NAIVE BAYES ON AMAZON FINE FOOD REVIEWS DATASET

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

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.It consist of data collected from past many years. This dataset consist of approx 550k reviews.

SNIPPET

1. Converted the reviews using NLP techniques i.e BOW, tf-IDF, Word2Vec and tf-IDF Word2Vec.
2. Applied Naive Bayes on the dataset with both techniques i.e Bernaulli Naive Bayes and Multinomial Naive Bayes.
3. Calculated Train Error, CV Error and Test Error to determine the performance and to ensure best fit.
4. Compared performance of each model using accuracy, f1-score, recall, precision.
5. Made confusion matrix between predicted and tested data.
6. Conclusion based on the obtained results.

DATA INFORMATION

- 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

Predict the polarity of the review using Naive Bayes and Compare both models i.e Bernaulli and Multinomial to find the best one and ensure that the model is neither overfitting nor underfitting.

LOADING

In [1]:

```
import sqlite3
import pandas as pd
```

In [2]:

```
conn=sqlite3.connect('./final.sqlite') # making a connection with sqlite
Data=pd.read_sql_query("""SELECT * FROM Reviews""",conn)
```

In [3]:

```
Data.head(3)
```

Out[3]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	positive
1	138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1	positive
2	138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1	positive

MAPPING

In [4]:

```
# function to map the polarity as 0 or 1
def sign(x):
```

```
    if x=='positive':
        return 1
    else:
        return 0

Data['Score']=Data['Score'].map(sign)
```

In [5]:

```
# Dimension
print(Data.shape)
```

```
(364171, 12)
```

In [6]:

```
Data['Score'].value_counts()
```

Out[6]:

```
1    307061
0     57110
Name: Score, dtype: int64
```

SORTING

In [7]:

```
# Sorting the data according to Time.
Data.sort_values('Time',inplace=True)
```

IMPORTING

In [93]:

```
import re
import gensim
import pickle
import numpy as np
import time
import seaborn as sns
from scipy import sparse
from prettytable import PrettyTable
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score
import statistics as s
from sklearn.naive_bayes import BernoulliNB
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn import preprocessing
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
import matplotlib.pyplot as plt
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
```

FUNCTIONS

1. Split Function

In [9]:

```
'''
This function is used to split that data into train and test.
It uses the function to split it into 70-30 %.
It does not shuffle so the data is distributed sequentially.
'''
def Split(d1,d2):
    a,b,c,d= train_test_split(d1,d2,test_size=0.3,shuffle=False) # Splitting it in 70-30 without sh
uffling.
    return a,b,c,d
```

2. Naive Bayes With Grid Search CV

In [10]:

```
'''
This function takes training data and algorithm as input and gives execution time, accuracy and th
e optimal value of alpha
on that data.
It uses GridSearch CV.
'''
def NB(X,Y,s):
    start = time.time()
    tscv = TimeSeriesSplit(n_splits=10)
    parameters = {'alpha':[0.00001,0.0001,0.001,0.01,0.02,0.08,0.1,0.2,0.25,0.3,0.35,0.4,0.45,0.5,1
,5,10,20,50,100,500,1000,10000]}
    if s=='B':
        clf = BernoulliNB()
    else:
        clf = MultinomialNB()
    g = GridSearchCV(clf,parameters,cv=tscv,return_train_score=True,n_jobs=-1)
    g.fit(X,Y)
    end = time.time()
    t=end-start
    return t,g
```

3. Hyperparameter vs Accuracy Plot

In [11]:

```
'''
This function takes Object of gridsearch cv and plots the graph for accuracy vs alpha's.
'''
def Accplot(h,nlp,algo):
    acu = h.cv_results_['mean_test_score']
    alp = [0.00001,0.0001,0.001,0.01,0.02,0.08,0.1,0.2,0.25,0.3,0.35,0.4,0.45,0.5,1,5,10,20,50,100,
500,1000,10000]
    sns.set_style("darkgrid")
    plt.plot(alp,acu,'b--')
    plt.xlabel("Alpha's",fontsize=15, color='black')
    plt.ylabel("Accuracy",fontsize=15, color='black')
    plt.title("Accuracy -" + nlp + algo,fontsize=15, color='black')
    plt.show()
```

4. Hyperparameter vs Error Plot

In [12]:

```
'''
This function takes the grid cv object and calculates CV accuracy and Training accuracy.
Output is train error and CV error.
It also plots the graph between Hyperparameters vs Errors.
'''

def Errorplot(h):
    alp = [0.00001,0.0001,0.001,0.01,0.02,0.08,0.1,0.2,0.25,0.3,0.35,0.4,0.45,0.5,1,5,10,20,50,100,
500,1000,10000]
```

```
    cv_acc = list(h.cv_results_['mean_test_score'])
    train_acc = list(h.cv_results_['mean_train_score'])
    a = [1 - x for x in cv_acc]
    b = [1 - x for x in train_acc]
    plt.plot(alp, a, '-b', label='CV Error')
    plt.plot(alp, b, '-r', label='Train Error')
    plt.legend(loc='lower right')
    plt.xlabel("Hyperparameters",fontsize=15, color='black')
    plt.ylabel("Train Error & Cv Error",fontsize=15, color='black')
    plt.title("Train vs CV Error on Hyperparameters" ,fontsize=15, color='black')
    plt.show()
    print("The Train Error is -: ",round(s.mean(b),3)*100,"%\n")
    print("The CV Error is -: ",round(s.mean(a),3)*100,"%\n")
```

5. Predicting On Best Hyperparameter

In [13]:

```
'''
It runs the desired algorithm on the optimal value of Alpha we get from training part.
It also returns predicted values.
'''
def predict(s,a,xtrain,ytrain,xtest):
    if s=='B':
        clf = BernoulliNB(alpha = a)
    else:
        clf = MultinomialNB(alpha = a)
    clf.fit(xtrain,ytrain)
    pred=clf.predict(xtest)
    return clf,pred
```

6. Performance Measurement

In [14]:

```
'''
It gives the performance in terms of accuracy, F1 Score, recall, precision and test error also.
'''
def Measure(test,pre):
    print("Accuracy on Test Data -: ",round(((accuracy_score(test,pre))*100),3),"% \n")
    print("F1 Score -:  ",round(((f1_score(test,pre))),3),"\n")
    print("Precision Score -: ",round(((precision_score(test,pre))),3),"\n")
    print("Recall Score -: ",round((recall_score(test,pre)),3),"\n")
    print("Test Error -: ",100-round(((accuracy_score(test,pre))*100),3))
```

7. Confusion Matrix

In [15]:

```
'''
It gives confusion matrix between actual and predicted values.
'''
def CF(test,pre):
    cf = confusion_matrix(test,pre)
    df =pd.DataFrame(cf,index=[0,1],columns=[0,1])
    sns.set(font_scale=1.5)
    sns.heatmap(df,annot=True,annot_kws={"size" :20},fmt='g')
    return plt.show()
```

