Install the required libraries and packages

```
#pip install keras-tuner --upgrade                    # Install Keras Tuner


#!pip install nltk==3.8.1                             # Install nltk library


#!pip install gensim==4.3.1                           # Install gensim library


#!pip install tensorflow==2.7.0                       # tensorflow library


#!pip intall keras==2.7.0                             # install keras library


#!pip install scikit-learn==1.2.2                     # install scikit-learn library
```

```
#The necessary libraries are imported

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import datetime
from tqdm.notebook import tqdm
import joblib
import seaborn as sns
import matplotlib.pyplot as plt
import time
import pyarrow


#import nltk
#nltk.download()      # Download the necessary packagesof nltk
```

To allow all the available columns in the dataframe to be displayed on screen

```
pd.set_option('display.max_columns',None)
```

The Amazon Musical Instruments Reviews tsv file is read into the Pandas Dataframe . The seperator is set to a raw tab value since the input file is of a format a tab seperated values

```
%%time
amazon= pd.read_table('amazon_reviews_us_Musical_Instruments_v1_00.tsv', sep=r'\t')
```

```
<timed exec>:1: ParserWarning: Falling back to the 'python' engine because the 'c' engine does not support regex separator
CPU times: total: 9.25 s
Wall time: 12.8 s
```

```
###### A brief info about the counts and datatypes of the features in the Amazon dataset

amazon.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 904765 entries, 0 to 904764
Data columns (total 15 columns):
 #   Column             Non-Null Count   Dtype 
---  ------             --------------   ----- 
 0   marketplace        904765 non-null  object
 1   customer_id        904765 non-null  int64 
 2   review_id          904765 non-null  object
 3   product_id         904765 non-null  object
 4   product_parent     904765 non-null  int64 
 5   product_title      904764 non-null  object
 6   product_category   904765 non-null  object
 7   star_rating        904765 non-null  int64 
 8   helpful_votes      904765 non-null  int64 
 9   total_votes        904765 non-null  int64 
 10  vine               904765 non-null  object
 11  verified_purchase  904765 non-null  object
```

```
 12  review_headline    904759 non-null  object
 13  review_body        904712 non-null  object
 14  review_date        904765 non-null  object
dtypes: int64(5), object(10)
memory usage: 103.5+ MB
```

Descriptive statistics of the amazon reviews dataset

```
amazon.describe()
```

	customer_id	product_parent	star_rating	helpful_votes	total_votes
count	9.047650e+05	9.047650e+05	904765.000000	904765.000000	904765.000000
mean	2.732872e+07	4.947710e+08	4.251103	1.861308	2.384755
std	1.551782e+07	2.887873e+08	1.216395	13.079296	13.886548
min	1.011300e+04	2.765700e+04	1.000000	0.000000	0.000000
25%	1.403545e+07	2.377961e+08	4.000000	0.000000	0.000000
50%	2.580814e+07	4.917281e+08	5.000000	0.000000	0.000000
75%	4.190720e+07	7.452023e+08	5.000000	1.000000	2.000000
max	5.309656e+07	9.999951e+08	5.000000	4709.000000	4805.000000

The first 5 rows of the amazon reviews dataset

```
amazon.head()
```

	marketplace	customer_id	review_id	product_id	product_parent	product
0	US	45610553	RMDCHWD0Y5OZ9	B00HH62VB6	618218723	AGP Isolatec 9V G
1	US	14640079	RZSL0BALIYUNU	B003LRN53I	986692292	Ser HD203 Heac
2	US	6111003	RIZR67JKUDBI0	B0006VMBHI	603261968	AudioC reco
3	US	1546619	R27HL570VNL85F	B002B55TRG	575084461	Hoh 56 Specia Ha
4	US	12222213	R34EBU9QDWJ1GD	B00N1YPXW2	165236328	Blue Y Micro E

Review having sentiment sentiment rating of 1

```
amazon[amazon['star_rating']==1].review_body[40]
```

```
'Really bad. Bought as a midi trigger kit but the latency from the module is ridiculous. Comlete waste of $$. A toy.'
```

Review having sentiment sentiment rating of 2

```
amazon[amazon['star_rating']==2].review_body[13]
```

```
'Bridge pickup was broken. I replace d the pickup and ok now. To cheap to send back.'
```

Review having sentiment sentiment rating of 3

```
amazon[amazon['star_rating']==3].review_body[0]
```

```
'Works very good, but induces ALOT of noise.'
```

Review having sentiment sentiment rating of 4

```
amazon[amazon['star_rating']==4].review_body[42]
```

```
'nice Microphone. good delivery'
```

Review having sentiment sentiment rating of 5

```
amazon[amazon['star_rating']==5].review_body[4]
```

```
'This is an awesome mic!'
```

The first 5 customer IDs are reviewed

```
amazon.customer_id[:5]
```

```
0    45610553
1    14640079
2     6111003
3     1546619
4    12222213
Name: customer_id, dtype: int64
```

```
# It is observed that there is only one product category

amazon.product_category.value_counts()
```

```
Musical Instruments    904765
Name: product_category, dtype: int64
```

```
# The range of helpful_votes
amazon[['helpful_votes']].value_counts()
```

```
helpful_votes
0                552441
1                152724
2                 64281
3                 36158
4                 22143
                  ...
353                   1
357                   1
358                   1
359                   1
4709                  1
Length: 414, dtype: int64
```

The various feature data types are cast into types of smaller memory for efficiency

```
amazon['customer_id']=amazon['customer_id'].astype('int32')
amazon['product_parent']=amazon['product_parent'].astype('int32')
amazon['star_rating']=amazon['star_rating'].astype('int8')
amazon['helpful_votes']=amazon['helpful_votes'].astype('int16')
amazon['total_votes']=amazon['total_votes'].astype('int16')
```

```
amazon['review_id']=amazon['review_id'].astype(str)
amazon['product_id']=amazon['product_id'].astype(str)
amazon['product_title']=amazon['product_title'].astype(str)
```

```
amazon['vine']=amazon['vine'].astype(str)
amazon['verified_purchase']=amazon['verified_purchase'].astype(str)
amazon['review_headline']=amazon['review_headline'].astype(str)
amazon['review_body']=amazon['review_body'].astype(str)
```

```
amazon['review_date']=pd.to_datetime(amazon['review_date'], dayfirst=True)
```

Check for Missing Values in the dataset

```
amazon.isna().sum()
```

```
marketplace          0
customer_id          0
review_id            0
product_id           0
product_parent       0
product_title        0
product_category     0
star_rating          0
helpful_votes        0
total_votes          0
vine                 0
verified_purchase    0
review_headline      0
review_body          0
review_date          0
dtype: int64
```

```
#### Drop all the unrequired features for the sentiment classification task at hand

amazon.drop(['marketplace','customer_id','product_title',
             'product_category','product_id','product_parent',
             'helpful_votes','total_votes','vine','verified_purchase'],inplace=True,axis=1)
```

```
amazon.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 904765 entries, 0 to 904764
Data columns (total 5 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   review_id        904765 non-null  object
 1   star_rating      904765 non-null  int8
 2   review_headline  904765 non-null  object
 3   review_body      904765 non-null  object
 4   review_date      904765 non-null  datetime64[ns]
dtypes: datetime64[ns](1), int8(1), object(3)
memory usage: 28.5+ MB
```

Number of reviews per year

We have reviews from the year 1999 till 2015

```
amazon['review_date'].max()
```

```
Timestamp('2015-08-31 00:00:00')
```

```
amazon['review_date'].min()
```

```
Timestamp('1999-12-13 00:00:00')
```

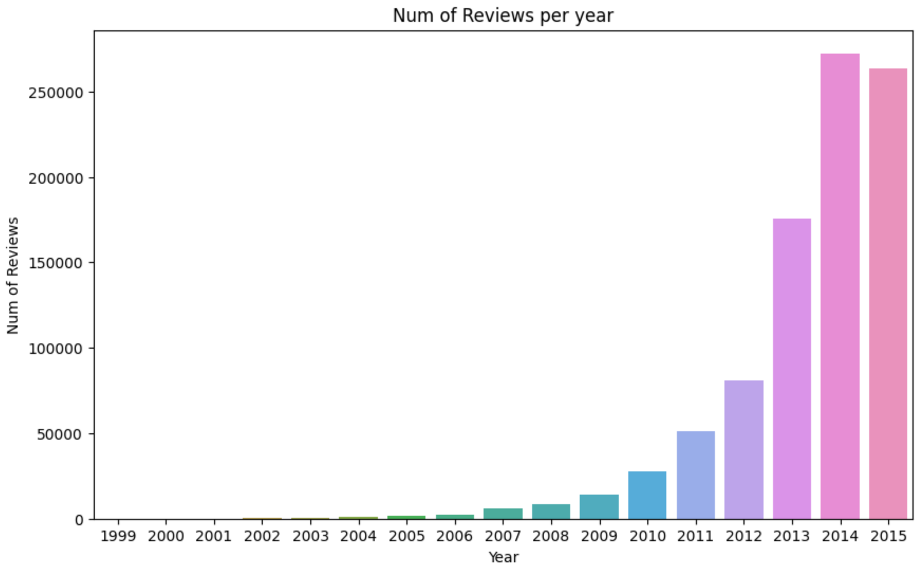
A function is defined to read all the reviews values from a particular year into a dictionary indexed by the year key. A barplot is plotted to visualize the counts of reviews per year

```
def Reviews_per_Year(df):

    global Reviews_per_Year_dict
    Reviews_per_Year_dict={}

    for year_ in range(1999,2016):
        Reviews_per_Year_dict[year_]=(df[df['review_date'].dt.year==year_].shape[0])

    year=list(Reviews_per_Year_dict.keys())

    review_year_count=list(Reviews_per_Year_dict.values())
```

```
plt.figure(figsize=(10, 6))

sns.barplot(x=year,y=review_year_count)

plt.xlabel('Year')
plt.ylabel('Num of Reviews')
plt.title('Num of Reviews per year')

plt.show()
```

It is noted that the number of reviews per year increases in an exponential manner with the year 1999 having the least reviews and 2015 having the most reviews

```
Reviews_per_Year(amazon)
```




```
#### A New Feature consisting of the year in which the review was posted is derived from
#### the original review date feature

amazon['Review_Year']=amazon['review_date'].dt.year

amazon['Review_Year']=amazon['Review_Year'].astype('int32')

amazon.drop('review_date',axis=1,inplace=True)
```

A function is defined to note the different review Star_Ratings and calculate the Percentage of star_ratings distributed in the dataset. A barplot is plotted to visualize the Percentage of star_ratings DIstribution

```
def Plot_Star_Rating(df):

        x_bar=list(df['star_rating'].astype('str').value_counts().index)
        total_count=df.shape[0]
        y_bar=list(((x/total_count)*100) for x in df['star_rating'].astype('str').value_counts().values)

        sns.barplot(x=x_bar,y=y_bar)

        plt.xlabel('Star_Rating')
        plt.ylabel('Percent Count')
        plt.title('Counts of Star_Rating')
```

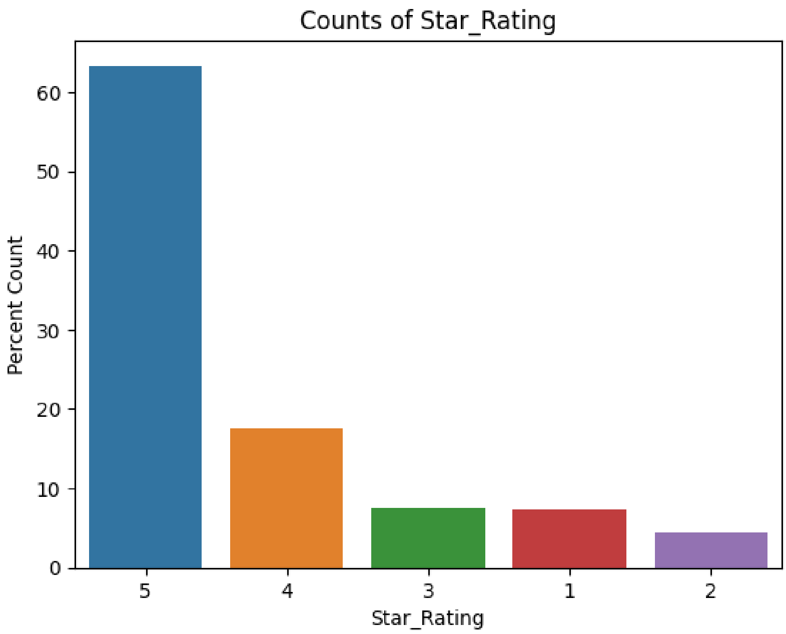
```
# Show the plot
plt.show()
```

The Star_Ratings are the ratings given by the customers per product purchase and can be considered a measure of the sentiment of the customer's review of the product. From the distrbution of star ratings it is noted that there are 5 different ratings:

- 5: Very Positive
- 4: Positive
- 3: Neutral
- 2: Negative
- 1: Very Negative

> We can see from the barplot below that the dataset is **highly imbalanced** in terms of **Star_rating** with a siginificant percentage of the dataset being 5 star rated reviews and the minority class being negative and very negative reviews

```
Plot_Star_Rating(amazon)
```



Duplicated Review Documents

```
from collections import Counter
```

```
#### The duplicate Review text rows

duplicates=amazon.duplicated(subset=['review_body'])
```

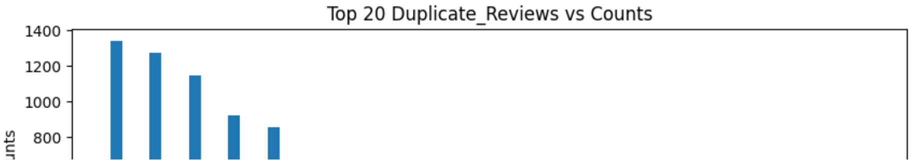
```
duplicated_counter=Counter(amazon.review_body[duplicates])
```

```
#### The most common duplicate reviews in descending counts order

duplicated_counter.most_common()
```

```
[('good', 1343),
 ('Good', 1277),
 ('Great', 1148),
 ('great', 917),
 ('Excellent', 852),
 ('Perfect', 564),
 ('ok', 544),
 ('Great!', 519),
 ('Works great', 507),
 ('Awesome', 478),
 ('Nice', 472),
 ('works great', 464),
 ('excellent', 462),
 ('Great product', 426),
```

```
('Works great!', 424),
('Love it', 423),
('nice', 394),
('very good', 389),
('perfect', 361),
('love it', 332),
('Very good', 330),
('Perfect!', 293),
('Excellent!', 278),
('Love it!', 269),
('Works great.', 252),
('Great product!', 252),
('Good product', 244),
('great product', 236),
('Thanks', 218),
('excelente', 205),
('Awesome!', 197),
('good product', 192),
('Excelente', 182),
('Excelent', 179),
('I love it', 164),
('Ok', 161),
('Works well', 161),
('Great product.', 159),
('works well', 156),
('A+', 156),
('thanks', 148),
('OK', 145),
('Works well.', 141),
('awesome', 139),
('Thank you', 138),
('Excellent product', 134),
('thank you', 133),
('Very nice', 132),
('Good quality', 129),
('Perfect.', 123),
('Excellent.', 119),
('GREAT', 115),
('works', 115),
('very nice', 105),
('excellent product', 100),
('excelent', 98),
('Good!', 97),
```

```
fig,ax = plt.subplots(figsize= (10,3))

categories=[text[0] for index,text
            in enumerate(duplicated_counter.most_common())
            if index<20]

values=[text[1] for index,text in
        enumerate(duplicated_counter.most_common())
       if index<20]

ax.bar(categories, values, width=0.3)

ax.set_xlabel('Duplicate_Reviews')
ax.set_ylabel('Counts')
ax.set_title('Top 20 Duplicate_Reviews vs Counts')

# Transpose x-axis labels
ax.tick_params(axis='x', rotation=90)

plt.show()
```




```
duplicate_indexes=[index for index in duplicates.index if duplicates[index]==True]
```

```
#### Total count of duplicate reviews

len(duplicate_indexes)
```

```
52976
```

```
#### Drop all the rows containing duplicate reviews

amazon.drop(duplicate_indexes, axis=0, inplace= True)
```

```
amazon.reset_index(drop=True, inplace= True)
```

```
amazon.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 851789 entries, 0 to 851788
Data columns (total 5 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   review_id        851789 non-null  object
 1   star_rating      851789 non-null  int8
 2   review_headline  851789 non-null  object
 3   review_body      851789 non-null  object
 4   review_date      851789 non-null  datetime64[ns]
dtypes: datetime64[ns](1), int8(1), object(3)
memory usage: 26.8+ MB
```

Number of Unique Reviews

```
amazon.review_body.unique().shape
```

```
(851789,)
```

Merging the multi class reviews into positive and negative sentiment reviews, while dropping the Neutral sentiment reviews.

```
for i in range(1,6):
    print('Star Rating ',i,':',amazon[amazon['star_rating']==i].shape[0])
```

```
Star Rating  1 : 65081
Star Rating  2 : 39779
Star Rating  3 : 65509
Star Rating  4 : 151681
Star Rating  5 : 529739
```

```
### NEUTRAL SENTIMENT REVIEWS

for review in amazon[amazon['star_rating']==3].review_body[0:5]:
    print(review, end='\n\n')
```

```
Works very good, but induces ALOT of noise.

removes dust. does not clean

Beautiful set. Only the sound not at long and deap.

There was only one clip in the box even though this is supposed to be a two pack.  The one we did receive works fine.  Not

I love these lights they are very bright vibrant colors. The remote hasn't worked on them but they change colors and they
```

```
### Indexes of the rows containing Neutral Sentiment Reviews

indexes_star_rating3= list(amazon[amazon['star_rating']==3].index)


### Dropping the rows containing Neutral sentiment reviews.

amazon.drop(indexes_star_rating3, axis=0, inplace=True)


amazon.reset_index(drop=True, inplace= True)


### Extracting the negative sentiment review rows and concatenating the
### dataframes along the row axis to get a Negative Sentiment Dataframe.
### This resulting Dataframe is set to sentiment 0 (Negative).

amazon_star_rating_1=amazon[amazon['star_rating']==1]
amazon_star_rating_2=amazon[amazon['star_rating']==2]

amazon_negative_sent= pd.concat((amazon_star_rating_1,amazon_star_rating_2),
                                 axis=0, ignore_index=True)

# Setting the negative class label as 0

amazon_negative_sent.star_rating = 0


amazon_negative_sent.head()
```

	review_id	star_rating	review_headline	review_body	review_date
0	R2HUWDNW62FOL3	0	Poor sound quality	I was hoping it would work well, but tried a s...	2015-08-31
1	RUPNDVAV1ESYP	0	It works well while it can. Mine failed when ...	It works well while it can. Mine failed when I...	2015-08-31
2	R3DMITMOKNZ2XW	0	DON'T Buy This	Really bad. Bought as a midi	2015-08-31

```
### Extracting the positive sentiment review rows and concatenating the
### dataframes along the row axis to get a Positive Sentiment Dataframe.
### This resulting Dataframe is set to sentiment 1 (Positive).

amazon_star_rating_4=amazon[amazon['star_rating']==4]
amazon_star_rating_5=amazon[amazon['star_rating']==5]

amazon_positive_sent= pd.concat((amazon_star_rating_4,amazon_star_rating_5),
                                 axis=0, ignore_index=True)

amazon_positive_sent.star_rating = 1


amazon_positive_sent.head()
```

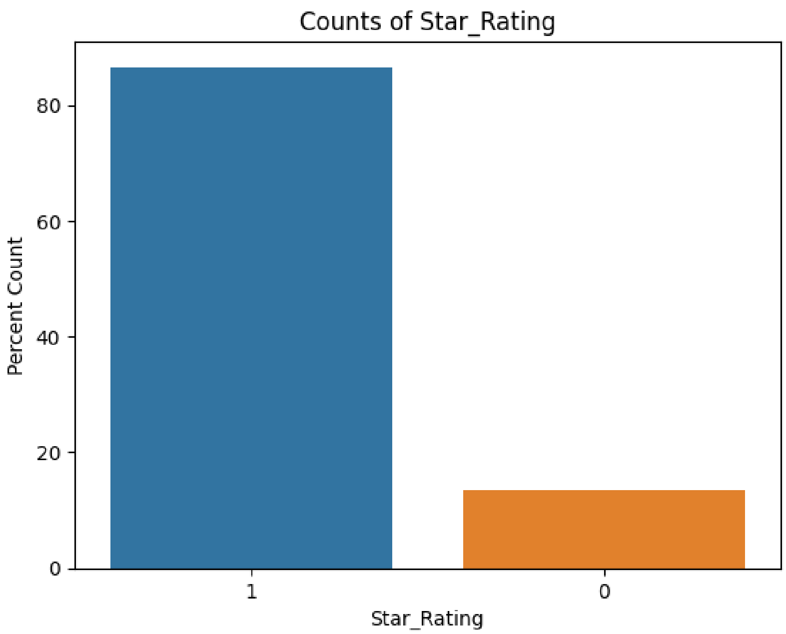
	review_id	star_rating	review_headline	review_body	review_date
0	R3H53KLLC210XI	1	Great pop filter - poor mount	by far the best pop filter i have used, extrem...	2015-08-31
1	R31OIOD3CP2FB1	1	Four Stars	Fit my cheep over seas pickup but will not fit...	2015-08-31
2	R3QZ914CIV184O	1	Four Stars	nice Microphone. good delivery	2015-08-31

```
amazon = pd.concat((amazon_negative_sent,amazon_positive_sent),
                                 axis=0, ignore_index=True)

# Shuffling the newly concatenated dataframe to avoid bias

amazon = amazon.sample(frac=1, random_state=41,
                              ignore_index=True)


amazon.reset_index(drop=True, inplace= True)
```

```
amazon['star_rating'].value_counts()
```

```
1    681420
0    104860
Name: star_rating, dtype: int64
```

```
Plot_Star_Rating(amazon)
```




```
amazon.head(5)
```

	review_id	star_rating	review_headline	review_body	review_date
0	R3AO39ZIHC23LW	1	Perfect. Just what I wanted.	Got this for my Mahalo Uke and it's work great...	2013-05-22
1	R22QPG1FZOPJCY	0	Look elsewhere for coated strings.	They sound decent enough, but they start deter...	2015-04-20
2	R1ZX1DVZT12UDU	0	Two of Three Sets	I bought three sets of these. I opened one	2011-12-07

```
amazon.shape
```

```
(786280, 5)
```

Balancing the target class distribution using Random undersampler

Considering computational power and timeframe the Dataset is large in size. It is undersampled while maintaining target class strata distribution using Random Undersampling. The majority class will be undersampled and as a result the sample target classes will be balanced in the train dataset.

Undersampling the majority class using Random Undersampler

```
from collections import Counter
from imblearn.under_sampling import RandomUnderSampler
```

```
rus = RandomUnderSampler(random_state=42)
X_res, y_res = rus.fit_resample(amazon[['review_body']],
                                amazon[['star_rating']])
```

```
# The input and target features are concatenated to get the undersampled dataset
```

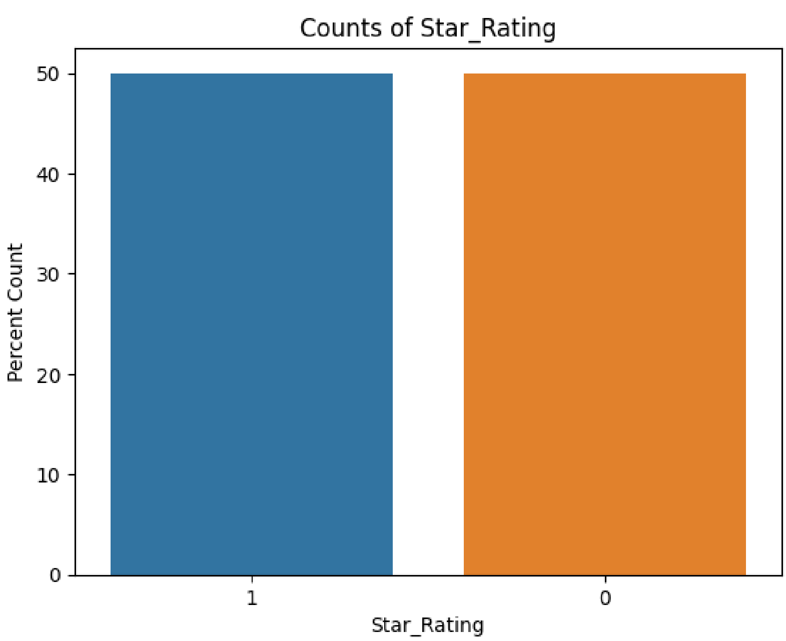
```
amazon=pd.concat((X_res,y_res),axis=1)

del(X_res, y_res)

# Shuffle the dataset

amazon=amazon.sample(frac=1, ignore_index=True, random_state=42)
amazon.reset_index(drop=True, inplace=True)

amazon.head(10)
```

	review_body	star_rating
0	Purchased by my son, he is very happy with thi...	1
1	Product seemed to look nice but 3 plugs in bac...	0
2	I bought these to replace a skull candy pair t...	1
3	I purchased this microphone because of its pri...	1
4	I read great things about these online so I fi...	0
5	Wish the flab thingy would stick to the screen!	0
6	My wife loves it.....Got it for her for Mother...	1
7	again, a gift for my nephew... very pleased	1
8	I own a few AXL guitars (El Dorado, Capricorn ...	0
9	I bought this cow bell on price, to use in a b...	0

```
amazon.shape
```

```
(209720, 2)
```

```
Plot_Star_Rating(amazon)
```



