



**HAL**  
open science

# Semantic organisation and generalisation mechanisms of abstract concepts

Dounia Lakhzoum

► **To cite this version:**

Dounia Lakhzoum. Semantic organisation and generalisation mechanisms of abstract concepts. Psychology. Université Clermont Auvergne; Laboratoire de Psychologie Sociale et Cognitive (LAPSCO), 2021. English. NNT: 2021UCFAL018 . tel-03879839

**HAL Id: tel-03879839**

**<https://hal.science/tel-03879839>**

Submitted on 30 Nov 2022

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License



Université Clermont Auvergne, U.F.R. Psychologie, Sciences Sociales et Sciences de l'Éducation

Laboratoire de Psychologie Sociale et Cognitive (LAPSCO) – CNRS, UMR 6024

École Doctorale Lettres, Sciences Humaines et Sociales

## THÈSE DE DOCTORAT

### **Semantic organisation and generalisation mechanisms of abstract concepts**

Présentée par LAKHZOUM Dounia,

En vue de l'obtention du titre de Docteur en Psychologie.

#### *Sous la direction de :*

**Marie IZAUTE** Professeure des Universités, Université Clermont Auvergne, Clermont-Ferrand

**Ludovic FERRAND** Directeur de Recherche CNRS, Université Clermont Auvergne, Clermont-Ferrand

#### *Membres du jury :*

<b>Simona BRAMBATI</b>	Professeure de Psychologie, Université de Montréal	Rapporteuse
<b>Marc BRYSSBAERT</b>	Professeur de Sciences Cognitives, Ghent University	Rapporteur
<b>Diane PECHER</b>	Professeure de Psychologie, Erasmus University, Rotterdam	Examinatrice
<b>René ZEELLENBERG</b>	Professeur Associé de Psychologie, Erasmus University, Rotterdam	Examineur

## Abstract

The study of semantic representation of abstract concepts entails answering some fundamental questions such as: (1) How is the meaning of the word represented? (2) How does it relate to other words whether similar or associated? (3) How does meaning relate to conceptual structure? (4) How is the meaning abstracted and generalised to all instances of the concept?

In order to answer such question, researchers need to have access to normed stimuli. The literature on abstract concepts still lacks from the availability of such stimuli. The first experimental chapter (Chapter 2) introduces a database of semantically similar pairs of French words with varying levels of abstractness. This database is to the best of our knowledge and at the time of writing this manuscript, the first to introduce semantically similar pairs of abstract words in the French language. Chapter 3 introduces another database for word associations between concepts using the same words as in the previous database. Correlation analyses revealed that cue words presented to the participants elicited response words of a similar level of concreteness meaning that concepts are organised in the mental lexicon according to a gradient of concreteness. Analyses from associative strength have shown that concrete concepts elicit stronger associations compared to abstract concepts. The large amount of data generated by the word association task allowed for the implementation of mathematical graph analyses. Consequently, Chapter 4 introduces the first semantic network built from French association data and the first to compare topological parameters for concrete and abstract concepts. Results have shown that the French mental lexicon is structured according to a small-world pattern characterised by a sparse density, a short average path length between nodes and a high clustering coefficient. Comparison analyses between the networks for concrete and abstract networks respectively have shown that concrete concepts are organised in denser communities compared to abstract concepts. In addition, the concrete word nodes are more influential in the network and can spread information better due to their position and patterns of connectivity.

In Chapter 5, we explored the richness of abstract concepts in a picture-word priming paradigm and compared the role of situational and intangible features in their processing. Results have shown that even when compared with situational picture primes, extraction mechanisms still occurred in the case of abstract pictures. We interpreted these results as further evidence of the richness of abstract concepts which can be composed from features other than lexical or situational, namely also abstract and intangible. These intangible features could be construed as evidence of abstracted representations from varied exemplars of concepts becoming generalised statistical traces in long-term memory. In Chapter 6, we investigated the effect of similarity and contextual diversity on the ability to generalise the meaning of abstract concepts to all instances. Results have shown that exposure to contextually diverse exemplars enhanced performance in the testing phase compared to similarity-based exposure.

We conclude this thesis by proposing a theoretical model based on our findings with the purpose of bridging the gap between levels of investigation of abstract concepts processing. Taken together, our findings describe a reversed pattern of processing with lower levels ruled by similarity-based processes while higher levels of processing are ruled by diversity-based mechanisms.

**Key-words:** abstract concepts processing, semantic similarity, verbal association, semantic network analysis, picture-word priming, abstraction, generalisation mechanisms.

## Résumé – Long summary in French

L'étude de la représentation des concepts a depuis longtemps été centrale au domaine de la psycholinguistique. Si cette étude a longtemps été centrée sur les mécanismes de représentation des concepts concrets tels que des entités vivantes et des objets non vivants mais tangibles (e.g., chat, table), l'étude des concepts abstraits (e.g., justice, liberté) n'a bénéficiée que depuis récemment d'un regain d'intérêt. Cette étude de la représentation des concepts en général demande de répondre à des questions de recherche fondamentale telles que (1) quelles sont les modes de représentation des concepts en mémoire ? (2) Comment les mécanismes de similarité et d'association verbale influent-ils sur la représentation des concepts dans le lexique mental ? (3) En quoi cette organisation du lexique mental est influencée par les caractéristiques structurelles du réseau qui leur sert de matrice ? (4) Comment le sens est-il généralisé à tous les exemples d'application d'un concept ?

L'étude de phénomènes psycholinguistiques repose sur l'emploi de stimuli normés afin de garantir le contrôle de potentielles variables confondues telles que la fréquence ou la longueur des mots. En effet, il existe en psycholinguistique, un intérêt important pour les normes de similarité en raison de leur utilisation dans des paradigmes d'amorçage sémantique qui permettent l'étude de l'organisation des concepts dans le lexique mental. Par exemple pour la langue anglaise, McRae et al. (2005) ont développé une base de données de traits sémantiques pour 541 concepts représentant des entités vivantes et objets concrets. Vinson et Vigliocco (2008) ont proposé une base de données similaire pour des objets concrets et verbes d'action. Baroni (2011) a collecté les propriétés sémantiques de concepts relationnels en Allemand et en Italien. En Espagnol, Moldovan et al. (2015) ont proposé 185 triplets de noms avec variation de distance sémantique entre les membres d'un même triplet. L'une des principales observations que nous avons pu faire concerne le manque de disponibilité de stimuli normés pour l'étude rigoureuse des concepts abstraits dans la langue française. Au moment de l'écriture de ce manuscrit, nous proposons la première base de données de paires de mots abstraits sémantiquement liés en Français. Dans l'objectif de répondre à ce manque dans la littérature, nous avons commencé par proposer une base de données de 630 paires de concepts sémantiquement liées qui varient selon un gradient de concrétude de très abstraits à très concrets dans 2 études indépendantes (voir Chapitre 1 partie expérimentale).

Nous avons fait le choix de joindre cette variable de concrétude afin de répondre aux observations de Crutch et Warrington (2011) qui suggèrent que le lexique mental est organisé selon un gradient de concrétude avec une organisation en fonction de la similarité sémantique pour les concepts concrets tandis que les concepts abstraits seraient organisés selon l'association verbale. La similarité sémantique signifie que les concepts d'une même paire possèdent une signification proche (e.g., table-chaise) tandis que des concepts sont associés verbalement lorsqu'ils sont fréquemment rencontrés ensemble dans le langage (e.g., miel-abeille). Les mesures de similarité sémantique ont été collectées auprès de 900 participants

dans une tâche de jugement pour laquelle les participants devaient répondre sur une échelle en 7 points. Nos données ont par la suite été croisées avec des bases de données de psycholinguistique française permettant aux utilisateurs de contrôler les potentielles variables confondues. Pour cela, nos données ont été croisées avec Lexique (New et al., 2004), the French Lexicon Project (Ferrand et al., 2010), Wordlex (Gimenes & New, 2016), and MEGALEX (Ferrand et al., 2018). Notre variable de concrétude peut être utilisée sous deux formats : continu ou catégoriel. La variable de concrétude continue représente les moyennes des jugements des participants donnés sur l'échelle en 7 points. Pour obtenir une variable catégorielle de la concrétude, nous avons implémenté un algorithme k-means (Wang & Song, 2011) qui a mis en évidence une organisation des paires sémantiques selon 3 clusters de concrétude. Les paires sémantiques peuvent ainsi être filtrées par l'utilisateur en fonction de 3 niveaux de concrétude de très abstraites à très concrètes.

Dans une étude d'amorçage sémantique avec décision lexicale, on présente au participant un mot d'amorce suivi d'un mot cible (Meyer & Schvaneveldt, 1971 ; McNamara, 1992 ; Plaut, 1995). La tâche des participants consiste à déterminer si la cible est un mot. L'effet d'amorçage sémantique est un phénomène très robuste qui a pu être répliqué des centaines de fois et qui correspond à une facilitation de traitement caractérisée par des temps de réponse plus courts et un pourcentage d'erreurs plus faible lorsque l'amorce et la cible sont reliées. Ce lien peut être sémantique (poney-cheval) ou d'association verbale (selle-cheval ; Hutchison et al., 2008, 2013). De précédentes études ont mis en évidence l'importance de strictement différencier entre ces deux types de lien et ont montré qu'il est possible d'obtenir un amorçage purement sémantique non-associé ou purement associé non sémantique (McRae & Boisvert, 1998 ; Perea & Rosa, 2002 ; Thompson-Schill, Kurtz, & Gabrieli, 1998 ; Lucas, 2000 ; Hutchison, 2003 ; Ferrand & New, 2003). L'application de cette stricte distinction a été empiriquement vérifiée par Ferrand et New (2003) qui ont obtenu un effet d'amorçage sémantique pur en utilisant des paires sémantiquement liées sans association verbale (e.g., <baleine> et <dauphin> sont sémantiquement liés mais non associés verbalement).

Afin de répondre à cette nécessité de distinguer entre ces deux formes de lien entre les concepts, nous avons proposé une seconde base de données d'association verbale qui repose sur les mêmes mots utilisés pour former la précédente base de données de paires sémantiques. De la même façon, cette base de données d'association verbale regroupe les réponses des participants pour 1100 mots cibles isolés variant selon un degré de concrétude de très abstrait à très concret. Les réponses des participants ont été collectées dans une tâche d'association verbale dans laquelle on présente un mot cible au participant qui doit répondre avec le premier mot qui lui vient à l'esprit. Cette tâche a l'avantage d'être très économique dans son implémentation et de pouvoir générer un très grand nombre de données. Nous avons ainsi pu obtenir plus de 92 000 mots réponses sur la base de 1100 mots cibles et 1200 participants recrutés en ligne. Ces données permettent dans un premier temps d'obtenir un pourcentage d'association entre le mot cible et les réponses données par les participants. Plus une réponse a été donnée fréquemment et plus elle est fortement associée au mot cible. Dans un premier temps, cette variable d'association verbale permet un croisement avec la précédente base de données de similarité sémantique pour assurer la création de matériel purement sémantique, purement associé ou au contraire avec un recouvrement entre ces deux types de lien pour les chercheurs qui souhaiteraient étudier l'effet d'un tel recouvrement.

Deuxièmement, cette base de données d'association verbale permet par l'introduction de la concrétude, d'étudier l'organisation du lexique mental pour les concepts abstraits comparativement aux concepts concrets. Ainsi, à partir de ces données, nous avons pu établir que les mots cibles abstraits génèrent des réponses plus faiblement associées comparativement aux concepts concrets. Cela confirme la théorie de Paivio (1971) selon laquelle les concepts abstraits sont plus faiblement associés à un grand nombre de contextes tandis que les concepts concrets sont plus fortement associés à un nombre restreint de contextes.

De plus, les résultats ont révélé une forte corrélation du niveau de concrétude entre mots cibles et réponses générées par les participants. Ainsi, les mots cibles abstraits présentés aux participants génèrent des réponses abstraites. De la même façon, les mots cibles concrets génèrent des réponses concrètes. Ces résultats suggèrent une organisation du lexique mental selon un gradient de concrétude avec une proximité des concepts abstraits d'une part et des concepts concrets d'autre part.

Enfin, la quantité de données générées nous a permis d'employer des méthodes empruntées à la théorie des graphes en mathématiques afin de construire le premier réseau sémantique d'associations verbales françaises et le premier réseau comparant l'organisation structurale des concepts abstraits et concrets toutes langues confondues. Cet emprunt de techniques à la théorie des graphes en mathématiques a donné lieu à un nouveau champ disciplinaire appelé science des réseaux cognitifs (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013 ; voir Siew, Wulff, Beckage, & Kenett, 2019 pour une revue de la littérature). Cette discipline appliquée à l'étude du langage, permet de modéliser l'organisation structurale du lexique mental sur une plus grande échelle comparativement à ce qu'il est possible de faire à partir de données comportementales obtenues sur la base de plans factoriels. Un réseau sémantique correspond à un graphe composé de nœuds liés entre eux par des liens qui indiquent la direction et la force de la connexion entre deux nœuds. Dans un réseau sémantique du lexique mental, les nœuds représentent des concepts (mots cibles et réponses des participants dans une tâche d'association verbale) et les liens indiquent une correspondance entre un mot cible et ses réponses. Ces liens sont également caractérisés par des poids qui représentent la fréquence d'association entre un mot cible et chacune de ses réponses. Plus une réponse est générée fréquemment par un grand nombre de participants et plus le poids du lien qui relie le mot cible à la réponse est élevé. L'analyse des réseaux sémantiques repose sur des paramètres d'intérêts tels que :

- Le diamètre du réseau qui correspond au chemin le plus long (en nombre de nœuds) qui relie deux nœuds du réseau ;
- Le chemin le plus court qui correspond au plus petit nombre de nœuds à parcourir pour passer d'un nœud à l'autre ;
- Le coefficient de clustering qui correspond à la probabilité que deux nœuds reliés entre eux possèdent également un nœud voisin en commun ;
- La densité du réseau qui correspond au nombre total de liens au sein du réseau

De précédentes études ont démontré par l'application de la science des réseaux aux données d'associations verbales que le lexique mental est caractérisé par une structure en « petit monde » ou « small-world » (Motter et al. 2002 ; Sigman & Cecchi 2002 ; de Jesus et al. 2004 ; Steyvers & Tenenbaum 2005 ; Bales & Johnson 2006 ; Borge-Holthoefer & Arenas 2010 ; Choudhury & Mukherjee 2009 ; Fukš & Krzemiński 2009 ; Veremyev, Semenov,

Pasillio & Boginski, 2019). Ce type de structure est caractérisé par une faible densité, un chemin plus court composé de peu de nœuds et un fort coefficient de clustering. Cela signifie que le lexique mental est structuré en clusters de nœuds fortement condensés qui permettent une distribution efficace de l'information (Borge-Holthoefer, Moreno, & Arenas, 2012 ; De Deyne et al. 2016). Notre étude a ainsi permis de construire le premier réseau sémantique du lexique mental français et de mettre en évidence sa structure en petit monde. Nous avons par la suite divisé ce réseau selon un gradient de concrétude avec un sous-réseau composé des concepts abstraits et un autre sous-réseau composé des concepts concrets. La comparaison des paramètres des deux réseaux suggère que le réseau des concepts abstraits est moins dense et plus diffus comparativement au réseau des concepts concrets. Une analyse supplémentaire des scores de diffusion de l'activation dans un réseau (voir Collins & Loftus, 1975) a démontré que les concepts abstraits ont un score de diffusion plus faible que les concepts concrets. Ces éléments permettent de mettre en évidence à un niveau structural des éléments de preuve selon lesquels les concepts abstraits sont organisés dans un pattern plus diffus comparativement aux concepts concrets. Ces éléments sont en accord avec de précédentes observations quand au déficit de traitement des concepts abstraits comparativement aux concepts concrets avec des concepts abstraits caractérisés par une lenteur de traitement et une apparente pauvreté de contenu dans les tâches de production de traits sémantiques (voir Recchia & Jones, 2012). Ceci coïncide également avec la proposition de Paivio (1971) selon laquelle les concepts abstraits sont faiblement connectés à une multitude de contextes tandis que les concepts concrets sont plus fortement connectés à un petit nombre de contextes.

Cette disparité structurelle dans l'organisation du lexique mental pour les concepts abstraits pose la question de la nature des traits sémantiques qui les composent et de leur mode de représentation (Barsalou, 2003 ; Borghi et al., 2017 ; Pecher, 2018 ; Lakhzoum et al., 2021). En effet, cette structure organisée dans un pattern plus diffus confirme la suggestion selon laquelle il n'existe pas de correspondance parfaite entre un concept abstrait et son référent. Les concepts abstraits font généralement référence à une multitude de situations complexes. Cette particularité des concepts abstraits a longtemps représenté un challenge pour l'étude de leur représentation d'un point de vue cognitif et cérébral dans la mesure où ils ne correspondent pas à des entités tangibles. Certaines études ont démontré que les concepts abstraits sont représentés dans des modalités situationnelles, émotionnelles, sociales, introspectives ou encore métacognitives (voir Borghi et al., 2017 pour une revue). De façon plus générale, ces études ont mis en évidence l'importance du contexte dans la représentation des concepts abstraits. D'autres part, plusieurs études ont exploré la représentation des concepts abstraits dans des tâches de production de listes de traits sémantiques (Barsalou & Wiemer-Hastings, 2005 ; Borghi et al., 2018 ; Kousta et al., 2011 ; Ferretti et al., 2001). Ces études suggèrent que les concepts abstraits peuvent eux-mêmes se décomposer en traits sémantiques abstraits. Pris ensemble, ces résultats semblent suggérer des implications contradictoires quand au mode de représentation des concepts abstraits avec certaines études suggérant un mode de représentation ancré dans des informations situationnelles tandis que d'autres suggèrent que les concepts abstraits se décomposent en traits sémantiques eux-mêmes abstraits.

Dans une étude récente McRae, Nedjadrassul, Pau, Pui-Hei et King (2018) ont utilisé un paradigme d'amorçage sémantique dans lequel des mots abstraits étaient amorcés par des

images illustrant chaque concept. Par exemple, le concept abstrait <discipline> était amorcé par une image montrant des enfants en rang. Le protocole expérimental consistait à présenter une image d'amorce puis un concept lexical abstrait dont le sens était soit lié sémantiquement à l'image soit non relié. Les résultats ont montré une facilitation de traitement avec des temps de réponse plus courts et un taux d'erreurs inférieur lorsque l'image d'amorce et le mot cible étaient reliés comparativement à lorsque ceux-ci n'étaient pas reliés. Ces résultats semblent confirmer une représentation des concepts abstraits selon un ancrage situationnel dans la mesure où la présentation de situations imagées en amorce facilite le traitement du concept abstrait lexical.

Dans une autre étude, Kuipers, Jones et Thierry (2018) ont utilisé un paradigme d'amorçage similaire dans lequel des concepts lexicaux abstraits étaient amorcés par des images abstraites. Ces auteurs ont cherché à explorer l'effet d'images abstraites dénuées de traits tangibles sur le traitement de concepts lexicaux abstraits. De la même façon, le protocole expérimental consistait à présenter une image d'amorce abstraite puis un concept lexical abstrait dont le sens était soit lié sémantiquement à l'image soit non relié. Les résultats ont montré pour les données comportementales un effet de facilitation avec des temps de réponse plus courts et un taux d'erreurs plus faible lorsque l'image d'amorce abstraite et le mot cible étaient reliés comparativement à lorsque ceux-ci n'étaient pas reliés. Les données d'EEG ont démontré une plus faible amplitude de la N400 pour les paires reliées comparativement aux paires non-reliées. Selon les auteurs, ces résultats suggèrent qu'il est possible d'activer des concepts abstraits en mémoire sur la base d'images abstraites dénuées de traits tangibles. Cela suggère donc que les concepts abstraits peuvent bénéficier d'un traitement sémantique même en l'absence d'information situationnelle.

Afin d'approfondir ces résultats qui semblent se contredire quand au rôle des informations situationnelles ou intangibles dans le traitement sémantique des concepts abstraits, nous avons réalisé une étude dans laquelle nous avons directement comparé ces deux conditions. Nous avons dans un premier temps répliqué l'étude de Kuipers et al. (2018) en Français afin de vérifier la faisabilité du protocole expérimental dans un contexte plurilinguistique. Comme Kuipers et al., (2018) nous avons formulé l'hypothèse selon laquelle nous devrions observer un effet de facilitation pour les paires images-mots reliées comparativement aux paires non-reliées. Les résultats ont confirmé ceux de Kuipers et al. (2018) et ont montré le même effet de facilitation pour les concepts abstraits amorcés par des images abstraites sémantiquement reliées comparativement aux paires non-reliées.

Dans un paradigme d'amorçage, nous avons présenté dans une première condition une série de paires de concepts lexicaux amorcés par des images abstraites dénuées de traits tangibles et dans une seconde condition, ces mêmes concepts lexicaux amorcés par des images riches en informations situationnelles. Nous avons formulé l'hypothèse selon laquelle l'effet de facilitation obtenu à partir des images situationnelles devrait être maintenu tandis que l'effet des images intangibles devrait disparaître. Nous avons donc fait l'hypothèse d'une stratégie de traitement préférentiel en faveur de traits situationnels comparativement à des traits intangibles. Les résultats ont montré un effet de facilitation pour chaque condition avec des temps de réponses plus courts et des taux d'erreurs plus faibles pour les paires images-mots reliées comparativement aux paires non-reliées, ceci pour les images situationnelles ainsi que pour les images abstraites. Cet effet de facilitation était plus fort pour les images

situationnelles comparativement aux images abstraites. Ces résultats ont permis d'approfondir les connaissances quand au rôle du type d'information permettant l'activation et le traitement des concepts abstraits. Ils suggèrent que même en présence d'informations situationnelles qui devraient stratégiquement faciliter le traitement des concepts dans la mesure où ils procurent un contexte d'ancrage, les participants ont continué d'extraire des traits sémantiques intangibles à partir des images abstraites. Une première interprétation de ces résultats au regard de l'étude de Kuipers et al. (2018) suggère que les concepts abstraits peuvent être décomposés en une série de traits qui peuvent être contextuels mais également abstraits. Cette première conclusion met ainsi l'accent sur la richesse des concepts abstraits et la variabilité de leurs modes de représentation qui va à l'encontre de précédentes suggestions concernant une pauvreté du contenu des concepts abstraits (voir Recchia & Jones, 2012).

Ces résultats peuvent également être interprétés en complément de ceux de Bolognesi et Vernillo (2019) qui proposent un traitement des concepts abstraits selon un mécanisme d'« abstraction par métonymie ». Celui-ci repose sur un processus d'abstraction des concepts partant de représentations tangibles vers des représentations plus abstraites. Nos résultats semblent suggérer un mécanisme opposé et complémentaire à celui-ci dans lequel les participants auraient extrait des traits sémantiques intangibles à partir desquels des représentations plus tangibles ont été inférées permettant l'activation des concepts lexicaux sémantiquement reliés.

Le traitement des concepts abstraits sur la base de ces traits intangibles pourrait également être interprété comme le résultat d'un processus de généralisation des concepts à partir d'une multitude d'exemples d'application dans des situations variées. En effet, les modèles de catégorisation cognitive décrivent la capacité des individus à faire abstraction des disparités situationnelles au travers de multiples exemples d'application situationnelle d'un concept afin d'en inférer un sens général. Cette capacité permet notamment de transférer le sens d'un concept à de nouvelles situations afin d'extraire les similitudes fondamentales dans la définition générale du concept. C'est grâce à cette aptitude que les individus sont capables de comprendre le sens d'un concept sans avoir besoin de faire l'expérience de toutes ses applications.

Dans le Chapitre 5, nous avons exploré ces capacités de généralisation du sens d'un concept à partir de la présentation d'une série d'exemples de situations d'application. La théorie de la catégorisation par l'exemplaire stipule que le sens des concepts est généralisé sur la base de la similarité entre un nouvel exemplaire et les exemplaires d'application stockés en mémoire. Par exemple, Gentner, Loewenstein et Hung (2007) ont montré que des enfants présentaient des facilitations de transfert de noms d'objets lorsqu'il existait une correspondance structurelle entre les exemplaires connus et le nouvel exemplaire d'objet à catégoriser. D'autres études ont toutefois remis en question cet effet de la similarité et suggèrent qu'elle pourrait porter atteinte à la capacité de transfert des caractéristiques communes d'une situation à une autre de par l'apprentissage de traits de surfaces idiosyncratiques (voir par exemple Braithwaite & Goldstone, 2015). Ces études préconisent l'effet de la diversité contextuelle lors de l'apprentissage d'un concept qui permettrait de faire abstraction de tels traits superficiels en faveur d'un traitement approfondi des bases communes aux exemplaires stockés en mémoire et le nouvel exemplaire à catégoriser. Par exemple, Braithwaite et Goldstone (2015) ont demandé aux participants d'apprendre une série de concepts

mathématiques abstraits dont les exemples étaient soit très similaires entre eux, soit présentaient des variations des traits de surface. Leurs résultats ont montré que les participants étaient mieux à même de généraliser leur apprentissage à de nouveaux exemplaires dans des conditions d'apprentissage sur la base d'une diversité contextuelle entre les exemplaires. Pagan et Nation (2019) ont utilisé un protocole similaire pour l'apprentissage de définitions de mots et ont également montré un effet de facilitation des capacités de transfert du sens à de nouveaux exemplaires d'un concept lorsque les exemples appris présentaient des variations contextuelles. Pris ensemble, ces études semblent générer des résultats contradictoires en termes d'impact des conditions de similarité ou de diversité contextuelle. C'est pourquoi, nous avons comparé ces deux contextes d'apprentissage dans une étude des capacités de généralisation du sens des concepts abstraits. Dans une première étude, nous avons construit une base de données de nouveaux concepts abstraits dont nous avons illustré le sens à travers une série d'exemples qui étaient soit très similaires entre eux soit qui présentaient des variations contextuelles. Dans une seconde étude, nous avons testé l'effet de la similarité et de la diversité contextuelle sur les capacités de généralisation du sens de concepts abstraits. Dans une première phase d'apprentissage, les participants étaient exposés à une série d'exemples soit similaires entre eux soit dissimilaires permettant d'illustrer un concept abstrait. Durant la phase de test, on présentait aux participants un nouvel exemple du concept appris. La tâche du participant consistait à déterminer dans quelle mesure le nouvel exemple était représentatif du sens du concept appris. Les résultats ont montré que les participants étaient d'avantage capables de généraliser le sens du concept à un nouvel exemple lorsque celui-ci était appris à partir d'exemples variés. Cette étude a donc permis de démontrer l'effet de facilitation de la diversité contextuelle comparativement à la similarité dans les mécanismes de généralisation du sens des concepts abstraits.

Pris ensemble, ces 5 chapitres expérimentaux permettent de répondre à une longue controverse en sciences cognitives concernant les effets de similarité et de diversité contextuelle. En conclusion de cette thèse, nous proposons un modèle théorique qui met en évidence un pattern renversé entre le traitement sémantique au niveau du mot comparativement à un niveau plus pragmatique centré sur le traitement sémantique d'exemplaires contextuels. Ce pattern révèle que les bas niveaux de traitement centrés sur le mot sont organisés selon un mécanisme de similarité tandis que les niveaux plus pragmatiques reposent sur un mécanisme centré sur la diversité contextuelle. Ce modèle suggère que ces modes de représentation selon la similarité ou la diversité contextuelle ne sont pas opposés mais correspondent aux extrêmes d'un processus hiérarchique de traitement sémantique.

Mots-clés : Concepts Abstraites, sémantique, amorçage, concrétude, généralisation

## Acknowledgment

I would like to thank Prof. Simona Brambati, Prof. Marc Brysbaert, Prof. Diane Pecher and Dr. René Zeelenberg for accepting to be members of the jury. I am honoured to have the privilege of their expertise and am very pleased to have such a diverse jury from around the world.

This research made in the FACTOLAB framework has been sponsored by Michelin Tyres Manufacturer, by the French government research programs "Investissements d'Avenir" through the IDEX-ISITE initiative 16-IDEX-0001 (CAP 20-25) and the IMobS3 Laboratory of Excellence (ANR-10-LABX-16-01).

## Publications

**Chapter 2 was published as** Lakhzoum, D., Izaute, M., & Ferrand, L. (2021). Semantic similarity and associated abstractness norms for 630 French word pairs. *Behavior Research Methods*, 53, 1166-1178. <https://doi.org/10.3758/s13428-020-01488-z>

Supplementary material: <https://osf.io/qsd4v/>

**Chapter 3 was submitted as:** Lakhzoum, D., Izaute, M., & Ferrand, L. (submitted). Word associations norms for 1,100 French words with varying levels of concreteness. *Journal of Psycholinguistic Research*.

Supplementary material: <https://osf.io/dhuqs/>

**Chapter 4 was submitted as the preprint** Lakhzoum, D., Izaute, M., & Ferrand, L. (2021). Semantic network analysis of abstract and concrete word associations.

<https://doi.org/10.31234/osf.io/epk47>

Supplementary material: <https://osf.io/4w69k/>

**Chapter 5 was published as** Lakhzoum, D., Izaute, M., & Ferrand, L. (2021). Intangible features extraction in the processing of abstract concepts: Evidence from picture-word priming. *Plos One*, 16, e0251448. <https://doi.org/10.1371/journal.pone.0251448>

Supplementary material: <https://osf.io/483tu/>

**Chapter 6 is in preparation for submission as** Lakhzoum et al. (in preparation). Generalisation mechanisms in the processing of abstract concepts.

Supplementary material: <https://osf.io/svm2p/>

## Table of content

Abstract.....	2
Résumé – Long summary in French .....	4
Acknowledgment.....	11
Publications.....	12
Foreword.....	21
Chapter 1. Theoretical Introduction .....	23
1. Models of semantic representation .....	23
Definition of semantic memory .....	23
Hierarchical and Network models .....	24
Feature models.....	26
2. Similarity, verbal association and semantic priming .....	29
3. Concepts concreteness .....	31
4. Distributional and grounded accounts of semantic representation .....	33
Distributed accounts of semantic representation .....	34
Grounded accounts of semantic representation.....	36
5. Abstraction and generalisation mechanisms in the processing of abstract concepts ..	40
Models of the prototype view of concept learning .....	41
Influential models of the exemplar theory .....	42
Challenges to the exemplar view .....	44
How does this relate to mechanisms of abstraction and generalisation in the processing of abstract concepts? .....	47
6. Network cognitive science .....	49
Historical account and classical models of network science .....	49
Network parameters and analysis .....	53
Cognitive network science approach to the mental lexicon.....	55
SYNTHESIS and INTRODUCTION TO EXPERIMENTAL CHAPTERS.....	59
Experimental Section .....	62
Chapter 2. Semantic similarity and associated abstractness norms for 630 French word pairs .....	64
ABSTRACT .....	65
INTRODUCTION .....	66
Accounts of semantic representation .....	66
Abstract concepts representation.....	70

Semantic priming and semantic similarity for concrete and abstract concepts.....	71
The present study: Semantic similarity norms for abstract words .....	76
METHOD.....	77
Participants.....	77
Stimuli.....	77
Procedure.....	79
RESULTS.....	80
DISCUSSION.....	86
CONCLUSION .....	89
REFERENCES .....	89
Chapter 3. Word associations norms for 1,100 French words with varying levels of concreteness .....	99
ABSTRACT .....	100
INTRODUCTION .....	101
Semantic and associative priming .....	101
Concreteness and organisation of the mental lexicon .....	102
Accounts of semantic representation.....	103
Word associations and normative datasets.....	104
The present study .....	106
METHOD.....	107
Participants.....	107
Stimuli.....	107
Procedure.....	107
RESULTS.....	108
DISCUSSION.....	114
REFERENCES .....	117
Chapter 4. Semantic network analysis of abstract and concrete word associations.....	128
ABSTRACT .....	129
INTRODUCTION .....	130
Network science and characteristics .....	130
Small-world structures and semantic networks.....	132
The present work .....	134
METHOD.....	135

Material and procedures.....	135
RESULTS.....	135
DISCUSSION.....	141
REFERENCES .....	144
Chapter 5. Intangible features extraction in the processing of abstract concepts:	
Evidence from picture-word priming.....	149
ABSTRACT .....	150
INTRODUCTION .....	151
Dimensions of abstract concepts .....	151
Theoretical accounts in the study of abstract concepts.....	152
Picture priming paradigms in the study of abstract concepts.....	154
The present study.....	154
Experiment 1 .....	155
MATERIALS and METHODS .....	155
Participants.....	155
Materials .....	156
Procedure .....	156
RESULTS.....	157
Reaction times .....	157
Errors.....	159
DISCUSSION.....	159
Experiment 2 .....	160
MATERIALS and METHODS .....	160
Participants.....	160
Materials .....	160
Procedure .....	160
RESULTS.....	162
Reaction times .....	162
Errors.....	164
DISCUSSION.....	164
GENERAL DISCUSSION .....	166
REFERENCES .....	168

Appendices: supplementary analyses .....	172
Chapter 6. Generalisation mechanisms in the processing of abstract concepts .....	175
INTRODUCTION .....	175
The prototype and exemplar accounts .....	176
The role of similarity and contextual diversity on abstraction and generalisation .....	178
Application to the generalisation of abstract concepts .....	180
The present work .....	181
EXPERIMENT 1a: selection of the NewAbstractConcepts database .....	183
METHOD.....	183
Participants .....	183
Materials and Procedure.....	183
RESULTS and DISCUSSION.....	184
EXPERIMENTS 1b and 1c: generating the NewAbstractConcepts database .....	185
METHOD.....	186
Participants .....	186
Materials and Procedure.....	186
RESULTS and DISCUSSION.....	187
METHOD.....	188
Participants .....	188
Materials and Procedure.....	189
RESULTS and DISCUSSION.....	189
EXPERIMENT 2.....	192
METHOD.....	192
Participants .....	192
Materials and Design .....	192
Procedure.....	193
RESULTS and DISCUSSION.....	194
GENERAL DISCUSSION .....	198
Chapter 7. General discussion and perspectives.....	203
Summary of results.....	203
A theoretical model and some implications for abstract concept processing .....	207
Implications for neural evidence .....	212

Implications for natural language processing .....	217
Conclusions and future work .....	220
REFERENCES.....	222

## List of Figures

### Chapter 1

---

**Figure 1.** Illustration of (left) the models of Collins & Quillian (1969) and (right) Collins & Loftus (1975).

**Figure 2.** Semantic Features Model (adapted from Smith et al. (1974)).

**Figure 3.** Graphical representation of the semantic vector space for the concepts dog, cat, van and car from Lenci (2018).

**Figure 4.** The hub-and-spoke model of semantic processing. Modality-specific spokes represent motion (yellow), colours (dark blue), shapes (green), names (orange), actions (light blue) and tasks (purple) which converge towards the amodal “hub” (red) represented in the anterior temporal lobe (ATL; Adapted from Patterson et al., 2007).

**Figure 5.** Schematic illustration of a category structure to explain the workings of the GCM

**Figure 6.** The two-step procedure to construct a category representation: (1) partition the category into clusters and (2) construct the centroid for each cluster. In this way, it is possible to construct the prototype representation (panel a), the exemplar representation (panel B), and a set of intermediate representations, one of which is illustrated in panel C (reproduced from Vanpaemel & Storms, 2008).

**Figure 7.** Euler's schema from ‘Solutio problematis ad geometriam situs pertinentis’.

**Figure 8.** Illustration of the Small-World Problem from Milgram (1967).

**Figure 9.** Small-world structure from Watts & Strogatz (1998). The small-world model was obtained by interpolation of a regular ring lattice and a random network, without altering the number of nodes or edges in the graph.

**Figure 10.** Three graphs of 20 nodes each generated with the Barabasi-Albert model (1990). The increasing value  $m$  represents the parameter of attachment. A high value of  $m$  signifies that the more connected a node is, the more it is susceptible to receive more links.

**Figure 11.** Proposed large-scale structures for semantic networks from Tenenbaum and Steyvers (2005): (a), a tree-structured hierarchy (e.g., Collins & Quillian, 1969); (b), an

arbitrary, unstructured graph (e.g., Collins & Loftus, 1975); **(c)**, a scale-free, small-world graph (e.g. Tenebaum & Steyvers, 2005).

**Figure 12.** Graphical representation of the scope of the present thesis.

## Chapter 3

---

**Figure 1.** Frequency spectrum on a logarithmic scale representing the number of types ( $V_m$ ) as a function of frequency class ( $m$ ). The class corresponding to  $m = 1$  corresponds to the hapax legomena.

**Figure 2.** Vocabulary Growth Curve (VGC) representing the increase of cue-response pairs as new responses are collected by comparing the VGC of our dataset (grey curve) to an empirical VGC obtained from the fZM model (red line). The vertical lines indicate the total number of observed tokens for our sample.

## Chapter 4

---

**Figure 1.** Visual representation of the whole network. Each point represents a word. The colour gradient from grey to red represents the distance between connected nodes the greyer the farther and the redder the closer (built with the software Gephi; Bastian, Heymann & Jacomy, 2009).

**Figure 2.** Visualisation of a portion of the network with a representation of the nodes degree where the larger and the darker green a node is and the more connection it has. The node with the most number of connection on this portion is the French concept “amour” or love in English. One of the nodes with the smallest degree is the French concept “ennui” or boredom in English (built with the software Gephi; Bastian, Heymann & Jacomy, 2009).

## Chapter 5

---

**Figure 1.** Trial procedure for the concept royalty (“royauté” in French).

**Figure 2.** Mean correct latencies (in ms with standard error bars) for Type of Image Prime and Type of Target Word (R = related pairs; NR = non-related pairs; \*\*p = 0.01; \*\*\*p < 0.001) in both Experiments 1 and 2.

**Figure A.1.** Results of the Bayes factor replication test applied to our replication attempt based on Kuipers et al. (2018).

## Chapter 6

---

**Figure 1.** Percentage of response for each choice.

**Figure 2.** Mean ratings for the similar and dissimilar conditions in Experiment 1c (\*  $p < 0.001$ ).

**Figure 3.** 2-dimensional graphical representation of the psychological space for concept SONDER. Each point represents an exemplar with coordinates  $x_{sonder_s}$  as the exemplar's mean similarity rating in the similar dimension and  $x_{sonder_d}$  as the exemplar's mean similarity rating in the dissimilar dimension.

**Figure 4.** Mean similarity judgments (on a scale from 0 to 100) as a function of reading phase exposure (similar vs. dissimilar exemplars;  $p < 0.001$ )

**Figure 5.** Prior and Posterior distribution for the paired samples t-test comparing the similar and dissimilar conditions.

**Figure 6.** Graphical model implementation of the GCM

## Chapter 7

---

**Figure 1.** Schematic representation of our theoretical model. Level I represents abstract concepts and features at the word levels. Concepts and features are activated following a threshold of activation. Thicker traits represent more influential nodes which possess a higher activation potential compared to thinner traits. Level II represents exemplars in memory as instances of a concepts. Level III represents the generalised concepts based on the processing of contextually diverse exemplars which allow for the recognition of novel instances.

**Figure 2.** Representation of the hub-and-spoke model with spoke regions which code for modality-specific components of concepts while the ATL is a semantic hub which aggregates across modalities and form amodal conceptual representations (see text for more details). From Lambon et al. (2017).

**Figure 3.** Advances in NLP research cross 3 major era following the syntactics, semantics and pragmatics curves (From Cambria & White, 2014).

## List of Tables

### Chapter 2

---

**Table 1.** Semantic similarity for word pairs and associated concreteness for prime and target words.

**Table 2.** Descriptive and behavioural data for target words.

**Table 3.** Descriptive and behavioural data for prime words.

**Table 4.** Correlation matrix between concreteness levels and lexical variables with significance levels (\*\* $p < 0.001$ ; \* $p < 0.01$ ; \* $p < 0.05$ ).

**Table 5.** Correlations of the present concreteness variable measures with those provided by other databases.

### Chapter 3

---

**Table 1.** Descriptive and behavioural data for cue words.

**Table 2.** Mean frequency and reaction times for response words

**Table 3.** Response frequencies and latencies according to cue concreteness

### Chapter 4

---

**Table 1.** Description of network characteristics used throughout the paper.

**Table 2.** Network statistics for the directed and undirected associative networks for the whole, concrete and abstract datasets.

### Chapter 5

---

**Table A.2.** Results of the Bayesian Replication Test.

### Chapter 6

---

**Table 1.** Examples of scenarios and exemplars for the concept SONDER.

**Table 2.** All combinations for the concept SONDER

## Foreword

*“When I use a word,” Humpty Dumpty said, in rather a scornful tone, “it means just what I choose it to mean—neither more nor less.”*

*“The question is,” said Alice, “whether you can make words mean so many different things.”*

*Alice in Wonderland, Lewis Carroll (1865).*

It is often said that language is the cornerstone of human cognition. This uniquely human trait requires assimilating mental representations or concepts that can be manipulated to make sense of the world. This feat has understandably fascinated philosophers and scientists alike for centuries who have pondered the question of how the mind generates such flexible yet stable representations from encountering very few positive examples. The mind can in the space of milliseconds understand a complex utterance and in turn produce words that will automatically generate an idea, an emotion in the mind of a listener or a reader. This ability is nothing short of miraculous as evidenced by an infant’s capacity to learn such an elaborate skill with virtually no formal teaching or training. What transpires is that the mind is a wired organ destined to learn and manipulate language. Some researchers posit that we develop in early infancy a common-sense core of knowledge built on intuitive theories about physics (forces, masses, gravity...) and psychology (desires, beliefs, intents...; see for example Gerstenberg & Tenenbaum, 2017). This core matrix is common to other species such as non-human primates but benefits from an enrichment and sophistication through language that is specific to humans. Intuitive theories are the tenets of featural patterns organised into a conceptual system from which semantic concepts can arise. The stability and flexibility of the semantic conceptual system is demonstrated by the mind’s ability to understand a statement even when intuitive theories are violated. To illustrate this point let us turn to the writer and mathematician Lewis Carroll (1832-1898) and his mastery of the nonsense literature, which

operates on its own intrinsic realm governed by the assumption that nothing exists outside the text. In *Alice's Adventures in Wonderland* and *Through the Looking Glass and What Alice Found There*, Alice enters a world of logical fallacies that ignore the laws of physics (e.g., “Either the well was very deep, or she fell very slowly [...]”), common sense (e.g., “Now, here, you see, it takes all the running you can do, to keep in the same place. If you want to get somewhere else, you must run at least twice as fast as that!”), semantic truths (e.g., "I've had nothing yet," Alice replied in an offended tone "so I can't take more. “You mean you can't take less," said the Hatter: "it's very easy to take more than nothing”) and semantic fallacies (e.g., "That's the reason they're called lessons," the Gryphon remarked: "because they lessen from day to day”) which implies a new meaning for the word lesson given by a phonological neighbour. Almost instantaneously, the reader is able to let go of mental representations acquired at the cost of many experiences and create new nonsensical ones in order to enjoy the story. This ability illustrates the complexity of the mental lexicon as a dynamic organ with constant interactions between its levels of processing from core featural properties to the understanding of complex statements.

Attempts to understand such semantic abilities have become the focal point for behavioural, computational and neurological investigations since the early phases of the cognitive revolution. The present thesis is a study of such semantic phenomena centered on abstract concepts from the organisation of concepts at the word-level in the mental lexicon to the mechanisms underlying our ability to generalise the meaning of concepts to novel instances.

## Chapter 1. Theoretical Introduction

Psycholinguistics has a long tradition of studying the representation of semantic concepts. This tradition has mainly been focused on the representation of concrete objects but in recent years, the focus has shifted to include the representation of abstract concepts. What does it entail to know the meaning of the word *owl* or *justice*? Answering this question raises some fundamental issues: (1) How is the meaning of the word represented? (2) How does it relate to other words whether similar or associated? (3) How does meaning relate to conceptual structure? (4) How is the meaning abstracted and generalised to all instances of the concept? The first part of this chapter is a review of semantic models from early hierarchal, network and feature models that have been the centre of attention starting from the 1960-70s to the more contemporary debate between the distributional and embodied accounts of semantic representation and their application to the challenge posed by abstract concepts. Next, we introduce the literature on abstraction and generalisation mechanisms of semantic concepts. Finally, the last section introduces the field of cognitive network science and its application to the issue of conceptual structure of the mental lexicon.

### 1. Models of semantic representation

#### Definition of semantic memory

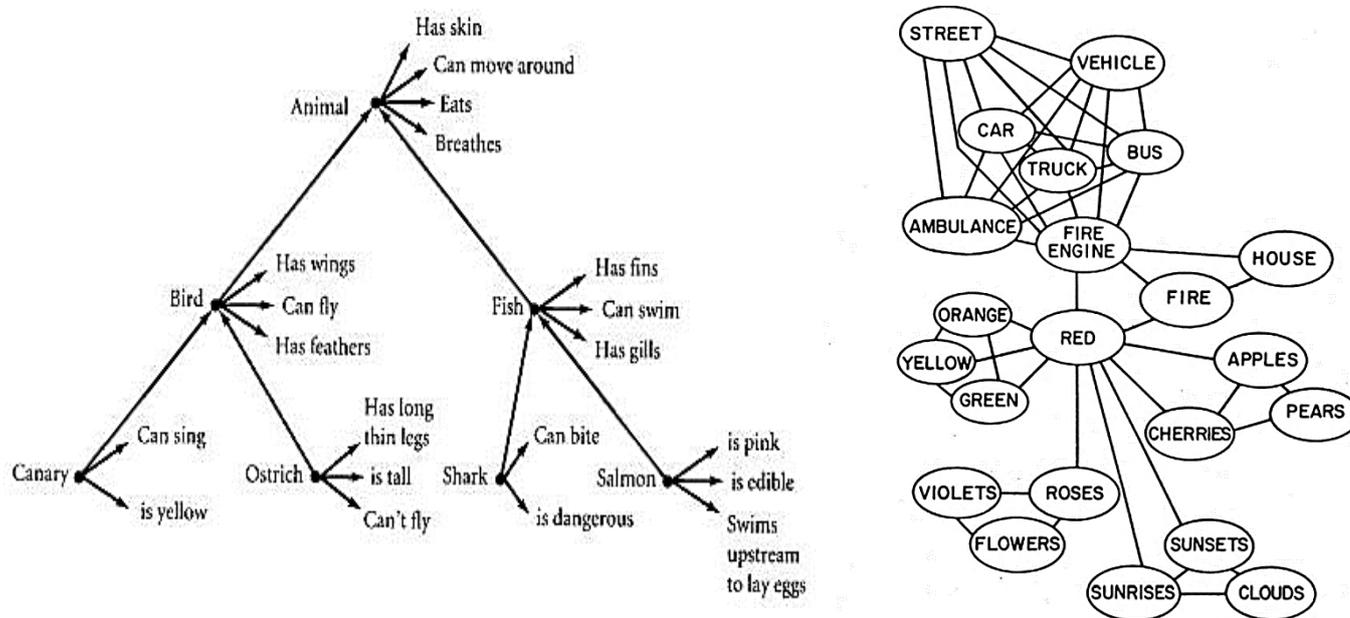
Concepts are the building blocks of higher-order cognition. They are the basis for our ability to form complex thoughts and generate abstract ideas. As such, philosophers and scientists have pondered the question of their representation in the mind and brain for millennia. During the last century, many influential models have been dedicated to the study of semantic concepts and the representation of meaning. In particular, Tulving (1972) built on Fodor's (1950) modular account of the cognitive system to propose a distinction between episodic and semantic memory that differ on the nature of the information they store.

Semantic memory is defined as a storage system for general knowledge of the world and their corresponding abstract symbols (e.g., what is a chair?). In contrast, episodic memory stores individual experiences tied to time, space and sensory impressions (e.g., a favourite reading chair). Early models of semantic memory can be divided in two categories: models that are centered on network representations of concepts and models that are centered on a featural (or decompositional) view of concepts (Collins & Loftus, 1975, see also Vigliocco & Vinson, 2005).

### **Hierarchical and Network models**

Semantic network theories draw on Fodor's (1980) holistic argument against the decomposition of concepts into a set of defining features and posit that the meaning of a concept is determined by its relationships with other concepts. Accordingly, this suggests that for every element of the world –be it an object, an event or property, etc. - there is a symbolic lexical equivalent that acts as a referent in the conceptual system of the mind (Fodor, Garrett, Walker & Parkes, 1980; Berg & Levelt, 1990; Roelofs, 1997; Levelt, Roelofs & Meyer, 1999). This was motivated by the work of Quillian (1962, 1967) who built a computer simulation of semantic search in a dictionary-like network where concepts were represented as nodes linked by hierarchical relations (Collins & Quillian, 1969 see Figure 1). Quillian's theory suggests that accessing a concept activates the whole network of related nodes, which gives the full meaning of the concept (Quillian, 1962, 1967). For instance, accessing the concept <machine> activates in turn the concepts <manufactured>, <composed of moving parts> and <a car> is an example of a machine. This computational view of semantic representation illustrates the complex structure of the conceptual system and the rich number of concepts that people must possess. However, Quillian was aware of the theoretical constraints put on the model due to its computational nature. Collins and Quillian (1969) tested the cognitive plausibility of this model in a series of True-False reaction-time experiments. Participants were presented with words and

properties and were asked to identify whether these properties belonged to the meaning of the word (for e.g. “A canary can fly”, “An ostrich is an animal”).



**Figure 1.** Illustration of (left) the models of Collins & Quillian (1969) and (right) Collins & Loftus (1975).

Results confirmed the hierarchical structure of semantic memory with an organisation comprising superordinate categories, which could account for a distance effect with longer latencies when more levels needed to be verified. The theory later influenced the development of several global theories of semantic network representation such as Schank’s conceptual dependency (Schank, 1972), the active structural networks of Norman and Rumelhart (1975) and Anderson and Bower’s associative network theory (Anderson & Bower 1983).

Collins and Loftus (1975) built upon this model and proposed a mechanism of semantic access by implementing their spreading of activation theory in a network. The theory posits that when a concept is processed, it activates the path between related nodes at a speed proportional to the strength of their similarity. This model corrected some of the hierarchical constraints of

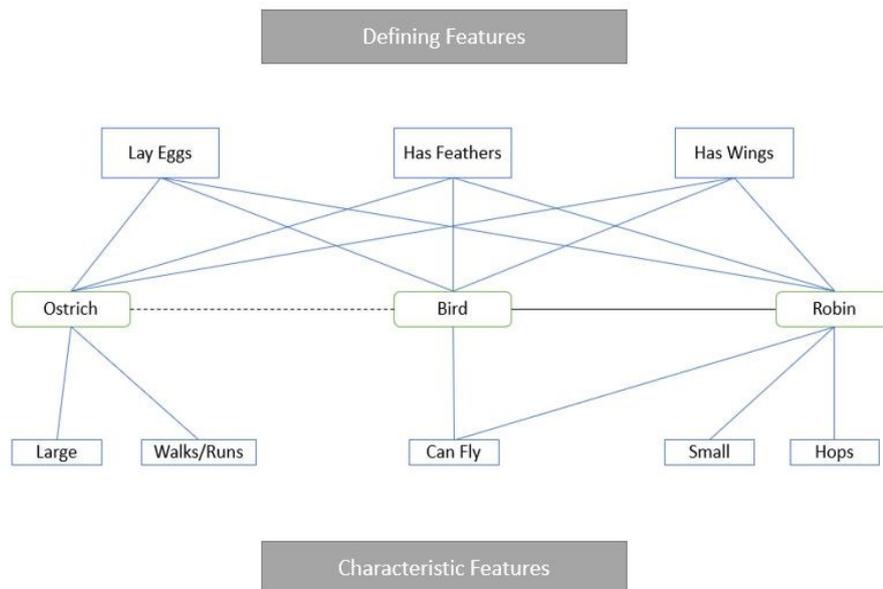
Collins and Quillian (1969) at the expense of less typical concepts (Carey, 1985; Rips, Shoben, & Smith, 1973; Sloman, 1998). The notion of semantic similarity is central to the model. The more properties two concepts have in common, the more links their nodes share and the closer their meaning. This assumption of semantic similarity in the spreading of activation theory accounts for both the strength of the link between nodes and the ensuing dynamics of activation for related concepts. For instance, accessing the concept *fire* would activate related nodes with decreasing levels of activation from the node *red* to the node *street* (see Figure 1). The theory was successful in explaining many empirical results such as free word association (Freedman & Loftus, 1971; Loftus, 1973a, 1973b), multiple category (Juola & Atkinson, 1971), sentence-verification (Conrad, 1972), categorization, semantic relatedness, typicality (Holyoak & Glass, 1975; Rips et al., 1973; Rosch, 1973; Smith et al., 1974), sentence processing (Traxler, Foss, Seely, Kaup, & Morris, 2000), errors in sentence production (Dell, 1986) and semantic priming effects (Balota & Lorch, 1986; de Wit & Kinoshita, 2015). The spreading of activation theory is still very influential today and has fuelled other disciplines that use networks to represent complex systems such as cognitive network science (see Siew, Wulff, Beckage & Kenett, 2019).

This one-to-one mapping between concepts and lexical referents that lay at the core of hierarchical and network models contrasts with the decompositional view of feature models.

### **Feature models**

The featural view posits that concepts can be decomposed into a set of properties or features that represent a diversity of semantic dimensions (e.g., Jackendoff, 1992; Vigliocco et al., 2004). The *Feature Comparison Model* developed by Smith, Shoben and Rips (1974) suggests two types of features: defining features referring to the core properties of a concept and characteristic features referring to informational but non-essential features (see Figure 2).

For instance, the concept *bird* would be decomposed into defining features such as <have wings> and <lay eggs> and characteristic features such as <can fly> because most but not all birds can fly.



**Figure 2.** Semantic Features Model (adapted from Smith et al. (1974)).

The notion of similarity is also important for feature models according to which the similarity between two concepts is given by the number of their overlapping features. The model assumes a two-stage process of comparison between two concepts. At stage 1, concepts are compared with respect to both feature types. If the first stage is not sufficient to produce a similarity judgment, a second stage reiterates the comparison based on defining features only. Despite the model's ability to account for categorisation data, the strict distinction between feature types represents an impractical constraint. For instance, based on a strict application of

the 2-stage process, a bird that would have had its wings removed would no longer be considered a bird (Collins & Loftus 1975).

This notion that meaning could be reduced to a definite set of defining features was heavily criticised for its impracticality (Fodor & Garrett, 1975; Fodor et al., 1980). Critics pointed that people seldom have knowledge of a concept's defining features, which calls into question the ecological validity of the model (Collins & Loftus, 1975). It can be argued that the model would also struggle to account for abstract concepts representation given that abstract concepts are more likely to be defined in relation with other concepts rather than as a set of features (Paivio, 1968; Crutch & Warrington, 2010).

Smith et al. (1974) argued that feature models could better explain empirical data compared to network models. Collins and Loftus (1975) expressed their opposition to this argument particularly due to Hollan's successful implementation of a feature model in a network (Hollan, 1975). This opposition between hierarchical network and feature representation models has yet to be resolved despite the accumulation of data mainly due to confounding variables such as familiarity and associations that have produced mixed results. More recently, Murphy, Hampton and Milovanovic (2012) have tested the validity of these models in a series of experiments based on novel materials to avoid such confounding variables. Their results provided evidence in favour of feature models and suggested that a hierarchical organisation of concepts is plausible but not the preferred option.

Despite early criticism, the featural assumption remains an elegant and effective model to account for semantic representation, which has benefited from a renewed interest for its ability to explain neuropsychological data (Allport, 1985). Warrington and McCarthy (1983) described the case of a patient who had difficulty identifying non-living things compared to living things while Warrington and Shallice (1984) described the case of a patient who

exhibited the opposite pattern. Consequently, it was possible to infer the existence of two dimensions of conceptual features that are the living vs. non-living dimensions (McRae et al., 2005).

The notion of similarity provides a consensus for both network and feature models. This explains the prevalence of semantic similarity in psycholinguistics as evidenced by its long tradition for developing semantic similarity norms and semantic priming paradigms.

## **2. Similarity, verbal association and semantic priming**

To gain insight into the nature of semantic processing, two main relationships between concepts have been extensively studied, namely semantic similarity and word association. Semantic similarity refers to the overlap between the defining features of concepts (for example <bee> and <wasp> are semantically similar) which is measured using a feature generation task or a similarity judgment of word pairs. Word association refers to the co-occurrence of words across language (for example <bee> and <honey>; McNamara, 1992; Plaut, 1995; Ferrand & Alario, 1998) which are obtained through a word association task.

In a feature generation task, participants are given a series of target words for which they are asked to list as many features of the word as possible. The more features two words have in common, the more similar they are (McRae, Cree, Seidenberg, & McNorgan, 2005; McRae, de Sa, & Seidenberg, 1997; Sánchez-Casas, Ferré, García-Albea & Guasch, 2006; Vigliocco, Vinson, Lewis & Garrett, 2004; Vinson & Vigliocco, 2008). However, the procedure can be very demanding due to the previously mentioned constraint regarding people's lack of systematic knowledge to decompose words into defining features as well as for its time-consuming nature (see McRae et al., 2005 for a discussion of these limitations). Researchers have more often resolved to generate semantically similar pairs of words that are

presented to participants and rated in a similarity judgment task (e.g., truck-car; Ferrand & New, 2003; Perea & Rosa, 2002; Ferrand & New, 2003; Sánchez-Casas et al., 2006).

In a word association task, participants are presented with a word (the cue) and asked to generate the first word that comes to mind (the response). In addition to providing normed stimuli to use in factorial designs, the task can unveil shared mental representations, language patterns and mechanisms of meaning extraction (Szalay & Deese, 1978; Prior & Bentin, 2008; Mollin, 2009, De Deyne et al., 2008, 2018). The amount of data generated also allow for the application of computationally rich models such as distributional statistics and network representation that provide insight into the structure of the mental lexicon (Steyvers & Tenenbaum, 2005; De Deyne et al., 2008, 2016, 2018). Both semantic similarity and word association have been used in semantic priming designs which are regarded as the gold standard for studying how semantic knowledge is organised (see Hutchinson, Balota, Cortese & Watson, 2008; Hutchison et al., 2013; Pulvermüller, 2013; Mandera, Keuleers & Brysbaert, 2017).

In a semantic priming study, participants are presented with a prime word followed by a target word (Meyer & Schvaneveldt, 1971; McNamara, 1992; Plaut, 1995). Semantic priming designs are often used with a lexical decision task for which participants must decide whether the target is a word. The semantic priming effect refers to the robust result, which has been replicated hundreds of times, showing that participants respond faster for related primes and targets –either semantically or verbal associates– compared to unrelated ones (Hutchison et al., 2008, 2013). Early studies of semantic priming have shown some discrepancies due to an overlap between semantic similarity and verbal association (for example <cat> and <dog> are semantically similar but also verbal associates; see Thompson-Schill et al., 1998, but also Hutchison, 2003). The importance of strictly differentiating between associative and semantic relations when studying the mental lexicon has long been established (for example <whale> and <dolphin>; McRae & Boisvert, 1998; Perea & Rosa, 2002; Thompson-Schill, Kurtz, &

Gabrieli, 1998; Lucas, 2000; Hutchison, 2003; Ferrand & New, 2003). Ferrand and New (2003) obtained a pure semantic priming effect by using stimuli that were semantically similar while controlling for verbal association (e.g., <dolphin> and <whale>). In reverse, they obtained a pure associative priming effect by using strongly associated stimuli that had no semantic similarity (e.g., <spider> and <web>). Consequently, word association norms are used either to select associated word pairs or to check that semantically similar pairs are not also verbally associated. This robustness of semantic and associative priming reported in the literature reflects fundamental rules of semantic organisation in the mental lexicon.

To focus only on similarity and verbal association does not provide a full picture of the organisation of semantic memory however as recent studies on concreteness have shown.

### **3. Concepts concreteness**

Concreteness is a prevalent lexical variable in psycholinguistics and refers to the degree of tangibility of a conceptual entity denoted by a word referent (Coltheart, 1980; Brysbaert, Warriner & Kuperman, 2014). According to the Dual Coding Theory (Paivio, Yuille & Madigan, 1968) concrete concepts refer to tangible entities that are perceptible via the senses, whereas abstract concepts are intangible. According to the Context Availability Theory (Schwanenflugel, Harnishfeger & Stowe, 1988) while concrete concepts refer to a definite number of contexts, abstract concepts are connected to varied contexts. The importance of this variable lies in its ability to predict the hemispheric lateralisation of semantic effects. Neuropsychological studies have shown a concreteness effect in the processing of concepts with a processing facilitation in the right hemisphere for abstract concepts compared to concrete concepts (e.g., Oliveira, Perea, Ladera & Gamito, 2013). Other studies have shown that concrete concepts are easier to retrieve from memory compared to abstract concepts (Newton & Barry, 1997; Hanley, Hunt, Steed, & Jackman, 2013) and have a higher emotional valence (Kousta, Vigliocco, Vinson, Andrews, & Del Campo, 2011; Paivio,

2013). In recent years, new elements of definition have emerged to describe abstract concepts in terms of intangible features such as events, social contexts and introspective states (e.g., Barsalou & Wiemer-Hastings, 2005; Harpaintner, Trumpp & Kiefer, 2018; see Borghi et al., 2017 for a review). The importance of the concreteness variable is further evidenced by the development of concreteness rating databases (Coltheart, 1981; Brysbaert, Warriner & Kuperman, 2014; Bonin et al., 2018) to use in semantic priming designs for instance.

