

# **Fake News Detection**

Submitted by:

Aditi Gupta

Internship 12

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Gratitude takes three forms-"A feeling from heart, an expression in words and a giving in return". We take this opportunity to express our feelings.

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#### INTRODUCTION

# Business Problem Framing

Fake news is a form of news consisting of delibrate disinformation or hoaxes spread via traditional news media or online social media. In this project, I have different natural language processing (NLP) based machine learning approaches to detect fake news fron news headlines and news.

# • Conceptual Background of the Domain Problem

The idea of fake news is often referred to as clickbait in social trends and is defined as a "made up story with an intention to deceive, geared towards getting clicks". Some news articles have titles which grab a reader's interest. Yet, the author only emphasizes a specific part of the article in the title. If the article itself does not focus on or give much truth to what the title had written, the new may be misleading.

#### Review of Literature

If we look at some scholar work shows the issue that the fake news has been concerned amongst scholar from various background. For instance, some authors have observed that fake news is no longer a preserve of the marketing and public relation departments. Instead there is an increasing risk of IT security, therefore IT department is premised on the idea that it would help avert the various risks associated with the problem. So, if we go deeply into it we could find that the hackers use clickbait with the help of fake news and make some professional of the organization download the malicious exploits in their system or leak sensitive information, albeit in an indirect manner. The user may be tricked into believing that they are helping to disseminate the news further when in the actual sence they are providing the perpetrators with access to their emails. So we need to implement more our research and extensive knowledge to solve the problem.

#### Motivation for the Problem Undertaken

This project is highly motivated project as it includes the real time problem of fake news which if we see is getting bigger, as there various concern as people do good things work hard to build a reputation and only one fake news is enough to ruin it all, it also have inverse effect on financial market as we observe there will be a good amount of fluctuation on stock market based on these news only.

#### PROBLEM STATEMENT

- Fake news irritating internet connection
- Critical news are missed and / or delayed.
- Millions of compromised computers
- Billions of dollars lost worldwide
- Identity theft
- Fake news can crash mail servers and fill up hard drives

#### OBJECTIVE

The objective of identification of fake news are:

- To give knowledge to the user about the fake news and relevant news
- To classify that newsis fake or not.

#### SCOPE OF THE PROJECT:

- It provides sensitivity to the client and adapts well to the future fake news techniques.
- It considers a complete news instead of single words with respect to its organization.
- It increases Security and Control.
- It reduces IT Administration Costs.
- It also reduce Network Resource Costs.

# **Analytical Problem Framing**

# Mathematical/ Analytical Modeling of the Problem

Machine Learning is defined by Tom Mitchell in his book as "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E". Supervised learning is when the output is known for the corresponding inputs, and is also provided for the machine to learn.

- Data Preprocessing
- EDA (Exploratory data analysis)
- Building Word Dictionary
- Feature Extraction
- Scoring & Metrics

#### Data Sources and their formats

The data is provided to us from our client database. It is hereby given to us for the exercise to improve the selection of mails for spam or not spam. It is given in the csv file format.

```
# Loading the dataset
df_news=pd.read_csv('train_news.csv')
df_news
```

|       | Unnamed: 0 | id    | headline                                       | written_by                 | news   | label |
|-------|------------|-------|--|----------------------------|--|-------|
| 0     | 0          | 9653  | Ethics Questions Dogged Agriculture Nominee as | Eric Lipton and Steve Eder | WASHINGTON — In Sonny Perdue's telling, Geo                                      | 0     |
| 1     | 1          | 10041 | U.S. Must Dig Deep to Stop Argentina's Lionel  | David Waldstein            | HOUSTON — Venezuela had a plan. It was a ta                                      | 0     |
| 2     | 2          | 19113 | Cotton to House: 'Do Not Walk the Plank and Vo | Pam Key                    | Sunday on ABC's "This Week," while discussing $\dots$                            | 0     |
| 3     | 3          | 6868  | Paul LePage, Besieged Maine Governor, Sends Co | Jess Bidgood               | $\label{eq:augusta} \mbox{AUGUSTA, Me.} \mbox{$-$ The beleaguered Republican g}$ | 0     |
| 4     | 4          | 7596  | A Digital 9/11 If Trump Wins                   | Finian Cunningham          | Finian Cunningham has written extensively on                                     | 1     |
|       |            |       |  |                            |  |       |
| 20795 | 20795      | 5671  | NaN  | NeverSurrender             | No, you'll be a dog licking of the vomit of yo                                   | 1     |
| 20796 | 20796      | 14831 | Albert Pike and the European Migrant Crisis    | Rixon Stewart              | By Rixon Stewart on November 5, 2016 Rixon Ste                                   | 1     |
| 20797 | 20797      | 18142 | Dakota Access Caught Infiltrating Protests to  | Eddy Lavine                | posted by Eddie You know the Dakota Access Pip                                   | 1     |
| 20798 | 20798      | 12139 | How to Stretch the Summer Solstice - The New Y | Alison S. Cohn             | It's officially summer, and the Society Boutiq                                   | 0     |
| 20799 | 20799      | 15660 | Emory University to Pay for '100 Percent' of U | Tom Ciccotta               | Emory University in Atlanta, Georgia, has anno                                   | 0     |
|       |            |       |  |                            |  |       |

# Data Preprocessing Done

The dataset that will be used to train the model has some challenges. Text Cleaning is a very important step in machine learning because your data may contains a lot of noise and unwanted character such as punctuation, white space, numbers, hyperlink and etc.

Some standard procedures are:

Checking and then Filling and dropping for the null values

```
Dataset contains any NaN/Empty cells : True

Total number of empty rows in each feature:

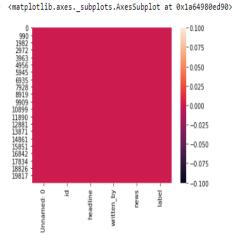
Unnamed: 0 0
id 0
headline 558
written_by 1957
news 39
label 0
dtype: int64
```

```
# Feature subject is having some null values, in here I am
# filling 'written_by' feature with unknown because sometimes there are anonymus authors,...
# filling up empty values in 'headline' feature as i will merge it further for further processing...
# Dropping empty values in rows because we are detecting fake news here and for this news is needed..

df_news['written_by'].fillna('Unknown ',inplace=True)
df_news['headline'].fillna('No Headline ',inplace=True)
df_news.dropna(subset=['news'],inplace=True)
df_news.head()
```

|   | Unnamed: 0 | id    | headline                                       | written_by                 | news   | label |
|---|------------|-------|--|----------------------------|--|-------|
| 0 | 0          | 9653  | Ethics Questions Dogged Agriculture Nominee as | Eric Lipton and Steve Eder | WASHINGTON — In Sonny Perdue's telling, Geo              | 0     |
| 1 | 1          | 10041 | U.S. Must Dig Deep to Stop Argentina's Lionel  | David Waldstein            | HOUSTON — Venezuela had a plan. It was a ta              | 0     |
| 2 | 2          | 19113 | Cotton to House: 'Do Not Walk the Plank and Vo | Pam Key                    | Sunday on ABC's "This Week," while discussing            | 0     |
| 3 | 3          | 6868  | Paul LePage, Besieged Maine Governor, Sends Co | Jess Bidgood               | ${\sf AUGUSTA}, {\sf MeThe\ beleasuered\ Republican\ g}$ | 0     |
| 4 | 4          | 7596  | A Digital 9/11 If Trump Wins                   | Finian Cunningham          | Finian Cunningham has written extensively on             | 1     |

```
# Hetmap for null values
sns.heatmap(df_news.isnull())
```



Adding two new column 'Content' by merging headlines and news
 Taking the length in new column 'content\_length'

```
# As we all know that title and text both are important for authenticity detection,
# thus here I am joining both title and text features to get some useful information while training...

df_news['Content'] = df_news[['headline', 'news']].apply(lambda x: ' '.join(x), axis = 1)

df_news

# New feature (length) contains length of the content feature..

df_news['content_length'] = df_news.Content.str.len()

df_news.head()
```

|   | id    | headline  | written_by                    | news  | label | Content   | content_length |
|---|-------|---|-------------------------------|---|-------|---|----------------|
| 0 | 9653  | Ethics Questions Dogged Agriculture<br>Nominee as | Eric Lipton and Steve<br>Eder | WASHINGTON — In Sonny Perdue's telling, Geo   | 0     | Ethics Questions Dogged Agriculture<br>Nominee as | 8021           |
| 1 | 10041 | U.S. Must Dig Deep to Stop<br>Argentina's Lionel  | David Waldstein               | HOUSTON — Venezuela had a plan. It was a ta   | 0     | U.S. Must Dig Deep to Stop<br>Argentina's Lionel  | 6185           |
| 2 | 19113 | Cotton to House: 'Do Not Walk the<br>Plank and Vo | Pam Key                       | Sunday on ABC's "This Week," while discussing | 0     | Cotton to House: 'Do Not Walk the<br>Plank and Vo | 526            |
| 3 | 6868  | Paul LePage, Besieged Maine<br>Governor, Sends Co | Jess Bidgood                  | AUGUSTA, Me. — The beleaguered Republican g   | 0     | Paul LePage, Besieged Maine<br>Governor, Sends Co | 6617           |
| 4 | 7596  | A Digital 9/11 If Trump Wins                      | Finian Cunningham             | Finian Cunningham has written extensively on  | 1     | A Digital 9/11 If Trump Wins Finian<br>Cunningh   | 9193           |

## Make a function for the following:

- Removing pos tags using wordnet
   (# Return the wordnet object value corresponding to the POS tag)
   (#Part-Of-Speech (POS) tagging: assign a tag to every word to define if it
   corresponds to a noun, a verb etc. using the WordNet lexical database)
- convert all letters to lower/upper case
- removing numbers
- removing punctuation
- removing white spaces
- removing hyperlink
- removing stop words such as a, about, above, down, doing and the list goes on... Sometimes, the extremely common word which would appear to be of very little value in helping select documents matching user need are excluded from the vocabulary entirely.
- Word lemmatizing: Lemmatizing is utilizing the dictionary of a particular language and tried to convert the words back to its base form. It will try to take into account of the meaning of the verbs and convert it back to the most suitable base form.

```
: # Return the wordnet object value corresponding to the POS tag
  #Part-Of-Speech (POS) tagging: assign a tag to every word to define if it corresponds to a noun, a verb etc. using the WordNet Le
  def get_wordnet_pos(pos_tag):
      if pos_tag.startswith('J'):
          return wordnet.ADJ
      elif pos_tag.startswith('V'):
          return wordnet.VERB
      elif pos_tag.startswith('N'):
          return wordnet.NOUN
      elif pos_tag.startswith('R'):
          return wordnet.ADV
          return wordnet.NOUN
  def clean_text(text):
      # lower text
      text = text.lower()
      text = re.sub("[^\w\s]", " ", text)
      # tokenize text and remove puncutation
      text = [word.strip(string.punctuation) for word in text.split(" ")]
      # remove words that contain numbers
      text = [word for word in text if not any(c.isdigit() for c in word)]
      # Remove Leading and trailing whitespace
#text=re.sub("[^\s+|\s+?$]"," ",text)
      # remove stop words
      stop = set(stopwords.words('english') + ['u', 'ü', 'ur', '4', '2', 'im', 'dont', 'doin', 'ure'])
      text = [x for x in text if x not in stop]
      # remove empty tokens
      text = [t for t in text if len(t) > 0]
      # pos tag text
      pos_tags = pos_tag(text)
      # Lemmatize text
      \texttt{text} = [\texttt{WordNetLemmatizer().lemmatize}(\texttt{t[0]}, \, \texttt{get\_wordnet\_pos}(\texttt{t[1]})) \, \, \texttt{for} \, \, \texttt{t} \, \, \texttt{in} \, \, \texttt{pos\_tags}]
      #text=stemmer.stem(text)
      # remove words with only two letter
      text = [t for t in text if len(t) > 2]
      # join all
      text = " ".join(text)
      return(text)
```

 Adding two new column 'clean\_content' by using the above function on content column and then 'clean\_column\_length' which contains the length of the column.

```
# cleaning the news and storing them in a separate feature...
df_news["clean_content"] = df_news["Content"].apply(lambda x: clean_text(x))

# New feature (Clean_length) contains length of the Clean_content feature after puncuations, stopwords removal..
df_news['clean_content_length'] = df_news.clean_content.str.len()
df_news.head()
```

|   | id    | headline  | written_by                    | news  | label | Content  | content_length | clean_content  | clean_content_length |
|---|-------|---|-------------------------------|---|-------|--|----------------|--|----------------------|
| 0 | 9653  | Ethics Questions<br>Dogged Agriculture<br>Nominee as    | Eric Lipton and<br>Steve Eder | WASHINGTON — In<br>Sonny Perdue's telling,<br>Geo | 0     | Ethics Questions<br>Dogged Agriculture<br>Nominee as | 8021           | ethic question dog<br>agriculture nominee<br>georgia | 4983                 |
| 1 | 10041 | U.S. Must Dig Deep<br>to Stop Argentina's<br>Lionel     | David Waldstein               | HOUSTON —<br>Venezuela had a plan. It<br>was a ta | 0     | U.S. Must Dig Deep to<br>Stop Argentina's<br>Lionel  | 6185           | must dig deep stop<br>argentina lionel messi<br>new  | 3886                 |
| 2 | 19113 | Cotton to House: 'Do<br>Not Walk the Plank<br>and Vo    | Pam Key                       | Sunday on ABC's "This Week," while discussing     | 0     | Cotton to House: 'Do<br>Not Walk the Plank<br>and Vo | 526            | cotton house walk plank<br>vote bill cannot pass     | 315                  |
| 3 | 6868  | Paul LePage,<br>Besieged Maine<br>Governor, Sends<br>Co | Jess Bidgood                  | AUGUSTA, Me. — The beleaguered Republican g       | 0     | Paul LePage,<br>Besieged Maine<br>Governor, Sends Co | 6617           | paul lepage besiege<br>maine governor send<br>confli | 4166                 |
| 4 | 7596  | A Digital 9/11 If Trump<br>Wins                         | Finian<br>Cunningham          | Finian Cunningham has written extensively on      | 1     | A Digital 9/11 If Trump<br>Wins Finian<br>Cunningh   | 9193           | digital trump win finian<br>cunningham write<br>exte | 6410                 |

# Change in date Before and After doing preprocessing

## **Before Preprocessing**

|   | Not Fake Words | Fake Words    |
|---|----------------|---------------|
| 0 | (the, 477787)  | (the, 338855) |
| 1 | (to, 245507)   | (of, 178429)  |
| 2 | (of, 238936)   | (to, 177382)  |
| 3 | (a, 221848)    | (and, 157269) |
| 4 | (and, 205457)  | (a, 123308)   |
| 5 | (in, 173291)   | (in, 108566)  |
| 6 | (that, 114656) | (that, 81347) |
| 7 | (for, 82760)   | (is, 78508)   |
| 8 | (on, 77853)    | (for, 54776)  |
| 9 | (is, 72281)    | (on, 45011)   |

## **After Preprocessing**

|   | Not Fake Words  | Fake Words       |
|---|-----------------|------------------|
| 0 | (say, 82086)    | (trump, 21708)   |
| 1 | (trump, 38454)  | (clinton, 21164) |
| 2 | (new, 26473)    | (say, 20839)     |
| 3 | (time, 24583)   | (people, 17072)  |
| 4 | (one, 23602)    | (one, 17054)     |
| 5 | (state, 23552)  | (state, 16670)   |
| 6 | (would, 22870)  | (would, 14610)   |
| 7 | (year, 21785)   | (hillary, 13814) |
| 8 | (people, 20124) | (make, 13081)    |
| 9 | (make, 19015)   | (time, 12910)    |

# **Building Word Dictionary**

```
# Tokenizing Documents..
data=[]
from nltk.tokenize import word_tokenize
for j,i in enumerate(df_news['clean_content']):
    a=word_tokenize(i, 'english')
    data.append(a)

# Making Word dictionary...
dictionary = corpora.Dictionary(data)
print(dictionary)

Dictionary(163632 unique tokens: ['acceptable', 'accompany', 'accord', 'act', 'action']...)
```

# Hardware and Software Requirements and Tools Used

Hardware: Since the computational aspect of the project is of importance to PANDA, it is important to know the hardware that was used in the evaluation process. The training and evaluation of the neural network model has been done on a Windows 10 computer using a quad-core CPU at i3.

Software: anaconda 3, windows 10, Microsoft office.

Tools used: python, machine learning libraries, Nltk, Nlp libraries.

#### Feature Extraction

```
# creating the TF-IDF(term frequency-inverse document frequency) vectorizer function in order to convert the tokens
# from the train documents into vectors so that machine can do further processing

def Tf_idf_train(text):
    tfid = TfidfVectorizer(min_df=3,smooth_idf=False)
    return tfid.fit_transform(text)

# Inserting vectorized values in a variable x, which will be used in training the model

x=Tf_idf_train(df_news['clean_content'])

# checking the shape of the data which is inserted in x which will be used for model training.

print("Shape of x: ",x.shape)

Shape of x: (20761, 54349)

# Assigning the label in y and checking it's shape
y = df_news['label'].values
print("Shape of y: ",y.shape)

Shape of y: (20761,)
```

