objective :

1. Applying naive bayes to classify the amazon food reviews.
2. Check for different types of scoring merrics
3. Getting the important features.

In [1]:
```
#importing all module
import sqlite3 as s
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.cross_validation import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import TimeSeriesSplit
from sklearn.metrics import confusion_matrix
```

```
C:\Users\himateja\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: D
eprecationWarning: This module was deprecated in version 0.18 in favor of the m
odel_selection module into which all the refactored classes and functions are m
oved. Also note that the interface of the new CV iterators are different from t
hat of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [2]:
```
con=s.connect("database.sqlite")
con
```

Out[2]:
```
<sqlite3.Connection at 0x23df96e8490>
```

In [3]:
```
data=pd.read_sql_query("SELECT * FROM Reviews WHERE Score!=3",con)
data.head(5)
```

Out[3]:

	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	
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	

In [4]:
```
#function to change the score to positive/negative
def change(x):
    if x<3:
        return 'negative'
    else:
        return 'positive'
```

In [5]:
```
a_s=data.Score
a_s=a_s.map(change)
data.Score=a_s
data.Score.head(5)
```

Out[5]:
```
0    positive
1    negative
2    positive
3    negative
4    positive
Name: Score, dtype: object
```

Data cleaning

The data needs to get clean as it may have some unwanted things such as duplicates.

In [6]:
```
#sorting the values by product ids
data=data.sort_values("ProductId")
```

In [7]:
```
#removing the duplicates from the data
final_data=data.drop_duplicates(subset={"UserId","Text","ProfileName","Time"},kee
```

In [8]:
```
print(final_data.shape)
print(final_data.Score.value_counts())
```

```
(364173, 10)
positive    307063
negative     57110
Name: Score, dtype: int64
```

In [9]:
```
p_data=final_data[final_data.Score=="positive"]
n_data=final_data[final_data.Score=="negative"]
```

In [10]:
```
#randomly selecting points
#p_data=p_data.sample(34000)
#n_data=n_data.sample(6000)
```

In [11]:
```
print(p_data.shape,n_data.shape)
```

```
(307063, 10) (57110, 10)
```

In [12]:
```
d=pd.concat((p_data,n_data))
```

In [13]:
```
print(d.shape)
```

```
(364173, 10)
```

In [14]:
```
#sorting according to time stamp
d=d.sort_values('Time')
```

In [15]:
```
print(d.Score.value_counts())
```

```
positive    307063
negative     57110
Name: Score, dtype: int64
```

Data preprocessing

The data should be preprocessed after cleaning it

In [16]:
```
import string
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
import re
```

In [17]:
```
#stopwords
stop_words=set(stopwords.words("english"))
#initializing snowball stemmer
sno=SnowballStemmer("english")
```

In [18]:
```
#function to remove html tags
def cleanhtml(s):
    cleanr=re.compile("<.*?>")
    cleant=re.sub(cleanr," ",s)
    return cleant
```

In [19]:
```
#funtion to remove punctuation and special character
def cleanpunc(s):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',s)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

In [20]:
```
i=0
final=[]

for s in d.Text.values:
    f=[]
    c=cleanhtml(s)
    for w in cleanpunc(c).split():
        if w.isalpha() and len(w)>2:
            if w not in stop_words:
                sne=(sno.stem(w.lower())).encode('utf-8')
                f.append(sne)

            else:
                continue
        else:
            continue
    te=b" ".join(f)
    final.append(te)
    i+=1
```

In [21]:
```
#adding the preprocessed data into another column
d["cleaned"]=final
```

In [22]:
```
#checking if new column is added
d.columns
```

Out[22]:
```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'cleaned'],
      dtype='object')
```

In [23]:
```
import sqlite3
conn=sqlite3.connect("future.sqlite")
c=conn.cursor()
conn.text_factory=str
d.to_sql('Reviews',conn,if_exists='replace',index=True)
```

In [24]:
```
#replacing positive and negative with 1,0 to make it work for different metrics
d=d.replace(['positive','negative'],[1,0])
d.head(10)
```

Out[24]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessD
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	
346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	
417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	
346116	374422	B00004CI84	A1048CYU0OV4O8	Judy L. Eans	2	
346041	374343	B00004CI84	A1B2IZU1JLZA6	Wes	19	
70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	
346141	374450	B00004CI84	ACJR7EQF9S6FP	Jeremy Robertson	2	
346094	374400	B00004CI84	A2DEE7F9XKP3ZR	jerome	0	

In [25]:
```
#importing the needed module
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import f1_score,make_scorer
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
```

Lets create functions for finding best parameter.

In [26]:
```
#function for multinomial naive bayes
def main(h,j,k,l):
    #gridsearchcv

    #params we need to try on classifier
    nb = MultinomialNB()
    param_grid = {'alpha':[0.0001,0.001,0.01,0.1,1,10,100]}
    #For time based splitting
    t = TimeSeriesSplit(n_splits=5)

    gsv = GridSearchCV(nb,param_grid,cv=t,n_jobs=-1,scoring='f1',refit=True)
    gsv.fit(h,j)
    print("Best HyperParameter: ",gsv.best_params_)
    #assinging best alpha to optimal
    optimal=gsv.best_params_['alpha']
    print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
    print("best estimator: ",gsv.estimator)
    nb_optimal=MultinomialNB(alpha=optimal)
    nb_optimal.fit(h,j)
    pred=nb_optimal.predict(k)

    #accuracy

    acc=accuracy_score(l,pred)*100
    print("\nthe accuracy is %.2f%%"%acc)

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

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

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

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

Bag of words

In [28]:
```
x_1, x_test, y_1, y_test = train_test_split(d.cleaned.values, d.Score, test_size=

#x_tr, x_cv, y_tr, y_cv = train_test_split(x_1, y_1, test_size=0.3)
```

In [29]:
```
print(x_1.shape,x_test.shape,y_1.shape,y_test.shape)
```

```
(254921,) (109252,) (254921,) (109252,)
```

In [30]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn import preprocessing
```

In [31]:
```
#bigrams
count_vect=CountVectorizer(ngram_range=(1,2))
```

In [32]:
```
#transforming the data
bdata=count_vect.fit_transform(x_1)
test_data=count_vect.transform(x_test)
print(bdata.shape,y_1.shape,test_data.shape,y_test.shape)
```

```
(254921, 2351349) (254921,) (109252, 2351349) (109252,)
```

In [33]:
```
%%time
main(bdata,y_1,test_data,y_test)
```

```
Best HyperParameter:  {'alpha': 0.001}
Best Accuracy: 93.70%
best estimator:  MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)

the accuracy is 88.85%

the recall is 98.24%
the precision is 89.32%
the f1 score is 93.57%
Wall time: 35 s
```

Feature importance

In [34]:
```
#getting all feature names
all_feat = count_vect.get_feature_names()
#model with optimal hyperparameter
clf=MultinomialNB(alpha=0.001)
clf.fit(bdata,y_1)
```

Out[34]: `MultinomialNB(alpha=0.001, class_prior=None, fit_prior=True)`

In [81]:
```
#probability of class given feature
log_probabilities=np.exp(clf.feature_log_prob_)
```

In [101]:
```
#dataframe for negative probabilities
negative_dataframe=pd.DataFrame({"word":all_feat,"negative_proba":log_probabiliti
negative_dataframe.head(4)
```

Out[101]:

	word	negative_proba
0	aa	3.087364e-10
1	aa pleas	3.087364e-10
2	aa state	3.087364e-10
3	aaa	3.090451e-07

In [103]:
```
#sorting in descending order
negative_dataframe=negative_dataframe.sort_values(by="negative_proba",ascending=F
negative_dataframe.head(4)
```

Out[103]:

	word	negative_proba
2028406	tast	0.007193
1159383	like	0.006632
2063012	the	0.005681
1587721	product	0.005608

In [105]:
```
#dataframe for positive probabilites
positive_dataframe=pd.DataFrame({"word":all_feat,"positive_proba":log_probabiliti
positive_dataframe.head(4)
```

Out[105]:

	word	positive_proba
0	aa	1.183994e-07
1	aa pleas	5.922928e-08
2	aa state	5.922928e-08
3	aaa	1.301802e-06

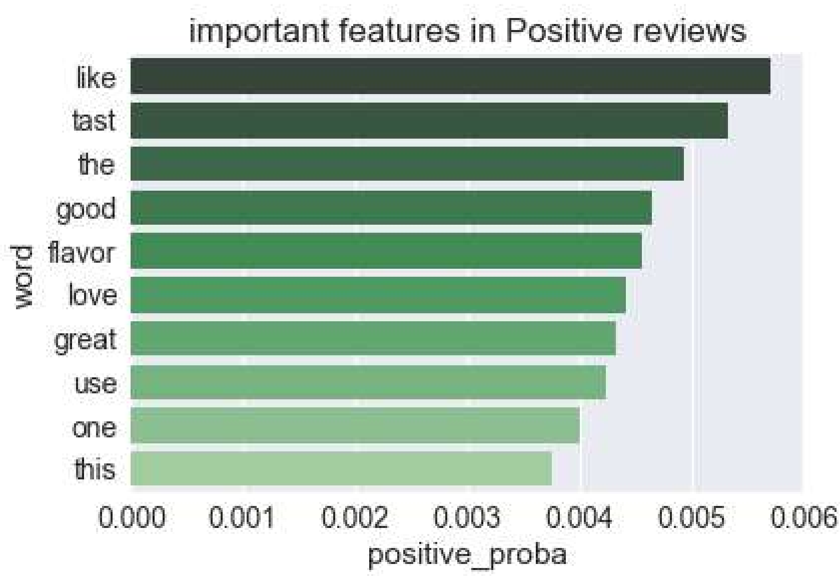
In [107]:
```
#sorting in descending order
positive_dataframe=positive_dataframe.sort_values(by="positive_proba",ascending=F
positive_dataframe.head(4)
```

Out[107]:

	word	positive_proba
1159383	like	0.005710
2028406	tast	0.005321
2063012	the	0.004941
881139	good	0.004649

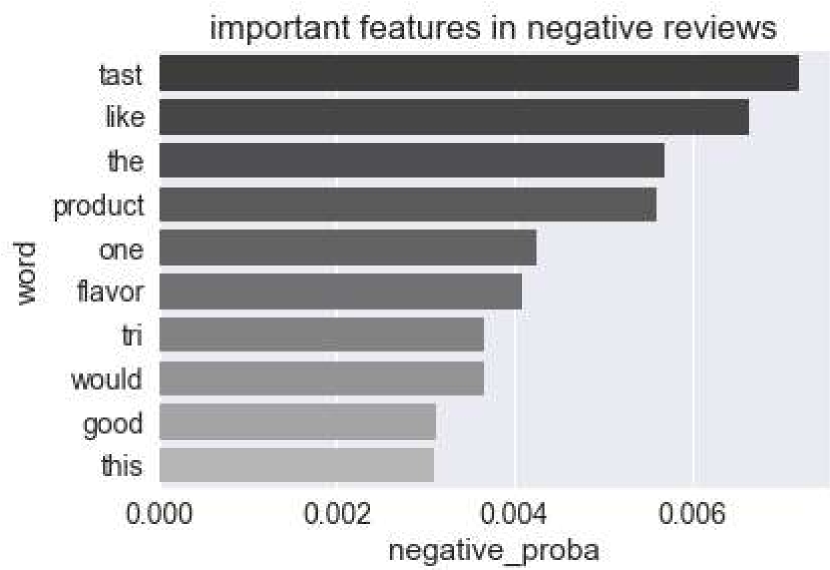
In [108]:
```
#barplot for positive feature importance
sns.barplot(y='word', x='positive_proba', data=positive_dataframe.head(10), palet
```

Out[108]:
```
Text(0.5,1,'important features in Positive reviews')
```



In [109]:
```
#barplot for negative feature importance
sns.barplot(y='word', x='negative_proba', data=negative_dataframe.head(10), palet
```

Out[109]: Text(0.5,1,'important features in negative reviews')



In [115]:
```
summary=pd.DataFrame({"accuracy":"88.85%","recall":"98.24%","precision":"89.32%",
summary=summary.T
summary
```

Out[115]:

	score
accuracy	88.85%
recall	98.24%
precision	89.32%
f1	93.57%

Tfidf

In [116]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [117]:
```
x_1, x_test, y_1, y_test = train_test_split(d.cleaned.values, d.Score, test_size=

#x_tr, x_cv, y_tr, y_cv = train_test_split(x_1, y_1, test_size=0.3)
```

In [118]:
```
#bigrams
tfidf=TfidfVectorizer(ngram_range=(1,2))
```

In [119]:
```
#transforming the data
tdata=tfidf.fit_transform(x_1)
test_data=tfidf.transform(x_test)
print(tdata.shape,test_data.shape)
```

```
(254921, 2351349) (109252, 2351349)
```

In [120]:
```
%%time
main(tdata,y_1,test_data,y_test)
```

```
Best HyperParameter:  {'alpha': 0.001}
Best Accuracy: 93.50%
best estimator:  MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)

the accuracy is 87.92%

the recall is 99.14%
the precision is 87.80%
the f1 score is 93.12%
Wall time: 32 s
```

In [121]:
```
#getting all feature names
all_feat = tfidf.get_feature_names()
#model with optimal hyperparameter
clf=MultinomialNB(alpha=0.001)
clf.fit(bdata,y_1)
```

Out[121]:
```
MultinomialNB(alpha=0.001, class_prior=None, fit_prior=True)
```

In [122]:
```
#probability of class given feature
log_probabilities=np.exp(clf.feature_log_prob_)
```

In [123]:
```
#dataframe for negative probabilities
negative_dataframe=pd.DataFrame({"word":all_feat,"negative_proba":log_probabiliti
negative_dataframe.head(4)
```

Out[123]:

	word	negative_proba
0	aa	3.087364e-10
1	aa pleas	3.087364e-10
2	aa state	3.087364e-10
3	aaa	3.090451e-07

In [124]:
```
#sorting in descending order
negative_dataframe=negative_dataframe.sort_values(by="negative_proba",ascending=F
negative_dataframe.head(4)
```

Out[124]:

	word	negative_proba
2028406	tast	0.007193
1159383	like	0.006632
2063012	the	0.005681
1587721	product	0.005608

In [125]:
```
#dataframe for positive probabilites
positive_dataframe=pd.DataFrame({"word":all_feat,"positive_proba":log_probabiliti
positive_dataframe.head(4)
```

Out[125]:

	word	positive_proba
0	aa	1.183994e-07
1	aa pleas	5.922928e-08
2	aa state	5.922928e-08
3	aaa	1.301802e-06

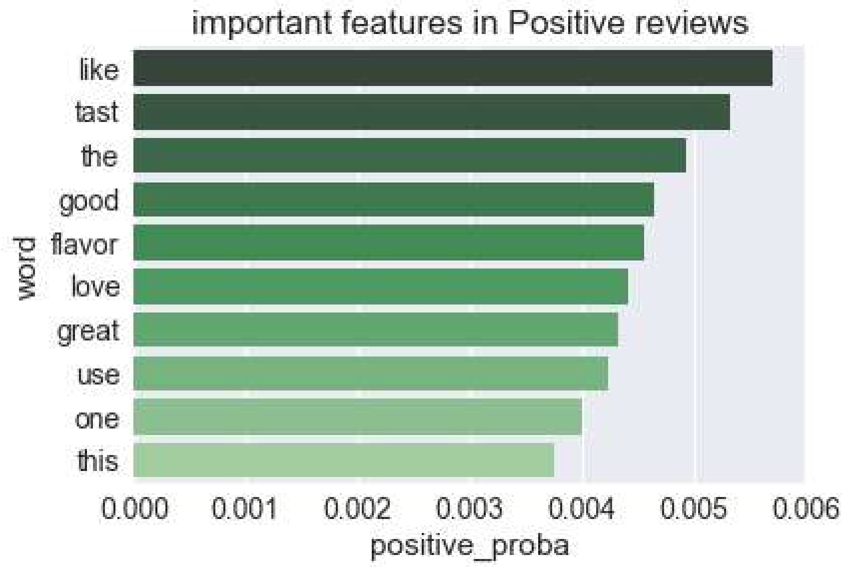
In [126]:
```
#sorting in descending order
positive_dataframe=positive_dataframe.sort_values(by="positive_proba",ascending=F
positive_dataframe.head(4)
```

Out[126]:

	word	positive_proba
1159383	like	0.005710
2028406	tast	0.005321
2063012	the	0.004941
881139	good	0.004649

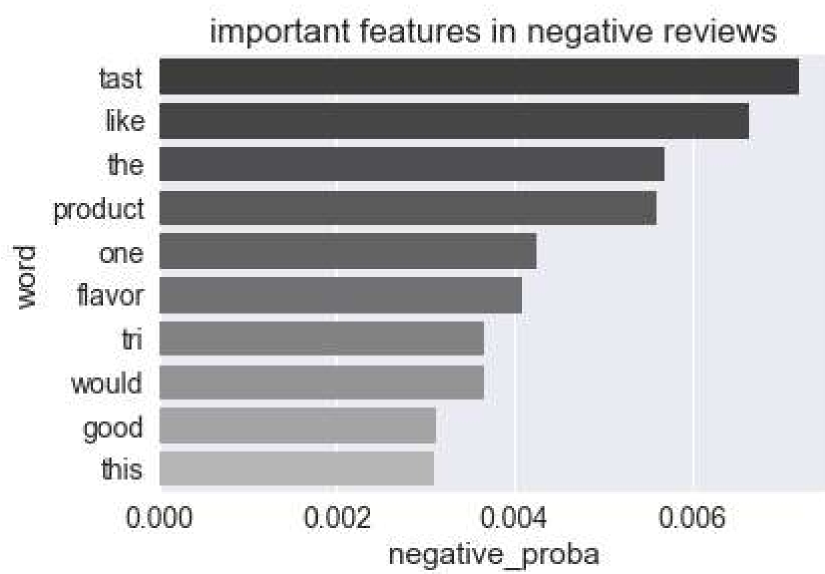
In [127]:
```
#barplot for positive feature importance
sns.barplot(y='word', x='positive_proba', data=positive_dataframe.head(10), palet
```

Out[127]: Text(0.5,1,'important features in Positive reviews')



In [128]:
```
#barplot for negative feature importance
sns.barplot(y='word', x='negative_proba', data=negative_dataframe.head(10), palet
```

Out[128]: Text(0.5,1,'important features in negative reviews')



In [131]:
```
summary=pd.DataFrame({"accuracy":"87.92%","recall":"99.14%","precision":"87.80%",
summary=summary.T
summary
```

Out[131]:

	score
accuracy	87.92%
recall	99.14%
precision	87.80%
f1	93.12%

Conclusion :
1.naive bayes works well ,when features are independent. That is why we have not done word2vec as feature are highly dependent.
2.time complexity of naive bayes is very less.(theortically o(n*d) n=number of points,d=no of features)
3.accuracy is not a good parameter to use in naive bayes

Both the above models are performing good as metrics have a good value.

In [ ]: