TOPICS
TOPICS IN COGNITIVE SCIENCE

Topics in Cognitive Science (2018) 1–23

ISSN:1756-8757 print / 1756-8765 online
DOI: 10.1111/tops.12335

This article is part of the topic "Abstract Concepts: Structure, Processing and Modeling," Marianna Bolognesi and Gerard Steen (Topic Editors). For a full listing of topic papers, see http://onlinelibrary.wiley.com/journal/10.1111/(ISSN)1756-8765/earlyview

# The Emotions of Abstract Words: A Distributional Semantic Analysis

Alessandro Lenci, Gianluca E. Lebani, Lucia C. Passaro

*Computational Linguistics Laboratory, Department of Philology, Literature, and Linguistics, University of Pisa*

Received 3 June 2017; received in revised form 17 February 2018; accepted 20 February 2018

**Abstract**

Recent psycholinguistic and neuroscientific research has emphasized the crucial role of emotions for abstract words, which would be grounded by affective experience, instead of a sensorimotor one. The hypothesis of affective embodiment has been proposed as an alternative to the idea that abstract words are linguistically coded and that linguistic processing plays a key role in their acquisition and processing. In this paper, we use distributional semantic models to explore the complex interplay between linguistic and affective information in the representation of abstract words. Distributional analyses on Italian norming data show that abstract words have more affective content and tend to co-occur with contexts with higher emotive values, according to affective statistical indices estimated in terms of distributional similarity with a restricted number of seed words strongly associated with a set of basic emotions. Therefore, the strong affective content of abstract words might just be an indirect byproduct of co-occurrence statistics. This is consistent with a version of representational pluralism in which concepts that are fully embodied either at the sensorimotor or at the affective level live side-by-side with concepts only indirectly embodied via their linguistic associations with other embodied words.

*Keywords:* Abstract words; Emotions; Contexts; Distributional semantics

Correspondence should be sent to Alessandro Lenci, Dipartimento di Filologia, Letteratura e Linguistica, via Santa Maria 36, I-56126 Pisa, Italy. E-mail: alessandro.lenci@unipi.it

## 1. Introduction

Behavioral and neuroimaging evidence shows that abstract and concrete words are organized, represented, and processed differently (Crutch & Warrington, 2005; Crutch, Connell, & Warrington, 2009; Crutch & Warrington, 2010; Wang, Conder, Blitzer, & Shinkareva, 2010; Hill, Korhonen, & Bentz, 2014; Troche, Crutch, & Reilly, 2014), but what is the *reason* of such difference? The importance of the answer we give to this question does not only lie in the possibility to explain a rich body of empirical data, but also in its deep consequences for our models of human cognition in general. According to the *Dual Coding Theory* (Paivio, 1991, 2007), concrete words are represented in two distinct systems, a linguistic system and a non-linguistic, imagistic, sensorimotor-based system, while abstract words are primarily or exclusively represented in the linguistic system. The *Context Availability Hypothesis* (Schwanenflugel, 1991) instead argues that all word meanings are represented in a single verbal code, but concrete words have stronger and denser associations to contextual knowledge than abstract ones. Despite their differences, both theories agree on the key role played by *linguistic information* for learning, representing, and processing abstract words. This is consistent with the fact that, lacking reference to externally perceivable entities, the meaning of abstract words is essentially acquired via language, for instance through distributional statistics extracted from the linguistic input. Moreover, neuroimaging studies have shown that the processing of abstract words is associated with higher activations in left hemispheric areas involved in linguistic processing such as the left inferior frontal gyrus and the superior temporal cortex (Binder et al., 2005; Binder, Desai, Graves, & Conant, 2009; Wang et al., 2010). The Dual Coding Theory and the Context Availability Hypothesis also share the view that concrete words are "semantically richer" than abstract ones, thereby explaining their processing advantage, the so-called *concreteness effect*. According to the former theory, the richness of concrete words depends on having access to imagistic information in addition to linguistic information, while for the latter it depends on their stronger contextual associations.

The linguistic nature of abstract word meanings directly challenges *embodied models of cognition*, in particular the "strong embodiment" claim that all concepts are inherently couched in sensorimotor representations (Meteyard, Cuadrado, Bahrami, & Vigliocco, 2012). In fact, the very existence of abstract words and concepts seems to call for some kind of *representational pluralism* (Dove, 2009, 2014). One version of this pluralism, which Scorolli et al. (2011) call *non-embodied multiple representation view*, assumes that concrete and abstract concepts have distinct representations, the former in the sensorimotor system and the latter in the linguistic system (Dove, 2009; Paivio, 1991). An alternative version of representational pluralism, the *embodied multiple representation view* (Scorolli et al., 2011), instead argues that all concepts are represented both in the language and in the sensorimotor domains, and that the difference between concrete and abstract words depends on the relative salience of embodied and linguistic information, the latter being more preponderant for the abstract domain. Various versions of this view have been proposed, such as the *Language and Situated Simulation* (LASS) theory

(Barsalou et al., 2008), the *Word as social tools* (WAT) theory (Borghi & Cimatti, 2009; Borghi & Binkofski, 2014), and the model of semantic representation by Vigliocco, Meteyard, Andrews, and Kousta (2009).

Embodied multiple representation models entail that (a) linguistic information is relevant for concrete concepts, in addition to experiential data, and conversely that (b) embodied information is present in abstract concepts too (though in a much less prominent way). The first statement has indeed found several significant empirical confirmations (Andrews, Frank, & Vigliocco, 2014); for instance, computational models integrating experiential features and distributional linguistic features have been shown to improve the semantic representation of concrete words (Andrews, Vigliocco, & Vinson, 2009; Johns & Jones, 2012; Riordan & Jones, 2011). The second statement is instead more puzzling, because it raises the question of the embodied component in abstract concepts. This must be different from zero, otherwise the embodied and the non-embodied multiple representation views would eventually conflate. Of course, one could claim that the experience of language is itself a kind of embodied experience, but this is surely not enough to call the representation of abstract words embodied (Scorolli et al., 2011).

Vigliocco et al. (2009) argue that the embodiment of abstract concepts is provided by *affective experience* (Kousta, Vigliocco, Vinson, Andrews, & Del Campo, 2011; Vigliocco, Kousta, Vinson, Andrews, & Del Campo, 2013; Vigliocco et al., 2014; Vinson et al., 2014). We will refer to this proposal as the *Affective Grounding Hypothesis* (AGH), which rests on the following assumptions:

1. All concepts are constituted by two types of information, *experiential* and *linguistic*. The latter comes in the form of distributional statistics extracted from the linguistic input. The former crucially includes sensory, motor, *and* affective information.
2. Sensorimotor information is preponderant for concrete word meanings, while affective and linguistic information is more preponderant in abstract word meanings.

The AGH is supported by the behavioral data in Kousta et al. (2011), who found that, once several variables are carefully controlled (like imageability and context availability) the concreteness effect disappears, with abstract words actually having an advantage over concrete ones. Kousta et al. (2011) show that the advantage of abstract words is due to their stronger affective associations, which have independently been proven to facilitate word processing in lexical recognition tasks (Kousta, Vinson, & Vigliocco, 2009). Further evidence comes from neuroimaging data, showing that abstract words produce a greater activation of areas associated with emotion processing (Vigliocco et al., 2014). The main novelty of the AGH is that emotion is considered to be another type of experiential information, side-by-side with sensorimotor data, and to be responsible for the grounding of abstract concepts, whose linguistic nature is therefore seriously downplayed. Indeed, Vigliocco et al. (2014: 1774) claim that their experimental data “argue against an exclusive (or even primary) role of linguistic information in the representation of abstract knowledge.”

Research in computational linguistics and psychology has shown the strong correlation between the affective content of words and their statistical co-occurrences. Bestgen and

Vincze (2012) and Recchia and Louwerse (2015) successfully exploited such correlation to predict the affective ratings (valence, arousal, and dominance) of the words in the ANEW norms (Bradley & Lang, 1999) with distributional semantic models (DSMs). Passaro and Lenci (2016) trained a DSM to measure the association of Italian words with the emotions in the taxonomy proposed by Plutchik (1994). The emotive scores were evaluated on human ratings collected with crowdsourcing, obtaining a very high precision. These results raise the possibility that the affective content of words is deeply influenced by their distribution in linguistic contexts. For instance, the negative valence of *pollution* may also depend on its distributional association with words such as *danger*, *sick*, *harm*, and so on.

The aim of this paper is to use distributional semantics to explore the AGH and the correlation between linguistic and affective information in abstract words. We present a regression study in which the abstractness ratings of the 417 Italian nouns in the norms by Della Rosa, Catricalà, Vigliocco, and Cappa (2010) are modeled with a set of corpus-based indices representing their affective content and context richness (i.e., context availability). Section 2 describes the distributional indices used as model predictors. Section 3 presents the results of the analysis, which in Section 4 are discussed within the broader issues of embodied cognition and the role of linguistic information in semantic representations.

## 2. Method

### *2.1. Distributional predictors of abstractness*

In our regression analyses, the abstractness ratings for the 417 Italian nouns normed by Della Rosa et al. (2010) are modeled by the four distributional predictors described in this section: an affective score of the target noun, a context affective score estimating the global affective content of the lexical contexts of the target noun, a measure of context richness, and word frequency. The abstractness ratings (ABS) were collected on a scale from 1 (*less abstract*) to 7 (*more abstract*), and then multiplied by 100 to produce a range from 100 to 700. The same norms contain concreteness ratings (CNC) on a scale from 1 (highly abstract) to 7 (highly concrete). For our study, we targeted the abstractness ratings because, according to the analysis in Della Rosa et al. (2010), they seem to be better at capturing differences in the abstract domain, which is our main focus of interest.

#### *2.1.1. Distributional affective score*

We computed the *Distributional Affective Score* (DAS) of the target nouns following the method described in Passaro and Lenci (2016), which computes emotive scores for Italian words using a DSM trained with a few set of seed items associated with emotions. Passaro and Lenci (2016) targeted nouns, verbs, and adjectives, but in the present work we only focus on the former class, because we are interested in modeling abstractness ratings for nouns.

Distributional semantics is grounded on the so-called *Distributional Hypothesis* (Harris, 1954), which states that semantically similar words tend to appear in similar contexts. DSMs represent each target word with a weighted feature vector, where features correspond to the statistical distribution of the target in contexts (Lenci, 2018). In order to account for the role of linguistic contexts to determine the affective content of a target word, we have generalized the basic principle of distributional semantics to emotions, proposing the following *Affective Distributional Hypothesis*:

> *A word* w *is associated with an emotion* e *if it co-occurs in similar contexts of other words associated with* e.

To implement this hypothesis, first we collected a small set of seed words highly associated with one of Plutchik's basic emotions: 60 Italian native speakers of different age groups and levels of education were asked to list, for each of the eight Plutchik's emotions, five nouns strongly associated with a given emotion. After removing all the nouns produced only once by subjects, we computed the distinctiveness of the collected words as their informativeness (i.e., the reciprocal of the number of emotions for which the word was generated), according to Devlin, Gonnerman, Andersen, and Seidenberg (1998). For example, the distinctiveness of the word *amore* "love" is 1/3, given the following hypothetical distribution of its production frequency (F): Joy (F = 2), Trust (F = 5), and Anticipation (F = 4). Finally, we selected only the nouns with a distinctiveness score equal to 1 (i.e., the words produced/evoked by a single emotion). In addition, we expanded this set of seeds with the names of the emotions (e.g., the nouns *gioia* "joy" and *rabbia* "anger") and their synonyms in the Italian MultiWordNet lexicon, WordNet Affect (Strapparava & Valitutti, 2004), and the Treccani Online Dictionary. Globally, we identified 163 affective noun seeds whose distribution is reported in Table 1. A small sample of such nouns is reported in Table 2, and the complete list, in which each seed is associated with its frequency and production frequency, is available in the Supplementary Material.

We then built a DSM by extracting from La Repubblica and itWaC corpora the list of the 30,000 most frequent nouns, verbs, and adjectives and recording their co-occurrences

Table 1
Distribution of the seed nouns

| Emotion | No. of Noun Seeds |
|---|---|
| Joy | 26 |
| Anger | 30 |
| Surprise | 17 |
| Disgust | 21 |
| Fear | 20 |
| Sadness | 22 |
| Trust | 21 |
| Anticipation | 22 |

Table 2
Sample of seed nouns

| Emotion | Nouns |
|---|---|
| Disgust | *terrore* "terror" |
| | *brivido* "chill" |
| | *panico* "panic" |
| Fear | *violenza* "violence" |
| | *odio* "hate" |
| | *collera* "wrath" |
| Sadness | *pianto* "cry" |
| | *amarezza* "bitterness" |
| | *infelicità* "misery" |

within a five-word symmetric window centered on the target word. Co-occurrences were reweighted with Positive Pointwise Mutual Information (PPMI). This is the standard Pointwise Mutual Information, but with negative values raised to 0:

$$\mathrm{PPMI}(x,y) = \max\left(0, \log_2 \frac{p(x,y)}{p(x)p(y)}\right)$$

Following Polajnar and Clark (2014), for each target word we selected the top 240 contexts ranked by PPMI, and then we applied Singular Value Decomposition, reducing the matrix to its top 300 latent dimensions.

Emotions were represented as centroid vectors built from the vectors of the seed nouns in the DSM. For each emotion $e$, we computed a word emotive score $\sigma_e$ by measuring the cosine similarity of the word vector in the DSM with the emotion vectors. This score measures the association of a noun with a given emotion. For instance, the amount of Joy associated with the noun *amore* "love" is estimated with the cosine similarity between the vector of *amore* and the centroid vector of Joy. Table 3 reports the nouns with the highest emotive score with respect to Disgust and Fear, as computed by the DSM.

Finally, the DAS of a word was computed as the sum of its emotive scores:

$$\mathrm{DAS}(x) = \sum_{e \in E} \sigma_e(x)n$$

In the present case, $E$ = {Joy, Anger, Disgust, Fear, Sadness, Trust }. We did not include Anticipation and Surprise because they were the least performing emotions in Passaro and Lenci (2016), probably because of the low reliability of the collected seeds.

DAS is a distributional measure of the global affective content of a word: the higher the DAS of a noun, the higher its emotive load. DAS does not take into account the affective valence, since it includes both positive and negative emotions. This is consistent with the U-shaped relationship between valence and concreteness reported by Vigliocco et al. (2014), with valenced words (either positive or negative) tending to be more abstract. Fig. 1 shows that there is a nonlinear, yet monotonic, relationship between the abstractness ratings collected by Della Rosa et al. (2010) and our distributional affective scores: higher DASes are associated with more abstract meanings, while concrete words concentrate in the lower DAS part of the graph.

The abstractness ratings (ABS) in Della Rosa et al. (2010) have a bimodal distribution, consistently with the view that abstract and concrete entities form two distinct categories. The category threshold (around ABS = 300) is close to the inflection point of the regression curve, showing that the DAS scores exhibit a similar categorical difference between

Table 3
Nouns with top emotive scores with respect to disgust and fear

| Emotion | Nouns | σ |
|---|---|---|
| Disgust | *fetore* "stink" | 0.84 |
| | *escremento* "excrement" | 0.83 |
| | *putrefazione* "rot" | 0.82 |
| | *carogna* "carcass" | 0.74 |
| | *miasma* "miasma" | 0.74 |
| Fear | *disorientamento* "disorientation" | 0.82 |
| | *angoscia* "anguish" | 0.81 |
| | *turbamento* "disruption" | 0.79 |
| | *prostrazione* "prostration" | 0.79 |
| | *inquietudine* "inquietude" | 0.78 |

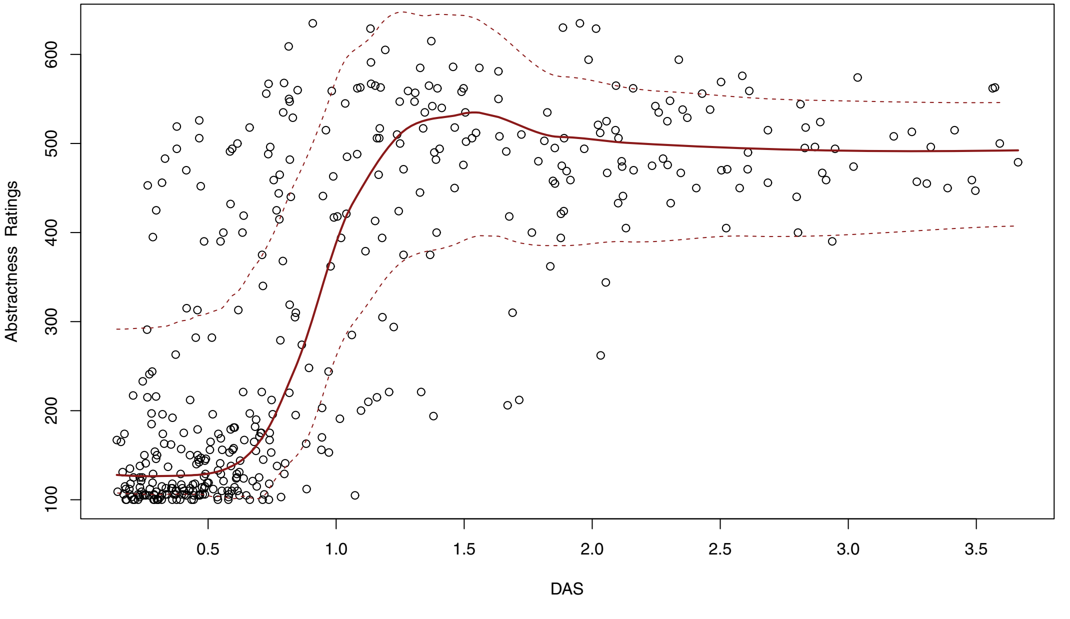


Fig. 1. Scatterplot of the abstractness rating from the Della Rosa et al. (2010) as a function of distributional affectiveness. Superimposed lines represent a nonparametric-regression curve obtained with a loess smoother (solid line), and the smoothed conditional spread (dashed lines).

abstract and concrete words. In fact, as shown in Fig. 2, when these are considered as distinct samples (we categorized as abstract all the words with ABS > 300), the DAS of abstract words is significantly higher than the DAS of concrete ones according to the Wilcoxon test ($W$ = 39.847, $p$ < .001).

### 2.1.2. Context affective score

We computed a *Context Affective Score* (CAS) as the mean of the DAS of the top $k$ context words of target nouns:

$$\mathrm{CAS}(x) = \frac{1}{k}\sum_{i=1}^{k}\mathrm{DAS}(c_i)$$

In this paper, we used the top $k$ contexts ranked according to their PPMI, with $k$ = 100. The contexts are the lexical co-occurrences used to build the DSM described in Section 2.1.1. Other types of context selection criteria and values of $k$ did not bring significant differences in the statistical model. CAS is a distributional measure of the affective content of the contexts of a target noun: the higher the CAS of a noun, the more emotive are the contexts it tends to co-occur with. Fig. 3 indicates that the nonlinear monotonic relationship between abstract ratings and context affectiveness has a similar shape than the one between DAS and abstractness.

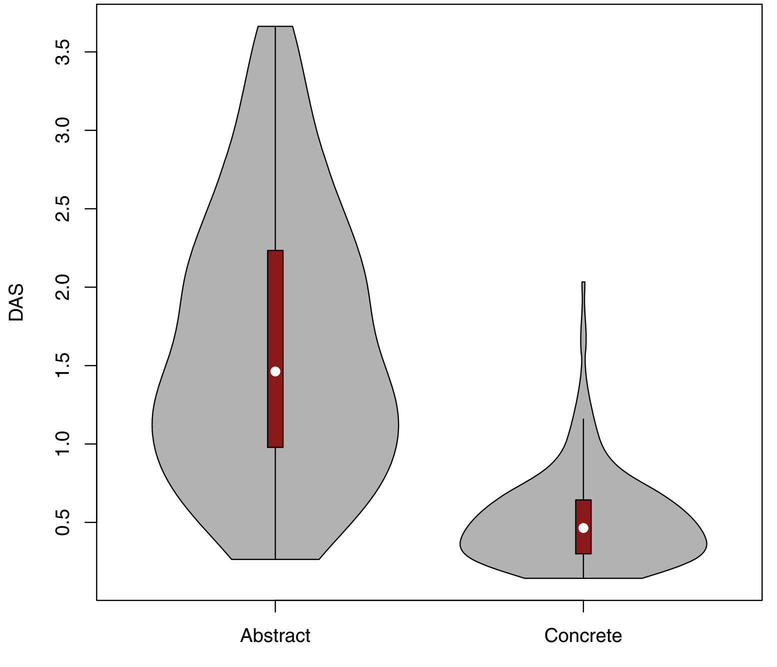


Fig. 2. Violin plots displaying the distribution of DAS values for the abstract (i.e., ABS > 300) and the concrete (i.e., ABS ≤ 300) words. The plots are obtained by combining a kernel density plots with boxplots indicating the median and quartiles with whiskers reaching up to 1.5 times the interquartile range.

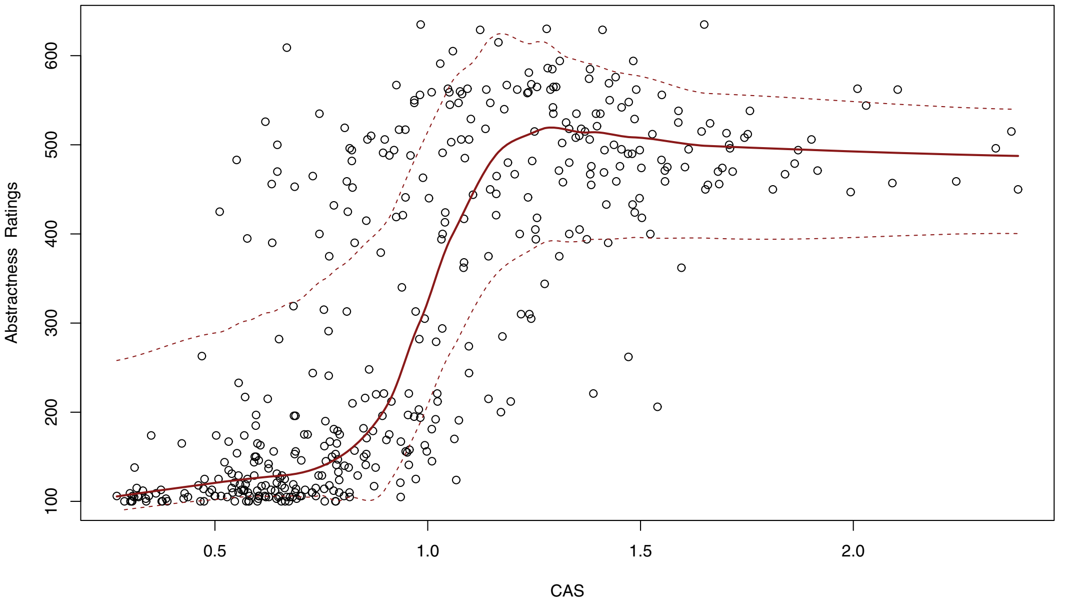


Fig. 3. Scatterplot of the abstractness rating from the Della Rosa et al. (2010) as a function of contextual affectiveness. Superimposed lines represent a nonparametric-regression curve obtained with a loess smoother (solid line), and the smoothed conditional spread (dashed lines).

Figure 4 shows that abstract words have a significantly higher CAS than concrete ones according to the Wilcoxon test ($W$ = 43,460, $p < .001$).

This resemblance between DAS and CAS is further confirmed by the high correlation between these scores ($r = .914$, $p < .001$), as shown by Fig. 5.

This suggests that strongly emotive words tend to co-occur with contexts that have a high affective content.

### *2.1.3. Context richness*

Following Recchia and Jones (2012), we computed an index of *Distributional of Context Richness* (DCR) using the context PMI, which measures the strength of its association with a target noun. The contexts were selected according to the same criteria adopted to compute the CAS values. After ranking the contexts by decreasing values of PPMI, we calculated DCR as the mean of the PPMI scores of the $k$ top contexts of the target noun:

$$\mathrm{DCR}(x) = \frac{1}{k}\sum_{i=1}^{k} \mathrm{PPMI}(x, c_i)$$

Like for CAS, we selected $k$ = 100. DCR is a distributional measure of the context richness (or context availability) of target nouns. As shown by Fig. 6, there is an inverse nonlinear relationship between abstractness and contextual richness, with a marked tendency for more concrete words to be associated with higher DCRs.

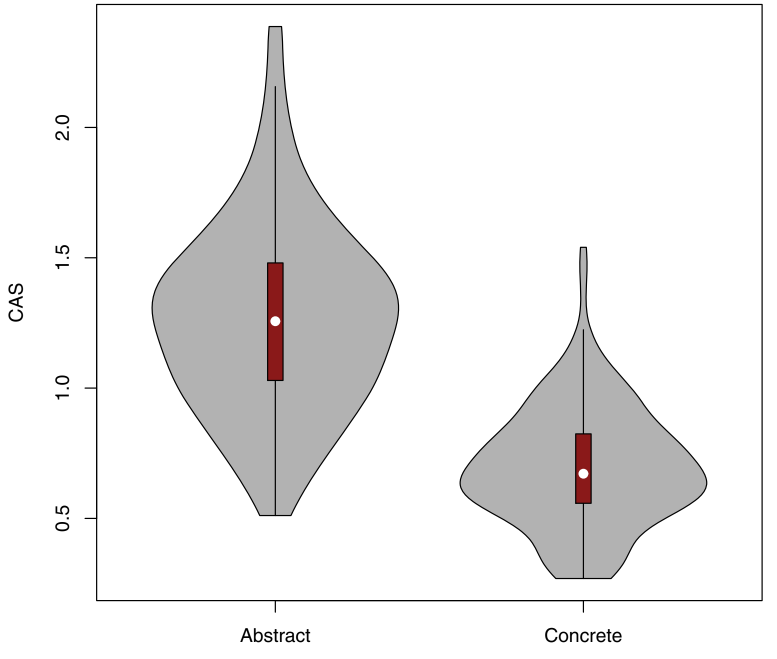


Fig. 4. Violin plots displaying the distribution of CAS values for the abstract (i.e., ABS > 300) and the concrete (i.e., ABS ≤ 300) words. The plots are obtained by combining a kernel density plot with boxplots indicating the median and quartiles with whiskers reaching up to 1.5 times the interquartile range.

Fig. 7 shows that, when treated as distinct samples, concrete words have a significantly higher DCR than abstract ones according to the Wilcoxon test ($W$ = 7,398, $p < .001$).

### 2.1.4. *Word frequency*

In our analysis we also considered the frequency of the stimuli rated by Della Rosa et al. (2010) to assess whether it is able to explain part of the ABS ratings variance. Word frequencies were estimated from a corpus built by concatenating the La Repubblica and itWaC corpora. In order to reduce the skewing of the distribution, the raw counts have been logarithmically transformed to approximate a normal distribution. Figs. 8 and 9 suggest an articulated picture in which abstract words have a higher log word frequency than concrete ones according to the Wilcoxon test ($W$ = 29,934, $p < .001$).

This inverse relation between the logarithm of the word frequency and DCR is confirmed by the high negative correlation between these scores ($r$ = -.784, $p < .001$), as shown by Fig. 10.

## 2.2. *Modeling abstractness with the distributional predictors*

In this analysis, we tested if and to what extent the distributional measures described in Section 2.1 can be used to model the abstractness ratings of the 417 Italian nouns

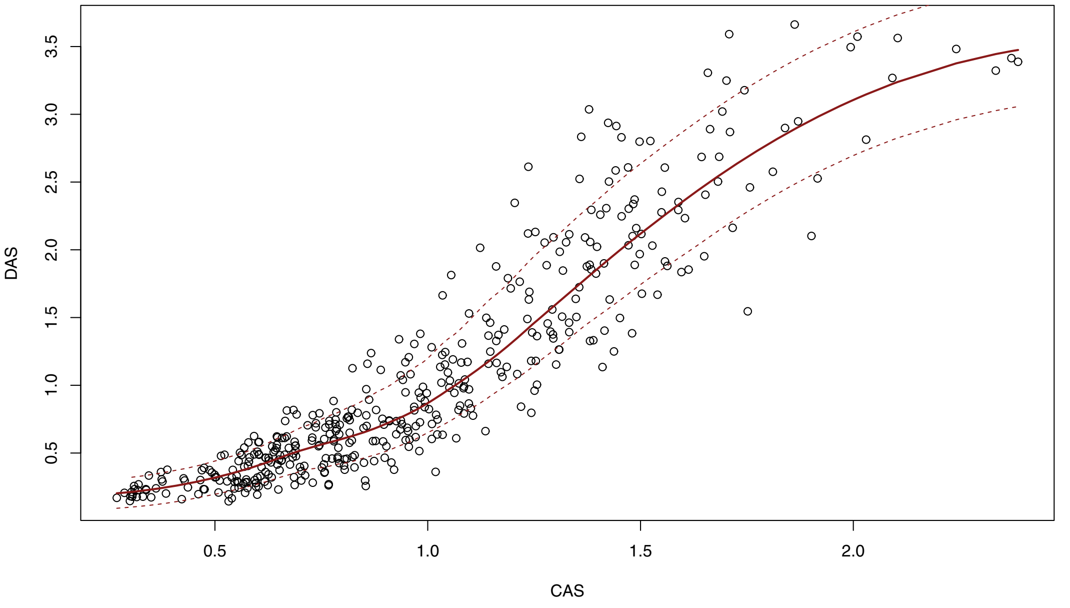


Fig. 5. Scatterplot of the distributional affectiveness as a function of contextual affectiveness. Superimposed lines represent a nonparametric-regression curve obtained with a loess smoother (solid line), and the smoothed conditional spread (dashed lines).

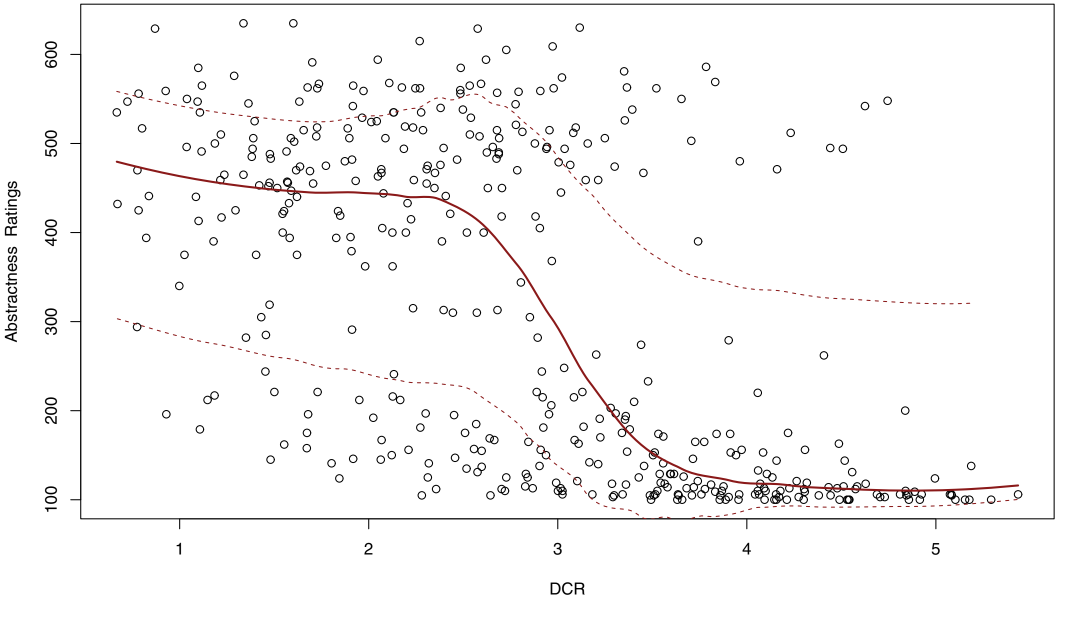


Fig. 6. Scatterplot of the abstractness rating from the Della Rosa et al. (2010) as a function of distributional context richness. Superimposed lines represent a nonparametric-regression curve obtained with a loess smoother (solid line), and the smoothed conditional spread (dashed lines).

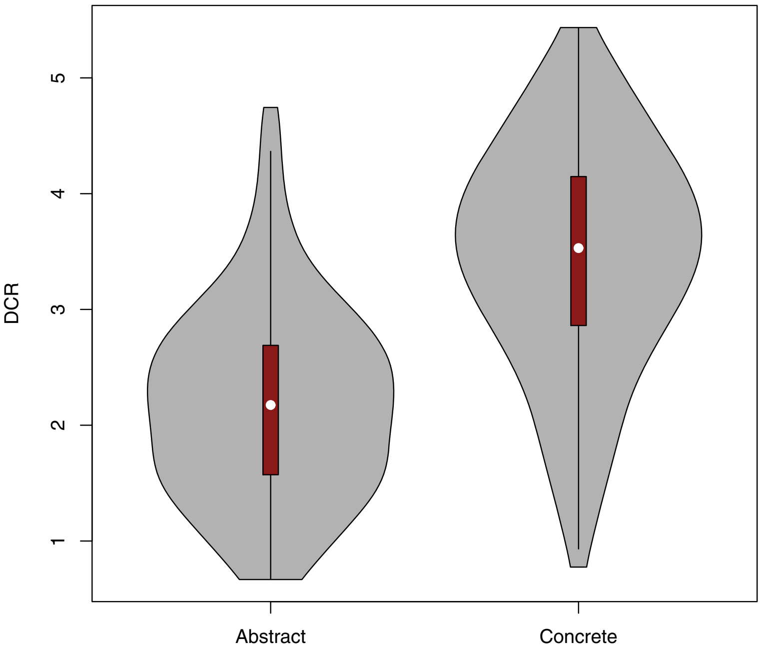


Fig. 7. Violin plots displaying the distribution of DCR values for the abstract (i.e., ABS > 300) and the concrete (i.e., ABS ≤ 300) words. The plots are obtained by combining a kernel density plots with boxplots indicating the median and quartiles with whiskers reaching up to 1.5 times the interquartile range.

normed by Della Rosa et al. (2010). A model including all the predictors described in Section 2.1 would suffer for a potentially harmful level of collinearity ($\kappa$ = 53.624), with large levels of variance inflation factors associated with DAS (*VIF* = 7.006) and CAS (*VIF* = 7.343), and moderate levels of collinearity for the DCR (*VIF* = 4.286) and the log frequency (*VIF* = 3.849). Yet an explorative hierarchical regression analysis suggests that the best performing model is the one including all the predictors ($R^2$ = .67, *adjusted* $R^2$ = .667, $F$ (4, 414) = 209.51, $p$ < .001). Inspection of condition indices and variance proportions reveals that the main sources of collinearity are the relation between CAS and DAS and the relation between the log frequency and DCR. As a consequence, we chose to reduce collinearity by means of principal component analysis (PCA). Accordingly, then, we applied PCA to our affective predictors (i.e., DAS and CAS) and choose to use as a regressor for our analysis only the first principal component, which accounts for 95.72% of the variance. The resulting predictor, affective.PC1, shows the same pattern of the original variables (cf. top scatterplot in Fig. 11). We applied PCA to our frequency-based predictors (i.e., DCR and the log frequency) as well, and we choose to use as regressors both principal components, which are plotted against our target ratings in the middle and in the bottom scatterplots of Fig. 11, respectively. The first component, distributional.PC1, accounts for 88.64% of the variance and is influenced by our two original variables with loadings of opposite sign. The second component, distributional.PC2,

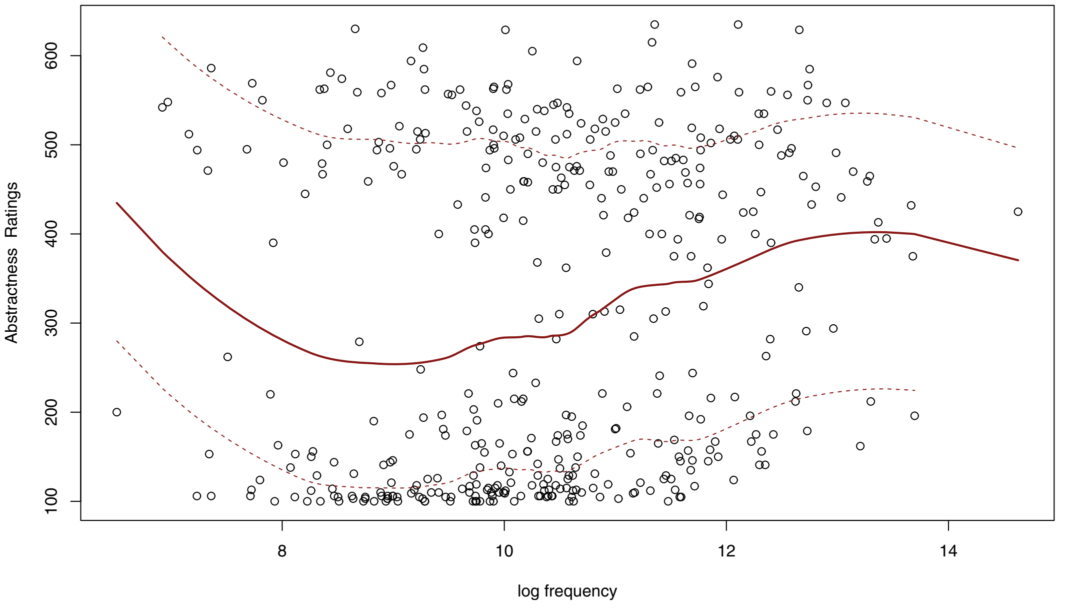


Fig. 8. Scatterplot of the abstractness rating from the Della Rosa et al. (2010) as a function of the logarithm frequency of the rated nouns estimated from a concatenation of the La Repubblica corpus and itWaC. Superimposed lines represent a nonparametric-regression curve obtained with a loess smoother (solid line), and the smoothed conditional spread (dashed lines).

accounts for the remaining 11.36% of the variance and is equally affected by DCR and by the log frequency. Both the condition number ($\kappa = 2.076$) and the variance inflation factors calculated on the data matrix composed by affective.PC1 (*VIF* = 1.636), distributional.PC1 (*VIF* = 1.026), and distributional.PC2 (*VIF* = 1.609) are reassuring.

In our regression analysis, we followed a four-step procedure. We first conducted a hierarchical regression analysis on the linear terms to assess if all our predictors are needed. Nested models were compared by means of F-tests, and the best fitting models ($R^2 = .67$, *adjusted* $R^2 = .668$, $F$ (3, 413) = 279.4, $p < .001$) turned to be the one including distributional.PC1 ($\Delta R^2 = .112$, $F = 140.21$, $p < .001$), distributional.PC2 ($\Delta R^2 = .062$, $F = 77.94$, $p < .001$), and affective.PC1 ($\Delta R^2 = .14$, $F = 174.84$, $p < .001$).[1]

In a second step, we modeled the nonlinear relations between the abstractness ratings and our distributional variables by means of restricted cubic splines (Harrell, 2001). We resorted to the AIC and BIC criteria to identify the optimal number of knots for each independent variable, which turned out to be four knots for affective.PC1 and three knots for distributional.PC1 and distributional.PC2. In the last step, we tested the presence of an interaction between our two predictors, finding evidence in support of the existence of an interaction involving all the nonlinear terms of distributional.PC1 and the linear term of affective.PC1. The overall fit of this model ($R^2 = .746$, *adjusted* $R^2 = .741$, $F$ (7, 409) = 171.24, $p < .001$) suggests that it is able to model our data reasonably well.

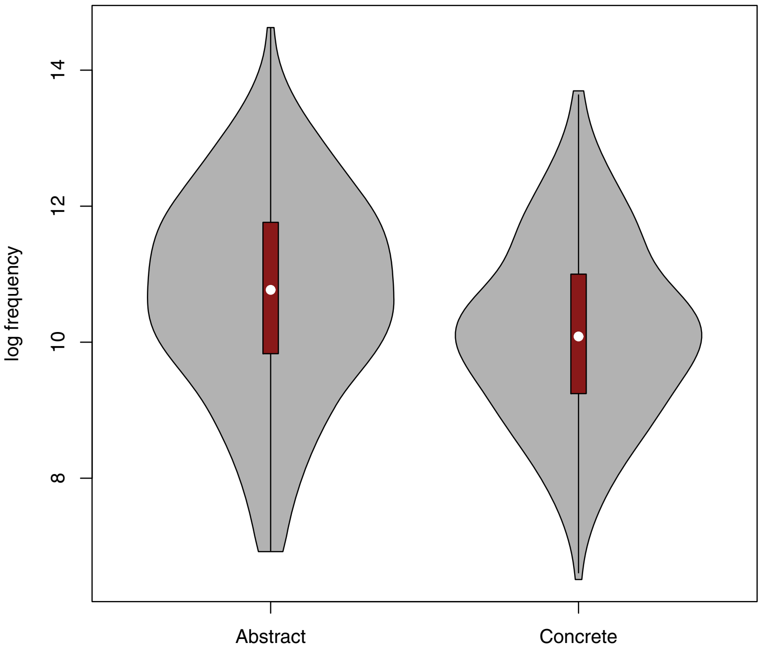


Fig. 9. Violin plots displaying the distribution of log frequencies for the abstract (i.e., ABS > 300) and the concrete (i.e., ABS ≤ 300) words. The plots are obtained by combining a kernel density plots with boxplots indicating the median and quartiles with whiskers reaching up to 1.5 times the interquartile range.

## 3. Result

Having determined our final model, we identified and removed 17 outliers. Such high leverage observations, constituting approximately 4% of our dataset, correspond to those data points whose absolute *dfbetas* exceed the 0.2 threshold (see Baayen, 2008). We then refitted the model obtaining the results that are reported in Table 4.

The removal of these outliers raises the fit of our final model ($R^2$ = .823, *adjusted* $R^2$ = .819, $F$ (9, 390) = 201.93, $p$ < .001), thus suggesting that our predictors can explain the biggest part of the variability shown by the abstractness ratings collected by Della Rosa and colleagues. In order to exclude overfitting, we performed 100,000 bootstrap runs to validate our regression model, in which the difference between the predictions in the training and in the test (a.k.a. "optimism," an estimate of overfitting sometimes) amounted to 0.0069. By taking optimism into consideration, we obtained a corrected $R^2$ of .8165. The low amount of optimism suggests that our model did not overfit the experimental data.

As can be seen from Table 4, in our final model all the predictors are significant, together with the interactions between affective.PC1 and distributional.PC1. Fig. 12 shows the partial effect of distributional.PC2, that is, its effect when the other predictors are held constant. Fig. 13 shows the partial effects of affective.PC1 at five different levels

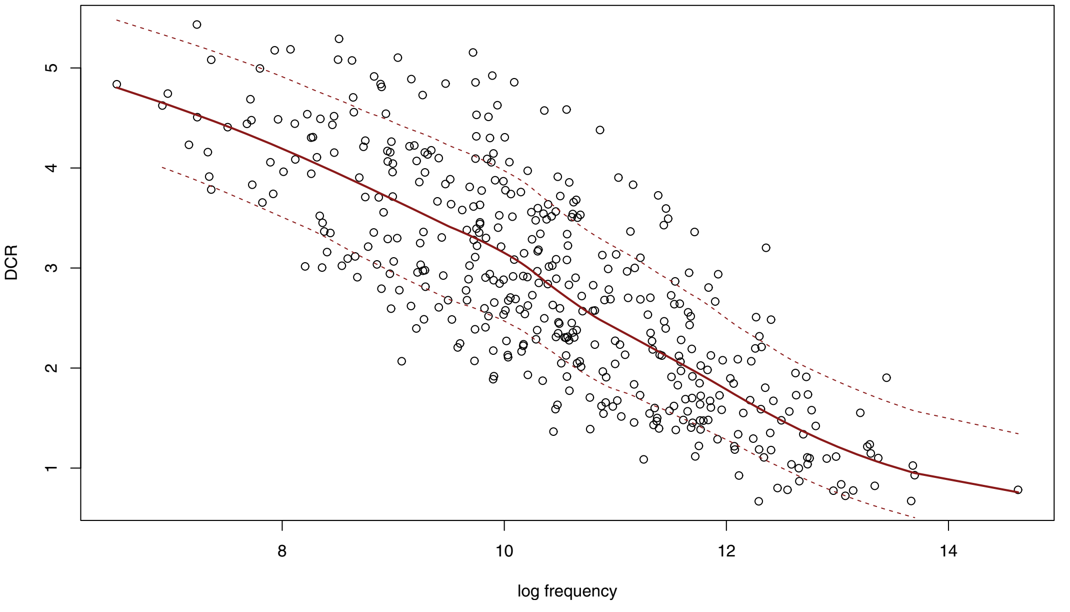


Fig. 10. Scatterplot of DCR as a function of the log word frequency. Superimposed lines represent a non-parametric-regression curve obtained with a loess smoother (solid line), and the smoothed conditional spread (dashed lines).

of distributional.PC1 (top), and of distributional.PC1 at five different levels of affective.PC1 (bottom). In both cases, distributional.PC2 is held constant at its median value.

The interaction between distributional.PC1 and affective.PC1 is particularly interesting because it supports a *multidimensional view* of the abstract versus concrete distinction (Dove, 2016; Troche et al., 2014; Zdrazilova & Pexman, 2013), with a strong interplay between context and affective dimensions. Since affective.PC1 also includes information about the affective content of contexts, from the analysis of the partial effects we can infer that abstract words are less contextually rich than concrete ones, but their most associated contexts have a higher affective content (cf. top rightmost plot in Fig. 13). By looking at the variation in distributional.PC1 (bottom plot in Fig. 13), as well as at the partial effect of distributional.PC2, we can instead observe that the highest values of our distributional principal components for concrete words correspond to very low values of affective content, again suggesting that concrete words tend to co-occur with strongly associated, but affectively poor contexts.

## 4. Discussion

Abstract and concrete nouns do not only differ at the neurocognitive level, but also for their linguistic properties. The distributional analyses on the data from Della Rosa et al. (2010) show that concrete words tend to occur with more associated linguistic contexts,

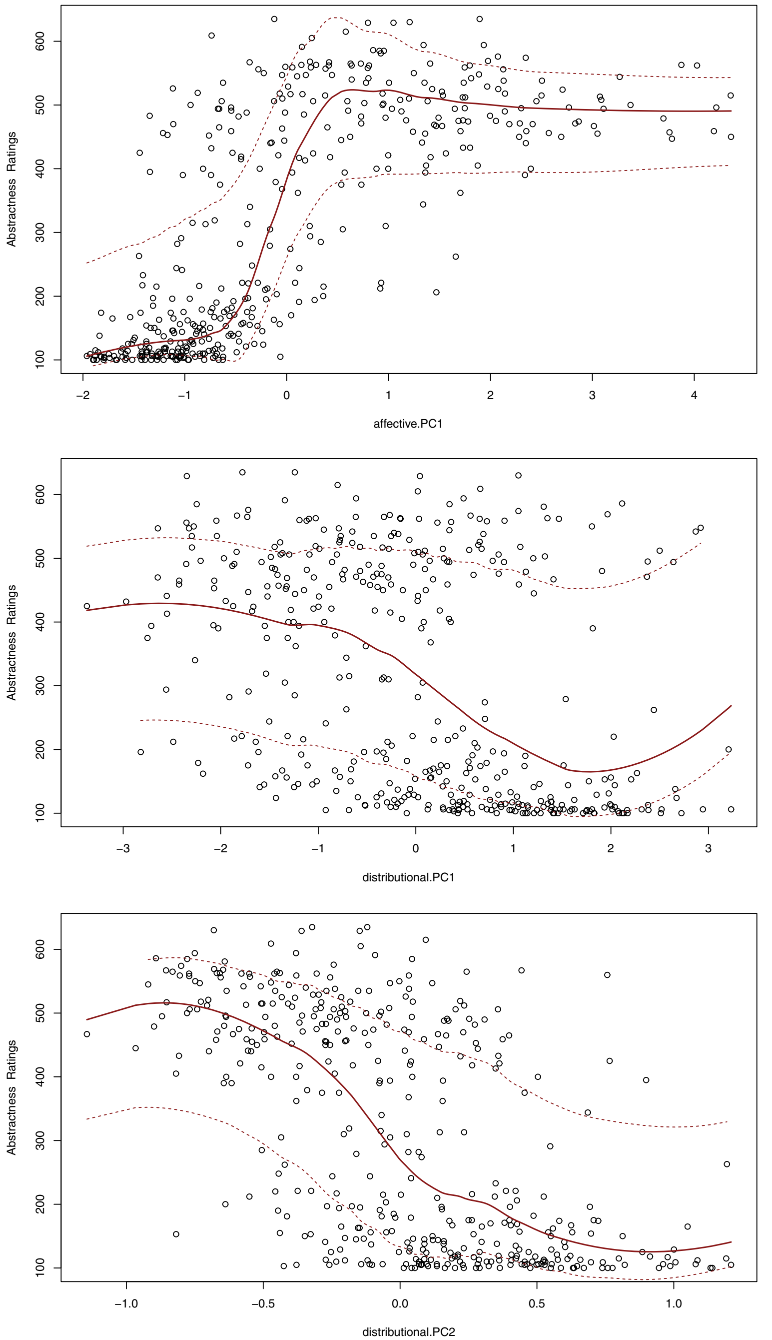


Fig. 11. Scatterplots of the distributional affectiveness as a function of the first Principal Component of the PCA on the distributional affective scores (above) and as a function of the first Principal Component of the PCA on the distributional scores (below). Superimposed lines represent a nonparametric-regression curve obtained with a loess smoother (solid line), and the smoothed conditional spread (dashed lines).

Table 4
Final model for the abstractness ratings collected by Della Rosa et al. (2010)

| | Estimate | Std. Error | *t*-value | *p* |
|---|---|---|---|---|
| Intercept | 24.116 | 27.025 | 0.89 | .373 |
| Affective.PC1 | −63.517 | 25.593 | −2.48 | .0135 |
| Affective.PC1' | 1293.893 | 137.747 | 9.39 | <.0001 |
| Affective.PC1'' | −2832.53 | 279.785 | −10.12 | <.0001 |
| Distributional.PC1 | −84.444 | 7.11 | −11.88 | <.0001 |
| Distributional.PC1' | 53.055 | 8.682 | 6.11 | <.0001 |
| Distributional.PC2 | −143.874 | 24.221 | −5.94 | <.0001 |
| Distributional.PC2' | 74.799 | 25.768 | 2.9 | .0039 |
| Affective.PC1 × distributional.PC1 | 30.435 | 6.721 | 4.53 | <.0001 |
| Affective.PC1 × distributional.PC1' | −21.179 | 7.304 | −2.9 | .0040 |

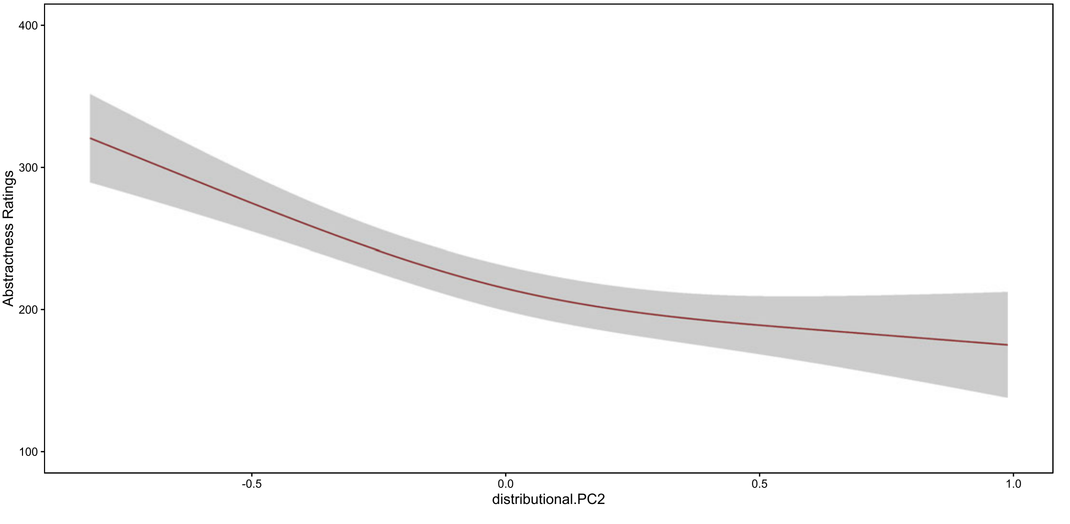


Fig. 12. Partial effect of distributional.PC2 holding the other two predictors constant. A 95% confidence interval is drawn around the estimated effect.

whose association strength is estimated with PPMI. Conversely, abstract words have more affective content and tend to co-occur with contexts with higher emotive value, according to statistical indices estimated in terms of distributional similarity with a restricted number of seed words strongly associated with a set of basic emotions. The first result brings direct support to the Context Availability model: Concrete words have stronger and richer contextual associations than abstract ones. The second result has instead much more complex consequences on the current debate on the affective embodiment of abstract words.

Kousta et al. (2011) have reported behavioral evidence that abstract words are more emotionally loaded than concrete ones, irrespectively of their valence, thereby gaining a processing advantage, when other psycholinguistic variables are controlled. This is considered to support what we have referred to as the *Affective Grounding Hypothesis*,

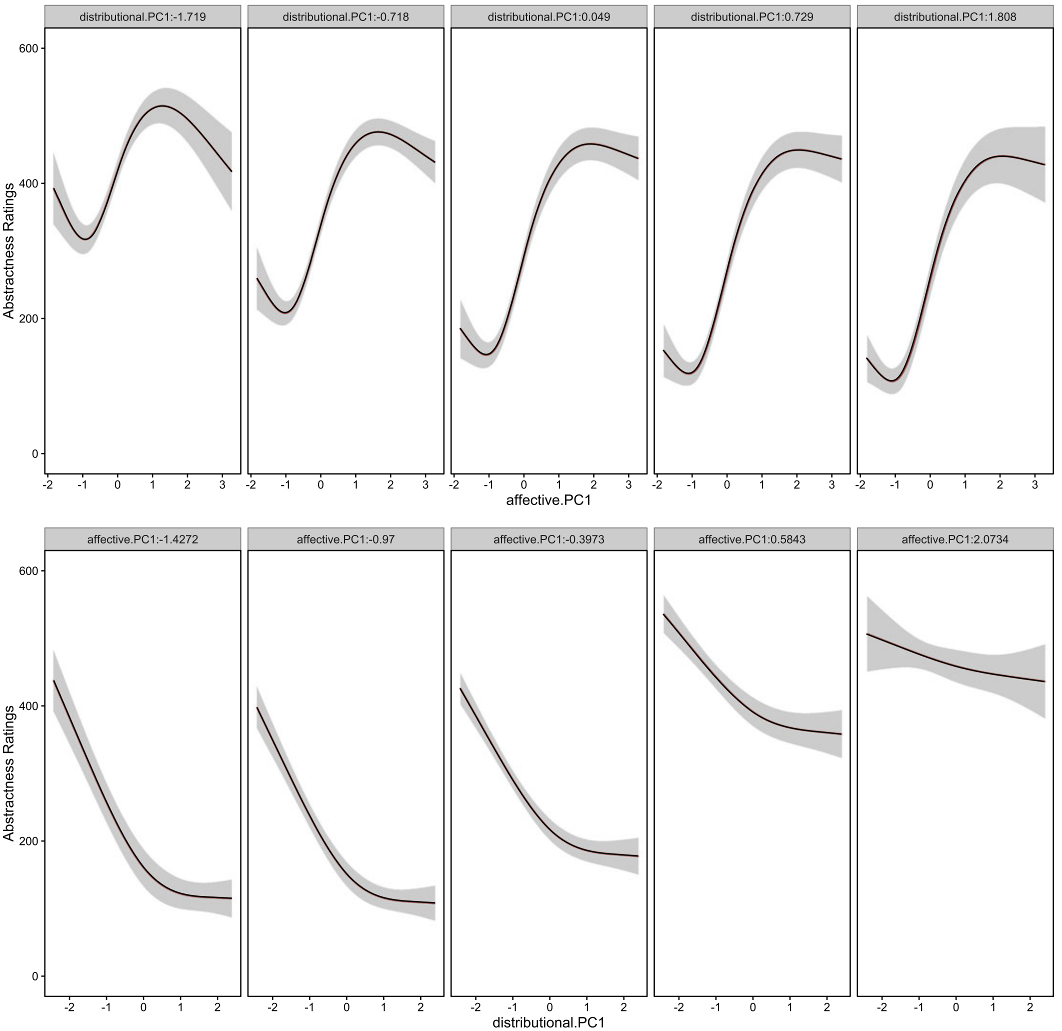


Fig. 13. Effect display for the interaction of distributional.PC1 and affective.PC1 in the final model. A 95% confidence interval is drawn around the estimated effect.

claiming that affective information provides the experiential grounding for abstract words. In our study, we have shown that the abstract nouns in Della Rosa et al. (2010) have indeed significantly higher emotive scores than concrete ones, and that such scores can be used to model abstractness ratings. On one hand, these results represent additional and complementary evidence to the one by Kousta et al. (2011). On the other hand, the main element of novelty of the present work is that, differently from Kousta et al. (2011), our emotive scores are derived from the statistical distribution of words in linguistic contexts.

The strong correlation between language and emotion, which is also the basis of the Affective Distributional Hypothesis, providing the theoretical foundation of the affective scores used in this study, is fully consistent with the idea that experiential and linguistic data are *interdependent* and one can be bootstrapped from the other (Andrews et al., 2014). The *Symbol Interdependency Hypothesis* by Louwerse (2008, 2011) claims that language encodes relations in the world, including embodied ones. The results we have presented here indeed support the possible reconcilement between distributional and embodied models of meanings.

However, Vigliocco et al. (2014: 1774) claim that the behavioral and neuroimaging evidence showing the key role of emotions for abstract words "argue against an exclusive (or even primary) role of linguistic information in the representation of abstract knowledge." Our distributional analysis instead suggests that this evidence might not suffice to downgrade the role of linguistic information. In fact, the *strong affective content of abstract words might itself be a consequence of their linguistic distribution*. We could even speculate that the affective richness of abstract words is a further proof of their strong (albeit obviously not exclusive) linguistic nature: If language brings affective associations, the high dependence of abstracts from linguistic information might produce the stronger emotive load for such words. In summary, we believe that the current evidence about the role of emotions with abstract words cannot be taken as a strong support for their generalized affective embodiment.

Embodied multiple representation views of semantic representations (Scorolli et al., 2011), like the one by Kousta et al. (2009), assume that all concepts, both concrete and abstract ones, contain experiential (i.e., embodied) and linguistic information, while they differ for the relative salience of these types of information, and also for the kind of experiential information. Lacking sensorimotor grounding, affective information is for Kousta et al. (2009, 2011) the cornerstone of the embodiment for abstract words. What if such affective information is itself linguistically derived (at least in a certain amount of cases)? We should probably countenance that some abstract concepts may indeed lack any type of experiential grounding, even an affective one, and being purely linguistically encoded, with their emotion actually an *indirect* byproduct of co-occurrence statistics. However, this claim entails neither that the emotional connotations of abstract words can *only* be inferred from text (e.g., at least for the early acquired abstract concepts the emotional connotations could be acquired by recognizing emotional states in others), nor that distributional information is more important for abstract than concrete words.

Meteyard et al. (2012) have classified current theories of semantic representations along a cline of embodiment, depending on how they describe conceptual knowledge (hence on the basis of how the different theories see concepts). The distributional analyses we have presented suggest that such a *cline of embodiment* might also exist at the level of conceptual representations themselves, with *strongly embodied concepts*, *weakly* or *indirectly embodied concepts*, up to possibly *fully symbolic* concepts. This means that concepts that are fully embodied either at the sensorimotor or at the affective level would live side-by-side with weakly embodied concepts, or concepts only indirectly embodied via their linguistic associations with other embodied words. As Scorolli et al. (2011) argue, the embodied nature of concepts might be crucially related to their *mode of acquisition*. Concepts acquired via the direct acquaintance with their referents would produce more strongly embodied representations, while concepts, like abstract ones but not only them, that are acquired primarily via language would result in weakly or indirectly embodied representations.

The cline of embodiment is obviously associated with, but also independent from, the concrete versus abstract opposition. Many concrete words are acquired only through language exposure, thereby being indirectly embodied: We can have the concept of *aardvark* as a small pig-like mammal with a long nose, without having had any direct experience of this animal (cf. the difference between *inferential* and *referential competence* of word meaning by Marconi, 1997). Congenital blind people acquire color terms and the color of objects via language. Indeed, behavioral evidence suggests that this mode of acquisition may result in significant differences in semantic representations (Connolly, Gleitman, & Thompson-Schill, 2007; Lenci, Baroni, Cazzolli, & Marotta, 2013). The weak or indirect embodiment would instead be dominant for abstract words. Some abstract words, for instance emotion words, might also be strongly embodied, but several abstract words, perhaps most of them, might be just weakly or indirectly embodied, via linguistic associations. This form of representational pluralism is consistent with the role of language as a cognitive scaffolding (Clark, 2006) that allows our semantic representations to be projected besides the proximal space of our direct sensorimotor or affective experiences.

## Note

1. The addition of the second affective Principal Component did not result in an improvement of the fitting of our model ($\Delta R^2$ = .0005. $F$ = 0.61, $p$ = .435)

## References

Andrews, M., Frank, S. L., & Vigliocco, G. (2014). Reconciling embodied and distributional accounts of meaning in language. *Topics in Cognitive Science*, *6*(3), 359–370.

Andrews, M., Vigliocco, G., & Vinson, D. P. (2009). Integrating experiential and distributional data to learn semantic representatedions. *Psychological Review*, *116*(3), 463–498.

Baayen, R. H. (2008). *Analyzing linguistic data. A Practical Introduction to Statistics Using R*. Cambridge, UK: Cambridge University Press.

Barsalou, L. W., Santos, A., Simmons, K. W., & Wilson, C. D. (2008). Language and simulations in conceptual processing. In M. De Vega, A. M. Glenberg, & A. C. Graesser (Eds.), *Symbols, embodiment and meaning* (pp. 245–284). Oxford, UK: Oxford University Press. http://dx.doi.org/10.1093/acprof:oso/9780199217274.003.0013 Barsalou.

Bestgen, Y., & Vincze, N. (2012). Checking and bootstrapping lexical norms by means of word similarity indexes. *Behavior Research Methods*, *44*(4), 998–1006.

Binder, J. R., Desai, R. H., Graves, W. W., & Conant, L. L. (2009). Where is the semantic system? A critical review and meta-analysis of 120 functional neuroimaging studies. *Cerebral Cortex*, *19*(12), 2767–2796.

Binder, J. R., Westbury, C. F., McKiernan, K. A., Possing, E. T., & Medler, D. A. (2005). Distinct brain systems for processing concrete and abstract concepts. *Journal of Cognitive Neuroscience*, *17*(6), 1–13.

Borghi, A. M., & Binkofski, F. (2014). *Words as Social Tools: An Embodied View on Abstract Concepts*. New York, NY: Springer.

Borghi, A. M., & Cimatti, F. (2009). Words as tools and the problem of abstract words meanings. In N. Taatgen & van Rijn H. (Eds.), *Proceedings of the 31st Annual Conference of the Cognitive Science Society* (pp. 2304–2309). Amsterdam: Cognitive Science Society.

Bradley, M. M., & Lang, P. J. (1999). Affective Norms for English Words (ANEW): Instruction Manual and Affective Ratings. Technical Report C-1, The Center for Research in Psychophysiology, University of Florida.

Clark, A. (2006). Language, embodiment, and the cognitive niche. *Trends in Cognitive Sciences*, *10*(8), 370–374.

Connolly, A. C., Gleitman, L. R., & Thompson-Schill, S. L. (2007). Effect of congenital blindness on the semantic representation of some everyday concepts. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(20), 8241–8246.

Crutch, S. J., Connell, S., & Warrington, E. K. (2009). The different representational frameworks underpinning abstract and concrete knowledge: Evidence from odd-one-out judgements. *The Quarterly Journal of Experimental Psychology*, *62*(7), 1377–1390.

Crutch, S. J., & Warrington, E. K. (2005). Abstract and concrete concepts have structurally different representational frameworks. *Brain*, *128*(3), 615–627.

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.

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.

Devlin, J. T., Gonnerman, L. M., Andersen, E. S., & Seidenberg, M. S. (1998). Category-specific semantic deficits in focal and widespread brain damage: A computational account. *Journal of cognitive Neuroscience*, *10*(1), 77–94.

Dove, G. (2009). Beyond perceptual symbols: A call for representational pluralism. *Cognition*, *110*(3), 412–431.

Dove, G. (2014). Thinking in words: Language as an embodied medium of thought. *Topics in Cognitive Science*, *6*(3), 371–389.

Dove, G. (2016). Three symbol ungrounding problems: Abstract concepts and the future of embodied cognition. *Psychonomic Bulletin & Review*, *23*(4), 1109–1121.

Harrell, F. E. (2001). *Regression modeling strategies with applications to linear models, logistic regression and survival analysis*. New York, NY: Springer.

Harris, Z. S. (1954). Distributional structure. *Word*, *10*(2–3), 146–162.

Hill, F., Korhonen, A., & Bentz, C. (2014). A quantitative empirical analysis of the abstract/concrete distinction. *Cognitive Science*, *38*(1), 162–177.

Johns, B. T., & Jones, M. N. (2012). Perceptual inference through global lexical similarity. *Topics in Cognitive Science*, *4*(1), 103–120. Retrieved from papers3://publication/doi/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.

Kousta, S. T., Vinson, D. P., & Vigliocco, G. (2009). Emotion words, regardless of polarity, have a processing advantage over neutral words. *Cognition*, *112*(3), 473–481.

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*(4), 1218–1233.

Louwerse, M. M. (2008). Embodied relations are encoded in language. *Psychonomic Bulletin & Review*, *15*(4), 838–844.

Louwerse, M. M. (2011). Symbol interdependency in symbolic and embodied cognition. *Topics in Cognitive Science*, *3*(2), 273–302.

Marconi, D. (1997). *Lexical competence*. Cambridge, MA: MIT Press.

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.

Paivio, A. (1991). Dual coding theory: Retrospect and current status. *Canadian Journal of Psychology*, *45*(3), 255–287.

Paivio, A. (2007). *The mind and its evolution: A dual coding theoretical approach*. Mahwah, NJ: Lawrence Erlbaum.

Passaro, L. C., & Lenci, A. (2016). Evaluating context selection strategies to build emotive vector space models. In: Nicoletta Calzolari et al. (Eds.), *Proceedings of the 10th International Conference on Language Resources and Evaluation* (pp. 2185–2191). Paris: LREC.

Plutchik, R. (1994). *The Psychology and Biology of Emotion*. New York, NY: Harper Collins.

Polajnar, T., & Clark, S. (2014). Improving distributional semantic vectors through context selection and normalisation. In: Daniel Marcu et al. (Eds.) *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics* (pp. 230–238). Baltimore, MD: EACL.

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.

Recchia, G., & Louwerse, M. M. (2015). Reproducing affective norms with lexical co-occurrence statistics: Predicting valence, arousal, and dominance. *The Quarterly Journal of Experimental Psychology*, *68*(8), 1584–1598.

Riordan, B., & Jones, M. N. (2011). Redundancy in perceptual and linguistic experience: Comparing feature-based and distributional models of semantic representation. *Topics in Cognitive Science*, *3*(2), 303–345.

Schwanenflugel, P. (1991). Why are abstract concepts hard to understand? In P. Schwanenflugel (Ed.), *The psychology of word meanings* (pp. 223–250). Hillsdale, NJ: Lawrence Erlbaum.

Scorolli, C., Binkofski, F., Buccino, G., Nicoletti, R., Riggio, L., & Borghi, A. M. (2011). Abstract and concrete sentences, embodiment, and languages. *Frontiers in Psychology*, *2*, 1–11. https://doi.org/10.3389/fpsyg.2011.00227.

Strapparava, C., & Valitutti, A. (2004). WordNet-affect: An affective extension of WordNet. In Nicoletta Calzolari et al. (Eds.), *Proceedings of the 4th International Conference on Language Resources and Evaluation* (pp. 1083–1086). Paris: LREC.

Troche, J., Crutch, S. J., & Reilly, J. (2014). Clustering, hierarchical organization, and the topography of abstract and concrete nouns. *Frontiers in Psychology*, *5*, 360. https://doi.org/10.3389/fpsyg.2014.00360.

Vigliocco, G., Kousta, S. T., Della Rosa, P. A., Vinson, D. P., Tettamanti, M., Devlin, J. T., & Cappa, S. F. (2014). The neural representation of abstract words: The role of emotion. *Cerebral Cortex*, *24*(7), 1767–1777.

Vigliocco, G., Kousta, S. T., Vinson, D. P., Andrews, M., Del Campo, E., et al. (2013). The representation of abstract words: What matters? Reply to Paivio's (2013) comment on Kousta et al. (2011). *Journal of Experimental Psychology: General*, *142*(1), 288–291.

Vigliocco, G., Meteyard, L., Andrews, M., & Kousta, S. T. (2009). Toward a theory of semantic representation. *Language and Cognition*, *1*(2), 219–247.

Vinson, D. P., Ponari, M., & Vigliocco, G. (2014). How does emotional content affect lexical processing? *Cognition & Emotion*, *28*(4), 737–746.

Wang, J., Conder, J. A., Blitzer, D. N., & Shinkareva, S. V. (2010). Neural representation of abstract and concrete concepts: A meta-analysis of neuroimaging studies. *Human Brain Mapping*, *31*(10), 1459–1468.

Zdrazilova, L., & Pexman, P. M. (2013). Grasping the invisible: Semantic processing of abstract words. *Psychonomic Bulletin & Review*, *20*(6), 1312–1318.

**Supporting Information**

Additional Supporting Information may be found online in the supporting information tab for this article:

**Data S1.** List of the seed nouns used for the construction of the centroid vectors representing the emotions.