SGD Algorithm to predict movie ratings

There will be some functions that start with the word "grader" ex: grader_matrix(), grader_mean(), grader_dim() etc, you should not change those function definition.

Every Grader function has to return True.

1. Download the data from _here_ (https://drive.google.com/open?id=1-1z7iDB52cB6_JpO7Dqa-eOYSs-mivpq)

2. The data will be of this format, each data point is represented as a triplet of user_id, movie_id and rating

user_id	movie_id	rating
77	236	3
471	208	5
641	401	4
31	298	4
58	504	5
235	727	5

Task 1

Predict the rating for a given (user_id, movie_id) pair

Predicted rating $\hat{y}_{ij}$ for user i, movied j pair is calcuated as $\hat{y}_{ij} = \mu + b_i + c_j + u_i^T v_j$, here we will be finding the best values of b_i and c_j using SGD algorithm with the optimization problem for N users and M movies is defined as

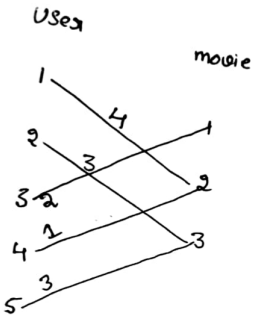
$$L = \min_{b,c,\{u_i\}_{i=1}^{N},\{v_j\}_{j=1}^{M}} \alpha\Big(\sum_j \sum_k v_{jk}^2 + \sum_i \sum_k u_{ik}^2 + \sum_i b_i^2 + \sum_j c_i^2\Big) + \sum_{i,j \in \mathcal{I}^{\text{train}}} (y_{ij} - \mu - b_i - c_j - u_i^T v_j)^2$$

- μ : scalar mean rating
- b_i : scalar bias term for user i
- c_j : scalar bias term for movie j
- u_i : K-dimensional vector for user i
- v_j : K-dimensional vector for movie j

*. We will be giving you some functions, please write code in that functions only.

*. After every function, we will be giving you expected output, please make sure that you get that output.

1. Construct adjacency matrix with the given data, assuming its weighted un-directed bi-partited graph (https://en.wikipedia.org/wiki/Bipartite_graph) and the weight of each edge is the rating given by user to the movie



The Adjacency matrix

	1	2	3
1	0	4	0
2	0	0	3
3	2	0	0
4	0	1	0
5	0	0	3

you can construct this matrix like $A[i][j] = r_{ij}$ here i is user_id, j is movie*id and $r{ij}$* $is rating given by user i to the movie$j$

Hint : you can create adjacency matrix using csr_matrix (https://docs.scipy.org/doc/scipy/reference/generated/scipy.sparse.csr_matrix.html)

1. We will Apply SVD decomposition on the Adjaceny matrix link1 (https://stackoverflow.com/a/31528944/4084039), link2 (https://machinelearningmastery.com/singular-value-decomposition-for-machine-learning/) and get three matrices $U, \sum, V$ such that $U \times \sum \times V^T = A$,
if A is of dimensions $N \times M$ then
U is of $N \times k$,
$\sum$ is of $k \times k$ and
V is $M \times k$ dimensions.

   *. So the matrix U can be represented as matrix representation of users, where each row u_i represents a k-dimensional vector for a user

*. So the matrix V can be represented as matrix representation of movies, where each row v_j represents a k-dimensional vector for a movie.

2. Compute μ , μ represents the mean of all the rating given in the dataset.(write your code in def m_u())
3. For each unique user initilize a bias value B_i to zero, so if we have N users B will be a N dimensional vector, the i^{th} value of the B will corresponds to the bias term for i^{th} user (write your code in def initialize())
4. For each unique movie initilize a bias value C_j zero, so if we have M movies C will be a M dimensional vector, the j^{th} value of the C will corresponds to the bias term for j^{th} movie (write your code in def initialize())
5. Compute dL/db_i (Write you code in def derivative_db())
6. Compute dL/dc_j(write your code in def derivative_dc()
7. Print the mean squared error with predicted ratings.

```
for each epoch:
    for each pair of (user, movie):
        b_i =  b_i - learning_rate * dL/db_i
        c_j =  c_j - learning_rate * dL/dc_j
predict the ratings with formula
```

$$\hat{y}_{ij} = \mu + b_i + c_j + \text{dot\_product}(u_i, v_j)$$

1. you can choose any learning rate and regularization term in the range 10^{-3} to 10^{2}
2. **bonus**: instead of using SVD decomposition you can learn the vectors u_i, v_j with the help of SGD algo similar to b_i and c_j

Task 2

As we know U is the learned matrix of user vectors, with its i-th row as the vector ui for user i. Each row of U can be seen as a "feature vector" for a particular user.

The question we'd like to investigate is this: do our computed per-user features that are optimized for predicting movie ratings contain anything to do with gender?

The provided data file user_info.csv (https://drive.google.com/open?id=1PHFdJh_4gIPiLH5Q4UErH8GK71hTrzlY) contains an is_male column indicating which users in the dataset are male. Can you predict this signal given the features U?

> **Note 1** : there is no train test split in the data, the goal of this assignment is to give an intution about how to do matrix factorization with the help of SGD and application of truncated SVD. for better understanding of the collabarative fillerting please check netflix case study.
>
> **Note 2** : Check if scaling of U, V matrices improve the metric

Reading the csv file

In [1]:
```
import pandas as pd
data=pd.read_csv('ratings_train.csv')
data.head()
```

Out[1]:

	user_id	item_id	rating
0	772	36	3
1	471	228	5
2	641	401	4
3	312	98	4
4	58	504	5

In [2]:
```
data.shape
```

Out[2]: (89992, 3)

Create your adjacency matrix

In [9]:
```
max(data.user_id), max(data.item_id)
```

Out[9]: (942, 1680)

In [10]:
```
from scipy.sparse import csr_matrix
adjacency_matrix = csr_matrix(
    (
        data['rating'].values, # data to be filled in the matrix
        (data['user_id'].values,data['item_id'].values) # rows and columns
    ),
    shape=(max(data.user_id)+1,max(data.item_id)+1) # shape of matrix (+1 is because index starts with 0)
)
```

In [11]:
```
adjacency_matrix.shape
```

Out[11]: (943, 1681)

Grader function - 1

In [12]:
```
def grader_matrix(matrix):
  assert(matrix.shape==(943,1681))
  return True
grader_matrix(adjacency_matrix)
```

Out[12]: True

SVD decompostion

Sample code for SVD decompostion

In [13]:
```
from sklearn.utils.extmath import randomized_svd
import numpy as np
matrix = np.random.random((20, 10))
U, Sigma, VT = randomized_svd(matrix, n_components=5,n_iter=5, random_state=None)
print(U.shape)
print(Sigma.shape)
print(VT.T.shape)
```

```
(20, 5)
(5,)
(10, 5)
```

Write your code for SVD decompostion

In [14]:
```
# Please use adjacency_matrix as matrix for SVD decompostion
# You can choose n_components as your choice

U, Sigma, VT = randomized_svd(adjacency_matrix, n_components=50, n_iter=10, random_state=43)
print(U.shape)
print(Sigma.shape)
print(VT.T.shape)
```

```
(943, 50)
(50,)
(1681, 50)
```

Compute mean of ratings

In [15]:
```
def m_u(ratings):
    '''In this function, we will compute mean for all the ratings'''
    # you can use mean() function to do this
    # check this (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.mean.html) link
for more details.
    return np.mean(ratings)
```

In [16]:
```
mu=m_u(data['rating'])
print(mu)
```

```
3.529480398257623
```

Grader function -2

In [17]:
```
def grader_mean(mu):
  assert(np.round(mu,3)==3.529)
  return True
mu=m_u(data['rating'])
grader_mean(mu)
```

Out[17]:
```
True
```

Initialize B_i and C_j

Hint : Number of rows of adjacent matrix corresponds to user dimensions(B_i), number of columns of adjacent matrix corresponds to movie dimensions (C_j)

In [32]:
```
def initialize(dim):
    '''In this function, we will initialize bias value 'B' and 'C'.'''
    # initalize the value to zeros
    # return output as a list of zeros
    B = np.zeros(dim)

    return list(B)
```

In [121]:
```
dim= adjacency_matrix.shape[0] # give the number of dimensions for b_i (Here b_i corresponds to users)
b_i=initialize(dim)
```

In [122]:
```
dim= adjacency_matrix.shape[1] # give the number of dimensions for c_j (Here c_j corresponds to movies)
c_j=initialize(dim)
```

Grader function -3

In [123]:
```
def grader_dim(b_i,c_j):
  assert(len(b_i)==943 and np.sum(b_i)==0)
  assert(len(c_j)==1681 and np.sum(c_j)==0)
  return True
grader_dim(b_i,c_j)
```

Out[123]: True

Compute dL/db_i

In [124]:
```
def derivative_db(user_id,item_id,rating,U,V,mu,alpha):
    '''In this function, we will compute dL/db_i'''

    db = 2*alpha*b_i[user_id] - 2*(rating- mu- b_i[user_id]- c_j[item_id]- (np.dot(U[user_id],V.T[item_id]
)))
    return db
```

Grader function -4

In [125]:
```
def grader_db(value):
    assert(np.round(value,3)==-0.931)
    return True
U1, Sigma, V1 = randomized_svd(adjacency_matrix, n_components=2,n_iter=5, random_state=24)
# Please don't change random state
# Here we are considering n_componets = 2 for our convinence
alpha=0.01
value=derivative_db(312,98,4,U1,V1,mu,alpha)
grader_db(value)
```

Out[125]: True

Compute dL/dc_j

In [126]:
```
def derivative_dc(user_id,item_id,rating,U,V,mu, alpha):
    '''In this function, we will compute dL/dc_j'''
    db = 2*alpha*c_j[item_id] - 2*(rating- mu- b_i[user_id]- c_j[item_id]- (np.dot(U[user_id],V.T[item_id]
)))
    return db
```

Grader function - 5

In [127]:
```
def grader_dc(value):
    assert(np.round(value,3)==-2.929)
    return True
U1, Sigma, V1 = randomized_svd(adjacency_matrix, n_components=2,n_iter=5, random_state=24)
# Please don't change random state
# Here we are considering n_componets = 2 for our convinence
r=0.01
value=derivative_dc(58,504,5,U1,V1,mu,r)
grader_dc(value)
```

Out[127]:
```
True
```

Compute MSE (mean squared error) for predicted ratings

for each epoch, print the MSE value

```
for each epoch:

    for each pair of (user, movie):

        b_i =  b_i - learning_rate * dL/db_i

        c_j =  c_j - learning_rate * dL/dc_j

predict the ratings with formula
```

$$\hat{y}_{ij} = \mu + b_i + c_j + \text{dot\_product}(u_i, v_j)$$

In [128]:
```
U2, Sigma2, V2 = randomized_svd(adjacency_matrix, n_components=50, n_iter=10, random_state=43)
lr = 0.01 # learning rate
```

In [129]:
```
from sklearn.metrics import mean_squared_error
```

In [148]:
```
from tqdm import trange
```

In [149]:
```
epoch=30 # no.of epoch
MSE = [] # list to store MSE for each epoch

# initializing B and C
b_i = initialize(adjacency_matrix.shape[0])
c_j = initialize(adjacency_matrix.shape[1])

mu=m_u(data['rating']) # finding mean value of all rating
alpha = 0.01
for e in trange(epoch): # for each epoch

    y_hat = [] # to store y_predicted for each epoch
    for i in range(len(data)): # for each datapoint
        u_id = data['user_id'].iloc[i]
        i_id = data['item_id'].iloc[i]
        rtng = data['rating'].iloc[i]
        b_i[u_id] = b_i[u_id] - lr * derivative_db(u_id, i_id, rtng, U2, V2, mu, alpha)
        c_j[i_id] = c_j[i_id] - lr * derivative_dc(u_id, i_id, rtng, U2, V2, mu, alpha)

        yij = mu + b_i[u_id] + c_j[i_id] + np.dot(U2[data.user_id.iloc[i]].T, V2.T[data.item_id.iloc[i]])
        y_hat.append(yij)

    mse = mean_squared_error(data.rating.values, y_hat)
    MSE.append(mse)
    print(mse)
```

```
  3%|          | 1/30 [00:09<04:31,
9.37s/it]

0.9016762989587581

  7%|          | 2/30 [00:18<04:19,
9.27s/it]

0.8188879205568885

 10%|          | 3/30 [00:27<04:09,
9.22s/it]

0.8036238580663191

 13%|          | 4/30 [00:36<04:00,
9.27s/it]

0.7972788259514956

 17%|          | 5/30 [00:46<03:55,
9.43s/it]

0.7939994020484421

 20%|          | 6/30 [00:56<03:49,
9.55s/it]

0.7920635023029331

 23%|          | 7/30 [01:06<03:39,
9.54s/it]

0.7908075366293013

 27%|          | 8/30 [01:15<03:27,
9.45s/it]

0.7899327617986935

 30%|          | 9/30 [01:24<03:16,
9.37s/it]

0.7892893604939921
```

```
 33%|███████████████████████▏                                                | 10/30 [01:33<03:05,
9.28s/it]

0.7887957233871079

 37%|██████████████████████████                                              | 11/30 [01:42<02:56,
9.27s/it]

0.7884042932188897

 40%|████████████████████████████▊                                           | 12/30 [01:51<02:44,
9.15s/it]

0.78808573129856

 43%|███████████████████████████████▍                                        | 13/30 [02:00<02:33,
9.05s/it]

0.7878210318047517

 47%|██████████████████████████████████▏                                     | 14/30 [02:09<02:26,
9.13s/it]

0.7875973536465711

 50%|████████████████████████████████████▊                                   | 15/30 [02:20<02:22,
9.48s/it]

0.7874057013370984

 53%|███████████████████████████████████████▍                                | 16/30 [02:29<02:11,
9.37s/it]

0.78723957478486

 57%|██████████████████████████████████████████▏                             | 17/30 [02:38<02:02,
9.43s/it]

0.7870941506008715

 60%|████████████████████████████████████████████▊                           | 18/30 [02:48<01:54,
9.52s/it]

0.7869657671828835
```

```
 63%|███████████████████████████████████████████████████▋                              | 19/30 [02:57<01:43, 9.37s/it]

0.7868515899952676

 67%|██████████████████████████████████████████████████████▋                           | 20/30 [03:06<01:33, 9.32s/it]

0.7867493874255046

 70%|█████████████████████████████████████████████████████████▍                        | 21/30 [03:15<01:22, 9.21s/it]

0.7866573766313585

 73%|████████████████████████████████████████████████████████████▏                     | 22/30 [03:24<01:12, 9.07s/it]

0.7865741149608929

 77%|██████████████████████████████████████████████████████████████▋                   | 23/30 [03:33<01:03, 9.03s/it]

0.786498421821607

 80%|██████████████████████████████████████████████████████████████████                 | 24/30 [03:42<00:54, 9.12s/it]

0.7864293213770439

 83%|████████████████████████████████████████████████████████████████████▍             | 25/30 [03:51<00:45, 9.01s/it]

0.786365999796551

 87%|███████████████████████████████████████████████████████████████████████            | 26/30 [04:00<00:35, 8.96s/it]

0.7863077728725967

 90%|█████████████████████████████████████████████████████████████████████████▋        | 27/30 [04:09<00:26, 8.90s/it]

0.7862540611544782
```

```
 93%|███████████████████████████████████████████████████████████████████████████      | 28/30 [04:17<00:17,
8.85s/it]

0.7862043706186114

 97%|████████████████████████████████████████████████████████████████████████████▌    | 29/30 [04:26<00:08,
8.83s/it]

0.7861582774762194

100%|█████████████████████████████████████████████████████████████████████████████| 30/30 [04:35<00:00,
9.18s/it]

0.78611541611349
```

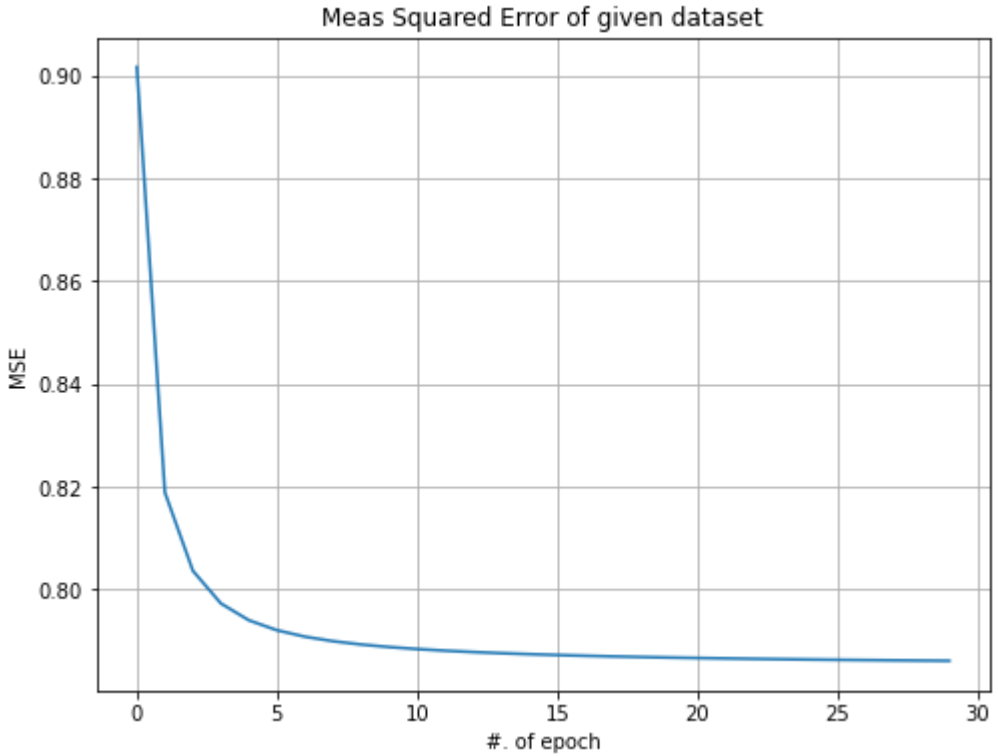
In [ ]:

Plot epoch number vs MSE

- epoch number on X-axis
- MSE on Y-axis

In [134]:
```
import matplotlib.pyplot as plt
```

In [140]:
```
plt.figure(figsize=(8,6))
plt.plot(list(range(epoch)), MSE)
plt.title('Meas Squared Error of given dataset')
plt.xlabel('#. of epoch')
plt.ylabel('MSE')
plt.grid(True)
plt.show()
```



In [ ]:
```

```

Task 2

In [143]:
```
U2[0]
```

Out[143]:
```
array([ 0.0662257 ,  0.00788852, -0.01253126, -0.08616387,  0.02486961,
        0.0066612 ,  0.08005114, -0.02756662,  0.06756802,  0.02042077,
       -0.02615953,  0.02650122, -0.03948423,  0.03992232, -0.01442573,
        0.00171249, -0.07894435,  0.01197095, -0.06763539, -0.05474592,
       -0.11436075, -0.01092713,  0.04383823, -0.05682249,  0.04246676,
        0.05950109, -0.09346606,  0.05188234,  0.00157581, -0.00749872,
       -0.04618425, -0.01912017,  0.10022757, -0.124795  ,  0.03214906,
        0.02922167, -0.03988895,  0.11293893, -0.03250723,  0.03664773,
       -0.02877647, -0.05587925,  0.01621883,  0.00082109,  0.11883379,
       -0.07604553, -0.02367046, -0.05205898, -0.0412519 , -0.06143904])
```

In [146]:
```
V2.T[0]
```

Out[146]:
```
array([ 0.09432076, -0.09365604, -0.00510748, -0.04886658, -0.15781319,
       -0.10065238,  0.08857685,  0.01377174, -0.08417885,  0.01251122,
        0.04529933,  0.06561506, -0.02090652,  0.02445128, -0.04001537,
       -0.07490333,  0.00961507,  0.01239697,  0.02700041, -0.00037579,
       -0.01629441, -0.10761141,  0.13925566,  0.06462811,  0.11077665,
        0.02480097, -0.08333359, -0.04316252, -0.17443817, -0.14669366,
       -0.08286182,  0.13359107,  0.0753128 , -0.0693474 , -0.08085442,
       -0.10298338,  0.01293713, -0.04579897, -0.03937351,  0.09870291,
       -0.02529772,  0.06006946,  0.033592  , -0.09808428,  0.02033945,
        0.07227342, -0.07508876, -0.04926345,  0.02038772, -0.08206805])
```

In [150]:
```
U2.shape, Sigma2.shape, V2.shape
```

Out[150]:
```
((943, 50), (50,), (50, 1681))
```

In [152]:
```
user_info = pd.read_csv('user_info.csv.txt')
user_info.head()
```

Out[152]:

	user_id	age	is_male	orig_user_id
0	0	24	1	1
1	1	53	0	2
2	2	23	1	3
3	3	24	1	4
4	4	33	0	5

In [180]:
```
Y = user_info['is_male'].values
```

In [181]:
```
Y.shape
```

Out[181]:
```
(943,)
```

In [233]:
```
def model_processing(modelName):
    model = modelName

    model.fit(X_train, y_train)

    y_hat = model.predict(X_test)
    x_hat = model.predict(X_train)
    print("Train accuracy of the model : ", accuracy_score(y_train, x_hat))
    print("*"*50)
    print("Test Accuracy of the model : ", accuracy_score(y_test, y_hat))
    print("*"*50)
    print("Confusion matrix of the model on test dataset:\n", confusion_matrix(y_test, y_hat))
    print("*"*50)
    print("Classification report of the model on test dataset:\n",classification_report(y_test, y_hat))
    temp_dict = {}
    temp_dict['train_accuracy'] = accuracy_score(y_train, x_hat)
    temp_dict['test_accuracy'] = accuracy_score(y_test, y_hat)
    temp_dict['confusion_matrix'] = confusion_matrix(y_test, y_hat)
    temp_dict['classification_report'] = classification_report(y_test,y_hat)
    return temp_dict
```

Logistic Regression

In [157]:
```
from sklearn.linear_model import LogisticRegression
```

In [158]:
```
model = LogisticRegression()
```

In [159]:
```
from sklearn.model_selection import train_test_split
```

In [182]:
```
X_train, X_test, y_train, y_test = train_test_split(U, Y, test_size=0.2, random_state=43)
```

In [183]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[183]: ((754, 50), (189, 50), (754,), (189,))

Logistic Regression without class balance

In [227]:
```
lr_result = model_processing(model)
```

```
Train accuracy of the model :  0.713527851458886
************************************************
Test Accuracy of the model :  0.6984126984126984
************************************************
Confusion matrix of the model on test dataset:
 [[  0  57]
 [  0 132]]
************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        57
           1       0.70      1.00      0.82       132

    accuracy                           0.70       189
   macro avg       0.35      0.50      0.41       189
weighted avg       0.49      0.70      0.57       189


C:\Users\localadmin\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1221: UndefinedMetricWarni
ng: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero
_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Above model is dumb means data is not linearly separable.

In [ ]:
```

```

In [228]:
```
lr_balanced_model = LogisticRegression(class_weight='balanced')
lr_balanced_model_result = model_processing(lr_balanced_model)
```

```
Train accuracy of the model :  0.7440318302387268
************************************************
Test Accuracy of the model :  0.6878306878306878
************************************************
Confusion matrix of the model on test dataset:
 [[36 21]
 [38 94]]
************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.49      0.63      0.55        57
           1       0.82      0.71      0.76       132

    accuracy                           0.69       189
   macro avg       0.65      0.67      0.66       189
weighted avg       0.72      0.69      0.70       189
```

Yeah, class_weight='balanced' works well

In [ ]:
```
```

KNN

In [247]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [248]:
```
knn = KNeighborsClassifier()
```

In [250]:
```
knn_result = model_processing(knn)
```

```
Train accuracy of the model :  0.7798408488063661
**************************************************
Test Accuracy of the model :  0.6613756613756614
**************************************************
Confusion matrix of the model on test dataset:
 [[ 18  39]
 [ 25 107]]
**************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.42      0.32      0.36        57
           1       0.73      0.81      0.77       132

    accuracy                           0.66       189
   macro avg       0.58      0.56      0.56       189
weighted avg       0.64      0.66      0.65       189
```

KNN weighted

In [251]:
```
knn_w = KNeighborsClassifier(weights='distance')
```

In [253]:
```
knn_w_result = model_processing(knn_w)
```

```
Train accuracy of the model :  1.0
************************************************
Test Accuracy of the model :  0.6613756613756614
************************************************
Confusion matrix of the model on test dataset:
 [[ 18  39]
 [ 25 107]]
************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.42      0.32      0.36        57
           1       0.73      0.81      0.77       132

    accuracy                           0.66       189
   macro avg       0.58      0.56      0.56       189
weighted avg       0.64      0.66      0.65       189
```

KNN with hyper-parameter K

In [254]:
```
neighbors = [1,3,5,7,11,15,20,25,35,40,50]
```

In [256]:
```
knn_results = []
for k in neighbors:
    print("#-"*50)
    print(" K = ",k)
    temp_model = KNeighborsClassifier(weights='distance', n_neighbors=k)
    knn_results.append(model_processing(temp_model))
    print("#-"*50)
```

```
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  1
Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.671957671957672
**************************************************
Confusion matrix of the model on test dataset:
 [[ 25  32]
 [ 30 102]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.45      0.44      0.45        57
           1       0.76      0.77      0.77       132

    accuracy                           0.67       189
   macro avg       0.61      0.61      0.61       189
weighted avg       0.67      0.67      0.67       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  3
Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.6984126984126984
**************************************************
Confusion matrix of the model on test dataset:
 [[ 19  38]
 [ 19 113]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.50      0.33      0.40        57
           1       0.75      0.86      0.80       132

    accuracy                           0.70       189
   macro avg       0.62      0.59      0.60       189
weighted avg       0.67      0.70      0.68       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
```

```
 K =  5
Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.6613756613756614
**************************************************
Confusion matrix of the model on test dataset:
 [[ 18  39]
 [ 25 107]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.42      0.32      0.36        57
           1       0.73      0.81      0.77       132

    accuracy                           0.66       189
   macro avg       0.58      0.56      0.56       189
weighted avg       0.64      0.66      0.65       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  7
Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.6349206349206349
**************************************************
Confusion matrix of the model on test dataset:
 [[ 13  44]
 [ 25 107]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.34      0.23      0.27        57
           1       0.71      0.81      0.76       132

    accuracy                           0.63       189
   macro avg       0.53      0.52      0.51       189
weighted avg       0.60      0.63      0.61       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  11
```

```
Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.6507936507936508
**************************************************
Confusion matrix of the model on test dataset:
 [[  9  48]
 [ 18 114]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.33      0.16      0.21        57
           1       0.70      0.86      0.78       132

    accuracy                           0.65       189
   macro avg       0.52      0.51      0.49       189
weighted avg       0.59      0.65      0.61       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  15
Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.6825396825396826
**************************************************
Confusion matrix of the model on test dataset:
 [[  9  48]
 [ 12 120]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.43      0.16      0.23        57
           1       0.71      0.91      0.80       132

    accuracy                           0.68       189
   macro avg       0.57      0.53      0.52       189
weighted avg       0.63      0.68      0.63       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  20
Train accuracy of the model :  1.0
```

```
**************************************************
Test Accuracy of the model :  0.7037037037037037
**************************************************
Confusion matrix of the model on test dataset:
 [[  9  48]
 [  8 124]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.53      0.16      0.24        57
           1       0.72      0.94      0.82       132

    accuracy                           0.70       189
   macro avg       0.63      0.55      0.53       189
weighted avg       0.66      0.70      0.64       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  25
Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.7037037037037037
**************************************************
Confusion matrix of the model on test dataset:
 [[  7  50]
 [  6 126]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.54      0.12      0.20        57
           1       0.72      0.95      0.82       132

    accuracy                           0.70       189
   macro avg       0.63      0.54      0.51       189
weighted avg       0.66      0.70      0.63       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  35
Train accuracy of the model :  1.0
**************************************************
```

```
Test Accuracy of the model :  0.7037037037037037
**************************************************
Confusion matrix of the model on test dataset:
 [[  3  54]
 [  2 130]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.60      0.05      0.10        57
           1       0.71      0.98      0.82       132

    accuracy                           0.70       189
   macro avg       0.65      0.52      0.46       189
weighted avg       0.67      0.70      0.60       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  40
Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.7037037037037037
**************************************************
Confusion matrix of the model on test dataset:
 [[  2  55]
 [  1 131]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.67      0.04      0.07        57
           1       0.70      0.99      0.82       132

    accuracy                           0.70       189
   macro avg       0.69      0.51      0.45       189
weighted avg       0.69      0.70      0.60       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
 K =  50
Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.6984126984126984
```

```
**************************************************
Confusion matrix of the model on test dataset:
 [[  1  56]
 [  1 131]]
**************************************************
Classification report of the model on test dataset:
               precision    recall  f1-score   support

           0       0.50      0.02      0.03        57
           1       0.70      0.99      0.82       132

    accuracy                           0.70       189
   macro avg       0.60      0.50      0.43       189
weighted avg       0.64      0.70      0.58       189

#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-#-
```

In [ ]:

In [ ]:

```
let's try Tree based model
```

DecisionTreeClassifier

without class balance

In [230]:
```
from sklearn.tree import DecisionTreeClassifier
tmodel = DecisionTreeClassifier()
tmodel_result = model_processing(tmodel)
```

```
Train accuracy of the model :  1.0
************************************************
Test Accuracy of the model :  0.6772486772486772
************************************************
Confusion matrix of the model on test dataset:
 [[ 20  37]
 [ 24 108]]
************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.45      0.35      0.40        57
           1       0.74      0.82      0.78       132

    accuracy                           0.68       189
   macro avg       0.60      0.58      0.59       189
weighted avg       0.66      0.68      0.66       189
```

let's try with weight='balanced'

DecisionTreeClassifier with class balanced

In [198]:
```
btmodel = DecisionTreeClassifier(class_weight='balanced')
```

In [231]:
```
bt_model_result = model_processing(btmodel)
```

```
Train accuracy of the model :  1.0
************************************************
Test Accuracy of the model :  0.656084656084656
************************************************
Confusion matrix of the model on test dataset:
 [[ 23  34]
 [ 31 101]]
************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.43      0.40      0.41        57
           1       0.75      0.77      0.76       132

    accuracy                           0.66       189
   macro avg       0.59      0.58      0.59       189
weighted avg       0.65      0.66      0.65       189
```

RandomForestClassifier

Let's try with ensemble models to increase test accuracy

RandomForest Classifier

without class balanced

In [206]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [232]:
```
rfmodel = RandomForestClassifier()
rfmodel_result = model_processing(rfmodel)
```

```
Train accuracy of the model :  1.0
************************************************
Test Accuracy of the model :  0.7301587301587301
************************************************
Confusion matrix of the model on test dataset:
 [[ 11  46]
 [  5 127]]
************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.69      0.19      0.30        57
           1       0.73      0.96      0.83       132

    accuracy                           0.73       189
   macro avg       0.71      0.58      0.57       189
weighted avg       0.72      0.73      0.67       189
```

Random Forest Classifier with class-weight='balanced'

In [234]:
```
rfmodel_weighted = RandomForestClassifier(class_weight='balanced')
```

In [235]:
```
rfmodel_weighted_result = model_processing(rfmodel_weighted)
```

```
Train accuracy of the model :  1.0
************************************************
Test Accuracy of the model :  0.7248677248677249
************************************************
Confusion matrix of the model on test dataset:
 [[  8  49]
 [  3 129]]
************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.73      0.14      0.24        57
           1       0.72      0.98      0.83       132

    accuracy                           0.72       189
   macro avg       0.73      0.56      0.53       189
weighted avg       0.73      0.72      0.65       189
```

In [ ]:
```

```

Let's try with Gradient boosting classifier

In [245]:
```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import VotingClassifier

models={
    'gradient boosting classifier':GradientBoostingClassifier(),
    'adaboost classifier':AdaBoostClassifier(),
    'Bagging classifier':BaggingClassifier(),
    'Extra tree classifier': ExtraTreesClassifier()
}
```

In [257]:
```
models_results = {}
for k, v in models.items():
    print("Model = ",k)
    print()
    models_results[k] = model_processing(v)
    print("*"*100)
```

```
Model =  gradient boosting classifier

Train accuracy of the model :  0.9708222811671088
************************************************
Test Accuracy of the model :  0.746031746031746
************************************************
Confusion matrix of the model on test dataset:
 [[ 20  37]
 [ 11 121]]
************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.65      0.35      0.45        57
           1       0.77      0.92      0.83       132

    accuracy                           0.75       189
   macro avg       0.71      0.63      0.64       189
weighted avg       0.73      0.75      0.72       189

********************************************************************************************************
Model =  adaboost classifier

Train accuracy of the model :  0.8713527851458885
************************************************
Test Accuracy of the model :  0.7354497354497355
************************************************
Confusion matrix of the model on test dataset:
 [[ 25  32]
 [ 18 114]]
************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.58      0.44      0.50        57
           1       0.78      0.86      0.82       132

    accuracy                           0.74       189
   macro avg       0.68      0.65      0.66       189
weighted avg       0.72      0.74      0.72       189

********************************************************************************************************
Model =  Bagging classifier
```

```
Train accuracy of the model :  0.9880636604774535
**************************************************
Test Accuracy of the model :  0.656084656084656
**************************************************
Confusion matrix of the model on test dataset:
 [[ 18  39]
 [ 26 106]]
**************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.41      0.32      0.36        57
           1       0.73      0.80      0.77       132

    accuracy                           0.66       189
   macro avg       0.57      0.56      0.56       189
weighted avg       0.63      0.66      0.64       189

**********************************************************************************************************
Model =  Extra tree classifier

Train accuracy of the model :  1.0
**************************************************
Test Accuracy of the model :  0.7195767195767195
**************************************************
Confusion matrix of the model on test dataset:
 [[  7  50]
 [  3 129]]
**************************************************
Classification report of the model on test dataset:
              precision    recall  f1-score   support

           0       0.70      0.12      0.21        57
           1       0.72      0.98      0.83       132

    accuracy                           0.72       189
   macro avg       0.71      0.55      0.52       189
weighted avg       0.71      0.72      0.64       189

**********************************************************************************************************
```

In [ ]:

Summary:
After training many models, I realized that the feature U that we get after Matrix decomposition is also represents the 'GENDER' with a good accuracy.

In [ ]: