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A SURVEY ON SUMMARIZATION OF LEGAL TEXTS

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1.Abstract - The task of summarizing legal texts is of paramount importance in facilitating access to legal knowledge. This survey paper critically reviews and analyzes diverse methodologies applied to the challenging task of summarizing legal texts. In the supervised realm, models such as GIST, SummaRuNNer, and BERTSUM have gained prominence, demonstrating prowess in extractive summarization techniques. Semi-supervised methods, leveraging innovative techniques such as TF-IDF Scores and Sentence Embeddings, have proven effective in handling the intricate structure of court judgments. Unsolicited approaches, CaseSummarizer and exemplified by USLT-LEGAL-BERT, address the challenges of summarization without the luxury of labeled data, showcasing their adaptability to diverse legal domains. Furthermore, the paper explores legal document retrieval strategies, incorporating document vector embeddings and deep learning techniques, underscoring the significance of domain-specific approaches. The study encompasses a variety of models, from Legal-BERT to hierarchical encoder decoder frameworks, showcasing their applicability in handling the complexity inherent in legal texts. Additionally, the survey delves into BERT-based techniques for legal classification tasks, emphasizing the crucial role of context and introducing innovative methods such as "Stride 64." In the realm of legal text simplification, the survey scrutinizes the KIS model and graph-based approaches, revealing nuanced trade-offs between readability, fluency, and meaning preservation. The research culminates with an exploration of the team's participation in LegalEval 2023 shared tasks, underscoring the prowess of deep learning models in tasks such as rhetorical role classification and legal named entity extraction.This survey paper provides a nuanced and comprehensive perspective on the evolving landscape of legal document summarization, offering valuable insights into current methodologies, challenges, and potential future directions for advancing the field.

Keywords- Legal text Summarization,Supervised Learning, Extractive Summarization,Semi-supervised methods,Deep learning Techniques,Legal Document retrieval.

2.INTRODUCTION

The legal landscape is intricately woven with vast volumes of texts, ranging from court judgments to statutes and legal opinions. Navigating this expansive sea of information poses a significant challenge for legal professionals, scholars, and even the general public seeking access to legal knowledge. Amid this challenge, the field of legal document summarization emerges as a crucial endeavor, aiming to distill the essence of complex legal texts into concise and comprehensible summaries. This survey paper embarks on a systematic exploration of the multifaceted approaches deployed in summarizing legal documents, offering a panoramic view of the current state of the art. As the legal domain is characterized by its unique language, structure, and depth, conventional natural language processing (NLP) techniques often fall short when applied directly to legal texts. The need for specialized methods tailored to the intricacies of legal language has fueled a surge in research and innovation within the realm of legal document summarization. This paper serves as a beacon, illuminating the diverse strategies and methodologies that researchers have devised to tackle the challenges inherent in summarizing legal content. Legal document summarization is not a one-size fitsall challenge; rather, it spans a spectrum of complexities dictated by the nature of the legal texts involved. From court judgments with nuanced legal reasoning to statutes laden with precise legislative language, the diversity of legal documents necessitates a nuanced understanding and treatment in the summarization process. The paper meticulously categorizes approaches based on supervised, semi-supervised, and unsupervised methods, unraveling the distinct strengths and limitations of each. Beyond summarization techniques, the paper delves into legal document retrieval strategies, exploring how document vector embeddings and deep learning methodologies can enhance the extraction of key legal information. By juxtaposing various models, including LegalBERT and hierarchical encoder-decoder frameworks, the survey underscores the importance of domain-specific considerations in legal document retrieval. Furthermore, the survey navigates through the realm of BERT-based techniques applied to legal classification tasks, where the context of legal texts plays a pivotal role. The paper discusses innovative methods like "Stride-64," shedding light on the evolving landscape of legal text analysis beyond traditional summarization. In the pursuit of accessibility and clarity, legal text simplification emerges as a critical aspect of legal document processing. The survey scrutinizes models such as the KIS model and graph-based approaches, offering a nuanced examination of the trade-offs between readability, fluency, and the preservation of meaning in simplified legal texts. The journey through legal document summarization culminates in a reflection on the participation in LegalEval 2023 shared tasks, showcasing the real world applicability of deep learning models in tasks like rhetorical role classification and legal named entity extraction. In essence, this survey paper embarks on a comprehensive exploration of the evolving landscape of legal document summarization, navigating through the intricate contours of legal language, structure, and semantics. Through this exploration, the paper seeks to contribute valuable insights, laying the groundwork for future advancements and innovations in the dynamic field of legal document processing.

3.LITERATURE SURVEY OVERVIEW

Organizing previous research works based on the various methods to understand how different approaches were used. This helps to understand common patterns, strengths, and weaknesses in applying different learning methods to summarize the legal texts. Including this breakdown in a survey paper adds context to how various learning techniques have been used.

3.1 Methods used to summarize legal text using supervised approach

Summarizing legal texts using supervised approaches involves utilizing machine learning models that have been trained on labeled datasets to understand the structure and content of legal documents.

GIST, SummaRuNNer andBERTSUM

This methods are used to train the model for extractive summarization[1] of legal texts using supervised approaches.In these the sentences are labelled 1 and 0.Sentences which are labeled 1are included for summarisation process and 0 labelled sentences are neglected.These labeling process is applied on the datasets of of Legal Information Institute of India (http://www.liiofindia.org/in/cases/cen/INSC/) and The UK Supreme court website (https://www. supremecourt.uk/decided-cases/) .Summarization models, during inference, are guided by a target summary length denoted as L,which is derived differently for various datasets. For IN-Ext documents, L is the average word count of two expert reference summaries, while for IN-Abs and UK-Abs, it's based on a single abstractive reference summary. Summaries are constrained to a length of at most ‘L’. words, and some algorithms rank sentences by summary-worthiness. Evaluation metrics encompass ROUGE-1, ROUGE-2, ROUGE-L F scores, and BertScore. Evaluation includes overall document-wide scores and, specifically for IN-Ext and UK-Abs datasets, a segment-wise assessment focusing on rhetorical segments. In segment-wise evaluation, only ROUGE Recall scores are reported, considering the summarization algorithms output characteristics.Notable performers for extractive summarization include DSDR which is unsupervised and SummaRuNNer. Legal-Pegasus stands out for abstractive summarization. Expert evaluations reveal that DSDR is preferred among legal practitioners. emphasizes the Interestingly, need for the study domain-specific evaluations and highlights the potential of fine tuning models for handling long legal documents. The correlation analysis suggests that automatic metrics might not fully capture the quality of legal summaries.

LETSUM

LetSum [6] categorizes the text into five themes through thematic segmentation, excluding less important units like case citations, selecting candidate units, and generating the summary. Sentences are assigned themes using hand engineered linguistic markers, and citation units are excluded with specific identifiers. Challenges in reproducibility stem from the varied structure of Indian case documents, different from Canadian ones, and the need to preserve citations in Indian legal case summaries. Cue phrases for theme identification in Indian legal texts are extracted through manual annotation and ranking of frequent n-grams. Despite an unspecified heuristic function, sentences are ranked based on TF-IDF scores, and issues with NLTK persist in this process.

GRAPHICAL

The prior workers employed Conditional Random Fields (CRF) to identify rhetorical roles in sentences, using features like cue phrases, word positions, and layout features [6]. The term distribution model, known as the k-mixture model, assigned probabilistic weights by summing term probability values. To generate the final summary, two re-ranking stages based on weights and evolved roles during CRF implementation were applied. Reproducibility challenges arose from cue phrase mismatches, leading to an automated identification process using n-grams and frequency analysis. Default CRF parameters were utilized, and sentence re-ranking, considering identified labels, avoided exceeding the desired summary length, with similar challenges encountered using NLTK.

3.2 Summarisation of legal texts using semi-supervised methods

In this study, the authors tackle the intricate task of extractive legal document summarization, focusing particularly on the unique structure of court judgments [11]. The dataset comprises Indian Supreme Court judgments, totaling around 10,000 cases, sourced primarily from judic.nic.in. The pre processing involved removing headers, punctuation, and employing tokenization, with an 80%-20% train-test split.

