LegalSum: Towards Tool for Evaluation for Extractive Summarization of Brazilian Lawsuits*

Daniela L. Freire[1] [0000−0002−5363−3608],
Alex M. G. de Almeida[2] [0000−0002−6805−3753],
Márcio de S. Dias[3] [0000−0003−1116−6965],
Adriano Rivolli[4] [0000−0001−6445−3007],
Fabíola S. F. Pereira[5] [0000−0003−2914−1803],
Giliard A. de Godoi[4] [0000−0002−1715−0852], and
Andre C. P. L. F. de Carvalho[1] [0000−0002−4765−6459]

[1] University of Sao Paulo, Sao Paulo, Brazil {danielalfrere,andre}@icmc.usp.br
[2] Ourinhos College of Technology, Brazil
alex.marino@fatecourinhos.edu.br
[3] Federal University of Catalan, Brazil
marciodias@ufcat.edu.br
[4] Federal Technological University of Paraná, Brazil
rivolli@utfpr.edu.br giliardgodoi@alunos.utfpr.edu.br
[5] Federal University of Uberlândia, Brazil
fabiola.pereira@ufu.br

Abstract. The increasing volume and complexity of legal documents have led to a growing interest in text summarizing for legal texts. In this context, this paper presents *LegalSum*, a tool for automatically summarizing lawsuits in Portuguese, aiming to improve the efficiency of legal professionals and researchers. The tool is equipped with a legal-domain expression dictionary, which enhances the accuracy of summarization. It provides various algorithms such as Word Frequency, KL-Sum, Reduction, Edmunson, LSA, LexRank, TextRank, and Pagerank, as well as a committee approach that combines multiple algorithms. The architecture of *LegalSum* is modular and flexible, allowing new algorithms to be easily integrated. The tool was evaluated using the metrics Rouge (Rouge-1, Rouge-2 and Rouge-L) obtaining promising results. This paper contributes to the development of summarization tools for the legal domain, offering a valuable resource for legal professionals and researchers in the field.

Keywords: Legal text summarization · Natural Processing Language · Extractive Summarizing · Rouge Metric · Real-world Application · Intelligent Technique.

* Supported by Tribunal de Justiça de São Paulo

1 Introduction

Text summarization techniques for legal documents have been on the rise in recent years, as highlighted by mainstream news outlets like Forbes [10]. AI-driven applications such as document review, legal research, due diligence, contract analysis, and legal outcome prediction all rely on text summarization, which offers potential benefits to law firms in terms of time savings and enhanced efficiency.

As legal documents become increasingly voluminous and complex, the demand for efficient and effective summarization tools is expected to grow. Legal professionals and researchers rely on text summarization to quickly identify and comprehend crucial information within intricate legal documents, ultimately saving substantial time compared to manual reading. Additionally, it helps mitigate the risk of overlooking critical details or misinterpreting the content [13]. The need for automated reading processes is particularly evident in the Sao Paulo Justice Court (Tribunal de Justiça de São Paulo - TJSP), which holds the highest number of lawsuits globally and has an 84% congestion rate with an average processing duration of seven years and five months. Automating this reading process not only saves time but also expedites lawsuit resolutions.

However, evaluating the quality of a summary presents challenges, as there is no universally accepted standard for summarization single documents or sets of documents [22]. Additionally, defining what constitutes a practical summary remains open-ended. Research indicates a need for more consensus among individuals when assessing and generating summaries. The absence of standardized assessment metrics and diverse evaluation criteria complicates summary evaluation.

This paper introduces *LegalSum*, a tool designed for automatically summarization Portuguese-language lawsuits. *LegalSum* incorporates a legal-domain expression dictionary for more precise summarization and offers various algorithms such as Word Frequency, KL-Sum, Luhn, Reduction, Edmunson, LSA, PageRank, TextRank, and LexRank. It also employs a committee of algorithms and features a modular and flexible architecture, allowing for integrating new algorithms. To assess its performance, we applied *LegalSum* to summarize lawsuit decisions in a real TJSP case, employing human evaluators and the Rouge performance metric.

The remainder of this paper is organized as follows: Section 2 reviews related works, while Section 3 provides background information and a brief overview of the techniques employed. Section 4 discusses the tool and presents a case study. Finally, Section 5 summarizes the main conclusions and outlines future research directions.

2 Related Work

Legal text summarization is a burgeoning field with the potential to transform legal document handling. Recent research explores various aspects of legal text summarization, including natural language processing techniques and specialized algorithms. Nunez-Robinson et al. [20] compared transformer-based models for legal text summarization, highlighting BART and T5 as top performers. The study emphasized the impact of training data size and fine-tuning. Bhattacharya et al. [4] evaluated summarization algorithms (LexRank, TextRank, LSA) on Brazilian legal cases. TextRank and LSA outperformed LexRank, demonstrating potential for combining NLP and ML. Huang et al. [12] introduced a two-stage approach using named entity recognition and supervised ML to summarize Chinese civil cases with high precision and recall. Jain et al. [14] proposed a deep clustering approach for legal document summarization, outperforming TextRank and LSA on Canadian legal cases. Begum et al. [3] assessed an automated summarization tool for Brazilian legal cases, noting its high recall but low precision when compared to human-generated summaries. Zhong et al. [28] used iterative masking of predictive sentences, outperforming traditional summarization techniques in summarization U.S. Supreme Court decisions. Sheik et al. [24] employed deep learning with masking to enhance summarization quality, showing promise in handling complex legal language and jargon in Canadian legal cases. Anand et al. [1] proposed a mask-based approach to focus on relevant sentences, improving accuracy and relevance in summarization legal texts. Deroy et al. [7] used ensemble methods and masking to improve extractive summarization for Indian legal case judgments, outperforming other techniques.

These studies collectively contribute to the advancement of legal text summarization, exploring various approaches and their potential impact on the field.

3 Background

Text summarization is a procedure that condenses a lengthy text document into a shorter and more comprehensible summary to highlight the essential points of the document. This task involves identifying and extracting the document's crucial information, which is then used to generate a brief and well-structured summary. The resulting summary must be coherent and fluent to convey the intended audience's key points effectively. Text summarization can be broadly categorized into two main approaches: extractive summarization and abstractive summarization. Extractive summarization involves selecting and condensing the most important sentences or phrases from a given document to create a summary. This approach typically involves ranking sentences based on relevance and importance and selecting the top-ranked sentences for inclusion in the summary. Extractive summarization is commonly used in news articles and a scientific papers summarization [23]. Abstractive summarization involves generating a summary that is not simply a subset of the original text but rather a new and original text that conveys the essential meaning of the original document. Abstractive summarization often involves using natural language processing (NLP) techniques to generate a fluent and coherent summary [2]. This study uses extractive summarization to reduce the analysis time of the lawsuit documents performed for TJSP force work.

3.1 Algorithms

Considering that *LegalSum* is a tool dedicated only to extractive techniques, we describe the techniques employed in this work next.

– **Word Frequency**: In this method, the frequency of all words in the text corpus is computed and recorded in a dictionary. Subsequently, the text corpus is tokenized, and the sentences that contain more frequently occurring words are retained for inclusion in the final summary data [11].
– **PageRank**: This is a well-known algorithm used to evaluate the significance of web pages by computing a ranking for each page. PageRank has been adapted for text summarization by treating sentences as nodes in a network and using the algorithm to identify the most important sentences in a document [5].
– **TextRank**: It is a graph-based ranking model for text processing, which leverages Google's PageRank algorithm to identify the most important sentences in a given text. The TextRank algorithm begins by segmenting the input text into individual sentences. Next, it constructs a graph where the nodes represent the sentences, and the edges between them indicate any overlapping words. Finally, by applying PageRank to this graph, TextRank identifies the most significant nodes, which correspond to the most important sentences in the text, forming the basis of the summary [19].
– **LexRank**: This algorithm is an unsupervised machine learning technique that leverages the TextRank method to summarise the input sentences. Specifically, the algorithm employs vector-based algorithms and cosine similarity measures to determine the minimum cosine distance among various words in the text corpus. The more similar words are grouped, forming the basis for generating the summary [9].
– **LSA (Latent Semantic Analyzer)**: The Latent Semantic Analyzer algorithm utilizes a technique known as data decomposition to transform the text data into a lower-dimensional space. This technique allows LSA to capture the semantic structure of the input text while generating a summary. By representing the text in a reduced dimensional space, LSA can identify and extract essential information while preserving the text's overall meaning [6].
– **Luhn**: This approach for text summarization relies on a frequency-based method that involves computing the term frequency-inverse document frequency (TF-IDF) of the words in the input text. This approach assigns weights to the words based on their frequency in the text and relevance to the entire corpus of documents [18].
– **KL–Sum**: This algorithm selects sentences with a similar word distribution to the original text. It aims to minimize the Kullback–Leibler divergence (KL–divergence), which measures the difference between two probability distributions. The algorithm employs a greedy optimization approach and iteratively adds sentences until the KL–divergence criterion decreases. By doing so, KL–Sum can produce a summary that preserves the original text's main ideas and fundamental concepts [15].

- **Edmunson**: This algorithm suggests a subjectively weighted combination of features instead of using feature weights derived from a corpus. In addition to the features commonly used in Luhn's method, Edmundson's algorithm also proposes the inclusion of several other features, such as position, word frequency, cue words, and document structure (such as headlines, titles, subtitles.) [8].
- **Graph Reduction**: This approach identifies the most important sentences from a single document by assigning importance to the vertices within a graph. The technique employs undirected and weighted graphs to implement text-based ranking, with documents or sentences represented as nodes and edges connecting nodes that share standard information. Sentence scoring is achieved by initializing weights to the nodes of the graph. The graph-based approach to text summarization is a powerful method that utilizes graph theory to extract essential information from a document or text [27].

3.2 Evaluation Metrics

When assessing the quality of a summary, various evaluation metrics come into play, involving both human evaluators and automated methods. These metrics consider coverage, grammatically, redundancy avoidance, essential content inclusion, structure, and coherence. One widely used automated evaluation metric is **ROUGE** [16]. ROUGE employs recall-oriented understudy methods to measure a summary's quality by comparing it to human reference summaries. Several variations of ROUGE exist, with the most common ones highlighted below:

- **ROUGE-n**: This metric evaluates the overlap of n-grams (typically two or three) between the reference and candidate summaries. The ROUGE-n score is calculated based on the number of common n-grams (p) and n-grams found only in the reference summary (q) using the formula $ROUGE - n = p/q$.
- **ROUGE-L**: ROUGE-L employs the longest common sub-sequence (LCS) to assess the similarity between the two text sequences. A higher LCS score indicates greater similarity between texts. It is important to note that this metric requires all n-grams to be consecutive sequences of words.
- **ROUGE-SU**: ROUGE-SU, or skip bi-gram and uni-gram ROUGE, evaluates both bi-grams and uni-grams. It allows for the insertion of words between the first and last words of bi-grams, accommodating non-consecutive word sequences.

4 Proposed Tool

This section describes our web tool *LegalSum*, which supports evaluating different algorithms in automatically summarising Portuguese lawsuit tasks.

4.1 Description

LegalSum has an easy-to-use graphical interface in Portuguese, c.f. shown in Fig.1. First, we describe every feature of the tool after we report detail regarding materials and methods used in tool development. We enumerate every feature in Fig.1, from 1 to 6, so explain next.

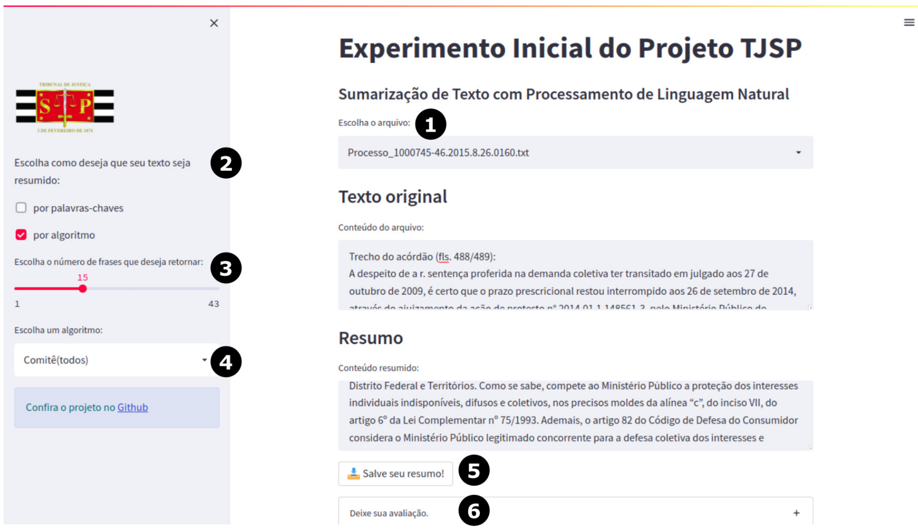

Fig. 1: *LegalSum* graphical interface.

1. File choice. The files to be summarised get in a specific folder. In this pop-up component, it is possible to choose which one.
2. Approach choice. There are two approaches to summarization. The former finds the keywords in the text, and the latter is by algorithms. It is possible to choose one of them or both. When the first checkbox is selected, the summarization takes into account keywords. Such keywords are saved in a specific folder file, where the users can update them whenever they deem it necessary. When the second checkbox is selected, the summarization is performed by a algorithm.
3. Number of sentences. This slider is a component that allows choosing the number of sentences the users want in their summary. The minimal number is one, and the maximal number is the number of sentences of text chosen.
4. Algorithm choice. There are nine options: Word Frequency, KL-Sum, Reduction, Edmunson, LSA, LexRank, TextRank, and Pagerank, more one that is a committee. The committee corresponds to execution of all algorithms, where they are choose, the sentences more frequent in summarization done by algorithms. New algorithms can be easily incorporated into the tool.
5. Saving. In this button, the user can download their summarize so with visualizing the document in format `.pdf`, with sentences selected highlighted.
6. Feedback. In this option, the user can test the summary produced by one of the algorithms or committees. The goal is improve the tuning of algorithms

that do not satisfied to users, or or even delete them of tool. There are three radio buttons with the option: “Bad”, “Regular”, and “Good”.

To build our tool, we used the open-source library *Streamlit*[6] (version 1.10.0) with Python (version 3.8.9) programming language. NLTK (Natural Language Toolkit) Python libraries (version 3.7) were used for classification, tokenization, stemming, tagging, parsing, and semantic reasoning tasks. Sumy Python library (version 0.11.0) was used to implement the summarization algorithms.

4.2 Case Study

One of the challenges encountered by the São Paulo Court of Justice is determining whether a lawsuit can be classified as repetitive. A repetitive theme refers to a legal concept denoting a category of legal cases under appeal characterized by identical theses founded on uniform questions of law. In such cases, multiple legal actions exhibit remarkable similarities in the core legal arguments and the legal issues at hand, indicating a recurring pattern or theme in the litigation process. These cases are typically grouped due to their common legal grounds, facilitating streamlined legal analysis and decision-making processes.[26]. Each day, civil servants at TJSP must read dozens of lengthy lawsuit decisions to determine which ones can be classified as repetitive.

Experimentation Setup TJSP civil servers selected five repetitive themes, and for every one of these themes, they selected three lawsuit decisions, totalizing fifteen documents to be summarized by *LegalSum*. Then, the structure of handled corpus is formatted by linear text from lawsuit decisions. TJSP civil servers highlighted essential parts of these documents and assigned a difficulty score. According to this score, a lawsuits decisions is considered “Easy”, when it explicitly indicates the repeating theme number; “Medium”, when it has a broad foundation, with keywords that are easier to find, although the text does not explicitly indicate the repetitive theme; “Hard” when it does not indicate the repetitive theme, presents few keywords.

The goal is to measure how much the summarization produced by *LegalSum* are similar to highlighted parts by TJSP civil servers. Then, we use ROUGE to check the tool’s performance.

Experimentation Results The Rouge metrics (1,2, L and S)[17] were calculated for all summarization algorithms of the proposed tool together with the three lawsuits decisions, of difficulty “Easy”, “Medium” and “Hard”, of one of repetitive themes, being these considered summaries of references for the evaluation experiment. In Table 1, the *F-score* value for Rouge-1, Rouge-2, Rouge-L and Rouge-S is listed for all summarizers of the tool.

According to Table 1, the LSA, Word Frequency and Edmundson algorithms have the best F-score value for the Lawsuit Decision - Easy in all Rouge metrics

[6] `https://streamlit.io/`

Table 1: F-score values for Rouge (1,2, L and S) for the repetitive theme.

	Lawsuit Decision - Easy				Lawsuit Decision - Medium				Lawsuit Decision - Hard			
Summarizers	Rouge-1	Rouge-2	Rouge-L	Rouge-S	Rouge-1	Rouge-2	Rouge-L	Rouge-S	Rouge-1	Rouge-2	Rouge-L	Rouge-S
Word Frequency	**0.6593**	**0.6312**	**0.6535**	**0.6564**	0.1453	0.0337	0.1038	0.1224	**0.2613**	**0.1538**	**0.1956**	**0.2124**
PageRank	0.1518	0.0462	0.1032	0.1138	0.1362	0.0296	0.0947	0.1173	0.1179	0.0125	0.0970	0.1031
TextRank	0.2804	0.2313	0.2653	0.2653	**0.1553**	0.0212	**0.1221**	**0.1286**	0.1131	0.0119	0.0828	0.0828
LexRank	0.1223	0.0502	0.1072	0.1175	0.0966	0.0115	0.0837	0.0837	0.0991	0.0097	0.0709	0.0709
LSA	**0.6593**	**0.6312**	**0.6535**	**0.6564**	0.1162	**0.0430**	0.1049	0.1049	0.2069	0.0705	0.1330	0.1330
Luhn	0.1473	0.0391	0.1023	0.1094	0.1202	0.0381	0.0789	0.1037	0.0678	0.0	0.0678	0.0678
KL-Sum	0.0800	0.0032	0.0567	0.0699	0.0541	0.0129	0.0445	0.0477	0.0694	0.0	0.0694	0.0694
Edmundson	**0.6593**	**0.6312**	**0.6535**	**0.6564**	0.1162	**0.0430**	0.1049	0.1049	0.2069	0.0705	0.1330	0.1330
Graph Reduction	0.4018	0.3229	0.3722	0.3797	**0.1553**	0.0212	**0.1221**	**0.1286**	0.1908	0.0824	0.1479	0.1479

considered in comparison to the values of the other summarization algorithms. This result can be explained by the nature of the algorithms that is related to the syntactic structure of the source text (position of words in the sentence, number of words, etc.), something that was better captured by these algorithms in Lawsuit Decision - Easy.

The Word Frequency algorithm also obtained a better F-score for all Rouge metrics compared to the other summary algorithms for Lawsuit Decision - Hard document. However, the TextRank and Graph Reduction algorithms obtained the best F-scores in Rouge-1, Rouge-L and Rouge-SE for Lawsuit Decision - Medium. But for Rouge-2, the LSA and Edmundson algorithms had the best F-scores for this document.

The use of Rouge metrics in this work is to show that the summarization algorithms used in the proposed tool can be useful to bring the most relevant information from a legal document. However, the F-score results are not high, which is to be expected given the nature of the reference summaries used. These summaries were generated with the aim of obtaining sentences that would facilitate the identification of repetitive themes and not to summarize the most important information in the source text.

5 Conclusion

Automatic Text Summarization has several advantages, including time-saving, instant response, and enhanced productivity. It has gained popularity across diverse fields, offering professionals an efficient means to achieve greater efficiency and accuracy in their work. Our tool, *LegalSum*, specifically supports summarization in the legal domain in Portuguese and was tested with lawsuits from the Sao Paulo Justice Court, the world's largest court[21]. Despite advancements, challenges remain in identifying important information and selecting critical sentences. With various expression forms, human language complexity poses difficulties for text summarization. Linguistic insights, while valuable, do not always determine the primary information for inclusion. Thus, further research is needed to develop more efficient methods addressing language complexity, information relevance, and context understanding. Automatic Text Summarization is valuable for processing vast amounts of information but requires ongoing development for efficiency and accuracy improvement. Enhancing text summarization techniques allows professionals to quickly identify critical information, leading to better decision-making and productivity. Therefore, continuous research and development in this field are essential to meet modern information processing demands. In future work, we plan to enhance summarization quality by employing advanced techniques, including state-of-the-art classifiers based on Large Language Models. Specifically, we leverage language models tailored for Brazilian Portuguese, like BERTimbau [25] expecting to improve coherence, informativeness, and overall summary quality significantly. This approach will make our summarization system more adept at handling complex legal texts and the linguistic nuances of Brazilian Portuguese legal documents.

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