AFR-Logistic Regression

September 17, 2018

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

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

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

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

0.1 Objective

1. Train, CV, Test split.

2. find right 'c' (1/Lambda) using gridsearchcv(), randomsearchcv().

3. Build logistic regression with featurisation techniques like BOW, TFIDF AVGW2V2 TFIDFW2V and use l1 or l2 regularizor.
4. get accuracy, precision scores, confusion matrrix, recall score, f1 score.
5. report what happens to sparsity when lamda increases using L1 regularizor.
6. get feature importance(check multicollinearity)

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

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

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

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

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

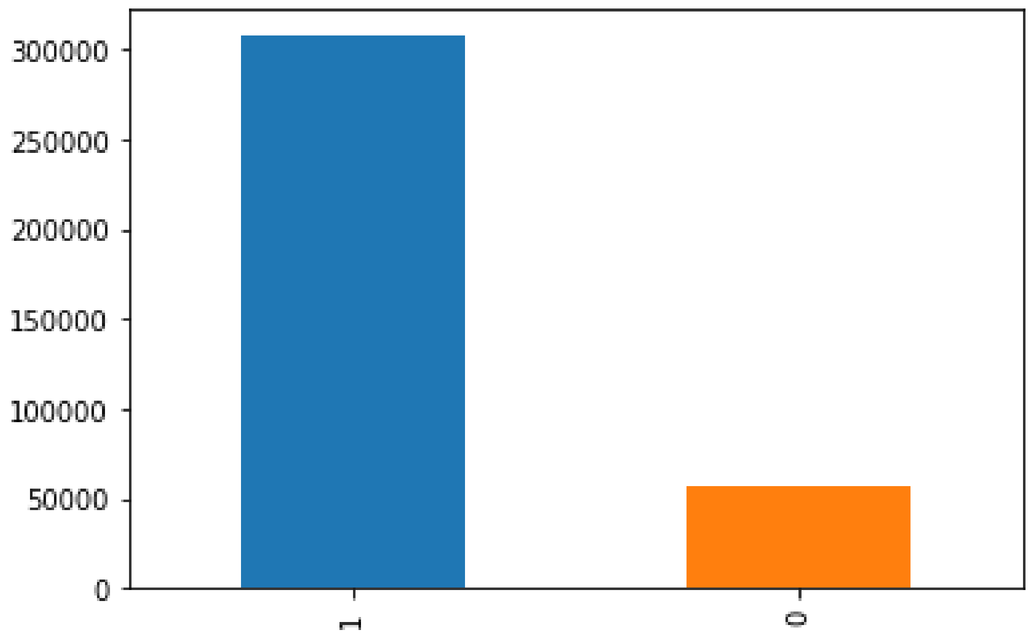
Out[8]:
```
    index      Id   ProductId          UserId                ProfileName  \
0  138706  150524  0006641040   ACITT7DI6IDDL            shari zychinski
1  138688  150506  0006641040  A2IW4PEEKO2R0U                      Tracy
2  138689  150507  0006641040  A1S4A3IQ2MU7V4      sally sue "sally sue"
3  138690  150508  0006641040     AZGXZ2UUK6X  Catherine Hallberg "(Kate)"
4  138691  150509  0006641040  A3CMRKGE0P909G                     Teresa

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

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

                                                Text  \
0  this witty little book makes my son laugh at l...
1  I grew up reading these Sendak books, and watc...
```

```
2  This is a fun way for children to learn their ...
3  This is a great little book to read aloud- it ...
4  This is a book of poetry about the months of t...

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

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

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

Out[9]: `<matplotlib.axes._subplots.AxesSubplot at 0x12eb55e7b00>`



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

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

```
Out[11]:       index      Id   ProductId          UserId              ProfileName  \
         0    138706  150524  0006641040   ACITT7DI6IDDL          shari zychinski
         30   138683  150501  0006641040   AJ46FKXOVC7NR       Nicholas A Mesiano
         424  417839  451856  B00004CXX9   AIUWLEQ1ADEG5         Elizabeth Medina
         330  346055  374359  B00004CI84  A344SMIA5JECGM          Vincent P. Ross
         423  417838  451855  B00004CXX9   AJH6LUC1UT1ON  The Phantom of the Opera

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

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

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

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

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

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

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

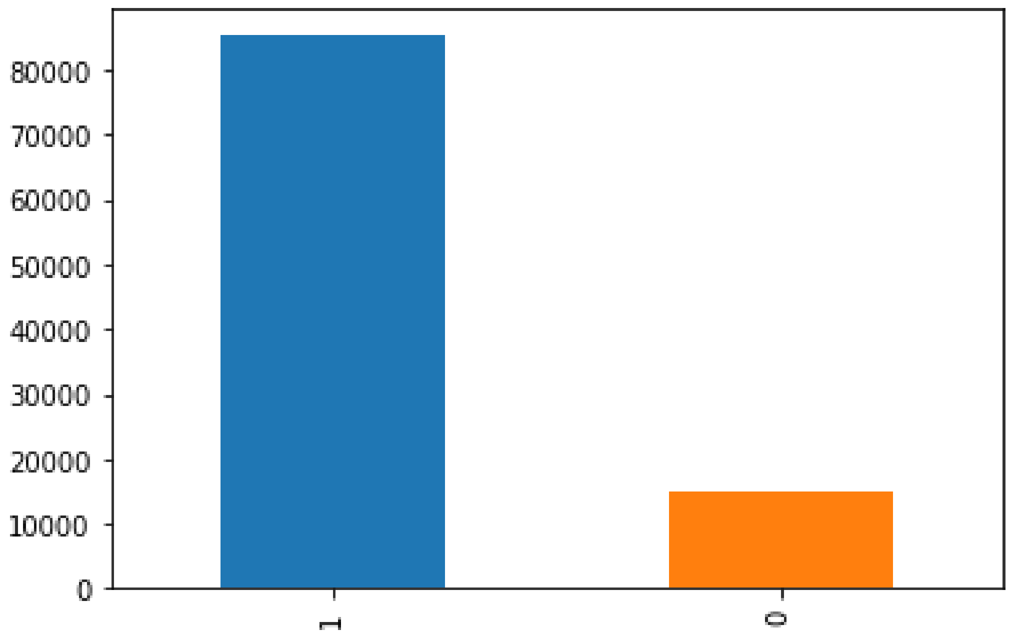
In [13]:
```
#lets check the total dataset values
df.shape
```

Out[13]: (364171, 2)

In [14]:
```
df_sample = df.head(100000)
print ('Number of +ve & -ve datapoints \n' ,df_sample['Score'].value_counts())
df_sample['Score'].value_counts().plot(kind='bar')
```

```
Number of +ve & -ve datapoints
 1    85197
0    14803
Name: Score, dtype: int64
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x12ebd1e6390>



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

```
(100000,)
(100000,)
```

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

```
X_train shape : (70000,)
y_train shape : (70000,)
X_test shape : (30000,)
y_test shape : (30000,)
```

0.1.1 check if rows are not shuffled since its time series data

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

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

