Project to Submit – Project 3

Movielens Case Study

Background of Problem Statement :

The GroupLens Research Project is a research group in the Department of Computer Science and Engineering at the University of Minnesota. Members of the GroupLens Research Project are involved in many research projects related to the fields of information filtering, collaborative filtering, and recommender systems. The project is led by professors John Riedl and Joseph Konstan. The project began to explore automated collaborative filtering in 1992 but is most well known for its worldwide trial of an automated collaborative filtering system for Usenet news in 1996. Since then the project has expanded its scope to research overall information by filtering solutions, integrating into content-based methods, as well as, improving current collaborative filtering technology.

Problem Objective :

Here, we ask you to perform the analysis using the Exploratory Data Analysis technique. You need to find features affecting the ratings of any particular movie and build a model to predict the movie ratings.

Domain: Entertainment

Analysis Tasks to be performed:

- Import the three datasets
- Create a new dataset [Master_Data] with the following columns MovieID Title UserID Age Gender Occupation Rating. (Hint: (i) Merge two tables at a time. (ii) Merge the tables using two primary keys MovieID & UserId)
- Explore the datasets using visual representations (graphs or tables), also include your comments on the following:
    1. User Age Distribution
    2. User rating of the movie “Toy Story”
    3. Top 25 movies by viewership rating
    4. Find the ratings for all the movies reviewed by for a particular user of user id = 2696
- Feature Engineering:

Use column genres:

1. Find out all the unique genres (Hint: split the data in column genre making a list and then process the data to find out only the unique categories of genres)
2. Create a separate column for each genre category with a one-hot encoding (1 and 0) whether or not the movie belongs to that genre.
3. Determine the features affecting the ratings of any particular movie.
4. Develop an appropriate model to predict the movie ratings

Dataset Description :

These files contain 1,000,209 anonymous ratings of approximately 3,900 movies made by 6,040 MovieLens users who joined MovieLens in 2000.

Ratings.dat

Format - UserID::MovieID::Rating::Timestamp

Field	Description
UserID	Unique identification for each user
MovieID	Unique identification for each movie
Rating	User rating for each movie

Timestamp	Timestamp generated while adding user review

- UserIDs range between 1 and 6040
- The MovieIDs range between 1 and 3952
- Ratings are made on a 5-star scale (whole-star ratings only)
- A timestamp is represented in seconds since the epoch is returned by time(2)
- Each user has at least 20 ratings

Users.dat
Format - UserID::Gender::Age::Occupation::Zip-code

Field	Description
UserID	Unique identification for each user
Genere	Category of each movie
Age	User's age
Occupation	User's Occupation
Zip-code	Zip Code for the user's location

All demographic information is provided voluntarily by the users and is not checked for accuracy. Only users who have provided demographic information are included in this data set.

- Gender is denoted by an "M" for male and "F" for female
- Age is chosen from the following ranges:

Value	**Description**
1	"Under 18"
18	"18-24"
25	"25-34"
35	"35-44"

45	"45-49"
50	"50-55"
56	"56+"

- Occupation is chosen from the following choices:

Value	Description
0	"other" or not specified
1	"academic/educator"
2	"artist”
3	"clerical/admin"
4	"college/grad student"
5	"customer service"
6	"doctor/health care"
7	"executive/managerial"
8	"farmer"
9	"homemaker"
10	"K-12 student"
11	"lawyer"

12	"programmer"
13	"retired"
14	"sales/marketing"
15	"scientist"
16	"self-employed"
17	"technician/engineer"
18	"tradesman/craftsman"
19	"unemployed"
20	"writer"

Movies.dat
Format - MovieID::Title::Genres

Field	Description
MovieID	Unique identification for each movie
Title	A title for each movie
Genres	Category of each movie

Titles are identical to titles provided by the IMDB (including year of release)

- Genres are pipe-separated and are selected from the following genres:
    1. Action
    2. Adventure
    3. Animation
    4. Children's
    5. Comedy
    6. Crime
    7. Documentary

8. Drama
9. Fantasy
10. Film-Noir
11. Horror
12. Musical
13. Mystery
14. Romance
15. Sci-Fi
16. Thriller
17. War
18. Western

- Some MovieIDs do not correspond to a movie due to accidental duplicate entries and/or test entries
- Movies are mostly entered by hand, so errors and inconsistencies may exist

Problem Objective :

Here, we ask you to perform the analysis using the Exploratory Data Analysis technique. You need to find features affecting the ratings of any particular movie and build a model to predict the movie ratings.

Domain: Entertainment

Analysis Tasks to be performed:

- Import the three datasets
- Create a new dataset [Master_Data] with the following columns MovieID Title UserID Age Gender Occupation Rating.
- Explore the datasets using visual representations (graphs or tables), also include your comments on the following:
    1. User Age Distribution
    2. User rating of the movie “Toy Story”
    3. Top 25 movies by viewership rating
    4. Find the ratings for all the movies reviewed by for a particular user of user id = 2696
- Feature Engineering:

  Use column genres:

    1. Find out all the unique genres (Hint: split the data in column genre making a list and then process the data to find out only the unique categories of genres)
    2. Create a separate column for each genre category with a one-hot encoding (1 and 0) whether or not the movie belongs to that genre.
    3. Determine the features affecting the ratings of any particular movie.
    4. Develop an appropriate model to predict the movie ratings

Write Up:

Analysis Tasks to be performed:

- Import the three datasets (Done) –
  - Movies.pd, Users.pd, Ratings.pd
- Create a new dataset [Master_Data] with the following columns MovieID Title UserID Age Gender Occupation Rating
  - First merging on **Common field MovieID** on Movies & Ratings database
  - Fields that we do not need are: Genre (column - 3) & Timestamp (column - 6)
  - Now merging User database with Master database
  - Dropping the field – Zip Code
  - Rearrange columns

From	To
'MovieID', 'Title', 'UserID', **'Rating'**, 'Gender', 'Age', 'Occupation', 'zip-code'	▪ MovieID – No Change ▪ Title - No Change ▪ UserID - No Change ▪ Age ▪ Gender ▪ Occupation - ▪ Rating – From No 4 to End

  -
- Explore the datasets using visual representations (graphs or tables), also include your comments on the following:
  - These graphs are made on the Master database that is just created
  5. User Age Distribution – Barchart
  6. User rating of the movie “Toy Story” – Barchart & line graph
  7. Top 25 movies by viewership rating – Table Representation
  8. Find the ratings for all the movies reviewed by for a particular user of user id = 2696 - Table Representation

- Feature Engineering:
  Use column genres:

  5. Find out all the unique genres
     - Here – using the original database Movies database
     - #Movie Genre does not house unique in terms of genre. It is showing the combines unique genre, like Drama|Romance, Horror|Suspense|Thriller etc.
     - Joining the dataset rating_df & movie_df – left join
  6. Create a separate column for each genre category with a one-hot encoding (1 and 0) whether or not the movie belongs to that genre.
     - Creating dummies for each possible genre, such as Sci-Fi or Drama, and having a single column for each. Creating dummies means creating 0s and 1s
  7. Determine the features affecting the ratings of any particular movie.
     - Using Correlation function the factor affecting was calculated
  8. Develop an appropriate model to predict the movie ratings
     - Linear model was not found to be good for this dataset.
       1. The accuracy was 5%
     - Logistic Regression was tested
       1. For Logistics Regression the accuracy is 35%

Code:

Project 2 Simpililearn Moviens - You need to find features affecting the ratings of any particular movie and build a model to predict the movie ratings.

Import Right Libraries

In [2]:

```
import numpy as np
import pandas as pd
from pandas import Series, DataFrame
import matplotlib.pyplot as plt
from matplotlib import style
import seaborn as sns
%matplotlib inline
```

• Import the three datasets

Movie Data base in movies_df

In [3]:

```
movies_df = pd.read_csv('D:\Alok-OneDrive\OneDrive\Knowledge Center\AI - ML\Python\Examples\Projects\\movies.dat', encoding='ISO-8859-1', sep='::', engine='python',
    names=['MovieID','Title','Genres'], header=None)
movies_df.head()
```

Out[3]:

	MovieID	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

Users Data base in users_df

In [4]:

```
users_df = pd.read_csv('D:\Alok-OneDrive\OneDrive\Knowledge Center\AI - ML\Python\Examples\Projects\\users.dat', encoding='ISO-8859-1', sep='::',engine='python',
    names=['UserID','Gender','Age', 'Occupation', 'zip-code'], header=None)
users_df.head()
```

Out[4]:

	UserID	Gender	Age	Occupation	zip-code
0	1	F	1	10	48067
1	2	M	56	16	70072
2	3	M	25	15	55117
3	4	M	45	7	02460
4	5	M	25	20	55455

Ratings Data base in ratings_df

In [5]:

```
ratings_df = pd.read_csv('D:\Alok-OneDrive\OneDrive\Knowledge Center\AI - ML\Python\Examples\Projects\\ratings.dat', encoding='ISO-8859-1', sep='::', engine='python',
    names=['UserID','MovieID','Rating', 'Timestamp'], header=None)
ratings_df.head()
```

Out[5]:

	UserID	MovieID	Rating	Timestamp
0	1	1193	5	978300760
1	1	661	3	978302109
2	1	914	3	978301968
3	1	3408	4	978300275
4	1	2355	5	978824291

• Create a new dataset [Master_Data] with the following columns MovieID Title UserID Age Gender Occupation Rating. (Hint: (i) Merge two tables at a time. (ii) Merge the tables using two primary keys MovieID & UserId)

First merging on Common field MovieID on Movies & Ratings database

In [6]:

```
Master_df = pd.merge(movies_df, ratings_df,
    on='MovieID')
Master_df.info()
```

```
Master_df.head()
Master_df = Master_df[['MovieID', 'Title', 'UserID', 'Rating']]
Master_df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns (total 6 columns):
 #   Column     Non-Null Count    Dtype
---  ------     --------------    -----
 0   MovieID    1000209 non-null  int64
 1   Title      1000209 non-null  object
 2   Genres     1000209 non-null  object
 3   UserID     1000209 non-null  int64
 4   Rating     1000209 non-null  int64
 5   Timestamp  1000209 non-null  int64
dtypes: int64(4), object(2)
memory usage: 53.4+ MB
```

Out[6]:

	MovieID	Title	UserID	Rating
0	1	Toy Story (1995)	1	5
1	1	Toy Story (1995)	6	4
2	1	Toy Story (1995)	8	4
3	1	Toy Story (1995)	9	5
4	1	Toy Story (1995)	10	5

Now merging on Common field MovieID on Master database on UserID

In [7]:

```
Master_df = pd.merge(Master_df, users_df,
    on='UserID')
Master_df.info()
Master_df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns (total 8 columns):
 #   Column      Non-Null Count    Dtype
---  ------      --------------    -----
 0   MovieID     1000209 non-null  int64
 1   Title       1000209 non-null  object
 2   UserID      1000209 non-null  int64
 3   Rating      1000209 non-null  int64
 4   Gender      1000209 non-null  object
 5   Age         1000209 non-null  int64
```

```
 6   Occupation  1000209 non-null  int64
 7   zip-code    1000209 non-null  object
dtypes: int64(5), object(3)
memory usage: 68.7+ MB
```

Out[7]:

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	zip-code
0	1	Toy Story (1995)	1	5	F	1	10	48067
1	48	Pocahontas (1995)	1	5	F	1	10	48067
2	150	Apollo 13 (1995)	1	5	F	1	10	48067
3	260	Star Wars: Episode IV - A New Hope (1977)	1	4	F	1	10	48067
4	527	Schindler's List (1993)	1	5	F	1	10	48067

Rearranged the Master database as per the requirement

In [8]:

```
# Get the DataFrame column names as a list
clist = list(Master_df.columns)
Master_df.reindex(columns=['MovieID',
 'Title',
 'UserID',
 'Age', 'Gender',
 'Occupation',
 'Rating' ])
Master_df.head()
```

Out[8]:

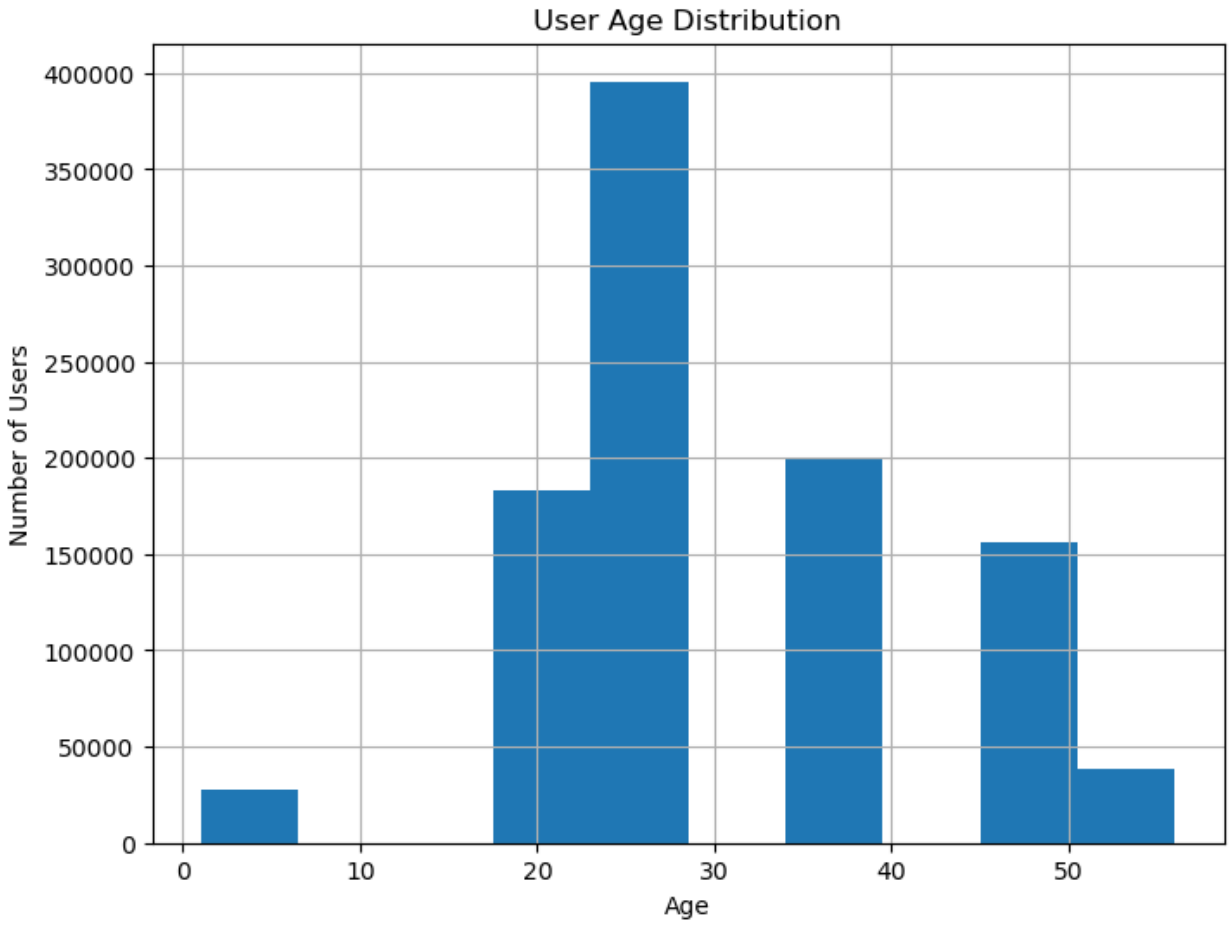
	MovieID	Title	UserID	Rating	Gender	Age	Occupation	zip-code
0	1	Toy Story (1995)	1	5	F	1	10	48067
1	48	Pocahontas (1995)	1	5	F	1	10	48067
2	150	Apollo 13 (1995)	1	5	F	1	10	48067
3	260	Star Wars: Episode IV - A New Hope (1977)	1	4	F	1	10	48067

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	zip-code
4	527	Schindler's List (1993)	1	5	F	1	10	48067

• Explore the datasets using visual representations (graphs or tables), also include your comments on the following: User Age Distribution These graphs are made on Master database that is currently created

In [9]:

```
plt.figure(figsize=(8,6))
Master_df.Age.hist()
plt.title('User Age Distribution')
plt.xlabel('Age')
plt.ylabel('Number of Users')
plt.show()
```



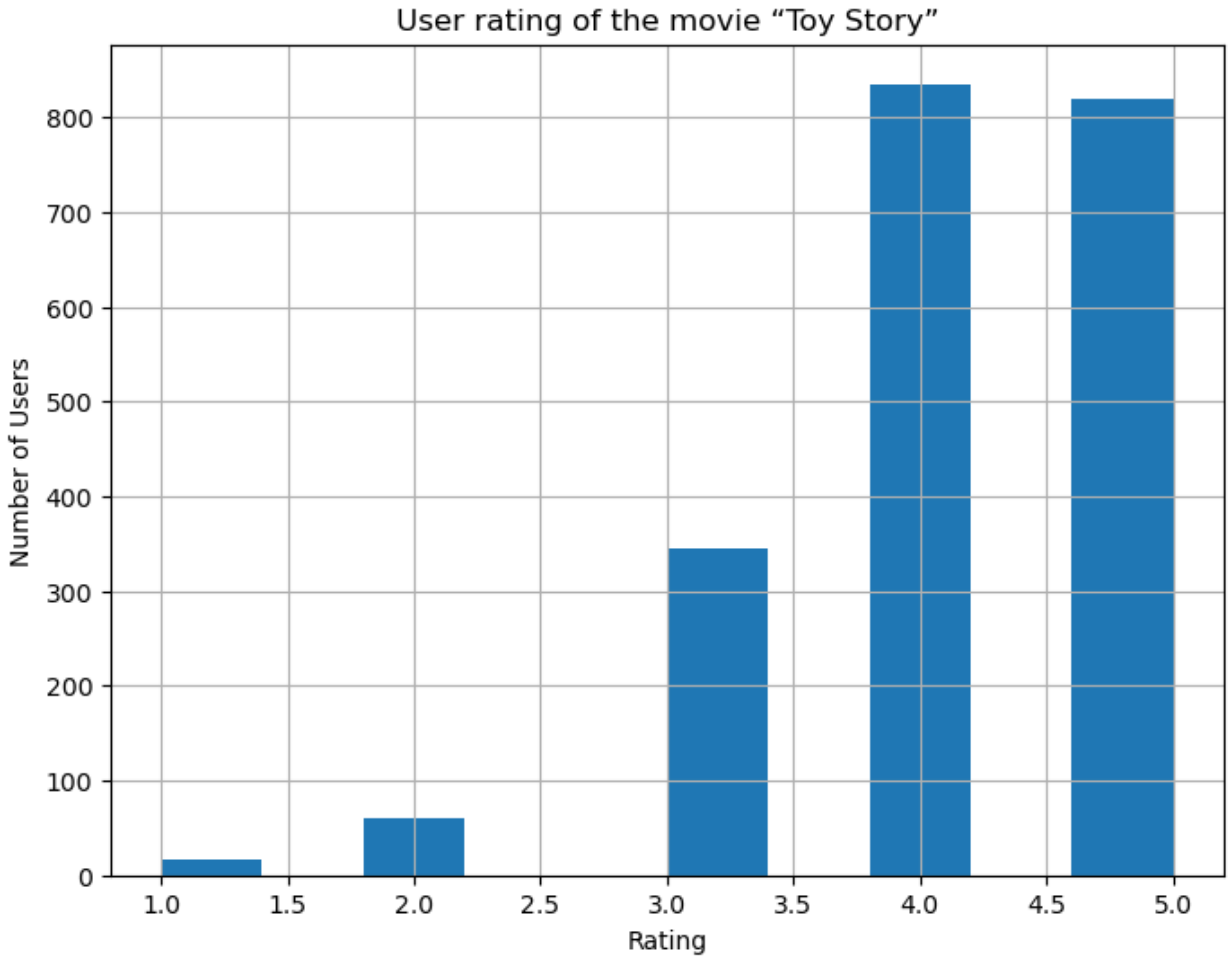
• Explore the datasets using visual representations (graphs or tables), also include your comments on the following: o These graphs are made on the Master database that is just created

1. User rating of the movie “Toy Story”

In [10]:

```
plt.figure(figsize=(8,6))
```

```
movies_grouped = Master_df.groupby('Title')
toy_story = movies_grouped.get_group('Toy Story (1995)')
toy_story['Rating'].hist()
plt.title('User rating of the movie "Toy Story"')
plt.xlabel('Rating')
plt.ylabel('Number of Users')
plt.show()
```



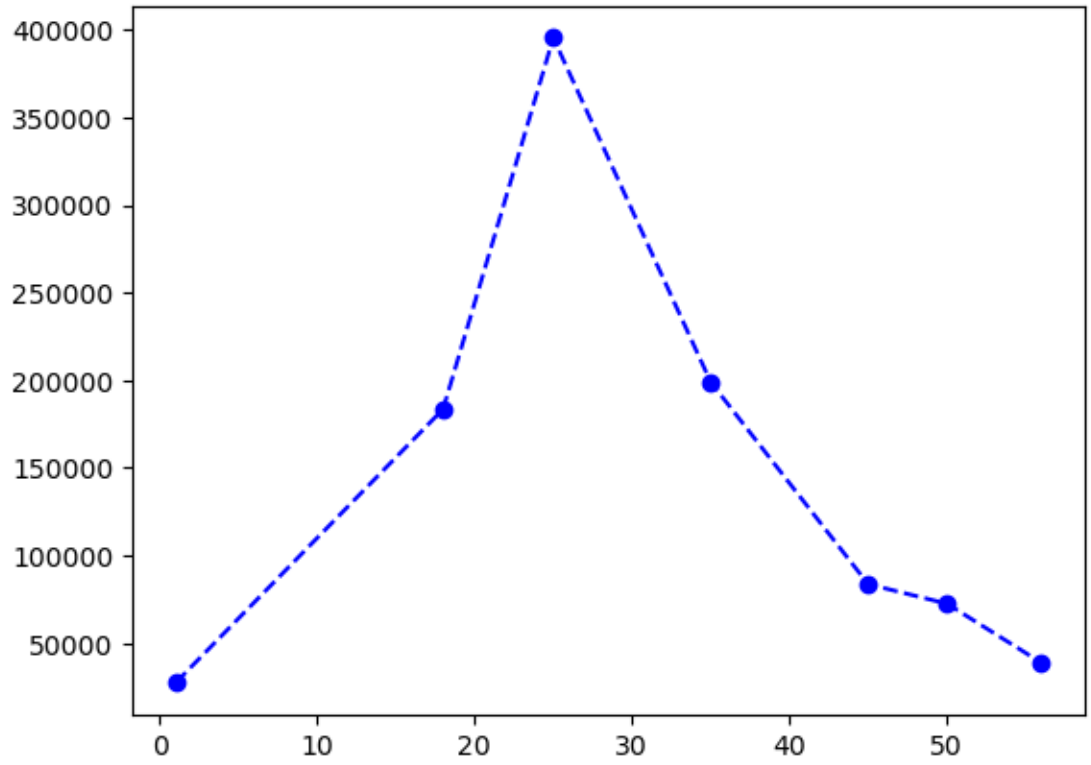
In [11]:

```
#User rating of the movie "Toy Story"
Master_df[Master_df.Title == "Toy Story (1995)"]

plt.plot(Master_df.groupby("Age")["MovieID"].count(),'--bo')
Master_df.groupby("Age")["MovieID"].count()
```

Out[11]:

```
Age
1      27211
18    183536
25    395556
35    199003
45     83633
50     72490
```

```
56     38780
Name: MovieID, dtype: int64
```



In [12]:

```
Master_df.groupby("Age")["MovieID"].count().describe()
```

Out[12]:

```
count         7.000000
mean     142887.000000
std      129954.446357
min       27211.000000
25%       55635.000000
50%       83633.000000
75%      191269.500000
max      395556.000000
Name: MovieID, dtype: float64
```

• Explore the datasets using visual representations (graphs or tables), also include your comments on the following: o These graphs are made on the Master database that is just created

1. Top 25 movies by viewership rating

In [13]:

```
rating_avg = Master_df.groupby('Title')['Rating'].mean()
rating_avg.head()
rating_avg = rating_avg.sort_values(ascending=False)
rating_avg[0:25]
```

Out[13]:

```
Title
```

```
Ulysses (Ulisse) (1954)                                                  5.0000
00
Lured (1947)                                                             5.0000
00
Follow the Bitch (1998)                                                  5.0000
00
Bittersweet Motel (2000)                                                 5.0000
00
Song of Freedom (1936)                                                   5.0000
00
One Little Indian (1973)                                                 5.0000
00
Smashing Time (1967)                                                     5.0000
00
Schlafes Bruder (Brother of Sleep) (1995)                                5.0000
00
Gate of Heavenly Peace, The (1995)                                       5.0000
00
Baby, The (1973)                                                         5.0000
00
I Am Cuba (Soy Cuba/Ya Kuba) (1964)                                      4.8000
00
Lamerica (1994)                                                          4.7500
00
Apple, The (Sib) (1998)                                                  4.6666
67
Sanjuro (1962)                                                           4.6086
96
Seven Samurai (The Magnificent Seven) (Shichinin no samurai) (1954)      4.5605
10
Shawshank Redemption, The (1994)                                         4.5545
58
Godfather, The (1972)                                                    4.5249
66
Close Shave, A (1995)                                                    4.5205
48
Usual Suspects, The (1995)                                               4.5171
06
Schindler's List (1993)                                                  4.5104
17
Wrong Trousers, The (1993)                                               4.5079
37
Dry Cleaning (Nettoyage à sec) (1997)                                    4.5000
00
Inheritors, The (Die Siebtelbauern) (1998)                               4.5000
00
Mamma Roma (1962)                                                        4.5000
00
Bells, The (1926)                                                        4.5000
00
Name: Rating, dtype: float64
```

In [14]:

```
rating_avg_count = pd.DataFrame(data=rating_avg)
rating_avg_count['number_of_ratings'] = pd.DataFrame(rating_avg_count)
rating_avg_count.head()
```

Out[14]:

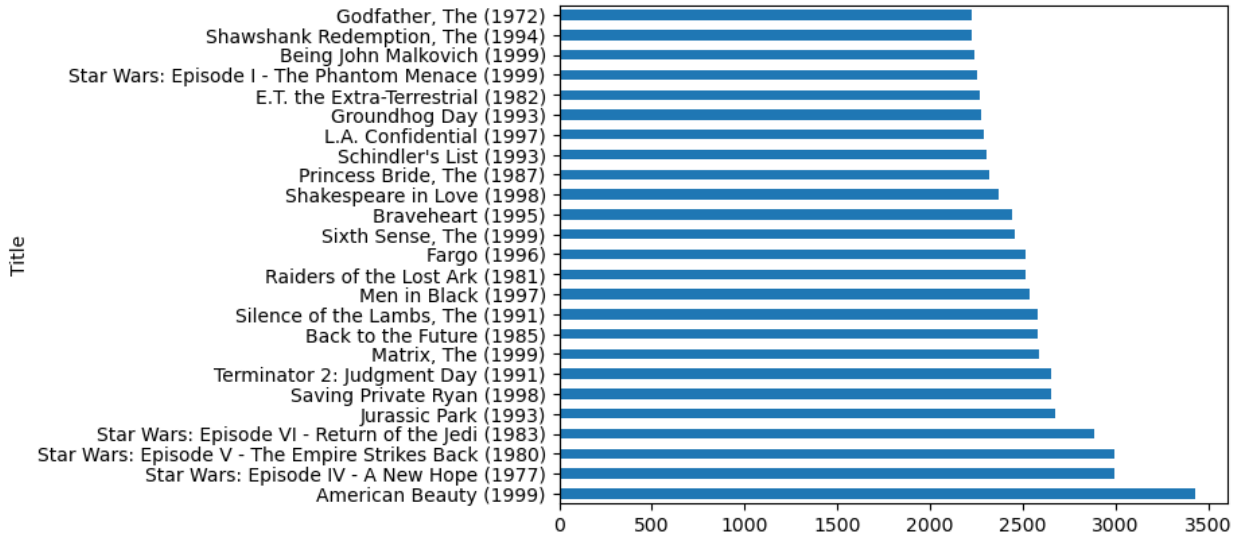
Title	Rating	number_of_ratings
Ulysses (Ulisse) (1954)	5.0	5.0
Lured (1947)	5.0	5.0
Follow the Bitch (1998)	5.0	5.0
Bittersweet Motel (2000)	5.0	5.0
Song of Freedom (1936)	5.0	5.0

In [15]:

```
#Top 25 movies by viewership rating

res = Master_df.groupby("Title").size().sort_values(ascending=False)[:25]
plt.ylabel("Title")
plt.xlabel("Viewership Count")
res.plot(kind="barh")
```

Out[15]:

```
<Axes: ylabel='Title'>
```



• Explore the datasets using visual representations (graphs or tables), also include your comments on the following: o These graphs are made on the Master database that is just created

1. Find the ratings for all the movies reviewed by for a particular user of user id = 2696

In [16]:

```
user_2696 = Master_df[Master_df['UserID'] == 2696]
user_2696
```

Out[16]:

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	zip-code
991035	350	Client, The (1994)	2696	3	M	25	7	24210
991036	800	Lone Star (1996)	2696	5	M	25	7	24210
991037	1092	Basic Instinct (1992)	2696	4	M	25	7	24210
991038	1097	E.T. the Extra-Terrestrial (1982)	2696	3	M	25	7	24210
991039	1258	Shining, The (1980)	2696	4	M	25	7	24210
991040	1270	Back to the Future (1985)	2696	2	M	25	7	24210
991041	1589	Cop Land (1997)	2696	3	M	25	7	24210
991042	1617	L.A. Confidential (1997)	2696	4	M	25	7	24210
991043	1625	Game, The (1997)	2696	4	M	25	7	24210
991044	1644	I Know What You Did Last Summer (1997)	2696	2	M	25	7	24210
991045	1645	Devil's Advocate, The (1997)	2696	4	M	25	7	24210
991046	1711	Midnight in the Garden of Good and Evil (1997)	2696	4	M	25	7	24210
991047	1783	Palmetto (1998)	2696	4	M	25	7	24210
991048	1805	Wild Things (1998)	2696	4	M	25	7	24210

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	zip-code
991049	1892	Perfect Murder, A (1998)	2696	4	M	25	7	24210
991050	2338	I Still Know What You Did Last Summer (1998)	2696	2	M	25	7	24210
991051	2389	Psycho (1998)	2696	4	M	25	7	24210
991052	2713	Lake Placid (1999)	2696	1	M	25	7	24210
991053	3176	Talented Mr. Ripley, The (1999)	2696	4	M	25	7	24210
991054	3386	JFK (1991)	2696	1	M	25	7	24210

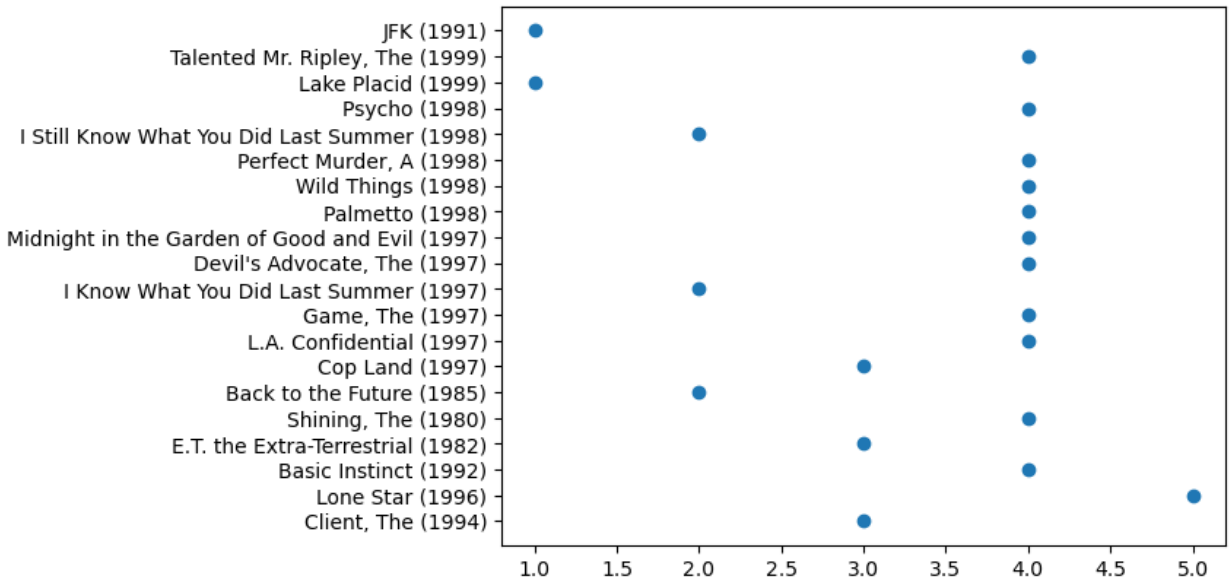
In [17]:

```
res = Master_df[Master_df.UserID == 2696]
plt.scatter(y=res.Title, x=res.Rating)
res
```

Out[17]:

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	zip-code
991035	350	Client, The (1994)	2696	3	M	25	7	24210
991036	800	Lone Star (1996)	2696	5	M	25	7	24210
991037	1092	Basic Instinct (1992)	2696	4	M	25	7	24210
991038	1097	E.T. the Extra-Terrestrial (1982)	2696	3	M	25	7	24210
991039	1258	Shining, The (1980)	2696	4	M	25	7	24210
991040	1270	Back to the Future (1985)	2696	2	M	25	7	24210
991041	1589	Cop Land (1997)	2696	3	M	25	7	24210

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	zip-code
991042	1617	L.A. Confidential (1997)	2696	4	M	25	7	24210
991043	1625	Game, The (1997)	2696	4	M	25	7	24210
991044	1644	I Know What You Did Last Summer (1997)	2696	2	M	25	7	24210
991045	1645	Devil's Advocate, The (1997)	2696	4	M	25	7	24210
991046	1711	Midnight in the Garden of Good and Evil (1997)	2696	4	M	25	7	24210
991047	1783	Palmetto (1998)	2696	4	M	25	7	24210
991048	1805	Wild Things (1998)	2696	4	M	25	7	24210
991049	1892	Perfect Murder, A (1998)	2696	4	M	25	7	24210
991050	2338	I Still Know What You Did Last Summer (1998)	2696	2	M	25	7	24210
991051	2389	Psycho (1998)	2696	4	M	25	7	24210
991052	2713	Lake Placid (1999)	2696	1	M	25	7	24210
991053	3176	Talented Mr. Ripley, The (1999)	2696	4	M	25	7	24210
991054	3386	JFK (1991)	2696	1	M	25	7	24210



• Feature Engineering: Use column genres: Find out all the unique genres

In [18]:

```
movies_df.head()
```

Out[18]:

	MovieID	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 [19]:

```
movies_df['Genres'].value_counts().head()
```

Out[19]:

```
Drama              843
Comedy             521
Horror             178
Comedy|Drama       162
Comedy|Romance     142
Name: Genres, dtype: int64
```

In [20]:

```
movies_df['Genres'].unique()
```

Out[20]:

```
array(["Animation|Children's|Comedy", "Adventure|Children's|Fantasy",
       'Comedy|Romance', 'Comedy|Drama', 'Comedy',
       'Action|Crime|Thriller', "Adventure|Children's", 'Action',
       'Action|Adventure|Thriller', 'Comedy|Drama|Romance',
       'Comedy|Horror', "Animation|Children's", 'Drama',
       'Action|Adventure|Romance', 'Drama|Thriller', 'Drama|Romance',
       'Thriller', 'Action|Comedy|Drama', 'Crime|Drama|Thriller',
       'Drama|Sci-Fi', 'Romance', 'Adventure|Sci-Fi', 'Adventure|Romance',
       "Children's|Comedy|Drama", 'Documentary', 'Drama|War',
       'Action|Crime|Drama', 'Action|Adventure', 'Crime|Thriller',
       "Animation|Children's|Musical|Romance", 'Action|Drama|Thriller',
       "Children's|Comedy", 'Drama|Mystery', 'Sci-Fi|Thriller',
       'Action|Comedy|Crime|Horror|Thriller', 'Drama|Musical',
       'Crime|Drama|Romance', 'Adventure|Drama', 'Action|Thriller',
       "Adventure|Children's|Comedy|Musical", 'Action|Drama|War',
       'Action|Adventure|Crime', 'Crime', 'Drama|Mystery|Romance',
       'Action|Drama', 'Drama|Romance|War', 'Horror',
       'Action|Adventure|Comedy|Crime', 'Comedy|War',
       'Action|Adventure|Mystery|Sci-Fi', 'Drama|Thriller|War',
       'Action|Romance|Thriller', 'Crime|Film-Noir|Mystery|Thriller',
       'Action|Adventure|Drama|Romance', "Adventure|Children's|Drama",
       'Action|Sci-Fi|Thriller', 'Action|Adventure|Sci-Fi',
       "Action|Children's", 'Horror|Sci-Fi', 'Action|Crime|Sci-Fi',
       'Western', "Animation|Children's|Comedy|Romance",
       "Children's|Drama", 'Crime|Drama',
       'Drama|Fantasy|Romance|Thriller', 'Drama|Horror', 'Comedy|Sci-Fi',
       'Mystery|Thriller', "Adventure|Children's|Comedy|Fantasy|Romance",
       'Action|Adventure|Fantasy|Sci-Fi', 'Drama|Romance|War|Western',
       'Action|Crime', 'Crime|Drama|Romance|Thriller',
       'Action|Adventure|Western', 'Horror|Thriller',
       "Children's|Comedy|Fantasy", 'Film-Noir|Thriller',
       'Action|Comedy|Musical|Sci-Fi', "Children's",
       'Drama|Mystery|Thriller', 'Comedy|Romance|War', 'Action|Comedy',
       "Adventure|Children's|Romance", "Animation|Children's|Musical",
       'Comedy|Crime|Fantasy', 'Action|Comedy|Western', 'Action|Sci-Fi',
       'Action|Adventure|Comedy|Romance', 'Comedy|Crime|Drama',
       'Comedy|Thriller', 'Horror|Sci-Fi|Thriller',
       'Mystery|Romance|Thriller', 'Comedy|Western', 'Drama|Western',
       'Action|Adventure|Crime|Thriller', 'Action|Comedy|War',
       'Comedy|Mystery', 'Comedy|Mystery|Romance', 'Comedy|Drama|War',
       'Action|Drama|Mystery', 'Comedy|Crime|Horror', 'Film-Noir|Sci-Fi',
       'Comedy|Romance|Thriller', "Action|Adventure|Children's|Sci-Fi",
       "Children's|Comedy|Musical", 'Action|Adventure|Comedy',
       'Action|Crime|Romance',
       "Action|Adventure|Animation|Children's|Fantasy",
       "Animation|Children's|Comedy|Musical", 'Adventure|Drama|Western',
       'Action|Adventure|Crime|Drama',
       'Action|Adventure|Animation|Horror|Sci-Fi', 'Action|Horror|Sci-Fi',
       'War', 'Action|Adventure|Mystery', 'Mystery',
       'Action|Adventure|Fantasy',
       "Adventure|Animation|Children's|Comedy|Fantasy", 'Sci-Fi',
```

```
'Documentary|Drama', 'Action|Adventure|Comedy|War',
'Crime|Film-Noir|Thriller', 'Animation',
'Action|Adventure|Romance|Thriller', 'Animation|Sci-Fi',
'Animation|Comedy|Thriller', 'Film-Noir', 'Sci-Fi|War',
'Adventure', 'Comedy|Crime', 'Action|Sci-Fi|War',
'Comedy|Fantasy|Romance|Sci-Fi', 'Fantasy',
'Action|Mystery|Thriller', 'Comedy|Musical',
'Action|Adventure|Sci-Fi|Thriller', "Children's|Drama|Fantasy",
'Adventure|War', 'Musical|Romance', 'Comedy|Musical|Romance',
'Comedy|Mystery|Romance|Thriller', 'Film-Noir|Mystery', 'Musical',
"Adventure|Children's|Drama|Musical",
'Drama|Mystery|Sci-Fi|Thriller', 'Romance|Thriller',
'Film-Noir|Romance|Thriller', 'Crime|Film-Noir|Mystery',
'Adventure|Comedy', 'Action|Adventure|Romance|War', 'Romance|War',
'Action|Drama|Western', "Children's|Comedy|Western",
"Adventure|Children's|Comedy", "Children's|Comedy|Mystery",
"Adventure|Children's|Fantasy|Sci-Fi",
"Adventure|Animation|Children's|Musical",
"Adventure|Children's|Musical", 'Crime|Film-Noir',
"Adventure|Children's|Comedy|Fantasy",
"Children's|Drama|Fantasy|Sci-Fi", 'Action|Romance',
'Adventure|Western', 'Comedy|Fantasy', 'Animation|Comedy',
'Crime|Drama|Film-Noir', 'Action|Adventure|Drama|Sci-Fi|War',
'Action|Sci-Fi|Thriller|War', 'Action|Western',
"Action|Animation|Children's|Sci-Fi|Thriller|War",
'Action|Adventure|Romance|Sci-Fi|War',
'Action|Horror|Sci-Fi|Thriller',
'Action|Adventure|Comedy|Horror|Sci-Fi', 'Action|Comedy|Musical',
'Mystery|Sci-Fi', 'Film-Noir|Mystery|Thriller',
'Adventure|Comedy|Drama', 'Action|Adventure|Comedy|Horror',
'Action|Drama|Mystery|Romance|Thriller', 'Comedy|Mystery|Thriller',
'Adventure|Animation|Sci-Fi|Thriller', 'Action|Drama|Romance',
'Action|Adventure|Drama', 'Comedy|Drama|Musical',
'Documentary|War', 'Drama|Musical|War', 'Action|Horror',
'Horror|Romance', 'Action|Comedy|Sci-Fi|War', 'Crime|Drama|Sci-Fi',
'Action|Romance|War', 'Action|Comedy|Crime|Drama',
'Action|Drama|Thriller|War', "Action|Adventure|Children's",
"Action|Adventure|Children's|Fantasy",
"Adventure|Animation|Children's|Comedy|Musical",
'Crime|Drama|Mystery', 'Action|Adventure|Comedy|Sci-Fi',
"Children's|Fantasy", 'Action|Mystery|Sci-Fi|Thriller',
'Action|Mystery|Romance|Thriller', 'Adventure|Thriller',
'Action|Thriller|War', 'Action|Crime|Mystery',
'Horror|Mystery|Thriller', 'Crime|Horror|Mystery|Thriller',
'Comedy|Drama|Thriller', 'Drama|Sci-Fi|Thriller',
'Drama|Romance|Thriller', 'Action|Adventure|Sci-Fi|War',
'Comedy|Crime|Drama|Mystery', 'Comedy|Crime|Mystery|Thriller',
'Film-Noir|Sci-Fi|Thriller', 'Adventure|Sci-Fi|Thriller',
'Crime|Drama|Mystery|Thriller', 'Comedy|Documentary',
'Documentary|Musical', 'Action|Drama|Sci-Fi|Thriller',
"Adventure|Animation|Children's|Fantasy",
'Adventure|Comedy|Romance', 'Mystery|Sci-Fi|Thriller',
'Action|Comedy|Crime', "Animation|Children's|Fantasy|War",
```

```
       'Action|Crime|Drama|Thriller', 'Comedy|Sci-Fi|Western',
       "Children's|Fantasy|Musical", 'Fantasy|Sci-Fi',
       "Children's|Comedy|Sci-Fi", "Action|Adventure|Children's|Comedy",
       "Adventure|Children's|Drama|Romance",
       "Adventure|Children's|Sci-Fi",
       "Adventure|Children's|Comedy|Fantasy|Sci-Fi",
       "Animation|Children's|Comedy|Musical|Romance",
       "Children's|Musical", 'Drama|Fantasy',
       "Animation|Children's|Fantasy|Musical", 'Adventure|Comedy|Musical',
       "Children's|Sci-Fi", "Children's|Horror", 'Comedy|Fantasy|Romance',
       'Comedy|Crime|Thriller', "Adventure|Animation|Children's|Sci-Fi",
       'Action|Crime|Mystery|Thriller', 'Adventure|Musical',
       "Animation|Children's|Drama|Fantasy", "Children's|Fantasy|Sci-Fi",
       'Adventure|Fantasy|Romance', 'Crime|Horror',
       'Action|Adventure|Horror', 'Adventure|Fantasy|Sci-Fi',
       'Drama|Film-Noir|Thriller', 'Action|Comedy|Fantasy',
       'Sci-Fi|Thriller|War', 'Action|Adventure|Sci-Fi|Thriller|War',
       'Action|Adventure|Drama|Thriller', 'Crime|Horror|Thriller',
       'Animation|Musical', 'Action|War',
       'Action|Comedy|Romance|Thriller', 'Comedy|Horror|Thriller',
       'Drama|Horror|Thriller', 'Action|Sci-Fi|Thriller|Western',
       'Drama|Romance|Sci-Fi', 'Action|Adventure|Horror|Thriller',
       'Comedy|Film-Noir|Thriller', 'Comedy|Horror|Musical|Sci-Fi',
       'Comedy|Romance|Sci-Fi', 'Action|Comedy|Sci-Fi|Thriller',
       'Action|Sci-Fi|Western', 'Comedy|Horror|Musical', 'Crime|Mystery',
       'Animation|Mystery', 'Action|Horror|Thriller',
       'Action|Drama|Fantasy|Romance', 'Horror|Mystery',
       "Adventure|Animation|Children's", 'Musical|Romance|War',
       'Adventure|Drama|Romance', 'Adventure|Animation|Film-Noir',
       'Action|Adventure|Animation', 'Comedy|Drama|Western',
       'Adventure|Comedy|Sci-Fi', 'Drama|Romance|Western',
       'Comedy|Drama|Sci-Fi', 'Action|Drama|Romance|Thriller',
       'Adventure|Romance|Sci-Fi', 'Film-Noir|Horror',
       'Crime|Drama|Film-Noir|Thriller', 'Action|Adventure|War',
       'Romance|Western', "Action|Children's|Fantasy",
       'Adventure|Drama|Thriller', 'Adventure|Fantasy', 'Musical|War',
       'Adventure|Musical|Romance', 'Action|Romance|Sci-Fi',
       'Drama|Film-Noir', 'Comedy|Horror|Sci-Fi',
       'Adventure|Drama|Romance|Sci-Fi', 'Adventure|Animation|Sci-Fi',
       'Adventure|Crime|Sci-Fi|Thriller'], dtype=object)
```

In [21]:

```
#However these are not not unique in terms of genre. It is showing the
combines unique genre
```

In [22]:

```
Master_df.head()
```

Out[22]:

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	zip-code
0	1	Toy Story (1995)	1	5	F	1	10	48067
1	48	Pocahontas (1995)	1	5	F	1	10	48067
2	150	Apollo 13 (1995)	1	5	F	1	10	48067
3	260	Star Wars: Episode IV - A New Hope (1977)	1	4	F	1	10	48067
4	527	Schindler's List (1993)	1	5	F	1	10	48067

In [23]:

```
#Joining the dataset
result = pd.merge(Master_df, movies_df,  how="left",  on='MovieID')
result.head()
result.columns
result = result[['MovieID', 'Title_x', 'UserID', 'Rating', 'Gender', 'Age',
'Occupation','Genres']]
result.head()
result.rename(columns = {'Title_x':'Title'}, inplace = True)
result.head()
```

Out[23]:

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	Genres
0	1	Toy Story (1995)	1	5	F	1	10	Animation|Children's|Comedy
1	48	Pocahontas (1995)	1	5	F	1	10	Animation|Children's|Musical|Romance
2	150	Apollo 13 (1995)	1	5	F	1	10	Drama
3	260	Star Wars: Episode IV - A New Hope (1977)	1	4	F	1	10	Action|Adventure|Fantasy|Sci-Fi

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	Genres
4	527	Schindler's List (1993)	1	5	F	1	10	Drama|War

Create a separate column for each genre category with a one-hot encoding (1 and 0) whether or not the movie belongs to that genre.

Creating dummies for each possible genre, such as Sci-Fi or Drama, and having a single column for each. Creating dummies means creating 0s and 1s

In [24]:

```
dummies = result['Genres'].str.get_dummies()
dummies.head()
```

Out[24]:

	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	1	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0
2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0
4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0

In [25]:

```
tidy_movie_ratings = (pd.concat([result, dummies], axis=1)
                        .drop([ "Genres"], axis=1)
                    )

tidy_movie_ratings.head()
```

Out[25]:

	MovieID	Title	UserID	Rating	Gender	Age	Occupation	Action	Adventure	Animation	...	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
0	1	Toy Story (1995)	1	5	F	1	10	0	0	1	...	0	0	0	0	0	0	0	0	0	0
1	48	Pocahontas (1995)	1	5	F	1	10	0	0	1	...	0	0	0	1	0	1	0	0	0	0
2	150	Apollo 13 (1995)	1	5	F	1	10	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	260	Star Wars: Episode IV - A New Hope (1977)	1	4	F	1	10	1	1	0	...	1	0	0	0	0	0	1	0	0	0
4	527	Schindler's List (1993)	1	5	F	1	10	0	0	0	...	0	0	0	0	0	0	0	0	1	0

5 rows × 25 columns

Now need to add column Year The year is the last 6 from left in Movie Title.

In [26]:
```
tidy_movie_ratings["Year"] = tidy_movie_ratings["Title"].str[-5:-1]
tidy_movie_ratings["movie_title"] = tidy_movie_ratings["Title"].str[:-7]
```

In [27]:
```
tidy_movie_ratings.reset_index(inplace=True)
tidy_movie_ratings=tidy_movie_ratings[['MovieID', 'Title', 'UserID',
'Rating', 'Gender', 'Age',
       'Occupation', 'Action', 'Adventure', 'Animation', "Children's",
       'Comedy', 'Crime', 'Documentary', 'Drama', 'Fantasy', 'Film-Noir',
       'Horror', 'Musical', 'Mystery', 'Romance', 'Sci-Fi', 'Thriller',
'War',
       'Western', 'Year']]
```

In [28]:
```
tidy_movie_ratings.columns
```

Out[28]:
```
Index(['MovieID', 'Title', 'UserID', 'Rating', 'Gender', 'Age', 'Occupation',
       'Action', 'Adventure', 'Animation', 'Children's', 'Comedy', 'Crime',
       'Documentary', 'Drama', 'Fantasy', 'Film-Noir', 'Horror', 'Musical',
       'Mystery', 'Romance', 'Sci-Fi', 'Thriller', 'War', 'Western', 'Year'],
      dtype='object')
```

In [29]:
```
tidy_movie_ratings.head()
tidy_movie_ratings.shape
```

Out[29]:
```
(1000209, 26)
```

Determine the features affecting the ratings of any particular movie. Removing few parameters like Title, User Id, Movie Id which

In [30]:
```
X_feature = tidy_movie_ratings[['Gender', 'Age', 'Occupation',
       'Action', 'Adventure', 'Animation', "Children's", 'Comedy', 'Crime',
       'Documentary', 'Drama', 'Fantasy', 'Film-Noir', 'Horror', 'Musical',
       'Mystery', 'Romance', 'Sci-Fi', 'Thriller', 'War', 'Western', 'Year']]
X_feature.shape
```

Out[30]:
```
(1000209, 22)
```

In [31]:
```
X_feature.head()
```

Out[31]:

	Gender	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	...	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western	Year
0	F	1	10	0	0	1	1	1	0	0	...	0	0	0	0	0	0	0	0	0	1995
1	F	1	10	0	0	1	1	0	0	0	...	0	0	1	0	1	0	0	0	0	1995
2	F	1	10	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	1995
3	F	1	10	1	1	0	0	0	0	0	...	0	0	0	0	0	1	0	0	0	1977
4	F	1	10	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	0	1993

5 rows × 22 columns

In [32]:

```
Y_target = tidy_movie_ratings[['Rating']]
```

In [33]:

```
#find the correlation using 'corr()' function.
#it returns a dataframe which contain the correlation between all the numeric columns.
data_corr = tidy_movie_ratings.corr()
data_corr
```

```
C:\Users\aranj\AppData\Local\Temp\ipykernel_17684\3636535412.py:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  data_corr = tidy_movie_ratings.corr()
```

Out[33]:

	MovieID	UserID	Rating	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
MovieID	1.000000	-0.017739	-0.064042	0.027575	0.008585	-0.042046	-0.082413	-0.014177	-0.071589	0.061667	...	-0.018792	-0.019655	0.057613	-0.059381	-0.028561	-0.118375	-0.011747	-0.058418	-0.081951	0.003940
UserID	-0.017739	1.000000	0.012303	0.034688	-0.026698	-0.000202	-0.000683	-0.000766	-0.000486	-0.000365	...	0.000221	0.000470	-0.000139	-0.000022	0.000433	0.000684	-0.000328	-0.000110	0.000350	0.000414
Rating	-0.064042	0.012303	1.000000	0.056869	0.006753	-0.047633	-0.036718	0.019670	-0.039829	-0.039622	...	-0.023312	0.006025	-0.094353	0.015643	0.015848	0.009644	-0.044487	-0.004806	0.007568	0.007311
Age	0.027575	0.034688	0.056869	1.000000	0.078371	-0.030975	-0.016730	-0.047020	-0.052858	-0.044046	...	-0.024222	0.033495	-0.023901	0.005158	0.024308	0.017503	-0.010879	-0.014100	0.038446	0.038177
Occupation	0.008585	-0.026698	0.006753	0.078371	1.000000	-0.018347	-0.014309	-0.003838	-0.006906	-0.006149	...	-0.001299	0.005246	-0.001439	-0.007312	0.002421	-0.014018	-0.026250	-0.008981	-0.010264	-0.005924

	MovieID	UserID	Rating	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
Action	-0.042046	-0.002023	-0.047633	-0.030975	0.018347	1.000000	0.374961	-0.110294	-0.141314	-0.268092	...	0.014551	-0.080288	-0.042733	-0.104332	-0.054084	-0.067830	0.319117	0.202756	0.135872	0.022242
Adventure	-0.082413	-0.000683	-0.036718	-0.016730	0.014309	0.374961	1.000000	0.000473	0.098283	-0.124960	...	0.227046	-0.014178	-0.057256	-0.022327	-0.043503	-0.024389	0.284190	-0.038423	0.016647	-0.011964
Animation	-0.014177	-0.007665	-0.019670	-0.047020	-0.003834	-0.110294	0.000473	1.000000	0.576204	0.018544	...	0.012025	-0.037013	-0.049730	-0.335231	-0.042488	-0.054540	-0.055526	-0.085713	-0.046114	-0.030908
Children's	-0.071589	-0.004862	-0.039829	-0.052858	-0.006906	-0.141314	0.098283	0.576204	1.000000	0.058711	...	0.263280	-0.038033	-0.077099	-0.312567	-0.052786	-0.084550	-0.038844	-0.132642	-0.066539	-0.031269
Comedy	0.061667	-0.003651	-0.039622	-0.044046	-0.006149	-0.268092	-0.124960	-0.018544	0.058711	1.000000	...	-0.000610	-0.101425	-0.093064	-0.030566	-0.105346	0.112843	-0.187079	-0.299501	-0.127101	0.007927

	MovieID	UserID	Rating	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
Crime	-0.061896	0.003469	0.003446	-0.007931	0.002821	0.088519	-0.045924	-0.062520	-0.081977	-0.078030	...	-0.033745	0.136237	-0.047899	-0.061179	0.008003	-0.073320	-0.083730	0.115095	-0.079715	-0.042711
Documentary	-0.000954	-0.001064	0.002809	0.004407	-0.002689	-0.052565	-0.035109	-0.018991	-0.024901	-0.040697	...	-0.017326	-0.012175	-0.025673	-0.007155	-0.018265	-0.037137	-0.038568	-0.043191	-0.016082	-0.012974
Drama	-0.030856	0.006572	0.012256	0.006385	-0.012326	-0.020241	-0.019457	-0.154479	-0.135707	-0.024984	...	-0.009629	-0.006729	-0.018955	-0.009477	-0.002769	0.023552	-0.021274	-0.015377	0.136582	-0.045945
Fantasy	-0.001879	0.002212	-0.002331	-0.002422	0.001299	0.014551	0.227046	0.012025	0.263280	-0.000601	...	1.000000	-0.002646	-0.005580	-0.002013	-0.003970	-0.014822	0.121843	-0.008737	-0.004492	-0.002819
Film-Noir	-0.019655	0.004701	0.006025	0.003495	0.005246	-0.008028	-0.014178	0.037013	-0.038033	-0.101425	...	-0.026464	1.000000	-0.003915	-0.002838	0.021535	-0.047351	-0.000406	0.115231	-0.003698	-0.001981

	MovieID	UserID	Rating	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
Horror	0.005763	-0.001392	-0.009435	-0.023901	0.001439	-0.004273	-0.007256	-0.049730	-0.077099	-0.093064	...	-0.055803	-0.039157	1.000000	-0.018924	-0.004242	-0.099434	0.056505	0.056629	-0.077985	-0.041784
Musical	-0.059381	-0.000022	0.001563	0.005158	-0.007312	-0.010043	-0.002231	0.335231	0.312567	0.030566	...	-0.002013	-0.002838	-0.001892	1.000000	-0.004258	0.023506	-0.006801	-0.010069	-0.003442	-0.003024
Mystery	-0.028561	0.000433	0.001584	0.002430	0.002421	-0.005408	-0.004350	-0.042488	-0.052786	-0.010534	...	-0.003970	0.021535	-0.000244	-0.004258	1.000000	-0.040162	-0.002827	0.022528	-0.005548	-0.002972
Romance	-0.118375	0.000683	0.000964	0.001750	-0.001418	-0.000678	-0.002438	-0.054540	-0.084550	0.112843	...	-0.001482	-0.004735	-0.009943	0.002350	-0.004016	1.000000	-0.013375	-0.008138	0.005334	-0.004465
Sci-Fi	-0.011747	-0.000328	-0.004487	-0.001087	0.002625	0.031911	0.028419	-0.055526	-0.038844	-0.187079	...	0.012184	-0.000406	0.005605	-0.006801	-0.002827	-0.013375	1.000000	0.010254	0.003931	-0.001093

	MovieID	UserID	Rating	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
Thriller	-0.058418	-0.001107	-0.000806	-0.001406	0.008981	0.202756	-0.038423	-0.085713	-0.132642	-0.299501	...	-0.087374	0.115231	0.056629	-0.100690	0.225281	-0.081384	0.102546	1.000000	-0.088018	-0.058897
War	-0.081951	0.003502	0.007568	0.038446	0.010264	0.135872	0.016647	-0.046114	-0.066539	-0.127101	...	-0.044928	-0.036984	-0.077985	-0.034429	-0.055482	0.053347	0.039314	-0.088018	1.000000	-0.019803
Western	0.003940	0.004114	0.007311	0.038177	0.005924	0.022242	-0.019164	-0.030908	-0.031269	0.007927	...	-0.028199	-0.019816	-0.041784	-0.030245	-0.029727	-0.046450	-0.010935	-0.058897	-0.019803	1.000000

23 rows × 23 columns

In [34]:

```
new_cor = data_corr[0:1]
new_cor
```

Out[34]:

	MovieID	UserID	Rating	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
MovieID	1.0	-0.017739	-0.064042	0.027575	0.008585	-0.042046	-0.082413	-0.014177	-0.071589	0.061667	...	-0.018792	-0.019655	0.057613	-0.059381	-0.028561	-0.118375	-0.011747	-0.058418	-0.081951	0.003944

1 rows × 23 columns

In [35]:

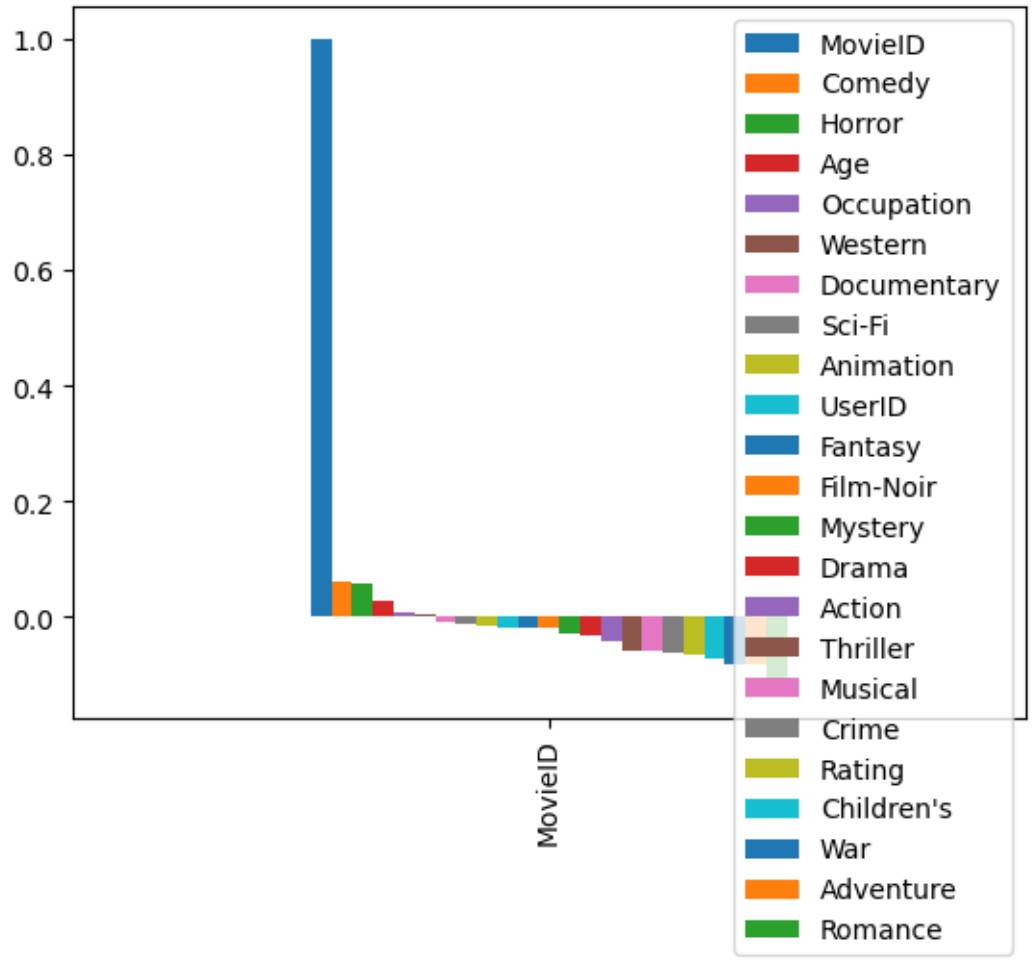
```
rslt_df = data_corr.sort_values(by = 'MovieID', axis = 1, ascending = False)
rslt_df = rslt_df[0:1]
```

In [36]:

```
rslt_df.plot.bar()
```

Out[36]:

```
<Axes: >
```



In [37]:

```
#The 3 factors affecting the rating are: Genre, Age & Occupation
#Overall - Rating is affected by 2 Genres - Horror & Comedy
#Genre - (2 of the Sub genre had been highest)
#Followed by Age       Occupation
```

In [38]:

```
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
#Split the dataset (by default, 75% is the training data and 25% is the
testing data)
#by default takin 75%-25% split
#Cross_validation got away from python 2
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X_feature, Y_target,
random_state=1)
```

In [39]:

```
number = LabelEncoder()
x_train.Gender = number.fit_transform(x_train["Gender"].astype("str"))
x_test.Gender = number.fit_transform(x_test["Gender"].astype("str"))
y_train = number.fit_transform(y_train.astype("int"))
```

```
y_test = number.fit_transform(y_test.astype("int"))
```

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\preprocessing\_label.py:11
6: DataConversionWarning: A column-vector y was passed when a 1d array was ex
pected. Please change the shape of y to (n_samples, ), for example using rave
l().
  y = column_or_1d(y, warn=True)
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\preprocessing\_label.py:11
6: DataConversionWarning: A column-vector y was passed when a 1d array was ex
pected. Please change the shape of y to (n_samples, ), for example using rave
l().
  y = column_or_1d(y, warn=True)
```

In [40]:

```
#Verify if the training and testing datasets are split correctly
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(750156, 22)
(750156,)
(250053, 22)
(250053,)
```

Logistic regression is best used for predicting categorical data

need to do logistic regression on the training data so we can see how well our test data does the prediction

The dataset kept throwing off a non-convergence error where max iterations had been reached. I used the code below to increase the max iter.

However, for test purpose showing how linear regression model witll fail

In [41]:

```
#Create a linear regression model
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
linreg.fit(x_train, y_train)
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
y_pred = linreg.predict(x_test)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[41], line 5
      3 linreg = LinearRegression()
      4 linreg.fit(x_train, y_train)
----> 5 LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
      6          normalize=False)
      7 y_pred = linreg.predict(x_test)

TypeError: LinearRegression.__init__() got an unexpected keyword argument 'no
rmalize'
```

In [ ]:

```
print(
```

```
    'y-intercept: ',
    linreg.intercept_
)
print(
    'Beta coefficients: ',
    linreg.coef_
)
```

In [ ]:

```
from sklearn import metrics

print(
    'Mean Abs Error  MAE: ',
    metrics.mean_absolute_error(y_test, y_pred)
)
print(
    'Mean Sq Error  MSE: ',
    metrics.mean_squared_error(y_test, y_pred)
)
print(
    'Root Mean Sq Error RMSE:',
    np.sqrt(metrics.mean_squared_error(y_test, y_pred))
)
print(
    'r2 value: ',
    metrics.r2_score(y_test, y_pred)
)
```

As we see the linear model is not the right model for this dataset Develop an appropriate model to predict the movie ratings

In [42]:

```
# Create a logistic regression model using the training set
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(x_train, y_train)
```

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:
458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regres
sion
  n_iter_i = _check_optimize_result(
```

Out[42]:

LogisticRegression

LogisticRegression()

In [43]:

```
#Make predictions using the testing set
y_pred = logreg.predict(x_test)
```

```
y_pred
```

Out[43]:

```
array([3, 3, 3, ..., 3, 3, 3], dtype=int64)
```

In [44]:

```
#Evaluate the accuracy of your model
print(logreg.intercept_)
print(logreg.coef_)
from sklearn import metrics
import numpy as np
print(metrics.mean_squared_error(y_test, y_pred))
from sklearn import metrics
metrics.accuracy_score(y_test,y_pred)
```

```
[-3.72911239e-05 -5.65842971e-05 -5.45592491e-05  2.62081779e-05
  1.22226492e-04]
[[ 1.23526965e-04 -1.68736754e-02 -2.44701381e-03  6.74231056e-04
   2.97300227e-04 -1.42370546e-04  5.51223708e-04  4.50621745e-04
  -4.11938206e-04 -5.46368622e-05 -2.51119580e-03  9.37765430e-05
  -2.42825115e-04  1.49548953e-03 -9.67548776e-05 -1.70485099e-04
  -6.36031008e-04  7.20702191e-04 -1.87337315e-04 -4.60275660e-04
  -2.07144237e-05 -2.93375828e-04]
 [ 6.36329084e-04 -2.91680233e-03  1.42350211e-04  1.16542314e-03
   6.95777556e-04 -3.95473120e-04  2.22067412e-04  7.89246682e-04
  -3.71832462e-04 -1.23840425e-04 -2.82996117e-03  2.39911608e-04
  -3.59845550e-04  1.17688745e-03 -2.30021381e-04 -8.79737592e-05
  -1.73466791e-04  1.08272938e-03  2.45195957e-04 -8.14791688e-04
  -8.20160591e-05 -1.72433042e-04]
 [ 4.59463515e-04  4.91744717e-03  3.74223100e-04  1.06257850e-03
   9.49359364e-04 -8.53344156e-05  5.05300083e-04  1.23232252e-03
  -4.27855569e-04 -2.10884523e-04 -2.59616289e-03  3.17553939e-04
  -5.19742401e-04  4.86357437e-04 -8.97403255e-05 -9.48512978e-05
   6.29113799e-04  5.61114125e-04  2.17630577e-04 -1.42452022e-03
  -1.27479455e-05  1.58110168e-04]
 [-3.95812618e-04  7.10438907e-03  1.79523201e-03 -1.01389841e-03
  -7.39245077e-04  2.67954810e-04 -3.99237138e-04 -1.80630693e-04
   2.38490624e-04  9.16185442e-05  2.48542160e-03 -2.64590354e-04
   1.65551570e-04 -1.48980050e-03  4.45756894e-05  5.87413237e-05
   5.91545527e-04 -1.36478149e-03  1.78227034e-04  6.95661035e-05
   3.41536972e-05  2.63647095e-04]
 [-8.23506947e-04  7.76864152e-03  1.35208493e-04 -1.88833429e-03
  -1.20319207e-03  3.55223271e-04 -8.79354065e-04 -2.29156025e-03
   9.73135614e-04  2.97743266e-04  5.45189826e-03 -3.86651736e-04
   9.56861496e-04 -1.66893391e-03  3.71940895e-04  2.94568832e-04
  -4.11161527e-04 -9.99764209e-04 -4.53716252e-04  2.63002146e-03
   8.13247311e-05  4.40516073e-05]]
1.425681755467841
```

Out[44]:

```
0.3506976520977553
```

In [45]:

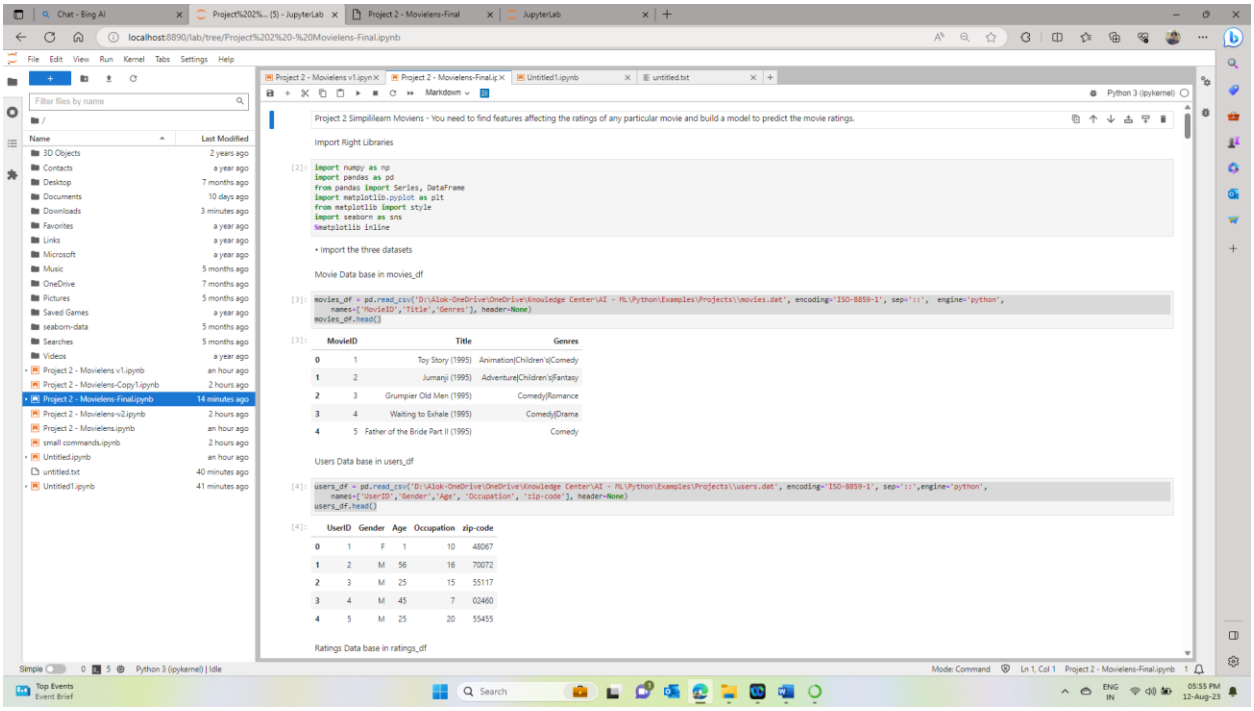
```
#Print the first 30 actual and predicted responses
print('Actual : ', y_test[0:30])
print('Predicted :', y_pred[0:30])
```

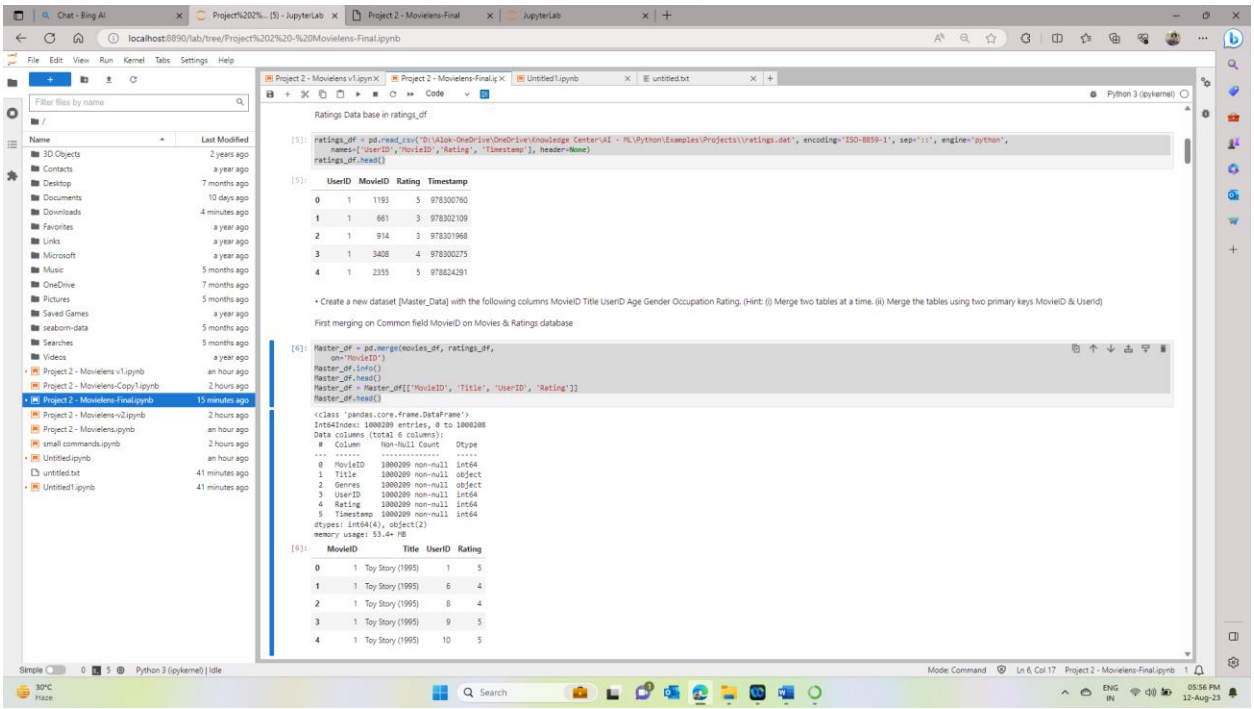
```
Actual :  [3 4 2 4 3 2 2 2 3 1 4 0 3 4 2 3 3 2 4 4 0 4 2 3 4 3 0 3 4 2]
Predicted : [3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3]
```

In [ ]:

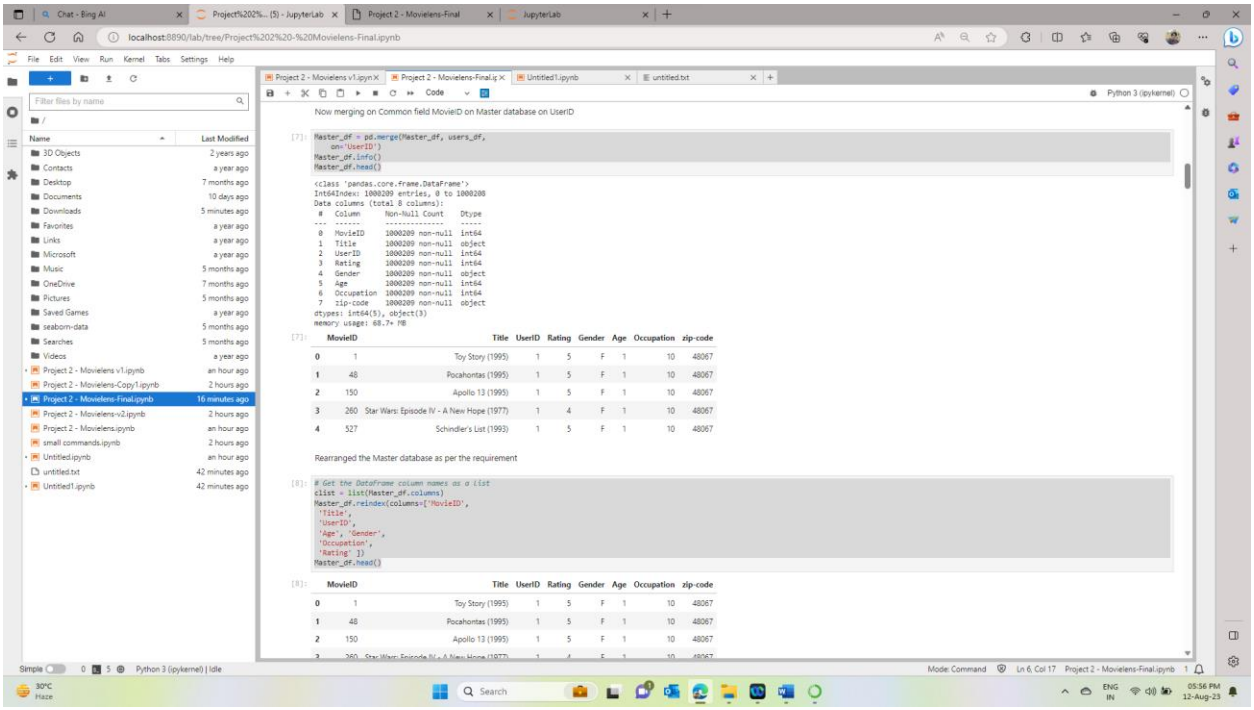
ScreenShots:

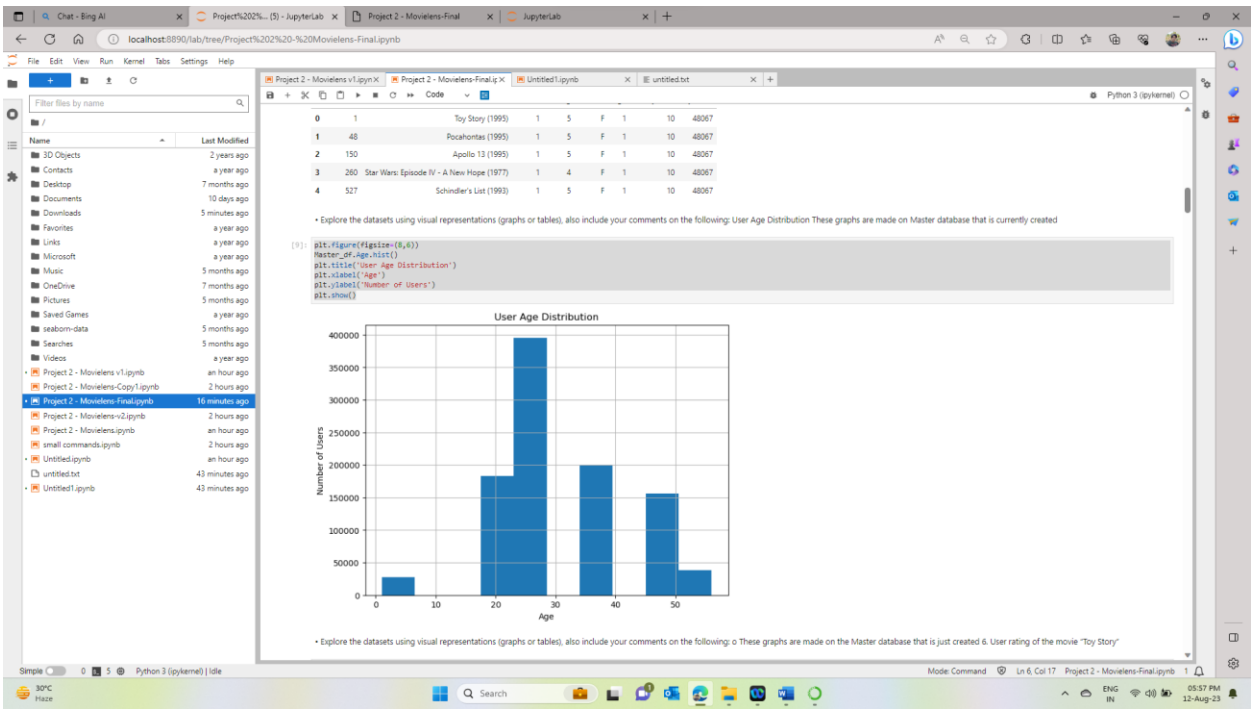
Import 3 datasets





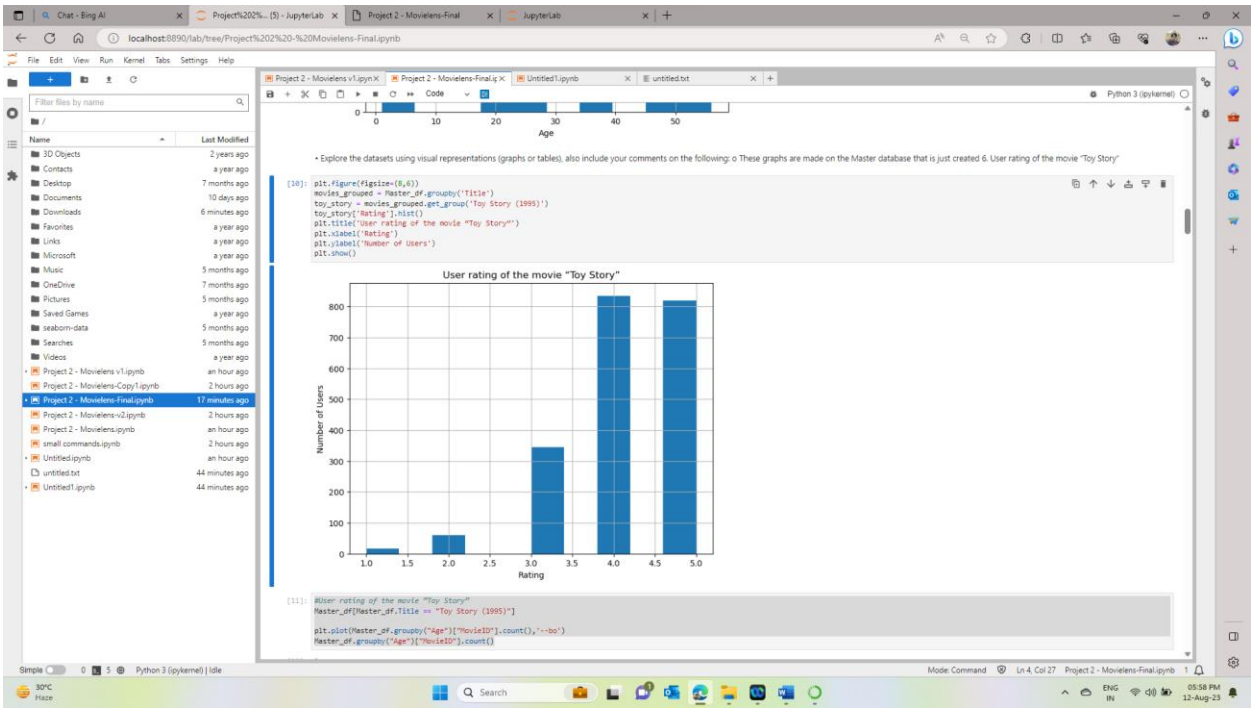
- Create a new dataset [Master_Data] with the following columns MovieID Title UserID Age Gender Occupation Rating.

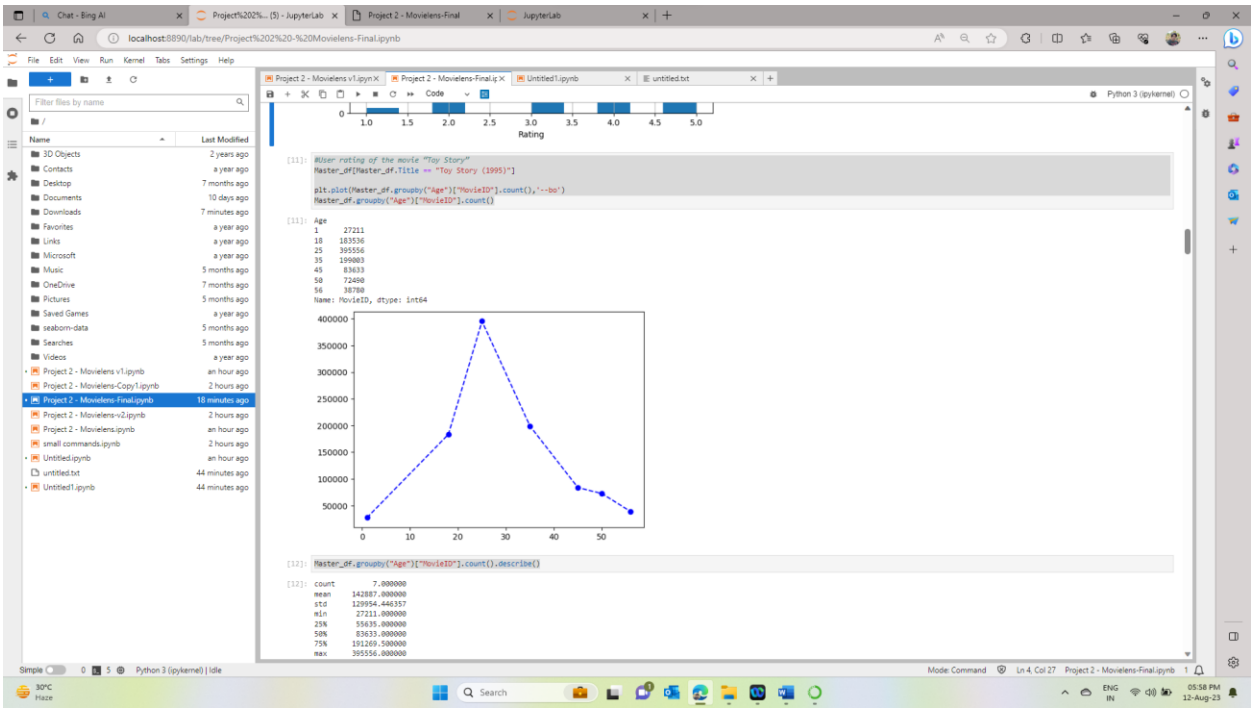




- Explore the datasets using visual representations (graphs or tables), also include your comments on the following:
    9. User Age Distribution
    10. User rating of the movie “Toy Story”

11. Top 25 movies by viewership rating
12. Find the ratings for all the movies reviewed by for a particular user of user id = 2696





```
[12]: Master_df.groupby("Age")["MovieID"].count().describe()

[12]: count       7.000000
      mean     142887.000000
      std      129954.446357
      min       27211.000000
      25%       55635.000000
      50%       83633.000000
      75%      191269.500000
      max      395556.000000
      Name: MovieID, dtype: float64
```

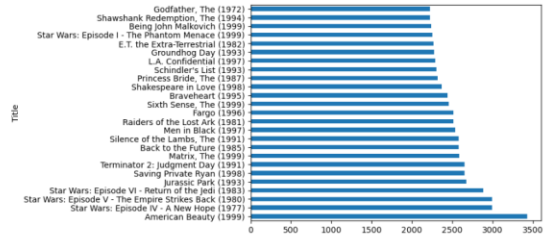
• Explore the datasets using visual representations (graphs or tables), also include your comments on the following: o These graphs are made on the Master database that is just created 7. Top 25 movies by viewership rating

```
[13]: rating_avg = Master_df.groupby('Title')['Rating'].mean()
      rating_avg.head()
      rating_avg = rating_avg.sort_values(ascending=False)
      rating_avg[0:25]

[13]: Title
      Ulysses (Ulisse) (1954)                                    5.000000
      Lured (1947)                                               5.000000
      Follow the Bitch (1998)                                    5.000000
      Bittersweet Motel (2000)                                   5.000000
      Song of Freedom (1936)                                     5.000000
      One Little Indian (1973)                                   5.000000
      Smashing Time (1967)                                       5.000000
      Schlafes Bruder (Brother of Sleep) (1995)                  5.000000
      Gate of Heavenly Peace, The (1995)                         5.000000
      Baby, The (1973)                                           5.000000
      I Am Cuba (Soy Cuba/Ya Kuba) (1964)                        4.800000
      Lamerica (1994)                                            4.750000
      Apple, The (Sib) (1998)                                    4.666667
      Sanjuro (1962)                                             4.608696
      Seven Samurai (The Magnificent Seven) (Shichinin no samurai) (1954)  4.560510
      Shawshank Redemption, The (1994)                           4.554558
      Godfather, The (1972)                                      4.524966
      Close Shave, A (1995)                                      4.520548
      Usual Suspects, The (1995)                                 4.517106
      Schindler's List (1993)                                    4.510417
      Wrong Trousers, The (1993)                                 4.507937
      Dry Cleaning (Nettoyage à sec) (1997)                      4.500000
      Inheritors, The (Die Siebtelbauern) (1998)                 4.500000
      Mamma Roma (1962)                                          4.500000
      Bells, The (1926)                                          4.500000
      Name: Rating, dtype: float64

[14]: rating_avg_count = pd.DataFrame(data=rating_avg)
      rating_avg_count['number_of_ratings'] = pd.DataFrame(rating_avg_count)
      rating_avg_count.head()

[14]:                                    Rating  number_of_ratings
```

```
      rating_avg_count.head()

[14]:
```

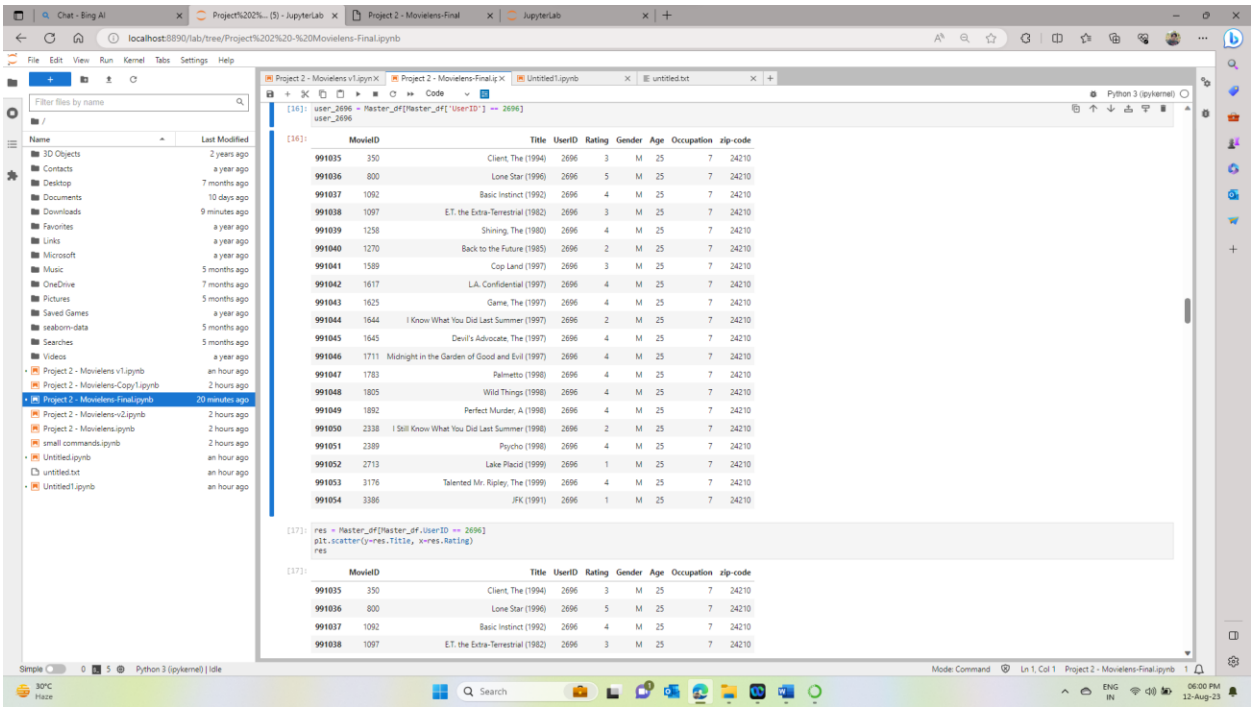
Title	Rating	number_of_ratings
Ulysses (Ulisse) (1954)	5.0	5.0
Lured (1947)	5.0	5.0
Follow the Bitch (1998)	5.0	5.0
Bittersweet Motel (2000)	5.0	5.0
Song of Freedom (1936)	5.0	5.0

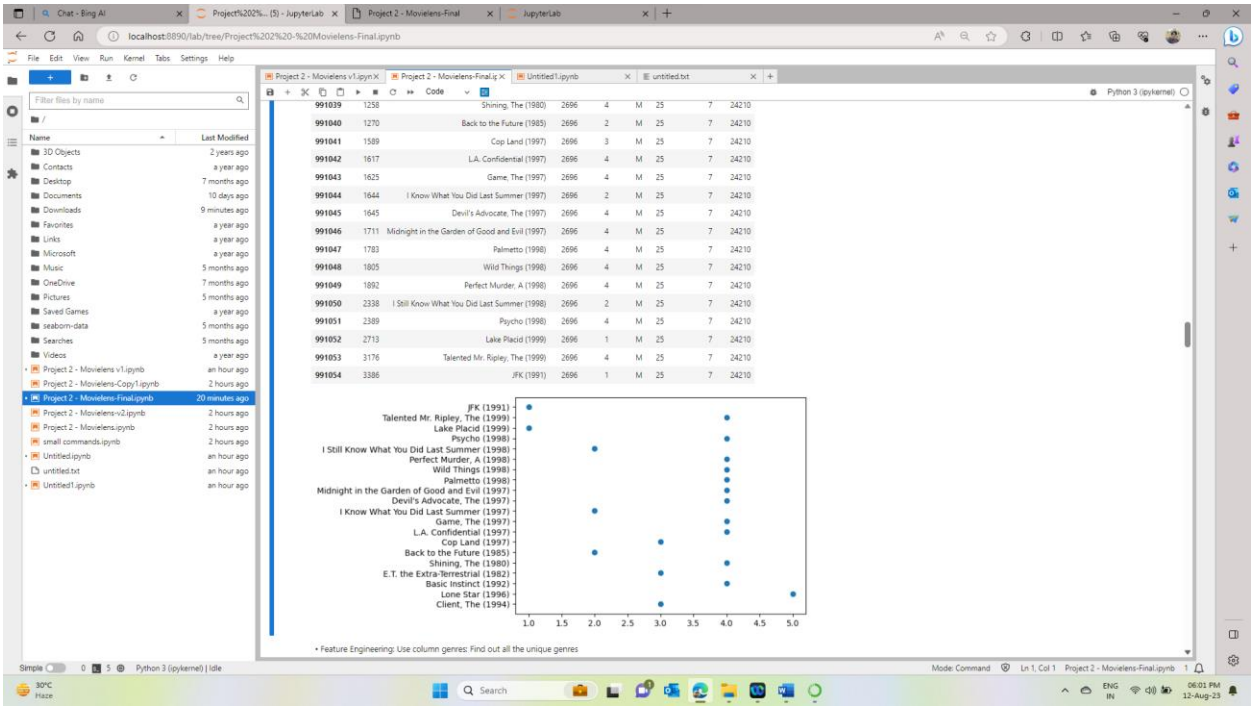
```
[15]: #Top 25 movies by viewership rating

      res = Master_df.groupby("Title").size().sort_values(ascending=False)[:25]
      plt.ylabel("Title")
      plt.xlabel("Viewership Count")
      res.plot(kind="barh")

[15]: <Axes: ylabel='Title'>
```



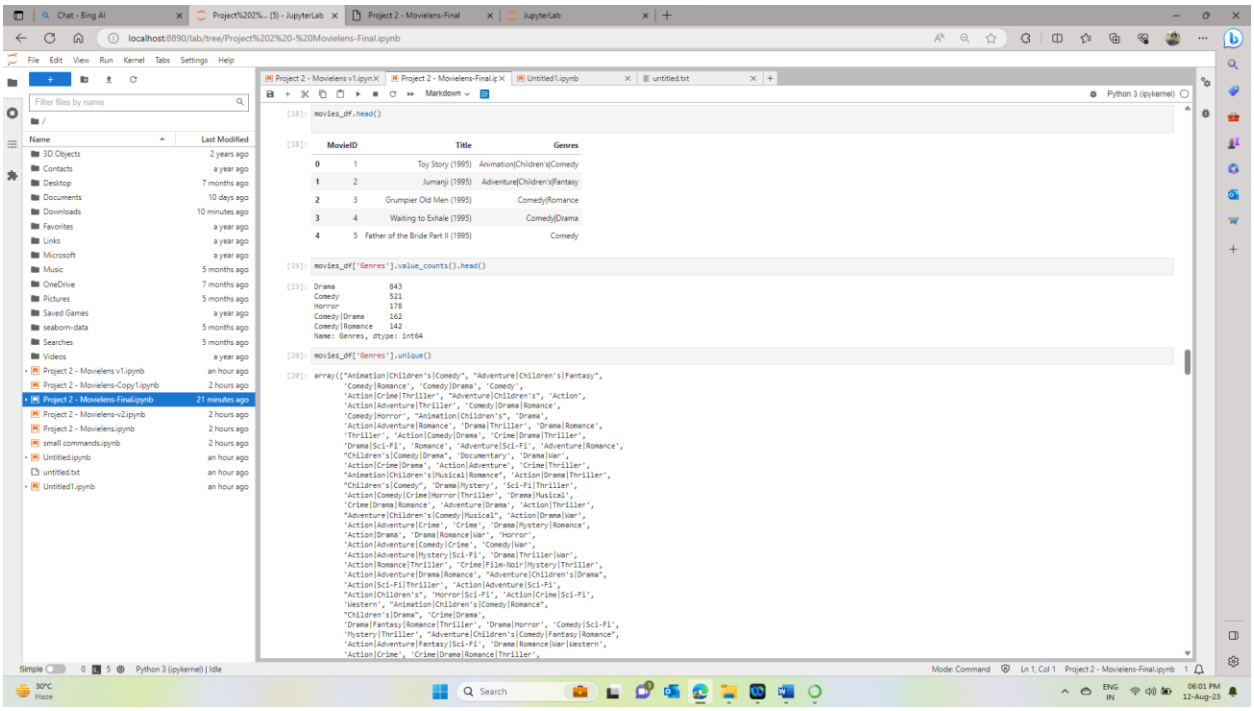
• Explore the datasets using visual representations (graphs or tables), also include your comments on the following: o These graphs are made on the Master database that is just created 8. Find the ratings for all the movies reviewed by for a particular user of user id = 2696

```
[16]: user_2696 = Master_df[Master_df['UserID'] == 2696]
```





- Feature Engineering:
  Use column genres:



```
movies_df.head()
```

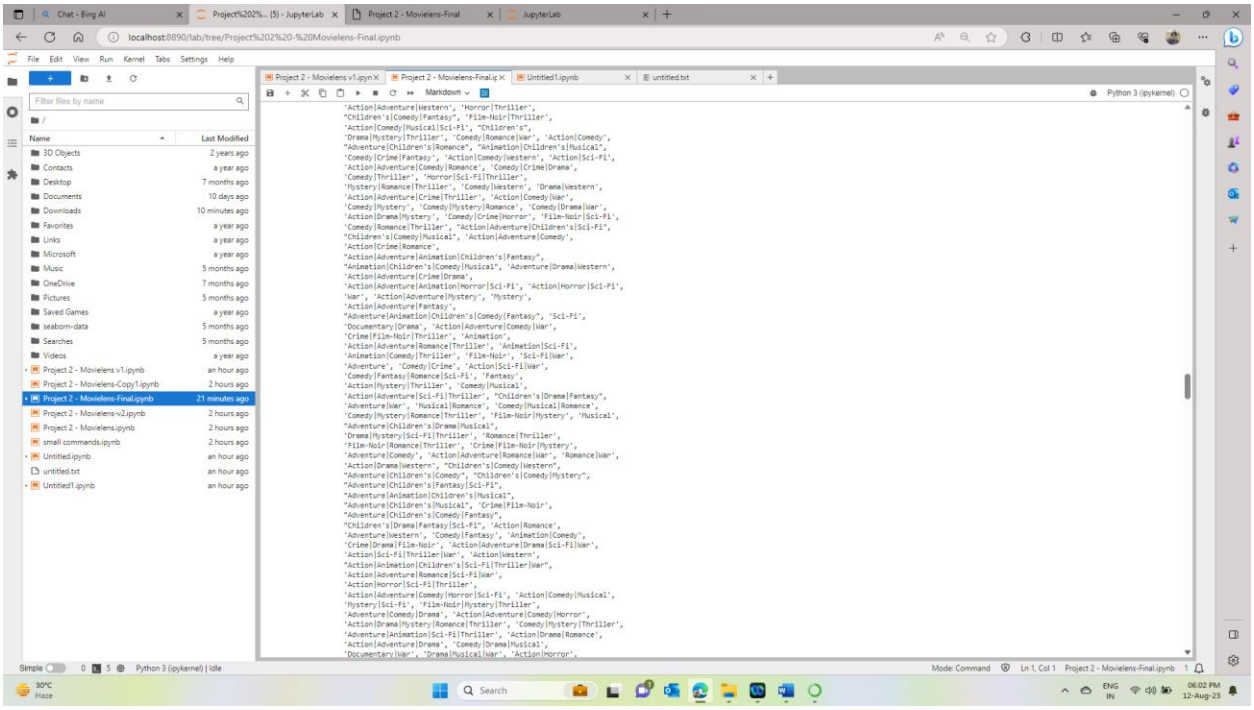
	MovieID	Title	Genres
0	1	Toy Story (1995)	Animation|Children's|Comedy
1	2	Jumanji (1995)	Adventure|Children's|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama
4	5	Father of the Bride Part II (1995)	Comedy

```
movies_df['Genres'].value_counts().head()
```

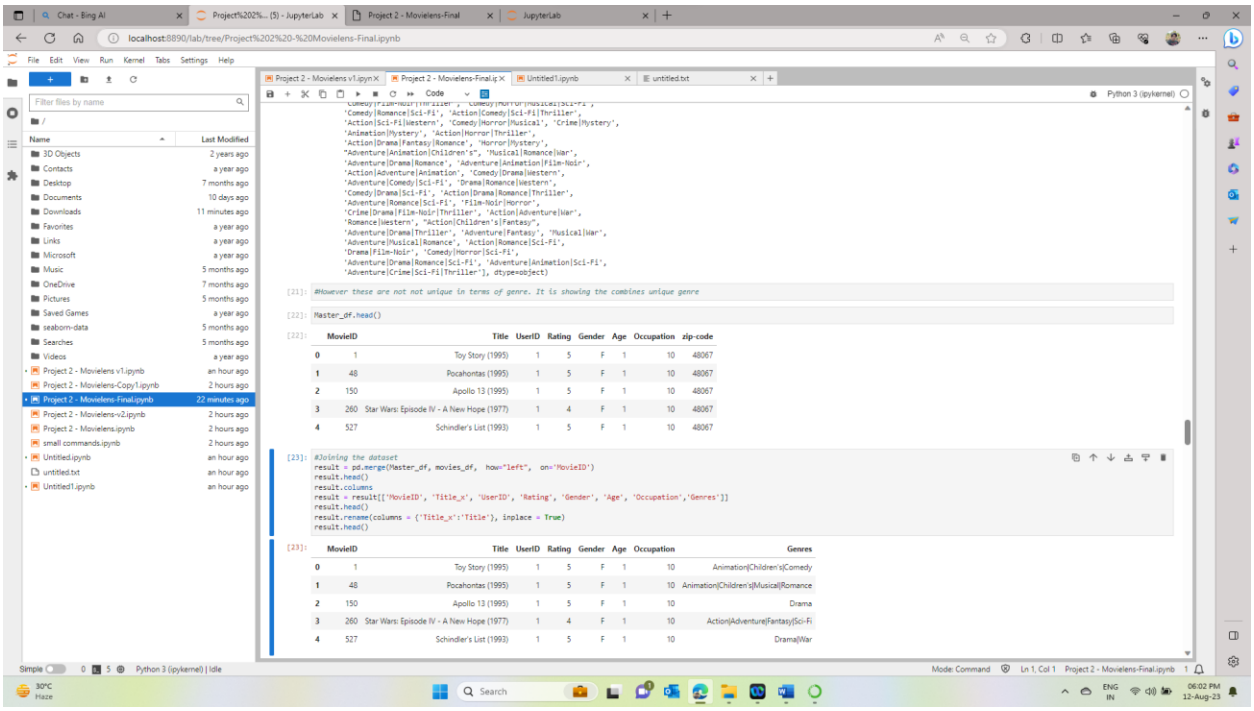
```
Drama              843
Comedy             521
Horror             178
Comedy|Drama       162
Comedy|Romance     142
Name: Genres, dtype: int64
```

```
movies_df['Genres'].unique()
```

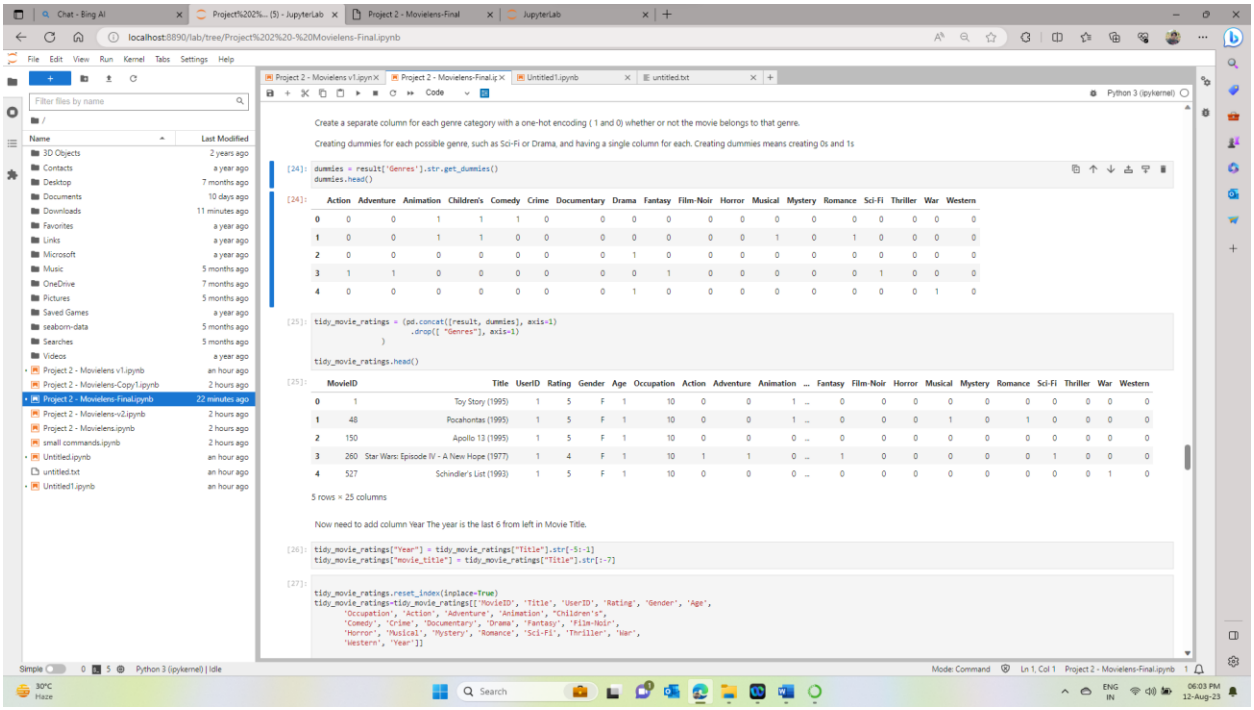
```
array(["Animation|Children's|Comedy", "Adventure|Children's|Fantasy",
       'Comedy|Romance', 'Comedy|Drama', 'Comedy',
       'Action|Crime|Thriller', "Adventure|Children's", 'Action',
       'Action|Adventure|Thriller', 'Comedy|Drama|Romance',
       'Comedy|Horror', "Animation|Children's", 'Drama',
       'Action|Adventure|Romance', 'Drama|Thriller', 'Drama|Romance',
       'Thriller', 'Action|Comedy|Drama', 'Crime|Drama|Thriller',
       'Drama|Sci-Fi', 'Romance', 'Adventure|Sci-Fi', 'Adventure|Romance',
       "Children's|Comedy|Drama", 'Documentary', 'Drama|War',
       'Action|Crime|Drama', 'Action|Adventure', 'Crime|Thriller',
       "Animation|Children's|Musical|Romance", 'Action|Drama|Thriller',
       "Children's|Comedy", 'Drama|Mystery', 'Sci-Fi|Thriller',
       'Action|Comedy|Crime|Horror|Thriller', 'Drama|Musical',
       'Crime|Drama|Romance', 'Adventure|Drama', 'Action|Thriller',
       'Adventure|Children's|Comedy|Musical", 'Action|Drama|War',
       'Action|Adventure|Crime', 'Crime', 'Drama|Mystery|Romance',
       'Action|Drama', 'Drama|Romance|War', 'Horror',
       'Action|Adventure|Comedy|Crime', 'Comedy|War',
       'Action|Adventure|Mystery|Sci-Fi', 'Drama|Thriller|War',
       'Action|Romance|Thriller', 'Crime|Film-Noir|Mystery|Thriller',
       'Action|Adventure|Drama|Romance', "Adventure|Children's|Drama",
       'Action|Sci-Fi|Thriller', 'Action|Adventure|Sci-Fi',
       "Action|Children's", 'Horror|Sci-Fi', 'Action|Crime|Sci-Fi',
       'Western', "Animation|Children's|Comedy|Romance",
       "Children's|Drama", 'Crime|Drama',
       'Drama|Fantasy|Romance|Thriller', 'Drama|Horror', 'Comedy|Sci-Fi',
       'Mystery|Thriller', "Adventure|Children's|Comedy|Fantasy|Romance",
       'Action|Adventure|Fantasy|Sci-Fi', 'Drama|Romance|War|Western',
       'Action|Crime', 'Crime|Drama|Romance|Thriller',
```

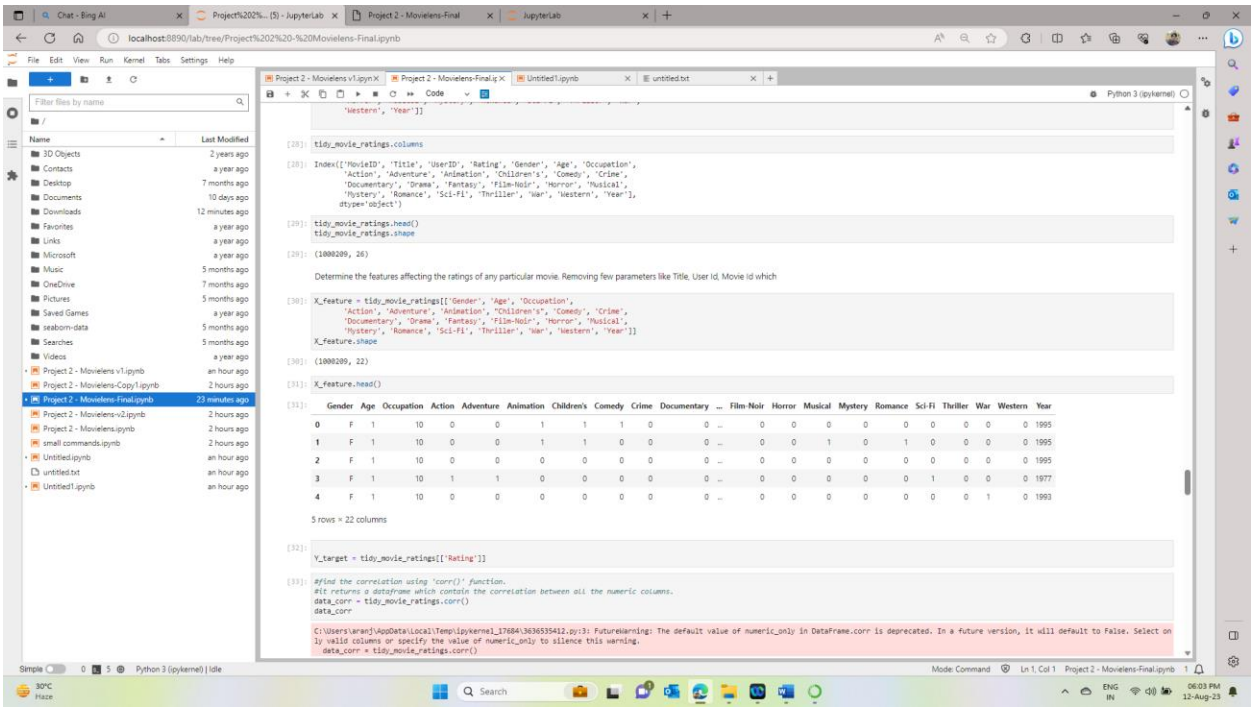


```
       'Action|Adventure|Western', 'Horror|Thriller',
       "Children's|Comedy|Fantasy", 'Film-Noir|Thriller',
       'Action|Comedy|Musical|Sci-Fi', "Children's",
       'Drama|Mystery|Thriller', 'Comedy|Romance|War', 'Action|Comedy',
       "Adventure|Children's|Romance", "Animation|Children's|Musical",
       'Comedy|Crime|Fantasy', 'Action|Comedy|Western', 'Action|Sci-Fi',
       'Action|Adventure|Comedy|Romance', 'Comedy|Crime|Drama',
       'Comedy|Thriller', 'Horror|Sci-Fi|Thriller',
       'Mystery|Romance|Thriller', 'Comedy|Western', 'Drama|Western',
       'Action|Adventure|Crime|Thriller', 'Action|Comedy|War',
       'Comedy|Mystery', 'Comedy|Mystery|Romance', 'Comedy|Drama|War',
       'Action|Drama|Mystery', 'Comedy|Crime|Horror', 'Film-Noir|Sci-Fi',
       'Comedy|Romance|Thriller', "Action|Adventure|Children's|Sci-Fi",
       "Children's|Comedy|Musical", 'Action|Adventure|Comedy',
       'Action|Crime|Romance',
       'Action|Adventure|Animation|Children's|Fantasy",
       "Animation|Children's|Comedy|Musical", 'Adventure|Drama|Western',
       'Action|Adventure|Crime|Drama',
       'Action|Adventure|Animation|Horror|Sci-Fi', 'Action|Horror|Sci-Fi',
       'War', 'Action|Adventure|Mystery', 'Mystery',
       'Action|Adventure|Fantasy',
       "Adventure|Animation|Children's|Comedy|Fantasy", 'Sci-Fi',
       'Documentary|Drama', 'Action|Adventure|Comedy|War',
       'Crime|Film-Noir|Thriller', 'Animation',
       'Action|Adventure|Romance|Thriller', 'Animation|Sci-Fi',
       'Animation|Comedy|Thriller', 'Film-Noir', 'Sci-Fi|War',
       'Adventure', 'Comedy|Crime', 'Action|Sci-Fi|War',
       'Comedy|Fantasy|Romance|Sci-Fi', 'Fantasy',
       'Action|Mystery|Thriller', 'Comedy|Musical',
       'Action|Adventure|Sci-Fi|Thriller', "Children's|Drama|Fantasy",
       'Adventure|War', 'Musical|Romance', 'Comedy|Musical|Romance',
       'Comedy|Mystery|Romance|Thriller', 'Film-Noir|Mystery', 'Musical',
       "Adventure|Children's|Drama|Musical",
       'Drama|Mystery|Sci-Fi|Thriller', 'Romance|Thriller',
       'Film-Noir|Romance|Thriller', 'Crime|Film-Noir|Mystery',
       'Adventure|Comedy', 'Action|Adventure|Romance|War', 'Romance|War',
       'Action|Drama|Western', "Children's|Comedy|Western",
       "Adventure|Children's|Comedy", "Children's|Comedy|Mystery",
       "Adventure|Children's|Fantasy|Sci-Fi",
       "Adventure|Animation|Children's|Musical",
       "Adventure|Children's|Musical", 'Crime|Film-Noir',
       "Adventure|Children's|Comedy|Fantasy",
       "Children's|Drama|Fantasy|Sci-Fi", 'Action|Romance',
       'Adventure|Western', 'Comedy|Fantasy', 'Animation|Comedy',
       'Crime|Drama|Film-Noir', 'Action|Adventure|Drama|Sci-Fi|War',
       'Action|Sci-Fi|Thriller|War', 'Action|Western',
       'Action|Animation|Children's|Sci-Fi|Thriller|War',
       'Action|Adventure|Romance|Sci-Fi|War',
       'Action|Horror|Sci-Fi|Thriller',
       'Action|Adventure|Comedy|Horror|Sci-Fi', 'Action|Comedy|Musical',
       'Mystery|Sci-Fi', 'Film-Noir|Mystery|Thriller',
       'Adventure|Comedy|Drama', 'Action|Adventure|Comedy|Horror',
       'Action|Drama|Mystery|Romance|Thriller', 'Comedy|Mystery|Thriller',
       'Adventure|Animation|Sci-Fi|Thriller', 'Action|Drama|Romance',
       'Action|Adventure|Drama', 'Comedy|Drama|Musical',
       'Documentary|War', 'Drama|Musical|War', 'Action|Horror',
```

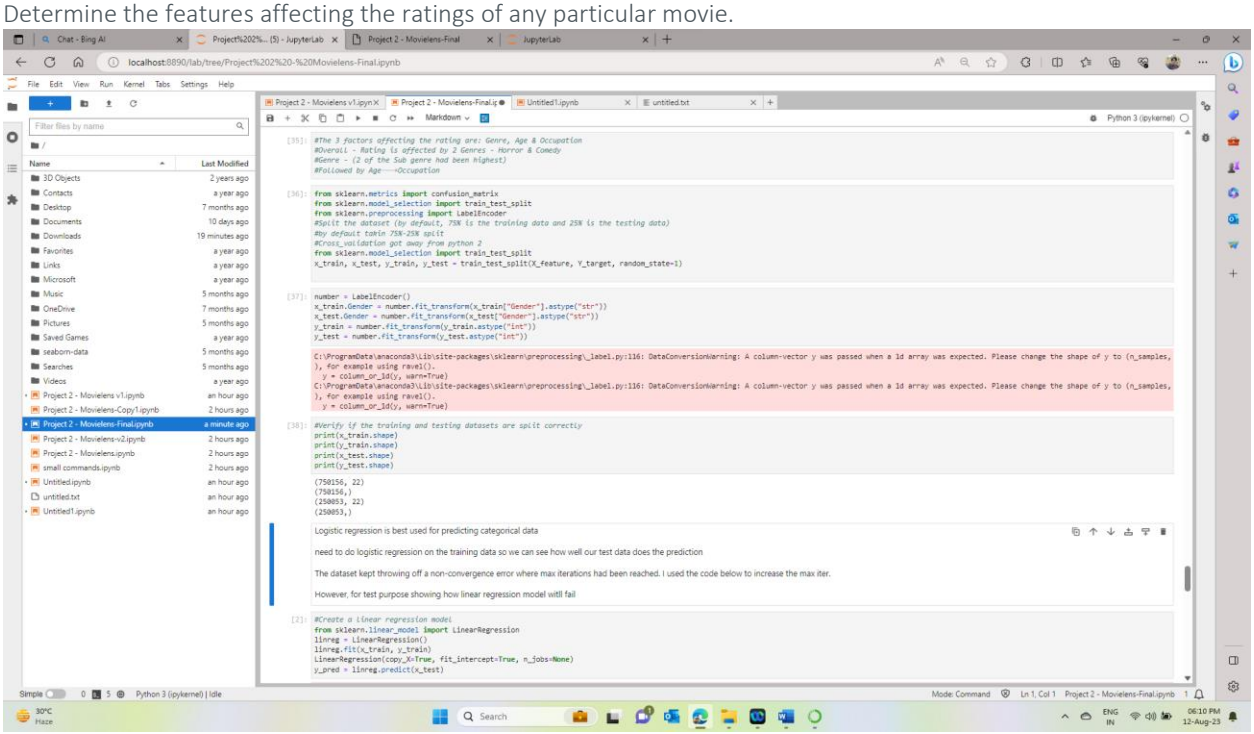


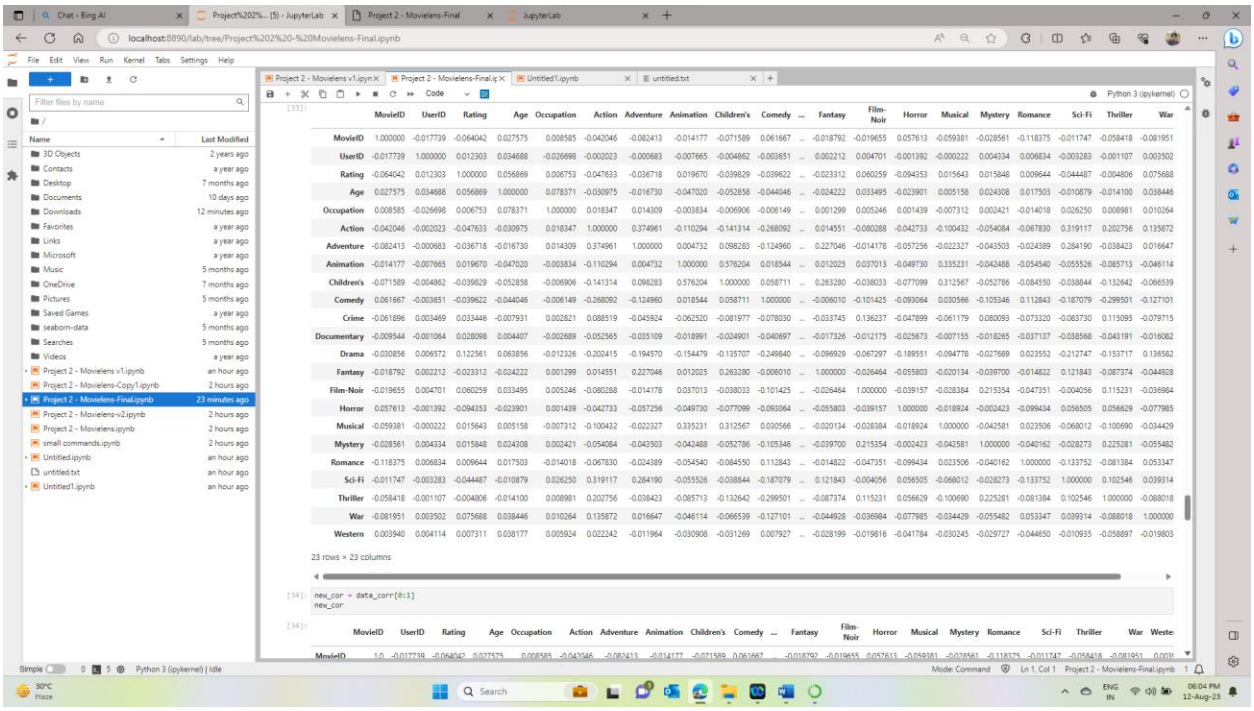
1. Create a separate column for each genre category with a one-hot encoding (1 and 0) whether or not the movie belongs to that genre.

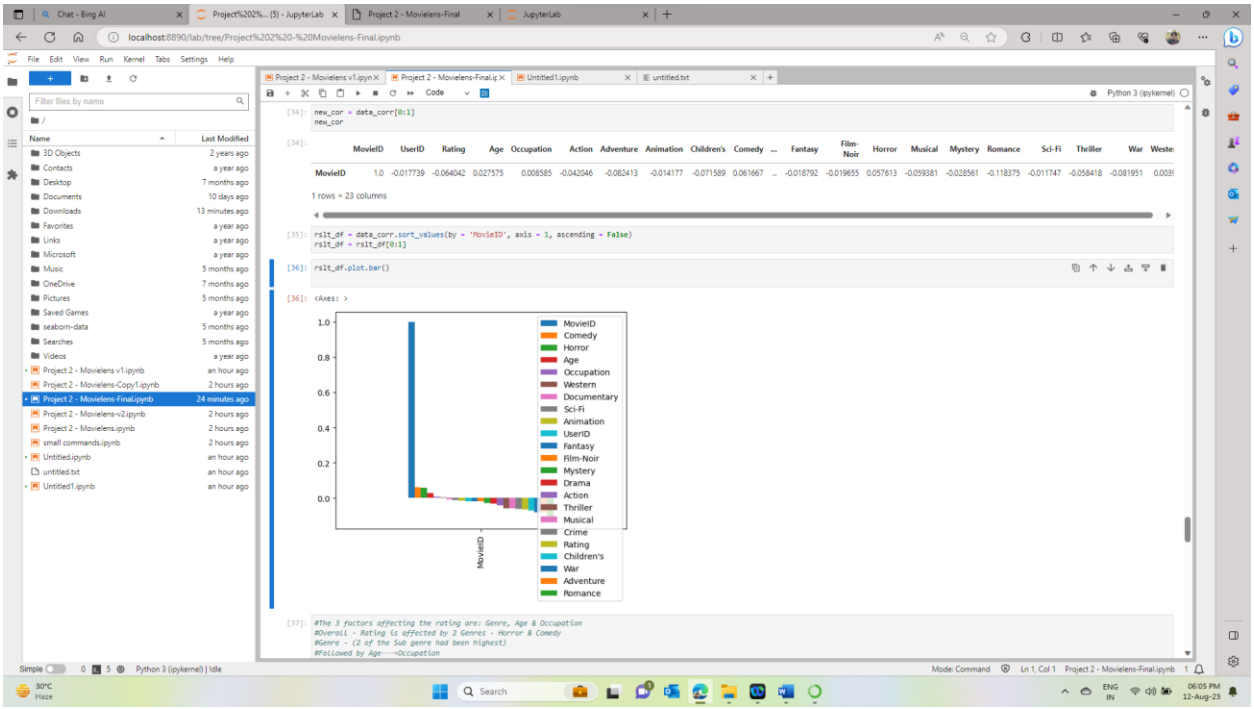




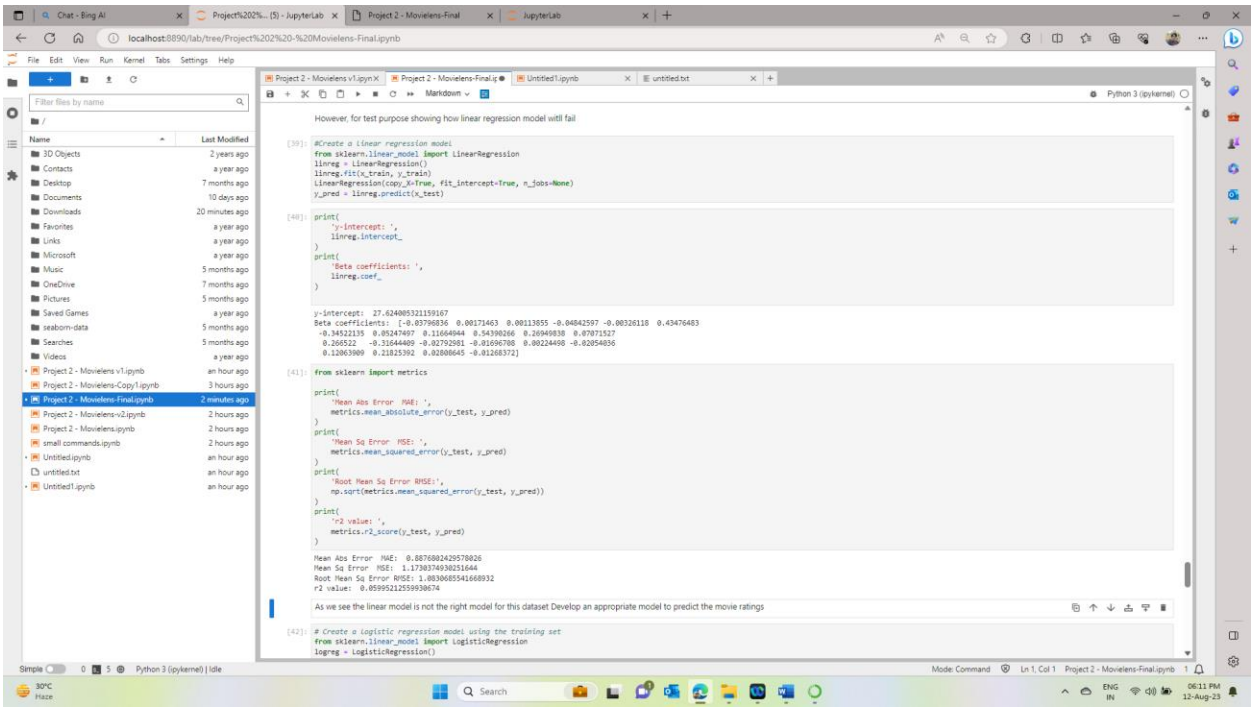
1. Determine the features affecting the ratings of any particular movie.

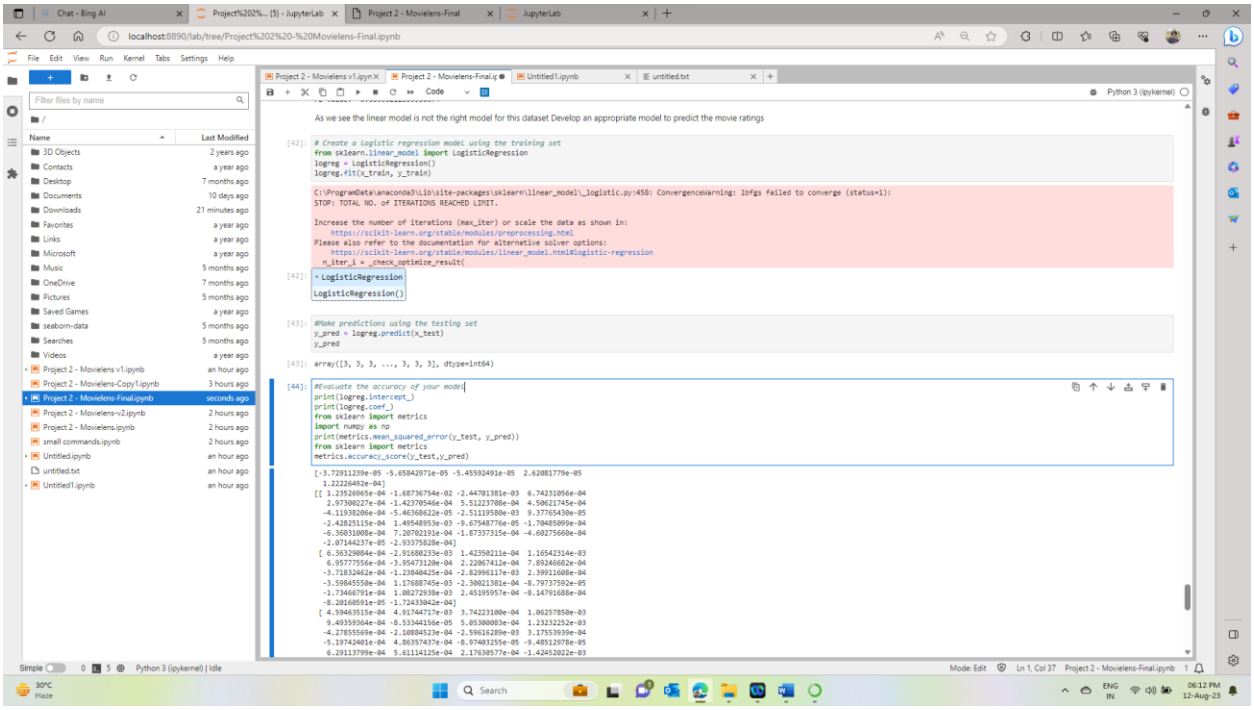


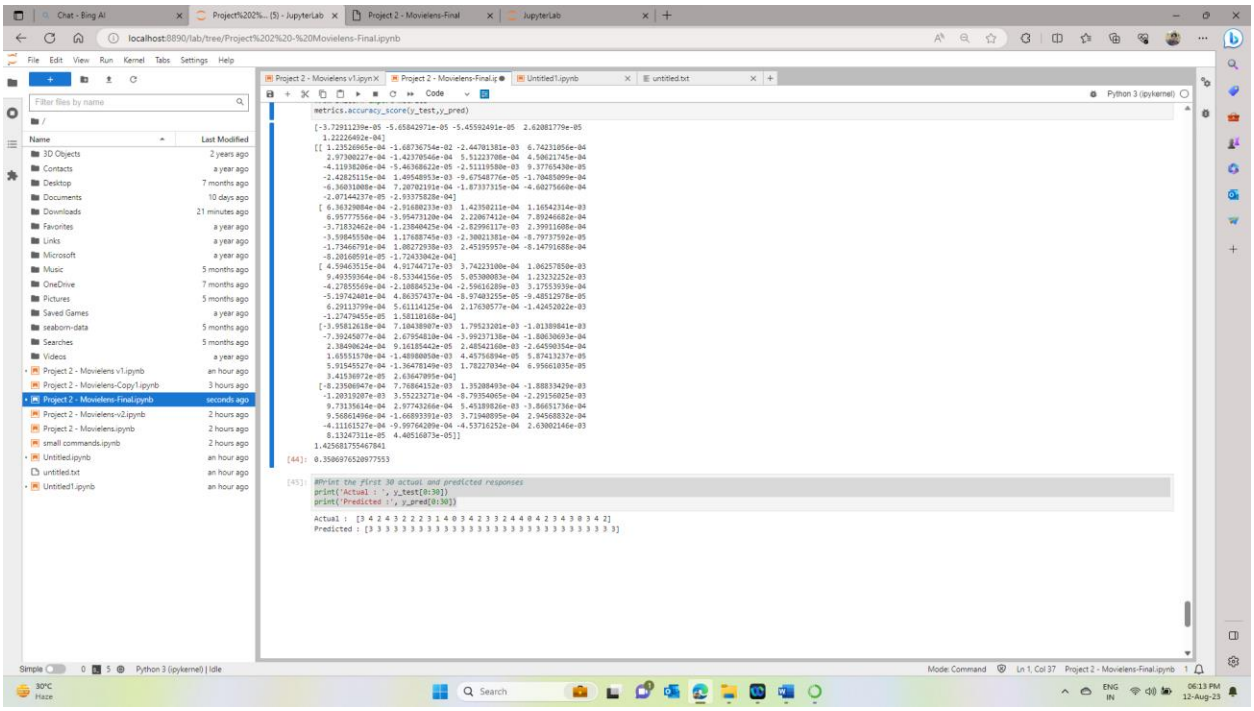




2. Develop an appropriate model to predict the movie ratings


However, for test purpose showing how linear regression model will fail
#Create a linear regression model
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
linreg.fit(x_train, y_train)
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None)
y_pred = linreg.predict(x_test)
print(
'y-intercept: ',
linreg.intercept_
)
print(
'Beta coefficients: ',
linreg.coef_
)
y-intercept: 27.624005321159167
Beta coefficients: [-0.03796836 0.00171463 0.00113855 -0.04042597 -0.00326118 0.43476483
-0.34522135 0.05247497 0.11664944 0.54390266 0.26949838 0.07071527
0.266522 -0.31644409 -0.02792981 -0.01696708 0.00224498 -0.02054036
0.12063909 0.21825392 0.02808645 -0.01268372]
from sklearn import metrics
print(
'Mean Abs Error MAE: ',
metrics.mean_absolute_error(y_test, y_pred)
)
print(
'Mean Sq Error MSE: ',
metrics.mean_squared_error(y_test, y_pred)
)
print(
'Root Mean Sq Error RMSE:',
np.sqrt(metrics.mean_squared_error(y_test, y_pred))
)
print(
'r2 value: ',
metrics.r2_score(y_test, y_pred)
)
Mean Abs Error MAE: 0.8876002429570026
Mean Sq Error MSE: 1.1730374930251644
Root Mean Sq Error RMSE: 1.0830685541668932
r2 value: 0.05995212559930674
As we see the linear model is not the right model for this dataset Develop an appropriate model to predict the movie ratings
# Create a logistic regression model using the training set
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()


As we see the linear model is not the right model for this dataset Develop an appropriate model to predict the movie ratings
# Create a logistic regression model using the training set
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(x_train, y_train)
C:\ProgramData\anaconda3\lib\site-packages\sklearn\linear_model_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max_iter) or scale the data as shown in:
https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
n_iter_i = _check_optimize_result(
LogisticRegression()
#Make predictions using the testing set
y_pred = logreg.predict(x_test)
y_pred
array([3, 3, 3, ..., 3, 3, 3], dtype=int64)
#Evaluate the accuracy of your model
print(logreg.intercept_)
print(logreg.coef_)
from sklearn import metrics
import numpy as np
print(metrics.mean_squared_error(y_test, y_pred))
from sklearn import metrics
metrics.accuracy_score(y_test,y_pred)
[-3.72911239e-05 -5.65842971e-05 -5.45592491e-05 2.62081779e-05
1.22226492e-04]
[[1.23520965e-04 -1.68736754e-02 -2.44701381e-03 6.74231056e-04
2.97300227e-04 -1.42370546e-04 5.51223708e-04 4.50621745e-04
-4.11938206e-04 -5.46368622e-05 -2.51119500e-03 9.37765430e-05
-2.42825115e-04 1.49548953e-03 -9.67548776e-05 -1.70485099e-04
-6.36031008e-04 7.20702191e-04 -1.87337315e-04 -4.60275660e-04
-2.07144237e-05 -2.93375828e-04]
[6.36329084e-04 -2.91680233e-03 1.42350211e-04 1.16542314e-03
6.95777556e-04 -3.95473120e-04 2.22067412e-04 7.89246682e-04
-3.71832462e-04 -1.23840425e-04 -2.82996117e-03 2.39911608e-04
-3.59845550e-04 1.17688745e-03 -2.30021381e-04 -8.79737592e-05
-1.73466791e-04 1.08272938e-03 2.45195957e-04 -8.14791688e-04
-8.20160591e-05 -1.72433042e-04]
[4.59463515e-04 4.91744717e-03 3.74223100e-04 1.06257850e-03
9.40359364e-04 -8.53344156e-05 5.05300083e-04 1.23232252e-03
-4.27855569e-04 -2.10884523e-04 -2.59616289e-03 3.17553939e-04
-5.19742401e-04 4.86357437e-04 -8.97403255e-05 -9.48512978e-05
6.29113799e-04 5.61114125e-04 2.17630577e-04 -1.42452022e-03



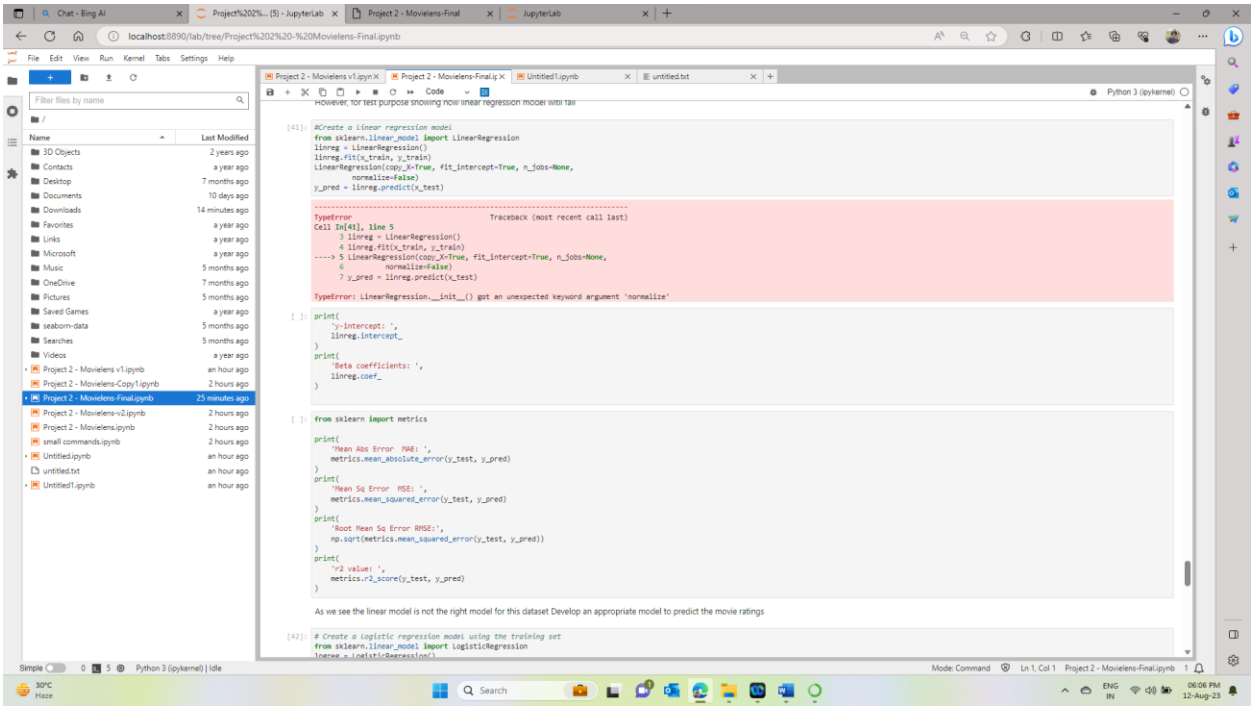
```
metrics.accuracy_score(y_test,y_pred)
```

```
[-3.72911239e-05 -5.65842971e-05 -5.45592491e-05  2.62081779e-05
  1.22226492e-04]
[[ 1.23526865e-04 -1.68736754e-02 -2.44701381e-03  6.74231056e-04
   1.97300227e-04 -1.42370546e-04  5.51223708e-04  4.50621745e-04
  -4.11938206e-04 -5.46368622e-05 -2.51119580e-03  9.37765430e-05
  -2.42825115e-04  1.49548953e-03 -9.67548776e-05 -1.70485099e-04
  -6.36031008e-04  7.28702191e-04 -1.87337315e-04 -4.60275660e-04
  -2.07144237e-05 -2.93375828e-04]
 [ 6.36329084e-04 -2.91680233e-03  1.42358211e-04  1.16542314e-03
   6.95777556e-04 -3.95473120e-04  2.22067412e-04  7.89246682e-04
  -3.71832462e-04 -1.23840425e-04 -2.82996117e-03  2.39911608e-04
  -3.59845550e-04  1.17688745e-03 -2.30021381e-04 -8.79737592e-05
  -1.73466791e-04  1.00272930e-03  2.45195957e-04 -8.14791688e-04
  -8.20168591e-05 -1.72433042e-04]
 [ 4.59463515e-04  4.91744717e-03  3.74223100e-04  1.06257850e-03
   9.49359364e-04 -8.53344156e-05  5.05300083e-04  1.23232252e-03
  -4.27855569e-04 -2.10884523e-04 -2.59616289e-03  3.17553930e-04
  -5.19742401e-04  4.86357437e-04 -8.97403255e-05 -9.48512978e-05
   6.29113799e-04  5.61114125e-04  2.17630577e-04 -1.42452022e-03
  -1.27479455e-05  1.58110168e-04]
 [-3.95812618e-04  7.10438907e-03  1.79523201e-03 -1.01389841e-03
  -7.39245077e-04  2.67954810e-04 -3.99237138e-04 -1.80630693e-04
   2.38490624e-04  9.16185442e-05  2.48542160e-03 -2.64590354e-04
   1.65551570e-04 -1.48980050e-03  4.45756894e-05  5.87413237e-05
   5.91545527e-04 -1.36478149e-03  1.78227034e-04  6.95661035e-05
   3.41536972e-05  2.63647095e-04]
 [-8.23506947e-04  7.76864152e-03  1.35208493e-04 -1.88833429e-03
  -1.20319207e-03  3.55223271e-04 -8.79354065e-04 -2.29156025e-03
   9.73135614e-04  2.97743266e-04  5.45189826e-03 -3.86651736e-04
   9.56861496e-04 -1.66893391e-03  3.71940895e-04  2.94568832e-04
  -4.11161527e-04 -9.99764289e-04 -4.53716252e-04  2.63002146e-03
   8.13247311e-05  4.40516073e-05]]
1.4256817554617841
```

```
0.3586976520977553
```

```
##Print the first 30 actual and predicted responses
print('Actual : ', y_test[0:30])
print('Predicted :', y_pred[0:30])
```

```
Actual :  [3 4 2 4 3 2 2 2 3 1 4 0 3 4 2 3 3 2 4 4 0 4 2 3 4 3 0 3 4 2]
Predicted : [3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3]
```



However, for test purpose showing how linear regression model with fail

```
#Create a linear regression model
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
linreg.fit(x_train, y_train)
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
y_pred = linreg.predict(x_test)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[41], line 5
      3 linreg = LinearRegression()
      4 linreg.fit(x_train, y_train)
----> 5 LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
      6          normalize=False)
      7 y_pred = linreg.predict(x_test)

TypeError: LinearRegression.__init__() got an unexpected keyword argument 'normalize'
```

```
print(
    'y-intercept: ',
    linreg.intercept_
)
print(
    'Beta coefficients: ',
    linreg.coef_
)
```

```
from sklearn import metrics

print(
    'Mean Abs Error  MAE: ',
    metrics.mean_absolute_error(y_test, y_pred)
)
print(
    'Mean Sq Error  MSE: ',
    metrics.mean_squared_error(y_test, y_pred)
)
print(
    'Root Mean Sq Error RMSE:',
    np.sqrt(metrics.mean_squared_error(y_test, y_pred))
)
print(
    'r2 value: ',
    metrics.r2_score(y_test, y_pred)
)
```

As we see the linear model is not the right model for this dataset Develop an appropriate model to predict the movie ratings

```
# Create a logistic regression model using the training set
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
```

Embedded File:

Phython File:

Project 2 - Movielens.ipynb

Code hosted on GitHub :
ks-alokranjan/Simplilearn-Project (github.com)