Amazon-Food-Reviews-Naive-Bayes

October 20, 2018

```
In [1]: %matplotlib inline

        #import all the modules
        import sqlite3
        import numpy as np
        import pandas as pd
        import nltk
        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.preprocessing import StandardScaler
        from sklearn.metrics import confusion_matrix,accuracy_score
        from sklearn import metrics
        #from sklearn.metrics import roc_curve,auc
        #from sklearn.manifold import TSNE
        from nltk.corpus import stopwords
        from nltk.stem.porter import PorterStemmer
        from nltk.stem import SnowballStemmer
        from nltk.stem.wordnet import WordNetLemmatizer
        from sklearn.naive_bayes import BernoulliNB,MultinomialNB
        from sklearn.model_selection import train_test_split,GridSearchCV
        from sklearn.cross_validation import cross_val_score
        from collections import Counter
        from sklearn import cross_validation
```

```
D:\Anaconda\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: This module w
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
In [2]: conn=sqlite3.connect('D:/Applied AI Course/final2.sqlite')
        conn.cursor()
        conn.commit()
        conn.text_factory=str
        #final_data.to_sql('Reviews',conn,schema=None,if_exists='replace')
```

```
In [3]: fd=pd.read_sql_query("""SELECT * FROM REVIEWS""",conn)
```

In [4]: `fd.head(3)`

Out[4]:
```
    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"

   HelpfulnessNumerator  HelpfulnessDenominator        Time  \
0                     0                       0   939340800
1                     1                       1  1194739200
2                     1                       1  1191456000

                                    Summary  \
0                  EVERY book is educational
1  Love the book, miss the hard cover version
2               chicken soup with rice 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 ...

                                         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...
```

In [5]: `conn2=sqlite3.connect('D:/Applied AI Course/final.sqlite')`

In [6]: `label_df=pd.read_sql_query("""SELECT * FROM REVIEWS""",conn2)`

In [7]: `label_df.head(3)`

Out[7]:
```
    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"

   HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
0                     0                       0  Positive   939340800
1                     1                       1  Positive  1194739200
2                     1                       1  Positive  1191456000

                                    Summary  \
0                  EVERY book is educational
1  Love the book, miss the hard cover version
2               chicken soup with rice 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 ...

                                         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...
```

In [8]:
```python
label_df=label_df.sort_values('Time',axis=0,inplace=False,kind='quicksort')
```

In [9]:
```python
fd=fd.sort_values('Time',axis=0,inplace=False,kind='quicksort')
```

In [10]:
```python
fd.head(3)
```

Out[10]:
```
      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

     HelpfulnessNumerator  HelpfulnessDenominator       Time  \
0                       0                       0  939340800
30                      2                       2  940809600
424                     0                       0  944092800

                                               Summary  \
0                                EVERY book is educational
30   This whole series is great way to spend time w...
424                                Entertainingl Funny!

                                                  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...

                                           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...
```

In [11]:
```python
label_df.shape
```

Out[11]:
```
(364173, 12)
```

In [12]:
```python
fd.shape
```

Out[12]:
```
(364173, 11)
```

1 Sampleset data

```
In [13]: d_pos=label_df[label_df["Score"] == 'Positive'].sample(n=20000)
         d_neg=label_df[label_df["Score"] == 'Negative'].sample(n=20000)
         finald=pd.concat([d_pos,d_neg])
         finald.shape
```

```
Out[13]: (40000, 12)
```

```
In [14]: finald.head(2)
         final_d=finald.sort_values(by='Time')
         final_d.head(3)
```

```
Out[14]:        index      Id   ProductId          UserId  \
         325   346094  374400  B00004CI84  A2DEE7F9XKP3ZR
         362   346077  374382  B00004CI84  A3C3BAQDZWH5YE
         1065  443667  479728  B00005U2FA   AR5RRP9N2UXDJ

                                            ProfileName  HelpfulnessNumerator  \
         325                                     jerome                     0
         362   Kushana no shinryaku (Kushana's invasion)                     0
         1065                             Boraxo "Boraxo"                    21

               HelpfulnessDenominator     Score        Time  \
         325                        3  Positive   959990400
         362                        1  Positive  1014681600
         1065                      23  Positive  1029196800

                                                Summary  \
         325   Research - Beatlejuice video - French version
         362                                          ...
         1065                               It really works

                                                        Text  \
         325   I'm getting crazy.I'm looking for Beatlejuice ...
         362   It was on the other night, and, having been a ...
         1065  I was very skeptical when I bought this item, ...

                                                 CleanedText
         325   get crazyim look beatlejuic french version vid...
         362   night big fan cartoon shown decid watch also t...
         1065  skeptic bought item imagin amaz discov actual ...
```

2 Bag of Words

```
In [91]: X=final_d["CleanedText"]
         X.shape
```

```
Out[91]: (40000,)
```

In [92]:
```
y=final_d["Score"]
y.shape
```

Out[92]:
```
(40000,)
```

In [93]:
```
#split the data into train and test fo bag of words

X_train,X_test,Y_train,Y_test=cross_validation.train_test_split(X,y,test_size=0.3,ranc
#split train into cross val train and cross val test
X_t,X_cv,Y_t,Y_cv=cross_validation.train_test_split(X_train,Y_train,test_size=0.3)
```

In [94]:
```
count_vect=CountVectorizer()
stdscaler=StandardScaler(with_mean=False)
#final_count=count_vect.fit_transform(test_data["CleanedText"].values)
X_train = count_vect.fit_transform(X_train)
X_test = count_vect.transform(X_test)
X_train=stdscaler.fit_transform(X_train)
X_test=stdscaler.fit_transform(X_test)
print("the type of count vectorizer is:",type(X_train))
#final_count.get_shape()
print(X_train.shape,X_test.shape)
```

```
D:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarning: Data witl
  warnings.warn(msg, DataConversionWarning)
D:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarning: Data witl
  warnings.warn(msg, DataConversionWarning)
D:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarning: Data witl
  warnings.warn(msg, DataConversionWarning)
D:\Anaconda\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarning: Data witl
  warnings.warn(msg, DataConversionWarning)


the type of count vectorizer is: <class 'scipy.sparse.csr.csr_matrix'>
(28000, 26755) (12000, 26755)
```

In [95]:
```
print(X_train.shape,Y_train.shape,X_test.shape,Y_test.shape)
```

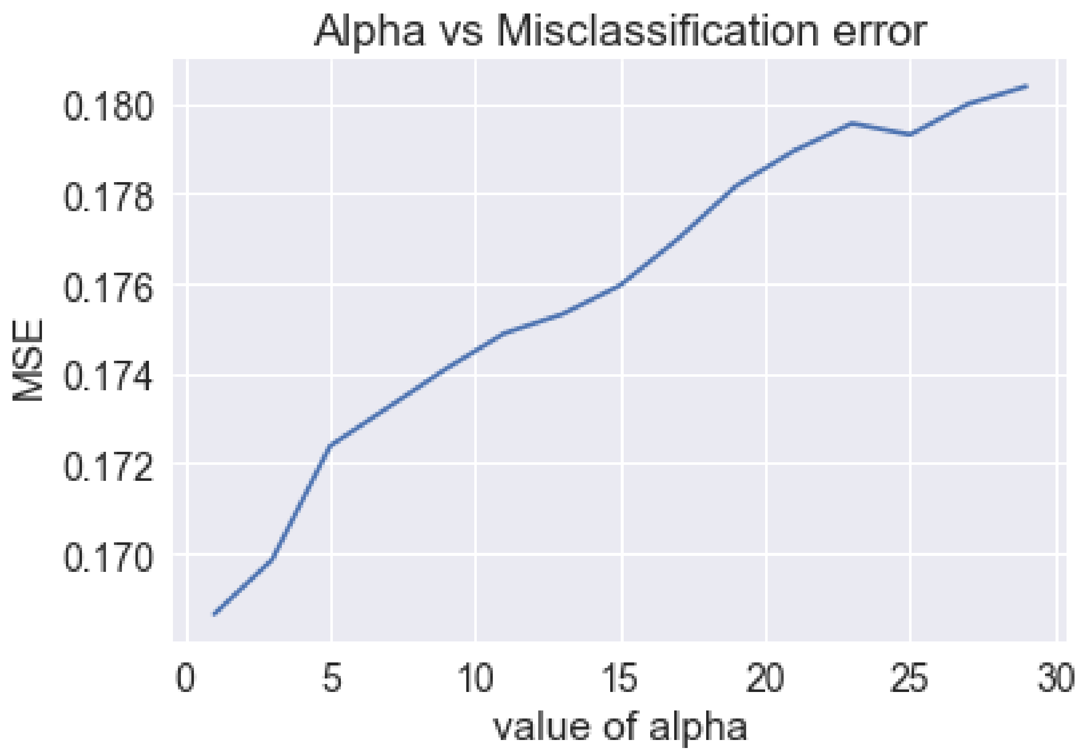
```
(28000, 26755) (28000,) (12000, 26755) (12000,)
```

3 Find the best alpha using cross validation for Laplace smoothing

In [46]:
```
#find the best alpha based on cv accuracy for bow
#l_a={'alpha':[1000,500,100,50,10,5,0.1,0.05,0.001]}
#alpha_set=list(range(float(1e-0,20,1e-4)))
#for i in alpha_set:
    # instantiate learning model (alpha = 10)
```

```python
bNB=BernoulliNB()
alpha_list = list(range(1,30,2))
cv_score = []
for i in alpha_list:
    bNB = BernoulliNB(alpha=i)
    scores = cross_val_score(bNB, X_train, Y_train, cv=3, scoring="accuracy")
    cv_score.append(scores.mean())

MSE = [1-x for x in cv_score]
optimal_alpha = alpha_list[MSE.index(min(MSE))]
print("Optimal alpha: ",optimal_alpha)
print('#'*100)
import matplotlib.pyplot as plt
plt.plot(alpha_list, MSE)
plt.title("Alpha vs Misclassification error")
plt.xlabel("value of alpha")
plt.ylabel("MSE")
plt.show()
#nB = BernoulliNB()
#cls=GridSearchCV(nB,l_a,cv=10)
    # fitting the model on crossvalidation train
#bNB.fit(X_train, Y_train)

    # predict the response on the crossvalidation train
#pred = bNB.predict(X_cv)

    # evaluate CV accuracy
#acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
#print("Best HyperParameter: ",cls.best_params_)
#print("Best Accuracy: %.2f%%"%(cls.best_score_*100))
#test accuracy
#nB = BernoulliNB(alpha=1000)
#nB.fit(X_train,Y_train)
#pred = nB.predict(X_test)
#acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
#print('\n****Test accuracy for alpha = 1000 is %d%%' % (acc))
```

```
Optimal alpha:  1
####################################################################################################
```