PreProcessing of Review_Body Text

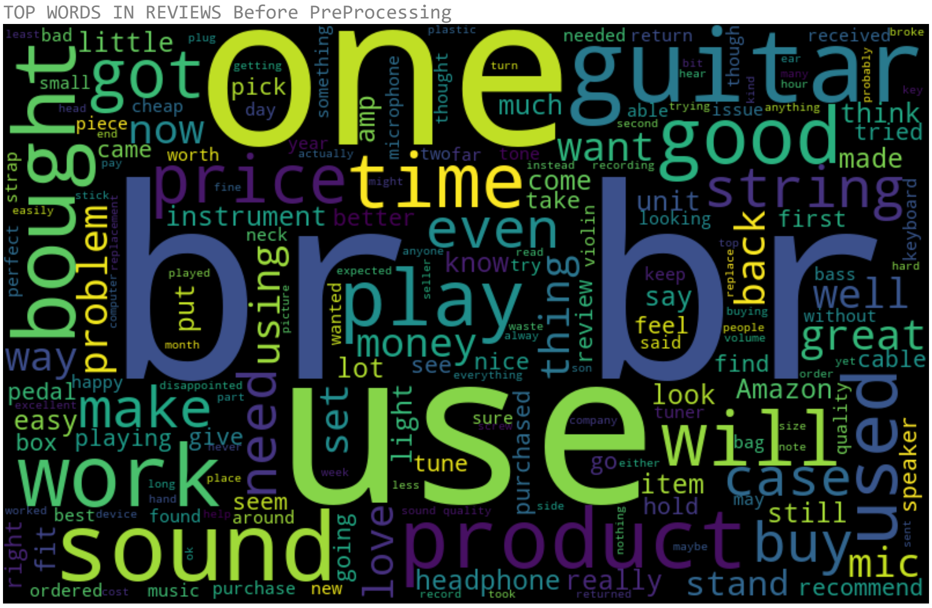
```
import nltk
import nltk.data
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import contractions
from nltk.probability import FreqDist
import re

from nltk.tokenize import wordpunct_tokenize
```

```
from wordcloud import WordCloud

import warnings
warnings.filterwarnings("ignore", category=UserWarning, module='nltk')


####Total number of stopwords in nltk

len(stopwords.words('english'))
```

```
179
```

```
text=' '.join(amazon['review_body'])


wordcloud = WordCloud(width=800, height=500)
wordcloud.generate(text)
print('TOP WORDS IN REVIEWS Before PreProcessing')
wordcloud.to_image()
```

```
TOP WORDS IN REVIEWS Before PreProcessing
```




```
#  Load the the nltk punkt sentence tokenizer

sent_detector = nltk.data.load('tokenizers/punkt/english.pickle')


# Regular expressions are used to search for web addresses in the reviews data. The pattern is compiled and matched in the data

pattern = re.compile(r'https?://\S+')


matches=pattern.finditer(text)


for i in matches:
    print(i)
    break
```

```
<re.Match object; span=(169654, 169741), match='http://www.amazon.com/gp/product/B0017H4EBG/ref=o>
```

A pre-preocessing class object is constructed which takes in the dataframe and the un-processed review column name as input. A cleaning function is created for this class which will take each review text, expand the contracted words, remove unwanted symbols,web-addresses, numbers and white spaces and convert the text to lowercase. Finally for each tokenized word, it will filter the stopwords and lemmatize the tokens to their base root form based on their part of speech. The main() method will apply this cleaning function to each of the reviews in the dataframe and return a processed dataframe containing an additional processed reviews column.

```
class txtprc():


    def __init__(self,df,raw=str(),target=str()):
        self.df = df
        self.raw = raw
        self.target = target


    def main(self):

        def clean(text):


            text=contractions.fix(text)   # Expand the contractions

            #remove website addres

            text_pr = re.compile(r'https?://\S+').sub('',str(text))
            text_pr = re.sub(r"e-mail","email",text_pr)

            #remove html text tags such as <br>
            text_pr=re.sub(r'<[\w\s\W]+>',' ',text,flags=re.IGNORECASE)

            #remove numbers and other characters such as Punctuation emoticons
            text_pr = re.sub(r'[^a-zA-Z!?]',' ',text_pr)

            text_pr = re.sub(r'\s+',' ',text_pr)  #remove white spaces, tabs, linebreaks
            text_pr=text_pr.lower()

            processed = []

           # Remove words like not nor and no from stopwords list as they are important
           # sentiment analysis

            stp_wrds=stopwords.words('english')
            for index,word in enumerate(['no','nor','not']):
                stp_wrds.remove(word)

            # We lemmatize the different forms of words to their root word to save memory
            #and improve classification efficiency

            lemmatizer = WordNetLemmatizer()

            for i in nltk.pos_tag(wordpunct_tokenize(text_pr)):               # Loop through word tokens

                    if i[0] not in stp_wrds:
                        if i[1].startswith('N'):
                            processed.append(lemmatizer.lemmatize(i[0],'n'))            # Lemmatization of tokens according to
                        elif i[1].startswith('V'):
                            processed.append(lemmatizer.lemmatize(i[0],'v'))            # token part of speech such as noun,verb
                        elif i[1].startswith('J'):
                            processed.append(lemmatizer.lemmatize(i[0],'a'))            # or adverb
                        elif i[1].startswith('R'):
                            processed.append(lemmatizer.lemmatize(i[0],'r'))
                        else:
                            processed.append(lemmatizer.lemmatize(i[0]))


            processed_str = ' '.join(processed)                                    # All the lemmatized clean tokens are joined
                                                                                   # as a string and returend by function
            return processed_str


        self.df['processed'] = self.df[self.raw].map(lambda x : clean(x).lower())        # Clean function applied to each review

        return self.df

processed_text=txtprc(amazon,raw='review_body',target='star_rating')

amazon_processed=processed_text.main()


amazon_processed.head()
```

	review_body	star_rating	processed
0	Purchased by my son, he is very happy with thi...	1	purchase son happy sing bowl sound produce
1	Product seemed to look nice but 3 plugs in bac...	0	product seem look nice plug back not work not ...
2	I bought these to replace a skull candy pair t...	1	buy replace skull candy pair come apart superi...

Drop the reviews which were null after being processed

```
amazon_processed[amazon_processed['processed']==''].head()
```

	review_body	star_rating	processed
1278	A++++	1	
4556	ㅎㅌㅊ	0	
5625	😡 👎	0	
17462	😤	0	
22813	90%	1	

```
amazon_processed.drop(list(amazon_processed[amazon_processed['processed']==''].index),
                            axis=0,
                            inplace=True)
```

```
amazon_processed.reset_index(drop=True, inplace=True)
```

The first two processed reviews

```
for index,review in enumerate(amazon_processed):
    if index<=1:
        print('Raw Review Text: ',)
        print(amazon_processed.review_body[index],'\n\n')
        print('Processed Review Text: ')
        print(amazon_processed.processed[index])
        print('----------------------','\n\n')
```

```
Raw Review Text:
Purchased by my son, he is very happy with this Singing Bowl and the sound it produces


Processed Review Text:
purchase son happy sing bowl sound produce
----------------------


Raw Review Text:
Product seemed to look nice but 3 plugs in back don't work I was not satisfied And the vu only works part of the time it wa


Processed Review Text:
product seem look nice plug back not work not satisfied vu work part time waste money
----------------------
```

```
# Saving the amazon preprocessed dataset
```

```
amazon_processed.to_csv('Applied_Research_Project.csv')
```

```
amazon_processed= pd.read_csv('Balanced_amazon_processed.parquet')
```

WordCloud for the most Common Words in the processed dataset

```
long_string = " ".join(amazon_processed['processed'])
wordcloud = WordCloud(width=800, height=500,background_color ='white')
print('Most Frequent Words in the Processed Reviews')
```

```
wordcloud.generate(long_string)
wordcloud.to_image()
```

Most Frequent Words in the Processed Reviews

Vocabulary size (Number of unique words) of the processed dataset

```
len(set(long_string.split()))
```

```
61137
```

Total Number of Words in the amazon processed reviews

```
len((long_string.split()))
```

```
6171327
```

Total Number of Documents in the Train Corpus

```
amazon_processed['processed'].shape[0]
```

```
209720
```

```
### WORD COUNTS IN DESCENDING ORDER
word_counts = pd.Series(' '.join(amazon_processed['processed'])
                        .lower().split()).value_counts()

word_counts
```

```
not           195100
use            68962
sound          66843
get            66714
one            61405
               ...
averagely          1
kurzweill          1
libary             1
defiency           1
kabeldirekt        1
Length: 61137, dtype: int64
```

Wrds that appear less than 10 times throughout the Entire Copus

```
# Example: Consider words that appear less than 10 times
# throughout the Corpus as Rare

threshold = 10
rare_words = word_counts[word_counts < threshold]

wordcloud = WordCloud(width=800,
                      height=400,
                      background_color='white').generate_from_frequencies(rare_words)

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```

Sentiment Classification using Machine Learning models

TfIDF Vectorizer

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
from sklearn.naive_bayes import MultinomialNB
```

```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import cross_validate
from tempfile import mkdtemp
from shutil import rmtree
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

Multinomial Naive Bayes Classifier

10 Fold Cross Validation of Multinomial Naive Bayes Classifier

```
from sklearn.model_selection import train_test_split
```

```
# Train-Test split
```

```
X_train,X_test,y_train,y_test= train_test_split(amazon_processed.processed,
```

```
                                                   amazon_processed.star_rating,
                                                   test_size=0.2,
                                                   stratify=amazon_processed.star_rating,
                                                   shuffle=True, random_state=42)
```

We develop a pipeline consisting of Tfidf vectorizer and the classifier. This will allow a streamlined flow of the feature vectorisation and classification process. It also helps in avoiding test data leakage as the tf-idf transformer will be fit on the training data and the same vectorizer will be used to transform the testset. The vectors obtained will be used to train the classifier and validate on the test set.

```
estimators = [('tfidf', TfidfVectorizer()),

              ('multinom_NB', MultinomialNB())]

cachedir = mkdtemp()          # Create a temp memory location to save
                              # the tf-idf transformer outputs once the transformer fits over all the datapoints.
                              #This helps in avoiding redundant computations in subsequent folds

pipe = Pipeline(estimators, memory=cachedir)
pipe
```

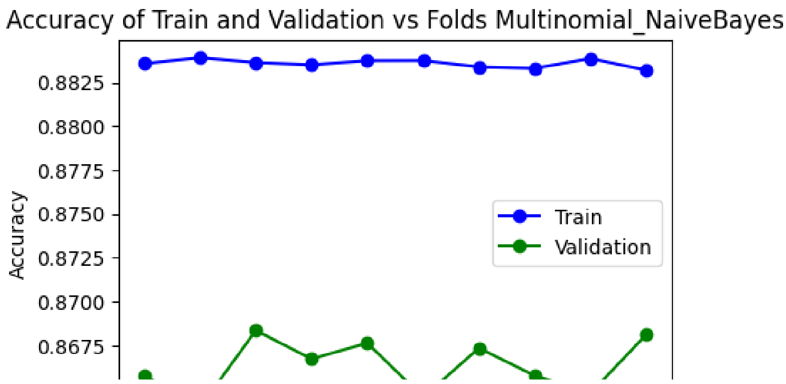
```
Pipeline
TfidfVectorizer
MultinomialNB
```

The pipe is passed as the estimator unit to the cross validator and 10 fold cross validation is implemented

```
from sklearn.metrics import (make_scorer, precision_score,
                             recall_score, f1_score)

prec_macro = make_scorer(precision_score, average='macro')         # The scoring metrics of the classifier are created and
rec_macro  = make_scorer(recall_score, average='macro')            # passed to the cross validator
f1_score   = make_scorer(f1_score, average='macro')

scoring = { 'acc': 'accuracy',
            'prec_macro': prec_macro,
            'rec_macro': rec_macro,
            'f1-score': f1_score}

X= amazon_processed.processed
Y= amazon_processed.star_rating

scores_Multinom_NB = cross_validate(pipe, X, Y,
                                    scoring=scoring,
                                    cv=10, return_train_score=True,
                                    verbose=2, n_jobs=-1)                # n-jobs is set to -1 to use all the CPU cores
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done   3 out of  10 | elapsed:   24.1s remaining:   56.4s
[Parallel(n_jobs=-1)]: Done  10 out of  10 | elapsed:   24.7s finished
```

```
# The accuracy of the classifier on the train and validation sets is plotted per fold

fig,ax= plt.subplots(figsize=(5,3.5))

folds=[1,2,3,4,5,6,7,8,9,10]

ax.plot(folds, scores_Multinom_NB['train_acc'], color='blue', label='Train', marker='o')
ax.plot(folds, scores_Multinom_NB['test_acc'], color='green', label='Validation', marker='o')
ax.set_xlabel('CV_Fold')
ax.set_ylabel('Accuracy')
ax.set_title('Accuracy of Train and Validation vs Folds Multinomial_NaiveBayes')
ax.legend()

plt.show()
```



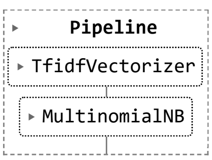

```
# A function is defined to retrieve the evaluation scores of the cross validator and return
# the mean of the scores for the 10 folds

def classification_metrics(score_dict):

    mean_test_acc       =  np.mean(score_dict['test_acc'])
    mean_test_recall    =  np.mean(score_dict['test_rec_macro'])
    mean_test_precision =  np.mean(score_dict['test_prec_macro'])
    mean_test_f1_score  =  np.mean(score_dict['test_f1-score'])
    mean_fit_time       =  np.mean(score_dict['fit_time'])
    mean_score_time     =  np.mean(score_dict['score_time'])

    return mean_test_acc,mean_test_recall,mean_test_precision,mean_test_f1_score,mean_fit_time,mean_score_time


test_acc,test_recall,test_precision,test_f1_score,fit_time,score_time=classification_metrics(scores_Multinom_NB)


print('10 FOLD CROSS VALIDATION TEST METRIC RESULTS MULTINOMIAL NAIVE BAYES CLASSIFIER','\n\n',\
      'test_accuracy: ',test_acc,'\n',\
      'test_recall: ',test_recall,'\n',\
      'test_precision: ',test_precision,'\n',\
      'test_f1_score: ',test_f1_score,'\n',\
       'Fit_time:', fit_time,'\n',\
       'Prediction_time:',score_time,sep='')
```

```
10 FOLD CROSS VALIDATION TEST METRIC RESULTS MULTINOMIAL NAIVE BAYES CLASSIFIER

test_accuracy: 0.8662979210375739
test_recall: 0.8662979210375739
test_precision: 0.8663045960521787
test_f1_score: 0.8662973112882207
Fit_time:12.340850472450256
Prediction_time:0.7715849637985229
```

```
rmtree(cachedir)               # Delete the temp directory
```

Tuning for the best Hyper-Parameters of MultinomialNB using Grid Search CV

```
# Estimator pipeline consisting of Tf-Idf transformer and Naive Bayes classifier is defined.
# It shall be passed to the Grid_search cross validator

estimators_grid = [('tfidf', TfidfVectorizer()),
              ('multinom_NB', MultinomialNB())]

cachedir = mkdtemp()

pipe_grid = Pipeline(estimators_grid, memory=cachedir)
pipe_grid
```




```
# The hyperparameter space is defined and is passed to the Grid-search 10-fold Cross validator

param_grid = dict(tfidf__ngram_range=[(1,1),(1,2),(1,3)],
```

```
                tfidf__min_df=[10,100],
                tfidf__max_df=[0.6,0.8],
                multinom_NB__alpha= [0.001,0.01,0.1, 1.0],    #Alpha is regularisation smoothing constant
                )
```

```
from sklearn.metrics import f1_score, make_scorer
```

```
# The F1-score is passed as scoring metric to Grid-search CV
```

```
f1 = make_scorer(f1_score, average='macro')
```

```
grid_search = GridSearchCV(pipe_grid,
                           param_grid=param_grid,
                           cv=10,
                           scoring=f1, n_jobs=10,
                           verbose=2)
```

```
grid_search.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 48 candidates, totalling 480 fits
C:\miniconda\lib\site-packages\sklearn\pipeline.py:359: UserWarning: Persisting input
If this happens often in your code, it can cause performance problems
(results will be correct in all cases).
The reason for this is probably some large input arguments for a wrapped
 function (e.g. large strings).
THIS IS A JOBLIB ISSUE. If you can, kindly provide the joblib's team with an
 example so that they can fix the problem.
  X, fitted_transformer = fit_transform_one_cached(
```

GridSearchCV

estimator: Pipeline

TfidfVectorizer

MultinomialNB

```
# The best hyperparameter obtained by Grid Search CV
```

```
grid_search.best_params_
```

```
{'multinom_NB__alpha': 1.0,
 'tfidf__max_df': 0.6,
 'tfidf__min_df': 10,
 'tfidf__ngram_range': (1, 3)}
```

```
# The best cross validated score obtained by the Grid Search CV
```

```
grid_search.best_score_
```

```
0.9024250854500506
```

```
# Time taken for the training of the model using the best hyperparameter set on the whole trainset
```

```
grid_search.refit_time_
```

```
52.204750537872314
```

```
# Time taken by the best model to predict the testset
```

```
start_time=time.time()
```

```
y_pred_MultiNB=grid_search.predict(X_test)
```

```
end_time=time.time()-start_time
```

```
print('Time taken by the best model to predict the testset:  ', end_time)
```

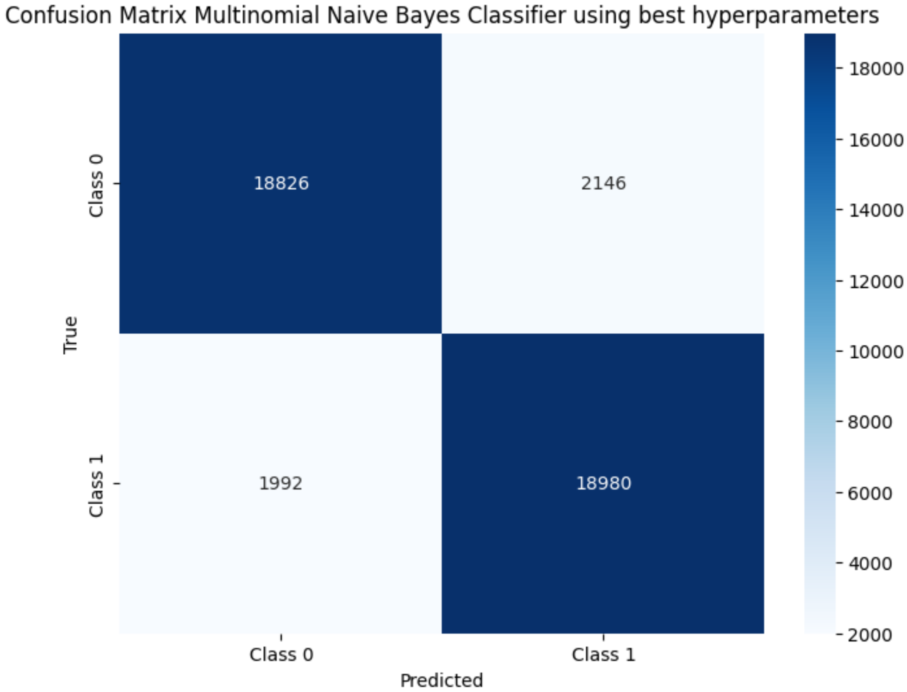
```
Time taken by the best model to predict the testset:   2.0999507904052734
```

Classification Report Multinomial Naive Bayes Classifier trained using best hyperparameters

```
print(classification_report(y_test,y_pred_MultiNB, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.9043    0.8977    0.9010     20972
           1     0.8984    0.9050    0.9017     20972

    accuracy                         0.9013     41944
   macro avg     0.9014    0.9013    0.9013     41944
weighted avg     0.9014    0.9013    0.9013     41944
```

```
# List of class labels
class_labels = ['Class 0', 'Class 1']

# Compute confusion matrix
cm = confusion_matrix(y_test,y_pred_MultiNB, labels= [0,1])

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=class_labels, yticklabels=class_labels)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix Multinomial Naive Bayes Classifier using best hyperparameters')
plt.show()
```




```
rmtree(cachedir)                        # Delete the temp directory
```

Logistic Regression Classifier

10 Fold Cross Validation of Log Reg Classifier

```
from sklearn.linear_model import LogisticRegression
```

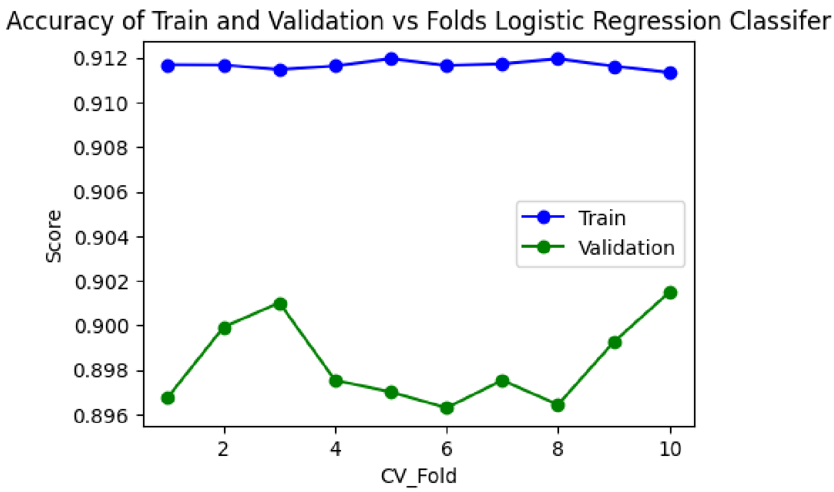
```
# A pipiline is contructed

estimators = [('tfidf', TfidfVectorizer()),
              ('lr', LogisticRegression(max_iter=1000))]   # Maximum number of iterations of model weight updation to converge
                                                           # to a minimal loss
cachedir = mkdtemp()

pipe = Pipeline(estimators, memory=cachedir)
pipe
```

Pipeline
TfidfVectorizer
LogisticRegression

```
from sklearn.metrics import (make_scorer, precision_score,
                             recall_score, f1_score)

prec_macro = make_scorer(precision_score, average='macro')           # The scoring metrics of the classifier are created and
rec_macro  = make_scorer(recall_score, average='macro')              # passed to the cross validator
f1_score   = make_scorer(f1_score, average='macro')

scoring = { 'acc': 'accuracy',
            'prec_macro': prec_macro,
            'rec_macro': rec_macro,
            'f1-score': f1_score}


scores_logreg = cross_validate(pipe, X,Y,                            # The verbosity is set to 2 to print the results during
                               scoring=scoring,                      # cross validation
                               cv=10, return_train_score=True,
                               verbose=2, n_jobs=10)
```

```
[Parallel(n_jobs=10)]: Using backend LokyBackend with 10 concurrent workers.
[Parallel(n_jobs=10)]: Done   3 out of  10 | elapsed:   31.8s remaining:  1.2min
[Parallel(n_jobs=10)]: Done  10 out of  10 | elapsed:   33.1s finished
```

```
# The Train and Validation accuracy of Logistic Regression Classifer is plotted per Fold

fig,ax= plt.subplots(figsize=(5,3.5))

folds=[1,2,3,4,5,6,7,8,9,10]

ax.plot(folds, scores_logreg['train_acc'], color='blue',
        label='Train', marker='o')
ax.plot(folds, scores_logreg['test_acc'], color='green',
        label='Validation', marker='o')

ax.set_xlabel('CV_Fold')
ax.set_ylabel('Score')
ax.set_title('Accuracy of Train and Validation vs Folds Logistic Regression Classifer')
ax.legend()

plt.savefig('Accuracy_CrossVal_LogReg.png')

plt.show()
```




```
test_acc_log,test_recall_log,test_precision_log,test_f1_score_log,fit_time_log,score_time_log=classification_metrics(scores_logr


print('10 FOLD CROSS VALIDATION TEST METRIC RESULTS Logistic Regression Classifer','\n\n',\
      'test_accuracy: ',test_acc_log,'\n',\
      'test_recall: ',test_recall_log,'\n',\
      'test_precision: ',test_precision_log,'\n',\
```

```
'test_f1_score: ',test_f1_score_log,'\n',\
 'Fit_time:', fit_time_log,'\n',\
 'Prediction_time:',score_time_log,sep='')
```

```
10 FOLD CROSS VALIDATION TEST METRIC RESULTS Logistic Regression Classifer

test_accuracy: 0.898321571619302
test_recall: 0.8983215716193019
test_precision: 0.8983262650215517
test_f1_score: 0.8983212741334089
Fit_time:20.609524512290953
Prediction_time:0.8587849378585816
```

```
rmtree(cachedir)                     # Delete the temp directory
```

Tuning for the best Hyper-Parameters of Logistic Regression using Grid Search CV

```
# Estimator pipeline consisting of Tf-Idf transformer and Logistic Regression classifier is defined.
# It shall be passed to the Grid_search cross validator

estimators_grid_Logreg = [('tfidf', TfidfVectorizer()),
              ('lr_clf', LogisticRegression(max_iter=1000))]

cachedir = mkdtemp()

pipe_grid_Logreg = Pipeline(estimators_grid_Logreg, memory=cachedir)
pipe_grid_Logreg
```

Pipeline

TfidfVectorizer

LogisticRegression

