# Project_Building User-Based Recommendation Model for Amazon

December 1, 2022

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.metrics.pairwise import cosine_similarity
import operator
```

[3]:
```
data  = pd.read_csv('Amazon - Movies and TV Ratings.csv')
data.head()
```

[3]:
```
          user_id  Movie1  Movie2  Movie3  Movie4  Movie5  Movie6  Movie7  \
0  A3R5OBKS7OM2IR     5.0     5.0     NaN     NaN     NaN     NaN     NaN
1   AH3QC2PC1VTGP     NaN     NaN     2.0     NaN     NaN     NaN     NaN
2  A3LKP6WPMP9UKX     NaN     NaN     NaN     5.0     NaN     NaN     NaN
3   AVIY68KEPQ5ZD     NaN     NaN     NaN     5.0     NaN     NaN     NaN
4  A1CV1WROP5KTTW     NaN     NaN     NaN     NaN     5.0     NaN     NaN

   Movie8  Movie9  …  Movie197  Movie198  Movie199  Movie200  Movie201  \
0     NaN     NaN  …       NaN       NaN       NaN       NaN       NaN
1     NaN     NaN  …       NaN       NaN       NaN       NaN       NaN
2     NaN     NaN  …       NaN       NaN       NaN       NaN       NaN
3     NaN     NaN  …       NaN       NaN       NaN       NaN       NaN
4     NaN     NaN  …       NaN       NaN       NaN       NaN       NaN

   Movie202  Movie203  Movie204  Movie205  Movie206
0       NaN       NaN       NaN       NaN       NaN
1       NaN       NaN       NaN       NaN       NaN
2       NaN       NaN       NaN       NaN       NaN
3       NaN       NaN       NaN       NaN       NaN
4       NaN       NaN       NaN       NaN       NaN

[5 rows x 207 columns]
```

[4]:
```
print('Shape of the dataset:',data.shape)
```

```
Shape of the dataset: (4848, 207)
```

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4848 entries, 0 to 4847
Columns: 207 entries, user_id to Movie206
dtypes: float64(206), object(1)
memory usage: 7.7+ MB
```

[6]:
```
data = data.drop('user_id',axis=1)
```

# 1 Exploratory Data Analysis:

- Which movies have maximum views/ratings?
- What is the average rating for each movie? Define the top 5 movies with the maximum ratings.
- Define the top 5 movies with the least audience.

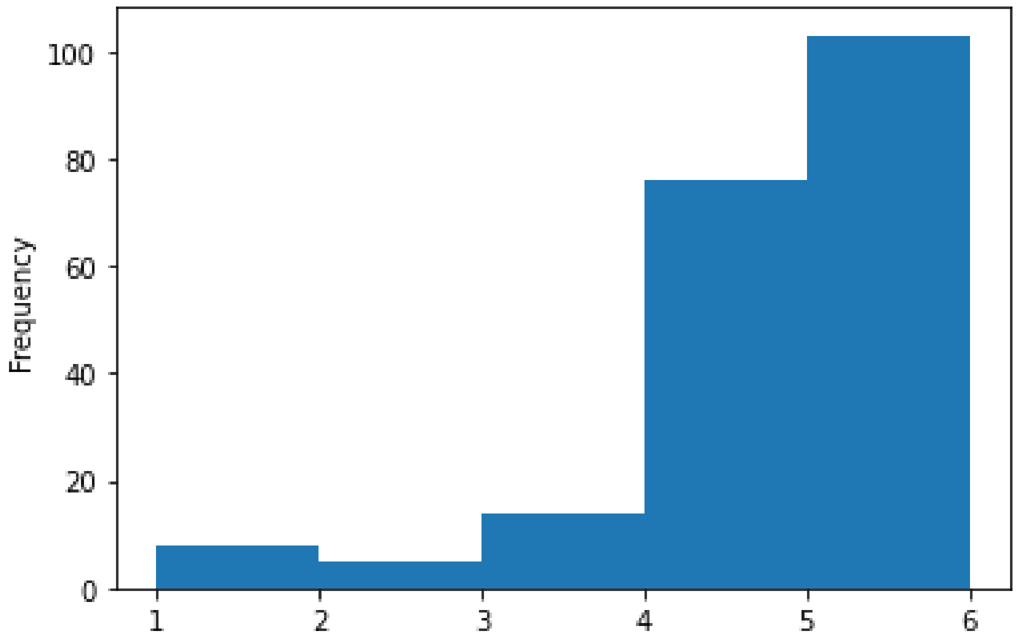
[7]:
```
data.describe().T
```

[7]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| Movie1 | 1.0 | 5.000000 | NaN | 5.0 | 5.00 | 5.0 | 5.0 | 5.0 |
| Movie2 | 1.0 | 5.000000 | NaN | 5.0 | 5.00 | 5.0 | 5.0 | 5.0 |
| Movie3 | 1.0 | 2.000000 | NaN | 2.0 | 2.00 | 2.0 | 2.0 | 2.0 |
| Movie4 | 2.0 | 5.000000 | 0.000000 | 5.0 | 5.00 | 5.0 | 5.0 | 5.0 |
| Movie5 | 29.0 | 4.103448 | 1.496301 | 1.0 | 4.00 | 5.0 | 5.0 | 5.0 |
| … | … | … | … | … | … | … | … | … |
| Movie202 | 6.0 | 4.333333 | 1.632993 | 1.0 | 5.00 | 5.0 | 5.0 | 5.0 |
| Movie203 | 1.0 | 3.000000 | NaN | 3.0 | 3.00 | 3.0 | 3.0 | 3.0 |
| Movie204 | 8.0 | 4.375000 | 1.407886 | 1.0 | 4.75 | 5.0 | 5.0 | 5.0 |
| Movie205 | 35.0 | 4.628571 | 0.910259 | 1.0 | 5.00 | 5.0 | 5.0 | 5.0 |
| Movie206 | 13.0 | 4.923077 | 0.277350 | 4.0 | 5.00 | 5.0 | 5.0 | 5.0 |

[206 rows x 8 columns]

[8]:
```
data.describe().T['mean'].plot(kind='hist',bins=[1,2,3,4,5,6])
plt.show()
```




### 1.0.1 Which movies have maximum views/ratings?

```
[9]: data_desc = pd.DataFrame(data.describe().T)
     data_desc['count'].sort_values(ascending=False).head(10).to_frame()
```

```
[9]:           count
     Movie127  2313.0
     Movie140   578.0
     Movie16    320.0
     Movie103   272.0
     Movie29    243.0
     Movie91    128.0
     Movie92    101.0
     Movie89     83.0
     Movie158    66.0
     Movie108    54.0
```

### 1.0.2 What is the average rating for each movie? Define the top 5 movies with the maximum ratings.

```
[10]: data_desc['mean'].sort_values(ascending=False).head(5).to_frame()
```

```
[10]:          mean
      Movie1    5.0
      Movie66   5.0
```

```
Movie76    5.0
Movie75    5.0
Movie74    5.0
```

#### 1.0.3 Define the top 5 movies with the least audience.

[11]:
```
data_desc['min'].sort_values(ascending=True).head(5).to_frame()
```

[11]:

| | min |
|---|---|
| Movie103 | 1.0 |
| Movie144 | 1.0 |
| Movie158 | 1.0 |
| Movie140 | 1.0 |
| Movie138 | 1.0 |

# 2 Recommendation Model: Some of the movies hadn't been watched and therefore, are not rated by the users. Netflix would like to take this as an opportunity and build a machine learning recommendation algorithm which provides the ratings for each of the users.

- Divide the data into training and test data
- Build a recommendation model on training data
- Make predictions on the test data

[12]:
```
data.fillna(0,inplace=True)
```

[13]:
```
data.head()
```

[13]:

| | Movie1 | Movie2 | Movie3 | Movie4 | Movie5 | Movie6 | Movie7 | Movie8 | Movie9 | \ |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 5.0 | 5.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| 1 | 0.0 | 0.0 | 2.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| 2 | 0.0 | 0.0 | 0.0 | 5.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| 3 | 0.0 | 0.0 | 0.0 | 5.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| 4 | 0.0 | 0.0 | 0.0 | 0.0 | 5.0 | 0.0 | 0.0 | 0.0 | 0.0 | |

| | Movie10 | … | Movie197 | Movie198 | Movie199 | Movie200 | Movie201 | Movie202 | \ |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.0 | … | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| 1 | 0.0 | … | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| 2 | 0.0 | … | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| 3 | 0.0 | … | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| 4 | 0.0 | … | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |

| | Movie203 | Movie204 | Movie205 | Movie206 |
|---|---|---|---|---|

```
0        0.0        0.0        0.0        0.0
1        0.0        0.0        0.0        0.0
2        0.0        0.0        0.0        0.0
3        0.0        0.0        0.0        0.0
4        0.0        0.0        0.0        0.0

[5 rows x 206 columns]
```

### 2.0.1 Divide the data into training and test data

[14]:
```
xtrain,xtest = train_test_split(data,test_size=0.2,random_state=41)
print(xtrain.shape,xtest.shape)
```

```
(3878, 206) (970, 206)
```

### 2.0.2 Build a recommendation model on training data

[15]:
```
def similar_users(user_id,matrix,k=5):

    # Create a data of just the current users
    user = matrix[matrix.index == user_id]

    # and data of all other users
    other_users = matrix[matrix.index != user_id]

    # Calculate cosine similarity between users and other users
    similarities = cosine_similarity(user,other_users)[0].tolist()

    # Create list of indices of these users
    indices = other_users.index.tolist()

    # Create key/value pairs of users index and their simolarities
    index_similarities = dict(zip(indices,similarities))

    # Sort by similarities
    index_similarities_sorted = sorted(index_similarities.items(),key=operator.
↪itemgetter(1))
    index_similarities_sorted.reverse()

    # Grab k userd of the top
    top_users_similarities = index_similarities_sorted[:k]
    users = [u[0] for u in top_users_similarities]

    return users
```

[16]:
```
ID = 1517
similar_users_indices = similar_users(ID,data,10)
similar_users_indices
```

[16]: [1520, 1519, 1518, 1516, 1515, 1514, 1513, 4847, 4846, 4845]

### 2.0.3 Make predictions on the test data

[17]:
```
def recommend_item(user_index,similar_uers_indices,matrix,items=12):

    # Load vector for similar users
    similar_users = matrix[matrix.index.isin(similar_uers_indices)]

    # Calculate average rating across the 3 similar users
    similar_users = similar_users.mean(axis=0)

    # Convert to dataframe so its easy to sort and filter
    similar_user_data = pd.DataFrame(similar_users,columns=['mean'])

    # Load vector for the current users
    user_data = matrix[matrix.index == user_index]

    # Transfer it so its easier to filter
    user_data_transpose = user_data.transpose()

    # Remae the column name at rating
    user_data_transpose.rename(columns={user_index:'rating'},inplace=True)

    # Remove any row without 0 value. Movies not saw yet
    user_data_transpose = user_data_transpose[user_data_transpose['rating'] ==␣
↪0]

    # Generate a list of books the user has not read
    movie_unseen = user_data_transpose.index.tolist()

    # Filter average rating of similar users for only books and the current␣
↪users not read
    similar_users_data_filter = similar_user_data[similar_user_data.index.
↪isin(movie_unseen)]

    # Order the dataframe
    similar_users_data_order = similar_user_data.
↪sort_values(by='mean',ascending=False)

    # Grab the to n movies
    top_n_movies = similar_users_data_order.head(items)
```

```python
    top_n_movies_indices = top_n_movies.index.tolist()

    # Lookup this Movies in the other dataframe to find names
    print('Top 12 recommended movies for users_id {} are'.format(ID))

    return top_n_movies_indices
```

[18]:
```python
recommend_item(ID,similar_users_indices,xtrain)
```

```
Top 12 recommended movies for users_id 1517 are
```

[18]:
```
['Movie119',
 'Movie206',
 'Movie130',
 'Movie132',
 'Movie133',
 'Movie134',
 'Movie135',
 'Movie136',
 'Movie137',
 'Movie138',
 'Movie139',
 'Movie140']
```

[ ]:
```python

```