# **Model/s Development and Evaluation**

## Models Used

```
# Importing useful libraries for model training
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
# Ensemble Techniques...
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.ensemble import AdaBoostClassifier
# Model selection libraries...
from sklearn.model_selection import cross_val_score, cross_val_predict, train_test_split
from sklearn.model_selection import GridSearchCV
# Importing some metrics we can use to evaluate our model performance....
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.metrics import roc_auc_score, roc_curve, auc
from sklearn.metrics import precision_score, recall_score, f1_score
# Creating instances for different Classifiers
RF=RandomForestClassifier()
LR=LogisticRegression()
MNB=MultinomialNB()
DT=DecisionTreeClassifier()
AD=AdaBoostClassifier()
XG=XGBClassifier()
```

```
Model = []
score = []
CVS=[]
rocscore=[]
for name, model in models:
   Model.append(name)
   model.fit(x_train,y_train)
   print(model)
   pre=model.predict(x_test)
   print('\n')
   AS=accuracy_score(y_test,pre)
   print('Accuracy_score = ',AS)
   score.append(AS*100)
   print('\n')
   sc = cross_val_score(model, x, y, cv=10, scoring='accuracy').mean()
   print('Cross_Val_Score = ',sc)
   cvs.append(sc*100)
   print('\n')
   false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,pre)
   roc_auc = auc(false_positive_rate, true_positive_rate)
   print ('roc_auc_score = ',roc_auc)
   rocscore.append(roc_auc*100)
   print('\n')
print('classification_report\n',classification_report(y_test,pre))
   print('\n')
   cm=confusion_matrix(y_test,pre)
   print(cm)
   print('\n')
   plt.figure(figsize=(10,40))
   plt.subplot(911)
   plt.title(name)
   print(sns.heatmap(cm,annot=True))
   plt.subplot(912)
   plt.title(name)
   plt.plot(false_positive_rate, true_positive_rate, label='AUC = %0.2f'% roc_auc)
   plt.plot([0,1],[0,1],'r--')
   plt.legend(loc='lower right')
   plt.ylabel('True Positive Rate')
   plt.xlabel('False Positive Rate')
   print('\n\n')
```

#### Run and Evaluate selected models

When it comes to evaluation of a data science model's performance, sometimes accuracy may not be the best indicator. Some problems that we are solving in real life might have a very imbalanced class and using accuracy might not give us enough confidence to understand the algorithm's performance.

In the fake news detection problem that we are trying to solve, the fake news is approximately 50% of our data. If our algorithm predicts all the email as non-spam, it will achieve an accuracy of 50%. And for some problem that has only 1% of positive data, predicting all the sample as negative will give them an accuracy of 99% but we all know this kind of model is useless in a real life scenario.

Precision & Recall is the common evaluation metrics that people use when they are evaluating class-imbalanced classification model.Let's try to understand what questions Precision & Recall is trying to answer,

- Precision: What proportion of positive identifications was actually correct?
- Recall: What actual proportion of actual positives was identified correctly?

So, precision is evaluating, when a model predict something as positive, how accurate the model is. On the other hand, recall is evaluating how well a model in finding all the positive samples.

#### **Confusion Matrix**

Confusion Matrix is a very good way to understand results like true positive, false positive, true negative and so on.

Sklearn documentation has provided a sample code of how to plot nice looking confusion matrix to visualize your result..

Confusion Matrix of the result

Max Accuracy Score corresponding to Random State 61 is: 0.9685342751645529

Learning Score : 0.9832782824112304 Accuracy Score : 0.9654840263284636 Cross Val Score : 0.9947618843675959 roc auc score : 0.965480538979566

#### Classification Report:

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.96      | 0.97   | 0.97     | 3116    |
| 1            | 0.97      | 0.96   | 0.97     | 3113    |
| accuracy     |           |        | 0.97     | 6229    |
| macro avg    | 0.97      | 0.97   | 0.97     | 6229    |
| weighted avg | 0.97      | 0.97   | 0.97     | 6229    |

Confusion Matrix: [[3031 85] [ 130 2983]]

MultinomialNB(alpha=1.0, class\_prior=None, fit\_prior=True)

Max Accuracy Score corresponding to Random State 71 is: 0.9181248996628673

Learning Score : 0.9364849986237269 Accuracy Score : 0.9081714560924707 Cross Val Score : 0.9843101497880349 roc auc score : 0.9081357135405091

#### Classification Report:

|                           | precision    | recall       | f1-score     | support      |
|---------------------------|--------------|--------------|--------------|--------------|
| 0                         | 0.86         | 0.98         | 0.91         | 3116         |
| 1                         | 0.98         | 0.83         | 0.90         | 3113         |
| accuracy                  |              |              | 0.91         | 6229         |
| macro avg<br>weighted avg | 0.92<br>0.92 | 0.91<br>0.91 | 0.91<br>0.91 | 6229<br>6229 |

