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)

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:\Users\himateja\Anaconda3\lib\site-packages\gensim\utils.py:1209: UserWarnin
g: 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')


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

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a ne
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	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	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	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...	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, inplac
```

In [9]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},
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 l
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 [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 i
t anymore.  Its very hard to find any chicken products made in the USA but they
are out there, but this one isnt.  Its too bad too because its a good product b
ut I wont take any chances till they know what is going on with the china impor
ts.
```

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)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying i
t anymore.  Its very hard to find any chicken products made in the USA but they
are out there, but this one isnt.  Its too bad too because its a good product b
ut I wont take any chances till they know what is going on with the china impor
ts.
==================================================
The Candy Blocks were a nice visual for the Lego Birthday party but the candy h
as 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 i
f you are afraid of the fishy smell, don't get it. But I think my dog likes it
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 him ove
r eating. Amazon's price was much more reasonable than any other retailer. You
can buy a 1 pound bag on Amazon for almost the same price as a 6 ounce bag at o
ther retailers. It's definitely worth it to buy a big bag if your dog eats them
a lot.
```

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 i
t anymore.  Its very hard to find any chicken products made in the USA but they
are out there, but this one isnt.  Its too bad too because its a good product b
ut I wont take any chances till they know what is going on with the china impor
ts.
```

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 [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 s
    preprocessed_reviews.append(sentance.strip())
```

```
100%|
| 87773/87773 [00:27<00:00, 3155.39it/s]
```

In [23]:
```
preprocessed_reviews[1500]
```

Out[23]:
```
'way hot blood took bite jig lol'
```

In [24]:
```
score=final.Score
```

In [25]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(preprocessed_reviews, score, test_
```

In [26]:
```
from sklearn import preprocessing
```

[4] Featurization

[4.1] BAG OF WORDS

In [27]:
```
#BoW
count_vect = CountVectorizer() #in scikit-learn
count_vect.fit(preprocessed_reviews)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)

final_counts = count_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_counts))
print("the shape of out text BOW vectorizer ",final_counts.get_shape())
print("the number of unique words ", final_counts.get_shape()[1])
```

```
some feature names  ['aa', 'aaa', 'aaaa', 'aaaaa', 'aaaaaaaaaaa', 'aaaaaaaaaaa
aaaa', 'aaaaaaahhhhhh', 'aaaaaaarrrrrggghhh', 'aaaaaawwwwwwwww', 'aaaaah']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (87773, 54904)
the number of unique words  54904
```

[4.2] Bi-Grams and n-Grams.

In [28]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-grams
# count_vect = CountVectorizer(ngram_range=(1,2))

count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
final_bigram_counts = count_vect.fit_transform(x_train)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_bi
final_bigram_counts=preprocessing.normalize(final_bigram_counts)
bdata=count_vect.transform(x_test)
bdata=preprocessing.normalize(bdata)
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (61441, 5000)
the number of unique words including both unigrams and bigrams  5000
```

[4.3] TF-IDF

In [29]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tdata=tf_idf_vect.fit_transform(x_train)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_
print('='*50)
tdata=preprocessing.normalize(tdata)

tfdata = tf_idf_vect.transform(x_test)
tfdata=preprocessing.normalize(tfdata)
print("the type of count vectorizer ",type(tdata))
print("the shape of out text TFIDF vectorizer ",tdata.get_shape())
print("the number of unique words including both unigrams and bigrams ", tdata.ge
```

```
some sample features(unique words in the corpus) ['aa', 'aafco', 'abandon', 'ab
dominal', 'ability', 'able', 'able add', 'able buy', 'able chew', 'able drink']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (61441, 36016)
the number of unique words including both unigrams and bigrams  36016
```

[4.4] Word2Vec

In [30]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
for sentance in preprocessed_reviews:
    list_of_sentance.append(sentance.split())
```

In [31]:
```
is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative3
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v = Tr
```

```
[('awesome', 0.8636060357093811), ('fantastic', 0.8518376350402832), ('terrifi
c', 0.8369103670120239), ('good', 0.8147627115249634), ('excellent', 0.81009835
00480652), ('wonderful', 0.7717774510383606), ('amazing', 0.7569868564605713),
('perfect', 0.7361234426498413), ('fabulous', 0.7135833501815796), ('nice', 0.7
113245725631714)]
==================================================
[('greatest', 0.7951724529266357), ('best', 0.7134156823158264), ('tastiest',
0.7073570489883423), ('coolest', 0.674415111541748), ('disgusting', 0.671094119
5487976), ('smoothest', 0.6416438817977905), ('closest', 0.6190751194953918),
('horrible', 0.6067203283309937), ('nastiest', 0.5920047760009766), ('terribl
e', 0.5882911086082458)]
```

In [32]:
```
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  17386
sample words  ['dogs', 'loves', 'chicken', 'product', 'china', 'wont', 'buyin
g', 'anymore', 'hard', 'find', 'products', 'made', 'usa', 'one', 'isnt', 'bad',
'good', 'take', 'chances', 'till', 'know', 'going', 'imports', 'love', 'saw',
'pet', 'store', 'tag', 'attached', 'regarding', 'satisfied', 'safe', 'infestati
on', 'literally', 'everywhere', 'flying', 'around', 'kitchen', 'bought', 'hopin
g', 'least', 'get', 'rid', 'weeks', 'fly', 'stuck', 'squishing', 'buggers', 'su
ccess', 'rate']
```

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

[4.4.1.1] Avg W2v

In [33]:
```
 #average Word2Vec
# compute average word2vec for each review.
def avg(l):

    sent_vectors = []; # the avg-w2v for each sentence/review is stored in this l
    for sent in tqdm(l): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length 50, you migh
        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 np.matrix(sent_vectors)
```

In [34]:
```
x_1, x_test, y_1, y_test = train_test_split(list_of_sentance, score, test_size=0.
```

In [35]:
```
x_1=avg(x_1)
x_test=avg(x_test)
```

