FLIP ROBO

NAME OF THE PROJECT

Fake News Project

SUBMITTED BY:

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ACKNOWLEDGMENT

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A huge thanks to “Data trained” who are the reason behind my Internship at Fliprobo.

Last but not least my parents who have been my backbone in every step of my life.

References use in this project:

- SCIKIT Learn Library Documentation
- Blogs from towards data science, Analytics Vidya, Medium Andrew Ng Notes on Machine Learning (GitHub)
- Data Science Projects with Python Second Edition by Packt
- Hands on Machine learning with scikit learn and tensor flow by Aurelien Geron
- Stackoverflow.com to resolve some project related queries.
- Predicting Credit Default among Micro Borrowers in Ghana Kwame Simpe Ofori, Eli Fianu Predicting Microfinance Credit Default: A Study of Nsoatreman Rural Bank, Ghana Ernest
- Yeboah Boateng

INTRODUCTION

1. Context

Fake news has become one of the biggest problems of our age. It has serious impact on our online as well as offline discourse. One can even go as far as saying that, to date, fake news poses a clear and present danger to western democracy and stability of the society.

2. What is a Fake News?

Fake news's simple meaning is to incorporate information that leads people to the wrong path.

Nowadays fake news spreading like water and people share this information without verifying it. This is often done to further or impose certain ideas and is often achieved with political agendas.

For media outlets, the ability to attract viewers to their websites is necessary to generate online advertising revenue. So it is necessary to detect fake news.

3. Workflow

In this project, we are using some machine learning and Natural language processing libraries like NLTK, re (Regular Expression), Scikit Learn.

Natural Language Processing:

Machine learning data only works with numerical features so we have to convert text data into numerical columns. So we have to preprocess the text and that is called natural language processing.

In-text preprocess we are cleaning our text by steaming, lemmatization, remove stopwords, remove special symbols and numbers, etc. After cleaning the data we have to feed this text data into a vectorizer which will convert this text data into numerical features.

Analytical Problem Framing

Mathematical/ Analytical Modelling of the Problem

- Cleaned Data by removing irrelevant features
- Pre-processing of text using NLPprocessing
- Used Word Counts
- Used Character Counts
- Used Count Vectorizer
- Split data into train and test
- Built Model
- Hyper parameter tunning

1. Data Sources and their formats

The data-set is in csv format: **Fake.csv and True.csv** Features of this dataset are:

```
fake = pd.read_csv("Fake.csv")
true = pd.read_csv("True.csv")
```

Data cleaning and preparation

In [7]:
```
# Add flag to track fake and real
fake['target'] = '0'
true['target'] = '1'
```

In [8]:
```
# Concatenate dataframes
data = pd.concat([fake, true]).reset_index(drop = True)
data.shape
```

Out[8]: (44898, 5)

In [9]:
```
# Shuffle the data
from sklearn.utils import shuffle
data = shuffle(data)
data = data.reset_index(drop=True)
```

In [10]:
```
# Check the data
data.head()
```

Out[10]:

	title	text	subject	date	target
0	Trump Wanted To Attack The LGBTQ Community; J...	Earlier in the week, there were leaked draft e...	News	February 3, 2017	0
1	U.S. Interior Secretary investigated over spee...	WASHINGTON (Reuters) - The U.S. Office of Spec...	politicsNews	October 3, 2017	1
2	Jordan border crossing with Iraq to reopen in ...	AMMAN (Reuters) - Jordan will open its main bo...	worldnews	August 29, 2017	1
3	PRESIDENT TRUMP Hits Back At Activist Judge On...	Judge Orrick in California ruled against Presi...	politics	Apr 26, 2017	0
4	Patrick Henningsen LIVE with guest Sean Stone ...	Join Patrick every week here at 21WIRE.TV for ...	US_News	December 8, 2016	0

[11]:
```
# Removing the date (we won't use it for the analysis)
data.drop(["date"],axis=1,inplace=True)
data.head()
```

