UoW: NLP Techniques Developed at the University of Wolverhampton for Semantic Similarity and Textual Entailment

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Abstract

This paper presents the system submitted by University of Wolverhampton for SemEval-2014 task 1. We proposed a machine learning approach which is based on features extracted using Typed Dependencies, Paraphrasing, Machine Translation evaluation metrics, Quality Estimation metrics and Corpus Pattern Analysis. Our system performed satisfactorily and obtained 0.711 Pearson correlation for the semantic relatedness task and 78.52% accuracy for the textual entailment task.

1 Introduction

The SemEval task 1 (Marelli et al., 2014a) involves two subtasks: predicting the degree of relatedness between two sentences and detecting the entailment relation holding between them. The task uses SICK dataset (Marelli et al., 2014b), consisting of 10000 pairs, each annotated with relatedness in meaning and entailment relationship holding between them. Similarity measures between sentences are required in a wide variety of NLP applications. In applications like Information Retrieval (IR), measuring similarity is a vital step in order to determine the best result for a related query. Other applications such as Paraphrasing and Translation Memory (TM) rely on similarity measures to weight results. However, computing semantic similarity between sentences is a complex and difficult task, due to the fact that the same meaning can be expressed in a variety of ways. For this reason it is necessary to have more than a surface-form comparison.

We present a method based on machine learning which exploits available NLP technology. Our approach relies on features inspired by deep semantics (such as parsing and paraphrasing), machine translation quality estimation, machine translation evaluation and Corpus Pattern Analysis (CPA). We use the same features to measure both semantic relatedness and textual entailment. Our hypothesis is that each feature covers a particular aspect of implicit similarity and entailment information contained within the pair of sentences. Training is performed in a regression framework for semantic relatedness and in a classification framework for textual entailment.

The remainder of the paper is structured as follows. In Section 2, we review the work related to our study and the existing NLP technologies used to measure sentence similarity. In Sections 3 and 4, we describe our approach and the similarity measures we used. In Section 5, we present the results and an analysis of our runs based on the test and training data provided by the SemEval-2014 task. Finally, our work is summed up in Section 6 with perspectives for future work we would like to explore.

2 Related Work

The areas of semantic relatedness and entailment have received extensive interest from the research community in the last decade. Earlier work in relatedness (Banerjee and Pedersen, 2003; Li et al., 2006) exploited WordNet in various ways to extract the semantic relatedness. Banerjee and Pedersen (2003) presented a measure using extended gloss overlap. This measure takes two WordNet synsets as input and uses the overlap of their WordNet glosses to compute their degree of semantic relatedness. Li et al. (2006) presented a semantic similarity metric based on the semantic similarity of words in a sentence. Recently, Wang and Cer (2012) presented an ap-
approach that uses probabilistic edit-distance to measure semantic similarity. The approach uses probabilistic finite state and pushdown automata to model weighted edit-distance where state transitions correspond to edit-operations. In some aspects, our work is similar to Bäär et al. (2012), who presented an approach which combines various text similarity measures using a log-linear regression model.

Entailment has been modelled using various approaches. The main approaches are based on logic inferencing (Moldovan et al., 2003), machine learning (Hickl et al., 2006; Castillo, 2010) and tree edit-distance (Kouylekov and Magnini, 2005). Most of the recent approaches employ various syntactic or tree edit models (Heilman and Smith, 2010; Mai et al., 2011; Rios and Gelbukh, 2012; Alabbas and Ramsay, 2013). Recently, Alabbas and Ramsay (2013) presented a modified tree edit distance approach, which extends tree edit distance to the level of subtrees. The approach extends Zhang-Shasha’s algorithm (Zhang and Shasha, 1989).

3 Features

Our system uses the same 31 features for both sub-tasks. This section explains them and the code which implements most of them can be found on GitHub².

3.1 Language Technology Features

We used existing language processing tools to extract features. Stanford CoreNLP³ toolkit provides lemma, parts of speech (POS), named entities, dependencies relations of words in each sentence.

We calculated Jaccard similarity on surface form, lemma, dependencies relations, POS and named entities to get the feature values. The Jaccard similarity computes sentence similarity by dividing the overlap of words on the total number of words of both sentences.

\[
\text{Sim}(s_1, s_2) = \frac{|s_1 \cap s_2|}{|s_1 \cup s_2|} \tag{1}
\]

where in equation (1), \(\text{Sim}(s_1, s_2)\) is the Jaccard similarity between sets of words \(s_1\) and \(s_2\).

We used the same toolkit to identify coreference relations and determine clusters of coreferential entities. The coreference feature value was calculated using clusters of coreferential entities. The intuition is that sentences containing coreferential entities should have some semantic relatedness. In order to extract clusters of coreferential entities, the pair of sentences was treated as a document. The coreference feature value using these clusters was calculated as follows:

\[
\text{Value}_{\text{coref}} = \frac{CC}{TC} \tag{2}
\]

where \(CC\) is the number of clusters formed by the participation of entities (at least one entity from each sentence of the pair) in both sentences and \(TC\) is the total number of clusters.

We calculated two separate feature values for dependency relations: the first feature concatenated the words involved in a dependency relation and the second used grammatical relation tags. For example, for the sentence pair “the kids are playing outdoors” and “the students are playing outdoors” the Jaccard similarity is calculated based on concatenated words “kids::the, playing::kids, playing::are, ROOT::playing, playing::outdoors” and “students::the, playing::students, playing::are, ROOT::playing, playing::outdoors” to get the value for the first feature and “det, nsubj, aux, root, dobj” and “det, nsubj, aux, root, dobj” to get the value for the second feature.

These language technology features try to capture the token based similarity and grammatical similarity between a pair of sentences.

3.2 Paraphrasing Features

We used the PPDB paraphrase database (Ganitkevitch et al., 2013) to get the paraphrases. We used lexical and phrasal paraphrases of “L” size. For each sentence of the pair, we created two sets of bags of n-grams \(1 \leq n \leq \text{length of the sentence}). We extended each set with paraphrases for each n-gram available from paraphrase database. We then calculated the Jaccard similarity (see Section 3.1) between these extended bag of n-grams to get the feature value. This feature capture the cases where one sentence is a paraphrase of the other.

3.3 Negation Feature

Our system does not attempt to model similarity with negation, but since negation is an important feature for contradiction in textual entailment, we designed a non-similarity feature. The system checks for the presence of a negation word such as ‘no’, ‘never’ and ‘not’ in the pair of sentences and

²https://github.com/rohitguptacs/wlvsimilarity
³http://nlp.stanford.edu/software/corenlp.shtml
returns “1” (“0” otherwise) if both or none of the sentences contain any of these words.

3.4 Machine Translation Quality Estimation Features

Seventeen of the features consist of Machine Translation Quality Estimation (QE) features, based on the work of (Specia et al., 2009) and used as a baseline in recent QE tasks (such as (Callison-Burch et al., 2012)). We extracted these features by treating the first set of sentences as the Machine Translation (MT) “source”, and the second set of sentences as the MT “target”. In Machine Translation, these features are used to access the quality of MT “target”. The QE features include shallow surface features such as the number of punctuation marks, the average length of words, the number of words. Furthermore, these features include n-gram frequencies and language model probabilities. A full list of the QE features is provided in the documentation of the QE system \(^4\) (Specia et al., 2009).

QE features relate to well-formedness and syntax, and are not usually used to compute semantic relatedness between sentences. We have used them in the hope that the surface features at least will show us some structural similarity between sentences.

3.5 Machine Translation Evaluation Features

Additionally, we used BLEU (Papineni et al., 2002), a very popular machine translation evaluation metric, as a feature. BLEU is based on n-gram counts. It is meant to capture the similarity between translated text and references for machine translation evaluation. The BLEU score over surface, lemma and POS was calculated to get three feature values. In a pair of sentences, one side was treated as a translation and another as a reference. We applied it at the sentence level to capture the similarity between two sentences.

3.6 Corpus Pattern Analysis Features

Corpus Pattern Analysis (CPA) (Hanks, 2013) is a procedure in corpus linguistics that associates word meaning with word use by means of semantic patterns. CPA is a new technique for mapping meaning onto words in text. It is currently being used to build a “Pattern Dictionary of English Verbs” (PDEV\(^5\)). It is based on the Theory of Norms and Exploitations (Hanks, 2013).

There are two features extracted from PDEV. They both make use of a derived resource called the CPA network (Bradbury and El Maarouf, 2013). The CPA network links verbs according to similar semantic patterns (e.g. both ‘pour’ and ‘trickle’ share an intransitive use where the subject is “liquid”).

The first feature value compares the main verbs in both sentences. When both verbs share a pattern, the system returns a value of “1” (otherwise “0”). The second feature extends the CPA network to compute the probability of a PDEV pattern, given a word. This probability is computed over the portion of the British National Corpus which is manually tagged with PDEV patterns. The probability of a pattern given each word of a sentence of the dataset is obtained by the product of those probabilities. The feature value is the (normalised) number of common patterns from the three most probable patterns in each sentence. These features try to capture similarity based on semantic patterns.

4 Predicting Through Machine Learning

4.1 Model Description

We used a support vector machine in order to build a regression model to predict semantic relatedness and a classification model to predict textual entailment. For the actual implementation we used LibSVM\(^6\) (Chang and Lin, 2011).

We used a regression model for the relatedness task that estimates a continuous score between 1 and 5 for each sentence. For the entailment task, we trained a classification model which assigns one of three different labels (ENTAILMENT, CONTRADICTION, NEUTRAL) to each sentence pair. We trained both systems on the 4500 sentence training set, augmented with the 500 sentence trial data. The values of C and \(\gamma\) have been optimised through a grid-search which uses a 5-fold cross-validation method.

The RBF kernel proved to be the best for both tasks.

5 Results and Analysis

We submitted 4 runs of our system (Run-1 to Run-4). Run-1 was submitted as primary run. Run-2, Run-3 and Run-4 systems were identical except

\(^4\)https://github.com/lspecia/quest
\(^5\)http://pdev.org.uk
\(^6\)http://www.csie.ntu.edu.tw/ cjlin/libsvm/
for some parameter differences for SVM training and the replacement of the values which were outside the boundaries (1-5). If relatedness values predicted by the system were less than 1 or greater than 5, these values were replaced by 1 and 5 respectively for Run-1, Run-2 and Run-4 and 1.5 and 4.5 respectively for Run-3. Our primary run also used one extra feature for relatedness, which was obtained by considering entailment judgement as a feature. Our hypothesis was that entailment judgement may help in measuring relatedness. In the actual test this feature was not helpful and we obtained Pearson correlation of 0.711 for the primary run, compared to 0.716 for Run-2. The details of runs are given in Table 1 and 2.

After training both models, we ran a feature selection algorithm to determine which features yielded the highest accuracy, and therefore had the highest impact on our system. Perhaps unsurprisingly, the QE features were not very useful in predicting semantic similarity or entailment. However, despite their focus on fluency rather than semantic correctness, the QE features still managed to contribute to some improvements in the textual entailment task (increasing accuracy by 1%), and the semantic relatedness task (0.027 increase in Pearson correlation).

In the entailment (classification) task, the strongest feature proved to be the negation feature with 70% accuracy (on the training set) when training on this feature only. This suggests that some measure of negation is crucial in determining whether a sentence contradicts or entails another sentence. Other strong features were lemma, paraphrasing and dependencies.

In the relatedness (regression) task, the lemma, surface, paraphrasing, dependencies, PDEV features were the strongest contributors to accuracy.

### Table 1: Results: Relatedness.

|       | Run-1 | Run-2 | Run-3 | Run-4 |
|-------|-------|-------|-------|-------|
| $C$   | 8     | 8     | 2     | 2     |
| $\gamma$ | 0.0441 | 0.0441 | 0.125 | 0.125 |
| Pearson | 0.7111 | 0.7166 | 0.6968 | 0.6975 |

### Table 2: Results: Entailment.

|       | Run-1 | Run-2 | Run-3 | Run-4 |
|-------|-------|-------|-------|-------|
| $C$   | 16    | 16    | 8     | 8     |
| $\gamma$ | 0.0625 | 0.0625 | 0.5   | 0.5   |
| Accuracy | 78.526 | 78.526 | 78.343 | 78.343 |

6 Conclusion and Future Work

We have presented an efficient approach to calculate semantic relatedness and textual entailment. One noticeable point of our approach is that we have used the same features for both tasks and our system performed well in each of these tasks. Therefore, our system captures reasonably good models to compute semantic relatedness and textual entailment.

In the future we would like to explore more features and particularly those based on tree edit distance, WordNet and PDEV. Our intuition suggests that tree edit distance seems to be more helpful for entailment, whereas WordNet and PDEV seem to be more helpful for similarity measurement. Additionally, we would like to combine our techniques for measuring relatedness and entailment with MT evaluation techniques. We would further like to apply these techniques cross-lingually, moving into other areas like machine translation evaluation and quality estimation.

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