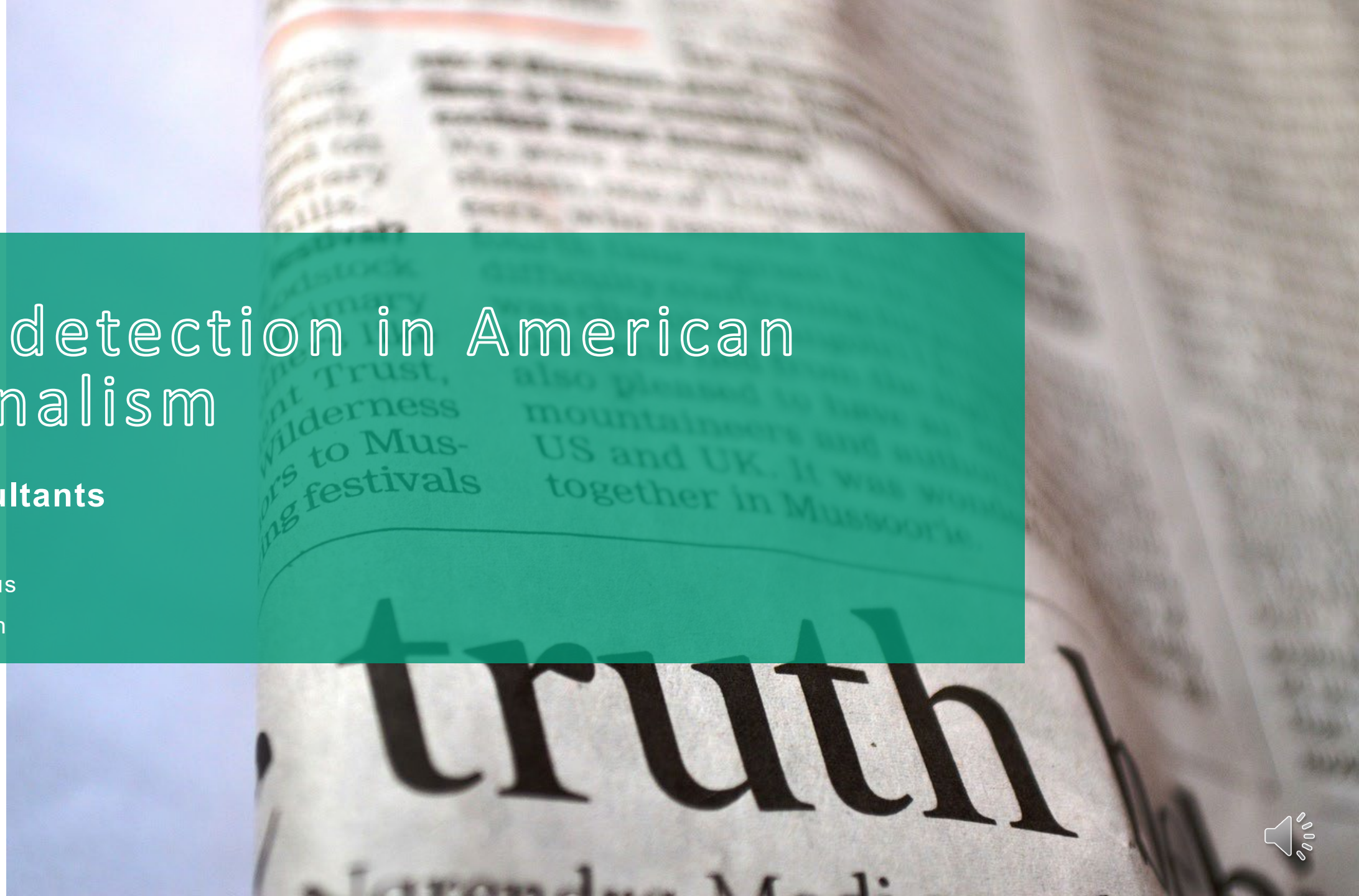
Bias detection in American Journalism

AI Consultants

Aaron Carr

Azucena Faus

Dave Friesen



Americans trust news that map to their point of view

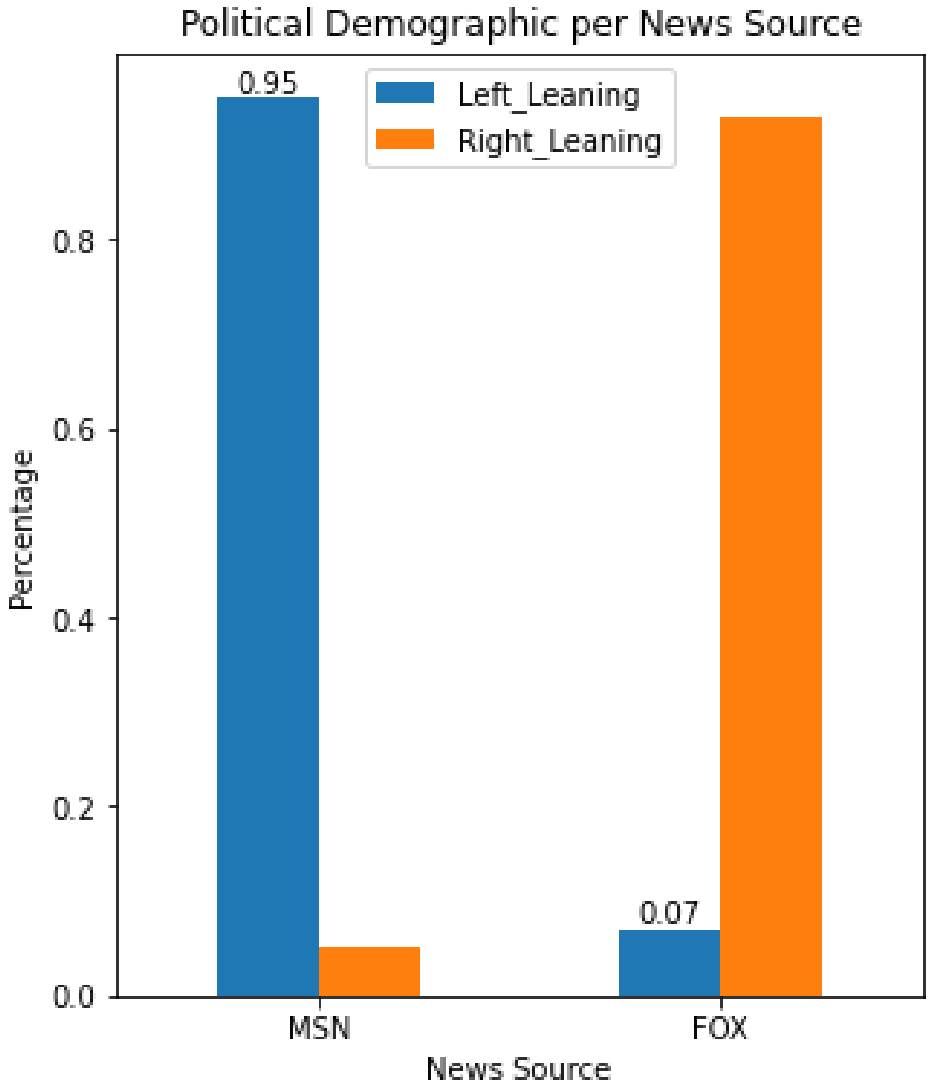
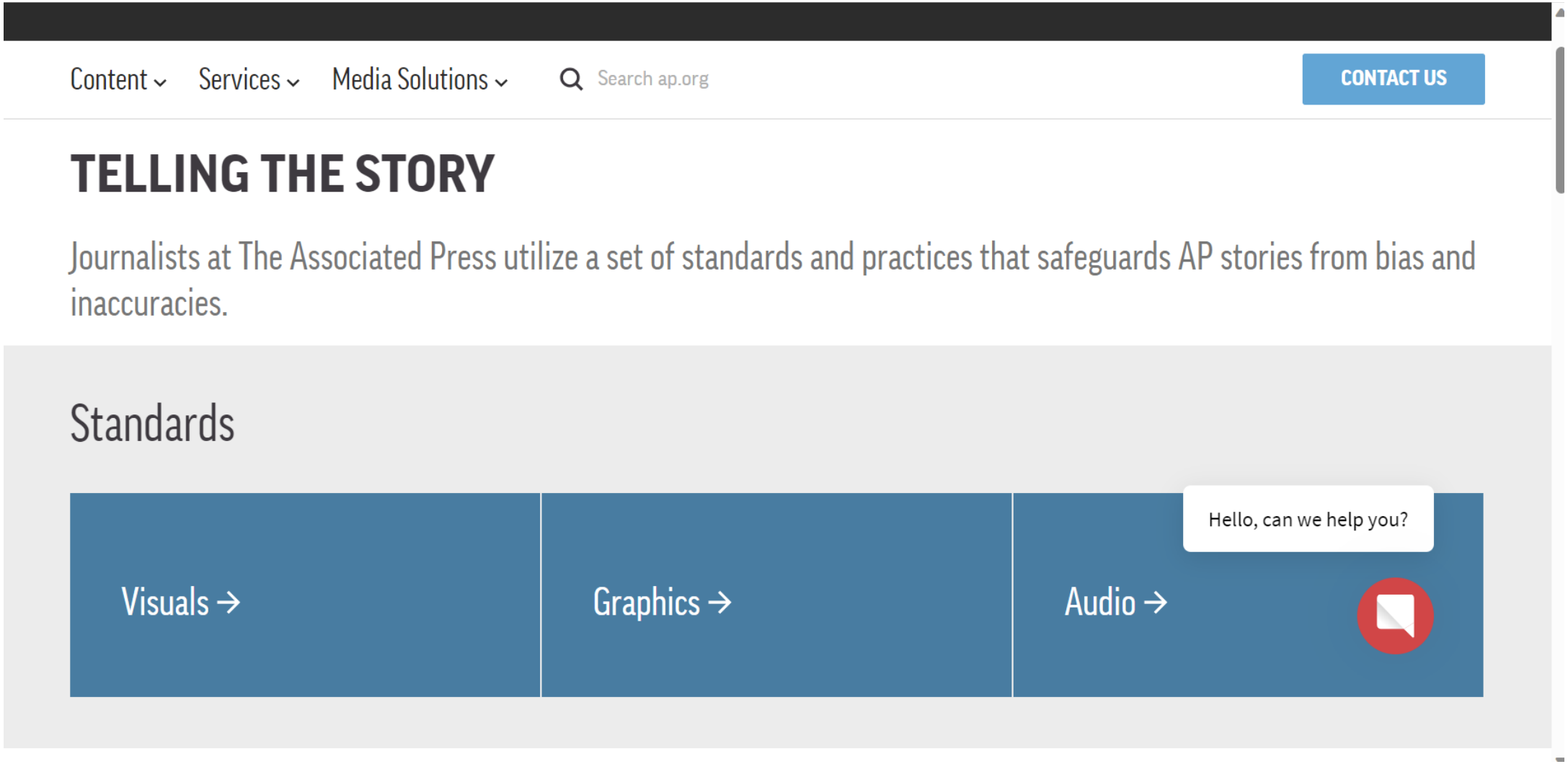


