Amazon Fine Food Reviews Analysis

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

EDA: 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 [0]:
```
%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
```

In [2]:

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

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?
client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleuser
content.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Aoob&scope=emai
l%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2
Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2
Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Faut
h%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
··········
Mounted at /content/drive
```

In [0]:
```
!cp "/content/drive/My Drive/final.sqlite" "final.sqlite"
```

In [5]:
```
import os
if os.path.isfile('final.sqlite'):
    conn = sqlite3.connect('final.sqlite')
    final = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score !=
 3 """, conn)
    conn.close()
else:
    print("Please the above cell")

print("Preprocessed Amzon fine food data columns  shape : ",final.shape
)
print("fPreprocessed Amzon fine food data columns       :",final.column
s.values)
```

```
Preprocessed Amzon fine food data columns  shape :  (364171, 12)
fPreprocessed Amzon fine food data columns       : ['index' 'Id' 'Produ
ctId' 'UserId' 'ProfileName' 'HelpfulnessNumerator'
 'HelpfulnessDenominator' 'Score' 'Time' 'Summary' 'Text' 'CleanedTex
t']
```

In [0]:
```
# 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 50
0000 data points
# you can change the number to any other number based on your computing
 power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Sco
re != 3 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score
 != 3 LIMIT 5000""", con)
```

```python
# Give reviews with Score>3 a positive rating(1), and reviews with a sc
ore<3 a negative rating(0).
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 (5000, 10)
```

Out[0]:

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

In [0]:

```python
display = pd.read_sql_query("""
```

```
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [0]:
```
print(display.shape)
display.head()
```

(80668, 7)

Out[0]:

	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 [0]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[0]:

UserId	ProductId	ProfileName	Time	Score	Text	COUNT(*)

	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 [0]:
```
display['COUNT(*)'].sum()
```

Out[0]:
```
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 [0]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[0]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenon
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 [0]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

In [0]:
```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

Out[0]: (4986, 10)

In [0]:
```
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

Out[0]: 99.72

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 [0]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[0]:

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

In [0]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [0]:
```
#Before starting the next phase of preprocessing lets see the number of
 entries left
print(final.shape)

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

```
(4986, 10)
```

Out[0]:
```
1    4178
0     808
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 [0]:

```
# 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)
```

```
Why is this $[...] when the same product is available for $[...] here?<
br />http://www.amazon.com/VICTOR-FLY-MAGNET-BAIT-REFILL/dp/B00004RBDY<
br /><br />The Victor M380 and M502 traps are unreal, of course -- tota
l fly genocide. Pretty stinky, but only right nearby.
==================================================
```

```
I recently tried this flavor/brand and was surprised at how delicious t
hese chips are.  The best thing was that there were a lot of "brown" ch
ips in the bsg (my favorite), so I bought some more through amazon and
shared with family and friends.  I am a little disappointed that there
are not, so far, very many brown chips in these bags, but the flavor is
still very good.  I like them better than the yogurt and green onion fl
avor because they do not seem to be as salty, and the onion flavor is b
etter.  If you haven't eaten Kettle chips before, I recommend that you
try a bag before buying bulk.  They are thicker and crunchier than Lays
but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I'm sorry; but t
hese reviews do nobody any good beyond reminding us to look  before ord
ering.<br /><br />These are chocolate-oatmeal cookies.  If you don't li
ke that combination, don't order this type of cookie.  I find the combo
quite nice, really.  The oatmeal sort of "calms" the rich chocolate fla
vor and gives the cookie sort of a coconut-type consistency.  Now let's
also remember that tastes differ; so, I've given my opinion.<br /><br /
>Then, these are soft, chewy cookies -- as advertised.  They are not "c
rispy" cookies, or the blurb would say "crispy," rather than "chewy."
I happen to like raw cookie dough; however, I don't see where these tas
te like raw cookie dough.  Both are soft, however, so is this the confu
sion?  And, yes, they stick together.  Soft cookies tend to do that.  T
hey aren't individually wrapped, which would add to the cost.  Oh yeah,
chocolate chip cookies tend to be somewhat sweet.<br /><br />So, if you
want something hard and crisp, I suggest Nabiso's Ginger Snaps.  If you
want a cookie that's soft, chewy and tastes like a combination of choco
late and oatmeal, give these a try.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.<br />Thi
s k cup is great coffee.  dcaf is very good as well
==================================================
```

In [0]:

```
# 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)
```

```
Why is this $[...] when the same product is available for $[...] here?<
br /> /><br />The Victor M380 and M502 traps are unreal, of course -- t
otal fly genocide. Pretty stinky, but only right nearby.
```

In [0]:

```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how
-to-remove-all-tags-from-an-element
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)
```

```
Why is this $[...] when the same product is available for $[...] here?
/>The Victor M380 and M502 traps are unreal, of course -- total fly gen
ocide. Pretty stinky, but only right nearby.
==================================================
I recently tried this flavor/brand and was surprised at how delicious t
hese chips are.  The best thing was that there were a lot of "brown" ch
ips in the bsg (my favorite), so I bought some more through amazon and
shared with family and friends.  I am a little disappointed that there
```

```
are not, so far, very many brown chips in these bags, but the flavor is
still very good.  I like them better than the yogurt and green onion fl
avor because they do not seem to be as salty, and the onion flavor is b
etter.  If you haven't eaten Kettle chips before, I recommend that you
try a bag before buying bulk.  They are thicker and crunchier than Lays
but just as fresh out of the bag.
==================================================
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I'm sorry; but t
hese reviews do nobody any good beyond reminding us to look  before ord
ering.These are chocolate-oatmeal cookies.  If you don't like that comb
ination, don't order this type of cookie.  I find the combo quite nice,
really.  The oatmeal sort of "calms" the rich chocolate flavor and give
s the cookie sort of a coconut-type consistency.  Now let's also rememb
er that tastes differ; so, I've given my opinion.Then, these are soft,
chewy cookies -- as advertised.  They are not "crispy" cookies, or the
blurb would say "crispy," rather than "chewy."  I happen to like raw co
okie dough; however, I don't see where these taste like raw cookie doug
h.  Both are soft, however, so is this the confusion?  And, yes, they s
tick together.  Soft cookies tend to do that.  They aren't individually
wrapped, which would add to the cost.  Oh yeah, chocolate chip cookies
tend to be somewhat sweet.So, if you want something hard and crisp, I s
uggest Nabiso's Ginger Snaps.  If you want a cookie that's soft, chewy
and tastes like a combination of chocolate and oatmeal, give these a tr
y.  I'm here to place my second order.
==================================================
love to order my coffee on amazon.  easy and shows up quickly.This k cu
p is great coffee.  dcaf is very good as well
```

In [0]:

```python
# 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)
```

```python
    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 [0]:
```python
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
Wow.  So far, two two-star reviews.  One obviously had no idea what the
y were ordering; the other wants crispy cookies.  Hey, I am sorry; but
these reviews do nobody any good beyond reminding us to look  before or
dering.<br /><br />These are chocolate-oatmeal cookies.  If you do not
like that combination, do not order this type of cookie.  I find the co
mbo quite nice, really.  The oatmeal sort of "calms" the rich chocolate
flavor and gives the cookie sort of a coconut-type consistency.  Now le
t is also remember that tastes differ; so, I have given my opinion.<br
/><br />Then, these are soft, chewy cookies -- as advertised.  They are
not "crispy" cookies, or the blurb would say "crispy," rather than "che
wy."  I happen to like raw cookie dough; however, I do not see where th
ese taste like raw cookie dough.  Both are soft, however, so is this th
e confusion?  And, yes, they stick together.  Soft cookies tend to do t
hat.  They are not individually wrapped, which would add to the cost.
Oh yeah, chocolate chip cookies tend to be somewhat sweet.<br /><br />S
o, if you want something hard and crisp, I suggest Nabiso is Ginger Sna
ps.  If you want a cookie that is soft, chewy and tastes like a combina
tion of chocolate and oatmeal, give these a try.  I am here to place my
second order.
==================================================
```

In [0]:
```python
#remove words with numbers python: https://stackoverflow.com/a/1808237
0/4084039
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
Why is this $[...] when the same product is available for $[...] here?<
br /> /><br />The Victor  and  traps are unreal, of course -- total fly
genocide. Pretty stinky, but only right nearby.
```

In [0]:
```python
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
Wow So far two two star reviews One obviously had no idea what they wer
e ordering the other wants crispy cookies Hey I am sorry but these revi
ews do nobody any good beyond reminding us to look before ordering br b
r These are chocolate oatmeal cookies If you do not like that combinati
on do not order this type of cookie I find the combo quite nice really
The oatmeal sort of calms the rich chocolate flavor and gives the cooki
e sort of a coconut type consistency Now let is also remember that tast
es differ so I have given my opinion br br Then these are soft chewy co
okies as advertised They are not crispy cookies or the blurb would say
crispy rather than chewy I happen to like raw cookie dough however I do
not see where these taste like raw cookie dough Both are soft however s
o is this the confusion And yes they stick together Soft cookies tend t
o do that They are not individually wrapped which would add to the cost
Oh yeah chocolate chip cookies tend to be somewhat sweet br br So if yo
u want something hard and crisp I suggest Nabiso is Ginger Snaps If you
want a cookie that is soft chewy and tastes like a combination of choco
late and oatmeal give these a try I am here to place my second order
```

In [0]:
```python
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'no
t'
# <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 step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'o
urs', 'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselve
s', 'he', 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'it
```

```
s', 'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'th
is', 'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', 'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
 'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between',
'into', 'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'h
ow', 'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 's
o', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',
"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
'didn', "didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "is
n't", 'ma', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
 "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [0]:

```
# 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 stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████████████████████████████████████████████| 4986/4986 [00:01<00:00, 3137.37it/s]
```

In [0]:
```
preprocessed_reviews[1500]
```

Out[0]:
```
'wow far two two star reviews one obviously no idea ordering wants cris
py cookies hey sorry reviews nobody good beyond reminding us look order
ing chocolate oatmeal cookies not like combination not order type cooki
e find combo quite nice really oatmeal sort calms rich chocolate flavor
gives cookie sort coconut type consistency let also remember tastes dif
fer given opinion soft chewy cookies advertised not crispy cookies blur
b would say crispy rather chewy happen like raw cookie dough however no
t see taste like raw cookie dough soft however confusion yes stick toge
ther soft cookies tend not individually wrapped would add cost oh yeah
chocolate chip cookies tend somewhat sweet want something hard crisp su
ggest nabiso ginger snaps want cookie soft chewy tastes like combinatio
n chocolate oatmeal give try place second order'
```

[3.2] Preprocessing Review Summary

In [0]:
```
## Similartly you can do preprocessing for review summary also.
```

[4] Featurization

[4.1] BAG OF WORDS

In [0]:
```
#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', 'aahhhs', 'aback', 'abandon', 'abates', 'abb
ott', 'abby', 'abdominal', 'abiding', 'ability']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words  12997
```

[4.2] Bi-Grams and n-Grams.

In [0]:

```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-gra
ms
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.
org/stable/modules/generated/sklearn.feature_extraction.text.CountVecto
rizer.html

# you can choose these numebrs min_df=10, max_features=5000, of your ch
oice
count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features
=5000)
final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_s
hape())
print("the number of unique words including both unigrams and bigrams "
, final_bigram_counts.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.3] TF-IDF

In [0]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[0:10])
print('='*50)

final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape
())
print("the number of unique words including both unigrams and bigrams "
, final_tf_idf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'a
ble find', 'able get', 'absolute', 'absolutely', 'absolutely deliciou
s', 'absolutely love', 'absolutely no', 'according']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

[4.4] Word2Vec

In [0]:

```
# 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 [0]:

```
# Using Google News Word2Vectors

# in this project we are using a pretrained model by google
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
```

```
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as val
ues
# To use this code-snippet, download "GoogleNews-vectors-negative300.bi
n"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edi
t
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17
SRFAzZPY
# you can comment this whole cell
# or change these varible according to your need

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
-negative300.bin', binary=True)
        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_trai
n_w2v = True, to train your own w2v ")
```

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('wond
erful', 0.9946032166481018), ('excellent', 0.9944332838058472), ('espec
ially', 0.9941144585609436), ('baked', 0.9940600395202637), ('salted',
0.994047224521637), ('alternative', 0.9937226176261902), ('tasty', 0.99
```

```
36816692352295), ('healthy', 0.9936649799346924)]
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325), ('p
opcorn', 0.9992750883102417), ('de', 0.9992610216140747), ('miss', 0.99
92451071739197), ('melitta', 0.999218761920929), ('choice', 0.999210238
4567261), ('american', 0.9991837739944458), ('beef', 0.999178051948547
4), ('finish', 0.9991567134857178)]
```

In [0]:

```
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  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'st
inky', 'right', 'nearby', 'used', 'ca', 'not', 'beat', 'great', 'receiv
ed', 'shipment', 'could', 'hardly', 'wait', 'try', 'love', 'call', 'ins
tead', 'removed', 'easily', 'daughter', 'designed', 'printed', 'use',
'car', 'windows', 'beautifully', 'shop', 'program', 'going', 'lot', 'fu
n', 'everywhere', 'like', 'tv', 'computer', 'really', 'good', 'idea',
'final', 'outstanding', 'window', 'everybody', 'asks', 'bought', 'mad
e']
```

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

[4.4.1.1] Avg W2v

In [0]:

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in
 this list
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, yo
u might need to change this to 300 if you use google's w2v
    cnt_words =0; # num of words with a valid vector in the sentence/re
```

```
view
    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)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|██████████████████████████████████████████████████
██████████| 4986/4986 [00:03<00:00, 1330.47it/s]
```

```
4986
50
```

[4.4.1.2] TFIDF weighted W2v

In [0]:

```
# 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 v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [0]:

```
# 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 ce
ll_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is st
ored in this list
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/r
```

```
eview
    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
```

```
100%|██████████████████████████████████████████████████
██████████| 4986/4986 [00:20<00:00, 245.63it/s]
```

[5] Assignment 4: Apply Naive Bayes

1. **Apply Multinomial NaiveBayes on these feature sets**
    - SET 1:Review text, preprocessed one converted into vectors using (BOW)
    - SET 2:Review text, preprocessed one converted into vectors using (TFIDF)

2. **The hyper paramter tuning(find best Alpha)**
    - Find the best hyper parameter which will give the maximum AUC value
    - Consider a wide range of alpha values for hyperparameter tuning, start as low as 0.00001
    - Find the best hyper paramter using k-fold cross validation or simple cross validation data
    - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning

3. **Feature importance**

    - Find the top 10 features of positive class and top 10 features of negative class for both feature sets Set 1 and Set 2 using values of `feature_log_prob_` parameter of MultinomialNB and print their corresponding feature names

4. **Feature engineering**

    - To increase the performance of your model, you can also experiment with with feature engineering like :
        - Taking length of reviews as another feature.
        - Considering some features from review summary as well.

5. **Representation of results**

    - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure. Here on X-axis you will have alpha values, since they have a wide range, just to represent those alpha values on the graph, apply log function on those alpha values.
    - Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
    - Along with plotting ROC curve, you need to print the confusion matrix with predicted and original labels of test data points. Please visualize your confusion matrices using seaborn heatmaps.

6. **Conclusion**

    - You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library link

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
4. For more details please go through this [link.]

Applying Multinomial Naive Bayes

[5.1] Applying Naive Bayes on BOW, SET 1

In [6]:
```
from sklearn.neighbors import  KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from tqdm import tqdm

preprocessed_reviews=final['CleanedText']
score=final['Score']
X_train, X_test, y_train, y_test = train_test_split(preprocessed_review
s, score, test_size=0.33, random_state=42)

X_train.shape
```

Out[6]: (243994,)

In [7]:
```
#BoW
count_vect = CountVectorizer(max_df=0.95, min_df=2,stop_words='english'
) #in scikit-learn
count_vect.fit(X_train)
print("some feature names ", count_vect.get_feature_names()[:10])
print('='*50)
```

```
X_train_bow = count_vect.transform(X_train)
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])

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

```
some feature names  ['aaa', 'aaaaah', 'aaaand', 'aaah', 'aachen', 'aa
f', 'aafco', 'aah', 'aamazoncom', 'aand']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (243994, 49398)
the number of unique words  49398
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (120177, 49398)
the number of unique words  49398
```

In [8]:
```
print(X_train_bow.shape,X_test_bow.shape,y_train.shape,y_test.shape)
```

```
(243994, 49398) (120177, 49398) (243994,) (120177,)
```

In [0]:
```
from sklearn.model_selection import cross_validate
#from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_validate
from tqdm import tqdm
def naive_bayes(X_train, Y_train,x_test,y_test):

    alpha_values = [0.0001,0.001,0.01,0.1,1,10,100]

