A Neurobiologically Motivated Analysis of Distributional Semantic Models

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Abstract

The pervasive use of distributional semantic models or word embeddings in a variety of research fields is due to their remarkable ability to represent the meanings of words for both practical application and cognitive modeling. However, little has been known about what kind of information is encoded in text-based word vectors. This lack of understanding is particularly problematic when word vectors are regarded as a model of semantic representation for abstract concepts. This paper attempts to reveal the internal information of distributional word vectors by the analysis using Binder et al.'s (2016) brain-based vectors, explicitly structured conceptual representations based on neurobiologically motivated attributes. In the analysis, the mapping from text-based vectors to brain-based vectors is trained and prediction performance is evaluated by comparing the estimated and original brain-based vectors. The analysis demonstrates that social and cognitive information is better encoded in text-based word vectors, but emotional information is not. This result is discussed in terms of embodied theories for abstract concepts.

Keywords: Distributional semantic models; Word vectors; Brain-based representation; Embodied cognition; Emotional and social information; Abstract concepts

Introduction

One of the most important advances in the study of semantic processing is the development of distributional semantic models for representing word meanings. In the distributional semantic model, words are represented as high-dimensional vectors, which can be learned from the distributional statistics of word occurrence in large collections of text. Any words that occur in the corpus can be learned regardless of their part-of-speech class, abstractness, novelty and familiarity. This is an important advantage of text-based distributional semantic models over other spatial models of semantic representation such as feature-based vectors (Andrews, Vigliocco, & Vinson, 2009) and image-based vectors (Silberer, Ferrari, & LaPata, 2017).

Word vectors have been employed in a variety of research fields and many successful results have been obtained. In the field of natural language processing (NLP), deep learning has recently been applied to a number of NLP tasks such as machine translation and automatic summarization, and achieved the impressive performance as compared to the traditional statistical methods. One of the reasons for the successful results is the use of word vectors as semantic representations for the input and output of recurrent neural networks (Goldberg, 2017). Research on cognitive science also benefits greatly from distributional semantic models (Jones, Willits, & Dennis, 2015). Word vectors have been demonstrated to explain a number of cognitive phenomena relevant to semantic memory or mental lexicon, such as word association (Jones, Gruenenfelder, & Recchia, 2017; Utsumi, 2015), semantic priming (Mandra, Keuleers, & Brysbaert, 2017), semantic transparency (Marelli & Baroni, 2015) and conceptual combination (Vecchi, Marelli, Zamparelli, & Baroni, 2017). Furthermore, recent brain imaging studies have demonstrated that distributional word vectors have a powerful ability to predict the neural brain activity evoked by lexical processing (Mitchell et al., 2008; Huth, de Heer, Griffiths, Theunissen, & Gallant, 2016; Güçlü & van Gerven, 2015). These voxel-wise modeling by word vectors is expected to open a door for brain-machine interfaces.

Despite the fact that successful results are obtained in many research fields, little has been known about what kind of information or knowledge is encoded in word vectors. This lack of understanding makes distributional semantic models unable to predict human language behavior and performance at the same level of detail and precision of other cognitive models. It also limits further improvements on the practical performance of word vectors for many NLP tasks.

In this paper, therefore, we attempt to reveal the internal information (or knowledge) encoded in text-based word vectors generated by distributional semantic models. Our approach to this problem is to simulate a brain-based semantic representation proposed by Binder et al. (2016) using text-based vectors. This semantic representation comprises 65 attributes based entirely on functional divisions in the human brain. Each word is represented as a 65-dimensional vector and each dimension represents the salience of the corresponding attribute, namely the degree to which the concept referred to by that word is related to that attribute. Because these attributes are based on not only sensorimotor experiences but also affective, social, and cognitive experiences, we can analyze distributional word vectors considering a wide variety of information. In the analysis, we trained the mapping from the text-based vectors to the brain-based vectors, by which brain-based vectors of untrained words are predicted. Prediction accuracy was measured for each attribute and word using a leave-one-out cross-validation.

The secondary purpose of this paper is to discuss the relationship between the embodied theory for abstract words and distributional semantic models from the results of the analysis. Recently it has been accepted that language or linguistic experience is much more important for abstract concepts than for concrete concepts, because abstract words are unlikely to be grounded in perceptual and sensorimotor experiences, in which concrete concepts are grounded (Borgh et al., 2017) A number of approaches have been proposed to explain the role of language as a simple shortcut (Balsalou, Santos, Simmons, & Wilson, 2008) or indirect grounding in perceptual or sensorimotor experiences (Louwerse, 2011; Dove, 2014), and the need for other information such as emotional (Kousta, Vigliocco, Vinson, Andrews, & Del Campo, 2011) and social information (Borgh & Binkofski, 2014). The analysis of in-
Table 1: Example of words represented as brain-based vectors

| Category  | Word       | Category  | Word       |
|-----------|------------|-----------|------------|
| plant     | apricot, rose, tree | human     | actor, girl, parent |
| vehicle   | car, subway, boat | social action | celebrate, help |
| place     | airport, lake, lab | visual property | black, new, dark |

Table 2: 65 attributes used in brain-based vectors

| Domain     | Attributes                              |
|------------|-----------------------------------------|
| Vision     | Vision, Bright, Dark, Color, Pattern, Large, Small, Motion, Biomotion, Fast, Slow, Shape, Complexity, Face, Body |
| Somatic    | Touch, Temperature, Texture, Weight, Pain |
| Audition   | Audition, Loud, Low, High, Sound, Music, Speech |
| Gustation  | Taste                                   |
| Olfaction  | Smell                                   |
| Motor      | Head, UpperLimb, LowerLimb, Practice    |
| Spatial    | Landmark, Path, Scene, Near, Toward, Away, Number |
| Temporal   | Time, Duration, Long, Short             |
| Causal     | Caused, Consequential                   |
| Social     | Social, Human, Communication, Self      |
| Cognition  | Cognition                               |
| Emotion    | Benefit, Harm, Pleasant, Unpleasant, Happy, Sad, Angry, Disgusted, Fearful, Surprised |
| Drive      | Drive, Needs                            |
| Attention  | Attention, Arousal                      |

formation encoded in text-based word vectors, which can be regarded as realizations of linguistic experiences, is expected to provide some implications for recent embodied approaches to abstract concepts.

Method

In order to examine what kind of information is encoded in distributional word vectors, we evaluated how accurately they can simulate Binder et al.’s (2016) brain-based vectors. The simulation was performed by training the mapping from text-based vectors to brain-based vectors and applying the trained mapping to the text-based vectors of untrained words. Prediction performance was evaluated by comparing the estimated brain-based vectors with the original brain-based vectors.

Brain-based Vectors

As mentioned above, we used Binder et al.’s (2016) brain-based componential representation of words as a gold standard. They provided 65-dimensional vectors of 535 words comprising 434 nouns, 62 verbs and 39 adjectives, some of which are listed in Table 1. The dimensions correspond to neurobiologically plausible attributes whose neural correlates have been well described. Table 2 lists 65 attributes (and 14 domains) used in Binder et al.’s (2016) brain-based vectors.

Word Vectors

In order to ensure the generality of the findings obtained through the analysis, we constructed six semantic spaces, which were obtained from the combinations of three distributional semantic models (SGNS, GloVe, PPMI) and two corpora (COCA and Wikipedia). As a distributional semantic model, we used three representative models, namely skip-gram with negative sampling (SGNS; Mikolov, Chen, Corrado, & Dean, 2013), GloVe (Pennington, Socher, & Manning, 2015) and positive pointwise mutual information (PPMI) with SVD (Bullinaria & Levy, 2007). SGNS and GloVe are prediction-based models that train word vectors by predicting context words on either side of a target word, while PPMI is a counting-based model that trains word vectors by counting and weighting word occurrences. We set a vector dimension $d = 300$ and a window size $w = 10$ for all semantic spaces.

Two corpora used in the analysis were English Wikipedia dump of enwiki-20160601 (Wiki) and Corpus of Contemporary American English (COCA). The Wiki and COCA corpora include 1.89G and 0.56G word tokens, respectively. We built a vocabulary from frequent words that occur 50 times or more in Wiki corpus \(^1\) or 30 times of more in COCA corpus. As a result, the vocabulary of Wiki and COCA contained 291,769 words and 108,230 words, respectively. These two corpora differ in that Wiki is a raw text corpus that is untagged and unlemmatized, while COCA is a fully tagged and lemmatized corpus. For Wiki corpus, raw texts were extracted from the dump files using WikipediaExtractor.py\(^2\) and no other preprocessing, such as lemmatization, was applied.

Training the Mapping from Text-based Vectors to Brain-based Vectors

We used two learning methods, namely linear transformation (LT) and multi-layer perceptron (MLP). LT trains a mapping matrix $M$ such that $B = WM$ where $B$ is the matrix with brain-based word vectors as rows and $W$ is a matrix with text-based word vectors as rows. MLP trains a neural network with one hidden layer comprising 150 sigmoid units and a linear output layer. In both methods, the mapping was trained by minimizing the mean squared error, and gradient descent with AdaGrad was used as an optimization method.

