In [1]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import re
import sklearn
from sklearn.linear_model import LogisticRegressionCV,LogisticRegression
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             roc_auc_score, confusion_matrix, classification_report,
                             roc_curve, f1_score, mean_squared_error)
from sklearn.model_selection import train_test_split, GridSearchCV, validation_curve, learning_curve
from sklearn.preprocessing import StandardScaler
```

Importing the three datasets and create a new dataset

In [2]:
```
ratings_df = pd.read_csv("C:\\Users\\Shawn Eng\\Desktop\\ratings.dat", delimiter="::", header=None, engine='python', e
users_df = pd.read_csv("C:\\Users\\Shawn Eng\\Desktop\\users.dat", delimiter="::", header=None, engine='python', encod
movies_df = pd.read_csv("C:\\Users\\Shawn Eng\\Desktop\\movies.dat", delimiter="::", header=None, engine='python', enc

ratings_df.columns = ['UserID', 'MovieID', 'Rating', 'Timestamp']
users_df.columns = ['UserID', 'Gender', 'Age', 'Occupation', 'Zip-code']
movies_df.columns = ['MovieID', 'Title', 'Genres']

Master_Data = pd.merge(ratings_df, users_df, on='UserID')
Master_Data = pd.merge(Master_Data, movies_df, on='MovieID')

#Read the new dataset df_Master_Data
df_Master_Data = pd.DataFrame(Master_Data)
df_Master_Data
```

2	12	1193	4	978220179	M	25	12	32793	One Flew Over the Cuckoo's Nest (1975)	Drama
3	15	1193	4	978199279	M	25	7	22903	One Flew Over the Cuckoo's Nest (1975)	Drama
4	17	1193	5	978158471	M	50	1	95350	One Flew Over the Cuckoo's Nest (1975)	Drama
...	...	...	...	...	...	...	...	...	...	...
1000204	5949	2198	5	958846401	M	18	17	47901	Modulations (1998)	Documentary
1000205	5675	2703	3	976029116	M	35	14	30030	Broken Vessels (1998)	Drama
1000206	5780	2845	1	958153068	M	18	17	92886	White Boys (1999)	Drama
1000207	5851	3607	5	957756608	F	18	20	55410	One Little Indian (1973)	Comedy|Drama|Western
1000208	5938	2909	4	957273353	M	25	1	35401	Five Wives, Three Secretaries and Me (1998)	Documentary

1000209 rows × 10 columns

In [3]:
```
df_Master_Data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns (total 10 columns):
 #   Column      Non-Null Count    Dtype 
---  ------      --------------    ----- 
 0   UserID      1000209 non-null  int64 
 1   MovieID     1000209 non-null  int64 
 2   Rating      1000209 non-null  int64 
 3   Timestamp   1000209 non-null  int64 
 4   Gender      1000209 non-null  object
 5   Age         1000209 non-null  int64 
 6   Occupation  1000209 non-null  int64 
 7   Zip-code    1000209 non-null  object
 8   Title       1000209 non-null  object
 9   Genres      1000209 non-null  object
dtypes: int64(6), object(4)
memory usage: 83.9+ MB
```

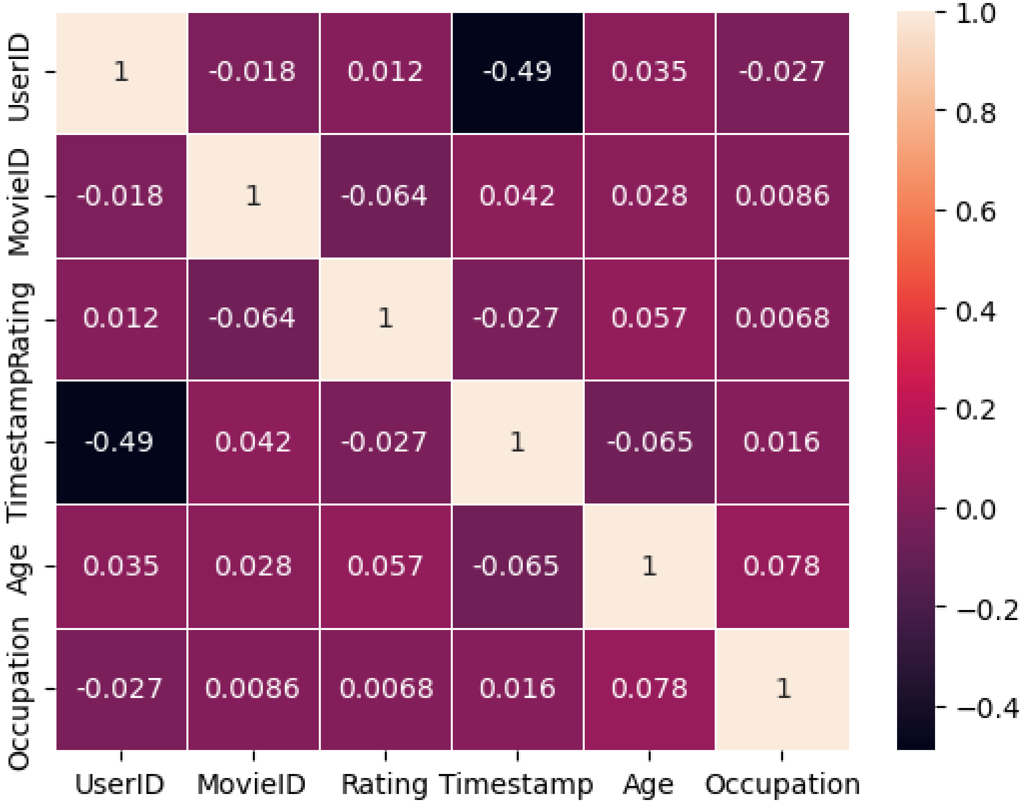
In [4]:
```
df_Master_Data.describe().round(3)
```

Out[4]:

	UserID	MovieID	Rating	Timestamp	Age	Occupation
count	1000209.000	1000209.000	1000209.000	1.000209e+06	1000209.000	1000209.000
mean	3024.512	1865.540	3.582	9.722437e+08	29.738	8.036
std	1728.413	1096.041	1.117	1.215256e+07	11.752	6.531
min	1.000	1.000	1.000	9.567039e+08	1.000	0.000
25%	1506.000	1030.000	3.000	9.653026e+08	25.000	2.000
50%	3070.000	1835.000	4.000	9.730180e+08	25.000	7.000
75%	4476.000	2770.000	4.000	9.752209e+08	35.000	14.000
max	6040.000	3952.000	5.000	1.046455e+09	56.000	20.000

In [5]:
```
df_Master_Data.shape
```
Out[5]:
```
(1000209, 10)
```

In [6]:
```
corr= df_Master_Data.corr()
sns.heatmap(corr, annot= True, linewidths=0.5)
```
Out[6]:
```
<Axes: >
```



In [7]:
```
# checking for NA Values in the DataFrame
print('NA Values in the Data Frame is : ')
def is_na(x):
    for i in x.columns:
        print(i,'column',' :', x[i].isna().sum(),'\n')
is_na(df_Master_Data)
```

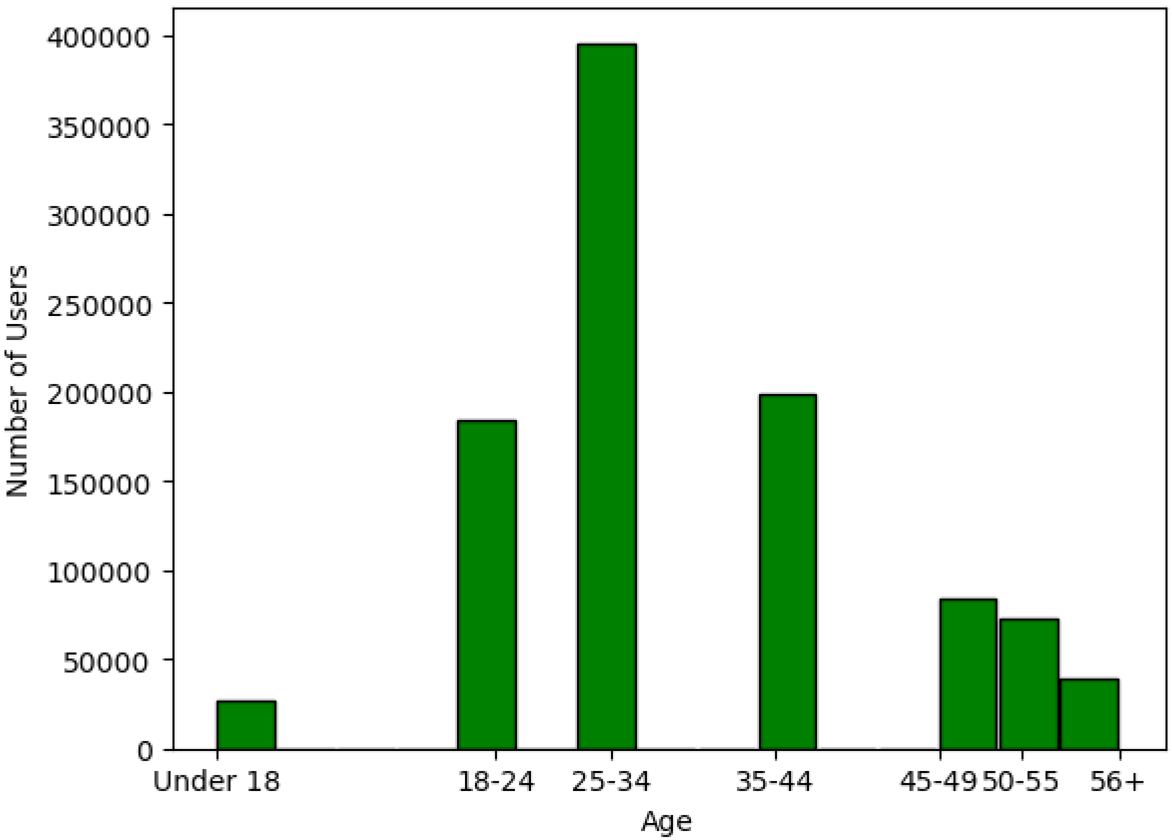
```
NA Values in the Data Frame is :
UserID column  : 0

MovieID column  : 0

Rating column  : 0

Timestamp column  : 0

Gender column  : 0

Age column  : 0

Occupation column  : 0

Zip-code column  : 0

Title column  : 0

Genres column  : 0
```

In [8]:
```
df_Master_Data.isna().value_counts()
```

Out[8]:
```
UserID  MovieID  Rating  Timestamp  Gender  Age    Occupation  Zip-code  Title  Genres
False   False    False   False      False   False  False       False     False  False     1000209
dtype: int64
```

Exploring the Datasets using Visual Representations

In [9]:
```
# User Age Distribution of Master_Data

plt.hist(df_Master_Data['Age'], bins=15, width=3.5, edgecolor='k', color='green')
plt.xlabel('Age')
plt.ylabel('Number of Users')
plt.xticks([1, 18, 25, 35, 45, 50, 56], ['Under 18', '18-24', '25-34', '35-44', '45-49', '50-55', '56+'])
plt.show()

## The user age distribution approximates a normal distribution curve with vast majority of the users in the dataset b
## their prime where they have the most time freedom and disposable income to watch movies as they are not yet respons
## paying house expenses or major responsibilities to shoulder. Vast Majority of MovieLens Users are younger as they a
## technologically savvy and able to naviagte MovieLens much easier than elders / seniors. People in elder years tend
## rewatch older movies that were popular in their youth and early adult years that can be watched for free on televis
```



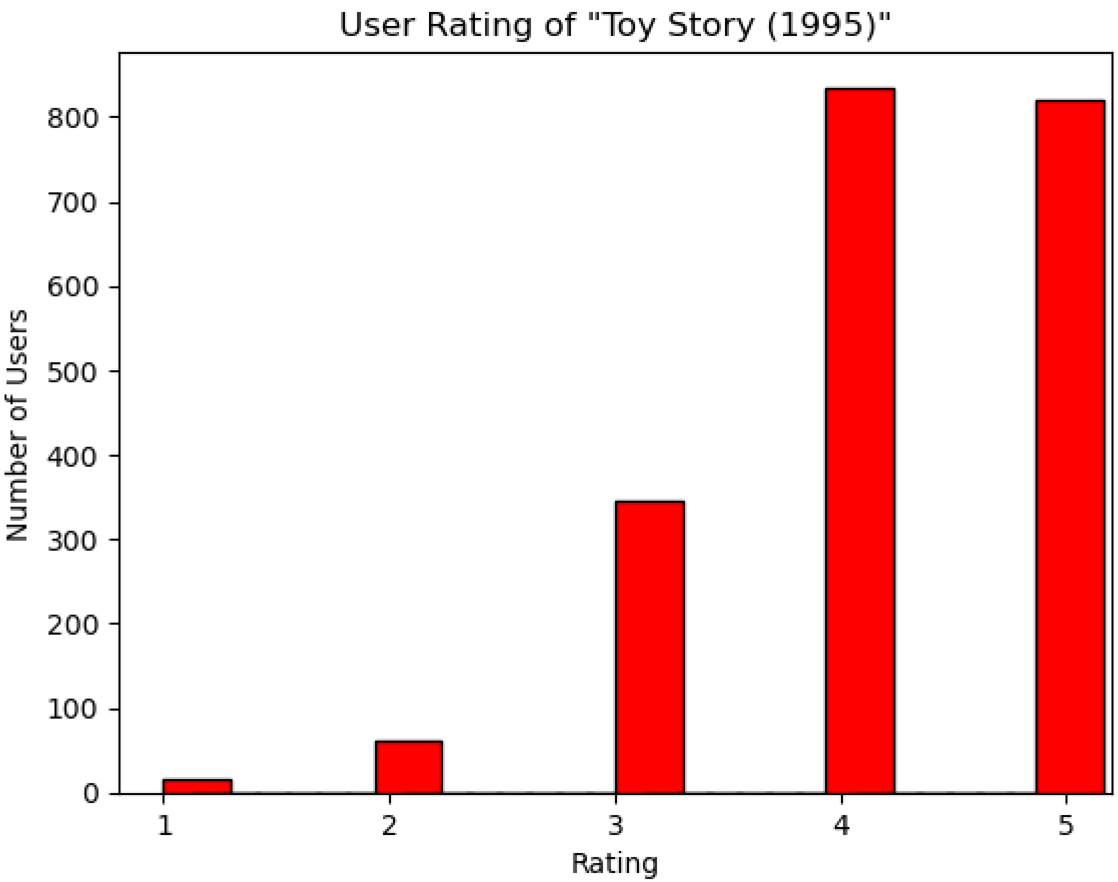
In [10]:
```
#User rating of the movie “Toy Story”
user_rating = ratings_df.groupby('UserID').size()
user_rating = df_Master_Data[df_Master_Data.Title == "Toy Story (1995)"]

user_rating
```

Out[10]:

	UserID	MovieID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Title	Genres
41626	1	1	5	978824268	F	1	10	48067	Toy Story (1995)	Animation|Children's|Comedy
41627	6	1	4	978237008	F	50	9	55117	Toy Story (1995)	Animation|Children's|Comedy
41628	8	1	4	978233496	M	25	12	11413	Toy Story (1995)	Animation|Children's|Comedy
41629	9	1	5	978225952	M	25	17	61614	Toy Story (1995)	Animation|Children's|Comedy
41630	10	1	5	978226474	F	35	1	95370	Toy Story (1995)	Animation|Children's|Comedy
...	...	...	...	...	...	...	...	...	...	...
43698	6022	1	5	956755763	M	25	17	57006	Toy Story (1995)	Animation|Children's|Comedy
43699	6025	1	5	956812867	F	25	1	32607	Toy Story (1995)	Animation|Children's|Comedy
43700	6032	1	4	956718127	M	45	7	55108	Toy Story (1995)	Animation|Children's|Comedy
43701	6035	1	4	956712849	F	25	1	78734	Toy Story (1995)	Animation|Children's|Comedy
43702	6040	1	3	957717358	M	25	6	11106	Toy Story (1995)	Animation|Children's|Comedy

2077 rows × 10 columns

In [11]:
```
# User rating of the movie "Toy Story":
Toy_Story_Ratings = df_Master_Data[df_Master_Data['Title'] == 'Toy Story (1995)']['Rating']
plt.hist(Toy_Story_Ratings, bins=30, width=0.3, edgecolor='k', color='red')
plt.xlabel('Rating')
plt.ylabel('Number of Users')
plt.title('User Rating of "Toy Story (1995)"')
plt.xticks([1, 2, 3, 4, 5])
plt.show()

## Toy Story was the first computer-animated feature film when it was released in 1995. The graphics of the film was c
## for its time which convinced many children & teenagers to watch it and its excellent storyline pulled in even adult
## as the film allows them to indulge in nostaligia of their childhood days playing with toys that their parents bough
## This led to near universal acclaim and high ratings from critics & audiences for the film. The user ratings of the
## story are heavily left-skewed as a result. This was the first of many movies to made by Pixar that accurately captu
## inner pains and joys of growing up which made subsequent movies very popular and perform very well in cinemas to th
## day.
```

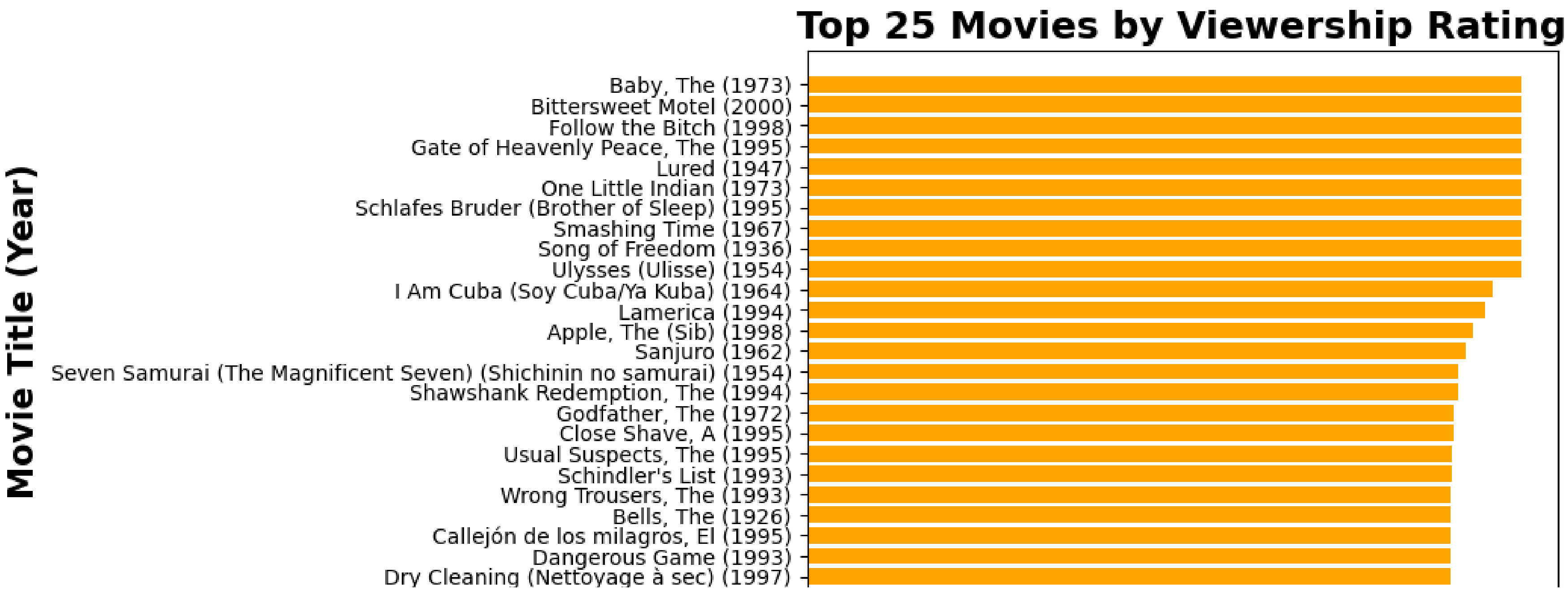

User Rating of "Toy Story (1995)"
Number of Users
0
100
200
300
400
500
600
700
800
1
2
3
4
5
Rating

In [12]:
```
movie_rating=ratings_df.groupby(['MovieID'])
avg_movie_rating=movie_rating.agg({'Rating':'mean'})
Top_25_movies=avg_movie_rating.sort_values('Rating',ascending=False).head(25)

pd.merge(Top_25_movies, movies_df, how='left', left_on=['MovieID'], right_on=['MovieID'])
```

Out[12]:

	MovieID	Rating	Title	Genres
0	989	5.000000	Schlafes Bruder (Brother of Sleep) (1995)	Drama
1	3881	5.000000	Bittersweet Motel (2000)	Documentary
2	1830	5.000000	Follow the Bitch (1998)	Comedy
3	3382	5.000000	Song of Freedom (1936)	Drama
4	787	5.000000	Gate of Heavenly Peace, The (1995)	Documentary
5	3280	5.000000	Baby, The (1973)	Horror
6	3607	5.000000	One Little Indian (1973)	Comedy|Drama|Western
7	3233	5.000000	Smashing Time (1967)	Comedy
8	3172	5.000000	Ulysses (Ulisse) (1954)	Adventure
9	3656	5.000000	Lured (1947)	Crime
10	3245	4.800000	I Am Cuba (Soy Cuba/Ya Kuba) (1964)	Drama
11	53	4.750000	Lamerica (1994)	Drama
12	2503	4.666667	Apple, The (Sib) (1998)	Drama
13	2905	4.608696	Sanjuro (1962)	Action|Adventure
14	2019	4.560510	Seven Samurai (The Magnificent Seven) (Shichin...	Action|Drama
15	318	4.554558	Shawshank Redemption, The (1994)	Drama
16	858	4.524966	Godfather, The (1972)	Action|Crime|Drama
17	745	4.520548	Close Shave, A (1995)	Animation|Comedy|Thriller
18	50	4.517106	Usual Suspects, The (1995)	Crime|Thriller
19	527	4.510417	Schindler's List (1993)	Drama|War
20	1148	4.507937	Wrong Trousers, The (1993)	Animation|Comedy
21	2309	4.500000	Inheritors, The (Die Siebtelbauern) (1998)	Drama
22	1795	4.500000	Callejón de los milagros, El (1995)	Drama
23	2480	4.500000	Dry Cleaning (Nettoyage à sec) (1997)	Drama
24	439	4.500000	Dangerous Game (1993)	Drama

In [13]:
```
# Top 25 movies by viewership rating:

Top_25_Movies = df_Master_Data.groupby('Title')['Rating'].mean().nlargest(25).sort_values(ascending=False)
plt.barh(Top_25_Movies.index, Top_25_Movies.values, color='orange')
plt.xlabel('Average Users Rating', fontweight='bold', fontsize=16)
plt.ylabel('Movie Title (Year)', fontweight='bold', fontsize=16)
plt.title('Top 25 Movies by Viewership Rating', fontweight='bold', fontsize=18)
plt.gca().invert_yaxis()
plt.show()

## The majority of the Top 25 movies by viewership rating in this Dataset can be clearly seen to be made in the 1990s
## with only 1 movie in this list coming out in then year 2000. This can be primarily attributed to the 18 years old t
## old age bracket forming vast majority of users as they are technologically savvy and able to interact with Movielen
##  which will be an issue for those in their 50s and above. With 11 of the Top 25 movies made in the 1920s to 1970s,
## clearly seen that MovieLens users in their 40s and 50s ae very actively giving high ratings to old movies that were
## when they were young. This might indicate that younger users as a whole are less likely to post reviews or give hig
##ratings to movies.
```



In [14]:
```
# The ratings for all the movies reviewed by for a particular user with the User ID of 2696
```

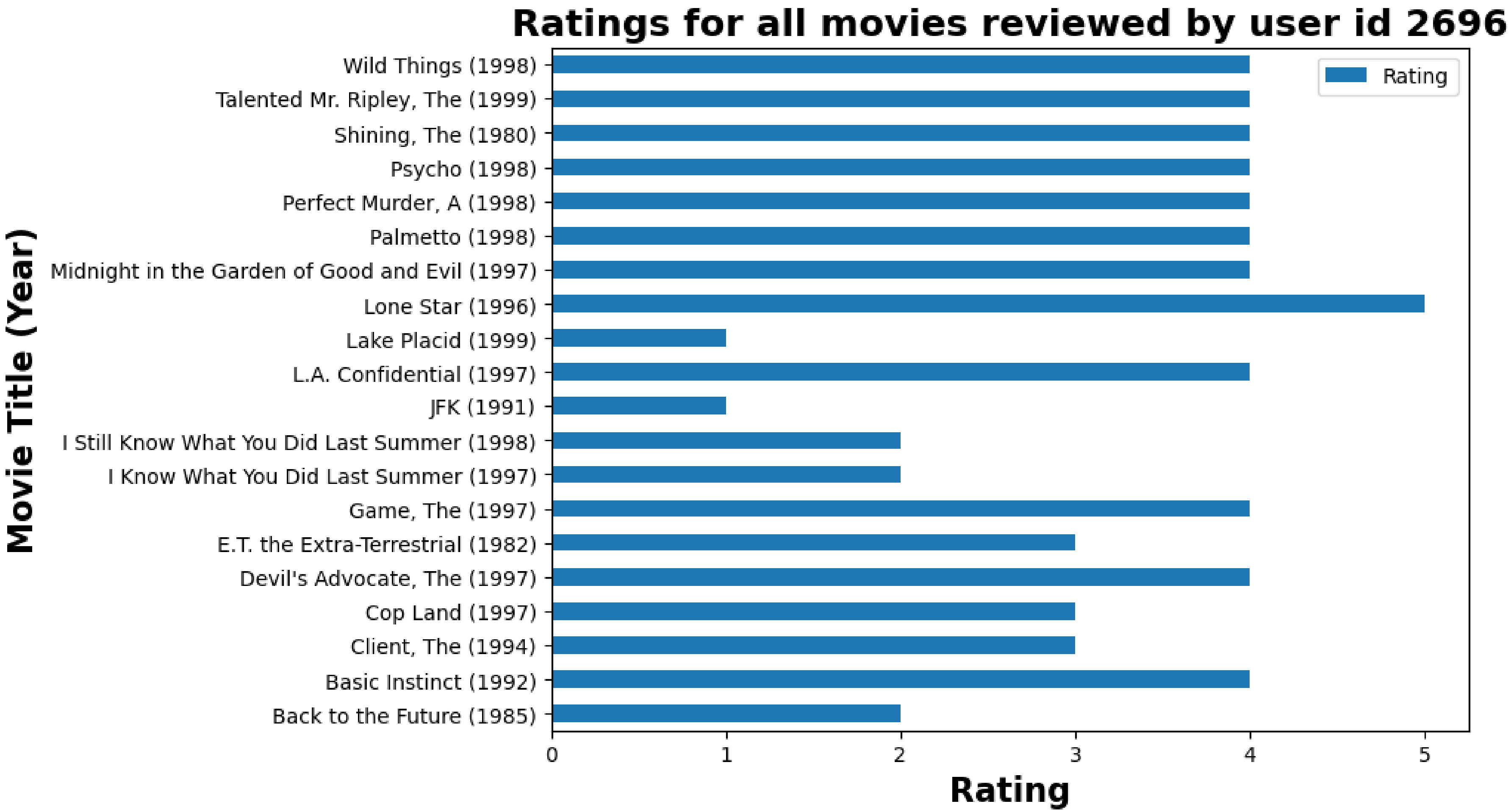
In [15]:
```
data_of_User_2696 = df_Master_Data[df_Master_Data['UserID']==2696]
```

In [16]:
```
data_of_User_2696.count()
```

Out[16]:
```
UserID        20
MovieID       20
Rating        20
Timestamp     20
Gender        20
Age           20
Occupation    20
Zip-code      20
Title         20
Genres        20
dtype: int64
```

In [17]:
```
#Plot the table with index title
plot_for_User_2696 = data_of_User_2696.pivot_table('Rating', index='Title')
```

In [18]:
```
#Plot rating data by User ID 2696

plot_for_User_2696.plot(kind='barh', figsize=(8, 6))
plt.xlabel('Rating', fontweight='bold', fontsize=16)
plt.ylabel('Movie Title (Year)', fontweight='bold', fontsize=16)
plt.title('Ratings for all movies reviewed by user id 2696', fontweight='bold', fontsize=18)
plt.show()

## There is a high probability that UserID 2696 is in his/her 20s to 30s at that point in time as all the movies revie
## this person came out in the 1980s and 1990s which are highly likely to be popular with younger people. UserID has s
## interest in Science Fiction, Crime, Action, Mystery and Horror Films as he/she gave good ratings to such films.
```

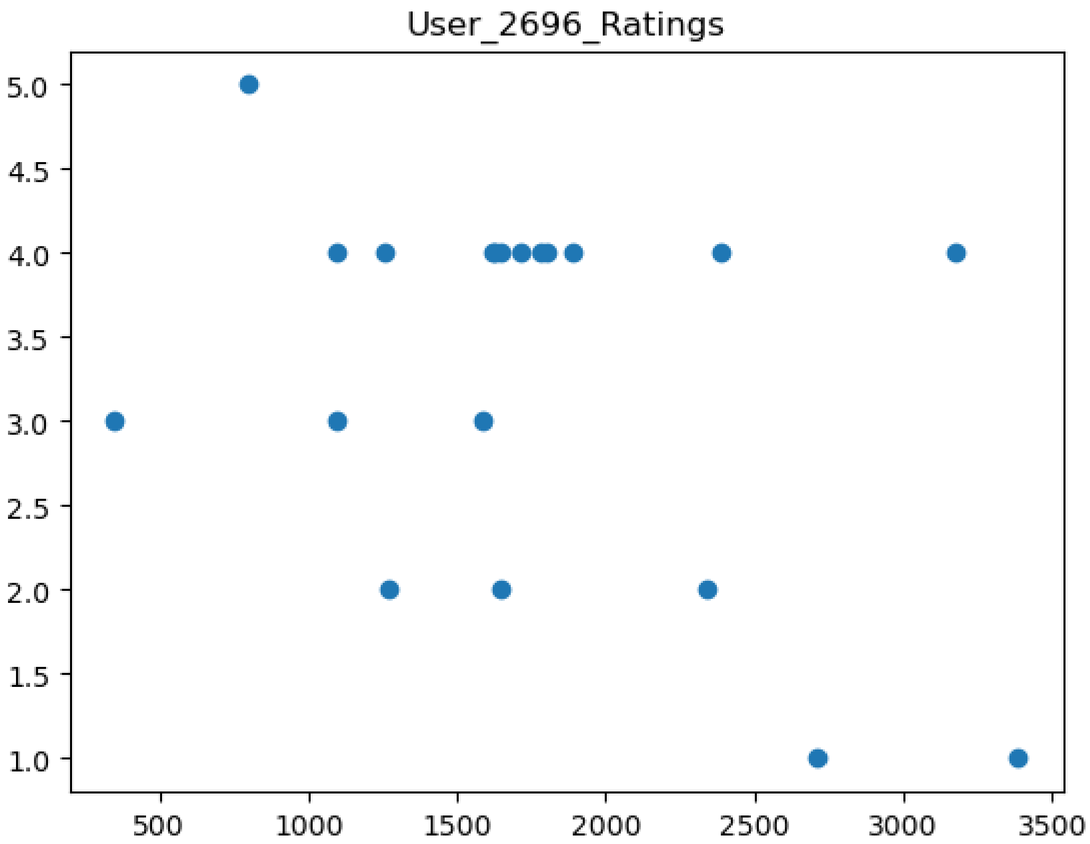

Ratings for all movies reviewed by user id 2696
Rating
Wild Things (1998)
Talented Mr. Ripley, The (1999)
Shining, The (1980)
Psycho (1998)
Perfect Murder, A (1998)
Palmetto (1998)
Midnight in the Garden of Good and Evil (1997)
Lone Star (1996)
Lake Placid (1999)
L.A. Confidential (1997)
JFK (1991)
I Still Know What You Did Last Summer (1998)
I Know What You Did Last Summer (1997)
Game, The (1997)
E.T. the Extra-Terrestrial (1982)
Devil's Advocate, The (1997)
Cop Land (1997)
Client, The (1994)
Basic Instinct (1992)
Back to the Future (1985)
Movie Title (Year)
0
1
2
3
4
5
Rating

In [19]:
```
# Find ratings for all movies reviewed by a particular user (user id = 2696):

User_2696_Ratings = df_Master_Data[df_Master_Data['UserID'] == 2696][['UserID', 'MovieID', 'Title', 'Rating']].sort_va
User_2696_Ratings
```

Out[19]:

	UserID	MovieID	Title	Rating
250014	2696	800	Lone Star (1996)	5
609204	2696	1625	Game, The (1997)	4
612552	2696	1645	Devil's Advocate, The (1997)	4
244232	2696	1617	L.A. Confidential (1997)	4
689379	2696	1258	Shining, The (1980)	4
277808	2696	3176	Talented Mr. Ripley, The (1999)	4
371178	2696	1711	Midnight in the Garden of Good and Evil (1997)	4
618708	2696	1092	Basic Instinct (1992)	4
598042	2696	1783	Palmetto (1998)	4
603189	2696	1892	Perfect Murder, A (1998)	4
616546	2696	1805	Wild Things (1998)	4
613486	2696	2389	Psycho (1998)	4
777089	2696	350	Client, The (1994)	3
29848	2696	1097	E.T. the Extra-Terrestrial (1982)	3
377250	2696	1589	Cop Land (1997)	3
611956	2696	1644	I Know What You Did Last Summer (1997)	2
697451	2696	2338	I Still Know What You Did Last Summer (1998)	2
24345	2696	1270	Back to the Future (1985)	2
621101	2696	2713	Lake Placid (1999)	1
273633	2696	3386	JFK (1991)	1

In [20]:
```
plt.scatter(x=User_2696_Ratings['MovieID'],y=User_2696_Ratings['Rating'])
plt.title('User_2696_Ratings')
plt.show()
```



In [21]:
```
Genres_List = df_Master_Data.Genres.tolist()
genre_list = []
i = 0
while (i<len(Genres_List)):
    genre_list+= Genres_List[i].split('|')
    i+=1
```

In [22]:
```
# Find out all the unique genres:
Unique_Genres = list(set(genre_list))
print(Unique_Genres)
print()
print("Number of the Unique Genres : ", len(Unique_Genres))
```

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

Number of the Unique Genres :  18
```

In [23]:
```
# 'Gender' - Label encoding
df_Master_Data.Gender.value_counts()
```

Out[23]:
```
M    753769
F    246440
Name: Gender, dtype: int64
```

In [24]:
```
# Gender Label Encode

Gender_Dict = {'F': 0 , 'M': 1}
df_Master_Data['Gender']= df_Master_Data['Gender'].map(Gender_Dict)
df_Master_Data.Gender.value_counts()
```

Out[24]:
```
1    753769
0    246440
Name: Gender, dtype: int64
```

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

In [25]:
```
New_Data = pd.concat([df_Master_Data,df_Master_Data.Genres.str.get_dummies()], axis=1)
print(New_Data.columns)
```

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

In [26]:
```
New_Data.head()
```

Out[26]:

	UserID	MovieID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Title	Genres	...	Fantasy	Film-Noir	Horror	Musical	Mystery	Roman
0	1	1193	5	978300760	0	1	10	48067	One Flew Over the Cuckoo's Nest (1975)	Drama	...	0	0	0	0	0	
1	2	1193	5	978298413	1	56	16	70072	One Flew Over the Cuckoo's Nest (1975)	Drama	...	0	0	0	0	0	
2	12	1193	4	978220179	1	25	12	32793	One Flew Over the Cuckoo's Nest (1975)	Drama	...	0	0	0	0	0	
3	15	1193	4	978199279	1	25	7	22903	One Flew Over the Cuckoo's Nest (1975)	Drama	...	0	0	0	0	0	
4	17	1193	5	978158471	1	50	1	95350	One Flew Over the Cuckoo's Nest (1975)	Drama	...	0	0	0	0	0	

5 rows × 28 columns

In [27]:
```
df_Master_Data_New = New_Data.drop(['Timestamp', 'Zip-code', 'Title', 'Genres'],  axis=1)
df_Master_Data_New
```

Out[27]:

	UserID	MovieID	Rating	Gender	Age	Occupation	Action	Adventure	Animation	Children's	...	Fantasy	Film-Noir	Horror	Musical	Myste
0	1	1193	5	0	1	10	0	0	0	0	...	0	0	0	0	
1	2	1193	5	1	56	16	0	0	0	0	...	0	0	0	0	
2	12	1193	4	1	25	12	0	0	0	0	...	0	0	0	0	
3	15	1193	4	1	25	7	0	0	0	0	...	0	0	0	0	
4	17	1193	5	1	50	1	0	0	0	0	...	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1000204	5949	2198	5	1	18	17	0	0	0	0	...	0	0	0	0	
1000205	5675	2703	3	1	35	14	0	0	0	0	...	0	0	0	0	
1000206	5780	2845	1	1	18	17	0	0	0	0	...	0	0	0	0	
1000207	5851	3607	5	0	18	20	0	0	0	0	...	0	0	0	0	
1000208	5938	2909	4	1	25	1	0	0	0	0	...	0	0	0	0	

1000209 rows × 24 columns

In [28]:
```
print(df_Master_Data_New.columns)
```

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

In [29]:
```
df_Master_Data_New.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns (total 24 columns):
 #   Column       Non-Null Count    Dtype
---  ------       --------------    -----
 0   UserID       1000209 non-null  int64
 1   MovieID      1000209 non-null  int64
 2   Rating       1000209 non-null  int64
 3   Gender       1000209 non-null  int64
 4   Age          1000209 non-null  int64
 5   Occupation   1000209 non-null  int64
 6   Action       1000209 non-null  int64
 7   Adventure    1000209 non-null  int64
 8   Animation    1000209 non-null  int64
 9   Children's   1000209 non-null  int64
 10  Comedy       1000209 non-null  int64
 11  Crime        1000209 non-null  int64
 12  Documentary  1000209 non-null  int64
 13  Drama        1000209 non-null  int64
 14  Fantasy      1000209 non-null  int64
 15  Film-Noir    1000209 non-null  int64
 16  Horror       1000209 non-null  int64
 17  Musical      1000209 non-null  int64
 18  Mystery      1000209 non-null  int64
 19  Romance      1000209 non-null  int64
 20  Sci-Fi       1000209 non-null  int64
 21  Thriller     1000209 non-null  int64
 22  War          1000209 non-null  int64
 23  Western      1000209 non-null  int64
dtypes: int64(24)
memory usage: 190.8 MB
```

Determine the features affecting the ratings of any particular movie.

In [30]:
```
#correlation
df_Master_Data_New.corr()
```

Out[30]:

	UserID	MovieID	Rating	Gender	Age	Occupation	Action	Adventure	Animation	Children's	...	Fantasy	Film-N
UserID	1.000000	-0.017739	0.012303	-0.035042	0.034688	-0.026698	-0.002023	-0.000683	-0.007665	-0.004862	...	0.002212	0.0047
MovieID	-0.017739	1.000000	-0.064042	0.021626	0.027575	0.008585	-0.042046	-0.082413	-0.014177	-0.071589	...	-0.018792	-0.0196
Rating	0.012303	-0.064042	1.000000	-0.019861	0.056869	0.006753	-0.047633	-0.036718	0.019670	-0.039829	...	-0.023312	0.0602
Gender	-0.035042	0.021626	-0.019861	1.000000	-0.003189	0.114974	0.094380	0.038645	-0.017719	-0.031662	...	0.002806	0.0051
Age	0.034688	0.027575	0.056869	-0.003189	1.000000	0.078371	-0.030975	-0.016730	-0.047020	-0.052858	...	-0.024222	0.0334
Occupation	-0.026698	0.008585	0.006753	0.114974	0.078371	1.000000	0.018347	0.014309	-0.003834	-0.006906	...	0.001299	0.0052
Action	-0.002023	-0.042046	-0.047633	0.094380	-0.030975	0.018347	1.000000	0.374961	-0.110294	-0.141314	...	0.014551	-0.0802
Adventure	-0.000683	-0.082413	-0.036718	0.038645	-0.016730	0.014309	0.374961	1.000000	0.004732	0.098283	...	0.227046	-0.0141
Animation	-0.007665	-0.014177	0.019670	-0.017719	-0.047020	-0.003834	-0.110294	0.004732	1.000000	0.576204	...	0.012025	0.0370
Children's	-0.004862	-0.071589	-0.039829	-0.031662	-0.052858	-0.006906	-0.141314	0.098283	0.576204	1.000000	...	0.263280	-0.0380
Comedy	-0.003651	0.061667	-0.039622	-0.040758	-0.044046	-0.006149	-0.268092	-0.124960	0.018544	0.058711	...	-0.006010	-0.1014
Crime	0.003469	-0.061896	0.033446	0.027065	-0.007931	0.002821	0.088519	-0.045924	-0.062520	-0.081977	...	-0.033745	0.1362
Documentary	-0.001064	-0.009544	0.028098	0.000234	0.004407	-0.002689	-0.052565	-0.035109	-0.018991	-0.024901	...	-0.017326	-0.0121
Drama	0.006572	-0.030856	0.122561	-0.052390	0.063856	-0.012326	-0.202415	-0.194570	-0.154479	-0.135707	...	-0.096929	-0.0672
Fantasy	0.002212	-0.018792	-0.023312	0.002806	-0.024222	0.001299	0.014551	0.227046	0.012025	0.263280	...	1.000000	-0.0264
Film-Noir	0.004701	-0.019655	0.060259	0.005152	0.033495	0.005246	-0.080288	-0.014178	0.037013	-0.038033	...	-0.026464	1.0000
Horror	-0.001392	0.057613	-0.094353	0.036566	-0.023901	0.001439	-0.042733	-0.057256	-0.049730	-0.077099	...	-0.055803	-0.0391
Musical	-0.000222	-0.059381	0.015643	-0.038051	0.005158	-0.007312	-0.100432	-0.022327	0.335231	0.312567	...	-0.020134	-0.0283
Mystery	0.004334	-0.028561	0.015848	-0.000905	0.024308	0.002421	-0.054084	-0.043503	-0.042488	-0.052786	...	-0.039700	0.2153
Romance	0.006834	-0.118375	0.009644	-0.091272	0.017503	-0.014018	-0.067830	-0.024389	-0.054540	-0.084550	...	-0.014822	-0.0473
Sci-Fi	-0.003283	-0.011747	-0.044487	0.072372	-0.010879	0.026250	0.319117	0.284190	-0.055526	-0.038844	...	0.121843	-0.0040
Thriller	-0.001107	-0.058418	-0.004806	0.038039	-0.014100	0.008981	0.202756	-0.038423	-0.085713	-0.132642	...	-0.087374	0.1152
War	0.003502	-0.081951	0.075688	0.025636	0.038446	0.010264	0.135872	0.016647	-0.046114	-0.066539	...	-0.044928	-0.0369
Western	0.004114	0.003940	0.007311	0.026397	0.038177	0.005924	0.022242	-0.011964	-0.030908	-0.031269	...	-0.028199	-0.0198

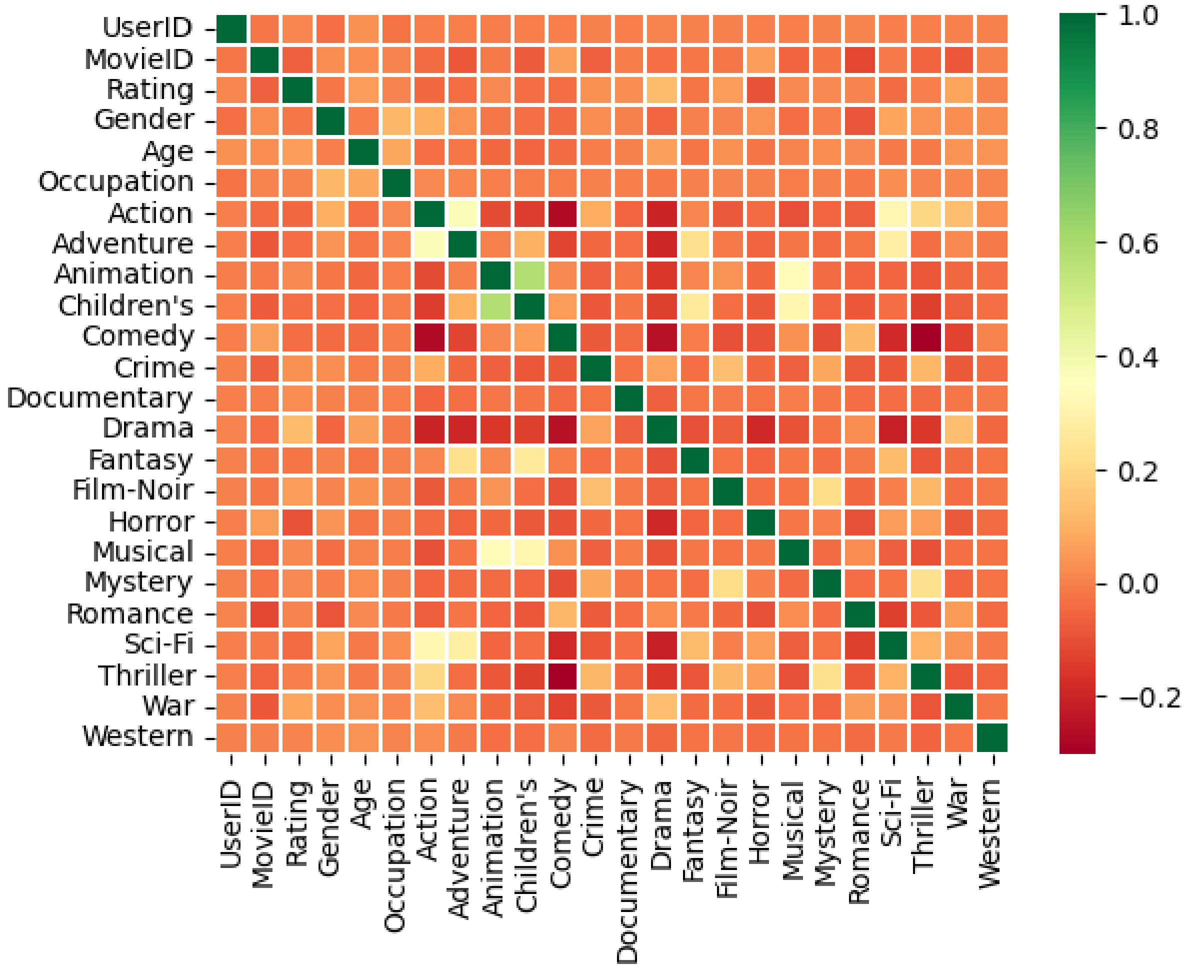
24 rows × 24 columns

In [31]:
```
# Calculate the correlation matrix
Correl_Matrix = df_Master_Data_New.corr(numeric_only=True)

# Display the correlation matrix with respect to the 'Rating' column
Correl_Matrix['Rating'].sort_values(ascending=False)
```

Out[31]:
```
Rating         1.000000
Drama          0.122561
War            0.075688
Film-Noir      0.060259
Age            0.056869
Crime          0.033446
Documentary    0.028098
Animation      0.019670
Mystery        0.015848
Musical        0.015643
UserID         0.012303
Romance        0.009644
Western        0.007311
Occupation     0.006753
Thriller      -0.004806
Gender        -0.019861
Fantasy       -0.023312
Adventure     -0.036718
Comedy        -0.039622
Children's    -0.039829
Sci-Fi        -0.044487
Action        -0.047633
MovieID       -0.064042
Horror        -0.094353
Name: Rating, dtype: float64
```

In [32]:
```
sns.heatmap(Correl_Matrix, xticklabels=True, yticklabels=True, annot= False, linewidths=0.05, cmap='RdYlGn')
```

Out[32]: <Axes: >



In [33]:
```
# Setting threshold of abs(0.8)
threshold = 0.8
```

In [34]:
```
from collections import defaultdict

df_Master_Data_New_corr = df_Master_Data_New.corr()

flag = False

corr_dict = defaultdict(list)

for row in df_Master_Data_New_corr.index:
    for col in df_Master_Data_New_corr.columns:
        if (col!=row) and (abs(df_Master_Data_New_corr.loc[row,col]) >= threshold):
            flag = True
            corr_dict[row].append(col)

if flag:
    print('High Correlation Present !')
    print(corr_dict)
else:
    print('No High Correlation Present !')
```

```
No High Correlation Present !
```

No pairs with correlation above 0.8

Looking at Variance Inflation Factor

In [35]:
```
# VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor

df_Master_Data_New_Rating = df_Master_Data_New.drop(['Rating'], axis=1)

for i, k in enumerate(df_Master_Data_New_Rating.columns):
    print(i+1,'. ', k,': ', round(variance_inflation_factor(df_Master_Data_New_Rating.values, i),2), sep='')
```

```
1. UserID: 3.58
2. MovieID: 3.53
3. Gender: 3.74
4. Age: 5.92
5. Occupation: 2.49
6. Action: 2.01
7. Adventure: 1.53
8. Animation: 1.71
9. Children's: 1.91
10. Comedy: 2.01
11. Crime: 1.18
12. Documentary: 1.03
13. Drama: 2.06
14. Fantasy: 1.23
15. Film-Noir: 1.14
16. Horror: 1.2
17. Musical: 1.23
18. Mystery: 1.16
19. Romance: 1.24
20. Sci-Fi: 1.47
21. Thriller: 1.55
22. War: 1.18
23. Western: 1.05
```

Develop an appropriate model to predict the movie ratings

In [36]:
```
# Seperate the dataset into features and target variables
X = df_Master_Data_New.drop(columns='Rating', axis=1)
y = df_Master_Data_New['Rating']
```

In [37]:
```
# Use sci-kit learn to split train and test dataset ~  70:30
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 42)

print("Train Dataset: {0}{1}".format(X_train.shape, y_train.shape))
print("Test Dataset: {0}{1}".format(X_test.shape, y_test.shape))
```

```
Train Dataset: (700146, 23)(700146,)
Test Dataset: (300063, 23)(300063,)
```

In [38]:
```
X_train.head()
```

Out[38]:

	UserID	MovieID	Gender	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	Horror	Musical	Myst
539061	1501	1220	1	25	11	1	0	0	0	1	...	0	0	0	1	
6514	1625	1197	1	45	0	1	1	0	0	1	...	0	0	0	0	
623156	3411	2722	1	18	4	1	0	0	0	0	...	0	0	0	0	
77441	4156	3578	1	56	20	1	0	0	0	0	...	0	0	0	0	
559047	5048	3448	0	35	7	0	0	0	0	1	...	0	0	0	0	

5 rows × 23 columns

In [39]:
```
# Feature Scaling

# Create an instance of StandardScaler()
sc= StandardScaler()

scale_cols = X_train.columns

# fit on training data and apply it to every feature set present
X_train[scale_cols] = sc.fit_transform(X_train[scale_cols])
X_test[scale_cols] = sc.transform(X_test[scale_cols])
```

In [40]:
```
# Explore scaled features training dataset
X_train.head()
```

Out[40]:

	UserID	MovieID	Gender	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	
539061	-0.881724	-0.589387	0.571671	-0.402968	0.453513	1.699397	-0.392950	-0.212717	-0.279573	1.342543	...	-0.194732	-0.13617	-0.:
6514	-0.809989	-0.610372	0.571671	1.299451	-1.230329	1.699397	2.544853	-0.212717	-0.279573	1.342543	...	-0.194732	-0.13617	-0.:
623156	0.223225	0.781047	0.571671	-0.998814	-0.618022	1.699397	-0.392950	-0.212717	-0.279573	-0.744855	...	-0.194732	-0.13617	-0.:
77441	0.654213	1.562067	0.571671	2.235781	1.831202	1.699397	-0.392950	-0.212717	-0.279573	-0.744855	...	-0.194732	-0.13617	-0.:
559047	1.170242	1.443454	-1.749257	0.448241	-0.158793	-0.588444	-0.392950	-0.212717	-0.279573	1.342543	...	-0.194732	-0.13617	-0.:

5 rows × 23 columns

Logistic Regression Model training, Iteration & Validation

In [41]:
```
# create instance of LogisticRegression()
lr = LogisticRegression()
```

In [42]:
```
# Fit model on training datasets
lr.fit(X_train, y_train)
```

Out[42]:
```
▾ LogisticRegression
LogisticRegression()
```

In [43]:
```
#Computing prediction on 'X-test' test dataset, outputs predicted labels
y_pred = lr.predict(X_test)
```

In [44]:
```
#Evaluating model on accuracy metric with 'accuracy_score()' method
print("Accuracy Score: {}".format(accuracy_score(y_test, y_pred)))
```

```
Accuracy Score: 0.3520394050582711
```

In [45]:
```
# Test predicted output value of model for first row example in the test dataset
# test dataset row 0 with output values rescaled

X_test.loc[[0]]
```

Out[45]:

	UserID	MovieID	Gender	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	Horror
0	-1.749485	-0.614022	-1.749257	-2.44587	0.300437	-0.588444	-0.39295	-0.212717	-0.279573	-0.744855	...	-0.194732	-0.13617	-0.287188

1 rows × 23 columns

In [46]:
```
print("Test dataset row 0: Actual Value: {}".format(y_test.values[0]))
print("Test dataset row 0: Predicted Output by the Model: {}".format(y_pred[0]))
```

```
Test dataset row 0: Actual Value: 3
Test dataset row 0: Predicted Output by the Model: 4
```

In [47]:
```
import statsmodels.formula.api as sm
import statsmodels.api as sm_api

X_train = sm_api.add_constant(X_train)
X_train.head()
```

Out[47]:

	const	UserID	MovieID	Gender	Age	Occupation	Action	Adventure	Animation	Children's	...	Fantasy	Film-Noir	Hor
539061	1.0	-0.881724	-0.589387	0.571671	-0.402968	0.453513	1.699397	-0.392950	-0.212717	-0.279573	...	-0.194732	-0.13617	-0.2871
6514	1.0	-0.809989	-0.610372	0.571671	1.299451	-1.230329	1.699397	2.544853	-0.212717	-0.279573	...	-0.194732	-0.13617	-0.2871
623156	1.0	0.223225	0.781047	0.571671	-0.998814	-0.618022	1.699397	-0.392950	-0.212717	-0.279573	...	-0.194732	-0.13617	-0.2871
77441	1.0	0.654213	1.562067	0.571671	2.235781	1.831202	1.699397	-0.392950	-0.212717	-0.279573	...	-0.194732	-0.13617	-0.2871
559047	1.0	1.170242	1.443454	-1.749257	0.448241	-0.158793	-0.588444	-0.392950	-0.212717	-0.279573	...	-0.194732	-0.13617	-0.2871

5 rows × 24 columns

In [48]:
```
X_test = sm_api.add_constant(X_test)
```

In [49]:
```
y_train_probs = [float(rating) / 5 for rating in y_train]

model = sm_api.Logit(y_train_probs, X_train)
result = model.fit()
result.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.526567
         Iterations 5
```

Out[49]:

Logit Regression Results

Dep. Variable:	y	**No. Observations:**	700146
Model:	Logit	**Df Residuals:**	700122
Method:	MLE	**Df Model:**	23
Date:	Wed, 26 Jul 2023	**Pseudo R-squ.:**	-0.3330
Time:	13:00:03	**Log-Likelihood:**	-3.6867e+05
converged:	True	**LL-Null:**	-2.7658e+05
Covariance Type:	nonrobust	**LLR p-value:**	1.000

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.9373	0.003	349.946	0.000	0.932	0.943
UserID	0.0099	0.003	3.689	0.000	0.005	0.015
MovieID	-0.0609	0.003	-22.157	0.000	-0.066	-0.056
Gender	-0.0142	0.003	-5.216	0.000	-0.020	-0.009
Age	0.0477	0.003	17.590	0.000	0.042	0.053
Occupation	0.0071	0.003	2.635	0.008	0.002	0.012
Action	-0.0429	0.003	-12.951	0.000	-0.049	-0.036
Adventure	0.0002	0.003	0.063	0.949	-0.006	0.006
Animation	0.0754	0.003	21.786	0.000	0.069	0.082
Children's	-0.0856	0.003	-24.676	0.000	-0.092	-0.079
Comedy	-0.0055	0.003	-1.640	0.101	-0.012	0.001
Crime	0.0221	0.003	7.748	0.000	0.017	0.028
Documentary	0.0378	0.003	12.674	0.000	0.032	0.044
Drama	0.1092	0.003	31.742	0.000	0.102	0.116
Fantasy	0.0132	0.003	4.637	0.000	0.008	0.019
Film-Noir	0.0664	0.003	20.610	0.000	0.060	0.073
Horror	-0.0690	0.003	-25.249	0.000	-0.074	-0.064

Musical	0.0265	0.003	9.011	0.000	0.021	0.032
Mystery	0.0003	0.003	0.103	0.918	-0.005	0.006
Romance	-0.0122	0.003	-4.327	0.000	-0.018	-0.007
Sci-Fi	-0.0119	0.003	-4.044	0.000	-0.018	-0.006
Thriller	0.0178	0.003	5.736	0.000	0.012	0.024
War	0.0748	0.003	24.952	0.000	0.069	0.081
Western	0.0138	0.003	5.046	0.000	0.008	0.019

In [50]:
```
# Predicted values
y_pred_orig = model.predict(params=result.params)
y_pred_orig
```

Out[50]:
```
array([0.7092602 , 0.68922851, 0.66251345, ..., 0.70045956, 0.6771519 ,
       0.69676561])
```

Model Iteration 1

In [51]:
```
#Deleting variables with high p-value
p_values = pd.DataFrame(result.pvalues).reset_index()
p_values = p_values.rename(columns={'index': 'Features', 0: 'p-value'})

# What features have p-values greater than 0.05 - remove them
alpha = 0.05

# Create a list of dropped columns from p-value
drop_cols_pval = list(p_values[p_values['p-value'] > alpha]['Features'])

dropped = drop_cols_pval

if(len(dropped)!=0):
    print("Dropping: {}".format(dropped))
else:
    print("No Dropping!")
```

```
Dropping: ['Adventure', 'Comedy', 'Mystery']
```

In [52]:
```
# Drop them
X_train2 = X_train.drop(columns=drop_cols_pval, axis=1)
X_test2 = X_test.drop(columns=drop_cols_pval, axis=1)
```

In [53]:
```
X_train2.shape
```

Out[53]:
```
(700146, 21)
```

In [54]:
```
X_test2.shape
```

Out[54]:
```
(300063, 21)
```

Model iteration 2

In [55]:
```
import statsmodels.api as sm

y_train_probs = [float(rating) / 5 for rating in y_train]

model2 = sm.Logit(y_train_probs, X_train2)
result2 = model2.fit()
result2.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.526567
         Iterations 5
```

Out[55]:

Logit Regression Results

Dep. Variable:	y	**No. Observations:**	700146
Model:	Logit	**Df Residuals:**	700125
Method:	MLE	**Df Model:**	20
Date:	Wed, 26 Jul 2023	**Pseudo R-squ.:**	-0.3330
Time:	13:00:07	**Log-Likelihood:**	-3.6867e+05
converged:	True	**LL-Null:**	-2.7658e+05
Covariance Type:	nonrobust	**LLR p-value:**	1.000

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.9373	0.003	349.945	0.000	0.932	0.943
UserID	0.0099	0.003	3.692	0.000	0.005	0.015
MovieID	-0.0610	0.003	-22.275	0.000	-0.066	-0.056
Gender	-0.0142	0.003	-5.200	0.000	-0.020	-0.009
Age	0.0479	0.003	17.676	0.000	0.043	0.053
Occupation	0.0071	0.003	2.626	0.009	0.002	0.012
Action	-0.0413	0.003	-13.736	0.000	-0.047	-0.035
Animation	0.0759	0.003	22.073	0.000	0.069	0.083
Children's	-0.0854	0.003	-24.737	0.000	-0.092	-0.079
Crime	0.0222	0.003	7.794	0.000	0.017	0.028
Documentary	0.0384	0.003	13.004	0.000	0.033	0.044
Drama	0.1117	0.003	36.657	0.000	0.106	0.118
Fantasy	0.0136	0.003	4.860	0.000	0.008	0.019
Film-Noir	0.0672	0.003	21.276	0.000	0.061	0.073
Horror	-0.0679	0.003	-25.698	0.000	-0.073	-0.063
Musical	0.0268	0.003	9.126	0.000	0.021	0.033
Romance	-0.0123	0.003	-4.387	0.000	-0.018	-0.007

Sci-Fi	-0.0110	0.003	-3.843	0.000	-0.017	-0.005
Thriller	0.0195	0.003	6.862	0.000	0.014	0.025
War	0.0752	0.003	25.239	0.000	0.069	0.081
Western	0.0140	0.003	5.144	0.000	0.009	0.019

In [56]:
```
#Deleting p-value high variables
p_values2 = pd.DataFrame(result2.pvalues).reset_index()
p_values2 = p_values2.rename(columns={'index': 'Features', 0: 'p-value'})

# What features have p-values greater than 0.05 - remove them
alpha = 0.05

# Create a list of dropped columns from p-value
drop_cols_pval2 = list(p_values2[p_values2['p-value'] > alpha]['Features'])

dropped2 = drop_cols_pval2

if(len(dropped2)!=0):
    print("Dropping: {}".format(dropped2))
else:
    print("No Dropping!")
```

```
No Dropping!
```

Model Statistics 2

In [57]:
```
# Predicted values
y_pred2 = model2.predict(params=result2.params)
y_pred2
```

Out[57]:
```
array([0.71083884, 0.69043522, 0.66283433, ..., 0.70015178, 0.67608783,
       0.69723063])
```

Final Model

In [58]:
```
y_train_probs = [float(rating) / 5 for rating in y_train]

model2 = sm.Logit(y_train_probs, X_train2)
result2 = model2.fit()
result2.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.526567
         Iterations 5
```

Out[58]:

Logit Regression Results

Dep. Variable:	y	**No. Observations:**	700146
Model:	Logit	**Df Residuals:**	700125
Method:	MLE	**Df Model:**	20
Date:	Wed, 26 Jul 2023	**Pseudo R-squ.:**	-0.3330
Time:	13:00:11	**Log-Likelihood:**	-3.6867e+05
converged:	True	**LL-Null:**	-2.7658e+05
Covariance Type:	nonrobust	**LLR p-value:**	1.000

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.9373	0.003	349.945	0.000	0.932	0.943
UserID	0.0099	0.003	3.692	0.000	0.005	0.015
MovieID	-0.0610	0.003	-22.275	0.000	-0.066	-0.056
Gender	-0.0142	0.003	-5.200	0.000	-0.020	-0.009
Age	0.0479	0.003	17.676	0.000	0.043	0.053
Occupation	0.0071	0.003	2.626	0.009	0.002	0.012
Action	-0.0413	0.003	-13.736	0.000	-0.047	-0.035
Animation	0.0759	0.003	22.073	0.000	0.069	0.083
Children's	-0.0854	0.003	-24.737	0.000	-0.092	-0.079
Crime	0.0222	0.003	7.794	0.000	0.017	0.028
Documentary	0.0384	0.003	13.004	0.000	0.033	0.044
Drama	0.1117	0.003	36.657	0.000	0.106	0.118
Fantasy	0.0136	0.003	4.860	0.000	0.008	0.019
Film-Noir	0.0672	0.003	21.276	0.000	0.061	0.073
Horror	-0.0679	0.003	-25.698	0.000	-0.073	-0.063
Musical	0.0268	0.003	9.126	0.000	0.021	0.033
Romance	-0.0123	0.003	-4.387	0.000	-0.018	-0.007

Sci-Fi	-0.0110	0.003	-3.843	0.000	-0.017	-0.005
Thriller	0.0195	0.003	6.862	0.000	0.014	0.025
War	0.0752	0.003	25.239	0.000	0.069	0.081
Western	0.0140	0.003	5.144	0.000	0.009	0.019

In [59]:
```
# Predicted Probability Values
y_pred_final = model2.predict(params=result2.params, exog=X_test2)
y_pred_final
```

Out[59]:
```
array([0.77541608, 0.72556935, 0.68981126, ..., 0.71592725, 0.78577954,
       0.79045549])
```

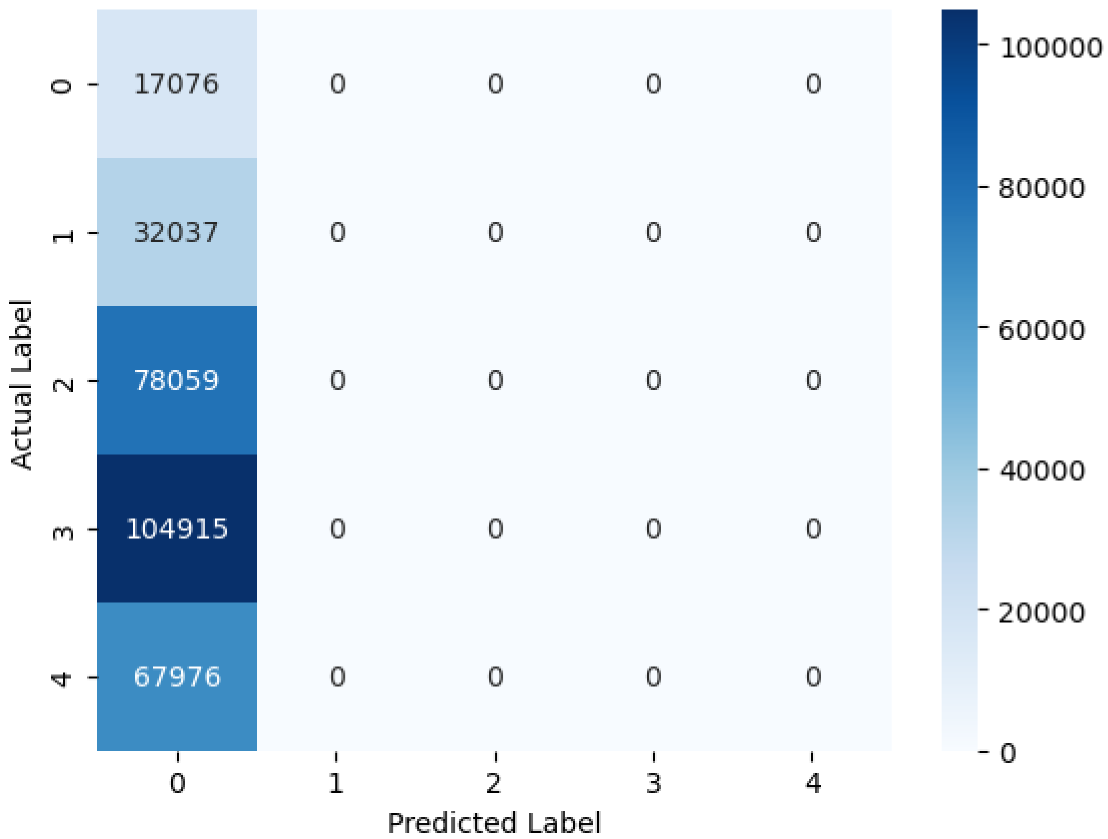
In [60]:
```
# Default (Random) Model threshold of 0.5
y_pred_labels = (y_pred_final>0.5).astype(int)
y_pred_labels
```

Out[60]:
```
array([1, 1, 1, ..., 1, 1, 1])
```

In [61]:
```
# Computing Various Evaluation Metrics - Scikit-Learn

print("Confusion Matrix")
print(confusion_matrix(y_test, y_pred_labels))
```

```
Confusion Matrix
[[ 17076      0      0      0      0]
 [ 32037      0      0      0      0]
 [ 78059      0      0      0      0]
 [104915      0      0      0      0]
 [ 67976      0      0      0      0]]
```

In [62]:
```
sns.heatmap(confusion_matrix(y_test, y_pred_labels), annot=True, cmap='Blues', fmt='g')
plt.ylabel('Actual Label')
_ = plt.xlabel('Predicted Label')
```



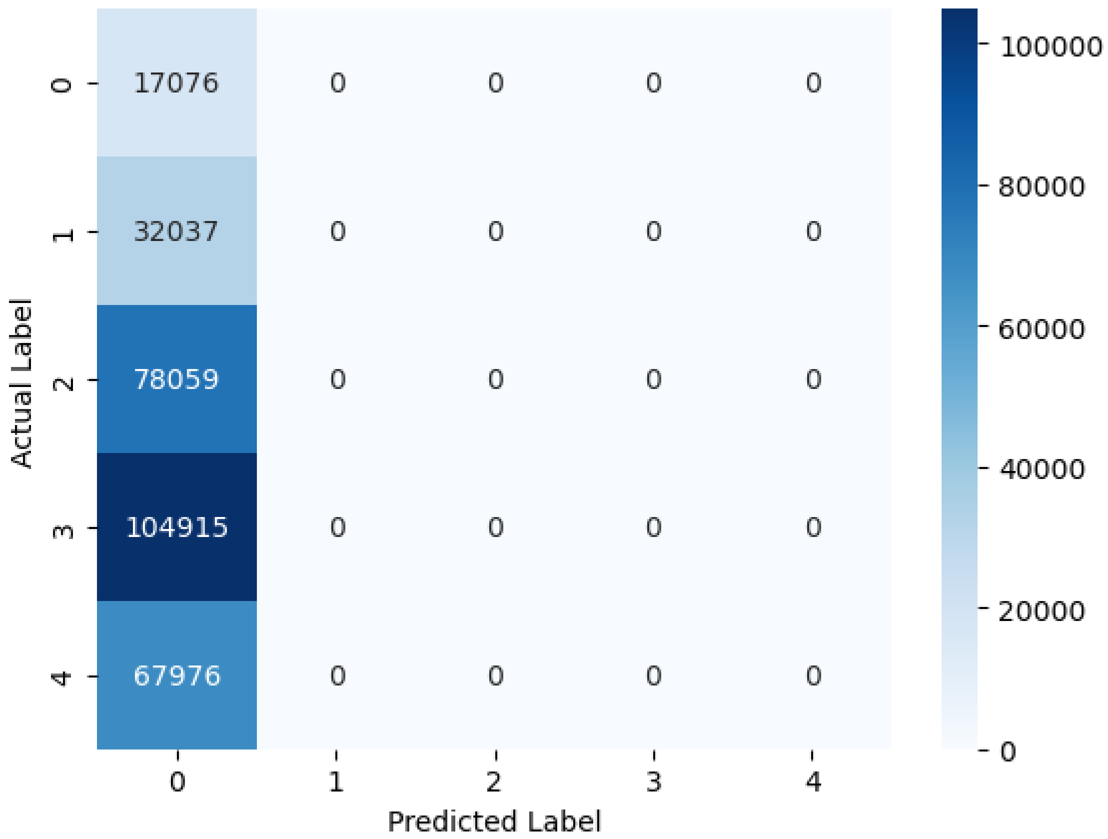
In [63]:
```
# % of FP and FN in output
conf_mat = confusion_matrix(y_test, y_pred_labels)
print("% of False Positive: {}".format(conf_mat[0][1]*100/(conf_mat[0][0] + conf_mat[0][1] + conf_mat[1][0] + conf_mat

print("% of False Negative: {}".format(conf_mat[1][0]*100/(conf_mat[0][0] + conf_mat[0][1] + conf_mat[1][0] + conf_mat
```

```
% of False Positive: 0.0
% of False Negative: 65.23120151487386
```

In [64]:
```
y_pred_labels2 = (y_pred_final>0.3).astype(int)
y_pred_labels2
```

Out[64]:
```
array([1, 1, 1, ..., 1, 1, 1])
```

In [65]:
```
sns.heatmap(confusion_matrix(y_test, y_pred_labels2), annot=True, cmap='Blues', fmt='g')
plt.ylabel('Actual Label')
_ = plt.xlabel('Predicted Label')
```



In [66]:
```
# % of FP and FN in output
conf_mat2 = confusion_matrix(y_test, y_pred_labels2)
print("% of False Positive: {}".format(conf_mat2[0][1]*100/(conf_mat2[0][0] + conf_mat2[0][1] + conf_mat2[1][0] + conf

print("% of False Negative: {}".format(conf_mat2[1][0]*100/(conf_mat2[0][0] + conf_mat2[0][1] + conf_mat2[1][0] + conf
```

```
% of False Positive: 0.0
% of False Negative: 65.23120151487386
```

In [67]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_pred_final, y_test)
rmse = np.sqrt(mse)

print("About 95% of the predictions are between -" + str(np.round(2*rmse,2)) + " and " + str(np.round(2*rmse, 2))
     + " of actual rating values")
```

```
About 95% of the predictions are between -6.15 and 6.15 of actual rating values
```

In [68]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score

# Generate Precision for the model
print(precision_score(y_test, y_pred, average='weighted'))

# Generate Recall of the model
print(recall_score(y_test, y_pred, average='weighted'))
```

```
0.2906953397053388
0.3520394050582711
```

In [69]:
```
confusion_matrix(y_test, y_pred)
```

Out[69]:
```
array([[    0,     0,  1995, 14838,   243],
       [    0,     0,  2704, 28655,   678],
       [    0,     0,  4980, 70828,  2251],
       [    2,     0,  4821, 95488,  4604],
       [    0,     0,  2386, 60424,  5166]], dtype=int64)
```