# Predicting Fake News Articles

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# ABSTRACT

Living in the age where  information quickly accessible on social media platforms exposes us and makes us susceptible to believing fake news articles. These articles underlying tone incites xenophobia and racism leading to polarized views fueled by lies. This problem is plentiful on this social media platform, the needs of which require us to experiment with machine learning and deep learning models to classify fake news to enhance user experience. This paper explores the methods, results and conclusions drawn from the analysis. It also makes recommendations for the future.

# Introduction

- Social Media companies need to have satisfied customers for it to be successful and this report looks at our ability to predict fake news articles on a social media platform and flag them as fake or real.
- The social media platform is the client and they are concerned about potentially losing current users from their platform.
- The client is interested in predicting which news articles circulating on their platform are real or fake, so users are aware of which articles are real or fake.
- A snapshot of the dataset below!

| | label | article_title | author | text | length | text_polarity |
|---|---|---|---|---|---|---|
| 0 | 1 | House Dem Aide: We Didn't Even See Comey's Let... | Darrell Lucus | House Dem Aide: We Didn't Even See Comey's Let... | 4886 | 0.001796 |
| 1 | 0 | FLYNN: Hillary Clinton, Big Woman on Campus - ... | Daniel J. Flynn | Ever get the feeling your life circles the rou... | 4143 | 0.100880 |
| 2 | 1 | Why the Truth Might Get You Fired | Consortiumnews.com | Why the Truth Might Get You Fired October 29, ... | 7670 | 0.056258 |
| 3 | 1 | 15 Civilians Killed In Single US Airstrike Hav... | Jessica Purkiss | Videos 15 Civilians Killed In Single US Airstr... | 3223 | 0.017497 |
| 4 | 1 | Iranian woman jailed for fictional unpublished... | Howard Portnoy | Print An Iranian woman has been sentenced to s... | 934 | -0.012500 |

# Methods

- Data Wrangling
- Exploring the data
- Inferential Statistical Analysis
- Modeling

# Data Wrangling

- Changed column names.
- Removed articles with less than 50 characters.
- Removed articles with null values.
- Added text_polarity column with values ranging between -1 and +1.

# Exploring the Data

In all news articles, without removal of stop words, the top word that occured was ‘the’. With the removal of stop words, the top word that occured was ‘said’. Similarly, without removal of stop words, the top bigram that occured was ‘of the’. With removal of stop words, the top bigram that occured was ‘mr trump’. Lastly, in all news articles, without removal of stop words the top trigram that occured was ‘the united states’. With the removal of stop words, the top trigram that occured was ‘new york times’.

In all fake articles, without removal of stop words, the top word that occured was ‘the’. With the removal of stop words, the top word that occured was ‘said’. Similarly, without removal of stop words, the top bigram that occured was ‘of the’. With removal of stop words, the top bigram that occured was ‘mr trump’. Lastly, in all news articles, without removal of stop words the top trigram that occured was ‘the united states’. With the removal of stop words, the top trigram that occured was ‘new york times’.

- For all (real and fake) articles, text polarity seemed normally distributed and had articles of values -1 and +1.
- Fake articles text polarity seemed normally distributed but did not contain articles with extreme values of -1 and +1.
- There was no correlation between the features in the dataset.
- Found the top unigram, bigrams and trigrams in all, real and fake articles.

# Inferential Statistical Analysis

```
Out[229]: Ttest_1sampResult(statistic=3.020018793001539, pvalue=0.0025337349388929752)
```

- **Hypothesis Testing:** Is there significant difference in the means of text polarity between articles that are fake and all text articles?
- **Null Hypothesis:** The null hypothesis would be there there is no difference in text polarity between articles that are fake and all text articles.
- **Alternate Hypothesis:** The alternative hypothesis would be that there is a difference in text polarity between fake articles and all articles.
- The low P-value of 0.0025 at a 5% confidence interval is a good indicator to reject the null hypothesis.

# Modeling

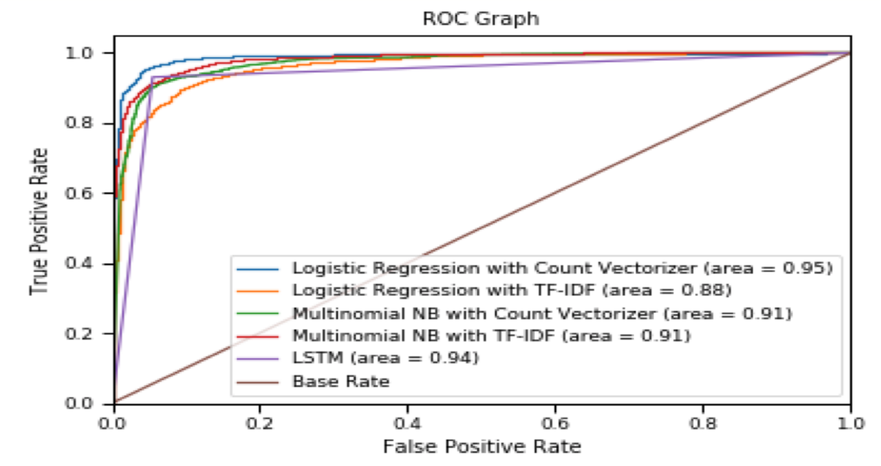
- CountVectorizer and TF-IDF Vectorizer to convert into input data for modeling
- Predicted with Logistic Regression and Multinomial Naive Bayes classifier
- Predicted with deep learning technique called Long Short Term Memory Neural Networks