4 Naive Bayes

In [49]:
```
#BernoulliNB with optimal k and test accuracy for bag of words

nB_opt=BernoulliNB(alpha=optimal_alpha)
#fit the model
nB_opt.fit(X_train,Y_train)
#predict the model
prediction=nB_opt.predict(X_test)

#the accuracy score
acc_score=accuracy_score(Y_test,prediction)* 100
print('\n the accuracy score for bag of words model with optimal a=%d is %f%%' % (opt
print('#'*100)
print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0]
print('%'*50)
training_accuracy = nB_opt.score(X_train, Y_train)
training_error = 1 - training_accuracy
test_accuracy = accuracy_score(Y_test, prediction)
test_error = 1 - test_accuracy

print("training error:%.2f%%" %training_error)
```

```
print('#'*100)
print("training accuracy:%.2f%%" %training_accuracy)
print('#'*100)
print("test error:%.2f%%" %test_error)
print('#'*100)
print("test accuracy:%.2f%%" %test_accuracy)
```

```
 the accuracy score for bag of words model with optimal a=1 is 83.225000%
####################################################################################################
Number of mislabeled points out of a total 28000 points : 2013
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
training error:0.13%
####################################################################################################
training accuracy:0.87%
####################################################################################################
test error:0.17%
####################################################################################################
test accuracy:0.83%
```

5 Feature importance

```
In [32]: #pred_proba = nB_opt.predict_proba(X_test)
         #words = np.take(count_vect.get_feature_names(), pred_proba.argmax(axis=1))

         feat_name=np.array(count_vect.get_feature_names())
         f_cnt=nB_opt.feature_count_
         log_prob = nB_opt.feature_log_prob_
         feature_prob = pd.DataFrame(log_prob, columns=feat_name).T
         #sorted_idx=nB_opt.coef_[0].argsort()
         #print("smallest coeffecient is: \n {} \n".format(feat_name[sorted_idx[:10]]))
         #print("largest coefficient is: \n {} \n".format(feat_name[sorted_idx[:-11:-1]]))
         top_positive = feature_prob[1].sort_values(ascending=False)[:10]
         top_negative = feature_prob[0].sort_values(ascending=False)[:10]
```

```
In [50]: def show_most_informative_features(vectorizer, clf, n=25):
             feature_names = vectorizer.get_feature_names()
             coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
             top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
             print("\t\t\tPositive\t\t\t\t\t\tNegative")
             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(count_vect,nB_opt)
```

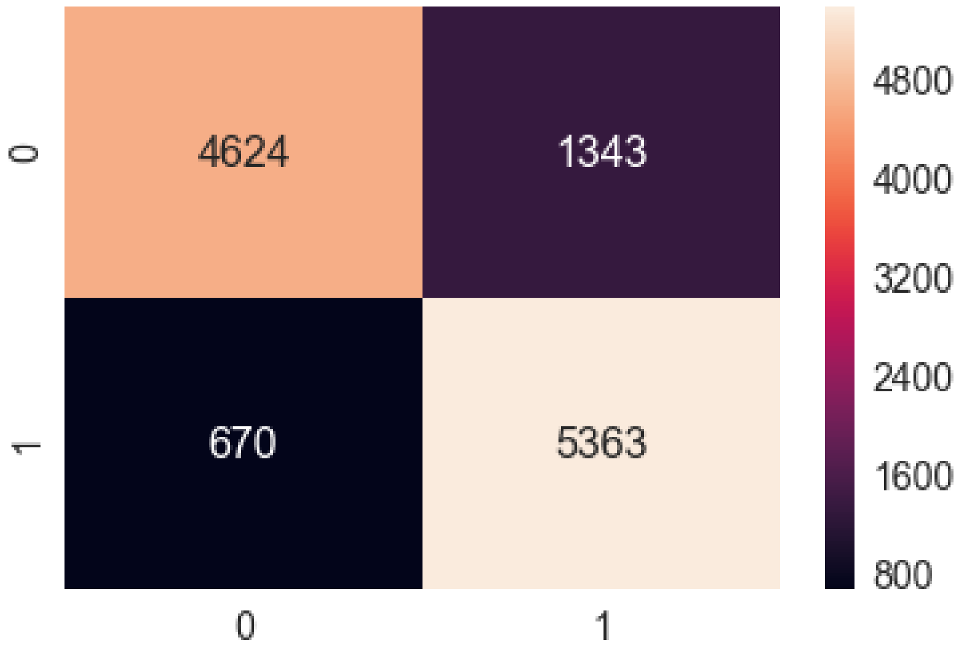
```
                        Positive                                                Negative
----------------------------------------------------------------------------------------------------
```

```
        -9.5446        aa                                          -1.1841        like
        -9.5446        aaaaaaarrrrrggghhh                            -1.2084        tast
        -9.5446        aachen                                      -1.2601        love
        -9.5446        abalon                                      -1.2754        good
        -9.5446        abbrevi                                     -1.3016        great
        -9.5446        abc                                         -1.4181        flavor
        -9.5446        aberr                                       -1.4904        one
        -9.5446        abhorr                                      -1.5000        use
        -9.5446        abid                                        -1.5352        tri
        -9.5446        abiet                                       -1.5493        product
        -9.5446        abnorm                                      -1.6585        make
        -9.5446        abod                                        -1.6953        get
        -9.5446        abort                                       -1.8859        buy
        -9.5446        abosolut                                    -1.9054        time
        -9.5446        abottl                                      -1.9175        realli
        -9.5446        abound                                      -1.9482        would
        -9.5446        abour                                       -1.9824        best
        -9.5446        aboutthi                                    -1.9971        price
        -9.5446        abras                                       -2.0298        much
        -9.5446        abrotanum                                   -2.0380        find
        -9.5446        absinthium                                  -2.0413        also
        -9.5446        absolutelt                                  -2.0614        eat
        -9.5446        absorbt                                     -2.0732        amazon
        -9.5446        absoslut                                    -2.1021        dont
        -9.5446        absout                                      -2.1175        littl
```

6 Confusion matrix

In [51]:
```
conf_matr_df = pd.DataFrame(confusion_matrix(Y_test, prediction), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(conf_matr_df, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[51]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20bd96a0>
```




```
In [52]: from sklearn.metrics import classification_report,precision_score,recall_score,f1_sco
         print(classification_report(Y_test,prediction))
```

```
             precision    recall  f1-score   support

   Negative       0.87      0.77      0.82      5967
   Positive       0.80      0.89      0.84      6033

avg / total       0.84      0.83      0.83     12000
```

7 Grid Search cross validation

```
In [77]: nB = BernoulliNB()
         param_grid = {'alpha':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.
         gsv=GridSearchCV(nB,param_grid,cv=3,verbose=1)
         gsv.fit(X_train,Y_train)
         print("Best HyperParameter: ",gsv.best_params_)
         print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 3 folds for each of 15 candidates, totalling 45 fits


[Parallel(n_jobs=1)]: Done  45 out of  45 | elapsed:   19.0s finished
```

```
Best HyperParameter:  {'alpha': 100}
Best Accuracy: 49.74%
```

```
In [78]: nB_opt=BernoulliNB(alpha=100)
         #fit the model
         nB_opt.fit(X_train,Y_train)
         #predict the model
         prediction=nB_opt.predict(X_test)

         #the accuracy score
         acc_score=accuracy_score(Y_test,prediction)* 100
         print('\n the accuracy score for bag of words model with optimal a=100 is %f%%' %acc_s
         print('#'*100)
         print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0]
         print('%'*50)
         training_accuracy = nB_opt.score(X_train, Y_train)
         training_error = 1 - training_accuracy
         test_accuracy = accuracy_score(Y_test, prediction)
         test_error = 1 - test_accuracy

         print("training error:%.2f%%" %training_error)
         print('#'*100)
         print("training accuracy:%.2f%%" %training_accuracy)
         print('#'*100)
         print("test error:%.2f%%" %test_error)
         print('#'*100)
         print("test accuracy:%.2f%%" %test_accuracy)
```

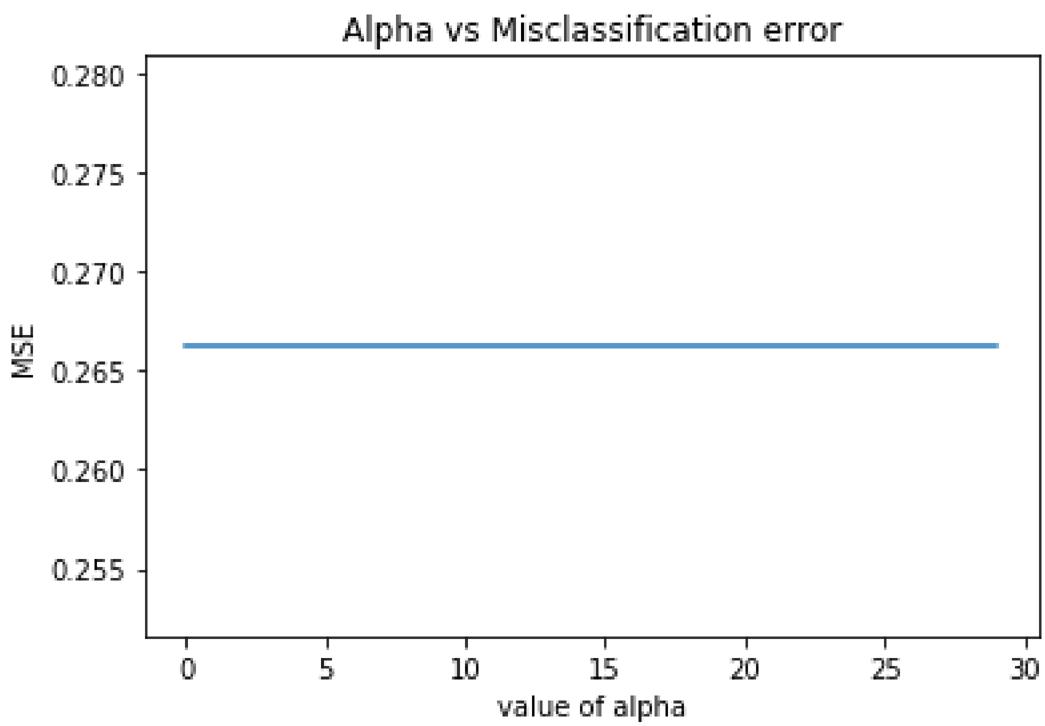
```
 the accuracy score for bag of words model with optimal a=100 is 49.475000%
###############################################################################################
Number of mislabeled points out of a total 28000 points : 6063
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
training error:0.49%
###############################################################################################
training accuracy:0.51%
###############################################################################################
test error:0.51%
###############################################################################################
test accuracy:0.49%
```

