Sentiment and Topics in North American News Media Coverage of Donald Trump

Group 62
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Introduction

We considered several political candidates to analyze in this report and settled on Donald Trump due to the large media coverage of the US elections that took place in November 2024. Donald Trump is a prominent American political figure and member of the Republican Party. He served as the 45th President of the United States from 2017 to 2021. A businessman and television personality before entering politics, Trump won the 2016 presidential election in an upset and is known for his unconventional rhetoric. After losing the 2020 presidential election to Joe Biden, he remained a significant and controversial figure in American political discourse, particularly following the events surrounding these results and subsequent legal challenges.

In the context of the 2024 election cycle, Trump emerged as a key Republican candidate, securing the party's nomination and positioning himself for a potential return to the presidency. On November 5, 2024, Trump won the US elections with a majority of electoral votes, marking a significant moment in contemporary American politics. Our report is an analysis of recent, English-language coverage of Donald Trump from across North American news outlets during this pivotal election period. Relevant stakeholders include our client, a media company that wants to understand how Donald Trump is being covered in the media.

By systematically examining news articles from diverse media outlets, we seek to understand two critical dimensions of media representation:

1. The primary topics and themes that dominate the narrative surrounding Donald Trump's electoral campaign in recent North American news outlets' coverage.
2. The sentiment of recent North American news outlets coverage' of Donald Trump; whether articles present Trump in a positive, negative, or neutral light.

Using a rigorous methodological approach that involves data collection, open coding, and systematic annotation, we provide insights into how North American news outlets portray President Trump. Our objective is to offer a nuanced understanding of his current media representation in the context of the recent US election period. We need to specify that "Donald Trump coverage" includes any articles that mention the political figure's name in the title or opening description. Further, "recent" defines a time frame of approximately one month, starting towards the end of October, 2024. Finally, "North American news outlets" refers to established, mainstream news sources based in the United States and Canada.

A thorough analysis of 500 articles led to the following key findings:

1. The majority of Donald Trump's coverage was of negative sentiment, particularly in economic policies, legal and institutional matters, and general public reception. On the other hand, his electoral victory indicates that mainstream coverage did not have a strong influence or did not accurately represent his broader public reception—a recurring theme in our analyses.
2. Media and Public reaction is the most frequently discussed topic in Trump's coverage. This is somewhat expected given his high-profile status prior to his political career and involvement in numerous controversies. However, his interviews on two of the top ten US podcasts (ranked by Spotify; *Joe Rogan Experience* and *This Past Weekend w/ Theo Von*) in October 2024 certainly played a role in the increased discussion in this topic. Notably, *Joe Rogan Experience*'s audience is 28x larger than that of CNN.
3. TF-IDF analysis of bigrams and trigrams revealed that Joe Rogan and Elon Musk's endorsements of Donald Trump were key talking points in articles surrounding the president-elect's campaign, economic messaging, and public reception. Further, trigrams such as "Joe Rogan endorses" and "Buzz Aldrin endorses" show that endorsement stories dominated coverage of Trump's campaign.
4. Trigram TF-IDF analysis of economic coverage highlights that rising grocery prices emerged as a key voter concern, significantly influencing support for Trump and dominating media narratives. Additionally, Bernie

Sanders featured prominently in the top bigrams for Campaign and Political Messaging, reflecting his agreement with Trump on economic policies, such as capping credit-card interest rates—a stance resonating with working-class voters. Elon Musk's endorsement further amplified Trump's pro-business appeal. Despite this, the largely negative media sentiment on economic issues underscores a disconnect between Trump's broad economic appeal and the tone of his media coverage.

5. Mark Cuban, a prominent entrepreneur and media personality, recently criticized Trump during a televised interview, stating that "you never see (Trump) around strong, intelligent women. Ever." This remark garnered significant media attention, and the phrase "strong, intelligent women" appeared in the top ten trigrams for the topic "Media and Public Reaction." Cuban's comment reflects broader critiques of Trump's political messaging, particularly concerning the underrepresentation of women in his inner circle and leadership roles, an issue that has repeatedly surfaced in media coverage. This highlights a persistent weak point in Trump's public perception among female voters and his broader political narrative.

Data

Our dataset is composed of 500 articles, drawn from NewsAPI.org. The features in our dataset are defined as follows:

- *author*: the author of the news article;
- *title*: the title of the news article;
- *description*: either the provided description/subtitle or a snippet from the news article;
- *source_name*: the display name of the source this news article came from;
- *source_id*: the unique identifier of the source this news article came from;
- *topic*: the topic of the article's content, obtained through the human annotation process;
- *sentiment*: the sentiment of the article's content, which is positive, negative, or neutral, obtained through the human annotation process.

We constructed this dataset through multiple rounds of data collection using NewsAPI.org's free plan, which imposed several constraints and necessitated additional design decisions:

1. The API's lookback period had a limit of 30 days, which limited our search to articles from around a week before the elections until the end of the month of November. We refined our research question to align with this time period, focusing on articles published during the election and specifying "recent" as articles from the past month.
2. The API returns a maximum of 100 results per request. We, therefore, had to query multiple pages to obtain enough articles for our project. Additionally, we queried the articles across two different time intervals.
3. The API does not provide a parameter to filter by country. This impacted our ability to search for only North American news media, so we had to modify our data collection algorithm. We started by using all NewsAPI.org's sources returned from our queries and hand annotating them by country. We then searched for articles using these sources to filter our query to only North American (US, Canada, and Mexico) articles.

Once we queried for the North American articles, we had to do some extra work, starting by filtering out duplicates. There were also some results from the response object that contained features set to "[Removed]," which are most likely articles that got deleted from the news outlet but were still found by the API.

To summarize, our data collection process was done in the following steps:

1. First, we collected US and Canadian-based sources for a total of 14 sources. This was done by doing an initial query "Donald Trump" via NewsAPI's /v2/everything endpoint. We then retrieved all the sources returned from this query, hand-annotated them by their country, and finally filtered out only American and Canadian sources (there were no Mexican sources). Finally, we sent the query to the same endpoint, with a filter on sources this time, to obtain a total of 638 articles across different North American sources in the past 30 days.
2. We then filtered any duplicate articles, as well as deleted articles. For the rest of the data science project, we were only interested in the "author," "title," "description," "source_name," and "source_id," so we filtered the data set to only include these relevant features. This left us with a total of 603 articles.
3. From this set of articles, we picked 500 articles using random sampling to mitigate bias (since the API returned articles in order of popularity), which created our final data set used for the data annotation process. This was the best solution available to us, as there were not enough articles such that a subset of at least 500 samples could be uniformly distributed among left-wing, right-wing, and center sources.

Methods

Open-Coding and Typology

We followed standard practices to categorize the *topic* and *sentiment* precisely and such that the resulting classes represent all of the data. For the topic, we started with open coding on 200 randomly sampled articles to reach a final typology after three rounds of coding. Due to this year's atypical election cycle, the first round of coding produced 16 topic categories. There was significant overlap between group members' categories, which often differed in names but shared similar meanings. After agreeing on the names and the definitions, we proceeded to the second round of coding, aiming to narrow down the topic to eight classes. There was disagreement over the merging of categories given the variety of related classes (e.g., Media reaction vs.

Public reaction), and an extensive conversation was needed to decide the most appropriate merging and final categories best characterizing all of the seen articles, and generalizable to potential edge cases on the remaining data. We were able to finally agree on 8 topics that will be described in the **Results** section. Finally, through the open-coding and annotation process, we were able to avoid a "catch-all" category like "Other," since our final set of topics for our typology encompassed all articles in our data set.

After completing the open coding as a team, we divided the remaining 300 articles among group members, resulting in each having 100 articles to annotate with the final typology. To mitigate potential human errors, we went through the annotation process multiple times to review each other's work.

As for the sentiment annotation, we independently annotated the entire dataset, using only the article title and opening paragraph. Each article was classified as either *Positive*, *Negative*, or *Neutral*. We classified the sentiment of the article's discussion of the given event rather than the event itself. After the individual annotations, we combined our results. In the case of disagreement, we would select the majority agreement as the final classification. In the case of complete disagreement (three distinct labels applied to the same sample), we got together to discuss and come to an agreement on these particular cases. For completeness, we defined the sentiment classes as follows:

- Positive Sentiment: Articles that present Donald Trump in a favorable light, highlighting his achievements, strengths, popular support, or positive policy outcomes. The tone is supportive and complimentary.
- Negative Sentiment: Articles that critically portray Donald Trump, emphasizing controversies, criticisms, legal challenges, policy failures, or personal shortcomings. The tone is disapproving or critical.
- Neutral Sentiment: Articles that present information about Donald Trump objectively, without evident bias. These articles focus on factual reporting, provide balanced perspectives, and avoid overtly positive or negative language.

TF-IDF Analysis

Part of our task was to characterize the topics by computing the ten words in each category with the highest TF-IDF scores, computing the inverse document frequency across all 500 articles. We preprocessed the title and description by converting all characters to lowercase, removing punctuation, and removing stop words with NLTK[1]'s stop word corpus. Finally, we utilized scikit-learn[2]'s TfidfVectorizer method to compute the TF-IDF scores with inverse document frequency across all 500 articles. Despite the document penalties, our first pass through the dataset placed numerous words in the top ten that were not conducive to driving insights; these words included: 'American', 'former', and 'president'. Thus, words that were generic in our task were added to the stopword corpus. In the second pass through the dataset, we obtained more meaningful words; however, much of the context was still missing as the analysis was limited to unigrams. For example, the terms "garbage" and "truck" appear among the top ten unigrams for Campaign and Political Messaging (Figure 2). This is likely due to Trump's recent appearance riding a garbage truck in an attempt to get back at Joe Biden for calling his supporters "garbage." Notably, the trigram "Puerto Rico remarks" was among the top ten for Media and Public Reaction, referencing comedian Tony Hinchcliffe's comments about garbage in Puerto Rico during Trump's New York rally. To address such ambiguities, we applied TF-IDF to unigrams, bigrams, and trigrams, which effectively highlighted key insights.

Aggregate Sentiment Analysis

For the sentiment analysis task, we aggregated rows along the three values in the sentiment column, computing the counts for each sentiment class. We then utilized matplotlib[3] to generate a pie chart representing the overall sentiment distribution. Moreover, we computed the distribution of sentiment for each topic, which was done by grouping the rows of the dataset by topic and then performing the count-aggregation along the sentiment column for each topic class.

Results

Typology Definitions

Through the open-coding process and development of our typology, we were able to narrow it down to the following eight topics:

1. **Election Outcome and Dynamics**: articles in this category would primarily focus on the results, implications, and analysis of elections involving Donald Trump. This includes discussions about election results, vote counts, electoral college distributions, Trump's performance in specific states or regions, and broader interpretations of how the election outcomes reflect political trends or shifts in voter preferences.
2. **Campaign and Political Messaging**: articles on this topic are encompassed by their concentration on Trump's campaign strategies, political rhetoric, public statements, and communication approaches. These articles would highlight his campaign rallies, speeches, political slogans, messaging tactics, and how he frames his political narrative and connects with his base of supporters.
3. **Policy and Governance Implications**: articles in this category would analyze Trump's policy proposals, governance approaches, executive actions, and potential or actual legislative impacts. This includes discussions about his policy stances on issues like immigration, foreign policy, healthcare, trade, and national security, and how these policies might affect different sectors of society or the broader political landscape.
4. **Media and Public Reaction**: this topic focuses on how the media and public perceive and respond to Trump's

[1]https://www.nltk.org
[2]https://scikit-learn.org
[3]https://matplotlib.org/

actions, statements, and political career. Articles would include media commentary, public opinion polls, social media reactions, public protests or support, and analysis of how different media outlets and demographic groups interpret and react to Trump's political activities.

5. **Legal and Institutional Context**: articles in this category would center on legal challenges, investigations, court cases, impeachment proceedings, and other institutional interactions involving Trump. This includes coverage of legal disputes, constitutional debates, interactions with government institutions, lawsuits, criminal investigations, and potential legal consequences of his actions.
6. **Economy**: articles on this topic would primarily discuss economic issues related to Trump, including his economic policies, impact on businesses, job market, trade relations, tax policies, and economic performance during his presidency or political career. This topic would cover economic indicators, business responses, and how his economic approaches affect different economic sectors and social groups.
7. **Demographic and Voter Shifts**: this topic analyzes changes in voter behavior, demographic trends, and political alignments associated with Trump. Articles would explore how different demographic groups (by age, race, income, education, geography) respond to Trump, shifts in political party loyalty, emerging voting patterns, and the broader sociopolitical implications of these demographic changes.
8. **Election Campaign Events**: articles in this category would provide detailed coverage of specific events during election campaigns. This includes reporting on campaign rallies, debates, fundraising events, campaign trail incidents, interactions with supporters and opponents, and the day-to-day dynamics of Trump's election campaigns.

TF-IDF Results

As described above, we have carried out a TF-IDF analysis for our sampled data, computing the top ten most representative words for each topic category. Figures 1-8 show the top ten words by TF-IDF scores across the eight topics.

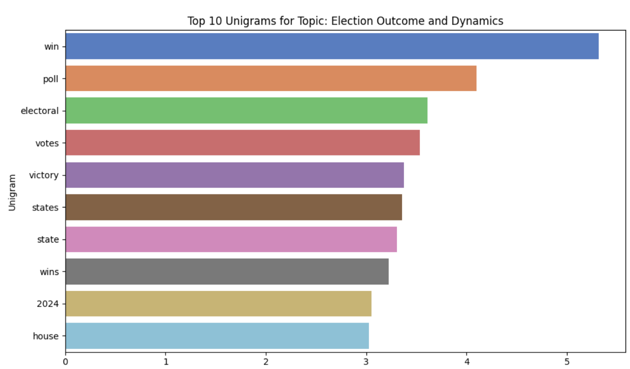

Figure 1: The top ten unigrams with the highest TF-IDF scores in articles categorized under "Election Outcome and Dynamics."

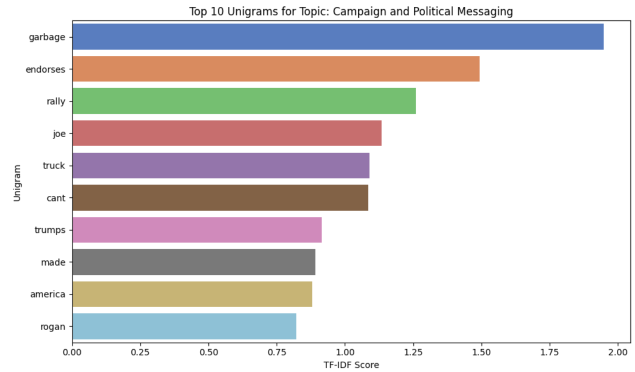

Figure 2: The top ten unigrams with the highest TF-IDF scores in articles categorized under "Campaign and Political Messaging."

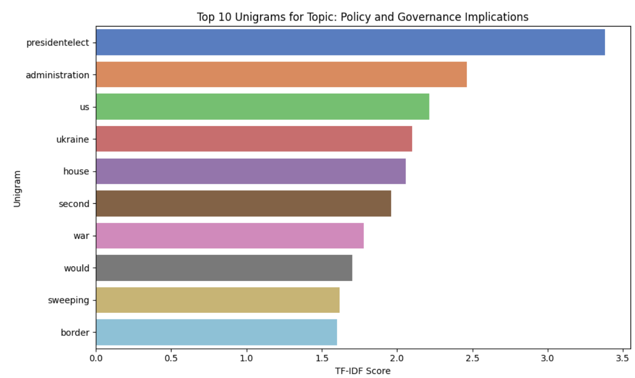

Figure 3: The top ten unigrams with the highest TF-IDF scores in articles categorized under "Policy and Governance Implications."

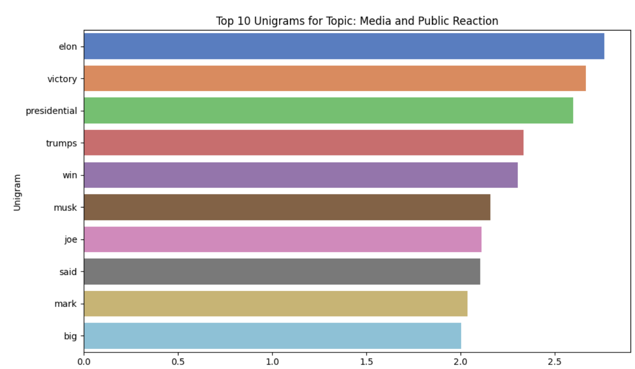

Figure 4: The top ten unigrams with the highest TF-IDF scores in articles categorized under "Media and Public Reaction."

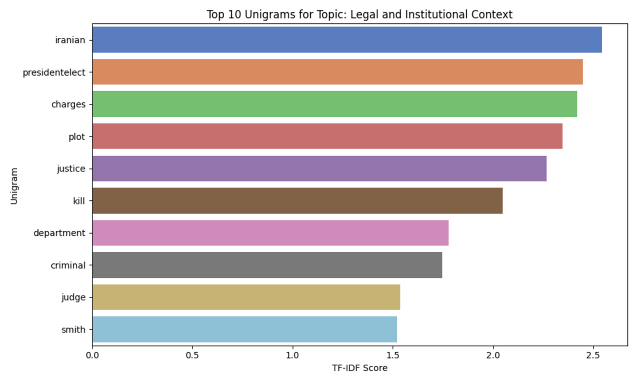

Figure 5: The top ten unigrams with the highest TF-IDF scores in articles categorized under "Legal and Institutional Context."

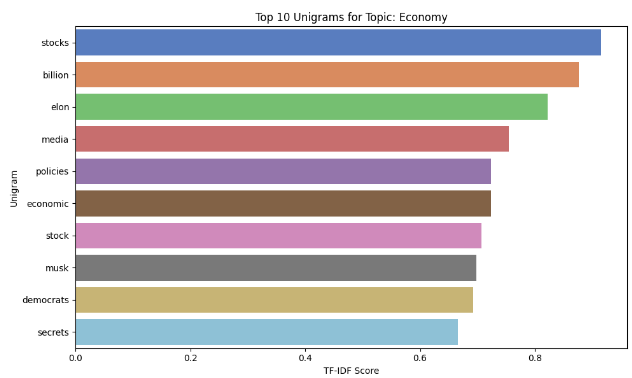

Figure 6: The top ten unigrams with the highest TF-IDF scores in articles categorized under "Economy."

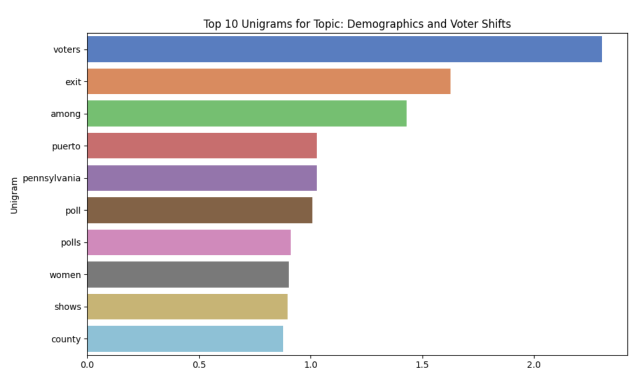

Figure 7: The top ten unigrams with the highest TF-IDF scores in articles categorized under "Demographics and Voter Shifts."

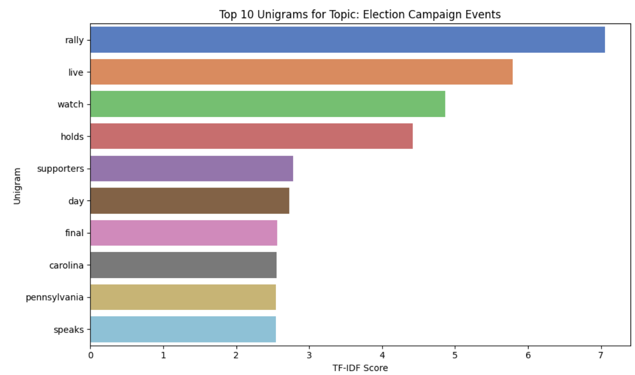

Figure 8: The top ten unigrams with the highest TF-IDF scores in articles categorized under "Election Campaign Events."

We also present the top ten bigrams and trigrams from some of the topics mentioned in our key findings in Figures 9 and 10.

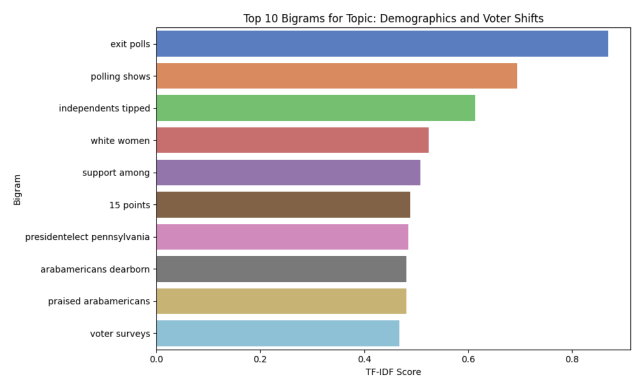

Figure 9: The top ten bigrams with the highest TF-IDF scores in articles categorized under "Demographics and Voter Shifts."

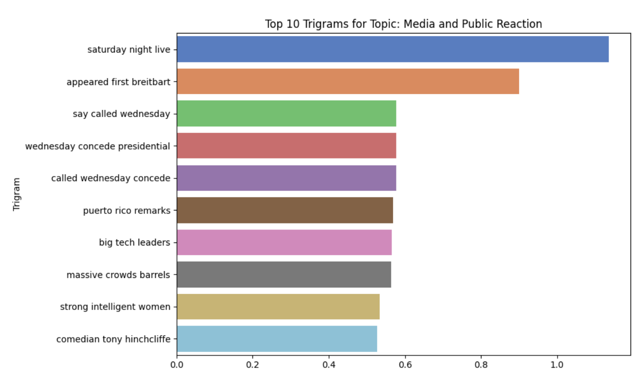

Figure 10: The top ten trigrams with the highest TF-IDF scores in articles categorized under "Media and Public Reaction."

Sentiment Results

By using the typology defined above to annotate the data, as well as the sentiment annotation, we compiled the sentiment distribution per topic, as shown in Figure 11. Relate this with Figure 12, showing the overall sentiment distribution across all articles. We see that coverage was not only negative in general but also negative in each topic.

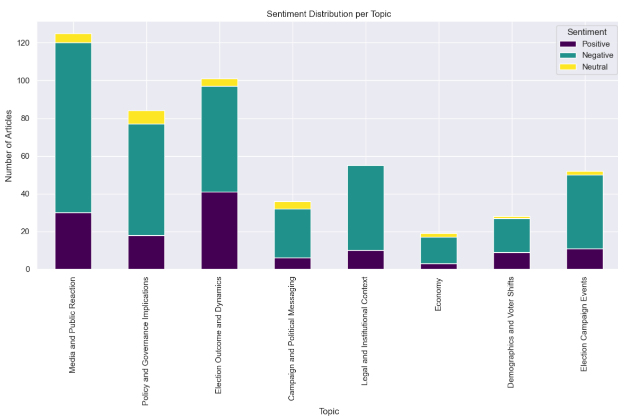

Figure 11: The distribution of sentiment (positive, neutral, and negative) across articles for each topic in the dataset.

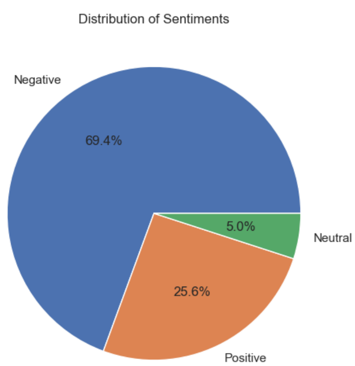

Figure 12: The overall sentiment distribution (positive, neutral, and negative) across all articles in the dataset.

Source Bias

We want to disclose and present any potential political bias in our dataset's news sources. Figure 13 shows the proportional distribution of the political bias (by source) in the articles, with most originating from a politically centered source, according to AllSides. This contrasts with Figure 12, which shows that the majority of articles have negative sentiment. However, it could be that the stories being covered are *absolutely* negative. Further, categorizing a news source as left-, right-, or center-leaning can be a subjective task (to what extent is the source left- or right-leaning?), and we attempt to mitigate subjectivity by using AllSides, which is a media bias rating website that helps readers understand the political leanings of various news sources. Thus, for the sake of transparency, we disclose the sources which occurred in our dataset: ABC News, Breitbart News, Business Insider, CBC News, CBS News, CNN, Fortune, MSNBC, NBC News, Newsweek, The Verge, Time, USA Today, Wired.

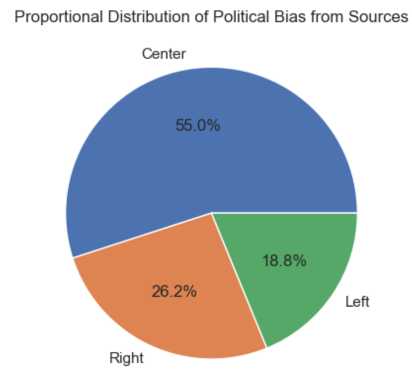

Figure 13: The distribution of articles by political bias of the news sources (left-leaning, center, and right-leaning) in the dataset.

Discussion

Our analysis set out to address two critical dimensions of Donald Trump's media representation: the primary topics dominating his media narrative and the sentiment of news coverage across these topics. The findings provide a nuanced understanding of how North American media portrayed Trump throughout a one-month period around the election.

First, the eight-topic typology reveals a multifaceted media approach to Trump's political presence. Contrary to potential expectations of a singular narrative, our analysis demonstrates the complexity of media representation.

"Election Outcome and Dynamics" and "Election Campaign Events" were prominent topics, reflecting the media's intense focus on the electoral process. This aligns with our initial research goal of understanding how Trump is being covered in the context of the recent election. The high frequency of terms like "electoral," "votes," and "states" indicates a deep commitment to explaining the technical and strategic aspects of the election.

The "Policy and Governance Implications" topic, with keywords like "administration," "Ukraine," and "war," suggests that media coverage extended beyond electoral mechanics to substantive international policy discussions. This demonstrates a media approach that seeks to contextualize Trump's electoral victory within broader geopolitical and domestic policy frameworks.

Intriguingly, some topics revealed unexpected narrative dimensions. The “Legal and Institutional Context” topic, with its surprising keywords like “Iranian,” “plot,” and “kill,” suggests that media coverage incorporated complex legal and potentially international dimensions to Trump’s political narrative.

The role of high-profile media and technology figures emerged as a significant narrative thread in our analysis. The prominent mentions of Joe Rogan and Elon Musk’s endorsements reveal the expanding influence of non-traditional media personalities in political discourse. These endorsements were not merely peripheral mentions but emerged as key talking points across multiple topics, particularly in campaign messaging and public reaction. This finding suggests a media landscape where celebrity endorsements and podcast influencers play an increasingly crucial role in shaping political narratives, blurring the lines between traditional media coverage and alternative information channels.

Economic messaging presented a particularly nuanced dimension of media coverage. Our TF-IDF analysis revealed that grocery prices were a critical concern for voters, potentially swaying electoral support for Trump. Interestingly, the economic coverage demonstrated an unexpected alignment between Trump and Bernie Sanders on certain economic policies, particularly regarding credit card interests. This finding highlights a complex economic narrative that contradicts the predominantly negative media coverage. It suggests that working-class economic concerns transcended traditional partisan divisions, with media coverage potentially underestimating the economic appeal of Trump’s messaging to certain voter demographics.

The analysis of demographic representation, particularly concerning women, unveiled significant challenges in Trump’s political messaging. Mark Cuban’s remarks about Trump not being around “strong and intelligent women” emerged as a notable trigram in media coverage. This finding underscores a persistent issue in Trump’s political communication – the perception of underrepresentation and potential marginalization of women. Combined with Trump’s historical remarks about women, our analysis reveals that his reception among female voters remained a critical and problematic aspect of media discourse.

As for our sentiment analysis, the results provide crucial insights into the emotional framing of Trump’s media representation.

The pie chart showing the overall sentiment distribution across all the articles indicates that the majority of articles (69.4%) have a negative sentiment towards Donald Trump, while only 25.6% have a positive sentiment, with the rest being neutral. This predominantly negative media representation of Donald Trump during the 2024 US elections, despite his electoral victory, suggests a media landscape where legacy outlets are not always representative of broader public sentiment and perhaps are starting to lose influence on election outcomes.

On the other hand, negative coverage of a given politician is not a novel occurrence in news media, and it may indicate that news coverage continues to prioritize critical discussion, seeking to maintain journalistic integrity through a skeptical approach to political narratives. Due to the misalignment between broader public sentiment and media coverage, exploration of Trump’s media coverage in a broader setting, one that includes independent journalism, social media, and podcasts, is necessary for accurately assessing Trump’s media coverage.

Examining the sentiment distribution across specific topics provides further nuance to the media’s coverage of Donald Trump’s presidency. The data reveals a more balanced approach in certain areas while highlighting a more critical tone in others. Topics such as “Election Outcome and Dynamics” as well as “Media and Public Reaction” exhibit a relatively balanced sentiment distribution, with both positive and negative articles represented. This suggests the media has taken a more nuanced stance in reporting on the technical aspects of the election process and the public’s response to Trump, examining multiple perspectives rather than adopting a singularly critical tone. In contrast, areas like “Economy” and “Campaign and Political Messaging” show a higher percentage of negative sentiment. This indicates the media has been more critical in its coverage of Trump’s economic policies and his communication and messaging strategies during the campaign and presidency. The prominence of negative sentiment in these core aspects of Trump’s agenda and approach suggests the media has closely scrutinized these elements, potentially highlighting shortcomings or controversies. The topic of “Legal and Institutional Context” also displays a mostly negative sentiment distribution, implying the media has adopted a critical stance in examining the legal and institutional controversies surrounding Trump’s actions and policies.

However, the prevalence of negative sentiment overall signals the media’s inclination to maintain a critical distance from Trump’s political narratives. Even in areas like “Legal and Institutional Context” and “Policy and Governance Implications,” where one might expect more neutral reporting (these topics are usually focused on more objective and technical details), the negative sentiment predominates. This indicates an ongoing media effort to scrutinize Trump’s dealings with governmental institutions and the policy ramifications of his administration.

The sentiment analysis, therefore, suggests a media landscape that is separating electoral success from positive perception. While Trump may have secured victory, the media appears determined to continue evaluating his actions, statements, and overall impact through a critical lens. This approach, while potentially contributing to a more skeptical public discourse, also demonstrates the media’s commitment to maintaining accountability and nuance in its political coverage.

Limitations and Potential Sources of Bias

The dataset used for this analysis shows a more balanced distribution of political bias across the articles, with 55.0% categorized as center, 26.2% as right or right-leaning, and 18.8% as left or left-leaning. This suggests the sample of news sources included a diverse range of political perspectives.

However, it is still important to acknowledge potential sources of bias that may have influenced our findings. The temporal limitations mentioned earlier, where the analysis was restricted to the US election time period, could have impacted the thematic focus and sentiment expressed in the articles. Additionally, the selection of news sources, even if balanced in their political leanings, may not fully represent the entire media landscape or broader public sentiment. In particular, we have only discussed one dimension of political bias (left or right); some outlets in our dataset, such as CNN and Breitbart News, are commercial entities and thus are prone to having financial interests (that are independent from the left-right spectrum) that may influence coverage and coverage sentiment. Thus, it is also important to weigh biases involving corporate interests and how they may conflict with those of the general public.

To mitigate this potential bias, future research should aim to include a more balanced and representative sample of data by considering other forms of media that cover political figures. Expanding the analysis to include non-traditional media sources, such as podcasts, social media, and independent journalism (Substack[4]) could offer additional insights into the broader public discourse surrounding Trump. This approach would provide a more comprehensive view of media representation and reduce the influence of inherent biases in individual outlets.

Finally, an inherent limitation of our analysis is its reliance solely on article titles and short descriptions, which are often crafted to maximize reader engagement through emotionally charged rhetoric. By contrast, the full content of articles tends to be more nuanced and balanced. As a result, our approach inherently skews toward more polarized sentiment, particularly emphasizing negativity. To reduce this potential bias in the future, we could perform an analysis of the entire content of each article, which is likely more nuanced.

Overall, acknowledging the limitations of the current dataset and identifying potential sources of bias is crucial for providing appropriate context and qualifications around the findings of this sentiment analysis. Implementing strategies to diversify the data sources in future iterations of this research will strengthen the validity and generalizability of the results.

[4]https://substack.com/

Conclusion

This data analysis project provided valuable insights into the framing and sentiment of recent North American media coverage surrounding Donald Trump during the 2024 US elections. By systematically examining 500 news articles, we uncovered a complex and multifaceted portrayal of the political figure.

Moving forward, further research could explore how this media framing evolves over time, expand the scope to include international and non-traditional media sources, and apply more advanced analytical techniques. Diversifying the data and methodologies would strengthen our understanding of the complex interplay between media representation, public perception, and the shifting political dynamics surrounding influential figures like Donald Trump.

Nevertheless, the results and discussion of our analysis generated many interesting findings and insights on Donald Trump for our media company client.

Group Member Contributions

All group members contributed significantly in the completion of this data science project. Here are the particular tasks each group member completed:

- Hamza Rashid: Open coding, discussion of the topics, TF-IDF, and sentiment analysis
- Samuel Ren: Data collection scripts, open coding, typology building, discussion of the topics, introduction
- Benjamin Saine: Data collection scripts, open coding, typology building, discussion of the topics, political bias

References

AllSides. https://www.allsides.com/media-bias/ratings. Accessed for news source political bias rating: 2024-12-05.

Fortune. "Billionaire Mark Cuban says strong, intelligent women intimidate Donald Trump and he doesn't like to be challenged by them." https://fortune.com/2024/11/01/mark-cuban-donald-trump-strong-intelligent-women-kamala-harris/. Accessed: 2024-12-06.

NewsAPI. Documentation. https://newsapi.org/docs. Accessed: 2024-11-26.

Newsweek. "'Joe Rogan Experience' podcast dominates Spotify subscribers, social media." https://www.newsweek.com/joe-rogan-experience-podcast-spotify-subscribers-social-media-1882984. Accessed: 2024-12-06.

Newsweek. "Donald Trump Gets Unexpected Praise from Bernie Sanders: 'Good Idea'" https://www.newsweek.com/bernie-sanders-donald-trump-credit-card-limit-interest-debt-1986463. Accessed: 2024-12-06.

Newsweek. “Republicans ‘disgusted’ by Tony Hinchcliffe’s Puerto Rico ‘garbage’ joke at Trump rally.” https://www.newsweek.com/republicans-tony-hinchcliffe-puerto-rico-garbage-joke-trump-rally-1975711. Accessed: 2024-12-06.

Newsweek. “Trump rides garbage truck to hammer Biden and Harris at Wisconsin rally.” https://www.newsweek.com/trump-garbage-truck-biden-harris-wisconsin-rally-1977663. Accessed: 2024-12-06.

Politico. “Elon Musk defends Trump’s return to Twitter/X ahead of the 2024 election.” https://www.politico.com/news/2024/11/05/elon-musk-trump-twitter-x-election-00187467. Accessed: 2024-12-05.

Spotify Podcast Charts. https://podcastcharts.byspotify.com/. Accessed for podcast rankings: 2024-12-06.

Wikipedia. “Breitbart News.” https://en.wikipedia.org/wiki/Breitbart_News. Accessed: 2024-12-05.

Wikipedia. “News Media in the United States.” https://en.wikipedia.org/wiki/News_media_in_the_United_States. Accessed: 2024-12-06.