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In [9]: ## COMP 8745 : Spring 2021
## Project: Recommendation System for Movie Ratings
## Due Date: April 23, 2021
## Team:
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## Implementation Algorithm: Item-Item Collaborative Filtering

# libraries
import numpy as np
import pandas as pd
import sklearn
from sklearn.metrics.pairwise import cosine_similarity
import scipy
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In [10]: # load dataset. This is an example dataset
columns = ['userID', 'movieID', 'Rating'] # We have added header to make it simple
user_movie_dataset = pd.read_csv('exampledataset/data_test.txt', delimiter=',',
user_movie_dataset # This is basically displaying the following table
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Out[10]:
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|   | userID | movieID | Rating |
|---|--------|---------|--------|
| 0 | 1      | 1       | 2      |
| 1 | 1      | 3       | 3      |
| 2 | 2      | 1       | 5      |
| 3 | 2      | 2       | 2      |
| 4 | 3      | 1       | 3      |
| 5 | 3      | 2       | 3      |
| 6 | 3      | 3       | 1      |
| 7 | 4      | 2       | 2      |
| 8 | 4      | 3       | 2      |

```
In [11]: # load actual dataset: Working Dataset
# User large dataset. rating.txt
columns = ['userID', 'movieID', 'Rating'] # Please do not remove this column.

user_movie_dataset = pd.read_csv('netflix/ratings.txt', delimiter=',', names=col
user_movie_dataset.head() # display first 5 entries of the dataset. We use it to
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Out[11]:
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|   | userID | movieID | Rating |
|---|--------|---------|--------|
| 0 | 28     | 1392773 | 4.0    |
| 1 | 28     | 1990901 | 5.0    |
| 2 | 28     | 765331  | 3.0    |
| 3 | 28     | 1987434 | 4.0    |
| 4 | 28     | 2193455 | 4.0    |

```
In [18]: # Step 1: make user-movie matrix
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user_movie_mat = user_movie_dataset.pivot(index='userID', columns='movieID', val
user_movie_mat.head()
# Note: This is creating a sparse matrix with the cell values 'NaN' if a particu

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Out[18]: movieID      7   79  199  481  769  906 1310 1333 1427 1442 ... 2648572 2648589 26
          userID

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|     |     |     |     |     |     |     |     |     |     |     |     |     |     |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 28  | 4.0 | NaN | NaN | NaN | NaN | 3.0 | 3.0 | 2.0 | NaN | 4.0 | ... | NaN | 3.0 |
| 48  | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN |
| 305 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 5.0 | ... | NaN | NaN |
| 577 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN |
| 595 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN |

5 rows × 28968 columns

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In [23]: # Python API 'cosine_similarity' does not work on undefined value. To get rid of
          user_movie_mat.fillna(0, inplace=True)
          user_movie_mat.head()

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Out[23]: movieID      7   79  199  481  769  906 1310 1333 1427 1442 ... 2648572 2648589 2648
          userID

```

|     |     |     |     |     |     |     |     |     |     |     |     |     |     |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 28  | 4.0 | 0.0 | 0.0 | 0.0 | 0.0 | 3.0 | 3.0 | 2.0 | 0.0 | 4.0 | ... | 0.0 | 3.0 |
| 48  | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 |
| 305 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 5.0 | ... | 0.0 | 0.0 |
| 577 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 |
| 595 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 |

5 rows × 28968 columns

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In [22]: user_movie_mat.shape

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Out[22]: (92, 28968)

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In [13]: # Step 2: Item-item similarity matrix using cosine similarity
          similarity_mat = cosine_similarity(user_movie_mat.T, user_movie_mat.T)
          similarity_mat

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Out[13]: array([[1.          , 0.43503212, 0.37994855, ..., 0.42237094, 0.3741104 ,
                0.55577001],
                [0.43503212, 1.          , 0.72314299, ..., 0.0951968 , 0.61113629,
                0.65693576],
                [0.37994855, 0.72314299, 1.          , ..., 0.          , 0.78132929,
                0.61589504],
                ...,
                [0.42237094, 0.0951968 , 0.          , ..., 1.          , 0.          ,
                0.11553664],
                [0.3741104 , 0.61113629, 0.78132929, ..., 0.          , 1.          ,
                0.5317937 ]],

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[0.55577001, 0.65693576, 0.61589504, ..., 0.11553664, 0.5317937 ,  
1.          ]])
```

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In [30]: # Step 3: predict rating  
def predict_rating(user_id, movie_id):  
    df = pd.DataFrame(user_movie_mat)  
  
    user_index = np.where(df.index.values==user_id)[0][0]  
    movie_index = np.where(df.columns.values==movie_id)[0][0]  
    # We are calculating predicted rating of an item by a particular user using  
    rating = np.sum(np.dot(user_movie_mat.iloc[user_index, :],similarity_mat[:,  
    # bounded rating between 1 and 5  
    rating = 1.0 if rating < 1 else rating;  
    rating = 5.0 if rating > 5 else rating;  
    rating = "{:.2f}".format(rating)  
    print ("Predicted rating by user {0} for movie {1} is {2}".format(user_id, m
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In [31]: predict_rating(28,7) # first parameter is userID and second parameter is movieID  
Predicted rating by user 28 for movie 7 is 2.08
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In [16]: ## Finally done
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