Movielens

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1.1 Project: 2

1.2 Project Name: Movielens Case Study

1.3 Domain: Entertainment

1.3.1 Objective

I have to perform the analysis using the Exploratory Data Analysis technique and to find features affecting the ratings of any particular movie. Building a model named Logistic Regression to predict the movie ratings

[1]:
```
import numpy as np
import pandas as pd
```

[2]:
```
#importing the datasets
movies=pd.read_csv("movies.dat", sep="::", header=None,␣
 ↪names=['MovieID','Title','Genres'],dtype={'MovieID':np.int32, 'Title':np.
 ↪str, 'Genres':np.str}, engine='python')
users=pd.read_csv("users.dat", sep="::", header=None,␣
 ↪names=['UserID','Gender','Age','Occupation','ZipCode'],dtype={'UserID':np.
 ↪int32, 'Gender':np.str, 'Age':np.int32, 'Occupation':np.str, 'ZipCode':np.
 ↪str}, engine='python')
ratings=pd.read_csv("ratings.dat", sep="::", header=None,␣
 ↪names=['UserID','MovieID','Rating','Timestamp'],dtype={'UserID':np.int32,␣
 ↪'MovieID':np.int32, 'Rating':np.int32, 'Timestamp':np.str},  engine='python')
```

[3]:
```
#UserData
users.head()
```

[3]:

	UserID	Gender	Age	Occupation	ZipCode
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

[4]:
```
users.info()
```

```
<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   object
 4   ZipCode     6040 non-null   object
dtypes: int32(2), object(3)
memory usage: 188.9+ KB
```

[5]:
```
#checking for null values
users.isnull().sum()
```

[5]:
```
UserID        0
Gender        0
Age           0
Occupation    0
ZipCode       0
dtype: int64
```

[6]:
```
#shape of the dataframe
users.shape
```

[6]:
```
(6040, 5)
```

[7]:
```
#Movies dataset
movies.head()
```

[7]:

	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

[8]:
```
movies.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
```

[9]:
```
#checking null values
movies.isnull().sum()
```

[9]:
```
MovieID    0
Title      0
Genres     0
dtype: int64
```

[10]:
```
#shape of the data frame
movies.shape
```

[10]:
```
(3883, 3)
```

[11]:
```
#rating dataset
ratings.head()
```

[11]:

	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

[12]:
```
ratings.info()
```

```
<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  int32
 2   Rating     1000209 non-null  int32
 3   Timestamp  1000209 non-null  object
dtypes: int32(3), object(1)
memory usage: 19.1+ MB
```

[13]:
```
#checkinng for null values
ratings.isnull().sum()
```

[13]:
```
UserID       0
MovieID      0
Rating       0
```

```
Timestamp    0
dtype: int64
```

[14]:
```
#shape of the datafreame
ratings.shape
```

[14]:
```
(1000209, 4)
```

[15]:
```
#merging users dataset and ratings dataset
users_ratings=pd.merge(users, ratings, on='UserID')
users_ratings.head()
```

[15]:

	UserID	Gender	Age	Occupation	ZipCode	MovieID	Rating	Timestamp
0	1	F	1	10	48067	1193	5	978300760
1	1	F	1	10	48067	661	3	978302109
2	1	F	1	10	48067	914	3	978301968
3	1	F	1	10	48067	3408	4	978300275
4	1	F	1	10	48067	2355	5	978824291

[16]:
```
#merging users_ratings dataset and movies dataset
users_ratings_movies=pd.merge(users_ratings, movies, on='MovieID')
users_ratings_movies.head()
```

[16]:

	UserID	Gender	Age	Occupation	ZipCode	MovieID	Rating	Timestamp	\
0	1	F	1	10	48067	1193	5	978300760	
1	2	M	56	16	70072	1193	5	978298413	
2	12	M	25	12	32793	1193	4	978220179	
3	15	M	25	7	22903	1193	4	978199279	
4	17	M	50	1	95350	1193	5	978158471	

	Title	Genres
0	One Flew Over the Cuckoo's Nest (1975)	Drama
1	One Flew Over the Cuckoo's Nest (1975)	Drama
2	One Flew Over the Cuckoo's Nest (1975)	Drama
3	One Flew Over the Cuckoo's Nest (1975)	Drama
4	One Flew Over the Cuckoo's Nest (1975)	Drama

[17]:
```
#preparing the required master dataset
master_data=users_ratings_movies.drop(['ZipCode','Timestamp'], axis=1)
```

[18]:
```
master_data=master_data[['UserID', 'Gender', 'Age', 'Occupation', 'MovieID',␣
↪'Title', 'Genres', 'Rating']]
master_data.head()
```

[18]:

	UserID	Gender	Age	Occupation	MovieID	\
0	1	F	1	10	1193	
1	2	M	56	16	1193	

```
2      12      M   25          12     1193
3      15      M   25           7     1193
4      17      M   50           1     1193

                                    Title Genres  Rating
0  One Flew Over the Cuckoo's Nest (1975)  Drama       5
1  One Flew Over the Cuckoo's Nest (1975)  Drama       5
2  One Flew Over the Cuckoo's Nest (1975)  Drama       4
3  One Flew Over the Cuckoo's Nest (1975)  Drama       4
4  One Flew Over the Cuckoo's Nest (1975)  Drama       5
```

[19]:
```
#data visualization
import matplotlib.pyplot as plt
from matplotlib import style
%matplotlib inline
```

[20]:
```
#user age distribution
age_count=users['Age'].value_counts()
age_count
```

[20]:
```
25    2096
35    1193
18    1103
45     550
50     496
56     380
1      222
Name: Age, dtype: int64
```

[21]:
```
age_category=('Under 18', '18-24', '25-34', '35-44', '45-49', '50-55', '55+')
x_pos=np.arange(len(age_category))
x_pos
```

