Project_3:- Movielence_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

Import the libraries

In [2]:
```
import pandas as pd
import numpy as np
```

```
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Loading all three datasets

In [3]:
```
movi_data = pd.read_csv('movies.dat' ,sep='::' ,header=None, names=['MovieID','Titl
rating_data = pd.read_csv('ratings.dat',sep='::',header=None, names=['UserID', 'Mov
user_data = pd.read_csv('users.dat', sep='::',header=None , names=['UserID', 'Gende
```

In [4]:
```
movi_data.head()
```

Out[4]:

	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 [5]:
```
movi_data.shape
```

Out[5]:
```
(3883, 3)
```

In [6]:
```
movi_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3883 entries, 0 to 3882
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   MovieID  3883 non-null   int32 
 1   Title    3883 non-null   object
 2   Genres   3883 non-null   object
dtypes: int32(1), object(2)
memory usage: 76.0+ KB
```

In [7]:
```
movi_data.isnull().sum()
```

Out[7]:
```
MovieID    0
Title      0
Genres     0
dtype: int64
```

In [8]:
```
#There are no empty colums in movi_data
```

In [9]:
```
rating_data.info()
rating_data.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 4 columns):
 #   Column     Non-Null Count    Dtype 
---  ------     --------------    ----- 
 0   UserID     1000209 non-null  int32 
 1   MovieID    1000209 non-null  int64 
 2   Rating     1000209 non-null  int32 
 3   Timestamp  1000209 non-null  object
dtypes: int32(2), int64(1), object(1)
memory usage: 22.9+ MB
```

Out[9]:
```
UserID       0
MovieID      0
Rating       0
Timestamp    0
dtype: int64
```

In [10]:
```
rating_data.head()
```

Out[10]:

	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

In [11]:
```
rating_data.shape
```

Out[11]:
```
(1000209, 4)
```

In [12]:
```
#There are no empty colums in rating_data
```

In [13]:
```
user_data.info()
user_data.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6040 entries, 0 to 6039
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   UserID      6040 non-null   int32 
 1   Gender      6040 non-null   object
 2   Age         6040 non-null   int32 
 3   Occupation  6040 non-null   int32 
 4   Zip_Code    6040 non-null   object
dtypes: int32(3), object(2)
memory usage: 165.3+ KB
```

Out[13]:
```
UserID        0
Gender        0
Age           0
Occupation    0
Zip_Code      0
dtype: int64
```

In [14]:
```
user_data.head()
```

Out[14]:

	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

In [15]:
```
user_data.shape
```
Out[15]:
```
(6040, 5)
```

In [16]:
```
#There are no empty colums in user_data
```

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

In [17]:
```
first_two_data_merging = pd.merge(movi_data, rating_data, on = 'MovieID')
first_two_data_merging
```

Out[17]:

	MovieID	Title	Genres	UserID	Rating	Timestamp
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 [18]:
```
all_Three_Data = pd.merge(first_two_data_merging, user_data, on = 'UserID')
all_Three_Data.head(10)
```

Out[18]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351	F
2	150	Apollo 13 (1995)	Drama	1	5	978301777	F
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	978300760	F
4	527	Schindler's List (1993)	Drama|War	1	5	978824195	F
5	531	Secret Garden, The (1993)	Children's|Drama	1	4	978302149	F
6	588	Aladdin (1992)	Animation|Children's|Comedy|Musical	1	4	978824268	F
7	594	Snow White and the Seven Dwarfs (1937)	Animation|Children's|Musical	1	4	978302268	F
8	595	Beauty and the Beast (1991)	Animation|Children's|Musical	1	5	978824268	F
9	608	Fargo (1996)	Crime|Drama|Thriller	1	4	978301398	F

In [19]:

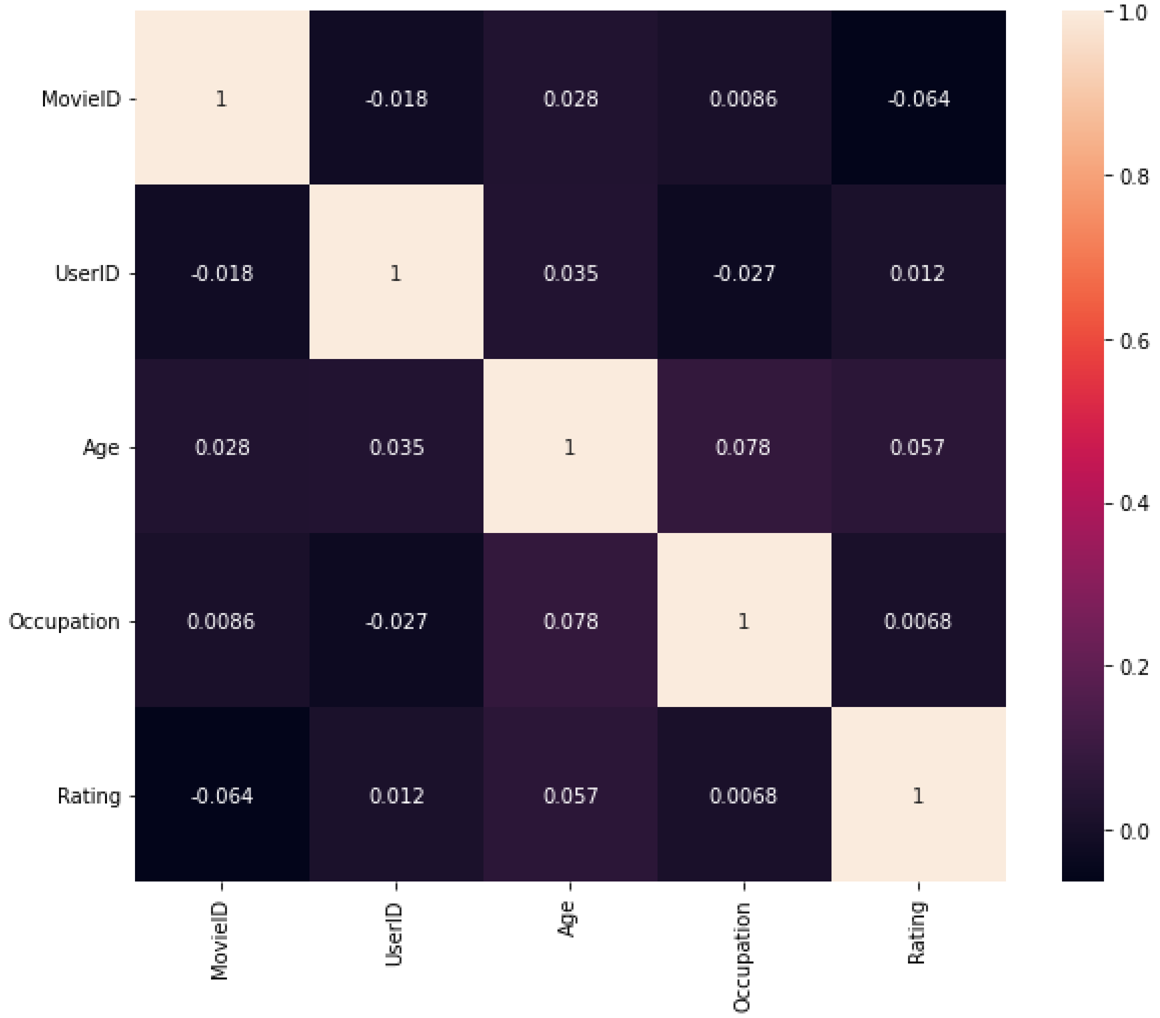
```
master_Data = all_Three_Data[['MovieID','Title','UserID','Age','Gender','Occupatio
master_Data.head(10)
```

Out[19]:

	MovieID	Title	UserID	Age	Gender	Occupation	Rating
0	1	Toy Story (1995)	1	1	F	10	5
1	48	Pocahontas (1995)	1	1	F	10	5
2	150	Apollo 13 (1995)	1	1	F	10	5
3	260	Star Wars: Episode IV - A New Hope (1977)	1	1	F	10	4
4	527	Schindler's List (1993)	1	1	F	10	5
5	531	Secret Garden, The (1993)	1	1	F	10	4
6	588	Aladdin (1992)	1	1	F	10	4
7	594	Snow White and the Seven Dwarfs (1937)	1	1	F	10	4
8	595	Beauty and the Beast (1991)	1	1	F	10	5
9	608	Fargo (1996)	1	1	F	10	4

In [48]:
```
correlation = master_Data.corr()
plt.figure(figsize=(10,8))
sns.heatmap(data=correlation,square=True,annot=True)
plt.yticks(rotation=0)
plt.xticks(rotation=90)
```

Out[48]:
```
(array([0.5, 1.5, 2.5, 3.5, 4.5]),
 [Text(0.5, 0, 'MovieID'),
  Text(1.5, 0, 'UserID'),
  Text(2.5, 0, 'Age'),
  Text(3.5, 0, 'Occupation'),
  Text(4.5, 0, 'Rating')])
```



In [20]:
```
master_Data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns (total 7 columns):
 #   Column      Non-Null Count    Dtype
---  ------      --------------    -----
 0   MovieID     1000209 non-null  int32
 1   Title       1000209 non-null  object
 2   UserID      1000209 non-null  int32
 3   Age         1000209 non-null  int32
 4   Gender      1000209 non-null  object
 5   Occupation  1000209 non-null  int32
 6   Rating      1000209 non-null  int32
dtypes: int32(5), object(2)
memory usage: 42.0+ MB
```

In [21]:
```
master_Data.shape
```

Out[21]:
```
(1000209, 7)
```

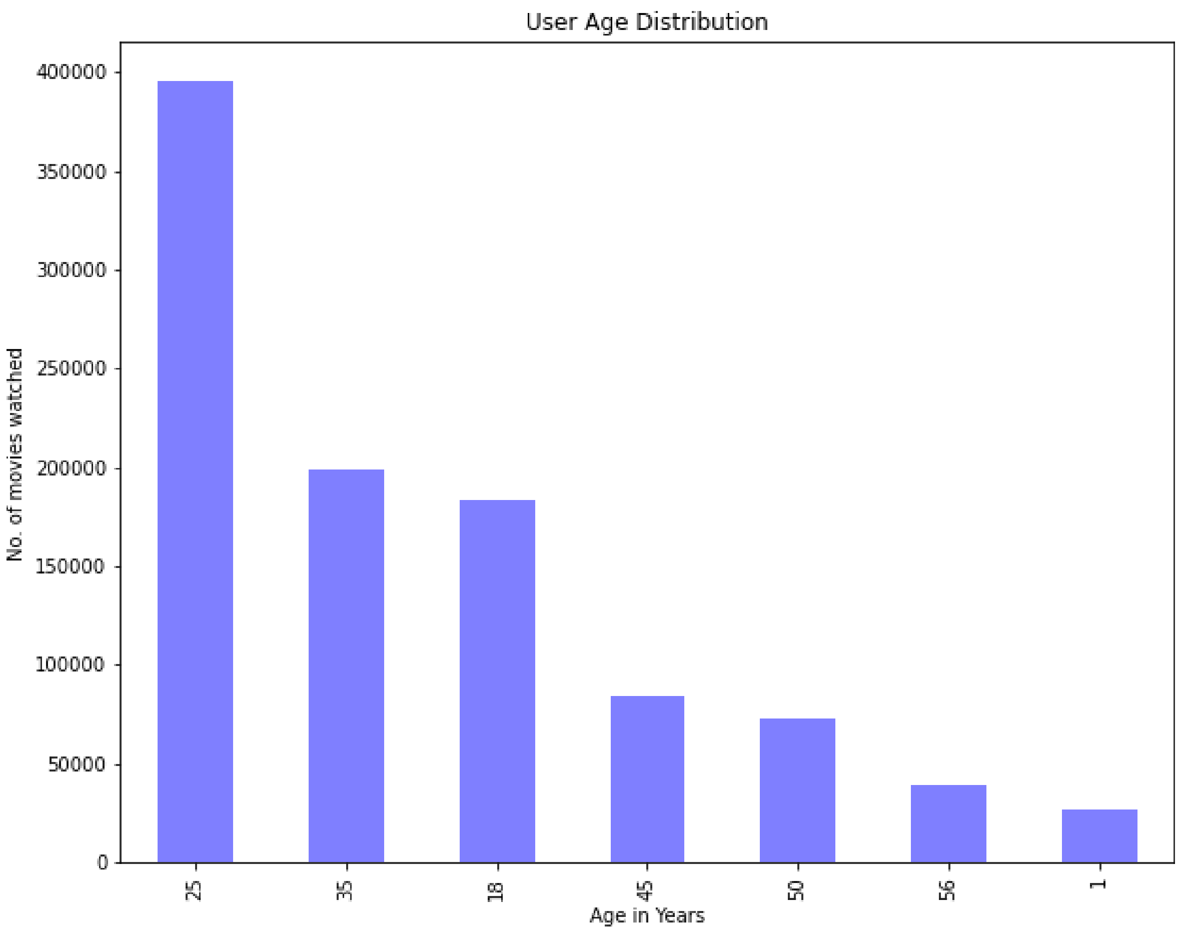
In [22]:
```
master_Data.isnull().sum()
```

Out[22]:
```
MovieID       0
Title         0
UserID        0
Age           0
Gender        0
Occupation    0
Rating        0
dtype: int64
```

Explore the datasets using visual representations (graphs or tables)

1. User Age Distribution

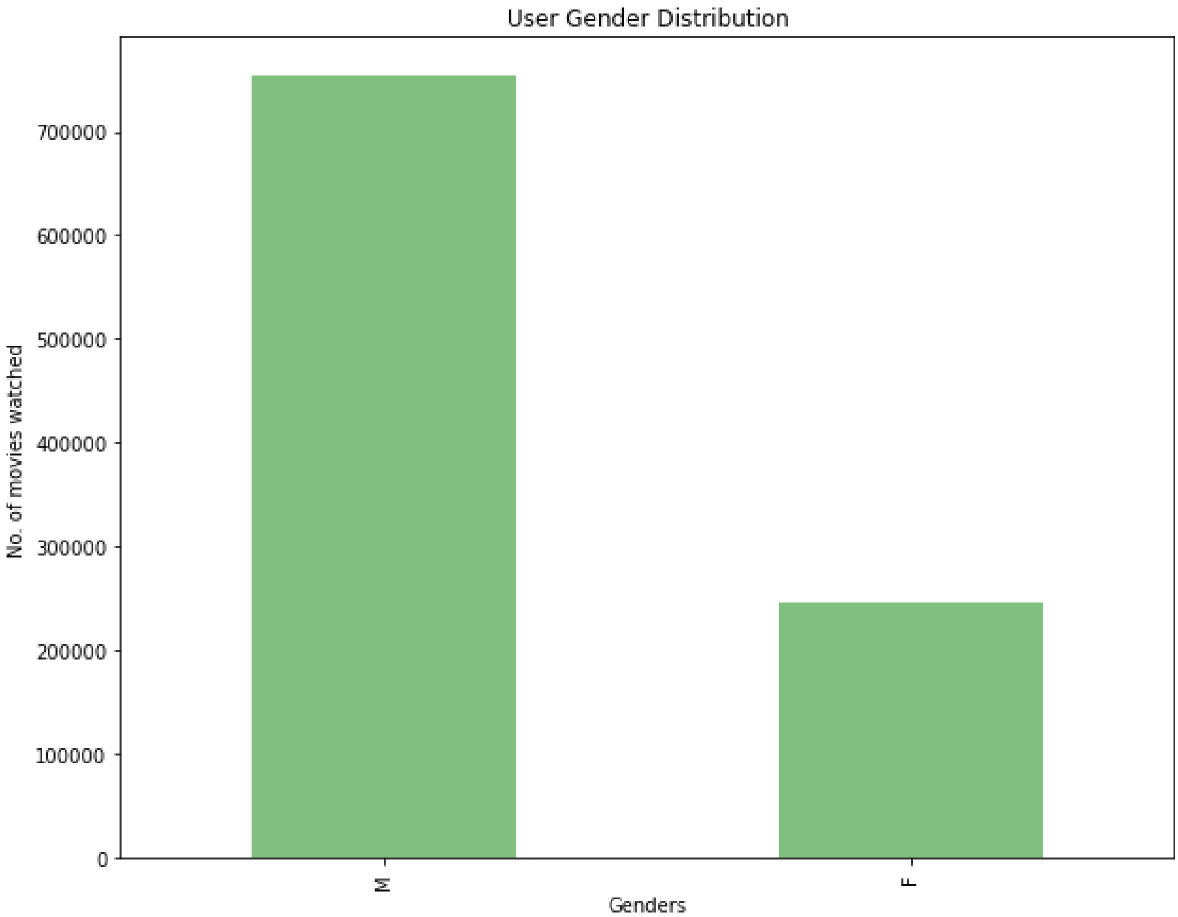
In [23]:
```
plt.figure(figsize=(10,8))
master_Data['Age'].value_counts().plot(kind='bar',color='b',alpha=0.50)
plt.xlabel('Age in Years')
plt.ylabel('No. of movies watched')
plt.title("User Age Distribution")
plt.show()
```



Comments:- Most movie watching age groups are 25 to 35 year old.

In [24]:
```
plt.figure(figsize=(10,8))
master_Data['Gender'].value_counts().plot(kind='bar',color='g',alpha=0.50)
plt.xlabel('Genders')
plt.ylabel('No. of movies watched')
```

```
plt.title("User Gender Distribution")
plt.show()
```



Comments:- Most movie watching by Male Genders.

2. User rating of the movie “Toy Story”

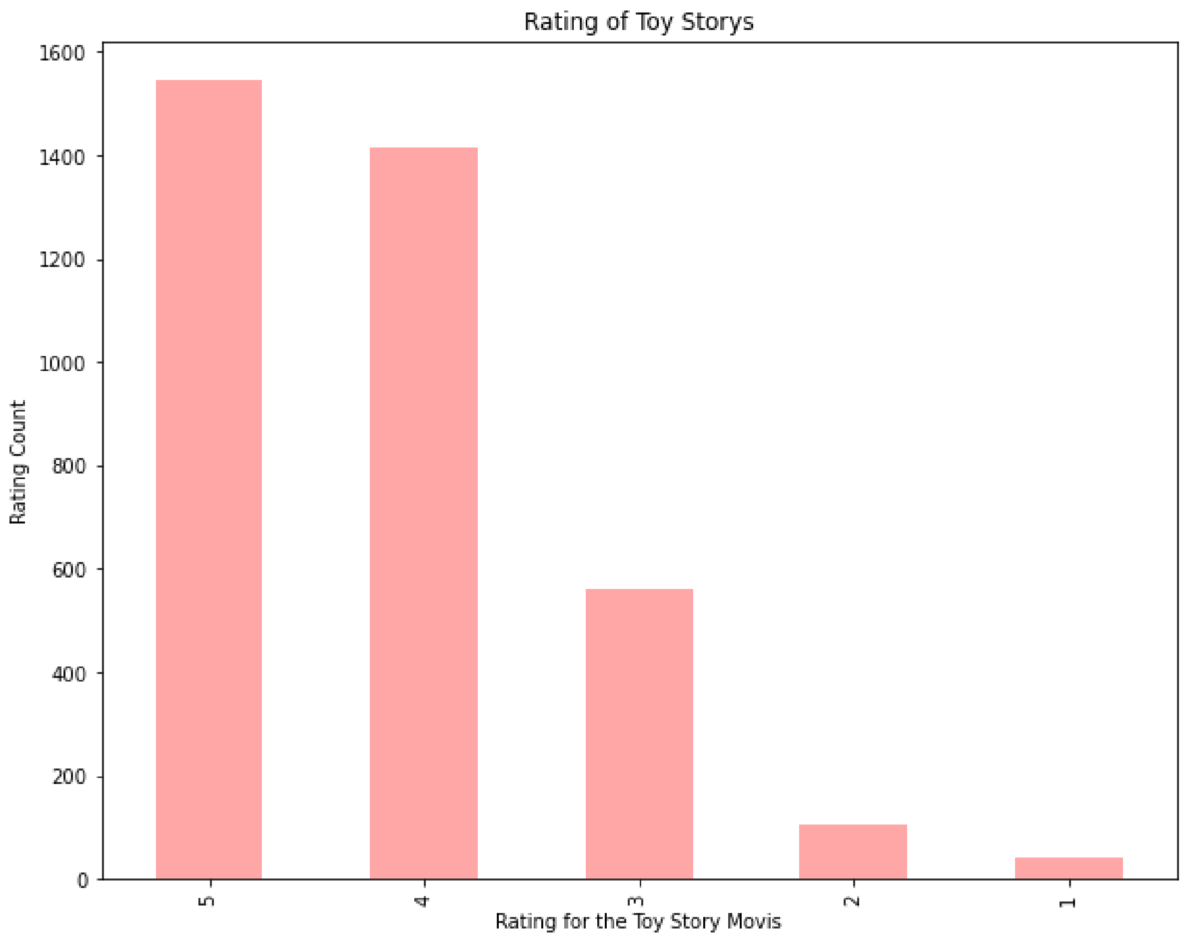
In [25]:
```
#creat datafram for toy story (1995)
Toy_story = master_Data.loc[master_Data['Title'].str.contains("Toy Story")]
print (Toy_story)
```

```
         MovieID              Title  UserID  Age Gender  Occupation  Rating
0              1   Toy Story (1995)       1    1      F          10       5
50          3114 Toy Story 2 (1999)       1    1      F          10       4
53             1   Toy Story (1995)       6   50      F           9       4
124            1   Toy Story (1995)       8   25      M          12       4
263            1   Toy Story (1995)       9   25      M          17       5
...          ...                ...     ...  ...    ...         ...     ...
998988      3114 Toy Story 2 (1999)    3023   25      F           7       4
999027      3114 Toy Story 2 (1999)    5800   35      M          18       5
999486      3114 Toy Story 2 (1999)    2189    1      M          10       4
999869      3114 Toy Story 2 (1999)     159   45      F           0       4
1000192     3114 Toy Story 2 (1999)    5727   25      M           4       5

[3662 rows x 7 columns]
```

In [26]:
```
#Count rating for Toy Story
Toy_story['Rating'].value_counts()
```

Out[26]:
```
5    1544
4    1413
3     559
2     105
1      41
Name: Rating, dtype: int64
```

In [27]:
```
plt.figure(figsize=(10,8))
Toy_story['Rating'].value_counts().plot(kind='bar',color='r',alpha=0.35)
plt.xlabel('Rating for the Toy Story Movis')
plt.ylabel('Rating Count')
plt.title("Rating of Toy Storys")
plt.show()
```



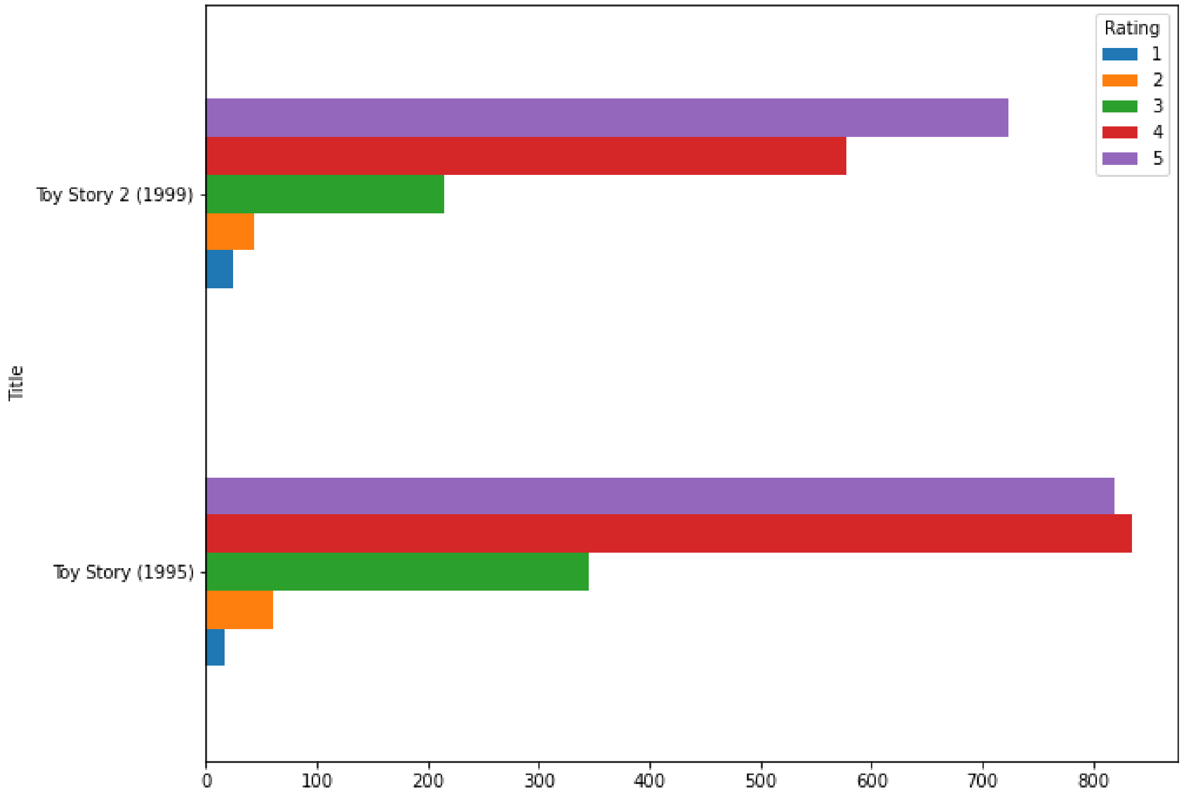
In [28]:
```
# Dictionary
df_movi_rating = {'Rating': ['5', '4', '3','2', '1'],'Rating Count': [1544, 1413, !
# Create a DataFrame
df_movi_rating = pd.DataFrame(df_movi_rating, columns = ['Rating','Rating Count'])

# Calculating Percentage
df_movi_rating['percent'] = (df_movi_rating['Rating Count'] /
                  df_movi_rating['Rating Count'].sum()) * 100

# Show the dataframe
df_movi_rating.head()
```

Out[28]:

	Rating	Rating Count	percent
0	5	1544	42.162753
1	4	1413	38.585472
2	3	559	15.264883
3	2	105	2.867286
4	1	41	1.119607

Comments:- According to data, 42% people have given 5 star rating and 38% people have given 4 star rating to Toystory Movi.

In [29]:
```
Toy_story.groupby(["Title","Rating"]).size().unstack().plot(kind='barh',stacked=Fa
plt.show()
```



In [ ]:
```
toy
```

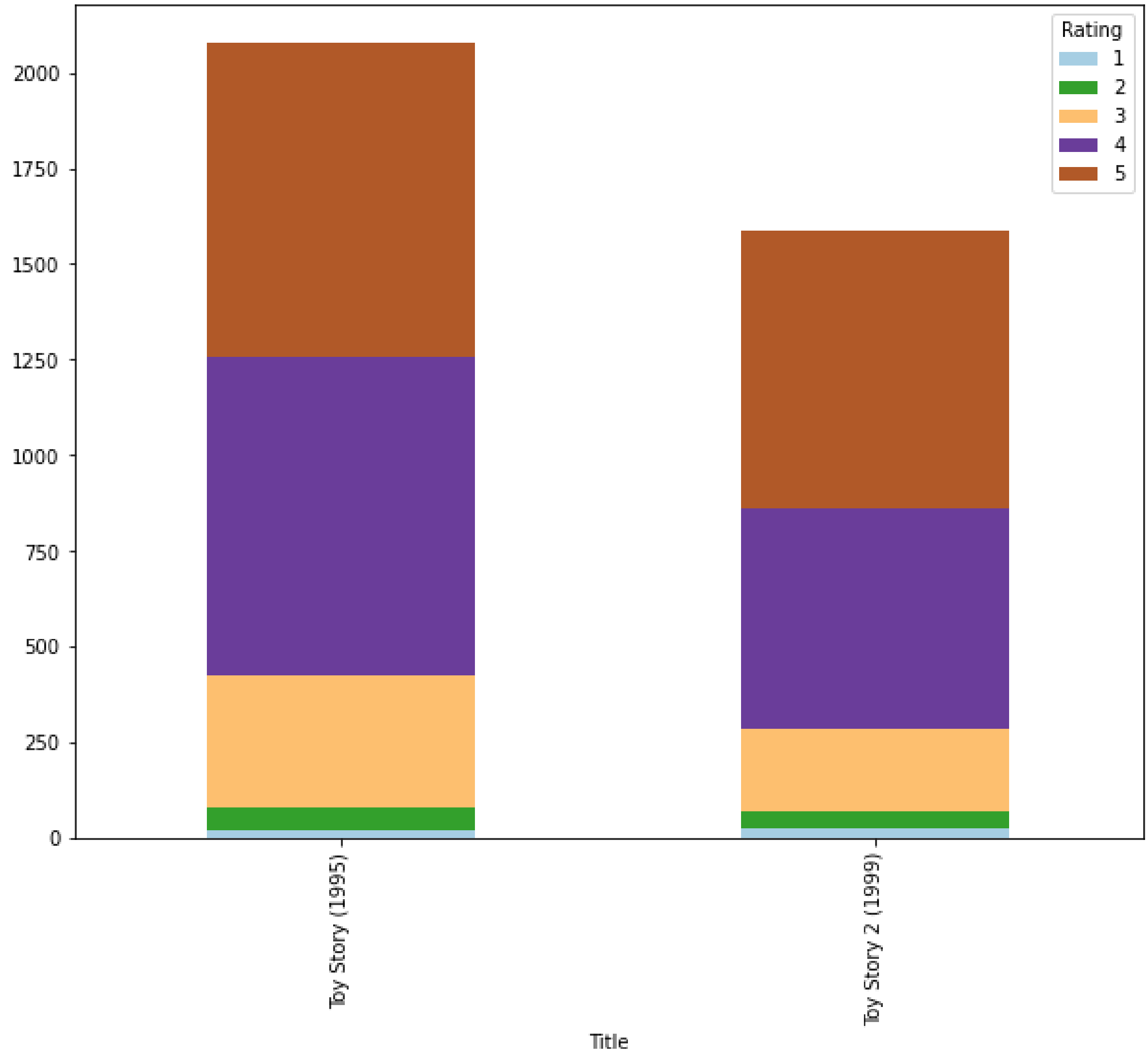
In [51]:
```
crosstab_toy_S = pd.crosstab(index=Toy_story['Title'],columns=Toy_story['Rating'])
crosstab_toy_S
```

Out[51]:

Rating	1	2	3	4	5
Title					
Toy Story (1995)	16	61	345	835	820
Toy Story 2 (1999)	25	44	214	578	724

In [53]:
```
crosstab_toy_S.plot(kind="bar", figsize=(10,8), stacked=True, colormap = 'Paired')
```

Out[53]: <AxesSubplot:xlabel='Title'>



3. Top 25 movies by viewership rating

In [61]:
```
# Explore Movi data for viewership by movie title
movi_data_count_by_rating = master_Data['Title'].value_counts()[0:25]
movi_data_count_by_rating
```

Out[61]:

```
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: Title, dtype: int64
```

In [32]:

```
# top 25 movis rating mean
Titalewise_mean = pd.DataFrame(master_Data.groupby('Title')['Rating'].mean())
Titalewise_mean.head()
```

Out[32]:

Title	Rating
$1,000,000 Duck (1971)	3.027027
'Night Mother (1986)	3.371429
'Til There Was You (1997)	2.692308
'burbs, The (1989)	2.910891
...And Justice for All (1979)	3.713568

In [33]:

```
Top_25 = Titalewise_mean.sort_values('Rating', ascending=False)
Top_25.head(25)
```

Out[33]:

	Rating
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

In [80]:
```
Top_25.shape
```

Out[80]:
```
(3706, 1)
```

In [86]:
```
Top_25_crosstab= pd.crosstab(index=master_Data['Title'],columns=master_Data['Ratin
Top_25_crosstab
```

Out[86]:

Rating	1	2	3	4	5
Title					
$1,000,000 Duck (1971)	3	8	15	7	4
'Night Mother (1986)	4	10	25	18	13
'Til There Was You (1997)	5	20	15	10	2
'burbs, The (1989)	36	69	107	68	23
...And Justice for All (1979)	2	12	65	82	38
...	...	...	...	...	...
Zed & Two Noughts, A (1985)	2	3	8	13	3
Zero Effect (1998)	7	32	72	108	82
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0	0	1	1	0
Zeus and Roxanne (1997)	5	6	8	3	1
eXistenZ (1999)	43	61	109	142	55

3706 rows × 5 columns

In [93]:

```
Top_25_ratting_count = master_Data.value_counts('Title').reset_index(name='counts'
Top_25_ratting_count
```

Out[93]:

	Title	counts
0	American Beauty (1999)	3428
1	Star Wars: Episode IV - A New Hope (1977)	2991
2	Star Wars: Episode V - The Empire Strikes Back...	2990
3	Star Wars: Episode VI - Return of the Jedi (1983)	2883
4	Jurassic Park (1993)	2672
...	...	...
3701	Target (1995)	1
3702	I Don't Want to Talk About It (De eso no se ha...	1
3703	An Unforgettable Summer (1994)	1
3704	Never Met Picasso (1996)	1
3705	Full Speed (1996)	1

3706 rows × 2 columns

In [95]:

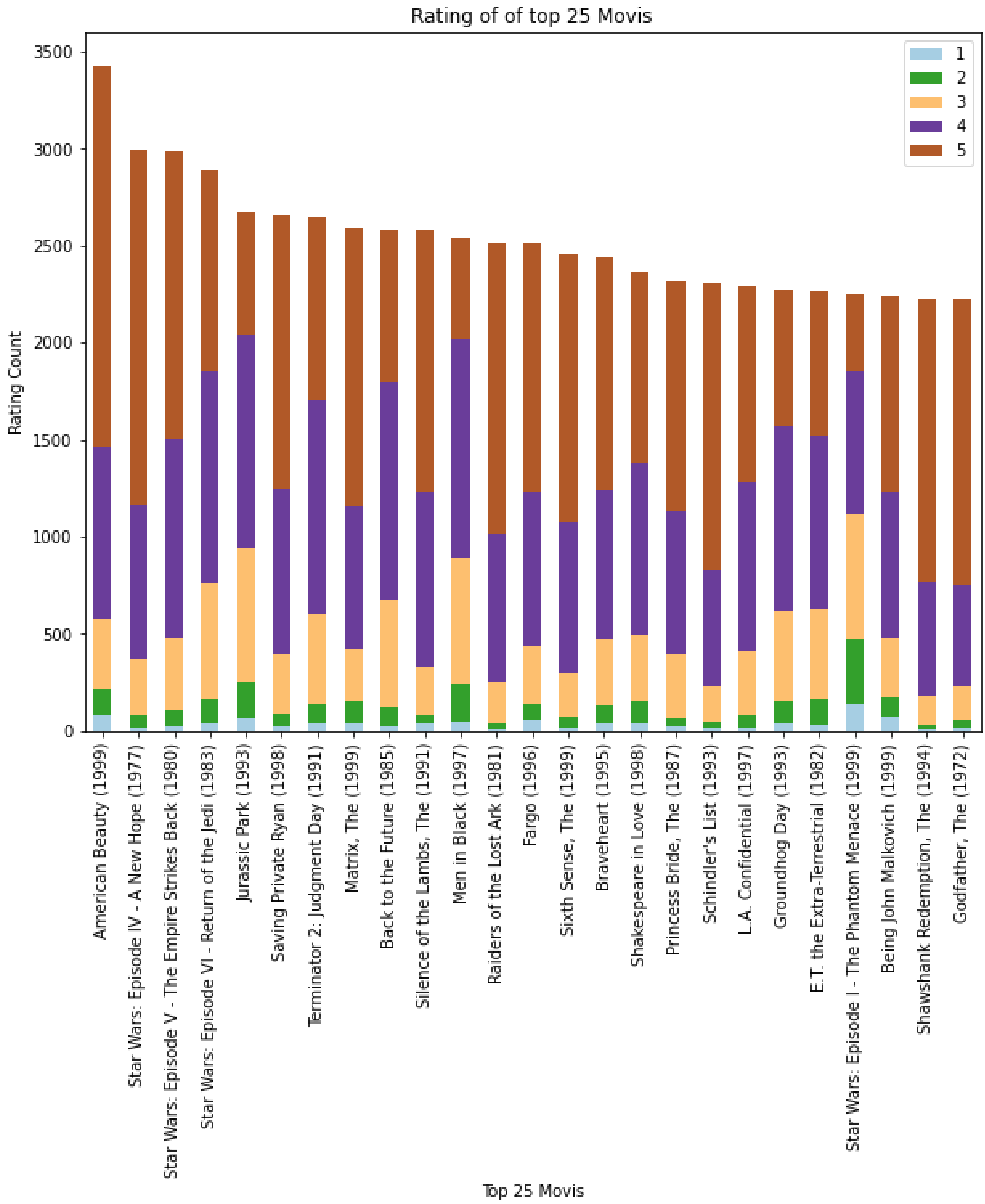
```
#merge top 25 movi coloum with Stacked datafram
top_25_Movi_rating_cross = pd.merge(Top_25_crosstab, Top_25_ratting_count, how="ri
top_25_Movi_rating_cross
```

Out[95]:

	Title	1	2	3	4	5	counts
0	American Beauty (1999)	83	134	358	890	1963	3428
1	Star Wars: Episode IV - A New Hope (1977)	19	62	288	796	1826	2991
2	Star Wars: Episode V - The Empire Strikes Back...	22	83	375	1027	1483	2990
3	Star Wars: Episode VI - Return of the Jedi (1983)	39	128	589	1099	1028	2883
4	Jurassic Park (1993)	62	197	683	1098	632	2672
5	Saving Private Ryan (1998)	25	67	301	855	1405	2653
6	Terminator 2: Judgment Day (1991)	42	98	465	1102	942	2649
7	Matrix, The (1999)	37	119	263	741	1430	2590
8	Back to the Future (1985)	20	103	550	1119	791	2583
9	Silence of the Lambs, The (1991)	37	43	246	902	1350	2578
10	Men in Black (1997)	47	194	653	1122	522	2538
11	Raiders of the Lost Ark (1981)	4	37	213	760	1500	2514
12	Fargo (1996)	57	85	297	796	1278	2513
13	Sixth Sense, The (1999)	16	58	222	778	1385	2459
14	Braveheart (1995)	37	92	337	771	1206	2443
15	Shakespeare in Love (1998)	37	119	336	890	987	2369
16	Princess Bride, The (1987)	22	44	328	738	1186	2318
17	Schindler's List (1993)	19	28	186	596	1475	2304
18	L.A. Confidential (1997)	17	61	334	867	1009	2288
19	Groundhog Day (1993)	36	121	460	958	703	2278
20	E.T. the Extra-Terrestrial (1982)	33	134	459	896	747	2269
21	Star Wars: Episode I - The Phantom Menace (1999)	143	324	651	732	400	2250
22	Being John Malkovich (1999)	69	106	307	752	1007	2241
23	Shawshank Redemption, The (1994)	8	25	148	589	1457	2227
24	Godfather, The (1972)	18	38	178	514	1475	2223

In [107…

```
#Stacked barplot for ratings and top 25 movis
top_25_Movi_rating_cross.drop(['counts'], axis=1).plot(x="Title" ,kind="bar", figs
plt.xlabel('Top 25 Movis')
plt.ylabel('Rating Count')
plt.title("Rating of of top 25 Movis")
plt.show()
```



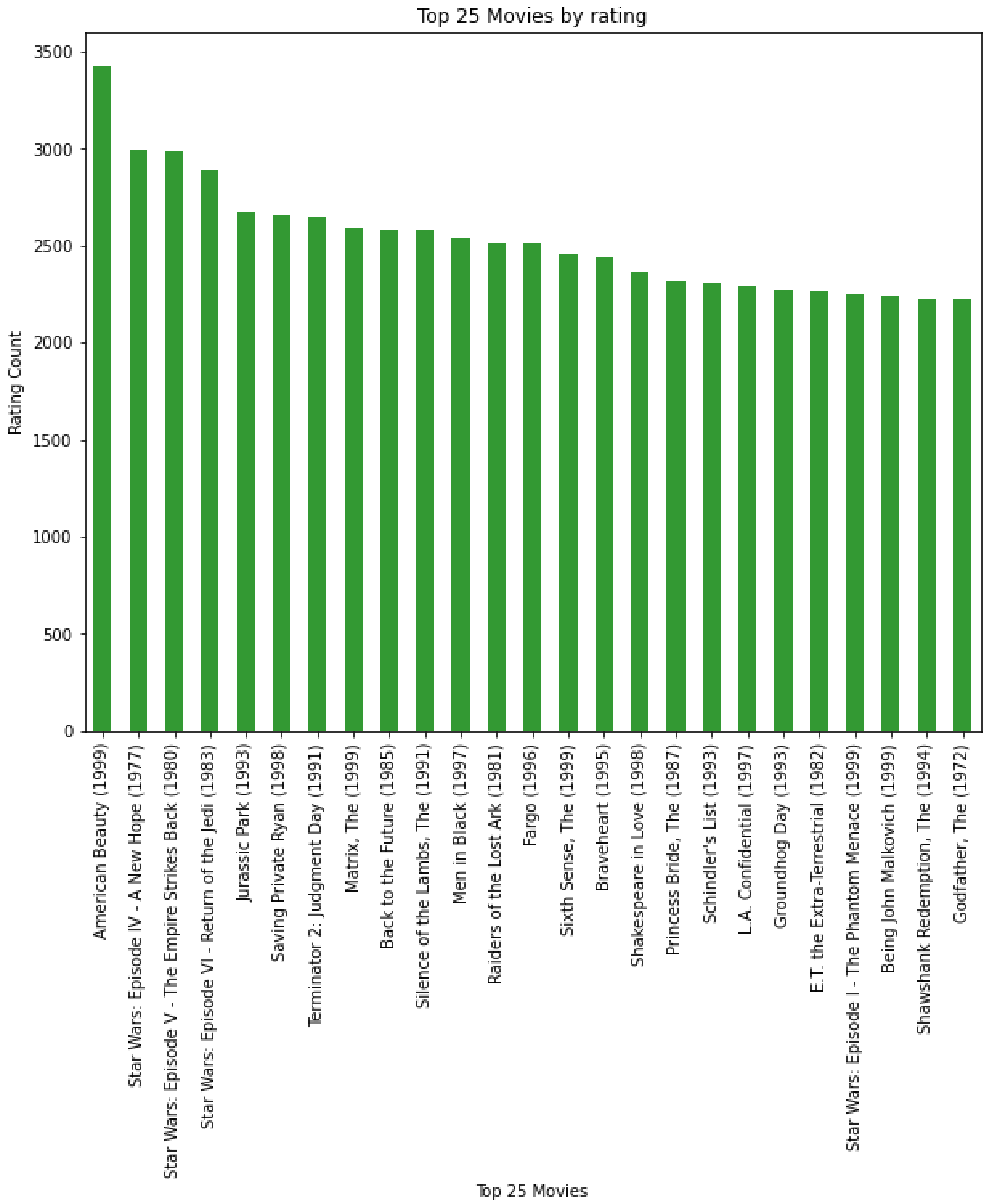
In [68]:
```
top_25_Movi_data = master_Data.groupby('Title').size().sort_values(ascending=False
top_25_Movi_data
```

Out[68]:
```
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
dtype: int64
```

In [69]:
```
top_25_Movi_data.shape
```

Out[69]:
```
(25,)
```

In [38]:
```
top_25_Movi_data.plot(kind='bar',color='g', alpha = 0.8,figsize=(10,8))
plt.xlabel("Top 25 Movies")
plt.ylabel("Rating Count")
plt.title("Top 25 Movies by rating")
plt.show()
```



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

In [39]:
```
data_of_2696 = master_Data[master_Data['UserID']==2696]
data_of_2696.info()
```

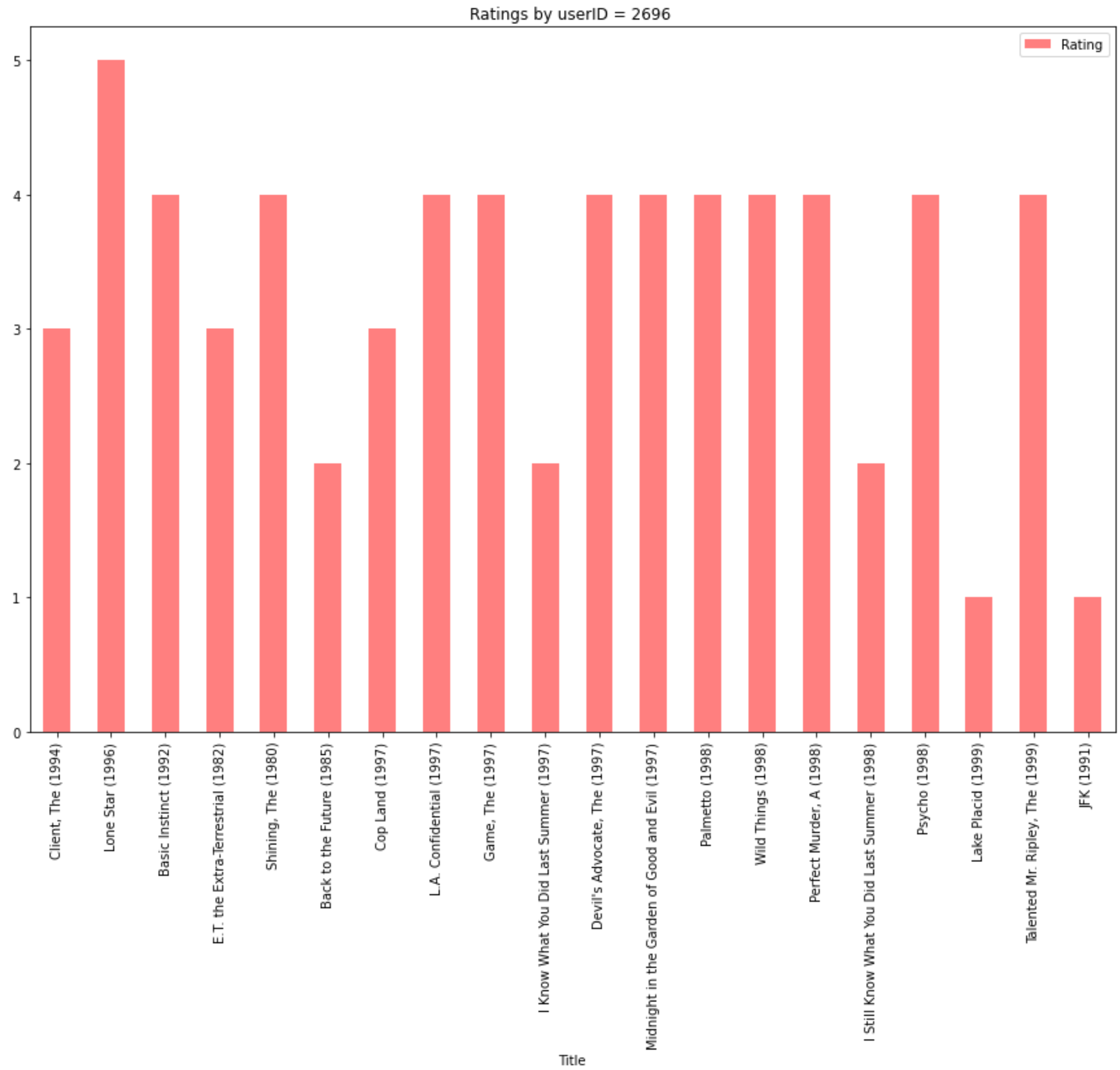
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20 entries, 991035 to 991054
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   MovieID     20 non-null     int32 
 1   Title       20 non-null     object
 2   UserID      20 non-null     int32 
 3   Age         20 non-null     int32 
 4   Gender      20 non-null     object
 5   Occupation  20 non-null     int32 
 6   Rating      20 non-null     int32 
dtypes: int32(5), object(2)
memory usage: 880.0+ bytes
```

In [42]:
```
print (data_of_2696)
```

```
        MovieID                                         Title  UserID  Age  \
991035      350                                 Client, The (1994)    2696   25
991036      800                                   Lone Star (1996)    2696   25
991037     1092                             Basic Instinct (1992)    2696   25
991038     1097                 E.T. the Extra-Terrestrial (1982)    2696   25
991039     1258                                Shining, The (1980)    2696   25
991040     1270                         Back to the Future (1985)    2696   25
991041     1589                                    Cop Land (1997)    2696   25
991042     1617                           L.A. Confidential (1997)    2696   25
991043     1625                                   Game, The (1997)    2696   25
991044     1644             I Know What You Did Last Summer (1997)    2696   25
991045     1645                       Devil's Advocate, The (1997)    2696   25
991046     1711  Midnight in the Garden of Good and Evil (1997)    2696   25
991047     1783                                    Palmetto (1998)    2696   25
991048     1805                                Wild Things (1998)    2696   25
991049     1892                          Perfect Murder, A (1998)    2696   25
991050     2338       I Still Know What You Did Last Summer (1998)    2696   25
991051     2389                                      Psycho (1998)    2696   25
991052     2713                                 Lake Placid (1999)    2696   25
991053     3176                     Talented Mr. Ripley, The (1999)    2696   25
991054     3386                                         JFK (1991)    2696   25

       Gender  Occupation  Rating
991035      M           7       3
991036      M           7       5
991037      M           7       4
991038      M           7       3
991039      M           7       4
991040      M           7       2
991041      M           7       3
991042      M           7       4
991043      M           7       4
991044      M           7       2
991045      M           7       4
991046      M           7       4
991047      M           7       4
991048      M           7       4
991049      M           7       4
991050      M           7       2
991051      M           7       4
991052      M           7       1
991053      M           7       4
991054      M           7       1
```

In [113…
```
data_of_2696.plot(x="Title",y="Rating",kind="bar", color='r', alpha=0.5, figsize=(
```

Out[113]:
```
<AxesSubplot:title={'center':'Ratings by userID = 2696 '}, xlabel='Title'>
```



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)

In [116…

```
Genres_data = all_Three_Data['Genres'].str.get_dummies('|')
print(Genres_data)
```

```
         Action  Adventure  Animation  Children's  Comedy  Crime  Documentary  \
0             0          0          1           1       1      0            0
1             0          0          1           1       0      0            0
2             0          0          0           0       0      0            0
3             1          1          0           0       0      0            0
4             0          0          0           0       0      0            0
...         ...        ...        ...         ...     ...    ...          ...
1000204       0          0          0           0       0      0            0
1000205       0          0          0           0       1      0            0
1000206       0          0          0           0       1      0            0
1000207       1          0          0           0       0      0            0
1000208       1          0          0           0       0      0            0

         Drama  Fantasy  Film-Noir  Horror  Musical  Mystery  Romance  Sci-Fi  \
0            0        0          0       0        0        0        0       0
1            0        0          0       0        1        0        1       0
2            1        0          0       0        0        0        0       0
3            0        1          0       0        0        0        0       1
4            1        0          0       0        0        0        0       0
...        ...      ...        ...     ...      ...      ...      ...     ...
1000204      1        0          0       0        0        0        0       0
1000205      0        0          0       1        0        0        0       0
1000206      0        0          0       0        0        0        1       0
1000207      0        0          0       0        0        0        0       0
1000208      1        0          0       0        0        0        0       0

         Thriller  War  Western
0               0    0        0
1               0    0        0
2               0    0        0
3               0    0        0
4               0    1        0
...           ...  ...      ...
1000204         1    0        0
1000205         1    0        0
1000206         0    0        0
1000207         1    0        0
1000208         0    0        0

[1000209 rows x 18 columns]
```

In [117…

```
Genres_data.columns
```

Out[117]:

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

Comments:- There are 18 unique genres are available in datasets.

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 [119…

```
model_data = all_Three_Data.join(all_Three_Data.pop('Genres').str.get_dummies('|'))
model_data.head()
```

Out[119]:

	MovieID	Title	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip_Code	Actio
0	1	Toy Story (1995)	1	5	978824268	F	1	10	48067	(
1	48	Pocahontas (1995)	1	5	978824351	F	1	10	48067	(
2	150	Apollo 13 (1995)	1	5	978301777	F	1	10	48067	(
3	260	Star Wars: Episode IV - A New Hope (1977)	1	4	978300760	F	1	10	48067	
4	527	Schindler's List (1993)	1	5	978824195	F	1	10	48067	(

5 rows × 27 columns

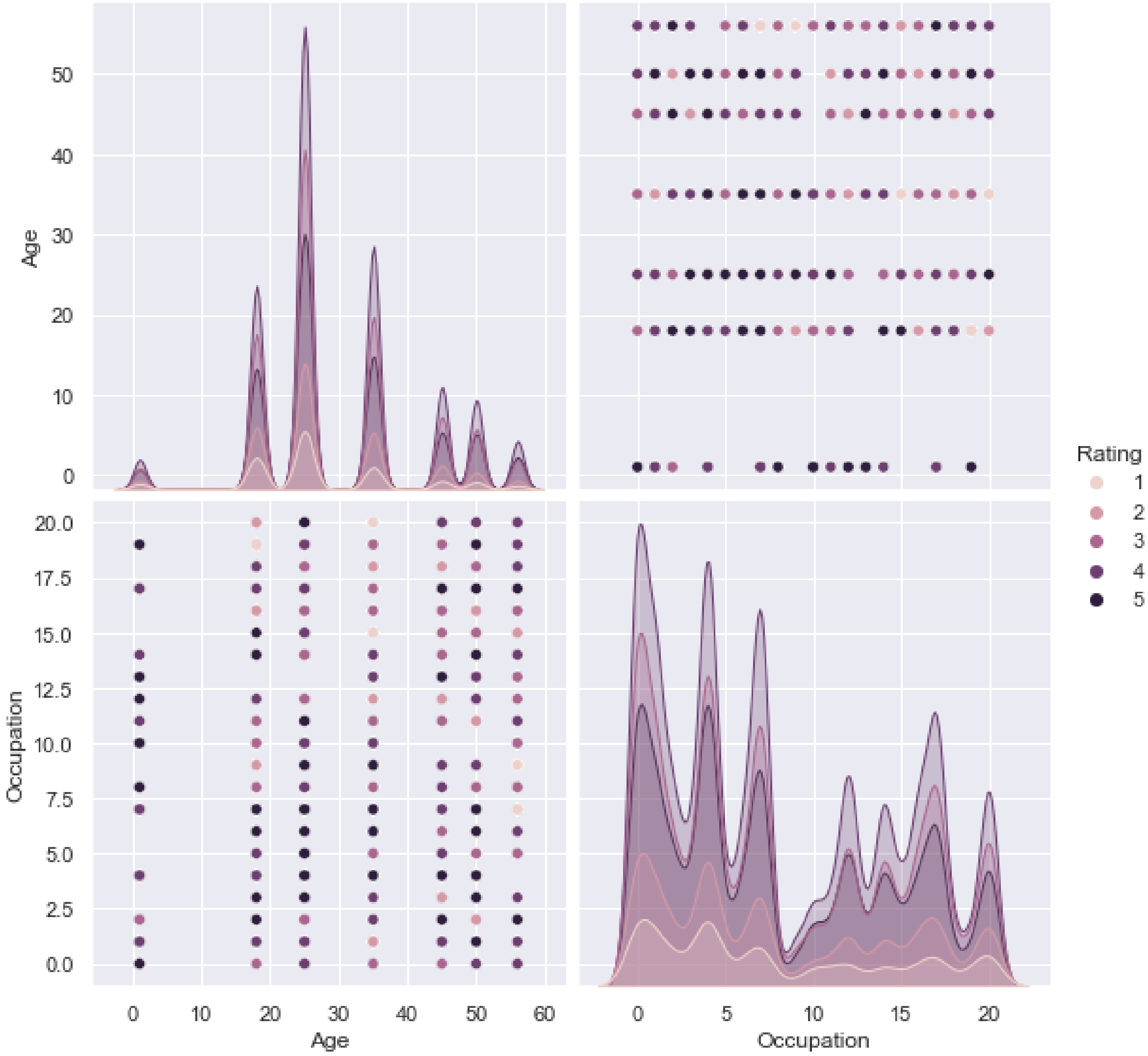
3. Determine the features affecting the ratings of any particular movie.

In [121…

```
sns.set()
sns.pairplot(all_Three_Data[['Age','Gender','Occupation','Rating']],hue = "Rating"
```

Out[121]:

```
<seaborn.axisgrid.PairGrid at 0x21ed36a8970>
```

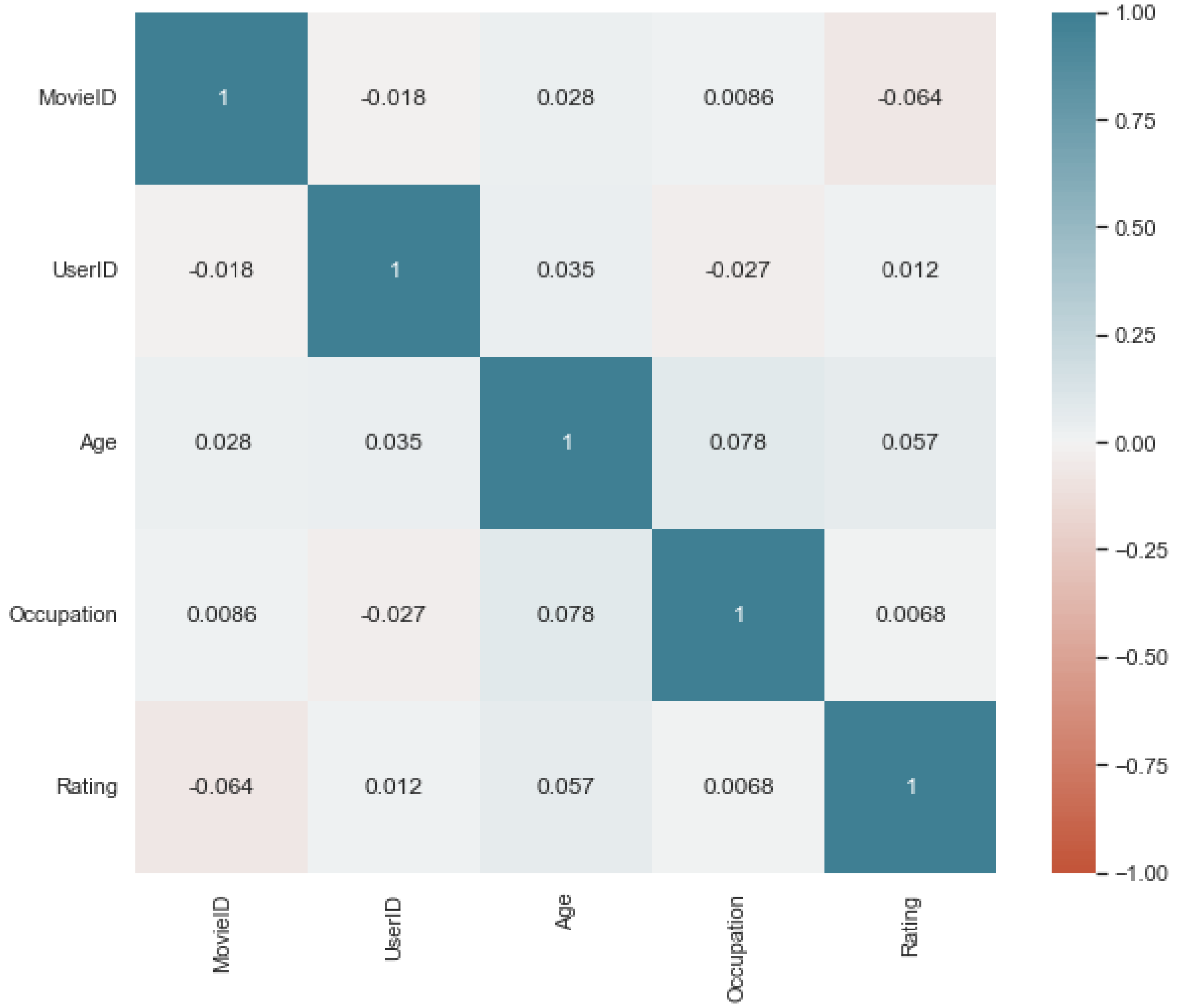


In [125…

```
correlation = master_Data.corr()
plt.figure(figsize=(10,8))
sns.heatmap(data=correlation,cmap=sns.diverging_palette(20, 220, n=200),vmin=-1, v
plt.yticks(rotation=0)
plt.xticks(rotation=90)
```

Out[125]:

```
(array([0.5, 1.5, 2.5, 3.5, 4.5]),
 [Text(0.5, 0, 'MovieID'),
  Text(1.5, 0, 'UserID'),
  Text(2.5, 0, 'Age'),
  Text(3.5, 0, 'Occupation'),
  Text(4.5, 0, 'Rating')])
```



Comments:- The pair plot and correlation plots are conclude that there is no feature affecting the ratings of any movie.

4. Develop an appropriate model to predict the movie ratings

In [153…

```
# selecting the features for building model
model_data_ML=all_Three_Data[['MovieID','Age','Gender','Occupation','Rating']]
model_data_ML.head()
model_data_ML.shape
```

Out[153]:

```
(1000209, 5)
```

In [154…

```
model_data_ML.dtypes
```

Out[154]:

```
MovieID         int32
Age             int32
Gender         object
Occupation      int32
Rating          int32
dtype: object
```

In [155…

```
def gentoint(x):
    if (x=='F'):
     return 0
    if (x=='M'):
     return 1
#gentoint('M')
```

In [156…
```
model_data_ML['Gender']= model_data_ML['Gender'].apply(gentoint)
```

In [157…
```
model_data_ML.dtypes
```

Out[157]:
```
MovieID       int32
Age           int32
Gender        int64
Occupation    int32
Rating        int32
dtype: object
```

In [158…
```
# features data
X_features=model_data_ML[['MovieID','Age','Gender','Occupation']]
```

In [159…
```
X_features
```

Out[159]:

	MovieID	Age	Gender	Occupation
0	1	1	0	10
1	48	1	0	10
2	150	1	0	10
3	260	1	0	10
4	527	1	0	10
...	...	...	...	...
1000204	3513	25	1	4
1000205	3535	25	1	4
1000206	3536	25	1	4
1000207	3555	25	1	4
1000208	3578	25	1	4

1000209 rows × 4 columns

In [160…
```
Y_target=model_data_ML['Rating']
```

In [161…
```
Y_target
```

Out[161]:
```
0          5
1          5
2          5
3          4
4          5
          ..
1000204    4
1000205    2
1000206    5
1000207    3
1000208    5
Name: Rating, Length: 1000209, dtype: int32
```

In [162…
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_features, Y_target, test_size
```

In [163…
```
# Create a logistic regression model using the training set
from sklearn.linear_model import LogisticRegression
```

```
logreg=LogisticRegression()
```

In [164…

```
logreg.fit(X_train,y_train)
```

Out[164]:

```
LogisticRegression()
```

In [165…

```
#Evaluate the accuracy of your model
y_ped=logreg.predict(X_test)
from sklearn import metrics
print(metrics.accuracy_score(y_test,y_ped))
# logistic regression model gives 34% accuracy
```

```
0.34904670019295947
```

In [166…

```
# use KNN classifier method - import it from sklearn
from sklearn.neighbors import KNeighborsClassifier
# instantiate the knn estimator
knn = KNeighborsClassifier(n_neighbors=6)
```

In [167…

```
# fit data into KNN model (estimator)
knn.fit(X_features,Y_target)
```

Out[167]:

```
KNeighborsClassifier(n_neighbors=6)
```

In [168…

```
#Evaluate the accuracy of your model
y_ped=knn.predict(X_test)
from sklearn import metrics
print(metrics.accuracy_score(y_test,y_ped))
#KNN model gives 46% accuracy
```

```
0.4680617070415213
```

Comments:- KNN is gives 46 % accuracy.

In [ ]: