Improving the Recall of a Discourse Parser by Constraint-based Postprocessing

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Abstract
We describe two constraint-based methods that can be used to improve the recall of a shallow discourse parser based on conditional random field chunking. These method uses a set of natural structural constraints as well as others that follow from the annotation guidelines of the Penn Discourse Treebank. We evaluated the resulting systems on the standard test set of the PDTB and achieved a rebalancing of precision and recall with improved F-measures across the board. This was especially notable when we used evaluation metrics taking partial matches into account; for these measures, we achieved F-measure improvements of several points.

Keywords: Discourse structure, constraint-based methods, evaluation

1. Introduction

Automatic analysis of the discourse structure of a text is a complex task with a wide range of potential applications. The release of the Penn Discourse Treebank (Prasad et al., 2008a) has resulted in a recent flurry of work in discourse parsing. In particular, there is a growing body of literature describing systems that extract arguments of explicit discourse connectives (Wellner and Pustejovsky, 2007; Elwell and Baldridge, 2008; Ghosh et al., 2011b; Ghosh et al., 2011a).

We previously presented a method for automatic argument extraction based on chunking with conditional random fields (Ghosh et al., 2011a). In contrast to previous approaches to argument extraction, our chunking system is very loosely coupled with the syntactic representation: It is completely straightforward to use one or more constituent, dependency, or shallow parsers in any combination since the argument boundaries are not tied to any particular constituent span. Other advantages include the simplicity of implementation by using standard chunking tools. The runtime of the system is also very low, with most of the processing time spent on feature extraction (i.e. running syntactic parsers).

However, while the chunking-based approach has the advantage of flexibility and speed, it is unable to take the global argument structural constraints into account. In particular, the PDTB annotation guidelines specify that exactly one Arg1 and one Arg2 must be annotated for every connective, while we often noticed that our system predicted no arguments. This causes our recall values to be low compared to the precision.

In this paper, we show that adding these constraints to the inference step improves the performance of the discourse parser. In particular, we see strong recall improvements. Global inference methods, including constraint-based as well as learning-based methods (often implemented as rerankers), have seen much use in NLP recently. Inference with constraints in particular has been successful in improving tasks such as semantic role labeling (Punyakanok et al., 2008). This approach may be seen as a simple way to introduce long-distance structural relationships while still keeping the machine learning models simple.

2. The Penn Discourse Treebank

The Penn Discourse Treebank (PDTB) is a resource containing one million words from the Wall Street Journal corpus (Marcus et al., 1993) annotated with discourse relations. While the PDTB is annotated on an English corpus, there are also preliminary efforts to annotate PDTB-style discourse treebanks in other languages including Hindi (Prasad et al., 2008b) and Turkish (Zeyrek and Webber, 2008).

Based on the observation that “no discourse connective has yet been identified in any language that has other than two arguments” (Webber et al. (2010), p. 15), connectives in the PTDB are treated as discourse predicates taking two text spans as arguments, i.e. parts of the text that describe events, propositions, facts, situations. These two types of arguments in the PDTB are called Arg1 and Arg2, with the numbering not necessarily corresponding to their order in text. Instead, Arg2 is the argument syntactically bound to the connective, while Arg1 is the other one. While the Arg2 is typically very close to the connective, the Arg1 may be much more distant, and may even occur in other
sentences. Table 1 shows some statistics about how often the Arg1 occurs intersententially.

In the PDTB, discourse relations can be either explicitly or implicitly expressed. However, in this paper we focus exclusively on explicit connectives and the identification of their arguments, including the exact spans. This kind of classification is very complex, since Arg1 and Arg2 can occur in many different configurations. In particular, an explicit connective can occur between two arguments (e.g., clauses connected by because) or at the beginning of the sentence (for example, when a sentence begins with since). It can also appear inside an argument, for instance with instead or however in sentence-internal position.

| Arg1 in same sentence as connective | 60.9% |
| Arg1 in previous, adjacent sentence | 30.1% |
| Arg1 in previous, non adjacent sentence | 9.0% |

Table 1: Statistics about the position of the Arg1 with respect to the explicit discourse connective. Taken from Prasad et al. (2008a).

3. Implementation

Our system for the automatic extraction of discourse arguments for explicit connectives (Ghosh et al., 2011a) consists of a pipeline, illustrated in Figure 1. Firstly, we assume that the explicit discourse connectives (and their high-level senses) are given to the system as input. They can be taken from the gold standard or automatically identified and disambiguated (Pitler and Nenkova, 2009), and for simplicity we used gold-standard connectives in this work. We then apply a module to extract the Arg2 arguments, which are the easiest to identify since they are syntactically connected to the discourse connectives. After the Arg2s have been identified, we finally apply the Arg1 extractor.

![Figure 1: Pipeline for argument detection given a connective.](image)

The Arg2 and Arg1 extractors are implemented as conditional random field sequence labelers, which use a set of syntactic and structural features (see Ghosh et al. (2011a) for a full discussion). In order to reduce the processing time, we apply the sequence labelers to the sentence containing the connective, and a context window of up to two sentences before and after.

3.1. Adding Constraints

In our evaluations (Ghosh et al., 2011a), recall was always lower than precision. We noticed that the system often failed to predict any argument at all. This was especially true for Arg1s, which are not always syntactically connected to the connective and thus typically more distant than the Arg2s. However, since the PDTB annotation guidelines specify that exactly one Arg1 and one Arg2 must be annotated for every connective, we may force the system to output arguments of each type. To improve the recall, we therefore implemented a weighted constraint-based postprocessor to make the system produce output satisfying the requirements defined by the annotation guidelines.

In order to find the best solution with a minimum of constraint violations, we generated the top k analyses output by the CRF for every sentence; these analyses can then be combined to form the k top analyses for the whole 5-sentence window around the connective. This combination is most efficiently carried out using a priority queue similar to a chart cell in the k-best parsing algorithm by Huang and Chiang (2005).

The algorithm then proceeds through the k-best list and outputs an argument segmentation with the minimal number of constraint violations. If there are more than one such segmentation, we select the one with the highest probability. We note that the search for the optimum could as well have been implemented directly in the CRF inference as a modified Viterbi procedure, with a slightly more complex dynamic programming table. We leave the implementation of this algorithm to future work.

We counted the following five conditions as constraint violations:

Overgeneration. This constraint is violated if an Arg1 or Arg2 is split over multiple sentences. However, due to the fact that an argument may be split into several pieces (because of attribution spans, nonprojective syntactic constructions, or embedded connectives), we allow an argument to be split into more than one part in the same sentence.

Undergeneration. Since every connective must have arguments of each type, this constraint is violated if an argument is missing.

Intersentential Arg2. We count every Arg2 outside the sentence containing the connective as a violation, since they are required to be syntactically connected to the connective.

Arg1 after the connective sentence. We count every Arg1 after the sentence containing the connective as a violation.

Argument overlapping with the connective. Arguments are not allowed to overlap with the connective, since PDTB uses discontinuous argument spans to encode situations where a connective is embedded in an argument span.

3.2. Soft Constraints

In addition, we investigated an implementation based on soft constraints. For a hypothesis h with a set of violated constraints $V(h)$, we define a scoring function $f(h)$ based on
on the score assigned by the base CRF and a set of constraint weights, with one weight $w_C$ for every violated constraint $C$. Our system then selects the hypothesis $h$ that maximizes $f(h)$.

$$f(h) = \log P_{CRF}(h) - \sum_{C \in V(h)} w_C$$

Based on tuning on a development set, we set all the constraint weights to 1, except the weight for Undergeneration which was set to 2.

4. Analysis

We first report the argument extraction performance for the constraint-based postprocessors and compare it to the baseline CRF, and then analyze various aspects of the performance.

4.1. Performance Measurements

Table 2 shows the performance of the baseline system (Ghosh et al., 2011a). As in that paper, we show precision and recall values using three evaluation protocols: exact, where an argument must have exactly the same boundaries to be counted as correct; overlap, where an argument is counted as correct if it overlaps with a gold standard argument; and partial, where a weight between 0 and 1 is used to measure the extent to which a segment corresponds to the gold standard (Johansson and Moschitti, 2010). As previously noted, the recall values are fairly low compared to the precision values.

| Arg2 | P   | R   | F1  |
|------|-----|-----|-----|
| Exact| 83.4| 75.1| 79.1|
| Partial| 93.4| 84.2| 88.6|
| Overlap| 97.2| 87.5| 92.1|

| Arg1 | P   | R   | F1  |
|------|-----|-----|-----|
| Exact| 69.9| 48.5| 57.3|
| Partial| 82.9| 61.7| 70.7|
| Overlap| 91.0| 65.1| 74.6|

Table 2: Performance of the baseline discourse parser.

Table 3 shows the effect of the postprocessing with hard constraints, using a $k$ of 8. We note that recall is improved in all settings, in particular for Arg1. The increased recall is offset by lower values of precision. However, F-measure always improves, especially for the partial and overlap measures.

| Arg2 | P   | R   | F1  |
|------|-----|-----|-----|
| Exact| 80.8| 77.9| 79.3|
| Partial| 92.8| 89.0| 90.9|
| Overlap| 96.9| 93.4| 95.1|

| Arg1 | P   | R   | F1  |
|------|-----|-----|-----|
| Exact| 58.9| 57.8| 58.4|
| Partial| 73.6| 75.7| 74.6|
| Overlap| 80.5| 79.0| 79.7|

Table 3: Results with constraint-based postprocessing.

Table 4 shows the corresponding table for the postprocessor using soft constraints, again with a $k$ of 8. This postprocessor strikes a middle ground between the precision-oriented baseline system and the postprocessor with hard constraints, which is very recall-oriented. We also note that this system scores achieves the highest exact F-measure, while the other postprocessor has higher values for partial and overlap F-measures.

| Arg2 | P   | R   | F1  |
|------|-----|-----|-----|
| Exact| 81.8| 77.1| 79.4|
| Partial| 93.0| 87.6| 90.2|
| Overlap| 97.1| 91.5| 94.2|

| Arg1 | P   | R   | F1  |
|------|-----|-----|-----|
| Exact| 66.8| 53.1| 59.2|
| Partial| 80.6| 68.0| 73.7|
| Overlap| 88.3| 70.1| 78.1|

Table 4: Results with postprocessing using soft constraints.

4.2. Intersentential Arguments

The most challenging arguments to extract are the intersentential Arg1. Table 5 shows the performance of the three systems on these arguments. For these arguments, the postprocessor with hard constraints stands out from the other two: it is much more recall-oriented, while the other two have fairly similar performances. However, the constraint-based systems always outperform the baseline for all types of F-measure.

| Baseline | P   | R   | F1  |
|----------|-----|-----|-----|
| Exact    | 52.9| 27.5| 36.2|
| Partial  | 68.6| 40.2| 50.7|
| Overlap  | 78.8| 41.0| 53.9|

| Postprocessing (hard) | P   | R   | F1  |
|-----------------------|-----|-----|-----|
| Exact                 | 39.1| 37.8| 38.5|
| Partial               | 55.9| 56.4| 56.1|
| Overlap               | 62.4| 60.3| 61.4|

| Postprocessing (soft) | P   | R   | F1  |
|----------------------|-----|-----|-----|
| Exact                | 49.2| 29.8| 37.1|
| Partial              | 65.9| 44.1| 52.7|
| Overlap              | 75.0| 45.5| 56.6|

Table 5: Intersentential Arg1 extraction results.

Because of our window-based pruning strategy, the constraints naturally lead to a certain amount of overgeneration: in about 6% of the cases, the gold-standard Arg1 is located outside the 5-sentence window, while the constraints still force the system to predict an Arg1 inside the window. This lowers the upper bound on the precision that our system can possible achieve.

4.3. The Effect of the Number of Hypotheses

In any method based on generation of multiple hypotheses from an underlying base system, it is important to investigate the question of how many hypotheses are needed to reach the best achievable performance, since generating a large set of hypotheses may be inefficient. Table 6 shows the effect of the $k$ value on the overlap F-measure for the task of Arg1 extraction, along with the oracle F-measure for the same task.
We have presented a constraint-based method that improves a shallow discourse parser based on chunking with conditional random fields. The method converts a severely unbalanced discourse parser to one that performs better with a plateau very quickly when increasing the hypothesis set size. This can be explained by the fact that our method immediately returns when finding a violation-free hypothesis. Table 7 shows the distribution of the positions of the first violation-free hypothesis. We note that a violation-free hypothesis was available among the four top-scored hypothesis in 97% of the cases.

Table 7: Distribution of the position in the k-best list of the first hypothesis without constraint violations.

| k  | 1 | 2 | 4 | 8 | 16 |
|----|---|---|---|---|----|
| F1 | 74.6 | 79.1 | 79.4 | 79.7 | 79.7 |
| Oracle F1 | 74.6 | 84.5 | 88.8 | 92.6 | 94.8 |

Table 6: Arg1 overlap F-measure for different values of k.

As is typical for these approaches, the largest gain is achieved immediately, when going from one to two hypotheses. However, in contrast to approaches based on reranking (see e.g. (Johansson and Moschitti, 2010)), our method immediately returns when finding a hypothesis without constraint violations. Table 7 shows the distribution of the positions of the first violation-free hypothesis. We note that a violation-free hypothesis was available among the four top-scored hypothesis in 97% of the cases.

Table 7: Distribution of the position in the k-best list of the first hypothesis without constraint violations.

| k  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | >8 |
|----|---|---|---|---|---|---|---|---|----|
| F1 | 108 | 370 | 55 | 35 | 15 | 10 | 5 | 3 | 10 |

5. Conclusion

We have presented a constraint-based method that improves a shallow discourse parser based on chunking with conditional random fields. The method converts a severely unbalanced discourse parser to one that performs better with a plateau very quickly when increasing the hypothesis set size. This can be explained by the fact that our method immediately returns when finding a violation-free hypothesis. Table 7 shows the distribution of the positions of the first violation-free hypothesis. We note that a violation-free hypothesis was available among the four top-scored hypothesis in 97% of the cases.

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