Out[11]:

	title	text	subject	target
0	Trump Wanted To Attack The LGBTQ Community; J...	Earlier in the week, there were leaked draft e...	News	0
1	U.S. Interior Secretary investigated over spee...	WASHINGTON (Reuters) - The U.S. Office of Spec...	politicsNews	1
2	Jordan border crossing with Iraq to reopen in ...	AMMAN (Reuters) - Jordan will open its main bo...	worldnews	1
3	PRESIDENT TRUMP Hits Back At Activist Judge On...	Judge Orrick in California ruled against Presi...	politics	0
4	Patrick Henningsen LIVE with guest Sean Stone ...	Join Patrick every week here at 21WIRE.TV for ...	US_News	0

In [12]:
```
# Removing the title (we will only use the text)
data.drop(["title"],axis=1,inplace=True)
data.head()
```

Out[12]:

	text	subject	target
0	Earlier in the week, there were leaked draft e...	News	0
1	WASHINGTON (Reuters) - The U.S. Office of Spec...	politicsNews	1
2	AMMAN (Reuters) - Jordan will open its main bo...	worldnews	1
3	Judge Orrick in California ruled against Presi...	politics	0
4	Join Patrick every week here at 21WIRE.TV for ...	US_News	0

In [13]:
```
# Convert to lowercase

data['text'] = data['text'].apply(lambda x: x.lower())
data.head()
```

Out[13]:

	text	subject	target
0	earlier in the week, there were leaked draft e...	News	0
1	washington (reuters) - the u.s. office of spec...	politicsNews	1
2	amman (reuters) - jordan will open its main bo...	worldnews	1
3	judge orrick in california ruled against presi...	politics	0
4	join patrick every week here at 21wire.tv for ...	US_News	0

In [14]:
```
# Remove punctuation

import string

def punctuation_removal(text):
    all_list = [char for char in text if char not in string.punctuation]
    clean_str = ''.join(all_list)
    return clean_str

data['text'] = data['text'].apply(punctuation_removal)
```

In [15]:
```
# Check
data.head()
```

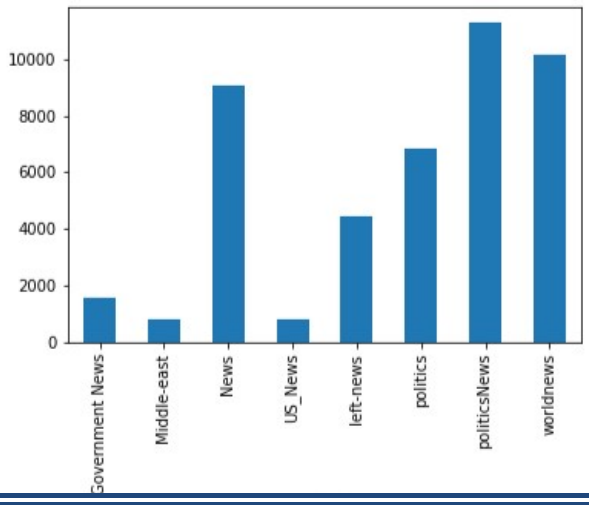
Out[15]:

	text	subject	target
0	earlier in the week there were leaked draft ex...	News	0
1	washington reuters the us office of special c...	politicsNews	1
2	amman reuters jordan will open its main borde...	worldnews	1
3	judge orrick in california ruled against presi...	politics	0
4	join patrick every week here at 21wiretv for n...	US_News	0

Basic data exploration

In [18]:
```
# How many articles per subject?
print(data.groupby(['subject'])['text'].count())
data.groupby(['subject'])['text'].count().plot(kind="bar")
plt.show()
```

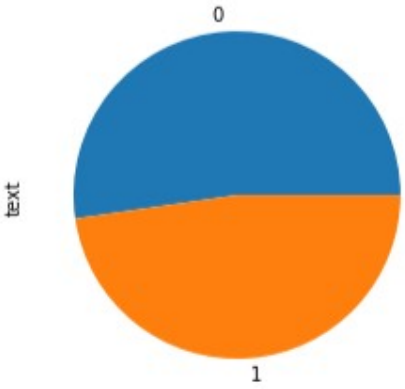
```
subject
Government News     1570
Middle-east          778
News                9050
US_News              783
left-news           4459
politics            6841
politicsNews       11272
worldnews          10145
Name: text, dtype: int64
```



In [19]:

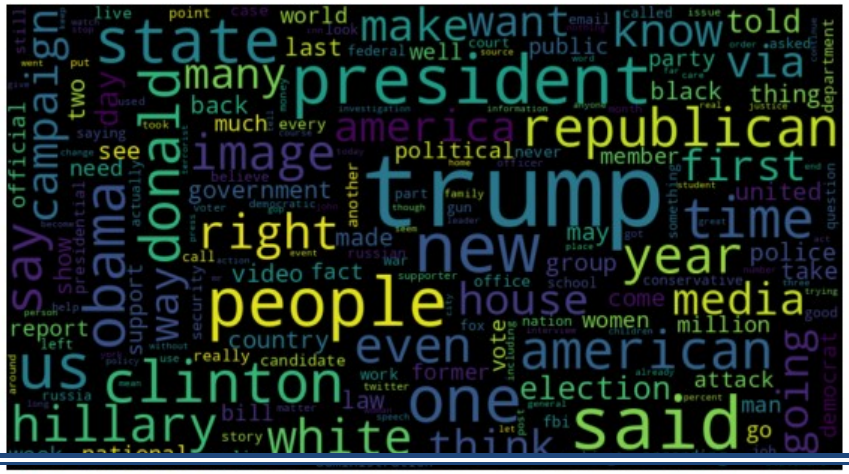
```
# How many fake and real articles?
print(data.groupby(['target'])['text'].count())
data.groupby(['target'])['text'].count().plot(kind="pie")
plt.show()
```

```
target
0    23481
1    21417
Name: text, dtype: int64
```



In [20]:

```
# Word cloud for fake news
from wordcloud import WordCloud

fake_data = data[data["target"] == "0"]
all_words = ' '.join([text for text in fake_data.text])

wordcloud = WordCloud(width= 900, height= 500,
                      max_font_size = 110,
                      collocations = False).generate(all_words)

plt.figure(figsize=(10,7))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```

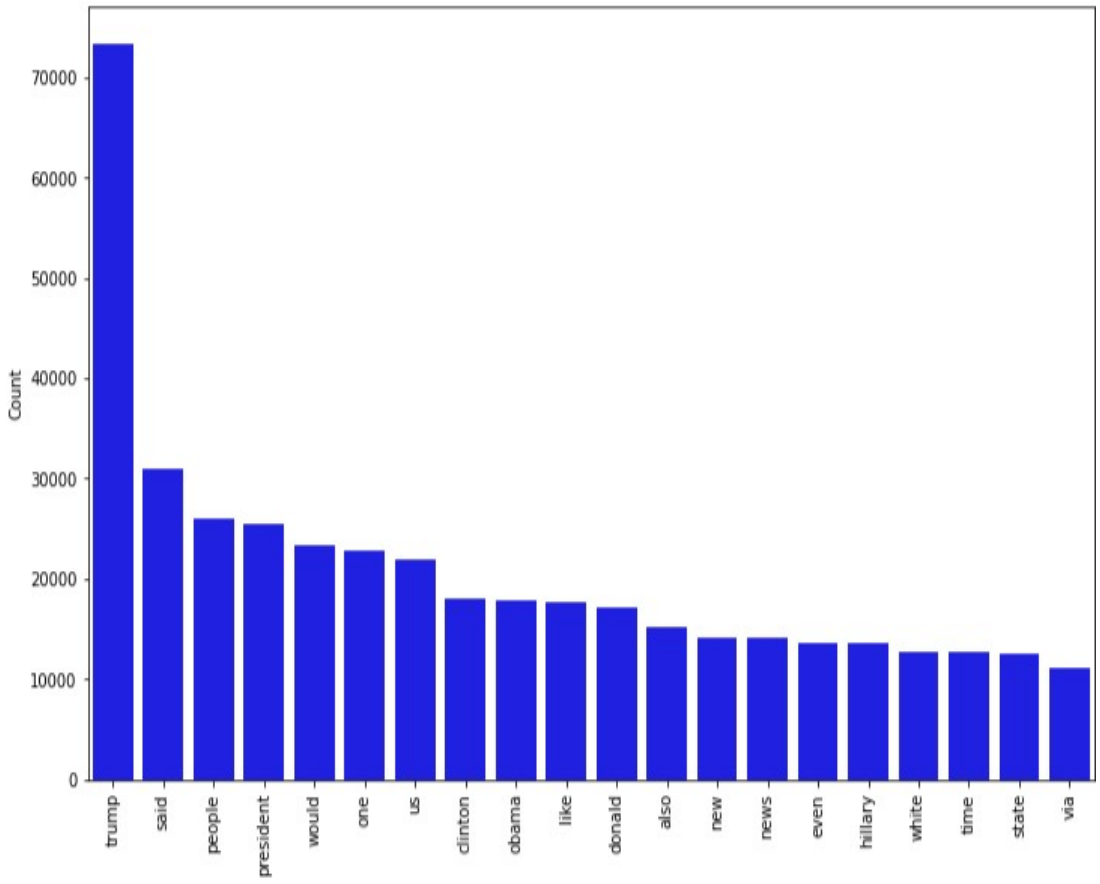


In [22]:

```
# Most frequent words counter
from nltk import tokenize

token_space = tokenize.WhitespaceTokenizer()

def counter(text, column_text, quantity):
    all_words = ' '.join([text for text in text[column_text]])
    token_phrase = token_space.tokenize(all_words)
    frequency = nltk.FreqDist(token_phrase)
    df_frequency = pd.DataFrame({"Word": list(frequency.keys()),
                                 "Frequency": list(frequency.values())})
    df_frequency = df_frequency.nlargest(columns = "Frequency", n = quantity)
    plt.figure(figsize=(12,8))
    ax = sns.barplot(data = df_frequency, x = "Word", y = "Frequency", color = 'blue')
    ax.set(ylabel = "Count")
    plt.xticks(rotation='vertical')
    plt.show()
```

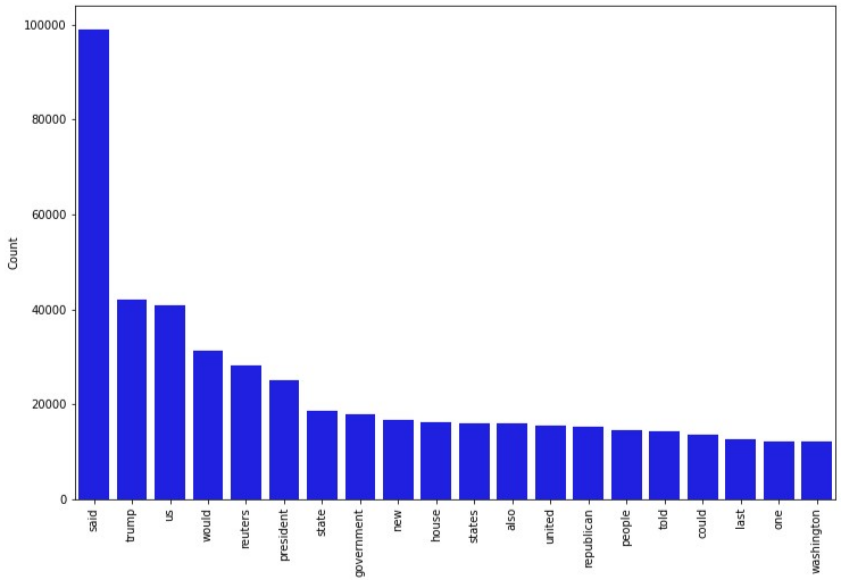
Most frequent words in fake news

```
counter(data[data["target"] == "0"], "text", 20)
```



Most frequent words in real news

```
counter(data[data["target"] == "1"], "text", 20)
```



Modeling

```
from sklearn import metrics
import itertools

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Greens):

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

Preparing the data

In [26]:
```
# Split the data
X_train,X_test,y_train,y_test = train_test_split(data['text'], data.target, test_size=0.2, random_state=42)
```

Naive Bayes

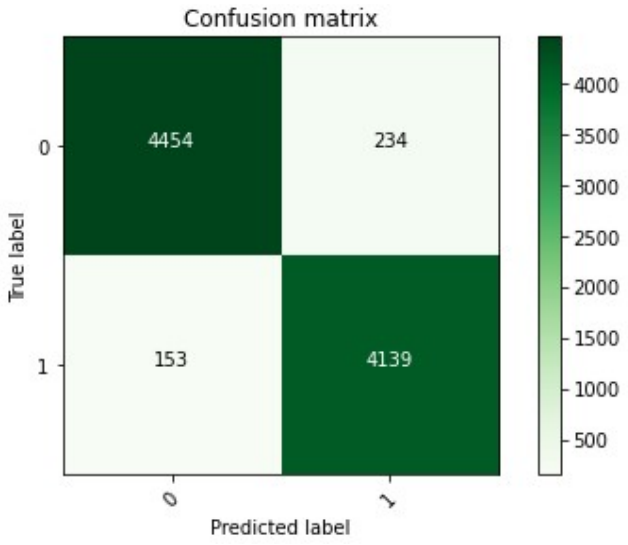
In [27]:
```
dct = dict()

from sklearn.naive_bayes import MultinomialNB

NB_classifier = MultinomialNB()
pipe = Pipeline([('vect', CountVectorizer()),
                 ('tfidf', TfidfTransformer()),
                 ('model', NB_classifier)])

model = pipe.fit(X_train, y_train)
prediction = model.predict(X_test)
print("accuracy: {}%".format(round(accuracy_score(y_test, prediction)*100,2)))

dct['Naive Bayes'] = round(accuracy_score(y_test, prediction)*100,2)
```

```
accuracy: 95.69%
```

In [28]:
```
cm = metrics.confusion_matrix(y_test, prediction)
plot_confusion_matrix(cm, classes=['0', '1'])
```

```
Confusion matrix, without normalization
```

Confusion matrix without normalization



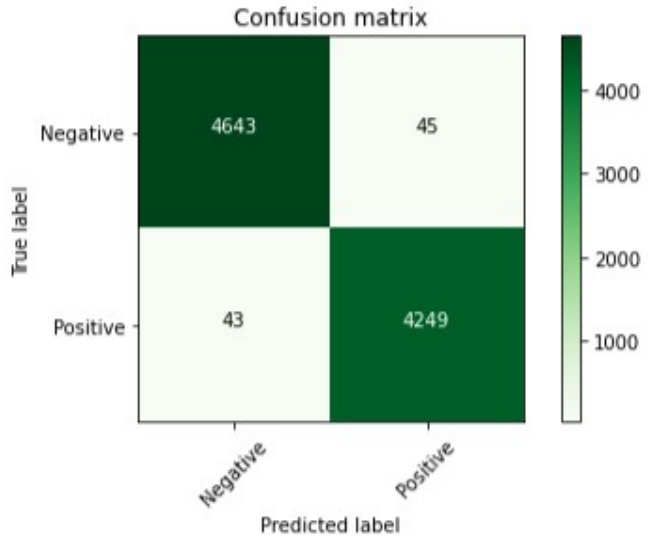
Logistic regression

In [29]:
```
# Vectorizing and applying TF-IDF
from sklearn.linear_model import LogisticRegression

pipe = Pipeline([('vect', CountVectorizer()),
                 ('tfidf', TfidfTransformer()),
                 ('model', LogisticRegression())])

# Fitting the model
model = pipe.fit(X_train, y_train)

# Accuracy
prediction = model.predict(X_test)
print("accuracy: {}%".format(round(accuracy_score(y_test, prediction)*100,2)))
dct['Logistic Regression'] = round(accuracy_score(y_test, prediction)*100,2)
```

```
accuracy: 99.02%
```

