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

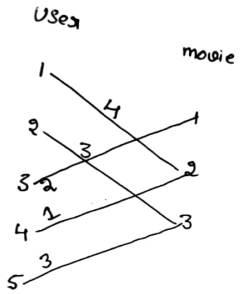
$$L = \min_{b,c,\{u_i\}_{i=1}^{N},\{v_j\}_{j=1}^{M}} \alpha \left(\right.$$

- 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 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

1. **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.**
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 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**

Loading Files

In [ ]:

```
from google.colab import files

uploaded = files.upload()
```

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```
Saving ratings_train (1).csv to ratings_train (1).csv
```

Reading Files

In [ ]:

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

Out[ ]:

	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 [ ]:

```
data.shape
```

Out[ ]:

```
(89992, 3)
```

In [ ]:

```
from scipy.sparse import csr_matrix
adjacency_matrix = csr_matrix((data.rating.values, (data.user_id.values,
                                                    data.item_id.values)))
```

In [ ]:

```
adjacency_matrix.shape
```

Out[ ]:

```
(943, 1681)
```

In [ ]:

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

Out[ ]:

```
True
```

In [ ]:

```
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)
```

Own code for SVD decompostion

In [ ]:

```
from sklearn.utils.extmath import randomized_svd
import numpy as np
U, Sigma, VT = randomized_svd(adjacency_matrix, n_components=10,n_iter=5, random_state=None)
print(U.shape)
print(Sigma.shape)
print(VT.T.shape)
```

```
(943, 10)
(10,)
(1681, 10)
```

Compute mean of ratings

In [ ]:

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

In [ ]:

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

```
3.529480398257623
```

In [ ]:

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

Out[ ]:

```
True
```

Initialize B_i and C_j

In [ ]:

```
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 np.zeros(dim)
```

In [ ]:

In [ ]:

```
adjacency_matrix.shape[0],adjacency_matrix.shape[1]
```

Out[ ]:

```
(943, 1681)
```

In [ ]:

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

In [ ]:

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

In [ ]:

```
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[ ]:

```
True
```

Compute dL/db_i

In [ ]:

```
def derivative_db(user_id,item_id,rating,U,V,mu,alpha):
    '''In this function, we will compute dL/db_i'''
   # total loss = loss + regularization
    total_loss=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 total_loss
```

In [ ]:

```
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=2
4)
# 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[ ]:

```
True
```

Compute dL/dc_j

In [ ]:

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

In [ ]:

```
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=2
4)
# 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,alpha)
grader_dc(value)
```

Out[ ]:

```
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 [ ]:

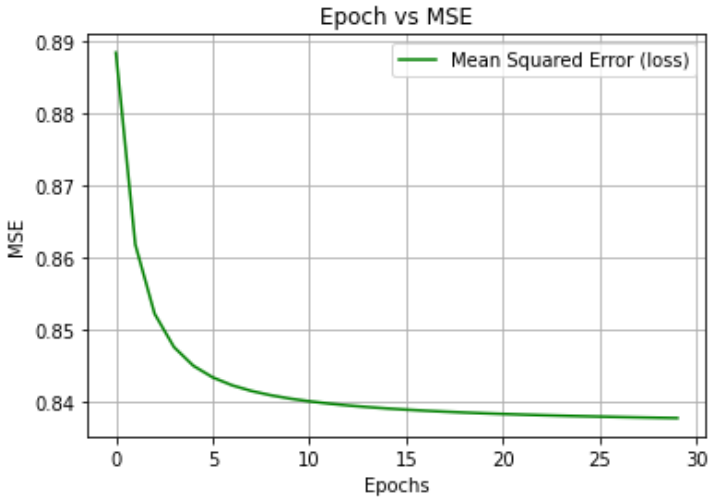
```
from sklearn.metrics import mean_squared_error
rate=.01
y_act=data["rating"]
epochs=[]
mse=[]
for epoch in range(30):
  epochs.append(epoch+1)
  predic=[]
  for user,item,rating in zip(data['user_id'], data['item_id'],data['rating']):
    d_b=derivative_db(user,item,rating,U,VT,mu,alpha)
    b_i[user]=b_i[user]-rate*d_b
    d_c=derivative_dc(user,item,rating,U,VT,mu,alpha)
    c_j[item]=c_j[item]-rate*d_c
  for user,item,rating in zip(data['user_id'], data['item_id'],data['rating']):
    pred=mu+b_i[user]+c_j[item]+np.dot(U[user],VT.T[item])
    predic.append(pred)
  m= mean_squared_error(y_act,predic)
  mse.append(m)
  print("--"+" "+ "EPOCH"+" "+str(epoch+1),"MSE :",m)
```

```
-- EPOCH 1 MSE : 0.8884185238398319
-- EPOCH 2 MSE : 0.8618663903699963
-- EPOCH 3 MSE : 0.8522569308967981
-- EPOCH 4 MSE : 0.8476521642296475
-- EPOCH 5 MSE : 0.84507034527215
-- EPOCH 6 MSE : 0.8434572317851666
-- EPOCH 7 MSE : 0.8423648799536154
-- EPOCH 8 MSE : 0.8415781854207115
-- EPOCH 9 MSE : 0.8409840054575606
-- EPOCH 10 MSE : 0.840518321979385
-- EPOCH 11 MSE : 0.8401426267342598
```

```
-- EPOCH 12 MSE : 0.8398325085924365
-- EPOCH 13 MSE : 0.8395717755484097
-- EPOCH 14 MSE : 0.8393492588535076
-- EPOCH 15 MSE : 0.8391569908414119
-- EPOCH 16 MSE : 0.8389891208875505
-- EPOCH 17 MSE : 0.83884124529328
-- EPOCH 18 MSE : 0.8387099784247682
-- EPOCH 19 MSE : 0.8385926695081191
-- EPOCH 20 MSE : 0.8384872102468957
-- EPOCH 21 MSE : 0.8383919007700268
-- EPOCH 22 MSE : 0.8383053540695737
-- EPOCH 23 MSE : 0.8382264264719244
-- EPOCH 24 MSE : 0.8381541661184472
-- EPOCH 25 MSE : 0.8380877741628353
-- EPOCH 26 MSE : 0.8380265751166688
-- EPOCH 27 MSE : 0.8379699938883168
-- EPOCH 28 MSE : 0.8379175377947381
-- EPOCH 29 MSE : 0.8378687823197244
-- EPOCH 30 MSE : 0.8378233597304671
```

In [ ]:

```
import matplotlib.pyplot as plt
plt.plot(mse,label='Mean Squared Error (loss)',color="green")
plt.xlabel('Epochs')
plt.ylabel('MSE')
plt.title('Epoch vs MSE')
plt.grid()
plt.legend()
plt.show()
```



Task 2

- **For this task you have to consider the user_matrix U and the user_info.csv file.**
- **You have to consider is_male columns as output features and rest as input features. Now you have to fit a model by posing this problem as binary classification task.**
- **You can apply any model like Logistic regression or Decision tree and check the performance of the model.**
- **Do plot confusion matrix after fitting your model and write your observations how your model is performing in this task.**
- **Optional work- You can try scaling your U matrix.Scaling means changing the values of n_componenets while performing svd and then check your results.**

In [ ]:

```
from google.colab import files
uploaded = files.upload()
```

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```
Saving user_info.csv.txt to user_info.csv.txt
```

In [ ]:

```
import pandas as pd
data1=pd.read_csv('user_info.csv.txt')
data1.head()
```

Out[ ]:

	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 [ ]:

```
y = data1['is_male'].values
x = U
```

Splitting Data into Train and Test

In [ ]:

```
X_train,X_test,y_train,y_test=train_test_split(x,y,stratify=y,random_state=10)
```

In [ ]:

```
from sklearn.linear_model import SGDClassifier
from seaborn import heatmap
clf = SGDClassifier(loss='log',random_state=23)
```

Model Fitting

In [ ]:

```
from sklearn import linear_model
clf = linear_model.SGDClassifier(alpha=0.0001,eta0=0.0001,max_iter=1000,loss='log',penalt
y='l2')
clf.fit(X_train,y_train)
```

Out[ ]:

```
SGDClassifier(eta0=0.0001, loss='log')
```

In [ ]:

```
print("Accuracy on train_data: {}".format(clf.score(X_train,y_train))) #imbalanced Datase
t
print("Accuracy on test_data: {}".format(clf.score(X_test,y_test)))
```

```
Accuracy on train_data: 0.7468175388967468
Accuracy on test_data: 0.75
```

In [ ]:

```
user_male_pred = clf.predict(U)
from sklearn.metrics import confusion_matrix
import seaborn as sns
def plot_confusion_matrix(test_y, predict_y):
```

```
 C = confusion_matrix(test_y, predict_y)

 A =(((C.T)/(C.sum(axis=1))).T)

 B =(C/C.sum(axis=0))
 plt.figure(figsize=(20,4))

 labels = [0,1]
 # representing A in heatmap format

 plt.subplot(1, 3, 1)
 sns.heatmap(C, annot=True, cmap='GnBu', fmt=".3f", xticklabels=labels, yticklabels=labe
ls)
 plt.xlabel('Predicted Class')
 plt.ylabel('Actual Class')
 plt.title("Confusion matrix")

 plt.subplot(1, 3, 2)
 sns.heatmap(B, annot=True, cmap='GnBu', fmt=".3f", xticklabels=labels, yticklabels=labe
ls)
 plt.xlabel('Predicted Class')
 plt.ylabel('Actual Class')
 plt.title("Precision matrix")

 plt.subplot(1, 3, 3)
 # representing B in heatmap format
 sns.heatmap(A, annot=True, cmap='GnBu', fmt=".3f", xticklabels=labels, yticklabels=labe
ls)
 plt.xlabel('Predicted Class')
 plt.ylabel('Actual Class')
 plt.title("Recall matrix")

 plt.show()
```

In [ ]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y,user_male_pred)
```

```
Train confusion_matrix
```