Project - Movielens Case Study

For this project we are using Google Colab as the dataset is very huge and some models will consume most of the CPU RAM during analysis

In [2]:

```
# Import the required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

In [3]:

```
# mount the drive
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive", force_remount=True).
```

In [4]:

```
# import the three datasets
movies = pd.read_csv('/content/gdrive/MyDrive/Colab Notebooks/movies.dat',sep='::',header=None,names=['MovieID','Title','Genres'])
ratings = pd.read_csv('/content/gdrive/MyDrive/Colab Notebooks/ratings.dat',sep="::",header=None,names=['UserID','MovieID','Rating
users = pd.read_csv('/content/gdrive/MyDrive/Colab Notebooks/users.dat',sep="::",header=None,names=['UserID','Gender','Age','Occup
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: ParserWarning: Falling back to the 'python' engine because the 'c'
engine does not support regex separators (separators > 1 char and different from '\s+' are interpreted as regex); you can avoid th
is warning by specifying engine='python'.
  """Entry point for launching an IPython kernel.
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: ParserWarning: Falling back to the 'python' engine because the 'c'
engine does not support regex separators (separators > 1 char and different from '\s+' are interpreted as regex); you can avoid th
is warning by specifying engine='python'.

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: ParserWarning: Falling back to the 'python' engine because the 'c'
engine does not support regex separators (separators > 1 char and different from '\s+' are interpreted as regex); you can avoid th
is warning by specifying engine='python'.
  This is separate from the ipykernel package so we can avoid doing imports until
```

In [5]:

```
# check shapes of datasets
```

```
print(movies.shape)
print(ratings.shape)
print(users.shape)
```

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

In [6]:

```
movies.head() # first 5 records
```

Out[6]:

	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 [7]:

```
ratings.head() # first 5 records
```

Out[7]:

	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 [8]:

```
users.head() # first 5 records
```

Out[8]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	48067

	UserID	Gender	Age	Occupation	Zip-code
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 [9]:

```
# Check the datatypes of data
print(movies.dtypes)
print(ratings.dtypes)
print(users.dtypes)
```

```
MovieID     int64
Title      object
Genres     object
dtype: object
UserID       int64
MovieID      int64
Rating       int64
Timestamp    int64
dtype: object
UserID         int64
Gender        object
Age            int64
Occupation     int64
Zip-code      object
dtype: object
```

In [9]:

```
# Check for na values in movies
movies.isnull().sum().sort_values(ascending=False)
```

Out[9]:

```
Genres     0
Title      0
MovieID    0
dtype: int64
```

In [10]:

```
# check for na values in ratings
ratings.isnull().sum().sort_values(ascending=False)
```

Out[10]:
```
Timestamp    0
Rating       0
MovieID      0
UserID       0
dtype: int64
```

In [11]:
```
# check for na values in users
users.isnull().sum().sort_values(ascending=False)
```

Out[11]:
```
Zip-code      0
Occupation    0
Age           0
Gender        0
UserID        0
dtype: int64
```

There are no missing values in the dataset

Analysis Task - Create a new dataset [Master_Data]

In [10]:
```
# Merging the 3 datasets to create a Master_Data
data = pd.merge(movies,ratings,on='MovieID')
Master_Data = pd.merge(data,users,on='UserID')
```

In [13]:
```
Master_Data.head() # first 5 records
```

Out[13]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	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

In [14]:
```
# to get number of rows and columns
Master_Data.shape
```

Out[14]:
```
(1000209, 10)
```

In [15]:
```
Master_Data.dtypes # check the datatypes
```

Out[15]:
```
MovieID        int64
Title         object
Genres        object
UserID         int64
Rating         int64
Timestamp      int64
Gender        object
Age            int64
Occupation     int64
Zip-code      object
dtype: object
```

In [16]:
```
Master_Data.isnull().sum().sort_values(ascending=False) # check for missing values
```

Out[16]:
```
Zip-code      0
Occupation    0
Age           0
Gender        0
Timestamp     0
Rating        0
UserID        0
Genres        0
Title         0
MovieID       0
dtype: int64
```

There are no missing values in the Master_Data

Explore the datasets using visual representations

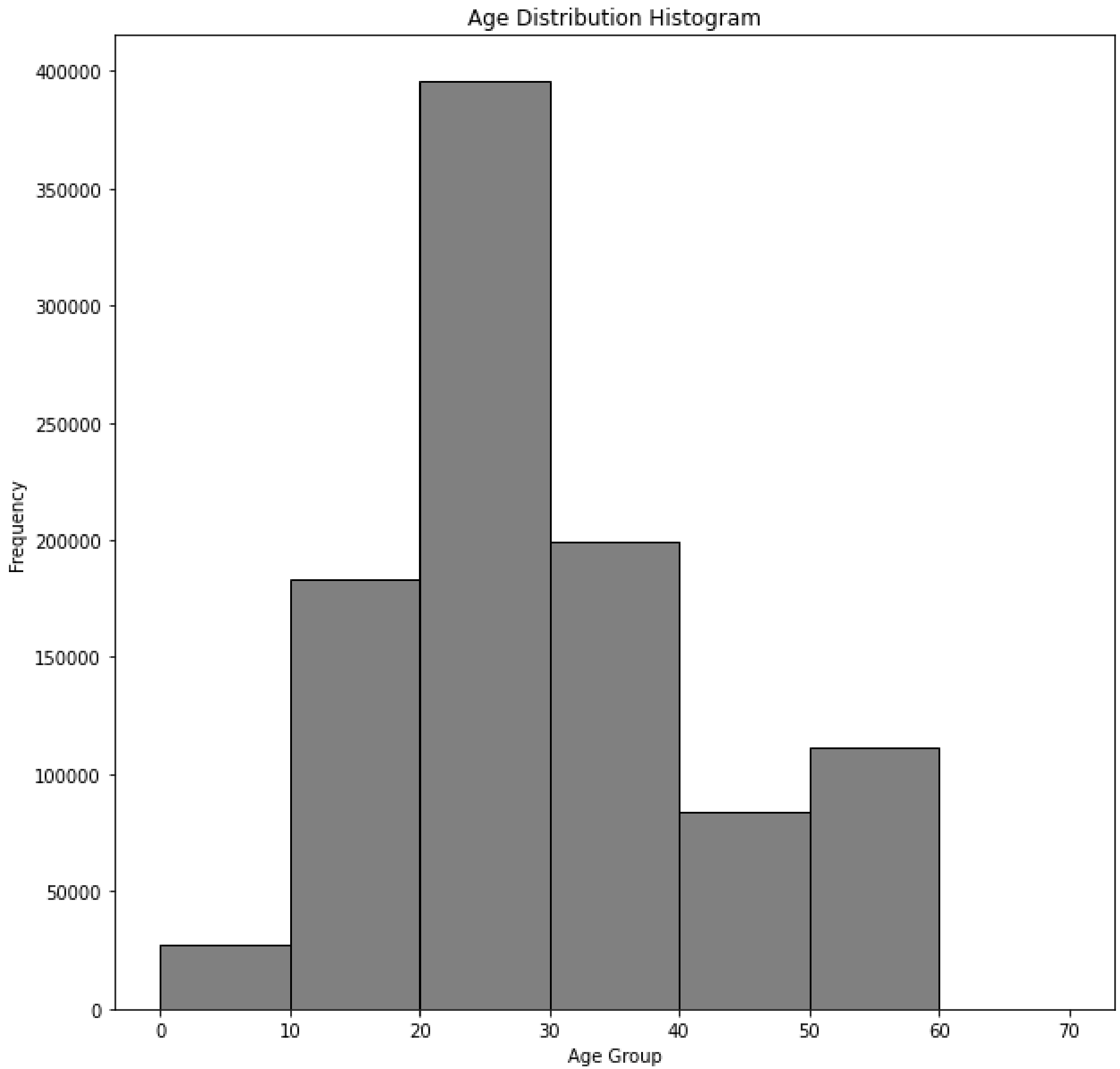
1. User Age Distribution

In [17]:

```
# creating a variable for age
age_data = Master_Data['Age']
```

In [18]:

```
# Let's create a Histogram of Age Distribution
plt.figure(figsize=(10,10))
plt.hist(age_data,bins=[0,10,20,30,40,50,60,70],color='grey',edgecolor='black')
plt.xlabel('Age Group')
plt.ylabel('Frequency')
plt.title('Age Distribution Histogram')
plt.grid(False)
plt.show()
```



From above histogram we found that the Master_Data has people from age group 20-30 who contribute highest and people from age

group 0-10 who contribute lowest when it comes to watch movies and also the movie ratings

2. User rating of the movie “Toy Story”

In [19]:
```
# Lets check for unique movie titles
Unique_Titles = Master_Data.Title.unique()
Unique_Titles
```

Out[19]:
```
array(['Toy Story (1995)', 'Pocahontas (1995)', 'Apollo 13 (1995)', ...,
       'Voyage to the Beginning of the World (1997)',
       'Project Moon Base (1953)', "Heaven's Burning (1997)"],
      dtype=object)
```

In [20]:
```
# check for toy story
Toy_Story = []
for i in Unique_Titles:
    if i.startswith('Toy Story')==True:
        Toy_Story.append(i)
print(Toy_Story)
```

```
['Toy Story (1995)', 'Toy Story 2 (1999)']
```

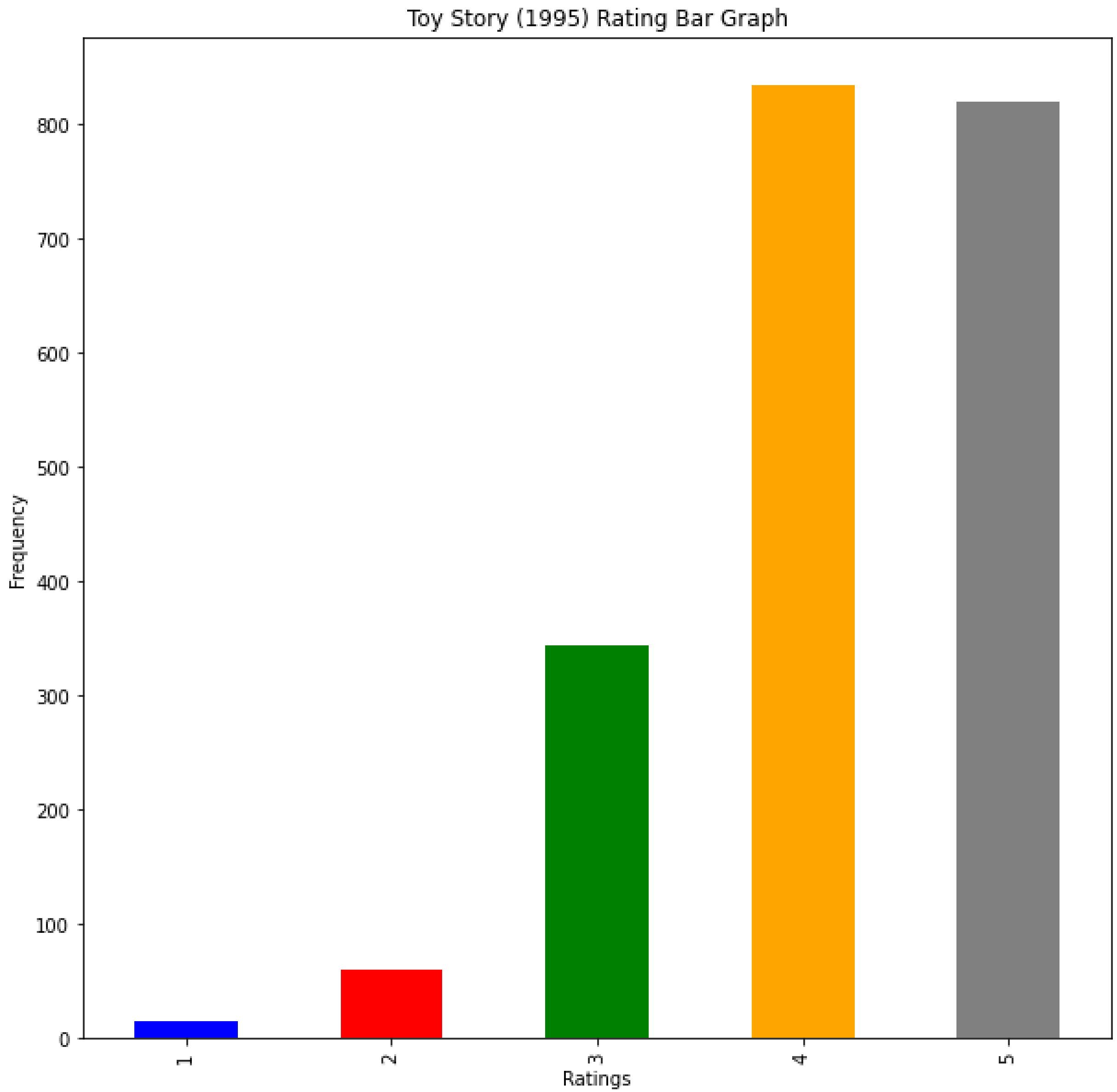
from above analysis we can see that there are two toy story movies : 'Toy Story (1995)', 'Toy Story 2 (1999)'

In [21]:
```
# Creating a separate data for the two toy sory versions
ToyStory1995 = Master_Data[Master_Data.Title=='Toy Story (1995)']
ToyStory1999 = Master_Data[Master_Data.Title=='Toy Story 2 (1999)']
```

In [22]:
```
# Now we will group Toy Story 1995 by ratings count the how many users provided the ratings
TS1995 = ToyStory1995.groupby('Rating')['UserID'].count()
TS1995
```

Out[22]:
```
Rating
1     16
2     61
3    345
4    835
5    820
Name: UserID, dtype: int64
```

In [23]:
```
# Lets create a Bar Graph of Toy Story (1995) Rating
plt.figure(figsize=(10,10))
TS1995.plot(kind='bar',color=['blue','red','green','orange','grey'])
plt.xlabel('Ratings')
plt.ylabel('Frequency')
plt.title('Toy Story (1995) Rating Bar Graph')
plt.show()
```

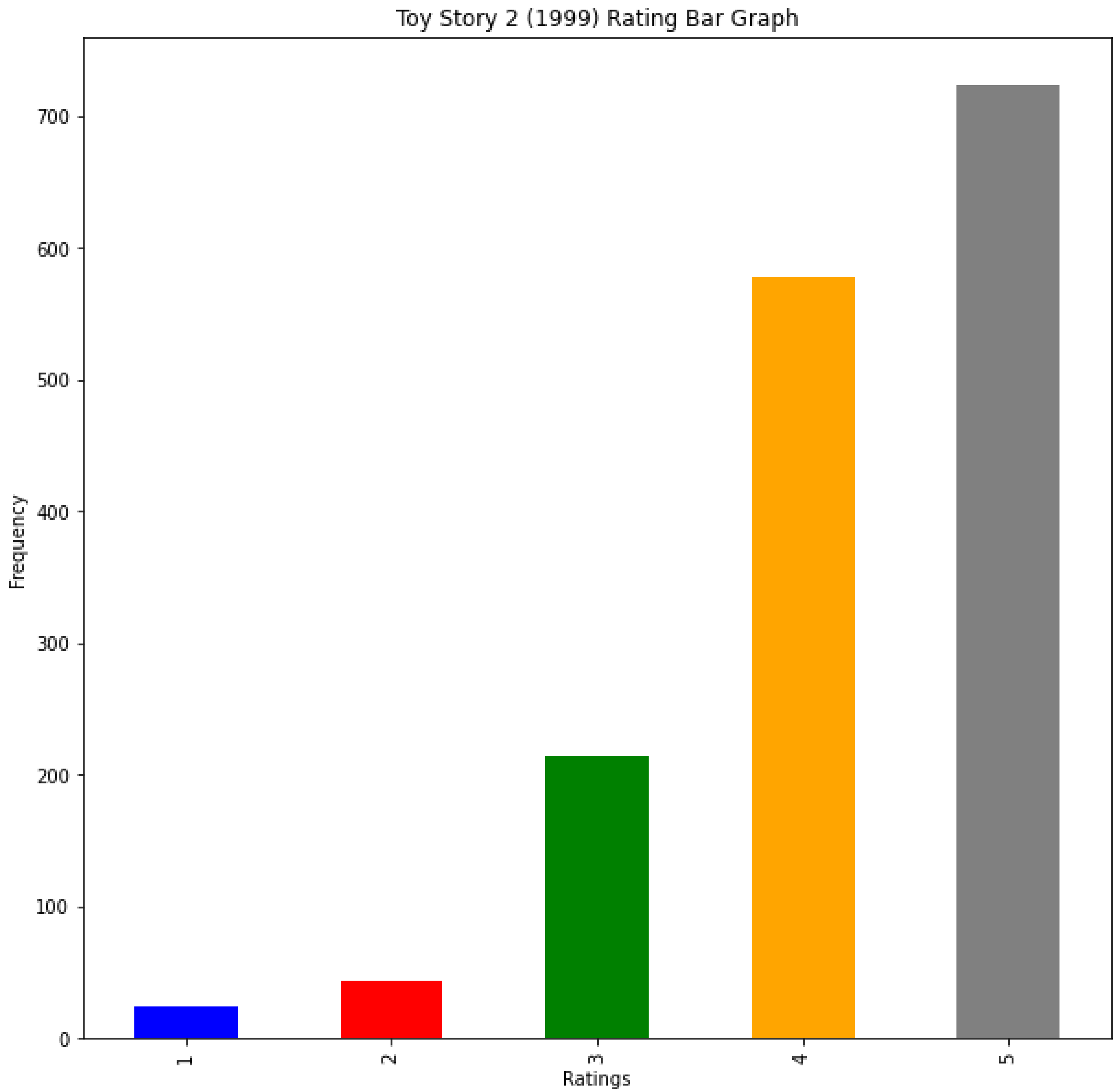


From above analysis we can see that for Toy Story 1995 maximum users gave rating 5 and minimum as rating 1

In [24]:
```
# Now we will group Toy Story 1999 by ratings count the how many users provided the ratings
TS1999 = ToyStory1999.groupby('Rating')['UserID'].count()
TS1999
```

Out[24]:
```
Rating
1     25
2     44
3    214
4    578
5    724
Name: UserID, dtype: int64
```

In [25]:
```
# Lets create a Bar Graph of Toy Story (1995) Rating
plt.figure(figsize=(10,10))
TS1999.plot(kind='bar',color=['blue','red','green','orange','grey'])
plt.xlabel('Ratings')
plt.ylabel('Frequency')
plt.title('Toy Story 2 (1999) Rating Bar Graph')
plt.show()
```



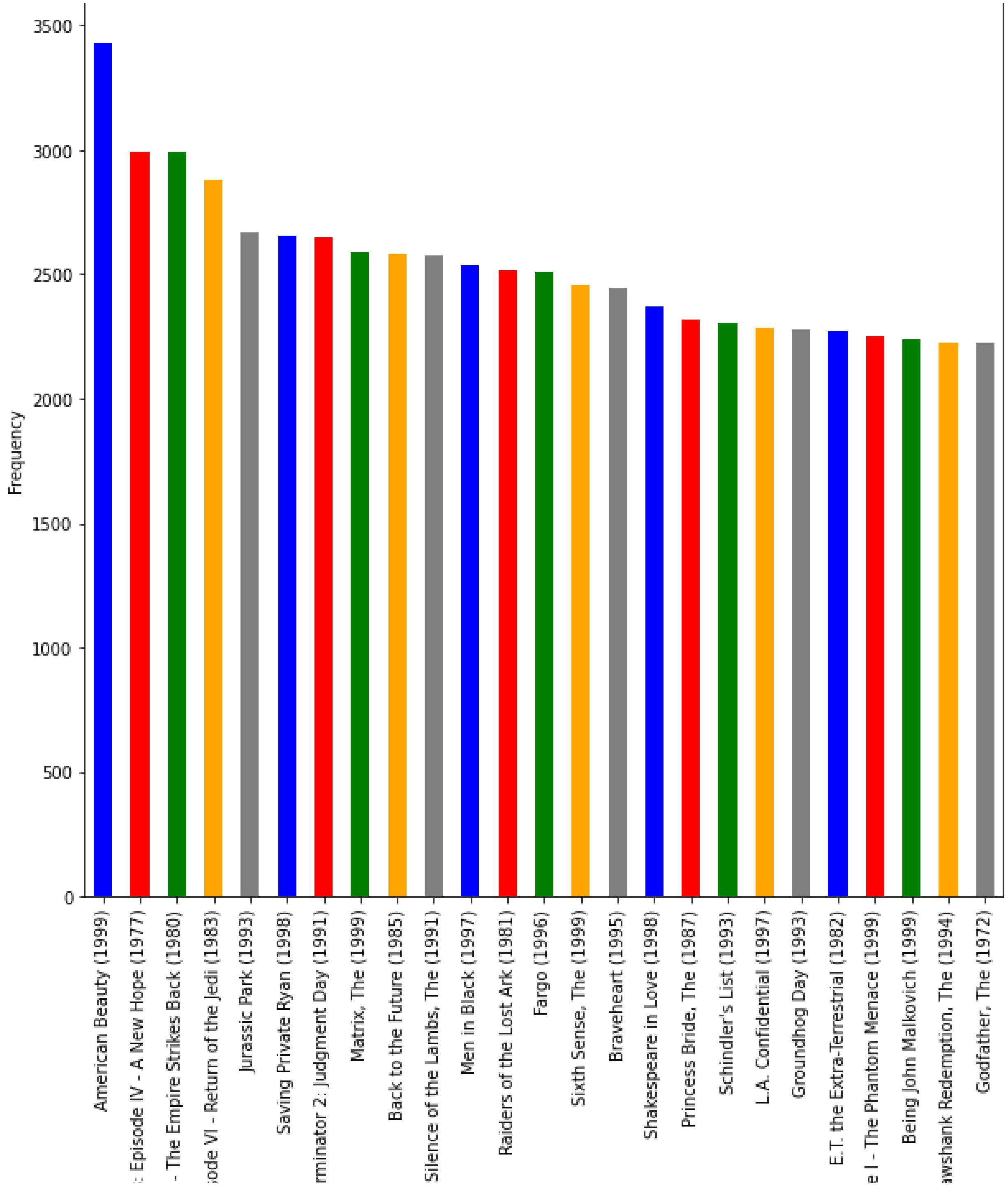
From above analysis we can see that for Toy Story 1999 maximum users gave rating 5 and minimum as rating 1

3. Top 25 movies by viewership rating

In [26]:
```
# Creating data for top 25 movies with higest number of ratings count
Top25 = Master_Data.groupby('Title')['Rating'].count().nlargest(25)
Top25
```

Out[26]:
```
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 [27]:
```
# Creating a Bar Graph of Top 25 Movies
plt.figure(figsize=(10,10))
Top25.plot(kind='bar',color = ['blue','red','green','orange','grey'])
plt.xlabel('Movie Title')
plt.ylabel('Frequency')
plt.title('Top 25 Movies Bar Graph')
plt.show()
```


Frequency
0
500
1000
1500
2000
2500
3000
3500
American Beauty (1999)
: Episode IV - A New Hope (1977)
- The Empire Strikes Back (1980)
ode VI - Return of the Jedi (1983)
Jurassic Park (1993)
Saving Private Ryan (1998)
rminator 2: Judgment Day (1991)
Matrix, The (1999)
Back to the Future (1985)
Silence of the Lambs, The (1991)
Men in Black (1997)
Raiders of the Lost Ark (1981)
Fargo (1996)
Sixth Sense, The (1999)
Braveheart (1995)
Shakespeare in Love (1998)
Princess Bride, The (1987)
Schindler's List (1993)
L.A. Confidential (1997)
Groundhog Day (1993)
E.T. the Extra-Terrestrial (1982)
e I - The Phantom Menace (1999)
Being John Malkovich (1999)
awshank Redemption, The (1994)
Godfather, The (1972)

From above analysis American Beauty (1999) has highest number of ratings and Godfather, The (1972) has lowest number of ratings

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

In [28]:

```
# Creating a data for user 2696
user_2696 = Master_Data[Master_Data.UserID==2696]
user_2696
```

Out[28]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code
991035	350	Client, The (1994)	Drama|Mystery|Thriller	2696	3	973308886	M	25	7	24210
991036	800	Lone Star (1996)	Drama|Mystery	2696	5	973308842	M	25	7	24210
991037	1092	Basic Instinct (1992)	Mystery|Thriller	2696	4	973308886	M	25	7	24210
991038	1097	E.T. the Extra-Terrestrial (1982)	Children's|Drama|Fantasy|Sci-Fi	2696	3	973308690	M	25	7	24210
991039	1258	Shining, The (1980)	Horror	2696	4	973308710	M	25	7	24210
991040	1270	Back to the Future (1985)	Comedy|Sci-Fi	2696	2	973308676	M	25	7	24210
991041	1589	Cop Land (1997)	Crime|Drama|Mystery	2696	3	973308865	M	25	7	24210
991042	1617	L.A. Confidential (1997)	Crime|Film-Noir|Mystery|Thriller	2696	4	973308842	M	25	7	24210

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code
991043	1625	Game, The (1997)	Mystery|Thriller	2696	4	973308842	M	25	7	24210
991044	1644	I Know What You Did Last Summer (1997)	Horror|Mystery|Thriller	2696	2	973308920	M	25	7	24210
991045	1645	Devil's Advocate, The (1997)	Crime|Horror|Mystery|Thriller	2696	4	973308904	M	25	7	24210
991046	1711	Midnight in the Garden of Good and Evil (1997)	Comedy|Crime|Drama|Mystery	2696	4	973308904	M	25	7	24210
991047	1783	Palmetto (1998)	Film-Noir|Mystery|Thriller	2696	4	973308865	M	25	7	24210
991048	1805	Wild Things (1998)	Crime|Drama|Mystery|Thriller	2696	4	973308886	M	25	7	24210
991049	1892	Perfect Murder, A (1998)	Mystery|Thriller	2696	4	973308904	M	25	7	24210
991050	2338	I Still Know What You Did Last Summer (1998)	Horror|Mystery|Thriller	2696	2	973308920	M	25	7	24210
991051	2389	Psycho (1998)	Crime|Horror|Thriller	2696	4	973308710	M	25	7	24210
991052	2713	Lake Placid (1999)	Horror|Thriller	2696	1	973308710	M	25	7	24210
991053	3176	Talented Mr. Ripley, The (1999)	Drama|Mystery|Thriller	2696	4	973308865	M	25	7	24210
991054	3386	JFK (1991)	Drama|Mystery	2696	1	973308842	M	25	7	24210

In [29]:

```
# Now we will group data by rating and its counts
user2696 = user_2696.groupby('Rating')['UserID'].count()
user2696
```

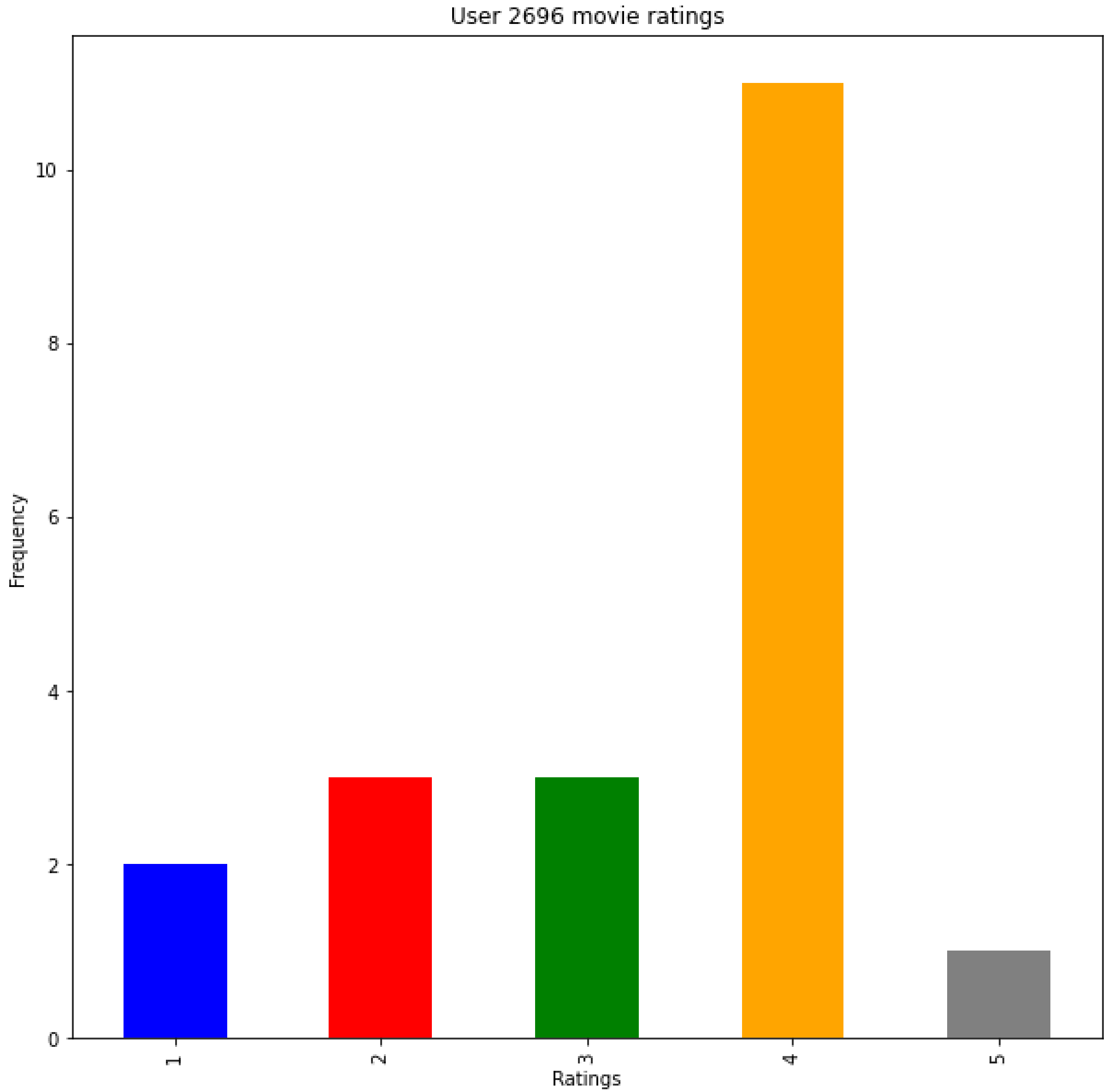
Out[29]:

```
Rating
1     2
2     3
3     3
4    11
5     1
Name: UserID, dtype: int64
```

In [30]:

```
# Creating a Bar Graph of User 2696 movie ratings
plt.figure(figsize=(10,10))
user2696.plot(kind='bar',color = ['blue','red','green','orange','grey'])
plt.xlabel('Ratings')
```

```
plt.ylabel('Frequency')
plt.title('User 2696 movie ratings')
plt.show()
```



From above analysis we can see that user 2696 gave maximum number of rating 4 and minimum number of rating 5 to the movies he watched

Feature Engineering

1. Find out all the unique genres

In [31]:

```
# checking of counts of each genre
Master_Data.Genres.value_counts()
```

Out[31]:

```
Comedy                      116883
Drama                       111423
Comedy|Romance               42712
Comedy|Drama                 42245
Drama|Romance                29170
                             ...  
Drama|Romance|Western           29
Children's|Fantasy              27
Comedy|Film-Noir|Thriller        5
Film-Noir|Horror                 2
Fantasy                          1
Name: Genres, Length: 301, dtype: int64
```

In [32]:

```
Master_Data.Genres.unique() # get unique names of genres
```

Out[32]:

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

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

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

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

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 [33]:

```
Genres_data = Master_Data['Genres']
```

```
Genres_data = Genres_data.str.get_dummies().add_prefix('Genre_')
Genres_data.head()
```

Out[33]:

	Genre_Action	Genre_Adventure	Genre_Animation	Genre_Children's	Genre_Comedy	Genre_Crime	Genre_Documentary	Genre_Drama	Genre_Fantasy	G
0	0	0	1	1	1	0	0	0	0	
1	0	0	1	1	0	0	0	0	0	
2	0	0	0	0	0	0	0	1	0	
3	1	1	0	0	0	0	0	0	1	
4	0	0	0	0	0	0	0	1	0	

So we have created 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 [34]:

```
Genres_data.shape # to check for rows and columns
```

Out[34]: (1000209, 18)

In [35]:

```
Master_Data.columns
```

Out[35]:

```
Index(['MovieID', 'Title', 'Genres', 'UserID', 'Rating', 'Timestamp', 'Gender',
       'Age', 'Occupation', 'Zip-code'],
      dtype='object')
```

In [36]:

```
# Lets create a duplicate of Master_Data with selected columns
Movie_data = Master_Data[['MovieID', 'Title', 'UserID', 'Rating', 'Gender','Age', 'Occupation']]
```

In [37]:

```
Movie_data_final = pd.concat([Movie_data,Genres_data],axis=1)
Movie_data_final.head()
```

Out[37]:

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

We have combined the genres_data with Movie_data with selected number of columns

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

In [11]:

```
Master_Data.head() # first 5 records
```

Out[11]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	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

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code
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

In [12]:
```
Master_Data.dtypes # check datatypes
```

Out[12]:
```
MovieID         int64
Title          object
Genres         object
UserID          int64
Rating          int64
Timestamp       int64
Gender         object
Age             int64
Occupation      int64
Zip-code       object
dtype: object
```

In [13]:
```
# converting Zip-code to string datatype
Master_Data['Zip-code'] = Master_Data['Zip-code'].astype(str)
```

In [14]:
```
# Now we will convert Zip-code to float for further analysis
Master_Data['Zip-code'] = Master_Data['Zip-code'].str.replace('-', '_').astype(float)
```

In [15]:
```
# Creating separate data for object columns and numeric columns
objectcols = Master_Data[['Title','Genres','Gender']]
numericcols = Master_Data.drop(['Title','Genres','Gender'],axis=1)
```

In [16]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

In [17]:
```
# Creating dummy of objectcols for further analysis
objectcolsdummy = objectcols.apply(le.fit_transform)
```

```
objectcolsdummy.head()
```

Out[17]:

	Title	Genres	Gender
0	3411	145	0
1	2598	153	0
2	195	239	0
3	3153	24	0
4	2901	262	0

In [18]:

```
# combining the data to form a final data for analysis
Master_Data_final = pd.concat([numericcols,objectcolsdummy],axis=1)
Master_Data_final.head()
```

Out[18]:

	MovieID	UserID	Rating	Timestamp	Age	Occupation	Zip-code	Title	Genres	Gender
0	1	1	5	978824268	1	10	48067.0	3411	145	0
1	48	1	5	978824351	1	10	48067.0	2598	153	0
2	150	1	5	978301777	1	10	48067.0	195	239	0
3	260	1	4	978300760	1	10	48067.0	3153	24	0
4	527	1	5	978824195	1	10	48067.0	2901	262	0

In [19]:

```
Master_Data_final.shape # rows and columns
```

Out[19]: (1000209, 10)

In [20]:

```
Master_Data_final.dtypes # check datatypes
```

Out[20]:

```
MovieID        int64
UserID         int64
Rating         int64
Timestamp      int64
Age            int64
```

```
Occupation      int64
Zip-code      float64
Title           int64
Genres          int64
Gender          int64
dtype: object
```

As our data is very huge i.e 1000209 rows we will split it into 4 parts and then we will perform analysis on the data¶

In [21]:
```
# Separating data into 4 parts for easy analysis
Master_Data_final1 = Master_Data_final.iloc[0:250000,:]
Master_Data_final2 = Master_Data_final.iloc[250000:500000,:]
Master_Data_final3 = Master_Data_final.iloc[500001:750001,:]
Master_Data_final4 = Master_Data_final.iloc[750001:1000210,:]
```

In [22]:
```
# Check shapes of each part
print(Master_Data_final1.shape)
print(Master_Data_final2.shape)
print(Master_Data_final3.shape)
print(Master_Data_final4.shape)
```

```
(250000, 10)
(250000, 10)
(250000, 10)
(250208, 10)
```

In [23]:
```
# import the required libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
```

Master_Data_final1

In [52]:
```
# Dependent (y1) and Independent (X1) variables
y1 = Master_Data_final1.Rating
X1 = Master_Data_final1.drop(['Rating'],axis=1)
```

In [53]:
```
# Split the data into train and test
X1_train,X1_test,y1_train,y1_test = train_test_split(X1,y1,test_size=0.25,random_state=42)
```

In [54]:
```
# Check shapes
print(X1_train.shape)
print(X1_test.shape)
print(y1_train.shape)
print(y1_test.shape)
```

```
(187500, 9)
(62500, 9)
(187500,)
(62500,)
```

In [56]:
```
# Linear Regression Model
print('Linear Regression :')
print()
linreg = LinearRegression()
linregmodel = linreg.fit(X1_train,y1_train)
regpredict = linregmodel.predict(X1_test)
print('Model Score :',linregmodel.score(X1_train,y1_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y1_test,regpredict))
print('Mean Squared Error :',mean_squared_error(y1_test,regpredict))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y1_test,regpredict)))
```

```
Linear Regression :

Accuracy:  1.014979655349313
Mean Absolute Error : 0.9307692688456111
Mean Squared Error : 1.2418534132439387
Root Mean Square Error : 1.1143847689393187
```

In [57]:
```
# Decision Tree Model
print('Decision Tree Model :')
print()
tree = DecisionTreeRegressor()
treemodel = tree.fit(X1_train,y1_train)
```

```
treepredict = treemodel.predict(X1_test)
print('Model Score :',treemodel.score(X1_train,y1_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y1_test,treepredict))
print('Mean Squared Error :',mean_squared_error(y1_test,treepredict))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y1_test,treepredict)))
```

```
Decision Tree Model :

Model Score : 100.0
Mean Absolute Error : 0.997232
Mean Squared Error : 1.80968
Root Mean Square Error : 1.3452434723870619
```

In [59]:

```
# Random Forest Model
print('Random Forest Model :')
print()
rf = RandomForestRegressor(n_estimators=500)
rfmodel = rf.fit(X1_train,y1_train)
rfpredict = rfmodel.predict(X1_test)
print('Model Score :',rfmodel.score(X1_train,y1_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y1_test,rfpredict))
print('Mean Squared Error :',mean_squared_error(y1_test,rfpredict))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y1_test,rfpredict)))
```

```
Random Forest Model :

Model Score : 89.9209659700578
Mean Absolute Error : 0.7650695679999999
Mean Squared Error : 0.918656814464
Root Mean Square Error : 0.9584658650489333
```

In [60]:

```
# Gradient Boosting Model
print('Gradient Boosting Model :')
print()
gbr = GradientBoostingRegressor(n_estimators=500)
gbrmodel = gbr.fit(X1_train,y1_train)
gbrpredict = gbrmodel.predict(X1_test)
print('Model Score :',gbrmodel.score(X1_train,y1_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y1_test,gbrpredict))
print('Mean Squared Error :',mean_squared_error(y1_test,gbrpredict))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y1_test,gbrpredict)))
```

```
Gradient Boosting Model :
```

```
Model Score : 23.55457086776539
Mean Absolute Error : 0.7943017533257478
Mean Squared Error : 0.9631827002018266
Root Mean Square Error : 0.9814187180820563
```

In [61]:

```
# Factors affecting ratings
print(list(zip(X1_train.columns,rfmodel.feature_importances_)))
```

```
[('MovieID', 0.1594805969612773), ('UserID', 0.1400025188072164), ('Timestamp', 0.17740815432847604), ('Age', 0.0532542997481916), ('Occupation', 0.08420693074027762), ('Zip-code', 0.16722081823278828), ('Title', 0.11329962973714408), ('Genres', 0.08743745638666045), ('Gender', 0.01768959505796832)]
```

Master_Data_final2

In [62]:

```
# Dependent (y2) and Independent (X2) variables
y2 = Master_Data_final2.Rating
X2 = Master_Data_final2.drop(['Rating'],axis=1)
```

In [63]:

```
# Split the data into train and test
X2_train,X2_test,y2_train,y2_test = train_test_split(X2,y2,test_size=0.25,random_state=42)
```

In [64]:

```
# Check shapes
print(X2_train.shape)
print(X2_test.shape)
print(y2_train.shape)
print(y2_test.shape)
```

```
(187500, 9)
(62500, 9)
(187500,)
(62500,)
```

In [65]:

```
# Linear Regression Model
print('Linear Regression :')
print()
linreg2 = LinearRegression()
linregmodel2 = linreg2.fit(X2_train,y2_train)
regpredict2 = linregmodel2.predict(X2_test)
print('Model Score :',linregmodel2.score(X2_train,y2_train)*100)
```

```
print('Mean Absolute Error :',mean_absolute_error(y2_test,regpredict2))
print('Mean Squared Error :',mean_squared_error(y2_test,regpredict2))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y2_test,regpredict2)))
```

```
Linear Regression :

Model Score : 1.3013223981213073
Mean Absolute Error : 0.9087647893596562
Mean Squared Error : 1.197846440036141
Root Mean Square Error : 1.094461712457837
```

In [66]:

```
# Decision Tree Model
print('Decision Tree Model :')
print()
tree2 = DecisionTreeRegressor()
treemodel2 = tree2.fit(X2_train,y2_train)
treepredict2 = treemodel2.predict(X2_test)
print('Model Score :',treemodel.score(X2_train,y2_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y2_test,treepredict2))
print('Mean Squared Error :',mean_squared_error(y2_test,treepredict2))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y2_test,treepredict2)))
```

```
Decision Tree Model :

Model Score : -85.05815208989615
Mean Absolute Error : 0.9864
Mean Squared Error : 1.786944
Root Mean Square Error : 1.3367662473297268
```

In [67]:

```
# Random Forest Model
print('Random Forest Model :')
print()
rf2 = RandomForestRegressor(n_estimators=500)
rfmodel2 = rf2.fit(X2_train,y2_train)
rfpredict2 = rfmodel2.predict(X2_test)
print('Model Score :',rfmodel2.score(X2_train,y2_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y2_test,rfpredict2))
print('Mean Squared Error :',mean_squared_error(y2_test,rfpredict2))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y2_test,rfpredict2)))
```

```
Random Forest Model :

Model Score : 89.92045546838978
Mean Absolute Error : 0.748560128
```

```
Mean Squared Error : 0.8902996811520001
Root Mean Square Error : 0.9435569305304264
```

In [68]:

```
# Gradient Boosting Model
print('Gradient Boosting Model :')
print()
gbr2 = GradientBoostingRegressor(n_estimators=500)
gbrmodel2 = gbr2.fit(X2_train,y2_train)
gbrpredict2 = gbrmodel2.predict(X2_test)
print('Model Score :',gbrmodel.score(X2_train,y2_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y2_test,gbrpredict2))
print('Mean Squared Error :',mean_squared_error(y2_test,gbrpredict2))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y2_test,gbrpredict2)))
```

```
Gradient Boosting Model :

Model Score : 6.1557438585355578
Mean Absolute Error : 0.785011842000925
Mean Squared Error : 0.9481626993842109
Root Mean Square Error : 0.9737364630043444
```

In [69]:

```
# Factors affecting ratings
print(list(zip(X2_train.columns,rfmodel2.feature_importances_)))
```

```
[('MovieID', 0.1566481026607614), ('UserID', 0.12916771619660924), ('Timestamp', 0.18403964498310527), ('Age', 0.054006355249512895), ('Occupation', 0.08379752671074138), ('Zip-code', 0.1694402230421053), ('Title', 0.11775044094636383), ('Genres', 0.08723560052227808), ('Gender', 0.017914389688522 71)]
```

Master_Data_final3

In [24]:

```
# Dependent (y3) and Independent (X3) variables
y3 = Master_Data_final3.Rating
X3 = Master_Data_final3.drop(['Rating'],axis=1)
```

In [25]:

```
# Split the data into train and test
X3_train,X3_test,y3_train,y3_test = train_test_split(X3,y3,test_size=0.25,random_state=42)
```

In [26]:

```
# Check shapes
print(X3_train.shape)
```

```
print(X3_test.shape)
print(y3_train.shape)
print(y3_test.shape)
```

```
(187500, 9)
(62500, 9)
(187500,)
(62500,)
```

In [27]:

```
# Linear Regression Model
print('Linear Regression :')
print()
linreg3 = LinearRegression()
linregmodel3 = linreg3.fit(X3_train,y3_train)
regpredict3 = linregmodel3.predict(X3_test)
print('Model Score :',linregmodel3.score(X3_train,y3_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y3_test,regpredict3))
print('Mean Squared Error :',mean_squared_error(y3_test,regpredict3))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y3_test,regpredict3)))
```

```
Linear Regression :

Model Score : 1.1120603235960647
Mean Absolute Error : 0.9379769486198766
Mean Squared Error : 1.2641260495382158
Root Mean Square Error : 1.124333602423327
```

In [28]:

```
# Decision Tree Model
print('Decision Tree Model :')
print()
tree3 = DecisionTreeRegressor()
treemodel3 = tree3.fit(X3_train,y3_train)
treepredict3 = treemodel3.predict(X3_test)
print('Model Score :',treemodel3.score(X3_train,y3_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y3_test,treepredict3))
print('Mean Squared Error :',mean_squared_error(y3_test,treepredict3))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y3_test,treepredict3)))
```

```
Decision Tree Model :

Model Score : 100.0
Mean Absolute Error : 1.016304
Mean Squared Error : 1.878384
Root Mean Square Error : 1.370541498824461
```

In [29]:

```
# Random Forest Model
print('Random Forest Model :')
print()
rf3 = RandomForestRegressor(n_estimators=500)
rfmodel3 = rf3.fit(X3_train,y3_train)
rfpredict3 = rfmodel3.predict(X3_test)
print('Model Score :',rfmodel3.score(X3_train,y3_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y3_test,rfpredict3))
print('Mean Squared Error :',mean_squared_error(y3_test,rfpredict3))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y3_test,rfpredict3)))
```

```
Random Forest Model :

Model Score : 89.8273094297585
Mean Absolute Error : 0.78138512
Mean Squared Error : 0.9572246026879998
Root Mean Square Error : 0.9783785579661892
```

In [30]:

```
# Gradient Boosting Model
print('Gradient Boosting Model :')
print()
gbr3 = GradientBoostingRegressor(n_estimators=500)
gbrmodel3 = gbr3.fit(X3_train,y3_train)
gbrpredict3 = gbrmodel3.predict(X3_test)
print('Model Score :',gbrmodel3.score(X3_train,y3_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y3_test,gbrpredict3))
print('Mean Squared Error :',mean_squared_error(y3_test,gbrpredict3))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y3_test,gbrpredict3)))
```

```
Gradient Boosting Model :

Model Score : 22.22118061851466
Mean Absolute Error : 0.8144027167114244
Mean Squared Error : 1.007279449712804
Root Mean Square Error : 1.00363312505756
```

In [31]:

```
# Factors affecting ratings
print(list(zip(X3_train.columns,rfmodel3.feature_importances_)))
```

```
[('MovieID', 0.1563262701429214), ('UserID', 0.13025379487269634), ('Timestamp', 0.1660020630569722), ('Age', 0.0597071921317613
2), ('Occupation', 0.0935707813073586), ('Zip-code', 0.17630721863573232), ('Title', 0.11138721788335078), ('Genres', 0.0879540238
7604936), ('Gender', 0.018491438093l5779)]
```

Master_Data_final4

In [32]:
```
# Dependent (y4) and Independent (X4) variables
y4 = Master_Data_final4.Rating
X4 = Master_Data_final4.drop(['Rating'],axis=1)
```

In [33]:
```
# Split the data into train and test
X4_train,X4_test,y4_train,y4_test = train_test_split(X4,y4,test_size=0.25,random_state=42)
```

In [34]:
```
# Check shapes
print(X4_train.shape)
print(X4_test.shape)
print(y4_train.shape)
print(y4_test.shape)
```

```
(187656, 9)
(62552, 9)
(187656,)
(62552,)
```

In [35]:
```
# Linear Regression Model
print('Linear Regression :')
print()
linreg4 = LinearRegression()
linregmodel4 = linreg4.fit(X4_train,y4_train)
regpredict4 = linregmodel4.predict(X4_test)
print('Model Score :',linregmodel4.score(X4_train,y4_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y4_test,regpredict4))
print('Mean Squared Error :',mean_squared_error(y4_test,regpredict4))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y4_test,regpredict4)))
```

```
Linear Regression :

Model Score : 1.8155346469467482
Mean Absolute Error : 0.888265978319701
Mean Squared Error : 1.1949406683917985
Root Mean Square Error : 1.0931334174709866
```

In [36]:
```
# Decision Tree Model
```

```
print('Decision Tree Model :')
print()
tree4 = DecisionTreeRegressor()
treemodel4 = tree4.fit(X4_train,y4_train)
treepredict4 = treemodel4.predict(X4_test)
print('Model Score :',treemodel4.score(X4_train,y4_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y4_test,treepredict4))
print('Mean Squared Error :',mean_squared_error(y4_test,treepredict4))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y4_test,treepredict4)))
```

```
Decision Tree Model :

Model Score : 100.0
Mean Absolute Error : 1.0161465660570406
Mean Squared Error : 1.8993157692799592
Root Mean Square Error : 1.3781566562912793
```

In [37]:

```
# Random Forest Model
print('Random Forest Model :')
print()
rf4 = RandomForestRegressor(n_estimators=500)
rfmodel4 = rf4.fit(X4_train,y4_train)
rfpredict4 = rfmodel4.predict(X4_test)
print('Model Score :',rfmodel4.score(X4_train,y4_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y4_test,rfpredict4))
print('Mean Squared Error :',mean_squared_error(y4_test,rfpredict4))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y4_test,rfpredict4)))
```

```
Random Forest Model :

Model Score : 89.07661056298622
Mean Absolute Error : 0.7861571812252207
Mean Squared Error : 0.9741089017777209
Root Mean Square Error : 0.9869695546356639
```

In [38]:

```
# Gradient Boosting Model
print('Gradient Boosting Model :')
print()
gbr4 = GradientBoostingRegressor(n_estimators=500)
gbrmodel4 = gbr4.fit(X4_train,y4_train)
gbrpredict4 = gbrmodel4.predict(X4_test)
print('Model Score :',gbrmodel4.score(X4_train,y4_train)*100)
print('Mean Absolute Error :',mean_absolute_error(y4_test,gbrpredict4))
```

```
print('Mean Squared Error :',mean_squared_error(y4_test,gbrpredict4))
print('Root Mean Square Error :',np.sqrt(mean_squared_error(y4_test,gbrpredict4)))
```

```
Gradient Boosting Model :

Model Score : 17.841000798708762
Mean Absolute Error : 0.8120149292123968
Mean Squared Error : 1.0143197795740913
Root Mean Square Error : 1.0071344396723265
```

In [39]:

```
# Factors affecting ratings
print(list(zip(X4_train.columns,rfmodel4.feature_importances_)))
```

```
[('MovieID', 0.14284055370022072), ('UserID', 0.13526504905604206), ('Timestamp', 0.16084878462274965), ('Age', 0.0621254974587008
85), ('Occupation', 0.1009485779110867), ('Zip-code', 0.19882355699997728), ('Title', 0.10382248354132333), ('Genres', 0.075448901
29958216), ('Gender', 0.01987659541031733)]
```

From above analysis we found that the Random Forest is the best model to predict ratings and MovieID, UserID, Timestamp, Zip-code,Title are the main factors that affect ratings

Summary :

1. People from age group 20-30 contribute more and age group 0-10 contribute less towards watching movies

2. Both Toy Story 1995 and Toy Story 1999 has maximum rating given as 5 and lowest as 1

3. American Beauty (1999) has highest number of ratings and Godfather, The (1972) has lowest number of ratings

4. User 2696 gave maximum number of rating 4 and minimum number of rating 5 to the movies he watched

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

6. Random Forest is the best model to predict ratings and MovieID, UserID, Timestamp, Zip-code,Title are the main factors that affect ratings