Evaluation of Word Embeddings for Sequence Tagging

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Abstract

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1 Introduction

Word embedding learning methods are the new generation of distributional semantics models. As with other learning methods, it is well known that the performance of machine learning algorithms heavily depends on their parameters optimization, the training data used and the applications they target. In this paper, we perform an extensive evaluation of three word embedding approaches under the same experiment conditions, and evaluate them in different sequence tagging tasks.

Expected contributions:

- Fair comparison of different word embedding algorithms. This includes running different word embeddings algorithms under controlled conditions, for example, chose algorithms and data sets that are publicly available, apply the same NLP pre-processing to all data sets, trained the algorithms with the same data sets, apply the learned word vectors to well defined tasks sequence labeling tasks such as POS-tagging and Named Entity Recognition.

- Influence of word embeddings in the sequence tagging tasks with semi-supervised settings. We considered the empirical evaluation in a semi-supervised setting because we conjecture that the word embeddings learned from unlabelled data could save a significant amount of labelled data, and thus, alleviate the cost of human annotation.

- Complete evaluation of word embeddings in sequence tagging tasks. Sequence labelling tasks is one of the meta problems NLP faced. Previous works have shown that learning word embeddings vector features improves the performance of sequence labelling task, but not fair and extensive comparison has been done so far. In this paper, we evaluated word embedding algorithms in several sequence labelling tasks and discuss their benefits, taking into account different aspects of sequence labelling problems such as row labelling (POS-tagging) and join segmentation and labelling (Named Entity Recognition).

- Multi-word expressions (MWE) identification using word embeddings. As far as we known, there is no work yet that used word embeddings vectors to identify MWE. The experiments carry out in this paper will tell which is the best word embedding algorithm to solve for the identification of MWE.

2 Related Work

In this section, we describe the four word embedding approaches we compared in the paper.

Word embeddings models are the new generation of distributional semantics models (DSMs), where the vectors weights are set to optimally predict the contexts in which the corresponding word tend to appear.

Describe each of the following word embeddings approaches

- Glove (Pennington et al., 2014)

- word2vec (Mikolov et al., 2013)

- Brown cluster (Brown et al., 1992)

- Pre-trained word embeddings (Turian et al., 2010a)

The mentioned methods were chosen because they are recent state-of-the-art word embedding learning and because their software is available.

3 Word Representations

Inspired by distributional semantics models, distributed word representation methods represent each word as a continuous vector, were similar words have a similar vector representation, therefore, capturing the similarity between words.

Example:

The resulting vectors can be used as features in many NLP applications and it has been shown that they outperform methods that treats words as atomic units ().

The estimation of the word vectors can be carry out with different models architectures. In this paper, we evaluate the word embedding learning methods presented in the next section and evaluate their utility in several sequence labelling tasks.

3.1 Word Embedding Learning Algorithms

- Glove (Pennington et al., 2014)
- Skig-gram (Mikolov et al., 2013)
- CBOW (Mikolov et al., 2013)
- Brown cluster (Brown et al., 1992)
- Neural language model (Turian et al., 2010a)

3.2 Experimental Setup

3.3 Materials

It is well known that the choice of a corpora have an important effect in the final accuracy of machine learning algorithms. Thus, we select different corpora to learn the word embedding vectors (Table 3.3). The main reason of choosing these data set is that they are publicly available.

Data set	Size	Words
UMBC	48.1GB	3 billions
One Billion	4.1GB	0.8 billions
Latest wikipedia dump	49.6GB	3 billions
Twiter		

Table 1: Corpus used to learn word embeddings

3.4 Preprocessing

In order to make the comparison of different word embedding approaches across different applications, we applied the same preprocessing to the data sets used. The preprocessing pipeline consist of a sentence splitter, a tokenizer, a POS-tagger and a lemmatizer. The pipeline is built with the UIMA architecture and the DKPro NLP tools.

3.5 Parameters

The performance of each approach heavily depends on their parameters optimization. In an ideal machine learning setup, grid search or random search would be applied in order to search for the best hyperparameters, for each approach. But, that is too time taken. Instead, we look for the shared parameters along the three approaches and vary these parameters deterministically? The rest of the parameters (the ones that are unique for each approach) are set to their optimal reported values. The parameters that we vary are:

- **Word vector size**: 25, 50, 100, 200, 300, 600.
- **Context window size**: 5, 10, 15.

Brown clustering: Number of clusters

4 Sequence Tagging Tasks

We evaluate different learning approaches of word embeddings in four different sequence tagging tasks: POS tagging, chunking, MWE identification, and name entity recognition. Because we can either update pre-trained word embeddings during training or not, through the evaluation, we want to answer the following questions:

- How well do different word embeddings perform in all tasks when supervised fine-tuning is *not* performed?
- How well do different word embeddings perform in all tasks when supervised fine-tuning is performed?
- How does the size of labeled training data affect the experimental results?
- How well do the word embeddings perform for unknown words?
- How do the key parameters of each word learning algorithms affect the experimental results?

For each task, we feed learned embeddings into the graph transformer trained with sentence tag criterion (Turian et al., 2010b). The graph transformer is equivalent to CRF, if we do not update word embeddings. For all tasks, we train Graph transformer with pre-trained word embeddings in the following two settings:

- CRF with conventional features.

- Graph transformer *does not* fine tune embeddings during training.
- Graph transformer fine tunes the embeddings during training.

For each task, we split the data into a training set, validation set, and a test set. The hyper parameters are tuned on the validation set with random search (Bergstra and Bengio, 2012). To be fair, for each model, we randomly choose 100 hyper parameter combinations and pick up the best one based on its performance on the validation set. Then each model is evaluated in a semi-supervised setting. We start with training models on 10% of the training data, and evaluate them on the test dataset. Then we incrementally add another 10% of the training data and evaluate them until all training data is used. We adopt per-word F1 scores as the evaluation metric for all tasks except POS tagging. We keep using per-word accuracy for POS tagging. In order to evaluate model performance on unknown words, we report also the average F1 scores for the words that do not occur in the training set.

In order to assess the influence of the key parameters of each word learning algorithms, we evaluate all embedding based models with varying key parameters on the full training set.Do we evaluate also combinations of the key parameters ,e.g. we measure model performance by incrementally augmenting the size of the training set at the same time as the word vector size.?

4.1 POS tagging

Almost the setting as (Collobert et al., 2011), except adding one more test set.

4.1.1 Option 1

Training set: 0-18 of WSJ.
Validation set: 19-21 of WSJ.
Test set: 22-24 of WSJ, and English Web Treebank. We report model performances on these two test sets respectively.
Feature space: the same set as in (Collobert et al., 2011)

4.1.2 Option 2

Use the experimental setting in (Owoputi et al., 2013) for twitter POS tagging. All word embeddings will be learned from the twitter corpus provided by Scott.

4.2 Chunking

The same setting as (Turian et al., 2010b)

Training set: WSJ train set.
Validation set: Randomly sampled 1000 sentences from the train set for development.
Test set: CoNLL2000 test set.
Feature space: the same set as in (Turian et al., 2010b)

4.3 MWE Identification

Training set: randomly sampled 500 documents from Nathanas corpus.
Validation set: randomly sampled 100 documents from Nathanas corpus.
Test set: remaining 123 documents from Nathanas corpus..
Feature space: the same set as in (Schneider et al., 2014)

4.4 Named entity recognition

Training set: CoNLL03 train set.
Validation set: CoNLL03 development set.
Test set: CoNLL03 test set and MUC7. We report model performances on these two test sets respectively.
Feature space: the same set as in (Turian et al., 2010b)

5 Experimental Results and Discussion

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