Analyzing U.S. Presidential Speeches: Sentiments, Topics, and Political Context

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This report presents a comprehensive analysis of U.S. presidential speeches by constructing a network of speeches based on their similarity, to find out how they correlate with outside factors such as parties, economic indicators and historical events. Using natural language processing (NLP) techniques, we uncover patterns in presidential rhetoric over time and how speeches align the political landscapes, economic conditions and significant historical events.

Political Communication | Social Networks | NLP | Economics | U.S. History

Presidential speeches are a valuable source of political and historical narratives. Analysing these speeches allows for the identification of underlying themes, the measurement of sentiment shifts and the understanding of the evolution of discourse in response to socio-political contexts. This study leverages natural language processing (NLP) and network analysis techniques to explore the linguistic elements of a dataset of US presidential speeches. Additionally, sentiment evaluation and topic analysis provide deeper insights into changes in rhetorical style, focus and their connection to social and economic factors. Each speech is represented as a node in an undirected network, with edges determined by the similarity between speeches, calculated using text embeddings and cosine similarity.

Results

Initial Network Analysis. Once the speeches network was constructed with 743 nodes and 5041 edges, a preliminary exploration was conducted to understand its structural properties. The network's degree distribution revealed that most nodes had low degrees, while only a few were highly connected. This suggests a high diversity of thematic connectivity across the speeches, with a few central speeches acting as key thematic hubs. Even though this is a typical aspect of scale-free networks, the network's degree distribution does not follow a power-law distribution and may resemble a random or exponential distribution.

Community analysis. The network's modularity, when considering the party affiliations of the presidents, yielded a score of 0.0767 suggesting a weak community structure. This result indicates that speeches delivered by presidents from the same political party are not significantly more similar to each other than to speeches delivered by presidents from other parties. The lack of clear clustering by party affiliation is further supported by the network visualization, see figure 1, where the blending of node colors suggests limited influence of party on speech similarity.

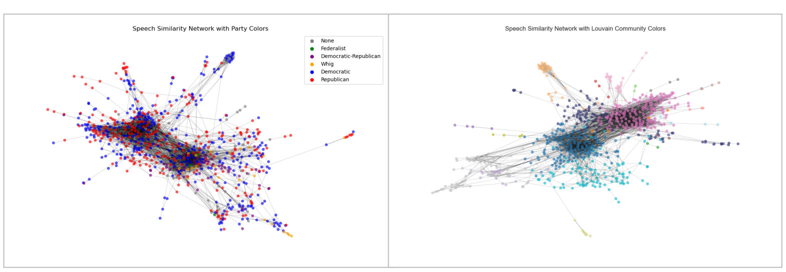

Fig. 1. Speech Similarity Network

In contrast, the modularity score for the Louvain partition was significantly higher (0.5496), indicating the presence of stronger and more meaningful community structures. The network visualization (figure 1) with nodes colored by their Louvain

Significance Statement

This study explores how economic factors and historical events shape the themes and sentiments of U.S. presidential speeches by constructing a network based on textual similarity. By integrating natural language processing with GDP data and key events in U.S. history, we delve into how economic and social conditions influence the topics and emotions of speeches. In addition, it investigates whether different party affiliations or groups of similarly themed speeches lead to distinct rhetorical strategies. Throughout this analysis, the research uncovers patterns that show how presidents adapt their messages over time, providing insights into the relationship between political communication, economics and social changes.

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Author contributions:
1 - Data preprocessing, network creation, initial network analysis, community detection and analysis, sentiment analysis (overall, by party and by community), sentiment vs. economy, sentiment vs. GDP growth, topic analysis (overall, by party and by community).
2 - Api data collection, data preprocessing, network creation, topic analysis, historical events vs. topic similarity and topic frequency.
3 - Sentiment Analysis, topic analysis, historical events and topic frequency

communities shows distinct clusters of tightly connected speeches. These clusters reflect thematic similarities that go beyond party lines, suggesting that factors such as political context, historical events or rhetorical style may play a more important role in shaping

Comparing the communities found by the Louvain algorithm with political party affiliations using the confusion matrix, revealed a limited alignment between the two. While some overlap exists for major parties, such as the Democratic and Republican parties, showed strong overlaps with specific communities (e.g., community 12), there was notable mixing between parties in several communities. This underscores the complexity of speech patterns, highlighting that party affiliation alone does not sufficiently explain the thematic groupings identified by the Louvain algorithm.

Sentiment Analysis. Plotting the histogram of sentiment scores showed a near-normal distribution centered around a positive range, with a slight right skew, representing a moderately positive tone, with minimal occurrences of lower sentiment scores. The average sentiment score across all speeches was 5.6384.

The 10 happiest speeches wordclouds' revealed recurring themes of patriotism, unity and progress, reflecting optimism and a forward-looking vision. Some speeches emphasize national pride and identity tied to pivotal historical moments, such as Ulysses S. Grant's 1876 speech commemorating the Hundredth Anniversary of Independence and Warren G. Harding's 1920 speech on *Americanism*. Ronald Reagan's 1988 speech honoring veterans highlighted sacrifice and devotion, where words like *eternal* and *wreath* signify tribute and respect. Religious themes featured in James Madison's 1813 speech and John Adams's 1798 speech, reflected national reflection and prayer, with words like *adoration* and *repentance*. The happiest speech, Donald Trump's 2020 *March for Life*, addressed controversial topics like abortion, but presented words like *applause* and *thank* showing emotional support for the event's themes.

On the other hand, in the top 10 saddest speeches' wordclouds, we can identify the somber tone of their topics, often recurring to war, conflict and national security. George W. Bush's 2003 speech on the Iraq War highlighted terms that reflected the gravity of the military conflict. Donald Trump's 2019 speech on the death of Abu Bakr al-Baghdadi included terms emphasized the somber tone of military operations, while George W. Bush's 2008 speech on the *War on Terror* mentioned words like *qaida* and *extremist*, signaling ongoing struggles in international conflicts. The recent Joe Biden's 2021 speech on Afghanistan addressed terms that underlined the tragic realities of the Afghanistan crisis. Non-military themes also emerge, such as Ulysses S. Grant's *Veto Message Regarding Restrictions on Rebellion Participants* speech, that featured terms like *oath* and *swear*, focusing on societal and legal challenges, as well as Herbert Hoover's 1930 speech, that mentioned words like *prisoner* and *prohibition*, reflecting economic struggles and law enforcement issues.

These findings underscore the emotional depth and complexity of presidential rhetoric, particularly during times of national or global crises. Additionally, it shows that similar sentiment scores can result from different themed discourse. This insight is supported by the lack of a clear association between thematic and sentiment similarity in our analysis.

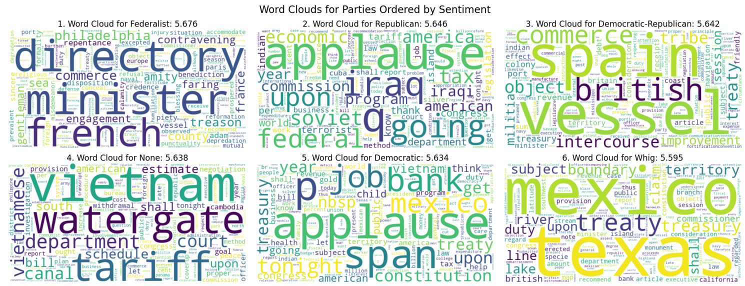

Fig. 2. Word Cloud Sentiment by Political Party

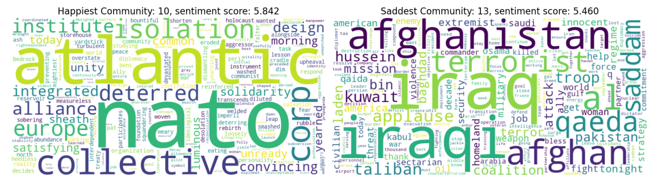

Fig. 3. Word Cloud Sentiment by Louvain Community

Sentiment Analysis by Political Party. The wordclouds in 2, reveal that the Federalist Party emerges as the "happiest" with the highest average sentiment score, emphasizing terms like *commerce* and *treaty*, which reflects their focus on international relations and trade. Conversely, the Whig Party ranks as the "saddest", with terms like *mexico* and *boundary*, highlighting territorial expansion and foreign policy challenges. The Democratic-Republican Party's wordcloud shows a strong focus on governance and diplomacy, with words like *commerce* and *militia*, while the Democratic party emphasizes financial and constitutional topics with terms like *bank*, *treasury* and *constitution*. The Republican speeches seem to be often centered on themes of economic policies and national identity, with words such as *iraq*, *tax* and *america*. The slight variations in average sentiment across parties indicate differences in tone and thematic emphasis, while also highlighting shared challenges and objectives reflected in presidential rhetoric.

Sentiment analysis by Louvain Community. The average sentiment of the six largest Louvain communities ranges from 5.543 to 5.713, a relatively narrow range, indicating a consistent emotional tone across these groups. The wordcloud for the "happiest" community (3) emphasizes themes of international cooperation and collective defense, with words like *atlantic*, *nato*, *corp* and *alliance*. In contrast, the "saddest" community (3) seems dominated by themes of war and conflict, particularly in the Middle East, using terms like *terrorist*, *qaeda* and *taliban* that relayte to military operations and terrorism.

Sentiment vs. Economy. Historical GDP data shows a clear upward trend in real GDP per capita, reflecting long-term economic growth. From 1790 to 1880, growth was stable and moderate. After this period, economic growth accelerated, accompanied by notable fluctuations during major historical events. Examples of economic downturns include the Great Depression in the 1930s, the financial crisis of 2008, and the COVID-19 pandemic in 2020. Periods of rapid economic expansion include the WWII boom (1939-1945) and the late 1990s economic surge.

Analyzing the distribution of speeches across GDP per capita, it appears that during periods of worse economic conditions (prior to 1940), presidential speeches were more frequent, likely as a means to address public concerns or garner support. For GDP values above 10,000, speeches are generally less frequent, likely reflecting shifts in communication methods over time. However, the frequency of speeches shows no strong relationship with GDP, as variations across GDP ranges remain relatively similar.

Sentiment analysis over time reveals that sentiment scores are mostly stable, with notable declines during crises such as the Great Depression and WWII. Interestingly, sentiment often peaks after these low points, suggesting a pattern of optimism and hope following periods of hardship.

Word clouds highlight contrasting themes in the happiest and saddest years. The happiest year, 1798, with an average sentiment score of 6.001, features religious and moralistic language such as repentance, benediction, and piety, reflecting a focus on spirituality and gratitude during the early formation of the U.S. The saddest year, 1904, with an average sentiment score of 5.435, emphasizes maritime conflict with terms like privateer, vessel, and belligerent, likely influenced by naval disputes during the Russo-Japanese War. These findings demonstrate how external events, such as wars, impact the tone of presidential rhetoric.

Despite exploring a potential relationship between GDP and sentiment, the results indicate no strong correlation. While GDP steadily increases over time, sentiment fluctuates independently, as reflected by a low correlation coefficient calculated between average yearly sentiment and GDP per capita, both for the current year and with a one-year lag. This suggests that factors influencing political discourse are more complex than economic performance alone.

Topic Analysis, Historical Relationship. The results of analysis of the normalized topic frequencies showed that politics, people and society, and war were the most prominent topics, while technology and the environment were the least discussed. Frequency distributions between political parties were similar, with differences mainly due to smaller speech sets from smaller or extinct parties, suggesting that major social and economic events, rather than party affiliations, shape presidential topics.

We also analysed the frequencies grouped by the communities in the network, found using the Louvain algorithm. In these results the most frequent topics remained similar to previous findings, however the distribution varied slightly more in different communities. For example in the largest community 12 *economy* swapped places with **war** and **people and society** took the first place from *politics*. This further supports the idea that the communities within the network reflect the varying topical focuses of the speeches rather than strictly aligning with political party affiliations.

Plotting the frequencies by time showed anticipated results. We expected to see the main topics being mostly dominant throughout the whole timeline, while others appearing periodically correlating with historical events and different periods in the U.S. history. As we can see on figure 4. the results are similar to what we expected. Topics like Politcs and War show many high peaks distributed on the whole X axis while others show lower numbers with some higher peaks. Looking more closely at each plot we can make some

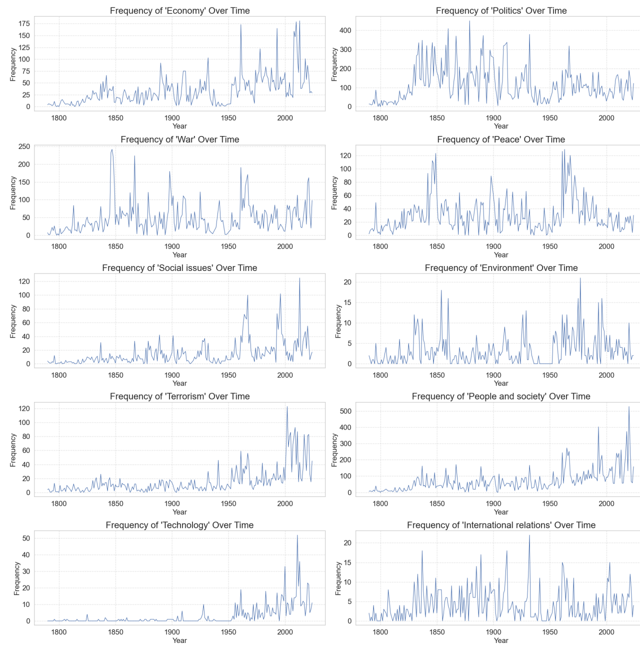

Fig. 4. Frequency of Topics by Time

interesting conclusions. We gathered data of the key historical events from multiple sources and used it to find correlations between topics in speeches and real world events.

Economy related topics frequently appear throughout the speeches for all years. However, we can see some significant peaks that can correlate to important financial events. For instance, the peak in 1878 coincides with the post-Civil War economic recovery and the efforts to stabilize the economy following the Panic of 1873. Another major peak in the 1890s aligns with the economic challenges faced during the Depression of 1893. The sharp increase around the 1930s falls during the Great Depression, as President Franklin D. Roosevelt introduced the New Deal to address unemployment and stimulate recovery, while the one around 1979 can be linked to inflation and the energy crisis that cause disturbance during President Jimmy Carter's administration. Lastly, the 2008 peak corresponds to the Great Recession, highlighting efforts to stabilize markets and prevent further economic collapse. Economic discussions in presidential speeches often show a reactive focus, prioritizing financial stability during crises and recovery periods.

Similar to economics, **Political** topics also dominate the speech dataset, showing a general slightly upwards trend in normalized frequency from the 1790s until around 1875. After that, it starts to decrease and seems to stabilize around 1990, continuing at a more consistent level. The 1790s shows a spike that can be tied to foundational discussions, including the Bill of Rights and early federal structures. Political discourse peaks again in 1860, during the the election of Abraham Lincoln and the Civil War era (1861-1865), reflecting the polarizing political climate surrounding slavery and secession. The high increase also observed around 1875, can be attributed to political discussions surrounding the end of Reconstruction and the changes that followed the Civil War. Smaller surges in the late 20th century align with moments such as Watergate in the 1970s and the Monica Lewinsky scandal in the 1990s.

War-related topics rise during major conflicts, such as the War of 1812, reflected in the peak during the 1810s, and the Civil War, as seen by the peak around 1860s. The highest peak is seen in the early 1900s, which could be reflecting military discussions related to the aftermath of the Spanish-American War (1898), including U.S. expansion in the Caribbean and the Pacific, as well as the construction of the Panama Canal. A major surge is observed from 1938 to 1942, during the lead-up to and early years of World War II (1941-1945), while smaller increases are also noted during the Vietnam War in the 1960s and 1970s.

Social issues become more dominant during periods of civil unrest. The highest peak is observed around 1800, potentially reflecting early debates about the institution of slavery and societal organization in the nascent United States. Afterward, the frequency remains somewhat stable but less pronounced, with slight increases during key periods. High normalized frequencies are seen between 1895 and 1910, coinciding with the Progressive Era and movements advocating for social reforms like labor rights and women's suffrage. We can see another peak in the 1960s, corresponding to the Civil Rights Movement and Martin Luther King Jr.'s assassination. More recent surges in 2013 and the 2020s correspond to movements like Black Lives Matter, highlighting ongoing struggles for equality and civil rights.

Terrorism-related topics show a slight upward trend starting from the 1930s, reflecting growing concerns about global conflicts and security threats. A considerable increase and more pronounced peaks occur from 2001 onward, dominating the discourse following the September 11 attacks. The War on Terror, initiated in response, continues to shape rhetoric in the early 21st centuryThese discussions reflect a heightened focus on national security and global stability in the post-9/11 era.

Technology-related discussions gain prominence in the late 20th century and early 21st century, reflecting rising technological advancements. Initial growth in the 1960s aligns with the Space Race and Apollo program, as technological innovation became a symbol of national progress. The more recent peaks reflect the digital revolution, cybersecurity concerns and the role of technology in modern governance.

Environmental topics remain minimal and relatively constant throughout history. A notable peak occurs in the 1970s, coinciding with the establishment of the Environmental Protection Agency in 1970 and the rise of environmental awareness during that era. Subsequent discussions align with global climate policies, such as the Kyoto Protocol (1997), reflecting a growing focus on environmental challenges.issues.

Discussions about **people and society** show an overall rising trend, marked by sharp edges in periods of societal change or crisis. Peaks in the 1800s and 1860s reflect the nation's early struggles with societal structures and the Civil War. The 1930s to 1950s highlight efforts to address unemployment during the Great Depression and post-war recovery. Recent increases in the 2020s correspond to movements for social justice and equity. These trends demonstrate how presidential rhetoric responds to public needs and social advocacy.

Speeches related to **international relations** are relatively constant, with minor fluctuations. This reflects the steady role of U.S. foreign policy in presidential speeches, where peaks align with increases in other topics such as war, peace and economy, but the focus on diplomacy and international engagement remains stable over time.

Discussion

This study offers a comprehensive exploration of US presidential speeches, revealing insights into their thematic structure, sentiment and relationships with economic conditions and historical events. The findings highlight important discoveries, such as the detection of the Louvain community by identifying groups orientated more by historical context than by party affiliation. Also, sentiment analysis showed that speeches predominantly maintain a positive tone, with happier speeches emphasizing unity and progress, and sadder ones reflecting war and crises. Economic analysis highlighted a weak positive correlation between GDP growth and sentiment, with speeches during economic downturns often adopting a somber tone. Topic analysis identified economy, politics, and war as dominant themes, aligning with major historical events, while newer topics like the environment, technology and international relations appeared less frequently.

Future research could explore contextual sentiment analysis, expanding the scope to include other political leaders or multimodal data, such as audience reactions. Additionally, detailed studies on specific historical periods, such as the Civil War or the Great Depression, could clarify how presidential speech shapes and responds to crucial moments in U.S. history.

Methods

Data Preprocessing and Network Creation. The dataset of US presidential speeches was retrieved from the Miller Centre API (1). To align with the available GDP data, only speeches from 1790 onwards were kept, resulting in a data set that runs from 1790 to 2024. In total, the dataset resulted in 1.055 speeches from 45 presidents. To construct a network of speeches based on their thematic similarity, a range of thresholds (0.3 to 0.9) was tested to determine the optimal similarity score for edge creation. Metrics as the largest connected component size, modularity, average degree and density were adopted to distinct communities and preserving network interpretability. As result, a threshold between 0.6 and 0.65 provided the best balance. Therefore, 0.625 was chosen as the similarity threshold for edge creation, ensuring distinct communities without significant loss in network size. This choice optimizes modularity while maintaining a sufficiently large largest connected component.

A U.S. presidential speeches network was created, where each node represents a speech, and weighted edges were formed between speeches that share a cosine similarity greater than 0.625. Each node includes attributes such as the speech title, president, date and transcript. The network was reduced to the largest connected component to focus on the most significant part of the network. Nodes with no connections were removed to enhance interpretability and relevance. To assess the network's structure, we examined the degree distribution, fitted it to a power-law model and performed a Log-Likelihood Ratio Test against an exponential distribution.

Community Detection. To perform community analysis on the network, the modularity score based on each speech's party affiliation was calculated. Modularity measures the strength of the community structure in the network by comparing the density of links within communities to what would be expected in a random network (2). The modularity score ranges from -1 to 1. For a more advanced community detection, the Louvain algorithm (3) was applied to partition the speech network, identifying communities that are more tightly connected. A confusion matrix D was created to compare the communities identified by the Louvain algorithm with the political party affiliations of the speeches. Each entry $D(i, j)$ represents the number of nodes that belong to party i and Louvain community j (out of the six most common ones).

Sentiment Analysis. Sentiment analysis is an important tool for understanding the emotional tone behind a piece of text. In this study, sentiment analysis was conducted on the presidential speeches to explore how tone and emotions in these speeches relate to political strategies, public perceptions, and societal issues. The LabMT S1 dataset (4) was used to calculate speech sentiment scores based on the average happiness ratings of its words, which reflect the emotional tone typically associated with them. The sentiment analysis involved processing the transcript of each speech, including tokenization, removing punctuation, converting text to lowercase, removing stopwords, and lemmatizing. It is important to note that this method evaluates the surface sentiment of words but does not fully capture audience reactions or the nuanced context of the speeches.

To analyse the relationship between thematic and sentiment similarity, a sentiment similarity matrix (absolute differences in sentiment scores) and a transcript similarity matrix (cosine similarity) were created, focusing only on connected nodes.

Additionally, to explore the emotional and linguistic patterns more deeply, a TF-IDF (Term Frequency-Inverse Document Frequency) analysis was applied to assess the importance of terms in each speech. TF measures how often a word appears in a document relative to the total number of terms, while IDF measures how rare a word is across all documents. This helps identify words that are more informative for each speech, giving less weight to common words. The TF-IDF scores were used to generate word clouds to easily visualize the most significant terms.

To conduct an analysis party and community based, the average sentiment of individual speeches per group was calculated, rather than combining all speeches per party. This approach ensures fairness by treating each speech independently, avoiding biases from speech length or frequency, providing a standardised measure of the tone associated with each group.

sentiment vs Economy. To incorporate economic relationship into the analysis, GDP data was used to explore how economic conditions may influence the tone, sentiment or topics of political speeches. Each speech was mapped to the real GDP per capita of its corresponding year, using data from MeasuringWorth.com (5), which provides comprehensive historical economic datasets. This mapping allowed GDP values to be assigned as attributes to the nodes in the network. A temporal visualisation of GDP was created, along with a bar chart illustrating its distribution between speeches, and the sentiment scores were analysed by year to relate to this data.

To examine thematic responses to economic sentiment, the happiest and saddest years, based on average sentiment, were identified, and the TF-IDF analysis was used to highlight distinctive terms from these periods. The correlation coefficient between sentiment and yearly GDP, and sentiment and GDP lagged by one year were obtained.

To go further, the analysis explored the relationship between GDP growth per presidential term and the sentiment expressed in presidential speeches. This approach based on the mandate years considered the possible influence of economic performance during a president's term, as sentiment can reflect both the challenges or successes encountered and the president's characteristic emotional tone. Sentiment scores were also calculated and analyzed by term.

Historical topic Analysis. To link historical events to topics in presidential speeches a keyword-based approach was used, in which topics such as economics, politics, war, social issues, the environment, terrorism, people and society, and violence were defined through predefined keyword groups. These groups were generated using ChatGPT (6), which provided descriptions and relevant keywords for each topic in a structured JSON format. The normalized frequency of each topic in the speeches was calculated by counting the occurrences of the associated keywords and dividing it by the total number of speeches in that year. This allowed a quantitative evaluation of the different topics in the presidential speech, accounting for variations in the number of speeches per year

Initial exploratory topic modeling using Latent Dirichlet Allocation (LDA) was attempted to uncover hidden topics. However, the results were discarded as the topics identified by LDA did not align with the predefined categories, making them unhelpful for the purposes of the research. So, to identify trends, the frequency of each topic was examined over time by plotting its occurrence per year. This temporal analysis provided insights into how the focus of presidential speeches has shifted in response to historical events.

The study analyzed topic frequency by political party and Louvain community. For each party, the top three topics (e.g., economy, politics, social issues) were identified. Similarly, the six largest Louvain communities were examined for dominant themes. The happiest and saddest communities, based on sentiment scores, were also analyzed to identify their top three topics, highlighting emotional tones.

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