```
# The hyperparameter space is defined and is passed to the Grid-search 10-fold Cross validator

param_grid = dict(tfidf__ngram_range=[(1,1),(1,2),(1,3)],
                tfidf__min_df=[10,100],
                  tfidf__max_df=[0.6,0.8],
                  lr_clf__C=[1e-4,0.001,0.01,0.1,1]       # C is regularisation constant and prevents the model
                  )                                       # from overfitting the data

from sklearn.metrics import f1_score, make_scorer
f1 = make_scorer(f1_score, average='macro')

grid_search_logreg = GridSearchCV(pipe_grid_Logreg, param_grid=param_grid,
                                  cv=10, scoring=f1, n_jobs=10,
                                  verbose=2)
```

```
grid_search_logreg.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 60 candidates, totalling 600 fits
C:\miniconda\lib\site-packages\sklearn\pipeline.py:359: UserWarning: Persisting input arguments took 18.54s to run.
If this happens often in your code, it can cause performance problems
(results will be correct in all cases).
The reason for this is probably some large input arguments for a wrapped
 function (e.g. large strings).
THIS IS A JOBLIB ISSUE. If you can, kindly provide the joblib's team with an
 example so that they can fix the problem.
  X, fitted_transformer = fit_transform_one_cached(
```

GridSearchCV

estimator: Pipeline

TfidfVectorizer

LogisticRegression

```
# The best hyperparameter obtained by Grid Search CV

grid_search_logreg.best_params_
```

```
{'lr_clf__C': 1,
 'tfidf__max_df': 0.6,
 'tfidf__min_df': 10,
 'tfidf__ngram_range': (1, 3)}
```

```
# The best cross validated score obtained by the Grid Search CV

grid_search_logreg.best_score_
```

```
0.916697815246927
```

```
# Time taken for the training of the model using the best hyperparameter set on the whole trainset

grid_search_logreg.refit_time_
```

```
56.356250047683716
```

```
# Time taken by the best model to predict the testset

start_time=time.time()

y_pred_logreg= grid_search_logreg.predict(X_test)

end_time=time.time()-start_time

print('Time taken by the best model to predict the testset:  ', end_time)
```

```
Time taken by the best model to predict the testset:   1.9021222591400146
```

Classification Report of Logistic Regression classifier trained using best Hyperparameter set

```
print(classification_report(y_test,y_pred_logreg, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.9161    0.9164    0.9163     20972
           1     0.9164    0.9161    0.9162     20972

    accuracy                         0.9162     41944
   macro avg     0.9162    0.9162    0.9162     41944
weighted avg     0.9162    0.9162    0.9162     41944
```

```
# List of class labels
class_labels = ['Class 0', 'Class 1']

# Compute confusion matrix
cm = confusion_matrix(y_test,y_pred_logreg, labels= [0,1])

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=class_labels, yticklabels=class_labels)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix Logistic Regression Classifier using best hyperparameters')
plt.show()
```


```
rmtree(cachedir)                             # Delete the temp directory
```

Show hidden output

Support Vector Classifier

```
from sklearn.svm import LinearSVC

estimators = [('tfidf', TfidfVectorizer()),
              ('SVC', LinearSVC())]

cachedir = mkdtemp()

pipe = Pipeline(estimators, memory=cachedir)
pipe
```

```
Pipeline
TfidfVectorizer
LinearSVC
```

```
from sklearn.model_selection import cross_validate

from sklearn.metrics import (make_scorer, precision_score,
                             recall_score, f1_score)

prec_macro = make_scorer(precision_score, average='macro')
rec_macro  = make_scorer(recall_score, average='macro')
f1_score   = make_scorer(f1_score, average='macro')

scoring = { 'acc': 'accuracy',
            'prec_macro': prec_macro,
            'rec_macro': rec_macro,
            'f1-score': f1_score}

X=amazon_processed.processed
Y=amazon_processed.star_rating

scores_SVC = cross_validate(pipe, X, Y,
                             scoring=scoring,
                             cv=10, return_train_score=True,
                             verbose=2, n_jobs=-1)
```

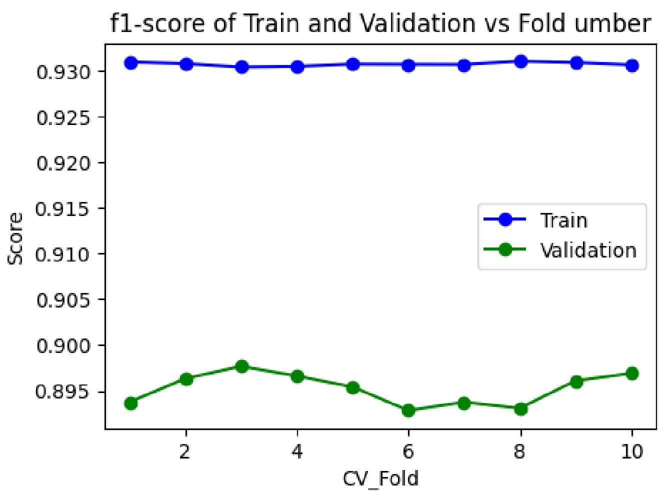
```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done   3 out of  10 | elapsed:   27.0s remaining:  1.1min
[Parallel(n_jobs=-1)]: Done  10 out of  10 | elapsed:   28.3s finished
```

```
test_acc_SVC,test_recall_SVC,test_precision_SVC,test_f1_score_SVC,fit_time,score_time=classification_metrics(scores_SVC)
```

```
print('10 FOLD CROSS VALIDATION TEST METRIC RESULTS','\n\n',\
      'test_accuracy: ',test_acc_SVC,'\n',\
      'test_recall: ',test_recall_SVC,'\n',\
      'test_precision: ',test_precision_SVC,'\n',\
      'test_f1_score: ',test_f1_score_SVC, '\n',\
      'fit_time: ', fit_time, '\n',\
      'score_time: ',score_time,sep='')
```

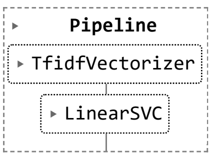
```
10 FOLD CROSS VALIDATION TEST METRIC RESULTS

test_accuracy: 0.8952555788670609
test_recall: 0.8952555788670609
test_precision: 0.8952641452435828
test_f1_score: 0.8952550171374934
fit_time: 15.61154134273529
score_time: 0.7426803112030029
```

```
fig,ax= plt.subplots(figsize=(5,3.5))

folds=[1,2,3,4,5,6,7,8,9,10]

ax.plot(folds, scores_SVC['train_f1-score'], color='blue', label='Train', marker='o')
ax.plot(folds, scores_SVC['test_f1-score'], color='green', label='Validation', marker='o')
ax.set_xlabel('CV_Fold')
ax.set_ylabel('Score')
ax.set_title('f1-score of Train and Validation vs Fold umber')
ax.legend()

plt.show()
```



Tuning for the best Hyper-Parameters of SVC using Grid Search CV

```
estimators_grid_SVC = [('tfidf', TfidfVectorizer()),
                       ('SVC', LinearSVC())]

cachedir = mkdtemp()

pipe_grid_SVC = Pipeline(estimators_grid_SVC, memory=cachedir)
pipe_grid_SVC
```




```
param_grid = dict(tfidf__ngram_range=[(1,1),(1,2),(1,3)],
                tfidf__min_df=[10,100],
                  tfidf__max_df=[0.6,0.8],
                  SVC__C=[1,1e-1, 1e-2, 1e-3,1e-4]           #C is regularisation constant which leads to smooth margin SVMs
                  )

from sklearn.metrics import f1_score, make_scorer
f1 = make_scorer(f1_score, average='macro')

grid_search_SVC = GridSearchCV(pipe_grid_SVC,
                               param_grid=param_grid,
                               cv=10, scoring=f1,
                               n_jobs=10,
                               verbose=2)
```

```
grid_search_SVC.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 60 candidates, totalling 600 fits
C:\miniconda\lib\site-packages\sklearn\pipeline.py:359: UserWarning: Persisting input
If this happens often in your code, it can cause performance problems
(results will be correct in all cases).
The reason for this is probably some large input arguments for a wrapped
 function (e.g. large strings).
THIS IS A JOBLIB ISSUE. If you can, kindly provide the joblib's team with an
 example so that they can fix the problem.
  X, fitted_transformer = fit_transform_one_cached(
```

▸ **GridSearchCV**

▸ **estimator: Pipeline**

▸ TfidfVectorizer

▸ LinearSVC

```
# The best cross validated score obtained by the Grid Search CV

grid_search_SVC.best_score_
```

```
0.9185098660114386
```

```
# The best hyperparameter obtained by Grid Search CV

grid_search_SVC.best_params_
```

```
{'SVC__C': 0.1,
 'tfidf__max_df': 0.6,
 'tfidf__min_df': 10,
 'tfidf__ngram_range': (1, 3)}
```

```
# Time taken for the training of the model using the best hyperparameter set on the whole trainset

grid_search_SVC.refit_time_
```

```
54.928555488586426
```

```
# Time taken by the best model to predict the testset

start_time=time.time()

y_pred_SVC=grid_search_SVC.predict(X_test)

end_time=time.time()-start_time

print('Time taken by the best model to predict the testset:  ', end_time)
```

```
Time taken by the best model to predict the testset:   2.005186080932617
```

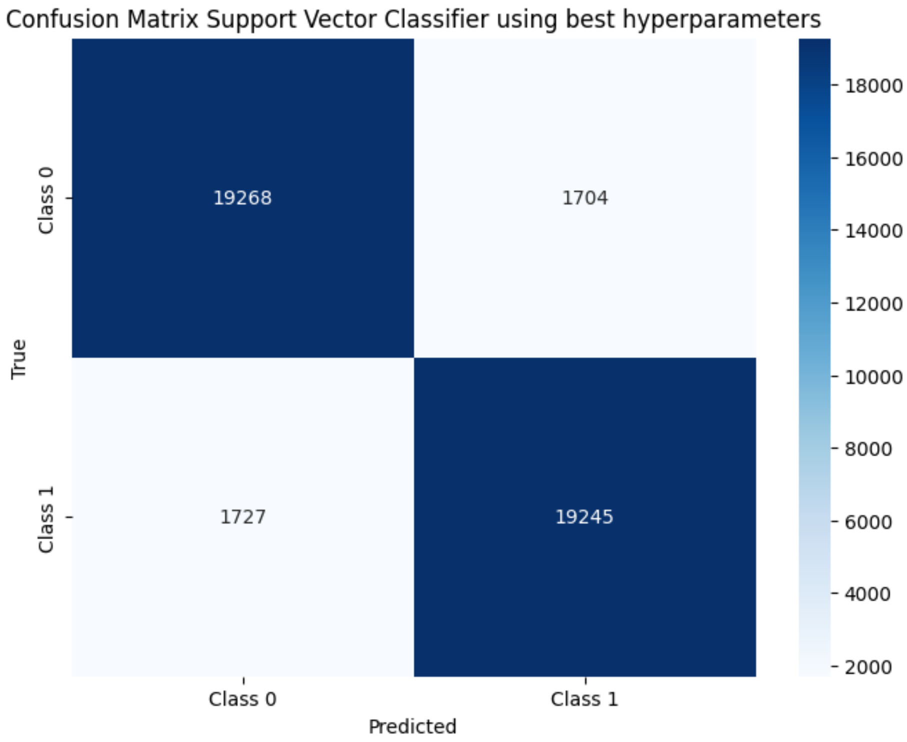
Classification Report Support Vector Classifier trained using best Hyperparameter set

```
print(classification_report(y_test,y_pred_SVC, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.9177    0.9187    0.9182     20972
           1     0.9187    0.9177    0.9182     20972

    accuracy                         0.9182     41944
   macro avg     0.9182    0.9182    0.9182     41944
weighted avg     0.9182    0.9182    0.9182     41944
```

```
# List of class labels
class_labels = ['Class 0', 'Class 1']

# Compute confusion matrix
cm = confusion_matrix(y_test,y_pred_SVC, labels= [0,1])

# Plot confusion matrix
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=class_labels, yticklabels=class_labels)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix Support Vector Classifier using best hyperparameters')
plt.show()
```




```
rmtree(cachedir)
```

Sentiment Classification using Deep Learning models

```
# Import tensorflow

import tensorflow as tf


print('Tensorflow version: ', tf.__version__)
```

```
     Tensorflow version:  2.7.0
```

```
from gensim.models import Word2Vec
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
```

To convert the text reviews into numeric vectors to feed into the neural network we will use the Word2Vec algorithm which is an unsupervised text vectorisation based on a neural network. We will import the pretrained Word2vec model trained on Google News.

```
import gensim.downloader

# Download the google pre-trained Word2Vec model

word2vec_model = gensim.downloader.load('word2vec-google-news-300')


# Save the download word2vec-google-news-300 model in binary format

from gensim.models import KeyedVectors
```

```
# Save the vectors to a file

word2vec_model.save_word2vec_format("word2vec_model.txt", binary=True)
```

```
from gensim.models import KeyedVectors

# Load the pre-trained Word2Vec model in binary format

word2vec = KeyedVectors.load_word2vec_format("word2vec_model.txt",
                                          binary=True)
```

There is a total of 300000 words and its vectors. Each vector has a dimension of 300 which captures the meaning of each word and its relation and context to other words

```
vocab=word2vec.key_to_index
print("The total number of words are : ",len(vocab))
```

```
The total number of words are :  3000000
```

```
word2vec_vector = word2vec.get_vector('king')
```

```
# Dimension of word2vec vecor

word2vec_vector.shape
```

```
(300,)
```

```
word2vec.most_similar('Guitar')
```

```
[('guitar', 0.6482495665550232),
 ('Guitars', 0.639025092124939),
 ('Piano', 0.5972932577133179),
 ('Autoharp', 0.5947816371917725),
 ('Mandolin', 0.5770671963691711),
 ('Guitar_Player', 0.5768842101097107),
 ('guitarists', 0.5736500024795532),
 ('Ukulele', 0.5734299421310425),
 ('Acoustic_Guitar', 0.5714870691299438),
 ('guitars', 0.5576277375221252)]
```

```
# Sme of the words in word2vec model

word2vec.index_to_key[20:26]
```

```
['I', 'have', 'he', 'will', 'has', '####']
```

```
# import punkt tokenizer

import nltk.data
sent_detector = nltk.data.load('tokenizers/punkt/english.pickle')
from nltk.tokenize import wordpunct_tokenize
```

We calculate the 85h percentile review length and shall pad truncate our reviews to that length

```
review_len= []

for review in amazon_processed.processed:
    length= len(wordpunct_tokenize(review))
    review_len.append(length)
```

```
# 85 percent and less of the documents have a Review length of 51

np.percentile(review_len,85)
```

```
51.0
```

Maximum Length of a review in processed dataset

```
np.percentile(review_len,100)
```

```
2199.0
```

```
# Import keras tokinzer and padder

from tensorflow.keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
```

```
X_train.shape, X_test.shape
```

```
((167776,), (41944,))
```

We will be using the Keras tokenizer which creates a vocabulary from the documents. It converts each and every document to a numeric vector with the words mapped to their numeric index in the vocabulary. We will fit the tokenizer on the train data only and then transform the train and test data from the trainset vocabulary. This prevents data leakage from the test set

All the reviews in the train and test datsets shall be padded with zeroes to convert them to vectors of the same size. This will facilitate the Neural Network fitting process

```
def padding_tokenizer(X_train, X_test, num_words, max_review_len):

    global vocab_size

    global tok

    tok = Tokenizer(num_words)                         # Reviews are tokenized using a vocabulary of 5000 most common words

    tok.fit_on_texts(X_train)

    vocab_size = len(tok.word_index) + 1               # total no of words in tokenizer vocabulary

    encd_reviews_train = tok.texts_to_sequences(X_train)       # Encoded Trainset

    encd_reviews_test = tok.texts_to_sequences(X_test)         # Encoded Testset

    # now padding to have a maximum length of 50

    pad_reviews_train= pad_sequences(encd_reviews_train,
                           maxlen=max_review_len,
                           padding='pre')                    # Pre-padding is used to pad the reviews with zeroes at the
                                                             # beginning of each review
    pad_reviews_test= pad_sequences(encd_reviews_test,
                           maxlen=max_review_len,
                           padding='pre')

    return pad_reviews_train,pad_reviews_test,
```

```
# Reviews are tokenized using a vocabulary of 5000 most common words and padded to have an uniform length of 50 tokens

pad_reviews_train,pad_reviews_test=padding_tokenizer(X_train=X_train,
                                                     X_test=X_test,
                                                     num_words= 5000,
                                                     max_review_len= 50 )
```

We can observe the padded reviews have the same word feature length of 50

```
pad_reviews_train.shape, pad_reviews_test.shape
```

```
((167776, 50), (41944, 50))
```

We will now create an embedding matrix which will contain the word2vec vectors corresponding to each word in the tokenized vocabulary such that each i-th vector in the matrix will correspond to the i-th indexed word in the vocabulary

```
 # total no of words

vocab_size = len(tok.word_index) + 1

# embedding dimension as choosen in word2vec constructor

embedd_dims=300

# max length of a review

max_review_len= 50
```

```
vocab_size
```

```
     54262
```

```
# now creating the Google embedding matrix

embedd_matrix_google=np.zeros(shape=(vocab_size,embedd_dims))

for word,i in tqdm(tok.word_index.items()):
        if word in word2vec.index_to_key:
            embedd_matrix_google[i]=word2vec.get_vector(word)
```

```
       0%|          | 0/54261 [00:00<?, ?it/s]
```

```
# The embedding matrix containing Google word2vec word embeddings is saved

np.save('embedding_matrix__google_word2vec.npy', embedd_matrix_google)
```

```
# Load the Google embedding matrix

embedd_matrix_google=np.load('embedding_matrix__google_word2vec.npy' )
```

```
embedd_matrix_google.shape
```

```
     (54262, 300)
```

We will check how many vectors of words were successfully extracted from the Google pretrained word2vec vector set. Some of the words in our corpus may be absent in the Google pretrained corpus.

```
all_zero_arrays = np.all(embedd_matrix_google == 0, axis=1)

# Find the indices of arrays where all elements are zero
indices_with_all_zeros = np.where(all_zero_arrays)[0]
```

```
# 21833 words were not found in the Google Pretrained corpus

indices_with_all_zeros.shape
```

```
     (22848,)
```

Custom Word Embedding by training Word2vec model on the Amazon Musical Instrument Review Dataset from scratch.

To train a Word2vec model it has to be passed sentences of each document, each sentence broken down into its constituent words. We build the preprocessing function.

```
def clean(text):


            text=contractions.fix(text)   # Expand the contractions

            text_pr = re.compile(r'https?://\S+').sub('',str(text)) #remove website addres
            text_pr = re.sub(r"e-mail","email",text_pr)
            text_pr=re.sub(r'<[\w\s\W]+>',' ',text_pr,flags=re.IGNORECASE)#remove html text tags such as <br>
            text_pr = re.sub(r'[^a-zA-Z!?]',' ',text_pr)  #remove numbers other characters such as Punctuation
```

```
        text_pr = re.sub(r'\s+',' ',text_pr)  #remove white spaces
        text_pr=text_pr.lower()

        processed = []

        stp_wrds=stopwords.words('english')
        for index,word in enumerate(['no','nor','not']):
            stp_wrds.remove(word)

        lemmatizer = WordNetLemmatizer()

        for i in nltk.pos_tag(wordpunct_tokenize(text_pr)):

                if i[0] not in stp_wrds:
                    if i[1].startswith('N'):
                        processed.append(lemmatizer.lemmatize(i[0],'n'))
                    elif i[1].startswith('V'):
                        processed.append(lemmatizer.lemmatize(i[0],'v'))
                    elif i[1].startswith('J'):
                        processed.append(lemmatizer.lemmatize(i[0],'a'))
                    elif i[1].startswith('R'):
                        processed.append(lemmatizer.lemmatize(i[0],'r'))


                    else:
                        processed.append(lemmatizer.lemmatize(i[0]))



        processed_str = ' '.join(processed)

        return processed_str
```

We pass each each sentence of corresponding reviews, preprocess them, break the preprocessed sentence into individual words and finally append these words as lists to the sentences list.

```
sent_tokenizer = nltk.data.load('tokenizers/punkt/english.pickle')

sentences=[]

sum=0

for review in tqdm(amazon_processed['processed']):

    sents=sent_tokenizer.tokenize(review.strip())

    sum+=len(sents)

    for sent in sents:
        processd_sent=clean(sent)
        sentences.append(processd_sent.split())

print(sum)
print(len(sentences))  # total no of sentences
```

```
100%|██████████████████████████████████████████████████████████████████████████| 199042/199042 [21:30<00:00, 154.29it/s]260
260255
```

The Word2vec model is initialized such that the output vectors will have dimension of 300.

The "window size" refers to the number of words surrounding a target word that are considered as context words for the purpose of training the model. The window size determines the range within which the model looks for context words when predicting the target word. (CBOW Continuous Bag of Words)

min_count parameter specifies the minimum number of times a word must appear in the corpus to be included in the vocabulary and considered for word embeddings.

```
import gensim
w2v_amazon=gensim.models.Word2Vec(sentences=sentences,
                                  vector_size=300,
```

```
                                  window=10,
                                  min_count=1)
```

Show hidden output

```
# training of Word2vec model on Amazon dataset

w2v_amazon.train(sentences,epochs=10,total_examples=len(sentences))
```

```
(51124190, 58499230)
```

```
w2v_amazon.save("word2vec_amazon.model")  # Save the saved Word2Vec model trained on Amamzzon dataset
```

```
# Load the saved Word2Vec model
w2v_amazon = Word2Vec.load("word2vec_amazon.model")
```

```
# Words present in the Custom trained word embeddings

w2v_amazon.wv.index_to_key
```

Show hidden output

We will create an embedding matrix and populate it with the word2vec word vectors trained on the Amazon Reviews dataset.

```
# now creating the empty embedding matrix

embedd_matrix_amazon=np.zeros(shape=(vocab_size,embedd_dims))

for word,i in tqdm(tok.word_index.items()):

        if word in w2v_amazon.wv.index_to_key:

            embedd_matrix_amazon[i]=w2v_amazon.wv.get_vector(word)
```

```
  0%|          | 0/54261 [00:00<?, ?it/s]
```

```
embedd_matrix_amazon.shape
```

```
(54262, 300)
```

Check how many word vectors could not be extracted in the amazon embedded matrix

```
all_zero_arrays = np.all(embedd_matrix_amazon == 0, axis=1)

# Find the indices of arrays where all elements are zero
indices_with_all_zeros = np.where(all_zero_arrays)[0]

indices_with_all_zeros.shape
```

```
(12489,)
```

```
# Save the NumPy embedding matrix to a binary file

np.save('embedding_matrix_amazon.npy', embedd_matrix_amazon)
```

```
# Load the embedded matrix

embedd_matrix_amazon= np.load('embedding_matrix_amazon.npy')
```

```
# Configure GPU memory growth
gpus = tf.config.experimental.list_physical_devices('GPU')
if gpus:
    for gpu in gpus:
        tf.config.experimental.set_memory_growth(gpu, True)

# Create a new session
sess = tf.compat.v1.Session(config=tf.compat.v1.ConfigProto())
```

Neural Network trained using Google pre-trained word embeddings

To input the padded vectors into the neural network, we define a Keras Embedding layer which shall accept the padded index vectors of dataset and map the index of the words to the corresponding word2vec vector in the embedding matrix as output. The input shape shall be (batch_size, padded_sentence length). The output shape shall be (batch_size,padded_sentence length, word2vec vector dimension).

The trainable parameter of embedding layer is set to false so as to avoid disturbing the pre trained weights

```
import keras
from tensorflow.keras.layers import Embedding
import keras_tuner
from keras.initializers import Constant
from keras.layers import Dropout,Flatten
from keras import layers
from tensorflow.keras.optimizers import Adam
```

Artificial Neural Network (ANN) Google word2vec word embeddings

The ANN hypermodel is constructed which consists of an initial embedding layer taking the review token sequences as input. The input shape is (batch_size, sequence_length=50) and for each word within the review, it shall do a lookup in the word2vec embedding matrix and output a sequence of word embeddings corresponding to the input sequence. The output shape is (batch_size=128, sequence_length=50, embedding_dim=300).

The hyperparameters are defined and the number of layers and the number of neurons per layer, dropout rate and the learning rate of the optimizer are tuned.

