```
In [150]: import numpy
          import pandas as pd
          import matplotlib.pyplot as plt
          from sklearn.metrics import confusion matrix
          from sklearn.metrics import accuracy score
          from sklearn.cross validation import cross val score
          from sklearn.cross validation import train test split
          from nltk.corpus import stopwords
          from nltk.stem import PorterStemmer
          import re
          import sqlite3
In [151]: | con = sqlite3.connect("./amazon-fine-food-reviews/database.sqlite")
          data = pd.read sql query('''
          SELECT *
          FROM REVIEWS
          WHERE SCORE != 3''', con)
          data.shape
Out[151]: (525814, 10)
In [152]: data = data[data.HelpfulnessNumerator <= data.HelpfulnessDenominator]</pre>
          data.shape
Out[152]: (525812, 10)
In [153]: data['Score'] = data["Score"].apply(lambda x: "positive" if x > 3 else
          "negative")
          sorted data = data.sort values('ProductId',axis = 0, inplace = False, k
          ind = 'quicksort',ascending = True)
          sorted data.head()
Out[153]:
                          ProductId
                                              Userld | ProfileName | HelpfulnessNumerator | He
                      ld
```

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	He	
138693	150511	0006641040	A1C9K534BCl9GO	Laura Purdie Salas	0	0	
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11	18	
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1	2	
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	
138705	150523	0006641040	A2P4F2UO0UMP8C	Elizabeth A. Curry "Lovely Librarian"	0	0	
4	←						

```
In [154]: filtered_data = sorted_data.drop_duplicates(subset = {'UserId','Profile
    Name','Time'} ,keep = 'first', inplace = False)
```

```
filtered data.shape
Out[154]: (328770, 10)
In [155]: filtered data['Score'].value counts()
Out[155]: positive
                      275650
          negative
                       53120
          Name: Score, dtype: int64
In [156]: final = filtered data.copy()
In [157]: import nltk
          nltk.download('stopwords')
          [nltk data] Downloading package stopwords to C:\Users\manish
          [nltk data]
                          dogra\AppData\Roaming\nltk data...
                        Package stopwords is already up-to-date!
          [nltk data]
Out[157]: True
In [158]: stop = set(stopwords.words("english"))
          st = PorterStemmer()
          st.stem('burned')
Out[158]: 'burn'
In [159]: def cleanhtml(sent):
              cleanr = re.compile('<.*?>')
              cleaned = re.sub(cleanr, ' ', sent)
              return cleaned
          def cleanpunc(sent):
              clean = re.sub(r'[?|!|$|#|\'|"|:]',r'',sent)
              clean = re.sub(r'[,|(|)|.|\|/]',r'',clean)
              return clean
In [160]: i=0
          all positive reviews =[]
```

```
all negative reviews = []
          final string = []
          stem data = " "
          for p in final['Text'].values:
              filtered sens = []#filtered word
              p = cleanhtml(p)
              for w in p.split():
                 # print(w)
                  punc = cleanpunc(w)
                  for s in punc.split():
                       #print(w)
                      if (s.isalpha()) & (len(s)>2):
                           if s.lower() not in stop:
                               stem data = (st.stem(s.lower())).encode('utf8')
                               #can we use lemmatizer and stemming altogether??
                               filtered sens.append(stem data)
                               if (final['Score'].values)[i] == 'positive':
                                   all positive reviews.append(stem data)
                               if (final['Score'].values)[i] == 'negative':
                                   all negative reviews.append(stem data)
                           else:
                               continue
                       else:
                           continue
              #print(filtered sens)
              str1 = b" ".join(filtered sens)
              #print(str1)
              final string.append(str1)
              i+=1
In [161]: final['CleanedText'] = final string
          final.head()
Out[161]:
                                              UserId | ProfileName | HelpfulnessNumerator | He
                          ProductId
                      ld
```

	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	Не
138693	150511	0006641040	A1C9K534BCl9GO	Laura Purdie Salas	0	0
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11	18
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1	2
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
138705	150523	0006641040	A2P4F2UO0UMP8C	Elizabeth A. Curry "Lovely Librarian"	0	0

In [162]: from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature extraction.text import CountVectorizer In [163]: final = final.sort values('Time',axis= 0,inplace = False , na position = 'last',ascending = True) X = final['CleanedText'].values X = X[:100000]y = final['Score'].values v = v[:100000]In [164]: X train ,X test,y train,y test = train test split(X,y,test size = 0.3,s tratifv = vLogistic regression on bow In [165]: count vect = CountVectorizer() #in scikit-learn bow train = count vect.fit transform(X train) bow test = count vect.transform(X test) #count vect.get feature names() bow train.shape Out[165]: (70000, 32539) In [166]: import numpy as np In [167]: x = np.random.normal(loc = 0 , scale = 0.1, size = 50)param distb = $\{'C': [y \text{ for } y \text{ in } x \text{ if } y > 0]\}$ print(param distb) {'C': [0.16698275797096984, 0.11398056947443365, 0.076115220379598142, 0.17229256023059686, 0.027907564007266322, 0.066047061540247629, 0.0178 07903972506894, 0.0031991558659850423, 0.006525179239134149, 0.11504336 398450735, 0.017970785538968106, 0.015577283888338659, 0.02837952027458 2549, 0.15682816393394053, 0.045687225669993524, 0.056541521764899655, 0.1314026855004789, 0.047455632742603837, 0.051550262477658176, 0.17422