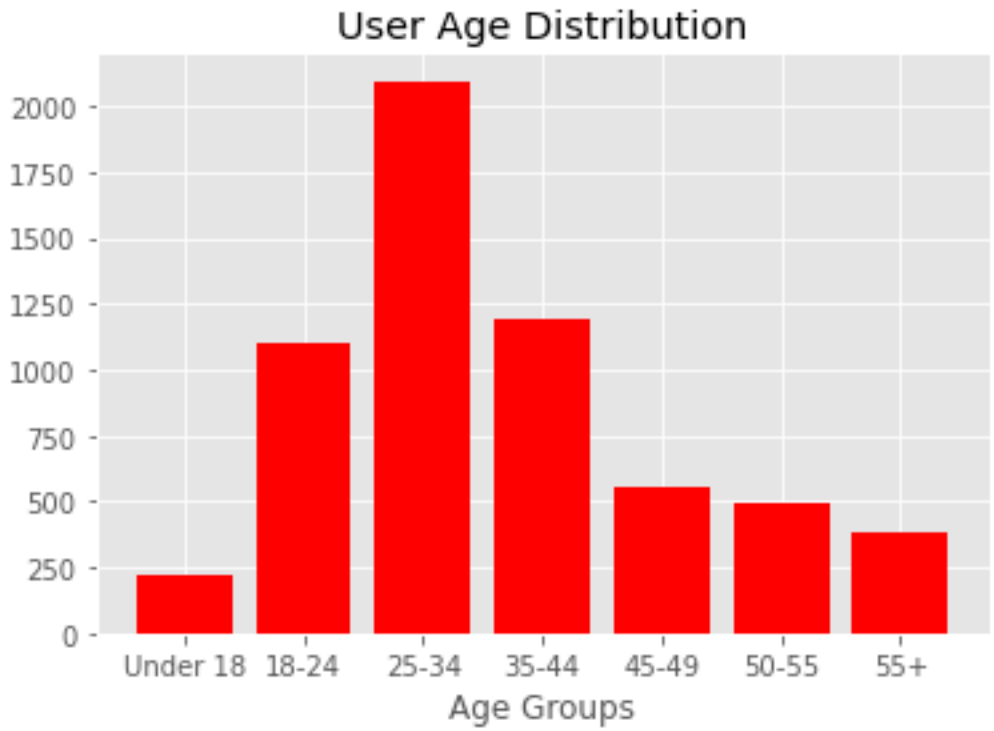
[21]:
```
array([0, 1, 2, 3, 4, 5, 6])
```

[22]:
```
age_values=[age_count[1], age_count[18], age_count[25], age_count[35],␣
 ↪age_count[45], age_count[50], age_count[56]]
age_values
```

[22]:
```
[222, 1103, 2096, 1193, 550, 496, 380]
```

[23]:
```
#plotting the bar chart
style.use('ggplot')
plt.bar(x_pos, age_values, align='center', color='r')
plt.xlabel('Age Groups')
plt.xticks(x_pos, age_category)
plt.title('User Age Distribution')
```

```
plt.show()
```



[24]:
```
#fetching the MovieID of the Toy Story (1995)
movies[movies['Title']=='Toy Story (1995)']['MovieID']
```

[24]:
```
0    1
Name: MovieID, dtype: int32
```

[25]:
```
toystory_data=ratings[ratings['MovieID']==1]
toystory_data.head(10)
```

[25]:

	UserID	MovieID	Rating	Timestamp
40	1	1	5	978824268
469	6	1	4	978237008
581	8	1	4	978233496
711	9	1	5	978225952
837	10	1	5	978226474
1966	18	1	4	978154768
2276	19	1	5	978555994
2530	21	1	3	978139347
2870	23	1	4	978463614
3405	26	1	3	978130703

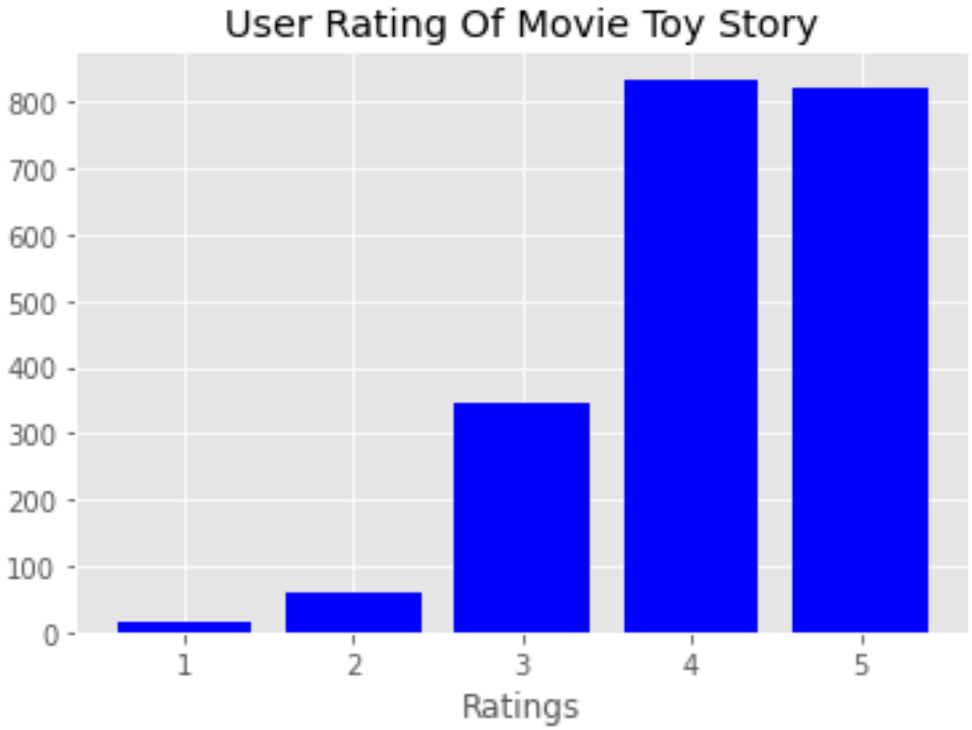
[26]:
```
movie_rating_toystory=toystory_data.groupby('Rating').size()
movie_rating_toystory
```

[26]:
```
Rating
1     16
2     61
3    345
4    835
5    820
dtype: int64
```

[27]:
```
ratings_type=('1', '2', '3', '4', '5')
x_pos1=np.arange(len(ratings_type))
x_pos1
```

[27]:
```
array([0, 1, 2, 3, 4])
```

[28]:
```
#plotting the barchart
style.use('ggplot')
plt.bar(x_pos1,movie_rating_toystory, align='center', color='b')
plt.xlabel('Ratings')
plt.xticks(x_pos1,ratings_type)
plt.title("User Rating Of Movie Toy Story")
plt.show()
```



[29]:
```
#finding top 25 movies by viwership rating
#fetching the data and rating of each movie by aggregate
movie_rating=master_data.groupby(['Title'], as_index=False)
average_movie_rating=movie_rating.agg({'Rating':'mean'})
average_movie_rating
```

[29]:

	Title	Rating
0	$1,000,000 Duck (1971)	3.027027
1	'Night Mother (1986)	3.371429
2	'Til There Was You (1997)	2.692308
3	'burbs, The (1989)	2.910891
4	…And Justice for All (1979)	3.713568
…	…	…
3701	Zed & Two Noughts, A (1985)	3.413793
3702	Zero Effect (1998)	3.750831
3703	Zero Kelvin (Kjærlighetens kjøtere) (1995)	3.500000
3704	Zeus and Roxanne (1997)	2.521739
3705	eXistenZ (1999)	3.256098

[3706 rows x 2 columns]

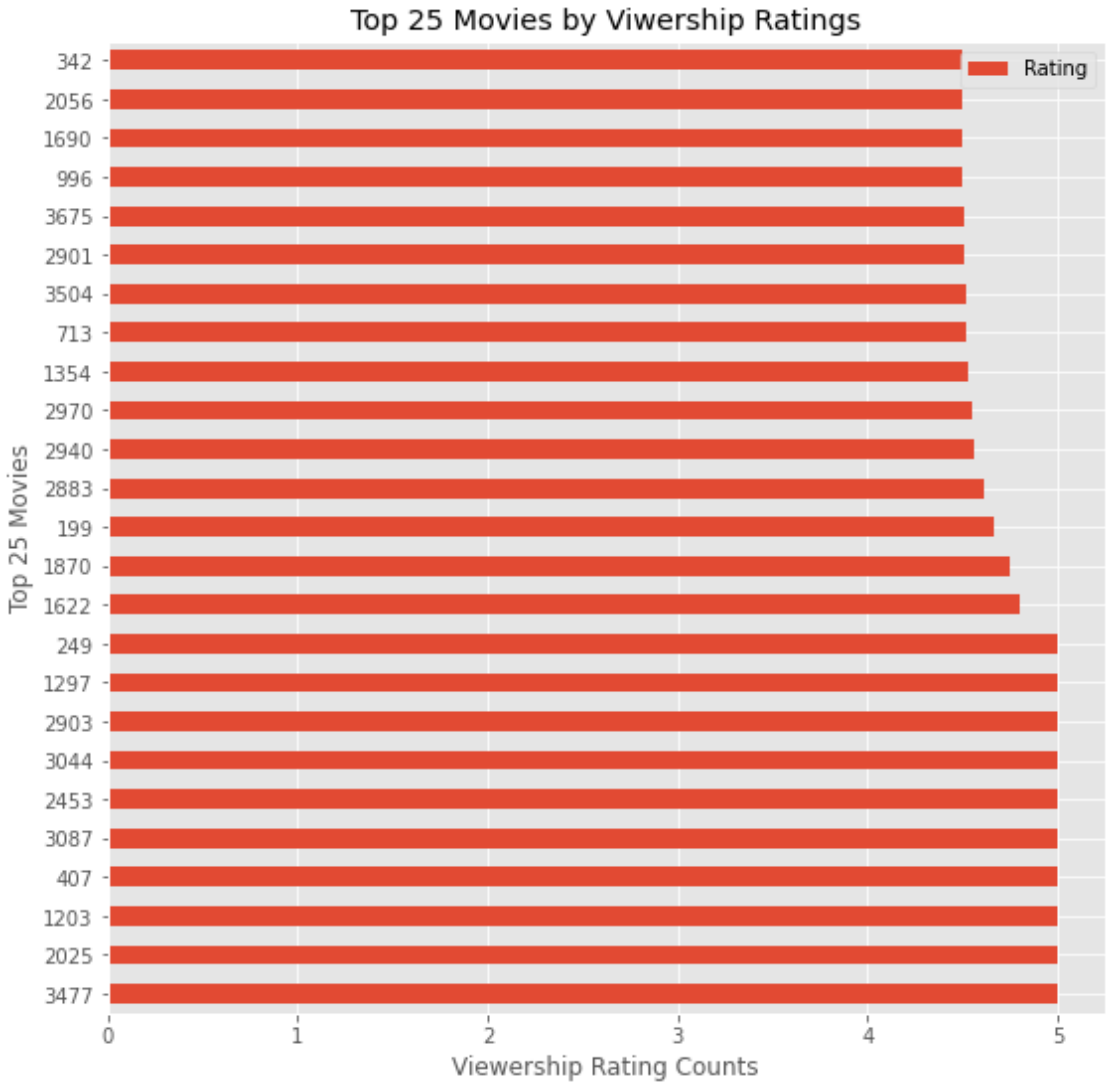
[30]:
```
top_25=average_movie_rating.sort_values('Rating', ascending=False).head(25)
top_25
```

[30]:

	Title	Rating
3477	Ulysses (Ulisse) (1954)	5.000000
2025	Lured (1947)	5.000000
1203	Follow the Bitch (1998)	5.000000
407	Bittersweet Motel (2000)	5.000000
3087	Song of Freedom (1936)	5.000000
2453	One Little Indian (1973)	5.000000
3044	Smashing Time (1967)	5.000000
2903	Schlafes Bruder (Brother of Sleep) (1995)	5.000000
1297	Gate of Heavenly Peace, The (1995)	5.000000
249	Baby, The (1973)	5.000000
1622	I Am Cuba (Soy Cuba/Ya Kuba) (1964)	4.800000
1870	Lamerica (1994)	4.750000
199	Apple, The (Sib) (1998)	4.666667
2883	Sanjuro (1962)	4.608696
2940	Seven Samurai (The Magnificent Seven) (Shichin…	4.560510
2970	Shawshank Redemption, The (1994)	4.554558
1354	Godfather, The (1972)	4.524966
713	Close Shave, A (1995)	4.520548
3504	Usual Suspects, The (1995)	4.517106
2901	Schindler's List (1993)	4.510417
3675	Wrong Trousers, The (1993)	4.507937

```
996                Dry Cleaning (Nettoyage à sec) (1997)  4.500000
1690         Inheritors, The (Die Siebtelbauern) (1998)  4.500000
2056                                  Mamma Roma (1962)  4.500000
342                                    Bells, The (1926)  4.500000
```

[31]:
```
#plotting bar for 25 top movies by viwerership
top_25.plot(kind='barh', figsize=(9,9))
plt.xlabel("Viewership Rating Counts")
plt.ylabel("Top 25 Movies")
plt.title("Top 25 Movies by Viwership Ratings")
plt.show()
```

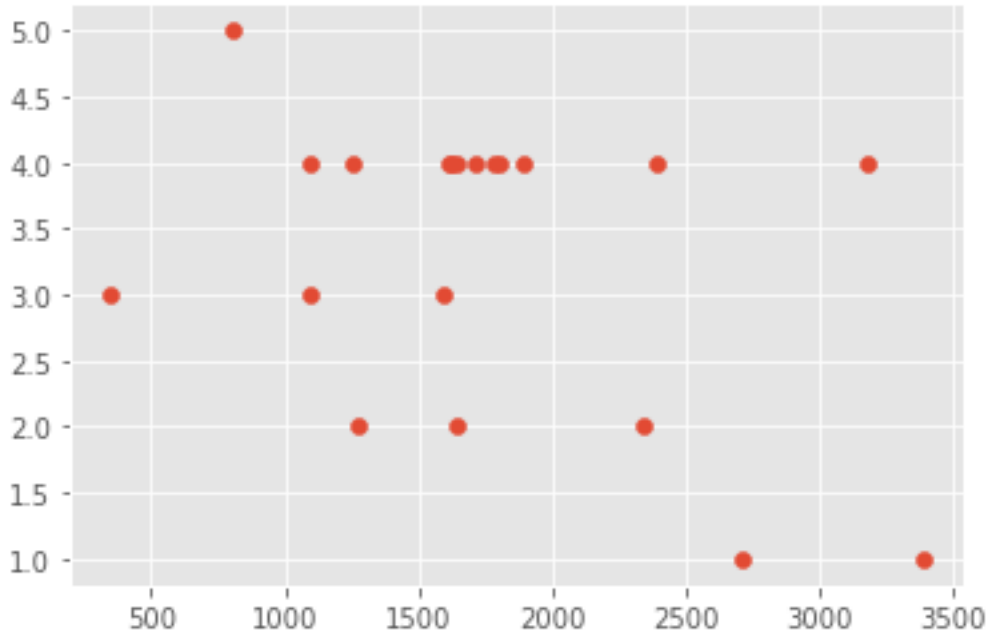


[32]:
```
#rating for all the movies by a particular user of UserID=2496
user_rating_data=master_data[master_data['UserID']==2696]
user_rating_data=user_rating_data[['UserID','MovieID','Title','Rating']]
user_rating_data.head(10)
```

[32]:

	UserID	MovieID	Title	Rating
24345	2696	1270	Back to the Future (1985)	2
29848	2696	1097	E.T. the Extra-Terrestrial (1982)	3
244232	2696	1617	L.A. Confidential (1997)	4
250014	2696	800	Lone Star (1996)	5
273633	2696	3386	JFK (1991)	1
277808	2696	3176	Talented Mr. Ripley, The (1999)	4
371178	2696	1711	Midnight in the Garden of Good and Evil (1997)	4
377250	2696	1589	Cop Land (1997)	3
598042	2696	1783	Palmetto (1998)	4
603189	2696	1892	Perfect Murder, A (1998)	4

[33]:
```
#plotting Movie and rating for the above particular user
plt.scatter(x=user_rating_data['MovieID'].head(20),␣
 ↪y=user_rating_data['Rating'].head(20))
plt.show()
```



[34]:
```
#Feature Ebgineering
```

[35]:
```
#Finding all the unique genres
genres=master_data['Genres'].str.split("|")
genres
```

[35]:
```
0                            [Drama]
1                            [Drama]
2                            [Drama]
3                            [Drama]
4                            [Drama]
                        …
1000204                [Documentary]
1000205                      [Drama]
1000206                      [Drama]
1000207    [Comedy, Drama, Western]
1000208                [Documentary]
Name: Genres, Length: 1000209, dtype: object
```

[36]:
```
unique_genres=set()
for i in genres:
    unique_genres=unique_genres.union(set(i))
unique_genres
```

[36]:
```
{'Action',
 'Adventure',
 'Animation',
 "Children's",
 'Comedy',
 'Crime',
 'Documentary',
 'Drama',
 'Fantasy',
 'Film-Noir',
 'Horror',
 'Musical',
 'Mystery',
 'Romance',
 'Sci-Fi',
 'Thriller',
 'War',
 'Western'}
```

[37]:
```
#Create a separate column for each genre category with a one-hot encoding ( 1␣
↪and 0)
one_hot_genre=master_data['Genres'].str.get_dummies("|")
one_hot_genre.head()
```

[37]:

	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	\
0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	

	Drama	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	\
0	1	0	0	0	0	0	0	0	
1	1	0	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	0	
4	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	0	0

[38]:
```
#merging one_hot_genre with master data
one_hot_genre=pd.concat([master_data,one_hot_genre], axis=1)
```

```
one_hot_genre.head()
```

[38]:
```
   UserID Gender  Age Occupation  MovieID  \
0       1      F    1         10     1193
1       2      M   56         16     1193
2      12      M   25         12     1193
3      15      M   25          7     1193
4      17      M   50          1     1193

                                  Title Genres  Rating  Action  Adventure  \
0  One Flew Over the Cuckoo's Nest (1975)  Drama       5       0          0
1  One Flew Over the Cuckoo's Nest (1975)  Drama       5       0          0
2  One Flew Over the Cuckoo's Nest (1975)  Drama       4       0          0
3  One Flew Over the Cuckoo's Nest (1975)  Drama       4       0          0
4  One Flew Over the Cuckoo's Nest (1975)  Drama       5       0          0

   …  Fantasy  Film-Noir  Horror  Musical  Mystery  Romance  Sci-Fi  \
0  …        0          0       0        0        0        0       0
1  …        0          0       0        0        0        0       0
2  …        0          0       0        0        0        0       0
3  …        0          0       0        0        0        0       0
4  …        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    0        0

[5 rows x 26 columns]
```

[39]:
```
#accessing all the  column names
one_hot_genre.columns
```

[39]:
```
Index(['UserID', 'Gender', 'Age', 'Occupation', 'MovieID', 'Title', 'Genres',
       'Rating', 'Action', 'Adventure', 'Animation', 'Children's', 'Comedy',
       'Crime', 'Documentary', 'Drama', 'Fantasy', 'Film-Noir', 'Horror',
       'Musical', 'Mystery', 'Romance', 'Sci-Fi', 'Thriller', 'War',
       'Western'],
      dtype='object')
```

[40]:
```
#Determine the features affecting the ratings of any particular movie.
```

