Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews)

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/ (https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/)

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [1]:
```
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os
```

```
C:\ProgramData\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWarning:
detected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [2]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data p
# you can change the number to any other number based on your computing power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIM
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 LIMIT

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a neg
def partition(x):
    if x < 3:
        return 0
    return 1

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (100000, 10)
```

Out[2]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominat
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	

In [3]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [4]:
```
print(display.shape)
display.head()
```

(80668, 7)

Out[4]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
0	#oc-R115TNMSPFT9I7	B005ZBZLT4	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ESG	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B005ZBZLT4	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ESG	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBEV0	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [5]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[5]:

	UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)
80638	AZY10LLTJ71NX	B001ATMQK2	undertheshrine "undertheshrine"	1296691200	5	I bought this 6 pack because for the price tha...	5

In [6]:
```
display['COUNT(*)'].sum()
```

Out[6]: 393063

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

In [7]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomir
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [8]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace
```

In [9]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, k
final.shape
```

Out[9]: (87775, 10)

In [10]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[10]: 87.775

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [11]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[11]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomir
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	

In [12]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [13]:
```
#Before starting the next phase of preprocessing lets see the number of entries le
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(87773, 10)
```

Out[13]:
```
1    73592
0    14181
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [14]:
```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[1000]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[1500]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[4900]
print(sent_4900)
print("="*50)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but th
ey are out there, but this one isnt.  Its too bad too because its a good produ
ct but I wont take any chances till they know what is going on with the china
imports.
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the candy
has little taste to it.  Very little of the 2 lbs that I bought were eaten and
I threw the rest away.  I would not buy the candy again.
==================================================
was way to hot for my blood, took a bite and did a jig  lol
==================================================
My dog LOVES these treats. They tend to have a very strong fish oil smell. So
if you are afraid of the fishy smell, don't get it. But I think my dog likes i
t because of the smell. These treats are really small in size. They are great
for training. You can give your dog several of these without worrying about hi
m over eating. Amazon's price was much more reasonable than any other retaile
r. You can buy a 1 pound bag on Amazon for almost the same price as a 6 ounce
bag at other retailers. It's definitely worth it to buy a big bag if your dog
eats them a lot.
==================================================
```

In [15]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
# sent_1000 = re.sub(r"http\S+", "", sent_1000)
# sent_150 = re.sub(r"http\S+", "", sent_1500)
# sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but th
ey are out there, but this one isnt.  Its too bad too because its a good produ
ct but I wont take any chances till they know what is going on with the china
imports.
```

In [16]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but th
ey are out there, but this one isnt.  Its too bad too because its a good produ
ct but I wont take any chances till they know what is going on with the china
imports.
==================================================
```

In [17]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [18]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
was way to hot for my blood, took a bite and did a jig  lol
==================================================
```

In [19]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but th
ey are out there, but this one isnt.  Its too bad too because its a good produ
ct but I wont take any chances till they know what is going on with the china
imports.
```

In [20]:
```
# remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
was way to hot for my blood took a bite and did a jig lol
```

In [21]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st ste

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ours
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'h
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that'
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has'
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because',
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'thr
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off'
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all',
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than',
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've"
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "did
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma',
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't
            'won', "won't", 'wouldn', "wouldn't"])
```

In [22]:
```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in st
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████████
█| 87773/87773 [00:40<00:00, 2147.00it/s]
```

In [23]:
```
preprocessed_reviews[100]
```

Out[23]:
```
'frenchbull given nylabone chew since weeks old safe strong bite not break larg
e pieces could choke dinosaur chew perfect many places hold bite dylabone produ
ct buy'
```

In [24]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [25]:
```
from sklearn.model_selection import train_test_split

print(type(final['Text']))
final['Text'] = preprocessed_reviews

# Created new feature TextLength (Length of Review) in our preprocessed data
final['TextLength'] = final['Text'].str.len()

X = final
Y = final['Score'].values

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3)

print(X_train.shape, Y_train.shape)
print(X_test.shape, Y_test.shape)
```

```
<class 'pandas.core.series.Series'>
(61441, 11) (61441,)
(26332, 11) (26332,)
```

[4] Featurization

[4.1] BAG OF WORDS

In [26]:
```
#BoW
from scipy.sparse import hstack

count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(X_train['Text'])
# print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

X_train_bow = count_vect.transform(X_train['Text'])
X_test_bow = count_vect.transform(X_test['Text'])

# Adding new feature Review Length to our featurized train and test data
X_train_bow=hstack([X_train_bow,np.matrix(X_train['TextLength'].values).reshape(X_
X_test_bow=hstack([X_test_bow,np.matrix(X_test['TextLength'].values).reshape(X_tes

# Adding new feature Review Length to list of features
feature_bow = count_vect.get_feature_names()
feature_bow.append('TextLength')

print("the type of count vectorizer ",type(X_train_bow))
print("the shape of out text BOW vectorizer ",X_train_bow.get_shape())
print("the number of unique words ", X_train_bow.get_shape()[1])
```

```
==================================================
the type of count vectorizer  <class 'scipy.sparse.coo.coo_matrix'>
the shape of out text BOW vectorizer  (61441, 46377)
the number of unique words  46377
```

[4.3] TF-IDF

In [27]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_train['Text'])
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_n
print('='*50)

X_train_tfidf = tf_idf_vect.transform(X_train['Text'])
X_test_tfidf = tf_idf_vect.transform(X_test['Text'])

# Adding new feature Review Length to our featurized train and test data
X_train_tfidf=hstack([X_train_tfidf,np.matrix(X_train['TextLength'].values).reshap
X_test_tfidf=hstack([X_test_tfidf,np.matrix(X_test['TextLength'].values).reshape(X

# Adding new feature Review Length to list of features
feature_tfidf = tf_idf_vect.get_feature_names()
feature_tfidf.append('TextLength')

final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of TFIDF vectorizer ",type(X_train_tfidf))
print("the shape of out text TFIDF vectorizer ",X_train_tfidf.get_shape())
print("the number of unique words including both unigrams and bigrams ", X_train_t
```

```
some sample features(unique words in the corpus) ['aa', 'aafco', 'abandoned',
'ability', 'able', 'able buy', 'able chew', 'able drink', 'able eat', 'able en
joy']
==================================================
the type of TFIDF vectorizer  <class 'scipy.sparse.coo.coo_matrix'>
the shape of out text TFIDF vectorizer  (61441, 36275)
the number of unique words including both unigrams and bigrams  36275
```

[4.4] Word2Vec

In [28]:
```
# Train your own Word2Vec model using your own text corpus
list_of_sentance_train=[]
for sentance in X_train['Text']:
    list_of_sentance_train.append(sentance.split())

w2v_model=Word2Vec(list_of_sentance_train,min_count=5,size=50, workers=2)
```

In [29]:
```
w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  14776
sample words  ['water', 'great', 'prefer', 'normal', 'flavor', 'passion', 'fru
it', 'version', 'good', 'stuff', 'workout', 'bike', 'ride', 'also', 'prevent',
'hangover', 'one', 'conclude', 'consumption', 'another', 'wake', 'seems', 'rep
lenish', 'necessary', 'minerals', 'etc', 'give', 'pleasant', 'recovery', 'pack
aging', 'boxes', 'simple', 'open', 'stay', 'cold', 'long', 'time', 'drawback',
'price', 'like', 'said', 'icing', 'happy', 'able', 'buy', 'online', 'family',
'favorite', 'shipped', 'arrived']
```

[4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

In [30]:
```
# average Word2Vec
# compute average word2vec for each review.
def avgw2v(list_of_sentance):
    sent_vectors = []; # the avg-w2v for each sentence/review is stored in this li
    for sent in tqdm(list_of_sentance): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might
        cnt_words =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in w2v_words:
                vec = w2v_model.wv[word]
                sent_vec += vec
                cnt_words += 1
        if cnt_words != 0:
            sent_vec /= cnt_words
        sent_vectors.append(sent_vec)
    return sent_vectors
```

In [31]:
```
sent_vectors_train = avgw2v(list_of_sentance_train)
print(len(sent_vectors_train[0]))
print(len(list_of_sentance_train))
```

```
100%|██████████████████████████████████████████████████
█| 61441/61441 [02:20<00:00, 436.41it/s]

50
61441
```

In [32]:
```
list_of_sentance_test=[]
for sentance in X_test['Text']:
    list_of_sentance_test.append(sentance.split())

sent_vectors_test = avgw2v(list_of_sentance_test)
print(len(sent_vectors_test))
print(len(sent_vectors_test[0]))
```

```
100%|██████████████████████████████████████████████████
█| 26332/26332 [01:03<00:00, 416.22it/s]

26332
50
```

[4.4.1.2] TFIDF weighted W2v

In [33]:
```
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))
```

In [34]:
```
# TF-IDF weighted Word2Vec
def tfidfw2v(list_of_sentance):
    tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
    # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val

    tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in
    row=0;
    for sent in tqdm(list_of_sentance): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length
        weight_sum =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in w2v_words and word in tfidf_feat:
                vec = w2v_model.wv[word]
    #           tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                # to reduce the computation we are
                # dictionary[word] = idf value of word in whole courpus
                # sent.count(word) = tf valeus of word in this review
                tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
        row += 1
    return tfidf_sent_vectors
```

In [35]:
```
tfidf_sent_vectors_train = tfidfw2v(list_of_sentance_train)
```

```
100%|
| 61441/61441 [31:13<00:00, 23.23it/s]
```

In [36]:
```
tfidf_sent_vectors_test = tfidfw2v(list_of_sentance_test)
```

```
100%|
| 26332/26332 [13:02<00:00, 25.65it/s]
```

[5] Assignment 9: Random Forests

[5.1] Applying RF

[5.1.1] Applying Random Forests on BOW, SET 1

In [37]:

```
%config IPCompleter.greedy=True
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, confusion_matrix
import seaborn as sns
# plot 3D Plotly
import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
```

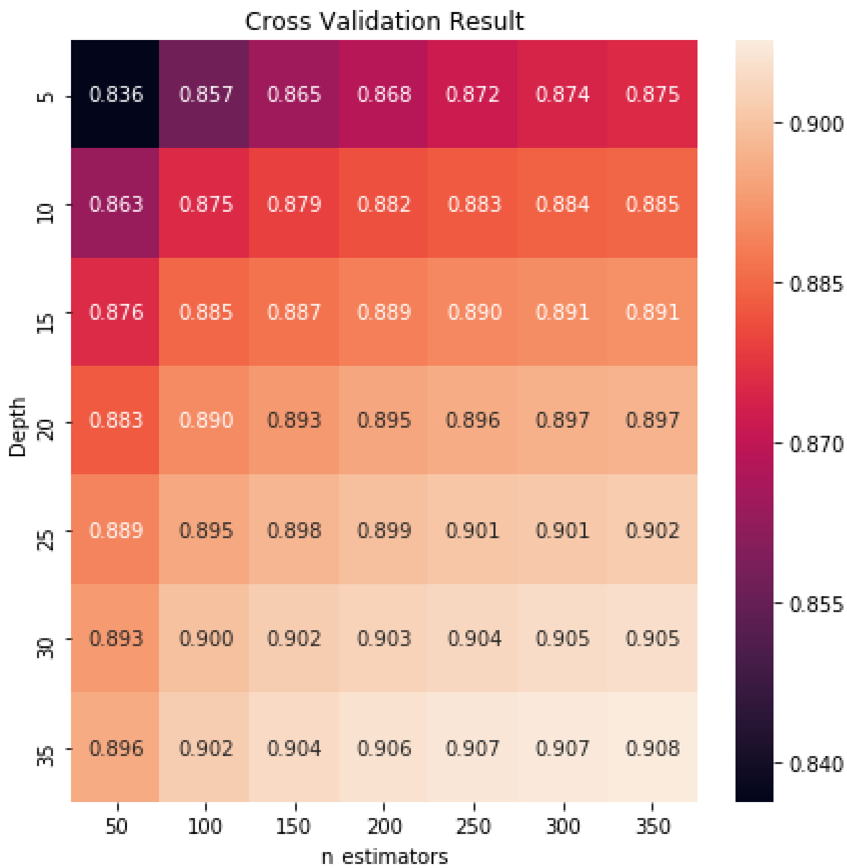
In [ ]:

```
# Plot 3rd graph for hyperparameters and AUC of train and test results
def D3_Plot(max_depth, base_learners, train_auc, test_auc):

    # https://plot.ly/python/3d-axes/
    train = go.Scatter3d(x=max_depth,y=base_learners,z=train_auc, name = 'train')
    test = go.Scatter3d(x=max_depth,y=base_learners,z=test_auc, name = 'Cross vali
    data = [train, test]

    layout = go.Layout(scene = dict(
            xaxis = dict(title='Max Depth'),
            yaxis = dict(title='Base_Learners'),
            zaxis = dict(title='AUC'),))

    fig = go.Figure(data=data, layout=layout)
    offline.iplot(fig, filename='3d-scatter-colorscale')
```

In [ ]:
```
def Get_Hyperparameters(X_train_vector):
    max_depth =  [5, 10, 15, 20, 25, 30, 35]
    base_learners =  [50, 100, 150, 200, 250, 300, 350]
    parameters = { 'max_depth' : max_depth, 'n_estimators' : base_learners}

    clf = RandomForestClassifier(random_state=0, n_jobs=-1)
    grid = GridSearchCV(clf, parameters, cv = 10, scoring='roc_auc')
    grid.fit(X_train_vector, Y_train)

    print("Best Estimator: ", grid.best_estimator_)
    print("Best param: ", grid.best_params_)
    print("Best Score: ", grid.best_score_)

    best_depth = grid.best_params_['max_depth']
    best_base_learner = grid.best_params_['n_estimators']

    train_auc= grid.cv_results_['mean_train_score']
    cv_auc = grid.cv_results_['mean_test_score']

    # Plot 3rd graph for hyperparameters and AUC of train and test results
    D3_Plot(max_depth, base_learners, train_auc, cv_auc)

    # Transform CV results(list of 100) to 10X10
    test_score = cv_auc.reshape(len(base_learners), len(max_depth))

    plt.figure(figsize=(7,7))
    sns.heatmap(test_score, annot=True, fmt=".3f", xticklabels=base_learners, ytic
    plt.xlabel("n_estimators")
    plt.ylabel("Depth")
    plt.title("Cross Validation Result")
    plt.show()
    return best_depth, best_base_learner
```

In [ ]:
```
best_max_depth_bow, best_base_learner_bow  = Get_Hyperparameters(X_train_bow)
```

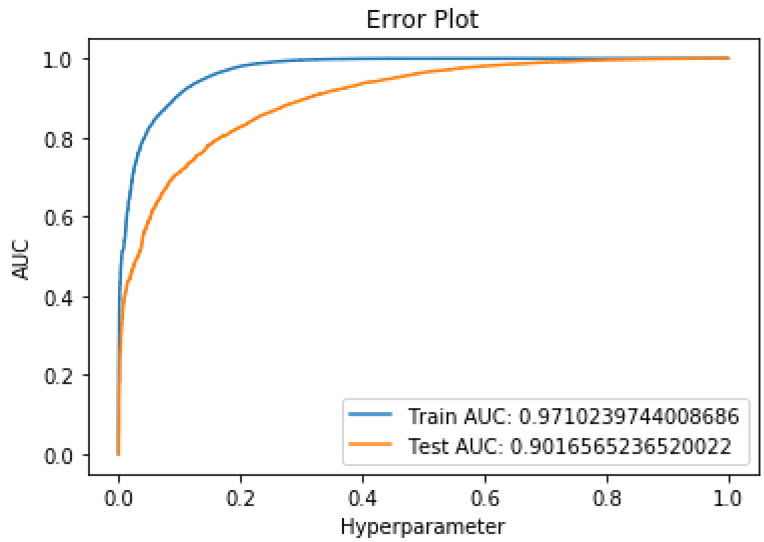
```
Best Estimator:  RandomForestClassifier(bootstrap=True, class_weight=None, cri
terion='gini',
            max_depth=35, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=350, n_jobs=-1,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
Best param:  {'max_depth': 35, 'n_estimators': 350}
Best Score:  0.9075509049081137
```

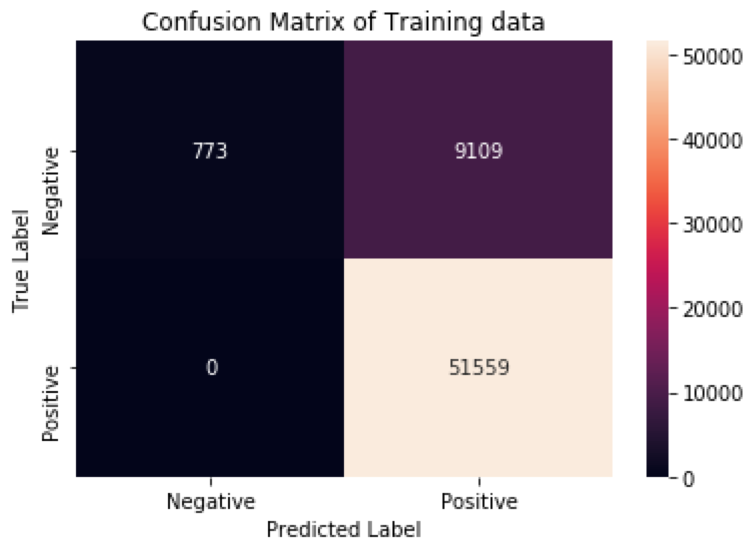


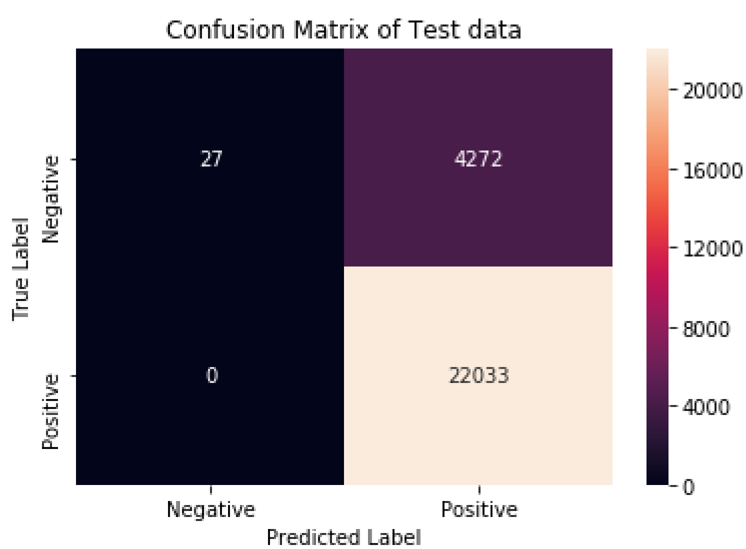
Cross Validation Result
Depth
n_estimators
5
10
15
20
25
30
35
50
100
150
200
250
300
350
0.836
0.857
0.865
0.868
0.872
0.874
0.875
0.863
0.875
0.879
0.882
0.883
0.884
0.885
0.876
0.885
0.887
0.889
0.890
0.891
0.891
0.883
0.890
0.893
0.895
0.896
0.897
0.897
0.889
0.895
0.898
0.899
0.901
0.901
0.902
0.893
0.900
0.902
0.903
0.904
0.905
0.905
0.896
0.902
0.904
0.906
0.907
0.907
0.908
0.900
0.885
0.870
0.855
0.840

In [ ]:
```
def RandomForest_Test(X_train_vector, X_test_vector, best_depth, best_base_learner

    clf = RandomForestClassifier(n_estimators = best_base_learner, max_depth=best_
    clf.fit(X_train_vector, Y_train)

    train_fpr, train_tpr, threshold = roc_curve(Y_train, clf.predict_log_proba(X_t
    test_fpr, test_tpr, threshold = roc_curve(Y_test, clf.predict_log_proba(X_test

    test_auc=auc(test_fpr,test_tpr)
    plt.plot(train_fpr, train_tpr, label="Train AUC: "+str(auc(train_fpr, train_tp
    plt.plot(test_fpr, test_tpr, label="Test AUC: "+str(test_auc))

    plt.legend()
    plt.xlabel("Hyperparameter")
    plt.ylabel("AUC")
    plt.title("Error Plot")
    plt.show()

    # Confusion Matrix of Training data
    class_labels = ['Negative', 'Positive']
    df_cm_train = pd.DataFrame(confusion_matrix(Y_train, clf.predict(X_train_vecto
    sns.heatmap(df_cm_train, annot=True, fmt="d")
    plt.title("Confusion Matrix of Training data")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()

    # Confusion Matrix of Test data
    df_cm_test = pd.DataFrame(confusion_matrix(Y_test, clf.predict(X_test_vector))
    sns.heatmap(df_cm_test, annot=True, fmt="d")
    plt.title("Confusion Matrix of Test data")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
    return test_auc, clf
```

In [ ]:
```
test_auc_bow, clf_bow = RandomForest_Test(X_train_bow, X_test_bow,
                                          best_max_depth_bow, best_base_learner_bo
```

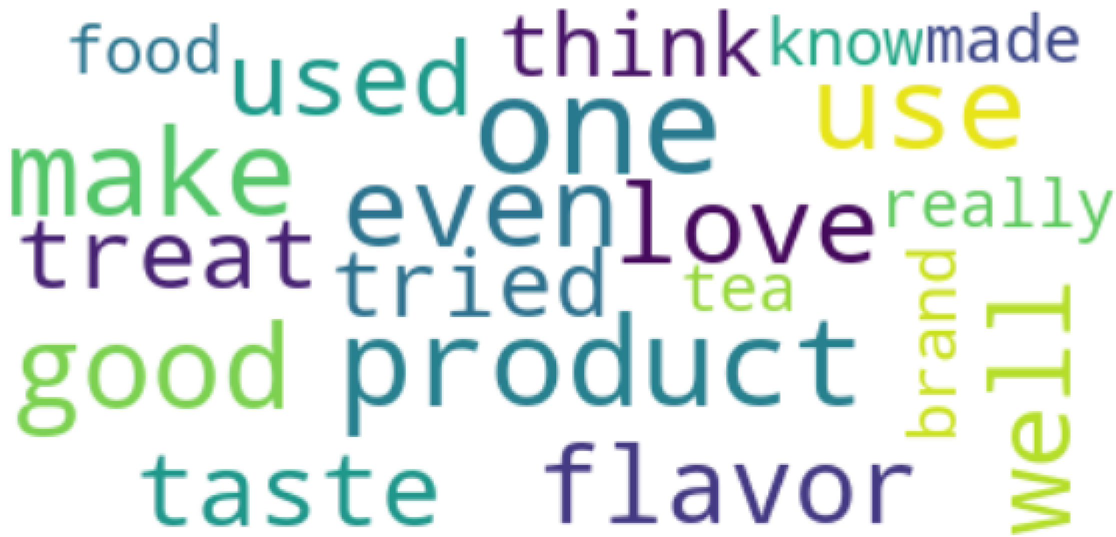






[5.1.2] Wordcloud of top 20 important features from SET 1

In [ ]:
```
from wordcloud import WordCloud

reviews = ' '.join(preprocessed_reviews)
wordcloud = WordCloud(max_font_size=50, max_words=20, background_color="white").ge
wordcloud.to_file("first_wordCloud.png")
plt.figure(figsize=(10,7))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()

features = count_vect.get_feature_names()
coefs = sorted(zip(clf_bow.feature_importances_, features))
n =20
top = coefs[:-(n+1):-1]

print("Top Features")
for (coef, feat) in top:
    print("%.4f\t%s" % (coef, feat))
```



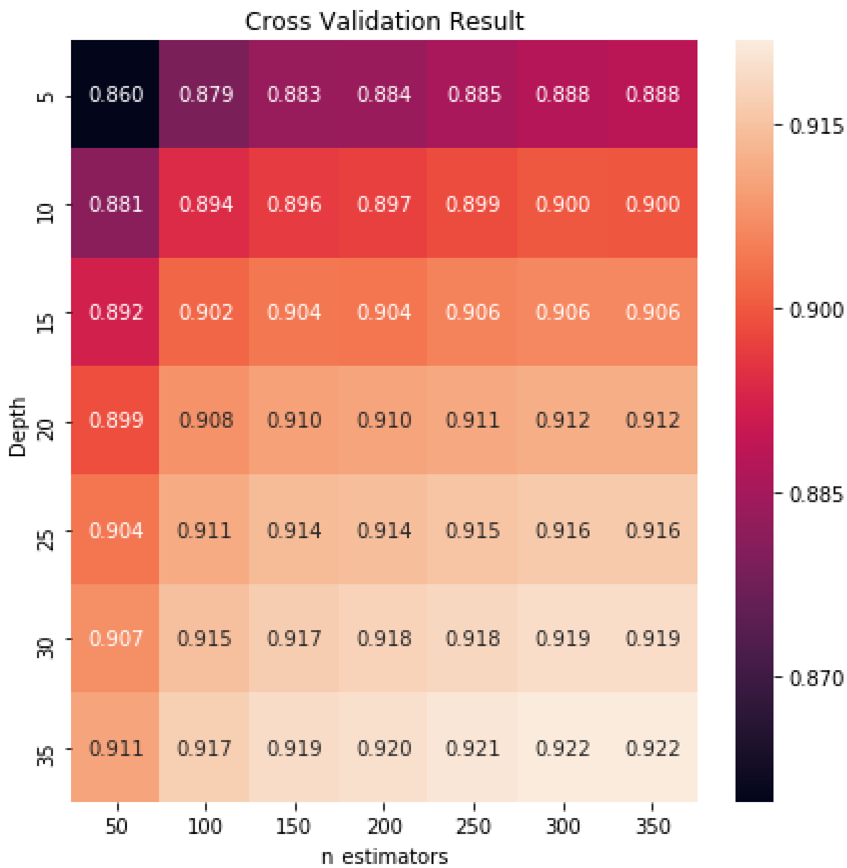

```
Top Features
0.0217	not
0.0144	disappointed
0.0138	great
0.0119	waste
0.0110	bad
0.0105	horrible
0.0089	awful
0.0087	threw
0.0086	return
0.0085	worst
0.0082	terrible
0.0079	money
0.0065	love
0.0062	would
0.0062	stale
0.0060	disappointing
0.0059	delicious
0.0057	refund
```

```
0.0057  disgusting
0.0055  best
```

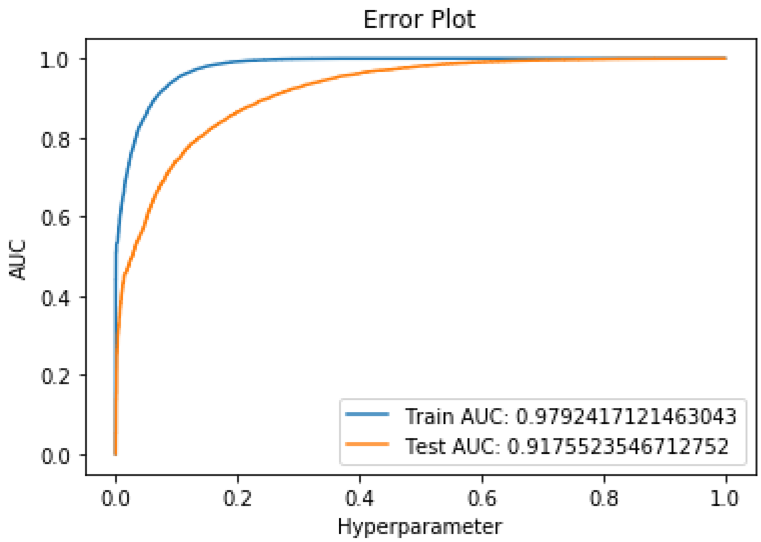
[5.1.3] Applying Random Forests on TFIDF, SET 2

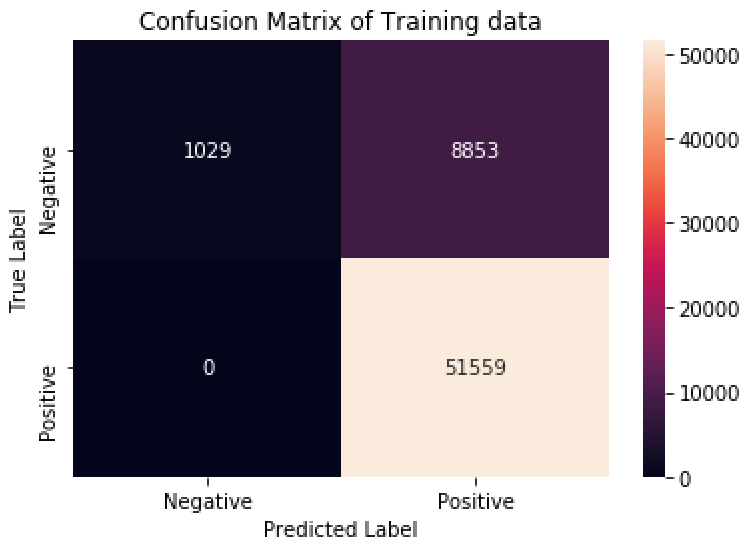
In [ ]:
```
best_max_depth_tfidf, best_base_learner_tfidf = Get_Hyperparameters(X_train_tfidf)
```

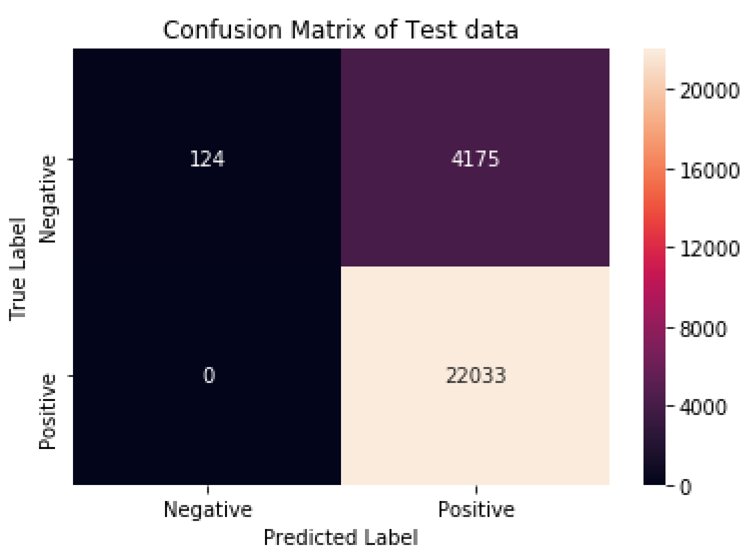
```
Best Estimator:  RandomForestClassifier(bootstrap=True, class_weight=None, cri
terion='gini',
            max_depth=35, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=350, n_jobs=-1,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
Best param:  {'max_depth': 35, 'n_estimators': 350}
Best Score:  0.9217492517636897
```


Cross Validation Result
Depth
n_estimators
5
10
15
20
25
30
35
50
100
150
200
250
300
350
0.860 0.879 0.883 0.884 0.885 0.888 0.888
0.881 0.894 0.896 0.897 0.899 0.900 0.900
0.892 0.902 0.904 0.904 0.906 0.906 0.906
0.899 0.908 0.910 0.910 0.911 0.912 0.912
0.904 0.911 0.914 0.914 0.915 0.916 0.916
0.907 0.915 0.917 0.918 0.918 0.919 0.919
0.911 0.917 0.919 0.920 0.921 0.922 0.922
0.915
0.900
0.885
0.870

In [ ]:
```
test_auc_tfidf, clf_tfidf = RandomForest_Test(X_train_tfidf, X_test_tfidf,
                                              best_max_depth_tfidf, best_base_lear
```

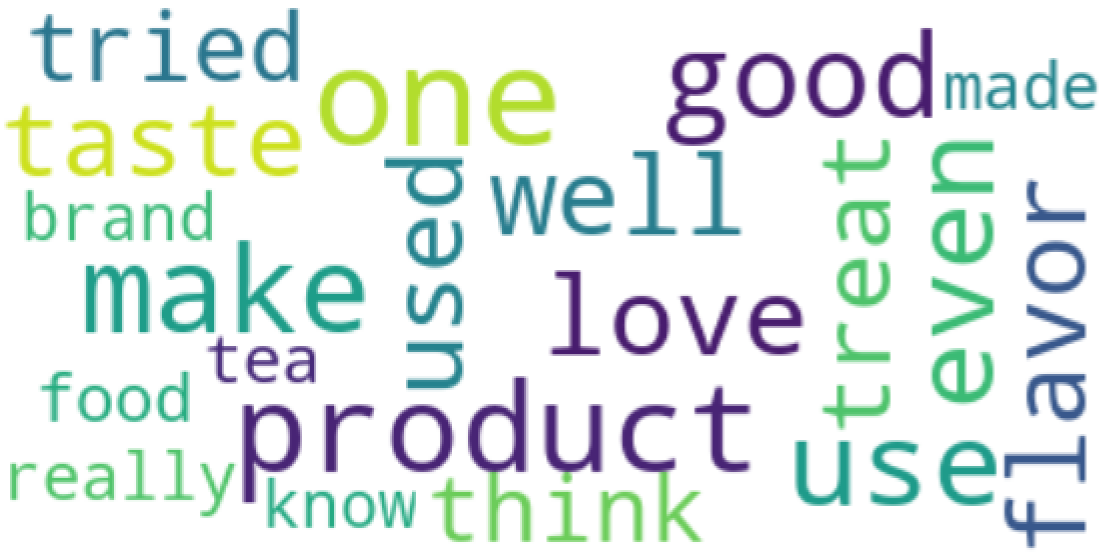






[5.1.4] Wordcloud of top 20 important features from SET 2

In [ ]:
```
reviews = ' '.join(preprocessed_reviews)
wordcloud = WordCloud(max_font_size=50, max_words=20, background_color="white").ge
wordcloud.to_file("first_wordCloud.png")
plt.figure(figsize=(10,7))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()

features = tf_idf_vect.get_feature_names()
coefs = sorted(zip(clf_tfidf.feature_importances_, features))
n =20
top = coefs[:-(n+1):-1]

print("Top Features")
for (coef, feat) in top:
    print("%.4f\t%s" % (coef, feat))
```

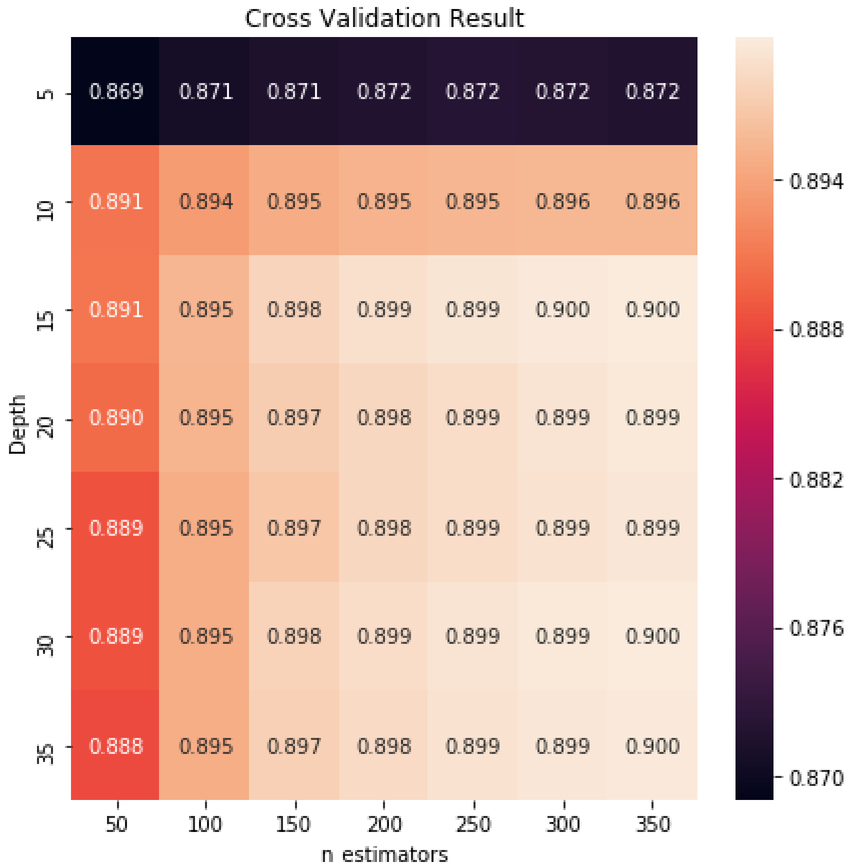



```
Top Features
0.0208  not
0.0130  great
0.0110  not buy
0.0107  worst
0.0104  disappointed
0.0100  horrible
0.0098  bad
0.0095  return
0.0090  waste money
0.0088  waste
0.0088  money
0.0083  awful
0.0080  not worth
0.0076  threw
0.0068  would not
0.0067  terrible
0.0064  disappointing
0.0058  stale
0.0057  not recommend
0.0056  thought
```

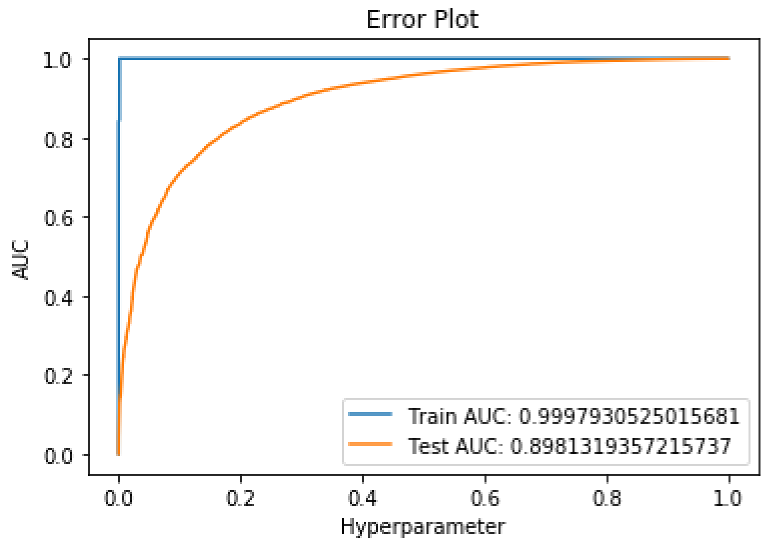
[5.1.5] Applying Random Forests on AVG W2V, SET 3

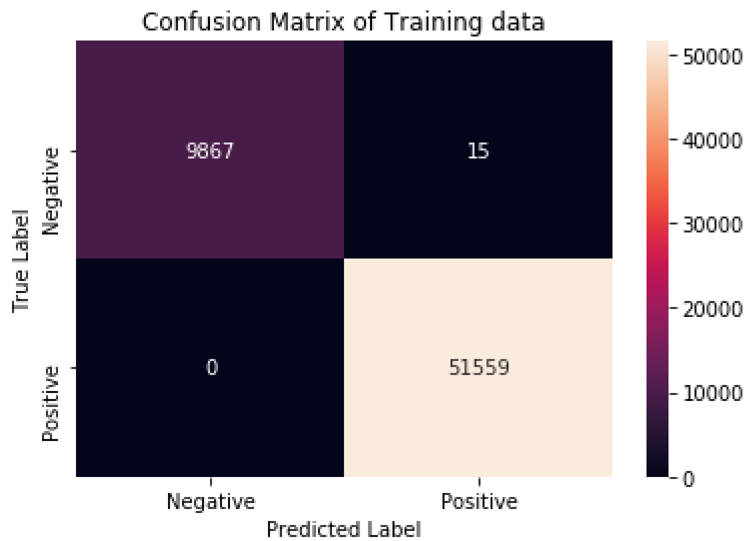
In [ ]:
```
best_max_depth_avgw2v, best_base_learner_avgw2v = Get_Hyperparameters(sent_vectors
```

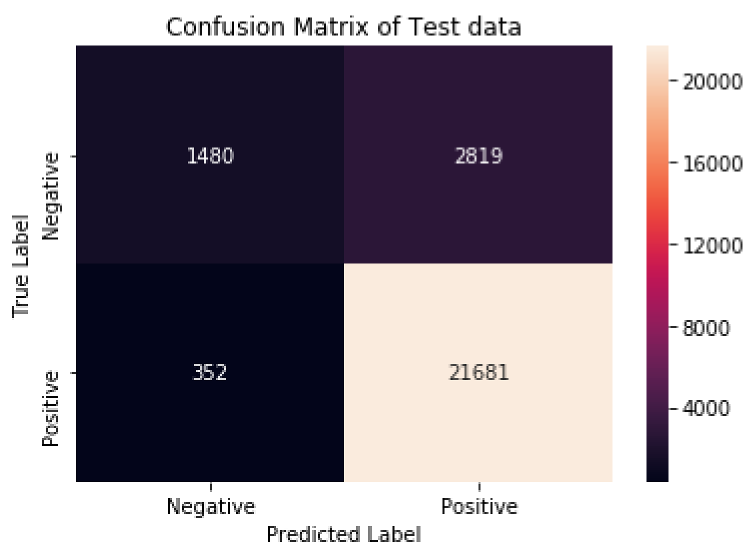
```
Best Estimator:  RandomForestClassifier(bootstrap=True, class_weight=None, cri
terion='gini',
            max_depth=30, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=350, n_jobs=-1,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
Best param:  {'max_depth': 30, 'n_estimators': 350}
Best Score:  0.8996990709338865
```


Cross Validation Result
Depth
5
10
15
20
25
30
35
0.869 0.871 0.871 0.872 0.872 0.872 0.872
0.891 0.894 0.895 0.895 0.895 0.896 0.896
0.891 0.895 0.898 0.899 0.899 0.900 0.900
0.890 0.895 0.897 0.898 0.899 0.899 0.899
0.889 0.895 0.897 0.898 0.899 0.899 0.899
0.889 0.895 0.898 0.899 0.899 0.899 0.900
0.888 0.895 0.897 0.898 0.899 0.899 0.900
50 100 150 200 250 300 350
n_estimators
0.894
0.888
0.882
0.876
0.870

In [ ]:
```
test_auc_avgw2v, clf_avgw2v = RandomForest_Test(sent_vectors_train, sent_vectors_t
                                                  best_max_depth_avgw2v, best_base_l
```



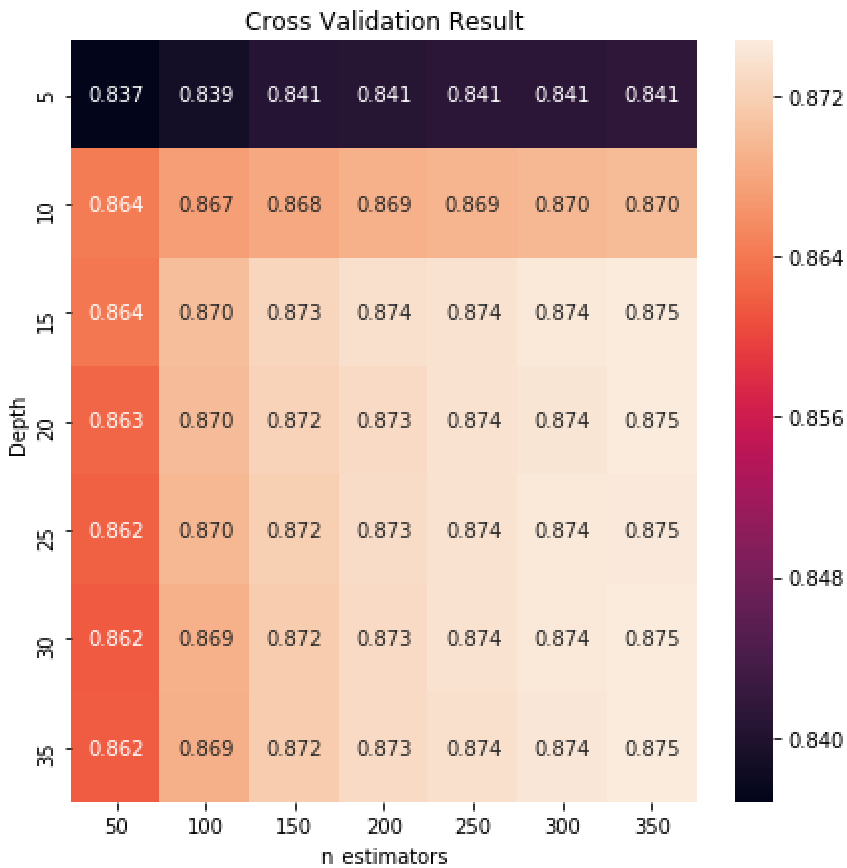




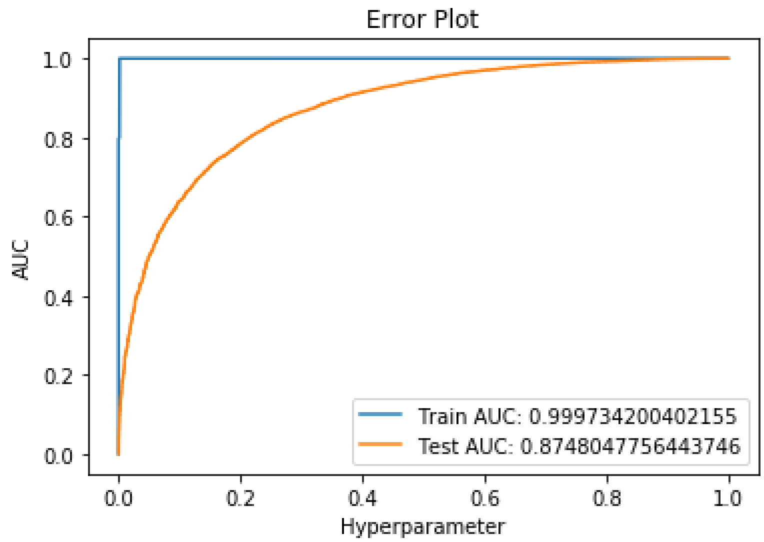
[5.1.6] Applying Random Forests on TFIDF W2V, SET 4

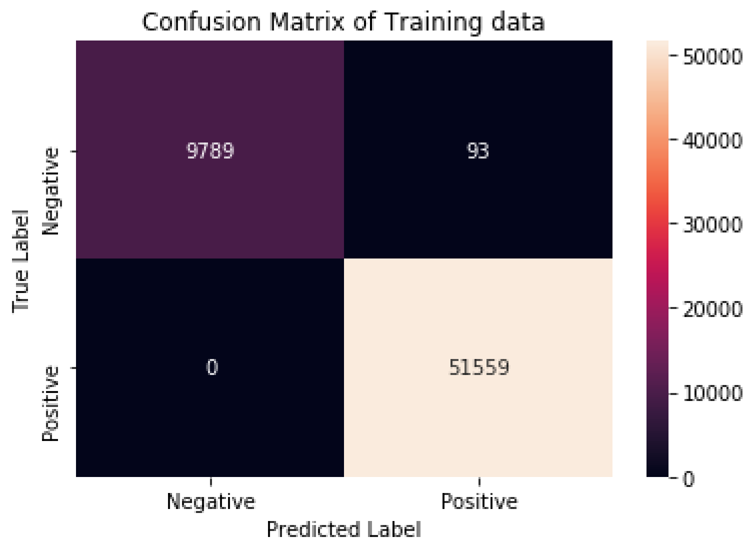
In [ ]:
```
best_max_depth_tfidfw2v, best_base_learner_tfidfw2v = Get_Hyperparameters(tfidf_se
```

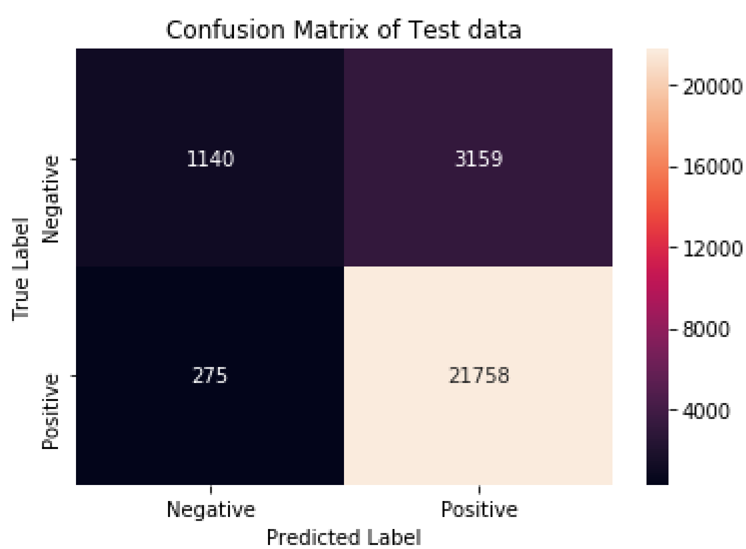
```
Best Estimator:  RandomForestClassifier(bootstrap=True, class_weight=None, cri
terion='gini',
            max_depth=20, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=350, n_jobs=-1,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
Best param:  {'max_depth': 20, 'n_estimators': 350}
Best Score:  0.8747279056599092
```


Cross Validation Result
Depth
5
10
15
20
25
30
35
n_estimators
50
100
150
200
250
300
350
0.837 0.839 0.841 0.841 0.841 0.841 0.841
0.864 0.867 0.868 0.869 0.869 0.870 0.870
0.864 0.870 0.873 0.874 0.874 0.874 0.875
0.863 0.870 0.872 0.873 0.874 0.874 0.875
0.862 0.870 0.872 0.873 0.874 0.874 0.875
0.862 0.869 0.872 0.873 0.874 0.874 0.875
0.862 0.869 0.872 0.873 0.874 0.874 0.875
0.872
0.864
0.856
0.848
0.840

In [ ]:
```
test_auc_tfidfw2v, clf_tfidfw2v = RandomForest_Test(tfidf_sent_vectors_train, tfid
                                                    best_max_depth_tfidfw2v, best_
```







[5.2] Applying GBDT using XGBOOST

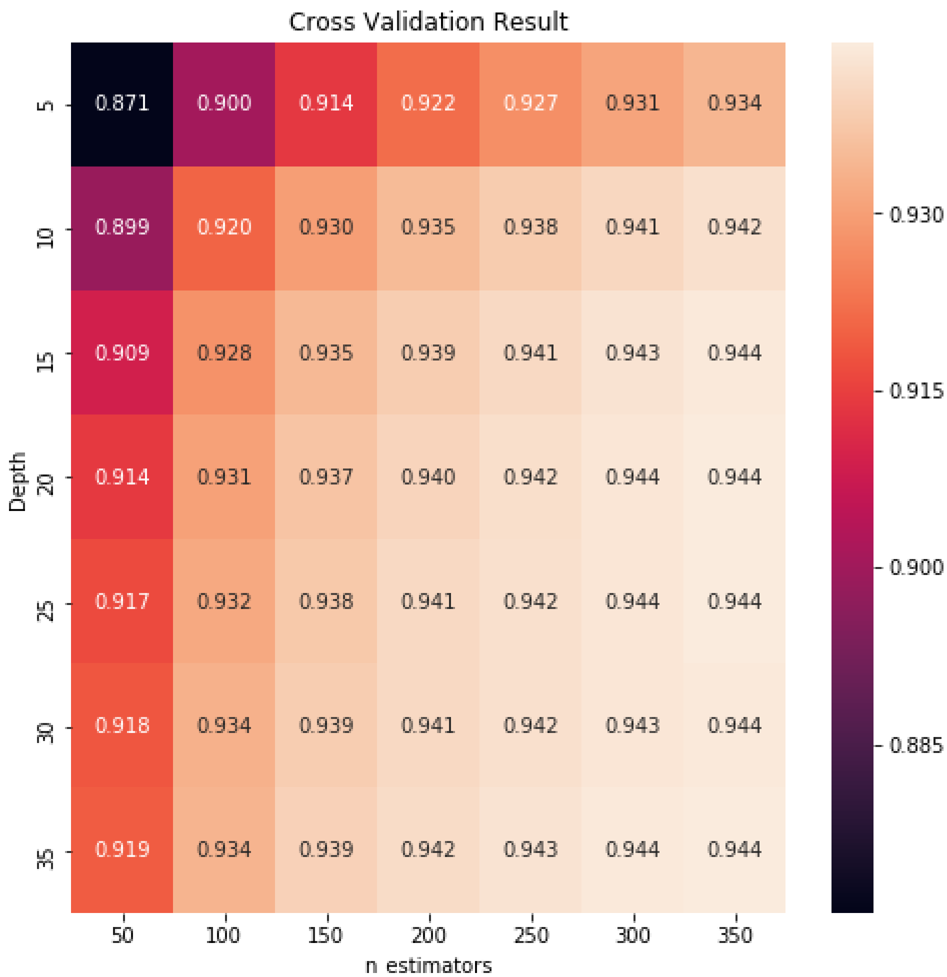
[5.2.1] Applying XGBOOST on BOW, SET 1

In [38]:
```
import warnings
warnings.filterwarnings('ignore')
from xgboost import XGBClassifier
# from sklearn.ensemble import GradientBoostingClassifier
```

In [39]:
```
def Get_Hyperparameters_GBDT(X_train_vector):
    max_depth =  [5, 10, 15, 20, 25, 30, 35]
    base_learners =  [50, 100, 150, 200, 250, 300, 350]
    parameters = { 'max_depth' : max_depth, 'n_estimators' : base_learners}

    clf = XGBClassifier(random_state=0, subsample=0.7, n_jobs=-1)
    grid = GridSearchCV(clf, parameters, cv = 10, scoring='roc_auc')
    grid.fit(X_train_vector, Y_train)

    print("Best Estimator: ", grid.best_estimator_)
    print("Best param: ", grid.best_params_)
    print("Best Score: ", grid.best_score_)

    best_depth = grid.best_params_['max_depth']
    best_base_learner = grid.best_params_['n_estimators']

    test_score = grid.cv_results_['mean_test_score'].reshape(len(base_learners), l

    plt.figure(figsize=(8,8))
    sns.heatmap(test_score, annot=True, fmt=".3f", xticklabels=base_learners, ytic
    plt.xlabel("n_estimators")
    plt.ylabel("Depth")
    plt.title("Cross Validation Result")
    plt.show()
    return best_depth, best_base_learner
```

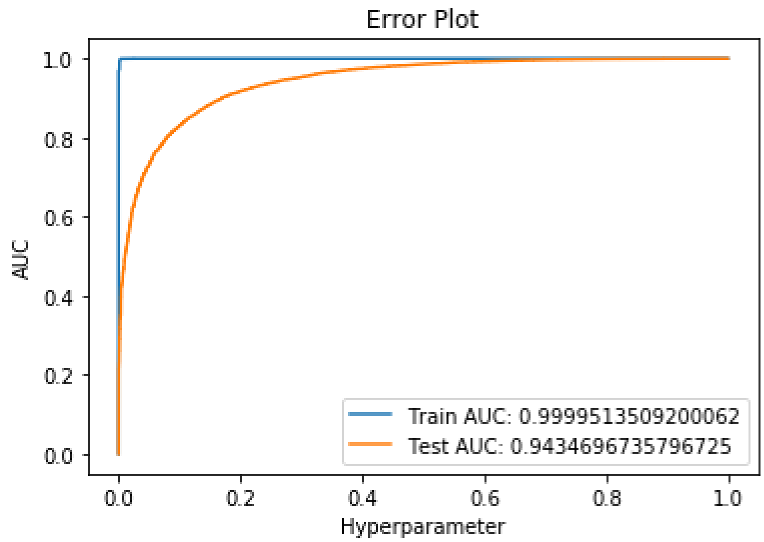
In [ ]:
```
best_depth_GBDT_bow, best_base_learner_GBDT_bow = Get_Hyperparameters_GBDT(X_train
```

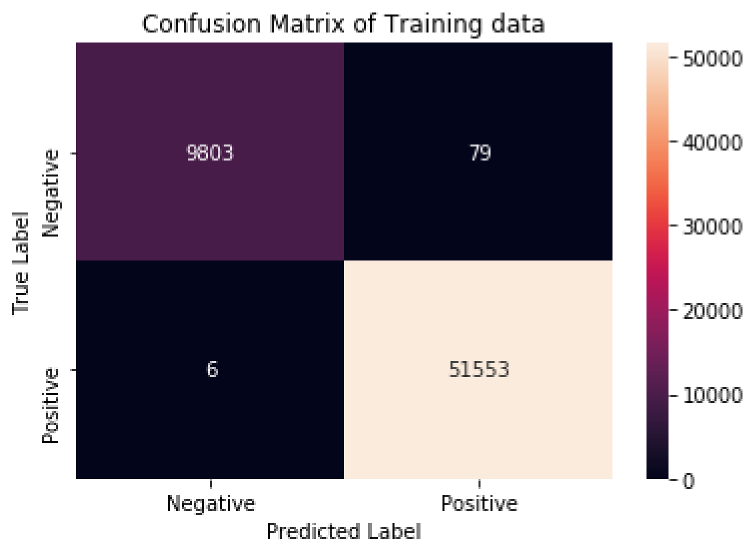
```
Best Estimator:  XGBClassifier(base_score=0.5, booster='gbtree', colsample_byl
evel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=35, min_child_weight=1, missing=None, n_estimators=350,
       n_jobs=-1, nthread=None, objective='binary:logistic',
       random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
       seed=None, silent=True, subsample=0.7)
Best param:  {'max_depth': 35, 'n_estimators': 350}
Best Score:  0.944460836463861
```

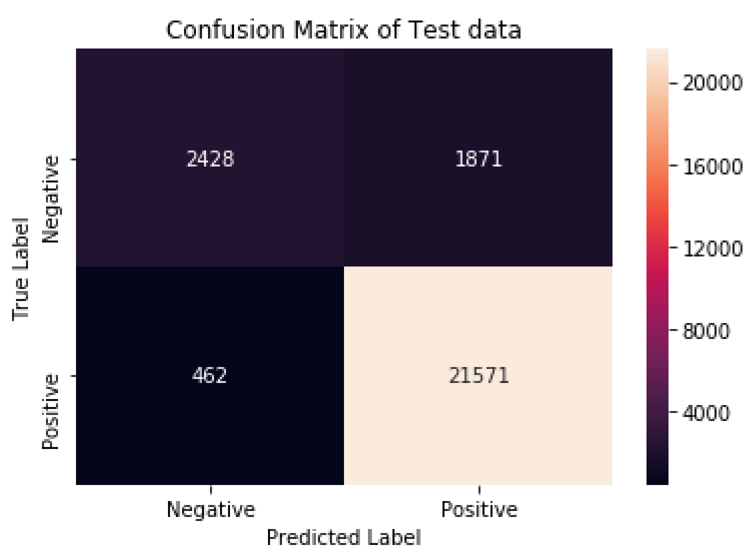


In [40]:
```
def GBDT_Test(X_train_vector, X_test_vector, best_depth, best_base_learner):

    clf = XGBClassifier(n_estimators = best_base_learner, max_depth=best_depth, ra
    clf.fit(X_train_vector, Y_train)

    train_fpr, train_tpr, threshold = roc_curve(Y_train, clf.predict_proba(X_train
    test_fpr, test_tpr, threshold = roc_curve(Y_test, clf.predict_proba(X_test_vec

    test_auc=auc(test_fpr,test_tpr)
    plt.plot(train_fpr, train_tpr, label="Train AUC: "+str(auc(train_fpr, train_tp
    plt.plot(test_fpr, test_tpr, label="Test AUC: "+str(test_auc))

    plt.legend()
    plt.xlabel("Hyperparameter")
    plt.ylabel("AUC")
    plt.title("Error Plot")
    plt.show()

    # Plotting confusion matrix to describe the performance of classifier
    # Confusion Matrix of Training data
    class_labels = ['Negative', 'Positive']
    df_cm_train = pd.DataFrame(confusion_matrix(Y_train, clf.predict(X_train_vecto
    sns.heatmap(df_cm_train, annot=True, fmt="d")
    plt.title("Confusion Matrix of Training data")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()

    # Confusion Matrix of Training data
    df_cm_test = pd.DataFrame(confusion_matrix(Y_test, clf.predict(X_test_vector))
    sns.heatmap(df_cm_test, annot=True, fmt="d")
    plt.title("Confusion Matrix of Test data")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
    return test_auc, clf
```

In [ ]:
```
test_auc_bow_GBDT, clf_bow_GBDT = GBDT_Test(X_train_bow, X_test_bow,
                                             best_depth_GBDT_bow, best_base_learner
```



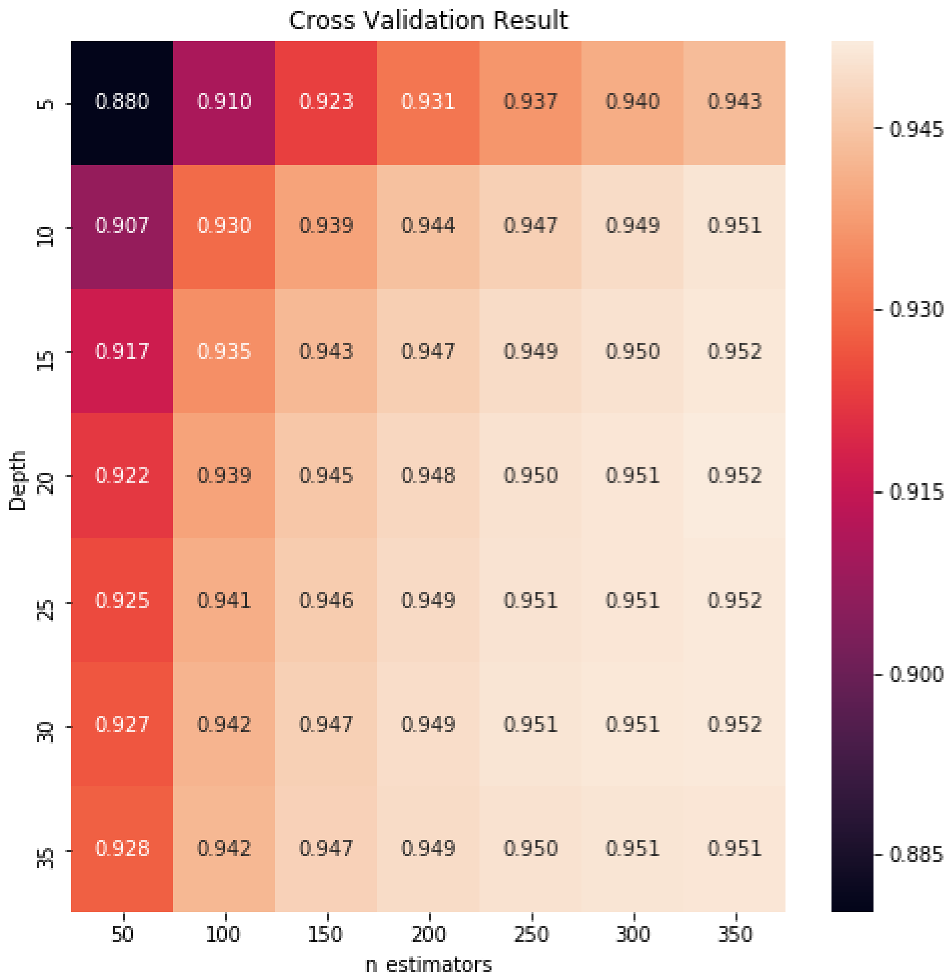




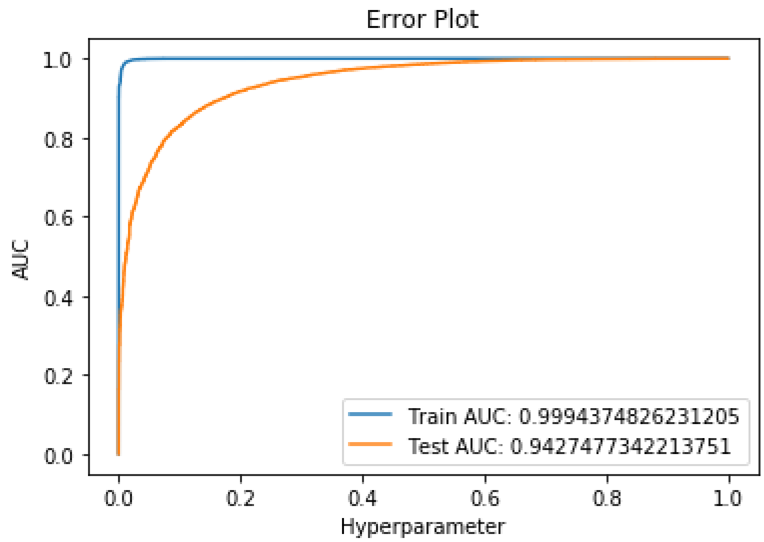
[5.2.2] Applying XGBOOST on TFIDF, SET 2

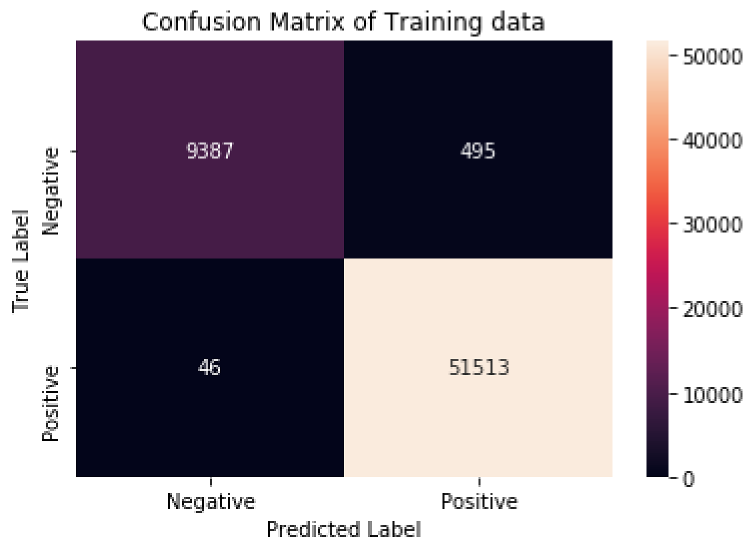
In [ ]:
```
best_depth_GBDT_tfidf, best_base_learner_GBDT_tfidf = Get_Hyperparameters_GBDT(X_t
```

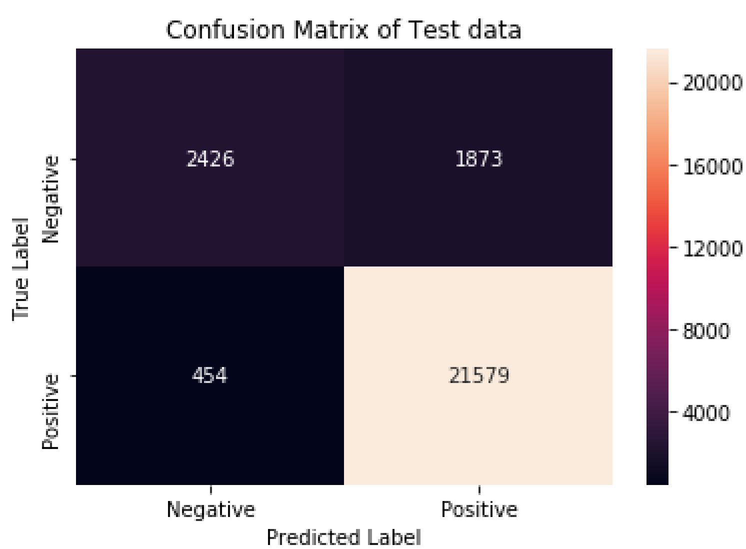
```
Best Estimator:  XGBClassifier(base_score=0.5, booster='gbtree', colsample_byl
evel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=20, min_child_weight=1, missing=None, n_estimators=350,
       n_jobs=-1, nthread=None, objective='binary:logistic',
       random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
       seed=None, silent=True, subsample=0.7)
Best param:  {'max_depth': 20, 'n_estimators': 350}
Best Score:  0.9521899745958528
```



In [ ]:
```
test_auc_tfidf_GBDT, clf_tfidf_GBDT = GBDT_Test(X_train_bow, X_test_bow,
                                                best_depth_GBDT_tfidf, best_base_l
```



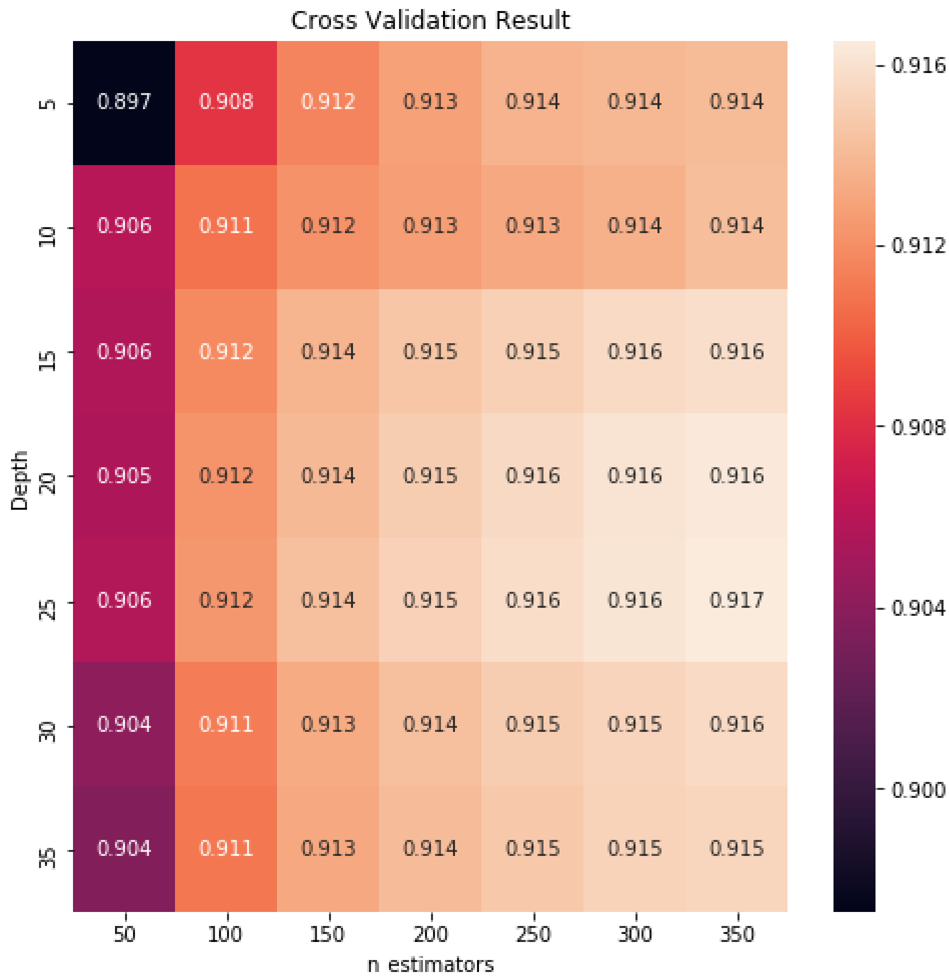




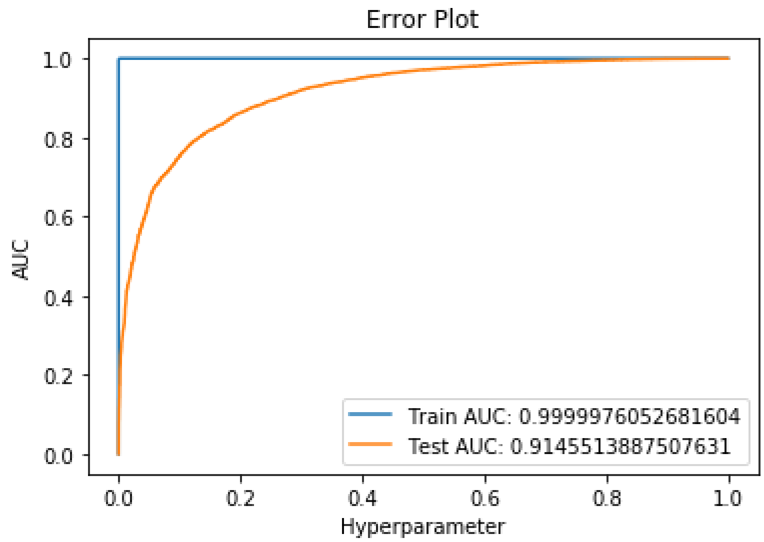
[5.2.3] Applying XGBOOST on AVG W2V, SET 3

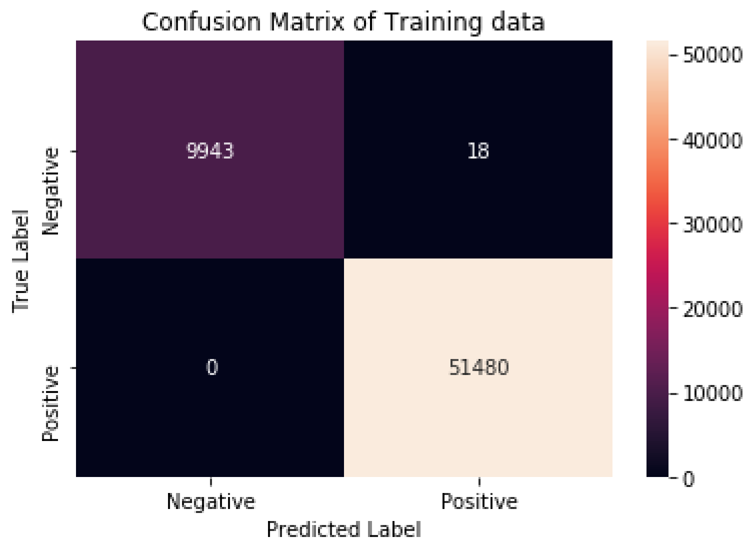
In [41]:
```
best_depth_GBDT_avgw2v, best_base_learner_GBDT_avgw2v = Get_Hyperparameters_GBDT(n
```

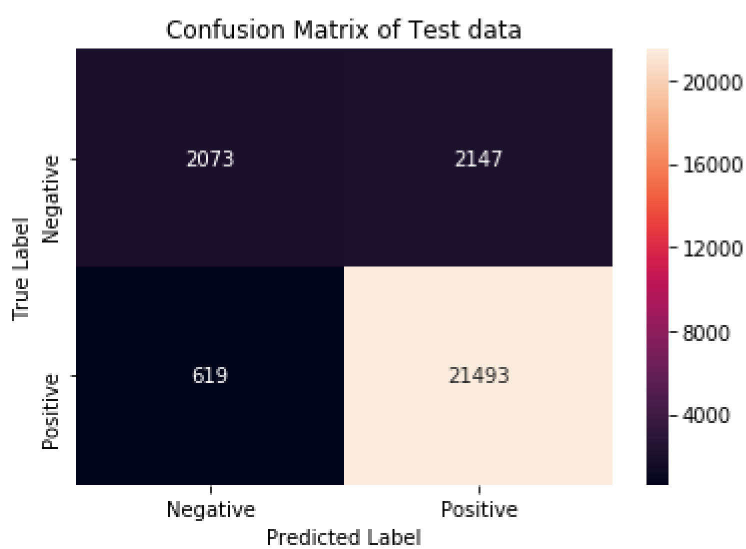
```
Best Estimator:  XGBClassifier(base_score=0.5, booster='gbtree', colsample_byl
evel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=25, min_child_weight=1, missing=None, n_estimators=350,
       n_jobs=-1, nthread=None, objective='binary:logistic',
       random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
       seed=None, silent=True, subsample=0.7)
Best param:  {'max_depth': 25, 'n_estimators': 350}
Best Score:  0.9165140139750995
```



In [42]:
```
test_auc_avgw2v_GBDT, clf_avgw2v_GBDT = GBDT_Test(np.array(sent_vectors_train), np
                                                   best_depth_GBDT_avgw2v, best_bas
```



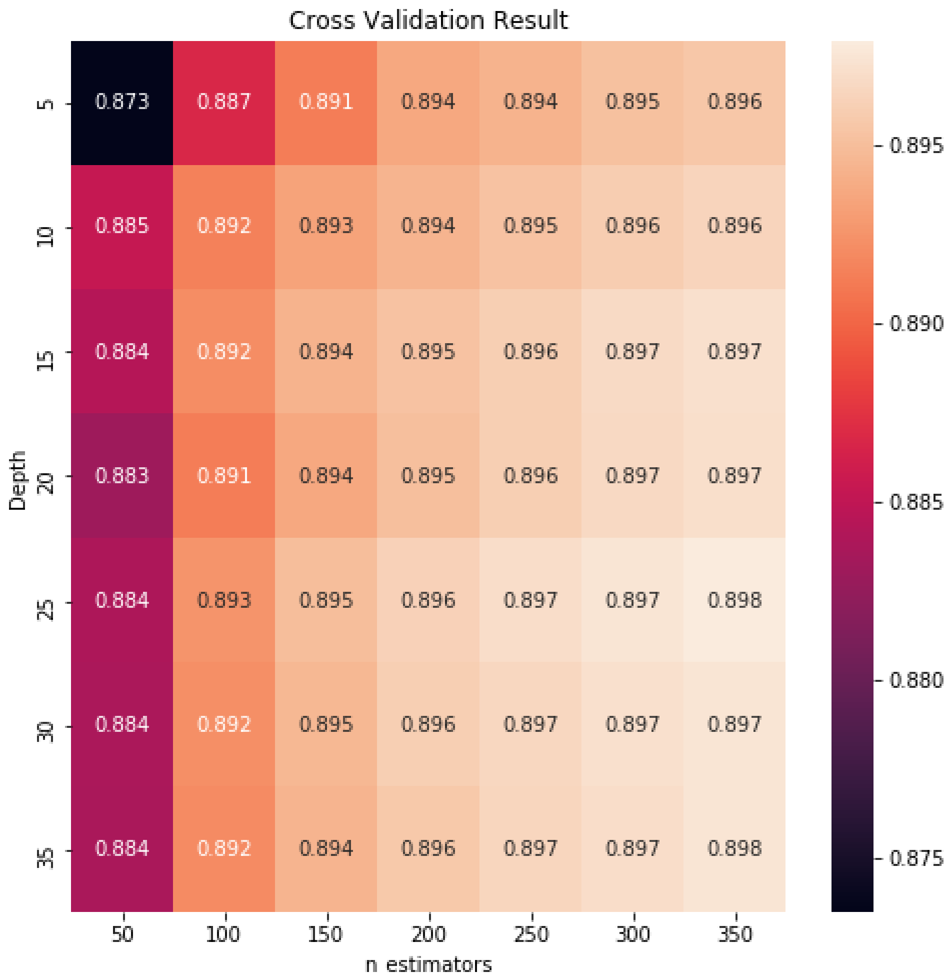




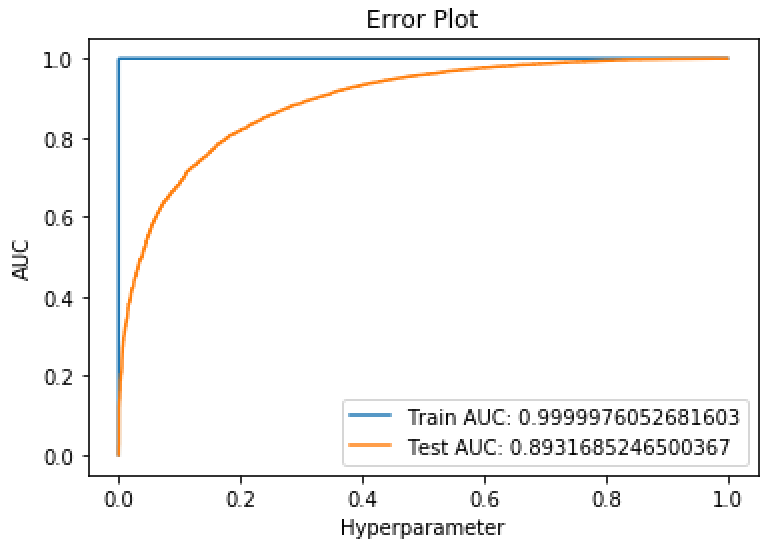
[5.2.4] Applying XGBOOST on TFIDF W2V, SET 4

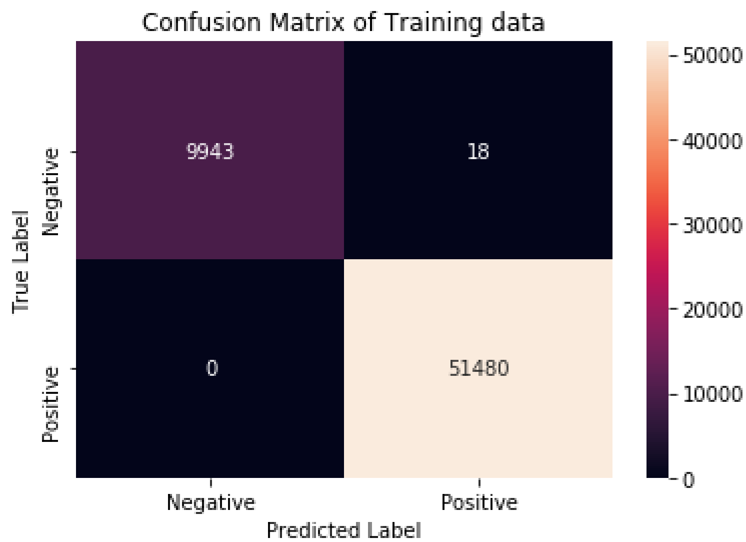
In [43]:
```
best_depth_GBDT_tfidfw2v, best_base_learner_GBDT_tfidfw2v = Get_Hyperparameters_GB
```

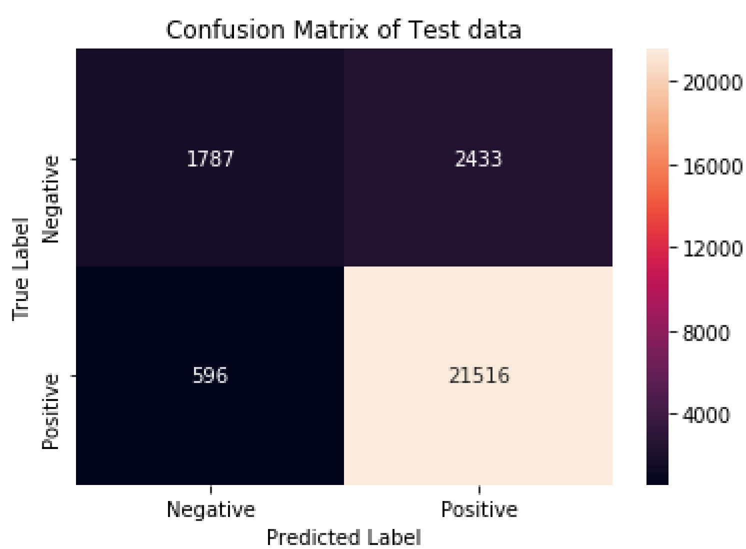
```
Best Estimator:  XGBClassifier(base_score=0.5, booster='gbtree', colsample_byl
evel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=25, min_child_weight=1, missing=None, n_estimators=350,
       n_jobs=-1, nthread=None, objective='binary:logistic',
       random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
       seed=None, silent=True, subsample=0.7)
Best param:  {'max_depth': 25, 'n_estimators': 350}
Best Score:  0.8979371596236952
```



In [44]:
```
test_auc_tfidfw2v_GBDT, clf_tfidfw2v_GBDT = GBDT_Test(np.array(tfidf_sent_vectors_
                                                    best_base_learner_GBDT_tfidf
```







[6] Conclusions

In [46]:
```
models = pd.DataFrame({
'Vectorizer': ["BOW", "TFIDF", "AVGW2V", "TFIDFW2V", "BOW", "TFIDF", "AVGW2V", "TF
'Model' : ['RandomForest', 'RandomForest', 'RandomForest', 'RandomForest', 'GBDT',
'Hyper Parameter(Max_Depth, BaseLearners)': [
    {'Depth': best_max_depth_bow, 'BaseLearners': best_base_learner_bow},
    {'Depth': best_max_depth_tfidf, 'BaseLearners': best_base_learner_tfidf},
    {'Depth': best_max_depth_avgw2v, 'BaseLearners': best_base_learner_avgw2v},
    {'Depth': best_max_depth_tfidfw2v, 'BaseLearners': best_base_learner_tfidfw2v}
    {'Depth': best_depth_GBDT_bow, 'BaseLearners': best_base_learner_GBDT_bow},
    {'Depth': best_depth_GBDT_tfidf, 'BaseLearners': best_base_learner_GBDT_tfidf}
    {'Depth': best_depth_GBDT_avgw2v, 'BaseLearners': best_base_learner_GBDT_avgw2
    {'Depth': best_depth_GBDT_tfidfw2v, 'BaseLearners': best_base_learner_GBDT_tfi
'AUC': [test_auc_bow, test_auc_tfidf, test_auc_avgw2v, test_auc_tfidfw2v,
       test_auc_bow_GBDT, test_auc_tfidf_GBDT, test_auc_avgw2v_GBDT, test_auc_tfid
columns = ["Vectorizer", "Model", "Hyper Parameter(Max_Depth, BaseLearners)", "AUC
print(models)
```

```
  Vectorizer         Model Hyper Parameter(Max_Depth, BaseLearners)       AUC
0        BOW  RandomForest       {'Depth': 35, 'BaseLearners': 350}  0.901000
1      TFIDF  RandomForest       {'Depth': 35, 'BaseLearners': 350}  0.917000
2     AVGW2V  RandomForest       {'Depth': 30, 'BaseLearners': 350}  0.898000
3   TFIDFW2V  RandomForest       {'Depth': 20, 'BaseLearners': 350}  0.874000
4        BOW          GBDT       {'Depth': 35, 'BaseLearners': 350}  0.943000
5      TFIDF          GBDT       {'Depth': 20, 'BaseLearners': 350}  0.942000
6     AVGW2V          GBDT       {'Depth': 25, 'BaseLearners': 350}  0.914551
7   TFIDFW2V          GBDT       {'Depth': 25, 'BaseLearners': 350}  0.893169
```

- Done the featurization of reviews using BOW, TFIDF, AVGW2V and TFIDF-W2V
- Created new feature of Review Length
- Define a function to get the optimized hyperparameters for maximum depth and number of base learners for all 4 featurization using cross-validation with GridSearchCV for both Random Forest (Bagging) and GBDT using XGBoost (Boosting).
- Define a function to plot 3D graph using plotly for hyperparamter and AUC (Train and Test)
- Created HeatMap for AUC using hyperparameter values
- Define a function to test Random Forest and GBDT on optimized/best hyperparameters for all 4 featurization and visually represent the errors vs hyperparameter plot.
- Used ROC-AUC and Confusion matrix as performance metric
- Calculated top 20 important features for BOW and TFIDF