8. Informative Features

In [16]:

```
'''
This functions draws a pretty table of important features among positive and negative classes each
according
to the probabilities.
'''
```

```
'''
def IF(c,co):
    a = c.feature_log_prob_
    f = co.get_feature_names()
    l1 = list(zip(a[0],f))
    l1 = sorted(l1,reverse=True)
    l2 = list(zip(a[1],f))
    l2 = sorted(l2,reverse=True)
    x = PrettyTable()
    x.field_names = ["Top Negative Features", "Probability_neg", "Top Positive Features",
"Probability_pos"]
    n=1
    for i in range(25):
        x.add_row([l1[i][1],l1[i][0],l2[i][1],l2[i][0]])
        n+=2
    print(x)
```

9. Using Pickle - File Handling

In [17]:

```
'''
These functions are used to save and retrieve the information and use it afterwards for future ref
erence.
'''

# Method to Save the data.
def save(o,f):
    op=open(f+".p","wb")
    pickle.dump(o,op)

# Method to retrieve the data.
def retrieve(f):
    op=open(f+".p","rb")
    ret=pickle.load(op)
    return ret
```

10. List Of Words

In [18]:

```
'''
This function takes sentences as input and it splits the sentence into words and makes list of wor
ds
for each and every review.
'''

def cleanpunc(sentence): #function to clean the word of any punctuation or special characters
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned

def LOW(l):
    i=0
    list_of_sent=[] # list to store all the lists.
    for sent in l:
        filtered_sentence=[] # list to store each review.
        for w in sent.split():
            for cleaned_words in cleanpunc(w).split():
                if(cleaned_words.isalpha()):
                    filtered_sentence.append(cleaned_words.lower())
                else:
                    continue
        list_of_sent.append(filtered_sentence)
    return list_of_sent
```

NAIVE BAYES MODEL ON BAG OF WORDS (BOW)

SPLITTING INTO TRAIN AND TEST

In [19]:

```
x_train, x_test, y_train, y_test = Split(Data['CleanedText'].values,Data['Score'].values)
```

In [20]:

```
print("-----------------------TRAIN DATA------------------------------------")
print(x_train.shape)
print(y_train.shape)
print("---------------------------------------------------------------------")
print("\n-----------------------TEST DATA-------------------------------------")
print(x_test.shape)
print(y_test.shape)
```

```
-----------------------TRAIN DATA------------------------------------
(254919,)
(254919,)
---------------------------------------------------------------------

-----------------------TEST DATA-------------------------------------
(109252,)
(109252,)
```

CONVERTING REVIEWS INTO VECTORS USING BOW

In [21]:

```
count = CountVectorizer(ngram_range=(1,2))
x_train = count.fit_transform(x_train)
x_test = count.transform(x_test)
```

In [22]:

```
print("Train Dataset Shape -: ",x_train.shape)
print("Test Dataset Shape -: ",x_test.shape)
```

```
Train Dataset Shape -:  (254919, 2290079)
Test Dataset Shape -:  (109252, 2290079)
```

NORMALIZING THE DATA

In [23]:

```
x_train = preprocessing.normalize(x_train)
x_test = preprocessing.normalize(x_test)
```

BERNAULLI NAIVE BAYES

classification
- Bernoulli model

Calling NB Function with training dataset

In [24]:

```
t, g = NB(x_train, y_train, 'B')
```

In [24]:

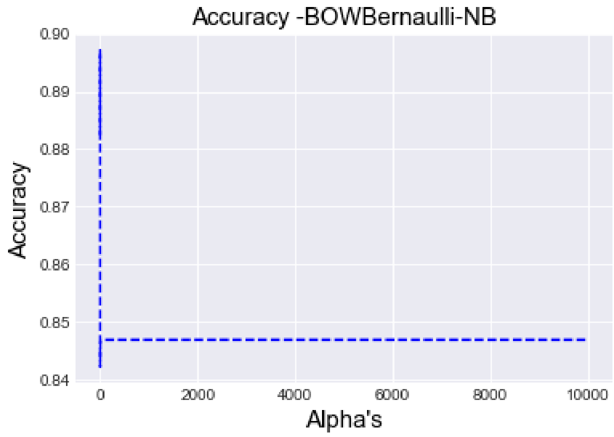
```
print("Time taken to complete -: ",t,"sec\n")
print("Best Hyperparameter -: ",g.best_params_,"\n")
print("Accuracy -: ",round(g.best_score_*100,3),"%")
```

```
Time taken to complete -:  229.48659324645996 sec

Best Hyperparameter -:  {'alpha': 0.001}

Accuracy -:  89.718 %
```

Alpha vs Accuracy Plot

In [25]:

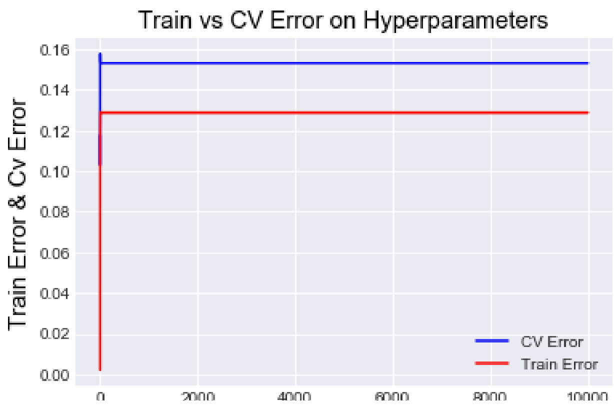
```
Accplot(g, 'BOW', 'Bernaulli-NB')
```



Hyperparameters vs Error Plot

In [26]:

```
Errorplot(g)
```




```
The Train Error is -:  7.3 %

The CV Error is -:  14.3 %
```

Predicting on Best Hyperparameter

In [27]:

```
clf, pred = predict('B', 0.001, x_train, y_train, x_test)
```

Measuring Performance

In [28]:

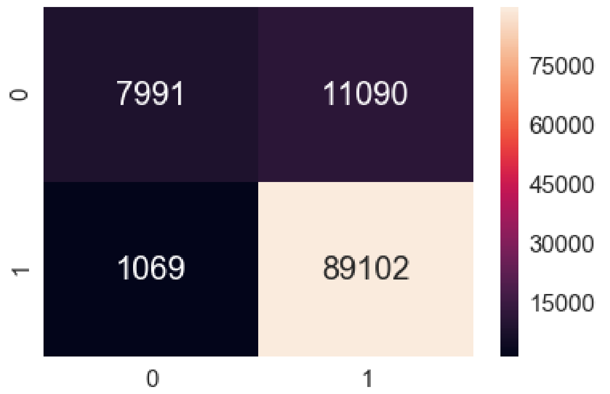
```
Measure(y_test,pred)
```

```
Accuracy on Test Data -:  88.871 %

F1 Score -:   0.936

Precision Score -:  0.889

Recall Score -:  0.988

Test Error -:  11.129
```

Confusion Matrix

In [29]:

```
CF(y_test,pred)
```



Top Informative Features With Probabilities

In [30]:

```
IF(clf,count)
```

Top Negative Features	Probability_neg	Top Positive Features	Probability_pos
not	-0.591495978586	not	-1.143502781
tast	-0.978229341871	like	-1.18976586811
like	-1.00029217837	tast	-1.20777610866
product	-1.20966002121	love	-1.27277138223
one	-1.35423340058	good	-1.27701143801

would	-1.42066838439	great	-1.29398558433
veri	-1.46121372351	flavor	-1.42895460263
tri	-1.46621430161	one	-1.47244014142
flavor	-1.53763527983	veri	-1.48742715634
good	-1.54512779078	use	-1.49067686533
buy	-1.60967452302	tri	-1.53436216381
get	-1.66774617814	product	-1.56418661232
use	-1.70958494361	make	-1.64635042798
dont	-1.75203714136	get	-1.69610144085
even	-1.82744062758	buy	-1.90621339099
order	-1.84675612379	time	-1.90972461953
much	-1.96368519443	amazon	-1.94814878644
make	-1.9729087875	would	-1.95812887643
realli	-2.02352549552	best	-1.95845564177
time	-2.02471976294	find	-1.97842626735
amazon	-2.03051224777	realli	-1.98494901107
love	-2.05587114284	price	-2.01631022762
look	-2.08632822577	much	-2.03264909073
eat	-2.09933341643	also	-2.04063584528
box	-2.10126661391	eat	-2.05001119211

MULTINOMIAL NAIVE BAYES

Calling NB Function with training dataset

In [31]:

```
t, g = NB(x_train, y_train, 'M')
```

In [32]:

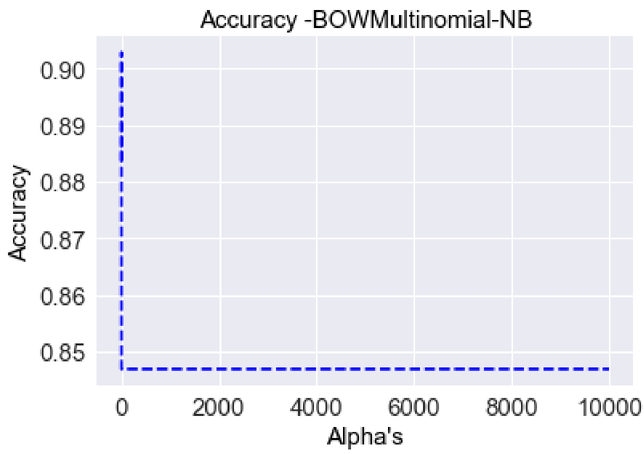
```
print("Time taken to complete -: ",t,"sec\n")
print("Best Hyperparameter -: ",g.best_params_,"\n")
print("Accuracy -: ",round(g.best_score_*100,3),"%")
```

```
Time taken to complete -:  195.02917623519897 sec

Best Hyperparameter -:  {'alpha': 0.001}

Accuracy -:  90.289 %
```

Alpha vs Accuracy Plot

In [33]:

```
Accplot(g, 'BOW', 'Multinomial-NB')
```

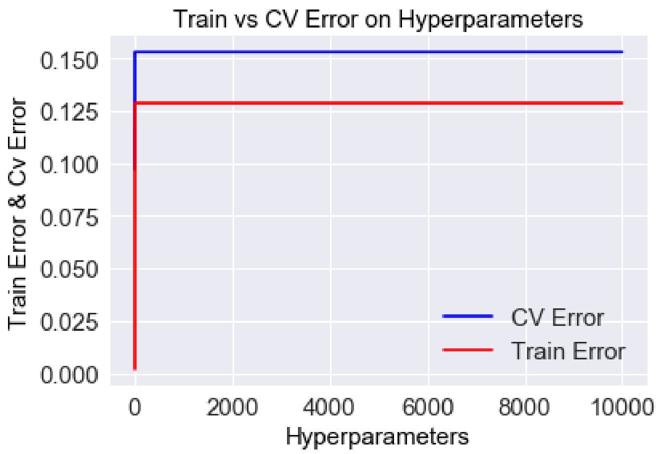


Hyperparameters vs Error Plot

Hyperparameters vs Error Plot

In [34]:

```
Errorplot(g)
```




```
The Train Error is -:  9.9 %

The CV Error is -:  14.1 %
```

Predicting on Best Hyperparameter

In [35]:

```
clf, pred = predict('M', 0.001, x_train, y_train, x_test)
```

Measuring Performance

In [36]:

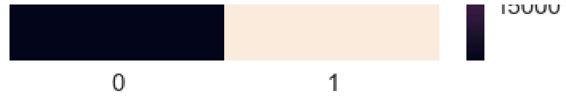
```
Measure(y_test,pred)
```

```
Accuracy on Test Data -:  88.916 %

F1 Score -:   0.937

Precision Score -:  0.886

Recall Score -:  0.993

Test Error -:  11.084
```

Confusion Matrix

In [38]:

```
CF(y_test,pred)
```



Top Informative Features With Probabilities

In [37]:

```
IF(clf,count)
```

Top Negative Features	Probability_neg	Top Positive Features	Probability_pos
not	-4.39456968128	not	-5.08733210663
tast	-4.80287504633	like	-5.11363424438
like	-4.93626209316	tast	-5.11587401159
product	-5.10272224388	love	-5.13784997904
flavor	-5.42163426918	great	-5.15135938134
one	-5.4258532145	good	-5.18779629708
veri	-5.50994836331	flavor	-5.30372976915
would	-5.54822196322	use	-5.41323068891
tri	-5.56735853717	veri	-5.42123614647
good	-5.66619844568	product	-5.42865616484
buy	-5.71337557934	one	-5.48721364629
coffe	-5.727499484	tri	-5.58453138364
order	-5.78450913137	tea	-5.59431023374
use	-5.80529900633	coffe	-5.63981788723
get	-5.82406096746	make	-5.69706371871
dont	-5.93893546279	get	-5.76234754565
box	-5.99473797207	buy	-5.91909748435
tea	-6.02787327741	best	-5.9521302228
even	-6.0611099655	amazon	-5.96719037773
amazon	-6.07515141709	price	-5.9747697241
food	-6.09507522235	time	-5.99674540941
much	-6.16233428554	find	-6.00644244085
realli	-6.18321642592	food	-6.01131130938
eat	-6.18853519616	realli	-6.03888192929
bag	-6.20366272502	order	-6.05820905687

tf-IDF

SPLITTING INTO TRAIN AND TEST

In [39]:

```
x_train, x_test, y_train, y_test = Split(Data['CleanedText'].values,Data['Score'].values)
```

In [40]:

```
print("-----------------------TRAIN DATA------------------------------------")
print(x_train.shape)
print(y_train.shape)
print("---------------------------------------------------------------------")
print("\n-----------------------TEST DATA------------------------------------")
print(x_test.shape)
print(y_test.shape)
```

```
------------------------TRAIN DATA------------------------------------
(254919,)
(254919,)
----------------------------------------------------------------------

------------------------TEST DATA-------------------------------------
(109252,)
(109252,)
```

CONVERTING REVIEWS INTO VECTORS USING tf-IDF

In [41]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
x_train = tf_idf_vect.fit_transform(x_train)
x_test = tf_idf_vect.transform(x_test)
```

In [42]:

```
print("Train Dataset Shape -: ",x_train.shape)
print("Test Dataset Shape -: ",x_test.shape)
```

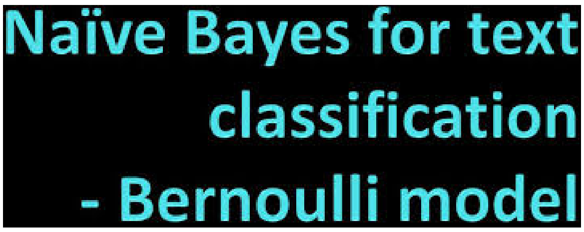
```
Train Dataset Shape -:  (254919, 2290079)
Test Dataset Shape -:  (109252, 2290079)
```

NORMALIZING THE DATA

In [43]:

```
x_train = preprocessing.normalize(x_train)
x_test = preprocessing.normalize(x_test)
```

BERNAULLI NAIVE BAYES



Calling NB Function with training dataset

In [44]:

```
t, g = NB(x_train, y_train, 'B')
```

In [45]:

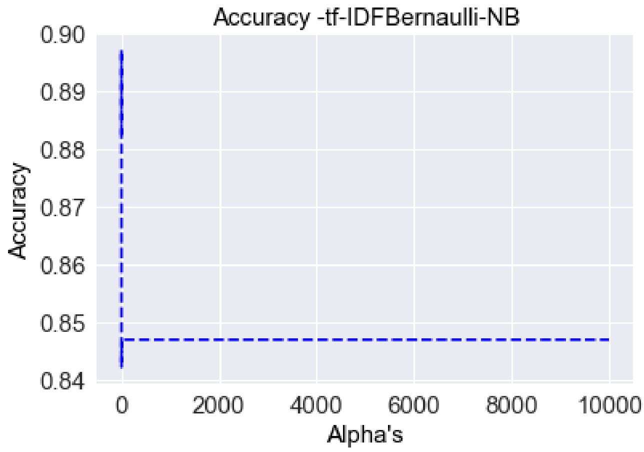
```
print("Time taken to complete -: ",t,"sec\n")
print("Best Hyperparameter -: ",g.best_params_,"\n")
print("Accuracy -: ",round(g.best_score_*100,3),"%")
```

```
Time taken to complete -:  264.5981376171112 sec

Best Hyperparameter -:  {'alpha': 0.001}

Accuracy -:  89.718 %
```

Alpha vs Accuracy Plot

In [46]:

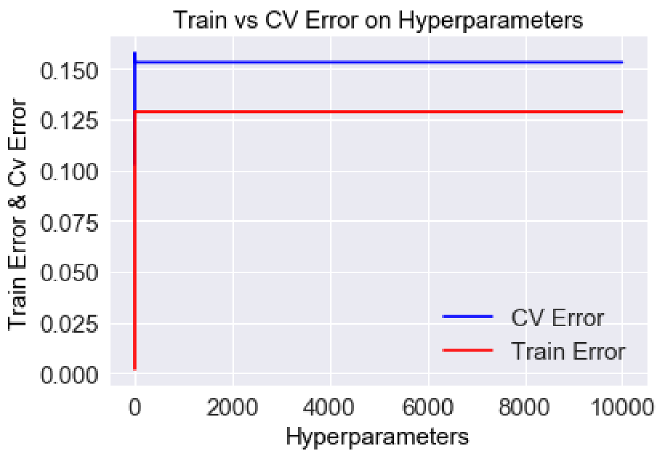
```
Accplot(g, 'tf-IDF', 'Bernaulli-NB')
```



Hyperparameters vs Error Plot

In [47]:

```
Errorplot(g)
```




```
The Train Error is -:  7.3 %

The CV Error is -:  14.3 %
```

Predicting on Best Hyperparameter

In [48]:

```
clf, pred = predict('B', 0.001, x_train, y_train, x_test)
```

Measuring Performance

In [49]:

```
Measure(y_test,pred)
```

```
Accuracy on Test Data -:  88.871 %

F1 Score -:   0.936

Precision Score -:  0.889
```

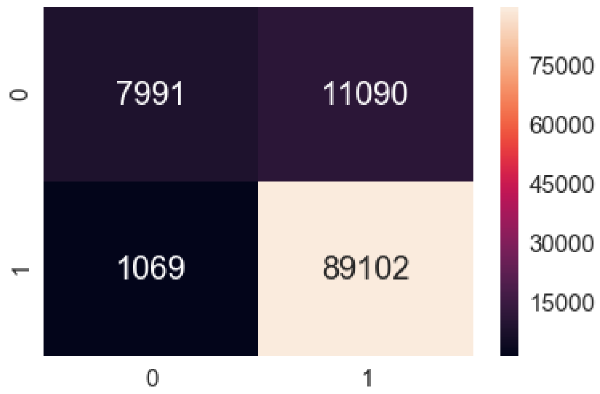
Recall Score -: 0.988

Test Error -: 11.129

Confusion Matrix

In [50]:

```
CF(y_test,pred)
```



Top Informative Features With Probabilities

In [51]:

```
IF(clf,tf_idf_vect)
```

Top Negative Features	Probability_neg	Top Positive Features	Probability_pos
not	-0.591495978586	not	-1.143502781
tast	-0.978229341871	like	-1.18976586811
like	-1.00029217837	tast	-1.20777610866
product	-1.20966002121	love	-1.27277138223
one	-1.35423340058	good	-1.27701143801
would	-1.42066838439	great	-1.29398558433
veri	-1.46121372351	flavor	-1.42895460263
tri	-1.46621430161	one	-1.47244014142
flavor	-1.53763527983	veri	-1.48742715634
good	-1.54512779078	use	-1.49067686533
buy	-1.60967452302	tri	-1.53436216381
get	-1.66774617814	product	-1.56418661232
use	-1.70958494361	make	-1.64635042798
dont	-1.75203714136	get	-1.69610144085
even	-1.82744062758	buy	-1.90621339099
order	-1.84675612379	time	-1.90972461953
much	-1.96368519443	amazon	-1.94814878644
make	-1.9729087875	would	-1.95812887643
realli	-2.02352549552	best	-1.95845564177
time	-2.02471976294	find	-1.97842626735
amazon	-2.03051224777	realli	-1.98494901107
love	-2.05587114284	price	-2.01631022762
look	-2.08632822577	much	-2.03264909073
eat	-2.09933341643	also	-2.04063584528
box	-2.10126661391	eat	-2.05001119211

MULTINOMIAL NAIVE BAYES

Calling NB Function with training dataset

In [52]:

```
t, g = NB(x_train, y_train, 'M')
```

In [53]:

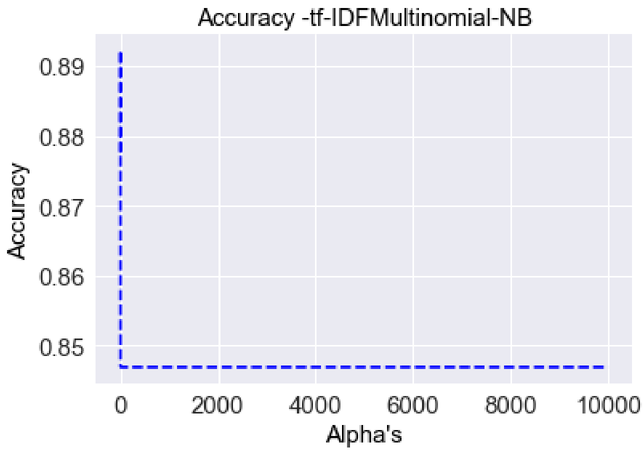
```
print("Time taken to complete -: ",t,"sec\n")
print("Best Hyperparameter -: ",g.best_params_,"\n")
print("Accuracy -: ",round(g.best_score_*100,3),"%")
```

```
Time taken to complete -:  213.79974484443665 sec

Best Hyperparameter -:  {'alpha': 0.02}

Accuracy -:  89.227 %
```

Alpha vs Accuracy Plot

In [54]:

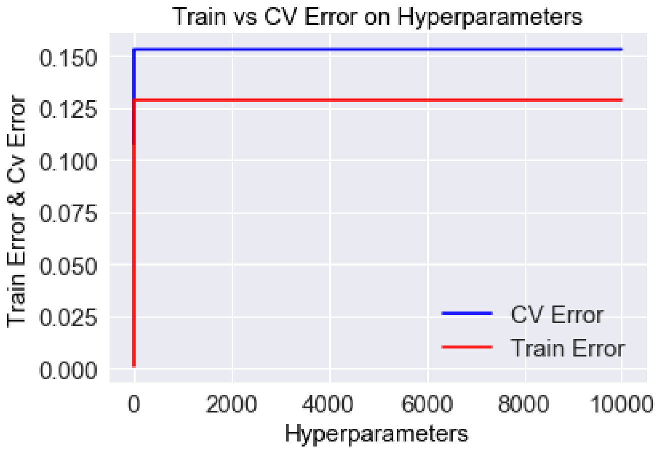
```
Accplot(g, 'tf-IDF', 'Multinomial-NB')
```



Hyperparameters vs Error Plot

In [55]:

```
Errorplot(g)
```




```
The Train Error is -:  9.1 %

The CV Error is -:  14.1 %
```

Predicting on Best Hyperparameter

In [56]:

```
clf, pred = predict('M', 0.02, x_train, y_train, x_test)
```

Measuring Performance

In [57]:

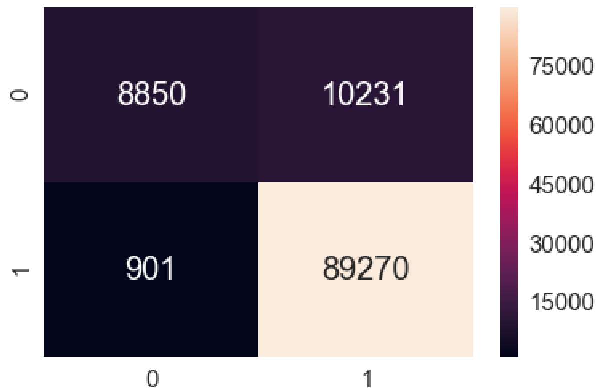
```
Measure(y_test,pred)
```

```
Accuracy on Test Data -:  89.811 %

F1 Score -:   0.941

Precision Score -:  0.897

Recall Score -:  0.99

Test Error -:  10.189
```

Confusion Matrix

In [58]:

```
CF(y_test,pred)
```



Top Informative Features With Probabilities

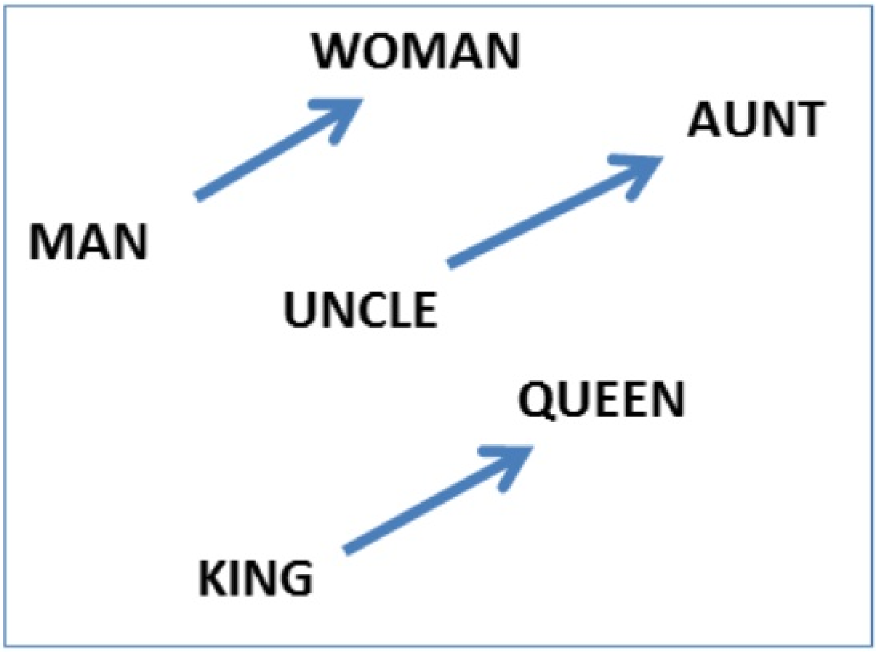
In [59]:

```
IF(clf,tf_idf_vect)
```

Top Negative Features	Probability_neg	Top Positive Features	Probability_pos
not	-5.80290394131	great	-6.2561340553
tast	-6.13678432729	love	-6.26498470791
like	-6.2789461342	tast	-6.31363447518
product	-6.32403385514	tea	-6.31801850573
would	-6.62441282194	like	-6.32230202326
flavor	-6.63971618579	good	-6.32603250711
coffe	-6.64264841499	not	-6.36144060994
one	-6.6625209448	flavor	-6.38468385105
veri	-6.72495979549	coffe	-6.4092940944
tri	-6.76714461039	veri	-6.48825821735
buy	-6.79400411565	use	-6.48859090922
order	-6.79790750356	product	-6.49926836251
box	-6.87928820739	one	-6.57928118858
tea	-6.88746923392	tri	-6.64481473256
good	-6.94759422312	make	-6.70547445688

good	-6.94759422312	make	-6.70547445688
disappoint	-6.95062363452	get	-6.77367362275
dont	-6.96643949338	best	-6.82138424462
get	-6.97742975786	price	-6.83058465018
use	-7.02383678788	food	-6.84868322585
even	-7.05586053304	buy	-6.85485392068
food	-7.07524851254	amazon	-6.86820317722
bag	-7.10177839986	find	-6.88254392257
bad	-7.10984888918	time	-6.91831772624
amazon	-7.13414135393	realli	-6.92455002247
purchas	-7.17455665139	order	-6.92501155692

Avg Word2Vec



SPLIT DATA INTO TRAIN AND TEST

In [25]:

```
'''
Here we are taking two lists and putting the data separate as Train in l4 and Test in l5.
'''

l4=[]
for i in range(254919):
    l1=Data['CleanedText'].values[i]
    l2=str(l1)
    l4.append(l2)

l5=[]
for i in range(254919,364171,1):
    l1=Data['CleanedText'].values[i]
    l2=str(l1)
    l5.append(l2)
```

MAKING LIST OF WORDS

In [26]:

```
Train = LOW(l4)
Test = LOW(l5)
```

In [27]:

```
print("Length of Train Dataset -: ",len(Train))
print("Length of Test Dataset -: ",len(Test))
```

```
Length of Train Dataset -:  254919
Length of Test Dataset -:  109252
```

In [28]:

```
print("____________________________________ TRAINING DATA
___________________________________________________")
print(Data['CleanedText'].values[3])

print("\n" + "*******************Converted these sentences into a list of words
each**********************\n ")

# First Review with breaking into words.
print(Train[3])

#--------------------------------------------------------------------------------------------------
-------------
print("-------------------------------------------------------------------------------------------------
---------------")

print("____________________________________ TEST DATA
___________________________________________________")

print(Data['CleanedText'].values[-1])

print("\n" + "*******************Converted these sentences into a list of words
each**********************\n ")

# First Review with breaking into words.
print(Test[-1])
```

```
____________________________________ TRAINING DATA
___________________________________________________
b'twist rumplestiskin captur film star michael keaton geena davi prime tim burton masterpiec rumbl
absurd wonder pace point not dull moment'

*******************Converted these sentences into a list of words each**********************

['btwist', 'rumplestiskin', 'captur', 'film', 'star', 'michael', 'keaton', 'geena', 'davi',
'prime', 'tim', 'burton', 'masterpiec', 'rumbl', 'absurd', 'wonder', 'pace', 'point', 'not', 'dull
', 'moment']
--------------------------------------------------------------------------------------------------
-------
____________________________________ TEST DATA ___________________________________________________
b'mix make good bread also use make pop over near made wheat wife celiac use bread popov pizza cru
st'

*******************Converted these sentences into a list of words each**********************

['bmix', 'make', 'good', 'bread', 'also', 'use', 'make', 'pop', 'over', 'near', 'made', 'wheat', '
wife', 'celiac', 'use', 'bread', 'popov', 'pizza', 'crust']
```

TRAINING THE MODEL ON TRAIN DATA

In [29]:

```
w2v_model=gensim.models.Word2Vec(Train,min_count=2,size=100, workers=4)
```

CONVERTING REVIEWS INTO VECTORS USING AVG WORD2VEC

In [30]:

```
'''
Converting the reviews into vectors by using the above trained model.
'''
```

```
#-------------------------------------- TRAIN DATASET -------------------------------------------------
------------------
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in Train: # for each review/sentence
    sent_vec = np.zeros(100) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors.append(sent_vec)

#------------------------------------- TEST DATASET ---------------------------------------------------
------------------
'''
Here we are converting reviews of test data using the vocabulary of training data to make the conc
ept of generalization
meaningful and fruitful.
'''
sent_vectors1 = []; # the avg-w2v for each sentence/review is stored in this list
for sent in Test: # for each review/sentence
    sent_vec = np.zeros(100) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors1.append(sent_vec)
```

```
C:\Users\15-AU008TX\Anaconda3\lib\site-packages\ipykernel_launcher.py:35: RuntimeWarning: invalid
value encountered in true_divide
```

CHECKING THE Nan VALUE

In [31]:

```
sent_vectors=np.array(sent_vectors)
print(np.isnan(sent_vectors).any())
sent_vectors1=np.array(sent_vectors1)
print(np.isnan(sent_vectors1).any())
```

```
False
True
```

In [32]:

```
'''
Here we are checking that at which index or at which review Nan values are coming.
'''
np.argwhere(np.isnan(sent_vectors1))
```

Out[32]:

```
array([[3254,    0],
       [3254,    1],
       [3254,    2],
       [3254,    3],
       [3254,    4],
       [3254,    5],
       [3254,    6],
       [3254,    7],
       [3254,    8],
       [3254,    9],
       [3254,   10],
```

```
[3254,   11],
[3254,   12],
[3254,   13],
[3254,   14],
[3254,   15],
[3254,   16],
[3254,   17],
[3254,   18],
[3254,   19],
[3254,   20],
[3254,   21],
[3254,   22],
[3254,   23],
[3254,   24],
[3254,   25],
[3254,   26],
[3254,   27],
[3254,   28],
[3254,   29],
[3254,   30],
[3254,   31],
[3254,   32],
[3254,   33],
[3254,   34],
[3254,   35],
[3254,   36],
[3254,   37],
[3254,   38],
[3254,   39],
[3254,   40],
[3254,   41],
[3254,   42],
[3254,   43],
[3254,   44],
[3254,   45],
[3254,   46],
[3254,   47],
[3254,   48],
[3254,   49],
[3254,   50],
[3254,   51],
[3254,   52],
[3254,   53],
[3254,   54],
[3254,   55],
[3254,   56],
[3254,   57],
[3254,   58],
[3254,   59],
[3254,   60],
[3254,   61],
[3254,   62],
[3254,   63],
[3254,   64],
[3254,   65],
[3254,   66],
[3254,   67],
[3254,   68],
[3254,   69],
[3254,   70],
[3254,   71],
[3254,   72],
[3254,   73],
[3254,   74],
[3254,   75],
[3254,   76],
[3254,   77],
[3254,   78],
[3254,   79],
[3254,   80],
[3254,   81],
[3254,   82],
[3254,   83],
[3254,   84],
[3254,   85],
[3254,   86],
[3254,   87],
```

```
       [3254,   88],
       [3254,   89],
       [3254,   90],
       [3254,   91],
       [3254,   92],
       [3254,   93],
       [3254,   94],
       [3254,   95],
       [3254,   96],
       [3254,   97],
       [3254,   98],
       [3254,   99]], dtype=int64)
```

In [33]:

```
'''
Here we are putting a constant in place of Nan values but we can also use mean, median etc values.

or we can remove this review as it will not effect performance of model as the no. of reviews with Nan
values is 1 only that's why we can remove it also.
'''
sent_vectors1[3254]=0
```

In [34]:

```
# Again checking the Nan values.
print(np.isnan(sent_vectors).any())
print(np.isnan(sent_vectors1).any())
```

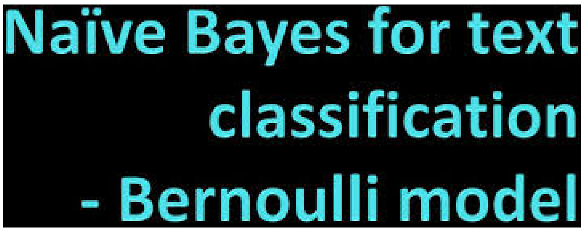
```
False
False
```

SAVING

In [35]:

```
# Saving for future assignments.
save(sent_vectors,"Word2Vec-Train")
save(sent_vectors1,"Word2Vec-Test")
```

BERNAULLI NAIVE BAYES



Calling NB Function with training dataset

In [36]:

```
t, g = NB(sent_vectors, y_train, 'B')
```

In [37]:

```
print("Time taken to complete -: ",t,"sec\n")
print("Best Hyperparameter -: ",g.best_params_,"\n")
print("Accuracy -: ",round(g.best_score_*100,3),"%")
```

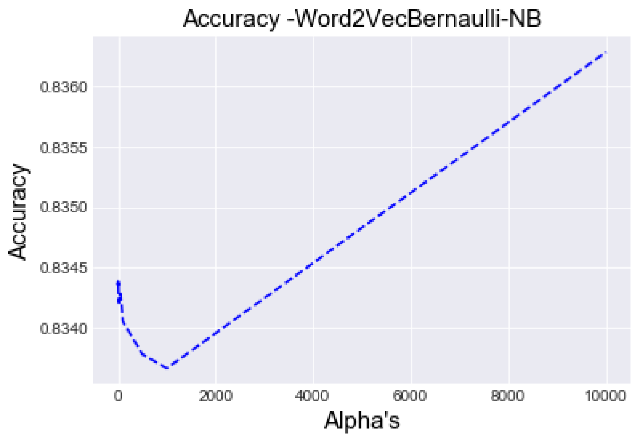
```
Time taken to complete -:  163.2255663871765 sec

Best Hyperparameter -:  {'alpha': 10000}
```

```
Accuracy -:  83.629 %
```

Alpha vs Accuracy Plot

In [38]:

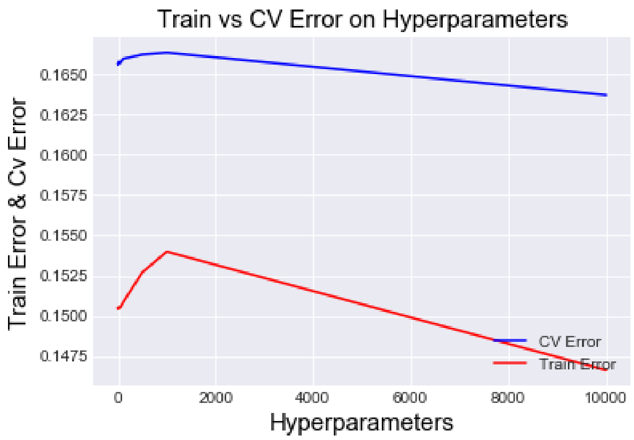
```
Accplot(g, 'Word2Vec', 'Bernaulli-NB')
```



Hyperparameters vs Error Plot

In [39]:

```
Errorplot(g)Errorplot(g)
```




```
The Train Error is -:  15.1 %

The CV Error is -:  16.6 %
```

Predicting on Best Hyperparameter

In [40]:

```
clf, pred = predict('B', 10000, sent_vectors, y_train, sent_vectors1)
```

Measuring Performance

In [41]:

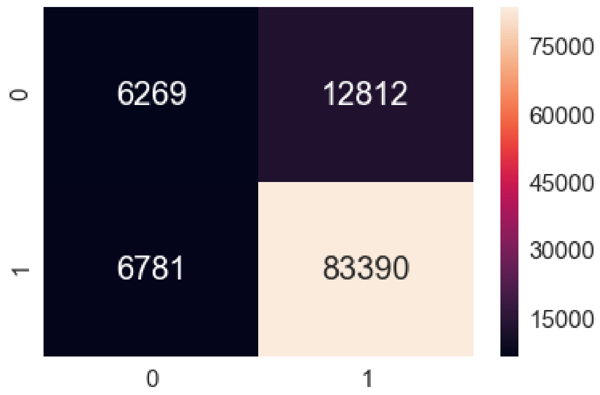
```
Measure(y_test,pred)
```

```
Accuracy on Test Data -:  82.066 %

F1 Score -:   0.895

Precision Score -:  0.867

Recall Score -:  0.925

Test Error -:  17.934
```

Confusion Matrix

In [42]:

```
CF(y_test,pred)
```



MULTINOMIAL NAIVE BAYES

Not possible, as multinomial naive bayes does not work with negative values.

tf-IDF Word2Vec

SPLITTING INTO TRAIN AND TEST

In [51]:

```
x_train, x_test, y_train, y_test = Split(Data['CleanedText'].values,Data['Score'].values)
```

CONVERTING REVIEWS INTO VECTORS USING tf-IDF

In [52]:

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,1))
x_train = tf_idf_vect.fit_transform(x_train)
x_test = tf_idf_vect.transform(x_test)
```

CONVERTING REVIEWS INTO VECTORS USING tf-IDF WORD2VEC

In [53]:

```
tfidf_feat = tf_idf_vect.get_feature_names()

tfidf_sent_vectors_train = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in Train: # for each review/sentence
```

```
    #print(row)
    sent_vec = np.zeros(100) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = x_train[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
```

```
C:\Users\15-AU008TX\Anaconda3\lib\site-packages\ipykernel_launcher.py:18: RuntimeWarning: invalid
value encountered in true_divide
```

In [54]:

```
tfidf_sent_vectors_test = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in Test: # for each review/sentence
    #print(row)
    sent_vec = np.zeros(100) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = x_test[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

```
C:\Users\15-AU008TX\Anaconda3\lib\site-packages\ipykernel_launcher.py:16: RuntimeWarning: invalid
value encountered in true_divide
  app.launch_new_instance()
```

Checking NaN Values

In [55]:

```
train_data = np.array(tfidf_sent_vectors_train)
test_data = np.array(tfidf_sent_vectors_test)
print(np.isnan(train_data).any())
print(np.isnan(test_data).any())
```

```
True
True
```

SAVING

In [75]:

```
# Saving for future assignments.
save(train_data,"tfidf-W2v-train")
save(test_data,"tf-idf-w2v-test")
```

In [76]:

```
# Creating new dataframes and putting array values in it.
train_d = pd.DataFrame(train_data)
test_d = pd.DataFrame(test_data)
```

In [79]:

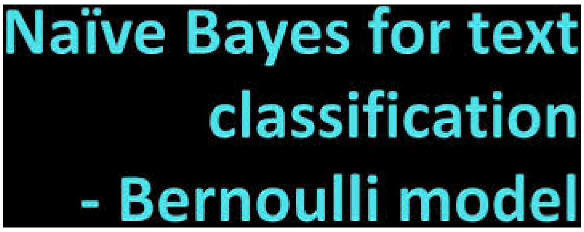
```
'''
replacing Nan values with constant in whole dataframes.
'''
train_d = train_d.fillna(0)
test_d = test_d.fillna(0)
```

In [80]:

```
print(train_d.shape)
print(test_d.shape)
```

```
(254919, 100)
(109252, 100)
```

BERNAULLI NAIVE BAYES



Calling NB Function with training dataset

In [85]:

```
t, g = NB(train_d, y_train, 'B')
```

In [86]:

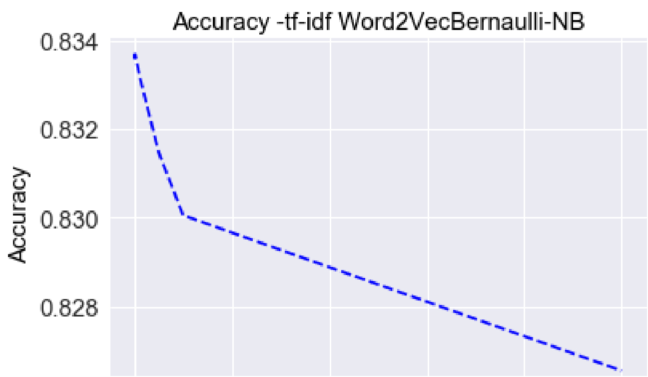
```
print("Time taken to complete -: ",t,"sec\n")
print("Best Hyperparameter -: ",g.best_params_,"\n")
print("Accuracy -: ",round(g.best_score_*100,3),"%")
```

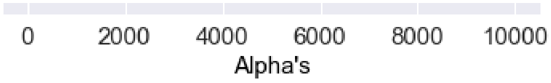
```
Time taken to complete -:  138.74359464645386 sec

Best Hyperparameter -:  {'alpha': 10}

Accuracy -:  83.369 %
```

Alpha vs Accuracy Plot

In [87]:

```
Accplot(g, 'tf-idf Word2Vec', 'Bernaulli-NB')
```

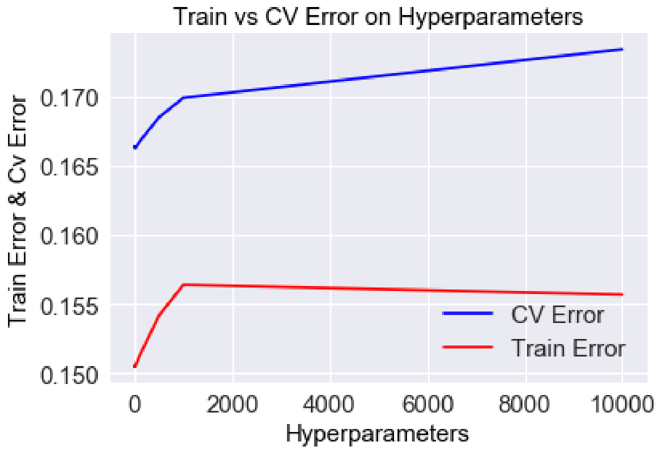




Hyperparameters vs Error Plot

In [88]:

```
Errorplot(g)
```




```
The Train Error is -:  15.1 %

The CV Error is -:  16.7 %
```

Predicting on Best Hyperparameter

In [89]:

```
clf, pred = predict('B', 10, train_d, y_train, test_d)
```

Measuring Performance

In [90]:

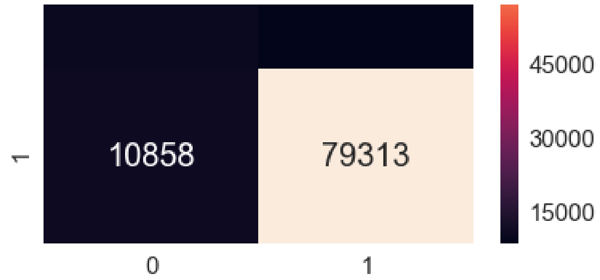
```
Measure(y_test,pred)
```

```
Accuracy on Test Data -:  82.247 %

F1 Score -:   0.891

Precision Score -:  0.903

Recall Score -:  0.88

Test Error -:  17.753
```

Confusion Matrix

In [91]:

```
CF(y_test,pred)
```



In [92]:

```
x = PrettyTable()

x.field_names = ["NLP Technique", "Algorithm", "Hyperparameter", "Accuracy(%)", "F1 Score", "Recall
Score", "Precision Score"]

x.add_row(["BOW", "Bernaulli NB", 0.001, 88.871, 0.936, 0.988, 0.889])
x.add_row(["BOW", "Multinomial NB", 0.001, 88.916, 0.937, 0.993, 0.886])
x.add_row(["tf-IDF", "Bernaulli NB", 0.001, 88.871, 0.936, 0.988, 0.889])
x.add_row(["tf-IDF", "Multinomial NB", 0.02, 89.811, 0.941, 0.990, 0.897])
x.add_row(["Avg Word2Vec", "Bernaulli NB", 10000, 82.066, 0.895, 0.925, 0.867])
x.add_row(["Avg Word2Vec", "Multinomial NB", "-", "-", "-", "-", "-"])
x.add_row(["tf-IDF Word2Vec", "Bernaulli NB", 10, 82.247, 0.891, 0.880, 0.903])
x.add_row(["tf-IDF Word2Vec", "Multinomial NB", "-", "-", "-", "-", "-"])

print(x)
```

```
+-----------------+----------------+----------------+-------------+----------+--------------+------
--------+
|  NLP Technique  |   Algorithm    | Hyperparameter | Accuracy(%) | F1 Score | Recall Score |
Precision Score |
+-----------------+----------------+----------------+-------------+----------+--------------+------
--------+
|       BOW       |  Bernaulli NB  |     0.001      |    88.871   |  0.936   |    0.988     |
.889       |
|       BOW       | Multinomial NB |     0.001      |    88.916   |  0.937   |    0.993     |
.886       |
|      tf-IDF     |  Bernaulli NB  |     0.001      |    88.871   |  0.936   |    0.988     |
.889       |
```

```
|      tf-IDF      | Multinomial NB |      0.02       |     89.811    |  0.941    |      0.99       |
.897       |
|   Avg Word2Vec   |  Bernaulli NB  |     10000       |     82.066    |  0.895    |     0.925       |
.867       |
|   Avg Word2Vec   | Multinomial NB |       -         |       -       |    -      |       -         |
-         |
| tf-IDF Word2Vec |  Bernaulli NB  |       10        |     82.247    |  0.891    |      0.88       |
.903       |
| tf-IDF Word2Vec | Multinomial NB |       -         |       -       |    -      |       -         |
-         |
+------------------+----------------+-----------------+---------------+-----------+-----------------+------
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```

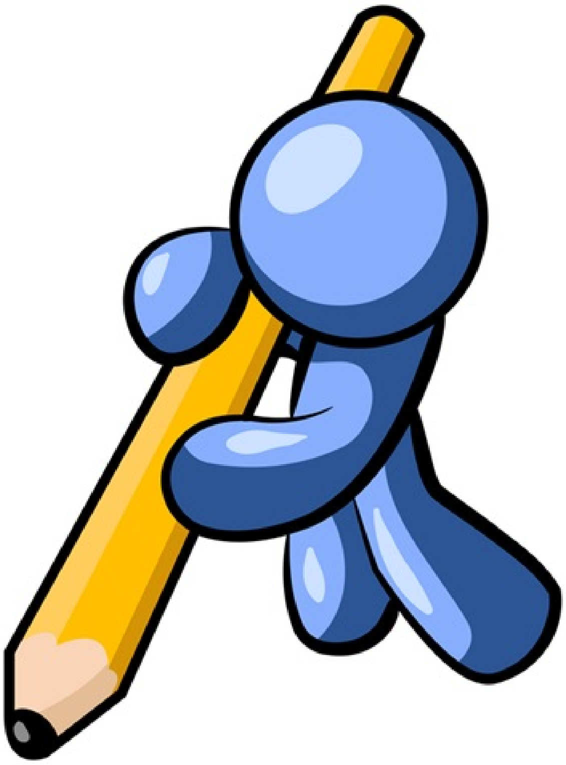

1. The comparison shows that tf-IDF is a good technique on Naive Bayes for this dataset with an accuracy of 89.811 %.

2. Therefore the best hyperparameter is 0.02 with an F1 Score of 0.941, recall Score of 0.99 and a precision of 0.897

3. Multinomial Naive Bayes is giving better results as compared to Bernaulli Naive Bayes.

4. Multinomial Naive Bayes is not good for the data set having negative values as it does not work with negative values.

5. The basic assumption of naive bayes is that features are independent and i think this is the reason that it does not perform well with Word2Vec or tf-IDF Word2Vec.

6. Naive Bayes is better than Knn as it is very fast as compared to Knn so it will be useful if we want the result in less time.