Figure 1.

(Brenan, 2020)

Many media sources play to this, but some consider themselves unbiased



(Brenan, 2020)

Build a classifier that detects left and right bias and try it on “centered” news

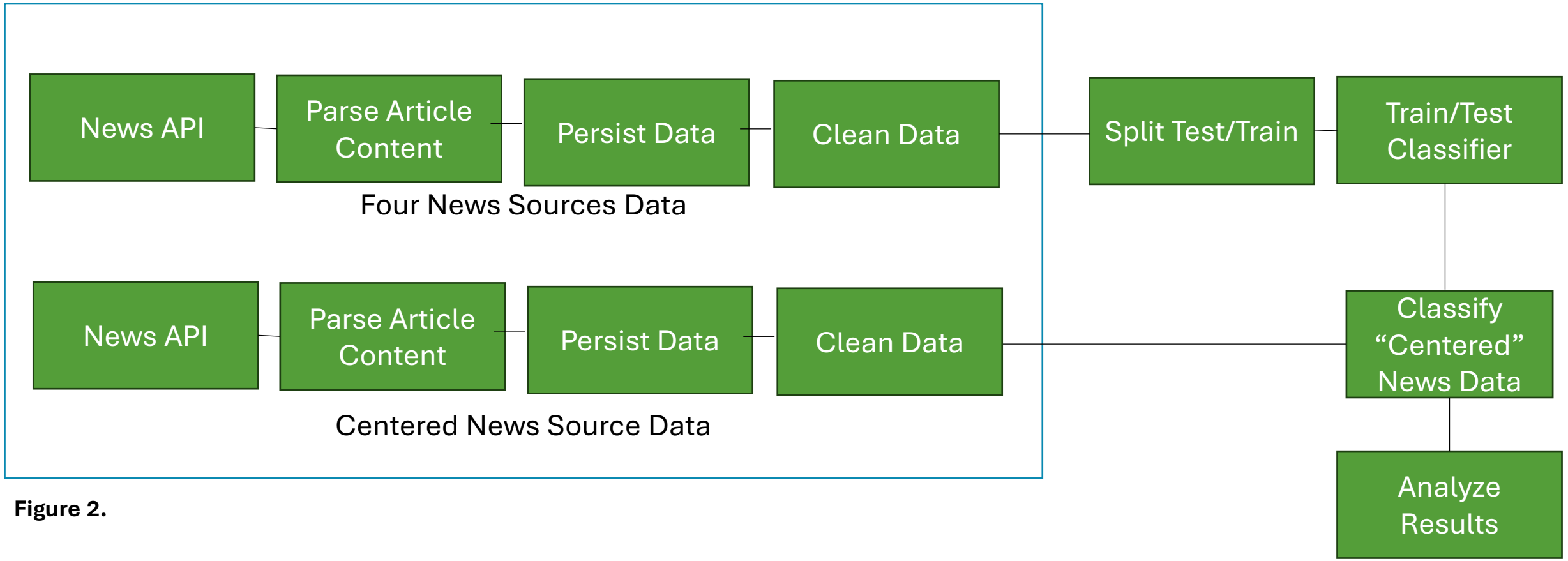
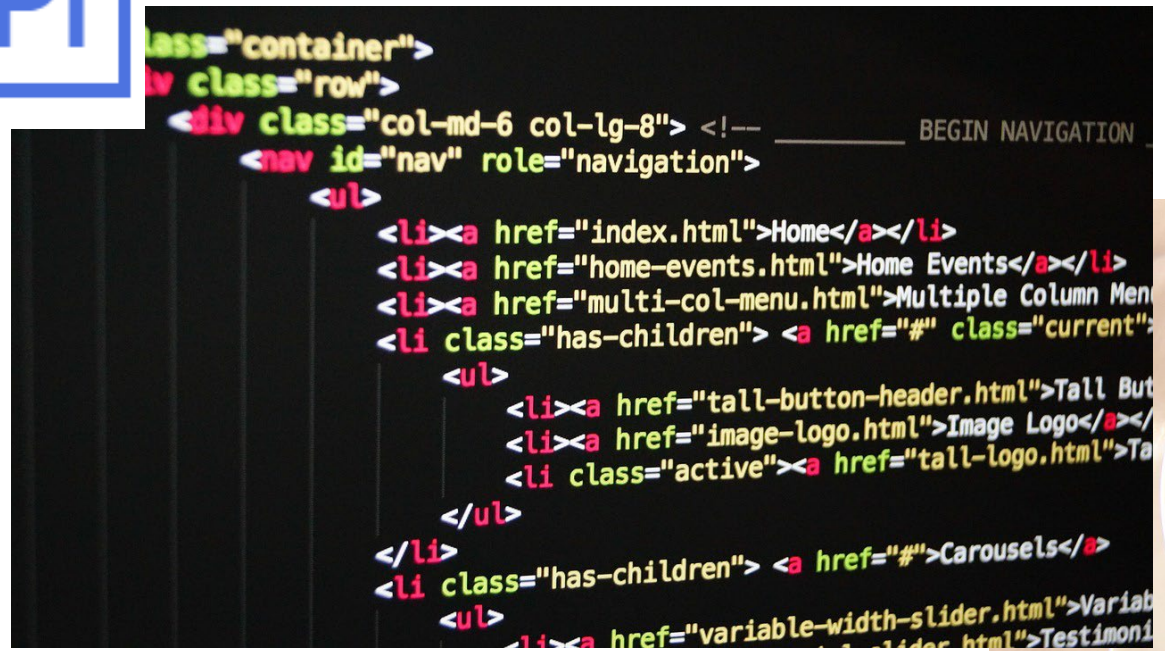


Figure 2.

Data collection involved using News API to collect URLs and webscraping

News API



Word Count distributions by news source

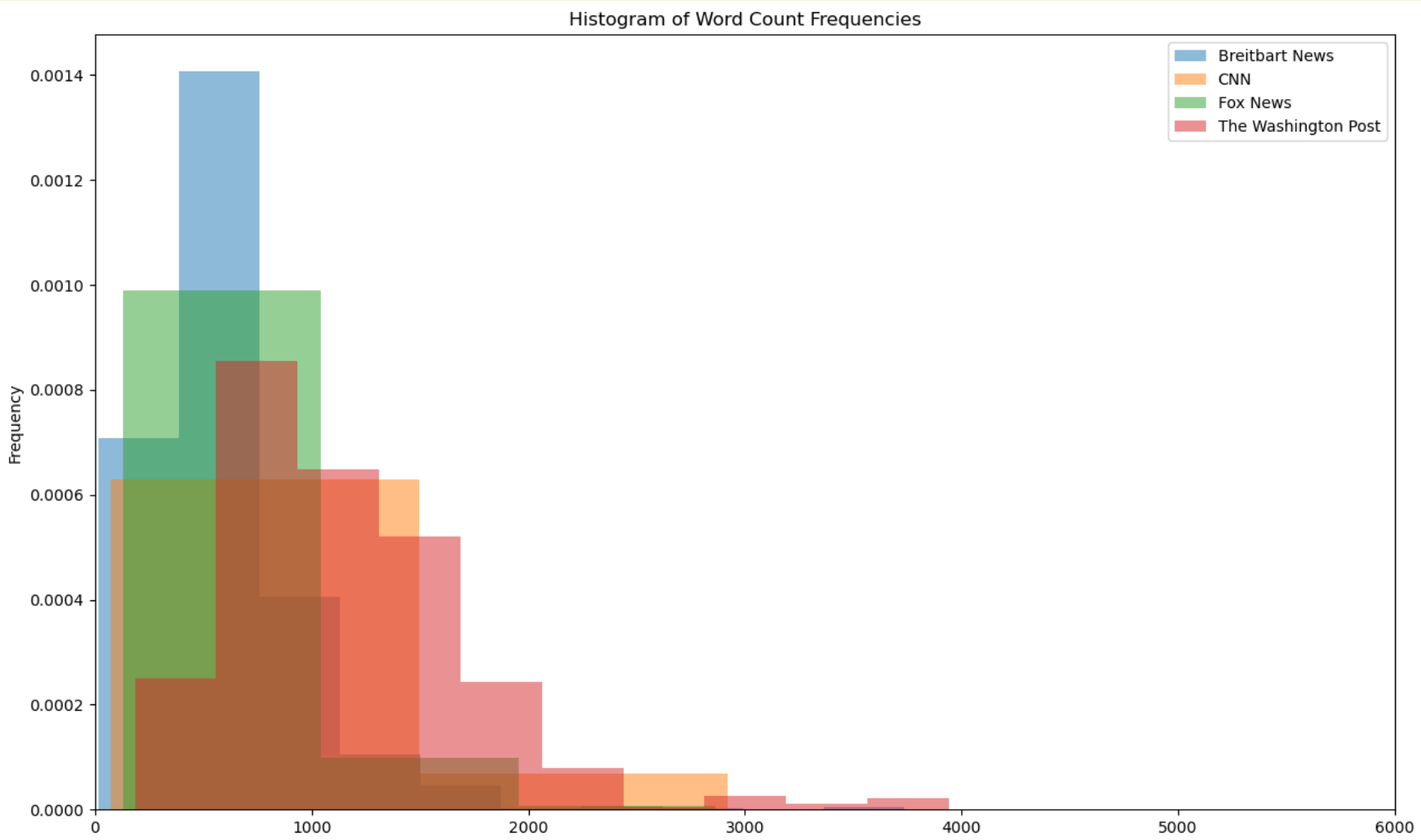


Figure 3.

Word Clouds reveal top words in Left and Right Leaning articles

Left Leaning Article WordCloud

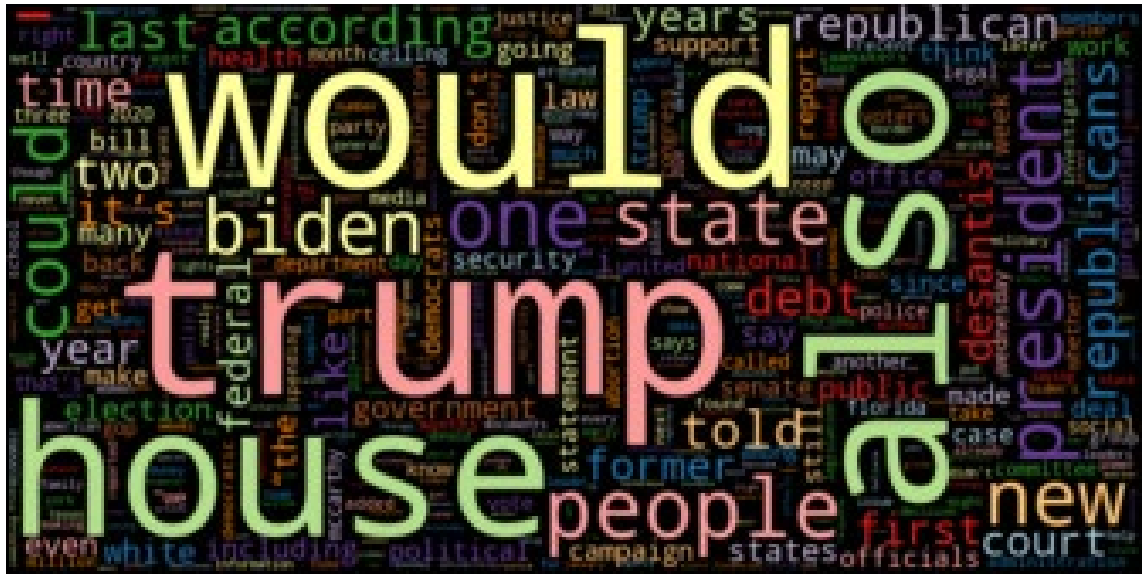


Figure 4a.

Right Leaning Article WordCloud

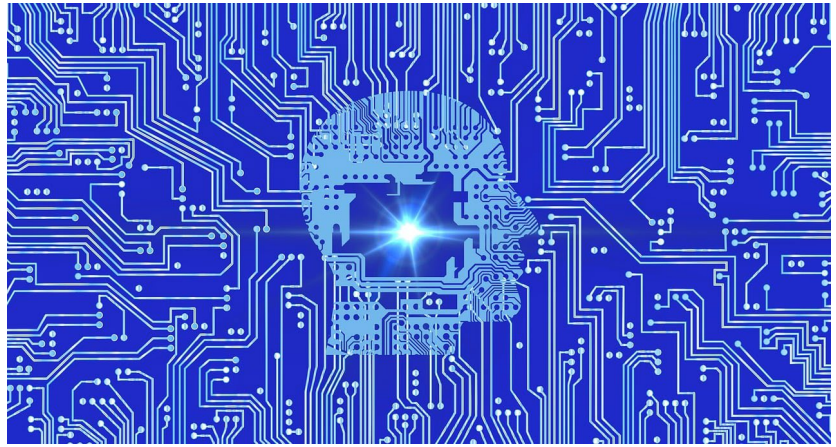
Figure 4b.

NMF Topic Modeling reveals topics covered in Left leaning sources

*

*By Gage Skidmore from Surprise, AZ, United States of America - [1], CC BY-SA 2.0, https://commons.wikimedia.org/w/index.php?curid=127920603

NMF Topic Modeling reveals topics covered in Right leaning sources



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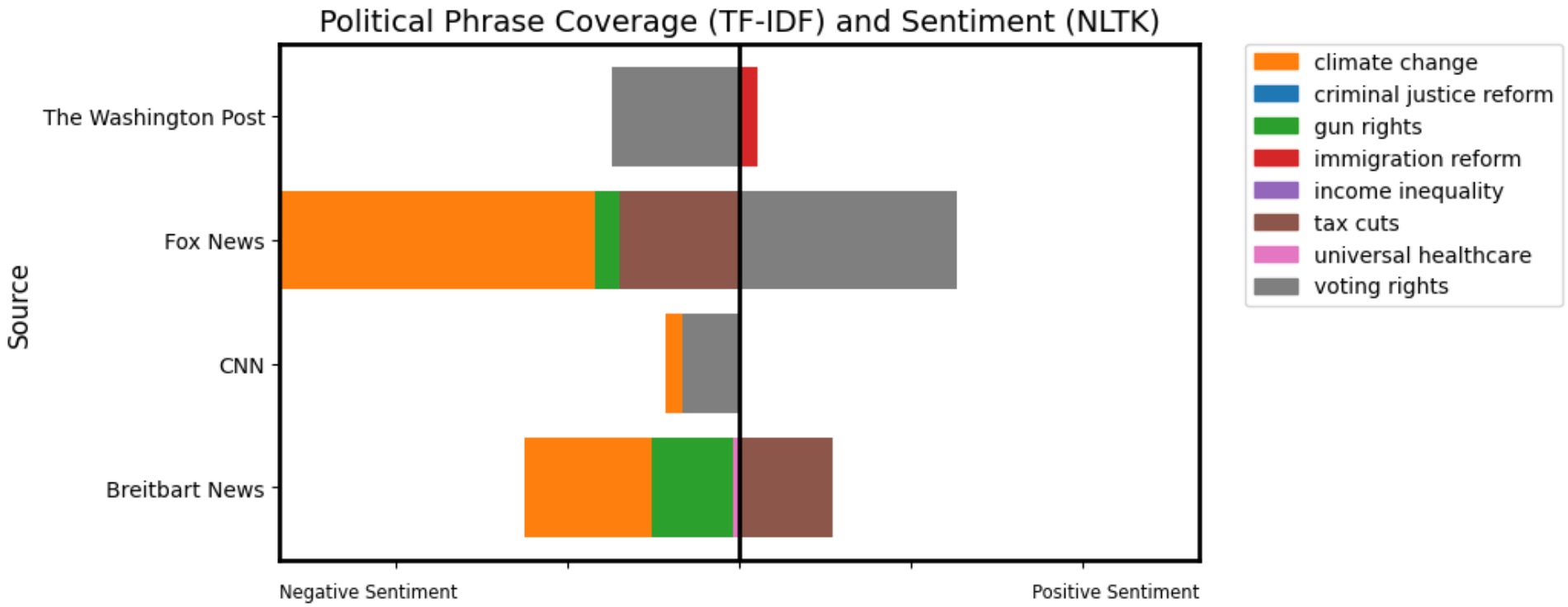
*By Gage Skidmore from Surprise, AZ, United States of America - [1], CC BY-SA 2.0, https://commons.wikimedia.org/w/index.php?curid=127920603

Sentiment Analysis – can it help understand “true” political lean or bias?

Figure 5.

“Classic” Sentiment Analysis approach

comparing words “around” political phrases with a sentiment lexicon

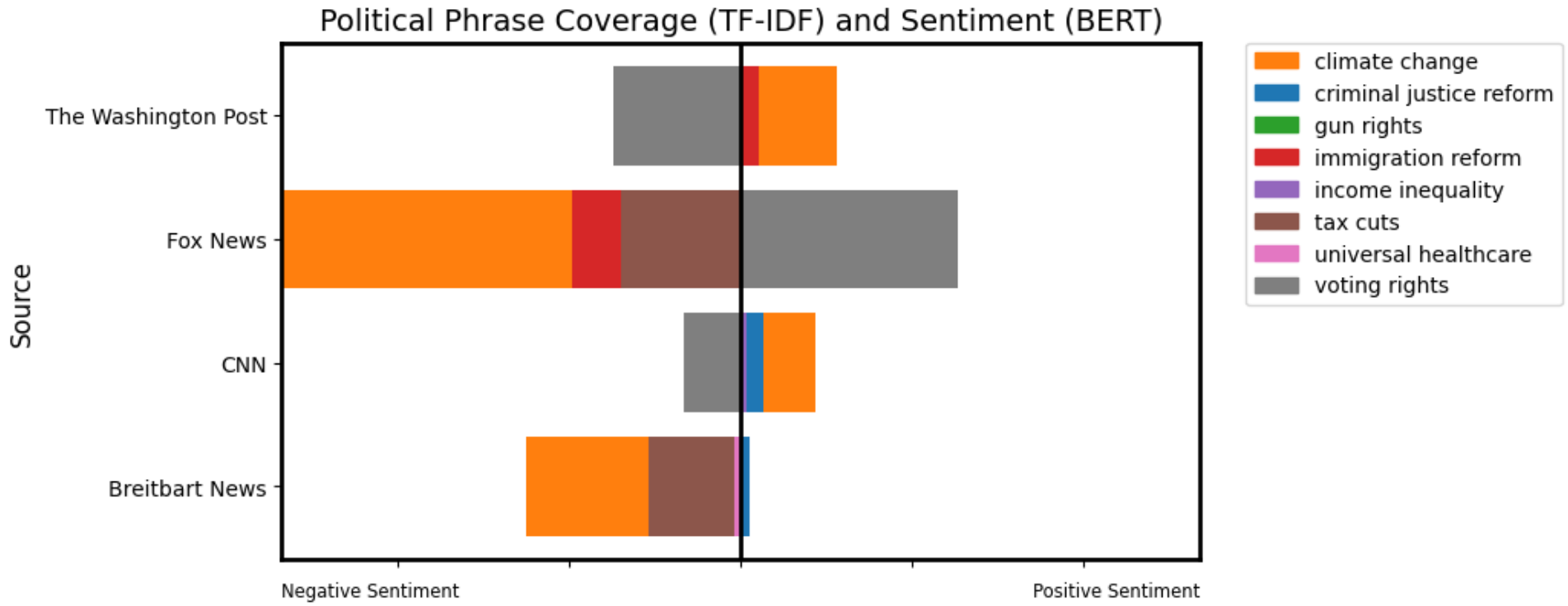


More Sentiment Analysis – newer approaches show promise

Figure 6.

“Contemporary” Sentiment Analysis approach

understanding semantic context around political phrases using a transformer-based approach



Concentration Ratios Between Labels

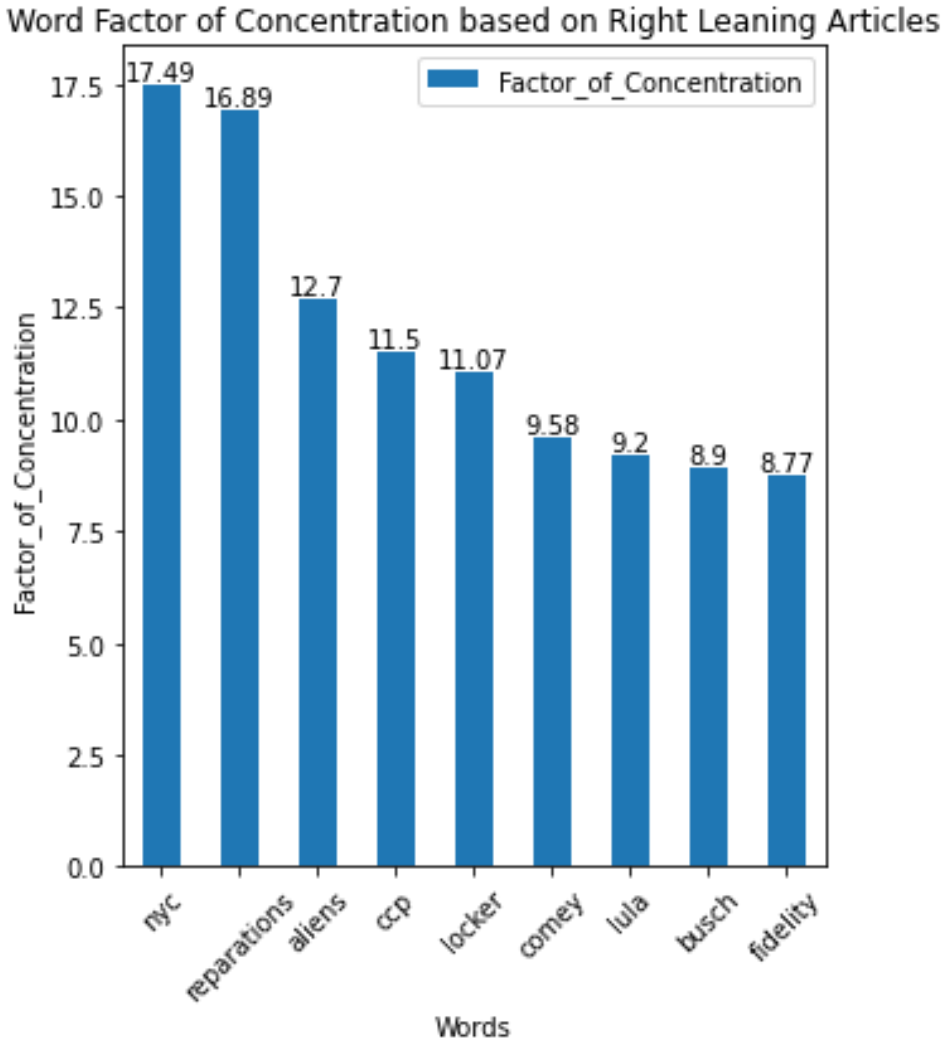


Figure 7a.

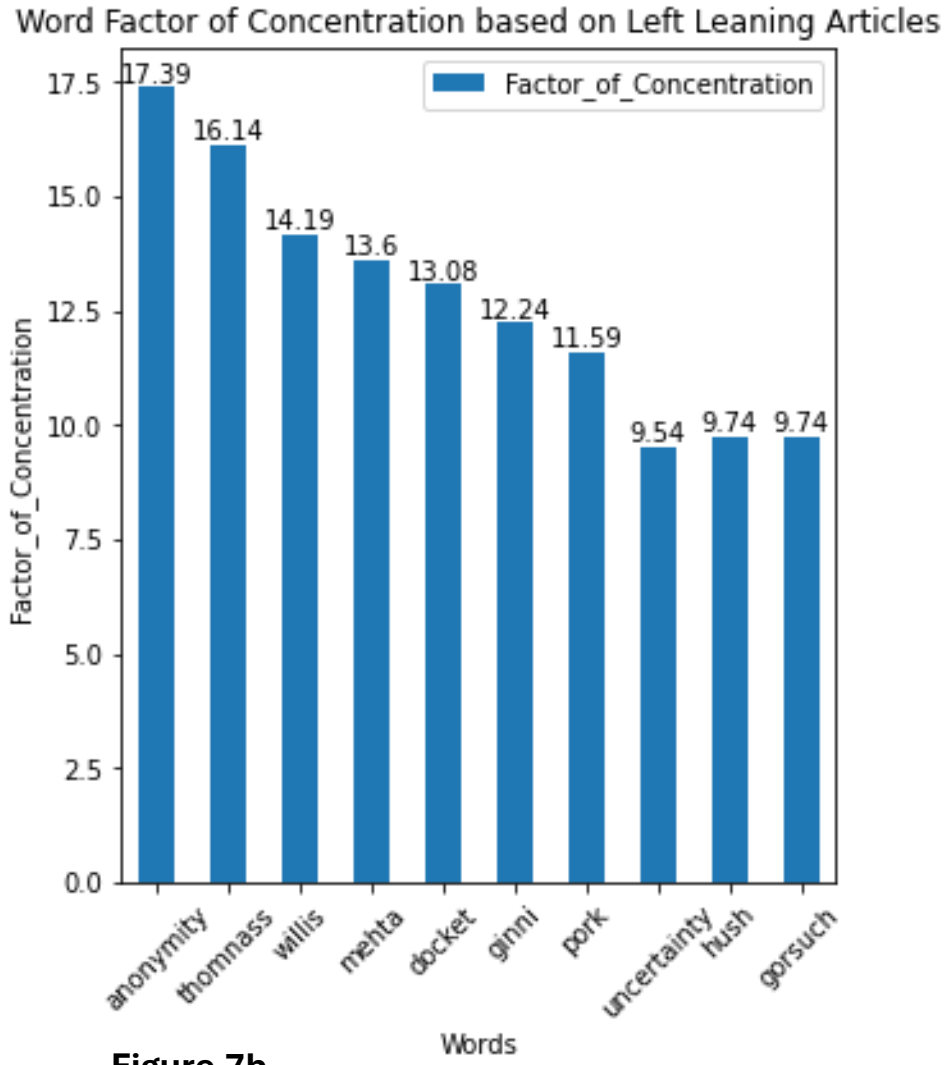
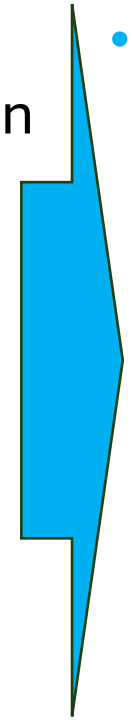


Figure 7b.

Text Preprocessing - Normalization

Multi-step text cleaning, normalization, and tokenization pipeline

- Case-loading
- Formatting normalization (textacy)
- Special characters & phrases removal; separate emojis
- Custom stop word removal
- Custom punctuation removal



- “they waited in saint—hélène 🌈”, fox news digital reported.
- "they waited in saint-helene 🌈", fox news digital reported.
- "they waited in saint helene 🌈", reported.
- "waited saint helene 🌈",.
- waited saint helene 🌈

Tokenization & Vectorization

- Train/test split
- Tokenization (split on whitespace) ['waited', 'saint', 'helene', '']
- TD-IDF vectorization:

Figure 8.

```
nlm_tfidf = TfidfVectorizer(encoding='utf-8',
                            analyzer='word',
                            stop_words=sw,
                            token_pattern=r'(?u)\b\w\w+\b',
                            ngram_range=(1,3),
                            max_df=.7,
                            min_df=5)

nlm_train_x01_mtx = nlm_tfidf.fit_transform(nlm_train_x01)
nlm_test_x01_mtx = nlm_tfidf.transform(nlm_test_x01)

display(nlm_train_x01_mtx)
display(nlm_test_x01_mtx)
```

Class Assignment

Figure 9.

- ✓ Fox News
- ✓ Breitbart

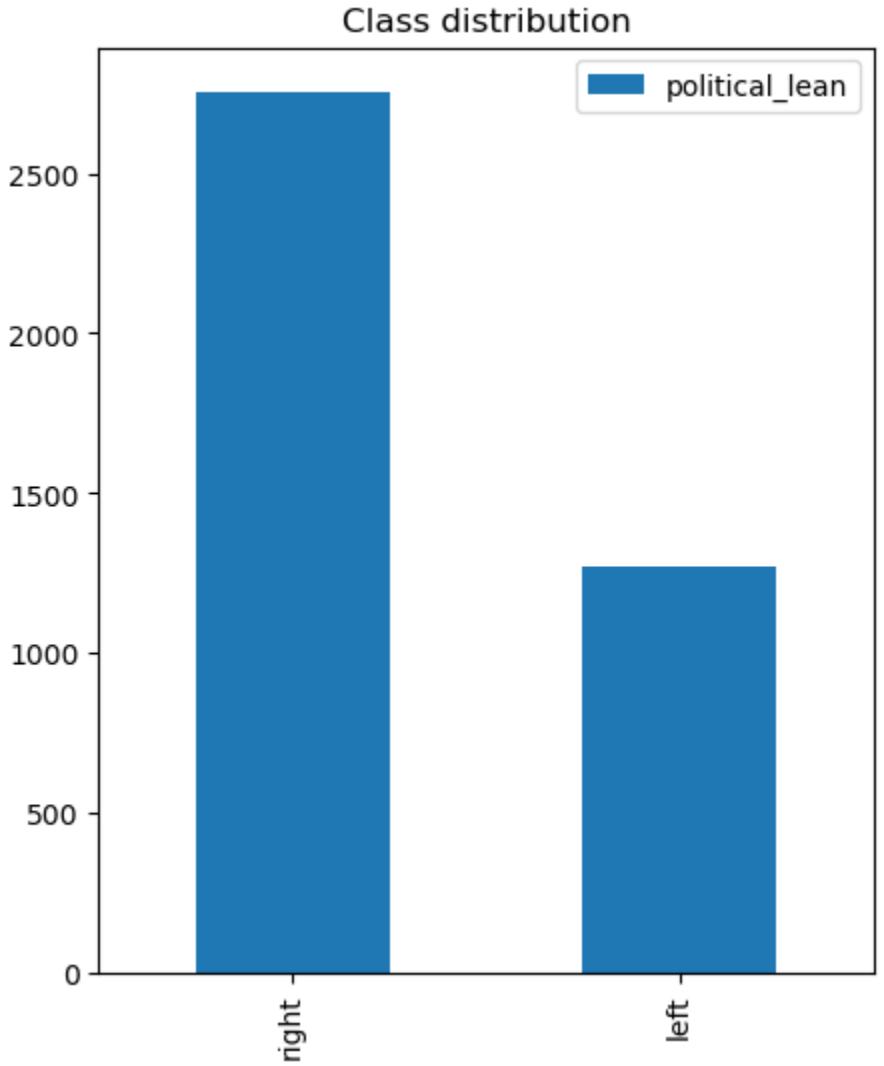
Label: right

- ✓ CNN
- ✓ Washington Post

Label: left

Class Distribution

Figure 10.



Modeling Approach

Two-fold aim

1. Develop binary text classification model

2. Use the model with highest performance (F_1 score) to predict lean distribution of client articles

Class (y) = 'left' or 'right'

Predicted Lean = ratio of 'left' / 'right'

ML Algorithms Implemented

Table 1.

Baseline Model

Classifier	Type	Key Hyperparameters	Training F_1
Nearest Centroid	Distance-base	metric = "euclidean"	0.76

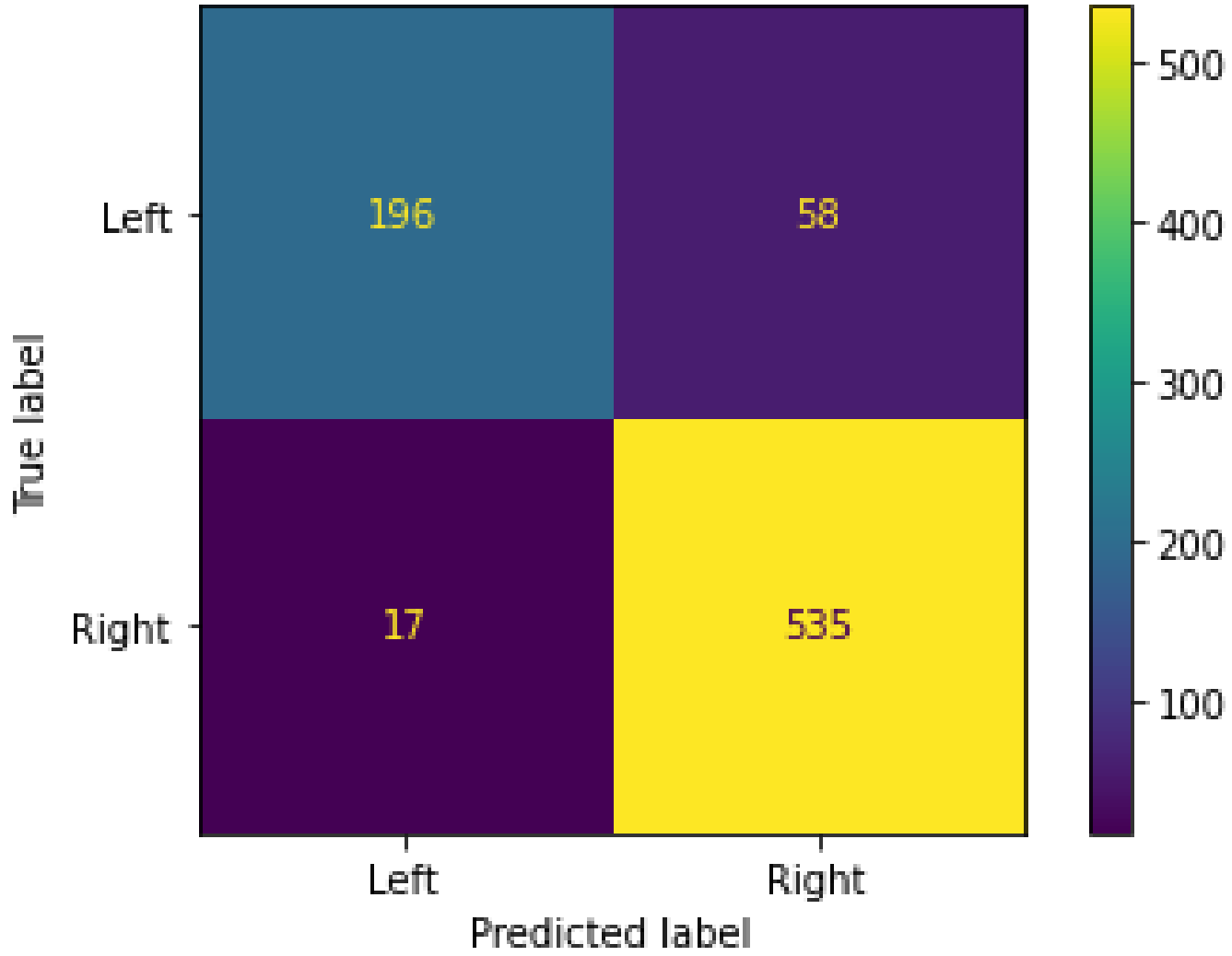
Tuned Models

Classifier	Type	Key Hyperparameters	Training F_1
Support Vector Classifier	Linear*, Discriminant	C: [0.1, 1, 6, 6.5, 8] penalty: ['l1', 'l2'] tol: [1e-7, 1e-5, 1e-4, 1e-3, 01e-2]	1.00***
Gradient Boosted Trees	Ensemble Decision Trees	loss: ['log_loss', 'exponential'] learning_rate: (1e-3, 1e3)** n_estimators: (1e2, 1e3)** min_samples_split: (.01, .95)** max_depth: (1, 20)** max_features: ['sqrt', 'log2', None]	1.00***

* Based on selected hyperparameter
** Selection using log-uniform distribution
*** Strongly indicates overfitting

Linear Support Vector Test Results

Figure 11.



Tuned Models' Performance Metrics

Figure 12a.

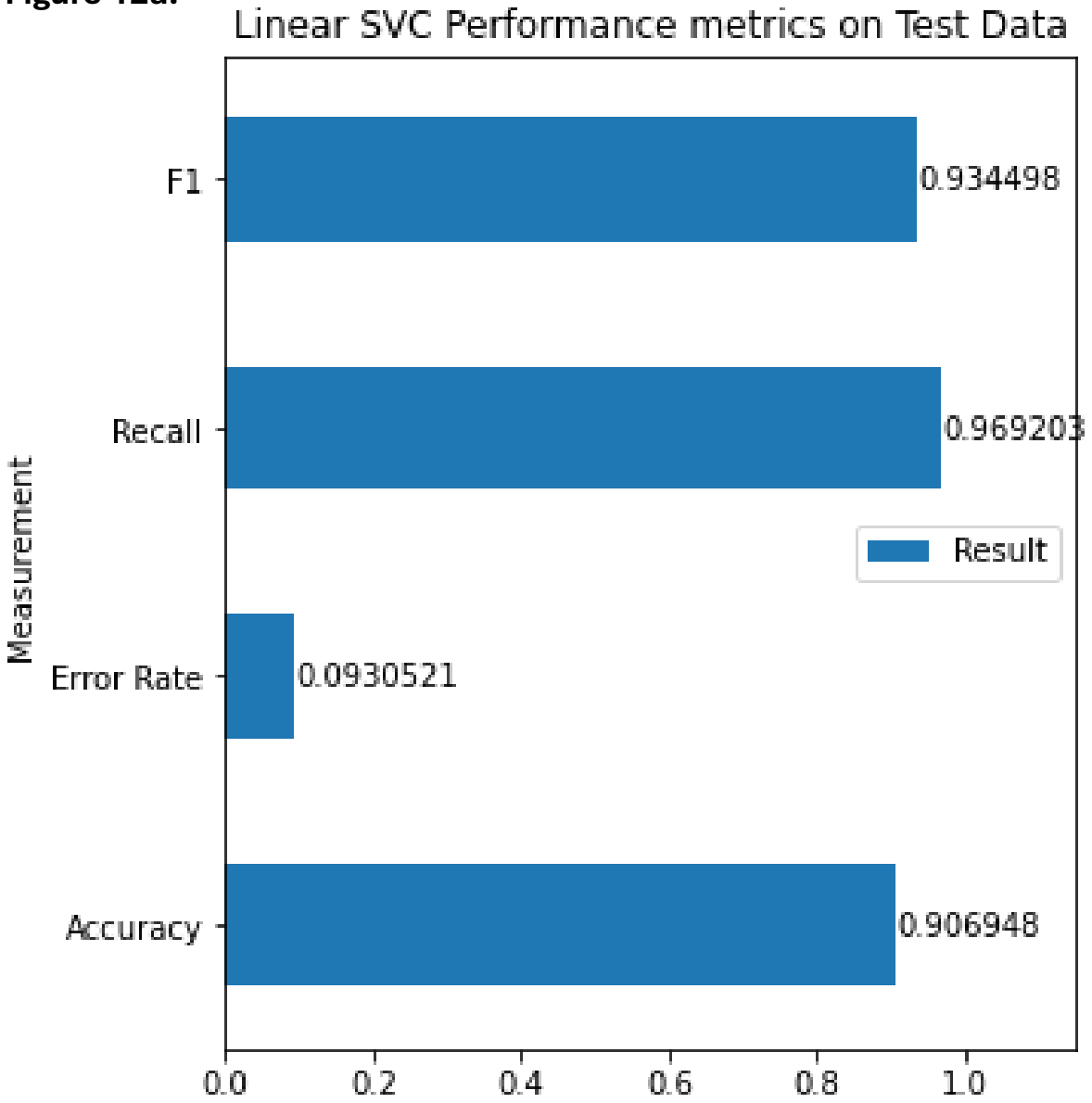
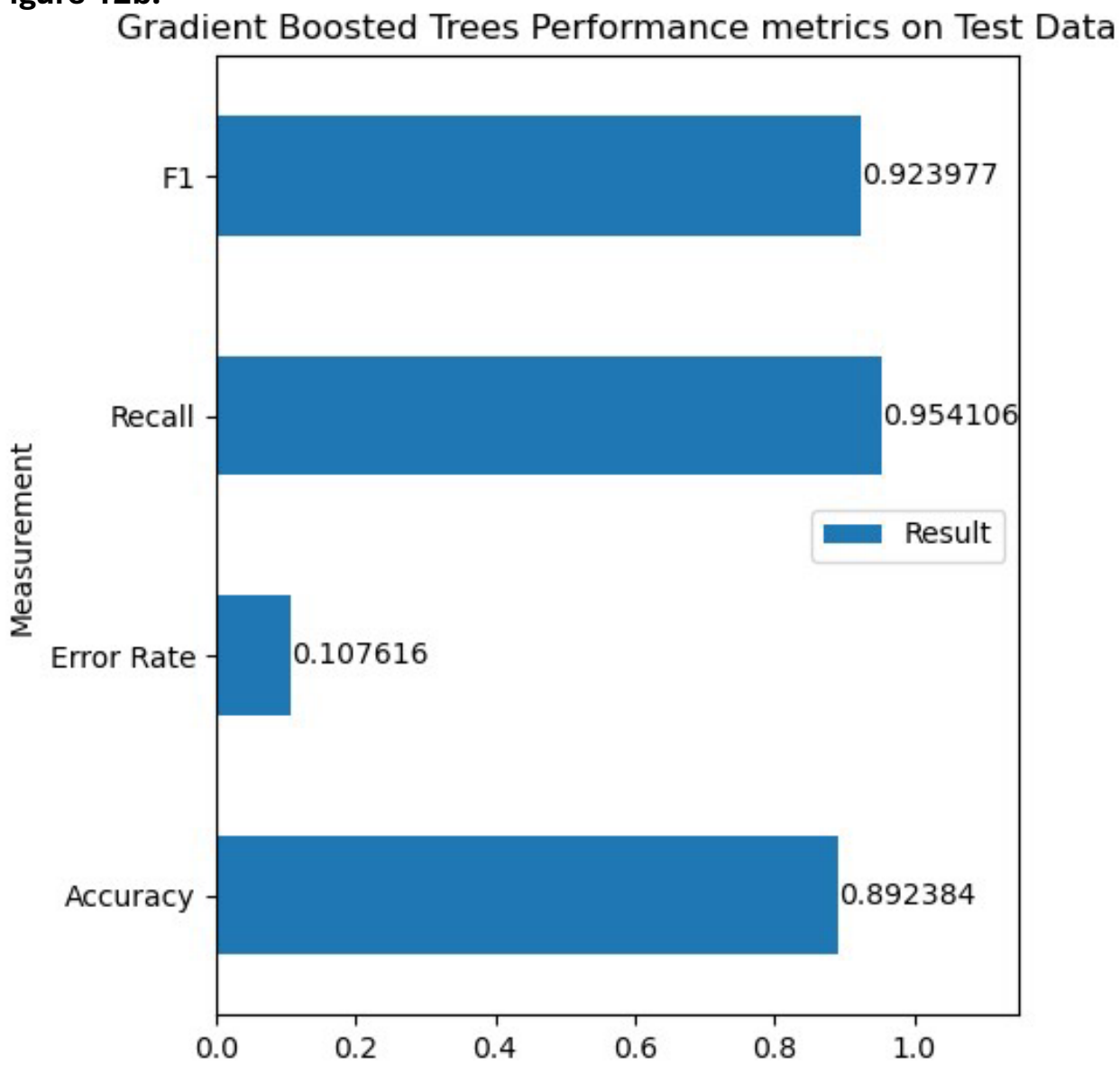
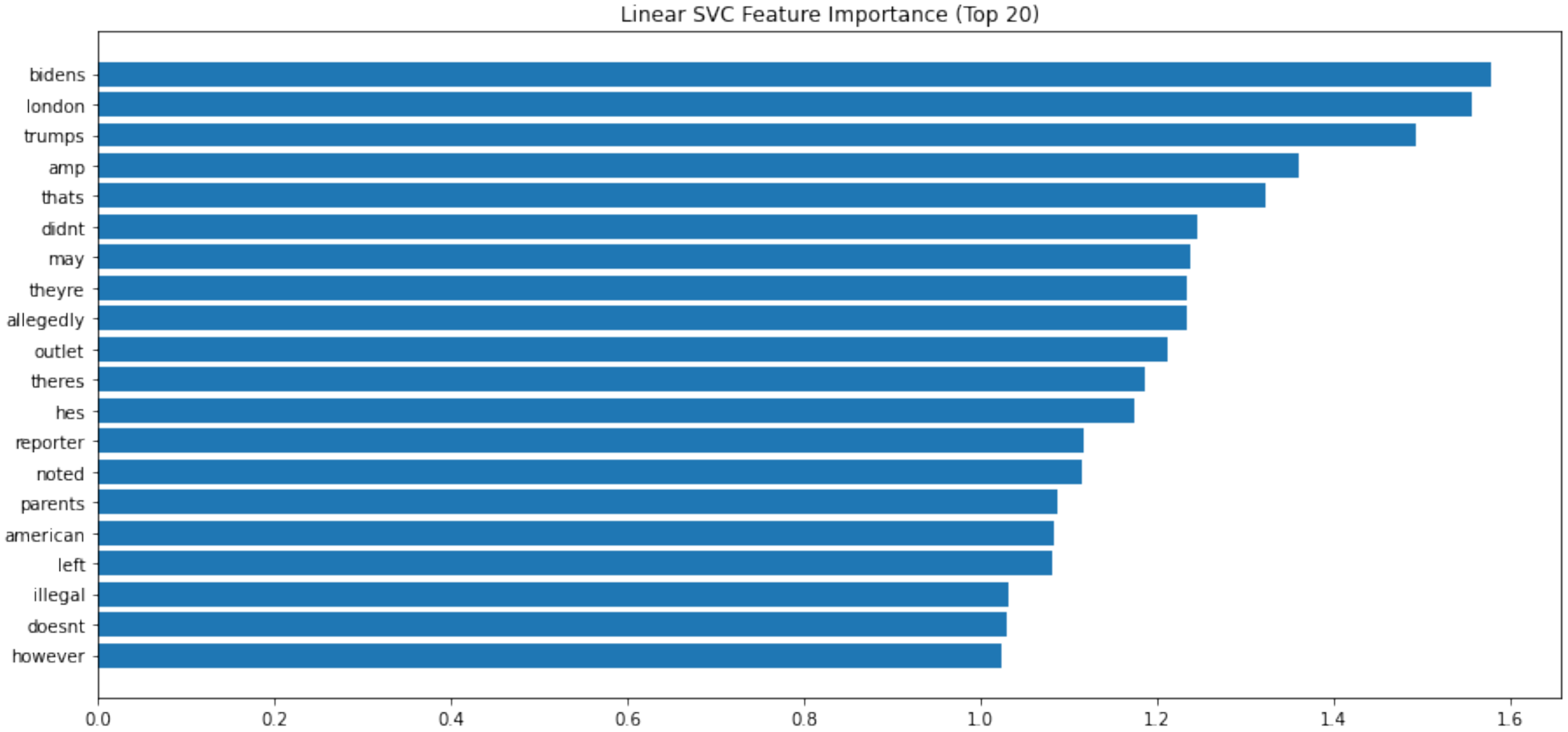