Estimation of brain-based vectors from text-based vectors was performed by a leave-one-out cross validation procedure. For each of the 535 words, we trained the mapping between brain-based and text-based vectors of the remaining 534 words and estimated a brain-based vector for the target word using the trained mapping. By repeating this procedure for all words as a target, we obtained $B$ with estimated brain-based vectors as rows.

Performance Measure

Prediction performance of the estimated vectors was measured using Spearman’s rank correlation $\rho$ between the estimated brain-based matrix $B$ and the original matrix $B$. \(^3\) We

\(^1\)Out of 535 words for brain-based vectors, only one word “joviality” was not selected as frequent words for Wiki corpus. Hence, we added it to the vocabulary for Wiki corpus.

\(^2\)http://media2lab.di.unipi.it/wiki/Wikipedia_Extractor

\(^3\)Mean squared error can also be a measure for prediction performance. However, we are interested in the similarity of order, rather than of absolute value, between the original and estimated vectors, and thus we used rank correlations in this paper.
performed two analyses: column-wise and row-wise matrix correlation. The column-wise matrix correlation indicates the estimation accuracy for each attribute, while the row-wise correlation indicates the accuracy for each word.

In addition, we performed a k-means clustering analysis in which 535 words were grouped into 28 clusters using the estimated brain-based vectors, and the obtained clustering result was compared with the 28-cluster solution computed using the original brain-based vectors by Binder et al. (2016). The clustering result was evaluated for each gold-standard cluster by the normalized entropy $H(G_i)$ as follows:

$$H(G_i) = \frac{-1}{\log|G_i|} \sum_{j=1}^{28} \frac{n_{ij}}{|G_i|} \log \frac{n_{ij}}{|G_i|}$$  \hspace{1cm} (1)

where $G_i$ is the $i$-th gold-standard cluster and $n_{ij}$ denotes the number of words in $G_i$ that were assigned to the $j$-th estimated cluster. The normalized entropy represents how diversely words in a word category are clustered by the estimated vectors. A lower entropy implies that more words in $G_i$ are grouped into the same cluster. If and only if all words in $G_i$ are grouped into one cluster, $H(G_i) = 0$.

### Result

#### Correlation Analysis by Attribute

We evaluated the prediction accuracy for attributes by computing column-wise matrix correlations between the estimated and original brain-based vector spaces. Figure 1 shows correlation coefficients for 65 attributes. In addition, these results are summarized in Figure 2, which depicts mean correlations averaged over attributes of the same domain.

Although in this paper we are not concerned with the overall performance of word vectors, Table 3 shows that SGNS achieved the best prediction performance, and word vectors trained using the COCA corpus were superior to those of the Wiki corpus. In addition, as expected, MLP trained better mappings than LT. Despite these differences of overall performance, Figures 1 and 2 demonstrate that relative performance among attributes did not significantly differ, regardless of distributional model, corpus and training method.

Attributes in causal, cognitive, social, and attentional domains were generally predicted with higher accuracy (i.e., their rank correlations of SGNS+COCA+MLP exceeded 0.7). In other words, the information of these attributes, which characterize abstract concepts, is likely to be encoded in text-based word vectors. It seems to suggest that abstract concepts can be largely acquired through linguistic experiences. On the other hand, sensorimotor and spatiotemporal attributes were relatively more difficult to predict from text-based word vectors. This result is consistent with the embodied view of cognition that perceptual or sensorimotor information for grounding concrete concepts cannot be acquired through lin-

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**Table 3: Mean correlations over all attributes**

|        | SGNS | GloVe | PPMI |
|--------|------|-------|------|
| Wikipedia | MLP  | 0.576 | 0.522 | 0.483 |
| LT     | 0.549 | 0.450 | 0.429 |
| COCA   | MLP  | 0.634 | 0.554 | 0.440 |
| LT     | 0.598 | 0.494 | 0.454 |

![Figure 1: Correlations between the estimated and original brain-based vectors for 65 attributes.](image-url)
linguistic experiences. Note that some perceptual attributes such as vision, pattern, shape, texture and sound were predicted as accurately as abstract attributes, suggesting that text-based word vectors can encode these kinds of information.

A somewhat surprising result was that emotional attributes were not predicted as accurately as social and cognitive ones, although a large number of NLP studies have demonstrated successful results of sentiment analysis (Taboada, 2016). From a cognitive science (or embodied cognition) perspective, however, this result suggests that emotional information is more likely to be acquired from direct emotional experiences than from linguistic ones, and it is consistent with the view that emotional experiences are required for grounding abstract concepts (Kousta et al., 2011; Vigliocco et al., 2014).

**Correlation Analysis by Word**

We computed row-wise matrix correlations between the estimated and original brain-based vector spaces, and then averaged these 535 correlations according to 47 word categories. These word categories are provided a priori by Binder et al. (2016) and reflect grammatical classes (i.e., noun, verb, adjective) and semantic classes. Figure 3 shows mean correlations per word category. As in the case of the attribute analysis, there were no crucial differences among semantic spaces and among training methods.

The overall result was that brain-based vectors for human-related categories such as mental action, social action, human and social event were relatively better predicted from text-based word vectors. Emotional and cognitive categories such as emotion and cognitive property were predicted well, but with lower accuracy than human-related categories. These results are consistent with the findings obtained by the attribute analysis. On the other hand, other abstract concepts, in particular many categories of action and property, were difficult to predict from text-based word vectors. Distributional semantic models may be insufficient for representing some kinds of abstract concepts, and other experiences than linguistic one would be required (e.g., Borghi et al., 2017).

Interestingly, many artifact categories such as instruments, food, and vehicle, and some natural objects such as plant and animal showed higher prediction performance. There is no doubt that, as the embodied theory of language argues, these concrete words or concepts are grounded in perceptual and sensorimotor experiences, but some kinds of concrete concepts, in particular artifacts, may be able to be represented (or indirectly grounded) by text-based word vectors.

**Cluster Analysis**

We performed a cluster analysis in which 535 words were clustered into 28 clusters by their estimated brain-based vec-

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Note that word categories provided online slightly differ from those shown in Binder et al.’s (2016) article. In this paper, we used the online version of word categories.
In this paper, we have demonstrated that text-based distributional word vectors can predict social and cognitive information quite accurately, but the accuracy of emotional information is not so high. Given the existing empirical findings on the importance of emotion for abstract concepts (Vigliocco et al., 2014; Buccino, Colagè, Gobbi, & Bonaccorso, 2016), this result suggests that direct emotional experiences are necessary for grounding abstract concepts, and thus may lend support to some embodied theories (Kousta et al., 2011; Vigliocco et al., 2014). On the other hand, some other embodied theories such as WAT theory (Borghi & Binkofski, 2014) have argued that social experiences also play an important role in representation of abstract concepts. However, the result of our analysis that social information can be conveyed by language may diminish the importance of social experiences for concrete concepts. Furthermore, the need of social-cognitive ability is not specific to abstract concepts; concrete concepts are acquired and processed through social abilities such as a Theory of Mind (e.g., Bloom, 2000).

It was also found from the analysis that perceptual, sensorimotor and spatiotemporal information is less likely to be encoded in word vectors. This is what is expected from a number of studies claiming that distributional semantic models learn only from co-occurrences of amodal symbols that are not grounded in the real world (Glenberg & Robertson, 2000). It is also consistent with the findings of multimodal distributional semantics that inclusion of visual information improves semantic representation for concrete words (e.g., Kiela, Hill, Korhonen, & Clark, 2014). At the same time, the analysis also suggested the possibility that some perceptual information can be derived from distributional semantic models. This result does not deny the embodied account that grounding in perceptual and sensorimotor experiences is necessary for representing and acquiring concrete concepts. For practical applications to NLP and AI, however, text-based word vectors can possibly provide enough information without considering the embodied nature of word meanings.

Of course, the analysis presented in this paper is not comprehensive and has some limitations. One important limitation is that the brain-based vectors represent the salience of attributes that characterize concepts, but do not necessarily represent the value of salient attributes. For some attributes such as Bright and Happy, their value is indistinguishable from their salience, but many other attributes such as Color and Human have distinct values independent of their salience. Hence, the analysis in this paper cannot examine the representational power of attribute values. Our analysis is also limited within a small set of vocabulary words. To generalize and refine the findings presented in this paper, we have to evaluate a much larger set of vocabulary words that are not included in Binder et al.’s (2016) dataset. It would be interesting and vital for further work to extend the analysis and to develop a novel analysis method so as to overcome these limitations.

**Discussion**

Figure 4: Normalized entropy of 28 word categories. A bar chart represents the result of the estimated brain-based vectors for SGNS+COCA+MLP, while a line graph represents the result obtained using the original SGNS+COCA vectors.
Acknowledgments
This research was supported by JSPS KAKENHI Grant Numbers JP15H02713 and SCAT Research Grant.

References
Andrews, M., Vigliocco, G., & Vinson, D. (2009). Integrating experiential and distributional data to learn semantic representations. Psychological Review, 116, 463–498.
Barsalou, L. W., Santos, A., Simmons, W. K., & Wilson, C. D. (2008). Language and simulation in conceptual processing. In M. de Vega, A. Glenberg, & A. Graesser (Eds.), Symbols and embodiment: Debates on meaning and cognition (pp. 245–283). New York: Oxford University Press.
Binder, J. R., Conant, L. L., Humphries, C. J., Fernandino, L., Simons, S. B., Aguilar, M., & Desai, R. H. (2016). Toward a brain-based compositional semantic representation. Cognitive Neuropsychology, 33(3–4), 130–174.
Bloom, P. (2000). How children learn the meanings of words. MIT Press.
Borghi, A. M., & Binkofski, F. (2014). Words as social tools: An embodied view on abstract concepts. New York: Springer.
Borghi, A. M., Binkofski, F., Castelfranchi, C., Cimatti, F., Scorolli, C., & Tumulini, L. (2017). The challenge of abstract concepts. Psychological Bulletin, 143(3), 263–292.
Buccino, G., Colagè, I., Gobbi, N., & Bonaccorso, G. (2016). Grounding meaning in experience: A broad perspective on embodied language. Neuroscience & Biobehavioral Reviews, 69, 69–78.
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.
Dove, G. (2014). Thinking in words: Language as an embodied medium of thought. Topics in Cognitive Science, 6, 371–389.
Glenberg, A., & Robertson, D. (2000). Symbol grounding and meaning: A comparison of high-dimensional and embodied theories of meaning. Journal of Memory and Language, 43, 379–401.
Goldberg, Y. (2017). Neural network methods for natural language processing. Morgan & Claypool Publishers.
Güçlü, U., & van Gerven, M. A. J. (2015). Semantic vector space models predict neural responses to complex visual stimuli. arXiv:1510.04738 [q-bio.NC].
Huth, A. G., de Heer, W. A., Griffiths, T. L., Theunissen, F. E., & Gallant, J. L. (2016). Natural speech reveals the semantic maps that tile human cerebral cortex. Nature, 532, 453–458.
Jones, M. N., Gruenfelder, T. M., & Recchia, G. (2017). In defense of spatial models of semantic representation. New Ideas in Psychology, in press.
Jones, M. N., Willits, J., & Dennis, S. (2015). Models of semantic memory. In J. R. Busemeyer, Z. Wang, J. T. Townsend, & A. Eidels (Eds.), Oxford handbook of mathematical and computational psychology (pp. 232–254). New York, NY: Oxford University Press.
Kiela, D., Hill, F., Korhonen, A., & Clark, S. (2014). Improving multi-modal representations using image dispersion: Why less is sometimes more. In Proceedings of the 52nd annual meeting of the association for computational linguistics (pp. 835–841).
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.
Louwerse, M. M. (2011). Symbol interdependency in symbolic and embodied cognition. Topics in Cognitive Science, 3, 273–302.
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.
Marelli, M., & Baroni, M. (2015). Affixation in semantic space: Modeling morpheme meanings with compositional distributional semantics. Psychological Review, 122(3), 485–515.
Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. In Proceedings of workshop at the international conference on learning representation (iclr).
Mitchell, T. M., Shinkareva, S. V., Carlson, A., Chang, K.-M., Malave, V. L., Mason, R. A., & Just, M. A. (2008). Predicting human brain activity associated with the meanings of nouns. Science, 320, 1191–1195.
Pennington, J., Socher, R., & Manning, C. D. (2015). GloVe: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (emnlp) (pp. 1532–1543).
Silberer, C., Ferrari, V., & Lapata, M. (2017). Visually grounded meaning representations. IEEE Transactions on Pattern Recognition and Machine Intelligence, 39(11), 2284–2297.
Taboada, M. (2016). Sentiment analysis: An overview from linguistics. Annual Review of Linguistics, 2, 325–347.
Utsumi, A. (2015). A complex network approach to distributional semantic models. PLoS ONE, 10(8), e0136277.
Vecchi, E. M., Marelli, M., Zamarelli, R., & Baroni, M. (2017). Spicy adjectives and nominal donkeys: Capturing semantic deviance using compositionality in distributional spaces. Cognitive Science, 41, 102–136.
Vigliocco, G., Kousta, S.-T., Rosa, P. A. D., 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, 1767–1777.