Easy-First Bottom-Up Discourse Parsing via Sequence Labelling

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Abstract

We propose a novel unconstrained bottom-up approach for rhetorical discourse parsing based on sequence labelling of adjacent pairs of discourse units (DUs), based on the framework of Koto et al. (2021). We describe the unique training requirements of an unconstrained parser, and explore two different training procedures: (1) fixed left-to-right; and (2) random order in tree construction. Additionally, we introduce a novel dynamic oracle for unconstrained bottom-up parsing. Our proposed parser achieves competitive results for bottom-up rhetorical discourse parsing.

1 Introduction

Discourse analysis aims to explain the relationship of texts beyond sentence boundaries, and has been modelled based on Rhetorical Structure Theory (RST: Mann and Thompson (1988)). In the RST framework, texts are modelled as a labelled hierarchy of discourse units (DU), with elementary discourse units (EDU) being the smallest unit (see Figure 1).

Although there has been a move from bottom-up (Hernault et al., 2010; Ji and Eisenstein, 2014; Joty et al., 2015; Li et al., 2016; Yu et al., 2018; Mabona et al., 2019) to top-down approaches (Lin et al., 2019; Zhang et al., 2020; Nguyen et al., 2021; Koto et al., 2021), we argue that the bottom-up paradigm is conceptually intuitive as humans analyse the structure of documents incrementally based on elementary structures. Furthermore, in contemporaneous work, Yu et al. (2022) have shown that bottom-up parsers built on a language model pre-trained at the EDU level outperform top-down parsers trained comparably.

In this paper, we revisit the bottom-up approach and introduce a novel unconstrained bottom-up discourse parsing $O(n^2)$ by adopting the sequence-labelling framework of Koto et al. (2021). Unconstrained means that we relax the fixed left-to-right direction of discourse tree construction, allowing us to make the easiest decisions first. Intuitively speaking, when it comes to making the harder decisions, the history of existing structures can be used to make more reliable predictions.

Goldberg and Elhadad (2010) introduced the non-directional easy-first algorithm to dependency parsing, which is a greedy, best-first parser, which relaxes the left-to-right order constraint of other bottom-up transition-based algorithms (Yu et al., 2018). Because the model is conditioned on existing parsed structures, we need to sample parsing trajectories to train the model, and compare two simple sampling methods: (1) left-to-right, and (2) random. To the best of our knowledge, we are the first to propose a bottom-up model for discourse parsing using the easy-first algorithm in a sequence labelling framework.

To summarize our contributions: (1) we propose a novel bottom-up context-sensitive parser; (2) we explore sampling methods for training a context-sensitive parser; and (3) we devise a novel dynamic oracle for our unconstrained bottom-up discourse...
2 Bottom-Up RST Parsing

We construct RST trees in a bottom-up fashion, starting with a sequence of EDUs and sequentially merging adjacent discourse units. At each stage, there are multiple merge points in the partially-parsed document that make up the gold discourse tree, and we define all such points to be gold merges. We impose no constraint on which gold merge needs to be executed first.

Following Koto et al. (2021), we frame the merging task as a sequence labeling problem. We train a merging model to assign a binary label $y \in \{0, 1\}$ to each discourse unit, where 1 indicates the unit and its right neighbour are subject to a gold merge. For each parse state, we train the model to label all gold merge points. At test time, we select the highest-probability merge point to construct the next parse state. We assign the discourse label and nuclearity relation separately with a second classifier after a merge is decided.

2.1 Model

Following Koto et al. (2021), our merging module consists of two blocks, as depicted in Figure 2. The first block is an EDU encoder. We use the hierarchical LSTM architecture of Yu et al. (2018), generating encodings with implicit syntax features. We obtain a suitable representation for each EDU text span $\{w_1, w_2, \ldots, w_m\}$ by using two Bi-LSTMs (Bi-LSTM$_1$ and Bi-LSTM$_2$). Bi-LSTM$_1$ is given the neural embedding of $w_i$ concatenated with the part of speech embedding as input. Bi-LSTM$_2$ is given the syntax embedding $s_i$ of each work as input. The syntax embedding comes from the syntax dependency parser from Dozat and Manning (2017). We also use an EDU type embedding $t_{E_j}$ to distinguish EDUs at the end of a paragraph from other EDUs. The final EDU encoding $g_{E_j}$ is the concatenation of the average output states for both Bi-LSTMs over the EDU and the EDU type embedding $t_{E_j}$:

$$x_i = w_i \oplus p_i$$
$$\{a^w_1, \ldots, a^w_p\} = \text{Bi-LSTM}_1(\{x_1, \ldots, x_p\})$$
$$\{a^s_1, \ldots, a^s_p\} = \text{Bi-LSTM}_2(\{s_1, \ldots, s_p\})$$
$$g_{E_j} = \text{Avg-Pool}(\{a^w_1, \ldots, a^w_p\}) \oplus \text{Avg-Pool}(\{a^s_1, \ldots, a^s_p\}) \oplus t_{E_j}$$

Given a sequence of independent EDU encodings, we use a third Bi-LSTM (Bi-LSTM$_3$) to capture relationships between EDUs and produce a contextualized encoding $h_{E_j}$:

$$\{h_{E_1}, \ldots, h_{E_q}\} = \text{Bi-LSTM}_3(g_{E_1}, \ldots, g_{E_q})$$

The second block (the top half of Figure 2) is the merger, and deviates from Koto et al. (2021). The parse state consists of a sequence of discourse units, each of which is represented by averaging the encodings of the component EDUs:

$$d_{D_k} = \text{Avg}(h_{E_{a_1}}, \ldots, h_{E_{b}})$$

where $D_k$ is a discourse unit with EDU span $E_{a:b}$.

We use a fourth Bi-LSTM (Bi-LSTM$_4$) to encode relationships between complex discourse units and assign a binary label to each merge.

$$\{d'_{D_1}, \ldots, d'_{D_n}\} = \text{Bi-LSTM}_4(d_{D_1}, \ldots, d_{D_n})$$

$$\hat{y}_{D_k} = \sigma(\text{MLP}(d'_{D_k}))$$
We predict the joint probability distribution of the nuclearity and discourse labels after a merge is chosen by feeding the encodings $d'_{ind}, d'_{ind+1}$ of the selected discourse units into an MLP layer, where $ind$ is the index of the left discourse unit chosen to be merged:

$$z_{nuc+dis} = \text{softmax}(\text{MLP}(d'_{ind}, d'_{ind+1}))$$

The final training loss of our model is the combination of the merging and nuclearity-discourse prediction loss: $L = L_{merge} + L_{nuc+dis}$.

### 2.2 Merge Order in Training

Because the model evaluates each merge candidate in the context of all previously parsed structures in the document, different permutations of parse states with discourse units not part of the merge candidate can lead to different predictions for that merge candidate. We propose to sample parse sequences for training. We evaluate two different sampling schemes: (1) merging gold pairs left to right; and (2) merging gold pairs at random.

### 2.3 Dynamic Oracle

In the standard training regimen, the model is only trained on parse states constructed by a sequence of correct merges. However, at test time, the model will often see error parse states, created by an incorrect merge in its history. Because the model is never trained on error states, it will struggle to recover after it has made a mistake.

We address this problem by training our model with a dynamic oracle, first introduced by Goldberg and Nivre (2012) and adopted for discourse parsers (Yu et al., 2018; Koto et al., 2021). Given an error state, a dynamic oracle provides the next set of merge actions that will minimize deviation between the gold tree and the final tree. The dynamic oracle is described in Algorithm 1. At each merging step in training, with probability $\alpha$ we execute the predicted merge instead of the sampled gold merge. In this manner, we introduce error states to the training set and teach the model to predict the next set of oracle actions, so the parser chooses the best actions even after a mistake.

In a document with $n$ EDUs, the oracle assigns a merge order to each $n-1$ cut separating adjacent EDUs. The merge order is defined as the earliest step discourse units to the left and right of the cut are merged in all possible gold merge sequences. If the merge order of a cut is lower than adjacent cuts, it is an oracle action to merge the two discourse units around the cut, because in such cases, other gold merges that involve the two discourse units must come after the oracle action.

### 3 Experiments

#### 3.1 Data

Following previous studies (Koto et al., 2021; Yu et al., 2018), we focus on the English language and use the RST Discourse Treebank for our experiments, binarizing all discourse trees in a right-heavy manner. It contains 347 annotated documents for training and 38 documents for testing. Our development set consists of the same 35 documents as Koto et al. (2021) and Yu et al. (2018), taken from the training set. Consistent to previous works, we use the same 18 coarse-grained discourse relationships and use the gold EDU segments for discourse tree construction.

#### 3.2 Set-Up

We use the standard Parseval metrics for RST parsing of Marcu (2000). Based on the recommendations of a recent replication study (Morey et al., 2017), we report micro-averaged F-1 scores on labeled attachment decisions (original Parseval) instead of macro-averaged F-1 scores (RST-Parseval). The Parseval metrics consist of: $\text{Span}$, $\text{Nuclearity}$, $\text{Relation}$, and $\text{Full}$.\footnote{\text{Span} evaluates the correctness of the predicted tree structure. $\text{Nuclearity}$ evaluates the tree skeleton together with nuclearity indications. $\text{Relation}$ evaluates the tree skeleton with the discourse relations. $\text{Full}$ evaluates the tree skeleton along with nuclearity indications and discourse relations.}
Table 1: Sampling strategy results over the dev set, based on the Full metric (micro-averaged F-score on labeled attachment decisions) and Bias (depth difference between the left and right end of the tree).

| Merge Order | Full | Bias |
|-------------|------|------|
| Left Merge  | 47.3 | 12.6 |
| Random Merge| 51.8 | 0.8  |

We adopt the hyperparameter settings used in Koto et al. (2021). GloVe embeddings (Pennington et al., 2014) are used to encode the words in each EDU. We use CoreNLP (Manning et al., 2014) to obtain POS tag, and initialize each POS encoding as a random vector. The embedding dimension of words, POS tags, EDU type and syntax features are 200, 200, 100 and 1200, respectively. The dimensionality of the Bi-LSTMs in the encoder is 256 and Bi-LSTM_4 in the merge classifier has a dimension of 128. We use batch size = 4, gradient accumulation = 2, learning rate = 0.001, dropout probability = 0.5, and optimizer = Adam (with epsilon of 1e-6). When training with a dynamic oracle, we activate the dynamic oracle after 50 epochs.

We tune the α value used in the dynamic oracle on the development set. We performed grid search on α values, each averaging the Full Parseval metric over three random seeds. For training with a dynamic oracle, we found that α = 0.8 resulted in the best Full Parseval score.

We use a single Tesla V100 SXM2 32 GB with 4 CPU cores to run our experiments. A run with static oracle takes around 14 hours in run time.

3.3 Results
We present analysis of the sampling strategy in Table 1. All results are averaged over three runs with different random seeds on the development set, with a static oracle. We compare training with left-first state sequences and randomly-sampled state sequences, and find that the latter result in an absolute +4.5 improvement over training with left-first state sequences. As such, we use random sampling for the remainder of the paper.

We benchmark our parser against previous state-of-the-art RST parsers over the test set. The results are presented in Table 2 (original Parseval).

| Method | S   | N   | R   | F   |
|--------|-----|-----|-----|-----|
| Bottom-Up: |     |     |     |     |
| Feng and Hirst (2014)† | 68.6 | 55.9 | 45.8 | 44.6 |
| Ji and Eisenstein (2014)† | 64.1 | 54.2 | 46.8 | 46.3 |
| Surdeanu et al. (2015)† | 65.3 | 54.2 | 45.1 | 44.2 |
| Joty et al. (2015) | 65.1 | 55.5 | 45.1 | 44.3 |
| Hayashi et al. (2016) | 65.1 | 54.6 | 44.7 | 44.1 |
| Li et al. (2016) | 64.5 | 54.0 | 38.1 | 36.6 |
| Braud et al. (2017) | 62.7 | 54.5 | 45.5 | 45.1 |
| Yu et al. (2018) (static)‡ | 71.1 | 59.7 | 48.4 | 47.4 |
| Yu et al. (2018) (dynamic)‡ | 71.4 | 60.3 | 49.2 | 48.1 |
| Mabona et al. (2019) | 67.1 | 57.4 | 45.5 | 45.0 |
| Yu et al. (2022) (XLNet) | **76.4** | **66.1** | **54.5** | **53.5** |
| Top-Down: |     |     |     |     |
| Zhang et al. (2020) | 67.2 | 55.5 | 45.3 | 44.3 |
| Nguyen et al. (2021) | 67.1 | 57.4 | 45.5 | 45.0 |
| Koto et al. (2021) (static)‡ | 72.7 | 61.7 | 50.5 | 49.4 |
| Koto et al. (2021) (dynamic)‡ | 73.1 | 62.3 | 51.5 | 50.3 |
| Our proposed Bottom-Up Method: |     |     |     |     |
| Static‡ | 73.3 | 62.0 | 50.1 | 49.1 |
| Dynamic‡ | 73.6 | 62.3 | 50.3 | 49.3 |

Table 2: Results over the test set calculated using micro-averaged F-1 on labeled attachment decisions (original Parseval). All metrics (S: Span, N: Nuclearity, R: Relation, F: Full) are averaged over three runs. “†” and “‡” denote that the model uses sentence and paragraph boundary features, respectively.

Algorithm, without the need for complex post-editing or a chart-parsing algorithm. The sequence labeling framework has the benefit of being conceptually simpler than transition parsers. Training with a dynamic oracle adds algorithmic complexity during training, but our inference procedure remains the same. Our parser is most comparable with the transition-based parser proposed by Yu et al. (2018), which shares the same LSTM-architecture as our work and also utilises implicit syntax features. Our results demonstrate that a parser with the context of the document structure outperforms parsers without structure context.

Compared to the top-down parser proposed by Koto et al. (2021) with the dynamic oracle, our results for Span and Nuclearity are superior or equivalent, but the relation classification results are slightly inferior, resulting in slightly lower results overall. It is important to note that, while noticeably superior to our approach, the methods of Yu et al. (2022) and Zhang et al. (2021) are heavily based on pre-trained LMs, where our method makes no use of pre-training, which we leave to future work.
3.4 Analysis

We perform bias analysis on discourse trees produced by models trained with left-first states against random states. We introduce a simple metric for detecting heaviness bias, by calculating the depth difference between the left-most and the right-most leaf nodes and subtracting the expected difference from the gold tree. A higher value indicates the predicted trees are more right-heavy than the gold trees.

\[ d_i = \text{Depth}_{\text{pred}}(EDU_i) - \text{Depth}_{\text{gold}}(EDU_i) \]

\[ b = d_n - d_1 \]

When the parser is trained with left-first examples, \( b = 12.6 \) (Table 1), indicating a bias towards right-heavy trees. This is expected due to right merges being merged last in the training examples, thus creating an imbalance in the number of correct merges in the left and right sides of the tree in the training examples. On the other hand, when trained with random sampling, there is no such imbalance in the training dataset. And we see that there is no significant bias, with \( b = 0.8 \).

4 Conclusion

In this work, we adapted the sequence labeling framework to bottom-up RST parsing, introducing an easy-first parser conditioned on past decisions. We investigated methods to sample training examples for a non-directional parser, and proposed a dynamic oracle for our bottom-up parsing. We demonstrated that our parser achieves competitive results for bottom-up RST parsing.

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A Additional Results

We also report the results in Table 3 with the RST-Parseval Procedure. We include the reported results from Guz and Carenini (2020) as a reference. Their reported RST-Parseval scores beat other works, but uses the pre-trained language model SpanBERT.

A.1 Evaluation with RST-Parseval Procedure

| Method                        | S   | N   | R   | F   |
|-------------------------------|-----|-----|-----|-----|
| **Bottom-Up**                 |     |     |     |     |
| Feng and Hirst (2014)*†       |  84.3 | 69.4 | 56.9 | 56.2 |
| Ji and Eisenstein (2014)*‡    |  82.0 | 68.2 | 57.8 | 57.6 |
| Surdeanu et al. (2015)*†      |  82.6 | 67.1 | 55.4 | 54.9 |
| Joty et al. (2015)*           |  82.6 | 68.3 | 55.8 | 54.4 |
| Hayashi et al. (2016)*        |  82.6 | 66.6 | 54.6 | 54.3 |
| Li et al. (2016)*             |  82.2 | 66.5 | 51.4 | 50.6 |
| Braud et al. (2017)*          |  81.3 | 68.1 | 56.3 | 56.0 |
| Yu et al. (2018) (1 run)*†‡   |  85.5 | 73.1 | 60.2 | 59.9 |
| Yu et al. (2018) (static)*‡    |  85.8 | 72.6 | 59.5 | 59.0 |
| Yu et al. (2018) (dynamic)*‡   |  85.6 | 72.9 | 59.8 | 59.3 |
| **Our Work:**                 |     |     |     |     |
| Static ‡                      |  86.7 | 73.2 | 60.5 | 60.0 |
| Dynamic‡                      |  86.8 | 73.6 | 60.6 | 60.1 |
| **Top-Down**                  |     |     |     |     |
| Kobayashi et al. (2020)*†‡    |  87.0 | 74.6 | 60.0 | -   |
| Koto et al. (2021) LSTM (static)‡ |  86.4 | 73.4 | 60.8 | 60.3 |
| Koto et al. (2021) LSTM (dynamic)‡ |  86.6 | 73.7 | 61.5 | 60.9 |
| **Using Pretrained LM**       |     |     |     |     |
| Guz and Carenini (2020) (SpanBERT-CorefFeats)*†‡ |  88.1 | 76.1 | 63.6 | -   |
| Human                         |  88.3 | 77.3 | 65.4 | 64.7 |

Table 3: Results over the test set calculated using micro-averaged F-1 on RST-Parseval. All metrics (S: Span, N: Nuclearity, R: Relation, F: Full) are averaged over three runs. “*” denotes reported performance. “†” and “‡” denote that the model uses sentence and paragraph boundary features, respectively.

A.2 Evaluation over Development Set

| Method | S   | N   | R   | F   |
|--------|-----|-----|-----|-----|
| Static |  71.8 | 62.2 | 52.6 | 51.8 |
| Dynamic|  71.6 | 62.0 | 53.0 | 52.2 |

Table 4: Results over the development set calculated using micro-averaged F-1 on labeled attachment decisions (original Parseval). All metrics are averaged over three runs.