Predicting Above-Sentence Discourse Structure using Distant Supervision from Topic Segmentation

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Abstract
RST-style discourse parsing plays a vital role in many NLP tasks, revealing the underlying semantic/pragmatic structure of potentially complex and diverse documents. Despite its importance, one of the most prevailing limitations in modern day discourse parsing is the lack of large-scale datasets. To overcome the data sparsity issue, distantly supervised approaches from tasks like sentiment analysis and summarization have been recently proposed. Here, we extend this line of research by exploiting distant supervision from topic segmentation, which can arguably provide a strong and oftentimes complementary signal for high-level discourse structures. Experiments on two human-annotated discourse treebanks confirm that our proposal generates accurate tree structures on sentence and paragraph level, consistently outperforming previous distantly supervised models on the sentence-to-document task and occasionally reaching even higher scores on the sentence-to-paragraph level.

1 Introduction
The Rhetorical Structure Theory (RST) (Mann and Thompson 1988) is arguably one of the most popular frameworks to represent the discourse structure of complete documents. As such, RST has received considerable attention over the past decades, being leveraged to benefit important NLP downstream tasks, such as text classification (Ji and Smith 2017), sentiment analysis (Bhatia, Ji, and Eisenstein 2015; Hogenboom et al. 2015; Nejat, Carenini, and Ng 2017; Huber and Carenini 2020a), summarization (Marcu 1999; Gerani et al. 2014; Xu et al. 2020; Xiao, Huber, and Carenini 2020) and argumentation analysis (Chakrabarty et al. 2019).

Compared to other competing discourse theories (e.g., PDTB (Prasad et al. 2008)), RST postulates complete discourse trees based on clause-like Elementary Discourse Units (abbreviated: EDUs), which are sentence fragments on an intermediate granularity level between words and sentences. With EDUs acting as leaf nodes in RST-style discourse trees, constituents are formed by aggregating EDUs into sub-trees containing: (1) a projective tree structure, (2) a nuclearity assignment for each internal node and (3) rhetorical relations between siblings. In this work, we focus on “plain” discourse tree structures and leave the exploration of nuclearity and relation classification for future work.

Due to the definition of complete discourse trees in the RST framework, tree structures become deeper as documents grow longer (as compared to the definition in PDTB, where the aggregation stops above sentence level). Furthermore, the defining factors for the tree aggregation on higher levels diverts considerably from the ones on lower levels (e.g., aggregating multiple paragraphs vs. combining EDUs) (Jiang et al. 2021). For example, suitable features for EDU level tree aggregations (i.e., low-levels) are mostly influenced by local syntactic and semantic signals, while the tree aggregation on paragraph level (i.e., high-levels) is likely to follow more global features, such as major topic shifts planned by the author for possibly complex communicative goals (Stede 2011).

Researchers working on RST-style discourse parsing take these considerations into account by either (1) proposing hard constraints to construct discourse trees on distinct textual levels by using varying feature sets (Ji and Eisenstein 2014; Joty, Carenini, and Ng 2015) or (2) as done in recent work by Wang, Li, and Wang (2017) and Guz and Carenini (2020a), by proposing soft constraints, encoding sentence-paragraph breaks as input features. Furthermore, recent work on tree-level dependent RST-style discourse parsing...
mostly focuses on high-level tree structures (Jiang et al. 2021). Ideally, an RST-style discourse parser should achieve good performance on all levels shown in Figure 1. However, as argued in Kobayashi et al. (2020), the performance on high-level constituency tree structures is especially important (green arrow in Figure 1) when converting these constituency trees into dependency structures, as typically done for key downstream applications (Marcus 1999; 2000; Ji and Smith 2017; Shiv and Quirk 2019; Huber and Carenini 2020a; Xiao, Huber, and Carenini 2021). Unfortunately, training samples for these critical high-level discourse structures are extremely limited (see red arrow in Figure 1). Not only does the largest available human-annotated treebank in English just contains 385 documents, but for each document, vastly more training samples are available for structures within sentences than for structures connecting sentences and paragraphs, since the number of nodes in a binary tree decreases exponentially from the leaves towards the root.

To tackle the data sparsity issue for discourse parsing, previous work has proposed to leverage distant supervision from tasks with naturally annotated and abundantly available training data, such as sentiment analysis (Huber and Carenini 2020b) and summarization (Xiao, Huber, and Carenini 2021). While we believe that both these auxiliary tasks capture some structural information, they are plausibly even more aligned with other aspects of discourse, such as salience for summarization and discourse relations (e.g., evidence, concession) for sentiment. In contrast, this paper focuses exclusively on high-level tree structure generation, by exploiting signals from the auxiliary task of topic segmentation. Training on the naturally occurring and abundantly available topic segmentation annotations (sections/paragraphs), we believe that valuable information on major topic shifts, an effective signal indicative for high-level discourse trees, can be learned (Stede 2011).

More specifically, we train the top-performing neural topic segmentation model proposed in Xing et al. (2020) and use the trained model to generate discourse structures, which we evaluate on two popular discourse parsing treebanks. Based on the sequential output of the topic segmentation model, we explore the generation of discourse trees using (1) a greedy top-down algorithm and (2) an optimal bottom-up CKY dynamic programming approach (Jurafsky and Martin 2014), predicting RST-style tree structures on above-sentence level.

To better understand and properly compare the performance of our discourse tree generation algorithm with previously published models, as well as a set of baselines, we evaluate all approaches on three partially overlapping discourse tree subsets from: sentence-to-paragraph (S-P), paragraph-to-document (P-D) and sentence-to-document (S-D). In our evaluation, we find that distant supervision from topic segmentation achieves promising results on the high-level tree structure generation task, consistently outperforming previous methods with distant supervision on sentence-to-document level and in some cases reaching superior performance compared to supervised models.

2 Related Work

Rhetorical Structure Theory (RST) (Mann and Thompson 1988) is one of the main guiding theories for discourse parsing. As such, the RST framework proposes complete constituency discourse trees by first splitting a document into Elementary Discourse Units (EDUs) and subsequently aggregating them into larger (internal) sub-trees. The generated, projective tree structure (also called tree-span) is further augmented with a local importance score (called salience), indicating a sub-tree as either a “Nucleus” (of primary importance) or a “Satellite” (of supplementary importance). Furthermore, rhetorical relations (e.g., evaluation, attribution and contrast) are assigned between adjacent sub-trees to represent the type of connection. In this paper, we follow the RST paradigm, generating above-sentence, “plain” constituency discourse trees (without salience and relations) through distant supervision from topic segmentation.

Building on top of the RST discourse theory, RST-style Discourse Parsing aims to automatically infer discourse trees for new and unseen documents. With only a few small RST-style discourse treebanks available in English (e.g., RST-DT (Carlson, Okurowski, and Marcu 2002), Instruction-DT (Subba and Di Eugenio 2009) and GUM (Zeldes 2017)), most research in supervised discourse parsing has been focused on traditional machine learning approaches, such as DPLP (Ji and Eisenstein 2014), CODRA (Joty, Carenini, and Negri 2015) and the Two-Stage parser (Wang, Li, and Wang 2017). More recently, a small number of neural solutions (Yu, Zhang, and Fu 2018; Kobayashi et al. 2020; Guz and Carenini 2020a,b) have also been proposed. However, due to the limited size of available treebanks, supervised models have been shown to not perform well when transferred across domains (Huber and Carenini 2020b). As a result, a stream of unsupervised approaches, such as (Kobayashi et al. 2019; Nishida and Nakayama 2020; Huber and Carenini 2021) and distantly supervised (Huber and Carenini 2019, 2020b; Xiao, Huber, and Carenini 2021) discourse parsers have been proposed to address the data sparsity issue. Typically, distantly supervised approaches leverage supervision signals learned from tasks with abundant training data (e.g., sentiment analysis and extractive summarization) to infer discourse structures. Unsupervised approaches, on the other hand, mostly exploit the document hierarchy and separately aggregate tree structures on different levels based on recursively computed dissimilarity scores (Kobayashi et al. 2019), syntactic knowledge (Nishida and Nakayama 2020) or using an auto-encoder objective (Huber and Carenini 2021). In this paper, we propose another distantly supervised approach, computing discourse structures from the task of topic segmentation. We thereby draw inspiration from the findings in Jiang et al. (2021), showing that a pre-trained topic segmenter can benefit supervised discourse parsers, especially on high-levels. However, instead of augmenting a supervised discourse parser with information obtained from a topic segmentation model, we explore the potential of directly inferring high-level discourse structures from the output of topic segmentation, bypassing the data sparsity issue of supervised models through the use of distant supervision from topic segmentation.
The topic segmentation task is commonly interpreted as a sequence labeling problem. Formally, given a document $d$ in the form of a sequence of sentences $\{s_1, s_2, \ldots, s_k\}$, a topic segmentation model assigns a probability score to each sentence $s_i$ for $i \in [1, \ldots, k-1]$, generating a sequence of probabilities $P = \{p(s_1), p(s_2), \ldots, p(s_{k-1})\}$ with $p(s_i) \in [0, 1]$ indicating how likely sentence $s_i$ is the end of a segment.

Based on the set of probability scores $P$ and an additional threshold $\tau$, determined on a held-out development set, topic segmentation models make binary predictions, labeling sentences with a probability larger than $\tau$ as the “end of segment”, or “within segment” otherwise. Here, instead of converting the probabilities into discrete sentence boundary labels, we utilize the real-valued probability scores as our signal for distant supervision to infer RST-style discourse trees.

The high-level architecture of the neural topic segmentation model proposed in (Xing et al. 2020), intrasentence task (EDU-to-sentence), as individually tackled by (Lin et al. 2019) with great success.

### 3.1 Topic Segmentation Model

The topic segmentation task is commonly interpreted as a sequence labeling problem. Formally, given a document $d$ in the form of a sequence of sentences $\{s_1, s_2, \ldots, s_k\}$, a topic segmentation model assigns a probability score to each sentence $s_i$ for $i \in [1, \ldots, k-1]$, generating a sequence of probabilities $P = \{p(s_1), p(s_2), \ldots, p(s_{k-1})\}$ with $p(s_i) \in [0, 1]$ indicating how likely sentence $s_i$ is the end of a segment.

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### 3.2 Tree Generation

To convert the sequential outputs of the topic segmentation model into tree structures, we follow the intuition that the value at position $i$ in the output of the topic segmentation model, namely the likelihood of $s_i$ being the end of
trees for large/small discount factors, respectively. As a re-
performance and resulting in heavily balanced/imbalanced
practice inferior to the greedy approach, showing unstable
the CKY approach, despite being theoretically superior, is in
In preliminary experiments, we found that this adaption of
merging low-probability sentences early on, and de-
property of the subtree aggregation (see Figure 5 for an example).
In order to address this issue, additional hyper-parameters
sent the document at hand, due to the commutativity prop-
merging any two consecutive units
sequence. The intuitive way to fill the CKY matrix is to start
Carenini (2020b) and Xiao, Huber, and Carenini (2021).
used for distantly supervised discourse parsing in Huber and
mal CKY dynamic programming algorithm, as previously
monly used tree-aggregation technique to convert a real-
p
0
s
i
of the former unit
s
i
and assigning the new (merged) span the aggregation score
of the latter, here
p(s
i
+1).
Applying
this strategy using the dynamic programming approach,
each tree-candidate receives the same likelihood to repre-
sing this strategy using the dynamic programming approach,
p
k
A natural way to ex-
plote the output of the topic segmentation model is to create
a binary discourse tree by applying a greedy top-down algo-
where text spans (i.e., sub-trees) are determined recur-
sively by splitting the two sentences with the largest topical
distance. A small-scale example for this approach is shown
Figure 4. Here, we first search for the sentence
s
max =
argmax
s
∈D
P(s)
with the maximum probability in
P,
making it our segmentation point. We then segment the sequence
P into two sub-sequences:
P1 = \{p(s1), p(s2), ..., p(s
max)\} (left portion) and
P2 = \{p(s
max+1), p(s
max+2), ..., p(s
k)\} (right portion). Next, we mark
s
max as a previously selected segmentation point by setting
p(s
max) = 0.0. We then re-
cursively repeat this process for the two sub-sequences in
a divide-and-conquer style, until all sentence probabilities
are set to 0.0. Noticeably, the bottom-up greedy strategy is
equivalent to the top-down approach in our case.

Besides the greedy approach described above, a com-
monly used tree-aggregation technique to convert a real-
valued sequence into a binary tree structure is the opti-
mal CKY dynamic programming algorithm, as previously
used for distantly supervised discourse parsing in Huber and
Carenini (2020b) and Xiao, Huber, and Carenini (2021).
However, applying the CKY algorithm to the real-valued
topic-break probabilities is problematic, since the output
of any topic segmentation model only contains a single se-
quency. The intuitive way to fill the CKY matrix is to start
merging any two consecutive units
s
i
and
s
i+1 with the score
p(s
i
) of the former unit
s
i
and assigning the new (merged)
span the aggregation score of the latter, here
p(s
i+1).
Applying
this strategy using the dynamic programming approach,
each tree-candidate receives the same likelihood to repre-
sent the document at hand, due to the commutativity prop-
erty of the subtree aggregation (see Figure 5 for an example).
In order to address this issue, additional hyper-parameters
can be introduced, such as an attribute to quantify the ben-
et of merging low-probability sentences early on, and de-
laying likely topic-breaks. We explore this extended version
of the CKY approach using a set of fixed discount factors.
In preliminary experiments, we found that this adaption of
the CKY approach, despite being theoretically superior, is in
practice inferior to the greedy approach, showing unstable
performance and resulting in heavily balanced/imbalanced
trees for large/small discount factors, respectively. As a re-
sult, we leave the task of finding a more effective discount-
function to future work and focus on the superior greedy
top-down approach (as illustrated in Figure 4) in this paper.

### 4 Evaluation

#### 4.1 Datasets

We use three diverse datasets to train the topic segmenta-
tion models. We randomly sample a subset of Wikipedia ar-
ticles from the Wikipedia dump[1][3] strictly following the sam-
ping scheme in Koshorek et al. (2018) (from here on called
Wiki). Our Wiki corpus consists of 20,000 documents, con-
sistent in size with previously proposed topic segmentation
training corpora, such as the Wiki-Section dataset (Arnold
et al. 2019), originally used in the top-performing model by
Xing et al. (2020). In contrast to the popular Wiki-Section
dataset, which extracts a strictly domain-limited subset of
Wikipedia, exclusively covering webpages on cities and dis-
cases, we lift this topic restriction by uniformly sampling
from all of Wikipedia. We split our Wiki dataset into training,
validation and test sets using the default 80%, 10%, 10%-
data-split. We further train the topic segmentation model
on the RST-DT (Carlson, Okurowski, and Marcu 2002) and
GUM (Zeldes 2017) corpora. While RST-DT exclusively
contains news articles from the Wall Street Journal dataset,
the additional GUM treebank used in our experiments covers
a mixture of 12 different genres, including interviews, news
stories, academic writing and conversations. Since the two
discourse corpora do not have any explicit human-annotated
topic segment boundaries, we use paragraph breaks con-
tained in the textual representation of the data as topic-shift
indicators for the training of topic segmentation models.
Please note that we do not use any human-annotated dis-
course structures during the training procedure of the topic
segmentation model.

The key statistics of all three datasets are presented in Ta-
ble 3.

#### 4.2 Baselines

We compare our distantly supervised model against three
sets of baselines: (1) Simple, but oftentimes competitive
structural and random baselines, including Right-Branching,
4.3 Experimental Design

Given that our newly proposed RST-style tree generation strategy can only be applied on and above sentence level, we cannot directly compare our model with results provided in the literature, generally evaluating complete discourse trees from EDU-to-document level. In order to fairly compare against baselines and previously proposed models, and to provide a better understanding of how our proposal performs on different textual levels of the document (as depicted in Figures 1 and 2), we design a set of comparisons extending the regular evaluation technique for complete discourse trees. More specifically, instead of just computing the micro-average performance for a complete document course trees, we aim to investigate the structural discounting. All trees receive the same final score.

**Leaky Sub-Tree Aggregation:** Following the approach presented in Sporleder and Lascarides (2004), we replace leaky sentences with a single node \( n = (sent(e_i), sent(e_j)) \) and attach it depending on the largest intra-sentence subtree (e.g., if for a sentence containing 5 EDUs a sub-tree containing the first 3 EDUs is attached to the previous sentence and the sub-tree containing the last 2 EDUs is combined with the following sentence, we attach it to the previous sentence). In case of ties we attach the sentence to the right neighbour, as done in Sporleder and Lascarides (2004).

**Restricting Trees to the Upper-Bound:** Regarding the restriction of trees to selected upper-bounds (here exemplified on paragraph level), we remove any node \( n \) covering sentences \( s_i \) to \( s_j \) if \( para(s_i) \neq para(s_j) \) with \( para(\cdot) \) returning the paragraph assignment of a sentence.

### 4.4 Experiments and Results

We show the RST parseval discourse structure performance of each model on the sentence-to-paragraph (S-P), paragraph-to-document (P-D) and finally sentence-to-

| Dataset | Wiki | RST-DT | GUM |
|---------|------|--------|-----|
| # of Docs. | 20,000 | 385 | 150 |
| # of Para./Doc. | 31.1 | 9.99 | 12.3 |
| # of Sents./Doc. | 144.9 | 22.5 | 49.3 |
| # of EDUs/Doc. | × | 56.6 | 114.2 |
| # of EDUs/Para. | × | 5.67 | 9.29 |
| # of EDUs/Sent. | × | 2.51 | 2.32 |

Table 2: Statistics of the three training/testing datasets.

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*We additionally show the results for two more supervised parsers proposed in Kobayashi et al. (2020) and Jiang et al. (2021) in Appendix A.*

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### Table 3: Evaluation results using the RST Parseval micro-average precision measure on the RST-DT dataset. Subscripts indicate training dataset. TS = Topic Segmentation Model. * = Average performance over 10 runs. Best performance per sub-table underlined, best performance per column bold.

| Model                  | S-P  | P-D  | S-D  |
|------------------------|------|------|------|
|                        | Baselines |      |      |
| Random*                | 77.11| 63.90| 60.20|
| Right-Branching        | 73.57| 65.50| 59.46|
| Left-Branching         | 72.41| 64.07| 58.07|
| **Supervised RST-style Parsers** |          |      |      |
| Two-StageGUM (2017)   | 88.82| 65.63| 69.58|
| Two-StageRST-DT (2017)| 90.64| 68.09| 72.11|
| SpanBERTGUM (2020b)   | **90.75**| **76.03**| **77.19**|
| **Distantly Supervised RST-style Parsers** |          |      |      |
| Xiao, Huber, and Carenni (2021) | 74.23| 66.15| 59.10|
| Two-StageMEGA-DT (2020b) | 85.00| 65.50| 66.99|
| TS_{RST-DT}           | 84.34| 62.52| 65.96|
| TS_{Wiki}             | 83.43| 69.78| 68.13|
| TS_{Wiki,RST-DT}      | 83.84| 66.54| 65.84|
| Ablation – TS_{Wiki}  | 83.51| 68.61| 67.47|

### Table 4: Evaluation results using the RST Parseval micro-average precision measure on the GUM dataset. Subscripts indicate training dataset. TS = Topic Segmentation Model. * = Average performance over 10 runs. Best performance per sub-table underlined, best performance per column bold.

| Model                  | S-P  | P-D  | S-D  |
|------------------------|------|------|------|
|                        | Baselines |      |      |
| Random*                | 67.53| 60.96| 57.99|
| Right-Branching        | 64.15| 72.71| 59.39|
| Left-Branching         | 62.07| 54.35| 51.56|
| **Supervised RST-style Parsers** |          |      |      |
| Two-StageRST-DT (2017)| 74.20| 63.29| 63.65|
| Two-StageGUM (2017)   | **76.70**| **72.94**| **68.38**|

Our results are thereby subdivided into sub-tables according to the type of supervision used. The top sub-tables contain unsupervised baselines generating either random trees or completely right-/left-branching structures on the evaluated levels. The second set of results (in the center sub-tables) contain supervised discourse parsers, and the bottom sub-tables show distantly supervised models, including our results. To evaluate the ability of our proposal to generate domain-independent discourse structures, we compare the Topic Segmenter (TS) trained on in-domain data (TS_{RST-DT,GUM}[^1]) with the out-of-domain Wiki corpus (TS_{Wiki}) as well as a “fine-tuned” approach, first trained on the Wiki corpus, and subsequently fine-tuned on RST-DT or GUM (TS_{Wiki,RST-DT,GUM}[^1]). Finally, to further assess the role of the context modeling component (coherence module and restricted self-attention) in regards to the performance of topic segmentation as the distant supervised task for discourse tree generation, we ablate the context modeling component (red/green parts in Figure 4) as “Ablation – TS_{Wiki}” in the last row of both tables.

Not surprisingly, when evaluating discourse structures on the RST-DT dataset (Table 3), supervised models generally outperform unsupervised baselines and distantly supervised models. Assessing the bottom sub-table in more detail, it becomes clear that while the Two-Stage parser trained on MEGA-DT achieves the best performance on the sentence-to-document level, our model solely trained on the Wiki dataset performs best on the paragraph-to-document and sentence-to-document level, showing that (1) obtaining discourse structures from topic segmentation effectively supports high-level discourse parsing and (2) general out-of-domain training on large-scale data (TS_{Wiki}) performs better than models trained or fine-tuned on in-domain data (TS_{RST-DT} and TS_{Wiki,RST-DT} respectively). We believe that a possible explanation for the surprising under-performance of the in-domain training described above could originate from the limited size of the RST-DT dataset, as well as the mismatch between the “granularity” of segment information in Wikipedia and RST-DT (see Table 2), where the average number of sentences per segment is about twice as large in Wikipedia than RST-DT. Plausibly, the larger segments in Wikipedia better support higher-level discourse structures (which cover larger text spans), leading to superior performance, with the RST-DT fine-tuning step (at finer granularity) introducing the mismatch, and therefore not delivering the expected benefits.

Our evaluation results on the GUM dataset (Table 4) show similar trends to the evaluation on RST-DT. Our in-domain trained and further fine-tuned models in the bottom sub-table do not achieve improved performances compared to the out-of-domain TS_{Wiki} model. We believe a possible explanation for this phenomenon is the mix of domains within the small GUM training portion, resulting in the fine-tuning step mixing noisy signals from different genres, hence not providing consistent improvements over Wikipedia. Interestingly however, there are some observations which differ from RST-DT: (1) Unlike for RST-DT, our distantly supervised model trained on Wiki even outperforms supervised approaches on sentence-to-document level. (2) Right-branching trees out-

[^1]: We present original parseval scores, as recommended in Morey, Müller, and Asher (2017) in Appendix A.

Please note that even though we use the RST-DT/GUM datasets, we do not use any discourse tree annotation.
| Genre            | RB  | 2S\textsubscript{GUM} | 2S\textsubscript{RST-DT} | TS\textsubscript{Wiki} | TS\textsubscript{GUM} |
|------------------|-----|------------------------|---------------------------|------------------------|------------------------|
| Travel guides    | 78.1| 75.0                   | 65.6                      | 53.1                   | 68.8                   |
| Biographies      | 75.0| 78.6                   | 60.7                      | 78.6                   | 71.4                   |
| Fiction          | 80.6| 80.6                   | 61.1                      | 61.1                   | 61.1                   |
| How-to guides    | 69.4| 64.3                   | 59.2                      | 66.3                   | 75.5                   |
| Academic writing | 70.4| 81.5                   | 74.1                      | 70.4                   | 63.0                   |
| News stories     | 57.4| 57.4                   | 61.8                      | 63.2                   | 69.1                   |
| Political speeches| 80.0| 85.0                   | 70.0                      | 60.0                   | 55.0                   |
| Textbooks        | 78.6| 71.4                   | 64.3                      | 57.1                   | 71.4                   |
| Interviews       | 78.8| 83.3                   | 66.7                      | 60.6                   | 60.6                   |

Table 5: RST Parseval micro-average precision on paragraph-to-document level for genres in the GUM corpus. Sample(s) in “Vlog” & “Conversation” only contain a single paragraph and are therefore omitted. RB=Right-Branching, 2S=Two-Stage parser, TS=Topic Segmentation model.

Figure 6: Positive example (wsj.1346) with 100% structural overlap between prediction and RST-DT gold-label annotation. Gold paragraphs $p_n$ are indicated by solid lines. Leaves are sentences.

Figure 7: Random example (wsj.1380) with 80.77% structural overlap between prediction (top) and RST-DT gold-label annotation (bottom). Gold paragraphs $p_n$ are indicated by solid lines. Leaves are sentences.

perform random trees, which hasn’t been the case on the RST-DT dataset and (3) the paragraph-to-document (P-D) level differs from previous results, with the right-branching baseline reaching a performance close to the best supervised model (Two-Stage\textsubscript{GUM}), outperforming the out-of-domain supervised model (Two-Stage\textsubscript{RST-DT}) and all distantly supervised approaches.

Regarding the ablation studies, our results shown in the last row of Tables 3 and 4 imply that the context modeling component, shown to boost the topic segmentation performance, can also consistently benefit the high-level discourse structure inference on S-D level.

We refer readers to Appendix A for results on additional evaluation levels (e.g., EDU-to-sentence and EDU-to-paragraph) using the RST and original parseval scores.

To further investigate the performance on paragraph-to-document level for the GUM corpus, we show a comparison by genre for the surprisingly high performing right-branching baseline, the two supervised models and our methods based on Wiki and GUM in Table 5. Right-branching trees thereby achieve the best performance in 3 out of the 9 genres, including textbooks and fiction. Supervised methods perform best on 5 out of the 9 genres, including highly structured domains such as academic writing and interviews. Our distantly supervised model trained on Wikipedia reaches the best performance on biographies and the topic segmentation model trained on GUM achieves the highest score on how-to guides and news articles. Furthermore, as expected, the supervised parser trained on RST-DT (i.e., the news domain) performs well on the news genre. Overall, while these mixed results appear to align well with our intuition on the prevalent structures in certain genres, further research is required to better understand the relationship between modelling decisions and their impact on different discourse structures across genres.

To complement our quantitative evaluation, we show a set of predicted trees and their respective gold-label structures for well captured above-sentence discourse (Figure 6), randomly selected documents (Figure 7) and poorly captured samples (Figure 8). Similar results for the GUM corpus are shown in Figures 9, 10 and 11 in Appendix B.

Overall, inspecting a large number of tree-structures along with their gold-labels, we recognize that the generated trees are slightly more balanced than the respective gold-label trees (see for example Figures 7 and 8), however generally represent non-trivial structures, oftentimes well-aligned with major topic shifts and high-level discourse.

5 Conclusions and Future Work

In this paper, we show that topic segmentation can provide useful signals for high-level discourse constituency tree structure generation. Comparing multiple aggregation approaches, our proposal using a greedy top-down algorithm performs well when applied on two popular gold-standard discourse treebanks, namely RST-DT and GUM. We provide a detailed evaluation based on textual levels in documents, giving insights into the strength and weaknesses of simple baselines, previously proposed models and our new, distantly supervised approach using topic segmentation, on sentence, paragraph and document level. We show addi-
Figure 8: Negative example (wsj_1365) with 55.56% structural overlap between prediction (top) and RST-DT gold-label annotation (bottom). Gold paragraphs $p_n$ are indicated by solid lines. Leaves are sentences.

tional insights into our modelling approach through an ablation study, per-genre evaluations and qualitative tree generation samples.

For the future, in the short term we plan to investigate alternative non-greedy tree aggregation strategies, such as variations of the CKY approach mentioned in section 3.2. Next, we want to explore if the synergy between discourse parsing and topic segmentation is bidirectional, incorporating discourse signals to improve topic segmentation models. Finally, inspired by the approach described in [Kobayashi et al. (2019)], we also plan to use dense representations of neural topic segmentation models to infer discourse structures with nuclearity and relation labels, to obtain more complete trees by solely exploiting distant supervision from topic segmentation.

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A Complete Quantitative Results

We show the complete quantitative results, including the previously shown Sentence-to-Paragraph (S-P), Paragraph-to-Document (P-D) and Sentence-to-Document (S-D) performance, as well as the additional EDU-to-Sentence (E-S), EDU-to-Paragraph (E-P), EDU-to-Document (E-D) and EDU-to-Sentence-to-Document (E-S-D) sub-tree results here. Tables 6 and 7 contain the RST parseval scores on the RST-DT and GUM corpus, respectively. Table 8 contains the full results of the original parseval score applied to RST-DT and Table 9 shows the original parseval performance on GUM. Besides the additional performance evaluations also covering low-level structures for the baseline models (E-S, E-P, E-D and E-S-D), we show an additional model, combining the out-of-the-box discourse segmenter by Wang, Li, and Yang (2018) with our above-sentence tree structures generated from topic-segmentation in the last row of Tables 6, 7, 8 and 9 (Combined – TSWiki/Disc-Seg). Since we combine strictly intra-sentence structures from the discourse segmenter with strictly above-sentence trees, this approach does not support leaky EDUs, and hence constitutes E-S-D structures (as compared to non sentence limited E-D trees).

| Model                | E-S | S-P | P-D | E-P | S-D | E-D | E-S-D |
|----------------------|-----|-----|-----|-----|-----|-----|-------|
| **Baselines**        |     |     |     |     |     |     |       |
| Random*              | 70.08 | 77.11 | 63.90 | 64.05 | 60.20 | 58.03 | 70.10 |
| Right-Branching      | 64.12 | 73.57 | 65.50 | 58.41 | 59.46 | 54.64 | 74.37 |
| Left-Branching       | 63.85 | 72.41 | 64.07 | 57.73 | 58.07 | 53.73 | 70.58 |

| **Supervised RST-style Parsers** |
|----------------------------------|
| Top-Down RST-DT (2020)           | ×   | ×   | ×   | ×   | 86.10 | 86.40 |
| Two-Stage GUM (2017)             | 92.57 | 88.82 | 65.63 | 88.62 | 69.58 | 81.24 | ×     |
| Two-Stage RST-DT (2017)          | 94.48 | 90.64 | 68.09 | 91.06 | 72.11 | 83.90 | ×     |
| SpanBERT RST-DT (2020a)          | **96.27** | **90.75** | **76.03** | **92.87** | **77.19** | **87.69** | ×     |

| **Distantly Supervised RST-style Parsers** |
|---------------------------------------------|
| Xiao, Huber, and Carenini (2021) CNN/DM     | 85.95 | 74.23 | 66.15 | 78.19 | 59.10 | 60.68 | 75.13 |
| Two-Stage MEGA-DT (2020b)                  | 89.57 | 85.00 | 65.50 | 84.73 | 66.99 | 77.90 | ×     |
| TS RST-DT                                   | ×   | 84.34 | 62.52 | ×   | 65.96 | ×   | ×     |
| TSWiki                                      | ×   | 83.43 | 69.78 | ×   | 68.13 | ×   | ×     |
| TSWiki + RST-DT                             | ×   | 83.84 | 66.54 | ×   | 65.84 | ×   | ×     |
| Ablation – TSWiki                           | ×   | 83.51 | 68.61 | ×   | 67.47 | ×   | ×     |
| Combined – TSWiki/Disc-Seg                  | 87.10 | 83.43 | 69.78 | 81.67 | 68.13 | ×   | **75.56** |

Table 6: Evaluation results using the RST Parseval micro-average precision measure on the RST-DT dataset. Subscripts indicate training dataset. TS=Topic Segmentation Model. Disc-Seg=Discourse Segmentation Model by Wang, Li, and Yang (2018). ×=Not feasible combination. *=Average performance over 10 runs. Best performance per sub-table underlined, best performance per column bold
| Model | E-S | S-P | P-D | E-P | S-D | E-D | E-S-D |
|-------|-----|-----|-----|-----|-----|-----|-------|
| **Baselines** |     |     |     |     |     |     |       |
| Random* | 72.16 | 67.53 | 60.96 | 61.60 | 57.99 | 57.24 | 69.93 |
| Right-Branching | 66.30 | 64.15 | 72.71 | 56.23 | 59.39 | 54.71 | 71.58 |
| Left-Branching | 65.96 | 62.07 | 54.35 | 55.08 | 51.56 | 50.77 | 64.57 |

| Supervised RST-style Parsers |     |     |     |     |     |     |       |
| Two-Stage_{RST-DT (2017)} | **93.51** | 74.20 | 63.29 | 82.74 | 63.65 | 77.16 |     |
| Two-Stage_{GUM (2017)} | 93.25 | 76.70 | **72.94** | **83.49** | **68.38** | **79.04** |     |

| Distantly Supervised RST-style Parsers |     |     |     |     |     |     |       |
| Xiao, Huber, and Carenini (2021)_{CNN-DM} | 88.09 | 67.89 | 57.80 | 76.52 | 53.82 | 59.28 | 72.39 |
| Two-Stage_{MEGA-DT (2020b)} | 88.78 | 73.37 | **69.88** | 78.35 | 64.69 | 73.89 |     |
| TS\_GUM | × | 72.54 | 67.60 | × | 62.79 | × | × |
| TS\_Wiki | × | **76.98** | 63.53 | × | 65.84 | × | × |
| TS\_Wiki\_GUM | × | 74.48 | 67.29 | × | 64.69 | × | × |
| Ablation – TS\_Wiki | × | 75.94 | 64.71 | × | 65.38 | × | × |
| Combined – TS\_Wiki\_Disc-Seg | 88.58 | 76.98 | 63.53 | 79.30 | 65.84 | × | **73.94** |

Table 7: Evaluation results using the RST Parseval micro-average precision measure on the GUM dataset. Subscripts indicate training dataset. TS=Topic Segmentation Model. Disc-Seg=Discourse Segmentation Model by Wang, Li, and Yang (2018). ×=Not feasible combination. *=Average performance over 10 runs. Best performance per sub-table underlined, best performance per column bold

| Model | E-S | S-P | P-D | E-P | S-D | E-D | E-S-D |
|-------|-----|-----|-----|-----|-----|-----|-------|
| **Baselines** |     |     |     |     |     |     |       |
| Random* | 19.35 | 22.55 | 30.61 | 17.13 | 21.83 | 16.06 | 41.07 |
| Right-Branching | 3.25 | 7.27 | 31.62 | 4.12 | 19.21 | 9.27 | 48.74 |
| Left-Branching | 2.53 | 3.20 | 28.79 | 2.56 | 16.45 | 7.45 | 41.16 |

| Supervised RST-style Parsers |     |     |     |     |     |     |       |
| MDParse – TS\_RST-DT (2021) | × | × | 40.52 | × | × | × | × |
| Two-Stage_{GUM (2017)} | 79.97 | 60.76 | 31.88 | 73.78 | 39.38 | 62.48 | × |
| Two-Stage_{RST-DT (2017)} | 85.10 | 67.44 | 36.76 | 79.40 | 44.54 | 70.97 | × |
| SpanBERT\_RST-DT (2020a) | **90.16** | **68.69** | **52.75** | **83.83** | **54.37** | **75.39** | × |

| Distantly Supervised RST-style Parsers |     |     |     |     |     |     |       |
| Xiao, Huber, and Carenini (2021)_{CNN-DM} | 62.11 | 9.59 | 32.09 | 49.72 | 18.49 | 21.36 | 49.21 |
| Two-Stage_{MEGA-DT (2020b)} | 71.87 | 47.38 | 31.62 | 64.81 | 34.21 | 55.81 | × |
| TS\_RST-DT | × | 45.06 | 28.02 | × | 32.17 | × | × |
| TS\_Wiki | × | 41.86 | 41.90 | × | 36.49 | × | × |
| TS\_Wiki\_RST-DT | × | 43.31 | 34.96 | × | 31.93 | × | × |
| Ablation – TS\_Wiki | × | 42.15 | 39.07 | × | 35.17 | × | × |
| Combined – TS\_Wiki\_Disc-Seg | 65.22 | 41.86 | 41.90 | 57.74 | 36.49 | × | **50.95** |

Table 8: Evaluation results using the original Parseval micro-average precision measure on the RST-DT dataset. Subscripts indicate training dataset. TS=Topic Segmentation Model. Disc-Seg=Discourse Segmentation Model by Wang, Li, and Yang (2018). ×=Not feasible combination. *=Average performance over 10 runs. Best performance per sub-table underlined, best performance per column bold
| Model                          | E-S | S-P | P-D | E-P | S-D | E-D | E-S-D |
|-------------------------------|-----|-----|-----|-----|-----|-----|-------|
| **Baselines**                 |     |     |     |     |     |     |       |
| Random*                       | 18.45 | 17.83 | 25.46 | 15.25 | 16.71 | 14.49 | 43.11 |
| Right-Branching               | 1.28  | 7.35  | 46.30 | 3.39  | 18.78 | 9.42  | 43.15 |
| Left-Branching                | 0.30  | 1.97  | 10.19 | 0.86  | 3.11  | 1.54  | 29.15 |
| **Supervised RST-style Parsers** |     |     |     |     |     |     |       |
| Two-Stage_{RST-DT} (2017)     | **81.00** | 33.69 | 27.78 | 61.90 | 27.53 | 54.33 | ×     |
| Two-Stage_{GUM} (2017)        | 80.22 | 39.78 | **46.76** | **63.56** | **36.75** | **58.08** | ×     |
| **Distantly Supervised RST-style Parsers** |     |     |     |     |     |     |       |
| Xiao, Huber, and Carenini (2021)_{CNN-DM} | 65.72 | 7.60  | 16.75 | 46.69 | 7.64  | 18.56 | 45.97 |
| Two-Stage_{MEGA-DT} (2020b)   | 67.13 | 31.36 | 40.74 | 52.22 | 29.49 | 47.79 | ×     |
| TS_{GUM}                      | ×    | 29.03 | 37.50 | ×    | 25.58 | ×    | ×     |
| TS_{Wiki}                     | ×    | **40.50** | 31.02 | ×    | 31.68 | ×    | ×     |
| TS_{Wiki} + GUM               | ×    | 34.05 | 37.04 | ×    | 29.38 | ×    | ×     |
| Ablation − TS_{Wiki}          | ×    | 37.81 | 33.33 | ×    | 30.76 | ×    | ×     |
| Combined − TS_{Wiki}/Disc-Seg | 66.54 | 40.50 | 31.02 | 54.32 | 31.68 | ×    | **47.81** |

Table 9: Evaluation results using the **original Parseval** micro-average precision measure on the GUM dataset. Subscripts indicate training dataset. TS=Topic Segmentation Model. Disc-Seg=Discourse Segmentation Model by Wang, Li, and Yang (2018). ×=Not feasible combination. *=Average performance over 10 runs. Best performance per sub-table underlined, best performance per column **bold**
B Qualitative Analysis on GUM

Figure 9: Positive example (GUM_bio_jespersen) with 76.92% structural overlap between prediction (left) and GUM gold-label annotation (right).

Figure 10: Random example (GUM_voyage_oakland) with 70.83% structural overlap between prediction (left) and GUM gold-label annotation (right).

Figure 11: Negative example (GUM_bio_dvorak) with 57.14% structural overlap between prediction (left) and GUM gold-label annotation (right).