Abstract

We propose a methodology that adapts graph embedding techniques (DeepWalk (Perozzi et al., 2014) and node2vec (Grover and Leskovec, 2016)) as well as cross-lingual vector space mapping approaches (Least Squares and Canonical Correlation Analysis) in order to merge the corpus and ontological sources of lexical knowledge. We also perform comparative analysis of the used algorithms in order to identify the best combination for the proposed system. We then apply this to the task of enhancing the coverage of an existing word embedding’s vocabulary with rare and unseen words. We show that our technique can provide considerable extra coverage (over 99%), leading to consistent performance gain (around 10% absolute gain is achieved with w2v-GN-500K cf.§3.3) on the Rare Word Similarity dataset.

1 Introduction

The prominent model for representing semantics of words is the distributional vector space model (Turney and Pantel, 2010) and the prevalent approach for constructing these models is the distributional one which assumes that semantics of a word can be predicted from its context, hence placing words with similar contexts in close proximity to each other in an imaginary high-dimensional vector space. Distributional techniques, either in their conventional form which compute co-occurrence matrices (Turney and Pantel, 2010; Baroni and Lenci, 2010) and learn high-dimensional vectors for words, or the recent neural-based paradigm which directly learns latent low-dimensional vectors, usually referred to as embeddings (LeCun et al., 2015), rely on a multitude of occurrences for each individual word to enable accurate representations. As a result of this statistical nature, words that are infrequent or unseen during training, such as domain-specific words, will not have reliable embeddings. This is the case even if massive corpora are used for training, such as the 100B-word Google News dataset (Mikolov et al., 2013a).

Recent work on embedding induction has mainly focused on morphologically complex rare words and has tried to address the problem by learning transformations that can transfer a word’s semantic information to its morphological variations, hence inducing embeddings for complex forms by breaking them into their sub-word units (Luong et al., 2013; Botha and Blunsom, 2014; Soricut and Och, 2015). However, these techniques are unable to effectively model single-morpheme words for which no sub-word information is available in the training data, essentially ignoring most of the rare
domain-specific entities which are crucial in the performance of NLP systems when applied to those domains.

On the other hand, distributional techniques generally ignore all the lexical knowledge that is encoded in dictionaries, ontologies, or other lexical resources. There exist hundreds of high coverage or domain-specific lexical resources which contain valuable information for infrequent words, particularly in domains such as health. Here, we present a methodology that merges the two worlds by benefiting from both expert-based lexical knowledge encoded in external resources as well as statistical information derived from large corpora, enabling vocabulary expansion not only for morphological variations but also for infrequent single-morpheme words. The contributions of this work are twofold: (1) we propose a technique that induces embeddings for rare and unseen words by exploiting the information encoded for them in an external lexical resource, and (2) we apply, possibly for the first time, vector space mapping techniques, which are widely used in multilingual settings, to map two lexical semantic spaces with different properties in the same language. We show that a transfer methodology can lead to consistent improvements on a standard rare word similarity dataset.

2 Methodology

We take an existing semantic space $S_C$ and enrich it with rare and unseen words on the basis of the knowledge encoded for them in an external knowledge base (KB) $K$. The procedure has two main steps: we first embed $K$ to transform it from a graph representation into a vector space representation (2.1), and then map this space to $S_C$ (2.2). Our methodology is illustrated in Figure 1.

In our experiments, we used WordNet 3.0 (Fellbaum, 1998) as our external knowledge base $K$. For word embeddings, we experimented with two popular models: (1) GLOVe embeddings trained by Pennington et al. (2014) on Wikipedia and Gigaword 5 (vocab: 400K, dim: 300), and (2) Word2vec (Mikolov et al., 2013) trained on the Google News dataset (vocab: 3M, dim: 300).

2.1 Knowledge Base Embedding

Our coverage enhancement starts by transforming the knowledge base $K$ into a vector space representation that is comparable to that of the corpus-based space $S_C$. To this end, we use two techniques for learning low-dimensional feature spaces from knowledge graphs: DeepWalk and node2vec. DeepWalk uses a stream of short random walks in order to extract local information for a node from the graph. By treating these walks as short sentences and phrases in a special language, the approach learns latent representations for each node. Similarly, node2vec learns a mapping of nodes to continuous vectors that maximizes the likelihood of preserving network neighborhoods of nodes. Thanks to a flexible objective that is not tied to a particular sampling strategy, node2vec reports...
improvements over DeepWalk on multiple classification and link prediction datasets. For both these systems we used the default parameters and set the dimensionality of output representation to 100. Also, note than nodes in the semantic graph of WordNet represent synsets. Hence, a polysemous word would correspond to multiple nodes. In our experiments, we use the MaxSim assumption of Reisinger and Mooney (2010) in order to map words to synsets.

To verify the reliability of these vector representations, we carried out an experiment on three standard word similarity datasets: RG-65 (Rubenstein and Goodenough, 1965), WordSim-353 similarity subset (Agirre et al., 2009), and SimLex-999 (Hill et al., 2015). Table 1 reports Pearson and Spearman correlations for the two KB embedding techniques (on WordNet’s graph) and, as baseline, for our two word embeddings, i.e. $W^2V$-GN and GLOVE. The results are very similar, with node2vec proving to be slightly superior. We note that the performances are close to those of state-of-the-art WordNet approaches (Pilehvar and Navigli, 2015), which shows the efficacy of these embedding techniques in capturing the semantic properties of WordNet’s graph.

### 2.2 Semantic Space Transformation

Once we have the lexical resource $K$ represented as a vector space $S_K$, we proceed with projecting it to $S_C$ in order to improve the word coverage of the latter with additional words from the former. In this procedure we make two assumptions. Firstly, the two spaces provide reliable models of word semantics; hence, the relative within-space distances between words in the two spaces are comparable. Secondly, there exists a set of shared words between the two spaces, which we refer to as semantic bridges, from which we can learn a projection that maps one space into another.

As for the mapping, we used two techniques which are widely used for the mapping of semantic spaces belonging to different languages, mainly with the purpose of learning multilingual semantic spaces: Least squares (Mikolov et al., 2013b; Dinu and Baroni, 2014, LS) and Canonical Correlation Analysis (Faruqui and Dyer, 2014; Upadhyay et al., 2016, CCA). These models receive as their input two vector spaces of two different languages and a seed lexicon for that language pair and learn a linear mapping between the two spaces. Ideally, words that are semantically similar across the two languages will be placed in close proximity to each other in the projected space. We adapt these models to the monolingual setting and for mapping two semantic spaces with different properties. As for the seed lexicon (to which in our setting we refer to as semantic bridges) in this monolingual setting, we use the set of monosemous words in the vocabulary which are deemed to have the most reliable semantic representations.

| KB/Word | RG-65 | WSS-353 | SimLex-999 |
|---------|-------|---------|------------|
| Embedding | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ | $\rho$ |
| node2vec | 0.88 | 0.86 | 0.67 | 0.70 | 0.36 | 0.39 | |
| DeepWalk | 0.86 | 0.86 | 0.69 | 0.70 | 0.35 | 0.38 | |
| W2V-GN | 0.75 | 0.77 | 0.77 | 0.76 | 0.44 | 0.45 | |
| GLOVE | 0.76 | 0.75 | 0.66 | 0.66 | 0.37 | 0.39 | |

Table 1: Pearson ($r$) and Spearman ($\rho$) correlation results on three word similarity datasets.
Specifically, let \( S_C \) and \( S_K \) be the corpus and KB semantic spaces, respectively, and \( S'_C \subset S_C \) and \( S'_K \subset S_K \) be their corresponding subset of semantic bridges, i.e., words that are monosemous according to the WordNet sense inventory. Note that \( S'_C \) and \( S'_K \) are vector matrices that contain representations for the same set of corresponding words, i.e., \( |S'_C| = |S'_K| \). LS views the problem as a multivariate regression and learns a linear function \( M \in \mathbb{R}^{d_K \times d_C} \) (where \( d_K \) and \( d_C \) are the dimensionalities of the KB and corpus spaces, respectively) on the basis of the following \( L_2 \)-regularized least squares error objective and typically using stochastic gradient descent:

\[
\min_{M \in \mathbb{R}^{d_K \times d_C}} ||S'_K M - S'_C||^2 + \lambda ||M||^2 \tag{1}
\]

The enriched space \( S^* \) is then obtained as a union of \( S_K M \) and \( S_C \). CCA, on the other hand, learns two distinct linear mappings \( M_1 \) and \( M_2 \) with the objective of maximizing the correlation between the dimensions of the projected vectors \( S'_C \) and \( S'_K \):

\[
M_1, M_2 = \text{CCA}(S'_C, S'_K) = \arg \max_{M_1, M_2} \rho(M_1 S'_C, M_2 S'_K) \tag{2}
\]

In this case, \( S^* \) is the union of \( M_1 S_C \) and \( M_2 S_K \). In the next section we first compare different KB embedding and transformation techniques introduced in this section and then apply our methodology to a rare word similarity task.

3 Experiments

3.1 Evaluation benchmark

To verify the reliability of the transformed semantic space, we propose an evaluation benchmark on the basis of word similarity datasets. Given an enriched space \( S^* \) and a similarity dataset \( D \), we compute the similarity of each word pair \( (w_1, w_2) \in D \) as the cosine similarity of their corresponding transformed vectors \( s_{w_1} \) and \( s_{w_2} \) from the two spaces, where \( s_{w_1} \in S_K M \) and \( s_{w_2} \in S_C \) for LS and \( s_{w_1} \in M_1 S_C \) and \( s_{w_2} \in M_2 S_K \) for CCA. A high performance on this benchmark shows that the mapping has been successful in placing semantically similar terms near to each other whereas dissimilar terms are relatively far apart in the space. We repeat the computation for each pair in the reverse direction.

3.2 Comparison Study

Figure 2 shows the performance of different configurations on our three similarity datasets and for increasing sizes of semantic bridge sets. We experimented with four different configurations: two KB embedding approaches, i.e. DeepWalk and node2vec, and two mapping techniques, i.e. LS and CCA (cf. §2). In general, the optimal performance is reached when around 3K semantic bridges are used for transformation. DeepWalk and node2vec prove to be very similar in their performance across the three datasets. Among the two transformation techniques, CCA consistently outperforms LS on all three datasets when provided with 1000 or more semantic bridges (with 500, however, LS always has an edge). In the remaining experiments we only report results for the best configuration: node2vec with CCA. We also set the size of semantic bridge set to 5K.

3.3 Rare Word Similarity

In order to verify the reliability of our technique in coverage expansion for infrequent words we did a set of experiments on the Rare Word similarity dataset (Luong et al., 2013). The dataset comprises 2034 pairs of rare words, such as ulcerate-change and nurturance-care, judged by 10 raters on a \([0,10]\) scale. Table 2 shows the results on the dataset for three pre-trained word embeddings (cf. §2), in their initial form as well as when enriched with additional words from WordNet.

\[\text{We used only monosemous nouns and adjectives as our semantic bridges (WordNet 3.0 has over 100K of these). Our experiments with sets up to 20K semantic bridges did not show any significant performance gain over 5K.}\]

\[\text{In addition to our two pre-trained embeddings, we also experimented with the top 500K words from w2v-gn in order to simulate a setting with limited vocabulary.}\]
Among the three initial embeddings, w2v-GN-500K provides the lowest coverage, with over 20% out-of-vocabulary pairs, whereas GloVE has a similar coverage to that of w2v-GN despite its significantly smaller vocabulary (400K vs. 3M). Upon enrichment, all the embeddings attain near full coverage (over 99%), thanks to the vocabulary expansion by rare words in WordNet. The enhanced coverage leads to consistent performance improvements according to both Pearson and Spearman correlations. The best performance gain is achieved for w2v-GN-500K (around 10% absolute gain) which proves the efficacy of our approach in inducing embeddings for rare words. The improvements are also statistically significant (p < 0.05) according to conducted one-tailed t-test (Cohen and Cohen, 1975), showing that the coverage enhancement could lead to improved performance even if lower-performing KB embedding and transformation are used.

### 4 Related Work

The main focus of research in embedding coverage enhancement has been on the morphologically complex forms (Alexandrescu and Kirchhoff, 2006). Luong et al. (2013) used recursive neural networks (RNNs) and neural language models in order to induce embeddings for morphologically complex words from their morphemes whereas Lazaridou et al. (2013) adapted phrase composition models for this purpose. Botha and Blunsom (2014) proposed a different model based on log-bilinear language models, mainly to have a compositional vector-based morphological representation that can be easily integrated into a machine translation decoder. These models often utilize a morphological segmentation toolkit, such as Morfessor (Creutz and Lagus, 2007), in order to break inflected words into their morphological structures and to obtain segmentations for words in the vocabulary. Soricut and Och (2015) put forward a technique that does not rely on any external morphological analyzer and instead, induces morphological rules and transformations, represented as vectors in the same embedding space. Based on these rules a morphological graph is constructed and representations are inferred by analyzing morphological transformations in the graph. However, all these techniques fall short in inducing representations for single-morpheme words that are not seen frequently during training as they base their modeling on information available on sub-word units. In contrast, our transformation-based model can also induce embeddings for single-morpheme words that are infrequent or unseen in the training data, such as domain-specific entities.

### 5 Conclusions and Future Work

We presented a methodology for merging distributional semantic spaces and lexical ontologies and applied it to the task of extending the vocabulary of the former with the help of information extracted from the latter. We carried out an analysis for different KB embedding and semantic space mapping techniques and also showed that our methodology can lead to considerable enrichment of two standard word embedding models, leading to consistent improvements on the rare word similarity dataset. One interesting property of our approach is that it can be used in the reverse direction and for the completion of knowledge bases using the distributional information derived from text corpora. In future work, we plan to investigate this direction. We also intend to experiment with domain-specific lexical resources and measure the impact of coverage enhancement on a downstream NLP application.
Acknowledgments

This research was supported by EPSRC Experienced Researcher Fellowship (Nigel Collier, Dimitri Kartsaklis, (EP/M005089/1)), MRC grant (Mohammad Taher Pilehvar, (MR/M025160/1)) We gratefully acknowledge the donation of a GPU card from the NVIDIA Grant Program.

References

Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. DeepWalk: Online learning of social representations. In Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD ’14, pages 701–710, 2014. ISBN 978-1-4503-2956-9. URL http://doi.acm.org/10.1145/2623330.2623732

Aditya Grover and Jure Leskovec. Node2vec: Scalable feature learning for networks. In Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD ’16, pages 855–864, 2016. ISBN 978-1-4503-4232-2.

Peter D. Turney and Patrick Pantel. From frequency to meaning: Vector space models of semantics. Journal of Artificial Intelligence Research, 37(1):141–188, 2010.

Marco Baroni and Alessandro Lenci. Distributional memory: A general framework for corpus-based semantics. Computational Linguistics, 36(4):673–721, 2010.

Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. Nature, 521(7553):436–444, 2015.

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. In Workshop at International Conference on Learning Representations, Scottsdale, Arizona, 2013a.

Thang Luong, Richard Socher, and Christopher Manning. Better word representations with recursive neural networks for morphology. In Proceedings of the Seventeenth Conference on Computational Natural Language Learning, pages 104–113, Sofia, Bulgaria, 2013.

Jan A. Botha and Phil Blunsom. Compositional Morphology for Word Representations and Language Modelling. In Proceedings of the 31st International Conference on Machine Learning (ICML), Beijing, China, 2014.

Radu Soricut and Franz Och. Unsupervised morphology induction using word embeddings. In Proceedings of NAACL-HLT, pages 1627–1637, Denver, Colorado, 2015.

Christiane Fellbaum, editor. WordNet: An Electronic Database. MIT Press, Cambridge, MA, 1998.

Jeffrey Pennington, Richard Socher, and Christopher Manning. Glove: Global vectors for word representation. In Proceedings of EMNLP 2014, pages 1532–1543, Doha, Qatar, 2014.

Joseph Reisinger and Raymond J. Mooney. Multi-prototype vector-space models of word meaning. In Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics, pages 109–117, Los Angeles, California, 2010.

Herbert Rubenstein and John B. Goodenough. Contextual correlates of synonymy. Communications of the ACM, 8(10):627–633, 1965.

Eneko Agirre, Enrique Alfonseca, Keith Hall, Jana Kravalova, Marius Pasca, and Aitor Soroa. A study on similarity and relatedness using distributional and WordNet-based approaches. In Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, pages 19–27, 2009.

Felix Hill, Roi Reichart, and Anna Korhonen. SimLex-999: Evaluating semantic models with (genuine) similarity estimation. Computational Linguistics, 41(4):665–695, 2015.

Mohammad Taher Pilehvar and Roberto Navigli. From senses to texts: An all-in-one graph-based approach for measuring semantic similarity. Artificial Intelligence, 228:95–128, 2015.

Mohammad Taher Pilehvar and Roberto Navigli. From senses to texts: An all-in-one graph-based approach for measuring semantic similarity. Artificial Intelligence, 228:95–128, 2015.

Tomas Mikolov, Quoc V. Le, and Ilya Sutskever. Exploiting similarities among languages for machine translation. CoRR, abs/1309.4168, 2013b. URL http://arxiv.org/abs/1309.4168

Georgiana Dinu and Marco Baroni. Improving zero-shot learning by mitigating the hubness problem. CoRR, abs/1412.6568, 2014. URL http://arxiv.org/abs/1412.6568
Manaal Faruqui and Chris Dyer. Improving vector space word representations using multilingual correlation. In *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics*, pages 462–471, Gothenburg, Sweden, 2014.

Shyam Upadhyay, Manaal Faruqui, Chris Dyer, and Dan Roth. Cross-lingual models of word embeddings: An empirical comparison. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1661–1670, Berlin, Germany, 2016.

Jacob Cohen and Patricia Cohen. *Applied multiple regression/correlation analysis for the behavioral sciences*. Lawrence Erlbaum Associates, 10 Industrial Avenue Mahwah, NJ 07430 United States, 1975.

Andrei Alexandrescu and Katrin Kirchhoff. Factored neural language models. In *Proceedings of the Human Language Technology Conference of the NAACL, Companion Volume: Short Papers*, pages 1–4, New York City, USA, 2006.

Angeliki Lazaridou, Marco Marelli, Roberto Zamparelli, and Marco Baroni. Compositional-ly derived representations of morphologically complex words in distributional semantics. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1517–1526, Sofia, Bulgaria, 2013.

Mathias Creutz and Krista Lagus. Unsupervised models for morpheme segmentation and morphology learning. *ACM Transactions on Speech and Language Processing*, 4(1):3:1–3:34, 2007.