# Results

- Model Evaluation

# Results

| Classifier | AUR-ROC Score | Accuracy |
|---|---|---|
| Multinomial NB (Count Vectorizer) | 0.91 | 0.91 |
| Multinomial NB (TF-IDF) | 0.91 | 0.91 |
| Logistic Regression (Count Vectorizer) | 0.95 | 0.95 |
| Logistic Regression (TF-IDF) | 0.88 | 0.88 |
| LSTM | 0.94 | 0.94 |




- Logistic Regression gave best result with 95% accuracy and 95% AUC-ROC score.
- LSTM model second best with 94% each in accuracy and AUC-ROC score.
- The worst model performance was also by Logistic Regression with TF-IDF Vectorizer achieving an accuracy and AUC-ROC score of 0.88.

# Evaluation

```
-- Logistic Regression Model --
-- Logistic Regression Model AUC = 0.95 --
-- Logistic Regression Model with Count Vectorizer Accuracy = 0.95 --
[[1942  126]
 [  72 1971]]
              precision    recall  f1-score   support

           0       0.96      0.94      0.95      2068
           1       0.94      0.96      0.95      2043

    accuracy                           0.95      4111
   macro avg       0.95      0.95      0.95      4111
weighted avg       0.95      0.95      0.95      4111
```

```
-- LSTM Neural Network on Tokenized Text --
-- LSTM Neural Network on Tokenized Text AUC = 0.94 --
-- LSTM Neural Network on Tokenized Text Accuracy = 0.94 --

[[1945  113]
 [ 142 1911]]

              precision    recall  f1-score   support

           0       0.93      0.95      0.94      2058
           1       0.94      0.93      0.94      2053

    accuracy                           0.94      4111
   macro avg       0.94      0.94      0.94      4111
weighted avg       0.94      0.94      0.94      4111
```

```
-- Multinomial NB Model with TF-IDF --
-- Multinomial NB Model with Count Vectorizer AUC = 0.91 --
-- Multinomial NB Model with Count Vectorizer Accuracy = 0.91 --

[[2023   45]
 [ 306 1737]]

              precision    recall  f1-score   support

           0       0.87      0.98      0.92      2068
           1       0.97      0.85      0.91      2043

    accuracy                           0.91      4111
   macro avg       0.92      0.91      0.91      4111
weighted avg       0.92      0.91      0.91      4111
```

```
-- Multinomial NB Model with Count Vectorizer AUC = 0.91 --
-- Multinomial NB Model with Count Vectorizer Accuracy = 0.91 --

[[1991   77]
 [ 282 1761]]

              precision    recall  f1-score   support

           0       0.88      0.96      0.92      2068
           1       0.96      0.86      0.91      2043

    accuracy                           0.91      4111
   macro avg       0.92      0.91      0.91      4111
weighted avg       0.92      0.91      0.91      4111
```

```
-- Logistic Regression Model --
-- Logistic Regression Model AUC = 0.88 --
-- Logistic Regression Model with TFIDF Accuracy = 0.88 --
[[1684  384]
 [ 102 1941]]
              precision    recall  f1-score   support

           0       0.94      0.81      0.87      2068
           1       0.83      0.95      0.89      2043

    accuracy                           0.88      4111
   macro avg       0.89      0.88      0.88      4111
weighted avg       0.89      0.88      0.88      4111
```

- Use Accuracy
- Use the AUC-ROC score which plots the True Positive Rate against the False Positive Rate.
- Take into consideration the False Positive and False Negative Errors to evaluate our models' performances.
- False Positives (Type I Error): You predict that the article is Fake but is Real.
- False Negatives (Type II Error): You predict that the article is Real but is Fake.

# Conclusion

- Potential Solutions
- Where do we go from here?

# Potential Solutions:

Solution 1:

We can rank the articles with a probability estimate of it being real or fake, indicating how confident we think a particular article is real or fake. This will provide the readers some context and enough to decide for themselves to be skeptical of the news or not. The social media platform isn't making the decision for their users but giving them the information to decide for themselves so it does not feel like the user is being coerced into believing something or not.

Solution 2:

Provide free training to the users of the social media platform to identify fake news. For example, tips and resources can be shared that discuss common ways one can fact check a news article. It can be as simple as copy pasting information from the article into google, and seeing if the information adds up.

# Where do we go from here?

1. This problem is about equipping the social media company with actionable knowledge regarding their ability to identify fake news on their platform and countering it. When modeling the data, we should not use the predictive metric as our final solution. Instead, we should use the information we get from modeling and arm the social media platform users so they can carry out informed decision making.

2. Once the model is deployed, as more and more articles get shared on the platform, our dataset will grow. This will help make our model more accurate over time by allowing us to even test out different techniques or other models that may perform better or are more computationally efficient for our use case. For now, this model will do as it is better to have some knowledge about an article's validity than to be completely in the dark in this age of misinformation.