Neobility at SemEval-2017 Task 1: An Attention-based Sentence Similarity Model

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Abstract
This paper describes a neural-network model which performed competitively (top 6) at the SemEval 2017 cross-lingual Semantic Textual Similarity (STS) task. Our system employs an attention-based recurrent neural network model that optimizes the sentence similarity. In this paper, we describe our participation in the multilingual STS task which measures similarity across English, Spanish, and Arabic.

1 Introduction
Semantic textual similarity (STS) measures the degree of equivalence between the meanings of two text sequences (Agirre et al., 2016). The similarity of the text pair can be represented as discrete or continuous values ranging from irrelevance (1) to exact semantic equivalence (5). It is widely applicable to many NLP tasks including summarization (Wong et al., 2008; Nenkova et al., 2011), generation and question answering (Vo et al., 2015), paraphrase detection (Fernando and Stevenson, 2008), and machine translation (Corley and Mihalcea, 2005).

In this paper, we describe a system that is able to learn context-sensitive features within the sentences. Further, we encode the sequential information with Recurrent Neural Network (RNN) and perform attention mechanism (Bahdanau et al., 2015) on RNN outputs for both sentences. Attention mechanism was performed to increase sensitivity of the system to words of similarity significance. We also optimize directly on the Pearson correlation score as part of our neural-based approach. Moreover, we include a pair feature adapter module that could be used to include more features to further improve performance. However, for this competition we include merely the TakeLab features (Šarić et al., 2012).

2 Related Works
Most proposed approaches in the past adopted a hybrid of varying text unit sizes ranging from character-based, token-based, to knowledge-based similarity measure (Gomaa and Fahmy, 2013). The linguistic depths of these measures often vary between lexical, syntactic, and semantic levels.

Most solutions include an ensemble of modules that employs features coming from different unit sizes and depths. More recent approaches generally include the word embedding-based similarity (Liebeck et al., 2016; Brychcın and Svoboda, 2016) as a component of the final ensemble. Top performing team in 2016 (Rychalska et al., 2016) uses an ensemble of multiple modules including recursive autoencoders with WordNet and monolingual aligner (Sultan et al., 2016). UMD-TTIC-UW (He et al., 2016) proposes the MPCNN model that requires no feature engineering and managed to perform competitively at 6th place. MPCNN is able to extract the hidden information using the Convolutional Neural Network (CNN) and added an attention layer to extract the vital similarity information.

3 Methods
3.1 Model
Given two sentences \( I_1 = \{w^1_1, w^1_2, ..., w^1_{n_1}\} \) and \( I_2 = \{w^2_1, w^2_2, ..., w^2_{n_2}\} \), where \( w^i_j \) denote the \( j \)th token of the \( i \)th sentence, embedded using a function \( \phi \) that maps each token to a \( D \)-dimension trainable vector. Two sentences are encoded with

\[S_i = \\phi(w^i_1), \phi(w^i_2), ..., \phi(w^i_{n_i})\]

where \( S_i \) is the sentence vector representation.

The similarity score is computed by taking the dot product of the sentence vectors:

\[sim(I_1, I_2) = \frac{S_1 \cdot S_2}{\|S_1\| \cdot \|S_2\|} \]

The attention mechanism is used to weigh the importance of each word in the sentences, allowing the model to focus on the most relevant parts of the text.

Our system and data is available at https://github.com/iamalbert/semval2017task1.
an attentive RNN to obtain sentence embeddings $u^1$, $u^2$, respectively.

**Sentence Encoder** For each sentence, the RNN firstly converts $w^j_i$ into $x^j_i \in R^{2H}$, using an bidirectional Gated Recurrent Unit (GRU) (Cho et al., 2014) by sequentially fed $w^j_i$ into the unit, forward and backward. The superscripts of $w, x, a, u, n$ are omitted for clear notation.

$$x^j_i = [x^F_i; x^B_i]$$

$$x^F_i = \text{GRU}(x^F_{i-1}, w_i)$$

$$x^B_i = \text{GRU}(x^F_{i+1}, w_i)$$

(1)

Then, we attend each word $x_j$ for different salience $a_j$ and blend the memories $x_{1:n}$ into sentence embedding $u$:

$$a_j \propto \exp(v^T \tanh(Wx_i))$$

$$u = \sum_{j=1}^{n} a_j x_j$$

(2)

**Surface Features** Inspired by the simple system described in (Šarić et al., 2012), We also extract surface features from the sentence pair as following:

- **Ngram Overlap Similarity**: These are features drawn from external knowledge like WordNet (Miller, 1995) and Wikipedia. We use both PathLen similarity (Leacock and Chodorow, 1998) and Lin similarity (Lin et al., 1998) to compute similarity between pairs of words $w^1_i$ and $w^2_j$ in $I_1$ and $I_2$, respectively. We employed the suggested pre-processing step (Šarić et al., 2012), and added both WordNet and corpus-based information to ngram overlap scores, which was obtained with the harmonic mean of the degree of overlap between the sentences.

- **Semantic Sentence Similarity**: We also computed token-based alignment overlap and vector space sentence similarity (Šarić et al., 2012). Semantic alignment similarity was computed greedily between all pairs of tokens using both the knowledge-based and corpus-based similarity. Scores are further enhanced with the aligned pair information. We obtained the weighted form of latent semantic analysis vectors (Turney and Pantel, 2010) for each word $w$, before computing the cosine similarity. As such, sentence similarity scores are enhanced with corpus-based information for tokens. The features are concatenated into a vector, denoted as $m$.

**Scoring** Let $S$ be a discrete random variable over $\{0, 1, 2, 3, 4, 5\}$ describing the similarity of the given sentence pair $\{I_1, I_2\}$. The representation of the given pair is the concatenation of $u^1$, $u^2$, and $m$, which is fed into an MLP with one hidden layer to calculate the estimated distribution of $S$.

$$p = \begin{bmatrix}
    P(S = 0) \\
    P(S = 1) \\
    \vdots \\
    P(S = 5)
\end{bmatrix} = \text{softmax}(V \tanh(U \begin{bmatrix}
    u^1 \\
    u^2 \\
    m
\end{bmatrix}))$$

(3)

Therefore, the score $y$ is the expected value of $S$:

$$y = E[S] = \sum_{i=0}^{5} i P(S = i) = v^T p$$

(4)

, where $v = [0, 1, 2, 3, 4, 5]^T$. The entire system is shown in Figure 1.
3.2 Word Embedding

We explored initializing word embeddings randomly or with pre-trained word2vec (Mikolov et al., 2013) of dimension 50, 100, 300, respectively. We found that the system works the best with 300-dimension word2vec embeddings.

3.3 Optimization

Let $p^n$, $y^n$ be the predicted probability density and expected score and $\hat{y}^n$ be the annotated gold score of the $n$-th sample. Most of the previous learning-based models are trained to minimize the following objectives on a batch of $N$ samples:

- Negative Log-likelihood (NLL) of $p$ and $\hat{p}$ (Aker et al., 2016). The task is viewed as a classification problem for 6 classes:

$$L_{\text{NLL}} = \sum_{n=1}^{N} - \log p^n_\hat{n}$$

, where $t^n$ is $\hat{y}^n$ rounded to the nearest integer.

- Mean square error (MSE) between $y^n$ and $\hat{y}^n$ (Brychcin and Svoboda, 2016).

$$L_{\text{MSE}} = \frac{1}{N} \sum_{n=1}^{N} (y^n - \hat{y}^n)^2$$

- Kullback-Leibler divergence (KLD) of $p$ and gold distribution $\hat{p}$ estimated by $\hat{y}^n$:

$$L_{KLD} = \sum_{n=1}^{N} \left( \sum_{i=1}^{6} \hat{p}^n_i \log \frac{\hat{p}^n_i}{p^n_i} \right)$$

where

$$\hat{p}^n_i = \begin{cases} 
\hat{y}^n - \lfloor \hat{y}^n \rfloor , & \text{if } i = \lfloor \hat{y}^n \rfloor + 1 \\
\lfloor \hat{y}^n \rfloor + 1 - \hat{y}^n , & \text{if } i = \lfloor \hat{y}^n \rfloor \\
0 , & \text{otherwise}
\end{cases}$$

(Li and Huang, 2016; Tai et al., 2015). For each $n$, there exists some $k$ such that $\hat{p}^n_k = 1$ and $\forall h \neq k, \hat{p}^n_h = 0$, KLD is identical to NLL.

However, the evaluation metric of this task is Pearson Correlation Coefficient (PCC), which is invariant to changes in location and scale of $y^n$ but none of the above objectives can reflect it. Here we use an example to illustrate that MSE and KLD can even report an inverse tendency. In Table 1, group A has lower MSE and KLD loss than group B, but its PCC is also lower.

To solve this problem, we train the model to maximize PCC directly. Hence, the loss function is given by:

$$L_{\text{PCC}} = - \frac{\sum_{n=1}^{N} (y^n - \hat{y})(\hat{y}^n - \bar{y})}{\sqrt{\sum_{n=1}^{N} (y^n - \bar{y})^2} \sqrt{\sum_{n=1}^{N} (\hat{y}^n - \bar{y})^2}}$$

(5)

where $\bar{y} = \frac{1}{N} \sum_{n=1}^{N} y^n$ and $\hat{y} = \frac{1}{N} \sum_{n=1}^{N} \hat{y}^n$. Since $N$ is fixed for every batch, $L_{\text{PCC}}$ is differentiable with respect to $\hat{y}^n$, which means we can apply back propagation to train the network. To the best of our knowledge, we are the first team to adopt this training objective.

| Group | A | B |
|-------|---|---|
| Gold Score | 3 | 4 | 5 | 3 | 4 | 5 |
| $P(S = 0)$ | 0.05 | 0.05 | 0.05 | 0.15 | 0.05 | 0.1 |
| $P(S = 1)$ | 0.05 | 0.05 | 0.05 | 0.3 | 0.2 | 0.1 |
| $P(S = 2)$ | 0.15 | 0.1 | 0.05 | 0.25 | 0.3 | 0.2 |
| $P(S = 3)$ | 0.5 | 0.35 | 0.0 | 0.1 | 0.25 | 0.3 |
| $P(S = 4)$ | 0.15 | 0.4 | 0.1 | 0.1 | 0.1 | 0.2 |
| $P(S = 5)$ | 0.1 | 0.05 | 0.7 | 0.1 | 0.1 | 0.1 |
| $E[S]$ | 2.95 | 3.15 | 4.2 | 2.0 | 2.45 | 2.7 |

Table 1: Example of lower MSE and KLD not indicating higher PCC.

4 Evaluation

4.1 Data

| Dataset | Pairs |
|---------|-------|
| Training | 22,401 |
| Validation | 5,601 |

Table 2: Training and validation Data sets (STS 2012-2016 and SICK).

We gathered dataset from SICK (Marelli et al., 2014) and past STS across years 2012, 2013, 2014, 2015, and 2016 (Agirre et al., 2012, 2013, 2014, 2015, 2016) for both cross-lingual and monolingual subtasks. We shuffled and splitting them according to the ratio 80:20 into training set and validation set, respectively. Table 2 indicates the size of training set and validation set. All non-English sentence appearing in training, validation, and test set are translated into English with Google Cloud Translation API.
4.2 Experiments

In the experiment, the size of output of GRU is set to be $H = 200$. We use ADAM algorithm to optimize the parameters with mini-batches of 125. The learning rate is set to $10^{-4}$ at the beginning and reduced by half for every 5 epochs. We trained the network for 15 epochs.

**Word embeddings** In Table 3, we demonstrate that the system performs better with pretrained word vectors (WI) than randomly initialized (RI).

|       | PCC on validation set |
|-------|-----------------------|
| RI    |                       |
| 50    | 0.7904                |
| 300   | 0.8091                |
| WI    |                       |
| 50    | 0.7974                |
| 300   | **0.8174**            |

Table 3: System performance with different dimensions of word embeddings, using either randomly initialized or pre-trained word embedding.

**Loss function** We display performances with systems optimized with KLD, MSE, and PCC. It shows that when using $L_{PCC}$ as the training objective, our system not only performs the best but also converges the fastest. As shown in Table 4 and Figure 2.

| Loss function | PCC  |
|---------------|------|
| $L_{KLD}$     | 0.6839 |
| $L_{MSE}$     | 0.7863 |
| $L_{PCC}$     | **0.8174** |

Table 4: Influence of different loss objectives on the system performance measured using PCC on our validation set.

4.3 Final System Results

We tune the model on validation set, and select the set of hyper-parameters that yields the best performance to obtain the scores of test data. We report the official provisional results in Table 5. There is an obvious performance drop in track 4b, which happens to all teams. We hypothesized that the sentences in track 4b (en-es) are collected from a special domain, due to the fact that the number of out-of-vocabulary words in track 4b is many times more than that in other tracks.

| Track | PCC | mean | median | max |
|-------|-----|------|--------|-----|
| Primary | 0.6171 | 0.660 | 0.350 | 28  |
| 1     | 0.6821 | 0.530 | 0      | 3   |
| 2     | 0.6459 | 0.500 | 0      | 3   |
| 3     | 0.7928 | 0.350 | 0      | 4   |
| 4a    | 0.7169 | 0.350 | 0      | 4   |
| 4b    | 0.0200 | 2.540 | 2      | 28  |
| 5     | 0.7927 | 0.360 | 0      | 4   |
| 6     | 0.6696 | 0.330 | 0      | 5   |

Table 5: Final system results and statistics of the number of OOV words within a pair.

5 Conclusion and Future Work

In conclusion, we propose a simple neural-based system with a novel means of optimization. We found that optimizing directly on PCC achieved the best scores, allowing the model to perform competitively on STS-2017. Moreover, we demonstrated that using randomly initialized word embedding does not harm the performance, but allowing it to achieve slightly higher scores against the pre-trained word embedding.

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