### Text summarization of congressional legislation

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#### Abstract

This project aims to address the issue of accessibility concerning Congressional legislation. Using a selection of House Resolutions from the 117th Congress Second Session, we conducted a text summarization task through an abstractive approach. We employed a pre-trained summarizer pipeline from sumy in python to generate summaries of 0.3 times the size of the bill. The success of this summary generation was evaluated through comparing readability scores and the cosine similarity of the bill text and their summaries. This evaluation revealed that the readability scores were very similar in both groups, with the scores of the summaries being slightly higher on average. Furthermore, the average cosine similarity was very strong, and most bill-summary pairs had high similarity.

**1. Introduction**

Many bills are over thousands of pages long and contain verbose language that many people do not have the time or bandwidth to decipher, which can lead to slow decision-making and fundamental misunderstandings of the content [1]. Furthermore, the summaries offered on Congress.gov are slow to appear and tend to be vague or very brief.

Creating accurate, automatic summarizations of these bills would not only be beneficial for the general public, but also for government officials who work in busy environments and need to make well-informed decisions about whether to vote in favor of or against a bill. Additionally, citizens will be more aware of what their representatives are voting for, as these summaries will be objective descriptions of the bills, rather than explanations filtered through the media that may have a partisan spin.

**2. Literature review**

There is a substantial collection of literature on text summarization for many professional areas, especially in the legal field. Manual drafting of case summaries is a long and grueling process that is slow and expensive. The process relies on a group of “specialized staffs whose task is to summarize cases” [3]. The number of legal documents produced every year seems to be comparable to the number of legislative documents our Congress produces as well, and methods used in this research may lead to similar results.

A study published in the Expert Systems With Applications international journal presents an unsupervised method for extractive multi-document summarization using a centroid approach and sentence embedding representation [6]. The authors utilize a sentence importance score that is a composite of three other scores to create summaries of the Multi-News dataset. After evaluating with cosine similarity and Recall-Oriented Understudy for Gisting Evaluation (ROUGE), they concluded that their approach is comparable to the current cannon of text summarization methods, including supervised deep learning [6].

Automatic summarization of Congressional bills is a relatively new field, and thus there is much room for improvement. In 2019, two researchers from FiscalNote Research created the first corpus for this task, titled “BillSum” [4]. In this study, they applied a “Document Context Model” (DOC) using TF-IDF, a “Summary Language Model” (SUM) using a BERT model, and an ensemble of both models to predict a label they created indicating whether or not it belongs in the summary.

We intend to build upon the aforementioned studies by implementing an unsupervised, centrality scoring approach to summarization of Congressional bills.

**3. DATA**

The data we are using for this project comes from the govinfo.gov web API [2]. We used this API to download only the House Resolution (HR) Bills from the 117th Congress Second Session that were “enrolled,” which means they were passed in identical form by both houses [5]. We chose to only evaluate this subset because the total number of HRs is slightly overwhelming for an experimental analysis such as this one.

In total, there were 4674 files containing different HRs as well as various iterations of each one based on its status in Congress. Our final data set included only 152 of these files, the ones that had been “enrolled.”

Since the files were originally in XML format, the first step was extracting the text elements using the ElementTree module of the xml package in python. This included parsing each file and extracting the root element, which identifies the heading of the file. Then, we located all elements that included text relevant to the bill and extracted them into a data frame. Each observation in the data frame consisted of an identifying row number, the raw bill text, and an initialized column to hold the generated summaries.

**4. METHODS**

**4.1. Summarization**

For text summarization tasks, there are two main approaches that can be used: Extractive and Abstractive. The Extractive approach uses simple and traditional algorithms that observe the frequency of words within the text and look for sentences that contain those high frequency words to use in the final summary. The Abstractive method attempts to make smaller sentences with the same semantic meaning as the original sentences, generally using deep learning transformers like the BERT method.

This project implements an Extractive approach through the LexRank summarizer from the sumy python library. This summarizer is an unsupervised, graph-based algorithm that uses eigenvector centrality to identify the most important sentences in a text. LexRank is based on the PageRank algorithm from Google that defines the relevance of each site in relation to the search. This method calculates an importance score for each token, or sentence in this case, in a bill. We then use these scores to extract the most important sentences and combine them to create a summary.

The LexRank summarizer has its own rules about what constitutes a sentence, and vectorizes sentences based on those rules. It also removes stop words, punctuation, and unnecessary characters. Therefore, we did not preprocess the raw bill text before applying the summarizer. We decided against lowercasing and stemming or lemmatization to preserve the grammatical accuracy, context, and proper governmental terms in the summary.

Capped the summaries at 0.3 times the length of the bill

**4.2. Evaluation**

Two of the most popular ways to evaluate the success of text summarization are readability scores and cosine similarity. We began with investigating readability, with the intention of producing summaries that are more readable than the original text. We utilized the textstat library

In order to evaluate the success of this task, we calculated readability scores and Cosine similarity between the bill and the summary

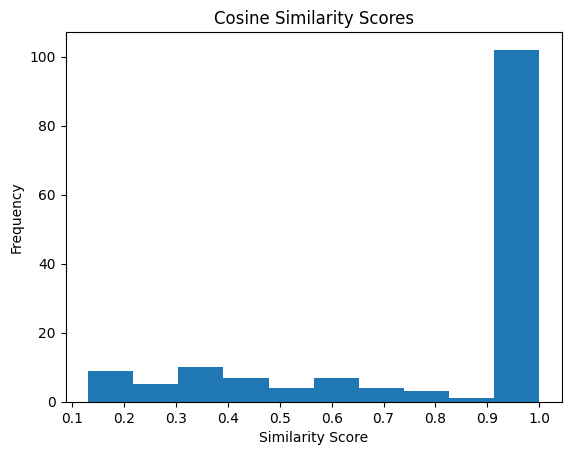
LexRank- eigenvectory centrality

From sumy package, using LexRankSummarizer:

5. Results

Chart, histogram

Description automatically generated

6. Discussion

**6.1. Conclusions**

There is statistically significant evidence that the proportion of exam failure among the Black or African American participants is greater than the proportion of failure among the White participants. Among the Black population, keeping all other variables constant, Pell Grant recipients have 0.94 times the odds of passing that non-Pell Grant recipients have, those with a GPA above 3.0 have 1.066 times the odds of the GPA below 3.0 group of passing, conditional accepts have 0.77 times the odds of regular accepts of passing, and the non-binary group has 1.24 times the odds of females of passing.

Furthermore, keeping all other variables constant, of the Black participants in DC, Pell Grant recipients have 1.059 the odds of never passing that non-Pell Grant recipients have, conditional accepts have 1.181 times the odds of never passing that regular accepts have, and males have 1.115 times the odds of never passing that females have. Of the Black participants in DFW, those with a GPA above 3.0 have 0.873 times the odds of never passing that those with a GPA below 3.0 have, and conditional accepts have 1.203 times the odds of never passing that regular accepts have. Of the Black participants in Baltimore, conditional accepts have 1.206 times the odds of never passing that regular accepts have.

As of now, there are mixed results about whether Mometrix use is statistically significant, and whether it has a positive or negative relationship with the odds of passing a content exam.

**6.2. Future research**

Given the results of this project, we are now aware of the vulnerable populations when it comes to passing licensure exams and ensuring that they can become educators. To build upon this research, future exploration and analysis should focus on the implementation of new policies to help these groups, and whether they are effective or not. In terms of the Mometrix analysis, investigation into a floor effect may indicate that a minimum amount of time using Mometrix products is required for improved likelihood of passing. A randomized experiment using Mometrix products would illuminate more about its effectiveness than the minimal data currently available.

For such a study to be statistically sound, there must be randomized treatment and control groups with a pre-test and a post-test. Additionally, as many other variables as possible must be held constant, such as time spent studying, study tools used, and courses taken. The ethical implications should be considered carefully, since some participants would be receiving more resources than others. These research endeavors will illuminate more about the populations that need more intervention to make it to the classroom while license exams are still required.

7. Closing REMARKS

**7.1. Limitations**

The limitations of this analysis include the extremely large available corpus, our processing power, and the subjective nature of text summarization. There are thousands of Congressional bills that have been written, and thus limiting our data to the second session of the 117th Congress excludes the vast majority of available data. Furthermore, due to limited processing power, we had to cap the length of a bill, which constrained our data. Additionally, text summarization is a nuanced task, and what one person thinks is a good summary may not be what another person thinks, and evaluation methods cannot capture every aspect of a summary.

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