[41]:
```
feature_data=master_data.copy()
feature_data
```

[41]:
```
         UserID Gender  Age Occupation  MovieID  \
0             1      F    1         10     1193
1             2      M   56         16     1193
2            12      M   25         12     1193
3            15      M   25          7     1193
4            17      M   50          1     1193
…           …    …  …         …       …
1000204    5949      M   18         17     2198
1000205    5675      M   35         14     2703
1000206    5780      M   18         17     2845
1000207    5851      F   18         20     3607
1000208    5938      M   25          1     2909

                                              Title                 Genres  \
0             One Flew Over the Cuckoo's Nest (1975)                  Drama
1             One Flew Over the Cuckoo's Nest (1975)                  Drama
2             One Flew Over the Cuckoo's Nest (1975)                  Drama
3             One Flew Over the Cuckoo's Nest (1975)                  Drama
4             One Flew Over the Cuckoo's Nest (1975)                  Drama
…                                                 …                      …
1000204                        Modulations (1998)            Documentary
1000205                      Broken Vessels (1998)                  Drama
1000206                          White Boys (1999)                  Drama
1000207                    One Little Indian (1973)  Comedy|Drama|Western
1000208  Five Wives, Three Secretaries and Me (1998)            Documentary

         Rating
0             5
1             5
2             4
3             4
4             5
…          …
1000204       5
1000205       3
1000206       1
1000207       5
1000208       4

[1000209 rows x 8 columns]
```

[42]:
```
#fetching the year which the movie was released
feature_data[["Title","Year"]]=feature_data.Title.str.extract("(.)\s\((.\d+)",␣
 ↪expand=True)
feature_data=feature_data.drop(['Title'], axis=1)
feature_data
```

[42]:

	UserID	Gender	Age	Occupation	MovieID	Genres	Rating	\
0	1	F	1	10	1193	Drama	5	
1	2	M	56	16	1193	Drama	5	
2	12	M	25	12	1193	Drama	4	
3	15	M	25	7	1193	Drama	4	
4	17	M	50	1	1193	Drama	5	
…	…	…	…	…	…	…	…	
1000204	5949	M	18	17	2198	Documentary	5	
1000205	5675	M	35	14	2703	Drama	3	
1000206	5780	M	18	17	2845	Drama	1	
1000207	5851	F	18	20	3607	Comedy|Drama|Western	5	
1000208	5938	M	25	1	2909	Documentary	4	

	Year
0	1975
1	1975
2	1975
3	1975
4	1975
…	…
1000204	1998
1000205	1998
1000206	1999
1000207	1973
1000208	1998

[1000209 rows x 8 columns]

[43]:
```
#calculating the age of movies
feature_data['Year']=feature_data.Year.astype(int)
feature_data['Movie_Age']=2022-feature_data['Year']
feature_data
```

[43]:

	UserID	Gender	Age	Occupation	MovieID	Genres	Rating	\
0	1	F	1	10	1193	Drama	5	
1	2	M	56	16	1193	Drama	5	
2	12	M	25	12	1193	Drama	4	
3	15	M	25	7	1193	Drama	4	
4	17	M	50	1	1193	Drama	5	
…	…	…	…	…	…	…	…	
1000204	5949	M	18	17	2198	Documentary	5	
1000205	5675	M	35	14	2703	Drama	3	
1000206	5780	M	18	17	2845	Drama	1	
1000207	5851	F	18	20	3607	Comedy|Drama|Western	5	
1000208	5938	M	25	1	2909	Documentary	4	

	Year	Movie_Age

```
0         1975         47
1         1975         47
2         1975         47
3         1975         47
4         1975         47
…          …          …
1000204   1998         24
1000205   1998         24
1000206   1999         23
1000207   1973         49
1000208   1998         24

[1000209 rows x 9 columns]
```

[44]:
```
#Making gender colums to integer type
feature_data['Gender']=feature_data.Gender.replace('F',1)
feature_data['Gender']=feature_data.Gender.replace('M',0)
feature_data['Gender']=feature_data.Gender.astype(int)
feature_data
```

[44]:
```
          UserID  Gender  Age Occupation  MovieID                 Genres  \
0              1       1    1         10     1193                  Drama
1              2       0   56         16     1193                  Drama
2             12       0   25         12     1193                  Drama
3             15       0   25          7     1193                  Drama
4             17       0   50          1     1193                  Drama
…           …      …  …          …       …                    …
1000204     5949       0   18         17     2198            Documentary
1000205     5675       0   35         14     2703                  Drama
1000206     5780       0   18         17     2845                  Drama
1000207     5851       1   18         20     3607  Comedy|Drama|Western
1000208     5938       0   25          1     2909            Documentary

          Rating  Year  Movie_Age
0              5  1975         47
1              5  1975         47
2              4  1975         47
3              4  1975         47
4              5  1975         47
…            …    …          …
1000204        5  1998         24
1000205        3  1998         24
1000206        1  1999         23
1000207        5  1973         49
1000208        4  1998         24

[1000209 rows x 9 columns]
```

[45]:
```
#checking the correlation of features with ratings
feature_data[['Gender','Occupation','Age','Movie_Age']].
 ↪corrwith(feature_data['Rating'])
```

[45]:
```
Gender       0.019861
Age          0.056869
Movie_Age    0.156946
dtype: float64
```

