The Role of Discourse Units in Near-Extractive Summarization

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Abstract

Although human-written summaries of documents tend to involve significant edits to the source text, most automated summarizers are extractive and select sentences verbatim. In this work we examine how elementary discourse units (EDUs) from Rhetorical Structure Theory can be used to extend extractive summarizers to produce a wider range of human-like summaries. Our analysis demonstrates that EDU segmentation is effective in preserving human-labeled summarization concepts within sentences and also aligns with near-extractive summaries constructed by news editors. Finally, we show that using EDUs as units of content selection instead of sentences leads to stronger summarization performance in near-extractive scenarios, especially under tight budgets.

1 Introduction

Document summarization has a wide variety of practical applications and is consequently a focus of much NLP research. When a human summarizes a document, they often edit its constituent sentences in order to succinctly capture the document’s meaning. For instance, Jing and McKeown (2000) observed that summary authors trimmed extraneous content, combined sentences, replaced phrases or clauses with more general or specific variants, etc. These abstractive summaries thus involve sentences which deviate from those of the source document in structure or content.

In contrast, automated approaches to summarization generally produce extractive summaries by selecting complete sentences from the source document (Nenkova and McKeown, 2011) in order to ensure that the output is grammatical. Extractive summarization techniques, which are widely used in practical applications, therefore address a substantially simpler problem than human summarization.

This leads to a natural question: can extractive summarization techniques be used to produce more human-like summaries? We hypothesize that automated methods can generate a wider range of summaries by extracting over sub-sentential units of meaning from the source documents rather than whole sentences. Specifically, in this paper we investigate whether elementary discourse units (EDUs) from Rhetorical Structure Theory (Mann and Thompson, 1988) comprise viable textual units for summarization. Our focus is on recovering salient summary content under ROUGE (Lin, 2004) while the composition of EDUs into fluent output sentences is left to future work.

We investigate this hypothesis in two complementary ways: by studying the compatibility of EDUs with human-labeled summarization units from pyramid evaluations (Nenkova et al., 2007) and by assessing their utility in reconstructing real-world document previews chosen by news editors in the New York Times corpus (Sandhaus, 2008). The contributions of this work include:

- A demonstration that EDU segmentation preserves human-identified conceptual units in the context of document summarization.
- New, large datasets proposed for research into extractive and compressive summarization of news articles.
- A study of the lexical omissions made by news editors in real-world compressive summarization.
- A comparative analysis of supervised single-document summarization over full sentences and over a range of budgets in extractive and near-extractive scenarios.
2 Background and related work

Discourse structure in summarization

Rhetorical Structure Theory (RST) (Mann and Thompson, 1988) represents the discourse in a document in the form of a tree (Figure 1). The leaf nodes of RST trees are elementary discourse units (EDUs) which are a segmentation of sentences into independent clauses, including dependencies such as clausal subjects and complements. The more central units to each RST relation are nuclei while the more peripheral are satellites.

Prior work in document compression (Daumé and Marcu, 2002) and single-document summarization (Marcu, 1999; Louis et al., 2010; Hirao et al., 2013; Kikuchi et al., 2014; Yoshida et al., 2014) has shown that the structure of discourse trees, especially the nuclearity of non-terminal discourse relations in the tree, is valuable for content selection in summarization.

The Penn Discourse Treebank (PDTB) (Prasad et al., 2008) on the other hand is theory-neutral and does not define a recursive structure for the entire document like RST. Discourse relations are lexically bound to explicit discourse connectives within a sentence or exist between adjacent sentences if there is no connective. Each relation is realized in two text arguments, which are similar to EDUs. However, unlike EDUs, PDTB relation arguments have flexibility in size, ordering and arrangement and do not form a complete segmentation of the text. They are therefore not easily interpretable as textual units that can be combined to form sentences and summaries.

In this paper, we focus on EDUs and explore their viability as basic units for summarization. We did not use PDTB-style arguments to make sure each part of a document belongs to a textual unit and that the units are strictly adjacent to each other. EDU segmentation, typically addressed as a tagging problem early in discourse parsing systems, has seen accuracy and speed improvements in recent years (Hernault et al., 2010; Joty et al., 2015). It is now practical to segment document sentences into EDUs at scale as a preprocessing step for automated summarization.

Textual units in summarization.

In extractive summarization, sentences are typically chosen as units to assemble output summaries because of their presumed grammaticality (Nenkova and McKeown, 2011). Finer-grained units such as n-grams are frequently used for quantifying content salience and redundancy prior to summarization over sentences (Filatova and Hatzivassiloglou, 2004; Thadani and McKeown, 2008; Gillick and Favre, 2009; Lin and Bilmes, 2011; Cao et al., 2015). In contrast, when the task at hand is more abstractive, the units are more fine-grained, e.g., n-grams and phrases in abstractive summarization (Kikuchi et al., 2014; Liu et al., 2015; Bing et al., 2015), n-grams and human-annotated concept units in summarization evaluation (Lin, 2004; Hovy et al., 2006). Recently, subject-verb-object triplets were used to automatically identify concept units (Yang et al., 2016) and in abstractive summarization (Li, 2015); however, this requires semantic processing while EDU segmentation is presently more accurate and scalable.

Here, we explore EDUs as a middle ground between fine-grained lexical units and full sentences. While EDUs have been used in prior work to directly assemble output summaries (Marcu, 1999; Hirao et al., 2013; Yoshida et al., 2014), the focus was on using discourse structure as features for sentence ranking, while our work is the first to examine the utility of EDUs themselves.

Datasets.

In this work, we address single-document summarization. Standard datasets for the task were created for the Document Understanding Conference (DUC) in 2001 and 2002. The datasets for each year were composed of about 600 documents accompanied by 100-word abstractive summaries. In addition, the RST Discourse Treebank (Carlson et al., 2003) contains abstractive summaries for 30 documents, which have been used for evaluation in RST-driven summarization (Hirao et al., 2013; Kikuchi et al., 2014; Yoshida et al., 2014).

In contrast, we propose the use of datasets de-
rived from the New York Times (NYT) corpus\(^1\) that are orders of magnitude larger than the DUC dataset, featuring thousands of article summaries with varying degrees of extractiveness. Although the summaries in this dataset typically contain fewer than 100 words and are sometimes intended to serve as a teaser for the article rather than a distillation of its content, they were nevertheless created by professional editors for a highly-trafficked news website. Prior work has also demonstrated the utility of this corpus for summarization (Hong et al., 2015; Nye and Nenkova, 2015). This dataset therefore enables the study of summarization in a realistic setting.

**Compressive summarization.** To explore the utility of EDUs in summarization, we examine near-extractive summaries in the NYT corpus which are drawn from sentences in the document but omit at least one word or phrase from them. This setting is also explored in the summarization literature for techniques which combine extractive sentence selection with sentence compression (Clarke and Lapata, 2007; Berg-Kirkpatrick et al., 2011; Woodsend and Lapata, 2012; Almeida and Martins, 2013; Kikuchi et al., 2014). These approaches are typically evaluated against abstractive summaries and have not been studied with a natural compressive dataset such as the ones proposed here. We do not address techniques to generate compressive summaries in this work but instead attempt to quantify how the omitted content in a summary relates to its EDU segmentation.

**3 EDUs as Concept Units in Summaries**

We first investigate whether EDUs from an RST parse of the document can serve as a middle ground between abstract units of information and the sentences in which they are realized. Specifically, given a dataset containing human-labeled concepts in each article, we examine their correspondence with the EDUs extracted automatically from the article in terms of both lexical coverage and content salience.

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\(^1\)Available from the LDC at [https://catalog.ldc.upenn.edu/LDC2008T19](https://catalog.ldc.upenn.edu/LDC2008T19)
Figure 4: Examples of sentences in which human-labeled concepts (indicated by connected lines) span EDUs (in square brackets).

Figure 5: Number of words in SCU contributors which remain uncovered by a single EDU in the DUC/TAC reference summary datasets.

3.2 Concept coverage

Figure 3 indicates the number of EDUs that overlap by one or more tokens with each SCU contributor in the data. Most concepts (62%) are covered by a single EDU. This is more pronounced for concepts which are realized in a contiguous text span (69%), while multi-part concepts are unsurprisingly more likely to overlap with two EDUs. On average, concepts overlap with 1.56 EDUs while EDUs overlap with 1.77 concepts, significantly fewer than the average number of concepts contained in whole sentences (2.18).

Because we consider an overlap of one token to be sufficient to associate an EDU with an SCU contributor, we also examine in Figure 5 the number of non-punctuation contributor words that would need to be deleted for each concept to be covered by a single EDU. The vast majority of SCU contributors are covered by a single EDU, while the remainder typically have 2–4 words uncovered. Fewer than 8% of concepts were observed to have more than 4 words outside their corresponding EDU.

In Figure 4 we show typical examples of sentences with concepts which cross EDU boundaries. A major source for breached boundaries lies within heads of clauses. For instance, the first example contains two verb phrases in separate EDUs which each mark a concept, but their shared head “American Bookseller Association” can be in only one EDU. Errors are also often caused by overly broad SCUs which contain too much content. In the second example, the second EDU holds a causal relation with the first EDU and is thus a satellite to the discourse relation, whereas the whole relation is combined into a single SCU contributor. These cases can potentially be resolved by taking into account the discourse relation and nuclearity status of the involved EDUs.

3.3 Salience via discourse structure

In addition to coverage of SCU contributors, we would like to see the extent to which EDUs are meaningful with respect to summarization concepts. One of the most intriguing aspects of EDUs is that they are not merely textual units but rather units in a discourse tree from which relative concept importance can be derived. In pyramid evaluations, the salience of an SCU is determined by the number of distinct contributors it has across all reference summaries for a topic, and thus each SCU in our dataset has an implicit weight indicating its importance. We therefore investigate the relationship between inter-document concept salience using these SCU weights and an intra-document counterpart from the EDUs in the discourse tree.

To calculate salience over EDUs, we use the scoring mechanism in Marcu (1999). Intuitively, each EDU which is a nucleus of a discourse relation (as opposed to a satellite) can be promoted one level up in the discourse tree. The score weights each EDU according to the depth that it can be promoted up to: the closer to the root, the more important the EDU is. For this analysis, we impute the discourse salience of a contributor by averaging the Marcu (1999) scores (normalized by tree depth) of the EDUs it overlaps with.

Table 1 shows the mean of these scores over all contributors with a particular SCU weight. In each group with weight \( w \), the average EDU-derived
### Table 1: Average salience scores of EDUs overlapping with SCU contributors, stratified by SCU weight.

| SCU weight | 1 | 2 | 3 | ≥4 |
|------------|---|---|---|----|
| Proportion of SCUs (%) | 54.3 | 21.6 | 13.0 | 11.2 |
| Mean Marcu (1999) score | 0.64 | 0.66 | 0.68 | 0.72 |

Differences between scores for each group are statistically significant under the Wilcoxon rank-sum test ($p < 0.05$).

The salience score is significantly higher ($p < 0.05$) compared to the group with weight $w - 1$. That is, the more important a SCU is across these documents, the more important its corresponding EDUs are within the discourse of each document. We infer that the human authors of these summaries make structural decisions to highlight important concepts, and that these choices are reflected in the derived discourse structure.

With a large fraction of concepts observed to be contained within EDUs, we find compelling evidence to support the notion of EDUs as operational units of summarization. Moreover, we find evidence that the RST discourse structure which typically accompanies EDU segmentation also provides a strong signal of salience, though further experimentation along these lines is left to future work. We now investigate the utility of EDUs in a practical news summarization task using a large dataset.

## 4 Near-extractive summarization

In order to investigate the viability of discourse units in a practical setting, we use the New York Times Annotated Corpus (Sandhaus, 2008) which contains over 1.8 million articles published between 1987 and 2007 as well as their metadata. We mine this corpus to recover near-extractive summaries of articles which reveal how human editors selectively omit information from article sentences in order to preview the article for potential readers. This presents a middle ground between purely extractive and fully abstractive summarization which is useful to study the role of sentential units in content selection.

### 4.1 Datasets

The NYT dataset contains editor-produced online lead paragraphs which accompany 284,980 articles featured prominently on the NYT homepage from 2001 onwards. They are explicitly intended for presentation to readers and usually consist of one or more complete sentences which serve as a brief summary or teaser for the full article.

We ensure that these online lead paragraphs—henceforth online summaries—are composed of complete sentences by filtering out cases which contain no verbs, omit sentence-terminating punctuation or are all-uppercase, respectively indicating summaries which are caption-like, truncated or merely topic/location descriptors. We also exclude articles with frequently repeated titles, first sentences and summaries which we observe to be template-like and thus not indicative of editorial input. Finally, we preprocess the remaining 244,267 summaries by stripping HTML artifacts and structured prefixes (e.g., bureau locations), normalizing Unicode symbols and fixing whitespace inserted within or deleted between tokens. We have released our data preparation code to facilitate future research on the NYT corpus.

Three mutually exclusive datasets are drawn from the processed document collection:

- **EX-SENT**: 38,921 fully extractive instances in which each summary sentence is drawn whole from the article when ignoring case, punctuation and whitespace.
- **NX-SPAN**: 15,646 near-extractive instances where one or more summary sentences form a contiguous span of tokens within an article sentence, and the remaining fit the definition above.
- **NX-SUBSEQ**: 25,381 near-extractive instances where one or more summary sentences form a non-contiguous token subsequence within an article sentence, and the remaining fit either of the definitions above.

The remaining 164,319 instances contain fully abstractive summaries with sentences that cannot be unambiguously mapped to those in the articles; these are not considered in the remainder of this section.

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2 Despite the name, these are typically not the same as the leading sentence or paragraph of the article.

3 Note that this differs from the abstracts used in prior summarization research (Yang and Nenkova, 2014; Hong et al., 2015; Nye and Nenkova, 2015). We observe that abstracts appear to serve more as high-level structured descriptions of articles (e.g., referring to type of the article and NYT sections, using present-tense and collapsed sentences) rather than narrative summaries intended for presentation to readers.

4 https://github.com/grimpil/nyt-summ

5 The NYT document IDs for these datasets are available at http://www.cs.columbia.edu/~kapil/datasets/docids_nytsumm.tgz
Now that their season is over, the New York Yankees are likely to shop for new players over the winter. They really should look for new fans.

The country’s appetite for real estate propelled sales of newly built homes to a record pace in April, adding to concerns that the housing market may be in overdrive.

Now that their season is over, the New York Yankees are likely to shop for new players over the winter, [and may even] [seek a new manager] [to take over from the estimable Joseph Paul Torre]. [What they really should look for are new fans.]

Table 2: Examples of reference summaries from NX-SPAN and NX-SUBSEQ alongside their source sentences from the article, segmented into EDUs. Tokens omitted by the summary are italicized.

| Dataset | Unit | # deleted | # added |
|---------|------|-----------|---------|
| NX-SPAN | Sent | 11.47 | 0.00 |
|         | EDU  | 1.24 | 0.39 |
| NX-SUBSEQ | Sent | 11.95 | 0.00 |
|          | EDU  | 1.94 | 0.77 |

Table 3: Average #tokens deleted and added from each type of unit in NX-SPAN and NX-SUBSEQ.
Comparison with lead. To validate this summarization framework, we first compare trained summaries to the gold standard model using features that are tailored to summarization units, such as discourse relation labels or discourse tree structure.