    # empty list that will hold cv scores
    train_score=[]
    test_score = []

    # perform 10-fold cross validation
```

```
    for alpha in tqdm(alpha_values):
        mnb = MultinomialNB(alpha = alpha)
        scores = cross_validate(mnb, X_train, Y_train, cv = 10,return_t
rain_score=True, scoring = 'roc_auc')
        #cv_scores.append(scores.mean())
        test_score.append(scores['test_score'].mean())
        train_score.append(scores['train_score'].mean())
        #scores = cross_validate(clf, iris.data, iris.target, scoring=s
coring,
        #                 cv=5, return_train_score=False)
        #sorted(scores.keys())

        #scores['test_recall_macro']

    test_score=list(map(lambda x:round(x,2),test_score))
    train_score=list(map(lambda x:round(x,2),train_score))

    # changing to misclassification error
    MSE_train = [1 - x for x in train_score]
    MSE_test  = [1 - x for x in test_score]
    #print(MSE)
    # determining best alpha
    optimal_alpha = alpha_values[MSE_test.index(min(MSE_test))]
    print('\nThe optimal number of alpha is %d.' % optimal_alpha)

    # plot misclassification error vs alpha
    plt.plot(alpha_values, MSE_train, marker = '*',color='red',label='t
rain')
    plt.plot(alpha_values, MSE_test, marker = '*',color='orange',label=
'test')

    #for xy in zip(alpha_values, np.round(MSE,3)):
        #plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
    plt.title("Misclassification Error vs alpha")
    plt.xlabel('value of alpha')
    plt.ylabel('Misclassification Error')
    plt.show()

    #print("the misclassification error for each value of alpha is : ",
```

```
np.round(MSE,3))
    #optimal_alpha_code(optimal_alpha,X_train,Y_train,x_test,y_test,vec
t_method)

    return optimal_alpha
```

In [0]:
```
naive_bayes(X_train_bow,y_train,X_test_bow,y_test)
```

```
100%|██████████| 7/7 [00:30<00:00,  4.34s/it]
```

```
The optimal number of alpha is 0.
```

Out[0]:
```
0.1
```

In [11]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
```

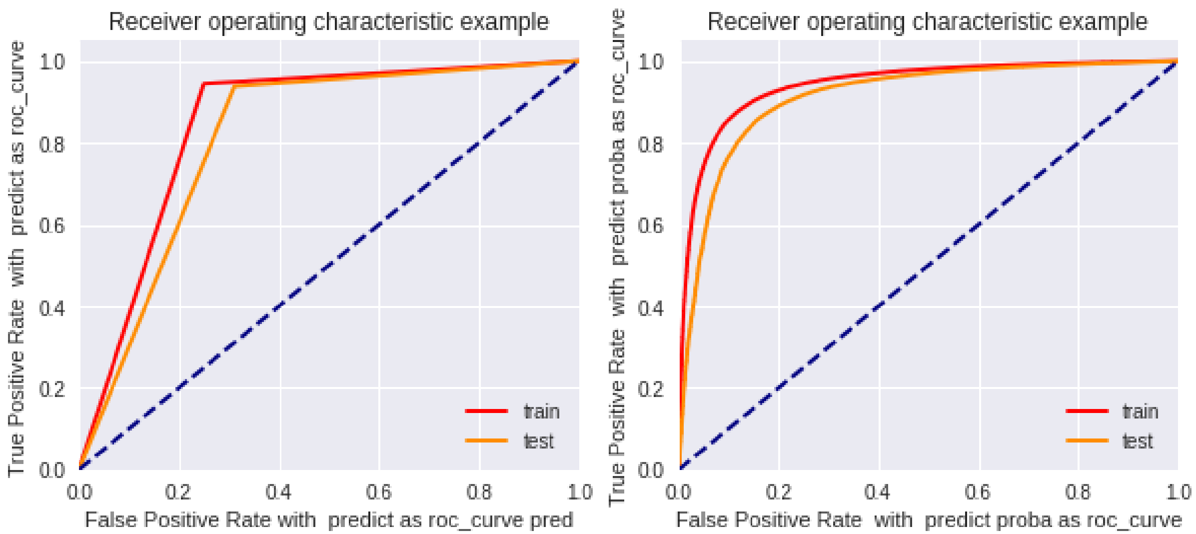
```
from sklearn.naive_bayes import MultinomialNB


clf1= MultinomialNB(alpha = 0.1)
clf1.fit(X_train_bow,y_train)
pred_train=clf1.predict(X_train_bow)
pred=clf1.predict(X_test_bow)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
print("Classification Report")
print(classification_report(y_test,pred))
print("        ")


fpr_train_pred,tpr_train_pred,thresholds_train=roc_curve(y_train,pred_t
rain)
print("AUC Score for train data  with roc_curve 2nd parameter as Predic
t :",metrics.auc(fpr_train_pred,tpr_train_pred))

fpr_pred,tpr_pred,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data with roc_curve 2nd parameter as Predict
 :",metrics.auc(fpr_pred,tpr_pred))

print("        ")

pred_proba=clf1.predict_proba(X_test_bow)
pred_proba_train=clf1.predict_proba(X_train_bow)

fpr_train_pred_proba,tpr_train_pred_proba,thresholds_train=roc_curve(y_
train,pred_proba_train[:,1])
print("AUC Score for train data  with roc_curve 2nd parameter as Predic
tProba :",metrics.auc(fpr_train_pred_proba,tpr_train_pred_proba))

fpr_pred_proba,tpr_pred_proba,thresholds=roc_curve(y_test,pred_proba[:,
```

```
1])
print("AUC Score for test data with roc_curve 2nd parameter as PredictP
roba :",metrics.auc(fpr_pred_proba,tpr_pred_proba))


print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()

pred_proba=clf1.predict_proba(X_test_bow)
print("RoC Score predict  :: ",roc_auc_score(y_test, pred))

print("RoC Score predictproba  :: ",roc_auc_score(y_test, pred_proba[:,
1]))





plt.figure(figsize=(10,4))

plt.subplot(121)
plt.plot(fpr_train_pred, tpr_train_pred,color='red',lw=2,label='train')
plt.plot(fpr_pred, tpr_pred,color='darkorange',lw=2,label='test')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate with  predict as roc_curve pred')
plt.ylabel('True Positive Rate  with  predict as roc_curve')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")

plt.subplot(122)
plt.plot(fpr_train_pred_proba, tpr_train_pred_proba,color='red',lw=2,la
bel='train')
plt.plot(fpr_pred_proba, tpr_pred_proba,color='darkorange',lw=2,label=
'test')
```

```
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate  with  predict proba as roc_curve')
plt.ylabel('True Positive Rate  with  predict proba as roc_curve')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()




print("       ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("        ")
print("        ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

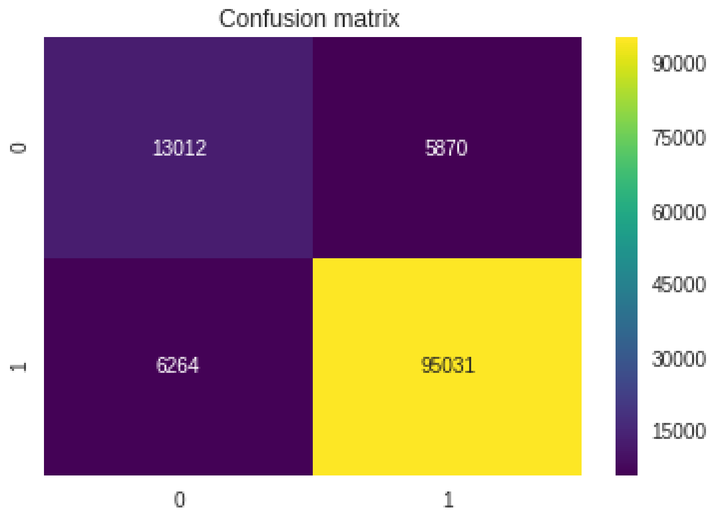
```
Accuracy Score :  89.9032260748729
Precision Score :  94.18241642798387
Recall Score :  93.81608174144824
F1 Score :  93.99889216403885

Classification Report
              precision    recall  f1-score   support

           0       0.68      0.69      0.68     18882
           1       0.94      0.94      0.94    101295
```

```
   micro avg       0.90      0.90      0.90    120177
   macro avg       0.81      0.81      0.81    120177
weighted avg       0.90      0.90      0.90    120177


AUC Score for train data  with roc_curve 2nd parameter as Predict : 0.8
474912507015196
AUC Score for test data with roc_curve 2nd parameter as Predict : 0.813
641366232927

AUC Score for train data  with roc_curve 2nd parameter as PredictProba
: 0.941883420826886
AUC Score for test data with roc_curve 2nd parameter as PredictProba :
0.9117527434509669

RoC Score predict  ::  0.813641366232927
RoC Score predictproba  ::  0.9117527434509669
```




```
TrueNegative : 13012
FalsePostive : 5870
FalseNegative : 6264
```

```
TruePostive  :  95031
```



[5.1.1] Top 10 important features of positive class from SET 1

In [12]:
```
features_name = count_vect.get_feature_names()

feat_count = clf1.feature_count_
#print("printing features score on class 0 and class 1 is :",feat_coun
t)
print("printing features score  rows {} and columns {} :".format(feat_c
ount.shape[0],feat_count.shape[1]))
    #print(nb_optimal.class_count_)

    #Feature probablity for a paticular class get by (feature_log_prob_
 or feature_count_ Attribute )
log_prob = clf1.feature_log_prob_
#print("printing probablity of features on class 0 and class 1 is : ",l
og_prob)
```

```
print("No.of Rows and column in log_prob : ",log_prob.shape)
print("Total number of features : ",len(features_name))

    #creating DataFrame with each word probabilty value
    #ie feature or word name(By bow_features )
    #ie each feature or word probablity value(score) of each class by f
eature_log_prob_
feature_prob = pd.DataFrame(feat_count, columns = features_name,index=[
'negative','postive'])
feature_prob
feature_prob_transpose = feature_prob.T
print("Dataframe for feature_Importance contain rows {},columns {}".for
mat(feature_prob_transpose.shape[0],feature_prob_transpose.shape[1]))

print("Top 20 Postive features : \n", feature_prob_transpose['postive']
.sort_values(ascending = False)[:20])
```

```
printing features score  rows 2 and columns 49398 :
No.of Rows and column in log_prob :  (2, 49398)
Total number of features :  49398
Dataframe for feature_Importance contain rows 49398,columns 2
Top 20 Postive features :
 like       92448.0
tast       84331.0
good       73484.0
love       71364.0
flavor     71080.0
use        68635.0
great      67658.0
veri       60157.0
product    59035.0
just       58240.0
tri        57164.0
tea        54815.0
coffe      51768.0
make       49732.0
food       42219.0
buy        35874.0
time       35854.0
realli     35104.0
```

```
eat         34352.0
onli        34098.0
Name: postive, dtype: float64
```

[5.1.2] Top 10 important features of negative class from SET 1

In [0]:

```
print("Top 20 Negative features : \n", feature_prob_transpose['negativ
e'].sort_values(ascending = False)[:20])
```

```
Top 20 Negative features :
 tast        22573.0
like        21569.0
product     18328.0
flavor      12649.0
just        12283.0
tri         11821.0
veri        11230.0
use         10125.0
coffe        9743.0
good         9731.0
buy          8995.0
order        8529.0
food         8165.0
dont         7741.0
tea          7558.0
box          6969.0
becaus       6800.0
onli         6720.0
make         6483.0
time         6394.0
Name: negative, dtype: float64
```

[5.2] Applying Naive Bayes on TFIDF, SET 2

In [0]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10, max_df=0.95
```

```
,stop_words='english',max_features=50000 )
tf_idf_vect.fit(X_train)
print("some sample features(unique words in the corpus)",tf_idf_vect.ge
t_feature_names()[0:10])
print('='*50)

X_train_tfidf= tf_idf_vect.transform(X_train)
print("the type of count 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_tfidf.get_shape()[1])

X_test_tfidf = tf_idf_vect.transform(X_test)
print("the type of count vectorizer ",type(X_test_tfidf))
print("the shape of out text TFIDF vectorizer ",X_test_tfidf.get_shape
())
print("the number of unique words ", X_test_tfidf.get_shape()[1])
```

```
some sample features(unique words in the corpus) ['aafco', 'aback', 'ab
andon', 'abc', 'abdomin', 'abil', 'abil make', 'abl', 'abl add', 'abl a
mazon']
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (243994, 50000)
the number of unique words including both unigrams and bigrams  50000
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (120177, 50000)
the number of unique words  50000
```

In [0]:

```
naive_bayes(X_train_tfidf,y_train,X_test_tfidf,y_test)
```

```
100%|██████████| 7/7 [00:37<00:00,  5.33s/it]
```

```
The optimal number of alpha is 0.
```

Out[0]: 0.1

In [0]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score



clf1= MultinomialNB(alpha = naive_bayes(X_train_bow,y_train,X_test_bow,
y_test))
clf1.fit(X_train_tfidf,y_train)
pred_train=clf1.predict(X_train_tfidf)
pred=clf1.predict(X_test_tfidf)

print("Accuracy Score : ",accuracy_score(y_test,pred)*100)
print("Precision Score : ",precision_score(y_test,pred)*100)
print("Recall Score : ",recall_score(y_test,pred)*100)
```

```
print("F1 Score : ",f1_score(y_test,pred)*100)

print("        ")
print("Classification Report")
print(classification_report(y_test,pred))
print("        ")


fpr_train_pred,tpr_train_pred,thresholds_train=roc_curve(y_train,pred_t
rain)
print("AUC Score for train data  with roc_curve 2nd parameter as Predic
t :",metrics.auc(fpr_train_pred,tpr_train_pred))

fpr_pred,tpr_pred,thresholds=roc_curve(y_test,pred)
print("AUC Score for test data with roc_curve 2nd parameter as Predict
 :",metrics.auc(fpr_pred,tpr_pred))

print("        ")

pred_proba=clf1.predict_proba(X_test_tfidf)
pred_proba_train=clf1.predict_proba(X_train_tfidf)

fpr_train_pred_proba,tpr_train_pred_proba,thresholds_train=roc_curve(y_
train,pred_proba_train[:,1])
print("AUC Score for train data  with roc_curve 2nd parameter as Predic
tProba :",metrics.auc(fpr_train_pred_proba,tpr_train_pred_proba))

fpr_pred_proba,tpr_pred_proba,thresholds=roc_curve(y_test,pred_proba[:,
1])
print("AUC Score for test data with roc_curve 2nd parameter as PredictP
roba :",metrics.auc(fpr_pred_proba,tpr_pred_proba))


print("        ")

#y_true = # ground truth labels
#y_probas = # predicted probabilities generated by sklearn classifier
#skplt.metrics.plot_roc_curve(y_true, y_probas)
#plt.show()
```

```
pred_proba=clf1.predict_proba(X_test_tfidf)
print("RoC Score predict  :: ",roc_auc_score(y_test, pred))

print("RoC Score predictproba  :: ",roc_auc_score(y_test, pred_proba[:,
1]))




plt.figure(figsize=(10,4))

plt.subplot(121)
plt.plot(fpr_train_pred, tpr_train_pred,color='red',lw=2,label='train')
plt.plot(fpr_pred, tpr_pred,color='darkorange',lw=2,label='test')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate with  predict as roc_curve pred')
plt.ylabel('True Positive Rate  with  predict as roc_curve')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")

plt.subplot(122)
plt.plot(fpr_train_pred_proba, tpr_train_pred_proba,color='red',lw=2,la
bel='train')
plt.plot(fpr_pred_proba, tpr_pred_proba,color='darkorange',lw=2,label=
'test')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate  with  predict proba as roc_curve')
plt.ylabel('True Positive Rate  with  predict proba as roc_curve')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

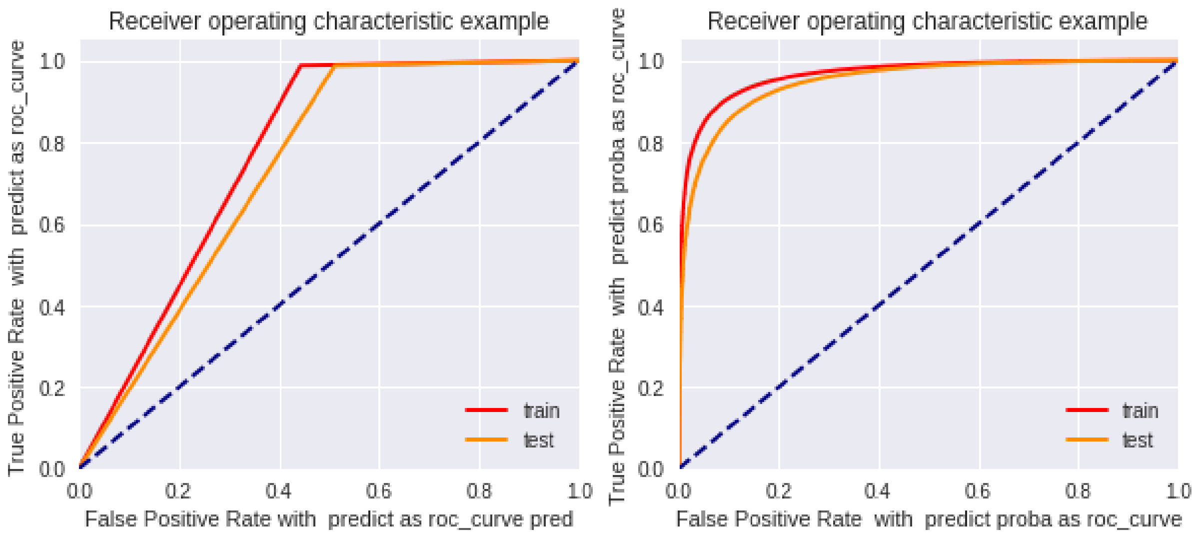
```
print("        ")

tn, fp, fn, tp=confusion_matrix(y_test,pred).ravel()
print("""
TrueNegative : {}
FalsePostive : {}
FalseNegative : {}
TruePostive  :  {}""".format(tn, fp, fn, tp))
print("         ")
print("         ")

confusionmatrix_DF=pd.DataFrame(confusion_matrix(y_test,pred),columns=[
'0','1'],index=['0','1'])
sns.heatmap(confusionmatrix_DF,annot=True,fmt='g',cmap='viridis')
plt.title("Confusion matrix ")
plt.show()
```

```
100%|██████████| 7/7 [00:31<00:00,  4.40s/it]
```

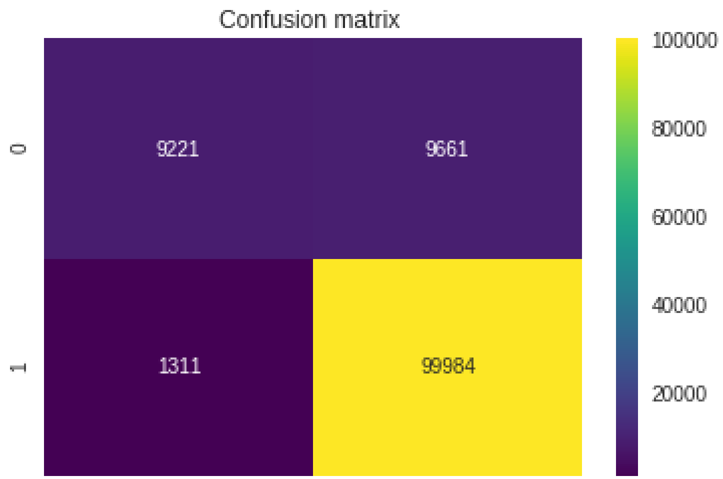
```
The optimal number of alpha is 0.
```


```
Accuracy Score :  90.87013322016692
```

```
Precision Score :  91.18883670025994
Recall Score :  98.70576040278395
F1 Score :  94.79852090641889

Classification Report
              precision    recall  f1-score   support

           0       0.88      0.49      0.63     18882
           1       0.91      0.99      0.95    101295

   micro avg       0.91      0.91      0.91    120177
   macro avg       0.89      0.74      0.79    120177
weighted avg       0.91      0.91      0.90    120177


AUC Score for train data  with roc_curve 2nd parameter as Predict : 0.7
720611854002382
AUC Score for test data with roc_curve 2nd parameter as Predict : 0.737
70314795185

AUC Score for train data  with roc_curve 2nd parameter as PredictProba
: 0.9657689486098211
AUC Score for test data with roc_curve 2nd parameter as PredictProba :
0.9481309134411939

RoC Score predict  ::  0.73770314795185
RoC Score predictproba  ::  0.9481309134411939
```




```
TrueNegative : 9221
FalsePostive : 9661
FalseNegative : 1311
TruePostive  :  99984
```



0 1

[5.2.1] Top 10 important features of positive class from SET 2

In [0]:

```
features_name = tf_idf_vect.get_feature_names()

feat_count = clf1.feature_count_
#print("printing features score on class 0 and class 1 is :",feat_coun
t)
print("printing features score  rows {} and columns {} :".format(feat_c
ount.shape[0],feat_count.shape[1]))
    #print(nb_optimal.class_count_)

    #Feature probablity for a paticular class get by (feature_log_prob_
 or feature_count_ Attribute )
log_prob = clf1.feature_log_prob_
#print("printing probablity of features on class 0 and class 1 is : ",l
og_prob)

print("No.of Rows and column in log_prob : ",log_prob.shape)
print("Total number of features : ",len(features_name))

    #creating DataFrame with each word probabilty value
    #ie feature or word name(By bow_features )
    #ie each feature or word probablity value(score) of each class by f
eature_log_prob_
feature_prob = pd.DataFrame(feat_count, columns = features_name,index=[
'negative','postive'])
feature_prob
feature_prob_transpose = feature_prob.T
print("Dataframe for feature_Importance contain rows {},columns {}".for
mat(feature_prob_transpose.shape[0],feature_prob_transpose.shape[1]))

print("Top 20 Postive features : \n", feature_prob_transpose['postive']
.sort_values(ascending = False)[:20])
```

```
printing features score  rows 2 and columns 50000 :

No.of Rows and column in log_prob :  (2, 50000)
```

```
No.of Rows and column in log_prob :  (2, 50000)
Total number of features :  50000
Dataframe for feature_Importance contain rows 50000,columns 2
Top 20 Postive features :
 love       4183.646829
great      4125.356815
like       3958.787766
tast       3920.160674
good       3897.722163
flavor     3623.042327
tea        3620.651829
coffe      3517.758644
use        3405.913935
product    3326.233755
veri       3312.847763
just       2900.210631
tri        2863.649954
make       2667.259052
food       2383.138801
best       2350.310181
buy        2330.421221
price      2293.076359
order      2210.567647
realli     2176.764949
Name: postive, dtype: float64
```

In [0]:
```
feature_prob_transpose
```

Out[0]:

	negative	postive
aafco	0.947531	1.906845
aback	1.117783	4.204955
abandon	2.434199	7.585749
abc	1.991237	4.653120
abdomin	3.703658	3.146549
abil	4.919758	43.786671

	negative	postive
abil make	0.128122	4.264919
abl	75.152074	656.068624
abl add	0.479430	5.750315
abl amazon	0.104561	25.762454
abl ani	1.200833	13.739107
abl anywher	0.513444	11.386949
abl buy	1.895426	78.821956
abl chew	2.157053	7.432982
abl cut	0.615961	4.478480
abl drink	3.904940	14.209929
abl eat	8.244002	37.547219
abl enjoy	1.693066	24.660621
abl feed	0.214754	5.193737
abl finish	3.997557	3.994015
abl good	0.998367	5.775365
abl groceri	0.399515	6.539074
abl handl	1.447147	4.809715
abl just	0.234937	8.413124
abl local	1.061262	25.353197
abl locat	0.735250	10.375881
abl make	4.377909	28.845148
abl onlin	0.158810	10.771177
abl open	0.305859	4.819479
abl order	0.438283	59.526225
...	...	...

	negative	postive
zico coconut	2.175910	4.087070
zinc	2.182496	13.747332
zinc sulfat	0.575077	1.962786
zing	3.021349	48.034568
zinger	1.761718	18.351144
zinger tea	0.397950	4.193430
zingi	0.298589	4.892098
zip	6.514845	63.645253
zip bag	0.522616	6.534916
zip lock	2.459238	27.213974
zipfizz	0.114807	7.096795
ziploc	2.523814	28.167183
ziploc bag	1.548193	17.294997
ziplock	4.346975	34.452863
ziplock bag	3.574484	19.650827
zipper	1.815100	13.060599
zippi	0.153364	5.553446
ziti	0.310917	7.991491
ziwipeak	1.315111	5.684001
zoe	0.856126	11.058875
zojirushi	0.856713	6.042700
zola	1.620302	7.325864
zombi	0.543720	7.978614
zone	2.865159	9.997233
zoo	0.290588	6.068601

	negative	postive
zoom	0.591534	3.778006
zucchini	1.608655	15.493792
zuke	3.135665	39.170036
zuke mini	0.430254	7.934223
zuke treat	0.863241	4.495055

50000 rows × 2 columns

[5.2.2] Top 10 important features of negative class from SET 2

In [0]:

```
print("Top 20 Negative features : \n", feature_prob_transpose['negative'].sort_values(ascending = False)[:20])
```

```
Top 20 Negative features :
 tast          1042.969769
like           933.261051
product        929.710468
flavor         621.432503
coffe          621.338371
veri           592.132235
just           585.193077
tri            572.218851
order          568.273353
buy            565.355694
box            495.721239
dont           474.230702
disappoint     473.555605
tea            471.593348
use            467.222169
good           466.385264
food           427.551118
bag            419.384582
bad            404.428912
```

```
purchas        398.204799
Name: negative, dtype: float64
```

[6] Conclusions

In [0]:
```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["NavieBayes with Different Vectorization", "alpha" ,
'Test_Accuracy','F1-Score','AUC_Score on TestData with Predict', 'AUC_S
core on TestData with PredictProba']

x.add_row([ "NaiveBayes with BOW" , "0.1" , 89.903  , 93.998  ,  81.36
,91.17 ])
x.add_row([ "NaiveBayes with TFIDF" , "0" , 90.8701  , 94.798 ,  73.77
,94.813 ])

print(x)
```

```
+-----------------------------------------+-------+---------------+----
------+-----------------------------------+--------------------------
--------------+
| NavieBayes with Different Vectorization | alpha | Test_Accuracy | F1-
Score | AUC_Score on TestData with Predict | AUC_Score on TestData with
PredictProba |
+-----------------------------------------+-------+---------------+----
------+-----------------------------------+--------------------------
--------------+
|           NaiveBayes with BOW           |  0.1  |     89.903    |  9
3.998  |               81.36                |                 91.17
               |
|          NaiveBayes with TFIDF          |   0   |    90.8701    |  9
4.798  |               73.77                |                 94.813
               |
+-----------------------------------------+-------+---------------+----
```

------+-----------------------------------+-------------------------
--------------+

- Amzon Fine food reviews with NavieBayes BOW have less AUC Score compare to the TFIDF
- Feature Importance of TF-idf and Bow have almost same
- after using all data in AmzonFinefoodreviews got AUC SCore has 94.813
- there i no OVERFIT or UNDERFIT in NavieBayes BOW as
  - AUC Score for train data 0.8474912507015196
  - AUC Score for test data : 0.813641366232927 there values are good enough
- Similray there ia also not OVERFIT or UNDERFIT in NavieBayes TFIDF as :
  - AUC Score for train data 0.7720611854002382
  - AUC Score for test data : 0.73770314795185

In [0]: