

Fake News Detection and Sentiment Analysis

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Abstract

In the world of social media, people are constantly exposed to and interacting with news and current events. We are constantly in front of a stream of news headlines about the pandemic, local, national, international elections, financial markets, and popular culture. This constantly flowing stream of data in the form of text influences people's thoughts, forms their opinion, and directs consumer behaviour. This input given to the user is in the form of raw textual data (Semi-Structured Data) in different languages and terms, which contains noise in data as well as critical information that allows a team to analyze the data to discover knowledge and patterns from the dataset available. Of late, the two most important aspects of news headlines and articles which are being analyzed are authenticity and sentiment. To discover this unknown information from the linguistic data, Natural Language Processing (NLP) and Data Mining techniques are the most focused research terms used for fake news detection and sentiment analysis. In our work, we have attempted to work at the intersection of fake news detection and sentiment analysis using machine learning techniques applied to news articles. We realized that the neutral sentiment for news articles is significantly high which clearly shows the limitations of our current work.

1 Introduction

Today's world is in a constant process of rapid transformation. The internet, social media, and the metaverse come with their advantages but it also has their demerits and challenges. There are different issues in this digital world. One of them is fake news. Fake news is spread to harm the reputation of a person or an organization. It can be propaganda against an entity that can be a person,

a group of people, a political party, or an organization. There are different online platforms where the person can spread fake news which include Instagram, Snapchat, Facebook, Twitter, etc.

One tool that can be used to tackle the issue of fake news is machine learning. Machine learning helps in making the systems that can learn and perform different actions. A variety of machine learning algorithms like supervised, unsupervised, reinforcement algorithms have to be trained with some data. Once trained, these algorithms can be used to perform different tasks. Most of the time machine learning algorithms are used for prediction purposes or to detect something hidden. The subset of ML called Natural language Processing - NLP is especially useful in detecting fake news.

Online platforms allow users to easily access news and information. At the same time, they allow cybercriminals to spread fake news through these platforms. This news can be proven harmful to a person or society. Readers read the news and start believing it without its verification. Detecting fake news is a big challenge, and if not detected early then the people can spread it to others and all the people will start believing it. Individuals, organizations, or political parties can be affected by fake news. For instance, it is said that people's opinions and decisions were affected by fake news in the US election of 2016.

We used 80% of our data to train the model and the remaining 20% to test it. We used a data model which classified the news as real or fake. We

evaluated our model by plotting the confusion matrix and the accuracy score. Our project will serve as a base for our independent study where we plan to incorporate fake news detection and sentiment analysis to determine whether a news article is fake or real and also analyze the sentiment of the article. The purpose of this project is not to decide for the reader whether or not the document is fake, but rather to alert them that they need to use extra scrutiny for some documents. Fake news detection, unlike spam detection, has many nuances that aren't as easily detected by text analysis. For example, a human actually needs to apply their knowledge of a particular subject in order to decide whether or not the news is true. The "fakeness" of an article could be switched on or off simply by replacing one person's name with another person's name. Therefore, the best we can do from a content-based standpoint is to decide if it is something that requires scrutiny.

Sentiment analysis is a process that involves the extraction of attitudes, opinions, views, and emotions from text, speech, tweets, and database sources through Natural Language Processing (NLP). Sentiment analysis involves classifying opinions in text into different categories like "positive" or "negative" or "neutral". It is also referred to as subjectivity analysis, opinion mining, and appraisal extraction. In this work, we apply similar techniques that people have used for Twitter sentiment detection to the news headlines.

2 Related Work

Machine learning (ML) is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions, relying on patterns and inference instead. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task. Machine learning is closely related to computational statistics, which focuses on making predictions using computers. In this project, we apply machine learning to solve a problem that has been a cause for concern in recent years- fake news detection. We also perform sentiment analysis of the text.

The 2016 U.S. The Presidential Election between Donald Trump and Hilary Clinton showed us not only the bad effects of fake news but also served as an example of challenges faced when we try to separate real news from fake news[1]. Fake news has been around at least since the appearance and popularity of polarized and partisan newspapers in the 19th century. Recent developments in technology and the spread of news through different types of media, especially social media have increased the spread of fake news today. The incidence of the fake news phenomenon has risen dramatically in the recent past and something must be done to prevent this from continuing in the future.

In the report by Nicole O' Brien, she outlined the three most prevalent motivations for spreading fake news[1]. The first motivation for writing fake news, which dates back to the 19th century one-sided party newspapers, is to influence public opinion. The second, which requires more recent advances in technology, is a display of fake headlines as clickbait making the user click so that they can make money. The third motivation for writing fake news, which is equally prominent yet arguably less dangerous, is satirical writing[1]. While all three subsets of fake news, namely, (a) clickbait[2], (b), influential[3], and (c) satire[4], share the common thread of being fictitious, their widespread effects are vastly different.

The definition of fake news chosen in [1] and the one we chose in our report will focus primarily on fake news as defined by politifact.com, "fabricated content that intentionally masquerades as news coverage of actual events." Satire can already be classified, by machine learning techniques according to [4]. Therefore, our goal is to move beyond these achievements and use machine learning to classify, at least as well as humans, more difficult discrepancies between real and fake news.

The dangerous effects of fake news, are made clear by events such as [5] in which a man attacked a pizzeria due to a widely circulated fake news article. This story along with analysis from [6] is a proof that humans are not efficient at detecting fake news, and hence we need to use mathematical and computational approaches for fake news detection, such as ML and NLP.

Previous studies and academic research has been done in the domain of fake news detection, for example by Bali et al. [7]. The authors addressed fake news detection from the angle of NLP and Machine Learning. Three representative datasets were assessed, each having its own set of features mined from the headlines and contents. According to the results of their study, gradient boosting surpassed all other classifiers. The accuracy and F-scores of seven alternative machine learning algorithms were investigated, but they all remained under 90%.[8]

Some researchers have also tried to uncover the different classes of strategies for fake news detection. In their publication, Conroy et al. [9] provided us with an overview of two significant classes of strategies for discovering fake/false news. The first overviewed class was involving linguistic techniques, in which the material of deceptive messages is removed and dissected to relate language designs with double-dealing. The second class of strategies which they overviewed was related to network approaches, in which network data, take for example, message metadata or organized information organization inquiries, could be compiled to produce total misdirection measures.

Another publication we looked at was written by Abdullah et al. [10] and this involved using deep learning models for the purpose of fake news detection. The study was used to detect fake news using a multimodal model. Still, its performance did not produce good results through a convolutional neural network (CNN), and long short-term memory (LSTM) approaches. The model training time was time taken, and the study was biased towards datasets.[8]

The challenge of detecting falsified sources of information through content based analysis has been addressed and solved previously in the field of spam detection [11], spam detection utilizes statistical machine learning techniques to classify text (i.e. tweets [12] or emails) as spam or legitimate. This has been accomplished by pre-processing of the text, feature extraction, and feature selection by determining the features that lead to the best performance on a test dataset. Once these features are obtained, they can be classified using a classifier like K-nearest neighbors

classifiers. The classifiers people have used are characteristic of supervised machine learning, defined by its use of labeled datasets to train algorithms that to classify data or predict outcomes accurately as in [13].

In the past few years, significant work has been done in the field of “Sentiment Analysis on Twitter” by several researchers. Early publications on this topic, intended to perform binary classification where they assigned opinions or reviews to bipolar classes such as positive or negative only. Pak and Paroubek [14] in their paper in 2010, conceptualized a model and used a sentiment-based classifier to classify tweets as objective, positive or negative. They created a Twitter data collection by collecting tweets using Twitter API and then automatically annotating those tweets using emoticons. Using that data set, they developed a sentiment classifier based on the multinomial Naive Bayes method that uses features like Ngram and Part Of Speech tags. Their training set was limited since it contained only tweets having emoticons. Parikh and Movassate [15] implemented two models, a Naive Bayes bigram model and a Maximum Entropy model to classify tweets. Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes’ theorem with the “naive” assumption of conditional independence between every pair of features given the value of the class variable. The principle of maximum entropy states that the probability distribution which best represents the current state of knowledge about a system is the one with the largest entropy, in the context of precisely stated prior data. It was found that the Naive Bayes classifiers worked much better than the Maximum Entropy model [16].

3 Implementation Details

Tools Used : PyCharm.

Libraries used: Pandas, sklearn, Flask, vaderSentiment, BeautifulSoup, TextBlob, urllib.request

Data Structures used: lists, dictionaries, files and dataframes.

Step 1: Predicting News Authenticity

- Made necessary imports
- Read dataset into data frames

- Extracted text and labels from the data, and divided the whole dataset into test and train subsets.
- Trained Passive Aggressive Classifier model and predicted results.
- Calculated accuracy for test data.
- Generated outputs for user data.

Step 2: News Sentiment Analysis

- Made necessary imports
- Used Vader Sentiment to analyze text/news, and TextBlob to find polarity of web-scraped news articles.
- Categorized results as 'positive', 'negative' or 'neutral' based on polarity values.

Step 3: Web scraping

- Made necessary imports
- Defined functions to:
 - Get news titles and links from newspaper's webpages based on class attributes of HTML elements.
 - Zip news titles and respective articles.
 - Extract text from each article and find it's polarity.
 - Output the result for each news article.
- Incorporated logics to work for two different websites: thehindu.com and thestar.com

Step 4: Developing Flask web application and implementing the first 3 steps

- Made the necessary imports.
- Created 3 HTML pages for the web application.
 - The Home Page
 - News Authenticity Page, where user would get to know the authenticity of news entered into the textbox, and its sentiment as well.
 - Sentiment Analysis Page, where user would get to know the sentiment of text entered into the textbox, or the sentiment of news posted on either of the two websites: thehindu.com or thestar.com.

- Implemented logic to trigger python functions and generate required results.
- Used stylesheet and bootstrap to improve the visuals of web application.

This website will act as a platform where the user will interact with an intention to check the credibility of news. The user enters a news article in the space provided. This text is passed on to the machine learning model to predict the credibility or sentiment of the article. After backend processing, the final results are displayed to the users.

We chose a web-based presentation with the hope that it will enable many users to view our results. The statistical analysis and machine learning module will make the judgements about a given article.

Work Flow:



Libraries and Data Structures:

Pandas: Pandas is a Python library for data analysis. It is built on top of two core Python libraries—matplotlib for data visualization and NumPy for mathematical operations. Pandas acts as a wrapper over these libraries, allowing you to access many of matplotlib's and NumPy's methods with less code.

Sklearn: Scikit-learn is probably the most useful library for machine learning in Python. The sklearn library contains a lot of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction.

Flask: Flask is a micro web framework written in Python. It is a lightweight WSGI web application framework. It is designed to make getting started quick and easy, with the ability to scale up to complex applications.

vaderSentiment: VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media, and works well on texts from other domains.

BeautifulSoup: BeautifulSoup is a Python library that is used for web scraping purposes to pull the data out of HTML and XML files. It creates a parse tree from page source code that can be used to extract data in a hierarchical and more readable manner.

TextBlob: Textblob is an open-source python library for processing textual data. It performs different operations on textual data such as noun phrase extraction, sentiment analysis, classification, translation.



4 Dataset:

We are using news.csv to train our model. We have taken this dataset from data-flair.training. This dataset has a shape of 7796×4. It consists of 4 columns, where one of them does not have a header but contains identifier for each news. The second column is ‘title’ which contains the headings of a news article, and the third column ‘text’ contains the body text of the particular article. The fourth column has labels denoting whether the news is Real or Fake. Here is what our dataset looks like:

```
In [11]: dataframe.head(10)
```

	Unnamed: 0	title	text	label
0	5876	You Can Spoil Hillary's Face	Charles Goodhart, a British Journalist Falls...	FAKE
1	10294	Watch The Exact Moment Paul Ryan Committed Pd...	Google Protester Sluggs Lincoln Reddix Shambles...	FAKE
2	3698	Kerry to go to Paris in gesture of sympathy	U.S. Secretary of State John F. Kerry said Mon...	REAL
3	10742	Bernie supporters on Twitter erupt in anger ag...	— Kanye West (@KanyeWest) November 9, 2016 T...	FAKE
4	679	The Battle of New York City This Primary Matters	It's primary day in New York and front runners...	REAL
5	1683	Tekken, USA	It's not an immigrant, but my grandparents...	FAKE
6	7341	Get Horrific At What She Watches Bayhead O...	Share This Bayless Luciani (left), Skolenski o...	FAKE
7	86	Britain's Schröder Dies at 100	A Czech stockbroker who saved more than 650 Je...	REAL
8	4988	Fact check: Trump and Clinton at the commande...	Hillary Clinton and Donald Trump made some ma...	REAL
9	2385	Iran reportedly makes new push for uranium cat...	Iranian negotiators reportedly have made a las...	REAL

5 Evaluation and Analysis:

We evaluated our model using two metrics: accuracy and confusion matrix. The model scored an accuracy of >90%. It was observed that model was working very well with the data from our dataset, though we were getting some false positives and false negatives for the actual news articles since the data in our dataset seemed to be have collected in the past and needs to be updated for better results.

We are using the confusion matrix to depict the overall performance of our model while testing our test data.

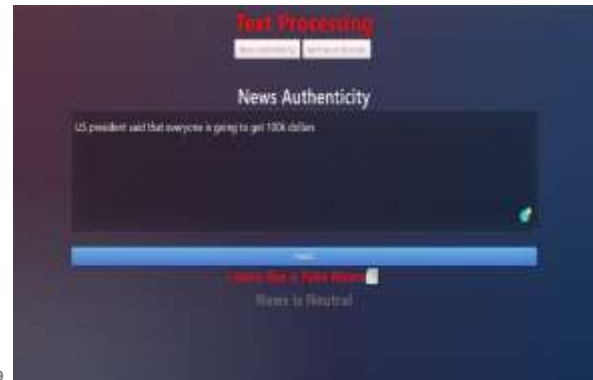
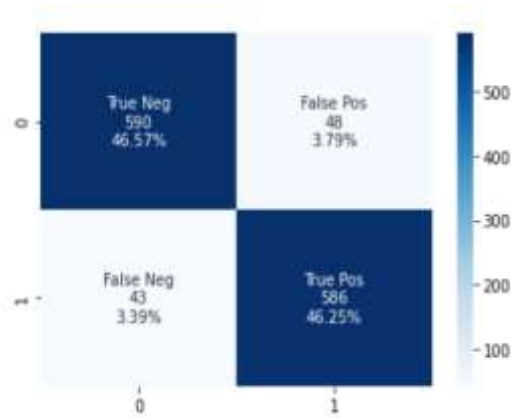
Here are the results that were recorded:

```
In [11]: score=accuracy_score(y_test,y_pred)
          print(score)

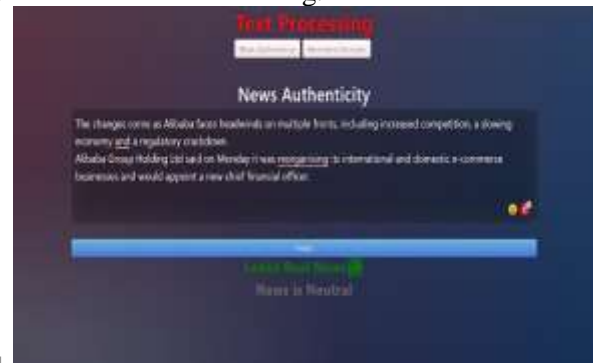
0.9265982636148382
```

```
In [21]: confusion_matrix(y_test,y_pred, labels=['FAKE', 'REAL'])

Out[21]: array([[598, 48],
                [ 43, 586]], dtype=int64)
```



Img.1



Img.2



Img.3



Img.4

6 Use Case

- Social media websites, news channels can benefit from a fake news detection system that filters out fake news.
- News websites and social media websites can provide a toggle/option to users to filter out articles based on sentiment.
- A standalone application can be made for use by organizations and educational institutions to avoid fake news being used for business purposes or academic citations

7 Results

After training our model and setting up the web application, we analyzed news articles from various news websites. Here are some of the results that we got:

- Image 1 shows a news being detected as Fake.
- Image 2 shows a news being detected as True.
- Image 3 shows a sentiment test being run on a text and the text being classified as Negative.
- Image 4 again shows a sentiment test being run on a text and the text being classified as Positive.
- Image 5 and 6 shows sentiment analysis of news articles from two different websites.



Img.5



Img.6

8 Future Work

In the future, we can improve two aspects of our project. The first one is we can improve our dataset and the second one is incorporating real-time processing functionality. A larger and updated dataset can remove any bias in our model that generally exists in smaller data sets. It is also possible to perform real-time fake news detection and sentiment analysis to the news articles. To achieve this, we have to implement the same data processing and machine learning algorithm on the cloud, which can boost the scale and the performance for sentiment analysis using Natural Language Processing (NLP) techniques. Creation of nodes on a cloud data platform like Hadoop that allow us to store the data on the cloud using HDFS (Hadoop File System) and Map-reduce concept to distribute the data processing algorithm on the cloud to load and process large size data set and real-time sentiment analysis for the linguistic data. This will enable real-time fake news detection and sentiment analysis in a cloud environment and will allow the user to fetch real time sentiment analysis from the input data.

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602 **10 Appendix**

603 Download the code here:

604 “[https://drive.google.com/file/d/1ozHNZxzVs](https://drive.google.com/file/d/1ozHNZxzVsLKI8pcSZLluhmjVI_5BW8gR/view?usp=sharing)
605 [LKI8pcSZLluhmjVI_5BW8gR/view?usp=sh](https://drive.google.com/file/d/1ozHNZxzVsLKI8pcSZLluhmjVI_5BW8gR/view?usp=sharing)
606 [aring](https://drive.google.com/file/d/1ozHNZxzVsLKI8pcSZLluhmjVI_5BW8gR/view?usp=sharing)”

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