AmazonReviewsClassificationLogisticRegression

June 23, 2018

1 AmazonReviews Logistic Regression Assignment

In [1]:
```
%matplotlib inline

import sqlite3
import pandas as pd #for data frames
import numpy as np #numpy array operations
import nltk #natural lang processing, for processing text
import string
import matplotlib.pyplot as plt
import seaborn as sns #for plotting
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 roc_curve, auc
from nltk.stem.porter import PorterStemmer
import pickle
import seaborn as sn

import matplotlib.pyplot as plt
from sklearn.cross_validation import train_test_split
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.model_selection import train_test_split

from sklearn.metrics import average_precision_score,f1_score,precision_score,recall_sc


from sklearn.model_selection import train_test_split
from sklearn.grid_search import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.datasets import *
from sklearn.linear_model import LogisticRegression
```

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

In [2]:
```
pickle_in=open("cleanedData.pickle","rb")
final = pickle.load(pickle_in)

pickle_in = open("BOW_tfidf_avgW2V_TfidfW2V.pickle","rb")
count_vect = pickle.load(pickle_in) #BOW
final_counts = pickle.load(pickle_in) #BOW

tf_idf_vect = pickle.load(pickle_in) #TFIDF
final_tf_idf = pickle.load(pickle_in) #TFIDF
features = pickle.load(pickle_in) #TFIDF
```

In [3]:
```
final.shape
```

Out[3]:
```
(364171, 11)
```

In [4]:
```
scores = final['Score'].get_values()
len(scores)
```

Out[4]:
```
364171
```

In [5]:
```
li = lambda x: 1 if x=='positive'  else 0
final_scores = []
for i in range(0,364171):
    final_scores.append(li(scores[i]))
```

In [6]:
```
def convToNpArray(arr):
    if(type(arr) == list):
        arr = np.array(arr)
        return arr
    else:
        return arr;
```

In [7]:
```
# Total data frame

x = final_counts[0:10000]


# this is only Score/rating  of data

y = final_scores[0:10000]


x_1, x_test, y_1, y_test = train_test_split(x,y, test_size=0.3, random_state=0)
```

```
x_1 = convToNpArray(x_1)
x_test = convToNpArray(x_test)
y_1 = convToNpArray(y_1)
y_test = convToNpArray(y_test)
```

```
In [22]: def confusionMatrix(y_test,pred):
             tn, fp, fn, tp = confusion_matrix(y_test, pred).ravel()
             tpr = tp/(fn+tp)
             tnr = tn/(tn+fp)
             fnr = fn/(fn+tp)
             fpr = fp/(tn+fp)

             print("\n######### Confusion Matrix #########")
             print("TPR :%f \t TNR : %f\nFPR : %f \t FNR: %f"%(tpr,tnr,fpr,fnr))
```

1.1 GridSearch CV

L2

```
In [23]: tuned_parameters = [{'C':[10**-2,10**0,10,10**2,10**4]}]

         lr_model = LogisticRegression(class_weight='balanced',penalty='l2');
         model = GridSearchCV(lr_model,tuned_parameters,
                              scoring='f1',cv=5,n_jobs=4)

         model.fit(x_1,y_1)

         print(model.best_estimator_)
         print("Score: ",model.score(x_test,y_test))
```

```
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)
Score:  0.9525976488433827
```

```
In [24]: Lr_Model = 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)
         Lr_Model.fit(x_1,y_1)
         pred = Lr_Model.predict(x_test)
         confusionMatrix(y_test,pred)
```

```
######### Confusion Matrix #########
TPR :0.951876          TNR : 0.659280
FPR : 0.340720          FNR: 0.048124
```

L1

```
In [25]: tuned_parameters = [{'C':[10**-2,10**0,10,10**2,10**4]}]

         model = GridSearchCV(LogisticRegression(class_weight='balanced',penalty='l1'),tuned_pa
                              scoring='f1',cv=5,n_jobs=4)

         model.fit(x_1,y_1)

         print(model.best_estimator_)
         print("Score: ",model.score(x_test,y_test))
```

```
LogisticRegression(C=10000, 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)
Score:  0.94859287054409
```

```
In [26]: Lr_Model = LogisticRegression(C=10000, 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)
         Lr_Model.fit(x_1,y_1)
         pred = Lr_Model.predict(x_test)
         confusionMatrix(y_test,pred)
```

```
######### Confusion Matrix #########
TPR :0.956423          TNR : 0.567867
FPR : 0.432133          FNR: 0.043577
```

1.2 RandomizedSearch CV

L2

```
In [27]: from scipy.stats import expon
         tuned_parameters = {'C':expon(scale=100)}

         model = RandomizedSearchCV(LogisticRegression(class_weight='balanced',penalty='l2'),tu
                              scoring='f1',cv=5,n_jobs=4)

         model.fit(x_1,y_1)

         print(model.best_estimator_)
         print("Score: ",model.score(x_test,y_test))

         Lr_Model = model.best_estimator_
```

```
Lr_Model.fit(x_1,y_1)
pred = Lr_Model.predict(x_test)
confusionMatrix(y_test,pred)
```

```
LogisticRegression(C=31.679052419676523, 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)
Score:  0.9509562582844158

######### Confusion Matrix #########
TPR :0.951497          TNR : 0.637119
FPR : 0.362881          FNR: 0.048503
```

L1

In [28]:
```
tuned_parameters = {'C':expon(scale=100)}

model = RandomizedSearchCV(LogisticRegression(class_weight='balanced',penalty='l1'),tu
                     scoring='f1',cv=5,n_jobs=4)

model.fit(x_1,y_1)

print(model.best_estimator_)
print("Score: ",model.score(x_test,y_test))

Lr_Model = model.best_estimator_
Lr_Model.fit(x_1,y_1)
pred = Lr_Model.predict(x_test)
confusionMatrix(y_test,pred)
```

```
LogisticRegression(C=196.0818344361864, 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)
Score:  0.9455987910842463

######### Confusion Matrix #########
TPR :0.948465          TNR : 0.581717
FPR : 0.418283          FNR: 0.051535
```

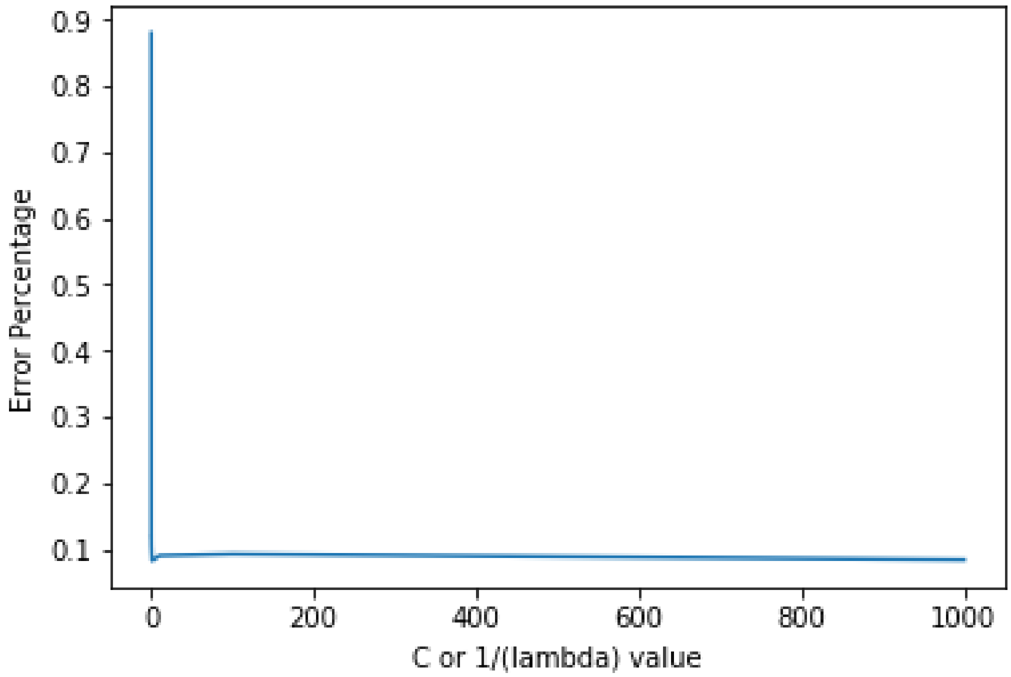
1.3 Checking Performance with different lambdas/C with L1

In [43]:
```
li_of_c_vals = [0.0001,0.001,0.01,0.1,1,10,100,1000]
li_of_errors=[]
for i in li_of_c_vals:
```

```
        model = LogisticRegression(C=i, penalty='l1')
        model.fit(x_1,y_1)
        w = model.coef_
        err_val = 1-model.score(x_test,y_test);
        print("C = ",i,", No.of non zero vals: ",np.count_nonzero(w))
        print("Score: ",(1-err_val)*100)
        print("Error: ",(err_val)*100)
        li_of_errors.append(err_val)

    plt.plot(li_of_c_vals,li_of_errors)
    plt.xlabel('C or 1/(lambda) value')
    plt.ylabel('Error Percentage')
    plt.show()
```

```
C =  0.0001 , No.of non zero vals:  0
Score:  12.033333333333333
Error:  87.96666666666667
C =  0.001 , No.of non zero vals:  3
Score:  87.96666666666667
Error:  12.033333333333333
C =  0.01 , No.of non zero vals:  13
Score:  87.96666666666667
Error:  12.033333333333333
C =  0.1 , No.of non zero vals:  171
Score:  89.53333333333333
Error:  10.466666666666669
C =  1 , No.of non zero vals:  842
Score:  91.73333333333333
Error:  8.266666666666666
C =  10 , No.of non zero vals:  1240
Score:  90.96666666666667
Error:  9.033333333333339
C =  100 , No.of non zero vals:  1358
Score:  90.73333333333333
Error:  9.266666666666667
C =  1000 , No.of non zero vals:  2674
Score:  91.60000000000001
Error:  8.399999999999997
```



Observation: As 'C' val decreases or Lambda val increases Error increases i.e model is underfitted.

2 Multi Collinearity Check

Adding Noise to the data

```
In [108]: from numpy.random import normal
          ep=normal(loc=0.0,scale = 0.01)
          print(ep)

          noisyData = final_tf_idf[0:10000]
          # adding noise to non zero elements.
          noisyData[noisyData!=0]+=ep;
```

```
-7.468860561221003e-05
```

```
In [109]: x = noisyData


          # this is only Score/rating  of data

          y = final_scores[0:10000]
```

```
x_1, x_test, y_1, y_test = train_test_split(x,y, test_size=0.3, random_state=0)

x_1 = convToNpArray(x_1)
x_test = convToNpArray(x_test)
y_1 = convToNpArray(y_1)
y_test = convToNpArray(y_test)
```

In [110]:
```
tuned_parameters = [{'C':[10**-2,10**0,10,10**2,10**4]}]

model = GridSearchCV(LogisticRegression(class_weight='balanced',penalty='l2'),tuned_p
                     scoring='f1',cv=5,n_jobs=4)

model.fit(x_1,y_1)

print(model.best_estimator_)
print("Score: ",model.score(x_test,y_test))
```

```
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)
Score:  0.9577256784197894
```

In [111]:
```
clf = 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)
clf.fit(x_1,y_1)

w_1 = clf.coef_
```

Data without Noise

In [112]:
```
x = final_tf_idf[0:10000]


# this is only Score/rating  of data

y = final_scores[0:10000]


x_1, x_test, y_1, y_test = train_test_split(x,y, test_size=0.3, random_state=0)

x_1 = convToNpArray(x_1)
x_test = convToNpArray(x_test)
```

```
y_1 = convToNpArray(y_1)
y_test = convToNpArray(y_test)
```

In [113]:
```
tuned_parameters = [{'C':[10**-2,10**0,10,10**2,10**4]}]

model = GridSearchCV(LogisticRegression(class_weight='balanced',penalty='l2'),tuned_
                     scoring='f1',cv=5,n_jobs=4)

model.fit(x_1,y_1)

print(model.best_estimator_)
print("Score: ",model.score(x_test,y_test))
```

```
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)
Score:  0.9577256784197894
```

In [114]:
```
clf = 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)
clf.fit(x_1,y_1)

w = clf.coef_
```

Difference between W's(without noise,with noise)

In [115]:
```
import numpy
#calculating euclidean distance between w and origin, w1 and origin
d_w = numpy.linalg.norm(w[0]-np.zeros(len(w[0])))
d_w1 = numpy.linalg.norm(w_1[0]-np.zeros(len(w_1[0])))

# calculating difference percentage of w,w1 if its more than 30% then they are Multi
# if its less than 30% not Multi Collinear then we can Use 'w' to get imp features,
# if val of 'wj' is zero its considered as not imp feature or else it imp feature.

diffPercentage=(abs(d_w-d_w1)/d_w)*100
print(diffPercentage)
```

```
0.033024648368667066
```

Observation: As there is no much difference(its less than 30%) after adding noise i.e after perturbation they are not Multi Collinear so we can directly calculate Important Features from 'Wj' if 'Wj' is 0 its not important else its important feature.

2.1 Important Features

```
In [116]: def getImpFeatures(vectorizer,w_vec,top_n_features):
              feature_names = vectorizer.get_feature_names()
              coefs_with_fns = sorted(zip(w_vec[0], feature_names))
              print("These are the top 20 important Features Which are most widely used in Posi
              pos_features = coefs_with_fns[len(feature_names)-top_n_features:len(feature_name
              neg_features = coefs_with_fns[0:top_n_features];
              print("\n")
              print("Positive: \t\t\t\t Negative:")
              print("\n")
              for i in range(20):
                  print(pos_features[i],"\t\t",neg_features[i])

In [117]: getImpFeatures(tf_idf_vect,w,20)
```

```
These are the top 20 important Features Which are most widely used in Positive and Negative Rev


Positive:                                   Negative:


(3.67269840222691, 'this is')                  (-11.022854495425578, 'not')
(3.830396378404382, 'not too')                  (-5.919702871446887, 'bad')
(3.8471012895105616, 'is the')                  (-5.203579659848787, 'was')
(3.8937270060700473, 've')                  (-4.82529152939797, 'horrible')
(3.906414952561781, 'well')                  (-4.7611614606687755, 'bland')
(3.9764711662140724, 'wonderful')                  (-4.633196132031222, 'not worth')
(3.9996887872215345, 'my')                  (-4.536424119124524, 'awful')
(4.098975896733789, 'you')                  (-4.454289620730527, 'worst')
(4.183771427232313, 'are')                  (-4.453348340689143, 'maybe')
(4.2302564482631775, 'perfect')                  (-4.265050192227308, 'at all')
(4.230877349078375, 'and')                  (-4.19376677640029, 'return')
(4.274160608860285, 'use')                  (-4.1467478388618195, 'were')
(4.579999278463121, 'good')                  (-4.096109095784286, 'instead')
(4.612639553658168, 'excellent')                  (-4.079439265526672, 'ok')
(4.671047024612496, 'love')                  (-4.0767977600891, 'the worst')
(4.6714602021905725, 'nice')                  (-4.057347473359296, 'disgusting')
(5.605323042033229, 'the best')                  (-4.030841934475372, 'terrible')
(5.680373400135534, 'best')                  (-3.8605807716607763, 'did')
(5.720677627127294, 'delicious')                  (-3.828510245689711, 'money')
(10.6774382514121, 'great')                  (-3.808510323002438, 'away')
```

2.2 Summary:

Performed Logistic Regression on Amazon Food Reviews, Used GridSearchCv and RandomSearchCv Observed that RandomSearchCV was fast, Used 2 types of Regularizations L2 and L1, Performed Multi Coliinearity Check and Observed that there is no much difference before and after adding Noise to the data so it can be said that Features are not multi collinear i.e Independent, so used 'W' to get the top 20 important features.

The Positive and Negative Features which we obtained are Perfect when compared to other technique like classifier.coef_ .

```
<tr>
    <th>Regularization</th>
    <th>CV</th>
    <th>Best HyperParameter(C)</th>
    <th>Accuracy</th>
</tr>
<tr>
    <td>L2</td>
    <td>GridSearch CV</td>
    <td>10</td>
    <td>95.2%</td>
</tr>
<tr>
    <td>L1</td>
    <td>GridSearchCV</td>
    <td>1000</td>
    <td>95.8%</td>
</tr>
<tr>
    <td>L2</td>
    <td>RandomSearch CV</td>
    <td>31.67</td>
    <td>95.09%</td>
</tr>
<tr>
    <td>L1</td>
    <td>RandomSearch CV</td>
    <td>196.08</td>
    <td>94.5%</td>
</tr>
```