# **Fake News Detection**

Summary	Fake new detection using NLP and performing sentiment analysis
URL	
Category	Machine Learning, Web
Environment	NA
Status	Version 1
Feedback Link	
Team No	7
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## Team 7

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# **Project goal**



Our goal is to explore how artificial intelligence technologies, particularly machine learning and natural language processing, might be leveraged to combat the fake news problem. We believe by using these technologies we can automate and help the users to determine if a story is real or a hoax. Our purpose is to use different machine learning models and identify the accurate model to determine if any news is fake or real. If a user comes across any random news site with some misleading content before actually believing it and spreading the news, he can use our model to identify the content. Our motive is to take a step to prevent the casualties

occurring due to the amount of fake information widespread in society by delivering a model having the highest accuracy of detecting the legit information.

# Implementation details

### Web scraping:

We first collect data by web scraping 3 newspaper sites WSJ, NYTimes, and TampaBay for legitimate news content. In order to collect fake news data we used an API and gathered fake news content. The data is collected in a standard format of id, title, publication, author, published date, category, URL, content.

### Data merging and Data Preprocessing:

All the data collected is merged using pandas to form a combined dataset under Final\_Data.csv. At the time of merging we label the data as "Real" and "Fake". Data is cleaned by removing all the null values, special characters, Unicode characters which are identified by performing exploratory data analysis on the merged data. This cleaned data is stored under a separate CSV named CleanData.

### **Data Cleansing**

- Removed characters from the content
- Updated empty rows with values
- Dropped Unwanted rows
- · Removed stop words from content
- · Punctuation has been handled

### Exploratory Data Analysis:

Exploratory data analysis usually performed to get an overview of the dataset gave us some insights about the data we had after merging. We realized a lot of data needs to be processed as shown in the below snapshot to generate a clean dataset.

	ID	Title	Publication	Author	Published	Year	Month	Category	URL	Content
0	1	What's News: Business & Finance	WSJ	O	01/02/18	2018	1	\r\r\n Whats News Busines	https://www.wsj.com/articles/whats- news-busine	The unemployment rate in some metro areas stan
1	2	A Browser You've Never Heard of Is Dethroning	WSJ	['Newley Purnell', 'Newley.Purnell Wsj.Com']	01/01/18	2018	1	Tech	https://www.wsj.com/articles/a-browser-youve-n	JAKARTA, Indonesia—A mobile browser rarely use
2	3	2017 Marked Safest Year in Commercial Aviation	WSJ	['Andy Pasztor', 'Andy.Pasztor Wsj.Com']	01/02/18	2018	1	U.S.	https://www.wsj.com/articles/2017- marked-safes	The global airline industry achieved a previou
3	4	Five Things to Know About the Iranian Protests	WSJ	['Farnaz Fassihi', 'Farnaz.Fassihi Wsj.Com']	12/31/17	2017	12	World	https://www.wsj.com/articles/economics-dissati	Protests erupted across Iran for a third day o
4	5	Photos of the Day: Jan. 1	WSJ	0	01/01/18	2018	1	None	https://www.wsj.com/articles/photos-of- the-day	Photos of the Day: Jan. 1 Children warm up by

We added a feature named 'Label' to denote the fake and real news. The data set looks like below after cleaning

### **Null Values**

## Quantity of non-empty rows

```
In [33]: N
              1 #Calcualing percetage of empty rows
                 def NaN_percent(df, column_name):
              2
                     row_count = df[column_name].shape[0]
              3
                     empty_values = row_count - df[column_name].count()
              4
                     return (100.0*empty_values)/row_count
              6 for i in list(df):
                     print(i +': ' + str(NaN percent(df,i))+'%')
             ID: 0.0%
             Title: 24.89328836363304%
             Publication: 0.0%
             Author: 20.924620910910637%
             Published: 0.0%
             Year: 0.0%
             Month: 0.0%
             Category: 0.0%
             URL: 0.0%
             Content: 0.0%
```

## **Null Values**

**Null Values Handling** 

# **Null Values**

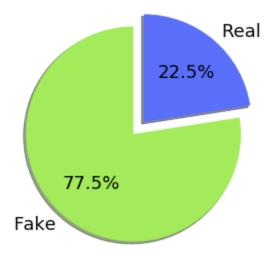
### Fake Data Word Cloud



### Real Data Word Cloud



So after data processing, we could come up to the conclusion that our dataset has a collection of real and fake news as shown in the pie chart below



### Vectorization:

It is a process of collecting discriminative information from a set of given samples. We used two approaches to extract our features Count Vectorization and Tfldf Vectorization. The training data is transformed to learn vocabulary dictionary and return term-document matrix and the test data is transformed to the document-term matrix for model analysis.

Count vectorizer: It counts the number of times a token shows up in the document and uses this value as its weight.

*TF-IDF Vectorizer*: TF-IDF stands for "term frequency-inverse document frequency", meaning the weight assigned to each token not only depends on its frequency in a document but also how recurrent that term is in the entire corpus.

### Generating models:

The approach to implementing our idea is pretty simple, our ultimate goal is to classify a given piece of information. To achieve this we tried 5 models for classification and evaluated them to get the best one

- Multinomial Naive Bayes
- Random Forest
- Support Vector Machine
- Logistic Regression
- XGBoost

# **Analysis of models**

### **Multinomial Naive Bayes:**

MNB is a commonly used machine-learning probabilistic classifier which uses a set of features and classes to determine the probability of features occurring in each class and returns the most

likely class in return. The probability is calculated using features generated from count vectorizer and tf-idf vectorizer and labels (fake and real). We train our model on these features and test the model on transformed data. For evaluation, we are computing metrics as follows

### **Random Forest**

Random forests create decision trees on randomly selected data samples, gets a prediction from each tree and selects the best solution by means of voting. The best solution is computed using features generated from count vectorizer and tf-idf vectorizer and labels(fake and real).

### XGBoost

Boosting is a sequential technique which works on the principle of an ensemble. It combines a set of weak learners and delivers improved prediction accuracy. At any instant t, the model outcomes are weighed based on the outcomes of previous instant t-1. The outcomes predicted correctly are given a lower weight and the ones miss-classified are weighted higher. Using features generated from count vectorizer and tf-idf vectorizer and labels(fake and real) for training the model

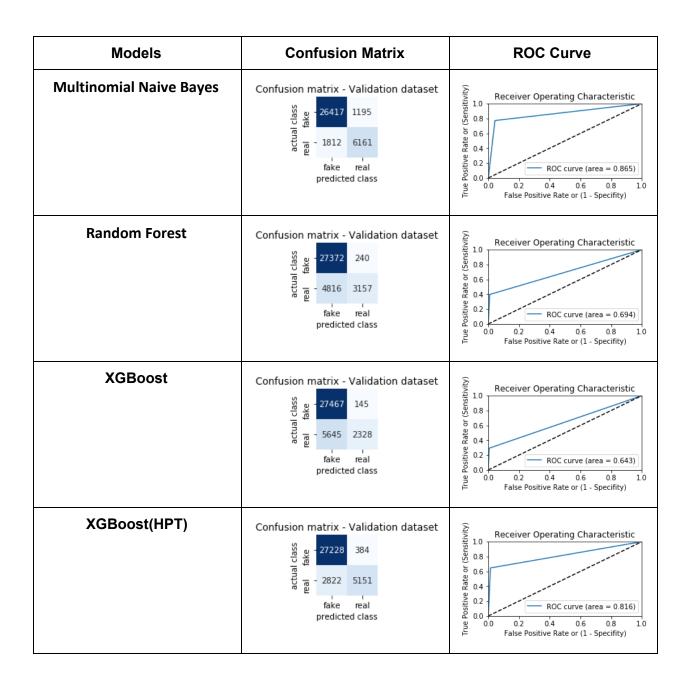
### **Logistic Regression**

It is the go-to method for binary classification problems (problems with two class values). Logistic regression is a classification algorithm used to assign observations to a discrete set of classes. Unlike linear regression which outputs continuous number values, logistic regression transforms its output using the logistic sigmoid function to return a probability value which can then be mapped to two or more discrete classes.

### **Support Vector Machine**

SVM is an algorithm to find a hyperplane in an n-dimensional space which distinctly classifies the data points. The model finds a place that has the maximum margin i.e. maximum distance between the data points of both the classes. The data points falling on either side of the hyperplane can be attributed to different classes Support vectors are data points that are closer to the hyperplane and influence the position and orientation of the hyperplane.

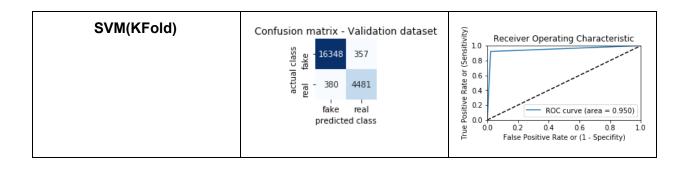
### **Confusion Matrix and ROC Curve using Count Vectorizer**



Logistic Regression	Confusion matrix - Validation dataset    Solution   Proceedings   Proceded	Receiver Operating Characteristic  Receiver Operating Characteristic  Receiver Operating Characteristic  ROC curve (area = 0.914)  False Positive Rate or (1 - Specifity)
SVM	Confusion matrix - Validation dataset  Set of the least o	Receiver Operating Characteristic  Box operation of the service of
SVM(KFold)	Confusion matrix - Validation dataset  Sep July - 16110 595  - 521 4340  fake real predicted class	Receiver Operating Characteristic  Receiver Operating Characteristic  ROC curve (area = 0.929)  ROC curve (area = 0.929)  False Positive Rate or (1 - Specifity)

# **Confusion Matrix and ROC Curve using TF-IDF Vectorizer**

Models	Confusion Matrix	ROC Curve		
Multinomial Naive Bayes	Confusion matrix - Validation dataset    Sea   Property   Property	Receiver Operating Characteristic  Receiver Operating Characteristic  ROC curve (area = 0.516)  ROC curve (area = 0.516)  False Positive Rate or (1 - Specifity)		
Random Forest	Confusion matrix - Validation dataset  27580 32  - 4485 3488  fake real predicted class	Receiver Operating Characteristic  Receiver Operating Characteristic  Receiver Operating Characteristic  ROC curve (area = 0.718)  ROC curve (area = 0.718)  False Positive Rate or (1 - Specifity)		
XGBoost	Confusion matrix - Validation dataset  Validation dataset  456  27156  456  - 2395  5578  fake real predicted class	Receiver Operating Characteristic  Receiver Operating Characteristic  ROC curve (area = 0.842)  ROC curve (area = 0.842)  False Positive Rate or (1 - Specifity)		
Logistic Regression	Confusion matrix - Validation dataset  Validation dataset  Validation dataset  10	Receiver Operating Characteristic  Receiver Operating Characteristic  Receiver Operating Characteristic  ROC curve (area = 0.888)  ROC curve (area = 0.888)  False Positive Rate or (1 - Specifity)		
SVM	Confusion matrix - Validation dataset    Section   Proceedings   Proceded   P	Receiver Operating Characteristic  1.0  Receiver Operating Characteristic  1.0  ROC curve (area = 0.942)  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0		



### Other metrics for models using Count Vectorizer

Models	F1 Score	F1 %	Accuracy	ROC-AUC
Multinomial Naive Bayes	0.946	94.615	0.915	0.864
Random Forest	0.907	90.737	0.842	0.655
XGBoost	0.944	94.440	0.909	0.816
XGBoost(HPT)	0.904	90.465	0.837	0.643
Logistic Regression	0.967	96.728	0.948	0.914
SVM	0.964	96.401	0.943	0.913
SVM(KFold)	0.966	96.652	0.948	0.928

Other metrics for models using TF-IDF Vectorizer

Models	F1 Score	F1 %	Accuracy	ROC-AUC
Multinomial Naive Bayes	0.877	87.729	0.782	0.515
Random Forest	0.915	91.545	0.857	0.693
Random Forest(HPT)	0.924	92.430	0.873	0.718
XGBoost	0.950	95.012	0.919	0.841
Logistic Regression	0.962	96.251	0.940	0.888
SVM	0.977	97.741	0.964	0.941
SVM(KFold)	0.977	97.795	0.965	0.950

### **Evaluation Metrics:**

We have implemented Random Forest, Multinomial Naive Bayes, Logistic Regression, Support Vector Machine(with 5 fold cross-validation) and XGBoost Models for both Count and TFIDF Vectorization.

Output for Support Vector Machine(with 5 fold cross validation) using TFIDF Vectorization is providing below values.

### **Confusion Matrix**

**True Positive** - We predicted that 16348 news as fake and they are fake.

False Positive - We predicted 357 news as fake but they are real

False Negative - We predicted 380 news as real but they are fake

**True Negative** - We predicted 4481 news are real and they are real

**Precision -** Precision is the ratio of correctly predicted positive observations of the total predicted positive observations. High precision relates to the low false positive rate.

### 0.9786291529482191

**Recall** - Recall is the ratio of correctly predicted positive observations to all observations in the actual class

### 0.9772835963653754

**F1 Score** - F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account.

#### 0.9779559118236474

### F1 % - 97.79559118236475

**Accuracy** - Accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0. It can also be calculated by 1 – ERR.

#### 0.965825836965594

### Error Rate - 0.034174163034406006

**ROC-AUC** - ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds.

#### 0.9502279687802193

Which is higher than any other values, and we are using the SVM model for our final prediction.

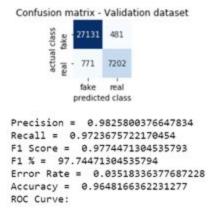
# **Pipeline Design**

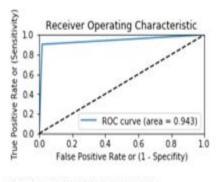
Luigi is a Python tool for workflow management. It has been developed at Spotify, to help building complex data pipelines of batch jobs

There are two core concepts to understand how we can apply Luigi to our own data pipeline: Tasks and Targets. A task is a unit of work, designed by extending the class luigi. Task and overriding some basic methods. The output of a task is a target, which can be a file on the local filesystem, a file on Amazon's S3, some piece of data in a database etc.

Dependencies are defined in terms of inputs and outputs, i.e. if TaskB depends on TaskA, it means that the output of TaskA will be the input of TaskB.

Our code does the Data Merging for all the newspapers csv's that we have and the MergeAllDataSingleFile() depends on four tasks for its input and to merge all of them into a single csv file. Later on the DataCleaning() depends on MergeAllDataSingle() and cleans the csv that is provided by it and stores into a csv. This acts as an input to our Model() where the metrics are calculated providing the accuracy of the model used for classification





ROC-AUC 0.9429393352753868

## **Details on how to run the Model**

```
tfidf vectorizer = TfidfVectorizer(stop words='english',
 2
                                       encoding='utf-8',
 3
                                       decode error='replace',
                                       strip_accents='unicode',
 4
 5
                                       analyzer='word',
                                       tokenizer=porter tokenizer,
 6
 7
                                       ngram range=(1,2),
                                       binary=False)
8
9
10 #testing the implementation
11 tfcon = df['Content'].loc[1]
12 | tfcon = [tfcon]
13
14 tfvect = tfidf vectorizer.fit(tfcon)
15 print(tfvect)
16
17 # Fit and transform the training data
18 tfidf train = tfidf vectorizer.fit transform(X train)
19
20 # Transform the test set
21 tfidf_test = tfidf_vectorizer.transform(X_test)
```

### **SVM Model using KFold Cross Validation**

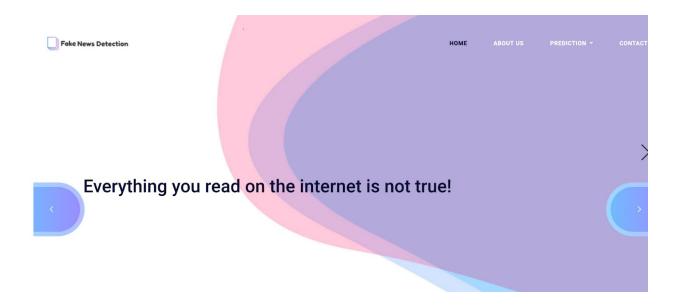
```
1 #K fold Cross Validation
 3 #Defining the split into 5 Fold
 4 from sklearn.model selection import StratifiedKFold
 6 le = LabelEncoder()
 7 le.fit(df['Label'])
 9 df labels = pd.DataFrame(np.array(le.transform(df['Label'])))
 skf = StratifiedKFold(n_splits = 5)
 for trn_indx, tst_indx in skf.split(df['Content'],df_labels):
        skf_X_train, skf_X_test = df['Content'].iloc[trn_indx], df['Content'].iloc[tst_indx]
 15
        skf_Y_train, skf_Y_test = df_labels.iloc[trn_indx], df_labels.iloc[tst_indx]
1 # Fit and transform the training data for count vector
 2 skf_count_train = count_vectorizer.fit_transform(skf_X_train)
 4 # Transform the test set
 5 skf count test = count vectorizer.transform(skf X test)
 7 # Fit and transform the training data for tfidf
 8 skf tfidf train = tfidf vectorizer.fit transform(skf X train)
 10 # Transform the test set
 skf tfidf test = tfidf vectorizer.transform(skf X test)
```

```
1 # print("TfIdf Vectorization")
 2 skf_clf2 = svm.LinearSVC()
4 skf_clf2.fit(skf_tfidf_train, skf_Y_train)
                                                                   # Fit SVM classifier according to X, y
 6 skf_predtf = skf_clf2.predict(skf_tfidf_test)
                                                                    # Perform classification on an array of test vectors X
8 skf_tf_roc_auc = roc_auc_score(skf_Y_test, skf_predtf, average= 'micro')
10 #confusion matrix for count vector
skf_tf_cm = metrics.confusion_matrix(skf_Y_test, skf_predtf, labels=[0,1])
13 #plot the confusion Matrix
14 plotConfusionMatrix(skf_tf_cm)
16 rocCurve(skf_Y_test, skf_predtf, skf_tf_roc_auc)
17
18 #Evaluation
19 evaluation(skf_tf_cm)
20
21 print("ROC-AUC", skf tf roc auc)
```

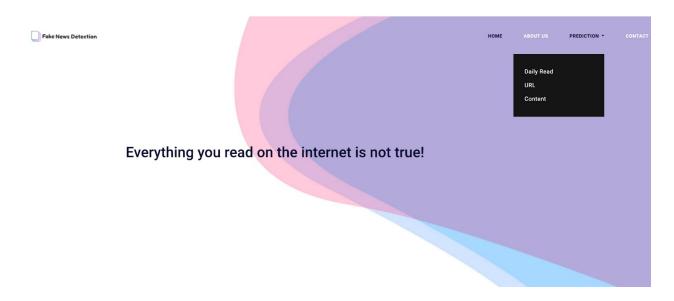
## **Details on how to run the Website**

Docker Image - docker run -p 5000:5000 sharavan27/ads\_fake\_news\_final1 Demo link -  $\frac{https://youtu.be/abbaa6noMpg}{}$ 

Step 1: Click on the website link.

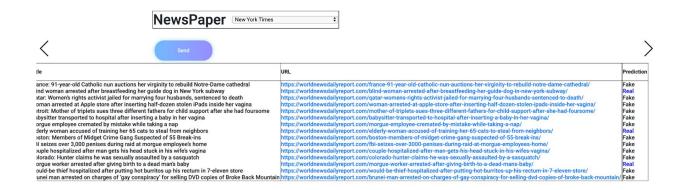


**Step 2:** Website is for predicting the news. Click on prediction drop down, three options are given.



Step 3: Select "Daily Read". This option will take you to the drop down of New papers list.

Select any one of Newspaper name.



It will provide a list of articles of the websites and whether they are Fake or Real along with URL list of the article.

**Step 4:** Again go back to Prediction, dropdown. Select the URL option.In the given textbox, provide URL of Newspaper articles, which you want to check whether legitimate or not.



This will provide whether the article's data is real or not.

Step 5: From the dropdown, select Content option.On the page, in the given text box provide content from any news and check whether is it Fake or Real.

### Content

Predict the news

### **Enter the Content:**

In the African-American neighborhoods near downtown Raleigh, the playfully painted doors signal what's coming. Colored in crimson, in coral, in seafoam, the doors accent newly renovated craftsman cottages and boxy modern homes that have replaced vacant lots.

To longtime residents, the doors mean higher home prices ahead, more investors knocking, more white neighbors.

Here, and in the center of cities across the United States, a kind of demographic change most often associated with gentrifying parts of

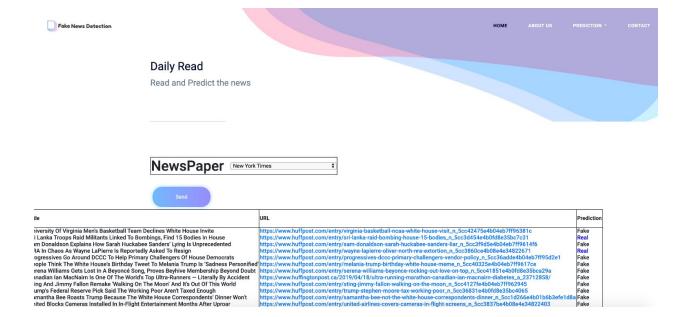


Real

# **Test Cases**

A reader is browsing through some site which has some hot news and wants to know whether the information is legitimate or not.

Input - From dropdown select Huffpost( <a href="https://www.huffpost.com/">https://www.huffpost.com/</a>)Output - List of articles with Label of Real or Fake



### A reader has read news content and wants to know if the content is fake or real

**Input -** Provide content to the textbox

**Output -** User will get the Label of the content.

### Content

Predict the news

### **Enter the Content:**

Russia in its efforts to interfere in the 2016 election. [In other words, no collusion.] ...

Democrats have clamored for the release of Mueller's full report and underlying evidence to Congress, accusing Barr of bias in the handling of the special counsel's report.

Read special counsel Robert Mueller's 448 page report on his two year investigation into the accusation that President Trump colluded with Russia "Report on the Investigation into Russian interference into the ..."



**Fake** 

A reader has come across a news article which he finds suspicious and can be unreal

**Input -** Provide URL of the article.

Output - User will get the Label of the content.



## **Citations**

https://github.com/rasbt/musicmood/blob/master/code/classify\_lyrics/nb\_init\_model.ipynb

https://github.com/rockash/Fake-news-Detection/blob/master/getEmbeddings.py

https://github.com/rastogi-s/Fake-News-Detection/blob/master/ModelRun/Driver.py

https://github.com/tommartensen/fake-news-detector/tree/master/feature\_generation

https://github.com/bedarkarpriyanka/NLP-Project-Fake-News-Detection/blob/master/NLPproject\_6.ipynb

https://github.com/nishitpatel01/Fake News Detection

https://github.com/ajayjindal/Fake-News-Detection/blob/master/final.py

https://www.kaggle.com/mrisdal/fake-news

https://towardsdatascience.com/sentiment-analysis-with-python-part-1-5ce197074184

https://github.com/chbrown/liwc-python