Evaluation of Word Embeddings for Sequence Tagging Tasks

A Anonymous **B Anonymous**

Abstract

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1 Introduction

Tim

In the last years, distributed word representations have been applied to several NLP tasks. Inspired by distributional semantics models, distributed word representation methods represent each word as a continuous vector, where similar words have a similar vector representation, therefore, capturing the similarity between words.

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 (). Their attractiveness relies in the ability to learn word representations in an unsupervised way, thus directly providing lexical features from big amounts of unlabelled data and, therefore, alleviating the cost of human annotations. It has been also claimed that word embeddings have the ability to connect out of vocabulary words to known ones. Hence, suggesting that word embeddings are a good resource for applications that need to be adapted to a certain domain, different from the one the application have been tuned for. For example,... Another property attribute to word embeddings is their capacity to encouraging common behaviour among related in-vocabulary words, for instance...

As with other learning methods, it is well known that the performance of machine learning algorithms heavily depends on parameter optimization, the size of the training data used and the applications they target. For example, (Turian et al., 2010) shows that the optimal word embedding dimensions are task specific. Moreover, there are several word embeddings methods, which used different algorithms and resources. Some methods involve feedback from the end task when learning (or fine-tuning) the word representations and others do not. Learning algorithm that involves fine-tuning are supposed to perform better since word representations become task-specific, at the cost of performing worst for out of vocabulary words. But still, there is not systematic comparison between these two methods.

In this paper, we perform an extensive evaluation of five word embedding approaches under fixed experiment conditions, and evaluate them over different sequence labelling tasks: POS-tagging, chunking, NER and MWE (Multi Word Expression Identification), within the following aims: (i) perform a fair comparison of different word embeddings algorithms. This includes running different word embeddings algorithms under controlled conditions, for example, use the same training set, the same preprocessing, etc.; (ii) measure the influence of word embeddings in sequence labeling tasks in semi-supervised settings (fine-tuning); (iii) systematically compared the usefulness of word embedding versus unigram features for sequence tagging. (iv) use word embeddings for MWE. To the best of our knowledge, word embeddings have not been used for this task before;

2 Related Work

Gabriela

Word embedding learning methods have been applied to several NLP tasks that we summaries in this section.

Collobert et al. (2011) proposed a neuronal network architecture that learn word embeddings and use them in POS-tagging, chunking, NER and SRL. Without specializing their architecture for the mentioned tasks, they achieve close state-of-the-art performance. After including specialized features (e.g., word suffixes for POS-tagging; Gazzeters for NER, etc.) and other tricks like cascading and ensambling classifiers, achieve competitive state-of-the-art performance. Similarly, Turian et al. (2010) explored the impact of using word features learned from cluster-based and word embeddings representations for NER and chunking. They conclude that unsupervised word representation improve NER and chunking, and that combining different word representations can further improve the performance. Word representation from Brown clusters have been also shown to enhance Twitter POS tagging Owoputi et al. (2013).

Schneider et al. (2014a) presented a MWE analyser that, among other features, used unsupervised word clusters. They observed that the clusters were useful for identifying words that usually belong to proper names, which are considered MWE in the data set used. Nevertheless, they mentioned that it is difficult to measure the impact of the word embeddings features, since other features may capture the same information.

Word embeddings have been also used as features for syntactic dependency parsing and constituent parsing. Bansal et al. (2014) used word embeddings as features for dependency parsing, which used the syntactic dependency context instead of the linear context in raw text. They found that simple attempts based on discretization of individual word vector dimensions do not improve parsing. Only when performing hierarchical clustering of the continuous word vectors then using features based on the hierarchy, they gain performance. They also pointed out that ensemble of different word embeddings representations improved performance. Within the same aim, Andreas and Klein (2014) explores the used of word embeddings for constituency parsing and conclude that the information they provide might be redundant with the one acquire by a syntactic parser trained with a small amount of data. Others that boost the performance when including word embeddings representations for syntactic parsing includes (Koo et al., 2008; Koo et al., 2010; Haffari et al., 2011; Tratz and Hovy, 2011).

Word embedding have also been applied to other (non-sequential NLP) tasks such as supersense tagging (Edouard Grave and Bach, 2013); grammar induction (Spitkovsky et al., 2011) and semantic task such as semantic relatedness, synonymy detection, concept categorization selection preferences and analogy (Baroni et al., 2014)

3 Self-taught Learning

Lizhen and Gabriela

The idea behind self-taught learning is to use unlabelled data for improving the performance on supervised learning tasks by learning a higher-order feature representation of the inputs using the unlabelled data (**?**)

3.1 Learning Word Representations

Based on the idea that a word is characterized by the company it keeps (Firth, 1957), distributed word representation methods represent a given word as a continuous vector, which consists of the most frequent contexts of that given word in a big corpus. Therefore, similar words have a similar vector representation.

Traditionally, the estimation of the vectors is done by initializing the vectors with co-occurrences counts. More recently, the vectors are learned in a supervised way, where the weights in the vectors are set to maximize the probability of the context in which the word is observed in the corpus. Note that the method does no require an annotated corpus since the contexts windows used for training are extracted from unannotated data.

More formally, learning a word vector $W : words \rightarrow \mathbb{R}^n$ is parametrized function that maps words to high-dimensional vectors, where W is initialized to have random vectors for each word and learn to have meaningful vectors to perform same task.

Learning the word vectors can be carry out with different models architectures. In this paper, we evaluated five different word embeddings learning algorithms, which are the following:

- Brown cluster (Brown et al., 1992)
- CBOW (Mikolov et al., 2013b)
- Glove (Pennington et al., 2014)
- Neural language model (Collobert et al., 2011)
- Skip-Gram (Mikolov et al., 2013a)

The above methods were chosen because they are recent state-of-the-art word embedding learning methods and because their software is available and all of them are neural networks architectures. The first method (Brown clusters) was selected as a benchmark word representation, which makes use of hard word clusters rather than a distributed representation.

Skip-Gram (Mikolov et al., 2013a) is a neuronal network language model, but it does not have a hidden layer, and instead predicting the target word, it predicts the context given the target word. These embeddings are faster to train than other neuronal embeddings. (and does not involve dense matrix multiplication).

The CBOW (Mikolov et al., 2013b) model learns to predict the word in the middle of a symmetric window based on the sum of the vector representations of the words in the window.

GloVe (Pennington et al., 2014) is essentially a log-bilinear model with a weighted least-squares objective. The main intuition underlying the model is the simple observation that ratios of word-word co-occurrence probabilities have the potential for encoding some form of meaning.

4 Sequence Tagging Tasks

Lizhen

We evaluate different word representations in four different sequence tagging tasks: POS tagging, chunking, NER and MWE identification.

4.1 Datasets

It is well known that the choice of a corpora have an important effect in the final accuracy of machine learning algorithms. Therefore, each word embedding method was trained with the same corpora (Table 1). The main reason of choosing the corpora 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

Table 1: Corpora used to learn word embeddings

4.2 Preprocessing

All text are preprocessed with Stanford sentence splitter and tokeniser. All consecutive digit substrings are replaced by NUMf, where f is the length of the digit substring. For example, "10.20" is replaced by "NUM2.NUM2".

For each task, we feed learned word representations into a first order linear-chain graph transformer (Collobert et al., 2011), and trained them by using the online learning algorithm AdaGrad (Duchi et al., 2011). If we do not update word representations during training, the graph transformer is equivalent to a linear-chain CRF. For each model taking distributed word representations as word features, we consider two settings:

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

For each task, we consider also CRF models with hand-crafted features, which use one-hot representation for each unigram.

For each task, we split the task specific corpus into a training set, validation set, and a test set (see Table 2). If a corpus already provides fixed splits, we reuse them. For POS tagging and NER, we also evaluate the models with a out-of-domain corpus, which has similar annotation schema as the respective training corpus.

In order to have fair and reproducible experimental results, we tuned the hyperparameters with random search (Bergstra and Bengio, 2012). We randomly sampled 50 distinct hyperparameter sets with the same random seed for the models that do not update word embeddings, and sampled 100 distinct hyperparameter sets for the models that update word embeddings. For each set of hyperparameters, we train a model on its training set and pick up the best one based on its performance on its validation set (Turian et al., 2010). Note that, we also consider word vector size and context window size of distributed word representation, and number of clusters of brown clustering as the hyperparameters. This is achieved by mapping each possible hyperparameter combination to the word representation files trained with these parameters. Their ranges are listed below.

- **Word vector size**: [25, 50, 100, 200].
- **Context window size**: [5, 10, 15].
- **Number of brown clusters**: [250, 500, 1000, 2000, 4000].

However, for the models that update word representations, we always found under-performed hyperparameters after trying out all hyperparameter combinations, because they have more hyperparameters than the models that do not update word representations. Then for each distributed word representations, we reuse all hyperparameters of the models that do not update word representations, only tune the hyperparameters of AdaGrad for the word representation layer. This method requires only 32 additional runs for each model updating embeddings and achieves consistently better results than 100 random draws.

The final evaluation is carried out in a semi-supervised setting. We split the training set into

	Training	Validation	Test	Feature space
POS-Tagging	0-18 WSJ	19-21 WSJ	22-24 of WSJ; English Web-Treebank	as in (Collobert et al., 2011)
Chunking	WSJ	1000 sentences WSJ	CoNLL-2000	as (Turian et al., 2010)
NER	CoNLL-2003 train set	CoNLL-2003 dev. set	CoNLL-2003 test set; MUC7	as in (Turian et al., 2010)
MWE	500 documents from	100 documents from	123 documents	as in (Schneider et al., 2014b)

Table 2: Datasets and features for each task

10 partitions at log scale. That means, the second smallest partition will be twice the size of the smallest partition. We created 10 training sets with incremental size by merging these partitions from the smallest one to the largest one, and evaluate them all on the same designated test sets.

We adopt the most commonly used F1 measures as the evaluation metric for all tasks except POS tagging, for which we use per-word accuracy. In order to evaluate model performance on unknown words, we report also the accuracy for the words that do not occur in the training set.

In addition, we also set up experiments to verify if CRF/graph transformer requires different feature design for different kinds of pre-trained word embeddings. This is achieved by adding a hidden layer between CRF and distributed word representations. For each context word, the hidden layer computes the element-wise multiplication of its embedding with the embedding of the current word embedding, and the representation of current word stays the same. The results of this approach are not plotted because this method leads only to marginal improvement.

5 Experimental Results and Discussion

Lizhen, Gabriela and Nathan?

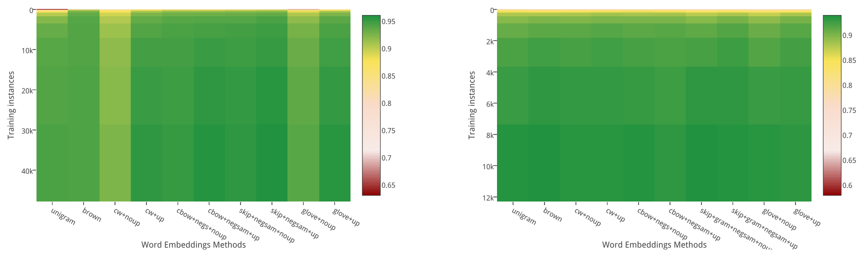
Because we can either update pre-trained word embeddings during training or not, through the evaluation, we want to answer the following questions:

- 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?

Table 3: Benchmark results vs. our best results

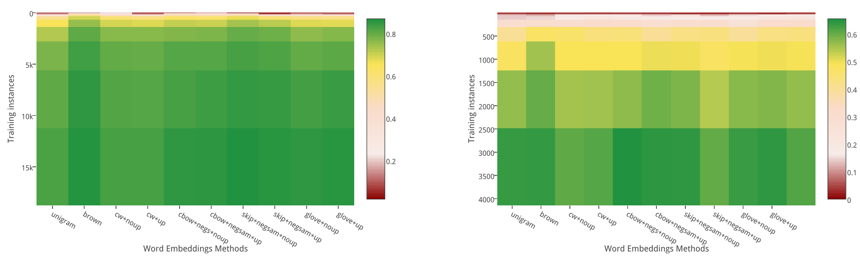
Task	**Benchmark**	**Us**
POS-Tagging	(Accuracy) 97.24 (Toutanova et al., 2003)	0.9592 (skip-gram negsam+up)
Chunking	(F1) 0.9429 (Sha and Pereira, 2003)	0.9386 (Brown cluster v2000+)
NER	(F1) 0.8931 (Ando and Zhang, 2005)	0.8686 (skip-gram negsam+noup)
MWE	(F1) 0.6253 (Schneider et al., 2014a)	0.6546 (cw+up)

Figure 1: Best results for each method for POS-Tagging and Chunking



(a) POS-Tagging Accuracy (b) Chunking F1-Measure

Figure 2: Best results for each method for NER and MWE



(a) NER F1-Measure (b) MWEs F1-Measure

5.1 Result tables

The first column of each table contains the number of training sentences.

5.1.1 Best hyperparameters for All Tasks

5.1.2 Out of Vocabulary results for All Tasks

5.1.3 Out of domain Results for NER and POS

6 Conclusion

Acknowledgments

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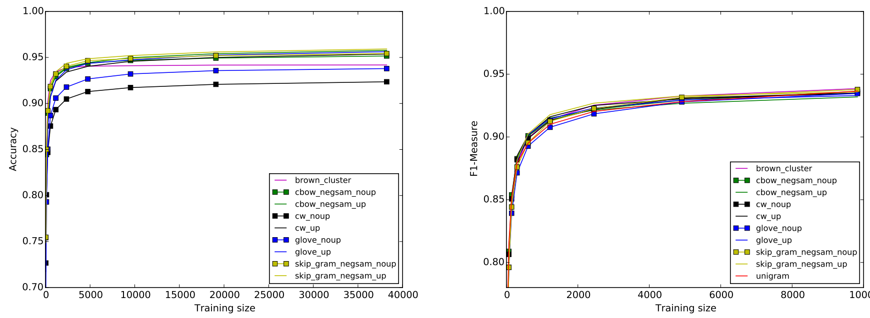
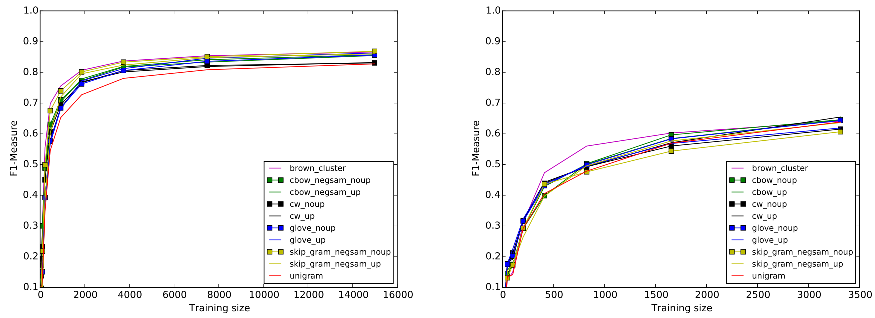
Figure 3: Best results for each method for POS-Tagging and Chunking



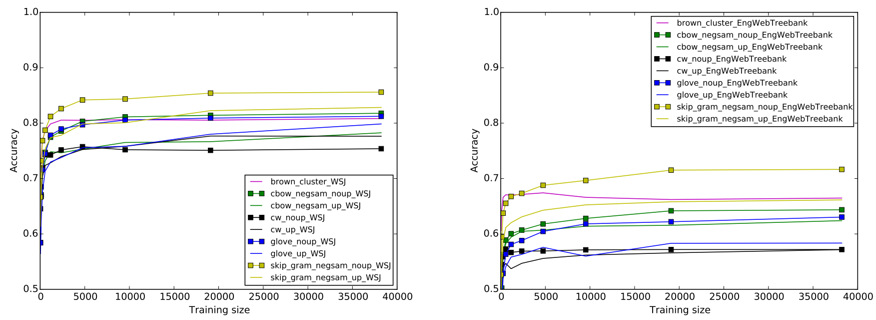
(a) POS-Tagging results (b) Chunking results

Figure 4: Best results for each method for NER and MWE



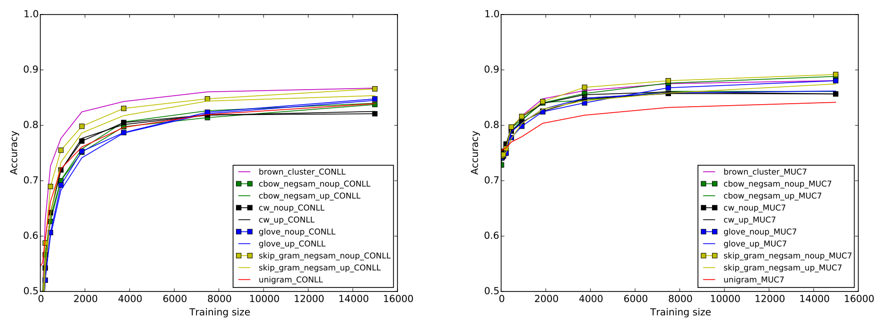
(a) NER results (b) MWE results

Figure 5: POS-Tagging out-of-vocabulary-words accuracy for *in-domain* and *out-of-domain* test sets



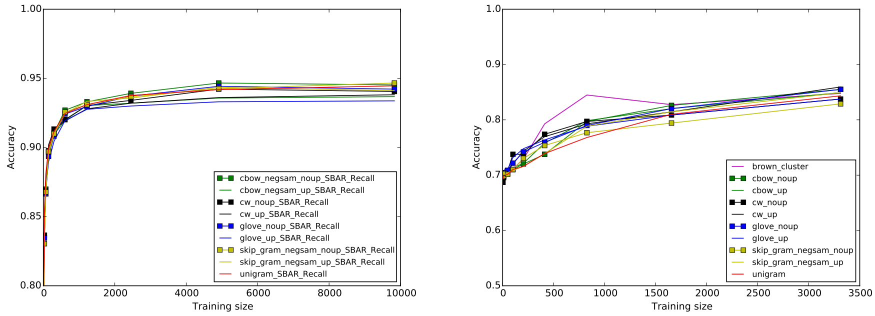
(a) *in domain* (b) *out-of-domain*

Figure 6: NER out-of-vocabulary-words accuracy for *in-domain* and *out-of-domain* test sets



(a) *in-domain* (b) *out-of-domain*

Figure 7: Chunking and MWE out-of-vocabulary-words accuracy for *in-domain* test set



(a) *in-domain* (b) *out-of-domain*

label	unigram	brown+cluster+v4000	cw+noupdated	cw+updated	cbow+negsam+noupdated	cbow+negsam+updated	skip+gram+negsam+noupdated	skip+gram+negsam+updated	glove+noupdated	glove+updated
38	0.6293	0.7687	0.7267	0.742	0.7543	0.7457	0.7547	0.7486	0.6861	0.7172
113	0.7387	0.8527	0.8009	0.8266	0.8446	0.8386	0.8501	0.8482	0.793	0.8178
262	0.8208	0.9019	0.8468	0.8818	0.8896	0.8877	0.8921	0.8953	0.8503	0.8737
561	0.8721	0.9249	0.8755	0.9076	0.9162	0.9159	0.9185	0.921	0.8869	0.9071
1,159	0.9039	0.9346	0.8933	0.9243	0.9293	0.9303	0.9321	0.9344	0.9059	0.9253
2,354	0.9215	0.9391	0.9048	0.9341	0.938	0.9392	0.9403	0.9437	0.9178	0.9366
4,745	0.933	0.9405	0.9129	0.9404	0.9439	0.9444	0.9465	0.9486	0.9266	0.9435
9,527	0.9382	0.941	0.9173	0.9458	0.9468	0.9498	0.9489	0.952	0.9321	0.9474
19,091	0.9413	0.9417	0.9208	0.95	0.9494	0.9541	0.9521	0.956	0.9357	0.9526
38,219	0.9432	0.9419	0.9236	0.9537	0.9516	0.9577	0.9543	0.9592	0.9379	0.9563

Table 4: Accuracy of POS tagging evaluated on WSJ test set

label	unigram	brown+cluster+v4000	cw+noupdated	cw+updated	cbow+negsam+noupdated	cbow+negsam+updated	skip+gram+negsam+noupdated	skip+gram+negsam+updated	glove+noupdated	glove+updated
15	0.0873	0.1345	0.1933	0.0524	0.0917	0.1424	0.0339	0.0173	0.0543	0.0707
44	0.0618	0.1441	0.1725	0.0529	0.1378	0.13	0.0972	0.0256	0.0702	0.0629
103	0.1332	0.3023	0.2318	0.1159	0.3003	0.2955	0.2184	0.0774	0.1508	0.1144
220	0.3469	0.5553	0.45	0.3909	0.4886	0.4751	0.4993	0.3852	0.3924	0.3749
455	0.5457	0.6983	0.606	0.58	0.6311	0.6214	0.6752	0.6037	0.5764	0.5694
923	0.6526	0.7557	0.6949	0.6848	0.7104	0.7033	0.7396	0.7198	0.6842	0.6813
1,861	0.7271	0.8068	0.7666	0.7691	0.7736	0.7786	0.8013	0.7954	0.7622	0.7722
3,736	0.7804	0.8369	0.8059	0.8013	0.8174	0.8192	0.8333	0.8237	0.8059	0.8121
7,487	0.8084	0.854	0.8224	0.819	0.8333	0.841	0.851	0.8481	0.8359	0.8462
14,987	0.8276	0.8663	0.8306	0.832	0.8547	0.8573	0.8686	0.8603	0.8565	0.8631

Table 5: F1 Measure of NER evaluated on CoNLL test set

label	unigram	brown+cluster+v2000	cw+noupdated	cw+updated	cbow+negsam+noupdated	cbow+negsam+updated	skip+gram+negsam+noupdated	skip+gram+negsam+updated	glove+noupdated	glove+updated
10	0.6386	0.6108	0.6123	0.6006	0.6247	0.6247	0.5778	0.5832	0.5963	0.5952
29	0.764	0.7424	0.7442	0.7376	0.744	0.7375	0.7325	0.7317	0.7306	0.726
68	0.8148	0.8001	0.8065	0.8051	0.8088	0.8061	0.7961	0.8012	0.7961	0.7971
145	0.8519	0.8492	0.8506	0.851	0.8538	0.8518	0.8442	0.8496	0.8392	0.8459
298	0.8791	0.879	0.8818	0.885	0.8826	0.8834	0.876	0.8818	0.8715	0.8806
606	0.8951	0.8992	0.8987	0.9015	0.9009	0.901	0.8955	0.9024	0.8927	0.9019
1,221	0.9101	0.9139	0.913	0.9161	0.9134	0.9151	0.9125	0.9178	0.9077	0.9145
2,451	0.9203	0.9253	0.9221	0.9251	0.9221	0.9214	0.9227	0.9269	0.9184	0.9231
4,910	0.9281	0.9326	0.931	0.9303	0.9292	0.9268	0.9316	0.9326	0.9279	0.9294
9,829	0.9365	0.9386	0.935	0.9348	0.9362	0.9319	0.9378	0.9359	0.9347	0.933

Table 6: F1 Measure of chunking evaluated on CoNLL test set

label	unigram	brown+cluster+v4000	brown+cluster+nathn	cw+noupdated	cw+updated	cbow+noupdated	cbow+updated	skipgram+noupdated	skipgram+updated	glove+noupdated	glove+updated
4	0.0241	0.0255	0.0232	0.0146	$8.2 \cdot 10^{-3}$	0.0122	0.0138	$8.4 \cdot 10^{-3}$	0	$3.4 \cdot 10^{-3}$	0.0111
10	0.0306	0.024	0.0239	0.0103	0.0172	0.0205	0.0206	0.0137	0.0206	0.0138	$6.8 \cdot 10^{-3}$
23	0.0505	0.0375	0.054	0.0564	0.0603	0.0505	0.0373	0.0374	0.0507	0.0374	0.0599
49	0.1354	0.1241	0.1623	0.1782	0.1825	0.1437	0.1573	0.1314	0.1544	0.1751	0.1782
101	0.1412	0.1494	0.1785	0.2121	0.192	0.1752	0.173	0.1723	0.1743	0.2021	0.2245
204	0.2933	0.311	0.3036	0.3173	0.3204	0.2921	0.2926	0.2926	0.2644	0.3156	0.3234
412	0.4054	0.4733	0.4658	0.439	0.4424	0.3985	0.4287	0.4358	0.3975	0.4312	0.4363
826	0.4785	0.5601	0.4929	0.493	0.493	0.5027	0.5011	0.4762	0.4959	0.4994	0.4955
1,655	0.5695	0.6025	0.5578	0.5602	0.5709	0.5965	0.5845	0.5437	0.5768	0.5836	0.5684
3,312	0.6384	0.6409	0.6077	0.6153	0.6546	0.6459	0.645	0.6067	0.6363	0.6434	0.619

Table 7: F1 Measure of MWE identification evaluated on MWE test set

label	unigram	brown+cluster+v4000	cw+noupdated	cw+updated	cbow+negsam+noupdated	cbow+negsam+updated	skip+gram+negsam+noupdated	skip+gram+negsam+updated	glove+noupdated	glove+updated
38	0.4546	0.7018	0.6455	0.6302	0.5844	0.5731	0.6665	0.6135	0.584	0.5644
113	0.525	0.7404	0.6851	0.6676	0.6705	0.6524	0.732	0.6782	0.6676	0.6215
262	0.6306	0.7691	0.7196	0.7036	0.7164	0.7047	0.7684	0.7229	0.716	0.6756
561	0.6815	0.7862	0.7429	0.7236	0.7473	0.732	0.7873	0.7538	0.7447	0.7135
1,159	0.717	0.7985	0.7425	0.7284	0.7745	0.7484	0.812	0.7738	0.7782	0.7298
2,354	0.7377	0.8055	0.7516	0.7396	0.7858	0.7465	0.8262	0.7782	0.7895	0.7378
4,745	0.7503	0.8051	0.7575	0.7524	0.8033	0.7531	0.8418	0.7985	0.7971	0.7556
9,527	0.7602	0.8062	0.752	0.7582	0.8113	0.7651	0.8436	0.8007	0.8055	0.7582
19,091	0.7673	0.8055	0.7509	0.7767	0.8142	0.7665	0.8542	0.8225	0.8091	0.78
38,219	0.7719	0.8084	0.7538	0.7764	0.8178	0.7825	0.856	0.8284	0.8124	0.7985

Table 8: Accuracy of POS tagging evaluated on out-of-vocabulary words in WSJ test set

label	unigram	brown+cluster+v4000	cw+noupdated	cw+updated	cbow+negsam+noupdated	cbow+negsam+updated	skip+gram+negsam+noupdated	skip+gram+negsam+updated	glove+noupdated	glove+updated
15	0.5468	0.4234	0.4728	0.4281	0.4351	0.4523	0.4091	0.4079	0.4102	0.4136
44	0.5478	0.4281	0.4406	0.4047	0.4351	0.4481	0.4263	0.4047	0.4099	0.411
103	0.5528	0.4986	0.4632	0.4221	0.4825	0.4994	0.47	0.4107	0.4245	0.4216
220	0.5948	0.6291	0.5425	0.5277	0.5664	0.5672	0.5875	0.542	0.5204	0.5266
455	0.6625	0.7265	0.6423	0.6423	0.6265	0.6345	0.6896	0.6395	0.6064	0.5999
923	0.7215	0.7764	0.7195	0.7187	0.7	0.7011	0.7551	0.7336	0.6922	0.6829
1,861	0.7609	0.8243	0.7715	0.7764	0.7515	0.7575	0.7983	0.7863	0.7531	0.7414
3,736	0.7962	0.843	0.805	0.8014	0.7975	0.8061	0.8305	0.8175	0.7868	0.7861
7,487	0.8194	0.8604	0.8188	0.8183	0.8139	0.8264	0.8479	0.8438	0.8238	0.8212
14,987	0.8392	0.8672	0.8209	0.8251	0.8375	0.8399	0.8659	0.8537	0.8477	0.8451

Table 9: Accuracy of NER evaluated on out-of-vocabulary words in CoNLL test set

label	unigram	brown+cluster+v2000	cw+noupdated	cw+updated	cbow+negsam+noupdated	cbow+negsam+updated	skip+gram+negsam+noupdated	skip+gram+negsam+updated	glove+noupdated	glove+updated
10	0.7958	0.7907	0.7849	0.7988	0.7751	0.7788	0.7744	0.774	0.7737	0.7717
29	0.8548	0.8447	0.8366	0.8468	0.8349	0.8393	0.8304	0.8366	0.8345	0.8383
68	0.8808	0.8719	0.8692	0.8733	0.8699	0.8753	0.8678	0.8675	0.8665	0.8702
145	0.8998	0.9001	0.8967	0.9018	0.8977	0.8974	0.897	0.895	0.8936	0.8896
298	0.9116	0.9096	0.9134	0.913	0.9106	0.9093	0.91	0.9093	0.9083	0.9045
606	0.9247	0.9212	0.9201	0.9191	0.9269	0.9198	0.9256	0.9246	0.9242	0.9195
1,221	0.931	0.931	0.9303	0.928	0.9331	0.9303	0.931	0.9334	0.9297	0.9276
2,451	0.9377	0.9354	0.9341	0.932	0.9392	0.932	0.9368	0.9358	0.9371	0.93
4,910	0.9419	0.9405	0.9422	0.9361	0.9467	0.9358	0.9426	0.9436	0.9443	0.9331
9,829	0.9446	0.9439	0.9405	0.9382	0.9453	0.9368	0.9467	0.9412	0.9422	0.9337

Table 10: Accuracy of Chunking evaluated on out-of-vocabulary words in CoNLL test set

label	unigram	brown+cluster+v4000	cw+noupdated	cw+updated	cbow+noupdated	cbow+updated	skipgram+noupdated	skipgram+updated	glove+noupdated	glove+updated
4	0.6942	0.6971	0.687	0.6971	0.6957	0.6971	0.6971	0.6971	0.6971	0.6986
10	0.6986	0.6986	0.6957	0.6986	0.7	0.7	0.6986	0.6986	0.6986	0.7
23	0.7	0.7	0.7043	0.7043	0.7014	0.7	0.7029	0.7014	0.7029	0.7116
49	0.7014	0.6986	0.7072	0.7072	0.7029	0.7043	0.7014	0.7043	0.7087	0.7101
101	0.7101	0.7116	0.7377	0.7203	0.7101	0.713	0.7101	0.7087	0.7217	0.7319
204	0.7159	0.729	0.7377	0.7435	0.7203	0.7217	0.7304	0.7159	0.742	0.7478
412	0.7391	0.7928	0.7739	0.7696	0.7377	0.758	0.7536	0.7391	0.7594	0.7638
826	0.7681	0.8449	0.7971	0.7928	0.7971	0.7986	0.7768	0.7884	0.7899	0.7884
1,655	0.8101	0.8275	0.8087	0.8145	0.8261	0.8203	0.7942	0.8145	0.8203	0.8087
3,312	0.8435	0.8478	0.8377	0.8594	0.8551	0.8493	0.829	0.8493	0.8551	0.8377

Table 11: Accuracy of MWE identification evaluated on out-of-vocabulary words in MWE test set

label	unigram	brown+cluster+v4000	cw+noupdated	cw+updated	cbow+negsam+noupdated	cbow+negsam+updated	skip+gram+negsam+noupdated	skip+gram+negsam+updated	glove+noupdated	glove+updated
38	0.5345	0.7106	0.6303	0.636	0.6854	0.6681	0.6786	0.6631	0.5931	0.6249
113	0.6448	0.7898	0.7151	0.7468	0.779	0.7632	0.7819	0.7781	0.7023	0.7407
262	0.7279	0.8537	0.7704	0.8219	0.8407	0.8341	0.8389	0.8433	0.7712	0.8148
561	0.7967	0.8772	0.8067	0.8481	0.8686	0.8624	0.8659	0.8675	0.816	0.8464
1,159	0.8318	0.8879	0.8303	0.8633	0.882	0.8782	0.8856	0.882	0.8426	0.865
2,354	0.8511	0.8916	0.8464	0.8728	0.8895	0.8855	0.8938	0.8891	0.8575	0.8766
4,745	0.8656	0.8942	0.8563	0.8825	0.8965	0.8908	0.901	0.8971	0.8701	0.886
9,527	0.873	0.8926	0.8614	0.8877	0.8994	0.8961	0.9054	0.9017	0.876	0.8912
19,091	0.877	0.8908	0.8656	0.8913	0.9029	0.9003	0.9084	0.9044	0.8804	0.8979
38,219	0.8796	0.8911	0.8681	0.8959	0.9045	0.902	0.9105	0.9064	0.8836	0.9009

Table 12: Accuracy of POS tagging evaluated on English web treebank.

label	unigram	brown+cluster+v4000	cw+noupdated	cw+updated	cbow+negsam+noupdated	cbow+negsam+updated	skip+gram+negsam+noupdated	skip+gram+negsam+updated	glove+noupdated	glove+updated
15	0.0424	0.0589	0.0679	0.0451	0.0562	0.0785	0.0223	0.023	0.0306	0.0296
44	0.0487	0.0624	0.0615	0.0465	0.0608	0.0609	0.032	0.0304	0.0494	0.0568
103	0.0503	0.0837	0.0825	0.0687	0.0996	0.123	0.0479	0.0395	0.0553	0.0539
220	0.1054	0.227	0.1925	0.1788	0.2089	0.2315	0.1423	0.1118	0.1311	0.1525
455	0.3051	0.434	0.3769	0.3787	0.4156	0.4262	0.3976	0.3621	0.34	0.3903
923	0.3955	0.5136	0.4403	0.468	0.4897	0.5024	0.4881	0.461	0.445	0.4708
1,861	0.48	0.5834	0.52	0.5346	0.5629	0.5666	0.5784	0.5464	0.5294	0.5342
3,736	0.5622	0.6465	0.6034	0.6201	0.6368	0.6118	0.6663	0.6114	0.6109	0.6155
7,487	0.5956	0.6726	0.6334	0.6425	0.6765	0.6529	0.6794	0.65	0.6602	0.6491
14,987	0.6288	0.7012	0.6391	0.6521	0.7148	0.6838	0.7364	0.6964	0.6929	0.6754

Table 13: F1 measure of NER evaluated on MUC7 test set