Confusion Matrix: [[3061 55] [ 517 2596]] \* DecisionTreeClassifier \*

DecisionTreeClassifier(ccp\_alpha=0.0, class\_weight=None, criterion='gini', max\_depth=None, max\_features=None, max\_leaf\_nodes=None, min\_impurity\_decrease=0.0, min\_impurity\_split=None, min\_samples\_leaf=1, min\_samples\_split=2,
min\_weight\_fraction\_leaf=0.0, presort='deprecated',
random\_state=None, splitter='best')

Max Accuracy Score corresponding to Random State 92 is: 0.9643602504414834

Learning Score : 1.0 Accuracy Score : 0.9616310804302456 Cross Val Score : 0.9597815499959201 roc auc score : 0.9616326952235996

Classification Report:

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.96      | 0.96   | 0.96     | 3116    |
| 1            | 0.96      | 0.96   | 0.96     | 3113    |
| accuracy     |           |        | 0.96     | 6229    |
| macro avg    | 0.96      | 0.96   | 0.96     | 6229    |
| weighted avg | 0.96      | 0.96   | 0.96     | 6229    |

Confusion Matrix: [[2986 130] [ 109 3004]]

\* RandomForestClassifier \*

RandomForestClassifier(bootstrap=True, ccp\_alpha=0.0, class\_weight=None, criterion='gini', max\_depth=None, max\_features='auto', max leaf nodes=None, max samples=None, min\_impurity\_decrease=0.0, min\_impurity\_split=None, min\_samples\_leaf=1, min\_samples\_split=2, min\_weight\_fraction\_leaf=0.0, n\_estimators=100, n\_jobs=None, oob\_score=False, random\_state=None, verbose=0, warm\_start=False)

Max Accuracy Score corresponding to Random State 43 is: 0.9717450634130679

Learning Score : 1.0

Accuracy Score : 0.9677315781024242 Cross Val Score : 0.9954496494545729 roc auc score : 0.9677273180875925

Classification Report:

| Clussification | precision | recall | f1-score | support |
|----------------|-----------|--------|----------|---------|
| 0              | 0.96      | 0.98   | 0.97     | 3116    |
| 1              | 0.98      | 0.96   | 0.97     | 3113    |
| accuracy       |           |        | 0.97     | 6229    |
| macro avg      | 0.97      | 0.97   | 0.97     | 6229    |
| weighted avg   | 0.97      | 0.97   | 0.97     | 6229    |
|                |           |        |          |         |

Confusion Matrix: [[3043 73] [ 128 2985]]

AdaBoostClassifier(algorithm='SAMME.R', base\_estimator=None, learning\_rate=1.0, n\_estimators=50, random\_state=None)

Max Accuracy Score corresponding to Random State 97 is: 0.9749558516615829

Learning Score : 0.9761904761904762 Accuracy Score : 0.9693369722266817 Cross Val Score : 0.99569414839702 roc auc score : 0.9693371970703831

Classification Report:

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.97      | 0.97   | 0.97     | 3116    |
| 1            | 0.97      | 0.97   | 0.97     | 3113    |
| accuracy     |           |        | 0.97     | 6229    |
| macro avg    | 0.97      | 0.97   | 0.97     | 6229    |
| weighted avg | 0.97      | 0.97   | 0.97     | 6229    |

Confusion Matrix: [[3019 97] [ 94 3019]]

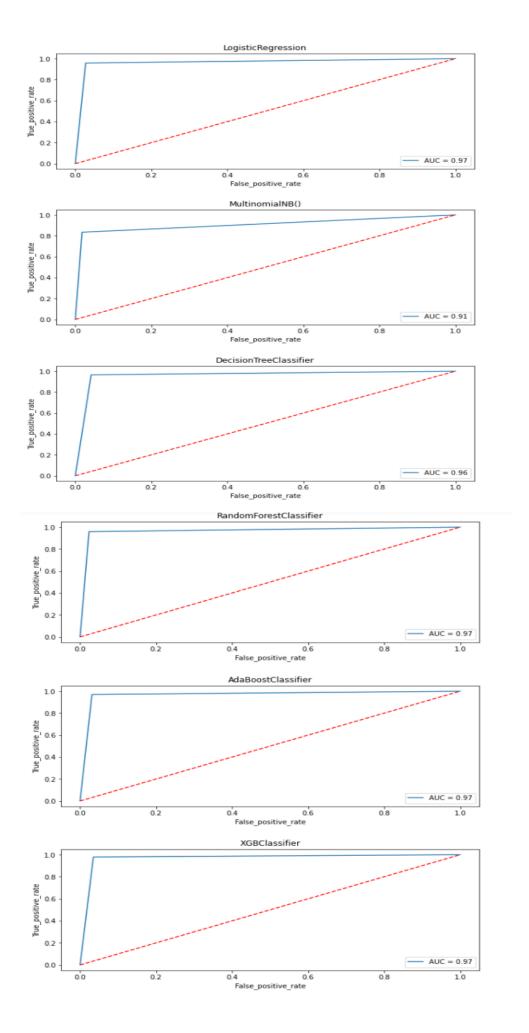
Max Accuracy Score corresponding to Random State 44 is: 0.9735109969497512

