# Logistic Regression on Amazon fine food dataset

Data Source: <a href="https://www.kaggle.com/snap/amazon-fine-food-reviews">https://www.kaggle.com/snap/amazon-fine-food-reviews</a> (<a href="https://www.kaggle.com/snap/amazon-fine-food-reviews">https://www.kaggle.com/snap/amazon

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012

Number of Attributes/Columns in data: 10

Attribute Information:

- 1. ld
- 2. Productld unique identifier for the product
- 3. UserId unqiue identifier for the user
- 4. ProfileName
- 5. HelpfulnessNumerator number of users who found the review helpful
- 6. HelpfulnessDenominator number of users who indicated whether they found the review helpful or not
- 7. Score rating between 1 and 5
- 8. Time timestamp for the review
- 9. Summary brief summary of the review
- 10. Text text of the review

## Objective:

To perform Logistic regression using L2 regularization on different vectors like BOW, Tf-idf, Avg-W2vec & Tf-idf W2vec.

```
%matplotlib inline
    import warnings
    warnings.filterwarnings("ignore")
    import sqlite3
    import pandas as pd
    import numpy as np
    import nltk
    import string
    import matplotlib.pyplot as plt
10
    import seaborn as sns
11
    from sklearn.feature extraction.text import TfidfTransformer
12
    from sklearn.feature_extraction.text import TfidfVectorizer
13
14
15
    from sklearn.feature extraction.text import CountVectorizer
16
    from sklearn.metrics import confusion matrix
    from sklearn import metrics
17
    from sklearn.metrics import roc_curve, auc
18
19
    from nltk.stem.porter import PorterStemmer
20
21
    import re
22
23
    import string
24
    from nltk.corpus import stopwords
25
    from nltk.stem import PorterStemmer
26
    from nltk.stem.wordnet import WordNetLemmatizer
27
28
    from gensim.models import Word2Vec
29
    from gensim.models import KeyedVectors
30
    import pickle
31
    from tqdm import tqdm
33
    import os
```

```
#Importing Train and test dataset
  train_data=pd.read_csv("E:/Applied AI assignments/Amazon_fine_train_data.csv")
  test_data=pd.read_csv("E:/Applied AI assignments/Amazon_fine_test_data.csv")
  train_data=train_data.astype(str)
  test_data=test_data.astype(str)
  train data.shape
(80000, 13)
  train_data['Score'].value_counts()
           70407
positive
negative
           9593
Name: Score, dtype: int64
  test_data.shape
(20000, 13)
  test_data['Score'].value_counts()
positive
          17322
negative
           2678
Name: Score, dtype: int64
  #Train data
  y_train = train_data['Score']
  x_train = train_data['CleanedText']
  #Test data
  y_test = test_data['Score']
  x_test = test_data['CleanedText']
```

```
#Replacing Positive score with 0 and negative score with 1
     y_train.replace('negative',1,inplace=True)
     y_train.replace('positive',0,inplace=True)
     y test.replace('negative',1,inplace=True)
     y_test.replace('positive',0,inplace=True)
     from sklearn.linear model import LogisticRegression
     from sklearn.model selection import RandomizedSearchCV
     from sklearn.model selection import TimeSeriesSplit
     from sklearn.metrics import accuracy score
     from sklearn.metrics import recall score
     from sklearn.metrics import precision_score
     from sklearn.metrics import f1 score
     from sklearn.metrics import make scorer
     from sklearn.metrics import confusion matrix
     from sklearn.cross validation import cross val score
 10
     from collections import Counter
 11
     from sklearn import cross validation
 12
 13
     from wordcloud import WordCloud
 14
     import matplotlib.pyplot as plt
 15
     from tqdm import tqdm
Applying L2 regularization
```

Randomised CV using L2

## **Binary Bow**

```
count_vect = CountVectorizer(binary=True)

#Train data
vocabulary = count_vect.fit(x_train) #in scikit-learn

Bow_x_train= count_vect.transform(x_train)

print("the type of count vectorizer ",type(Bow_x_train))

print("the shape of out text BOW vectorizer ",Bow_x_train.get_shape())

print("the number of unique words ", Bow_x_train.get_shape()[1])

the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (80000, 33433)
the number of unique words 33433
```

```
#Test data
      Bow x test = count vect.transform(x test)
      print("the type of count vectorizer ",type(Bow_x_test))
      print("the shape of out text BOW vectorizer ",Bow_x_test.get_shape())
      print("the number of unique words ", Bow_x_test.get_shape()[1])
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (20000, 33433)
the number of unique words 33433
      #Standardizing Bow x train and Bow x test
      from sklearn.preprocessing import StandardScaler
      Scaler=StandardScaler(with mean=False)
      Bow_x_train = Scaler.fit_transform(Bow_x_train)
     Bow_x_test = Scaler.transform(Bow_x_test)
      print(Bow x train.shape)
      print(Bow x test.shape)
(80000, 33433)
(20000, 33433)
Fitting Grid Search CV on BOW
      grid.fit(Bow x train, y train)
     # examine the best model
     print(grid.best_score_)
      print(grid.best params )
0.6401387857438695
```

{'class\_weight': 'balanced', 'C': 0.0001}

```
#Plotting C v/s CV_error
     a=pd.DataFrame(grid.cv_results_)[['mean_test_score', 'std_test_score', 'params']]
     a['C'] = [d.get('C') for d in a['params']]
     b=a.sort_values(['C'])
     CV_Error=1-b['mean_test_score']
     C =b['C']
     plt.plot(C,CV_Error)
 10
    plt.xlabel('C')
    plt.ylabel('Cross-Validated Error')
  Text(0,0.5,'Cross-Validated Error')
  0.52 -
  0.50
  0.48
Cross-Validated Error
  0.46
  0.44
  0.42
  0.40
  0.38
  0.36
                                              40
                  10
                           20
                                     30
                                                        50
                                С
```

```
#{'class_weight': 'balanced', 'C': 0.0001}
      LR optimal=LogisticRegression(penalty='l2',C=0.0001,class weight='balanced')
     # fitting the model
     LR optimal.fit(Bow x train, y train)
     # predict the response
     pred bow = LR optimal.predict(Bow x test)
  10
     # evaluate f1_score
 11
     f1_score = f1_score(y_test, pred_bow)
  12
 13
     # Train & Test Error
 14
     print("The overall f1 score for the Train Data is : ", metrics.f1 score(y train,LR optimal.predict(Bow )
 15
     print("The overall f1 score for the Test Data is : ", metrics.f1 score(y test,pred bow))
  16
The overall f1 score for the Train Data is : 0.8089229382604777
The overall f1_score for the Test Data is : 0.675998091299507
Pertubation test
     # Re-training the model after adding noise
     Epsilon = np.random.normal(loc=0,scale =0.01)
     Noise_Bow_x_train=Bow_x_train
     Noise_Bow_x_train.data+=Epsilon
     Noise Bow x train.shape
   (80000, 33433)
```

```
#{'class_weight': 'balanced', 'C': 0.0001}
      LR optimal noise=LogisticRegression(penalty='l2',C=0.0001,class weight='balanced')
     # fitting the model
     LR_optimal_noise.fit(Noise_Bow_x_train, y_train)
     # predict the response
     pred bow = LR optimal noise.predict(Bow x test)
  10
     # evaluate f1_score
 11
 12 f1_score = f1_score(y_test, pred_bow)
 13
     # Train & Test Error
 14
     print("The overall f1 score for the Train Data is : ", metrics.f1 score(y train,LR optimal.predict(Noise
 15
     print("The overall f1 score for the Test Data is : ", metrics.f1 score(y test,pred bow))
  16
The overall f1 score for the Train Data is : 0.8088692595430168
The overall f1_score for the Test Data is : 0.675998091299507
     #Features
     feature names = np.array(vocabulary.get feature names())
     feature names.shape
   (33433,)
     #Weights before adding noise
     LR_optimal.coef_.shape
   (1, 33433)
```

1 #Weights after adding noise
2 LR\_optimal\_noise.coef\_.shape
(1, 33433)

```
merge_arr = np.concatenate([LR_optimal.coef_, LR_optimal_noise.coef_], axis=0)
merge=pd.DataFrame(data=merge_arr,columns=feature_names).transpose()
merge[2]=((merge[1]-merge[0])/merge[0])*100
merge
merge
```

	0	1	2
aaa	-0.001722	-0.001722	0.002999
aaaaaaaagghh	-0.002087	-0.002087	-0.012497
aaaaah	-0.002006	-0.002006	0.005672
aaaaahhhhhhhhhhhhhhhh	-0.000765	-0.000765	0.000203
aaaah	-0.000964	-0.000964	-0.003298
aaah	-0.001224	-0.001224	-0.004986
aachen	0.005927	0.005927	-0.008612
aad	-0.000364	-0.000364	-0.071263
aadp	-0.001017	-0.001017	-0.024636
aafco	-0.000879	-0.000878	-0.090446
aagh	-0.003549	-0.003549	-0.004424
aah	-0.002004	-0.002004	0.000561
aahh	-0.001183	-0.001182	-0.024529
aand	-0.001929	-0.001929	-0.005073
aardvark	-0.003908	-0.003909	0.014199
aarrgh	0.009679	0.009679	0.000378
ab	-0.002795	-0.002795	0.003201
aback	-0.006500	-0.006501	0.003168
abandon	0.003590	0.003590	-0.012733
abaolut	-0.001443	-0.001442	-0.028476
abattoir	-0.000879	-0.000880	0.026223
abba	-0.002686	-0.002686	-0.004696
abbey	-0.002013	-0.002013	0.001276
abbi	-0.003064	-0.003064	-0.006595

	0	1	2
abbott	-0.000479	-0.000479	-0.044658
abbrevi	-0.000541	-0.000541	-0.002948
abc	0.000694	0.000695	0.252658
abcstor	-0.001687	-0.001687	0.020410
abd	-0.001774	-0.001774	-0.028242
abdomen	0.000109	0.000109	-0.001692
zot	-0.008788	-0.008788	0.005860
zotz	-0.004918	-0.004919	0.003821
zour	0.002518	0.002518	0.000398
zout	-0.001946	-0.001946	-0.022958
zowi	-0.000718	-0.000718	-0.045905
zreport	-0.004741	-0.004741	0.000733
zsweet	-0.002095	-0.002094	-0.028194
zuc	-0.002182	-0.002182	-0.009051
zucchini	0.004017	0.004017	0.002359
zuccini	-0.004626	-0.004625	-0.005549
zuccnini	-0.000321	-0.000321	-0.013392
zuchinni	-0.003164	-0.003164	0.001102
zuke	-0.001739	-0.001739	-0.015763
zulu	-0.001037	-0.001037	-0.007865
zum	-0.000321	-0.000320	-0.059621
zummi	-0.000321	-0.000320	-0.059621
zune	-0.003632	-0.003632	-0.002227
zupreem	-0.000610	-0.000610	-0.001370
zurich	-0.001767	-0.001767	-0.010648
zwar	-0.000111	-0.000111	0.007019
zwieback	0.003339	0.003340	0.018697
zwiebeck	-0.002276	-0.002275	-0.025352

```
0
                                                         2
                             -0.001672 -0.001672 0.003113
    zydeco
                             -0.002309 -0.002309 0.006540
    ZZZZZS
                            -0.000076 -0.000076 -0.063760
    ZZZZZZ
                            0.007196  0.007195  -0.003373
    ZZZZZZZ
                            -0.000630 -0.000630 0.014911
    ZZZZZZZZ
                            -0.000379 -0.000379 -0.081017
    ZZZZZZZZZZ
                            -0.002822 -0.002822 0.004119
    ZZZZZZZZZZZ
                            -0.001229 -0.001229 -0.016318
    çay
   33433 rows \times 3 columns
      merge[merge[2]>30].shape
   (3, 3)
3 features out of 33433 shows percentage change > 30 post pertubation test i.e 0.0089%
We can say that our data isn't much affected by multicollinearity
      feature_names = np.array(vocabulary.get_feature_names())
      sorted_coef_index = LR_optimal.coef_[0].argsort()
      #Top 20 positive features
      p=feature_names[sorted_coef_index[:20]]
      sp = ""
      for i in p:
          sp += str(i)+","
   6
      print(sp)
great,love,best,delici,perfect,excel,good,favorit,nice,wonder,find,tasti,easi,amaz,thank,addict,alway,keep,year,snack,
```

```
1    n=feature_names[sorted_coef_index[:-21:-1]]
2    3    sn = ""
4    for i in n:
5         sn += str(i)+","
6    print(sn)

disappoint,worst,terribl,thought,bad,aw,horribl,bland,unfortun,stale,would,money,return,wast,threw,didnt,mayb,weak,sorri,ho pe,
```

```
print("******** Top 20 Negative words ************")
     wordcloud = WordCloud(width = 800, height = 800,
                     background_color ='black',
                     min font size = 10).generate(sn)
  4
     # plot the WordCloud image
     plt.figure(figsize = (5,5), facecolor = None)
     plt.imshow(wordcloud)
     plt.axis("off")
     plt.tight_layout(pad = 0)
 10
     plt.show()
 11
 12
 13
     print("******** Top 20 Positive words ************")
 14
     wordcloud = WordCloud(width = 800, height = 800,
 15
                    background color ='black',
 16
                    min font size = 10).generate(sp)
 17
 18
 19
     # plot the WordCloud image
     plt.figure(figsize = (5,5), facecolor = None)
 20
     plt.imshow(wordcloud)
    plt.axis("off")
 22
     plt.tight_layout(pad = 0)
 23
 24
     plt.show()
****** Top 20 Negative words *********
```



