Exploring phrase-compositionality in skip-gram models

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Abstract

In this paper, we introduce a variation of the skip-gram model which jointly learns distributed word vector representations and their way of composing to form phrase embeddings. In particular, we propose a learning procedure that incorporates a phrase-compositionality function which can capture how we want to compose phrases vectors from their component word vectors. Our experiments show improvement in word and phrase similarity tasks as well as syntactic tasks like dependency parsing using the proposed joint models.

1 Introduction

Distributed word vector representations learned from large corpora of unlabeled data have been shown to be effective in a variety of NLP tasks, such as POS tagging (Collobert et al., 2011), parsing (Chen and Manning, 2014), Durrett and Klein, 2015, and machine translation (Devlin et al., 2014; Liu et al., 2014; Sutskever et al., 2014; Kalchbrenner and Blunsom, 2013). One of the most widely used approaches to learn these vector representations is the skip-gram model described in Mikolov et al. (2013a) and Mikolov et al. (2013b). The skip-gram model optimizes the probability of predicting words in the context given the current center word. Figure 1 shows a standard skip-gram structure. Ling et al. (2015) present a variation of skip-gram which captures the relative position of context words by using a different weight matrix to connect the hidden layer to the context word at each relative position.

Word embeddings are usually hard to scale to larger units due to data sparsity. Recent work (Mitchell and Lapata, 2008; Baroni and Zamparelli, 2010; Coecke et al., 2010; Fyshe et al., 2015) deals with this issue by constructing distributional representations for phrases from word embeddings. Socher et al. (2013) use a recursive neural network to learn weight matrices that capture compositionality. However, the learning procedure is limited to the labeled Penn Treebank and the phrasal information from the unlabeled data is not utilized.

Lebret and Collobert (2015) propose a learning schedule which learns distributed vector representations for words and phrases jointly. However, they haven’t used the context information during the optimization procedure. Recently Yu and Dredze (2015) propose a feature-rich compositional transformation (FCT) model which learns weighted combination of word vectors to compose phrase vectors, where they mainly focus on bigram NPs.

In this paper, we extend the skip-gram model to use the phrase structure in a large corpus to capture phrase compositionality and positional information of both words and phrases. We jointly model words in the context of words and phrases in the context of phrases. Additionally, we enforce a compositionality constraint on both the input and output phrase embedding spaces which indicates how we build the distributed vector representations for phrases from their component word vectors. Our results show
that using phrase level context information provides
gains in both word similarity and phrase similarity
tasks. Additionally, if we model phrase-level
skip-gram over syntactic phrases, it would be helpful
for syntactic tasks like syntactic analogy and depend-
pency parsing.

2 Skip-gram model

The skip-gram model learns distributed vector rep-
resentations for words by maximizing the prob-
bility of predicting the context words given the current
word. According to the word2vec implementation of
Mikolov et al. (2013b), each input word \( w \) is associ-
ated with a \( d \)-dimensional vector \( v_w \in \mathbb{R}^d \) called the
input embedding and each context word \( w_O \) is associ-
ated with a \( d \)-dimensional vector \( v_{w_O} \in \mathbb{R}^d \) called the
output embedding. \( w, w_O \) are words from a vo-
cabulary \( V \) of size \( W \). The probability of observing
\( w_O \) in the context of \( w \) is modeled with a softmax
function:

\[
P(w | w_O) = \frac{\exp(v_{w_O}^T v_w)}{\sum_{i=1}^W \exp(v_{w_i}^T v_w)} \tag{1}
\]

The denominator of this function involves a sum-
mation over the whole vocabulary, which is imprac-
tical. One alternative to deal with the complexity
issue is to sample several negative samples to avoid
computing all the vocabulary. The objective func-
tion after using negative sampling is:

\[
E_w = \sum_{w \in s} \left( \log \sigma(v_{w_O}^T v_w) + \sum_{i=1}^K \log \sigma(-v_{w_{i-1}}^T v_w) \right) \tag{2}
\]

where \( s \) is a chunked sentence. \( w_i, i = 1, 2, \ldots, K \),
are negative samples sampled from the following
distribution:

\[
P(w) = \frac{\tilde{P}(w)^{\frac{3}{4}}}{Z} \tag{3}
\]

where \( \tilde{P}(w) \) is the unigram distribution of words and
\( Z \) is the normalization constant. The exponent \( \frac{3}{4} \) is
set empirically.

3 Compositionality-aware skip-gram

model

To capture the way of composing phrase embed-
dings from distributed word vector representations,
we extend the skip-gram model to include informa-
tion from context of phrases and learn their composi-
tionality from word vectors during the optimization
procedure. Our phrase-level skip-gram structure is
shown in Figure 1b.

3.1 Phrase-level skip-gram model

The word-level skip-gram model predicts the con-
text words given the current word vector. Our
approach further models the prediction of context
phrases given the vector representation of the cur-
rent phrase vector (Figure 1b). Assume \( v_p \in \mathbb{R}^d \)
to be the \( d \)-dimensional input embedding for current
phrase \( p \) and \( v_{pO} \in \mathbb{R}^d \) to be the output embedding
for context phrase \( p_O \). Using negative sampling, we
model the phrase-level probability with:

\[
E_p = \sum_{p \in s} \left( \log \sigma(v_{pO}^T v_p) + \sum_{i=1}^N \log \sigma(-v_{p_i}^T v_p) \right) \tag{4}
\]

where \( p_i, i = 1, 2, \ldots, N \), are negative samples
sampled according to the unigram probability of
phrases raised to the same exponent \( \frac{3}{4} \).

In this paper, we jointly model word-level skip-
gram and phrase-level skip-gram for each sentence:

\[
E = E_w + \beta E_p \tag{5}
\]

where \( \beta > 0 \) adjusts the relative importance of
the word-level and the phrase-level skipgram.

3.2 Compositional model

Assume a phrase \( p \) is composed of words
\( w_1, \ldots, w_{nP} \), where \( n_p \) is the number of component
words. The vector representation for \( p \) is computed
as:

\[
v_p = \Phi(\sigma(v_{w_1}), \ldots, \sigma(v_{w_i})) \tag{6}
\]
where $v_p$ is the vector representation for $p$. The function $\sigma$ is a component-wise manipulation over each dimension. The symbol $\oplus$ is an operator over the component word vectors, which can be linear combination, summation, concatenation etc. The mapping function $\Phi$ is a linear or non-linear manipulation over the resulting vector after the $\oplus$ operation. The same composition function is used to compute the output phrase embeddings $v'_{pO}$ and $v'_{pI}$, except that the component word vectors are $v'_{wi}$ instead of $v_{wi}$.

To show the effect of modeling phrase embeddings, we experiment with a composition function where $\oplus$ is linear combination and $\Phi$ is passing the resulting matrix to the left of a weight vector $l^p = [l^p_1, l^p_2, \ldots, l^p_n]$ associated with each phrase $p$. This manipulation can be interpreted as adjusting dimensional values of word vectors to the phrase vector space.

Stochastic gradient ascent is used to update the word vectors. In equation (4) for each word $w_j$ in $p'$, either context phrase $p_O$ or negative phrase sample $p_I$, the gradient is:

$$
\frac{\partial E_p}{\partial v'_{w_j}} = \nabla \sigma(v'_{w_j})(l^p_j(y - \sigma(v'_p T v_p))v_p)
$$

where $y = 1$ for each word in $p_O$ and 0 for each word in $p_I$, $\nabla \sigma(v'_{w_j})$ is a diagonal matrix where the $i$-th diagonal value is $\phi'(v'_{w_j})$. For each word $w_j$ in the current phrase $p$, the gradient is:

$$
\frac{\partial E_p}{\partial v_{w_j}} = \nabla \sigma(v_{w_j})(l^p_j(1 - \sigma(v'_p T v_p))v_p + \sum_{i=1}^{N} (-\sigma(v'_p T v_p))v_p))
$$

### 3.3 Output phrase embedding space

Following Ling et al. (2015), we use separate output embeddings to capture phrase-compositionality (we call this compositional model). That is, we have a separate component word vector $v''$ to compose the phrase vectors in the context and the negative samples instead of using $v'$. The intuition is that we don’t want the compositionality information in the context or negative sample layer to be distorted by word-level updates.

We further extend the phrase-level skipgram to include the order information, which uses different output word embeddings to compose phrases at each relative position. Phrases at the same relative position share the same output embeddings (we call this model positional+compositional). Without loss of generality, we experiment with the composition described in Equation (7). The coefficients $l^p_j$'s are set to be $\frac{1}{n_p}$.

### 4 Experiments

We train the skip-gram model with negative sampling using word2vec as our baseline. We used an April 2010 snapshot of the Wikipedia corpus (Shaoul and Westbury, 2010), which contains approximately 2 million articles and 990 million tokens. We remove all words that have a frequency less than 20 and use a context window size of 5 (5 words before and after the word occurrence). We set the number of negative samples to be 10 and the dimensionality of vectors to be 300. For phrase-level skip-gram, we also use a context window size of 5 (5 phrases before and after the phrase occurrence).

#### 4.1 Phrase compositionality

We first evaluate the compositional model on the intransitive verb disambiguation dataset provided by Mitchell and Lapata (2008). The dataset consists of pairs of subject and intransitive verb and a landmark intransitive verb is provided for each pair.

| Model                  | $\rho$ |
|------------------------|--------|
| Mitchell and Lapata (2008) | 0.19   |
| word2vec               | 0.23   |
| compositional          | 0.25   |
| positional             | 0.23   |
| compositional + positional | 0.26   |

Table 1: Spearman’s correlation using different embeddings
For example, this task requires one to identify when taking “sale” as the subject, reference “slump” and landmark “decline” are close to each other while “slump” and landmark “slouch” are not. Each pair has multiple human ratings indicating how similar the pairs are.

We use the senna toolkit to extract the POS tag labels for each sentence and combine adjacent noun-verb pairs. As the evaluation dataset is lemmatized, we also lemmatize the Wikipedia corpus to avoid sparsity. We evaluate the cosine similarity between the composed reference subject intransitive verb pair and its landmarks. Then we compute the Spearman’s correlation between the similarity scores and the human ratings. Table 1 shows the result. We can see that the compositions of subject and intransitive verbs can be learned using the compositional model and the best performance is achieved using the joint model. We use $\alpha = 1$ and varying $\alpha$ does not change much of the performance.

### 4.2 Word similarity and word analogy

We also consider word similarity and analogy tasks for evaluating the quality of word embeddings. Word similarity measures Spearman’s correlation coefficient between the human scores and the embeddings’ cosine similarities for word pairs. Word analogy measures the accuracy on syntactic and semantic analogy questions.

Here we extract phrases that contain syntax information, in the hope of learning additional syntactic information by modeling phrase-level skip-gram. We use the senna toolkit to identify the constituent chunks in each sentence. We run the chunker on 20 CPUs, and it takes less than 2 hours to chunk the Wikipedia 2010 corpus we use. The extracted phrases are labeled with NP, VP, PPs etc.

We evaluate similarity on two tasks, WordSim-353 and men, respectively containing 353 and 3000 word pairs. We use two word analogy datasets that we call SYN (8000 syntactic analogy questions) and MIXED (19544 syntactic and semantic analogy questions).

On the WordSim-353 task, Neelakantan et al. (2014) reported a Spearman’s correlation of 0.709, while their word2vec baseline is 0.704. From Table 2 we can see that positional information actually degrades the performance on the similarity task, while only adding compositional information performs the best. For syntactic and mixed analogy tasks which involves syntax information, we can see that using phrase-level skip-gram and positional information both help and combining both gives the best performance.

### 4.3 Dependency parsing

We use the same preprocessing procedure as in the previous task. The evaluation on dependency parsing is performed on the English PTB, with the standard train, dev and test splits with Stanford Dependencies. We use a neural network as described in Chen and Manning (2014). As we are using embeddings with a different dimensionality, we tune the hidden layer size and learning rate parameters for the neural network parser by grid search for each model and train for 15000 iterations. The other parameters are using the default settings. Evaluation is performed with the labeled (LAS) and unlabeled (UAS) attachment scores. We run each parameter setting for 3 times and then average to prevent randomness. We can see that by modeling phrase-level skip-gram over syntactic phrases, the performance on the dependency parsing task can be improved.

### 5 Conclusion

In this paper, we have presented a variation of skip-gram model which learns compositionality of phrase embeddings. Our results show that modeling phrase-level co-occurrence and phrase composi-
compositionality helps improve word and phrase similarity tasks. If the phrases contain syntactic information, it would also help improve syntactic tasks. As our compositionality function is very general, it would be interesting to see different variations and choices of composition function in different applications.

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