```
def build_model_ANN_google(hp):                             # hp is the keras hyperparamter object

    model_ANN = keras.Sequential()

    model_ANN.add(Embedding(input_dim=vocab_size,
                    output_dim=embedd_dims,
                    input_length=max_review_len,
                    embeddings_initializer=Constant(embedd_matrix_google), # Set pre-trained vectors as initial weights
                    trainable=False))                               # Keep the pre-trained weights fixed during training

    model_ANN.add(Flatten())

    for i in range(hp.Int('num_layers', 2, 20)):
        model_ANN.add(layers.Dense(units=hp.Int('units_' + str(i),
                                            min_value=32,
                                            max_value=512,
                                            step=32),
                                            activation='relu'))


    model_ANN.add(layers.Dropout(rate=hp.Choice('dropout_rate',[0.2,0.3,0.5])))    # Prevent model model overfitting

    model_ANN.add(layers.Dense(1, activation='sigmoid'))

    learning_rate = hp.Choice('learning_rate', [1e-2, 1e-3, 1e-4])

    model_ANN.compile(optimizer=Adam(learning_rate=learning_rate),
                                 loss='binary_crossentropy',
                                 metrics=['accuracy'])

    return model_ANN

build_model_ANN_google(keras_tuner.HyperParameters())
```

```
<keras.engine.sequential.Sequential at 0x18ecc2f7e50>
```

```
# The Keras Random tuner object is instantiated.The random search tuner is set to run for 10 trials such that
# for each trial two models with the same set of hyperparameters will be evaluated
```

```
tuner_ANN_google = keras_tuner.RandomSearch(hypermodel=build_model_ANN_google,
                                            objective="val_accuracy",
                                            max_trials=10,
                                            executions_per_trial=2,
                                            directory="Research_Project",
                                            project_name="Amazon_ANN")
```

```
INFO:tensorflow:Reloading Tuner from Research_Project\Amazon_ANN\tuner0.json
```

```
# Hyperparameter search pace summary

tuner_ANN_google.search_space_summary()
```

```
Search space summary
Default search space size: 5
num_layers (Int)
{'default': None, 'conditions': [], 'min_value': 2, 'max_value': 20, 'step': 1, 'sampling': 'linear'}
units_0 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step': 32, 'sampling': 'linear'}
units_1 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step': 32, 'sampling': 'linear'}
dropout_rate (Choice)
{'default': 0.2, 'conditions': [], 'values': [0.2, 0.3, 0.5], 'ordered': True}
learning_rate (Choice)
{'default': 0.01, 'conditions': [], 'values': [0.01, 0.001, 0.0001], 'ordered': True}
```

```
from tensorflow.keras.callbacks import EarlyStopping

# Define the early stopping callback
early_stopping = EarlyStopping(monitor='val_accuracy', patience=3, restore_best_weights=True)
```

```
tuner_ANN_google.search(pad_reviews_train, y_train,
                 epochs=20,
                 validation_data=(pad_reviews_test, y_test),
                 callbacks= [early_stopping])
```

```
Trial 10 Complete [00h 02m 53s]
val_accuracy: 0.5

Best val_accuracy So Far: 0.8515520691871643
Total elapsed time: 00h 29m 21s
INFO:tensorflow:Oracle triggered exit
```

ANN Hyperparamter tuning results summary

```
tuner_ANN_google.results_summary()
```

```
Results summary
Results in Research_Project\Amazon_ANN
Showing 10 best trials
Objective(name="val_accuracy", direction="max")

Trial 07 summary
Hyperparameters:
num_layers: 5
units_0: 448
units_1: 160
dropout_rate: 0.2
learning_rate: 0.0001
units_2: 64
units_3: 32
units_4: 224
units_5: 64
units_6: 224
units_7: 160
units_8: 288
units_9: 352
units_10: 416
units_11: 448
units_12: 448
units_13: 416
units_14: 480
units_15: 64
units_16: 32
units_17: 480
units_18: 384
Score: 0.8515520691871643

Trial 03 summary
Hyperparameters:
num_layers: 19
units_0: 160
units_1: 480
dropout_rate: 0.5
learning_rate: 0.0001
units_2: 480
units_3: 512
units_4: 416
units_5: 512
units_6: 352
units_7: 288
units_8: 32
units_9: 384
units_10: 480
units_11: 256
units_12: 384
units_13: 64
units_14: 32
units_15: 384
units_16: 32
units_17: 32
units_18: 32
Score: 0.8483811616897583
```

```
# Get the best ANN model

final_model_ANN_google= tuner_ANN_google.get_best_models()[0]


final_model_ANN_google.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
```

```
 embedding (Embedding)       (None, 50, 300)           16278600

 flatten (Flatten)           (None, 15000)             0

 dense (Dense)               (None, 448)               6720448

 dense_1 (Dense)             (None, 160)               71840

 dense_2 (Dense)             (None, 64)                10304

 dense_3 (Dense)             (None, 32)                2080

 dense_4 (Dense)             (None, 224)               7392

 dropout (Dropout)           (None, 224)               0

 dense_5 (Dense)             (None, 1)                 225

=================================================================
Total params: 23,090,889
Trainable params: 6,812,289
Non-trainable params: 16,278,600
_________________________________________________________________
```

```
# Predict the test set using best ANN model trained using Google word embeddings

y_pred_ANN=final_model_ANN_google.predict(pad_reviews_test)
```

```
# Output predicted probabilities greater than 0.5 is pridicted to be positive and negative otherwise

for index,pred in enumerate(y_pred_ANN):
    if pred>0.5:
        y_pred_ANN[index]=1
    else:
        y_pred_ANN[index]=0


# List of class labels
class_labels = ['Class 0', 'Class 1']

# Compute confusion matrix
cm = confusion_matrix(y_test,y_pred_ANN, labels= [0,1])

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=class_labels, yticklabels=class_labels)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

Classification report of best ANN model trained using Google word embeddings

```
print(classification_report(y_test,y_pred_ANN, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8354    0.8782    0.8563     20972
           1     0.8716    0.8269    0.8487     20972

    accuracy                         0.8526     41944
   macro avg     0.8535    0.8526    0.8525     41944
weighted avg     0.8535    0.8526    0.8525     41944
```

LSTM Google Word2vec word embeddings

```
from keras.layers import Dropout,LSTM
```

The LSTM hypermodel is built which will tune the number of layers (max of 3 layers) and the number of memory cells per LSTM layer

```
from keras.layers import Dropout,LSTM

def build_model_LSTM_google(hp):

    model_LSTM = keras.Sequential()

    model_LSTM.add(Embedding(input_dim=vocab_size,
                             output_dim=embedd_dims,
                             input_length=max_review_len,
                    embeddings_initializer=Constant(embedd_matrix_google), # Set pre-trained vectors as initial weights
                    trainable=False))                                      # Keep the pre-trained weights fixed during training


    for i in range(0,hp.Int('num_layers', min_value=0, max_value=2, step=1)):

        model_LSTM.add(LSTM(units=hp.Int('units_' + str(i),
                                          min_value=16,              # Number of memory cells per layer ranging from
                                          max_value=96,              # 16 cells to 96 cells with a step size of 16
                                          step=16),
                                          return_sequences=True))



    model_LSTM.add(LSTM(units=hp.Int('units_final_LSTM',              # Final LSTM Layer
                                      min_value=16,
                                      max_value=96,
                                      step=16)))


    model_LSTM.add(layers.Dropout(rate=hp.Choice('dropout_rate',[0.2,0.3,0.5]))) # Dropout rate tuning to prevent model overfitt

    model_LSTM.add(layers.Dense(1, activation='sigmoid'))

    learning_rate = hp.Choice('learning_rate', [1e-2, 1e-3, 1e-4])

    model_LSTM.compile(optimizer=Adam(learning_rate=learning_rate),
                                        loss='binary_crossentropy',
                                        metrics=['accuracy'])

    return model_LSTM


build_model_LSTM_google(keras_tuner.HyperParameters())
```

```
<keras.engine.sequential.Sequential at 0x1fd26527ca0>
```

```
# The Keras Random tuner object is instantiated.


tuner_LSTM_google = keras_tuner.RandomSearch(hypermodel=build_model_LSTM_google,
                                             objective="val_accuracy",
                                             max_trials=10,
                                             executions_per_trial=2,
                                             directory="Research_Project",
                                             project_name="Research_LSTM_Tuner_Amazon")
```

```
INFO:tensorflow:Reloading Tuner from Research_Project\Research_LSTM_Tuner_Amazon\tuner0.json
```

```
tuner_LSTM_google.search_space_summary()
```

```
Search space summary
Default search space size: 6
num_layers (Int)
{'default': None, 'conditions': [], 'min_value': 0, 'max_value': 2, 'step': 1, 'sampling': 'linear'}
units_final_LSTM (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 96, 'step': 16, 'sampling': 'linear'}
dropout_rate (Choice)
{'default': 0.2, 'conditions': [], 'values': [0.2, 0.3, 0.5], 'ordered': True}
learning_rate (Choice)
{'default': 0.01, 'conditions': [], 'values': [0.01, 0.001, 0.0001], 'ordered': True}
units_0 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 96, 'step': 16, 'sampling': 'linear'}
units_1 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 96, 'step': 16, 'sampling': 'linear'}
```

```
from tensorflow.keras.callbacks import EarlyStopping

# Define the early stopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)
```

```
tuner_LSTM_google.search(pad_reviews_train,
                  y_train,
                  batch_size=128,
                  epochs=50,
                  validation_data=(pad_reviews_test, y_test),
                  callbacks=[early_stopping])
```

```
Trial 10 Complete [00h 07m 08s]
val_accuracy: 0.9153037369251251

Best val_accuracy So Far: 0.9189633727073669
Total elapsed time: 00h 54m 54s
INFO:tensorflow:Oracle triggered exit
```

```
tuner_LSTM_google.save()
```

```
tuner_LSTM_google.results_summary()       # LSTM tuning results summary
```

```
Results summary
Results in Research_Project\Research_LSTM_Tuner_Amazon
Showing 10 best trials
Objective(name="val_accuracy", direction="max")

Trial 08 summary
Hyperparameters:
num_layers: 0
units_final_LSTM: 80
dropout_rate: 0.2
learning_rate: 0.001
units_0: 80
units_1: 48
Score: 0.9189633727073669

Trial 06 summary
Hyperparameters:
num_layers: 2
units_final_LSTM: 64
dropout_rate: 0.5
learning_rate: 0.0001
units_0: 80
units_1: 16
Score: 0.9162931442260742

Trial 00 summary
```

```
Hyperparameters:
num_layers: 2
units_final_LSTM: 16
dropout_rate: 0.5
learning_rate: 0.001
units_0: 16
units_1: 16
Score: 0.9160666465759277

Trial 03 summary
Hyperparameters:
num_layers: 2
units_final_LSTM: 48
dropout_rate: 0.3
learning_rate: 0.0001
units_0: 48
units_1: 96
Score: 0.9157209396362305

Trial 09 summary
Hyperparameters:
num_layers: 2
units_final_LSTM: 48
dropout_rate: 0.2
learning_rate: 0.0001
units_0: 48
units_1: 16
Score: 0.9153037369251251

Trial 05 summary
Hyperparameters:
num_layers: 2
```

```
final_model_LSTM_google= tuner_LSTM_google.get_best_models()[0]    # Get the best LSTM model
```

```
final_model_LSTM_google.summary()                                  # Best LSTM summary
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 50, 300)           16278600

 lstm (LSTM)                 (None, 80)                121920

 dropout (Dropout)           (None, 80)                0

 dense (Dense)               (None, 1)                 81

=================================================================
Total params: 16,400,601
Trainable params: 122,001
Non-trainable params: 16,278,600
_________________________________________________________________
```

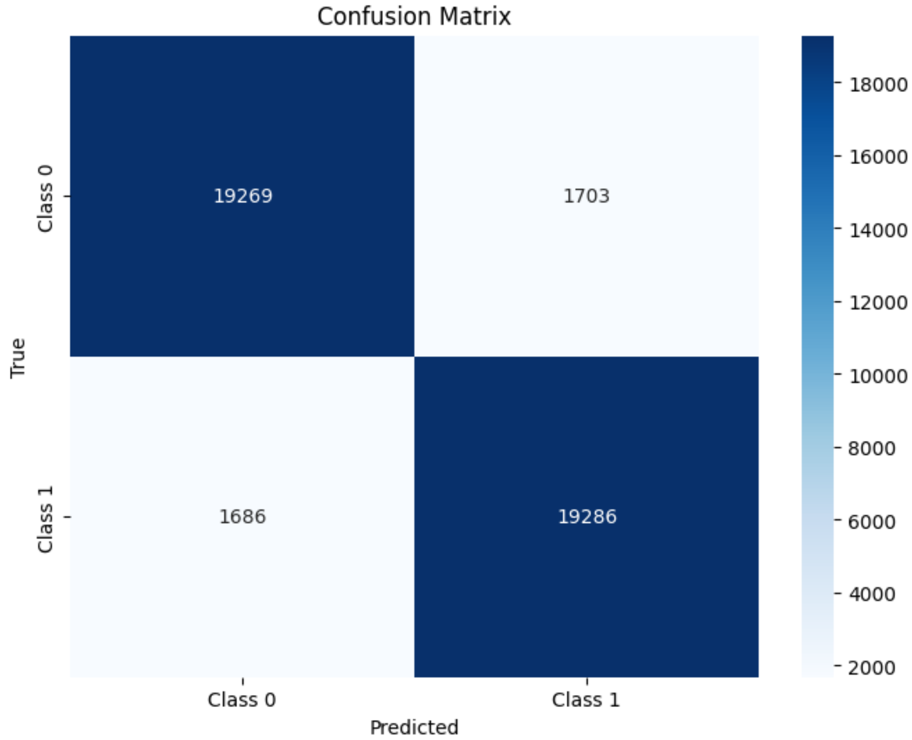
```
# Predict the test set using the best LSTM model trained using Google word embeddings

y_pred_LSTM=final_model_LSTM_google.predict(pad_reviews_test)
```

```
# Output predicted probabilities greater than 0.5 is pridicted to be positive and negative otherwise
```

```
for index,pred in enumerate(y_pred_LSTM):
    if pred>0.5:
        y_pred_LSTM[index]=1
    else:
        y_pred_LSTM[index]=0
```

```
# List of class labels
class_labels = ['Class 0', 'Class 1']

# Compute confusion matrix
cm = confusion_matrix(y_test,y_pred_LSTM, labels= [0,1])

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=class_labels, yticklabels=class_labels)
plt.xlabel('Predicted')
plt.ylabel('True')
```

```
plt.title('Confusion Matrix')
plt.show()
```



Classification report of best LSTM model trained using Google word embeddings

```
print(classification_report(y_test,y_pred_LSTM,digits=4))
```

```
              precision    recall  f1-score   support

           0     0.9195    0.9188    0.9192     20972
           1     0.9189    0.9196    0.9192     20972

    accuracy                         0.9192     41944
   macro avg     0.9192    0.9192    0.9192     41944
weighted avg     0.9192    0.9192    0.9192     41944
```

Neural Network trained using Custom trained Word2vec word embeddings

ANN

```
# ANN hypermodel is built to tune the hyperparameters
#The hyperparameters are defined and the number of layers and the number of neurons per layer,
# dropout rate and the learning rate of the optimizer are tuned.

def build_model_ANN_amazon(hp):

    model_ANN = keras.Sequential()

    model_ANN.add(Embedding(input_dim=vocab_size,
                    output_dim=embedd_dims,
                    input_length=max_review_len,
                    embeddings_initializer=Constant(embedd_matrix_amazon), # Set pre-trained vectors as initial weights
                    trainable=False))  # Keep the pre-trained weights fixed during training

    model_ANN.add(Flatten())

    for i in range(hp.Int('num_layers', 2, 20)):
        model_ANN.add(layers.Dense(units=hp.Int('units_' + str(i),
                                            min_value=32,
                                            max_value=512,
```

```
                                                step=32),
                                                activation='relu'))


    model_ANN.add(layers.Dropout(rate=hp.Choice('dropout_rate',[0.2,0.3,0.5])))

    model_ANN.add(layers.Dense(1, activation='sigmoid'))

    learning_rate = hp.Choice('learning_rate', [1e-2, 1e-3, 1e-4])

    model_ANN.compile(optimizer=Adam(learning_rate=learning_rate),
                                    loss='binary_crossentropy',
                                    metrics=['accuracy'])

    return model_ANN
```

```
build_model_ANN_amazon(keras_tuner.HyperParameters())
```

```
<keras.engine.sequential.Sequential at 0x1fd23b9d490>
```

```
# Keras Random search tuner is instantiated
```

```
tuner_ANN_amazon = keras_tuner.RandomSearch(hypermodel=build_model_ANN_amazon,
                                    objective="val_accuracy",
                                    max_trials=10,
                                    executions_per_trial=2,
                                    directory="Research_Project",
                                    project_name="Amazon_ANN_word2vec_new")
```

```
tuner_ANN_amazon.search_space_summary()
```

```
Search space summary
Default search space size: 5
num_layers (Int)
{'default': None, 'conditions': [], 'min_value': 2, 'max_value': 20, 'step': 1, 'sampling': 'linear'}
units_0 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step': 32, 'sampling': 'linear'}
units_1 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step': 32, 'sampling': 'linear'}
dropout_rate (Choice)
{'default': 0.2, 'conditions': [], 'values': [0.2, 0.3, 0.5], 'ordered': True}
learning_rate (Choice)
{'default': 0.01, 'conditions': [], 'values': [0.01, 0.001, 0.0001], 'ordered': True}
```

```
from tensorflow.keras.callbacks import EarlyStopping

# Define the early stopping callback
early_stopping = EarlyStopping(monitor='val_accuracy', patience=3, restore_best_weights=True)
```

```
tuner_ANN_amazon.search(pad_reviews_train, y_train,
                 epochs=50,
                 validation_data=(pad_reviews_test, y_test),
                 callbacks= [early_stopping])
```

```
Trial 10 Complete [00h 03m 43s]
val_accuracy: 0.5

Best val_accuracy So Far: 0.8795536756515503
Total elapsed time: 00h 35m 52s
INFO:tensorflow:Oracle triggered exit
```

```
tuner_ANN_amazon.results_summary()
```

```
Results summary
Results in Research_Project\Amazon_ANN_word2vec_new
Showing 10 best trials
Objective(name="val_accuracy", direction="max")

Trial 06 summary
Hyperparameters:
num_layers: 13
units_0: 448
units_1: 256
dropout_rate: 0.2
learning_rate: 0.0001
```

```
units_2: 64
units_3: 224
units_4: 320
units_5: 96
units_6: 32
units_7: 384
units_8: 32
units_9: 512
units_10: 32
units_11: 160
units_12: 128
units_13: 416
units_14: 480
units_15: 480
units_16: 224
units_17: 416
Score: 0.8795536756515503

Trial 01 summary
Hyperparameters:
num_layers: 2
units_0: 352
units_1: 384
dropout_rate: 0.3
learning_rate: 0.001
units_2: 448
units_3: 96
units_4: 288
units_5: 416
Score: 0.878635823726654

Trial 04 summary
Hyperparameters:
num_layers: 16
units_0: 288
units_1: 128
dropout_rate: 0.5
learning_rate: 0.0001
units_2: 320
units_3: 288
units_4: 384
units_5: 160
units_6: 96
units_7: 352
units_8: 160
units_9: 512
```

```
# Best ANN model tuned using the Custom trained word2vec word embeddings
```

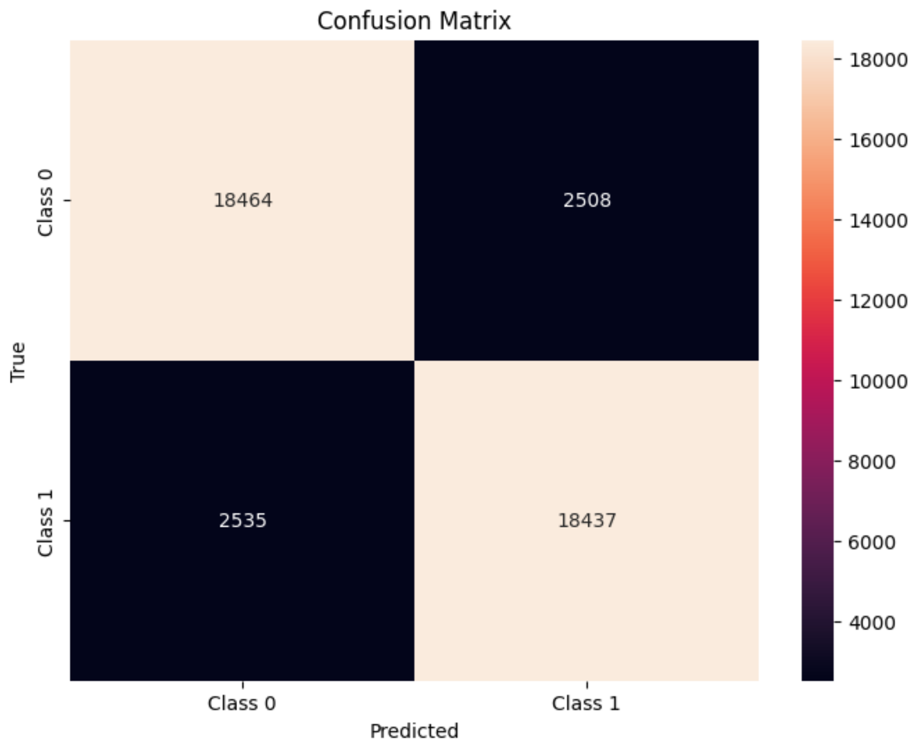
```
final_model_ANN_amazon= tuner_ANN_amazon.get_best_models()[0]
```

```
final_model_ANN_amazon.summary()                  # ANN model summary
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 50, 300)           16278600

 flatten (Flatten)           (None, 15000)             0

 dense (Dense)               (None, 448)               6720448

 dense_1 (Dense)             (None, 256)               114944

 dense_2 (Dense)             (None, 64)                16448

 dense_3 (Dense)             (None, 224)               14560

 dense_4 (Dense)             (None, 320)               72000

 dense_5 (Dense)             (None, 96)                30816

 dense_6 (Dense)             (None, 32)                3104

 dense_7 (Dense)             (None, 384)               12672

 dense_8 (Dense)             (None, 32)                12320

 dense_9 (Dense)             (None, 512)               16896

 dense_10 (Dense)            (None, 32)                16416
```

```
 dense_11 (Dense)            (None, 160)               5280

 dense_12 (Dense)            (None, 128)               20608

 dropout (Dropout)           (None, 128)               0

 dense_13 (Dense)            (None, 1)                 129

=================================================================
Total params: 23,335,241
Trainable params: 7,056,641
Non-trainable params: 16,278,600
_________________________________________________________________
```

```
# Predict the test set using best ANN model trained using custom word embeddings


y_pred_ANN= final_model_ANN_amazon.predict(pad_reviews_test)


# Output predicted probabilities greater than 0.5 is pridicted to be positive and negative otherwise

for index,pred in enumerate(y_pred_ANN):
    if pred>0.5:
        y_pred_ANN[index]=1
    else:
        y_pred_ANN[index]=0


# List of class labels
class_labels = ['Class 0', 'Class 1']

# Compute confusion matrix
cm = confusion_matrix(y_test,y_pred_ANN, labels= [0,1])

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d",  xticklabels=class_labels, yticklabels=class_labels)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



Classification Report ANN model trained using custom trained word embeddings

```
print(classification_report(y_test,y_pred_ANN, digits=4))
```

```
              precision    recall  f1-score   support

           0     0.8793    0.8804    0.8798     20972
           1     0.8803    0.8791    0.8797     20972

    accuracy                         0.8798     41944
   macro avg     0.8798    0.8798    0.8798     41944
weighted avg     0.8798    0.8798    0.8798     41944
```

LSTM Hyperparameter Tuning using custom trained word2vec word embeddings

The LSTM hypermodel is built which will tune the number of layers (max of 3 layers) and the number of memory cells per LSTM layer

```
from keras.layers import Dropout,LSTM

def build_model_LSTM_amazon(hp):

    model_LSTM = keras.Sequential()

    model_LSTM.add(Embedding(input_dim=vocab_size,
                             output_dim=embedd_dims,
                             input_length=max_review_len,
                    embeddings_initializer=Constant(embedd_matrix_amazon), # Set pre-trained vectors as initial weights
                    trainable=False))  # Keep the pre-trained weights fixed during training


    for i in range(0,hp.Int('num_layers', min_value=0, max_value=2, step=1)):

        model_LSTM.add(LSTM(units=hp.Int('units_' + str(i),              # Number of memory cells per layer ranging from
                                          min_value=16,                  # 16 to 96
                                          max_value=96,
                                          step=16),
                                          return_sequences=True))                # The hidden state sequences are returned
                                                                                 # for next layer


    model_LSTM.add(LSTM(units=hp.Int('units_final_LSTM',                         # final LSTM Layer
                                      min_value=16,
                                      max_value=96,
                                      step=16)))


    model_LSTM.add(layers.Dropout(rate=hp.Choice('dropout_rate',[0.2,0.3,0.5])))    # Dropout tuning to prevent model overfit

    model_LSTM.add(layers.Dense(1, activation='sigmoid'))

    learning_rate = hp.Choice('learning_rate', [1e-2, 1e-3, 1e-4])

    model_LSTM.compile(optimizer=Adam(learning_rate=learning_rate),
                                                 loss='binary_crossentropy',
                                                 metrics=['accuracy'])

    return model_LSTM


build_model_LSTM_amazon(keras_tuner.HyperParameters())
```

```
<keras.engine.sequential.Sequential at 0x14334b14e50>
```

```
tuner_LSTM_amazon = keras_tuner.RandomSearch(hypermodel=build_model_LSTM_amazon,
                                     objective="val_accuracy",
                                     max_trials=10,
                                     executions_per_trial=2,
                                     directory="Research_Project",
                                     project_name="Research_LSTM_Tuner_Amazon_Word2vec")


tuner_LSTM_amazon.search_space_summary()
```

```
Search space summary
Default search space size: 4
```