Movielens Case Study

Project 1 DESCRIPTION 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.

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
```

---

import the three dataset

In [1]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# Users data import
print("-------------- USER Data ----------------------")
users = pd.read_csv("users.dat",delimiter="::",header = None)
users.columns = ['User_id','Gender','Age','Occupation','Zip_code']
print(users.head(),"\n")
# Ratings data import
ratings = pd.read_csv("ratings.dat",sep="::", names = ['User_id','Movie_id','Rating','Timestaemp'] )
print("-------------- Rating Data ----------------------")
print(ratings.head(),"\n")
# Movies data import
Movies = pd.read_csv("movies.dat",sep="::",names=['Movie_id','Title','Genres'])
print("-------------- Movie Data ----------------------")
print(Movies.head())
```

```
-------------- USER Data ----------------------
   User_id 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

-------------- Rating Data ----------------------
   User_id  Movie_id  Rating  Timestaemp
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

-------------- Movie Data ----------------------
   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 [3]:
```
print(users.shape)
print(ratings.shape)
print(Movies.shape)
```

```
(6040, 5)
(1000209, 4)
(3883, 3)
```

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)

In [4]:
```
data_1 = pd.merge(left = Movies , right = ratings ,how='inner', on='Movie_id' )
```

In [5]:
```
data_1
```

Out[5]:

	Movie_id	Title	Genres	User_id	Rating	Timestaemp
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268
1	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008
2	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496
3	1	Toy Story (1995)	Animation|Children's|Comedy	9	5	978225952
4	1	Toy Story (1995)	Animation|Children's|Comedy	10	5	978226474
...	...	...	...	...	...	...
