Abstract

The results obtained by the BUAP team at Task 1 of SemEval 2014 are presented in this paper. The run submitted is a supervised version based on two classification models: 1) We used logistic regression for determining the semantic relatedness between a pair of sentences, and 2) We employed support vector machines for identifying textual entailment degree between the two sentences. The behaviour for the second subtask (textual entailment) obtained much better performance than the one evaluated at the first subtask (relatedness), ranking our approach in the 7th position of 18 teams that participated at the competition.

1 Introduction

The Compositional Distributional Semantic Models (CDSM) applied to sentences aim to approximate the meaning of those sentences with vectors summarizing their patterns of co-occurrence in corpora. In the Task 1 of SemEval 2014, the organizers aimed to evaluate the performance of this kind of models through the following two tasks: semantic relatedness and textual entailment. Semantic relatedness captures the degree of semantic similarity, in this case, between a pair of sentences, whereas textual entailment allows to determine the entailment relation holding between two sentences.

2 Description of the Distributional Semantic Model Used

Given a sentence $S = w_1 w_2 \cdots w_{|S|}$, with $w_i$ a sentence word, we have calculated different correlated terms $(t_{i,j})$ or a numeric vector $(V_i)$ for each word $w_i$ as follows:

1. $\{t_{i,j} | relation(t_{i,j}, w_i)\}$ such as “relation” is one the following dependency relations: “object”, “subject” or “property”.
2. $\{t_{i,j} | t_{i,j} = c_k \cdots c_{k+n} \}$ with $n = 2, \ldots, 5$, and $c_k \in w_i$; these tokens are also known as $n$-grams of length $n$.
3. $\{t_{i,j} | t_{i,j} = c_k \cdots c_{k+(n-1)r} \}$ with $n = \cdots$
2, · · · , 5, \( r = 2, \cdots, 5 \), and \( c_k \in w_i \); these tokens are also known as skip-grams of length \( n \).

4. \( V_i \) is obtained by applying the Latent Semantic Analysis (LSA) algorithm implemented in the R software environment for statistical computing and graphics. \( V_i \) is basically a vector of values that represent relation of the word \( w_i \) with it context, calculated by using a corpus constructed by us, by integrating information from Europarl, Project-Gutenberg and Open Office Thesaurus.

3 A Classification Model for Semantic Relatedness and Textual Entailment based on DSM

Once each sentence has been represented by means of a vectorial representation of patterns, we constructed a single vector, \( \vec{v} \), for each pair of sentences with the aim of capturing the semantic relatedness on the basis of a training corpus.

The entries of this representation vector are calculated by obtaining the semantic similarity between each pair of sentences, using each of the DSM shown in the previous section. In order to calculate each entry, we have found the maximum similarity between each word of the first sentence with respect to the second sentence and, thereafter, we have added all these values, thus, \( \vec{v} = \{f_1, \cdots, f_9\} \).

Given a pair of sentences \( S_1 = w_{1,1}w_{2,1} \cdots w_{|S_1|,1} \) and \( S_2 = w_{1,2}w_{2,2} \cdots w_{|S_2|,2} \), such as each \( w_{i,k} \) is represented according to the correlated terms or numeric vectors established at Section 2, the entry \( f_i \) of \( \vec{v} \) is calculated as: \( f_i = \max_{j=1, \ldots, |S_2|} \{\text{sim}(w_{i,1}, w_{j,2})\} \), with \( j = 1, \ldots, |S_2| \).

The specific similarity measure (\( \text{sim()} \)) and the correlated term or numeric vector used for each \( f_i \) is described as follows:

1. \( f_1 : w_{i,k} \) is the “object” of \( w_i \) (as defined in 2), and \( \text{sim()} \) is the maximum similarity obtained by using the following six WordNet similarity metrics offered by NLTK: Leacock & Chodorow (Leacock and Chodorow, 1998), Lesk (Lesk, 1986), Wu & Palmer (Wu and Palmer, 1994), Resnik (Resnik, 1995), Lin (Lin, 1998), and Jiang & Conrath\(^1\) (Jiang and Conrath, 1997).

2. \( f_2 : w_{i,k} \) is the “subject” of \( w_i \), and \( \text{sim()} \) is the maximum similarity obtained by using the same six WordNet similarity metrics.

3. \( f_3 : w_{i,k} \) is the “property” of \( w_i \), and \( \text{sim()} \) is the maximum similarity obtained by using the same six WordNet similarity metrics.

4. \( f_4 \) is numeric vector containing \( w_i \), and \( \text{sim()} \) is the cosine similarity measure.

5. \( f_5 : w_{i,k} \) is an skip-gram containing \( w_i \), and \( \text{sim()} \) is the cosine similarity measure.

6. \( f_6 : w_{i,k} \) is numeric vector obtained with LSA, and \( \text{sim()} \) is the Rada Mihalcea semantic similarity measure (Mihalcea et al., 2006).

7. \( f_7 : w_{i,k} \) is numeric vector obtained with LSA, and \( \text{sim()} \) is the cosine similarity measure.

8. \( f_8 : w_{i,k} \) is numeric vector obtained with LSA, and \( \text{sim()} \) is the euclidean distance.

9. \( f_9 : w_{i,k} \) is numeric vector obtained with LSA, and \( \text{sim()} \) is the Chebyshev distance.

All these 9 features were introduced to a logistic regression classifier in order to obtain a classification model which allows us to determine the value of relatedness between a new pair of sentences\(^2\). Here, we use as supervised class, the value of relatedness given to each pair of sentences on the training corpus.

The obtained results for the relatedness subtask are given in Table 1. In columns 2, 3 and 5, a large value signals a more efficient system, but a large MSE (column 4) means a less efficient system. As can be seen, our run obtained the rank 12 of 17, with values slightly below the overall average.

3.1 Textual Entailment

In order to calculate the textual entailment judgment, we have enriched the vectorial representation previously mentioned with synonyms, antonyms and cue-
### Table 1: Results obtained at the substask “Relatedness” of the Semeval 2014 Task 1

| TEAM ID | PEARSON | SPEARMAN | MSE   | Rank |
|---------|---------|----------|-------|------|
| ECNU_run1 | 0.82795 | 0.76892 | 0.32504 | 1    |
| StanfordNLP_run5 | 0.82723 | 0.75594 | 0.32300 | 2    |
| The_Meaning_Factory_run1 | 0.82680 | 0.77219 | 0.32237 | 3    |
| UNAL-NLP_run1 | 0.80432 | 0.74582 | 0.35933 | 4    |
| Illinois-LH_run1 | 0.79925 | 0.75378 | 0.36915 | 5    |
| CECL_ALL_run1 | 0.78044 | 0.73166 | 0.39819 | 6    |
| SemantiKLUE_run1 | 0.78019 | 0.73598 | 0.40347 | 7    |
| CNGL_run1 | 0.76391 | 0.68769 | 0.42906 | 8    |
| UTexas_run1 | 0.71455 | 0.67444 | 0.49900 | 9    |
| UoW_run1 | 0.71116 | 0.67870 | 0.51137 | 10   |
| FBK-TR_run3 | 0.70892 | 0.64430 | 0.59135 | 11   |
| **BUAP_run1** | **0.69698** | **0.64524** | **0.52774** | **12** |
| UANLPcourse_run2 | 0.69327 | 0.60269 | 0.54225 | 13   |
| UQeResearch_run1 | 0.64185 | 0.62565 | 0.82252 | 14   |
| ASAP_run1 | 0.62780 | 0.59709 | 0.66208 | 15   |
| Yamraj_run1 | 0.53471 | 0.53561 | 2.66520 | 16   |
| asjai_run5 | 0.47952 | 0.46128 | 1.10372 | 17   |
| overall average | 0.71876 | 0.67159 | 0.63852 | 8-9  |

Our difference against the overall average: -2% / -3% / 11% / -

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words (“no”, “not”, “nobody” and “none”) for detecting negation at the sentences. Thus, if some of these new features exist on the training pair of sentences, we add a boolean value of 1, otherwise we set the feature to zero.

This new set of vectors is introduced to a support vector machine classifier, using as class the textual entailment judgment given on the training corpus.

The obtained results for the textual entailment subtask are given in Table 2. Our run obtained the rank 7 of 18, with values above the overall average. We consider that this improvement over the relatedness task was a result of using other features that are quite important for semantic relatedness, such as lexical relations (synonyms and antonyms), and the consideration of the negation phenomenon in the sentences.

### 4 Conclusions

This paper describes the use of compositional distributional semantic models for solving the problems of semantic relatedness and textual entailment. We proposed different features and measures for that purpose. The obtained results show a competitive approach that may be further improved by considering more lexical relations or other type of semantic similarity measures.

In general, we obtained the 7th place in the official ranking list from a total of 18 teams that participated in the textual entailment subtask. The result at the semantic relatedness subtask could be improved if we were considered to add the new features taken into consideration at the textual entailment subtask, an idea that we will implement in the future.

### References

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Table 2: Results obtained at the substask “Textual Entailment” of the Semeval 2014 Task 1

| TEAM ID         | ACCURACY | Rank |
|-----------------|----------|------|
| Illinois-LH_run1 | 84.575   | 1    |
| ECNU_run1       | 83.641   | 2    |
| UNAL-NLP_run1   | 83.053   | 3    |
| SemantiKLUE_run1| 82.322   | 4    |
| The_Meaning_Factory_run1 | 81.591 | 5 |
| CECL_ALL_run1   | 79.988   | 6    |
| BUAP_run1       | 79.663   | 7    |
| UoW_run1        | 78.526   | 8    |
| CDT_run1        | 77.106   | 9    |
| UIO-Lien_run1   | 77.004   | 10   |
| FBK-TR_run3     | 75.401   | 11   |
| StanfordNLP_run5 | 74.488 | 12 |
| UTexas_run1     | 73.229   | 13   |
| Yamraj_run1     | 70.753   | 14   |
| asjai_run5      | 69.758   | 15   |
| haLF_run2       | 69.413   | 16   |
| CNGL_run1       | 67.201   | 17   |
| UANLPCourse_run2 | 48.731 | 18 |
| Overall average | 75.358   | 11–12|
| Our difference against the overall average | 4.31% |      |

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