PROJECT - (23rd April, 2021 - 09th May, 2021)

→ 1. PART ONE

```
from google.colab import drive
drive.mount('/content/drive')
    Mounted at /content/drive
%tensorflow_version 2.x
import tensorflow
tensorflow.__version__
    '2.4.1'
project_path = '/content/drive/MyDrive/My Files/AIML Workbooks'
import os
                            # Importing os library
                            # To read the data set
import pandas as pd
import numpy as np
                            # Importing numpy library
import seaborn as sns
                            # For data visualization
import matplotlib.pyplot as plt
                                     # Necessary library for plotting graphs
from glob import glob
                            # Importing necessary library
import tensorflow as tf
                           # Importing library
%matplotlib inline
sns.set(color codes = True)
from sklearn import metrics
                                     # Importing metrics
from sklearn.model_selection import train_test_split
                                                           # Splitting data into
from sklearn.metrics import classification report, accuracy score, recall score,
from sklearn.preprocessing import StandardScaler
                                                           # Importing to standa
from sklearn.impute import SimpleImputer
                                                           # Importing to fill i
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import PolynomialFeatures
                                                           # Importing polynomia
from sklearn.decomposition import PCA
                                                # Importing to run pca analysis
from sklearn import svm
                                     # Importing necessary library for model bui
from sklearn.ensemble import RandomForestClassifier
                                                           # Importing necessary
from sklearn.neighbors import KNeighborsClassifier
                                                           # Importing necessary
from sklearn import preprocessing
                                                # Importing preprocessing librar
```

```
from sklearn: model_selection import GFoldearchev_valacomisedsearchev # Importing
from sklearn.cluster import KMeans
                                                # For KMeans cluster model build
from scipy.stats import zscore
                                     # Import zscore library
from scipy.spatial.distance import cdist
                                                # Importing cdist functionality
import tensorflow
                           # Importing tensorflow library
from tensorflow.keras.models import Sequential, Model
                                                                    # Importing
from tensorflow.keras.utils import to_categorical
                                                           # Importing tensorflo
from tensorflow.keras import optimizers
                                                           # Importing optimizer
from tensorflow.keras.layers import Dense, Dropout, Activation, BatchNormalizati
from tensorflow.keras.applications.mobilenet import preprocess input
from tensorflow.python.keras.preprocessing.text import Tokenizer
                                                                    # Importing
from tensorflow.python.keras.preprocessing.sequence import pad_sequences
from tensorflow.python.keras.models import load model
                                                                    # Importing
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLRO
from tensorflow.keras.applications.mobilenet import MobileNet
                                                                    # Importing
from tensorflow.keras.losses import binary_crossentropy
                                                                    # Importing
                                                           # Importing necessary
from tensorflow.keras.backend import log, epsilon
from keras.utils import np_utils  # Importing necessary library
                                    # Importing necessary library for model bui
from sklearn import svm
                                    # Import svc library for model building
from sklearn.svm import SVC
from skimage.color import rgb2gray
                                                # Loading color library
from sklearn.preprocessing import OneHotEncoder
                                                           # Library for one hot
from sklearn.metrics import confusion_matrix
                                                           # Loading necessary l
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img, i
from keras.preprocessing import image
                                               # Importing necessary image libr
from tensorflow import keras
                                     # Loading keras libaray
from tensorflow.keras.optimizers import Adam, SGD
                                                           # Importing optimizer
import cv2
                           # Importing necessary library
from PIL import ImageFile
                                     # Importing image library
from tgdm import tgdm
                                     # Importing necessary library
import time
                           # Importing time library
from mpl_toolkits.axes_grid1 import ImageGrid
                                                           # Importing necessary
from PIL import Image
                           # Importing image library
                           # Importing regular expression library
import re
                            # Import necessary library
import nltk
from nltk.corpus import stopwords
                                                # Importing necessary library
from sklearn.feature_extraction.text import CountVectorizer
                                                                     # Importing
                                                       # Imorting necessary
from sklearn.preprocessing import MultiLabelBinarizer
                           # Importing json to import file
import json
import urllib
                           # Importing necessary library
from tensorflow.keras.preprocessing.text import Tokenizer
                                                                     # Importing
from tensorflow.keras.preprocessing.sequence import pad_sequences
                                # Importing necessary library
from wordcloud import WordCloud
nltk.download("stopwords")
                                    # Loading necessary datasets from nltk
nltk.download("punkt")
                                     # Loading necessary datasets from nltk
nltk.download('punkt')
                                     # Loadiing necessary datasets from nltk
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data] Package punkt is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data] Package punkt is already up-to-date!
True
```

Loading and checking the data

df = pd.read_csv('/content/drive/MyDrive/My
Files/AIML Workbooks/IMDB Dataset.cs
df.head()

	review	sentiment
0	One of the other reviewers has mentioned that	positive
1	A wonderful little production. The	positive
2	I thought this was a wonderful way to spend ti	positive
3	Basically there's a family where a little boy	negative
4	Petter Mattei's "Love in the Time of Money" is	positive

df.tail()

	review	sentiment
995	I thought this movie did a down right good job	positive
996	Bad plot, bad dialogue, bad acting, idiotic di	negative
997	I am a Catholic taught in parochial elementary	negative
998	I'm going to have to disagree with the previou	negative
999	No one expects the Star Trek movies to be high	negative

```
df.shape
```

(50000, 2)

df.size

100000

df.columns

Index(['review', 'sentiment'], dtype='object')

df.isnull().sum()

review 6 sentiment 6 dtype: int64

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 2 columns):

Column Non-Null Count Dtype
--- 0 review 50000 non-null object

1 sentiment 50000 non-null object

dtypes: object(2)

memory usage: 781.4+ KB

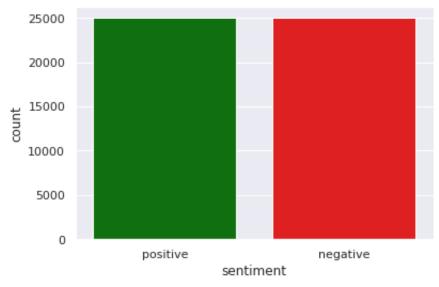
df.describe()

	review	sentiment
count	50000	50000
unique	49582	2
top	Loved today's show!!! It was a variety and not	positive
freq	5	25000

Visualizing the positive and negative sentiments

```
sns.countplot(df['sentiment'], palette = ['green','red'])
plt.show()
print(df.sentiment.value_counts())
```

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWar: FutureWarning



positive 25000 negative 25000

Name: sentiment, dtype: int64

We can observe from the above graphical representation that both positive and negative sentiments are equal.

Converting our sentiments into integer values

df.sentiment = [1 if each == 'positive' else 0 for each in df.sentiment]

df.head()

	review	sentiment
0	One of the other reviewers has mentioned that	1
1	A wonderful little production. The	1
2	I thought this was a wonderful way to spend ti	1
3	Basically there's a family where a little boy	0
4	Petter Mattei's "Love in the Time of Money" is	1

df.tail()

	review	sentiment
49995	I thought this movie did a down right good job	1
49996	Bad plot, bad dialogue, bad acting, idiotic di	0
49997	I am a Catholic taught in parochial elementary	0
49998	I'm going to have to disagree with the previou	0
49999	No one expects the Star Trek movies to be high	0

Checking to see if the sentiments have been coverted to integer values

Cleaning the dataset

Process of clearing punctuation marks in data.

Cleaning unnecessary marks in data.

Capitalization to lowercase.

Cleaning extra spaces.

Removal of stopwords in sentences.

[] \hookrightarrow 4 cells hidden

Splitting data into train and test set

[] \hookrightarrow 12 cells hidden

Model Buidling

```
model = Sequential()
embedding_size = 50

model.add(Embedding(input_dim = 10000, output_dim = embedding_size, input_length
model.add(LSTM(units = 16, return_sequences = True))
model.add(Dropout(0.1))

model.add(LSTM(units = 8, return_sequences= True))
model.add(Dropout(0.1))

model.add(LSTM(units = 4))
model.add(Dropout(0.1))

model.add(Dense(1, activation = 'sigmoid'))

optimizer = Adam(lr = 1e-3)
model.compile(loss = 'binary_crossentropy', metrics = ['accuracy'], optimizer = 10000, output_dim = embedding_size, input_length
model.add(LSTM(units = 16, return_sequences = True))
model.add(Dropout(0.1))
```

model.summary()

Model: "sequential_1"

Layer (type)	Output Shape	Param #
embedding_layer (Embedding)	(None, 272, 50)	500000
lstm_3 (LSTM)	(None, 272, 16)	4288
dropout_3 (Dropout)	(None, 272, 16)	0
lstm_4 (LSTM)	(None, 272, 8)	800
dropout_4 (Dropout)	(None, 272, 8)	0
lstm_5 (LSTM)	(None, 4)	208
dropout_5 (Dropout)	(None, 4)	0
dense_1 (Dense)	(None, 1)	5 =======

Total params: 505,301 Trainable params: 505,301 Non-trainable params: 0

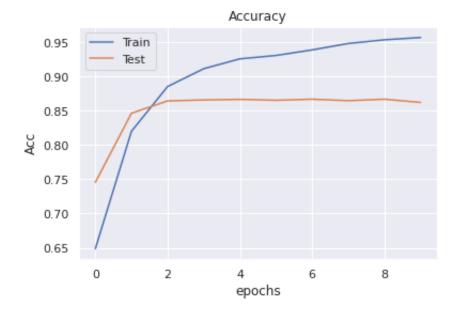
history = model.fit(x_train_pad, y_train, validation_split = 0.3, batch_size = 1

```
Epoch 1/10
Epoch 2/10
28/28 [============== ] - 3s 117ms/step - loss: 0.5824 - acc
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
28/28 [============== ] - 3s 117ms/step - loss: 0.2261 - acc
Epoch 10/10
28/28 [============== ] - 3s 117ms/step - loss: 0.2018 - acc
```

```
result = model.evaluate(x_test_pad, y_test)
   x = model.predict(x_test_pad)
print(x)
    [[0.9118545]
    [0.9136807]
    [0.08736128]
    [0.9157319]
    [0.86391574]
    [0.8981884]]
y = []
a = 0
for i in x:
 if i >= 0.5:
   a = 1
 else:
   a = 0
 y append(a)
print(y)
    [1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0,
```

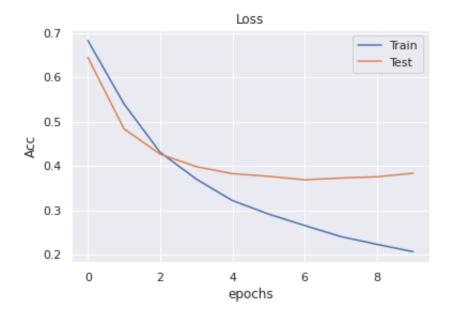
Visualizing accuracy through graphical representation

```
plt.figure()
plt.plot(history.history["accuracy"], label = "Train")
plt.plot(history.history["val_accuracy"], label = "Test")
plt.title("Accuracy")
plt.ylabel("Acc")
plt.xlabel("epochs")
plt.legend()
plt.show()
```



Visualizing loss through graphical representation

```
plt.figure()
plt.plot(history.history["loss"], label = "Train")
plt.plot(history.history["val_loss"], label = "Test")
plt.title("Loss")
plt.ylabel("Acc")
plt.xlabel("epochs")
plt.legend()
plt.show()
```



```
dataset_predict = df.copy()
dataset_predict = pd.DataFrame(dataset_predict)
dataset_predict.columns = ['review']
dataset_predict = dataset_predict.reset_index()
dataset_predict = dataset_predict.drop(['index'], axis=1)
dataset_predict.head()
```

review

- **0** one reviewers mentioned watching oz episode ho...
- **1** wonderful little production br br filming tech...
- 2 thought wonderful way spend time hot summer we...
- 3 basically family little boy jake thinks zombie...
- 4 petter mattei love time money visually stunnin...

```
test_actual_label = sentiment.copy()
test actual label = pd.DataFrame(test actual label)
test_actual_label.columns = ['sentiment']
test_actual_label['sentiment'] = test_actual_label['sentiment'].replace({1: 'pos
test actual label['sentiment'].head()
    0
         positive
    1
         positive
    2
         positive
    3
         negative
         positive
    Name: sentiment, dtype: object
test_predicted_label = y.copy()
test_predicted_label = pd.DataFrame(test_predicted_label)
test_predicted_label.columns = ['predicted_sentiment']
test_predicted_label['predicted_sentiment'] = test_predicted_label['predicted_se
```

test_result = pd.concat([dataset_predict, test_actual_label, test_predicted_labe
test_result.head()

	review	sentiment	predicted_sentiment
0	one reviewers mentioned watching oz episode ho	positive	positive
1	wonderful little production br br filming tech	positive	positive
2	thought wonderful way spend time hot summer we	positive	negative
3	basically family little boy jake thinks zombie	negative	positive
4	petter mattei love time money visually stunnin	positive	negative

2. PART TWO

from google.colab import drive
drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly remount, ca

```
%tensorflow version 2.x
import tensorflow
tensorflow.__version__
    '2.4.1'
project_path = '/content/drive/MyDrive/My Files/AIML Workbooks'
                            # Importing os library
import os
                            # To read the data set
import pandas as pd
import numpy as np
                            # Importing numpy library
                            # For data visualization
import seaborn as sns
                                     # Necessary library for plotting graphs
import matplotlib.pyplot as plt
from glob import glob
                            # Importing necessary library
import tensorflow as tf
                            # Importing library
%matplotlib inline
sns.set(color_codes = True)
from sklearn import metrics
                                     # Importing metrics
from sklearn.model selection import train test split
                                                           # Splitting data into
from sklearn.metrics import classification_report, accuracy_score, recall_score,
from sklearn.preprocessing import StandardScaler
                                                           # Importing to standa
from sklearn.impute import SimpleImputer
                                                           # Importing to fill i
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import PolynomialFeatures
                                                           # Importing polynomia
from sklearn.decomposition import PCA
                                                # Importing to run pca analysis
                                     # Importing necessary library for model bui
from sklearn import svm
from sklearn.ensemble import RandomForestClassifier
                                                           # Importing necessary
from sklearn.neighbors import KNeighborsClassifier
                                                           # Importing necessary
from sklearn import preprocessing
                                                # Importing preprocessing librar
from sklearn.model_selection import KFold, cross_val_score
                                                                     # Importing
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.cluster import KMeans
                                                # For KMeans cluster model build
from scipy.stats import zscore
                                     # Import zscore library
from scipy.spatial.distance import cdist
                                                # Importing cdist functionality
import tensorflow
                            # Importing tensorflow library
from tensorflow.keras.models import Sequential, Model
                                                                    # Importing
from tensorflow.keras.utils import to_categorical
                                                           # Importing tensorflo
from tensorflow.keras import optimizers
                                                           # Importing optimizer
from tensorflow.keras.layers import Dense, Dropout, Activation, BatchNormalizati
from tensorflow.keras.applications.mobilenet import preprocess_input
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLRO
from tensorflow.keras.applications.mobilenet import MobileNet
                                                                    # Importing
from tensorflow.keras.losses import binary_crossentropy
                                                                    # Importing
from tensorflow.keras.backend import log, epsilon
                                                           # Importing necessary
```

```
from keras.utils import np_utils
from sklearn import svm
                                       # Importing necessary library
# Importing necessary library for model bui
                                       # Import svc library for model building
from sklearn.svm import SVC
from skimage.color import rgb2gray
                                                  # Loading color library
                                                              # Library for one hot
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import confusion_matrix
                                                              # Loading necessary l
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img, i
from keras.preprocessing import image
                                                  # Importing necessary image libr
from tensorflow import keras
                                       # Loading keras libaray
from tensorflow.keras.optimizers import Adam, SGD
                                                              # Importing optimizer
import cv2
                             # Importing necessary library
from PIL import ImageFile
                                       # Importing image library
from tgdm import tgdm
                                       # Importing necessary library
import time
                             # Importing time library
from mpl toolkits.axes grid1 import ImageGrid
                                                              # Importing necessary
from PIL import Image
                             # Importing image library
import re
                             # Importing regular expression library
import nltk
                             # Import necessary library
from nltk.corpus import stopwords
                                                  # Importing necessary library
from sklearn.feature_extraction.text import CountVectorizer
                                                                        # Importing
from sklearn.preprocessing import MultiLabelBinarizer
                                                             # Imorting necessary
import json
                             # Importing json to import file
import urllib
                             # Importing necessary library
from tensorflow.keras.preprocessing.text import Tokenizer
                                                                        # Importing
from tensorflow.keras.preprocessing.sequence import pad_sequences
from wordcloud import WordCloud
                                      # Importing necessary library
def parse_data(file):
  for I in open(file, 'r'):
    yield ison.loads(I)
df = list(parse_data('/content/drive/MyDrive/My Files/AIML Workbooks/Sarcasm_Hea
len(df)
    26709
```

df[0:10]

The dataset is a list of dictionaries as seen below

```
[{'article link': 'https://www.huffingtonpost.com/entry/versace-black-code
        'headline': "former versace store clerk sues over secret 'black code' for
       'is sarcastic': 0},
      {'article_link': '<a href="https://www.huffingtonpost.com/entry/roseanne-revival-re">https://www.huffingtonpost.com/entry/roseanne-revival-re</a>
        'headline': "the 'roseanne' revival catches up to our thorny political mo
        'is_sarcastic': 0},
      {'article_link': 'https://local.theonion.com/mom-starting-to-fear-son-s-we
       'headline': "mom starting to fear son's web series closest thing she will
       'is sarcastic': 1},
      {'article_link': '<a href="https://politics.theonion.com/boehner-just-wants-wife-to">https://politics.theonion.com/boehner-just-wants-wife-to</a>
        'headline': 'boehner just wants wife to listen, not come up with alternat
       'is sarcastic': 1},
      {'article_link': '<a href="https://www.huffingtonpost.com/entry/jk-rowling-wishes-s">https://www.huffingtonpost.com/entry/jk-rowling-wishes-s</a>
       'headline': 'j.k. rowling wishes snape happy birthday in the most magical
        'is sarcastic': 0},
      {'article_link': 'https://www.huffingtonpost.com/entry/advancing-the-world
        'headline': "advancing the world's women",
       'is_sarcastic': 0},
      {'article_link': 'https://www.huffingtonpost.com/entry/how-meat-is-grown-i
        'headline': 'the fascinating case for eating lab-grown meat',
       'is sarcastic': 0},
      {'article link': 'https://www.huffingtonpost.com/entry/boxed-college-tuiti
        'headline': 'this ceo will send your kids to school, if you work for his
        'is sarcastic': 0},
      {'article_link': 'https://politics.theonion.com/top-snake-handler-leaves-s
        'headline': 'top snake handler leaves sinking huckabee campaign',
       'is_sarcastic': 1},
      {'article_link': 'https://www.huffingtonpost.com/entry/fridays-morning-ema
        'headline': "friday's morning email: inside trump's presser for the ages"
        'is sarcastic': 0}]
# Seperating data into features and labels for futher processing
headline_tmp = []
labels = []
for items in df:
  headline tmp.append(items['headline'])
  labels.append(items['is_sarcastic'])
```

headline_tmp[0:10]

```
["former versace store clerk sues over secret 'black code' for minority sho
     "the 'roseanne' revival catches up to our thorny political mood, for bette
     "mom starting to fear son's web series closest thing she will have to gran
      'boehner just wants wife to listen, not come up with alternative debt-redu
     'j.k. rowling wishes snape happy birthday in the most magical way',
     "advancing the world's women",
      'the fascinating case for eating lab-grown meat',
      'this ceo will send your kids to school, if you work for his company',
      'top snake handler leaves sinking huckabee campaign',
     "friday's morning email: inside trump's presser for the ages"]
labels[0:10]
    [0, 0, 1, 1, 0, 0, 0, 0, 1, 0]
# Steps to remove stopwords and punctuations
nltk.download('stopwords')
stop = list(stopwords.words('english'))
# Remove stopwords from the headlines
headline = []
for sent in headline_tmp:
   filtered_list = []
   for word in sent.split():
     if not word in stop:
       filtered_list.append(word)
   join_str = ' '.join([str(ele) for ele in filtered_list])
   headline.append(join str)
     [nltk_data] Downloading package stopwords to /root/nltk_data...
    [nltk data] Package stopwords is already up-to-date!
headline[0:10]
     ["former versace store clerk sues secret 'black code' minority shoppers",
     "'roseanne' revival catches thorny political mood, better worse",
     "mom starting fear son's web series closest thing grandchild",
     'boehner wants wife listen, come alternative debt-reduction ideas',
      'j.k. rowling wishes snape happy birthday magical way',
     "advancing world's women",
      'fascinating case eating lab-grown meat',
      'ceo send kids school, work company',
      'top snake handler leaves sinking huckabee campaign',
     "friday's morning email: inside trump's presser ages"]
```

→ Word Cloud

Creating a dataframe from the oirginal json file
sarcastic = pd.read_json('/content/drive/MyDrive/My Files/AIML Workbooks/Sarcasm
sarcastic.head()

	article_link	headline	is_sarcastic
0	https://www.huffingtonpost.com/entry/versace-b	former versace store clerk sues over secret 'b	0
1	https://www.huffingtonpost.com/entry/roseanne	the 'roseanne' revival catches up to our thorn	0
2	https://local.theonion.com/mom-starting-to-fea	mom starting to fear son's web series closest	1

sarcastic.tail()

is_sarcastic	headline	article_link	
0	american politics in moral free-fall	https://www.huffingtonpost.com/entry/american	26704
0	america's best 20 hikes	https://www.huffingtonpost.com/entry/americas	26705
0	reparations and obama	https://www.huffingtonpost.com/entry/reparatio	26706
	israeli ban targeting		

Remvoing the article column from the dataframe we do not require it for out an
sarcastic.drop('article_link', axis =1, inplace = True)

sarcastic.head()

	headline	is_sarcastic
0	former versace store clerk sues over secret 'b	0
1	the 'roseanne' revival catches up to our thorn	0
2	mom starting to fear son's web series closest	1
3	boehner just wants wife to listen, not come up	1
4	j.k. rowling wishes snape happy birthday in th	0

Filtering rows to display is_sarcastic = 1
sarcastic[sarcastic.is_sarcastic == 1]

	headline	is_sarcastic
2	mom starting to fear son's web series closest	1
3	boehner just wants wife to listen, not come up	1
8	top snake handler leaves sinking huckabee camp	1
15	nuclear bomb detonates during rehearsal for 's	1
16	cosby lawyer asks why accusers didn't come for	1
26693	new bailiff tired of hearing how old bailiff d	1
26694	breaking: 'the onion' in kill range of boston	1
26695	seaworld crowd applauds for dolphin playfully	1
26702	pentagon to withhold budget figures out of res	1
26703	pope francis wearing sweater vestments he got	1

11724 rows × 2 columns

Filtering rows to display is_sarcastic = 0 sarcastic[sarcastic.is_sarcastic == 0]

	headline	is_sarcastic
0	former versace store clerk sues over secret 'b	0
1	the 'roseanne' revival catches up to our thorn	0
4	j.k. rowling wishes snape happy birthday in th	0
5	advancing the world's women	0
6	the fascinating case for eating lab-grown meat	0
26704	american politics in moral free-fall	0
26705	america's best 20 hikes	0
26706	reparations and obama	0
26707	israeli ban targeting boycott supporters raise	0
26708	gourmet gifts for the foodie 2014	0

14985 rows × 2 columns

Defining a word cloud for 1000 most frequent words in sarcastic headlines

```
wc = WordCloud(background_color='white', max_words = 1000, width= 1400, height =
wc.generate(' '.join(sarcastic[sarcastic.is_sarcastic == 1]['headline']))

print('Word cloud for 1000 most frequent words in sarcastic headline')
plt.figure(figsize = (12,12))
plt.imshow(wc, interpolation= 'bilinear')
plt.axis('off')
plt.show()
```

Word cloud for 1000 most frequent words in sarcastic headline



Defining a word cloud for 1000 most frequent words in non saracatic headlines
wc = WordCloud(background_color = 'white', max_words = 1000, width = 1400, heigh
wc.generate(' '.join(sarcastic[sarcastic.is_sarcastic == 0]['headline']))
print('Words cloud for 1000 most frequent words in non sarcastic headlines')
plt.figure(figsize = (12,12))
plt.imshow(wc, interpolation = 'bilinear')
plt.axis('off')
plt.show()

Words cloud for 1000 most frequent words in non sarcastic headlines



Distribution of Labels

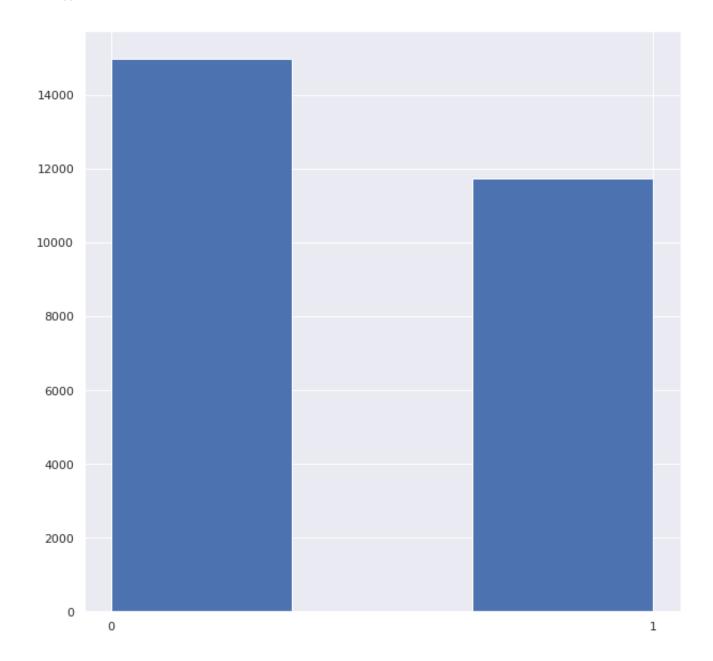
sarcastic['is_sarcastic'].value_counts()

0 149851 11724

Name: is_sarcastic, dtype: int64

Visualizing the count via histogram plot

```
plt.figure(figsize = (10,10))
plt.hist(sarcastic['is_sarcastic'], bins = 3)
plt.xticks([0,1])
plt.show()
```



Distribution of length of headlines

Creating a new column in the dataframe with the number of words for each headl
sarcastic['headline_length'] = sarcastic['headline'].apply(lambda x: len(x.split

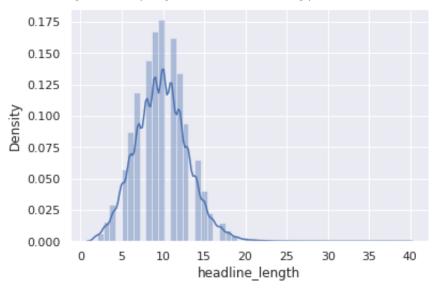
sarcastic['headline_length'].head()

Name: headline_length, dtype: int64

Visualizing density plot of headline lengths

sns.distplot(sarcastic['headline_length']);

/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: Futurwarnings.warn(msg, FutureWarning)



sarcastic['headline_length'].describe()

26709.000000 count 9.845820 mean std 3.168955 min 2.000000 25% 8.000000 50% 10.000000 75% 12.000000 39.000000 max

Name: headline_length, dtype: float64

```
# Getting the 99.99th percentile using quantile method
sarcastic['headline_length'].quantile(0.9999)
30.32919999999649
```

▼ Data Processing

```
# Define parameters
#embedding dim = the dimnesion to which each of the words in the sentence will b
#max length = Maximum length to be retained of each sentence(headline) for the t
#trunc_type = trucate(suffix) the sentence from the back if the sentence length
#padding_type = pad(suffix) the sentence with 0's at the back if the sentence le
#oov_token = Out Of Vocubulary token to be used if the word is not part of the v
embedding_dim = 100
max_length = 32
trunc type='post'
padding_type='post'
oov tok = "<00V>"
training_size = 20000
# Split data into training and validation datasets using the training_size param
train_sentences = headline[:training_size]
train labels = labels[:training size]
validation_sentences = headline[training_size:]
validation_labels = labels[training_size:]
print(training_size)
print(len(train_sentences))
print(len(train labels))
print(len(validation_sentences))
print(len(validation_labels))
    20000
    20000
    20000
    6709
    6709
```

```
# Use tokenizer from Keras to tokenize and transform the words into numerical da
# Use pad_sequences from keras to pad the data to make it of same length(max_len
tokenizer = Tokenizer(oov_token= oov_tok)
tokenizer.fit on texts(headline)
word_index = tokenizer.word_index
training sequences = tokenizer.texts to sequences(train sentences)
training_padded = pad_sequences(training_sequences, maxlen = max_length, padding
validation_sequences = tokenizer.texts_to_sequences(validation_sentences)
validation padded = pad sequences(validation sequences, maxlen = max length, pad
# Vocabulary size will be the total number of the words in the word_index identi
len(word_index)
    29590
training_sequences[0]
     [216, 15046, 572, 3237, 2192, 287, 2472, 15047, 2473, 8352]
training_padded[0]
    array([ 216, 15046,
                            572, 3237,
                                         2192,
                                                 287,
                                                       2472, 15047,
                                                                      2473,
             8352,
                       0,
                              0,
                                     0,
                                            0.
                                                    0,
                                                           0,
                                                                  0,
                                                                         0,
                0,
                              0,
                                     0,
                       0,
                                            0,
                                                    0,
                                                                  0,
                                                                         0,
                                     0,
                0,
                                            0], dtype=int32)
                              0,
```

Convert into numpy array

```
training_padded = np.array(training_padded)
validation_padded = np.array(validation_padded)
training_labels_pad = np.array(train_labels)
validation_labels_pad = np.array(validation_labels)
```

▼ Model 1. Using default embedding layer of of keras

```
# Define model
vocab_size = len(word_index)
tf.keras.backend.clear_session()
tf.random.set_seed(51)
np.random.seed(51)
# Defining early stopping if validation accuracy does not change within 5 epochs
callback = EarlyStopping(patience = 5, verbose = 1, monitor = 'val_accuracy', re
model = tf.keras.Sequential([
    tf.keras.layers.Embedding(vocab_size+1, embedding_dim, input_length=max_leng
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(64, return_sequences=True
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32, return_sequences = Tr
    tf.keras.layers.GlobalAveragePooling1D(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')])
optimizer = tf.keras.optimizers.Adam()
model.compile(loss = 'binary_crossentropy', metrics = ['accuracy'], optimizer =
```

model.summary()

Model: "sequential"

Layer (type)	Output	Shape	Param #
embedding (Embedding)	(None,	32, 100)	2959100
dropout (Dropout)	(None,	32, 100)	0
bidirectional (Bidirectional	(None,	32, 128)	84480
dropout_1 (Dropout)	(None,	32, 128)	0
bidirectional_1 (Bidirection	(None,	32, 64)	41216
<pre>global_average_pooling1d (Gl</pre>	(None,	64)	0
dense (Dense)	(None,	256)	16640
dropout_2 (Dropout)	(None,	256)	0
dense_1 (Dense)	(None,	128)	32896
dense_2 (Dense)	(None,	1)	129
T + 1			

Total params: 3,134,461 Trainable params: 3,134,461 Non-trainable params: 0

history = model.fit(training_padded, training_labels_pad, validation_data=(valid

```
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
```

```
Epoch 11/30
Epoch 12/30
Epoch 13/30
Epoch 14/30
Epoch 15/30
Epoch 16/30
Epoch 17/30
Epoch 18/30
Epoch 19/30
Epoch 20/30
Epoch 21/30
Epoch 22/30
Epoch 23/30
Epoch 24/30
Epoch 25/30
Epoch 26/30
Epoch 27/30
Epoch 28/30
Epoch 29/30
Epoch 30/30
157/157 [______
   _____1 /c 26mc/c+on
         1000 6 E1E00 04
```

→ Model 2. Using Glove Embeddings

```
vocab_size = len(word_index) #30813
# for each line in the glove embedding text file, the first value is the word an
# Store the values into a dictionary
embeddings index = \{\}
with open('/content/drive/MyDrive/My Files/AIML Workbooks/glove.6B.100d.txt') as
    for line in f:
        values = line.split()
        word = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        embeddings_index[word]=coefs
# initialize a matrix of zeros and then assign the encoding for the words in the
embeddings_matrix = np.zeros((vocab_size+1, embedding_dim))
for key in sorted(word_index, key=word_index.get)[:vocab_size]:
    embedding vector = embeddings index.get(key)
    if embedding vector is not None:
        embeddings_matrix[word_index[key]] = embedding_vector
embeddings_matrix.shape
     (29591, 100)
# First 10 words and the corresponding index from the word_index dictionary whic
for key in sorted(word_index, key=word_index.get)[:10]:
  print(key,end=' ')
  print(word index.get(key))
    <00V>1
    new 2
    trump 3
    man 4
    one 5
     report 6
    vear 7
    area 8
    donald 9
    u 10
# Embeddings for the first 10 words
for key in sorted(word_index, key=word_index.get)[:10]:
  print(key,end=' ')
  print(embeddings_index.get(key))
    <00V> None
```

```
1.8936e-01 6.6110e-01 -4.9007e-01 3.2211e-01 -3.4161e-0
new I-4.3959e-02
 -6.8480e-02 3.1364e-01 -7.1142e-01
                                       5.7436e-01 -3.3588e-01 -5.2279e-01
-3.9075e-01 -8.9694e-02
                          4.6371e-01 -3.5610e-01
                                                  8.4576e-01 -2.6188e-02
-1.9328e-01 -8.3846e-02
                          3.1806e-01 -1.9812e-01
                                                  3.0009e-01
                                                                6.9189e-02
  5.4470e-01 -5.9193e-01
                          5.4221e-01 -6.2876e-01 -5.3447e-01
                                                                4.2334e-01
  3.0869e-02
                                      4.5752e-02 -5.7100e-01
             9.7164e-01 -5.6222e-01
                                                                8.0185e-02
 -8.1434e-02 -6.0260e-01
                          1.6466e-01 -4.0281e-01 -4.7701e-01 -5.1950e-01
  1.2777e-01 -4.3775e-01
                                       4.8752e-01 -6.0220e-02 -5.2622e-01
                          2.6602e-01
  3.7687e-01 -1.8007e-01
                          3.0166e-02 -9.4577e-02
                                                   1.6330e-01
                                                                5.9041e-01
 -4.8877e-01 -3.4230e+00
                          1.3113e-01 -8.0386e-02
                                                   1.8978e+00
                                                                1.8857e-01
 -5.7300e-01
              8.6358e-01
                          2.1116e-03
                                      3.6060e-01
                                                   8.0475e-01 -1.3954e-01
 -5.3935e-02
              3.8873e-01
                          3.0673e-01 -3.1395e-01
                                                   8.3238e-02 -4.1737e-01
-1.0998e+00 -8.8005e-01
                          2.1550e-01 -2.6132e-01 -1.0091e-01
                                                                7.9584e-02
 -1.2341e+00 -6.5281e-01
                          6.3363e-01 -9.8491e-02
                                                  3.3518e-01
                                                                2.6332e-01
-9.6427e-01 -1.4150e-02
                          3.0849e-01 -3.1418e-01 -4.0793e-01 -4.2900e-01
  8.5451e-02 -2.0073e-01
                          5.5050e-02 -4.0922e-02 -9.4015e-01
                                                                6.9544e-02
 -4.5397e-01 -1.4168e-01
                          9.2789e-01
                                       5.9058e-01]
trump [-0.15731 -0.75503]
                             0.36845
                                     -0.18958 \quad -0.16896
                                                          -0.23157 -0.22658
            0.24372
                                 0.58995
 -0.30186
                      0.61896
                                           0.047638 - 0.055164 - 0.70211
  0.22084
           -0.69232
                      0.49419
                                 1.4285
                                          -0.25362
                                                     0.20031
                                                              -0.26192
  0.05315
           -0.048418 -0.44982
                                 0.54644
                                          -0.014645 - 0.015531 - 0.61197
                                                                0.10532
-0.91964
           -0.7528
                      0.64843
                                 1.0934
                                           0.052682
                                                     0.33345
  0.59517
            0.023104 - 0.37105
                                 0.29749
                                          -0.23683
                                                     0.079566 - 0.10326
  0.35885
           -0.28935
                     -0.19881
                                 0.22908
                                          -0.061435
                                                     0.56127
                                                               -0.017115
           -0.78417
                                 0.34944
                                                    -0.061168 - 1.3106
-0.32868
                     -0.49375
                                           0.16278
                     -0.20873
                                -0.18473
                                          -0.56184
  0.39152
            0.124
                                                     0.55693
                                                                0.012114
-0.54545
           -0.31409
                      0.1
                                 0.31543
                                           0.74757
                                                    -0.47734
                                                               -0.18332
                     -0.30697
 -0.65623
            0.40768
                                -0.47247
                                          -0.7421
                                                    -0.44978
                                                               -0.078122
-0.52673
           -0.70633
                      1.3271
                                 0.26298
                                          -0.91
                                                     0.91632
                                                               -0.51643
  0.20284
           -0.25402
                     -1.2566
                                 0.20271
                                           0.92105
                                                    -0.57574
                                                               -0.15105
                                                     0.38794
-0.24831
            0.36673
                     -0.53987
                                 0.18534
                                           0.25713
                                                               -0.54137
  0.67817
           -0.17251
man [ 3.7293e-01 3.8503e-01
                             7.1086e-01 -6.5911e-01 -1.0128e-03 9.2715e-0
  2.7615e-01 -5.6203e-02 -2.4294e-01
                                      2.4632e-01 -1.8449e-01
                                                                3.1398e-01
  4.8983e-01
              9.2560e-02
                          3.2958e-01
                                       1.5056e-01
                                                   5.7317e-01 -1.8529e-01
                                       3.1001e-02 -1.6246e-01 -4.0567e-01
                          9.2038e-01
-5.2277e-01
              4.6191e-01
  7.8621e-01
              5.7722e-01 -5.3501e-01 -6.8228e-01
                                                  1.6987e-01
                                                                3.6310e-01
                                                   1.7543e-01 -3.7573e-01
              4.7233e-01
                          2.7806e-02 -1.4951e-01
 -7.1773e-02
                          8.6859e-01
                                      3.1445e-02 -4.5897e-01 -4.0917e-02
-7.8517e-01
              5.8171e-01
                          1.3045e-01
                                       2.7434e-01 -6.9485e-02
  9.5897e-01 -1.6975e-01
                                                                2.2402e-02
  2.4977e-01 -2.1536e-01 -3.2406e-01 -3.9867e-01
                                                   6.8613e-01
                                                                1.7923e+00
 -3.7848e-01 -2.2477e+00 -7.7025e-01
                                      4.6582e-01
                                                   1.2411e+00
                                                                5.7756e-01
              8.4328e-01 -5.4259e-01 -1.6715e-01
                                                   7.3927e-01 -9.3477e-02
  4.1151e-01
                                                   1.5443e-01 -2.9432e-01
  9.0278e-01
              5.0889e-01 -5.0031e-01
                                       2.6451e-01
                          3.5438e-01
  1.0906e-01 -2.6667e-01
                                      4.9079e-02
                                                   1.8018e-01 -5.8590e-01
 -5.5542e-01 -2.8987e-01
                          7.4278e-01
                                      3.4530e-01 -2.8757e-02 -2.2646e-01
 -1.3113e+00 -5.7190e-01 -5.2306e-01 -1.2670e-01 -9.8678e-02 -5.3463e-01
  2.8607e-01 -3.7501e-01
                                      4.5975e-02 -2.4675e-01 4.5656e-02
                          4.5742e-01
                          3.9138e-02 -5.3911e-01]
 -3.8302e-01 -9.3711e-01
one [-0.22557
                0.49418
                           0.4861
                                    -0.4332
                                               0.13738
                                                          0.50617
                                                                    0.26058
           -0.091486
                                                     0.22303
  0.30103
                      0.10876
                                 0.3058
                                           0.051028
                                                                0.054236
                               -0.082203 -0.28866
  0.068838 - 0.24701
                      0.32689
                                                     0.3734
                                                                0.73804
 -0.040969
                                 0.69987
                                          -0.49745
                                                    -0.06755
                                                               -0.42599
            0.040201
                      0.11384
           -0.010697 -0.01479
                                                     0.053053
 -0.10725
                                 0.55976
                                           0.3064
                                                                0.058034
```

```
0.32756
          -0.37233
                      0.46513
                                 0.14285
                                          -0.085003 - 0.45476
                                                                 0.19773
 0.6383
          -0.31148
                      0.10858
                                 0.31557
                                           0.36682
                                                     -0.35135
                                                               -0.48414
-0.33235
          -0.33816
                     -0.39678
                                 0.1908
                                           1.3513
                                                     -0.39044
                                                               -2.8795
-0.14276
          -0.087754
                                 0.99332
                                          -0.14129
                                                      0.94389
                                                                 0.050897
                      1.7713
 A 17272
           A 06207
                      A 16167
                                 A 67100
                                           V EJJ/1
                                                      α 1//20
                                                                 0 0 5 5 1 0 1
```