Learning Score : 0.9755023396641894 Accuracy Score : 0.9719056028254937 Cross Val Score : 0.9964623358557286 roc auc score : 0.9719089210140752

Classification Report:

|                           | precision    | recall       | f1-score     | support      |
|---------------------------|--------------|--------------|--------------|--------------|
| 0                         | 0.98         | 0.97         | 0.97         | 3116         |
| 1                         | 0.97         | 0.98         | 0.97         | 3113         |
| accuracy                  |              |              | 0.97         | 6229         |
| macro avg<br>weighted avg | 0.97<br>0.97 | 0.97<br>0.97 | 0.97<br>0.97 | 6229<br>6229 |

Confusion Matrix: [[3007 109] [ 66 3047]]

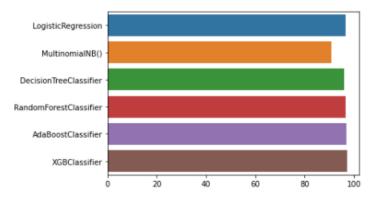


# Key Metrics for success in solving problem under consideration

|   | Model                  | Learning Score | Accuracy Score | Cross Val Score | Roc_Auc_curve |
|---|------------------------|----------------|----------------|-----------------|---------------|
| 0 | LogisticRegression     | 98.327828      | 96.548403      | 99.476188       | 96.548054     |
| 1 | MultinomialNB()        | 93.648500      | 90.817146      | 98.431015       | 90.813571     |
| 2 | DecisionTreeClassifier | 100.000000     | 96.163108      | 95.978155       | 96.163270     |
| 3 | RandomForestClassifier | 100.000000     | 96.773158      | 99.544965       | 96.772732     |
| 4 | AdaBoostClassifier     | 97.619048      | 96.933697      | 99.569415       | 96.933720     |
| 5 | XGBClassifier          | 97.550234      | 97.190560      | 99.646234       | 97.190892     |

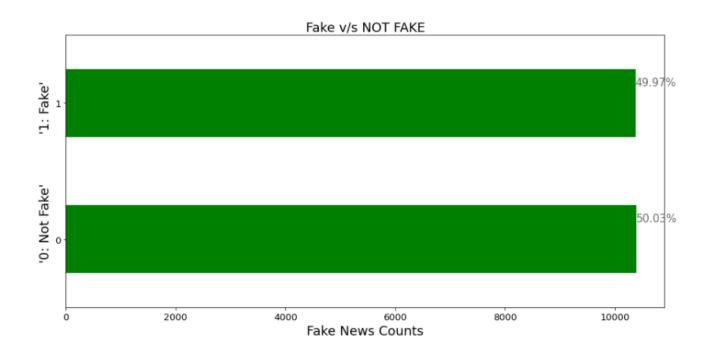
```
# visualisation of Accuracy Score
sns.barplot(y=Model,x=Acc_score)
```

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fe195104750>



## Visualizations

#### 1. Count for Fake and Not Fake News



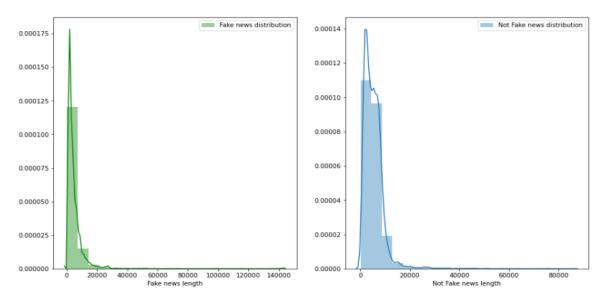
## 2. Fake Words before Cleaning



3. Not Fake Words before Cleaning



4. Length Distribution of Fake and Not Fake before cleaning



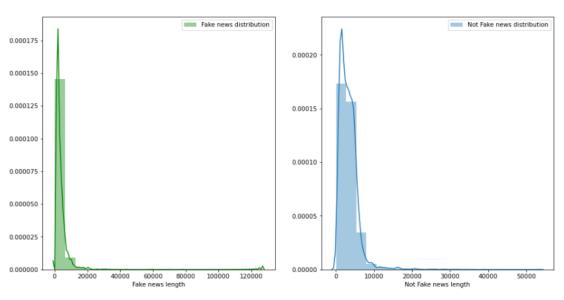
## 5. Fake Words after Cleaning

```
em dakota catch de Tump array key exists ength vomit digital make state november official access live infiltrate leavemigrant out come neadlineex te retaliate lick alabama what ever expect crisis constants chifitie proper constants chifitie rixon finian collision people elec cunning ham mind win putin dtype russian reuters protest dog president chinese warn
```

## 6. Not Fake Words after Cleaning

```
new governor assad lionel suburban dig pass pollution passed bill stretch y undocumented to be study paul rapid georgia free aim america dtype taim patrol aim patrol america dtype taim patrol aim patrol aim arrocities one question evolution historywalk send ength percents ave summer lepage york stop official messi energy in the page of the
```

# 7. Length Distribution of Fake and Not Fake after cleaning

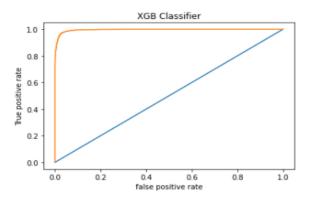


# • Interpretation of Result

#### **Final Model**

XGB Classifier is giving an accuracy of 97% . So now I am making a final model using XGB Classifier.

```
# Using XGBClassifier for final model...
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=83,test_size=.30)
XG=XGBClassifier()
XG.fit(x_train,y_train)
XG.score(x_train,y_train)
XGpred=XG.predict(x_test)
print('Accuracy Score:',accuracy_score(y_test,XGpred))
print('Confusion Matrix:',confusion_matrix(y_test,XGpred))
print('Classification Report:','\n',classification_report(y_test,XGpred))
Accuracy Score: 0.9691764328142559
Confusion Matrix: [[2991 128]
    64 3046]]
Classification Report:
                   precision
                                    recall f1-score
              0
                        0.98
                                     0.96
                                                  0.97
                                                               3119
              1
                        0.96
                                     0.98
                                                  0.97
                                                               3110
     accuracy
                                                  0.97
                                                               6229
    macro avg
                        0.97
                                     0.97
                                                  0.97
                                                               6229
weighted avg
                        0.97
                                     0.97
                                                  0.97
                                                               6229
```



roc\_auc\_score = 0.9962263236732856

#### Prediction of y\_test data

```
# Printing predicted values
test=pd.DataFrame(data=y_test,)
test['Predicted values']=XGpred
test
# On the lest side values are those which are taken by machine for test...
```

|      | 0 | Predicted values |
|------|---|------------------|
| 0    | 1 | 1                |
| 1    | 0 | 0                |
| 2    | 1 | 1                |
| 3    | 0 | 0                |
| 4    | 0 | 0                |
|      |   |                  |
| 6224 | 0 | 0                |
| 6225 | 1 | 1                |
| 6226 | 1 | 1                |
| 6227 | 1 | 1                |
| 6228 | 1 | 1                |

6229 rows × 2 columns

# **CONCLUSION**

# Key Findings and Conclusions of the Study

From the whole evaluation we can see that the maximum number of fake words used are Trump and Clinton and we can interrupt that it was due to election campaign held during US Presidential election and we know this adverse effect of the voters which were influenced by the fake news and the real had said trump and president and the fake news which was cleared by Trump's campaign but can hardly see clarity or real news from the side of Clinton and due to which the impact we already saw on election results and regarding the election advertisement and news Facebook's CEO Mark Zuckerberg also got extensively questioned by congress.

## • Learning Outcomes of the study with respect to Data science

So from the word frequency chart we can clearly see that most of the news is related to US Presidential election between Trump ad Clinton and by implementing passive aggressive algorithms we can see that we can achieved a good score as it calculates the error and updates its own learning rate which makes our model more reliable.

# • Limitations of this Work and Scope for Future Work

- I have also tried machine learning algorithm Gradient boosting Classifier which took enormous time more than a day (though not completed that's why I don't opt) to build the model.
- Using hyperparameter tuning for XGB can increase our score.
- Using Deep learning techniques may give some more good results.