Fake News Detection

GETTING TO THE TRUTH IN AN ERA OF MISINFORMATION

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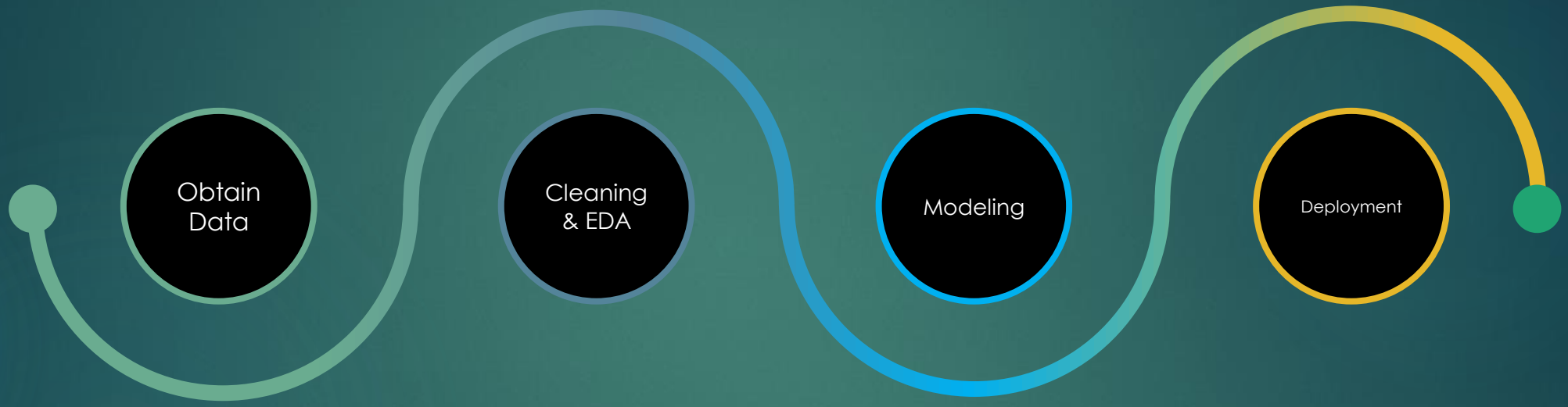
Business Case

- Fake news has been on the rise this past decade
- Denying the 2020 election results
- Spreading misinformation about the COVID vaccine
- Breakdown of shared reality
- One of the main sources of fake news is social media, such as Facebook and Twitter
- 2019: 8 percent of engagement with the 100 top-performing news sources on social media was dubious
- 2020: this number more than doubled
- Most popular news platform on Facebook in 2021: The Daily Wire
- A fake news detection system like the one I aim to produce can be used by social media companies to filter out misinformation.

Modeling Roadmap



MILESTONE 1

- Download the data from Kaggle

MILESTONE 2

- Preprocess data
- Perform EDA

MILESTONE 3

- Create simple models
- Optimize models through hyperparameter tuning

MILESTONE 4

- Create a web app using Streamlit

Data Understanding

- Date source: ‘Fake and real news dataset’ from Kaggle.
- 21,417 real articles from Reuters
- 23,481 fake articles from various sources.
- Period covered: January 2017 to December 2017.

Data Preparation

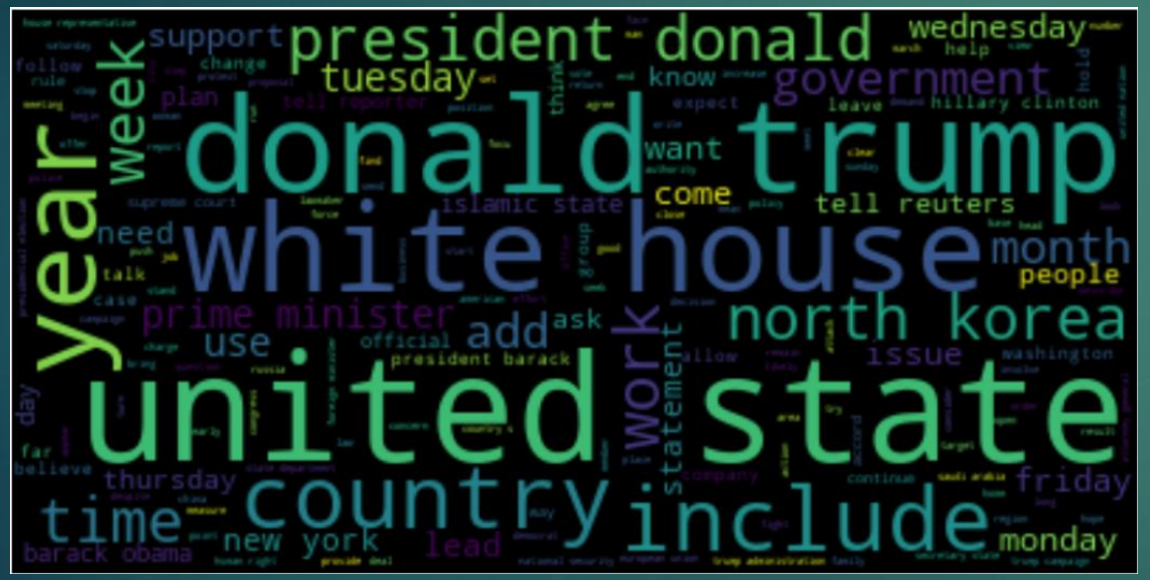
- Only looking at the articles, not the titles, subject or date.
- Data preparation steps:

1. Use regex to remove the names of the news outlet and city of origin from the real articles.

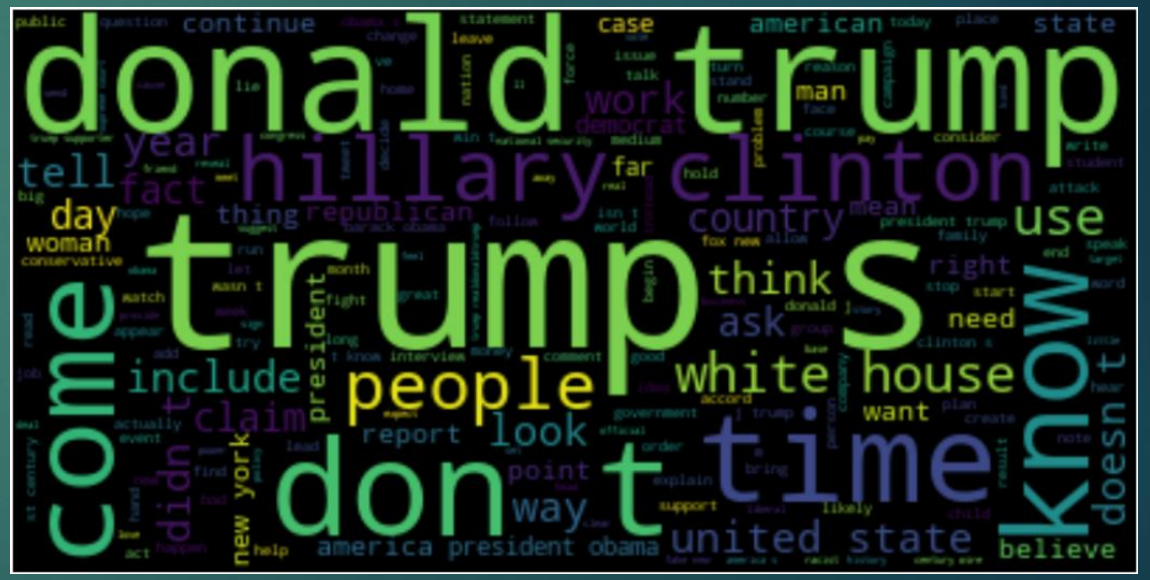
2. Use Spacy to tokenize the text of the articles and remove stop words.

World Cloud Visualization

Real Articles

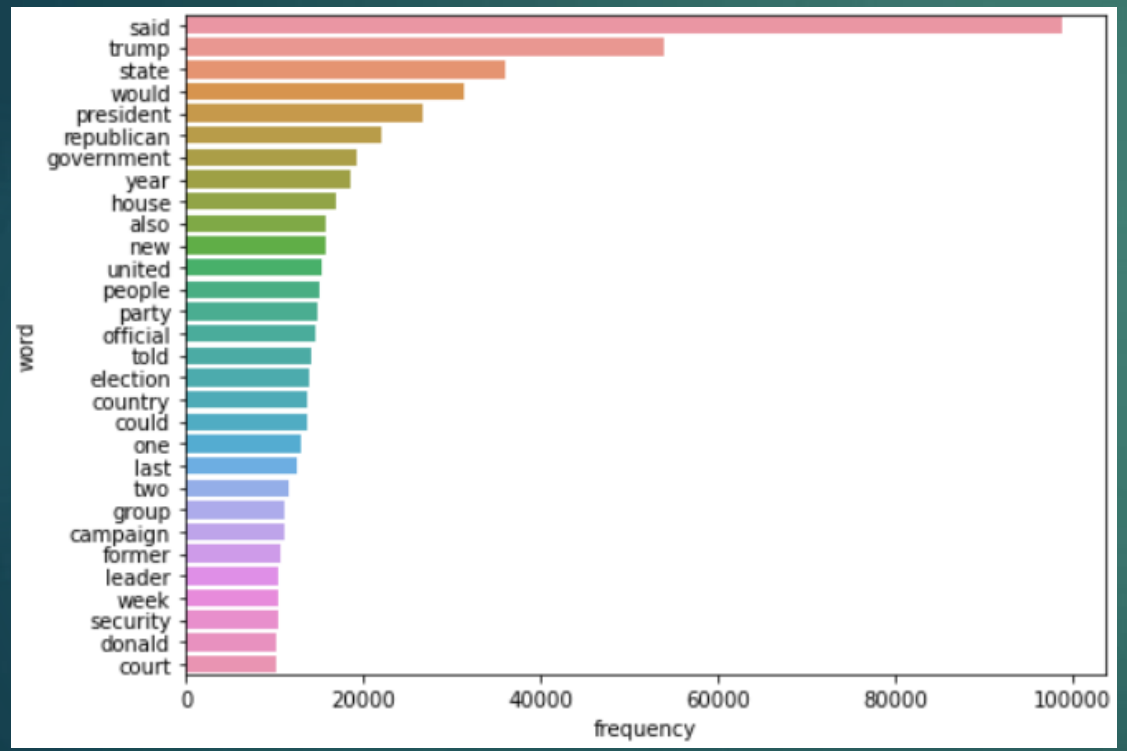


Fake articles

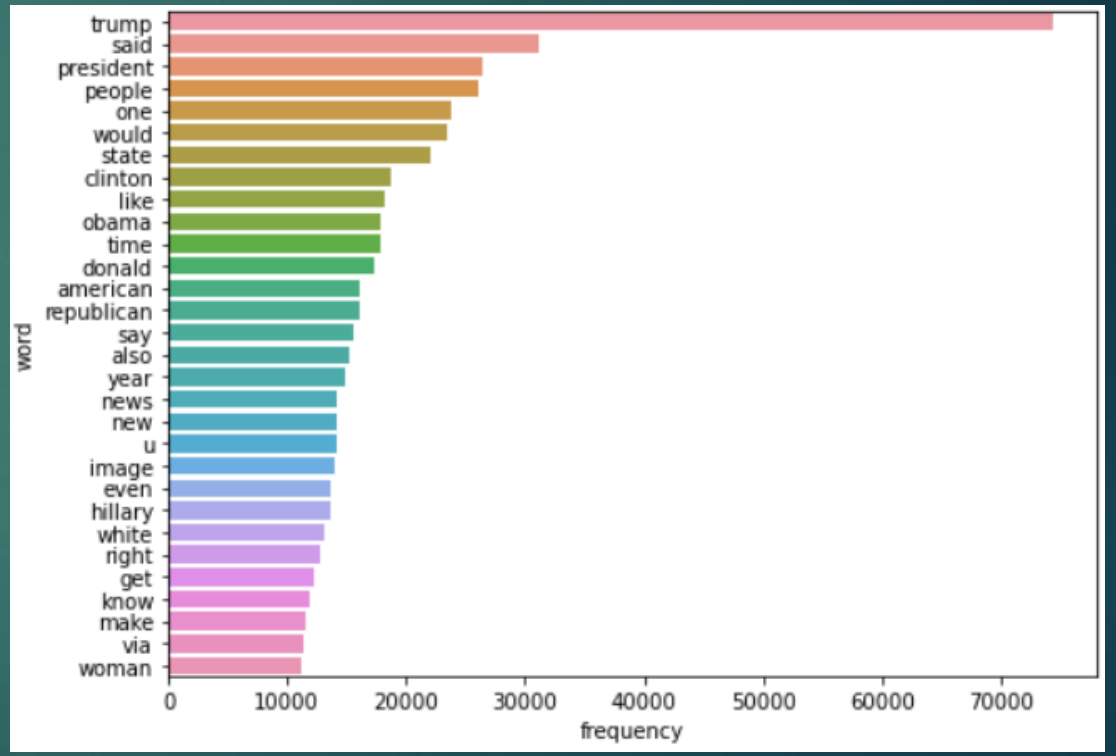


Unigram Frequency Distribution

Real Articles

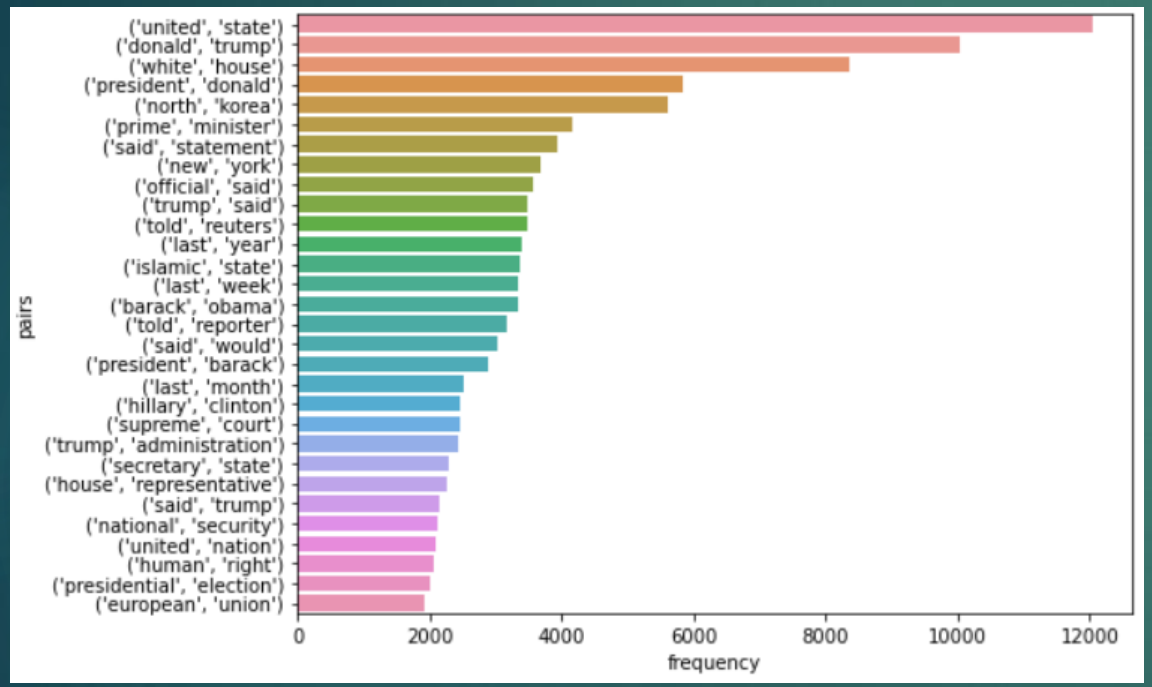


Fake Articles

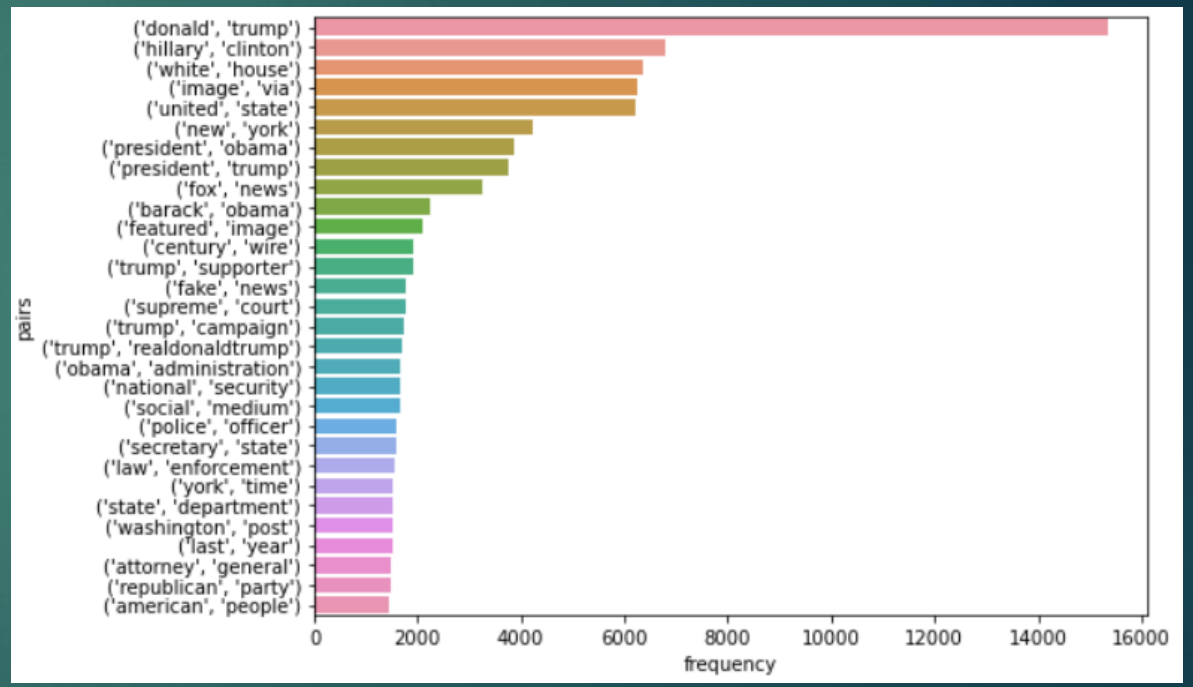