8 Multinomial Naive Bayes

```
In [23]: mNB=MultinomialNB()
         alpha_list = list(range(0,30,1))
         #alpha=list(filter(lambda x: x % 2 != 0, alpha_list))
```

```
cv_score = []
for i in alpha_list:
    bNB = MultinomialNB(alpha=i)
    scores = cross_val_score(mNB, X_train, Y_train, cv=10, scoring="accuracy")
    cv_score.append(scores.mean())

MSE = [1-x for x in cv_score]
optimal_alpha = alpha_list[MSE.index(min(MSE))]
print("Optimal alpha: ",optimal_alpha)
print('#'*100)
import matplotlib.pyplot as plt
plt.plot(alpha_list, MSE)
plt.title("Alpha vs Misclassification error")
plt.xlabel("value of alpha")
plt.ylabel("MSE")
plt.show()
```

```
Optimal alpha:  0
####################################################################################################
```




```
In [24]: mNB_opt=MultinomialNB(alpha=0)
         #fit the model
         mNB_opt.fit(X_train,Y_train)
```

```
        #predict the model
        prediction=nB_opt.predict(X_test)

        #the accuracy score
        acc_score=accuracy_score(Y_test,prediction)* 100
        print('\n the accuracy score for bag of words model with optimal a=%d is %f%%' % (opt
        print('#'*100)
        print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0]
        print('%'*50)
        training_accuracy = mNB_opt.score(X_train, Y_train)
        training_error = 1 - training_accuracy
        test_accuracy = accuracy_score(Y_test, prediction)
        test_error = 1 - test_accuracy

        print("training error:%.2f%%" %training_error)
        print('#'*100)
        print("training accuracy:%.2f%%" %training_accuracy)
        print('#'*100)
        print("test error:%.2f%%" %test_error)
        print('#'*100)
        print("test accuracy:%.2f%%" %test_accuracy)
```

```
e:\sofs\python3.6\lib\site-packages\sklearn\naive_bayes.py:472: UserWarning: alpha too small w
  'setting alpha = %.1e' % _ALPHA_MIN)



 the accuracy score for bag of words model with optimal a=0 is 75.125000%
################################################################################################
Number of mislabeled points out of a total 28000 points : 2985
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
training error:0.10%
################################################################################################
training accuracy:0.90%
################################################################################################
test error:0.25%
################################################################################################
test accuracy:0.75%
```

9 Feature Importance

```
In [26]: feat_name=np.array(count_vect.get_feature_names())
        f_cnt=mNB_opt.feature_count_
        log_prob = mNB_opt.feature_log_prob_
        feature_prob = pd.DataFrame(log_prob, columns=feat_name).T
        #sorted_idx=nB_opt.coef_[0].argsort()
        #print("smallest coeffecient is: \n {} \n".format(feat_name[sorted_idx[:10]]))
```

```
#print("largest coefficient is: \n {} \n".format(feat_name[sorted_idx[:-11:-1]]))
top_positive = feature_prob[1].sort_values(ascending=False)[:10]
top_negative = feature_prob[0].sort_values(ascending=False)[:10]

def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")
    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(count_vect,mNB_opt)
```

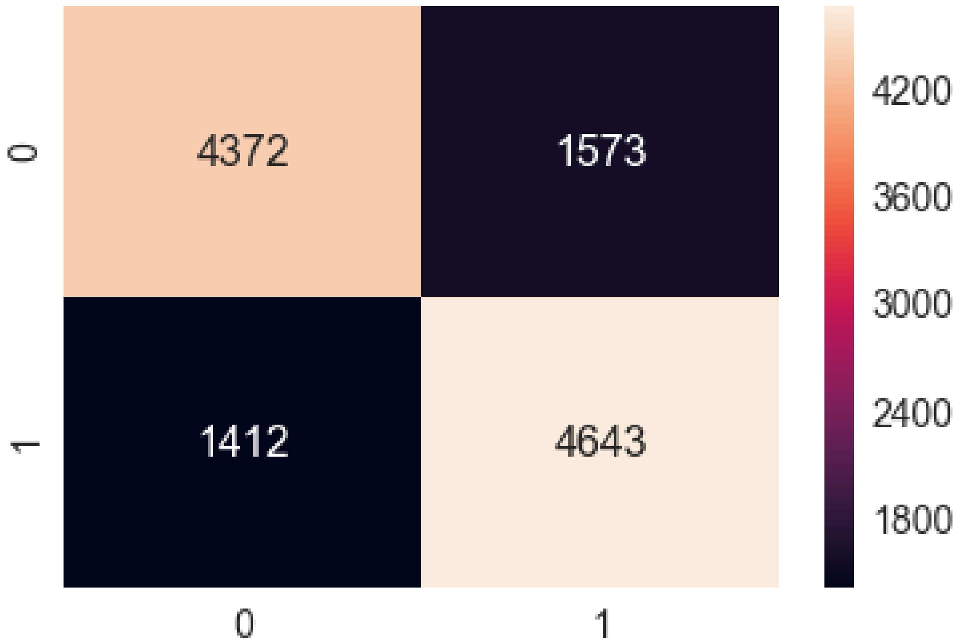
```
                              Positive                                                Negative
-----------------------------------------------------------------------------------------------------------
               -38.5609        aaa                                              -6.4315        great
               -38.5609        aaaaaaarrrrrggghhh                                  -6.4760        love
               -38.5609        aaaaaahhhhhyaaaaaa                                  -6.5612        good
               -38.5609        aaaahhhhhh                                       -6.6575        like
               -38.5609        aafco                                            -6.7617        use
               -38.5609        aamzon                                           -6.7703        tast
               -38.5609        aarrgh                                           -6.7900        make
               -38.5609        aauc                                             -6.8084        tri
               -38.5609        abbott                                           -6.8227        one
               -38.5609        abbrevi                                          -6.8245        flavor
               -38.5609        abdomen                                          -6.8600        best
               -38.5609        abdomin                                          -6.8723        get
               -38.5609        aberr                                            -6.9032        find
               -38.5609        abhor                                            -6.9565        time
               -38.5609        abhorr                                           -6.9669        littl
               -38.5609        abject                                           -6.9861        store
               -38.5609        abov                                             -6.9973        delici
               -38.5609        abt                                              -7.0078        also
               -38.5609        abut                                             -7.0280        much
               -38.5609        abysmali                                         -7.0280        well
               -38.5609        acacia                                           -7.0432        price
               -38.5609        acaigreen                                        -7.0476        buy
               -38.5609        accesori                                         -7.0480        recommend
               -38.5609        accross                                          -7.0585        realli
               -38.5609        acct                                             -7.0658        perfect
```

10 Confusion matrix

```
In [27]: conf_matr_df = pd.DataFrame(confusion_matrix(Y_test, prediction), range(2),range(2))
         sns.set(font_scale=1.4)#for label size
```

```
sns.heatmap(conf_matr_df, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x215c2198>




```
In [28]: from sklearn.metrics import classification_report,precision_score,recall_score,f1_sco
         print(classification_report(Y_test,prediction))
```

```
             precision    recall  f1-score   support

   Negative       0.76      0.74      0.75      5945
   Positive       0.75      0.77      0.76      6055

avg / total       0.75      0.75      0.75     12000
```

Observation:
with optimal alpha being 1 the Bernoulli Naive Bayes for BagOfWords approach has precision 84with optimal alpha being 0 the Multinomial Naive Bayes for BoW has precision and recall at 75

11 Multinomial Naive Bayes with feature selction by GridSearch

```
In [96]: mNB=MultinomialNB()
         param_grid = {'alpha':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0
         gsv=GridSearchCV(nB,param_grid,cv=3,verbose=1)
```

```
        gsv.fit(X_train,Y_train)
        print("Best HyperParameter: ",gsv.best_params_)
        print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 3 folds for each of 15 candidates, totalling 45 fits


[Parallel(n_jobs=1)]: Done  45 out of  45 | elapsed:   10.8s finished


Best HyperParameter:  {'alpha': 100}
Best Accuracy: 84.08%
```

```
In [97]: mNB_opt=MultinomialNB(alpha=100)
         #fit the model
         mNB_opt.fit(X_train,Y_train)
         #predict the model
         prediction=mNB_opt.predict(X_test)

         #the accuracy score
         acc_score=accuracy_score(Y_test,prediction)* 100
         print('\n the accuracy score for bag of words model with optimal a=%d is %f%%' % (opt
         print('#'*100)
         print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0]
         print('%'*50)
         training_accuracy = mNB_opt.score(X_train, Y_train)
         training_error = 1 - training_accuracy
         test_accuracy = accuracy_score(Y_test, prediction)
         test_error = 1 - test_accuracy

         print("training error:%.2f%%" %training_error)
         print('#'*100)
         print("training accuracy:%.2f%%" %training_accuracy)
         print('#'*100)
         print("test error:%.2f%%" %test_error)
         print('#'*100)
         print("test accuracy:%.2f%%" %test_accuracy)
```

```
 the accuracy score for bag of words model with optimal a=1 is 78.083333%
####################################################################################################
Number of mislabeled points out of a total 28000 points : 2630
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
training error:0.09%
####################################################################################################
training accuracy:0.91%
####################################################################################################
test error:0.22%
```

```
########################################################################################
test accuracy:0.78%
```

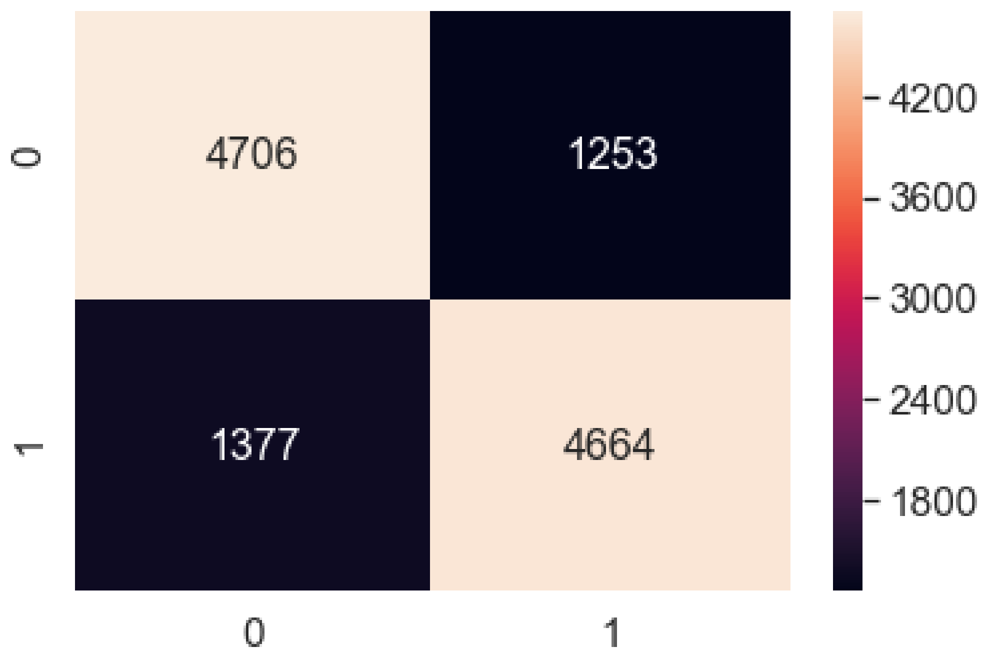
```
In [98]: feat_name=np.array(count_vect.get_feature_names())
         f_cnt=mNB_opt.feature_count_
         log_prob = mNB_opt.feature_log_prob_
         feature_prob = pd.DataFrame(log_prob, columns=feat_name).T
         #sorted_idx=nB_opt.coef_[0].argsort()
         #print("smallest coeffecient is: \n {} \n".format(feat_name[sorted_idx[:10]]))
         #print("largest coefficient is: \n {} \n".format(feat_name[sorted_idx[:-11:-1]]))
         top_positive = feature_prob[1].sort_values(ascending=False)[:10]
         top_negative = feature_prob[0].sort_values(ascending=False)[:10]

         def show_most_informative_features(vectorizer, clf, n=25):
             feature_names = vectorizer.get_feature_names()
             coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
             top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
             print("\t\t\tPositive\t\t\t\t\t\tNegative")
             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(count_vect,mNB_opt)
```

```
                        Positive                                                Negative
________________________________________________________________________________________________
        -11.3241        aafco                                           -6.8062         great
        -11.3241        aamazoncom                                      -6.8311         love
        -11.3241        aarrgh                                          -6.9023         good
        -11.3241        abbey                                           -7.0438         like
        -11.3241        abdomen                                         -7.1338         tast
        -11.3241        aberr                                           -7.1469         use
        -11.3241        abhor                                           -7.1603         make
        -11.3241        abhorr                                          -7.1826         one
        -11.3241        ablet                                           -7.1948         tri
        -11.3241        abolut                                          -7.2003         flavor
        -11.3241        abomin                                          -7.2108         best
        -11.3241        abosolut                                        -7.2637         get
        -11.3241        abouit                                          -7.2871         find
        -11.3241        abreast                                         -7.3435         littl
        -11.3241        abrupt                                          -7.3569         delici
        -11.3241        absolv                                          -7.3586         also
        -11.3241        absorbedconsid                                  -7.3731         time
        -11.3241        absorbt                                         -7.3736         buy
        -11.3241        absoulut                                        -7.3805         realli
        -11.3241        abysm                                           -7.3830         recommen
        -11.3241        acaigreen                                       -7.3976         well
```

-11.3241	acaii	-7.4003	much
-11.3241	acceptalbl	-7.4020	store
-11.3241	accidentley	-7.4030	price
-11.3241	accod	-7.4157	product

In [99]:
```
conf_matr_df = pd.DataFrame(confusion_matrix(Y_test, prediction), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(conf_matr_df, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[99]: <matplotlib.axes._subplots.AxesSubplot at 0x6fdae358>



In [100]:
```
from sklearn.metrics import classification_report,precision_score,recall_score,f1_sco
print(classification_report(Y_test,prediction))
```

```
             precision    recall  f1-score   support

   Negative       0.77      0.79      0.78      5959
   Positive       0.79      0.77      0.78      6041

avg / total       0.78      0.78      0.78     12000
```

Observation 1 The difference between cross validation and Grid Search CV for Bag of Words leads to a slight increase in precision and recall being 78

12 Tf_IDF

In [101]:
```
X=final_d["CleanedText"]
X.shape
```

Out[101]: (40000,)

In [102]:
```
y=final_d["Score"]
y.shape
```

Out[102]: (40000,)

In [103]:
```
X_train,X_test,Y_train,Y_test=cross_validation.train_test_split(X,y,test_size=0.30,ra
#split train into cross val train and cross val test
X_t,X_cv,Y_t,Y_cv=cross_validation.train_test_split(X_train,Y_train,test_size=0.3)
```

In [83]:
```
print(X_train.shape,X_test.shape,Y_train.shape,Y_test.shape)
```

```
(28000,) (12000,) (28000,) (12000,)
```

In [104]:
```
tf_idf_vect=TfidfVectorizer()
final_tfidf_vect=tf_idf_vect.fit_transform(X_train)
final_test_tfidf_vect=tf_idf_vect.transform(X_test)
```

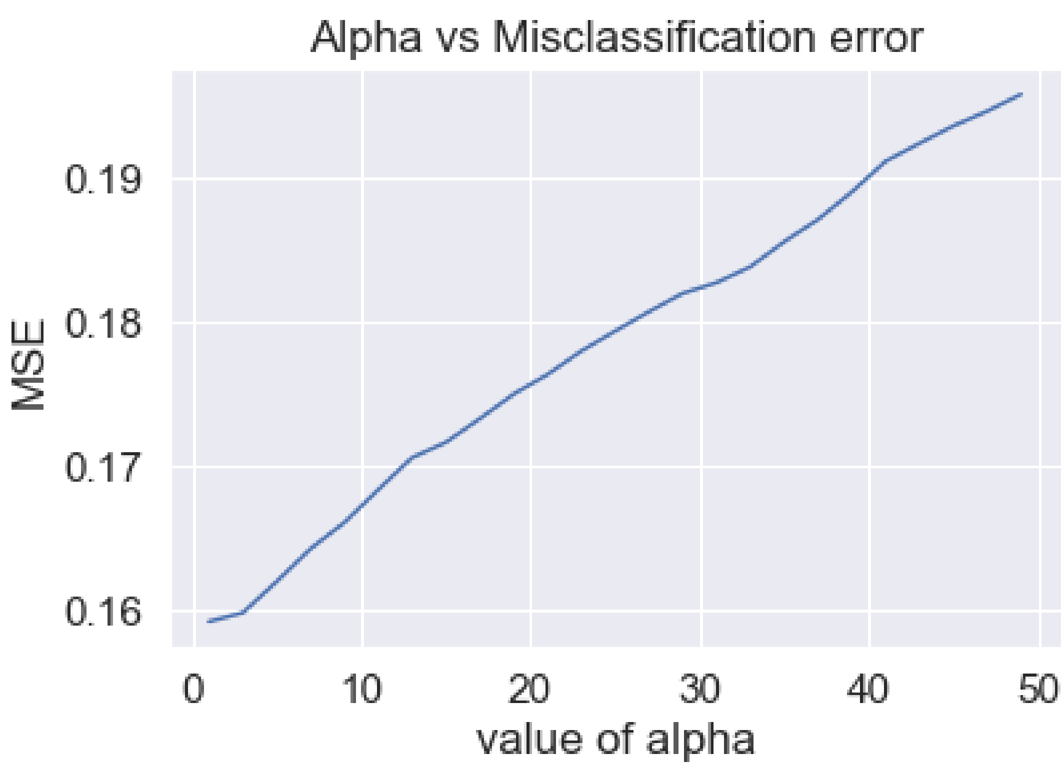
In [105]:
```
X_train=final_tfidf_vect
X_test=final_test_tfidf_vect
```

13 To find the best alpha using cross validation

In [86]:
```
bNB=BernoulliNB()
alpha_list = list(range(1,50,2))
cv_score = []
for i in alpha_list:
    bNB = BernoulliNB(alpha=i)
    scores = cross_val_score(bNB, X_train, Y_train, cv=10, scoring="accuracy")
    cv_score.append(scores.mean())

MSE = [1-x for x in cv_score]
optimal_alpha = alpha_list[MSE.index(min(MSE))]
print("Optimal alpha: ",optimal_alpha)

import matplotlib.pyplot as plt
plt.plot(alpha_list, MSE)
plt.title("Alpha vs Misclassification error")
plt.xlabel("value of alpha")
plt.ylabel("MSE")
plt.show()
```

```
#l_a={'alpha':[1000,500,100,50,10,5,0.1,0.05,0.001]}
#alpha_set=[1e-3, 1e-2,1e-1, 1e-0, 1e2, 1e3, 1e4]
#for i in alpha_set:
    # instantiate learning model (alpha = 10)
#nB = BernoulliNB()
#cls=GridSearchCV(nB,l_a,cv=10)
    # fitting the model on crossvalidation train
#cls.fit(X_train, Y_train)

    # predict the response on the crossvalidation train
#pred = cls.predict(X_cv)

    # evaluate CV accuracy
#acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
#print("Best HyperParameter: ",cls.best_params_)
#print("Best Accuracy: %.2f%%"%(cls.best_score_*100))
#test accuracy
#nB = BernoulliNB(alpha=1000)
#nB.fit(X_train,Y_train)
#pred = nB.predict(X_test)
#acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
#print('\n****Test accuracy for alpha = 1000 is %d%%' % (acc))
```

```
Optimal alpha:  1
```



```
In [87]: nB_opt=BernoulliNB(alpha=optimal_alpha)
         #fit the model
         nB_opt.fit(X_train,Y_train)
         #predict the model
         prediction=nB_opt.predict(X_test)

         #the accuracy score
         acc_score=accuracy_score(Y_test,prediction)* 100
         print('\n the accuracy score for TfIDf model with optimal a=%d is %f%%' %(optimal_alpl

         print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0]

         training_accuracy = nB_opt.score(X_train, Y_train)
         training_error = 1 - training_accuracy
         test_accuracy = accuracy_score(Y_test, prediction)
         test_error = 1 - test_accuracy

         print("training error:%.2f%%" %training_error)
         print('#'*100)
         print("training accuracy:%.2f%%" %training_accuracy)
         print('#'*100)
         print("test error:%.2f%%" %test_error)
         print('#'*100)
         print("test accuracy:%.2f%%" %test_accuracy)
```

```
 the accuracy score for TfIDf model with optimal a=1 is 83.908333%
Number of mislabeled points out of a total 28000 points : 1931
training error:0.12%
###############################################################################################
training accuracy:0.88%
###############################################################################################
test error:0.16%
###############################################################################################
test accuracy:0.84%
```

14 Feature importance

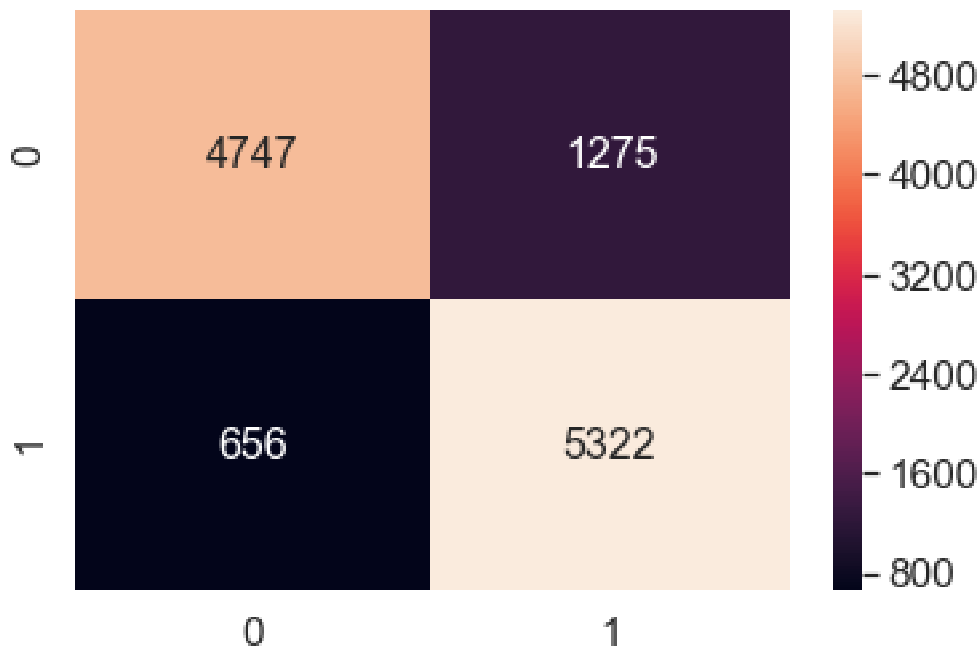
```
In [88]: feat_name=np.array(tf_idf_vect.get_feature_names())
         f_cnt=nB_opt.feature_count_
         log_prob = nB_opt.feature_log_prob_
         feature_prob = pd.DataFrame(log_prob, columns=feat_name).T
         #sorted_idx=nB_opt.coef_[0].argsort()
         #print("smallest coeffecient is: \n {} \n".format(feat_name[sorted_idx[:10]]))
```

```python
#print("largest coefficient is: \n {} \n".format(feat_name[sorted_idx[:-11:-1]]))
top_positive = feature_prob[1].sort_values(ascending=False)[:10]
top_negative = feature_prob[0].sort_values(ascending=False)[:10]

def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")
    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(tf_idf_vect,nB_opt)
```

```
                  Positive                                              Negative
-----------------------------------------------------------------------------------------------
        -9.5485         aaaaaaarrrrrggghhh                                 -1.1621        like
        -9.5485         aachen                                          -1.1955         tast
        -9.5485         aafco                                           -1.2681         good
        -9.5485         aarrgh                                          -1.2734         love
        -9.5485         aback                                           -1.3148         great
        -9.5485         abat                                            -1.4523         flavor
        -9.5485         abbey                                           -1.4593         one
        -9.5485         abdomen                                         -1.4817         use
        -9.5485         abdomin                                         -1.5292         tri
        -9.5485         aberr                                           -1.5468         product
        -9.5485         abhor                                           -1.6681         make
        -9.5485         abhorr                                          -1.7031         get
        -9.5485         ablet                                           -1.8908         buy
        -9.5485         abod                                            -1.9234         time
        -9.5485         abolut                                          -1.9308         would
        -9.5485         abomin                                          -1.9786         realli
        -9.5485         abosolut                                        -2.0016         price
        -9.5485         abottl                                          -2.0079         much
        -9.5485         abouit                                          -2.0186         best
        -9.5485         aboutbut                                        -2.0202         find
        -9.5485         abrupt                                          -2.0337         also
        -9.5485         absinth                                         -2.0463         eat
        -9.5485         absolutelt                                      -2.0608         dont
        -9.5485         absoprt                                         -2.0880         littl
        -9.5485         absorbedconsid                                  -2.0950         amazon
```

In [89]:
```python
conf_matr_df = pd.DataFrame(confusion_matrix(Y_test, prediction), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(conf_matr_df, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[89]: <matplotlib.axes._subplots.AxesSubplot at 0x6838f588>




```
In [90]: from sklearn.metrics import classification_report
         print(classification_report(Y_test,prediction))
```

```
             precision    recall  f1-score   support

   Negative       0.88      0.79      0.83      6022
   Positive       0.81      0.89      0.85      5978

avg / total       0.84      0.84      0.84     12000
```

15 GridSearch CV feature selection

```
In [106]: nB = BernoulliNB()
          param_grid = {'alpha':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0
          gsv=GridSearchCV(nB,param_grid,cv=3,verbose=1)
          gsv.fit(X_train,Y_train)
          print("Best HyperParameter: ",gsv.best_params_)
          print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 3 folds for each of 15 candidates, totalling 45 fits


[Parallel(n_jobs=1)]: Done  45 out of  45 | elapsed:   10.6s finished
```

```
Best HyperParameter:  {'alpha': 1}
Best Accuracy: 84.49%
```

In [107]:
```
nB_opt=BernoulliNB(alpha=1)
#fit the model
nB_opt.fit(X_train,Y_train)
#predict the model
prediction=nB_opt.predict(X_test)

#the accuracy score
acc_score=accuracy_score(Y_test,prediction)* 100
print('\n the accuracy score for TfIDf model with optimal a=%d is %f%%' %(optimal_al

print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0

training_accuracy = nB_opt.score(X_train, Y_train)
training_error = 1 - training_accuracy
test_accuracy = accuracy_score(Y_test, prediction)
test_error = 1 - test_accuracy

print("training error:%.2f%%" %training_error)
print('#'*100)
print("training accuracy:%.2f%%" %training_accuracy)
print('#'*100)
print("test error:%.2f%%" %test_error)
print('#'*100)
print("test accuracy:%.2f%%" %test_accuracy)
```

```
 the accuracy score for TfIDf model with optimal a=1 is 84.725000%
Number of mislabeled points out of a total 28000 points : 1833
training error:0.11%
###############################################################################################
training accuracy:0.89%
###############################################################################################
test error:0.15%
###############################################################################################
test accuracy:0.85%
```

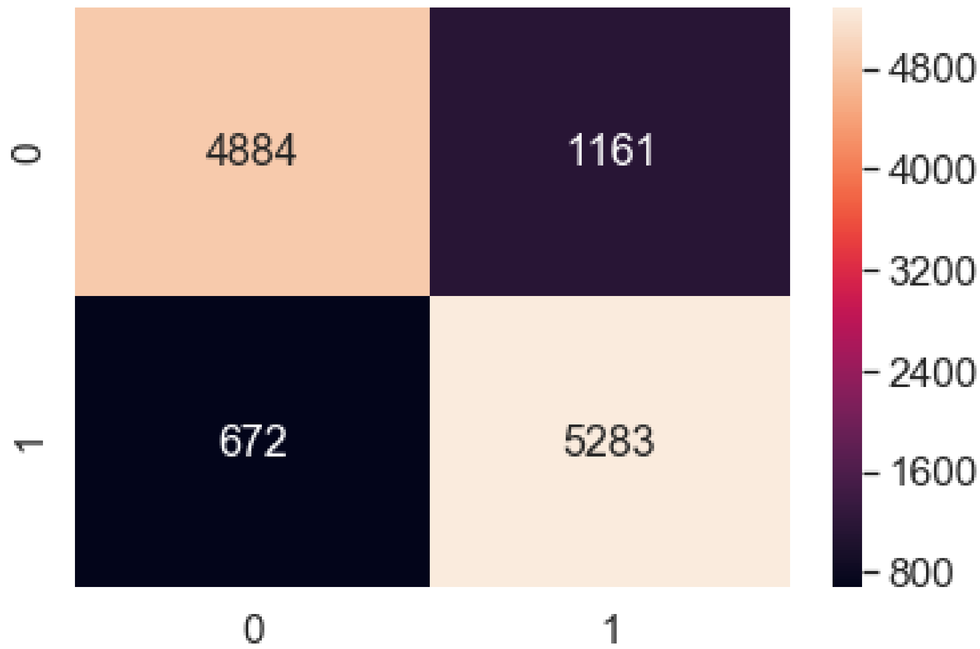
In [108]:
```
feat_name=np.array(tf_idf_vect.get_feature_names())
f_cnt=nB_opt.feature_count_
log_prob = nB_opt.feature_log_prob_
feature_prob = pd.DataFrame(log_prob, columns=feat_name).T
#sorted_idx=nB_opt.coef_[0].argsort()
#print("smallest coeffecient is: \n {} \n".format(feat_name[sorted_idx[:10]]))
#print("largest coefficient is: \n {} \n".format(feat_name[sorted_idx[:-11:-1]]))
```

```
top_positive = feature_prob[1].sort_values(ascending=False)[:10]
top_negative = feature_prob[0].sort_values(ascending=False)[:10]

def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")
    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(tf_idf_vect,nB_opt)
```

```
                        Positive                                                Negative
----------------------------------------------------------------------------------------------
        -9.5502         aachen                                          -1.1692         like
        -9.5502         aafco                                           -1.2078         tast
        -9.5502         aamazoncom                                      -1.2644         love
        -9.5502         aarrgh                                          -1.2684         good
        -9.5502         aauc                                            -1.3127         great
        -9.5502         abat                                            -1.4337         flavor
        -9.5502         abbey                                           -1.4709         one
        -9.5502         abdomen                                         -1.4755         use
        -9.5502         aberr                                           -1.5279         tri
        -9.5502         abhorr                                          -1.5505         product
        -9.5502         abject                                          -1.6785         make
        -9.5502         ablet                                           -1.7189         get
        -9.5502         abolut                                          -1.9019         buy
        -9.5502         abomin                                          -1.9458         would
        -9.5502         abottl                                          -1.9478         time
        -9.5502         abouit                                          -1.9953         best
        -9.5502         aboutbut                                        -1.9958         much
        -9.5502         abrupt                                          -1.9979         realli
        -9.5502         absolutelt                                      -2.0095         price
        -9.5502         absoprt                                         -2.0234         find
        -9.5502         absoulut                                        -2.0343         also
        -9.5502         acaigreen                                       -2.0737         eat
        -9.5502         acceptal                                        -2.0754         dont
        -9.5502         accod                                           -2.0834         amazon
        -9.5502         accountit                                       -2.0879         littl
```

In [109]:
```
conf_matr_df = pd.DataFrame(confusion_matrix(Y_test, prediction), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(conf_matr_df, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[109]: <matplotlib.axes._subplots.AxesSubplot at 0x6c83e940>




```
In [110]: from sklearn.metrics import classification_report
          print(classification_report(Y_test,prediction))
```

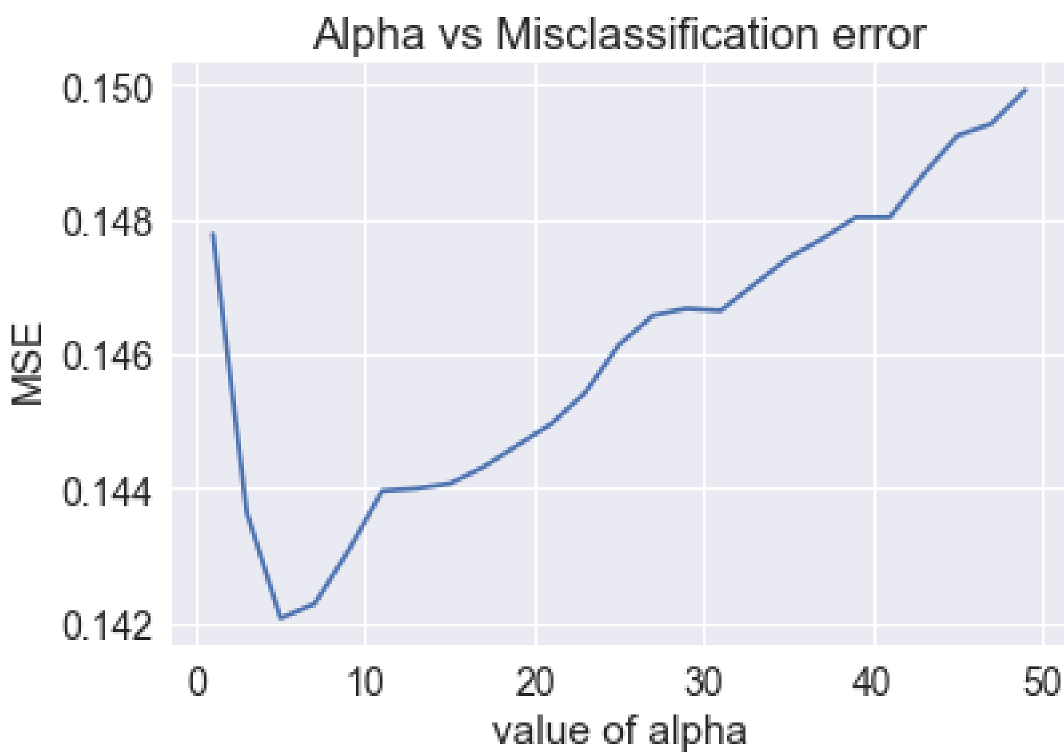
```
             precision    recall  f1-score   support

   Negative       0.88      0.81      0.84      6045
   Positive       0.82      0.89      0.85      5955

avg / total       0.85      0.85      0.85     12000
```

16 Multinomial Naive Bayes

```
In [45]: mNB=MultinomialNB()
         alpha_list = list(range(1,50,2))
         cv_score = []
         for i in alpha_list:
             mNB = MultinomialNB(alpha=i)
             scores = cross_val_score(mNB, X_train, Y_train, cv=10, scoring="accuracy")
             cv_score.append(scores.mean())

         MSE = [1-x for x in cv_score]
         optimal_alpha = alpha_list[MSE.index(min(MSE))]
```

```
print("Optimal alpha: ",optimal_alpha)

import matplotlib.pyplot as plt
plt.plot(alpha_list, MSE)
plt.title("Alpha vs Misclassification error")
plt.xlabel("value of alpha")
plt.ylabel("MSE")
plt.show()
```

```
Optimal alpha:  5
```




```
In [46]: mNB_opt=MultinomialNB(alpha=optimal_alpha)
         #fit the model
         mNB_opt.fit(X_train,Y_train)
         #predict the model
         prediction=mNB_opt.predict(X_test)

         #the accuracy score
         acc_score=accuracy_score(Y_test,prediction)* 100
         print('\n the accuracy score for bag of words model with optimal a=%d is %f%%' % (opt
         print('#'*100)
         print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0]
```

```
print('%'*50)
training_accuracy = mNB_opt.score(X_train, Y_train)
training_error = 1 - training_accuracy
test_accuracy = accuracy_score(Y_test, prediction)
test_error = 1 - test_accuracy

print("training error:%.2f%%" %training_error)
print('#'*100)
print("training accuracy:%.2f%%" %training_accuracy)
print('#'*100)
print("test error:%.2f%%" %test_error)
print('#'*100)
print("test accuracy:%.2f%%" %test_accuracy)
```

```
 the accuracy score for bag of words model with optimal a=5 is 85.608333%
################################################################################################
Number of mislabeled points out of a total 28000 points : 1727
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
training error:0.12%
################################################################################################
training accuracy:0.88%
################################################################################################
test error:0.14%
################################################################################################
test accuracy:0.86%
```

In [47]:
```
feat_name=np.array(tf_idf_vect.get_feature_names())
f_cnt=mNB_opt.feature_count_
log_prob = mNB_opt.feature_log_prob_
feature_prob = pd.DataFrame(log_prob, columns=feat_name).T
#sorted_idx=nB_opt.coef_[0].argsort()
#print("smallest coeffecient is: \n {} \n".format(feat_name[sorted_idx[:10]]))
#print("largest coefficient is: \n {} \n".format(feat_name[sorted_idx[:-11:-1]]))
top_positive = feature_prob[1].sort_values(ascending=False)[:10]
top_negative = feature_prob[0].sort_values(ascending=False)[:10]

def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")
    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(tf_idf_vect,mNB_opt)
```

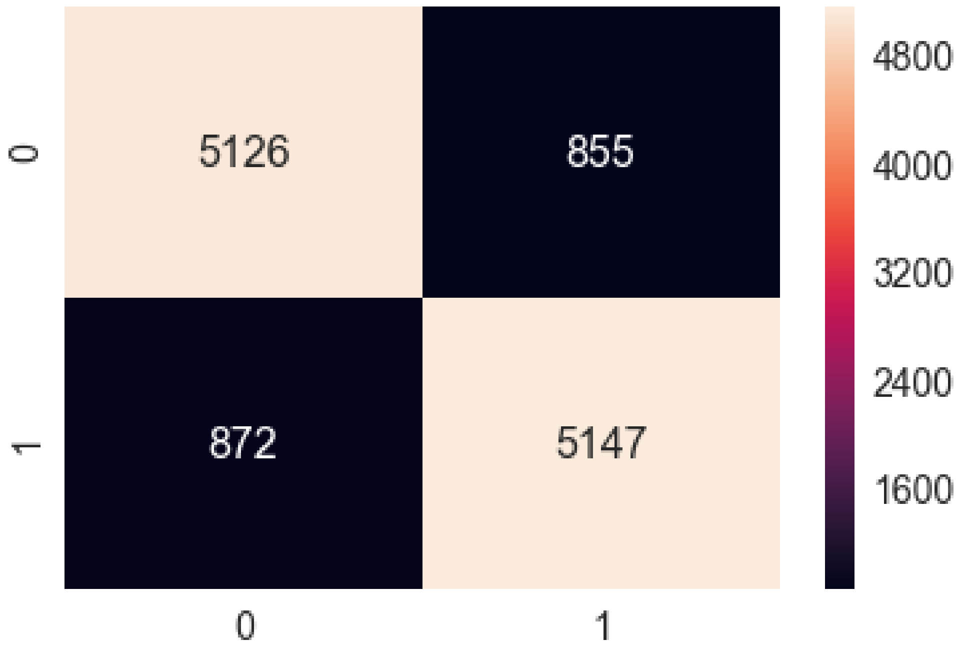
```
                     Positive                                                        Negative
------------------------------------------------------------------------------------------------
       -10.5935        aaaaaaarrrrrggghhh                                     -6.0647        great
       -10.5935        aaaaaahhhhhyaaaaaa                                     -6.1096        love
       -10.5935        aaaahhhhhh                                          -6.2190        good
       -10.5935        aarrgh                                              -6.2721        like
       -10.5935        aasanfoodcom                                        -6.2789        tast
       -10.5935        aauc                                                -6.2986        flavor
       -10.5935        abalon                                              -6.3113        tea
       -10.5935        abbazabba                                           -6.3667        coffe
       -10.5935        abbott                                              -6.3686        use
       -10.5935        abbrevi                                             -6.4578        product
       -10.5935        abdomen                                             -6.5235        one
       -10.5935        abhor                                               -6.6260        tri
       -10.5935        abhorr                                              -6.6290        make
       -10.5935        abiet                                               -6.6754        best
       -10.5935        abit                                                -6.7045        get
       -10.5935        abject                                              -6.7468        price
       -10.5935        aboutbut                                            -6.7847        find
       -10.5935        abov                                                -6.7914        food
       -10.5935        absolutelt                                          -6.7938        time
       -10.5935        absolutley                                          -6.8087        buy
       -10.5935        absorbt                                             -6.8357        realli
       -10.5935        abut                                                -6.8670        store
       -10.5935        abysm                                               -6.8711        eat
       -10.5935        abysmali                                            -6.8761        order
       -10.5935        acaigreen                                           -6.9104        dog
```

In [48]:

```python
conf_matr_df = pd.DataFrame(confusion_matrix(Y_test, prediction), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(conf_matr_df, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x44e223c8>
```




```
In [49]: from sklearn.metrics import classification_report
         print(classification_report(Y_test,prediction))

             precision    recall  f1-score   support

   Negative       0.85      0.86      0.86      5981
   Positive       0.86      0.86      0.86      6019

avg / total       0.86      0.86      0.86     12000
```

Observation:
with alpha being 1 for BernoulliNB we get precision and recall at 85# Word2Vec

```
In [17]: import gensim
         from gensim.models import word2vec,KeyedVectors

D:\Anaconda\lib\site-packages\gensim\utils.py:1209: UserWarning: detected Windows; aliasing chu
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")

In [40]: X=final_d["Text"]
         X.shape

Out[40]: (40000,)
```

In [41]:
```
y=final_d["Score"]
y.shape
```

Out[41]: (40000,)

In [42]:
```
X_train,X_test,Y_train,Y_test=cross_validation.train_test_split(X,y,test_size=0.30,ra
#split train into cross val train and cross val test
X_t,X_cv,Y_t,Y_cv=cross_validation.train_test_split(X_train,Y_train,test_size=0.3)
```

In [23]:
```
print(X_train.shape,X_test.shape,Y_train.shape,Y_test.shape)
```

```
(28000,) (12000,) (28000,) (12000,)
```

In [43]:
```
i=0
list_of_sentence=[]
for sent in X_train.values:
    filtered_sentence=[]
    list_of_sentence.append(sent.split())
    #sent=cleanhtml(sent)
    #for w in sent.split():
      #   for cleaned in cleanpunc(w).split():
      #      if(cleaned.isalpha()):
       #         filtered_sentence.append(cleaned.lower())
        #    else:
         #       continue
#list_of_sentence.append(filtered_sentence)
#print(X["CleanedText"].values[0])
#print('##########')
#print(list_of_sentence[0])
w2v_model=gensim.models.Word2Vec(list_of_sentence,min_count=5,size=50,workers=4)

words=list(w2v_model.wv.vocab)
print(len(words))
```

```
19582
```

In [25]:
```
w2v_model.wv.most_similar('like')
```

```
D:\Anaconda\lib\site-packages\gensim\matutils.py:737: FutureWarning: Conversion of the second
  if np.issubdtype(vec.dtype, np.int):
```

Out[25]:
```
[('like,', 0.6465601325035095),
 ('like.', 0.5829551219940186),
 ('prefer', 0.567816972732544),
 ('notice', 0.5240753889083862),
 ('great,', 0.5214934349060059),
```

```
 ('mind', 0.5159530639648438),
 ('think', 0.5159229636192322),
 ('okay', 0.5143426656723022),
 ('expect', 0.5121126174926758),
 ('care', 0.5057751536369324)]
```

```
In [44]: #word2vec for test
         i=0
         list_of_sentences=[]
         for sent in X_test.values:
             filtered_sentences=[]
             list_of_sentences.append(sent.split())
             #sent=cleanhtml(sent)
             #for w in sent.split():
              #   for cleaned in cleanpunc(w).split():
               #      if(cleaned.isalpha()):
                #         filtered_sentence.append(cleaned.lower())
                 #    else:
                  #       continue
         #list_of_sentences.append(filtered_sentence)
         #print(X_train.values[0])
         #print('##########')
         print(list_of_sentences[0])
         w2v_model_test=gensim.models.Word2Vec(list_of_sentences,min_count=5,size=50,workers=4)

         words_test=list(w2v_model_test.wv.vocab)
         print(len(words_test))
```

```
["I'm", 'just', 'going', 'to', 'say', 'it:', 'These', 'CHIPS', 'Taste', 'like', 'DETERGENT.<br
11071
```

```
In [45]: from tqdm import tqdm
```

```
In [505]: import re


          def cleanhtml(sentence):
              cleantext = re.sub('<.*>', '', sentence)
              return cleantext


          def cleanpunc(sentence):
              cleaned = re.sub(r'[?|!|\'|#|@|.|,|)|(|\|/]', r'', sentence)
              return cleaned
```

```
In [509]: print(train_w2v_words.shape, test_w2v_words.shape)
```

```
(2408, 50) (1534, 50)
```

17 Avg-Word2Vec

```
In [46]: sent_vectors = []
         for sent in tqdm(list_of_sentence): # 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
                 try:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
                 except:
                     pass

             if cnt_words != 0:
                 sent_vec /= cnt_words
             sent_vectors.append(sent_vec)
         print(len(sent_vectors))
         print(len(sent_vectors[0]))


         train_vectors=np.nan_to_num(sent_vectors)
```

```
100%|| 28000/28000 [00:09<00:00, 2987.14it/s]


28000
50
```

```
In [47]: test_vectors = []
         for sent in tqdm(list_of_sentences):
             sent_vec = np.zeros(50)
             cnt_words = 0
             for word in sent:
                 try:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
                 except:
                     pass
             sent_vec /= cnt_words
             test_vectors.append(sent_vec)
         test_vectors = np.nan_to_num(test_vectors)
```

```
100%|| 12000/12000 [00:03<00:00, 3021.25it/s]
```

```
In [111]: X_train=train_vectors
          X_test=test_vectors
```

In [112]: X_train.shape

Out[112]: (28000, 50)

In [113]: Y_train.shape

Out[113]: (28000,)

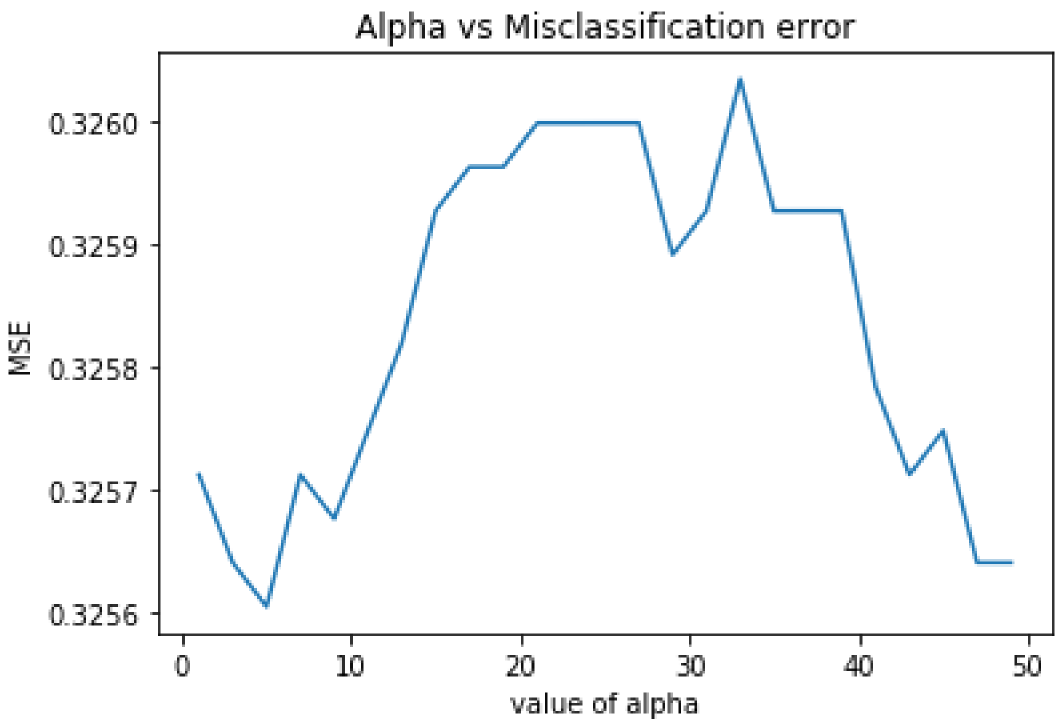
In [303]: #model=word2vec.Word2Vec.load('w2vmodel')

18 alpha value using old-cross validation approach

In [33]:
```
bNB=BernoulliNB()
alpha_list = list(range(1,50,2))
cv_score = []
for i in alpha_list:
    bNB = BernoulliNB(alpha=i)
    scores = cross_val_score(bNB, X_train, Y_train, cv=10, scoring="accuracy")
    cv_score.append(scores.mean())

MSE = [1-x for x in cv_score]
optimal_alpha = alpha_list[MSE.index(min(MSE))]
print("Optimal alpha: ",optimal_alpha)

import matplotlib.pyplot as plt
plt.plot(alpha_list, MSE)
plt.title("Alpha vs Misclassification error")
plt.xlabel("value of alpha")
plt.ylabel("MSE")
plt.show()









#l_a={'alpha':[1000,500,100,50,10,5,0.1,0.05,0.001]}
#alpha_set=[1e-3, 1e-2,1e-1, 1e-0, 1e2, 1e3, 1e4]
#for i in alpha_set:
    # instantiate learning model (alpha = 10)
#nB = BernoulliNB()
#cls=GridSearchCV(nB,l_a,cv=10)
    # fitting the model on crossvalidation train
#cls.fit(X_train, Y_train)

    # predict the response on the crossvalidation train
```

```
#pred = cls.predict(X_cv)

    # evaluate CV accuracy
#acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
#print("Best HyperParameter: ",cls.best_params_)
#print("Best Accuracy: %.2f%%"%(cls.best_score_*100))
#test accuracy
#nB = BernoulliNB(alpha=1000)
#nB.fit(X_train,Y_train)
#pred = nB.predict(X_test)
#acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
#print('\n****Test accuracy for alpha = 1000 is %d%%' % (acc))
```

```
Optimal alpha:  5
```



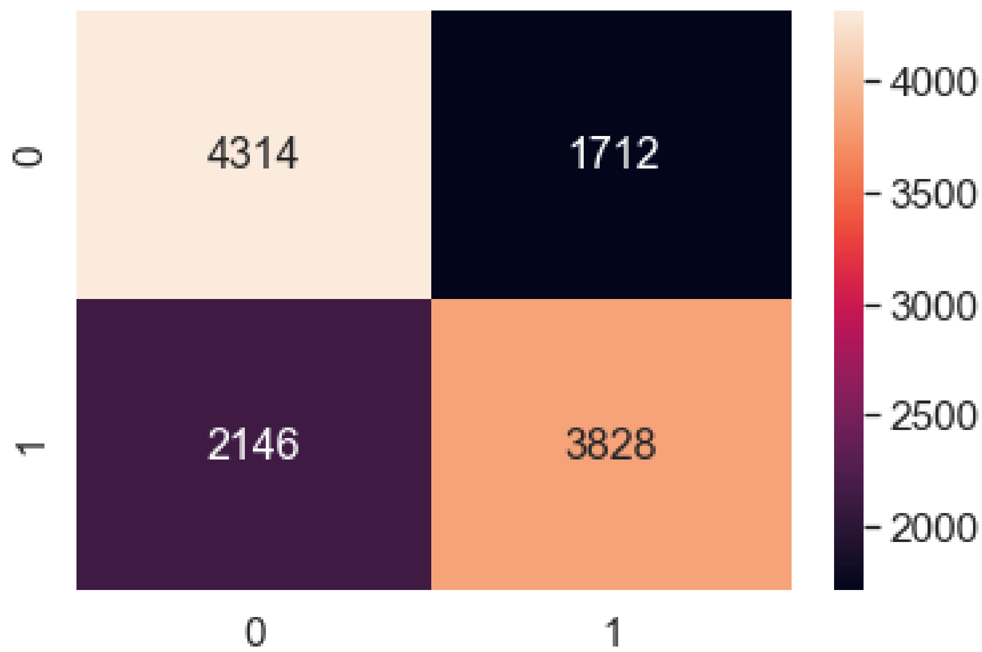
In [34]:
```
nB_opt=BernoulliNB(alpha=optimal_alpha)
#fit the model
nB_opt.fit(X_train,Y_train)
#predict the model
prediction=nB_opt.predict(X_test)

#the accuracy score
acc_score=accuracy_score(Y_test,prediction)* 100
```

```
print('\n the accuracy score for bag of words model with optimal a=%d is %f%%' %(opti

print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0]

training_accuracy = nB_opt.score(X_train, Y_train)
training_error = 1 - training_accuracy
test_accuracy = accuracy_score(Y_test, prediction)
test_error = 1 - test_accuracy

print("training error:%.2f%%" %training_error)
print('#'*100)
print("training accuracy:%.2f%%" %training_accuracy)
print('#'*100)
print("test error:%.2f%%" %test_error)
print('#'*100)
print("test accuracy:%.2f%%" %test_accuracy)
```

```
 the accuracy score for bag of words model with optimal a=5 is 67.850000%
Number of mislabeled points out of a total 28000 points : 3858
training error:0.33%
################################################################################################
training accuracy:0.67%
################################################################################################
test error:0.32%
################################################################################################
test accuracy:0.68%
```

In [36]:
```
conf_matr_df = pd.DataFrame(confusion_matrix(Y_test, prediction), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(conf_matr_df, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[36]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x63e676d8>
```



19 Grid Search CV feature selection

```
In [114]: nB = BernoulliNB()
          param_grid = {'alpha':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0
          gsv=GridSearchCV(nB,param_grid,cv=3,verbose=1)
          gsv.fit(X_train,Y_train)
          print("Best HyperParameter: ",gsv.best_params_)
          print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Fitting 3 folds for each of 15 candidates, totalling 45 fits


[Parallel(n_jobs=1)]: Done  45 out of  45 | elapsed:   14.0s finished


Best HyperParameter:  {'alpha': 1000}
Best Accuracy: 50.15%
```

```
In [115]: nB_opt=BernoulliNB(alpha=1000)
          #fit the model
          nB_opt.fit(X_train,Y_train)
          #predict the model
          prediction=nB_opt.predict(X_test)
```

```
        #the accuracy score
        acc_score=accuracy_score(Y_test,prediction)* 100
        print('\n the accuracy score for bag of words model with optimal a=%d is %f%%' %(opt

        print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0

        training_accuracy = nB_opt.score(X_train, Y_train)
        training_error = 1 - training_accuracy
        test_accuracy = accuracy_score(Y_test, prediction)
        test_error = 1 - test_accuracy

        print("training error:%.2f%%" %training_error)
        print('#'*100)
        print("training accuracy:%.2f%%" %training_accuracy)
        print('#'*100)
        print("test error:%.2f%%" %test_error)
        print('#'*100)
        print("test accuracy:%.2f%%" %test_accuracy)
```

```
 the accuracy score for bag of words model with optimal a=1 is 49.283333%
Number of mislabeled points out of a total 28000 points : 6086
training error:0.49%
#############################################################################################
training accuracy:0.51%
#############################################################################################
test error:0.51%
#############################################################################################
test accuracy:0.49%
```

20 Weighted Tf-IDf Word2Vec

```
In [55]: model = TfidfVectorizer()
         tf_idf_matrix = model.fit_transform(final_d['CleanedText'].values)
         # we are converting a dictionary with word as a key, and the idf as a value
         dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))

In [56]: X=final_d["CleanedText"]
         X.shape

Out[56]: (40000,)

In [57]: y=final_d["Score"]
         y.shape

Out[57]: (40000,)
```

```
In [59]: X_train,X_test,Y_train,Y_test=cross_validation.train_test_split(X,y,test_size=0.30,ra
         #split train into cross val train and cross val test
         X_t,X_cv,Y_t,Y_cv=cross_validation.train_test_split(X_train,Y_train,test_size=0.3,rand
```

```
In [60]: print(X_train.shape,X_test.shape,Y_train.shape,Y_test.shape)
```

```
(28000,) (12000,) (28000,) (12000,)
```

```
In [61]: tfidf_vect = TfidfVectorizer()
         train_tfidf_w2v = tfidf_vect.fit_transform(X_train)
         test_tfidf_w2v = model.transform(X_test)
```

```
In [62]: print(train_tfidf_w2v.shape,test_tfidf_w2v.shape)
```

```
(28000, 26916) (12000, 32822)
```

```
In [63]: tfidf_feat = model.get_feature_names() # tfidf words/col-names
         # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

         tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this l
         row=0;
         for sent in tqdm(list_of_sentence): # 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]
         #            tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                     # to reduce the computation we are
                     # dictionary[word] = idf value of word in whole courpus
                     # sent.count(word) = tf valeus of word in this review
                     tf_idf = dictionary[word]*sent.count(word)
                     sent_vec += (vec * tf_idf)
                     weight_sum += tf_idf
                 except:
                     pass

             if weight_sum != 0:
                 sent_vec /= weight_sum
             tfidf_sent_vectors.append(sent_vec)
             row += 1
```

```
100%|| 28000/28000 [00:11<00:00, 2402.95it/s]
```

```
In [64]: tfidf_feat = model.get_feature_names() # tfidf words/col-names
         # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
```

```
tfidf_sent_vectors_test = []; # the tfidf-w2v for each sentence/review is stored in th
row=0;
for sent in tqdm(list_of_sentences): # 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]
            tf_idf = dictionary[word]*sent.count(word)
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass

#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review

    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

```
100%|| 12000/12000 [00:04<00:00, 2474.46it/s]
```

In [65]:
```
X_train=np.array(tfidf_sent_vectors)
X_test=np.array(tfidf_sent_vectors_test)
```

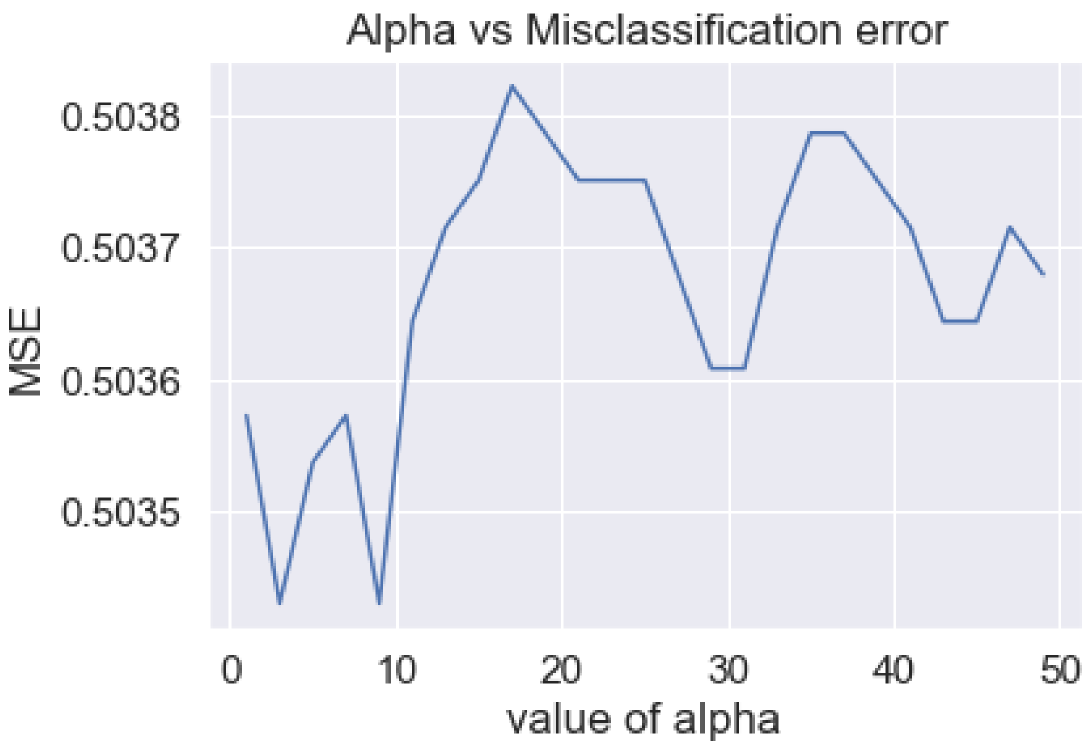
21 alpha value using GridSearch Cross-validation

In [67]:
```
bNB=BernoulliNB()
alpha_list = list(range(1,50,2))
cv_score = []
for i in alpha_list:
    bNB = BernoulliNB(alpha=i)
    scores = cross_val_score(bNB, X_train, Y_train, cv=10, scoring="accuracy")
    cv_score.append(scores.mean())

MSE = [1-x for x in cv_score]
optimal_alpha = alpha_list[MSE.index(min(MSE))]
print("Optimal alpha: ",optimal_alpha)
#l_a={'alpha':[1000,500,100,50,10,5,0.1,0.05,0.001]}
#alpha_set=[1e-3, 1e-2,1e-1, 1e-0, 1e2, 1e3, 1e4]
#for i in alpha_set:
    # instantiate learning model (alpha = 10)
```

```
#nB = BernoulliNB()
#cls=GridSearchCV(nB,l_a,cv=10)
    # fitting the model on crossvalidation train
#cls.fit(X_train, Y_train)

    # predict the response on the crossvalidation train
#pred = cls.predict(X_cv)

    # evaluate CV accuracy
#acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
#print("Best HyperParameter: ",cls.best_params_)
#print("Best Accuracy: %.2f%%"%(cls.best_score_*100))
#test accuracy
#nB = BernoulliNB(alpha=1)
#nB.fit(X_train,Y_train)
#pred = nB.predict(X_test)
#acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
#print('\n****Test accuracy for alpha = 1000 is %d%%' % (acc))
```

```
Optimal alpha:  3
```

In [69]:
```
import matplotlib.pyplot as plt
plt.plot(alpha_list, MSE)
plt.title("Alpha vs Misclassification error")
plt.xlabel("value of alpha")
plt.ylabel("MSE")
plt.show()
```



In [68]:
```
nB_opt=BernoulliNB(alpha=optimal_alpha)
#fit the model
nB_opt.fit(X_train,Y_train)
#predict the model
prediction=nB_opt.predict(X_test)

#the accuracy score
acc_score=accuracy_score(Y_test,prediction)* 100
print('\n the accuracy score for bag of words model with optimal a=%d is %f%%' %(opti

print("Number of mislabeled points out of a total %d points : %d" % (X_train.shape[0]


training_accuracy = nB_opt.score(X_train, Y_train)
training_error = 1 - training_accuracy
test_accuracy = accuracy_score(Y_test, prediction)
test_error = 1 - test_accuracy

print("training error:%.2f%%" %training_error)
print('#'*100)
print("training accuracy:%.2f%%" %training_accuracy)
print('#'*100)
print("test error:%.2f%%" %test_error)
```

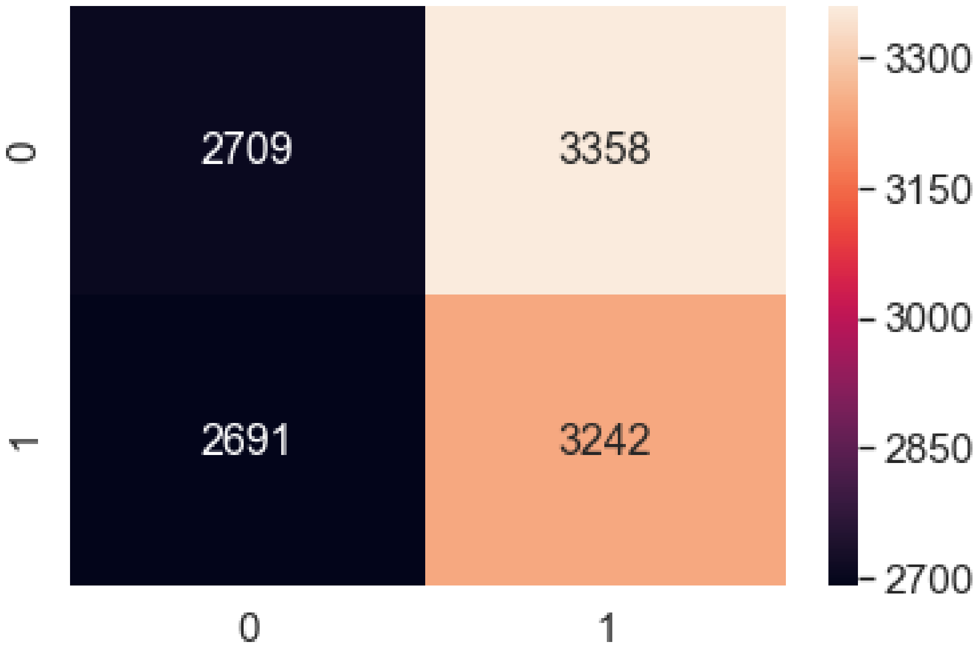
```
print('#'*100)
print("test accuracy:%.2f%%" %test_accuracy)
```

```
 the accuracy score for bag of words model with optimal a=3 is 49.591667%
Number of mislabeled points out of a total 28000 points : 6049
training error:0.49%
####################################################################################################
training accuracy:0.51%
####################################################################################################
test error:0.50%
####################################################################################################
test accuracy:0.50%
```

22 Confusion matrix

In [72]:
```
conf_matr_df = pd.DataFrame(confusion_matrix(Y_test, prediction), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(conf_matr_df, annot=True,annot_kws={"size": 16}, fmt='g')

print("----------------------------------------------------------------------------------

from sklearn.metrics import classification_report
print(classification_report(Y_test,prediction))
```

```
----------------------------------------------------------------------------------------------------
             precision    recall  f1-score   support

   Negative       0.50      0.45      0.47      6067
   Positive       0.49      0.55      0.52      5933

avg / total       0.50      0.50      0.49     12000
```



23 Observations & Conclusions

1) We get a 83-85% accurate model with BoW and Tf-Idf with GridSearch CV used for feature selection(with precision and recall at 85%/83%). while for AvgWord2Vec and WeightedTfIdf Word2Vec model,the acuracy level is low compared to BoW and Tf-Idf