Abstract

Prepositions are highly polysemous, and their variegated senses encode significant semantic information. In this paper we match each preposition’s complement and attachment and their interplay crucially to the geometry of the word vectors to the left and right of the preposition. Extracting such features from the vast number of instances of each preposition and clustering them makes for an efficient preposition sense disambiguation (PSD) algorithm, which is comparable to and better than state-of-the-art on two benchmark datasets. Our reliance on no external linguistic resource allows us to scale the PSD algorithm to a large WikiCorpus and learn sense-specific preposition representations – which we show to encode semantic relations and paraphrasing of verb particle compounds, via simple vector operations.

1 Introduction

Prepositions form a closed class showing no inflectional variation and are some of the most frequent words. Yet, they remain largely under-explored in computational linguistics owing to their highly polysemous nature and frequent participation in idiomatic expressions (Saint-Dizier, 2006). In this paper, we study the problem of sense disambiguation for prepositions and the related problem of their distributed representation.

Computationally, two different views of prepositions are standard: sometimes they are treated as being semantically vacuous and other times as being indiscriminate in association owing to their polysemy. Language processing tasks operating at a surface level of words treat them as stop words and disregard them (e.g., bag-of-words models), whereas those harnessing the syntax and semantics of words resort to the latter. In doing so, the latter tackles the challenges brought about by prepositional ambiguity in tasks such as prepositional phrase attachment (Ratnaparkhi et al., 1994; Collins and Brooks, 1995), semantic role labeling (Srikumar and Roth, 2013) and downstream applications such as grammatical error correction (Chodorow et al., 2007) and machine translation (Shilon et al., 2012).

The highly polysemous nature of prepositions drives several syntactic and semantic processes. For instance, the preposition with has 18 senses listed in The Preposition Project (TPP) (Litkowski and Hargraves, 2005), examples of which, are shown in Table 1. We notice that with indicates an emotional state in with confusion and refers to an accompanier in combine with, while it suggests the idea of a tool or means in wash with water. Thus, preposition sense disambiguation (PSD) is vital for natural language understanding and a closer look at the function of prepositions in specific contexts is an important computational step.

Antecedent approaches to PSD (for instance, (Ye and Baldwin, 2007; Hovy et al., 2011)) have relied on linguistic tools and resources (the minimum of which involves dependency parsers and POS taggers) to capture the crucial contextual information of prepositions. We depart by using no linguistic resources or tools other than a set of word representations (trained on a large corpus). We interpret preposition senses as groups of similar contexts, where each instance of the preposition ‘sense’ is represented as vectors of context-dependent features. We find that a simple feature extraction that creatively harnesses the geometry of word representations yields a scalable algorithm that can reach near and even beat state-of-the-art performance on two benchmark datasets (SemEval 2007 and OEC); this is true in both un-
supervised and supervised PSD settings.

| Sentence (TPP sense)                  |
|--------------------------------------|
| She blinked with confusion. (Manner & Mood) |
| His band combines professionalism with humor. (Accompanier) |
| He washed a small red teacup with water. (Means) |

Table 1: Examples showing polysemous behavior of with

A PSD algorithm that efficiently scales to a large corpus naturally paves the way for distributed representations of the preposition senses: we enrich the corpus with sense-specific information of prepositions using our PSD algorithm.

Next, we repurpose an off-the-shelf word representation algorithm (Word2vec (Mikolov et al., 2013a)) to relearn word representations with the key aspect that the length of the context surrounding prepositions is crucially reduced. Sense-specific preposition representations thus learnt are strongly validated using intrinsic evaluation tasks on datasets derived from standard benchmarks and by comparing them with their monosemous (i.e., original Word2vec) representations.

Our experiments reveal two curious properties exhibited by sense-specific preposition representations; they encode semantic relations and aid paraphrasing of phrasal verbs when used in a simplistic compositional manner. This compositional-ity brings forth not only the non-trivial amount of semantic information encoded in prepositions, but also suggests that it can be harnessed using basic algebraic operations on word representations.

We summarize our contributions below:

**Resource-independent Disambiguation:** We rely only on a set of trained word representations and not any external linguistic resource – almost all prior approaches have included at least POS tagging and dependency parsing. We are comparable to, or better than, state-of-the-art on two standard benchmarks.

**Preposition Sense Representation Learning:** To the best of our knowledge, this is the first work on preposition sense representation. The power of our sense representation is reflected by the finding that the embedding of ‘in’ in the sense of “things enclosed”, is captured via the linear-algebraic relationship: in + America ∼ American, while the global representation of ‘in’ fails in such tasks. Again, using a sense-specific word embedding of ‘for’ yields a paraphrase of the phrasal verb, ‘fight for’ to be ‘defend,’ derived via a simple additive model of composition.

A key contribution of this work is in the selectional aspects of the context that best represent the sense of a preposition, where we match classical ideas from linguistics with the appropriate geometry of word embeddings; this is discussed next.

## 2 Preposition Sense Disambiguation

The key intuition behind our sense disambiguation approach is the modern descriptive linguistic view (Huddleston, 1984; DeCarrico, 2000): prepositional sense in any sentence is driven by both its attachment and its complement; classical prescriptive linguistics had focused only on the latter (Beal, 2004), pp. 110, (Cobbett, 1823), pp. 16, (Lowth, 1762), pp. 8, 91.

An example is in Table 1: italic words determine the sense of “with”. In the first sentence, ‘confusion’ to the right of the preposition (i.e., “right context”) is the complement of ‘with’, from which we infer that ‘with’ encodes the sense of “manner”. In the second sentence, the accompanier sense of ‘with’ is because of its governor, the verb ‘combine’ (i.e., the left context). In the last sentence, the sense of ‘with’ is “by means of” and is determined by both the verb in its left context and the argument in its right context. Consider a new sentence with changed right context: ‘He washed a small cup with a handle.’ Here ‘with’ functions as an attribute. Again, changing its left context we get the sentence ‘He asked for a small cup with water’, where ’with’ serves as an attribute instead of encoding the sense of means.

That the left and right contexts and their interplay are critical to prepositional sense disambiguation is also well established in the literature (Hovy et al., 2011; Litkowski and Hargraves, 2007). Our key intellectual contribution is in matching these linguistic properties to appropriate geometric objects within the vector space of word embeddings; the word embeddings are borrowed off-the-shelf – this work uses word2vec exclusively. We describe this next, focusing first on the left context, next on the right context and then on their interplay.

**Left context feature** $v_L$ is the average of the vectors of the left $k_L$ words (here $k_L$ is a parameter roughly taking values 1 through 4). This simple geometric operation is motivated by recent works (Faruqui et al., 2015; Kenter et al., 2016; Yu et al., 2014) representing a sentence by the average of its constituent words robustly and successfully in
Table 2: Performance of the unsupervised PSD compared with the state-of-the-art. \((\ell,\text{inter}), (\ell, r)\) and \((r,\text{inter})\) correspond to feature ablation results.

| System | State-of-art | \(k\)-means clustering |
|--------|--------------|-------------------------|
|        | \[\text{average}\]| \((\ell, r)\) | \((\ell, i)\) | \((r, i)\) | \((\ell, r, i)\) |
|        | \[0.56\]     | \[0.555\] | \[0.561\] | \[0.565\] | \[0.534\] | \[0.584\] |

Table 3: Supervised disambiguation on SemEval and OEC Datasets.

| Feature Type | SemEval Dataset | OEC dataset |
|--------------|-----------------|-------------|
|              | \(\ell, r\)     | \((\ell, i)\) | \((r, i)\) | \((\ell, r, i)\) |
| SVM          | 0.712           | 0.765 | 0.775 | 0.700 | 0.782 | 0.305 | 0.330 | 0.333 | 0.325 | 0.351 |
| MLP          | 0.712           | 0.758 | 0.780 | 0.704 | 0.777 | 0.322 | 0.353 | 0.353 | 0.347 | 0.375 |
| Weighted \(k\)-NN | 0.731 | 0.781 | 0.792 | 0.733 | \[0.804\] | 0.329 | 0.341 | 0.380 | 0.367 | \[0.400\] |

a variety of downstream settings. Although prior work (Hovy et al., 2010) points out that fixed window sizes are insufficient, when compared to using specific syntactic features (example: POS tagging and dependency parsing—common techniques in prior works), we will see that the semantic information embedded in word vectors largely compensates for this limitation.

**Right context feature** \(v_r\) is the average of the vectors of the right \(k_r\) words (here \(k_r\) is a parameter roughly taking values 1 through 4). This is identical to the method adopted for the left context.

**Context-interplay feature** \(v_{\text{inter}}\) is the vector closest to both the subspace spanned by the left context word vectors and the subspace spanned by the right context word vectors. This geometric representation appears crucial to capture the prepositional-sense when the interplay between the contexts matters decisively, as seen empirically in our extensive experiments. This feature represents one of the key findings of this paper. Let \(v^\ell_i\) and \(v^r_j\) be left and right context word vectors respectively. A precise mathematical definition of \(v_{\text{inter}}\) is below:

\[
v_{\text{inter}} = \arg \min_v \frac{1}{\|v\|_2} \left( \sum_{k_r} \alpha_i \|v - v^\ell_i\|_2^2 + \sum_{k_r} \beta_i \|v - v^r_i\|_2^2 \right)
\]

These three feature vectors, \(v_{\ell}, v_{r}\) and \(v_{\text{inter}}\), are used in both unsupervised and supervised preposition sense disambiguation.

**Unsupervised learning** of senses of a given preposition is conducted by clustering the 3 feature vectors harnessing the very vast number of instances of each preposition in the large Wikicorpus (here we fix \(k_{\ell} = k_r = 2\) and use standard \(k\)-means clustering). If the features do capture the prepositional sense efficiently, then a majority of the same-sense instances belong to the same cluster, which is now represented by the dominant label of its instances.

**Supervised learning** of the senses using the three feature vectors is readily conducted based on the training examples provided in benchmark PSD datasets. We do this using the standard support vector machines (SVM) (Cortes and Vapnik, 1995), multilayer perceptron (MLP) (Glorot and Bengio, 2010) and weighted \(k\)-nearest neighbor (\(k\)-NN) (Andoni and Indyk, 2006) classifiers. Each of these allows potentially different weighting of the three features in a context dependent way. The parameters are tuned to maximize the disambiguation accuracy on the development set provided in the benchmark PSD datasets. These experiments are discussed in detail next.

### 3 Experiments on Sense Disambiguation

The PSD algorithms were validated using two publicly available datasets derived from TPP. The **SemEval Dataset** consisting of 34 prepositions instantiated by 24,663 sentences covering 323 senses. Among them, 16,557 sentences are used as training instances (semtrain) and 8096 sentences are test instances (semtest) for the preposition disambiguation task.

The **OEC dataset** consists of 7,650 sentences collected from the Oxford English Corpus. Since these sentences included more prepositions than those in the SemEval dataset, we chose 3,587 sentences that included the same 33 prepositions as
used in the SemEval task.

Word embeddings. The word embeddings we used in our experiments were trained on the English WikiCorpus with Word2Vec CBOW model (Mikolov et al., 2013a), with dimension 300.

Unsupervised PSD is conducted by clustering the SemEval dataset’s training instances using \( k \)-means. In the evaluation phase, each test instance was assigned to the closest cluster, and its sense was the dominant training sense within this cluster. For a fair comparison with the state-of-the-art unsupervised technique, we report the disambiguation accuracy on \textit{semtest} as shown in Table 2, a new state-of-the-art result.

Supervised PSD is conducted by first conducting a 80/20 split of \textit{semtrain} into training and development sets. Disambiguation accuracy calculated on both \textit{semtest} and OEC datasets are reported in Table 3, using standard off-the-shelf classifiers. We used the SVM classifier with a linear kernel and its penalty parameter \( C \) as a tunable parameter, the MLP classifier with one hidden layer, and the number of neurons as a tunable parameter, and the \( k \)-NN classifier (weighted \( k \)-NN), with the number of nearest neighbors and the feature weights as tunable parameters; all tunable parameters were tuned using the development set. Additionally, the context window sizes \( k_L \) and \( k_R \) were parameters for all the three classifiers, each tuned on the development set.

Baseline. Recent works have shown that the average word embedding serves as a good representation of the compositional sentential semantics (Faruqui et al., 2015; Kenter et al., 2016; Yu et al., 2014), and this single feature – the average of all context word vectors (both to the left and the right) – serves as a natural baseline.

Results. In both the unsupervised and supervised disambiguation settings, the best performance is achieved by using all three features, \( v_L \), \( v_R \) and \( v_i \). As summarized in Table 2, our unsupervised method achieves a 2.4\% improvement (4.2\% relative) over state-of-art (Hovy et al., 2011).

The results in the supervised setting, tabulated in Table 3 reveal that the weighted \( k \)-NN classifier performs best. Denoting left, right and interplay features by \( \ell, r, i \) respectively, Table 2 and 3 report our experimental results using only subset combinations of these features on the two disambiguation tasks.

An ablation analysis of the features reveals that the context-interplay feature is most beneficial to the model when testing on the OEC dataset, but on the SemEval dataset, the left context feature appears to be the most beneficial. A likely explanation to this behavior is that several instances in \textit{semtrain} and \textit{semtest} share the governors the prepositions attach to. Hence the left feature with the governor information helps disambiguation on \textit{semtest}. The governors and complements in OEC instances differ from those in \textit{semtrain}. Therefore, the context-interplay feature provides more general context information than provided by the left and right context features by themselves for sense disambiguation on the OEC dataset.

A side-by-side comparison of the performance of our supervised approach with related prior approaches is shown in Table 4. From the table we note that the accuracy of our system was significantly better than that of the best PSD system in SemEval 2007 (11% higher accuracy), and 7.5% (absolute) higher on the OEC dataset. It is noteworthy that while (Litkowski, 2013) fared better than our system with the SemEval data, our system outperformed (Litkowski, 2013) on the OEC dataset. It is also noteworthy that we achieve per-

| Dataset | System | Resources | Accuracy |
|---------|--------|-----------|----------|
|         | Our system | English corpus | 0.81 |
| (Litkowski, 2013) | lemmatizer, dependency parser, WordNet | 0.86 |
| (Srikumar and Roth, 2013) | dependency parser, WordNet | 0.85 |
| (Gonen and Goldberg, 2016) | multilingual corpus, aligner, dependency parser | 0.81 |
| (Ye and Baldwin, 2007) | chunker, dependency parser, named entity extractor, WordNet | 0.69 |
|      | Our system | English corpus | 0.40 |
| (Litkowski, 2013) | lemmatizer, dependency parser, WordNet | 0.32 |

Table 4: Preposition Disambiguation Performance Comparison on SemEval and OEC dataset
formance comparable to the recent work (Gonen and Goldberg, 2016) which also used word embeddings, but had access to a multilingual translation corpus (and linguistic tools). Again, we note that our performance is achieved with complete non-reliance on linguistic resources.

4 Preposition Sense Representation

Standard embedding methods do not account for the inherent polysemy in words – this is exacerbated in the context of prepositions. Indeed, to the best of our knowledge, no linguistic properties of the standard embeddings (say, word2vec (Mikolov et al., 2013a) or GloVe (Pennington et al., 2014)) are known for preposition vectors. Recent works that learn sense-specific embeddings inherently use the distinct “topics” the senses of a given word can take (example: (Rothe and Schütze, 2015) explicitly uses Wordnet senses) and have only been validated with respect to nouns and verbs.

In this work, we provide the first sense-specific prepositional representations and validate them by creatively repurposing datasets meant for other tasks. This is the focus of this section. Toward this, we used the trained $k$-NN classifier (described in Section 2) to disambiguate each preposition token in the large WikiCorpus. Now each preposition instance in the corpus has a sense-label. We then used Word2Vec (Mikolov et al., 2013a) to re-learn word embeddings on the preposition-sense-tagged corpus; this time we arrive at sense-specific embeddings of prepositions.

The sense-specific representations are readily interpreted in terms of the extensive-resources of TPP – a detailed description of our sense representations and their connections to TPP senses can be found in Tables 8,9,10,11,12 of the supplementary material, including the words nearest to the preposition sense and corresponding example sentences for five common prepositions: in, over, for, or, with.

Below, we validate the quality of the sense representations in two tasks, where prepositional senses play an important semantic role: (a) semantic analogy task and (b) paraphrasing task.

| Embedding                | Global | Sense | Difference |
|--------------------------|--------|-------|------------|
| Capital-country          | 0.17   | 0.54  | 0.95       |
| City-state               | 0.32   | 0.67  | 0.91       |
| Nationality-adjective    | 0.73   | 0.85  | 0.95       |

Table 5: Accuracy on relation approximation

4.1 Preposition senses as relations

Task. Prepositions indicate a relation between the noun or pronoun and another word, which may be a verb, an adjective, or another noun or pronoun (Huddleston et al., 2002). While previous studies have found that simple arithmetic operations between word vectors capture the relation between word pairs fairly well (Mikolov et al., 2013a,b), in this study we explored the ability of sense-specific preposition embeddings to encode two noun-noun relations and one noun-adjective relation. The rationale here is explained with an example.

Prepositions such as ‘in’ and ‘from’ encode a spatial relation (in America) and hence the location sense of these prepositions could potentially capture the nationality relation that in America ≈ American. If the prepositional sense embedding can indeed capture this spatial relation, then the adjective can be predicted from the country via the addition operation as follows. Let a particular sense embedding of ‘in’ be $v_{in}^\text{sense}$. Given the country, we predict the nationality-adjective by finding the nearest word of $v_{adjective}^\text{sense} \approx v_{in}^\text{sense} + v_{country}$. Likewise, we explored whether country names (resp. state) could also be predicted from their capital (resp. city) names via the addition operation.

Datasets: We use the popular semantic analogy datasets (Pennington et al., 2014) and focus on the following three relations: (1) capital-world with 116 (capital, country) pairs, e.g., (Cairo, Egypt); (2) city-in-state with 69 (city, state) pairs, e.g., (Houston, Texas); (3) gram6-nationality-adjective with 41 (country, nationality-adjective) pairs, e.g., (Albania, Albanian).

Baselines. (a) Lower baseline: the “global” preposition embedding (i.e., original word2vec representation), $v_{in}^\text{global}$, is one baseline in our experiments, e.g., we predict the adjective through $v_{adjective}^\text{global} \approx v_{in}^\text{global} + v_{country}$.

(b) Upper baseline: since the difference between two words in the first analogy pair are shown to efficiently capture the relation, we took the average difference vector among all word pairs in the dataset corresponding to a relation, as the second baseline, $v_{diff}$. The adjective is then predicted via $v_{adjective}^\text{diff} \approx v_{diff} + v_{country}$.

We used from to approximate capital-country relation, and in for city-state and nationality-adjective relations. For each relation, we evaluated the outcome of adding the preposition vector to the base word by checking if the answer occurs
among the closest three words of the sum vector. For example, if American appears among the closest words to the sum of the vectors of America and in, we considered it to be a correct approximation.

**Results.** Table 5 reports the accuracy of finding the target word (country, state or adjective) in the top 3 neighbors corresponding to the use of the global embedding, the sense-specific embedding of (‘in’ and ‘from’) and the difference embedding. The accuracy achieved by using the preposition sense representation is significantly close to that of the difference embedding compared to the global representation. This shows that the sense representation is good at approximating the relations between capital-state, capital-country and country-nationality.

### 4.2 Preposition senses aid paraphrasing

**Task.** Prepositions encode non-trivial semantic information. For example, switch on and switch off show opposite meanings owing to the prepositions that follow the common verb switch. Another setting in which we validate the sense-specific preposition representation is by understanding its role in phrasal verbs.

Specifically, our goal is to infer the meaning of verb-particle constructions (VPC)—a head verb with one or more obligatory particles—in the form of intransitive prepositions (e.g., hand in). We focused exclusively on prepositions serving as particles due to their high productivity, and mainly consider compositional VPCs (McCarthy et al., 2003; Bannard et al., 2003). This allows us to highlight the value of the vector representation of the preposition sense in terms of playing a non-trivial role in phrasal verb semantics (Brinton, 1985).

**Experiments.** We explore the task of inferring the meaning of the phrasal verb from its components, i.e., the verb and preposition sense representation, casting this as a lexical paraphrasing task of finding one word that captures the meaning of the VPC (e.g., climb down = descend).

**Dataset.** Because a dataset for paraphrasing of VPCs was not available, we created a dataset ¹. It consists of 91 phrasal verbs, extracted from the VPC datasets in (Baldwin, 2005), (McCarthy et al., 2003) and the online Oxford dictionary². Given that the meaning of VPCs is context-sensitive (as discussed in (Gong et al., 2016) for example), we provide three sentences for each VPC to ascertain the paraphrase, while ensuring that the VPC has the same sense in all three sentences.

For each VPC instance, we first disambiguated the preposition sense in the given context using the supervised method described in Section 2. Because the meaning of a compositional phrase can be inferred from the meaning of its component words, we approximate the word representation of a VPC as the sum of the vectors of its verb and its preposition. Thus, we have, $v_{vp} = v_{verb} + v_{prep}$. We consider such an approximation under three settings:

1. **Global embedding baseline:** In this simplistic compositional model of the phrasal verb, we add the verb and the global preposition embedding to approximate the phrasal verb embedding, i.e., $v_{vp}^{global} = v_{verb} + v_{prep}^{global}$.

2. **Simplex embedding baseline:** Here the assumption is that the verb alone is contributing to the meaning of the phrasal verb. Hence, we use the verb embedding alone, to approximate the phrasal verb embedding, i.e., $v_{vp}^{simplex} = v_{verb}$.

3. **Sense-specific embedding:** Here we use our sense-specific preposition embedding to yield $v_{vp}^{sense} = v_{verb} + v_{prep}^{sense}$.

For each approximate phrasal embedding ($v_{vp}^{sense}$, $v_{vp}^{global}$, $v_{vp}^{simplex}$), we list the nearest three verbs (excluding the verb in the phrase) as its paraphrase. Here, the distance is measured in terms of the cosine similarity between the word vectors. Examples of phrasal verb paraphrasing are shown in Table 6. In the sentence, “The teaching was carried on in the form of folklore”, the nearest neighbor of carry on is conduct using the preposition sense embedding, laid using the global embedding and placed with the simplex verb.

Two human annotations set the gold standard for whether the paraphrase is valid or not (for polysemous verbs, we consider the verb as a valid paraphrase if it conveys the meaning in any of its senses). The agreed upon annotations constitute the dataset. We use accuracy as evaluation metric, which is the percent of phrasal verbs with a valid paraphrase among three candidates. A more detailed evaluation is in the supplementary material.

**Results.** We report the results in Table 7, where we notice that paraphrasing with the preposition sense embedding has a much higher precision than the two baselines. This validates the sense-specific
The teaching is **carried on** in the form of folklore.

He **brought in** new ideas in the discussion.

| sentence                                                                 | phrasal verb   | paraphrasing |
|--------------------------------------------------------------------------|----------------|--------------|
| The teaching is **carried on** in the form of folklore.                  | carried on     | conducted    |
|                                                                          | placed         | laid          |
|                                                                          |                |              |
| He **brought in** new ideas in the discussion.                           | brought in     | introduced    |
|                                                                          | placed         |               |
|                                                                          |                | came          |

Table 6: Paraphrasing of Phrasal Verbs

| Embedding | Global | Simplex | Sense |
|-----------|--------|---------|-------|
| Accuracy  | 0.44   | 0.44    | 0.73  |

Table 7: Accuracy on Phrasal Verbs Paraphrasing.

Comparing the different phrasal verb approximation methods on an instance-by-instance basis yields a closer view of the results. Of the 91 phrasal verbs, there were 31 instances where a sense-based approximation was better than that using a global-embedding, 32 instances where sense-based was better than simplex, and 19 instances where sense-based was better than both global and simplex. This shows that the role of sense-specific preposition embeddings in capturing the meanings of phrasal verbs is non-trivial.

**Sense embeddings outperform simplex** ones in instances where: (a) prepositions are important in aspectual phrases (where the particle provides the verb with an endpoint, suggesting that the action described by the verb is performed completely, thoroughly or continuously), e.g., "go against"; (b) prepositions help disambiguate the verb, e.g., "carried" has multiple senses, sense 1: support the weight of something, sense 2: Assume or accept (responsibility or blame). In vector representation, "carried" is close to "laid", "wiped" and "phased", while sense "on" drives "carry on" much closer to "conducted".

**Sense embeddings outperform global** ones since the latter only represent the semantics of dominant sense while sense embedding is better at capturing the true sense. For example, the global embedding of **down** is close to **destroyed** and **crashed**, and thus in phrase **put down**, global method gives paraphrases such as **slammed** and **snapped**. Sense embedding provides its sense of “downward direction”, and gives the paraphrases **laid** and **tossed**.

**Sense embeddings encode phrasal verb** semantics even though the preposition in the phrasal verb has lost its functional aspect; we see that computationally (and in a vector space), the sense-tagged preposition remains inside a phrasal verb. This is more pronounced in compositional phrasal verbs and in aspectual ones, and less so in idiomatic ones (see Section A.3 for a discussion (Villavicencio, 2006)).

5 Discussion

**Resource-independence**: Previous approaches to PSD relied on a dependency parser to extract words modified by a preposition and those that the preposition modifies. In general, these words occur in the preposition’s local context. We have allowed the context window to be a tunable parameter so that the classifier can learn to cover informative words in the context, and thus effectively captures the dependency information in a resource-independent fashion.

**Novel context feature**: The context averaging approach, which disregards context word order, suffers in accuracy compared to models that use left and right context words. This indicates that information about the order relative to the preposition is useful in preposition disambiguation, since the left (resp. right) context generally corresponds to attachment (resp. complement) information. Additionally, our use of the context-interplay feature combines the information on both sides of the preposition to infer its underlying sense. Suppose a cup of medicine, professor of humanity and professor of mathematics are in the training corpus, and senses of preposition of are ‘contents’, ‘possessor’ and ‘field’. Given a test instance professor of medicine, it would be hard for the method with only the left or the right feature to decide the preposition sense since the test instance has the same word as each of the training instance, and their features in these two baselines are similar. However, the interplay vector in professor of medicine is closer to that in “professor of mathematics” than to other two training instances. The interplay feature prompts that of in test instance refers to a field (or species) instead of contents or possessor.

**Data-driven insights into context dependence:**
Knowing the weights on the context features in our supervised PSD model, the weighted $\kappa$-NN, we can infer the extent to which prepositions rely on the complement and the attachment. For example, we found that in the case of the prepositions behind (occurring in, “shut behind her”, “dip behind clouds”), to (e.g., “testify to the depth”, “mumbling to himself”), and with (e.g., “amalgamated with her old school”, and “rub with bare hands”), the verbs they attach to strongly influence their sense. For other prepositions such as during (e.g., “during the incident”, “during his lifetime”, “during the day”) and on (e.g., “on his hands”, “on the ground”), the complement has more influence on the senses.

**Sense encodes relations:** Sense-specific representations outperform the global preposition representation in terms of encoding semantic relations—thus prepositional sense-specificity captures the encoded semantics better than its sense-generic version. Working with the small VPC dataset and the simplistic model of compositionality, we interpret the results as positive indicators of the viability of using sense-specific prepositional embeddings to paraphrase VPCs. We observe that in the case of light verbs, whose meaning is determined by the particles they combine with, (e.g., come down $\sim$ fall), a valid paraphrase is found in the top 3 candidates when the sense-specific representation is used, and not when the simplex or the global representation is used.

As pointed out in (Navigli, 2006), a potential limiting factor of the sense-specific representation could be the fine-grained sense distinctions in the training set. Future work could explore preposition sense representation learned from a coarse-grained training set.

### 6 Related Works

**Preposition Sense Disambiguation:** Preposition disambiguation has been explored on the SemEval dataset via various methods and external resources (part of speech taggers, chunkers, dependency parsers, named entity extractors, WordNet based supersense taggers and semantic role labelers) since 2007 (Yuret, 2007; Ye and Baldwin, 2007; Tratz and Hovy, 2009; Hovy et al., 2011; Popescu et al., 2007; Tratz and Hovy, 2011; Srikumar and Roth, 2013).

More recently, Gonen and Goldberg (2016) use word embeddings and other resources including a multilingual parallel corpus processed using sequence to sequence neural networks for preposition disambiguation and achieve an accuracy within 5% of the state-of-the-art, which includes (Litkowski, 2013; Hovy et al., 2010; Srikumar and Roth, 2013). We note that we achieve the comparable performance as (Gonen and Goldberg, 2016) using only word embeddings.

**Preposition Representation:** Word embeddings such as Word2vec (Mikolov et al., 2013a) and GloVe (Pennington et al., 2014) have been widely recognized for their ability to capture linguistic regularities (including syntactic and semantic relations). On the other hand, no linguistic property of their prepositional embeddings are known; to the best of our knowledge, we propose the first sense-specific prepositional embeddings and demonstrate their linguistic regularities. Distantly related is (Hashimoto and Tsuruoka, 2015), which learns embeddings of prepositions acting as verb adjuncts by tensor factorization of a predicate matrix. Similarly, Belinkov et al. (2014) explore the use of preposition representations optimized for the task of prepositional phrase attachment, but do not analyze the semantic contribution or sense-specificity of preposition embeddings.

**Sense-specific Embedding:** Recent works have proposed polysemy disambiguation, using external resources such as Wordnet (Rothe and Schütze, 2015) or in an unsupervised way (Arora et al., 2016; Neelakantan et al., 2014); both the unsupervised approaches are limited in the number of senses they can represent (about 4) and are validated for only nouns and verbs. The approach of (Neelakantan et al., 2014) is roughly similar to our baseline method using the average context vector.

### 7 Conclusion

This paper encodes attachment and complement properties of prepositions into context features, disambiguating senses of preposition. The method relies on no external resources (all prior works use at least a dependency parser), and performs very well on two standard PSD datasets. The disambiguation readily scales to a large corpus and the resulting sense-specific representations have been shown to capture lexical relationships and aid phrasal paraphrasing. Evaluating the utility of the preposition representations in downstream NLP applications (specifically question-answering) is left to future work.
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A Preposition Sense Representation

A.1 Word similarity task

We learn preposition sense representations, and explore the semantic information they carry. A straightforward approach is to examine the nearest neighboring words, corresponding to each sense of each representation. Our results on this exploration for five exemplar prepositions are here: in (Table 8), over (Table 9), for (Table 11), of (Table 11), and with (Table 12). We enumerate senses for a preposition in each table, and also provide their closest words, TPP semantic type and example sentences for each sense.

| sense number | 1                  | 2                  | 3                  | 4                  |
|--------------|--------------------|--------------------|--------------------|--------------------|
| closest words | backwards, reverse, angles, diagonal, between, forward | wearing, dress, hats, dresses, trousers, sleeves, pants, jacket | back, inside, underneath, from, into, where, onto | where, near, from, at, southern, northern,during |
| example      | in all directions, move in, differ in | dress in black, in leather, in size | in the mail, in most cases, in confined space | in military aircraft, in the UK, in Argentina |
| TPP sense    | Manner,or,Degree | VariableQuality    | ThingEntered       | ThingEnclosed      |

| sense number | 5                  | 6                  | 7                  | 8                  |
|--------------|--------------------|--------------------|--------------------|--------------------|
| closest words | until, during, subsequently, following, after, late, since | university, graduate, college, teaching, faculty, school | economic, systematic, growth, technological | wearing, dressed, costume, wears, clothes, jacket |
| example      | in 1978, in may 1993, in 2002, in the weeks | in a lecture, in graduate studies, in college | focus in science, growth in sales, vocals in her pieces | in the costume, in the jacket, in a gown |
| TPP sense    | Timeframe          | ProfessionAspect   | Attribute           | Garment            |

| sense number | 9                  | 10                 | 11                 | 12                 |
|--------------|--------------------|--------------------|--------------------|--------------------|
| closest words | explicitly, interpretation, discourse, fundamental, notion, principles | prosecutor, prosecution, criminal, judicial, justice | onwards, for, wherein | violent, betrayal, bloody, brutal, bitter, fearful |
| example      | in a diagram, in this process, in different ways, in the work | in a constitution, in military justice, in court | in computer graphics, in engineering projects, in the war | result in, in custody, involved in, participate in |
| TPP sense    | Medium             | Activity           | FramingEntity      | Condition          |

Table 8: Senses of Preposition “in”

In Table 8, we notice that the nearest neighbors can be the words semantically similar to the given sense. For example, until, during and since are close to TimeFrame sense of in. The nearest words might be the governors of a preposition. For example, when in carries the sense of Garment, verbs such as dressed are close to it. Also, the nearest words can also be complements of this preposition. For example, nouns such as university, college and school are neighbors to in’s sense of ProfessionAspect.

For the sense representations of over in Table 9, we see that the nearest neighbors are indeed synonymous. For example, crossed is close to over’s sense of ThingsSurmounted, about close to the sense of SubjectConsidered, onto close to the sense of ThingsCovered, against close to the sense of ResistantSurface. Senses are interchangeable with synonymous neighbors. “bridge over the river” is similar to “bridge crossed the river”, “ponder over the reply” similar to “ponder about the reply”, and “drizzling ketchup over chicken” similar to “drizzling ketchup onto chicken”, and “broke a chair over me” similar to “broke a chair against me”. Besides synonyms, nearest words also include governors and complements specific to over’s senses since they co-occur so frequently. Word broke is a governor in “broke a chair over me”, and it is also a nearest neighbor given over’s sense as ResistantSurface. In another sentence “cooking the dumplings over a medium heat”, heat is a complement, and also close to over, given its sense as ThingsSurmounted.
| sense number | 0                                      | 1                                      | 2                                      | 3                                      |
|--------------|----------------------------------------|----------------------------------------|----------------------------------------|----------------------------------------|
| closest words | around, upwards, across, outwards, vertically, surface | crossed, foot, paces, straightened, stretch, spanning, river | about, around, intervening, estimated | onto, grabbed, inside, top, apiece,      |
| example      | glance over her shoulder, look over the gymnasium | bridge over the river, leaned over her shoulder | brood over it, pondered over the reply | flung a net over me, drizzling ketchup over his grilled chicken |
| TPP sense    | ThingsSurveyed                         | ThingsSurmounted                       | SubjectConsidered                      | ThingsCovered                          |
| sense number | 4                                      | 5                                      | 6                                      | 7                                      |
| closest words | heat, coated, oven, insulation, heaters | spanning, stretch, crosses, spans, longest, reaching | notching, yards, shut-out, scampered | across, traversing, meters, submerged, traversed, inland |
| example      | cook the dumplings over a medium heat, the fighting over England, | crossed one foot over another | discarded the broken spar over the side | clambered over the fallen rocks |
| TPP sense    | ThingsSurmounted                       | PlaceSurpassed                         | ThingDescendedFrom                     | ThingNegotiated                        |
| sense number | 8                                      | 9                                      |                                        |                                        |
| closest words | scored, unbeaten, against, beating, hat-trick, rule | hit, against, on, broke, smashed       |                                        |                                        |
| example      | reigned over Bangkok ’s economy, rule over it | broke a chair over me                  |                                        |                                        |
| TPP sense    | ThingControlled                        | ResistantSurface                       |                                        |                                        |

Table 9: Senses of Preposition *over*
| sense number | 0 | 1 | 2 | 3 |
|--------------|---|---|---|---|
| closest words | within, its, constituting, comprising, combined | cups, pot, basket, bucket, bowls | featured, wonderful, amazing, shows, laugh | concerning, regarding, furthermore |
| example | colonies of insects, bunches of grain | a can of milk, the envelop of photographs | a smile of delight, a frown of doubt | purchase of copyright, smuggling of oil |
| TPP sense | Whole | Contents | Defining Quality | Recipient |
| sense number | 4 | 5 | 6 | 7 |
| closest words | specific, particular, common, generic | measured, maximum, decreases, increases, proportional | triangular, outer, underneath, adjacent | appointed, deputy, treasurer, whose, chief, governed |
| example | a type of, all kinds of | length of 7 cm, an increase of 1% | top of the slope, face of a man | descendant of humans, sisters of this girl |
| TPP sense | Exemplar | ScaleValue | Whole | Possessor |
| sense number | 8 | 9 | 10 | 11 |
| closest words | corrupted, enlightened, regards, owes | gender, male, female, adolescent, adult | containing, packaged, handmade, contained | acknowledge, asserts, argues, conceived, believes |
| example | tell of the experience, enlightenment of participants | infants of the same age, women of nineteen | stick of furniture, the firms of solicitors | ashamed of, conceived of, know of |
| TPP sense | Object | Age | Constituent | MentalContents |
| sense number | 12 | 13 | 14 | 15 |
| closest words | died, buried, survived, pleaded, dying, arrested | seeming, utter, sincere, religious | consequent, upon, regarding, subsequent | emphasize, concerning, embodied, academic, faculty |
| example | died of a coronary, convict the farmer of pollution | afraid of, religious of, shy of | belief of people, presumption of the courts | expression of, announcement of a discovery |
| TPP sense | Cause | Concomitant | Possessor | Species |
| sense number | 16 |
| closest words | written, novels, adaptations, narrated, edited |
| example | diary of Bob, poetry of Shakespeare |
| TPP sense | Creator |

**Table 10: Senses of Preposition of**
Seventeen senses are enumerated for preposition of in Table 10. Synonymous words can be found in of’s nearest neighbors. For example, concerning is close to the sense Recipient, upon is close to the sense Possessor, and containing is close to the sense Constituent. These neighbors can paraphrase of’s corresponding senses. The sentence “purchase of copyright” can be paraphrased as “purchase concerning copyright”, “presumption of the courts” paraphrased as “presumption upon the courts”, and “the firms of solicitors” as “the firms containing solicitors”. We again observe that the nearest neighbors also reflect the attachment and complement properties of specific senses. When of carries the sense of Contents, words such as cups, pot and bowls are neighbors of the sense Contents. When of carries the sense of Cause, governors such died and arrested are its closest neighbors.

| sense number | 0 | 1 | 2 | 3 |
|--------------|---|---|---|---|
| closest words | purchase, buy, rental, lease | rovers, starting, southend | promotional, showcase, featuring, music, advertise, commercial | generic, terminology, describe, denote, definitions, defined |
| example | bought it for $200 | headed for the bathroom, made for the orchard | feel pity for, be worried for, be embarrassed for | a synonym for coordination, an expression for the energy |
| TPP sense | Price | Destination | Beneficiary | Referent |
| sense number | 4 | 5 | 6 | 7 |
| closest words | harshly, repeatedly, insisting, admitting, accusing, behalf | economical, because, therefore, considering, practical, ensure | team, league, win, championship, scoring, match, final | overseeing, consultant, supervising, executive, deputy, assistant |
| example | adored him for his personality, despising herself for her eagerness | is costly for the firms, is fantastic for a little boy | desire for friendship, eager for challenge, urge for food | a good chief for the clan, work for a company |
| TPP sense | Cause | Experincer | Beneficiary | Employer |
| sense number | 8 | 9 | 10 | 11 |
| closest words | outstanding, best, award, exemplary, achievement, recognizing, exceptional | during, spent, beforehand, before, after | fees, expenses, payment, dues, money, pay, taxes, allowance, subsidy | facilitate, assist, enable, using, simplify, simulate, ensure, optimize, purpose |
| example | outstanding for cuisine, proclivity for risk | for the end of this year, forecast for 1993 | higher prices for goods, charge drives for emission tests | defer the issue for later discussion, excellent for this purpose |
| TPP sense | Concomitant | TimePeriod | SwapGoal | Purpose |
| sense number | 12 |
| closest words | hence, because, ample, adequate, consequently |
| example | suffice for a murder conviction, adequate for flow |
| TPP sense | ReferentNorm |

Table 11: Senses of Preposition for

Table 11 provides for’s senses. First look at the synonyms among the nearest neighbors. Word during corresponds to the sense TimePeriod, and “forecast for 1993” can be replaced with “forecast during 1993”. Then we can find the governors and complements as neighbors. For example, buy is a governor in phrase “buy it for $200”, and also close to the sense Price. Word definitions governs the preposition in phrase “definition for the term” and stay close to the sense Referent. Word outstanding is also a governor
in “outstanding for a cuisine”, and close to for’s sense Concomitant. As for complements, purpose acts as an complement in “excellent for this purpose”, and appears close to for’s sense of Purpose.

| sense number | 0     | 1                      | 2                        | 3                      |
|--------------|-------|------------------------|--------------------------|------------------------|
| closest words| pair, featuring, twisted, assorted | using, stacked, resembling, molded, mechanically, adding | signed, contract, professional, manager, career, full-time | switches, microphones, setup, installing, radios, audio |
| example      | rubble with bare hands, nudged Graham with her elbow | healed them with our doctor’s hand, treatment with laser | stint with Somerset, manager with The Northern Echo | a wooden cart with small wheels, the envelope with her resignation |
| TPP sense    | MeansName | MeansName | Employer | Accountrement |
| sense number | 4     | 5            | 6            | 7            |
| closest words| scholar, studies, professor, doctoral | treasurer, leader elected, deputy | while, alongside, mutual, befriend, interpersonal | community, voluntary, facilitate, implementing |
| example      | studies literature with the Open University | the value of benefits rises with income, fantastic with the day | partner with systems integrators, conspire with enemy | complied with their obligation, conform with the legislation |
| TPP sense    | Partner | Coreconsultant | Accompanier | Harmonizer |
| sense number | 8     | 9            | 10           | 11           |
| closest words| express, emotional, jealousy, fearful | against, teammate, throwing, punching | news, reporter, press, interviewing, announcing | collar, wears, shoulders, waist, belly, neck |
| example      | glistened with dew, shimmers with crystals | the showdown with his father, collided with a bus | contact me with ideas, call me with an arrangement | people with disabilities, a lady with a pale face |
| TPP sense    | FeatureCause | Opponent | Message | Attribute |
| sense number | 12    | 13           | 14           |              |
| closest words| mutual, mutually, resulting, when, thus, meanwhile | symptoms, prognosis, syndrome, abnormalities | dazed, furiously, relentlessly, taunt |              |
| example      | reason with her, compatible with autonomy | woke with a heavy head, awoke with a start | forecast with certainty, express it with passionate intensity |              |
| TPP sense    | Concomitant | Malady | Manner&Mood |              |

Table 12: Senses of Preposition with

The senses of with are listed in Table 12. A nearest neighbor of sense MeansName is using, and sentence “treatment with laser” can be rewritten as “treatment using laser”. A nearest neighbor of sense Accompanier is alongside, and “partner with systems integrators” can be understood as “partner alongside systems integrators”. Against is synonymous to the sense Opponent, and “collided with a bus” can be paraphrased as “collided against a bus”. Besides semantically similar words, governors and complements can be included as nearest words. Abnormalities is a governor in “woke with abnormalities”, and is one neighbor of sense Malady. News is a complement in “contact me with the recent news”, and close to of’s sense Message.

These tables of sense representations show us that preposition sense-specific embedding carries non-trivial lexical semantics. Nearest neighbors give a qualitative evaluation of these representations in terms of word similarity. We do observe semantically-similar words are included as nearest neighbors, which can be treated as definitions of the specific preposition sense. We also find that these nearest words
reveal the attachment and complement properties of prepositions. Governors and complements may appear close to the given sense.

### A.2 Preposition senses as relations

In this section, we use preposition sense to model lexical relations, and predict one word (e.g., country) from the other (e.g., capital). Three candidate predictions are generated from the approximate embedding. In Fig. 1, we report the accuracy of finding the target word (country, state or adjective) in the top $k$ ($k = 1, 2, 3$) neighbors corresponding to the use of the global embedding, the sense-specific embedding of (‘in’ and ‘from’) and the difference embedding.

Figure 1: Sense specific preposition embeddings serve as good approximations of three semantic relations.

### A.3 Preposition senses aid paraphrasing

| sentence                                                                 | phrasal verb | paraphrasing |
|-------------------------------------------------------------------------|--------------|--------------|
| She could not keep from crying, and agitated on the chair.              | keep from    | avoid, get,  |
|                                                                          |              | maintain     |
| Without a word he leaned forward and switched on the engine.            | switched on   | starting,    |
|                                                                          |              | shifted,     |
|                                                                          |              | reverted     |
| I have certainly been kicked in the teeth by those bastards.            | kicked in     | knocked,     |
|                                                                          |              | throw        |
| I have chosen to block off the easy track and so turn it into a dead end.| block off    | stopped,     |
|                                                                          |              | cleared,     |
|                                                                          |              | cleared      |
| The Rishon Le Zion killings sparked off a wave of sympathy protests.    | sparked off   | ensued,      |
|                                                                          |              | spurred,     |
|                                                                          |              | ignited      |
| Stanley put down his paper and glared at her.                          | put down     | laid,        |
|                                                                          |              | slammed,     |
|                                                                          |              | brought      |

Table 13: Paraphrasing of Phrasal Verbs

In the experiment on phrasal verb paraphrasing, we use preposition global embedding, simplex embedding and our sense-specific preposition embedding to approximate the representation of phrasal verbs. The nearest verbs of the phrasal representation are used (excluding the verb in the phrase) as its paraphrases. Some examples of phrasal verbs and paraphrases are shown in Table 13, and valid paraphrases are highlighted.

For each approximate phrasal embedding $(v_{\text{sense}}^{vp}, v_{\text{global}}^{vp}, v_{\text{simplex}}^{vp})$, we list the nearest three verbs (excluding the verb in the phrase) as candidate paraphrases. Here, the distance is measured in terms of the cosine similarity between the word vectors.

Since we listed the top three candidate paraphrases for a phrasal verb and consider the validity, we choose metric precision at $k$ $(\text{prec}@k)$ which is defined as:

$$\text{prec}@k = \frac{1}{N} \sum_{i=1}^{N} \text{Precision}(i, k),$$

where $N$ is the number of phrasal verbs, and $\text{Precision}(i, k)$ is the percent of good paraphrases among the top $k$ paraphrases for phrase $i$. The precision metrics for each method are reported in Fig. 2. As we
can see, our sense-specific preposition embedding has a significantly better performance than global and simplex embeddings, in terms of all the three prec@1, prec@2 and prec@3 metrics.

We notice that paraphrasing is closely related with the nature of phrasal verbs. A three way classification is adopted in (Dehé, 2002; Jackendoff, 2002; Emonds, 1985; Villavicencio, 2006), where verb particle compounds (VPC) can be classified into compositional, idiomatic or aspectual. For the compositional VPCs, the meaning of the construction is determined by the literal interpretations of the particle and the verb (e.g., throw out). Idiomatic VPCs, however, cannot have their meaning determined by their component words (e.g., get through meaning ‘manage to deal with’). The third class, aspectual VPCs, have the particle providing the verb with an endpoint, describing the action in more details (e.g., tear up).

The dataset of English phrasal verbs consists of 91 phrases, in which there are 54 compositional phrases, 16 aspectual phrases and 21 noncompositional phrases in our dataset. Here we report the precision@k (k=1,2,3) of different methods on these three types of verb phrases respectively.

As is shown in Table 14, the precision of paraphrasing with preposition sense embedding is higher than baselines with preposition global embedding and verb embedding on three types of phrases. As we can see from the table, the precision improvement of sense embedding over global embedding is larger on aspectual phrases than on compositional phrases. The reason might be that preposition plays a more important semantic role in aspectual phrases than in compositional phrases.

We also observe that the precision achieved by simplex embedding is close to precision by global embedding. It means the phrasal verb representations with and without global embedding do not differ too much, which indicates that global embedding does not provide necessary semantic information of prepositions in paraphrasing phrasal verbs.

Also, we find that paraphrasing of compositional or aspectual phrasal verbs is better than that of idiomatic ones. This is because component words do not give much information about the semantics of idiomatic phrases. Hence addition of components is not a good approximation of idiomatic phrasal representation.

Empirically, phrasal approximation using addition of verb and particle gives good paraphrasing mainly in the following cases:

1. verb dominates the phrasal meaning, e.g., focus on (∼ focus), carry in (∼ carry);
2. preposition dominates the phrasal meaning, e.g., go against (∼ against), keep from (∼ from, one
Table 14: Precision on Verb Phrase Paraphrasing

| phrase type | Compositional | Aspectual | Idiomatic |
|-------------|---------------|-----------|-----------|
| embedding   | global simplex sense | global simplex sense | global simplex sense |
| prec@1      | 0.125 0.232 0.482 | 0.0625 0.0625 0.5 | 0.190 0.143 0.333 |
| prec@2      | 0.196 0.277 0.429 | 0.125 0.0625 0.406 | 0.238 0.167 0.429 |
| prec@3      | 0.220 0.268 0.417 | 0.188 0.042 0.438 | 0.190 0.159 0.381 |

sense of 'from' is close to 'stop' and 'prevent');

3. verb is polysemous, and preposition helps disambiguate the verb. For example, "headed down" where the verb "headed" have two senses: "chaired/led" and "approached". The phrase "headed down" prompts that "headed" should have the sense "approached".