Figure 12b.



Variable Importance

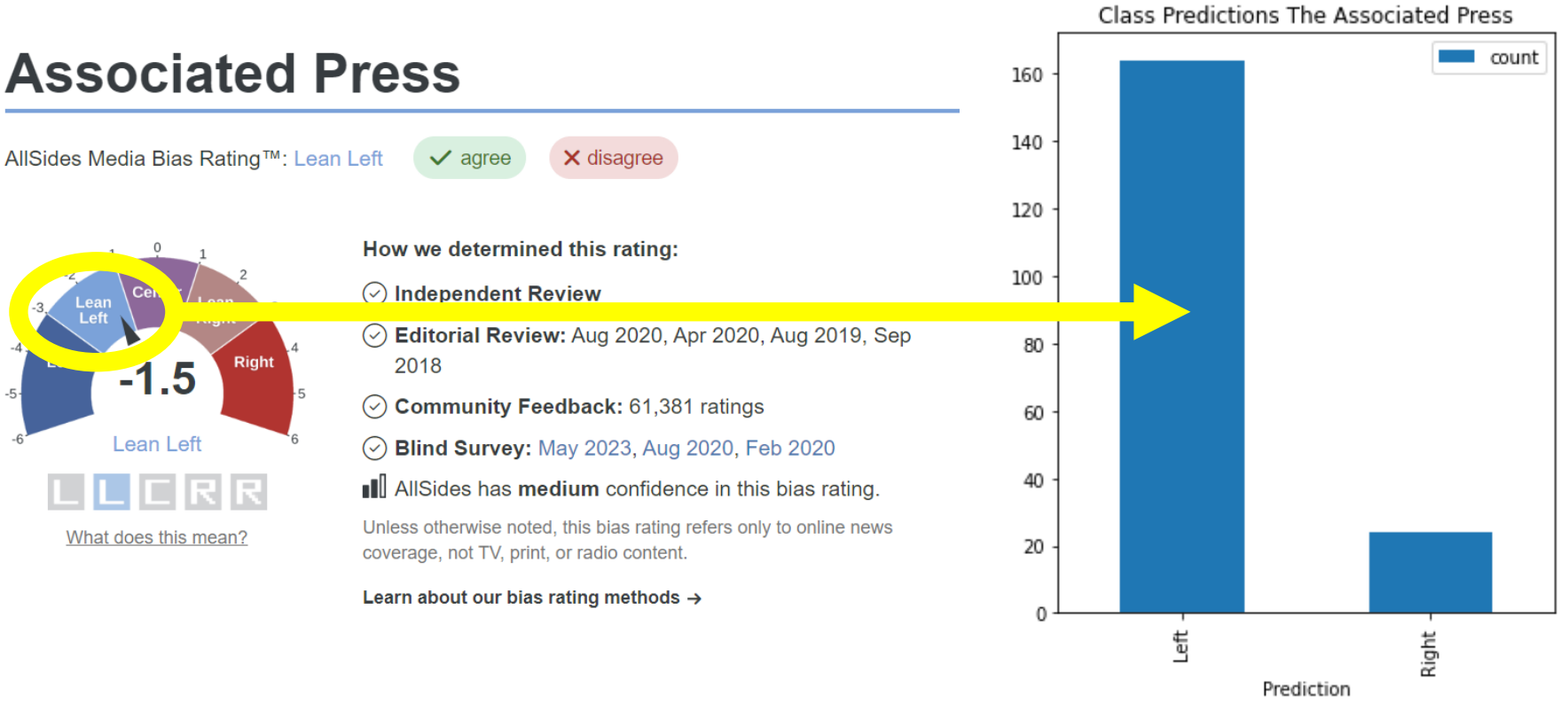
Figure 13.

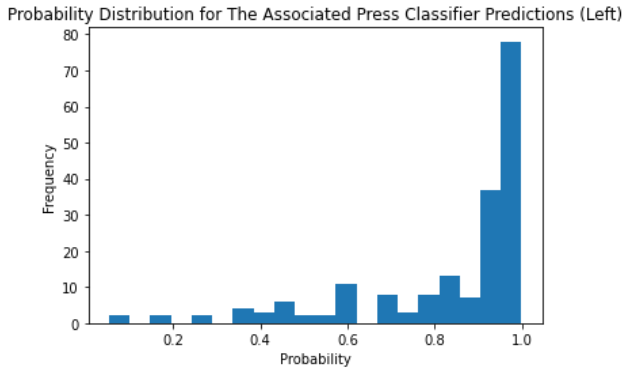


Do results from unseen news sources correlate with AllSides ratings?

Figure 14.

Independent News Bias Rating → **Classified** → **. . . with confidence,**
confirming it's finding
a "left" pattern

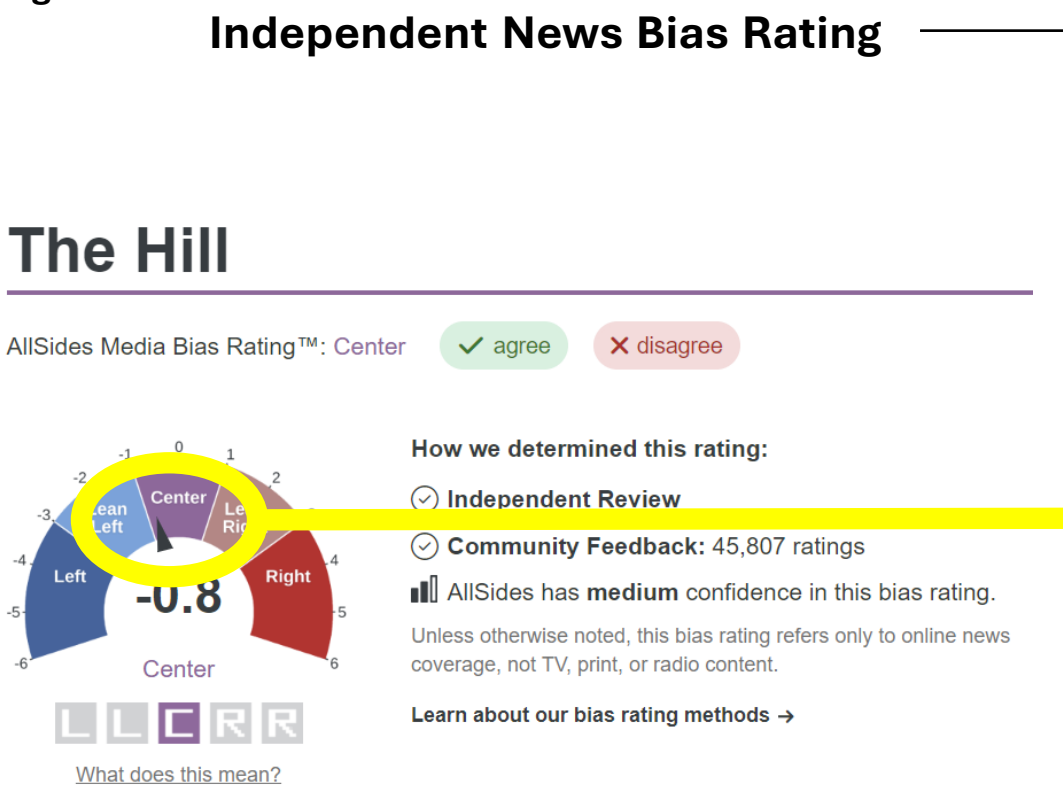


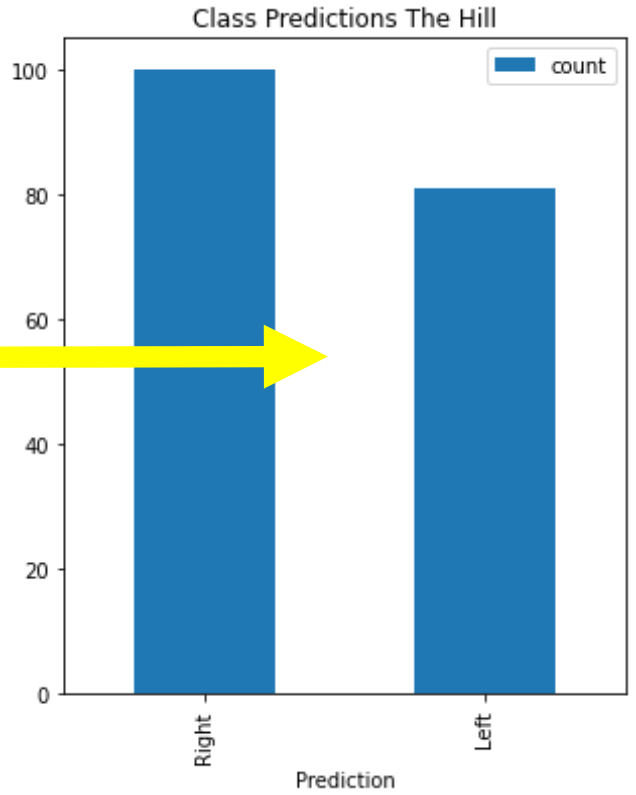


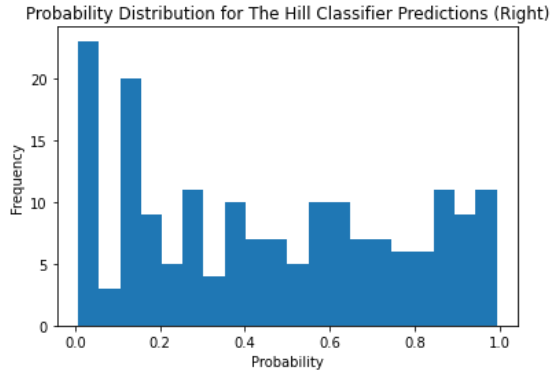
. . . and a more challenging “centrist” example

Figure 15.

Independent News Bias Rating → **Classified** → **. . . not as confidently**
left or right,
reflecting “centricity”





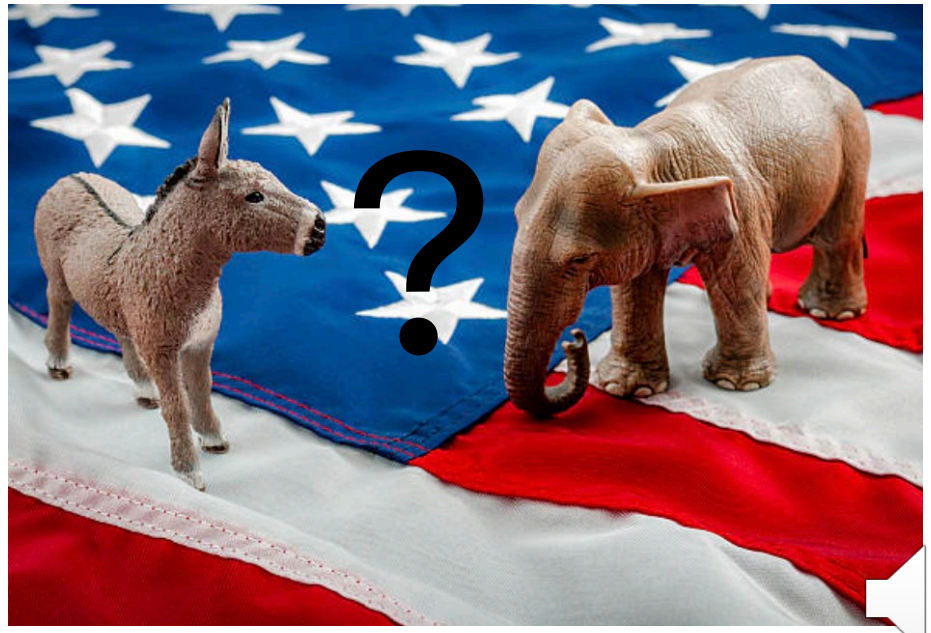


Conclusion

News consumers and advertisers ***highly interested*** **in news bias**

Project demonstrated *effective* left/right/center ***classification*** vs. independent bias ratings

. . . and highlighted opportunities with advanced NLP capabilities



Opportunities

Expand classifier training data, both source and time window

Consider lemmatization to limit noise and improve performance

Pursue **transformers**, including newer pre-training models and corpora, for deeper bias understanding

Thank you!

References

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