```
In [18]: X_test.head()
```

```
Out[18]: 70000    introduc madhava agav sister back jan diabet r...
         70001    love nectar wish amazon would quit rais price ...
         70002    purchas particular item twice price local heal...
         70003    madhava agav nectar low calori natur kosher sw...
         70004    bought replac honey tendenc crystal winter mon...
         Name: CleanedText, dtype: object
```

```
In [19]: X_train.tail()
```

```
Out[19]: 69995    madhava agav nectar amber bottl pack use agav ...
         69996    forget aspartam artifici sweetner agav nectar ...
         69997    ferment agav nectar realli refresh drink twist...
         69998    love stuff liquid dissolv easier low gci proba...
         69999    start eat healthier one ago biggest step chang...
         Name: CleanedText, dtype: object
```

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

```
Out[20]: 99995    delici sugar pretti light brown color delici a...
         99996    sugar raw flavor profil much better white suga...
         99997    use buy sugar year eat much sugar still sugar ...
         99998    product exact advertis save least half retail ...
         99999    love sugar also get muscavado sugar great use ...
         Name: CleanedText, dtype: object
```

1 Functions to find Hyperparameter & Use Logistic Regression

```
In [21]: #c=1/lambda, lambda = 0.001,0.002,0.01,0.02,0.1,0.2,1,2,10,20,100,200,1000,2000,10000
         def log_reg_best_params (X_train, y_train) :
             #c=1/lambda, lambda = 0.001,0.002,0.01,0.02,0.1,0.2,1,2,10,20,100,200,1000,2000,1
             clf = LogisticRegression(n_jobs=-1)
             cv= TimeSeriesSplit(n_splits=10)
             param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.
                           'penalty':['l1', 'l2']}
             grid_cv = GridSearchCV(clf, param_grid, cv=cv, verbose=1, n_jobs=-1)
             grid_cv.fit(X_train,y_train)
             print("Best HyperParameter: ",grid_cv.best_params_)
             print("Best Accuracy: ", (grid_cv.best_score_*100))
```

```
In [22]: def log_reg(C, penalty, X_train, y_train, X_test, y_test) :
             clf = LogisticRegression(C=C, penalty=penalty, n_jobs=-1)
             clf.fit(X_train, y_train)
             y_pred=clf.predict(X_test)
             print('accuracy_score =', accuracy_score(y_test, y_pred))
             print('precision_score =', precision_score(y_test, y_pred))
             print('recall_score =', recall_score(y_test, y_pred))
             cm = confusion_matrix(y_test, y_pred)
             sns.heatmap(cm, annot=True, fmt="d")
             return y_pred
```

```
In [23]: #c=1/lambda, lambda = 0.001,0.002,0.01,0.02,0.1,0.2,1,2,10,20,100,200,1000,2000,10000
         def log_reg_best_params_rand (X_train, y_train) :
             #c=1/lambda, lambda = 0.001,0.002,0.01,0.02,0.1,0.2,1,2,10,20,100,200,1000,2000,1
             clf = LogisticRegression(n_jobs=-1)
             cv= TimeSeriesSplit(n_splits=10)
             param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.
                           'penalty':['l1', 'l2']}
             rand_cv = RandomizedSearchCV(clf, param_grid, cv=cv, verbose=1, n_jobs=-1)
             rand_cv.fit(X_train,y_train)
             print("Best HyperParameter: ",rand_cv.best_params_)
             print("Best Accuracy: ", (rand_cv.best_score_*100))
```

```
In [24]: def log_reg_rand(C, penalty, X_train, y_train, X_test, y_test) :
             clf = LogisticRegression(C=C, penalty=penalty, n_jobs=-1)
             clf.fit(X_train, y_train)
             y_pred=clf.predict(X_test)
             print('accuracy_score =', accuracy_score(y_test, y_pred))
             print('precision_score =', precision_score(y_test, y_pred))
             print('recall_score =', recall_score(y_test, y_pred))
             cm = confusion_matrix(y_test, y_pred)
             sns.heatmap(cm, annot=True, fmt="d")
             return y_pred
```

2 BAG of WORDS

```
In [25]: vect = CountVectorizer()
```

```
In [26]: from sklearn import preprocessing
         bow_X_train = vect.fit_transform(X_train)
         bow_X_train = preprocessing.normalize(bow_X_train)
         bow_X_train
```

```
Out[26]: <70000x32149 sparse matrix of type '<class 'numpy.float64'>'
                 with 2162199 stored elements in Compressed Sparse Row format>
```

```
In [27]: bow_X_test = vect.transform(X_test)
         bow_X_test = preprocessing.normalize(bow_X_test)
         bow_X_test
```

```
Out[27]: <30000x32149 sparse matrix of type '<class 'numpy.float64'>'
                 with 880827 stored elements in Compressed Sparse Row format>
```

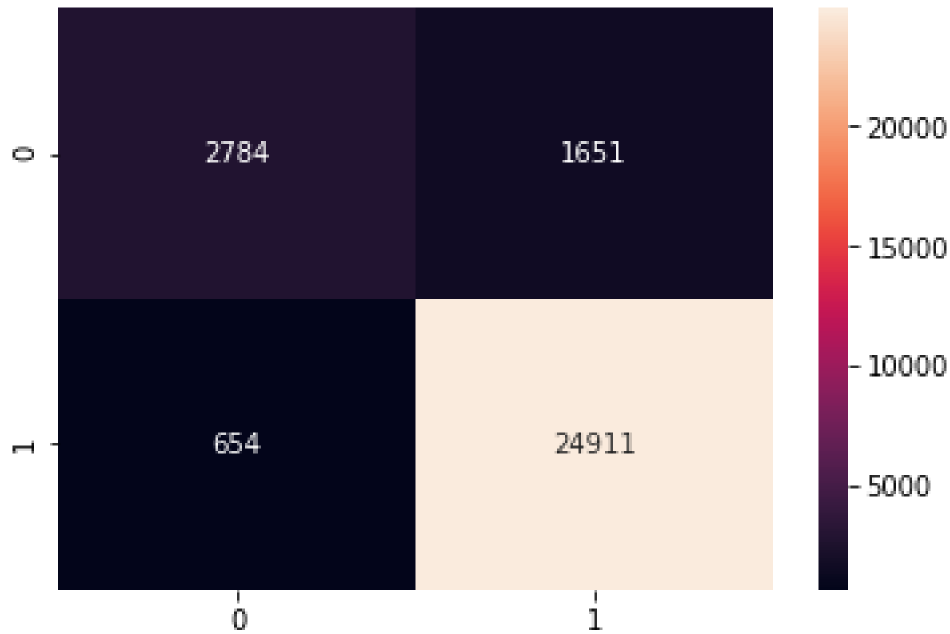
```
In [28]: log_reg_best_params(bow_X_train, y_train)
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed:  2.6min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:  2.8min finished