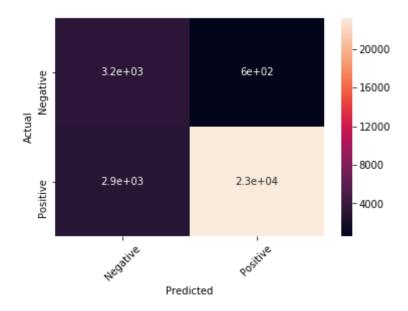
332503357488, 0.064818656695836085, 0.13720030020819388, 0.109886253096

```
47977, 0.10114463373321468, 0.064679822096676692, 0.014860127257105109,
          0.07087264327765079, 0.094597354879467896, 0.04957879513728862]}
In [168]: from sklearn.model selection import RandomizedSearchCV
          from sklearn.linear model import LogisticRegression
          model random = RandomizedSearchCV(LogisticRegression(class weight = 'ba
          lanced',penalty = 'l1'),param distb,cv = 10 ,scoring = 'accuracy')
          model random.fit(bow train,y train)
          print(model random.best estimator )
          pred = model random.predict(bow test)
          print('Accuracy ',accuracy score(y test,pred)*100)
          LogisticRegression(C=0.17422332503357488, class weight='balanced', 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)
          Accuracy 88.203333333
         from sklearn.metrics import classification report
In [169]:
          print(classification report(y test,pred))
                                    recall f1-score
                                                       support
                       precision
             negative
                            0.52
                                      0.84
                                                0.64
                                                          3811
                                                0.93
                            0.97
                                      0.89
             positive
                                                         26189
          avg / total
                                                0.89
                            0.92
                                      0.88
                                                         30000
In [170]: from sklearn.metrics import recall score , precision score , roc auc sc
          ore ,roc curve
          print('RECALL SCORE')
          print(recall score(y test,pred,pos label = 'positive'))
          print(recall score(y test,pred,pos label= 'negative') )
          print('\n')
          print('PRECISION SCORE')
          print(precision score(y test,pred,pos label = 'positive'))
          print(precision score(y test,pred,pos label = 'negative'))
```

```
RECALL SCORE
           0.887853679026
           0.842036210968
           PRECISION SCORE
           0.97476314245
           0.522128213472
In [171]: change = lambda x : 1 if x == 'positive' else 0
           y true = np.array([change(x) for x in y test])
           y pred = model random.predict proba(bow test)[:,1]
           fpr,tpr,thresholds = roc curve(y true, y pred)
           plt.plot(fpr,tpr,'r--')
           plt.ylabel('True Positive Rate')
           plt.xlabel('False Positive Rate')
           plt.legend()
           plt.show()
             1.0
              0.8
            True Positive Rate
              0.2
              0.0
                         0.2
                                 0.4
                                         0.6
                                                 0.8
                                                         1.0
                  0.0
                                False Positive Rate
In [172]: print(roc_auc_score(y_true,y_pred))
           0.932468206735
```

```
In [173]: from sklearn.metrics import confusion_matrix
import seaborn as sns
confusion = confusion_matrix(y_test , pred)
print(confusion)
df_cm = pd.DataFrame(confusion , index = ['Negative','Positive'])
sns.heatmap(df_cm ,annot = True)
plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

[[ 3209 602]
[ 2937 23252]]
```



Logistic Regression on BOW with L1

- Optimal C = 0.174
- Accuracy = 88.203

```
• Precision = 0.974(positive), 0.522(negative)

    Recall = 0.887, 0.842

            • AUC = 0.932

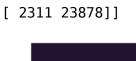
    TN = 3209

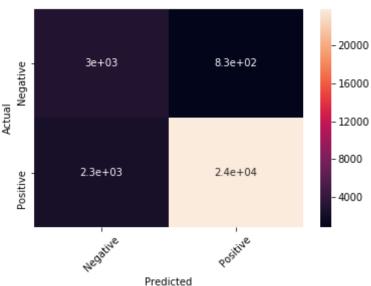
            • TP = 23252
In [174]: clf = LogisticRegression(penalty = 'l1', C = 0.1, class weight = 'balanc
          ed')
          clf.fit(bow train,y train)
          pred = clf.predict(bow test)
          pred train = clf.predict(bow train)
          test error = 1-accuracy score(y test,pred)
          train error = 1-accuracy score(y train,pred train)
In [175]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = clf.coef
          print('Sparsity', np.count nonzero(w)-len(w))
          Error on test 12.2433333333
          Error on train 11.3757142857
          Sparsity 1275
In [176]: clf = LogisticRegression(penalty = 'll', C = 1, class weight = 'balance
          d')
          clf.fit(bow train,y train)
          pred = clf.predict(bow test)
          pred train = clf.predict(bow train)
          test error = 1-accuracy score(y test, pred)
          train error = 1-accuracy score(y train,pred train)
In [177]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = clf.coef
          print('Sparsity', np.count nonzero(w)-len(w))
          Error on test 10.7066666667
```

```
Error on train 6.48571428571
          Sparsity 5098
In [178]: clf = LogisticRegression(penalty = 'l1', C = 10, class weight = 'balance
          d')
          clf.fit(bow train,y_train)
          pred = clf.predict(bow test)
          pred train = clf.predict(bow train)
          test error = 1-accuracy score(y test,pred)
          train error = 1-accuracy score(y train,pred train)
In [179]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = clf.coef
          print('Sparsity',np.count nonzero(w)-len(w))
          Error on test 11.0633333333
          Error on train 2.44857142857
          Sparsity 9747
          Result with L1
            1. C = 0.1, ERROR ON TEST - 12.24, ERROR IN TRAIN - 11.375, SPARSITY - 1275
            2. C = 1, ERROR ON TEST - 10.7, ERROR IN TRAIN - 6.48, SPARSITY - 5048
            3. C = 10, ERROR ON TEST - 11.06, ERROR IN TRAIN - 2.448, SPARSITY - 9747
In [180]: tunned param = [\{'C': [10** -4, 10**-3, 10**-2, 10**-1, 1, 10, 100, 1000, 100]]
          00]}]
          from sklearn.linear model import LogisticRegression
          from sklearn.model selection import GridSearchCV
          model = GridSearchCV(LogisticRegression(class weight = 'balanced'),tun
          ned param , scoring = 'accuracy',cv = 10,n jobs = -1)
          model.fit(bow train,y train)
          print(model.best estimator )
          pred = model.predict(bow test)
          print('Accuracy ',accuracy score(y test,pred)*100)
```

```
LogisticRegression(C=1, class weight='balanced', 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)
          Accuracy 89.54
In [181]: from sklearn.metrics import classification report
          print(classification report(y test,pred))
                       precision
                                    recall f1-score
                                                       support
             negative
                            0.56
                                      0.78
                                                0.66
                                                          3811
             positive
                            0.97
                                      0.91
                                                0.94
                                                         26189
          avg / total
                            0.92
                                      0.90
                                                0.90
                                                         30000
In [182]: from sklearn.metrics import recall score , precision score , roc auc sc
          ore ,roc curve
          print('RECALL SCORE')
          print(recall score(y test,pred,pos label = 'positive'))
          print(recall score(y test,pred,pos label= 'negative') )
          print('\n')
          print('PRECISION SCORE')
          print(precision score(y test,pred,pos label = 'positive'))
          print(precision score(y test,pred,pos label = 'negative'))
          RECALL SCORE
          0.911756844477
          0.782996588822
          PRECISION SCORE
          0.96652499494
          0.563550519358
In [183]: change = lambda x : 1 if x == 'positive' else 0
          v true = np.array([change(x) for x in y test])
          y pred = model.predict proba(bow test)[:,1]
```

```
fpr,tpr,thresholds = roc_curve(y_true, y_pred)
           plt.plot(fpr,tpr,'r--')
           plt.ylabel('True Positive Rate')
           plt.xlabel('False Positive Rate')
           plt.legend()
           plt.show()
             1.0
              0.8
            True Positive Rate
              0.6
              0.4
              0.2
              0.0
                         0.2
                                 0.4
                                         0.6
                                                 0.8
                                                        1.0
                 0.0
                                False Positive Rate
In [184]: print(roc auc score(y true,y pred))
           0.920404717222
In [185]: from sklearn.metrics import confusion matrix
           import seaborn as sns
           confusion = confusion matrix(y test , pred)
           print(confusion)
           df cm = pd.DataFrame(confusion , index = ['Negative','Positive'])
           sns.heatmap(df cm ,annot = True)
           plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
           plt.xlabel("Predicted")
           plt.ylabel("Actual")
           plt.show()
           [[ 2984
                     8271
```





Logistic Regression on BOW with L2

- Optimal C = 1
- Accuracy = 89.84
- Precision = 0.96(positive), 0.56(negative)
- Recall = 0.91,0.78
- AUC = 0.92
- TN = 2984
- TP = 23878

```
In [186]: clf = LogisticRegression(class_weight = 'balanced',C = 1)
    clf.fit(bow_train,y_train)
```

```
multi class='ovr', n jobs=1, penalty='l2', random state=None,
                    solver='liblinear', tol=0.0001, verbose=0, warm start=False)
In [187]: w = clf.coef
          print(w)
          [[ -6.92004818e-03 7.78286830e-02 5.95620395e-06 ....
                                                                      9.93296045e
          - 02
             -7.35283969e-02 3.43243715e-05]]
          Multicollinearity check
In [188]: rand = np.random.normal(loc = 0, scale = 0.01, size = 1)
          bow train.data = bow train.data + rand
In [190]: mod = GridSearchCV(LogisticRegression(class weight = 'balanced'), tunne
          d param , scoring = 'accuracy',cv = 10,n_jobs = -1)
          mod.fit(bow train,y train)
          print(model.best estimator )
          LogisticRegression(C=1, class weight='balanced', 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)
In [191]: | clf noise = LogisticRegression(class weight = 'balanced', C = 1)
          clf noise.fit(bow train,y train)
Out[191]: LogisticRegression(C=1, class weight='balanced', 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)
In [192]: w noise = clf noise.coef
          print(w noise)
          [[ -6.94135146e-03 7.83005056e-02
                                                6.15526665e-06 ...,
                                                                      9.97149823e
```

```
- 02
             -7.36787442e-02 3.34816168e-05]]
In [193]: per = ((w noise[0] - w[0])/abs(w[0]))
          per = abs(per)
          len per = len(per)
          change = []
          for i in per:
              if i > 0.3:
                   change.append(i)
          len change = len(change)
In [195]: print(len per)
          print(len change)
          print('Multicollinearity exists in features for change greater than 30%
           is',(len change/len per)*100,'%')
          32539
          2100
          Multicollinearity exists in features for change greater than 30% is 6.4
          53793908847843 %
In [196]: change = []
          for i in per:
              if i > 0.4:
                   change.append(i)
          len change = len(change)
In [198]: print(len per)
          print(len change)
          print('Multicollinearity exists in features for change greater than 40%
           is',(len change/len per)*100,'%')
          32539
          1954
          Multicollinearity exists in features for change greater than 40% is 6.0
          05101570423185 %
```

```
In [199]: indices = w.argsort()[::-1][:10]
    print(np.take(count_vect.get_feature_names(),indices))

[['worst' 'perricon' 'secondli' ..., 'skeptic' 'downsid' 'pleasantli']]
```

Logistic regression on tfidf

```
In [200]: tfidf vect = TfidfVectorizer()
          tfidf train = tfidf vect.fit transform (X train)
          tfidf test = tfidf vect.transform(X test)
          from sklearn.preprocessing import StandardScaler
          sc = StandardScaler(with mean = False)
          X tr = sc.fit transform(tfidf train)
          X te = sc.transform(tfidf test)
          param = [\{'C':[10**i \text{ for } i \text{ in } range(-3,4)]\}]
          qd = GridSearchCV(LogisticRegression(class weight = 'balanced', penalty
          = 'l1'),param,cv = 10, scoring = 'accuracy',n jobs = -1)
          qd.fit(X tr,y train)
          print(qd.best estimator )
          pred = gd.predict(X te)
          print('Accuracy is ',accuracy score(y test,pred)*100)
          LogisticRegression(C=0.01, class weight='balanced', 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)
          Accuracy is 89.406666667
In [201]: from sklearn.metrics import classification report
          print(classification report(y test,pred))
          print('\n')
          print('Recall for positive', recall score(y test, pred, pos label = 'posit
          ive'))
          print('Recall for negative', recall score(y test, pred, pos label = 'negat
          ive'))
```

```
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
  'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
  'negative'))
```

	precision	recall	fl-score	support
negative positive	0.56 0.97	0.81 0.91	0.66 0.94	3811 26189
avg / total	0.92	0.89	0.90	30000

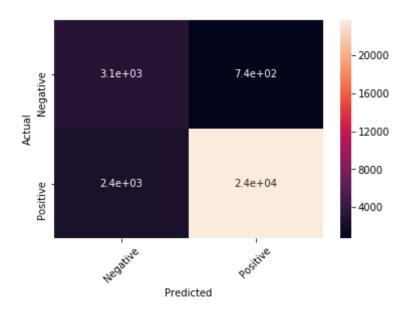
Recall for positive 0.906869296269 Recall for negative 0.806087641039

Precision for postive 0.96982318592 Precision for negative 0.557430593359

```
In [203]: print('ROC Score',roc_auc_score(y_true,y_pred))
    print('\n')
    confusion = confusion_matrix(y_test , pred)
    print(confusion)
    df_cm = pd.DataFrame(confusion , index = ['Negative','Positive'])
    sns.heatmap(df_cm ,annot = True)
    plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()
```

ROC Score 0.936580162457

```
[[ 3072 739]
[ 2439 23750]]
```



Logistic Regression on Tfidf with L1

- Optimal C = 0.01
- Accuracy = 89.4
- Precision = 0.96(positive), 0.55(negative)
- Recall = 0.90 ,0.8
- AUC = 0.93
- TN = 3072
- TP = 23750

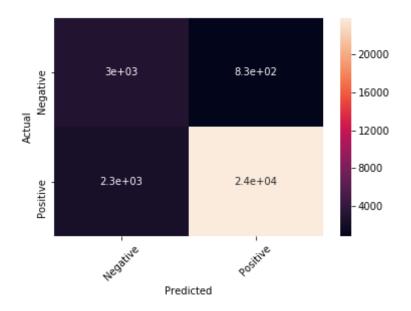
```
In [204]: lr_clf = LogisticRegression(penalty = 'l1', C = 0.1,class_weight = 'bal
anced')
lr_clf.fit(X_tr,y_train)
pred = lr_clf.predict(X_te)
pred_train = lr_clf.predict(X_tr)
test_error = 1-accuracy_score(y_test,pred)
train_error = 1-accuracy_score(y_train,pred_train)
```

```
In [205]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
          print('Sparsity', np.count nonzero(w)-len(w))
          Error on test 11.65
          Error on train 2.64428571429
          Sparsity 12879
In [206]: | lr clf = LogisticRegression(penalty = 'l1', C = 1,class weight = 'balan
          ced')
          lr clf.fit(X tr,y train)
          pred = lr clf.predict(X te)
          pred train = lr clf.predict(X tr)
          test error = 1-accuracy score(y test, pred)
          train error = 1-accuracy score(y train,pred train)
In [207]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
          print('Sparsity', np.count_nonzero(w) -len(w))
          Error on test 13.65
          Error on train 1.79571428571
          Sparsity 14055
In [208]: | lr clf = LogisticRegression(penalty = 'l1', C = 10, class weight = 'bala
          nced')
          lr clf.fit(X tr,y train)
          pred = lr clf.predict(X te)
          pred train = lr clf.predict(X tr)
          test error = 1-accuracy_score(y_test,pred)
          train error = 1-accuracy score(y train,pred train)
In [209]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
          print('Sparsity',np.count nonzero(w)-len(w))
```

```
Error on test 14.3666666667
           Error on train 1.58714285714
          Sparsity 14596
In [210]: | lr clf = LogisticRegression(penalty = 'l1', C = 100, class weight = 'bal
           anced')
          lr clf.fit(X tr,y train)
           pred = lr clf.predict(X te)
           pred train = lr clf.predict(X tr)
           test error = 1-accuracy score(y test,pred)
           train error = 1-accuracy score(y train,pred train)
In [211]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
           print('Sparsity',np.count nonzero(w)-len(w))
           Error on test 14.5733333333
           Error on train 1.55714285714
           Sparsity 15651
          Result with L1
            1. C = 0.1, ERROR ON TEST - 11.65, ERROR IN TRAIN - 2.64, SPARSITY - 12879
            2. C = 1, ERROR ON TEST - 13.65, ERROR IN TRAIN - 1.79, SPARSITY - 14055
            3. C = 10, ERROR ON TEST - 14.3, ERROR IN TRAIN - 1.5, SPARSITY - 14596
            4. C = 100, ERROR ON TEST - 14.57, ERROR IN TRAIN - 1.55, SPARSITY - 15651
          model = GridSearchCV(LogisticRegression(class weight = 'balanced'),tun
In [212]:
          ned param , scoring = 'accuracy', cv = 10, n jobs = -1)
          model.fit(bow train,y train)
           print(model.best estimator )
           pred = model.predict(bow test)
           print('Accuracy ',accuracy score(y_test,pred)*100)
          LogisticRegression(C=1, class weight='balanced', 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)
          Accuracy 89.53
In [213]: print(classification report(y test,pred))
          print('\n')
          print('Recall for positive', recall score(y test, pred, pos label = 'posit
          ive'))
          print('Recall for negative', recall score(y test, pred, pos label = 'negat
          ive'))
          print('\n')
          print('Precision for postive', precision score(y test, pred, pos label =
          'positive'))
          print('Precision for negative',precision score(y test,pred,pos label =
           'negative'))
                                    recall f1-score
                       precision
                                                        support
             negative
                            0.56
                                      0.78
                                                 0.66
                                                           3811
             positive
                            0.97
                                      0.91
                                                 0.94
                                                          26189
          avg / total
                            0.92
                                      0.90
                                                 0.90
                                                          30000
          Recall for positive 0.911604108595
          Recall for negative 0.783258987142
          Precision for postive 0.966558704453
          Precision for negative 0.56320754717
In [214]: y pred = gd.predict proba(X te)[:,1]
          fpr,tpr,thresholds = roc curve(y true, y pred)
          plt.plot(fpr,tpr,'r--')
          plt.ylabel('True Positive Rate')
          plt.xlabel('False Positive Rate')
```

```
plt.legend()
            plt.show()
              1.0
              0.8
            True Positive Rate
               0.6
               0.2
               0.0
                          0.2
                                                            1.0
                   0.0
                                   0.4
                                           0.6
                                                    0.8
                                  False Positive Rate
In [215]: print('ROC Score', roc_auc_score(y_true, y_pred))
            print('\n')
            confusion = confusion_matrix(y_test , pred)
            print(confusion)
            df cm = pd.DataFrame(confusion , index = ['Negative', 'Positive'])
            sns.heatmap(df cm ,annot = True)
            plt.xticks([0.\overline{5}, 1.5], ['Negative', 'Positive'], rotation = 45)
            plt.xlabel("Predicted")
            plt.ylabel("Actual")
            plt.show()
           ROC Score 0.936580162457
            [[ 2985 826]
             [ 2315 23874]]
```



Logistic Regression on Tfidf with L2

- Optimal C = 1
- Accuracy = 89.53
- Precision = 0.96(positive), 0.56(negative)
- Recall = 0.91 ,0.78
- AUC = 0.93
- TN = 2985
- TP = 23874

```
In [216]: clf = LogisticRegression(C = 1 ,class_weight = 'balanced')
    clf.fit(X_tr,y_train)
    w_tfidf = clf.coef_
    print(w_tfidf)
    X_tr.data = X_tr.data + rand

[[ -1.25793095e-02    1.76258923e-02    -1.30055807e-04 ...,    8.56353978e
    -03
```

Multicollinearity check

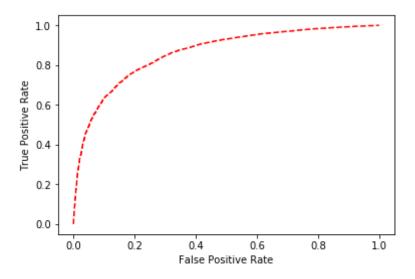
```
In [217]: | mod = GridSearchCV(LogisticRegression(class weight = 'balanced'), tunne
         d param , scoring = 'accuracy',cv = 10,n jobs = -1)
         mod.fit(X tr,y train)
         print(model.best estimator )
         LogisticRegression(C=1, class weight='balanced', dual=False,
                  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)
In [218]: clf noise = LogisticRegression(class weight = 'balanced',C = 1)
         clf noise.fit(X tr,y_train)
         w d = clf noise.coef
         print(w d)
         - 03
            -2.55559428e-02 2.79360564e-0611
In [219]: tf per = ((w d - w tfidf)/abs(w tfidf))
         tf per = abs(tf per)[0]
         ch tfidf = []
         for i in tf per:
             if i > 0.3:
                 ch tfidf.append(i)
In [221]: print(len(ch tfidf))
         print(len(tf per))
         print(print('Multicollinearity exists in features for change greater th
         an 30% is',(len(ch tfidf)/len(tf per))*100,'%'))
         9564
         32539
```

```
Multicollinearity exists in features for change greater than 30% is 29.
          392421402009894 %
          None
In [222]: ch tfidf = []
          for i in tf per:
              if i > 0.4:
                  ch tfidf.append(i)
In [224]: print(len(ch tfidf))
          print(len(tf per))
          print(print('Multicollinearity exists in features for change greater th
          an 40% is',(len(ch tfidf)/len(tf per))*100,'%'))
          9357
          32539
          Multicollinearity exists in features for change greater than 40% is 28.
          75626171670918 %
          None
          Top 10 Features
In [225]: index = w tfidf.argsort()[::-1][:10]
          print(np.take(tfidf vect.get feature names(),index))
          [['worst' 'disappoint' 'tast' ..., 'highli' 'love' 'great']]
          Logistic Regression on Avg W2Vec
In [226]: list of sent train = []
          for i in X train:
              sent = []
              for word in i.split():
                  sent.append(word.decode('utf-8'))
              list of sent train.append(sent)
```

```
In [227]: from gensim.models import Word2Vec
          w2v model = Word2Vec(list of sent train,min count = 5, size = 50, workers
           = 4)
          sent vectors train = []
          for sent in list_of_sent_train:
              sent vec = np.zeros(50)
              cnt word = 0
              for word in sent:
                  try:
                      vec = w2v model.wv[word]
                      sent vec += vec
                      cnt word += 1
                  except:
                       pass
              sent vec /= cnt word
              sent vectors train.append(sent vec)
          print(len(sent vectors train))
          70000
In [228]: list of sent test = []
          for i in X_test:
              sent = []
              for word in i.split():
                  sent.append(word.decode('utf-8'))
              list of sent test.append(sent)
In [229]: import warnings
          warnings.filterwarnings("ignore")
          from gensim.models import Word2Vec
          w2v model = Word2Vec(list of sent test,min count = 5, size = 50, workers
          = 4)
          sent vectors test = []
          for sent in list of sent test:
              sent vec = np.zeros(50)
              cnt word = 0
              for word in sent:
                  try:
```

```
vec = w2v model.wv[word]
                       sent vec += vec
                       cnt word += 1
                   except:
                       pass
              sent vec /= cnt word
              sent vectors test.append(sent vec)
          print(len(sent vectors test))
          30000
In [230]: np.where(np.isnan(sent vectors test))
Out[230]: (array([], dtype=int64), array([], dtype=int64))
In [231]: sc = StandardScaler()
          w2v train = sc.fit transform(sent vectors train)
          w2v test = sc.transform(sent vectors test)
          param = [\{'C':[10**i \text{ for } i \text{ in } range(-3,4)]\}]
          w2v model = GridSearchCV(LogisticRegression(class weight = 'balanced',p
          enalty = 'l1'),param,scoring = 'accuracy',cv = 10,n jobs = -1,)
          w2v model.fit(w2v train,y train)
          print(w2v model.best estimator )
          pred = w2v model.predict(w2v test)
          acc = accuracy score(y test,pred)
          print('accuracy is',acc*100)
          LogisticRegression(C=10, class weight='balanced', 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)
          accuracy is 87.6833333333
In [232]: from sklearn.metrics import classification report
          print(classification report(y test,pred))
          print('\n')
          print('Recall for positive', recall score(y test, pred, pos label = 'posit
          ive'))
          print('Recall for negative', recall score(y test, pred, pos label = 'negat
```

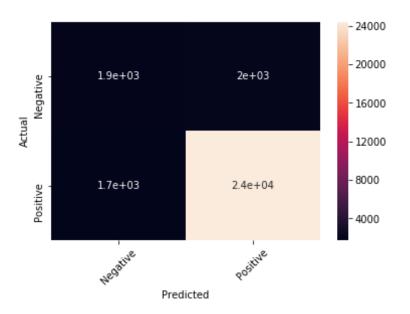
```
ive'))
          print('\n')
          print('Precision for postive', precision score(y test, pred, pos label =
          'positive'))
          print('Precision for negative', precision score(y test, pred, pos label =
          'negative'))
                                    recall f1-score
                       precision
                                                        support
                            0.52
                                                 0.50
             negative
                                       0.49
                                                           3811
             positive
                            0.93
                                      0.93
                                                 0.93
                                                          26189
          avg / total
                            0.87
                                       0.88
                                                 0.88
                                                          30000
          Recall for positive 0.933483523617
          Recall for negative 0.487536079769
          Precision for postive 0.926022727273
          Precision for negative 0.516111111111
In [233]: change = lambda x : 1 if x == 'positive' else 0
          y true = np.array([change(x) for x in y test])
          y pred = w2v model.predict proba(w2v test)[:,1]
          fpr,tpr,thresholds = roc curve(y true, y pred)
          plt.plot(fpr,tpr,'r--')
          plt.ylabel('True Positive Rate')
          plt.xlabel('False Positive Rate')
          plt.legend()
          plt.show()
```



```
In [234]: print('ROC Score',roc_auc_score(y_true,y_pred))
    print('\n')
    confusion = confusion_matrix(y_test , pred)
    print(confusion)
    df_cm = pd.DataFrame(confusion , index = ['Negative','Positive'])
    sns.heatmap(df_cm ,annot = True)
    plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()
```

ROC Score 0.862073848079

```
[[ 1858 1953]
[ 1742 24447]]
```



Logistic Regression on Tfidf with L1

- Optimal C = 10
- Accuracy = 87.68
- Precision = 0.92(positive), 0.51(negative)
- Recall = 0.93,0.48
- AUC = 0.86
- TN = 1858
- TP = 24447

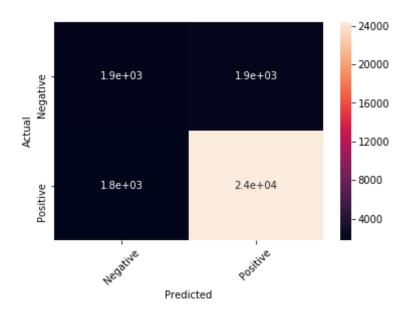
```
In [235]: lr_clf = LogisticRegression(penalty = 'l1', C = 0.1,class_weight = 'bal
anced')
lr_clf.fit(w2v_train,y_train)
pred = lr_clf.predict(w2v_test)
pred_train = lr_clf.predict(w2v_train)
test_error = 1-accuracy_score(y_test,pred)
train_error = 1-accuracy_score(y_train,pred_train)
```

```
In [236]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
          print('Sparsity', np.count nonzero(w)-len(w))
          Error on test 13.1233333333
          Error on train 19.1542857143
          Sparsity 49
In [237]: | lr clf = LogisticRegression(penalty = 'll', C = 1,class weight = 'balan
          ced')
          lr clf.fit(w2v train,y train)
          pred = lr clf.predict(w2v test)
          pred train = lr clf.predict(w2v train)
          test error = 1-accuracy score(y test,pred)
          train error = 1-accuracy score(y train,pred train)
In [238]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
          print('Sparsity', np.count nonzero(w)-len(w))
          Error on test 12.3566666667
          Error on train 19.1171428571
          Sparsity 49
In [239]: | lr clf = LogisticRegression(penalty = 'l1', C = 10, class weight = 'bala
          nced')
          lr clf.fit(w2v train,y train)
          pred = lr clf.predict(w2v test)
          pred train = lr clf.predict(w2v train)
          test error = 1-accuracy score(y test,pred)
          train error = 1-accuracy score(y train,pred train)
In [240]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
          print('Sparsity',np.count nonzero(w)-len(w))
```

```
Error on test 12.3166666667
           Error on train 19.1157142857
           Sparsity 49
In [241]: | lr clf = LogisticRegression(penalty = 'l1', C = 100, class weight = 'bal
           anced')
          lr clf.fit(w2v train,y train)
           pred = lr clf.predict(w2v test)
           pred train = lr clf.predict(w2v train)
           test error = 1-accuracy score(y test,pred)
           train error = 1-accuracy score(y train,pred train)
In [242]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
           print('Sparsity',np.count nonzero(w)-len(w))
           Error on test 12.3066666667
           Error on train 19.1171428571
          Sparsity 49
          Result with L1
            1. C = 0.1, ERROR ON TEST - 11.65, ERROR IN TRAIN - 2.64, SPARSITY - 12879
            2. C = 1, ERROR ON TEST - 13.65, ERROR IN TRAIN - 1.79, SPARSITY - 14055
            3. C = 10, ERROR ON TEST - 14.3, ERROR IN TRAIN - 1.5, SPARSITY - 14596
            4. C = 100, ERROR ON TEST - 14.57, ERROR IN TRAIN - 1.55, SPARSITY - 15651
In [243]: model = GridSearchCV(LogisticRegression(class weight = 'balanced'),par
           am , scoring = 'accuracy', cv = 10, n jobs = -1)
          model.fit(w2v train,y train)
           print(model.best estimator )
           pred = model.predict(w2v test)
           print('Accuracy ',accuracy score(y_test,pred)*100)
          LogisticRegression(C=1, class weight='balanced', 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)
          Accuracy 87.6533333333
In [244]: from sklearn.metrics import classification report
          print(classification report(y test,pred))
          print('\n')
          print('Recall for positive', recall score(y test, pred, pos label = 'posit
          print('Recall for negative', recall score(y test, pred, pos label = 'negat
          ive'))
          print('\n')
          print('Precision for postive', precision score(y test, pred, pos label =
           'positive'))
          print('Precision for negative', precision score(y test, pred, pos label =
          'negative'))
                       precision
                                     recall f1-score
                                                        support
             negative
                             0.51
                                       0.49
                                                 0.50
                                                           3811
             positive
                            0.93
                                      0.93
                                                 0.93
                                                          26189
                                                 0.88
          avg / total
                            0.87
                                       0.88
                                                          30000
          Recall for positive 0.93279621215
          Recall for negative 0.489897664655
          Precision for postive 0.926288249346
          Precision for negative 0.514750482492
In [245]: y pred = model.predict proba(w2v test)[:,1]
          fpr,tpr,thresholds = roc curve(y true, y pred)
          plt.plot(fpr,tpr,'r--')
          plt.vlabel('True Positive Rate')
          plt.xlabel('False Positive Rate')
```

```
plt.legend()
            plt.show()
              1.0
              0.8
            True Positive Rate
               0.6
               0.2
               0.0
                                                            1.0
                   0.0
                           0.2
                                   0.4
                                           0.6
                                                    0.8
                                  False Positive Rate
In [246]: print('ROC Score', roc_auc_score(y_true, y_pred))
            print('\n')
            confusion = confusion_matrix(y_test , pred)
            print(confusion)
            df cm = pd.DataFrame(confusion , index = ['Negative', 'Positive'])
            sns.heatmap(df cm ,annot = True)
            plt.xticks([0.\overline{5}, 1.5], ['Negative', 'Positive'], rotation = 45)
            plt.xlabel("Predicted")
            plt.ylabel("Actual")
            plt.show()
           ROC Score 0.86208826601
            [[ 1867 1944]
             [ 1760 24429]]
```



Logistic Regression on Tfidf with L2

- Optimal C = 1
- Accuracy = 87.65
- Precision = 0.92(positive), 0.51(negative)
- Recall = 0.93,0.48
- AUC = 0.86
- TN = 1867
- TP = 24429

Multicollinearity check

```
In [248]: | mod = GridSearchCV(LogisticRegression(class weight = 'balanced'),tunne
          d param , scoring = 'accuracy', cv = 10, n jobs = -1)
          mod.fit(w2v train,y train)
          print(mod.best estimator )
          LogisticRegression(C=1, class weight='balanced', 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)
In [249]: clf noise = LogisticRegression(class weight = 'balanced', C = 1)
          clf noise.fit(w2v train,y train)
          w = clf noise.coef
          [[ 0.37074169 -0.21480769  0.14271536  0.29113785 -0.59122114 -0.398021
          31
            -0.06539209 - 0.12408598 0.20794021 0.21387863 0.61894129 0.036370
            -0.03264708 -0.04245962 -0.40218067 0.11351973 0.23688174 -0.139121
          12
```

```
0.32180065 - 0.06119811 \ 0.22544015 \ 0.41544074 \ 0.15219955 \ 0.256023
          52
             0.21988354 0.08731498 -0.45795553 0.47673351 0.08619895 -0.120791
          57
            -0.28587255 - 0.15766967 - 0.33169755 - 0.3070821 - 0.80750977 - 0.125764
          39
            -0.35391471 -0.14552967 -0.18356721 0.40294866 -0.1525602
                                                                          0.028226
             -0.34162572  0.07689781  0.09730443  -0.38530197  -0.14786992  -0.420982
          23
             0.6251021 -0.49948318]]
In [250]: w per = ((w - w w2v)/abs(w w2v))
          w per = abs(w per)[0]
          ch w = []
          for i in w per:
              if i > 0.3:
                  ch w.append(i)
In [252]: print(len(ch w))
          print(len(w per))
          print(print('Multicollinearity exists in features for change greater th
          an 30% is',(len(ch w)/len(w per))*100,'%'))
          0
          50
          Multicollinearity exists in features for change greater than 30% is 0.0
          None
In [253]: ch w = []
          for i in w_per:
              if i > 0.4:
                  ch_w.append(i)
In [255]: print(len(ch w))
          print(len(w per))
```

```
print(print('Multicollinearity exists in features for change greater th
an 40% is',(len(ch_w)/len(w_per))*100,'%'))

0
50
Multicollinearity exists in features for change greater than 40% is 0.0
%
None
```

Top 10 features

```
In [256]: sr = sorted(w_w2v)[0]
    print(sr[::-1][:10])

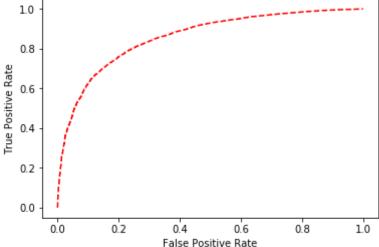
[-0.4994952     0.62512785 -0.42100114 -0.14788566 -0.38529685     0.0972886
4
     0.07688974 -0.34163162     0.02824109 -0.15255126]
```

Logistic Regression on Tfidf W2Vec

```
tfidf sent vec train.append(sent vec)
               row += 1
In [262]: tf idf feat = tfidf vect.get feature names()
          tfidf_sent vec test = []
           row = 0
          for sent in list of sent test:
               sent vec = np.zeros(50)
              weight sum = 0
              for word in sent:
                   trv:
                       vec = w2v model.wv[word]
                       tfidf = tfidf test[row,tf idf feat.index(word)]
                       sent vec += (vec*tfidf)
                       weight sum += tfidf
                   except:
                       pass
               sent vec/= weight sum
              tfidf sent vec test.append(sent vec)
               row += 1
In [263]: np.where(np.isnan(tfidf sent vec train))
Out[263]: (array([], dtype=int64), array([], dtype=int64))
In [264]: #del tfidf sent vec train[10706]
In [265]: #y train = np.delete(y train, 10706)
In [266]: sc = StandardScaler()
          tfidf w2v train = sc.fit transform(tfidf sent vec train)
          tfidf w2v test = sc.transform(tfidf sent vec test)
          param = [\{'C':[10**i \text{ for } i \text{ in } range(-3,4)]\}]
          wv model = GridSearchCV(LogisticRegression(class weight = 'balanced',pe
          nalty = 'l1'),param,scoring = 'accuracy',cv = 10,n jobs = -1,)
          wv model.fit(tfidf w2v train,y train)
          print(wv model.best estimator )
```

```
pred = wv model.predict(tfidf w2v test)
          acc = accuracy score(y_test,pred)
          print('accuracy is',acc*100)
          LogisticRegression(C=0.1, class weight='balanced', 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)
          accuracy is 76.4133333333
In [267]: from sklearn.metrics import classification report
          print(classification report(y test,pred))
          print('\n')
          print('Recall for positive', recall score(y test, pred, pos label = 'posit
          ive'))
          print('Recall for negative', recall score(y test, pred, pos label = 'negat
          ive'))
          print('\n')
          print('Precision for postive', precision score(y test, pred, pos label =
           'positive'))
          print('Precision for negative', precision score(y test, pred, pos label =
          'negative'))
                       precision
                                    recall f1-score
                                                        support
             negative
                             0.33
                                       0.80
                                                 0.46
                                                           3811
                            0.96
                                       0.76
                                                 0.85
                                                          26189
             positive
          avg / total
                            0.88
                                       0.76
                                                 0.80
                                                          30000
          Recall for positive 0.758906411089
          Recall for negative 0.800052479664
          Precision for postive 0.963076028493
          Precision for negative 0.325643490334
```

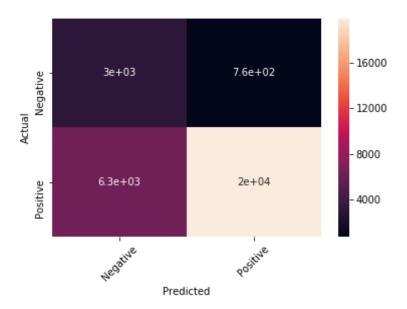
```
In [268]: change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = wv_model.predict_proba(tfidf_w2v_test)[:,1]
fpr,tpr,thresholds = roc_curve(y_true, y_pred)
plt.plot(fpr,tpr,'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```



```
In [269]: print('ROC Score',roc_auc_score(y_true,y_pred))
    print('\n')
    confusion = confusion_matrix(y_test , pred)
    print(confusion)
    df_cm = pd.DataFrame(confusion , index = ['Negative','Positive'])
    sns.heatmap(df_cm ,annot = True)
    plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()
```

ROC Score 0.858007651002

```
[[ 3049 762]
[ 6314 19875]]
```



Logistic Regression on Tfidf with L1

- Optimal C = 0.1
- Accuracy = 79.41
- Precision = 0.96(positive), 0.32(negative)
- Recall = 0.75,0.80
- AUC = 0.85
- TN = 3049
- TP = 19875

```
In [270]: lr_clf = LogisticRegression(penalty = 'l1', C = 0.1,class_weight = 'bal
anced')
lr_clf.fit(tfidf_w2v_train,y_train)
pred = lr_clf.predict(tfidf_w2v_test)
```

```
pred train = lr clf.predict(tfidf w2v train)
          test error = 1-accuracy score(y test, pred)
          train error = 1-accuracy score(y train,pred train)
In [271]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
          print('Sparsity', np.count nonzero(w)-len(w))
          Error on test 23.5866666667
          Error on train 23,6903384334
          Sparsity 48
In [272]: | lr clf = LogisticRegression(penalty = 'l1', C = 1,class weight = 'balan
          ced')
          lr clf.fit(tfidf w2v train,y train)
          pred = lr clf.predict(tfidf w2v test)
          pred train = lr clf.predict(tfidf w2v train)
          test error = 1-accuracy score(y test,pred)
          train error = 1-accuracy score(y train,pred train)
In [273]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
          print('Sparsity',np.count_nonzero(w)-len(w))
          Error on test 23.5566666667
          Error on train 23.6774811069
          Sparsity 49
In [274]: | lr clf = LogisticRegression(penalty = 'l1', C = 10, class weight = 'bala
          nced')
          lr clf.fit(tfidf w2v train,y train)
          pred = lr clf.predict(tfidf w2v test)
          pred train = lr clf.predict(tfidf w2v train)
          test error = 1-accuracy score(y_test,pred)
          train error = 1-accuracy score(y train,pred train)
```

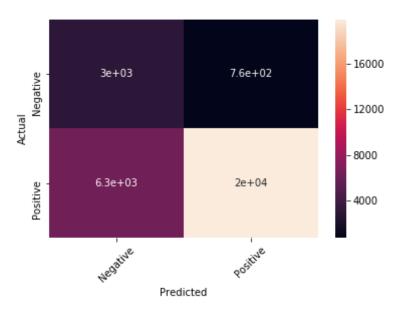
```
In [275]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
           print('Sparsity', np.count nonzero(w)-len(w))
           Error on test 23.5433333333
          Error on train 23.6774811069
          Sparsity 49
In [276]: | lr clf = LogisticRegression(penalty = 'l1', C = 100, class weight = 'bal
           anced')
          lr clf.fit(tfidf w2v train,y train)
          pred = lr clf.predict(tfidf w2v test)
           pred train = lr clf.predict(tfidf w2v train)
           test error = 1-accuracy score(y test, pred)
           train error = 1-accuracy score(y train,pred train)
In [277]: print('Error on test', test error*100)
          print('Error on train', train error*100)
          w = lr clf.coef
          print('Sparsity', np.count nonzero(w)-len(w))
           Error on test 23.5433333333
           Error on train 23.6789096987
          Sparsity 49
          Result with L1
            1. C = 0.1, ERROR ON TEST - 23.58, ERROR IN TRAIN - 23.69, SPARSITY - 48
            2. C = 1, ERROR ON TEST - 23.55, ERROR IN TRAIN - 23.67, SPARSITY - 49
            3. C = 10, ERROR ON TEST - 23.54, ERROR IN TRAIN - 23.67, SPARSITY - 49
            4. C = 100, ERROR ON TEST - 23.54, ERROR IN TRAIN - 23.67, SPARSITY - 49
In [278]: model = GridSearchCV(LogisticRegression(class weight = 'balanced'),par
           am , scoring = 'accuracy', cv = 10, n jobs = -1)
          model.fit(tfidf w2v train,y train)
```

```
print(model.best estimator )
          pred = model.predict(tfidf w2v test)
          print('Accuracy ',accuracy score(y test,pred)*100)
          LogisticRegression(C=10, class weight='balanced', 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)
          Accuracy 76.4533333333
In [279]: from sklearn.metrics import classification report
          print(classification report(y test,pred))
          print('\n')
          print('Recall for positive', recall score(y test, pred, pos label = 'posit
          ive'))
          print('Recall for negative', recall score(y test, pred, pos label = 'negat
          ive'))
          print('\n')
          print('Precision for postive', precision score(y test, pred, pos label =
           'positive'))
          print('Precision for negative', precision score(y test, pred, pos label =
          'negative'))
                       precision
                                    recall f1-score
                                                        support
             negative
                             0.33
                                       0.80
                                                 0.46
                                                           3811
                            0.96
                                       0.76
                                                 0.85
                                                          26189
             positive
          avg / total
                            0.88
                                       0.76
                                                 0.80
                                                          30000
          Recall for positive 0.759364618733
          Recall for negative 0.800052479664
          Precision for postive 0.963097486561
          Precision for negative 0.326061383809
```

```
In [280]: change = lambda x : 1 if x == 'positive' else 0
           y true = np.array([change(x) for x in y test])
           y pred = model.predict proba(tfidf w2v test)[:,1]
           fpr,tpr,thresholds = roc curve(y true, y pred)
           plt.plot(fpr,tpr,'r--')
           plt.ylabel('True Positive Rate')
           plt.xlabel('False Positive Rate')
           plt.legend()
           plt.show()
             1.0
              0.8
           True Positive Rate
              0.2
              0.0
                         0.2
                 0.0
                                                0.8
                                                        1.0
                                False Positive Rate
In [281]: print('ROC Score', roc auc score(y true, y pred))
           print('\n')
           confusion = confusion matrix(y test , pred)
           print(confusion)
           df cm = pd.DataFrame(confusion , index = ['Negative', 'Positive'])
           sns.heatmap(df cm ,annot = True)
           plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
           plt.xlabel("Predicted")
           plt.ylabel("Actual")
           plt.show()
```

ROC Score 0.858033961971

```
[[ 3049 762]
[ 6302 19887]]
```



Logistic Regression on Tfidf with L2

- Optimal C = 10
- Accuracy = 76.45
- Precision = 0.96(positive), 0.32(negative)
- Recall = 0.75,0.80
- AUC = 0.85
- TN = 3049
- TP = 19887

```
In [282]: clf = LogisticRegression(C = 10 ,class_weight = 'balanced')
    clf.fit(tfidf_w2v_train,y_train)
    w_tw = clf.coef_
    print(w_tw)
```

```
[ 0.02227554 0.24687819 0.37823166 0.57594705 -0.37873557 0.021310
65
   0.41199441 - 0.35374098 - 0.07554398 - 0.10735884  0.35796675 - 0.178627
1
   0.35220381 \quad 0.11873004 \quad -0.60147544 \quad -0.33643168 \quad 0.21301264 \quad -0.020921
32
   0.8381591 0.04104244 0.31729943 -0.09284939 0.51619522 0.587219
11
  0.16106774 - 0.03312721 - 0.29633354 \ 0.38546997 - 0.6728411 - 0.051906
  -0.06456107 -0.18990998 -0.58129387 -0.46385552 -0.15921694 -0.049612
11
   0.07228252 - 0.04166887 - 0.17267261 0.23475067 - 0.0980782
                                                                  0.531995
  -0.18634539 0.29089368 0.14593808 -0.28221459 -0.09264809 0.014357
54
  0.5253343 -0.4886633911
```

Multicollinearity check

```
13
            0.41202389 - 0.35377543 - 0.07555119 - 0.10733927 0.35800868 - 0.178657
         69
            0.35222731 0.11876977 -0.6015311 -0.33645107 0.21307016 -0.020942
         91
            0.83826889 \quad 0.04105077 \quad 0.31733588 \quad -0.09290468 \quad 0.51623758 \quad 0.587275
         85
            0.16108844 -0.03314105 -0.29636022 0.3854946 -0.67294777 -0.051923
         12
            -0.06457251 -0.18989387 -0.58131874 -0.46386346 -0.15919052 -0.049583
         19
            0.07229074 -0.04170776 -0.17267676 0.2348406 -0.09809837 0.532056
         Θ7
            -0.1863495 0.29092362 0.14590847 -0.28223304 -0.09264245 0.014417
            0.52538131 -0.4887001911
In [286]: wtf per = ((w wtf - w tw)/abs(w tw))
         wtf_per = abs(wtf per)[0]
         print(wtf per)
         ch wtf = []
         for i in wtf per:
             if i > 0.3:
                 ch wtf.append(i)
          [ 1.09822497e-04
                            2.52366338e-04
                                            1.09911554e-04
                                                             2.33259080e-05
            4.18341479e-05
                            1.57098133e-03
                                            7.15593607e-05
                                                             9.73690660e-05
            9.53398298e-05
                            1.82255387e-04
                                            1.17134438e-04
                                                             1.71240654e-04
            6.67344312e-05
                            3.34591349e-04
                                             9.25333561e-05
                                                             5.76574121e-05
                            1.03194882e-03
                                            1.30985958e-04
            2.70000531e-04
                                                            2.02880216e-04
            1.14865993e-04
                            5.95412093e-04
                                            8.20600471e-05 9.66239089e-05
            1.28513274e-04
                            4.17729780e-04
                                            9.00062465e-05
                                                             6.38805811e-05
            1.58544089e-04
                            3.11565842e-04
                                            1.77207071e-04
                                                             8.48254522e-05
                            1.71053273e-05
                                            1.65953184e-04
                                                             5.82769907e-04
            4.27799415e-05
            1.13723288e-04
                            9.33269889e-04
                                            2.40314159e-05
                                                             3.83092080e-04
            2.05589943e-04
                            1.14221496e-04
                                            2.20758018e-05 1.02915392e-04
                                             6.08768805e-05
                                                             4.15526724e-03
            2.02901015e-04
                            6.53562489e-05
            8.94889490e-05
                            7.53096503e-051
```

```
In [288]:
          print(len(ch wtf))
          print(len(wtf per))
          print(print('Multicollinearity exists in features for change greater th
          an 30% is',(len(ch wtf)/len(wtf per))*100,'%'))
          0
          50
          Multicollinearity exists in features for change greater than 30% is 0.0
          None
In [289]: ch wtf = []
          for i in wtf per:
              if i > 0.4:
                  ch wtf.append(i)
In [291]: print(len(ch wtf))
          print(len(wtf per))
          print(print('Multicollinearity exists in features for change greater th
          an 40% is',(len(ch wtf)/len(wtf per))*100,'%'))
          0
          50
          Multicollinearity exists in features for change greater than 40% is 0.0
          None
          Top 10 features
In [292]: sort = sorted(w tw)[0]
          print(sort[::-1][:10])
          [-0.48866339 0.5253343
                                    0.01435754 -0.09264809 -0.28221459 0.1459380
            0.29089368 -0.18634539 0.5319953 -0.0980782 1
```