27.17.Amazon_food_review_logistic_regression

June 14, 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 [1]: 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)
```

```
C:\Users\suman\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning:
  "This module will be removed in 0.20.", DeprecationWarning)
C:\Users\suman\Anaconda3\lib\site-packages\sklearn\grid_search.py:42: DeprecationWarning: This
  DeprecationWarning)
```

4 Data preprocessing

```
In [2]: 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 eleme
        sorted_data=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},
```

```
In [38]: #take only 50000 data
         print(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 = 50000, stratify = sorted_da
         clean_data['Score'].value_counts()
```

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

Out[38]:
```
positive    42159
negative     7841
Name: Score, dtype: int64
```

In [39]:
```python
# 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'))
```

In [40]:
```python
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
```

In [41]:
```
clean_data['CleanedText']=final_string
#store for future use
#conn = sqlite3.connect('clean_data.sqlite')
#c=conn.cursor()
#conn.text_factory = str
#clean_data.to_sql('Reviews1', conn, flavor=None, schema=None, if_exists='replace', i
#con = sqlite3.connect('clean_data.sqlite')
#clean_data = pd.read_sql_query("""SELECT * FROM Reviews1 WHERE Score != 3""", con)
#clean_data['CleanedText'].sample(15)
clean_data.shape
#Sort data on timestamp
clean_data=clean_data.sort_values(by=['Time'],ascending=False)
#clean_data
clean_data['CleanedText'].sample(2)
```

Out[41]:
```
286076    b'pleasant surpris fresh tast orang bar realli...
171848    b'best product make bread bread machin everyth...
Name: CleanedText, dtype: object
```

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

In [42]:
```
#now convert CleanedText to TDM
count_vect = CountVectorizer() #in scikit-learn
final_counts = count_vect.fit_transform(clean_data['CleanedText'].values)
print(final_counts.get_shape())
print(type(final_counts))
#print(final_counts[[1]])
print("new")
#print(final_counts[0,:])# this is stored like dict format only non zero values. spar
#x = pd.DataFrame(final_counts.toarray())#this is stored like dataframe format all 0 
# sparse matrix in csr format works faster compare to dense format
#print(x.shape,x.loc[0])
```

```
(50000, 27310)
<class 'scipy.sparse.csr.csr_matrix'>
```

new

```
In [43]: from sklearn.preprocessing import StandardScaler
         x=final_counts
         y =clean_data['Score']


         #Standarize the features
         #below not working
         #sc = StandardScaler(with_mean=False)
         # this is sparse matrix so standarization is required differently
         from sklearn.preprocessing import normalize
         x = normalize(x, norm='l1', axis=0)


         #sc = StandardScaler()
         #x = sc.fit_transform(x)
         print(x.get_shape())
         print(type(x))
         #print(x[[1]])


         n=x.shape[0]
         n1=int(n*.3)
         #X_test = x[0:n1]
         #X_train= x[n1:n+1]

         #y should be changed to binary

         from sklearn.preprocessing import label_binarize
         encoded_column_vector = label_binarize(y, classes=['negative','positive']) # negative
         encoded_labels = np.ravel(encoded_column_vector) # Reshape array
         y=encoded_labels

         y_test=y[0:n1]
         y_train=y[n1:n+1]


         X_test = x[0:n1,:]
         X_train= 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.shape, X_test.shape,y_trai
         #print("positive and negative review in train and test\n",y_train.value_counts(),"\n"

(50000, 27310)
<class 'scipy.sparse.csc.csc_matrix'>
```

```
size of X_train, X_test, y_train , y_test  (35000, 27310) (15000, 27310) (35000,) (15000,)
```

```
In [44]: 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=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)
<class 'scipy.sparse.csc.csc_matrix'> <class 'numpy.ndarray'>
```

```
In [45]: #build model with best parameter
         model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
         model.fit(X_train, y_train)

         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)
```

```
Count of non zero element in coefficient 4938
Model train and test score C and penalty 0.911971428571 0.8382 10 l1
```

6 Apply Random search

```
In [46]: # Random search
         from sklearn.model_selection import RandomizedSearchCV

         #tuned_parameters = [{'penalty' : ['l1', 'l2']},

         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, sco

         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)


         # Print coefficients
         # check no of parameter
         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.sc
         bb=pd.DataFrame({'type':['Random search BOW'],'train_score':[model.score(X_train,y_tra
         aa=aa.append(bb)
         print(aa)
```

```
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='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Count of non zero element in coefficient 12072
Model train and test score C and penalty 0.968942857143 0.863933333333 100 l1
     C penalty  test_score  train_score               type
0   10      l1    0.838200     0.911971    Grid search BOW
0  100      l1    0.863933     0.968943  Random search BOW
```

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

```
In [47]: 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 0 (1, 27310) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.01 0 (1, 27310) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.1 0 (1, 27310) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1 0 (1, 27310) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10 4967 (1, 27310) 0.912714285714 0.838333333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 100 12065 (1, 27310) 0.968942857143 0.863933333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1000 11175 (1, 27310) 0.992228571429 0.858466666667
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10000 9626 (1, 27310) 0.998428571429 0.824533333333
```

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

```
In [49]: #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 -3077.2179721 disappoint
0 -1652.9975165 bad
0 -1213.63238997 thought
0 -1204.21845854 aw
0 -1146.3880296 terribl
0 -1128.70382556 money
0 -1121.39663435 horribl
0 -1077.38007019 worst
0 -1042.36105164 return
0 -1027.37078209 unfortun
```

```
1 5440.0 great
1 5017.96549989 love
1 4804.31139217 best
1 3362.15637588 perfect
1 3353.73812941 delici
1 1974.53175044 excel
1 1579.62281001 tasti
1 1563.1358183 favorit
1 1259.92774809 nice
1 1196.04334525 keep
```

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

The noise is with mean 0 and sd=.0001

```
In [50]: # 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 [51]: #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 [52]: 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 -3077.10091129 disappoint
0 -1624.83929695 bad
0 -1230.52805736 aw
0 -1183.08374384 terribl
0 -1132.23714539 horribl
0 -1130.43471644 money
0 -1078.19914821 return
0 -1077.81626203 worst
0 -1056.94920513 unfortun
0 -1053.09605742 noth


1 3400.0 best
1 3372.80909943 great
1 3140.52489553 delici
1 3102.76664556 perfect
1 1922.60193055 excel
1 1871.4953013 love
1 1580.31088605 good
1 1463.46979206 favorit
1 1452.09431946 tasti
1 1079.79385601 easi
```

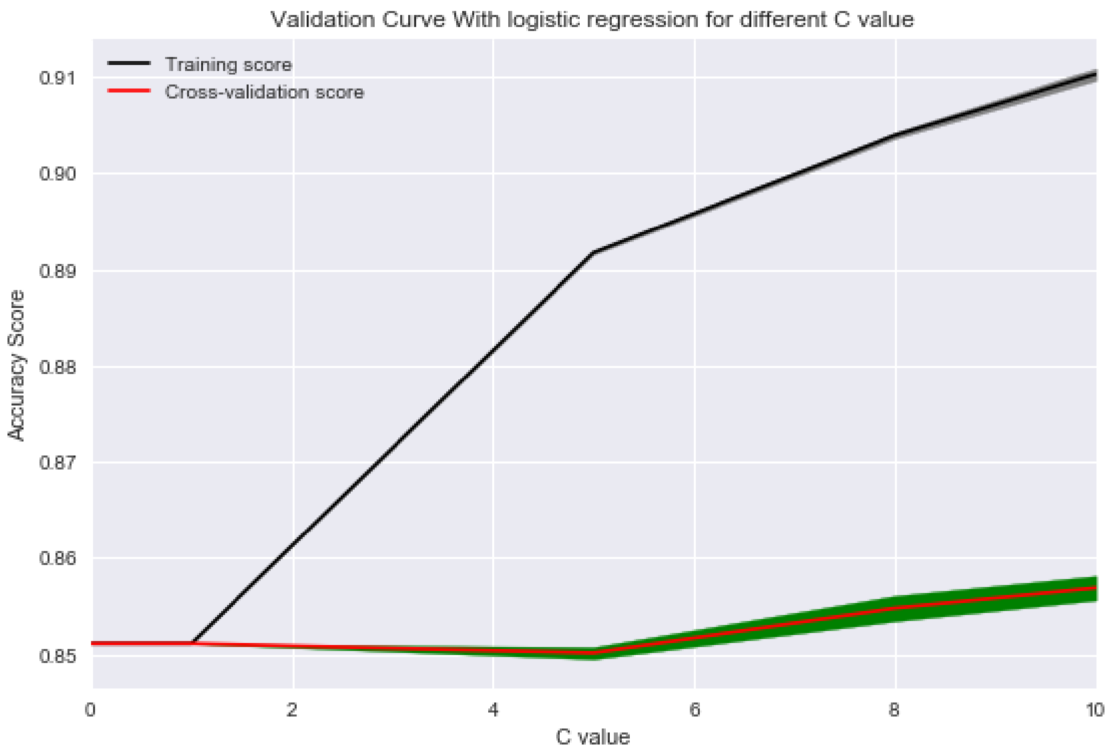
So we can see after adding noise the weights of top 20 words are almost same as earlier, so multicolinearity doesnot exist

In [ ]:

9 Plot traing and CV error with C and l1 penalty

In [53]:
```
#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()
```



10 Plot traing and CV error with C and l2 penalty

In [54]:
```
#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 +

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()
```

In [55]:
```
aa
```

Out[55]:

	C	penalty	test_score	train_score	type
0	10	l1	0.838200	0.911971	Grid search BOW
0	100	l1	0.863933	0.968943	Random search BOW

In [56]:
```
aa
```

Out[56]:

	C	penalty	test_score	train_score	type
0	10	l1	0.838200	0.911971	Grid search BOW
0	100	l1	0.863933	0.968943	Random search BOW

11 TFIDF

In [57]:
```
# 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(clean_data['CleanedText'].values)
from sklearn.preprocessing import StandardScaler
x=final_counts
y =clean_data['Score']
from sklearn.preprocessing import normalize
x = normalize(x, norm='l1', axis=0)
n=x.shape[0]
```

```
n1=int(n*.3)
from sklearn.preprocessing import label_binarize
encoded_column_vector = label_binarize(y, classes=['negative','positive']) # negative
encoded_labels = np.ravel(encoded_column_vector) # Reshape array
y=encoded_labels
y_test=y[0:n1]
y_train=y[n1:n+1]
X_test = x[0:n1,:]
X_train= 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.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 TFIDF'],'train_score':[model.score(X_train,y_tra
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.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_
aa=aa.append(bb)
```

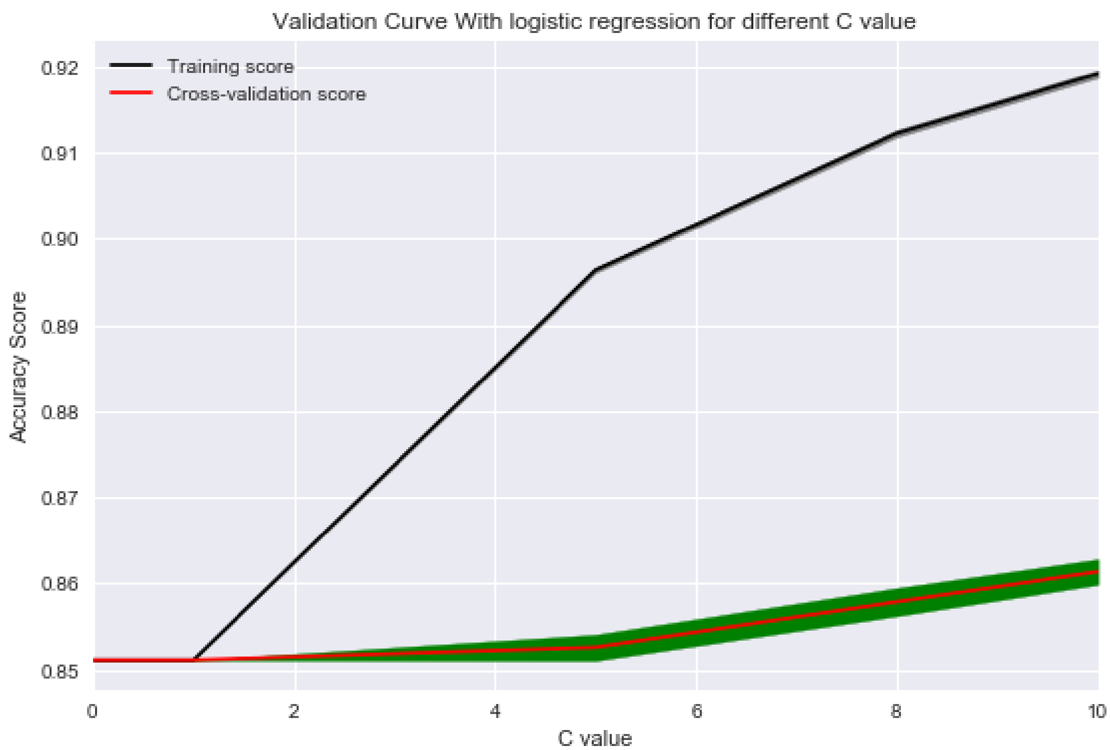
```
print(aa)
#try increasing lambda
for i in [.001,.01,.1,1,10,100,1000,10000]:
  model = LogisticRegression(C=i,penalty='l1')
  model.fit(X_train, y_train)
  w = model.coef_
  print('Count of non zero, total element (l1), coefficient ( C or 1/lambda),train acc
#See top features
coefs = np.abs(model.coef_[0])
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_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
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_train
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
```

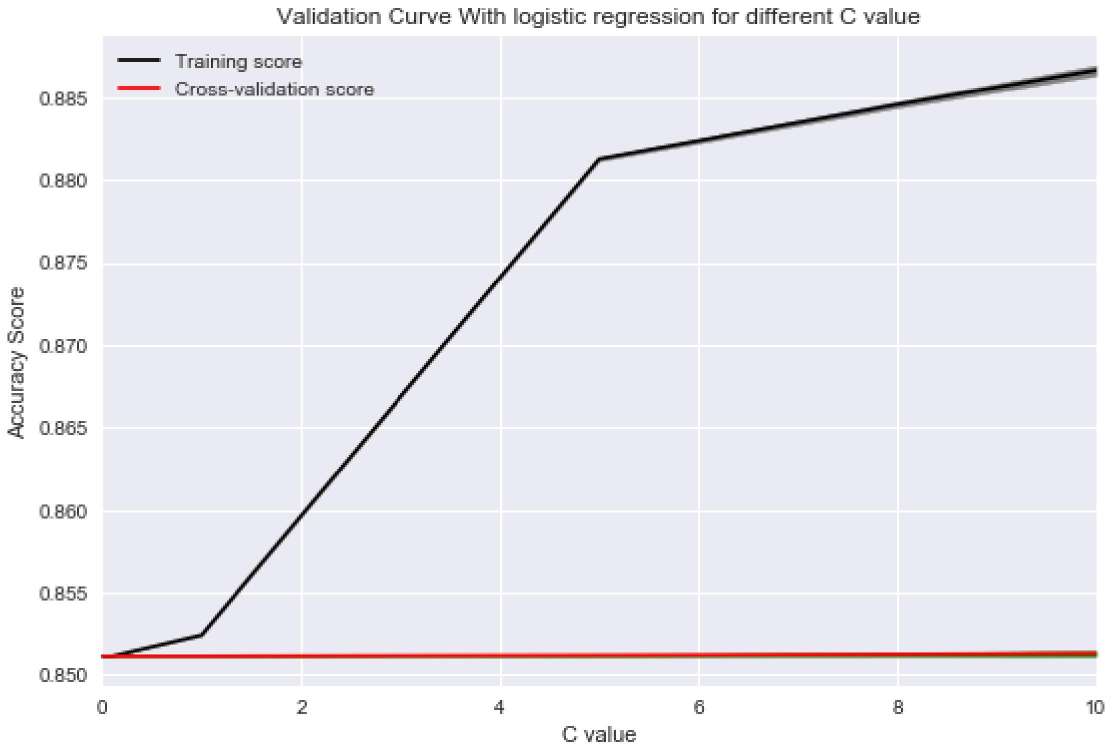
```
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.plot(param_range, train_scores_mean, label="Training score", color="black")
    plt.plot(param_range, test_scores_mean, label="Cross-validation score", color="red")
    #Plot accurancy bands 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  (35000, 27310) (15000, 27310) (35000,) (15000,)
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 5272
Model train and test score C and penalty 0.921028571429 0.845133333333 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='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Count of non zero element in coefficient 13833
Model train and test score C and penalty 0.975514285714 0.862733333333 100 l1
     C penalty  test_score  train_score                 type
0   10      l1    0.838200     0.911971      Grid search BOW
0  100      l1    0.863933     0.968943    Random search BOW
0   10      l1    0.845133     0.921029    Grid search TFIDF
0  100      l1    0.862733     0.975514  Random search TFIDF
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.001 0 (1, 27310) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.01 0 (1, 27310) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.1 0 (1, 27310) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1 0 (1, 27310) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10 5419 (1, 27310) 0.921514285714 0.846733333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 100 13858 (1, 27310) 0.975514285714 0.862666666667
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
```

```
 1000 12047 (1, 27310) 0.996171428571 0.848466666667
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10000 9601 (1, 27310) 0.999885714286 0.818533333333
Top 10 words for both review 0 negative 1 positive with weights

0 -2139.38157289 disappoint
0 -1343.79150145 bad
0 -1018.63082006 thought
0 -889.616419324 worst
0 -870.133829618 aw
0 -865.1849819 horribl
0 -839.381927857 money
0 -839.139526293 didnt
0 -814.130563045 terribl
0 -811.599707981 noth


1 7241.52363849 great
1 3234.56182544 best
1 3127.84986407 love
1 2663.20685441 perfect
1 2468.75754499 delici
1 1328.68194528 excel
1 1137.793068 tasti
1 980.712306274 favorit
1 937.424975827 nice
1 810.669191614 carri
Top 10 words for both review 0 negative 1 positive with weights

0 -2112.40818779 disappoint
0 -1407.87021874 bad
0 -990.737502145 thought
0 -952.187102874 didnt
0 -915.717401709 worst
0 -896.234827143 aw
0 -858.238564517 horribl
0 -831.674797692 terribl
0 -831.411063051 noth
0 -813.053910623 money


1 2558.71549498 great
1 2389.42052379 delici
1 2375.80330702 perfect
1 2323.78249038 best
1 1332.07445746 love
1 1244.82913667 excel
1 1015.93231255 tasti
```

```
1 809.771239605 carri
1 776.265706882 favorit
1 759.309715496 nice
```





12 AVG W2V

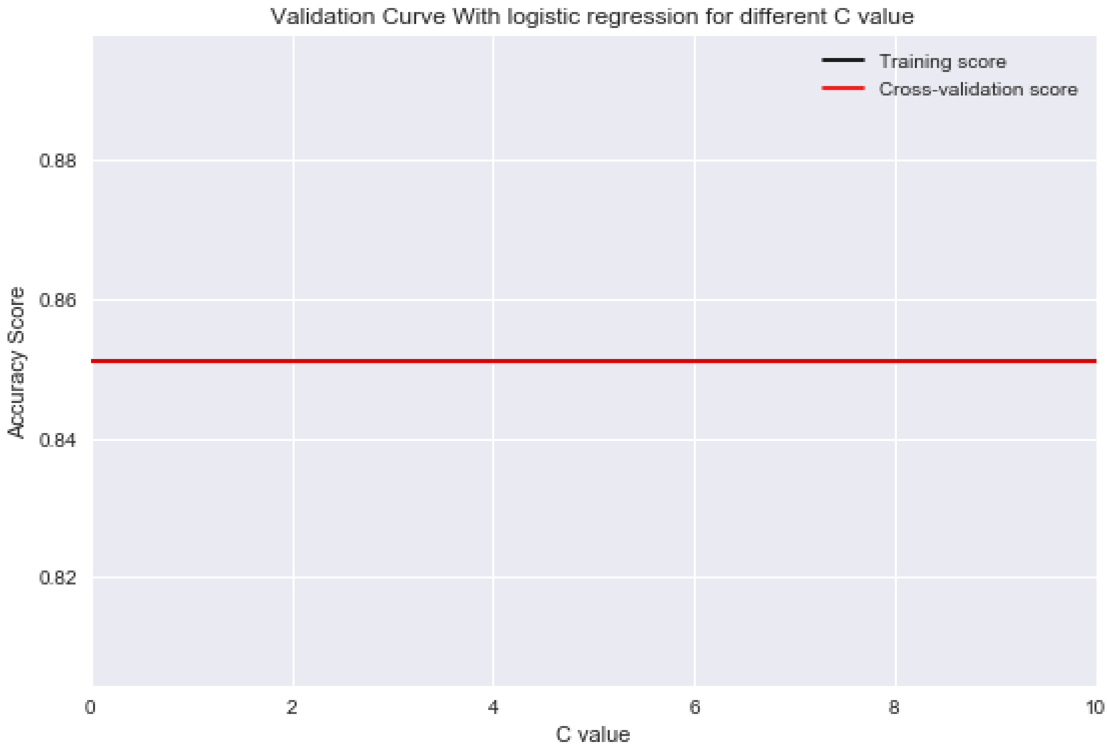
In [58]:
```
#ignore warning
import warnings
warnings.filterwarnings('ignore')


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
i=0
#create a list of list to be used in W2V
list_of_sent=[]
for sent in 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()):
```

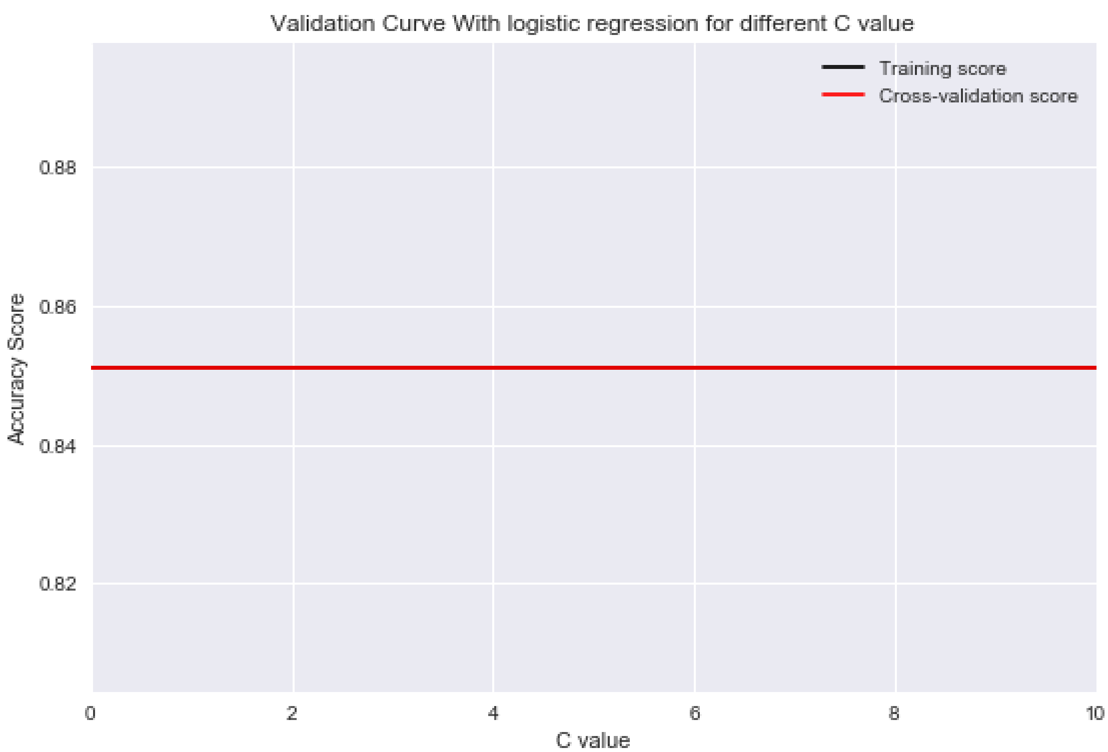
```
                filtered_sentence.append(cleaned_words.lower().decode('utf8'))
            else:
                continue
    list_of_sent.append(filtered_sentence)
#convert each sentence's words to a vector of 50 dimension. Dont construct vec if wor
#and 4 core processor
w2v_model=gensim.models.Word2Vec(list_of_sent,min_count=5,size=50, 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 = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors.append(sent_vec)

#Sent_vectors ready for tsne



x=sent_vectors
y =clean_data['Score']
from sklearn.preprocessing import normalize
x = normalize(x, norm='l1', axis=0)
n=x.shape[0]
n1=int(n*.3)
from sklearn.preprocessing import label_binarize
encoded_column_vector = label_binarize(y, classes=['negative','positive']) # negative
encoded_labels = np.ravel(encoded_column_vector) # Reshape array
y=encoded_labels
y_test=y[0:n1]
y_train=y[n1:n+1]
X_test = x[0:n1,:]
X_train= 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.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)
#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  (35000, 50) (15000, 50) (35000,) (15000,)
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='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Count of non zero element in coefficient 0
Model train and test score C and penalty 0.851142857143 0.8246 0.001 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='l1', 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 0.892885714286 0.8832 10000 l1
           C penalty  test_score  train_score                 type
0     10.000      l1    0.838200     0.911971       Grid search BOW
0    100.000      l1    0.863933     0.968943     Random search BOW
0     10.000      l1    0.845133     0.921029     Grid search TFIDF
0    100.000      l1    0.862733     0.975514   Random search TFIDF
0      0.001      l1    0.824600     0.851143    Grid search AVGW2V
0  10000.000      l1    0.883200     0.892886  Random search AVGW2V
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.001 0 (1, 50) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.01 0 (1, 50) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.1 0 (1, 50) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1 0 (1, 50) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10 0 (1, 50) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 100 20 (1, 50) 0.874028571429 0.857733333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1000 47 (1, 50) 0.882285714286 0.868333333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10000 50 (1, 50) 0.886742857143 0.872533333333
```


Validation Curve With logistic regression for different C value
Training score
Cross-validation score
Accuracy Score
0.88
0.86
0.84
0.82
0
2
4
6
8
10
C value


Validation Curve With logistic regression for different C value
Training score
Cross-validation score
Accuracy Score
0.88
0.86
0.84
0.82
0
2
4
6
8
10
C value

13 TFIDF AVGW2V

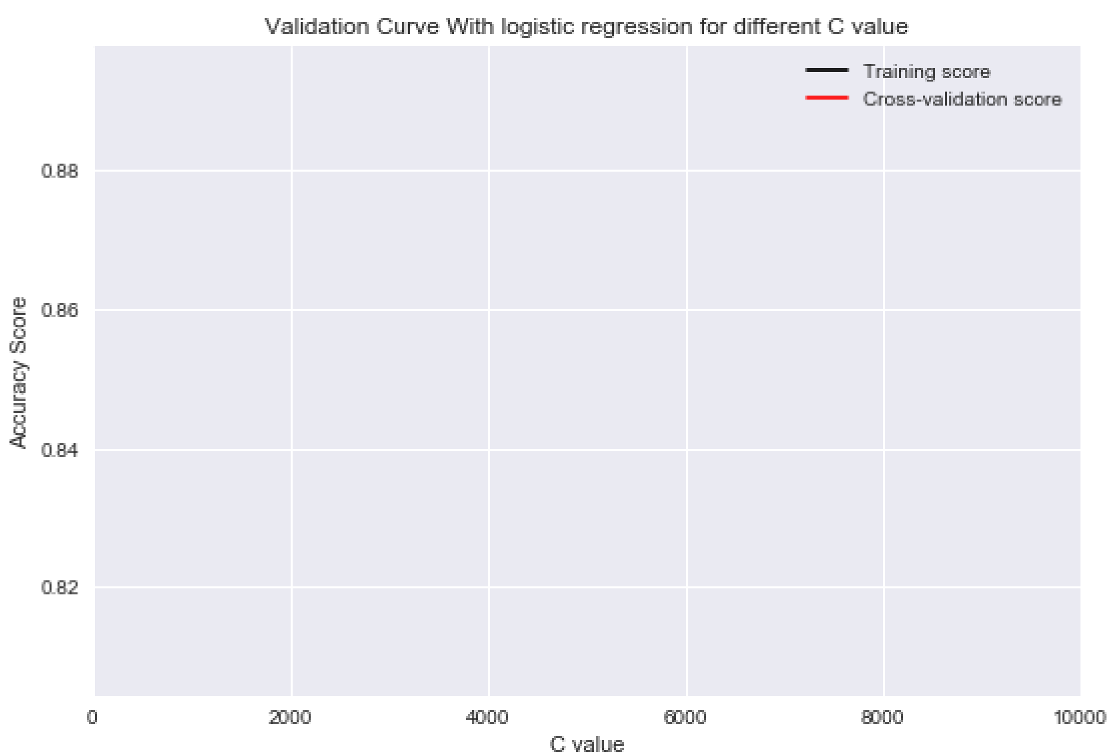
In [61]:
```
tf_idf_vect = TfidfVectorizer()
final_tf_idf=tf_idf_vect.fit_transform(clean_data['CleanedText'].values)
tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this l
row=0;
#calculate avg tfidf score for each sentences
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]#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.append(sent_vec)
    row += 1
#tfidf_sent_vectors.


x=tfidf_sent_vectors
y =clean_data['Score']
from sklearn.preprocessing import normalize
x = normalize(x, norm='l1', axis=0)
n=x.shape[0]
n1=int(n*.3)
from sklearn.preprocessing import label_binarize
encoded_column_vector = label_binarize(y, classes=['negative','positive']) # negative
encoded_labels = np.ravel(encoded_column_vector) # Reshape array
y=encoded_labels
y_test=y[0:n1]
y_train=y[n1:n+1]
X_test = x[0:n1,:]
X_train= 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.shape, X_test.shape,y_trai
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import validation_curve
```

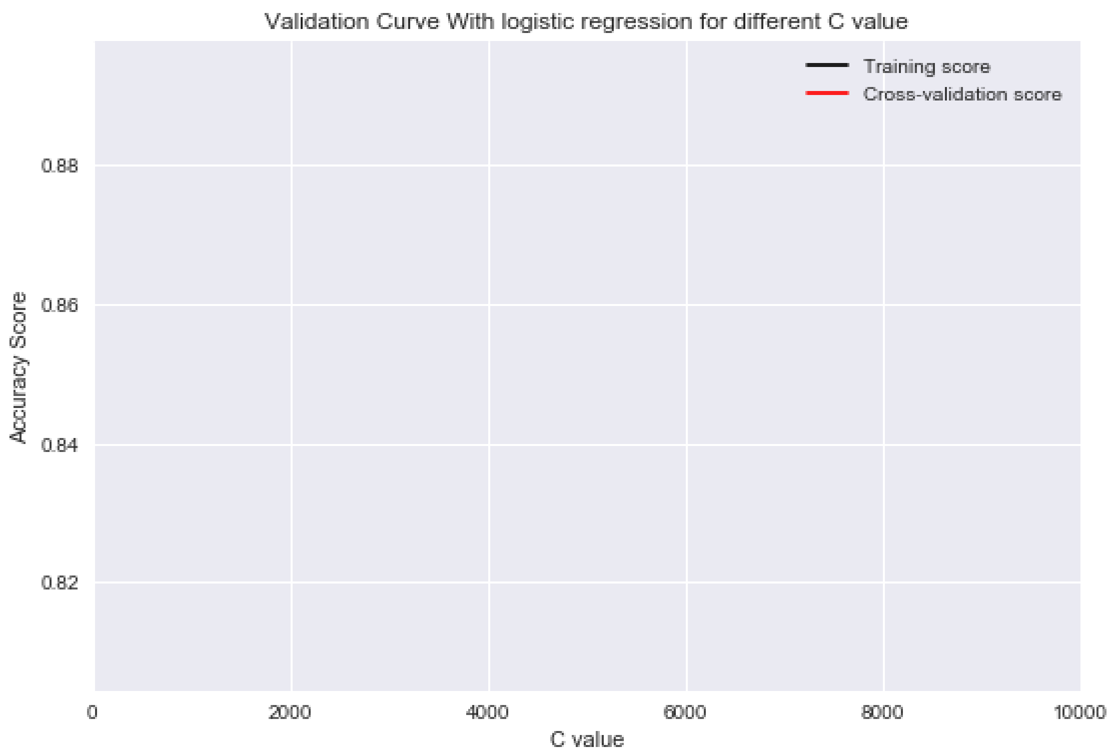
```
C=[10**-3, 10**-2, 10**-1, 1,10]
penalty=['l1', 'l2']
tuned_parameters=dict(penalty=penalty,C=C)
model = GridSearchCV(LogisticRegression(), tuned_parameters, scoring = 'f1', cv=5)
model.fit(X_train, y_train)
print('Best parameters \n',model.best_estimator_)
optimumc=model.best_estimator_.C
optimumpenalty=model.best_estimator_.penalty
#build model with best parameter
model = LogisticRegression(C=optimumc,penalty=optimumpenalty)
model.fit(X_train, y_train)
bb=pd.DataFrame({'type':['Grid search AVGW2VTFIDF'],'train_score':[model.score(X_trai
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 AVGW2VTFIDF'],'train_score':[model.score(X_tr
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 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(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 +
plt.title("Validation Curve With logistic regression for different C value")
plt.xlabel("C value")
plt.ylabel("Accuracy Score")
plt.xlim(.0001,10000)
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(.0001,10000)
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```

```
size of X_train, X_test, y_train , y_test  (35000, 50) (15000, 50) (35000,) (15000,)
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='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Count of non zero element in coefficient 0
Model train and test score C and penalty 0.851142857143 0.8246 0.001 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='l1', 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 0.880971428571 0.869 10000 l1
          C penalty  test_score  train_score                        type
0     10.000      l1    0.838200     0.911971            Grid search BOW
0    100.000      l1    0.863933     0.968943          Random search BOW
0     10.000      l1    0.845133     0.921029          Grid search TFIDF
0    100.000      l1    0.862733     0.975514        Random search TFIDF
0      0.001      l1    0.824600     0.851143         Grid search AVGW2V
0  10000.000      l1    0.883200     0.892886       Random search AVGW2V
0      0.001      l1    0.824600     0.851143    Grid search AVGW2VTFIDF
0  10000.000      l1    0.868867     0.880971  Random search AVGW2VTFIDF
0      0.001      l1    0.824600     0.851143    Grid search AVGW2VTFIDF
0  10000.000      l1    0.869000     0.880971  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) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.01 0 (1, 50) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 0.1 0 (1, 50) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1 0 (1, 50) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10 0 (1, 50) 0.851142857143 0.8246
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 100 21 (1, 50) 0.862771428571 0.839666666667
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 1000 44 (1, 50) 0.8788 0.864333333333
Count of non zero, total element (l1), coefficient ( C or 1/lambda),train accuracy and test acc
 10000 50 (1, 50) 0.874257142857 0.8594
Top 10 words for both review 0 negative 1 positive with weights

0 -44148.6776947 abject
0 -34912.5191701 abd
0 -24886.6383054 aberr
0 -24850.9542093 abiet
```

```
0 -24687.0231284 abit
0 -18365.4512478 aboard
0 -18005.3536612 abl
0 -16383.2147701 abandn
0 -13020.5610446 abomin
0 -12862.4413119 abid


1 26703.0402706 aaaah
1 26233.433247 abil
1 23400.7809441 aback
1 19917.4485339 abhor
1 17978.3121422 abhorr
1 16205.5972376 abot
1 14013.4267517 abnormalitywith
1 12715.6304794 aauc
1 11132.174957 aboslut
1 8965.68548098 abdomen
```





14 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 [64]: aa
```

Out[64]:

	C	penalty	test_score	train_score	type
0	10.000	l1	0.838200	0.911971	Grid search BOW
0	100.000	l1	0.863933	0.968943	Random search BOW
0	10.000	l1	0.845133	0.921029	Grid search TFIDF
0	100.000	l1	0.862733	0.975514	Random search TFIDF
0	0.001	l1	0.824600	0.851143	Grid search AVGW2V
0	10000.000	l1	0.883200	0.892886	Random search AVGW2V
0	0.001	l1	0.824600	0.851143	Grid search AVGW2VTFIDF
0	10000.000	l1	0.868867	0.880971	Random search AVGW2VTFIDF