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Speech Sentiment Across the Aisle

Introduction

Recent occurrences of extremist fringe groups have placed a spotlight on how media and news are portrayed. These fringe groups isolate themselves into "echo chambers" which serve to both solidify and intensify these beliefs. Echo chambers primarily exist on social media, but news outlets are often used as a tool further this isolation, as members of these groups listen to outlets which identify closely with their beliefs. The tone of a text often matters more than the actual content, or the truth or accuracy of the account (Young & Soroka (2012)). Sentiment in politics and in the media is paramount, and can be quantified with sentiment analysis.

Sentiment analysis is a useful tool to observe the method in which media outlets communicate with their audience . Appeals can be hopeful, promising that everything will resolve itself, or disparaging, convincing listeners that they should fear certain policies or movements. Some news is rightfully negative, such as coverage of mass shootings or the death of a prominent figure, but in the current media environment even these stories often have a positive or negative spin. This paper hopes to analyze this spin and quantify how news is portrayed. To do this, a total of roughly 600 article summaries were scraped from news websites, from six outlets, ten topics per outlet, and ten articles per topic. This sample size should eliminate bias where a topic is inherently positive or negative and give insight to the overall tone of an outlet. To determine sentiment, these articles were processed through the NLP model Bert (Devlin et al., 2018) and tagged as either positive or negative.

Far-right news outlets play off echo chambers and rely on fear mongering and the vilification of groups to appeal to their base and keep them in the group. This will cause the right-leaning outlets to be more negative overall than the left. The left-leaning news outlets can certainly be negative, but do not seem to rely on negativity as a singular appeal, which can be argued for the far-right. Sentiment Analysis will likely show more positive sentiment expressed from far-left outlets and more negative sentiment expressed from far-right outlets.

Background

Previous work into sentiment analysis in news is primarily focused on politics or political speeches, as these topics are especially contingent on tone. This paper focuses partially on explicit political topics, but also includes topics and search phrasings which are less polarized. A study by Burscher et al. (2016) examined emphasis framing in news articles covering nuclear power. Sentiment analysis with an NLP model was among the methods used to determine the emphasis framing in this study. This shows that sentiment analysis does not evaluate the author's opinion about the subject, but simply how the subject is framed. Inferences can then be made about the author's intent, but the only output of sentiment analysis is the subject's framing. Emphasis framing, the focus on certain elements of an issue to shape public opinion, will therefore be a focus of this paper as well. Sentiment analysis alone is not enough to empirically determine the emphasis framing of an outlet, but emphasis framing is a useful tool to interpret the sentiment.

The political affiliation of selected outlets will show whether trends in the sentiment of news are outlet-specific or party-specific. If trends are party specific, it may provide insight for the beliefs and overall sentiment of a party. News outlets are not the only place Americans get their news, considering the exponential rise of social media, but roughly 80% of people claim they often get their news from outlets, both on television and online (Shearer, 2020). This data highlights the importance of accountability for these outlets. If an outlet is portraying content with a goal in mind, their audience is likely to adopt this viewpoint. Most, if not all news outlets are profit-driven, so this goal would be to maximize viewership and click rates. Results may also show if a positive or negative portrayal is more profitable, or whether this varies by political affiliation.

Sentiment used solely for its ability to generate traffic or increase profits will likely be positive. A study by Alvarez and Strover showed that for facebook ads run by Russians misinformation campaigns, those classified as positive by sentiment analysis had a significantly higher click rate (2020). This is not a direct equivalency to the news articles being analyzed in this paper, but data is likely related for news articles, as both aim to appeal to a similar demographic and have the goal of generating clicks. If this proves true, larger and more profitable news outlets would have higher rates of positive sentiment, so outlets such as CNN and Fox would lead the others. Even if the large outlets do not outperform in positive sentiment, a positive tone is still likely more profitable. This paper may provide insight into this, but a conclusion would have to be drawn from a study designed specifically to test the phenomenon.

Methods

In the gathered dataset, there are six news outlets, ten topics, and ten articles per topic. News outlets were selected for their political affiliation, three left leaning and three right leaning. Four are more extreme and two are closer to the center. Outlet affiliation was determined from two sources, the Allsides Media Bias Chart(2020), and Pew Research's Ideological Profile of Sources (Mitchell et al., 2020). Outlets selected had consistent ratings between the two, and were large enough to gather significant data from. The final six outlets and their affiliations were as follows:

1. Slate - Consistently Liberal
2. New Yorker - Consistently Liberal
3. CNN - Left Leaning
4. Fox - Right Leaning
5. Breitbart - Consistently Conservative
6. The Blaze - Consistently Conservative

The news outlets selected vary greatly in content, so topics and search terms with broad coverage and high traction were needed. For this purpose, The Hill's "The 10 Biggest News Stories of the Year" (Swanson, 2020) was used as the base for initial data gathering. The topics in the article were reduced to a single keyword for use in a search function. For instance, the search term "Biden" would derive from the topic: "Democrats fight over Biden agenda". This article included topics from 2021, some of which were outdated and replaced. Topics were also replaced if the search function returned an insufficient number of articles, or no articles at all. These changes were made to the initial list:

1. Abortion → Protest
2. Afghanistan → - Trump
3. Climate Change → Democrat
4. January 6 → Republican

Replacements were selected based on the popularity of their use in media, and for search terms relating to both political parties. Some outlets such as CNN and Fox, consistently returned complete data, but outlets such as The New Yorker, with a slower output of articles, struggled with topics that were not immediately relevant. Search failures also happened because of the search function itself, which was limited to articles published in the past 14 days. Final selected topics returned a significant number of articles for all six outlets:

1. Biden
2. Trump
3. Democrat
4. Republican
5. Election
6. Protest
7. Pandemic
8. Vaccine
9. Ukraine
10. Inflation

Articles were then gathered for these search terms using the Python package "Newscatcherapi" (Sugonyaka & Bugara, 2020), which scrapes news articles and returns relevant information. The package offers a "summary" function which was chosen instead of accessing the full text of the article. This was done to keep the token count low, as the Bert model can only accept 512 tokens at a time, and many articles ranged into the thousands. There is no documentation on the method Newscatcher uses to summarize, but anecdotally it appears to return the first one hundred words. This summary still contains much of the sentiment of the article, and previous studies such as Burscher (2016) have used headlines alone to determine an article's sentiment. A flaw of the api was limiting searches to the past two weeks, which excluded many articles from the less prolific outlets. A total of sixty search functions were performed for each topic and outlet. Full code for search functions can be found in Appendix A. The search function returned a text file of ten article summaries for each topic, which was then converted to a list input for the Bert Model.

Sentiment analysis was performed by Hugging Face's Bert Model for natural language processing. The specific version used was TFBertForSequenceClassification-uncased, a pre-trained model for sentiment analysis which does not take the case of a letter into account. Case was not a significant factor for semantic meaning in the articles. Bert was chosen as the model for this paper because of its bidirectional approach to contextual analysis and because it is pre-trained on a huge quantity of data. For this paper, Bert was fine-tuned in Google Colabs using Stanford's IMDB dataset (Andrew et al., 2011), a dataset containing 100,000 IMDB movie reviews. Of these, 25,000 were used to train Bert to save processing time and computing resources. Full code for fine-tuning can be found in Appendix B. This sample is pre-tagged with positive and negative sentiments, so Bert can return an accuracy score after training on the dataset. After training for two epochs, Bert returned an accuracy score of 97%. Accuracy and loss data can be found in Appendix C. Code for fine-tuning Bert was borrowed from Orhan Yalçın's article on the topic (2021).

Results

Processed the samples were assigned positive or negative tags, then converted to integers, with a positive score equal to a value of one and a negative score equal to a value of zero. It was then possible to calculate average scores for each outlet and topic. These average scores represent the positivity score of an item, where an item is positive if above 0.5, and negative if below it. A positivity score of 0.5 indicated complete neutrality. Overall positivity scores were also calculated for each of the six outlets, denoting how positive each outlet was on average for each of the ten topics. Figure 1 shows these scores, where The New Yorker has the highest overall positivity score, and The Blaze has the lowest. The two far-right news outlets have the lowest positivity scores, while the two far-left outlets have the highest positivity scores. Fox news is the outlier among right-leaning outlets with a higher positivity score than CNN. Only one news outlet, the New Yorker, has positive framing overall. Slate has neutral framing and the other four outlets frame their news negatively, by varying amounts.

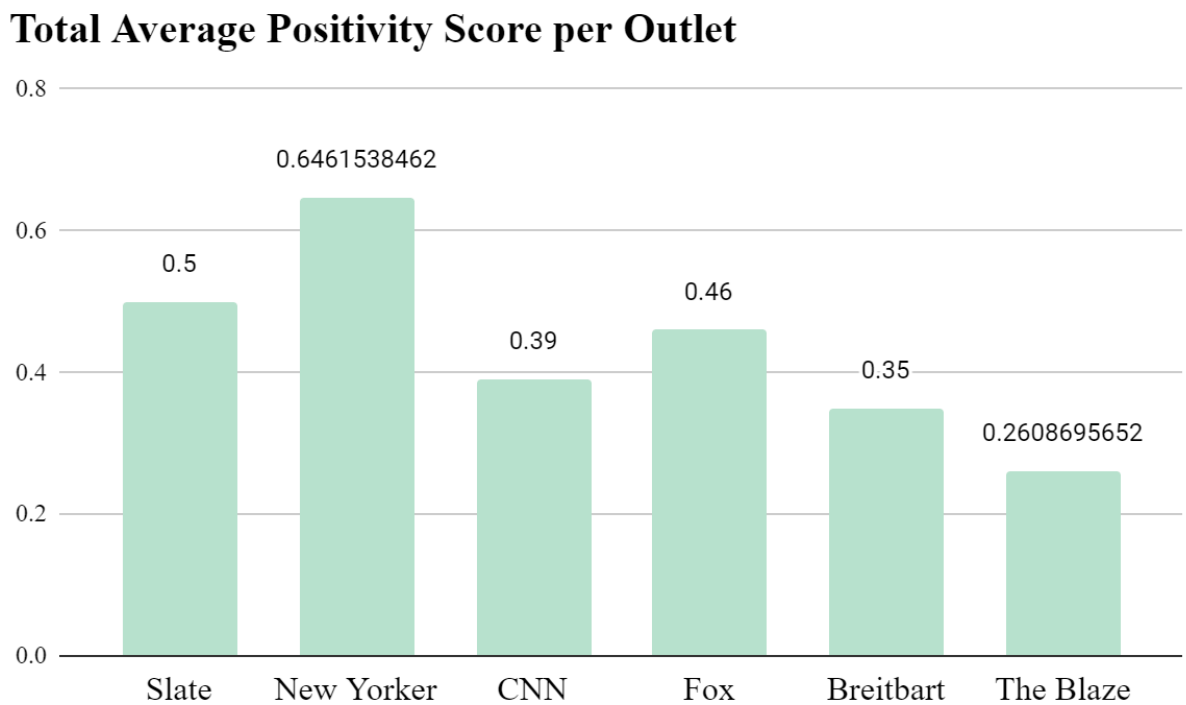


figure 1

Positivity scores varied greatly between topics. Figure 2 shows that Inflation had the highest positivity score, and Protest had the lowest. Pandemic and Vaccine have very similar scores, but overall both are viewed negatively. Trump and Biden also had similar scores, with Biden slightly higher and both just below neutral. The most positive scores were Democrat, Ukraine, and Inflation. Inflation was the most favorable topic by a large margin. Overall, the emphasis framing of pandemic-related topics seems to be very negative, and slightly negative for political parties and figures. Democrats are the exception to this as the only favorably portrayed political item.

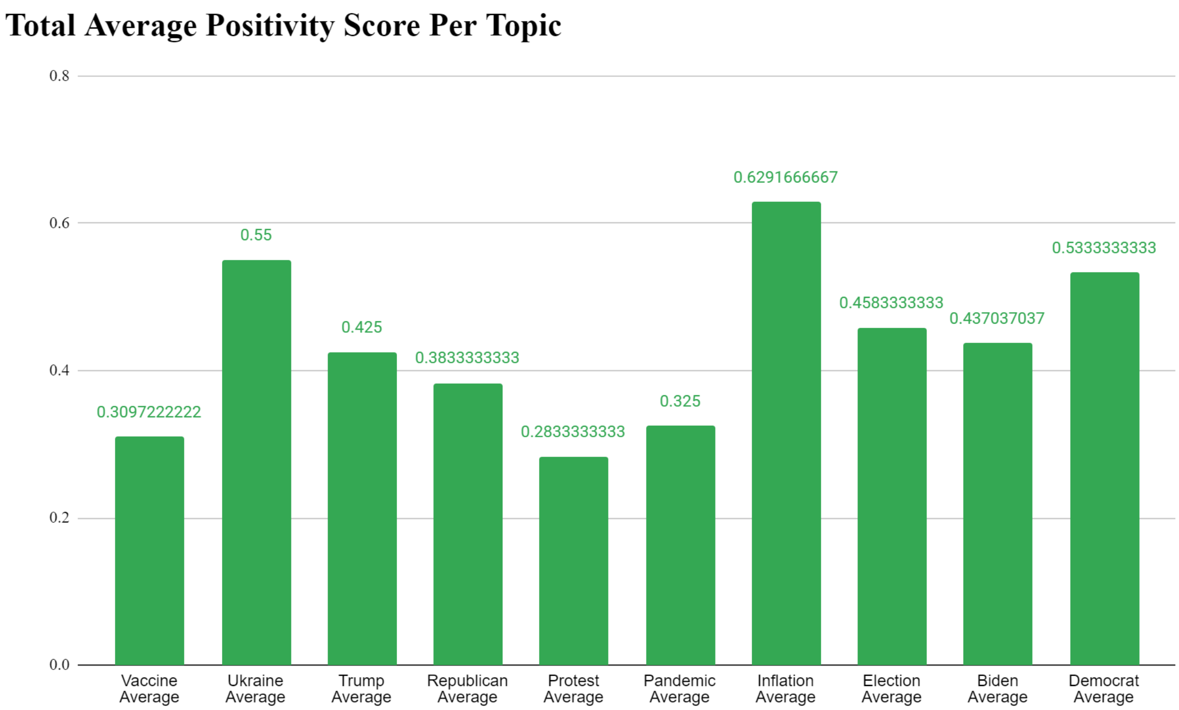


figure 2

The total sample size for this data is 522 articles. Three outlets returned ten articles for each topic, resulting in exactly 100 articles, but some returned few articles for multiple topics:

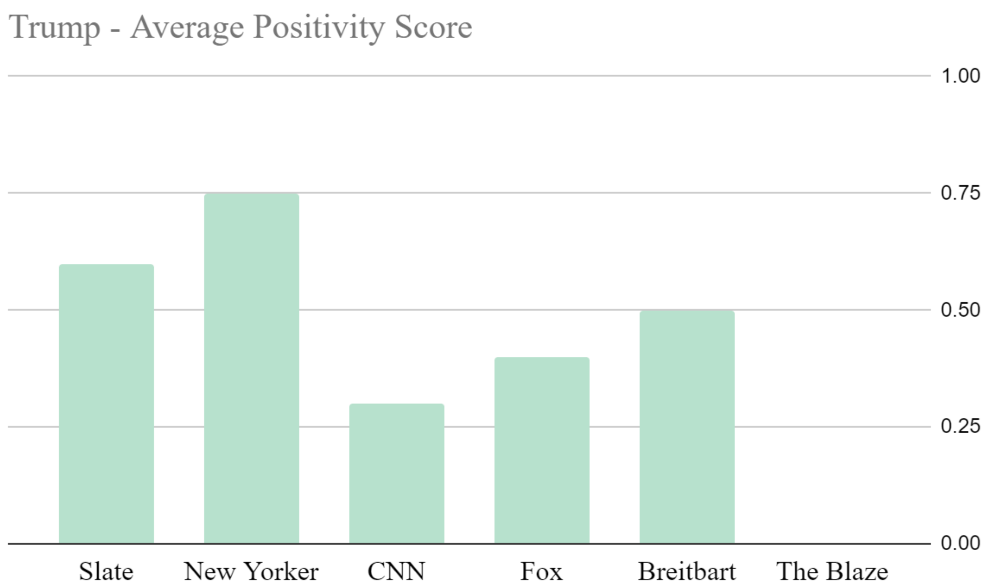
Slate	New Yorker	CNN	Fox	Breitbart	The Blaze
88	65	100	100	100	69

The New Yorker had the smallest sample size of 65, followed closely by The Blaze at 69. For the entire sample, across all 522 data points, the overall positivity score was 0.429. This is less than a neutral score of 0.5, meaning that the overall framing of news from the sampled outlets was negative. Full results and raw data can be found in Appendix D.

