Is it all fake?
Fake News Detection

Gopalika Sharma and Surya Menon

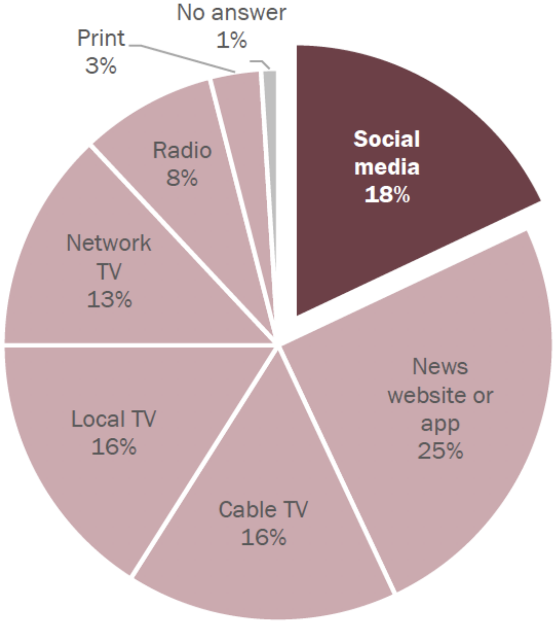
Background

- The prevalence of fake news has been exacerbated by **social media**
  - More news sources than ever before
  - Confirmation bias
- Far-reaching consequences in society
  - Dissemination of propaganda
  - Undermining democratic institutions
  - Erosion of trust

Pew Research Center 2019 Survey

About one-in-five U.S. adults say they get their political news primarily through social media

% of U.S. adults who say the most common way they get political and election news is ...



Source: Survey of U.S. adults conducted Oct. 29-Nov. 11, 2019.
"Americans Who Mainly Get Their News on Social Media Are Less Engaged, Less Knowledgeable"

PEW RESEARCH CENTER

Problem Statement

Improve how individuals engage with news stories:

- Identify general strategies to evaluate article authenticity
- Detect fake news articles using ML and NLP methods
  - Topic-specific models

Datasets:

- IEEE Fake News Inference Dataset (FNID)
- Combined Topics Dataset
  - FakeNewsNet (PolitiFact, GossipCop), COVID-19, Disasters

FNID Dataset

Feature	Description	Type
Date	Article Date	Interval
Speaker	Person/organization to whom text relates	Nominal
Sources	Article publication	Nominal
Article Text	Article raw text	Nominal
Fake News Class (label_fnn)	Real or Fake	Nominal

N = 17326

Sample Text Snippet

```
'With all eyes on Iowa for the Republican caucuses in the first
days of 2012, the Democratic contender for president reminded w
atchers of his own Iowa win — and what he has done to keep his
campaign promises.\nObama for America bought banner ads across
the home page of the online Des Moines Register on Jan. 3, 201
2, with a link to highlights from Obama\'s 2008 victory speech
.\nMusic plays as candidate Barack Obama promises action on hea
lth care, taxes, energy independence and the war in Iraq. Betwe
en clips, white text across the screen highlights President Oba
ma\'s policy accomplishments.\nFor example, after candidate Oba
ma declares, "I\'ll be a president who harnesses the ingenuity
of farmers and scientists and entrepreneurs to free this nation
from the tyranny of oil once and for all!" the next three scree
ns show an image of him driving a car and the words: "Put in pl
ace historic fuel efficiency standards for cars and trucks to l
ower costs at the pump and reduce dependence on foreign oil."\n
We wondered, did Obama do that?\nNew standards\nObama has annou
nced new fuel economy standards — more than once — taking part
in the bipartisan practice of updating rules in place since the
1970s Arab oil embargo .\nThe most recent update, announced in
July 2011, covers cars and light trucks made from 2017-2025, re
quiring an average of 54.5 miles per gallon in 2025.\nThe year
before, a new rule required cars and light trucks combined to g
```

Combined Topics Data

Feature	Description	Type
News Topic (ID)	5 values	Nominal
Title	Article title (if provided)	Nominal
Article Text	Article raw text	Nominal
Source	Article publication	Nominal
Fake News Class (target)	Real or Fake	Nominal

N = 29052

Sample Text Snippet

'Buried the hatchet! AnnaLynne McCord spoke to Us Weekly excl usively about what she thinks caused her feud with her costar Shenae Grimes on the set of 90210.McCord recently revealed on The Wendy Williams Show that they didn't get along while film ing The CW reboot, and she told Us ego had a lot to do with i t. "There was just discrepancies, ego, so much ego," she said at the premiere of her movie First We Take Brooklyn on Wednes day, February 7. "When you're that young – Shenae was 18, I w as 20 – we got this crazy show that had so much hype around i t and our egos were out of this world.""When that happens, yo u're kind of thrown into this limelight of Hollywood and earl y success, and all those things and you're dealing with your own demons, which she and I both were, secretly," she continu ed. "Our hidden stories were very much a big part of what cau sed us to be the people that perhaps we were."McCord, 30, rev ealed to Williams on Tuesday, February 6, that after five yea rs of being "at each other's throats," Grimes, 28, called her the day before the show wrapped in 2013. They have since put their differences aside and are friends now. McCord attended Grimes' wedding to model Josh Beech that same year, and the a ctresses even have dinner dates together."Obviously we've tal ked about it a million times now that we're friends. We hang out at the hot tub at her place," she told Us. "Last time I w

Exploratory Data Analysis

Methods

Article Features

- Frequencies/Distributions
  - Article length
  - Title length
  - Year
  - Speaker
- Publication sources
- Changes over time

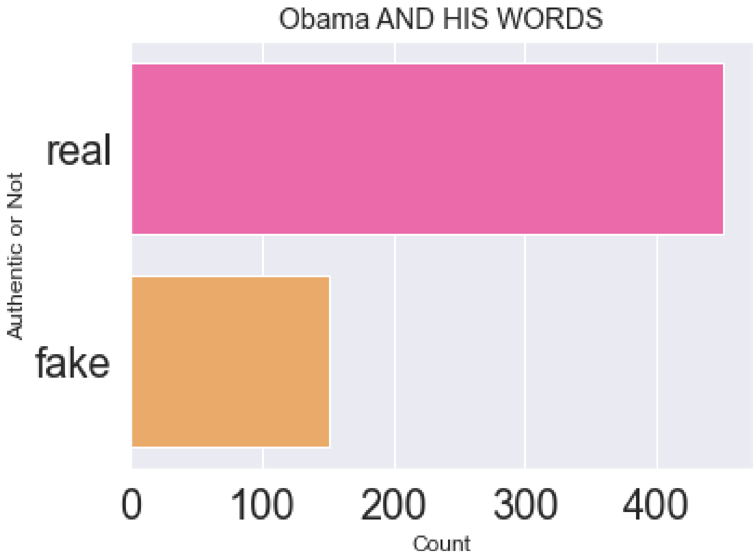
Text Analysis

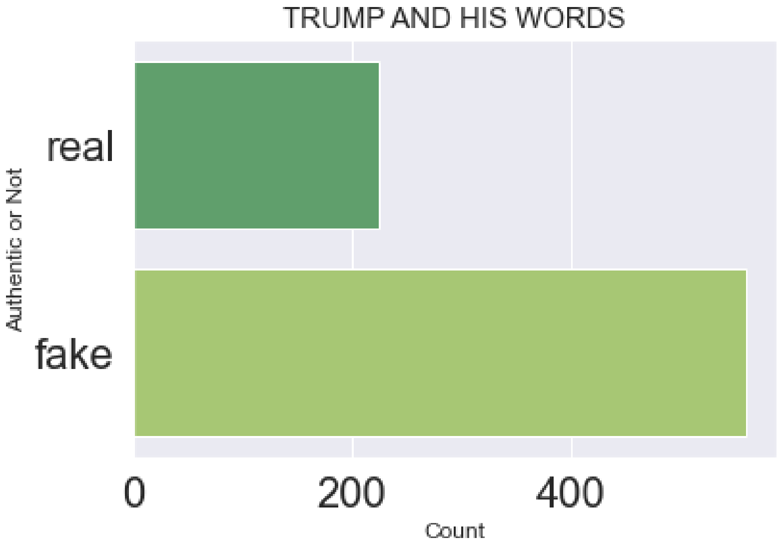
- Word frequency
  - Word clouds
  - N-grams
- Sentiment analysis
- Topic modeling
  - Latent Dirichlet allocation

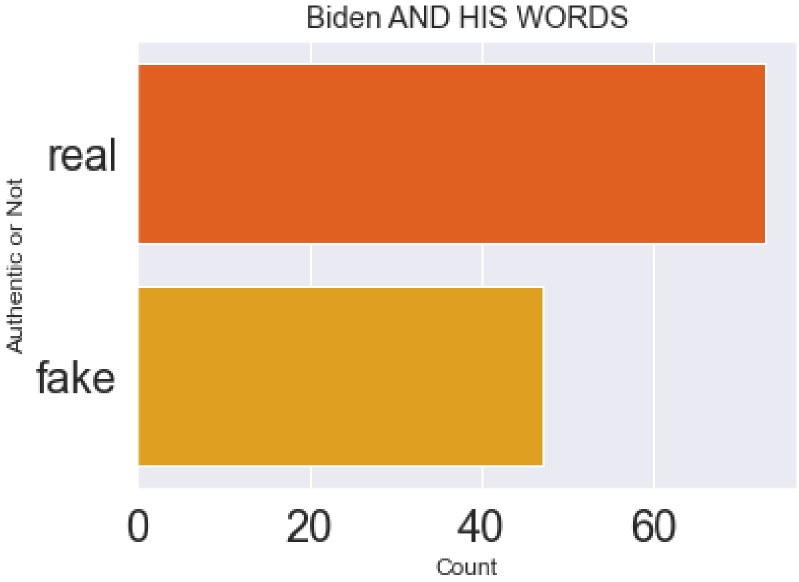
FNID Dataset

The speaker matters

FNID Data

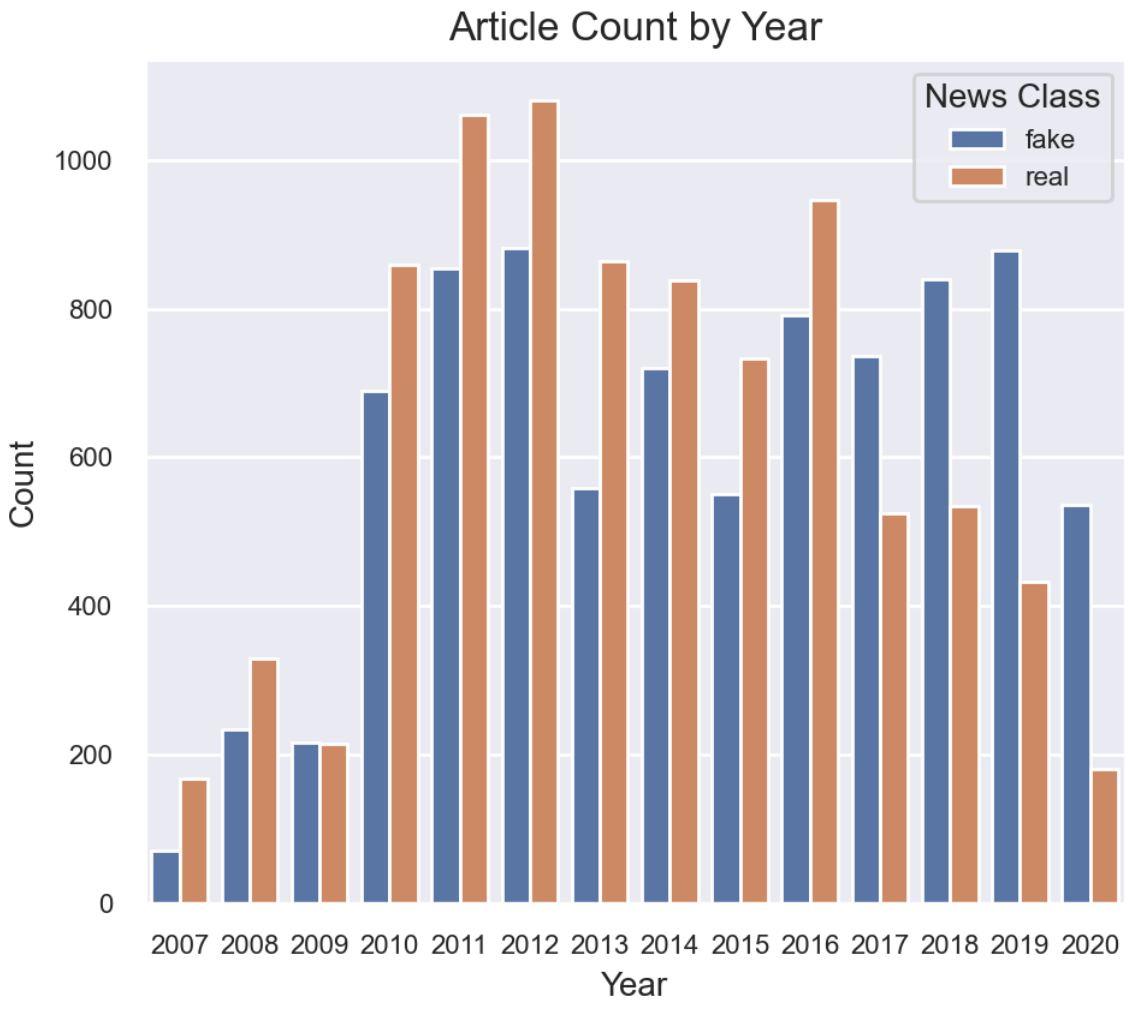


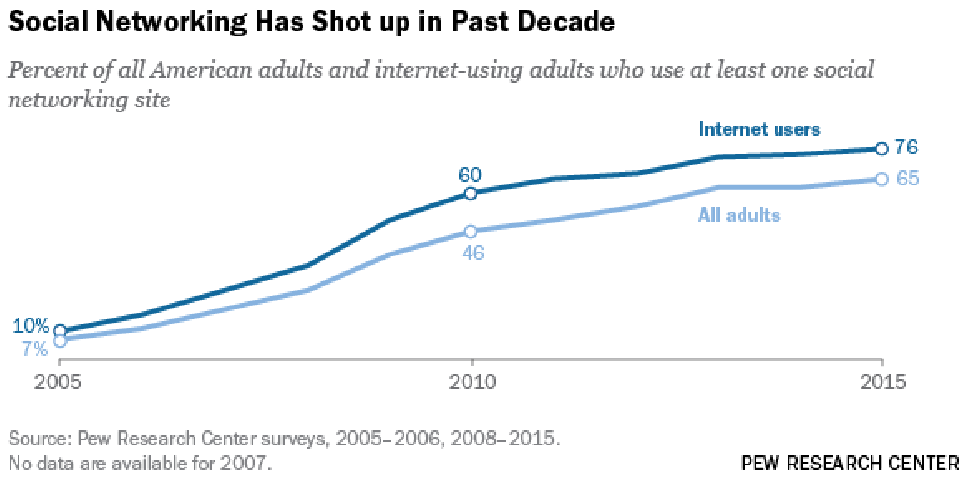




Amount of fake news has risen

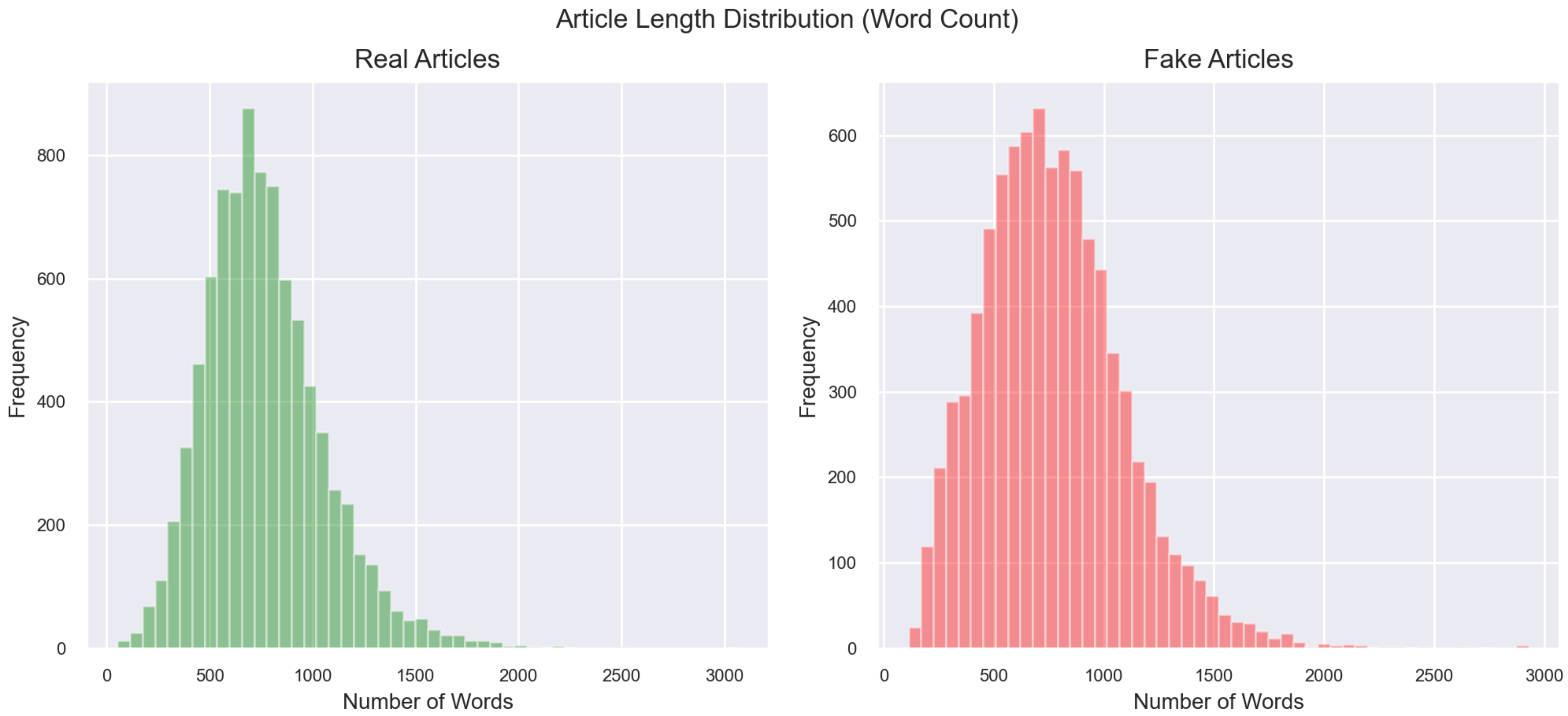
FNID Data





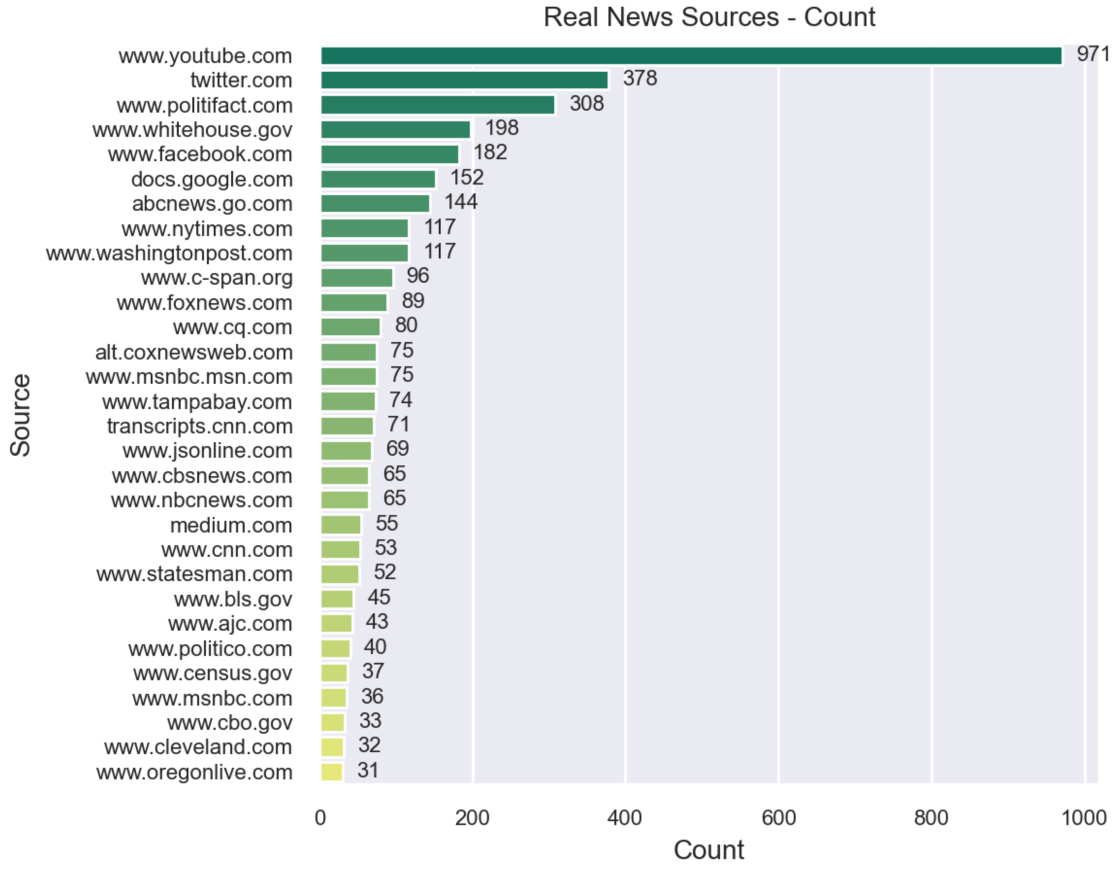
Fake news tends to be longer

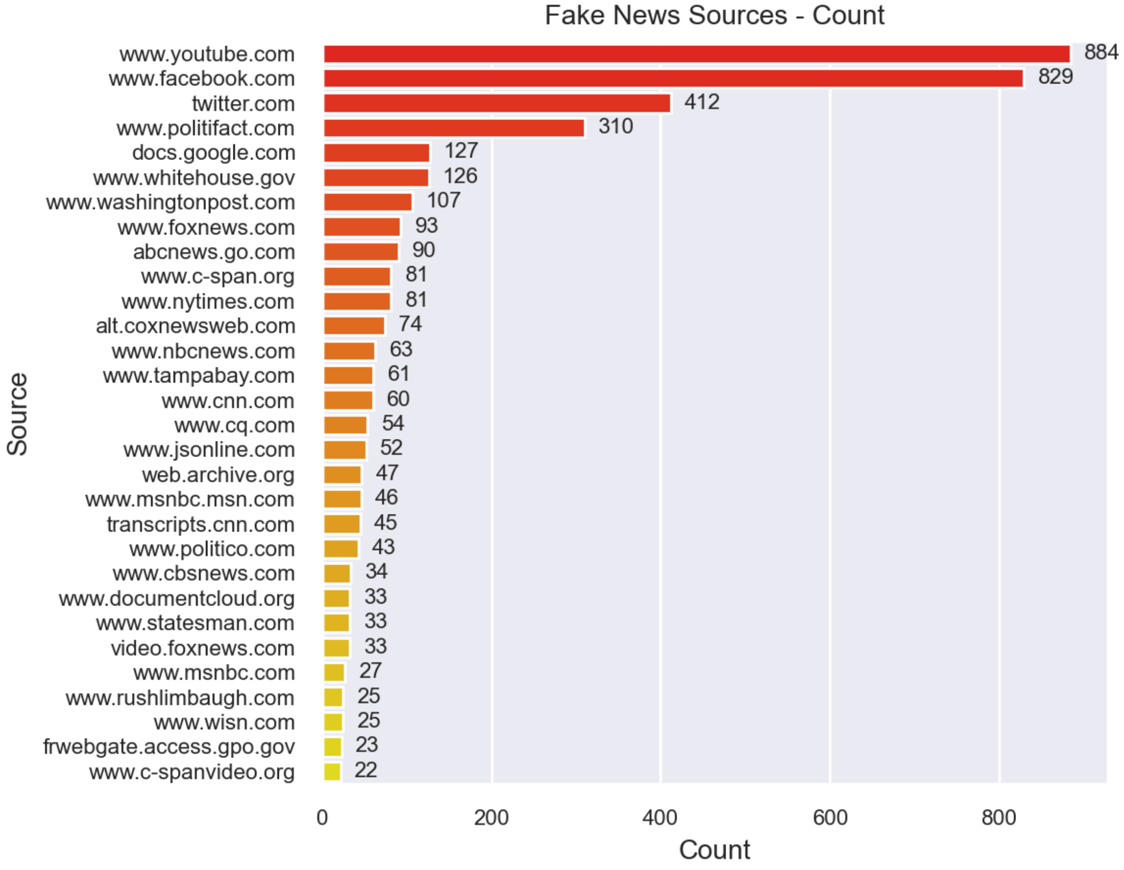
FNID Data



Question your source...

