Legislative Narratives on Gun Control in the United States: A Sentiment Analysis Approach

I. Introduction & Literature Review

(Introduces the research question, reviews previous work in the field, and presents a gap in the field)

II. Methodology

(Provides an explanation of and justification for the chosen method or process)

A. Data Collection

As this study focuses on congressional legislation, all legislative data was sourced from Congress.gov, the official website for legislative information. Using the advanced search function with specific search terms and filters, I was able to identify the legislation relevant to the gun control debate. The search term "gun" and the legislation category option were used to capture a comprehensive list of relevant legislation. To further refine my search, I specified a time-frame spanning congressional sessions 101-117 (January 3rd, 1989, to January 3rd, 2023). The starting point of 1989 was chosen because legislation text prior to this session is unavailable, while the ending point in 2023 reflects the on-going nature of the 118th congressional session, which has not yet concluded and continues to generate new legislative content. Lastly, the status of legislation was set to all options, including failed legislation, as although unsuccessful legislation lacks real-world impact, its value lies in understanding legislators' framing of issues. Even failed legislation can be beneficial as it provides additional insights from legislators.

After conducting the search, I then used the bulk download feature to extract relevant data on each piece of legislation. Using this option, I received the Legislation Number, URL, Congressional Session, Title, Party of Sponsors, and Date of Introduction of each legislation, all of which have a purpose in this study. The Legislation Number serves as a unique identifier, differentiating each piece of legislation and providing information on its origin, including the chamber in which it was introduced and the type of legislation. The URL is used later on as part of a web scraper to gather the text for each piece of legislation. The Date of Introduction is used later on in the analysis to determine how legislation sentiment changes over time, while the Party of Sponsors will be used to determine the side (pro-control or pro-rights) each political party is on.

While the bulk download feature provides much useful information, it does not provide the actual legislative text to conduct the sentiment analysis. Therefore, I created a web scraper to use the URLs from the bulk download to retrieve the textual data. Using the Selenium Python library, I simulated a Google Chrome browser to open a modified URL link that points directly to the website with the legislative link and retrieve the HTML source code, which contains all the elements of the website including the text. I then parsed the HTML code to extract the relevant legislation text using the BeautifulSoup4 Python library. Before saving the text in a CSV file with all of the other information from the bulk download feature on Congress.gov, I created a script to pre-process the text to prepare it for sentiment analysis. The script finds and removes the header and signatories' information before the actual legislation text. Next, the script conducts a series of pre-processing methods as detailed in [1]. This involves replacing grammatical contractions with their expanded forms, removing URL links, removing numbers, expanding acronyms to their full form, and removing stop words. Stop words, including "the", "is", and "at", are words that are very common and have no sentiment, which is why they are removed before the sentiment analysis step. The stop words removed from the script were taken from [2]. With the text pre-processed, it is saved and ready for its classification and sentiment analysis.

B. Data Classification

After gathering the legislative data, I classified each piece of legislation as pro-control and pro-rights using the OpenAI Generative Pre-trained Transformer (GPT) Large Language Model (LLM). LLMs are machine learning models with the capability to comprehend and generate human language text after being trained on massive collections of textual data, such as books, articles, and websites [3]. As shown through the experiment [4], LLM's have had phenomenal results in fields from vision to coding to math to even societal influences, such as bias, misinformation, human expertise, etc. LLMs have the ability to address a wide range of tasks, which sets them apart from earlier models limited to handling particular tasks. GPT uses a wide variety of natural language processing techniques and deep learning methods, as well as the ability to retain information from previous user-interactions, to prove personalized humanized responses to each user. I specifically chose the latest OpenAI model, GPT-4, as it was trained on an unparalleled amounts

of data [5] such that many researchers believe it to be a step towards more general intelligence compared to previous AI models.

Using the OpenAI API to access GPT-4, I gave it the following prompt: "You will be provided with a legislative text regarding firearms, and your task is to classify it as pro-control or pro-rights. Your response can be one of two things: 'control' or 'rights'." The prompt explains the input that the model will be receiving, which is a legislative text, as well as its task, to categorize it as either pro-control or pro-rights. To further improve the accuracy of the model, the model's temperature hyperparameter was changed to get the most direct output. The sampling temperature, a value from 0.0 to 2.0, determines how random a response from the model can be. Higher values make the output more random, while lower values are more focused and concentrated. The study [6] showed that the GPT-4 model has extremely similar performance values when changing the sampling temperature, but as I wanted the model to return only one word and nothing else as it would impact the script that saves the output, I set the temperature to 0.0. The other hyperparameters were set to default as they wouldn't have any significant impact on the accuracy in this particular use case. The API was then given the legislation texts to classify and saved in a CSV files to be used later in the analysis of my results.

III. RESULTS / FINDINGS

(Presents findings or results)

IV. DISCUSSION / ANALYSIS

(Interprets the significance of results in the context of the research question)

V. CONCLUSION & FUTURE DIRECTIONS

(Highlights a new understanding, the limitations of your methodology, possible implications of your project, and future research that could be accomplished)

REFERENCES

[1] Z. Jianqiang and G. Xiaolin, "Comparison Research on Text Pre-processing Methods on Twitter Sentiment Analysis," *IEEE Access*, vol. 5, no. , pp. 2870–2879, 2017, doi: 10.1109/ACCESS.2017.2672677.

[2] C. Fox, "A stop list for general text."

[3] B. Almarie, P. E. P. Teixeira, K. Pacheco-Barrios, C. A. Rossetti, and F. Fregni, "Editorial – The Use of Large Language Models in Science: Opportunities and Challenges," *Principles and practice of clinical research (2015)*, vol. 9, no. 1, pp. 1–4, Jul. 2023, doi: 10.21801/ppcrj.2023.91.1.

[4] S. Bubeck *et al.*, "Sparks of Artificial General Intelligence: Early experiments with GPT-4." 2023.

[5] OpenAI *et al.*, "GPT-4 Technical Report." 2024.

[6] M. Renze and E. Guven, "The Effect of Sampling Temperature on Problem Solving in Large Language Models." 2024.