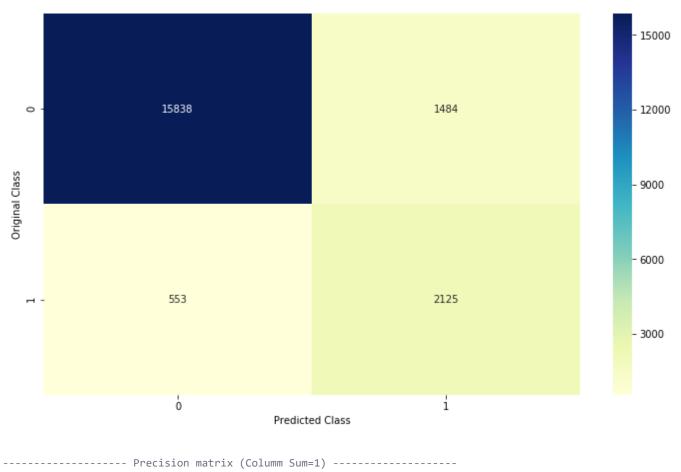
\*\*\*\*\*\*\* Top 20 Positive words \*\*\*\*\*\*\*\*\*\*\*

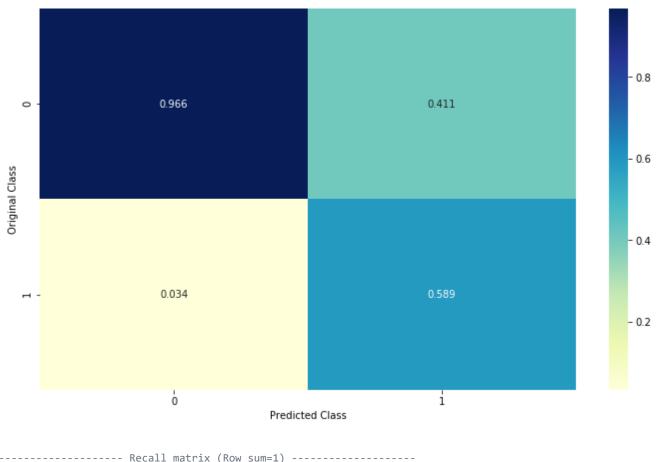


```
#Confusion matrix
C = confusion_matrix(y_test, pred_bow)
A = (((C.T)/(C.sum(axis=1))).T)
B = (C/C.sum(axis=0))
labels = [0,1]
```

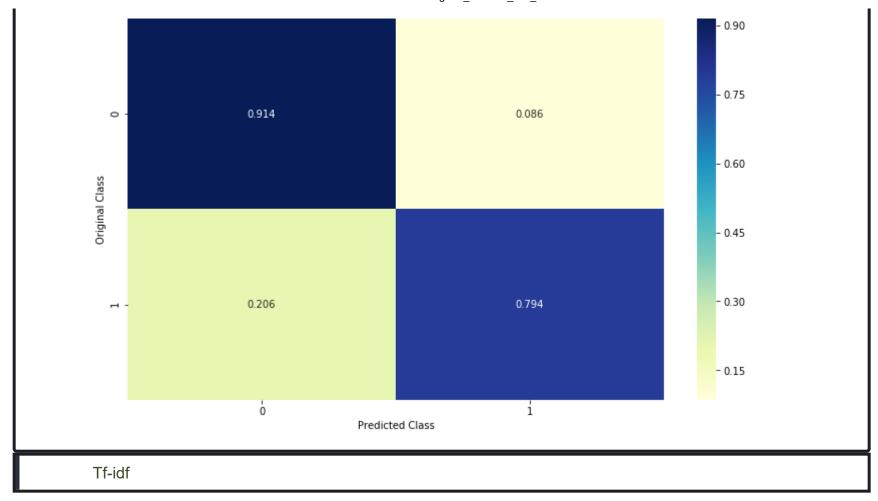
```
print("-"*20, "Confusion matrix", "-"*20)
 1
    plt.figure(figsize=(12,7))
   sns.heatmap(C, annot=True, cmap="YlGnBu", fmt="g", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
   plt.show()
   print("-"*20, "Precision matrix (Column Sum=1)", "-"*20)
    plt.figure(figsize=(12,7))
   sns.heatmap(B, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
10
    plt.xlabel('Predicted Class')
11
   plt.ylabel('Original Class')
12
13
   plt.show()
14
        # representing B in heatmap format
15
   print("-"*20, "Recall matrix (Row sum=1)", "-"*20)
16
    plt.figure(figsize=(12,7))
17
   sns.heatmap(A, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
18
19
   plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
20
21
   plt.show()
```

----- Confusion matrix -----





----- Recall matrix (Row sum=1) -----



```
#Initiating Vectorizer
      count vect = TfidfVectorizer(ngram range=(1,2))
      #Train data
      vocabulary = count vect.fit(x train)
     Tfidf x train= count vect.transform(x train)
     print("the type of count vectorizer ",type(Tfidf x train))
     print("the shape of out text BOW vectorizer ",Tfidf x train.get shape())
     print("the number of unique words ", Tfidf x train.get shape()[1])
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (80000, 1013943)
the number of unique words 1013943
      #Test data
     Tfidf x test= count vect.transform(x test)
     print("the type of count vectorizer ",type(Tfidf x test))
     print("the shape of out text BOW vectorizer ",Tfidf x test.get shape())
      print("the number of unique words ", Tfidf x test.get shape()[1])
the type of count vectorizer <class 'scipy.sparse.csr.csr matrix'>
the shape of out text BOW vectorizer (20000, 1013943)
the number of unique words 1013943
      #Standardizing
      from sklearn.preprocessing import StandardScaler
     Standard=StandardScaler(with mean=False)
     Tfidf x train = Standard.fit transform(Tfidf x train)
     Tfidf x test = Standard.transform(Tfidf x test)
     print(Tfidf x train.shape)
      print(Tfidf x test.shape)
(80000, 1013943)
(20000, 1013943)
```

# Fitting Randomsearch on Tf-ldf 1 grid.fit(Tfidf\_x\_train, y\_train) 2 3 # examine the best model 4 print(grid.best\_score\_) 5 print(grid.best\_params\_) 0.5390181835332085 {'class\_weight': 'balanced', 'C': 1e-07}

```
#Plotting C v/s CV_error
     a=pd.DataFrame(grid.cv_results_)[['mean_test_score', 'std_test_score', 'params']]
     a['C'] = [d.get('C') for d in a['params']]
     b=a.sort_values(['C'])
     CV_Error=1-b['mean_test_score']
     C =b['C']
     plt.plot(C,CV_Error)
 10
    plt.xlabel('C')
    plt.ylabel('Cross-Validated Error')
  Text(0,0.5,'Cross-Validated Error')
  1.0
  0.9
0.8 0.8 0.7 0.6
  0.5
                                                     50
                10
                         20
                                  30
                              С
```

```
#{'class_weight': 'balanced', 'C': 1e-07}
      LR optimal=LogisticRegression(penalty='12',C=0.0000001,class weight='balanced')
     # fitting the model
     LR optimal.fit(Tfidf x train, y train)
     # predict the response
     pred tfidf = LR optimal.predict(Tfidf x test)
  10
     # evaluate accuracy
 11
     f1_score = f1_score(y_test, pred_tfidf)
  12
 13
     # Train & Test Error
 14
     print("The overall f1 score for the Train Data is : ", metrics.f1 score(y train,LR optimal.predict(Tfid-
 15
     print("The overall f1 score for the Test Data is : ", metrics.f1 score(y test,pred tfidf))
  16
The overall f1 score for the Train Data is : 0.9030708364732479
The overall f1_score for the Test Data is : 0.5339728217426059
```

### Pertubation test

```
# Re-training the model after adding noise
Epsilon = np.random.normal(loc=0,scale =0.01)
Noise_Tfidf_x_train=Tfidf_x_train
Noise_Tfidf_x_train.data+=Epsilon
```

```
#{'class_weight': 'balanced', 'C': 1e-07}
     LR_optimal_noise=LogisticRegression(penalty='12',C=0.0000001,class_weight='balanced')
     # fitting the model
     LR_optimal_noise.fit(Noise_Tfidf_x_train, y_train)
     # predict the response
     pred tfidf = LR optimal noise.predict(Tfidf x test)
  10
     # evaluate accuracy
 11
     f1_score = f1_score(y_test, pred_tfidf)
  12
 13
     # Train & Test Error
 14
     print("The overall f1 score for the Train Data is : ", metrics.f1 score(y train,LR optimal noise.predict
  15
     print("The overall f1 score for the Test Data is : ", metrics.f1 score(y test,pred tfidf))
 16
The overall f1 score for the Train Data is : 0.9030283049969386
The overall f1_score for the Test Data is : 0.5340948029697316
     #Features
     feature names = np.array(vocabulary.get feature names())
     feature names.shape
   (1013943,)
     LR_optimal.coef_.shape
   (1, 1013943)
     LR_optimal_noise.coef_.shape
   (1, 1013943)
```

```
merge_arr = np.concatenate([LR_optimal.coef_, LR_optimal_noise.coef_], axis=0)
merge=pd.DataFrame(data=merge_arr,columns=feature_names).transpose()
merge[2]=((merge[1]-merge[0])/merge[0])*100
merge
```

	0	1	2
aaa	-0.000010	-0.000010	0.003393
aaa condit	-0.000008	-0.000008	0.002404
aaa perfect	-0.000008	-0.000008	0.000782
aaaaaaaagghh	-0.000008	-0.000008	0.000995
aaaaah	-0.000011	-0.000011	0.002724
aaaaah awak	-0.000008	-0.000008	0.000999
aaaaah satisfi	-0.000008	-0.000008	0.002002
aaaaahhhhhhhhhhhhhhhh	-0.000008	-0.000008	0.001810
aaaaahhhhhhhhhhhhhhhh angel	-0.000008	-0.000008	0.001810
aaaah	-0.000007	-0.000007	-0.000594
aaaah snob	-0.000007	-0.000007	-0.000594
aaah	-0.000013	-0.000013	0.002666
aaah inhal	-0.000008	-0.000008	0.000134
aaah miss	-0.000008	-0.000008	0.000481
aaah sip	-0.000008	-0.000008	0.000763
aachen	0.000045	0.000045	0.000334
aachen munich	0.000045	0.000045	0.000334
aad	-0.000008	-0.000008	-0.001176
aad sausag	-0.000008	-0.000008	-0.001176
aadp	-0.000008	-0.000008	0.000288
aafco	0.000002	0.000002	0.041650
aafco also	-0.000007	-0.000007	-0.002049
aafco certifi	0.000018	0.000018	0.001439
aafco countri	-0.000007	-0.000007	-0.002049