Discussion

Splitting the positivity scores by political affiliation does show that left-leaning outlets have more positive framing overall than right-leaning outlets. Left-leaning outlets have an average positivity score of 0.51, essentially neutral, while right-leaning outlets have a score of 0.36, which is considerably negative. Breitbart and The Blaze having the most negative scores follows earlier predictions , as does Slate and the New Yorker having the highest scores. The outlier is CNN, which has a considerably more negative score than other left-leaning outlets, and is more negative than Fox by a significant margin. The New Yorker was extremely positive, especially compared to other outlets, but this may be skewed because of its smaller data pool.

Some outlets had sentiment scores for certain topics that were not logical. For instance, the Trump topic, which would likely be framed very positively by right-leaning outlets, was most positively framed by the two far-left outlets. In fact, The Blaze was negative for every single article in this topic and returned an average score of zero:



This positive coverage from the far-left could be from discussing the fact that he is no longer in office, or the discussion could simply be about their positive outlook on a future without Trump. The pattern is odd, but the results from this search term show that a positivity score does not refer to the outlet's perception of a topic, as it is clear that right-leaning outlets would have higher scores than their counterparts. The positivity score is instead a measure of the tone of articles written on a topic, so these left-leaning outlets must be writing articles mentioning Trump that are framed positively. Considering this pattern, there is likely a common framing among the two most left leaning outlets that is not shared by any other outlet. CNN notably has the lowest positivity score, which does follow a more expected trend.

One issue that could affect the validity of this data is that some search functions did not return a complete list for every topic, and some outlets had only a few articles for a given topic. These topics were not replaced if the incomplete list was limited to only one outlet. Some graphs and representations for individual topics may be compromised because there are only a few data points for one outlet. This should have no effect on the overall positivity rates of the outlets as a whole as the sample size is large enough to smooth out the missing data points.

Another issue is the selection of topics, as this could skew certain outlets to be especially positive or negative. Selected topics had an equal number of political keywords, split evenly across affiliations, but in a few instances the search function would return the same article for a different keyword. Search terms such as Democrat and Republican may not be the most optimal, as many articles that mention one also mention the other.

Conclusion

In this paper, Newscatcherapi was used to scrape article summaries from six news outlets for ten topics per outlet. Article summaries were then fed to the NLP model Bert for sentiment analysis, where they were assigned a tag of negative or positive. Negative scores were then converted to zeros and positives scores were converted to ones to quantify the overall positive framing of a topic or outlet. Initial predictions were correct that left-leaning news outlets have a more positive overall framing than right-leaning news outlets. These outlets followed initial predictions for the most part, except for CNN, which had more negative framing than Fox news. This could mean that the tone of an article does not significantly affect the amount of traffic it generates for an outlet. Future studies could incorporate the profitability and click rate of articles with varying sentiments and determine if sentiment has a significant effect on click rate.

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Appendix A

Newscatcher web scraping code:

https://github.com/farveg/Speech-Sentiment-Across-the-Aisle/tree/main/NEWS%20SCRAPER

Appendix B

Bert code:

https://github.com/farveg/Speech-Sentiment-Across-the-Aisle/blob/main/BERT/bert.py

Appendix C

Epoch 1/2

1250/1250 [==============================] - 2161s 2s/step - loss: 0.2627 - accuracy: 0.8891 - val_loss: 0.3220 - val_accuracy: 0.8726

Epoch 2/2

1250/1250 [==============================] - 2128s 2s/step - loss: 0.0771 - accuracy: 0.9736 - val_loss: 0.4472 - val_accuracy: 0.8778

Appendix D

Full results dataset:
https://github.com/farveg/Speech-Sentiment-Across-the-Aisle/blob/main/DATA/RESULTS/Semantic%20Analysis%20Results.xlsx