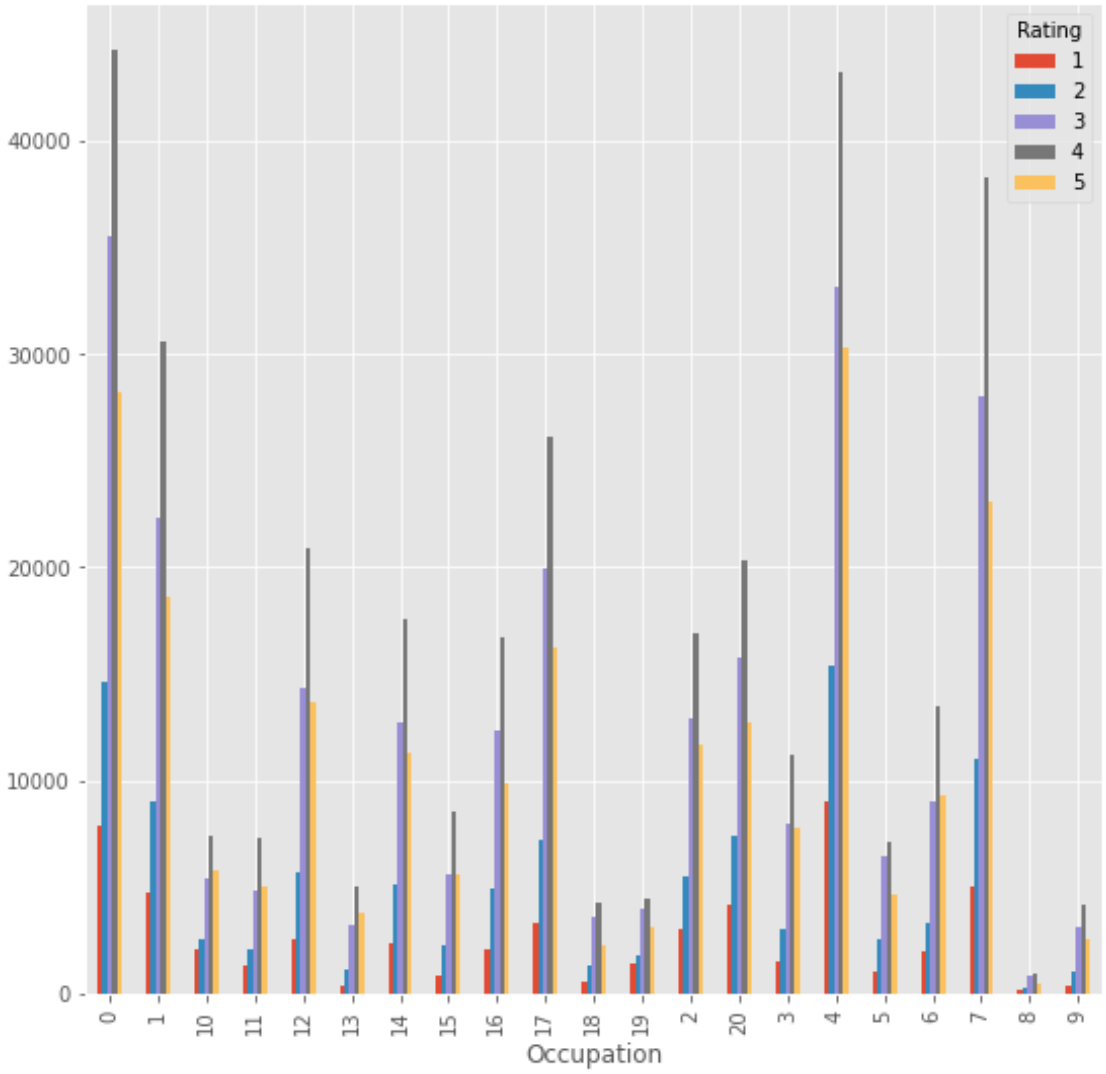
[46]:
```
#here movie age has the positive realtionship with rating
```

[47]:
```
#checking Occupation relationship with Rating
occupation_rating=feature_data.groupby(['Occupation','Rating']).size().unstack()
occupation_rating
```

[47]:

Rating	1	2	3	4	5
Occupation					
0	7892	14679	35494	44256	28178
1	4756	9054	22361	30577	18603
10	2058	2570	5392	7448	5822
11	1337	2056	4814	7287	5069
12	2578	5675	14382	20909	13670
13	405	1176	3274	5060	3839
14	2345	5160	12696	17593	11315
15	887	2271	5571	8568	5654
16	2051	4980	12355	16733	9902
17	3351	7193	19908	26155	16209
18	583	1295	3655	4238	2315
19	1417	1835	3991	4482	3179
2	3062	5486	12919	16899	11702
20	4166	7427	15748	20312	12744
3	1521	3083	7958	11236	7825
4	9004	15418	33119	43219	30272
5	1070	2552	6446	7127	4655
6	2046	3332	9058	13500	9269
7	5076	10978	28054	38273	23044
8	176	292	820	929	489
9	393	1045	3182	4170	2555

[48]:
```
#plotting the graph for relationship between occupation and ratings
occupation_rating.plot(kind='bar', stacked=False, legend=True, figsize=(9,9))
plt.show()
```

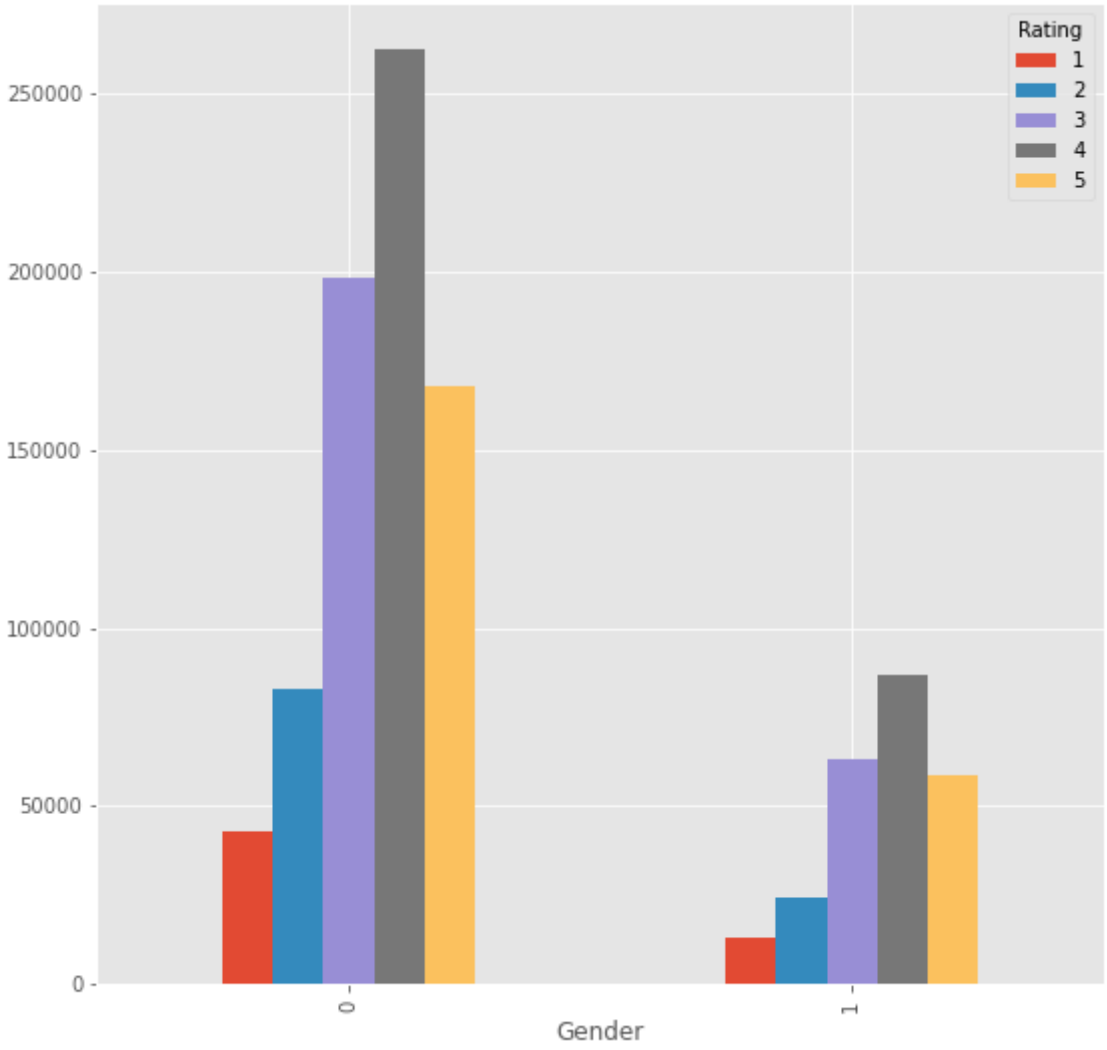


[49]:
```
#checking gender realtion with ratings
gender_rating=feature_data.groupby(['Gender','Rating']).size().unstack()
gender_rating
```

[49]:

Rating	1	2	3	4	5
Gender					
0	42827	83009	198231	261938	167764
1	13347	24548	62966	87033	58546

[50]:
```
#plotting the graph showing realtionship between gender and ratings
gender_rating.plot(kind='bar',stacked=False, legend=True, figsize=(9,9))
plt.show()
```

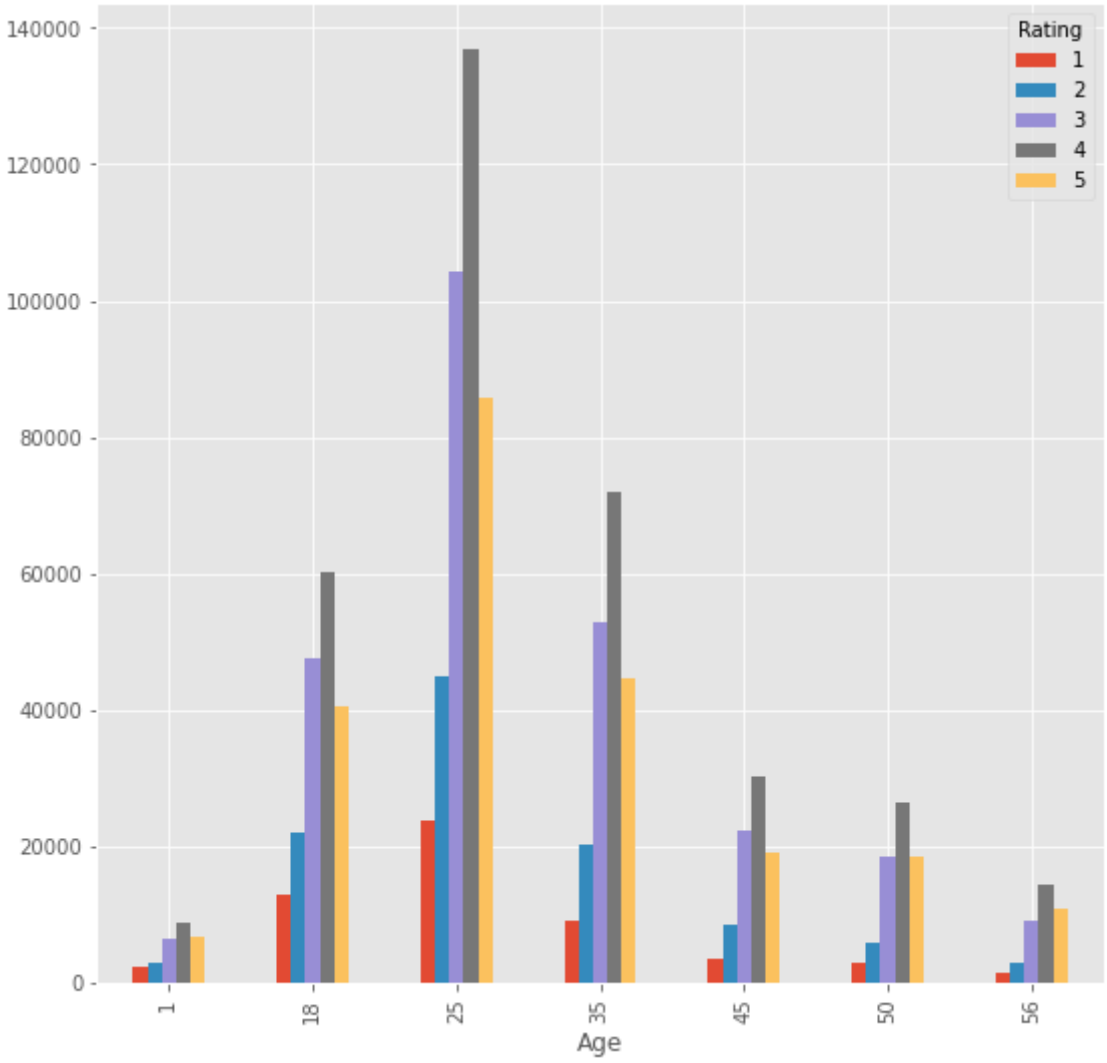


[51]:
```
#checking age realtioship with ratings
age_rating=feature_data.groupby(['Age','Rating']).size().unstack()
age_rating
```

[51]:

Rating	1	2	3	4	5
Age					
1	2238	2983	6380	8808	6802
18	13063	22073	47601	60241	40558
25	23898	44817	104287	136824	85730
35	9067	20253	52990	71983	44710
45	3409	8437	22311	30334	19142
50	2948	5993	18465	26484	18600
56	1551	3001	9163	14297	10768

[52]:
```
#plotting the graph showing relationship between age and ratings
age_rating.plot(kind='bar',stacked=False, legend=True, figsize=(9,9))
plt.show()
```



[53]:
```
#checking relationship between movie age and ratings
movieage_rating=feature_data.groupby(['Movie_Age','Rating']).size().unstack()
movieage_rating
```

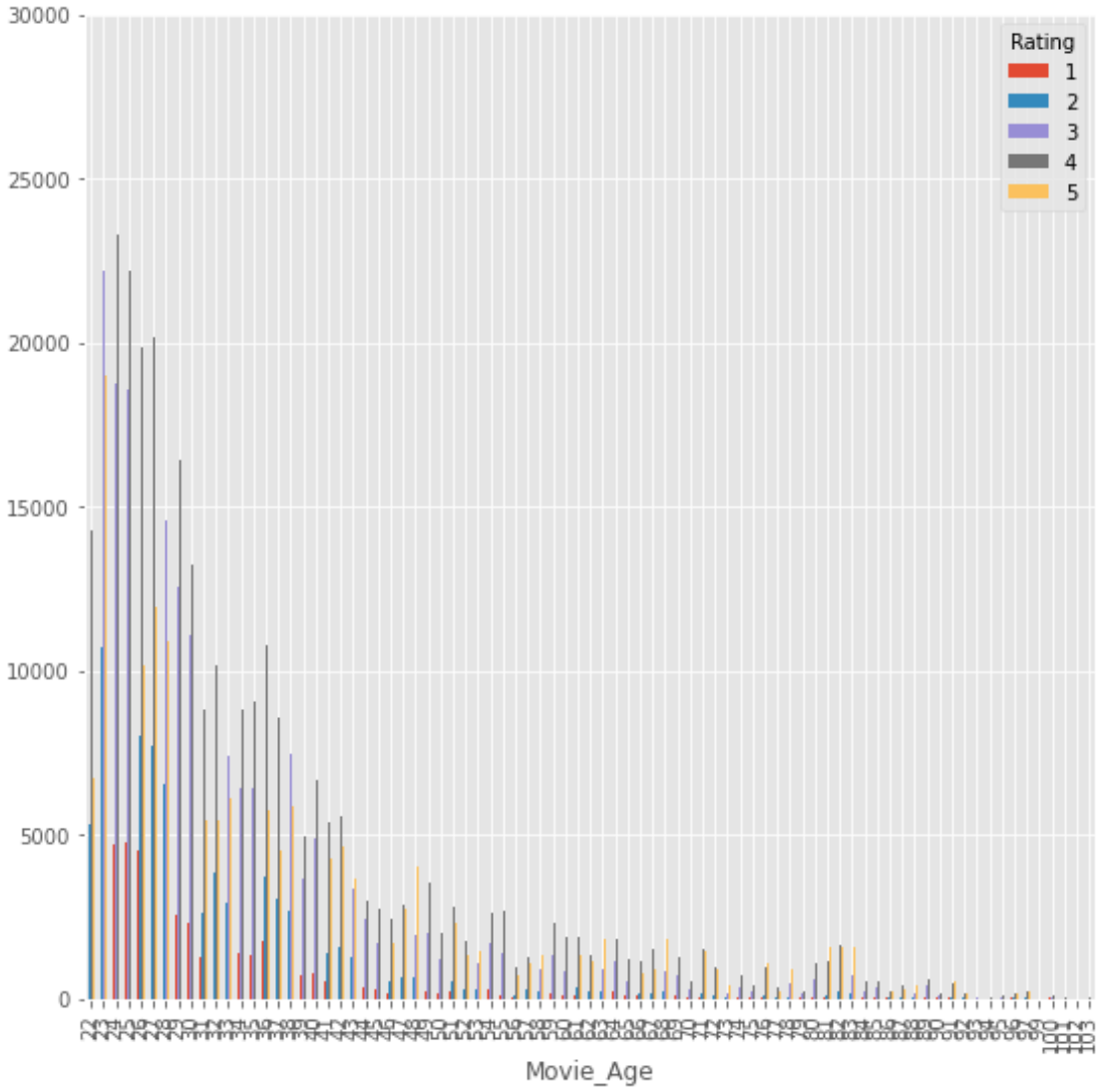
[53]:

Rating	1	2	3	4	5
Movie_Age					
22	3551.0	5313.0	11125.0	14300.0	6711.0
23	6386.0	10704.0	22158.0	28585.0	19000.0
24	4709.0	8525.0	18751.0	23310.0	12931.0
25	4738.0	8533.0	18563.0	22204.0	11364.0

```
26          4540.0    8001.0   16852.0   19827.0   10162.0
…              …         …        …         …         …
99             4.0       2.0      2.0       6.0       3.0
100           12.0      10.0     42.0      78.0      96.0
101            3.0       5.0     10.0      28.0      16.0
102            2.0       3.0      4.0       7.0       8.0
103            3.0       3.0     15.0      18.0       6.0

[81 rows x 5 columns]
```

[54]:
```
#plotting the graph showing the realtionship between movie_age and ratings
movieage_rating.plot(kind='bar',stacked=False, legend=True, figsize=(9,9))
plt.show()
```



[55]:
```
#developing Logistic regression model to predict the movie rating
```

[56]:
```
#assigning independent variable and dependent variable to Xand Y
x=master_data[['Age','Occupation','MovieID']]
y=master_data['Rating']
x
y
```

[56]:
```
0          5
1          5
2          4
3          4
4          5
          ..
1000204    5
1000205    3
1000206    1
1000207    5
1000208    4
Name: Rating, Length: 1000209, dtype: int32
```

[57]:
```
#checking the shape of x and y
x.shape
```

[57]:
```
(1000209, 3)
```

[58]:
```
y.shape
```

[58]:
```
(1000209,)
```

[59]:
```
#splitting the dataset into testing and training dataset at 70:30
import sklearn
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test=sklearn.model_selection.
 ↪train_test_split(x,y,random_state=1,test_size=0.3)
```

[60]:
```
#using the logistic regression
from sklearn.linear_model import LogisticRegression
logreg=LogisticRegression()
```

[61]:
```
#fitting data into logistic regression
logreg.fit(x_train,y_train)
```

```
C:\Users\sssun\anaconda3\lib\site-
packages\sklearn\linear_model\_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

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

[61]:
```
LogisticRegression()
```

[62]:
```
#predicting the outcome using logistic regression
y_pred=logreg.predict(x_test)
```

[63]:
```
y_pred
```

[63]:
```
array([4, 4, 4, …, 4, 4, 4])
```

[64]:
```
#calculate the accuracy of the model
from sklearn.metrics import accuracy_score
accuracy_score(y_pred,y_test)
```

[64]:
```
0.3500264944361684
```

[65]:
```
#check model perormance on new dataset
#crewate example object with new values for prediction
x_new=[[25,7,1193],[18,17,2198]]
```

[66]:
```
logreg.predict(x_new)
```

[66]:
```
array([4, 4])
```

[67]:
```
from sklearn import metrics
print(metrics.confusion_matrix(y_test, y_pred))
print(metrics.classification_report(y_test, y_pred))
```

```
[[     0      0      0  16833      0]
 [     0      0      0  31872      0]
 [     0      0      0  78277      0]
 [     0      0      0 105030      0]
 [     0      0      0  68051      0]]
C:\Users\sssun\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support
```

```
              1       0.00      0.00      0.00     16833
              2       0.00      0.00      0.00     31872
              3       0.00      0.00      0.00     78277
              4       0.35      1.00      0.52    105030
              5       0.00      0.00      0.00     68051

       accuracy                           0.35    300063
      macro avg       0.07      0.20      0.10    300063
   weighted avg       0.12      0.35      0.18    300063
```

[ ]: