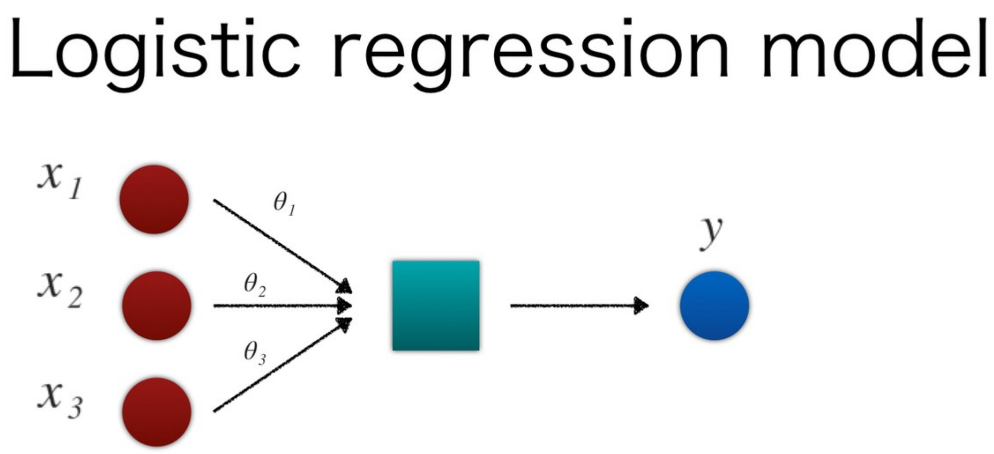
LOGISTIC REGRESSION ON AMAZON FINE FOOD REVIEWS DATASET

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 Logistic Regression on the dataset with both CV techniques i.e GridSearchCV as well as RandomSearchCV.
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. Shown the variation of Error & Sparsity with increse in lambda.
7. Performed Perturbation Testing.
8. 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 Logistic Regression and Compare both CV techniques and regularizers i.e GridSearchCV & RandomSearchCV to find the best one and ensure that the model is neither overfitting nor underfitting. Moreover to check that the features are dependent or related to each other or not.

IMPORTING

In [2]:

```
import re
import time
import gensim
import pickle
import sqlite3
import warnings
warnings.filterwarnings("ignore")
import numpy as np
import pandas as pd
import seaborn as sns
import statistics as s
from scipy import sparse
from scipy.sparse import find
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn.model_selection import RandomizedSearchCV
from prettytable import PrettyTable
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
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
from sklearn.metrics import accuracy_score
from sklearn.model_selection import TimeSeriesSplit
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
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
```

LOADING

In [3]:

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

In [4]:

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

Out[4]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score
0								

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score
	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 [5]:

```
# 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 [6]:

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

```
(364171, 12)
```

In [7]:

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

Out[7]:

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

SORTING

In [8]:

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

FUNCTIONS

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
```

GridSearchCV & RandomizedSearchCV

In [10]:

```
'''
This function takes training data and algorithm as input and gives execution time, accuracy and
the optimal value of alpha
on that data.
It uses GridSearch CV.
'''
def LR(X,Y,s):
    tscv = TimeSeriesSplit(n_splits=10)
    tuned_parameters = {'C': [0.001, 0.01, 1, 10, 100, 1000], 'penalty':['l1','l2']}
    clf = LogisticRegression()
    if s=='Grid':
        start = time.time()
        model = GridSearchCV(clf, tuned_parameters, cv=tscv)
        model.fit(X,Y)
        end = time.time()
        t=end-start
        print("Time taken to complete -: ",t,"sec\n")
        print("Best Hyperparameter -: ",model.best_params_,"\n")
        print("Accuracy -: ",round(model.best_score_*100,3),"%")
        return model
    else:
        start = time.time()
        model = RandomizedSearchCV(clf, tuned_parameters, cv=tscv)
        model.fit(X,Y)
        end = time.time()
        t=end-start
        print("Time taken to complete -: ",t,"sec\n")
        print("Best Hyperparameter -: ",model.best_params_,"\n")
        print("Accuracy -: ",round(model.best_score_*100,3),"%")
        return model
```

Hyperparameters vs Accuracy

In [11]:

```
'''
Calculates the accuracy on l1 & l2 regularizer and plot it against hyperparameters.
'''
def Accplot(h,nlp):
    l1=[]
    l2=[]
    j=0
    #print(h.cv_results_)
    acu = h.cv_results_['mean_test_score']
    alp = [0.001, 0.01, 1, 10, 100, 1000]
    for i in acu:
        if j%2==0:
            l1.append(i)
        else:
            l2.append(i)
        j+=1
    sns.set_style("darkgrid")
    plt.figure(figsize=(17,5))
    plt.figure(1)
    plt.subplot(121)
```

```
    plt.plot(alp,l1,'b--')
    plt.xlabel("Hyperparameter",fontsize=15, color='black')
    plt.ylabel("Accuracy",fontsize=15, color='black')
    plt.title("Accuracy -" + nlp + " -l1 regularizer",fontsize=15, color='black')
    plt.subplot(122)
    plt.plot(alp,l2,'r--')
    plt.xlabel("Hyperparameter",fontsize=15, color='black')
    plt.ylabel("Accuracy",fontsize=15, color='black')
    plt.title("Accuracy -" + nlp + " -l2 regularizer",fontsize=15, color='black')
    plt.show()
    print("\n")
    print("Average Accuracy on l1 reg -: ",round(s.mean(l1),3)*100)
    print("Average Accuracy on l2 reg -: ",round(s.mean(l2),3)*100)
```

Hyperparameter vs Error

In [12]:

```
'''
Calculates Error on both l1 regularizer as well as l2 regularizer and plots the train and Cv error
against
hyperparameters for each l1 & l2.
'''
def Errorplot(h):

    l1_test = []
    l1_train = []
    l2_test = []
    l2_train = []
    j=0
    j1=0

    alp = [0.001, 0.01, 1, 10, 100, 1000]

    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]

    for i in a:
        if j%2==0:
            l1_test.append(i)
        else:
            l2_test.append(i)
        j+=1

    for k in b:
        if j1%2==0:
            l1_train.append(k)
        else:
            l2_train.append(k)
        j1+=1


    plt.figure(figsize=(17,5))
    plt.figure(1)
    plt.subplot(121)
    plt.plot(alp, l1_test, '-b', label='CV Error')
    plt.plot(alp, l1_train, '-r', label='Train Error')
    plt.legend(loc='upper 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 l1 regularizer" ,fontsize=15, color='black')
    plt.subplot(122)
    plt.plot(alp, l2_test, '-b', label='CV Error')
    plt.plot(alp, l2_train, '-r', label='Train Error')
    plt.legend(loc='upper right')
    plt.xlabel("Hyperparameters",fontsize=15, color='black')
    plt.ylabel("Train Error vs Cv Error",fontsize=15, color='black')
    plt.title("Train vs CV Error on l2 regularizer" ,fontsize=15, color='black')
    plt.show()

    x = PrettyTable()
```

```
    x.field_names = ["Regularizer", "CV Error", "Train Error"]

    x.add_row(["L1", round(s.mean(l1_test),3)*100, round(s.mean(l1_train),3)*100])
    x.add_row(["L2", round(s.mean(l2_test),3)*100, round(s.mean(l2_train),3)*100])

    print("\n")
    print(x)
```

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(c,p,x_tr,y_tr,ts):
    clf = LogisticRegression(C = c, penalty = p)
    clf.fit(x_tr, y_tr)
    pred=clf.predict(ts)
    return clf,pred
```

Performance Measurement

In [14]:

```
'''
It gives the performance in terms of accuracy, F1 Score, recall, precision and test error also.
It gives confusion matrix between actual and predicted values.
'''
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))
    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()
```

Sparsity & Error with l1 Regularizer

In [15]:

```
'''
It takes hyperparameter values and regularizer and train & test datasets.
It returns error and sparsity.
'''
def Spar(c,x_tr,y_tr,x_ts,y_ts):
    clf = LogisticRegression(C = c, penalty = 'l1')
    clf.fit(x_tr, y_tr)
    pred=clf.predict(x_ts)
    print("\nFOR C = ",c)
    print("Error -: ",100-(round(((accuracy_score(y_ts,pred))*100),3)),"%")
    print("Sparsity -: ",np.count_nonzero(clf.coef_),"\n")
    print("________________________________")
```

MultiCollinearity Check

In [31]:

```
'''
This function checks multicollinearity or the realtion between the features.
'''
```

```
# _______________________________ Reference From StackOverflow
__________________________________________________

def muc(c, p, cnt, x_tr, y_tr, x_ts, y_ts):
    clf = LogisticRegression(C = c, penalty = p)
    clf.fit(x_tr, y_tr)
    pred=clf.predict(x_ts)
    print("__________________________ Without Adding Weights _____________________________")
    print("Accuracy -: ",round(((accuracy_score(y_ts,pred))*100),3),"%")
    print("Sparsity -: ",np.count_nonzero(clf.coef_),"\n")
    w1=find(clf.coef_[0])[2]
    print("__________________________ Weights Before Adding Noise _____________________________")
    print(w1[20:40])
    x_tr_t = x_tr
    s = find(x_tr_t)[0].size
    noise = np.random.uniform(low = -0.0001, high=0.0001, size=s)
    i,j,k = find(x_tr_t)
    x_tr_t[i,j] = noise + x_tr_t[i,j]
    clf = LogisticRegression(C = c, penalty = p)
    clf.fit(x_tr_t, y_tr)
    pred=clf.predict(x_ts)
    print("__________________________ After Adding Weights _____________________________")
    print("Accuracy -: ",round(((accuracy_score(y_ts,pred))*100),3),"%")
    print("Sparsity -: ",np.count_nonzero(clf.coef_),"\n")
    w2=find(clf.coef_[0])[2]
    print("__________________________ Weights After Adding Noise _____________________________")
    print(w2[20:40])
    w_diff = (abs(w1-w2)/w1)*100

    # I have varied the percentage for different models.

    f = w_diff[np.where(w_diff > 20)].size
    print("\n")
    print("The no. of features which are changing greater than 20% - : ",f)
    print("\n")
    if f>0:
        IF(clf,cnt)
    else:
        print("Therefore, the features are not multicollinear")
        print("\n")
```

Important Features

In [30]:

```
'''
This functions draws a pretty table of important features according to the Weights.
'''
def IF(c,co):
    a = c.coef_[0]
    f = co.get_feature_names()
    l1 = list(zip(a,f))
    l1 = sorted(l1,reverse=True)
    x = PrettyTable()
    x.field_names = ["Rank","Most Important Features", "Weight"]
    for i in range(25):
        x.add_row([i+1,l1[i][1],l1[i][0]])
    print(x)
```

Using Pickle

In [18]:

```
'''
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
```

LOGISTIC REGRESSION 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)
```

CONVERTING REVIEWS INTO VECTORS USING BOW

In [20]:

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

In [21]:

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

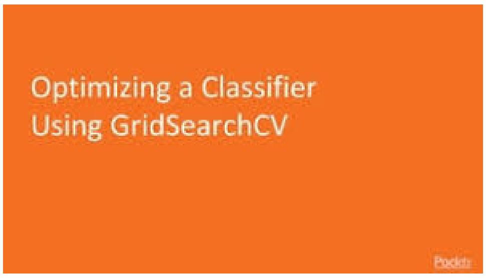
```
Train Dataset Shape -:  (254919, 2290079)
Test Dataset Shape -:  (109252, 2290079)
```

NORMALIZING THE DATA

In [22]:

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

GridSearchCV



HyperParameter Tuning

In [23]:

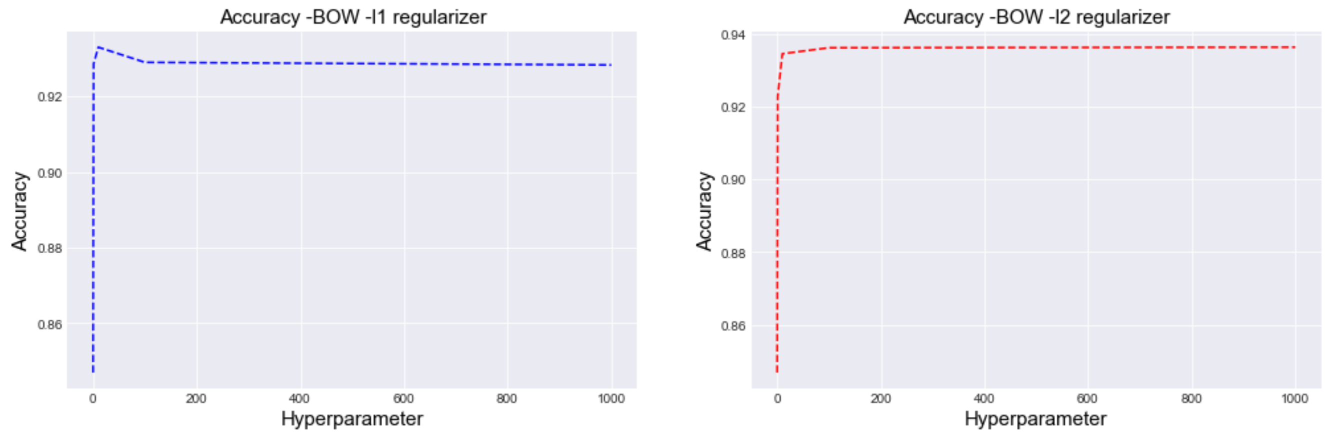
```
m = LR(x_train,y_train,'Grid')
```

```
Time taken to complete -:  2147.6635541915894 sec

Best Hyperparameter -:  {'C': 1000, 'penalty': 'l2'}

Accuracy -:  93.636 %
```

Hyperparameter vs Accuracy plot

In [24]:

```
Accplot(m,"BOW")
```

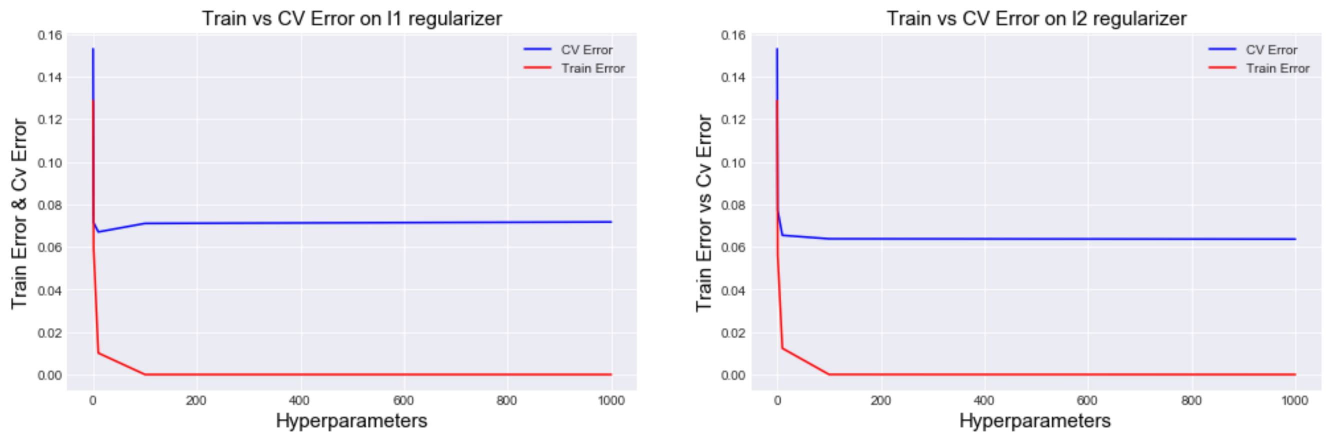



```
Average Accuracy on l1 reg -:  90.3
Average Accuracy on l2 reg -:  90.5
```

Hyperparameter vs Error Plot

In [25]:

```
Errorplot(m)
```



Regularizer	CV Error	Train Error
L1	9.7	5.4
L2	9.5	5.4

```
+-------------+----------+-------------+
```

Predicting on best Hyperparameter

In [26]:

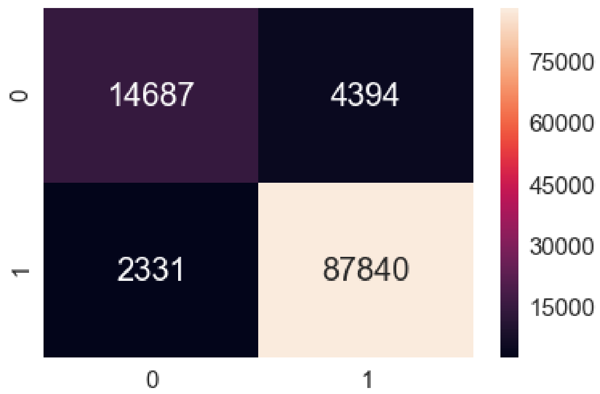
```
cl, pr = predict(1000,'l2',x_train,y_train,x_test)
```

Performance Measurement

In [27]:

```
Measure(y_test,pr)
```

```
Accuracy on Test Data -:  93.845 %

F1 Score -:   0.963

Precision Score -:  0.952

Recall Score -:  0.974

Test Error -:  6.155
```



RandomSearchCV

HyperParameter Tuning

In [28]:

```
m = LR(x_train,y_train,'Random')
```

```
Time taken to complete -:  1940.7424070835114 sec

Best Hyperparameter -:  {'penalty': 'l2', 'C': 1000}

Accuracy -:  93.636 %
```

Predict on Best Hyperparameter

In [110]:

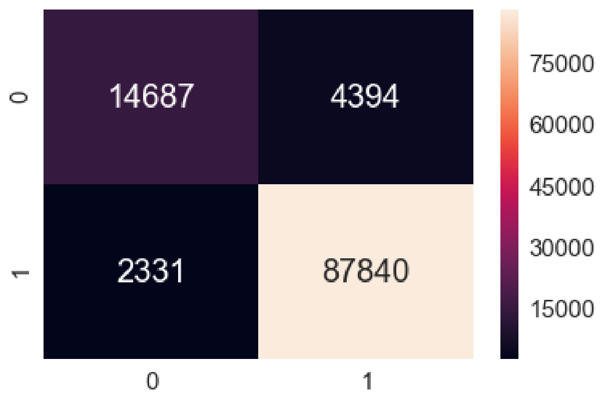
```
cl, pr = predict(1000,'l2',x_train,y_train,x_test)
```

Performance Measurement

In [111]:

```
Measure(y_test,pr)
```

```
Accuracy on Test Data -:  93.845 %

F1 Score -:   0.963

Precision Score -:  0.952

Recall Score -:  0.974

Test Error -:  6.155
```



Perturbation Testing & Most Important Features

In [158]:

```
muc(100,'l2',count,x_train,y_train,x_test,y_test)
```

```
__________________________ Without Adding Weights _____________________________
Accuracy -:  93.848 %
Sparsity -:  2290079

__________________________ Weights Before Adding Noise ____________________________
[ 0.03148651  0.00073087  0.00072889 -0.1176949  -0.11682553  0.00047818
  0.00047912  0.02590252  0.02576515  0.02625819  0.02636826 -0.10202166
 -0.10270304  0.00065026  0.00065027  0.00073295  0.00073478  0.02104627
  0.00343749  0.01751685]
__________________________ After Adding Weights _____________________________
Accuracy -:  93.849 %
Sparsity -:  2290079

__________________________ Weights After Adding Noise ____________________________
[ 0.03170446  0.0008444   0.00084155 -0.11819555 -0.11710487  0.00056001
  0.0005614   0.02579992  0.02562869  0.02624327  0.02638048 -0.10160746
 -0.10245528  0.00073456  0.00073458  0.00084741  0.00085006  0.02157005
  0.00357672  0.01787577]


The no. of features which are changing greater than 45% - :  1058
Therefore, the features are multicollinear




+------+------------------------+---------------+
| Rank | Most Important Features |     Weight    |
+------+------------------------+---------------+
|  1   |     not disappoint      | 36.4888980682 |
|  2   |    wont disappoint      | 22.9286291075 |
|  3   |       four star         | 22.3045466572 |
|  4   |     high recommend      | 20.5661521681 |
|  5   |      not overpow        | 20.1878946005 |
|  6   |    pleasant surpris     |  19.479181032 |
|  7   |       veri pleas        | 18.5076717285 |
|  8   |        skeptic          |  18.48538805  |
```

```
|  9   |      never disappoint      | 17.8893788386 |
|  10  |           delici           | 17.8237239249 |
|  11  |            hook            | 17.7900360811 |
|  12  |       not overwhelm        | 16.4691033854 |
|  13  |         not bitter         | 16.2426136023 |
|  14  |        right amount        | 15.8806423808 |
|  15  |          not weak          | 15.7845434612 |
|  16  |          perfect           | 15.2592540859 |
|  17  |          not bad           | 15.1765061171 |
|  18  |           addict           | 14.9960733986 |
|  19  |         wont sorri         | 14.8989421479 |
|  20  |            amaz            | 14.8925408812 |
|  21  |           excel            | 14.6725370909 |
|  22  |         cant wrong         | 14.6499793641 |
|  23  |         wasnt sure         |  14.646643426 |
|  24  |           awesom           | 14.4595837864 |
|  25  |         noth wrong         | 14.1007767654 |
+------+----------------------------+---------------+
```

LOGISTIC REGRESSION MODEL ON tf-IDF

SPLITTING INTO TRAIN AND TEST

In [159]:

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

CONVERTING REVIEWS INTO VECTORS USING tf-IDF

In [160]:

```
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 [161]:

```
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 [162]:

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

GridSearchCV

HyperParameter Tuning

In [164]:

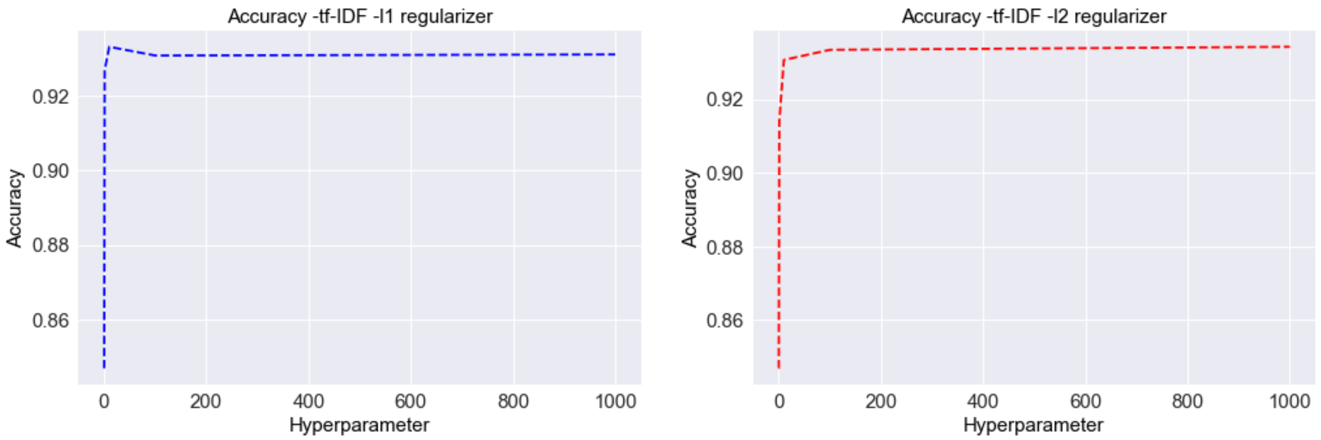
```
m = LR(x_train,y_train,'Grid')
```

```
Time taken to complete -:  1353.2826647758484 sec

Best Hyperparameter -:  {'C': 1000, 'penalty': 'l2'}

Accuracy -:  93.429 %
```

Hyperparameter vs Accuracy plot

In [167]:

```
Accplot(m,"tf-IDF")
```

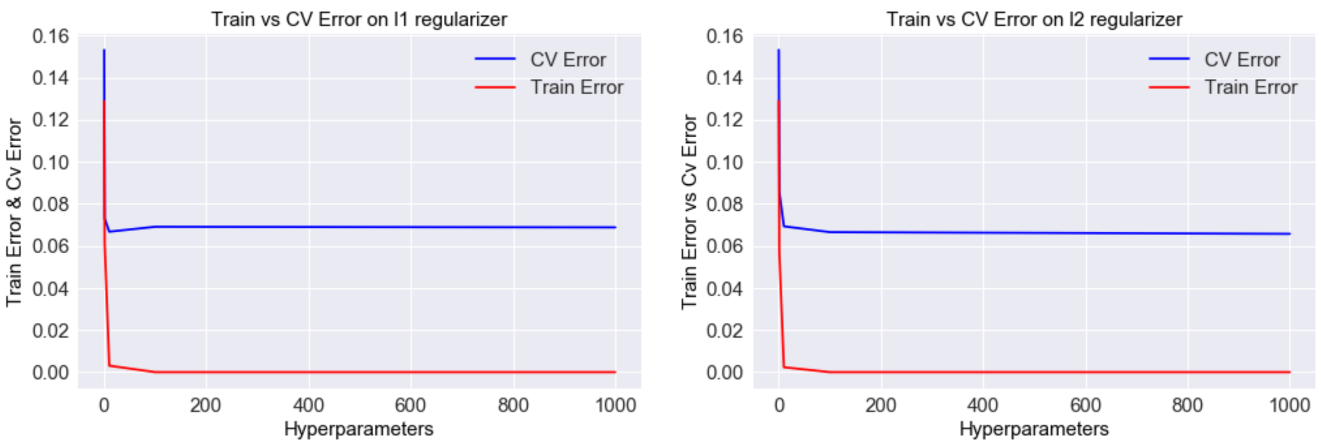



```
Average Accuracy on l1 reg -:  90.3
Average Accuracy on l2 reg -:  90.1
```

Hyperparameter vs Error Plot

In [168]:

```
Errorplot(m)
```



Regularizer	CV Error	Train Error
L1	9.7	5.4
L2	9.9	5.3

Predicting on best Hyperparameter

In [169]:

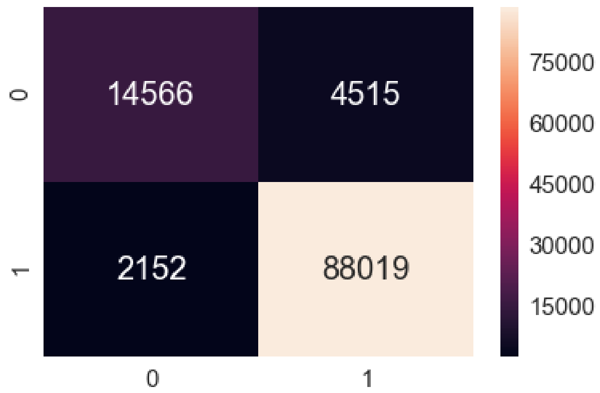
```
cl, pr = predict(1000,'l2',x_train,y_train,x_test)
```

Performance Measurement

In [170]:

```
Measure(y_test,pr)
```

```
Accuracy on Test Data -:  93.898 %

F1 Score -:   0.964

Precision Score -:  0.951

Recall Score -:  0.976

Test Error -:  6.102
```



RandomSearchCV

HyperParameter Tuning

In [171]:

```
m = LR(x_train,y_train,'Random')
```

```
Time taken to complete -:  1148.8976826667786 sec

Best Hyperparameter -:  {'penalty': 'l2', 'C': 1000}

Accuracy -:  93.429 %
```

Predicting on best Hyperparameter

In [172]:

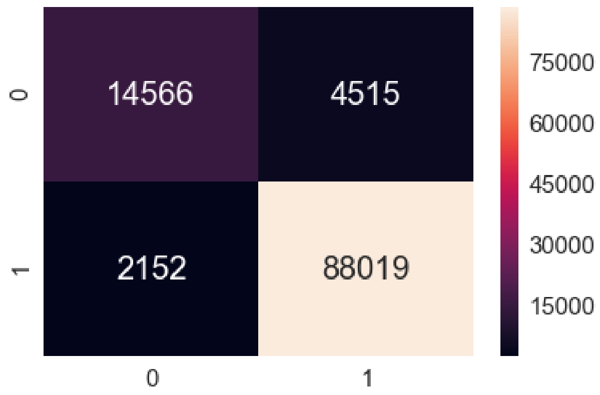
```
cl, pr = predict(1000,'l2',x_train,y_train,x_test)
```

Performance Measurement

In [173]:

```
Measure(y_test,pr)
```

```
Accuracy on Test Data -:  93.898 %

F1 Score -:   0.964

Precision Score -:  0.951

Recall Score -:  0.976

Test Error -:  6.102
```



Perturbation Testing & Most Important Features

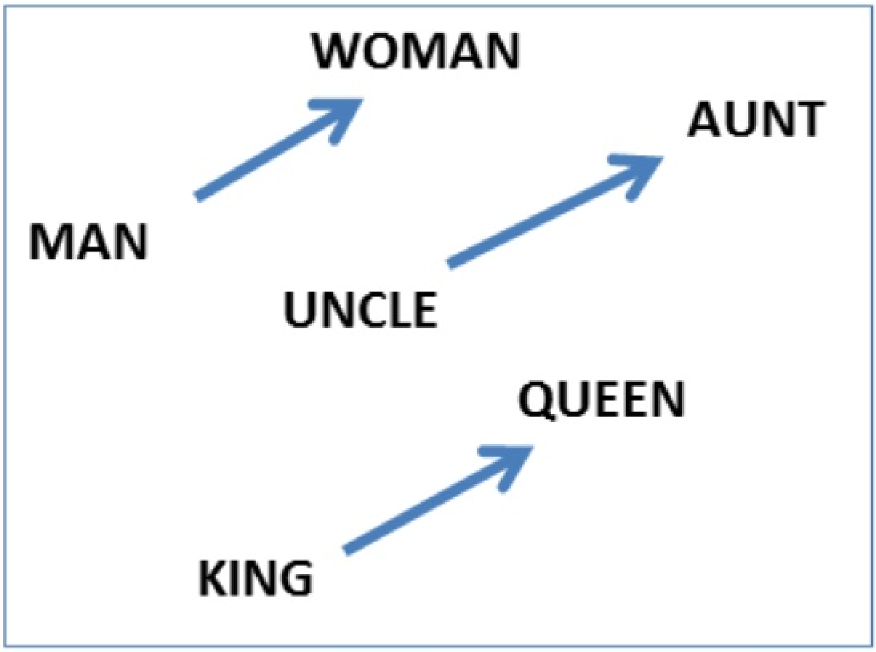
In [175]:

```
muc(1000,'l2',count,x_train,y_train,x_test,y_test)
```

```
__________________________ Without Adding Weights _____________________________
Accuracy -:  93.898 %
Sparsity -:  2290079

__________________________ Weights Before Adding Noise _____________________________
[ 0.02002966  0.00899722  0.00899722 -0.29669962 -0.29669962  0.00782466
  0.00782466  0.04067399  0.04067399  0.04067399  0.04067399 -0.19896223
 -0.19896223  0.00381418  0.00381418  0.00899722  0.00899722  0.07032526
  0.01165108  0.06098302]
__________________________ After Adding Weights _____________________________
Accuracy -:  93.897 %
Sparsity -:  2290079

__________________________ Weights After Adding Noise _____________________________
[ 0.02012778  0.00900098  0.00899655 -0.29713966 -0.29679242  0.00784464
  0.00784732  0.04045345  0.04041887  0.04054299  0.0405707  -0.19917217
 -0.19940993  0.00381575  0.00381577  0.00900565  0.00900977  0.07056717
  0.01166215  0.06116929]


The no. of features which are changing greater than 45% - :  224
Therefore, the features are multicollinear




+------+-------------------------+---------------+
| Rank | Most Important Features |     Weight    |
+------+-------------------------+---------------+
|  1   |          great          | 52.3630679374 |
|  2   |      not disappoint     | 50.4487266416 |
|  3   |          delici         | 48.9219650623 |
|  4   |           best          | 41.6275842281 |
|  5   |           love          | 40.6020040497 |
|  6   |         perfect         | 40.3694787044 |
|  7   |      high recommend     | 39.0835074114 |
|  8   |          excel          | 35.6073114593 |
|  9   |           good          | 34.6374096333 |
|  10  |           amaz          | 31.5810296627 |
```

```
|  11  |      wont disappoint     | 30.7952536126 |
|  12  |          awesom          | 27.8381684494 |
|  13  |          happi           | 27.7729795824 |
|  14  |          addict          | 27.3728283387 |
|  15  |          yummi           | 27.1973177899 |
|  16  |         favorit          | 26.9485405379 |
|  17  |           hook           | 26.7420606633 |
|  18  |        veri pleas        | 26.2754042232 |
|  19  |         fantast          |  26.136676439 |
|  20  |        four star         | 26.0739362273 |
|  21  |         not bad          | 25.2953598582 |
|  22  |          tasti           | 25.2389106226 |
|  23  |           nice           | 24.4594323043 |
|  24  |       not overpow        | 24.4435167537 |
|  25  |     pleasant surpris     | 24.0065823029 |
+------+--------------------------+---------------+
```

LOGISTIC REGRESSION MODEL ON Avg Word2Vec



Loading Data From File

In [244]:

```
x_train = retrieve("Word2Vec-Train")
x_test = retrieve("Word2Vec-Test")
```

In [245]:

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

```
Train Dataset Shape -:  (254919, 100)
Test Dataset Shape -:  (109252, 100)
```

In [246]:

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

GridSearchCV

HyperParameter Tuning

In [183]:

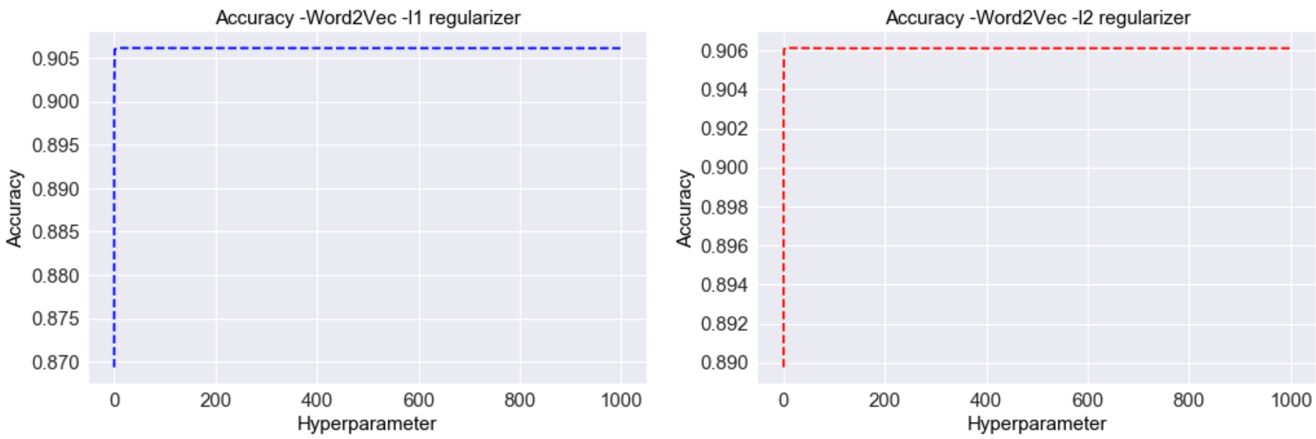
```
m = LR(x_train,y_train,'Grid')
```

```
Time taken to complete -:  1866.907469034195 sec

Best Hyperparameter -:  {'C': 10, 'penalty': 'l1'}

Accuracy -:  90.613 %
```

Hyperparameter vs Accuracy plot

In [184]:

```
Accplot(m,"Word2Vec")
```

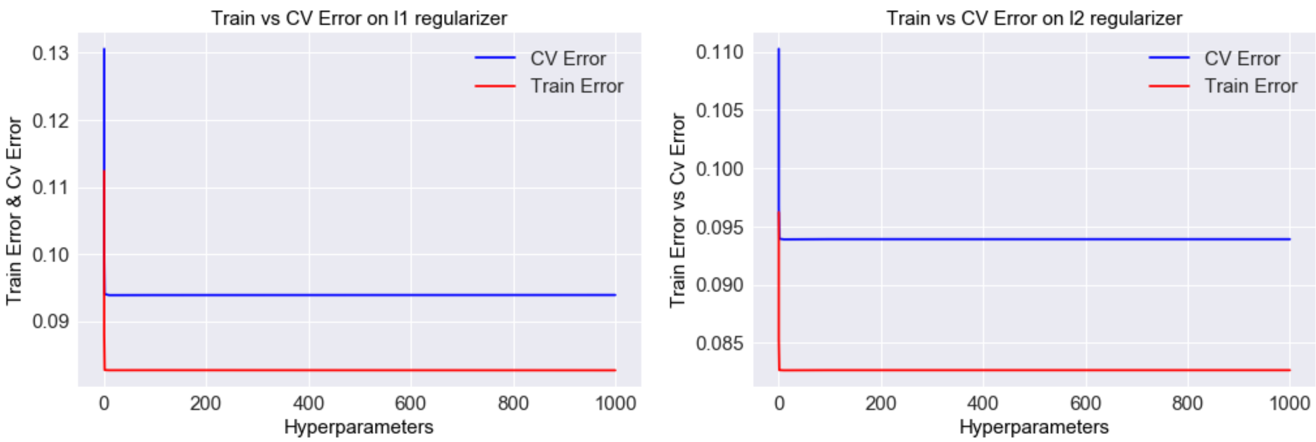



```
Average Accuracy on l1 reg -:  89.9
Average Accuracy on l2 reg -:  90.3
```

Hyperparameter vs Error Plot

In [185]:

```
Errorplot(m)
```




```
+-------------+----------+-------------+
| Regularizer | CV Error | Train Error |
+-------------+----------+-------------+
```

```
|      L1      |   10.1   |     8.9     |
|      L2      |   9.7    |     8.5     |
+--------------+----------+-------------+
```

Predicting on best Hyperparameter

In [186]:

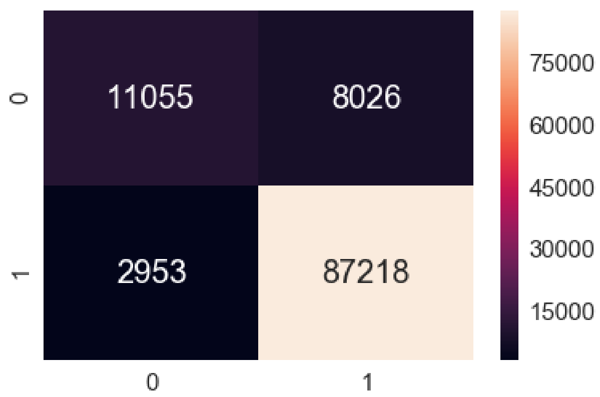
```
cl, pr = predict(10,'l1',x_train,y_train,x_test)
```

Performance Measurement

In [187]:

```
Measure(y_test,pr)
```

```
Accuracy on Test Data -:  89.951 %

F1 Score -:   0.941

Precision Score -:  0.916

Recall Score -:  0.967

Test Error -:  10.049
```



RandomSearchCV

HyperParameter Tuning

In [191]:

```
m = LR(x_train,y_train,'Random')
```

```
Time taken to complete -:  1255.9150743484497 sec

Best Hyperparameter -:  {'penalty': 'l1', 'C': 100}

Accuracy -:  90.613 %
```

Predicting on best Hyperparameter

In [192]:

```
cl, pr = predict(100,'l1',x_train,y_train,x_test)
```

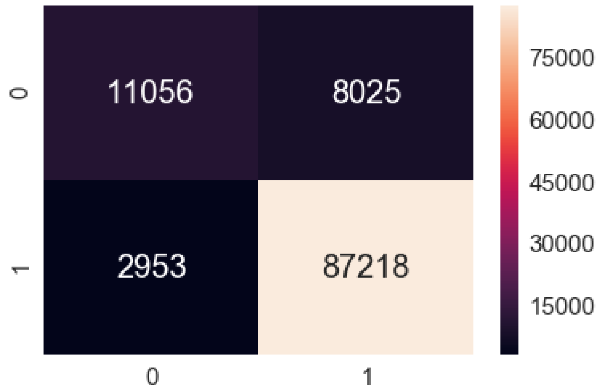
Performance Measurement

Performance Measurement

In [193]:

```
Measure(y_test,pr)
```

```
Accuracy on Test Data -:  89.952 %

F1 Score -:   0.941

Precision Score -:  0.916

Recall Score -:  0.967

Test Error -:  10.048
```



Perturbation Testing & Most Important Features

In [248]:

```
muc(10,'l1',count,x_train,y_train,x_test,y_test)
```

```
__________________________ Without Adding Weights _____________________________
Accuracy -:  90.079 %
Sparsity -:  100

__________________________ Weights Before Adding Noise _____________________________
[-0.65328423  4.30807754  2.75024395  0.7504924   4.66648608 -3.91403971
  3.1598497   3.63224149  1.50035848  1.32009116  1.31141728 -3.84303892
 -1.06954065 -1.85355511  0.66127268  1.84013293  2.6620992   4.33684717
  0.58927849 -1.80202248]
__________________________ After Adding Weights _____________________________
Accuracy -:  90.079 %
Sparsity -:  100

__________________________ Weights After Adding Noise _____________________________
[-0.65264396  4.30672336  2.75060328  0.75085858  4.66567812 -3.91399743
  3.16143489  3.63322853  1.50077616  1.32082567  1.31192407 -3.84329915
 -1.07015799 -1.85242117  0.66271248  1.84079513  2.66226709  4.33954868
  0.58822809 -1.80177214]


The no. of features which are changing greater than 40% - :  0
Therefore, the features are not multicollinear
```

LOGISTIC REGRESSION MODEL ON tf-IDF Word2Vec

LOADING DATA FROM FILE

In [195]:

```
x_train = retrieve("tfidf-W2v-train")
x_test = retrieve("tf-idf-w2v-test")
```

In [196]:

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

```
Train Dataset Shape -:  (254919, 100)
Test Dataset Shape -:  (109252, 100)
```

In [198]:

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

In [199]:

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

In [200]:

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

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

In [203]:

```
# Saving for future assignments.
save(x_train,"tfidf_w2v_train")
save(x_test,"tfidf_w2v_test")
```

Normalizing the Data

In [204]:

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

GridSearchCV

HyperParameter Tuning

In [205]:

```
m = LR(x_train,y_train,'Grid')
```

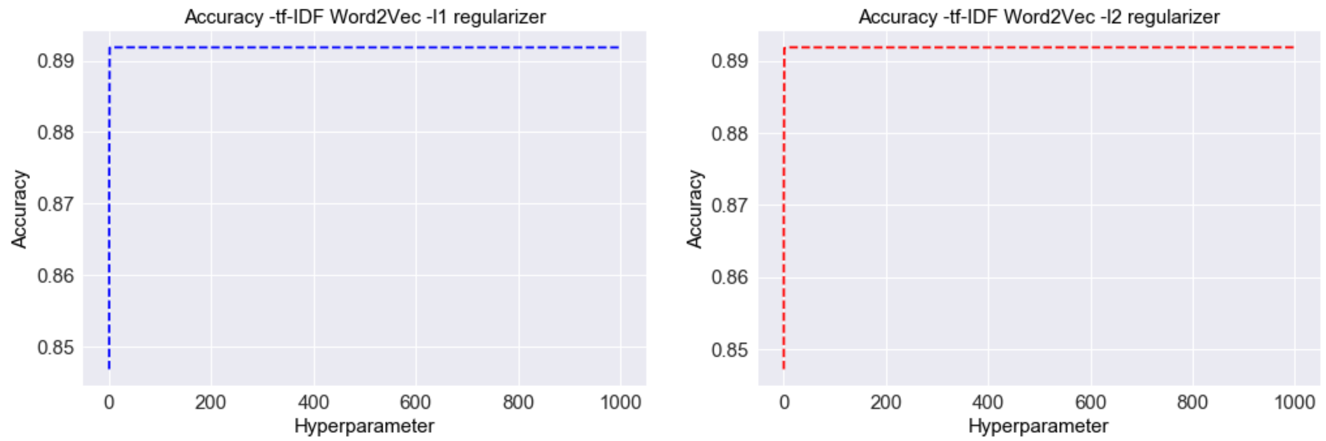
```
Time taken to complete -:  834.3468735218048 sec

Best Hyperparameter -:  {'C': 10, 'penalty': 'l2'}

Accuracy -:  89.185 %
```

Hyperparameter vs Accuracy plot

Hyperparameter vs Accuracy plot

In [206]:

```
Accplot(m,"tf-IDF Word2Vec")
```

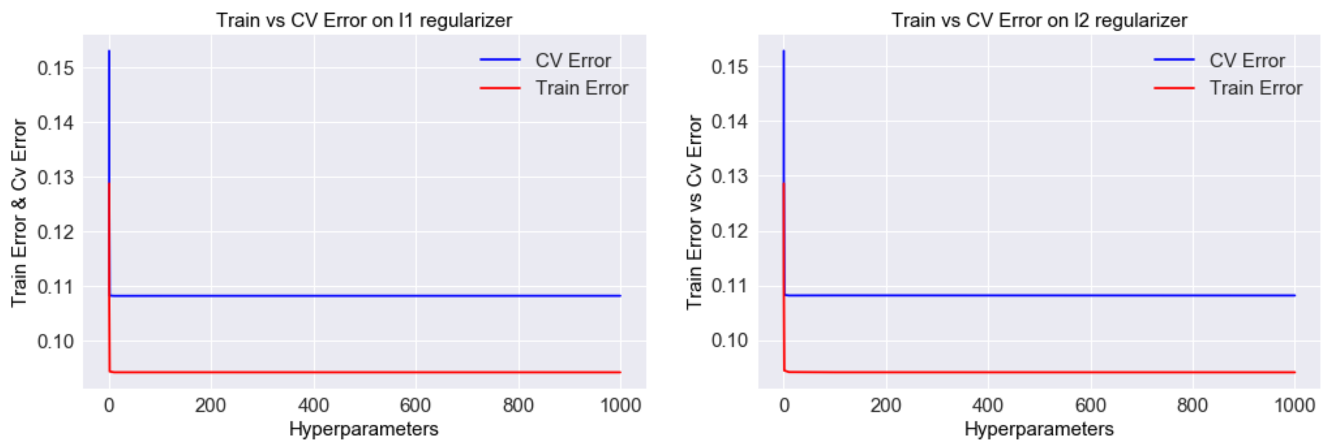



```
Average Accuracy on l1 reg -:  88.1
Average Accuracy on l2 reg -:  88.1
```

Hyperparameter vs Error Plot

In [207]:

```
Errorplot(m)
```




```
+-------------+----------+-------------+
| Regularizer | CV Error | Train Error |
+-------------+----------+-------------+
|      L1     |   11.9   |     10.2    |
|      L2     |   11.9   |     10.3    |
+-------------+----------+-------------+
```

Predicting on best Hyperparameter

In [208]:

```
cl, pr = predict(10,'l2',x_train,y_train,x_test)
```

Performance Measurement

In [209]:

```
Measure(y_test,pr)
```

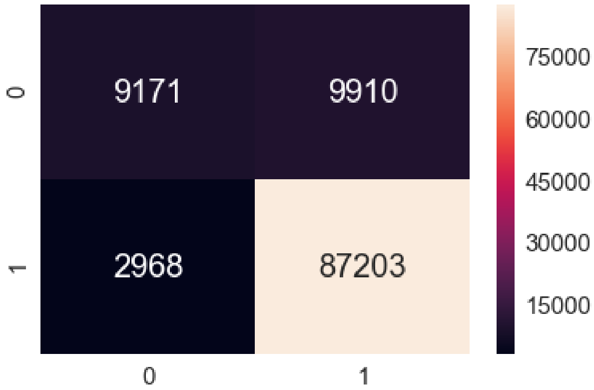
Accuracy on Test Data -: 88.213 %

F1 Score -:   0.931

Precision Score -: 0.898

Recall Score -: 0.967

Test Error -: 11.787



RandomSearchCV

HyperParameter Tuning

In [210]:

```
m = LR(x_train,y_train,'Random')
```

Time taken to complete -: 703.25212931633 sec

Best Hyperparameter -: {'penalty': 'l2', 'C': 1000}

Accuracy -: 89.185 %

Predicting on best Hyperparameter

In [211]:

```
cl, pr = predict(1000,'l2',x_train,y_train,x_test)
```

Performance Measurement

In [212]:

```
Measure(y_test,pr)
```

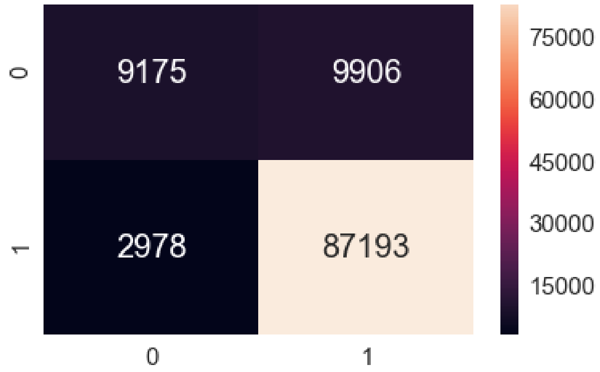
Accuracy on Test Data -: 88.207 %

F1 Score -:   0.931

Precision Score -: 0.898

Recall Score -: 0.967

Test Error -: 11.793



Perturbation Testing & Most Important Features

In [226]:

```
muc(10,'l2',count,x_train,y_train,x_test,y_test)
```

```
__________________________ Without Adding Weights _____________________________
Accuracy -:  88.213 %
Sparsity -:  100

__________________________ Weights Before Adding Noise ____________________________
[-1.50491463  4.12457625  1.8145111   0.56468903  3.62400594 -4.05997015
  2.65292544  3.88932183  1.40524758  0.49444092  0.94394901 -3.21870626
 -0.45658308 -1.37685048  0.62665631  1.22169452  2.13516832  3.15228367
 -0.42686414 -1.3344293 ]
__________________________ After Adding Weights _____________________________
Accuracy -:  88.213 %
Sparsity -:  100

__________________________ Weights After Adding Noise ____________________________
[-1.50395916  4.12481309  1.81556218  0.56452883  3.62891696 -4.06088593
  2.65063101  3.88818585  1.40405688  0.49288106  0.94383467 -3.21946672
 -0.4590658  -1.37541519  0.62872374  1.21931655  2.13589464  3.15593736
 -0.42699785 -1.33466254]


The no. of features which are changing greater than 15% - :  0
Therefore, the features are not multicollinear
```

ANALYZING ERROR & SPARSITY

In [242]:

```
Spar(100,x_train,y_train,x_test,y_test)
Spar(10,x_train,y_train,x_test,y_test)
Spar(1,x_train,y_train,x_test,y_test)
Spar(0.1,x_train,y_train,x_test,y_test)
Spar(0.01,x_train,y_train,x_test,y_test)
```

```
FOR C =  100
Error -:  11.789 %
Sparsity -:  100

_______________________________

FOR C =  10
Error -:  11.789 %
Sparsity -:  100

_______________________________

FOR C =  1
```

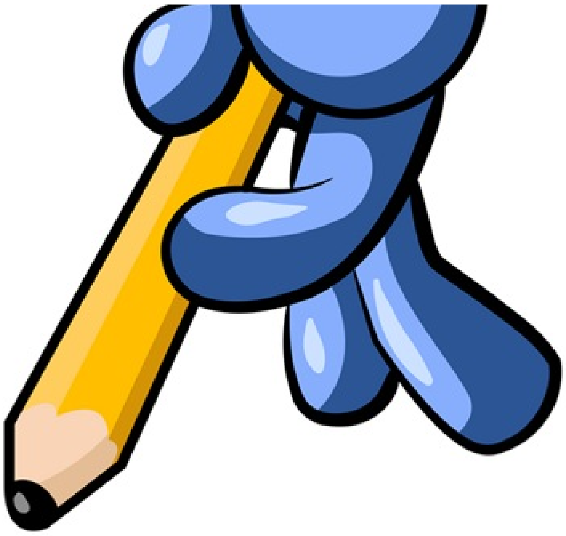
```
Error -:  11.799 %
Sparsity -:  100

________________________________

FOR C =  0.1
Error -:  11.873 %
Sparsity -:  98

________________________________

FOR C =  0.01
Error -:  12.656 %
Sparsity -:  58

________________________________
```

As we can analyze above that as the c value decreases error increases and sparsity also decreases.

In [230]:

```
x = PrettyTable()

x.field_names = ["NLP Technique", "CV", "Hyperparameter", "Regularizer", "Accuracy(%)"]

x.add_row(["BOW", "GridSearchCV", 100, "l2", 93.721])
x.add_row(["BOW", "RandomSearchCV", 1000, "l2", 93.845])
x.add_row(["tf-IDF", "GridSearchCV", 1000,"l2", 93.898])
x.add_row(["tf-IDF", "RandomSearchCV", 1000,"l2", 93.898])
x.add_row(["Avg Word2Vec", "GridSearchCV", 10,"l2",89.951])
x.add_row(["Avg Word2Vec", "RandomSearchCV",100,"l1",89.952 ])
x.add_row(["tf-IDF Word2Vec", "GridSearchCV", 10,"l2",88.213])
x.add_row(["tf-IDF Word2Vec", "RandomSearchCV",1000,"l2",88.207])

print(x)
```

```
+-----------------+----------------+----------------+-------------+-------------+
|  NLP Technique  |       CV       | Hyperparameter | Regularizer | Accuracy(%) |
+-----------------+----------------+----------------+-------------+-------------+
|       BOW       |  GridSearchCV  |      100       |      l2     |    93.721   |
|       BOW       | RandomSearchCV |      1000      |      l2     |    93.845   |
|      tf-IDF     |  GridSearchCV  |      1000      |      l2     |    93.898   |
|      tf-IDF     | RandomSearchCV |      1000      |      l2     |    93.898   |
|   Avg Word2Vec  |  GridSearchCV  |       10       |      l2     |    89.951   |
|   Avg Word2Vec  | RandomSearchCV |      100       |      l1     |    89.952   |
| tf-IDF Word2Vec |  GridSearchCV  |       10       |      l2     |    88.213   |
| tf-IDF Word2Vec | RandomSearchCV |      1000      |      l2     |    88.207   |
+-----------------+----------------+----------------+-------------+-------------+
```



1. The comparison shows that tf-IDF is a good technique on Logistic Regression for this dataset with an accuracy of 93.898 %.

2. Therefore the best hyperparameter is 1000 with an F1 Score of 0.964, recall Score of 0.976 and a precision of 0.951

3. RandomSearchCV is giving better results as compared to GridSearchCV.

4. We can analyze that features in BOW and tf-IDF are changing massively therefore they are multicollinear but the features in Word2Vec are not changing at that extent.

5. As C decreases the sparsity also decreases but error increases.

6. Logistic Regression is better than Knn and Naive Bayes on this dataset as it is giving better accuracy.