The methodology unfolds in two main phases. First, for labeled dataset generation, the study proposes novel techniques. These include TF-IDF Scores (STFIDF) for similarity measurement, Rouge-L Scores (SROUGE) utilizing the Rouge-L metric, and Sentence Embeddings (SSE) using InferSent and Sent2Vec. SSE, leveraging deep learning advances, outperforms other methods in labeled data creation.

Moving to summary generation, the study employs various techniques. Feed Forward Neural Networks (FFNN) come in two variants, namely InferSent + FFNN and Sent2Vec-FFNN, with training based on labeled data generated by SSE. Long Short-Term Memory (LSTM) architecture, combining 1D Convolutional NN (CNN) and RNN/LSTM, is explored with Glove and Word2Vec embeddings, resulting in variants LSTMGlove and LSTM Word2Vec. Additionally, traditional machine learning classifiers such as Naive Bayes and Random Forest, along with a baseline summarization method are included for comparison.

Evaluation encompasses both extrinsic and intrinsic measures. Extrinsic evaluation utilizes Rouge measures (Rouge-1, Rouge2, and Rouge-L), while intrinsic evaluation employs Precision, Recall, and F-Measure. Results indicate that labeled data generated using SSE outperforms other methods. The LSTM with Glove word embedding emerges as the most effective in achieving high coherence in summaries without the need for explicit feature engineering.

In conclusion, the proposed semi-supervised approach, driven by neural network architectures, exhibits promise in the challenging domain of extractive legal document summarization. By eliminating the need for expert-labeled data and demonstrating effectiveness in generating coherent summaries from complex legal texts, the study opens avenues for future exploration. Subsequent work may involve evaluating the method on human-generated legal text summaries and exploring sentence simplification techniques to enhance interpretability.

3.3 Summarisation of legal texts using unsupervised methods .

CASESUMMARIZER

The original CaseSummarizer method, designed for Australian documents, ranks sentences based on a score calculation [6]. The score considers TF-IDF values of words, sentence length normalization, the presence of dates, named entities, and whether the sentence starts a section. In adapting this method for Indian case documents (IN-Ext and IN-Abs), lacking structured sections, we substituted section information with a count of legal terms. To address the absence of clear entity identification details, we used the Stanford NER Tagger. This adjustment ensures a fair comparison, and the same approach was applied to the UK-Abs dataset.

CaseSummarizer performs less effectively. This reduced performance of CaseSummarizer may be attributed to its heavy reliance on accurately identifying named entities, a challenge in legal documents when using standard NLP tools, as mentioned earlier.

USLT-LEGAL-BERT

This study introduces an unsupervised method for simplifying legal texts by analyzing and altering both lexical and syntactic elements [2]. It identifies complex words based on frequency and complexity measures like the Zipf Scale. Using transformer based language models, masked-out word prediction generates substitution candidates, ranked by various features, with the highest-ranking candidate replacing the complex word. Sentence splitting is then employed to enhance legibility. Experimental results reveal the method's superiority over general methods, especially when applied to legal language using domain-specific corpora and transformer models in USLT. With its state-of-the art transformer models, USLT outputs are expected to be compatible with various high-level legal NLP tasks. On the datset They randomly selected 500 legal cases from the Caselaw Access Project and generated a test dataset comprising 500 sentences, each randomly chosen from distinct cases within the US Supreme Court cases. The quantitative experiments, specifically the comparison of the US Legal Text dataset (USLT) with other methods, were conducted using sentences extracted from the aforementioned US Supreme Court cases.

The Flesch–Kincaid Grade Level (FKGL) and Dale-Chall Score (DC) are employed as readability metrics in the legal domain. FKGL generates a grade level score indicating text readability, calculated based on the number of sentences (nS), words (nw), and syllables (nsyl). DC assesses comprehension difficulty using familiar words and considers the number of difficult words (ndw), total words (nw), and sentences (nS). Semantic Difference (SD) measures output sentence preservation of original semantics, employing vector embeddings and cosine similarity. A non parametric Wilcoxon signed-rank test is used for statistical significance in comparing scores of different methods in reported experimental results.

Multilingual Unsupervised Simplification by Mining Paraphrases

This study focuses on using Transformers in ATS for Language Processing (NLP). Researchers trained the "bertimbaulaw-base Portuguese-cased" model on 13,288 sentence pairs for 10 epochs [5]. The Multilingual Unsupervised Sentence Simplification by Mining Paraphrases (MUSS) method, without the need for parallel datasets, was explored. It offers fine control over attributes like compression rate and linguistic complexity. Virtual Box 6.1.38 on Ubuntu 22.04.1 64x, with Python 3.10.6, was used for tests. Neural Machine Translation (NMT) with attention mechanisms was also studied, treating simplification as a translation task. The model was trained from scratch on 132,879 sentence pairs for 100 epochs with a batch size of 128.

3.4 Legal Document Retrieval using Document Vector Embeddings and Deep Learning

The researchers embarked on a study focused on legal document summarization, starting by collecting over 2500 legal case documents from the FindLaw website. These documents formed the basis of their investigation, aiming to develop an effective system for extracting key information from legal texts.

To structure their methodology, the researchers proposed a system which involved creating three distinct document vector models [12]. The first model utilized raw document references, the second employed a neural network, and the third was based on sentence ranking derived from semantic similarity measures.

In the process of establishing relevance among legal cases, the researchers faced challenges related to variations and abbreviations in legal case names. To address this, they implemented regex-based Information Extraction and conducted extensive searches on the FindLaw platform to accurately map document references.

To capture the semantic structure of legal documents, the researchers employed a sentence similarity graph network. This approach focused on the importance of sentences in understanding the overall semantics of the documents, using the TextRank algorithm to highlight the most crucial sentences.

Ensuring the quality of their data, the researchers applied text preprocessing techniques to clean the document corpus. This involved the removal of unwanted characters and common words, employing lemmatization and case-folding for effective natural language processing.

Creating a robust foundation for document representation, the researchers applied TF-IDF to generate a weight matrix. They introduced a Global Term Frequency (GTF) approach to identify and prioritize words that held significant importance in the legal domain.

Building on this foundation, the researchers employed the Node2vec algorithm to develop a scalable feature learning model (doc2vecNV). Additionally, they introduced the doc2vecNN model, a neural network model trained by incorporating features from both doc2vecNV and another model based on sentence similarity measures.

In conducting experiments, the researchers compared the accuracy levels of these models by varying the dimension (p) of the document base vector. The results demonstrated that the doc2vecNN model outperformed the other models, supporting their hypothesis regarding the effectiveness of domain-specific techniques in legal document retrieval.

Concluding their study, the researchers suggested future work should consider the frequency of case mentions for a more nuanced understanding of relevance. Furthermore, they proposed extending their model to other domains for the development of information retrieval systems, emphasizing the significance of domain-specific approaches in this field.

This study leverages sentence embeddings for NLP tasks, employing a BERT model with mean-pooling token embeddings for a fixed-size representation. Legal-BERT [10], tailored for the legal domain and trained on the Harvard Law case corpus, provides domain-specific embeddings. To address class imbalance in extractive summarization, a weighted crossentropy loss is introduced, emphasizing positive labels. Maximal Marginal Relevance (MMR) is employed for sentence selection, balancing relevance and diversity. Xiao and Carenini (2020) address redundancy issues with a redundancy loss term (LRD) in the cross-entropy loss function, controlled by the parameter β. Extractive summarization, treated as a binary classification problem, involves Bidirectional Gated Recurrent Units (Bi-GRU) for encoding sentence embeddings in both directions, aiming to generate informative summaries for Reasoning/Evidence sentences in legal documents.

3.5 Other Approches used to summarize legal texts

KIS MODEL

It employs the KIS model [4] trained on 67K legal text sentences randomly selected from the LEDGAR dataset, not present in the test data. Evaluation is conducted on the LEDGAR dataset, comprising Securities and Exchange Commission (SEC) contracts. The evaluation metrics include meaning preservation, syntactic simplicity, fluency, hallucination, and readability measures. The models compared include BERT-LS, DISSIM, MWS, KIS, SBM-CONT, and human evaluations by legal experts. Results show that lexical simplification methods like BERT-LS focus on complex word replacements, while sentence splitting methods (DISSIM, MWS) improve readability but may sacrifice fluency. KIS achieves good readability and fluency but may compromise meaning preservation. Human evaluations highlight disagreements among legal experts on simplicity, indicating challenges in defining simplicity in legal texts. Correlation with automatic metrics reveals varied effectiveness across different metrics. This study concludes that legal text simplification remains a challenging area in NLP, and further research is needed for a better understanding of simplicity criteria in the legal domain.

GRAPHBASED

Experiments were conducted on two large-scale corpora, namely CNN and DailyMail [3]. These datasets are widely used in neural document summarization tasks. The datasets were originally constructed by collecting human-generated abstractive highlights from news stories on the respective websites. Methods: The proposed method adopts an encoderdecoder framework, commonly used in machine translation and dialog systems. Specifically, a hierarchical encoder decoder framework. The method introduces a graph-based attention mechanism and a hierarchical decoding algorithm to address challenges in abstractive summary generation.

The encoder's goal is to map the input document to a vector representation. A hierarchical encoder framework is utilized, consisting of a word encoder and a sentence encoder. Long Short-Term Memory (LSTM) is employed for both the word encoder and sentence encoder.

The decoder, responsible for generating output sentences, is based on an LSTM-based hierarchical decoder framework. An attention mechanism is used to allow the decoder to focus on different parts of the input during generation. The study introduces a graph-based attention mechanism inspired by graph-based extractive summarization models like TextRank and LexRank.

Results: Experimental results demonstrate the effectiveness of the proposed method. On the CNN dataset, the abstractive method outperforms traditional extractive methods and a distraction based abstractive model (Distraction-M3). On the DailyMail dataset, the proposed method achieves considerable improvement over neural abstractive baselines and outperforms state-of-the-art neural extractive methods. Human evaluation results also support the superiority of the proposed method . The study utilizes a dataset consisting of legal documents related to criminal and tax cases in India. The dataset includes 247 training documents and 30 development documents, with one training document being a duplicate [7]. The corpus covers various court judgments, including those from the Supreme Court of India, High Courts, and Tribunal courts. The data is categorized into 12 fine-grained rhetorical roles (RRs) and a NONE label. Key statistics of the dataset, such as document distribution, sentence distributions, are presented.

The models employed in this are based on pre trained transformer-based language models, particularly focusing on BERT (Bidirectional Encoder Representations from Transformers). Three main model variants are explored: LegalBERT, InCaseLawBERT, and ensemble embeddings of LegalBERT with Latent Dirichlet Allocation (LDA) or RoBERTa. These embeddings are combined with various machine learning (ML) and neural classification heads, such as Logistic Regression, Support Vector Machine, Multi-Layer Perceptron, and others.

For model evaluation, experiments are conducted both with and without fine-tuning the pre-trained transformers. The performance of the models is assessed using metrics like micro F1 score. The study observes that certain classes, particularly those with lower representation, face challenges in accurate classification. The conclusion suggests that enriching the embeddings and incorporating a Conditional Random Field (CRF) layer for the classifier could enhance the results.

In summary, this study explores the application of pre-trained transformer-based models on a legal dataset, experimenting with different embeddings and classifiers. The findings highlight the importance of richer embeddings for improved accuracy, while acknowledging challenges related to class imbalance in certain rhetorical labels.

BERT-BASEDTECHNIQUES

The study revolves around the classification of the US Supreme Court decisions dataset obtained from the Washington University School of Law. The dataset includes documents categorized by topic with 15 broad category labels and 279 finegrained category labels. The researchers discusses the dataset's characteristics, emphasizing its imbalances in terms of

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points per label [9]. Pre-processing involves removing footnotes, and challenges arise due to the larger average document length compared to other legal datasets.

The researchers explored various BERT-based techniques for classification, using models such as BERT, RoBERTa, and Legal-BERT. Techniques like "Best-512" involve analyzing different chunks of 512 tokens in each document, while "Summarization-512" summarizes documents to fit within 512 tokens. "Concat-512" combines the outputs of multiple BERT models trained on different chunks, and "Ensemble" combines predictions from multiple models. "Stride-64" identifies shared chunks between consecutive 512 token segments. Additionally, "Long Sequence Models (LSMs)" and other transformer-based models are explored for sequences longer than 512 tokens.

Results indicate that BERT-based models trained on legal data consistently outperform others. Among techniques, "Stride-64" stands out, followed by "Concat-512," "Summarization-512," "Best 512," "Ensemble," and finally "LSMs." The study highlights the impact of context beyond the first 512 tokens on classification tasks. Future work could involve leveraging knowledge from references in the dataset, employing graph structures, and exploring greedy approaches for summarization and ensemble techniques.

The team participated in the LegalEval 2023 shared tasks, addressing four subtasks[8]: A, B, C-1, and C-2. For Sub-task A, they worked on classifying sentences in Indian Court Judgements into 13 rhetorical roles, using methods like Hierarchical BiLSTM-CRF and transformer-based models. They achieved the best results with the BiLSTM-CRF model using GPT2 embeddings.

In Sub-task B, focused on Legal Named Entities Extraction, they employed a BERT-based model, achieving an F1-score of 0.87 and ranking sixth in the shared task. The dataset consisted of various entity types found in legal documents. For Sub-task C-1 (Legal Judgment Prediction), the team experimented with domain-specific.

4.RESULTS OF THE RELATED WORKS

Table-1 showing the result of algorithm used.R-ROUGE

Algorithm	R-1	R-2	R-L	BertScore
SummaRunner[1]	0.502	0.205	0.237	0.846
Gist[1]	0.427	0.132	0.215	0.819
Legal-Pegasus	0.465	0.211	0.279	0.842
DSDR	0.485	0.222	0.27	0.848
Case-Summarizer	0.198	0.094	0.154	-
LetSum	0.408	0.112	0.371	-
LSTM+Glove[11]	0.436	0.245	0.382	-

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Table-2 Shows the result of unsupervised methods used for simplification of legal texts

First/Second model	FKGL	DC
USLT/Original Text	<0.005	
USLT/ACCESS	<0.005	
USLT/MUSS	<0.005	
USLT/REC-LS	<0.005	
USLT/LS-Bert	<0.005	0.009(LS_Bert)
USLT/LSBertCWI	0.009	0.042(LS-BertCWI)

Table-3 Shows the result of court Judgement Prediction results on the validation dataset.

	P	R	FI	Accuracy
CaseLawBERT+ BiGRU DET [8]	0.78	0.74	0.76	0.74

5. CONCLUSION

This survey encapsulates the diverse landscape of legal document summarization, offering insights into methodologies and advancements within legal informatics. Supervised methods like GIST and BERTSUM, along with performers like DSDR and Legal-Pegasus, highlighted the efficacy of machine learning in extractive summarization. Semi supervised techniques, including TF-IDF Scores and Sentence Embeddings, exhibited promise, while unsupervised approaches like CaseSummarizer and USLT-LEGAL-BERT underscored challenges in handling legal language complexities. 0.74 0.76 0.74 Beyond summarization, legal document retrieval using document vector embeddings showcased the success of the doc2vecNN model. BERT-based techniques excelled in legal classification tasks, pushing boundaries with innovations like "Stride 64." Legal text simplification models, like KIS and graph-based approaches, emphasized ongoing challenges in achieving a balance between readability, fluency, and meaning preservation. Participation in LegalEval 2023 demonstrated real world applicability, highlighting the synergy between deep learning models and tasks like rhetorical role classification and legal named entity extraction. In essence, this survey serves as a foundational guide to the evolving field, emphasizing the importance of domain-specific considerations. As legal informatics advances, this survey aims to inspire further exploration at the intersection of law and technology.

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