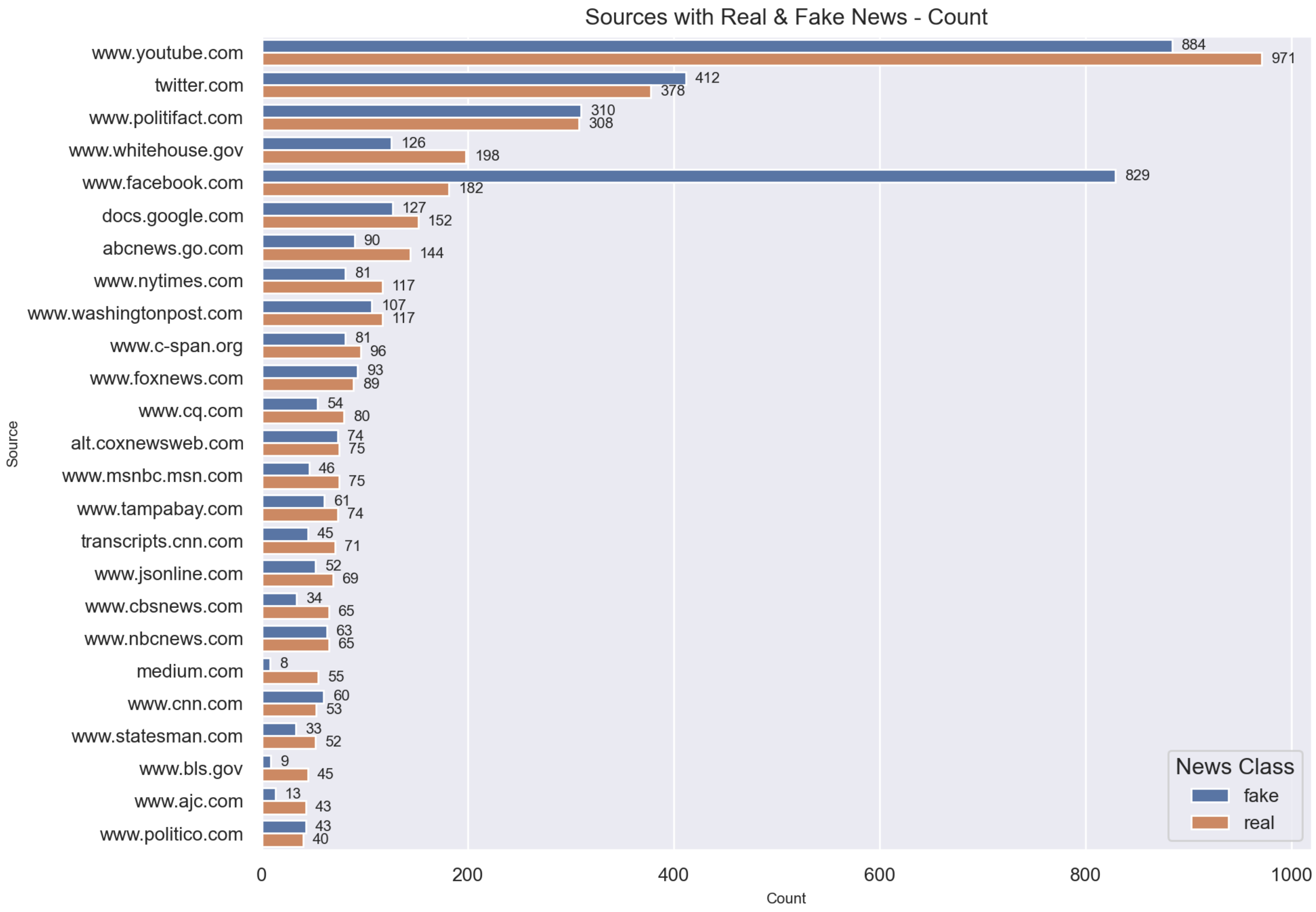
FNID Data





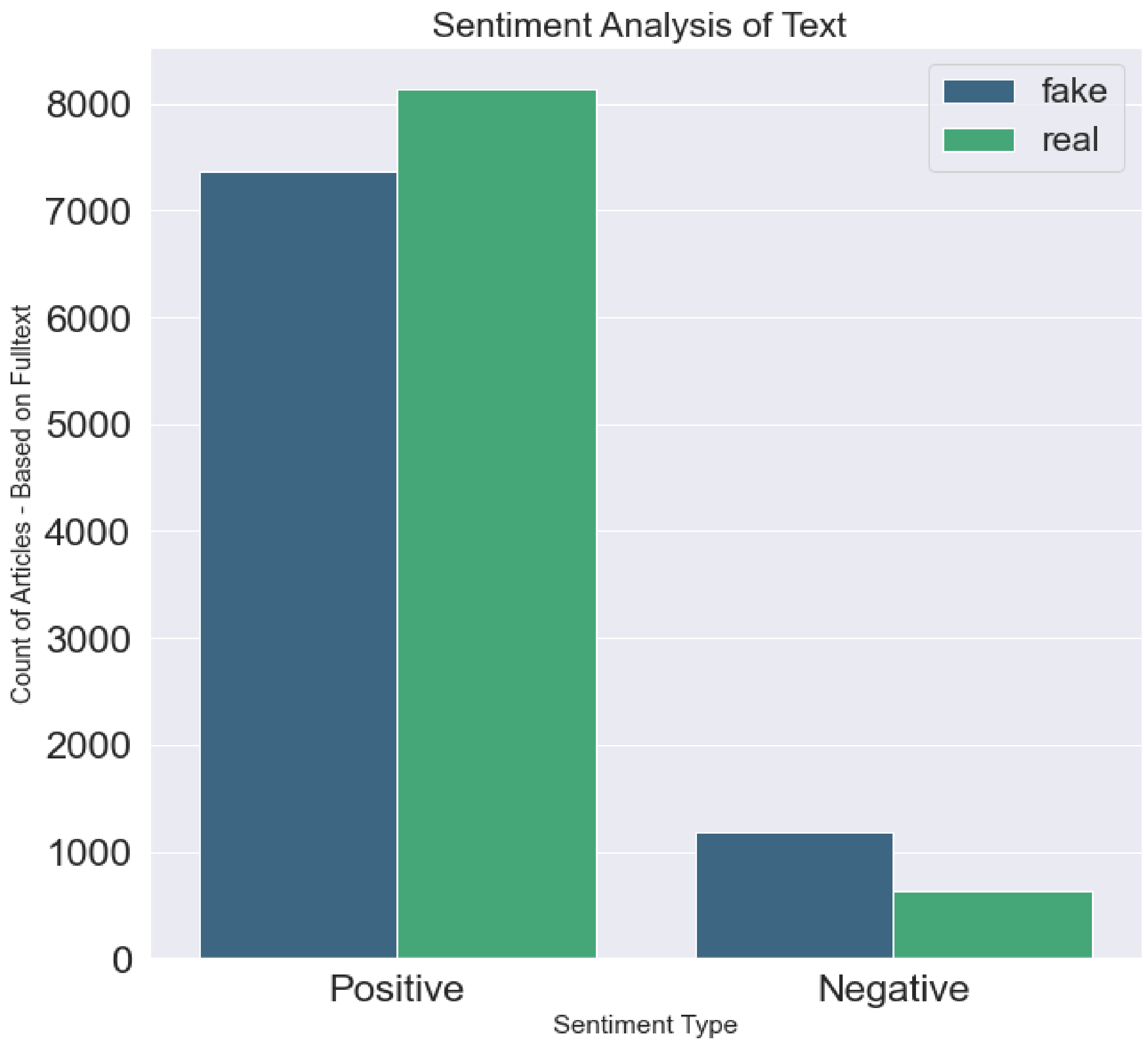
...even the "trusted" ones

FNID Data



Fake news is more negative

FNID Data



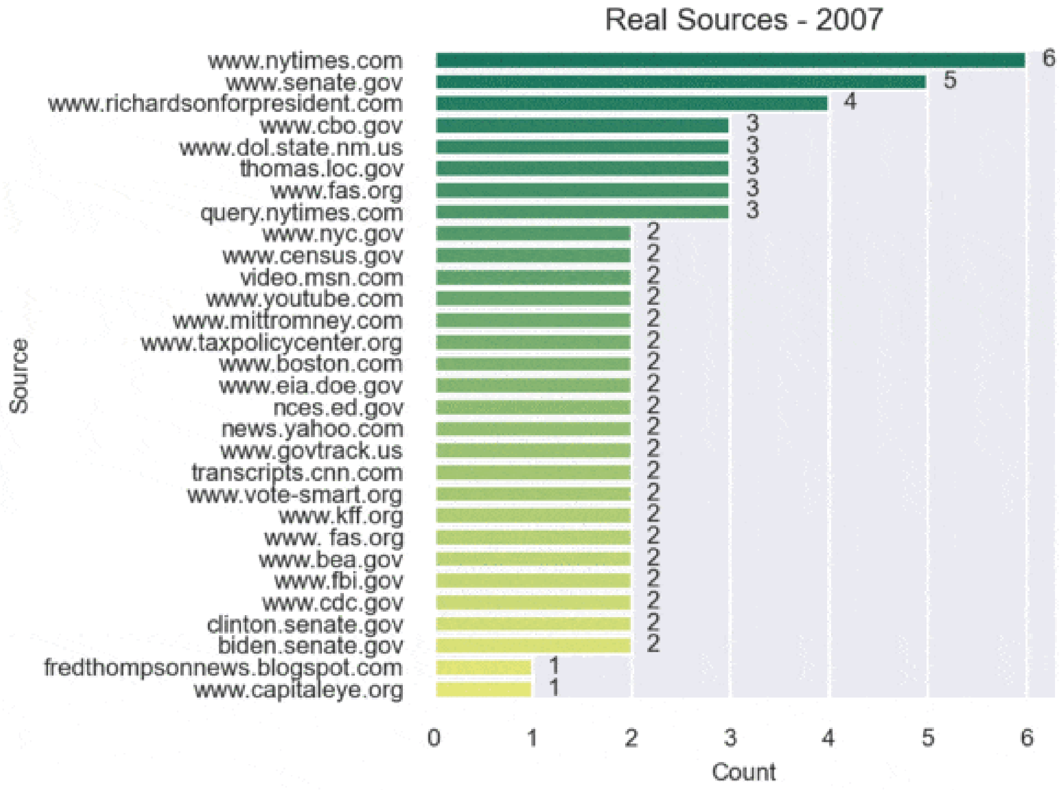
Topic Modeling

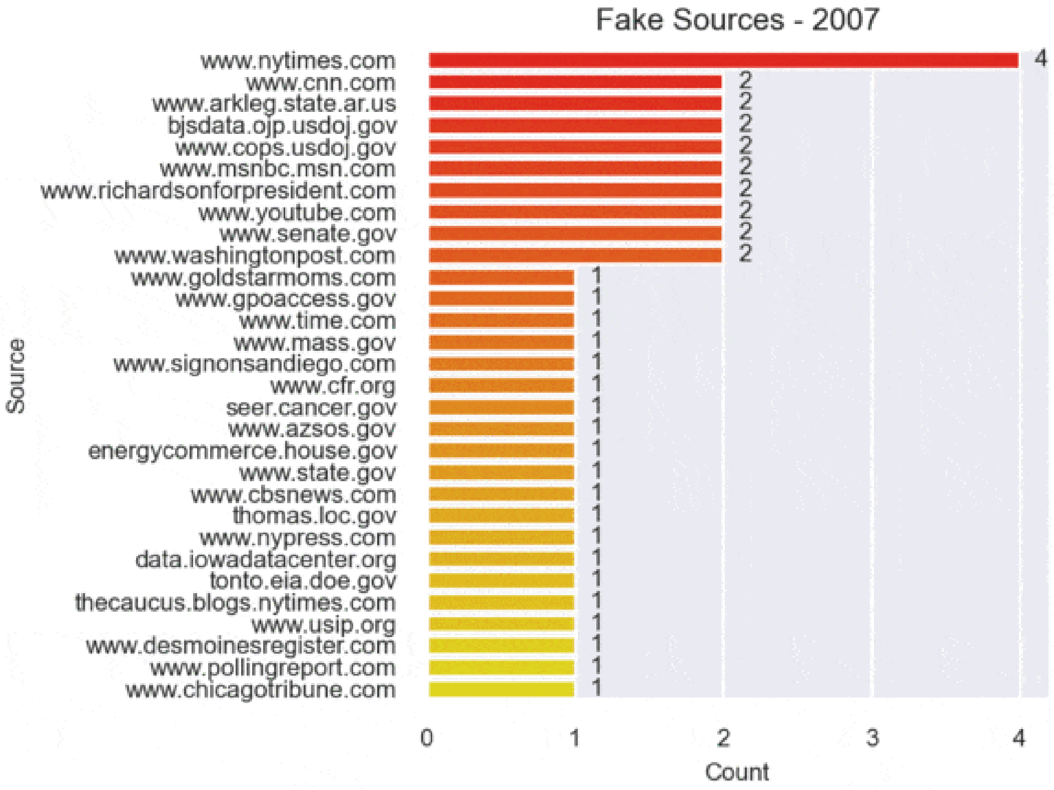
Latent Dirichlet allocation results

- Found distinct sub-topics
- HTML file

FNID Data

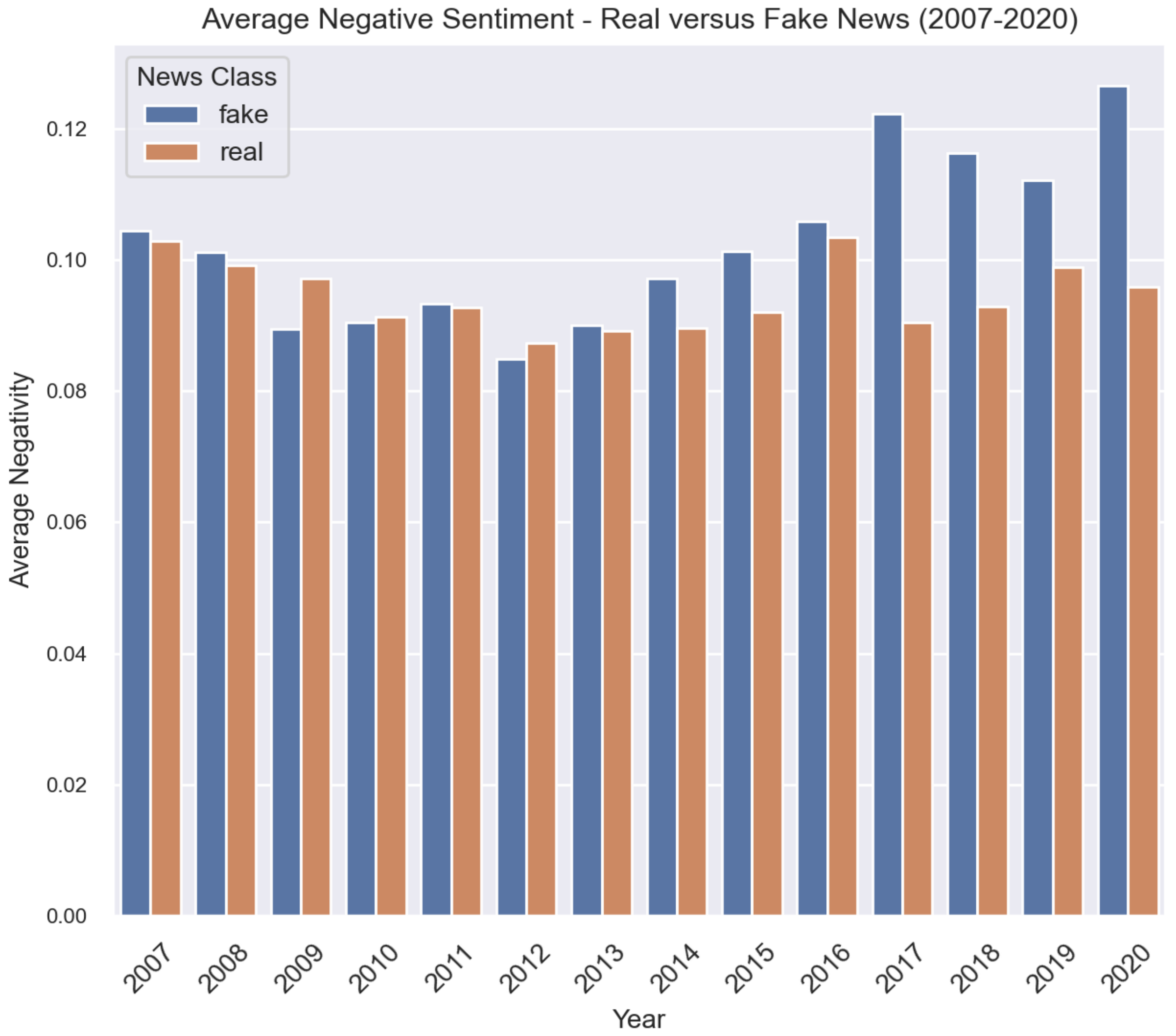
Real and fake sources over time





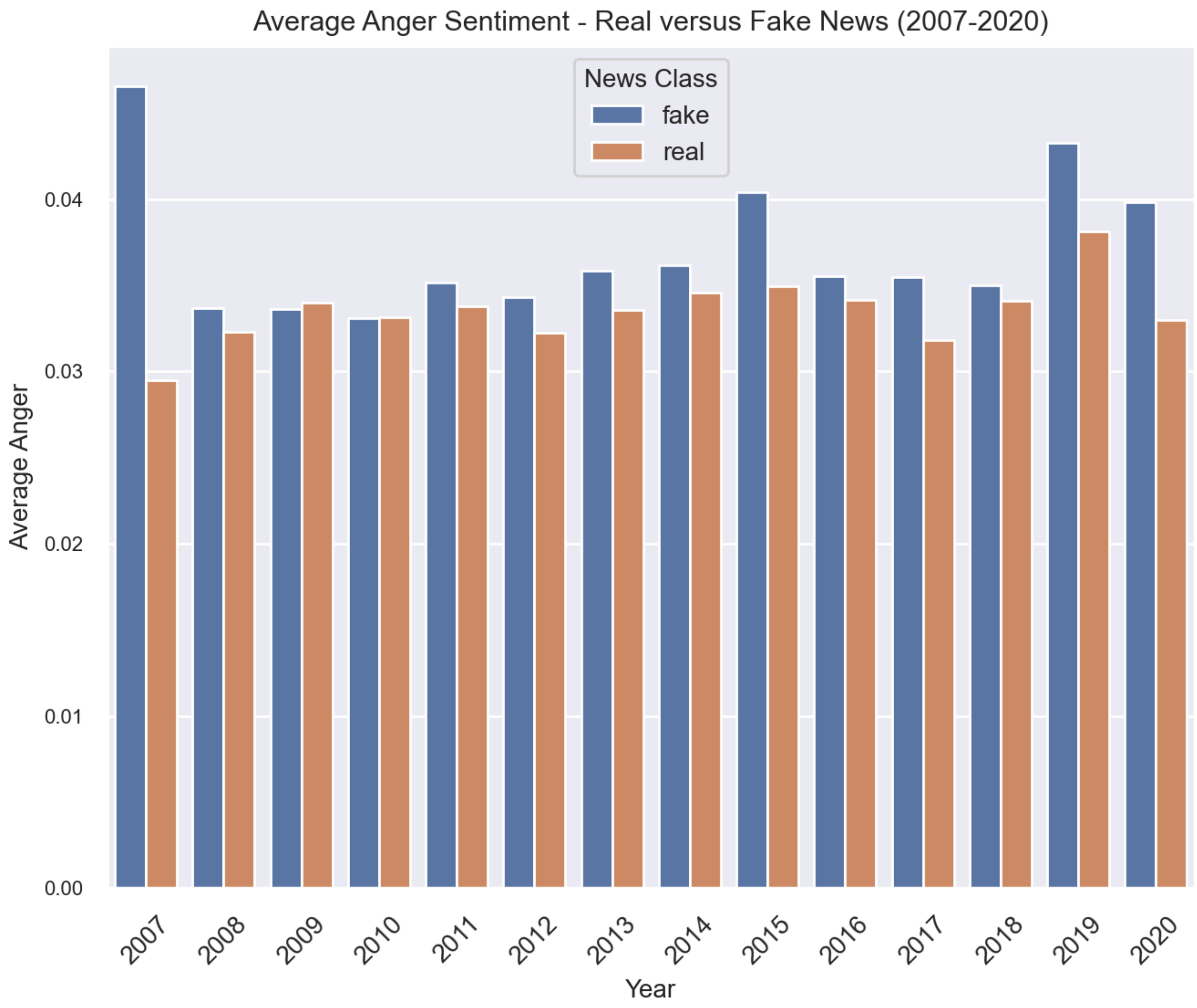
Fake news has become more negative

FNID Data



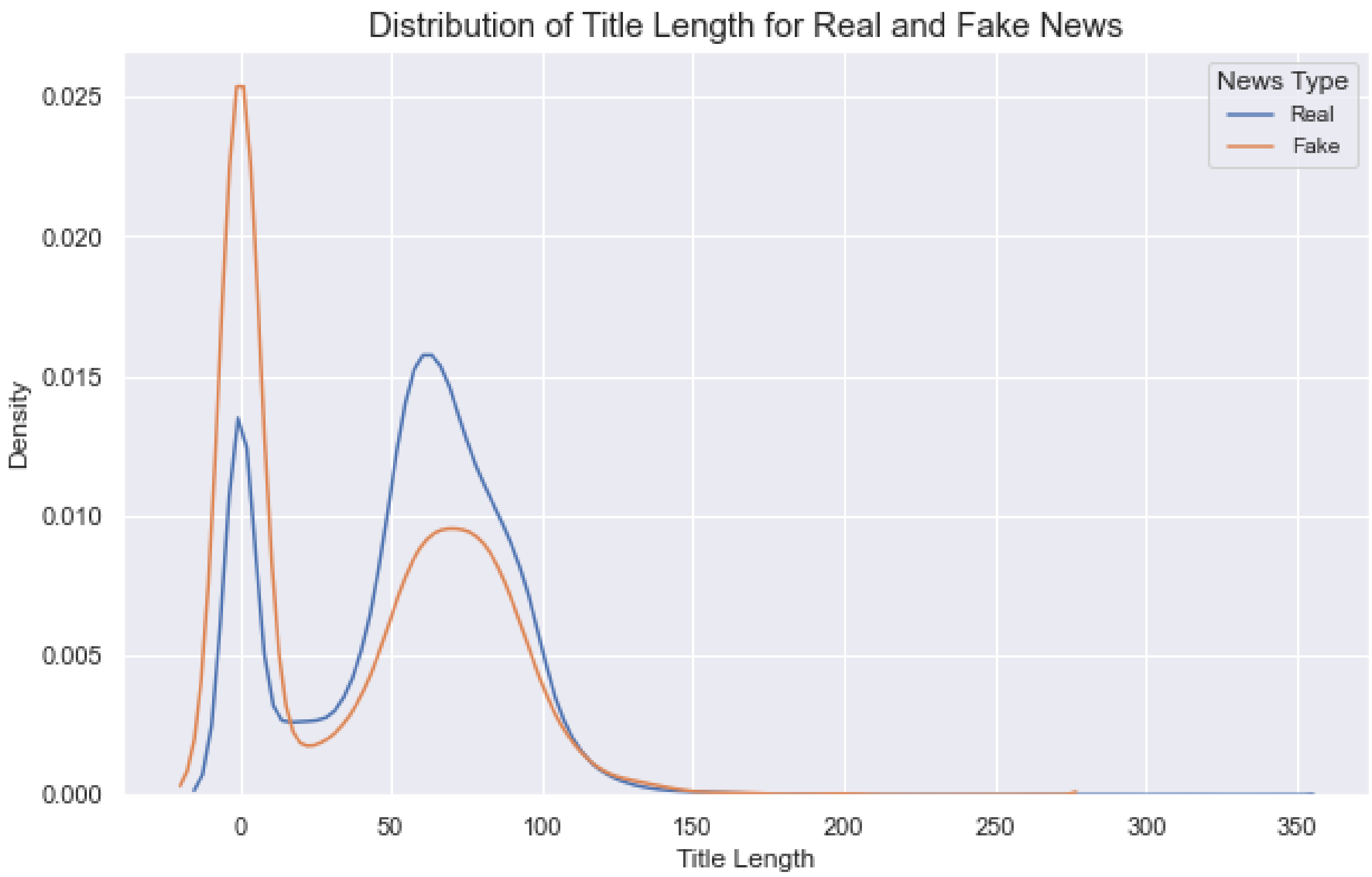
Average anger over time

FNID Data



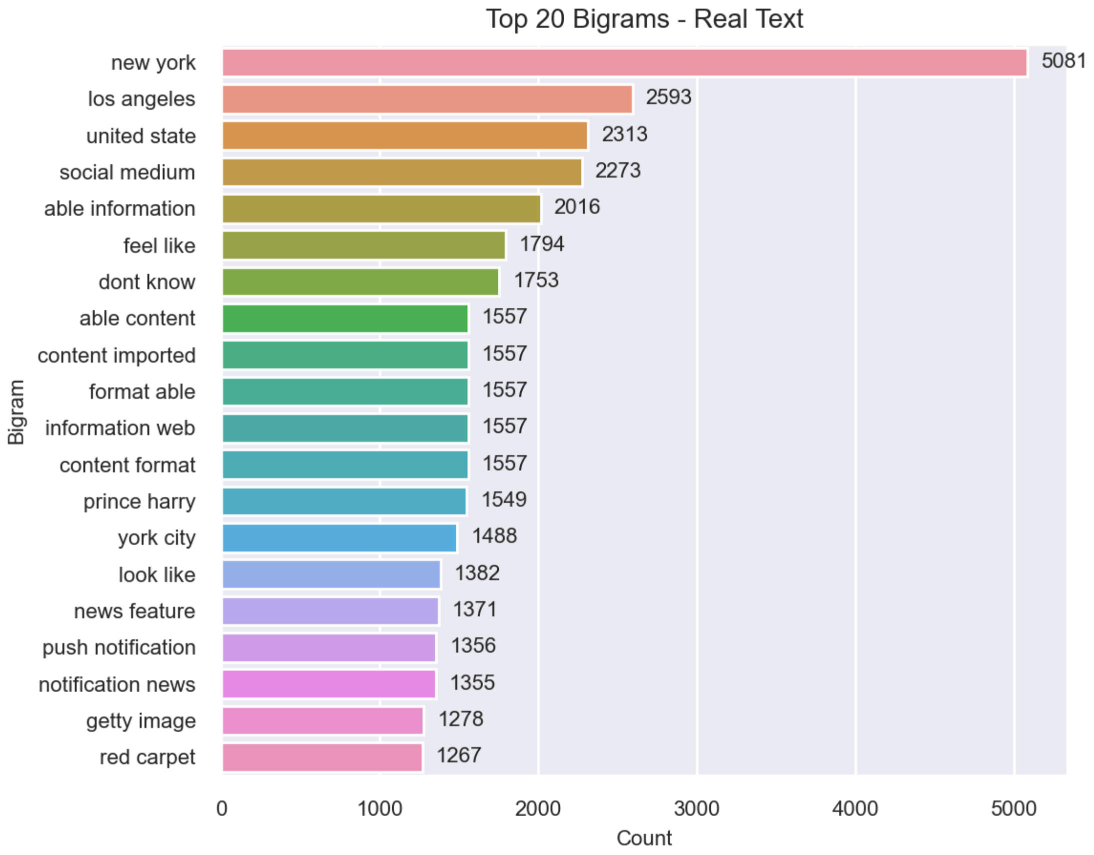
Combined Topics Dataset

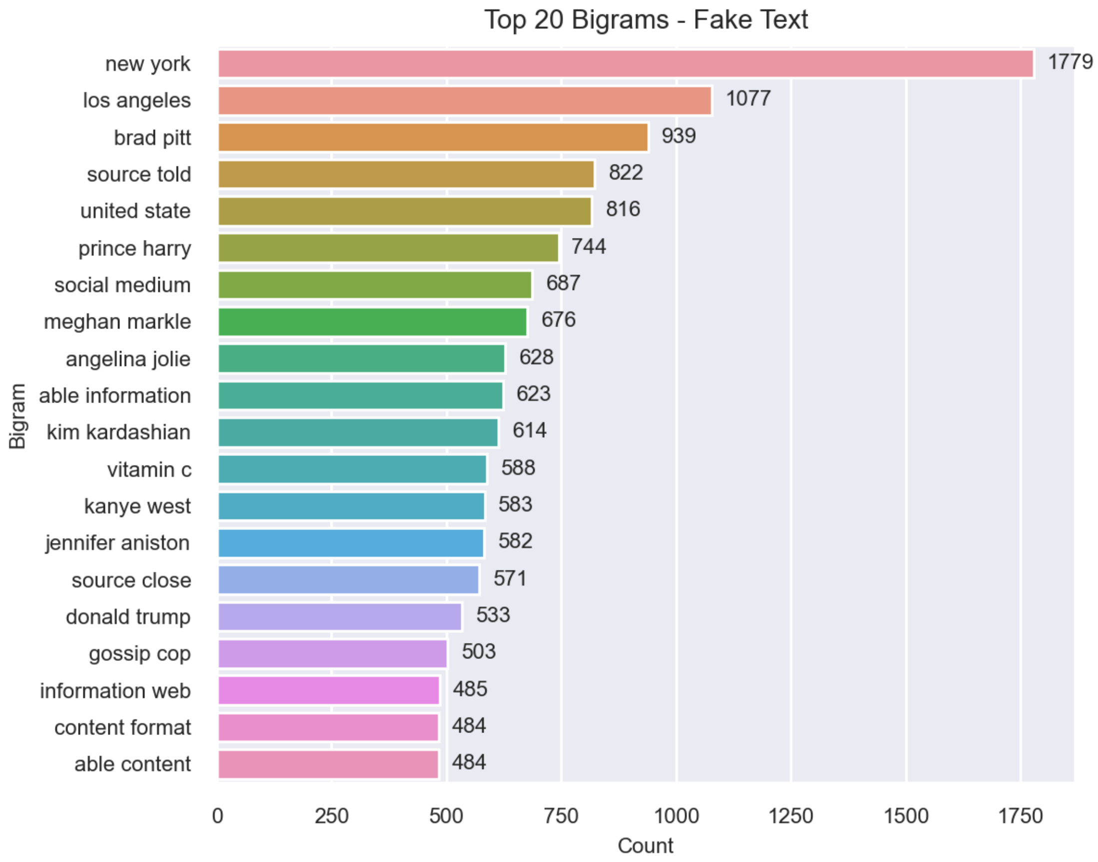
Fake news stories have shorter titles



Fake stories often mention "sources"

Topics Data





Quotation Marks (Proxy for Sources/References)

Article Text

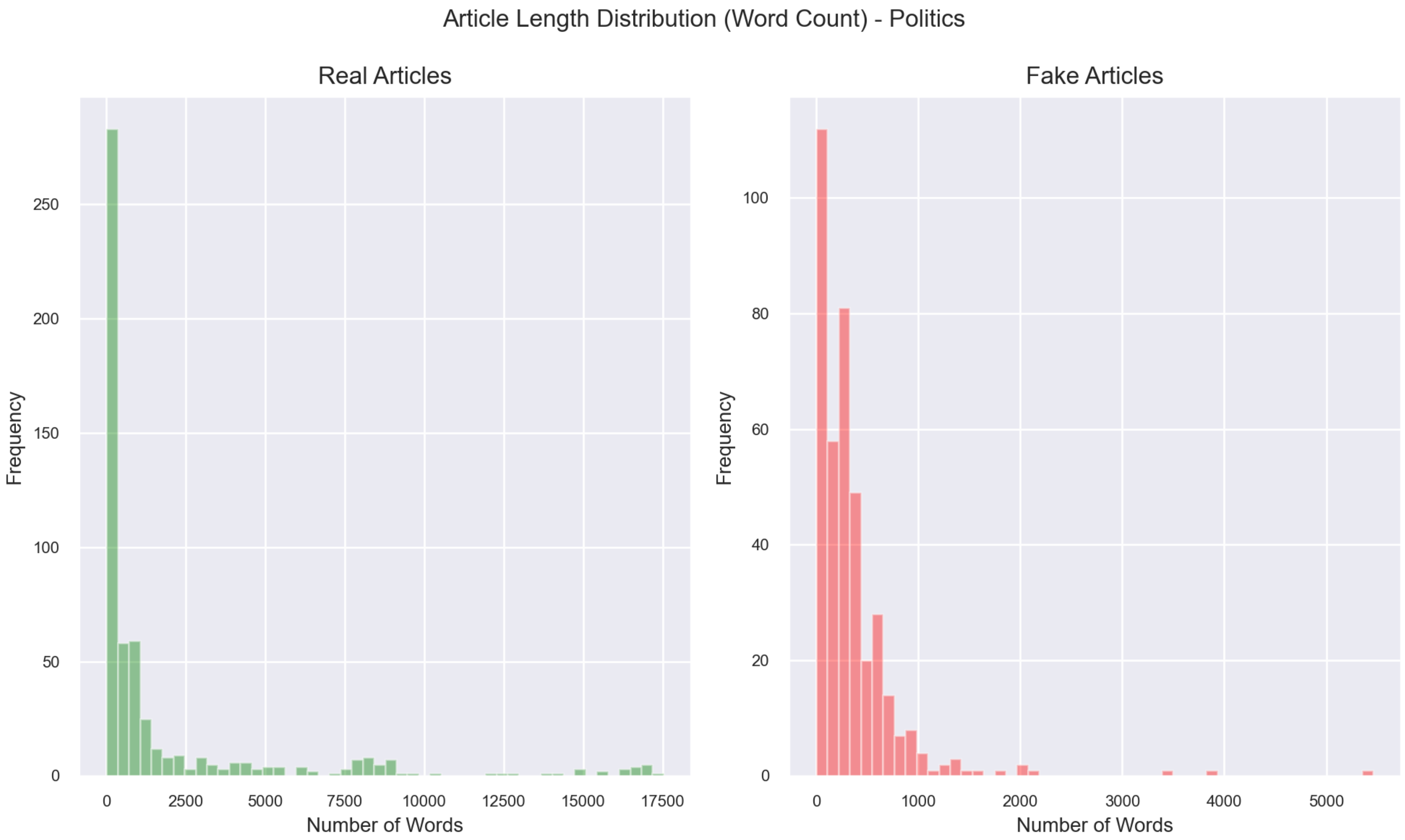
News Type	Total Number of Quotations	Mean Number of Quotations
Real	110613	5.89
Fake	33014	3.20

Article Title Text

News Type	Total Number of Quotations	Mean Number of Quotations
Real	763	0.041
Fake	236	0.023

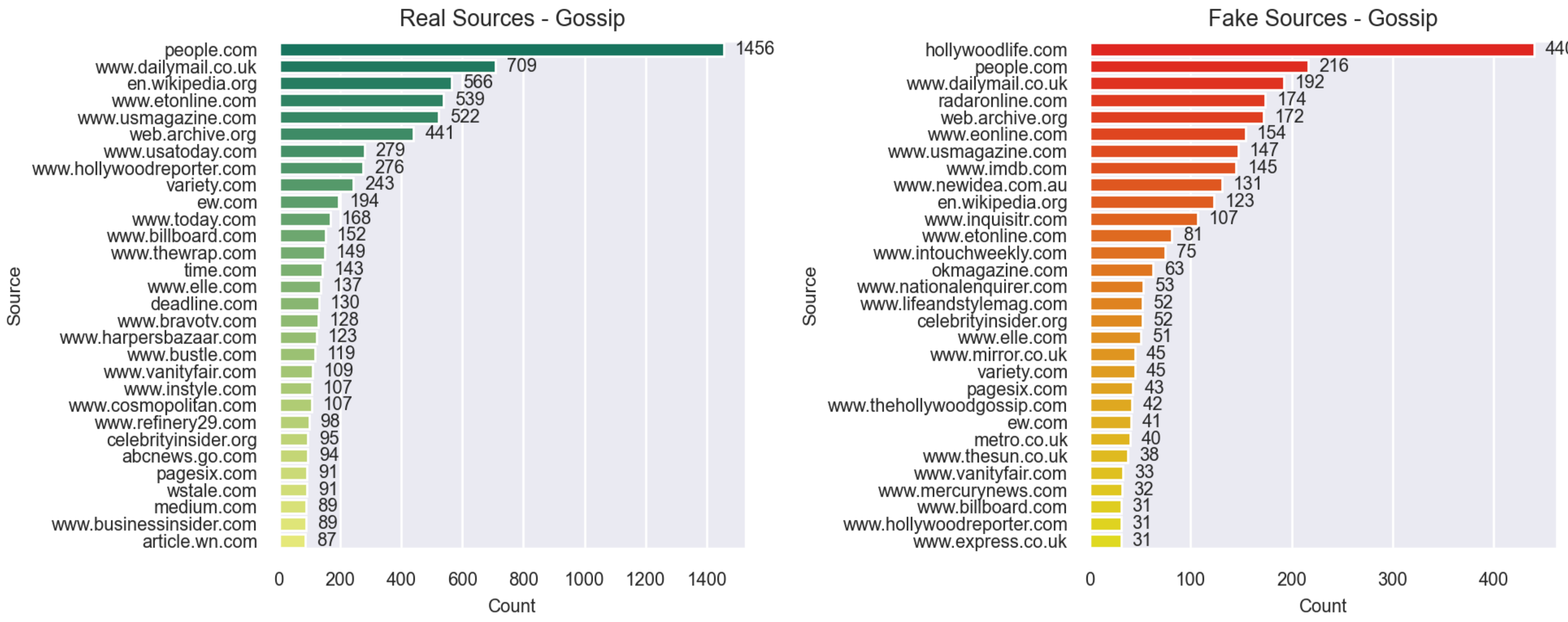
Article Length – Political News

Topics Data



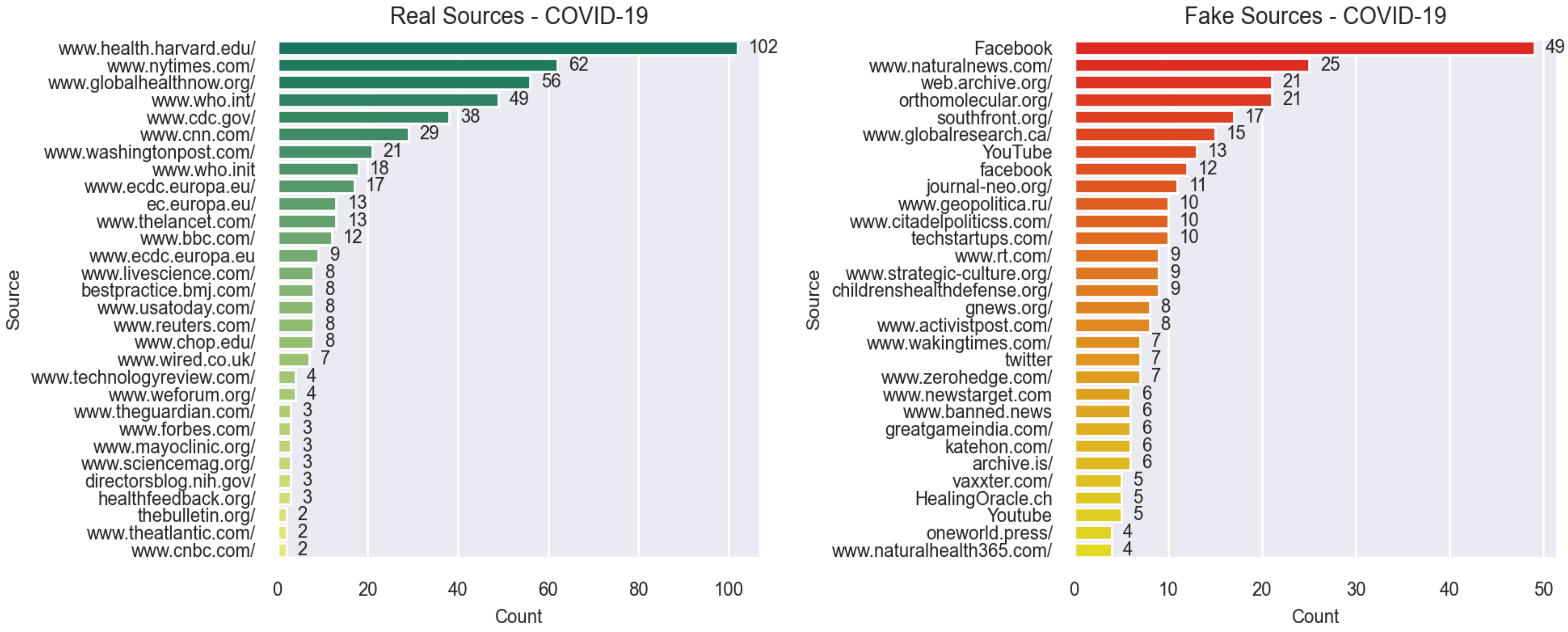
Topics Data

Article Sources – Gossip News



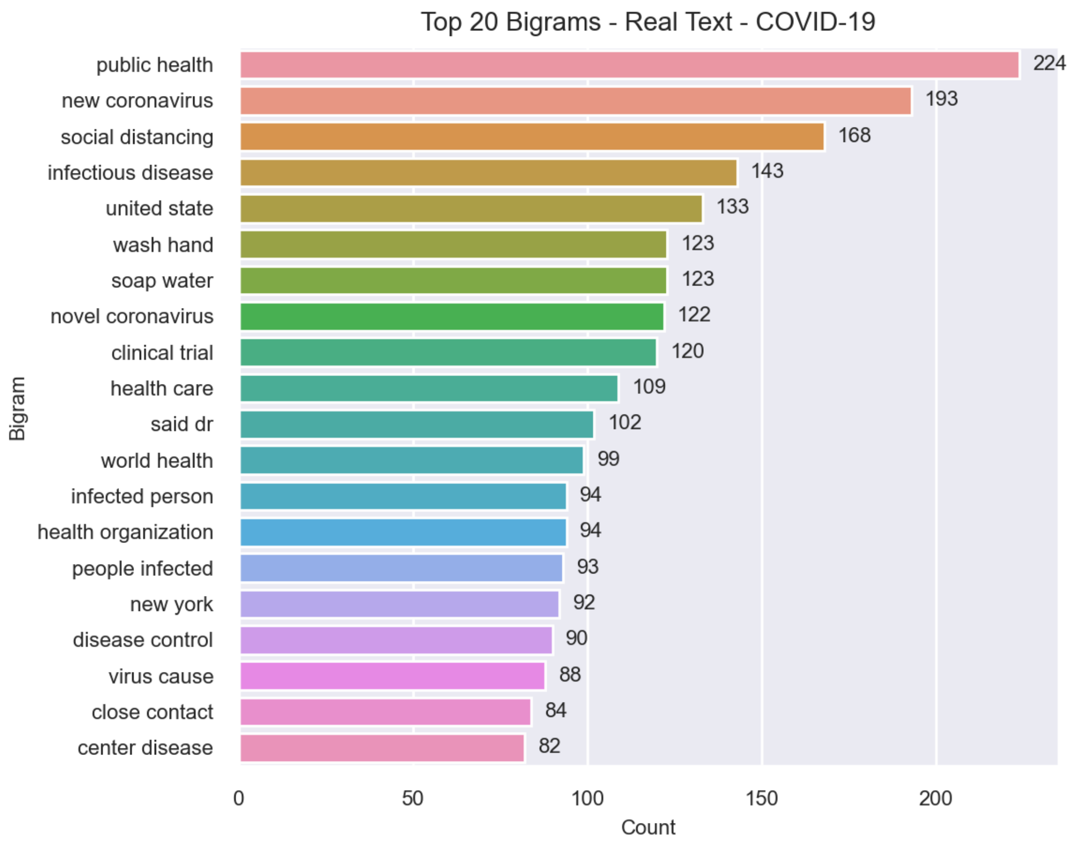
Article Sources – COVID-19 News

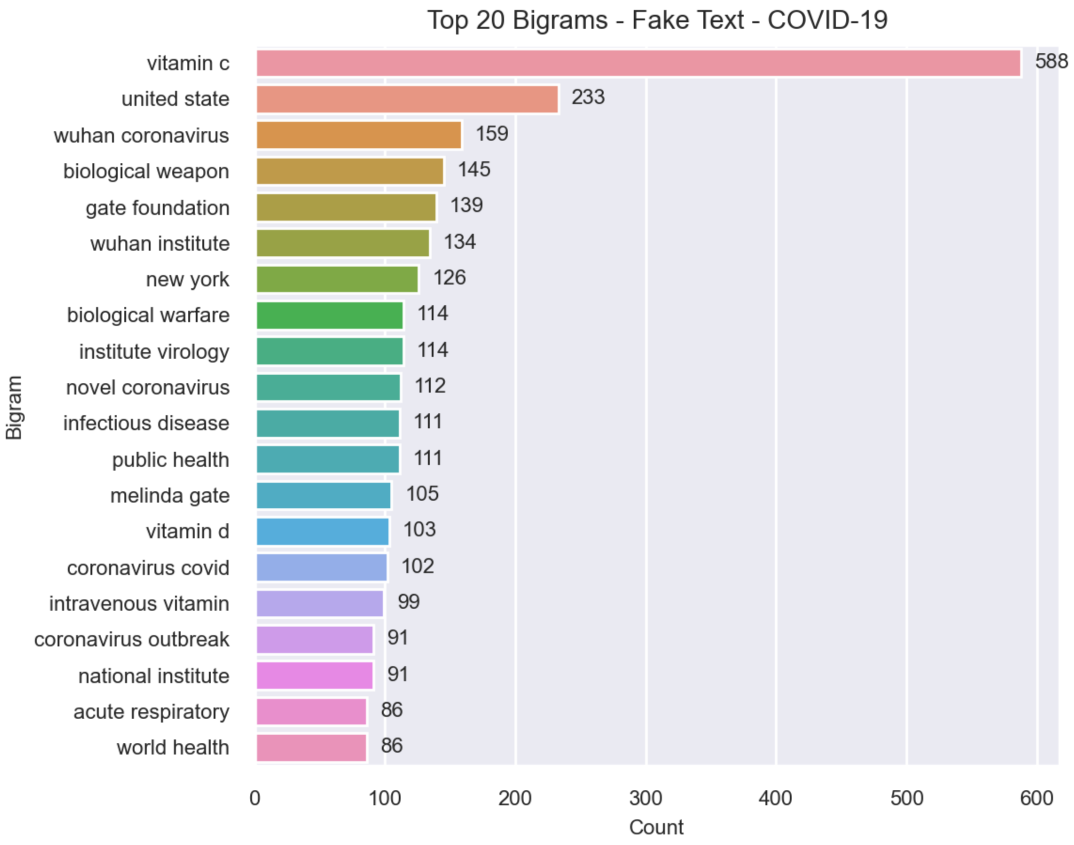
Topics Data



Topics Data

Top Bigrams – COVID-19 News





Takeaways

Key Strategies

- Credibility matters
  - But be cautious!
- Check emotional response
  - Biases, buzz words
- Be wary of headlines
- Notice punctuation
  - Quotations, exclamations

Other General Advice

- Check web domain
  - .com.co
- Multiple sources on topic
- Are there references?
- Publication date
- Consult fact checkers
  - Snopes, PolitiFact
  - Images

Predictive Modeling

Methods

Fake News classifier

- Text preprocessing
  - FNID and Topics Data
- Document-term matrix
- General classifiers
  - Cross-validation
- Pre-trained NLP models
  - BERT, RoBERTa

Topic-specific models

- Topics Data
  - Politics, Gossip, COVID-19, Disasters
- Class balance
- General classifiers

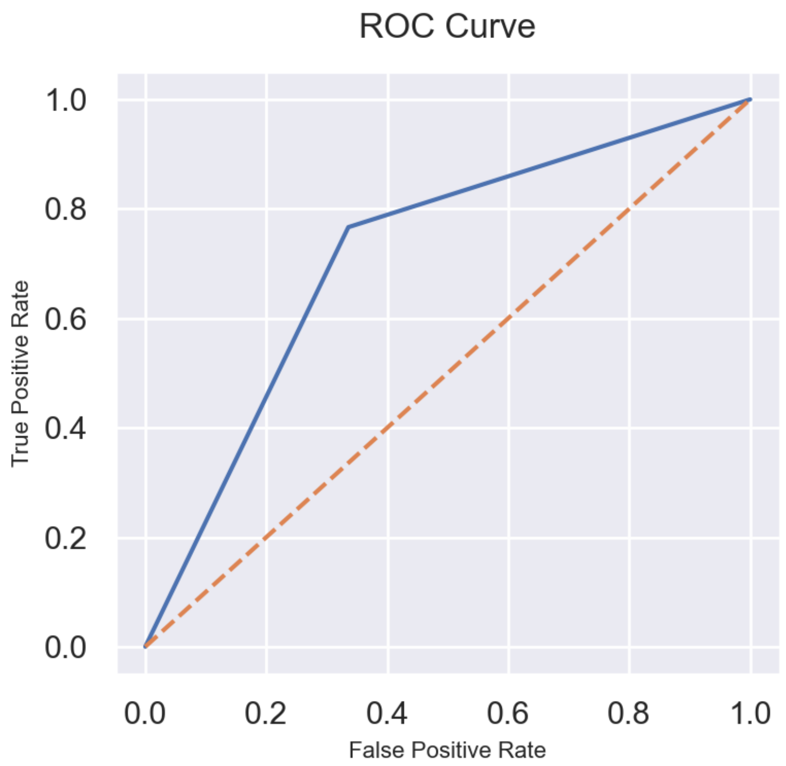
FNID Dataset

General Fake News Detection

FNID Data

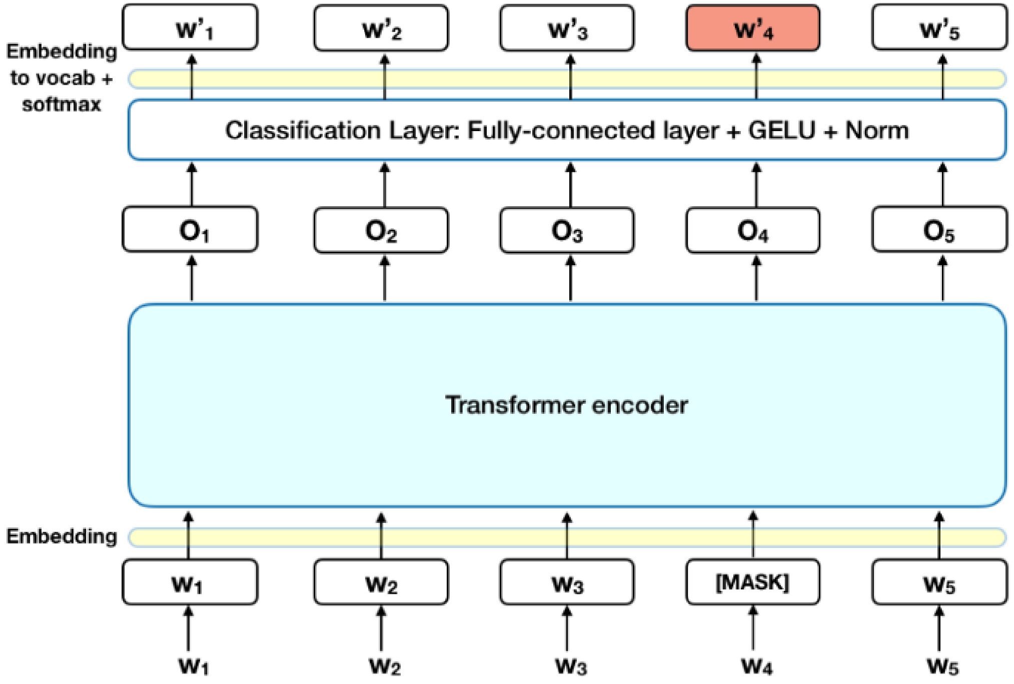
Classifier	Test Accuracy	Test Precision	Test Recall
Logistic Regression	0.72	0.72	0.715
Naïve Bayes	0.65	0.66	0.65
Passive Aggressive	0.68	0.67	0.67
Random Forest	0.70	0.71	0.695
Gradient Boosting	0.71	0.72	0.71
XGBoost	0.72	0.72	0.72

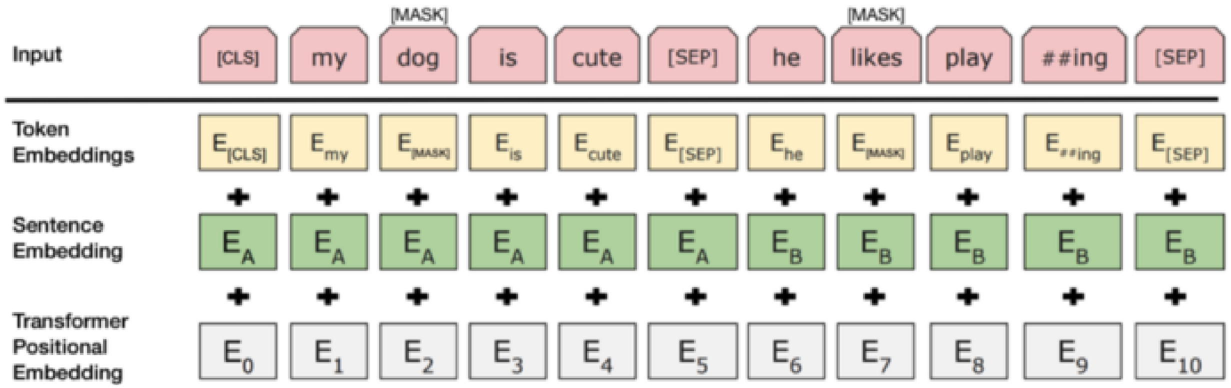
XGBoost Test ROC



Test AUC: 0.718

Bidirectional Encoder Representation from Transformer (BERT) and RoBERTa (Robustly Optimized BERT approach)



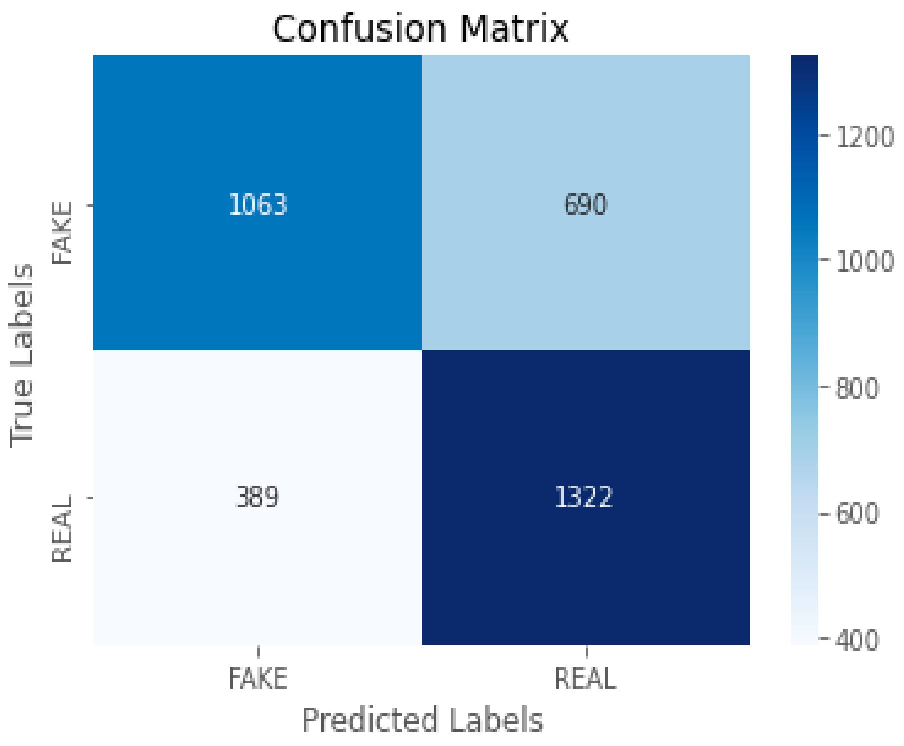


General Fake News Detection – BERT/RoBERTa

FNID Data

Classifier	Test Accuracy	Test Precision	Test Recall
BERT	0.64	0.65	0.63
RoBERTa	0.69	0.69	0.68

RoBERTa Test Confusion Matrix



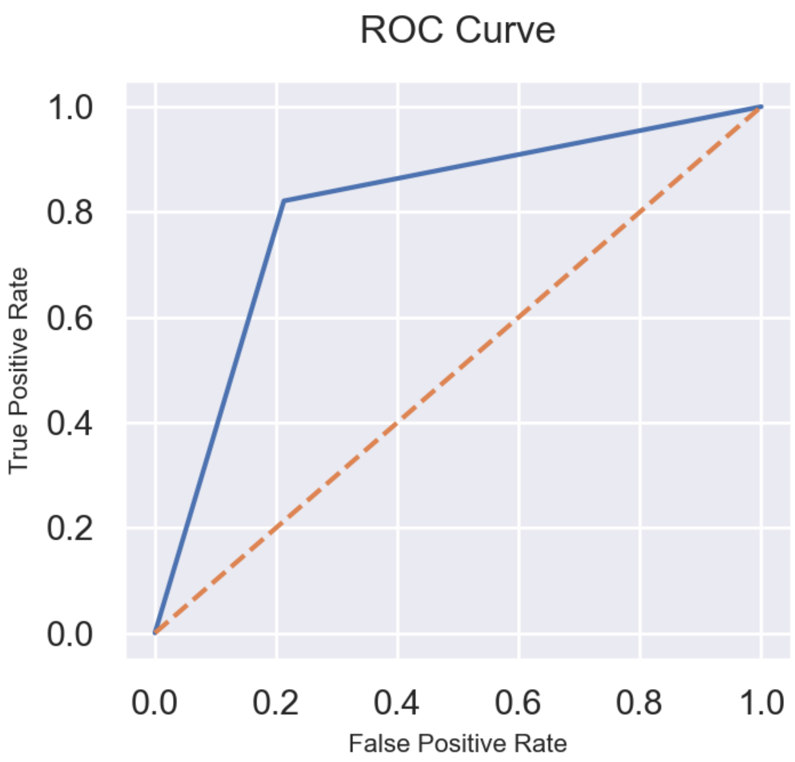
Combined Topics Dataset

General Fake News Detection

Topics Data

Classifier	Test Accuracy	Test Precision	Test Recall
Logistic Regression	0.80	0.805	0.81
Naïve Bayes	0.76	0.79	0.76
Passive Aggressive	0.76	0.76	0.76
Random Forest	0.78	0.79	0.78
XGBoost	0.77	0.77	0.77
RoBERTa	0.78	0.77	0.77

Logistic Regression Test ROC



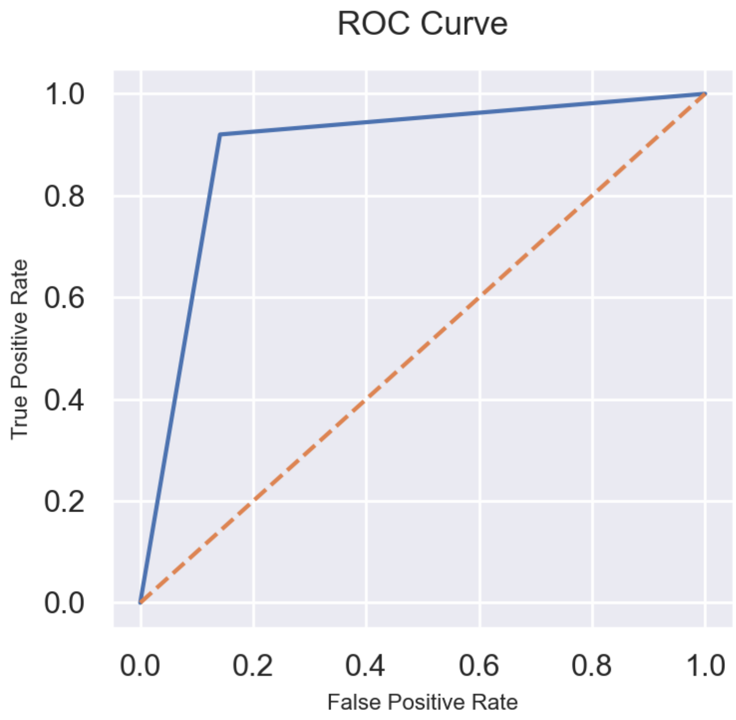
Test AUC: 0.805

Politics Fake News Detection

Topics Data

Classifier	Test Accuracy	Test Precision	Test Recall
Logistic Regression	0.87	0.87	0.87
Naïve Bayes	0.76	0.79	0.77
Passive Aggressive	0.88	0.88	0.88
Random Forest	0.83	0.84	0.83
Gradient Boosting	0.81	0.82	0.81
XGBoost	0.89	0.88	0.89

XGBoost Test ROC



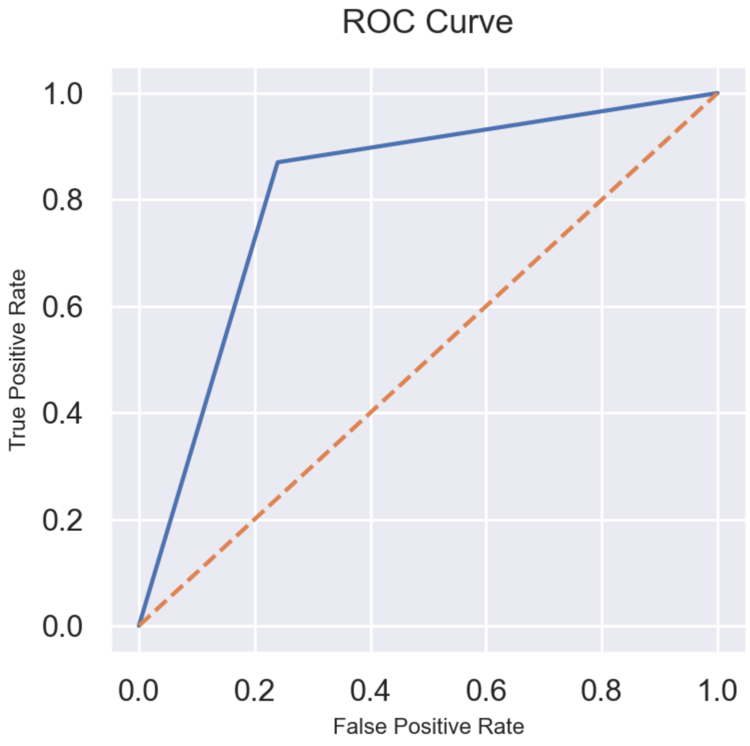
Test AUC: 0.888

Gossip Fake News Detection

Topics Data

Classifier	Test Accuracy	Test Precision	Test Recall
Logistic Regression	0.82	0.82	0.82
Naïve Bayes	0.81	0.805	0.81
Passive Aggressive	0.785	0.79	0.79
Random Forest	0.80	0.81	0.80
Gradient Boosting	0.75	0.77	0.76
XGBoost	0.79	0.80	0.79

Logistic Regression Test ROC



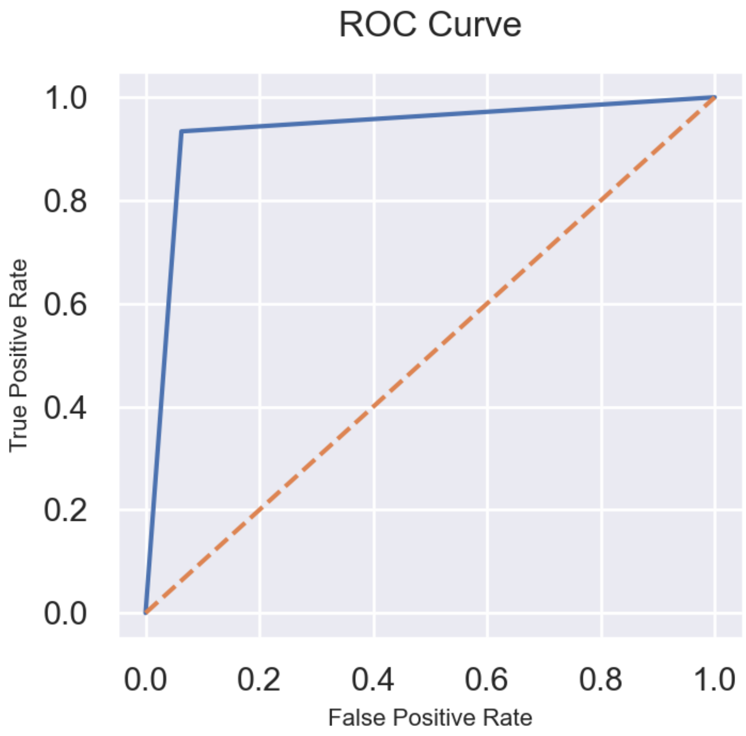
Test AUC: 0.820

COVID-19 Fake News Detection

Topics Data

Classifier	Test Accuracy	Test Precision	Test Recall
Logistic Regression	0.92	0.92	0.915
Naïve Bayes	0.89	0.89	0.89
Passive Aggressive	0.93	0.94	0.93
Random Forest	0.90	0.91	0.90
Gradient Boosting	0.86	0.87	0.86
XGBoost	0.86	0.86	0.86

Passive Aggressive Test ROC



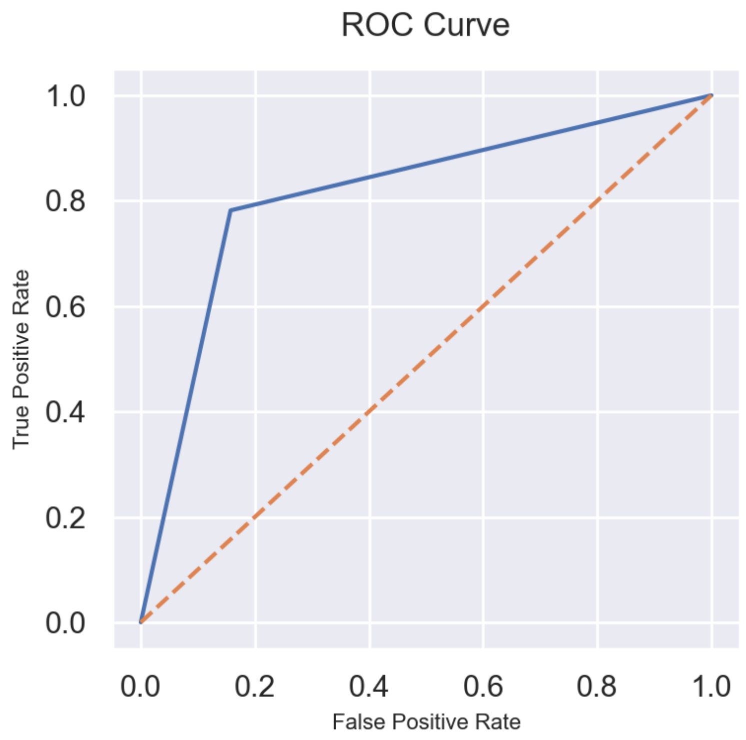
Test AUC: 0.935

Disasters Fake News Detection

Topics Data

Classifier	Test Accuracy	Test Precision	Test Recall
Logistic Regression	0.81	0.82	0.81
Naïve Bayes	0.80	0.805	0.80
Passive Aggressive	0.76	0.76	0.76
Random Forest	0.79	0.80	0.79
Gradient Boosting	0.72	0.75	0.72
XGBoost	0.77	0.78	0.77

Logistic Regression Test ROC

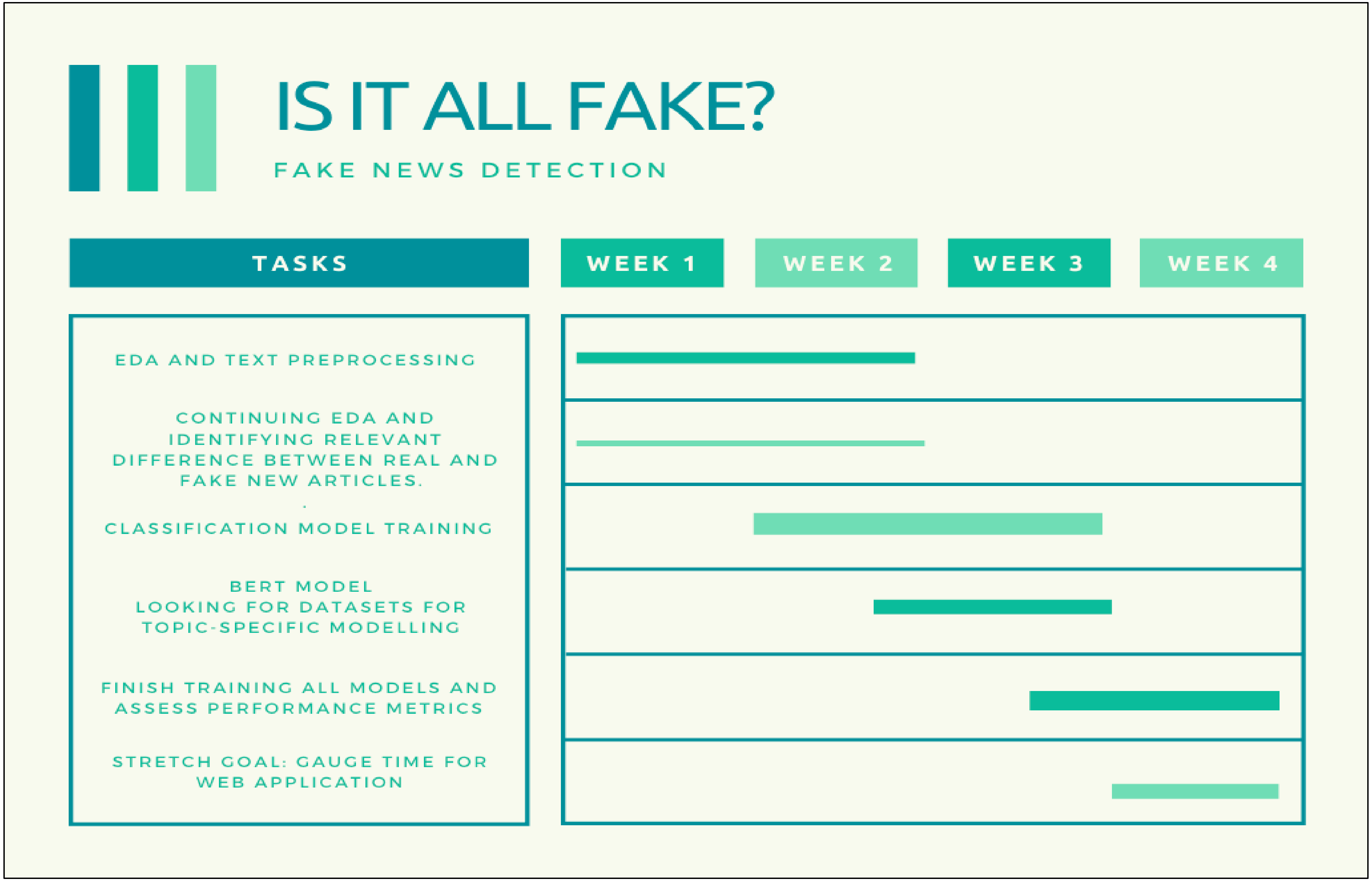


Test AUC: 0.814

Discussion

Conclusions

- Project outcomes
  - Strategies to determine authenticity
  - Fake news detection
    - Language-based
    - Topic dependent
- No "one" solution to combat fake news
  - Variations in fake news
  - Human monitoring and algorithm detection


IS IT ALL FAKE?
FAKE NEWS DETECTION
TASKS
WEEK 1
WEEK 2
WEEK 3
WEEK 4
EDA AND TEXT PREPROCESSING
CONTINUING EDA AND IDENTIFYING RELEVANT DIFFERENCE BETWEEN REAL AND FAKE NEW ARTICLES.
CLASSIFICATION MODEL TRAINING
BERT MODEL
LOOKING FOR DATASETS FOR TOPIC-SPECIFIC MODELLING
FINISH TRAINING ALL MODELS AND ASSESS PERFORMANCE METRICS
STRETCH GOAL: GAUGE TIME FOR WEB APPLICATION

Future Work

- Web application
- Focus on just social media (e.g., Facebook, Twitter)
  - Fake accounts/bots
  - Emojis
- Left versus right-leaning news sources
- International news
- Other types of fake media content
  - Deep fake

Thanks!

Any questions?

Datasets

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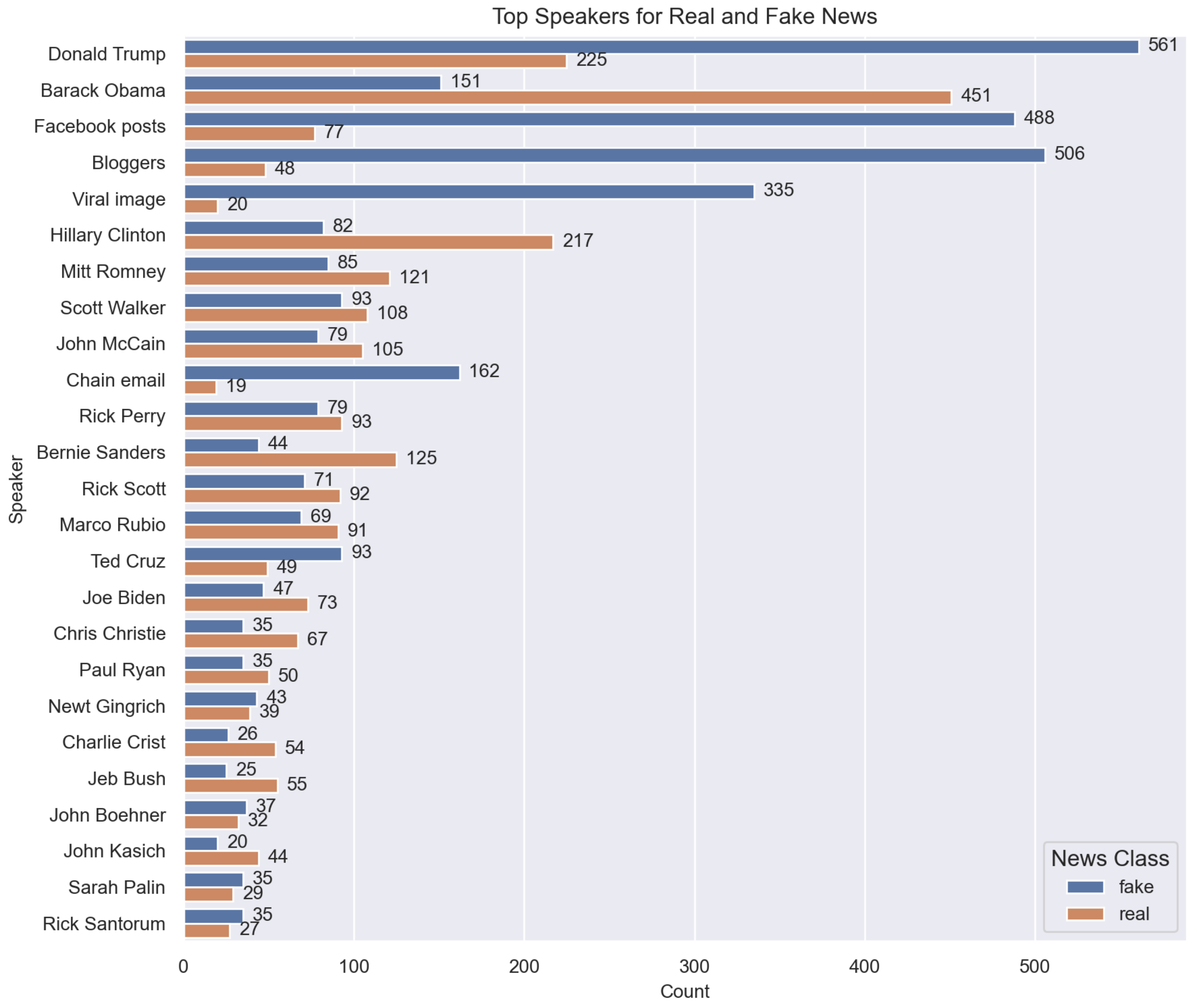
Appendix

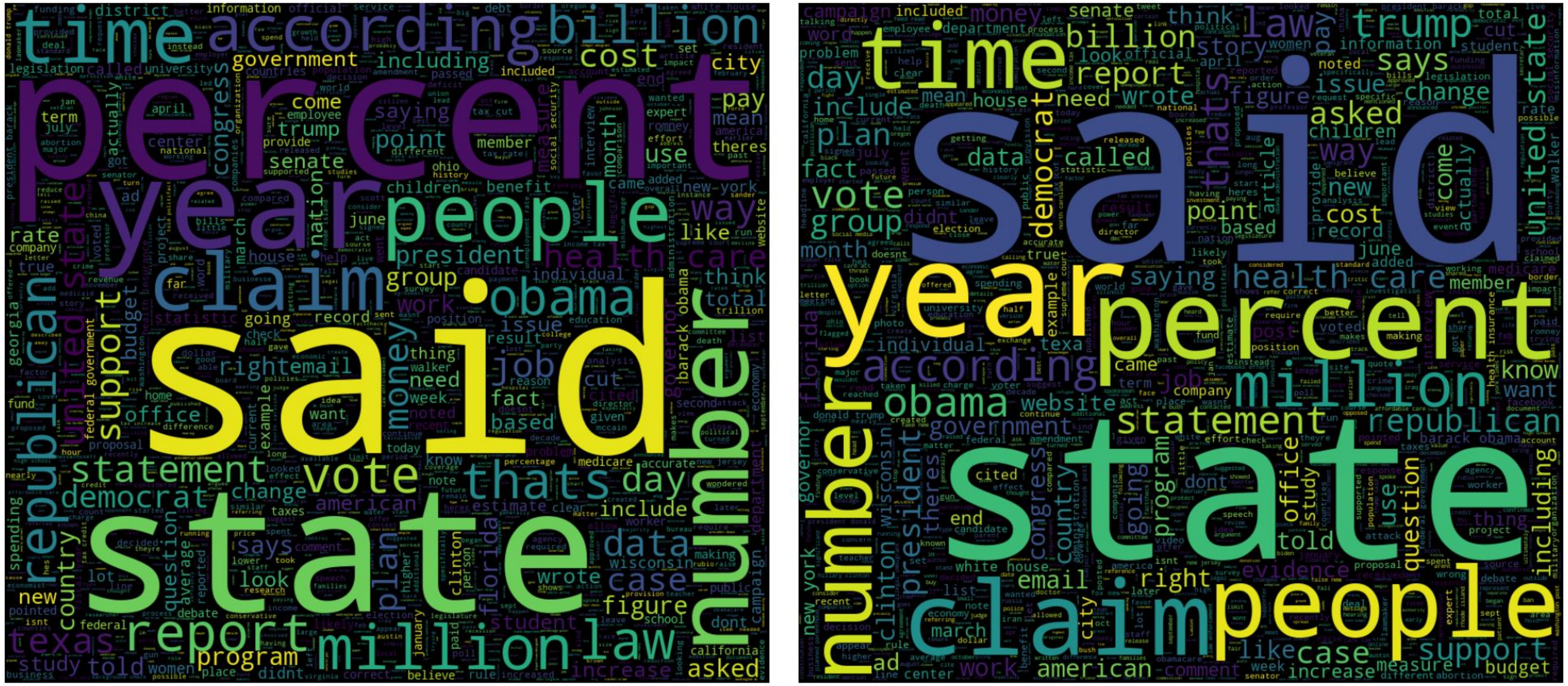
Top speakers for real and fake news



Frequent words

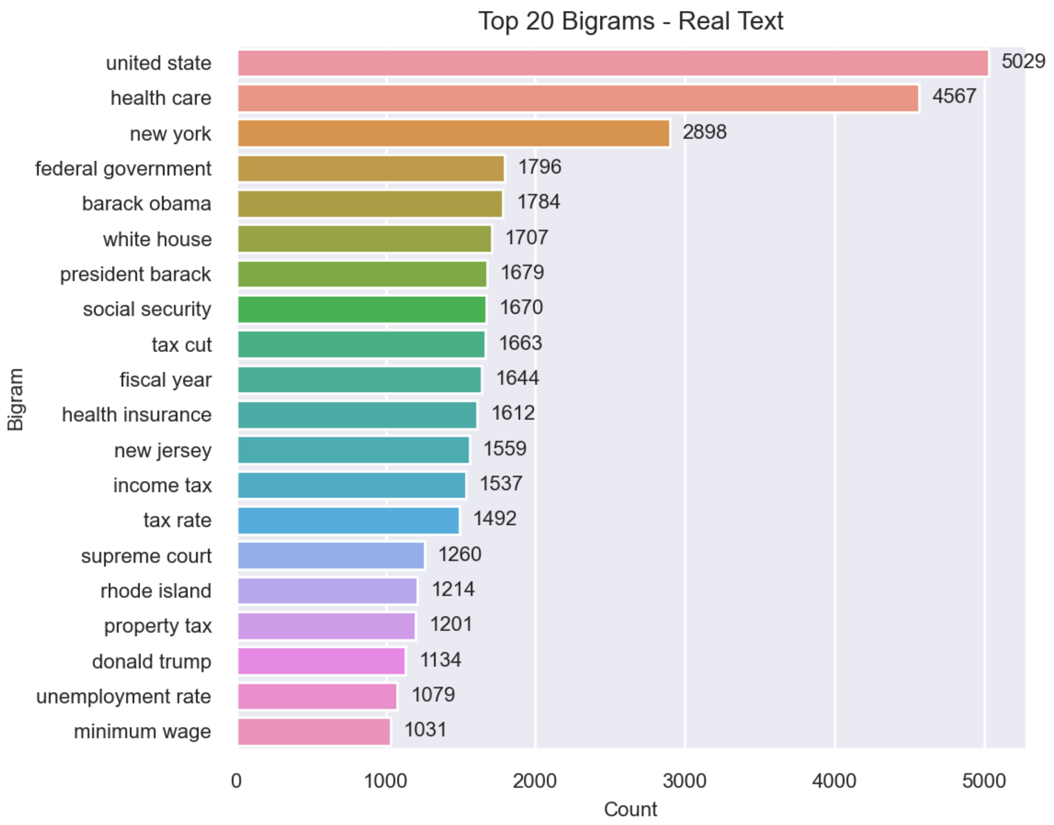
Word Clouds - Real versus Fake

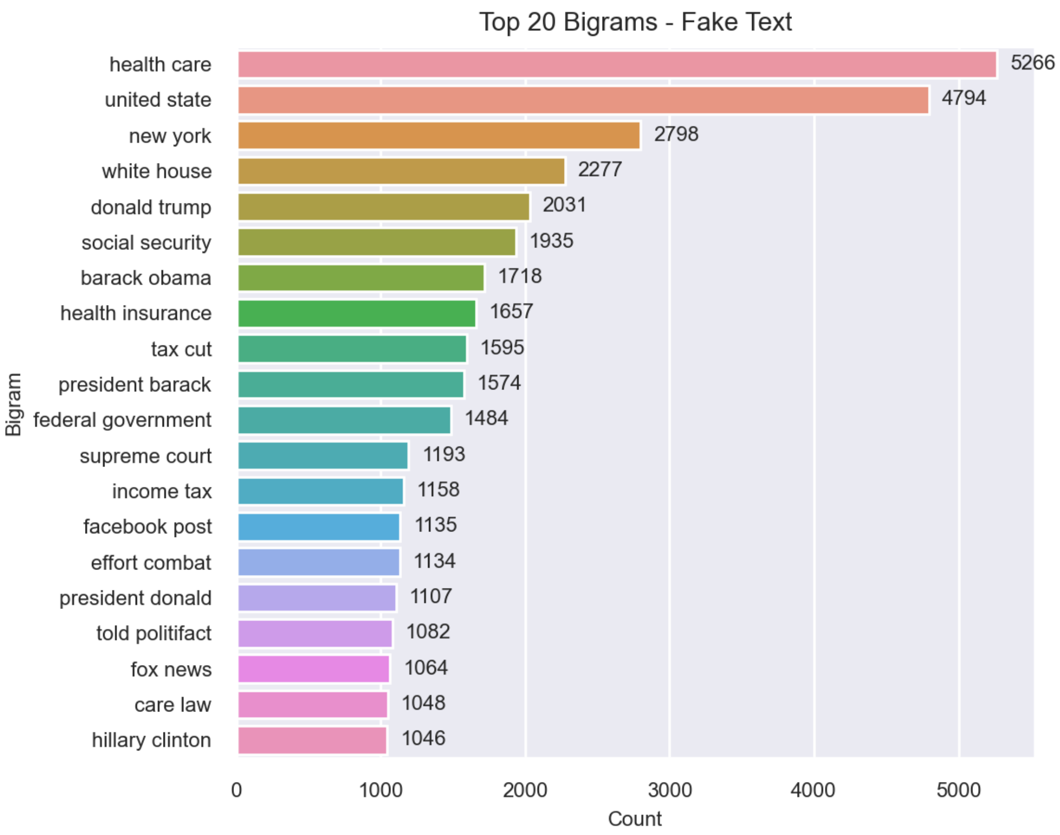
Real News Fake News



Top bigrams overlap in real and fake news

FNID Data





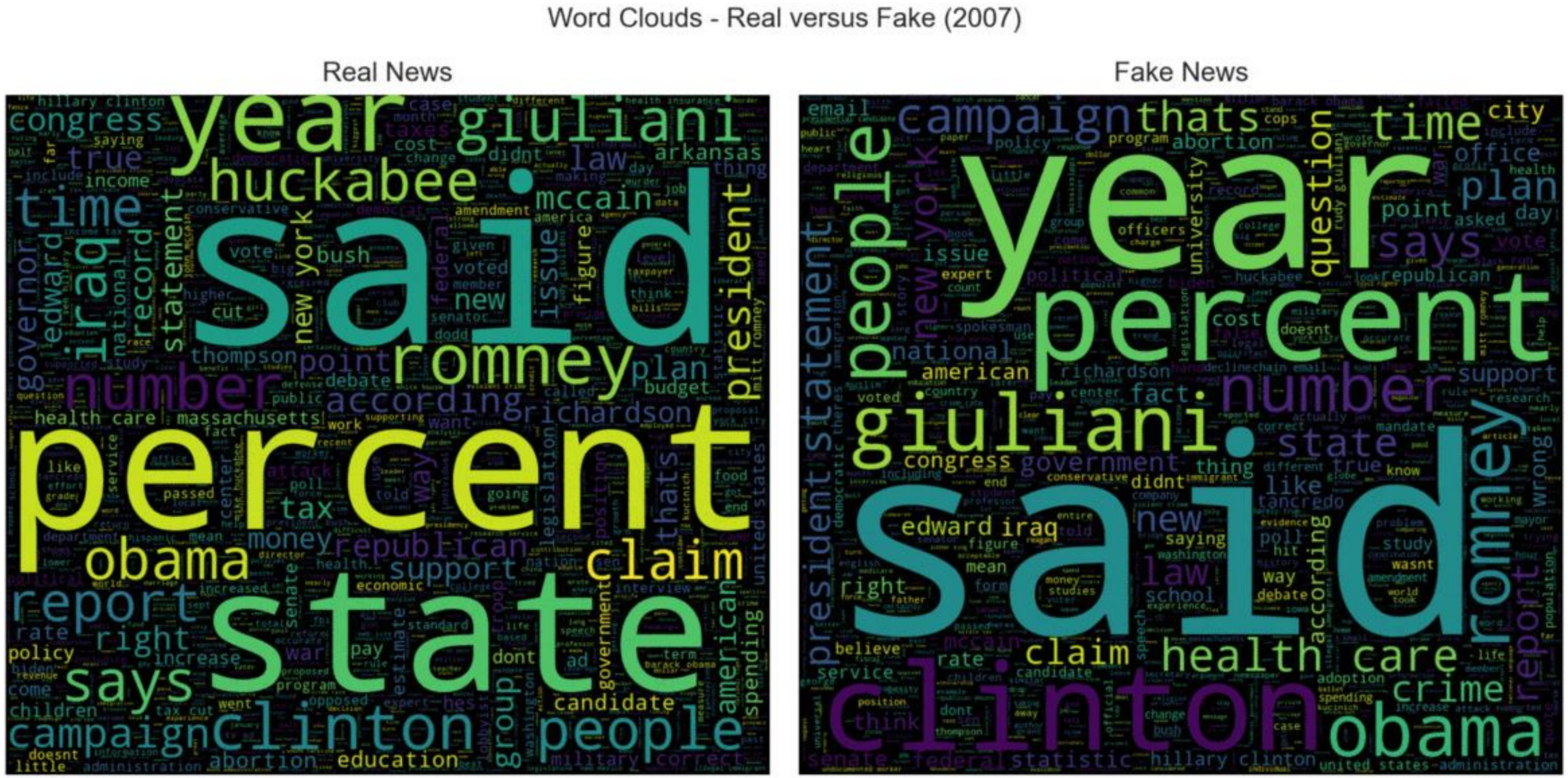
Punctuation statistics

Article Text

News Type	Total Number of Quotations	Mean Number of Quotations	Total Number of Exclamations	Mean Number of Exclamations
Real	40850	4.66	652	0.074
Fake	40213	4.70	1794	0.21

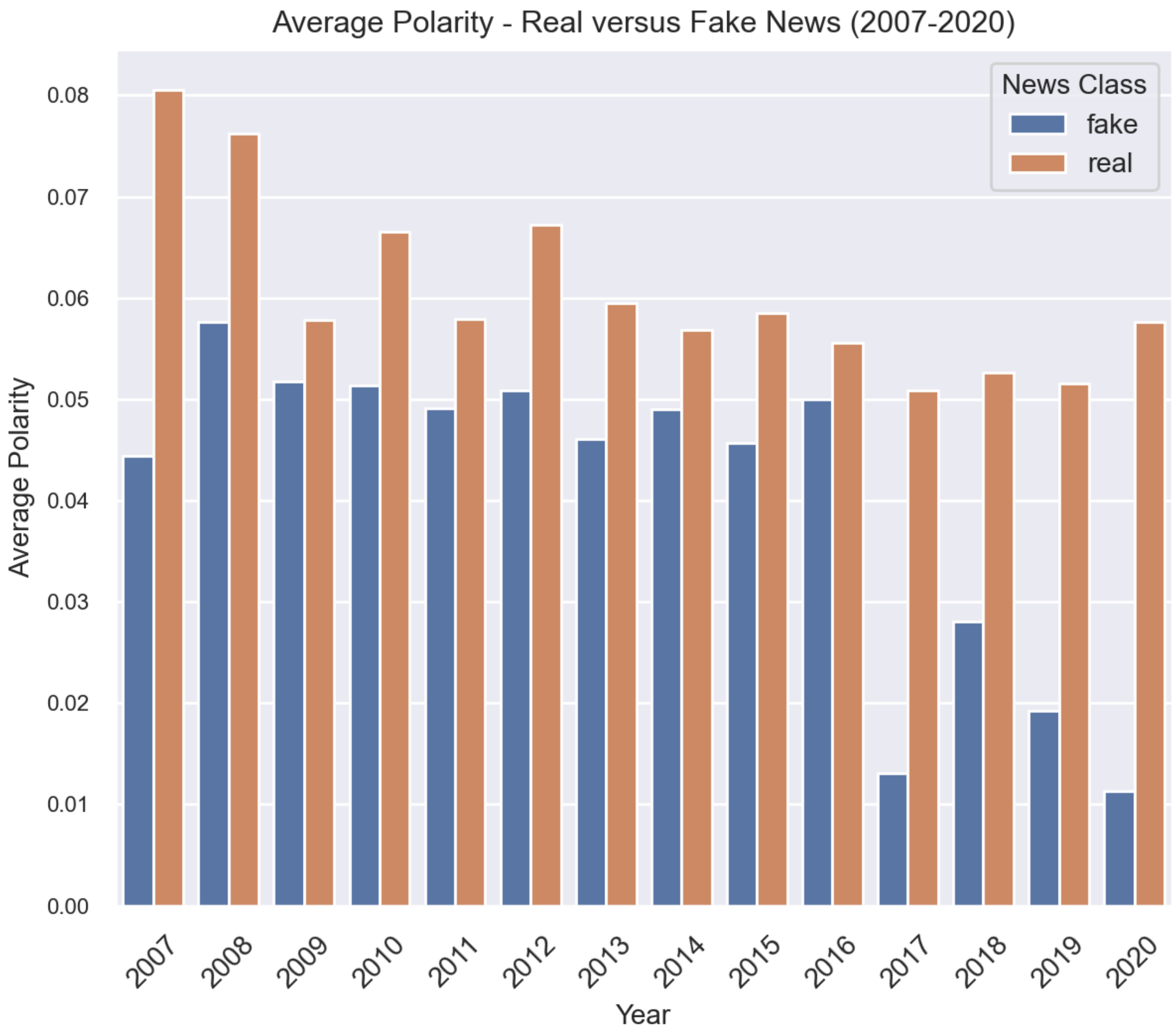
Common words diverge over time

FNID Data

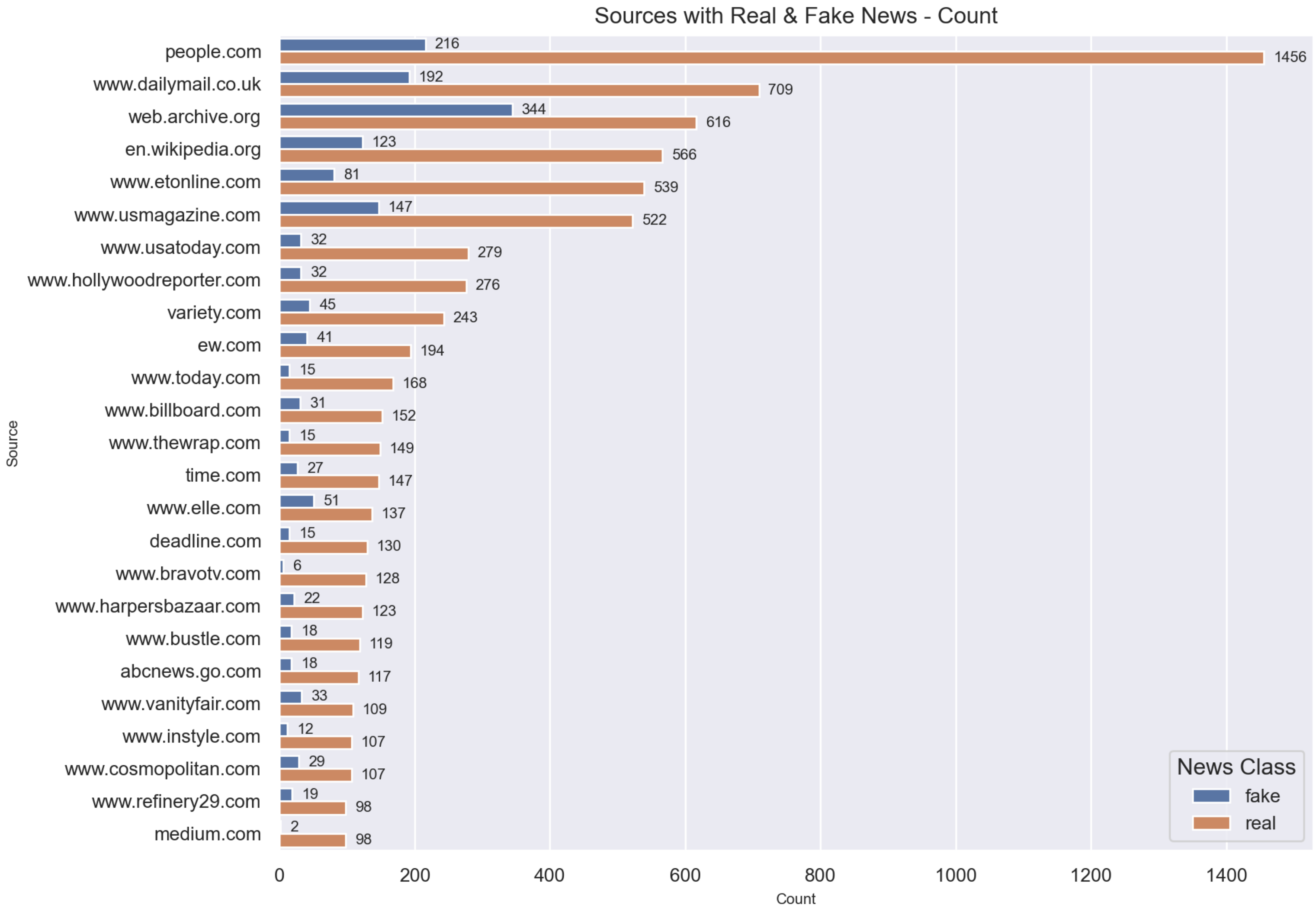


Average polarity over time

FNID Data



Common sources for real and fake news



Exclamation statistics

Article Text

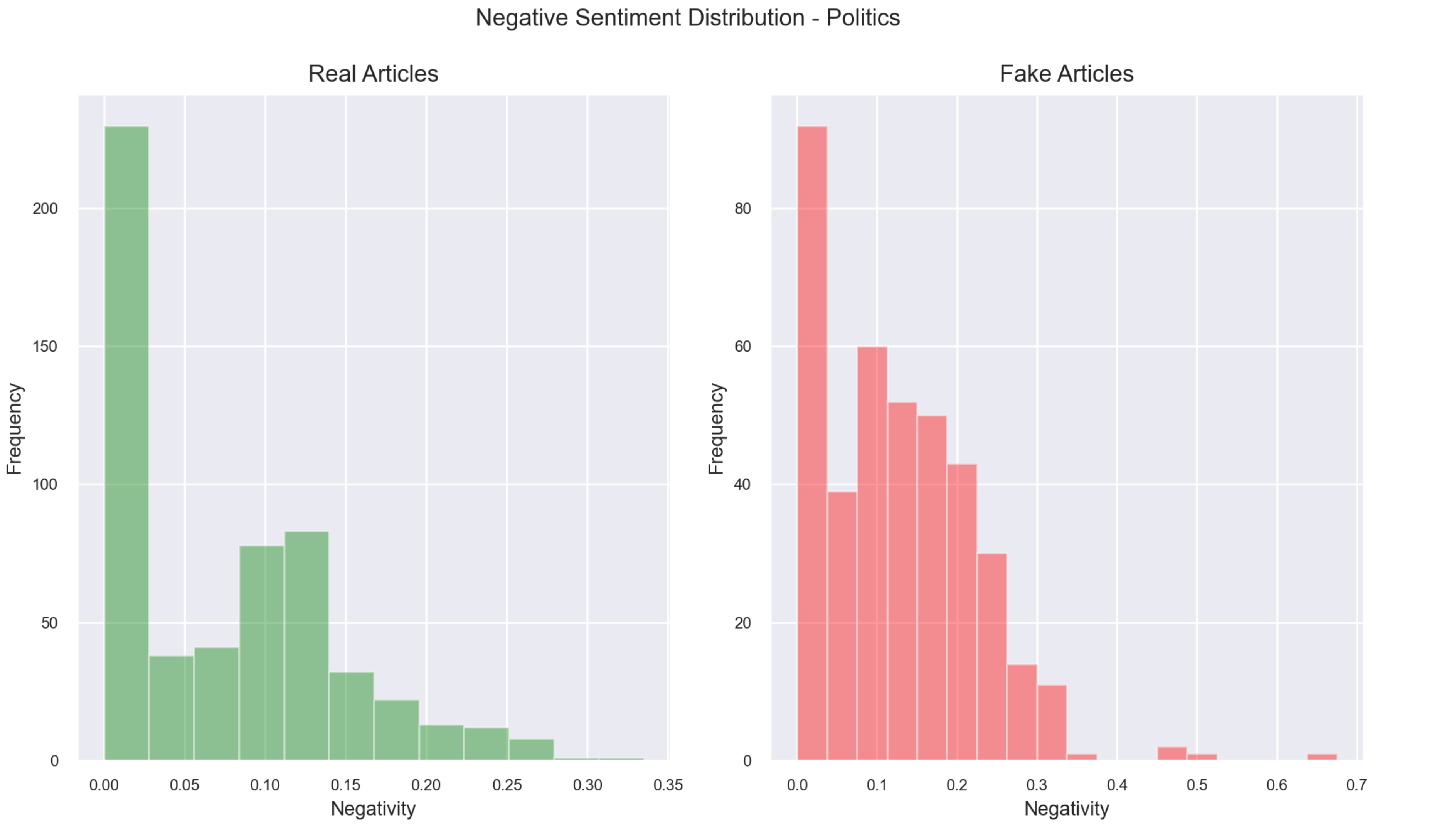
News Type	Total Number of Exclamations	Mean Number of Exclamations
Real	23198	0.951
Fake	9794	1.24

Article Title Text

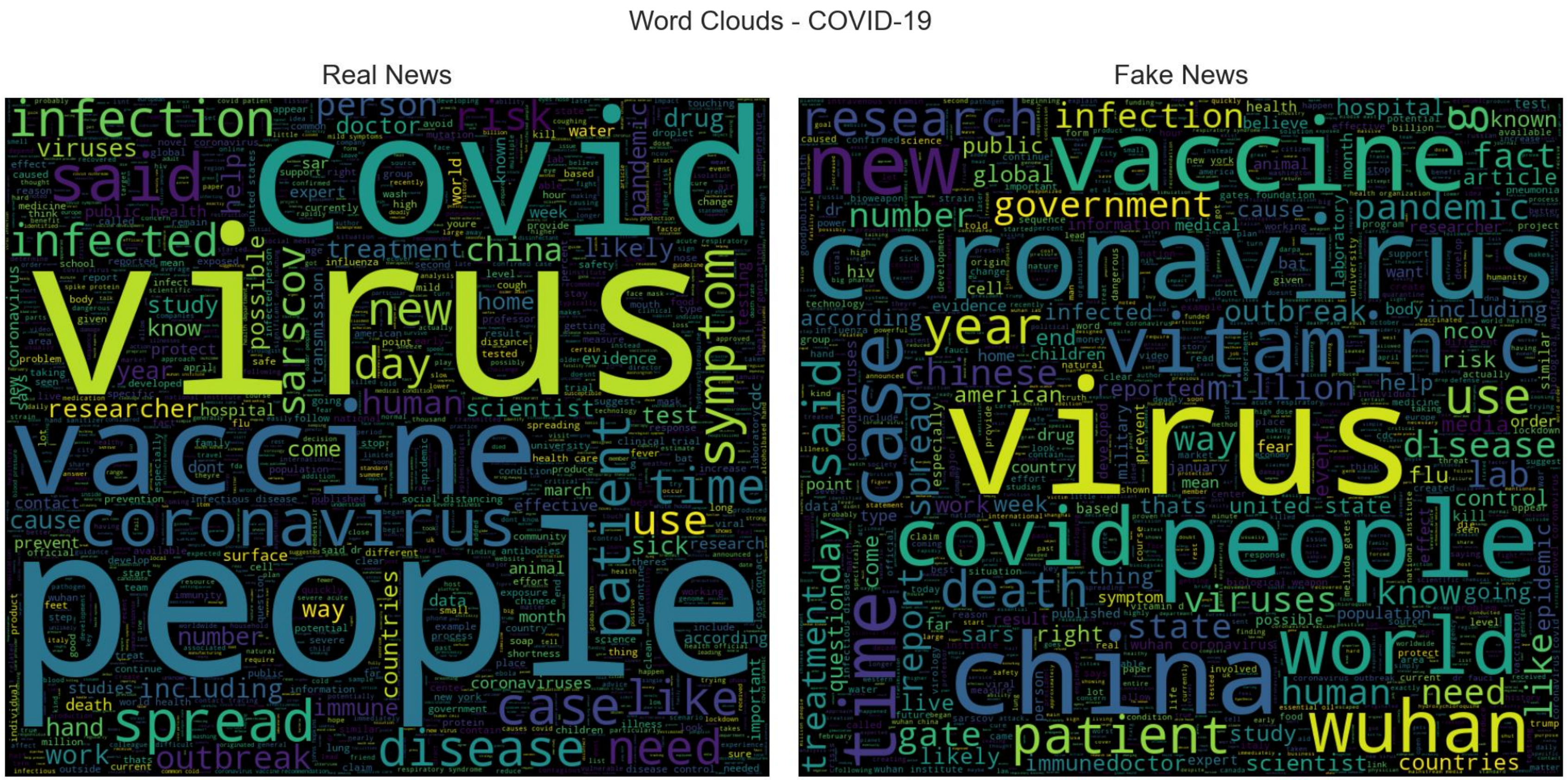
News Type	Total Number of Exclamations	Mean Number of Exclamations
Real	768	0.041
Fake	437	0.042

Article Negativity – Political News

Topics Data



Frequent words – COVID-19 News



BERT and RoBERTa Performance

	BERT	RoBERTa	DistilBERT	XLNet
Size (millions)	**Base**: 110 **Large**: 340	**Base**: 110 **Large**: 340	**Base**: 66	**Base**: ~110 **Large**: ~340
Training Time	**Base**: 8 x V100 x 12 days* **Large**: 64 TPU Chips x 4 days (or 280 x V100 x 1 days*)	**Large**: 1024 x V100 x 1 day; 4-5 times more than BERT.	**Base**: 8 x V100 x 3.5 days; 4 times less than BERT.	**Large**: 512 TPU Chips x 2.5 days; 5 times more than BERT.
Performance	Outperforms state-of-the-art in Oct 2018	2-20% improvement over BERT	3% degradation from BERT	2-15% improvement over BERT
Data	16 GB BERT data (Books Corpus + Wikipedia). 3.3 Billion words.	160 GB (16 GB BERT data + 144 GB additional)	16 GB BERT data. 3.3 Billion words.	**Base**: 16 GB BERT data **Large**: 113 GB (16 GB BERT data + 97 GB additional). 33 Billion words.
Method	BERT (Bidirectional Transformer with MLM and NSP)	BERT without NSP**	BERT Distillation	Bidirectional Transformer with Permutation based modeling