```
100%|
| 61441/61441 [01:45<00:00, 582.84it/s]
100%|
| 26332/26332 [00:48<00:00, 541.76it/s]
```

In [36]:
```
#changing nan values if any
atrain=np.nan_to_num(x_1)
atest=np.nan_to_num(x_test)
```

[4.4.1.2] TFIDF weighted W2v

In [37]:
```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(preprocessed_reviews)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [38]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = t

def tw2v(l,d,t=tfidf_feat):
    tfidf_sent_vectors = [] # the tfidf-w2v for each sentence/review is stored in
    row=0
    for sent in tqdm(l): # 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 t:
                vec = w2v_model.wv[word]
                tf_idf = tf_idf_matrix[row, t.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 = d[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 np.matrix(tfidf_sent_vectors)
```

In [39]:
```
x_1=tw2v(x_1,dictionary)
x_test=tw2v(x_test,dictionary)
```

```
100%|████████████████████████████████████████████████████████████████| 61441/61441 [31:39<00:00, 32.35it/s]
100%|████████████████████████████████████████████████████████████████| 26332/26332 [13:39<00:00, 32.14it/s]
```

In [40]:
```
# changing 'NaN' to numeric value
train=np.nan_to_num(x_1)
test=np.nan_to_num(x_test)
```

In [48]:
```
from sklearn.ensemble import RandomForestClassifier
#importing needed
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score as roc
import random
from sklearn.model_selection import RandomizedSearchCV
import scipy
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import GridSearchCV
```

In [170]:
```
#function for finding optimal parameters
def clfg(xtrain,ytrain,xtest,ytest):

    #using the gridsearchcv for finding the best c
    rf = RandomForestClassifier()
    n_estimators=[10,50,60,80,100,125,150]
    max_depth=[5,7,9,11,13,15,17]
    param_grid = {'n_estimators':[10,50,60,80,100,125,150],'max_depth':[5,7,9,11,
    #For time based splitting
    t = TimeSeriesSplit(n_splits=3)

    gsv = GridSearchCV(rf,param_grid,cv=t,n_jobs=-1,verbose=1,scoring="roc_auc")
    gsv.fit(xtrain,ytrain)
    print("Best HyperParameter: ",gsv.best_params_)
    #assinging best alpha to optimal print("Best Accuracy: %.2f%%"%(gsv.best_scor
    print("best estimator: ",gsv.estimator)
    #print("cv results :",gsv.cv_results_)

    es=gsv.best_params_['n_estimators']
    md=gsv.best_params_['max_depth']


    rf=RandomForestClassifier(n_estimators=es,max_depth=md)
    rf.fit(xtrain,ytrain)
    pred=rf.predict(xtest)
    #different metrics
    acc=accuracy_score(y_test,pred)*100
    print("\nthe accuracy is %.2f%%"%acc)

    re=recall_score(y_test,pred,) * 100
    print("\nthe recall is %.2f%%"%re)

    pre=precision_score(y_test,pred) * 100
    print("the precision is %.2f%%"%pre)

    f1=f1_score(y_test,pred) * 100
    print("the f1 score is %.2f%%"%f1)

    df_cm=pd.DataFrame(confusion_matrix(y_test,pred))
    #sns.set(font_scale=1.4)
    sns.heatmap(df_cm,annot=True,fmt="d")

    print('\n\n')
    plt.figure(figsize=(8, 6))
    scores = gsv.cv_results_['mean_test_score'].reshape(len(n_estimators),len(max_
    testing = sns.heatmap(scores, annot=True)

    plt.xlabel('n_estimators')
    plt.ylabel('max_depth')

    plt.xticks(np.arange(len(n_estimators)), n_estimators, rotation=45)
    plt.yticks(np.arange(len(max_depth)), max_depth)
    plt.title('Cross Validation accuracy')
    plt.show()
```

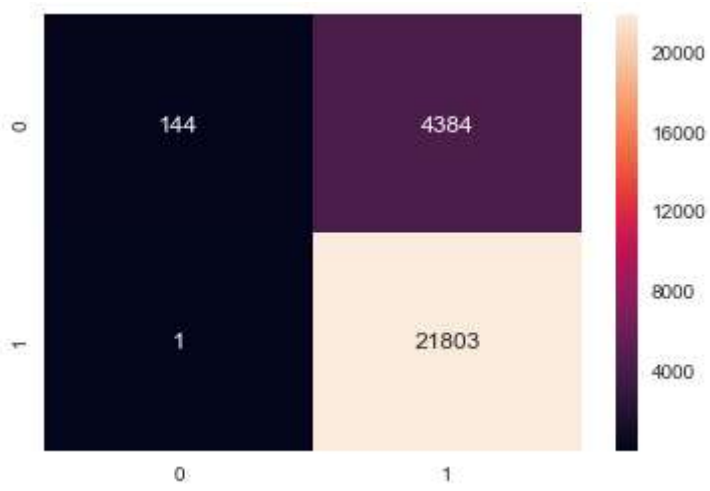
[5.1] Applying RF

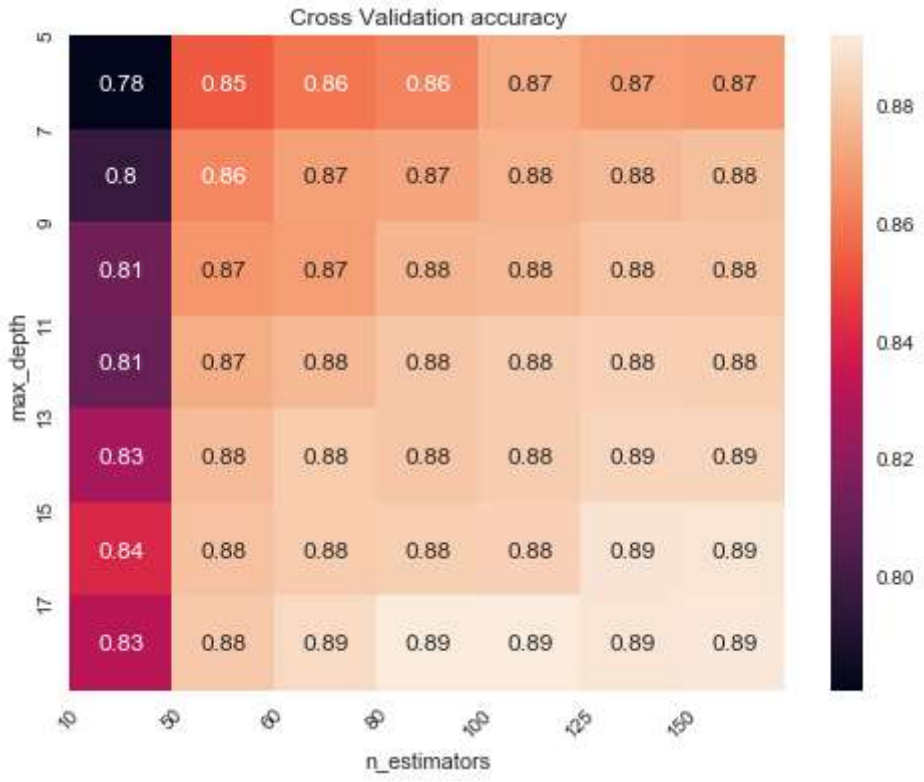
[5.1.1] Applying Random Forests on BOW

In [171]:
```
# Please write all the code with proper documentation
```

In [172]:
```
%%time
clfg(final_bigram_counts,y_train,bdata,y_test)
```

```
Fitting 3 folds for each of 49 candidates, totalling 147 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   19.8s
[Parallel(n_jobs=-1)]: Done 147 out of 147 | elapsed:  1.8min finished

Best HyperParameter:  {'max_depth': 17, 'n_estimators': 100}
best estimator:  RandomForestClassifier(bootstrap=True, class_weight=None, crit
erion='gini',
            max_depth=None, 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=10, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

the accuracy is 83.35%

the recall is 100.00%
the precision is 83.26%
the f1 score is 90.86%
```






```
Wall time: 2min 6s
```

[5.1.2] Wordcloud of top 20 important features

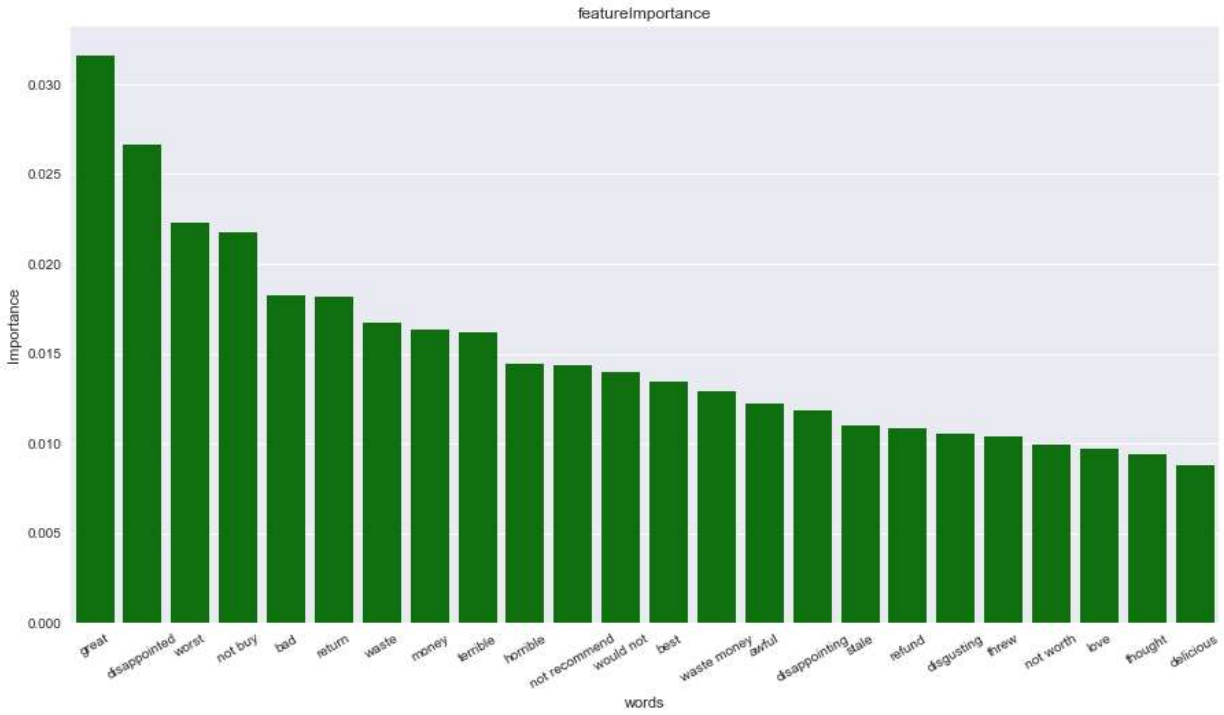
In [173]:
```
# Please write all the code with proper documentation
```

In [174]:
```
rrf=RandomForestClassifier(n_estimators=150,max_depth=15)
rrf.fit(final_bigram_counts,y_train)
```

Out[174]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=15, 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=150, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [175]:
```
all_feat=count_vect.get_feature_names()
```

In [176]:
```
imp_features = rrf.feature_importances_

# sorting the weight indices
imp_sorted =  np.argsort(imp_features)[::-1]

# top features
imp = np.take(all_feat, imp_sorted[1:25])
val = np.take(imp_features, imp_sorted[1:25])
#plotting
sns.set()
plt.figure(figsize=(15, 8))
imp_plot = sns.barplot(imp, val, color="green")
imp_plot.set_xticklabels(imp, rotation=30)
plt.ylabel('Importance')
plt.xlabel('words')
plt.title('featureImportance')
plt.show()
```



In [177]:
```
#wordcloud formation
from wordcloud import WordCloud,STOPWORDS
impo=list(imp)
imp_text=" ".join(impo)
cloud=WordCloud().generate(imp_text)
plt.figure(figsize=(8,8))
plt.imshow(cloud)
plt.grid(False)
plt.axis('off')
plt.show()
```

The model performed decent.

[5.1.3] Applying Random Forests on TFIDF

In [178]:
```
# Please write all the code with proper documentation
```

In [180]:
```
%%time
clfg(tdata,y_train,tfdata,y_test)
```

```
Fitting 3 folds for each of 49 candidates, totalling 147 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   24.8s
[Parallel(n_jobs=-1)]: Done 147 out of 147 | elapsed:  2.2min finished

Best HyperParameter:  {'max_depth': 17, 'n_estimators': 125}
best estimator:  RandomForestClassifier(bootstrap=True, class_weight=None, crit
erion='gini',
            max_depth=None, 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=10, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

the accuracy is 82.83%

the recall is 100.00%
the precision is 82.82%
the f1 score is 90.60%
```


```
Wall time: 2min 23s
```

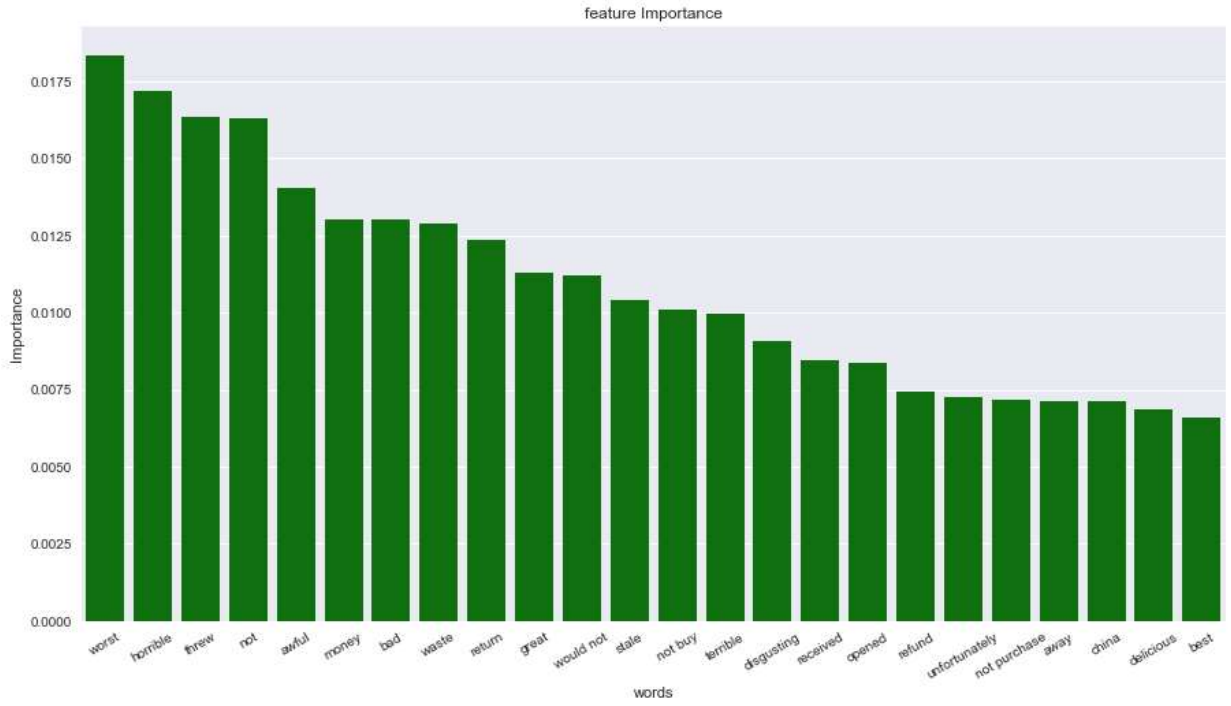
[5.1.4] Wordcloud of top 20 important features

In [0]:
```
# Please write all the code with proper documentation
```

In [181]:
```
rrf=RandomForestClassifier(n_estimators=125,max_depth=15)
rrf.fit(tdata,y_train)
```

Out[181]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=15, 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=125, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [183]:
```
all_feat=tf_idf_vect.get_feature_names()
imp_features = rrf.feature_importances_

# sorting the weight indices
imp_sorted =  np.argsort(imp_features)[::-1]

# top features
imp = np.take(all_feat, imp_sorted[1:25])
val = np.take(imp_features, imp_sorted[1:25])

# plotting
sns.set()
plt.figure(figsize=(15, 8))
imp_plot = sns.barplot(imp, val, color="green")
imp_plot.set_xticklabels(imp, rotation=30)
plt.ylabel('Importance')
plt.xlabel('words')
plt.title('feature Importance')
plt.show()
```



In [184]:
```
#forming wordcloud
impo=list(imp)
imp_text=" ".join(impo)
cloud=WordCloud().generate(imp_text)
plt.figure(figsize=(8,8))
plt.imshow(cloud)
plt.grid(False)
plt.axis('off')
plt.show()
```

The model performs decent.

[5.1.5] Applying Random Forests on AVG W2V

In [185]:
```
# Please write all the code with proper documentation
```

In [186]:
```
%%time
clfg(atrain,y_1,atest,y_test)
```

```
Fitting 3 folds for each of 49 candidates, totalling 147 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   56.5s
[Parallel(n_jobs=-1)]: Done 147 out of 147 | elapsed:  7.3min finished

Best HyperParameter:  {'max_depth': 11, 'n_estimators': 150}
best estimator:  RandomForestClassifier(bootstrap=True, class_weight=None, crit
erion='gini',
            max_depth=None, 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=10, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

the accuracy is 86.88%

the recall is 98.68%
the precision is 87.17%
the f1 score is 92.57%
```


```
Wall time: 8min 50s
```

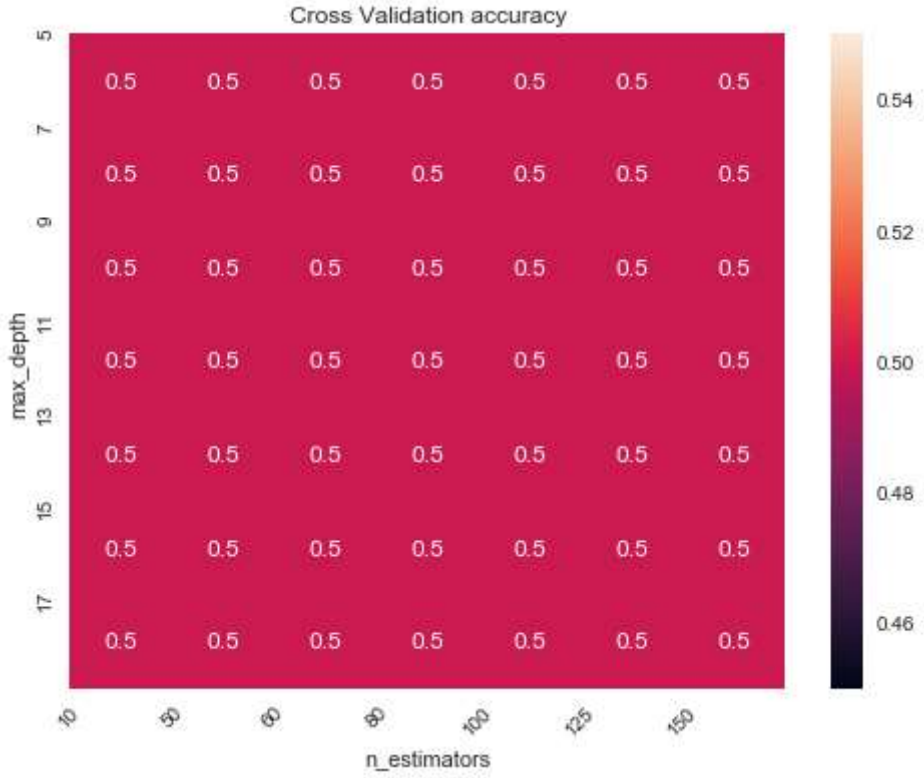
The model here performs better than models on BOW and TFIDF

[5.1.6] Applying Random Forests on TFIDF W2V

In [187]:
```
# Please write all the code with proper documentation
```

In [188]:
```
%%time
clfg(train,y_1,test,y_test)
```

```
Fitting 3 folds for each of 49 candidates, totalling 147 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   24.2s
[Parallel(n_jobs=-1)]: Done 147 out of 147 | elapsed:  1.6min finished

Best HyperParameter:  {'max_depth': 5, 'n_estimators': 10}
best estimator:  RandomForestClassifier(bootstrap=True, class_weight=None, crit
erion='gini',
            max_depth=None, 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=10, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

the accuracy is 82.80%

the recall is 100.00%
the precision is 82.80%
the f1 score is 90.59%
```




```
Wall time: 1min 36s
```

This model is a dumb model.

[5.2] Applying GBDT using XGBOOST

In [44]:
```
from xgboost import XGBClassifier
```

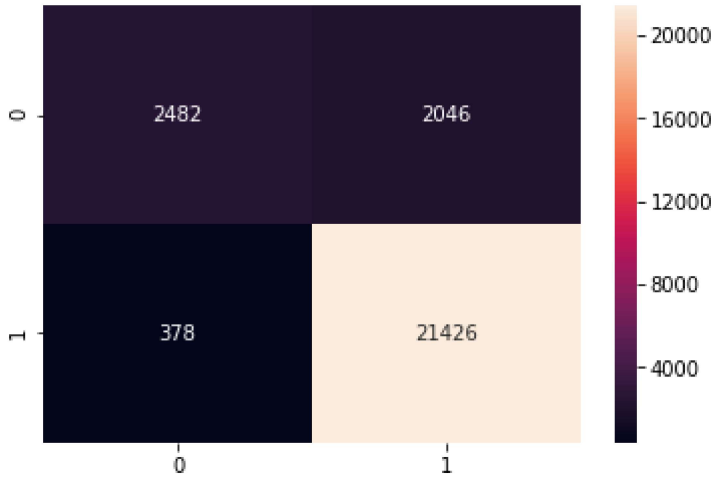
In [49]:
```
#function for finding optimal parameters
def xclfg(xtrain,ytrain,xtest,ytest):

    #using the gridsearchcv for finding the best c
    xc = XGBClassifier()
    n_estimators=[50,60,80,100,125,150]
    max_depth=[3,5,7,9,11,13]
    param_grid = {'n_estimators':[50,60,80,100,125,150],'max_depth':[3,5,7,9,11,1
    #For time based splitting
    t = TimeSeriesSplit(n_splits=3)

    gsv = GridSearchCV(xc,param_grid,cv=t,n_jobs=-1,verbose=1,scoring="roc_auc")
    gsv.fit(xtrain,ytrain)
    print("Best HyperParameter: ",gsv.best_params_)
    #assinging best alpha to optimal print("Best Accuracy: %.2f%%"%(gsv.best_scor
    print("best estimator: ",gsv.estimator)
    #print("cv results :",gsv.cv_results_)

    es=gsv.best_params_['n_estimators']
    md=gsv.best_params_['max_depth']


    xc=XGBClassifier(n_estimators=es,max_depth=md)
    xc.fit(xtrain,ytrain)
    pred=xc.predict(xtest)
    #different metrics
    acc=accuracy_score(y_test,pred)*100
    print("\nthe accuracy is %.2f%%"%acc)

    re=recall_score(y_test,pred,) * 100
    print("\nthe recall is %.2f%%"%re)

    pre=precision_score(y_test,pred) * 100
    print("the precision is %.2f%%"%pre)

    f1=f1_score(y_test,pred) * 100
    print("the f1 score is %.2f%%"%f1)

    df_cm=pd.DataFrame(confusion_matrix(y_test,pred))
    #sns.set(font_scale=1.4)
    sns.heatmap(df_cm,annot=True,fmt="d")

    print('\n\n')
    plt.figure(figsize=(8, 6))
    scores = gsv.cv_results_['mean_test_score'].reshape(len(n_estimators),len(max_
    testing = sns.heatmap(scores, annot=True)

    plt.xlabel('n_estimators')
    plt.ylabel('max_depth')

    plt.xticks(np.arange(len(n_estimators)), n_estimators, rotation=45)
    plt.yticks(np.arange(len(max_depth)), max_depth)
    plt.title('Cross Validation accuracy')
    plt.show()
```

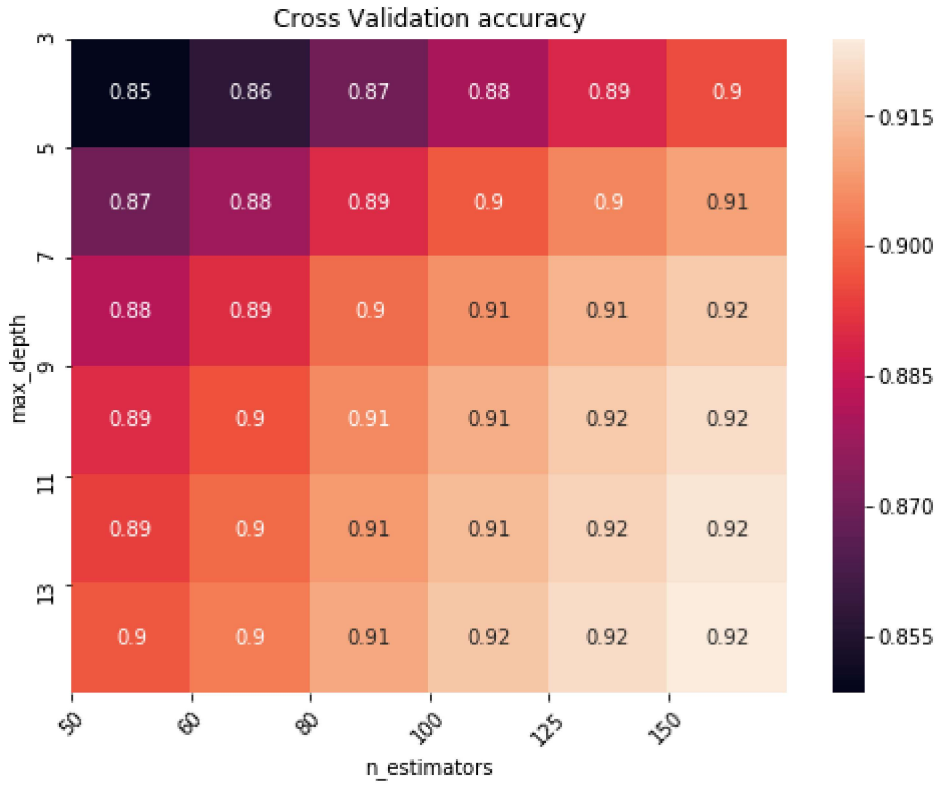
[5.2.1] Applying XGBOOST on BOW

In [50]:
```
# Please write all the code with proper documentation
```

In [51]:
```
%%time
xclfg(final_bigram_counts,y_train,bdata,y_test)
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  3.0min
[Parallel(n_jobs=-1)]: Done 108 out of 108 | elapsed: 19.5min finished

Best HyperParameter:  {'max_depth': 13, 'n_estimators': 150}
best estimator:  XGBClassifier(base_score=0.5, booster='gbtree', colsample_byle
vel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       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=1)

C:\Users\himateja\Anaconda3\lib\site-packages\sklearn\preprocessing\label.py:15
1: DeprecationWarning: The truth value of an empty array is ambiguous. Returnin
g False, but in future this will result in an error. Use `array.size > 0` to ch
eck that an array is not empty.
  if diff:


the accuracy is 90.79%

the recall is 98.27%
the precision is 91.28%
the f1 score is 94.65%
```






```
Wall time: 24min 34s
```

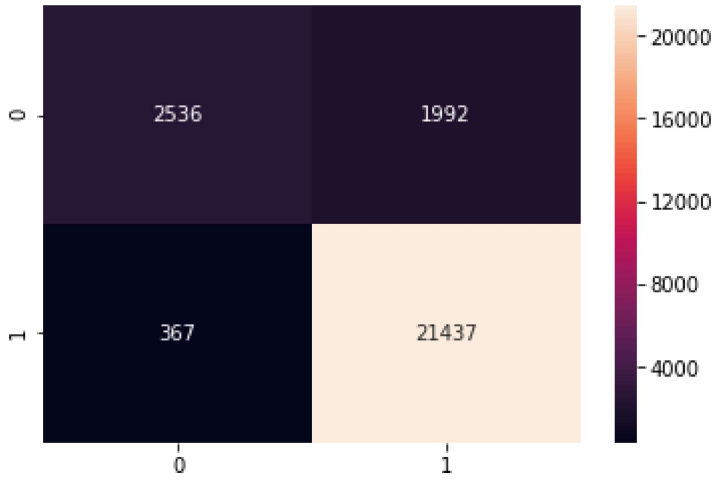
The XGBoost model performs better than Random forest for BOW.

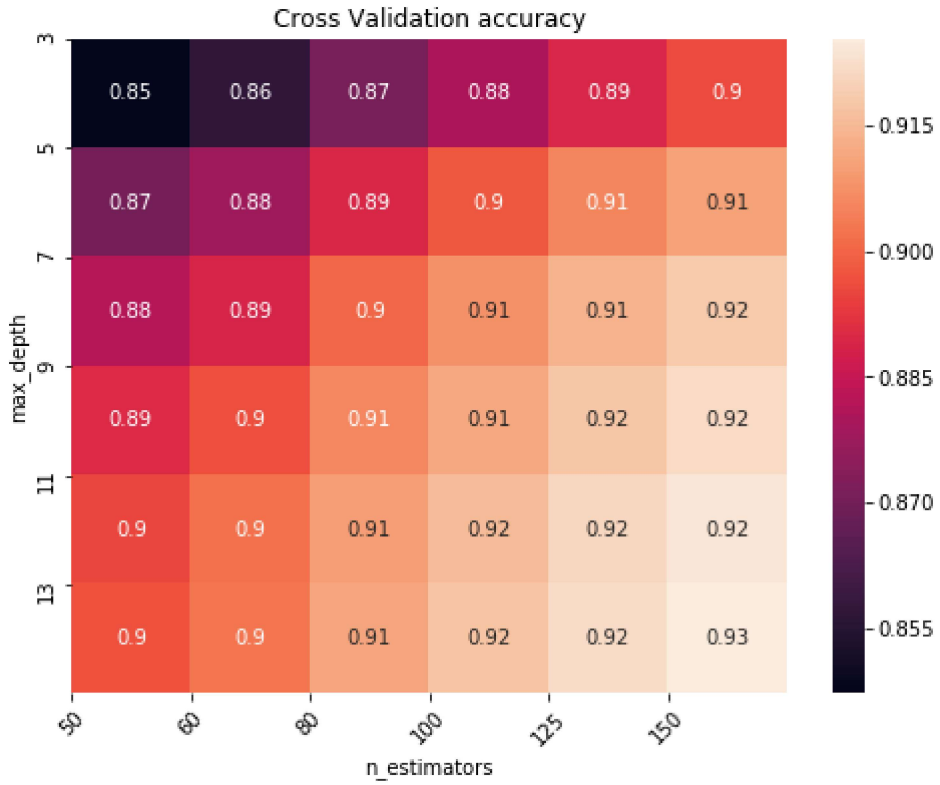
[5.2.2] Applying XGBOOST on TFIDF

In [52]:
```
# Please write all the code with proper documentation
```

In [53]:
```
%%time
xclfg(tdata,y_train,tfdata,y_test)
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed: 12.3min
[Parallel(n_jobs=-1)]: Done 108 out of 108 | elapsed: 50.5min finished

Best HyperParameter:  {'max_depth': 13, 'n_estimators': 150}
best estimator:  XGBClassifier(base_score=0.5, booster='gbtree', colsample_byle
vel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       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=1)

C:\Users\himateja\Anaconda3\lib\site-packages\sklearn\preprocessing\label.py:15
1: DeprecationWarning: The truth value of an empty array is ambiguous. Returnin
g False, but in future this will result in an error. Use `array.size > 0` to ch
eck that an array is not empty.
  if diff:


the accuracy is 91.04%

the recall is 98.32%
the precision is 91.50%
the f1 score is 94.78%
```






```
Wall time: 59min 7s
```

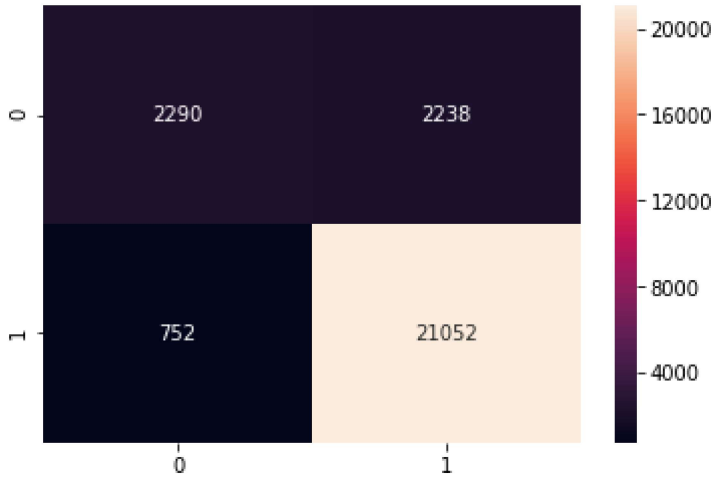
The XGBoost model performs better than Random forest on TFIDF

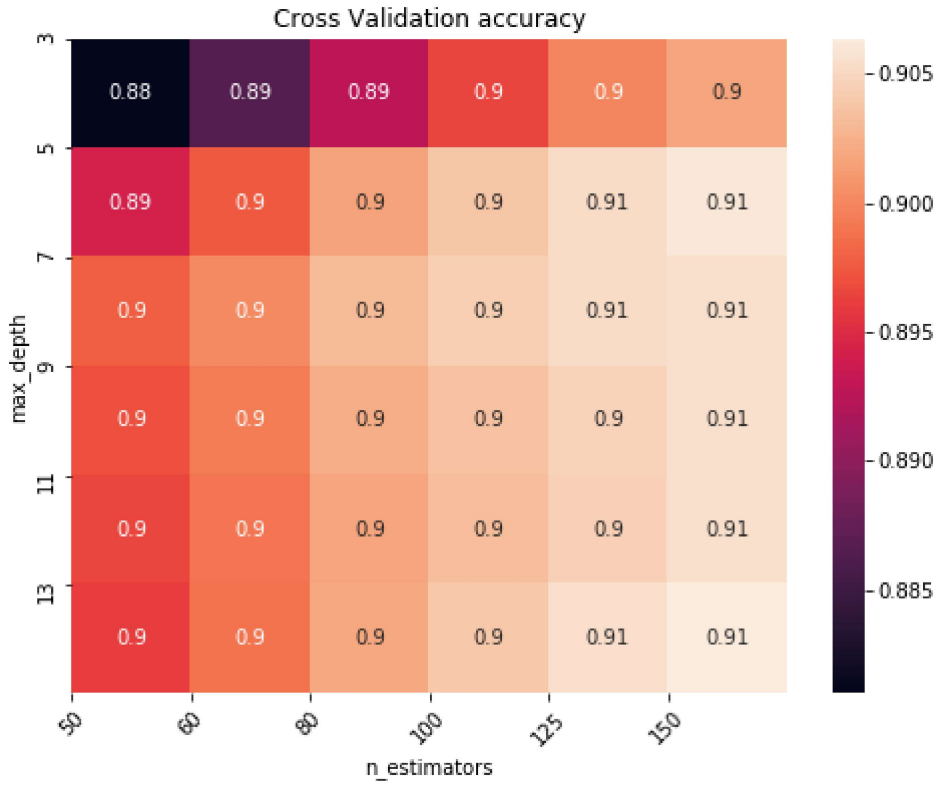
[5.2.3] Applying XGBOOST on AVG W2V

In [54]:
```
# Please write all the code with proper documentation
```

In [55]:
```
%%time
xclfg(atrain,y_1,atest,y_test)
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  2.9min
[Parallel(n_jobs=-1)]: Done 108 out of 108 | elapsed: 20.3min finished

Best HyperParameter:  {'max_depth': 13, 'n_estimators': 150}
best estimator:  XGBClassifier(base_score=0.5, booster='gbtree', colsample_byle
vel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       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=1)

C:\Users\himateja\Anaconda3\lib\site-packages\sklearn\preprocessing\label.py:15
1: DeprecationWarning: The truth value of an empty array is ambiguous. Returnin
g False, but in future this will result in an error. Use `array.size > 0` to ch
eck that an array is not empty.
  if diff:


the accuracy is 88.64%

the recall is 96.55%
the precision is 90.39%
the f1 score is 93.37%
```






```
Wall time: 26min 6s
```

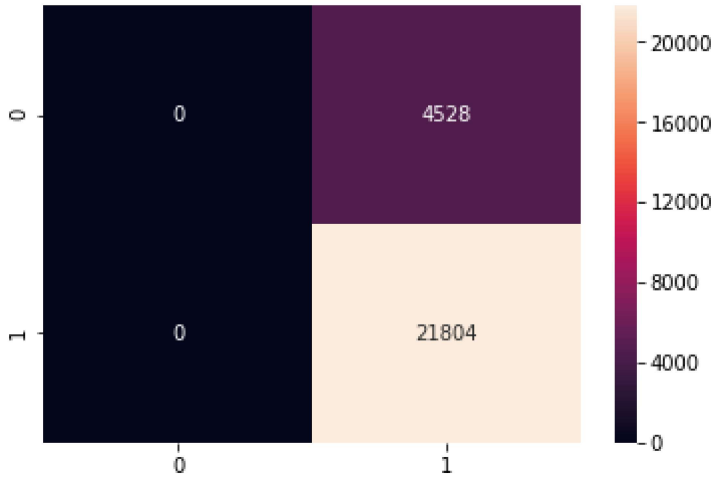
The performance of the model is good.

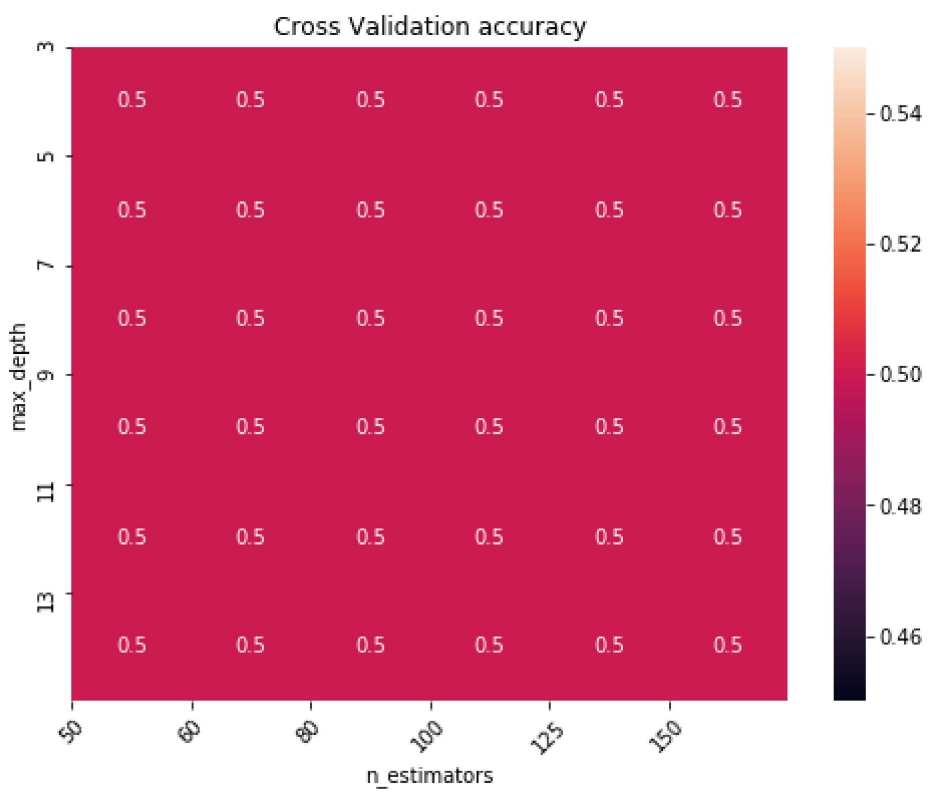
[5.2.4] Applying XGBOOST on TFIDF W2V

In [0]:
```
# Please write all the code with proper documentation
```

In [56]:
```
%%time
xclfg(train,y_1,test,y_test)
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 108 out of 108 | elapsed:  3.3min finished

Best HyperParameter:  {'max_depth': 3, 'n_estimators': 50}
best estimator:  XGBClassifier(base_score=0.5, booster='gbtree', colsample_byle
vel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       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=1)

C:\Users\himateja\Anaconda3\lib\site-packages\sklearn\preprocessing\label.py:15
1: DeprecationWarning: The truth value of an empty array is ambiguous. Returnin
g False, but in future this will result in an error. Use `array.size > 0` to ch
eck that an array is not empty.
  if diff:


the accuracy is 82.80%

the recall is 100.00%
the precision is 82.80%
the f1 score is 90.59%
```






```
Wall time: 3min 24s
```

This model is a dumb model.

[6] Conclusions

In [58]:
```
# Please compare all your models using Prettytable library
from prettytable import PrettyTable
```

Random Forest

In [67]:
```
x=PrettyTable()
```

In [68]:
```
x.field_names = ['feature_set','n_estimators','max_depth','ROC']
```

In [69]:
```
x.add_row(["BOW",'100','17','83.35%'])
x.add_row(["TFIDF",'125','17','82.35%'])
x.add_row(["AVG_W2v",'150','11','86.88%'])
x.add_row(["TFIDF_w2V",'10','5','82.80%'])
```

In [70]:
```
print(x)
```

```
+-------------+--------------+-----------+--------+
| feature_set | n_estimators | max_depth |  ROC   |
+-------------+--------------+-----------+--------+
|     BOW     |     100      |     17    | 83.35% |
|    TFIDF    |     125      |     17    | 82.35% |
|   AVG_W2v   |     150      |     11    | 86.88% |
|  TFIDF_w2V  |      10      |     5     | 82.80% |
+-------------+--------------+-----------+--------+
```

XGBoost

In [71]:
```
y=PrettyTable()
```

In [72]:
```
y.field_names = ['feature_set','n_estimators','max_depth','ROC']
```

In [73]:
```
y.add_row(["BOW",'150','13','90.79%'])
y.add_row(["TFIDF",'150','13','91.04%'])
y.add_row(["AVG_W2v",'150','13','86.64%'])
y.add_row(["TFIDF_w2V",'50','3','82.80%'])
```

In [74]:
```
print(y)
```

```
+-------------+--------------+-----------+--------+
| feature_set | n_estimators | max_depth |  ROC   |
+-------------+--------------+-----------+--------+
|     BOW     |     150      |     13    | 90.79% |
|    TFIDF    |     150      |     13    | 91.04% |
|   AVG_W2v   |     150      |     13    | 86.64% |
|  TFIDF_w2V  |      50      |     3     | 82.80% |
+-------------+--------------+-----------+--------+
```

In [ ]:
```

```