Joint Syntacto-Discourse Parsing and the Syntacto-Discourse Treebank [*]

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Abstract

Discourse parsing has long been treated as a stand-alone problem independent from constituency or dependency parsing. Most attempts at this problem rely on annotated text segmentations (Elementary Discourse Units, EDUs) and sophisticated sparse or continuous features to extract syntactic information. In this paper we propose the first end-to-end discourse parser that jointly parses in both syntax and discourse levels, as well as the first syntactic-discourse treebank by integrating the Penn Treebank and the RST Treebank. Built upon our recent span-based constituency parser, this joint syntactic-discourse parser requires no preprocessing efforts such as segmentation or feature extraction, making discourse parsing more convenient. Empirically, our parser achieves the state-of-the-art end-to-end discourse parsing accuracy.

1 Introduction

Distinguishing the semantic relations between segments in a document can be greatly beneficial to many high-level NLP tasks, such as summarization (Louis et al., 2010; Yoshida et al., 2014), sentiment analysis (Voll and Taboada, 2007; Somasundaran et al., 2009; Bhatia et al., 2015), question answering (Ferrucci et al., 2010; Jansen et al., 2014), and textual quality evaluation (Tetreault et al., 2013; Li and Jurafsky, 2016).

There has been a variety of research on discourse parsing (Marcu, 2000a; Soricut and Marcu, 2003; Pardo and Nunes, 2008; Hernault et al., 2010; da Cunha et al., 2012; Joty et al., 2013; Joty and Moschitti, 2014; Feng and Hirst, 2014; Ji and Eisenstein, 2014; Li et al., 2014a,b; Heilman and Sagae, 2015; Wang et al., 2017). But the majority of them aim to improve the discourse-level parsing accuracy with little focus on the efficiency and practical use: 1) they exploit sophisticated sparse/continuous features, which are usually extracted with some extra techniques such as constituency parsing or word embedding; 2) they also need additional tools for text segmentation when dealing with raw text, since they all assume the basic processing units to be text segments.

In this paper we propose the first *joint syntactic and discourse treebank*, by building up a framework to unify the constituency and discourse tree representations. Based on this, we further propose the first *end-to-end* incremental parser that jointly parses at constituency level and discourse level. Following Cross and Huang (2016), our algorithm employs the strong generalization power of bi-directional LSTM network, and parses efficiently and robustly with a simple feature set. In addition, the new parser does not require binarization of the discourse trees.

We make the following contributions:

1. We develop a combined representation of the constituency trees and discourse trees to facilitate parsing at both levels without explicit conversion mechanism. Using this representation, we build and release a joint treebank based on the Penn Treebank (Marcus et al., 1993) and RST Treebank (Marcu, 2000a,b). (Section 2)

2. We propose a novel joint parser that parses at both constituency and discourse levels. Our parser performs discourse parsing in an end-to-end manner, which greatly reduces the ef-

[*] The source code and the joint treebank are available at https://github.com/kaayy/josydipa.

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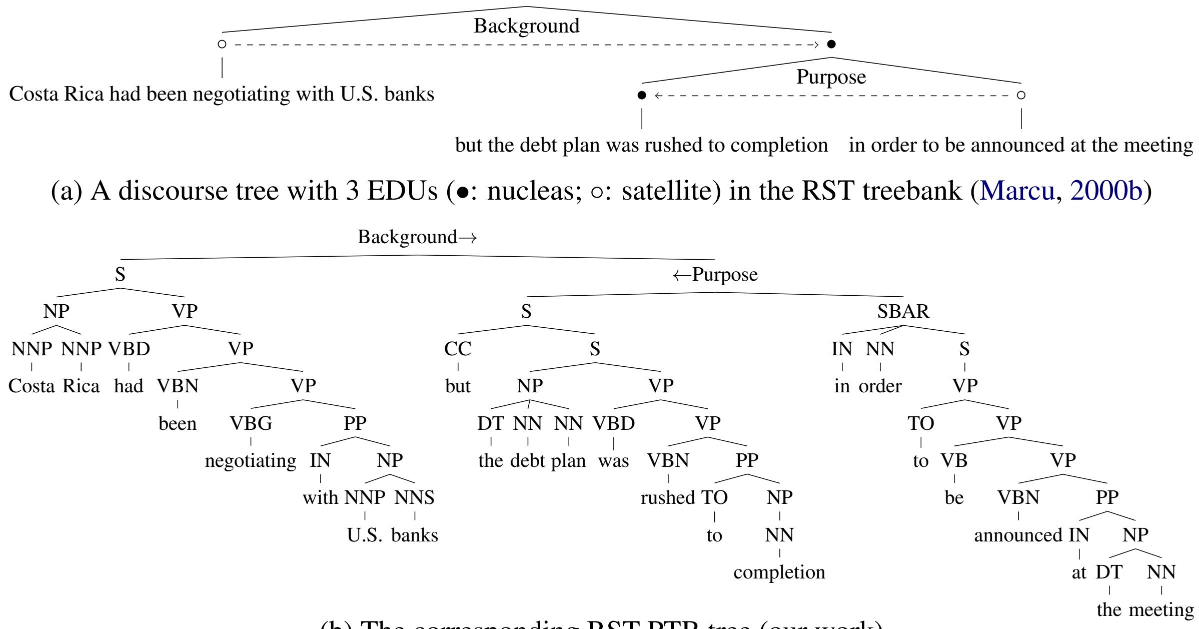


(a) A discourse tree with 3 EDUs (●: nucleas; ○: satellite) in the RST treebank (Marcu, 2000b)

(b) The corresponding RST-PTB tree (our work)

Figure 1: Examples of the RST discourse treebank and our syntacto-discourse treebank (PTB-RST).

forts required in preprocessing the text for segmentation and feature extraction, and, to our best knowledge, is the first end-to-end discourse parser in literature. (Section 3)

3. Following Cross and Huang (2016), our incremental parser actually deos *not* require to design any explicit syntactic feature when predicting the output structure, thanks to the strong feature representing power of bidirectional LSTM. Besides this, our parser does not require binarization of the discourse trees, which simplifies the parsing mechanism. (Section 3)

4. Empirical evaluations show that our end-to-end parser outperforms the traditional pipeline-based discourse parsing algorithms. In ablation experiment, when the gold EDUs are provided, our parser is also competitive to other existing approaches with sophisticated features. (Section 4)

2 Combined Representation & Treebank

We first briefly review the discourse trees in Rhetorical Structure Theory (Mann and Thompson, 1988), and then discuss how to unify the discourse tree and constituency tree, which gives rise to our syntacto-discourse treebank PTB-RST.

2.1 Review: RST Discourse Tree

In RST, structure, i.e., the discourse tree. There are two types of branchings in a discourse tree. Most of the internal discourse tree nodes are binary branching, with one *nucleus* child containing the core semantic meaning of the current node, and one *satellite* child semantically decorating the nucleus. Like dependency labels, there is a *relation* annotated between each satellite-nucleus pair, such as “Background” or “Purpose”. Figure 1(a) shows an example RST tree. There are also non-binary-branching internal nodes whose children are conjunctions, e.g., a “List” of semantically similar EDUs (which are all nucleus nodes); see Figure 2(a) for an example.

2.2 Syntacto-Discourse Representation

It is widely recognized that lower-level lexical and syntactic information can greatly help determining both the boundaries of the EDUs (i.e., discourse segmentation) (Bach et al., 2012) as well as the semantic relations between EDUs (Soricut and Marcu, 2003; Hernault et al., 2010; Joty and Moschitti, 2014; Feng and Hirst, 2014; Ji and Eisenstein, 2014; Li et al., 2014a; Heilman and Sagae, 2015). While these previous approaches rely on pre-trained tools to provide both EDU segmentations and intra-EDU syntactic parse trees, we instead propose to directly determine the low-level segmentations, the syntactic parses, and the high-

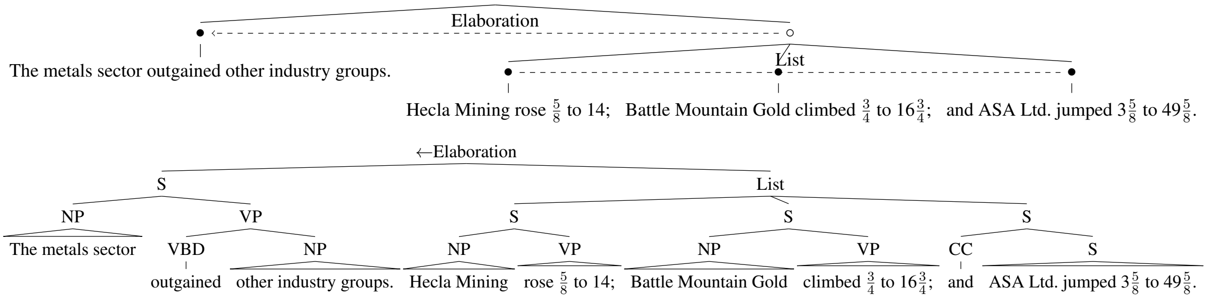
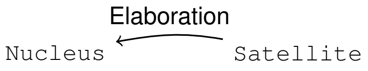

Elaboration
The metals sector outgained other industry groups.
List
Hecla Mining rose $\frac{5}{8}$ to 14;
Battle Mountain Gold climbed $\frac{3}{4}$ to $16\frac{3}{4}$;
and ASA Ltd. jumped $3\frac{5}{8}$ to $49\frac{5}{8}$.
←Elaboration
S
NP
VP
The metals sector
VBD
outgained
NP
other industry groups.
List
S
NP
Hecla Mining
VP
rose $\frac{5}{8}$ to 14;
S
NP
Battle Mountain Gold
VP
climbed $\frac{3}{4}$ to $16\frac{3}{4}$;
S
CC
and
S
ASA Ltd. jumped $3\frac{5}{8}$ to $49\frac{5}{8}$.

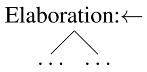
Figure 2: Another example of RST vs. PTB-RST, demonstrating a discourse tree over two sentences and a non-binary relation (List). The lower levels of the PTB-RST tree are collapsed due to space contraints.

level discourse parses using a single joint parser. This parser is trained on the combined trees of constituency and discourse structures.

We first convert the RST trees to the constituency tree structures as defined in the Penn Treebank (Marcus et al., 1993). For each binary branching node with a nucleus child and a satellite child, we use the relation as the label of the converted parent node. The nucleus/satellite relation (either ← or →, pointing from satellite to nucleus) is then attached to the label as a suffix. For example, the top level relation in Figure 2,



is converted into



For each conjunctive branch, we simply use the relation as the label of the converted parent node.

After converting the RST trees into constituency tree format, we then align the constituency trees for each EDU span to the converted discourse tree leaves. Given that the RST Treebank (Marcu, 2000b) is a subset of the Penn Treebank, we can always find the corresponding constituency subtrees for each EDU leaf node. For the most cases, each EDU corresponds to one single (sub)tree in the Penn Treebank, since the semantic units highly correlate with the syntactic units. In some other cases, one EDU leaf node may correspond to multiple subtrees in the Penn Treebank, and for these EDUs we simply treat them as multiple-branching nodes in the converted trees.

Figure 2 shows an example of a discourse tree and its combined tree.

2.3 Joint Treebank

Using the conversion strategy described in the previous subsection, we build the first joint syntactic and discourse treebank based on Penn Treebank (Marcus et al., 1993) and RST Treebank (Marcu, 2000a,b). This treebank is released as a set of tools to generate the joint trees given Penn Treebank and RST Treebank data. During the alignment between the RST trees and the constituent trees, we only keep the common parts of the two trees.

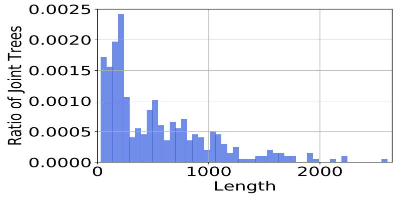


Figure 3: PTB-RST: length distribution (# tokens).

We follow the training/testing splitting strategy of RST Treebank. In the training set, there are 347 joint trees with 17,837 tokens in total, in which the lengths of the discourses vary from 30 to 2,199. In the testing set, there are 38 joint trees with 4,819 tokens in total, in which the lengths of the discourses vary from 45 to 2,607. Figure 3 shows the distribution of the discourse lengths over the whole dataset.

3 Joint Syntacto-Discourse Parsing

Given the combined syntactic and discourse treebank, we now propose a joint parser that can perform end-to-end discourse parsing. Later in this section we will briefly discuss the underlying recurrent neural models and the training of the parser.

3.1 Extending Span-based Parsing

Due to efficiency considerations for a long sequence of words in a document, we resort to incremental parsing. The deductive system for our joint parsing algorithm (Figure 4) is inspired by the span-based constituency parser of Cross and Huang (2016).

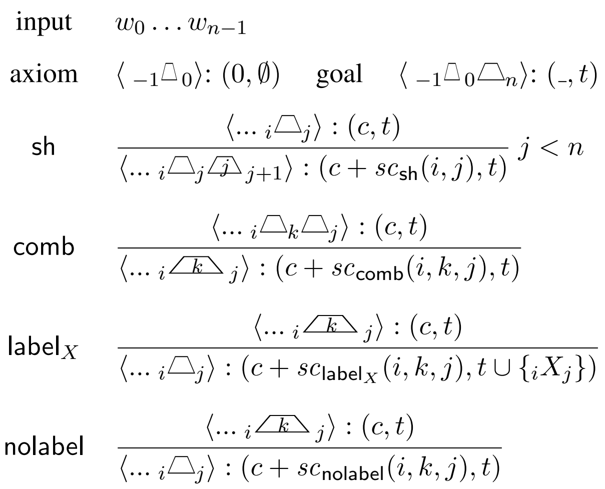


Figure 4: Deductive system for joint syntactic and discourse parsing. $sc_{\mathsf{sh}}(\cdot,\cdot)$, $sc_{\mathsf{comb}}(\cdot,\cdot,\cdot)$, $sc_{\mathsf{label}_X}(\cdot,\cdot,\cdot)$, and $sc_{\mathsf{nolabel}}(\cdot,\cdot,\cdot)$ are scoring functions evaluated in the neural network.

At each parsing step, we maintain a configuration that is a triple $\langle z, \sigma, k\rangle$, where z is the number of parsing actions performed, σ is a stack, and k is the previous branching position.In traditional incremental parsing, the stack σ stores the subtrees that have been constructed during the parsing. However, in the span-based constituency parsing, the stack σ only needs to store the boundaries of the subtrees, which are actually a list of indexes representing the spans of the subtrees. Please refer Cross and Huang (2016) for details of the span-based constituency parsing.

The actions we can perform at each step is conditioned on whether the current step is even or odd. For even steps, we perform structural actions, i.e., either shift (sh) or combine (comb); and for odd steps, we perform label actions, i.e., either mark the top span with a label, or mark a nolabel for multiple branching nodes.

Different from Cross and Huang (2016), in the combine action, we choose to keep the last branching point k. This is because in our parsing mechanism, the discourse relation between two EDUs is actually determined after the previous combine action. We need to keep the splitting point to clearly find the spans of the two EDUs to determine their relations.

The nolabel action makes the binarization of the discourse/constituency tree unnecessary, because nolabel actually combines the top two spans on the stack σ into one span, but without annotating the new span a label. This greatly simplifies the pre-processing and post-processing efforts needed.

	Prec.	Recall	F1
Constituency	87.6	86.9	87.2
Discourse	46.5	40.2	43.0
Overall	83.5	81.6	82.5

Table 1: Accuracies on PTB-RST at constituency and discourse levels.

Note that our parser actually does not rely on any explicit syntactic features when predicting the discourse-level structures and labels. It predicts soloy based on the span feature representations from underlying bi-directional LSTM.

3.2 Recurrent Neural Models and Training

The scoring functions in the deductive system (Figure 4) are calculated by an underlying neural model, which is similar to the bi-directional LSTM model in Cross and Huang (2016) that evaluates based on span boundary features.

During the decoding time, a document is firstly passed into a two-layer bi-directional LSTM model, then the outputs at each text position of the two layers of the bi-directional LSTMs are concatenated as the positional features. The spans at each parsing step can be represented as the feature vectors at the boundaries. The span features are then passed into fully connected networks with softmax to calculate the likelihood of performing the corresponding action or marking the corresponding label.

We use the "training with exploration" strategy (Goldberg and Nivre, 2013) and the dynamic oracle mechanism described in Cross and Huang (2016) to make sure the model can handle unseen parsing configurations properly.

4 Empirical Evaluations

We use the treebank described in Section 2 for empirical evaluation. We randomly choose 30 documents from the training set as the development set.

We tune the hyperparameters of the neural model on the development set. For most of the hyperparameters we settle with the same values suggested by Cross and Huang (2016). To alleviate the overfitting problem for training on the relative small RST Treebank, we use a dropout of 0.5.

One particular hyperparameter is that we use a value β to balance the chances between training following the exploration (i.e., the best action chosen by the neural model) and following the correct

	description	syntactic feats.	segmentation	structure	+nuclearity	+relation
Bach et al. (2012)	segmentation only	Stanford	95.1	-	-	-
Hernault et al. (2010)	end-to-end pipeline	Penn Treebank	94.0	72.3	59.1	47.3
joint syntactic & discourse parsing		-	**95.4**	**78.8**	**65.0**	**52.2**

Table 2: F1 scores of end-to-end systems. "+nuclearity" indicates scoring of tree structures with nuclearity included. "+relation" has both nuclearity and relation included (e.g., ←Elaboration).

		syntactic feats	structure	+nuclearity	+relation
human annotation (Ji and Eisenstein, 2014)		-	88.7	77.7	65.8
sparse	Hernault et al. (2010)	Penn Treebank	83.0	68.4	54.8
	Joty et al. (2013)	Charniak (retrained)	82.7	68.4	55.7
	Joty and Moschitti (2014)	Charniak (retrained)	-	-	57.3
	Feng and Hirst (2014)	Stanford	85.7	71.0	58.2
	Heilman and Sagae (2015)	ZPar (retraied)	83.5	68.1	55.1
	Wang et al. (2017)	Stanford	**86.0**	**72.4**	59.7
neural	Li et al. (2014a)	Stanford	82.4	69.2	56.8
	+ sparse features		84.0	70.8	58.6
	Ji and Eisenstein (2014)	MALT	80.5	68.6	58.3
	+ sparse features		81.6	71.1	**61.8**
	span-based discourse parsing	-	84.2	67.7	56.0

Table 3: Experiments using gold segmentations. The column of "syntactic feats" shows how the syntactic features are calculated in the corresponding systems. Note that our parser predicts solely based on the span features from bi-directionaly LSTM, instead of any explicitly designed syntactic features.

path provided by the dynamic oracle. We find that $\beta = 0.8$, i.e., following the dynamic oracle with a probability of 0.8, achieves the best performance. One explanation for this high chance to follow the oracle is that, since our combined trees are significantly larger than the constituency trees in Penn Treebank, lower β makes the parsing easily divert into wrong trails that are difficult to learn from.

Since our parser essentially performs both constituency parsing task and discourse parsing task. We also evaluate the performances on sentence constituency level and discourse level separately. The result is shown in Table 1. Note that in constituency level, the accuracy is not directly comparable with the accuracy reported in Cross and Huang (2016), since: a) our parser is trained on a much smaller dataset (RST Treebank is about 1/6 of Penn Treebank); b) the parser is trained to optimize the discourse-level accuracy.

Table 2 shows that, in the perspective of end-to-end discourse parsing, our parser first outperforms the state-of-the-art segmentator of Bach et al. (2012), and furthermore, in end-to-end parsing, the superiority of our parser is more pronounced comparing to the previously best parser of Hernault et al. (2010).

On the other hand, the majority of the conventional discourse parsers are not end-to-end: they rely on gold EDU segmentations and pre-trained tools like Stanford parsers to generate features. We perform an experiment to compare the performance of our parser with them given the gold EDU segments (Table 3). Note that most of these parsers do not handle multi-branching discourse nodes and are trained and evaluated on binarized discourse trees (Feng and Hirst, 2014; Li et al., 2014a,b; Ji and Eisenstein, 2014; Heilman and Sagae, 2015), so their performances are actually not directly comparable to the results we reported.

5 Conclusion

We have presented a neural-based incremental parser that can jointly parse at both constituency and discourse levels. To our best knowledge, this is the first end-to-end parser for discourse parsing task. Our parser achieves the state-of-the-art performance in end-to-end parsing, and unlike previous approaches, needs little pre-processing effort.

Acknowledgments

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