Abstract

This paper describes the Georgia Tech team’s approach to the CoNLL-2016 supplementary evaluation on discourse relation sense classification. We use long short-term memories (LSTM) to induce distributed representations of each argument, and then combine these representations with surface features in a neural network. The architecture of the neural network is determined by Bayesian hyperparameter search.

1 Introduction

Our approach to discourse relation classification is to combine strong surface features with a distributed representation of each discourse unit. This follows prior work demonstrating that distributed representations can improve generalization for this task (Ji and Eisenstein, 2014; Ji and Eisenstein, 2015; Braud and Denis, 2015). We combine these two disparate representations in a neural network architecture. Our approach is shaped by two main design decisions: the use of long short-term memory recurrent networks (Hochreiter and Schmidhuber, 1997) to induce representations of each discourse unit, and the use of Bayesian optimization (Snoek et al., 2012) for tuning the neural network architecture.

2 System Overview

The overall architecture is shown in Figure 1. The same architecture is used for both explicit and non-explicit relations, but with different parameters. The output of the classifier is a softmax layer, which takes as input a series of dense layers. These dense layers allow nonlinear interactions between surface features and elements of the distributed representations. Dropout is employed to reduce overfitting (Srivastava et al., 2014). The overall architecture is trained to minimize cross-entropy. The implementation is in Keras (Chollet, 2015), and training takes several hours on a standard CPU. We now describe of the subcomponents of the classifier in detail.

2.1 Distributed representations for discourse units

First, we induce representations for each unit in each discourse relation. This component of the model is shown in the dotted part of Figure 1 for the first discourse argument. Prior work has explored a variety of ways for inducing representations of discourse units, including average pooling (Ji and Eisenstein, 2014; Braud and Denis, 2015) and recursive neural networks on syntactic parse trees (Li et al., 2014; Ji and Eisenstein, 2015). We take a recurrent neural network approach, characterizing
each discourse unit by a recurrently-updated state vector (Li et al., 2015), with the input consisting of pre-trained word embeddings GoogleNews-vectors-negative300.bin from the word2vec page.\footnote{https://code.google.com/archive/p/word2vec/}

Specifically, our recurrent architecture is a long short-term memory (LSTM), which uses a combination of gates to better handle long-term dependencies, as compared with the more straightforward recurrent neural network (Hochreiter and Schmidhuber, 1997). Following Graves and Schmidhuber (2005), we employ a bidirectional LSTM, in which each training sequence is presented forwards and backwards to two separate recurrent nets, both of which are connected to the same output layer. We combine the output of these bidirectional LSTMs in a multilayer perceptron with the extracted surface features.

2.2 Surface features

In addition to the distributed representations of the discourse units, we use some of the most successful surface features from prior work. These features are implemented using the Natural Language Toolkit (Bird et al., 2009) and scikit-learn (Pedregosa et al., 2011). In general, these features were inspired by the system from Wang and Lan (2015), which obtained best performance on the PDTB test set in the 2015 shared task (Xue et al., 2015).

2.2.1 Features for explicit relations

Connective Text The connective itself is a strong feature for sense classification of explicit discourse relations (Pitler et al., 2008). This feature alone yields F1 of 0.8862 for our classifier.

Sentiment Value The Vader Sentiment analysis package (Hutto and Gilbert, 2014) was used to calculate sentiment score for both arguments. The feature then reports whether the two arguments have the same sentiment.

Trigrams We used trigram features for the final three words of arg1, and for the first three words of arg2.

2.2.2 Features for non-explicit relations

We used the same trigrams features from the explicit relation classifier, as well as the following additional features on pairs of linguistic elements in arg1 and arg2.

Word Pairs We formed word pairs from the cross product of all words appearing in arg1 and arg2, following much of the prior work in discourse parsing (Marcu and Echihabi, 2003; Pitler et al., 2009). We then replaced the words in each pair with a cluster identity (Rutherford and Xue, 2014). Specifically, we used the GoogleNews-vectors-negative skipgram word embeddings to form 1000 clusters.

Part-of-Speech Pairs Similarly, we formed part-of-speech pairs from the tags appearing in the two arguments (Rutherford and Xue, 2014).

Production Rules Pairs Using the syntactic analysis of each argument, we form pairs of production rules appearing in the two arguments (Lin et al., 2009).

Adverb Pairs Adverbs are particularly relevant for non-explicit discourse relations, so we compute features from pairs of adverbs appearing the two arguments.

2.3 Hyperparameter tuning

The best set of hyperparameters for the classifiers were found using spearmint (Snoek et al.,

| Hyperparameter        | Range   | Best  |
|-----------------------|---------|-------|
| **Number of hidden nodes** |         |       |
| lstm1                 | 64-320  | 259   |
| lstm2                 | 64-100  | 75    |
| lstm3                 | 64-320  | 263   |
| lstm4                 | 64-320  | 127   |
| lstm5                 | 64-100  | 89    |
| lstm6                 | 64-320  | 150   |
| dense1                | 64-320  | 269   |
| dense2                | 64-100  | 69    |
| **Percentage of dropout** |         |       |
| dropout1              | 0-0.9   | 0.11  |
| dropout2              | 0-0.9   | 0.57  |
| **Learning Rate**     |         |       |
| SGD                   | 0.001-0.5 | 0.1549 |

Table 1: Hyperparameters selected by Spearmint from the provided ranges, for non-explicit discourse relations
Figure 2: Progress of Bayesian optimization over hyperparameter space

| Feature Type      | $F1$ |
|-------------------|------|
| Distributed       | 0.3485 |
| + Argument 2 first 3 | 0.3872 |
| + Argument 1 last 3 | 0.3044 |
| + Word Pairs      | 0.3672 |
| + Parts of Speech | 0.3672 |
| + Adverbs         | 0.3979 |
| + Inquirer        | 0.3979 |
| + Production Rule | 0.4072 |

Table 2: Evaluation as the features are added incrementally to the purely distributed model.

Evaluation was performed using the evaluation script provided by the conll16 task organizers. In Table 3, the performance of our system is compared to the best-performing systems from this year’s shared task. Our system was particularly competitive on the blind test set. (The best performance on non-explicit relations on the blind test set was from ttr, but this system did not attempt to classify explicit relations, and so did not obtain an overall score for all relations.) This suggests that our approach suffered less from overfitting to the dev data. On the other hand, our system’s performance on explicit relations was further behind the best systems, suggesting the need for additional features to handle this case.

Results are broken down by individual relation types in Table 4, again using the shared task evaluation script. In addition, the contribution of each feature is indicated in Table 2, in which features are incrementally added to a baseline model containing only the distributed representations of each argument.

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Table 3: Discourse sense classification results, measured by F1, in comparison with the most competitive systems from the shared task.

| System          | Dev All | Explicit | Non-expl. | Test All | Explicit | Non-expl. | Blind All | Explicit | Non-expl. |
|-----------------|---------|----------|-----------|----------|----------|-----------|-----------|----------|-----------|
| tbmihaylov      | 0.641   | 0.912    | 0.403     | 0.633    | 0.898    | 0.392     | 0.546     | 0.782    | 0.345     |
| ecnuc           | 0.680   | 0.926    | 0.464     | 0.643    | 0.901    | 0.409     | 0.541     | 0.774    | 0.342     |
| gtnlp (this paper) | 0.639   | 0.903    | 0.407     | 0.609    | 0.895    | 0.350     | 0.543     | 0.750    | 0.368     |

Table 4: Dev set evaluation for explicit and non-explicit (Implicit, EntRel, AltLex) discourse relations

|                    | Explicit |          |          |          |          |          |          |          |          |
|--------------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|                    | Micro-Average |        |          |          |          |          |          |          |          |
|                    | precision | recall   | F1       | precision | recall   | F1       | precision | recall   | F1       |
| Comparison.Concession | 0.9029  | 0.9029   | 0.9029   | 0.4072   | 0.4072   | 0.4072   |          |          |          |
| Comparison.Contrast   | 1.0000   | 0.0833   | 0.1538   | 1.0000   | 0.0000   | 0.0000   |          |          |          |
| Contingency.Cause.Reason | 0.9387  | 0.9563   | 0.9474   | 0.2391   | 0.2619   | 0.2500   |          |          |          |
| Contingency.Cause.Result | 0.8235  | 0.6829   | 0.7467   | 0.3714   | 0.1688   | 0.2321   |          |          |          |
| Contingency.Condition | 1.0000   | 0.8421   | 0.9143   | 0.3714   | 0.1688   | 0.2321   |          |          |          |
| EntRel              | 0.9778  | 0.9362   | 0.9565   | -        | -        | -        |          |          |          |
| Expansion.Alternative | 0.8571  | 1.0000   | 0.9231   | -        | -        | -        |          |          |          |
| Expansion.Alternative.Chosen alternative | 1.0000   | 0.8333   | 0.9091   | 1.0000   | 0.0000   | 0.0000   |          |          |          |
| Expansion.Conjunction  | 0.9286  | 0.9891   | 0.9579   | 0.3298   | 0.5122   | 0.4013   |          |          |          |
| Expansion.Instantiation | 1.0000   | 1.0000   | 1.0000   | 0.4783   | 0.2292   | 0.3099   |          |          |          |
| Expansion.Restatement  | 0.3750  | 0.2621   | 0.3086   | 0.3750   | 0.2621   | 0.3086   |          |          |          |
| Temporal.Asynchronous.Precedence | 0.9608   | 1.0000   | 0.9800   | 0.2857   | 0.0800   | 0.1250   |          |          |          |
| Temporal.Asynchronous.Succession  | 1.0000   | 0.6667   | 0.8000   | 1.0000   | 0.0000   | 0.0000   |          |          |          |
| Temporal.Synchrony     | 0.6842  | 0.9420   | 0.7927   | 1.0000   | 0.0000   | 0.0000   |          |          |          |

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