Multi-Context Term Embeddings: 
the Use Case of Corpus-based Term Set Expansion

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Abstract

In this paper, we present a novel algorithm that combines multi-context term embeddings using a neural classifier and we test this approach on the use case of corpus-based term set expansion. In addition, we present a novel and unique dataset for intrinsic evaluation of corpus-based term set expansion algorithms. We show that, over this dataset, our algorithm provides up to 5 mean average precision points over the best baseline.

1 Introduction

Term set expansion is the task of expanding a given seed set of terms into a more complete set of terms that belong to the same semantic class. For example, given a seed of personal assistant application terms like ‘Siri’ and ‘Cortana’, the expanded set is expected to include additional terms such as ‘Amazon Echo’ and ‘Google Now’.

Most prior work on corpus-based term set expansion is based on distributional similarity, where early work is primarily based on using sparse vectors while recent work is based on word embeddings. The prototypical term set expansion methods utilize corpus-based semantic similarity between seed terms and candidate expansion terms. To the best of our knowledge, each of the prior methods used a single context type for embedding generation, and there are no reported comparisons of the effectiveness of embedding different context types. Moreover, the lack of a publicly available dataset hinders the replicability of previous work and method comparison.

In this paper, we investigate the research question of whether embeddings of different context types can complement each other and enhance the performance of computational semantics tasks like term set expansion. To address this question, we propose an approach that combines term embeddings over multiple contexts for capturing different aspects of semantic similarity. The algorithm uses 5 different context types, 3 of which were previously proposed for term set expansion and additional two context types that were borrowed from the general distributional similarity literature. We show that combining the different context types yields improved results on term set expansion. In addition to the algorithm, we developed a dataset for intrinsic evaluation of corpus-based set expansion algorithms, which we propose as a basis for future comparisons.

Code, demonstration system, dataset and term embeddings pre-trained models are distributed as part of NLP Architect by Intel AI Lab.¹

2 Related Work

Several works have addressed the term set expansion problem. We focus on corpus-based approaches based on the distributional similarity hypothesis (Harris, 1954). State-of-the-art techniques return the k nearest neighbors around the seed terms as the expanded set, where terms are represented by their co-occurrence or embedding vectors in a training corpus according to different context types, such as linear window context (Pantel et al., 2009; Shi et al., 2010; Rong et al., 2016; Zaheer et al., 2017; Gyllensten and Sahlgren, 2018; Zhao et al., 2018), explicit lists (Roark and Charniak, 1998; Sarmento et al., 2007; He and Xin, 2011), coordinational patterns (Sarmento et al., 2007) and unary patterns (Rong et al., 2016; Shen et al., 2017). In this work, we generalize coordinational patterns, look at additional context types and combine multiple context-type embeddings.

We did not find any suitable publicly available dataset to train and evaluate our set ex-

¹http://nlp_architect.nervanasys.com/term_set_expansion.html
pansion algorithm. The INEX Entity Ranking track (Demartini et al., 2009) released a dataset for the list completion task. However, it addresses a somewhat different task: in addition to seed terms, an explicit description of the semantic class is supplied as input to the algorithm and is used to define the ground truth expanded set. Some works like (Pantel et al., 2009) provide an evaluation dataset that does not include any training corpus, which is required for comparing corpus-based approaches. Sarmento et al. (2007) use Wikipedia as training corpus, but exploit meta-information like hyperlinks to identify terms; in our work, we opted for a dataset that matches real-life scenarios where terms have to be automatically identified.

Systems based on our approach are described by (Mamou et al., 2018a,b).

3 Term Representation

Our approach is based on representing any term in a (unlabeled) training corpus by its word embeddings in order to estimate the similarity between seed terms and candidate expansion terms. Different techniques for term extraction are described in detail by Moreno and Redondo (2016). We follow Kageura and Umino (1996) who approximate terms by noun phrases (NPs),\(^2\) extracting them using an NP chunker. We use term to refer to such extracted NP chunk and unit to refer to either a term or a word.

As preprocessing, term variations, such as aliases, acronyms and synonyms, which refer to the same entity, are grouped together.\(^3\) Next, we use term groups as input elements for embedding training (the remaining corpus words are left intact); this enables obtaining more contextual information compared to using individual terms, thus enhancing embedding model robustness. In the remainder of this paper, by language abuse, term will be used instead of term group.

While word2vec originally uses a linear window context around the focus word, the literature describes other possible context types. For each focus unit, we extract context units of different types, as follows (see a typical example for each type in Table 1\(^4\)).

3.1 Linear Context (Lin)

This context is defined by neighboring context units within a fixed length window of context units, denoted by \(\text{win}\), around the focus unit. word2vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014) and fastText (Joulin et al., 2016) are state-of-the-art implementations.

3.2 Explicit Lists

Context units consist of terms co-occurring with the focus term in textual lists such as comma separated lists and bullet lists (Roark and Charniak, 1998; Sarmento et al., 2007).

3.3 Syntactic Dependency Context (Dep)

This context is defined by the syntactic dependency relations in which the focus unit participates (Levy and Goldberg, 2014; MacAvaney and Zeldes, 2018). The context unit is concatenated with the type and the direction of the dependency relation.\(^5\) This context type has not yet been used for set expansion. However, Levy and Goldberg (2014) showed that it yields more functional similarities of a co-hyponym nature than linear context and thus may be relevant to set expansion.

3.4 Symmetric Patterns (SP)

Context units consist of terms co-occurring with the focus term in symmetric patterns (Schwartz et al., 2015). We follow Davidov and Rapporot (2006) for automatic extraction of SPs from the textual corpus.\(^6\) For example, the symmetric pattern ‘X rather than Y’ captures certain semantic relatedness between the terms X and Y. This context type generalizes coordinational patterns (‘X and Y’, ‘X or Y’), which have been used for set expansion.

\(^2\)Our algorithm can be used for terms with other part-of-speech or with other term extraction methods.

\(^3\)For that, we use a heuristic algorithm based on text normalization, abbreviation web resources, edit distance and word2vec similarity. For example, New York, New-York, NY, NYC and New York City are grouped.

\(^4\)We preferred showing in the example the strength of each context type with a good example, rather than providing a common example sentence across all the context types.

\(^5\)Given a focus unit \(t\) with modifiers \(m_i\) and a head \(h\), the context of \(t\) consists of the pairs \((m_i, l_i)\), where \(l_i\) is the type of the dependency relation between the head \(h\) and the modifier \(m_i\); the context stores also \((h/l_i)\) where \(l_i\) marks the inverse-relation between \(t\) and \(h\).

\(^6\)SPs are automatically extracted using the \(\text{dr06}\) library available at https://homes.cs.washington.edu/~roysch/software/dr06/dr06.html.
3.5 Unary Patterns (UP)

This context is defined by the unary patterns in which the focus term occurs. Context units consist of \( n \)-grams of terms and other words, where the focus term occurs; ‘\( - \)’ denotes the placeholder of the focus term in Table 1. Following Rong et al. (2016), we extract six \( n \)-grams per focus term.\(^7\)

We show in Section 7 that different context types complement each other by capturing different types of semantic relations. As explained in Section 2, to the best of our knowledge, several of these context types have been used for set expansion, except for syntactic dependency context and symmetric patterns. We train a separate term embedding model for each of the 5 context types and thus, for each term, we obtain 5 different vector representations. When training for a certain context type, for each focus unit in the corpus, corresponding \(<\text{focus unit}, \text{context unit}>\) pairs are extracted from the corpus and are then fed to the word2vec toolkit that can train embeddings on arbitrary contexts, except for linear context for which we use the word2vec toolkit. Only terms representations are stored in the embedding models while other word representations are pruned.

| Cont. type | Example sentence | Context units |
|------------|------------------|---------------|
| Lin \( \text{win} = 5 \) | Siri uses voice queries and a natural language user interface. | uses, voice queries, natural language user interface |
| List       | Experience in image processing, signal processing, computer vision. | signal processing, computer vision |
| Dependency | Turing studied as an undergraduate ... at King’s College, Cambridge. | (Turing/nsubj), (undergraduate/prep-as), (King’s College/prep-at) |
| SP         | Apple and Orange juice drink ... | Orange |
| UP         | In the U.S. state of Alaska ... | U.S. state of _ |

Table 1: Examples of extracted context units per context type. Focus units appear in bold.

4 Multi-Context Seed-Candidate Similarity

For a given context type embedding and a seed term list, we compute two similarity scores between the seed terms and each candidate term, based on cosine similarity.\(^8\) First, we apply the centroid scoring method (\textit{cent}), commonly used for set expansion (Pantel et al., 2009). The centroid of the seed is represented by the average of the term embedding vectors of the seed terms. Candidate terms become the \( k \) terms\(^9\) that are the most similar, by cosine similarity, to the centroid of the seed. Second, the CombSUM scoring method (\textit{csum}) is commonly used in Information Retrieval (Shaw et al., 1994). We first produce a candidate term set for each individual seed term: candidate terms become the \( k' \) terms\(^9\) that are the most similar, according to the term embedding cosine similarity, to the seed term. The CombSUM method scores the similarity of a candidate term to the seed terms by averaging over all the seed terms the normalized pairwise cosine similarities\(^10\) between the candidate term and the seed term.

