Measuring Bias in COVID-19 News Articles

Andrew Pagtakhan, Kwan Bo Shim, Cinthia Jazmin Trejo Medina

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Contents

1 Preface

The full code and dataset can be found here: https://github.com/ajpag/US-News-NLP

All analysis was completed in R.

2 Research Question

2.1 Background

The means in which informaton is communicated with regards to the COVID-19 pandemic has had major influence on how we read and learn about the virus through a multitude of media outlets. Some of these major sources include television, YouTube, social media forums, and major news companies. Major news companies in particular carry large influence based on the audiences it can reach. For example, Fox News Channel averaged 2.5 million primetime viewers (8pm - 11pm) in February 2021, and CNN averaged 1.7 million during the same time period. *Source: https://www.foxnews.com/media/fox-news-finishes-february-most-watched-primetime-network.*

According to King G. & et. al., "...the exposure to news media causes Americans to take public stands on specific issues, join national policy conversation, and express themselves publicly". Furthermore, Holman E. & et. al, suggest a correlation between raising level of stress and prolonged media exposure to "community-based traumas (e.g., mass shootings, natural disasters". Recently, Holman has suggested the COVID-19 is a particular case to study; since multiple stressors have arose at the same time. To mention some: financial crisis, elections, health crisis, among others. It can be said that news can influence the decisions, general views and metal health of Americans. *Source: https://science.sciencemag.org/content/358/6364/776* Source: https://www.pnas.org/content/111/1/93 *Source: https://www.universityofcalifornia.edu/news/how-and-why-coronavirus-changing-our-sense-time* Source: https://www.bbc.com/future/article/20200512-how-the-news-changes-the-way-we-think-and-behave

I would like to connect this ideas, but I am unsure how to do it... ###########JTM

Since major news companies have a large influence in how information is commmunicated to its audiences, it is vital to quantify how different these sources are in relation to COVID-19 news. By measuring potential bias in relation to each source, this analysis examines how different major news sources are when reporting on COVID-19. It is also insightful to see if there are underlying patterns such as subtopics within COVID-19 that are published more in news sources over others. This would help identify if there are patterns that are predictive of which news source the article came from.

2.2 Research Question

Are there underlying patterns in news articles related to COVID-19 across major news sources that suggest bias, and are these patterns predictive of which news source it is likely from?

I think we should think further what is the importance of predicting the source. If it is because it help us evaluate the patterns, probably they are not the question but the methodology to anwer our question... ###########JTM

2.3 Use Cases

By quantifying underlying differences on COVID-19 reporting and examining the predictive power of these patterns to identify the news source, this study can be useful for a number of use cases. For example, understanding biases in article text can help the reader understand inherent idealogical leanings towards certain news sources, which can help equip them with greater understanding and critical examination of news consumption. #####In the same way, selective news consumption could potentially lead to less stress impact due to news sources.#####

From a policy perspective, greater impact and studies could be conducted to place more standardized regulations in an effort to influence more objective reporting. We acknowledge this second use case can be difficult from business and philosophical perspectives, especially in relation to the First Amendement of the US Constitution in relation to the freedom of speech.

I think this statement can be less extreme, such as just having transparency towards the bias that each news source could have… ###### I like this article: https://www.americanpressinstitute.org/journalism-essentials/bias-objectivity/understanding-bias/ and this statement: ###### What if journalists acknowledged that bias does exist, that it is built into the choices they make when deciding what to leave in and what to leave out? That bias is embedded in the culture and language of the society on which the journalist reports? And that "news judgment" does reflect the journalist's background as well as the news organization's mission and business model? ###### I think that acknowledging is a step to give information to the consumer when choosing which news to read ###########JTM

2.4 Methodology

2.4.1 Data Sourcing

In order to choose major news sources to analyze, the figure below created by the Pew Research Center shows where on the US political spectrum various news companies fall. In order to get a mix of sources across the conservative and liberal spectrum, while balancing limitations of computing resources, the following news sources were used to procure a dataset.

Source: https://www.journalism.org/2014/10/21/political-polarization-media-habits/pj_14-10-21_mediapolarization-08/

- BBC
- CNN
- The Wall Street Journal
- Reuters

Note: Due to legal restrictions, Fox News data was not scraped

3 Data Cleaning

Leveraging the **GNews API**, news article data related to COVID-19 were pulled for the following major news sources noted in the previous section (filtered to US articles).

3.1 GNews API

A total of 5,360 articles between the time period 1/1/2020 - 4/9/2021 were called from the API (20 articles per week and news source, for 67 weeks). The API call returned 3,454 records for article-related data. Below are some of the key fields from the API call, with an example:

- `article url`: https://www.cnn.com/2021/02/08/health/covid-19-antigen-tests-states-cnn-analysis/index.html
- `article description`: "Covid-19 antigen tests not counted among cases in some states, CNN analysis shows - CNN"
- `date and time of article publication`: 2021-02-08T08:00:00Z
- `article source name`: CNN

3.2 Web Scraping

After gathering the article URLs, the full news text for each article was pulled. Each data source carried unique idiosyncrasies in its html structure. The next section highlights unique aspects web scraping each data source.

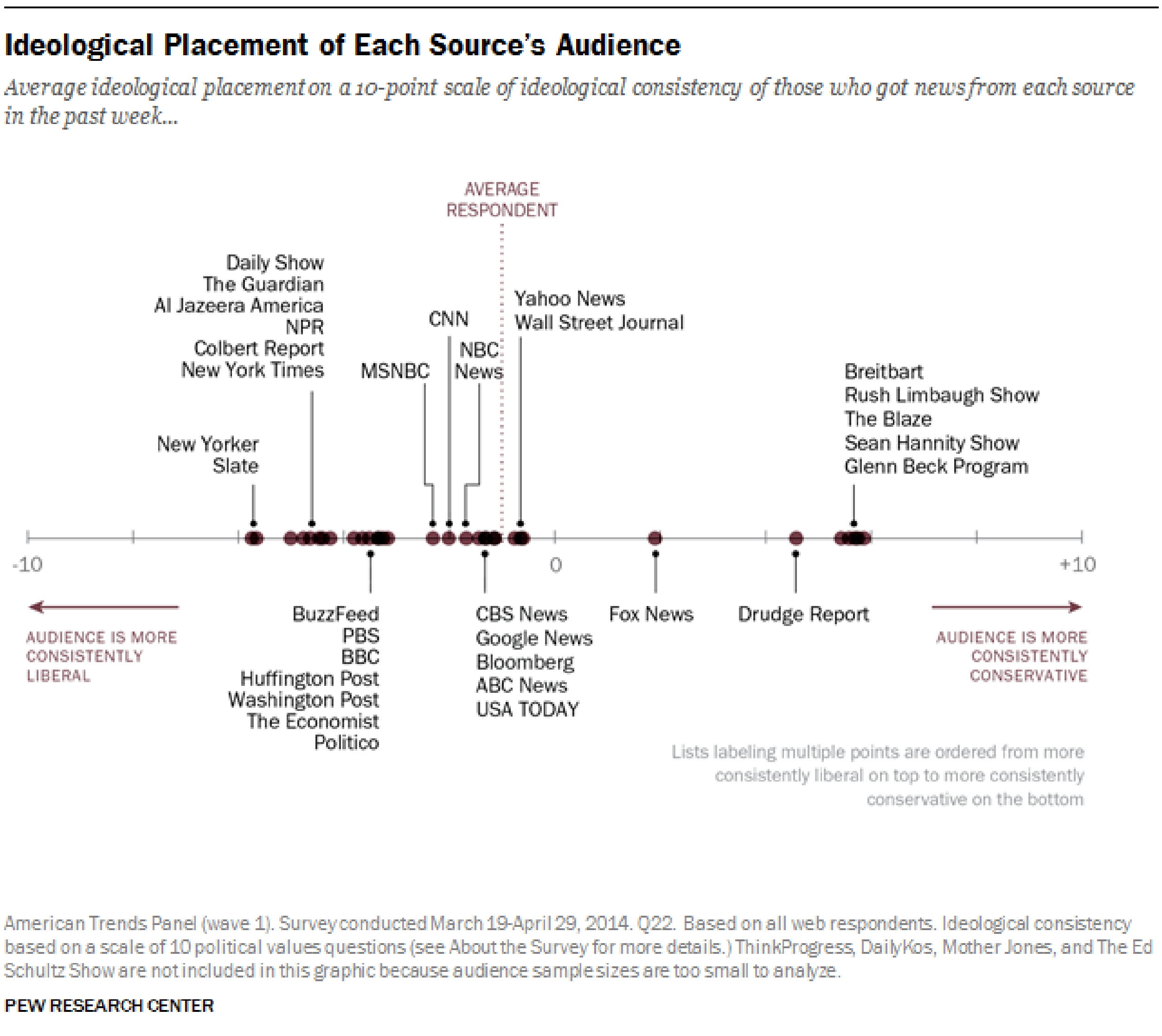

Figure 1: Source: Pew Research Center

3.2.1 BBC

3.2.2 CNN

There were two distinct HTML structures. One for the first sentence, and another for the remainder of the article. Additional cleaning needed to be done to remove the “(CNN)” and “(CNN Business)” text at the beginning of each article, as well as additional escape characters scattered throughout the article.

3.2.3 Reuters

This was relatively streamlined compared to the other news sources. One unique aspect of Reuters was that a number of their articles were not text articles in the traditional sense, but slideshows. For example this article:

https://www.reuters.com/news/picture/coronavirus-outbreak-spreads-in-china-idUSRTS2ZART

3.2.4 The Wall Street Journal

4 Exploratory Data Analysis

4.1 Sentiment Analysis

To better understand the data, sentiment analysis utilizing various lexicons were explored. Key visualizations of the data are illustrated:

BBC had the least average words per article, whereas CNN had the most words per article.

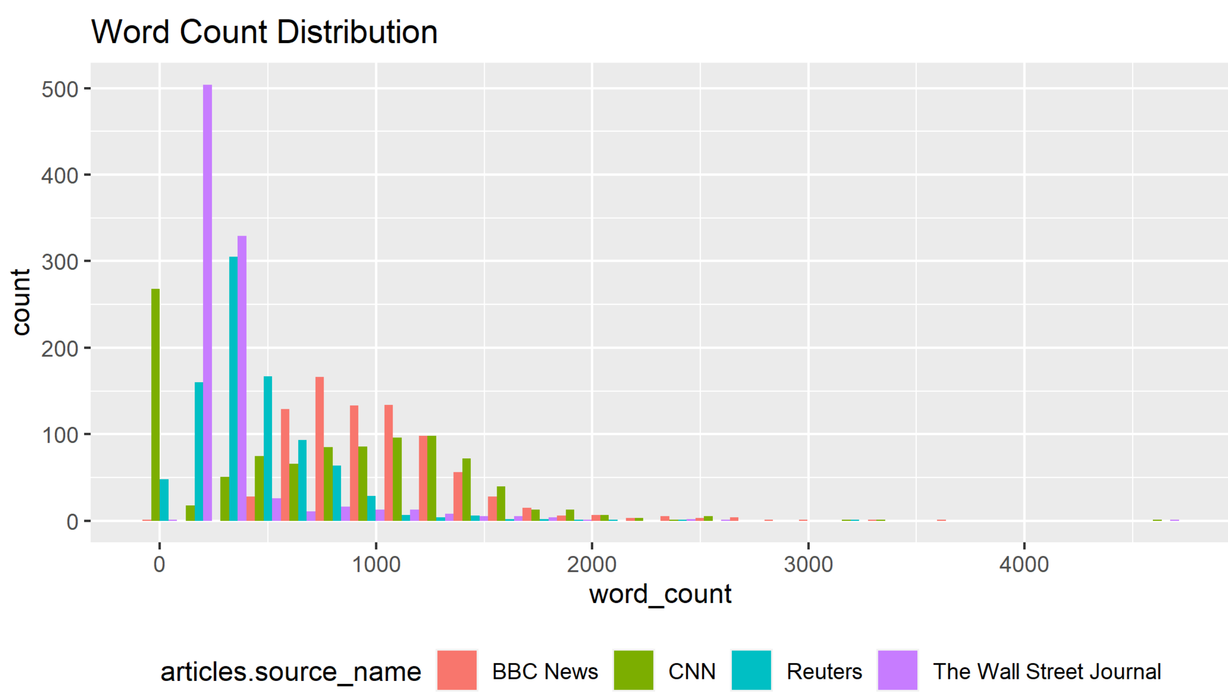

Figure 2: Words Per Article

BBC News had a larger variety of top words compared to the other news sources.

All news sources had average weekly sentiment mainly hovering between -1 to 0, using the Afinn lexicon. This means that average sentiment was slightly negative.

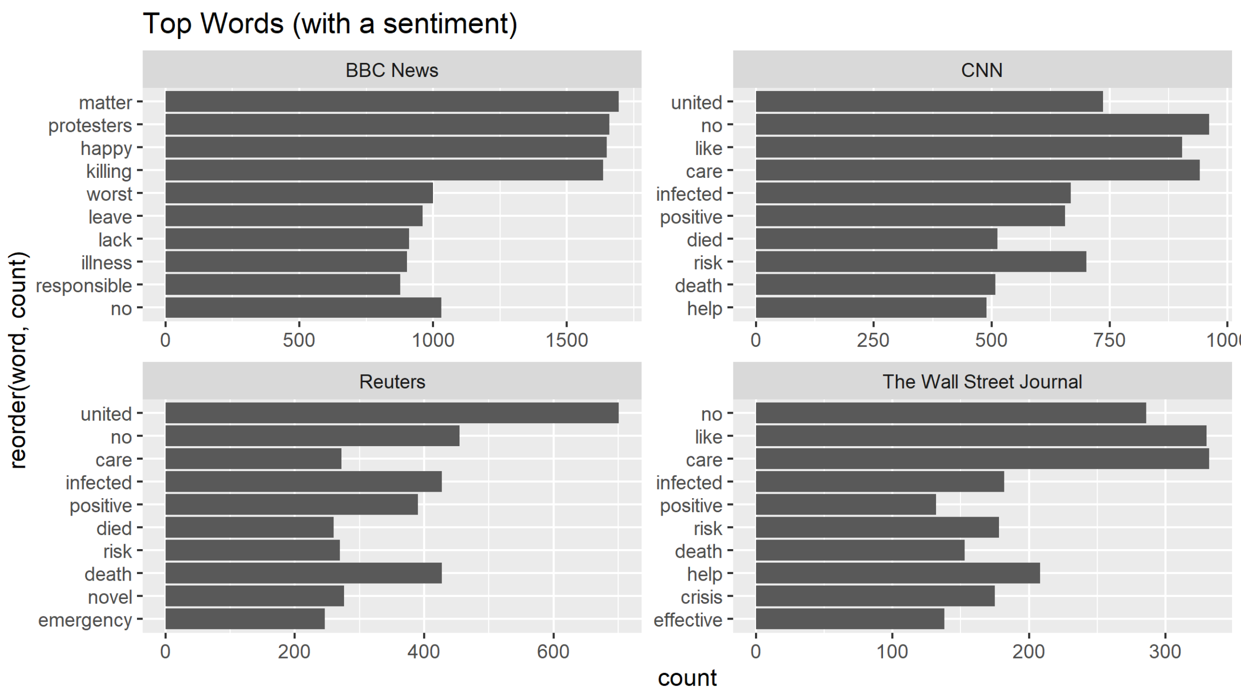

Figure 3: Top Words with a sentiment

The Wall Street Journal had the largest range in average weekly sentiment. It is plausible there is some correlation between this sentiment and the stock market, and would require further analysis outside of this study.

Afinn lexicon: https://www.tidytextmining.com/sentiment.html

5 Feature Engineering

In order to create features to build classification models for predicting a news source based on text, the below features were generated.

5.1 Average Sentiment and Word counts

One feature was generated for each article:

- average sentiment by word
- average sentiment by sentence
- word count
- word count with a sentiment

5.2 Keyword features

As a baseline, keyword features based on the researchers' prior knowledge on the following topics was used to generate average Afinn sentiment for articles. One feature was generated for each term below (noted in quotes).

- Politics: "Trump", "Biden"
- Business: "stock market", "financial"

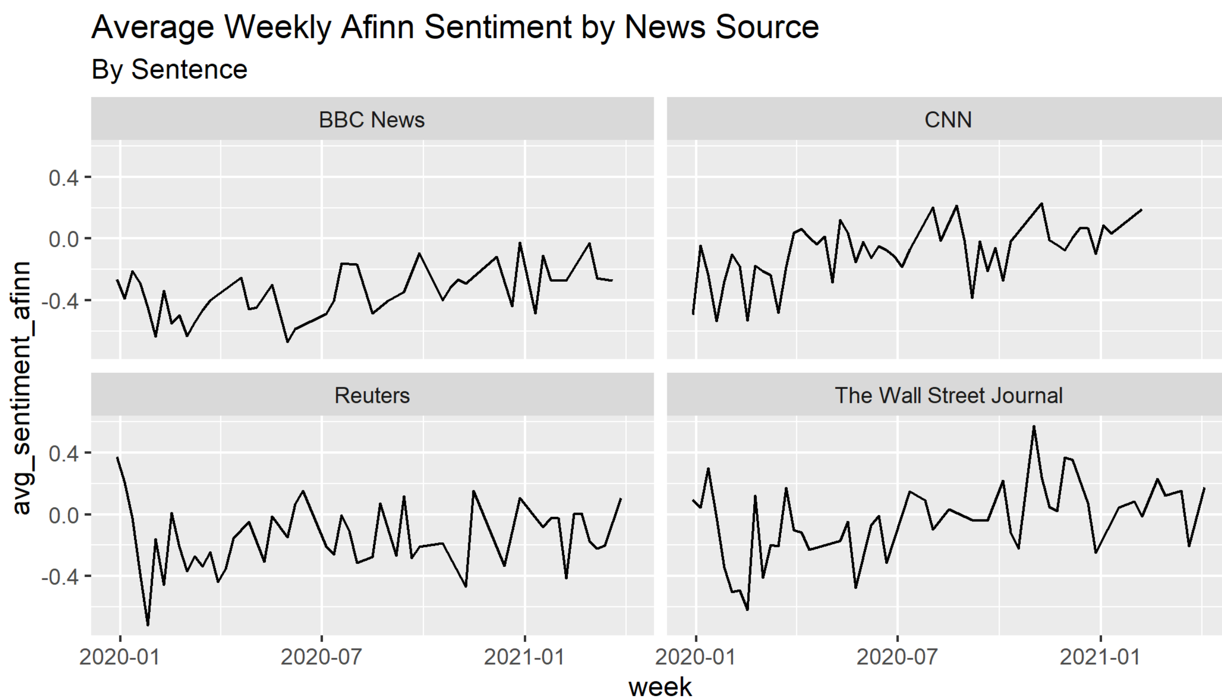

Figure 4: Average Sentiment by Week

- Pandemic: "death", "pandemic", "disease", "illness"

5.3 Topic features from prior research

Leveraging prior studies, the following features were generated by topic using keyword. Specific keywords used for each topic can be found here:

https://github.com/ajpag/US-News-NLP/blob/53faa3e31d901386b12ea0459586ac6bd0785f1e/analysis/feature_engineering_ap.R#L280

Source: "Politicization and Polarization in COVID-19 News Coverage" https://journals.sagepub.com/doi/full/10.1177/1075547020950735

- COVID 19
- Scientist
- Republican
- Democrat

Source: "Polarization in elite communication on the COVID-19 pandemic" https://advances.sciencemag.org/content/6/28/eabc2717

- Republican Words
- Democrat Words

5.4 Topic Modeling: Latent Dirichlet Allocation

To assess commonalities in topics and article text across articles, Latend Dirichlet Allocation was applied. After experimentation, it was decided that 7 topics was the optimal number, based on interpretabilty and overlap of topics. The VEM method was used: https://www.tidytextmining.com/topicmodeling.html

Topics:

Table 1: Topics from LDA

topic_number	topic
1	Politics
2	Reported deaths and cases
3	China / Wuhan
4	Outbreaks and infections by country
5	Patients and Symptoms
6	Vaccines and Research
7	Business and Economy

6 Measuring Bias Across News Sources

Performing a chi-square test to measure differences in signifances across news sources, the following metrics were used. The chi-square test for all three metrics suggest that there is a indeed a bias in article text across the news sources.

6.1 Topic Probabilities

Following intuition, The Wall Street Journal has the highest average topic probability for Business and Economy articles. It is interesting that Reuters has the highest probability of China / Wuhan related articles. CNN has the lowest probability of articles pertaining to vaccines and research.

The chi-square test ($p < 1\%$) indicates there are correlations across each news source in relation to average topic probabilities.

Note: Probabilities were multiplied by a factor of 100 prior to running the test

6.2 Average Sentiment

The chi-square test ($p < 1\%$) indicates there are correlations across each news source in relation to average Afinn sentiment.

Note: Sentiment scores were multiplied by a factor of 100 and converted to positive integers prior to running the test

6.3 Word Count

The chi-square test ($p < 1\%$) indicates there are correlations across each news source in relation to average word count.

Note: Average word counts were converted to positive integers prior to running the test

7 Classification

For each of the 5 algorithms run, 4 models were run using different sets of features:

- **Topic Modeling features**: per section 5.4
- **Keyword features**: per section 5.2

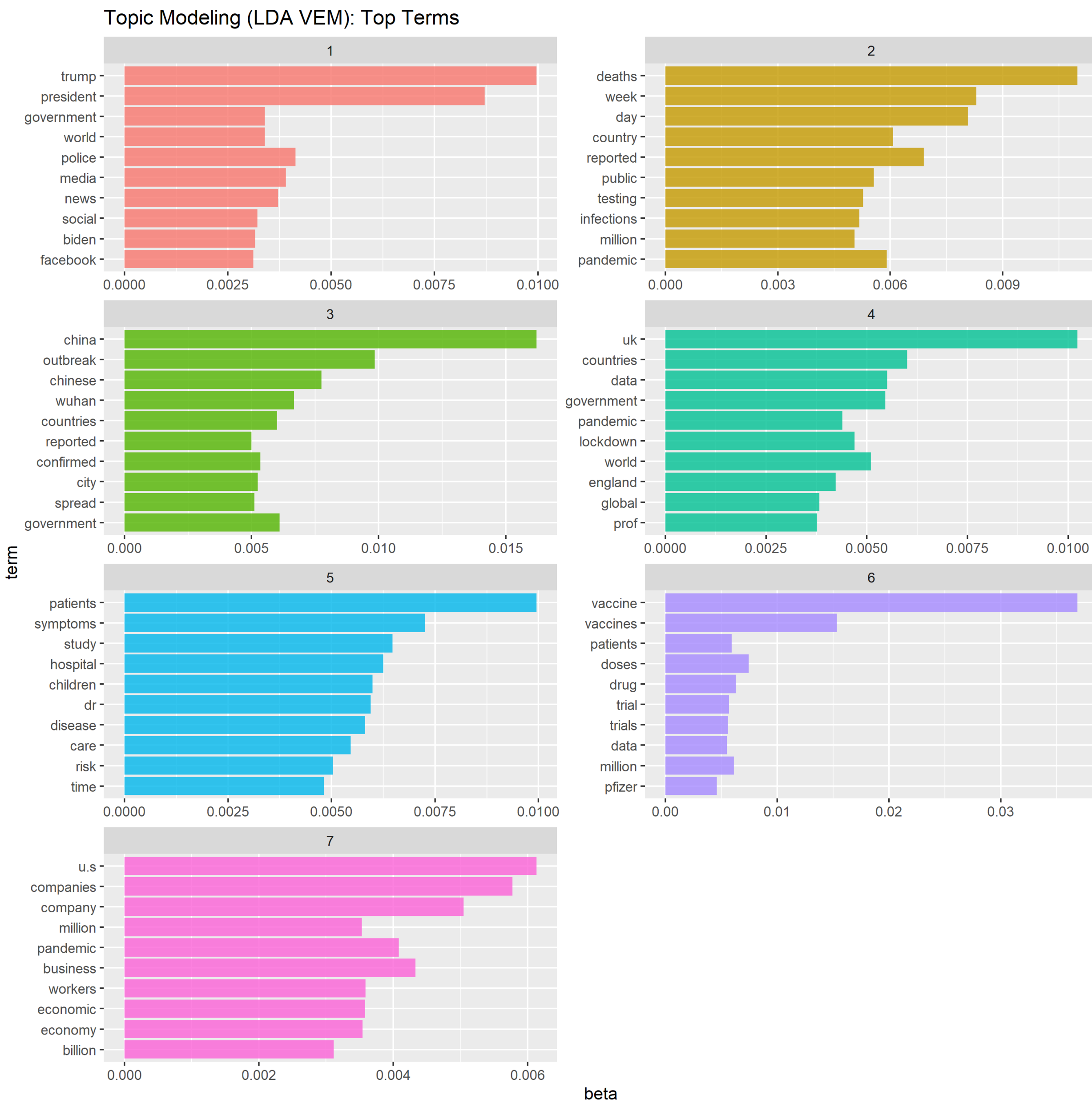

Figure 5: Topic Modeling: Top Words

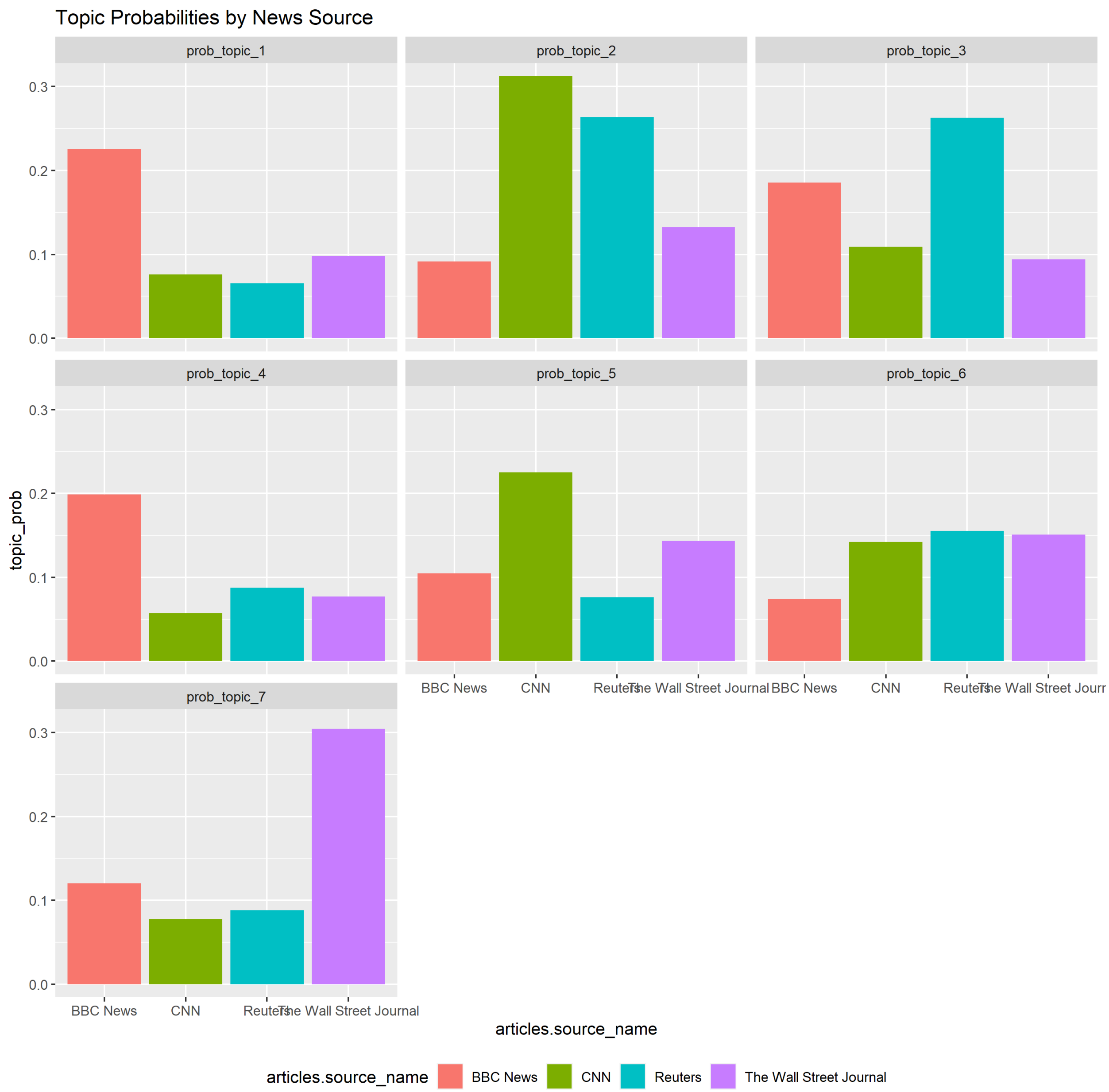

Figure 6: Topic Modeling Probabilities

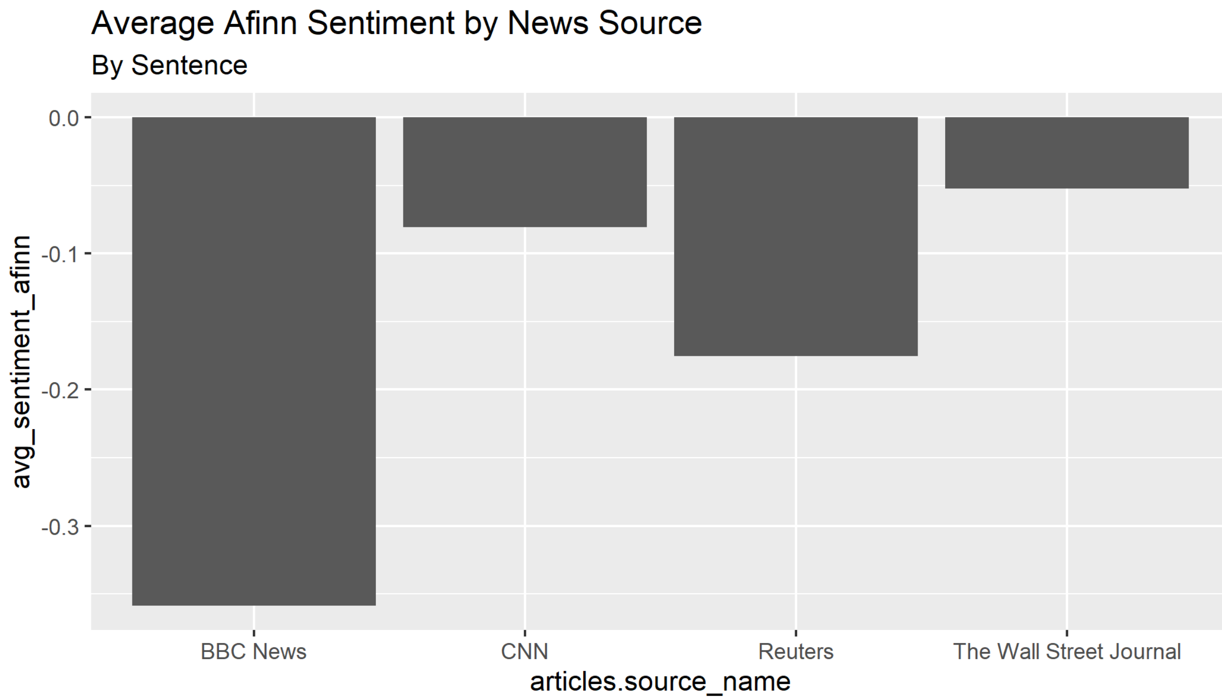

Figure 7: Avg sentiment by sentence across articles

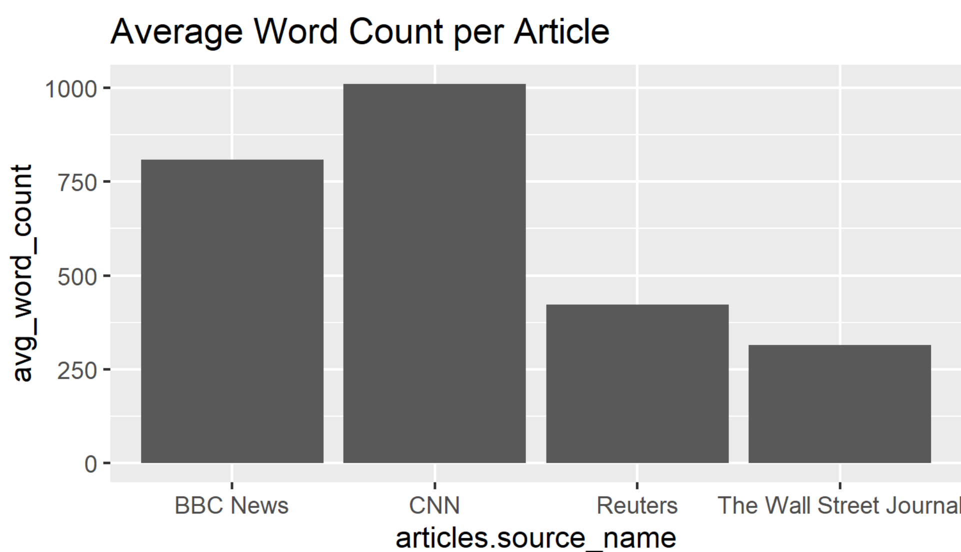

Figure 8: Avg word count across articles

- **Topic keyword features**: per section 5.3
- All features

Table 2: Classification Model Results

model	test_accuracy	auc
rf_all	0.89	0.98
rf_topic	0.81	0.94
gbm_all_features	0.80	0.94
rf_paper	0.76	0.92
logreg_all_political	0.72	0.84
svm_all	0.68	0.87
gbm_topic_lda	0.68	0.89
logreg_all	0.64	0.85
gbm_topic_keywods	0.61	0.84
rf_keyword	0.57	0.57
nb_all	0.56	0.81
logreg_paper	0.52	0.92
svm_topic	0.51	0.76
logreg_topic	0.49	0.75
svm_paper	0.49	0.77
nb_paper	0.49	0.74
nb_topic	0.46	0.72
gbm_keywords	0.45	0.71
svm_keywords	0.37	0.61
logreg_keyword	0.33	0.57
nb_keywords	0.29	0.57

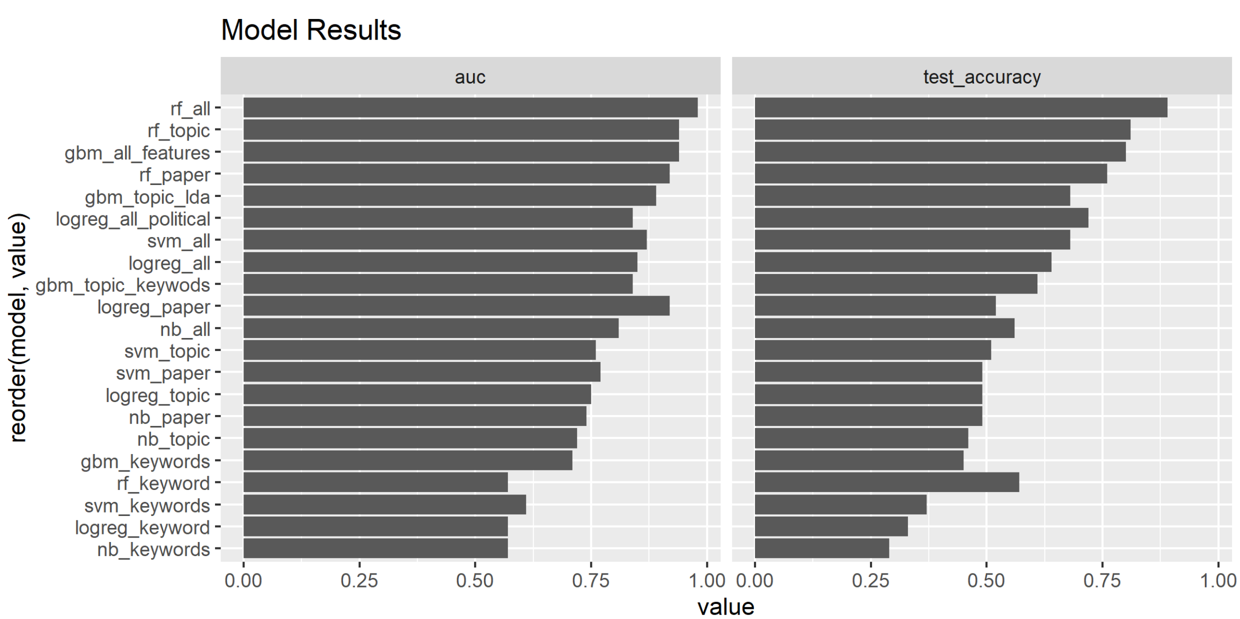

Figure 9: Model Results

8 Results

8.1 Conclusion and Next Steps

Maybe we could divide this section in 4 paragraphs ###### JTM

Paragraph 1: There is different patterns accross news sources chi-sq ###### JTM

Paragraph 2: Summary of the results of all the models ###### JTM

Paragraph 3: Explain why we think the best algorithm is working and why the least one is performing that way ###### JTM

Paragraph 4: Follow-up analysis: WSJ negative sentiment associated with stock marcket, Add information of more conservative sources, expand news without COVID-19 filter? ###### JTM

8.2 Limitations:

- Selection bias in news articles analyzed: Due to legal restrictions, more conservative news sources, such as Fox News, were not scraped. Also due to legal restrictions, the articles of The Wall Street Journal were not able to be fully scrapped.
- Context limitations in sentiment: The sentiment method used, Afinn, only parsed words individually, and not into context of the entire article. So, the sentence sentiment was calculated using the average sentiment of words.
- Parsing limitations: There are many edge cases in which breaking down articles by sentences did not parse successfully. For example, `tidytext::unnest_functions()` incorrectly parsed the following sentence into two since `Ms.` has a period:

Original sentence: `"The manager's decision to send Ms. Coleman home for wearing the headscarf was due to a lack of training," Warren said.`

Parsed sentence(s)

- `"The manager's decision to send Ms."`
- `"Coleman home for wearing the headscarf was due to a lack of training," Warren said."`