In [30]:
```
cm = metrics.confusion_matrix(y_test, prediction)
plot_confusion_matrix(cm, classes=['Negative', 'Positive'])
```

```
Confusion matrix, without normalization
```



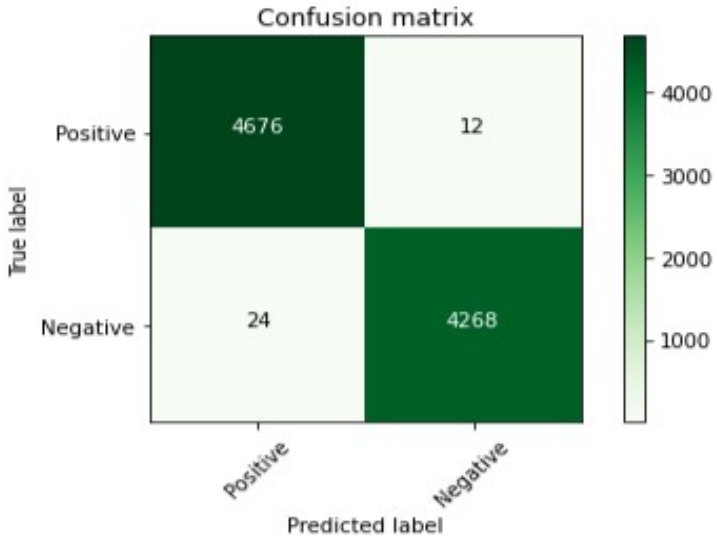
Decision Tree

In [31]:
```
from sklearn.tree import DecisionTreeClassifier

# Vectorizing and applying TF-IDF
pipe1 = Pipeline([('vect', CountVectorizer()),
                  ('tfidf', TfidfTransformer()),
                  ('model', DecisionTreeClassifier(criterion= 'entropy',
                                                   max_depth = 20,
                                                   splitter='best',
                                                   random_state=42))])
# Fitting the model
model = pipe1.fit(X_train, y_train)

# Accuracy
prediction = model.predict(X_test)
print("accuracy: {}%".format(round(accuracy_score(y_test, prediction)*100,2)))
dct['Decision Tree'] = round(accuracy_score(y_test, prediction)*100,2)
```

```
accuracy: 99.6%
```

In [32]:
```
cm = metrics.confusion_matrix(y_test, prediction)
plot_confusion_matrix(cm, classes=['Positive', 'Negative'])
```

```
Confusion matrix, without normalization
```



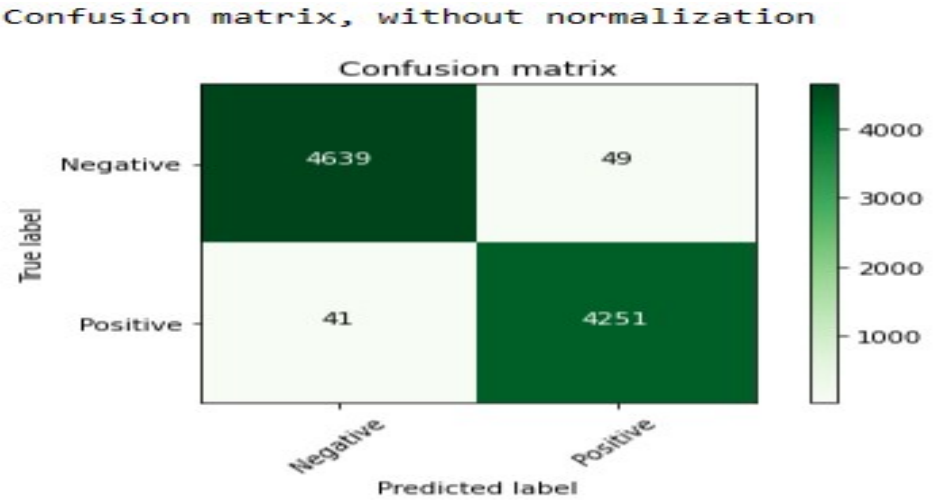
Random Forest

In [33]:
```
from sklearn.ensemble import RandomForestClassifier

pipe = Pipeline([('vect', CountVectorizer()),
                 ('tfidf', TfidfTransformer()),
                 ('model', RandomForestClassifier(n_estimators=50, criterion="entropy"))])

model = pipe.fit(X_train, y_train)
prediction = model.predict(X_test)
print("accuracy: {}%".format(round(accuracy_score(y_test, prediction)*100,2)))
dct['Random Forest'] = round(accuracy_score(y_test, prediction)*100,2)
```

```
accuracy: 99.0%
```

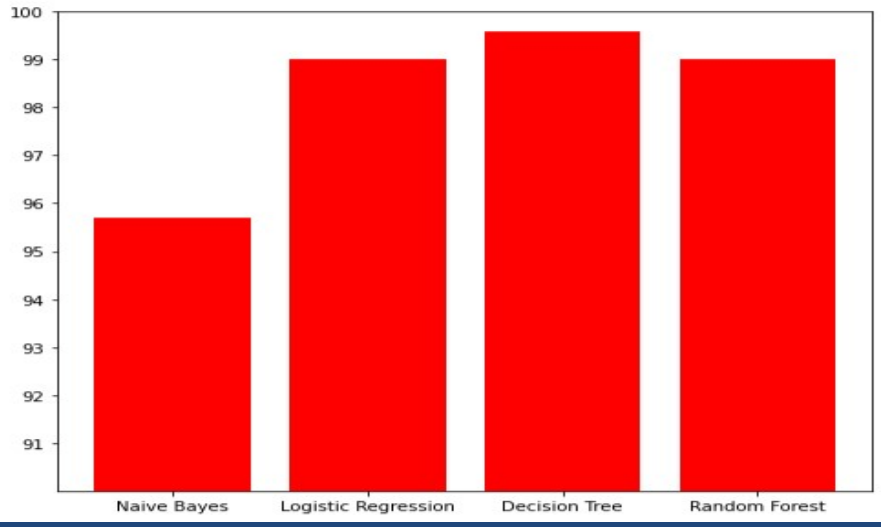
In [34]:
```
cm = metrics.confusion_matrix(y_test, prediction)
plot_confusion_matrix(cm, classes=['Negative', 'Positive'])
```

```
Confusion matrix, without normalization
```



Comparing Different Models

In [35]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(8,7))
plt.bar(list(dct.keys()),list(dct.values()),color='red')
plt.ylim(90,100)
plt.yticks((91, 92, 93, 94, 95, 96, 97, 98, 99, 100));
```



Saving the model

```
In [37]: import pickle
         filename = "finalized_model.pkl"
         pickle.dump(pipe1, open(filename, 'wb'))
```

The few challenges while working on this project were: -

- Using NLP to find punctuations & stop words, it took time in giving the result.

The data set took time to run some algorithms & to check the cross- validation score.

Interpretation of the Results

- Through Pre-processing it is interpretated that all texts are converted to lower case, removed Punctation, replaced extra space, removed stop- words, Calculated length of sentence, words, and characters, converted text using Counter-Vectorize.
- Natural Language Processing and Machine Learning is used in this project.

Learning Outcomes of the Study in respect ofData Science

- This project has demonstrated the importance ofNLP.
- Through different powerful tools of visualization, we were able to analyze and interpret the huge data and with the help of pie plot, count plot & word cloud, I can see the distribution of spam and ham messages.
- Through data cleaning we were able to remove unnecessary columns, values, stop-words and punctuation from our dataset due to which our model would have suffered from overfitting or underfitting.