Introduction:

Explain the properties of the chosen data set and what you will be doing with it:

There are two data sets, one of them contains all the fake news, and the other contains all the true or verified news. Using these data sets, we will create 3 working machine learning models for data classification between fake and true news, with the help of natural language processing (NLP).

Mention the two (or more) machine learning techniques that you will be using:

We will be using 3 machine learning models:

Logistic Regression Support Vector Machine Naive Bayes

Background:

Describe the mechanics of the selected machine learning techniques:

Logistic Regression:

Logistic regression is a simple yet very effective classification algorithm so it is commonly used for many binary classification tasks. Logistic regression uses an equation as the representation, very much like linear regression. Input values (x) are combined linearly using weights or coefficient values (referred to as the Greek capital letter Beta) to predict an output value (y).

Support Vector Machine: Classification

SVM or Support Vector Machine is a linear model for classification and regression problems. It can solve linear and non-linear problems and work well for many practical problems. The idea of SVM is simple: The algorithm creates a line or a hyperplane which separates the data into classes.

Naive Bayes:

It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.

Describe what rescaling and normalisation are and why they are important:

Normalization is a technique for organizing data in a database. It is important that a database is normalized to minimize redundancy (duplicate data) and to ensure only related data is stored in each table. It also prevents any issues stemming from database modifications such as insertions, deletions, and updates.

Describe what cross validation is:

Cross-Validation is a statistical method of evaluating and comparing learning algorithms by dividing data into two segments: one used to learn or train a model and the other used to validate the model. It is a resampling technique with the fundamental idea of splitting the dataset into 2 parts- training data and test data. Train data is used to train the model and the unseen test data is used for prediction. If the model performs well over the test data and gives good accuracy, it means the model hasn't overfitted the training data and can be used for prediction. Here we split our data into K parts, let's use K=3 for a toy example. If we have 3000 instances in our dataset, We split it into three parts, part 1, part 2 and part 3. We then build three different models, each model is trained on two parts and tested on the third. Our first model is trained on part 1 and 2 and tested on part 3. Our second model is trained to on part 1 and part 3 and tested on part 2 and so on.

Describe what dimensionality reduction and feature selection methods are:

Feature selection is simply selecting and excluding given features without changing them. Dimensionality reduction transforms features into a lower dimension.

Explain the quantitative measurements that you will be using to quantify the results

We will be using accuracy score as our measurement. Accuracy score is:

Accuracy Score: Accuracy is one metric for evaluating classification models. Informally, accuracy is the fraction of predictions our model got right. Formally, accuracy has the following definition:

Accuracy = [Number of correct predictions / Total number of predictions]

In [1]:

```
1 # Importing necessary libraries.
```

In [2]:

```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

In [3]:

```
# Importing the fake dataset.
fake = pd.read_csv('Fake.csv', nrows = 5000)
fake
```

Out[3]:

	title	text	subject	date
0	Donald Trump Sends Out Embarrassing New Year'	Donald Trump just couldn t wish all Americans	News	December 31, 2017
1	Drunk Bragging Trump Staffer Started Russian	House Intelligence Committee Chairman Devin Nu	News	December 31, 2017
2	Sheriff David Clarke Becomes An Internet Joke	On Friday, it was revealed that former Milwauk	News	December 30, 2017
3	Trump Is So Obsessed He Even Has Obama's Name	On Christmas day, Donald Trump announced that	News	December 29, 2017
4	Pope Francis Just Called Out Donald Trump Dur	Pope Francis used his annual Christmas Day mes	News	December 25, 2017
4995	FBI Warns Republicans: Do Not Leak Clinton Em	It s no secret Republicans are salivating to f	News	August 18, 2016
4996	Justice Department Announces It Will No Longe	Republicans are about to lose a huge source of	News	August 18, 2016
4997	WATCH: S.E. Cupp Destroys Trump Adviser's 'Fa	A pawn working for Donald Trump claimed that w	News	August 18, 2016
4998	WATCH: Fox Hosts Claim Hillary Has Brain Dama	Fox News is desperate to sabotage Hillary Clin	News	August 18, 2016
4999	CNN Panelist LAUGHS In Corey Lewandowski's Fa	As Donald Trump s campaign continues to sink d	News	August 18, 2016

5000 rows × 4 columns

In [4]:

```
# Importing the true dataset.
true = pd.read_csv('True.csv', nrows = 5000)
true
```

Out[4]:

	title	text	subject	date
0	As U.S. budget fight looms, Republicans flip t	WASHINGTON (Reuters) - The head of a conservat	politicsNews	December 31, 2017
1	U.S. military to accept transgender recruits o	WASHINGTON (Reuters) - Transgender people will	politicsNews	December 29, 2017
2	Senior U.S. Republican senator: 'Let Mr. Muell	WASHINGTON (Reuters) - The special counsel inv	politicsNews	December 31, 2017
3	FBI Russia probe helped by Australian diplomat	WASHINGTON (Reuters) - Trump campaign adviser	politicsNews	December 30, 2017
4	Trump wants Postal Service to charge 'much mor	SEATTLE/WASHINGTON (Reuters) - President Donal	politicsNews	December 29, 2017
4995	U.S. Agriculture secretary nominee submits eth	(Reuters) - U.S. President Donald Trump's nomi	politicsNews	March 13, 2017
4996	Trump aides attack agency that will analyze he	WASHINGTON (Reuters) - Aides to U.S. President	politicsNews	March 12, 2017
4997	Highlights: The Trump presidency on March 12 a	(Reuters) - Highlights of the day for U.S. Pre	politicsNews	March 12, 2017
4998	Obama lawyers move fast to join fight against	WASHINGTON (Reuters) - When Johnathan Smith re	politicsNews	March 13, 2017
4999	Mike Pence to tour Asia next month amid securi	JAKARTA (Reuters) - U.S. Vice President Mike P	politicsNews	March 13, 2017

5000 rows × 4 columns

In [5]:

1 # Concatinating title and text column for the final datasets.

```
In [6]:
```

```
fake['Description'] = fake['title'] + " " + fake['text']
fake['Description']
#fake['Description'][0]
```

Out[6]:

```
0
         Donald Trump Sends Out Embarrassing New Year'...
1
         Drunk Bragging Trump Staffer Started Russian ...
2
         Sheriff David Clarke Becomes An Internet Joke...
         Trump Is So Obsessed He Even Has Obama's Name...
3
4
         Pope Francis Just Called Out Donald Trump Dur...
4995
         FBI Warns Republicans: Do Not Leak Clinton Em...
4996
         Justice Department Announces It Will No Longe...
4997
         WATCH: S.E. Cupp Destroys Trump Adviser's 'Fa...
4998
         WATCH: Fox Hosts Claim Hillary Has Brain Dama...
         CNN Panelist LAUGHS In Corey Lewandowski's Fa...
4999
Name: Description, Length: 5000, dtype: object
```

In [7]:

```
1 true['Description'] = true['title'] + " " + true['text']
2 true['Description']
3 #true['Description'][0]
```

Out[7]:

```
0
        As U.S. budget fight looms, Republicans flip t...
1
        U.S. military to accept transgender recruits o...
2
        Senior U.S. Republican senator: 'Let Mr. Muell...
3
        FBI Russia probe helped by Australian diplomat...
4
        Trump wants Postal Service to charge 'much mor...
4995
        U.S. Agriculture secretary nominee submits eth...
4996
        Trump aides attack agency that will analyze he...
4997
        Highlights: The Trump presidency on March 12 a...
        Obama lawyers move fast to join fight against ...
4998
        Mike Pence to tour Asia next month amid securi...
4999
Name: Description, Length: 5000, dtype: object
```

In [8]:

```
1 # Adding label: 1, for all the true descriptions.
```

In [9]:

```
1 true['label'] = 1
2 true
```

Out[9]:

	title	text	subject	date	Description	label
0	As U.S. budget fight looms, Republicans flip t	WASHINGTON (Reuters) - The head of a conservat	politicsNews	December 31, 2017	As U.S. budget fight looms, Republicans flip t	1
1	U.S. military to accept transgender recruits o	WASHINGTON (Reuters) - Transgender people will	politicsNews	December 29, 2017	U.S. military to accept transgender recruits o	1
2	Senior U.S. Republican senator: 'Let Mr. Muell	WASHINGTON (Reuters) - The special counsel inv	politicsNews	December 31, 2017	Senior U.S. Republican senator: 'Let Mr. Muell	1
3	FBI Russia probe helped by Australian diplomat	WASHINGTON (Reuters) - Trump campaign adviser	politicsNews	December 30, 2017	FBI Russia probe helped by Australian diplomat	1
4	Trump wants Postal Service to charge 'much mor	SEATTLE/WASHINGTON (Reuters) - President Donal	politicsNews	December 29, 2017	Trump wants Postal Service to charge 'much mor	1
4995	U.S. Agriculture secretary nominee submits eth	(Reuters) - U.S. President Donald Trump's nomi	politicsNews	March 13, 2017	U.S. Agriculture secretary nominee submits eth	1
4996	Trump aides attack agency that will analyze he	WASHINGTON (Reuters) - Aides to U.S. President	politicsNews	March 12, 2017	Trump aides attack agency that will analyze he	1
4997	Highlights: The Trump presidency on March 12 a	(Reuters) - Highlights of the day for U.S. Pre	politicsNews	March 12, 2017	Highlights: The Trump presidency on March 12 a	1
4998	Obama lawyers move fast to join fight against	WASHINGTON (Reuters) - When Johnathan Smith re	politicsNews	March 13, 2017	Obama lawyers move fast to join fight against	1
4999	Mike Pence to tour Asia next month amid securi	JAKARTA (Reuters) - U.S. Vice President Mike P	politicsNews	March 13, 2017	Mike Pence to tour Asia next month amid securi	1

5000 rows × 6 columns

In [10]:

1 # Adding Label: 0, for all the fake descriptions.

In [11]:

fake['label'] = 0
fake

Out[11]:

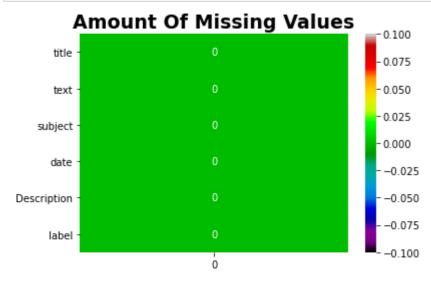
	title	text	subject	date	Description	label
0	Donald Trump Sends Out Embarrassing New Year'	Donald Trump just couldn t wish all Americans	News	December 31, 2017	Donald Trump Sends Out Embarrassing New Year'	0
1	Drunk Bragging Trump Staffer Started Russian 	House Intelligence Committee Chairman Devin Nu	News	December 31, 2017	Drunk Bragging Trump Staffer Started Russian	0
2	Sheriff David Clarke Becomes An Internet Joke	On Friday, it was revealed that former Milwauk	News	December 30, 2017	Sheriff David Clarke Becomes An Internet Joke	0
3	Trump Is So Obsessed He Even Has Obama's Name	On Christmas day, Donald Trump announced that	News	December 29, 2017	Trump Is So Obsessed He Even Has Obama's Name	0
4	Pope Francis Just Called Out Donald Trump Dur	Pope Francis used his annual Christmas Day mes	News	December 25, 2017	Pope Francis Just Called Out Donald Trump Dur	0
4995	FBI Warns Republicans: Do Not Leak Clinton Em	It s no secret Republicans are salivating to f	News	August 18, 2016	FBI Warns Republicans: Do Not Leak Clinton Em	0
4996	Justice Department Announces It Will No Longe	Republicans are about to lose a huge source of	News	August 18, 2016	Justice Department Announces It Will No Longe	0
4997	WATCH: S.E. Cupp Destroys Trump Adviser's 'Fa	A pawn working for Donald Trump claimed that w	News	August 18, 2016	WATCH: S.E. Cupp Destroys Trump Adviser's 'Fa	0
4998	WATCH: Fox Hosts Claim Hillary Has Brain Dama	Fox News is desperate to sabotage Hillary Clin	News	August 18, 2016	WATCH: Fox Hosts Claim Hillary Has Brain Dama	0
4999	CNN Panelist LAUGHS In Corey Lewandowski's Fa	As Donald Trump s campaign continues to sink d	News	August 18, 2016	CNN Panelist LAUGHS In Corey Lewandowski's Fa	0

5000 rows × 6 columns

Checking for any missing values on both the datasets.

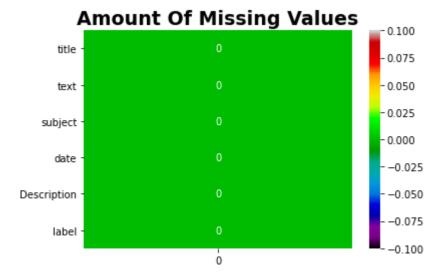
In [12]:

```
plt.title('Amount Of Missing Values',fontsize=19,fontweight='bold')
sns.heatmap(fake.isna().sum().to_frame(),annot=True,cmap='nipy_spectral')
plt.show()
```



In [13]:

```
plt.title('Amount Of Missing Values',fontsize=19,fontweight='bold')
sns.heatmap(true.isna().sum().to_frame(),annot=True,cmap='nipy_spectral')
plt.show()
```



Creating a new data frame only with the required columns.

In [14]:

```
1 true_final = true[['Description', 'label']]
2 true_final
```

Out[14]:

	Description	label
0	As U.S. budget fight looms, Republicans flip t	1
1	U.S. military to accept transgender recruits o	1
2	Senior U.S. Republican senator: 'Let Mr. Muell	1
3	FBI Russia probe helped by Australian diplomat	1
4	Trump wants Postal Service to charge 'much mor	1
4995	U.S. Agriculture secretary nominee submits eth	1
4996	Trump aides attack agency that will analyze he	1
4997	Highlights: The Trump presidency on March 12 a	1
4998	Obama lawyers move fast to join fight against	1
4999	Mike Pence to tour Asia next month amid securi	1

5000 rows × 2 columns

In [15]:

```
fake_final = fake[['Description', 'label']]
fake_final
```

Out[15]:

	Description	label
0	Donald Trump Sends Out Embarrassing New Year'	0
1	Drunk Bragging Trump Staffer Started Russian	0
2	Sheriff David Clarke Becomes An Internet Joke	0
3	Trump Is So Obsessed He Even Has Obama's Name	0
4	Pope Francis Just Called Out Donald Trump Dur	0
4995	FBI Warns Republicans: Do Not Leak Clinton Em	0
4996	Justice Department Announces It Will No Longe	0
4997	WATCH: S.E. Cupp Destroys Trump Adviser's 'Fa	0
4998	WATCH: Fox Hosts Claim Hillary Has Brain Dama	0
4999	CNN Panelist LAUGHS In Corey Lewandowski's Fa	0

5000 rows × 2 columns

In [16]:

```
df = pd.concat([true_final, fake_final])
df.head(5)
```

Out[16]:

	Description	label
0	As U.S. budget fight looms, Republicans flip t	1
1	U.S. military to accept transgender recruits o	1
2	Senior U.S. Republican senator: 'Let Mr. Muell	1
3	FBI Russia probe helped by Australian diplomat	1
4	Trump wants Postal Service to charge 'much mor	1

In [17]:

```
1 df.tail(5)
```

Out[17]:

	Description	label
4995	FBI Warns Republicans: Do Not Leak Clinton Em	0
4996	Justice Department Announces It Will No Longe	0
4997	WATCH: S.E. Cupp Destroys Trump Adviser's 'Fa	0
4998	WATCH: Fox Hosts Claim Hillary Has Brain Dama	0
4999	CNN Panelist LAUGHS In Corey Lewandowski's Fa	0

In [18]:

1 df

Out[18]:

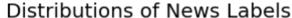
	Description	label
0	As U.S. budget fight looms, Republicans flip t	1
1	U.S. military to accept transgender recruits o	1
2	Senior U.S. Republican senator: 'Let Mr. Muell	1
3	FBI Russia probe helped by Australian diplomat	1
4	Trump wants Postal Service to charge 'much mor	1
4995	FBI Warns Republicans: Do Not Leak Clinton Em	0
4996	Justice Department Announces It Will No Longe	0
4997	WATCH: S.E. Cupp Destroys Trump Adviser's 'Fa	0
4998	WATCH: Fox Hosts Claim Hillary Has Brain Dama	0
4999	CNN Panelist LAUGHS In Corey Lewandowski's Fa	0

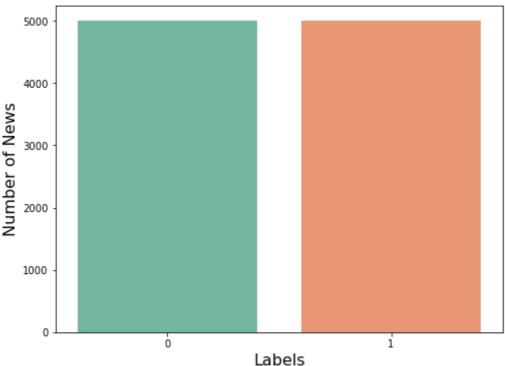
10000 rows × 2 columns

In [19]:

```
# Final Labels Countplot

plt.figure(figsize=(8,6))
sns.countplot(df.label, palette='Set2')
plt.title('Distributions of News Labels',fontsize=20)
plt.xlabel('Labels', fontsize=16)
plt.ylabel('Number of News', fontsize=16)
plt.show()
```





Cleaning the dataset:

https://medium.com/analytics-vidhya/data-cleaning-in-natural-language-processing-1f77ec1f6406 (https://medium.com/analytics-vidhya/data-cleaning-in-natural-language-processing-1f77ec1f6406)

- · Removing Puntuations
- · Stopword Removal
- · Lemmatizing the cleaned description column
- Normalizing the data
- Using principal components to extract the features
- · Creating X and y training and testing sets

In [20]:

```
# Importing necessarry libraries to clean the data set
import nltk
import string
import re
```

In [21]:

```
# Removing Puntuation:

def remove_punct(text):
    text = "".join([char for char in text if char not in string.punctuation])
    text = re.sub('[0-9]+', '', text)
    return text
```

In [22]:

```
# Stopword Removal:

from nltk.corpus import stopwords
", ".join(stopwords.words('english'))

STOPWORDS = set(stopwords.words('english'))

def remove_stopwords(text):
    """custom function to remove the stopwords"""
    return " ".join([word for word in str(text).split() if word not in STOPWORDS])
```

In [23]:

```
# Applying all the defined functions in the data

df['Description'] = df['Description'].apply(lambda x: remove_punct(x))

df['clean_Description'] = df['Description'].apply(lambda text: remove_stopwords(text))

df.head(5)
```

Out[23]:

	Description	label	clean_Description
0	As US budget fight looms Republicans flip thei	1	As US budget fight looms Republicans flip fisc
1	US military to accept transgender recruits on	1	US military accept transgender recruits Monday
2	Senior US Republican senator Let Mr Mueller do	1	Senior US Republican senator Let Mr Mueller jo
3	FBI Russia probe helped by Australian diplomat	1	FBI Russia probe helped Australian diplomat ti
4	Trump wants Postal Service to charge much more	1	Trump wants Postal Service charge much Amazon

In [24]:

In [25]:

True

```
# Lemmatizing the cleaned description column
   # Stemming uses the stem of the word, while lemmatization uses the context in which the
   # Lemmatization carries out a morphological analysis of the words, the chatbot is able
 4
 5
   from nltk.corpus import wordnet
   from nltk.stem import WordNetLemmatizer
 6
 8
   lemmatizer = WordNetLemmatizer()
   wordnet map = {"N":wordnet.NOUN, "V":wordnet.VERB, "J":wordnet.ADJ, "R":wordnet.ADV}
9
10
11
   def lemmatize words(text):
       pos_tagged_text = nltk.pos_tag(text.split())
12
       return " ".join([lemmatizer.lemmatize(word, wordnet_map.get(pos[0], wordnet.NOUN))
13
14
   df["Description lemmatized"] = df["clean Description"].apply(lambda text: lemmatize wor
15
   df.head(5)
16
```

Out[25]:

	Description	label	clean_Description	Description_lemmatized
0	As US budget fight looms Republicans flip thei	1	As US budget fight looms Republicans flip fisc	As US budget fight loom Republicans flip fisca
1	US military to accept transgender recruits on	1	US military accept transgender recruits Monday	US military accept transgender recruit Monday
2	Senior US Republican senator Let Mr Mueller do	1	Senior US Republican senator Let Mr Mueller jo	Senior US Republican senator Let Mr Mueller jo
3	FBI Russia probe helped by Australian diplomat	1	FBI Russia probe helped Australian diplomat ti	FBI Russia probe help Australian diplomat tipo
4	Trump wants Postal Service to charge much more	1	Trump wants Postal Service charge much Amazon	Trump want Postal Service charge much Amazon s

In [26]:

1 df.head(20)

Out[26]:

	Description	label	clean_Description	Description_lemmatized
0	As US budget fight looms Republicans flip thei	1	As US budget fight looms Republicans flip fisc	As US budget fight loom Republicans flip fisca
1	US military to accept transgender recruits on	1	US military accept transgender recruits Monday	US military accept transgender recruit Monday
2	Senior US Republican senator Let Mr Mueller do	1	Senior US Republican senator Let Mr Mueller jo	Senior US Republican senator Let Mr Mueller jo
3	FBI Russia probe helped by Australian diplomat	1	FBI Russia probe helped Australian diplomat ti	FBI Russia probe help Australian diplomat tipo
4	Trump wants Postal Service to charge much more	1	Trump wants Postal Service charge much Amazon	Trump want Postal Service charge much Amazon s
5	White House Congress prepare for talks on spen	1	White House Congress prepare talks spending im	White House Congress prepare talk spend immigr
6	Trump says Russia probe will be fair but timel	1	Trump says Russia probe fair timeline unclear	Trump say Russia probe fair timeline unclear N
7	Factbox Trump on Twitter Dec Approval rating	1	Factbox Trump Twitter Dec Approval rating Amaz	Factbox Trump Twitter Dec Approval rating Amaz
8	Trump on Twitter Dec Global Warming The foll	1	Trump Twitter Dec Global Warming The following	Trump Twitter Dec Global Warming The following
9	Alabama official to certify Senatorelect Jones	1	Alabama official certify Senatorelect Jones to	Alabama official certify Senatorelect Jones to
10	Jones certified US Senate winner despite Moore	1	Jones certified US Senate winner despite Moore	Jones certify US Senate winner despite Moore c
11	New York governor questions the constitutional	1	New York governor questions constitutionality	New York governor question constitutionality f
12	Factbox Trump on Twitter Dec Vanity Fair Hil	1	Factbox Trump Twitter Dec Vanity Fair Hillary	Factbox Trump Twitter Dec Vanity Fair Hillary
13	Trump on Twitter Dec Trump Iraq Syria The fo	1	Trump Twitter Dec Trump Iraq Syria The followi	Trump Twitter Dec Trump Iraq Syria The followi
14	Man says he delivered manure to Mnuchin to pro	1	Man says delivered manure Mnuchin protest new	Man say deliver manure Mnuchin protest new US
15	Virginia officials postpone lottery drawing to	1	Virginia officials postpone lottery drawing de	Virginia official postpone lottery draw decide
16	US lawmakers question businessman at Trump To	1	US lawmakers question businessman Trump Tower	US lawmaker question businessman Trump Tower m
17	Trump on Twitter Dec Hillary Clinton Tax Cut	1	Trump Twitter Dec Hillary Clinton Tax Cut Bill	Trump Twitter Dec Hillary Clinton Tax Cut Bill
18	US appeals court rejects challenge to Trump vo	1	US appeals court rejects challenge Trump voter	US appeal court reject challenge Trump voter f
19	Treasury Secretary Mnuchin was sent giftwrappe	1	Treasury Secretary Mnuchin sent giftwrapped bo	Treasury Secretary Mnuchin send giftwrapped bo

In [27]:

!pip install transformers

```
Requirement already satisfied: transformers in c:\users\karsten\anaconda3\li
b\site-packages (4.14.1)
Requirement already satisfied: pyyaml>=5.1 in c:\users\karsten\anaconda3\lib
\site-packages (from transformers) (5.3.1)
Requirement already satisfied: sacremoses in c:\users\karsten\anaconda3\lib
\site-packages (from transformers) (0.0.46)
Requirement already satisfied: filelock in c:\users\karsten\anaconda3\lib\si
te-packages (from transformers) (3.0.12)
Requirement already satisfied: packaging>=20.0 in c:\users\karsten\anaconda3
\lib\site-packages (from transformers) (21.3)
Requirement already satisfied: regex!=2019.12.17 in c:\users\karsten\anacond
a3\lib\site-packages (from transformers) (2020.6.8)
Requirement already satisfied: huggingface-hub<1.0,>=0.1.0 in c:\users\karst
en\anaconda3\lib\site-packages (from transformers) (0.2.1)
Requirement already satisfied: requests in c:\users\karsten\anaconda3\lib\si
te-packages (from transformers) (2.24.0)
Requirement already satisfied: tqdm>=4.27 in c:\users\karsten\anaconda3\lib
\site-packages (from transformers) (4.47.0)
Requirement already satisfied: numpy>=1.17 in c:\users\karsten\anaconda3\lib
\site-packages (from transformers) (1.18.5)
Requirement already satisfied: tokenizers<0.11,>=0.10.1 in c:\users\karsten
\anaconda3\lib\site-packages (from transformers) (0.10.3)
Requirement already satisfied: typing-extensions>=3.7.4.3 in c:\users\karste
n\anaconda3\lib\site-packages (from huggingface-hub<1.0,>=0.1.0->transformer
```

Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\users\karsten \anaconda3\lib\site-packages (from packaging>=20.0->transformers) (2.4.7)
Requirement already satisfied: chardet<4,>=3.0.2 in c:\users\karsten\anacond a3\lib\site-packages (from requests->transformers) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in c:\users\karsten\anaconda3\lib\site-packages (from requests->transformers) (2.10)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\karsten\anaconda3\lib\site-packages (from requests->transformers) (2020.6.20)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in c:\users\karsten\anaconda3\lib\site-packages (from requests->transformers)

(1.25.9)
Requirement already satisfied: click in c:\users\karsten\anaconda3\lib\sitepackages (from sacremoses->transformers) (7.1.2)

Requirement already satisfied: six in c:\users\karsten\anaconda3\lib\site-pa ckages (from sacremoses->transformers) (1.15.0)

Requirement already satisfied: joblib in c:\users\karsten\anaconda3\lib\site -packages (from sacremoses->transformers) (0.16.0)

https://www.youtube.com/watch?v=VFp38yj8h3A (https://www.youtube.com/watch?v=VFp38yj8h3A)

In natural language processing most of the data that we handle consists of raw text however machine learning models cannot read or understand text in its raw form they can only work with numbers so the tokenizer's objective will be to translate the text into numbers there are several possible approaches to this conversion and the objective is to find the most meaningful representation we'll take a look at three distinct tokenization algorithms we compare them one to one:

- Word-based tokenizers: https://www.youtube.com/watch?v=nhJxYji1aho (<a href="https://www.youtube.com/watch?v=nhJxYji1aho (<a href="https://www.youtube.com/watch?v=nhJxYji1aho (<a href="https://www.youtube.com/watch?v
- Character-based tokenizers: https://youtu.be/ssLg EK2jLE (https://youtu.be/ssLg EK2jLE)

• Subword-based tokenizers: https://youtu.be/zHvTiHr506c (https://youtu.be/zHvTiHr506c (https://youtu.be/zHvTiHr506c) <- We Use as more accuracte, it produces more meaningful subwords

https://www.youtube.com/watch?v=xI0HHN5XKDo (https://www.youtube.com/watch?v=xI0HHN5XKDo)

BERT was trained using the WordPiece tokenization. It means that a word can be broken down into more than one sub-words. To tokenize our texts. BERT was trained using the WordPiece tokenization. It means that a word can be broken down into more than one sub-words. This kind of tokenization is beneficial when dealing with out of vocabulary words, and it may help better represent complicated words. The sub-words are constructed during the training time and depend on the corpus the model was trained on. We could use any other tokenization technique of course, but we'll get the best results if we tokenize with the same tokenizer the BERT model was trained on.

https://www.analyticsvidhya.com/blog/2021/09/an-explanatory-guide-to-bert-tokenizer/ (https://www.analyticsvidhya.com/blog/2021/09/an-explanatory-guide-to-bert-tokenizer/)

In [28]:

```
import numpy as np
 1
   from transformers import BertTokenizer
   tokenizer=BertTokenizer.from_pretrained('bert-base-uncased')
 5
   def sen_to_vec(sentence):
       tokens=tokenizer.tokenize(sentence)
 6
 7
       tokens = ['[CLS]'] + tokens + ['[SEP]']
 8
       T=1519
       padded_tokens=tokens +['[PAD]' for _ in range(T-len(tokens))]
 9
       attn_mask=[ 1 if token != '[PAD]' else 0 for token in padded_tokens ]
10
       seg_ids=[0 for _ in range(len(padded_tokens))]
11
12
       sent_ids=tokenizer.convert_tokens_to_ids(padded_tokens)
13
       return np.array(sent ids)
```

None of PyTorch, TensorFlow >= 2.0, or Flax have been found. Models won't be available and only tokenizers, configuration and file/data utilities can be used.

In [29]:

```
df["Array"]=df["Description_lemmatized"].apply(sen_to_vec)
df.head()
```

Out[29]:

	Description	label	clean_Description	Description_lemmatized	Array
0	As US budget fight looms Republicans flip thei	1	As US budget fight looms Republicans flip fisc	As US budget fight loom Republicans flip fisca	[101, 2004, 2149, 5166, 2954, 8840, 5358, 1064
1	US military to accept transgender recruits on	1	US military accept transgender recruits Monday	US military accept transgender recruit Monday	[101, 2149, 2510, 5138, 16824, 13024, 6928, 20
2	Senior US Republican senator Let Mr Mueller do	1	Senior US Republican senator Let Mr Mueller jo	Senior US Republican senator Let Mr Mueller jo	[101, 3026, 2149, 3951, 5205, 2292, 2720, 2677
3	FBI Russia probe helped by Australian diplomat	1	FBI Russia probe helped Australian diplomat ti	FBI Russia probe help Australian diplomat tipo	[101, 8495, 3607, 15113, 2393, 2827, 11125, 59
4	Trump wants Postal Service to charge much more	1	Trump wants Postal Service charge much Amazon	Trump want Postal Service charge much Amazon s	[101, 8398, 2215, 10690, 2326, 3715, 2172, 973

In [30]:

```
1 df_for_model = df[["Array","label"]]
```

In [31]:

```
df_final_for_model=pd.concat([df_for_model.pop('Array').apply(pd.Series), df_for_model|
df_final_for_model=df_final_for_model.fillna(0)
df_final_for_model
```

Out[31]:

	0	1	2	3	4	5	6	7	8	9	
0	101.0	2004.0	2149.0	5166.0	2954.0	8840.0	5358.0	10643.0	11238.0	10807.0	
1	101.0	2149.0	2510.0	5138.0	16824.0	13024.0	6928.0	20864.0	2899.0	26665.0	
2	101.0	3026.0	2149.0	3951.0	5205.0	2292.0	2720.0	26774.0	3105.0	2899.0	
3	101.0	8495.0	3607.0	15113.0	2393.0	2827.0	11125.0	5955.0	7245.0	6396.0	
4	101.0	8398.0	2215.0	10690.0	2326.0	3715.0	2172.0	9733.0	22613.0	5862.0	
4995	101.0	8495.0	19428.0	10643.0	2079.0	2025.0	17271.0	7207.0	10373.0	6764.0	
4996	101.0	3425.0	2533.0	17472.0	2009.0	2097.0	2053.0	2936.0	2224.0	2797.0	
4997	101.0	3422.0	7367.0	2452.0	2361.0	20735.0	8398.0	11747.0	1521.0	1055.0	
4998	101.0	3422.0	4419.0	6184.0	4366.0	18520.0	2038.0	4167.0	4053.0	2138.0	
4999	101.0	13229.0	5997.0	2923.0	11680.0	1999.0	18132.0	24992.0	28574.0	10344.0	

10000 rows × 3354 columns

```
In [32]:
```

```
# Creating X and y variable
X = df_final_for_model.drop('label', axis=1)
y = df_final_for_model.label
```

In [33]:

```
1 X
```

Out[33]:

	0	1	2	3	4	5	6	7	8	9	
0	101.0	2004.0	2149.0	5166.0	2954.0	8840.0	5358.0	10643.0	11238.0	10807.0	•
1	101.0	2149.0	2510.0	5138.0	16824.0	13024.0	6928.0	20864.0	2899.0	26665.0	
2	101.0	3026.0	2149.0	3951.0	5205.0	2292.0	2720.0	26774.0	3105.0	2899.0	
3	101.0	8495.0	3607.0	15113.0	2393.0	2827.0	11125.0	5955.0	7245.0	6396.0	
4	101.0	8398.0	2215.0	10690.0	2326.0	3715.0	2172.0	9733.0	22613.0	5862.0	
4995	101.0	8495.0	19428.0	10643.0	2079.0	2025.0	17271.0	7207.0	10373.0	6764.0	
4996	101.0	3425.0	2533.0	17472.0	2009.0	2097.0	2053.0	2936.0	2224.0	2797.0	
4997	101.0	3422.0	7367.0	2452.0	2361.0	20735.0	8398.0	11747.0	1521.0	1055.0	
4998	101.0	3422.0	4419.0	6184.0	4366.0	18520.0	2038.0	4167.0	4053.0	2138.0	
4999	101.0	13229.0	5997.0	2923.0	11680.0	1999.0	18132.0	24992.0	28574.0	10344.0	

10000 rows × 3353 columns

In [34]:

1 y

Out[34]:

```
0
         1
1
         1
2
         1
3
         1
         1
4995
         0
4996
        0
4997
        0
4998
         0
4999
```

Name: label, Length: 10000, dtype: int64

```
In [35]:
```

```
# Normalizing the data
 2
   # Initialize a MinMaxScaler and scale the features to between -1 and 1 to normalize the
   # The MinMaxScaler transforms features by scaling them to a given range.
 5
   # The fit_transform() method fits to the data and then transforms it. We don't need to
   # Scale the features to between -1 and 1
 7
   # Scaling is important in the algorithms such as support vector machines (SVM) and k-ne
9
   # between the data points is important.
10
11
   from sklearn.preprocessing import MinMaxScaler
12
13
   scaler = MinMaxScaler((0,1))
14 | X = scaler.fit_transform(X)
```

In [36]:

```
# Using principal components to extract the features explaining up to 90% of variance
   # Applying Feature Engineering
   # Applying PCA
   # The code below has .90 for the number of components parameter.
 5
   # It means that scikit-learn choose the minimum number of principal components such the
 7
   from sklearn.decomposition import PCA
8
9
   pca = PCA(.90)
10
   X_PCA=pca.fit_transform(X)
11
   print(X.shape)
12
13
   print(X_PCA.shape)
```

```
(10000, 3353)
(10000, 373)
```

In [37]:

```
1 X_PCA.shape[1]
```

Out[37]:

373

In [38]:

```
from sklearn.feature_selection import SelectKBest, chi2
selector = SelectKBest(chi2, k=X_PCA.shape[1])
X_kbest = selector.fit_transform(X, y)
```

Scikit Learn

Implementing different kinds of model based on third-party libraries

In [39]:

```
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score, core
   #from sklearn.tree import DecisionTreeClassifier
 3 from sklearn import metrics
4 from sklearn.model selection import GridSearchCV, cross val score
 5 from sklearn.preprocessing import StandardScaler
 6 from sklearn.metrics import classification report
   from sklearn.svm import SVC
 7
   from sklearn.linear_model import LogisticRegression
9 #from sklearn.linear model import SGDClassifier
10 #from sklearn.ensemble import BaggingClassifier, RandomForestClassifier, AdaBoostClass
11 import plotly.graph_objects as go
12 #import xgboost as xgb
13 from sklearn.metrics import roc_curve, auc
14 #from sklearn.ensemble import GradientBoostingClassifier
15 | from sklearn.naive_bayes import GaussianNB
```

In [40]:

```
1 # Creating the function consisting 3 ML techniques
```

In [41]:

```
#Now,split the dataset into training and testing sets keeping 20% of the data for testing
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

X_train_PCA,X_test_PCA,y_train_PCA,y_test_PCA=train_test_split(X_PCA, y, test_size=0.2, X_train_kbest,X_test_kbest,y_train_kbest,y_test_kbest=train_test_split(X_kbest, y, test_size=0.2)
```

In [42]:

```
1
   def func(X_train,y_train,X_test, y_test):
        model_names = ['LogisticRegression', 'SupportVectorMachine', 'NaiveBayes']
 2
 3
        train_scores = []
 4
       test_scores = []
 5
 6
        models = [LogisticRegression,SVC,GaussianNB]
 7
 8
        for model in models:
 9
            mod = model()
10
            model_fit = mod.fit(X_train, y_train)
11
12
            train_scores.append(model_fit.score(X_train, y_train))
            test_scores.append(model_fit.score(X_test, y_test))
13
14
        # dictionary of lists
15
16
        dd = {'Model': model_names , 'Training_score': train_scores, 'Testing_score': test
17
18
        result = pd.DataFrame(dd)
19
20
        return result
```

In [43]:

```
1 #Thrird party library results
```

```
In [44]:
```

```
func(X_train_PCA,y_train_PCA,X_test_PCA, y_test_PCA)
```

Out[44]:

	Model	Training_score	Testing_score
0	LogisticRegression	0.877125	0.8505
1	SupportVectorMachine	0.965000	0.8675
2	NaiveBayes	0.618375	0.6025

In [45]:

```
func(X_train_kbest,y_train_kbest,X_test_kbest, y_test_kbest)
```

Out[45]:

	Model	Training_score	Testing_score
0	LogisticRegression	0.865375	0.8475
1	SupportVectorMachine	0.950500	0.8685
2	NaiveBayes	0.698125	0.6900

In [46]:

```
1 X_train,X_test,y_train,y_test=train_test_split(X_kbest, y, test_size=0.2, random_state=
```

Cross validation divides the data repeatedly based on k value we give and generates accuracies for them then takes the mean of it. This will help us compare between kfold cross validation models and scikit learn library models

In [48]:

```
from sklearn.model_selection import cross_val_score

models = [LogisticRegression,SVC,GaussianNB]
for model in models:
    #model_names = ['LogisticRegression', 'SupportVectorMachine', 'NaiveBayes']
    cross_validation = cross_val_score(model(), X_train, y_train, cv=5, scoring="accuracy print(f"Mean accuracy of {str(model)} is: {np.mean(cross_validation)}")
```

```
Mean accuracy of <class 'sklearn.linear_model._logistic.LogisticRegression'>
is: 0.840125000000001

Mean accuracy of <class 'sklearn.svm._classes.SVC'> is: 0.8595

Mean accuracy of <class 'sklearn.naive_bayes.GaussianNB'> is: 0.697125
```

Models Based on First Principle

Logistic Regression Manual Implementation

Using our Function to train the Model

In [49]:

```
# to compare our model's accuracy with sklearn model
   from sklearn.linear_model import LogisticRegression
   # Logistic Regression
 4
   class LogitRegression() :
        def __init__( self, learning_rate, iterations ) :
 5
 6
            self.learning_rate = learning_rate
 7
            self.iterations = iterations
 8
        # Function for model training
 9
        def fit( self, X, Y ) :
10
11
            # no_of_training_examples, no_of_features
12
            self.m, self.n = X.shape
            # weight initialization
13
14
            self.W = np.zeros( self.n )
15
            self.b = 0
            self.X = X
16
            self.Y = Y
17
18
19
            # gradient descent Learning
20
21
            for i in range( self.iterations ) :
22
                self.update_weights()
23
            return self
24
25
        # Helper function to update weights in gradient descent
26
        def update_weights( self ) :
27
28
            A = 1 / (1 + np.exp( - (self.X.dot(self.W) + self.b)))
29
30
            # calculate gradients
31
            tmp = (A - self.Y.T)
32
            tmp = np.reshape( tmp, self.m )
33
            dW = np.dot( self.X.T, tmp ) / self.m
34
            db = np.sum( tmp ) / self.m
35
36
            # update weights
37
            self.W = self.W - self.learning_rate * dW
38
            self.b = self.b - self.learning rate * db
39
            return self
40
41
42
        # Hypothetical function h(x)
43
44
        def predict( self, X ) :
45
            Z = 1 / (1 + np.exp( - (X.dot(self.W) + self.b)))
            Y = np.where(Z > 0.5, 1, 0)
46
            return Y
47
```

In [50]:

```
1 model = LogitRegression(learning_rate = 0.01, iterations = 1000)
2 model.fit(X_train, y_train)
```

Out[50]:

```
<__main__.LogitRegression at 0x22dd5ede5b0>
```

```
In [51]:

1 y_pred = model.predict( X_test )
```

We are creating our own accuracy fuction called 'accurate' to be used for all other models as well:

```
In [52]:
```

```
def accurate(y_true, y_pred):
    accuracy = np.sum(y_true == y_pred) / len(y_true)
    return accuracy
```

In [53]:

```
train_predictions = model.predict(X_train)
print("Logit Clasifier Training Accuracy: ",accurate(y_train,train_predictions)*100 )

test_predictions = model.predict(X_test)
print("Logit Clasifier Testing Accuracy: ",accurate(y_test,test_predictions)*100 )
```

```
Logit Clasifier Training Accuracy: 74.8375
Logit Clasifier Testing Accuracy: 74.4
```

Support Vector Machine Manual Implementation:

In [54]:

```
class SVM:
 2
 3
        def __init__(self, learning_rate=0.001, lambda_param=0.01, n_iters=1000):
            self.lr = learning rate
 4
 5
            self.lambda_param = lambda_param
            self.n_iters = n_iters
 6
 7
            self.w = None
 8
            self.b = None
 9
10
11
        def fit(self, X, y):
12
            n_samples, n_features = X.shape
13
            y_{-} = np.where(y == 0, 0, 1)
14
15
            self.w = np.zeros(n_features)
16
            self.b = 0
17
18
            for _ in range(self.n_iters):
19
                for idx, x_i in enumerate(X):
20
21
                     condition = y_{int} = y_{int} * (np.dot(x_i, self.w) - self.b) >= 1
22
                     if condition:
                         self.w -= self.lr * (2 * self.lambda param * self.w)
23
                     else:
24
25
                         self.w -= self.lr * (2 * self.lambda_param * self.w - np.dot(x_i, y
                         self.b -= self.lr * y_[idx]
26
27
28
        def predict(self, X):
29
            approx = np.dot(X, self.w) - self.b
30
31
            return np.sign(approx)
```

In [55]:

```
1 model = SVM()
2 model.fit(X_train, y_train)
```

In [56]:

```
1 train_predictions = model.predict(X_train)
2 print("SVM Clasifier Training Accuracy: ",accurate(y_train,train_predictions)*100 )
3
4 test_predictions = model.predict(X_test)
5 print("SVM Clasifier Testing Accuracy: ",accurate(y_test,test_predictions)*100 )
```

SVM Clasifier Training Accuracy: 49.95 SVM Clasifier Testing Accuracy: 50.2

Implementing Naive Bayes Algorithm from Scratch:

In [57]:

```
1
   class NaiveBayes:
 2
 3
        def fit(self, X, y): # X is a numpy array, y is a 1D vector
 4
            n samples, n features = X.shape # n samples are Rows, n features are Columns
 5
            self._classes = np.unique(y) # Unique Classes
 6
            n_classes = len(self._classes)
 7
 8
            # Calculating Mean variace and Prior for each class
9
            self._mean = np.zeros((n_classes, n_features),dtype=np.float64)
            self. var = np.zeros((n classes, n features),dtype=np.float64)
10
11
            self._priors = np.zeros(n_classes,dtype=np.float64)
12
13
14
            for idx, c in enumerate(self._classes):
                X_c = X[y==c]
15
                self._mean[idx, :] = X_c.mean(axis=0)
16
17
                self._var[idx, :] = X_c.var(axis=0)
                self._priors[idx] = X_c.shape[0] /float(n_samples)
18
19
20
21
        def predict(self,X):
22
            y_pred = [self._predict(x) for x in X] # Using List Comprehension
23
            return np.array(y pred)
24
25
        def predict(self,x):
26
            posteriors = [] # Adding all the values to choose maximum value for posterior |
27
            # Calculating posterior probability for each class
28
29
            for idx, c in enumerate(self. classes):
                prior = np.log(self._priors[idx])
30
                posterior = np.sum(np.log(self._pdf(idx,x)))
31
32
                posterior = prior + posterior
33
                posteriors.append(posterior)
34
35
            # Return class with Highest posterior probability
36
            return self._classes[np.argmax(posteriors)]
37
38
39
        def _pdf(self, class_idx, x):
40
            mean = self. mean[class idx]
            var = self._var[class_idx]
41
42
            numerator = np.exp(-(x-mean)**2 / (2 * var))
43
            denominator = np.sqrt(2 * np.pi * var)
            return numerator / denominator
44
```

In [58]:

```
1  nb = NaiveBayes()
2  nb.fit(X_train, y_train)
```

In [59]:

```
train_predictions = nb.predict(X_train)
print("Naive Bayes Clasifier Training Accuracy: ",accurate(y_train,train_predictions)*:

test_predictions = nb.predict(X_test)
print("Naive Bayes Clasifier Testing Accuracy: ",accurate(y_test,test_predictions)*100
```

```
Naive Bayes Clasifier Training Accuracy: 69.8125
Naive Bayes Clasifier Testing Accuracy: 69.0
```

Experiments:

Describe the steps that you used to process the data set:

To process the data set:

- After importing both the data sets; consists of true and fake news with upto 5000 rows
- · We created a text based description column
- Labels for each type of news has been added, where 1 represents true news and 0 represents fake news.
- After checking for any missing values, the final data frame has been created using only the description and label columns.
- With the final data set, we used NLP techniques to clean to data by removing all the stop words and punctuations. Then we used lemmatization and Bert tokenization to get the array form required.
- For the last experiment we checked the cross-validation score, and it didn't provide much help, as accuracies for every model remains similar to that of sklearn methods.

Describe the experiments that you carried out

- first we scale the predictor variables using Minmaxscaler
- Used PCA to get the most important features that explains upto 90% of the variance
- then we used kbest method for feature selection to compare between PCA and kBest methods

Describe the implementation of the 3 ML techniques chosen

- For all three models, that is Logistic, Support Vector and Naive Bayes' we used our own models. The models are build from scratch based on the first principle of python language
- · For accuracy we used own accuracy model on all of them to get the result
 - def accurate(y true, y pred):
 - accuracy = np.sum(y_true == y_pred) / len(y_true)
 - return accuracy

Compare your implementation of these techniques using the dataset against a third-party implementation of the same techniques.

The comparision of the results:

- For Logistic the training and testing accuracies using third party libraries are: 86% & 84% and using the first principle is: 74.8% & 74.4%.
- For SVM the training and testing accuracies using third party libraries are: 95% & 86% and using the first principle is: 49.9% & 50.0%
- For Naive Bayes the training and testing accuracies using third party libraries are: 69.8% & 69% and using the first principle is: 69.8% & 69%.

Conclusion:

Draw conclusions from your experiments

- Feature Selection:
 - Feature selection with kbest and PCA doesn't give any clear recommendation about which model is better as both of the models gives almost same result when comparing logistic and SVM accuracies at: 86% and 95% respectively. But while comparing Naive Bayes kbest method gives higher accuracy at 69% compared to 60% when using PCA.
- · Model Selection:
 - Logistic regression provided maximum accuracy for training and testing when using both first principle python languages and third party lbibraries at 74.8% & 74.4% with 86% & 84% respectively.
- · First Principle vs Third party libraries:
 - Naive bayes model from scratch provided most similar result then other models, so we can conclude that naive bayes from scratch was the best when comes to first principle language, although in most of the cases third party languages provided much higher accuracies.
- Cross Validation:
 - Using cross validation did not provided much improvement in the model, as all the accuracies remains almost similar.
- SVM:
 - The support vector machine model provides the least accuracy at 50% compared to its alternative version using sklearn, which gives accuracy at 95%.
- Further Improvements:
 - To further improve the moddel we could have used hyper parater tuning or different machine learning techniques, that might have improved our results.