OBJECTIVE :

1. APPLYING LOGISTIC REGRESSION WITH BOW VECTORIZATION
   - PERFORMING PERTUBATION TEST TO CHECK WHETHER OUR DATA FEATURES ARE COLLINER OR NOT AND PLOTTING THE RESULT
   - FINDING THE BEST HYPERPARAMETER USING GRIDSEARCHCV WITH TRAIN DATA AND CROSS-VALIDATION DATA BY PLOTTING THE RESLUTS OF VAROIUS TRAIN DATA AND CROSS VALIDATION DATA
   - USING THE APROPRIATE VALUE OF HYPERPARAMETER ,TESTING ACCURACY ON TEST DATA USING F1-SCORE
   - PLOTTING THE CONFUSION MATRIX TO GET THE PRECISOIN ,RECALL VALUE WITH HELP OF HEATMAP
   - PRINTING THE TOP 20 FEATURES FOR BOTH POSITIVE AND NEGATIVE WORDS #

In [2]:
```
from sklearn.model_selection import train_test_split          #importin
g the necessary libraries
from sklearn.model_selection import RandomizedSearchCV
from sklearn.datasets import *
from sklearn import naive_bayes
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
import pandas as pd
from sklearn import *
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
final_processed_data=pd.read_csv("C:/Users/Mayank/Desktop/machine learn
ing/appliedaicourse data/lecture 18  knn/final_new_data.csv")#loading t
he preprocessed data  with 100k points into dataframe
```

```
In [4]: # getting the counts of 0 and 1 in "SCORE" column to know whether it is
         unbalanced data or not
        count_of_1=0
        count_of_0=0
        for i in final_processed_data['Score']:
           if i==1:
            count_of_1+=1
           else:
            count_of_0+=1
        print(count_of_1)
        print(count_of_0)
        #it is an imbalanced dataset
```

```
88521
11479
```

```
In [5]: #spliiting the data into train and test data
        x_train,x_test,y_train,y_test=model_selection.train_test_split(final_pr
        ocessed_data['CleanedText'].values,final_processed_data['Score'].values
        ,test_size=0.2,shuffle=False)
```

```
In [6]: vectorizer=CountVectorizer(min_df=10)#building the vertorizer with word
         counts equal and more then 2
        train_bow=vectorizer.fit_transform(x_train)#fitting the model on traini
        ng data
        print(train_bow.shape)
```

```
(80000, 7677)
```

```
In [7]: from sklearn.preprocessing import StandardScaler #standarizing the trai
        ning  data
        x_train_data=StandardScaler( with_mean=False).fit_transform(train_bow)
        print(x_train_data.shape)
```

```
(80000, 7677)
```

```
In [8]: test_bow=vectorizer.transform(x_test)#fitting the bow model on test dat
        a
        print("shape of x_test after bow vectorization ",test_bow.shape)
```

```
x_test_data=StandardScaler( with_mean=False).fit_transform(test_bow)#standarizing the test data
print("shape of x_test after standardization ",x_test_data.shape)
```

```
shape of x_test after bow vectorization  (20000, 7677)
shape of x_test after standardization  (20000, 7677)
```

In [9]:
```
#using time series split method for cross-validation score
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)
from sklearn.linear_model import LogisticRegression
from scipy.stats import uniform
data=[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]#range of hyperparameter
```

In [10]:
```
lr=LogisticRegression(penalty='l2',class_weight={1:.5,0:.5})#building logistic regression model
tuned_parameters=[{'C':data}]
```

In [10]:
```
#applying the model of logistic regression and using gridsearchcv to find the best hyper parameter
%time
from sklearn.model_selection import GridSearchCV
model = GridSearchCV(lr, tuned_parameters, scoring = 'f1', cv=tscv,n_jobs=-1)#building the gridsearchcv model
model.fit(x_train_data, y_train)#fiitting the training data

print(model.best_estimator_)#printing the best_estimator
print(model.score(x_test_data, y_test))#predicting  f1 score on test data
```

```
Wall time: 0 ns
LogisticRegression(C=0.001, class_weight={1: 0.5, 0: 0.5}, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
0.952504987808
```

In [11]:
```
lr=LogisticRegression(C=0.001,penalty='l2',class_weight={1:.5,0:.5},n_j
obs=-1)#again building the model to find best hyperparameter
lr.fit(x_train_data,y_train)#fitting the training data
z=lr.decision_function(x_train_data)#checking the signed distance of a
 point from hyperplane
print(z)#printing the signed distance
```

```
[ 3.55845076  2.26483878  1.98815951 ...,  7.38021825 -2.68550859
  4.84653495]
```

In [12]:
```
wieght_vector=lr.coef_#getting the weight vector
print(wieght_vector.shape)#wieght vector shape
print(wieght_vector[:20])
```

```
(1, 7677)
[[-0.00404381 -0.0055471  -0.00635504 ...,  0.0277215  -0.00865251
   0.00910158]]
```

PERFORMING SPARSITY CHECK WITH L1 REGULARIZATION

In [11]:
```
first_20k_points=x_train_data[:20000] #first 20k points
```

In [12]:
```
#using time series split method for cross-validation score
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)
from sklearn.linear_model import LogisticRegression
from scipy.stats import uniform
data=[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]#range
 of hyperparameter
```

In [13]:
```
lr=LogisticRegression(penalty='l1',class_weight={1:.5,0:.5})#building l
ogistic regression model
tuned_parameters=[{'C':data}]
```

In [14]:
```
#applying the model of logistic regression and using gridsearchcv to fi
nd the best hyper parameter
%time
from sklearn.model_selection import GridSearchCV
model = GridSearchCV(lr, tuned_parameters, scoring = 'f1', cv=tscv,n_jo
bs=-1)#building the gridsearchcv model
model.fit(first_20k_points, y_train[:20000])#fiitting the training data

print(model.best_estimator_)#printing the best_estimator
```

```
Wall time: 0 ns
LogisticRegression(C=0.1, class_weight={1: 0.5, 0: 0.5}, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l1', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

In [15]:
```
lr=LogisticRegression(C=0.1,penalty='l1',class_weight={1:.5,0:.5},n_job
s=-1)#again building the model to find best hyperparameter
lr.fit(first_20k_points,y_train[:20000])#fitting the training data
```

Out[15]:
```
LogisticRegression(C=0.1, class_weight={1: 0.5, 0: 0.5}, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l1', random_state=Non
e,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

In [16]:
```
wieght_vector=lr.coef_#getting the weight vector
print(wieght_vector.shape)#wieght vector shape
print(wieght_vector[:20])
```

```
(1, 7677)
[[ 0.          0.00692072  0.         ...,  0.          0.          0.
       ]]
```

In [17]:
```
np.count_nonzero(wieght_vector)
```

Out[17]:
```
1625
```

THUS HERE ONLY 1625 FEATURES ARE NON_ZERO AND REST OF FEATURES WIEGHTS HAVE BECOME ZERO..SPARSITY CHECK IS POSITIVE

PERTUBATION TEST :

```
AIM:    TO CHECK FOR MULTI COLLINEARITY  OF FEATURES
STEPS
```

1. **GETTING THE WIEGHT VECTOR FROM MODEL AND SAVING IT**
2. **ADDING NOISE TO THE TRAINING DATA TO GET NEW TRAINING DATA**
3. **FITTING THE MODEL AGAIN ON NEW DATA**
4. **GETTING THE WIEGHT VECTOR FROM THIS MODEL 5.ADDING SMALL VALUE TO WEIGHT VECTOR OF BOTH TRAINNG DATA TO REMOVE ANY ERROR**
5. **FINDING THE PERCENTAGE CHANGE VECTOR**
6. **GEETING HOW MANY GEATURE HAS CHANGED USING SOME THRESHOLD VALUE(HERE TAKING IT AS 100)**
7. **PLOTTING THE QUANTILES WITH THIER PERCENTAGE WIGHT VALUE TO CHECK IF COLLINEARITY EXITS OR NOT**

 # RESULT : TO KNOW WHETHER FEATURES ARE MULTICOLLINEAR OR NOT # # AND TO KNOW WHETHER MODEL IS RELIABLE OR NOT #

In [19]:
```
#here,we are adding noise to the data
from scipy.stats import norm
noise=norm.rvs(size=1)#noise
x_train_data.data+=noise#adding noise
```

In [20]:
```
print('shape of our new train data  after adding noise is : ',x_train_d
ata.shape)#printing shape of new training data
```

```
shape of our new train data  after adding noise is :  (80000, 7677)
```

In [21]:
```
#uilding the model using timeSeriesSplit
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10) # 10 spilts cross validation
from sklearn.linear_model import LogisticRegression
from scipy.stats import uniform
data=[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]#value
 range of hyper parameter for grid searchcv
lr=LogisticRegression(penalty='l2',class_weight={1:.5,0:.5},n_jobs=-1)#
building the model
tuned_parameters=[{'C':data}]
```

In [22]:
```
%time
from sklearn.model_selection import GridSearchCV
model = GridSearchCV(lr, tuned_parameters, scoring = 'f1', cv=tscv,n_jo
bs=-1)#building the gridsearchcv model
model.fit(x_train_data, y_train)#fiitting the training data

print('best estimator of our new data is: ',model.best_estimator_)#prin
ting the best_estimator
```

```
Wall time: 0 ns
best estimator of our new data is:  LogisticRegression(C=0.001, class_w
eight={1: 0.5, 0: 0.5}, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=Non
e,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

In [23]:
```
# again building the model for finding the wieght vector of the words f
rom model
lr=LogisticRegression(C=0.001,penalty='l2',class_weight={1:.5,0:.5},n_j
obs=-1)#building the logistic regression model
lr.fit(x_train_data,y_train)#fiting the training model
```

```
new_wieght_vector=lr.coef_
print(new_wieght_vector.shape)#printing shape of wieght vector
```

```
(1, 7677)
```

In [24]:
```
percent_change_vec=np.ones((1,17204))#generating the percent_change_vet
or to store the percentage change  values for each word
```

In [25]:
```
wieght_vector=wieght_vector+10**-6 #adding some values to wieght vector
 to avoid error while division

new_wieght_vector=new_wieght_vector+10**-6 #adding some values to wiegh
t vector to avoid error while division

percent_change_vec=abs((wieght_vector-new_wieght_vector)/wieght_vector)
*100#calculating the percentage change in the vector
```

In [26]:
```
x=(wieght_vector[0][2]-new_wieght_vector[0][2])/wieght_vector[0][2]#jus
t checking randomly that every value is positve in percent_change_vecto
r
print(x)
```

```
6124.13518164
```

In [27]:
```
print('shape of percent change wieght vector is', percent_change_vec.sh
ape)#printing shape of percent_change_vector
```

```
shape of percent change wieght vector is (1, 7677)
```

In [28]:
```
per_change_df=pd.DataFrame(percent_change_vec.T,columns=['CHANGE'])#bui
lding a dataframe from wight vector
```

In [29]:
```
per_change_df.head()#getting first 5 values
```

Out[29]:

	CHANGE
0	4.114007e+05

	CHANGE
1	1.793059e+02
2	6.124135e+05
3	6.546318e+05
4	1.072202e+06

In [30]:

```
sorted_Df=per_change_df.sort_values('CHANGE',ascending=True,axis=0)#sorting the dataframe to calculate the quantiles values
sorted_Df.describe()#describe function
```

Out[30]:

	CHANGE
count	7.677000e+03
mean	8.163010e+05
std	8.943429e+05
min	3.020788e-01
25%	6.567501e+04
50%	5.955684e+05
75%	1.224095e+06
max	1.119868e+07

In [31]:

```
quantiles=list( i/100 for i in range(0,101,5))#building the list of quantiles value
for i in quantiles:
  print('sorted_Data {:.2f}th quantiles is {:7.3f}'.format(i,sorted_Df['CHANGE'].quantile(i)))#printing the quantiles and thier coreesponding values
```

```
sorted_Data 0.00th quantiles is   0.302
sorted_Data 0.05th quantiles is  36.889
sorted_Data 0.10th quantiles is  62.904
sorted_Data 0.15th quantiles is 102.959
sorted_Data 0.20th quantiles is 528.746
sorted_Data 0.25th quantiles is 65675.014
sorted_Data 0.30th quantiles is 180460.231
sorted_Data 0.35th quantiles is 279055.538
sorted_Data 0.40th quantiles is 378386.003
sorted_Data 0.45th quantiles is 482543.855
sorted_Data 0.50th quantiles is 595568.425
sorted_Data 0.55th quantiles is 703414.610
sorted_Data 0.60th quantiles is 811447.629
sorted_Data 0.65th quantiles is 937978.515
sorted_Data 0.70th quantiles is 1076080.247
sorted_Data 0.75th quantiles is 1224094.822
sorted_Data 0.80th quantiles is 1410348.577
sorted_Data 0.85th quantiles is 1629372.501
sorted_Data 0.90th quantiles is 1950475.872
sorted_Data 0.95th quantiles is 2545719.779
sorted_Data 1.00th quantiles is 11198680.280
```

In [32]:

```
quantiles=list( i/100 for i in range(95,101,1))#printing the last perce
ntiles values because this region is showing abrupt change
percent_change_list=[]#empty percent_change
for i in quantiles:
  print('sorted_Data {:.2f}th quantiles is {:7.3f}'.format(i,sorted_Df[
'CHANGE'].quantile(i)))
  percent_change_list.append(sorted_Df['CHANGE'].quantile(i))#building
 the list
```

```
sorted_Data 0.95th quantiles is 2545719.779
sorted_Data 0.96th quantiles is 2740753.344
sorted_Data 0.97th quantiles is 2907890.640
sorted_Data 0.98th quantiles is 3243208.220
```

```
sorted_Data 0.99th quantiles is 3921466.304
sorted_Data 1.00th quantiles is 11198680.280
```

In [33]:

```
print(percent_change_list)
my_formatted_list = [ '%.2f' % elem for elem in percent_change_list ]#formatted list with string values in it
my_formatted_list=[float(i) for i in my_formatted_list]#formatted list with flaot values in it
print(my_formatted_list)#printing formatted list
print(quantiles)#printing quantiles
```

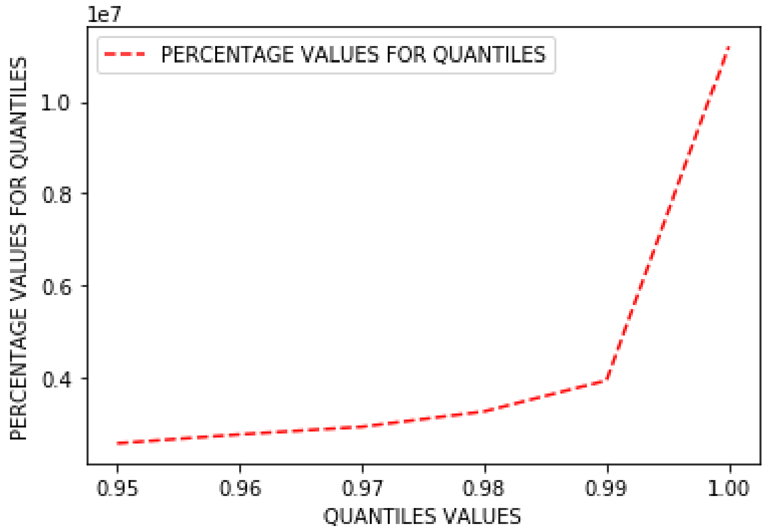
```
[2545719.778685397, 2740753.3441018667, 2907890.6404516995, 3243208.219537627, 3921466.30395979, 11198680.279986566]
[2545719.78, 2740753.34, 2907890.64, 3243208.22, 3921466.3, 11198680.28]
[0.95, 0.96, 0.97, 0.98, 0.99, 1.0]
```

In [34]:

```
%matplotlib inline
import matplotlib.pyplot as plt
plt.show()
plt.xlabel('QUANTILES VALUES')
plt.ylabel('PERCENTAGE VALUES FOR QUANTILES')
plt.plot(quantiles,my_formatted_list,'r--' ,label='PERCENTAGE VALUES FOR QUANTILES')
plt.legend(loc='best')
```

Out[34]:

```
<matplotlib.legend.Legend at 0x15e71d05358>
```



FROM THE ABOVE VISUALIZATION , MAIN POINTS ARE:.

1. THAT ONLY 1% OF FEATURES GOT AFFECTED AFTER ADDING NOISE TO THE DATA.
2. VERY LESS COLLINEARITY OF DATA IS PRESENT ,BECAUSE MOST OF THE WEIGHT VECTORS VALUES REMAINS SAME 3.THERFORE, OUR MODEL IS RELIABLE AND WE CAN PROCEED FURTHER TO CHECK ACCURACY ON TEST DATA

CALCULATING THE BEST HYPERPARAMETER ON TRAIN DATA AND CALCULATING THE ACCURACY USING F1-SCORE AND PLOTTING IT

In [35]:
```
#using time series split method for cross-validation score
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)
from sklearn.linear_model import LogisticRegression
from scipy.stats import uniform
```

```
data=[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]#range
 of hyperparameter
```

In [36]:
```
lr=LogisticRegression(penalty='l2',class_weight={1:.5,0:.5},n_jobs=-1)#
building logistic regression model
tuned_parameters=[{'C':data}]
```

In [37]:
```
#applying the model of logistic regression and using gridsearchcv to fi
nd the best hyper parameter
from sklearn.model_selection import GridSearchCV
model = GridSearchCV(lr, tuned_parameters, scoring = 'f1', cv=tscv,n_jo
bs=-1)#building the gridsearchcv model
model.fit(x_train_data, y_train)#fiitting the training data
```

Out[37]:
```
GridSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=10),
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight={1: 0.5, 0: 0.
5}, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=Non
e,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=-1,
       param_grid=[{'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 1
0000]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='f1', verbose=0)
```

In [38]:
```
results=pd.DataFrame(model.cv_results_)# getting varoius cv_scores and
 train_scores various values of alpha given as parameter and storing it
 in a dataframe
results#printing the dataframe
```

Out[38]:

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_C	parar
0	1.371375	0.009375	0.947138	0.957927	0.0001	{'C': 0.000

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_C	parar
1	2.322609	0.007812	0.956032	0.979998	0.001	{'C': 0.001
2	4.062930	0.001562	0.954233	0.991260	0.01	{'C': 0.01}
3	7.760476	0.007813	0.946258	0.995863	0.1	{'C': 0.1}
4	14.133621	0.007087	0.937421	0.997608	1	{'C':
5	19.005972	0.009486	0.932540	0.997968	10	{'C': 10}
6	19.856343	0.007924	0.927830	0.998044	100	{'C': 100}
7	26.530732	0.009849	0.925073	0.998082	1000	{'C': 1000
8	30.367647	0.004799	0.923287	0.998256	10000	{'C': 1000

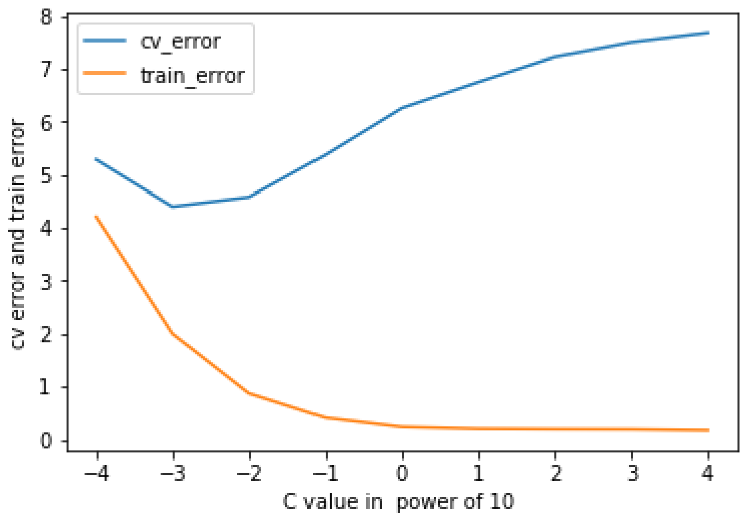
9 rows × 31 columns

In [39]:
```
%matplotlib inline
import matplotlib.pyplot as plt


mean_test_score=list(results['mean_test_score'])#taking mean_test_score
 values of various alpha into a list
mean_train_score=list(results['mean_train_score'])#taking mean_train_sc
ore values of varoius alpha into a list
cv_error_list=[]
train_error_list=[]
for i  in mean_test_score:
```

```
    i=1-i
    i=i*100
    cv_error_list.append(i)#appending the list with cv_error
for i  in mean_train_score:
    i=1-i
    i=i*100
    train_error_list.append(i)#appending  the list with train_error

print(cv_error_list)
C_values_in_10_power=[-4,-3,-2,-1,0,1,2,3,4]#list of alpha values in po
wer of 10
plt.plot(C_values_in_10_power,cv_error_list,label='cv_error')#plotting
 alpha with cv_error
plt.plot(C_values_in_10_power,train_error_list,label='train_error')#plo
tting aplhawith train_error
plt.xlabel('C value in  power of 10 ')
plt.ylabel('cv error and train error')
plt.legend(loc='best')
```

```
[5.2862463174302876, 4.3968129672200318, 4.5767022275204798, 5.37416529
13736448, 6.2578765329667103, 6.7460040101474439, 7.2170415778466062,
7.4926855714309131, 7.6713443582323571]
```

Out[39]: <matplotlib.legend.Legend at 0x15e72866b70>



From here,the best hyperparameter value is c=0.001 or alpha=1000

NOW GETTING THE TOP 30 FEATURES WORDS FOR POSITIVE AND NEGATIVE WORDS

In [40]:

```
#building the model using timeSeriesSplit
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10) # 10 spilts cross validation
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression(C=0.001,penalty='l2',class_weight={1:.5,0:.5},n_j
obs=-1)#building logistic regression model
lr.fit(x_train_data,y_train)
```

Out[40]:

```
LogisticRegression(C=0.001, class_weight={1: 0.5, 0: 0.5}, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=-1, penalty='l2', random_state=Non
e,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

In [41]:

```
z=lr.coef_[0]#getting the wieght of the vector
print(z)#printing the wieght of the vector
```

```
[-0.00411401 -0.00549033 -0.00612414 ...,  0.02776355 -0.00862934
  0.00916463]
```

In [42]:

```
a=z.argsort()
print('shape of wieght vector is:',a.shape)
top_30_positive=np.take(vectorizer.get_feature_names(),a[17174:])
top_30_negative=np.take(vectorizer.get_feature_names(),a[:30])
```

```
shape of wieght vector is: (7677,)
```

In [43]:
```
print("POSITVE WORDS\t|\tNEGATIVE WORDS")
for i,j in zip(top_30_positive,top_30_negative):
    print( '{}\t\t|\t\t{}'.format(i,j) )#printing the postive and negat
ive words
```

```
POSITVE WORDS	|	NEGATIVE WORDS
```

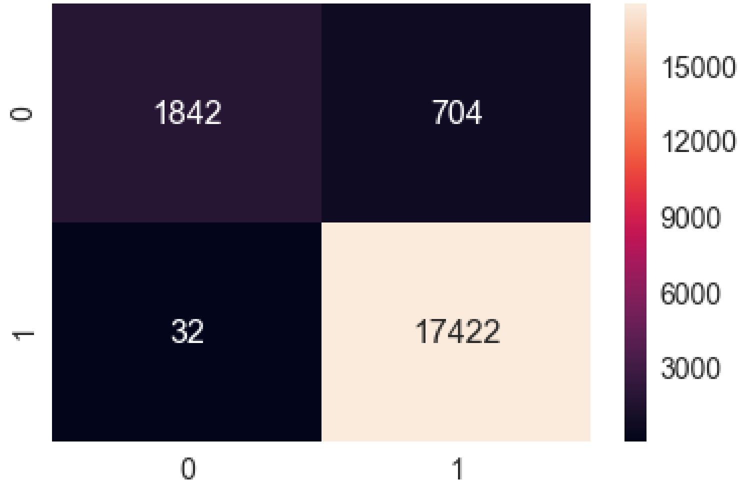
USING BEST HYPERPARAMETER VALUE ON TEST DATA AND PLOTTING THE CONFUSION MATRIX WITH HEATMAP

In [44]:
```
#Testing Accuracy on Test data
import seaborn as sns #importing seaborn as sns
from sklearn.metrics import *#importing varoius metrics from sklearn
#building the model
lr.fit(x_test_data,y_test)
y_pred = lr.predict(x_test_data)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*1
00))#printing accuracy
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
#printing precision score
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred))) #prin
ting recall
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2
)) #generating the heatmap for confusion matrix
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 96.320%
Precision on test set: 0.961
Recall on test set: 0.998
F1-Score on test set: 0.979
Confusion Matrix of test set:
 [ [TN  FP]

 [FN TP] ]
```

[FN TP]]

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x15e77d4bef0>



FROM THE ABOVE OBSERVATIONS ,IT IS FOUND THAT THE BEST HYPERPARAMETER IS FOUND AS APLHA=1000 AND IT IS ALSO HAVING HIGH PRECISION,RECALL VALUE ON TEST DATA

In [45]:
```
#BOW VECTORIZATION IS COMPLETED FOR LOGISTIC REGRESSION
```