Improving a Pipeline Architecture for Shallow Discourse Parsing

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Abstract

We present a system that implements an end-to-end discourse parser. The system uses a pipeline architecture with seven stages: preprocessing, recognizing explicit connectives, identifying argument positions, identifying and labeling arguments, classifying explicit and implicit connectives, and identifying attribution structures. The discourse structure of a document is inferred based on these components. For NLP analysis, we use Illinois NLP software\(^1\) and the Stanford Parser. We use lexical and semantic features based on function words, sentiment lexicons, brown clusters, and polarity features. Our system achieves an F1 score of 0.2492 in overall performance on the development set and 0.1798 on the blind test set.

1 Introduction

The Illinois discourse parsing system builds on existing approaches, using a series of classifiers to identify different elements of discourse structures such as argument boundaries and types along with discourse connectives and senses. In developing the components of this pipeline, we investigated different kinds of features to try to improve abstraction while retaining sufficient expressivity. To that end, we investigated a combination of parse and lexical (function word) features; brown clusters; and relations between verb-argument structures in consecutive sentences.

2 System Description

In this section, we describe the system we developed, and introduce the features we used in each component. For our starting point, we implemented a pipeline architecture based on the description in Lin et al. (2014), then investigated features and inference approaches to improve the system. The pipeline includes seven components. After a preprocessing step, the system identifies explicit connectives, determines the positions of the arguments relative to the connective, identifies and labels arguments, classifies explicit and implicit connectives, and identifies attribution structures. The system architecture is presented in Figure 1. All the classifiers are built based on LibLinear (Fan et al., 2008) via the interface of Learning Based Java (LBJava) (Rizzolo and Roth, 2010).

2.1 Preprocessing

The preprocessing stage identifies tokens, sentences, part-of-speech (Roth and Zelenko, 1998), shallow parse chunks (Punyakanok and Roth, 2001), lemmas\(^2\), syntactic constituency parse (Klein and Manning, 2003), and dependency parse (de Marneffe et al., 2006). This stage also generates a mapping from our own token indexes to those provided in the gold standard data, to allow evaluation with the official shared task scoring code.

2.2 Recognizing Explicit Connectives

To recognize explicit connectives, we construct a list of existing connectives labeled in the Penn Discourse Treebank (Prasad et al., 2008a). Since not all the words of the connective list are necessarily true connectives when they appear in text, we build a binary classifier to determine when a word matching an entry in the list represents an actual connective. We only focus on the connectives with consecutive tokens and ignore the non-consecutive connectives. We generate lexico-syntactic and path features associated with the

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\(^1\)http://cogcomp.cs.illinois.edu/page/software

\(^2\)http://cogcomp.cs.illinois.edu/page/software_view/illinois-lemmatizer
connectives following Lin et al. (2014).

2.3 Identifying Arguments and Argument Positions

For each explicit connective, we first identify the relevant argument positions – whether Arg1 is in the previous sentence relative to the connective or in the same sentence. We build a classifier incorporating the contextual lexico-syntactic features. We then detect the spans of Arg1 and Arg2 based on these two decisions. The features used are similar to those of Lin et al. (2014).

To generate candidate arguments, we enumerate all subtrees in the parse tree of each sentence. We then classify the subtrees to be Arg1, Arg2, or None. In addition to the features used by Lin et al. (2014), we also add function words to the path features. If we detect a word which is in the lexicon of function words, we replace the corresponding tag used in the path with the word’s surface string.

2.4 Classifying Explicit Connectives

To classify explicit connectives, we build a multi-class classifier to identify the senses. In addition to the features used by Lin et al. (2014), we also incorporate Brown cluster (Brown et al., 1992) features generated by Liang (2005). The Brown clustering algorithm produces a binary tree, where each word can be uniquely identified by its path from the root, and this path can be compactly represented with a bit string. Different lengths of the prefix of this root-to-leaf path provide different levels of word abstraction. In this implementation, we set the length of the prefix to 6.

2.5 Classifying Implicit Connectives

We classify the sense of implicit connectives based on four sets of features. We follow Lin et al. (2014) to generate the product rules of both constituent parse and dependency parse features, and to generate the word pair features to enumerate all the word pairs in each pair of sentences. In addition, similar to Rutherford and Xue (2014), we incorporate Brown cluster pairs by replacing each word with its Brown cluster prefixes (length of 4) in the way described in Section 2.4. We also use another rich source of information - the polarity of context, which has been previously shown to be useful for coreference problems (Peng et al., 2015). We extract polarity information using the data provided by Wilson et al. (2005) given the predicates of two discourse arguments. The data contains 8221 words, each of which is labeled with a polarity of positive, negative, or neutral. We use
the extracted polarity values to construct three features: Two individual polarities of the two predicates and the conjunction of them. We also implement feature selection to remove the features that are active in the corpus less than five times. As a result, we have 16,989 parse tree features, 4,335 dependency tree features, 77,677 word pair features, and 67,204 Brown cluster features.

2.6 Identifying Attribution Structures
We train two classifiers for attribution identification based on the original PDTB data (sections 2-21). The first classifier is similar to that developed by Lin et al. (2014). We use the patterns proposed by Skadhauge and Hardt (2005) to enumerate all the candidate attribution spans. The coverage of our implementation is 59.8%, which means that we can only enumerate the candidates that contain the attribution covering 59.8% of the annotation. We then build a classifier following Lin et al. (2014) to decide whether the candidate is a valid attribution or not. Using the sentences that contain the attribution(s), we also train a tagger. The tagger is designed following the features used in Illinois Chunker (Punyakanok and Roth, 2001).

3 Evaluation and Results
In this section, we present the data we used and results of the evaluation based on both cross-validation on the training data (computed within our software) and using the official CoNLL 2015 Shared Task evaluation framework of Xue et al. (2015).

3.1 Data
The data we used is provided through the CoNLL-2015 shared task (Xue et al., 2015), which is a modification of Penn Discourse Treebank (PDTB) (Prasad et al., 2008b) sections 2 through 21. The training data for attribution identification is obtained from the original PDTB release, also sections 2 through 21.

3.2 Cross-Validation Results
We first present the cross validation results for each component using the training data (Table 1). All the results are averaged over 10-fold cross validation of all the examples we generated, using our own predicted features and our own evaluation code. Each component is evaluated in isolation, assuming the inputs are from gold data (for example: for connective classification, it is assumed we have the correct connective and arguments provided as input). This means that these results are higher than they would be if evaluated using inputs generated by previous stages of the system, although in this evaluation they still use the predicted part-of-speech, chunk, and parse information.

Table 1: Cross validation results of all the components.

| Component               | P    | R    | F1   |
|-------------------------|------|------|------|
| Explicit Connectives    | 92.97| 93.91| 93.44|
| Argument Positions      | 98.15| 98.15| 98.15|
| Exact Arg1              | 64.41| 64.95| 64.68|
| Exact Arg2              | 87.06| 86.06| 86.56|
| Partial Arg1            | 77.02| 77.66| 77.34|
| Partial Arg2            | 94.74| 93.65| 94.19|
| Explicit Sense          | 83.18| 83.18| 83.18|
| Implicit Sense          | 34.58| 34.58| 34.58|
| Attribution Identification | 82.94 | 58.02 | 68.27 |
| Attribution Tagger      | 59.75| 56.49| 58.08|

3.3 CoNLL Results
We also present the results evaluated by the CoNLL-2015 shared task scorer on dev, test, and blind sets in Tables 2, 3, and 4. The results are consistent with the cross validation results, allowing for the fact that components are working with predicted inputs rather than gold annotations. The sense performance reported here is the macro-average of explicit and implicit senses.

Compared with the best results on the blind set, which is shown in Table 5, our main weaknesses lie in the sense classifier and argument detector. Since we presently ignore the disjoint connectives, our results can be improved if we incorporate those missing connectives. We do not presently incorporate the argument information in connective detection and sense classification for the explicit parser. Connective detection and classification can be improved if we also incorporate more features from arguments or perform joint learning.

4 Discussion
In this section we point to some types of errors in our system’s predictions and the complications of working on the provided corpus.
4.1 Error Analysis

We provide examples of the errors in the system’s predictions that show where the system can be improved, but also some that may indicate possible improvements in the task annotations themselves.

The argument boundaries in our system are predicted based on parse tree constituents. Some mistakes occur when an argument is non-contiguous, and some extraneous content is included. However, the UI-CCG system also generated correct arguments with erroneous token offsets due to tokenization differences.

Although the shared task specification indicates that attribution detection is not evaluated, our results suggest that it is helpful for some cases in order to obtain the correct argument boundaries.

4.2 Task-specific Complications

Since we wanted to use our own NLP software and to build a general-purpose system that will process raw text from new sources, we parsed the raw text files provided for the PDTB data. However, the shared task formulation requires outputs to be specified in terms of token indexes. We must therefore align our tokenization to that of the task-provided parse files, which were based on the gold tokenization of the Penn Treebank. We found alternative explanation. The issue of whether connectives should be included in arguments seems somewhat hard to pin down.

We also found examples where it is hard to make sense of the gold token offsets.

In some cases, there seems to be a legitimate
some disagreements in tokenization decisions by our NLP tools with the gold standard which introduced unwelcome complications and consequent errors. Possibly, character spans from the original text might provide an accurate but less constraining basis for evaluating system outputs, although the gold standard tokenization appears to omit terminal periods from abbreviated words.

5 Extending the Submitted System

Comparing the experimental results of other participating systems in the shared task to our model, it seems that sense disambiguation is the critical step in our pipeline that requires further improvements. We designed an initial model for making global decisions for the sequence of senses that can occur in a paragraph. The idea is to consider the label of the neighboring senses when predicting the sense of any implicit or explicit discourse relation candidate. To implement this idea we designed a constrained conditional model (CCM) (Chang et al., 2012) in LBJava. In this model two basic classifiers are trained. A first classifier, $C_1$, is trained to predict the sense of each candidate explicit/implicit relation and a second classifier $C_2$ is trained to predict the cooccurrence of the senses of any neighboring pair of candidate explicit/implicit relations. These classifiers are trained independently using features similar to those in the previous pipeline model. At prediction time, using $C_1$ and $C_2$ we make a global decision for the whole paragraph by modeling the component decisions as a sequence tagging task formulated as a CCM. In this model, the sequential joint prediction is made by adding two global constraints on the predictions made by $C_1$ and $C_2$: a) $C_2$ is applied on all pairs of neighboring relation candidates contained in a paragraph and the label assignments to any pair should be consistent with the label assignments made by $C_1$ to the relations in that pair. b) For any two neighboring pairs in a paragraph that share a relation, the label assignments should be consistent; that is, if a pair $p_1$ contains relation $i$ and relation $i+1$ and the next pair $p_2$ contains relation $i+1$ and relation $i+2$ then the assignments to the shared relation, $i+1$, should be the same. This constraint should hold for the whole paragraph. Using this model, we consider both emission and transition factors in making a global decision for the whole sequence of senses in a paragraph. However, this initial experiment on joint inference did not yield a significant improvement when tested on the sense prediction layer given all ground-truth labels of the previous layers in the pipeline.

6 Conclusions and Future Work

We have built a reasonably effective discourse parser using a pipeline architecture, and identified some features that improve performance over the previous reported state-of-the-art, including features based on Brown Clusters and on argument polarity information. We have also begun investigating the use of constrained conditional models for global inference.

Two natural extensions are: a) Improved features for sense classification. Our sense classification accuracy is relatively low. We need to improve the features we extract from the candidate arguments, and ideally these will reflect a higher level of semantic abstraction than the brown cluster features we used here. b) Global inference over multiple component decisions using Constrained Conditional Models.

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