embeddings_matrix[word_index['new']]

```
array([-4.39589992e-02, 1.89359993e-01, 6.61099970e-01, -4.90069985e-01,
                                                          3.13639998e-01.
        3.22109997e-01, -3.41610014e-01, -6.84799999e-02,
       -7.11420000e-01, 5.74360013e-01, -3.35880011e-01, -5.22790015e-01,
       -3.90749991e-01, -8.96940008e-02,
                                         4.63710010e-01, -3.56099993e-01,
        8.45759988e-01, -2.61879992e-02, -1.93279997e-01, -8.38460028e-02,
        3.18060011e-01, -1.98119998e-01, 3.00089985e-01, 6.91889971e-02,
        5.44700027e-01, -5.91929972e-01.
                                         5.42209983e-01. -6.28759980e-01.
                                         3.08689997e-02. 9.71639991e-01.
       -5.34470022e-01. 4.23339993e-01.
                                                         8.01850036e-02.
                       4.57520001e-02, -5.70999980e-01,
       -5.62219977e-01,
       -8.14339966e-02, -6.02599978e-01,
                                          1.64660007e-01, -4.02810007e-01,
       -4.77010012e-01, -5.19500017e-01,
                                          1.27770007e-01, -4.37750012e-01,
        2.66020000e-01, 4.87520009e-01, -6.02199994e-02, -5.26220024e-01,
        3.76870006e-01, -1.80069998e-01,
                                          3.01660001e-02, -9.45769995e-02,
        1.63299993e-01,
                        5.90409994e-01, -4.88770008e-01, -3.42300010e+00,
                                          1.89779997e+00,
        1.31129995e-01, -8.03859979e-02,
                                                          1.88569993e-01,
       -5.73000014e-01, 8.63579988e-01,
                                          2.11160001e-03.
                                                          3.60599995e-01,
        8.04750025e-01, -1.39540002e-01, -5.39349988e-02,
                                                          3.88729990e-01,
        3.06730002e-01, -3.13950002e-01,
                                          8.32379982e-02, -4.17369992e-01,
       -1.09979999e+00, -8.80050004e-01,
                                          2.15499997e-01, -2.61319995e-01,
       -1.00910001e-01, 7.95840025e-02, -1.23409998e+00, -6.52809978e-01,
                                                         2.63319999e-01.
                                         3.35180014e-01.
        6.33629978e-01, -9.84909981e-02,
       -9.64269996e-01, -1.41500002e-02, 3.08490008e-01, -3.14179987e-01,
       -4.07929987e-01, -4.28999990e-01, 8.54509994e-02, -2.00729996e-01,
        5.50500005e-02, -4.09220010e-02, -9.40150023e-01, 6.95440024e-02,
       -4.53969985e-01, -1.41680002e-01, 9.27890003e-01, 5.90579987e-01])
```

```
# Define model
vocab_size = len(word_index)
tf.keras.backend.clear_session()
tf.random.set_seed(51)
np.random.seed(51)
# Defining early stopping if validation accuracy does not change within 5 epochs
callback = EarlyStopping(patience = 5, verbose = 1, monitor = 'val_accuracy', re
model ge = tf.keras.Sequential([
    tf.keras.layers.Embedding(vocab_size+1, embedding_dim, input_length=max_leng
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(64, return_sequences=True
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32, return_sequences = Tr
    tf.keras.layers.GlobalAveragePooling1D(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')])
optimizer_ge = tf.keras.optimizers.Adam()
model_ge.compile(loss = 'binary_crossentropy', metrics = ['accuracy'], optimizer
```

model_ge.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 32, 100)	2959100
dropout (Dropout)	(None, 32, 100)	0
bidirectional (Bidirectional	(None, 32, 128)	84480
dropout_1 (Dropout)	(None, 32, 128)	0
bidirectional_1 (Bidirection	(None, 32, 64)	41216
global_average_pooling1d (Gl	(None, 64)	0
dense (Dense)	(None, 256)	16640
dropout_2 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32896
dense_2 (Dense)	(None, 1)	129
Total paramet 2 124 461		

Total params: 3,134,461 Trainable params: 3,134,461 Non-trainable params: 0

history_ge = model_ge.fit(training_padded, training_labels_pad, batch_size = 128

```
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Restoring model weights from the end of the best epoch.
Epoch 00007: early stopping
```

```
# Saving the model
model.save("sarcasm_glove_mymodel.h5")
# Retrieve and evaluate the model with the validation set
model = keras.models.load_model('sarcasm_glove_mymodel.h5')
model.evaluate(validation_padded,validation_labels_pad)
    [2.6552867889404297, 0.7707557082176208]
# Prediction using the same validation dataset to plot confusion matrix
pred = (model.predict(validation_padded) > 0.5).astype("int32")
# Confusion Matrix
from sklearn import metrics
cm = metrics.confusion_matrix(validation_labels_pad,pred)
print(cm)
    [[3155 624]
     [ 914 2016]]
```

