Cross-Lingual Generation and Evaluation of a Wide-Coverage Lexical Semantic Resource

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Abstract

Neural word embedding models trained on sizable corpora have proved to be a very efficient means of representing meaning. However, the abstract vectors representing words and phrases in these models are not interpretable for humans by themselves. In this paper we present the Thing Recognizer, a method that assigns explicit symbolic semantic features from a finite list of terms to words present in an embedding model, making the model interpretable for humans and covering the semantic space by a controlled vocabulary of semantic features. We do this in a cross-lingual manner, applying semantic tags taken form lexical resources in one language (English) to the embedding space of another (Hungarian).

Keywords: semantic lexicon induction, word embedding models, cross-lingual resource generation

1. Introduction

A recently very popular and efficient method for the distributional representation of words is using word embedding (WE) models (Mikolov et al., 2013c). In this paper we present a method that creates the WE model of a large text corpus and inserts the corresponding embedding vectors of a limited set of abstract semantic features into the same space. The embedding vectors for semantic features are built from automatically reorganized lexical resources (that may be in a language different from our target language) and are transformed to the target WE space. Then, a nearest neighbor approach is applied to find the most relevant features for a query word. The assigned features can also be used as a searchable semantic annotation of the original corpus the WE model was created from, because our model assigns semantic features to any (even non-standard/slang or misspelled) word in a text in a language-independent manner, regardless of whether these are present in a lexical resource or not, and whether any such resource is available for the target language. The organization of categories and the way they are actually assigned to words by the algorithm is in accordance with the actual usage of these words as manifested by their distribution in a large corpus. The method is demonstrated for English and Hungarian, but it can easily be applied to other languages as well.

2. Related Work

WE models have frequently been used to represent word meaning efficiently (Mikolov et al., 2013b; Pennington et al., 2014). There are also approaches that replace WE with sense embedding (Bordes et al., 2012; Neelakantan et al., 2014; Tian et al., 2014; Li and Jurafsky, 2015; Bartunov et al., 2015). Huang et al. (2012) applied clustering algorithms to create single prototype embedding. Some have tried to match WE’s to entities in existing lexical resources, for example to BabelNet entries (Panchenko, 2016) or WordNet synsets (Chen et al., 2014; Soricut andottie, 2006). Rothe and Schütze (2015) combines WE vectors to obtain Wordnet synset representations in the original WE space. Labutov and Lipson (2013) also try to take existing WE’s and use labeled data to produce WE’s in the same space in order to tune or adapt the original representation. Other approaches try to exploit knowledge bases to improve WE’s. Yu and Dredze (2014) aim at predicting related words in a knowledge base to WE’s. Others compute vector representations of word senses directly from knowledge base (Bordes et al., 2011; Camacho-Collados et al., 2015).

3. Word Embedding Models for Morphologically Rich Languages

We built WE models for Hungarian, an agglutinative language with complex morphology. In order to incorporate the information encoded in the morphological structure of word forms, full morphological disambiguation was applied to the input words, and the tag sequence following the main PoS tag of each word was detached and included as a separate token following the token consisting of the lemma and the PoS tag in the text. The following example shows the representation of the sentence Szeretlek, kedvesem. ‘I love you, dear’: 

szeret#V #1Sg.<2Sg ,#, kedves#N #Poss1Sg
love [I, you] , dear [my]

Thus, while no information was lost, we managed to improve the quality of the WE model compared to that created from surface word forms in two ways: by assigning a separate representation to lexical items of different part of speech; and by effectively reducing data sparseness problems following from the great variety of rare inflected word forms (Sziklósi, 2016).

Although morphological annotation has a less pronounced impact on the quality of the model in English (the language of the lexical resources we used to extract semantic features – see Section 4), we applied the same method to the English text as well to make the two models compatible.
by introducing PoS-based sense distinctions and thus improving the quality of mapping between the models (see Section 5).

For building the WE models, we used the word2vec tool. The Hungarian model was trained on a web-crawled corpus of 3.18 billion tokens (127.49 M token types) that was annotated using the PurePos (Orosz and Novák, 2013) tagger, augmented with the Humor Hungarian morphological analyzer (Novák, 2014; Novák et al., 2016). We trained the English WE model on the English Wikipedia dump of 2.25 billion tokens (8.24 M token types) that was analyzed using Stanford tagger (Toutanova et al., 2003). We created a CBOW model for both languages with the radius of the context window set to 5 and the number of dimensions to 300 and using a token frequency limit of 5. The vocabulary size of the English model was 2,057,592 items and that of the Hungarian one was 2,266,389 items. While only 6 items in the English vocabulary are detached inflectional tags (like [PL] for plural), the Hungarian model contains 2340 such items. These abstract entries representing grammatical morpheme combinations play an important role as context while building the models. The rest are lemmas annotated by their corresponding PoS tag.

4. Lexical Resources

In order to assign semantic labels to the words in the embedding models, we needed some lexical resource to induce the tags from. A widely used, although quite dated, system of concepts is Roget’s Thesaurus (Chapman, 1977). Its digitally available third edition contains 990 semantic categories, each further partitioned along five parts-of-speech (noun, verb, adjective, adverb, phrase/interjection). The thesaurus lists a set of related words for each applicable part-of-speech within each category. The original thesaurus includes 91,608 words and multiword expressions. After intersecting it with the vocabulary of the English WE model built from Wikipedia, 51,108 words remained – we lost all MWE’s, dated words, and ones with incorrectly marked PoS (see Section 5.1). The online version of the digital edition of Longman Dictionary of Contemporary English (LDOCE) (Summers, 2005) includes a resource similar to Roget’s Thesaurus. However, it contains a much more recent vocabulary and a modern categorization of words. In the online version, words are associated with 213 semantic categories. Part-of-speech is also indicated for each headword. Thus, it could easily be converted to the same format as Roget’s Thesaurus, i.e. headwords listed for each part-of-speech in each category. The size of this resource before intersecting with the English WE model was 213 categories and 28,257 example words and multiword entries, which was reduced to 21,546 words after the intersection with the English Wikipedia vocabulary.

The third resource we used, 4lang, is also based on LDOCE. The definitions of LDOCE’s defining vocabulary were transformed into a formal description (Kornai et al., 2015) illustrated by the following examples:

\[
\text{bread: food, FROM/2742 flour, bake MAKE} \\
\text{show: =AGT CAUSE=DAT LOOK =PAT1, communicate}
\]

We further transformed this format so that we have a similar one to the previous ones. This was achieved by segmenting the formal descriptions into single tokens (by splitting at spaces and brackets) and treating each token as a category label. Then, all words that had the particular token in their definition were listed for that label. This resulted in 1489 category labels and 12,507 words listed for them. 4lang includes some affixes and inflected forms, which are not present in the Wikipedia model, so the intersection resulted in 11,039 words.

We also created another model from 4lang, in which we did not segment predicates with more than one argument into further parts, so e.g. HAS[four.(legs)] remained an atomic feature. Further processing of this model, to which we refer as 4lang2 in the paper, was identical to that of the 4lang model. The first four columns of Table 1 summarize the main characteristics of the resources, while Table 2 shows some examples from each resource.

| Resource | Original | After \& clustering |
|----------|----------|---------------------|
|          | cats     | words               | w/c     | cats | words | w/c     |
| LDOCE    | 213      | 28257               | 132.66  | 3069 | 21546 | 7.02    |
| Roget’s  | 3077     | 91608               | 29.77   | 7066 | 51108 | 7.23    |
| 4lang    | 1489     | 12507               | 8.39    | 2249 | 11039 | 4.91    |
| 4lang2   | 4172     | 12507               | 2.99    | 4256 | 11039 | 2.59    |

Table 1: Characteristics of the three lexical resources (number of different category labels, number of words and the average number of words per category, before and after intersection with the English embedding model and clustering).

One of the most popular semantic resources for English is WordNet (Fellbaum, 1998; Miller, 1995). However, WordNet has been criticized for its too high granularity at the bottom level and its generality at the top level (Brown, 2008). Selecting an appropriate set of concepts from WordNet that could be used as semantic features is far from trivial. There is a high level categorization into which WordNet synsets are organized (“supersenses”), and these could be used as features similarly to the ones derived from the resources mentioned before. However, there are only 45 supersenses, which seems to be an extremely low-grained categorization to be useful for practical purposes. Due to these problems, although we consider using WordNet in the future both as a resource and as a possible benchmark, we did not use it in the experiments presented in this paper.

5. Method

The goal of this research was to create a tool that is able to assign semantic features to words, even if the target word is not included in any semantic lexicon or if such a lexicon does not even exist in the given language. Thus, two problems had to be handled: assigning features and, if needed, bridging the language gap.
Table 2: Examples from each resource after transforming them to the same format

| Resource | Category | Example words in the original resource |
|----------|----------|----------------------------------------|
| LDOCE   | Cooking  | allspice#NN, bunke#VB, barbecue#VB, baster#VB, blanch#VB, boil#VB, bottle#VB, bouillon#NN, etc. |
| LDOCE   | Mythology| centaur#NN, chimera#NN, Cyclops#NN, deity#NN, demigod#NN, faun#NN, god#NN, griffin#NN, gryphon#NN, etc. |
| 4LANG   | Food     | sandwich#NN, fat#NN, bread#NN, pepper#NN, meal#NN, fork#NN, egg#NN, bowl#NN, salt#NN, etc. |
| 4LANG2  | PART_OF | body#NN, tongue#NN, back#NN, neck#NN, shoulder#NN, bone#NN, skirt#NN, wrist#NN, buttock#NN, etc. |
| 4LANG2  | -AGTHAS | mouth#NN |

Figure 1: The 3 nearest features assigned to the words pianist, teacher, turner, maid from the LDOCE and Roget’s models arranged in semantic space

5.1. Semantic Feature Space

As described in Section 4, we used three lexical resources in this experiment using the category labels in these lexicons as semantic features. However, some categories were too broad and the set of words listed for them was too heterogeneous. To handle this problem, a hierarchical agglomerative clustering algorithm was applied to the set of words in those categories that contained at least five words (for details of the clustering algorithm, see Siklósi, 2016). Each cluster was then labeled with the original category label and a numeric index. Since the clustering algorithm used the distance between the embedding vectors of words trained from the English Wikipedia corpus, only words present in the Wikipedia model could be used from the original resources. How this intersection and the clustering of words affected the representations in each lexical resource is shown in Table 1.

We used a simple but effective method for representing each semantic feature in the same semantic space as that of the English PoS-tagged WE model: we assigned the average of the embedding vectors of clustered example words to each indexed semantic label. To find the relevant features for a query word tagged with its appropriate part-of-speech, its representational vector is retrieved from the WE model and its nearest neighbors are taken from each feature model. Figure 1 shows how four words (pianist, teacher, turner, maid) and the 3 nearest features assigned to them from the LDOCE and Roget’s models are organized in semantic space.

5.2. Cross-Lingual Mapping of the Models

It has been shown that WE spaces can effectively be mapped across languages. One mapping method is to use a word-aligned bilingual parallel corpus to build an embedding model that contains vector representations of words in both languages (Luong et al., 2015). We applied another approach instead, where the projection is achieved by learning a piecewise linear transformation based on a seed dictionary, through which a monolingual WE space can be mapped to another monolingual space (Mikolov et al., 2013a). The transformation maps each word vector in the source language space to a point in the vicinity of the vector of its translation in the target language space.

We used a subset of the 4lang dictionary (built from the defining vocabulary of LDOCE) containing 3477 English-Hungarian word pairs as the seed dictionary to calculate the transformation matrix. We used pairs where both the English and the Hungarian word had a frequency over 10000 in the two corpora. Manual evaluation of the transformation on an additional 100 words resulted in 0.38 precision for the first-ranked translation and precision=0.69/0.81 for the first 5/10 top-ranked translations (indicating whether a correct translation of the target word was found in the set of the first five/ten most similar words in the transformed space). We used this transformation matrix to map the English semantic label vectors to the Hungarian WE space. Then, the same nearest neighbor algorithm could be applied to the query word as in the case of searching the English semantic space. This made it possible to input a Hungarian word as a query to our system and receive semantic features based on originally English resources without the expensive and labor-intensive task of translating them. Moreover, since instead of exact matching, nearest neighbors are searched for, out-of-vocabulary words (with respect to the original lexical resources) can also be assigned semantic labels.

6. Experiments and Results

When looking at the output of the models, we found that even though the LDOCE features seemed to be the most meaningful, the Roget’s, 4lang and 4lang2 models also turned out to be useful. E.g. adjectives have a much richer categorization in Roget’s than what we obtain from the LDOCE model. Since LDOCE and Roget’s seemed to perform well in complementary regions, we decided to unify these two models (ROLSD).

We carried out two kinds of quantitative analysis of the performance of our model. First, we checked the robustness of the model by performing a sanity check on the original English resources. In the other scenario, we selected 280 words randomly from a predefined list of Hungarian words in which each word was assigned to one of 28 semantic domains (e.g. food, vehicles, locations, occupations, etc.) and manually checked the accuracy of the semantic features assigned to these words by each model.
6.1. Sanity Check

For each word present in the original 4lang dictionary, we calculated how many of the semantic features present in the original definition were retrieved among the top N features returned by the model (feature recall, R_w) and the percentage of words for which all features were retrieved (word recall, R_w(poss)). The results are shown in Table 3 as a function of N. Recall was also calculated ignoring words having more than N features (R_w(poss)) and features over the N limit (R_f(pos)). As no definition contained more than 10 terms, R_w(poss) is identical to R_w and R_f(pos) is identical to R_f for N ≥ 10. The last column of the table shows the mean reciprocal rank of features (terms) present in the original definitions. Reciprocal rank is calculated as \( i/Rank \) for the \( i \)th feature returned by the model that is also present in the original definition, it is zero if no valid feature was retrieved. MRR is calculated as the average of the reciprocal rank of all expected features retrieved for all words.

| N | R_w | R_w(poss) | R_f | R_f(poss) | MRR |
|---|-----|-----------|-----|-----------|-----|
| 1 | 0.1508 | 0.8504 | 0.2691 | 0.9455 | 0.9455 |
| 5 | 0.5472 | 0.6574 | 0.7614 | 0.8445 | 0.9586 |
| 10 | 0.7049 | 0.7080 | 0.8756 | 0.8785 | 0.9237 |
| 20 | 0.8187 | 0.8187 | 0.9316 | 0.9316 | 0.9292 |

Table 3: Performance (recall) of the three models for English tested on the original resources.

6.2. Standard Language Use

After the sanity check, we tested our system on standard Hungarian. In order to do this, we collected groups of words belonging to different semantic categories. These categories were defined manually and the test words were collected by a semi-automatic algorithm as described in (Siklósi, 2016). Finally, each group was manually checked resulting in 28 groups containing 39,050 words altogether. We randomly selected 10 words from each group, and the top 10 semantic features were generated using the models 4lang, 4lang2 and ROLD. The list of randomly selected words also included misspelled and very rare words. Features that were partitioned and indexed when building the models (see Section 5.1) were joined after lookup. Two annotators checked the generated semantic feature sets, and marked each feature that was inappropriate for the given lexical item (e.g. the domain of \texttt{HAS.horn} is animals) and completely inappropriate features (e.g feature \texttt{dig} for \texttt{csár} “barn” in the buildings group) were not differentiated: they were all simply marked wrong. Inter-annotator agreement was found to be substantial (Cohen’s kappa=0.734).

6.3. Proper Names and Non-standard Language

The WE models our method is based on also reflect world knowledge as represented in the corpus from which they are generated from. This enables our model to assign features to proper names of various types, such as names of people, institutions, fictional creatures, or even abbreviations as shown in Table 5 in the names section of the table, some famous people are shown, one of them is Hungarian (Béla Bartók, a Hungarian composer). It can be seen the extended abstract.
Table 5: Examples of features returned for proper names and abbreviations of names of institutions from the models that each person is assigned features that provide information about them. Thus, the model can be queried even for names one is not familiar with, and relevant features will be provided. This also holds for names with lower frequency in the corpus, as long as the name itself is unique.

Table 5 also contains the abbreviated name of some organizations. **ELTE** is for Eötvös Loránd University, while **PPKE** is for Pázmány Péter Catholic University. While both of them are educational institutions, **ELTE** is a state university, but **PPKE** is catholic, and this difference is reflected by the set of features assigned to them in addition to their relation to science and education.

The same applies to slang terms, including many short diminutive forms. These are abundant in the web-crawled corpus, mainly coming from often heated discussions in user comments and fora, and many of them have strong emotional connotations. These are neatly reflected by the set of features assigned to them in addition to the ones reflecting the basic meaning of the term, e.g. 'Deceiver', 'Obstinance', 'Ignorance', 'Thief', 'Crime', 'Politics' 'Race relations' 'Psychology, Psychiatry', 'stupid', 'criminal' in addition to 'person' for derogative terms like 'Gypsy', 'proletarian', 'bolshevik' or 'cigó'.

### 7. Conclusions

We have shown that the meaning implicitly represented in word embedding models can be transformed into a set of symbolic features that can be used as semantic annotation. This can also be done across languages, thus relevant semantic tags can be assigned to words in a language that lacks appropriate semantic resources. Despite its simplicity, our system, the Thing Recognizer, performs this surprisingly efficiently also for names and words that cannot be expected to be included in manually created lexical semantic resources.

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