Bi-gram Frequency Distribution

Real

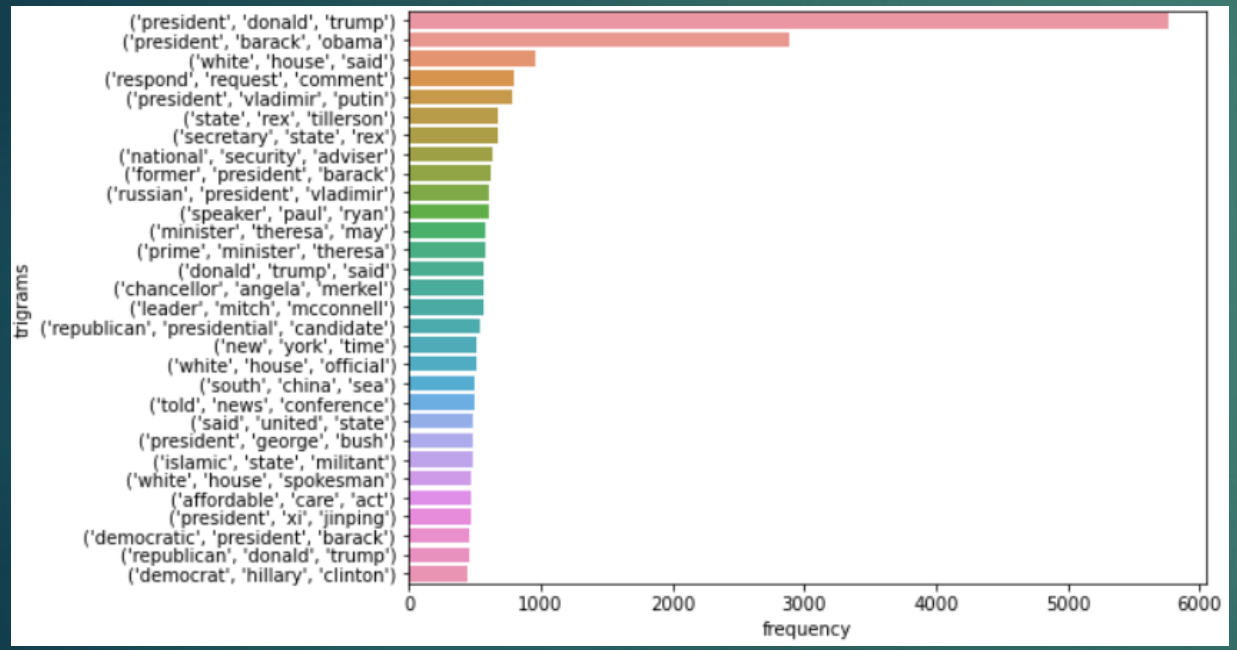


Fake

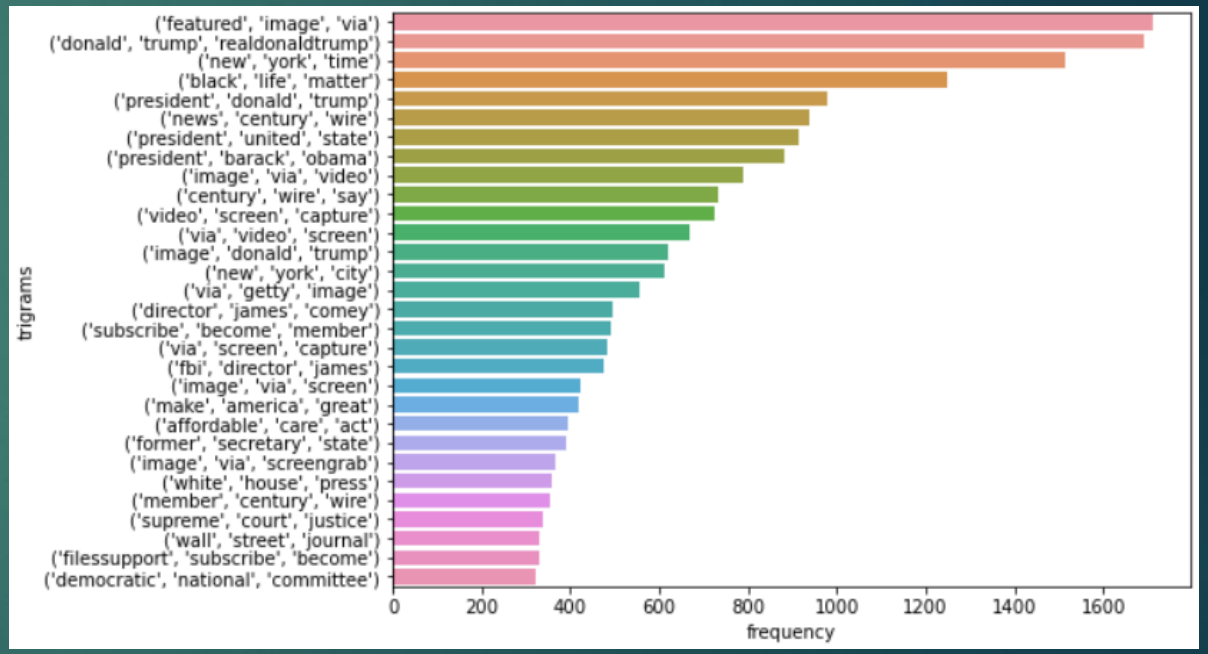


Tri-Gram Frequency Distribution

Real



Fake



Modeling

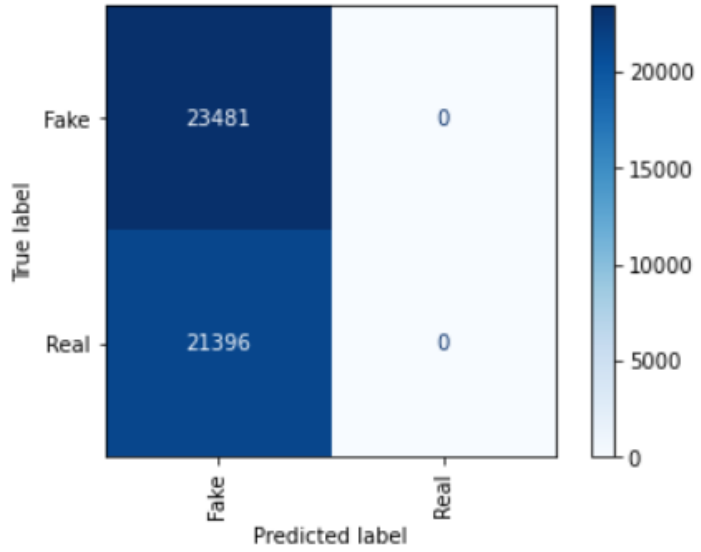
- 1. dummy classifier to check the baseline score.
- 2. LogisticRegression
- 3. Multinomial Naïve Bayes
- 4. Random Forest
- 5. Voting classifier (LogisticRegression, Multinomial Naïve Bayes and Random Forest)
- Best Results: LogisticRegression
- Scoring: f1 (not overly concerned with false positives or negatives)
- Initial split: 0.25, which resulted in an f1 score of 0.99.
- Subsequent split (to address overfitting): 0.5, which resulted in an f1 score of 0.98

Modeling Results

Model	Training F1-Score	Testing F1-Score
Logistic Regression	1	0.99
Multinomial Naïve Bayes	0.96	0.94
Random Forest Classifier	1	0.95
Voting Classifier	1	0.98

Dummy Classifier

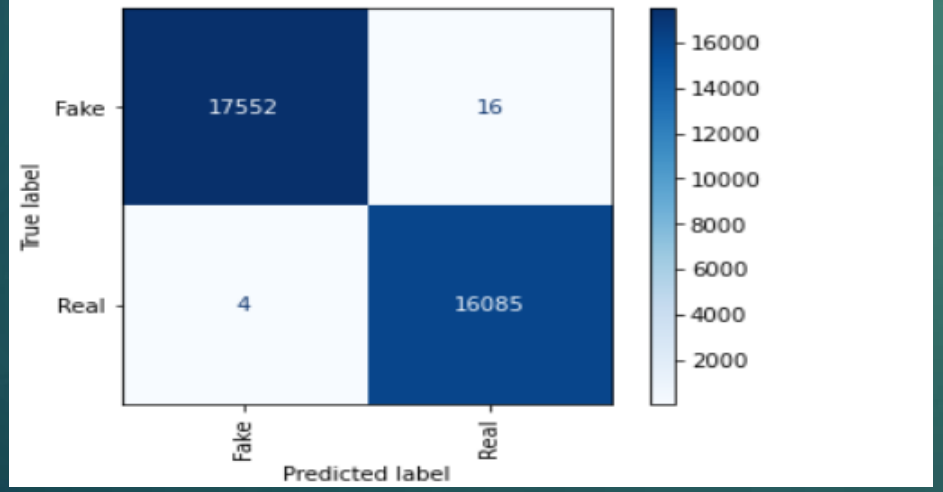
	precision	recall	f1-score	support
Fake	0.52	1.00	0.69	23481
Real	0.00	0.00	0.00	21396
accuracy			0.52	44877
macro avg	0.26	0.50	0.34	44877
weighted avg	0.27	0.52	0.36	44877



Logistic Regression Gridsearch Results with Split Set to 0.25

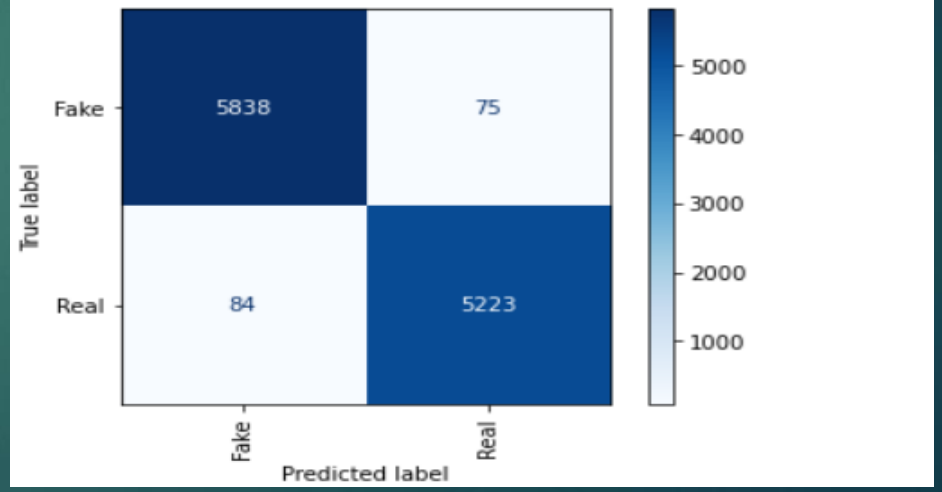
Training Set

	precision	recall	f1-score	support
Fake	1.00	1.00	1.00	17568
Real	1.00	1.00	1.00	16089
accuracy			1.00	33657
macro avg	1.00	1.00	1.00	33657
weighted avg	1.00	1.00	1.00	33657



Test Set

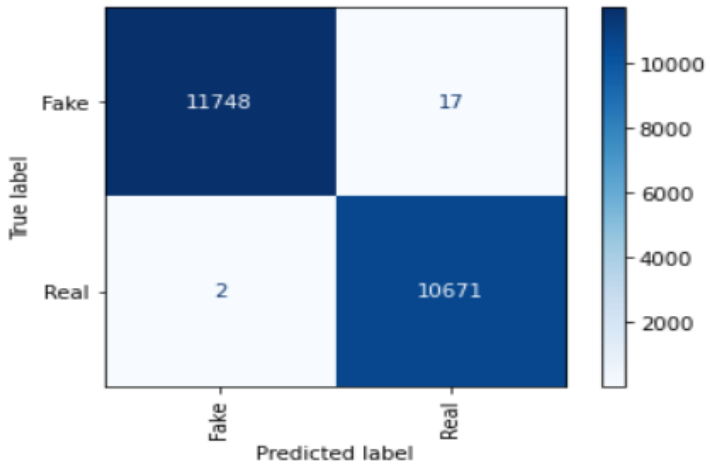
	precision	recall	f1-score	support
Fake	0.99	0.99	0.99	5913
Real	0.99	0.98	0.99	5307
accuracy			0.99	11220
macro avg	0.99	0.99	0.99	11220
weighted avg	0.99	0.99	0.99	11220



Logistic Regression Gridsearch Results with Split Set to 0.5

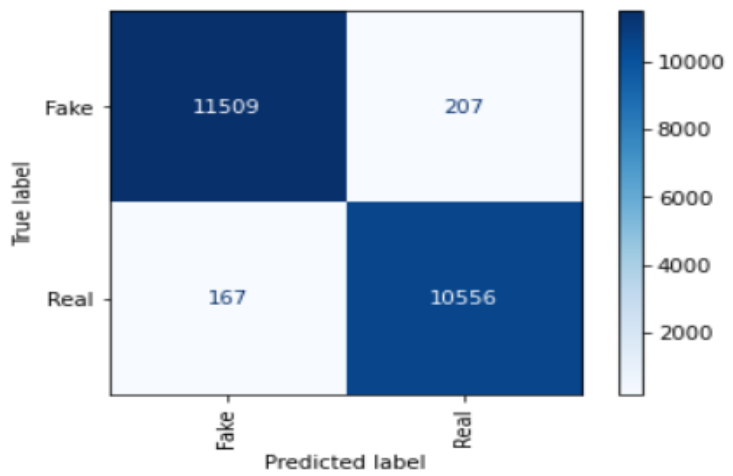
Training Set

	precision	recall	f1-score	support
Fake	1.00	1.00	1.00	11765
Real	1.00	1.00	1.00	10673
accuracy			1.00	22438
macro avg	1.00	1.00	1.00	22438
weighted avg	1.00	1.00	1.00	22438



Test Set

	precision	recall	f1-score	support
Fake	0.99	0.98	0.98	11716
Real	0.98	0.98	0.98	10723
accuracy			0.98	22439
macro avg	0.98	0.98	0.98	22439
weighted avg	0.98	0.98	0.98	22439



Next Steps

- Deploy web app so that anyone can verify if an article is real or fake.
- Train model on newer articles to keep it up to date.

Thank you

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