We adopt a supervised structured prediction approach to extractive single-document summarization. Summaries are produced through greedy search-based inference with features defined over units in the document as well as over units and partial summaries, resulting in a feature-based generalization of Carbonell and Goldstein (1998). In order to focus on the role of summarization units, we work with a simple standard model using features that are neutral to the benefits and/or drawbacks of either sentences or EDUs:

- Position of the unit
- Position of the unit in the paragraph
- Position of the paragraph containing the unit
- TF-IDF-weighted cosine similarity of the summary with the unit added and the document centroid;
- Whether the unit is adjacent to the previous unit added
- Whether the sentence containing the unit is adjacent to the sentence containing the previous unit added
- Position of the paragraph containing the unit
- TF-IDF-weighted cosine similarity of the summary with the unit added and the document centroid;
- Whether the sentence containing the unit is adjacent to the sentence containing the previous unit added
- Position of the paragraph containing the unit
- TF-IDF-weighted cosine similarity of the summary with the unit added and the document centroid;
- Whether the sentence containing the unit is adjacent to the sentence containing the previous unit added

Feature weights are estimated using the structured perceptron (Collins, 2002) with parameter averaging for generalization. As inference is carried out via search, we employ a max-violation update policy (Huang and Feyong, 2012) to improve convergence speed and performance.

Data and settings. We use the extractive and near-extractive subsets from the NYT corpus described in Section 4.1 to train and evaluate our summarizer. To aid replicability for benchmarking, we partition all datasets by date rather than random sampling. Articles published in 2006–2007 are assigned to a held-out test partition while articles prior to 2005 are used for training, leaving articles from 2005 for a development partition.

The mean and standard deviation of summary lengths (specifically the number of characters) from our three NYT datasets are: EX-SENT 194.0 ± 92.6, NX-SPAN 134.6 ± 31.3, NX-SUBSEQ 143.3 ± 27.9. Summarization budgets are chosen to cover this range and set to 100, 150, 200, 250 and 300 characters. The lower bound (100 characters) is approximately one standard deviation below the mean across all three datasets, while the upper bound (300 characters) is approximately one standard deviation above the mean for EX-SENT, which features the longest summaries.

Comparison with lead. To validate this summarization framework, we first compare trained sum-

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Table 4: ROUGE-1 of lead sentences vs. the supervised summarizer under a 200-char budget.

| Dataset   | EDU  | Sentence |
|-----------|------|----------|
| EX-SENT   | 0.65 | 0.55     |
| NX-SPAN   | 0.46 | 0.32     |
| NX-SUBSEQ | 0.54 | 0.37     |

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6We also experimented with beam search but did not observe improvements, as was also found in prior work (McDonald, 2007).

7For example, we do not use features related to nuclearity, discourse relation labels or discourse tree structure.

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Figure 6: Proportion of source sentences and EDUs with the number of tokens deleted and added to recover summaries from NX-SPAN and NX-SUBSEQ. Cases with zero tokens added/deleted are omitted.

Figure 7: Average number of deleted tokens per instance in NX-SPAN and NX-SUBSEQ.
We experimented with all other aforementioned budgets with consistent results.

Table 5: ROUGE results for EDU- and sentence-based summarization.

| Budget | ROUGE-1 EDU | ROUGE-1 Sent | ROUGE-2 EDU | ROUGE-2 Sent | ROUGE-4 EDU | ROUGE-4 Sent |
|--------|-------------|--------------|-------------|--------------|-------------|--------------|
| EX-SENT |             |              |             |              |             |              |
| 300    | 0.80        | 0.78         | 0.70        | 0.71         | 0.59        | 0.71         |
| 250    | 0.75        | 0.69         | 0.64        | 0.62         | 0.54        | 0.61         |
| 200    | 0.67        | 0.58         | 0.56        | 0.49         | 0.47        | 0.48         |
| 150    | 0.54        | 0.41         | 0.43        | 0.32         | 0.35        | 0.31         |
| 100    | 0.35        | 0.21         | 0.26        | 0.13         | 0.20        | 0.12         |
| NX-SPAN |             |              |             |              |             |              |
| 300    | 0.61        | 0.58         | 0.45        | 0.44         | 0.37        | 0.42         |
| 250    | 0.56        | 0.50         | 0.41        | 0.36         | 0.33        | 0.34         |
| 200    | 0.48        | 0.36         | 0.33        | 0.20         | 0.27        | 0.18         |
| 150    | 0.38        | 0.22         | 0.25        | 0.08         | 0.19        | 0.06         |
| 100    | 0.24        | 0.14         | 0.13        | 0.04         | 0.09        | 0.03         |
| NX-SUBSEQ |             |              |             |              |             |              |
| 300    | 0.70        | 0.69         | 0.53        | 0.55         | 0.38        | 0.46         |
| 250    | 0.66        | 0.59         | 0.49        | 0.44         | 0.35        | 0.37         |
| 200    | 0.56        | 0.40         | 0.40        | 0.24         | 0.28        | 0.20         |
| 150    | 0.43        | 0.22         | 0.28        | 0.08         | 0.19        | 0.05         |
| 100    | 0.29        | 0.14         | 0.17        | 0.04         | 0.11        | 0.02         |

Our results also highlight a need for future work.
Ref: Manager Willie Randolph did not see what the big deal was. All he did before last night’s game against San Diego at Shea Stadium was drop Mike Piazza in the batting order to sixth from fifth and promote David Wright to fifth from sixth. But the swap led to a barrage of questions from reporters.

EDU: [Manager Willie Randolph did not see what the big deal was.] [All] [he did before last night’s game against San Diego at Shea Stadium] [was drop Mike Piazza in the batting order to sixth from fifth]

Sent: Manager Willie Randolph did not see what the big deal was. But the swap led to a barrage of questions from reporters. Was Piazza being demoted permanently? How had Piazza and Wright handled the moves?

Ref: Big, cheap and somewhere in Manhattan. Those were the starting criteria for Kelli Grant, who was desperate to escape a long bus commute between Midtown and southern New Jersey.

EDU: [Big, cheap] [and somewhere in Manhattan.] [Those were the starting criteria for Kelli Grant.] [and for her boyfriend, James Darling.] [to be with her.]

Sent: Big, cheap and somewhere in Manhattan. At that early, uninformed stage, big meant two bedrooms, they hoped. Cheap meant up to $1,500 a month.

Ref: The plan, which rivals the scope of Battery Park City, would rezone a 175-block area of Greenpoint and Williamsburg.

EDU: [The plan.] [which rivals the ambition and scope of the creation of Battery Park City.] [would rezone a 175-block area of Greenpoint and Williamsburg, two neighborhoods]. [and led to intense pressure]

Sent: The plan, which is expected to be approved by the full City Council next week, imposes some novel requirements for developers seeking to build the housing.

Table 6: Examples of NYT reference and system-generated summaries using EDUs and sentences from (A) EX-SENT, (B) NX-SPAN, (C) NX-SUBSEQ. An “...” separates EDUs from different source sentences.

in composing EDUs to form fluent sentences. As suggested by the coverage analysis in Section 3.2, it is very likely that this can be accomplished robustly. For instance, Daumé and Marcu (2002) demonstrated that an EDU-based document compression system can improve over sentence extraction in both grammaticality and coherence.

7 Conclusion

In this work, we explore the potential of elementary discourse units (EDUs) from Rhetorical Structure Theory in extending extractive summarization techniques to produce a wider range of human-like summaries. We first demonstrate that EDU segmentation is effective in preserving concepts extracted from a document. We also analyze summaries in the New York Times corpus whose content is extracted from parts of their original sentences. When recovering the summaries using EDUs, the amount of extraneous information in the form of content words is dramatically reduced compared to their original sentences. Finally, we demonstrate that using EDUs as units of content selection instead of sentences leads to stronger summarization performance on these near-extractive datasets under standard evaluation measures, particularly when summarization budgets are tight.

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