A Cognitive Linguistics analysis of Phrasal Verbs' representation in Distributional Semantics

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Abstract
Phrasal Verbs (PVs) constitute a peculiar feature of the English language and represent a challenge for both language learners and computational models because of their complex and idiomatic nature, which has made them appear unsystematic and unpredictable. Recently, Cognitive Linguistics has offered a more systematic explanation of the semantics of PVs by relating their non-compositional meanings to the metaphorical extensions of the particle's meaning. In order to assess the computational suitability of this approach using Distributional Semantics, we analyzed three different semantic spaces to understand how PVs and particles are represented and whether any of the embeddings capture the significance of particles in the semantics of the entire construction. The results indicate that phrase embeddings are effective in representing the meanings of PV constructions, while word embeddings excel at capturing particle meanings and additionally support the Cognitive Linguistics hypothesis. Since improving the semantic representation of PVs can benefit various NLP applications, further research is necessary to validate these findings.

Keywords
Phrasal Verbs, Cognitive Linguistics, Distributional Semantics

1. Introduction

Phrasal Verbs (PVs) represent a distinctive peculiarity of the English language and are defined as a lexicon unit composed of a verb (e.g. *look*) and a particle (e.g. *out*), whose meaning is often non-compositional (e.g. *look out* means 'to beware') [1, 2]. PVs comprise a significant portion of the verb vocabulary [3] and are commonly used in everyday language, particularly in spoken and informal contexts [4, 5]. In addition, they are highly productive, with new ones continually being coined to reflect societal changes (e.g. *google up*) [6]. They are also characterized by their polysemy, with each phrasal verb having multiple meanings on average [5]. To further enhance their complexity, for a long time, linguists and grammarians have claimed that the selection of verb and particle in the PV construction is totally unsystematic and unpredictable [6, 7, 8], therefore the traditional pedagogical approach to PVs has always been based on memorization of the verb-particle combination and the corresponding meaning causing a general discouragement of learners around PVs. Recent research in Cognitive Linguistics, however, has proposed a more systematic explanation of the association between these verb-particle combinations and their apparently randomly assigned idiomatic meaning, by suggesting that it is the particle (in particular its metaphorically extended meaning [9]) that plays a crucial role in shaping the overall meaning of the PV [2]. Given that this approach has shown promising results in language learning [10], and that computational models of language face difficulties that are similar to English as a Second Language (ESL) learners in understanding the semantic complexity of PVs, we wanted to examine whether such Cognitive Linguistics account holds also from a Distributional Semantics perspective, where the representation of words' meanings and semantic relationship have repeatedly been proved to be similar to the way they are represented in the human cognitive system [11]. With this aim, we analysed three different semantic spaces –word embeddings, phrase embeddings and POS-tagged embeddings– to determine the most accurate way of representing PVs and particles and whether the Cognitive Linguistics hypothesis was accounted for in any of them. The importance of the particle in shaping the meaning of PVs was confirmed but the results appeared to vary across the different semantic spaces, suggesting the need for further and more detailed research.

2. Related Works

Phrasal Verbs have for long been a hot topic among linguists and lexicographers who have largely debated on their definition and classification, proposing various theories based on their syntactic and semantic features [6, 12, 4, 13, 14]. Corpus linguistics has also played a crucial role in studying PVs, providing insights into their frequency and meaning distribution, thus aiding language

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teacher by identifying the most frequently used PVs and their meanings [4, 5, 15, 16, 17]. However, to develop effective teaching strategies for PVs, it is essential to consider the cognitive processes involved in storing and retrieving these structures from the mental lexicon and that is where the Cognitive Linguistics approach comes into play offering a new perspective that considers PVs as conceptually motivated constructions rather than arbitrary combinations [18, 19, 20, 2, 21]. This account is based on one of the cornerstones of Cognitive Linguistics which is Metaphor Theory. According to this view, metaphors play a fundamental role in conceptualization and thinking as they allow us to understand and experience abstract concepts by mapping them onto concrete entities that we can bodily perceive [9]. In the case of PVs, the Cognitive Linguistics account considers the metaphorical extension of the particle's literal meaning as responsible for the idiomatic meaning of the entire construction [2, 22], unlike traditional approaches that often neglect the semantic role of particles, and function words more in general [23]. According to this view, the prototypical meaning of particles, which is usually related to spatial locations and orientations, can be metaphorically extended to abstract non-physical domains that are thought of in terms of space, such as attitudes, knowledge, completion, or increase [2]. For example, the particle "UP" literally denotes a physical upward motion (e.g. *to pick up*), but can be used to denote a number of abstract domains that we categorize assigning (spatial) values along a vertical line such as temperature, ranks, attitudes, knowledge etc. Therefore, the metaphorical extension of 'UP' can indicate improvement (e.g. *to brush up*), higher visibility and accessibility (e.g. *to turn up*), completion (e.g. *to fill up*), and reaching a a boundary (e.g. *to be fed up*) [2]. This perspective allows to get insights into the systematicity and predictability of PVs' semantics and demonstrates that idiomatic and polysemous meanings of PVs are connected through a network of senses derived from the prototypical meaning of the particle. Empirical studies have shown that adopting this more cognitively plausbile approach in the instruction of PVs can benefit ESL learners as it helps them grasp the relationship between idiomatic and literal meanings of PVs thus facilitating the processing and acquisition of these constructions [24, 25, 26, 27, 10]. Having briefly discussed the Cognitive Linguistics perspective concerning the semantics of PVs, we now briefly explore how the meaning of PVs is processed computationally, adopting a Distributional Semantics approach. Distributional Semantics is a computational approach to language meaning where words are represented as distributional vectors in a semantic space based on their contextual usage. The underlying assumption, referred to as the Distributional Hypothesis [28], is that words that occur in similar contexts tend to purport similar meanings and that the semantic similarity between two words can be measured as the geometrical distance between the vectors representing such words (for a more detailed explanation of the different frameworks see [11]; [29]). Even though this approach works extremely well for representing the meaning of single words, it faces some challenges when representing the meaning of PVs and multi-word expressions more in general due to their non-compositional and often polysemous meaning. Most studies addressed this issue by developing strategies to detect compositionality using dictionary-based [30, 31] and distributional similarity methods [32, 33, 34]. While providing effective working solutions, these compensation strategies do not fix the root problem at the level of semantic representation. Recently, DS has been extended to incorporate larger units, such as multi-word expressions and phrases, thus creating more informative embeddings and leading to better performance in NLP tasks [35, 36, 37, 38]. It is against this background that we framed our research questions and decided to investigate which type of embeddings could better represent the complex semantics of PVs and whether the distributional semantic space manages to capture the role of the particle's meaning in shaping the meaning of the entire construction, as posited by the Cognitive Linguistics account.

3. Methodology

In order to investigate how the semantics of PVs is represented within the Distributional Semantics framework, and more specifically to test whether distributed representations can capture the importance of particles in PV constructions, as suggested by the Cognitive approach, we analyzed three types of embeddings:

Word embeddings: we selected the pre-trained word vectors released by Google[1], which are 300-dimensional vectors trained using a Skip-gram model on a portion of the Google News dataset, with a window-size of 5. The Skip-gram model was selected because it has shown superior performance in semantic tasks compared to other models like CBOW, NNLM, and RNNLM [39]. The window-size of 5 allows capturing broader semantic information beyond immediate context, which is suitable for investigating the semantics of PVs with separable particles [40]. The vector size of 200-300 dimensions strikes a balance between informativeness and computational complexity [41].

Phrase embeddings: we selected the embeddings for generalized phrases introduced by [38]. They collected two-word phrases, categorized them as continuous or discontinuous, and trained a Skip-gram model to learn

[1] https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTT-lSS21pQmM/edit?resourcekey=0-wjGZdNAUop6WykTtMip30g

embeddings for both words and phrases. They showed that phrase embeddings outperformed word embeddings in semantic tasks, demonstrating their better representative power for such multi-word expressions, because considering them as linguistic units allows to capture the attributes of their real contexts of usage and thus to create accurate semantic representations that account for their non-compositional meaning.

POS-tagged embeddings: we included POS-tagged embeddings in our analysis to test whether building isolate representations for particles, distinguishing their occurrences in PV constructions from those of the same words used as prepositions or adverbs, would lead to more accurate semantic representation of the entire PV and could account for the Cognitive Linguistics hypothesis. We selected the English TreeTagger [42] trained on the PENN Treebank [43], which includes a specific tag for particles (RP) and used the BNC corpus for training. To ensure accurate identification of particles, we cross-checked the TreeTagger annotations comparing it with the dependency parsing annotation performed with SpaCy Dependency Parser [44] and corrected any misclassifications. Finally, we trained Word2vec on the double-checked POS-tagged BNC data with a Skip-gram architecture, a window size of 5, and 300-dimensional vectors. In compliance with the hyperparameter setting of word embeddings, we adopted the Skip-gram architecture, setting the window-size to 5 and the vectors' dimension to 300 [39].

4. Experiments

We conducted exploratory analyses on the three different semantic spaces to investigate how PV constructions and particles are distributionally represented. We selected as target verbs the 150 most frequent PVs identified by previous corpus-based studies [15]. To determine the meanings of these PVs, we referred to the PHaVE List [16], which provides key meaning senses based on frequency distributions. Similarly, we addressed the challenge of representing particle meanings, which are often overlooked in Distributional Semantics, by turning to [2] work for detailed meaning descriptions of particles and we selected simplified synonyms to evaluate the accuracy of particles' semantic representations. For both PVs and particles, we evaluated their meaning representation using cosine similarity measures. The final lists of particle meanings used in our analysis can be found in Appendix A, while in Appendix B we reported a sample of PVs that were used in our analysis with the corresponding meanings selected from the PHaVE List [16]. Having defined the meaning of reference for PVs and particles, we designed three types of analyses to answer our research questions.

4.1. Semantic representation of PVs

In order to examine how the meaning of PVs is represented in the different semantic spaces, we measured the cosine similarity between the PV vectors and the vectors representing their possible meanings, as adapted from the PHaVE List [16] (see Appendix B for a few examples). If a single meaning consisted of multiple synonyms (e.g. for the PV *look out* the first meaning is represented by the pair *observe/contemplate*), we obtained the similarity score by summing the similarities of the PV with each synonym (i.e. sim(*look_out* - meaning 1) = sim(*look_out* - *observe*) + sim(*look_out* - *contemplate*)). In cases where the selected synonyms were multi-word expressions (e.g. for the PV *give out* the meaning 2 *make public*), in word and POS-tagged embeddings we obtained the vectors by summing the individual word vectors (i.e. vect(*make_public* = vect(*make)* + vect(*public*)), while for phrase embeddings, we checked if the multi-word expression was represented as a generalized phrase in the embeddings. If so, we used the corresponding embedding; otherwise, we obtained the vector through summation, similar to word and POS-tagged embeddings (for an explanation of the additive property of vectors see [39]).

4.2. Semantic representation of particles

In order to examine if and how the meaning of particles is represented in the different semantic spaces, similarly to the analysis conducted for PVs, we computed the cosine similarity between the vectors representing each particle and their possible meanings, adapted from [2]. If the meanings of particles consisted of multi-word expressions (e.g., for the particle *up* the corresponding meaning *positive verticality*), we obtained the vectors for the entire phrase by summing the individual word vectors (e.g., vect(*positive_verticality* = vect(*positive*) + vect(*verticality*)). Likewise, if the meaning of a particle was described by multiple synonyms (e.g., for the particle *on* the pair *contact/continuation*), also in this case we computed the similarity score by summing the similarity of the particle with each synonym (i.e., sim(*on* - meaning) = sim(*on* - *contact*) + sim(*on* - *continuation*)) [39].

4.3. Verb vs particle in the semantic representation of PVs

In order to test whether the distributional representations of meanings successfully capture the cognitive peculiarity of PVs' semantics, specifically the fact that particles play a significant role in shaping the meaning of the entire construction compared to the verb proper [2], we compared the similarity between the particle and the verb proper with the whole PV construction. For instance, considering the PV *set up* if the distributional representation effectively captures the Cognitive Linguistics account of PVs' semantics, we would expect the cosine similarity score between the entire PV and the particle (sim(*set up*–*up*)) to be higher than that between the PV and the verb proper (sim(*set up*–*set*)). In other words, the vector representing the meaning of the PV should be more similar, and therefore closer, to the vector representing the particle than to the vector representing the verb proper.

5. Results

Since one of the primary objectives of this work was to understand what could be the most appropriate way to build a distributional semantic representation of PVs that truthfully accounts for their complex semantics, we will now briefly[2] present and discuss the results of the three types of analyses that were carried out comparing the results obtained with the three semantic spaces.

5.1. Semantic representation of PVs

When evaluating the similarity between the PVs and their meanings to assess the quality of the semantic representation, overall significance was not high in any embeddings. However, phrase embeddings outperformed the others as they showed higher similarity scores for PV-meaning pairs (32%) compared to word (27%) and POS-tagged (17%) embeddings (see Table 1 for an example). This might be explained by the fact that phrase embeddings treat PVs as a single unit, capturing their real contexts of usage and therefore represent their semantic complexity more accurately. Conversely, word and POS-tagged embeddings, which summed the verb and particle vectors, fell short in capturing the full meaning of PVs. In conclusion, phrase embeddings proved to be the most suitable for representing PV semantics.

Table 1
Sample of our results showing the similarity scores obtained with the three different embeddings for the PV *take out* and its corresponding three meanings *remove, invite, obtain*. The highest similarity scores highlighted in bold are obtained, in all three cases, with phrase embeddings.

Meanings *take out*	Similarity scores		
	Word-e	Phrase-e	POS tag-e
remove	0.2918	**0.3894**	0.2422
invite	0.2773	**0.3491**	0.0819
obtain	0.2153	**0.2319**	0.0467

[2]For the sake of brevity, just a sample of the results is reported herein, for a comprehensive overview and a more detailed analysis see [45].

5.2. Semantic representation of particles

When evaluating the similarity between the particles and their meanings, we obtained similarity scores that were overall below the 0.5 significance threshold across the three types of embeddings. Surprisingly, comparing the results, word embeddings performed best, followed by phrase embeddings, while POS-tagged embeddings showed very poor performance (see Table 2 for a sample of the results). This was unexpected because it is only in POS-tagged embeddings that we could represent particles in isolated vectors, therefore they were supposed to capture more precisely their meaning. Conversely, in word embeddings the meaning representation of particles was collapsed in a single vector that included also occurrences of the same words when used with different syntactic functions (i.e. prepositions or adverbs), while in phrase embeddings the vectors representing the particle was actually built excluding the occurrences of the words as particles because those where captured within the phrase-vectors themselves. These findings point to two possible conclusions which are not mutually exclusive but rather complementary: on the one hand, they suggest that for building distributional representation of words that occur frequently in different syntactic roles –such as particles, and function words more in general– collapsing all the occurrences within a single vector representation might lead to better capturing their meaning, and on the other, they hint that particles used in PVs may have a core (prototypical) meaning that transcends their syntactic role, aligning with the Cognitive Linguistics hypothesis [2].

Table 2
Sample of our results showing the similarity scores obtained with the three types of embeddings for the particle *on* and its corresponding two meanings *contact* (m1) and *continuation* (m2), as well as the total meaning obtained by computing the similarity between the particle and the collapsed vector of the two meanings (see Section 4.2) The highest similarity scores, highlighted in bold, are obtained with word embeddings.

Meanings *on*	Similarity scores		
	Word-e	Phrase-e	POS tag-e
contact	**0.0388**	0.0284	-0.0122
continuation	**0.1421**	0.1075	-0.0345
tot meaning v(m1) + v(m2)	**0.1809**	0.1359	-0.0467

5.3. Verb vs particle in the semantic representation of PVs

In the final analysis, we compared the similarity between the PV and the particle and the PV and the verb across the three types of embeddings to test whether any of them

Table 3
Sample of our results showing the similarity scores obtained with the three types of embeddings for the verb *take out* compared to the verb proper (*take*) and the particle (*out*). The highest similarity scores, highlighted in bold, are obtained with word embeddings.

		Similarity scores	
PV	Embeddings	PV – v	PV – prt
take out	word	**0.784**	0.714
	phrase	**0.476**	0.373
	POS-tagged	0.645	**0.685**

supported the Cognitive Linguistics hypothesis about the role of particles in PV semantics. Broadly speaking, as expected word and POS-tagged embeddings performed better than phrase embeddings. They both gave overall significant similarity scores but showed the opposite patterns of similarity (see Table 3 for an example). Indeed, while in word embeddings it is the verb proper that resulted to be more similar to the PV compared to the particle, the opposite is true for POS-tagged embeddings where it is the particle that resulted to be more similar to the PV compared to the verb proper. These contrasting patterns align respectively with the traditional view and with the Cognitive Linguistics view (Section 2) on PVs meaning, and suggest that in a semantic space in which particles are accurately (i.e. separately) represented, the Cognitive Linguistic view claiming the higher significance of the particle (vs the verb proper) in shaping the PVs meaning, is supported and accounted for.

6. Conclusion and Future Directions

The aim of this work was to analyze the distributional representation of PVs from a Cognitive Linguistics perspective. More specifically we wanted to examine three different semantic spaces (word embeddings, phrase embeddings and POS-tagged embeddings) using simple vector combination (sum) and mathematical computations (cosine similarity) to evaluate whether: 1) the meaning of the PV construction is properly represented; 2) the particles' embeddings truthfully capture their meaning; 3) the greater role of the particle in shaping the semantics of the PV, as posited by the Cognitive Linguistics approach, is accounted for. The current results showed that, as expected, phrase embeddings performed best in capturing the complex semantics of PVs, supporting the idea of treating PVs as single tokens when training the embeddings so as to capture the true context of occurrence and obtain more accurate meaning representation that account also for the less compositional meanings.

As far as particles are concerned, word embeddings outperformed both phrase and POS-tagged embeddings. These results were unexpected because we anticipated better performance from POS-tagged embeddings, which were designed to isolate particle occurrences. We identified different possible explanations for these results, including limitations in integrating POS-tag information (that reduces the number of occurrences) compared to including occurrences with different syntactic functions, the issues related to the general difficulty of representing function words and also the possibility that words used as particles carry a unique core meaning regardless of their syntactic functions. Further research is needed, along these lines, to disentangle these factors and understand what could be the most effective way to represent particles and function words in Distributional Semantics.

Finally, the results of the third and last type of analysis, that was designed precisely to test the Cognitive Linguistics claim on the role of the particle, showed that when separate vector representations are built for particles, i.e. distinguishing the occurrences of the same words with other syntactic functions, as was the case with POS-tagged embeddings, particles do appear to play a greater role than the verbs proper in the semantics of the PVs. Conversely, when the vector representation of particles is less accurate, i.e. includes occurrences of the same words with other syntactic functions, as it was the case with word embeddings, it is the verb proper that appears to be more crucial in the semantics of the PV in most cases.

Overall our findings align with the literature, in that they support the idea that vectors for PVs should be treated as single tokens rather than splitting them into individual words [38] and that representing the meaning of particles is challenging, justifying their removal in many NLP applications [46]. However, we believe that understanding how to build appropriate semantic representations for particles is crucial for analyzing their contribution to larger constructions, such as PVs. In order to do so, future studies can explore different types of embeddings and testing whether refining POS-tagged embeddings (for example by weighting each POS-tag feature according to the task or alternatively using Neural Networks for combining these features into a unique meaningful hidden representation) could improve representation accuracy and thus lead to better performance of the models in specific semantic tasks.

Last but not least, our results provide initial evidence supporting the Cognitive Linguistics account of PV semantics from a Distributional Semantic perspective, although further confirmation is needed. Adopting the Cognitive Linguistics approach to PVs in education and leveraging NLP applications in this direction can facilitate the acquisition of this complex English structure for ESL learners. Additionally, capturing and representing PV meanings and the semantic roles of their components can benefit NLP tasks involving semantic and morphosyntactic relations (such as machine translation, question-answering, summarization, automatic synonym detection, etc.). For these reasons, we hope this work stimulates further advanced research in this area, leveraging the insights from Cognitive Linguistics and Computational Linguistics.

A. Appendix A. Particle's meanings

List of particles' meanings adapted from [2] that were used for the analysis.

Particles	Meanings
on	contact/continuation
up	positive verticality/increasing/completing
back	returning/past
out	leaving/exhaustion
in	entering/being inside
down	negative verticality/decreasing/ending
off	separation
ahead	progressing
over	crossing/overcoming
a/round	vicinity/proximity
through	crossing/completing
about	dispersion
along	parallel/accompanying

B. Appendix B. Sample of PVs' meanings

Small sample of PVs-meanings pairs as extracted from the PHaVE list [16].

PV	Meaning 1	Meaning 2	Meaning 3
get up	rise		
take out	remove	invite	obtain
go down	move	decrease	go
look out	observe / contemplate	take care / protect	
give out	give	make public	collapse / fail

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