Despite the robustness of the semantic priming effect with concrete concepts, results have been inconsistent with abstract concepts. Crutch (2005; Crutch, Conell & Warrington, 2009; Crutch & Warrington, 2010) showed that while concrete concepts are organized according to semantic similarity, abstract concepts are organized according to verbal association. Several studies tried to replicate these results but revealed discrepancies (e.g., Hamilton & Coslett, 2008; Duñabeitia, Avilés, Afonso, Scheepers & Carreiras, 2009; Geng & Schnur, 2015). Indeed, these studies have attempted to replicate the results according to which concrete and abstract concepts have different dependencies upon semantic similarity and associative strength. They have failed however to find any such difference in the organization of concrete and abstract concepts. A more recent study found that both semantic similarity and verbal association elicited a priming effect for concrete concepts whereas for abstract concepts it was only found with verbal association (Ferré, Guasch, García-Chico & Sánchez-Casas, 2015). Crutch and Jackson (2011) suggested the relationship between concreteness and association type could explain these disparities. They presented evidence based on data from healthy and neuropsychological patients showing that when presented with triplets of low, middle and high-levels of concreteness, the effect of semantic similarity increased with concreteness while the effect of verbal association decreased with concreteness. Furthermore, they suggested that concreteness be used as a graded variable rather than a binary one especially when studying its effect on the organization of semantic memory.

In recent years, the representation of abstract concepts has gained extra interest and became the focus of the debate between two seemingly opposite accounts of the nature of semantic representation, namely the distributional and the embodiment accounts. They differ from each other in respect to the information used to represent meaning. While distributional semantics relies on symbolic and linguistic features, embodiment relies on perceptual and sensory-motor states. According to this definition, the distributional account can easily explain the representation of abstract concepts while embodiment struggles to account for their representation due to their intangible nature. Both the distributional and embodied assumptions can account for priming effects, which results from the activation of features shared between the prime and the target (Mahon & Caramazza, 2008; Dove, 2009; Andrews, Frank & Vigliocco, 2014; Carota, Kriegeskorte, Nili & Pulvermüller, 2017). Where these accounts differ, however, is in the nature of the features. The distributional account suggests the priming effect results from the activation of linguistic features, the embodied account that it results from the activation of shared sensorimotor states. Recently, a hybrid account has emerged as a consensus to suggest that both linguistic and perceptual features are responsible for this phenomenon.

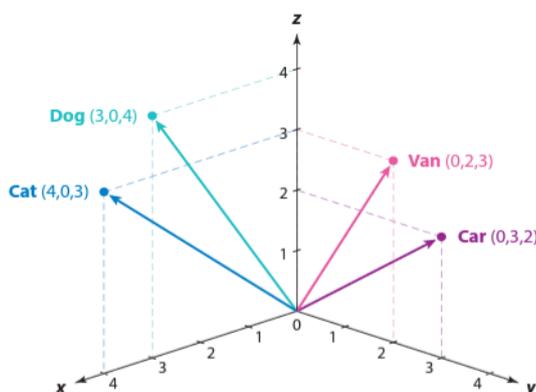
#### **4. Distributional and grounded accounts of semantic representation**

The symbolic or experiential nature of conceptual features is a question that dates back to ancient philosophers. On the *rationalist* end of the debate, philosophers such as Descartes, Leibnitz and Kant -building on ideas from Platon- had developed the notion that concepts are detached from sensory matters and reside in the mind as symbolic entities. On the *empiricist* end of the debate, philosophers such as Hume and Locke building on assumptions from Aristotle had suggested that concepts represent impressions of the sensory environment (see

Markie, 2008, Machery, 2009; 2016). This opposition has fuelled the current debate between distributional and grounded accounts of semantic representation.

### Distributed accounts of semantic representation

The distributional hypothesis originated from the field of computational linguistics that represents meaning in a semantic vector space (Lenci, 2018; see Figure 3). According to models of distributional semantics, meaning is the result of the statistical distribution of words across written and spoken language (Andrew, Frank & Vigliocco, 2014; Lenci, 2018; Lund & Burgess, 1996; Landauer & Dumais, 1997; Griffiths, Steyvers & Tenenbaum, 2007; Mandera, Keuleers & Brysbaert, 2017). The core tenet of this hypothesis lies in Harris' principle according to which words occurring in similar contexts have similar meanings (Harris, 1954; see also Firth, 1957). Similarity lies at the core of the model and the meaning of concepts is given by the co-occurrence of its vector across similar contexts. For instance, Figure 3 shows that the concepts <cat> and <dog> are represented by close coordinates in a vector space because they occur in similar contexts and therefore have similar meanings. The meaning of words is therefore defined in relation to other words, depending on their shared symbolic and linguistic features.



**Figure 3.** Graphical representation of the semantic vector space for the concepts dog, cat, van and car from Lenci (2018).

This hypothesis later became influential in cognitive psychology as distributional analysis methods were considered a suitable foundation to represent semantic similarity (Miller, 1967). Miller and Charles (1991) formulated a definition of semantic similarity within the distributional framework and described it as a “function of the contexts in which words are used” (Miller & Charles, 1991, p.3). The reliance of this framework on large text corpora to extract semantic representations across written language provided much insights into the linguistic environment from which the mental lexicon is acquired and expanded (McRae & Jones, 2013; Jones et al., 2015). In contrast, the use of distributional analysis on behavioural data such as word associations established a framework for modelling the impact of linguistic environment on the mental lexicon. This allowed for the modelling of various distributional phenomena such as word frequency and centrality in the mental lexicon as well as vocabulary growth defined as the probability of generating novel words as the number of responses in a word association task increases (Herdan, 1964; Baroni, 2006; Evert & Baroni, 2007).

Distributional models of semantics are defined according to two main dimensions: the type of context used and the learning algorithm for distributional vectors (see Bullinaria & Levy, 2007; Riordan & Jones, 2011 for reviews). Accordingly, three major models have proved to be very influential in computational linguistics and cognitive psychology alike: LSA (Latent Semantic Analysis; Landauer & Dumais, 1997), HAL (Hyperspace Analogue of Language; Burgess 1998) and the Topic models (Griffiths, Steyvers & Tenenbaum, 2007). The LSA and HAL algorithms describe the statistical distribution of concepts according to their frequency of co-occurrence with other words. In addition, these models produced close performances when comparing with behavioural data. This suggests that they are able, to some extent, to mimic the extraction of semantic representation from language (see Andrews et al., 2009; Binder, Conant, Humphries, Fernandino, Simons, Aguilar & Desai, 2016). In

particular, the distance values between similar vectors obtained from the LSA and HAL models were able to predict reaction times for semantic priming effects and synonym recognition tests respectively. More recently, Griffiths and colleagues (2007) developed a Bayesian model of distributional statistics, which outperformed the LSA and HAL models on predicting a series of semantic phenomena such as semantic similarity and word associations.

This account of semantic representation based on linguistic features finds no issue in explaining the representation of abstract concepts. This prevalence of linguistic features is further evidenced by the late age of acquisition of abstract concepts, which suggests that they are more likely to be acquired through language exposure (Della Rosa et al., 2010). In addition, neuropsychological data have shown that the processing of abstract words shows higher levels of activation in the left hemisphere associated with linguistic processing (Binder et al., 2005; Binder, Desai, Graves, & Conant, 2009; Wang et al., 2010). This view of distributional semantics using amodal linguistic symbols as a proxy for representing meaning has been under fire, particularly from researchers subscribing to the theory of embodiment, for its lack of grounding in perceptual and motor states.

### **Grounded accounts of semantic representation**

According to the embodied account of semantic representation, concepts gain their meaning from internal simulation of the perceptual and sensorimotor features that define them (Barsalou, 1999; 2012; Borghi et al., 2017; Gallese & Lakoff, 2005; Glenberg, 1997; Zwaan, 2004; Kiefer & Pulvermüller, 2012; Meteyard, Cuadrado, Bahrami & Vigliocco, 2012). For example, the concept <lemon> acquires its meaning from a re-enactment of features such as the colour yellow, the texture of the peel and the acidic taste. Pulvermüller, Shtyrov, and Ilmoniemi (2005) used brain-imaging techniques to show that brain areas responsible for motor actions of the face and leg are activated when action words such as kick or lick are

processed. This evidence struggles, however, to explain the grounding mechanisms for abstract concepts such as *justice* or *freedom* which do not refer to direct perceptual features or sensory-motor states (see Borghi & Pecher, 2011; Borghi, Binkofski, Castelfranchi, Cimatti, Scorolli & Tummolini, 2017, Pecher, 2018 for reviews; Dove, 2009, 2011, 2014; Machery, 2016). However, several hypotheses, from strongly to weakly embodied, have been developed as explanations for the grounding mechanisms of abstract concepts.

According to strong embodiment assumptions abstract concepts are as grounded and reliant on sensory-motor states as concrete concepts are (e.g., Glenberg & Kaschak, 2002; see Borghi et al., 2017 for a review). For instance, the conceptual metaphor theory describes the grounding of abstract concepts according to 'image schemas' corresponding to mental representations (e.g., Lakoff & Johnson, 1980; Gallese & Lakoff, 2005). More precisely, studies have shown that abstract concepts of valence and power are grounded in schemas described by spatial vectors using vertical vectors to represent positions of power while horizontal vectors represent valence concepts (see Pecher, 2018 for a review). As these schemas establish a mapping between abstract concepts and metaphors the Conceptual Metaphor Theory is limited by the availability of such metaphors to represent the richness of abstract concepts.

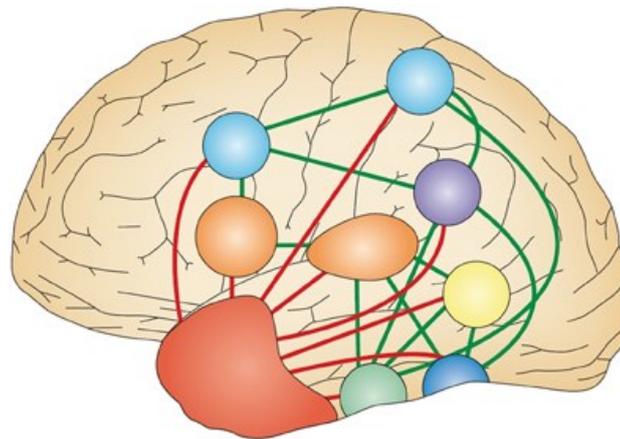
According to weak embodiment assumptions abstract concepts are grounded via both sensorimotor and linguistic modes of representation. Several studies have shown that abstract concepts activate social and introspective aspects of situations (Barsalou & Wiemer-Hastings, 2005), emotional features (Kousta, Vigliocco, Vinson, Andrews & Del Campo, 2011; Lenci, Lebani & Passaro, 2018), information about events and thematic roles (Ferretti, McRae & Hatherell, 2001). They have also found that linguistic information can act as a shortcut to conceptual simulation (Barsalou, Santos, Simmons & Wilson, 2008). Such results suggest that abstract concepts are grounded according to mechanisms which place a great emphasis on the

context in which they are used (e.g., Barsalou, 1999; 2003; Wiemer-hasting and Xu, 2005).

Contrary to strongly embodied accounts, these assumptions are sufficiently general to apply to a variety of abstract concepts.

The strongly and weakly embodied accounts represent the extremes of a theoretical continuum. Middle-ground theories, have also been formulated to account for the representation of abstract concepts which consider that both linguistic and grounded features contribute to their representation. For instance, Dove's representation pluralism (Dove 2009, 2011, 2014; see also Borghi et al., 2017; Pecher, 2018) is a hybrid account, according to which abstract concepts activate both linguistic and modality-specific features. Andrews, Vigliocco and Vinson (2009) integrated both distributional and experiential data in a probabilistic model which learned semantic representations in an attempt to reconcile the distributional and embodied accounts. The model revealed an interdependency of linguistic and sensory information. In another study, Lenci, Lebani and Passaro (2018) showed a similar statistical co-occurrence between linguistic and affective information in the representation of abstract words by applying distributional analyses on norming data.

Finally, the hub-and-spoke model provides some neurological evidence in accordance with hybrid accounts of conceptual representation (Patterson et al., 2007, 2015; Mahon & Caramazza, 2009; Lambon Ralph et al., 2010; Martin et al., 2014; Martin, 2016). The hub-and-spoke model posits that semantic concepts are processed in a distributed network of modality-specific areas called spokes connected through cortical routes to hub regions that integrate all modalities (Figure 4).



**Figure 4.** The hub-and-spoke model of semantic processing. Modality-specific spokes represent motion (yellow), colours (dark blue), shapes (green), names (orange), actions (light blue) and tasks (purple) which converge towards the amodal “hub” (red) represented in the anterior temporal lobe (ATL; Adapted from Patterson et al., 2007).

Neuropsychological data from patients with semantic dementia (SD) identify the ATL (anterior temporal lobe, see Figure 4) as a semantic hub region (see for example Patterson et al., 2007) due to a cross-modality pattern of semantic impairment found in SD patients. Consequently, this deficit has been construed as evidence of the amodal nature of the ATL and its role as a convergence zone for amodal conceptual representations (Patterson et al., 2007, Rogers et al., 2004; Rogers & McClelland, 2004). Few studies have investigated the role of the ATL in the representation of abstract concepts specifically. However, recently, Hoffman, Binney and Lambon Ralph (2015) found an activation of the ATL for both concrete and abstract concepts with a graded shift as regards to the conceptual information relevant to each type. Accordingly, concrete concepts elicited stronger patterns of activation for ventromedial areas closely associated with visual regions while abstract concepts elicited a stronger activation in dorsolateral areas associated with auditory-verbal regions. Taken together, these patterns of activation suggest that the ATL is a hub for both abstract and concrete concepts across all modalities with stronger connections to related regions according to conceptual content.

## Conclusion

Since the early research of the 1960-70s, psycholinguistics has tried to establish a pattern of organisation of the mental lexicon first as a computational prospect with network models and later to make sense of neuropsychological and behavioural data. Major advances have been made over the decades as researchers established that similarity, whether computed as the overlap of features or co-occurrence in similar contexts plays a key role in the organisation of conceptual knowledge. In recent years, the nature of the conceptual features has been at the centre of attention in order to answer the challenge posed by abstract concept representation. Neuropsychological, computational and behavioural evidence have shown that the nature of features can be linguistic as well as grounded in modality-specific information. Neural evidence has also suggested the existence of hubs that abstract specific features in favor of similar core components of concepts (Patterson & Lambon Ralph, 2016). Evidence from the amodal hubs suggests a mechanism of abstraction which allows for the generalisation of conceptual meaning beyond encoded idiosyncratic features. As a result, the question of how concepts are represented is impossible to treat without considering how meaning is abstracted and generalised to all instances of a concept.

## **5. Abstraction and generalisation mechanisms in the processing of abstract concepts**

Mechanisms of categorisation address a core tenet of conceptual knowledge in exploring how the meaning of concepts is generalised from isolated exemplars to all instances. Generalisation refers to the process of extracting features across multiple instances of a concept so that common features are given more weight in the representation of meaning compared to idiosyncratic features which become abstracted (see Murphy, 2002; Glenberg, 2006; Altmann, 2017; Yee, 2019). This process is a cognitive feat without which it would not be possible to reason, make inferences and more generally make sense of the world. Many similarities exist in the respective literatures for concept representation and generalisation

which suggests that both rely on related mechanisms. As Murphy (2013) observed, this literature is still set in the prototype vs. exemplar debate as it has been for decades and without the perspective of a clear resolution in sight.

### **Models of the prototype view of concept learning**

What is the nature of the mental representation that comes to mind when we think of a category word such as furniture or emotion? According to the prototype theory of Rosch (1975; Rosch & Mervis, 1975), such mental representations require a summary description of the core properties which define a category. Concepts are categorised according to their similarity with the most prototypical member of the category. In a series of priming experiments, Rosch (1975) found a facilitation effect for members of categories that presented a pattern with many properties in common with other members of the category and few properties in common with other categories. Consequently, researchers have adopted an interpretation of the prototype view according to which categories are represented by a set of features with some features being more important than others are (Posner & Keele, 1968; Hampton, 1979; Rosch & Mervis, 1975; Smith & Medin, 1981; Murphy, 2002; 2016). In these terms, the prototype view is in accordance with the featural view of concept representation and distributional approaches including feature-based models (e.g., Rogers et al., 2004; Rosch & Mervis, 1975; Smith, Rips, & Shoben, 1974) and hierarchical network models (e.g., Collins & Quillian, 1969). According to this account, concepts are defined as an unstructured list of features with associated weights called schemata (plural of schema; Cohen & Murphy, 1984; Smith & Osherson, 1984). Rumelhart and Ortony (1977) described schemata as data structures that represent generalised concepts underlying objects, situations, events and network relations with other concepts (see Murphy, Hampton & Milovanovic, 2012, for example).

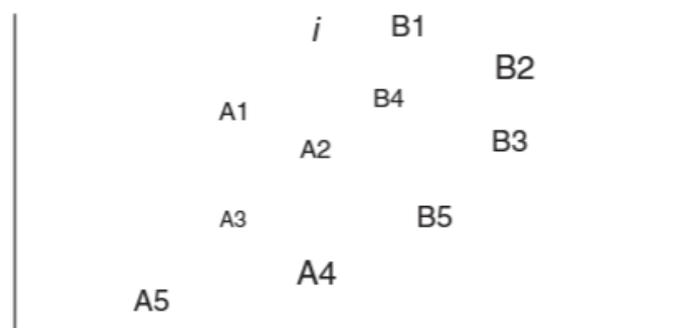
This prototype view became dominant after challenging the classical “all-or-none view” of concepts according to which concepts are categorized based on necessary and sufficient rules of membership (see Katz, 1972 for example). Despite its initial success, this account fell out of favour to the benefit of an exemplar view of concept learning which offered a better fit of empirical data (see Nosofsky, 1992 for a review). The major argument against the prototype view lies in its failure to represent the variety of correlated features that compose the examples encountered during concept learning (Fried & Holyoak, 1984; Medin, Altom, Edelson & Freko, 1982; Rips, 1989).

The exemplar theory of categorisation is an alternative to the prototype view according to which such rules of membership are not necessary. The exemplar theory represents category membership according to stored situations where the concept applies (Medin & Schaffer, 1978; Blair & Homa, 2001; Medin & Schwanenflugel, 1981; Murphy, 2002; 2005). The generalisation of a category label from encountering a set of examples is dependent on the similarity of the examples and each member of the category (Medin & Schaffer, 1978; Nosofsky, 1986). For instance, a child that would encounter three instances of a bird and recognise it as such would have formed three “bird” exemplars that can be generalised to all instances and serve for later classifications (Barsalou, Huttenlocher, & Lamberts, 1998; Nosofsky, 1988). Contrary to the prototype theory, exemplar models suggest that all exemplars are stored and retrieved in concept learning.

### **Influential models of the exemplar theory**

One of the most influential models of the exemplar account is the Generalised Context Model (GCM) of Nosofsky (1986) which posits that people store and classify concepts based on a vast collection of exemplars. New elements are stored and classified on the basis of their similarity to previously encountered exemplars. The model uses multidimensional scaling to represent similarity (MDS; see Shepard, 1958; 1987) which defines exemplars as points in a

psychological space. Similarity is measured as the distance between exemplar points. The shorter the distance between points, the more similar the exemplars they represent are. Figure 5 illustrates the conceptual idea behind the model. Each point represents an exemplar which can vary along two main dimensions A and B. Exemplar A2 and B4 are positioned very closely in the dimensional space compared to exemplars A5 and B2. According to the illustrated case, A2 and B4 would be computed as highly similar compared to A5 and B2 that would be computed as highly dissimilar. The model can compute the categorisation of a novel item  $i$  by summing up its similarity to all exemplar in category A and in category B to determine its category membership.



**Figure 5.** Schematic illustration of a category structure to explain the workings of the GCM (adapted from Nosofsky, 2012).

The GCM model theoretically derives from the Medin-Schaffer context model (1978) which considered exemplars based on two dimensions only. In contrast, the GCM offers a more varied account of exemplars domains represented in the multidimensional scale. This flexibility largely contributed to the model's influence as evidenced by the numerous extensions that have been proposed over the years. For example, Kruschke's (1992) highly influential ALCOVE (attention-learning covering map) model implemented building blocks of the GCM such as the exemplar-based dimensionality and similarity principles in a connectionist framework. In this way, classification mechanisms are not only modelled but

rather learned on a trial-by-trial basis. The compelling account of the GCM model is illustrated in the number of extensions that have been proposed over the years which include Nosofsky and Palmeri's (1997) exemplar based random walk (EBRW) and Lambert's (2000) extended generalised context model for response times (EGCM-RT) which all provide predictive data. However, like the prototype view of concept learning, the exemplar view did not remain unchallenged.

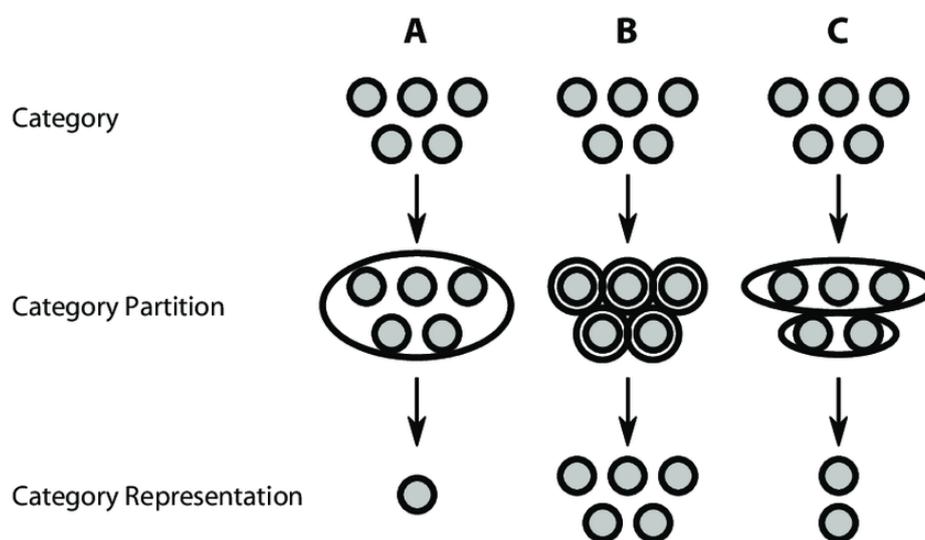
### **Challenges to the exemplar view**

The main challenges to the exemplar view concern the issue of cognitive economy (Rosch, 1978). Exemplar accounts posit that every encountered exemplar is stored and retrieved from memory. Both assumptions seem impractical as they violate the economical strategies of cognitive processes (Feldman, 2003). More recently, Murphy (2016) reviewed the literature on exemplar models and concluded that despite their ability to explain data from many concept-learning experiments, it is not adequate to describe real-world category and concept learning. Murphy (2016) objected to the idea that category learning experiments can faithfully provide an ecological representation of the cognitive mechanisms involved in concept learning. In contrast with the prototype view, the exemplar view cannot account for the hierarchical structures of semantic networks (Quillian & Loftus, 1969; Collins & Loftus, 1975). To account for such hierarchies would require that every exemplar be encoded along with its category membership which would contradict the cognitive economy principle. However, the exemplar view has an advantage over the prototype theory in its ability to garner a sufficient amount of information to represent and learn concepts that would be lost in a prototypical account.

Taken in isolation, neither the prototype nor the exemplar theory can provide a compelling account of concept learning. The major debate opposes the loss of information in

a prototype account to the violation of cognitive economy in the exemplar view (Komatsu, 1992; Vanpaemel & Ons, 2005; see Vanpaemel & Storms, 2008 for a discussion).

To answer these challenges, Vanpaemel and Storms (2008) proposed the Varying Abstraction Model (VAM) that combines both the information of the exemplar account and the cognitive economy of the prototype account. They viewed the debate between exemplar and prototype accounts as a debate on abstraction mechanisms. The VAM model posits that the prototype and the exemplar accounts exist on a continuum of abstraction where exemplars represent minimal abstraction whereas prototypes represent maximal abstraction. The model describes a two-steps procedure with varying levels of abstraction. On Figure 6, panel A represents a mechanism of abstraction based on the prototype end of the continuum while panel B represents a mechanism based on the exemplar end of the spectrum. Finally, panel C represents a middle-ground position that consists of subprototypes obtained from the abstraction of a subset of exemplars.



**Figure 6.** The two-step procedure to construct a category representation: (1) partition the category into clusters and (2) construct the centroid for each cluster. In this way, it is possible to construct the prototype representation (panel a), the exemplar representation (panel B), and a set of intermediate representations, one of which is illustrated in panel C (reproduced from Vanpaemel & Storms, 2008).

Despite the emergence of models to find a middle ground between these two views, the debate has yet to be resolved and no consensus has been reached. More recently, Ambridge (2020) argued against stored abstractions and proposed instead a radical exemplar model based on a strict dichotomy between the exemplar view and the process of abstraction. This dichotomy is rooted in the original debate on prototype and exemplar theories which defined prototypes as abstracted core features that represent a category while exemplar accounts assumed a position against abstraction based on the storage of every exemplar. This exemplar vs. abstraction dichotomy has been explored in studies on concept learning in children. For instance, Ambridge (2016) took position in favour of the prototype view and explained that children form and store a semantic construction prototype. This position has been challenged by recent models and experiments which suggest that the assumptions of storing exemplars and abstraction are not contradictory. Studies have shown that children develop more abstract representations as their language grows until they are able to generalise across common features of meaning (Savage, Lieven, Theakston & Tomasello, 2006; Rowland, Chang, Ambridge, Pine & Lieven, 2012). In addition, hybrid models posit that abstracted representation are composed of stored exemplars (Abbot-Smith & Tomasello, 2006; Goldberg, 2006; Langacker, 1988). Even Ambridge (2020) reversed his position and proposed that word meanings are composed of exemplars, rather than represented as prototypes based on a central meaning. Most of the literature on concept learning and categorisation has been focused on concrete objects and generic concepts (e.g., triangles, faces, etc). These assumptions can also be applied to the study of abstraction mechanisms in the learning of abstract concepts.

## **How does this relate to mechanisms of abstraction and generalisation in the processing of abstract concepts?**

In recent years, much work has been focused on solving the challenge posed by abstract concepts (see Borghi et al., 2017; Pecher, 2011, 2018 for reviews) especially in light of their variety and complexity which make them difficult to classify in well-defined categories. Little is known about how abstract concepts are learned, categorised and generalised to all instances of a particular concept. Studies have shown that the preferred mechanism of abstraction depends on the structure of the category. According to Minda and Smith (2001), the prototype account is better suited for large categories whereas Feldman (2003) suggests that the exemplar account is more adequate for complex categories. More broadly, the literature on concept learning explores the mechanisms of abstraction that aggregate individual instances of a concept such that common features gain prominence while idiosyncratic features carry little weight (see Yee, 2019 for a review).

Abstraction mechanisms are discussed in terms of categorisation levels from lower levels to higher levels of abstraction (e.g., robin -> bird -> animal). This hierarchy is more difficult to establish for abstract concepts that can themselves be decomposed into a set of abstract features and generally refer to complex situations (Borghi et al., 2017; Recchia & Jones, 2012). How are the concepts of joy, fantasy or justice categorised for instance? The literature on abstract concepts has described several large domains to define abstract concepts rather than the categories used to classify concrete objects. These domains can broadly be described as number concepts, morals and aesthetics, the social and cultural dimension as well as emotion. These domains can be grounded in dimensions of sociality, language, interoception, perception and action, and finally metacognition (see Borghi, Barca, Binsofsky & Tummolini, 2018 for a review of these domains and dimensions of abstract concepts). This

complexity of abstract concepts mean that little is known about their mechanisms of abstraction.

In recent years, Gentner and Asmuth (2017) have proposed a process of abstraction they call Career of Metaphor which describes how abstract meaning can be generalised through figurative language. For example, they consider the abstract relational meaning of the concept <anchor> that can be abstracted through figurative expressions such as <religion is an anchor>. Repeated exposure to such figurative instances would highlight the common features between the concepts <anchor> and <religion> by abstracting the meaning of the metaphor in favour of an underlying common relational structure which can be extended to other situations that share similar structures. The major limitation to the metaphorical account for abstraction is similar to the one found in the Conceptual Metaphor Theory for the grounding of abstract concepts which is that there cannot be a one-to-one mapping between each abstract concept and relational metaphors (see Pecher, 2018 for a discussion).

### **Conclusion**

The literature on concept learning is made complex by a lack of consensus between the prototype and exemplar views on the one hand and the exemplars and abstraction dichotomy on the other hand. This literature is made even more complex for psycholinguistics research due to a lack of studies that have used semantic concepts in favour of more generic concepts such as lines, triangles, faces which are easier to generate, to norm and to diversify along chosen dimensions. The combination of word learning experiments and concept learning provides a powerful framework for studying how semantic concepts are abstracted and generalised to all instances. While this framework has been successfully applied to studying the abstraction mechanisms of concrete objects, very little is known about how abstract concepts are abstracted and generalised. This is mainly due to the fact that the literature on abstract concepts is rather recent and the majority of studies and models have

been dedicated to their representation and grounding mechanisms that have always represented a challenge. The complexity of abstract concepts and their lack of clear-cut categories make them even more of a challenge. The previous sections of this theoretical chapter have introduced the behavioural and neural evidence on the representation of abstract concepts. Although cognitive and neuroscientific approaches often have little to say about how concepts are structured, the newly prolific class of cognitive network models are an important exception.

## **6. Network cognitive science**

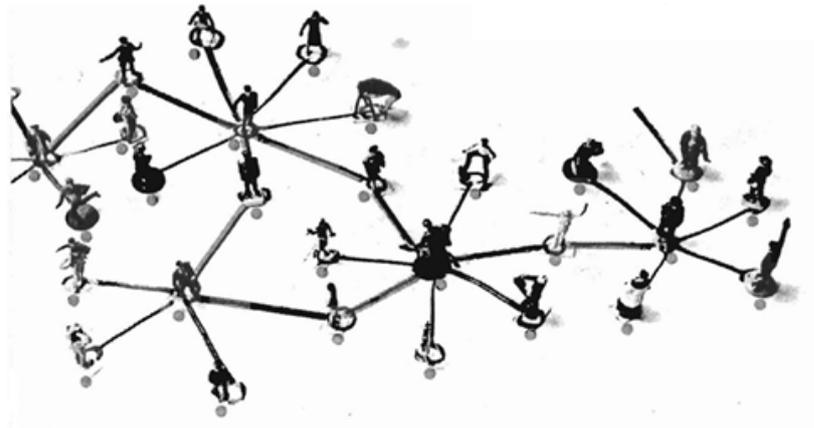
Networks are used to explore the intrinsic structural design of many real-world phenomena. The last two decades have generated a wider interest for their application to study complex systems across all domains of science. This section is divided in three parts. The first part retraces the historical roots of network science and introduces the three most commonly encountered models of networks: the Erdős-Renyi model (1959), the Watts-Strogatz model (1998) and the Barabasi-Albert model (1999). The second part exposes the main mathematical parameters that allow for inferential network analyses. Finally, the third part is an overview of cognitive network science or the application of graph theory to the study of human cognition with an emphasis on the mental lexicon.

### **Historical account and classical models of network science**

Network science stems from the mathematical graph theory but its historical roots are much older. The earliest known paper written by the mathematician Euler (1735) provided a solution to the famous Königsberg bridge problem. In this paper, Euler transcribed the map of the Prussian town of Königsberg into what is now known as a network to prove that it was not possible to cross each bridge of the town exactly once (Figure 7). This solution described for the first time the notions of nodes –or vertices- and edges that are central to the field of



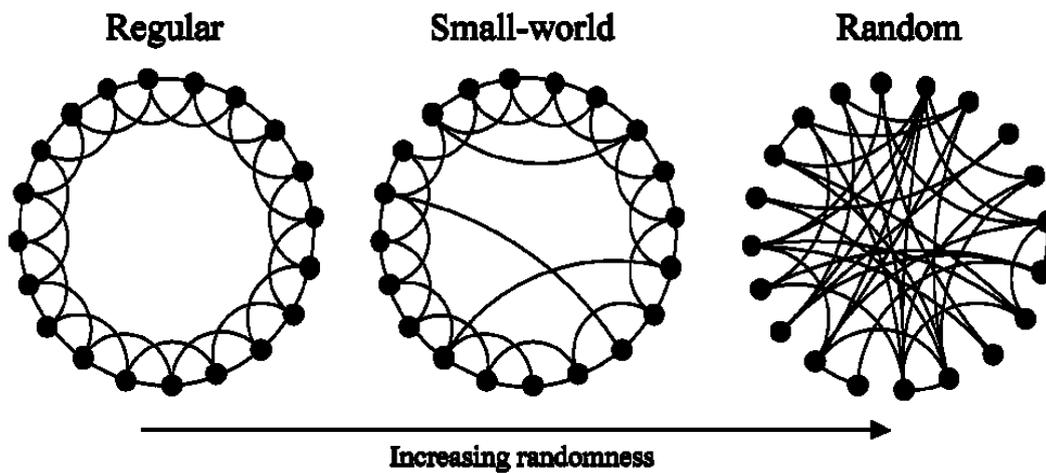
Massachusetts using their own social connections. Results showed that on average, only six intermediary social connections were needed for the letter to reach its destination. This model so named because it illustrates the saying *we live in a small world* lies at the origin of the six-degree-separation principle (Guare, 1990). Milgram formulated the following small-world problem: “[...] starting with any two people in the world, what is the probability that they will know each other? ...while persons X and Z may not know each other, they may share a mutual acquaintance- that is a person who knows both of them.” Milgram (1967, p.4).



**Figure 8.** Illustration of the Small-World Problem from Milgram (1967).

This principle became very influential in most fields that use network science for its ability to model real world phenomena. **Watts and Strogatz (1998)** explored the dynamics of self-organising systems further and established that most complex systems such as biological, technological or social networks present structural characteristics that lie between regular networks and random networks. In a regular network, every node is connected to every neighbour while a random network is characterised by a random pattern of connections between nodes. These middle-ground models can be highly clustered -with a high number of connections between nodes- like regular networks yet have small path lengths like random networks (Figure 9). A combination of high clustering and small path lengths became the

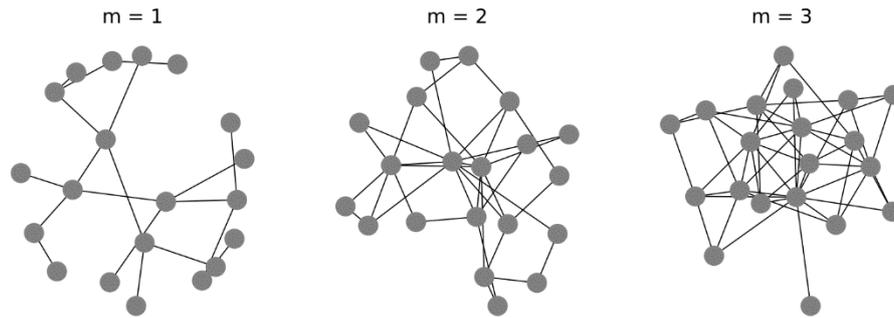
hallmark of a small-world structure based on an analogy with Milgram's small world phenomenon.



**Figure 9.** Small-world structure from Watts & Strogatz (1998). The small-world model was obtained by interpolation of a regular ring lattice and a random network, without altering the number of nodes or edges in the graph.

Later studies confirmed these small-world properties in social networks (e.g., Watts & Strogatz, 1998; Kitsak et al., 2010), epidemiology of infectious diseases (e.g., Keeling & Rohani, 2008), spread of computer viruses (e.g., Pastor-Satorras & Vespignani, 2001), protein interaction (e.g., Bork et al., 2004), gene expression (e.g., van Noort, Snel & Huynen, 2004), neural (e.g., Bassett & Bullmore, 2017) and semantic networks (e.g., Steyvers & Tenenbaum, 2005).

The benefit of using network representation for complex systems lies in their ability to represent not only structural characteristics but also dynamic processes of growth over time. For instance, according to the **Barabasi-Albert model (1999)**, every time a node is added to a network, it connects either to an existing hub of influential nodes or to a community of nodes that are close to each other following a mechanism of preferential attachment (Figure 10).



**Figure 10.** Three graphs of 20 nodes each generated with the Barabasi-Albert model (1999). The increasing value  $m$  represents the parameter of attachment. A high value of  $m$  signifies that the more connected a node is, the more it is susceptible to receive links.

These characteristics generate self-organising systems with a high level of information transfer and provide powerful structural and dynamic models to explain real world phenomena from the World Wide Web to human cognition. Network models also provide powerful mathematical parameters based on graph theory to draw quantitative inferences about structural and growth mechanisms.

### **Network parameters and analysis**

A network is a graph composed of connected nodes also called vertices. The links between nodes can provide three types of information: (1) the existence of a connection between two given nodes for which case, the link is called an edge in an undirected network, (2) the direction of this connection from the source node to the destination node for which case, the link is represented by an arrow called an arc in a directed network, and (3) the weight of this connection. Nodes can be made to represent any entity of a complex system such as grids, airports, people, protein, etc. In the same way, the weights correspond to any value of the complex systems such as distance between locations, force of interaction, etc. These characteristics provide the fundamental topology of a network. Network modelling proposes

parameters and measures that are used to draw inferences. Inferences are not based on statistical significance as it is usually the case when manipulating behavioural data but rather draws on the comparison of the network of interest with a comparable random network that can be generated with the Erdős-Renyi model (1959).

The macrostructure of the network is given by its diameter ( $D$ ) measured as the longest path between two nodes. The average shortest path length ( $ASPL$ ) refers to the average minimum number of steps from one node to another. The Erdős-Renyi (1959) and Watts-Strogatz (1998) models have established the importance of the  $ASPL$  for random and small-world networks which is often used to assess the small-world structure of a network. On a more empiric viewpoint, the  $ASPL$  has been used in semantic networks to model lexical parameters such as semantic similarity and verbal association (see Kenett, Levi, Anaki & Faust, 2017). The density ( $d$ ) is defined as a ratio of the number of edges in the network to the number of all possible edges.

At the microscopic level, nodes are characterised by their degree or number of connections. In a directed network, each node has an in-degree ( $k^{in}$ ) that is the number of incoming arcs and an out-degree ( $k^{out}$ ) that is the number of outgoing arcs. An undirected network only has degree  $k$  corresponding to the number of edges of a node. The average degree  $\langle k \rangle$  describes the overall connectivity of the network. The clustering coefficient ( $CC$ ) is the probability that two nodes are interconnected knowing they both are connected to a common neighbour (Table 1). The microscopic description of a network can assess the effectiveness of flow of information in the network. Studies have shown the impact of the clustering coefficient on word recognition (Chan & Vitevitch, 2009; Yates, 2013; Siew, 2018) and recall (Vitevitch, Chan & Roodenrys, 2012).

**Table 3.** Network parameters and description

network characteristics	Description
$D$	the diameter of the network
$ASLP$	the average length of shortest path
$CC$	the clustering coefficient
$\langle k \rangle$	average degree
$k, k^{in}, k^{out}$	the degree, in-degree, and out-degree
$d$	density of the network

At the mesoscopic level, nodes can be organised into sub-network communities. Communities are defined as a group of nodes that are tightly interconnected but have few connections with the rest of the network. This community structure is best captured by the modularity measure established by Newman (2006). A network with a high modularity measure is formed of an important number of communities.

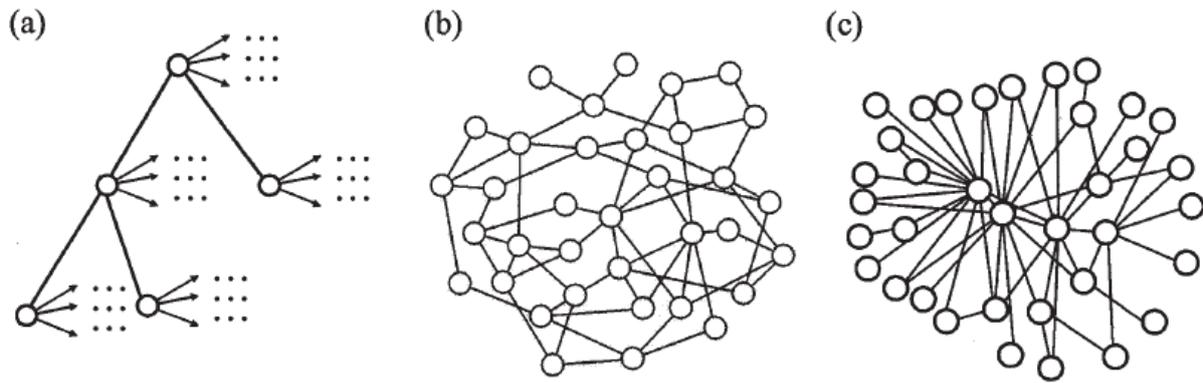
The described network parameters have been applied to uncover structural principles of human cognition. More particularly, semantic network analysis has been used to great extent in the seminal work of Tenenbaum and Steyvers (2005) to establish the small-world structure of semantic networks.

### **Cognitive network science approach to the mental lexicon**

Cognitive science has a long tradition of exploring the structural substrates of human cognition as evidenced by the development of symbolic, connectionist and neural models (Anderson, 1996; McClelland, McNaughton and O'Reilly, 1995; Dell, Chang & Griffin, 1999). It has emerged in recent years as a new mathematical framework to analyse behavioural and neural data (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013; see Siew, Wulff, Beckage, & Kenett, 2019 for a review). Much of this approach has been dedicated to modelling the structural principles and growth mechanisms of the mental lexicon (see Tenenbaum & Steyvers, 2005).

Network representation of semantic memory is rooted in Collins and Quillians' seminal work (1969) which predates this new interest for cognitive network science. Collins and Quillian (1969) suggested that semantic memory is organised in a hierarchical tree-like structure with categories and features represented as nodes (see Figure 11a). Their model stated that the retrieval efficiency of the semantic fact <a canary can fly> for example lies in the generalisation of stored features such as <a canary is a bird> and <birds can fly>. This model puts much constraint on lexical access based on hierarchical relations at the expense of less typical concepts (Carey, 1985; Rips, Shoben, & Smith, 1973; Sloman, 1998). Collins and Loftus (1975) proposed an alternative to this hierarchical network structure (Figure 11b). Their model represented a large-scale unstructured network where nodes correspond to words or concepts linked by patterns of similarity. The model described a retrieval mechanism based on spreading activation able to predict many lexical phenomena such as retrieval from memory, priming and interference effects (Deese, 1965; Collins & Loftus, 1975; Anderson, 2000; Nelson, McKinney, Gee & Janczura, 1998). Despite the efficiency of the model of Collins and Loftus (1975), it fails to render the dynamic processes governing the organisation and growth of the mental lexicon.

More recently, Tenenbaum and Steyvers (2005) studied the structural principles of human semantic knowledge using semantic network analysis on word association data. They found that semantic networks have a small-world structure (Figure 11c).



**Figure 11.** Proposed large-scale structures for semantic networks from Tenenbaum and Steyvers (2005): **(a)**, a tree-structured hierarchy (e.g., Collins & Quillian, 1969); **(b)**, an arbitrary, unstructured graph (e.g., Collins & Loftus, 1975); **(c)**, a scale-free, small-world graph (e.g. Tenenbaum & Steyvers, 2005).

In a word association task, participants are presented with a series of cue-words to which they must respond with the first word that comes to mind. In a network based on association data, the nodes correspond to words connected by an undirected edge or a directed arc. A directed network provides additional information about the direction of the association from cue to response words. The weights of the arcs and edges represent the frequency or strength of association.

Tenenbaum and Steyvers (2005) constructed a directed network from word association data collected by Nelson, McEvoy and Schreiber (1999) comprising 5,000 cue-words. Their analyses focused on the number of connections per word or degree ( $\langle k \rangle$ ,  $k^{\text{in}}$ ,  $k^{\text{out}}$ ), the average shortest path length (ASPL) between two words and the clustering coefficient (CC). When comparing the word association network to a random network generated with the **Erdős-Renyi model (1959)**, the word association network showed a combination of highly clustered nodes and a small average shortest path length characteristic of a small-world structure described by Milgram (1967) and **Watts and Strogatz (1998)**. In addition, a focus on the mesoscopic level showed the presence of many hubs of highly interconnected nodes that share few connections with the rest of the network. This pattern of connectivity testifies

to the nature of growth mechanism taking place in the network over time. It suggests a scale-free organisation in which new nodes tend to join already existing hubs and communities following the same mechanism of preferential attachment described by **Barabasi and Albert (1999)**.

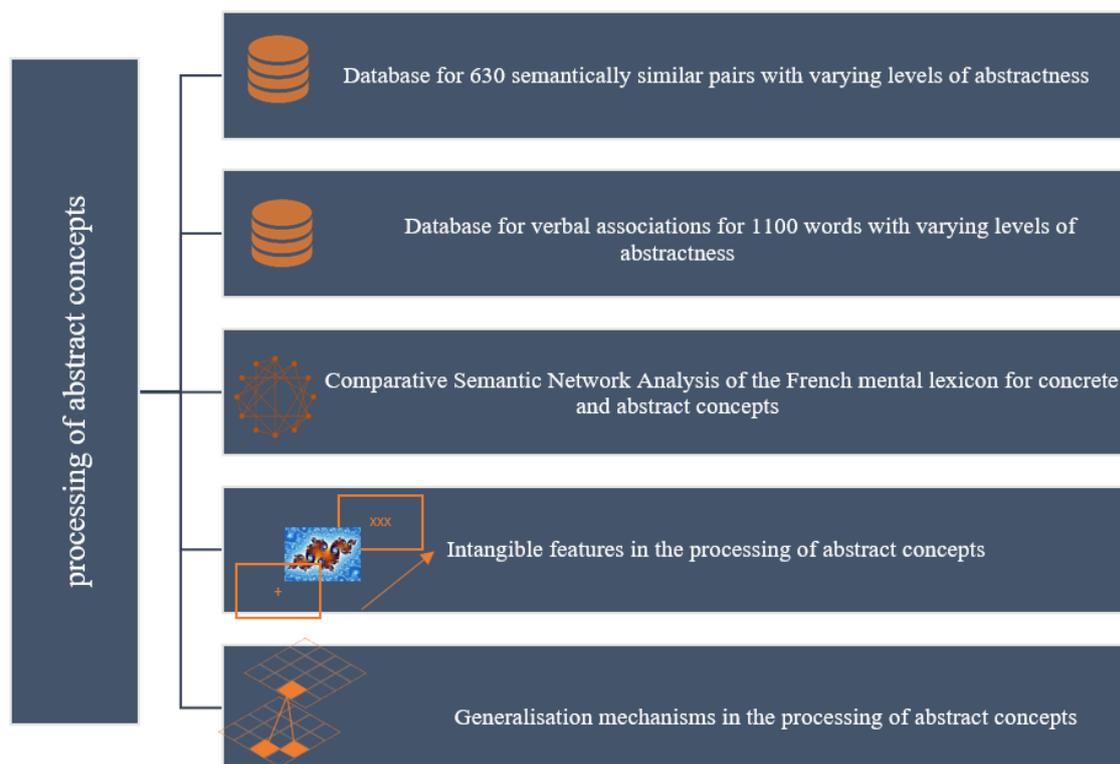
De Deyne and Storms (2008) later confirmed the small-world properties of semantic networks using a continuous word association task. They found that the centrality of nodes within the network related to the age of acquisition of the word with a denser pattern of connection for words acquired early. This supports the view of how the mental lexicon grows over time suggested by the model of Tenenbaum and Steyvers (2005). More recently, De Deyne, Navarro and Storms (2013) constructed a network based 12,000 cues using a multiple-response procedure that covered a large portion of the mental lexicon and which allowed for better prediction of lexical access and semantic similarity (see also De Deyne, Navarro, Perfors, Brysbaert & Storms, 2019).

## **Conclusion**

The network modelling approach has proven its ability to provide additional insights by representing language processing on a larger and more dimensional scale, which was not possible with previous methods and models. This approach aims to provide a complementary account of the organisation and dynamic of the mental lexicon. It proves to be a powerful tool that empirically outperforms the prediction ability of more linear databases. Finally, network science can be applied to study brain connectivity using the same parameters (Siew et al., 2019 for a review). This behavioural account of the mental lexicon could therefore be completed with network analyses of brain patterns of connectivity to link the behavioural data to the neural substrates that generated the structure and dynamic of the mental lexicon.

## SYNTHESIS and INTRODUCTION TO EXPERIMENTAL CHAPTERS

Research on abstract conceptual knowledge has recently become the focus of interest and benefitted from a long tradition of studying psycholinguistic phenomena which translates into a diversity of approaches, models and theories. In the present thesis, we set out to explore fundamental questions about abstract conceptual knowledge spanning from the processing of the word-level to the higher levels of processing which allow for the representation of generalised abstract concepts. Figure 12 provides an overview of the scope of the levels of investigation that we explored.



**Figure 12.** Graphical representation of the scope of the present thesis.

The second chapter draws from the longest psycholinguistic tradition and provides a much-needed database for 630 semantically-similar word pairs in French. The main incentive for the development of this database was methodological and practical as it aims to bridge the gap in the French literature as regards to the availability of normed stimuli for abstract semantic word pairs. Similarly, Chapter 3 provides a complementary database comprising the same isolated words from the previous database which were presented in a word association task. The aim for this database was to provide users with the ability to have control over the nature of crafted stimuli with respect to purely semantic, purely associated or with an overlap in the relationship between chosen stimuli. These two chapters focus on the representation of semantic abstract concepts at the word-level. As such, they provide insights as to the linguistic variables that can impact the processing of lexical concepts but are rather limited when it comes to the structural organisation of the mental lexicon. The rich amount of data generated by the word association task allowed for the use of methods borrowed from corpus linguistics and the mathematical graph theory. In Chapter 4, we used these data to build the first semantic network of the French mental lexicon at the time of writing this manuscript which provides novel insights as to the difference in structural organisation for abstract concepts compared to concrete concepts.

During the last two decades, the interest for the representation of abstract concepts has intensified. In the past however, assumptions had been made as to an assumed paucity of content characterising abstract concepts compared to concrete concepts. In Chapter 5, we explored the richness of abstract concepts and the nature of their features. We used a novel type of stimuli composed of abstract pictures devoid of tangible features in a well-established picture-word priming paradigm. This allowed us to study the role of situational information compared to intangible information in the processing of abstract concepts. This chapter

provides insights as to the featural nature of abstract concepts beyond their situational and linguistic components.

In chapter 6, we explored a higher level of processing focused on the mechanisms that come into play in the generalisation of meaning to novel instances of abstract concepts. We introduced a database of 42 novel abstract concepts each illustrated by 9 exemplars of scenarios. The database was presented to participants who rated the similarity between exemplars. The database was then used in a word learning experiment where participants were introduced to a series of exemplars of each abstract concept that were either similar or dissimilar to each other. The combination of word learning experiments and concept learning provided a powerful framework for studying how abstract semantic concepts are generalised to all instances of meaning.

Finally, we conclude this thesis by proposing a theoretical model based on our findings with the purpose of bridging the gap between levels of investigation of abstract concepts processing. Taken together, our findings describe a reversed pattern of processing with lower levels ruled by similarity-based processes while higher levels of processing are ruled by diversity-based mechanisms.

## **Experimental Section**

The study of the representation of concepts at the word-level requires access to normed stimuli to insure the control of potentially confounded variables. This study of semantic concepts has long been centered on the representation of concrete concepts. However, in recent years, this focus has shifted to the representation of abstract concepts. This means that abstract concepts have not benefitted from the long tradition of developing psycholinguistic norms to the same extent that concrete concepts have. Consequently, there is a gap in the literature as regards to the availability of normed stimuli for abstract concepts. In order to address this gap in the literature, the following chapter introduces a database of semantically similar pairs of French words with varying levels of abstractness. This database is to the best of our knowledge and at the time of writing this manuscript, the first to introduce semantically similar pairs of abstract words in the French language. In addition, we collected semantic similarity and concreteness judgments to address the suggestion of Crutch and Warrington (2011) about different patterns of organisation in the mental lexicon for concrete and abstract concepts. The database was cross-referenced with other known psycholinguistic databases to allow for the control of lexical variables in the crafting of experimental stimuli. A first cluster analysis has shown that the word pairs could be organised according to three levels of concreteness. Further descriptive and correlational results have shown that the prime and target words shared the same level of concreteness and were well-matched across all lexical variables. The entire database is available on the OSF framework.

## Chapter 2. Semantic similarity and associated abstractness norms for 630 French word pairs

Dounia Lakhzoum, Marie Izaute, and Ludovic Ferrand

Université Clermont Auvergne, CNRS, LAPSCO, F-63001 Clermont-Ferrand, France

**Chapter 2 was published under the reference:** Lakhzoum, D., Izaute, M., & Ferrand, L. (2021). Semantic similarity and associated abstractness norms for 630 French word pairs. *Behavior Research Methods*, 53, 1166-1178.

Supplementary material: <https://osf.io/qs4v/>

Running-title: Semantic similarity and associated abstractness norms

**Corresponding author:** Dounia Lakhzoum or Ludovic Ferrand, Université Clermont Auvergne, CNRS LAPSCO, 34 avenue Carnot TSA 60401- 63001 Clermont-Ferrand Cedex 1, France

Phone: + 33 4 73 40 62 57 – Fax: + 33 4 73 40 64 82

Email: [dounia.lakhzoum@uca.fr](mailto:dounia.lakhzoum@uca.fr) ; [ludovic.ferrand@uca.fr](mailto:ludovic.ferrand@uca.fr)

### Author's note

This research was financed by the French government IDEX-ISITE initiative 16-IDEX-0001 (CAP 20-25).

### ACKNOWLEDGMENT

This work was sponsored by a public grant overseen by the French National Research Agency as part of the “Investissements d’Avenir” through the IDEX-ISITE initiative CAP 20-25 (ANR-16-IDEX-0001).

## **ABSTRACT**

The representation of abstract concepts remains a challenge, justifying the need for further experimental investigation. To that end, we introduce a normative database for 630 semantically-similar French word pairs and associated levels of abstractness for 1260 isolated words based on data from 900 subjects. The semantic similarity and abstractness norms were obtained in two studies using 7-points scales. The database is organized according to word-pair semantic similarity, abstractness, and associated lexical variables such as word length (in number of letters), word frequency, and other lexical variables to allow for matching of experimental material. The associated variables were obtained by cross-referencing our database with other known psycholinguistic databases such as Lexique (New et al., 2004), the French Lexicon Project (Ferrand et al., 2010), Wordlex (Gimenes & New, 2016), and MEGALEX (Ferrand et al., 2018). We introduced sufficient diversity to allow researchers to select pairs with varying levels of semantic similarity and abstractness. In addition, it is possible to use these data as continuous or discrete variables. The full data are available in the supplementary materials as well as on OSF (<https://osf.io/qsd4v/>).

**Keywords:** Semantic similarity norms, Concreteness, Normative ratings, Abstract concepts, French word pairs.

## INTRODUCTION

Conceptual representation has been the focus of much study and debate for decades in the fields of semantics and psycholinguistics. In contrast with the holistic and non-decompositional view held by Collins and Loftus (1975), at the heart of the debate now are two seemingly opposite accounts of semantic representation: the distributional and the embodied accounts of conceptual representation (Harris, 1954; Firth, 1957; see Lenci, 2008; Andrews, Vigliocco & Vinson, 2009; Andrews, Frank & Vigliocco, 2014; Bruni, Tran & Baroni, 2014; Lenci, 2018 for reviews of the distributional account. See Glenberg, 1997; Barsalou, 1999; Zwaan, 2004; Meteyard, Cuadraro, Bahrami & Vigliocco, 2012; Pulvermüller, 2013; Ostarek & Huettig, 2019 for reviews of the embodied account). Both these accounts consider that feature and property overlap play a major role in the processing of meaning (see Vigliocco & Vinson, 2007; Vigliocco, Meteyard, Andrews & Kousta for reviews). Indeed, there is much evidence of this from semantic priming studies, widely regarded as the gold standard for studying semantic representation in the mind and brain (e.g., Hitchison et al., 2013; Kim, Yap & Goh, 2019). However, for both sides of the spectrum the representation of abstract concepts remains a challenge, hence the need for a database of source material enabling us to further our understanding of abstract concepts representation.

### **Accounts of semantic representation**

#### *Holistic view and spreading of activation*

According to the holistic view of semantic representation, for every element of the world – be it an object, an event, property, etc. - there is an abstract and symbolic lexical equivalent that acts as a referent in the conceptual system of the mind (Fodor, Garrett, Walker & Parkes, 1980; Berg & Levelt, 1990; Roelofs, 1997; Levelt, Roelofs & Meyer, 1999). In this view of one-to-one mapping, each referent represents a single node in a semantic network, with nodes linked

according to their semantic similarity. For instance, the concept *fire* would be represented by a single node linked to related concepts or properties, such as *red*, also represented by a single node. Collins and Loftus (1975) described the mechanisms of semantic processing based on their theory of the spreading of activation in a network, according to which a concept, when it is processed, activates the path between related nodes at a speed proportional to the strength of the link between them. The assumption of semantic similarity in the spreading of activation theory accounts for both the strength of the link between nodes and the ensuing dynamics of activation for related concepts. Given that in this holistic view, each property or feature of a concept is represented by a single node, it is a view which contrasts with the decompositional or featural view.

### ***Featural view***

According to the featural view of semantic representation, words can be decomposed into a set of defining features or properties reflecting the meaning of the concept to which they relate (Smith, Shoben & Rips, 1974). For instance, the concept *fire* would be decomposed according to its defining features such as <is hot> and <is red>. As with the holistic view, at the core of the featural view is semantic similarity, but in this case it is measured by the number of features two concepts have in common (Plaut, 1995; McRae, de Sa & Seidenberg, 1997; Cree, McRae & McNorgan, 1999; Vigliocco, Vinson, Lewis & Garrett, 2004; Kiefer & Pulvermüller, 2012). The more features they share, the more semantically similar they are. In recent years, two seemingly opposite accounts of this featural view have dominated the debate on the nature of semantic representation, namely the distributional and the embodiment accounts. They differ from each other in respect of the information used to represent meaning. While distributional semantics relies on symbolic and linguistic features, embodiment relies on perceptual and sensory-motor states.

According to models of distributional semantics, meaning is the result of the statistical distribution of words across written and spoken language (see Andrew, Frank & Vigliocco, 2014; Lenci, 2018 for reviews of this account, see also Lund & Burgess, 1996; Landauer & Dumais, 1997; Griffiths, Steyvers & Tenenbaum, 2007; Mandera, Keuleers & Brysbaert, 2017). The meaning of words is therefore defined in relation to other words, depending on their shared symbolic and linguistic features. According to the distributional hypothesis, words occurring in similar contexts have similar meanings (Harris, 1954). This use of intralinguistic relationships was successfully implemented in computational models of semantics (e.g., Hoffman, McClelland & Lambon Ralph, 2018). Motivation for using algorithms such as LSA (latent semantic analysis; Landauer & Dumais, 1997) is the notion that meaning can be extracted by computing semantic similarities between concepts (Louwerse, 2008; 2011; Louwerse & Jeuniaux, 2008; 2010; Rogers & McClelland, 2004; Kintsch, McNamara, Dennis & Landauer, 2007). In addition, the close performance between computational models and human behaviour suggests these models are able, to some extent, to mimic the extraction of semantic representation from language (see Andrews et al., 2009; Binder, Conant, Humphries, Fernandino, Simons, Aguilar & Desai, 2016).

This view of distributional semantics using amodal linguistic symbols as a proxy for representing meaning has been under fire, particularly from researchers subscribing to the theory of embodiment, for its lack of grounding in perceptual and motor states.

The embodied account of semantic representation defines meaning as grounded in perceptual and motor states derived from an individual's sensory experience (Barsalou, 1999; Glenberg, 1997; Zwaan, 2004; Kiefer & Pulvermüller, 2012; Meteyard, Cuadrado, Bahrami & Vigliocco, 2012). For instance, Pulvermüller, Shtyrov, and Ilmoniemi (2005) used brain-imaging techniques to show that brain areas responsible for motor actions of the face and leg are activated when action words such as *kick* or *lick* are processed. Evidence like this struggles,

however, to explain the grounding mechanisms for abstract concepts, where there are no physical and sensory features (see Borghi & Pecher, 2011; Borghi, Binkofski, Castelfranchi, Cimatti, Scorolli & Tummolini, 2017 for reviews).

The dichotomy between abstract and concrete concepts is not clear-cut (Della Rosa et al., 2010). The most commonly invoked criterion is tangibility, with concrete concepts referring to tangible entities that are perceptible via the senses, whereas abstract concepts are intangible. According to the Dual Coding Theory (Paivio, Yuille & Madigan, 1968), concrete concepts trigger processing based on two informational systems, one visual, the other verbal, whereas abstract concepts are processed only in the verbal system. The Context Availability Theory (Schwanenflugel, Harnishfeger, Stowe, 1988) posits that while concrete concepts refer to a definite number of contexts, abstract concepts are connected to varied contexts. Although true, this distinction can be considered reductive and contributes to the view that abstract concepts are poor in terms of features. More recently, with the interest shown in abstract concepts by grounded cognition, new elements of definition have emerged according to which abstract concepts refer to intangible features such as emotions, events, social contexts and introspective states (e.g., Barsalou & Wiemer-Hastings, 2005; Harpainter et al., 2018; see Borghi, 2017 for a review). This latter definition reflects a new interest in their grounding mechanisms and semantic representation.

The tangibility criterion is best represented by the concreteness variable defining the distinction between concrete and abstract concepts based on the dual coding and context availability theories. It plays a key role in psycholinguistic research, as well as providing an explanation for many phenomena, such as hemispheric lateralisation in the processing of concrete and abstract concepts (Oliveira, Perea, Ladera, & Gamito, 2013), or ease of retrieval of concrete words compared to abstract ones (Mate, Allen, & Baques, 2012; Nishiyama, 2013).

The importance of the concreteness variable is further borne out by the development of several widely used databases containing concreteness rating norms (Coltheart, 1981) and, more recently, 40 000 words in English (Brysbaert, Warriner & Kuperman, 2014) and 1659 words in French (Bonin et al., 2018).

### **Abstract concepts representation**

The embodied account has yet to propose a unified theory for the representation of abstract concepts such as *justice* or *freedom* which do not refer to direct perceptual features or sensory-motor states (Dove, 2009, 2011, 2014; Machery, 2016; see Pecher, 2018 for a review). However, several hypotheses, ranging from strongly to weakly embodied, have been put forward as explanations for the grounding mechanisms of abstract concepts. The strong embodiment assumptions make no allowance for multiple representations and consider abstract concepts to be as grounded and reliant on sensory-motor systems as concrete concepts are (e.g., Glenberg & Kaschak, 2002; see Borghi et al., 2017 for a review). For instance, according to the conceptual metaphor theory, abstract concepts are grounded through image schemas corresponding to mental representations (e.g., Lakoff & Johnson, 1980; Gallese & Lakoff, 2005). Several studies have shown that abstract concepts of *valence* and *power* are grounded in two-dimensional spatial schema with the higher point of a vertical vector representing positions of power while the left-hand side of a horizontal vector represents negative concepts (see Pecher, 2018 for a review). However, the need for one-to-one mapping between abstract concepts and concrete metaphors means there are limits to the availability of such metaphors for every type of abstract concept.

At the other end of the spectrum, according to weak embodiment assumptions abstract concepts are grounded via multiple representations of meaning with the involvement of both

sensorimotor and linguistic processing. These grounding mechanisms place a greater emphasis on the context in which abstract concepts are used (e.g., Barsalou, 1999; 2003; Wiemer-hasting and Xu, 2005). Several studies have shown that abstract concepts activate social and introspective aspects of situations (Barsalou & Wiemer-Hastings, 2005), emotional features (Kousta, Vigliocco, Vinson, Andrews & Del Campo, 2011; Lenci, Lebani & Passaro, 2018), information about events, and thematic roles (Ferretti, McRae & Hatherell, 2001), and, more generally, linguistic information acting as a shortcut to conceptual simulation (Barsalou, Santos, Simmons & Wilson, 2008). Such assumptions have the advantage of being sufficiently general to apply to a variety of abstract concepts.

Whether seen from the distributional or embodied end of the spectrum, all accounts agree on the importance of relationships between concepts for the organisation of semantic knowledge. Two kinds of relationships have been widely investigated: semantic similarities (theft-burglary) and verbal association (theft-prison), and a lot of effort has gone into creating databases of material to use in semantic priming studies regarded as the gold standard for studying how semantic knowledge is organised (see Hutchinson, Balota, Cortese & Watson, 2008; Hutchison et al., 2013; Pulvermüller, 2013; Mandera, Keuleers & Brysbaert, 2017).

## **Semantic priming and semantic similarity for concrete and abstract concepts**

### ***Semantic priming***

In a semantic priming study, participants are presented with a prime word followed by a target word (Meyer & Schvaneveldt, 1971). The relationship between the two words is one of either semantic similarity, where the two words belong to the same superordinate category (e.g., prime: *eagle*; target: *owl*), or verbal association, where the two words are frequently found together across spoken and written language (e.g., prime: *fireman*; target: *truck*; McNamara, 1992; Plaut, 1995). In a lexical decision task, participants make a decision on the target by

indicating whether or not it is a word. The semantic priming effect refers to the robust result, which has been replicated hundreds of times, showing that participants respond faster for related primes and targets compared to unrelated ones (Hutchison et al., 2008, 2013). This phenomenon has been widely studied as it provides considerable insight into the organisation and mechanisms of semantic knowledge. In actual fact, each theoretical view discussed above can account for this priming effect. According to the holistic view (Fodor et al., 1980; Berg & Levelt, 1990; Roelofs, 1997), the priming effect is the result of spreading activation from the prime to the target along strongly linked nodes, whereas according to the distributional, embodied and hybrid accounts, it results from the activation of features shared between the prime and the target (Mahon & Caramazza, 2008; Dove, 2009; Andrews, Frank & Vigliocco, 2014; Carota, Kriegeskorte, Nili & Pulvermüller, 2017). Where these last accounts differ, however, is in the nature of the features. The distributional account suggests the priming effect results from the activation of linguistic features, the embodied account that it results from the activation of shared sensorimotor states, and the hybrid account that both linguistic and perceptual features are responsible for this phenomenon.

Despite the robustness of the semantic priming effect with concrete concepts, with abstract concepts results have been inconsistent. Crutch (2005; Crutch, Conell & Warrington, 2009; Crutch and Warrington, 2010) showed that while concrete concepts are organized according to semantic similarity, abstract concepts are organized according to verbal association. Several studies tried to replicate these results but revealed discrepancies (e.g., Hamilton & Coslett, 2008; Duñabeitia, Avilés, Afonso, Scheepers & Carreiras, 2009; Geng & Schnur, 2015). Indeed, these studies have attempted to replicate the results according to which concrete and abstract concepts have different dependencies upon semantic similarity and associative strength. They have however failed to find any such difference in the organization of concrete and abstract concepts. A more recent study found that both semantic similarity and verbal

association elicited a priming effect for concrete concepts whereas for abstract concepts it was only found with verbal association (Ferré, Guasch, García-Chico, & Sánchez-Casas, 2015). Crutch and Jackson (2011) suggested the relationship between concreteness and association type could explain these disparities. They presented evidence based on data from healthy and neuropsychological patients showing that when presented with triplets of low, middle and high-levels of concreteness, the effect of semantic similarity increased with concreteness while the effect of verbal association decreased with concreteness. Furthermore, they suggested that concreteness be used as a graded variable rather than a binary one especially when studying its effect on the organization of semantic memory. Accordingly, this calls for a shift in the way abstract concepts are studied, to place more emphasis on the type and associated level of concreteness for selected abstract concepts. Two different procedures are used to generate material for semantic similarity and priming studies: feature generation tasks and semantic similarity ratings.

### ***Semantic similarity: feature generation and semantic pairs***

In a feature generation task, participants are given a list of words for which they are required to provide a list of features defining each word. The procedure provides measures of semantic similarity by comparing the feature overlap between two words. The more features two words have in common, the more similar they are (McRae, Cree, Seidenberg, & McNorgan, 2005; McRae, de Sa, & Seidenberg, 1997; Sánchez-Casas, Ferré, García-Albea & Guasch, 2006; Vigliocco, Vinson, Lewis and Garrett, 2004; Vinson & Vigliocco, 2008). However, it is a procedure which is highly time-consuming and which has limitations (see McRae et al., 2005 for a discussion of these limitations). For instance, in feature naming, participants may provide only a linguistic approximation of conceptual content. It is fair to assume, therefore, that some parts of the concepts would be lost in verbalisation. This criticism appears to be particularly relevant in the case of abstract concepts which may themselves be decomposed into abstract

features. Indeed, many authors have suggested that, compared to concrete concepts, abstract concepts appear to be semantically impoverished, with their representation requiring associations with other concepts or grounding simulations in introspective and social states (Barsalou et al., 2008; Borghi, Scorolli, Caligiore, Baldassare & Tummolini, 2013; Borghi, Barca, Binkofski, Castelfranchi, Pezzulo & Tummolini, 2019, see also Recchia & Jones, 2012).

On the other hand, Wiemer-Hastings and Xu (2005) suggested that this apparent paucity of features for abstract concepts is due mainly to the instructions given to participants during a feature generation task. In the original method, Wiemer-Hastings and Xu (2005) asked participants only to generate features defining the concept, whereas later they instructed them to provide context features. The results showed that the difference between abstract and concrete concepts in terms of semantic richness disappeared when participants were encouraged to provide context features. By using the same method of property listing as Wiemer-Hastings and Xu (2005), Harpainter, Trumpp and Kiefer (2018) gathered properties for close to 300 abstract concepts. By doing so, they further demonstrated the richness and heterogeneity of abstract concepts showing that they can elicit affective, introspective, social and sensory-motor properties. This heterogeneity of abstract concepts was further investigated by Villani, Lugli, Liuzza and Borghi (2019) who evaluated more than 400 abstract concepts on 15 dimensions. Their results provided further support for a multiple representation view of abstract concepts.

In addition, Bolognesi, Pilgram and van den Heerik (2017) adapted Wu and Barsalou's taxonomy (2009) to include 20 feature categories belonging to four main dimensions (concept properties, situation properties, introspections, and taxonomic properties) that must be distinguished to convey the full semantic richness of concepts. Recchia and Jones (2012) have not, however, been able to determine whether such distinctions in respect of semantic features could benefit abstract concept representation. They invoked the shallowness of lexical decision

tasks in semantic processing. Consequently, future studies will need to reach conclusions on the role of feature categories for abstract concept representation.

Another, less costly, way of creating material for semantic representation studies is to generate semantically similar word pairs. This option relies on a similarity-rating task where participants are presented with pairs of words formed by the researcher with a view to obtaining concepts either belonging to the same category or being similar in meaning (e.g., *truck-car*; Ferrand & New, 2003; Perea & Rosa, 2002). Participants must rate the semantic similarity of the pairs on a scale (Ferrand & New, 2003; Sánchez-Casas et al., 2006). Studies have shown that the pairs rated as being highly similar produced a strong priming effect (e.g., McRae & Boisvert, 1998; Plaut & Booth, 2000; Hutchison, 2003; Andrews, Lo & Xia, 2017). In addition, studies have shown a strong correlation between the measures from similarity-rating tasks and feature generation ensuring the legitimacy of this latter technique (e.g., McRae, De Sa & Seidenberg, 1997). More recently, Maki, Krinsky and Muñoz (2006) used a semantic rating task to show that ratings were a good predictor of feature overlap for existing semantic feature norms.

### ***Normative databases for semantic similarity***

Given the importance of carefully crafted material for studying semantic representation, much effort has been directed towards building normative databases to provide the research community with the material it needs. The most commonly found datasets gather English feature norms. McRae and collaborators (2005), for instance, provides feature norms for 541 living and non-living concepts. Subsequently, Buchanan, Holmes, Teasley and Hutchison (2013) built a searchable web portal based on the work of McRae and collaborators (2005), facilitating the search for experimental stimuli in their dataset. Buchanan, Valentine and Maxwell (2019) expanded previous databases and provided features for more than 4000 words. Vinson and Vigliocco (2008) provided an interesting dataset based on concrete object nouns

and verb events that allow semantic representation to be studied beyond the usual focus on concrete concepts. Devereux, Tyler, Geertzen, and Randall (2014) built on McRae and colleagues' work by adding features produced by at least two participants compared to McRae and collaborator's (2005) 5-feature threshold for inclusion. In other languages, De Deyne and Storms (2008) and De Deyne and colleagues (2008) collected normative features among Dutch participants. Lebani, Bondielli and Lenci (2015) collected thematic role features to study the semantic content of Italian verbs. Also in Italian, Lenci, Baroni, Cazzolli and Marotta (2013) collected semantic features from congenitally-blind and sighted participants, making it possible to study the role of perceptual information in concept processing. Kremer and Baroni (2011) collected properties and semantic relation types for German and Italian. More recently, Vivas, Vivas, Comesaña, Coni and Vorano (2017) published the first Spanish semantic feature production norms for living and non-living concepts.

Researchers have used similarity-rating tasks to a lesser extent to produce such norms. Buchanan and collaborators (2013) compiled a English dataset comprising 1 808 words paired according to semantic similarity. In Spanish, Moldovan, Ferré, Demestre, and Sánchez-Casas (2015) collected normative ratings for 185 Spanish noun triplets with variation of semantic distance within each triplet. However, much of the effort in developing databases has been focused on concrete concepts. To the best of our knowledge, the present work offers the first database of semantically-similar abstract word pairs in French.

### **The present study: Semantic similarity norms for abstract words**

The present work introduces a dataset comprising semantic similarity ratings for abstract word pairs obtained from French participants. We have added a measure of the concreteness of each word from each pair to allow for the selection of abstract concepts in line with Crutch and Jackson's (2011) suggestion that there is a relationship between graded levels of concreteness

and semantic organisation. To provide a dataset of experimental stimuli according to the significant lexical variables and lexical latencies previously discussed, we have combined our list of words with existing databases such as the French Lexicon Project (FLP, Ferrand et al., 2010), Lexique (New et al., 2001, 2004, 2007), MEGALEX (Ferrand et al., 2018), and Wordlex (Gimenes & New, 2016).

## **METHOD**

### **Participants**

Both the similarity- and concreteness-rating tasks were presented as online questionnaires. Participants for the two studies were all French native speakers and between 18 and 45 years old. We collected data from 373 participants (334 women;  $M_{\text{age}} = 26.43$ ;  $SD = 8.34$ ) for the similarity-rating task, and 529 (486 women;  $M_{\text{age}} = 29.7$ ;  $SD = 9.03$ ) for the concreteness-rating task. Participants volunteered in response to an announcement posted on Facebook group walls and no compensation was paid. Participants took part in only one of the tasks in an attempt to ensure their ratings were not influenced by previous exposure to the items which are common to both tasks. Both studies obtained the approval of the Université Clermont Auvergne Research Ethics Committee.

### **Stimuli**

To have some guarantee of the level of abstractness<sup>1</sup> of our material before collecting our own ratings, we selected 1020 words having a low level of concreteness (range between 100 and 600) from Coltheart's (1981) concreteness norms. We then translated the selected words into French following a back-translation procedure (Sperber, Devellis & Boehlecke, 1994),

---

<sup>1</sup> Both "abstractness" and "concreteness" words are used across this paper. The use of these notions is not arbitrary. Abstractness is a central notion to the present work as it aimed at introducing abstract stimuli whereas concreteness is used to refer to other studies that introduce or deal with the concreteness variable.

following which 174 words were excluded. We also added the material from Ferrand (2001) comprising 260 French abstract words.

Based on our linguistic intuition, we then formed semantically similar pairs (e.g., joie-bonheur; [*joy-happiness*]). To the best of our ability (see below), we ensured that the semantic pairs were non-associates (according to McRae & Boisvert, 1998), and were not linked by either a super/supra-ordinate, part/whole or antonym relationships. The material was then divided into 6 lists of pairs, and 30% of fillers (unrelated pairs, e.g., défaut-frisson; [*flaw-chill*]) were added per list. So that the participants would be sensitive to the abstractness of the pairs, we also added concrete words from Ferrand and Alario (1998) and formed semantic pairs. Accordingly, we were able to form 628 semantically related pairs (460 noun pairs, 99 adjective pairs and 69 verb pairs). Both prime and target words had the same grammatical status within each semantically-similar pair. To ensure the pairs were semantically similar and not associated, we translated the target words back into English and checked for forward strength in the Small World of Words database<sup>2</sup> (SWOW, De Deyne, Navarro, Perfors, Brysbaert & Storms, 2019). We identified all pairs for which the prime and target presented a forward associative strength of higher than 10%. Seventy pairs were identified as both associated and semantically similar (e.g., anxiety-fear). We kept them in the main database with the possibility to filter them out. In addition, we created a secondary database containing only the semantically similar and associated word pairs. As suggested by De Deyne et al. (2019), association data are not to be discarded and provide a strong indication of meaning similarity.

For the concreteness-rating task, the pairs were separated, and the lists of individual words were presented in another experiment. Given the added material from Ferrand and Alario (1998),

---

<sup>2</sup> We used the Small World of Words database because there are no databases large enough in French.

participants were presented with stimuli ranging from abstract to concrete, thereby ensuring their sensitivity to the task and avoiding learned response patterns.

## **Procedure**

The stimuli (fillers included) were randomly divided into 6 lists of word pairs and 10 lists of isolated words respectively for the similarity-rating and concreteness-rating tasks. The motivation for dividing the pairs into different lists was twofold. Firstly, we wanted to keep the experiment concise so as to not overwhelm participants. Secondly, some words appear several times in different pairs, which is why we used semi-randomization to ensure that participants never saw pairs with the same words. The pairs and words were presented one by one on the screen in a randomized order. The experiment was conducted online using the Qualtrics software (2020). The design of the interface for this experiment allowed participants to complete the task on either a computer or smartphone.

Once they had given their consent and registered their demographic information, participants were randomly assigned to one of the lists. Their task was to judge the similarity between the two words presented for the similarity ratings and whether the words were more abstract or concrete for the concreteness ratings. Both tasks used a 7-point Likert-like scale ranging from 1 = “not at all similar” (“*pas du tout similaires*” in French) to 7 = “totally similar” (“*tout à fait similaires*”) for the similarity-rating tasks and from 1 = “very abstract” (“*très abstrait*”) to 7 = “very concrete” (“*très concret*”) for the concreteness-rating task. The words appeared one by one on the screen and were replaced as soon as participants had rated them. They were presented in the middle of the screen in Arial 12 font against a white background. We provided examples of items and their possible ratings in the instructions. No training was given before the tasks started. Both studies were self-paced, with no time limit for either the stimulus presentation

(word pair or isolated pair) or participant's answer. Both tasks took about 12 minutes to complete.

## RESULTS

We first computed general statistics for the entire dataset. The general statistics collected for the semantic similarity and concreteness variable are shown in Table 1<sup>3</sup>. Tables 2 and 3 provide the means for associated lexical variables computed by crossing our dataset with the Lexique (New et al., 2004), FLP (Ferrand et al., 2010), MEGALEX (Ferrand et al., 2018) and Wordlex (Gimenes & New, 2016) databases.

**Table 1.** Semantic similarity for word pairs and associated concreteness for prime and target words.

	Pair Semantic Similarity	Prime Word Concreteness	Target Word Concreteness
Mean	4.43	4.41	4.40
SD	1.63	1.48	1.54
Min	1.13	1.63	1.51
Max	6.93	6.92	6.95
Median	4.65	4.43	4.47
Range	5.80	5.29	5.44
Skewness	-0.52	-0.31	-0.35
Q1	3.37	3.44	3.38
Q3	5.60	5.40	5.46

It is apparent from the general statistics in Table 1 that the semantic similarity ratings range from 1.13 to 6.93 on a 7-points scale. This shows participants used the full range of the scale but also reflects the diversity of the word pairs in terms of semantic similarity. Separating very similar ( $M = 5.13$ ;  $SD = 0.41$ ) and less similar ( $M = 3.67$ ;  $SD = 0.59$ ) pairs based on the median revealed a significant effect of semantic similarity [ $t(300) = 35.78$ ,  $p < 0.001$ ,  $d = 2.06$ ]. This

<sup>3</sup>The semantic similarity variable reported in Table 1 corresponds to the mean similarity ratings for word pairs. The concreteness variable corresponds to the mean concreteness for the prime word and target word separately as ratings were obtained on individual words for concreteness and on pairs of words for semantic similarity.

effect is particularly large, given that Cohen's  $d$  suggests the difference is greater than 2 standard deviations. This will allow for the use of semantic similarity either as a continuous or categorical variable for researchers who would wish to study the effect of variation in semantic similarity. Concerning the concreteness variable, the means for prime and target are very close to one another, showing a good concreteness match within each pair (Mean prime concreteness = 4.41; Mean target concreteness = 4.40). A paired-samples T-test showed no significant difference between the mean concreteness ratings for prime and target words ( $t(628) = 0.27$ ,  $p = 0.80$  ns). This close match is further demonstrated in the correlation we computed between prime and target words with a strong and highly significant correlation [ $r = .87$ ,  $t(628) = 44.50$ ,  $p < 0.001$ ].

**Table 2.** Descriptive and behavioural data for target words.

	<i>min</i>	<i>max</i>	<i>M</i>	<i>SD</i>
<b>Movie Subtitles Frequency</b>	0.00	2751.99	56.21	186.30
<b>Book Frequency</b>	0.00	4696.15	64.51	286.62
<b>Blog Frequency</b>	0.06	3095.93	84.85	279.23
<b>Twitter Frequency</b>	0.00	4070.02	77.11	309.32
<b>Newspaper Frequency</b>	0.00	3782.26	78.54	295.09
<b>N-letters</b>	3.00	13.00	6.88	2.03
<b>N-orthographic Neighbours</b>	0.00	23.00	2.52	3.73
<b>OLD20</b>	1.00	5.40	2.06	0.62
<b>Reaction Times (FLP)</b>	515.54	915.85	653.09	62.71
<b>Reaction Times (MEGALEX)</b>	473.48	747.84	549.10	43.01

Note. OLD20: orthographic Levenshtein distance (Yarkoni, Balota, & Yap, 2008); Movie subtitles frequency (from Lexique ; New et al., 2004).

**Table 3.** Descriptive and behavioural data for prime words.

	<i>min</i>	<i>max</i>	<i>M</i>	<i>SD</i>
<b>Movie Subtitles Frequency</b>	0.00	986.59	31.02	81.43
<b>Book Frequency</b>	0.00	835.47	35.36	81.71
<b>Blog Frequency</b>	0.15	2866.60	53.28	150.60
<b>Twitter Frequency</b>	0.07	4070.02	46.79	189.88
<b>Newspaper Frequency</b>	0.00	1556.37	46.37	118.08
<b>N-letters</b>	3.00	14.00	6.99	2.00
<b>N-orthographic Neighbours</b>	0.00	20.00	2.43	3.58
<b>OLD20</b>	1.00	4.55	2.10	0.60
<b>Reaction Times (FLP)</b>	515.54	1005.15	657.94	67.18
<b>Reaction Times (MEGALEX)</b>	473.92	738.03	553.11	44.78

Note. OLD20: orthographic Levenshtein distance (Yarkoni, Balota, & Yap, 2008); Movie subtitles frequency (from Lexique ; New et al., 2004).

Table 2 and 3 display the lexical characteristics for the primes and targets composing our word pairs. The statistics presented in Table 2 and 3 were obtained by cross-referencing our dataset with Lexique (New et al., 2001, 2004, 2007), the French Lexicon Project (Ferrand et al., 2010), Wordlex (Gimenes & New, 2016), and MEGALEX (Ferrand et al., 2018). Movie Subtitles Frequency corresponds to the *freqfilms2* variable from Lexique and refers to word frequency based on movie subtitles. The other frequencies were computed from books (Lexique: New et al., 2004), blog posts, Twitter and Newspapers (Wordlex: Gimenes & New, 2016).

We also computed correlations between semantic similarity for the pair and lexical variables as well as concreteness levels for the prime and target respectively. Such correlations were all non-significant except for the correlation between semantic similarity and concreteness. Indeed, the concreteness level of the prime and target respectively was negatively and moderately correlated to the semantic similarity of the pair ( $R_{\text{prime\_concreteness}} = -0.26$ ;  $R_{\text{target\_concreteness}} = -0.28$ ,  $p < 0.001$ ), suggesting that the higher the semantic similarity, the lower the level of concreteness. However, the mean concreteness is not as different for highly similar pairs ( $M_{\text{concreteness}} = 4.14$ ;

$SD = 1.59$ ) as for less similar pairs ( $M_{\text{concreteness}} = 4.78$ ;  $SD = 1.39$ ). This means researchers using the present database will be able to study phenomena of semantic similarity and their relationship with graded levels of concreteness without having to worry that the concreteness variable and the lexical variables might act as confounding variables.

In addition, we computed correlations between the concreteness variable and other lexical variables. It is clear from Table 4 that the concreteness variable shows a negative correlation to frequencies based on blog posts and Twitter. Such correlations are rather weak ( $r = -0.10$ ), however, and should not be cause for concern as regards potential confounding variables. The concreteness variable is also moderately and negatively correlated with the number of letters and orthographic similarity, but positively correlated with the number of orthographic neighbours. All lexical variables are significantly intercorrelated, a result which replicates previous findings from the psycholinguistic norms literature. Indeed, upon comparing the correlations shown in Table 4 with those reported in MEGALEX (Ferrand et al., 2018), we found that the correlations between lexical variables were similar in size and significance levels, which further validates our dataset. For example, and among the most widely used, word frequencies computed from books are highly correlated to other word frequencies computed from subtitles ( $r=.78$ ), blogposts ( $r=.73$ ), Twitter ( $r=.63$ ) and newspapers ( $r=.68$ , see Table 4).

We computed correlations between our concreteness variable and those collected by Bonin et al. (2018) in French and Brysbaert, Warriner and Kuperman (2014) and Coltheart (1981) in English. Table 5 shows that the correlations are strong and highly significant, ensuring thus the validity of the concreteness variable we collected.

**Table 4.** Correlation matrix between concreteness levels and lexical variables with significance levels (\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ ).

	Concreteness	Movie Subtitles Frequency	Book Frequency	Blog Frequency	Twitter Frequency	Newspaper Frequency	N-letters	N-orthographic neighbours	OLD20
Concreteness	1								
Movie Subtitles Frequency	-0.03	1							
Book Frequency	-0.003	0.78***	1						
Blog Frequency	-0.10**	0.73***	0.73***	1					
Twitter Frequency	-0.10**	0.63***	0.45***	0.87***	1				
Newspaper Frequency	-0.06	0.68***	0.78***	0.89***	0.66***	1			
N-letters	-0.24***	-0.23***	-0.20***	-0.23***	-0.22***	-0.19***	1		
N-orthographic neighbours	0.18***	0.24***	0.24***	0.23***	0.24***	0.19***	-0.59***	1	
OLD20	-0.21***	-0.19***	-0.17***	-0.18***	-0.18***	-0.16***	0.79***	-0.68***	1

**Table 5.** Correlations of the present concreteness variable measures with those provided by other databases.

Language	Study	Correlation with the present study	
		<i>r</i>	<i>N</i>
French	Bonin et al. (2018)	.95	257
English	Coltheart (1981)	.91	1256
English	Brysbaert et al. (2014)	.91	1256

Note. N: number of items in common. All correlations are significant at the  $p < .0001$  level

Finally, to investigate the concreteness variable further, we implemented the package `Ckmeans.1d.dp` in R studio, an unsupervised learning algorithm for clustering univariate data (Wang & Song, 2011). Based on a Bayesian information criterion, the algorithm suggested the concreteness variable be split according to 3 clusters of abstractness, with cluster 1 the most abstract and cluster 3 the least abstract. The cluster variable is particularly important in relation to the previously discussed need to control the concreteness variable when manipulating semantic similarity. It is a variable which will therefore allow experimenters to select stimuli with matching concreteness levels. We have provided the cluster variable in the supplementary material.

#### Availability of the database

The dataset for the present study is available in excel format on the BRM and OSF websites (<https://osf.io/qsd4v/>). The main database is organized according to the following variables: Word Pairs in French, word-pairs translation in English, word-pair mean concreteness, cluster variable based on word-pair mean concreteness, verbal association strength based on the SWOW, and mean pair similarity with associated general statistics (SD, min, max, median, range, skewness, Q1, Q3). The rest of the database is divided according to Prime word and Target word for the following variables: Mean concreteness and associated general statistics, lexical variables (grammatical category, number of letters, phonemes, orthographic and

phonemic neighbours), reaction times (based on FLP and MEGALEX) and frequencies per million (movie subtitles, books, blogs, Twitter and newspapers). The secondary database is organized following the same variables but contains only the 70 word pairs that are semantically similar as well as verbally associated.

## **DISCUSSION**

The present study aimed to produce French norms of semantic similarity for abstract concepts. Based on our statistical analyses, we can provide material with varying levels of semantic similarity. In addition, based on our collection of concreteness ratings and the implementation of the k-means clustering algorithm (Wang & Song, 2011), we organized the semantic pairs according to three clusters of abstractness. Our ultimate aim is for this database to be used to design material for studies such as semantic priming studies and other language-based paradigms (see, for example, Hutchison et al., 2013). The cross-references we computed with previously mentioned lexical databases allow stimuli to be matched on the basis of frequencies and other lexical variables. The analysis based on this cross-referencing also provides information about the potentially confounding variables that could create noise in an experimental design.

The comparison of prime and target words across the concreteness and lexical variables produced highly significant correlations, thus ensuring a good match within each pair. Further comparisons between semantic similarity and lexical variables resulted, however, in either very weak or non-significant correlations. This suggests there is no need to be particularly careful to avoid confounding lexical variables when using the similarity ratings. The strong and significant correlation in concreteness levels within word pairs, along with the cluster variable we introduced were aimed at addressing Crutch and Jackson's (2011) suggestion that discrepancies found when studying the organization of semantic memory according to similarity or association might be due to a binary, rather than graded definition of concreteness

levels. Indeed, when considering the organization of semantic memory at the extremes of concrete vs. abstract concepts, we lose substantial evidence for the concepts in-between these two extremes. This limitation can be addressed by considering graded levels of concreteness. Previous findings have shown that concepts are organized according to semantic similarity when concreteness increases and according to verbal association when abstractness increases.

Finally, we suggest that, when creating materials, researchers pay attention to the moderate but significant correlation between semantic similarity and the concreteness variable, insofar as results have shown that more abstract pairs are also perceived as more similar than concrete pairs.

The aim of this database was also to fill a gap in the French literature regarding norms for abstract concepts. We therefore consider the present work to be a good starting point for developing other French-language databases focusing on abstract concepts such as verbal association.

Indeed, studies using word stimuli tend to focus primarily on pairing stimuli according to word frequency, word length, and age of acquisition. However, such variables fail to capture fully the effect of word processing by the human mind, as best illustrated by the percentage of variance explained in norming studies and megastudies, which stagnates between .20 and .50 (Balota, Yap, Hutchison, Cortese, Kessler, Loftis & Treiman, 2007; Keuleers, Brysbaert & New, 2010; Ferrand, New, Brysbaert, Bonin & Pallier, 2010; Brysbaert, Mandera & Keuleers, 2018). Newly-developed variables have therefore been introduced with a view to capturing more of the word-processing phenomena. For instance, Brysbaert, Mandera, McCormick and Keuleers (2019) introduced the word prevalence variable (the proportion of people who know a particular word), first in Dutch (Brysbaert, Stevens, Mandera, and Keuleers, 2016; Keuleers, Stevens, Mandera, & Brysbaert, 2015), and then in English (Brysbaert et al., 2019). This

variable was shown to explain an additional 6-10 percent of the variance in response latencies in a lexical decision task.

In addition, we consider that most norming studies have focused mainly on concrete concepts, although, as shown by Recchia and Jones (2012), abstract concepts have a richness of their own which warrants further study. For instance, Chedid, Brambati, Bedetti, Rey, Wilson and Vallet (2019) recently introduced a perceptual strength variable for Canadian French, which aims to identify auditory and visual involvement in conceptual knowledge. In addition, the Sensory Experience ratings variable (SER, Juhasz & Yap, 2013; Bonin et al., 2015; 2018) was introduced as a measure of the extent to which a word can elicit sensory and perceptual experiences. The correlation analyses between our concreteness variable and the SER variable based on the 257 items in common is .33. This rather low correlation goes to show that the SER variable cannot capture the same psycholinguistic phenomena as the concreteness variable, thus ensuring the relevance of the latter. We also computed the correlation between our concreteness variable and the Perceptual Strength variable (Chedid, Brambati, Bedetti, Rey, Wilson & Vallet, 2019) and found that  $r=.80$  based on 507 items in common. Although this correlation value appears rather high, it is consistent with the findings of Chedid and colleagues, who reported a correlation value of  $r=.76$  between Perceptual Strength and Bonin and colleagues' concreteness variables. According to Chedid et al. (2019), however, this new variable cannot be regarded as another form of concreteness since it made an independent contribution to the prediction of word latencies in word processing.

Until recently, grounding has mainly been studied in concrete concepts, owing to a previous consensus that abstract concepts are not grounded. However, several studies have shown that abstract concepts can be grounded in perceptual situations and events. In addition, Connell, Lynott and Banks (2018) consider interoception a forgotten modality for abstract concepts and report a facilitation effect of interoceptive strength. Future work will therefore focus on

developing norms that capture these modalities for abstract concepts to further our knowledge about their representation.

## CONCLUSION

The present study aimed to provide French semantic similarity norms for 630 word pairs with varying levels of similarity and associated concreteness. The database is organized in such a way that semantic similarity and concreteness may be used as either continuous or categorical variables. The continuous variables correspond to the ratings we collected, whereas the categorical variables correspond to the cluster variable we computed for concreteness and the median for semantic similarity. The database also provides frequency and lexical variables for matching pairs in stimuli set design. We anticipate that it will be very useful for researchers working on memory and language, especially given the growing interest for studying abstract concepts representation.

### Open Practices Statement

In line with an open data policy, all data discussed in this article are freely available on our web site on the Open Science Framework web site (<https://osf.io/qs4v/>).

## REFERENCES

- Andrews, M., Frank, S., & Vigliocco, G. (2014). Reconciling embodied and distributional accounts of meaning in language. *Topics in Cognitive Science*, *6*, 359–370. <https://doi.org/10.1111/tops.12096>
- Andrews, S., Lo, S., & Xia, V. (2017). Individual differences in automatic semantic priming. *Journal of Experimental Psychology: Human Perception and Performance*, *43*, 1025–1039. <https://doi.org/10.1037/xhp0000372>
- Andrews, M., Vigliocco, G., & Vinson, D. (2009). Integrating experiential and distributional data to learn semantic representations. *Psychological Review*, *116*, 463–498. <https://doi.org/10.1037/a0016261>
- Balota, D. A., Yap, M. J., Cortese, M. J., Hutchison, K. A., Kessler, B., Loftis, B., ... Treiman, R. (2007). The English Lexicon Project. *Behavior Research Methods*. Springer New York LLC. <https://doi.org/10.3758/BF03193014>

- Barsalou, L. W. (1999). Perceptions of perceptual symbols. *Behavioral and Brain Sciences*, 22, 577-660. <https://doi.org/10.1017/S0140525X99532147>
- Barsalou, L. W. (2003). Abstraction in perceptual symbol systems. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 358, 1177-1187. <https://doi.org/10.1098/rstb.2003.1319>
- Barsalou, L. W., Santos, A., Simmons, W.K., & Wilson, C. D. (2008). Language and simulation in conceptual processing. In M. De Vega, A. M. Glenberg, & A. C. Graesser (Eds.), *Symbols embodiment, and meaning* (pp.245-283). Oxford: University Press. <https://doi.org/10.1093/acprof:oso/9780199217274.003.0013>
- Barsalou, L. W., & Wiemer-Hastings, K. (2005). Situating abstract concepts. In D. Pecher & R. Zwaan (Eds.), *Grounding Cognition: The Role of Perception and Action in Memory, Language, and Thinking* (pp. 129-163). New York, NY: Cambridge University Press. <https://doi.org/10.1017/CBO9780511499968.007>
- Berg, T., & Levelt, W. J. M. (1990). Speaking: From intention to articulation. *The American Journal of Psychology*, 103, 409-418. <https://doi.org/10.2307/1423219>
- Binder, J. R., Conant, L. L., Humphries, C. J., Fernandino, L., Simons, S. B., Aguilar, M., & Desai, R. H. (2016). Toward a brain-based componential semantic representation. *Cognitive Neuropsychology*, 33, 130–174. <https://doi.org/10.1080/02643294.2016.1147426>
- Bolognesi, M., Pilgram, R., & van den Heerik, R. (2017). Reliability in content analysis: The case of semantic feature norms classification. *Behavior Research Methods*, 49, 1984–2001. <https://doi.org/10.3758/s13428-016-0838-6>
- Bonin, P., Méot, A., Ferrand, L., & Bugajska, A. (2015). Sensory experience ratings (SERs) for 1,659 French words: Relationships with other psycholinguistic variables and visual word recognition. *Behavior Research Methods*, 47, 813–825. <https://doi.org/10.3758/s13428-014-0503-x>
- Bonin, P., Méot, A., & Bugajska, A. (2018). Concreteness norms for 1,659 French words: Relationships with other psycholinguistic variables and word recognition times. *Behavior Research Methods*, 50, 2366–2387. <https://doi.org/10.3758/s13428-018-1014-y>
- Borghi, A. M., Barca, L., Binkofski, F., Castelfranchi, C., Pezzulo, G., & Tummolini, L. (2019). Words as social tools: Language, sociality and inner grounding in abstract concepts. *Physics of Life Reviews*, 29, 120–153. <https://doi.org/10.1016/j.plrev.2018.12.001>
- Borghi, A. M., Binkofski, F., Castelfranchi, C., Cimatti, F., Scorolli, C., & Tummolini, L. (2017). The challenge of abstract concepts. *Psychological Bulletin*, 143, 263–292. <https://doi.org/10.1037/bul0000089>
- Borghi, A. M., & Pecher, D. (2011). Introduction to the special topic embodied and grounded cognition. *Frontiers in Psychology*, 2. <https://doi.org/10.3389/fpsyg.2011.00187>
- Borghi, A. M., Scorolli, C., Caligiore, D., Baldassarre, G., & Tummolini, L. (2013). The embodied mind extended: Using words as social tools. *Frontiers in Psychology*, 4. <https://doi.org/10.3389/fpsyg.2013.00214>
- Bruni, E., Tran, N. K., & Baroni, M. (2014). Multimodal distributional semantics. *Journal of Artificial Intelligence Research*, 49, 1–47. <https://doi.org/10.1613/jair.4135>
- Brysbaert, M., Mandera, P., & Keuleers, E. (2018). The word frequency effect in word processing: An updated review. *Current Directions in Psychological Science*, 27, 45–50. <https://doi.org/10.1177/0963721417727521>
- Brysbaert, M., Mandera, P., McCormick, S. F., & Keuleers, E. (2019). Word prevalence norms for 62,000 English lemmas. *Behavior Research Methods*, 51, 467–479. <https://doi.org/10.3758/s13428-018-1077-9>

- Brysbaert, M., Stevens, M., Mander, P., & Keuleers, E. (2016). How many words do we know? Practical estimates of vocabulary size dependent on word definition, the degree of language input and the participant's age. *Frontiers in Psychology, 7*.  
<https://doi.org/10.3389/fpsyg.2016.01116>
- Brysbaert, M., Warriner, A. B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand generally known English word lemmas. *Behavior Research Methods, 46*, 904–911.  
<https://doi.org/10.3758/s13428-013-0403-5>
- Buchanan, E. M., Holmes, J. L., Teasley, M. L., & Hutchison, K. A. (2013). English semantic word-pair norms and a searchable Web portal for experimental stimulus creation. *Behavior Research Methods, 45*, 746–757. <https://doi.org/10.3758/s13428-012-0284-z>
- Buchanan, E. M., Valentine, K. D., & Maxwell, N. P. (2019). English semantic feature production norms: An extended database of 4436 concepts. *Behavior Research Methods, 51*, 1849–1863. <https://doi.org/10.3758/s13428-019-01243-z>
- Carota, F., Kriegeskorte, N., Nili, H., & Pulvermüller, F. (2017). Representational similarity mapping of distributional semantics in left inferior frontal, middle temporal, and motor cortex. *Cerebral Cortex, 27*, 294–309. <https://doi.org/10.1093/cercor/bhw379>
- Chedid, G., Brambati, S. M., Bedetti, C., Rey, A. E., Wilson, M. A., & Vallet, G. T. (2019). Visual and auditory perceptual strength norms for 3,596 French nouns and their relationship with other psycholinguistic variables. *Behavior Research Methods, 51*, 2094–2105. <https://doi.org/10.3758/s13428-019-01254-w>
- Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review, 82*, 407–428. <https://doi.org/10.1037/0033-295X.82.6.407>
- Coltheart, M. (1981). The MRC psycholinguistic database. *The Quarterly Journal of Experimental Psychology Section A, 33*, 497–505.  
<https://doi.org/10.1080/14640748108400805>
- Connell, L., Lynott, D., & Banks, B. (2018). Interoception: The forgotten modality in perceptual grounding of abstract and concrete concepts. *Philosophical Transactions of the Royal Society B: Biological Sciences, 373*. <https://doi.org/10.1098/rstb.2017.0143>
- Cree, G. S., McRae, K., & McNorgan, C. (1999). An attractor model of lexical conceptual processing: Simulating semantic priming. *Cognitive Science, 23*, 371–414.  
[https://doi.org/10.1207/s15516709cog2303\\_4](https://doi.org/10.1207/s15516709cog2303_4)
- Crutch, S. J. (2005). Abstract and concrete concepts have structurally different representational frameworks. *Brain, 128*, 615–627. <https://doi.org/10.1093/brain/awh349>
- Crutch, S. J., Connell, S., & Warrington, E. K. (2009). The different representational frameworks underpinning abstract and concrete knowledge: evidence from odd-one-out judgements. *Quarterly Journal of Experimental Psychology, 62*, 1377–1388, 1388–1390.  
<https://doi.org/10.1080/17470210802483834>
- Crutch, S. J., & Jackson, E. C. (2011). Contrasting graded effects of semantic similarity and association across the concreteness spectrum. *Quarterly Journal of Experimental Psychology, 64*, 1388–1408. <https://doi.org/10.1080/17470218.2010.543285>
- Crutch, S. J., & Warrington, E. K. (2010). The differential dependence of abstract and concrete words upon associative and similarity-based information: Complementary semantic interference and facilitation effects. *Cognitive Neuropsychology, 27*, 46–71.  
<https://doi.org/10.1080/02643294.2010.491359>
- De Deyne, S., Navarro, D. J., Perfors, A., Brysbaert, M., & Storms, G. (2019). The “Small World of Words” English word association norms for over 12,000 cue words. *Behavior Research Methods, 51*, 987–1006. <https://doi.org/10.3758/s13428-018-1115-7>
- De Deyne, S., & Storms, G. (2008). Word associations: Norms for 1,424 Dutch words in a continuous task. *Behavior Research Methods, 40*, 198–205.  
<https://doi.org/10.3758/BRM.40.1.198>

- De Deyne, S., Verheyen, S., Ameel, E., Vanpaemel, W., Dry, M. J., Voorspoels, W., & Storms, G. (2008). Exemplar by feature applicability matrices and other Dutch normative data for semantic concepts. *Behavior Research Methods*, *40*, 1030–1048. <https://doi.org/10.3758/BRM.40.4.1030>
- Della Rosa, P. A., Catricalà, E., Vigliocco, G., & Cappa, S. F. (2010). Beyond the abstract-concrete dichotomy: Mode of acquisition, concreteness, imageability, familiarity, age of acquisition, context availability, and abstractness norms for a set of 417 Italian words. *Behavior Research Methods*, *42*, 1042–1048. <https://doi.org/10.3758/BRM.42.4.1042>
- Devereux, B. J., Tyler, L. K., Geertzen, J., & Randall, B. (2014). The Centre for Speech, Language and the Brain (CSLB) concept property norms. *Behavior Research Methods*, *46*, 1119–1127. <https://doi.org/10.3758/s13428-013-0420-4>
- Dove, G. (2009). Beyond perceptual symbols: A call for representational pluralism. *Cognition*, *110*, 412–431. <https://doi.org/10.1016/j.cognition.2008.11.016>
- Dove, G. (2011). On the need for embodied and dis-embodied cognition. *Frontiers in Psychology*, *1*. <https://doi.org/10.3389/fpsyg.2010.00242>
- Dove, G. (2014). Thinking in words: Language as an embodied medium of thought. *Topics in Cognitive Science*, *6*, 371–389. <https://doi.org/10.1111/tops.12102>
- Duñabeitia, J. A., Avilés, A., Afonso, O., Scheepers, C., & Carreiras, M. (2009). Qualitative differences in the representation of abstract versus concrete words: Evidence from the visual-world paradigm. *Cognition*, *110*, 284–292. <https://doi.org/10.1016/j.cognition.2008.11.012>
- Ferrand, L. (2001). Normes d'associations verbales pour 260 mots « abstraits » [Word association norms for 260 “abstract” words]. *L'Année Psychologique*, *101*, 683–721. <https://doi.org/10.3406/psy.2001.29575>
- Ferrand, L., & Alario, F. X. (1998). Word association norms for 366 names of objects. [Word association norms for 366 concrete objects words]. *L'Année Psychologique*, *98*, 659–709. <https://doi.org/10.3406/psy.1998.28564>
- Ferrand, L., Méot, A., Spinelli, E., New, B., Pallier, C., Bonin, P., ... Grainger, J. (2018). MEGALEX: A megastudy of visual and auditory word recognition. *Behavior Research Methods*, *50*, 1285–1307. <https://doi.org/10.3758/s13428-017-0943-1>
- Ferrand, L., & New, B. (2003). Associative and semantic priming in the mental lexicon. In P. Bonin (Ed.), *The mental lexicon: Some words to talk about words* (pp. 25–43). New York: Nova Science Publishers.
- Ferrand, L., New, B., Brysbaert, M., Keuleers, E., Bonin, P., Méot, A., ... Pallier, C. (2010). The French Lexicon Project: Lexical decision data for 38,840 French words and 38,840 pseudo words. *Behavior Research Methods*, *42*, 488–496. <https://doi.org/10.3758/BRM.42.2.488>
- Ferré, P., Guasch, M., García-Chico, T., & Sánchez-Casas, R. (2015). Are there qualitative differences in the representation of abstract and concrete words? Within-language and cross-language evidence from the semantic priming paradigm. *Quarterly Journal of Experimental Psychology*, *68*, 2402–2418. <https://doi.org/10.1080/17470218.2015.1016980>
- Ferretti, T. R., McRae, K., & Hatherell, A. (2001). Integrating verbs, situation schemas, and thematic role concepts. *Journal of Memory and Language*, *44*, 516–547. <https://doi.org/10.1006/jmla.2000.2728>
- Firth, J. R. (1957). Applications of general linguistics. *Transactions of the Philological Society*, *56*, 1–14. <https://doi.org/10.1111/j.1467-968X.1957.tb00568.x>
- Fodor, J. A., Garrett, M. F., Walker, E. C. T., & Parkes, C. H. (1980). Against definitions. *Cognition*, *8*, 263–367. [https://doi.org/10.1016/0010-0277\(80\)90008-6](https://doi.org/10.1016/0010-0277(80)90008-6)

- Gallese, V., & Lakoff, G. (2005). The brain's concepts: The role of the sensory-motor system in conceptual knowledge. *Cognitive Neuropsychology*, *22*, 455-479. <https://doi.org/10.1080/02643290442000310>
- Geng, J., & Schnur, T. T. (2015). The representation of concrete and abstract concepts: Categorical versus associative relationships. *Journal of Experimental Psychology: Learning Memory and Cognition*, *41*, 22-41. <https://doi.org/10.1037/a0037430>
- Gimenes, M., & New, B. (2016). Worldlex: Twitter and blog word frequencies for 66 languages. *Behavior Research Methods*, *48*, 963-972. <https://doi.org/10.3758/s13428-015-0621-0>
- Glenberg, A. M. (1997). Mental models, space, and embodied cognition. In T. B. Ward & S. M. Smith (Eds.), *Creative thought: An investigation of conceptual structures and processes* (pp. 495-522). Washington, DC: American Psychological Association.
- Glenberg, A. M., & Kaschak, M. P. (2002). Grounding language in action. *Psychonomic Bulletin and Review*, *9*, 558-565. <https://doi.org/10.3758/BF03196313>
- Griffiths, T. L., Steyvers, M., & Tenenbaum, J. B. (2007). Topics in semantic representation. *Psychological Review*, *114*, 211-244. <https://doi.org/10.1037/0033-295X.114.2.211>
- Hamilton, A. C., & Coslett, H. B. (2008). Refractory access disorders and the organization of concrete and abstract semantics: Do they differ? *Neurocase*, *14*, 131-140. <https://doi.org/10.1080/13554790802032218>
- Harpaintner, M., Trumpp, N. M., & Kiefer, M. (2018). The semantic content of abstract concepts: A property listing study of 296 abstract words. *Frontiers in Psychology*, *9*. <https://doi.org/10.3389/fpsyg.2018.01748>
- Harris, Z. S. (1954). Distributional Structure. *Distributional Structure, Word*, *10*, 146-162. <https://doi.org/10.1080/00437956.1954.11659520>
- Hoffman, P., McClelland, J. L., & Lambon Ralph, M. A. (2018). Concepts, control, and context: A connectionist account of normal and disordered semantic cognition. *Psychological Review*, *125*, 293-328. <https://doi.org/10.1037/rev0000094>
- Hutchison, K. A. (2003). Is semantic priming due to association strength or feature overlap? A microanalytic review. *Psychonomic Bulletin and Review*, *10*, 785-813. <https://doi.org/10.3758/BF03196544>
- Hutchison, K. A., Balota, D. A., Cortese, M. J., & Watson, J. M. (2008). Predicting semantic priming at the item level. *Quarterly Journal of Experimental Psychology*, *61*, 1036-1066. <https://doi.org/10.1080/17470210701438111>
- Hutchison, K. A., Balota, D. A., Neely, J. H., Cortese, M. J., Cohen-Shikora, E. R., Tse, C. S., ... Buchanan, E. (2013). The semantic priming project. *Behavior Research Methods*, *45*, 1099-1114. <https://doi.org/10.3758/s13428-012-0304-z>
- Juhasz, B. J., & Yap, M. J. (2013). Sensory experience ratings for over 5,000 mono- and disyllabic words. *Behavior Research Methods*, *45*, 160-168. <https://doi.org/10.3758/s13428-012-0242-9>
- Keuleers, E., Brysbaert, M., & New, B. (2010). SUBTLEX-NL: A new measure for Dutch word frequency based on film subtitles. *Behavior Research Methods*, *42*, 643-650. <https://doi.org/10.3758/BRM.42.3.643>
- Keuleers, E., Stevens, M., Mandera, P., & Brysbaert, M. (2015). Word knowledge in the crowd: Measuring vocabulary size and word prevalence in a massive online experiment. *Quarterly Journal of Experimental Psychology*, *68*, 1665-1692. <https://doi.org/10.1080/17470218.2015.1022560>
- Kiefer, M., & Pulvermüller, F. (2012). Conceptual representations in mind and brain: Theoretical developments, current evidence and future directions. *Cortex*, *48*, 805-825. <https://doi.org/10.1016/j.cortex.2011.04.006>

- Kim, S. Y., Yap, M. J., & Goh, W. D. (2019). The role of semantic transparency in visual word recognition of compound words: A megastudy approach. *Behavior Research Methods*, *51*, 2722–2732. <https://doi.org/10.3758/s13428-018-1143-3>
- Kintsch, W., McNamara, D. S., Dennis, S., Landauer, T. K., McNamara, D. S., Dennis, S., & Landauer, T. K. (2007). LSA and meaning: in theory and application, 479–492. <https://doi.org/10.4324/9780203936399-32>
- Kousta, S. T., Vigliocco, G., Vinson, D. P., Andrews, M., & Del Campo, E. (2011). The representation of abstract words: Why emotion matters. *Journal of Experimental Psychology: General*, *140*, 14–34. <https://doi.org/10.1037/a0021446>
- Kremer, G., & Baroni, M. (2011). A set of semantic norms for German and Italian. *Behavior Research Methods*, *43*, 97–109. <https://doi.org/10.3758/s13428-010-0028-x>
- Lakoff, G., & Johnson, M. (1980). Conceptual metaphor in everyday language. *The Journal of Philosophy*, *77*, 453. <https://doi.org/10.2307/2025464>
- Landauer, T. K., & Dumais, S. T. (1997). A solution to Plato's problem: The Latent Semantic Analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review*, *104*, 211–240. <https://doi.org/10.1037/0033-295X.104.2.211>
- Lebani, G. E., Bondielli, A., & Lenci, A. (2015). You are what you do: An empirical characterization of the semantic content of the thematic roles for a group of Italian verbs. *Journal of Cognitive Science*, *16*, 399–428.
- Lenci, A. (2008). Distributional semantics in linguistic and cognitive research. *Italian Journal of Linguistics*, *20*, 1–31.
- Lenci, A. (2018). Distributional models of word meaning. *Annual Review of Linguistics*, *4*, 151–171. <https://doi.org/10.1146/annurev-linguistics-030514-125254>
- Lenci, A., Baroni, M., Cazzolli, G., & Marotta, G. (2013). BLIND: A set of semantic feature norms from the congenitally blind. *Behavior Research Methods*, *45*, 1218–1233. <https://doi.org/10.3758/s13428-013-0323-4>
- Lenci, A., Lebani, G. E., & Passaro, L. C. (2018). The emotions of abstract words: A distributional semantic analysis. *Topics in Cognitive Science*, *10*, 550–572. <https://doi.org/10.1111/tops.12335>
- Levelt, W. J. M., Roelofs, A., & Meyer, S. (1999). A theory of lexical access in speech production. *Behavioral and Brain Sciences*, *22*, 1–38. <https://doi.org/10.1017/s0140525x99001776>
- Louwerse, M. M. (2008). Embodied relations are encoded in language. *Psychonomic Bulletin and Review*, *15*, 838–844. <https://doi.org/10.3758/PBR.15.4.838>
- Louwerse, M. M. (2011). Symbol interdependency in symbolic and embodied cognition. *Topics in Cognitive Science*, *3*, 273–302. <https://doi.org/10.1111/j.1756-8765.2010.01106.x>
- Louwerse, M., & Jeuniaux, P. (2008). Language comprehension is both embodied and symbolic. In *Symbols and Embodiment Debates on meaning and cognition* (pp. 309–326). Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199217274.003.0015>
- Louwerse, M. M., & Jeuniaux, P. (2010). The linguistic and embodied nature of conceptual processing. *Cognition*, *114*, 96–104. <https://doi.org/10.1016/j.cognition.2009.09.002>
- Lund, K., & Burgess, C. (1996). Producing high-dimensional semantic spaces from lexical co-occurrence. *Behavior Research Methods, Instruments, & Computers*, *28*, 203–208.
- Machery, E. (2016). The amodal brain and the offloading hypothesis. *Psychonomic Bulletin and Review*, *23*, 1090–1095. <https://doi.org/10.3758/s13423-015-0878-4>
- Mahon, B. Z., & Caramazza, A. (2008). A critical look at the embodied cognition hypothesis and a new proposal for grounding conceptual content. *Journal of Physiology-Paris*, *102*, 59–70. <https://doi.org/10.1016/j.jphysparis.2008.03.004>

- Maki, W. S., Krinsky, M., & Muñoz, S. (2006). An efficient method for estimating semantic similarity based on feature overlap: Reliability and validity of semantic feature ratings. *Behavior Research Methods, 38*, 153–157. <https://doi.org/10.3758/BF03192761>
- Mandera, P., Keuleers, E., & Brysbaert, M. (2017). Explaining human performance in psycholinguistic tasks with models of semantic similarity based on prediction and counting: A review and empirical validation. *Journal of Memory and Language, 92*, 57–78. <https://doi.org/10.1016/j.jml.2016.04.001>
- Mate, J., Allen, R. J., & Baqués, J. (2012). What you say matters: exploring visual-verbal interactions in visual working memory. *Quarterly Journal of Experimental Psychology, 65*, 395–400. <https://doi.org/10.1080/17470218.2011.644798>
- McNamara, T. P. (1992). Theories of Priming: I. Associative Distance and Lag. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18*, 1173–1190. <https://doi.org/10.1037/0278-7393.18.6.1173>
- McRae, K., & Boisvert, S. (1998). Automatic semantic similarity priming. *Journal of Experimental Psychology: Learning Memory and Cognition, 24*, 558–572. <https://doi.org/10.1037/0278-7393.24.3.558>
- McRae, K., Cree, G. S., Seidenberg, M. S., & McNorgan, C. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behavior Research Methods, 37*, 547–559. <https://doi.org/10.3758/BF03192726>
- McRae, K., De Sa, V. R., & Seidenberg, M. S. (1997). On the nature and scope of featural representations of word meaning. *Journal of Experimental Psychology: General, 126*, 99–130. <https://doi.org/10.1037/0096-3445.126.2.99>
- Meteyard, L., Cuadrado, S. R., Bahrami, B., & Vigliocco, G. (2012). Coming of age: A review of embodiment and the neuroscience of semantics. *Cortex, 48*, 788–804. <https://doi.org/10.1016/j.cortex.2010.11.002>
- Meyer, D. E., & Schvaneveldt, R. W. (1971). Facilitation in recognizing pairs of words: Evidence of a dependence between retrieval operations. *Journal of Experimental Psychology, 90*, 227–234. <https://doi.org/10.1037/h0031564>
- Moldovan, C. D., Ferré, P., Demestre, J., & Sánchez-Casas, R. (2015). Semantic similarity: normative ratings for 185 Spanish noun triplets. *Behavior Research Methods, 47*, 788–799. <https://doi.org/10.3758/s13428-014-0501-z>
- New, B., Brysbaert, M., Veronis, J., & Pallier, C. (2007). The use of film subtitles to estimate word frequencies. *Applied Psycholinguistics, 28*, 661–677. <https://doi.org/10.1017/S014271640707035X>
- New, B., Ferrand, L., Pallier, C., & Brysbaert, M. (2006). Reexamining the word length effect in visual word recognition: New evidence from the English Lexicon Project. *Psychonomic Bulletin and Review, 13*, 45–52. <https://doi.org/10.3758/BF03193811>
- New, B., Pallier, C., Brysbaert, M., & Ferrand, L. (2004). Lexique 2: A new French lexical database. *Behavior Research Methods, Instruments, and Computers, 36*, 516–524. <https://doi.org/10.3758/BF03195598>
- New, B., Pallier, C., Ferrand, L., & Matos, R. (2001). A lexical database for contemporary French on Internet : LEXIQUE. *L'Année Psychologique, 101*, 447–462. <https://doi.org/10.3406/psy.2001.1341>
- Nishiyama, R. (2013). Dissociative contributions of semantic and lexical-phonological information to immediate recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 39*, 642–648. <https://doi.org/10.1037/a0029160>
- Oliveira, J., Perea, M. V., Ladera, V., & Gamito, P. (2013). The roles of word concreteness and cognitive load on interhemispheric processes of recognition. *Laterality, 18*, 203–215. <https://doi.org/10.1080/1357650X.2011.649758>

- Ostarek, M., & Huettig, F. (2019). Six challenges for embodiment research. *Current Directions in Psychological Science*, 28, 593–599. <https://doi.org/10.1177/0963721419866441>
- Paivio, A., Yuille, J. C., & Madigan, S. A. (1968). Concreteness, imagery, and meaningfulness values for 925 nouns. *Journal of Experimental Psychology*, 76, 1–25. <https://doi.org/10.1037/h0025327>
- Pecher, D. (2018). Curb your embodiment. *Topics in Cognitive Science*, 10, 501–517. <https://doi.org/10.1111/tops.12311>
- Perea, M., & Rosa, E. (2002). The effects of associative and semantic priming in the lexical decision task. *Psychological Research*, 66, 180–194. <https://doi.org/10.1007/s00426-002-0086-5>
- Plaut, D. C. (1995). Semantic and associative priming in a distributed attractor network. In Cognitive Science Society (Ed.), *Proceedings of the Seventeenth Annual Conference of the Cognitive Science Society* (pp. 37–42). Hillsdale, NJ: Erlbaum
- Plaut, D. C., & Booth, J. R. (2000). Individual and developmental differences in semantic priming: Empirical and computational support for a single-mechanism account of lexical processing. *Psychological Review*, 107, 786–823. <https://doi.org/10.1037/0033-295X.107.4.786>
- Pulvermüller, F. (2013). How neurons make meaning: Brain mechanisms for embodied and abstract-symbolic semantics. *Trends in Cognitive Sciences*, 17, 458–470. <https://doi.org/10.1016/j.tics.2013.06.004>
- Pulvermüller, F., Shtyrov, Y., & Ilmoniemi, R. (2005). Brain signatures of meaning access in action word recognition. *Journal of Cognitive Neuroscience*, 17, 884–892. <https://doi.org/10.1162/0898929054021111>
- Qualtrics (2020) Qualtrics.com. Available at: <http://www.qualtrics.com/>
- Recchia, G., & Jones, M. N. (2012). The semantic richness of abstract concepts. *Frontiers in Human Neuroscience*, 6. <https://doi.org/10.3389/fnhum.2012.00315>
- Roelofs, A. (1997). The WEAVER model of word-form encoding in speech production. *Cognition*, 64, 249–284. [https://doi.org/10.1016/S0010-0277\(97\)00027-9](https://doi.org/10.1016/S0010-0277(97)00027-9)
- Rogers, T. T., & McClelland, J. L. (2004). *Semantic cognition: A parallel distributed processing approach*. Cambridge, MA: MIT Press.
- Sánchez-Casas, R., Ferré, P., García-Albea, J. E., & Guasch, M. (2006). The nature of semantic priming: Effects of the degree of semantic similarity between primes and targets in Spanish. *European Journal of Cognitive Psychology*, 18, 161–184. <https://doi.org/10.1080/09541440500183830>
- Schwanenflugel, P. J., Harnishfeger, K. K., & Stowe, R. W. (1988). Context availability and lexical decisions for abstract and concrete words. *Journal of Memory and Language*, 27, 499–520. [https://doi.org/10.1016/0749-596X\(88\)90022-8](https://doi.org/10.1016/0749-596X(88)90022-8)
- Smith, E. E., Shoben, E. J., & Rips, L. J. (1974). Structure and process in semantic memory: A featural model for semantic decisions. *Psychological Review*, 81, 214–241. <https://doi.org/10.1037/h0036351>
- Sperber, A. D., Devellis, R. F., & Boehlecke, B. (1994). Cross-cultural translation. *Journal of Cross-Cultural Psychology*, 25, 501–524. <https://doi.org/10.1177/0022022194254006>
- Vigliocco, G., Meteyard, L., Andrews, M., & Kousta, S. (2009). Toward a theory of semantic representation. *Language and Cognition*, 1, 219–247. <https://doi.org/10.1515/langcog.2009.011>
- Vigliocco, G., Vinson, D. P., Lewis, W., & Garrett, M. F. (2004). Representing the meanings of object and action words: The featural and unitary semantic space hypothesis. *Cognitive Psychology*, 48, 422–488. <https://doi.org/10.1016/j.cogpsych.2003.09.001>

- Vigliocco, G., & Vinson, D. P. (2007). Semantic representation. In G. Gaskell & G. Altmann (Eds.), *The Oxford handbook of psycholinguistics* (pp. 195–215). Oxford, England: Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780198568971.013.0012>
- Villani, C., Lugli, L., Liuzza, M. T., & Borghi, A. M. (2019). Varieties of abstract concepts and their multiple dimensions. *Language and Cognition, 11*, 403–430. <https://doi.org/10.1017/langcog.2019.23>
- Vinson, D. P., & Vigliocco, G. (2008). Semantic feature production norms for a large set of objects and events. *Behavior Research Methods, 40*, 183–190. <https://doi.org/10.3758/BRM.40.1.183>
- Vivas, J., Vivas, L., Comesaña, A., Coni, A. G., & Vorano, A. (2017). Spanish semantic feature production norms for 400 concrete concepts. *Behavior Research Methods, 49*, 1095–1106. <https://doi.org/10.3758/s13428-016-0777-2>
- Wiemer-Hastings, K., & Xu, X. (2005). Content differences for abstract and concrete concepts. *Cognitive Science, 29*, 719–736. [https://doi.org/10.1207/s15516709cog0000\\_33](https://doi.org/10.1207/s15516709cog0000_33)
- Wang, H. & Song, M. (2011). Ckmeans.1d.dp: optimal k-means clustering in one dimension by dynamic programming. *R Journal, 3*, 29–33.
- Wu, L., & Barsalou, L. W. (2009). Perceptual simulation in conceptual combination: Evidence from property generation. *Acta Psychologica, 132*, 173–189. <https://doi.org/10.1016/j.actpsy.2009.02.002>
- Yap, M. J., & Balota, D. A. (2009). Visual word recognition of multisyllabic words. *Journal of Memory and Language, 60*, 502–529. <https://doi.org/10.1016/j.jml.2009.02.001>
- Yarkoni, T., Balota, D., & Yap, M. (2008). Moving beyond Coltheart's N: A new measure of orthographic similarity. *Psychonomic Bulletin and Review, 15*, 971–979. <https://doi.org/10.3758/PBR.15.5.971>
- Zwaan, R. A. (2004). The immersed experienter: Toward an embodied theory of language comprehension. *Psychology of Learning and Motivation - Advances in Research and Theory, 44*, 35–62. [https://doi.org/10.1016/S0079-7421\(03\)44002-4](https://doi.org/10.1016/S0079-7421(03)44002-4)

The previous chapter was intended to bridge the gap in the French literature as regards to the availability of semantically similar pairs for abstract concepts. As such, it proposed the first French database composed of abstract semantically similar pairs of concepts. The database also included a concreteness variable in order to answer the suggestion of Crutch and Warrington (2011) about a difference in the organisation of the mental lexicon in terms of semantic similarity and verbal association for concrete and abstract concepts respectively. In addition, previous findings have established the need to systematically differentiate between these two major types of relationships (McRae & Boisvert, 1998). Ferrand and New (2003) have applied this strict distinction between semantic similarity and verbal association by using pairs of concepts that were semantically similar but not verbally associated and obtained a pure semantic effect in a priming experiment. These results illustrate the need to have access to controlled stimuli and to provide the ability to researchers to check the link between chosen materials. In order to address such a need, the next chapter introduces a database for word associations between concepts using the same words as in the previous database. Users will be able to craft materials that is controlled on both the semantically similar and associative dimensions.

The amount of data generated by the word association task allowed for the use of techniques borrowed from distributional statistics from which a vocabulary growth curve was plotted. Correlation analyses revealed that cue words presented to the participants elicited response words of a similar level of concreteness meaning that concepts are organised in the mental lexicon according to a gradient of concreteness. Analyses from associative strength have shown that concrete concepts elicited stronger associations compared to abstract concepts. Finally, association frequencies were computed to predict semantic processing and showed that the more salient a word is in the mental lexicon, the less time it takes to be processed. The entire database is available on OSF.

## Chapter 3. Word associations norms for 1,100 French words with varying levels of concreteness

Dounia Lakhzoum, Marie Izaute, and Ludovic Ferrand

**Chapter 3 was submitted as:** Lakhzoum, D., Izaute, M., & Ferrand, L. (submitted). Word associations norms for 1,100 French words with varying levels of concreteness. *Journal of Psycholinguistic Research*.

Supplementary material: <https://osf.io/dhuqs/>

Université Clermont Auvergne, CNRS, LAPSCO, F-63001 Clermont-Ferrand, France

**Corresponding author:** Dounia Lakhzoum or Ludovic Ferrand, Université Clermont Auvergne, CNRS LAPSCO, 34 avenue Carnot TSA 60401- 63001 Clermont-Ferrand Cedex 1, France

Phone: + 33 4 73 40 62 57 – Fax: + 33 4 73 40 64 82

Email: [dounia.lakhzoum@uca.fr](mailto:dounia.lakhzoum@uca.fr) ; [ludovic.ferrand@uca.fr](mailto:ludovic.ferrand@uca.fr)

Author's note

This research was financed by the French government IDEX-ISITE initiative 16-IDEX-0001 (CAP 20-25).

ACKNOWLEDGMENT

This work was sponsored by a public grant overseen by the French National Research Agency as part of the “Investissements d’Avenir” through the IDEX-ISITE initiative CAP 20-25 (ANR-16-IDEX-0001).

## **ABSTRACT**

The organization of concepts in the mental lexicon is a widely studied phenomenon in experimental psychology. For instance, several studies have shown that whereas concrete concepts are organized according to semantic similarity, abstract concepts are organized according to verbal association. However, these results are not systematically replicated, mainly because there is no normative database for studying the phenomenon. This is particularly true for the French language. To that end, we compiled a French word association database of 1 100 cues with varying levels of concreteness from abstract to concrete concepts. First results revealed stronger association strength for concrete concepts than abstract concepts, confirming the existence of different organisation patterns, with concrete concepts more closely connected to a small number of contexts while abstract concepts are more loosely connected to a high number of varied contexts. Additional results revealed that cues and responses were organised according to a concreteness and perceptual strength gradient. These results provide insights into the rules governing organisation of the mental lexicon. The full data are available in the supplementary materials as well as on OSF (<https://osf.io/dhuqs/>).

**Keywords:** Word association norms, Concreteness, Normative ratings, French words.

## INTRODUCTION

Psycholinguistic experiments rely on normative stimuli. Two types of norms have a long tradition in the field: semantic similarity and word association norms. Semantic similarity refers to the overlap between the defining features of concepts (for example <bee> and <wasp> are semantically similar). In the case of word associations, two words are considered associates when they frequently occur together across language (for example <bee> and <honey> are verbal associates; McNamara, 1992; Plaut, 1995; Ferrand & Alario, 1998).

### **Semantic and associative priming**

The development of datasets addresses the crucial need to access carefully crafted material when studying cognitive phenomena such as free recall (Nelson, McEvoy & Schreiber, 2004), age-related lexical access (Taconnat et al., 2009), metamemory (Eakin, 2005; Bugajska, Morson, Moulin & Souchay, 2011; West & Mulligan, 2019), or clinical pathologies such as schizophrenia (Kircher, Whitney, Krings, Huber & Weis, 2008) and semantic refractory access dysphasia (Crutch & Warrington, 2005).

For language study in particular, the importance of strictly differentiating between associative and semantic relations when studying the mental lexicon has long been established (McRae & Boisvert, 1998; Perea & Rosa, 2002; Thompson-Schill, Kurtz, & Gabrieli, 1998; Lucas, 2000; Hutchison, 2003; Ferrand & New, 2003). The semantic priming effect is one of the most robust effects for studying the mental lexicon. Historically, at least two types of major lexical relations have been used in psycholinguistic experiments, associative and semantic relations, occasionally with some overlaps between relation types (for example <cat> and <dog> are semantically similar but also verbal associates). As a result, several discrepancies have been reported in the literature as regards semantic and associative-priming effects (see, for example, Thompson-Schill et al., 1998, but also Hutchison, 2003). McRae

and Boisvert (1998) suggested we use semantically similar pairs that are not associates (for example <whale> and <dolphin>). On the basis of this suggestion, Ferrand and New (2003) obtained a pure semantic priming effect by using stimuli that were semantically similar while controlling for verbal association (e.g., <dolphin> and <whale>). Conversely, they were able to obtain a pure associative priming effect by using strongly associated stimuli with no semantic similarity (e.g., <spider> and <web>). Hence, researchers rely heavily on word association norms either to select associated word pairs or to check that semantically similar pairs are not also verbally associated. This robustness of semantic and associative priming reported in the literature reflects how the mental lexicon is organised. More recently, the debate on the nature of what is measured by associations and similarity has evolved to include distributional semantic models derived from co-occurrences compared to word association models (Schloss & Li, 2016). Recent evidence has shown that word associations collected from human participants usually outperform text models (De Deyne, Verheyen & Storms, 2016; Van Rensbergen et al., 2016; Vankrunkelsven et al., 2018). This addition to the debate also served to re-establish the place of word associations as a way of studying psychological meaning rather than as just a tool for creating only semantically similar pairs. Recent studies have shown, for instance, how it is possible to compute cosine similarity based on word-association data (see De Deyne, Navarro, Perfors, Brysbaert & Storms, 2019 for an example). With the introduction of algorithms based on distributional statistics, the frontier between associative strength and semantic similarity is no longer needed. To focus exclusively on the two aforementioned modes of organisation of the mental lexicon would not provide as full a picture, however, as recent studies on concreteness have shown.

### **Concreteness and organisation of the mental lexicon**

Recent studies have shown that concreteness must be taken into account in addition to association strength and semantic similarity in order to have a fuller picture of how the mental

lexicon is organised. Crutch and colleagues (2005; Crutch, Connell & Warrington, 2009; Crutch and Warrington, 2010) reported a case study of a patient with symptoms of semantic refractory access dysphasia. They found that, for this patient, concrete concepts elicited only a semantic priming effect and no associative priming effect, whereas abstract concepts elicited the opposite pattern. This finding suggests that while concrete concepts are organised according to semantic similarity, abstract concepts are organized according to verbal association. Several studies tried to replicate this pattern with discrepancies (e.g., Hamilton & Coslett, 2008; Duñabeitia, Avilés, Afonso, Scheepers & Carreiras, 2009; Geng & Schnur, 2015). Crutch and Jackson (2011) suggested the disparities might be due to how the concreteness variable was operationalised. In two semantic odd-one-out judgement and matching-to-sample paradigms, they used triplets of low, middle and high levels of concreteness. Results showed that the semantic effect increased with concreteness while the associative effect decreased. Furthermore, they suggested that concreteness be used as a graded variable rather than a binary one, especially when studying its effect on the organisation of semantic representation.

### **Accounts of semantic representation**

In recent years, two main accounts of the nature of semantic representation have been debated, namely the distributional and embodiment accounts. They differ in terms of the information used to represent meaning. While distributional semantics relies on symbolic and linguistic features, embodiment relies on modality-specific information.

According to the distributional hypothesis, words occurring in similar contexts have similar meanings (Harris, 1954). The meaning of both abstract and concrete concepts can therefore be derived from statistical co-occurrences across large corpora. Hence, this account makes great use of variables, such as semantic and relatedness variables, that describe associations between words (see Louwerse & Jeuniaux, 2010; Andrews, Frank & Vigliocco,

2014; Borghi, Binkofski, Castelfranchi, Cimatti, Scorolli & Tummolini, 2017). It is an account which has come under attack in recent years, however, because it fails to explain how concepts are grounded in world referents.

The embodied account, on the other hand, defines semantic representation as being grounded in perceptual and motor states (Barsalou, 1999; Glenberg, 1997; Zwaan, 2004; Kiefer & Pulvermüller, 2012; Meteyard, Cuadrado, Bahrami & Vigliocco, 2012). Studies of this account usually show evidence of behavioural and brain activation of modality-specific processes, which makes it better suited to explain the processing of concrete concepts over abstract concepts. Recent hypotheses have been formulated to account for the processing of abstract concepts within the embodied framework, with studies showing that abstract concepts are grounded in social and introspective aspects of situations (Barsalou & Wiemer-Hastings, 2005), emotional features (Kousta, Vigliocco, Vinson, Andrews & Del Campo, 2011; Lenci, Lebani & Passaro, 2018), information about events, and thematic roles (Ferretti, McRae & Hatherell, 2001).

To capture relations other than word associations for both abstract and concrete concepts new variables have emerged. For example, the perceptual strength variable developed by Chedid, Brambati, Bedetti, Rey, Wilson & Vallet (2019) aims to yield information about perceptual experiences. It represents the extent to which a concept relies on sensorimotor traits for its representation. Accordingly, their dataset comprises perceptual strength norms for more than 3 000 nouns. It contributes to the study of relations between word associations and perceptual modalities.

### **Word associations and normative datasets**

In a word association task, participants are presented with a word (the cue) and asked to generate the first word that comes to mind (the response). The task is particularly effective

and powerful because it demands barely any cognitive cost and is easily gamified, and yet it can unveil shared mental representations, language patterns and mechanisms of meaning extraction (Prior & Bentin, 2008; Mollin, 2009, De Deyne & Storms, 2008; De Deyne et al., 2019). Word association norms have mostly been collected in English. The *Edinburgh Associative Thesaurus* (Kiss, Armstrong, Milroy & Piper, 1972), with more than 8 000 cues, is one of the most commonly used. More recently, Moss and Older (1996) introduced the *Birkbeck norms* with over 2 600 cues in British English. The more recent set of *University of South Florida norms* (Nelson et al., 2004) introduced free association data for 72 000 word pairs and is the most widely used, with more than 2 000 citations from psycholinguistics to computational linguistics. Even more recently, De Deyne et al. (2019) launched the *Small World of Words* project (*SWOW-EN*), an ongoing megastudy which aims to capture most word associations. It consists of over 12 000 cue words, each of which has elicited 300 responses from half a million participants at the time of writing this paper, making this dataset the most comprehensive one to date. This particular project followed a similar one by De Deyne, Navarro & Storms (2013) which consisted of 16 000 cues in Dutch (*SWOW-NL*). Other languages also have word association datasets. The number of cues is still significant, albeit reduced, and the datasets are still highly valuable for researchers studying these languages, such as Korean (Jung, Na & Akama, 2010), Japanese (Joyce, 2005) and Chinese (Kwong, 2013). In Spanish, Fernández, Díez, Alonso & Beato (2004) introduced free-association norms for 247 frequent words, and, more recently, Barron-Martinez and Arias-Trejo (2014) presented the *Spanish Word Association Norms* for 234 concrete nouns in Mexican Spanish. In French, Ferrand and Alario (1998) introduced word associations for 366 concrete nouns. They were quickly followed by a new dataset of 260 abstract words (Ferrand, 2001). Later on, Duscherer and Mounoud (2006) collected free association data for 151 French action verbs, and, more recently, Bonin, Méot, Ferrand & Bugajska (2013) collected

word associations for 520 concrete words. As evidenced by all these datasets, the history of the collection of word associations in French is rather spread out in time, making the present study the first for nearly a decade and the one involving the largest number of cues from the largest number of participants for the French language.

### **The present study**

The present study introduces a dataset comprising word association norms for 1 100 cues obtained from French participants. The method used allowed only one response per word, whereas other studies such as De Deyne et al., (2019) used several. Nelson, McEvoy and Dennis (2000) reported a high reliability coefficient computed from the correlation between the probability of a single-response task and that of a first-response when two responses were collected. This high level of reliability suggests the discrete responses collected for the present dataset are sufficient to capture stable association strength. The cues on the concreteness spectrum varied, and we added a measure of cue word concreteness collected in a previous study (Lakhzoum et al., 2021) which will allow researchers who study the organisation of the mental lexicon to select abstract and concrete concepts for cues. To provide a dataset of experimental stimuli according to the significant lexical variables and lexical latencies previously discussed, we have combined our list of words with existing databases such as the French Lexicon Project (FLP, Ferrand et al., 2010), Lexique (New et al., 2004), Megalex (Ferrand et al., 2018), and Wordlex (Gimenes & New, 2016). In response to Crutch and colleagues' observations, our dataset includes the levels of concreteness for the cues previously collected by Lakhzoum, Izaute and Ferrand (2021). With the exception of Ferrand et al., 2001, to the best of our knowledge this is the first time a deliberate effort has been made to include abstract concepts in a French word association dataset.

## **METHOD**

### **Participants**

The word association task was presented as an online questionnaire. All the participants were native French-speakers aged between 18 and 45 years old. We collected data from 1 200 participants (627 women;  $M_{\text{age}} = 29.30$ ;  $SD = 7.48$ ). Participants volunteered in response to an announcement posted on Facebook group walls and received no payment. The study was approved by the Research Ethics Committee of Clermont Auvergne University.

### **Stimuli**

The stimuli were composed of the isolated words used to create the materials in Lakhzoum, Izaute and Ferrand (2021), which were originally based on Coltheart's (1981) concreteness norms so as to ensure that varying levels of concreteness were included, with abstract words *monarchy* and *joy* as well as concrete words such as *dress* and *bee*. The words had been back-translated and used to form semantically similar pairs. For the present study, the pairs were dissociated; cue and target were separated in different lists so that participants would not see two words that shared semantic features to avoid influencing their responses. To that end, and to keep the task short, since participants' focus in online tasks tends to be less than in non-online tasks, we divided the material into 11 lists of 100 words each.

### **Procedure**

The stimuli were divided into 11 lists of 100 isolated cues. Each participant was randomly assigned to only one of the lists. The experiment was conducted online using Qualtrics software (2020). The experiment interface was designed to allow participants to complete the task on either a computer or smartphone. Their task was to read the word that appeared on the screen and to answer in the space below with the first word that came to mind as quickly as possible. The cue words appeared on the screen one after another. They were replaced as soon as the participant had answered. To avoid unacceptable responses, when

participants could not think of an answer they were given the opportunity of leaving a blank and moving onto the next cue. The cues were presented in the middle of the screen in Arial 12 font against a white background. No training was given before the tasks started. The study was self-paced, with no time limit for either the stimulus presentation or the participant's answer. The task took about 15 minutes to complete.

## RESULTS

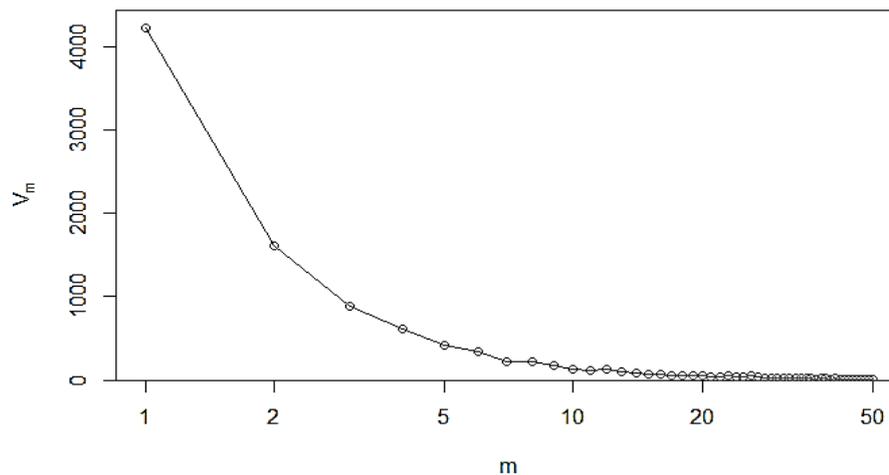
### Data Pre-processing

Before performing any analysis, the dataset was cleaned to remove any responses that failed to meet our criteria for inclusion. Symbols and punctuation such as tags, quotes, final punctuation and double spaces were removed. We also removed responses that seemed to indicate participants did not know what to answer. For instance, they sometimes entered “rien”, “aucune réponse” or “aucun mot” in French (*nothing, no response and no word*), indicating that no response came to mind, instead of leaving a blank as the procedure allowed them to do. Finally, responses that were phrases intended to describe what the cue brought to mind were removed. This concerned 523 responses. The responses were then spell-checked and lemmatized by cross-referencing the dataset with Lexique (New et al., 2004). By the end of the process, 2.5% of the data had been removed. Analyses were performed on the remaining 89 707 unique responses or *tokens*.

### Distributional statistics

A first exploration of the dataset focused on its distributional characteristics. When all responses were aggregated, there were 10 604 distinct words or *types*, 4 233 of which appeared only once. The responses occurring only once are known as *hapax legomena* responses. In accordance with De Deyne et al. (2013, 2018, but see Nelson et al., 2004), we decided to keep these responses because they reflect the long tail of the frequency spectrum. When sorting the

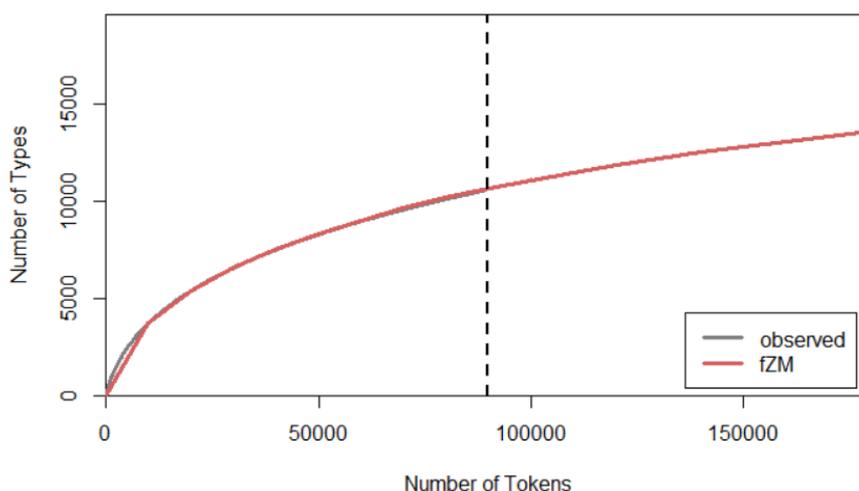
responses according to cue median concreteness, the hapax legomena were equally distributed at 53% for the responses elicited by abstract cues and 55% for the responses elicited by concrete cues. These aspects of quantitative linguistics can be a good tool for capturing common linguistic phenomena across datasets of varying sizes. For instance, Figure 1 is a frequency spectrum of the distribution of the number of types ( $V_m$ ) as a function of frequency class ( $m$ ).



**Figure 1.** Frequency spectrum on a logarithmic scale representing the number of types ( $V_m$ ) as a function of frequency class ( $m$ ). The class corresponding to  $m = 1$  corresponds to the hapax legomena.

Figure 1 shows that there are more than 4 000 words in frequency class  $V_1$ , which represents the *hapax legomena*, but very few words in frequency class  $V_{50}$ . This pattern, characterized by few exemplars in low frequency classes and many exemplars in high frequency classes and is consistently found across corpora and languages (Evert & Baroni, 2005). The frequency spectrum indicates that the process for the present word association task is productive, meaning that if we were to sample more responses from participants the number of types would also increase. This phenomenon is best captured by Herdan's law (1964), which describes a bounded exponential relation between the number of types and corpus size. The process can be illustrated by a vocabulary growth curve, which plots how the number of distinct cue-response pairs evolves as the number of collected responses increases. The  $V$  and  $V_m$  estimates of the

frequency spectrum can be extrapolated using a finite Zipf-Mandelbrot model<sup>4</sup> (fZM, Evert & Baroni, 2007; Baroni & Evert, 2006) to obtain estimates of vocabulary growth at arbitrary sample sizes (see Figure 2). It is customary to generate a vocabulary growth curve for about twice the size of the observed sample (here  $N = 180,000$ ).



**Figure 2.** Vocabulary Growth Curve (VGC) representing the increase of cue-response pairs as new responses are collected by comparing the VGC of our dataset (grey curve) to an empirical VGC obtained from the fZM model red line). The vertical lines indicate the total number of observed tokens for our sample.

The vocabulary growth curve compares the empirical growth obtained from the fZM model with the observed growth in our dataset. For the present word-association task, the curves express how the number of types (here, distinct cue-response pairs) increases as a function of the number of tokens (here, the responses collected). According to Figure 2, the observed and extrapolated curves almost completely overlap, providing a clear visual assessment of the model's goodness of fit for items sampled from our dataset.

<sup>4</sup> The finite ZM model was preferred to the ZM model because the latter is founded on the unlikely assumption of an infinite vocabulary size (Evert, 2004).

### Cue Descriptive statistics

General statistics were first computed for the cue words. The mean concreteness variable reported was taken from the Lakhzoum et al. (2021) concreteness study. The general statistics for the lexical variables presented in Table 1 were obtained by cross-referencing the present cue words with the Lexique (New et al., 2004), FLP (Ferrand et al., 2010), MEGALEX (Ferrand et al., 2018) and Wordlex (Gimenes & New, 2016) databases. The concreteness statistics indicate that the present dataset contains cue words of varying levels of concreteness ranging from 2.10 to 6.58 on a 7-point scale allowing users to study responses elicited by both abstract and concrete concepts. Separating very concrete cue words ( $M = 3.12$ ;  $SD = 0.44$ ) from very abstract ones ( $M = 5.52$ ;  $SD = 0.92$ ) based on the median revealed a significant effect of concreteness [ $t(910) = 56.71$ ;  $p < 0.0001$ ]. This will allow concreteness to be used as either a continuous or categorical variable by researchers wishing to study the effect of variation in concreteness of the cues that elicited the associated responses.

**Table 1.** Descriptive and behavioural data for cue words.

	<i>min</i>	<i>max</i>	<i>M</i>	<i>SD</i>
Mean Concreteness	2.10	6.58	5.17	1.57
Movie Frequency	0.00	2752.00	440.15	136.47
Book Frequency	0.00	4696.15	44.92	172.65
Blog Frequency	0.06	3095.93	61.24	193.06
Twitter Frequency	0.00	4070.02	55.45	232.49
Newspaper Frequency	0.00	3782.26	57.49	200.59
N-letters	3.00	14.00	7.00	2.02
N-orthographic Neighbours	0.00	23.00	2.42	3.60
OLD20	1.00	5.40	2.09	0.62
Reaction Times (FLP)	515.54	1005.15	658.41	65.67
Reaction Times (Megalex)	473.48	747.84	553.05	44.18

Note. OLD20: orthographic Levenshtein distance (Yarkoni, Balota, & Yap, 2008); Movie subtitles frequency (from Lexique ; New et al., 2004) and Mean concreteness (from Lakhzoum et al., 2021).

A more extensive description of the cues can be found in Lakhzoum et al., (2021).

### Cue concreteness and Response frequency analyses

General statistics were then computed for the responses following a similar cross-referencing process. Table 2 shows the aggregated statistics for all the responses

**Table 2.** Mean frequency and reaction times for response words

	<i>M</i>	<i>SD</i>
Movie Subtitles Frequency	29.85	349.18
Book Frequency	33.38	450.23
Blog Frequency	57.59	746.03
Twitter Frequency	55.60	646.61
Newspaper Frequency	55.26	797.73
Reaction Times (FLP)	690.32	79.01
Reaction Times (Megalex)	574.11	53.04

With respect to the responses, frequency and reaction time data were our main interest. Additional analyses compared the frequency and reaction time data for responses elicited by abstract and concrete cue words. They revealed an effect of movie subtitle frequencies with more frequent response words corresponding to abstract cue words ( $M = 87.44$ ;  $SD = 462.69$ ) than more concrete cue words ( $M = 72.40$ ;  $SD = 418.31$ ) –  $t(37146) = 3.36$ ;  $p < 0.001$ . The focus on movie subtitle frequencies was due mainly to the fact that they are commonly used, particularly when it comes to norming stimuli in language experiments. An additional analysis revealed an effect of reaction times, with shorter latencies for words elicited by concrete cue words ( $M = 647.00$ ;  $SD = 64.85$ ) than abstract cue words ( $M = 651.12$ ;  $SD = 65.72$ ) –  $t(34184) = 5.83$ ;  $p < 0.001$ . Taken together, the analyses revealed that abstract cue words elicited more frequent responses but with longer latencies (see Table 3).

**Table 3.** Response frequencies and latencies according to cue concreteness

	abstract cues	concrete cues
response frequencies	87.44 (462.69)	72.40 (418.31)
response latencies	651.12 (65.72)	647.00 (64.85)

Note. Mean (SD). All reported means are statistically significant ( $p < 0.0001$ )

### Cue-response organisation according to concreteness and perceptual gradients

An additional study was designed to establish whether cue words prompted responses of similar concreteness levels. Using the same protocol as Lakhzoum et al., (2021), we conducted an additional concreteness study where the responses from the 150 most strongly associated pairs were submitted to an independent group of 50 French native-speakers ( $M_{age} = 26.63$ ;  $SD = 7.64$ ). The collected concreteness levels for both cues and responses are presented in Table A1. Results showed a strong correlation between cue and response concreteness levels ( $r = .73$ ) –  $t(147) = 13.00$ ;  $p < 0.001$ . An additional independent t-test showed no statistical difference between cue and response concreteness ( $t(292) = 0.64$ ;  $p = 0.52$  ns). Taken together, these results show that concrete cue words tend to elicit concrete responses and abstract cue words tend to elicit abstract responses. Aggregating across all responses, cue-response pairs elicited by concrete cues were more strongly associated ( $M = 3.10$ ;  $SD = 5.60$ ) than pairs elicited by abstract cues ( $M = 2.45$ ;  $SD = 3.97$ ) –  $t(35861) = 13.00$ ;  $p < 0.001$ .

Finally, we considered the effect of the modality-specific perceptual strength variable developed by Chedid et al. (2019). A comparison of perceptual strength between cues and responses gave an overall moderate correlation ( $r = .41$ ) –  $t(6466) = 35.70$ ;  $p < 0.001$ .

However, when only pairs that are verbally associated (association strength  $\geq .10$ ) are considered, the correlation increases considerably ( $r = .67$ ) –  $t(359) = 17.00$ ;  $p < 0.001$ , signifying that participants tend to produce responses of similar perceptual strength to the cues that elicited said responses. This result is similar to the one obtained with the concreteness variable, suggesting modality-specific variables can also capture patterns of organisation of the mental lexicon. We then estimated the ability of perceptual strength to predict semantic latencies, obtaining a moderate negative correlation ( $r = -.20$ ) –  $t(1822) = 8.90$ ;  $p < 0.001$ .

#### Use of association frequencies to predict semantic processing

We verified that response frequency – i.e., the number of times word  $j$  is given as a response to cue word  $i$  – is correlated to the association strength between cues and responses. Results showed a strong correlation between frequency and strength ( $r = .98$ ) –  $t(39911) = 1032$ ;  $p < 0.001$ . Response frequency offers up additional information to strength insofar as it emphasises the lexical centrality or saliency of a response, and thus of a word, in the mental lexicon. It is therefore often used to estimate other measures of semantic relatedness, such as reaction latencies (see De Deyne et al., 2019). The comparison between response lexical centrality and lexical latencies from MEGALEX (Ferrand et al., 2018) showed a substantial negative correlation ( $r = -.55$ )<sup>5</sup> –  $t(5722) = 47.70$ ,  $p < 0.001$ ) which means that the more salient the less time it takes to be processed.

## **DISCUSSION**

The present study aimed to produce French word-association norms with a focus on abstract concepts. The task yielded a sizeable number of responses that allowed for an exploration of the dataset's distributional characteristics. Frequency spectrum analyses

---

<sup>5</sup> De Deyne et al. (2018) reported a correlation of  $-.59$  based on the SWOW dataset.

revealed that the dataset displayed the same commonly found pattern across language and corpora (Evert & Baroni, 2005). In addition, the vocabulary growth curves highlighted the productivity of the task, meaning that with continuous response collection, the number of types (or unique responses) would exponentially increase, an illustration of the fact that new words are constantly coined (Baayen, 2001). Taken together, the frequency spectrum and vocabulary growth curve reflect the productivity of the human language and the fact that new word types are continuously produced, be it in the context of a word-association task or as a broader linguistic phenomenon.

We reported the previously collected concreteness variable for the cue words, which allowed for a comparison of response statistics between words prompted by an abstract cue or a concrete cue. The presence of the concreteness variable in this dataset, even if it is reserved for the cue words, is of the utmost importance when considering the previously reported discrepancies in the literature as to the role of concreteness in the organisation of the mental lexicon (see Crutch & Warrington, 2010 for example). The additional study used to collect response concreteness revealed a high correlation between cue and response concreteness and no significant difference in concreteness levels between the two words of a pair. These important results shed more light on how the mental lexicon is organised according to abstract and concrete concepts, in that they suggest abstract concepts are closely coded in the semantic network if an abstract cue tends to prompt an abstract response, but, in addition, they also allow for a deeper exploration of the link between concreteness and frequency. For example, the results showed that, in comparison with concrete cues, abstract cues prompted responses that are more frequently distributed across movie subtitles. At first sight this result might seem to be a rather counterintuitive, insofar as concrete concepts appear to be more common in language use. In actual fact, the vast majority of meaningful words used in everyday language tend to be more abstract, as illustrated in particular by the regular use of abstract

verbs such as *think*, *feel*, and *want* to express volition and states of mind. According to the British National Corpus (Leech, Garside & Bryant, 1994), 72 % of the noun or verb tokens in British English are more abstract than the noun *war*. Nevertheless, given that previous language norms and studies have relied heavily on concrete concepts, it is not surprising these results seem counterintuitive when in fact they provide more of an incentive to further the study of abstract concepts.

The introduction of a modality-specific variable such as perceptual strength is further testament to the intricate nature of abstract concepts. Results showed that cue words elicited responses of a similar level of not only concreteness but also perceptual strength. This result is important in light of the seeming chiasm between the distributional and grounded accounts of concept representation. The suggestion is that the organisation of the mental lexicon follows statistical patterns that can be captured by variables that are historically distributional, such as semantic similarity, frequency and relatedness, and by variables that are closer to the grounded end of the spectrum, such as concreteness and perceptual strength. Our analyses in respect of the latter were constrained, however, by the limited number of items between our cue-response pairs and the items present in Chedid and colleagues' database. This is a further indication of the need to develop larger normative datasets based on these modality-specific variables and with an emphasis on abstract concepts.

The aim of this dataset was to fill a gap in the French literature as regards word association norms by introducing 1 100 cues of varying levels of concreteness that elicited more than 89k responses from over a 1 000 participants. To the best of our knowledge, this is the first dataset since Bonin et al., (2013), nearly a decade ago, and also the most recent since Ferrand et al., (2001), two decades ago, to attempt to focus on abstract concepts as well. We anticipate that it will be very useful for researchers working on language- and memory-related tasks, especially those wishing to control for association when working on semantic similarity

or on the impact of concreteness in the organisation of the mental lexicon. The correlation between lexical centrality and word latencies guarantees the validity of the dataset and its ability to predict semantic processing.

### Open Practices Statement

In line with an open data policy, all data discussed in this article are freely available on our web site on the Open Science Framework web site (<https://osf.io/dhuqs/>).

## REFERENCES

- Andrews, M., Frank, S., & Vigliocco, G. (2014). Reconciling embodied and distributional accounts of meaning in language. *Topics in Cognitive Science, 6*, 359–370. <https://doi.org/10.1111/tops.12096>
- Baayen, R. H. (2001). *Word frequency distributions* (Vol. 18). Springer Science & Business Media.
- Baroni, M., & Evert, S. (2006). The zipfR package for lexical statistics: A tutorial introduction. <http://zipfr.r-forge.r-project.org>.
- Barrón-Martínez, J. B., & Arias-Trejo, N. (2014). Word association norms in Mexican Spanish. *The Spanish Journal of Psychology, 17*, 1-13. <https://doi.org/10.1017/sjp.2014.91>.
- Barsalou, L. W. (1999). Perceptual symbol systems. *Behavioral and Brain Sciences, 22*, 577-660. <https://doi.org/10.1017/S0140525X99002149>
- Barsalou, L. W., & Wiemer-Hastings, K. (2005). Situating abstract concepts. In *Grounding Cognition: The Role of Perception and Action in Memory, Language, and Thinking* (pp. 129–163). Cambridge University Press. <https://doi.org/10.1017/CBO9780511499968.007>
- Bonin, P., Méot, A., Ferrand, L., & Bugaïska, A. (2013). Normes d'associations verbales pour 520 mots concrets et étude de leurs relations avec d'autres variables psycholinguistiques. *L'Année Psychologique, 113*, 63–92.
- Borgi, A. M., Binkofski, F., Castelfranchi, C., Cimatti, F., Scorolli, C., & Tummolini, L. (2017). The challenge of abstract concepts. *Psychological Bulletin, 143*, 263–292. <https://doi.org/10.1037/bul0000089>
- Bugaïska, A., Morson, S., Moulin, C. J. A., & Souchay, C. (2011). Metamemory, recollection and familiarity in Alzheimer's disease. *Revue Neurologique, 167*, 3–13. <https://doi.org/10.1016/j.neuro.2010.03.001>
- Chedid, G., Brambati, S. M., Bedetti, C., Rey, A. E., Wilson, M. A., & Vallet, G. T. (2019). Visual and auditory perceptual strength norms for 3,596 French nouns and their relationship with other psycholinguistic variables. *Behavior Research Methods, 51*, 2094–2105. <https://doi.org/10.3758/s13428-019-01254-w>
- Coltheart, M. (1981). The MRC Psycholinguistic Database. *The Quarterly Journal of*

- Experimental Psychology Section A*, 33, 497–505.  
<https://doi.org/10.1080/14640748108400805>
- Crutch, S. J., Connell, S., & Warrington, E. K. (2009). The different representational frameworks underpinning abstract and concrete knowledge: Evidence from odd-one-out judgements. *Quarterly Journal of Experimental Psychology*, 62, 1377–1390.  
<https://doi.org/10.1080/17470210802483834>
- Crutch, S. J., & Jackson, E. C. (2011). Contrasting graded effects of semantic similarity and association across the concreteness spectrum. *Quarterly Journal of Experimental Psychology*, 64, 1388–1408. <https://doi.org/10.1080/17470218.2010.543285>
- Crutch, S. J., & Warrington, E. K. (2005). Abstract and concrete concepts have structurally different representational frameworks. *Brain*, 128, 615–627.  
<https://doi.org/10.1093/brain/awh349>
- Crutch, S. J., & Warrington, E. K. (2010). The differential dependence of abstract and concrete words upon associative and similarity-based information: Complementary semantic interference and facilitation effects. *Cognitive Neuropsychology*, 27, 46–71.  
<https://doi.org/10.1080/02643294.2010.491359>
- De Deyne, S., Navarro, D. J., Perfors, A., Brysbaert, M., & Storms, G. (2019). Measuring the associative structure of English: The “Small World of Words” norms for word association. *Behavior Research Methods*, 51, 987–1006.
- De Deyne, S., Navarro, D. J., & Storms, G. (2013). Better explanations of lexical and semantic cognition using networks derived from continued rather than single-word associations. *Behavior Research Methods*, 45, 480–498. <https://doi.org/10.3758/s13428-012-0260-7>
- De Deyne, S., & Storms, G. (2008). Word associations: Network and semantic properties. *Behavior Research Methods*, 40, 213–231. <https://doi.org/10.3758/BRM.40.1.213>
- Deyne, S. De, Verheyen, S., & Storms, G. (2016). Structure and organization of the mental lexicon: A network approach derived from syntactic dependency relations and word associations. *Understanding Complex Systems*, 99, 47–79. [https://doi.org/10.1007/978-3-662-47238-5\\_3](https://doi.org/10.1007/978-3-662-47238-5_3)
- Duñabeitia, J. A., Avilés, A., Afonso, O., Scheepers, C., & Carreiras, M. (2009). Qualitative differences in the representation of abstract versus concrete words: Evidence from the visual-world paradigm. *Cognition*, 110, 284–292.  
<https://doi.org/10.1016/j.cognition.2008.11.012>
- Duscherer, K., & Mounoud, P. (2006). Normes d’associations verbales pour 151 verbes d’action. *L’Année Psychologique*, 106, 397–413.
- Eakin, D. K. (2005). Illusions of knowing: Metamemory and memory under conditions of retroactive interference. *Journal of Memory and Language*, 52, 526–534.  
<https://doi.org/10.1016/j.jml.2005.01.009>
- Evert, S., & Baroni, M. (2005). Testing the extrapolation quality of word frequency models. In *Proceedings of Corpus Linguistics*.
- Evert, S., & Baroni, M. (2007). zipfR: Word frequency distributions in R. In *Proceedings of the 45th annual meeting of the ACL on interactive poster and demonstration sessions*

- (pp. 29–32).
- Fernández, Á., Díez, E., Alonso, M. Á., & Beato, M. S. (2004). Free-association norms for the Spanish names of the Snodgrass and Vanderwart pictures. *Behavior Research Methods, Instruments, & Computers*, *36*, 577–583.
- Ferrand, L. (2001). Normes d'associations verbales pour 260 mots « abstraits ». *L'Année Psychologique*, *101*, 683–721. <https://doi.org/10.3406/psy.2001.29575>
- Ferrand, L., & Alario, F. X. (1998). Word association norms for 366 names of objects. *L'Année Psychologique*, *98*, 659–709. <https://doi.org/10.3406/psy.1998.28564>
- Ferrand, L., Méot, A., Spinelli, E., New, B., Pallier, C., Bonin, P., Dufau, S., Mathôt, S., & Grainger, J. (2018). MEGALEX: A megastudy of visual and auditory word recognition. *Behavior Research Methods*, *50*, 1285–1307. <https://doi.org/10.3758/s13428-017-0943-1>
- Ferrand, L., & New, B. (2003). Semantic and associative priming in the mental lexicon. *Mental Lexicon: Some Words to Talk about Words*, 25–43.
- Ferrand, L., New, B., Brysbaert, M., Keuleers, E., Bonin, P., Méot, A., Augustinova, M., & Pallier, C. (2010). The French lexicon project: Lexical decision data for 38,840 French words and 38,840 pseudo words. *Behavior Research Methods*, *42*, 488–496. <https://doi.org/10.3758/BRM.42.2.488>
- Ferretti, T. R., McRae, K., & Hatherell, A. (2001). Integrating Verbs, Situation Schemas, and Thematic Role Concepts. *Journal of Memory and Language*, *44*, 516–547. <https://doi.org/10.1006/jmla.2000.2728>
- Geng, J., & Schnur, T. T. (2015). The representation of concrete and abstract concepts: Categorical versus associative relationships. *Journal of Experimental Psychology: Learning Memory and Cognition*, *41*, 22–41. <https://doi.org/10.1037/a0037430>
- Gimenes, M., & New, B. (2016). Worldlex: Twitter and blog word frequencies for 66 languages. *Behavior Research Methods*, *48*, 963–972.
- Glenberg, A. M. (1997). What memory is for. *Behavioral and Brain Sciences*, *20*, 1–19.
- Hamilton, A. C., & Coslett, H. B. (2008). Refractory access disorders and the organization of concrete and abstract semantics: Do they differ? *Neurocase*, *14*, 131–140. <https://doi.org/10.1080/13554790802032218>
- Harris, Z. (1954). Distributional hypothesis. *Word World*, *10*, 146–162.
- Herdan, G. (1964). *Quantitative Linguistics*. London: Butterworths.
- Joyce, T. (2005). Constructing a large-scale database of Japanese word associations. *Glottometrics*, *10*, 82–99.
- Jung, J., Li, N., & Akama, H. (2010). Network analysis of Korean word associations. *Proceedings of the NAACL HLT 2010 First Workshop on Computational Neurolinguistics*, 27–35. <http://www.aclweb.org/anthology/W/W10/W10-0604>
- Kiefer, M., & Pulvermüller, F. (2012). Conceptual representations in mind and brain: Theoretical developments, current evidence and future directions. *Cortex*, *48*, 805–825. <https://doi.org/10.1016/j.cortex.2011.04.006>
- Kircher, T., Whitney, C., Krings, T., Huber, W., & Weis, S. (2008). Hippocampal dysfunction during free word association in male patients with schizophrenia. *Schizophrenia Research*, *101*, 242–255. <https://doi.org/10.1016/j.schres.2008.02.003>

- Kiss, G. R., Armstrong, C., Milroy, R., & Piper, J. (1972). The Edinburgh Associative Thesaurus. *The Edinburgh Associative Thesaurus*. <https://w3id.org/associations/eat.nt.gz>.
- Kousta, S. T., Vigliocco, G., Vinson, D. P., Andrews, M., & Del Campo, E. (2011). The representation of abstract words: Why emotion matters. *Journal of Experimental Psychology: General*, *140*, 14–34. <https://doi.org/10.1037/a0021446>
- Kwong, O. Y. (2013). Exploring the Chinese mental lexicon with word association norms. *27th Pacific Asia Conference on Language, Information, and Computation, PACLIC 27*, 153–162.
- Lakhzoum, D., Izaute, M., & Ferrand, L. (2021). Semantic similarity and associated abstractness norms for 630 French word pairs. *Behavior Research Methods*, *53*, 1166–1178.
- Leech, G., Garside, R., & Bryant, M. (1994). CLAWS4: The tagging of the British National Corpus. *Proceedings of the 15th International Conference on Computational Linguistics*, 622–628.
- Lenci, A., Lebani, G. E., & Passaro, L. C. (2018). The emotions of abstract words: A distributional semantic analysis. *Topics in Cognitive Science*, *10*, 550–572. <https://doi.org/10.1111/tops.12335>
- Louwerse, M. M., & Jeuniaux, P. (2010). The linguistic and embodied nature of conceptual processing. *Cognition*, *114*, 96–104. <https://doi.org/10.1016/j.cognition.2009.09.002>
- McNamara, T. P. (1992). Theories of priming: I. Associative distance and lag. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *18*, 1173–1190. <https://doi.org/10.1037/0278-7393.18.6.1173>
- McRae, K., & Boisvert, S. (1998). Automatic semantic similarity priming. *Journal of Experimental Psychology: Learning Memory and Cognition*, *24*, 558–572. <https://doi.org/10.1037/0278-7393.24.3.558>
- Meteyard, L., Cuadrado, S. R., Bahrami, B., & Vigliocco, G. (2012). Coming of age: A review of embodiment and the neuroscience of semantics. *Cortex*, *48*, 788–804. <https://doi.org/10.1016/j.cortex.2010.11.002>
- Mollin, S. (2009). Combining corpus linguistic and psychological data on word co-occurrences: Corpus collocates versus word associations, *Corpus Linguistics and Linguistic Theory*, *5*, 175–200. <https://doi.org/10.1515/CLLT.2009.008>
- Moss, H., Older, L., & Older, L. (1996). *Birkbeck word association norms*. Psychology Press.
- Nelson, D. L., McEvoy, C. L., & Dennis, S. (2000). What is free association and what does it measure? *Memory and Cognition*, *28*, 887–899.
- Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (2004). The University of South Florida free association, rhyme, and word fragment norms. *Behavior Research Methods, Instruments, and Computers*. Psychonomic Society Inc. <https://doi.org/10.3758/BF03195588>
- New, B., Pallier, C., Brysbaert, M., & Ferrand, L. (2004). Lexique 2: A new French lexical database. *Behavior Research Methods, Instruments, and Computers*. Psychonomic Society Inc. <https://doi.org/10.3758/BF03195598>

- Plaut, D. C., & Erlbaum Associates, L. (1995). *Semantic and Associative Priming in a Distributed Attractor Network*.
- Prior, A., & Bentin, S. (2008). Word associations are formed incidentally during sentential semantic integration. *Acta Psychologica, 127*, 57–71.
- Qualtrics (2020). Qualtrics.com. <http://www.qualtrics.com/>
- Schloss, B., & Li, P. (2016). Disentangling narrow and coarse semantic networks in the brain: The role of computational models of word meaning. *Behavior Research Methods, 49*, 1582–1596. <https://doi.org/10.3758/s13428-016-0807-0>
- Taconnat, L., Raz, N., Toczé, C., Bouazzaoui, B., Sauzéon, H., Fay, S., & Isingrini, M. (2009). Ageing and organisation strategies in free recall: The role of cognitive flexibility. *European Journal of Cognitive Psychology, 21*, 347–365. <https://doi.org/10.1080/09541440802296413>
- Thompson-Schill, S. L., Kurtz, K. J., & Gabrieli, J. D. E. (1998). Effects of semantic and associative relatedness on automatic priming. *Journal of Memory and Language, 38*, 440–458.
- West, J. T., & Mulligan, N. W. (2019). Prospective Metamemory, Like Retrospective Metamemory, Exhibits Underconfidence With Practice. *Journal of Experimental Psychology: Learning Memory and Cognition, 45*. <https://doi.org/10.1037/xlm0000708>
- Yarkoni, T., Balota, D., & Yap, M. (2008). Moving beyond Coltheart's N: A new measure of orthographic similarity. *Psychonomic Bulletin and Review, 15*, 971–979. <https://doi.org/10.3758/PBR.15.5.971>
- Zwaan, R. A. (2004). The Immersed Experiencer: Toward an embodied theory of language comprehension. *Psychology of Learning and Motivation - Advances in Research and Theory, 44*, 35–62. [https://doi.org/10.1016/S0079-7421\(03\)44002-4](https://doi.org/10.1016/S0079-7421(03)44002-4)

## APPENDIX

**Table A1.** First 150 most associated pairs with cue and response mean concreteness

cue	translation	response	translation	%strength	cue_concreteness	response_concreteness
crainte	fright	peur	fear	85.71	2.95	2.37
omelette	omelet	œuf	egg	82.05	6.67	6.61
chorégraphie	choregraphy	danse	dance	79.49	5.12	4.71
poivre	pepper	sel	salt	78.57	6.55	6.10
croquis	sketch	dessin	drawing	74.39	5.46	5.57
ruche	hive	abeille	bee	72.73	6.43	6.67
brasier	inferno	feu	fire	72.37	5.75	5.76
question	question	réponse	answer	72.00	3.93	2.94
homme	man	femme	woman	71.88	6.26	5.78
selle	saddle	cheval	horse	71.43	6.46	6.63
luge	sledge	neige	snow	70.42	6.58	6.29
primate	primate	singe	monkey	70.27	5.36	6.43
soucoupe	saucer	volant	flying	69.77	5.90	5.61
égaré	misplaced	perdre	loose	69.57	3.49	2.86
prévision	forecast	météo	weather	69.57	2.74	3.88
avalanche	avalance	neige	snow	69.14	6.17	6.29
aéroport	airport	avion	plane	67.95	6.24	6.63
nid	nest	oiseau	bird	67.86	6.31	6.69
effroi	dread	peur	fear	66.67	3.16	2.37
robinet	faucet	eau	water	65.52	6.61	6.22
tendance	tendency	mode	fashion	64.84	2.57	2.82
rouge-gorge	robin	oiseau	bird	64.71	6.58	6.69
cacao	cocoa	chocolat	chocolate	64.37	6.23	6.59
ancre	anchor	bateau	boat	62.35	6.14	6.63
chlore	chlorine	piscine	pool	62.12	5.41	6.49
bibliothèque	library	livre	book	61.97	6.48	6.63
baril	barrel	pétrole	oil	61.33	6.34	5.88
périr	perish	mourir	die	61.29	4.11	3.51
riche	wealthy	pauvre	poor	61.29	3.48	2.94
flamme	flame	feu	fire	61.11	5.94	5.76
réponse	answer	question	question	60.53	3.92	3.00
cliché	stereotype	photo	picture	60.44	3.71	5.73
bravoure	bravery	courage	courage	60.26	2.97	2.69
cercle	circle	rond	round	60.24	5.21	4.82
ampoule	bulb	lumière	light	59.55	6.78	4.76
gare	train station	train	train	59.46	6.19	6.55
frère	brother	sœur	sister	59.21	5.94	5.67
roi	king	reine	queen	59.15	5.59	5.31
oncle	uncle	tante	aunt	58.82	6.46	5.75

pacifique	peaceful	océan	ocean	58.75	3.64	5.82
bien	good	mal	bad	58.11	2.60	2.22
décret	decree	loi	law	57.97	4.26	3.04
tablier	apron	cuisine	kitchen	57.69	6.53	5.73
tonneau	cask	vin	wine	57.69	6.63	6.35
vie	life	mort	death	57.69	3.74	3.45
femme	woman	homme	man	57.33	5.86	5.57
grand	large	petit	small	57.14	4.59	3.88
soulier	shoe	chaussure	shoe	56.99	6.69	6.45
réfléchir	reflect	penser	think	56.63	3.62	2.82
moineau	sparrow	oiseau	bird	56.47	6.48	6.69
célébration	celebration	fête	party	55.95	3.97	4.06
égalité	equality	fraternité	fraternity	55.95	3.05	2.49
étincelle	sparke	feu	fire	55.26	5.58	5.76
après	after	avant	before	55.13	3.77	2.45
terrier	burrow	lapin	rabbit	54.67	6.43	6.65
monarchie	monarchy	roi	king	53.73	4.04	5.43
berceau	crib	bébé	baby	53.41	6.60	6.20
anatomie	anatomy	corps	body	53.09	5.82	5.96
sapin	fir	noël	christmas	52.63	6.76	3.88
trébucher	stumble	tomber	fall	52.63	5.26	4.12
capture	capture	écran	screen	52.44	3.75	6.41
rusé	cunning	renard	fox	52.05	3.27	6.73
lait	milk	vache	cow	51.81	6.48	6.67
astronomie	astronomy	étoile	stars	51.76	4.59	5.59
émissaire	emissary	bouc	goat	51.47	4.33	6.29
abdomen	abdomen	ventre	belly	51.32	6.53	6.14
privé	private	public	public	51.28	3.31	3.84
bulle	buble	savon	soap	51.16	5.71	6.43
flore	flora	faune	fauna	50.77	5.24	4.47
existence	existence	vie	life	50.55	3.52	3.14
palpitation	palpitation	coeur	fever	50.53	4.87	5.47
album	album	photo	photo	50.00	6.23	5.73
tentative	attempt	essai	test	50.00	3.37	3.35
navire	ship	bateau	boat	49.44	6.51	6.63
problème	problem	solution	solution	49.41	3.47	3.10
tasse	cup	café	coffee	49.37	6.68	6.43
source	source	eau	water	49.30	4.20	6.22
liquide	liquide	eau	water	49.21	5.34	6.22
torchon	napkin	serviette	towel	48.84	6.41	6.47
panique	panic	peur	fear	48.78	3.49	2.37
brise	breeze	vent	wind	48.65	4.51	4.92
rectangle	rectangle	carré	square	48.61	6.56	3.55
pauvre	poor	riche	wealthy	48.53	3.83	3.25

Pâque	Easter	œuf	egg	48.44	3.97	6.61
bizarre	weird	étrange	strange	48.24	2.50	2.27
épave	wreck	bateau	boat	47.89	5.80	6.63
dévoré	devour	manger	eat	47.76	4.20	4.82
démence	dementia	folie	madness	47.56	2.87	2.10
étrange	strange	bizarre	weird	47.52	2.49	2.02
bouée	buoy	sauvetage	rescue	47.50	6.51	3.82
forêt	forest	arbre	tree	47.44	6.00	6.67
chouette	owl	hibou	owl	47.37	5.97	6.49
aisé	convenient	riche	wealthy	47.13	3.26	3.25
solution	solution	problème	problem	46.99	3.91	2.80
coïncidence	coincidence	hasard	chance	46.91	2.77	2.27
hibou	owl	chouette	owl	46.48	6.78	5.53
pinceau	brush	peinture	paint	46.39	6.56	5.92
arrivée	arrival	départ	departure	46.38	4.07	3.51
soi	self	moi	me	46.34	2.84	4.12
avoir	to have	être	to be	46.25	3.49	2.08
entrée	entrance	sortie	exit	45.65	4.56	3.67
geler	congeal	froid	cold	45.65	5.05	3.80
timbre	stamp	poste	post office	45.59	6.35	4.80
planète	planet	terre	earth	45.56	5.68	5.98
célébrité	fame	star	star	45.35	3.33	4.06
bon	good	mauvais	bad	45.26	3.13	2.51
monter	go up	descendre	come down	45.24	4.50	3.82
soir	evening	nuît	night	45.00	4.84	2.63
auteur	author	livre	book	44.93	5.54	6.63
poignée	handle	porte	door	44.59	5.95	6.47
vache	cow	lait	milk	44.58	6.89	6.45
budget	budget	argent	money	44.44	5.03	5.24
finance	finance	argent	money	44.30	3.45	5.24
cage	cage	oiseau	bird	44.29	6.31	6.69
collège	middle school	lycée	high school	44.29	6.17	5.71
divertir	entertain	amuser	amuse	43.94	3.35	2.88
compte	account	banque	bank	43.90	4.44	5.47
individu	individual	personne	person	43.90	5.10	4.71
mauvais	bad	bon	good	43.84	3.26	2.71
mélancolie	melancoly	tristesse	sadness	43.84	2.69	2.61
béton	concrete	armer	reinforced	43.68	6.52	3.92
propre	clean	sale	dirty	43.62	3.98	3.73
cartable	schoolbag	école	school	43.59	6.78	5.96
pyramide	pyramid	Egypte	Egypt	43.53	6.31	5.31
avenir	future	futur	future	43.48	3.04	2.27
plage	beach	sable	sand	43.43	6.09	6.49
velouté	chowder	soupe	soup	43.43	5.35	6.33

faiblesse	weakness	force	strength	43.42	2.72	3.04
neveu	nephew	nièce	niece	43.18	6.20	5.67
pays	country	France	France	42.86	5.66	4.94
maximum	maximum	minimum	minimum	42.71	3.04	2.96
mal	bad	bien	good	42.47	3.14	2.53
ricaner	giggle	rire	laugh	42.47	4.51	3.90
berger	shepherd	mouton	sheep	42.45	6.10	6.65
aérien	aerial	avion	plane	42.19	4.21	6.63
action	action	réaction	reaction	42.17	4.09	2.86
poignard	dagger	couteau	knife	42.17	6.39	6.61
lit	bed	dormir	sleep	41.98	6.84	4.37
adulte	adult	enfant	child	41.94	4.40	5.86
émeraude	emerald	vert	green	41.94	6.21	4.37
gravir	climb	monter	ascend	41.94	4.94	3.90
courgette	zucchini	légume	vegetable	41.46	6.76	6.12
abeille	bee	miel	honey	41.38	6.64	6.33
printemps	spring	été	summer	41.38	4.38	3.80
orner	adorn	décorer	decorate	41.05	4.61	3.82
horreur	horror	film	movie	41.03	3.00	5.69
célébrer	showcase	fêter	celebrate	40.82	3.89	3.75
part	piece	gâteau	cake	40.74	3.82	6.31
colonie	colony	vacance	vacation	40.63	4.30	3.73

The aim of the previous chapter was twofold. Firstly, we wanted to provide an update to the availability of word association for French abstract concepts because the most recent database was introduced by Ferrand et al. (2001). Secondly, we developed this database in order to provide control for researchers over the crafting of materials when studying processes related to semantic similarity and verbal association. The implementation of a word association task produced a large amount of data which allowed for the use of methods borrowed from distributional statistics. Main results have shown that concepts are organised in the mental lexicon according to a gradient of concreteness and that concrete concepts elicit stronger associations compared to abstract concepts.

The large amount of data generated by the word association task allowed for the application of semantic network analyses borrowed from the mathematical graph theory. A key advantage of cognitive network science is that it renders possible the exploration of large-scale semantic phenomena from a structural level. The next chapter introduces the first semantic network built from French association data and the first to compare topological parameters for concrete and abstract concepts. Results have shown that the mental lexicon is structured according to a small-world pattern characterised by a sparse density, a short average path length between nodes and a high clustering coefficient.

Comparison analyses between the networks for concrete and abstract networks respectively have shown that concrete concepts are organised in denser communities compared to abstract concepts. Additional analyses have shown that the concrete word nodes are more influential in the network due to their position and patterns of connectivity. This means that concrete nodes have a higher ability to spread information in the network compared to abstract nodes. We relate these characteristics to the assumptions of Paivio (1971) according to which concrete concepts are strongly connected to a limited number of

contexts while abstract concepts are more loosely connected to a great number of contexts.

Semantic network analyses have confirmed these assumptions on a larger scale based on the structural parameters of the mental lexicon.

## Chapter 4. Semantic network analysis of abstract and concrete word associations.

Dounia Lakhzoum, Marie Izaute, and Ludovic Ferrand

**Chapter 4 was submitted as a preprint under the reference:**

Lakhzoum, D., Izaute, M., & Ferrand, L. (2021). Semantic network analysis of abstract and concrete word associations. <https://doi.org/10.31234/osf.io/epk47>

Supplementary material: <https://osf.io/4w69k/>

Université Clermont Auvergne, CNRS, LAPSCO, F-63001 Clermont-Ferrand, France

**Corresponding author:** Dounia Lakhzoum or Ludovic Ferrand, Université Clermont Auvergne, CNRS LAPSCO, 34 avenue Carnot TSA 60401- 63001 Clermont-Ferrand Cedex 1, France

Email: [dounia.lakhzoum@ext.uca.fr](mailto:dounia.lakhzoum@ext.uca.fr)

### Author's note

This research was financed by the French government IDEX-ISITE initiative 16-IDEX-0001 (CAP 20-25).

### ACKNOWLEDGMENT

This work was sponsored by a public grant overseen by the French National Research Agency as part of the “Investissements d’Avenir” through the IDEX-ISITE initiative CAP 20-25 (ANR-16-IDEX-0001).

## **ABSTRACT**

In recent years, a new interest for the use of graph-theory based networks has emerged within the field of cognitive science. This has played a key role in mining the large amount of data generated by word association norms. In the present work, we applied semantic network analyses to explore norms of French word associations for concrete and abstract concepts (Lakhzoum et al., 2021). Graph analyses have shown that the network exhibits high clustering coefficient, sparse density, and small average shortest path length for both the concrete and abstract networks. These characteristics are consistent with a small-world structure.

Comparisons between local node statistics and global structural topology showed that abstract and concrete concepts present a similar local connectivity but different overall patterns of structural organisation with concrete concepts presenting an organisation in densely connected communities compared to abstract concepts. These patterns confirm previously acquired knowledge about the dichotomy of abstract and concrete concepts on a larger scale. To the best of our knowledge, this is the first attempt to confirm the generalisability of these properties to the French language and with an emphasis on abstract and concrete concepts.

## INTRODUCTION

In recent years, a new interest has emerged within the field of cognitive science for mathematical models such as graph-theory based science networks (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013; see Siew, Wulff, Beckage, & Kenett, 2019 for a review). More specifically, the use of semantic network analysis on word association offers a powerful computational technique for the modelling of structures like the mental lexicon (De Deyne & Storms, 2008; De Deyne, Verheyen & Storms, 2016; De Deyne, Navarro, Perfors, Brysbaert & Storms, 2019; Stella, Beckage, Brede, & De Domenico, 2018). Models have shown that word associations are organised according to the same small-world structure found in many natural phenomena (Steyvers & Tenenbaum, 2005).

### Network science and characteristics

A network is built as a graph that consists of nodes linked by edges or arcs. In a network based on association data, the nodes correspond to words connected by an undirected edge or a directed arc. A directed network provides additional information about the direction of the association from cue to response words. The arcs and edges can have weights to represent the frequency of association. Adjacent nodes are directly connected by an arc or edge whereas nonadjacent nodes are connected by a path. Based on this macroscopic structure, it is possible to compute network statistics of interest. The macrostructure of the network can be described in terms of its diameter ( $D$ ), which gives the largest path length between two nodes. The average shortest path length ( $ASPL$ ) that links two nodes is also of interest. It refers to the average minimum number of steps from one node to another. Nodes are characterised by the degree corresponding to their number of connections. In a directed network, each node has an in-degree ( $k^{in}$ ) that is the number of incoming arcs and an out-degree ( $k^{out}$ ) that is the number of outgoing arcs. An undirected network only has degree  $k$  corresponding to the number of

edges of a node. The average degree  $\langle k \rangle$  of the network can provide valuable information about the connectivity of the network itself but also about nodes centrality within the network. The clustering coefficient ( $CC$ ) constitutes such a measure of centrality. It is the probability that two nodes are interconnected knowing they both are connected to a common neighbour. Finally, the density ( $d$ ) is defined as a ratio of the number of edges in the network to the number of all possible edges (Steyvers & Tenenbaum, 2005; De Deyne & Storms, 2008; Csardi & Nepusz, 2006; Kolaczyk & Csardi, 2014; see Table 1 for a summary of all network statistics described above).

**Table 4.** Description of network characteristics used throughout the paper.

network characteristics	Description
$D$	the diameter of the network
$ASLP$	the average length of shortest path
$CC$	the clustering coefficient
$\langle k \rangle$	average degree
$k, k^{in}, k^{out}$	the degree, in-degree, and out-degree
$d$	density of the network
$S$	Smallworldness

Based on these characteristics, some networks exhibit small-world properties when compared to similar random networks (Milgram, 1967; Watts & Strogatz, 1998; Steyvers & Tenenbaum, 2005). Humphries and Gurney (2008) introduced a quantitative measure called smallworldness ( $S$ ) aimed to assess the small-world properties of a network. This measure corresponds to the ratio of the clustering coefficient ( $CC$ ) to the average shortest path length ( $ASPL$ ). The network is considered smallworlded when  $S$  is higher

Based on these characteristics, some networks exhibit small-world properties when compared to similar random networks (Milgram, 1967; Watts & Strogatz, 1998; Steyvers & Tenenbaum, 2005). Humphries and Gurney (2008) introduced a quantitative measure called smallworldness ( $S$ ) aimed to assess the small-world properties of a network. This measure

corresponds to the ratio of the clustering coefficient (CC) to the average shortest path length (ASPL). The network is considered smallworlded when  $S$  is higher than 3 (Humphries & Gurney, 2008). A small-world network when compared to a random network of equal size and number of edges would have a lower average shortest path length but a higher clustering coefficient (Erdős & Rényi, 1960; Watts & Strogatz, 1998; Steyvers & Tenenbaum, 2005; De Deyne & Storms, 2008). Smallworld networks represent a vast collection of models that can be found in multiple real-world phenomena.

### **Small-world structures and semantic networks**

Milgram (1967), in an experiment on social networks tested the principle according to which people are on average separated by only six social connections. He asked a group of participants (origin node) to send a letter to a stockbroker (destination node) using their own social connections. Results suggested a small degree of separation between any two people living in the United States at the same time. According to Milgram (1967), this suggested an organisation of social connections according to a small-world structure.

Other studies later confirmed these small-world properties in social networks (e.g., Watts & Strogatz, 1998; Kitsak et al., 2010), epidemiology of infectious diseases (e.g., Keeling & Rohani, 2008), spread of computer viruses (e.g., Pastor-Satorras & Vespignani, 2001), protein interaction (e.g., Bork et al., 2004), gene expression (e.g., van Noort, Snel & Huynen, 2004), neural (e.g., Basset & Bullmore, 2017) and semantic networks (e.g., Steyvers & Tenenbaum, 2005).

The use of semantic networks for the study of language corpora has a long history as evidenced by the development of influential computational models such as LSA (Latent Semantic Analysis, Landauer & Dumais, 1997). It models the assumption that words that co-occur in similar contexts share the same meaning (Firth, 1968). This corpus approach relies

on the mining of large text corpora that provide a good representation of the linguistic environment from which language is acquired and processed (De Deyne et al. 2016). The use of co-occurrence to define meaning is limited however because it does not distinguish between similarity-based co-occurrences and purely verbal associates as it is the case for psycholinguistic models of semantics. The use of word associations collected from human participants can address this limitation by providing large-scale networks to study the mental lexicon from data that are psychologically plausible.

The word association task is a simple yet powerful tool that can generate a large amount of data to gain insights into the organization of the mental lexicon. Traditionally, these data are used to create word association norms that are applied in factorial designs to study varied cognitive phenomena such as visual word recognition, memory recall, and semantic and lexical decision tasks (Balota, Cortese, Sergent-Marshall, Spieler & Yap, 2004; Hutchison, 2003; McNamara, 2005). The modelling of these data using network science not only is interesting because it provides psychologically plausible data or the ability to explore semantic memory on a larger scale than what is possible to achieve with factorial designs but is also theoretically sound. This technique is embedded in the seminal work of Collins and Loftus (1975) who established the network structure of the mental lexicon. In addition to the structural properties, semantic networks have the ability to model functional properties such as the spreading activation process that takes place when a node is activated in the network and all nodes that are connected to it are activated in turn. It is also possible to consider the weights and paths length in a directed network to model activation decay as a function of time and distance (Collins & Loftus, 1975; Den Heyer, & Briand, 1986; Kenett, Levi, Anaki & Faust, 2017).

Many studies have investigated the above-mentioned characteristics of semantic networks (Motter, Moura, Lai & Dasgupta, 2002; Sigman & Cecchi 2002; Steyvers &

Tenenbaum 2005; Bales & Johnson 2006; Borge-Holthoefer & Arenas 2010; Choudhury & Mukherjee 2009; Fukš & Krzemiński 2009; Veremyev, Semenov, Pasiliao & Boginski, 2019).

Steyvers and Tenenbaum (2005) analysed semantic networks based on behavioural word associations and large text corpora. They showed that they all have a small-world structure characterized by sparse connectivity, short average path lengths, and a strong clustering coefficient. These small-world properties reflect an organisation of the lexicon in highly connected hubs that allow efficient information distribution and contributes to the robustness of the structure as a whole (Borge-Holthoefer, Moreno, & Arenas, 2012; De Deyne et al. 2016). It also provides insights into the network growth mechanisms as newly acquired concepts join tightly connected hubs over time (Steyvers, and Tenenbaum, 2005). These results were later replicated in Dutch (De Deyne et al., 2008), German and Spanish (Borge-Holthoefer & Arenas, 2010), Hebrew (Kenett et al., 2017) and most recently in Persian (Karimkhani et al., 2021) showing that these properties still hold for Semitic languages.

### **The present work**

In the present work, we applied techniques of semantic network analyses on behavioural abstract and concrete word associations previously collected from French native speakers (Lakhzoum et al., submitted). The first aim of this work is to replicate the network analyses and small-world properties found by Steyvers and Tenenbaum (2005) and generalise their results to the French language. A second aim is to explore potential differences in network properties when separating abstract and concrete word associations in two distinct networks. This is, to the best of our knowledge, the first attempt to study the characteristics of abstract and concrete networks and the first attempt to generalise small world properties to the French language.

## METHOD

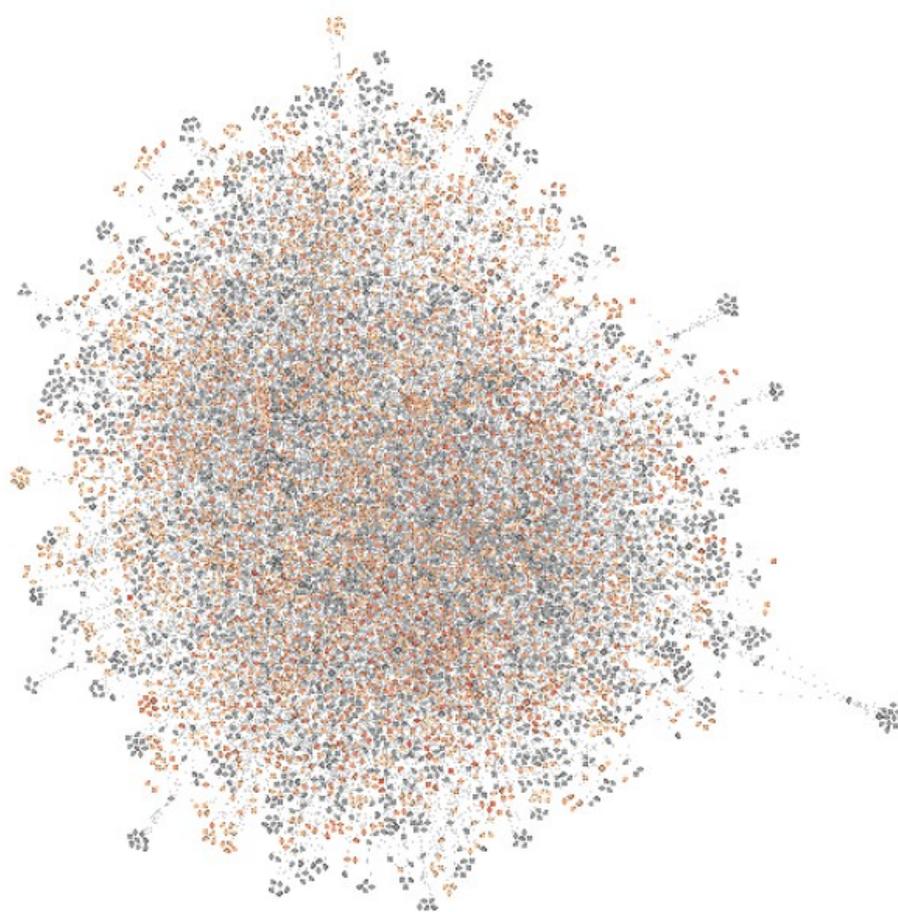
### Material and procedures

A detailed description of the French word association data is provided in Lakhzoum et al., (submitted). The word associations were based on 1100 cues with varying levels of concreteness from very abstract to very concrete on a 7-points scale. They were collected in an online experiment among 1200 French native speakers. This resulted in a dataset of 92000 responses. Following the procedure of De Deyne et al. (2019), only the responses suggested by at least two participants were kept. For the remaining data, a weighted adjacency matrix was computed. The cue words and associated responses were used to create the nodes in the networks. The links between cue and responses were used as the directed arcs and the association strength values were represented in the weights of the arcs. The whole network was later divided into the concrete and abstract networks based on the median level of concreteness of the cues.

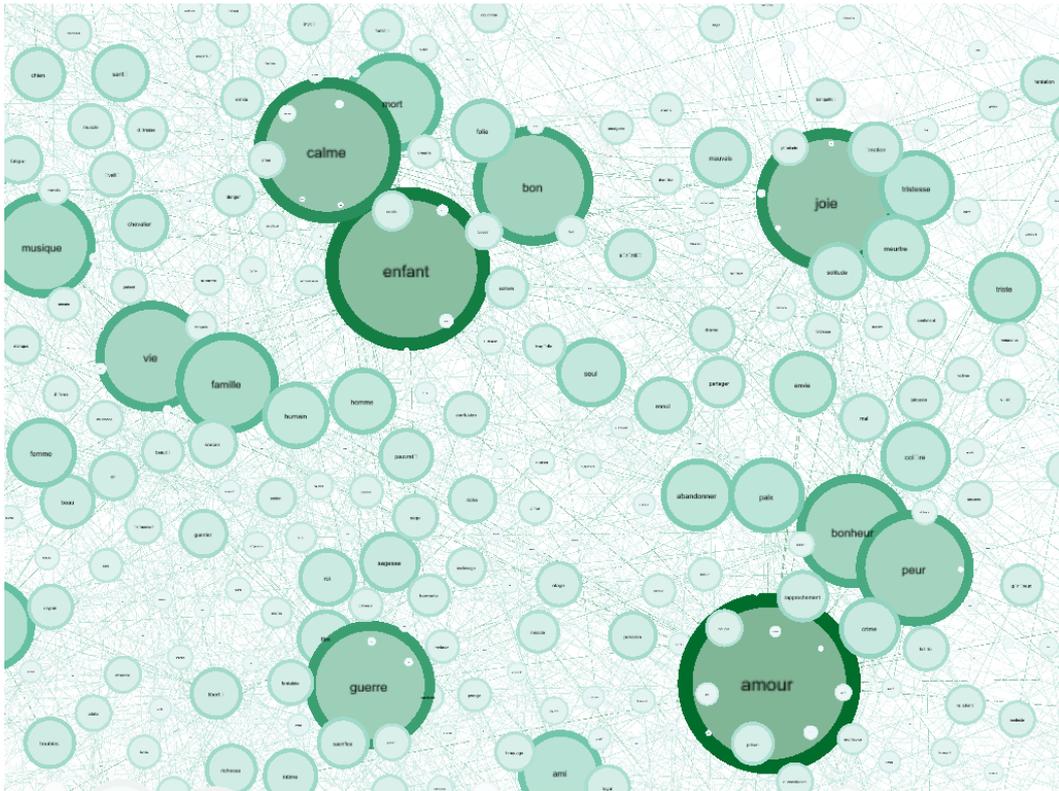
## RESULTS

Semantic network analyses do not rely on techniques of hypothesis testing, as it is the case for factorial designs (Moreno & Neville, 2013). The insights about the data are drawn from comparisons of directed and undirected networks with random networks of comparable size, density and mean connectivity  $\langle k \rangle$ . More specifically, the benchmark random networks used to estimate smallworldness (ASPL and CC parameters) were generated with the same size and mean connectivity that provided the parameters  $ASPL_{\text{random}}$  and  $CC_{\text{random}}$  (see Table 1). Most of the literature on semantic networks relies on unweighted, undirected networks. However, considering the present application in word association data, the direction of the edges and the frequency of the association are of importance. The following analyses are based on directed and undirected weighted graphs. The variable  $n$  refers to the number of

nodes corresponding to the word association dataset (Lakhzoum et al., submitted). The whole network corresponds to the graph representation of the entire dataset (see Figure 1 for a representation of the whole network; see Figure 2 for a more focused visualisation of the network)



**Figure 1.** Visual representation of the whole network. Each point represents a word. The colour gradient from grey to red represents the distance between connected nodes the greyer the farther and the redder the closer (built with the software Gephi; Bastian, Heymann & Jacomy, 2009).



**Figure 2.** Visualisation of a portion of the network with a representation of the nodes degree were the larger and the darker green a node is and the more connection it has. The node with the most number of connection on this portion is the French concept “amour” or love in English. One of the nodes with the smallest degree is the French concept “ennui” or boredom in English (built with the software Gephi; Bastian, Heymann & Jacomy, 2009).

Based on our previous study, we were able to determine that concrete and abstract cue words tend to elicit responses of the same level of concreteness (Lakhzoum et al., submitted) which justified our choice to explore both levels in separate networks. The concrete and abstract networks correspond to the datasets for the concrete and abstract cue words respectively.

The first parameter of interest is the diameter ( $D$ ) of the network that defines the maximum distance between two nodes. It provides information about the macrostructure of the network and an estimation of the overall connectivity as it relates to the density parameter ( $d$ ). For the whole network, the diameter shows that the most distant nodes are separated by

20 (directed) and 9 (undirected) connections. In the concrete network, the most distant nodes are separated by 24 (directed) and 9 (undirected) connections. Finally, in the abstract network, the most distant nodes are separated by 19 (directed) and 10 (undirected) connections. These diameters are overall higher than the ones found in the Leven dataset (De Deyne et al., 2008) which is explained by the higher density of their network.

**Table 2.** Network statistics for the directed and undirected associative networks for the whole, concrete and abstract datasets.

variables	Whole network		Concrete network		Abstract network	
	directed	undirected	directed	undirected	directed	undirected
$n$	4,758		2,961		2,827	
$D$	20	9	24	9	19	10
$d$	$5.10^{-3}$		$6.10^{-3}$		$7.10^{-3}$	
$ASPL$	7.07	4.90	8.46	5.13	7.20	5.00
$ASPL_{random}$	10.00	7.05	10.21	6.63	10.13	6.58
$k_{in/out}$	2.46	-	1.97	-	2.07	-
$\langle k \rangle$	4.92	4.92	3.94	3.94	4.13	4.13
$CC$	0.15	0.07	0.15	0.07	0.14	0.06
$CC_{random}$	0.0005	0.0005	0.001	0.0008	0.0007	0.001
$S$	682		925		657	
$Q$	0.62		0.70		0.64	

Note.  $n$  = the number of nodes;  $D$  = the diameter of the network;  $\langle k \rangle$  = the average number of connections;  $ASPL$  = the average shortest path length;  $CC$  = clustering coefficient;  $ASPL_{random}$  = the average shortest path length with random graph of same size and density;  $CC_{random}$  = the clustering coefficient for a random graph of same size and density.

The density of the network serves two purposes. Firstly, it allows to create a comparable random network to provide a benchmark for small-world analyses. Secondly, it serves to check the sparseness of the network. The sparseness of the whole network is shown by a very low density of  $5.10^{-3}$ . This means that about 0.05% of all possible associations between words are represented. When comparing the density of the concrete and abstract

networks, the concrete network presents an even lower density, which is in accordance with its higher diameter. This extreme sparseness can be explained by the variety of the dataset in terms of levels of concreteness of the cues. We expect that the concrete and abstract data share very few connections and belong to separate clusters. The sparseness of these networks -very low density- is the first mark of their small-world structure.

Based on the average shortest path length (ASPL), there was an average of 7.07 (directed) and 4.90 (undirected) steps from one node to another in the whole network. This average number of steps was higher in the concrete network (8.46 for the directed and 5.13 for the undirected) compared to the abstract network (7.20 for the directed and 5.00 for the undirected). This pattern is in accordance with the diameter. A series of random networks were generated with comparable size  $n$  and mean connectivity  $\langle k \rangle$  to serve as benchmark for smallworldness estimation. All networks had the same density as their corresponding random benchmarks. According to Table 2, the ASPL statistics were consistently smaller for the actual networks compared to the randomly generated ones. A small ASPL is a fundamental characteristic of a small-world structure.

The clustering coefficient is a measure of the probability that associates of a word are also connected to each other. This parameter is evaluated against a comparable random network. Table 2 shows that associates of a word in the directed networks were also connected to each other about 15% of the times for the whole and concrete networks and 14% of the times for the abstract network. For the undirected networks, this probability dropped to approximately 6-7 % of the time. The clustering coefficients of the whole, concrete and abstract networks were very high compared to the ones found for the benchmark random networks that ranged from 0.05 to 0.1% probability to find a link between two nodes that have a neighbour in common. The clustering coefficient is among the most important indicator of a

small-world structure. It suggests that when additional nodes are introduced in the network, they join a tightly connected hub, which insures the stability of the entire network.

Taken together, the sparseness, average short path lengths and clustering coefficient show that the present networks exhibit the same small-world properties found by Steyvers and Tenenbaum (2005). A final measure established by Humphries and Gurney (2008) was computed for each network and their corresponding random networks to evaluate their smallworldness. Based on this parameter, Humphries and Gurney (2008) indicated that an S measure  $> 3$  indicates a small-world structure. All the networks presented a very high S measure.

Finally, the modularity measure (Q) introduced by Newman (2006) indicates the extent to which a network is composed of sub-communities. Communities are non-overlapping groups of nodes with a high number of within community connections and a low number of between-community connections. The concrete network is more modular (Q = 0.70) compared to the abstract network (Q = 0.64).

Network analysis is rooted in the seminal work of Collins and Loftus (1975) who described the spreading of activation according to which the activation of concepts in memory spreads and activates other closely related concepts. This process is fundamental in cognitive science for its ability to explain many phenomena related to the mental lexicon (see Siew et al., 2019 for a review). Given the structural differences we have found in the concrete and abstract networks, it is fair to assume that the two types of concepts would exhibit different patterns of spreading scores. In the same way that spreading activation mimics the diffusion of discrete events such as the spread of disease among individuals, it is possible to identify initial “infected” nodes and their ability to spread the discrete event which is modelled (Siew et al., 2019). Salavaty, Ramialison and Currie (2020) have proposed a computational method

to identify the most influential nodes in a network that have a higher spreading scores for each node. Spreading scores are an indication of the capacity for a node to spread information within the network. The algorithm was used for each abstract and concrete network and generated a vector of spreading scores for each node. Comparison of spreading scores for abstract and concrete nodes respectively showed that abstract nodes ( $M=2.56$ ;  $SD=4.75$ ) have a lower spreading score compared to concrete nodes ( $M=3.72$ ;  $SD = 6.57$ ) –  $t(5390) = 7.70$ ;  $p < 0.001$ . These results suggest that the abstract nodes in the network are less influential and have a lesser ability to spread information within the network compared to concrete nodes.

## DISCUSSION

In the present work, the data obtained from word associations was represented as several networks using graph-theory based principles. This aimed at extracting structural and organisational patterns of the mental lexicon that would not be possible to gain from the raw dataset (De Deyne & Storms, 2008; Csardi & Nepusz, 2006; Kolaczyk & Csardi, 2014). The whole network represented the entire dataset. Next, based on a previously established pattern of cues eliciting responses of the same level of concreteness (Lakhzoum et al., 2021), the whole network was divided into a concrete and an abstract network by using the median concreteness level to separate them. A first series of analyses used random networks of a similar density and connectivity as benchmark (Lerner, Ogrocki, & Thomas, 2009).

Comparisons between the present networks and comparable random ones showed that the networks exhibited a small ASPL and a high clustering coefficient characteristic of a small-world structure (Watts & Strogatz, 1998; Steyvers & Tenenbaum, 2005; De Deyne & Storms, 2008). The small world structure provides valuable information not only about the structural characteristics of the networks but also about the way the networks will expand with the addition of new nodes. In a small-world network, when new nodes are included they join an already established cluster of existing nodes. This means that the network does not expand

proportionally with the addition of new nodes. This small-world effect insures that networks present a highly robust architecture that is resistant to change and disturbances (Peng, Tan, Wu & Holme, 2016).

When comparing the topological properties of the concrete and abstract networks, the concrete networks seems more spread out (higher ASPL), more connected (higher S measure), more modular (higher Q measure) than the abstract network. This pattern of densely connected but loosely interconnected nodes for the concrete network concurs with the pattern found in association strength with concrete cues eliciting stronger associates compared to the abstract ones. It also concurs with the dichotomy established by Paivio (Paivio, Yuille & Madigan, 1968; but see Della Rosa, Catricalà, Vigliocco & Cappa, 2010) between concrete and abstract concepts with concrete concepts being more highly connected to a smaller number of contexts while abstract concepts are more loosely connected to a higher number of contexts. This pattern of abstract concepts was confirmed in previous studies on feature-listing norms (Recchia & Jones, 2012) and now on a larger scale as evidence by a smaller modularity measure in the abstract network.

Taken together with previous findings, these local node statistics suggest that abstract and concrete concepts do not differ in their pattern of connectivity but rather on the strength of these connections with concrete concepts presenting stronger association compared to abstract concepts (Lakhzoum et al., submitted). This pattern of weaker connection for abstract nodes compared to concrete nodes is further reflected in their respective spreading scores with abstract nodes presenting a lesser ability to spread information in the network compared to concrete nodes. These scores are reflective of the position of the nodes in the network and influenced by clustering and modularity as well as the weights of their connections. This suggests that abstract concepts, due to their more diffuse pattern of organisation and weaker connections given by associative strength from the word association data have a lesser ability

to spread semantic activation in the mental lexicon. This is in accordance with previous findings according to which abstract concepts present a processing disadvantage compared to concrete concepts as evidenced by the longer response times they elicit (see Borghi, Binkofski, Castelfranchi, Cimatti, Scorolli & Tummolini, 2017).

Taken together, these characteristics suggest that the local organisation of abstract and concrete concepts is similar while their structural position within the network shows a different pattern with concrete concepts presenting a more modular pattern compared to abstract concepts.

## FUTURE WORK

The present work represents a first attempt to study the structural dichotomy in the organisation of concrete and abstract concepts in the mental lexicon. A future project will have to replicate the same analyses using an English word association dataset such as the SWOW-EN database of De Deyne and colleagues (2019). This will allow for a replication on a higher scale because the database contains 12.000 cues for more than 4 million responses. Realising the same network in English will also provide a baseline comparison for the research community and the opportunity to compare between English and other languages. By cross-referencing with concreteness ratings norms (Brysbaert, Warriner & Kuperman, 2014), it will be possible to understand the same structural organisation of abstract and concrete concepts on a larger scale.

Additionally, it must be kept in mind that the present network representation is not a neural network and does not yield any insights into the mapping of abstract and concrete concepts representation in the human brain. Network science can be applied to study brain connectivity based on the same techniques and parameters used in the present work (Siew et al., 2019 for a review). Based on recording of brain activity during a word association task for

abstract and concrete concepts, it will be possible to map the cognitive patterns obtained in the present work to the neural substrates that generated said cognitive patterns.

## REFERENCES

- Baronchelli, A., Ferrer-i-Cancho, R., Pastor-Satorras, R., Chater, N., & Christiansen, M. H. (2013). Networks in cognitive science. *Trends in Cognitive Sciences*, *17*, 348–360. <https://doi.org/10.1016/j.tics.2013.04.010>
- Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: an open source software for exploring and manipulating networks. In *Third international AAAI conference on weblogs and social media*.
- Bassett, D. S., & Bullmore, E. T. (2017). Small-World Brain Networks Revisited. *Neuroscientist*, *23*, 499–516. <https://doi.org/10.1177/1073858416667720>
- Borge-Holthoefer, J., & Arenas, A. (2010). Semantic networks: Structure and dynamics. *Entropy*, *12*, 1264–1302. <https://doi.org/10.3390/e12051264>
- Borge-Holthoefer, J., Moreno, Y., & Arenas, A. (2012). Topological versus dynamical robustness in a lexical network. *International Journal of Bifurcation and Chaos*, *22*, 1–9. <https://doi.org/10.1142/S021812741250157X>
- Borghi, A. M., Binkofski, F., Castelfranchi, C., Cimatti, F., Scorolli, C., & Tummolini, L. (2017). The challenge of abstract concepts. *Psychological Bulletin*, *143*, 263–292. <https://doi.org/10.1037/bul0000089>
- Bork, P., Jensen, L. J., Von Mering, C., Ramani, A. K., Lee, I., & Marcotte, E. M. (2004). Protein interaction networks from yeast to human. *Current Opinion in Structural Biology*, *14*, 292–299. <https://doi.org/10.1016/J.SBI.2004.05.003>
- Brysbaert, M., Warriner, A. B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand English word lemmas. *Behavior Research Methods*, *46*, 904–911.
- Choudhury, M., & Mukherjee, A. (2009). The Structure and Dynamics of Linguistic Networks. *Modeling and Simulation in Science, Engineering and Technology*, *42*, 145–166. [https://doi.org/10.1007/978-0-8176-4751-3\\_9](https://doi.org/10.1007/978-0-8176-4751-3_9)
- Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review*, *82*, 407–428. <https://doi.org/10.1037/0033-295X.82.6.407>
- Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal Complex Systems*, 1695. Retrieved from <http://igraph.sf.net>
- De Deyne, S., Navarro, D. J., Perfors, A., Brysbaert, M., & Storms, G. (2019). The “Small World of Words” English word association norms for over 12,000 cue words. *Behavior Research Methods*, *51*, 987–1006. <https://doi.org/10.3758/s13428-018-1115-7>
- De Deyne, S., & Storms, G. (2008). Word associations: Network and semantic properties. *Behavior Research Methods*, *40*, 213–231. <https://doi.org/10.3758/BRM.40.1.213>
- Della Rosa, P. A., Catricalà, E., Vigliocco, G., & Cappa, S. F. (2010). Beyond the abstract-concrete dichotomy: Mode of acquisition, concreteness, imageability, familiarity, age of acquisition, context availability, and abstractness norms for a set of 417 Italian words. *Behavior Research Methods*, *42*, 1042–1048. <https://doi.org/10.3758/BRM.42.4.1042>
- den Heyer, K., & Briand, K. (1986). Priming Single Digit Numbers: Automatic Spreading Activation Dissipates as a Function of Semantic Distance. *The American Journal of Psychology*, *99*, 315–340. <https://doi.org/10.2307/1422488>
- Deyne, S. De, Verheyen, S., & Storms, G. (2016). Structure and Organization of the Mental Lexicon: A Network Approach Derived from Syntactic Dependency Relations and Word

- Associations. *Understanding Complex Systems*, 99, 47–79. [https://doi.org/10.1007/978-3-662-47238-5\\_3](https://doi.org/10.1007/978-3-662-47238-5_3)
- Erdos, P., & Rényi, A. (1960). On the evolution of random graphs. *Publications of the Mathematical Institute of the Hungarian Academy of Sciences*, 5, 17–60.
- Fuks, H., & Krzemiński, M. (2009). Topological structure of dictionary graphs. *Journal of Physics A: Mathematical and Theoretical*, 42, 375101. <https://doi.org/10.1088/1751-8113/42/37/375101>
- Humphries, M. D., & Gurney, K. (2008). Network ‘Small-World-Ness’: A Quantitative Method for Determining Canonical Network Equivalence. *PLOS ONE*, 3, e0002051. <https://doi.org/10.1371/JOURNAL.PONE.0002051>
- Hutchison, K. A. (2003). Is semantic priming due to association strength or feature overlap? A microanalytic review. *Psychonomic Bulletin & Review*, 10, 785–813. <https://doi.org/10.3758/BF03196544>
- Karimkhani, F., Rahmani, H., Zare, A., Saheb Nassagh, R., & Aghakasiri, K. (2021). Tarvajah: Word Association Norms for Persian Words. *Journal of Psycholinguistic Research*, 50, 863–882. <https://doi.org/10.1007/s10936-020-09751-2>
- Keeling, M., & Rohani, P. (2011). *Modeling infectious diseases in humans and animals*. Princeton: New York University Press. <https://doi.org/https://doi.org/10.1515/9781400841035>
- Kenett, Y. N., Levi, E., Anaki, D., & Faust, M. (2017). The semantic distance task: Quantifying semantic distance with semantic network path length. *Journal of Experimental Psychology: Learning Memory and Cognition*, 43, 1470–1489. <https://doi.org/10.1037/XLM0000391>
- Kitsak, M., Gallos, L. K., Havlin, S., Liljeros, F., Muchnik, L., Stanley, H. E., & Makse, H. A. (2010). Identification of influential spreaders in complex networks. *Nature Physics* 2010 6:11, 6, 888–893. <https://doi.org/10.1038/nphys1746>
- Kolaczyk, E. D., & Csárdi, G. (2014). *Statistical Analysis of Network Data with R*. New York: Springer. Cham: Springer International Publishing. <https://doi.org/10.1007/978-3-030-44129-6>
- Landauer, T. K., & Dumais, S. T. (1997). A Solution to Plato’s Problem: The Latent Semantic Analysis Theory of Acquisition, Induction, and Representation of Knowledge. *Psychological Review*, 104, 211–240. <https://doi.org/https://doi.org/10.1037/0033-295X.104.2.211>
- Lerner, A. J., Ogrocki, P. K., & Thomas, P. J. (2009). Network graph analysis of category fluency testing. *Cognitive and Behavioral Neurology*, 22, 45–52. <https://doi.org/10.1097/WNN.0B013E318192CCAF>
- M, S., & JB, T. (2005). The large-scale structure of semantic networks: statistical analyses and a model of semantic growth. *Cognitive Science*, 29, 41–78. [https://doi.org/10.1207/S15516709COG2901\\_3](https://doi.org/10.1207/S15516709COG2901_3)
- McNamara, T. P. (2005). *Semantic priming: Perspectives from memory and word recognition*. *Semantic priming: Perspectives from memory and word recognition*. New York, NY, US: Psychology Press. <https://doi.org/10.4324/9780203338001>
- Milgram, S. (1967). The small world problem. *Psychology Today*, 2, 60–67.
- Moreno, S., & Neville, J. (2013). Network Hypothesis Testing Using Mixed Kronecker Product Graph Models. In *2013 IEEE 13th International Conference on Data Mining* (pp. 1163–1168). <https://doi.org/10.1109/ICDM.2013.165>
- Motter, A., Moura, A., Lai, Y.-C., & Dasgupta, P. (2002). Topology of the conceptual network of language. *Physical Review. E, Statistical, Nonlinear, and Soft Matter Physics*, 65, 65102. <https://doi.org/10.1103/PhysRevE.65.065102>

- Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences of the United States of America*, *103*, 8577–8582. <https://doi.org/10.1073/pnas.0601602103>
- Paivio, A., Yuille, J. C., & Madigan, S. A. (1968). Concreteness, imagery, and meaningfulness values for 925 nouns. *Journal of Experimental Psychology*, *76*, 1–25. <https://doi.org/10.1037/h0025327>
- Pastor-Satorras, R., & Vespignani, A. (2001). Epidemic spreading in scale-free networks. *Physical Review Letters*, *86*, 3200–3203. <https://doi.org/10.1103/PhysRevLett.86.3200>
- Peng, G. S., Tan, S. Y., Wu, J., & Holme, P. (2016). Trade-offs between robustness and small-world effect in complex networks. *Scientific Reports*, *6*, 1–10. <https://doi.org/10.1038/srep37317>
- Recchia, G., & Jones, M. N. (2012). The semantic richness of abstract concepts. *Frontiers in Human Neuroscience*, *6*, 315. <https://doi.org/10.3389/fnhum.2012.00315>
- Salavaty, A., Ramialison, M., & Currie, P. D. (2020). Integrated Value of Influence: An Integrative Method for the Identification of the Most Influential Nodes within Networks. *Patterns*, *1*, 100052. <https://doi.org/10.1016/j.patter.2020.100052>
- Siew, C. S. Q., Wulff, D. U., Beckage, N. M., & Kenett, Y. N. (2019). Cognitive Network Science: A Review of Research on Cognition through the Lens of Network Representations, Processes, and Dynamics. *Complexity*, *2019*, 2108423. <https://doi.org/10.1155/2019/2108423>
- Sigman, M., & Cecchi, G. A. (2002). Global organization of the Wordnet lexicon. *Proceedings of the National Academy of Sciences*, *99*(3), 1742–1747. <https://doi.org/10.1073/PNAS.022341799>
- Stella, M., Beckage, N. M., Brede, M., & De Domenico, M. (2018). Multiplex model of mental lexicon reveals explosive learning in humans. *Scientific Reports*, *8*, 1–11. <https://doi.org/10.1038/s41598-018-20730-5>
- van Noort, V., Snel, B., & Huynen, M. A. (2004). The yeast coexpression network has a small-world, scale-free architecture and can be explained by a simple model. *EMBO Reports*, *5*, 280–284. <https://doi.org/10.1038/sj.embor.7400090>
- Veremyev, A., Semenov, A., Pasiliao, E. L., & Boginski, V. (2019). Graph-based exploration and clustering analysis of semantic spaces. *Applied Network Science*, *4*(1). <https://doi.org/10.1007/s41109-019-0228-y>
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’ networks. *Nature*, *393*, 440–442. <https://doi.org/10.1038/30918>
- Siew, C. S. Q., Wulff, D. U., Beckage, N. M., & Kenett, Y. N. (2019). Cognitive Network Science: A Review of Research on Cognition through the Lens of Network Representations, Processes, and Dynamics. *Complexity*, *2019*, 2108423. <https://doi.org/10.1155/2019/2108423>

The previous chapter was an application of the mathematical graph-theory on French word association data for concrete and abstract networks. Graph analyses have extended previous findings as regards to the small-world structure of the mental lexicon characterised by a sparse density, a short average path length and a high clustering coefficient to the French language. Comparison of the concrete and abstract networks have shown that abstract concepts are organised in a more diffuse pattern of connectivity compared to concrete concepts which confirms our findings about the weaker associative strength exhibited by abstract concepts compared to concrete concepts on a larger scale and on a structural level. Additional comparison of spreading scores for abstract and concrete nodes have shown that concrete concepts are more influential in the network compared to abstract concepts meaning they have a higher ability to spread information in the network. These results are providing some insights as regards to the apparent paucity in semantic content of abstract concepts compared to concrete concepts and the processing advantage of concrete concepts over abstract concepts (Paivio et al., 1986, but see Borghi et al., 2017 for a discussion).

More recent studies have explored the richness of abstract concepts and have found that what abstract concepts lack in physical features they gain in other types of features such as emotion, social, introspective and metacognitive (see for example Recchia & Jones, 2012). The next chapter builds on the work of McRae et al. (2018) who used a picture-word paradigm and provided evidence for the extraction of situational features in abstract concept processing. In contrast, Kuipers et al. (2018) showed that abstract concepts can be activated by abstract pictures, which lack such tangible situational features. In a series of experiments, we compared the role of situational and intangible features in the processing of abstract concepts. Results have shown that even when compared with situational picture primes, extraction mechanisms still occurred in the case of abstract pictures. We interpreted these

results as further evidence of the richness of abstract concepts which can be activated from features other than lexical or situational, namely also abstract and intangible.

## Chapter 5. Intangible features extraction in the processing of abstract concepts: Evidence from picture-word priming

Dounia Lakhzoum<sup>1\*</sup>, Marie Izaute<sup>1</sup>, and Ludovic Ferrand<sup>1\*</sup>

<sup>1</sup>Université Clermont Auvergne, CNRS, LAPSCO, Clermont-Ferrand, France

**Chapter 5 was published under the reference** Lakhzoum, D., Izaute, M., & Ferrand, L. (2021). Intangible features extraction in the processing of abstract concepts: Evidence from picture-word priming. *Plos One*, 16, e0251448.

Supplementary material: <https://osf.io/483tu/>

\*Corresponding authors: Dounia Lakhzoum or Ludovic Ferrand, Université Clermont

E-mail: [dounia.lakhzoum@uca.fr](mailto:dounia.lakhzoum@uca.fr) (DL); [ludovic.ferrand@uca.fr](mailto:ludovic.ferrand@uca.fr) (LF)

## ABSTRACT

Over the last decade, hypotheses ranging from linguistic symbol processing to embodiment have been formulated to account for the content and mechanisms responsible for the representation of abstract concepts. Results of recent studies have suggested that abstract concepts, just like concrete ones, can benefit from knowledge of real-world situational context, but that they can also be processed based on abstract pictures devoid of such situational features. This paper presents two semantic priming experiments to explore such mechanisms further. The first experiment replicates Kuipers, Jones, and Thierry (2018) in a cross-linguistic setting which shows that abstract concepts can be processed from abstract pictures devoid of tangible features. In the second experiment, we studied extraction mechanisms that come into play when participants are presented with abstract and concrete pictures that provide situational information to illustrate target abstract concepts. We expected this facilitatory effect to be limited to concrete picture primes. Our data analysed with both Bayesian and Frequentist tests showed however that even when presented with tangible situational information, the extraction of features still occurred for abstract pictures. We discuss the implications of this with respect to future avenues for studying the processing of abstract concepts.

## INTRODUCTION

Abstract concepts have long been a riddle for the brain and cognitive sciences. The past decade saw a greatly enhanced research effort as regards abstract concepts representation (e.g., [1]; see [2] for a review). In spite of such efforts, challenging questions remain as to how abstract concepts convey meaning and the type of information in which their representation is encoded.

### Dimensions of abstract concepts

With abstract concepts, there is no one-to-one matching between the concept–word and a single referent. Usually they refer to complex situations involving multiple objects and entities [3–5]. Until recently, their definition was formulated primarily in opposition to concrete concepts, therefore constraining the scope of the debate because the dichotomy between abstract and concrete concepts is not clear-cut [6]. For a long time, the most commonly used dimension was imageability, with concrete concepts referring to highly imageable entities that can be perceived through the senses and abstract concepts having low imageability. This dimension is the direct consequence of Paivio’s Dual Coding Theory (DCT, [7]) according to which concrete concepts trigger processing based on two informational systems, one visual, the other verbal, whereas abstract concepts are processed only in the verbal system. More specifically, imageability is the ability of “words [to] arouse sensory experience” (Paivio et al., 1968, p.4; see also [8]). In that sense, it is implicitly equated with abstractness, so much so, in fact, that abstract concepts stimuli were often chosen among words with low imageability ratings.

A closely related dimension used to distinguish abstract concepts comes from the Context Availability Theory (CAT, [9]) according to which concrete concepts refer to a set number of contexts whereas abstract concepts are loosely connected to a variety of contexts.

The argument here is that the availability of a strong network of highly defined features provides concrete concepts with a processing advantage over abstract concepts. This distinction perpetuates the inaccurate view that abstract concepts are poor in features. It has been somewhat invalidated, however, by recent evidence showing that although abstractness is highly correlated with imageability, the two dimensions are not equivalent. Kousta, Vigliocco, Vinson, Andrews, and Del Campo (2011) found a processing advantage in favour of abstract concepts once the imageability and context variables were controlled, a finding which intensified the perceived need to uncover more dimensions to define abstract concepts [10]. To that end, Villani et al., (2019) introduced a novel database of 15 dimensions clustered around sensorimotor, linguistic, inner, social states and hand and mouth effectors [5]. The database offers researchers the ability to select abstract stimuli along more defined dimensions and allows for better-controlled experiments.

The study of abstract concepts is benefiting from the greater emphasis placed on their variety, dimensions and richness. Not only has this intensified interest been concerned with defining their dimensional content, it has also produced theoretical accounts to explain how they are processed. Several theories on a spectrum ranging from amodal to grounded assumptions have been formulated to answer questions about processing mechanisms for abstract concepts.

### **Theoretical accounts in the study of abstract concepts**

At the amodal end of the spectrum, traditional accounts of semantics use symbolic representations to define the meaning of concepts [11–14]. In recent years, this account has been integrated in models of distributional semantics able to extract meaning from statistical distribution across corpora (see [15] for a review of these models). Given that word co-occurrences can be computed for concrete and abstract concepts alike, this account finds no

issue with explaining the representation of abstract concepts. However, use of amodal linguistic symbols as a proxy for representing meaning has been under fire for its lack of grounding in modality-specific brain areas [16–20].

At the grounded end of the spectrum, the meaning of concepts is derived from perceptual and motor states [21–23]. For instance, Pulvermüller, Shtyrov, and Ilmoniemi (2005) used MEG techniques to show that brain areas responsible for motor actions of the face or leg are activated when action words such as *lick* or *kick* are processed [24]. Such evidence is challenged, however, when faced with abstract concepts such as *truth* or *freedom*, as they do not refer directly to physical features of the world. That explains why the embodied account had to be extended to include hypotheses for the grounding of abstract concepts.

Several studies have investigated the representation of abstract concepts through feature-listing paradigms and have demonstrated that abstract concepts also benefit from some form of representation in modality-specific. For example, abstract concepts activate social and introspective aspects of situations [25,26], emotional features [27], event information and thematic roles [28]. More generally, these studies unveiled representation mechanisms for abstract concepts that place greater emphasis on the context in which they are used (e.g., [29–31]). For instance, Wilson-Mendenhall, Martin, Simmons and Barsalou (2013) performed a task requiring deep conceptual processing of abstract concepts such as *convince* [32]. They observed neural activation patterns of non-linguistic brain areas associated with mentalizing and social cognition. In a more recent study, Harpainter et al. (2020) studied brain activation patterns for visual and motor abstract concepts such as *beauty* and *fight* [33]. In line with the grounding of representation framework, their results suggest some categories of abstract concepts benefit from a similar grounding mechanism to concrete concepts. Middle-ground theories, however, consider that both amodal and grounded content contribute to the

representation of abstract concepts. For instance, Dove's representation pluralism ([34–36] see also [2] and [37] for a review) represents just such a hybrid approach, according to which abstract concepts activate both linguistic and modality-specific features.

### **Picture priming paradigms in the study of abstract concepts**

The representation of abstract concepts in situations and contexts has been further investigated in recent years [25,29,30]. More recently, McRae, Nédjardrasul, Pau, Pui-Hei Lo and King (2018) presented abstract target words primed by pictures depicting scenes either related or unrelated to the target words [38]. For example, the concept *discipline* was primed by the picture of students lined up. When target words were preceded by related pictures, lexical decision latencies were shorter than when unrelated pictures were shown. Such results support the assumption of extraction of situational features in abstract concept processing.

In another recent study, Kuipers, Jones and Thierry (2018) used a similar priming paradigm, but with abstract picture primes, which lack tangible situational features [39]. The results showed shorter manual latencies and a smaller N400 amplitude in the EEG data for related abstract picture-word pairs than unrelated ones. The authors inferred that the abstract pictures conveyed the same meaning as the abstract words. The fact that abstract images devoid of situational context elicited an activation pattern similar to the abstract concepts they primed suggests the need for further investigation of the mechanisms involved in abstract concept processing.

### **The present study**

After norming the abstract picture-word pairs from Kuipers et al. (2018) with French participants, we replicated their study in French in a first experiment to make sure their findings remained valid in a cross-linguistic setting. In a second experiment, we expanded on

their study by comparing abstract picture primes to concrete ones within the same experiment [39]. For the first experiment, we expected to find the same facilitatory effect as in English, with shorter manual latencies for related abstract picture-word pairs than for unrelated ones. In a second experiment, we compared concrete picture primes allowing for situational grounding to abstract picture primes composed of intangible features. For this second experiment, in which concrete and abstract picture primes were presented together we also expected shorter latencies for related picture-word pairs than for unrelated ones in the concrete picture condition. However, and in line with the previously discussed role of situational features in the representation of abstract concepts, we expected this facilitatory effect to be limited to concrete picture primes, insofar as they allow for a more tangible form of situational or contextual information, and to disappear in respect of abstract picture primes (see [38]). Tangible features, as opposed to intangible ones, should allow for easier processing [40]. We expected that when presented with both types of features the participants would develop a strategy by allocating more resources to extracting tangible features, to the detriment of intangible ones.

## **Experiment 1**

### **MATERIALS and METHODS**

#### **Participants**

The same number of participants were tested in Experiment 1 as were tested by Kuipers et al. (2018) [39]. Twenty native French speakers from Université Clermont Auvergne, France, took part in this experiment (4 males;  $M_{\text{age}} = 24$ ,  $SD = 3$ ). All participants were right-handed with corrected-to-normal vision. They all gave their informed written consent before taking part in the study. They were rewarded for their participation with a 10€

gift card. The study was approved by the local ethics committee (Comité d'éthique de la Recherche IRB-UCA).

## Materials

The material used in Experiment 1 was crafted on the basis of the norming study described hereafter. For Experiment 1, the purpose was to create a set of semantically related and unrelated picture-word combinations based on the stimuli used in [39]. We obtained the abstract images and words collected for their study by contacting the authors. The materials consisted of 100 abstract images, each paired with one related and one unrelated abstract word. We translated the words into French and submitted the picture-word combinations to a group of 166 French participants (56 men,  $M_{\text{age}} = 21.7$ ,  $SD = 4.6$ ) using Qualtrics (2020) in a preliminary study. As in Kuipers et al. (2018), participants were asked, "How strongly does the word below match the above picture?" (on a scale of 0 to 10) [39]. We kept only the 71 picture-word combinations that elicited the highest scores for the related conditions, and those that elicited the lowest scores for the unrelated conditions ( $M_{\text{Related}} = 6.5$ ,  $SD = 1.0$ ;  $M_{\text{Non\_Related}} = 2.2$ ,  $SD = 1.1$ ;  $t(70) = 21.6$ ,  $p < 0.001$ ,  $d = 2.6$ , 95CI [2.1-3.0], see Figure 1 for an example of combination).

## Procedure

Experiment 1 used exactly the same procedure as Kuipers et al. (2018), except that we recorded only reaction times, and not EEG. We presented abstract image-word combinations that were either semantically related or unrelated (see Figure 1 for example stimuli) [39]. Both the related and unrelated modalities were presented in a within-subjects design. Stimuli were presented using E-prime software v2.1 on a 15-inch Dell PC colour monitor with a refresh rate of 60 ms and connected to an AZERTY keyboard. Participants were seated at a distance

of 50 cm from the monitor. Each trial began with a fixation cross, displayed in the middle of the screen for 300ms followed by an abstract picture that remained on the screen for 5000ms. The fixation cross was then replaced with an abstract target word, which stayed on the screen until the participant answered, or until 5000ms had elapsed. The participant's task was to indicate, using the D and K keys on the AZERTY keyboard, whether the target word was semantically related or unrelated to the previous picture. Response latencies were recorded, as well as accuracy. The experiment took approximately 20 minutes to complete.

## RESULTS

### Reaction times

Latencies  $> 3$  SDs above or below each participant's mean latencies for each condition were excluded from the analyses (less than 2% of the data). Mean correct latencies were analysed by means of a one-sided paired-samples t-test testing the same directional hypothesis as Kuipers et al., (2018). We conducted analyses within a Bayesian framework relying on prior specification of theoretical knowledge which includes effect sizes and the direction of hypotheses [33], see also [41]. The analysis revealed an effect of Target Word Type with shorter latencies for the related pairs than the unrelated ones ( $M_{\text{Related}} = 1411$  ms;  $SD = 429$ ;  $M_{\text{Non\_Related}} = 1529$  ms;  $SD = 464$ ; Mean Difference = 118 ms; 95CI [21, 214];  $t(19) = 2.55$ ,  $p = 0.01$ , Cohen's  $d = 0.57$ , see Figure 2). We conducted a Bayesian paired-samples t-test using JASP [42]. For the informed prior we used Oosterwijk's recommendation (t-distribution with location 0.350, scale 0.102, and 3 degrees of freedom), because it is considered a good prior for small-to-medium effect sizes (see [43]). This analysis showed a Bayes Factor of 10.93 (median = 0.39; 95CI [0.19-0.67]). This means the results are about 11 times more likely under the alternative hypothesis compared to the null. Taken together, the Bayesian analyses

show substantial to strong support for the finding that abstract images can elicit a semantic priming effect [44].

Yet, this effect is somewhat surprising and rather counter-intuitive with respect to the role of situational grounding in concept representation. We therefore conducted supplementary analyses in a Bayesian replication framework to test for the robustness of such an effect. To that end, we applied a Replication Test in Rstudio [45] (ReplicationBF package [46]) which can be used to assess the success or failure of a replication attempt by testing whether the effect identified in previous studies is present or absent in the replication attempt [46], whether the effect size in the replication is equal to that found in the original study [47], and whether the effect is present when the data are pooled in a meta-analysis [48]. The replication test relies on sample sizes and t-values and requires no specification of a prior distribution, thus escaping the influence of a researcher's choice of priors, but it uses the posterior distribution of the original study as a prior for the replication attempt ([49,50] but see [51]). The results of the replication tests are reported in the supplementary analyses. For the equality-of-effect size Bayes factor, support for the null hypothesis, according to which there is no difference between effect sizes, is indicative of a successful replication. The tests provided substantial support for the equality of effect sizes (Equality B01  $\approx$  5; see Table A.1), with the fixed-effect meta-analysis Bayes factor test showing strong support for the presence of an overall effect (Meta B10  $\approx$  30). Finally, the new Bayes factor for replication shown in Figure A.1 indicates that the results are about 12.5 times more likely under the proponent's hypothesis that the effect is consistent with the one found in the original study as opposed to the sceptic's hypothesis that the effect is spurious [46].

## Errors

A paired-samples t-test showed no effect of Target Word Types for the errors ( $t(19) = 0.14$ ;  $p = 0.90$  *ns*).

## DISCUSSION

The aim of Experiment 1 was first to extend the replicability of Kuipers et al. (2018) to another language before considering expanding it in a follow-up experiment [39]. As in the study by Kuipers and colleagues, we obtained shorter latencies for related combinations than for unrelated ones. They interpreted their results in terms of meaning processing and concluded that it was possible that abstract pictures can convey the same meaning as lexical abstract concepts. Given the counter-intuitive results obtained by Kuipers et al. (2018), especially given the important role of situational information, we decided to conduct Bayesian analyses [46], the results of which provided strong evidence in favour of Kuipers and colleagues' alternative hypothesis, according to which abstract pictures can convey the same meaning as abstract concepts. Furthermore, we conducted a supplementary replication test to ensure our attempt at replication was successful. We demonstrated therefore that the effect of picture-word priming using abstract pictures could be replicated in a cross-linguistic setting using different abstract images. Despite our analyses confirming the evidence uncovered by Kuipers and colleagues we do not rule out other possible interpretations (see General Discussion). Having confirmed the replicability of a study using such stimuli, we are now keen to expand Experiment 1 in a paradigm that would allow abstract concepts to be extracted from situational pictures. Experiment 2 aimed to implement such a paradigm. To that end, we kept the abstract priming pictures from Experiment 1 and added a condition for which participants were presented with concrete priming pictures that provided situational information.

## Experiment 2

### MATERIALS and METHODS

#### Participants

An independent group of 90 students from Université Clermont Auvergne who met the same criteria as for Experiment 1 took part in Experiment 2 (18 males;  $M_{age} = 20.2$ ;  $SD = 2.86$ ). They all gave their informed written consent before taking part in the study. The study was approved by the local ethics committee (Comité d'éthique de la Recherche IRB-UCA).

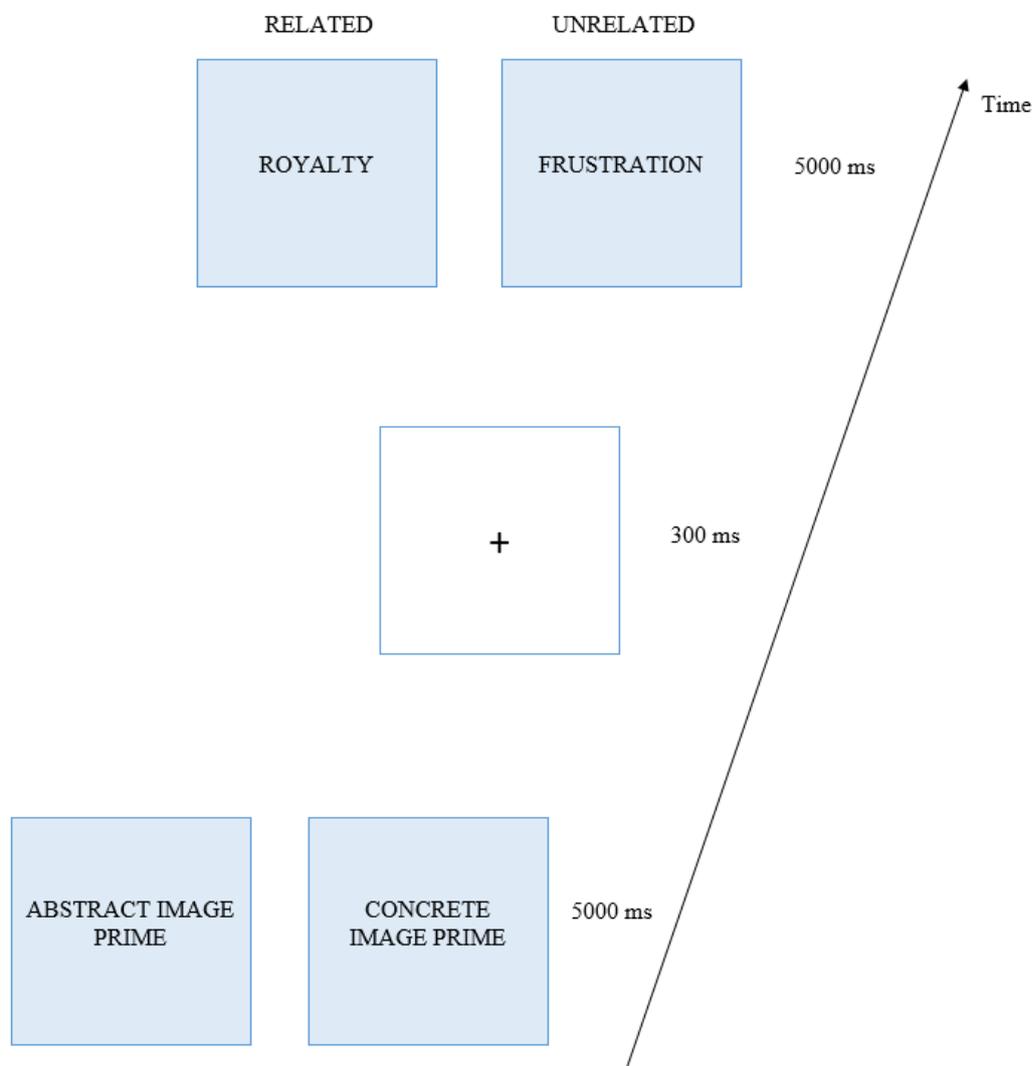
#### Materials

The materials used for Experiment 2 were the result of a second norming study. The purpose of the norming study for Experiment 2 was to find corresponding concrete images for each picture-word combination in Experiment 1. To that end, we searched online databases for images likely to elicit the same meaning as the abstract words. For each word, we selected two potential images which we then submitted to an independent group of 146 French participants (38 men,  $M_{age} = 22.4$ ,  $SD = 5.6$ ) using Qualtrics. Participants were asked, "How strongly does the word below match the above picture?" (on a scale of 0 to 10). Picture-word combinations that obtained a low score ( $< 5$  on a scale of 0 to 10) for both image options were discarded. The remaining 56 stimuli combinations (abstract/concrete image-related/unrelated word) were used in Experiment 2 (see Figure 1 for an example of stimuli).

#### Procedure

We used a similar procedure as for Experiment 1, but expanded it with 2 within-subjects variables: Priming Image Type (abstract vs. concrete) and Target Word Type (related

vs. unrelated). The stimuli were divided in a Latin square with 4 modalities: abstract prime images, concrete prime images, semantically-related target words and unrelated target words. Following this Latin-square design, the pictures were divided into two lists so that each picture presented in the related condition to participant 1 was also presented to participant 2 in the unrelated condition. Participants were exposed to all variables but saw only one of the 4 possible types of picture-word combination for each stimulus (see Figure 1 for an illustration of the trial procedure with an example of stimuli).



**Figure 1.** Trial procedure for the concept royalty (“royauté” in French).

Note. For this concept, each participant was exposed to either the abstract or the concrete image prime followed by the related or unrelated target word. The trial procedure for Experiment 1 consisted of only the abstract images paired with related or unrelated words, whereas Experiment 2 also had

concrete images in addition to the abstract pictures. The abstract image stimulus is a fractal created by Sven Geier (<http://www.sgeier.net/fractals/fractals/07/The%20Road%20Ahead.jpg>) and the concrete image stimulus is a coronation picture credited to the National Film Board of Canada. Photothèque. Library and Archives Canada, PA-196667; CC BY 2.0; <https://tinyurl.com/pxfvv8p7>).

## RESULTS

### Reaction times

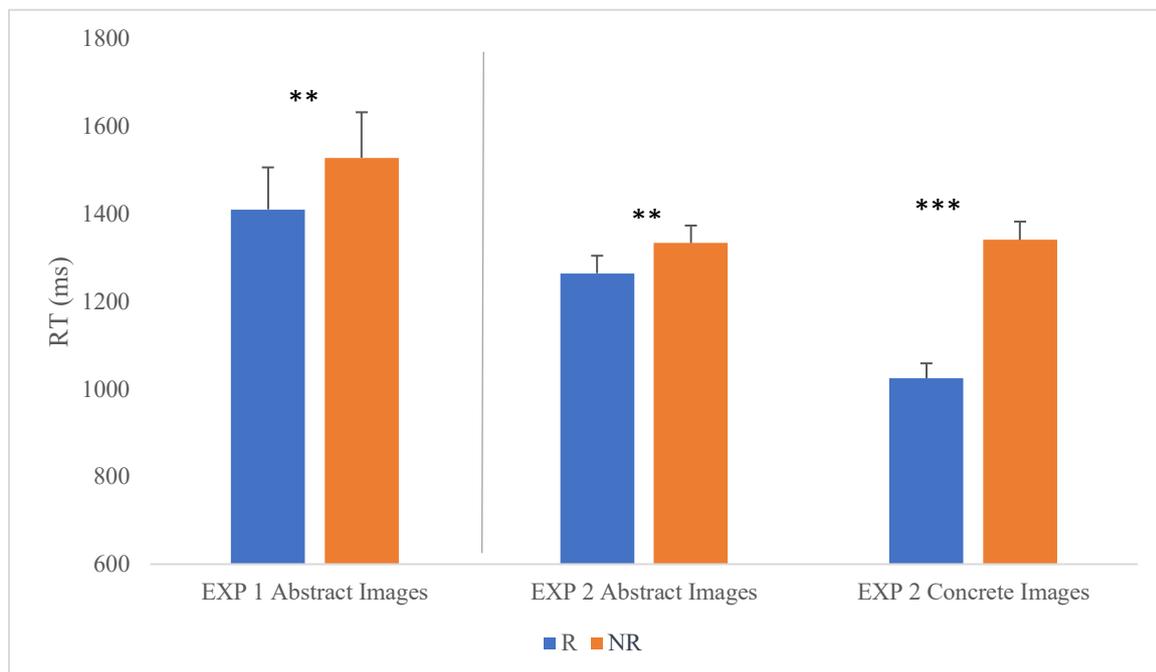
Latencies  $> 3$  SDs above or below each participant's mean latencies for each condition were excluded from the analyses (i.e.  $\sim 2\%$  of the total data). Data from 3 participants were discarded based on z-scores that showed very slow RTs in all conditions (z-scores  $> 2.99$ ).

The following analyses are based on the data from 87 participants.

Mean correct latencies are presented in Figure 2. Mean correct latencies were analysed with a 2(Priming Image Type = Concrete vs. Abstract) \* 2(Target Word Type = Related vs. Unrelated) repeated measures ANOVA.

This analysis revealed a main effect of Priming Image Type with shorter latencies for concrete images compared to abstract images (respectively,  $M_{\text{Concrete\_Image}} = 1183$  ms;  $SD = 357$ ;  $M_{\text{Abstract\_Image}} = 1338$  ms;  $SD = 383$ ; Mean Difference = 116 ms; 95CI [80, 152];  $F(1, 86) = 40.65$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.32$ ). The results also showed a main effect of Target Word Type with shorter latencies for the related targets compared to unrelated targets ( $M_{\text{Related}} = 1144$  ms;  $SD = 346$ ;  $M_{\text{Non\_Related}} = 1300$  ms;  $SD = 372$ ; Mean Difference = 193 ms; CI [145, 241];  $F(1, 86) = 63.74$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.43$ ). The results showed an interaction effect between Priming Image Type and the Target Word Type ( $F(1, 86) = 70.48$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.45$ ). Contrast analyses were conducted to investigate this interaction further. There was a significant effect of word type within each level of image type, with shorter latencies for the related targets compared to unrelated targets for the abstract images ( $M_{\text{Abstract\_Related}} = 1265$ ;  $SE = 40$ ; 95CI

[1185, 1344];  $M_{\text{Abstract\_NonRelated}} = 1334$ ;  $SE = 40$ ;  $CI [1255, 1414]$ ;  $t(86) = 2.33$ ;  $p = 0.011$ ;  $d = 0.3$ ;  $CI [0.04, 0.5]$ ) and concrete images ( $M_{\text{Concrete\_Related}} = 1025$ ;  $SE = 34$ ;  $CI [957, 1093]$ ;  $M_{\text{Concrete\_NonRelated}} = 1341$ ;  $SE = 42$ ;  $CI [1258, 1426]$ ;  $t(86) = 12.00$ ;  $p < 0.001$ ;  $d = 1.3$ ;  $CI [0.99, 1.56]$ , see Figure 2). The semantic facilitatory effect was therefore present for both types of prime stimuli.



**Figure 2.** Mean correct latencies (in ms with standard error bars) for Type of Image Prime and Type of Target Word (R = related pairs; NR = non-related pairs; \*\* $p = 0.01$ ; \*\*\* $p < 0.001$ ) in both Experiments 1 and 2.

A Bayesian repeated measures ANOVA compared four models to the null model. We kept the default JAPS prior for fixed effects ( $r$  scale prior width = 0.5; [47,48]). Based on Bayes Factors, the model including only the types of priming images was 5770 times more likely than the null model. There is therefore strong evidence for the type of prime model. There was also strong evidence for the model including only the type of word target ( $BF = 1.902 \times 10^{13}$ ), for the model including both main effects ( $BF = 2.990 \times 10^{18}$ ), and for the interaction model ( $BF = 2.551 \times 10^{25}$ ). Finally, we compared the main effects model to the

interaction model ( $2.551 \times 10^{25} / 2.990 \times 10^{18} = 8.533 \times 10^6$ ; based on the Baws Factor suggested by Mathôt, 2017 [52]) and obtained strong evidence for the interaction model.

We used a Bayesian paired-samples t-test to explore this interaction, with an informed prior following Oosterwijk's recommendation. The analysis showed a Bayes Factor of 7.67 (median = 0.30; CI [0.13, 0.45]) in favour of the alternative hypothesis for the difference between related and unrelated target words in the abstract picture primes condition, and a Bayes Factor of  $4.42 \times 10^{15}$  (median = 1.19; CI [0.89, 1.48]) in favour of the alternative hypothesis for the difference between related and unrelated target words in the concrete picture primes. These Bayesian analyses concur with the ones obtained from traditional paired-samples t-test and confirm substantial evidence for the effect of the abstract picture primes and extreme evidence for the concrete ones.

## Errors

Given the difficulty of the task, especially concerning the abstract image condition, we expected larger rates of errors overall, but more specifically for the abstract image primes.

Indeed, a repeated measures ANOVA revealed a main effect of Priming Image Type with a higher percentage of errors for the abstract images compared to the concrete images

( $M_{\text{Abstract\_Image}} = 29\%$ ;  $SD = 16.5$ ;  $M_{\text{Concrete\_Image}} = 12\%$ ;  $SD = 10$ ;  $F(1,87) = 189.87$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.69$ ). As for Experiment 1, the results showed no main effect of Target Word Type.

## DISCUSSION

Experiment 2 expanded on Experiment 1 by comparing abstract to concrete pictures priming abstract lexical concepts. We opted for a semantic, as opposed to a lexical decision task given that Recchia and Jones (2012) suggested the latter did not yield deep semantic

processing and therefore accounted for the discrepancies between results in the abstract concept processing literature [53]. Recognising this might be a concern, however, we checked for such surface features based on analyses of emotional valence in an additional study. We presented the pictures to an independent pool of 49 participants online and asked them to rate the emotional valence of the pictures on a scale of 0-10. We then used this valence variable in a *post-hoc* analysis and found it failed to explain the variance in latencies for semantic priming (based on a repeated measures ANOVA ( $F(2, 48) = 1.76 ; p = .19$  ns)). Based on this analysis we can rule out a shallow picture-word association based only on surface physical features.

This facilitatory effect was significantly stronger for concrete pictures than for abstract ones. However, it was weaker in relation to Experiment 1, although it did not disappear for abstract pictures.

This result expands on those obtained by Kuipers et al. (2018), showing that abstract concepts can be processed on the basis of abstract and concrete pictures alike and more broadly from tangible and intangible features. The Bayesian models provide decisive evidence in favour of the alternative hypothesis of semantic priming. The error rates obtained were quite high compared to traditional effects in the semantic priming literature. We were not surprised by these rates, however, as the task was more difficult in comparison to traditional priming studies. We asked Kuipers et al. (2018) for the error rates for their study (27% error rates for the related and 31% for the unrelated items), which confirmed our intuition that such stimuli would elicit higher error rates compared to more traditional semantic priming studies.

## GENERAL DISCUSSION

The aim of the present studies was to investigate conceptual processing mechanisms based on picture-word combinations in terms of the role of situational features compared to intangible abstract features.

In the first experiment and in line with Kuipers and colleagues, we investigated conceptual processing mechanisms in relation to abstract pictures. The results showed participants were able to process concepts from abstract pictures devoid of tangible features (therefore replicating Kuipers et al., 2018 results and extending them to the French language). To the best of our knowledge, Kuipers et al. (2018) were the first to provide evidence that abstract pictures can activate the meaning of abstract concepts. The data of Experiment 1 which was analysed using a Bayesian replication framework, corroborated their findings. This fact alone broadens the scope of conceptual representation beyond the usual debate of linguistic vs. situational features (see for e.g., [14,25,34]). It also goes to show that abstract concepts are even richer and activate features beyond their linguistic or situational components [53].

In a second experiment, we gave participants an opportunity to extract situational features (see also [38]). Results showed a stronger facilitatory effect for concrete picture-words pairs compared to abstract ones. Participants relied more heavily on the priming pictures with distinguishable features. Our results support previous findings according to which some types of abstract concepts are grounded in situations and events [25,32,40].

From the evidence from the two experiments, it appears that is possible to represent abstract concepts based on abstract and intangible pictures as well as on concrete and tangible ones. McRae et al. (2018) showed that in a picture-priming paradigm similar to our “concrete images” condition, participants could process the meaning of abstract concepts derived from

pictures depicting scenes. Kuipers et al. (2018) showed how this processing could also be derived from abstract pictures that differ from the stimuli used by McRae and colleagues because they are devoid of tangible features. In the present study, and based on the assumption that it is costlier to extract intangible features when tangible ones are available, we showed that extraction mechanisms still occurred in the case of abstract pictures.

The immediate interpretation of these results refers to how Kuipers and colleagues and McRae and colleagues interpreted meaning processing based on tangible and intangible features. This initial interpretation infers that there is a semantic level of processing and implies a featural view of semantic representation according to which concepts can be broken up into a set of defining features that represent their meaning (see [54] for an account of the featural view). If confirmed, this assumption would mean such features can be other than lexical or situational, namely also abstract and intangible.

For instance, Bolognesi and Vernillo (2019) proposed ‘Abstraction by Metonymy’ as a novel grounding mechanism for abstract concepts in the pictorial mode, where they use verbo-pictorial metaphors to investigate people’s ability to illustrate abstract concepts [55]. According to their hypothesis, this abstraction process allows for an inferential mechanism that moves from concretely depicted entities to more abstract ones. In the present studies, the reverse mechanism seems to have occurred. It might be that in the abstract image condition, participants extracted intangible features and inferred a more tangible representation of the concept. Therefore, these results could be construed as complementing the Abstraction by Metonymy.

In conclusion, by directly comparing the two types of features for representation, we were able to show that abstract concepts can be processed based on situational features and

abstract ones. For us, these conclusions signal the need to explore further the mechanisms of concept representation and abstraction.

### Acknowledgments

This research conducted within the FACTOLAB framework has been sponsored by: Michelin tyre manufacturer, the French government research programs "Investissements d'Avenir," the IDEX-ISITE initiative 16-IDEX-0001 (CAP 20-25), and the IMobS3 Laboratory of Excellence (ANR-10-LABX-16-01).

This work received technical support from the CNRS and UCA of Clermont-Ferrand. The authors would like thank Gillian Wakenhut for reviewing and editing the language of the manuscript. The authors would also like to thank Jan R. Kuipers for giving us access to his data and stimuli.

### REFERENCES

1. Lakhzoum D, Izaute M, Ferrand L. Semantic similarity and associated abstractness norms for 630 French word pairs. . doi:10.3758/s13428-020-01488-z
2. Borghi AM, Binkofski F, Castelfranchi C, Cimatti F, Scorolli C, Tummolini L. The challenge of abstract concepts. *Psychol Bull.* 2017;143: 263–292. doi:10.1037/bul0000089
3. Barsalou LW. Abstraction in perceptual symbol systems. *Philosophical Transactions of the Royal Society B: Biological Sciences.* Royal Society; 2003. pp. 1177–1187. doi:10.1098/rstb.2003.1319
4. Pulvermüller F. Neural reuse of action perception circuits for language, concepts and communication. *Progress in Neurobiology.* Elsevier Ltd; 2018. pp. 1–44. doi:10.1016/j.pneurobio.2017.07.001
5. Villani C, Lugli L, Liuzza MT, Borghi AM. Varieties of abstract concepts and their multiple dimensions. *Lang Cogn.* 2019;11: 403–430. doi:10.1017/langcog.2019.23
6. Della Rosa PA, Catricalà E, Vigliocco G, Cappa SF. Beyond the abstract-concrete dichotomy: Mode of acquisition, concreteness, imageability, familiarity, age of acquisition, context availability, and abstractness norms for a set of 417 Italian words. *Behav Res Methods.* 2010;42: 1042–1048. doi:10.3758/BRM.42.4.1042
7. Paivio A, Yuille JC, Madigan SA. Concreteness, imagery, and meaningfulness values for 925 nouns. *J Exp Psychol.* 1968;76: 1–25. doi:10.1037/h0025327
8. Dellantonio S, Job R, Mulatti C. Imageability: Now you see it again (albeit in a different form). *Frontiers in Psychology.* Frontiers Media SA; 2014. p. 991. doi:10.3389/fpsyg.2014.00279
9. Schwanenflugel PJ, Harnishfeger KK, Stowe RW. Context availability and lexical

- decisions for abstract and concrete words. *J Mem Lang*. 1988;27: 499–520.  
doi:10.1016/0749-596X(88)90022-8
10. Kousta ST, Vigliocco G, Vinson DP, Andrews M, Del Campo E. The Representation of Abstract Words: Why Emotion Matters. *J Exp Psychol Gen*. 2011;140: 14–34.  
doi:10.1037/a0021446
  11. Collins AM, Loftus EF. A spreading-activation theory of semantic processing. *Psychol Rev*. 1975;82: 407–428. doi:10.1037/0033-295X.82.6.407
  12. Pylyshyn ZW. Cognitive representation and the process-architecture distinction: Cognitive representation and the process-architecture distinction. *Behavioral and Brain Sciences*. Cambridge University Press; 1980. pp. 154–169.  
doi:10.1017/S0140525X00002302
  13. Fodor JA, M.I.T. Press. *The mind doesn't work that way: the scope and limits of computational psychology*. MIT Press; 2001.
  14. Mahon BZ, Caramazza A. Concepts and Categories: A Cognitive Neuropsychological Perspective. *Annu Rev Psychol*. 2009;60: 27–51.  
doi:10.1146/annurev.psych.60.110707.163532
  15. Andrews M, Frank S, Vigliocco G. Reconciling Embodied and Distributional Accounts of Meaning in Language. *Top Cogn Sci*. 2014;6: 359–370. doi:10.1111/tops.12096
  16. Gallese V, Lakoff G. The brain's concepts: The role of the sensory-motor system in conceptual knowledge. *Cognitive Neuropsychology*. 2005. pp. 455–479.  
doi:10.1080/02643290442000310
  17. Pulvermüller F. Brain mechanisms linking language and action. *Nature Reviews Neuroscience*. Nature Publishing Group; 2005. pp. 576–582. doi:10.1038/nrn1706
  18. Barsalou LW. Grounded Cognition. *Annu Rev Psychol*. 2008;59: 617–645.  
doi:10.1146/annurev.psych.59.103006.093639
  19. Borghi AM, Cimatti F. Embodied cognition and beyond: Acting and sensing the body. *Neuropsychologia*. 2010;48: 763–773. doi:10.1016/j.neuropsychologia.2009.10.029
  20. Meteyard L, Cuadrado SR, Bahrami B, Vigliocco G. Coming of age: A review of embodiment and the neuroscience of semantics. *Cortex*. 2012;48: 788–804.  
doi:10.1016/j.cortex.2010.11.002
  21. Barsalou LW. Perceptual symbol systems. *Behavioral and Brain Sciences*. 1999. pp. 577–609. doi:10.1017/S0140525X99002149
  22. Glenberg AM. Mental models, space, and embodied cognition. *Creative thought: An investigation of conceptual structures and processes*. American Psychological Association; 2004. pp. 495–522. doi:10.1037/10227-018
  23. Zwaan RA. The Immersed Experiencer: Toward An Embodied Theory Of Language Comprehension. *Psychol Learn Motiv - Adv Res Theory*. 2004;44: 35–62.  
doi:10.1016/S0079-7421(03)44002-4
  24. Pulvermüller F, Shtyrov Y, Ilmoniemi R. Brain signatures of meaning access in action word recognition. *J Cogn Neurosci*. 2005;17: 884–892.  
doi:10.1162/0898929054021111
  25. Barsalou LW, Wiemer-Hastings K. Situating abstract concepts. *Grounding Cognition: The Role of Perception and Action in Memory, Language, and Thinking*. Cambridge University Press; 2005. pp. 129–163. doi:10.1017/CBO9780511499968.007
  26. Borghi AM, Barca L, Binkofski F, Castelfranchi C, Pezzulo G, Tummolini L. Words as social tools: Language, sociality and inner grounding in abstract concepts. *Phys Life Rev*. 2018;29: 120–153. doi:10.1016/j.pprev.2018.12.001
  27. Kousta ST, Vigliocco G, Vinson DP, Andrews M, Del Campo E. The Representation of Abstract Words: Why Emotion Matters. *J Exp Psychol Gen*. 2011;140: 14–34.  
doi:10.1037/a0021446

28. Ferretti TR, McRae K, Hatherell A. Integrating Verbs, Situation Schemas, and Thematic Role Concepts. *J Mem Lang*. 2001;44: 516–547. doi:10.1006/jmla.2000.2728
29. Barsalou LW. Perceptions of perceptual symbols. *Behavioral and Brain Sciences*. 1999. pp. 637–660. doi:10.1017/S0140525X99532147
30. Barsalou LW. Situated simulation in the human conceptual system. *Language and Cognitive Processes*. Psychology Press Ltd ; 2003. pp. 513–562. doi:10.1080/01690960344000026
31. Wiemer-Hastings K, Xu X. Content differences for abstract and concrete concepts. *Cogn Sci*. 2005;29: 719–736. doi:10.1207/s15516709cog0000\_33
32. Wilson-Mendenhall CD, Simmons WK, Martin A, Barsalou LW. Contextual processing of abstract concepts reveals neural representations of nonlinguistic semantic content. *J Cogn Neurosci*. 2013;25: 920–935. doi:10.1162/jocn\_a\_00361
33. Harpaintner M, Sim EJ, Trumpp NM, Ulrich M, Kiefer M. The grounding of abstract concepts in the motor and visual system: An fMRI study. *Cortex*. 2020;124: 1–22. doi:10.1016/j.cortex.2019.10.014
34. Dove G. Beyond perceptual symbols: A call for representational pluralism. *Cognition*. 2009;110: 412–431. doi:10.1016/j.cognition.2008.11.016
35. Dove G. On the need for Embodied and Dis-Embodied Cognition. *Front Psychol*. 2011;1: 242. doi:10.3389/fpsyg.2010.00242
36. Dove G. Thinking in Words: Language as an Embodied Medium of Thought. *Top Cogn Sci*. 2014;6: 371–389. doi:10.1111/tops.12102
37. Pecher D. Curb Your Embodiment. *Top Cogn Sci*. 2018;10: 501–517. doi:10.1111/tops.12311
38. McRae K, Nedjadrassul D, Pau R, Lo BPH, King L. Abstract Concepts and Pictures of Real-World Situations Activate One Another. *Top Cogn Sci*. 2018;10: 518–532. doi:10.1111/tops.12328
39. Kuipers JR, Jones MW, Thierry G. Abstract images and words can convey the same meaning. *Sci Rep*. 2018;8: 1–6. doi:10.1038/s41598-018-25441-5
40. McRae K, Nedjadrassul D, Pau R, Lo BP-H, King L. Abstract Concepts and Pictures of Real-World Situations Activate One Another. *Top Cogn Sci*. 2018 [cited 19 Mar 2018]. doi:10.1111/tops.12328
41. Lee MD, Vanpaemel W. Determining informative priors for cognitive models. *Psychon Bull Rev*. 2018;25: 114–127. doi:10.3758/s13423-017-1238-3
42. JASP - A Fresh Way to Do Statistics. [cited 20 Oct 2020]. Available: <https://jasp-stats.org/>
43. Gronau QF, Ly A, Wagenmakers E-J. Informed Bayesian t -Tests . *Am Stat*. 2019; 1–14. doi:10.1080/00031305.2018.1562983
44. Ly A, Verhagen J, Wagenmakers EJ. Harold Jeffreys’s default Bayes factor hypothesis tests: Explanation, extension, and application in psychology. *J Math Psychol*. 2016;72: 19–32. doi:10.1016/j.jmp.2015.06.004
45. RStudio | Open source & professional software for data science teams - RStudio. [cited 20 Oct 2020]. Available: <https://rstudio.com/>
46. Verhagen J, Wagenmakers E-J. Bayesian Tests to Quantify the Result of a Replication Attempt. 2014 [cited 10 Mar 2020]. doi:10.1037/a0036731
47. Bayarri MJ, Mayoral AM. Bayesian Design of “Successful” Replications. *The American Statistician*. Taylor & Francis, Ltd.American Statistical Association; pp. 207–214. doi:10.2307/3087300
48. Rouder JN, Morey RD. A Bayes factor meta-analysis of Bem’s ESP claim. *Psychon Bull Rev*. 2011;18: 682–689. doi:10.3758/s13423-011-0088-7
49. Kruschke JK. Bayesian data analysis. *Wiley Interdiscip Rev Cogn Sci*. 2010;1: 658–

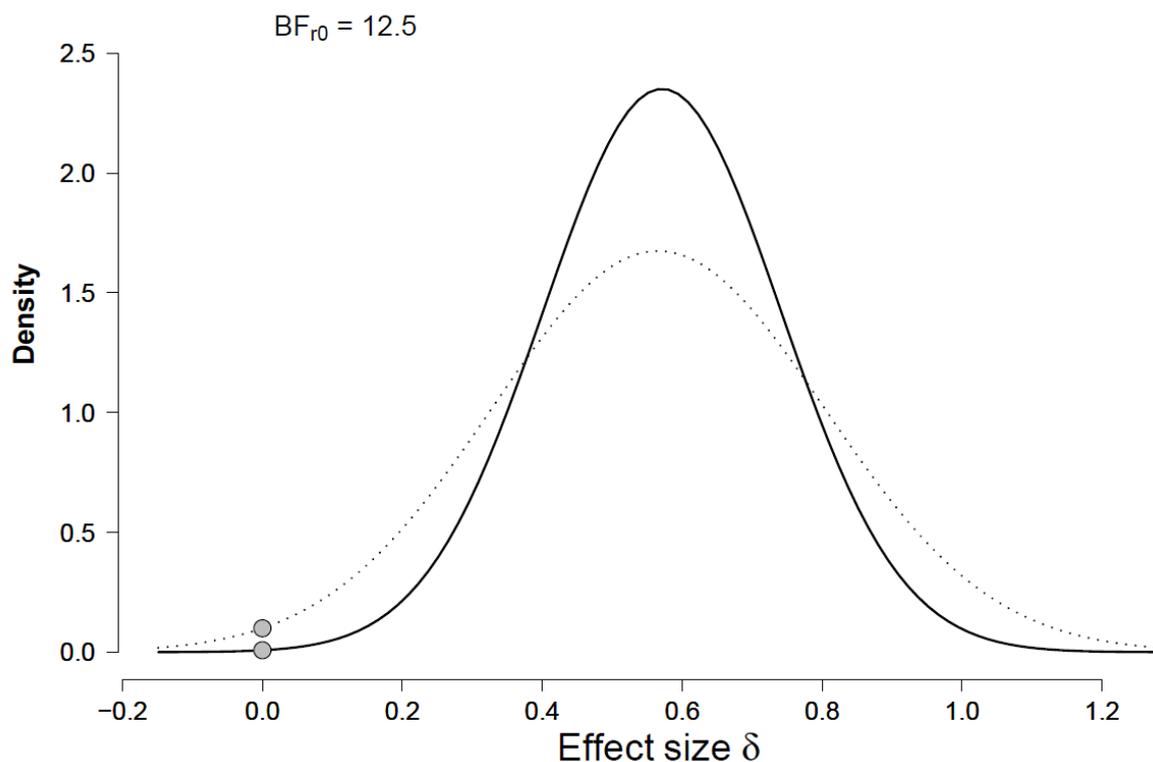
676. doi:10.1002/wcs.72
50. Liu CC, Aitkin M. Bayes factors: Prior sensitivity and model generalizability. *J Math Psychol.* 2008;52: 362–375. doi:10.1016/j.jmp.2008.03.002
  51. Vanpaemel W. Prior sensitivity in theory testing: An apologia for the Bayes factor. *J Math Psychol.* 2010;54: 491–498. doi:10.1016/j.jmp.2010.07.003
  52. Mathôt S. Mathôt S. (2017). Bayes Like a Baws: Interpreting Bayesian Repeated Measures in JASP. [Google Scholar] - Recherche Google. [cited 20 Oct 2020]. Available: [https://www.google.com/search?q=Mathôt+S.+\(2017\).+Bayes+Like+a+Baws%3A+Interpreting+Bayesian+Repeated+Measures+in+JASP.+%5BGoogle+Scholar%5D&ie=utf-8&oe=utf-8&aq=t](https://www.google.com/search?q=Mathôt+S.+(2017).+Bayes+Like+a+Baws%3A+Interpreting+Bayesian+Repeated+Measures+in+JASP.+%5BGoogle+Scholar%5D&ie=utf-8&oe=utf-8&aq=t)
  53. Recchia G, Jones MN. The semantic richness of abstract concepts. *Front Hum Neurosci.* 2012;6. doi:10.3389/fnhum.2012.00315
  54. Smith EE, Shoben EJ, Rips LJ. Structure and process in semantic memory: A featural model for semantic decisions. *Psychol Rev.* 1974;81: 214–241. doi:10.1037/h0036351
  55. Bolognesi M, Vernillo P. How abstract concepts emerge from metaphorical images: The metonymic way. *Lang Commun.* 2019;69: 26–41. doi:10.1016/j.langcom.2019.05.003

## Appendices: supplementary analyses

**Table A.5.** Results of the Bayesian Replication Test.

	$BF_{r0}$	Equality $B_{01}$	Meta $B_{10}$
<b>Original</b>	<i>N/A</i>	<i>N/A</i>	
<b>Replication</b>	12.5	5.0	30.3

Note. “Rep  $B_{r0}$ ” is the new Bayes factor test for replication; “Equality  $B_{01}$ ” is the equality-of-effect-size Bayes factor test; and “Meta  $B_{10}$ ” is the fixed-effect meta-analysis Bayes factor test.



**Figure A.1.** Results of the Bayes factor replication test applied to our replication attempt based on Kuipers et al. (2018).

Note. The dotted line represents the posterior from the original study, which was used as the prior for the effect sizes in the replication tests. The solid line represents the posterior distributions once data from the present replication attempt have been taken into account. The grey dots indicate the ordinates of this prior and posterior for the null hypothesis according to which the effect size is zero. The ratio between these two ordinates gives the result of the replication test [46].

The previous chapter introduced a series of experiments which compared the role of situational information with intangible features in the processing of abstract concepts. Results have shown that even when compared with situational picture primes, extraction mechanisms still occurred in the case of abstract pictures. We interpreted these results as further evidence of the richness of abstract concepts which can be composed of features other than lexical or situational, namely also abstract and intangible. These intangible features could be construed as evidence of abstracted representations from varied exemplars of concepts becoming generalised statistical traces in long-term memory (see for example Barsalou, 2003). In this context, we draw the distinction between two dimensions of abstraction, one referring to a form of content, the other to a mechanism. The first dimension is a horizontal abstraction that refers to the type abstract concepts such as '*justice*'. The abstraction in this case refers to the featural content of the concept. The second dimension is vertical and refers to a mechanism of generalisation through abstraction in concept learning tasks for instance. As such, abstraction refers to the process of extracting features across multiple instances of a concept so that common features can be generalised to novel instances. The question of concept processing is closely related to the latter mechanisms of abstraction and generalisation.

In the next chapter, we introduce a database of novel abstract concepts in a series of experiments to investigate the effect of similarity and contextual diversity on the ability to generalise the meaning of abstract concepts to all instances. An important question that we aim to address is what would be the optimal set of training exemplars to learn a concept so that it generalises to new exemplars. In the case of similarity-based generalisation, participants are expected to better generalise the meaning of concepts when exposed to similar exemplars. In contrast, contextual diversity assumes a generalisation of meaning to novel instances based on exposure to contextually diverse exemplars. Results have shown that

exposure to contextually diverse exemplars enhanced performance in the testing phase compared to similarity-based exposure.

## Chapter 6. Generalisation mechanisms in the processing of abstract concepts

**Chapter 6 is in preparation as** Lakhzoum et al. (in preparation). Generalisation mechanisms in the processing of abstract concepts.

Supplementary material: <https://osf.io/svm2p/>

### INTRODUCTION

The question of how concepts are represented is impossible to treat without addressing mechanisms of *abstraction* and *generalisation*. Abstraction refers to the process of extracting features across multiple instances of a concept so that common features are given more weight in the representation of meaning compared to idiosyncratic features (see Murphy, 2002; Glenberg, 2006; Altmann, 2017; Yee, 2019). The resulting abstracted representations can be generalised to all instances of a concept that become aggregated under a common *categorisation* label (Thorndike, 1924; Thorndike & Woodworth, 1901, see also Gardner, 1987; Goldstone, Kersten, Carvalho & 2018). This ability to extract meaningful representations from a few exemplars and generalise to novel situations is the hallmark of human cognition. During the last decade, this feat has been emphasised especially when comparing human performances to those of computational models, which are constantly outperformed due to their failure to implement efficient rules of generalisation (see Cambria, & White, 2014 for a review). Since the early 20<sup>th</sup> century, this particular cognitive ability has been the object of much work in the concept learning literature focused on abstraction mechanisms. Yet, despite more than a century worth of research, the cognitive principles that give rise to such mechanisms are still poorly understood. In order to elucidate these

principles, two major questions need to be answered: (1) What sort of features are acquired during the learning of concepts through exposure to a set of exemplars? (2) How are these features generalised to novel instances? As Murphy (2013) observed, the literature on concept learning is still dominated by the debate opposing prototype and exemplar models of abstraction as it has been for decades. This debate has been fuelled by many experiments and models that simulate the categorisation of concepts as the result of an abstraction process.

### **The prototype and exemplar accounts**

According to the prototype theory of Rosch (1975; Rosch & Mervis, 1975; see also Barsalou, 1990), mental representations require a summary description of fundamental properties that form a category. The categorisation of concepts is determined by their similarity with the most prototypical member or ideal example of the category. In a series of priming experiments, Rosch showed a facilitation effect for members of categories that had the most properties in common with other members of the category and the least properties in common with other categories (Posner & Keele, 1968; Hampton, 1979; Rosch & Mervis, 1975; Smith & Medin, 1981; Murphy, 2002; 2016).

Exemplar models are an alternative theory according to which prototypes are not necessary. According to exemplar theories, categories are represented by memories of instances and situations where the concept applies (Medin & Schaffer, 1978). Generalisation based on exemplars offers a better explanation compared to prototypes especially for poorly defined categories (Blair & Homa, 2001; Medin & Schwanenflugel, 1981; Murphy, 2002; 2005). The probability of generalising a category label from encountering a set of examples is a function of the similarity between the examples and each member of the category (Medin & Schaffer, 1978; Nosofsky, 1986). A child that would encounter three instances of a bird and recognise it as such would have formed three “bird” exemplars that can be generalised to all instances and serve for classification (Barsalou, Huttenlocher, & Lamberts, 1998; Nosofsky,

1988). One of the most influential models of the exemplar account is the GCM (generalised categorisation model) of Nosofsky (1986). In the GCM, similarity is modelled according to a multidimensional scaling (MDS; see Kruskal, 1984; Shepard, 1958; 1987) that represent exemplars as points in a multidimensional psychological space. Similarity is a function of the distance between exemplar points: the closer they are, the more similar. In recent years, Vanpaemel and Storms (2008) proposed the VAM (varying abstraction model) as a middle-ground position that combined both the rich amount of stored informational features from the exemplar account and the cognitive economy of the prototype account. The model is rooted in the assumption that prototype and exemplar exist on a continuum where exemplars represent minimal abstraction whereas prototypes represent maximal abstraction.

This notion of a dichotomy between exemplar account and abstraction process has been challenged by recent models and experiments which suggest that both assumptions of storing exemplars and abstraction process are not contradictory. For instance, studies of concept learning in children have shown that they develop more abstract representation as their language grows until they are able to generalise across common features of meaning (Savage, Lieven, Theakston & Tomasello, 2006; Rowland, Chang, Ambridge, Pine & Lieven, 2012). In addition, hybrid models posit that abstracted representations are composed of stored exemplars (Abbot-Smith & Tomasello, 2006; Goldberg, 2006; Langacker, 1988).

Most of the literature on concept learning and abstraction has been dedicated to learning generic concepts such as lines, triangles, faces that are easier to generate, to norm and to diversify along chosen dimensions which provides the researchers with an opportunity to simulate the underlying mechanisms in a computational model such as GCM or VAM for instance. The combination of word learning experiments and concept learning can provide a powerful framework for studying how semantic concepts are abstracted and generalised. Most of the literature points to seemingly opposite assumptions to explain these mechanisms

namely similarity-based generalisation and contextual diversity. One view proposes that generalisation happens when the set of training exemplars of a category are relatively similar; the other view proposes that generalisation happens when the set of training exemplars is relatively diverse.

## **The role of similarity and contextual diversity on abstraction and generalisation**

### ***Similarity-based generalisation***

Similarity is one of the core tenets of cognitive processes (Medin, Goldstone & Gentner, 1993; Goldstone, 1994; Goldstone & Son, 2012). The seminal work of Gentner (1987) established similarity as a key parameter of a successful generalisation process. According to this account, similarity refers to a mental experience sparked by a current situation similar to a prior experience stored in memory. Gentner, Loewenstein and Hung (2007) tested this similarity principle in children's ability to name parts of objects and found that children showed a facilitated process of structure-mapping when presented with set of similar exemplars. Structure-mapping refers to a process of finding commonalities between conceptual representations based on relational similarities through structural alignment (Gentner, 2003; Gentner & Markman, 2007). Gentner has shown that this alignment can strengthen the ability to generalised extracted common relational features to novel objects and situations (Gentner & Namy, 2016; Gentner, 2010; Gentner, Anggoro, & Klibanoff, 2011; Gentner, Loewenstein, & Hung, 2007; Kotovsky & Gentner, 1996).

The benefit of similarity in generalisation depends on the weight attributed to shared underlying structure at the expense of variations in superficial features (Braithwaite & Goldstone, 2015; Hammer, Bar-Hillel, Hertz, Weinshall, & Hochstein, 2008). Other accounts have shown that a high degree of similarity between stored exemplars can hinder the ability to generalise to new instances of a concept. This can be explained by a failure to recall relevant examples particularly when stored exemplars and the novel instance differ in surface features

(Gick & Holyoak, 1980; Keane, 1988; Holyoak & Koh, 1987; Simon & Hayes, 1976; Weisberg, DiCamillo, & Phillips, 1978; Gentner, Loewenstein & Thompson, 2003; Gentner & Bowdle, 2008; Braithwaite & Goldstone, 2015). Studies have shown that exposure to exemplars presenting a diversity of superficial features can emphasise common underlying structures, thereby promoting generalisation (Gomez, 2002; Onnis, Monaghan, Christiansen, & Chater, 2004; Perry, Samuelson, Malloy and Schiffer, 2010; Rost & McMurray, 2010). In recent years, many studies have reported the importance of contextual diversity on the representation and abstraction of semantic concepts (see Jones, Dye, & Johns, 2017 for a review).

### ***Contextual diversity and generalisation***

The importance of diversity for generalisation stems from the work of Posner and Keele (1968) on the classification of abstract patterns. They have shown that when learning a set of abstract patterns, the ability to classify new instances correctly increases with the variability of memorised patterns. More broadly, the hypothesis of generalisation from stored exemplars to novel instances assumes a presentation of common core features between exemplars while idiosyncratic surface features may vary (Belenky & Schalk, 2014; Day & Goldstone, 2012; Gentner, 1983; Gick & Holyoak, 1983). In this way, stable concept representations rely on a common core of overlapping features while varied superficial surface features become anecdotic information. This assumption also insures the flexibility of conceptual representations as learners become able to overlook such anecdotic features as noise and recognise the core meaning of a concept (see Braithwaite & Goldstone, 2015).

Context generalisation studies have shown that children exposed to multiple exemplars of novel words across varied contexts can better abstract over training examples and generalise meaning to novel test exemplars (Vlach & Sandhofer, 2011; Goldenberg & Sandhofer, 2013; Twomey & Westermann, 2018, Sandhofer & Schonberg, 2020). Smith and

Handy (2014) examined the decontextualization of memories in adult learners and found that acquisition trials presented in varied situations resulted in memory retrieval independently of context. Braithwaite and Goldstone (2015) built on the assumptions that learning abstract concepts through concrete examples could inhibit abilities to generalise to novel instances. In a series of experiments, they showed that varying superficial features of exemplars resulted in better transfer abilities from learned examples to new situations.

Finally, Pagan and Nation (2019) examined the effect of contextual diversity in a word learning experiment where participants had to learn the meaning of low-frequency words through exposure to varied or similar situations. They found that although words presented in diverse contexts were acquired more slowly, participants had more facility answering inferential questions about word meaning compared to similar contexts which they interpreted as better performances of generalisation.

Taken together, the literature centered on similarity and contextual diversity provides inconsistent evidence as regards to the underlying mechanisms involved in abstraction and generalisation in concept learning. Most of the literature is centered on the use of generic concepts such as faces, triangles and dot patterns. Consequently, there is little evidence as regards to the generalisation mechanisms of semantic concepts. This is even truer for abstract concepts such as *fantasy* or *justice*.

### **Application to the generalisation of abstract concepts**

The variety and complexity of abstract concepts makes them difficult to classify in categories with clear-cut boundaries. This complexity represents even more of a challenge mainly due to the fact that the literature on abstract concepts is rather young and the majority of studies and models have been dedicated to their representation and grounding (see Pecher, 2011; Borghi et al., 2017; Pecher, 2011, 2018 for reviews). Studies have shown that the

preferred mechanism of abstraction depends on the structure of the category. For instance, Minda and Smith (2001) have shown that the prototype account provides a better explanation for large categories. In contrast, Feldman (2003) suggests that the exemplar account provides a better explanation for complex categories. Instead of categories, the literature on abstract concepts representation has established some domains which are number concepts, morals, aesthetics, social and cultural dimensions, as well as emotion that can be grounded in dimensions such as sociality, language, interoception, perception-action, and metacognition (see Barsalou, 2003; Borghi, Barca, Binsofsky & Tummolini, 2018 for a review of these domains and dimensions of abstract concepts). As a result, little is known about how abstract concepts are generalised to all instances of a concept. Given this complexity and lack of clear categorisation for abstract concepts, we suggest that the exemplar end of the exemplar-prototype continuum would provide a better explanation for their mechanisms of generalisation than a prototype view would (see Vanpaemel & Storms, 2008). According to Paivio's Dual Coding Theory (DCT, 1968, 1971), abstract concepts are more loosely related to a multitude of contexts compared to concrete concepts. Taken together the exemplar view and the DCT would suggest that the generalisation of abstract concepts could benefit from exposure to multiple exemplars in diverse contexts.

### **The present work**

The combination of word learning experiments and concept learning models provides a powerful framework for studying how semantic concepts can be generalised to all instances. While this framework has been applied successfully to studying the abstraction mechanisms of concrete objects, very little is known about how abstract concepts are abstracted and generalised. The present project was intended as an attempt to bridge this gap in the literature.

The literature on conceptual representation tends to consider the keywords “concept” and “word” as interchangeable on principles (Murphy, 2002). This is not strictly true however

and a distinction does exist between the two notion (Murphy, 2002). A conceptual view based on a strict one-to-one mapping between words and concepts would mean that for each mental representation there is one and only one word and that each word of the mental lexicon is associated with a single mental representation. This view of one-to-one mapping between concepts and words is oversimplified and impractical as it cannot account for the complexity of abstract concepts. On the theoretical and empirical levels, this distinction is of little importance to the ability of researcher to design and conduct experiments. It becomes important in the context of the present project however, which takes advantage of this lack of one-to-one mapping between words and concepts to introduce the NewAbstractConcepts database. This database was motivated by the difficulty to craft experimental stimuli for word learning experiments in adults. In contrast with children, adults present a vast knowledge of concepts. Introducing concepts that have no word referent provides some control of participants' background knowledge compared to previous studies that have used existing low-frequency words (see for example Pagan & Nation, 2019).

In the present project, we introduce a database of 42 novel abstract concepts which describe situations that are commonly encountered in an everyday setting but for which no word label exists. Each abstract concept is composed of 9 exemplars of scenarios (3 sets of scenarios composed of 3 exemplars each). The database was presented to participants who rated the similarity between exemplars. On the basis of these similarity judgments, a psychological space similar to GCM model of Nosofsky (1986, 1992, 2014) was built. This attempt aimed to establish a proof of concept for the use of semantic concepts composed of linguistic exemplars in computational models such as GCM that are usually applied to generic concepts. The database was then used in a word learning experiment for which participants were exposed to a series of exemplars that were either similar or dissimilar to each other.

## **EXPERIMENT 1a: selection of the NewAbstractConcepts database**

To create the database, samples were selected from the book *That should be a word* by author Lizzie Skurnick (Skurnick, 2015). The book is a collection of fake words and their definition that correspond to situations and feelings that people can relate to on an everyday basis but that do not have words to label them. For instance, one such word is JOUSKA coined by Skurnick (2015) and which described *A hypothetical conversation that you compulsively play in your head*. The samples were presented to participants in Experiment 1a in order to ensure that people could relate to the concepts.

## **METHOD**

### **Participants**

Eighty psychology students took part in this experiment (6 males;  $M_{\text{age}} = 20.55$ ,  $SD = 4.99$ ) presented online using Qualtrics (2020). They all gave their informed consent before taking part in the study. They were awarded course credits for their participation.

### **Materials and Procedure**

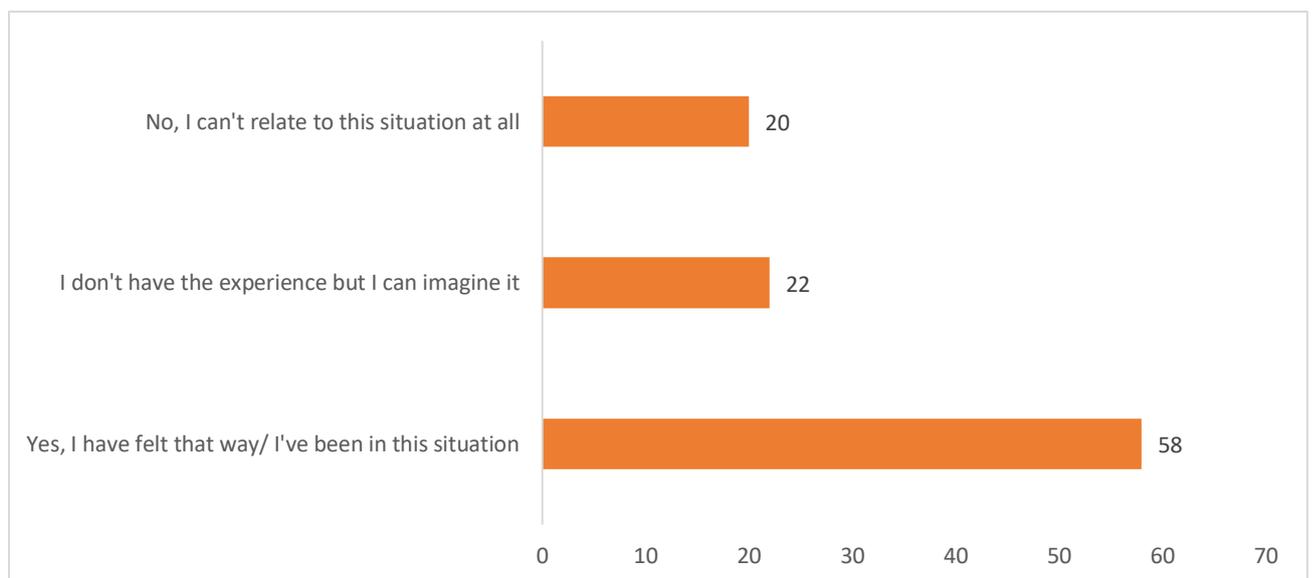
The material consisted of 76 concepts with description selected from the book *That should be a word* (Skurnick, 2015). The fake word labels composed by the author such as *Jouska*, *Sonder* or *Gistake* were not presented to the participants as they had not been normed and could influence the perception of the concepts. Each concept was presented as a description of a situation or feeling (e.g., A hypothetical conversation that you compulsively play in your head; The realisation that each passer-by has a life as vivid and complex as your own; Using incorrect words that still get the point across).

For each concept, participants were asked to indicate in a forced multiple-choice questionnaire whether they had experienced the described situation, or had not experienced but could image the situation, or if they could neither relate to nor imagine the situation. They

were then asked to provide an example where the described concept could apply in a free text entry question to ensure that they understood the concept. Participants were randomly presented with 20 out of the 76 concepts. The concepts were presented one-by-one on the screen. The study was self-paced and could be completed in about 30 minutes.

## RESULTS and DISCUSSION

We aggregated the percentage of response from all the participants for each choice. According to Figure 1, 80% of responses indicated that the concept had been experienced or imagined by the participant. Only 20% of responses indicated that the participant could not relate at all to the concept.



**Figure 1.** Percentage of response for each choice.

On the basis of this first analysis, the concepts that were not understood by participants were removed. The concepts for which at least 25% of the responses indicated that the participant could not relate were removed. As a result, 26 concepts out of 76 such as *The art of saying "no" by seeming overly pleased* were removed. In contrast, 7 concepts were judged as relatable or understood by all participants such as *A hypothetical conversation that you compulsively play out in your head* or *The desire to care less about things*. After removing

concepts that were the least understood or relatable, the remaining 50 concepts were used to generate the database.

## EXPERIMENTS 1b and 1c: generating the NewAbstractConcepts database

For each selected concept, 3 different scenarios where the concept could apply were generated. Each scenario was then described by 3 different exemplars of statements that were similar to each other. This process resulted in 9 different exemplars to describe each concept. For instance, the concept *SONDER* described as *The realization that each passer-by has a life as vivid and complex as your own* was described by 3 scenarios each of them, illustrated exemplars presented in Table 1. For the concept *SONDER*, the first scenario described a stranger on a train; scenario 2 described a colleague who speaks a different language and finally scenario 3 described a teacher in a private setting.

**Table 1.** Examples of scenarios and exemplars for the concept *SONDER*.

Scenarios	Exemplars	Descriptive statements
1	A	On the train, he looked at the woman in the opposite seat as she opened her laptop and wondered what type of work she might do.
1	B	The man on the train was looking at sheet music and humming to himself and she thought he might be a musician travelling all over the country to give concerts.
1	C	She kept thinking that the woman sitting across the aisle on the train might be a scientist because she was studying papers with complicated looking graphs.
2	A	Listening to her colleague answer the phone in his mother tongue, she suddenly realized that he grew up in a tropical country.
2	B	She heard the office manager talk to his children in a foreign language and started daydreaming about how their upbringing might have differed from her own.
2	C	When he heard the team manager answer her phone in fluent Japanese, he imagined what it was like growing up in the Japanese culture.
3	A	It was strange to see the math teacher in the dairy section but he realized that the teacher must have a family too.
3	B	At the concert he became aware of the coach's private life when he saw him dressed for a party rather than in his usual sports outfit.
3	C	When the history teacher proudly told them he ran the New York City marathon, they knew he must have spent a lot of his free time training.

The triplets of statements generated for each scenario were made to provide a within-scenario similarity. The exemplars were then reorganised by mixing the scenarios to generate dissimilar combinations as shown in Table 2.

**Table 2.** All combinations for the concept SONDER

	Version 1	Version 2	Version 3
similar	1A/1B/1C	2A/2B/2C	3A/3B/3C
dissimilar	1A/2C/3B	1B/2B/3C	1C/2A/3A

The within-scenarios similarity and between-scenarios dissimilarity were tested in Experiment 1b using a paradigm of paired similarity judgments.

## METHOD

### Participants

Seventy-one British native speakers were recruited online using the Prolific platform to take part in this experiment (32 males;  $M_{\text{age}} = 27.01$ ,  $SD = 5.13$ ) presented online using Qualtrics (2020). They all gave their informed consent before taking part in the study. They received £2.50 for their participation.

### Materials and Procedure

The material was composed of the exemplars from 50 concepts organised by pairs that were either similar to each other or dissimilar. For instance, for the concept *SONDER*, the pairs were organised as described in Table 3 below so as to obtain 9 pairs in each similar or dissimilar condition.

**Table 3.** Example of similar and dissimilar pairs for the concept SONDER

Similar pairs	Dissimilar pairs
1A-1B	1A-2C
1A-1C	1A-3B
1B-1C	2C-3B
2A-2B	1B-2B
2A-2C	1B-3C
2B-2C	2B-3C
3A-3B	1C-2A
3A-3B	1C-3A
3B-3C	2A-3A

The material was composed of 900 exemplars that were divided into 16 blocks of 6 or 7 concepts for a total of 54 to 63 pairs per block (due to some blocks having 1 additional concept with 9 more pairs). The concept labels such as *SONDER* were never shown to the participants. The material was divided so that each participant saw only 1 condition for each concept either similar or dissimilar. Each participant was randomly assigned to only one block. The order of the pairs within a block was also randomised. For each pair, participants were asked to rate on a scale from 0 to 100 to what extent the two statements describe similar situations. Pairs of exemplars appeared one by one on the screen. The study was self-paced and took about 20 minutes to complete.

## RESULTS and DISCUSSION

The aim of this similarity judgment study was twofold. Firstly, it was designed to ensure that the distance between pairs could reflect the similar and dissimilar conditions meaning that the similar and dissimilar pairs constructed by the researchers were also judged similar and dissimilar by an external pool of participants. Secondly, the similarity judgment were embedded in a psychological space that reflected Euclidian distances between exemplars (see Shepard, 1991 for a review).

For the first objective to adjust the database only the concepts that elicited the highest similarity ratings for the similar pairs and the lowest ratings for the dissimilar pairs were kept. Mean similarity between pairs were analysed to build the similar and dissimilar conditions for the whole concepts. For the entire dataset, mean similarity ratings for similar and dissimilar combinations were compared by means of a paired-samples t-test. The analysis revealed that the constructed similar pairs elicited higher similarity ratings compared to the dissimilar pairs ( $M_{\text{Similar}} = 70.08$ ;  $SD = 12.28$ ;  $M_{\text{Dissimilar}} = 44.74$ ;  $SD = 6.61$ ; Mean Difference = 25.29; 95CI [24, 27];  $t(449) = 29.00$ ,  $p < 0.001$ , Cohen's  $d = 1.32$ ). These results were satisfactory as they validated the pairs generated based on the researcher's intuition. Although this analysis provided satisfactory results, a closer examination on a qualitative level of each concept revealed that some combinations presented a reversed pattern with dissimilar pairs showing a higher similarity rating compared to similar pairs. According to this qualitative examination, 25 concepts presented a reversed pattern for some combinations. The reversed pairs were reworked so as to increase within-scenario similarity compared to between-scenario dissimilarity. Although, sometimes only 1 pair from a concept was problematic, the 25 concepts were re-tested in their entirety so as to ensure the validity of the combinations after modifications were applied. The new version of the concepts was presented in Experiment 1c to a new pool of participants.

## **METHOD**

### **Participants**

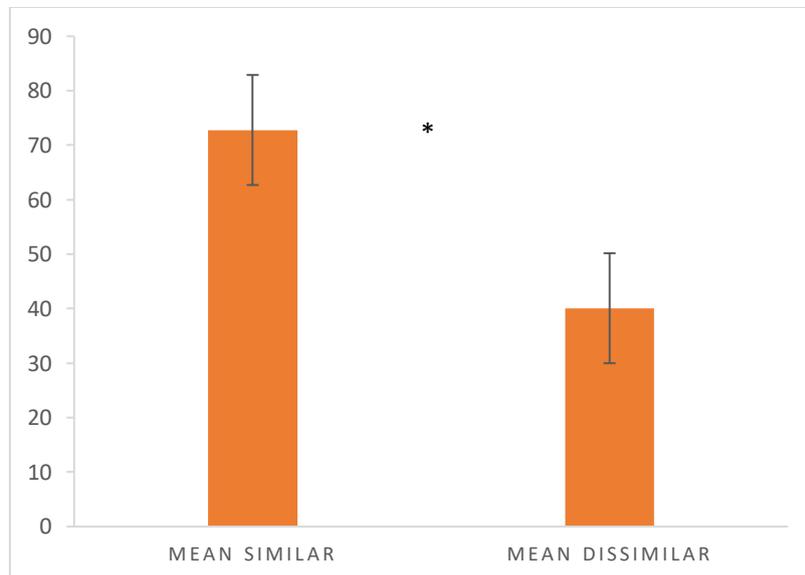
One hundred and twelve British native speakers were recruited online using the Prolific platform to take part in this experiment (34 males;  $M_{\text{age}} = 30.01$ ,  $SD = 6.63$ ) presented online using Qualtrics (2020). They all gave their informed consent before taking part in the study. They received £2.50 for their participation.

## Materials and Procedure

The material was composed of the exemplars from 25 modified concepts organised by pairs that were either similar to each other or dissimilar. The procedure was the same as Experiment 1b.

## RESULTS and DISCUSSION

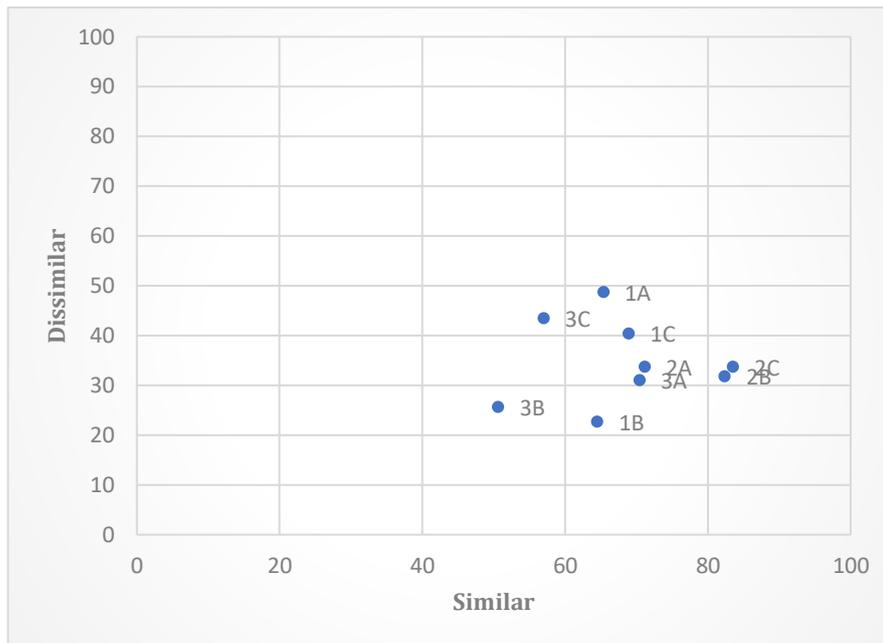
A first qualitative exploration of the data revealed that 8 concepts still presented a reversed pattern of similarity with some dissimilar pairs showing a higher similarity rating compared to dissimilar pairs. The rest of the analyses is based on the remaining 42 concepts. As shown in Figure 2, the analysis revealed that the constructed similar pairs elicited higher similarity ratings compared to the dissimilar pairs ( $M_{\text{similar}} = 72.80$ ;  $SD = 10.10$ ;  $M_{\text{Dissimilar}} = 40.08$ ;  $SD = 12.13$ ; Mean Difference = 32.72; 95CI [31, 34];  $t(383) = 49.63$ ,  $p < 0.0001$ , Cohen's  $d = 2.53$ ).



**Figure 2.** Mean ratings for the similar and dissimilar conditions in Experiment 1c (\*  $p < 0.001$ ).

These results showed an improvement of all the statistics compared to Experiment 1b. The mean rating for the similar condition was higher while the mean rating for the dissimilar condition was lower compared to the same statistics obtained from Experiment 1b. Overall mean difference between the similar and dissimilar conditions was higher compared to Experiment 1b ( $M_{\text{diff}_{1b}} = 25.29$ ;  $M_{\text{diff}_{1c}} = 32.72$ ). The consistency of the similarity pattern for pairs in the similar and dissimilar condition was established upon visual inspection of the concepts and was statistically confirmed by the increase in the effect size from Experiment 1b to 1c (Cohen's  $d_{1b} = 1.32$ ; Cohen's  $d_{1c} = 2.53$ ). Taken together, these statistics indicate that the database is composed of a robust combination of stimuli. These similarity ratings were then used to build the psychological space as a graphical representation of the Euclidian distance between similar and dissimilar dimension for each exemplar.

According to the GCM model, stimuli can be represented as points in a multidimensional psychological space (Nosofsky, 1986, 1992, 2011, 2014). This geometric representation of exemplars is based on a multidimensional space (MDS) algorithm developed by Kruskal (1964; see also Shepard, 1987). The MDS represents the pairwise similarities obtained from a similarity rating task. For instance, when considering the concept *SONDER*, the coordinates are given by the similarity rating of exemplar 1A in the similar condition and in the dissimilar condition (see Figure 3). The similar and dissimilar conditions represent the 2 dimensions of the psychological space which reflects the stored exemplars in memory that are the basis for comparison in a categorisation task. In the present case, let  $x_{\text{sonder}} = (x_{\text{sonder}_s} ; x_{\text{sonder}_d})$  be the coordinate locations for concept *SONDER* in the 2-D psychological space with  $x_{\text{sonder}_s}$  the exemplars' mean similarity rating in the similar dimension and  $x_{\text{sonder}_d}$  the exemplars' mean similarity rating in the dissimilar dimension.



**Figure 3.** 2-dimensional graphical representation of the psychological space for concept SONDER. Each point represents an exemplar with coordinates  $x_{sonder_s}$  as the exemplar's mean similarity rating in the similar dimension and  $x_{sonder_d}$  as the exemplar's mean similarity rating in the dissimilar dimension.

This psychological space is a graphical representation of the exemplars that are stored in memory. Each concept was described by 9 exemplars that could be combined so as to have similar or dissimilar combinations. In a second experiment, the NewAbstractConcepts database was used to test the ability to generalise the meaning of concepts learned through exposure to either similar or dissimilar combinations to a novel test exemplar. Studies have produced incoherent results as regards to the mechanisms involved in the generalisation of meaning to novel situations. The literature has suggested two opposite mechanisms that are similarity-based generalisation and contextual diversity. According to similarity accounts, generalisation mechanisms are dependent on commonalities between conceptual representations. In contrast, contextual diversity posits that a diversity of superficial features can emphasise common underlying structures, thereby promoting generalisation. Experiment 2 aimed at testing these two hypotheses using abstract concepts that have no word referent but are described by exemplars either similar to each other or contextually diverse.

## **EXPERIMENT 2**

### **METHOD**

#### **Participants**

Seventy-two British native speakers were recruited online using the Prolific platform to take part in this experiment (16 males;  $M_{\text{age}} = 30.29$ ;  $SD = 8.29$ ) presented online using Qualtrics (2020). They all gave their informed consent before taking part in the study. They received £2.50 for their participation.

#### **Materials and Design**

The material was composed of 42 NewAbstractConcepts from the database developed in the previous Experiment 1. For each concept 9 exemplars were constructed following 3 different scenarios. The triplet of exemplars belonging to one scenario were constructed as similar to each other. The dissimilar triplets of exemplars were obtained from reordering the scenarios so as to create combinations of exemplars that are different from one another. The concepts were then divided in 2 lists of 3 blocks each. Each block was composed of 3 exemplars either similar or dissimilar. Participants were randomly assigned to a single block following a Latin Square design meaning that each participant was presented with 1 triplet of similar or dissimilar exemplars from 1 scenario for each concept (see Table 4). Participants were all presented with the similar and dissimilar conditions.

**Table 4.** Latin square for Experiment 2 following a mixed design with exemplars presented as between-subjects while the similar and dissimilar conditions were presented in a within-subject design.

	LIST A			LIST B		
	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6
Concept 1	1A-1B-1C	2A-2B-2C	3A-3B-3C	1A-2C-3B	1B-2B-3C	1C-2A-3A
Concept 2	1B-2A-3B	1C-2A-3C	1A-2B-3A	1A-1B-1C	2A-2B-2C	3A-3B-3C

...

For each concept, a pseudo-word was generated using Wuggy (Keuleers & Brysbaert, 2010) to serve as a referent label (e.g., Remation, Unglith). The pseudo-words were generated based on the English language and were matched for lexicality and number of letters. For each concept, a test exemplar that corresponded to a novel scenario composed of a single exemplar was constructed (e.g., When he entered the living room, he saw a picture on a mantelpiece and was astonished that his neighbour had apparently met Bill Gates). Finally, nonsensical sentences were constructed to serve as filler in an attention check during the reading phase. The fillers were constructed following the same rules as for the actual exemplars but contained unrelated words to create a sense of semantic ambiguity (e.g., Getting upstairs, she could not remember whether she had poisoned the front door). The experiment contained a proportion of 18% fillers which were also presented with a pseudo-word generated using Wuggy that served as a referent.

## Procedure

During the reading phase, participants were presented with a pseudo-word (e.g., REMATION) and 3 exemplars -either similar or dissimilar- that appeared one by one on the screen. Participants were never provided with a definition of the concepts but were asked to pay attention to the pseudo-word and the corresponding exemplars that were meant to illustrate their meaning. Each exemplar was presented alongside its pseudo-word referent. To make sure that they were paying attention, nonsensical sentences were randomly scattered

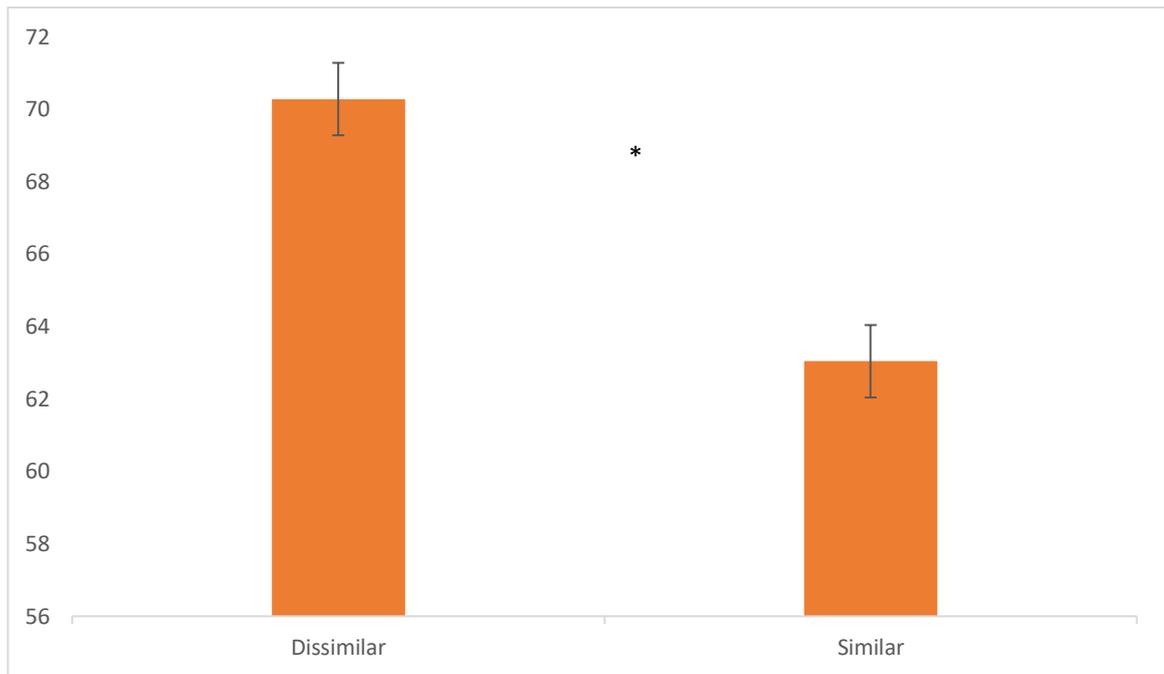
during the reading phase. After reading each exemplar, participants had to choose the “next” button to go to the next trial or the “nonsensical” button to indicate that they had spotted a nonsensical sentence. The blocks were divided in series of 7 concepts. The presentation of exemplars and their corresponding pseudo-word were all randomised within each series. Following each series of 7 concepts, participants entered a testing phase.

During the testing phases, participants were presented with a novel test exemplar that was constructed as part of a 4<sup>th</sup> scenario for each concept. The test exemplars were presented alongside their corresponding pseudo-word. The task of the participants was to judge on a scale from 0 to 100 whether this novel exemplar was a good example to describe the pseudo-word.

The study was self-paced and took about 30 minutes to complete.

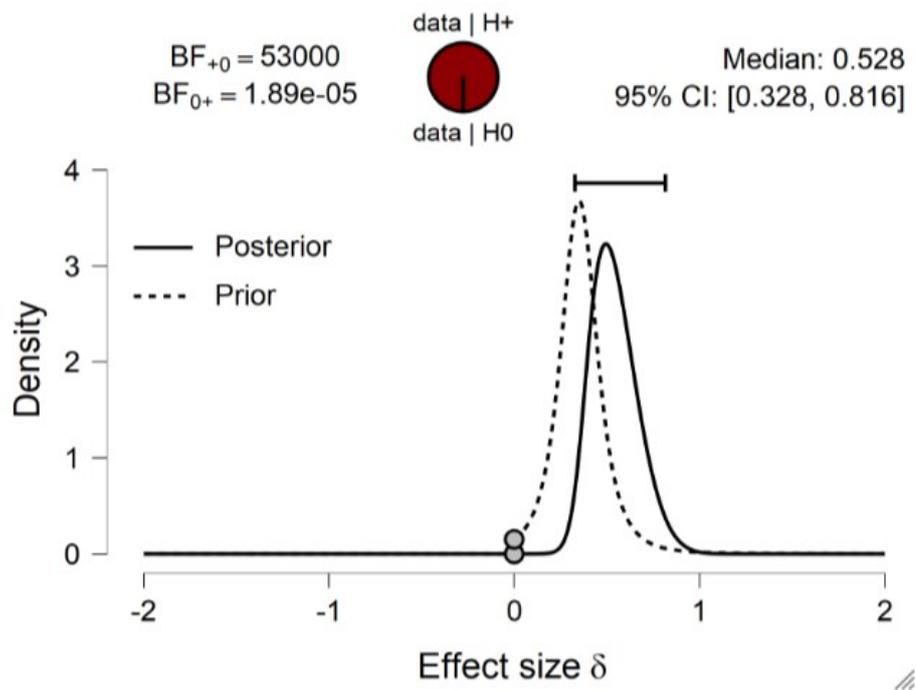
## **RESULTS and DISCUSSION**

The similarity judgments of novel exemplars to those stored during the reading phase were compared by means of a paired samples t-test. The analysis revealed that the test exemplars were judged as better examples of the concepts when participants were exposed to dissimilar exemplars during the reading phase ( $M_{\text{Dissimilar}} = 70.28$ ;  $SD = 7.54$ ) compared to when they were exposed to similar exemplars ( $M_{\text{Similar}} = 63.04$ ;  $SD = 9.06$ ) -  $t(71) = 5.66$ ,  $p < 0.001$ ; Mean Difference = 7.20; 95CI [4.65, 9.74]; Cohen’s  $d = 0.71$ ; see Figure 4).



**Figure 4.** Mean similarity judgments (on a scale from 0 to 100) as a function of reading phase exposure (similar vs. dissimilar exemplars;  $p < 0.001$ )

We conducted a Bayesian paired-samples t-test using JASP (2020). For the informed prior we used Oosterwijk's recommendation (t-distribution with location 0.350, scale 0.102, and 3 degrees of freedom), because it is considered a good prior for small-to-medium effect sizes (see Gronau & Wagenmakers, 2019). This analysis showed a Bayes Factor of 51900 (median = 0.53; 95CI [0.33-0.82]; see Figure 5). This means the results are about 51900 times more likely under the alternative hypothesis compared to the null.



**Figure 5.** Prior and Posterior distribution for the paired samples t-test comparing the similar and dissimilar conditions.

The aim of Experiment 2 was to test for the generalisation of meaning on the basis of exposure to similar or contextually diverse exemplars. According to the account of similarity-based generalisation, participants were expected to better generalise the meaning of concepts when exposed to similar exemplars. In contrast, the account of contextual diversity assumes a facilitation of generalisation to novel exemplars when participants are exposed to contextually diverse exemplars.

Results have shown that exposure to contextually diverse exemplars enhanced performance in the testing phase. Participants had less difficulty identifying the novel test exemplars presented as a 4<sup>th</sup> scenario when stored exemplars were learned through exposure to diverse exemplars. This result could be explained by the fact that contextual diversity during reading allows for the representation of words to become more context independent (e.g., Bolger et al., 2008; Pagan & Nation, 2019).

These results are in accordance with previous studies on the importance of diversity for generalisation. Posner and Keele (1968) have demonstrated that the ability to classify new instances of learned concepts correctly increased with the variability of stored patterns. More broadly, the hypothesis of generalisation from stored exemplars to novel instances assumes a mechanism of abstraction of idiosyncratic surface features while common core features are better identified in diverse contexts (Belenky & Schalk, 2014; Day & Goldstone, 2012; Gentner, 1983; Gick & Holyoak, 1983). This mechanism of abstraction assumes an attention parameter with more attention allocated to well attended dimensions compared to unattended ones. This assumption is at the core of GCM model of Nosofsky (1986, 1992, 2014; Vanpaemel, 2009). The model posits a set of selective-attention weights that modify the dimensions of the psychological space in which the exemplars are embedded (Carroll & Wish, 1974; Nosofsky, 2014). These results are in accordance with accounts of exemplar-based abstraction which posit a process of extracting features across multiple instances of a concept so that idiosyncratic features provide representation that are context independent (see Yee, 2019 for a review).

The literature on abstract concepts is rather young and most of it has been dedicated to their mechanisms of representation and grounding (see Borghi, 2017; Pecher, 2018 for reviews). As a result, little is known about how abstract concepts are generalised to all instances of a particular concept. Gentner and Asmuth (2017) have suggested a process of abstraction they refer to as Career of Metaphor that describes how abstract meaning can be generalised through figurative language. For example, they consider that the abstract relational meaning of the concept <anchor> can be abstracted through figurative expressions such as <religion is an anchor>. Repeated exposure to such figurative instances would highlight the common features between the concepts <anchor> and <religion> by abstracting

the meaning of the metaphor in favour of an underlying common relational structure which can be extended to other situations that share similar structures.

This process of abstraction through metaphors seems compatible with an assumption of exemplar-based generalisation particularly as it assumes exposure to multiple instances of a concepts in diverse contexts. However, studies have shown that learning abstract concepts through metaphors could hinder the ability to grasp the full richness of abstract concepts and in turn the ability to generalise (see for e.g., Braithwaite and Goldstone, 2015; Pecher, Boot & Van Dantzig, 2011). In addition, this assumption of learning relational similarities between concepts through metaphors is limited by a lack of one-to-one mapping between abstract concepts and metaphors (Pecher, 2018). The assumption of generalising abstract concepts from exposure to multiple exemplars in diverse contexts seems to offer a better account. This is particularly true when considering Paivio's Dual Coding Theory (DCT, 1968, 1971) according to which abstract concepts are more loosely related to a multitude of contexts compared to concrete concepts. Taken together, contextual diversity and the DCT would suggest that the generalisation of abstract concepts could benefit from exposure of exemplars in diverse contexts.

## **GENERAL DISCUSSION**

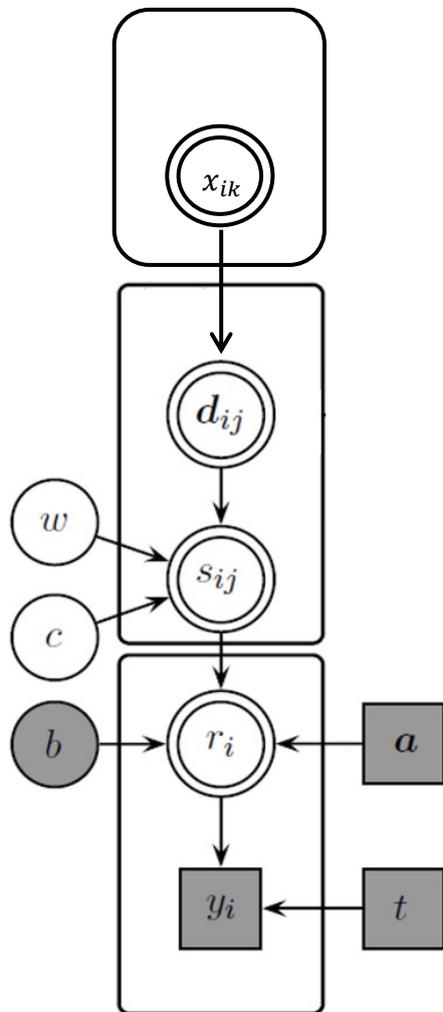
The ability to extract meaningful representations from a few exemplars and generalise to novel situations has been the object of much work in the concept learning literature focused on abstraction mechanisms. This process of abstraction is a cognitive feat without which it would not be possible to make sense of the world. Many accounts have been proposed to explain the mechanisms underlying such an ability. The literature has long been dominated by the debate opposing prototype and exemplar models of generalisation (Murphy, 2013). The prototype account assumes a mechanism of generalisation based on the similarity of novel instances to the most prototypical exemplar stored in memory (Rosch, 1975; Rosch & Mervis,

1975). This assumption does not provide a good explanation for the generalisation of abstract concepts due to their complexity and lack of organisation in clear-cut categories (Borghi, Barca, Binsofsky & Tummolini, 2018; Minda & Smith, 2001). As a result, this account has mostly been abandoned in favour of an exemplar view of concept learning (Feldman, 2003; Yee, 2019).

The exemplar view is best illustrated by the GCM model which posits that generalisation is a function of similarity between stored exemplars and novel instances (Medin & Schaffer, 1978; Nosofsky, 1986). This assumption suggests that the exemplar view provides a better explanation for mechanisms underlying the generalisation of abstract concepts as it allows for more flexibility in the description of how abstract concepts are categorised. The present studies have attempted to uncover such mechanisms by introducing a custom-made database of concepts called *NewAbstractConcepts* which refer to situations that are familiar to everybody but for which no word referent exist. The introduction of the database had many advantages. First, it offers a set of normed stimuli that would allow for the design of experiments to study mechanisms of concept learning, abstraction and generalisation for abstract concepts, which is a crucial aspect that has been missing from the abstract concept literature. Secondly, the introduction of stimuli that have no word referent avoids issues of background knowledge when testing adult participants in word learning experiments. Finally, crafting and testing such materials allowed for a better control of the exemplars that could be embedded in a psychological space that varied along two dimensions of similarity. Experiments 1a to 1c were designed to create such a psychological space following a technique of multidimensional scaling (MDS; Kruskal, 1964; Shepard, 1987). As a result, it was possible to represent the exemplars of the database in a psychological pace that varied along two dimensions on a similarity gradient from similar to dissimilar. Experiment 2 showed that dissimilar exemplars produced better performances of generalisation in the

processing of abstract concepts. The use of the psychological space and a Bayesian account of the GCM model (see Vanpaemel, 2009; Lee & Wagenmakers, 2014) provides a powerful framework to answer the two questions that this project set out to answer: (1) What sort of features are acquired during the learning of concepts through exposure to a set of exemplars? (2) How are these features generalised to novel instances of an abstract concept?

The creation of this psychological space answers a first assumption of the GCM model as regards to the dimensions of stored exemplars. In the present case, the similar and dissimilar dimensions were obtained from a series of similarity rating tasks and the exemplars of the NewAbstractConcepts concepts were learned and stored during the reading phase of experiment 2. A second assumption of the GCM model relates to selective attention weights allocated to chosen dimensions. According to the results of Experiment 2 which showed better performances for generalisation to novel instances, when stored exemplars were dissimilar to each other, the attention parameter allocated more weight to the dissimilar dimension compared to the similar dimension. This might seem counter-intuitive to allocate more attention to the dissimilar dimension when from a theoretical viewpoint, results from Experiment 2 suggest an abstraction of idiosyncratic surface features compared to common core features. However, this parameter of selective-attention strategy is implemented to model the influence of each dimension on classification predictions (Nosofsky, 2014). Experiment 2 suggests that contextual diversity is a better predictor of people's ability to recognise the novel exemplars as a good example of a previously stored concept and as such should receive a higher attention weight. Taken together, the psychological space obtained from Experiment 1a to 1c and the attention parameters from Experiment 2 provides the necessary background information to build a generalisation model for abstract concepts using the GCM model in a Bayesian framework which allows for flexible parameter estimation (see Figure 6).



**Figure 6.** Graphical model implementation of the GCM

Let  $x_i = (x_{i1}, x_{i2})$  denote the coordinate locations of stimulus  $x_i$  in a 2-D psychological space.

The first dimension  $x_{i1}$  has attention weight  $w$  with  $0 \leq w_d \leq 1$  and the second dimension  $x_{i2}$  has attention  $(1 - w)$ . Given the coordinate of the stimulus, the distance between stimuli  $x_i$  and  $x_j$  is computed according to the Minkowski metric:

$$d(x_i, x_j) = \left[ w |x_{i1} - x_{j1}|^r + (1 - w) |x_{i2} - x_{j2}|^r \right]^{1/r}$$

With  $r$  is a Euclidean metric ( $r = 2$ ) used for stimuli varying on integral dimensions (see Shepard, 1991 for a review).

Similarity between the  $i^{th}$  stored exemplar and  $j^{th}$  test exemplar is modelled as a decaying function of the distance between the stimuli:

$$s(x_i, x_j) = \exp\{-cd(x_i, x_j)\}$$

where  $c$  is a generalisation parameter such as  $c \sim Uniform(0,5)$

The overall probability that a test exemplar will be recognised as a good example of the NewAbstractConcepts is given by:

$$r_i = \frac{bs_{iA}}{(bs_{iA} + (1 - b)s_{iB})} \text{ with } b = 0.5$$

The observed decision is given by

$$y_i \sim Binomial(r_i, t)$$

with  $t$ , the total number of trial presentations.

The benefit of a Bayesian implementation of the GCM model lies in its ability to represent dependencies between mechanisms involved in the overall process of exemplar generalisation to novel instances. The stored exemplars are embedded in a dimensional space that represent the 2 salient dimensions of similarity or contextual diversity. The model also allows to allocate selective-attention weights to these dimensions with the idea a parameter

that can “stretch” attended dimensions and “shrink” unattended ones (Nosofsky, 2014).

Finally, the overall probability of generalisation meaning that people would be able to correctly recognise new instances of a concept is dependent on this psychological space, the attention and generalisation parameters which reflect prior knowledge established on the basis of the results obtained from Experiment 2 according to which abstract concepts such as those defined in the NewAbstractConcepts database are better generalised to new instances when learned through exposure to contextually diverse exemplars.

## CONCLUSION and FUTURE WORK

The present project provides a stepping stone for the study of generalisation mechanisms in the processing of abstract concepts. When considering the variability and complexity of abstract concepts, it is fair to assume that many other studies will need to be implemented in order to get a fuller picture of these mechanisms especially as regards to particular types of abstract concepts illustrated by the dimensions proposed by Borghi and colleagues (2018) about the variety of abstract concepts. It can be expected that the present model would require to implement more complex parameters especially as regards to the attention parameter. For emotion concepts for instance, generalisation could not only rely on the similar vs. dissimilar dimensions but emotional valence could also play a role. In using novel abstract concepts, the issue of the complexity of abstract concepts was side-stepped in order to propose a general-purpose model that could be used as a template for richer assumptions of generalisation of abstract concepts. The availability of the NewAbstractConcepts database will also provide an opportunity to implement other assumptions of the GCM model that were not specifically tested in the present project but also to use other models as a framework referent. With this project, we hoped to provide a satisfactory articulation of the literature on abstract concepts representation and generalisation mechanisms in concept learning which has mainly been missing in the literature.

## Chapter 7. General discussion and perspectives

Research on abstract conceptual knowledge is rooted in a long tradition which translates into a diversity of approaches, models and theories that aim to answer the fundamental questions we set out to explore in the present thesis such as (1) How is the meaning of abstract concepts represented? (2) How does it relate to other concepts whether similar or associated? (3) How does meaning relate to conceptual structure? (4) How is meaning generalised to all instances of the concept? The following chapter offers an overview of the results that were obtained to answer these questions. Such questions are a testament to the different levels of exploration that we set out to investigate in our study of the abstract concept phenomenon. More broadly, the long tradition of studying the semantic processing of concepts has often been compartmentalised into separate levels from semantics dealing with conceptual entities at the word-level to pragmatics dealing with complex utterances and statements (Cruse, 2010; Aitchison, 2012; Yule, 2020). As a result, the present chapter introduces a theoretical model of the semantic organisation and generalisation mechanisms of abstract concept processing. We consider this model to be an attempt to bridge the gap between different levels of investigation of psycholinguistic phenomena.

### Summary of results

The first two chapters of this thesis introduced normative databases that bridged the gap in the French literature as regards to the availability of normed stimuli used to study abstract concepts processing at the word level. As such, their main incentive was methodological and practical. The first database (Chapter 2) measured semantic similarity between pairs of French abstract concepts while the second database (Chapter 3) measured associative strength generated in a word association task. A second motivation for the creation of the two databases was to address previous findings that have shown that concepts are organized according to semantic similarity when concreteness increases and according to verbal

association when abstractness increases (see Crutch & Jackson, 2011). To address this observation, both databases included a variable of graded levels of concreteness. The computed descriptive statistics revealed stronger association strength for concrete concepts compared to abstract concepts, which confirmed different organisation patterns where concrete concepts are more tightly connected to a few contexts while abstract concepts are more loosely connected to a larger number of varied contexts (Chapter 3). In addition, word associations have shown a high correlation between cue and response concreteness which shed more light on the organisation of the mental lexicon as a function of concreteness that suggests abstract concepts are closely represented in the mental lexicon.

We then used the large amount of data generated by the word association task to build a graphical representation of the mental lexicon and apply methods of cognitive network science (Chapter 4). This was introduced as the first instance of building a semantic network based on French word association data and the first to explore structural differences between concrete and abstract concepts in the mental lexicon for any language. Graph analyses have shown that the network exhibits a high clustering coefficient, sparse density, and a small average shortest path length for both the concrete and abstract networks which is consistent with a small-world structure therefore confirming seminal findings of Steyvers and Tenenbaum (2005). Comparisons between local node statistics and global structural topology have shown that abstract and concrete concepts present different overall patterns of structural organisation with concrete concepts presenting an organisation in densely connected communities compared to abstract concepts. These patterns confirmed previously acquired knowledge about the differences between abstract and concrete concepts on a larger scale.

Previous studies have used simulations of spreading activation to derive highly predictive judgments of similarity (see for example Kenett, Levi, Anaki & Faust, 2017; De Deyne et al., 2018). As such, when considering the word level of semantic processing, both semantic

similarity and verbal association can refer to similarity-based processes. Taken together, this suggests that the mental lexicon is organised according to patterns of similarity whether measured in terms of semantic similarity between pairs of words in a database or as node coordinates extracted by an algorithm of spreading activation in a semantic network built from word association data. In Chapter 4, simulations of spreading activation have shown that abstract and concrete concepts present different thresholds of activation with abstract concepts being less influential in the network and therefore exhibiting lower activation levels compared to concrete concepts. This pattern confirmed findings obtained from graph analyses according to which abstract concepts are organised in a more diffuse pattern in the mental lexicon. This also confirms previous findings according to which abstract concepts are more loosely connected to a diversity of contexts (Paivio et al., 1968).

Many authors have suggested that, compared to concrete concepts, abstract concepts appear to be semantically impoverished, with their representation requiring associations with other concepts (Barsalou et al., 2008; Borghi, Scorolli, Caligiore, Baldassare & Tummolini, 2013; Borghi, Barca, Binkofski, Castelfranchi, Pezzulo & Tummolini, 2019, see also Recchia & Jones, 2012). In Chapter 5, we explored the richness of abstract concepts and the nature of their features. In a preliminary norming task, we constructed a set of pictures to illustrate a list of lexical abstract concepts. The pictures were either concrete pictorial depictions of the chosen lexical concepts or abstract pictures devoid of tangible features. These materials were then used to form picture-word pairs where each lexical concept was paired with a picture either concrete or abstract. The main hypothesis posited that participants would use a strategy when presented with both picture-types and process the meaning of abstract concepts based only on clear depictions rather than intangible pictures. On the contrary, results have shown that participants continued to process concepts from abstract pictures devoid of tangible features even when presented with more concrete ones. This suggested abstract pictures can

convey the same meaning as lexical abstract concepts which we took as evidence of the richness of abstract concepts as they activate features beyond their linguistic or situational components. These results were complementary to those of Bolognesi and Vernillo (2019) who proposed a process of abstraction based on an inferential mechanism that moves from concretely depicted entities to more abstract ones. These intangible features could be construed as evidence of abstracted representations from varied exemplars of concepts becoming generalised statistical traces in long-term memory (Barsalou, 2003).

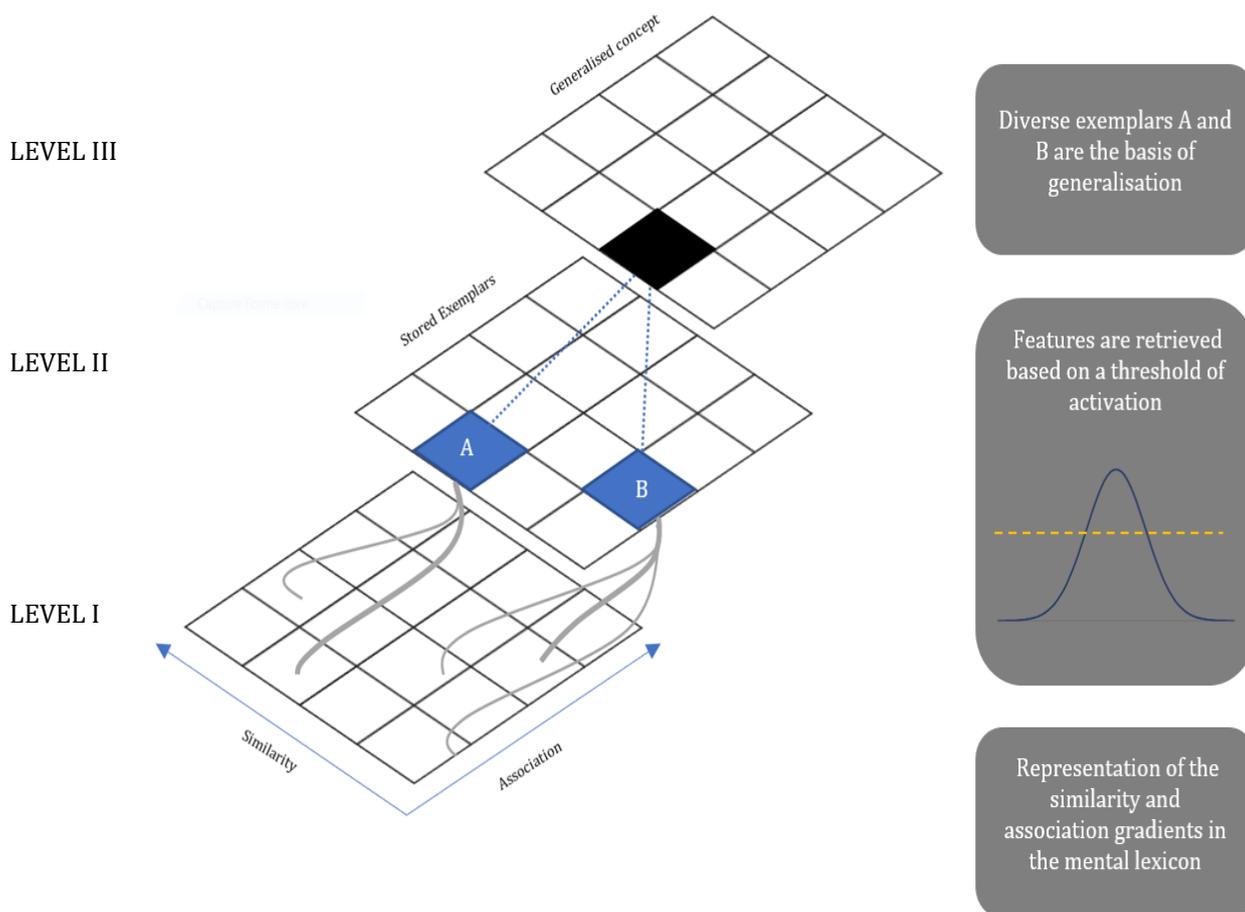
This process of generalisation refers to an ability to extract meaningful representations from exemplars and transfer to novel situations which reflects a higher-level mechanism with pragmatic implications. In Chapter 6, we explored generalisation mechanisms in the processing of abstract concepts by introducing a novel database of new abstract concepts which were used to test whether abstract concepts are generalised based on patterns of similarity or contextual diversity. A first series of norming studies aimed to build the database composed of novel abstract concepts described by exemplars that were paired into similar or dissimilar combinations. The abstract concepts were then presented to participants in a similarity judgment task (Chapter 6, Experiment 2). Experiment 2 showed that dissimilar exemplars produced better performances of generalisation compared to similar exemplars. Exposure to contextually diverse exemplars enhanced participants abilities to generalised learned abstract concepts to novel instances of said concepts. These results were construed as evidence of the role of contextually diverse patterns for the processing of abstract concepts at a higher level of complexity.

Taken together, results from all empirical chapters reveal a reversed pattern when moving up in levels from the semantics of the word-level databases which revealed a pattern of similarity to complex abstract exemplars which are generalised on the basis of contextual diversity. The complexity of psycholinguistics phenomena means that scientific explorations

of the mental lexicon are often compartmentalised with studies focusing on a single identified level of processing. The present thesis is evidence of this complexity with several studies each focused on one single level. Further exploration will need to account for the link between levels of processing. The present chapter summarises the findings across our empirical data into a theoretical model as an attempt to render a fuller picture of the semantic organisation and generalisation of abstract concepts.

### **A theoretical model and some implications for abstract concept processing**

A central controversy in cognitive science concerns the roles of similarity versus contextual diversity. To gain some insights on this issue, we propose a theoretical model that draws on the results from the present thesis. The model posits that similarity-versus diversity-based processes can be characterized as extremes in a multilevel space with similarity-based organisation at the word level and contextual diversity at the pragmatic level. The transition from similarity-based to diversity-based processing is conceptualized as a transition through levels.



**Figure 1.** Schematic representation of our theoretical model. Level I represents abstract concepts and features at the word levels. Concepts and features are activated following a threshold of activation. Thicker traits represent more influential nodes which possess a higher activation potential compared to thinner traits. Level II represents exemplars in memory as instances of a concepts. Level III represents the generalised concepts based on the processing of contextually diverse exemplars which allow for the recognition of novel instances.

The theoretical model presented in Figure 1 suggests a hierarchical structure based on an integration across levels of processing from features to generalised concepts. This hierarchical structure posits a reverse pattern of processing with the lowest level relying on similarity while the highest level describes a pattern of contextual diversity. At the word level, features are activated when they reach the required threshold. This notion of activation threshold comes from the modelling of a semantic network of the mental lexicon (Chapter 4). Results

from Chapter 4 revealed that some concepts are more influential than others due to their structural position in the network meaning that they facilitate the spread of activation within the network. Levels of activation are also determined by the weights attributed to links between nodes. In a network built from word association data, weights reflect the strength of word associations. Other aspects such as the number of inward or outward connections also impact the influence of a node and consequently the spread of activation. The comparison of node influence in the network suggested that abstract concepts have a lower threshold of activation compared to concrete concepts meaning that more features need to be activated in order to reach the required threshold. This notion of activation threshold is illustrated in Figure 1 by the thickness of traits that link the first and second levels of the model with thicker traits for more influential concepts. One aspect that could not be shown on the Figure is the nature of the features that activate a concept which could be intangible as well (Chapter 5). This has been confirmed by previous feature naming tasks according to which participants may provide only a linguistic approximation of conceptual content of abstract concepts which may themselves be decomposed into abstract features (McRae, Cree, Seidenberg, & McNorgan, 2005; McRae, de Sa, & Seidenberg, 1997; Sánchez-Casas, Ferré, García-Albea & Guasch, 2006; Vigliocco, Vinson, Lewis & Garrett, 2004; Vinson & Vigliocco, 2008). This has been previously regarded as a limitation of feature naming tasks but in light of the results obtained from Chapter 5, this could also be construed as evidence of the intangible nature of certain features that compose abstract concepts (see McRae et al., 2005 for a discussion of these limitations).

To the best of our knowledge, the semantic network we build in Chapter 4 was the first attempt in the French language and the first to investigate the structural properties of abstract and concrete concepts in a network. This attempt provided important insights as to the structural differences between abstract and concrete concepts. In a future project, we aim

to test the replicability of these findings in a larger English database by using the Small World of Words data collected by De Deyne et al. (2019).

While the passage from level I to level II in the model was determined by similarity-based processes, the passage between level II and level III is determined by diversity-based processes which reflects a reversed pattern from lower to higher-level processing. The overall incentive of studying conceptual knowledge is aimed to explore the ability to extract meaningful representations from encountering a few instances of a concept. In Chapter 6, we explored this ability for abstract concepts. When studying the acquisition of concepts, researchers encounter some methodological difficulties such as the necessity to control people's background knowledge. In order to avoid such difficulties, we introduced a database of novel abstract concepts described by several exemplars that were either similar or dissimilar to each other. Abstract concepts present such complexity and diversity that they cannot be precisely arranged in categories with clear-cut boundaries. As a result, we suggested that the processing of abstract concepts would be better described using an exemplar account of generalisation (see Feldman, 2003). The newly introduced database was first used to create a psychological space based on two within exemplars dimensions which were similarity and dissimilarity. The materials were then used in a word-learning experiment where participants were presented with a pseudo-word to label the novel abstract concept along with a set of exemplars that were either similar or dissimilar. In the test phase, they were presented with a novel instance of each abstract concept and were asked whether this could be construed as a new example of the learned concept. Participants performed better at recognising the novel instances as an example when the abstract concepts were learned through dissimilar set compared to similar sets of exemplars. We took these results as evidence that abstract concepts are generalised following a mechanism based on contextual diversity. Taken together with the previous level, this suggests that the more abstracted

conceptual knowledge becomes and the more its processing relies on a reversed pattern that moves from a similarity-based mechanism for lower-levels of processing to a diversity-based mechanism for higher-levels of processing.

When considering a broader cognitive framework, this reversed pattern is not specific to the processing of semantic abstract concepts. The CAL model (Category Abstraction Learning) developed by Schlegelmilch and von Helversen (2021) is a model that combines similarity-based lower-level processes with dissimilarity-based higher abstraction processes to explain many phenomena of category and reinforcement learning. Their model was aimed to answer a major limitation present in most models of category learning which are unable to explain the underlying generalisation mechanisms from features to exemplars to generalised concepts. The model builds on the principle of stimulus generalisation (Shepard, 1987) according to which the presentation of a stimulus activates stored exemplars in memory with a level of activation that decays following the psychological distance between a novel stimulus and exemplars stored in memory.

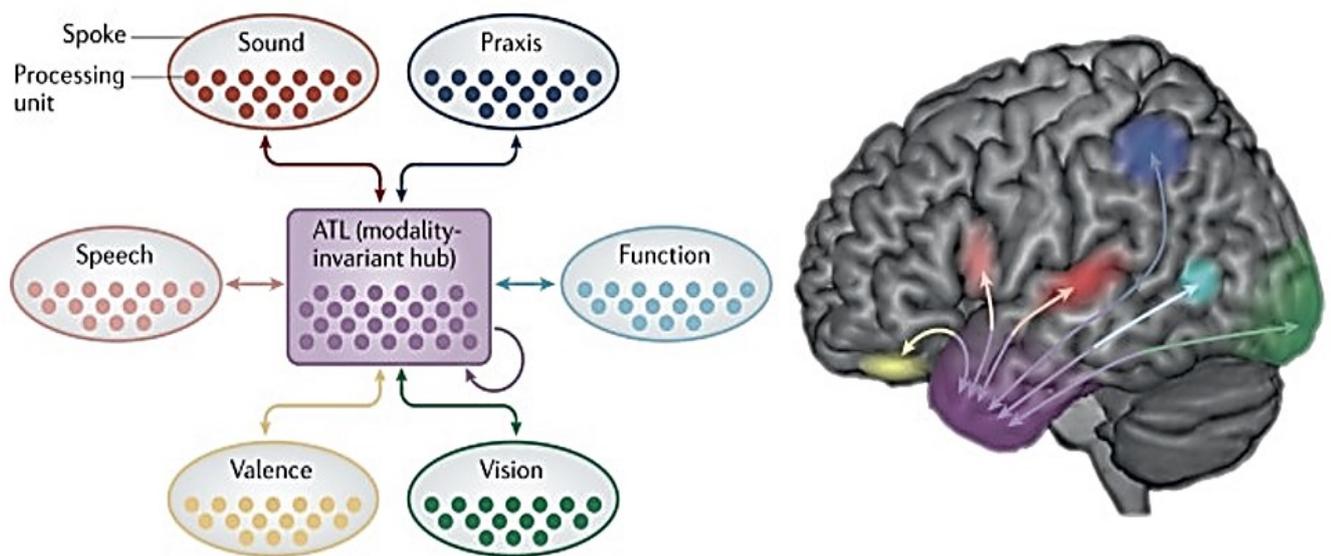
The parallel between the reversed pattern inferred from the results of our model to the one described in the broader cognitive framework proposed by Schlegelmilch and von Helversen (2021) highlights the importance of explaining language mechanisms within a larger cognitive framework. This observation is in line with our attempt in Chapter 6 to describe the mechanism for the generalisation of abstract concepts using the GCM model. This pertains to the maturity of the cognitive science in general and its ability to grapple with the challenge of defining unified models and theories without losing sight of specificities that are intrinsic to a specific level of explanation.

The present observations have been centered on psycholinguistic phenomena at the behavioural level of explanation. Our results present some implications for neural and computational levels.

## Implications for neural evidence

Network semantic analyses have shown a structural difference in the activation patterns for abstract and concrete concepts (Chapter 4). Previous studies have confirmed the impact of this concreteness gradient in neurological data. The literature on the neurological profile of semantic processing has established that language is represented in a distributed neural network (Patterson et al., 2007; Binder & Desai, 2011; Han et al., 2013; Martin, 2016; Huth et al., 2016). The literature however has not reached a consensus on the nature of the semantic neural network and proposes two distribution patterns which are debated namely: the distributed-only models and the hub-and-spoke hypothesis (Patterson et al., 2007, 2015; Mahon & Caramazza, 2009; Lambon Ralph et al., 2010; Martin et al., 2014; Martin, 2016). According to distributed-only theories, conceptual knowledge is represented in a modality-specific pattern which put an emphasis on the role of sensorimotor modalities such as shapes, colours, sounds and actions which coincide with a grounded view of cognition (Martin, 2007; Barsalou, 1999; 2008; Binder et al., 2009). The hub-and-spoke hypothesis posits the existence of amodal hubs of processing in addition to modality-specific regions (Lambon Ralph, 2014; Lambon Ralph & Patterson, 2008; Lambon Ralph, Sage, Jones, & Mayberry, 2010; Patterson, Nestor, & Rogers, 2007; Rogers et al., 2004). In the hub-and-spoke model, some regions called spokes process the modality-specific features of concepts which are connected through cortical routes to hub regions. These hubs code for similarity-based processes that abstract specific features in favour of similar core components of concepts (Patterson & Lambon Ralph, 2016). In light of results from Chapter 6, this role of the hub regions coincides with the description of the exemplar theory which posits a mechanism responsible for the abstraction of idiosyncratic features in the generalisation of abstract concepts.

Neuropsychological data such as profiles of semantic dementia (SD) provide support for the hub-and-spoke hypothesis and identify the ATL (anterior temporal lobe) as a semantic hub region (see for example Patterson et al., 2007). Semantic dementia is a neurodegenerative disorder characterised by a selective loss of conceptual knowledge regardless of their modality and can be associated with bilateral lesions to the ATL (Hodges et al., 1992; Patterson et al., 2007; Binney et al., 2010; Gainotti, 2012; Hoffman et al., 2014; Lambon Ralph, 2014; Rice et al., 2015; Zhao et al., 2017). As a result, SD patients exhibit a poor comprehension of conceptual items presented in every modality (Bozeat et al., 2000, Coccia et al., 2004, Luzzi et al., 2007). Consequently, this pattern of cross-modality deficit has been construed as evidence of the amodal nature of the ATL and its role as a convergence zone which form amodal conceptual representations (see Figure 2; Patterson et al., 2007, Rogers et al., 2004; Rogers & McClelland, 2004).



**Figure 2.** Representation of the hub-and-spoke model with spoke regions which code for modality-specific components of concepts while the ATL is a semantic hub which aggregates across modalities and form amodal conceptual representations (see text for more details). From Lambon et al. (2017).

Despite such evidence, the specific role of the ATL remains unclear. For instance, Loiselle et al. (2012) have explored the comprehension of concrete and abstract concepts in patients with a selective ATL resection. Typically, the concreteness effect refers to the robust behavioural phenomena found in neurologically intact participants which describes a facilitated processing of concrete concepts compared to abstract concepts in terms of speed and accuracy in varied tasks such as memory retrieval and lexical decision (see Paivio, 1991 for a review). In contrast, patients who exhibit patterns of semantic dementia have been known to present a reversed concreteness effect with a facilitated processing in favour of abstract concepts compared to concrete concepts (Breedin et al., 1994; Cipolotti & Warrington, 1995; Macoir, 2009; Papagno, Capasso, & Miceli, 2009; Warrington, 1975; Yi, Moore, & Grossman, 2007). It remains unclear whether this greater impairment for concrete concepts originates from damage to the ATL in SD patients or from degraded visuo-perceptual features from damaged inferior temporal lobe in SD patients (Desgranges et al., 2007; Nestor, Fryer, & Hodges, 2006). This latter hypothesis emerged from the role of the inferior temporal lobe in the processing of visual objects that often present lesions in SD patients. To test these two hypotheses, Loiselle et al. (2012) compared the processing of abstract and concrete concepts using a semantic judgment task in patients who underwent a selective ATL surgical resection and patients with selective medial temporal lobe damage sparing the ATL. Results have shown that both groups exhibited impaired processing for both concept types compared to the control group. Comprehension of concrete concepts were significantly more impaired for patients with selective ATL resection while both concept types were equally impaired in other patients. Loiselle et al. (2012) interpreted these results in relation with the dichotomy between abstract and concrete concepts with concrete concepts that are more dependent on similarity-based patterns while abstract concepts are inscribed in more diffuse associative patterns. This concurs with Paivio's assumption (Paivio, 1991)

according to which concrete concepts show stronger connections to a smaller number of contexts while abstract concepts are more loosely connected to a larger number of contexts. In the case of a lesion to the ATL, this loose pattern becomes an advantage as more diffuse statistical memory traces are maintained for abstract concepts while stronger and more localised connections are lost as a whole in the case of concrete concepts. These results confirm our conclusions on a neurological level of explanation which showed that abstract concepts present weaker associative connections (Chapter 3), are organised in a diffuse structural pattern in a semantic network which resulted in lower activation levels (Chapter 4), and can be processed and decomposed based on intangible features that leave memory traces which can be activated even when the concept is not clearly depicted but evoked based on pictures devoid of tangible features (Chapter 5).

Other studies have shown the existence of an abstract-to-concrete gradient in the ATL with concrete concepts represented in the medial-ventral ATL while abstract concepts are represented in the dorsal-lateral ATL (Lambon Ralph et al., 2017). More recently, Vignali, Turini, Collignon, Crepaldi and Bottini (2020) have explored the time course of the abstract and concrete concepts convergence in the ATL. They have shown the existence of a dorsal-to-medial and abstract-to-concrete gradient in the ATL which emerges in late stages of processing. According to this time course, abstract and concrete concepts are initially encoded in posterior temporal regions before converging in the ATL. These results provide additional evidence of the fact that semantic information for concrete and abstract concepts travel along different cortical routes with concrete concepts that originate from the ventral stream before converging to the ventral-medial ATL while abstract concepts originate from the posterior STG (superior temporal gyrus) and the orbito-frontal cortex before converging to the dorsal-lateral ATL.

Taken together, evidence from SD patients and the graded convergence in the ATL seem to suggest that the ATL could act as a lever between newly processed concepts grounded in modal and linguistic features to generalised concepts in the form of amodal conceptual representations through a mechanism responsible for the abstraction of idiosyncratic features (Patterson & Lambon Ralph, 2016). However, several questions on the role of the ATL in the processing of abstract concepts need to be answered. The processing advantage of abstract concepts in the ATL would suggest that being composed of abstract features themselves, abstract concepts should benefit from a faster mechanism of generalisation. Time course analyses of concrete and abstract concepts have not produced faster convergence for the abstract concepts compared to the concrete concepts however (Loiselle et al., 2012). In addition, the hub-and-spoke mechanisms are said to be similarity-based whereas we have seen in Chapter 6 that concepts were more easily generalised on the basis of dissimilar exemplars. A way to elucidate these seemingly contradictory assumptions would be to test for the processing of abstract concepts by replicating the experiments from Chapter 5 and 6 using fMRI techniques. In Chapter 5, we have seen that abstract concepts could be activated by intangible pictures. An fMRI implementation of this experiment would provide some evidence as to the nature of these features based on brain activation during the processing of the pictures and the retrieval of the corresponding abstract concepts. Results from chapter 6 have shown that abstract concepts are better generalised from dissimilar exemplars. We propose an implementation of the newAbstractConcepts database in an experiment that would test for the effect of similar and dissimilar exemplars on the activation of the ATL using fMRI techniques to explore whether dissimilar exemplars produce higher levels of activation of the ATL given that they should facilitate generalisation.

Our study and findings of such psycholinguistic phenomena were meant to advance our knowledge of language processing in the human cognitive system and provide insight as

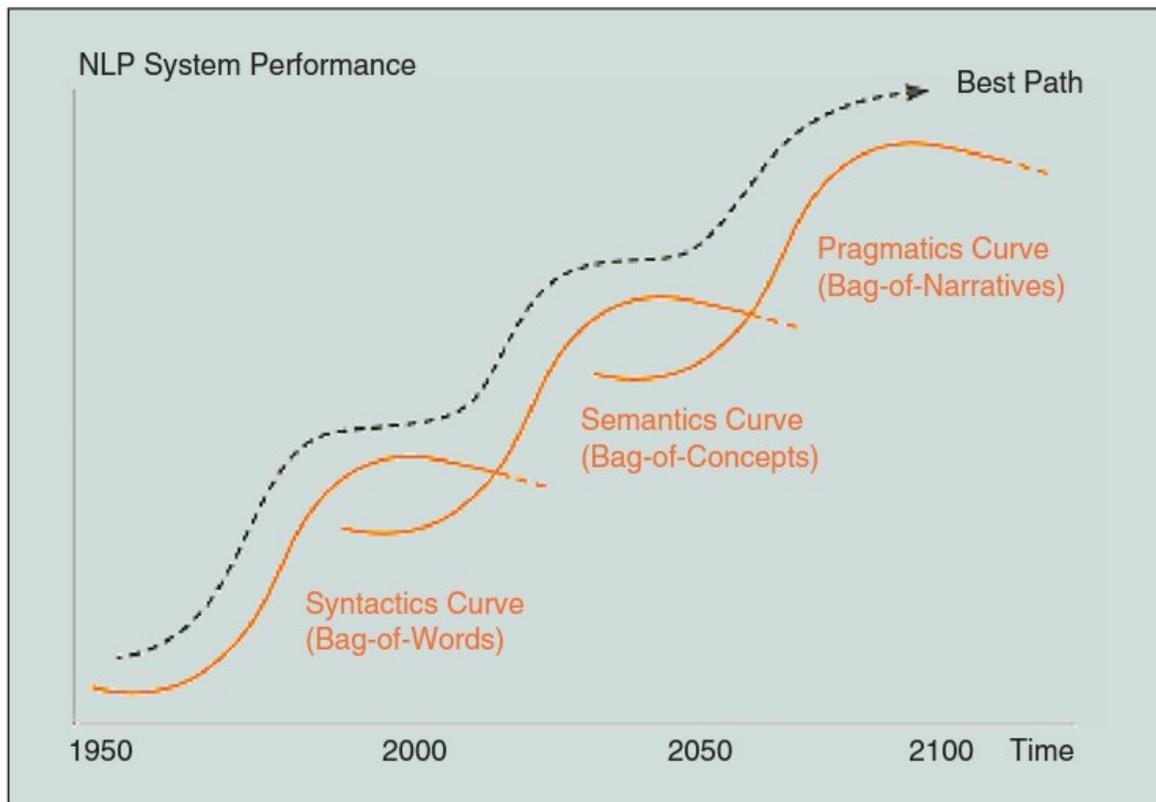
to the challenge posed by abstract concepts. Due to the interdisciplinary nature of the cognitive sciences, these findings can be interpreted on a larger scale beyond the frontiers of psycholinguistics or even cognitive psychology. In the next section, we deal with the implications of the present findings for natural language processing which falls under the umbrella of the cognitive sciences due to its ties to the field of computer science.

## **Implications for natural language processing**

Natural language processing (NLP) is a field of Artificial Intelligence (AI) motivated by the comprehension of human language by machines which uses computational techniques to analyse, represent and reproduce human language. From the advent of the Internet and the Social Web, a vast amount of unstructured linguistic content has been generated so much so that it becomes impossible to manipulate using traditional techniques. This vast amount of information has also provided us with an opportunity. Never before have we had access to such a wealth of data which provides insights into the ecological use of language by humans. For instance, the use of large linguistic corpora obtained from the mining of social media platforms has allowed for the development of word frequency databases such as Wordlex (Gimenes & New, 2016) which provides a more accurate and up-to-date picture of the common use of language compared to previous databases which were computed from books.

The unstructured nature of linguistic information generated by humans for humans presents a major challenge for machines as it is not directly processable to them. That is why, NLP uses algorithms able to mine, aggregate and parse large text corpora but which are unable to interpret their meaning (Allen, 1987; Dyer, 1994; Cambria & White, 2014). According to Dyer (1994), these limitations are due to the lack of high-level symbolic capabilities of NLP algorithms. Such capabilities would require the acquisition of lexical

semantic representation, grounding language in perceptual and motor experiences and the ability to abstract and generalise conceptual knowledge. This lack of capabilities keeps NLP models from achieving human-level language understanding despite major advances since the advent of the field in the 1950s.



**Figure 3.** Advances in NLP research cross 3 major era following the syntactics, semantics and pragmatics curves (From Cambria & White, 2014).

In recent years, more efforts of collaboration between cognitive and computational fields have been put forward in order to achieve psychologically plausible NLP models. Cambria and White (2014) envisioned the advance of NLP research according to three major eras represented as overlapping curves (see Figure 3). The leap between the syntactic and semantic curves represent the current interest for the use of cognitively plausible models at the word level which have been used as a paradigm shift from models centered on words as single linguistic units to the notion of concepts as meaningful representation grounded in

actions, events and situations (Cambria & Hussain, 2012). One example of this collaborative effort is the development of semantic networks which were first motivated by the need to represent semantic concepts in a computer memory slot (Quillian, 1969; Chapter 1). On the other side of this collaboration, psycholinguistics researchers borrowed powerful computational tools for the representation of the semantic information on a large scale (see Chapter 4).

The semantics curve includes the representation of common-sense knowledge built on intuitive theories about physics (forces, masses, gravity...) and psychology (desires, beliefs, intents...; see for example Gerstenberg & Tenenbaum, 2017). This interest for the representation of common sense is inscribed within a larger goal to build machines that learn and think like humans do (Lake, Ullman, Tenenbaum, & Gershman, 2017). The field of AI as a whole has become aware of the invaluable blueprint that the human mind can provide in its ability to learn quickly and flexibly new concepts in relation to previously acquired concepts (Lupyan & Bergen, 2016; Lupyan & Clark, 2015). This ability when implemented in intelligent systems using deep learning techniques can provide a powerful framework for tasks of scene understanding based on object recognition and the comprehension of intent in acting agents (Karpathy & Fei-Fei, 2015; Vinyals et al., 2014; K. Xu et al., 2015). Current algorithms have made tremendous progress in object recognition but still struggle with scene understanding which would allow for a leap between semantics and pragmatics curves (Figure 3). This leap would require the implementation of causality, intuitive physics and intuitive psychology in computational models (Lake et al. 2017). In chapter 6, we developed a database of novel abstract concepts to study mechanisms of generalisation to novel instances. This human capacity requires the ability to recognise a pattern between memorised exemplars and novel instances of a concept. Future work in cognitive sciences will have to provide answers as to the role such intuitive theories about psychology and physics come into play in the

representation, acquisition and generalisation of concepts in the mind which would benefit for both cognitive and computational sciences. Cognitive systems provide blueprints for the development of intelligent systems while computational implementation represent an additional incentive to apply a sense of mathematical formalism to verbal theories and test them in a computational framework.

## **Conclusions and future work**

The present thesis was designed to study the representation of abstract concepts according to several levels of processing. We first explored the word level of processing and proposed two databases of semantically similar and verbally associated word pairs. Our findings have put an emphasis on the importance to consider concreteness as a graded variable and revealed the role of concreteness as a gradient of organisation in the mental lexicon. The data from the associative database was then used to build a multidimensional semantic network which allowed us to explore the structural organisation of the mental lexicon and its impact on the processing of concepts. These databases and network used only the verbal modality for the representation of concepts. The next study used both the verbal and visual modality of abstract concepts to explore the featural nature of abstract concepts and found that abstract concepts can be activated by pictures devoid of tangible features. We interpreted this activation as evidence of statistical memory traces which can be activated even in the absence of the clear depiction of a concept. We construed these findings as a part of mechanisms of abstraction and generalisation mechanisms. We used this study as a transition to the study of generalisation in the processing of abstract concept within the framework of the exemplar theory and found that abstract concepts are more easily abstracted from their idiosyncratic features and generalised to novel instances on the basis of contextual diversity. This accumulation of evidence revealed a reversed pattern of organisation from

similarity-based processes at the word-level to diversity-based processes at the level of generalised concepts. This reversed pattern was summarised in a theoretical model which represented the three levels of processing from the word-level to pragmatics considerations. Finally, we explored the implications for neural and computational evidence.

The present thesis represents a snapshot of our reflection on the processing of abstract concepts at the time of writing which can be construed as a launchpad for future projects. For instance, the techniques of semantic network analysis are common to both the exploration of behavioural data and neurological data. This means that it would be possible to create a database of verbal association using a neurological association task and create a neural network of the same data to explore the parallels between the structural and neural organisation of the mental lexicon. More importantly, the reversed pattern illustrated in the theoretical model in particular provided an incentive to incorporate all levels of processing in a same experiment. This experiment would use the framework already developed in Chapter 5 and the newAbstractConcepts database. This follow-up study would attempt to replicate the previous findings according to which abstract concepts are better generalised on the basis of contextual diversity in a first phase and in a second phase, the pseudowords used to label these novel concepts would be used in a semantic priming experiment to explore the role of generalisation mechanisms at the word-level also. Finally, we hope that the availability of the databases and network we have proposed will serve for future researchers and students interested in the study of the French mental lexicon for abstract concepts.

## REFERENCES

- Andrews, M., Frank, S., & Vigliocco, G. (2014). Reconciling embodied and distributional accounts of meaning in language. *Topics in Cognitive Science*, 6(3), 359–370. <https://doi.org/10.1111/tops.12096>
- Andrews, M., Vigliocco, G., & Vinson, D. (2009). Integrating Experiential and Distributional Data to Learn Semantic Representations. *Psychological Review*, 116(3), 463–498. <https://doi.org/10.1037/a0016261>
- Andrews, S., Lo, S., & Xia, V. (2017). Individual differences in automatic semantic priming. *Journal of Experimental Psychology: Human Perception and Performance*, 43(5), 1025–1039. <https://doi.org/10.1037/xhp0000372>
- Baayen, R. H. (2001). *Word frequency distributions* (Vol. 18). Springer Science & Business Media.
- Bales, M. E., & Johnson, S. B. (2006). Graph theoretic modeling of large-scale semantic networks. *Journal of Biomedical Informatics*, 39(4), 451–464. <https://doi.org/10.1016/J.JBI.2005.10.007>
- Balota, D. A., Cortese, M. J., Sergent-Marshall, S. D., Spieler, D. H., & Yap, M. J. (2004). Visual word recognition of single-syllable words. *Journal of Experimental Psychology: General*, 133(2), 283–316. <https://doi.org/10.1037/0096-3445.133.2.283>
- Balota, D. A., Yap, M. J., Cortese, M. J., Hutchison, K. A., Kessler, B., Loftis, B., ... Treiman, R. (2007). The english lexicon project. *Behavior Research Methods*. Springer New York LLC. <https://doi.org/10.3758/BF03193014>
- Baronchelli, A., Ferrer-i-Cancho, R., Pastor-Satorras, R., Chater, N., & Christiansen, M. H. (2013). Networks in cognitive science. *Trends in Cognitive Sciences*, 17(7), 348–360. <https://doi.org/10.1016/j.tics.2013.04.010>
- Baroni, M., & Evert, S. (2006). The zipfR package for lexical statistics: A tutorial introduction.
- Barrón-Martínez, J. B., & Arias-Trejo, N. (2014). Word association norms in Mexican Spanish. *The Spanish Journal of Psychology*, 17.
- Barsalou, L. W. (1999). Perceptions of perceptual symbols. *Behavioral and Brain Sciences*. <https://doi.org/10.1017/S0140525X99532147>
- Barsalou, L. W. (2003). *Situated Conceptualization: Theory and Application*.
- Barsalou, L. W. (2003). Situated simulation in the human conceptual system. *Language and Cognitive Processes*. Psychology Press Ltd. <https://doi.org/10.1080/01690960344000026>
- Barsalou, L. W. (1999). Perceptual symbol systems. *Behavioral and Brain Sciences*. <https://doi.org/10.1017/S0140525X99002149>
- Barsalou, L. W. (2008). Grounded Cognition. *Annual Review of Psychology*, 59(1), 617–645. <https://doi.org/10.1146/annurev.psych.59.103006.093639>
- Barsalou, L. W. (2003). Abstraction in perceptual symbol systems. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 358(1435), 1177–1187. <https://doi.org/10.1098/rstb.2003.1319>
- Barsalou, L. W. (2003, July 29). Abstraction in perceptual symbol systems. *Philosophical Transactions of the Royal Society B: Biological Sciences*. Royal Society. <https://doi.org/10.1098/rstb.2003.1319>
- Barsalou, L. W., Santos, A., Simmons, W. K., & Wilson, C. D. (2012). Language and simulation in conceptual processing. In *Symbols and Embodiment: Debates on Meaning*

- and Cognition*. Oxford University Press.  
<https://doi.org/10.1093/acprof:oso/9780199217274.003.0013>
- Barsalou, L. W., & Wiemer-Hastings, K. (2005). Situating abstract concepts. In *Grounding Cognition: The Role of Perception and Action in Memory, Language, and Thinking* (pp. 129–163). Cambridge University Press.  
<https://doi.org/10.1017/CBO9780511499968.007>
- Bassett, D. S., & Bullmore, E. T. (2017). Small-World Brain Networks Revisited. *Neuroscientist*, 23(5), 499–516. <https://doi.org/10.1177/1073858416667720>
- Bayarri, M. J., & Mayoral, A. M. (n.d.). Bayesian Design of “Successful” Replications. *The American Statistician*. Taylor & Francis, Ltd. American Statistical Association.  
<https://doi.org/10.2307/3087300>
- Berg, T., & Levelt, W. J. M. (1990). Speaking: From Intention to Articulation. *The American Journal of Psychology*, 103(3), 409. <https://doi.org/10.2307/1423219>
- Bimler, D. L., Snellock, M., & Paramei, G. V. (2019). Art expertise in construing meaning of representational and abstract artworks. *Acta Psychologica*, 192, 11–22.  
<https://doi.org/10.1016/j.actpsy.2018.10.012>
- Binder, J. R., Conant, L. L., Humphries, C. J., Fernandino, L., Simons, S. B., Aguilar, M., & Desai, R. H. (2016). Toward a brain-based componential semantic representation. *Cognitive Neuropsychology*, 33(3–4), 130–174.  
<https://doi.org/10.1080/02643294.2016.1147426>
- Bolognesi, M., Pilgram, R., & van den Heerik, R. (2017). Reliability in content analysis: The case of semantic feature norms classification. *Behavior Research Methods*, 49(6), 1984–2001. <https://doi.org/10.3758/s13428-016-0838-6>
- Bolognesi, M., & Vernillo, P. (2019). How abstract concepts emerge from metaphorical images: The metonymic way. *Language and Communication*, 69, 26–41.  
<https://doi.org/10.1016/j.langcom.2019.05.003>
- Bonin, P., Méot, A., & Bugajska, A. (2018). Concreteness norms for 1,659 French words: Relationships with other psycholinguistic variables and word recognition times. *Behavior Research Methods*, 50(6), 2366–2387. <https://doi.org/10.3758/s13428-018-1014-y>
- Bonin, P., Méot, A., Ferrand, L., & Bugajska, A. (2013). Normes d’associations verbales pour 520 mots concrets et étude de leurs relations avec d’autres variables psycholinguistiques. *L’Année Psychologique*, 113, 63–92.
- Bonin, P., Méot, A., Ferrand, L., & Bugajska, A. (2015). Sensory experience ratings (SERs) for 1,659 French words: Relationships with other psycholinguistic variables and visual word recognition. *Behavior Research Methods*, 47(3), 813–825.  
<https://doi.org/10.3758/s13428-014-0503-x>
- Borge-Holthoefer, J., & Arenas, A. (2010). Semantic networks: Structure and dynamics. *Entropy*, 12(5), 1264–1302. <https://doi.org/10.3390/e12051264>
- Borge-Holthoefer, J., Moreno, Y., & Arenas, A. (2012). Topological versus dynamical robustness in a lexical network. *International Journal of Bifurcation and Chaos*, 22(7), 1–9. <https://doi.org/10.1142/S021812741250157X>
- Borghi, A. M., Barca, L., Binkofski, F., Castelfranchi, C., Pezzulo, G., & Tummolini, L. (2018). Words as social tools: Language, sociality and inner grounding in abstract concepts. *Physics of Life Reviews*, 29, 120–153.  
<https://doi.org/10.1016/j.plrev.2018.12.001>
- Borghi, A. M., Binkofski, F., Castelfranchi, C., Cimatti, F., Scorolli, C., & Tummolini, L. (2017). The challenge of abstract concepts. *Psychological Bulletin*, 143(3), 263–292.  
<https://doi.org/10.1037/bul0000089>

- Borghi, A. M., & Cimatti, F. (2010). Embodied cognition and beyond: Acting and sensing the body. *Neuropsychologia*, *48*(3), 763–773.  
<https://doi.org/10.1016/j.neuropsychologia.2009.10.029>
- Borghi, A. M., & Pecher, D. (2011). Introduction to the special topic Embodied and Grounded Cognition. *Frontiers in Psychology*. <https://doi.org/10.3389/fpsyg.2011.00187>
- Borghi, A. M., Scorolli, C., Caligiore, D., Baldassarre, G., & Tummolini, L. (2013). The embodied mind extended: Using words as social tools. *Frontiers in Psychology*, *4*.  
<https://doi.org/10.3389/fpsyg.2013.00214>
- Borghi, A., Tummolini, L., & Borghi, A. M. (2020). Behavioral and Brain Sciences-Commentary on Gilead, Trope & Liberman Touch me if you can: the intangible but grounded nature of abstract concepts. <https://doi.org/10.1017/S0140525X19003091>
- Bork, P., Jensen, L. J., Von Mering, C., Ramani, A. K., Lee, I., & Marcotte, E. M. (2004). Protein interaction networks from yeast to human. *Current Opinion in Structural Biology*, *14*(3), 292–299. <https://doi.org/10.1016/J.SBI.2004.05.003>
- Bruni, E., Tran, N. K., & Baroni, M. (2014). Multimodal distributional semantics. *Journal of Artificial Intelligence Research*, *49*, 1–47. <https://doi.org/10.1613/jair.4135>
- Brybaert, M., Mandera, P., & Keuleers, E. (2018). The Word Frequency Effect in Word Processing: An Updated Review. *Current Directions in Psychological Science*, *27*(1), 45–50. <https://doi.org/10.1177/0963721417727521>
- Brybaert, M., Mandera, P., McCormick, S. F., & Keuleers, E. (2019). Word prevalence norms for 62,000 English lemmas. *Behavior Research Methods*, *51*(2), 467–479.  
<https://doi.org/10.3758/s13428-018-1077-9>
- Brybaert, M., Stevens, M., Mandera, P., & Keuleers, E. (2016). How Many Words Do We Know? Practical Estimates of Vocabulary Size Dependent on Word Definition, the Degree of Language Input and the Participant's Age. *Frontiers in Psychology*, *7*.  
<https://doi.org/10.3389/fpsyg.2016.01116>
- Brybaert, M., Warriner, A. B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand generally known English word lemmas. *Behavior Research Methods*, *46*(3), 904–911.  
<https://doi.org/10.3758/s13428-013-0403-5>
- Brybaert, M., Warriner, A. B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand English word lemmas. *Behavior Research Methods*, *46*(3), 904–911.
- Buchanan, E. M., Holmes, J. L., Teasley, M. L., & Hutchison, K. A. (2013). English semantic word-pair norms and a searchable Web portal for experimental stimulus creation. *Behavior Research Methods*, *45*(3), 746–757. <https://doi.org/10.3758/s13428-012-0284-z>
- Buchanan, E. M., Valentine, K. D., & Maxwell, N. P. (2019). English semantic feature production norms: An extended database of 4436 concepts. *Behavior Research Methods*, *51*(4), 1849–1863. <https://doi.org/10.3758/s13428-019-01243-z>
- Bugajska, A., Morson, S., Moulin, C. J. A., & Souchay, C. (2011). Metamemory, recollection and familiarity in Alzheimer's disease. *Revue Neurologique*, *167*(1), 3–13.  
<https://doi.org/10.1016/j.neuro.2010.03.001>
- Carota, F., Kriegeskorte, N., Nili, H., & Pulvermüller, F. (2017). Representational Similarity Mapping of Distributional Semantics in Left Inferior Frontal, Middle Temporal, and Motor Cortex. *Cerebral Cortex (New York, N.Y. : 1991)*, *27*(1), 294–309.  
<https://doi.org/10.1093/cercor/bhw379>
- Chedid, G., Brambati, S. M., Bedetti, C., Rey, A. E., Wilson, M. A., & Vallet, G. T. (2019). Visual and auditory perceptual strength norms for 3,596 French nouns and their relationship with other psycholinguistic variables. *Behavior Research Methods*, *51*(5), 2094–2105. <https://doi.org/10.3758/s13428-019-01254-w>
- Chedid, G., Wilson, M. A., Bedetti, C., Rey, A. E., Vallet, G. T., & Brambati, S. M. (2019). Norms of conceptual familiarity for 3,596 French nouns and their contribution in lexical

- decision. *Behavior Research Methods*, 51(5), 2238–2247.  
<https://doi.org/10.3758/s13428-018-1106-8>
- Choudhury, M., & Mukherjee, A. (2009). The Structure and Dynamics of Linguistic Networks. *Modeling and Simulation in Science, Engineering and Technology*, 42, 145–166. [https://doi.org/10.1007/978-0-8176-4751-3\\_9](https://doi.org/10.1007/978-0-8176-4751-3_9)
- Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review*, 82(6), 407–428. <https://doi.org/10.1037/0033-295X.82.6.407>
- Coltheart, M. (1981). The MRC Psycholinguistic Database. *The Quarterly Journal of Experimental Psychology Section A*, 33, 497–505.  
<https://doi.org/10.1080/14640748108400805>
- Connell, L., Lynott, D., & Banks, B. (2018). Interoception: The forgotten modality in perceptual grounding of abstract and concrete concepts. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 373(1752).  
<https://doi.org/10.1098/rstb.2017.0143>
- Cree, G. S., McRae, K., & McNorgan, C. (1999). An Attractor Model of Lexical Conceptual Processing: Simulating Semantic Priming. *Cognitive Science*, 23(3), 371–414.  
[https://doi.org/10.1207/s15516709cog2303\\_4](https://doi.org/10.1207/s15516709cog2303_4)
- Crutch, S. J. (2005). Abstract and concrete concepts have structurally different representational frameworks. *Brain*, 128(3), 615–627.  
<https://doi.org/10.1093/brain/awh349>
- Crutch, S. J., Connell, S., & Warrington, E. K. (2009). The different representational frameworks underpinning abstract and concrete knowledge: Evidence from odd-one-out judgements. *Quarterly Journal of Experimental Psychology*, 62(7), 1377–1390.  
<https://doi.org/10.1080/17470210802483834>
- Crutch, S. J., & Jackson, E. C. (2011). Contrasting graded effects of semantic similarity and association across the concreteness spectrum. *Quarterly Journal of Experimental Psychology*, 64(7), 1388–1408. <https://doi.org/10.1080/17470218.2010.543285>
- Crutch, S. J., & Warrington, E. K. (2010). The differential dependence of abstract and concrete words upon associative and similarity-based information: Complementary semantic interference and facilitation effects. *Cognitive Neuropsychology*, 27(1), 46–71.  
<https://doi.org/10.1080/02643294.2010.491359>
- Crutch, S. J., & Warrington, E. K. (2005). Abstract and concrete concepts have structurally different representational frameworks. *Brain*, 128(3), 615–627.  
<https://doi.org/10.1093/brain/awh349>
- Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal Complex Systems, Complex Sy*, 1695. Retrieved from <http://igraph.sf.net>
- De Deyne, S., Navarro, D. J., & Storms, G. (2013). Better explanations of lexical and semantic cognition using networks derived from continued rather than single-word associations. *Behavior Research Methods*, 45(2), 480–498.  
<https://doi.org/10.3758/s13428-012-0260-7>
- De Deyne, S., Navarro, D. J., Perfors, A., Brysbaert, M., & Storms, G. (2019). The “Small World of Words” English word association norms for over 12,000 cue words. *Behavior Research Methods*, 51(3), 987–1006. <https://doi.org/10.3758/s13428-018-1115-7>
- De Deyne, S., Navarro, D. J., Perfors, A., Brysbaert, M., & Storms, G. (2019). Measuring the associative structure of English: The “Small World of Words” norms for word association. *Behavior Research Methods*, 51(3), 987–1006. Retrieved from [http://compcogscisydney.org/publications/DeDeyneNPBS\\_swow.pdf](http://compcogscisydney.org/publications/DeDeyneNPBS_swow.pdf)
- De Deyne, S., & Storms, G. (2008). Word associations: Network and semantic properties. *Behavior Research Methods*, 40(1), 213–231. <https://doi.org/10.3758/BRM.40.1.213>

- De Deyne, S., & Storms, G. (2008). Word associations: Norms for 1,424 Dutch words in a continuous task. *Behavior Research Methods*, *40*(1), 198–205. <https://doi.org/10.3758/BRM.40.1.198>
- de Deyne, S., Verheyen, S., Ameel, E., Vanpaemel, W., Dry, M. J., Voorspoels, W., & Storms, G. (2008). Exemplar by feature applicability matrices and other Dutch normative data for semantic concepts. *Behavior Research Methods*, *40*(4), 1030–1048. <https://doi.org/10.3758/BRM.40.4.1030>
- De Vega, M., Glenberg, A., & Graesser, A. (2008). *Symbols and embodiment: Debates on meaning and cognition*. *Symbols and Embodiment: Debates on Meaning and Cognition*. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199217274.001.0001>
- Deerwester, S., Dumais, S. T., Furnas, G. W., Landauer, T. K., & Harshman, R. (1990). Indexing by latent semantic analysis. *Journal of the American Society for Information Science*, *41*(6), 391–407. [https://doi.org/10.1002/\(SICI\)1097-4571\(199009\)41:6<391::AID-ASI1>3.0.CO;2-9](https://doi.org/10.1002/(SICI)1097-4571(199009)41:6<391::AID-ASI1>3.0.CO;2-9)
- Della Rosa, P. A., Catricalà, E., Vigliocco, G., & Cappa, S. F. (2010). Beyond the abstract-concrete dichotomy: Mode of acquisition, concreteness, imageability, familiarity, age of acquisition, context availability, and abstractness norms for a set of 417 Italian words. *Behavior Research Methods*, *42*(4), 1042–1048. <https://doi.org/10.3758/BRM.42.4.1042>
- Dellantonio, S., Job, R., & Mulatti, C. (2014). Imageability: Now you see it again (albeit in a different form). *Frontiers in Psychology*. Frontiers Media SA. <https://doi.org/10.3389/fpsyg.2014.00279>
- den Heyer, K., & Briand, K. (1986). Priming Single Digit Numbers: Automatic Spreading Activation Dissipates as a Function of Semantic Distance. *The American Journal of Psychology*, *99*(3), 315–340. <https://doi.org/10.2307/1422488>
- Devereux, B. J., Tyler, L. K., Geertzen, J., & Randall, B. (2014). The Centre for Speech, Language and the Brain (CSLB) concept property norms. *Behavior Research Methods*, *46*(4), 1119–1127. <https://doi.org/10.3758/s13428-013-0420-4>
- Deyne, S. De, Verheyen, S., & Storms, G. (2016). Structure and Organization of the Mental Lexicon: A Network Approach Derived from Syntactic Dependency Relations and Word Associations. *Understanding Complex Systems*, *99*, 47–79. [https://doi.org/10.1007/978-3-662-47238-5\\_3](https://doi.org/10.1007/978-3-662-47238-5_3)
- Dove, G. (2009). Beyond perceptual symbols: A call for representational pluralism. *Cognition*, *110*(3), 412–431. <https://doi.org/10.1016/j.cognition.2008.11.016>
- Dove, G. (2011). On the need for Embodied and Dis-Embodied Cognition. *Frontiers in Psychology*, *1*. <https://doi.org/10.3389/fpsyg.2010.00242>
- Dove, G. (2014). Thinking in Words: Language as an Embodied Medium of Thought. *Topics in Cognitive Science*, *6*(3), 371–389. <https://doi.org/10.1111/tops.12102>
- Duñabeitia, J. A., Avilés, A., Afonso, O., Scheepers, C., & Carreiras, M. (2009). Qualitative differences in the representation of abstract versus concrete words: Evidence from the visual-world paradigm. *Cognition*, *110*(2), 284–292. <https://doi.org/10.1016/j.cognition.2008.11.012>
- Duscherer, K., & Mounoud, P. (2006). Word association norms for 151 action verbs. *Année Psychologique*, *106*(3), 397–413. <https://doi.org/10.4074/S0003503306003046>
- Eakin, D. K. (2005). Illusions of knowing: Metamemory and memory under conditions of retroactive interference. *Journal of Memory and Language*, *52*(4), 526–534. <https://doi.org/10.1016/j.jml.2005.01.009>
- Erdos, P., & Rényi, A. (1960). On the evolution of random graphs. *Publications of the Mathematical Institute of the Hungarian Academy of Sciences*, *5*(1), 17–60.

- Evert, S., & Baroni, M. (2007). zipfR: Word frequency distributions in R. In *Proceedings of the 45th annual meeting of the ACL on interactive poster and demonstration sessions* (pp. 29–32).
- Evert, S., & Baroni, M. (2005). Testing the extrapolation quality of word frequency models. In *Proceedings of Corpus Linguistics* (Vol. 2006).
- Fernández, Á., Díez, E., Alonso, M. Á., & Beato, M. S. (2004). Free-association norms for the Spanish names of the Snodgrass and Vanderwart pictures. *Behavior Research Methods, Instruments, & Computers*, *36*, 577–583. <https://doi.org/10.3758/BF03195604>
- Ferrand, L. (2001). Normes d'associations verbales pour 260 mots « abstraits » [Word association norms for 260 “abstract” words]. *Annee Psychologique*, *101*(4), 683–721. <https://doi.org/10.3406/psy.2001.29575>
- Ferrand, L., & Alario, F. X. (1998). Word association norms for 366 names of objects. *Annee Psychologique*, *98*(4), 659–709. <https://doi.org/10.3406/psy.1998.28564>
- Ferrand, L., & Alario, F. X. (1998). Word association norms for 366 names of objects. [Word association norms for 366 concrete objects words]. *Annee Psychologique*, *98*(4), 659–709. <https://doi.org/10.3406/psy.1998.28564>
- Ferrand, L., Méot, A., Spinelli, E., New, B., Pallier, C., Bonin, P., ... Grainger, J. (2018). MEGALEX: A megastudy of visual and auditory word recognition. *Behavior Research Methods*, *50*(3), 1285–1307. <https://doi.org/10.3758/s13428-017-0943-1>
- Ferrand, L., & New, B. (2003). Semantic and associative priming in the mental lexicon. *Mental Lexicon: Some Words to Talk about Words*, 25–43.
- Ferrand, L., New, B., Brysbaert, M., Keuleers, E., Bonin, P., Méot, A., ... Pallier, C. (2010). The French lexicon project: Lexical decision data for 38,840 French words and 38,840 pseudo words. *Behavior Research Methods*, *42*(2), 488–496. <https://doi.org/10.3758/BRM.42.2.488>
- Ferré, P., Guasch, M., García-Chico, T., & Sánchez-Casas, R. (2015). Are there qualitative differences in the representation of abstract and concrete words? Within-language and cross-language evidence from the semantic priming paradigm. *Quarterly Journal of Experimental Psychology* (2006), *68*(12), 2402–2418. <https://doi.org/10.1080/17470218.2015.1016980>
- Ferretti, T. R., McRae, K., & Hatherell, A. (2001). Integrating Verbs, Situation Schemas, and Thematic Role Concepts. *Journal of Memory and Language*, *44*(4), 516–547. <https://doi.org/10.1006/jmla.2000.2728>
- Firth, J. R. (1957). Applications of General Linguistics. *Transactions of the Philological Society*, *56*(1), 1–14. <https://doi.org/10.1111/j.1467-968X.1957.tb00568.x>
- Fischer, M. H., & Zwaan, R. A. (2008). Embodied language: A review of the role of the motor system in language comprehension. *Quarterly Journal of Experimental Psychology*, *61*(6), 825–850. <https://doi.org/10.1080/17470210701623605>
- Fodor, J. A., & M.I.T. Press. (2001). *The mind doesn't work that way: the scope and limits of computational psychology*. MIT Press.
- Fukús, H., & Krzemiński, M. (2009). Topological structure of dictionary graphs. *Journal of Physics A: Mathematical and Theoretical*, *42*(37), 375101. <https://doi.org/10.1088/1751-8113/42/37/375101>
- Gallese, V., & Lakoff, G. (2005). The brain's concepts: The role of the sensory-motor system in conceptual knowledge. *Cognitive Neuropsychology*. <https://doi.org/10.1080/02643290442000310>
- Geng, J., & Schnur, T. T. (2015). The representation of concrete and abstract concepts: Categorical versus associative relationships. *Journal of Experimental Psychology: Learning Memory and Cognition*, *41*(1), 22–41. <https://doi.org/10.1037/a0037430>

- Gerstenberg, T., & Tenenbaum, J. B. (2017). Intuitive theories. In *The Oxford handbook of causal reasoning*. (pp. 515–547). New York, NY, US: Oxford University Press.
- Gilead, M., Liberman, N., & Maril, A. (2012). Construing counterfactual worlds: The role of abstraction. *European Journal of Social Psychology, 42*(3), 391–397. <https://doi.org/10.1002/ejsp.1862>
- Gimenes, M., & New, B. (2016). Worldlex: Twitter and blog word frequencies for 66 languages. *Behavior Research Methods, 48*(3), 963–972. <https://doi.org/10.3758/s13428-015-0621-0>
- Glenberg, A. M. (1997). What memory is for. *Behavioral and Brain Sciences, 20*(1), 1–19.
- Glenberg, A. M. (2004). Mental models, space, and embodied cognition. In *Creative thought: An investigation of conceptual structures and processes*. (pp. 495–522). American Psychological Association. <https://doi.org/10.1037/10227-018>
- Glenberg, A. M., & Kaschak, M. P. (2002). Grounding language in action. *Psychonomic Bulletin and Review, 9*(3), 558–565. <https://doi.org/10.3758/BF03196313>
- Goldstone, R. L., & Rogosky, B. J. (2002). Using relations within conceptual systems to translate across conceptual systems. *Cognition, 84*(3), 295–320. [https://doi.org/10.1016/S0010-0277\(02\)00053-7](https://doi.org/10.1016/S0010-0277(02)00053-7)
- Griffiths, T. L., Steyvers, M., & Tenenbaum, J. B. (2007). Topics in semantic representation. *Psychological Review, 114*(2), 211–244. <https://doi.org/10.1037/0033-295X.114.2.211>
- Gronau, Q. F., Ly, A., & Wagenmakers, E.-J. (2019). Informed Bayesian t -Tests. *The American Statistician, 1*–14. <https://doi.org/10.1080/00031305.2018.1562983>
- Hamilton, A. C., & Coslett, H. B. (2008). Refractory access disorders and the organization of concrete and abstract semantics: Do they differ? *Neurocase, 14*(2), 131–140. <https://doi.org/10.1080/13554790802032218>
- Harpaintner, M., Sim, E. J., Trumpp, N. M., Ulrich, M., & Kiefer, M. (2020). The grounding of abstract concepts in the motor and visual system: An fMRI study. *Cortex, 124*, 1–22. <https://doi.org/10.1016/j.cortex.2019.10.014>
- Harpaintner, M., Trumpp, N. M., & Kiefer, M. (2018). The semantic content of abstract concepts: A property listing study of 296 abstract words. *Frontiers in Psychology, 9*. <https://doi.org/10.3389/fpsyg.2018.01748>
- Harris, Z. S. (1954). Distributional Structure. *Distributional Structure, WORD, 10*(3), 146–162. <https://doi.org/10.1080/00437956.1954.11659520>
- Herdan, G. (1964). *Quantitative Linguistics*. London: Butterworths.
- Heyman, T., De Deyne, S., Hutchison, K. A., & Storms, G. (2015). Using the speeded word fragment completion task to examine semantic priming. *Behavior Research Methods, 47*(2), 580–606. <https://doi.org/10.3758/s13428-014-0496-5>
- Hill, F., & Korhonen, A. (n.d.). *Learning Abstract Concept Embeddings from Multi-Modal Data: Since You Probably Can't See What I Mean*.
- Hoffman, P., Binney, R. J., & Lambon Ralph, M. A. (2015). Differing contributions of inferior prefrontal and anterior temporal cortex to concrete and abstract conceptual knowledge. *Cortex, 63*, 250–266. <https://doi.org/https://doi.org/10.1016/j.cortex.2014.09.001>
- Hoffman, P., McClelland, J. L., & Lambon Ralph, M. A. (2018). Concepts, control, and context: A connectionist account of normal and disordered semantic cognition. *Psychological Review, 125*(3), 293–328. <https://doi.org/10.1037/rev0000094>
- Hu, J., Chen, Y., Zhuo, S., ... H. C.-B. of, & 2017, undefined. (n.d.). Word association norms and associated responses: Reference index for 1200 two-character Chinese words. *Psycnet.Apa.Org*. Retrieved from <https://psycnet.apa.org/record/2017-52184-003>

- Humphries, M. D., & Gurney, K. (2008). Network ‘Small-World-Ness’: A Quantitative Method for Determining Canonical Network Equivalence. *PLOS ONE*, 3(4), e0002051. <https://doi.org/10.1371/JOURNAL.PONE.0002051>
- Hutchison, K. A. (2003). Is semantic priming due to association strength or feature overlap? A microanalytic review. *Psychonomic Bulletin & Review* 2003 10:4, 10(4), 785–813. <https://doi.org/10.3758/BF03196544>
- Hutchison, K. A., Balota, D. A., Neely, J. H., Cortese, M. J., Cohen-Shikora, E. R., Tse, C. S., ... Buchanan, E. (2013). The semantic priming project. *Behavior Research Methods*, 45(4), 1099–1114. <https://doi.org/10.3758/s13428-012-0304-z>
- Hutchison, K. A., Balota, D. A., Cortese, M. J., & Watson, J. M. (2008). Predicting semantic priming at the item level. *Quarterly Journal of Experimental Psychology* (2006), 61(7), 1036–1066. <https://doi.org/10.1080/17470210701438111>
- Jenkins, J. J. (1970). THE 1952 MINNESOTA WORD ASSOCIATION NORMS. In *Norms of Word Association* (pp. 1–38). Elsevier. <https://doi.org/10.1016/b978-0-12-563050-4.50004-2>
- Jones, M. N., & Mewhort, D. J. K. (2007). Representing word meaning and order information in a composite holographic lexicon. *Psychological Review*, 114(1), 1–37. <https://doi.org/10.1037/0033-295X.114.1.1>
- Joyce, T. (2005). Constructing a Large-Scale Database of Japanese Word Associations. *Glottometrics*, 10, 82–99.
- Juhasz, B. J., & Yap, M. J. (2013). Sensory experience ratings for over 5,000 mono- and disyllabic words. *Behavior Research Methods*, 45(1), 160–168. <https://doi.org/10.3758/s13428-012-0242-9>
- Jung, J., Li, N., & Akama, H. (2010). Network Analysis of Korean Word Associations. *Proceedings of the NAACL HLT 2010 First Workshop on Computational Neurolinguistics*, 27–35. Retrieved from <http://www.aclweb.org/anthology/W/W10/W10-0604>
- Karimkhani, F., Rahmani, H., Zare, A., Saheb Nassagh, R., & Aghakasiri, K. (2021). Tarvajeh: Word Association Norms for Persian Words. *Journal of Psycholinguistic Research*, 50(4), 863–882. <https://doi.org/10.1007/s10936-020-09751-2>
- Wiemer-Hastings, K., & Xu, X. (2005). Content Differences for Abstract and Concrete Concepts. *Cognitive Science*, 29(5), 719–736. [https://doi.org/10.1207/s15516709cog0000\\_33](https://doi.org/10.1207/s15516709cog0000_33)
- Keeling, M., & Rohani, P. (2011). *Modeling infectious diseases in humans and animals* (Princeton:). <https://doi.org/https://doi.org/10.1515/9781400841035>
- Kenett, Y. N., Levi, E., Anaki, D., & Faust, M. (2017). The semantic distance task: Quantifying semantic distance with semantic network path length. *Journal of Experimental Psychology: Learning Memory and Cognition*, 43(9), 1470–1489. <https://doi.org/10.1037/XLM0000391>
- Keuleers, E., Brysbaert, M., & New, B. (2010). SUBTLEX-NL: A new measure for Dutch word frequency based on film subtitles. *Behavior Research Methods*, 42(3), 643–650. <https://doi.org/10.3758/BRM.42.3.643>
- Keuleers, E., Stevens, M., Mandera, P., & Brysbaert, M. (2015). Word knowledge in the crowd: Measuring vocabulary size and word prevalence in a massive online experiment. *Quarterly Journal of Experimental Psychology* (2006), 68(8), 1665–1692. <https://doi.org/10.1080/17470218.2015.1022560>
- Kiefer, M., & Pulvermüller, F. (2012). Conceptual representations in mind and brain: Theoretical developments, current evidence and future directions. *Cortex*, 48(7), 805–825. <https://doi.org/10.1016/j.cortex.2011.04.006>

- Kim, S. Y., Yap, M. J., & Goh, W. D. (2019). The role of semantic transparency in visual word recognition of compound words: A megastudy approach. *Behavior Research Methods*, *51*(6), 2722–2732. <https://doi.org/10.3758/s13428-018-1143-3>
- Kintsch, W., McNamara, D. S., Dennis, S., Landauer, T. K., McNamara, D. S., Dennis, S., & Landauer, T. K. (2007). LSA and Meaning: in Theory and Application, 479–492. <https://doi.org/10.4324/9780203936399-32>
- Kircher, T., Whitney, C., Krings, T., Huber, W., & Weis, S. (2008). Hippocampal dysfunction during free word association in male patients with schizophrenia. *Schizophrenia Research*, *101*(1–3), 242–255. <https://doi.org/10.1016/j.schres.2008.02.003>
- Kiss, G. R., Armstrong, C., Milroy, R., & Piper, J. (1972). The Edinburgh Associative Thesaurus. *The Edinburgh Associative Thesaurus*. Retrieved from url: <https://w3id.org/associations/eat>. nt. gz.
- Kitsak, M., Gallos, L. K., Havlin, S., Liljeros, F., Muchnik, L., Stanley, H. E., & Makse, H. A. (2010). Identification of influential spreaders in complex networks. *Nature Physics* *2010* 6:11, *6*(11), 888–893. <https://doi.org/10.1038/nphys1746>
- Kolaczyk, E. D., & Csárdi, G. (2014). *Statistical Analysis of Network Data with R*. New York: Springer. Cham: Springer International Publishing. <https://doi.org/10.1007/978-3-030-44129-6>
- Kousta, S. T., Vigliocco, G., Vinson, D. P., Andrews, M., & Del Campo, E. (2011). The Representation of Abstract Words: Why Emotion Matters. *Journal of Experimental Psychology: General*, *140*(1), 14–34. <https://doi.org/10.1037/a0021446>
- Kremer, G., & Baroni, M. (2011). A set of semantic norms for German and Italian. *Behavior Research Methods*, *43*(1), 97–109. <https://doi.org/10.3758/s13428-010-0028-x>
- Kruschke, J. K. (2010). Bayesian data analysis. *Wiley Interdisciplinary Reviews: Cognitive Science*, *1*(5), 658–676. <https://doi.org/10.1002/wcs.72>
- Kuipers, J. R., Jones, M. W., & Thierry, G. (2018). Abstract images and words can convey the same meaning. *Scientific Reports*, *8*(1), 1–6. <https://doi.org/10.1038/s41598-018-25441-5>
- Kwong, O. Y. (2013). Exploring the chinese mental lexicon with word association norms. *27th Pacific Asia Conference on Language, Information, and Computation, PACLIC 27*, 153–162.
- Lakhzoum, D., Izaute, M., & Ferrand, L. (2021). Semantic similarity and associated abstractness norms for 630 French word pairs. *Behavior Research Methods*, *53*, 1166–1178. <https://doi.org/10.3758/s13428-020-01488-z>
- Lakoff, G., & Johnson, M. (1980). Conceptual Metaphor in Everyday Language. *The Journal of Philosophy*, *77*(8), 453. <https://doi.org/10.2307/2025464>
- Landauer, T. K., & Dumais, S. T. (1997). A Solution to Plato’s Problem: The Latent Semantic Analysis Theory of Acquisition, Induction, and Representation of Knowledge. *Psychological Review*, *104*(2), 211–240. <https://doi.org/https://doi.org/10.1037/0033-295X.104.2.211>
- Laws, J., & Ryder, C. (2018). Register variation in spoken British English. *International Journal of Corpus Linguistics*, *23*(1), 1–27. <https://doi.org/10.1075/ijcl.16036.law>
- Lebani, G. E., Bondielli, A., & Lenci, A. (2015). *You Are What you Do. An Empirical Characterization of the Semantic Content of the Thematic Roles for a Group of Italian Verbs*. *Journal of Cognitive Science* (Vol. 16).
- Lee, M. D., & Vanpaemel, W. (2018). Determining informative priors for cognitive models. *Psychonomic Bulletin and Review*, *25*(1), 114–127. <https://doi.org/10.3758/s13423-017-1238-3>

- Leech, G., Garside, R., & Bryant, M. (1994). CLAWS4: The tagging of the British National Corpus. *Proceedings of the 15th International Conference on Computational Linguistics*, 622–628.
- Lenci, A. (2008). Distributional semantics in linguistic and cognitive research. *Italian Journal of Linguistics*, 20, 1–31.
- Lenci, A. (2018). Distributional Models of Word Meaning. *Annual Review of Linguistics*, 4(1), 151–171. <https://doi.org/10.1146/annurev-linguistics-030514-125254>
- Lenci, A., Baroni, M., Cazzolli, G., & Marotta, G. (2013). BLIND: A set of semantic feature norms from the congenitally blind. *Behavior Research Methods*, 45(4), 1218–1233. <https://doi.org/10.3758/s13428-013-0323-4>
- Lenci, A., Lebani, G. E., & Passaro, L. C. (2018). The Emotions of Abstract Words: A Distributional Semantic Analysis. *Topics in Cognitive Science*, 10(3), 550–572. <https://doi.org/10.1111/tops.12335>
- Lerner, A. J., Ogrocki, P. K., & Thomas, P. J. (2009). Network graph analysis of category fluency testing. *Cognitive and Behavioral Neurology*, 22(1), 45–52. <https://doi.org/10.1097/WNN.0B013E318192CCAF>
- Levelt, W. J. M.; Willem J. M. (1989). *Speaking: from intention to articulation*. MIT Press.
- Levelt, W. J. M., Roelofs, A., & Meyer, S. (1999). *A theory of lexical access in speech production Ant je*. Retrieved from [www.mpi.nl](http://www.mpi.nl)
- Levelt, W. J. M., Roelofs, A., & Meyer, A. S. (1999). A theory of lexical access in speech production. *Behavioral and Brain Sciences*. <https://doi.org/10.1017/S0140525X99001776>
- Liu, C. C., & Aitkin, M. (2008). Bayes factors: Prior sensitivity and model generalizability. *Journal of Mathematical Psychology*, 52(6), 362–375. <https://doi.org/10.1016/j.jmp.2008.03.002>
- Louwerse, M. M. (2011). Symbol Interdependency in Symbolic and Embodied Cognition. *Topics in Cognitive Science*, 3(2), 273–302. <https://doi.org/10.1111/j.1756-8765.2010.01106.x>
- Louwerse, M. M. (2008). Embodied relations are encoded in language. *Psychonomic Bulletin and Review*, 15(4), 838–844. <https://doi.org/10.3758/PBR.15.4.838>
- Louwerse, M. M. (2011). Symbol interdependency in symbolic and embodied cognition. *Topics in Cognitive Science*, 3(2), 273–302. <https://doi.org/10.1111/j.1756-8765.2010.01106.x>
- Louwerse, M. M., & Jeuniaux, P. (2010). The linguistic and embodied nature of conceptual processing. *Cognition*, 114(1), 96–104. <https://doi.org/10.1016/j.cognition.2009.09.002>
- Louwerse, M., & Jeuniaux, P. (2008). Language comprehension is both embodied and symbolic. In *Symbols and Embodiment Debates on meaning and cognition* (pp. 309–326). Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199217274.003.0015>
- Ly, A., Verhagen, J., & Wagenmakers, E. J. (2016). Harold Jeffreys's default Bayes factor hypothesis tests: Explanation, extension, and application in psychology. *Journal of Mathematical Psychology*, 72, 19–32. <https://doi.org/10.1016/j.jmp.2015.06.004>
- M, S., & JB, T. (2005). The large-scale structure of semantic networks: statistical analyses and a model of semantic growth. *Cognitive Science*, 29(1), 41–78. [https://doi.org/10.1207/S15516709COG2901\\_3](https://doi.org/10.1207/S15516709COG2901_3)
- Machery, E. (2016). The amodal brain and the offloading hypothesis. *Psychonomic Bulletin and Review*, 23(4), 1090–1095. <https://doi.org/10.3758/s13423-015-0878-4>
- Mahon, B. Z., & Caramazza, A. (2009). Concepts and Categories: A Cognitive Neuropsychological Perspective. *Annual Review of Psychology*, 60(1), 27–51. <https://doi.org/10.1146/annurev.psych.60.110707.163532>

- Maki, W. S., Krinsky, M., & Muñoz, S. (2006). An efficient method for estimating semantic similarity based on feature overlap: Reliability and validity of semantic feature ratings. *Behavior Research Methods*, *38*(1), 153–157. <https://doi.org/10.3758/BF03192761>
- Mandera, P., Keuleers, E., & Brysbaert, M. (2017). Explaining human performance in psycholinguistic tasks with models of semantic similarity based on prediction and counting: A review and empirical validation. *Journal of Memory and Language*, *92*, 57–78. <https://doi.org/10.1016/j.jml.2016.04.001>
- Mate, J., Allen, R. J., & Baqués, J. (2012). What you say matters: exploring visual-verbal interactions in visual working memory. *Quarterly Journal of Experimental Psychology* (2006), *65*(3), 395–400. <https://doi.org/10.1080/17470218.2011.644798>
- Mathôt, S. (n.d.). Mathôt S. (2017). Bayes Like a Baws: Interpreting Bayesian Repeated Measures in JASP. [Google Scholar] - Recherche Google. Retrieved October 20, 2020, from [https://www.google.com/search?q=Mathôt+S.\(2017\).+Bayes+Like+a+Baws%3A+Interpreting+Bayesian+Repeated+Measures+in+JASP.+%5BGoogle+Scholar%5D&ie=utf-8&oe=utf-8&aq=t](https://www.google.com/search?q=Mathôt+S.(2017).+Bayes+Like+a+Baws%3A+Interpreting+Bayesian+Repeated+Measures+in+JASP.+%5BGoogle+Scholar%5D&ie=utf-8&oe=utf-8&aq=t)
- McNamara, T. P. (2005). *Semantic priming: Perspectives from memory and word recognition*. *Semantic priming: Perspectives from memory and word recognition*. New York, NY, US: Psychology Press. <https://doi.org/10.4324/9780203338001>
- McNamara, T. P. (1992). Theories of Priming: I. Associative Distance and Lag. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *18*(6), 1173–1190. <https://doi.org/10.1037/0278-7393.18.6.1173>
- McRae, K., & Boisvert, S. (1998). Automatic semantic similarity priming. *Journal of Experimental Psychology: Learning Memory and Cognition*, *24*(3), 558–572. <https://doi.org/10.1037/0278-7393.24.3.558>
- McRae, K., Cree, G. S., Seidenberg, M. S., & McNorgan, C. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behavior Research Methods*, *37*(4), 547–559. <https://doi.org/10.3758/BF03192726>
- McRae, K., De Sa, V. R., & Seidenberg, M. S. (1997). On the Nature and Scope of Featural Representations of Word Meaning. *Journal of Experimental Psychology: General*, *126*(2), 99–130. <https://doi.org/10.1037/0096-3445.126.2.99>
- McRae, K., Nedjadrasul, D., Pau, R., Lo, B. P. H., & King, L. (2018). Abstract Concepts and Pictures of Real-World Situations Activate One Another. *Topics in Cognitive Science*, *10*(3), 518–532. <https://doi.org/10.1111/tops.12328>
- Meteyard, L., Cuadrado, S. R., Bahrami, B., & Vigliocco, G. (2012). Coming of age: A review of embodiment and the neuroscience of semantics. *Cortex*, *48*(7), 788–804. <https://doi.org/10.1016/j.cortex.2010.11.002>
- Meteyard, L., Rodriguez Cuadrado, S., Bahrami, B., & Vigliocco, G. (n.d.). *Coming of age: a review of embodiment and the neuroscience of semantics*.
- Meyer, D. E., & Schvaneveldt, R. W. (1971). Facilitation in recognizing pairs of words: Evidence of a dependence between retrieval operations. *Journal of Experimental Psychology*, *90*(2), 227–234. <https://doi.org/10.1037/h0031564>
- Milgram, S. (1967). The small world problem. *Psychology Today*, *2*(1), 60–67.
- Mitchell, M. (2019). Artificial Intelligence Hits the Barrier of Meaning. *Information*, *10*(2), 51. <https://doi.org/10.3390/info10020051>
- Mitchell, M. (2019). Artificial Intelligence Hits the Barrier of Meaning. *Information*. Retrieved from [https://pdxscholar.library.pdx.edu/compsci\\_fac/194](https://pdxscholar.library.pdx.edu/compsci_fac/194)
- Moldovan, C. D., Ferré, P., Demestre, J., & Sánchez-Casas, R. (2015). Semantic similarity: normative ratings for 185 Spanish noun triplets. *Behavior Research Methods*, *47*(3), 788–799. <https://doi.org/10.3758/s13428-014-0501-z>

- Mollin, S. (2009). Combining corpus linguistic and psychological data on word co-occurrences: Corpus collocates versus word associations, *5*, 175–200. <https://doi.org/https://doi.org/10.1515/CLLT.2009.008>
- Moreno, S., & Neville, J. (2013). Network Hypothesis Testing Using Mixed Kronecker Product Graph Models. In *2013 IEEE 13th International Conference on Data Mining* (pp. 1163–1168). <https://doi.org/10.1109/ICDM.2013.165>
- Moss, H., Older, L., & Older, L. (1996). *Birkbeck word association norms*. Psychology Press.
- Motter, A., Moura, A., Lai, Y.-C., & Dasgupta, P. (2002). Topology of the conceptual network of language. *Physical Review. E, Statistical, Nonlinear, and Soft Matter Physics*, *65*, 65102. <https://doi.org/10.1103/PhysRevE.65.065102>
- Neely, J. H., & Kahan, T. A. (2004). Is semantic activation automatic? A critical re-evaluation. In *The nature of remembering: Essays in honor of Robert G. Crowder*. (pp. 69–93). American Psychological Association. <https://doi.org/10.1037/10394-005>
- Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (2004). The University of South Florida free association, rhyme, and word fragment norms. *Behavior Research Methods, Instruments, and Computers*. Psychonomic Society Inc. <https://doi.org/10.3758/BF03195588>
- Nelson, D. L., McEvoy, C. L., & Dennis, S. (2000). What is free association and what does it measure? *Memory & Cognition*, *28*, 887–899.
- New, B., Brysbaert, M., Veronis, J., & Pallier, C. (2007). The use of film subtitles to estimate word frequencies. *Applied Psycholinguistics*, *28*(4), 661–677. <https://doi.org/10.1017/S014271640707035X>
- New, B., Ferrand, L., Pallier, C., & Brysbaert, M. (2006). Reexamining the word length effect in visual word recognition: New evidence from the English Lexicon Project. *Psychonomic Bulletin and Review*, *13*(1), 45–52. <https://doi.org/10.3758/BF03193811>
- New, B., Pallier, C., Brysbaert, M., & Ferrand, L. (2004). Lexique 2: A new French lexical database. *Behavior Research Methods, Instruments, and Computers*. Psychonomic Society Inc. <https://doi.org/10.3758/BF03195598>
- New, B., Pallier, C., Ferrand, L., & Matos, R. (2001). A lexical database for contemporary french on internet : LEXIQUE. *Annee Psychologique*, *101*(3), 447–462. <https://doi.org/10.3406/psy.2001.1341>
- Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(23), 8577–8582. <https://doi.org/10.1073/pnas.0601602103>
- Nishiyama, R. (2013). Dissociative contributions of semantic and lexical-phonological information to immediate recognition. *Journal of Experimental Psychology: Learning Memory and Cognition*, *39*(2), 642–648. <https://doi.org/10.1037/a0029160>
- Nosofsky, R. M. (2012). The generalized context model: an exemplar model of classification. *Formal Approaches in Categorization*, 18–39. <https://doi.org/10.1017/cbo9780511921322.002>
- Oliveira, J., Perea, M. V., Ladera, V., & Gamito, P. (2013). The roles of word concreteness and cognitive load on interhemispheric processes of recognition. *Laterality*, *18*(2), 203–215. <https://doi.org/10.1080/1357650X.2011.649758>
- Ostarek, M., & Huettig, F. (2019). Six Challenges for Embodiment Research. *Current Directions in Psychological Science*, *28*(6), 593–599. <https://doi.org/10.1177/0963721419866441>
- Paivio, A., Yuille, J. C., & Madigan, S. A. (1968). Concreteness, imagery, and meaningfulness values for 925 nouns. *Journal of Experimental Psychology*, *76*, 1–25. <https://doi.org/10.1037/h0025327>

- Paradis, C., Willners, C., & Jones, S. (2009). Good and bad opposites: Using textual and experimental techniques to measure antonym canonicity. *The Mental Lexicon*, 4(3), 380–429. <https://doi.org/10.1075/ml.4.3.04par>
- Pastor-Satorras, R., & Vespignani, A. (2001). Epidemic spreading in scale-free networks. *Physical Review Letters*, 86(14), 3200–3203. <https://doi.org/10.1103/PhysRevLett.86.3200>
- Pecher, D. (2018). Curb Your Embodiment. *Topics in Cognitive Science*, 10(3), 501–517. <https://doi.org/10.1111/tops.12311>
- Peng, G. S., Tan, S. Y., Wu, J., & Holme, P. (2016). Trade-offs between robustness and small-world effect in complex networks. *Scientific Reports*, 6, 1–10. <https://doi.org/10.1038/srep37317>
- Perea, M., & Rosa, E. (2002). The effects of associative and semantic priming in the lexical decision task. *Psychological Research*, 66(3), 180–194. <https://doi.org/10.1007/s00426-002-0086-5>
- Plaut, D. C., & Booth, J. R. (2000). Individual and developmental differences in semantic priming: Empirical and computational support for a single-mechanism account of lexical processing. *Psychological Review*, 107(4), 786–823. <https://doi.org/10.1037/0033-295X.107.4.786>
- Plaut, D. C., & Erlbaum Associates, L. (1995). *Semantic and Associative Priming in a Distributed Attractor Network*.
- Prior, A., & Bentin, S. (2008). Word associations are formed incidentally during sentential semantic integration. *Acta Psychologica*, 127(1), 57–71.
- Pulvermüller, F. (2005). Brain mechanisms linking language and action. *Nature Reviews Neuroscience*. Nature Publishing Group. <https://doi.org/10.1038/nrn1706>
- Pulvermüller, F. (2018). Neural reuse of action perception circuits for language, concepts and communication. *Progress in Neurobiology*. Elsevier Ltd. <https://doi.org/10.1016/j.pneurobio.2017.07.001>
- Pulvermüller, F. (2013, September). How neurons make meaning: Brain mechanisms for embodied and abstract-symbolic semantics. *Trends in Cognitive Sciences*. <https://doi.org/10.1016/j.tics.2013.06.004>
- Pulvermüller, F., Shtyrov, Y., & Ilmoniemi, R. (2005). Brain signatures of meaning access in action word recognition. *Journal of Cognitive Neuroscience*, 17(6), 884–892. <https://doi.org/10.1162/0898929054021111>
- Pylyshyn, Z. W. (1980). Cognitive representation and the process-architecture distinction: Cognitive representation and the process-architecture distinction. *Behavioral and Brain Sciences*. Cambridge University Press. <https://doi.org/10.1017/S0140525X00002302>
- Recchia, G., & Jones, M. N. (2012). The semantic richness of abstract concepts. *Frontiers in Human Neuroscience*, 6. <https://doi.org/10.3389/fnhum.2012.00315>
- Richardson, J. T. E. (1975). Concreteness and Imageability. *Quarterly Journal of Experimental Psychology*, 27(2), 235–249. <https://doi.org/10.1080/14640747508400483>
- Roelofs, A. (1997). The WEAVER model of word-form encoding in speech production. *Cognition*, 64(3), 249–284. [https://doi.org/10.1016/S0010-0277\(97\)00027-9](https://doi.org/10.1016/S0010-0277(97)00027-9)
- Rogers, T. T., & McClelland, J. L. (2004). *Semantic Cognition: A Parallel Distributed Processing Approach*.
- Rouder, J. N., & Morey, R. D. (2011). A Bayes factor meta-analysis of Bem's ESP claim. *Psychonomic Bulletin and Review*, 18(4), 682–689. <https://doi.org/10.3758/s13423-011-0088-7>

- Salavaty, A., Ramialison, M., & Currie, P. D. (2020). Integrated Value of Influence: An Integrative Method for the Identification of the Most Influential Nodes within Networks. *Patterns, 1*(5), 100052. <https://doi.org/10.1016/j.patter.2020.100052>
- Sánchez-Casas, R., Ferré, P., García-Albea, J. E., & Guasch, M. (2006). The nature of semantic priming: Effects of the degree of semantic similarity between primes and targets in Spanish. *European Journal of Cognitive Psychology, 18*(2), 161–184. <https://doi.org/10.1080/09541440500183830>
- Schepman, A., & Rodway, P. (2019). Shared Meaning in Representational and Abstract Visual Art: An Empirical Study. *Psychology of Aesthetics, Creativity, and the Arts. https://doi.org/10.1037/aca0000279*
- Schloss, B., & Li, P. (2016). Disentangling narrow and coarse semantic networks in the brain: The role of computational models of word meaning. *Behavior Research Methods, 49*(5), 1582–1596. <https://doi.org/10.3758/s13428-016-0807-0>
- Schwanenflugel, P. J., Harnishfeger, K. K., & Stowe, R. W. (1988). Context availability and lexical decisions for abstract and concrete words. *Journal of Memory and Language, 27*(5), 499–520. [https://doi.org/10.1016/0749-596X\(88\)90022-8](https://doi.org/10.1016/0749-596X(88)90022-8)
- Schwanenflugel, P. J., Harnishfeger, K. K., & Stowe, R. W. (1988). Context availability and lexical decisions for abstract and concrete words. *Journal of Memory and Language, 27*(5), 499–520. [https://doi.org/10.1016/0749-596X\(88\)90022-8](https://doi.org/10.1016/0749-596X(88)90022-8)
- Shallice, T., & Cooper, R. P. (2013). Is there a semantic system for abstract words? *Frontiers in Human Neuroscience, 7*, 175. <https://doi.org/10.3389/fnhum.2013.00175>
- Siew, C. S. Q., Wulff, D. U., Beckage, N. M., & Kenett, Y. N. (2019). Cognitive Network Science: A Review of Research on Cognition through the Lens of Network Representations, Processes, and Dynamics. *Complexity, 2019*, 2108423. <https://doi.org/10.1155/2019/2108423>
- Sigman, M., & Cecchi, G. A. (2002). Global organization of the Wordnet lexicon. *Proceedings of the National Academy of Sciences, 99*(3), 1742–1747. <https://doi.org/10.1073/PNAS.022341799>
- Smith, E. E., Shoben, E. J., & Rips, L. J. (1974). Structure and process in semantic memory: A featural model for semantic decisions. *Psychological Review, 81*(3), 214–241. <https://doi.org/10.1037/h0036351>
- Sperber, A. D., Devellis, R. F., & Boehlecke, B. (1994). Cross-Cultural Translation. *Journal of Cross-Cultural Psychology, 25*(4), 501–524. <https://doi.org/10.1177/0022022194254006>
- Stanfield, R. A., & Zwaan, R. A. (2001). The effect of implied orientation derived from verbal context on picture recognition. *Psychological Science, 12*(2), 153–156. <https://doi.org/10.1111/1467-9280.00326>
- Stella, M., Beckage, N. M., Brede, M., & De Domenico, M. (2018). Multiplex model of mental lexicon reveals explosive learning in humans. *Scientific Reports 2018 8:1*, 8(1), 1–11. <https://doi.org/10.1038/s41598-018-20730-5>
- Taconnat, L., Raz, N., Toczé, C., Bouazzaoui, B., Sauzéon, H., Fay, S., & Isingrini, M. (2009). Ageing and organisation strategies in free recall: The role of cognitive flexibility. *European Journal of Cognitive Psychology, 21*, 347–365. <https://doi.org/10.1080/09541440802296413>
- Thompson-Schill, S. L., Kurtz, K. J., & Gabrieli, J. D. E. (1998). Effects of semantic and associative relatedness on automatic priming. *Journal of Memory and Language, 38*(4), 440–458.
- van Noort, V., Snel, B., & Huynen, M. A. (2004). The yeast coexpression network has a small-world, scale-free architecture and can be explained by a simple model. *EMBO Reports, 5*(3), 280–284. <https://doi.org/10.1038/sj.embor.7400090>

- Vanpaemel, W. (2010). Prior sensitivity in theory testing: An apologia for the Bayes factor. *Journal of Mathematical Psychology*, 54(6), 491–498. <https://doi.org/10.1016/j.jmp.2010.07.003>
- Veremyev, A., Semenov, A., Pasiliao, E. L., & Boginski, V. (2019). Graph-based exploration and clustering analysis of semantic spaces. *Applied Network Science*, 4(1). <https://doi.org/10.1007/s41109-019-0228-y>
- Verhagen, J., & Wagenmakers, E.-J. (2014). Bayesian Tests to Quantify the Result of a Replication Attempt. <https://doi.org/10.1037/a0036731>
- Vigliocco, G., Meteyard, L., Andrews, M., & Kousta, S. (2009). Toward a theory of semantic representation. *Language and Cognition*, 1(2), 219–247. <https://doi.org/10.1515/langcog.2009.011>
- Vigliocco, G., & Vinson, D. P. (2012). Semantic representation. In *The Oxford Handbook of Psycholinguistics*. Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780198568971.013.0012>
- Vigliocco, G., Vinson, D. P., Lewis, W., & Garrett, M. F. (2004). Representing the meanings of object and action words: The featural and unitary semantic space hypothesis. *Cognitive Psychology*, 48(4), 422–488. <https://doi.org/10.1016/j.cogpsych.2003.09.001>
- Vigliocco, G., Vinson, D., Andrews, M., & Del Campo, E. (2013). The Representation of Abstract Words: What Matters? Reply to Paivio's (2013) Comment on Kousta et al. (2011). *Association*, 142(1), 288–291. <https://doi.org/10.1037/a0028749>
- Villani, C., Lugli, L., Liuzza, M. T., & Borghi, A. M. (2019). Varieties of abstract concepts and their multiple dimensions. *Language and Cognition*, 11(3), 403–430. <https://doi.org/10.1017/langcog.2019.23>
- Vinson, D. P., & Vigliocco, G. (2008). Semantic feature production norms for a large set of objects and events. *Behavior Research Methods*, 40(1), 183–190. <https://doi.org/10.3758/BRM.40.1.183>
- Vivas, J., Vivas, L., Comesaña, A., Coni, A. G., & Vorano, A. (2017). Spanish semantic feature production norms for 400 concrete concepts. *Behavior Research Methods*, 49(3), 1095–1106. <https://doi.org/10.3758/s13428-016-0777-2>
- Wang, H., & Song, M. (n.d.). *Ckmeans.Id.dp: Optimal k-means Clustering in One Dimension by Dynamic Programming*.
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature* 1998 393:6684, 393, 440–442. <https://doi.org/10.1038/30918>
- West, J. T., & Mulligan, N. W. (2019). Prospective Metamemory, Like Retrospective Metamemory, Exhibits Underconfidence With Practice. *Journal of Experimental Psychology: Learning Memory and Cognition*, 45. <https://doi.org/10.1037/xlm0000708>
- Wiemer-Hastings, K., & Xu, X. (2005). Content differences for abstract and concrete concepts. *Cognitive Science*, 29(5), 719–736. [https://doi.org/10.1207/s15516709cog0000\\_33](https://doi.org/10.1207/s15516709cog0000_33)
- Wilson-Mendenhall, C. D., Simmons, W. K., Martin, A., & Barsalou, L. W. (2013). Contextual processing of abstract concepts reveals neural representations of nonlinguistic semantic content. *Journal of Cognitive Neuroscience*, 25(6), 920–935. [https://doi.org/10.1162/jocn\\_a\\_00361](https://doi.org/10.1162/jocn_a_00361)
- Wu, L. ling, & Barsalou, L. W. (2009). Perceptual simulation in conceptual combination: Evidence from property generation. *Acta Psychologica*, 132(2), 173–189. <https://doi.org/10.1016/j.actpsy.2009.02.002>
- Yap, M. J., & Balota, D. A. (2009). Visual word recognition of multisyllabic words. *Journal of Memory and Language*, 60(4), 502–529. <https://doi.org/10.1016/j.jml.2009.02.001>

- Yarkoni, T., Balota, D., & Yap, M. (2008). Moving beyond Coltheart's N: A new measure of orthographic similarity. *Psychonomic Bulletin and Review*, 15(5), 971–979. <https://doi.org/10.3758/PBR.15.5.971>
- Yee Kwong, O. (2013). *Exploring the Chinese Mental Lexicon with Word Association Norms*. *aclweb.org*. Retrieved from <https://www.aclweb.org/anthology/Y13-1013.pdf>
- Zwaan, R. A. (2004). The Immersed Experiencer: Toward An Embodied Theory Of Language Comprehension. *Psychology of Learning and Motivation - Advances in Research and Theory*, 44, 35–62. [https://doi.org/10.1016/S0079-7421\(03\)44002-4](https://doi.org/10.1016/S0079-7421(03)44002-4)