1000204	3952	Contender, The (2000)	Drama|Thriller	5812	4	992072099
1000205	3952	Contender, The (2000)	Drama|Thriller	5831	3	986223125
1000206	3952	Contender, The (2000)	Drama|Thriller	5837	4	1011902656
1000207	3952	Contender, The (2000)	Drama|Thriller	5927	1	979852537
1000208	3952	Contender, The (2000)	Drama|Thriller	5998	4	1001781044

1000209 rows × 6 columns

In [6]:
```
Master_data= data_1.merge(users, on = 'User_id', how = 'inner')
Master_data
```

Out[6]:

	Movie_id	Title	Genres	User_id	Rating	Timestaemp	Gender	Age	Occupation	Zip_code
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	1	10	48067
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351	F	1	10	48067
2	150	Apollo 13 (1995)	Drama	1	5	978301777	F	1	10	48067
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	978300760	F	1	10	48067
4	527	Schindler's List (1993)	Drama|War	1	5	978824195	F	1	10	48067
...	...	...	...	...	...	...	...	...	...	...
1000204	3513	Rules of Engagement (2000)	Drama|Thriller	5727	4	958489970	M	25	4	92843
1000205	3535	American Psycho (2000)	Comedy|Horror|Thriller	5727	2	958489970	M	25	4	92843
1000206	3536	Keeping the Faith (2000)	Comedy|Romance	5727	5	958489902	M	25	4	92843
1000207	3555	U-571 (2000)	Action|Thriller	5727	3	958490699	M	25	4	92843
1000208	3578	Gladiator (2000)	Action|Drama	5727	5	958490171	M	25	4	92843

1000209 rows × 10 columns

In [7]:
```
Master_data.columns=['MovieID','Title','Genres','UserID','Rating','Timestaemp','Gender','Age','Occupation','Zip_code']
```

In [8]:
```
Master_data
```

Out[8]:

	MovieID	Title	Genres	UserID	Rating	Timestaemp	Gender	Age	Occupation	Zip_code
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	1	10	48067
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351	F	1	10	48067
2	150	Apollo 13 (1995)	Drama	1	5	978301777	F	1	10	48067
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	978300760	F	1	10	48067
4	527	Schindler's List (1993)	Drama|War	1	5	978824195	F	1	10	48067
