Data 698: Mid-Term Draft Project

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Research Question:

Do publications negatively portray certain candidates more than other candidates?

1. Introduction

A news organization's role in society is to gather, write and distribute key information to the masses. Depending on the news organization's specialty, its journalists aim is to keep the public informed on foreign and domestic issues and events. Given their expansive audiences, news media organizations have long been utilized to influence public perception on important issues and help propagate many political initiatives.

Freedom of the press, the First Amendment of the United States Constitution, is a key pillar in American democracy. The amendment has played an important role in politics since its creation as its intended purpose is to help the American people make informed decisions without government intervention. Thus, the role of American news organizations is to help cultivate the opinions of the American society. Given this power, a news organization plays a significant role in each election cycle based on how it covers each candidate and political party. This project aims to assess whether news organizations have abused this influence by negatively portraying certain candidates in the United States 2020 presidential primary.

During the presidential primary, a news media organization tailors the public's perception of the candidates through its delivered content. The content could possess a certain level of bias toward candidates due to factors such as frequency of coverage, data journalism, connotation, verbiage, and selection of images.

The frequency of coverage alone can greatly affect society's perceptions on a candidate or political party. Name recognition is cited as having a very large influence on each election and respective primary. When news coverage is mainly centered on a singular or selection of candidates, other candidates and their proposed policy changes can be virtually invisible to the American people. Being for-profit institutions, disproportionate candidate coverage may have more to do with revenue than intentional institutional bias of its journalists. Clicks, up votes, comments, re-tweets, citing and republication tends to favor the more polarizing candidates.

Catering to the partisan audience is another way a news organization can influence its readership during an election period and may affect how a news outlet portrays certain candidates and political parties. Based on a study by the Pew Institute, the perceived political slant of a news organization aligns with the political affiliation of its consumers [1]. This facilitation of ideological bias by its consumers may influence how a story is politicized and sensationalized by the news organization's employed journalists. Bias can become a self-perpetuating cycle, sustained by both the consumers and the news organizations. During an election or primary, this partisan coverage can force a news organization to place emphasis on the candidates that are winning, losing, or posing the largest threat to the organization's desired candidate.

Word choice is another key tool a news organization may utilize to subtly convey its feelings toward the candidates. Words are powerful and are intentionally selected to help evoke a certain feeling resulting from their connotations. For example, a news article may use words with violent connotations to help describe a certain candidate's proposed policy change. The violent words subtly imply that the constituents would be victimized by the policy change. In conjunction with aforementioned point on the partisan consumer, the audience may not realize or care about the content's intentionally biased wording.

Similarly, the images that a journalist or editor uses are intentionally selected to fit the connotation of the accompanying article. Visuals can evoke feelings ranging from fear and ridicule to happiness and acceptance. As people tend to be more visually inclined, the reader can be influenced to feel a certain way about the highlighted issue. The inclusion of candidate visuals for articles is a tactic many news organizations use in elections and primaries to influence their consumers.

Data journalism has been wielded as a weapon by news organizations, especially during the election periods. During the presidential primary, candidates are frequently asked questions about their proposed policy initiatives and stances on certain issues. As technology has improved, the concept of live fact-checking has come into vogue. The news organizations have started employing these fact-checking techniques to facilitate the jockeying of certain candidates.

In addition to fact-checking, news organizations have historically incorporated polling data into their delivered content. The polling data acts as a mechanism to influence voter perception and can also impact the amount of coverage the candidate receives by the news organization. Due to the nature of media coverage, the inclusion of polling data becomes a self-perpetuating cycle. Media flocks to the front-runners, who in turn receive more media coverage, and consequentially, may climb even higher in the polls.

While the intended goal of a news media organization is to help inform the people, the objectivity of its reporting should be questioned based on the aforementioned analysis. To assess whether news organizations have negatively portrayed certain candidates in the presidential primary, the team will focus on candidate biases created based on word choice. The project will employ a sentiment analysis model to determine the subjectivity and the overall emotional bias of candidate articles from a selection of news outlets.

In this paper, the Literature Review section focuses on academic research pertaining to news media biases. The Data Set and Sentiment Analysis section reviews the methodologies employed to cultivate and assess the sentiment of media content. The System Design section focuses on model used to measure bias. Lastly, the Results section provides a summary of the insights derived from the team's analysis.

2. Literature Review:

The Literature Review section focuses on a selection of published literature and analyses that define political bias and identify ways of measuring and quantifying these biases. The section is divided into three key components: causes of bias, consequences of bias, and the measurement of bias.

Causes of Bias:

Several papers, such as Sutter [2] and Baron [3], focus on the factors that propagate political biases. Sutter [2] compares the incentives for bias in universities versus those in for-profit organizations. He concludes that the forces that sustain bias in academia differ than those in commercial organizations since the stakeholders and accountability structures are vastly different.

For Bernhardt [4], media bias is a result of the general public's preference for "partisan" or biased news. Baron [3] concludes that news bias is a self-perpetuating cycle where journalistic biases lower subscription prices, forcing the news organization to survive only by hiring and paying journalists lower wages.

Gentzkow et al [6] aligns the causation of political bias to the production and dissemination of news: supplyside and demand-side, respectively. The supply-side biases can be attributed to the production of news media content, such as practices of management or labor in news media organizations. The demand-side biases originate and perpetuate from consumers' perceptions and preferences.

For bias to persist, there must be factors that sustain, or even strengthen it. The task of identifying factors that sustain bias across the adaptive and dynamic environment of news media organizations is the focus of papers such as Sutter [2], Baron [3], Bernhardt [4], Baum and Groeling [5].

Sutter [2] suggests that journalism, the main transmission engine for ideas and information in society, is inherently subjective and often reflects the opinions of the journalist and/or news outlet. However, the evidence to prove the existence of bias is circumstantial, making the measurement and quantification of these biases very difficult. Sutter notes that revenue is a controlling force for limiting or reducing bias in privately-owned news media organizations. He argues that the inclusion of too much bias in reporting can adversely affect the readership and advertising revenue for the news organizations.

Like Sutter, Baron [3] submits that profit-maximizing, competitive pressures, consumer preferences, and the general economic and financial landscapes impact the role of bias in news media. Unlike Sutter, Baron theorizes that there are strong correlations between political biases and consumer expectations, operational costs, and the ideological alignments of the employed journalists. Baron's findings show that several forces combine to ensure the presence and prevalence of unbalanced reporting.

Bernhardt [4] also suggests that profit-maximization may influence a news media outlet to cater to a more partisan audience by suppressing or doctoring some pertinent information in its news reporting.

Baum and Groeling [5] submits that the advent of internet media removed the professional editorial process from news content. The new "partisan" styled editorial system of internet news, paired with the public's adoption of the internet, produced a more fragmented audience.

Consequences of Bias:

Several authors explain the different ways that political bias causes harm. Bernhardt [4] cautions that the impact of media bias is more powerful and determinative than commonly presumed, since its effect cannot be nullified, even to a rational consumer. Baum and Groeling's [5] study found that left-skewed and right-skewed political biases exist in internet news media. This shift from bipartisan to partisan coverage has important implications for political discourse in America and may impact the decision making for many Americans.

Like Baum and Groeling, Gentzkow and Shapiro [6] believe that media bias can have large effects on voter behavior, public perception and political outcomes. However, it is very difficult to determine the actual impact of these biases.

Stone [7] presents the counterintuitive thesis that bias can be more prevalent in certain competitive media markets than in some less competitive ones. Stone presents formal proof that consumers can, for example, be less informed in some media duopolies than in some monopolies. Thus, one must guard against simplistic prescriptions on how to counter bias, since its correlations with market conditions can be contrary to intuition.

Sheth's [8] initial findings are that media coverage is broadly anti-conservative. His model also concludes that the news outlets, regardless of political affiliations, are resoundingly negative and critical of the opposition instead of championing its respective candidates. The Sheth model findings align with the general public's perception of media bias.

Lin, Bagrow and Lazer [9] prove that internet blogs are, more "social" as they are more connected and consequently more influenced by site connections. Being more connected makes the internet blogs more "exogenous", or more influenced by external factors, such as election cycles.

Measuring Bias:

Many researchers have grappled with the difficulty of precisely measuring or documenting bias. A number of papers, such as Sheth[8], Lin [9], and O'Connor [10], focus on the problem of quantifying media bias in networks, and present models that can be used to quantify political bias.

Sheth [8] proposes a model for measuring ideological bias in news coverage by mainstream media outlets. Terms in the news articles are classified based on detected political affiliations: pro-conservative, anti-conservative, pro-liberal and anti-liberal. Once classified, the model detects the overall measurement of political bias in each article.

Lin, Bagrow and Lazer [9] propose a method of quantifying bias in both traditional news media and internet blogs. The method primarily compares the number of media references to members of the United States congress. This method helps reduce errors due to subjective criteria, such as sentiment or degrees of bias. The presented method can also account for the variance in bias over time.

O'Connor, Balasubramanyan, Routledge and Smith [10] test how well Twitter sentiment correlates with consumer confidence, presidential and election polling data. The highlighted sentiment analysis model uses a lexicon from OpinionFinder on a tailored subset of Twitter data relating to several political topics between the years 2008 and 2009. The topics include key words such as "jobs", "Obama", "McCain", etc. The model calculates a sentiment score based on the ratio of positive to negative words. Smoothing averages techniques remove sentiment score noise and can help to determine correlation. O'Connor, Balasubramanyan, Routledge and Smith note that techniques like stemming caused dangerous misclassification over the model's lexicon, but did not substantially affect the aggregated scoring composites. The model proved effective with predicting economic indicators, but exhibited difficulty predicting the presidential approval polls.

The model described by Groseclose and Milyo [11] calculates an ADA (Americans for Democratic Action) score for various news outlets across the political spectrum. In Groseclose and Milyo's research, ADA is coterminous with political slant or liberal affiliation. The ADA score is calculated from the number of times the news media outlet cites various think-tanks in articles, compared against the number of times Congress cites the same think-tanks in Congressional speeches. The citation patterns frequency determines the news media outlet's political slant. In the study, editorials or traditional opinionated pieces are omitted as these pieces intend to exhibit biased reporting.

3. Data Set & Sentiment Analysis:

Data Sources:

Our project aims to measure bias in news media coverage for the candidates in the United States 2020 Democratic Presidential Primary. Given the abundance of news media organizations, the group assessed the perceived political affiliations of the major outlets and selected a small subset that could theoretically represent the complete political ideological spectrum. The selected news organizations include: The Washington Post, The New York Times, New York Magazine, The Huffington Post, The Wall Street Journal, and Breitbart News Network.

The Democratic Party's first presidential debate ahead of the 2020 United States presidential election was held on June 26, 2019, drawing a total of twenty qualified candidates. As the primary race's qualifying thresholds increase with each debate, there are currently twelve presidential hopefuls left in the race, with polling above 3.0%. In addition to filtering the news media sources, the team has selected front-running candidates that encompass the spectrum of Democratic ideology, ranging from more progressive to more mainstream. The candidates included are: Joe Biden, Pete Buttigieg, Kamala Harris, Bernie Sanders, and Elizabeth Warren.

Finally, for this analysis the group considered articles from the aforementioned news media organizations and candidates from September through October 2019. Given the importance of the primary to the United States population and consequently the popularity in its coverage, the group believes that a one-month period is material for the bias analysis.

Data Acquisition:

After selecting the pertinent news article parameters, the group interacted with News API, newsapi.org, which enables a user to search and retrieve news articles from a multitude of different sources based on specific user-entered criteria. This REST API service interacts with the group's Python script and retrieves articles that contain the candidate's search terms in the article's title or URL. By providing these specifications in the load script, the group pre-filtered the qualifying articles for this analysis.

Sentiment Overview:

Political bias in news articles can present itself in many different forms. As mentioned in the introduction, this project focuses on candidate biases created due to word choice. Words can convey a variety of emotions due to the connotations they carry. To programmatically measure bias, the sentiment of an article or its individual components needs to be assessed.

Sentiment analysis leverages natural language processing, NLP, technology to measure the underlying opinion, mood or emotion of the communicator. For this project, the analyzed data can quantify the journalist's feelings toward certain candidates and can measure the degree of partiality present at the selected news media organizations.

To measure sentiment, the selected algorithm must be trained to understand the relevant grammatical and linguistic nuances of political articles. The article's text also needs to be vetted to remove punctuation, stop words, and to tokenize the strings. If properly trained and vetted, the sentiment analysis can capture the categorical and quantitative sentiment measures, polarity and degree, respectively. *Polarity* describes the analyzed text as positive, neutral or negative. *Degree* is an outputted score which quantifies the article from extremely negative to very positive.

Sentiment Algorithm – Bag of Words:

The bag-of-words approach is a type of sentiment analysis which describes the occurrences of words within a piece of text. The model leverages a fed vocabulary of known words and measures the presence of these words within the observed document. The approach is considered both simple and flexible as it only considers the presence or absence of words and discards any information about the words' order or grammatical structure. Given its simplicity, the bag-of-words approach was employed as the group's first sentiment analysis model. More complex sentiment analysis models utilize network relationships of words, topic modeling, or deep learning techniques. Should the current bag-of-words model prove too simplistic or present too many limitations, the group may explore one of these more complex approaches as a supplementary model.

As mentioned above, the bag-of-words model leverages a fed vocabulary of known words. The group utilized a movie review database containing 25,000 previously classified negative and positive reviews as the base dataset. The group hypothesized that the words present in the movie reviews are not dissimilar to the ones that can be present in normal news articles. Given that assumption, the sentiment analysis model trained a Naive Bayesian Classifier to assess whether a sentence has positive or negative sentiment.

To construct the bag-of-words model, the group extracted the most frequently occurring words in the base review dataset. Once isolated, feature sets were constructed for each review fed into the model. The feature sets are key value pair vectors which assess the presence or absence of the common words, indicated by Boolean true/false values. The Naive Bayesian classification model then assigned a positive or negative label to the review based on the associated binary values in each feature vector. Once trained on the review dataset, the model was ready to perform binary classification on any string of text. The group trained the Naive Bayesian model on a general-purpose desktop machine and did not require specialized hardware such as additional GPUs.

4. System Design Bag-of-Words:

Use of Regular Expressions:

After constructing and implementing the bag-of-words model using the base review training dataset, the model could be applied to the news article corpus. While simple, the model could attribute a positive or negative identifier to each article. Before applying the model, the data needs to be organized by publication with the candidates identified. Additionally, the group needs to assess the proper level of text granularity to feed into the model: sentence, paragraph, full article, etc. Once all the preemptive measures are considered, the bag-of-words model is applied and a ratio score of positive to negative sentiment values can be computed for each inputted string.

While the data acquisition process calls the newsapi on the candidate level, the texts' contents may include many themes, candidate references, and vary in context. To a human reader, the shift in context and scope is implicitly understood. A human can partition the articles into definitive groupings based on the themes of each article's text or subtext. Given that the model is simplistic, the group layered regular expression techniques to explicitly tag each text piece with the intended candidate.

The regular expression identification process is a brute force approach that requires careful consideration of word combinations. As the news outlets considered in the analysis are all reputable, the articles contained in the corpus are not likely to contain shorthand naming substitutions like “Liz” or colloquial names like “Joey,”” making the regex approach computationally cheap. First name associations for Kamala Harris and Bernie Sanders are fine as their first names are uncommon in the United States. For candidates with common first names like Elizabeth Warren and Joe Biden, the text association would need to be a combination of the first and last name. An additional consideration was made for Bernie Sanders, as his last name may create false association with the current White House press secretary Sarah Huckabee Sanders.

Given the combination of candidates and news outlets considered, the group used eight search terms in its regular expression layer, which ran instantaneously over the dataset. Some potential drawbacks of regular expressions include false associate and data loss. As the regular expression tagging validation process is automatic and lacks transparency, the group may monitor the data on a more granular level to ensure it yields the most accurate candidate associations.

Granularity:

After associating candidates to each article in the corpus, the group needed to explore which subcomponent(s) of articles to apply the bag-of-words model. The sentiment analysis input structure is flexible to apply the bag-of-words to any length object.

The first option is to run the analysis at the full article level. As the article’s body can address many candidates and topics, there are inherent issues with applying the bag-of-words at this level. To help mitigate these issues, the group may explore layering topic modeling techniques or apply a custom scorer to ensure that the full article can be scored either positively or negatively at the candidate level. This approach may be explored later, but it was not deployed in the initial naïve model.

Another option is to evaluate the corpora on a paragraph level. When successful, this approach can measure the sentiment spanning multiple sentences, allowing for a more meaningful assessment of bias. However, in formal writing, pronouns are often used to take the place of nouns to make sentences clearer, less awkward, and smoother. For example, in a paragraph featuring Bernie Sanders, the paragraph will likely mention Bernie Sanders’ name once in the beginning, and then refer to Sanders by the him/his/he pronouns. From a modeling perspective, this can prove problematic if the paragraph were to feature more than one candidate. Simply assigning the paragraph’s scored sentiment value to all candidates mentioned in the paragraph could lead to an inaccurate assessment of candidate bias. A simple solution is to exclude paragraphs that mention more than one candidate. However, this could potentially lead to sample size issues. Another potential optimizing solution is to use coreference resolution to rename pronouns with their proper nouns. This approach was out of scope for the initial modeling but may be explored in later iterations.

The last approach is to assess candidate sentiment at the sentence level in each article. Due to the additional modeling considerations that would be needed to accommodate the paragraph and full article level analyses, the group select the sentence level granularity for its initial bag-of-words model. The advantage of deploying the initial data segregation and sentiment analysis on the sentence level is the amount of data that is retained in the results. As articles are comprised of many paragraphs and paragraphs are comprised of sentences, the sentence level will yield more data points and allow for a stronger scoring system.

The group constructed two scoring systems to measure sentiment at this level of granularity. Both aim to measure the ratio of positive to negative sentiment values for each inputted string. The first scoring system is candidate agnostic and applies the computed sentiment ratio score to any candidate mentioned in the sentence. The second system calculates the same sentiment ratio but excludes any sentences that mention multiple candidates. The second approach aims to mitigate any misattribution of sentiment scoring to the candidates. After reviewing the results, it was determined that the first and second approaches yield similar results, indicating that segregation of data is not too impactful to the overall scoring.

Initial Results:

After employing the sentence level naive bag-of-words model, the group was able to determine the sentiment toward the different candidates across the selected news outlets. The New York Times proved the most positive for candidate Joe Biden, with a calculated sentiment ratio of 57.0%. Biden was closely followed by candidates Elizabeth Warren at 50.0%, and Bernie Sanders at 46.0%. The CNN articles seem to exhibit the most balanced coverage, with every candidate landing in the 45.0-47.0% positive sentiment ratio range. Fox News allocated front-runner Biden more positive coverage at 51.0%, while Sanders and Warren hover around 45.0% and 46.0%, respectively. The Washington Post appears to favor Biden with 49.0% positive coverage, while Bernie and Warren receive around 44.0%. Please view the appendix for the full listing of candidate sentiment ratios per news media outlet.

Next Steps:

The results are preliminary but encouraging. The order of candidate sentiment at each news outlet closely mirrors the individual candidate’s rank in the public polling data. It is not surprising the front-runner and more moderate candidate, Joe Biden, universally receives a more positive sentiment score across each news outlet. For example, it is possible that a more traditionally conservative news outlet like Fox News uses harsher language with more progressive candidates, like Warren and Sanders. In the next iterations of this analysis, the group will focus on the publications that have exhibited more bias in the initial scoring and assess whether additional modeling refinements are needed.

This election season has been highly contentious due to the current political environment and many of the candidates’ proposed policy changes. The group also aims to explore the inclusion and associated impact of politically charged language in the text. The group believes that these proposed policies are ubiquitous in political articles and should be analyzed. With an enhancement to the existing implementation utilizing NLTK, the model would be able to identify adjective usage around these politically charged topics such as Medicare for All, taxes, electability, age, and bi-partisan. The topics will be explored visually with word clouds and distributions.

5. References:

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6. Appendix:

The following figures display the candidate sentiment ratio scores per news media outlet. The below also provides the mean score per candidate.

	level_0	level_1	pos	neg	Percent_positive
4	Breitbart News	Bernie	484.0	538.0	0.473581
8	CNN	Bernie	276.0	306.0	0.474227
12	Fox News	Bernie	482.0	574.0	0.456439
16	Google News	Bernie	20.0	30.0	0.4
20	MSNBC	Bernie	32.0	38.0	0.457143
24	New York Magazine	Bernie	190.0	198.0	0.489691
28	The New York Times	Bernie	145.0	171.0	0.458861
32	The Wall Street Journal	Bernie	26.0	15.0	0.634146
36	The Washington Post	Bernie	1059.0	1330.0	0.443282
MEAN	NA	NA	NA	NA	0.458911

	level_0	level_1	pos	neg	Percent_positive
5	Breitbart News	Biden	1473.0	1525.0	0.491328
9	CNN	Biden	883.0	962.0	0.478591
13	Fox News	Biden	2126.0	2044.0	0.509832
17	Google News	Biden	13.0	24.0	0.351351
21	MSNBC	Biden	119.0	113.0	0.512931
25	New York Magazine	Biden	414.0	434.0	0.488208
29	The New York Times	Biden	348.0	264.0	0.568627
33	The Wall Street Journal	Biden	82.0	67.0	0.550336
37	The Washington Post	Biden	3074.0	3295.0	0.48265
MEAN	NA	NA	NA	NA	0.494322

	level_0	level_1	pos	neg	Percent_positive
6	Breitbart News	Kamala	216.0	205.0	0.513064
10	CNN	Kamala	100.0	121.0	0.452489
14	Fox News	Kamala	193.0	244.0	0.441648
18	Google News	Kamala	5.0	4.0	0.555556
22	MSNBC	Kamala	14.0	8.0	0.636364
26	New York Magazine	Kamala	57.0	73.0	0.438462
30	The New York Times	Kamala	33.0	34.0	0.492537
34	The Wall Street Journal	Kamala	4.0	7.0	0.363636
38	The Washington Post	Kamala	402.0	594.0	0.403614
MEAN	NA	NA	NA	NA	0.442524

	level_0	level_1	pos	neg	Percent_positive
7	Breitbart News	Warren	519.0	602.0	0.462979
11	CNN	Warren	387.0	434.0	0.471376
15	Fox News	Warren	624.0	726.0	0.462222
19	Google News	Warren	20.0	41.0	0.327869
23	MSNBC	Warren	32.0	40.0	0.444444
27	New York Magazine	Warren	243.0	263.0	0.480237
31	The New York Times	Warren	198.0	200.0	0.497487
35	The Wall Street Journal	Warren	45.0	44.0	0.505618
39	The Washington Post	Warren	1295.0	1645.0	0.440476
MEAN	NA	NA	NA	NA	0.457054