CASESUMM: A Large-Scale Dataset for Long-Context Summarization from U.S. Supreme Court Opinions

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Abstract

This paper introduces CASESUMM, a novel dataset for long-context summarization in the legal domain that addresses the need for longer and more complex datasets for summarization evaluation. We collect 25.6K U.S. Supreme Court (SCOTUS) opinions and their official summaries, known as "syllabuses." Our dataset is the largest open legal case summarization dataset, and is the first to include summaries of SCOTUS decisions dating back to 1815.

We also present a comprehensive evaluation of LLM-generated summaries using both automatic metrics and expert human evaluation, revealing discrepancies between these assessment methods. Our evaluation shows Mistral 7b, a smaller open-source model, outperforms larger models on most automatic metrics and successfully generates syllabus-like summaries. In contrast, human expert annotators indicate that Mistral summaries contain hallucinations. The annotators consistently rank GPT-4 summaries as clearer and exhibiting greater sensitivity and specificity. We find that LLM-based evaluations are not more correlated with human evaluations than traditional automatic metrics. Furthermore, our analysis identifies specific hallucinations in generated summaries, including precedent citation errors and misrepresentations of case facts. These findings demonstrate the limitations of current automatic evaluation methods for legal summarization and highlight the critical role of human evaluation in assessing summary quality, particularly in complex, high-stakes domains.

CASESUMM is available on HuggingFace.[1]

1 Introduction

Although large language models (LLMs) are claimed to handle long contexts (GPT-4 Team, 2024; Bubeck et al., 2023; Claude Team, 2024), including summarizing very long inputs, how well they perform long-context summarization is an open question.

Evaluating long-context summarization is challenging for several reasons. First, human ground-truth summaries are often not available (Cao et al., 2024; Chang et al., 2024). Moreover, it's unclear whether we should trust human abilities to even create ground-truth summaries. Second, what makes a good summary in one setting may not generalize to other settings. For example, what's relevant in a legal text is different than what's relevant in a novel. Lastly, identifying salient information in complex domains often requires expertise.

We address these challenges by introducing a new dataset where "ground-truth" summaries are available and conducting a comprehensive human evaluation to benchmark existing models. In particular, we build CASESUMM, a legal case summarization dataset consisting of 25.6K U.S. Supreme Court cases and their official summaries, called syllabuses. Syllabuses, written by Court-employed attorneys and approved by Justices, serve as the gold standard for majority opinion summaries. We obtain the opinions from Public Resource Org's archive[2] and extract syllabuses from the official opinions published in the U.S. Reporter and hosted by the Library of Congress. Our dataset is 25% larger, spans 3 times as many years (1815-2019), and is more accessible with fewer copyright restrictions (Fang et al., 2023; Trivedi et al., 2024).

Beyond the legal domain, several datasets have been introduced to improve evaluation of long-context summarization (Kryściński et al., 2022; Sharma et al., 2019; Eidelman, 2019; Huang et al., 2021). CASESUMM continues the trend of larger datasets with both longer source and summary texts, where the summaries represent high quality ground-truths. Unlike prior work, however, our dataset spans over two centuries, demonstrating unique

[1]https://huggingface.co/datasets/ChicagoHAI/CaseSumm

[2]https://public.resource.org/

Findings of the Association for Computational Linguistics: NAACL 2025, pages 1917–1942

variation in the lengths and compression rates of summaries, while also reflecting a high-stakes and useful domain for summarization.

To highlight the opportunities and challenges of our dataset, we present both automatic and human expert evaluations of LLM-generated summaries of SCOTUS opinions and include two "control" human-written summaries from Westlaw and Oyez. According to both human and automatic metrics, fine-tuning Mistral successfully guides the model to more accurately mimic the official syllabuses and reflect the lexical and semantic content within them, than other much larger models.

Automatic metrics fail to align with human judgments, and LLM-based evaluation fares no better. Fine-tuned Mistral excels in automatic metrics but scores lower with human evaluators, whereas GPT-4 ranks highly in human assessments despite average automatic scores. Notably, GPT-4 summaries often surpass human-written ones—except in factual accuracy—challenging the concept of human ground-truth summaries.

Finally, we conduct an error analysis of hallucinations in GPT-4- and Mistral- generated summaries and identify factual errors ranging from precedent citation errors to misrepresentations of the facts of the case and procedural history as recounted in the source opinions.

In sum, we make the following contributions:

- We introduce a new large-scale dataset for long-context summarization in the legal domain, consisting of 25.6K U.S. Supreme Court cases and their official syllabuses from 1815-2019.
- We present a comprehensive evaluation of LLM-generated summaries using both automatic metrics and expert human evaluation, revealing discrepancies between these assessment methods.
- We provide a comparative analysis of summaries generated by fine-tuned models and larger, general-purpose models, offering insights into their relative strengths and weaknesses in legal summarization tasks.

2 Related Work

Evaluation for summarization. ROUGE (Lin, 2004) has been the dominant summarization metric, despite criticism of its high lexical dependence (Schluter, 2017; Cohan and Goharian, 2016). Newer metrics like BERTScore (Zhang et al., 2019) and BARTScore (Yuan et al., 2021) aim to capture semantic similarities. However, automatic metrics often don't correlate well with human judgments (Yuan et al., 2021; Fabbri et al., 2021; Bhandari et al., 2020). Despite LLM progress, we show that better high-stakes summarization metrics remain necessary. Chang et al. (2024) expanded LLM-based evaluation to books but overlooked expert judgments and remains slow and costly. Cao et al. (2024) developed a framework for characterizing LLM summaries of financial documents. Our work extends this research by evaluating and comparing model- and human-generated summaries in the legal domain. Addressing factual discrepancies in model-generated summaries, recent work has developed automatic methods for evaluating faithfulness in summarization (Krishna et al., 2023; Chang et al., 2024; Falke et al., 2019; Laban et al., 2022; Wang et al., 2020; Fabbri et al., 2022).

NLP and summarization in the Legal Domain. Natural language processing has been applied to various legal tasks, including summarization (Bauer et al., 2023), discovery (Zou and Kanoulas, 2020), redaction (Garat and Wonsever, 2022), case outcome prediction (Medvedeva et al., 2023; Cui et al., 2023), and Bar Exam performance (Katz et al., 2023a). For comprehensive surveys of NLP in the legal domain, see Katz et al. (2023b) and Kapoor et al. (2024).

Datasets in the legal domain. Our dataset uniquely includes U.S. Supreme Court opinions with syllabuses, unlike others (Chalkidis et al., 2022; Henderson et al., 2022; Law, 2024). Fang et al. (2023) introduce Super-SCOTUS, a dataset with a limited number of unverified, web-scraped syllabus-opinion pairs. In contrast, our CASESUMM dataset is more comprehensive, with cleaned and curated pairs.

For each decision PDF, we identify and extract the syllabus and majority opinion, which syllabuses are intended to summarize. We remove headers and concurrent and dissenting opinions, while properly including footnotes. As Table 1 shows, CASESUMM is a strict super-set of Super-SCOTUS with descriptive statistics that reflect our improved data processing pipeline. CASESUMM extends further back to 1815 and, by being extracted directly from source opinions, provides the community with a readily available summarization resource with fewer copyright restrictions.

3 Dataset

When the Supreme Court resolves a case, it publishes a majority "opinion" announcing the outcome and reasoning for their decision. The Court will also disseminate a summary of the opinion called the "syllabus", which is written by an attorney employed by the Court and approved by the Justices. The syllabus must include the main elements of the opinion: the facts of the case, the procedural history, the legal question to be decided, and the answer to that question. Accurately summarizing each of these sections requires (1) understand sophisticated legal reasoning and (2) identify the most salient aspects of the case.

As one of the longest-standing U.S. institutions, the Supreme Court has published thousands of opinions and syllabuses over 200 years. Looking at cases from 1815 to 2019, we collect 25.6K opinion-syllabus pairs for our dataset, available under a CC BY-NC 4.0 license.

Dataset construction We compile our dataset from multiple sources. Opinions published in U.S. Reports Volume 15-546 (years 1815-2005) and Volumes 546-591 (2005 through *Trump v. Vance* (2019)) are obtained from Public Resource Org's online archive (Public Resource Org, 2024) and the Super-SCOTUS data set (Fang et al., 2023), respectively. We extract syllabuses from PDFs of the opinions hosted on the Library of Congress's website (Library of Congress, 2024).

Extracting syllabuses from PDFs is challenging due to changing SCOTUS formatting and low-quality historical scans. These issues constrain the rules or signals we can use to reconstruct text structure, requiring alternative approaches. For example, while syllabuses have a smaller font size than the decision and could be a straightforward heuristic, this information is often misencoded in OCR data.

To ensure accurate syllabus extraction, we process the PDFs in multiple ways. First, we design a set of regular expressions to identify the start of the syllabus, providing coverage of decisions with different styles. Then, we develop an algorithm based on open-source computer vision software (Bradski, 2000) to identify continuous lines, allowing us to distinguish footers from the main text of a page. Finally, we take advantage of differences in line density, a measure that is more robust to OCR and scan quality, combined with regular expressions to determine when the syllabus ends.

Dataset	# Docs.	# Words	
		Source	Summary
Super-SCOTUS (1955-2019)	6.6k	9.3k	791
BillSum (1993-2018)	22.2k	1.8k	208
GovReport*	18.5k	9.4k	553
Multi-LexSum**	4.5k	75.5k	647
Oyez (1955-2012)***	622	4.8k	356
Westlaw (1956-2011)	156	4.5k	143
CASESUMM (1815-2019)	25.6k	2.6k	314
CASESUMM (1955-2019)	7.2k	4.9k	745
CASESUMM (1815-1955)	18.4k	3.4k	289

Table 1: Comparison of CASESUMM and related long-context summarization datasets in the legal domain. *GovReport does not specify years covered. **Multi-LexSum is a multi-document summarization dataset. ***Oyez summaries are a subset of SuperSCOTUS.

Since we build a new dataset, there are no accessible ground-truths to automatically evaluate our technique for extracting syllabuses from PDFs. Instead, we randomly sample 100 cases and manually evaluate the extracted syllabus by comparing them to the original PDFs. We find that 96 of the 100 are perfect extractions while the remaining 4 syllabuses are partially truncated. These results highlight the quality of our dataset as a rich resource for long-context summarization.

Descriptive statistics To demonstrate the value of our dataset as a resource for abstractive summarization, we compare the lengths of the opinions and their syllabuses.

Supreme Court opinions average 2,612 words, with syllabuses averaging 314 words (21.8%). Figure 1 shows lengths have risen over time. Since 1980, both have nearly doubled to 4,151 and 731 words respectively. Although compression rates, defined as the ratio of words in a syllabus to words in an opinion have been relatively stable over time, averaging 21.8% from 1815-2019, the Pearson correlation between the length of an opinion and its syllabus, while variable, has increased over time. Whereas this correlation was just 0.46 before 1920, it has been 0.68 since then. Given the changes in opinion and syllabus lengths and in the correlation between syllabus and opinion lengths, this data set is a valuable resource for modeling and evaluating expert summaries, especially in the legal domain.

4 Experiment Setup

In this section, we introduce our summarization task setup and evaluation strategies.

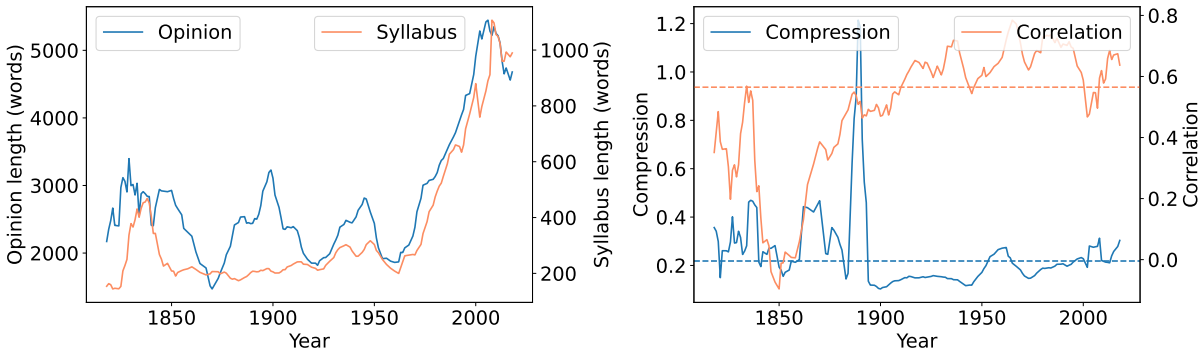

Figure 1: Opinion and syllabus lengths, compression rates by syllabuses, and correlations between opinion and syllabus lengths, 1815-2019. Dashed blue and orange lines give average compression rate and correlation. Lines are smoothed with 5-year moving-average.

4.1 Data and Modeling

Data preprocessing and splits. We use syllabuses as a supervision signal in our summarization modeling experiment and as reference summaries for evaluating the human and model-generated summaries.

As discussed in §3, the substance and style of syllabuses have changed over time. Therefore, the supervision signal has changed over time. The motivating use case in our summarization task is a legal professional conduction research. For such a professional, while concision has value, comprehensiveness is more valuable. By manually studying summaries, we determine that more comprehensive syllabuses begin with a summary of the facts of the case, followed by a new section—marked by the text "Held:"—containing details about the issues, analyses, and conclusions that the opinion commented on. Modern syllabuses consistently adhere to this structure.

Therefore, we filter our dataset to include only opinion/syllabus pairs where the syllabus contains the pattern "Held:". We call this subset of the dataset "structured". We find that the length of structured syllabuses is more strongly correlated with the length of their respective opinions ($r = 0.65$) than the length of unstructured syllabuses is with the length of their opinions ($r = 0.46$). Furthermore, structured syllabuses are on average 2.5x longer than the unstructured syllabuses. Overall, the structured dataset contains 6,683 case/syllabus pairs. We split these into a training set (n=5,455), validation set (n=606), and test set (n=622).

Modeling. We test two approaches for completing our legal case summarization task. The first is zero-shot prompting with proprietary and open-source LLMs. The proprietary LLM we use is GPT-4 Turbo (`gpt-4-1106-preview`) (GPT-4 Team, 2024), and the open-source LLM is Mistral 7b Instruct (`Mistral-7b-Instruct-v0.1`) (Jiang et al., 2023). The opinions in our dataset average 4,983 tokens, and the syllabuses 755 tokens. The second approach is instruction fine-tuning (Wei et al., 2021) the open-source model, Mistral 7b Instruct, using syllabuses in our training dataset. We refer to models used in a zero-shot setting by name: Mistral Base and GPT-4, and to the fine-tuned Mistral model as Mistral FT.

For Mistral in both settings, we design a prompt following best practices suggested by its authors.[3] For GPT-4, we optimize prompt-selection using DSPy (Khattab et al., 2023) with 10 opinion/syllabus pairs from the training set and ROUGE-2 as the optimization metric.

For fine-tuning, our input consists of a short instruction, the opinion, and the syllabus. We do standard auto-regressive language modeling but only backpropagate the language modeling loss for the syllabus. We use LoRA-based Parameter-Efficient Fine-Tuning (PEFT) (Hu et al., 2021) to train a subset of the parameters. We include additional implementation details in Appendix A.

4.2 Evaluation strategies

"Control group" summaries. We benchmark our three machine-generated summaries (Mistral Base, Mistral FT, and GPT-4 Turbo) along with two additional human-generated sources for purposes of having a control group of human-written summaries not explicitly intended to mimic syllabuses. First, we collect public Oyez summaries from the

[3] https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.1

Method	ROUGE-1 ↑			ROUGE-2 ↑			ROUGE-L ↑			BERTScore ↑		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
GPT-4 Turbo	71.2	37.1	45.1	31.1	15.5	19.2	34.9	18.1	21.9	**67.4**	62.2	**64.6**
Mistral Base	64.3	13.4	20.0	23.4	4.6	7.0	41.1	7.8	11.8	61.3	48.5	54.0
Mistral FT	63.3	**43.1**	**48.1**	30.1	**20.5**	**23.0**	34.9	**23.6**	**26.4**	66.0	**64.4**	**65.1**
Oyez	64.0	35.1	41.6	28.5	15.0	18.1	34.4	18.6	22.1	64.2	61.8	62.9
Westlaw	**71.5**	20.5	29.4	**32.7**	9.1	13.2	**42.3**	11.8	17.0	65.0	55.7	59.9

Table 2: Automatic evaluation of model-generated and human-written summaries, where official syllabuses are the reference summaries. Sample includes 622 Supreme Court cases. There are 622 observations on each type of summary except Westlaw, for which we only have 156 observations. For each metric, we report precision (P), recall (R), and F1-score (F1). For each metric, we **bold** the best score(s) and underline the second best score(s).

Super-SCOTUS dataset (Fang et al., 2023). Oyez summaries are composed of three sections: Facts of the Case, Question, and Conclusion. Second, we collect Westlaw's commercial summaries of cases via their online interface.[4] Because manual download is slow, our sample size for Westlaw downloads was smaller: whereas our test set has 622 instances of model-generated summaries and Oyez summaries, we have 156 Westlaw summaries.[5]

Automatic Evaluation. Following recent work on summarization (Koh et al., 2022), we use ROUGE and BERTScore (Lin, 2004; Zhang et al., 2019) as our automated metrics for evaluating generated summaries against the reference syllabuses. With this, we assess the *relevance* of the summaries. We breakdown each of the metrics by their precision, recall, and F1-score, highlighting how models balance trade-offs between coverage and concision. We also experimented with BARTscore (Yuan et al., 2021) (see Appendix B.3) but exclude it from our main analysis due to its sensitivity to whether text is in- or out-of- distribution relative to the scoring model. Since we compare Mistral after fine-tuning on syllabuses to models that were not fine-tuned, we expect unreliable results.

To further characterize the summaries, we compare them based on *compression rate*, defined as syllabus words over opinion words, and *correlation* between opinion and summary lengths. We use compression to measure brevity and correlation to assess how responsive summaries are to content changes.

Human Evaluation. For human evaluation, we recruited and paid[6] second- and third-year law students to read opinions and 5 summaries of each (Mistral FT[7], GPT-4, official syllabus, Westlaw, and Oyez). Students ranked summaries (1-5) on *sensitivity* (inclusion of relevant information), *specificity* (exclusion of irrelevant information), *clarity*, and professional legal *style*. Finally, we asked students to report the number of facts in the summary that were false based on their reading of the opinion (*error*). Students were not told the source of each summary.[8] See Appendix C for additional details on the annotation interface and procedure.

In total, students read 57 opinions. Our sample of opinions and summaries included 33 unique cases, and the median student read 5 cases. Given that we ask students to rank opinions from 1 to 5 (implying a mean of 3 and variance of 2), our minimum detectable effect, with 95% confidence and 80% power, was 0.52 rank points.

Experimenting with LLM-based evaluations. Metrics like ROUGE and BERTScore provide a baseline for assessing lexical and semantic alignment between a candidate and reference text. However, they can miss deeper qualities that humans value in a good summary. LLMs offer a new way to evaluate summaries and to address some of these

[4]We obtain these manually to avoid legal risks under our Westlaw subscription license.

[5]We initially included summaries from Justia, another publicly available legal resource, as a human baseline but, after manually inspecting 5 randomly sample summaries, we determine that they were largely derivative of the Court syllabuses and copied significant quantities of text from them. This was further validated by finding that Justia summaries achieved 0.97 ROUGE-1 score, which is exceedingly alike in a long-form summarization task such as this.

[6]Participants received $20/hr, $4 above RA minimum. See Appendix C.3 for instructions & consent.

[7]We exclude Mistral base due to poor performance on automatic metrics, reducing participants' cognitive load.

[8]This evaluation was deemed exempt from IRB review by our institution's IRB (IRB24-0277).

shortcomings (Liu et al., 2023; Song et al., 2024). Still, their results are variable and sensitive to their prompts. In this work, we study how well G-Eval (Liu et al., 2023), a GPT-4-based evaluation tool, agrees with human ratings compared to ROUGE and BERTScore. This helps us understand whether G-Eval offers a better way to evaluate summaries when a reference is unavailable or when traditional metrics fall short. We test both the default implementation of G-Eval, as well as an adapted version to more closely reflect our human evaluation setup.

Correlation between automatic and human rankings. In Section 5.3, we discuss differences and similarities in how various evaluation methods, including G-Eval, correlate with human judgments. For each opinion, we convert the ROUGE, BERTScore, and G-Eval scores for the various candidate summaries into rankings. Then, we compute the Spearman correlation between each ranking and the human ranking, and average these correlations.

5 Results

Our results reveal both consistencies and discrepancies between automatic and human evaluations. Model-generated summaries outperform control human-written summaries in automatic relevance metrics and match or exceed them in human evaluation. However, while automatic metrics favor Mistral FT summaries over GPT-4, expert humans generally rank GPT-4 higher.

Furthermore, we show all summaries are shorter than their reference syllabuses and correlate less with opinion lengths. Despite this, humans prefer GPT-4 summaries, revealing that its summaries may represent a more desirable trade-off between concision and comprehensiveness

5.1 Automated Evaluation Favors Fine-tuned Mistral Summaries

We start by looking at the results in Table 2 of automatic evaluation between summaries and official syllabuses for the three generated summaries (Mistral Base, Mistral FT, and GPT-4) and for two human summaries. Overall, we find that fine-tuning Mistral is particularly effective at improving the recall scores across all the metrics: ROUGE recall scores increase by an average of 21 points, BERTScore recall by 15 points. However, effects of fine-tuning on precision are weaker and more mixed. Perhaps fine-tuning sacrifices brevity for inclusion of more words in a syllabus.

Method	Length	Compression	Correlation
Opinion	6640	-	-
Syllabus	750	0.176	0.676^{***}
GPT-4	321	0.092	0.088^{*}
Mistral Base	126	0.034	0.151^{***}
Mistral FT	447	0.121	0.179^{***}
Oyez	332	0.096	0.094^{*}
Westlaw	142	0.044	0.025

Table 3: Descriptive statistics on summaries in test set (n=622). Length is number of words. Compression rate is ratio of words in syllabus to words in opinion. Smaller number is more compression. Opinion included as reference. ($^{*}p < 0.05$ $^{**}p < 0.01$, $^{***}p < 0.001$)

Control summaries help highlight effects of style differences on automatic metrics. By comparing against the two control human-written summaries, we can clearly see that Westlaw is an outlier. While GPT-4 and Mistral FT scores mostly resemble Oyez, Westlaw's recall scores are particularly low, only surpassing Mistral base. This poor performance on recall, but strong performance on precision, may be a product of how short those summaries are.

5.2 Summaries do not Scale with Opinion Length as much as Official Syllabuses

A unique aspect of CASESUMM is that it includes SCOTUS cases dating back to more than two centuries ago. This breadth enables researchers to investigate summaries from many different angles. In this subsection, we characterize candidate summaries through the lens of length and compression and explore how these variables may affect summary quality over time.

Length & Compression. In our dataset, both the opinion and syllabus lengths systematically co-vary across time. Table 3 shows that syllabuses in our sample have an average compression rate of 17.6%, meaning they tend to be about one-sixth the length of the original opinions. We find that in generated summaries, Mistral FT produces summaries closest in length to these syllabuses, even outperforming GPT-4, which was also prompt-optimized to mimic syllabuses. Westlaw produced the shortest summaries, followed by Mistral without fine-tuning.

Regarding the correlation between summary and opinion lengths, syllabuses demonstrate the strongest relationship with opinion lengths: doubling opinion length increases syllabus length by nearly 2/3. In contrast, Mistral FT summaries show

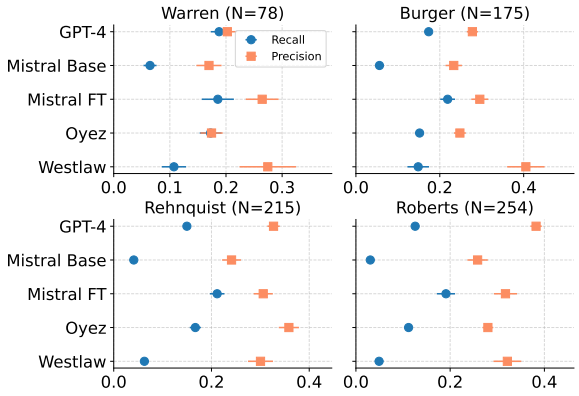

Figure 2: ROUGE-2 evaluation of model-generated and human summaries, by Chief Justice of SCOTUS when the opinion was written. Markers are means and whiskers are 95% confidence intervals.

a weaker correlation, with doubling opinion length increasing summary length by only 18%. Westlaw summaries exhibit almost no correlation with opinion length, maintaining a consistent target length of approximately 150 words. These findings highlight our dataset as a rich resource for future work in investigating how automatic summarization methods may adapt to varying source document lengths, ensuring that all salient information is captured regardless of length.

Precision & recall diverge over time. We use the Supreme Court Data Base[9], which contains metadata on SCOTUS cases, to see if any particular metadata can explain variation in summarization quality. While we do not find notable variation across most of these features, we observe one exception: the divergence between recall and precision across all summaries increases over time. Figure 2 illustrates this trend, comparing summaries for opinions based on the Chief Justice of the Supreme Court at the time an opinion was issued. Summaries of earlier opinions, e.g., under the Warren Court, have greater parity between recall and precision compared to summaries from later opinions. One possible explanation for this trend is that opinions and syllabuses have become longer over time (Figure 1 and Table 3), while the summaries we evaluate show a growing disparity between their lengths and opinion/syllabus lengths over time.

[9]We obtain data on features of cases by downloading case metadata from Washington University Law School's Supreme Court Data Base (SCDB).

Metric	Sensitivity	Specificity	Clarity	Style
ROUGE-1	0.54	-0.28	-0.02	0.40
ROUGE-2	0.55	-0.32	0.02	0.39
ROUGE-L	0.57	-0.26	0.04	0.47
BERTScore	0.45	-0.11	0.01	0.43

(a) ROUGE & BERTScore correlations with human rankings.

G-Eval	Sensitivity	Specificity	Clarity	Style
Consistency	0.26	0.06	0.25	0.11
Relevance	0.45	0.09	0.26	0.30
Coherence	0.42	0.05	0.28	0.33
Fluency	0.43	-0.15	0.08	0.30

(b) Default G-Eval criteria and prompts used for GPT-4o-based evaluation.

G-Eval	Sensitivity	Specificity	Clarity	Style
Sensitivity	0.43	-0.01	0.19	0.23
Specificity	0.51	0.06	0.24	0.38
Clarity	0.38	-0.02	0.23	0.21
Style	0.42	-0.07	0.08	0.34

(c) Human evaluation criteria used for GPT4o-based evaluation. G-Eval criteria and prompts adapted accordingly.

Table 4: Spearman correlations between various automatic scoring methods and human summary rankings. Interval scores from automatic methods are converted to rankings. Human rankings for the same set of summaries are averaged.

5.3 Human Evaluation Disagrees with Automatic Evaluation

The results of our human evaluation, presented in Figure 3 are distinctly different than those of our automatic evaluation. Whereas under automatic evaluation, Mistral FT outperforms other models as well as the control human-written summaries, we find that humans most commonly prefer GPT-4 summaries. GPT-4 particularly excels on *clarity*, a crucial yet difficult to measure desideratum for the summarization task. Nonetheless, Mistral FT remains an above-average performer, successfully matching the original opinion syllabuses on every dimension except, importantly, number of errors. Evaluators report that roughly 20% of Mistral FT summaries have at least 1 factual error, with a total of 10 errors identified across all evaluations. However, we see that these factual errors, or *hallucinations*, are not necessarily a product of using LLMs, as GPT-4 has performance on par with syllabuses and Oyez in terms of factual correctness.

Surprisingly, the human evaluation also revealed that all three human-written summaries, including the official syllabuses, often performed worse than

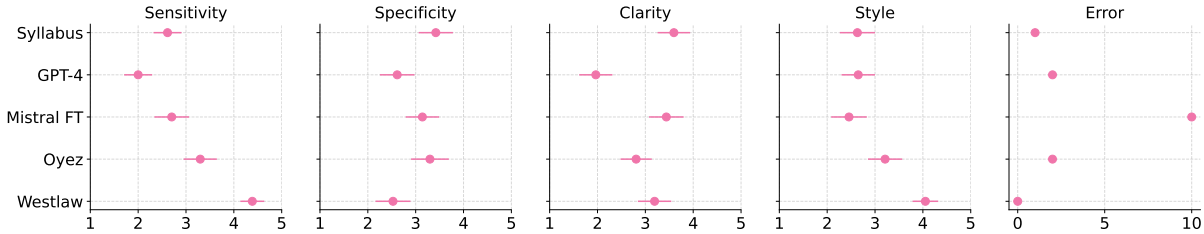

Figure 3: Human evaluation of model-generated and human summaries. x-axis is a rank, where 1 is best and 5 is worst. For **Error**, x-axis shows counts of the total number of errors identified by participants for each summary method. See Appendix C.1 for explanation of each dimension.

GPT-4. Westlaw summaries, despite being a paid service designed for legal professionals, ranked below average on sensitivity, clarity, and style. Even more intriguingly, the official syllabuses only matched or under-performed the LLM-generated summaries on all metrics except, crucially, factual correctness (*error*). This result both challenges the assumption that human-written summaries are inherently superior, while also revealing opportunities and challenges in using LLMs for generating concise, correct, and accessible summaries.

LLM-based evaluation does not correlate better with human evaluations than traditional automatic metrics. The human correlation results in Table 4 illustrate differences in how well various evaluation strategies align with human preferences.

First, ROUGE and BERTScore better capture other aspects of summary quality, particularly sensitivity and style. ROUGE-L has the highest correlation with human judgments of style (0.47), and ROUGE-1/2/L outperform G-Eval on sensitivity. Despite its limitations, ROUGE provides useful signals for evaluating how well summaries balance content inclusion and exclusion and convey proper legal style. Notably, ROUGE shows the strongest negative correlation with specificity.

Second, G-Eval shows significantly stronger correlations with human rankings of *clarity* (Tables 4b, 4c) compared to BERTScore and ROUGE. This suggests that G-Eval better captures attributes like readability and logical flow, which are valued by human evaluators.

Third, G-Eval, while generally more consistent, performs similarly in its default and adapted versions, with only modest differences across dimensions. For instance, the adapted G-Eval slightly improves correlations with human judgements of style and specificity but shows no significant advantage for clarity or sensitivity. This suggests that while adapting prompts can impact G-Eval's results, it does not drastically alter its overall effectiveness.[10]

These findings highlight the need for evaluation metrics, whether LLM-based or not, that are more closely aligned with human preferences and capable of capturing granular dimensions, such as clarity, specificity, and style, that matter in human judgment of summaries.

5.4 Error Analysis

Mistral hallucinates more conspicuously than GPT-4. We conduct further analysis of each summary flagged as containing factual errors according to the participants in the human evaluation. We compare each such summary to the original opinion to identify specific factual errors. Recent work has often referred to errors of this type as "hallucinations" (Huang et al., 2023).

Table 5 presents example errors. Fine-tuned mistral contained the most errors in its summaries. Furthermore, these errors were more egregious than any produced in the GPT-4 Turbo summaries. These errors include simple factual errors (examples 1), incorrect citations (example 2), temporal understanding errors (example 3), as well as procedural history outcome errors (examples 4).

In contrast, GPT-4 Turbo errs in a more subtle way, failing to properly convey the legal analysis presented in the opinion (example 5) or misrepresenting background details (example 6). While the opinion indeed reverses the judgement of the court below, it does not reject its reasoning. Rather, the ruling is reversed due to a superseding issue of constitutionality. The summary generated by GPT-4 Turbo is thus incorrect in its characterization of the Supreme Courts decision.

Lexical variation. We define *lexical variation* as the percentage of unique words in the summary not

[10] In this analysis we focus on G-Eval's agreement with human judgments. Complete G-Eval scores are included in Appendix B.4 for reference.

Hallucination in Summary	Explanation
Fine-tuned Mistral	
1. "Petitioner, a Negro, applied for admission to the University of Washington Law School, a state-operated institution."	The opinion indicates the petitioner is not a member of a "favored group" nor a "minority applicant". This strongly implies the petitioner is white and rules out the petitioner to be "a negro". 416 U.S. 312, 332, 325 (1974).
2. "Sherbert v. Velelline, 416 U. S. 456"	The opinion cites "Sherbert v. Verner, 374 U.S. 398" 494 U.S. 872, 875 (1990).
3. "He was held incommunicado for some five or seven days after signing the statement."	Petitioner Haynes testified he was held incommunicado until some five or seven days after his arrest. 373 U.S. 503, 504 (1963).
4. "The District Court ultimately entered judgment for petitioner, holding that the Texas death penalty scheme was unconstitutional."	While the District Court initially stayed the execution pending judgement, it ultimately "filed its findings and conclusions, rejecting each of the several grounds asserted by petitioner. The writ was accordingly denied; also, the stay of petitioner's death sentence was vacated." 463 U.S. 880, 885 (1983).
GPT-4 Turbo	
5. "The Court rejected the State's interest in [...] preserving the flag as an unalloyed symbol of the nation"	The Supreme Court did not reject the State's interest. They "assume[d], arguendo, that it is [valid]" but found "[t]he statute is nonetheless unconstitutional as applied to appellant's activity". 418 U.S. 405, 414 (1974).
6. "The PCAOB is a regulatory body that oversees the audits of public companies"	The PCAOB was created to govern the entire industry of accounting, including "hiring and professional development, promotion, supervision of audit work, the acceptance of new business and the continuation of old, internal inspection procedures, professional ethics rules, and 'such other requirements as the Board may prescribe.'" 561 U.S. 477, 485 (2010).

Table 5: Comparison of model hallucinations and their explanations.

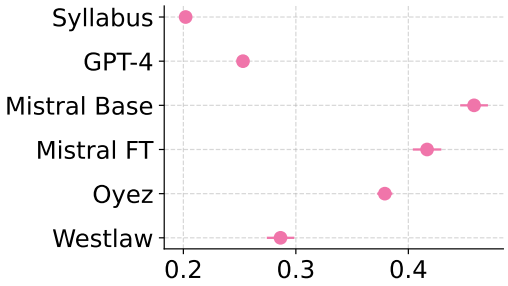

Figure 4: Lexical Variation. Measures the fraction of words in summary that are not in opinion.

present in the opinion and consider it a measure of summary style. Mirroring our comparison of compression rates, syllabuses are shown to exhibit the lowest percentage of lexical variation from the original opinion. Surprisingly, the fine-tuned Mistral summaries have the highest average percentage of lexical variation at 41.7%, even surpassing those written by Oyez (37.9%). This is unexpected because Mistral FT is trained on legal syllabuses, while Oyez summaries are written for a general audience and might borrow less from the opinion. The high lexical variation rate of Mistral FT may be related to its higher rate of factual errors.

6 Conclusion

This paper introduces CASESUMM, a novel dataset for long-context summarization in the legal domain, comprising 25.6K U.S. Supreme Court opinions and their official syllabuses. Our comprehensive evaluation of LLM-generated summaries, using automatic metrics and expert human evaluation, reveals discrepancies between these methods. While fine-tuned Mistral 7b outperforms larger models on automatic metrics, human experts rank GPT-4 summaries higher in clarity and accuracy.

Our evaluation also showed GPT-4 summaries often outperformed human-written ones, including official syllabuses and professional services, in several metrics except factual correctness. LLM-based evaluation, such as G-Eval, may be promising for reference-free evaluation, but our results show it does not correlate with human judgments better than traditional metrics.

Our findings highlight the limitations of current automatic evaluation methods for legal summarization and underscore the importance of human evaluation, particularly in complex, high-stakes domains like law. This work contributes to the ongoing dialogue on NLP evaluation methodologies and opens avenues for research in legal text summarization.

7 Limitations

First, the sample size of our human evaluation limits the conclusions we can draw. Second, while we are able to offer insight into the value of fine-tuning, at least with respect to the open-source Mistral model, we are unable to estimate the value of prompt-engineering even the GPT-4 model because we do not have a natural benchmark, non-optimized prompt for that model. A related weakness is that our evaluation of fine-tuning Mistral does not tell us the value of fine-tuning other models, such as GPT-4. It is possible that the benefit to fine-tuning the latter may be lower than the former because GPT-4 is trained on more data and has far more estimated parameters. Third, we experiment with one LLM-based evaluation framework. While G-Eval is commonly cited and used, other LLM-based approaches could yield different results. Finally, while we demonstrate through a manual evaluation that our PDF extraction procedure is largely accurate (96%), it is not perfect. A fraction of syllabuses, particularly those extracted from low-quality scans from SCOTUS opinions in the early 1800s, may not be fully correct.

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A Summary Generation

A.1 Mistral Fine-tuning and Generation Implementation Details

In our fine-tuning experiments, we use a batch size of 56. We select the best performing learning rate out of $\{2e-5, 2e-4, 2e-3\}$ and early stop based on dev loss convergence. We conduct our experiments on 7 A100 80GB GPUs, with each fine-tuning run taking approximately 2 hours. During summary generation, we don't use sampling and set max tokens to 1500. We truncate opinions which exceed Mistral's 32768 context-length limit. In approximately 10% of Mistral generations, the generation stops due to the length limit, rather than an `<eot>` token being generated. In such cases, we fallback to sampling a generation with `repetition_penalty = 1.3` and `top_p = 0.9`. This ensures a complete summary is produced and reduces degenerated summaries from the model.

A.2 GPT-4 Generation Details

To generate summaries based on majority opinions, we use the DSPy optimized prompt in Listing 2. The initial, unoptimized prompt, is included in Listing 1.

We run DSPy using `gpt-4-1106-preview`. We use the `SignatureOptimizer` (now called `COPRO`) with ROUGE-2 as the optimization metric along with a development set of reference syllabuses. Otherwise, we use default parameters.

For generating the final summaries after DSPy, we use `gpt-4-1106-preview` with `temperature = 0` and `max_tokens = 1000`. All other parameters are set to the OpenAI API defaults.

B Automatic Evaluation

B.1 ROUGE Implementation Details

We use the ROUGE implementation from the HuggingFace `evaluate` Python package. We set `use_stemmer = True` and `use_aggregator = True`.

B.2 BERTScore implementation Details

We use the `bert-score` PyPI package. We use the default `bert-base-uncased` scoring model and all other default settings.

B.3 BARTScore

See results in Table 6.

B.4 G-Eval LLM Evaluation

B.4.1 Generation Parameters

We use use `gpt-4-0613` with `temperature = 1` and `n = 10`. All other parameters are set to the OpenAI API defaults.

B.4.2 Default Prompts

Consistency: see Listing 3.
Coherence: see Listing 5.
Relevance: see Listing 4.
Fluency: see Listing 6.

B.4.3 Adapted Prompts

Sensitivity: see Listing 7.
Specificity: see Listing 8.
Clarity: see Listing 9.
Style: see Listing 10.

B.4.4 Default & Adapted G-Eval Scores

Table 7 presents all the G-Eval scores.

C Human Evaluation

C.1 Dimensions of Summary Quality

Sensitivity: Does this summary include all relevant information required to understand the facts, judgment and reasoning? Outcome is a rank, where 1 is best, rank 5 is worst. Ranks are mutually exclusive: only one case per rank.

Specificity: Does this summary exclude irrelevant information that is not required to understand the facts, judgment and reasoning? Rank from 1 to 5.

Clarity: Is this summary clear and easy to read? Rank from 1 to 5.

Style: Does this summary have a legal style, defined as something written by a well-trained lawyer? Rank from 1 to 5. For all measures where the outcome is rank, we mark the mean rank identically 3) with a red dashed line.

Factuality: Does this summary contain any factual errors? (Yes/No).

C.2 Annotation Interface

Figure 5 is a screenshot of the annotation interface that participants used to read the opinions and summaries then rank them.

C.3 Instructions & Consent Materials for Participants

Figure 6 shows the consent form presented to participants.
Figure 7 shows the email with annotation instructions sent to participants.

Listing 1: Initial GPT-4 Turbo summarization prompt used as input to DSPy.

```
Summarize the Supreme Court Opinion.

Opinion: {{OPINION}}
Summary:
```

Listing 2: DSPy optimized GPT-4 Turbo summarization prompt.

```
Review the provided Supreme Court opinion text. Deliver a concise, neutral
    summary that captures the essence of the legal reasoning, main points of law
    , conclusions drawn, and the implications of the decision, all whilst
    adhering to comprehensible language suitable for an educated general
    audience.

Opinion: {{OPINION}}

Summary of Supreme Court Opinion:
```

	BARTScore ↓		
Method	P	R	F1
GPT-4 Turbo	**256.0**	335.1	**289.5**
Mistral Base	277.0	380.1	316.8
Mistral FT	297.9	**312.3**	298.1
Oyez	346.5	334.6	339.3
Westlaw	307.8	345.2	323.5

Table 6: BARTScores of model-generated and human-written summaries, where official syllabuses are the reference summaries. Sample includes 622 Supreme Court cases. There are 622 observations on each type of summary except Westlaw, for which we only have 156 observations. We report precision (P), recall (R), and F1-score (F1). BARTScores are negative log-likelihoods, so lower scores are better. We **bold** the best score(s) and underline the second best score(s). For the scoring model, we use `facebook/bart-large-cnn`, the default model used in Yuan et al. (2021)

Method	**Default ↑**				**Adapted ↑**			
	Consistency	**Relevance**	**Coherence**	**Fluency**	**Sensitivity**	**Specificity**	**Clarity**	**Style**
Syllabus	4.1	3.6	4.0	**3.0**	3.3	3.6	3.8	**3.0**
GPT-4 Turbo	**4.4**	**4.2**	**4.5**	**3.0**	**3.9**	**3.8**	**4.3**	**3.0**
Mistral FT	3.1	3.1	3.5	2.8	2.8	3.0	3.8	2.6
Oyez	3.7	3.3	3.8	**3.0**	3.1	3.2	4.0	2.8
Westlaw	3.8	3.2	3.6	**3.0**	3.0	3.0	3.8	2.7

Table 7: G-Eval, default and adapted, LLM-based evaluation of model-generated and human-written summaries. Sample includes the 33 Supreme Court cases used for human evaluation. For each metric, we **bold** the best score(s) and underline the second best score(s).

Listing 3: Consistency prompt.

```
You will be given one summary written for a U.S. Supreme Court opinion.


Your task is to rate the summary on one metric.

Please make sure you read and understand these instructions carefully. Please keep this document open while reviewing, and refer to it as needed.


Evaluation Criteria:

Consistency (1-5) - the factual alignment between the summary and the summarized source. A factually consistent summary contains only statements that are entailed by the source document. Annotators were also asked to penalize summaries that contained hallucinated facts.

Evaluation Steps:

1. Read the opinion carefully and identify the main facts and details it presents.
2. Read the summary and compare it to the opinion. Check if the summary contains any factual errors that are not supported by the opinion.
3. Assign a score for consistency based on the Evaluation Criteria.

Opinion Text:

{{Document}}

Summary:

{{Summary}}


Evaluation Form (scores ONLY):

- Consistency:
```

Listing 4: Relevance prompt.

```
You will be given one summary written for a U.S. Supreme Court opinion.

Your task is to rate the summary on one metric.

Please make sure you read and understand these instructions carefully. Please
    keep this document open while reviewing, and refer to it as needed.

Evaluation Criteria:

Relevance (1-5) - selection of important content from the source. The summary
    should include only important information from the source document.
    Annotators were instructed to penalize summaries which contained
    redundancies and excess information.

Evaluation Steps:

1. Read the summary and the source document carefully.
2. Compare the summary to the source document and identify the main points of
    the opinion.
3. Assess how well the summary covers the main points of the opinion, and how
    much irrelevant or redundant information it contains.
4. Assign a relevance score from 1 to 5.


Opinion Text:

{{Document}}

Summary:

{{Summary}}


Evaluation Form (scores ONLY):

- Relevance:
```

Listing 5: Coherence prompt.

```
You will be given one summary written for a U.S. Supreme Court opinion.

Your task is to rate the summary on one metric.

Please make sure you read and understand these instructions carefully. Please
    keep this document open while reviewing, and refer to it as needed.

Evaluation Criteria:

Coherence (1-5) - the collective quality of all sentences. We align this
    dimension with the DUC quality question of structure and coherence whereby "
    the summary should be well-structured and well-organized. The summary should
     not just be a heap of related information, but should build from sentence
    to a coherent body of information about a topic."

Evaluation Steps:

1. Read the opinion carefully and identify the main topic and key points.
2. Read the summary and compare it to the opinion. Check if the summary covers
    the main topic and key points of the opinion, and if it presents them in a
    clear and logical order.
3. Assign a score for coherence on a scale of 1 to 5, where 1 is the lowest and
    5 is the highest based on the Evaluation Criteria.

Opinion Text:

{{Document}}

Summary:

{{Summary}}


Evaluation Form (scores ONLY):

- Coherence:
```

Listing 6: Fluency prompt.

```
You will be given one summary written for a U.S. Supreme Court opinion.

Your task is to rate the summary on one metric.

Please make sure you read and understand these instructions carefully. Please keep this document open while reviewing, and refer to it as needed.


Evaluation Criteria:

Fluency (1-3): the quality of the summary in terms of grammar, spelling, punctuation, word choice, and sentence structure.

- 1: Poor. The summary has many errors that make it hard to understand or sound unnatural.
- 2: Fair. The summary has some errors that affect the clarity or smoothness of the text, but the main points are still comprehensible.
- 3: Good. The summary has few or no errors and is easy to read and follow.

Summary:

{{Summary}}


Evaluation Form (scores ONLY):

- Fluency:
```

Listing 7: Sensitivity prompt.

```
You will be given one summary written for a U.S. Supreme Court opinion.


Your task is to rate the summary on one metric.

Please make sure you read and understand these instructions carefully. Please keep this document open while reviewing, and refer to it as needed.


Evaluation Criteria:

Sensitivity (1-5) - the informativeness of the summary with respect to the opinion. An informative summary contains all relevant information required to understand the facts, judgement, and reasoning of the opinion.

Evaluation Steps:

1. Read the opinion carefully and identify the main facts, judgements, and reasoning it presents.
2. Read the summary and compare it to the opinion. Check if the summary misses relevant information presented in the opinion.
3. Assign a score for sensitivity based on the Evaluation Criteria.


Opinion Text:

{{Document}}

Summary:

{{Summary}}


Evaluation Form (scores ONLY):

- Sensitivity:
```

Listing 8: Specificity prompt.

```
You will be given one summary written for a U.S. Supreme Court opinion.

Your task is to rate the summary on one metric.

Please make sure you read and understand these instructions carefully. Please keep this document open while reviewing, and refer to it as needed.

Evaluation Criteria:

Specificity (1-5) - selection of important content from the source. The summary should include only important information from the source document and exclude irrelevant information that is not required to understand the facts, judgement, and reasoning. Annotators were instructed to penalize summaries which contained irrelevant and excess information.

Evaluation Steps:

1. Read the summary and the opinion carefully.
2. Compare the summary to the opinion and identify the main points of the opinion.
3. Assess how much irrelevant or redundant information it contains.
4. Assign a Specificity score from 1 to 5.

Opinion Text:

{{Document}}

Summary:

{{Summary}}


Evaluation Form (scores ONLY):

- Specificity:
```

Listing 9: Clarity prompt.

```
You will be given one summary written for a U.S. Supreme Court opinion.

Your task is to rate the summary on one metric.

Please make sure you read and understand these instructions carefully. Please keep this document open while reviewing, and refer to it as needed.


Evaluation Criteria:

Clarity (1-5): the quality of the summary in terms of grammar, word choice, and sentence structure. The summary should be well-structured and well-organized. The summary should not just be a heap of related information, but should build from sentence to a coherent body of information about a topic. Is this summary clear and easy to read?

- 1: Very Poor. The summary is riddled with errors, making it very hard to understand. It may be disorganized to the point of confusion.
- 2: Poor. The summary has noticeable errors that impede clarity. It might be difficult to follow the central points or the flow of information.
- 3: Fair. The summary conveys the main points, but there are a few errors or awkward phrases. Overall, it is understandable but not polished.
- 4: Good. The summary is clear, well-structured, and mostly free of errors. The information is presented smoothly and cohesively.
- 5: Excellent. The summary is highly polished, with virtually no errors. It flows naturally, is easy to read, and effectively communicates the key information.


Summary:

{{Summary}}


Evaluation Form (scores ONLY):

- Clarity:
```

Listing 10: Style prompt.

```
You will be given one summary written for a U.S. Supreme Court opinion.

Your task is to rate the summary on one metric.

Please make sure you read and understand these instructions carefully. Please keep this document open while reviewing, and refer to it as needed.

Evaluation Criteria:

Style (1-3) - Does this summary have a legal style, defined as something written by a well-trained lawyer?

- 1: Poor. The summary does not read like something a trained lawyer would write. It may be overly casual, contain imprecise or incorrect legal terminology, or lack the logical structure and clarity typically found in legal writing.
- 2: Fair. The summary attempts a legal style and may use some appropriate terminology or reasoning, but it isn't fully polished. It might occasionally drift into non-legal language or lack the cohesive logic and precision expected from professional legal writing.
- 3: Good. The summary is stylistically consistent with something a trained lawyer would write. The language is precise, the reasoning is well-structured, and the tone is appropriately professional. It closely resembles the style commonly found in formal legal documents.

Evaluation Steps:

1. Read the summary and the opinion carefully.
2. Consider the style of the summary: Does it exhibit a tone, language, and structure similar to that of a well-trained lawyer (e.g., careful use of terminology, logical organization, professional tone)?
3. Compare the summary's style to the evaluation criteria. Assign a rating (1-3) based on how closely it aligns with a professional legal style, using the provided definitions for each level.

Opinion Text:

{{Document}}

Summary:

{{Summary}}


Evaluation Form (scores ONLY):

- Style:
```

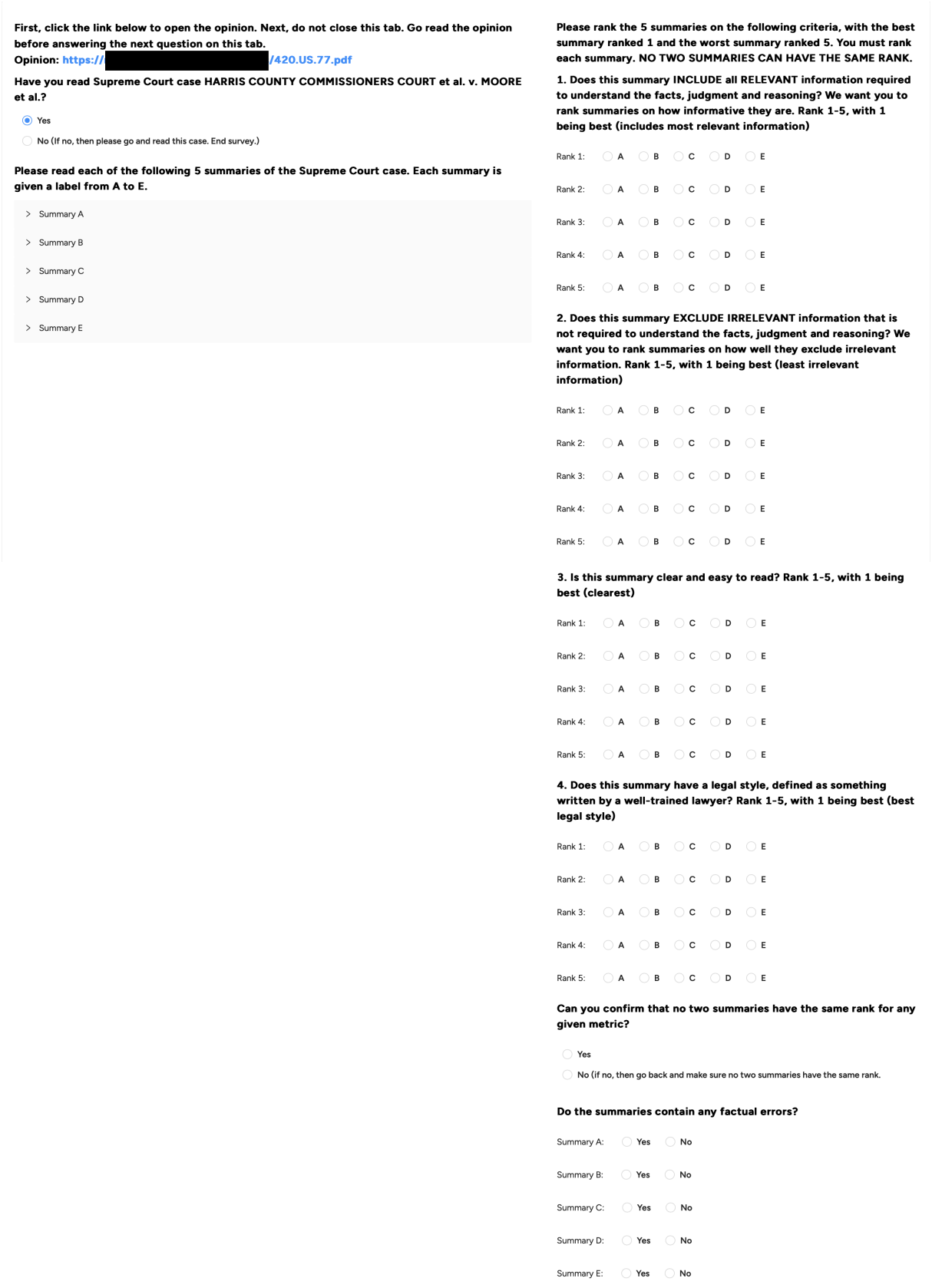

Figure 5: Labelstudio Annotation Interface

Online Consent Form for Research Participation

Study Title: Investigating the quality of automatic legal case summarization
Researcher(s): [redacted]

Description: We are researchers at [redacted] doing a research study that uses artificial intelligence (large-language models or LLMs) to summarize US legal cases. The purpose of this research is to develop tools to facilitate legal research. One step in this research is to assess the quality of these summaries. We are recruiting research assistants to do that. We will ask research assistants to (a) read a Supreme Court case that we have summarized, read 5 summaries of this cases, and (c) rank the 5 summaries on accuracy, clarity, and legal style. Together these 3 steps are called a "case summary analysis". We will not ask any personal questions about you, except your name, so that we can pay you for participating. Each case summary analysis will take roughly 45 minutes. We may do as many cases analyses as you like, though we request you complete a minimum of 4. You are eligible to be a research assistant on this study if you are a 2L or 3L law student at [redacted] Law School. Your participation is voluntary.

Incentives: We will pay you $15 per case summary, which equals $20/hour because each case summary analysis should take 45 minutes. You will be paid per case summary analysis completed. You will not be paid for partial case analyses as these are not usable for the research study.

Risks and Benefits: Your participation in this study does not involve any risk to you beyond that of everyday life.

Confidentiality: We will maintain a file that includes your name and a randomly generated ID number. You will use that ID number to log into a server that contains your case assignment, the 5 summaries associated with that case, and a web-form for ranking the 5 summaries. Each completed case analyses and your associated ID will be shared with Professor [redacted] who will connect your ID to your name for the purpose of paying you for the "case summary analysis". The data connecting your ID to your name will be maintained on the secure, encrypted [redacted] Box server. We will not use any identifiable data from you for the research analysis. Such data is only used for purposes of paying you compensation for your research assistance. We will not use data or identifiers from any case analysis summaries that are incomplete. You may stop working as a research assistant at any time. If you stop working as a research assistant, data collected up until the point of withdrawal may still be included in the analysis. No identifiable data will be used in future research. De-identified data may be used in future research and shared with other researchers for future research without additional informed consent.

Contacts & Questions:
If you have questions or concerns about the study, you can contact the researchers by reaching out to [redacted].

If you have any questions about your rights as a participant in this research, feel you have been harmed, or wish to discuss other study-related concerns with someone who is not part of the research team, you can contact the [redacted]

Institutional Review Board (IRB) Office by phone at [redacted] or by email at [redacted].

Consent:
Participation is voluntary. Refusal to participate or withdrawing from the research will involve no penalty or loss of benefits to which you might otherwise be entitled.

By clicking "Agree" below, you confirm that you have read the consent form, are at least 18 years old, and agree to participate in the research. Please print or save a copy of this page for your records.

☐ I agree to participate in the research
☐ I do NOT agree to participate in the research

Figure 6: Consent form for research participation.

Dear X,

Thanks for helping with our AI legal summarization project! As a reminder, you are going to evaluate the quality of the summaries produced by our AI-based tool for summarizing Supreme Court decisions. We hope that you are able to begin this work as soon as possible, ideally even today. Moreover, we request that you complete at least 4 evaluations, though we would be very happy for you to complete as many as you can. Remember, we pay $20/hour: because we expect each case evaluation to take you 45 minutes, this means we will pay $15 for every case evaluation you complete.

There are 3 steps to begin work as an RA.

1/ Please read and answer the attached consent form. While you are an RA, computer science projects have a norm of registering human evaluations with the IRB. Please email me back your completed consent form.

2/ Once you do that, I will send you a link to a custom survey that will give you a case, some summaries, and ask some questions. Once you complete one survey, you will be given a another one. Again, please try to complete at least 4 surveys. However, you may complete more.

3/ Once you are done, do let us know. The system will tabulate how many forms you have completed, and I will have the law school issue an RA payment to you. (The law school may need some additional paperwork, but it should not be onerous. Just the usual RA paperwork.)

If you have any questions, about the project, the consent form, or the survey, do reach out. The best way to reach me is via email at [redacted].

Figure 7: Email with instructions sent to participants.