Fake News Detection

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Abstract

Fake news can be defined as news pieces which are intentionally created to be false and misleading. Fake news detection has gained a lot of attention over the years with an increase in the spread of fake news through online social networks such as Facebook, Twitter, etc. Because of the various inherent social and political biases, the fake news on social media platforms can spread rapidly. The motives for spreading fake content are manipulating public opinion, trolling, bullying, manipulating the market and causing panic amongst the masses to create chaos and distrust. For instance, fake news during the 2016 Presidential Election was used to manipulate the outcomes of an election and Brexit was used to manipulate the sentiments of the people (Bessi and Ferrara, 2016).

1 Introduction

1.1 Problem Statement

For our project, we try to analyze how various aspects of a news piece affect the prediction of fake news articles. For this we try to model the information regarding the author, the title of the news article and the text given for the news article. We aim to find the most important aspect, or a combination of aspects, and try to reason the logic behind the results obtained.

1.2 Motivation

One of the motivating factors in pursuing this field is the non-trivial nature of fake news. Fake news detection is dependent on a number of factors such as the social engagement of the spreader, the intention of spreading the fake news, and the audience that the fake news is able to garner. This makes the problem challenging and pursuable. We were motivated to analyze that for the given dataset, how different features would affect the probability of a given news article to be fake.

1.3 Online Deployment link

Deployed on local machine due to unavailability of server.

1.4 Project Pipeline Summary

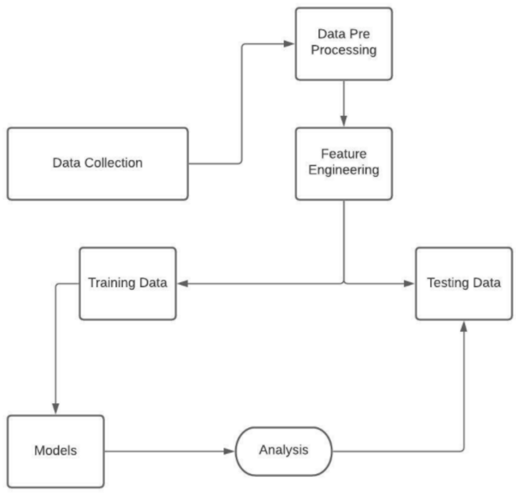

Figure 1: Pipeline of the data.

For all the machine learning models, we follow the general process. This involves data collection (Kaggle dataset), followed by data pre-processing, and feature engineering. We then derive the information relevant for our project, and then train various machine learning models to get the results and analysis.

2 Related Work

Though there is no general consensus on the definition of fake news, (Shu et al., 2017) have narrowed it down to “news articles that are intentionally and verifiably false and could mislead readers”. They have defined features for fake news detection into News Content Feature and Social Context Features. In the field of fake news detection, we see that with the advent of deep learning and increasing com-

plexity of the models, there has been a significant improvement in accuracy. However machine learning models and their ensemble also perform very well on these tasks(Ahmad et al., 2020). We see that (Ahmad et al., 2020) have extensively used machine learning ensembles to analyse their efficiencies on fake news tasks.
Since for our project, we have stuck to mostly machine learning models, most of our literature survey was based around machine learning models in natural language processing tasks. (Agarwalla et al., 2019) use Naive Bayes Classifier for the task of fake news detection. Their accuracies show the efficiency of a Naive Bayes Classifier in this task. (Conroy et al., 2015), discuss linguistic and network based approaches in fake news detection.While linguistic approaches are based on finding language "leakage" where verbal aspects can be considered, network approaches are based on real time network properties to identify deceptive language and behaviour through various network properties.

3 Methodology

3.1 Data Visualization

3.1.1 Percentage of Data for each labels

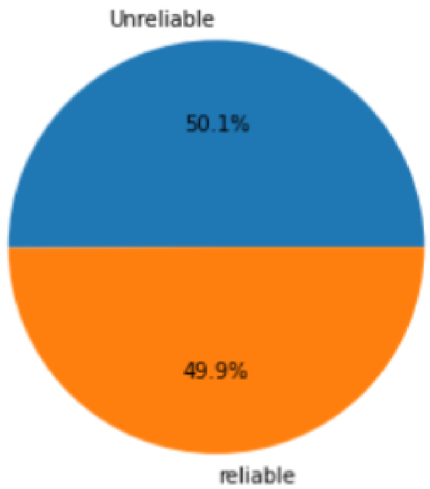

Figure 2: This picture represents percentage of data which is categorized as unreliable (fake news) and reliable (non fake news). As we can see that the data set is balanced and contains an almost equal amount of fake vs non fake samples.

3.1.2 Percentage of fake news spread by authors with the most number of publication

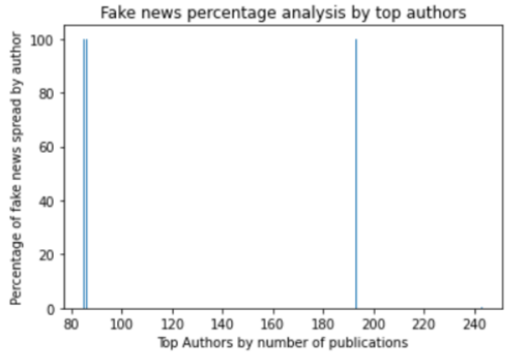

Figure 3: This picture represents authors who have more than 80 publications in our given dataset. As we can see there are very few authors with higher publication rates and high percentage of fake news. Hence, we can safely interpret from the data that most top authors do not spread fake news.

3.1.3 Grouping the number of publications and displaying the percentage of fake news in a bucket

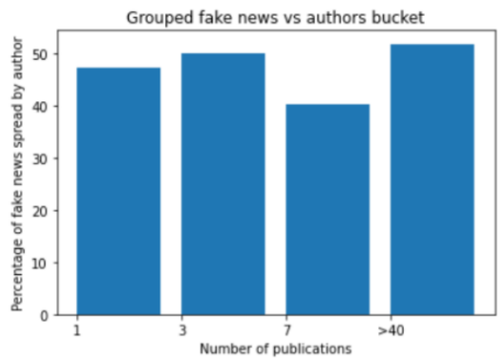

Figure 4: depicts that there is almost an equal percentage of fake news with the given bucket sizes, and from this we can infer that the top authors who have more than 80 publications must be very less as compared to 40-80.

3.1.4 Length of titles in our data set

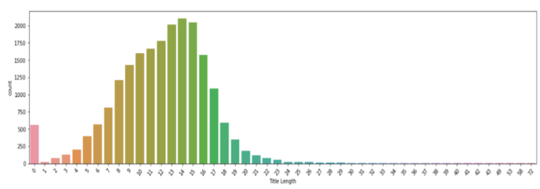

Figure 5: The frequency plot of number of tokens in a title.

3.1.5 Wordcloud for reliable news

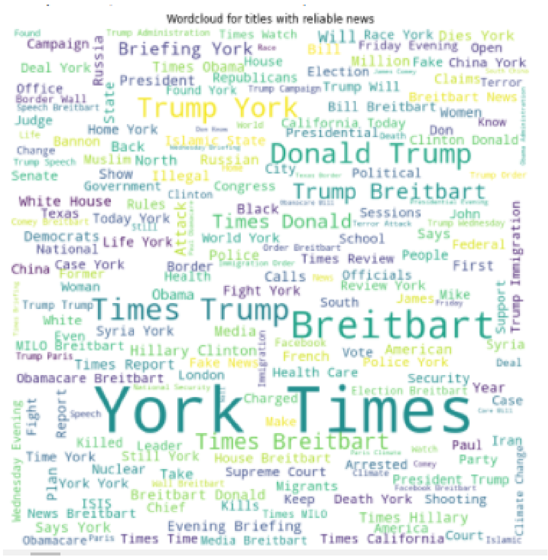

Figure 6: Top 250 words in reliable news.

3.1.6 Wordcloud for unreliable news

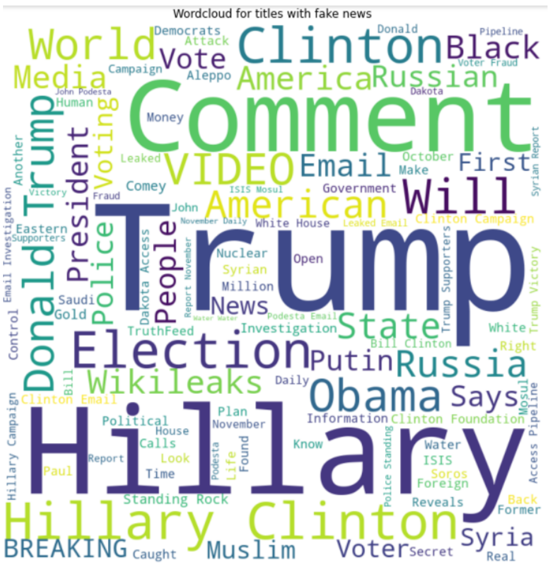

Figure 7: Top 250 words in fake news.

3.2 Data Preprocessing

For pre-processing data, we will first remove all rows which have undefined labels. For titles, authors and texts, instead of removing the nan values, we have replaced them with a space because we can still make a good prediction in case one or two of the columns are not present as we have later shown in the Experiment section.

After dealing with the nan values, we have removed the stop words and stemmed the words for some of our models which use one hot or bag of word implemenations. Also, punctuation have also been formatted from the feature labels.

3.3 Feature Extraction

We have used the following techniques for feature extraction:

1. Count vectorizer
2. Tfidf vectorizer
3. Word embeddings

3.4 Models Used

We have used the following models:

1. Multinomial Naive Bayes(MNB): Multinomial Naive Bayes is a probabilistic model based on the assumption that all the features are independent of each other.

2. Logistic Regression(LR) : In Fake News Detection, Logistic Regression gives us the probability of the ground truth values.

3. Decision Trees(DT): A decision tree classifier has a tree like structure with each node representing an attribute.

4. Random Forests(RF): Random Forest uses an ensemble of decision tree classifiers for improving the results obtained from a Decision Tree Classifier.

5. LSTM: It is an improved version of RNN model which controls the flow of information using recurrent units.

4 Experiments

4.1 Feature Selection

4.1.1 Taking each title (Ti) , author (Au) and text (Te) individually into account and applying baseline models such as Naive Bayes, Logistic Regression, Decision Tree.

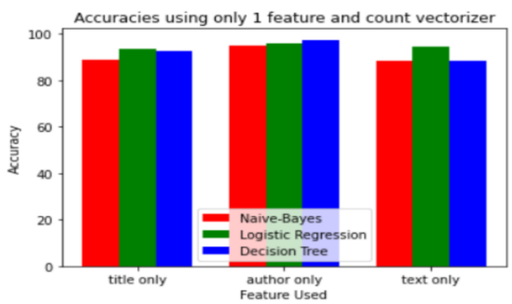

Figure 8: Using count-vectorizer.

Below is the table of accuracy .

Accuracy using Count Vectorizer			
Model	Ti	Te	Au
MNB	89.7%	89.0%	95.5%
LR	92.7%	94.9%	96.0%
DT	92.2%	89.5%	97.6%

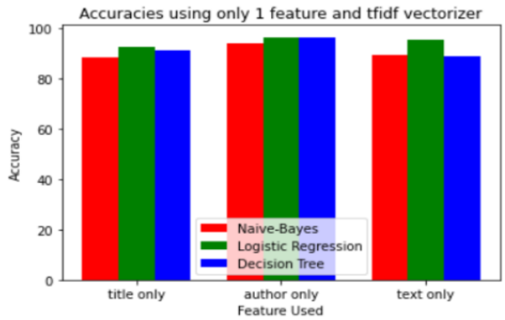

Figure 9: Using tfidf-vectorizer.

Below is the table of accuracy .

Accuracy using TFIDF Vectorizer			
Model	Ti	Au	Te
MNB	87.3%	93.2%	89.3%
LR	93.5%	96.4%	94.6%
DT	91.7%	96.7%	89.5%

From this, we can observe that we are getting a good enough accuracy (more than 85in every case using even individual features. Hence we cannot drop any features and all the features play an important role in the final classification.

4.1.2 Concatenating two features at a time and applying the baselines models so as to obtain accuracy and interpret coherence of concatenation

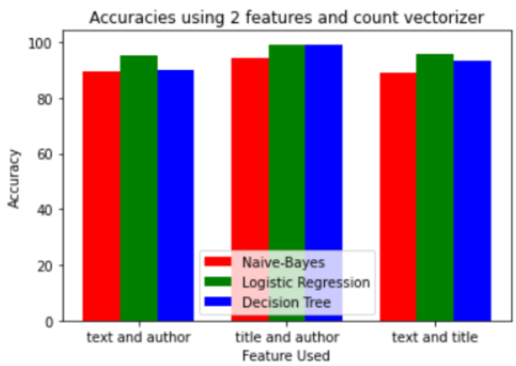

Figure 10: Using count vectorizer.

Below is the table of accuracy .

Accuracy using Count Vectorizer			
Model	Te+Au	Ti+Au	Ti+Te
MNB	89.2%	96.4%	89.8%
LR	95.6%	98.2%	95.8%
DT	89.1%	98.2%	93.1%

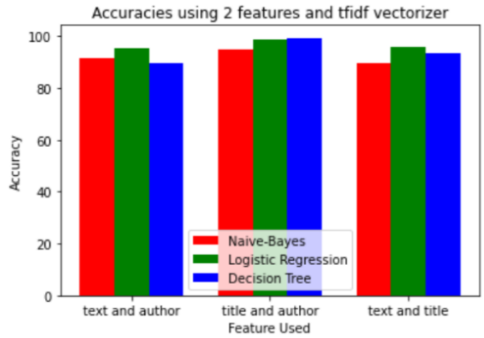

Figure 11: Using tfidf-vectorizer.

Below is the table of accuracy .

Accuracy using TFIDF Vectorizer			
Model	Te+Au	Ti+Au	Ti+Te
MNB	90.4%	97.7%	89.7%
LR	95.3%	98.4%	96.0%
DT	89.1%	97.3%	93.4%

4.1.3 Concatenating all the features in one go and applying baseline models to obtain accuracy.

Accuracy after combining all features .

Accuracy using Count Vectorizer	
Model	Au+Ti+Te
MNB	89.63%
LR	96.87%
DT	93.99%
RF	97.18%

Accuracy after combining all features .

Accuracy using TFIDF Vectorizer	
Model	Au+Ti+Te
MNB	91.39%
LR	96.85%
DT	95.57%
RF	97.74%

4.2 Using Word embeddings on LSTMs

Accuracy for Model + Embedding	
Model+Embedding	Accuracy
LSTM + one-hot	90.24%
LSTM + Glove	93.25%
BiLSTM, CNN + Glove	94.63%

5 Results and Analysis

When we applied baseline models to individual columns we observed that the results had accuracy of around 90% in all the columns and the Author column performed best in term of accuracy, which can be linked to the fact that if an author is known then the chances of knowing the label are higher for the author. Also, title and text give good accuracy hence we cannot drop off features and go ahead with combining two of them at a time.

When we applied concatenation operation on two models at a time we observed that Title+author column gave out the best accuracy which can be attributed to the occurrences of certain authors and catchy titles which is linked to more fake news and hence produces a better accuracy.

Now coming onto word embedding, we see that LSTM + one-hot performs the worst among all other models, this is because one hot encoding does not preserve context where as Glove embedding does and then Bidirection LSTM performs even better which is expected as it is able to capture the context in an even better manner.

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