AMAZON LOGISTIC REGRESSION

January 27, 2019

1 Amazon Fine Food Reviews Analysis

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

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

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: Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative? [Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

2 [1]. Reading Data

3 [1.1] Loading the data

The dataset is available in two forms 1. .csv file 2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [1]:
```
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc

# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import re
import string
from nltk.corpus import stopwords            #importing stopwords
from nltk.stem import SnowballStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from sklearn.model_selection import train_test_split
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV

from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
import math
import pickle
```

In [2]:
```
data = pd.read_csv('Reviews.csv')
print (data.head(2))
print(data.shape)
```

```
   Id   ProductId          UserId ProfileName  HelpfulnessNumerator  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW  delmartian                     1
1   2  B00813GRG4  A1D87F6ZCVE5NK      dll pa                     0
```

```
   HelpfulnessDenominator  Score        Time                Summary  \
0                       1      5  1303862400  Good Quality Dog Food
1                       0      1  1346976000      Not as Advertised

                                                Text
0  I have bought several of the Vitality canned d...
1  Product arrived labeled as Jumbo Salted Peanut...
(568454, 10)
```

3.1 [2] Data Cleaning: Deduplication and Nan features

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

```
In [3]: #checking for Nan values in data. True indicates Nan values are present along the colu
        data.isnull().any()
```

```
Out[3]: Id                        False
        ProductId                 False
        UserId                    False
        ProfileName                True
        HelpfulnessNumerator      False
        HelpfulnessDenominator    False
        Score                     False
        Time                      False
        Summary                    True
        Text                      False
        dtype: bool
```

```
In [4]: # checking for Nan values along 'profilename' column
        #data[data['ProfileName'].isnull()].head()
```

```
In [5]: # checking for Nan values along 'summary' column
        #data[data['Summary'].isnull()]
```

```
In [6]: #Dropping Nan values
        data = data.dropna()
```

```
In [7]: #printing shape of data after dropping Nan values
        print (data.shape)
```

```
(568411, 10)
```

```
In [8]: #Review score should lie between 1 to 5
        #Returns True if all the scores lie between 1 to 5(inclusive)
        list1 = data['Score'].map(lambda x: True if x in [1,2,3,4,5] else False)
        list1.all()
```

Out[8]: True

```
In [9]: filtered_data = data.loc[data['Score']!=3].copy()
        #print (filtered_data.head())
        print (filtered_data.shape)
```

```
(525773, 10)
```

```
In [10]: #mapping positive(>3) and negative(<3) reviews based on scores of the data.
         pos_negative = filtered_data['Score'].map(lambda x: 1 if int (x)>3  else 0)
         filtered_data['Score'] = pos_negative
         print ('shape of filtered_data')
         print (filtered_data.shape)
         print (filtered_data.head(2))
```

```
shape of filtered_data
(525773, 10)
   Id   ProductId          UserId ProfileName  HelpfulnessNumerator  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW  delmartian                     1
1   2  B00813GRG4  A1D87F6ZCVE5NK      dll pa                     0

   HelpfulnessDenominator  Score        Time                Summary  \
0                       1      1  1303862400  Good Quality Dog Food
1                       0      0  1346976000      Not as Advertised

                                                Text
0  I have bought several of the Vitality canned d...
1  Product arrived labeled as Jumbo Salted Peanut...
```

```
In [11]: #arranging data with increasing productid
         sorted_data = filtered_data.sort_values('ProductId',axis=0,ascending=True,inplace=Fals

In [12]: #finding the duplicates in our data
         #If the same person gives for the same product at the same time we call it as suplica
         #sorted_data.loc[sorted_data.duplicated(["UserId","ProfileName","Time","Text"],keep =

In [13]: #counting number of duplicates present in our data
         sorted_data.duplicated(["UserId","ProfileName","Time","Text"]).sum()
```

Out[13]: 161612

```
In [14]: #dropping all duplicates keeping the first one
         final = sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},kee
         final.shape
```

Out[14]: (364161, 10)

```
In [15]: #helpfulness numerator denotes number of people who found the review helpful
         #helpfulness denominator denotes number of people who indicated whether or not the re
         #so, helpfulness numerator should be less than denominator
         final = final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

```
In [16]: #final shape of data after preprocessing
         final.shape
```

```
Out[16]: (364159, 10)
```

```
In [17]: #arranging data with increasing productid
         final = final.sort_values('Time',axis=0,ascending=True,inplace=False,kind='quicksort'
```

```
In [18]: final['Score'].value_counts()
```

```
Out[18]: 1    307054
         0     57105
         Name: Score, dtype: int64
```

```
In [19]: final_data = final.iloc[0:100000,:].copy()
```

```
In [20]: final_data.shape
```

```
Out[20]: (100000, 10)
```

```
In [21]: final_data['Score'].value_counts()
```

```
Out[21]: 1    87730
         0    12270
         Name: Score, dtype: int64
```

4 [3] Preprocessing

5 [3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [98]:
```
stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer
not_words = re.findall(r'\w*n[\'|o]t',str (stop)) #finding NOT words in stop words
not_words.append('n\'t')
not_words.append('no')
print (not_words)
stop_words = stop - set (not_words)  #removing  NOT words from stop words
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r'\w*n[\'|o]t', "not", phrase)
    # general
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
def cleanhtmlpunc(sentence): #function to clean the word of any html-tags
    clean = re.compile('<.*?>')
    clean = re.sub(clean, ' ', sentence)
    clean = re.sub(r"(http|www)\S+", "", clean)
    clean = re.sub(r"\S+com", "",clean)
    #clean = re.sub(r"\(\w+\)","",clean)
    clean = re.sub(r"\."," ",clean)
    cleaned = re.sub(r'[?+|!+|\'+|"+|#+|:+]',r' ',clean)
    cleantext = re.sub(r'[\.+|,+|)+|(+|\+|/+]',r' ',cleaned)
    return cleantext
#def cleanpunc(sentence): #function to clean the word of any punctuation or special c
   # return  cleaned
print('************************************')
print(stop_words)
```

```
["weren't", "didn't", "won't", "aren't", "hadn't", "wouldn't", "mustn't", "couldn't", "mightn'
************************************
{'how', 'before', 'yourselves', 'if', 'is', 'have', 'during', 'same', 'our', 'some', 'hers', '
```

In [23]:
```
def cleanedtext(reviews):
    str1=' '
    final_string=[]
    s=''
    for sent in reviews:
        filtered_sentence=[]
```

```
            sent=cleanhtmlpunc(decontracted(sent)) # remove HTMl tags
            for w in sent.split():
                for cleaned_words in w.split():
                    if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                        if((cleaned_words.lower() not in stop_words)):
                            s=(sno.stem(cleaned_words.lower())).encode('utf8')
                            filtered_sentence.append(s)
                        else:
                            continue
                    else:
                        continue
            str1 = b" ".join(filtered_sentence) #final string of cleaned words for review
            final_string.append(str1)
        return final_string
```

```
In [24]: final_string = cleanedtext(final_data['Text'].values)
```

6 Applying Logistic Regression

7 [4.1] Logistic Regression on BOW, SET 1

7.1 [4.1.1] Applying Logistic Regression with L2 regularization on BOW, SET 1

```
In [2]: import pickle
        with open("final_data.pkl", "rb") as f:
            final_data = pickle.load(f)
```

```
In [3]: final_data = final_data.iloc[0:100000,:]
```

```
In [4]: final_data.shape
```

```
Out[4]: (100000, 13)
```

```
In [5]: #https://stackoverflow.com/questions/38640109/logistic-regression-python-solvers-defin
```

```
In [5]: # split the data set into train and test
        X_train, X_test, y_train, y_test = train_test_split(final_data['CleanedText'].values, 
                                                             test_size=0.3, random_sta
```

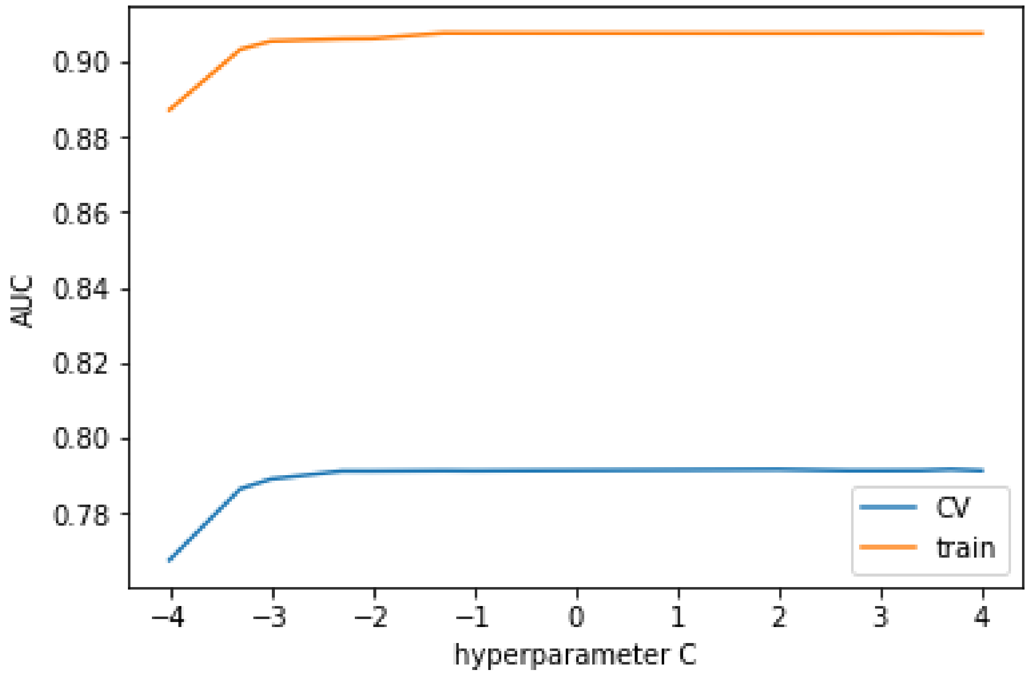
```
In [6]: model = CountVectorizer(dtype=float)
        final_counts= model.fit_transform(X_train)
```

```
In [7]: #standardizing the bag of words
        standardizing  = StandardScaler(with_mean = False)
        final_std_data = standardizing.fit_transform(final_counts)
        final_std_data.shape
```

```
Out[7]: (70000, 31094)
```

```
In [10]: from sklearn.metrics import make_scorer
         from sklearn.model_selection import cross_val_score
         from sklearn.metrics import roc_auc_score
         # creating list for hyperparameter alpha
         alpha_values = [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,100,500,1000,2500,5000,10000]
         # empty list that will hold cv scores

         cv_scores = []
         train_auc_values = []

         # perform 10-fold cross validation
         for alpha in alpha_values:
             log_reg = LogisticRegression(C=alpha,solver='saga',max_iter=10000)
             auc = make_scorer(roc_auc_score,greater_is_better=True,
                                          needs_threshold=True)
             auc_scores = cross_val_score(log_reg, final_std_data, y_train, cv=10, scoring=auc)
             log_reg.fit(final_std_data,y_train)
             y_pred_proba = log_reg.predict_proba(final_std_data)[::,1]
             train_auc = roc_auc_score(y_train, y_pred_proba)
             train_auc_values.append(train_auc)
             cv_scores.append(auc_scores.mean())

         print ('train scores')
         print (train_auc_values)
         print ('*'*50)
         print ('CV scores')
         print (cv_scores)

         # changing to misclassification error

         log = [math.log10(x) for x in alpha_values]
         # plot misclassification error vs alpha
         plt.plot(log, cv_scores,label='CV')
         #plt.label('cv_f1')
         plt.plot(log,train_auc_values,label='train')
         #plt.label('train_f1')
         plt.legend()
         plt.xlabel('hyperparameter C')
         plt.ylabel('AUC')
         plt.show()
```

```
train scores
[0.8872166258768911, 0.9032958584075139, 0.9055026416848345, 0.9060861740180313, 0.906182462039
**************************************************
CV scores
[0.7675376832793198, 0.786533751980348, 0.7891311431371723, 0.791253547700876, 0.79125445831950
```




```
In [11]: log_reg = LogisticRegression(C=100,solver='saga',max_iter=10000,tol=0.001,n_jobs=-1)
         log_reg.fit(final_counts,y_train)
```

```
Out[11]: LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=10000, multi_class='ovr',
                   n_jobs=-1, penalty='l2', random_state=None, solver='saga',
                   tol=0.001, verbose=0, warm_start=False)
```

```
In [12]: print('accuracy = {0}'.format(log_reg.score(standardizing.transform(model.transform(X_
```

```
accuracy = 92.5
```

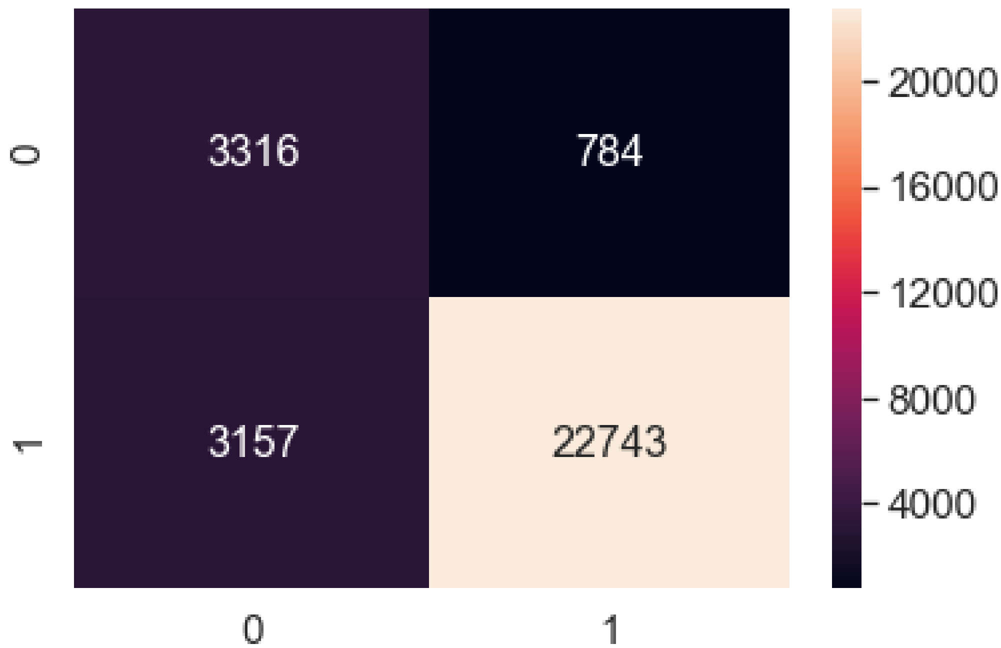
```
In [13]: predictions = log_reg.predict(standardizing.transform(model.transform(X_test)))
```

```
In [14]: precision = precision_score(y_test, predictions,pos_label=1)
         Recall = recall_score(y_test, predictions,pos_label=1)
         f1 = f1_score(y_test, predictions,pos_label=1)
         print ('precision = {0}'.format(precision))
         print ('Recall={0}'.format(Recall))
         print ('f1_score={0}'.format(f1))
```

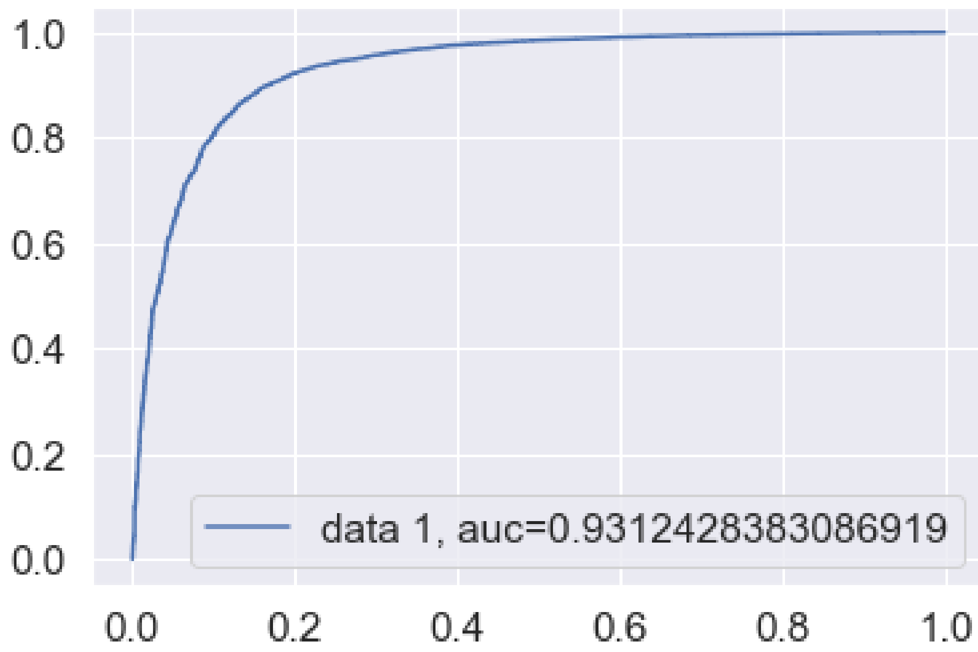
```
precision = 0.9666765843498959
Recall=0.8781081081081081
f1_score=0.9202662512392012
```

```
In [15]: from sklearn.metrics import confusion_matrix
         import seaborn as sns
         result = confusion_matrix(y_test,predictions)
         #print(result)
         sns.set(font_scale=1.4)#for label size
         sns.heatmap(result, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x4496e6f6d8>
```




```
In [16]: y_pred_proba = log_reg.predict_proba(model.transform(X_test))[::,1]
         fpr, tpr, _ = roc_curve(y_test, y_pred_proba,pos_label=1 )
         #auc = roc_auc_score(y_test, y_pred_proba)
         auc = np.trapz(tpr,fpr)
         plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
         plt.legend(loc=4)
         plt.show()
```



7.1.1 [4.1.1.1] Pertubation Test

```
In [17]: #clf = LogisticRegression(C=model.best_params_['C'], penalty='l2')
         #clf.fit(final_std_data, y_train)
         weights_before = log_reg.coef_
         print ('weights_before={0}'.format(weights_before))
```

```
weights_before=[[ 1.67703901e-02  5.14711165e-03 -5.38907139e-02 ...  6.79927908e-03
   6.29820289e-05  6.85599065e-04]]
```

```
In [18]: from scipy.sparse import find
         eps = np.random.normal(scale=0.01)
         print ('noise adding to weight vector is = {0}'.format(eps))
         X_train1 = final_counts
         a,b,c = find(X_train1)
         X_train1[a,b] = X_train1[a,b]+eps
         log_reg.fit(X_train1,y_train)
         weights_after = log_reg.coef_
         print ('weights_after adding noise = {0}'.format(weights_after))
```

```
noise adding to weight vector is = 0.006139962498737992
weights_after adding noise = [[ 1.66861339e-02  5.18499791e-03 -5.34311971e-02 ...  6.90404251e
   4.97940225e-05  7.01490370e-04]]
```

```
In [19]: per_weights_diff = abs((weights_before - weights_after)/weights_before)*100
         per_weights_diff = per_weights_diff[0]

In [20]: for i in range(0,110,10):
             print ('{0}  percentile value is {1}'.format(i,np.percentile(per_weights_diff,i)))
```

```
0  percentile value is 0.00016873855680106447
10  percentile value is 0.17566958318672576
20  percentile value is 0.3708582422088057
30  percentile value is 0.588400474177819
40  percentile value is 0.8893549312443004
50  percentile value is 1.3493502065878444
60  percentile value is 2.144811872848045
70  percentile value is 3.7624360694869883
80  percentile value is 7.594158041619698
90  percentile value is 21.302181988035613
100  percentile value is 1359298.8626627645
```

```
In [21]: for i in range(0,11,1):
             print ('{0}  percentile value is {1}'.format(60+i,np.percentile(per_weights_diff,6
```

```
60  percentile value is 2.144811872848045
61  percentile value is 2.254222670672485
62  percentile value is 2.370316193944895
63  percentile value is 2.494914457111536
64  percentile value is 2.6422856736299014
65  percentile value is 2.786969047610154
66  percentile value is 2.959162340942017
67  percentile value is 3.1436518761189367
68  percentile value is 3.3479251476185516
69  percentile value is 3.5527140753665396
70  percentile value is 3.7624360694869883
```

```
In [22]: for i in range(0,11,1):
             print ('{0}  percentile value is {1}'.format(63+i*0.1,np.percentile(per_weights_di
```

```
63.0  percentile value is 2.494914457111536
63.1  percentile value is 2.513683703079929
63.2  percentile value is 2.53208235928024
63.3  percentile value is 2.5436407867107893
63.4  percentile value is 2.5554346956896175
63.5  percentile value is 2.573439426220451
63.6  percentile value is 2.5871164719424375
63.7  percentile value is 2.6020419986022927
63.8  percentile value is 2.6134030229436798
63.9  percentile value is 2.629241177161071
64.0  percentile value is 2.6422856736299014
```

```
In [23]: feat_names = model.get_feature_names()

In [24]: per_weights_diff[per_weights_diff>2.5].size

Out[24]: 11492

In [25]: (per_weights_diff[per_weights_diff>2.5].size)*100/weights_before.size

Out[25]: 36.958898822924034

In [26]: index = per_weights_diff>2.5

In [27]: colli_features = [feature for feature,bol in zip(feat_names,index) if bol==True]

In [28]: colli_features[0:10]

Out[28]: ['aaaah',
          'aaah',
          'aad',
          'aadp',
          'aahh',
          'ab',
          'abandon',
          'abaolut',
          'abba',
          'abbi']
```

7.1.2 [4.1.1.2] Feature Importance

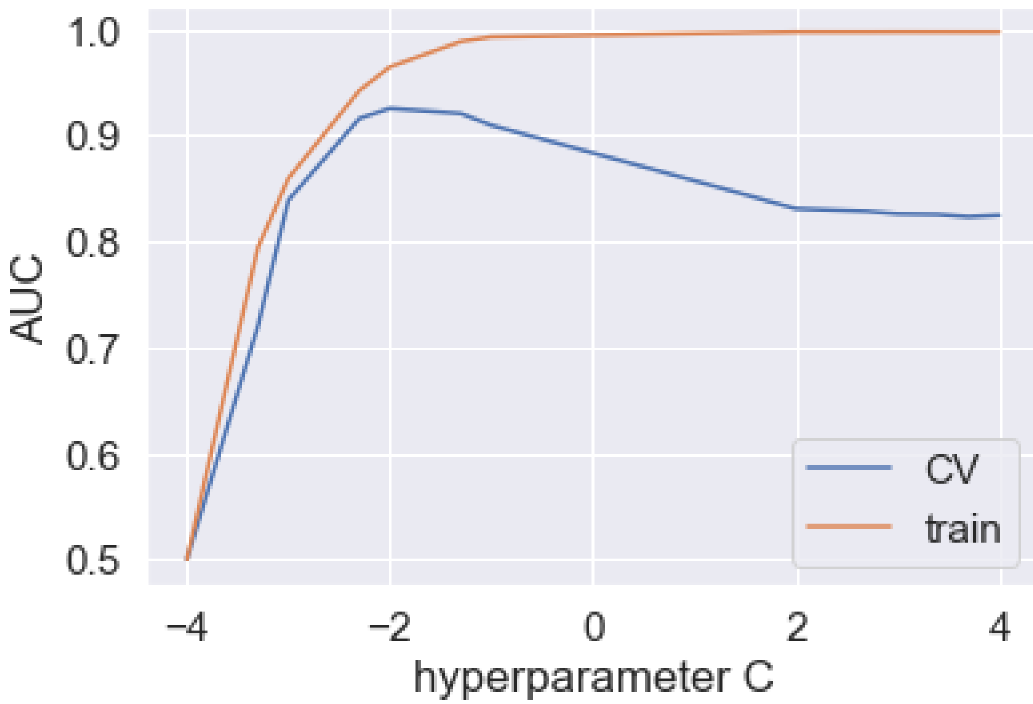
```
In [29]: indices = list (np.argsort(weights_before[0]))

In [30]: pos_indices = indices[-10:]
         neg_indices = indices[0:10]

In [31]: print ('top 10 positive features\t\t\ttop 10 negative features')
         print ('-'*100)
         for id1,id2 in zip(pos_indices,neg_indices):
             print ('\t{0}\t\t\t\t\t\t\t{1}'.format(feat_names[id1],feat_names[id2]))
```

```
top 10 positive features                       top 10 negative features
----------------------------------------------------------------------------------------------------
        awesom                                                      worst
        fantast                                                      terribl
        yummi                                                      aw
        addict                                                      bland
        great                                                      horribl
        amaz                                                      disappoint
        best                                                      threw
        perfect                                                      unfortun
        excel                                                      stale
        delici                                                      tasteless
```

7.2 [4.1.2] Applying Logistic Regression with L1 regularization on BOW, SET 1

In [32]:
```
from sklearn.metrics import make_scorer
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score
# creating list for hyperparameter alpha
alpha_values = [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,100,500,1000,2500,5000,10000]
# empty list that will hold cv scores

cv_scores = []
train_auc_values = []

# perform 10-fold cross validation
for alpha in alpha_values:
    log_reg = LogisticRegression(C=alpha,penalty='l1',max_iter=10000)
    auc = make_scorer(roc_auc_score,greater_is_better=True,
                              needs_threshold=True)
    auc_scores = cross_val_score(log_reg, final_std_data, y_train, cv=10, scoring=auc
    log_reg.fit(final_std_data,y_train)
    y_pred_proba = log_reg.predict_proba(final_std_data)[::,1]
    train_auc = roc_auc_score(y_train, y_pred_proba)
    train_auc_values.append(train_auc)
    cv_scores.append(auc_scores.mean())

print ('train scores')
print (train_auc_values)
print ('*'*50)
print ('CV scores')
print (cv_scores)

# changing to misclassification error

log = [math.log10(x) for x in alpha_values]
# plot misclassification error vs alpha
plt.plot(log, cv_scores,label='CV')
#plt.label('cv_f1')
plt.plot(log,train_auc_values,label='train')
#plt.label('train_f1')
plt.legend()
plt.xlabel('hyperparameter C')
plt.ylabel('AUC')
plt.show()
```

```
train scores
[0.5, 0.7940562566329163, 0.8592942388920859, 0.9422173038918453, 0.9645540175998825, 0.98852
**************************************************
CV scores
[0.5, 0.719741226931902, 0.8386816934576604, 0.9158721469675113, 0.9254130744246624, 0.920591
```




```
In [ ]: #http://rnowling.github.io/data/science/2016/09/04/comparing-lr-regularization-and-opt
```

```
In [33]: log_reg = LogisticRegression(C=0.005,penalty='l1',max_iter=5000,tol=0.001)
         log_reg.fit(final_counts,y_train)
```

```
Out[33]: LogisticRegression(C=0.005, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=5000, multi_class='ovr', n_jobs=1,
                   penalty='l1', random_state=None, solver='liblinear', tol=0.001,
                   verbose=0, warm_start=False)
```

```
In [34]: predictions = log_reg.predict(standardizing.transform(model.transform(X_test)))
```

```
In [36]: print('accuracy = {0}'.format(log_reg.score(standardizing.transform(model.transform(X_
```

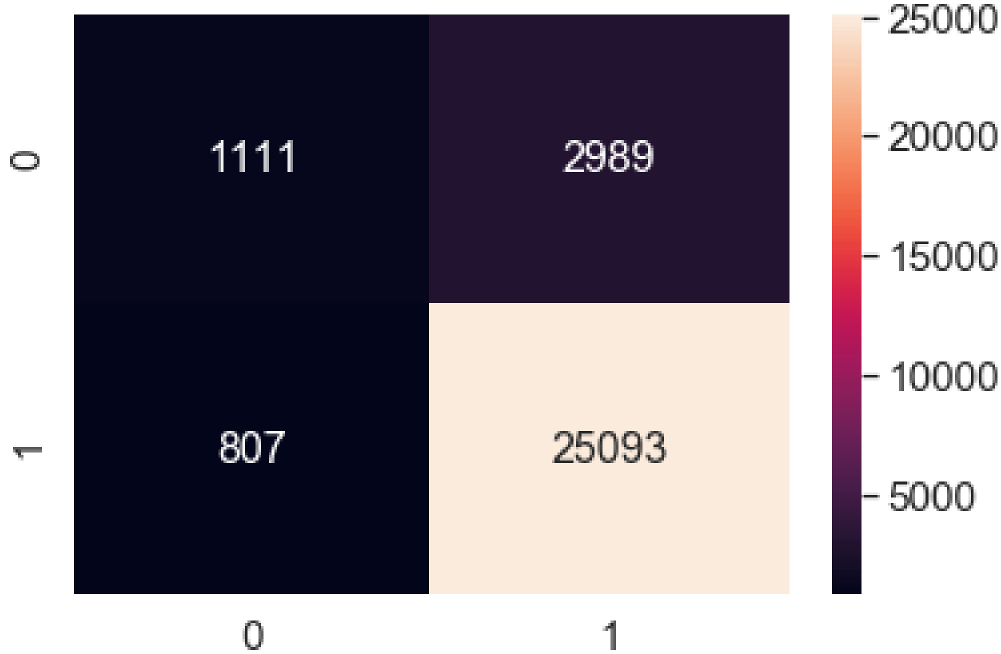
```
accuracy = 87.34666666666666
```

```
In [37]: precision = precision_score(y_test, predictions,pos_label=1)
         Recall = recall_score(y_test, predictions,pos_label=1)
         f1 = f1_score(y_test, predictions,pos_label=1)
         print ('precision = {0}'.format(precision))
         print ('Recall={0}'.format(Recall))
         print ('f1_score={0}'.format(f1))
```

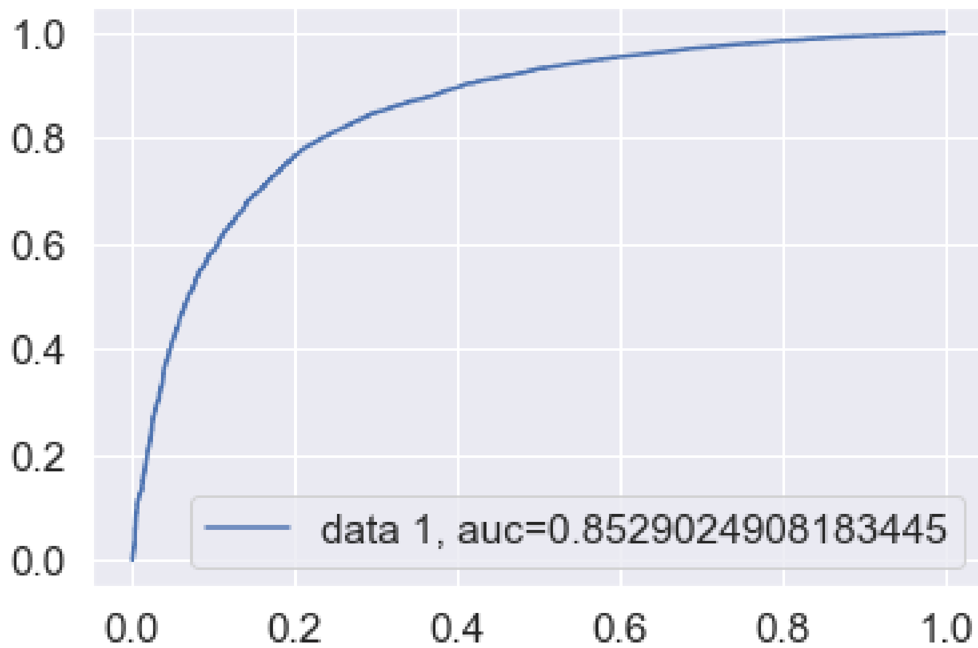
```
precision = 0.8935617121287658
Recall=0.9688416988416988
f1_score=0.9296802637916342
```

In [38]:
```python
from sklearn.metrics import confusion_matrix
import seaborn as sns
result = confusion_matrix(y_test,predictions)
#print(result)
sns.set(font_scale=1.4)#for label size
sns.heatmap(result, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x44818f5940>
```



In [39]:
```python
y_pred_proba = log_reg.predict_proba(model.transform(X_test))[::,1]
fpr, tpr, _ = roc_curve(y_test, y_pred_proba,pos_label=1 )
#auc = roc_auc_score(y_test, y_pred_proba)
auc = np.trapz(tpr,fpr)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



7.2.1 [4.1.2.1] Pertubation Test

```
In [40]: from scipy.sparse import find
         weights_before = log_reg.coef_
         print ('weights_before={0}'.format(weights_before))
         eps = np.random.normal(scale=0.01)
         print ('noise adding to weight vector is = {0}'.format(eps))
         X_train1 = final_counts
         a,b,c = find(X_train1)
         X_train1[a,b] = X_train1[a,b]+eps
         log_reg.fit(X_train1,y_train)
         weights_after = log_reg.coef_
         print ('weights_after adding noise = {0}'.format(weights_after))
```

```
weights_before=[[0. 0. 0. ... 0. 0. 0.]]
noise adding to weight vector is = -0.013766085204073575
weights_after adding noise = [[0. 0. 0. ... 0. 0. 0.]]
```

```
In [41]: weights_before = weights_before[0]+0.000001
```

```
In [42]: weights_after = weights_after[0]+0.000001
```

```
In [43]: per_weights_diff = abs((weights_before - weights_after)/weights_before)*100
         per_weights_diff = per_weights_diff[0]
```

```
In [44]: for i in range(0,110,10):
             print ('{0}  percentile value is {1}'.format(i,np.percentile(per_weights_diff,i)))
```

```
0  percentile value is 0.0
10  percentile value is 0.0
20  percentile value is 0.0
30  percentile value is 0.0
40  percentile value is 0.0
50  percentile value is 0.0
60  percentile value is 0.0
70  percentile value is 0.0
80  percentile value is 0.0
90  percentile value is 0.0
100  percentile value is 0.0
```

```
In [45]: (per_weights_diff[per_weights_diff>2.5].size)*100/weights_before.size
```

```
Out[45]: 0.0
```

7.2.2 [4.1.2.2] Calculating sparsity on L1 regulrization

```
In [46]: print ('Hyper Parameters(C) \t Num of non Zero elments')
         alpha_values = [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,100,500,1000,2500,5000,10000]
         for c in alpha_values:
             clf = LogisticRegression(C=c, penalty='l1',tol=0.01)
             clf.fit(final_counts, y_train)
             w = clf.coef_
             print ('\t{0}\t\t\t{1}'.format(c,np.count_nonzero(w)))
```

```
Hyper Parameters(C)          Num of non Zero elments
        0.0001                        0
        0.0005                        2
        0.001                        7
        0.005                        51
        0.01                        118
        0.05                        451
        0.1                        744
        100                        13555
        500                        15953
        1000                        16784
        2500                        19333
        5000                        20597
        10000                        23894
```

7.2.3 [4.1.2.3]Feature Importance

```
In [48]: feat_names = model.get_feature_names()
         weights_before = log_reg.coef_
```

```
indices = list (np.argsort(weights_before[0]))
pos_indices = indices[-10:]
neg_indices = indices[0:10]
print ('top 10 positive features\t\t\ttop 10 negative features')
print ('-'*100)
for id1,id2 in zip(pos_indices,neg_indices):
    print ('\t{0}\t\t\t\t\t{1}'.format(feat_names[id1],feat_names[id2]))
```

```
top 10 positive features                              top 10 negative features
-----------------------------------------------------------------------------------------------
        find                                            disappoint
        favorit                                            money
        excel                                            bad
        good                                            not
        nice                                            product
        perfect                                            thought
        love                                            would
        delici                                            tast
        best                                            receiv
        great                                            bought
```

8 [4.2] Logistic Regression on TFIDF, SET 2

[4.2.1] Applying Logistic Regression with L2 regularization on TFIDF, SET 2

In [49]:
```
# split the data set into train and test
tfidf_train, tfidf_test, y_train, y_test = train_test_split(final_data['CleanedText']
                                                            test_size=0.3, random_st
```

In [50]:
```
vector = TfidfVectorizer(ngram_range = (1,1))
tf_idf_vector = vector.fit_transform(tfidf_train)
```

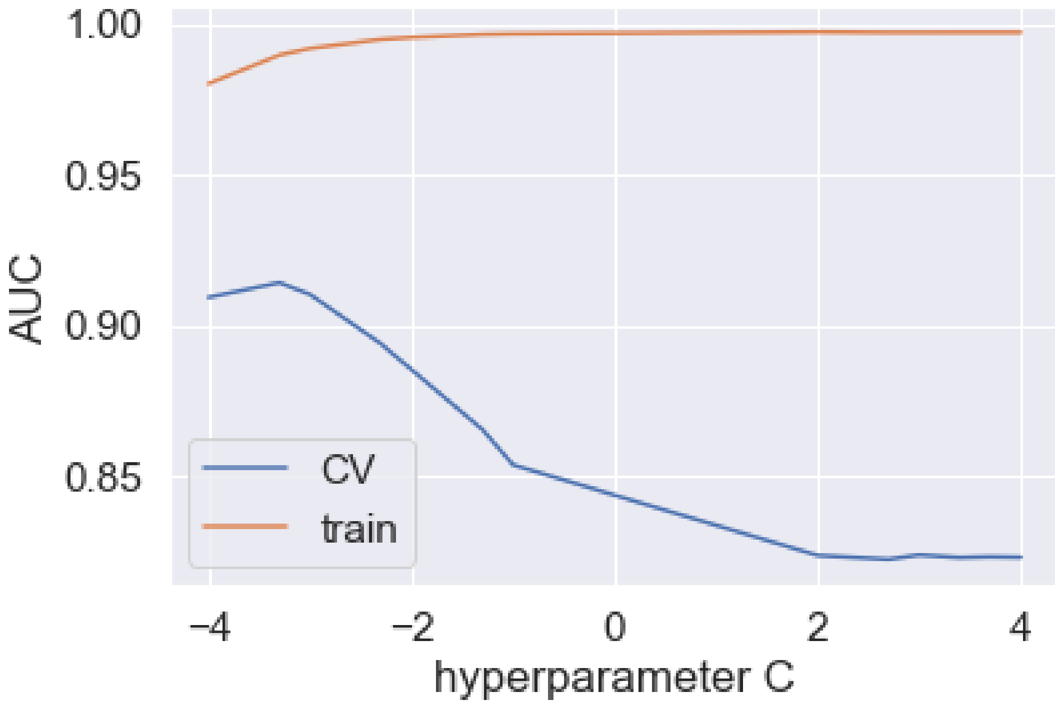
In [51]:
```
standardizing  = StandardScaler(with_mean = False)
final_std_data = standardizing.fit_transform(tf_idf_vector)
final_std_data.shape
```

Out[51]: (70000, 31094)

In [61]:
```
from sklearn.metrics import make_scorer
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score
# creating list for hyperparameter alpha
alpha_values = [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,100,500,1000,2500,5000,10000]
# empty list that will hold cv scores

cv_scores = []
```

```
train_auc_values = []

# perform 10-fold cross validation
for alpha in alpha_values:
    log_reg = LogisticRegression(C=alpha,penalty='l2',max_iter=10000)
    auc = make_scorer(roc_auc_score,greater_is_better=True,
                          needs_threshold=True)
    auc_scores = cross_val_score(log_reg, final_std_data, y_train, cv=10, scoring=auc
    log_reg.fit(final_std_data,y_train)
    y_pred_proba = log_reg.predict_proba(final_std_data)[::,1]
    train_auc = roc_auc_score(y_train, y_pred_proba)
    train_auc_values.append(train_auc)
    cv_scores.append(auc_scores.mean())

print ('train scores')
print (train_auc_values)
print ('*'*50)
print ('CV scores')
print (cv_scores)

# changing to misclassification error

log = [math.log10(x) for x in alpha_values]
# plot misclassification error vs alpha
plt.plot(log, cv_scores,label='CV')
#plt.label('cv_f1')
plt.plot(log,train_auc_values,label='train')
#plt.label('train_f1')
plt.legend()
plt.xlabel('hyperparameter C')
plt.ylabel('AUC')
plt.show()
```

```
train scores
[0.9801327058379166, 0.989632704947094, 0.9918192724909438, 0.9947721691588912, 0.995414761048
**************************************************
CV scores
[0.9092294068052114, 0.9140867851223128, 0.910187268720191, 0.893801488307162, 0.885249146245
```




```
In [62]: log_reg = LogisticRegression(C=0.0005,max_iter=10000,tol=0.001)
         log_reg.fit(final_std_data,y_train)
```

```
Out[62]: LogisticRegression(C=0.0005, class_weight=None, dual=False,
                   fit_intercept=True, intercept_scaling=1, max_iter=10000,
                   multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
                   solver='liblinear', tol=0.001, verbose=0, warm_start=False)
```

```
In [63]: print('accuracy = {0}'.format(log_reg.score(standardizing.transform(vector.transform(t
```

```
accuracy = 90.47
```

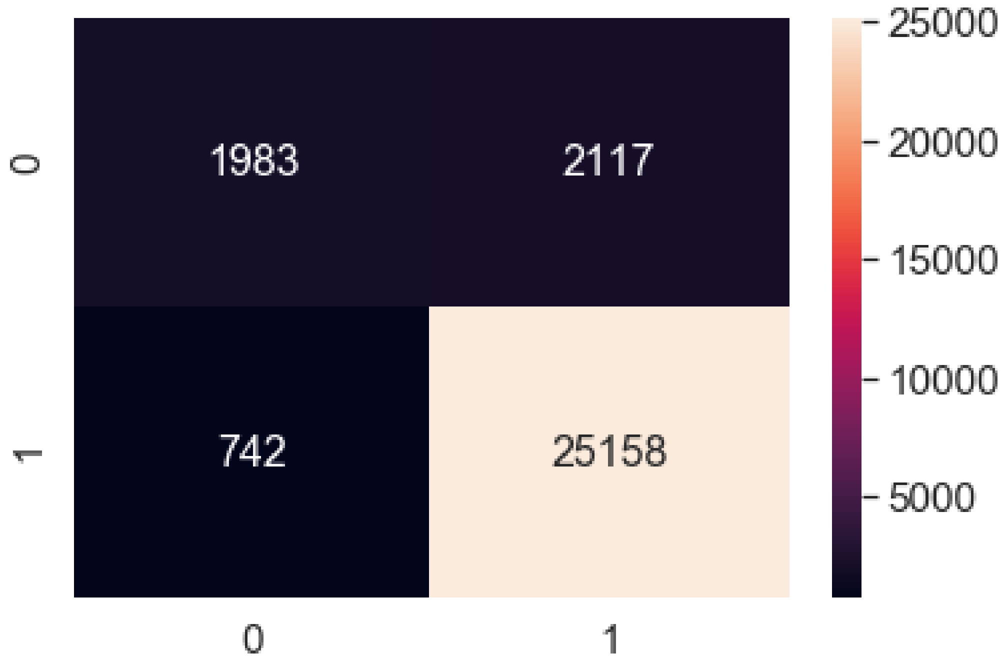
```
In [64]: predictions = log_reg.predict(standardizing.transform(vector.transform(tfidf_test)))
```

```
In [65]: precision = precision_score(y_test, predictions,pos_label=1)
         Recall = recall_score(y_test, predictions,pos_label=1)
         f1 = f1_score(y_test, predictions,pos_label=1)
         print ('precision = {0}'.format(precision*100))
         print ('Recall={0}'.format(Recall*100))
         print ('f1_score={0}'.format(f1*100))
```

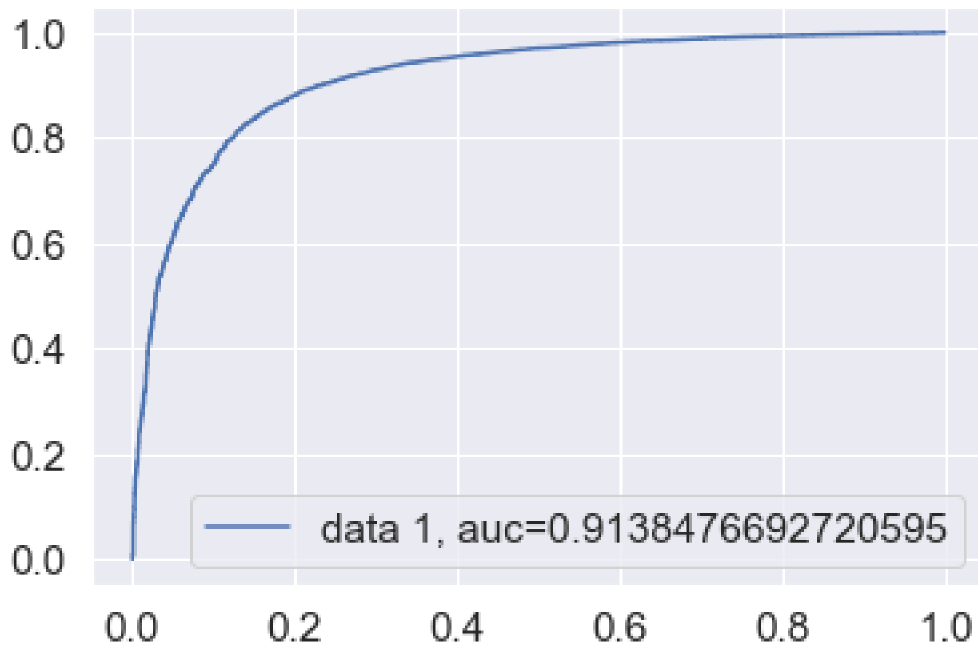
```
precision = 92.23831347387717
Recall=97.13513513513513
f1_score=94.62341325811
```

```
In [66]: from sklearn.metrics import confusion_matrix
         import seaborn as sns
         result = confusion_matrix(y_test,predictions)
         #print(result)
         sns.set(font_scale=1.4)#for label size
         sns.heatmap(result, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x4485e46da0>
```




```
In [67]: y_pred_proba = log_reg.predict_proba(standardizing.transform(vector.transform(tfidf_te
         fpr, tpr, _ = roc_curve(y_test, y_pred_proba,pos_label=1 )
         #auc = roc_auc_score(y_test, y_pred_proba)
         auc = np.trapz(tpr,fpr)
         plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
         plt.legend(loc=4)
         plt.show()
```



8.0.1 [4.2.1.1] Feature Importance of TFIDF with l2 Regularizer

```
In [68]: pos_indices = []
         neg_indices = []
         feat_names = vector.get_feature_names()
         weights_before = log_reg.coef_
         indices = list (np.argsort(weights_before[0]))
         pos_indices = indices[-10:]
         neg_indices = indices[0:10]
         print ('top 10 positive features\t\t\ttop 10 negative features')
         print ('-'*100)
         for id1,id2 in zip(pos_indices,neg_indices):
             print ('\t{0}\t\t\t\t\t\t{1}'.format(feat_names[id1],feat_names[id2]))
```

```
top 10 positive features                          top 10 negative features
----------------------------------------------------------------------------------------------------
        find                                          not
        nice                                          disappoint
        favorit                                          worst
        excel                                          aw
        perfect                                          terribl
        delici                                          horribl
        good                                          unfortun
        best                                          stale
```

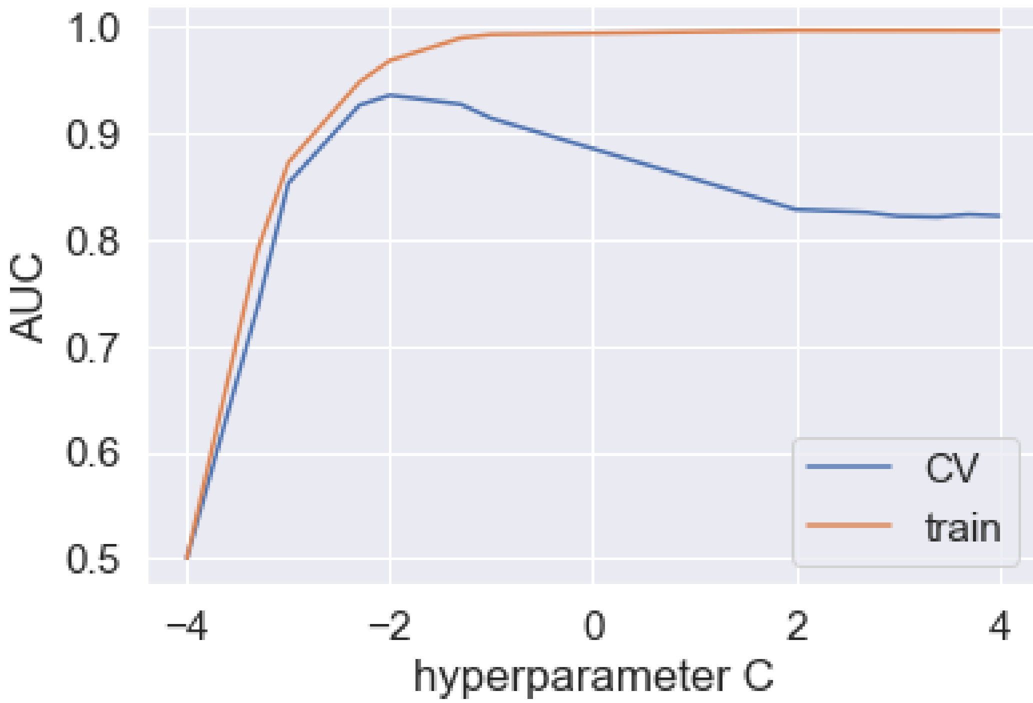
```
love                                    bland
great                                    return
```

8.0.2 [4.2.2] Applying Logistic Regression with L1 regularization on TFIDF, SET 2

```
In [69]: from sklearn.metrics import make_scorer
         from sklearn.model_selection import cross_val_score
         from sklearn.metrics import roc_auc_score
         # creating list for hyperparameter alpha
         alpha_values = [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,100,500,1000,2500,5000,10000]
         # empty list that will hold cv scores

         cv_scores = []
         train_auc_values = []

         # perform 10-fold cross validation
         for alpha in alpha_values:
             log_reg = LogisticRegression(C=alpha,penalty='l1',max_iter=10000)
             auc = make_scorer(roc_auc_score,greater_is_better=True,
                                          needs_threshold=True)
             auc_scores = cross_val_score(log_reg, final_std_data, y_train, cv=10, scoring=auc)
             log_reg.fit(final_std_data,y_train)
             y_pred_proba = log_reg.predict_proba(final_std_data)[::,1]
             train_auc = roc_auc_score(y_train, y_pred_proba)
             train_auc_values.append(train_auc)
             cv_scores.append(auc_scores.mean())

         print ('train scores')
         print (train_auc_values)
         print ('*'*50)
         print ('CV scores')
         print (cv_scores)

         # changing to misclassification error

         log = [math.log10(x) for x in alpha_values]
         # plot misclassification error vs alpha
         plt.plot(log, cv_scores,label='CV')
         #plt.label('cv_f1')
         plt.plot(log,train_auc_values,label='train')
         #plt.label('train_f1')
         plt.legend()
         plt.xlabel('hyperparameter C')
         plt.ylabel('AUC')
         plt.show()
```

```
train scores
```

```
[0.5, 0.7909062733902787, 0.8726965565352625, 0.9483963491319725, 0.9687353694765786, 0.9898758
**************************************************
CV scores
[0.5, 0.737474643725412, 0.8531336020054198, 0.9265739647008588, 0.9360879546733643, 0.92751454
```




```
In [70]: log_reg = LogisticRegression(C=0.005,penalty='l1',max_iter=10000,tol=0.001)
         log_reg.fit(final_std_data,y_train)
```

```
Out[70]: LogisticRegression(C=0.005, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=10000, multi_class='ovr', n_jobs=1,
                   penalty='l1', random_state=None, solver='liblinear', tol=0.001,
                   verbose=0, warm_start=False)
```

```
In [71]: print('accuracy = {0}'.format(log_reg.score(standardizing.transform(vector.transform(t
```

```
accuracy = 91.13333333333333
```

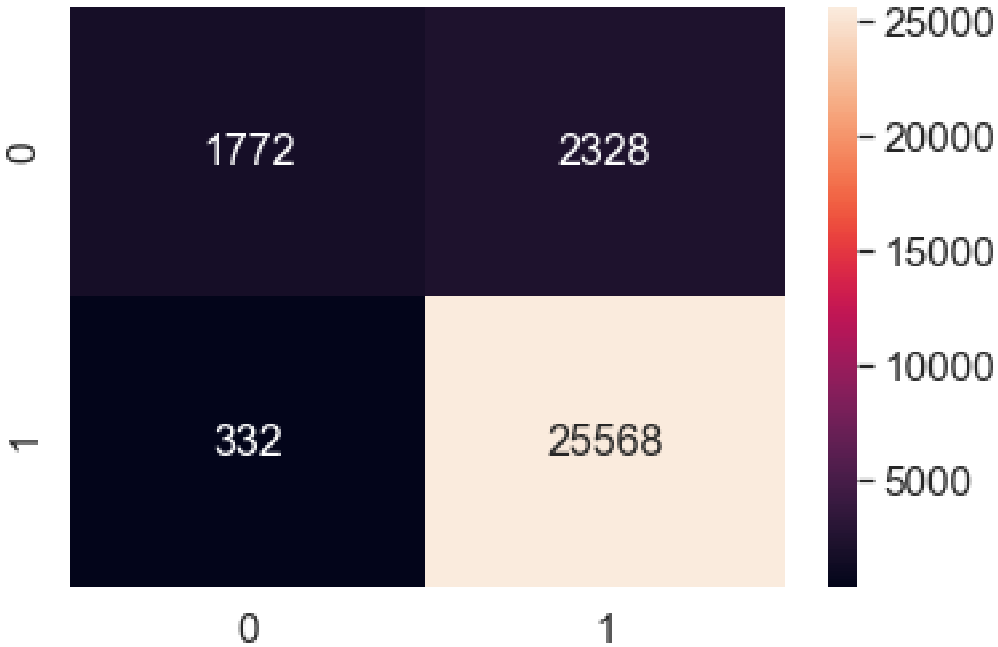
```
In [72]: predictions = log_reg.predict(standardizing.transform(vector.transform(tfidf_test)))
```

```
In [73]: precision = precision_score(y_test, predictions,pos_label=1)
         Recall = recall_score(y_test, predictions,pos_label=1)
         f1 = f1_score(y_test, predictions,pos_label=1)
         print ('precision = {0}'.format(precision))
         print ('Recall={0}'.format(Recall))
         print ('f1_score={0}'.format(f1))
```

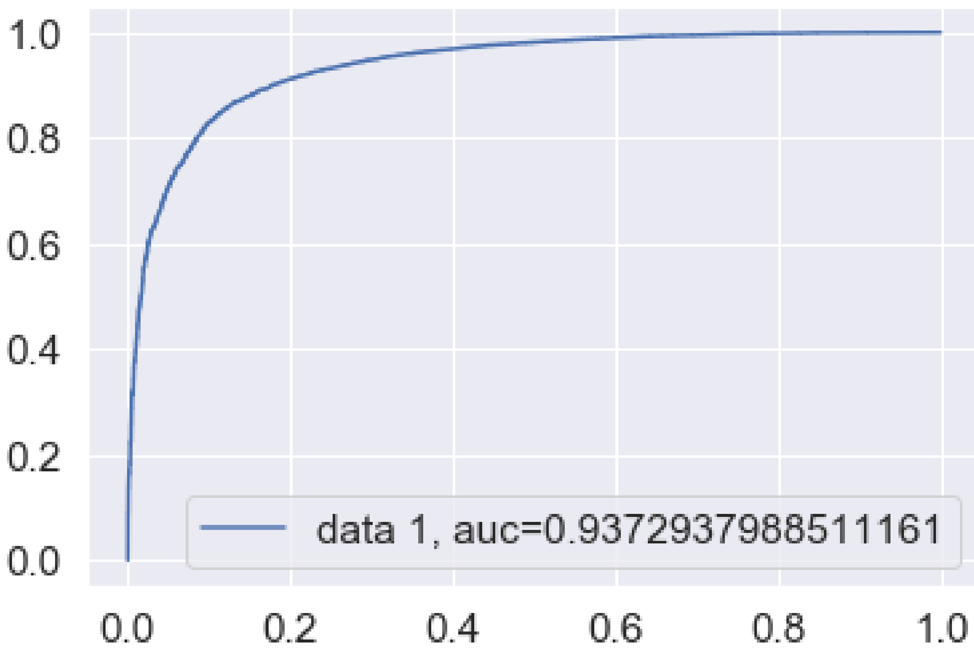
```
precision = 0.916547175222254
Recall=0.9871814671814672
f1_score=0.9505539445311919
```

In [74]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
result = confusion_matrix(y_test,predictions)
#print(result)
sns.set(font_scale=1.4)#for label size
sns.heatmap(result, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[74]: <matplotlib.axes._subplots.AxesSubplot at 0x448149f780>



In [75]:
```
y_pred_proba = log_reg.predict_proba(standardizing.transform(vector.transform(tfidf_te
fpr, tpr, _ = roc_curve(y_test, y_pred_proba,pos_label=1 )
#auc = roc_auc_score(y_test, y_pred_proba)
auc = np.trapz(tpr,fpr)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



8.0.3 [4.2.2.1]Feature Importance of TFIDF with l1 regularization

```
In [76]: pos_indices = []
         neg_indices = []
         feat_names = vector.get_feature_names()
         weights_before = log_reg.coef_
         indices = list (np.argsort(weights_before[0]))
         pos_indices = indices[-10:]
         neg_indices = indices[0:10]
         print ('top 10 positive features \t\t top 10 negative features')
         print ('-'*100)
         for id1,id2 in zip(pos_indices,neg_indices):
             print ('\t{0}\t\t\t\t\t{1}'.format(feat_names[id1],feat_names[id2]))
```

```
top 10 positive features                  top 10 negative features
----------------------------------------------------------------------------------------------------
        find                                        not
        nice                                        disappoint
        favorit                                        worst
        excel                                        terribl
        good                                        aw
        perfect                                        horribl
        delici                                        return
        love                                        money
```

```
best                                                threw
great                                                unfortun
```

9 [4.3] Logistic Regression on AVG W2V, SET 3

9.1 [4.3.1] Applying Logistic Regression with L2 regularization on AVG W2V SET 3

```
In [77]: import pickle
         with open("avg_w2v_train_data.pkl", "rb") as f:
             avg_w2v_train_data = pickle.load(f)
```

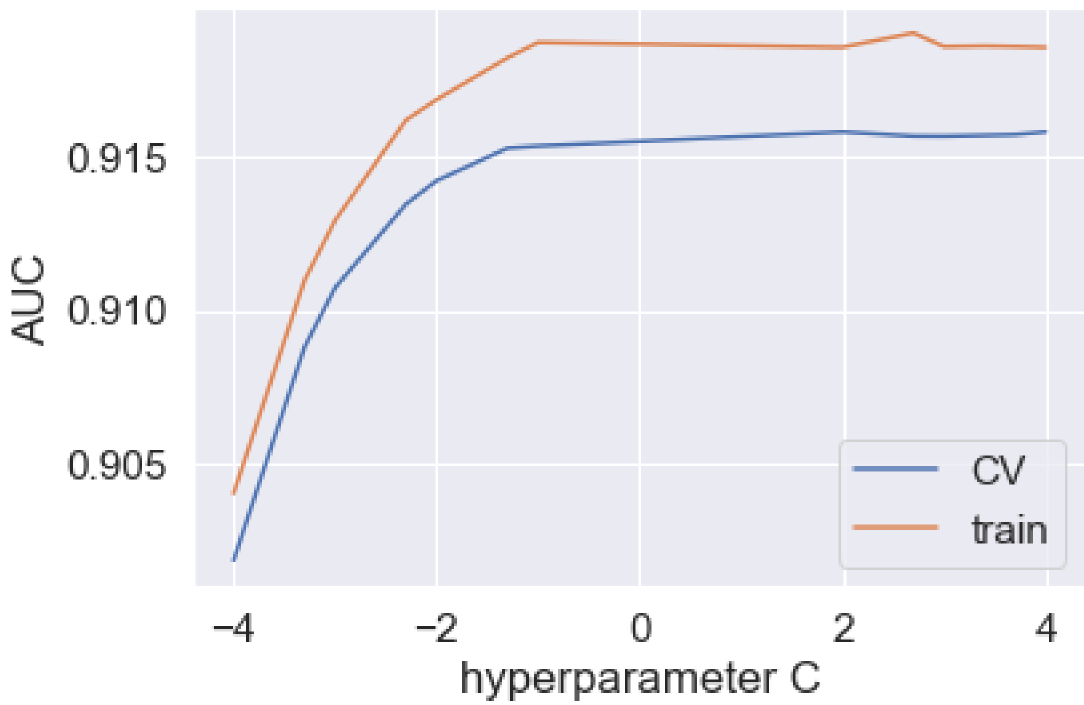
```
In [78]: import pickle
         with open("avg_w2v_test_data.pkl", "rb") as f:
             avg_w2v_test_data = pickle.load(f)
```

```
In [79]: standardizing  = StandardScaler(with_mean = False)
         avg_w2v_std_train_data = standardizing.fit_transform(avg_w2v_train_data)
         avg_w2v_std_train_data.shape

Out[79]: (70000, 300)
```

```
In [80]: from sklearn.metrics import make_scorer
         from sklearn.model_selection import cross_val_score
         from sklearn.metrics import roc_auc_score
         # creating list for hyperparameter alpha
         alpha_values = [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,100,500,1000,2500,5000,10000]
         # empty list that will hold cv scores

         cv_scores = []
         train_auc_values = []

         # perform 10-fold cross validation
         for alpha in alpha_values:
             log_reg = LogisticRegression(C=alpha,penalty='l2',max_iter=10000)
             auc = make_scorer(roc_auc_score,greater_is_better=True,
                                          needs_threshold=True)
             auc_scores = cross_val_score(log_reg, avg_w2v_std_train_data, y_train, cv=10, sco
             log_reg.fit(avg_w2v_std_train_data,y_train)
             y_pred_proba = log_reg.predict_proba(avg_w2v_std_train_data)[::,1]
             train_auc = roc_auc_score(y_train, y_pred_proba)
             train_auc_values.append(train_auc)
             cv_scores.append(auc_scores.mean())

         print ('train scores')
         print (train_auc_values)
         print ('*'*50)
         print ('CV scores')
```

```
    print (cv_scores)

    # changing to misclassification error

    log = [math.log10(x) for x in alpha_values]
    # plot misclassification error vs alpha
    plt.plot(log, cv_scores,label='CV')
    #plt.label('cv_f1')
    plt.plot(log,train_auc_values,label='train')
    #plt.label('train_f1')
    plt.legend()
    plt.xlabel('hyperparameter C')
    plt.ylabel('AUC')
    plt.show()
```

```
train scores
[0.9039903001300007, 0.9109722605770828, 0.912938977070425, 0.9162205654902067, 0.916893399816
***************************************************
CV scores
[0.9017952549247147, 0.9087825405111462, 0.910729067005892, 0.9134717315274579, 0.914239264251
```




```
In [81]: log_reg = LogisticRegression(C=0.05,penalty='l2',max_iter=10000,tol=0.001)
         log_reg.fit(avg_w2v_std_train_data,y_train)
```

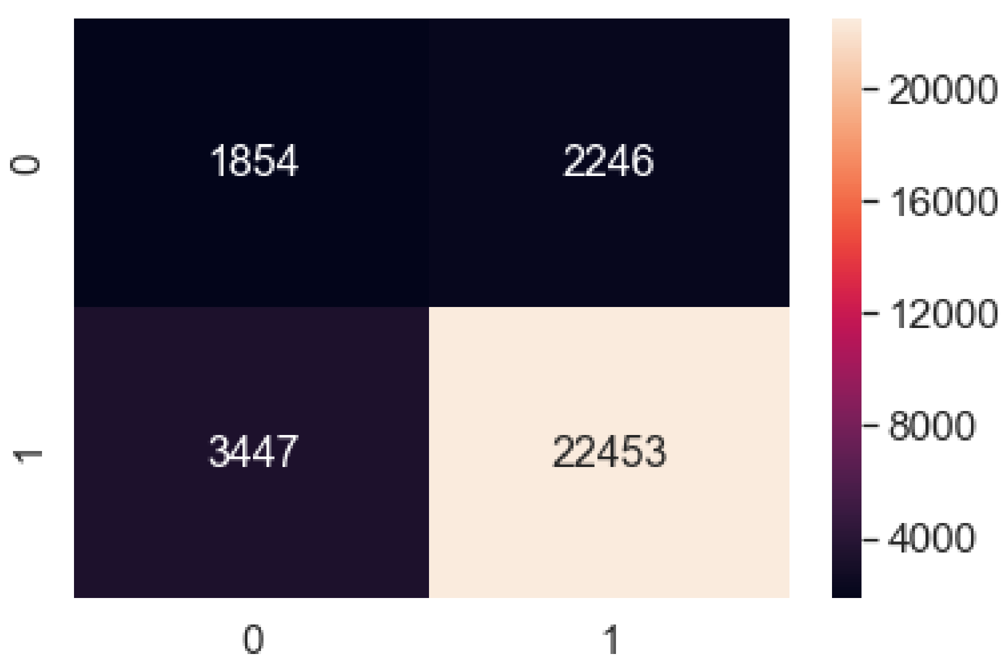
```
Out[81]: LogisticRegression(C=0.05, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=10000, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.001,
                   verbose=0, warm_start=False)
```

```
In [82]: predictions = log_reg.predict(standardizing.transform(avg_w2v_test_data))
         print('accuracy = {0}'.format(log_reg.score(standardizing.transform(avg_w2v_test_data
         precision = precision_score(y_test, predictions,pos_label=1)
         Recall = recall_score(y_test, predictions,pos_label=1)
         f1 = f1_score(y_test, predictions,pos_label=1)
         print ('precision = {0}'.format(precision))
         print ('Recall={0}'.format(Recall))
         print ('f1_score={0}'.format(f1))
```

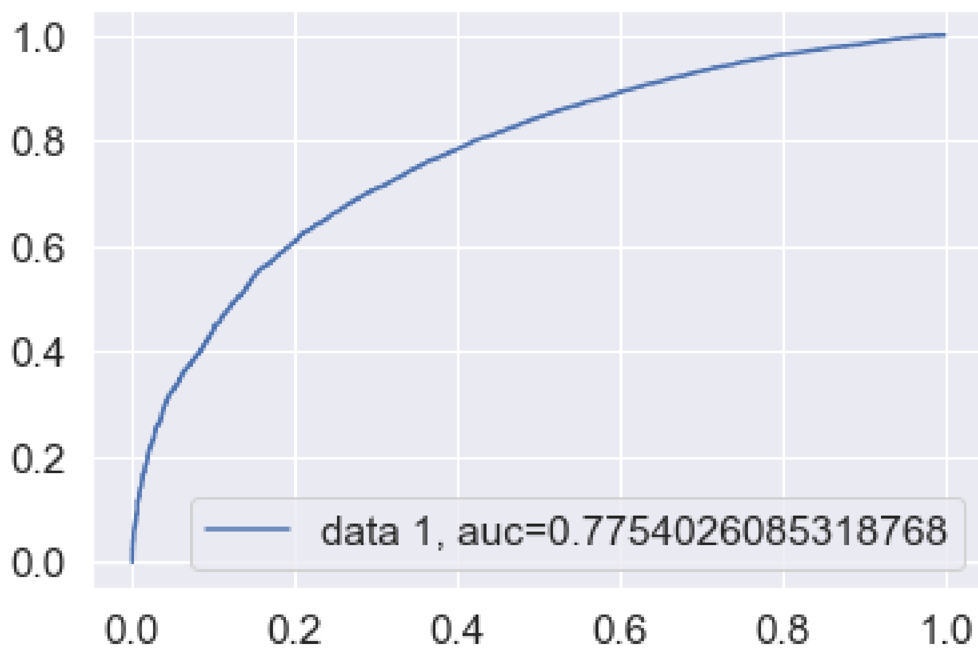
```
accuracy = 81.02333333333334
precision = 0.9090651443378275
Recall=0.8669111969111969
f1_score=0.8874878950176881
```

```
In [83]: from sklearn.metrics import confusion_matrix
         import seaborn as sns
         result = confusion_matrix(y_test,predictions)
         #print(result)
         sns.set(font_scale=1.4)#for label size
         sns.heatmap(result, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Out[83]: <matplotlib.axes._subplots.AxesSubplot at 0x44800a20b8>
```



In [84]:
```
y_pred_proba = log_reg.predict_proba(standardizing.transform(avg_w2v_test_data))[::,1]
fpr, tpr, _ = roc_curve(y_test, y_pred_proba,pos_label=1 )
#auc = roc_auc_score(y_test, y_pred_proba)
auc = np.trapz(tpr,fpr)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

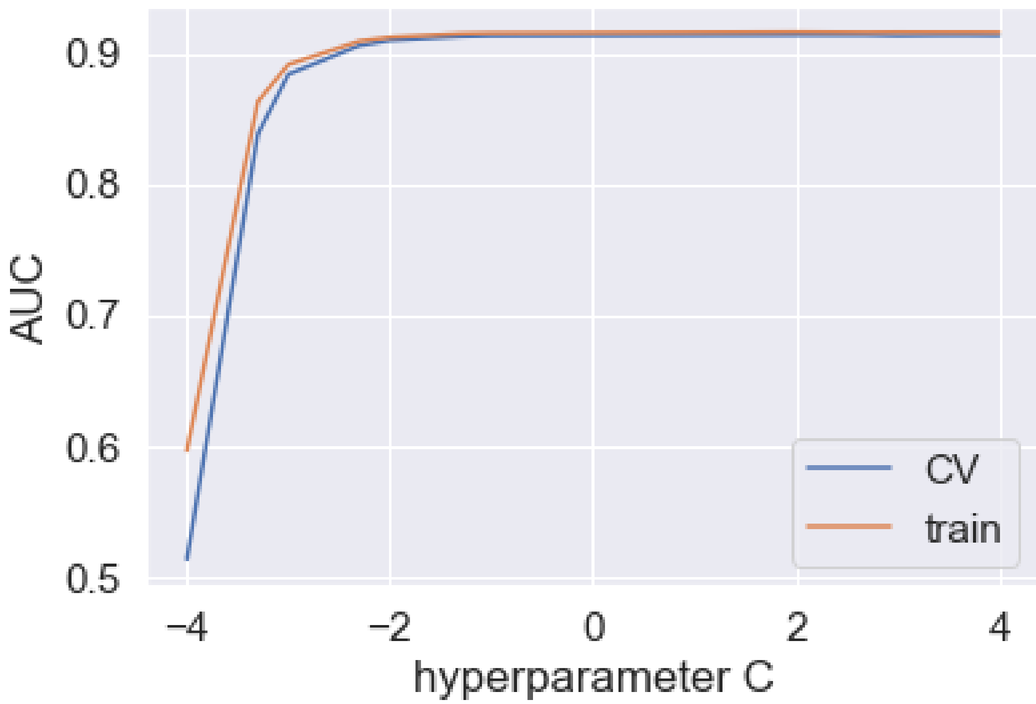


9.2 [4.3.2] Applying Logistic Regression with L1 regularization on AVG W2V, SET 3

In [85]:
```
from sklearn.metrics import make_scorer
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score
# creating list for hyperparameter alpha
alpha_values = [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,100,500,1000,2500,5000,10000]
# empty list that will hold cv scores

cv_scores = []
train_auc_values = []

# perform 10-fold cross validation
for alpha in alpha_values:
```

```
            log_reg = LogisticRegression(C=alpha,penalty='l1',max_iter=10000,)
            auc = make_scorer(roc_auc_score,greater_is_better=True,
                                         needs_threshold=True)
            auc_scores = cross_val_score(log_reg, avg_w2v_std_train_data, y_train, cv=10, sco
            log_reg.fit(avg_w2v_std_train_data,y_train)
            y_pred_proba = log_reg.predict_proba(avg_w2v_std_train_data)[::,1]
            train_auc = roc_auc_score(y_train, y_pred_proba)
            train_auc_values.append(train_auc)
            cv_scores.append(auc_scores.mean())

        print ('train scores')
        print (train_auc_values)
        print ('*'*50)
        print ('CV scores')
        print (cv_scores)

        # changing to misclassification error

        log = [math.log10(x) for x in alpha_values]
        # plot misclassification error vs alpha
        plt.plot(log, cv_scores,label='CV')
        #plt.label('cv_f1')
        plt.plot(log,train_auc_values,label='train')
        #plt.label('train_f1')
        plt.legend()
        plt.xlabel('hyperparameter C')
        plt.ylabel('AUC')
        plt.show()
```

```
train scores
[0.596049529536806, 0.8629598876454986, 0.891350149489925, 0.9090660408341188, 0.9120050109759
**************************************************
CV scores
[0.5127810767906871, 0.8380087759880162, 0.8837906321494697, 0.905839213257182, 0.909713212541
```




```
In [89]: log_reg = LogisticRegression(C=0.05,penalty='l1',max_iter=10000,tol=0.001)
         log_reg.fit(avg_w2v_std_train_data,y_train)
```

```
Out[89]: LogisticRegression(C=0.05, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=10000, multi_class='ovr', n_jobs=1,
                   penalty='l1', random_state=None, solver='liblinear', tol=0.001,
                   verbose=0, warm_start=False)
```

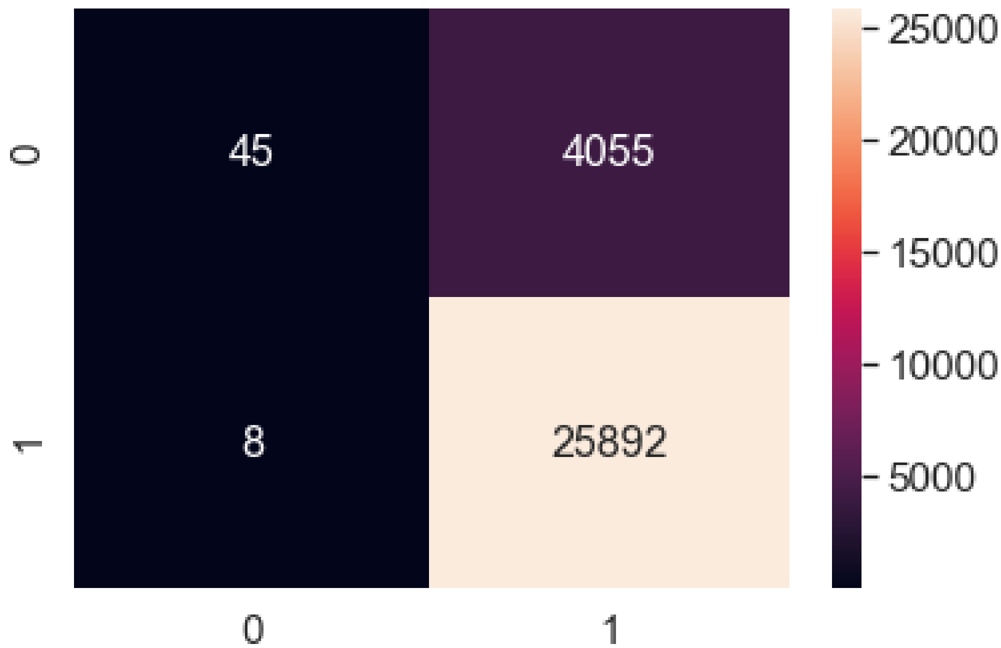
```
In [90]: predictions = log_reg.predict(standardizing.transform(avg_w2v_test_data))
         print('accuracy = {0}'.format(log_reg.score(standardizing.transform(avg_w2v_test_data
         precision = precision_score(y_test, predictions,pos_label=1)
         Recall = recall_score(y_test, predictions,pos_label=1)
         f1 = f1_score(y_test, predictions,pos_label=1)
         print ('precision = {0}'.format(precision))
         print ('Recall={0}'.format(Recall))
         print ('f1_score={0}'.format(f1))
```

```
accuracy = 86.45666666666668
precision = 0.8645941162720807
Recall=0.9996911196911197
f1_score=0.9272476587820296
```

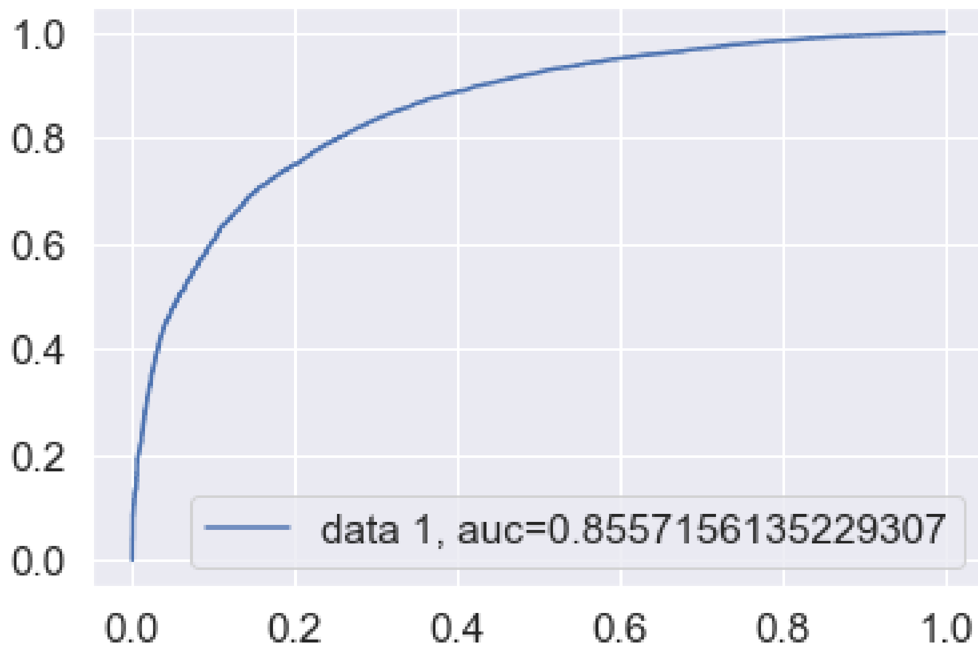
```
In [92]: from sklearn.metrics import confusion_matrix
         import seaborn as sns
```

```
result = confusion_matrix(y_test,predictions)
#print(result)
sns.set(font_scale=1.4)#for label size
sns.heatmap(result, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[92]: <matplotlib.axes._subplots.AxesSubplot at 0x4485e20358>



In [93]:
```
y_pred_proba = log_reg.predict_proba(standardizing.transform(avg_w2v_test_data))[::,1]
fpr, tpr, _ = roc_curve(y_test, y_pred_proba,pos_label=1 )
#auc = roc_auc_score(y_test, y_pred_proba)
auc = np.trapz(tpr,fpr)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



10 [4.4] Logistic Regression on TFIDF W2V, SET 4

10.1 [4.4.1] Applying Logistic Regression with L2 regularization on TFIDF W2V, SET 4

In [95]:
```
import pickle
with open("tfidf_w2v_train_data.pkl", "rb") as f:
    tfidf_w2v_train_data = pickle.load(f)
```

In [96]:
```
import pickle
with open("tfidf_w2v_test_data.pkl", "rb") as f:
    tfidf_w2v_test_data = pickle.load(f)
```

In [97]:
```
standardizing  = StandardScaler(with_mean = False)
tfidf_w2v_std_train_data = standardizing.fit_transform(tfidf_w2v_train_data)
tfidf_w2v_std_train_data.shape
```

Out[97]:
```
(70000, 300)
```

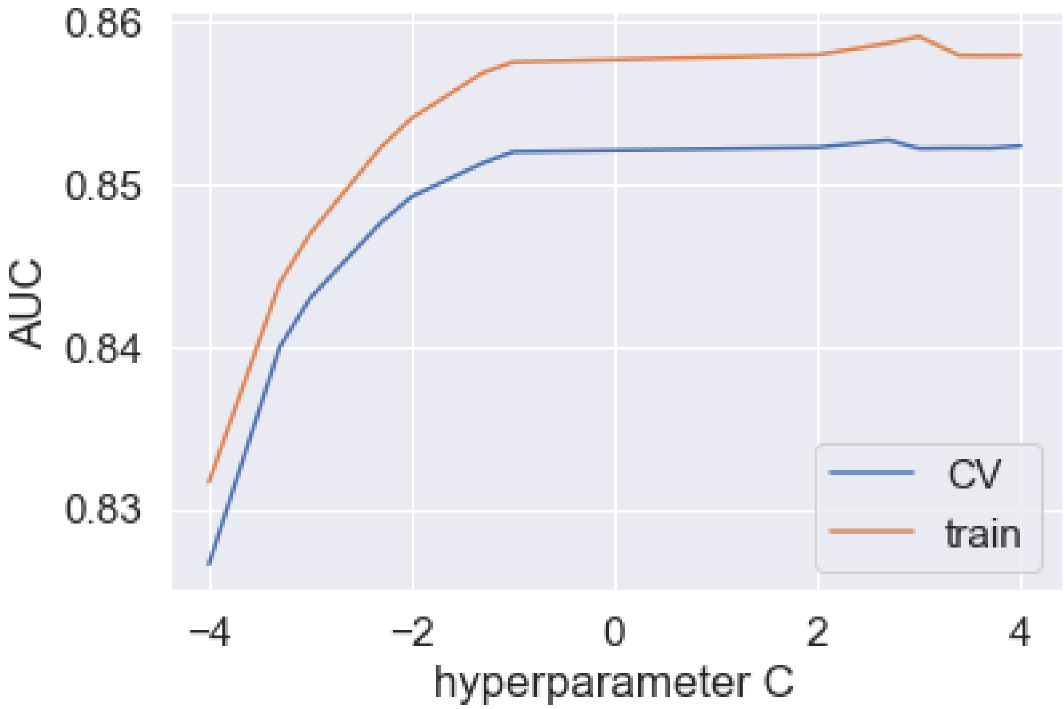
In [98]:
```
tfidf_w2v_std_train_data.mean()
```

Out[98]:
```
0.0071627058222749704
```

In [99]:
```
from sklearn.metrics import make_scorer
from sklearn.model_selection import cross_val_score
```

```python
from sklearn.metrics import roc_auc_score
# creating list for hyperparameter alpha
alpha_values = [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,100,500,1000,2500,5000,10000]
# empty list that will hold cv scores

cv_scores = []
train_auc_values = []

# perform 10-fold cross validation
for alpha in alpha_values:
    log_reg = LogisticRegression(C=alpha,penalty='l2',max_iter=10000)
    auc = make_scorer(roc_auc_score,greater_is_better=True,
                          needs_threshold=True)
    auc_scores = cross_val_score(log_reg, tfidf_w2v_std_train_data, y_train, cv=5, sc
    log_reg.fit(tfidf_w2v_std_train_data,y_train)
    y_pred_proba = log_reg.predict_proba(tfidf_w2v_std_train_data)[::,1]
    train_auc = roc_auc_score(y_train, y_pred_proba)
    train_auc_values.append(train_auc)
    cv_scores.append(auc_scores.mean())

print ('train scores')
print (train_auc_values)
print ('*'*50)
print ('CV scores')
print (cv_scores)

# changing to misclassification error

log = [math.log10(x) for x in alpha_values]
# plot misclassification error vs alpha
plt.plot(log, cv_scores,label='CV')
#plt.label('cv_f1')
plt.plot(log,train_auc_values,label='train')
#plt.label('train_f1')
plt.legend()
plt.xlabel('hyperparameter C')
plt.ylabel('AUC')
plt.show()
```

```
train scores
[0.8316270587156991, 0.843892458117977, 0.8469494345355281, 0.8522581075246595, 0.854040093152
**************************************************
CV scores
[0.8265845605404006, 0.8399606573161972, 0.8429660551070757, 0.8476368060962354, 0.849205900967
```



In [110]:
```
log_reg = LogisticRegression(C=0.01,penalty='l2',max_iter=10000,tol=0.001)
log_reg.fit(tfidf_w2v_std_train_data,y_train)
```

Out[110]:
```
LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=10000, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.001,
          verbose=0, warm_start=False)
```

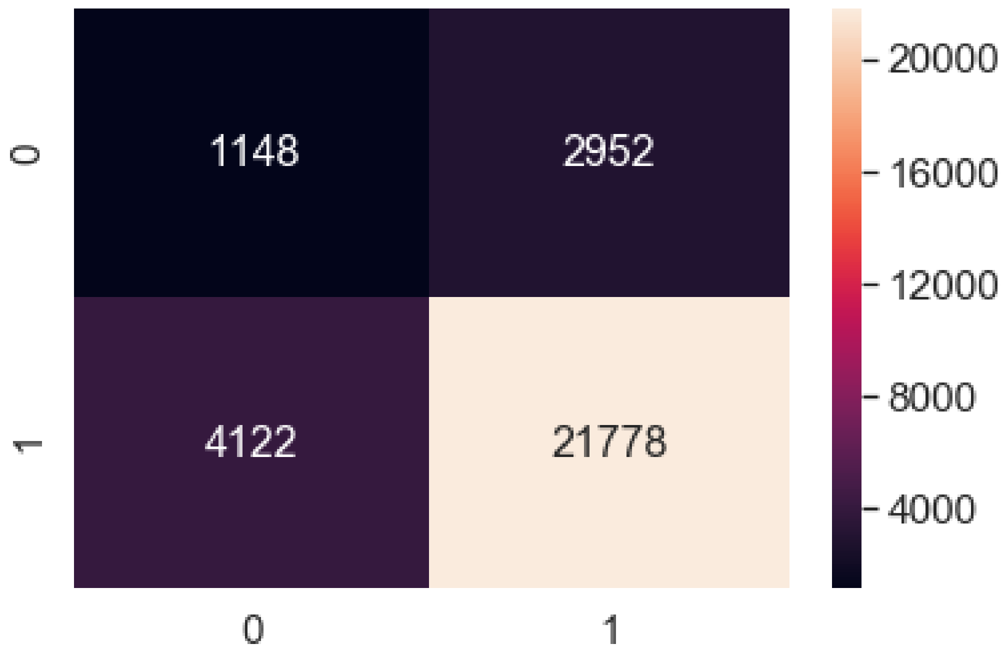
In [111]:
```
predictions = log_reg.predict(standardizing.transform(tfidf_w2v_test_data))
print('accuracy = {0}'.format(log_reg.score(standardizing.transform(tfidf_w2v_test_da
precision = precision_score(y_test, predictions,pos_label=1)
Recall = recall_score(y_test, predictions,pos_label=1)
f1 = f1_score(y_test, predictions,pos_label=1)
print ('precision = {0}'.format(precision))
print ('Recall={0}'.format(Recall))
print ('f1_score={0}'.format(f1))
```

```
accuracy = 76.42
precision = 0.8806308127780025
Recall=0.8408494208494208
f1_score=0.8602804661268022
```

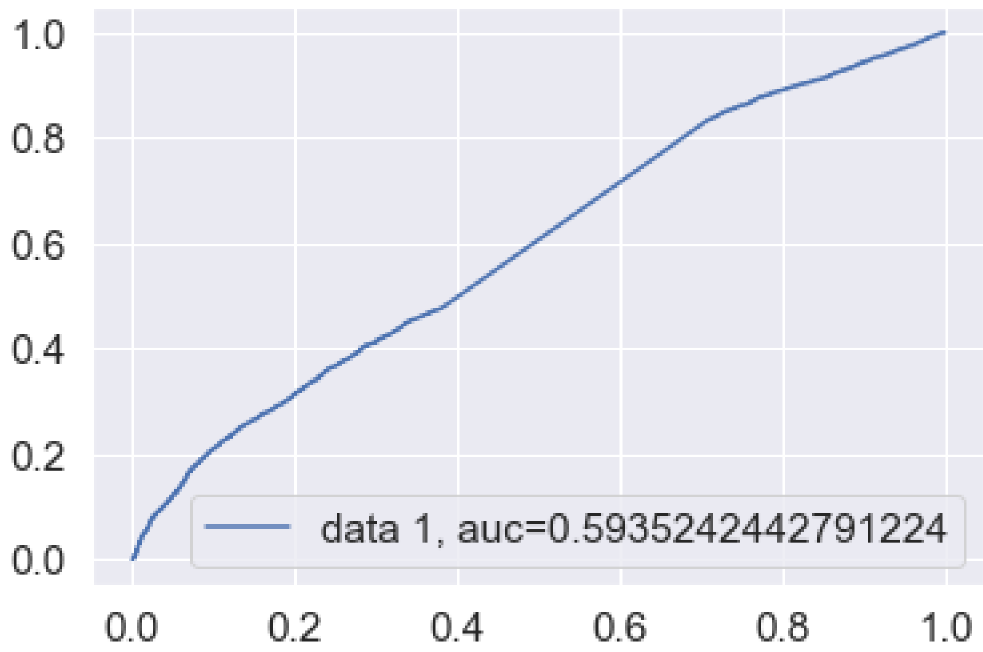
In [112]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
```

```
result = confusion_matrix(y_test,predictions)
#print(result)
sns.set(font_scale=1.4)#for label size
sns.heatmap(result, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0x449631beb8>



In [113]:
```
y_pred_proba = log_reg.predict_proba(standardizing.transform(tfidf_w2v_test_data))[:
fpr, tpr, _ = roc_curve(y_test, y_pred_proba,pos_label=1 )
#auc = roc_auc_score(y_test, y_pred_proba)
auc = np.trapz(tpr,fpr)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

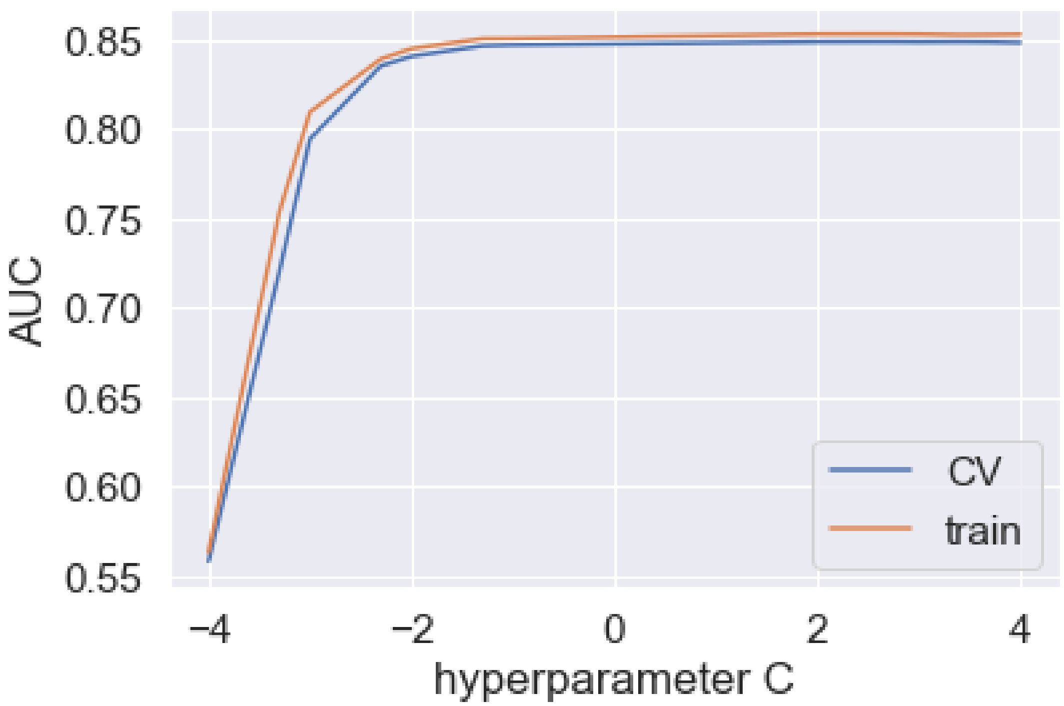


10.2 [4.4.2] Applying Logistic Regression with L1 regularization on TFIDF W2V, SET 4

In [114]:
```
from sklearn.metrics import make_scorer
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score
# creating list for hyperparameter alpha
alpha_values = [0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,100,500,1000,2500,5000,10000]
# empty list that will hold cv scores

cv_scores = []
train_auc_values = []

# perform 10-fold cross validation
for alpha in alpha_values:
    log_reg = LogisticRegression(C=alpha,penalty='l1',max_iter=10000)
    auc = make_scorer(roc_auc_score,greater_is_better=True,
                          needs_threshold=True)
    auc_scores = cross_val_score(log_reg, tfidf_w2v_std_train_data, y_train, cv=5, sc
    log_reg.fit(tfidf_w2v_std_train_data,y_train)
    y_pred_proba = log_reg.predict_proba(tfidf_w2v_std_train_data)[::,1]
    train_auc = roc_auc_score(y_train, y_pred_proba)
    train_auc_values.append(train_auc)
    cv_scores.append(auc_scores.mean())
```

```
print ('train scores')
print (train_auc_values)
print ('*'*50)
print ('CV scores')
print (cv_scores)

# changing to misclassification error

log = [math.log10(x) for x in alpha_values]
# plot misclassification error vs alpha
plt.plot(log, cv_scores,label='CV')
#plt.label('cv_f1')
plt.plot(log,train_auc_values,label='train')
#plt.label('train_f1')
plt.legend()
plt.xlabel('hyperparameter C')
plt.ylabel('AUC')
plt.show()
```

```
train scores
[0.5633358424835658, 0.7540617737940192, 0.8097770102846455, 0.8395026884035292, 0.845292490702
**************************************************
CV scores
[0.5582377926129428, 0.7205708054481125, 0.7946056041449776, 0.8355777409967038, 0.840934187810
```



In [115]:
```
log_reg = LogisticRegression(C=0.05,penalty='l1',max_iter=10000,tol=0.001)
log_reg.fit(tfidf_w2v_std_train_data,y_train)
```

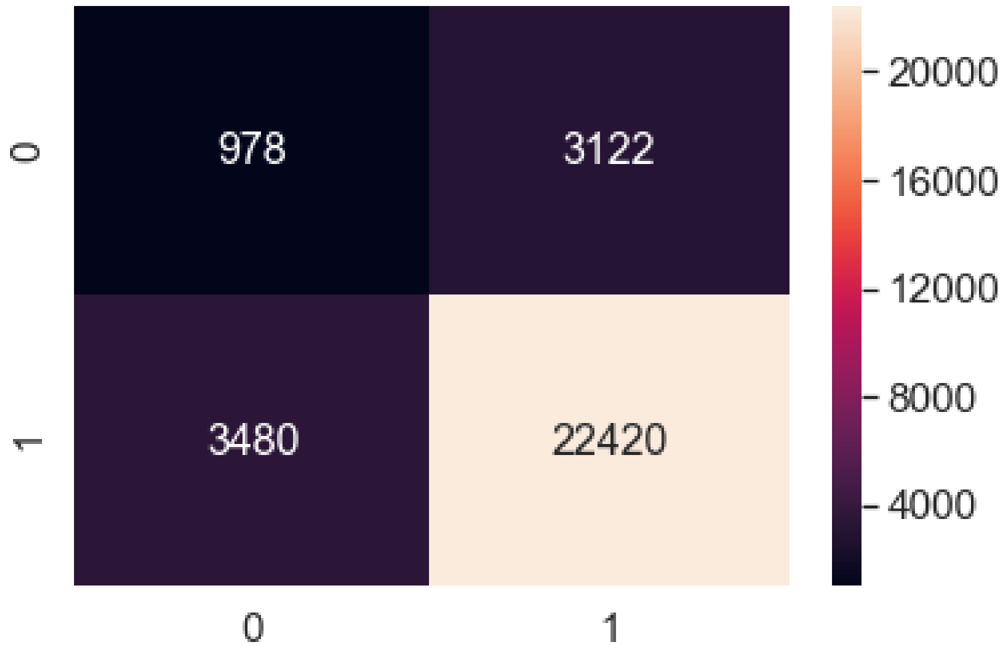
Out[115]:
```
LogisticRegression(C=0.05, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=10000, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.001,
          verbose=0, warm_start=False)
```

In [116]:
```
predictions = log_reg.predict(standardizing.transform(tfidf_w2v_test_data))
print('accuracy = {0}'.format(log_reg.score(standardizing.transform(tfidf_w2v_test_da
precision = precision_score(y_test, predictions,pos_label=1)
Recall = recall_score(y_test, predictions,pos_label=1)
f1 = f1_score(y_test, predictions,pos_label=1)
print ('precision = {0}'.format(precision))
print ('Recall={0}'.format(Recall))
print ('f1_score={0}'.format(f1))
```

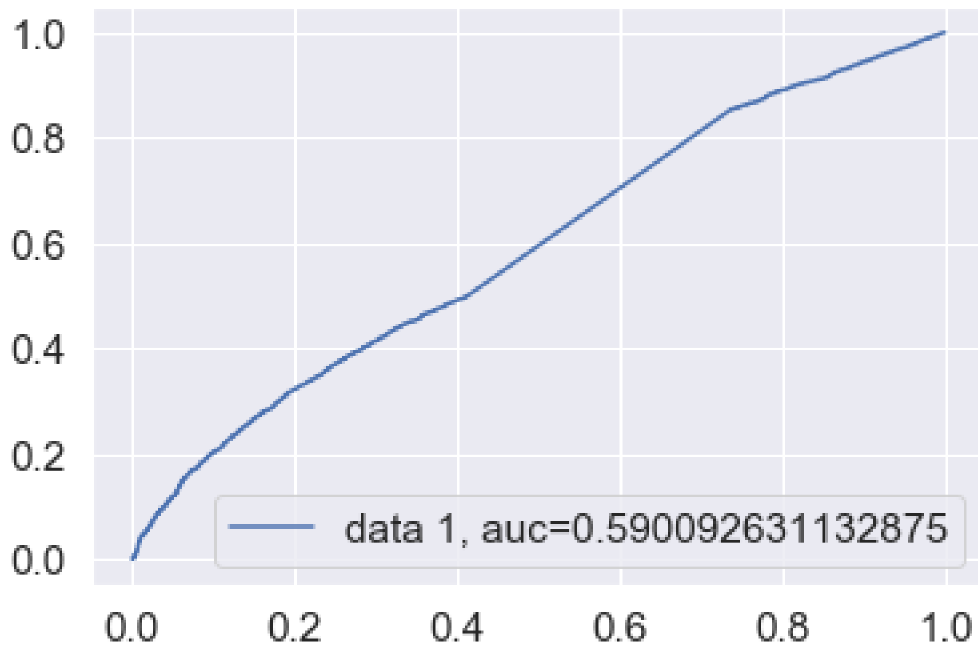
```
accuracy = 77.99333333333334
precision = 0.8777699475373894
Recall=0.8656370656370657
f1_score=0.8716612884413515
```

In [117]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
result = confusion_matrix(y_test,predictions)
#print(result)
sns.set(font_scale=1.4)#for label size
sns.heatmap(result, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[117]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x449d2f7a58>
```




```
In [118]: y_pred_proba = log_reg.predict_proba(standardizing.transform(tfidf_w2v_test_data))[:
          fpr, tpr, _ = roc_curve(y_test, y_pred_proba,pos_label=1 )
          #auc = roc_auc_score(y_test, y_pred_proba)
          auc = np.trapz(tpr,fpr)
          plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
          plt.legend(loc=4)
          plt.show()
```



11 5) Tabular form of Results

```
In [119]: from prettytable import PrettyTable

          x = PrettyTable()

          x.field_names = ['Featurization','regularization','accuracy','AUC',
                           'precision','recall','f1_score']
          x.add_row(['BOW','l2','92.51','0.931','0.9667','0.8784','0.9202'])
          x.add_row(['BOW','l1','87.346','0.8829','0.8935','0.9688','0.9291'])
          x.add_row(['TFIDF','l2','90.47','0.9138','0.9223','0.9713','0.9462'])
          x.add_row(['TF-IDF','l1','91.13','0.937','0.916','0.9878','0.9505'])
          x.add_row(['Avg W2V','l2','81.023','0.7754','0.9091','0.86','0.8875'])
          x.add_row(['Avg W2V','l1','86.45','0.8557','0.86459','0.9974','0.9272'])
          x.add_row(['TFIDF W2V','l2','76.42','0.593','0.8808','0.8408','0.8602'])
          x.add_row(['TFIDF W2V','l1','77.99','0.590','0.8777','0.8656','0.8716'])
          print (x)
```

Featurization	regularization	accuracy	AUC	precision	recall	f1_score
BOW	l2	92.51	0.931	0.9667	0.8784	0.9202
BOW	l1	87.346	0.8829	0.8935	0.9688	0.9291
TFIDF	l2	90.47	0.9138	0.9223	0.9713	0.9462

TF-IDF	l1	91.13	0.937	0.916	0.9878	0.9505
Avg W2V	l2	81.023	0.7754	0.9091	0.86	0.8875
Avg W2V	l1	86.45	0.8557	0.86459	0.9974	0.9272
TFIDF W2V	l2	76.42	0.593	0.8808	0.8408	0.8602
TFIDF W2V	l1	77.99	0.590	0.8777	0.8656	0.8716

12 6) Conclusions

1) TFIDF with l1 regularizer Values has high values of preacision, recall , f1 score and it also has highest AUC.
2) BOW with l2 regularizer has auc close to TFIDF,but low recall and f1_score and there is high multicollinearity in BOW with l2 regularizer
3) so, TFIDF with l1 regularizer is a best vector.