Best HyperParameter:  {'C': 5, 'penalty': 'l2'}
Best Accuracy:  91.42857142857143
```

```
In [29]: %time log_reg(5, 'l2', bow_X_train, y_train, bow_X_test, y_test)
```

```
accuracy_score = 0.9231666666666667
precision_score = 0.9378435358783224
recall_score = 0.974418149814199
Wall time: 2.25 s
```

```
Out[29]: array([1, 1, 1, ..., 0, 1, 1], dtype=int64)
```



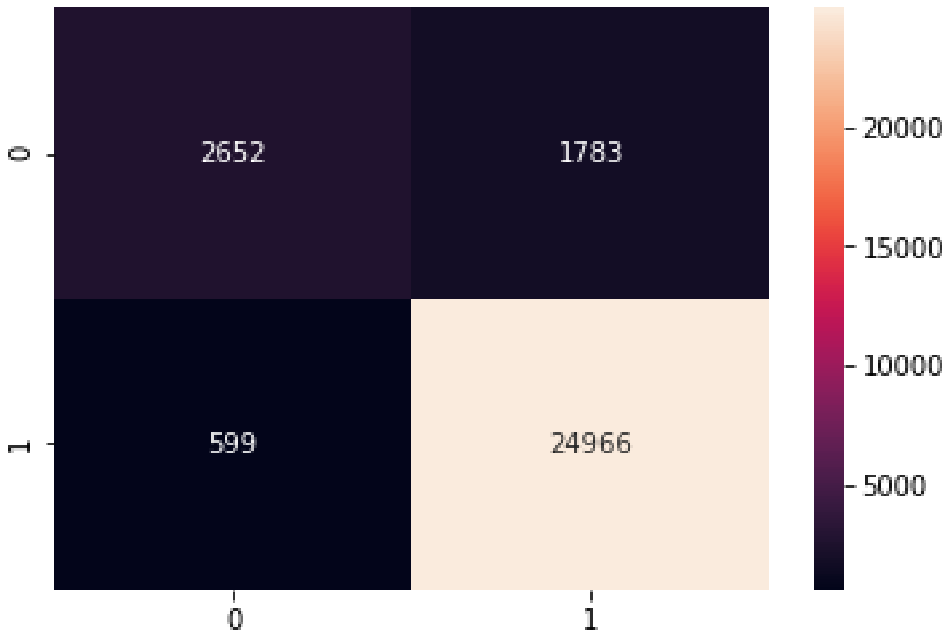
In [30]: log_reg_best_params_rand(bow_X_train, y_train)

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:   43.1s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  1.7min finished


Best HyperParameter:  {'penalty': 'l1', 'C': 1}
Best Accuracy:  91.05296243910105
```

In [31]: log_reg_rand(1,'l1', bow_X_train, y_train, bow_X_test, y_test)

```
accuracy_score = 0.9206
precision_score = 0.9333433025533665
recall_score = 0.9765695286524545
```

Out[31]: array([1, 1, 1, ..., 1, 1, 1], dtype=int64)



2.0.1 Most Important Features BOW

```
In [48]: clf = LogisticRegression(C=5, penalty='l2')
         clf.fit(bow_X_train, y_train)
         y_pred=clf.predict(bow_X_test)
         w = clf.coef_ #get weights

In [49]: bow_1 = CountVectorizer()
         bow_2 = bow_1.fit_transform(X_train.values)
         clf = LogisticRegression(n_jobs=-1)
         #clf = LogisticRegression('C'=5, penalty='l2', n_jobs=-1)
         def show_most_informative_features(vectorizer, clf, n=25):
             feature_names = vectorizer.get_feature_names()
             coefs_with_fns = sorted(zip(w[0], feature_names))
             top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
             print("\t\t\tNegative\t\t\t\t\t\tPositive")
             print("_______________________________________________________________________________________
             for (coef_1, fn_1), (coef_2, fn_2) in top:
                 print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

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

```
                        Negative                                                Positive
-----------------------------------------------------------------------------------------------
        -10.8883        worst                                           8.3558          delici
```

-9.0912	aw	7.9516	excel
-8.7896	terribl	7.4456	best
-8.2298	unfortun	7.3381	perfect
-8.2175	disappoint	7.3207	addict
-8.1568	horribl	7.1499	great
-7.5653	return	6.1712	awesom
-7.2720	threw	5.7523	amaz
-6.7309	wors	5.6065	love
-6.2133	weak	5.5125	fantast
-6.2112	poor	5.4617	smooth
-6.2098	refund	5.4452	wonder
-6.1006	disgust	5.4398	satisfi
-6.0980	cancel	5.3226	favorit
-6.0715	money	5.2587	beat
-5.5979	tasteless	5.1586	hook
-5.5589	stale	5.0264	hit
-5.5399	bland	4.6959	nice
-5.3023	lack	4.6386	glad
-5.1666	vomit	4.6243	delight
-5.1101	mess	4.5357	worri
-4.9157	sad	4.5340	yummi
-4.8549	bare	4.5079	easier
-4.8440	sorri	4.3902	uniqu
-4.8240	concept	4.3679	happi

3 TFIDF

In [33]:
```
vect = TfidfVectorizer()
```

In [34]:
```
from sklearn import preprocessing
tfidf_X_train = vect.fit_transform(X_train)
tfidf_X_train = preprocessing.normalize(tfidf_X_train)
tfidf_X_train
```

Out[34]:
```
<70000x32149 sparse matrix of type '<class 'numpy.float64'>'
        with 2162199 stored elements in Compressed Sparse Row format>
```

In [35]:
```
tfidf_X_test = vect.transform(X_test)
tfidf_X_test = preprocessing.normalize(tfidf_X_test)
tfidf_X_test
```

Out[35]:
```
<30000x32149 sparse matrix of type '<class 'numpy.float64'>'
        with 880827 stored elements in Compressed Sparse Row format>
```

In [36]:
```
log_reg_best_params(tfidf_X_train, y_train)
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

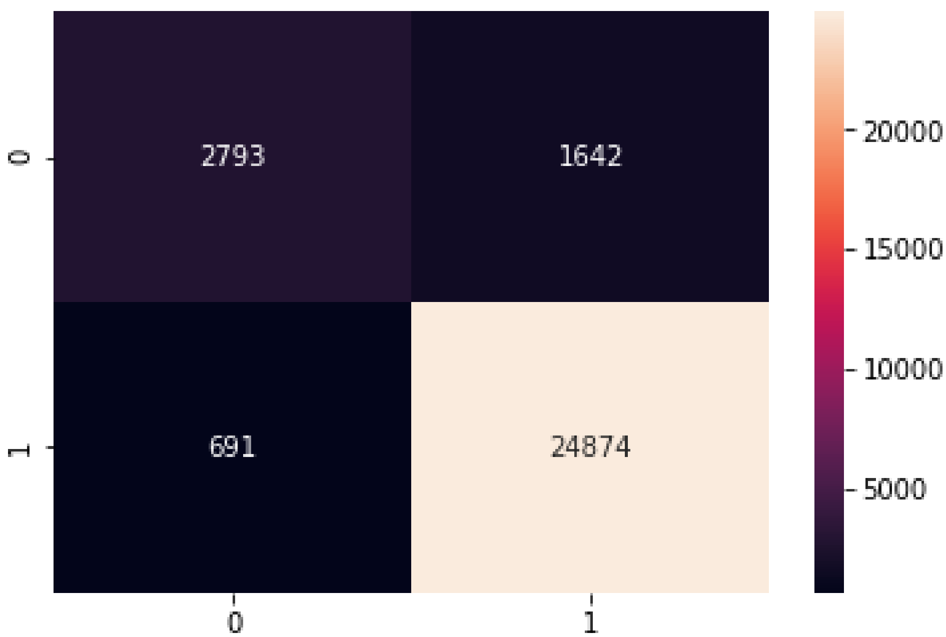
```
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed:  2.7min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:  2.9min finished
```

```
Best HyperParameter:  {'C': 5, 'penalty': 'l2'}
Best Accuracy:  91.4018544711614
```

In [37]:
```
log_reg(5, 'l2', tfidf_X_train, y_train, tfidf_X_test, y_test)
```

```
accuracy_score = 0.9222333333333333
precision_score = 0.9380751244531603
recall_score = 0.9729708585957364
```

Out[37]:
```
array([1, 1, 1, ..., 0, 1, 1], dtype=int64)
```



In [38]:
```
log_reg_best_params_rand(tfidf_X_train, y_train)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

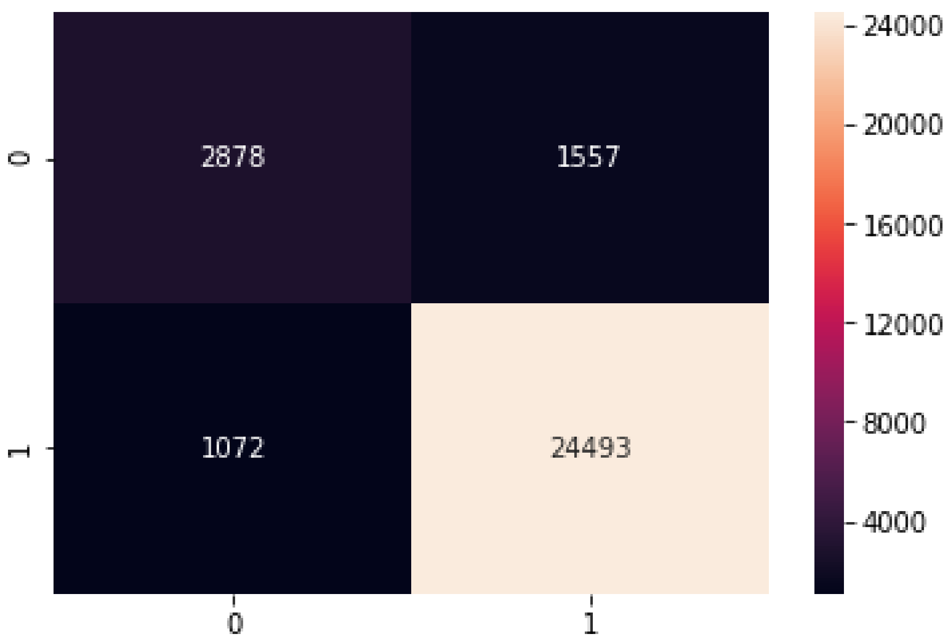
```
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:   12.0s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:   54.1s finished
```

```
Best HyperParameter:  {'penalty': 'l1', 'C': 10}
Best Accuracy:  90.54691183404054
```

```
In [39]: log_reg_rand(10,'l1', tfidf_X_train, y_train, tfidf_X_test, y_test)
```

```
accuracy_score = 0.9123666666666667
precision_score = 0.9402303262955855
recall_score = 0.9580676706434579
```

```
Out[39]: array([1, 1, 1, ..., 0, 1, 1], dtype=int64)
```



3.0.1 TFIDF most important features

```
In [51]: clf = LogisticRegression(C=5, penalty='l2')
         clf.fit(tfidf_X_train, y_train)
         y_pred=clf.predict(tfidf_X_test)
         w = clf.coef_ #get weights
```

```
In [52]: tfidf_1 = TfidfVectorizer()
         tfidf_2 = tfidf_1.fit_transform(X_train.values)
         def show_most_informative_features(vectorizer, clf, n=25):
             feature_names = vectorizer.get_feature_names()
             coefs_with_fns = sorted(zip(w[0], feature_names))
             top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
```

```
    print("\t\t\tNegative\t\t\t\t\t\tPositive")
    print("________________________________________________________________________________
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

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

```
                        Negative                                                        Positive
________________________________________________________________________________________________
        -9.7700         worst                                           12.9037         great
        -8.8200         disappoint                                      10.4799         love
        -8.0956         terribl                                         10.4246         best
        -8.0913         aw                                              10.1971         delici
        -7.6322         unfortun                                        8.7546         perfect
        -7.5516         horribl                                         8.6312         excel
        -7.3554         return                                          6.9972         addict
        -6.5018         threw                                           6.5298         wonder
        -6.2286         wors                                            6.4494         favorit
        -6.1854         money                                           5.9668         good
        -5.8390         cancel                                          5.9133         amaz
        -5.8279         poor                                            5.7594         awesom
        -5.7092         refund                                          5.5030         nice
        -5.3804         disgust                                         5.4475         fantast
        -5.3183         weak                                            5.1223         hook
        -4.9975         bland                                           5.1192         satisfi
        -4.9177         lack                                            5.1091         beat
        -4.8338         tasteless                                       5.0436         smooth
        -4.6710         vomit                                           4.9358         hit
        -4.6214         stale                                           4.8897         find
        -4.5550         unpleas                                         4.8709         definit
        -4.5338         concept                                         4.8645         keep
        -4.3705         sorri                                           4.7808         alway
        -4.3510         mislead                                         4.7724         easi
        -4.3118         didnt                                           4.6995         happi
```

4 WORD2VECTOR Model

In [40]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sent=[]
for sent in X_train.values:
    list_of_sent.append(sent.split())
```

In [41]:
```
print(X_train.values[0])
print("*****************************************************************")
print(list_of_sent[0])
```

```
witti littl book make son laugh loud recit car drive along alway sing refrain hes learn whale i
*****************************************************************
['witti', 'littl', 'book', 'make', 'son', 'laugh', 'loud', 'recit', 'car', 'drive', 'along', 'a
```

```
In [42]: # min_count = 5 considers only words that occured atleast 5 times
         w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

```
In [43]: w2v_words = list(w2v_model.wv.vocab)
         print("number of words that occured minimum 5 times ",len(w2v_words))
         print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  10848
sample words  ['littl', 'book', 'make', 'son', 'laugh', 'loud', 'recit', 'car', 'drive', 'along
```

5 AVGW2V

5.0.1 AVGW2V on train data

```
In [44]: # average Word2Vec
         # compute average word2vec for each review.
         %time train_vectors = []; # the avg-w2v for each sentence/review is stored in this li
         for sent in list_of_sent: # for each review/sentence
             sent_vec = np.zeros(50) # 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
                 if word in w2v_words:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
             if cnt_words != 0:
                 sent_vec /= cnt_words
             train_vectors.append(sent_vec)
         print(len(train_vectors))
         print(len(train_vectors[0]))
```

```
Wall time: 0 ns
70000
50
```

```
In [45]: avgw2v_train = preprocessing.normalize(train_vectors)
```

5.0.2 AVGW2V on test data

```
In [46]: # Train your own Word2Vec model using your own text corpus
         i=0
         list_of_sent_in_test=[]
```

```
        for sent in X_test.values:
            list_of_sent_in_test.append(sent.split())
```

```
In [47]: print(X_test.values[0])
         print("*****************************************************************")
         print(list_of_sent_in_test[0])
```

```
introduc madhava agav sister back jan diabet run famili decid use tea coffe cereal cold hot pa
*****************************************************************
['introduc', 'madhava', 'agav', 'sister', 'back', 'jan', 'diabet', 'run', 'famili', 'decid', '
```

```
In [48]: # average Word2Vec
         # compute average word2vec for each review.
         test_vectors = []; # the avg-w2v for each sentence/review is stored in this list

         for sent in list_of_sent_in_test : # for each review/sentence
             sent_vec = np.zeros(50) # 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
                 if word in w2v_words:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
             if cnt_words != 0:
                 sent_vec /= cnt_words
             test_vectors.append(sent_vec)
         print(len(test_vectors))
         print(len(test_vectors[0]))
```

```
30000
50
```

```
In [49]: avgw2v_test = preprocessing.normalize(test_vectors)
```

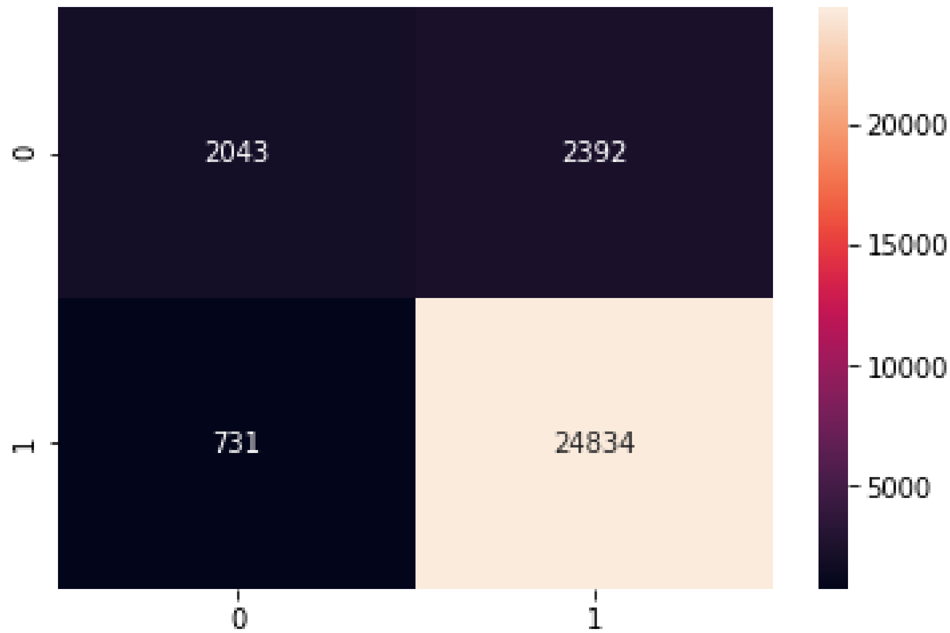
```
In [50]: log_reg_best_params(avgw2v_train, y_train)
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:   22.3s
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed:  2.3min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:  2.6min finished


Best HyperParameter:  {'C': 100, 'penalty': 'l2'}
Best Accuracy:  89.2990727644193
```

```
In [51]: log_reg(100, 'l2', avgw2v_train, y_train, avgw2v_test, y_test)
```

```
accuracy_score = 0.8959
precision_score = 0.9121428046720047
recall_score = 0.9714062194406415
```

```
Out[51]: array([1, 1, 1, ..., 1, 1, 1], dtype=int64)
```



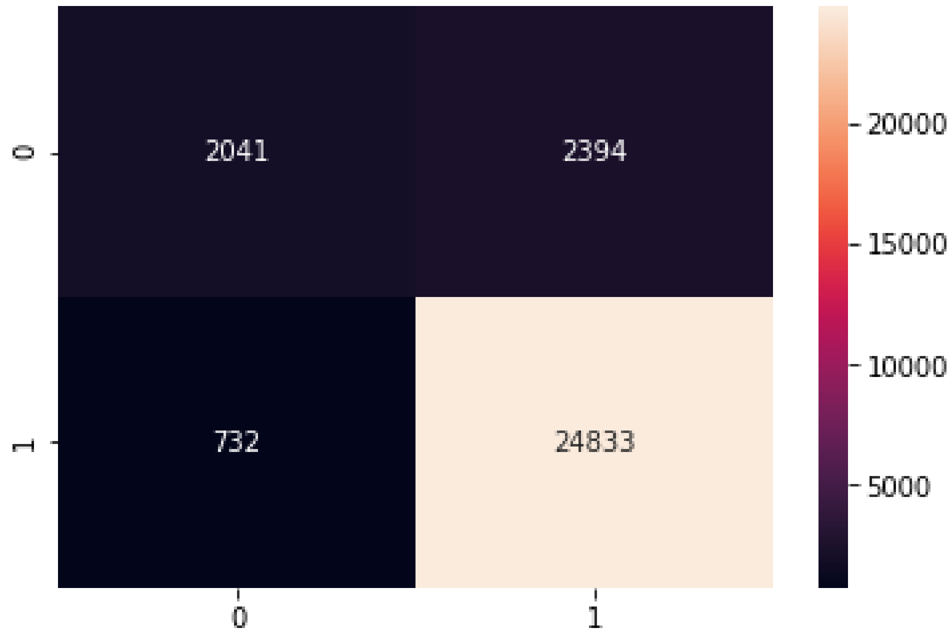

```
In [52]: log_reg_best_params_rand(avgw2v_train, y_train)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:   15.6s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:   42.4s finished


Best HyperParameter:  {'penalty': 'l1', 'C': 10}
Best Accuracy:  89.2990727644193
```

```
In [53]: log_reg_rand(10,'l1', avgw2v_train, y_train, avgw2v_test, y_test)
```

```
accuracy_score = 0.8958
precision_score = 0.9120725750174459
recall_score = 0.9713671034617641
```

Out[53]: array([1, 1, 1, ..., 1, 1, 1], dtype=int64)



