```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
```

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 
2. The data will be of this format, each data point is represented as a triplet c
```

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

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

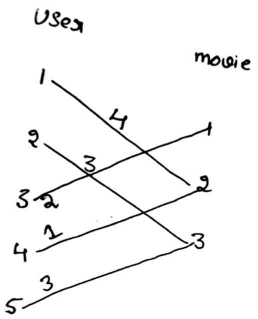
- μ : scalar mean rating
- b_i : scalar bias term for user i
- c_j : scalar bias term for movie j

- 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]() and the weight of each edge is the rating given by user to the movie



the Adjacency matrix

$$\begin{array}{c|ccc} & 1 & 2 & 3 \\ \hline 1 & 0 & 4 & 0 \\ 2 & 0 & 0 & 3 \\ 3 & 2 & 0 & 0 \\ 4 & 0 & 1 & 0 \\ 5 & 0 & 0 & 3 \end{array}$$

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]()

2. We will Apply SVD decomposition on the Adjaceny matrix [link1](), [link2]() 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.

3. Compute μ , μ represents the mean of all the rating given in the dataset.(write your code in def m_u())
4. 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())
5. 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())
6. Compute dL/db_i (Write you code in def derivative_db())
7. Compute dL/dc_j(write your code in def derivative_dc()
8. 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
```

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

9. you can choose any learning rate and regularization term in the range 10^{-3} to 10^{2}
10. **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 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

```
path = '/content/drive/MyDrive/AAIC/ASSIGN_15/'
```

```
import pandas as pd
data=pd.read_csv(path+'ratings_train.csv')
data.head()
```

	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

```
data.shape
```

```
(89992, 3)
```

Create your adjacency matrix

```
from scipy.sparse import csr_matrix
adjacency_matrix =  csr_matrix((data['rating'],(data['user_id'],data['item_id'
```

```
adjacency_matrix.shape
```

```
(943, 1681)
```

Grader function - 1

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

```
True
```

SVD decompostion

Sample code for SVD decompostion

```
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=No
print(U.shape)
print(Sigma.shape)
print(VT.T.shape)
```

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

Write your code for SVD decompostion

```
# 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=5,n_iter=5, rando
print(U.shape)
print(Sigma.shape)
print(VT.T.shape)

```

```
(943, 5)
(5,)
(1681, 5)
```

Compute mean of ratings

```
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/p


    return ratings.mean()
```

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

```
3.529480398257623
```

Grader function -2

```
def grader_mean(mu):
  assert(np.round(mu,3)==3.529)
  return True
```

```
mu=m_u(data['rating'])
grader_mean(mu)
```

```
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)

```
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



    return [0]*dim
```

```
dim= adjacency_matrix.shape[0]# give the number of dimensions for b_i (Here b_
b_i=initialize(dim)
```

```
dim=adjacency_matrix.shape[1] # give the number of dimensions for c_j (Here c_
c_j=initialize(dim)
```

Grader function -3

```
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)
```

```
True
```

Compute dL/db_i

```
def derivative_db(user_id,item_id,rating,U,V,mu,alpha):
    '''In this function, we will compute dL/db_i'''
    sam = alpha*b_i[user_id] - (rating - mu -b_i[user_id] -c_j[item_id] -np.do
    sam = 2*sam


    return sam

```

Grader function -4

```
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, rand
# 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)
```

```
True
```

Compute dL/dc_j

```
def derivative_dc(user_id,item_id,rating,U,V,mu, alpha):
    '''In this function, we will compute dL/dc_j'''
    sam = alpha*c_j[item_id] - (rating - mu -b_i[user_id] -c_j[item_id] -np.do
    sam = 2*sam


    return sam

```

Grader function - 5

```
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, rand
# 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)
```

```
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
```

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

```
from sklearn.metrics import mean_squared_error

epochs = 50
n_com = 900
alpha = 0.1
r = 0.1
lr = 0.00001

U1, Sigma, V1 = randomized_svd(adjacency_matrix, n_components=n_com ,n_iter=30
print(U1.shape)
print(V1.shape)

print(adjacency_matrix.shape)
pred_rating = np.zeros(adjacency_matrix.shape)
print(pred_rating.shape)

MSE = []

for epoch in range(epochs):
    for i in range(len(b_i)):
        for j in range(len(c_j)):
            b_i[i] = b_i[i] - lr * derivative_db(i,j,adjacency_matrix[i,j],U1,
            c_j[j] = b_i[i] - lr * derivative_dc(i,j,adjacency_matrix[i,j],U1,
            pred_rating[i,j] = mu+b_i[i]+c_j[j]+np.dot(U1[i,:],V1[:,j])

    mse = mean_squared_error(adjacency_matrix.toarray(), pred_rating)
    print(str(epoch)+':'+str(mse))

    MSE.append(mse)

print(MSE)
```

```
(943, 900)
(900, 1681)
(943, 1681)
(943, 1681)
0:11.081639815739358
1:9.775472602438578
2:8.63708262171535
3:7.644682236313814
4:6.779327453915718
5:6.024550205990485
6:5.366033566234692
7:4.79132965228029
8:4.289614595754088
9:3.851475704775306
10:3.468726584693329
```

```
11:3.1342465401035384
12:2.841841065058673
13:2.586120648574663
14:2.3623954874001303
15:2.1665840148599376
16:1.9951334297188275
17:1.8449506479320774
18:1.7133423076240857
19:1.5979626378028902
20:1.4967681577738337
21:1.4079783100804288
22:1.33004124778561
23:1.2616040993656636
24:1.2014871234660027
25:1.1486612430373466
26:1.102228515473803
27:1.061405153649037
28:1.0255067633551218
29:0.9939355065997977
30:0.966168938387937
31:0.9417502977628163
32:0.9202800626730204
33:0.9014086032351388
34:0.8848297896790509
35:0.87027543012412
36:0.8575104297166949
37:0.8463285768881519
38:0.8365488748515882
39:0.8280123471901668
40:0.8205792557146482
41:0.8141266768673107
42:0.8085463899853603
43:0.8037430368489372
44:0.7996325172484309
45:0.7961405899185212
46:0.7932016521937589
47:0.7907576752221848
48:0.7887572745985232
49:0.7871548989069016
[11.081639815739358, 9.775472602438578, 8.63708262171535, 7.644682236313814, 6
```

```
1   print(pred_rating) #we can observe that more users have given high rating for
```

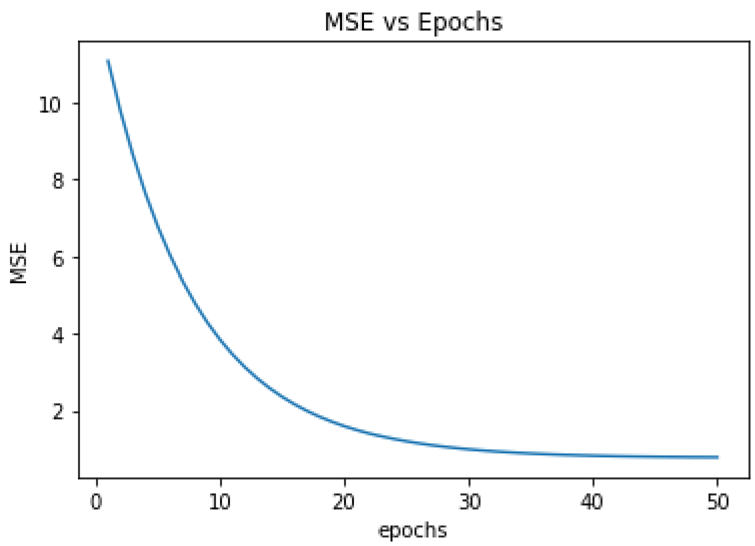
```
[[0.84586645 0.79213059 0.90521759 ... 0.81976166 0.82091536 0.81456016]
 [0.17519634 0.07535668 0.1021043  ... 0.11674885 0.11294922 0.11073341]
 [0.43795425 0.42786313 0.44363028 ... 0.44003585 0.42612667 0.44050006]
 ...
 [0.12487719 0.1533799  0.15844136 ... 0.16803064 0.15081865 0.1564356 ]
 [0.57371379 0.55645492 0.5743767  ... 0.5886821  0.59116511 0.59296929]
 [0.5518566  0.6904083  0.52637912 ... 0.5692556  0.56415896 0.57291178]]
```

Plot epoch number vs MSE

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

```
1   from matplotlib import pyplot as plt
```

```
plt.plot([i for i in range(1,epochs+1)],MSE)
plt.xlabel('epochs')
plt.ylabel('MSE')
plt.title('MSE vs Epochs')
plt.show()
```



Task 2

```
usr_data=pd.read_csv(path+'user_info.csv.txt')
usr_data.head()
```

	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

```
X = np.concatenate((U1,usr_data['age'].to_numpy(dtype=int).reshape(-1,1)),axis
y = usr_data['is_male'].to_numpy()
print(X.shape,y.shape)
```

```
(943, 901) (943,)
```

```
print(X)
```

```
[[ 6.62257023e-02  7.88851791e-03 -1.25312581e-02 ...  8.56543082e-03
   1.16203130e-02  2.40000000e+01]
 [ 1.36443174e-02 -4.88950212e-02  5.65537222e-02 ... -4.94073518e-02
  -9.17120326e-03  5.30000000e+01]
 [ 5.43826120e-03 -2.51277980e-02  2.00277398e-02 ...  5.30614847e-02
   4.81935436e-02  2.30000000e+01]
 ...
```

```
 [ 7.38924381e-03 -2.59737536e-02  6.34329873e-03 ...  2.85958049e-02
   1.43866607e-01  2.00000000e+01]
 [ 2.49992387e-02  4.47791436e-03  2.60564574e-02 ... -1.52048244e-03
   1.35618371e-02  4.80000000e+01]
 [ 4.33734106e-02 -2.81487169e-03 -6.07778951e-02 ... -4.09969180e-03
   3.81988884e-03  2.20000000e+01]]
```

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(random_state=0).fit(X, y)
print(clf.predict(X[:2, :]))
print(clf.predict_proba(X[:2, :]))
print(clf.score(X, y))
```

```
[1 1]
[[0.23973849 0.76026151]
 [0.41763493 0.58236507]]
0.7104984093319194
```

- clf.score returns the mean accuracy on the given test data and labels
- As in the above code cell we have given the training data to the classifier(Logistic Regression) it is giving the accuracy of 71%.
- So we can conclude that the user_representation makes prediction of is_male upto 71% and the accuracy might increase if we get a better representation of user by increasing the no of components in truncated_svd.

- Checking whehter only user vectors make differnce in is_male classification.

```
X = ((U1))
y = usr_data['is_male'].to_numpy()
print(X.shape,y.shape)
```

```
(943, 900) (943,)
```

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(random_state=0).fit(X, y)
print(clf.predict(X[:2, :]))
print(clf.predict_proba(X[:2, :]))
print(clf.score(X, y))
```

```
[1 1]
[[0.23641657 0.76358343]
 [0.42568659 0.57431341]]
0.7104984093319194
```

- We can observe that there is not much variation observed in the final accuracy of clf.