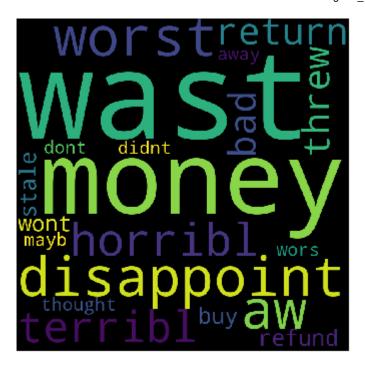
	0	1	2
aafco definit	0.000042	0.000042	0.001049
aafco dog	-0.000008	-0.000008	0.000260
aafco guidelin	-0.000008	-0.000008	-0.000410
aafco requir	-0.000008	-0.000008	0.001271
aagh	-0.000008	-0.000008	0.002790
aagh yelp	-0.000008	-0.000008	0.002790
zum heal	-0.000008	-0.000008	0.000441
zummi	-0.000008	-0.000008	0.000441
zummi love	-0.000008	-0.000008	0.000441
zummi tast	-0.000008	-0.000008	0.000441
zummi tri	-0.000008	-0.000008	0.000441
zune	-0.000008	-0.000008	0.002882
zune video	-0.000008	-0.000008	0.002882
zupreem	-0.000008	-0.000008	0.000569
zupreem ferret	-0.000008	-0.000008	0.000569
zurich	-0.000008	-0.000008	0.001963
zurich schnatzlet	-0.000008	-0.000008	0.001963
zwar	-0.000007	-0.000007	0.002107
zwar billig	-0.000007	-0.000007	0.002107
zwieback	0.000022	0.000022	0.004092
zwieback toast	0.000022	0.000022	0.004092
zwiebeck	-0.000008	-0.000008	0.001889
zwiebeck toast	-0.000008	-0.000008	0.001889
zydeco	-0.000008	-0.000008	0.001634
zydeco saturday	-0.000008	-0.000008	0.001634
ZZZZZS	-0.000011	-0.000011	0.002403
zzzzzs larg	-0.000008	-0.000008	0.002258
ZZZZZZ	-0.000007	-0.000007	-0.001191

```
0
                                                               2
                                   -0.000007 -0.000007 -0.001191
    zzzzzz say
                                   0.000053
                                             0.000053
                                                        0.001704
    ZZZZZZZ
    zzzzzz high
                                   0.000053 0.000053 0.001704
                                   -0.000007 -0.000007 0.002698
    ZZZZZZZZ
                                   -0.000008 -0.000008 -0.000450
    ZZZZZZZZZZ
    zzzzzzzzz final
                                   -0.000008 -0.000008 -0.000450
                                   -0.000008 -0.000008 0.001947
    ZZZZZZZZZZZ
                                   -0.000008 -0.000008 0.000097
    çay
   1013943 \text{ rows} \times 3 \text{ columns}
      merge[merge[2]>30].shape
   (1, 3)
1 features out of 1013943 shows percentage change > 30 post pertubation test i.e 0%
We can say that our data isn't affected by multicollinearity
      feature_names = np.array(vocabulary.get_feature_names())
      sorted_coef_index = LR_optimal.coef_[0].argsort()
      #Top 20 positive features
      p=feature_names[sorted_coef_index[:20]]
      sp = ""
      for i in p:
          sp += str(i)+","
      print(sp)
great,love,best,delici,perfect,favorit,good,find,make,high recommend,easi,excel,wonder,nice,use,snack,alway,keep,add,tasti,
```

```
1    n=feature_names[sorted_coef_index[:-21:-1]]
2    3    sn = ""
4    for i in n:
5         sn += str(i)+","
6    print(sn)

disappoint,wast money,worst,wast,aw,horribl,terribl,return,threw,money,bad,refund,stale,wont buy,thought,mayb,didnt,dont wast,away,wors,
```

```
print("******** Top 20 Negative words ************")
     wordcloud = WordCloud(width = 800, height = 800,
                     background_color ='black',
                     min font size = 10).generate(sn)
  4
     # plot the WordCloud image
     plt.figure(figsize = (5,5), facecolor = None)
     plt.imshow(wordcloud)
     plt.axis("off")
     plt.tight_layout(pad = 0)
 10
     plt.show()
 11
 12
 13
     print("******** Top 20 Positive words ************")
 14
     wordcloud = WordCloud(width = 800, height = 800,
 15
                    background color ='black',
 16
                    min font size = 10).generate(sp)
 17
 18
 19
     # plot the WordCloud image
     plt.figure(figsize = (5,5), facecolor = None)
 20
     plt.imshow(wordcloud)
    plt.axis("off")
 22
     plt.tight_layout(pad = 0)
 23
 24
     plt.show()
****** Top 20 Negative words *********
```



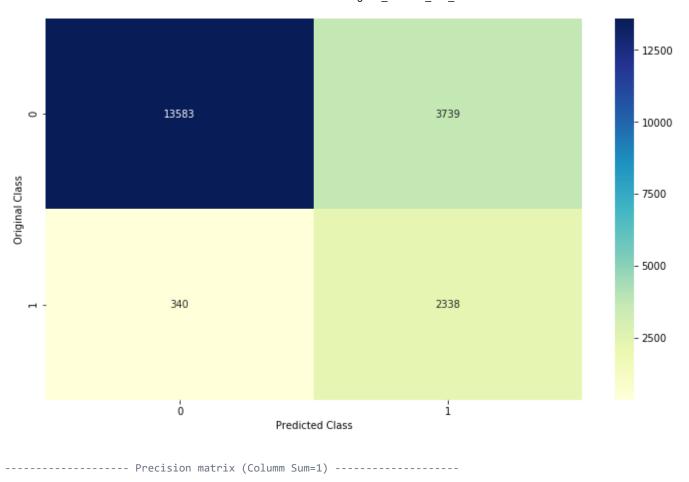
\*\*\*\*\*\*\* Top 20 Positive words \*\*\*\*\*\*\*\*\*\*\*



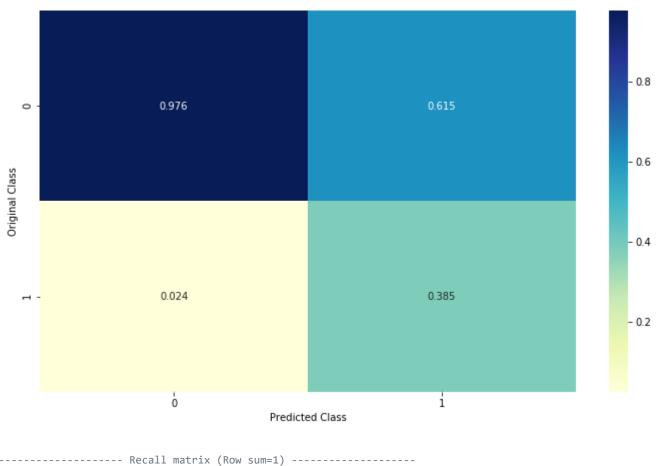
```
1 #Confusion matrix
2 C = confusion_matrix(y_test, pred_tfidf)
3 A =(((C.T)/(C.sum(axis=1))).T)
4 B =(C/C.sum(axis=0))
5 labels = [0,1]
```

```
print("-"*20, "Confusion matrix", "-"*20)
 1
    plt.figure(figsize=(12,7))
   sns.heatmap(C, annot=True, cmap="YlGnBu", fmt="g", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
   plt.show()
   print("-"*20, "Precision matrix (Column Sum=1)", "-"*20)
    plt.figure(figsize=(12,7))
   sns.heatmap(B, annot=True, cmap="YIGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
10
    plt.xlabel('Predicted Class')
11
   plt.ylabel('Original Class')
12
13
   plt.show()
14
        # representing B in heatmap format
15
   print("-"*20, "Recall matrix (Row sum=1)", "-"*20)
16
    plt.figure(figsize=(12,7))
17
   sns.heatmap(A, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
18
19
   plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
20
21
   plt.show()
```

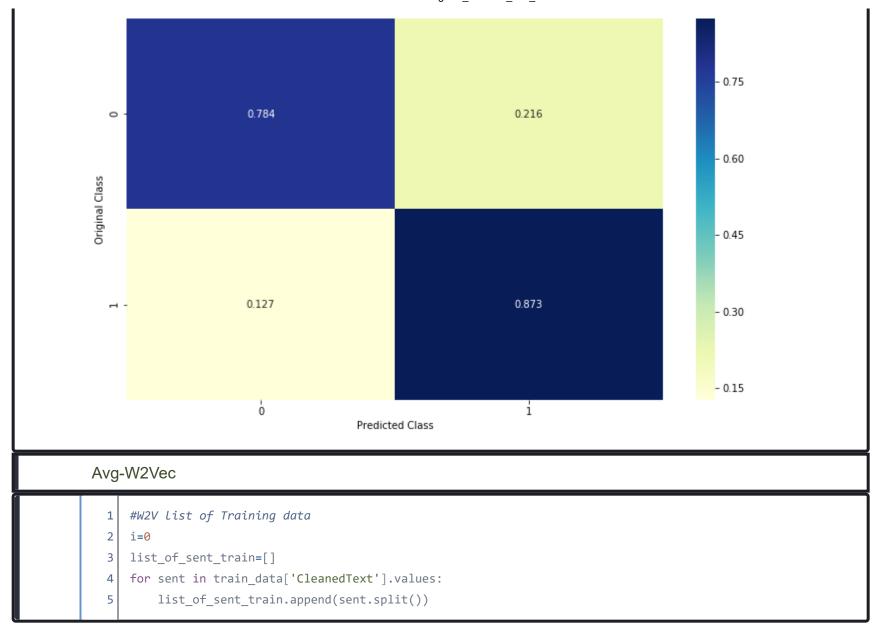
----- Confusion matrix -----



http://localhost:8888/notebooks/Documents/Applied%20AI%20assignments/6.%20Logistic%20on%20Amazon%20fine%20food/Logistic\_amazon\_fine\_L2.ipynb



----- Recall matrix (Row sum=1) -----



```
#W2V List of Test data
      i=0
      list_of_sent_test=[]
      for sent in test data['CleanedText'].values:
           list of sent test.append(sent.split())
      #Training W2V train model
      # min count = 5 considers only words that occured atleast 5 times
      w2v model train=Word2Vec(list of sent train,min count=5,size=50, workers=6)
      w2v words train = list(w2v model train.wv.vocab)
      print("number of words that occured minimum 5 times ",len(w2v words train))
      print("sample words ", w2v words train[0:50])
number of words that occured minimum 5 times 11361
sample words ['witti', 'littl', 'book', 'make', 'son', 'laugh', 'loud', 'car', 'drive', 'along', 'alway', 'sing', 'refrai
n', 'hes', 'learn', 'whale', 'india', 'droop', 'love', 'new', 'word', 'introduc', 'silli', 'classic', 'will', 'bet', 'stil
l', 'abl', 'memori', 'colleg', 'rememb', 'see', 'show', 'air', 'televis', 'year', 'ago', 'child', 'sister', 'later', 'bough
t', 'day', 'thirti', 'someth', 'use', 'seri', 'song', 'student', 'teach', 'preschool']
```

```
#Train data
     # average Word2Vec
     # compute average word2vec for each review.
     sent_vectors_train_avgw2v = []; # the avg-w2v for each sentence/review is stored in this list
      for sent in list of sent train: # for each review/sentence
          sent vec = np.zeros(50) # as word vectors are of zero length
   6
          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
   8
  9
              if word in w2v words train:
                  vec = w2v_model_train.wv[word]
  10
  11
                  sent_vec += vec
                  cnt words += 1
 12
          if cnt words != 0:
 13
 14
              sent vec /= cnt words
 15
          sent vectors train avgw2v.append(sent vec)
 16
     print(len(sent vectors train avgw2v))
  17
     print(len(sent vectors train avgw2v[0]))
80000
50
```

```
#Test data
     # average Word2Vec
     # compute average word2vec for each review.
      sent vectors test avgw2v = []; # the avg-w2v for each sentence/review is stored in this list
      for sent in list of sent test: # for each review/sentence
          sent vec = np.zeros(50) # as word vectors are of zero length
          cnt words =0; # num of words with a valid vector in the sentence/review
          for word in sent: # for each word in a review/sentence
   9
              if word in w2v words train:
  10
                  vec = w2v_model_train.wv[word]
                  sent vec += vec
  11
                  cnt words += 1
  12
  13
          if cnt words != 0:
  14
              sent vec /= cnt words
          sent_vectors_test_avgw2v.append(sent_vec)
  15
  16
     print(len(sent vectors test avgw2v))
      print(len(sent vectors test avgw2v[0]))
  17
20000
50
      #Standardizing Avg-W2v
      from sklearn.preprocessing import StandardScaler
     Standard=StandardScaler()
      sent vectors train avgw2v = Standard.fit transform(sent vectors train avgw2v)
      sent vectors test avgw2v = Standard.transform(sent vectors test avgw2v)
     print(sent_vectors_train_avgw2v.shape)
     print(sent_vectors_test_avgw2v.shape)
(80000, 50)
(20000, 50)
```

Fitting grid search on Avg-W2V

```
grid.fit(sent_vectors_train_avgw2v, y_train)

# examine the best model
print(grid.best_score_)
print(grid.best_params_)

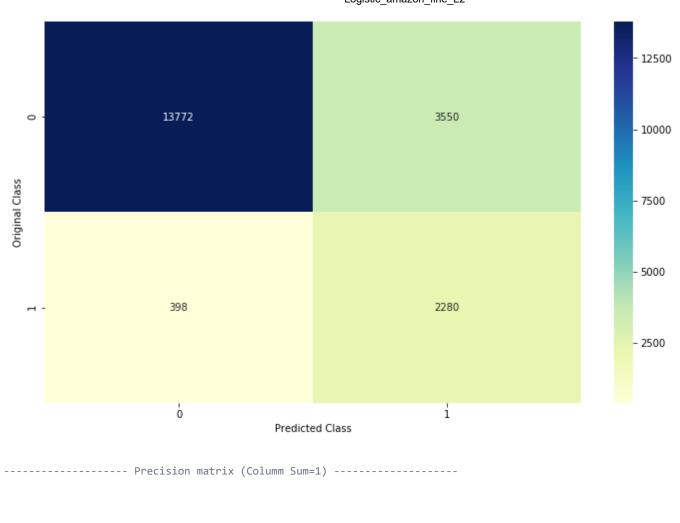
0.5134126417862019
{'class_weight': 'balanced', 'C': 50}
```

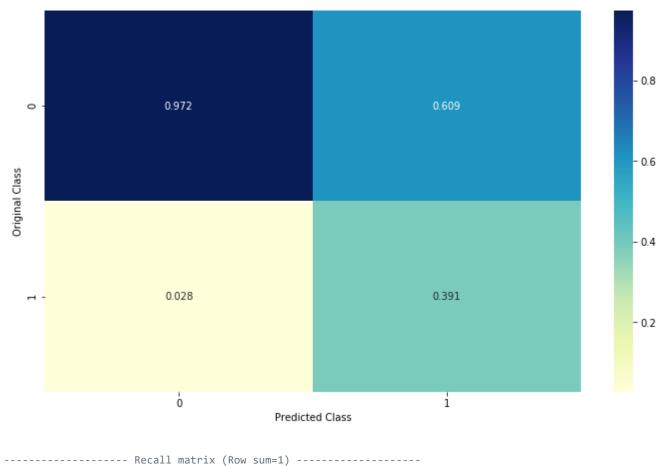
```
#Plotting C v/s CV_error
       a=pd.DataFrame(grid.cv_results_)[['mean_test_score', 'std_test_score', 'params']]
       a['C'] = [d.get('C') for d in a['params']]
       b=a.sort_values(['C'])
       CV_Error=1-b['mean_test_score']
       C =b['C']
       plt.plot(C,CV_Error)
   10
       plt.xlabel('C')
       plt.ylabel('Cross-Validated Error')
    Text(0,0.5,'Cross-Validated Error')
     0.675 -
     0.650
0.625
0.600
0.57!
0.55
0.55
     0.525
     0.500
                                                           50
                     10
                              20
                                        30
                                                 40
                                    C
```

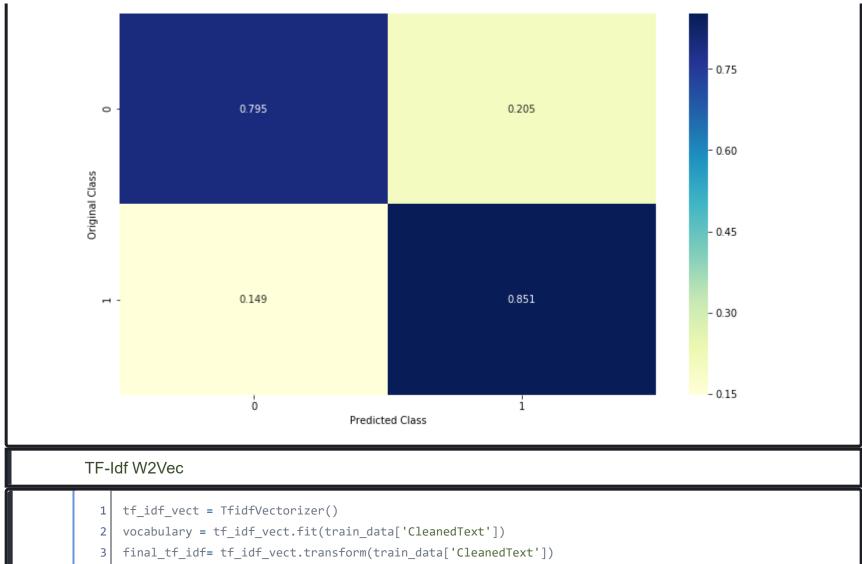
```
#{'class_weight': 'balanced', 'C': 50}
     LR_optimal=LogisticRegression(penalty='12',C=50,class_weight='balanced')
     # fitting the model
     LR optimal.fit(sent vectors train avgw2v, y train)
     # predict the response
     pred avg w2v = LR optimal.predict(sent vectors test avgw2v)
  10
 11 # evaluate f1_score
 12 f1_score = f1_score(y_test, pred_avg_w2v)
 13
 14 # Train & Test Error
     print("The overall f1 score for the Train Data is : ", metrics.f1 score(y train,LR optimal.predict(sent
 15
     print("The overall f1 score for the Test Data is : ", metrics.f1 score(y test,pred avg w2v))
  16
The overall f1 score for the Train Data is : 0.5152863591253961
The overall f1_score for the Test Data is : 0.535966149506347
     #Confusion matrix
     C = confusion_matrix(y_test, pred_avg_w2v)
  3 A = (((C.T)/(C.sum(axis=1))).T)
     B = (C/C.sum(axis=0))
     labels = [0,1]
```

```
print("-"*20, "Confusion matrix", "-"*20)
 1
    plt.figure(figsize=(12,7))
   sns.heatmap(C, annot=True, cmap="YlGnBu", fmt="g", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
   plt.show()
   print("-"*20, "Precision matrix (Column Sum=1)", "-"*20)
    plt.figure(figsize=(12,7))
   sns.heatmap(B, annot=True, cmap="YIGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
10
    plt.xlabel('Predicted Class')
11
   plt.ylabel('Original Class')
12
13
   plt.show()
14
        # representing B in heatmap format
15
   print("-"*20, "Recall matrix (Row sum=1)", "-"*20)
16
    plt.figure(figsize=(12,7))
17
   sns.heatmap(A, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
18
19
   plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
20
21
   plt.show()
```

----- Confusion matrix -----







```
tf_idf_vect = TfidfVectorizer()
vocabulary = tf_idf_vect.fit(train_data['CleanedText'])
final_tf_idf= tf_idf_vect.transform(train_data['CleanedText'])

# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(vocabulary.get_feature_names(), list(tf_idf_vect.idf_)))
```

```
# TF-IDF weighted Word2Vec
   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 w2v sent vectors train = []; # the tfidf-w2v for each sentence/review is stored in this list
 6
    row=0;
    for sent in tqdm(list of sent train): # for each review/sentence
        sent vec = np.zeros(50) # as word vectors are of zero length
 8
 9
        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
10
            if word in w2v words train:
11
                vec = w2v model train.wv[word]
12
                 tf idf = tf idf matrix[row, tfidf feat.index(word)]
13
                # to reduce the computation we are
14
                # dictionary[word] = idf value of word in whole courpus
15
                # sent.count(word) = tf valeus of word in this review
16
               tf idf = dictionary[word]*(sent.count(word)/len(sent))
17
               sent_vec += (vec * tf_idf)
18
19
                weight sum += tf idf
        if weight sum != 0:
20
21
            sent vec /= weight sum
22
        tfidf w2v sent vectors train.append(sent vec)
23
        row += 1
                                                       | 80000/80000 [01:11<00:00, 1113.33it/s]
```

```
final_tf_idf= tf_idf_vect.transform(test_data['CleanedText'])
     tfidf w2v sent vectors test = []; # the tfidf-w2v for each sentence/review is stored in this list
     row=0;
     for sent in tqdm(list of sent test): # for each review/sentence
          sent vec = np.zeros(50) # as word vectors are of zero length
          weight sum =0; # num of words with a valid vector in the sentence/review
          for word in sent: # for each word in a review/sentence
  9
              if word in w2v words train:
                  vec = w2v_model_train.wv[word]
 10
                  # obtain the tf idfidf of a word in a sentence/review
 11
                  tf idf = dictionary[word]*(sent.count(word)/len(sent))
 12
 13
                  sent vec += (vec * tf idf)
                  weight sum += tf idf
 14
 15
          if weight sum != 0:
 16
              sent vec /= weight sum
 17
          tfidf w2v sent vectors test.append(sent vec)
 18
          row += 1
                                                                        20000/20000 [00:18<00:00, 1080.47it/s]
     #Standardizing
     from sklearn.preprocessing import StandardScaler
     Standard=StandardScaler()
     tfidf w2v sent vectors train = Standard.fit transform(tfidf w2v sent vectors train)
     tfidf_w2v_sent_vectors_test = Standard.transform(tfidf_w2v_sent_vectors_test)
     print(tfidf w2v sent vectors train.shape)
     print(tfidf w2v sent vectors test.shape)
(80000, 50)
(20000, 50)
```

Fitting grid search cv on tfidf-w2vec

```
grid.fit(tfidf_w2v_sent_vectors_train, y_train)

# examine the best model
print(grid.best_score_)
print(grid.best_params_)

0.47618209651423954
{'class_weight': 'balanced', 'C': 0.5}
```

```
#Plotting C v/s CV_error
     a=pd.DataFrame(grid.cv_results_)[['mean_test_score', 'std_test_score', 'params']]
     a['C'] = [d.get('C') for d in a['params']]
     b=a.sort_values(['C'])
     CV_Error=1-b['mean_test_score']
     C =b['C']
     plt.plot(C,CV_Error)
 10
    plt.xlabel('C')
     plt.ylabel('Cross-Validated Error')
  Text(0,0.5,'Cross-Validated Error')
  0.80
0.75 0.70 0.70 0.65 0.60
  0.55
                                             12
```

```
#{'class_weight': 'balanced', 'C': 0.5}
      LR optimal=LogisticRegression(penalty='12',C=0.5,class weight='balanced')
     # fitting the model
     LR optimal.fit(tfidf w2v sent vectors train, y train)
     # predict the response
     pred tfidf w2v sent vectors test = LR optimal.predict(tfidf w2v sent vectors test)
  10 # evaluate f1_score
 f1 f1_score = f1_score(y_test, pred_tfidf_w2v_sent_vectors_test)
  12
 13 # Train & Test Error
 print("The overall f1 score for the Train Data is: ", metrics.f1 score(y train,LR optimal.predict(tfid-
     print("The overall f1 score for the Test Data is : ", metrics.f1 score(y test,pred tfidf w2v sent vector
  15
The overall f1_score for the Train Data is : 0.47774873135475937
The overall f1_score for the Test Data is : 0.5006821282401092
     #Confusion matrix
     C = confusion_matrix(y_test, pred_tfidf_w2v_sent_vectors_test)
     A = (((C.T)/(C.sum(axis=1))).T)
     B = (C/C.sum(axis=0))
     labels = [0,1]
```

```
print("-"*20, "Confusion matrix", "-"*20)
 1
    plt.figure(figsize=(12,7))
   sns.heatmap(C, annot=True, cmap="YlGnBu", fmt="g", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
   plt.show()
   print("-"*20, "Precision matrix (Column Sum=1)", "-"*20)
    plt.figure(figsize=(12,7))
   sns.heatmap(B, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
10
    plt.xlabel('Predicted Class')
11
   plt.ylabel('Original Class')
12
13
   plt.show()
14
        # representing B in heatmap format
15
   print("-"*20, "Recall matrix (Row sum=1)", "-"*20)
16
    plt.figure(figsize=(12,7))
17
   sns.heatmap(A, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
18
19
   plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
20
   plt.show()
21
```

----- Confusion matrix -----