6 TFIDFW2V

6.0.1 TFIDFW2V on Train data

In [58]:
```
#calculate TFIDF
tf_idf_vect = TfidfVectorizer()
final_tf_idf = tf_idf_vect.fit_transform(X_train.values)
final_tf_idf = tf_idf_vect.transform(X_test.values)
```

In [55]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
np.seterr(divide='ignore', invalid='ignore')
tfidf_train_vectors = []; # the tfidf-w2v for each sentence/review is stored in this
row=0;
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50) # 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 = final_tf_idf[row, tfidf_feat.index(word)]
```

```
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
            except:
                pass
        sent_vec /= weight_sum
        tfidf_train_vectors.append(sent_vec)
        row += 1
print(len(tfidf_train_vectors))
print(len(tfidf_train_vectors[0]))
```

```
70000
50
```

In [56]:
```
tfidfw2v_train = preprocessing.normalize(tfidf_train_vectors)
tfidfw2v_train.shape
```

Out[56]:
```
(70000, 50)
```

6.0.2 TFIDFW2V on Test Data

In [59]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
np.seterr(divide='ignore', invalid='ignore')
tfidf_test_vectors = []; # the tfidf-w2v for each sentence/review is stored in this l
row=0;
for sent in list_of_sent_in_test: # for each review/sentence
    sent_vec = np.zeros(50) # 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 = final_tf_idf[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sent_vec /= weight_sum
    tfidf_test_vectors.append(sent_vec)
    row += 1
print(len(tfidf_test_vectors))
print(len(tfidf_test_vectors[0]))
```

```
30000
50
```

```
In [60]: tfidfw2v_test = preprocessing.normalize(tfidf_test_vectors)
         tfidfw2v_test.shape
```

```
Out[60]: (30000, 50)
```

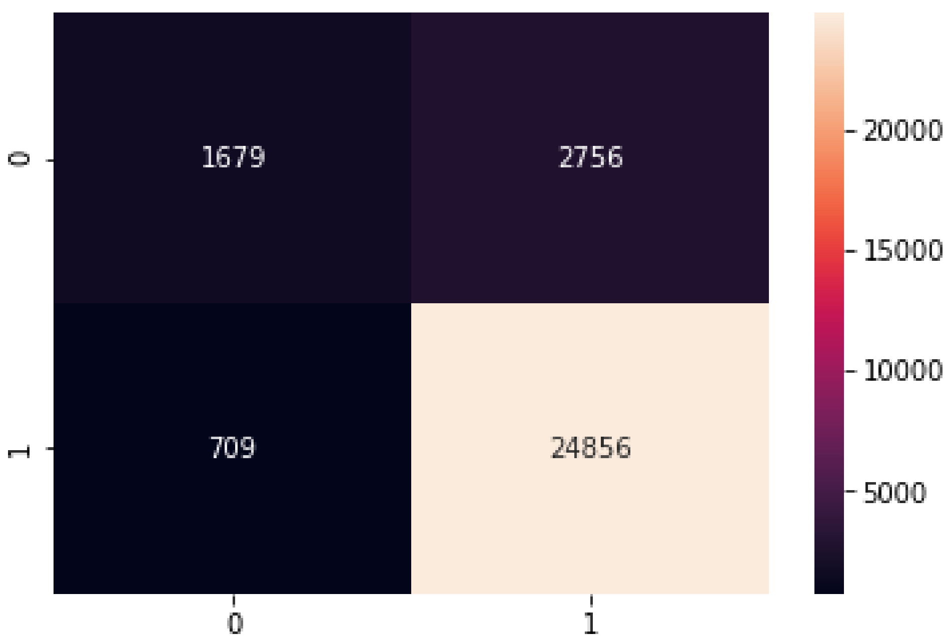
```
In [61]: log_reg_best_params(tfidfw2v_train, y_train)
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:   19.7s
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed:  2.1min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:  2.5min finished


Best HyperParameter:  {'C': 5, 'penalty': 'l1'}
Best Accuracy:  88.23353763947823
```

```
In [62]: log_reg(5, 'l1', tfidfw2v_train, y_train, tfidfw2v_test, y_test)
```

```
accuracy_score = 0.8845
precision_score = 0.9001883239171374
recall_score = 0.9722667709759437
```

```
Out[62]: array([1, 1, 1, ..., 1, 1, 1], dtype=int64)
```



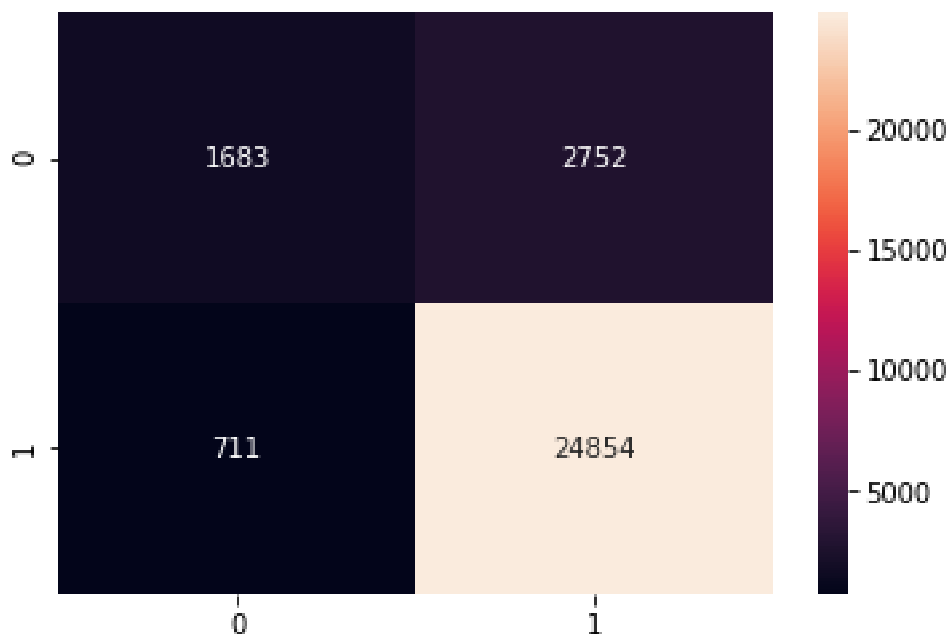
```
In [63]: log_reg_best_params_rand(tfidfw2v_train, y_train)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits


[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:    8.9s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  1.1min finished


Best HyperParameter:  {'penalty': 'l1', 'C': 500}
Best Accuracy:  88.23196605374824
```

```
In [64]: log_reg_rand(500,'l1', tfidfw2v_train, y_train, tfidfw2v_test, y_test)
```

```
accuracy_score = 0.8845666666666666
precision_score = 0.9003115264797508
recall_score = 0.9721885390181889
```

```
Out[64]: array([1, 1, 1, ..., 1, 1, 1], dtype=int64)
```



7 1.5 report what happens to sparsity when lamda increases using L1 regularizor.

Theory: as lambda increases sparsity increases(number of zeros in a vector increases) typical lambda values = #c=1/lambda, lambda = 0.001,0.002,0.01,0.02,0.1,0.2,1,2,10,20,100,200,1000,2000,10000.

C = 1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001

```
In [65]: c = [1000, 100, 50, 10, 0.1]
         for i in c :
             clf = LogisticRegression(C=i, penalty='l1')
             clf.fit(bow_X_train, y_train)
             w = clf.coef_ #get weights
             print(f'Number of Non-Zero values in vector for C = {i} with L1 regularization :'
```

```
Number of Non-Zero values in vector for C = 1000 with L1 regularization : 13717
Number of Non-Zero values in vector for C = 100 with L1 regularization : 10856
Number of Non-Zero values in vector for C = 50 with L1 regularization : 9552
Number of Non-Zero values in vector for C = 10 with L1 regularization : 5403
Number of Non-Zero values in vector for C = 0.1 with L1 regularization : 201
```

Observation
as we can see number of non zero values decrease i.e number of zeros in a vector increases

8 1.7 get feature importance(check multicollinearity) - Perturbation test

THEORY

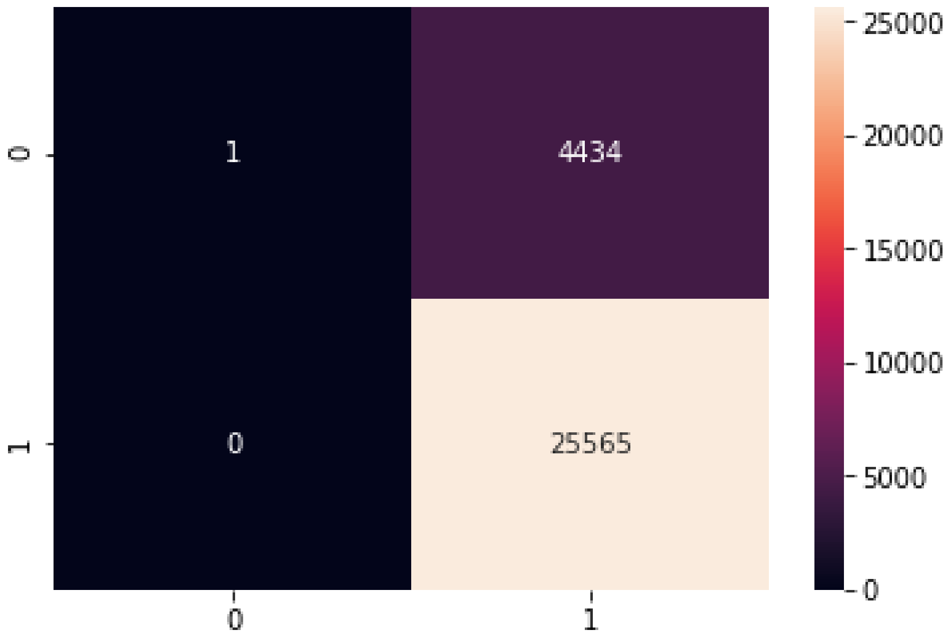
1. calculate weights vector for the original dataset
2. add some noise to the datapoints

add some noise to our train data points and compare its weight vector with original train dataset

```
In [77]: clf = LogisticRegression(C= 5, penalty= 'l2')
         clf.fit(bow_X_train,y_train)
         y_pred = clf.predict(bow_X_test)
         print('accuracy_score =', accuracy_score(y_test, y_pred))
         print('precision_score =', precision_score(y_test, y_pred))
         print('recall_score =', recall_score(y_test, y_pred))
         print('number of non-zero elements :', np.count_nonzero(clf.coef_))
         cm=confusion_matrix(y_test, y_pred)
         sns.heatmap(cm, annot=True, fmt='d')
```

```
accuracy_score = 0.8522
precision_score = 0.8521950731691056
recall_score = 1.0
number of non-zero elements : 32149
```

Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x12ef4a9c358>




```
In [78]: #Returns non zero elements in a matrix
         from scipy.sparse import find #prints only non zero values of sparse vector
         #Weights before adding random noise
         weights1 = find(clf.coef_[0])[2] #index '0' contains clf, index '1' contains column n
         print(weights1[:50])
```

```
[ 4.09979608e-01  3.97203109e-01 -1.52229597e-03 -1.06615872e-01
  3.45842758e-02  8.20446874e-01 -7.07117433e-01 -7.18519081e-03
  6.68225901e-01  8.27436375e-01 -9.03246688e-02 -1.23465802e+00
 -6.51253244e-02 -3.02791487e-01  7.47239649e-01 -2.35880129e-01
  7.39477572e-02  1.46699966e-01  2.51788983e-01 -9.70569911e-01
  5.95557116e-01  1.77738743e-01  1.25064587e-01 -7.72560048e-02
 -3.74635734e-01 -1.16315742e-01  1.84433998e-01  3.60463431e-01
 -1.06198312e-01  3.90122897e-01  3.91813740e-01 -8.39466264e-02
  1.48051807e+00 -1.38402366e+00  6.84210237e-01  2.20717506e-01
 -8.43710814e-02 -1.17113584e+00  1.15669705e-01  7.03571844e-01
 -2.57068924e+00 -1.08390632e-02  4.97262905e-01  8.48665036e-01
  1.89640309e-01 -4.47008524e-01 -3.68047821e-02  7.71324910e-01
  7.85315190e-01 -1.44494762e-01]
```

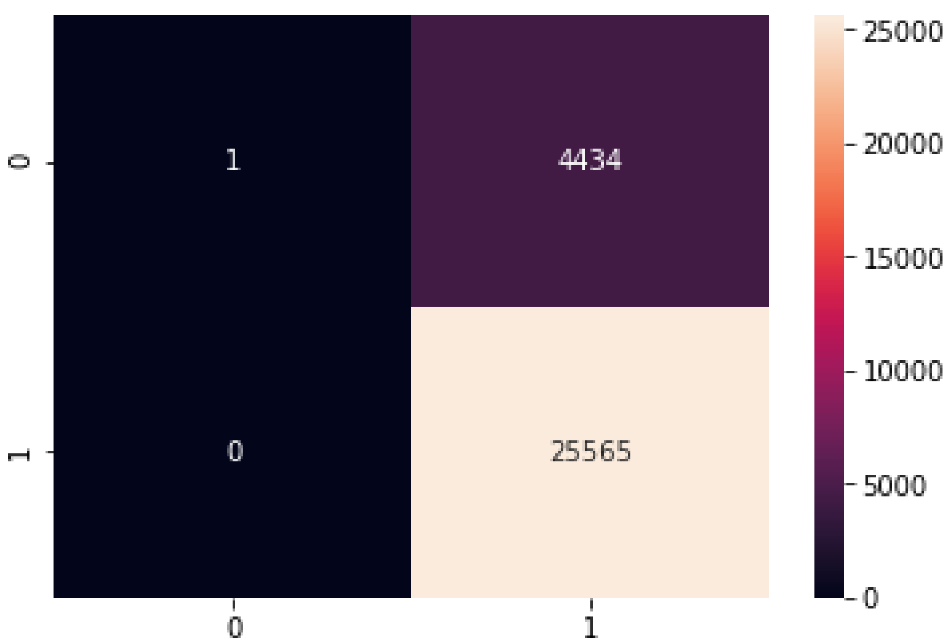
```
In [79]: x_train_t = bow_X_train
         #Random noise
         epsilon = np.random.normal(loc=0, scale=1, size=(find(x_train_t)[0].size,))
```

```
        #Getting the postions(row and column) and value of non-zero datapoints
        a,b,c = find(x_train_t)
        #Introducing random noise to non-zero datapoints
        x_train_t[a,b] = epsilon + x_train_t[a,b]
```

```
In [80]: clf = LogisticRegression(C=5, penalty='l2')#c, l2 most outcome hyperparameter
         clf.fit(x_train_t, y_train)
         y_pred=clf.predict(bow_X_test)
         print('accuracy_score =', accuracy_score(y_test, y_pred))
         print('precision_score =', precision_score(y_test, y_pred))
         print('recall_score =', recall_score(y_test, y_pred))
         print('number of non-zero elements :', np.count_nonzero(clf.coef_))
         cm=confusion_matrix(y_test, y_pred)
         sns.heatmap(cm, annot=True, fmt='d')
```

```
accuracy_score = 0.8522
precision_score = 0.8521950731691056
recall_score = 1.0
number of non-zero elements : 32149
```

```
Out[80]: <matplotlib.axes._subplots.AxesSubplot at 0x12ef47ee1d0>
```




```
In [81]: from scipy.sparse import find
         #Weights after adding random noise
         weights2 = find(clf.coef_[0])[2]
         print(weights2[:50])
```

```
[ 0.10929824 -0.35071215 -0.13453866  0.01445846  0.0221669   0.815576
 -0.61465652 -0.06074554  0.20227202  0.42113223 -0.22281701 -0.85095391
 -1.24475461  0.3641009   0.27552457 -0.02410019  0.35196598  0.66865629
  0.28560336  0.76106481 -0.62758307 -0.29645228  0.14901169 -0.13929226
 -0.16133379 -0.30672453  0.56055953  0.25337559 -0.41626678  0.05131717
 -1.18133401 -0.38214096  0.73622731 -0.81980495 -0.46188004  0.29895028
  0.07374555 -2.0231383   0.1522279   0.14681588 -1.02726654 -0.09718674
  0.39095755  1.47426486  0.95612056 -0.2700209  -0.16172987  0.23775194
  1.12352552 -0.63485173]
```

```
In [82]: print(weights1.shape)
         print(weights2.shape)
```

```
(32149,)
(32149,)
```

```
In [83]: weights_diff = (abs(weights1 - weights2)/weights1) * 100
         print(weights_diff[np.where(weights_diff > 30)].size)
```

```
14151
```

There are 14151 features that has significantly changed 30% since w1 and w2 have changed significantly that means multi-collinearity exists in our data.

9 RESULTS

```
In [86]: from prettytable import PrettyTable
         x = PrettyTable()
         x.field_names = ["MODEL", "C & PENALTY", "ACCURACY", "PRECISION", "RECALL" ]
         #BOW
         x.add_row(['BOW with LOGISTIC REGRESSION GridSearch', '5 & L2', 0.92, 0.93, 0.97])
         x.add_row(["BOW with LOGISTIC REGRESSION Random", '1 & L1', 0.92, 0.93, 0.97])
         x.add_row(['--'*5,'-'*5,'-'*8,'-'*5, '--'*5])
         #TFIDF
         x.add_row(['TFIDF with LOGISTIC REGRESSION GridSearch', '5 & L2', 0.92, 0.93, 0.97])
         x.add_row(["TFIDF with LOGISTIC REGRESSION Random", '10 & L1' ,0.91, 0.94, 0.95])
         x.add_row(['--'*5,'-'*8,'-'*8,'-'*5, '--'*5])
         #AVGW2V
         x.add_row(['AVGW2V with LOGISTIC REGRESSION GridSearch', '100 & L2', 0.89, 0.90, 0.97
         x.add_row(["AVGW2V with LOGISTIC REGRESSION Random", '10 & L1', 0.89, 0.90, 0.97])
         x.add_row(['--'*5,'-'*8,'-'*8,'-'*5, '--'*5])
         #TFIDFW2V
         x.add_row(['BOW with LOGISTIC REGRESSION GridSearch', '5 & L1', 0.87, 0.88, 0.97])
         x.add_row(["BOW with LOGISTIC REGRESSION Random", '500 & L1', 0.88, 0.90, 0.97])
         print(x)
```

MODEL	C & PENALTY	ACCURACY	PRECISION	RECALL
BOW with LOGISTIC REGRESSION GridSearch	5 & L2	0.92	0.93	0.97
BOW with LOGISTIC REGRESSION Random	1 & L1	0.92	0.93	0.97
----------	-----	--------	-----	----------
TFIDF with LOGISTIC REGRESSION GridSearch	5 & L2	0.92	0.93	0.97
TFIDF with LOGISTIC REGRESSION Random	10 & L1	0.91	0.94	0.95
----------	--------	--------	-----	----------
AVGW2V with LOGISTIC REGRESSION GridSearch	100 & L2	0.89	0.9	0.97
AVGW2V with LOGISTIC REGRESSION Random	10 & L1	0.89	0.9	0.97
----------	--------	--------	-----	----------
BOW with LOGISTIC REGRESSION GridSearch	5 & L1	0.87	0.88	0.97
BOW with LOGISTIC REGRESSION Random	500 & L1	0.88	0.9	0.97

In [84]:
```
#number of positive and negative values in test data
y_test.value_counts()
```

Out[84]:
```
1    25565
0     4435
Name: Score, dtype: int64
```

OBSERVATIONS

since AVGW2v and TFIDFW2V took too much time for converting to a vector. the total number of datapoints used are limited to 100K. also, the BOW & TFIDF were trained on all data and the confusion matrix and accuracy score were same in percentages. so, having extra data didn't give any significant improvement in overall results so only 100k datapoints are used.

1. The best results were obtained from BOW & TFIDF with closely 2.3k mis-classifications out of 30k datapoints.

2. Logistic Regression model works fantastic in comparison with Naive bayes. where in NB highest accuracy was 88%. but in Logistic Regression it is 92%. Also in Bow the misclassification rate is much lower compared to naive bayes(MultinomialNB)

3. in comparison GridSearchCV() takes more time than RandomizedSearchCV(). but random search was able to produce results faster and in comparison the misclassification is 100 extra with random hyperparameter search.

4. Perturbation test show that there are 14k features that are collinear. may be removing them might give considerable increase in misclassification rate.

5. since this data is imbalanced, there are large amount of data for positive reviews. so, the False positive rate is very high on almost all the vectorizers. W2V perfom very bad on this.