27.17.Amazon_food_review_logistic_regression_v1.0

June 30, 2018

1 Amazon food review dataset apply Logistic regression

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

2 Objective

1. Try predicting review using SVM grid and random search gamma and c
2. Get lambda 1 2(L1 and L2) using grid search and random search CV
3. For L1 regularization try increasing lambda and see error. Get non zero element in w
4. Get features importance check for multicolinearity by adding small value
5. Plot accuracy and hyperparameter

3 Import data and libraries

```
In [12]: from sklearn.manifold import TSNE
         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
         from nltk.stem.porter import PorterStemmer
         from sklearn.cross_validation import train_test_split,KFold
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.metrics import accuracy_score
         from sklearn.cross_validation import cross_val_score
         from collections import Counter
         from sklearn.metrics import accuracy_score
         from sklearn import cross_validation
```

```
from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression

con = sqlite3.connect('database.sqlite')

#get only +ve and -ve review
raw_data = pd.read_sql_query("""SELECT * FROM Reviews WHERE Score != 3""", con)
```

4 Data preprocessing

```
In [13]: filtered_data=raw_data
         # Score>3 a positive rating, and score<3 a negative rating.
         def partition(x):
             if x < 3:
                 return 'negative'
             return 'positive'

         #changing reviews with score less than 3 to be positive and vice-versa
         actualScore = filtered_data['Score']
         positiveNegative = actualScore.map(partition)
         filtered_data['Score'] = positiveNegative

         filtered_data.sample(5)
         filtered_data['Score'].value_counts()

         #Sorting data according to ProductId in ascending order
         sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fal

         #Deduplication of entries for same profilename,userid, time, text and take first elem
         sorted_data=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}
```

```
In [14]: #take only 50000 data
         print('total data \n',sorted_data['Score'].value_counts())
         #clean_data=sorted_data.sample(frac=1).groupby('Score').head(10000)
         #take stratified sampling i.e. positive and negative reviews are proportionate to raw
         _ , clean_data = train_test_split(sorted_data, test_size = 30000, random_state=0,stra
         clean_data['Score'].value_counts()
```

```
total data
 positive    307063
negative     57110
Name: Score, dtype: int64
```

```
Out[14]: positive    25295
         negative     4705
         Name: Score, dtype: int64
```

In [15]:
```
# Clean html tag and punctuation
import re
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

#substitute html tag and punctuation
def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special ch
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
#print(sno.stem('tasty'))

i=0
str1=' '
mystop={'of','four','one','would'}
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
#Create new catagory as Cleanedtext after removing htmltag and punctuation and upperc
for sent in clean_data['Text'].values:
    #change later
    #sent=sent[:20]
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if((cleaned_words.lower() not in stop) & (cleaned_words.lower() not i
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (clean_data['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to descr
                    if(clean_data['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to descr
                else:
                    continue
            else:
```

```
                continue
        str1 = b" ".join(filtered_sentence) #final string of cleaned words

        final_string.append(str1)
        i+=1

clean_data['CleanedText']=final_string
print(clean_data.shape)
#Sort data on timestamp
clean_data=clean_data.sort_values(by=['Time'],ascending=False)
#clean_data
clean_data['CleanedText'].sample(2)
```

```
(30000, 11)
```

```
Out[15]: 167691    b'realli happi tea ran tea purchas europ felt ...
         239691    b'love bake mix famili love thank pamela muell...
         Name: CleanedText, dtype: object
```

5 Split train and test

```
In [16]: x=clean_data['CleanedText'].values
         y = clean_data['Score']
         n=x.shape[0]
         n1=int(n*.3)
         X_test_raw = x[0:n1]
         X_train_raw= x[n1:n+1]
         y_test=y[0:n1]
         y_train=y[n1:n+1]
         print('size of X_train, X_test, y_train , y_test ',X_train_raw.shape, X_test_raw.shap
         print("positive and negative review in train and test\n",y_train.value_counts(),"\n",y
```

```
size of X_train, X_test, y_train , y_test  (21000,) (9000,) (21000,) (9000,)
positive and negative review in train and test
 positive    17832
negative     3168
Name: Score, dtype: int64
 positive    7463
negative    1537
Name: Score, dtype: int64
```

6 Create BOW and try grid search for logistic regreession with penalty l1 and l2

```
In [17]: #now convert CleanedText to TDM
         count_vect = CountVectorizer() #in scikit-learn
```

```
X_train = count_vect.fit_transform(X_train_raw)

#use the same vectors to convert test data
X_test=count_vect.transform(X_test_raw)
print(X_train.get_shape(),X_test.get_shape())
```

```
(21000, 18278) (9000, 18278)
```

In [18]:
```
from sklearn.preprocessing import StandardScaler

#Use scale of train and apply to test
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler(with_mean=False).fit(X_train)
X_train = scaler.transform(X_train)
X_test  = scaler.transform(X_test)

from sklearn.preprocessing import label_binarize

encoded_column_vector = label_binarize(y_train, classes=['negative','positive']) # ne
encoded_labels = np.ravel(encoded_column_vector) # Reshape array
y_train=encoded_labels

encoded_column_vector = label_binarize(y_test, classes=['negative','positive']) # neg
encoded_labels = np.ravel(encoded_column_vector) # Reshape array
y_test=encoded_labels


print('size of X_train, X_test, y_train , y_test ',X_train.shape, X_test.shape,y_trai
#print("positive and negative review in train and test\n",y_train.value_counts(),"\n"
```

```
size of X_train, X_test, y_train , y_test  (21000, 18278) (9000, 18278) (21000,) (9000,)
```

In [19]:
```
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import validation_curve

# Use grid search for L2
C=[10**-3, 10**-2, 10**-1, 1,10]

#param_range=C;

#c1=np.arrange(1, 250, 20)
penalty=['l1', 'l2']

tuned_parameters=dict(penalty=penalty,C=C)

#Using GridSearchCV
```

```
model = GridSearchCV(LogisticRegression(), tuned_parameters, scoring = 'f1', cv=5)
model.fit(X_train, y_train)
print('Best parameters \n',model.best_estimator_)
#print('Model test score', model.score(X_test, y_test))

optimumc=model.best_estimator_.C
optimumpenalty=model.best_estimator_.penalty
print(type(X_train),type(y_train))
```

```
Best parameters
 LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
<class 'scipy.sparse.csr.csr_matrix'> <class 'numpy.ndarray'>
```

In [20]:
```
#build model with best parameter
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
#confusion matrix
pred2 = model.predict(X_test)
mat=pd.crosstab(y_test, pred2, rownames=['Actual'], colnames=['Predicted'], margins=T
print('confusion matrix\n',mat)
aa=pd.DataFrame({'type':['Grid search BOW'],'train_score':[model.score(X_train,y_trai
#print(aa)

# Print coefficients
# check no of parameter
w = model.coef_
print('Count of non zero element in coefficient',np.count_nonzero(w))
print('Model train and test score C and penalty',model.score(X_train,y_train),model.s
#print(model.coef_[0],model.coef_[8])
#print(model.coef_)
#print(model.C,model.penalty)
```

```
confusion matrix
 Predicted    0     1   All
Actual
0          747   790  1537
1          179  7284  7463
All        926  8074  9000
Count of non zero element in coefficient 18278
Model train and test score C and penalty 0.974571428571 0.892333333333 0.001 l2
```

try random search

7 Apply Random search

In [21]:
```
# Random search
from sklearn.model_selection import RandomizedSearchCV
C=[10**-4, 10**-2, 10**0, 10**2, 10**4]
penalty=['l1', 'l2']
tuned_parameters=dict(C=C, penalty=penalty)
#Using random search
model = RandomizedSearchCV(LogisticRegression(), tuned_parameters, random_state=1, sc
model.fit(X_train, y_train)
#print('Model best extimator \n',model.best_estimator_)
#print(model.score(X_test, y_test))
optimumc=model.best_estimator_.C
optimumpenalty=model.best_estimator_.penalty
# create model with the best parameter from random search
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
w = model.coef_
print('Count of non zero element in coefficient',np.count_nonzero(w))
#print('Model test score',model.score(X_test,y_test))
print('Model train and test score C and penalty',model.score(X_train,y_train),model.s
bb=pd.DataFrame({'type':['Random search BOW'],'train_score':[model.score(X_train,y_tr
aa=aa.append(bb)
#confusion matrix
pred2 = model.predict(X_test)
mat=pd.crosstab(y_test, pred2, rownames=['Actual'], colnames=['Predicted'], margins=T
print('confusion matrix\n',mat)
print(aa)
```

```
Count of non zero element in coefficient 18278
Model train and test score C and penalty 0.990857142857 0.885777777778 0.01 l2
confusion matrix
 Predicted     0     1   All
Actual
0           875   662  1537
1           366  7097  7463
All        1241  7759  9000
       C penalty  test_score  train_score               type
0  0.001      l2    0.892333     0.974571    Grid search BOW
0  0.010      l2    0.885778     0.990857  Random search BOW
```

8 Try increasing lambda for L1 and see error and sparcity(non 0 element of w)

In [22]:
```
for i in [.001,.01,.1,1,10,100,1000,10000]:
    model = LogisticRegression(C=i,penalty='l1')
```

```
    model.fit(X_train, y_train)
    w = model.coef_

    print('Count of non zero, total element (l1), coefficient ( C or 1/lambda),train acc
    #print('model score',model.score(X_test,y_test))

#print(w)
```

```
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.001 4 (1, 18278) 0.849142857143 0.829222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.01 888 (1, 18278) 0.909 0.886555555556
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.1 4178 (1, 18278) 0.984714285714 0.895777777778
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1 5115 (1, 18278) 0.998714285714 0.873222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10 5145 (1, 18278) 1.0 0.859111111111
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 100 5674 (1, 18278) 1.0 0.852666666667
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1000 8359 (1, 18278) 1.0 0.833222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10000 10494 (1, 18278) 1.0 0.821
```

So We can see as C decreases i.e. lambda increases more coefficients are getting 0 and test accuracy increases when C too low accuracy decreases again if C is too low # See top features using the weights

```
In [23]: #print(model.coef_[1])
         coefs = np.abs(model.coef_[0])
         indices = np.argsort(coefs)[::-1]
         #print(indices)
         #print(count_vect.get_feature_names())
```

```
In [24]: #create optimum model
         model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
         model.fit(X_train, y_train)


         def most_informative_feature_for_binary_classification(vectorizer, classifier, n=10):
             class_labels = classifier.classes_
             feature_names = vectorizer.get_feature_names()
             topn_class1 = sorted(zip(classifier.coef_[0], feature_names))[:n]
             #negative words are sorted with -ve
             topn_class2 = sorted(zip(classifier.coef_[0], feature_names))[-n:]

             top_pos_fet=[]
```

```
    top_neg_fet=[]
    for coef, feat in topn_class1:
        print (class_labels[0], coef, feat)
        top_pos_fet.append(feat)

    print("\n")

    for coef, feat in reversed(topn_class2):
        print (class_labels[1], coef, feat)
        top_neg_fet.append(feat)

    return top_pos_fet,top_neg_fet

print("Top 10 words for both review 0 negative 1 positive with weights\n")
top_pos_fet,top_neg_fet=most_informative_feature_for_binary_classification(count_vect
```

```
Top 10 words for both review 0 negative 1 positive with weights

0 -0.298581527223 disappoint
0 -0.272111698062 worst
0 -0.224411686657 return
0 -0.203266486941 threw
0 -0.201739922058 aw
0 -0.192431243904 terribl
0 -0.18740445635 unfortun
0 -0.183026389691 wast
0 -0.175135513463 bland
0 -0.167223006745 didnt


1 0.555265011304 love
1 0.552539174726 great
1 0.476073414311 best
1 0.380479651656 delici
1 0.343530048721 good
1 0.306126878833 excel
1 0.294409265085 perfect
1 0.282933263072 favorit
1 0.249492790648 nice
1 0.213313608528 find
```

9 Check multicolinearity with perbutation test by adding small noise to sparse matrix

The noise is with mean 0 and sd=.0001

In [25]:
```
# Check VIF score of the above selected variables
#vif = pd.DataFrame()
#print(x.toarray().shape,x.shape[1])
#vif["VIF Factor"] = [variance_inflation_factor(x.toarray(), i) for i in range(x.shap
#vif["features"] = count_vect.get_feature_names()
#print(vif)
#for i in top_pos_fet:
#  print(vif[(vif[["features"]]==i).values])

#for i in top_neg_fet:
#  print(vif[(vif[["features"]]==i).values])

# creating VIF is giving a lot of inf
```

In [26]:
```
#refer https://medium.com/@dhwajraj/learning-python-regression-analysis-part-9-tests-
# to find colinearity by eigen value
#corr=np.corrcoef(x,rowvar=0)
#W,V=np.linalg.eig(corr)
#If at least one of the eigen values of the correlation matrix is close to zero then

#The eigen values at index 3,4 and 5 are close to zero. There corresponding eigen vec

#in the output produced above, column index 2 and 3 have near zero values in all thre
```

In [27]:
```
from scipy import *
import random
from scipy.sparse import *

#print(X_train)
#print(X_train.data.shape[0])
#X_train.todense()
#print("hi")
#X_train.data+=X_train
#X_train.todense()
X_train.data += np.random.normal(0,.0001,X_train.data.shape[0])
#print(X_train)

# Create model after adding some noise and check weights
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)

print("Top 10 words for both review 0 negative 1 positive with weights\n")
top_pos_fet,top_neg_fet=most_informative_feature_for_binary_classification(count_vect
```

```
Top 10 words for both review 0 negative 1 positive with weights

0 -0.298578263487 disappoint
0 -0.272111605877 worst
```

```
0 -0.22441091346 return
0 -0.203269639429 threw
0 -0.201738894913 aw
0 -0.192427443842 terribl
0 -0.187401989428 unfortun
0 -0.18302463223 wast
0 -0.175133105309 bland
0 -0.167222053226 didnt


1 0.555272463126 love
1 0.552549898008 great
1 0.476072518536 best
1 0.380481253714 delici
1 0.343537267526 good
1 0.306128981766 excel
1 0.29440825798 perfect
1 0.282933667135 favorit
1 0.24949603434 nice
1 0.21331462335 find
```

So we can see after adding noise the weights of top 20 words are almost same as earlier, so multicolinearity doesnot exist

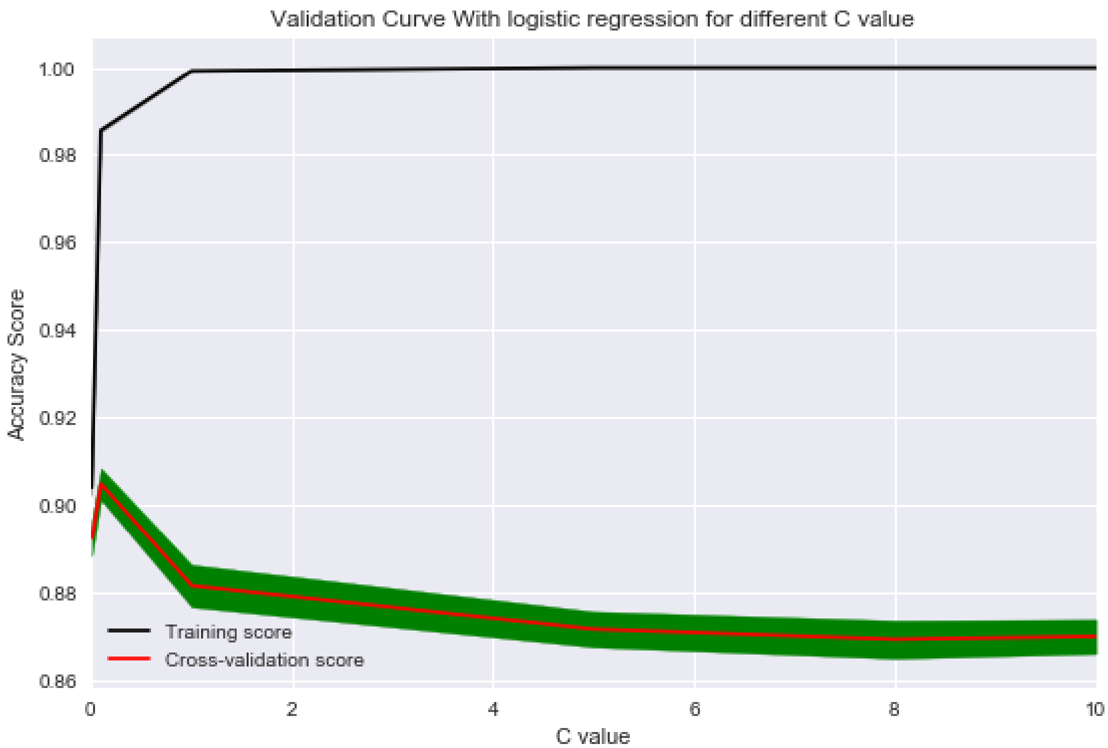
In [ ]:

10 Plot traing and CV error with C and l1 penalty

In [28]:

```
#create plot for training and test validation
# Calculate accuracy on training and test set using range of parameter values
C=[10**-2, 10**-1, 1,5,8,10]
param_range=[10**-2, 10**-1, 1,5,8,10]


train_scores, test_scores = validation_curve(LogisticRegression(penalty='l1'), X_trai

train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)

plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")

#Plot accurancy bands for training and test sets
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean +
```

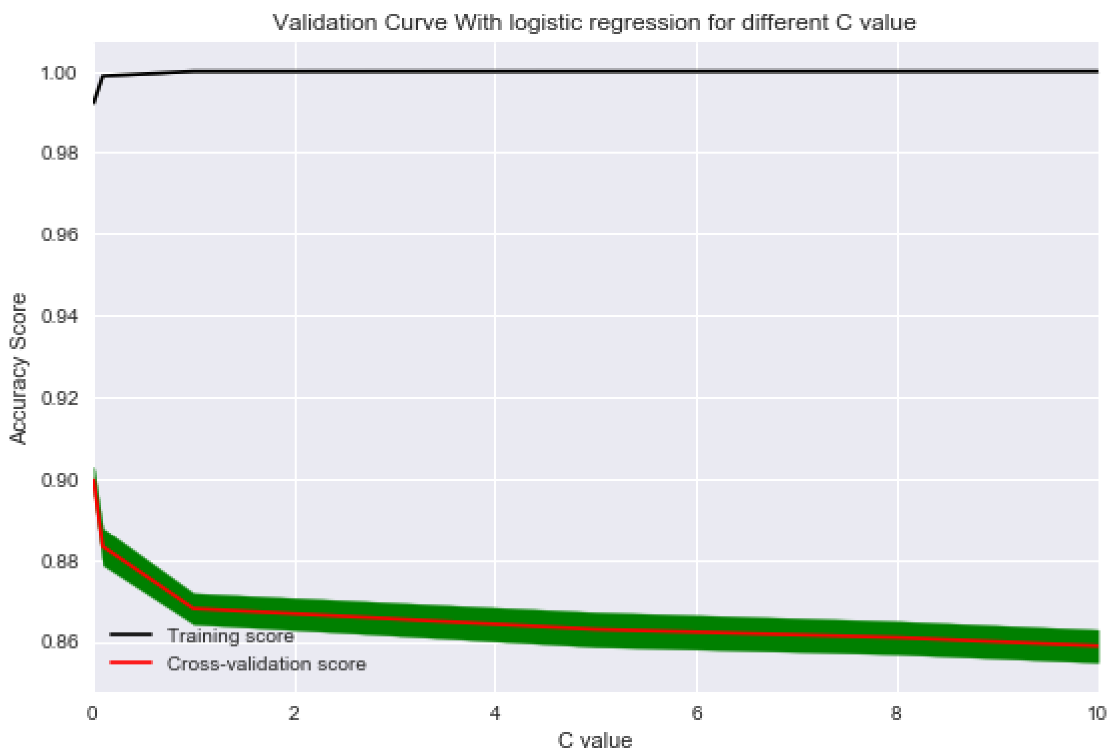
```
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```



11 Plot traing and CV error with C and l2 penalty

```
In [29]: #create plot for training and test validation
         # Calculate accuracy on training and test set using range of parameter values
         C=[10**-2, 10**-1, 1,5,8,10]
         param_range=[10**-2, 10**-1, 1,5,8,10]


         train_scores, test_scores = validation_curve(LogisticRegression(penalty='l2'), X_trai

         train_scores_mean = np.mean(train_scores, axis=1)
         train_scores_std = np.std(train_scores, axis=1)
         test_scores_mean = np.mean(test_scores, axis=1)
```

```
test_scores_std = np.std(test_scores, axis=1)

plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")

#Plot accurancy bands for training and test sets
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean + t

plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```



12 TFIDF

```
In [30]: # Create BOW and try grid search for logistic regreession with penalty l1 and l2
         tf_idf_vect = TfidfVectorizer()
         final_counts = tf_idf_vect.fit_transform(X_train_raw)
```

```
#use the same vectors to convert test data
X_test=count_vect.transform(X_test_raw)
print(X_train.get_shape(),X_test.get_shape())
#Use scale of train and apply to test
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler(with_mean=False).fit(X_train)
X_train = scaler.transform(X_train)
X_test  = scaler.transform(X_test)
#below already done
#encoded_column_vector = label_binarize(y_train, classes=['negative','positive']) # n
#encoded_labels = np.ravel(encoded_column_vector) # Reshape array
#y_train=encoded_labels
#encoded_column_vector = label_binarize(y_test, classes=['negative','positive']) # ne
#encoded_labels = np.ravel(encoded_column_vector) # Reshape array
#y_test=encoded_labels

import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import validation_curve
C=[10**-3, 10**-2, 10**-1, 1,10]
penalty=['l1', 'l2']
tuned_parameters=dict(penalty=penalty,C=C)
model = GridSearchCV(LogisticRegression(), tuned_parameters, scoring = 'f1', cv=5)
model.fit(X_train, y_train)
print('Best parameters \n',model.best_estimator_)
optimumc=model.best_estimator_.C
optimumpenalty=model.best_estimator_.penalty
#build model with best parameter
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
bb=pd.DataFrame({'type':['Grid search TFIDF'],'train_score':[model.score(X_train,y_tra
aa=aa.append(bb)
#confusion matrix
pred2 = model.predict(X_test)
mat=pd.crosstab(y_test, pred2, rownames=['Actual'], colnames=['Predicted'], margins=Tr
print('confusion matrix\n',mat)

w = model.coef_
print('Count of non zero element in coefficient',np.count_nonzero(w))
print('Model train and test score C and penalty',model.score(X_train,y_train),model.sc
# Random search
from sklearn.model_selection import RandomizedSearchCV
C=[10**-4, 10**-2, 10**0, 10**2, 10**4]
penalty=['l1', 'l2']
tuned_parameters=dict(C=C, penalty=penalty)
model = RandomizedSearchCV(LogisticRegression(), tuned_parameters, random_state=1, sco
model.fit(X_train, y_train)
print('Model best extimator \n',model.best_estimator_)
```

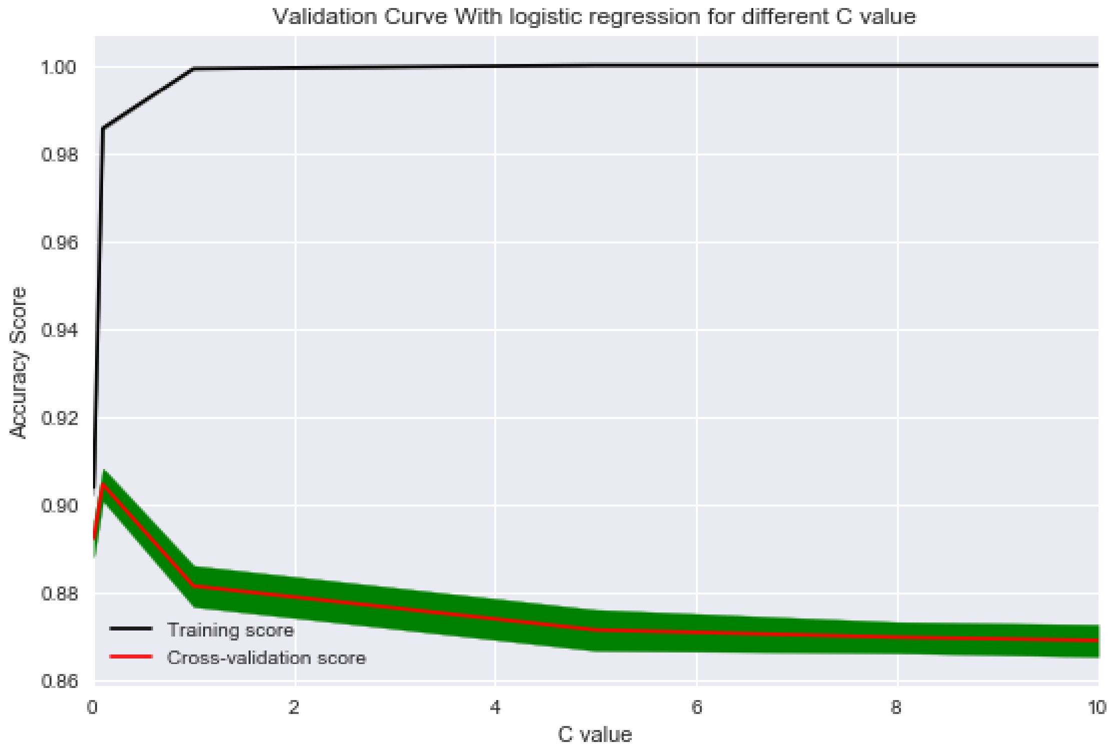
```
optimumc=model.best_estimator_.C
optimumpenalty=model.best_estimator_.penalty
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
w = model.coef_
print('Count of non zero element in coefficient',np.count_nonzero(w))
print('Model train and test score C and penalty',model.score(X_train,y_train),model.sc
bb=pd.DataFrame({'type':['Random search TFIDF'],'train_score':[model.score(X_train,y_t
aa=aa.append(bb)
print(aa)
#confusion matrix
mat=pd.crosstab(y_test, model.score(X_test,y_test), rownames=['Actual'], colnames=['Pr

#try increasing lambda
for i in [.001,.01,.1,1,10,100,1000,10000]:
  model = LogisticRegression(C=i,penalty='l1')
  model.fit(X_train, y_train)
  w = model.coef_
  print('Count of non zero, total element (l1), coefficient ( C or 1/lambda),train acc
#See top features
coefs = np.abs(model.coef_[0])
indices = np.argsort(coefs)[::-1]
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
print("Top 10 words for both review 0 negative 1 positive with weights\n")
top_pos_fet,top_neg_fet=most_informative_feature_for_binary_classification(tf_idf_vect
#Check multicolinearity
from scipy import *
import random
from scipy.sparse import *
X_train.data += np.random.normal(0,.0001,X_train.data.shape[0])
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
print("Top 10 words for both review 0 negative 1 positive with weights\n")
top_pos_fet,top_neg_fet=most_informative_feature_for_binary_classification(tf_idf_vect
#plot training and cv error with c and l1
C=[10**-2, 10**-1, 1,5,8,10]
param_range=[10**-2, 10**-1, 1,5,8,10]
train_scores, test_scores = validation_curve(LogisticRegression(penalty='l1'), X_train
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean + t
```

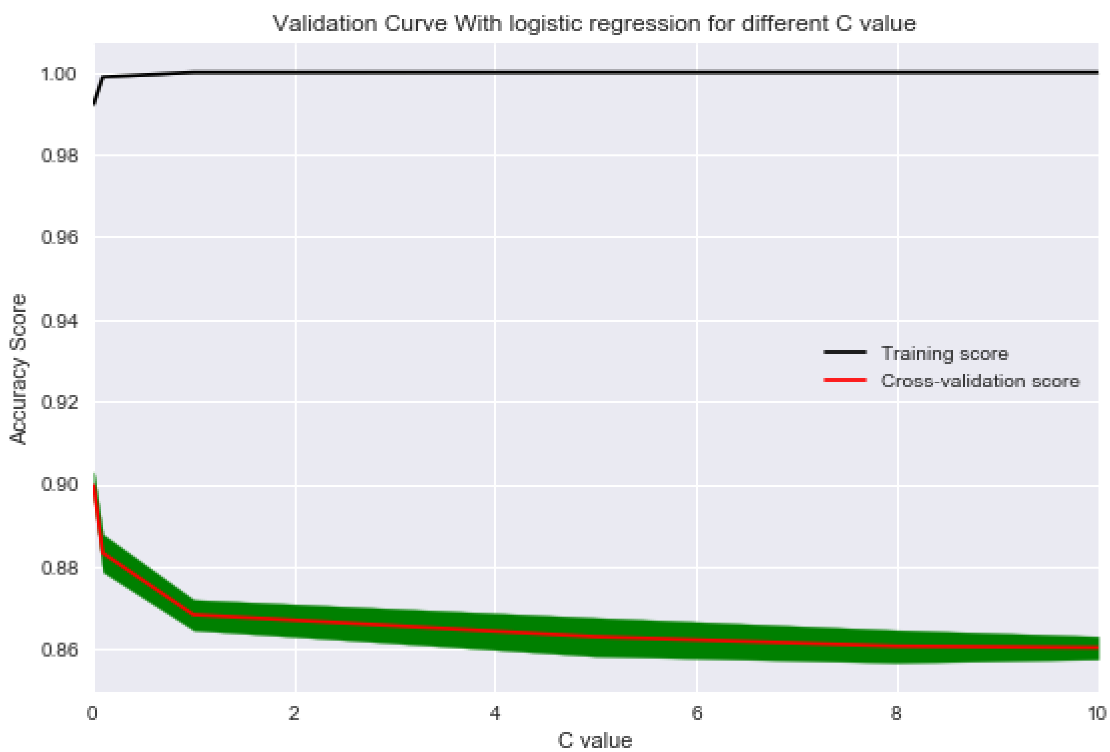
```python
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
#plot training and cv with c and l2
C=[10**-2, 10**-1, 1,5,8,10]
param_range=[10**-2, 10**-1, 1,5,8,10]
train_scores, test_scores = validation_curve(LogisticRegression(penalty='l2'), X_trai
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
#Plot accurancy bands for training and test sets
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean +
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```

```
(21000, 18278) (9000, 18278)
Best parameters
 LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
confusion matrix
 Predicted   0     1   All
Actual
0           14  1523  1537
1            0  7463  7463
All         14  8986  9000
Count of non zero element in coefficient 18278
Model train and test score C and penalty 0.974571428571 0.830777777778 0.001 l2
Model best extimator
 LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Count of non zero element in coefficient 18278
```

```
Model train and test score C and penalty 0.990857142857 0.838333333333 0.01 l2
       C penalty  test_score  train_score                type
0  0.001      l2    0.892333     0.974571      Grid search BOW
0  0.010      l2    0.885778     0.990857    Random search BOW
0  0.001      l2    0.830778     0.974571    Grid search TFIDF
0  0.010      l2    0.838333     0.990857  Random search TFIDF
Predicted  0.8383333333333334   All
Actual
0                        1537  1537
1                        7463  7463
All                      9000  9000
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.001 4 (1, 18278) 0.849142857143 0.829222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.01 906 (1, 18278) 0.908952380952 0.829555555556
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.1 4165 (1, 18278) 0.984714285714 0.838666666667
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1 5150 (1, 18278) 0.998714285714 0.856
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10 5101 (1, 18278) 1.0 0.859444444444
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 100 5813 (1, 18278) 1.0 0.858333333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1000 8490 (1, 18278) 1.0 0.857222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10000 11652 (1, 18278) 1.0 0.857888888889
Top 10 words for both review 0 negative 1 positive with weights

0 -0.298582615786 disappoint
0 -0.272109835239 worst
0 -0.224408772377 return
0 -0.203264362104 threw
0 -0.201742293535 aw
0 -0.192434543906 terribl
0 -0.187394363819 unfortun
0 -0.183021312381 wast
0 -0.17513417848 bland
0 -0.16722807824 didnt


1 0.555255387998 love
1 0.552541056562 great
1 0.476079226796 best
1 0.380471058226 delici
1 0.343522971193 good
1 0.306128580322 excel
1 0.294412869739 perfect
```

```
1 0.282932829763 favorit
1 0.249495263914 nice
1 0.213322131514 find
Top 10 words for both review 0 negative 1 positive with weights

0 -0.298579747097 disappoint
0 -0.272109370239 worst
0 -0.224412000299 return
0 -0.203266375619 threw
0 -0.201742968298 aw
0 -0.192429914179 terribl
0 -0.18740646361 unfortun
0 -0.183026822063 wast
0 -0.175136268515 bland
0 -0.167226921201 didnt


1 0.555267941325 love
1 0.55254199632 great
1 0.47607515665 best
1 0.38047992972 delici
1 0.343533581962 good
1 0.306128200565 excel
1 0.29440679309 perfect
1 0.282936121058 favorit
1 0.249492257381 nice
1 0.213308701372 find
```


Validation Curve With logistic regression for different C value
Accuracy Score
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
Training score
Cross-validation score
0
2
4
6
8
10
C value


Validation Curve With logistic regression for different C value
Accuracy Score
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
Training score
Cross-validation score
0
2
4
6
8
10
C value

13 AVG W2V

```
In [31]: #ignore warning
         import warnings
         warnings.filterwarnings('ignore')


         from gensim.models import Word2Vec
         from gensim.models import KeyedVectors
         import pickle
         model = KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin.gz', bi
         import gensim
         #convert W2V train data
         i=0
         #create a list of list to be used in W2V
         list_of_sent_train=[]
         for sent in X_train_raw:  #clean_data['CleanedText'].values:
             filtered_sentence=[]
             #sent=cleanhtml(sent)
             for w in sent.split():
                 #for cleaned_words in cleanpunc(w).split():
                  for cleaned_words in w.split():
                     if(cleaned_words.isalpha()):
                         filtered_sentence.append(cleaned_words.lower().decode('utf8'))
                     else:
                         continue
             list_of_sent_train.append(filtered_sentence)
         #convert each sentence's words to a vector of 50 dimension. Dont construct vec if wor
         #and 4 core processor
         w2v_model=gensim.models.Word2Vec(list_of_sent_train,min_count=5,size=50, workers=4)

         # average Word2Vec
         # for each sentence make average of vectors by (vectors of each words)/(total no of w
         # compute average word2vec for each review.
         sent_vectors_train = []; # the avg-w2v for each sentence/review is stored in this lis
         for sent in list_of_sent_train: # 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
             sent_vec /= cnt_words
             sent_vectors_train.append(sent_vec)
```

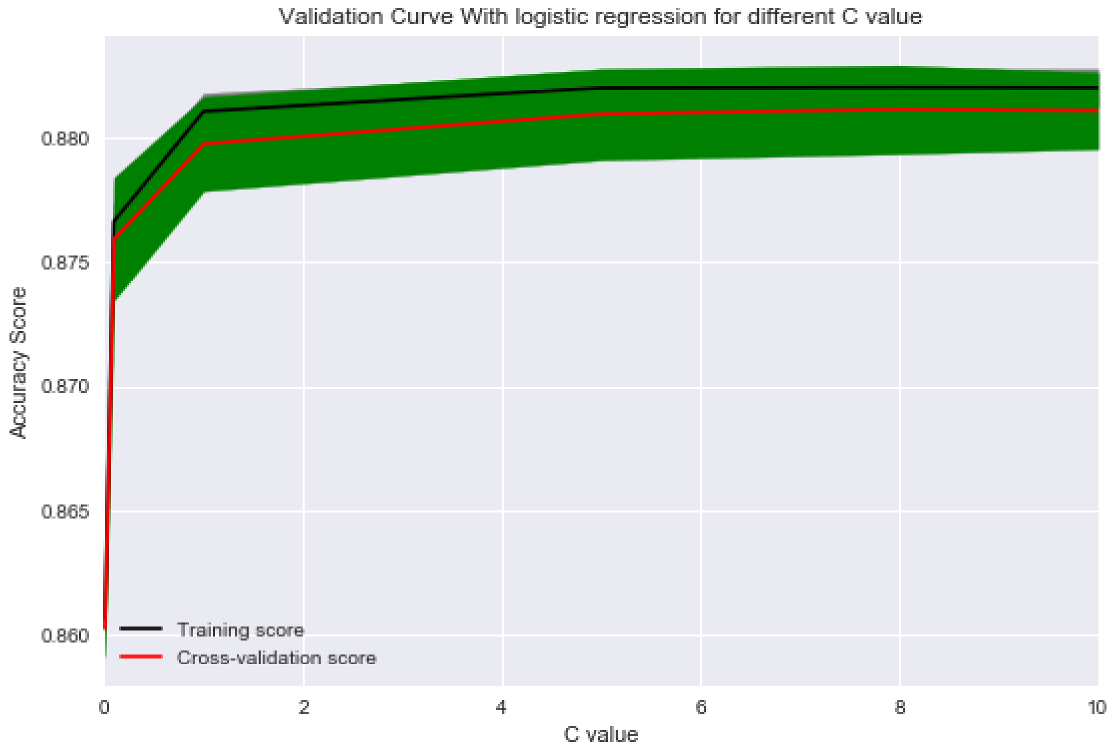
```
#convert W2V test data
i=0
#create a list of list to be used in W2V
list_of_sent_test=[]
for sent in X_test_raw:  #clean_data['CleanedText'].values:
    filtered_sentence=[]
    #sent=cleanhtml(sent)
    for w in sent.split():
        #for cleaned_words in cleanpunc(w).split():
         for cleaned_words in w.split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower().decode('utf8'))
            else:
                continue
    list_of_sent_test.append(filtered_sentence)
#convert each sentence's words to a vector of 50 dimension. Dont construct vec if wor
#and 4 core processor
w2v_model=gensim.models.Word2Vec(list_of_sent_test,min_count=5,size=50, workers=4)

# average Word2Vec
# for each sentence make average of vectors by (vectors of each words)/(total no of w
# compute average word2vec for each review.
sent_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)

# try
X_train = pd.DataFrame(sent_vectors_train)
X_test = pd.DataFrame(sent_vectors_test)

print('size of X_train, X_test, y_train , y_test ',X_train.shape, X_test.shape,y_trai
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import validation_curve
C=[10**-3, 10**-2, 10**-1, 1,10]
penalty=['l1', 'l2']
tuned_parameters=dict(penalty=penalty,C=C)
```

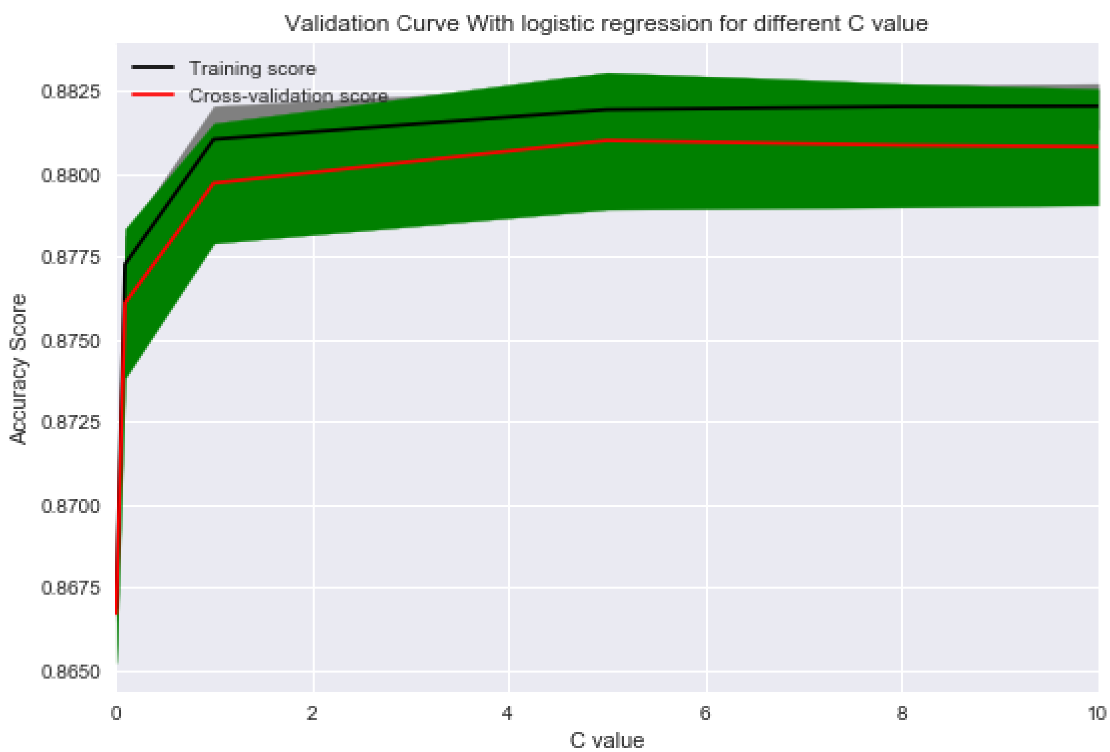
```
model = GridSearchCV(LogisticRegression(), tuned_parameters, scoring = 'f1', cv=5)
model.fit(X_train, y_train)
print('Best parameters \n',model.best_estimator_)
optimumc=model.best_estimator_.C
optimumpenalty=model.best_estimator_.penalty
#build model with best parameter
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
bb=pd.DataFrame({'type':['Grid search AVGW2V'],'train_score':[model.score(X_train,y_t
aa=aa.append(bb)
w = model.coef_
print('Count of non zero element in coefficient',np.count_nonzero(w))
print('Model train and test score C and penalty',model.score(X_train,y_train),model.s
# Random search
from sklearn.model_selection import RandomizedSearchCV
C=[10**-4, 10**-2, 10**0, 10**2, 10**4]
penalty=['l1', 'l2']
tuned_parameters=dict(C=C, penalty=penalty)
model = RandomizedSearchCV(LogisticRegression(), tuned_parameters, random_state=1, sc
model.fit(X_train, y_train)
print('Model best extimator \n',model.best_estimator_)
optimumc=model.best_estimator_.C
optimumpenalty=model.best_estimator_.penalty
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
w = model.coef_
print('Count of non zero element in coefficient',np.count_nonzero(w))
print('Model train and test score C and penalty',model.score(X_train,y_train),model.s
bb=pd.DataFrame({'type':['Random search AVGW2V'],'train_score':[model.score(X_train,y
aa=aa.append(bb)
print(aa)
#confusion matrix
pred2 = model.predict(X_test)
mat=pd.crosstab(y_test, pred2, rownames=['Actual'], colnames=['Predicted'], margins=T
print('confusion matrix\n',mat)

#try increasing lambda
for i in [.001,.01,.1,1,10,100,1000,10000]:
  model = LogisticRegression(C=i,penalty='l1')
  model.fit(X_train, y_train)
  w = model.coef_
  print('Count of non zero, total element (l1), coefficient ( C or 1/lambda),train ac
#See top features
coefs = np.abs(model.coef_[0])
indices = np.argsort(coefs)[::-1]
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
#print("Top 10 words for both review 0 negative 1 positive with weights\n")
```

```
#top_pos_fet,top_neg_fet=most_informative_feature_for_binary_classification(sent_vect
#Check multicolinearity
from scipy import *
import random
from scipy.sparse import *
#X_train.data += np.random.normal(0,.0001,X_train.data.shape[0])
#model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
#model.fit(X_train, y_train)
#print("Top 10 words for both review 0 negative 1 positive with weights\n")
#top_pos_fet,top_neg_fet=most_informative_feature_for_binary_classification(sent_vect
#plot training and cv error with c and l1
C=[10**-2, 10**-1, 1,5,8,10]
param_range=[10**-2, 10**-1, 1,5,8,10]
train_scores, test_scores = validation_curve(LogisticRegression(penalty='l1'), X_trai
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean +
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
#plot training and cv with c and l2
C=[10**-2, 10**-1, 1,5,8,10]
param_range=[10**-2, 10**-1, 1,5,8,10]
train_scores, test_scores = validation_curve(LogisticRegression(penalty='l2'), X_trai
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
#Plot accurancy bands for training and test sets
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean +
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
plt.legend(loc="best")
```

```
        plt.show()
```

```
size of X_train, X_test, y_train , y_test  (21000, 50) (9000, 50) (21000,) (9000,)
Best parameters
 LogisticRegression(C=10, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Count of non zero element in coefficient 47
Model train and test score C and penalty 0.881714285714 0.829111111111 10 l1
Model best extimator
 LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Count of non zero element in coefficient 50
Model train and test score C and penalty 0.881714285714 0.829111111111 100 l2
         C penalty  test_score  train_score                 type
0    0.001      l2    0.892333     0.974571       Grid search BOW
0    0.010      l2    0.885778     0.990857     Random search BOW
0    0.001      l2    0.830778     0.974571     Grid search TFIDF
0    0.010      l2    0.838333     0.990857   Random search TFIDF
0   10.000      l1    0.829111     0.881714    Grid search AVGW2V
0  100.000      l2    0.829111     0.881714  Random search AVGW2V
confusion matrix
 Predicted  0     1   All
Actual
0          0  1537  1537
1          1  7462  7463
All        1  8999  9000
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.001 0 (1, 50) 0.849142857143 0.829222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.01 14 (1, 50) 0.863428571429 0.829333333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.1 33 (1, 50) 0.876761904762 0.829333333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1 47 (1, 50) 0.881095238095 0.829222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10 47 (1, 50) 0.881714285714 0.829111111111
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 100 50 (1, 50) 0.881714285714 0.829111111111
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1000 50 (1, 50) 0.881714285714 0.829111111111
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10000 50 (1, 50) 0.881714285714 0.829111111111
```


Validation Curve With logistic regression for different C value
Accuracy Score
0.880
0.875
0.870
0.865
0.860
Training score
Cross-validation score
0
2
4
6
8
10
C value


Validation Curve With logistic regression for different C value
Training score
Cross-validation score
Accuracy Score
0.8825
0.8800
0.8775
0.8750
0.8725
0.8700
0.8675
0.8650
0
2
4
6
8
10
C value

14 TFIDF AVGW2V

In [32]:
```
tf_idf_vect = TfidfVectorizer()
final_tf_idf=tf_idf_vect.fit_transform(X_train_raw)
tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

tfidf_sent_vectors_train = []; # the tfidf-w2v for each sentence/review is stored in
row=0;
#calculate avg tfidf score for each sentences
for sent in list_of_sent_train: # 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]#calculate w2v for each word
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = final_tf_idf[row, tfidf_feat.index(word)]#get tfidf score of each
            sent_vec += (vec * tf_idf) # multiply vec with tfidf of each word and cum
            weight_sum += tf_idf # also add tfidf sums in each sentence
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
#tfidf_sent_vectors.

# do for test
final_tf_idf=tf_idf_vect.transform(X_test_raw)
tfidf_sent_vectors_test = []; # the tfidf-w2v for each sentence/review is stored in th
row=0;
#calculate avg tfidf score for each sentences
for sent in list_of_sent_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]#calculate w2v for each word
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = final_tf_idf[row, tfidf_feat.index(word)]#get tfidf score of each
            sent_vec += (vec * tf_idf) # multiply vec with tfidf of each word and cum
            weight_sum += tf_idf # also add tfidf sums in each sentence
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

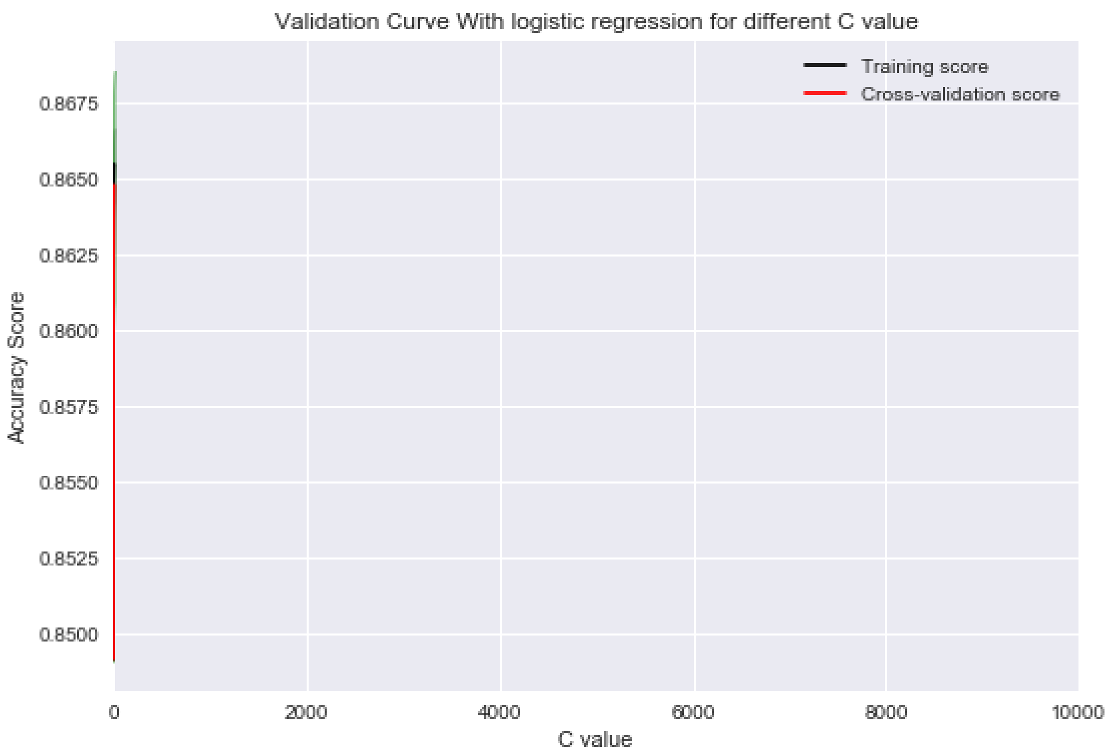
```
#x=tfidf_sent_vectors
#y = clean_data['Score']
#n=len(x)
#n1=int(n*.3)
#X_test = x[0:n1]
#X_train= x[n1:n+1]
#y_test=y[0:n1]
#y_train=y[n1:n+1]
#print('X y train test ',len(X_train),len(X_test),y_train.shape,y_test.shape)
X_train = pd.DataFrame(tfidf_sent_vectors_train)
X_test = pd.DataFrame(tfidf_sent_vectors_test)
print('size of X_train, X_test, y_train , y_test ',X_train.shape, X_test.shape,y_train

import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import validation_curve
C=[10**-3, 10**-2, 10**-1, 1,10]
penalty=['l1', 'l2']
tuned_parameters=dict(penalty=penalty,C=C)
model = GridSearchCV(LogisticRegression(), tuned_parameters, scoring = 'f1', cv=5)
model.fit(X_train, y_train)
print('Best parameters \n',model.best_estimator_)
optimumc=model.best_estimator_.C
optimumpenalty=model.best_estimator_.penalty
#build model with best parameter
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
bb=pd.DataFrame({'type':['Grid search AVGW2VTFIDF'],'train_score':[model.score(X_trai
aa=aa.append(bb)
#confusion matrix
pred2 = model.predict(X_test)
mat=pd.crosstab(y_test, pred2, rownames=['Actual'], colnames=['Predicted'], margins=T
print('confusion matrix\n',mat)

w = model.coef_
print('Count of non zero element in coefficient',np.count_nonzero(w))
print('Model train and test score C and penalty',model.score(X_train,y_train),model.s
# Random search
from sklearn.model_selection import RandomizedSearchCV
C=[10**-4, 10**-2, 10**0, 10**2, 10**4]
penalty=['l1', 'l2']
tuned_parameters=dict(C=C, penalty=penalty)
model = RandomizedSearchCV(LogisticRegression(), tuned_parameters, random_state=1, sc
model.fit(X_train, y_train)
print('Model best extimator \n',model.best_estimator_)
optimumc=model.best_estimator_.C
```

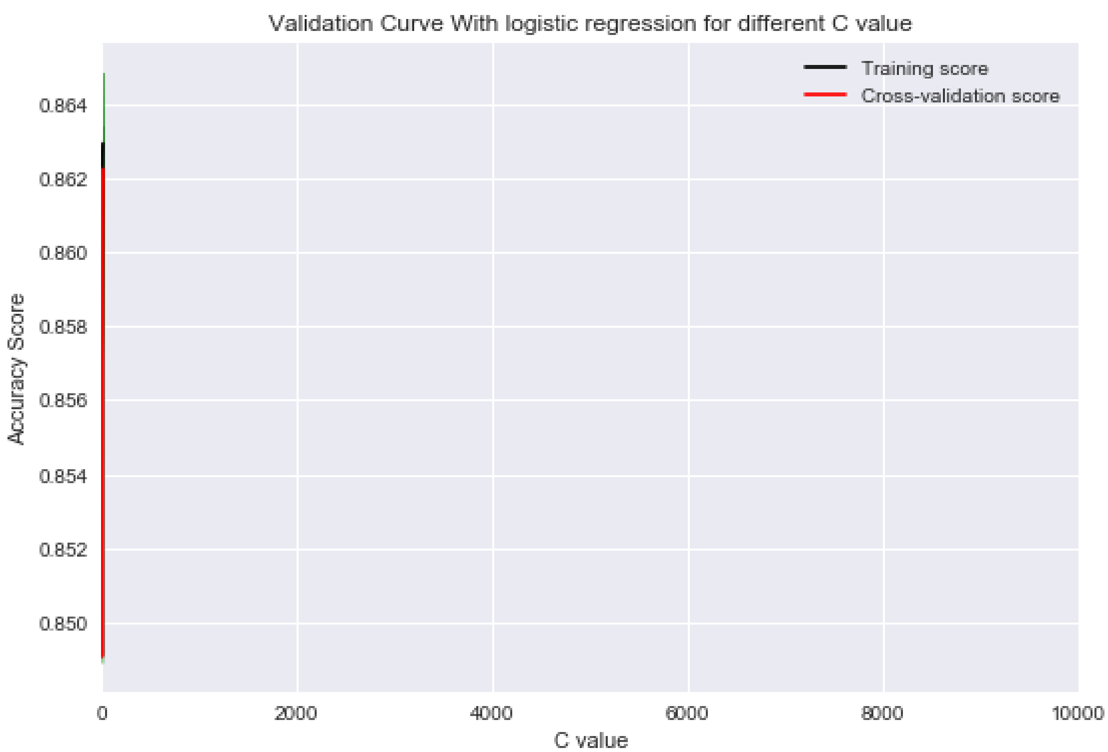
```
optimumpenalty=model.best_estimator_.penalty
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
w = model.coef_
print('Count of non zero element in coefficient',np.count_nonzero(w))
print('Model train and test score C and penalty',model.score(X_train,y_train),model.sc
bb=pd.DataFrame({'type':['Random search AVGW2VTFIDF'],'train_score':[model.score(X_tra
aa=aa.append(bb)
print(aa)
#try increasing lambda
for i in [.001,.01,.1,1,10,100,1000,10000]:
  model = LogisticRegression(C=i,penalty='l1')
  model.fit(X_train, y_train)
  w = model.coef_
  print('Count of non zero, total element (l1), coefficient ( C or 1/lambda),train acc
#See top features
coefs = np.abs(model.coef_[0])
indices = np.argsort(coefs)[::-1]
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
print("Top 10 words for both review 0 negative 1 positive with weights\n")
top_pos_fet,top_neg_fet=most_informative_feature_for_binary_classification(tf_idf_vec
#Check multicolinearity
from scipy import *
import random
from scipy.sparse import *
#X_train.data += np.random.normal(0,.0001,X_train.data.shape[0])
#model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
#model.fit(X_train, y_train)
#print("Top 10 words for both review 0 negative 1 positive with weights\n")
#top_pos_fet,top_neg_fet=most_informative_feature_for_binary_classification(tf_idf_ve
#plot training and cv error with c and l1
C=[10**-2, 10**-1, 1,5,8,10]
param_range=[10**-2, 10**-1, 1,5,8,10]
train_scores, test_scores = validation_curve(LogisticRegression(penalty='l1'), X_trai
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean + t
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
```

```
plt.legend(loc="best")
plt.show()
#plot training and cv with c and l2
C=[10**-2, 10**-1, 1,5,8,10]
param_range=[10**-2, 10**-1, 1,5,8,10]
train_scores, test_scores = validation_curve(LogisticRegression(penalty='l2'), X_trai
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
#Plot accurancy bands for training and test sets
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean + t
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```

```
size of X_train, X_test, y_train , y_test  (21000, 50) (9000, 50) (21000,) (9000,)
Best parameters
 LogisticRegression(C=10, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
confusion matrix
 Predicted    0     1   All
Actual
0           387  1150  1537
1           196  7267  7463
All         583  8417  9000
Count of non zero element in coefficient 46
Model train and test score C and penalty 0.865523809524 0.850444444444 10 l1
Model best extimator
 LogisticRegression(C=10000, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Count of non zero element in coefficient 50
Model train and test score C and penalty 0.86619047619 0.850333333333 10000 l2
           C penalty  test_score  train_score                       type
0      0.001      l2    0.892333     0.974571             Grid search BOW
0      0.010      l2    0.885778     0.990857           Random search BOW
0      0.001      l2    0.830778     0.974571           Grid search TFIDF
```

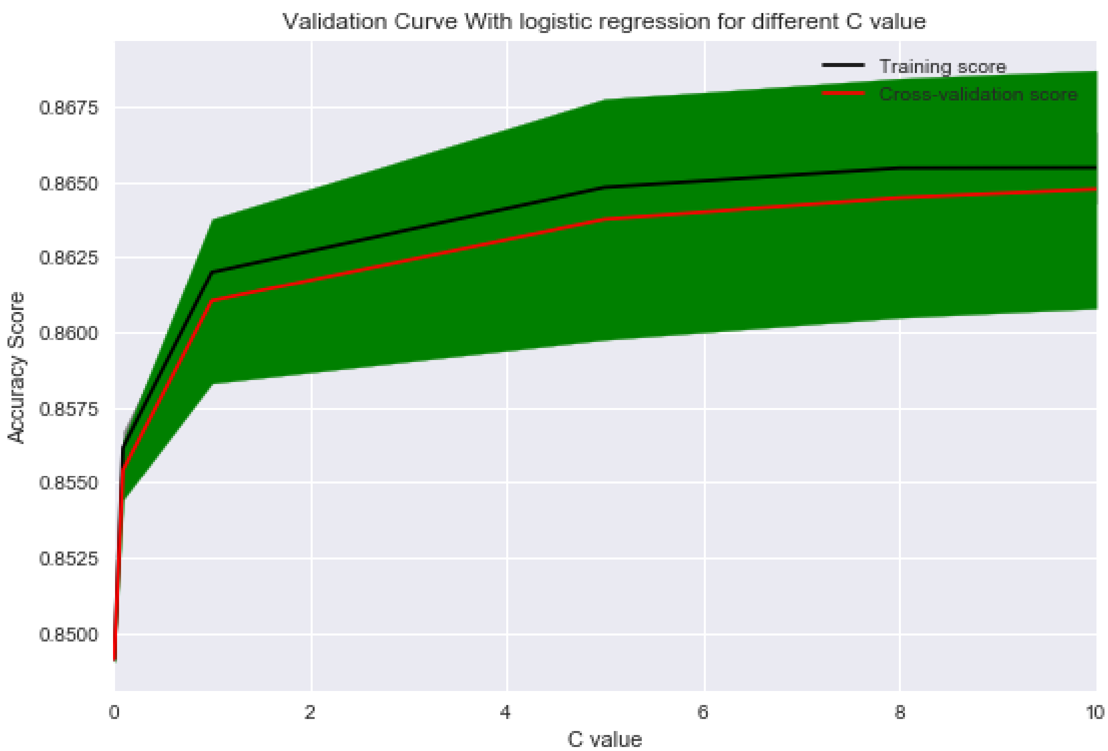
```
0      0.010      l2    0.838333     0.990857        Random search TFIDF
0     10.000      l1    0.829111     0.881714         Grid search AVGW2V
0    100.000      l2    0.829111     0.881714       Random search AVGW2V
0     10.000      l1    0.850444     0.865524    Grid search AVGW2VTFIDF
0  10000.000      l2    0.850333     0.866190  Random search AVGW2VTFIDF
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.001 0 (1, 50) 0.849142857143 0.829222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.01 5 (1, 50) 0.849142857143 0.829222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.1 20 (1, 50) 0.857523809524 0.834888888889
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1 30 (1, 50) 0.862142857143 0.847222222222
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10 46 (1, 50) 0.865238095238 0.850333333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 100 50 (1, 50) 0.866333333333 0.85
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1000 50 (1, 50) 0.866428571429 0.849888888889
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10000 50 (1, 50) 0.866523809524 0.85
Top 10 words for both review 0 negative 1 positive with weights

0 -24.8624174466 abnorm
0 -21.9495858481 abraham
0 -14.581004651 aberr
0 -12.8762018263 abiiiti
0 -11.6580628856 abett
0 -11.5960367598 absolutelli
0 -9.21736170044 absenc
0 -8.08649601681 abililti
0 -8.06268461972 absolut
0 -7.7369448004 abl


1 20.3647201227 abras
1 18.4357928796 absent
1 17.1738724428 abita
1 15.7728820151 aafco
1 14.788445502 aborio
1 13.3250782965 abiet
1 12.8564773183 absolutament
1 12.5631417672 aaaah
1 8.01473583945 abil
1 7.55987075871 aah
```

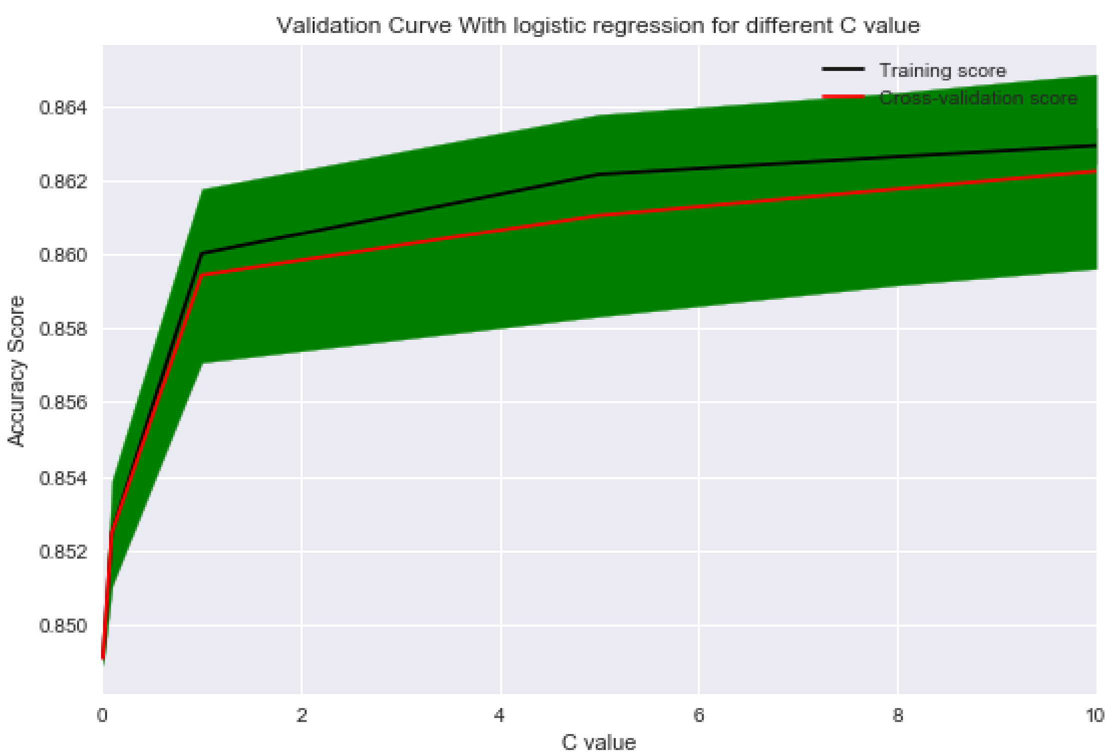

Validation Curve With logistic regression for different C value
Training score
Cross-validation score
0.8675
0.8650
0.8625
0.8600
0.8575
0.8550
0.8525
0.8500
Accuracy Score
0
2000
4000
6000
8000
10000
C value


Validation Curve With logistic regression for different C value
Training score
Cross-validation score
0.864
0.862
0.860
0.858
0.856
0.854
0.852
0.850
Accuracy Score
0
2000
4000
6000
8000
10000
C value

Ignore the above 2 plots those plots are plotted below again

In [34]:
```
C=[10**-2, 10**-1, 1,5,8,10]
param_range=[10**-2, 10**-1, 1,5,8,10]
train_scores, test_scores = validation_curve(LogisticRegression(penalty='l1'), X_trai
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean +
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
#plot training and cv with c and l2
C=[10**-2, 10**-1, 1,5,8,10]
param_range=[10**-2, 10**-1, 1,5,8,10]
train_scores, test_scores = validation_curve(LogisticRegression(penalty='l2'), X_trai
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.plot(param_range, train_scores_mean, label="Training score", color="black")
plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
#Plot accurancy bands for training and test sets
plt.fill_between(param_range, train_scores_mean - train_scores_std, train_scores_mean
plt.fill_between(param_range, test_scores_mean - test_scores_std, test_scores_mean +
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```


Validation Curve With logistic regression for different C value
Training score
Cross-validation score
0.8675
0.8650
0.8625
0.8600
0.8575
0.8550
0.8525
0.8500
Accuracy Score
0
2
4
6
8
10
C value


Validation Curve With logistic regression for different C value
Training score
Cross-validation score
0.864
0.862
0.860
0.858
0.856
0.854
0.852
0.850
Accuracy Score
0
2
4
6
8
10
C value

15 Conclusion

1. Increasing C We can see as C decreases i.e. lambda increases more coefficients are getting 0 and test accuracy increases when C too low accuracy decreases again
2. Multicolinearity After adding some noise on data the weights are almost same so multicolinearity doesnot exist
3. The most important words for positive and negatives are making sense Accuracy scores are below

```
In [33]: aa
```

```
Out[33]:           C penalty  test_score  train_score                    type
         0      0.001      l2    0.892333     0.974571         Grid search BOW
         0      0.010      l2    0.885778     0.990857       Random search BOW
         0      0.001      l2    0.830778     0.974571       Grid search TFIDF
         0      0.010      l2    0.838333     0.990857     Random search TFIDF
         0     10.000      l1    0.829111     0.881714      Grid search AVGW2V
         0    100.000      l2    0.829111     0.881714    Random search AVGW2V
         0     10.000      l1    0.850444     0.865524  Grid search AVGW2VTFIDF
         0  10000.000      l2    0.850333     0.866190  Random search AVGW2VTFIDF
```

16 Steps followed

Only !=3 reviews are taken Mark >3 as positive and <3 as negative. Sort data as per product id in ascending order Deduplication of entries for same profilename,userid, time, text and take first element Get stratified sampling of 50k data Clean html and punctuation Convert to uppercase and word<3 are rejected data sorted on time Split the data in train and test to 70:30

BOW

BOW BOW vec created using train data test data is converted using above X is standarize on train and same applied to test y is converted to 1 and 0 from positive and negative do grid search and random search for different value of c and penalty best model is established with best hyperparameter. model metric is stored in dataframe and crosstable is printed print the non zero element of weights try increasing lambda and see sparsity difference see top +ve and -ve features using weights sorted in descendng order Check if multicolinearity exist using pertubation test plot cv error with C and penalty

TFIDF form tfidf vec using train same is used in test to convert rest are same

AVG W2V gensim is used to convert train and test text to W2V AVG seperately rest are same

AVG TFIDF form tfidf vec using train same is used in test to convert gensim and above tfidf is used to convert train and test text to W2V AVG seperately