To combine multi-context embeddings, we follow the general idea of Berant et al. (2012) who train an SVM to combine different similarity score features to learn textual entailment relations. Similarly, we train a Multilayer Perceptron (MLP) binary classifier that predicts whether a candidate term should be part of the expanded set based on 10 similarity scores (considered as input features), using the above 2 different scoring methods for each of the 5 context types. Note that our MLP

\(^7\)Given a sentence fragment \( c_{-3} c_{-2} c_{-1} t c_1 c_2 c_3 \) where \( t \) is the focus term and \( c_i \) are the context units, the following \( n \)-grams are extracted: \( (c_{-3} c_{-2} c_{-1} t c_1), (c_{-2} c_{-1} t c_1 c_2), (c_{-2} c_{-1} t c_1), (c_{-1} t c_1 c_2 c_3), (c_{-1} t c_1 c_2), (c_{-1} t c_1). \)

\(^8\)Sarmento et al. (2007) and Pantel et al. (2009) use first-order semantic similarities for explicit list and coordinational pattern context types, respectively. However, Schwartz et al. (2015) showed that for the symmetric patterns context type, word embeddings similarity (second-order) performs generally better. We opted for term embeddings similarity (second-order) for all the context types.

\(^9\)Optimal values for \( k \) and \( k' \) are tuned on the training term list. Other terms are assigned a similarity score of 0 for normalization and combination purpose.

\(^10\)For any seed term, cosine similarities are normalized among the candidate terms in order to combine cosine similarity values estimated on different seed terms for the same candidate term, as suggested by Wu et al. (2006).
classifier polynomially combines different semantic similarity estimations and performs better than their linear combination. We also tried to concatenate the multi-context term embeddings in order to obtain a single vector representing all the context types. We trained an MLP classifier with concatenated vectors of candidate and seed terms as input features, but it performed worst (see Section 7).

5 Dataset

Given the lack of suitable standard dataset for training and testing term set expansion models, we used Wikipedia to develop a standard dataset. Our motivation for using Wikipedia is two-fold. First, Wikipedia contains human-generated lists of terms (‘List of’ pages) that cover many domains; these lists can be used for supervised training (MLP training in our approach) and for evaluating set expansion algorithms. Second, it contains textual data that can be used for unsupervised training of corpus-based approaches (multi-context term embedding training in our approach). We thus extracted from an English Wikipedia dump a set of term lists and a textual corpus for term embedding training.

5.1 Term Lists

A Wikipedia ‘List of’ page contains terms belonging to a specific class, where a term is defined to be the title of a Wikipedia article. We selected term lists among ‘List of’ pages containing between fifty and eight hundred terms in order to cover both specific and more common classes (e.g., list of chemical elements vs. list of countries). Moreover, we selected term lists that define purely a semantic class, with no additional constraints (e.g., skipping list of biblical names starting with ‘N’). Since there can be some problems with some Wikipedia ‘List of’ pages, 28 term lists have been validated manually and are used as ground truth in the evaluation. Here are some few examples of term lists: Australian cities, chemical elements, countries, diplomatic missions of the United Kingdom, English cities in the United Kingdom, English-language poets, Formula One drivers, French artists, Greek mythological figures, islands of Greece, male tennis players, Mexican singers, oil exploration and production companies.

Terms having a frequency lower than 10 in the training corpus are pruned from the lists since their embeddings cannot be learned properly; note that these terms are generally less interesting in most of real case applications. Term variations are grouped according to Wikipedia redirect information.

On average, a term list contains 328 terms, of which 3% are not recognized by the noun phrase chunker; the average frequency of the terms in the corpus is 2475.

The set of term lists is split into train, development (dev) and test sets with respectively 5, 5 and 18 lists for MLP training, hyperparameters tuning and evaluation. Each term list is randomly split into seed and expanded term sets, where we are interested in getting enough samples of seed and expanded term sets. Thus, given a term list, we randomly generate 15 seed sets (5 seed sets for each seed size of 2, 5 and 10 terms) where seed terms are sampled among the top 30 most frequent terms within the list. For the train set, the non-seed terms (expanded term set) provide the positive samples; we randomly select candidate terms that occur in the corpus but not in the list as negative samples; positive and negative classes are balanced.

5.2 Textual Corpus

The corpus contains all the textual parts of Wikipedia articles except ‘List of’ pages. It is used for training the multi-context embedding models. 3% of the terms appearing in the term lists are not recognized by our NP chunker in the corpus. It contains 2.2 billion words, and 12 million unique terms are automatically extracted.

5.3 Public Release

We use enwiki-20171201 to develop the dataset. Full dataset will be released upon publication and it will include train, dev and test sets including the split into seed and expanded terms, and negative samples for the train set; the textual corpus along with NP chunks and grouped term variations; term embedding model for each context type.

6 Implementation Details

Code is distributed under the Apache license as part of NLP Architect by Intel AI Lab, an open-source Python library for exploring state-of-the-art
deep learning topologies and techniques for natural language processing and natural language understanding.

We used the following tools for the implementation and for the development of the dataset: spaCy\textsuperscript{14} for tokenization, noun phrase chunking and dependency parsing; textacy\textsuperscript{15} for text normalization; word2vec\textsuperscript{16} and fastText\textsuperscript{17} to model term embeddings of linear context type; word2vecf\textsuperscript{18} to model term embeddings of other context types; WikiExtractor\textsuperscript{19} to extract textual part of Wikipedia dump; Keras\textsuperscript{20} to implement the MLP classifier.

Similarity scores are softmax-normalized over all the candidate terms per context type and per scoring method, in order to combine them with the MLP classifier. Our MLP network consists of one hidden layer. The input and hidden layers have respectively ten and four neurons.

7 Experiments

Following previous work (Sarmento et al., 2007), we report the Mean Average Precision at several top $n$ values (MAP@$n$) to evaluate ranked candidate lists returned by the algorithm. When computing MAP, a candidate term is considered as matching a gold term if they both appear in the same term variations group. We first compare the different context types; then, we report results on their combination.

7.1 Context Type Analysis

We provide a comparison of the different context types in Table 2. These context types are baselines and we compare them to the linear context that is more standard. Note that the dependency context type is affected by the performance of the dependency parser.\textsuperscript{21} Linear context with centroid scoring yields consistently best performance of at least 19 MAP@10 points and is consistently more stable looking at standard deviation. However, other context types achieve better performance than linear context type for 55% of the term lists, suggesting that the different context types complement each other by capturing better different types of semantic relations and that their combination may improve the quality of the expanded set.

In addition, performance consistently increases with the number of seed terms e.g., MAP@10, MAP@20 and MAP@50 of the linear context are respectively .66, .58 and .51 with 2 seed terms.

7.2 Context Combination

We provide in Table 3 MAP@$n$ for the centroid scoring of the linear context and for the MLP classification with 5 seed terms. For comparison, we report in ‘Concat.’ row the performance for the MLP binary classification on the concatenation of the multi-context term embeddings. In addition, we report oracle performance assuming we have an oracle that chooses, for each term list, the best context type with the best scoring method. Oracle performance shows that the context types are indeed complementary. The MLP classifier which combines all the context types, yields additional improvement in the MAP@$n$ compared to the baseline linear context. Moreover, we observed that the improvement of the MLP combination over the linear context is preserved with 2 and 10 seed terms. Yet, looking at the oracle, the MLP combination still does not optimally integrate all the information captured by the term embeddings.

8 Conclusion

We proposed a novel approach to combine different context embedding types and we showed that it achieved improved results for the corpus-based term set expansion use case. In addition, we publish a dataset and a companion corpus that enable comparability and replicability of work in this field.

| Context | Scor. | MAP@10 | stdev | best % |
|---------|-------|--------|-------|--------|
| Lin     | cent  | .78    | .22   |        |
| List    | csum  | .59    | .30   | 20     |
| Dep     | cent  | .53    | .31   | 15     |
| SP      | csum  | .48    | .32   | 10     |
| UP      | csum  | .47    | .36   | 10     |

Table 2: Comparison of the different context types. For each context type, we report the scoring method with higher MAP@10 on dev set, MAP@10 with 5 seed terms, its standard deviation among the different test term lists, the percentage of the test term lists where the context type achieves best performance.
| Method | MAP@10 | MAP@20 | MAP@50 |
|--------|--------|--------|--------|
| Linear | .78    | .71    | .59    |
| Concat.| .68    | .65    | .56    |
| MLP    | .83    | .74    | .63    |
| Oracle | .89    | .82    | .73    |

Table 3: MAP@$n$ performance evaluation of the linear context, concatenation, MLP binary classification and oracle, with 5 seed terms.

For future work, we plan to run similar experiments using recently introduced contextual embeddings, (e.g., ELMo (Peters et al., 2018), BERT (Devlin et al., 2018), OpenAI GPT-2 (Radford et al., 2019)), which are expected to implicitly capture more syntax than context-free embeddings used in the current paper. We plan also to investigate the contribution of multi-context term embeddings to other tasks in computational semantics.

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