SGD Algorithm to predict movie ratings

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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 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

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

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

you can construct this matrix like $A[i][j] = r_{ij}$ here i is user_id, j is movie*id and* $r{ij}$isratinggivenbyuseritothemoviej$

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

Reading the csv file

In [3]:
```python
from tqdm import tqdm
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
```

In [4]:
```python
data=pd.read_csv('ratings_train.csv')
data.head()
```

Out[4]:

	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

Create your adjacency matrix

In [5]:
```python
u_i = data.user_id
v_j = data.item_id

rating_details = data.rating.tolist()
actual_rating = data.rating.tolist()
user_details = u_i.tolist()
movie_details = v_j.tolist()
```

In [6]:
```python
from scipy.sparse import csr_matrix

adjacency_matrix_ = csr_matrix((rating_details, (user_details, movie_details)))
```

In [7]:
```python
adjacency_matrix_df = pd.DataFrame(adjacency_matrix_.todense())
```

Grader function - 1

In [8]:
```python
def grader_matrix(matrix):
  assert(matrix.shape==(943,1681))
  return True
grader_matrix(adjacency_matrix_)
```

Out[8]: True

SVD decompostion

Sample code for SVD decompostion

In [9]:
```python
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 [10]:
```python
# Please use adjacency_matrix as matrix for SVD decompostion
# You can choose n_components as your choice
```

In [15]:
```python
import numpy as np
adjacency_matrix_array = adjacency_matrix_.toarray( )
U, Sigma, VT = randomized_svd(adjacency_matrix_array, n_components=300,n_iter=5, random_state=None)
print(U.shape)
print(Sigma.shape)
print(VT.T.shape)
```

```
(943, 300)
(300,)
(1681, 300)
```

Compute mean of ratings

In [16]:
```python
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
```

In [17]:
```python
def m_u(ratings):
    '''In this function, we will compute mean for all the ratings'''

    ratings_mean = np.round(np.mean(ratings), 3)
    # 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 ratings_mean
```

Grader function -2

In [18]:
```python
def grader_mean(mu):
  assert(np.round(mu,3)==3.529)
  return True
mu=m_u(data['rating'])
grader_mean(mu)
```

Out[18]: 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 [19]:
```python
def initialize(dim):
    '''In this function, we will initialize bias value 'B' and 'C'.'''
    initializer = [0 for i in range(dim)]
    # initalize the value to zeros
    # return output as a list o

    return initializer
```

In [20]:
```python
dim= adjacency_matrix_.shape[0]
b_i=initialize(dim)
```

In [21]:
```python
dim= adjacency_matrix_.shape[1]
c_j=initialize(dim)
```

Grader function -3

In [22]:
```python
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[22]: True

Compute dL/db_i

In [23]:
```python
def derivative_db(user_id,item_id,rating,U,VT,mu,alpha):
    '''In this function, we will compute dL/db_i'''
    #b_ = 2*((alpha + 1)*b_i[user_id] - rating + mu + c_j[item_id] + np.dot(U[user_id], VT.T[item_id]))
    b_ = (2*alpha*b_i[user_id])-(2*(rating-mu-b_i[user_id]-c_j[item_id]-np.dot(U[user_id],VT.T[item_id])))

    return b_
```

Grader function -4

In [24]:
```python
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)
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
<ipython-input-24-bae5fdcb0ca4> in <module>
      7 alpha=0.01
      8 value=derivative_db(312,98,4,U1,V1,mu,alpha)
----> 9 grader_db(value)

<ipython-input-24-bae5fdcb0ca4> in grader_db(value)
      1 def grader_db(value):
----> 2     assert(np.round(value,3)==-0.931)
      3     return True
      4 U1, Sigma, V1 = randomized_svd(adjacency_matrix_, n_components=2,n_iter=5, random_state=24)
      5 # Please don't change random state

AssertionError:
```

In [25]:
```python
value=derivative_db(312,98,4,U1,V1,mu,alpha)
value
```

Out[25]: -0.9317891723925795

For derivative_db

- The Desired value = **-0.931**
- The value which I am getting is = **-0.9317891723925795**
- After rounding it to 3, it becomes -0.932 (assertation error).

As per Email conversation with team@appliedai the values I am getting are correct.

Ignoring Grader function -4

Compute dL/dc_j

In [26]:
```python
def derivative_dc(user_id,item_id,rating,U,VT,mu, alpha):
    '''In this function, we will compute dL/dc_j'''
    c_ = 2*((alpha + 1)*c_j[item_id] - rating + mu + b_i[user_id] + np.dot(U[user_id], VT.T[item_id]))
    #c_ = (2*alpha*c_j[item_id])-(2*(rating-mu-c_j[item_id]- b_i[user_id]-np.dot(U[user_id],VT.T[item_id])))
    return c_
```

Grader function - 5

In [27]:
```python
def grader_dc(value):
    assert(value==-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
alpha=0.01
value=derivative_dc(58,504,5,U1,V1,mu, alpha)
grader_dc(value)
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
<ipython-input-27-86c51b9a2d3b> in <module>
      7 alpha=0.01
      8 value=derivative_dc(58,504,5,U1,V1,mu, alpha)
----> 9 grader_dc(value)

<ipython-input-27-86c51b9a2d3b> in grader_dc(value)
      1 def grader_dc(value):
----> 2     assert(value==-2.929)
      3     return True
      4 U1, Sigma, V1 = randomized_svd(adjacency_matrix_, n_components=2,n_iter=5, random_state=24)
      5 # Please don't change random state

AssertionError:
```

In [28]:
```python
value=derivative_dc(58,504,5,U1,V1,mu, alpha)
value
```

Out[28]: -2.930039507958737

For derivative_db

- Value to assertain = **-2.929**
- I am getting = **-2.930039507958737**
- After rounding it to 3, it becomes -0.932 (assertation error).

As per Email conversation with team@appliedai the values I am getting are correct.

Ignoring Grader function -5

Compute MSE (mean squared error) for predicted ratings

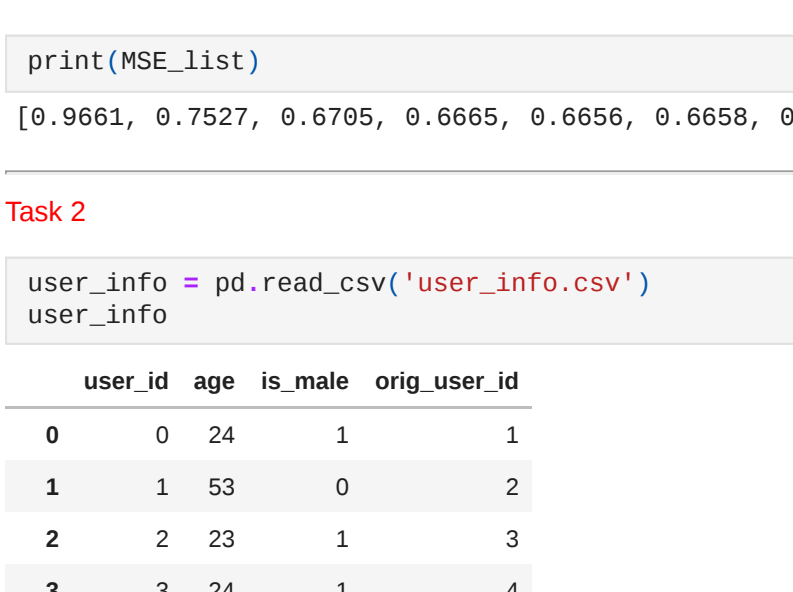
for each epoch, print the MSE value

```
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 [29]:
```python
#%%time

#dim= adjacency_matrix.shape[0]
#b_i=initialize(dim)


#dim= adjacency_matrix.shape[1]
#c_j=initialize(dim)


#adjacency_matrix = np.array(adjacency_matrix_)

epochs = 10
lr = 0.001
MSE_list = []

#actual_rating = pd.DataFrame(adjacency_matrix)

for e in tqdm(range(epochs)):
    all_users_ratings = []

    for i in range(U.shape[0]):
        user_ratings = []
        for j in range(VT.shape[1]):

            b_value=derivative_db(i,j,adjacency_matrix_array[i][j],U,VT,mu,alpha)
            b_i[i] = b_i[i] - lr*b_value

            c_value = derivative_dc(i,j,adjacency_matrix_array[i][j],U,VT,mu, alpha)
            c_j[j] = c_j[i] - lr*c_value

            y_pred = mu + b_i[i] + c_j[j] + np.dot(U[i], VT.T[j])
            user_ratings.append(y_pred)
        all_users_ratings.append(user_ratings)

    predicted_ratings = pd.DataFrame(all_users_ratings)
    actual_rating = pd.DataFrame(adjacency_matrix_array)
    MSE = np.round((np.square(np.array(predicted_ratings) - np.array(actual_rating)).mean(axis=None)), 4)
    MSE_list.append(MSE)


plt.plot([i for i in range(epochs)], MSE_list,
                                    color='green', marker='o', linestyle='--',
                                    linewidth=2, markersize=8)

plt.grid(color='y', linestyle='--', linewidth=0.5)
plt.xlabel("Epoch")
plt.ylabel("MSE")
plt.title("Epoch vs MSE ")
#plt.xkcd()
plt.show()
```

```
100%|████████████████████████████████████████| 10/10 [08:59<00:00, 53.96s/it]
```



In [30]:
```python
print(MSE_list)
```

```
[0.9661, 0.7527, 0.6705, 0.6665, 0.6656, 0.6658, 0.6662, 0.6664, 0.6667, 0.6669]
```

Task 2

In [31]:
```python
user_info = pd.read_csv('user_info.csv')
user_info
```

Out[31]:

	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
...	...	...	...	...
938	938	26	0	939
939	939	32	1	940
940	940	20	1	941
941	941	48	0	942
942	942	22	1	943

943 rows × 4 columns

In [32]:
```python
user_matrix = pd.DataFrame(U)
user_matrix['Is_Male'] = user_info.is_male
user_matrix.head()
```

Out[32]:

	0	1	2	3	4	5	6	7	8	9	...	291	292	293	294	295	296	297	298
0	0.066226	0.007889	-0.012531	-0.086164	0.024870	0.006661	0.080051	-0.027567	0.067568	0.020422	...	0.042233	-0.028445	0.011708	0.036218	-0.005871	0.047418	0.035521	-0.031427
1	0.013644	-0.048895	0.056554	0.015809	-0.012036	0.017731	0.010708	-0.010217	0.028434	-0.009383	...	0.075701	-0.025913	-0.041233	0.016309	0.021350	0.010320	0.044103	-0.029068
2	0.005438	-0.025128	0.020028	0.032832	0.035080	0.001919	0.007690	-0.000996	-0.021169	-0.003201	...	0.012493	-0.026614	0.038926	-0.027825	0.040551	0.004009	-0.009401	-0.005497
3	0.005704	-0.018211	0.010898	0.021867	0.013920	-0.014180	0.012246	-0.009111	-0.012774	0.006112	...	-0.007032	-0.059955	0.045249	0.020849	-0.028334	-0.028730	-0.000499	0.006983
4	0.034122	0.009005	-0.044054	-0.016049	0.004326	-0.021502	0.095574	0.079504	-0.017152	0.029360	...	-0.058646	0.051648	-0.039851	0.049883	0.063785	0.008650	-0.033055	0.033556

5 rows × 301 columns

In [33]:
```python
y = user_matrix.Is_Male
X = user_matrix.drop('Is_Male', axis=1)
```

Applying classification model without data scaling.

In [34]:
```python
from sklearn.linear_model import LogisticRegression

clf_logistic = LogisticRegression()
clf_logistic.fit(X, y)

y_pred = clf_logistic.predict(X)
y_pred[0:10]
```

Out[34]: array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1], dtype=int64)

Dumb Model as the model is predicting everything as 1.

Lets try to scale the data and apply Logistic Regression.

In [35]:
```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)
pd.DataFrame(X_scaled).head()
```

Out[35]:

	0	1	2	3	4	5	6	7	8	9	...	290	291	292	293	294	295	296	297
0	1.958621	0.590646	-0.651603	-2.795768	0.765587	0.392285	2.350677	-0.805625	2.122283	0.573709	...	0.414251	1.295367	-0.842886	0.363447	1.118968	-0.182385	1.467988	1.081397
1	-0.523289	-1.248412	1.537517	0.361269	-0.367732	0.737953	0.204032	-0.272371	0.919312	-0.342898	...	1.373237	2.323114	-0.765068	-1.262310	0.507582	0.653540	0.328700	1.344939
2	-0.910626	-0.478659	0.380105	0.888286	1.079118	0.244221	0.110625	0.011024	-0.605473	-0.152772	...	0.901704	0.382104	-0.786627	1.199269	-0.847743	1.243151	0.134902	-0.298134
3	-0.898067	-0.254636	0.090823	0.548809	0.429329	-0.258505	0.251661	-0.238393	-0.347414	0.133623	...	0.010399	-0.217466	-1.810974	1.393419	0.646994	-0.872185	-0.870542	-0.024764
4	0.443279	0.626795	-1.650473	-0.625034	0.134735	-0.487132	2.831201	2.485191	-0.481991	0.848592	...	-1.017612	-1.802440	1.617823	-1.219857	1.538604	1.956648	0.277434	-1.024538

5 rows × 300 columns

In [36]:
```python
clf_logistic.fit(X_scaled, y)
y_pred_scaled = clf_logistic.predict(X_scaled)
y_pred_scaled[0:10]
```

Out[36]: array([1, 0, 1, 1, 0, 1, 1, 1, 1, 1], dtype=int64)

In [48]:
```python
import seaborn as sns
import matplotlib.pyplot as plt
def plot_cmatrics(Y_true_cv, Y_predicted_cv):
    print("Confusion Matrics :")

    #reference: https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30fea

    confusion_matrix_cv = metrics.confusion_matrix(Y_true_cv, Y_predicted_cv)
    group_names = ['True Neg','False Pos','False Neg','True Pos']
    group_counts = ['{0:0.0f}'.format(value) for value in
                    confusion_matrix_cv.flatten()]
    group_percentages = ['{0:.2%}'.format(value) for value in
                         confusion_matrix_cv.flatten()/np.sum(confusion_matrix_cv)]
    labels = [f'{v1}\n{v2}\n{v3}'for v1, v2, v3 in
              zip(group_names,group_counts,group_percentages)]
    labels = np.asarray(labels).reshape(2,2)
    sns.heatmap(confusion_matrix_cv, annot=labels, fmt='', cmap='BuPu', ax=None,
                xticklabels=['Predicted NO', 'Predicted YES'], yticklabels=['Actual NO', 'Actual YES'],
                linecolor='black', linewidths=0.5)

    plt.show()
    print('-'*45)

    #return confusion_matrix_cv
```

In [50]:
```python
from sklearn import metrics
print(metrics.classification_report(y, y_pred_scaled))
plot_cmatrics(y, y_pred_scaled)
```

```
              precision    recall  f1-score   support

           0       0.89      0.86      0.87       273
           1       0.94      0.96      0.95       670

    accuracy                           0.93       943
   macro avg       0.92      0.91      0.91       943
weighted avg       0.93      0.93      0.93       943

Confusion Matrics :
```



```
---------------------------------------------
```

Observation

- It is observed that as we have applied classification model to the computed user metrics, model has predicted correct gender with 92% accuracy and high TP and TN values. Therefore we can conclude that the feature "Gender" has a significant impact on the ratings given by the user to specific movie.