Sentence Similarity Learning by Lexical Decomposition and Composition

Zhiguo Wang and **Haitao Mi** and **Abraham Ittycheriah**
IBM T.J. Watson Research Center
Yorktown Heights, NY, USA
{zhigwang, hmi, abei}@us.ibm.com

Abstract

Most conventional sentence similarity methods only focus on similar parts of two input sentences, and simply ignore the dissimilar parts, which usually give us some clues and semantic meanings about the sentences. In this work, we propose a model to take into account both the similarities and dissimilarities by decomposing and composing lexical semantics over sentences. The model represents each word as a vector, and calculates a semantic matching vector for each word based on all words in the other sentence. Then, each word vector is decomposed into a similar component and a dissimilar component based on the semantic matching vector. After this, a two-channel CNN model is employed to capture features by composing the similar and dissimilar components. Finally, a similarity score is estimated over the composed feature vectors. Experimental results show that our model gets the state-of-the-art performance on the answer sentence selection task, and achieves a comparable result on the paraphrase identification task.

1 Introduction

Sentence similarity is a fundamental metric to measure the degree of likelihood between a pair of sentences. It plays an important role for a variety of tasks in both NLP and IR communities. For example, in paraphrase identification task, sentence similarity is used to determine whether two sentences are paraphrases or not (Yin and Schütze, 2015; He et al., 2015). For question answering and information retrieval tasks, sentence similarities between query-answer pairs are used for assessing the relevance and ranking all the candidate answers (Severyn and Moschitti, 2015; Wang and Ittycheriah, 2015).

However, sentence similarity learning has following challenges:

1. There is a lexical gap between semantically equivalent sentences. Take the E_1 and E_2 in Table 1 for example, they have the similar meaning but with different lexicons.

2. Semantic similarity should be measured at different levels of granularity (word-level, phrase-level and syntax-level). E.g., “not related” in E_2 is an indivisible phrase when matching with “irrelevant” in E_1 (shown in square brackets).

3. The dissimilarity (shown in angle brackets) between two sentences is also a significant clue (Qiu et al., 2006). For example, by judging the dissimilar parts, we can easily identify that E_3 and E_5 share the similar meaning “The study is about salmon”, because “sockeye” belongs to the salmon family, and “flounder” does not. Whereas the meaning of E_4 is quite different from E_3, which emphasizes “The study is about red (a special kind of) salmon”, because both “sockeye” and “coho” are in the salmon family. How we can extract and utilize those information becomes another challenge.

In order to handle the above challenges, researchers have been working on sentence similarity algorithms for a long time. To bridge the lexical gap (challenge 1), some word similarity metrics were proposed to match different but semantically related words. Examples include knowledge-based metrics (Resnik, 1995) and corpus-based metrics (Jiang and Conrath, 1997; Yin and Schütze, 2015; He et al., 2015). To measure sentence similarity from various granularities (challenge 2), researchers have explored features extracted from n-grams, continuous phrases, discontinuous phrases, and parse trees (Yin and Schütze, 2015; He et al., 2015; Heilman and Smith, 2010). The third challenge did not get much

E_1	The research is [irrelevant] to sockeye.
E_2	The study is [not related] to salmon.
E_3	The research is relevant to salmon.
E_4	The study is relevant to sockeye, $\langle$instead of coho$\rangle$.
E_5	The study is relevant to sockeye, $\langle$rather than flounder$\rangle$.

Table 1: Examples for sentence similarity learning, where sockeye means "red salmon", and coho means "silver salmon". "coho" and "sockeye" are in the salmon family, while "flounder" is not.

attention in the past, the only related work of Qiu et al. (2006) explored the dissimilarity between sentences in a pair for paraphrase identification task, but they require human annotations in order to train a classifier, and their performance is still below the state of the art.

In this paper, we propose a novel model to tackle all these challenges jointly by decomposing and composing lexical semantics over sentences. Given a sentence pair, the model represents each word as a low-dimensional vector (challenge 1), and calculates a semantic matching vector for each word based on all words in the other sentence (challenge 2). Then based on the semantic matching vector, each word vector is decomposed into two components: a similar component and a dissimilar component (challenge 3). We use similar components of all the words to represent the similar parts of the sentence pair, and dissimilar components of every word to model the dissimilar parts explicitly. After this, a two-channel CNN operation is performed to compose the similar and dissimilar components into a feature vector (challenge 2 and 3). Finally, the composed feature vector is utilized to predict the sentence similarity. Experimental results on two tasks show that our model gets the state-of-the-art performance on the answer sentence selection task, and achieves a comparable result on the paraphrase identification task.

In following parts, we start with a brief overview of our model (Section 2), followed by the details of our end-to-end implementation (Section 3). Then we evaluate our model on answer sentence selection and paraphrase identifications tasks (Section 4).

2 Model Overview

In this section, we propose a sentence similarity learning model to tackle all three challenges (mentioned in Section 1). To deal with the first challenge, we represent each word as a distributed vector, so that we can calculate similarities for formally different but semantically related words. To tackle the second challenge, we assume that each word can be semantically matched by several words in the other sentence, and we calculate a semantic matching vector for each word vector based on all the word vectors in the other side. To cope with the third challenge, we assume that each semantic unit (word) can be partially matched, and can be decomposed into a similar component and a dissimilar component based on its semantic matching vector.

Figure 1 shows an overview of our sentence similarity model. Given a pair of sentences S and T, our task is to calculate a similarity score $sim(S, T)$ in following steps:

Word Representation. Word embedding of Mikolov et al. (2013) is an effective way to handle the lexical gap challenge in the sentence similarity task, as it represents each word with a distributed vector, and words appearing in similar contexts tend to have similar meanings (Mikolov et al., 2013). With those pre-trained embeddings, we transform S and T into sentence matrixes $S = [s_1, ..., s_i, ..., s_m]$ and $T = [t_1, ..., t_j, ..., t_n]$, where s_i and t_j are d-dimension vectors of the corresponding words, and m and n are sentence length of S and T respectively.

Semantic Matching. In order to judge the similarity between two sentences, we need to check whether each semantic unit in one sentence is covered by the other sentence, or vice versa. For example, in Table 1, to check whether E_2 is a paraphrase of E_1, we need to know the single word "irrelevant" in E_1 is matched or covered by the phrase "not related" in E_2. In our model, we treat each word as a primitive semantic unit, and calculate a semantic matching vector $\hat{s_i}$ for each word s_i by composing part or full word vectors in the other sentence T. In this way, we can match a word s_i to a word or phrase in T.

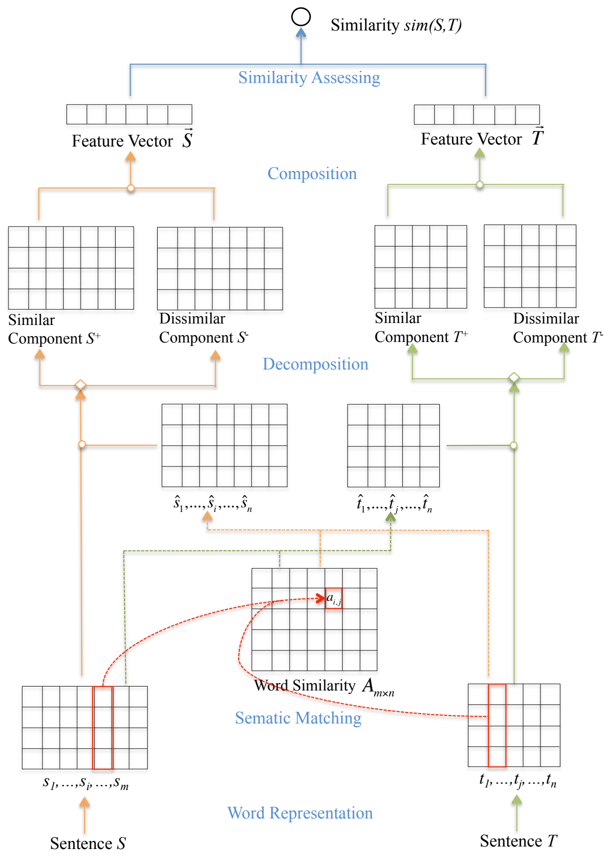


Figure 1: Model overview.

Similarly, for the reverse direction, we also calculate all semantic matching vectors $\hat{t_j}$ in T.

$$\begin{aligned} \hat{s_i} &= f_{match}(s_i, T) \qquad \forall s_i \in S \\ \hat{t_j} &= f_{match}(t_j, S) \qquad \forall t_j \in T \end{aligned} \tag{1}$$

We explore different f_{match} functions later in Section 3.

Decomposition. After the semantic matching phase, we have the semantic matching vectors of $\hat{s_i}$ and $\hat{t_j}$. We interpret $\hat{s_i}$ (or $\hat{t_j}$) as a semantic coverage of word s_i (or t_j) by the sentence T (or S). However, it is not necessary that all the semantics of s_i (or t_j) are fully covered by $\hat{s_i}$ (or $\hat{t_j}$). Take the E_1 and E_2 in Table 1 for example, the word "sockeye" in E_1 is only partially matched by the word "salmon" (the similar part) in E_2, as the full meaning of "sockeye" is "red salmon" (the semantic meaning of "red" is the dissimilar part). Motivated by this phenomenon, our model further decomposes word s_i (or t_j), based on its semantic matching vector $\hat{s_i}$ (or $\hat{t_j}$), into two components: similar component s_i^+ (or t_j^+) and dissimilar component s_i^- (or t_j^-). Formally, we define the decomposition function as:

$$\begin{aligned} [s_i^+; s_i^-] &= f_{decomp}(s_i, \hat{s_i}) \qquad \forall s_i \in S \\ [t_j^+; t_j^-] &= f_{decomp}(t_j, \hat{t_j}) \qquad \forall t_j \in T \end{aligned} \tag{2}$$

Composition. Given a similar component matrix $S^+ = [s_1^+, ..., s_m^+]$ (or $T^+ = [t_1^+, ..., t_n^+]$) and a dissimilar component matrix $S^- = [s_1^-, ..., s_m^-]$ (or $T^- = [t_1^-, ..., t_n^-]$), our goal in this step is how to utilize those information. Besides the suggestion from Qiu et al. (2006) that the significance of the dissimilar parts alone between two sentences has a great effect of their similarity, we also think that the dissimilar and similar components have strong connections. For example, in Table 1, if we only look at the dissimilar or similar part alone, it is hard to judge which one between E_4 and E_5 is more similar to E_3. We can easily identify that E_5 is more similar to E_3, when we consider both the similar and dissimilar parts. Therefore, our model composes the similar component matrix and dissimilar component matrix into a feature vector $\vec{S}$ (or $\vec{T}$) with the composition function:

$$\begin{aligned}\vec{S} &= f_{comp}(S^+, S^-)\\ \vec{T} &= f_{comp}(T^+, T^-)\end{aligned} \tag{3}$$

Similarity assessing. In the final stage, we concatenate the two feature vectors ($\vec{S}$ and $\vec{T}$) and predict the final similarity score:

$$sim(S, T) = f_{sim}(\vec{S}, \vec{T}) \tag{4}$$

3 An End-to-End Implementation

Section 2 gives us a glance of our model. In this section, we describe details of each phase.

3.1 Semantic Matching Functions

This subsection describes our specifications for the semantic matching function f_{match} in Eq. (1). The goal of f_{match} is to generate a semantic matching vector $\hat{s_i}$ for s_i by composing the vectors from T.

For a sentence pair S and T, we first calculate a similarity matrix $A_{m\times n}$, where each element $a_{i,j} \in A_{m\times n}$ computes the cosine similarity between words s_i and t_j as

$$a_{i,j} = \frac{s_i^T t_j}{\|s_i\| \cdot \|t_j\|} \qquad \forall s_i \in S, \forall t_j \in T. \tag{5}$$

Then, we define three different semantic matching functions over $A_{m\times n}$:

$$f_{match}(s_i, T) = \begin{cases} \frac{\sum_{j=0}^{n} a_{i,j} t_j}{\sum_{j=0}^{n} a_{i,j}} & \textit{global} \\ \frac{\sum_{j=k-w}^{k+w} a_{i,j} t_j}{\sum_{j=k-w}^{k+w} a_{i,j}} & \textit{local-w} \\ t_k & \textit{max} \end{cases} \tag{6}$$

where $k = \text{argmax}_j\, a_{i,j}$. The idea of the *global* function is to consider all word vectors t_j in T. A semantic matching vector $\hat{s_i}$ is a weighted sum vector of all words t_j in T, where each weight is the normalized word similarity $a_{i,j}$. The *max* function moves to the other extreme. It generates the semantic matching vector by selecting the most similar word vector t_k from T. The *local-w* function takes a compromise between *global* and *max*, where w indicates the size of the window to consider centered at k (the most similar word position). So the semantic matching vector is a weighted average vector from t_{k-w} to t_{k+w}.

3.2 Decomposition Functions

This subsection describes the implementations for the decomposition function f_{decomp} in Eq. (2). The intention of f_{decomp} is to decompose a word vector s_j based on its semantic matching vector $\hat{s_j}$ into a similar component s_i^+ and a dissimilar component s_i^-, where s_i^+ indicates the semantics of s_i covered by $\hat{s_i}$ and s_i^- indicates the uncovered part. We implement three types of decomposition function: *rigid*, *linear* and *orthogonal*.

The *rigid* decomposition only adapts to the *max* version of f_{match}. First, it detects whether there is an exactly matched word in the other sentence, or s_i equal to $\hat{s_i}$. If yes, the vector s_i is dispatched to the similar component s_i^+, and the dissimilar component is assigned with a zero vector **0**. Otherwise, the vector s_i is assigned to the dissimilar component s_i^-. Eq. (7) gives the formal definition:

$$\begin{array}{ll} [s_i^+ = s_i;\ s_i^- = \mathbf{0}] & if\ s_i = \hat{s_i} \\ [s_i^+ = \mathbf{0};\ s_i^- = s_i] & otherwise \end{array} \tag{7}$$

The motivation for the *linear* decomposition is that the more similar between s_i and $\hat{s_i}$, the higher proportion of s_i should be assigned to the similar component. First, we calculate the cosine similarity

α between s_i and $\hat{s_i}$. Then, we decompose s_i linearly based on α. Eq. (8) gives the corresponding definition:

$$\begin{aligned} \alpha &= \frac{s_i^T \hat{s_i}}{\|s_i\| \cdot \|\hat{s_i}\|} \\ s_i^+ &= \alpha s_i \\ s_i^- &= (1-\alpha) s_i \end{aligned} \tag{8}$$

The *orthogonal* decomposition is to decompose a vector in the geometric space. Based on the semantic matching vector $\hat{s_i}$, our model decomposes s_i into a parallel component and a perpendicular component. Then, the parallel component is viewed as the similar component s_i^+, and perpendicular component is taken as the dissimilar component s_i^-. Eq. (9) gives the concrete definitions.

$$\begin{aligned} s_i^+ &= \frac{s_i \cdot \hat{s_i}}{\hat{s_i} \cdot \hat{s_i}} \hat{s_i} \qquad && parallel \\ s_i^- &= s_i - s_i^+ && perpendicular \end{aligned} \tag{9}$$

3.3 Composition Functions

The aim of composition function f_{comp} in Eq. (3) is to extract features from both the similar component matrix and the dissimilar component matrix. We also want to acquire similarities and dissimilarities of various granularity during the composition phase. Inspired from Kim (2014), we utilize a two-channel convolutional neural networks (CNN) and design filters based on various order of n-grams, e.g., unigram, bigram and trigram.

The CNN model involves two sequential operations: *convolution* and *max-pooling*. For the *convolution* operation, we define a list of filters $\{w_o\}$. The shape of each filter is $d \times h$, where d is the dimension of word vectors and h is the window size. Each filter is applied to two patches (a window size h of vectors) from both similar and dissimilar channels, and generates a feature. Eq. (10) expresses this process.

$$c_{o,i} = f(w_o * S^+_{[i:i+h]} + w_o * S^-_{[i:i+h]} + b_o) \tag{10}$$

where the operation $A * B$ sums up all elements in B with the corresponding weights in A, $S^+_{[i:i+h]}$ and $S^-_{[i:i+h]}$ indicate the patches from S^+ and S^-, b_o is a bias term and f is a non-linear function (we use *tanh* in this work). We apply this filter to all possible patches, and produce a series of features $\vec{c_o} = [c_{o,1}, c_{o,2}, ..., c_{o,O}]$. The number of features in $\vec{c_o}$ depends on the shape of the filter w_o and the length of the input sentence. To deal with variable feature size, we perform a *max-pooling* operation over $\vec{c_o}$ by selecting the maximum value $c_o = max\ \vec{c_o}$. Therefore, after these two operations, each filter generates only one feature. We define several filters by varying the window size and the initial values. Eventually, a vector of features is captured by composing the two component matrixes, and the feature dimension is equal to the number of filters.

3.4 Similarity Assessment Function

The similarity assessment function f_{sim} in Eq. (4) predicts a similarity score by taking two feature vectors as input. We employ a linear function to sum up all the features and apply a *sigmoid* function to constrain the similarity within the range [0, 1].

3.5 Training

We train our sentence similariy model by maximizing the likelihood on a training set. Each training instance in the training set is represented as a triple (S_i, T_i, L_i), where S_i and T_i are a pair of sentences, and $L_i \in \{0, 1\}$ indicates the similarity between them. We assign $L_i = 1$ if T_i is a paraphrase of S_i for the paraphrase identification task, or T_i is a correct answer for S_i for the answer sentence selection task. Otherwise, we assign $L_i = 0$. We implement the mathematical expressions with Theano (Bastien et al., 2012) and use Adam (Kingma and Ba, 2014) for optimization.

4 Experiment

4.1 Experimental Setting

We evaluate our model on two tasks: answer sentence selection and paraphrase identification. The answer sentence selection task is to rank a list of candidate answers based on their similarities to a question sentence, and the performance is measured by mean average precision (MAP) and mean reciprocal rank (MRR). We experiment on two datasets: *QASent* and *WikiQA*. The statistics of the two datasets can be found in Yang et al. (2015), where *QASent* (Wang et al., 2007) was created from the TREC QA track, and *WikiQA* (Yang et al., 2015) is constructed from real queries of Bing and Wikipedia. The paraphrase identification task is to detect whether two sentences are paraphrases based on the similarity between them. The metrics include the accuracy and the positive class F_1 score. We experiment on the Microsoft Research Paraphrase corpus (MSRP) (Dolan et al., 2004), which includes 2753 true and 1323 false instances in the training set, and 1147 true and 578 false instances in the test set. We build a development set by randomly selecting 100 true and 100 false instances from the training set. In all experiments, we set the size of word vector dimension as d =300, and pre-train the vectors with the *word2vec* toolkit (Mikolov et al., 2013) on the English Gigaword (LDC2011T07).

4.2 Model Properties

There are several alternative options in our model, e.g., the semantic matching functions, the decomposition operations, and the filter types. The choice of these options may affect the final performance. In this subsection, we present some experiments to demonstrate the properties of our model, and find a good configuration that we use to evaluate our final model. All the experiments in this subsection were performed on the *QASent* dataset and evaluated on the development set.

First, we evaluated the effectiveness of various semantic matching functions. We switched the semantic matching functions among {*max*, *global*, *local-l*}, where $l \in \{1, 2, 3, 4\}$, and fixed the other options as: the *linear* decomposition, the filter types including {unigram, bigram, trigram}, and 500 filters for each type. Figure 2 (a) presents the results. We found that the *max* function worked better than the *global* function on both MAP and MRR. By increasing the window size, the *local-l* function acquired progressive improvements when the window size is smaller than 4. But after we enlarged the window size to 4, the performance dropped. The *local-3* function worked better than the *max* function in term of the MAP, and also got a comparable MRR. Therefore, we use the *local-3* function in the following experiments.

Second, we studied the effect of various decomposition operations. We varied the decomposition operation among {*rigid*, *linear*, *orthogonal*}, and kept the other options unchanged. Figure 2 (b) shows the performance. We found that the *rigid* operation got the worst result. This is reasonable, because the *rigid* operation decomposes word vectors by exactly matching words. The *orthogonal* operation got a similar MAP as the *linear* operation, and it worked better in term of MRR. Therefore, we choose the *orthogonal* operation in the following experiments.

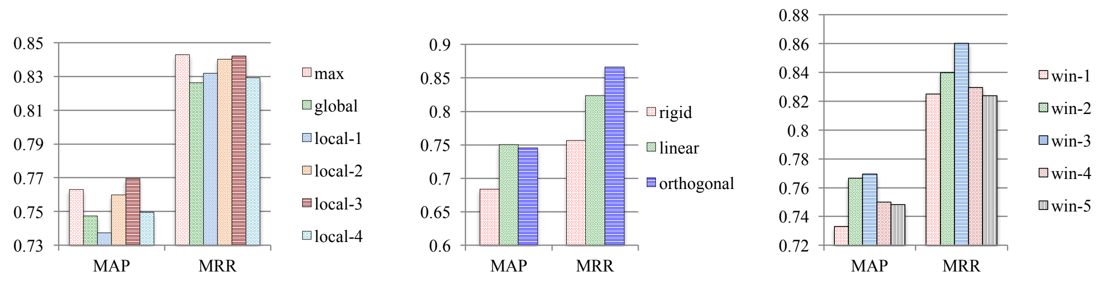
Third, we tested the influence of various filter types. We constructed 5 groups of filters: *win-1* contains only the unigram filters, *win-2* contains both unigram and bigram filters, *win-3* contains all the filters in *win-2* plus trigram filters, *win-4* extends filters in *win-3* with 4-gram filters, and *win-5* adds 5-gram filters into *win-4*. We generate 500 filters for each filter type (with different initial values). Experimental results are shown in Figure 2 (c). At the beginning, adding higher-order ngram filters was helpful for the performance. The performance reached to the peak, when we used the *win-3* filters. After that, adding more complex filters decreased the performance. Therefore, the trigram is the best granularity for our model. In the following experiments, we utilize filter types in *win-3*.

4.3 Comparing with State-of-the-art Models

In this subsection, we evaluated our model on the test sets of *QASent*, *WikiQA* and *MSRP*.

***QASent* dataset.** Table 2 presents the performances of the state-of-the-art systems and our model, where the performances were evaluated with the standard trec_eval-8.1 script [1]. Given a pair of sentences,

[1]http://trec.nist.gov/trec_eval/



(a) Semantic matching. (b) Decomposition. (c) Filter types in composition.

Figure 2: Influence of different configuration.

Models	MAP	MRR
Severyn and Moschitti (2015) (CNN only)	0.6709	0.7280
Severyn and Moschitti (2015) (CNN + sparse features)	0.7459	0.8078
Wang and Ittycheriah (2015) (Word embedding alignment)	0.7460	0.8200
dos Santos et al. (2016) (Attention-based CNN)	0.7530	**0.8511**
This work	**0.7714**	0.8447

Table 2: Results on the QASent dataset.

Models	MAP	MRR
Yang et al. (2015) (2-gram CNN)	0.6520	0.6652
dos Santos et al. (2016) (Attention-based CNN)	0.6886	0.6957
Miao et al. (2015) (Attention-based LSTM)	0.6886	0.7069
Yin et al. (2015) (Attention-based CNN)	0.6921	0.7108
This work	**0.7058**	**0.7226**

Table 3: Results on the WikiQA dataset.

Severyn and Moschitti (2015) employed a CNN model to compose each sentence into a vector separately, and joined the two sentence vectors to compute the sentence similarity. Because only the sentence-level granularity was used, the performance is much lower (the second row of Table 2). After adding some word overlap features between the two sentences, the performance was improved significantly (the third row of Table 2). Therefore, the lower-level granularity is an indispensable factor for a good performance. Wang and Ittycheriah (2015) conducted word alignment for a sentence pair based on word vectors, and measured the sentence similarity based on a couple of word alignment features. They got a slightly better performance (the fourth row of Table 2), which indicates that the vector representation for words is helpful to bridging the lexical gap problem. dos Santos et al. (2016) introduced the attention mechanism into the CNN model, and learnt sentence representation by considering the influence of the other sentence. They got better performance than all the other previous work. Our model makes use of all these useful factors and also considers the dissimilarities of a sentence pair. We can see that our model (the last row of Table 2) got the best MAP among all previous work, and a comparable MRR than dos Santos et al. (2016).

***WikiQA* dataset.** Table 3 presents the results of our model and several state-of-the-art models. Yang et al. (2015) constructed the dataset and reimplemented several baseline models. The best performance (shown at the second row of Table 3) was acquired by a bigram CNN model combining with the word overlap features. Miao et al. (2015) models the sentence similarity by enriching LSTMs with a latent stochastic attention mechanism. The corresponding performance is given at the fourth row of Table 3. Yin et al. (2015) introduced the attention mechanism into the CNN model, and captured the best performance (the fifth row of Table 3). The semantic matching phase in our model is similar to the attention mechanism. But different from the previous models, our model utilizes both the similarity and dissimilarity simultaneously. The last row of Table 3 shows that our model is more effective than the other models.

***MSRP* dataset.** Table 4 summarized the results from our model and several state-of-the-art models. Yin and Schütze (2015) employed a CNN model to learn sentence representations on multiple level of

Models	Acc	F1
Yin and Schütze (2015) (without pretraining)	72.5	81.4
Yin and Schütze (2015) (with pretraining)	78.4	84.6
He et al. (2015) (without POS embeddings)	77.8	N/A
He et al. (2015) (without Para. embeddings)	77.3	N/A
He et al. (2015) (POS and Para. embeddings)	78.6	84.7
Yin et al. (2015) (with sparse features)	78.9	84.8
Ji and Eisenstein (2013)	**80.4**	**86.0**
This work	78.4	84.7

Table 4: Experimental results for paraphrase identification on MSRP corpus.

granularity and modeled interaction features at each level for a pair of sentences. They obtained their best performance by pretraining the model on a language modeling task (the 3rd row of Table 4). However, their model heavily depends on the pretraining strategy. Without pretraining, they got a much worse performance (the second row of Table 4). He et al. (2015) proposed a similar model to Yin and Schütze (2015). Similarly, they also used a CNN model to extract features at multiple levels of granularity. Differently, they utilized some extra annotated resources, e.g., embeddings from part-of-speech (POS) tags and PARAGRAM vectors trained from the Paraphrase Database (Ganitkevitch et al., 2013). Their model outperformed Yin and Schütze (2015) without the need of pretraining (the sixth row of Table 4). However, the performance was reduced after removing the extra resources (the fourth and fifth rows of Table 4). Yin et al. (2015) applied their attention-based CNN model on this dataset. By adding a couple of sparse features and using a layerwise training strategy, they got a pretty good performance. Comparing to these neural network based models, our model obtained a comparable performance (the last row of Table 4) without using any sparse features, extra annotated resources and specific training strategies. However, the best performance so far on this dataset is obtained by Ji and Eisenstein (2013). In their model, they just utilized several hand-crafted features in a Support Vector Machine (SVM) model. Therefore, the deep learning methods still have a long way to go for this task.

5 Related Work

The semantic matching functions in subsection 3.1 are inspired from the attention-based neural machine translation (Bahdanau et al., 2014; Luong et al., 2015). However, most of the previous work using the attention mechanism in only LSTM models. Whereas our model introduces the attention mechanism into the CNN model. A similar work is the attention-based CNN model proposed by Yin et al. (2015). They first build an attention matrix for a sentence pair, and then directly take the attention matrix as a new channel of the CNN model. Differently, our model uses the attention matrix (or similarity matrix) to decompose the original sentence matrix into a similar component matrix and a dissimilar component matrix, and then feeds these two matrixes into a two-channel CNN model. The model can then focus much on the interactions between similar and dissimilar parts of a sentence pair.

6 Conclusion

In this work, we proposed a model to assess sentence similarity by decomposing and composing lexical semantics. To bridge the lexical gap problem, our model represents each word with its context vector. To extract features from both the similarity and dissimilarity of a sentence pair, we designed several methods to decompose the word vector into a similar component and a dissimilar component. To extract features at multiple levels of granularity, we employed a two-channel CNN model and equipped it with multiple types of ngram filters. Experimental results show that our model is quite effective on both the answer sentence selection task and the paraphrase identification task .

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