Movie Recommendation System

By Shreeyansh Das | SIC : 20BCSD50

1. Importing Libraries and Datasets

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn
```

In [2]:

```
#timestamp feature ignored

movies = pd.read_csv('movies.csv', sep = '\t', usecols = ['movie_id', 'title', 'genr
ratings = pd.read_csv('ratings.csv', sep = '\t', usecols = ['user_id', 'movie_id', '
users = pd.read_csv('users.csv', sep = '\t', usecols=['user_id', 'gender', 'zipcode'
```

2. Data Visualization and Exploration

Movies DataFrame

In [3]:

```
movies.head()
```

Out[3]:

	movie_id	title	genres
0	1	Toy Story (1995)	Animation|Children's|Comedy
1	2	Jumanji (1995)	Adventure|Children's|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama
4	5	Father of the Bride Part II (1995)	Comedy

In [4]:

```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3883 entries, 0 to 3882
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   movie_id  3883 non-null   int64 
 1   title     3883 non-null   object
 2   genres    3883 non-null   object
dtypes: int64(1), object(2)
memory usage: 91.1+ KB
```

In [5]:

```
movies.describe()
```

Out[5]:

	movie_id
count	3883.000000
mean	1986.049446

	movie_id
std	1146.778349
min	1.000000
25%	982.500000
50%	2010.000000
75%	2980.500000
max	3952.000000

Users DataFrame

In [6]:

```
users.head()
```

Out[6]:

	user_id	gender	zipcode	age_desc	occ_desc
0	1	F	48067	Under 18	K-12 student
1	2	M	70072	56+	self-employed
2	3	M	55117	25-34	scientist
3	4	M	02460	45-49	executive/managerial
4	5	M	55455	25-34	writer

In [7]:

```
users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6040 entries, 0 to 6039
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   user_id   6040 non-null   int64 
 1   gender    6040 non-null   object
 2   zipcode   6040 non-null   object
 3   age_desc  6040 non-null   object
 4   occ_desc  6040 non-null   object
dtypes: int64(1), object(4)
memory usage: 236.1+ KB
```

Ratings DataFrame

In [8]:

```
ratings.head()
```

Out[8]:

	user_id	movie_id	rating
0	1	1193	5
1	1	661	3
2	1	914	3
3	1	3408	4
4	1	2355	5

```
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 3 columns):
 #   Column    Non-Null Count    Dtype
---  ------    --------------    -----
 0   user_id   1000209 non-null  int64
 1   movie_id  1000209 non-null  int64
 2   rating    1000209 non-null  int64
dtypes: int64(3)
memory usage: 22.9 MB
```

In [10]:

```
ratings.describe()
```

Out[10]:

	user_id	movie_id	rating
count	1.000209e+06	1.000209e+06	1.000209e+06
mean	3.024512e+03	1.865540e+03	3.581564e+00
std	1.728413e+03	1.096041e+03	1.117102e+00
min	1.000000e+00	1.000000e+00	1.000000e+00
25%	1.506000e+03	1.030000e+03	3.000000e+00
50%	3.070000e+03	1.835000e+03	4.000000e+00
75%	4.476000e+03	2.770000e+03	4.000000e+00
max	6.040000e+03	3.952000e+03	5.000000e+00

In [11]:

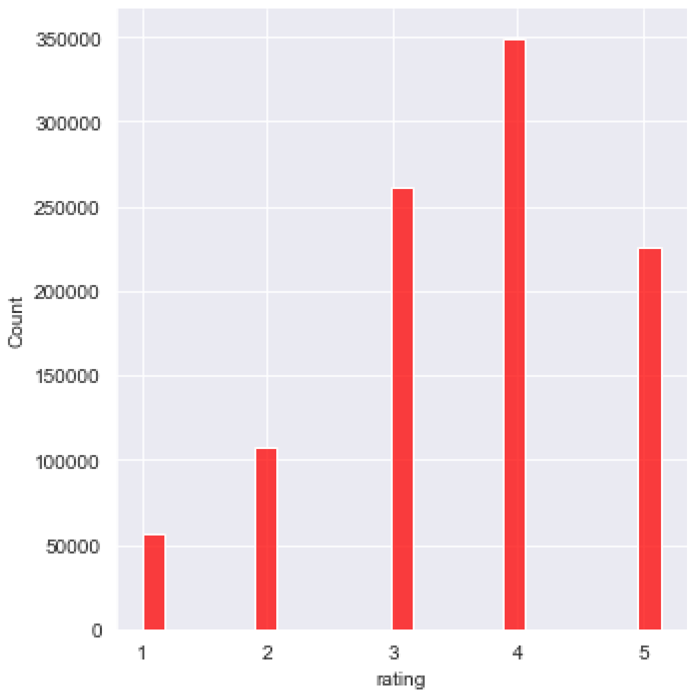
```
sns.set_style('darkgrid')
plt.figure(figsize = (9,5))

sns.displot(ratings['rating'].fillna(ratings['rating'].median), color = 'red', binwi
```

Out[11]:

```
<seaborn.axisgrid.FacetGrid at 0x1ebae20c610>
```

```
<Figure size 648x360 with 0 Axes>
```



In [12]:

```
ratings['rating'].describe()
```

Out[12]:

```
count    1.000209e+06
mean     3.581564e+00
std      1.117102e+00
min      1.000000e+00
25%      3.000000e+00
50%      4.000000e+00
75%      4.000000e+00
max      5.000000e+00
Name: rating, dtype: float64
```

Average rating given by all users is 3.58 out of 5. with a standard deviation of 1.11. 25% of the movies have been rated 3 out of 5 (2,50,00 people rated 3 which is approx 25% of 1,000,000) while 50~75 % of the movies have been rated 4 out of 5 which showcases that overall all users have rated most of the movies good.

In [13]:

```
df = pd.merge(pd.merge(movies, ratings),users)
df.head()
```

Out[13]:

	movie_id	title	genres	user_id	rating	gender	zipcode	age_
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	F	48067	Und
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	F	48067	Und
2	150	Apollo 13 (1995)	Drama	1	5	F	48067	Und
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	F	48067	Und
4	527	Schindler's List (1993)	Drama|War	1	5	F	48067	Und

In [14]:

```
df[['title','genres','rating']].sort_values(by = 'rating', ascending = False).head(5
```

Out[14]:

	title	genres	rating
0	Toy Story (1995)	Animation|Children's|Comedy	5
489283	American Beauty (1999)	Comedy|Drama	5
489259	Election (1999)	Comedy	5
489257	Matrix, The (1999)	Action|Sci-Fi|Thriller	5
489256	Dead Ringers (1988)	Drama|Thriller	5

Top 5 movies with highest ratings are Toy Story, American Beauty, Election, The Matrix and Dead Ringers.

4. Data Pre-processing

Handling for NaN's

In [15]:

```
ratings['user_id'] = ratings['user_id'].fillna(0)
ratings['movie_id'] = ratings['movie_id'].fillna(0)

# Replace NaN values in rating column with average of all values
ratings['rating'] = ratings['rating'].fillna(ratings['rating'].mean())
```

5. Implementation

In [16]:

```
from sklearn.model_selection import train_test_split
# Sampling 2% of Dataset
actual_dataset = ratings.sample(frac = 0.02)
```

Split the Dataset in a 7:3 train:test ratio using `train_test_split`

In [17]:

```
train, test = train_test_split(actual_dataset, test_size = 0.2)
```

Create two User-Item matrices for the training data and test data.

In [18]:

```
train.head()
```

Out[18]:

	user_id	movie_id	rating
196573	1207	1391	3
299635	1778	805	4
85539	558	223	3
866193	5223	1573	3
997433	6023	527	5

Convert to numpy array for ease-of-use.

In [19]:

```
train_matrix = train.to_numpy()
test_matrix = test.to_numpy()

print(train_matrix.shape)
print(test_matrix.shape)
```

```
(16003, 3)
(4001, 3)
```

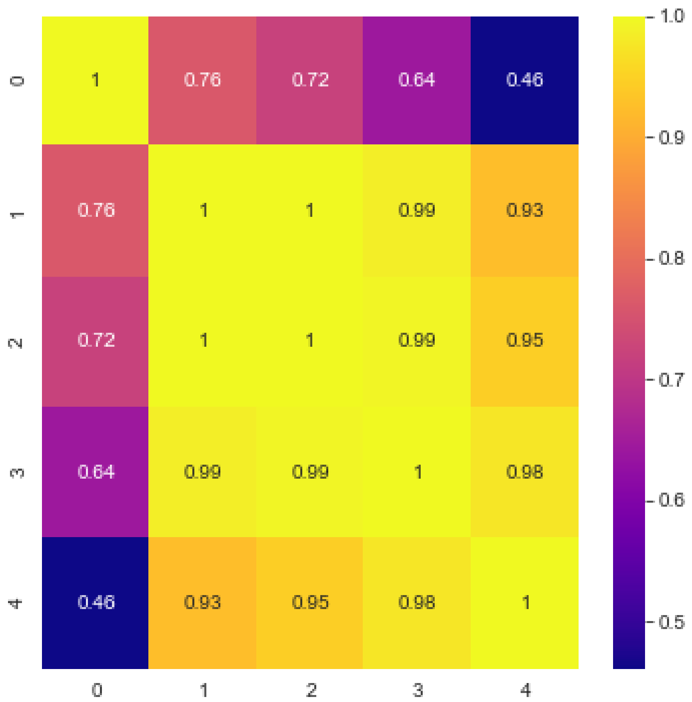
User Based CF: Calculate Pearson Correlation between users

In [20]:

```
from sklearn.metrics.pairwise import pairwise_distances

user_matrix = 1 - pairwise_distances(train, metric = 'correlation')
user_matrix[np.isnan(user_matrix)] = 0
print(user_matrix[:4, :4])
```

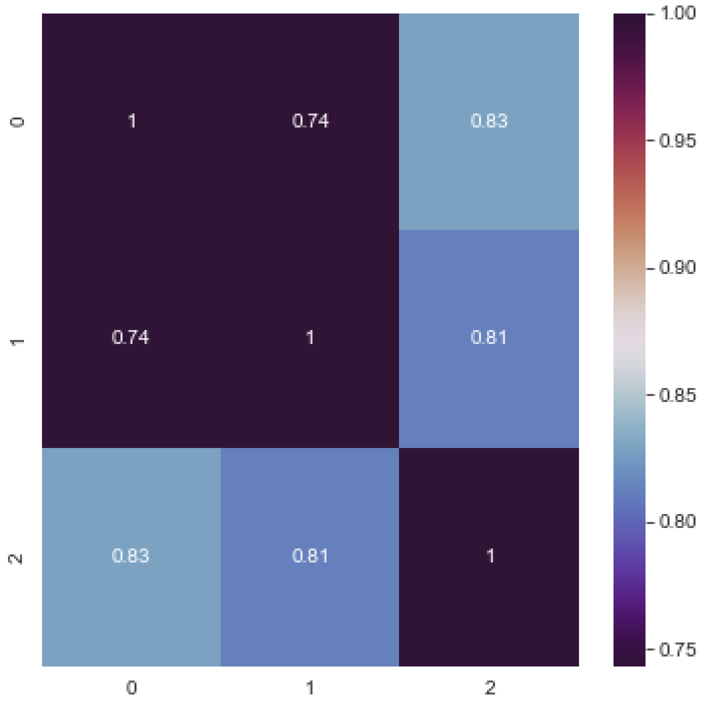
```
[[1.         0.76364379 0.72137942 0.64325078]
 [0.76364379 1.         0.99800695 0.98555063]
 [0.72137942 0.99800695 1.         0.99427502]
 [0.64325078 0.98555063 0.99427502 1.        ]]
```

In [21]:
```
user_matrix.shape
```
Out[21]:
```
(16003, 16003)
```
In [22]:
```
print(user_matrix[:5,:5])
```
```
[[1.         0.76364379 0.72137942 0.64325078 0.46144407]
 [0.76364379 1.         0.99800695 0.98555063 0.92516893]
 [0.72137942 0.99800695 1.         0.99427502 0.94727654]
 [0.64325078 0.98555063 0.99427502 1.         0.97609037]
 [0.46144407 0.92516893 0.94727654 0.97609037 1.        ]]
```
In [23]:
```
plt.figure(figsize = (6,6))
sns.heatmap(user_matrix[:5,:5], annot = True, cmap = 'plasma')
```
Out[23]:
```
<AxesSubplot:>
```


Item Based CF: Calculate Cosine between items

In [35]:
```
item_matrix = 1 - pairwise_distances(train_matrix.T, metric = 'cosine')
item_matrix[np.isnan(item_matrix)] = 0
```
In [36]:
```
item_matrix.shape
```
Out[36]:
```
(3, 3)
```
In [37]:
```
item_matrix
```
Out[37]:
```
array([[1.        , 0.74340932, 0.82908321],
       [0.74340932, 1.        , 0.81261005],
       [0.82908321, 0.81261005, 1.        ]])
```
In [38]:
```
plt.figure(figsize = (6,6))
sns.heatmap(item_matrix, annot = True, cmap = 'twilight_shifted')
```

Out[38]: <AxesSubplot:>



Make Predictions

1. For User Based CF :

- Find average rating of target user
- Calculate Similarity with all users
- Predict rating

2. For Item based CF :

- Find Item-Item similarity (cosine, here)
- Predict rating

In [39]:

```
def predict(ratings, similarity, type='user'):
    if type == 'user':
        mean_user_rating = ratings.mean(axis=1)
        # Use np.newaxis so that mean_user_rating has same format as ratings
        ratings_diff = (ratings - mean_user_rating[:, np.newaxis])
        pred = mean_user_rating[:, np.newaxis] + similarity.dot(ratings_diff) / np.a
    elif type == 'item':
        pred = ratings.dot(similarity) / np.array([np.abs(similarity).sum(axis=1)])
    return pred
```

Evaluation with R.M.S.E.

In [40]:

```
from sklearn.metrics import mean_squared_error
from math import sqrt


def RMSE(pred, actual):
    pred = pred[actual.nonzero()].flatten()
    actual = actual[actual.nonzero()].flatten()
    return sqrt(mean_squared_error(pred, actual))
```

```
user_prediction = predict(train_matrix, user_matrix, type ='user')
item_prediction = predict(train_matrix, item_matrix, type ='item')
```

In [43]:

```
print('Performance on Test Set\r')
print('User-based CF RMSE: ' + str(RMSE(user_prediction, test_matrix)))
print('Item-based CF RMSE: ' + str(RMSE(item_prediction, test_matrix)))
```

```
Performance on Test Set
User-based CF RMSE: 1411.6413341206628
Item-based CF RMSE: 1785.8244004035546
```

In [44]:

```
print('Performance on Training Set\r')
print('User-based CF RMSE: ' + str(RMSE(user_prediction, train_matrix)))
print('Item-based CF RMSE: ' + str(RMSE(item_prediction, train_matrix)))
```

```
Performance on Training Set
User-based CF RMSE: 695.6797089926853
Item-based CF RMSE: 1465.3545713653043
```

END

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