...	...	...	...	...	...	...	...	...	...	...
1000204	3513	Rules of Engagement (2000)	Drama|Thriller	5727	4	958489970	M	25	4	92843
1000205	3535	American Psycho (2000)	Comedy|Horror|Thriller	5727	2	958489970	M	25	4	92843
1000206	3536	Keeping the Faith (2000)	Comedy|Romance	5727	5	958489902	M	25	4	92843
1000207	3555	U-571 (2000)	Action|Thriller	5727	3	958490699	M	25	4	92843
1000208	3578	Gladiator (2000)	Action|Drama	5727	5	958490171	M	25	4	92843

1000209 rows × 10 columns

In [9]:
```
#Master_data.rename(columns={'MOVIE_ID':'MovieID',  'USER_ID':'UserID','AGE':'Age','GENDER': 'Gender', 'Occupation':'Occupation' ,'Rating':'Rating'},inplace = True)
```

In [10]:
```
Master_data.isna().sum()
```

Out[10]:
```
MovieID       0
Title         0
Genres        0
UserID        0
Rating        0
Timestaemp    0
Gender        0
Age           0
Occupation    0
Zip_code      0
dtype: int64
```

In [11]:
```
#Master_data.drop(['Zip_code','Timestaemp','Genres'],axis=1,inplace=True)
#Master_data
```

In [12]:
```
Master_Data = Master_data.reindex(columns=['MovieID', 'Title', 'UserID', 'Age','Zip_code','Timestaemp', 'Gender', 'Occupation' ,'Genres','Rating'])
Master_Data
```

Out[12]:

	MovieID	Title	UserID	Age	Zip_code	Timestaemp	Gender	Occupation	Genres	Rating
0	1	Toy Story (1995)	1	1	48067	978824268	F	10	Animation|Children's|Comedy	5
1	48	Pocahontas (1995)	1	1	48067	978824351	F	10	Animation|Children's|Musical|Romance	5
2	150	Apollo 13 (1995)	1	1	48067	978301777	F	10	Drama	5
3	260	Star Wars: Episode IV - A New Hope (1977)	1	1	48067	978300760	F	10	Action|Adventure|Fantasy|Sci-Fi	4
4	527	Schindler's List (1993)	1	1	48067	978824195	F	10	Drama|War	5
...	...	...	...	...	...	...	...	...	...	...
1000204	3513	Rules of Engagement (2000)	5727	25	92843	958489970	M	4	Drama|Thriller	4
1000205	3535	American Psycho (2000)	5727	25	92843	958489970	M	4	Comedy|Horror|Thriller	2
1000206	3536	Keeping the Faith (2000)	5727	25	92843	958489902	M	4	Comedy|Romance	5
1000207	3555	U-571 (2000)	5727	25	92843	958490699	M	4	Action|Thriller	3
1000208	3578	Gladiator (2000)	5727	25	92843	958490171	M	4	Action|Drama	5

Explore the datasets using visual representations (graphs or tables), also include your comments on the following:

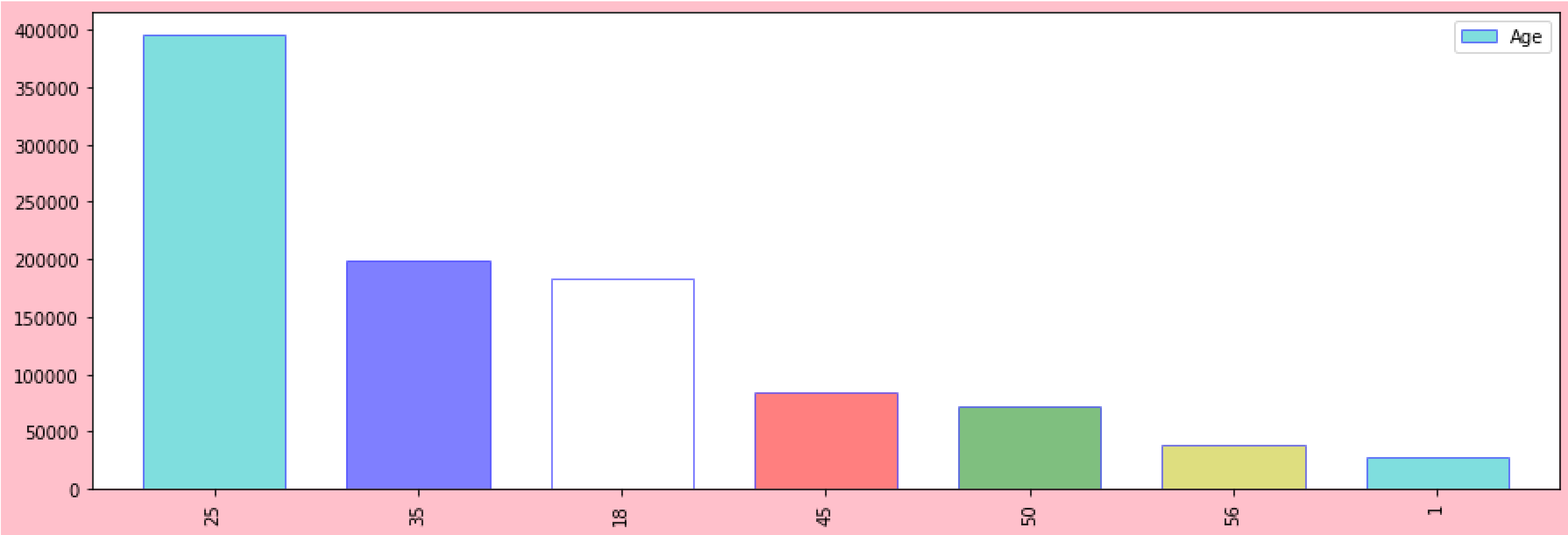
1. User Age Distribution
2. User rating of the movie “Toy Story”
3. Top 25 movies by viewership rating
4. Find the ratings for all the movies reviewed by for a particular user of user id = 2696 • Feature Engineering:

1 User Age Distribution

In [13]:
```
import matplotlib.pyplot as plt
```

In [14]:
```
plt.figure(figsize=(15,5),facecolor='pink',edgecolor='B',)
Master_data.Age.value_counts().plot.bar(alpha=0.5,edgecolor='b',width=0.7,color=['c','b','w','r','g','y'])
plt.legend()
```

Out[14]:
```
<matplotlib.legend.Legend at 0x1cc0a266e48>
```



2. User rating of the movie “Toy Story”

In [15]:
```
#User rating of the movie “Toy Story”
Master_data[Master_data.Title.str.contains("Toy Story")]['Title'].unique()
```

Out[15]:
```
array(['Toy Story (1995)', 'Toy Story 2 (1999)'], dtype=object)
```

In [16]:
```
Master_data[Master_data.Title == 'Toy Story (1995)'].groupby('Rating')['MovieID'].count()
```

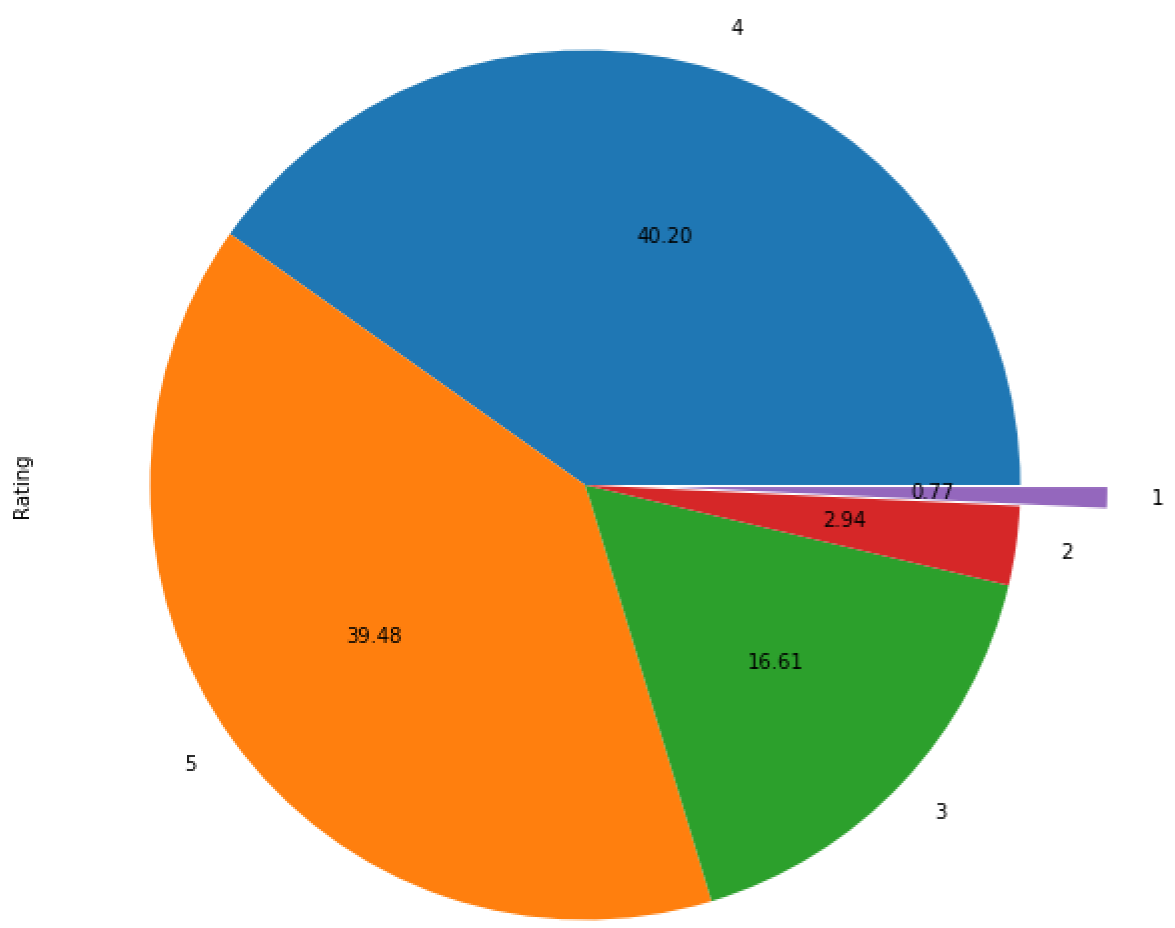
Out[16]:
```
Rating
1     16
2     61
3    345
4    835
5    820
Name: MovieID, dtype: int64
```

In [17]:
```
Master_data[Master_data.Title=='Toy Story (1995)'].Rating.value_counts()
```

Out[17]:
```
4    835
5    820
3    345
2     61
1     16
Name: Rating, dtype: int64
```

In [18]:
```
Master_data[Master_data.Title=='Toy Story (1995)'].Rating.value_counts().plot.pie(explode=[0,0,0,0,0.2] ,
                                                                                  autopct="%0.02f",
                                                                                  figsize=(10,10))
```

Out[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1cc0a24ba90>
```



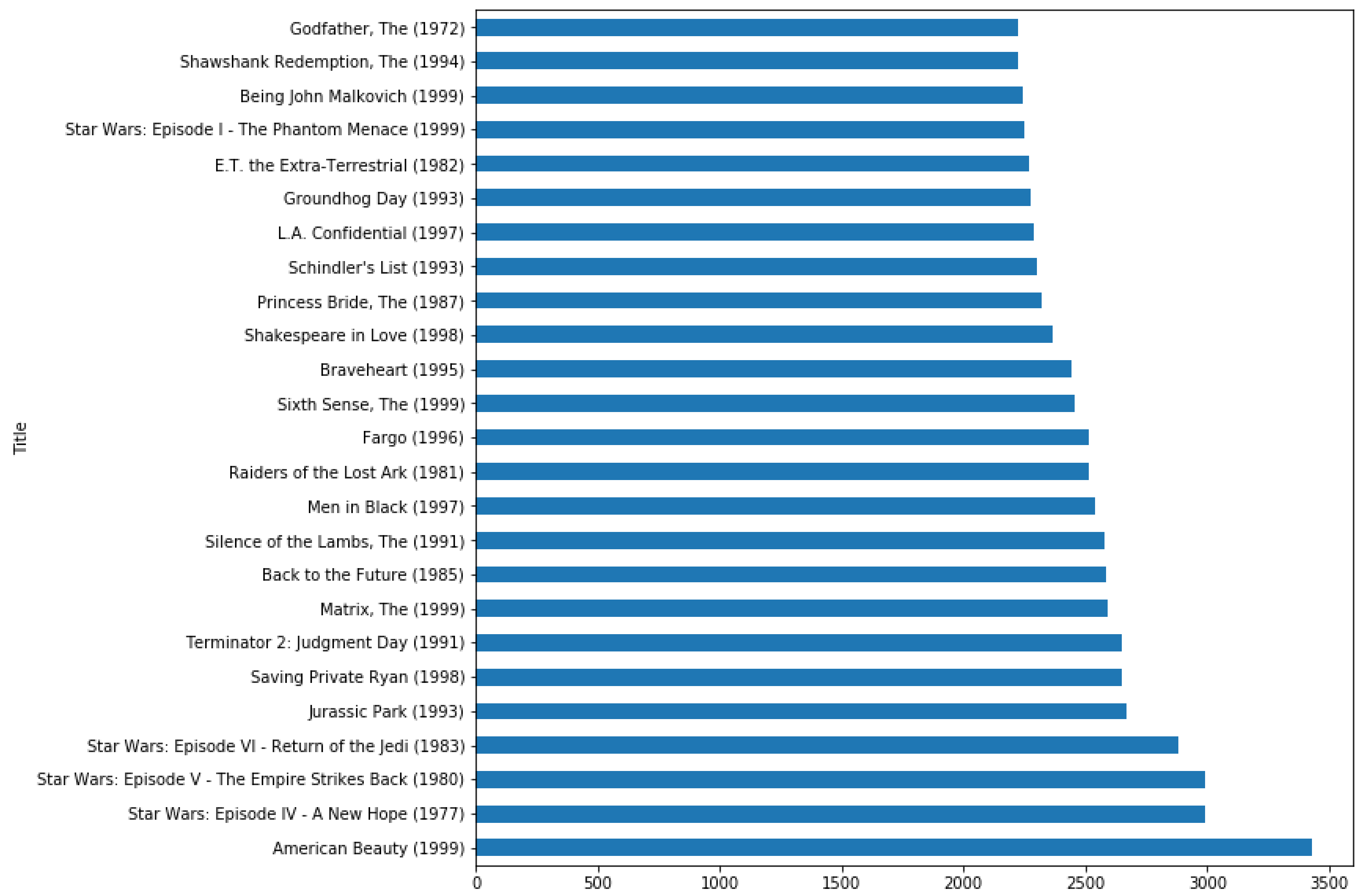
3 Top 25 movies by viewership rating

In [19]:
```
Top_rating = Master_data.groupby(['Title']).Rating.count().nlargest(25)
Top_rating
```

Out[19]:
```
Title
American Beauty (1999)                                   3428
Star Wars: Episode IV - A New Hope (1977)                2991
Star Wars: Episode V - The Empire Strikes Back (1980)    2990
Star Wars: Episode VI - Return of the Jedi (1983)        2883
Jurassic Park (1993)                                     2672
Saving Private Ryan (1998)                               2653
Terminator 2: Judgment Day (1991)                        2649
Matrix, The (1999)                                       2590
Back to the Future (1985)                                2583
Silence of the Lambs, The (1991)                         2578
Men in Black (1997)                                      2538
Raiders of the Lost Ark (1981)                           2514
Fargo (1996)                                             2513
Sixth Sense, The (1999)                                  2459
Braveheart (1995)                                        2443
Shakespeare in Love (1998)                               2369
Princess Bride, The (1987)                               2318
Schindler's List (1993)                                  2304
L.A. Confidential (1997)                                 2288
Groundhog Day (1993)                                     2278
E.T. the Extra-Terrestrial (1982)                        2269
Star Wars: Episode I - The Phantom Menace (1999)         2250
Being John Malkovich (1999)                              2241
Shawshank Redemption, The (1994)                         2227
Godfather, The (1972)                                    2223
Name: Rating, dtype: int64
```

In [20]:
```
Top_rating.plot.barh(figsize=(10,10))
```

Out[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1cc0a238fd0>
```



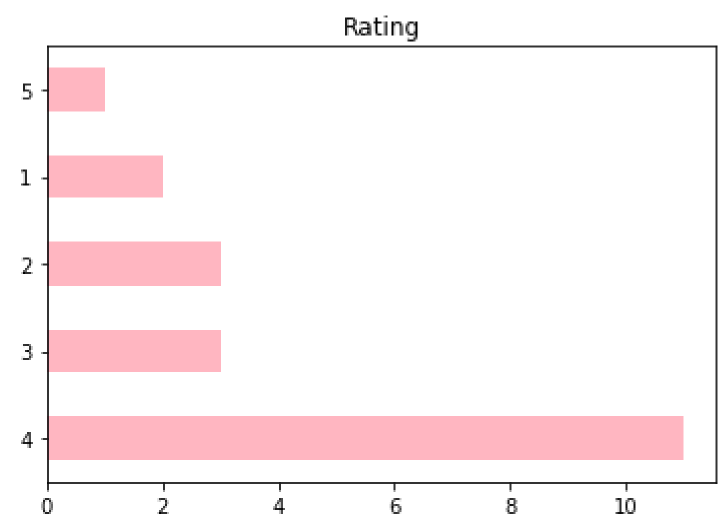
4 Find the ratings for all the movies reviewed by for a particular user of user id = 2696 • Feature Engineering

In [21]:
```
user_Rating =Master_data[(Master_data['UserID']==2696)].Rating.value_counts()
user_Rating
```

Out[21]:
```
4    11
3     3
2     3
1     2
5     1
Name: Rating, dtype: int64
```

In [22]:
```
user_Rating.plot.barh(color='lightpink')
plt.title("Rating")
```

Out[22]:
```
Text(0.5, 1.0, 'Rating')
```



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

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)

In [23]:
```
lst =Master_data.Genres.str.split("|").tolist()
final=[]
for i in lst:
    for j in i:
        final.append(j)
```

In [24]:
```
list(set(final))
```

Out[24]:
```
['Action',
 'Film-Noir',
 'Drama',
 'Musical',
 'War',
 'Fantasy',
 'Horror',
 'Mystery',
 'Crime',
 'Documentary',
 'Animation',
 'Sci-Fi',
 'Western',
 'Thriller',
 'Romance',
 'Comedy',
 "Children's",
 'Adventure']
```

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.

In [25]:
```
#Create a separate column for each genre category with a one-hot encoding ( 1 and 0)
Master_data.Genres.str.get_dummies("|")
```

Out[25]:

	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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1000204	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0
1000205	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0
1000206	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0
1000207	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
1000208	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0

1000209 rows × 18 columns

In [26]:
```
finalOHEDF = pd.concat([Master_data.Genres.str.get_dummies("|") , Master_data.iloc[:,[0,1,3,7,8,9,5,6,4]]] , axis=1)
```

In [27]:
```
finalOHEDF
```

Out[27]:

	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	...	Western	MovieID	Title	UserID	Age	Occupation	Zip_code	Timestaemp	Gender	Rating
0	0	0	1	1	1	0	0	0	0	0	...	0	1	Toy Story (1995)	1	1	10	48067	978824268	F	5
1	0	0	1	1	0	0	0	0	0	0	...	0	48	Pocahontas (1995)	1	1	10	48067	978824351	F	5
2	0	0	0	0	0	0	0	1	0	0	...	0	150	Apollo 13 (1995)	1	1	10	48067	978301777	F	5
3	1	1	0	0	0	0	0	0	1	0	...	0	260	Star Wars: Episode IV - A New Hope (1977)	1	1	10	48067	978300760	F	4
4	0	0	0	0	0	0	0	1	0	0	...	0	527	Schindler's List (1993)	1	1	10	48067	978824195	F	5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1000204	0	0	0	0	0	0	0	1	0	0	...	0	3513	Rules of Engagement (2000)	5727	25	4	92843	958489970	M	4
1000205	0	0	0	0	1	0	0	0	0	0	...	0	3535	American Psycho (2000)	5727	25	4	92843	958489970	M	2
1000206	0	0	0	0	1	0	0	0	0	0	...	0	3536	Keeping the Faith (2000)	5727	25	4	92843	958489902	M	5
1000207	1	0	0	0	0	0	0	0	0	0	...	0	3555	U-571 (2000)	5727	25	4	92843	958490699	M	3
1000208	1	0	0	0	0	0	0	1	0	0	...	0	3578	Gladiator (2000)	5727	25	4	92843	958490171	M	5

1000209 rows × 27 columns

3 Determine the features affecting the ratings of any particular movie

In [28]:
```
Master_Data1=Master_data[Master_data.Title=='American Beauty (1999)']
Master_Data1.head()
```

Out[28]:

	MovieID	Title	Genres	UserID	Rating	Timestaemp	Gender	Age	Occupation	Zip_code
103	2858	American Beauty (1999)	Comedy|Drama	6	1	978236809	F	50	9	55117
236	2858	American Beauty (1999)	Comedy|Drama	8	5	978229817	M	25	12	11413
342	2858	American Beauty (1999)	Comedy|Drama	9	4	978225333	M	25	17	61614
691	2858	American Beauty (1999)	Comedy|Drama	10	3	978224627	F	35	1	95370
1022	2858	American Beauty (1999)	Comedy|Drama	18	5	978156168	F	18	3	95825

In [29]:
```
from scipy.stats import chi2_contingency

ctMovieId = pd.crosstab(Master_Data1.MovieID,Master_Data1.Rating)
ctTitle = pd.crosstab(Master_Data1.Title,Master_Data1.Rating)
ctUserID = pd.crosstab(Master_Data1.UserID,Master_Data1.Rating)
ctGender = pd.crosstab(Master_Data1.Gender,Master_Data1.Rating)
ctAge = pd.crosstab(Master_Data1.Age,Master_Data1.Rating)
ctOccupation = pd.crosstab(Master_Data1.Occupation,Master_Data1.Rating)
ctZipCode = pd.crosstab(Master_Data1['Zip_code'],Master_Data1.Rating)
```

In [30]:
```
from scipy.stats import chi2_contingency

list1 = [ctTitle,ctTitle,ctUserID,ctGender,ctAge,ctOccupation,ctZipCode]

for i in list1:
    stat,pvalue,dof,expected_R = chi2_contingency(i)
    if pvalue <= 0.05:
        print("Alternate Hypothesis passed. {0:10} and Rating have Relationship  pvalue = {1:2}".format(i.index.name,pvalue))
    else:
        print("Null hypothesis passed. {} and Profit doesnot have  Relationship".format(i.index.name))
```

```
Null hypothesis passed. Title and Profit doesnot have  Relationship
Null hypothesis passed. Title and Profit doesnot have  Relationship
Null hypothesis passed. UserID and Profit doesnot have  Relationship
Alternate Hypothesis passed. Gender     and Rating have Relationship  pvalue = 0.006693963902916528
Alternate Hypothesis passed. Age        and Rating have Relationship  pvalue = 1.7165792272634493e-09
Alternate Hypothesis passed. Occupation and Rating have Relationship  pvalue = 0.0015706433878116685
Null hypothesis passed. Zip_code and Profit doesnot have  Relationship
```

4 .Create a model using above features

In [31]:
```
features = Master_Data1.loc[:,["Gender","Occupation","Age"]].values
label = Master_Data1.loc[:,'Rating'].values
```

In [32]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
le = LabelEncoder()
features[:,0] = le.fit_transform(features[:,0])

ohe = OneHotEncoder(categorical_features=[0])
features = ohe.fit_transform(features).toarray()
```

```
C:\Users\nilesh\Anaconda3\lib\site-packages\sklearn\preprocessing\_encoders.py:451: DeprecationWarning: The 'categorical_features' keyword is deprecated in version 0.20 and will be removed in 0.22. You can use the ColumnTransformer instead.
  "use the ColumnTransformer instead.", DeprecationWarning)
```

In [33]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(features, label,
                                                 test_size = 0.2,
                                                 random_state=1)
```

In [34]:
```
features.shape
```

Out[34]:
```
(3428, 4)
```

xgboost

In [35]:
```
from xgboost import XGBRFClassifier
xgb =  XGBRFClassifier(n_estimators=200)
xgb.fit(x_train,y_train)
```

Out[35]:
```
XGBRFClassifier(base_score=0.5, colsample_bylevel=1, colsample_bynode=0.8,
                colsample_bytree=1, gamma=0, learning_rate=1, max_delta_step=0,
                max_depth=3, min_child_weight=1, missing=None, n_estimators=200,
                n_jobs=1, nthread=None, objective='multi:softprob',
                random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
                seed=None, silent=None, subsample=0.8, verbosity=1)
```

In [36]:
```
xgb.score(x_train,y_train)
```

Out[36]:
```
0.5725747629467542
```

In [37]:
```
xgb.score(x_test,y_test)
```

Out[37]:
```
0.5728862973760933
```

KNN

In [38]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(features, label,
                                                 test_size = 0.2,
                                                 random_state=3)

from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=20)
knn.fit(x_train,y_train)
print(knn.score(x_train,y_train))
print(knn.score(x_test,y_test))
```

```
0.5681983953318746
0.5685131195335277
```

Random Forest

In [39]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(features, label,
                                                 test_size = 0.2,
                                                 random_state=4)

from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=200)
rf.fit(x_train,y_train)
print(rf.score(x_train,y_train))
print(rf.score(x_test, y_test))
```

```
0.587527352297593
0.575801749271137
```

In [ ]: