How well do similarity measures predict priming in abstract and concrete concepts?

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Acknowledgements

We thank Simon De Deyne for supplying the association strength values and Armand Rotaru for providing his script for the extraction of the lexical co-occurrence.

Funding: This work was supported by the European Union's Horizon 2020 [grant number 702655].

Declarations of interest: none.

Abstract

Models of semantic representation predict that automatic priming is determined by associative and co-occurrence relations (i.e., spreading activation accounts), or to similarity in words' semantic features (i.e., featural models of semantic representation). Although, these three factors are correlated to some extent in characterizing semantic representation, they are not entirely overlapping and seem to tap different aspects of word meaning.

The authors designed two lexical decision experiments to dissociate these three different types of meaning similarity. For unmasked primes, they observed priming only due to association strength and not the other two measures; and no evidence for differences in priming effects for concrete and abstract concepts. For masked primes there was no priming effect regardless of the semantic relation. These results challenge theoretical accounts of automatic priming. Rather, they are in line with the idea that priming may be due to participants' controlled strategic processes, such as prospective expectancy generation. Together, these results provide important insight about the nature of priming effects and how association strength, as determined from word-association norms, relates to the nature of semantic representation.

Keywords: priming effect, association strength, lexical co-occurrence, semantic similarity, concreteness, masked prime

1. Introduction

Lexical priming provides rich information about organisation of semantic representations: responses to a target word are faster if it is preceded by a “related” prime word than if it follows an “unrelated” prime, although there is conflicting evidence about what kind of relation predicts priming (for reviews: Hutchison, 2003; Lucas, 2000). Within spreading activation theories, priming reflects relations based on word use: reflecting temporal contiguity of word pairs in verbal/written language, vs. word meaning *per se*. This can be reflected in the probability of one word to evoke another in a free word-association task (henceforth, *association strength*; De Deyne & Storms, 2008; Nelson, McEvoy, & Schreiber, 2004), or in the frequency of two words' co-occurrence in similar linguistic contexts across different sources (henceforth, *lexical co-occurrence*; Bullinaria & Levy, 2007; Griffiths, Steyvers, & Tenenbaum, 2007). Under such views, priming is caused by passive spread of activation from an activated prime to associated nodes including the target. In contrast, featural models assume that words are represented as patterns of activity across semantic features (Cree, McNorgan, & McRae, 2006). Related words share semantic features obtained from a feature-listing task (henceforth, *semantic similarity*; McRae, de Sa, & Seidenberg, 1997; Montefinese, Vinson & Ambrosini, 2018; Montefinese, Ambrosini, Fairfield, & Mammarella, 2013; Montefinese, Zannino, & Ambrosini, 2015; Vinson & Vigliocco, 2008). Under this view, priming occurs because a prime activates shared features that facilitate responses to related targets. Despite different assumptions, both views posit that priming is automatic and reflects the structure of semantic representation (Thompson-Schill, Kurtz, & Gabrieli, 1998), and studies seem to show that all three types of relatedness predict priming: association strength (Heyman, Van Rensbergen, Storms, Hutchison, & De Deyne, 2015; Perea & Rosa, 2002), lexical co-occurrence (Brunellière, Perre, Tran, & Bonnotte, 2017; Günther, Dudschig, & Kaup, 2016) and semantic similarity (McRae et al., 1997;

Vigliocco, Vinson, Lewis, & Garrett, 2004). However, although these three factors are correlated in characterizing semantic representation (De Deyne, Navarro, & Storms, 2013; Guida & Lenci, 2007; Spence & Owens, 1990), they seem to tap different aspects of meaning and are not entirely overlapping (Maki & Buchanan, 2008).

These relations are also related to word concreteness: how directly a word represents a concept related to sensorial experience (Brysbaert, Warriner, & Kuperman, 2014). While concrete words have direct sensory referents (Crutch & Warrington, 2005) and greater availability of contextual information, abstract words tend to be more emotionally valenced (Kousta, Vigliocco, Vinson, Andrews, & Del Campo, 2011). Different organisational principles have also been argued to govern semantic representations of concrete and abstract words: concrete words predominantly organized by semantic similarity, and abstract words by associative relations (Crutch & Warrington, 2005). Benko (2015) tested this claim in a priming study using prime-target pairs related only by semantic similarity or by association strength, finding that priming was not modulated by word concreteness.

Here, we formally test whether priming is differentially sensitive to all three measures: semantic similarity, association strength and lexical co-occurrence for concrete and abstract words, maximising the difference between relation type conditions. If they are differentially represented we expect different measures to predict priming.

However, priming may also arise due to controlled processes not necessarily reflecting properties of semantic representation, such as prospective expectancy generation and retrospective relatedness checking strategies (Thompson-Schill et al., 1998). While controlled processes seem to be hindered/reduced by using stimulus onset asynchrony (SOA: interval between prime and target onset) ≤ 250 milliseconds and briefly displayed visually masked primes, meta-analysis highlighted inconsistencies between

studies (Hutchison, 2003; Lucas, 2000). For example, Lucas (2000) showed that priming can occur for category coordinates at SOAs <250ms, without high association strength, Hutchison (Hutchison, 2003) showed no priming at SOAs <250ms for these items when strategic processing was controlled (e.g. with subliminal presentation).

We carried out two lexical decision experiments (decide if the target is a word or not), presenting stimuli with a 250ms SOA (to eliminate some strategic effects: McRae & Boisvert, 1998). We manipulated the prime presentation between experiments (unmasked in Experiment 1, masked in Experiment 2). In Experiment 1 we expected priming for abstract words related by lexical co-occurrence and association strength, and priming for concrete words related by semantic similarity only. Furthermore, if masking a prime prevents the use of strategic processes involved in priming, in Experiment 2 we predicted a reduction in magnitude of the priming effect observed in Experiment 1 for both abstract and concrete concepts, along with a significant between-experiment modulation of it.

2 Method

2.1 Participants

Forty-eight healthy native English speakers (30 females; mean age = 26.02 years, $SD = 8.87$ years) took part in Experiment 1. Another group of forty-eight healthy native English speakers (37 females; mean age = 23.42 years, $SD = 5.44$ years) took part in Experiment 2 (see supplementary materials for further information)¹.

¹ Experiment 2 was preregistered as part of the Center for Open Science's Preregistration Challenge (cos.io/prereg/). All of the supplementary materials and set of stimuli can be found in our project on the Open Science Framework (osf.io/pd3nj). The preregistration can be retrieved from osf.io/f8j9m (Montefinese, Buchanan & Vinson, 2018, 26 March 2018). Where applicable, deviations from pre-registration are noted.

2.2 Stimuli

For both experiments we selected 80 abstract and 80 concrete target-prime pairs from English feature-listing norms (Buchanan, Holmes, Teasley, & Hutchison, 2013; McRae, Cree, Seidenberg, & McNorgan, 2005; Vinson & Vigliocco, 2008). Word pairs were assigned to abstract/concrete type by performing a tertile split on concreteness ratings (Brysbaert et al., 2014) for all words in the English semantic norms (Buchanan et al., 2013). Abstract and concrete pairs were selected from the top and bottom thirds of the concreteness distributions. 40 target words (20 abstract, 20 concrete) were paired with four types of word primes: unrelated (CHARM - *culture*) or related by one relation measure only (association strength, e.g., CHARM - *flirt*; lexical co-occurrence, e.g., CHARM - *talent*; semantic similarity, e.g., CHARM - *virtue*). We maximised the difference between related conditions by ensuring that pairs had high similarity values only according to one of the three measures and not the other two, thus testing their contribution to priming as independently as possible. Unrelated pairs had low similarity across all three measures. To operationalize semantic similarity, we used cosine angle between vectors for the two words, by summing the multiplication of matching feature frequencies divided by the products of each word's vector length (Buchanan et al., 2013). Lexical co-occurrence was computed as the natural logarithm of each word pair's co-occurrence frequency (+1) in a symmetrical 5-word window in the British National Corpus (Leech, Garside, & Bryant, 1994). Association strength was computed as the proportion of participants that gave the target response to a given cue word (De Deyne, Navarro, Perfors, Brysbaert & Storms, 2018). We matched our experimental conditions as closely as possible for several possible confounding variables: word length, word frequency, number of orthographical and phonological neighbours (Balota et al., 2007), age of acquisition (Brysbaert & Biemiller, 2016), valence, arousal and dominance (Warriner, Kuperman, & Brysbaert, 2013). ANOVA on each variable testing for Word Type (Abstract, Concrete) $\times$ Relation Type

(Association Strength, Lexical Co-occurrence, Semantic Similarity, Unrelated): all $ps > .126$. We additionally included these variables as predictors in analyses, see Results). 160 target nonwords (selected from Balota et al., 2007) matched to the target words for number of letters and orthographic neighbours were selected for filler trials and were paired with the same primes as the target words (see supplementary materials for stimuli). Sixteen additional prime-target pairs were selected for practice. All primes and targets, in lower case, were presented at the centre of the screen in white 24-point Consolas font against a black background.

2.3 Procedure

In Experiment 1, a trial included a yellow fixation cross (appearing for 250ms), the prime (200ms), a blank screen (50ms), and the target, which remained on screen until the participant responded (or until 3000ms). The ITI (a white fixation cross) lasted 1500ms. In Experiment 2 after the fixation cross (250ms), a forward mask (a random string of symbols: e.g. %\$@ \$#&€\$ the same length as the prime) for 100ms, then the prime (33ms), immediately followed by a backward mask (a different random string of symbols the same length of the prime) for 167 ms (Ortells, Kiefer, Castillo, Megías, & Morillas, 2016), thus resulting in the same 250ms SOA of Experiment 1. Target presentation and ITI were the same as Experiment 1. Participants were asked to indicate as quickly and accurately as possible whether the letter string (the target) was a word or nonword by pressing a key on the keyboard (“N” for word and “M” for nonword).

2.2 Data analysis

Latency and response accuracy were recorded. Trials with reaction times (RTs) faster than 150ms or incorrect responses (9.40 and 5.87% of the trials in Experiment 1

and 2, respectively), were discarded from analyses. The remaining RTs were log-transformed.

RTs from each experiment were analysed with linear mixed effects modelling, using a data-driven procedure to determine the best model (Bayeen, 2008; Montefinese, Ambrosini, Fairfield, & Mammarella, 2014; and supplementary materials for more detailed description). In a second analysis, we combined data from both experiments and tested the same model that we found to be the best for Experiment 1, but also including a between-experiments Masking factor (Unmasked vs. Masked prime). In the final models, the random part included three parameters for random factors of Subjects and Concepts and by-subjects random slopes for Trial, while the fixed factors included parameters for the effects of Intercept and Trial.

We tested whether inclusion of parameters in the linear mixed models was justified by performing likelihood ratio tests. Final models were re-fitted after excluding observations with absolute standardized residuals greater than 2.5 (always <3.02% of analysed trials). We assessed statistical significance of the predictors of primary theoretical interest by means of one-sided t tests with Satterthwaite's approximation to degrees of freedom. The alpha level was set at .05. We reported the estimated coefficient (b), standard error (SE), t and p values for each parameter included in the final model. Descriptive statistics are reported in the supplementary materials.

3 Results

3.1 Experiment 1

The final model and relative statistics are shown in Supplementary Materials Table S-1. The Relation Type factor significantly modulated participants' RTs. Specifically, there was priming only for association strength, controlling for confounding

lexico-semantic variables² (see Supplementary Materials Table S.2 for descriptive statistics). Importantly, this effect was not modulated by word concreteness: inclusion of the parameters for Concreteness $\times$ Word Type interaction was not justified ($\chi^2_{(4)} = 7.18$, $p = .127$).

Table 1. Estimated parameters and statistics of mixed-effects modelling for Experiment 1.

	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>
(Intercept)	6.43	.02	282.85	<.001
cTrial	-.02	.01	-2.22	.032
TAoA	.04	.01	7.79	<.001
PPhoNei	<.01	.01	.51	.614
TPhoNei	.01	.01	1.94	.054
PDom	-.01	.01	-2.27	.025
RelationType _{Ass} ^a	-.03	.01	-1.90	.030
RelationType _{Coo} ^a	-.01	.01	-.68	.250
RelationType _{Sim} ^a	<.01	.01	<.01	.500

cTrial = zero-centered vector for the trial effect, TAoA = age of acquisition of the target, PPhoNei = number of phonological neighbours of the prime, TPhoNei = number of phonological neighbours of the target, PDom = dominance of the target, Ass = association strength, Coo = Lexical co-occurrence, Sim = semantic similarity, ^a = each predictor is a pairwise comparison against unrelated pairs.

3.3 Experiment 2: Confirmatory analyses

This analysis aimed to test whether priming due to association strength was replicated when

² This result was confirmed ($b = -.02$, $SE = .01$, $t = -1.83$, $p = .034$) by a control analysis in which we excluded the parameter for the effect of phonological neighbours of the prime, which was not significant (the exclusion of this parameter was justified: $\chi^2_{(1)} = .18$, $p = .669$).

the prime was presented subliminally (i.e., masked). Unlike Experiment 1, the Relation Type factor was not significant and inclusion of parameters for Word Type was justified ($\chi^2_{(4)} = 12.32, p = .015$), with faster RTs for abstract words compared to the concrete ones (see Table 2 and Supplementary Table S.2 for descriptive statistics).

Table 2. Estimated parameters and statistics of mixed-effects modelling for Experiment 2.

	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>
(Intercept)	6.44	.02	308.98	<.001
cTrial	-.02	.01	-2.82	.007
TAoA	.04	<.01	8.94	<.001
PAoA	-.019	<.01	-2.34	.021
TPhoNei	.01	<.01	1.23	.220
RelType _{Ass} ^a	.01	.02	.64	.740
RelType _{Coo} ^a	-.01	.02	-.45	.327
RelType _{Sim} ^a	<-.01	.02	-.13	.450
WordType _{Concrete}	.04	.02	2.53	.013
RelationType _{Ass} :WordType _{Concrete} ^a	-.03	.02	-1.39	.168
RelationType _{Coo} :WordType _{Concrete} ^a	-.01	.02	-.49	.628
RelationType _{Sim} :WordType _{Concrete} ^a	-.01	.02	-.48	.633

cTrial = zero-centered vector for the trial effect, TAoA = age of acquisition of the target, PAoA = age of acquisition of the prime, TPhoNei = number of phonological neighbours of the target, Ass = association strength, Coo = Lexical co-occurrence, Sim = semantic similarity, ^a = each predictor is a pairwise comparison against unrelated pairs.

3.2 Between-Experiments effects: Confirmatory analyses

To test whether the masked prime prevented the use of strategic processes involved in associative priming, reducing the magnitude of the significant priming effect that we observed in Experiment 1, we performed linear mixed-effect models on data from

both experiments and added the Masking factor (Unmasked vs. Masked) to the best model explaining participants' RTs in Experiment 1. The final model showed a main effect of Association Strength and its interaction with Masking, as shown in Table 3.³ Follow up comparisons showed a significant difference between unmasked and masked prime conditions for the Association Strength factor only ($b = .029$, $SE = .019$, $t = 2.20$, $p = .014$). No masking-related differences were observed for Lexical Co-occurrence ($b = <-.01$, $SE = .01$, $t = -.27$, $p = .608$) and Semantic Similarity ($b = -.017$, $SE = .01$, $t = -.73$, $p = .768$) (see Fig. 1).

³ These results were again corroborated by exploratory control analyses in which we excluded the parameter for the effect of Phonological Neighbours and Dominance of the prime, which were not significant (Association Strength: $b = -.02$, $SE = .01$, $t = 2.08$, $p = .042$; Association Strength $\times$ Masking: $b = .02$, $SE = .01$, $t = 1.69$, $p = .019$). Note that the likelihood ratio test showed that the exclusion of these parameters at this stage was justified ($\chi^2_{(1)} = .02$, $p = .89$, and $\chi^2_{(1)} = 3.33$, $p = .068$), for Phonological Neighbours and Dominance of the prime, respectively).

Table 3. Estimated parameters and statistics of mixed-effects modelling on RT combined data from both experiments.

	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>
(Intercept)	6.40	.019	329.74	<.001
cTrial	-.02	.01	-4.32	<.001
TAoA	.04	<.01	9.81	<.001
PPhoNei	<.01	<.01	.55	.585
TPhoNei	.01	<.01	2.63	.009
PDom	-.01	<.01	-1.75	.081
RelationType _{Ass} ^a	-.02	.01	-1.93	.028
RelationType _{Coo} ^a	-.01	.01	-.61	.272
RelationType _{Sim} ^a	<.01	.01	.08	.532
Masking _{Masked}	.04	.03	1.33	.187
RelationType _{Ass} :Masking _{Masked} ^a	.02	.01	2.21	.014
RelationType _{Coo} :Masking _{Masked} ^a	<-.01	.01	-.25	.598
RelationType _{Sim} :Masking _{Masked} ^a	-.01	.01	-.76	.776

cTrial = zero-centered vector for the trial effect, TAoA = age of acquisition of the target, PPhoNei = number of phonological neighbours of the prime, TPhoNei = number of phonological neighbours of the target, PDom = dominance of the target, Ass = association strength, Coo = lexical co-occurrence, Sim = semantic similarity. ^a = each predictor is a pairwise comparison against unrelated pairs, ^a = each predictor is a pairwise comparison against unrelated pairs.

Fig. 1. Interaction between Relation Type and Masking. Log-transformed reaction times are shown as a function of Masking (Unmasked, Masked) and Relation Type (Unrelated, Association Strength, Lexical Co-occurrence, Semantic Similarity) factors. Error bars indicate standard error of the mean. * = $p < .05$.

4. Discussion

We designed two lexical decision experiments to dissociate three different types of meaning similarity used in previous priming studies: association strength, lexical co-occurrence and semantic similarity. Unexpectedly, for unmasked primes (Experiment 1) priming occurred for association strength only, and did not differ for concrete and abstract concepts. For masked primes (Experiment 2) there was no priming regardless of semantic relation. Potentially confounding lexico-semantic variables were partly controlled via item selection and also entered into analyses: target word age of acquisition was the only predictor consistently significant across analyses (with faster responses for earlier learnt words; see e.g. Ghyselinck, Custers, & Brysbaert, 2004).

Taken together, these results provide important insight about semantic representation. In particular, they bring some clarity to the longstanding debate about how association strength, as determined from word-association norms, relates to the nature of semantic representations (McRae, Khalkhali, & Hare, 2012). On the one hand, the

operationalization of association strength may affect the degree to which it captures conceptual semantic information. Indeed, the word-association task reflects some semantic relations, especially taxonomic relations for concrete concepts and verbs (Guida & Lenci, 2007; Santos, Chaigneau, Simmons, & Barsalou, 2011), which share many semantic features. This is particularly likely when a continuous word-association task is employed (i.e., when participants are asked to produce three associates for each cue stimulus) vs. a discrete word-association task (i.e., when participants are asked to produce just one associate), as in our case. Compared to lexical co-occurrence, association strength also is better at capturing words' affective features (Van Rensbergen, De Deyne, & Storms, 2016), which especially characterize abstract concepts (Kousta et al., 2011). A further asset of word association is that every association reflects a meaningful relation with a high signal-to-noise ratio, in contrast to co-occurrence in text corpora characterized by a low signal-to-noise ratio (Van Rensbergen et al., 2016). Associations are also clearly linguistically based, as they are provided in response to a word (in contrast to the standard feature-listing task which requires participants to explicitly consider the concept that the word refers to rather than the word itself), and reflect patterns of co-occurrence in semantic representation of both abstract and concrete concepts (Hoffman, McClelland, & Lambon Ralph, 2018).

The more comprehensive nature of association strength may be framed within theoretical models advocating hybrid views of semantic representation incorporating both featural and linguistic aspects (Anderson, Bruni, Bordinon, Poesio, & Baroni, 2013; Andrews, Vigliocco, & Vinson, 2009; Durda, Buchanan, & Caron, 2009; Johns & Jones, 2012; Steyvers, 2010; Vigliocco, Meteyard, Andrews, & Kousta, 2009). For example, the featural and unitary semantic space account (FUSS) by Vigliocco and colleagues (2004) assumes that lexicosemantic representations are conceived as intermediate: binding

conceptual representation (characterized by featural representations) and lexical representations (characterized by orthographic/phonological and other linguistic information). In this scenario, we propose that association strength reflects information about relations between words at this level of representation. Indeed, association strength could capture the meaning of abstract (affective and linguistically-based) and concrete (sensorimotor and linguistically-based) word pairs to a similar extent in the lexical decision task. We do not intend to suggest that association strength completely describes conceptual representation; rather, while association strength conveys different kinds of information to some degree, lexical co-occurrence and semantic similarity convey other kinds of information not used to make a lexical decision (whether it is a word or a nonword).

This fact may also explain the lack of differences in priming for concrete vs. abstract words we observed, and is consistent with a recent model by Hoffman et al. (2018), representing abstract and concrete words in a common semantic space sensitive to different relations between words. It is also consistent with neuropsychological evidence indicating that many aspects of semantic representation may be supported by a transmodal hub cortex in the ventral anterior temporal lobe (Hoffman, Binney, & Lambon Ralph, 2015; Jefferies, Patterson, & Ralph, 2008).

However, we observed associative priming only with conscious exposure to the prime only; it disappeared with subliminal exposure. This suggests that associative priming is not automatic. Although we used a brief SOA (250ms) to prevent the use of some controlled processes, these results seem to speak against spreading activation theory and featural distributed models of semantic representation given the lack of a significant effect of semantic similarity and lexical co-occurrence. Rather, our results may be best accounted for by a controlled process, such as prospective expectancy generation (McRae &

Boisbert, 1998; see also Wit and Kinoshita, 2015, for a similar alternative). This would occur when participants notice that some prime-target pairs are related, so when a prime is presented they generate possible related targets. Priming occurs when the target's representation overlaps with the predicted one. This strategy requires awareness of the prime's identity, which is prevented when primes are masked. Consistent with this, masking the prime eliminated associative priming in Experiment 2.

On the whole, by carefully decorrelating meaning similarity measures based on word association, lexical co-occurrence and semantic similarity, we found that only word association predicted priming in lexical decision at brief SOA, and even this effect was eliminated when prime was presented briefly and masked. These findings are thus consistent in many ways with priming at long SOAs, in that they largely appear to be related to participants' strategies and expectations rather than directly revealing the nature of semantic representations. While these results can still be accommodated within theoretical perspectives incorporating both conceptual and linguistic representations, we suggest that more explicitly semantic tasks are more likely to be informative about the nature of these representations.

References

- Anderson, A. J., Bruni, E., Bordinon, U., Poesio, M., & Baroni, M. (2013). Of Words, Eyes and Brains: Correlating Image-Based Distributional Semantic Models with Neural Representations of Concepts. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing* (pp. 1960–1970).
- 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>
- Balota, D. A., Yap, M. J., Hutchison, K. A., Cortese, M. J., Kessler, B., Loftis, B., ... Treiman, R. (2007). The English Lexicon Project. *Behavior Research Methods*, 39(3), 445–459. <https://doi.org/10.3758/BF03193014>
- Brunellière, A., Perre, L., Tran, T., & Bonnotte, I. (2017). Co-occurrence frequency evaluated with large language corpora boosts semantic priming effects. *Quarterly Journal of Experimental Psychology*, 70(9), 1922–1934. <https://doi.org/10.1080/17470218.2016.1215479>
- Brysbaert, M., & Biemiller, A. (2016). Test-based age-of-acquisition norms for 44 thousand English word meanings. *Behavior Research Methods*, (September). <https://doi.org/10.3758/s13428-016-0811-4>
- Brysbaert, 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>
- 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>

- Bullinaria, J. a, & Levy, J. P. (2007). Extracting semantic representations from word co-occurrence statistics: A computational study. *Behavior Research Methods*, 39(3), 510–526. <https://doi.org/10.3758/BF03193020>
- Cree, G. S., McNorgan, C., & McRae, K. (2006). Distinctive features hold a privileged status in the computation of word meaning: Implications for theories of semantic memory. *Journal of Experimental Psychology: Learning Memory and Cognition*. <https://doi.org/10.1037/0278-7393.32.4.643>
- 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>
- 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., & 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>
- Durda, K., Buchanan, L., & Caron, R. (2009). Grounding co-occurrence: Identifying features in a lexical co-occurrence model of semantic memory. *Behavior Research Methods*, 41(4), 1210–1223. <https://doi.org/10.3758/BRM.41.4.1210>
- Ghyselinck, M., Custers, R., & Brysbaert, M. (2004). The Effect of Age of Acquisition in Visual Word Processing: Further Evidence for the Semantic Hypothesis. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 30(2), 550–554. <https://doi.org/10.1037/0278-7393.30.2.550>
- 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>
- Guida, A., & Lenci, A. (2007). Semantic properties of word associations to Italian verbs. *Italian Journal of Linguistics*, 19(2), 293–326.
- Günther, F., Dudschig, C., & Kaup, B. (2016). Latent semantic analysis cosines as a cognitive similarity measure: Evidence from priming studies. *Quarterly Journal of Experimental Psychology*, 69(4), 626–653.
<https://doi.org/10.1080/17470218.2015.1038280>
- Heyman, T., Van Rensbergen, B., Storms, G., Hutchison, K. a, & De Deyne, S. (2015). The influence of working memory load on semantic priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 41(3), 911–920.
<https://doi.org/10.1037/xlm0000050>
- 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/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>
- Hutchison, K. A. (2003). Is semantic priming due to association strength or feature overlap? A microanalytic review. *Psychonomic Bulletin & Review*, 10(4), 785–813.
<https://doi.org/10.3758/BF03196544>
- Jefferies, E., Patterson, K., & Ralph, M. A. L. (2008). Deficits of knowledge versus executive control in semantic cognition: Insights from cued naming. *Neuropsychologia*, 46(2), 649–658.
<https://doi.org/10.1016/j.neuropsychologia.2007.09.007>

- Johns, B. T., & Jones, M. N. (2012). Perceptual Inference Through Global Lexical Similarity. *Topics in Cognitive Science*, 4(1), 103–120. <https://doi.org/10.1111/j.1756-8765.2011.01176.x>
- 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>
- Leech, G., Garside, R., & Bryant, M. (1994). CLAWS4. In *Proceedings of the 15th conference on Computational linguistics* - (Vol. 1, p. 622). Morristown, NJ, USA: Association for Computational Linguistics. <https://doi.org/10.3115/991886.991996>
- Lucas, M. (2000). Semantic priming without association: A meta-analytic review. *Psychonomic Bulletin & Review*, 7(4), 618–630. <https://doi.org/10.3758/BF03212999>
- Maki, W. S., & Buchanan, E. (2008). Latent structure in measures of associative, semantic, and thematic knowledge. *Psychonomic Bulletin & Review*, 15(3), 598–603. <https://doi.org/10.3758/PBR.15.3.598>
- McRae, K., & Boisvert, S. (1998). Automatic semantic similarity priming. *Journal of Experimental Psychology: Learning Memory and Cognition*. <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., Khalkhali, S., & Hare, M. (2012). Semantic and associative relations in

- adolescents and young adults: Examining a tenuous dichotomy. *The Adolescent Brain: Learning, Reasoning, and Decision Making*. <https://doi.org/10.1037/13493-002>
- Montefinese, M., Ambrosini, E., Fairfield, B., & Mammarella, N. (2013). Semantic memory: A feature-based analysis and new norms for Italian. *Behavior Research Methods*, 45(2), 440–461. <https://doi.org/10.3758/s13428-012-0263-4>
- Montefinese, M., Ambrosini, E., Fairfield, B., & Mammarella, N. (2014). Semantic significance: a new measure of feature salience. *Memory & Cognition*, 42(3), 355–369. <https://doi.org/10.3758/s13421-013-0365-y>
- Montefinese, M., Vinson, D., & Ambrosini, E. (2018). Recognition memory and featural similarity between concepts: The pupil's point of view. *Biological Psychology*, 135, 159–169. <https://doi.org/10.1016/j.biopsycho.2018.04.004>
- Montefinese, M., Zannino, G. D., & Ambrosini, E. (2015). Semantic similarity between old and new items produces false alarms in recognition memory. *Psychological Research*, 79(5), 785–794. <https://doi.org/10.1007/s00426-014-0615-z>
- 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, & Computers*, 36(3), 402–407. <https://doi.org/10.3758/BF03195588>
- Ortells, J. J., Kiefer, M., Castillo, A., Megías, M., & Morillas, A. (2016). The semantic origin of unconscious priming: Behavioral and event-related potential evidence during category congruency priming from strongly and weakly related masked words. *Cognition*, 146, 143–157. <https://doi.org/10.1016/j.cognition.2015.09.012>
- 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>

- Santos, A., Chaigneau, S. E., Simmons, W. K., & Barsalou, L. W. (2011). Property generation reflects word association and situated simulation. *Language and Cognition*, 3(01), 83–119. <https://doi.org/10.1515/langcog.2011.004>
- Spence, D. P., & Owens, K. C. (1990). Lexical co-occurrence and association strength. *Journal of Psycholinguistic Research*, 19(5), 317–330. <https://doi.org/10.1007/BF01074363>
- Steyvers, M. (2010). Combining feature norms and text data with topic models. *Acta Psychologica*, 133(3), 234–243. <https://doi.org/10.1016/j.actpsy.2009.10.010>
- 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. <https://doi.org/10.1006/jmla.1997.2559>
- Van Rensbergen, B., De Deyne, S., & Storms, G. (2016). Estimating affective word covariates using word association data. *Behavior Research Methods*, 48(4), 1644–1652. <https://doi.org/10.3758/s13428-015-0680-2>
- Vigliocco, G., Meteyard, L., Andrews, M., & Kousta, S. (2009). Toward a theory of semantic representation. *Language and Cognition*, 1(02), 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*. <https://doi.org/10.1016/j.cogpsych.2003.09.001>
- 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>
- Warriner, A. B., Kuperman, V., & Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behavior Research Methods*, 45(4), 1191–

1207. <https://doi.org/10.3758/s13428-012-0314-x>