IST664 - Natural Language Processing

Fall 2023 - Final Project

From Rhetoric to Reality: Analyzing Presidential Debates

Group Members

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Abbreviations and Acronyms

AI: Artificial Intelligence
BERT: Bidirectional Encoder Representations from Transformers
CapsNet: Capsule Network
CNN: Convolutional Neural Network
DL: Deep Learning
LDA: Latent Dirichlet Allocation
LLMs: Large Language Models
LSA: Latent Semantic Analysis
LSTM: Long Short-Term Memory
LSVC: Linear Support Vector Classifier
MNB: Multinomial Naïve Bayes
ML: Machine Learning
NLP: Natural Language Processing
NLU: Natural Language Understanding
SVM: Support Vector Machine
VGG: Visual Geometry Group

Introduction

In recent years, there has been a growing fascination with leveraging the capabilities of NLP and AI techniques to forecast election outcomes. This interest spans diverse methodologies including sentiment analysis, fake news identification, fact-checking, and topic modeling. Advanced models intertwine deep learning with foundational statistical approaches.

Our study delves into the thematic fabric of primary Presidential campaign debates, employing sentiment analysis to gauge the emotional tone of each speech, organizing sentiments by respective candidates. Additionally, we explore topic modeling and honesty classification among candidates. Our goal involves thoroughly analyzing these debates using a wide range of ML and NLP techniques. This encompasses various practices like topic modeling, sentiment analysis, and text classification among others.

Literature Review

Before delving into our project’s specifics, it is crucial to review the most recent research and advancements in NLP techniques pertinent to this domain.

Katalinić et al. [1] examined the 2022 US midterm elections by analyzing tweets from Democratic and Republican candidates (52,688 tweets in total). Using sentiment analysis, topic modeling, and party classification techniques, they uncovered nuanced political dynamics across Senate, Gubernatorial, and House elections. Their methods included Python’s Tweepy for data collection, MNB for party-based tweet classification, and sentiment analysis using TextBlob and VADER libraries. Gensim’s LDA was employed for topic modeling. The study highlighted heightened subjectivity, polarization, and classification disparities among elections, emphasizing the influence of social media and regional variations in shaping political narratives and outcomes.

Gode et al. [2] also delved into US political polarization using language models and a Wikipedia-derived dataset spanning 120 years. Employing Longformer, a Transformer model, they assessed polarization levels and identified divisive words. Their study led to the creation of a website estimating a politician’s polarization based on Longformer’s analysis of nearest neighbors. Findings highlighted distinct campaign topics for Democrats and Republicans, fostering polarization due to high subjectivity. Issues like *elections*, *cost of living*, and *jobs* were central, forming polarized voting blocs and showcasing the fragmentation within US political discourse.

Olabanjo et al. [3] directed their focus on Nigeria’s 2023 presidential election, specifically harnessing public opinion expressed through Twitter data. This research, unlike the previous studies, underlines the pivotal role of social media in shaping contemporary elections, employing advanced NLU techniques, notably focusing on the BERT model for sentiment analysis. The methodology involved identifying election-related keywords, hashtags, and Twitter accounts. Data scraping via the Twitter API, followed by meticulous cleaning to refine the dataset, was executed using Python. Three ML models - LSTM, BERT, and LSVC - trained on an IMDB dataset, were utilized for sentiment modeling. Furthermore, the study leveraged NLU techniques like sentence polarity analysis, topic modeling, entity extraction, word frequency analysis, and word clouds for comprehensive insight. Though specific findings weren’t explicitly detailed, this research presents a thorough exploration at the intersection of political analysis and advanced NLP technologies, shedding light on public sentiment regarding Nigeria’s political landscape.

Węcel et al. [4] examined the influence of LLMs, specifically ChatGPT, on fake news operations. Focusing on AI’s role in generating and detecting fake news, they explored how LLMs like BERT and GPT-3 influence misinformation identification. The study revealed that while BERT is commonly used in fake news detection models due to its effectiveness in tasks like sentiment analysis and named entity recognition, LLMs such as GPT-3 do not significantly enhance fake news detection rates. Results indicated a marginal performance improvement over random guessing, with various prompts affecting the accuracy and introducing biases in answers without significantly altering accuracy rates. The study also highlighted the issue of "*hallucinations*" where the models provided answers that were close but not entirely accurate. Additionally, the research explored the robustness of LLMs over time, finding that the models performed comparably wrong irrespective of data period, suggesting a need for continual adaptation to evolving information. Limitations in model confidence assessment and reliance on past knowledge were identified, prompting future directions like combining LLMs with knowledge graphs for up-to-date facts and investigating the impact of newer language models beyond GPT-3.

Mayopu et al. [5] carried out a groundbreaking investigation that centered on analyzing online fake news through the utilization of LSA. Unlike prior computer science-oriented approaches, this research aimed to develop an effective method, blending NLP and LSA techniques, to assist social scientists in dissecting fake news elements. The researchers analyzed the features of real and fake news articles, using the 2016 US presidential campaign to showcase the efficiency of their methodology. Their typologies of fake news included *Misinformation*, *Disinformation*, *Clickbait*, *Rumors*, *Propaganda*, *Satire*, *Parody*, and *Fabrication*. Employing LSA aided in examining significant sentences from input documents, unveiling latent structures, and exploring word-concept relationships using Singular Value Decomposition. The study identified five concepts through LSA analysis, revealing five topics crucial for identifying fake news during Presidential Elections: *Coalition*, *Politic*, *Future*, *Statement*, and *Issues*.

The extensive review authored by **Hamed et al. [6]** scrutinizes the landscape of fake news detection, highlighting key challenges and innovative approaches utilized in this critical area. The article emphasized key components and challenges in this realm, addressing approaches like data augmentation, feature extraction, and data fusion to bolster accuracy. Recognizing five types of fake news - *Rumor, Disinformation, Misinformation, Hoax*, and *Clickbait* - the study highlighted the crucial role of datasets, stressing that no benchmark dataset currently encompasses all necessary resources. The dataset's size, diversity, richness, and noise level significantly impact model performance in identifying fake news. The review categorized studies based on their employment of ML and DL methods. The review outlined various ML-based models like Logistic Classifier, Random Forest, and ensemble solutions. Additionally, it highlighted several DL-based models such as LSTM, CNN, CapsNet, among others. Limitations observed in fake news detection models encompassed overfitting, imbalanced datasets, ineffective feature representation, and inadequate data fusion. Prominent techniques used in these models included dataset augmentation techniques like Generative Adversarial Networks, feature extraction through models like BERT and VGG-19, and multimodal fusion methods including Early Fusion, Joint Fusion, and Late Fusion.

Our Process

Data Collection & Preprocessing

Data collection was carried out by scraping the transcript of the three *Republican Presidential Debates* into CSV files and creating a combined dataset with all three debates and an indicator variable for which debate the statement came from.

For precision, our analysis excludes the speeches of moderators to ensure a focused dataset aligned with the original topics discussed. We specifically focus on the candidates participating in all three debate rounds.

To preprocess the data and ensure quality analysis we used:

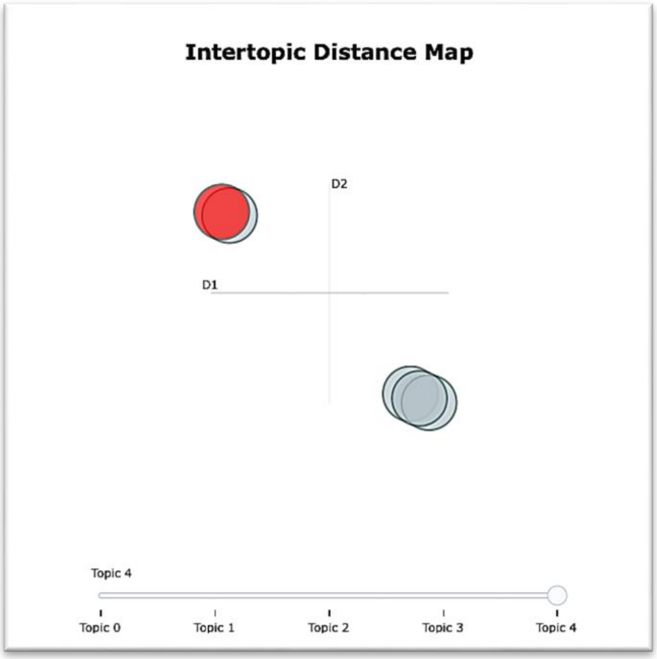
- Tokenization
- Lowercasing
- Punctuation and Numbers Removal
- Stop Words Removal
- Lemmatization

Topic Modelling

Our project delves into the realm of topic modeling, a powerful method for uncovering concealed themes within extensive text datasets. Techniques such as LSA, PLSA, and the widely popular LDA serve to reveal abstract topics by scrutinizing distributions of words and topics within documents. LDA, particularly favored, has proven its worth in various fields like software engineering and political science, offering valuable insights that span scientific content analysis, sentiment evaluation, and financial domains.

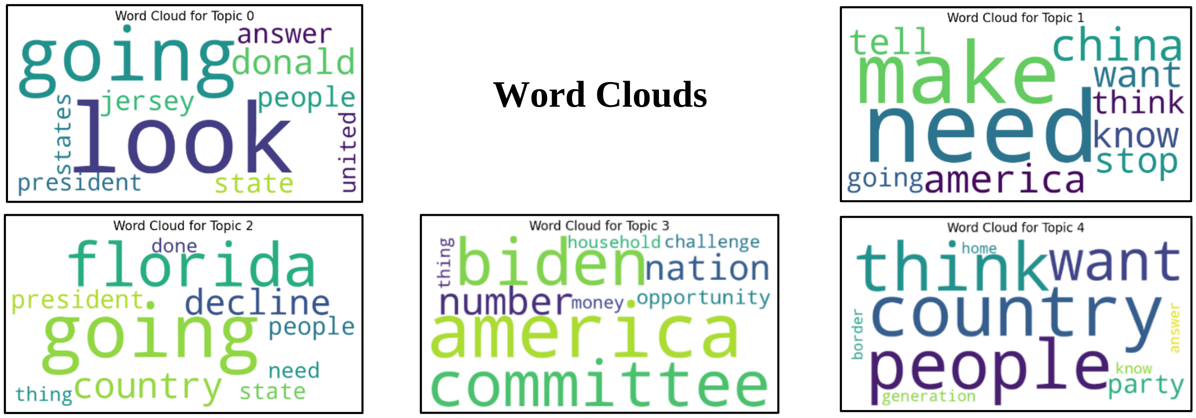
This project was built upon the robust capabilities of BERTopic, complemented by the SentenceTransformer "all-MiniLM-L6-v2" model, which empowered us to extract and scrutinize topics from a textual dataset. The fusion of BERTopic and SentenceTransformer facilitated a comprehensive representation of textual data through embeddings, while UMAP aided in refining the process by reducing dimensionality, thus enabling a deeper understanding of the content.
Critical to our methodology was the evaluation of topic coherence. Leveraging the CoherenceModel, we discovered that BERTopic exhibited approximately 10% higher coherence than traditional LDA methods, signifying its proficiency in extracting more meaningful and coherent topics.

Moreover, our approach personalized the analysis for each speaker in the dataset, employing unique BERTopic models. This tailored strategy allowed for a nuanced exploration of topic distributions, reflecting individual disparities within the textual data. This amalgamation of advanced NLP techniques and personalized topic modeling granted us profound insights into underlying themes and patterns within the data.



Our analysis highlighted distinct relationships among topics. Notably, Topics 1 and 5, "*future*" and "*hope*", showed high correlation, while Topics 2-4 centered on negative aspects such as "*demands*", "*fears*", and "*constraints*". Topic 4, "*constraints*", offered intriguing insights into discussions revolving around challenges, money, and opportunities, often linked to current President Biden, possibly reflecting attempts by Republican candidates to differentiate themselves from his policies.

Topic 1, "Future", shed light on discussions encompassing words like "look", "going", and "answer", revealing deliberations about former President Donald Trump's potential role in the party's future leadership. Despite his absence from debates, his presence in discussions indicated the party's contemplation about his future influence.

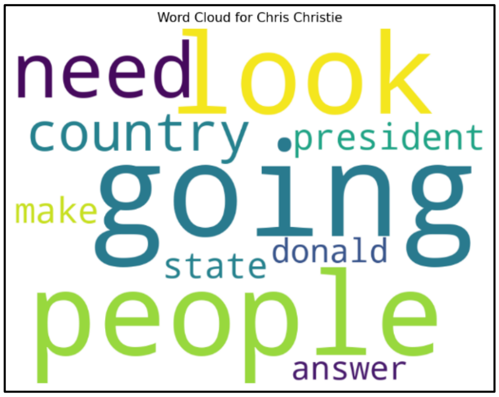


Word Clouds

Topic Modelling Per Candidate

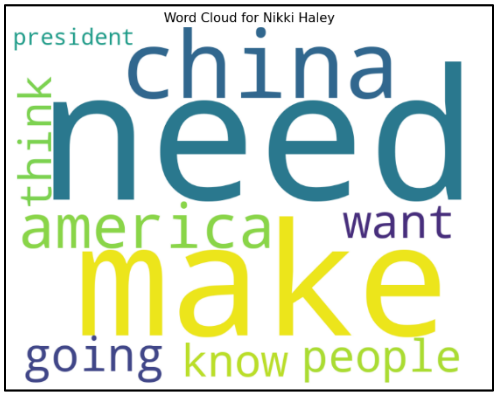
A. Chris Christie

Candidate-specific modeling suggests that Chris Christie was highly focused on where the country is going. He frequently referenced former President Donald Trump. Similar to Topic 1: "*future*", Christie's interest appears to be on looking toward the future and assessing whether or not former President Trump is the most qualified candidate for the Republican Presidential nomination.



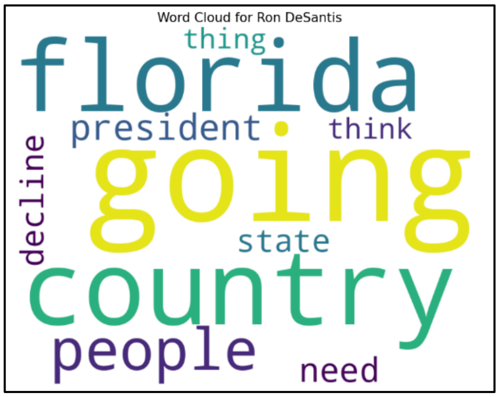
B. Nikki Haley

The most negative candidate across all three debates, Nikki Haley's specific language suggests a focus on what people need and want. Her frequent references to "*China*" and "*America*" suggest a focus on international affairs that is consistent with her history as the UN Ambassador for the US. Additionally, her frequent use of the word "*make*" implies a level of force not present in other candidates' language.

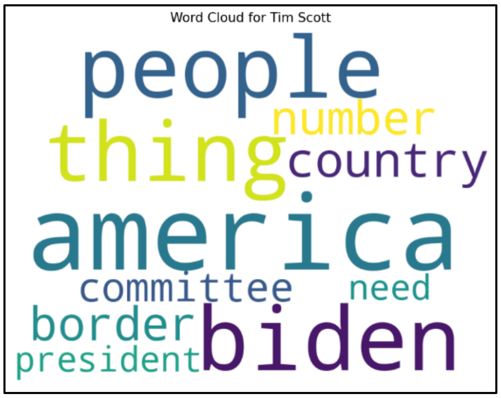


C. Ron DeSantis

Ron DeSantis' language reveals that he relied heavily on his experience as a Florida governor to talk about the country as a whole. In fact, "*florida*" and "*country*" appear to be used almost the same amount, suggesting that DeSantis may have leveraged the debates as an opportunity to market how his tenure in Florida can be exported to a national level. He also relies on future-looking language with "*going*", but his use of "*decline*" and "*need*" suggests negativity in his outlook.

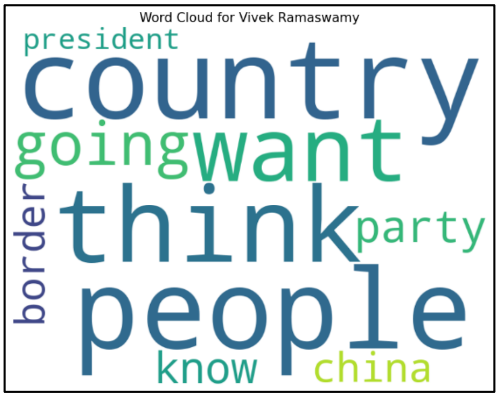


D. Tim Scott



While immigration is a high-profile issue in the United States, only Tim Scott and Vivek Ramaswamy have an explicitly immigration-related word on their most frequently used list. Scott frequently used both "*border*", "*America*", and "*country*", suggesting that he is particularly focused on migration into the US. Additionally, his high use of "*Biden*" suggests that he may have been raising immigration as a way to lodge a critique at current President Biden. Tim Scott has not stepped out of the primary race. However, his participation in the debates is still useful for demonstrating that a high focus on immigration throughout all three debates was not a winning strategy for this particular candidate, despite its salience to the Republican Party.

E. Vivek Ramaswamy



Vivek Ramaswamy, like Tim Scott, frequently used the word "*border*", however, he also frequently used "*China*" rather than "*America*". Like Nikki Haley, he may be particularly interested in foreign affairs. However, unlike Nikki Haley, who focused entirely on countries in her most frequently used words, Ramaswamy's high use of the word "*border*" suggests that he is particularly interested in immigration. Additionally, his use of "*think*", "*want*", and "*people*" far and above other words suggests that Ramaswamy may be relying on populist rhetoric for his campaign.

Sentiment Analysis

Our project also explores sentiment analysis, a technique pivotal in categorizing sentiments as positive, negative, or neutral, offering crucial insights into aligning information with entities. While recent advancements in machine learning and deep learning have bolstered sentiment analysis algorithms, the labor-intensive nature of manually classifying sentiment words remains a challenge.

In the context of elections, detecting sarcasm emerges as a persistent obstacle, urging continuous research endeavors. Despite these challenges, sentiment analysis stands as a crucial tool, especially in unraveling the intricate nuances within political conversations during pivotal events.

Our project included an exhaustive sentiment analysis and misinformation detection exercise on a text dataset, employing advanced NLP techniques. In light of this, we deployed a sentiment analysis pipeline that segmented the text data into manageable chunks to accommodate the pipeline's limitations. Each chunk underwent sentiment analysis, and an average sentiment score was derived to portray the overall sentiment of the text. This approach, applied across texts associated with different speakers, facilitated the aggregation of sentiment scores by candidate, unveiling a nuanced understanding of each speaker's expressed sentiment within the dataset.

Simultaneously, we addressed the challenge of misinformation detection, utilizing a labeled dataset that distinguished between fake and real news. After preprocessing steps like handling missing values and splitting the data into training and test sets, we crafted a machine learning pipeline amalgamating a TF-IDF vectorizer with an SVM classifier, a proven approach in text classification. The classifier was trained on the training data and subsequently employed to predict labels on the test set, culminating in a comprehensive classification report assessing its performance.

Applying this trained misinformation detection model to our dataset allowed us to assign predicted labels to each text, creating a summary of the "honesty" of each speaker based on the proportion of their texts classified as real or fake news. This dual approach, embracing both sentiment analysis and misinformation detection, yielded a comprehensive perspective on the textual data, providing insights into both the emotional tenor and the factual reliability of the content.

Our analysis revealed a pervasive negativity across topics and candidates during the Republican debates, consistent with sentiment analysis findings. Despite minor variations, the sentiment analysis identified all candidates as consistently expressing highly negative sentiments throughout the three debates. Notably, Nikki Haley's comments garnered the most negative classification, while Vivek Ramaswamy and Tim Scott exhibited relatively less negativity. Overall, the Republican debates depicted a predominantly negative outlook on American affairs, reflecting the sentiment prevalent in the debates.

Nikki Haley	NEGATIVE	0.97
Chris Christie	NEGATIVE	0.96
Ron DeSantis	NEGATIVE	0.95
Tim Scott	NEGATIVE	0.93
Vivek Ramaswamy	NEGATIVE	0.93

Sentiment Analysis

Chris Christie	1.0
Nikki Haley	1.0
Ron DeSantis	1.0
Tim Scott	1.0
Vivek Ramaswamy	1.0

Honesty Classification

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