

Computing and Exploiting Document Structure to Improve Unsupervised Extractive Summarization of Legal Case Decisions

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Abstract

Though many algorithms can be used to automatically summarize legal case decisions, most fail to incorporate domain knowledge about how important sentences in a legal decision relate to a representation of its document structure. For example, analysis of a legal case summarization dataset demonstrates that sentences serving different types of argumentative roles in the decision appear in different sections of the document. In this work, we propose an unsupervised graph-based ranking model that uses a reweighting algorithm to exploit properties of the document structure of legal case decisions. We also explore the impact of using different methods to compute the document structure. Results on the Canadian Legal Case Law dataset show that our proposed method outperforms several strong baselines.

1 Introduction

Single document summarization aims at rephrasing a long text into a shorter version while preserving the important information (Nenkova and McKeown, 2011). While recent years have witnessed a blooming of abstractive summarization models that can generate fluent and coherent new wordings (Rush et al., 2015; Zhang et al., 2020b; Lewis et al., 2020), abstractive summaries often contain hallucinated facts (Kryscinski et al., 2019). In contrast, extractive summarization models directly select sentences/phrases from the source document to form a summary. In certain domains such as the law or science (Bhattacharya et al., 2019; Dong et al., 2021), using exact wordings may be needed.

In this work, we focus on *extractive summarization of legal case decisions*. Different from texts in the news domain, case texts tend to be longer (e.g., in Canadian legal case decisions (Xu et al., 2021) there are on average 3.9k words, while standard news articles (Nallapati et al., 2016) range from 400 - 800 words) and also have more complicated

document structures (e.g., legal cases are likely to be split into sections while news articles are not). In contrast to scientific domains, which also have long and structured texts, large training sets of case decisions and reference summaries are generally not freely available given the restrictions of the legal field. A currently used case dataset has less than 30k training examples (Xu et al., 2021), which is ten times less than scientific datasets such as arXiv and PubMed (Cohan et al., 2018). Thus, for the legal domain, it is not surprising that *unsupervised* extractive summarization methods are of interest. Unfortunately, when researchers (Saravanan et al., 2006; Bhattacharya et al., 2019) have attempted to directly apply standard unsupervised models to legal data, they have obtained mediocre results.

However, most such attempts have failed to utilize the *document structure of legal texts*. In case law, important sentences about the issues versus the decisions of the court occur in different places in the document structure. In contrast, summarization algorithms typically flatten any structure during initial processing (i.e., they concatenate sentences from different sections/paragraphs of a document to form a sentence list), or select sentences using structural biases from other domains (e.g., the importance of leading sentences in news (Zheng and Lapata, 2019)). As shown in Figure 1, while LexRank correctly extracts the legal issue from the beginning of the source text, it incorrectly extracts several redundant sentences (i.e., [20], [21] and [22] which talk about similar content) as well as ignores a large part of the article (e.g., no sentences are extracted from the last section of the original case: *RECAPITULATION OF CALCULATION OF DAMAGES*). In contrast, the human summary focuses on sentences related to the argument of the legal decision (e.g., what are the issues, reasoning and conclusions of this court case?), which tend to be spread across the document structure.

Recently, the HipoRank model was proposed

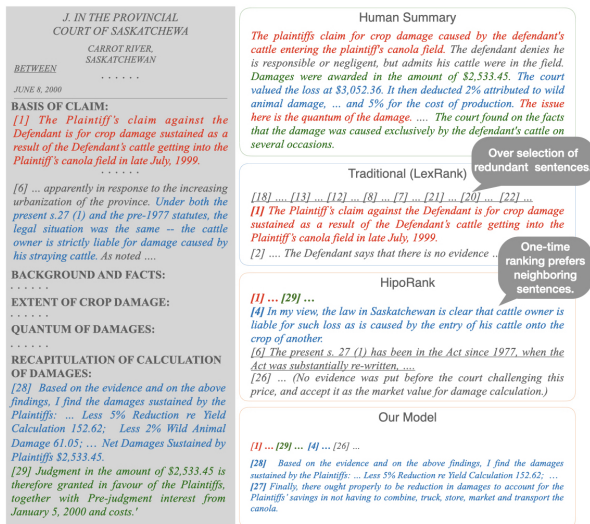


Figure 1: An example case law document-summary pair (ID: 3_2000canlii19612) and different summarization system outputs, where sentences are annotated with *argumentative* Issue, Reason, and Conclusion labels. Our method better extracts argumentative sentences from the source document by exploiting its structure.

to exploit discourse structure patterns during unsupervised extractive summarization (Dong et al., 2021). However, the model was designed for long scientific articles, and the experiments were based on data where the articles were already split into document sections. For case decisions, document structures are generally either missing or only implicitly conveyed by text formatting. For example, in Figure 1, document sections are conveyed by bolding in the source HTML file. Moreover, algorithms such as PACSUM and HipoRank compute sentence centrality just once and greedily select the top-k candidates as the extractive summary. Such a greedy selection algorithm fails to match the distribution of the argumentative sentences that ultimately appear in human case law summaries.

To address these limitations, we investigate the utility of different methods for automatically segmenting the sentences of legal case decisions into the sections of a document structure. We posit that incorporating *better views of document structure* could bring improvements in summarization quality when discourse-aware methods such as HipoRank are applied to legal case decisions. We also propose a novel *reweighting algorithm* to improve how HipoRank selects sentences when creating extractive summaries of legal decisions. The algorithm takes the history of already selected summary sentences into account, and gradually updates

the importance score of a sentence. We posit that reweighting will decrease the selection of redundant sentences as well as increase the selection of argumentative sentences from less-represented document segments (e.g., in the middle).

We evaluate our proposed method¹ for summarizing legal decisions using an annotated Canadian case summarization dataset (CanLII) (Xu et al., 2021). Based on the belief that *argumentative sentences* will capture the important sentences to summarize in a legal decision (Xu et al., 2021; Elaraby and Litman, 2022), a portion of the CanLII dataset comes with gold-standard sentence-level labels identifying which sentences are related to the issue/reasoning/conclusion of the court’s decision in both source and summary documents. We use these labels to additionally propose a metric that can better evaluate the quality of the generated summary from a legal expert’s perspective. Empirical results show that our method improves performance over previous unsupervised models (Zheng and Lapata, 2019; Dong et al., 2021; Erkan and Radev, 2004) in automatic evaluation.

2 Related Work

Supervised Extractive Summarization Using Discourse Information Graph-based methods have been exploited for extractive summarization tasks to better model the inter-sentence relations based on document structure. Xu et al. (2020) applied a GCN layer to aggregate information from the document’s discourse graph based on RST trees and dependencies. More recently, HiStruct+ (Ruan et al., 2022) and HEGEL (Zhang et al., 2020a) started to incorporate the hierarchical structure and topic structure of scientific articles into supervised model training, respectively. However, HiStruct+ relied on the relatively fixed and explicit document structure of scientific articles², while HEGEL relied on a large training set to identify the topic distributions. *Our work uses an unsupervised extractive summarization approach in a lower-resource setting, as well as studies the effects of computing different types of document structures.* We leave the exploration of the aforementioned supervised approaches on legal domain texts for future work.

¹Our code is available at <https://github.com/cs329yangzhong/DocumentStructureLegalSum>

²Section titles following a shared pattern (introduction, method ... and conclusion) are encoded to provide structural information. However, in our dataset, sectioning is often missing or not meaningful (e.g., titles such as "section 1").

Unsupervised Extractive Summarization Traditional extractive summarization methods are mostly unsupervised (Radev et al., 2000; Yin and Pei, 2015; Hirao et al., 2013), where a large portion apply the graph-based algorithms (Salton et al., 1997; Steinberger and Jezek, 2004; Erkan and Radev, 2004) or are based on term frequencies such as n-gram overlaps (Nenkova et al., 2005) to rank the sentences’ importance. More recently, pretrained transformer-based models (Devlin et al., 2019; Lewis et al., 2020; Zhang et al., 2020b) have provided better sentence representations. For instance, Zheng and Lapata (2019) built directed unsupervised graph-based models on news articles using BERT-based sentence representations and achieved comparable performance to supervised models on multiple benchmarks. Dong et al. (2021) augmented the document graph of Zheng and Lapata (2019) with sentence position and section hierarchy to reflect the document structure of scientific articles. *Different from these two works which are based on assumptions of news and scientific article structures, our method uses reweighting to better utilize the document structure of legal cases.*

Extractive Summarization of Legal Texts Despite the success of supervised neural network models in news and scientific article summarization (Zhang et al., 2020b; Lewis et al., 2020; Zaheer et al., 2020), they face challenges in legal document summarization given the longer texts, distinct document structure, and limited training data (Bhattacharya et al., 2019). Instead, prior work has tackled legal extractive summarization by applying domain independent unsupervised algorithms (Luhn, 1958; Erkan and Radev, 2004; Saravanan et al., 2006), or designing domain specific supervised approaches (Saravanan et al., 2006; Polsley et al., 2016; Zhong et al., 2019). One recent work (Bhattacharya et al., 2021) frames the task as Integer Linear Programming and demonstrates the importance of in-domain structure and legal knowledge. In another line of research, Xu et al. (2021) propose a sentence classification task with the hope of exploiting the court decision’s *argument structure* by making explicit its issues, conclusions, and reasons (i.e., argument triples). *Our work is unsupervised and implicitly reveals the relations between argument triples to generate better summaries.*

Case length (avg. # words)	3,971
Summary length (avg. # words)	266
Training set (# case/summary pairs)	27,241
Testing set (# case/summary pairs)	1,049

Table 1: Dataset statistics of CanLII.

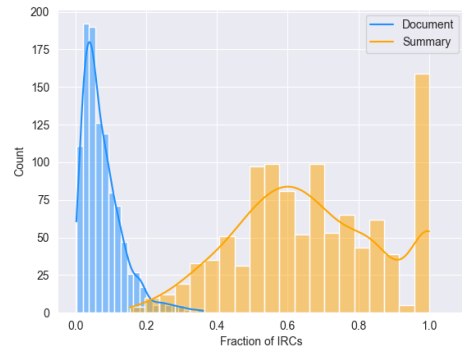


Figure 2: Fraction of sentences annotated as argumentative (using the IRC scheme) in the case documents versus in the summaries of the CanLII test set. Though only a small fraction of sentences in the original document are annotated as IRCs, IRCs are a large fraction of the human-written summaries.

3 Case Decision Summarization Dataset

Recent work has introduced a number of legal document summarization or salient information identification tasks with associated datasets, e.g., for bill summarization (Kornilova and Eidelman, 2019) and for case sentence argumentative classification (Xu et al., 2021) and rhetorical role prediction (Malik et al., 2022). Similarly to Xu et al. (2021), we use the **CanLII** (Canadian Legal Information Institute) dataset of legal case decisions and summaries³. Full corpus statistics are provided in Table 1, while an example case/summary pair from the test set is provided in Figure 6 in Appendix D.

Xu et al. (2021) only used a small portion of this dataset for their work in argumentative classification. Conjecturing that explicitly identifying the decision’s argumentative components would be crucial in case summarization, they annotated 1,049 case and human-written summary pairs curated from the full dataset. In particular, they recruited legal experts to annotate the document on the sentence level, adopting an **IRC scheme** (see Figure 6 in Appendix D) which classifies individual sen-

³The data was obtained through an agreement with the Canadian Legal Information Institute (CanLII) (<https://www.canlii.org/en/>).

tences into one of four categories: **Issue** (legal question addressed in the case), **Conclusion** (court’s decisions for the corresponding issue), **Reason** (text snippets explaining why the court made such conclusion) and **Non_IRC** (none of the above). The distributions of the IRC labels in the cases and summaries are shown in Figure 2 and illustrate that argumentative sentences do indeed play an important role in human summaries. We utilized the unannotated 27,241 pairs to train a supervised model baseline and the 1049 annotated pairs as our test set. While none of our summarization methods use the IRC annotations, they are used during testing as the basis of a domain-specific evaluation metric.

4 Method and Models

We propose a reweighting model that employs a graph-based ranking algorithm to exploit the structures encoded in long legal case decisions.

4.1 Discourse-Aware Backbone Model

The HipoRank (Hierarchical and Positional Ranking) model recently developed by Dong et al. (2021) constructs a directed graph for document representation using document section and sentence hierarchies. HipoRank computes the centrality score of each sentence as

$$c(s_i^I) = \mu_1 c_{inter}(s_i^I) + c_{intra}(s_i^I) \quad (1)$$

where s_i^I refers to the i -th sentence in I -th section. μ_1 is a tunable hyper-parameter, $c_{inter}(s_i^I)$ computes the sentence’s similarity to other section representations and $c_{intra}(s_i^I)$ computes the average similarity of the current sentence with all others in the same section. HipoRank then selects the top-K ranked sentences as the summary. More details of the algorithm are provided in Appendix A. Directly applying HipoRank to our data yielded multiple challenges (e.g., redundant neighboring sentences (recall Figure 1) as well as too many sentences from the ends of the article were selected).

4.2 Multiple Views of Document Structure

Before creating a HipoRank document graph, the document must be split into sections and sentences. The scientific datasets previously used with HipoRank were already split (Dong et al., 2021). We investigate *the summarization impact of using different approaches to automatically compute linear sections of the document structure*. Figure 3 shows different structures for the same case.

Original Document Structure This approach extracts the structure by processing the *HTML files*. We use a heuristic to mark the section names with an italic and bold format as the boundaries and segment the documents into multiple continuous sections. It is worth noting that 297 of the 1049 test case documents do not come with explicit section splits, thus we treat them as whole text spans⁴.

Topic Segment View Meanwhile, we also explore using a traditional, *domain-independent linear text segmentation* algorithm. We use C99 (Choi, 2000) but with advanced sentence representation from SBERT (Reimers and Gurevych, 2019) to group neighboring sentences into topic blocks.

Thematic Stage View Early studies found that legal documents tend to have well-defined, *domain-dependent thematic structures* (Farzindar and Lapalme, 2004) or rhetorical roles (Saravanan et al., 2008). Following work that extracts stage views in conversations (introductions → problem exploration → problem solving → wrap up) (Chen and Yang, 2020), we extract thematic stages through a Hidden Markov Model (HMM). A fixed order of stages is imposed and only consecutive transitions are allowed between neighboring stages. We again represent the sentences using SBERT (Reimers and Gurevych, 2019) and set the number of stages as 5, including the starting Decision Data, Introduction, Context, Judicial Analysis, and Conclusion, as introduced by Farzindar and Lapalme (2004).

CanLII Header Removing Preliminary analysis demonstrated that the raw CanLII documents fail to distinguish the less important headers at the beginning (i.e., the descriptive text before the main content, for example, the content above the grey splitting line and BASIS OF CLAIM in Figure 1). Generated summaries also tend to cover a large portion of such information. We thus propose a legal case decision preprocessing procedure following certain heuristics⁵ to remove those headers, and demonstrate the improved summarization quality (for all views of document structure) in Section 6.

4.3 Reweighting the Centrality Score

The HipoRank document graph will not change once built, and the important sentences are greedily

⁴The Original Structure method processed HTML source files and split sentences using a legal sentence splitter (https://github.com/jsavelka/luima_sbd). The Topic and Thematic views used non-HTML data preprocessed by Xu et al. (2021), but used the same sentence splitter.

⁵See Appendix D.3 for details.

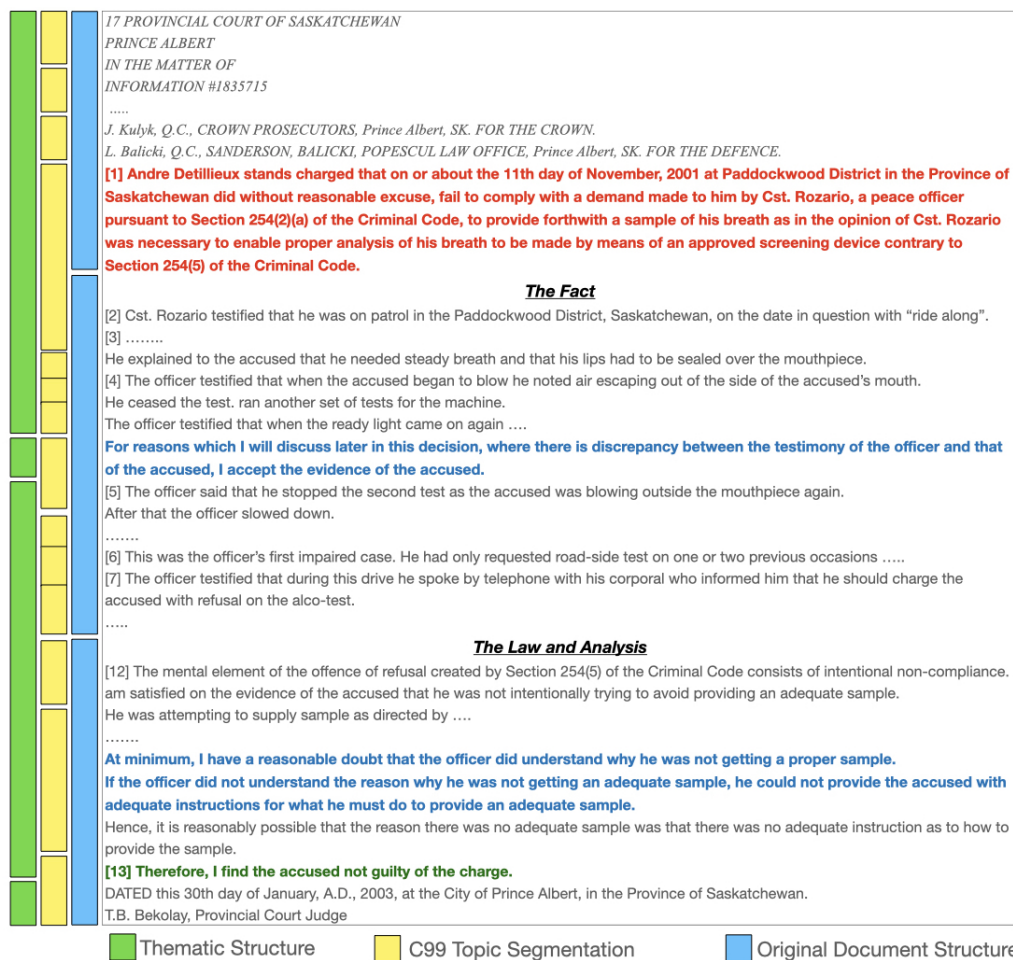


Figure 3: Different document structure views of a legal case decision (ID: c_2003skpc17) from our CANLLI test set. Original case sentences are annotated with **Issue**, **Reason**, and **Conclusion** labels. On the left side, the **green**, **yellow** and **blue** boxes refer to thematic stage, topic segmentation and the original document structure, respectively. The boxes mean the corresponding sentences on the right hand side are grouped into the same segments. For instance, for the first blue box, the original article is split by the italicized and bolded section name of "The Fact".

selected based on the aggregated centrality scores. This may introduce redundancies in selecting similar sentences and ignore the contents in the middle of the source case decisions that are more important once the argumentative sentences at the beginning and end are taken into account. We propose a novel reweighting approach that can tackle this problem. A prior attempt (Tao et al., 2021) on multi-round selection looked at the local similarity between selected sentences. They iteratively recompute the sentence to sentence similarities between the selected summary sentences and recompute the final sentence centrality scores after each sentence selection. Instead, we are focusing on modeling the relationship between the selected sentence and the other candidate sentences. Their method is also not directly applicable to longer text due to the n^2 time complexity of computation given large numbers of

sentences (on average 205 sentences for CanLII dataset).

Our approach can be divided into two phases, as shown in Algorithm 1. In the first phase, we assume that important argumentative sentences at the two ends of the document can be easily detected (as shown in Figures 1 and 3, legal case documents generally start by introducing the issues and end with conclusions). A quantitative analysis of the top-5 selected sentences in CanLII in fact provides an 80% coverage of issue or conclusion sentences. We thus set up a threshold to pick the first k sentences based on the original document graphs. Afterward, we gradually downweight the sentence's centrality score using the location of the latest selected sentence, that is, we set a penalty score for sentences that are placed as a neighbor of the current sentence selected for the summary. Our

Algorithm 1 Reweighting Algorithm

Require: computed centrality score $c(s_i^I)$ for all sentence s , $c_{intra}(d)$ for different section d 's embedding, and a threshold g for phase transition and maximum summary length max_{len} .

$Summ \leftarrow []$

PHASE 1

while $len(Summ) \leq g * max_{len}$ **do**

$Summ.append(topK(\{c(s_i^I)\}))$

end while

PHASE 2

while $len(Summ) \leq max_{len}$ **do**

$c(s_i^I) \leftarrow c(s_i^I) - sim(c_{intra}(I), c_{intra}(J)) * \mu_2$

$\triangleright J$ is the section index of last selected sentence, μ_2 is a hyperparameter

$Summ.append(top - 1(c(s_i^I)))$

end while

Return $Summ$

rationale is that reasoning sentences are more likely to be located in different sections in the middle that are not shared with issues and conclusions.

5 Experimental Setup

For supervised models, we split the training data in an 80:20 ratio for training and validation. For unsupervised models, we tune the hyperparameters on the validation set. Model training details can be found in Appendix B.

Upper Bound Oracles Based on Figure 2, we create a domain-dependent **IRC_Oracle** model where test sentences manually annotated with the IRC labels are concatenated to form the summary. Following Nallapati et al. (2017), we also report results for **EXT_Oracle**, a domain-independent summarizer which greedily selects sentences from the original document based on the ROUGE-L scores compared to the abstractive human summary.

Extractive Baselines For unsupervised models, we compare with LSA (Steinberger and Jezek, 2004), LexRank (Erkan and Radev, 2004), TextRank (Barrios et al., 2016), and PACSUM (Zheng and Lapata, 2019). We also include HipoRank (Dong et al., 2021) with document views. For supervised methods, we compare with BERT_EXT (Liu and Lapata, 2019). Although not our focus, abstractive baselines are in Appendix D.4.

Automic Evaluation Metrics We report ROUGE-1 (R-1), ROUGE-2 (R-2), and ROUGE-

L (R-L) F1 scores, as well as BERTScore (BS) (Zhang et al., 2020c). We also propose metrics to measure the recall value of the annotated IRC types in the test set, which exploits the structure of case documents. More details are in Section 6.2.

6 Results

In this section, we aim to deal with three research questions: **RQ1**. How well do the extractive baselines including the HipoRank backbone deal with legal documents? **RQ2**. How well do the different views of document structures perform with the HipoRank backbone? **RQ3**. Can the reweighting algorithm help select important argumentative sentences and improve summary quality?

6.1 Automatic Summarization Evaluation

Table 2 compares our methods with prior extractive models. See Appendix D.1 for example summaries.

RQ1. Table 2 shows that there is still a gap between oracle models (rows 1 and 2) and current extractive baselines. There are around 20 points differences on R-1, R-2, and R-L. Among the baselines, the supervised model works best only for R-1 and R-L. Unsupervised methods obtain the highest BS (row 4) and R-2 (row 5), possibly due to the higher coverage of n-grams benefitting from longer extracted summaries (row 3 model generated summaries have an average length of 250; row 4-6 models generate on average 400-word summaries; row 7 and 8 models have a limit of 220 words). Without reweighting, the HipoRank backbone never outperforms the best extractive baseline. However, if only unsupervised baselines are considered, HipoRank in row 12 does show the best performance for 3 of the 4 evaluation metrics.

RQ2. To examine the effects of the document views in Section 4.2, we split the document into different types of linear segments and then used HipoRank to generate summaries. Recall that HipoRank is the only model to exploit document structure, and as noted for RQ1, with the right structure could obtain the best unsupervised R-1, R-L, and BS baseline scores. When naively constructing different document structures from the CanLII dataset without header removal, using NLP algorithms (rows 9 - 10) versus just using the HTML formatting (row 8) generally degraded results. However, when we experimented with a modified version of the input documents (rows 11-13) where the headers were filtered through heuristics before computing the

ID	Model	R-1	R-2	R-L	BS
Oracles					
1	IRC	58.04	36.02	55.28	87.94
2	EXT (ROUGE-L, F1)	59.38	38.77	56.94	87.85
Extractive baselines (no document structure)					
<i>supervised</i>					
3	BERT_EXT	<i>43.44</i>	17.84	<i>40.36</i>	84.47
<i>unsupervised</i>					
4	LSA	37.22	17.82	34.87	84.48
5	LexRank	37.90	<u>18.17</u>	35.62	84.32
6	TextRank	36.70	16.19	34.00	83.51
7	PACSUM	40.01	15.68	37.37	83.52
HipoRank backbone (with different computed document structures)					
8	Original Structure	41.61	17.13	38.73	83.55
9	C99-topic	41.33	16.48	38.45	83.53
10	HMM-stage	40.71	15.64	37.93	83.57
11	Original Structure w/o header	42.58	18.01	39.63	83.62
12	C99-topic w/o header	<u>43.25</u>	18.02	<u>40.25</u>	84.48
13	HMM-stage w/o header	42.64	17.38	39.76	83.57
Ours (HipoRank backbone + Reweighting Algorithm)					
14	Original Structure w/o header	43.14	18.46	40.23	84.20
15	C99-topic w/o header	43.90	18.67	41.00	84.34
16	HMM-stage w/o header	43.28	17.80	40.40	84.22

Table 2: The automatic evaluation results on the CanLLI test set. **Bold** represents the best non-oracle score, *italic* the best baseline/backbone score, and underline the best unsupervised baseline/backbone score.

document structure, the scores in rows 11-13 were higher (or in one case the same) than the comparable scores in rows 8-10. Also, without headers, the C99 topic segmentation algorithm (row 12) now outperforms the use of HTML (row 11) (obtaining an average improvement of 0.5 points across ROUGE and 0.8 for BS), suggesting that better structures can improve summarization. As shown in Table 3 (and earlier in Figure 3), C99 creates many small sections (average number of sentences per section is 3.39 with standard deviation of 0.67). We hypothesize that this encourages the selection of sentences from more fine-grained segments. In contrast, the other two methods create lengthy sections (average of more than 50 sentences) with a large standard deviation (135.40 for original structure without headers). In sum, with improvements in automatic metrics, we find that document structures play an important role in summarizing cases.

Model	avg. # secs	avg. # sents per sec
with header		
Original Structure	4.83 (6.44)	83.82 (118.78)
C99-topic	63.47 (70.34)	3.38 (0.71)
HMM-stage	4.00(0.83)	54.32 (64.80)
without header		
Original Structure	3.67 (5.51)	102.99 (135.40)
C99-topic	59.74 (69.91)	3.39 (0.67)
HMM-stage	3.16 (1.08)	70.19 (119.39)

Table 3: Statistics about the average number of sections (avg. # secs) and average number of sentences per section (avg. # sents per sec) across the documents with different computed document structures (standard deviation in parenthesis).

RQ3. The final block of Table 2 presents the reweighting results (using the "w/o header" version of the CanLLI documents as they performed best in the prior block). By downweighting sentences that appear under the same section as previously se-

lected ones, we observe an F1 improvement of 0.65, 0.65, and 0.75 on R-1, R-2, and R-L, respectively, on the previously best-performing topic segmented document (row 12 versus 15). Row 15 in fact has the best non-oracle results for all ROUGE scores. This observation regarding the value of reweighting also holds for the original structure (row 11 vs. 14) and the HMM-stage segments (row 13 vs. 16).

Finally, to better understand the behavior of different enhancements to the HipoRank backbone model, Figure 4 visualizes the positions of IRC sentences in the original article that are selected by a particular summarization method. Plot (a) shows that the human-annotated IRC sentences in the summary tend to span across the source documents, with issues appearing in the beginning and conclusions in the end. Plot (b) shows that although HipoRank using the original document structure can successfully pick middle section sentences, the darkest band at the starting positions shows that the model still heavily relies on the inductive bias to pick the beginning sentences. Plot (c) shows that removing the headers reduces the starting sentence bias. Finally, plot (d) shows that reweighting reduces the number of sentences appearing on both ends. Further analyses on the complete automatic evaluation results⁶ suggest that the improvements come from higher recall values.

6.2 Argumentative Sentence Coverage

Taking advantage of the sentence-level IRC annotations, we propose recall metrics to better measure the summary quality from a legal argumentation perspective (RQ3). We compute the recall of “IRC” sentences extracted from the original case as source IRC coverage (src. IRC). We similarly compute the coverage of IRC sentences in the human-written summaries as target IRC coverage (tgt. IRC) and all sentences as target sentence coverage (trg. cov.). To do so we apply the oracle summarizer (Section 5) to map the generated extractive summaries to the human-written abstractive summaries.

We report these values for the IRC oracle, an unsupervised (LexRank) and supervised (BERT_EXT) baseline, the discourse-aware HipoRank with the original structure, and our best reweighting model using C99-topic segmentation. Table 4 shows that our model obtains the highest target IRC recall and coverage, suggesting that the summaries are more similar to the references with

⁶See Appendix C for ROUGE precision and recall.

Model	src. IRC	tgt. IRC	trg. cov.
<i>Oracle</i>			
IRC	1 (0.00)	0.918 (0.18)	0.820 (0.25)
<i>Baselines</i>			
BERT_EXT	0.804 (0.27)	0.846 (0.23)	0.833 (0.23)
LexRank	0.912 (0.19)	0.811 (0.26)	0.800 (0.27)
HipoRank	0.800 (0.25)	0.851 (0.24)	0.844 (0.22)
<i>Ours</i>	0.823 (0.26)	0.866 (0.20)	0.850 (0.21)

Table 4: Average recall of IRC sentences matched in the original case (src. IRC), gold summary (tgt. IRC), as well as target sentences coverage (trg. cov.) for each document (standard deviation in parenthesis).

respect to the decision’s argumentation. Another unsupervised model, LexRank, obtains the highest source IRC, but its off-the-shelf package requires a fixed sentence ratio selected from the source. This produced longer summaries than other approaches and thus captured more IRCs in the source.

6.3 Human Evaluation Discussion

As a first step towards human evaluation, we tried to extend the HipoRank setup in Dong et al. (2021) and designed a human evaluation protocol as follows. We asked human judges⁷ to read the human-written reference summary and presented extracted sentences from different summarization systems. The judges were asked to evaluate a system-extracted sentence according to two criteria: (1) *Content Coverage* - whether the presented sentence contained content from the human summary, and (2) *Importance* - whether the presented sentence was important for a goal-oriented reader even if it was not in the human summary⁸. The sentence selection was anonymized and randomly shuffled. We used the same sampling strategy in Dong et al. (2021) to pick ten reference summaries where the system outputs were neutral (i.e., had similar R-2 scores compared to the human reference). However, initial annotation on a small set by a legal expert demonstrated that the selected sentences may not reflect the model’s capability. Most sampled system outputs had low ROUGE-2 F1 scores compared to the reference (normally below 10% while the average model performance is 17%), and the human evaluator reported that some

⁷All judges should be native English speakers who are at least pursuing a JD degree in law school and have experience in understanding case law.

⁸Here we assumed the goal-oriented reader as the lawyers or law students seeking information from the case.

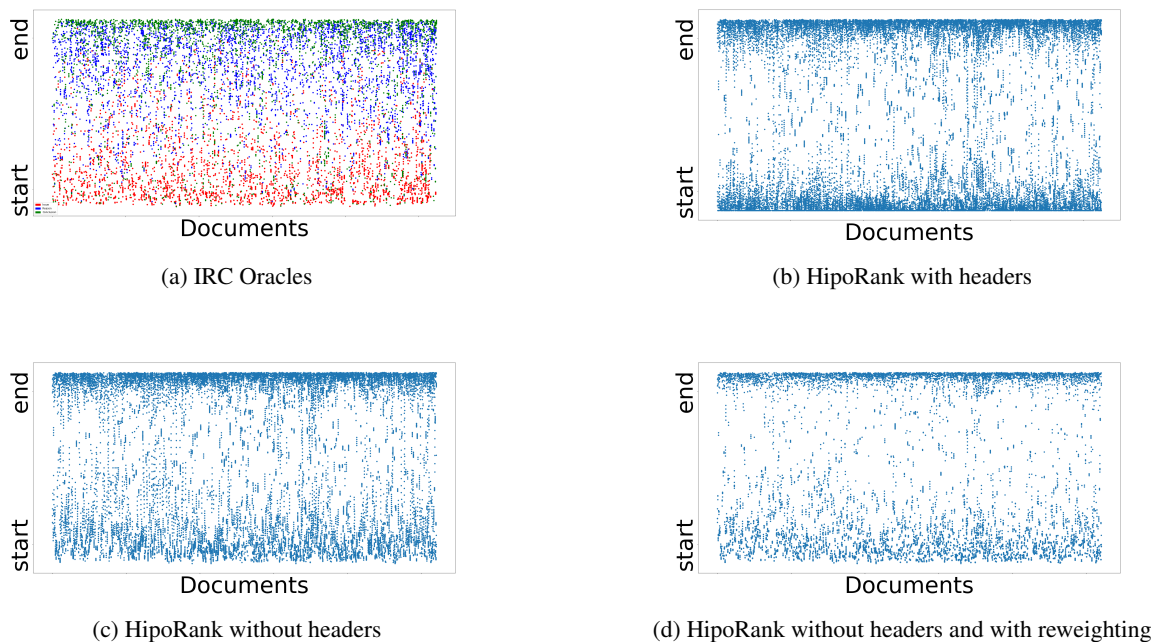


Figure 4: Sentence positions in source cases for extractive summaries generated by different models using the original document structure on the test set. For (b) (c) (d), documents on the x-axis are sorted in the same order. For IRC Oracles, **Issue**, **Reasoning** and **Conclusion** sentences are colored accordingly.

of the selected sentences were not meaningful. We thus propose that a more careful sampling technique will be required for legal annotation tasks such as ours.

To further guide our future work, we also reviewed how prior legal domain research has performed human evaluations when automatically summarizing legal documents (Polsley et al., 2016; Zhong et al., 2019; Salaün et al., 2022). Due to the burden of reading lengthy original documents, as in our human evaluation, most prior work evaluated summary quality using reference summaries rather than source documents. In addition, legal evaluations have typically been small-scale (5-20 summaries) due to the need to have evaluators with particular types of expertise (e.g., law graduate students or law professors), which was a similar constraint in our exploratory human evaluation. Researchers have also designed new types of legally-relevant evaluation questions that evaluate the summary for task-specific properties that go beyond more typical properties such as grammar, readability, and style. In our case, we would like legal experts to assess IRC coverage in the future.

7 Conclusion

We presented an unsupervised graph-based model for the summarization of long legal case decisions. Our proposed approach incorporated diverse views of the document structure of legal cases and utilized a reweighting scheme to better select argumentative sentences. Our exploration of document structure demonstrates how using different types of document structure impacts summarization performance. Moreover, a document structure inspired reweighting scheme yields performance gain on the CanLII case dataset.

Ethical Considerations

The utilization of the generated summary results of legal documents remains important. Current extractive methods avoid the problem of generating hallucinated information (Kryscinski et al., 2020; Maynez et al., 2020), which has been observed in abstractive methods that use large-scale pre-trained language models. The extracted sentences, however, may not capture the important contents of the legal documents. Meanwhile, CanLII has taken measures to limit the disclosure of defendants' identities (such as blocking search indexing). Thus, using the dataset may need to be taken good care of and avoid impacting those efforts.

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Limitations

The dataset we used has a relatively small scale (1K) test set. Meanwhile, the automatic evaluation metrics may fall short compared to human evaluations, thus unfaithfully representing the final quality of generated summaries. Although lightweight, there is still a large performance gap between our unsupervised method and both the extractive oracles as well as abstractive models (Appendix D.4), especially given the small-scale training data. There are more graph-based methods to aggregate information from the built graphs and we would like to explore and include more graph-based methods but selected the most relevant one in this work. Moreover, our proposed reweighting paradigm heavily relied on observations about the structure of legal cases. Many other legal document types, such as bills and statutes, have inherently distinct structures. Our results also show the importance of finding the correct structure and weights, which can vary depending on the corpus. This will require more advanced methods to find the correct structure and weights for a dataset.

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A The HipoRank Algorithm

In this section, we provide a detailed recap of the HipoRank algorithm (Dong et al., 2021). Our approach mainly modifies the obtained document graphs by building a *section-section* graph and changes the final summary selection algorithms.

A.1 Hierarchical Document Graph Creation

The document is first split into its sections, then into sentences. Two levels of connections are allowed in the built hierarchical graph: intra-sectional connections and inter-sectional connections. Following the original paper, we display a toy example of these two types of connections in Figure 5.

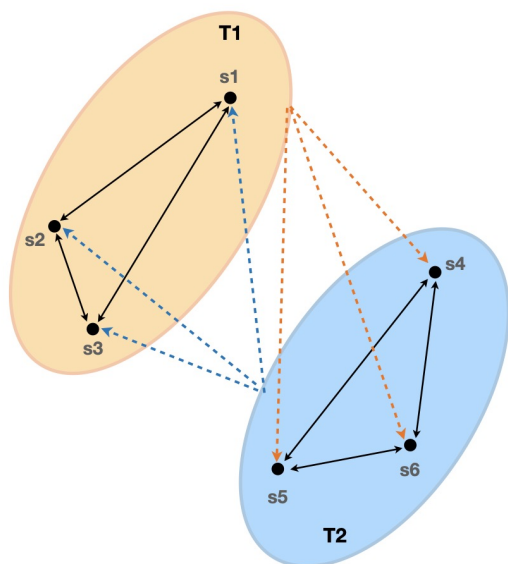


Figure 5: (Reproduced from (Dong et al., 2021)) An example of a hierarchical document graph constructed by HipoRank approach on a toy document, which contains two sections {T1, T2}, each containing three sentences for a total of six sentences {s1, . . . , s6}. In the graph, each double-headed arrow represents two edges with opposite directions. The solid and dashed arrows indicate intra-sectional and inter-sectional connections respectively.

Intra-sectional connections are designed to measure a sentence’s importance score inside its section. The authors built a fully-connected sub-graph over all sentences in the same section, allowing for *sentence-sentence* edges, which are measured by a weighted version of the similarities of sentence embeddings.

Inter-sectional connections “aim to model the global importance of a sentence with respect to

other topics/sections in the document”, according to Dong et al. (2021). To reduce the expensive computation of all sentence-sentence connections spanning across a document, HipoRank’s authors introduce section nodes on top of sentence nodes, and only allow for *sentence-section* edges to model the global information.

A.2 Asymmetric Edge Weighting by Boundary Functions

In order to compute the weight of an edge, HipoRank measures the similarity of sentence-sentence pairs by computing the cosine similarity of encoded sentence embeddings. Similarly, for sentence-section pairs, it averages the sentences’ representations in the same section, uses it as the section vector, and further computes the cosine similarity. Taking two discourse hypotheses of long scientific documents into account ((1) important sentences are near the boundaries (start or end) of a text (Baxendale, 1958) and (2) sections near the text boundaries (start or end) are more important (Teufel, 1997)), the authors of HipoRank capture this asymmetry by making their hierarchical graph directed and inject asymmetric edge weighting over intra-sectional and inter-sectional connections. We refer to the original paper for more detailed setups and algorithm details.

A.3 Importance Computation and Summary Generation

We talk about the importance computation approach and summary generation details in §4.1.

B Training Details and Hyperparameters

All of our experiments are conducted on Quadro RTX 5000 GPUs, each of which has 16 GB RAM. For the extractive oracle baseline, we use the python package of rouge⁹ to compute the ROUGE-L scores for sentence scoring.

Document Segmentation We provide details of segmentation methods mentioned in §4.2 below. For sentence encoding, we use the sentence_transformer library¹⁰, and the checkpoint of “bert-base-nli-stsb-mean-tokens” for sentence representations. For the HMM stage segmentation, we train a GaussianHMM model

⁹<https://pypi.org/project/rouge/>

¹⁰<https://www.sbert.net/>

with `hmmlearn`¹¹, setting the number of the components at 5 and train the model for 50 iterations on the validation set. For C99 algorithm, we use an implementation¹² shared from [Chen and Yang \(2020\)](#) in their original paper. We set the window size of 4 and `std_coefficient` as 1. All data processing scripts are publicly available in a combined package in <https://github.com/cs329yangzhong/DocumentStructureLegalSum>.

Supervised Model We build our BERT_EXT, the extractive model, on top of the official code base of the work of [Liu and Lapata \(2019\)](#)¹³. Since many original documents’ lengths go beyond the 512 token limits, we break the full document into different chunks and train the model to extract the top-3 sentences. For hyperparameters, we use 4 GPUs, set the learning rate of 2e-3, and save the best checkpoints at every 5,000 steps. We set the batch size as 3,000, the maximum training step at 100,000, and warm-up steps at 10,000.

Unsupervised Models We use off-the-shelf packages for most traditional models. We use LSA¹⁴, TextRank¹⁵, and LexRank¹⁶ accordingly.

For PACSUM model, we follow the re-implementation¹⁷ of ([Dong et al., 2021](#)) and keep the hyperparameters fixed with the original setup. BERT-based sentence embeddings are extracted using the fine-tuned BERT model released from the original paper ([Zheng and Lapata, 2019](#)). We also experimented with LEGAL-BERT ([Chalkidis et al., 2020](#)) in the early stages of our research but found it degraded performance on the baselines.

For HipoRank, we use the publicly available code base¹⁸. We experimented with various hyperparameter settings on the validation set but we find that the original hyperparameters used in the original paper for PubMed dataset seem to be the most stable and produce the best results. ($\lambda_1 = 0.0$, $\lambda_2 = 1.0$, $\alpha = 1.0$, with $\mu_1 = 0.5$.)

¹¹<https://hmmlearn.readthedocs.io/en/latest/>

¹²<https://github.com/GT-SALT/Multi-View-Seq2Seq/blob/master/data/C99.py>

¹³<https://github.com/nlpyang/PreSumm>

¹⁴<https://github.com/luisfredgs/LSA-Text-Summarization>

¹⁵<https://github.com/summanlp/textrank>

¹⁶<https://github.com/crabcamp/lexrank>

¹⁷<https://github.com/mirandrom/HipoRank>

¹⁸<https://github.com/mirandrom/HipoRank>

We build our reweighting model on top of the HipoRank dataset. We search the threshold g (for phase transition between phases 1 and 2) between [0.3, 0.5, and 0.7], finding that 0.5 is the best for the CanLII dataset.

C The Effects of Reweighting Algorithm

We study the effects of our reweighting algorithm by comparing different models’ performances on the input documents with original structures. As shown in Table 5, with a minor sacrifice of precision, the recall values are greatly improved with the reweighting algorithm, thus resulting in the final improvements of F1 scores.

D Examples

D.1 Summary Generation Results

We show the reference, best baseline, and our model’s output on the C99-topic view of the without header version of documents in Table 6.

D.2 IRC Annotation

We show the IRC annotation of both a case and its human summary in Figure 6.

D.3 Document Cleaning Heuristics

The heuristics for filtering the headers from cases are provided below for replication purposes; we also provide the code¹⁹ to process the CanLII data (although it requires that the data must first be obtained through an agreement with the Canadian Legal Information Institute).

1. Cut the document until the sentence begins with “Introduction”.
2. Cut the document until the sentence starts with an ordered number such as (1), [1].
3. Remove rows until the judge’s name or case date appeared.

D.4 Comparing to Abstractive Summarization

For supervised abstractive baselines, we experiment with BART ([Lewis et al., 2020](#)) and Longformer-Encoder-Decoder (LED) ([Beltagy et al., 2020](#)). The latter model can process longer input documents up to 16k tokens. The results in Table 7 show that there still exists a gap between the extractive and abstractive models.

¹⁹<https://github.com/cs329yangzhong/DocumentStructureLegalSum>

Document Structures	ROUGE-1			ROUGE-2			ROUGE-L		
	P	R	F1	P	R	F1	P	R	F1
w/o header	45.24	47.39	42.58	19.23	20.12	18.01	42.25	43.95	39.63
w/o header + Reweighting	44.13	49.80	43.14	18.97	21.35	18.46	41.29	46.26	40.23

Table 5: The Precision (P), Recall (R) and F1 of ROUGE-1/2/L scores for the inputs with original document structures, with and without reweighting algorithm. We find that the reweighting algorithm improves the recall, suggesting that more argumentative sentences in the references are covered.

Model	Summary
Reference	FIAT: The defendants, Sims, Garbriel and Dumurs, bring separate motions, pursuant to Queen’s Bench Rule 41(a), for severance of the claims against them or for an order staying the claims against them until the plaintiffs’ claim against the primary defendant, Walbaum have been heard and decided. HELD: 1) The Court will look at all of the circumstances in deciding whether to grant an application for severance. In this case the plaintiffs should not be precluded from adducing evidence related to Walbaum’s dealings with each of the applicants or required to segregate the evidence into two, three or four separate trials. Given the likelihood that the applicants will be required to attend portions of the trial in respect of the Walbaum Group in any event, severance would not necessarily result in a significant saving of time and expense. 2) The plaintiffs acknowledge that only relatively small portion of trial time (perhaps less than 1 day) will pertain to the claims against any one of the Sims, Gabriel or Dumurs. It would be unfair to require all of the applicants to participate in all of the trial when very little of it will be relevant to them. Specific dates and times should be set aside for the plaintiff to call evidence with respect to its claims against each applicant group. The applicants should be relieved from attending the trial at any other time.
HipoRank	QUEEN’S BENCH FOR SASKATCHEWAN 2007 SKQB 296 Judicial Centre: Regina DUN-RITE PLUMBING & HEATING LTD. (d) Robert Dumur 593340 Saskatchewan Ltd., carrying on business as Dumur Industries (herein “the Dumurs”) [2] The Sims, Gabriel and the Dumurs bring separate motions, pursuant to Queen’s Bench Rule 41(a) for severance of the claims against them or for orders staying the claims until the plaintiffs’ claims against the Walbaum Group have been heard and decided. ANALYSIS [12] T applications are brought pursuant to Queen’s Bench Rule 41 which states: 41 (1) Where the joinder of multiple claims or parties in the same action may unduly complicate or delay the trial, or cause undue prejudice to a party, the court may: (a) order separate trials; [21] It will also be left to the trial judge (or the pre-trial management judge) to designate specific days on which defence evidence may be adduced during the trial and argument presented with respect to each claim. All defendants other than those comprising the Walbaum Group shall be relieved from attending the trial on any date not designated by counsel for the plaintiffs or designated by the trial judge for adducing defence evidence and presenting argument. [22] Costs will be in the cause. D.P. Ball
Ours	FIAT BALL J. August 14, 2007 [1] The plaintiff brings this action against nine defendants (the claim against the defendant Albert Fazakas has been discontinued) who can be separated into four groups: All-Rite Plumbing Heating Ltd. [18] Although choeounsel for the plaintiffs asserts that the evidence against all of the defendants can be adduced in no more than two and one-half days, given the number and complexity of the claims against the Walbaum Group this estimate seems very unrealistic. [19] The plaintiffs acknowledge that only relatively small portion of trial time (perhaps less than one day) will pertain to the claims against any one of the Sims, Gabriel or the Dumurs. It would be unfair to require all of the applicants to participate in all of the trial when very little of it will be relevant to them. The applicants should be relieved from attending the trial at any other time. The plaintiffs shall not call evidence in respect of those claims on any other date without leave of the court. All defendants other than those comprising the Walbaum Group shall be relieved from attending the trial on any date not designated by counsel for the plaintiffs or designated by the trial judge for adducing defence evidence and presenting argument.

Table 6: Generated summaries for a CanLII case decision (ID: 2_2007skqb296), we use special symbol “||” to mark the sentence boundaries.

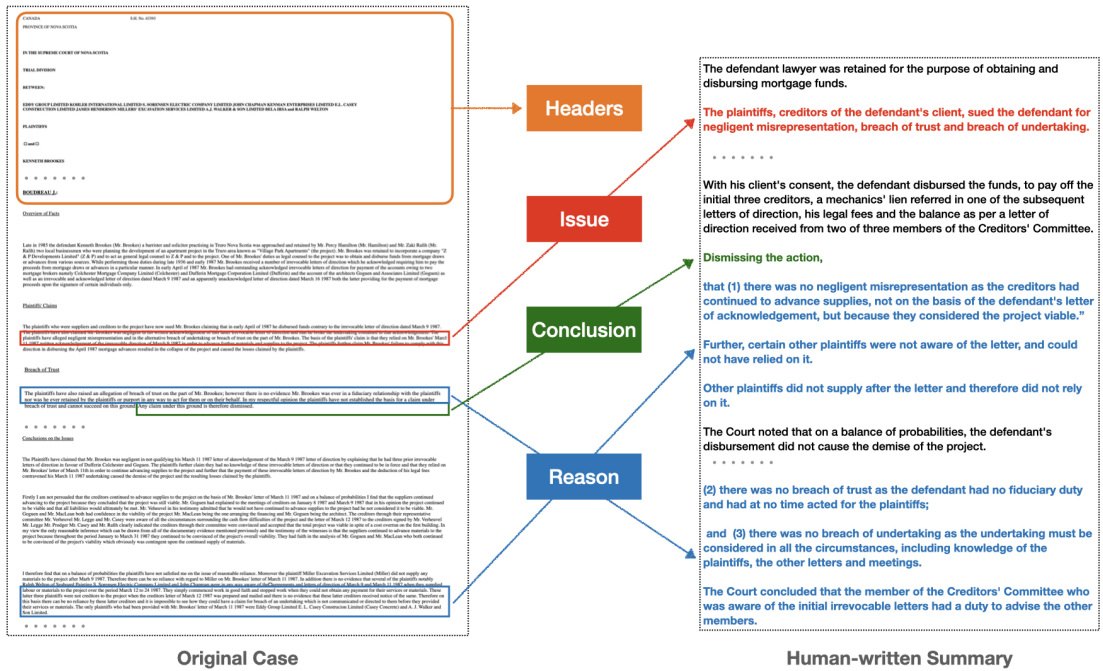


Figure 6: An example of the annotated **Issue**, **Reason**, and **Conclusion** sentences in CanLII dataset's case and summary pair (ID: 1991canlii4370). A portion of the beginning sentences in the case are not as important as the main document, including the meta-data of the case such as the participants' names, time, locations, etc. Thus, we treated them as headers and filtered them out using a heuristic introduced in Appendix D.3.

ID	Model	CanLII	
		R1/R2/RL	BS
Oracles			
1	IRC	58.04/36.02/55.28	87.94
2	EXT	59.38/38.77/56.94	87.85
Supervised Extractive			
3	BERT_extractor	43.44/17.84/40.36	84.47
Supervised Abtractive			
4	BART	50.50/25.58/46.82	87.25
5	LED	53.72/28.75/ 50.17	87.55

Table 7: The automatic evaluation results on the CanLII test set with supervised abstractive models.