AFR-NB

September 15, 2018

```
In [1]: #main libraries
        import sqlite3
        import pandas as pd
        import numpy as np
        import seaborn as sns
        import matplotlib.pyplot as plt
        import warnings
        warnings.filterwarnings("ignore")
```

```
In [2]: #vectorizors
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.feature_extraction.text import CountVectorizer
        import gensim
        from gensim.models import Word2Vec
        from gensim.models import KeyedVectors
        import pickle
```

```
In [3]: #performence metrics
        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import f1_score
        from sklearn.metrics import precision_score
        from sklearn.metrics import recall_score
```

```
In [4]: #modules for building ML model
        from sklearn.model_selection import train_test_split
        from sklearn.naive_bayes import BernoulliNB
        from sklearn.naive_bayes import MultinomialNB
        from sklearn.model_selection import GridSearchCV
        from sklearn.model_selection import RandomizedSearchCV
        from sklearn.model_selection import TimeSeriesSplit
```

0.1 Objective

1. use BernoulliNB(), MultinomialNB().
2. find right 'alpha' using 10fold cv.

3. Build Naive bayes with featurisation techniques like BOW, TFIDF AVGW2V2 TFIDFW2V.
4. get accuracy, precision scores, confusion matrrix, recall score, f1 score.
5. get important features for +ve and -ve class.

In [5]:
```
#connect sql database
con = sqlite3.connect('final.sqlite')
```

In [6]:
```
#read sql data using pandas
data = pd.read_sql("SELECT * FROM REVIEWS", con)
```

In [7]:
```
def partition(x) :
    if x == 'positive' :
        return 1
    return 0

actualscore = data['Score']
positivenegative = actualscore.map(partition)
data['Score'] = positivenegative
```

In [8]:
```
data.head()
```

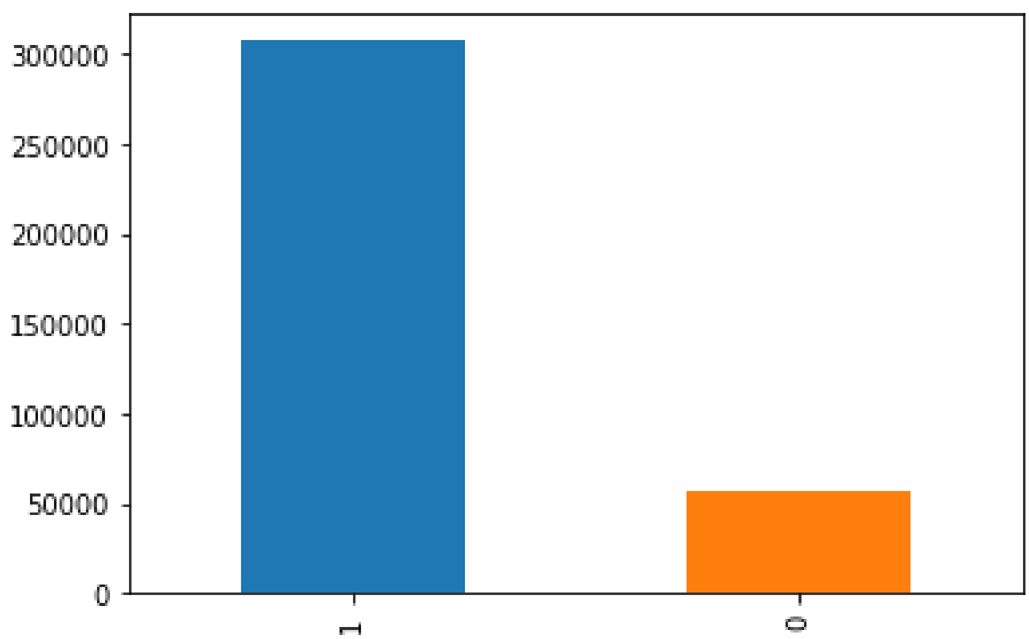
Out[8]:
```
    index      Id   ProductId          UserId                ProfileName  \
0  138706  150524  0006641040   ACITT7DI6IDDL            shari zychinski
1  138688  150506  0006641040  A2IW4PEEKO2R0U                      Tracy
2  138689  150507  0006641040  A1S4A3IQ2MU7V4        sally sue "sally sue"
3  138690  150508  0006641040     AZGXZ2UUK6X  Catherine Hallberg "(Kate)"
4  138691  150509  0006641040  A3CMRKGEOP909G                     Teresa

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     0                       0      1   939340800
1                     1                       1      1  1194739200
2                     1                       1      1  1191456000
3                     1                       1      1  1076025600
4                     3                       4      1  1018396800

                                      Summary  \
0                      EVERY book is educational
1  Love the book, miss the hard cover version
2                 chicken soup with rice months
3      a good swingy rhythm for reading aloud
4             A great way to learn the months

                                                Text  \
0  this witty little book makes my son laugh at l...
1  I grew up reading these Sendak books, and watc...
2  This is a fun way for children to learn their ...
3  This is a great little book to read aloud- it ...
```

```
4  This is a book of poetry about the months of t...

                                         CleanedText
0  witti littl book make son laugh loud recit car...
1  grew read sendak book watch realli rosi movi i...
2  fun way children learn month year learn poem t...
3  great littl book read nice rhythm well good re...
4  book poetri month year goe month cute littl po...
```

In [9]:
```
print ('Number of positive & negative data points are \n',data['Score'].value_counts()
data['Score'].value_counts().plot(kind='bar')
```

```
Number of positive & negative data points are
 1    307061
0    57110
Name: Score, dtype: int64
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x29907782d30>



In [10]:
```
#sort data based on time
df_time_sorted = data.sort_values('Time', kind ='quicksort')
```

In [11]:
```
df_time_sorted.head()
```

Out[11]:
```
    index      Id  ProductId         UserId          ProfileName  \
0  138706  150524  0006641040  ACITT7DI6IDDL      shari zychinski
```

```
30   138683  150501  0006641040   AJ46FKXOVC7NR       Nicholas A Mesiano
424  417839  451856  B00004CXX9   AIUWLEQ1ADEG5          Elizabeth Medina
330  346055  374359  B00004CI84  A344SMIA5JECGM           Vincent P. Ross
423  417838  451855  B00004CXX9   AJH6LUC1UT1ON  The Phantom of the Opera

     HelpfulnessNumerator  HelpfulnessDenominator  Score       Time  \
0                       0                       0      1  939340800
30                      2                       2      1  940809600
424                     0                       0      1  944092800
330                     1                       2      1  944438400
423                     0                       0      1  946857600

                                               Summary  \
0                            EVERY book is educational
30   This whole series is great way to spend time w...
424                              Entertainingl Funny!
330                           A modern day fairy tale
423                                         FANTASTIC!

                                                  Text  \
0    this witty little book makes my son laugh at l...
30   I can remember seeing the show when it aired o...
424  Beetlejuice is a well written movie ... ever...
330  A twist of rumplestiskin captured on film, sta...
423  Beetlejuice is an excellent and funny movie. K...

                                           CleanedText
0    witti littl book make son laugh loud recit car...
30   rememb see show air televis year ago child sis...
424  beetlejuic well written movi everyth excel act...
330  twist rumplestiskin captur film star michael k...
423  beetlejuic excel funni movi keaton hilari wack...
```

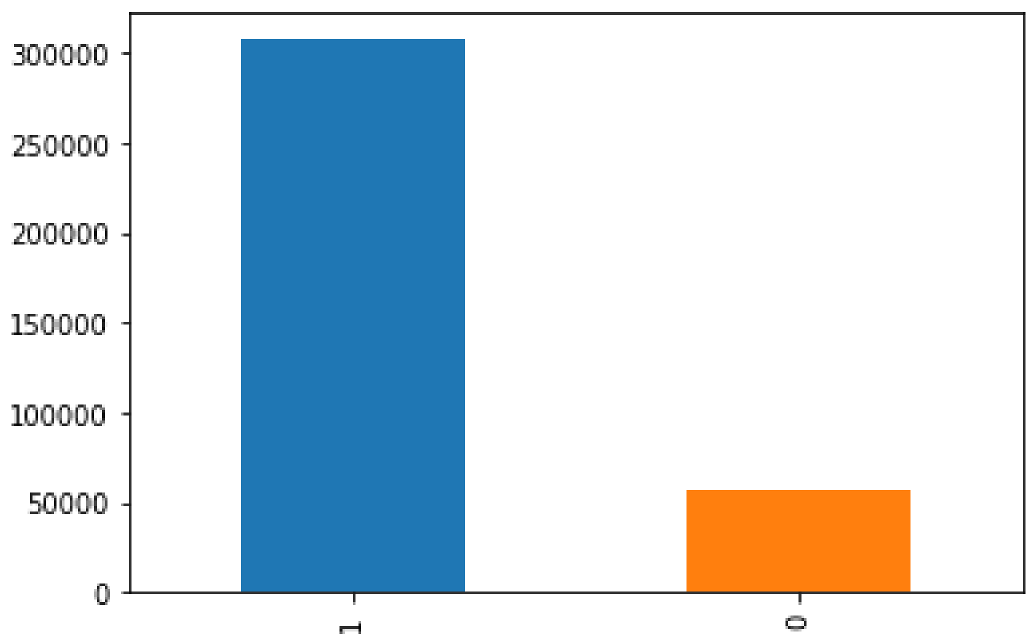
The important piece of information from dataset for building ML models are text reviews and their Scores if they are positive or negative so lets seperate only those two columns into a seperate dataframe using pandas

In [12]:
```python
df = pd.DataFrame(data, columns=['CleanedText', 'Score'])
df.head()
```

Out[12]:
```
                                         CleanedText  Score
0  witti littl book make son laugh loud recit car...      1
1  grew read sendak book watch realli rosi movi i...      1
2  fun way children learn month year learn poem t...      1
3  great littl book read nice rhythm well good re...      1
4  book poetri month year goe month cute littl po...      1
```

In [13]:
```python
#lets check the total dataset values
df.shape
```

```
Out[13]: (364171, 2)

In [14]: df_sample = df
         print ('Number of +ve & -ve datapoints \n' ,df_sample['Score'].value_counts())
         df_sample['Score'].value_counts().plot(kind='bar')

Number of +ve & -ve datapoints
 1    307061
0     57110
Name: Score, dtype: int64


Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x2990e54f1d0>
```




```
In [15]: X = df_sample['CleanedText']
         y = df_sample['Score']
         print (X.shape)
         print (y.shape)

(364171,)
(364171,)
```

Since the data is time based. we split the data into test-train in temporal manner and not random. where first 80% of data is taken into train and rest 20% into test.

To achieve this in test_train_split we use shuffle=False. so the data doesnt split in random manner.

```
In [16]: #test-train-split
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,shuffle=False)
         print('X_train shape :' ,X_train.shape)
         print('y_train shape :' ,y_train.shape)
         print('X_test shape :' ,X_test.shape)
         print('y_test shape :' ,y_test.shape)
```

```
X_train shape : (254919,)
y_train shape : (254919,)
X_test shape : (109252,)
y_test shape : (109252,)
```

```
In [17]: X_train.head()
```

```
Out[17]: 0    witti littl book make son laugh loud recit car...
         1    grew read sendak book watch realli rosi movi i...
         2    fun way children learn month year learn poem t...
         3    great littl book read nice rhythm well good re...
         4    book poetri month year goe month cute littl po...
         Name: CleanedText, dtype: object
```

```
In [18]: X_train.tail()
```

```
Out[18]: 254914       havent found decaff serv challah one give rebb
         254915    purchas coffe base posit feedback either got b...
         254916    drank communiti coffe mani year recent becam c...
         254917    bought pack give other kept one tri glad great...
         254918    love communiti coffe yummi strong without grea...
         Name: CleanedText, dtype: object
```

```
In [19]: X_test.head()
```

```
Out[19]: 254919    word want reduc caffienn brand best choic use ...
         254920    louisiana nativ like peopl louisiana drink com...
         254921    drink number brand coffe definit dont enjoy fi...
         254922    purchas great price amazon pleas flavor buddi ...
         254923    love coffe still block form fresh communiti co...
         Name: CleanedText, dtype: object
```

```
In [20]: X_test.head()
```

```
Out[20]: 254919    word want reduc caffienn brand best choic use ...
         254920    louisiana nativ like peopl louisiana drink com...
         254921    drink number brand coffe definit dont enjoy fi...
         254922    purchas great price amazon pleas flavor buddi ...
         254923    love coffe still block form fresh communiti co...
         Name: CleanedText, dtype: object
```

```
In [21]: #get train and cv 10fold shapes
         cv= TimeSeriesSplit(n_splits=10)
         for train, cv in cv.split(X_train):
             print(X_train[train].shape, X_train[cv].shape)
```

```
(23179,) (23174,)
(46353,) (23174,)
(69527,) (23174,)
(92701,) (23174,)
(115875,) (23174,)
(139049,) (23174,)
(162223,) (23174,)
(185397,) (23174,)
(208571,) (23174,)
(231745,) (23174,)
```

1 NAIVE-BAYES

1. Naive bayes are based on principle of Conditional independence i.e each features(words) are completly independent to each other.
2. Naive bayes classifier in SKlearn has two functions BernoulliNB() & MultinomialNB.
3. BernoulliNB is used when word occurences are counted as binary (i.e if a word is present it gives value 1, if not present then 0). if CountVectorizer(binary=True), TfidfVectorizer(binary=True).
4. MultinomialNB takes the number of occurences of words in documents. most generally MultinomialNB() is used in Naive-Bayes.
5. word2vec fails drastically fails on Naive-Bayes since the words are sematically co-realted vectors.

2 Functions to find Hyperparameter & Use Naive-Bayes

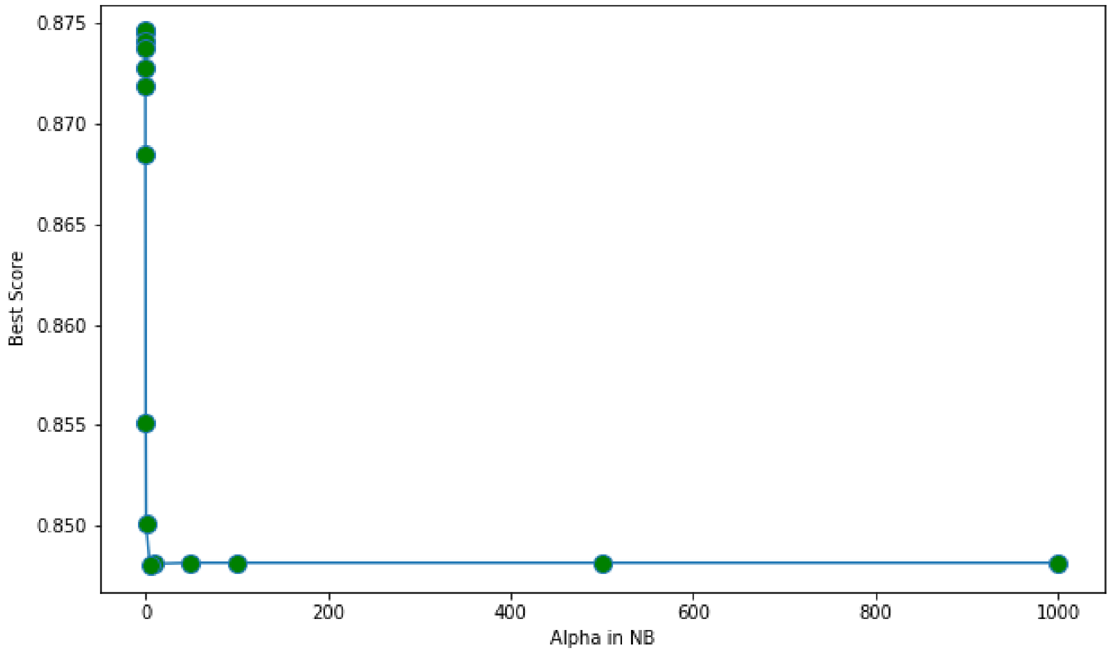
```
In [22]: #c=1/lambda, lambda = 0.001,0.002,0.01,0.02,0.1,0.2,1,2,10,20,100,200,1000,2000,10000
         def MNB_best_params (X_train, y_train) :
             clf = MultinomialNB()
             cv= TimeSeriesSplit(n_splits=10)
             param_grid = {'alpha':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005
             grid_cv = GridSearchCV(clf, param_grid, cv=cv, verbose=1, n_jobs=-1)
             grid_cv.fit(X_train,y_train)
             print("Best HyperParameter: ",grid_cv.best_params_)
             print("Best Accuracy: ", (grid_cv.best_score_*100))
             #Function for cv_error vs alpha plot
             plt.figure(figsize=(10,6))
             plt.xlabel('Alpha in NB')
```

```
        plt.ylabel('Best Score')
        plt.plot(param_grid['alpha'], grid_cv.cv_results_['mean_test_score'], marker='o',m
```

```
In [23]: def MNB(alpha, X_train, y_train, X_test, Y_test) :
             clf = BernoulliNB(alpha=alpha)
             clf.fit(X_train, y_train)
             y_pred = clf.predict(X_test)
             print("Accuracy: ", (metrics.accuracy_score(y_test, y_pred)*100))
             print("F1-Score: ",round(f1_score(y_test, y_pred) * float(100)))
             print("Precision-Score: ",round(precision_score(y_test, y_pred) * float(100)))
             print("Recall-Score : ",round(recall_score(y_test, y_pred) * float(100)))
             cm = confusion_matrix(y_test, y_pred)
             sns.heatmap(cm, annot=True, fmt='d')
```

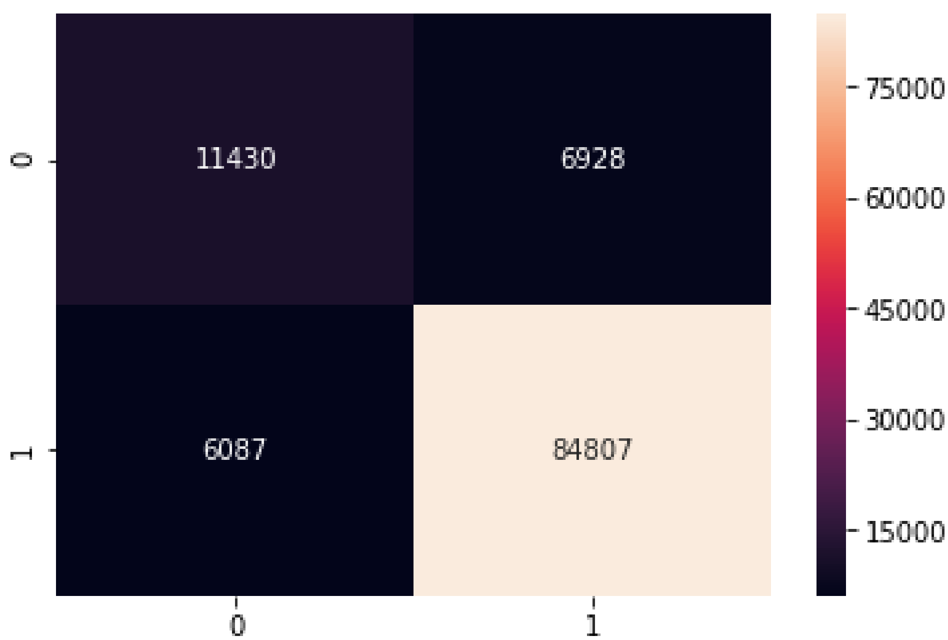
3 BAG of WORDS

```
In [24]: vect = CountVectorizer()

In [25]: from sklearn import preprocessing
         bow_X_train = vect.fit_transform(X_train)
         bow_X_train = preprocessing.normalize(bow_X_train)
         bow_X_train

Out[25]: <254919x59601 sparse matrix of type '<class 'numpy.float64'>'
                 with 7863068 stored elements in Compressed Sparse Row format>

In [26]: bow_X_test = vect.transform(X_test)
         bow_X_test = preprocessing.normalize(bow_X_test)
         bow_X_test

Out[26]: <109252x59601 sparse matrix of type '<class 'numpy.float64'>'
                 with 3581565 stored elements in Compressed Sparse Row format>

In [27]: MNB_best_params(bow_X_train, y_train)

Fitting 10 folds for each of 15 candidates, totalling 150 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:   12.9s
[Parallel(n_jobs=-1)]: Done 150 out of 150 | elapsed:   43.4s finished


Best HyperParameter:  {'alpha': 0.005}
Best Accuracy:  87.46051609562441
```




```
In [28]: MNB(0.005, bow_X_train, y_train, bow_X_test, y_test)
```

```
Accuracy:  88.08717460549921
F1-Score:  93.0
Precision-Score:  92.0
Recall-Score :  93.0
```



In [33]:
```
### Most Important Features
```

In [35]:
```
bow_1 = CountVectorizer()
bow_2 = bow_1.fit_transform(X_train.values)
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tNegative\t\t\t\t\t\tPositive")
    print("_______________________________________________________________________________
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(bow_1,NB)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informat
```

```
                        Negative                                                Positive
_______________________________________________________________________________________________
        -10.4069        aachen                                  -1.2896         love
        -10.4069        abbrevi                                 -1.2964         like
        -10.4069        aberr                                   -1.3265         great
        -10.4069        abouit                                  -1.3415         tast
        -10.4069        acc                                     -1.3606         good
        -10.4069        accusatori                              -1.3710         use
        -10.4069        acknowleg                               -1.5057         one
        -10.4069        actal                                   -1.5501         product
        -10.4069        addag                                   -1.5862         tri
        -10.4069        addicitv                                -1.6016         flavor
        -10.4069        adio                                    -1.6240         make
        -10.4069        adovada                                 -1.6878         get
        -10.4069        adress                                  -1.8521         time
        -10.4069        adver                                   -1.9693         best
        -10.4069        adverag                                 -1.9821         buy
        -10.4069        adversis                                -1.9868         find
        -10.4069        advertiz                                -1.9897         tea
        -10.4069        aegean                                  -2.0219         realli
        -10.4069        aer                                     -2.0334         much
        -10.4069        afer                                    -2.0352         would
        -10.4069        affront                                 -2.0450         also
        -10.4069        afi                                     -2.0896         well
        -10.4069        aftercar                                -2.0926         dont
        -10.4069        agribusi                                -2.1278         store
        -10.4069        ahora                                   -2.1328         eat
```

4 TFIDF

```
In [29]: vect = TfidfVectorizer()
```

```
In [30]: from sklearn import preprocessing
         tfidf_X_train = vect.fit_transform(X_train)
         tfidf_X_train = preprocessing.normalize(tfidf_X_train)
         tfidf_X_train
```

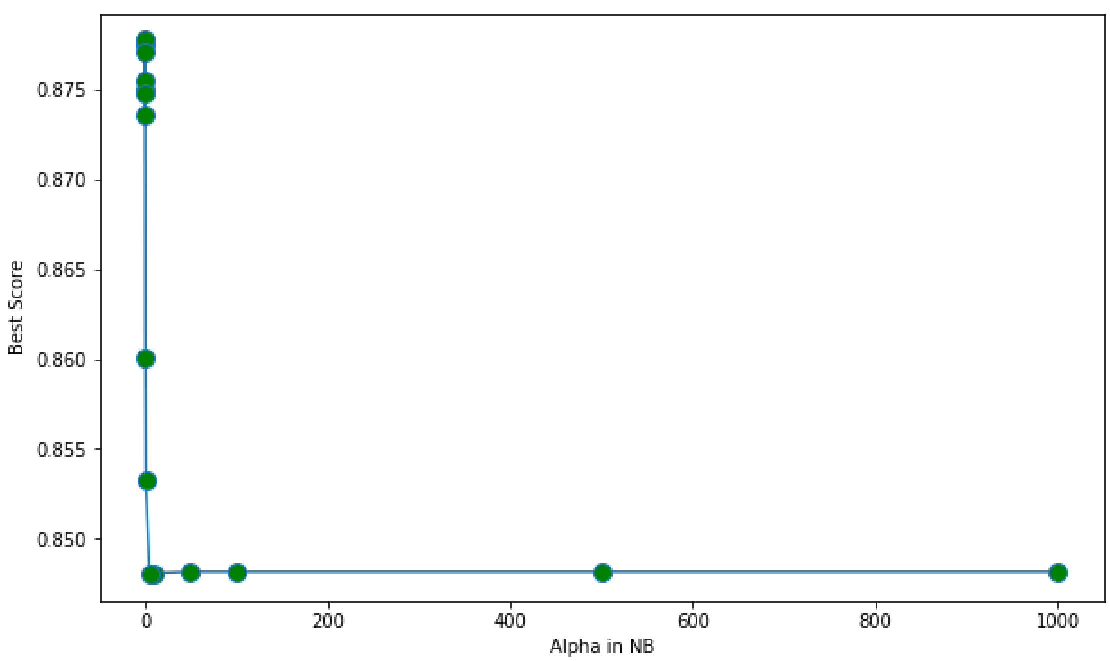
```
Out[30]: <254919x59601 sparse matrix of type '<class 'numpy.float64'>'
                 with 7863068 stored elements in Compressed Sparse Row format>
```

```
In [31]: tfidf_X_test = vect.transform(X_test)
         tfidf_X_test = preprocessing.normalize(tfidf_X_test)
         tfidf_X_test
```

```
Out[31]: <109252x59601 sparse matrix of type '<class 'numpy.float64'>'
                 with 3581565 stored elements in Compressed Sparse Row format>
```

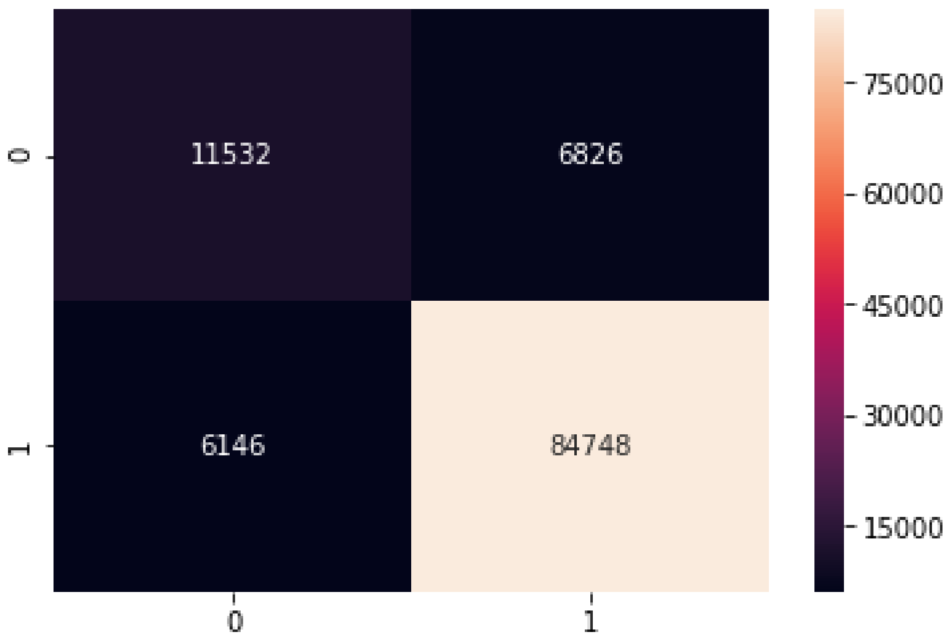
```
In [32]: MNB_best_params(tfidf_X_train, y_train)
```

```
Fitting 10 folds for each of 15 candidates, totalling 150 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:   12.7s
[Parallel(n_jobs=-1)]: Done 150 out of 150 | elapsed:   43.9s finished


Best HyperParameter:  {'alpha': 0.01}
Best Accuracy:  87.77164063174247
```



```
In [33]: MNB(0.01, tfidf_X_train, y_train, tfidf_X_test, y_test)
```

```
Accuracy:  88.12653315271116
F1-Score:  93.0
Precision-Score:  93.0
Recall-Score :  93.0
```



4.0.1 TFIDF most important features

```
In [34]: tfidf_1 = TfidfVectorizer()
         tfidf_2 = tfidf_1.fit_transform(X_train.values)
         def show_most_informative_features(vectorizer, clf, n=25):
             feature_names = vectorizer.get_feature_names()
             coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
             top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
             print("\t\t\tNegative\t\t\t\t\t\tPositive")
             print("________________________________________________________________________________
             for (coef_1, fn_1), (coef_2, fn_2) in top:
                 print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

         show_most_informative_features(tfidf_1,NB)
         #Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informat
```

```
                        Negative                                                       Positive
------------------------------------------------------------------------------------------------
        -10.4069        aachen                                         -1.2896        love
        -10.4069        abbrevi                                        -1.2964        like
        -10.4069        aberr                                          -1.3265        great
        -10.4069        abouit                                         -1.3415        tast
        -10.4069        acc                                            -1.3606        good
        -10.4069        accusatori                                     -1.3710        use
        -10.4069        acknowleg                                      -1.5057        one
        -10.4069        actal                                          -1.5501        product
        -10.4069        addag                                          -1.5862        tri
        -10.4069        addicitv                                       -1.6016        flavor
        -10.4069        adio                                           -1.6240        make
        -10.4069        adovada                                        -1.6878        get
        -10.4069        adress                                         -1.8521        time
        -10.4069        adver                                          -1.9693        best
        -10.4069        adverag                                        -1.9821        buy
        -10.4069        adversis                                       -1.9868        find
        -10.4069        advertiz                                       -1.9897        tea
        -10.4069        aegean                                         -2.0219        realli
        -10.4069        aer                                            -2.0334        much
        -10.4069        afer                                           -2.0352        would
        -10.4069        affront                                        -2.0450        also
        -10.4069        afi                                            -2.0896        well
        -10.4069        aftercar                                       -2.0926        dont
        -10.4069        agribusi                                       -2.1278        store
        -10.4069        ahora                                          -2.1328        eat
```

5 NAIVE-BAYES WITH BERNOULLINB()

In [34]:
```
#c=1/lambda, lambda = 0.001,0.002,0.01,0.02,0.1,0.2,1,2,10,20,100,200,1000,2000,10000
def NB_best_params (X_train, y_train) :
    clf = BernoulliNB()
    cv= TimeSeriesSplit(n_splits=10)
    param_grid = {'alpha':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005
    grid_cv = GridSearchCV(clf, param_grid, cv=cv, verbose=1, n_jobs=-1)
    grid_cv.fit(X_train,y_train)
    print("Best HyperParameter: ",grid_cv.best_params_)
    print("Best Accuracy: ", (grid_cv.best_score_*100))
    #Function for cv_error vs alpha plot
    plt.figure(figsize=(10,6))
    plt.xlabel('Alpha in NB')
    plt.ylabel('Best Score')
    plt.plot(param_grid['alpha'], grid_cv.cv_results_['mean_test_score'], marker='o',r
```

In [35]:
```
def NB(alpha, X_train, y_train, X_test, Y_test) :
    clf = BernoulliNB(alpha=alpha)
```

```
        clf.fit(X_train, y_train)
        y_pred = clf.predict(X_test)
        print("Accuracy: ", (metrics.accuracy_score(y_test, y_pred)*100))
        print("F1-Score: ",round(f1_score(y_test, y_pred) * float(100)))
        print("Precision-Score: ",round(precision_score(y_test, y_pred) * float(100)))
        print("Recall-Score : ",round(recall_score(y_test, y_pred) * float(100)))
        cm = confusion_matrix(y_test, y_pred)
        sns.heatmap(cm, annot=True, fmt='d')
```

6 BAG of WORDS

```
In [36]: vect = CountVectorizer(binary=True)
```

```
In [37]: from sklearn import preprocessing
         bow_X_train = vect.fit_transform(X_train)
         bow_X_train = preprocessing.normalize(bow_X_train)
         bow_X_train
```

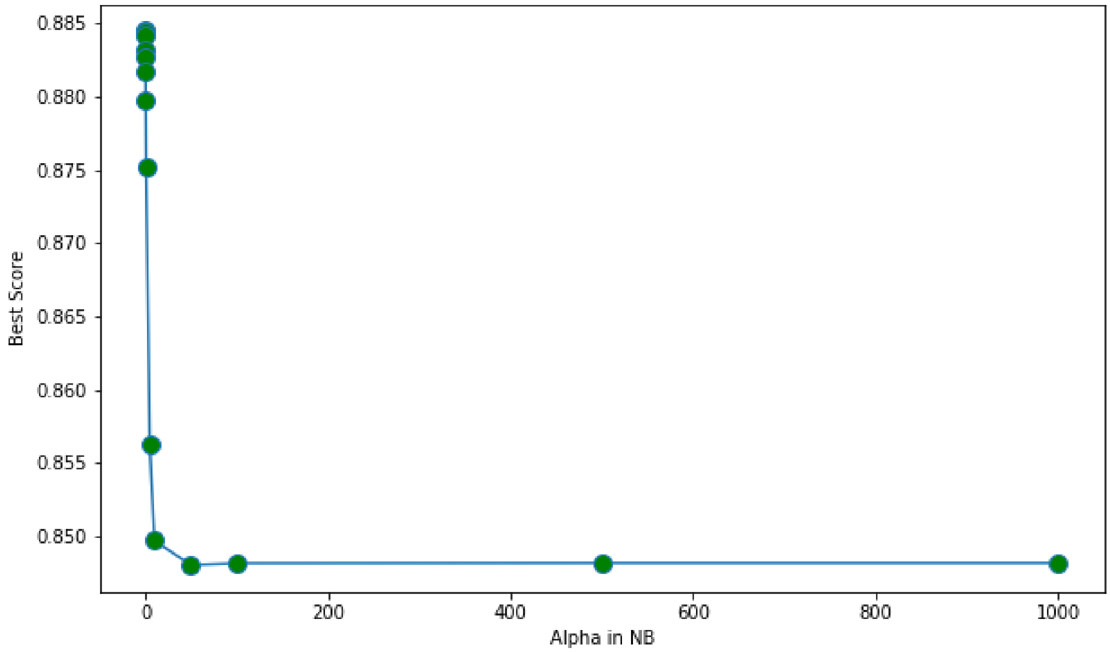
```
Out[37]: <254919x59601 sparse matrix of type '<class 'numpy.float64'>'
                 with 7863068 stored elements in Compressed Sparse Row format>
```

```
In [38]: bow_X_test = vect.transform(X_test)
         bow_X_test = preprocessing.normalize(bow_X_test)
         bow_X_test
```

```
Out[38]: <109252x59601 sparse matrix of type '<class 'numpy.float64'>'
                 with 3581565 stored elements in Compressed Sparse Row format>
```

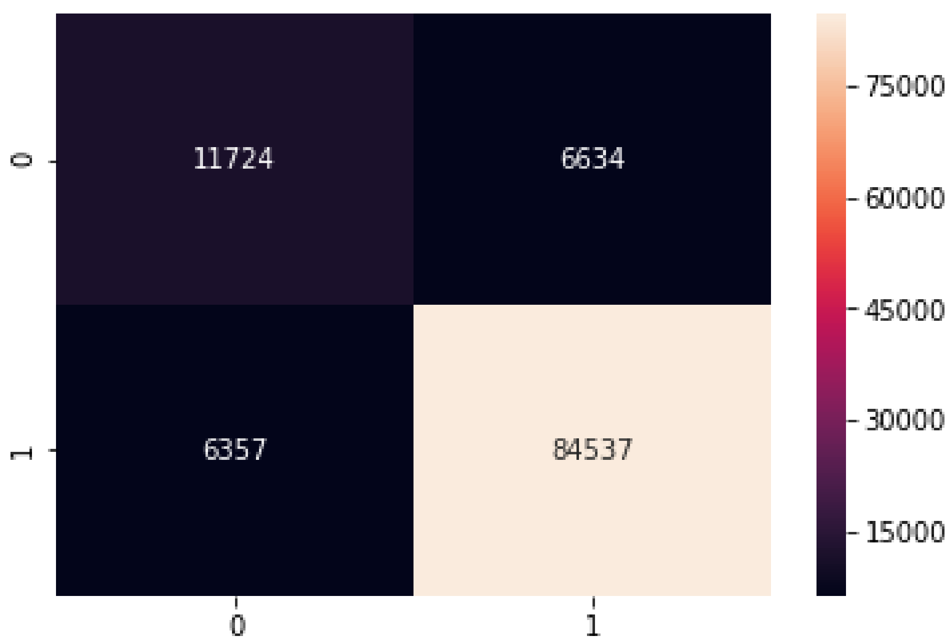
```
In [39]: NB_best_params(bow_X_train, y_train)
```

```
Fitting 10 folds for each of 15 candidates, totalling 150 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:   14.2s
[Parallel(n_jobs=-1)]: Done 150 out of 150 | elapsed:   48.3s finished


Best HyperParameter:  {'alpha': 0.05}
Best Accuracy:  88.44869250021577
```




```
In [40]: NB(0.05, bow_X_train, y_train, bow_X_test, y_test)
```

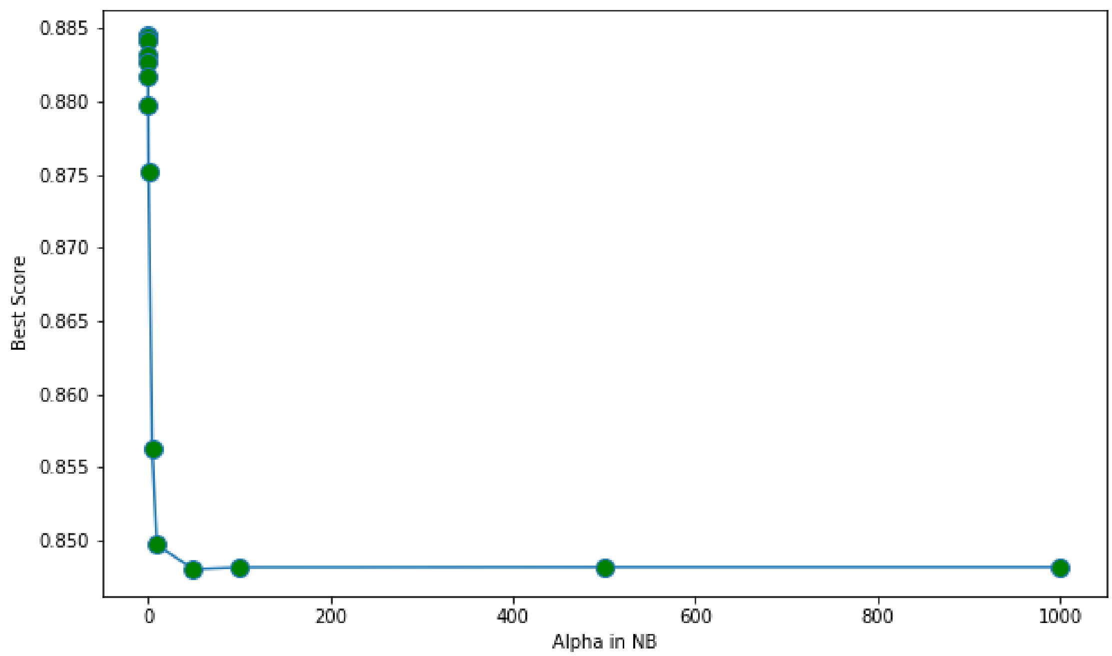
```
Accuracy:  88.10914216673379
F1-Score:  93.0
Precision-Score:  93.0
Recall-Score :  93.0
```



7 TFIDF

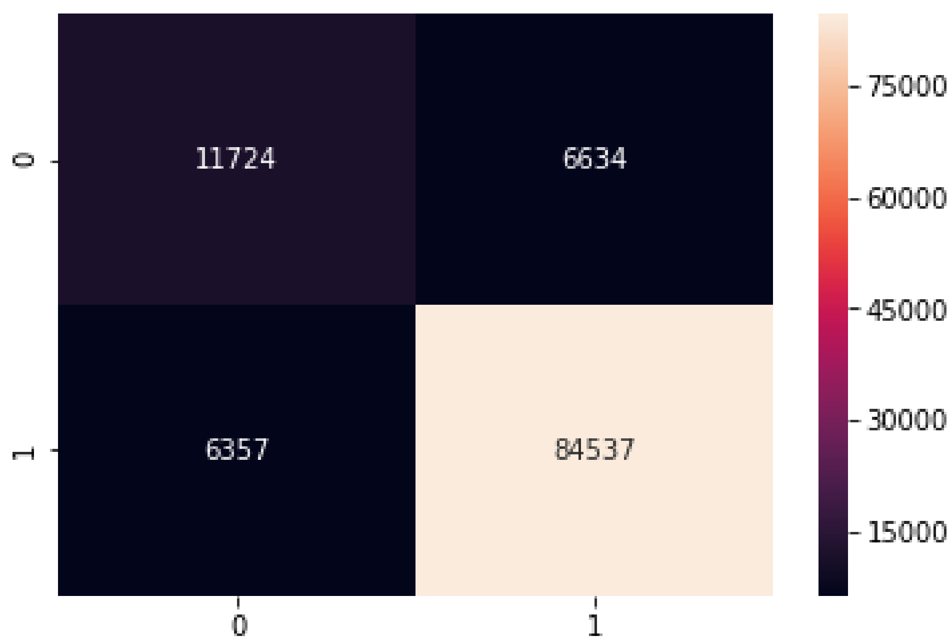
```
In [41]: vect = TfidfVectorizer(binary=True)

In [42]: from sklearn import preprocessing
         tfidf_X_train = vect.fit_transform(X_train)
         tfidf_X_train = preprocessing.normalize(tfidf_X_train)
         tfidf_X_train

Out[42]: <254919x59601 sparse matrix of type '<class 'numpy.float64'>'
                 with 7863068 stored elements in Compressed Sparse Row format>

In [43]: tfidf_X_test = vect.transform(X_test)
         tfidf_X_test = preprocessing.normalize(tfidf_X_test)
         tfidf_X_test

Out[43]: <109252x59601 sparse matrix of type '<class 'numpy.float64'>'
                 with 3581565 stored elements in Compressed Sparse Row format>

In [44]: NB_best_params(tfidf_X_train, y_train)
```

```
Fitting 10 folds for each of 15 candidates, totalling 150 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:   13.2s
[Parallel(n_jobs=-1)]: Done 150 out of 150 | elapsed:   45.4s finished


Best HyperParameter:  {'alpha': 0.05}
Best Accuracy:  88.44869250021577
```




```
In [45]: NB(0.05, tfidf_X_train, y_train, tfidf_X_test, y_test)
```

```
Accuracy:  88.10914216673379
F1-Score:  93.0
Precision-Score:  93.0
Recall-Score :  93.0
```



8 Feature Imporatnce

```
In [164]: nb = MultinomialNB(alpha=0.005)
          nb.fit(bow_X_train, y_train)

Out[164]: MultinomialNB(alpha=0.005, class_prior=None, fit_prior=True)

In [165]: #get first 10 features
          vect.get_feature_names()[:10]

Out[165]: ['aa',
           'aaa',
           'aaaa',
           'aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa',
           'aaaaaaaaaaaaaaaaaaaargh',
           'aaaaaaaaagghh',
           'aaaaaaarrrrrggghhh',
           'aaaaaah',
           'aaaaaahhhhhyaaaaaa',
           'aaaaaand']

In [166]: #get all features
          vect.get_feature_names()[4990:5000]

Out[166]: ['bewteen',
           'bewtter',
           'beyon',
           'beyond',
           'beyondhealth',
           'beyound',
           'bezo',
           'bezzera',
           'bfast',
           'bff']

In [167]: # number of times a word occur in each class
          nb.feature_count_

Out[167]: array([[0.        , 0.10846523, 0.        , ..., 0.        , 0.        ,
                  0.        ],
                 [0.18390036, 1.85169547, 0.17149859, ..., 0.21821789, 0.21821789,
                  0.18569534]])

In [168]: # number of times a word occur in negative class
          negative = nb.feature_count_[0]
          negative
```

Out[168]: array([0.   , 0.10846523, 0.   , ..., 0.   , 0.   ,
        0.   ])

In [169]:
```
# number of times a word occur in positive class
positive = nb.feature_count_[1]
positive
```

Out[169]: array([0.18390036, 1.85169547, 0.17149859, ..., 0.21821789, 0.21821789,
        0.18569534])

In [170]:
```
words = pd.DataFrame({'words': vect.get_feature_names(), 'negative': negative, 'posi
words.head()
```

Out[170]:

	words	negative	positive
0	aa	0.000000	0.183900
1	aaa	0.108465	1.851695
2	aaaa	0.000000	0.171499
3	aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa	0.000000	0.250000
4	aaaaaaaaaaaaaaaaaaaaaargh	0.000000	0.149071

In [171]:
```
# lets find #1 important word found in most of documents
imp_positive_word = words.iloc[words['positive'].argmax()]
imp_negative_word = words.iloc[words['negative'].argmax()]
print('Positive: \n' ,imp_positive_word)
print('--'*10)
print('Negative: \n' ,imp_negative_word)
```

```
Positive:
 words         love
negative    768.44
positive     12488
Name: 30590, dtype: object
--------------------
Negative:
 words          tast
negative    3057.34
positive    12155.8
Name: 51562, dtype: object
```

In [172]:
```
# lets add weights of each feature to dataframe
w = nb.coef_
print((w).T.shape)
print(words.shape)
words['weights'] = (w).T
words.head()
```

```
(59601, 1)
(59601, 3)
```

```
Out[172]:                                      words  negative  positive    weights
          0                                       aa  0.000000  0.183900 -15.522352
          1                                      aaa  0.108465  1.851695 -13.237018
          2                                     aaaa  0.000000  0.171499 -15.590259
          3  aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa  0.000000  0.250000 -15.222308
          4                     aaaaaaaaaaaaaaaaaaaaargh  0.000000  0.149071 -15.726157
```

```
In [173]: words.loc[words['weights'].argmax()]
```

```
Out[173]: words          love
          negative     768.44
          positive      12488
          weights    -4.42329
          Name: 30590, dtype: object
```

8.0.1 Most Important Words of Positive Class

```
In [178]: # important words of positive class
          sorted_words_positive = words.sort_values('positive', ascending=False)
          sorted_words_positive.drop('negative', axis=1).head(25)
```

```
Out[178]:          words      positive   weights
          30590     love  12488.037027 -4.423290
          22487    great  12278.876101 -4.440180
          51562     tast  12155.794395 -4.450255
          29913     like  12129.118940 -4.452452
          22002     good  11811.024980 -4.479027
          19348   flavor   9803.080638 -4.665364
          55665      use   9712.166215 -4.674681
          41146  product   9601.030360 -4.686190
          36723      one   8510.302003 -4.806783
          51711      tea   8128.262396 -4.852713
          53747      tri   7664.535819 -4.911457
          31198     make   7027.431888 -4.998239
          10498    coffe   6761.480835 -5.036819
          21276      get   6616.729822 -5.058459
          7258       buy   5827.013763 -5.185556
          4893      best   5523.162566 -5.239110
          40925    price   5490.367070 -5.245065
          19698     food   5457.163942 -5.251131
          1650    amazon   5408.886192 -5.260017
          52836     time   5398.541467 -5.261931
          19045     find   5285.353991 -5.283121
          37015    order   5149.511738 -5.309158
          16094      eat   4945.739769 -5.349534
          42669   realli   4859.922000 -5.367038
          58458    would   4730.966764 -5.393931
```

```
In [177]: # important words of negative class
          sorted_words_negative = words.sort_values('negative', ascending=False)
          sorted_words_negative.drop('positive', axis=1).head(25)
```

Out[177]:

	words	negative	weights
51562	tast	3057.336209	-4.450255
29913	like	2694.375407	-4.452452
41146	product	2522.880493	-4.686190
36723	one	1718.840329	-4.806783
19348	flavor	1567.082971	-4.665364
58458	would	1505.043411	-5.393931
53747	tri	1436.285639	-4.911457
22002	good	1354.542007	-4.479027
7258	buy	1342.526150	-5.185556
37015	order	1257.054977	-5.309158
55665	use	1254.921546	-4.674681
21276	get	1148.528400	-5.058459
15271	dont	1045.567577	-5.565799
10498	coffe	1012.800695	-5.036819
51711	tea	1001.403308	-4.852713
19698	food	983.297124	-5.251131
6201	box	953.869685	-5.921045
17621	even	902.680438	-5.719566
1650	amazon	884.899586	-5.260017
16094	eat	860.791259	-5.349534
3775	bag	838.970784	-5.663030
52836	time	832.514786	-5.261931
34169	much	809.315203	-5.471004
31198	make	779.321079	-4.998239
30590	love	768.439956	-4.423290

9 Lets compare the reviews with their probability to which class it belongs

```
In [139]: nb.predict_proba(bow_X_test).shape
```

```
Out[139]: (109252, 2)
```

```
In [156]: words_with_probailitites = pd.DataFrame({'words': X_test, 'negative probability':nb.p
          words_with_probailitites.head()
```

Out[156]:

	words \
254919	word want reduc caffienn brand best choic use ...
254920	louisiana nativ like peopl louisiana drink com...
254921	drink number brand coffe definit dont enjoy fi...
254922	purchas great price amazon pleas flavor buddi ...
254923	love coffe still block form fresh communiti co...

```
        negative probability  positive probability  true_class
254919              0.080737              0.919263           1
254920              0.052268              0.947732           1
254921              0.064091              0.935909           1
254922              0.041237              0.958763           0
254923              0.078502              0.921498           1
```

In [157]:
```
#reviews that are actually negative
words_with_probailitites[words_with_probailitites['true_class'] == 0].head()
```

Out[157]:
```
                                                    words  \
364097  unimpress almond clovey musti tast expect swee...
364114  spice tast harsh raw weird tast mayb much asaf...
364125  realli gross tast like calori worth chocol pea...
364141  trader joe product good qualiti buy straight t...
364144  wateri tasteless pinot noir planet cali tool m...

        negative probability  positive probability  true_class
364097              0.396581              0.603419           0
364114              0.187941              0.812059           0
364125              0.328486              0.671514           0
364141              0.387797              0.612203           0
364144              0.464924              0.535076           0
```

In [144]:
```
#reviews that are actually positive
words_with_probailitites[words_with_probailitites['true_class'] == 1].head()
```

Out[144]:
```
                                                    words  \
254919  word want reduc caffienn brand best choic use ...
254920  louisiana nativ like peopl louisiana drink com...
254921  drink number brand coffe definit dont enjoy fi...
254923  love coffe still block form fresh communiti co...
254924  truli wonder high suggest flavor mild alway fe...

        negative probability  positive probability  true_class
254919              0.080737              0.919263           1
254920              0.052268              0.947732           1
254921              0.064091              0.935909           1
254923              0.078502              0.921498           1
254924              0.040961              0.959039           1
```

10 RESULTS

In [49]:
```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["MODEL", "BEST alpha", "ACCURACY", "F1-SCORE", "PRECISION", "RECALL"
#BOW
x.add_row(['BOW with BERNOULLINB', 0.05, 88.1, 93, 93, 93 ])
```

```
x.add_row(["BOW with MULTINOMIALNB", 0.005, 88.12, 93, 92, 93 ])
x.add_row(['--'*5,'-'*5,'-'*8,'-'*5, '--'*5, '--'*5])
#TFIDF
x.add_row(['TFIDF with BERNOULLINB', 0.05, 88.08, 93, 93, 93 ])
x.add_row(["TFIDF with MULTINOMIALNB", 0.01, 88.10, 93, 93, 93 ])
x.add_row(['--'*5,'-'*8,'-'*8,'-'*5, '--'*5, '--'*5])
#AVGW2V
x.add_row(['AVGW2V with BERNOULLINB', '---' , '---', '---', '---', '---'])
x.add_row(["AVGW2V with MULTINOMIALNB", '---' ,'---' ,'---' ,'---', '---'])
x.add_row(['--'*5,'-'*8,'-'*8,'-'*5, '--'*5, '--'*5])
#TFIDFW2V
x.add_row(['TFIDFW2V with BERNOULLINB', '---' , '---', '---', '---', '---' ])
x.add_row(["TFIDFW2V with MULTINOMIALNB", '---' , '---', '---', '---', '---'])
print(x)
```

```
+------------------------------+------------+----------+----------+------------+------------+
|            MODEL             | BEST alpha | ACCURACY | F1-SCORE | PRECISION  |   RECALL   |
+------------------------------+------------+----------+----------+------------+------------+
|     BOW with BERNOULLINB     |    0.05    |   88.1   |    93    |     93     |     93     |
|    BOW with MULTINOMIALNB    |   0.005    |  88.12   |    93    |     92     |     93     |
|          ----------          |   -----    | -------- |  -----   | ---------- | ---------- |
|    TFIDF with BERNOULLINB    |    0.05    |  88.08   |    93    |     93     |     93     |
|   TFIDF with MULTINOMIALNB   |    0.01    |   88.1   |    93    |     93     |     93     |
|          ----------          |  --------  | -------- |  -----   | ---------- | ---------- |
|   AVGW2V with BERNOULLINB    |    ---     |   ---    |   ---    |    ---     |    ---     |
|  AVGW2V with MULTINOMIALNB   |    ---     |   ---    |   ---    |    ---     |    ---     |
|          ----------          |  --------  | -------- |  -----   | ---------- | ---------- |
|  TFIDFW2V with BERNOULLINB   |    ---     |   ---    |   ---    |    ---     |    ---     |
| TFIDFW2V with MULTINOMIALNB  |    ---     |   ---    |   ---    |    ---     |    ---     |
+------------------------------+------------+----------+----------+------------+------------+
```

In [50]:
```
#number of positive and negative values in test data
y_test.value_counts()
```

Out[50]:
```
1    90894
0    18358
Name: Score, dtype: int64
```

OBSERVATIONS

1. the test error is showing same over all the vectorisations but actual results are known by seeing confusion matrix.
2. confusion matrix = [tn fp] [fn tp]

```
tn - actual class and predicted class are both negative

tp - actual class and predicted class are both positive
```

```
fn - actual class is positive but model wrongly classified as negative[Falsdely classifiec

fp - actual class is negative model,wrongly classified as positive. [falsely classified
```

3. The Accuracy is same for all vectorizers, But the Precision is high with MultinomialNB() on TFIDF.
4. tried with Word2Vec too, But it failed with MultinomialNB() it pointed out errors as negative value. it may be because words are corellated and conditional independence principle not satisfied.

4. this current model is so much biased towards positive data since large amount of points belongs to positive class. this can be little bit solved using upsampling.