Movielens Case Study

DESCRIPTION

Background of Problem Statement :

The GroupLens Research Project is a research group in the Department of Computer Science and Engineering at the University of Minnesota. Members of the GroupLens Research Project are involved in many research projects related to the fields of information filtering, collaborative filtering, and recommender systems. The project is led by professors John Riedl and Joseph Konstan. The project began to explore automated collaborative filtering in 1992 but is most well known for its worldwide trial of an automated collaborative filtering system for Usenet news in 1996. Since then the project has expanded its scope to research overall information by filtering solutions, integrating into content-based methods, as well as, improving current collaborative filtering technology.

Problem Objective :

Here, we ask you to perform the analysis using the Exploratory Data Analysis technique. You need to find features affecting the ratings of any particular movie and build a model to predict the movie ratings.

Domain: Entertainment

Analysis Tasks to be performed:

- Import the three datasets
- Create a new dataset [Master_Data] with the following columns MovieID Title UserID Age Gender Occupation Rating. (Hint: (i) Merge two tables at a time. (ii) Merge the tables using two primary keys MovieID & UserId)
- Explore the datasets using visual representations (graphs or tables), also include your comments on the following:

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

  Use column genres:

  1. Find out all the unique genres (Hint: split the data in column genre making a list and then process the data to find out only the unique categories of genres)
  2. Create a separate column for each genre category with a one-hot encoding (1 and 0) whether or not the movie belongs to that genre.
  3. Determine the features affecting the ratings of any particular movie.
  4. Develop an appropriate model to predict the movie ratings

Dataset Description :

These files contain 1,000,209 anonymous ratings of approximately 3,900 movies made by 6,040 MovieLens users who joined MovieLens in 2000.

Ratings.dat

```
Format - UserID::MovieID::Rating::Timestamp
```

Users.dat

```
Format -  UserID::Gender::Age::Occupation::Zip-code
```

Movies.dat

```
Format - MovieID::Title::Genres
```

##

The DataFrame variables used in this project are as below

- Users_df = Users.dat
- Movies_df = Movies.dat
- Ratings_df = Ratings.dat
- Master_Data = Marging of all the 3 raw dataset
- Master_DataModiGenr = Modified "Genres" column in "Master_Data" with one hot encoding
- Master_DataModiGenrGendr = Modified "Gender" column in "Master_DataModiGenr" with one hot encoding
- Master_DataModiGenrGendrAge = Modified "Age" column in "Master_DataModiGenrGendr" with LebelEncoder
- Master_DataClean = Copy of "Master_DataModiGenrGendrAge" with selected feature for modeling
- Master_DataCleanCopy = Copy of "Master_DataClean" with MinMaxScaler for X_Features

In [1]:
```
#import all the required packages for data import and EDA
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
# Create different dataset column headers
Ratings_header = "UserID::MovieID::Rating::Timestamp".split("::")
Users_header = "UserID::Gender::Age::Occupation::Zip-code".split("::")
Movies_header = "MovieID::Title::Genres".split("::")

print('Ratings_header', Ratings_header)
print('Users_header',Users_header)
print('Movies_header',Movies_header)
```

```
Ratings_header ['UserID', 'MovieID', 'Rating', 'Timestamp']
Users_header ['UserID', 'Gender', 'Age', 'Occupation', 'Zip-code']
Movies_header ['MovieID', 'Title', 'Genres']
```

In [3]:
```
#Import the 3 dataset and assign the headers
Users_df = pd.read_csv('users.dat', sep='::', names = Users_header, engine ='python')
Movies_df = pd.read_csv('movies.dat', sep='::', names = Movies_header, engine ='python')
Ratings_df = pd.read_csv('ratings.dat', sep='::', names = Ratings_header, parse_dates=['Timestamp'], engin
e ='python')
```

In [4]:
```
# view the fist 5 data of Users_df
Users_df.head()
```

Out[4]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	48067
1	2	M	56	16	70072
2	3	M	25	15	55117
3	4	M	45	7	02460
4	5	M	25	20	55455

In [5]:
```
#view the shape of the Users_df
Users_df.shape
```

Out[5]: (6040, 5)

In [6]:
```
# view the fist 5 data of Movies_df
Movies_df.head()
```

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]:
```
#view the shape of the Movies_df
Movies_df.shape
```

Out[7]: (3883, 3)

In [8]:
```
# view the fist 5 data of Ratings_df
Ratings_df.head()
```

Out[8]:

	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 [9]:
```
#view the shape of the Ratings_df
Ratings_df.shape
```

Out[9]: (1000209, 4)

In [10]:
```
# Convert the epoch time to proper date time format
Ratings_dfCopy = Ratings_df.copy()
Ratings_dfCopy['Converted Date Time'] = pd.to_datetime(Ratings_dfCopy['Timestamp'],unit='s')
Ratings_dfCopy.head()
```

Out[10]:

	UserID	MovieID	Rating	Timestamp	Converted Date Time
0	1	1193	5	978300760	2000-12-31 22:12:40
1	1	661	3	978302109	2000-12-31 22:35:09
2	1	914	3	978301968	2000-12-31 22:32:48
3	1	3408	4	978300275	2000-12-31 22:04:35
4	1	2355	5	978824291	2001-01-06 23:38:11

In [11]:
```
# Merge the Ratings_df and Movies_df data on MovieID
movie_rating_df = pd.merge(Movies_df,Ratings_df,on='MovieID')
movie_rating_df.head()
```

Out[11]:

	MovieID	Title	Genres	UserID	Rating	Timestamp
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268
1	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008
2	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496
3	1	Toy Story (1995)	Animation|Children's|Comedy	9	5	978225952
4	1	Toy Story (1995)	Animation|Children's|Comedy	10	5	978226474

In [12]:
```
#view the shape of movie_rating_df
movie_rating_df.shape
```

Out[12]: (1000209, 6)

In [13]:
```
# Merge the Users_df and movie_rating_df on UserID
Master_Data = pd.merge(movie_rating_df,Users_df, on='UserID')
Master_Data.head()
```

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]:
```
#view the shape of Master_Data
Master_Data.shape
```

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

In [15]:
```
#check if there is NaN value
Master_Data.isnull().sum()
```

Out[15]:
```
MovieID       0
Title         0
Genres        0
UserID        0
Rating        0
Timestamp     0
Gender        0
Age           0
Occupation    0
Zip-code      0
dtype: int64
```

In [16]:
```
#find if there is a Duplicate entry
duplicateDFRow = Master_Data[Master_Data.duplicated(['MovieID','UserID'])]
duplicateDFRow.shape
```

Out[16]:
```
(0, 10)
```

##

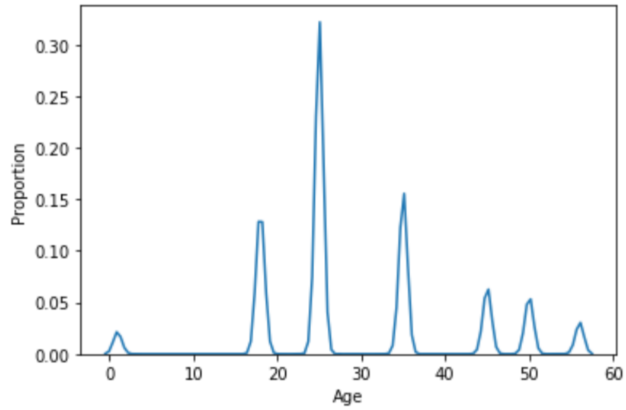
EDA using visual representations (graphs or tables)

1. User Age Distribution

In [17]:
```
# group the data w.r.t "Age" and view the size of each group
age_group = Master_Data.groupby('Age').size()
age_group
```

Out[17]:
```
Age
1      27211
18    183536
25    395556
35    199003
45     83633
50     72490
56     38780
dtype: int64
```

In [18]:
```
# density plot to view the data distribution w.r.t "Age" group
plt.ylabel('Proportion')
sns.distplot(Master_Data['Age'],hist=False)
plt.show()
```



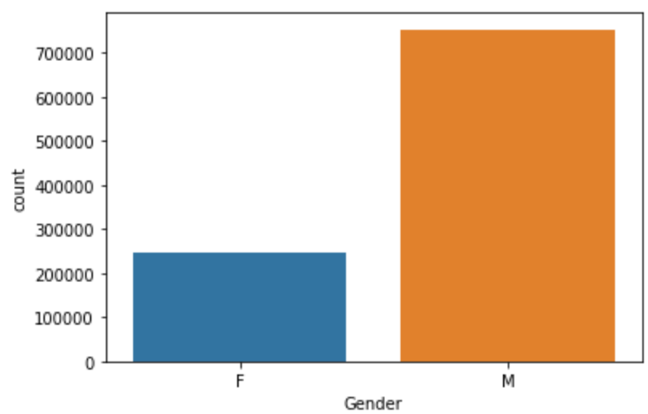
From the above density plot it is evedent that most of the viewers are of Age Group = "25-34", since this age group has value of 25.

1.1 Gender Distribution

In [19]:
```
#view the "Gender" distribution in Movie viewership
gender_group = Master_Data.groupby('Gender').size()
gender_group
```

Out[19]:
```
Gender
F    246440
M    753769
dtype: int64
```

In [20]:
```
# count plot to view the data distribution w.r.t "Gender" group
sns.countplot(Master_Data.Gender)
plt.show()
```



The above distribution shows that most of the users are Males

##

2. User rating of the movie “Toy Story”

In [21]:
```
# Make the dataframe grouped by MovieID as movie id is unique
grouped_movie = Master_Data.groupby(['MovieID'])
ToyStory_Grp = grouped_movie.get_group(1) # getting only the Toy Story movie data whose movie id is 1
ToyStory_Grp.head()
```

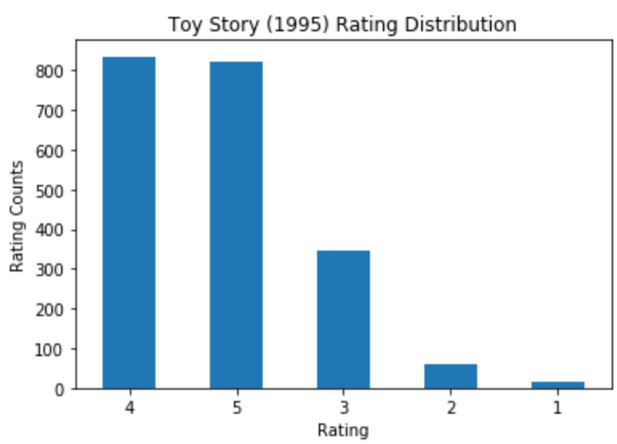
Out[21]:

	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
53	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008	F	50	9	55117
124	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496	M	25	12	11413
263	1	Toy Story (1995)	Animation|Children's|Comedy	9	5	978225952	M	25	17	61614
369	1	Toy Story (1995)	Animation|Children's|Comedy	10	5	978226474	F	35	1	95370

In [22]:
```
# find rating counts for Toy Story Movie
ToyStory_Grp['Rating'].value_counts()
```

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

In [23]:
```
# Plot the rating counts for Toy Story Movie
plt.title('Toy Story (1995) Rating Distribution')
plt.xlabel('Rating')
plt.ylabel('Rating Counts')
ToyStory_Grp['Rating'].value_counts().plot(kind='bar')

# Plot 'x' on current axes and rotate label
x = plt.gca().xaxis
for item in x.get_ticklabels():
    item.set_rotation(0)
plt.show()
```



> ***"Toy Story (1995)" has got Maximum number of 4 star ratings followed by 5 star ratings. Very less number of 1 and 2 star ratings.***

##

3. Top 25 movies by viewership rating

In [24]:

```
# create a dataset grouped by 'MovieID'
movie_rating = Master_Data.groupby(['MovieID'], as_index=False)

#create a dataframe with calculated mean of every group's 'Rating'
average_movie_ratings = movie_rating.agg({'Rating':'mean'})

# sort the dataframe based on calculated mean 'Rating' in decending order and show 1st 25 value
top_25_movies = average_movie_ratings.sort_values('Rating', ascending=False).head(25)
top_25_movies
```

Out[24]:

	MovieID	Rating
926	989	5.000000
3635	3881	5.000000
1652	1830	5.000000
3152	3382	5.000000
744	787	5.000000
3054	3280	5.000000
3367	3607	5.000000
3010	3233	5.000000
2955	3172	5.000000
3414	3656	5.000000
3021	3245	4.800000
51	53	4.750000
2309	2503	4.666667
2698	2905	4.608696
1839	2019	4.560510
309	318	4.554558
802	858	4.524966
708	745	4.520548
49	50	4.517106
513	527	4.510417
1066	1148	4.507937
2117	2309	4.500000
1626	1795	4.500000
2287	2480	4.500000
425	439	4.500000

In [25]:
```
#The below list shows top 25 movies by viewership data
pd.merge(top_25_movies, Movies_df, how='left', on=['MovieID'])
```

Out[25]:

	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

##

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

In [26]:
```
# Find the list of all movie reviewed by user id = 2696
user2696_df = Master_Data[Master_Data['UserID'] == 2696]

user2696_df.shape  # Find the number of observation with user id = 2696
```

Out[26]: (20, 10)

In [27]:
```
# show the movie list which is rated by user id = 2696
list(user2696_df.Title)
```

Out[27]:
```
['Client, The (1994)',
 'Lone Star (1996)',
 'Basic Instinct (1992)',
 'E.T. the Extra-Terrestrial (1982)',
 'Shining, The (1980)',
 'Back to the Future (1985)',
 'Cop Land (1997)',
 'L.A. Confidential (1997)',
 'Game, The (1997)',
 'I Know What You Did Last Summer (1997)',
 "Devil's Advocate, The (1997)",
 'Midnight in the Garden of Good and Evil (1997)',
 'Palmetto (1998)',
 'Wild Things (1998)',
 'Perfect Murder, A (1998)',
 'I Still Know What You Did Last Summer (1998)',
 'Psycho (1998)',
 'Lake Placid (1999)',
 'Talented Mr. Ripley, The (1999)',
 'JFK (1991)']
```

##

Feature Engineering:

1. Find out all the unique genres

In [28]:
```
Master_Data['Genres'].describe(include='all')
```

Out[28]:
```
count     1000209
unique        301
top        Comedy
freq       116883
Name: Genres, dtype: object
```

In [29]:
```
# define a empty list
genres = []

# create a list of all Genres available in the dataset
for string in Master_Data['Genres']:
    genres.extend(string.split('|'))

# print all Genres
print("total number of Genres count with repetition: ",len(genres))

# create a unique list of Genres using set()
unique_genres = list(set(genres))
print("\nUnique number of Genres count: ",len(unique_genres))
print("\nThe Unique Genres list are: \n", unique_genres)
```

```
total number of Genres count with repetition:  2101815

Unique number of Genres count:  18

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

##

2. Create a separate column for each genre category with a one-hot encoding (1 and 0)

In [30]:
```
# View the Master_Data
Master_Data.head()
```

Out[30]:

	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 [31]:
```
#copy the Master_Data into another data frame
Master_DataModiGenr = Master_Data.copy()
print(id(Master_DataModiGenr))
print(id(Master_Data))
```

```
2417193326536
2417192972104
```

In [32]:
```
# The splited 'Genres' add in different feature columns and assign 1 or 0 for a particular movie

unique_genres.sort()          # sort the genres list
for i in unique_genres:
    Master_DataModiGenr[i] = Master_DataModiGenr['Genres'].str.contains(i)*1
```

In [33]:
```
pd.set_option('display.max_columns', None)  # set option to view all the columns
Master_DataModiGenr.head()
```

Out[33]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Action	Adventure
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	1	10	48067	0	0
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351	F	1	10	48067	0	0
2	150	Apollo 13 (1995)	Drama	1	5	978301777	F	1	10	48067	0	0
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	978300760	F	1	10	48067	1	1
4	527	Schindler's List (1993)	Drama|War	1	5	978824195	F	1	10	48067	0	0

##

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

In [34]:
```
#get the Gender counts
Master_Data['Gender'].value_counts()
```

Out[34]:
```
M    753769
F    246440
Name: Gender, dtype: int64
```

In [35]:
```
# Converting a catagorical "Gender" variable to discrete numarical value
dummy_variable_1 = pd.get_dummies(Master_DataModiGenr["Gender"])

# renaming columns
dummy_variable_1.rename(columns={'F':'Gender_F', 'M':'Gender_M'}, inplace=True)
dummy_variable_1.head()
```

Out[35]:

	Gender_F	Gender_M
0	1	0
1	1	0
2	1	0
3	1	0
4	1	0

In [36]:
```
# merge "Master_DataModiGenr" and "dummy_variable_1"
Master_DataModiGenrGendr = pd.concat([Master_DataModiGenr, dummy_variable_1], axis=1)

# drop original column "Gender" from "Master_DataModiGenrGendr"
Master_DataModiGenrGendr.drop("Gender", axis = 1, inplace=True)
```

In [37]:
```
# View the data distribustion of "Age" feature
Master_DataModiGenrGendr['Age'].value_counts()
```

Out[37]:
```
25    395556
35    199003
18    183536
45     83633
50     72490
56     38780
1      27211
Name: Age, dtype: int64
```

In [38]:
```
# preprocess "Age" variable to sequencial value

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

le.fit(Master_DataModiGenrGendr['Age'])
x_age = le.transform(Master_DataModiGenrGendr['Age'])
```

In [39]:
```
#create a copy of the dataset
Master_DataModiGenrGendrAge = Master_DataModiGenrGendr.copy()

# assign new label encode age "x_age" in "Master_DataModiGenrGendr"
Master_DataModiGenrGendrAge['New Age'] = x_age

# drop original column "Age" from "Master_DataModiGenrGendrAge"
Master_DataModiGenrGendrAge.drop("Age", axis = 1, inplace=True)

Master_DataModiGenrGendrAge.head()
```

Out[39]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Occupation	Zip-code	Action	Adventure	Animation	Chi
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	10	48067	0	0	1	
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351	10	48067	0	0	1	
2	150	Apollo 13 (1995)	Drama	1	5	978301777	10	48067	0	0	0	
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	978300760	10	48067	1	1	0	
4	527	Schindler's List (1993)	Drama|War	1	5	978824195	10	48067	0	0	0	

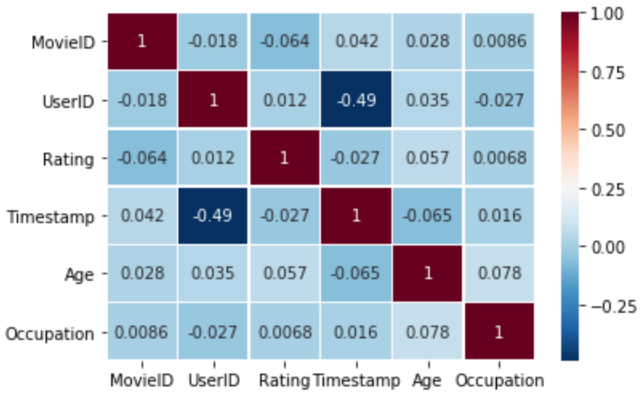
In [ ]:

In [40]:
```
# Checking the correlation of the "Master_Data" which affects Rating
Master_Data.corr()
```

Out[40]:

	MovieID	UserID	Rating	Timestamp	Age	Occupation
MovieID	1.000000	-0.017739	-0.064042	0.041632	0.027575	0.008585
UserID	-0.017739	1.000000	0.012303	-0.490383	0.034688	-0.026698
Rating	-0.064042	0.012303	1.000000	-0.026770	0.056869	0.006753
Timestamp	0.041632	-0.490383	-0.026770	1.000000	-0.064562	0.015646
Age	0.027575	0.034688	0.056869	-0.064562	1.000000	0.078371
Occupation	0.008585	-0.026698	0.006753	0.015646	0.078371	1.000000

In [41]:
```
# plot the heat map to view the relation
sns.heatmap(Master_Data.corr(),linewidths=.5,annot=True,cmap='RdBu_r')
plt.show()
```



From the above ***(Main Master_Data)*** *correlation matrix "Rating" has some visible correlation with*

- "Age" = 0.057
- "MovieID" = -0.064
- "Timestamp" = -0.027

"Occupation" has very very low correlation. So we can ignore it.

==

In [42]:
```
# Checking the correlation of the modified "Master_DataModiGenr" which affects Rating
Master_DataModiGenr.corr()
```

Out[42]:

	MovieID	UserID	Rating	Timestamp	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	C
MovieID	1.000000	-0.017739	-0.064042	0.041632	0.027575	0.008585	-0.042046	-0.082413	-0.014177	-0.071589	0.061667	-0.061
UserID	-0.017739	1.000000	0.012303	-0.490383	0.034688	-0.026698	-0.002023	-0.000683	-0.007665	-0.004862	-0.003651	0.003
Rating	-0.064042	0.012303	1.000000	-0.026770	0.056869	0.006753	-0.047633	-0.036718	0.019670	-0.039829	-0.039622	0.033
Timestamp	0.041632	-0.490383	-0.026770	1.000000	-0.064562	0.015646	-0.032990	-0.023252	0.000840	-0.000991	0.006064	-0.009
Age	0.027575	0.034688	0.056869	-0.064562	1.000000	0.078371	-0.030975	-0.016730	-0.047020	-0.052858	-0.044046	-0.007
Occupation	0.008585	-0.026698	0.006753	0.015646	0.078371	1.000000	0.018347	0.014309	-0.003834	-0.006906	-0.006149	0.002
Action	-0.042046	-0.002023	-0.047633	-0.032990	-0.030975	0.018347	1.000000	0.374961	-0.110294	-0.141314	-0.268092	0.088
Adventure	-0.082413	-0.000683	-0.036718	-0.023252	-0.016730	0.014309	0.374961	1.000000	0.004732	0.098283	-0.124960	-0.045
Animation	-0.014177	-0.007665	0.019670	0.000840	-0.047020	-0.003834	-0.110294	0.004732	1.000000	0.576204	0.018544	-0.062
Children's	-0.071589	-0.004862	-0.039829	-0.000991	-0.052858	-0.006906	-0.141314	0.098283	0.576204	1.000000	0.058711	-0.081
Comedy	0.061667	-0.003651	-0.039622	0.006064	-0.044046	-0.006149	-0.268092	-0.124960	0.018544	0.058711	1.000000	-0.078
Crime	-0.061896	0.003469	0.033446	-0.009597	-0.007931	0.002821	0.088519	-0.045924	-0.062520	-0.081977	-0.078030	1.000
Documentary	-0.009544	-0.001064	0.028098	0.009029	0.004407	-0.002689	-0.052565	-0.035109	-0.018991	-0.024901	-0.040697	-0.026
Drama	-0.030856	0.006572	0.122561	0.010374	0.063856	-0.012326	-0.202415	-0.194570	-0.154479	-0.135707	-0.249840	0.070
Fantasy	-0.018792	0.002212	-0.023312	-0.011237	-0.024222	0.001299	0.014551	0.227046	0.012025	0.263280	-0.006010	-0.033
Film-Noir	-0.019655	0.004701	0.060259	-0.008664	0.033495	0.005246	-0.080288	-0.014178	0.037013	-0.038033	-0.101425	0.136
Horror	0.057613	-0.001392	-0.094353	-0.007079	-0.023901	0.001439	-0.042733	-0.057256	-0.049730	-0.077099	-0.093064	-0.047
Musical	-0.059381	-0.000222	0.015643	0.000378	0.005158	-0.007312	-0.100432	-0.022327	0.335231	0.312567	0.030566	-0.061
Mystery	-0.028561	0.004334	0.015848	-0.006836	0.024308	0.002421	-0.054084	-0.043503	-0.042488	-0.052786	-0.105346	0.080
Romance	-0.118375	0.006834	0.009644	-0.004799	0.017503	-0.014018	-0.067830	-0.024389	-0.054540	-0.084550	0.112843	-0.073
Sci-Fi	-0.011747	-0.003283	-0.044487	-0.024150	-0.010879	0.026250	0.319117	0.284190	-0.055526	-0.038844	-0.187079	-0.083
Thriller	-0.058418	-0.001107	-0.004806	-0.011591	-0.014100	0.008981	0.202756	-0.038423	-0.085713	-0.132642	-0.299501	0.115
War	-0.081951	0.003502	0.075688	-0.014109	0.038446	0.010264	0.135872	0.016647	-0.046114	-0.066539	-0.127101	-0.079
Western	0.003940	0.004114	0.007311	-0.006230	0.038177	0.005924	0.022242	-0.011964	-0.030908	-0.031269	0.007927	-0.042

*From the above **(Master_DataModiGenr)** correlation matrix "Rating" has some visible correlation with*

- "Age" = 0.0568
- "Timestamp" = -0.0267
- "MovieID" = -0.064
- "Action" = -0.0476
- "Adventure" = -0.037
- "Children's" = -0.0398
- "Comedy" = -0.0396
- "Crime" = 0.033
- "Drama" = 0.123
- "Documentary" = 0.028
- "Film-Noir" = 0.060
- "Horror" = -0.094
- "Sci-Fi" = -0.044
- "War" = 0.076

"Occupation" has very very low correlation and others also doesn't have very good correlation. So we can ignore it.

==

In [43]:
```
# Checking the correlation of the modified "Master_DataModiGenrGendr" which affects Rating

Master_DataModiGenrGendr.corr()
```

Out[43]:

	MovieID	UserID	Rating	Timestamp	Age	Occupation	Action	Adventure	Animation	Children's	Comedy	C
MovieID	1.000000	-0.017739	-0.064042	0.041632	0.027575	0.008585	-0.042046	-0.082413	-0.014177	-0.071589	0.061667	-0.06
UserID	-0.017739	1.000000	0.012303	-0.490383	0.034688	-0.026698	-0.002023	-0.000683	-0.007665	-0.004862	-0.003651	0.00
Rating	-0.064042	0.012303	1.000000	-0.026770	0.056869	0.006753	-0.047633	-0.036718	0.019670	-0.039829	-0.039622	0.03
Timestamp	0.041632	-0.490383	-0.026770	1.000000	-0.064562	0.015646	-0.032990	-0.023252	0.000840	-0.000991	0.006064	-0.00
Age	0.027575	0.034688	0.056869	-0.064562	1.000000	0.078371	-0.030975	-0.016730	-0.047020	-0.052858	-0.044046	-0.00
Occupation	0.008585	-0.026698	0.006753	0.015646	0.078371	1.000000	0.018347	0.014309	-0.003834	-0.006906	-0.006149	0.00
Action	-0.042046	-0.002023	-0.047633	-0.032990	-0.030975	0.018347	1.000000	0.374961	-0.110294	-0.141314	-0.268092	0.08
Adventure	-0.082413	-0.000683	-0.036718	-0.023252	-0.016730	0.014309	0.374961	1.000000	0.004732	0.098283	-0.124960	-0.04
Animation	-0.014177	-0.007665	0.019670	0.000840	-0.047020	-0.003834	-0.110294	0.004732	1.000000	0.576204	0.018544	-0.06
Children's	-0.071589	-0.004862	-0.039829	-0.000991	-0.052858	-0.006906	-0.141314	0.098283	0.576204	1.000000	0.058711	-0.08
Comedy	0.061667	-0.003651	-0.039622	0.006064	-0.044046	-0.006149	-0.268092	-0.124960	0.018544	0.058711	1.000000	-0.07
Crime	-0.061896	0.003469	0.033446	-0.009597	-0.007931	0.002821	0.088519	-0.045924	-0.062520	-0.081977	-0.078030	1.00
Documentary	-0.009544	-0.001064	0.028098	0.009029	0.004407	-0.002689	-0.052565	-0.035109	-0.018991	-0.024901	-0.040697	-0.02
Drama	-0.030856	0.006572	0.122561	0.010374	0.063856	-0.012326	-0.202415	-0.194570	-0.154479	-0.135707	-0.249840	0.07
Fantasy	-0.018792	0.002212	-0.023312	-0.011237	-0.024222	0.001299	0.014551	0.227046	0.012025	0.263280	-0.006010	-0.03
Film-Noir	-0.019655	0.004701	0.060259	-0.008664	0.033495	0.005246	-0.080288	-0.014178	0.037013	-0.038033	-0.101425	0.13
Horror	0.057613	-0.001392	-0.094353	-0.007079	-0.023901	0.001439	-0.042733	-0.057256	-0.049730	-0.077099	-0.093064	-0.04
Musical	-0.059381	-0.000222	0.015643	0.000378	0.005158	-0.007312	-0.100432	-0.022327	0.335231	0.312567	0.030566	-0.06
Mystery	-0.028561	0.004334	0.015848	-0.006836	0.024308	0.002421	-0.054084	-0.043503	-0.042488	-0.052786	-0.105346	0.08
Romance	-0.118375	0.006834	0.009644	-0.004799	0.017503	-0.014018	-0.067830	-0.024389	-0.054540	-0.084550	0.112843	-0.07
Sci-Fi	-0.011747	-0.003283	-0.044487	-0.024150	-0.010879	0.026250	0.319117	0.284190	-0.055526	-0.038844	-0.187079	-0.08
Thriller	-0.058418	-0.001107	-0.004806	-0.011591	-0.014100	0.008981	0.202756	-0.038423	-0.085713	-0.132642	-0.299501	0.11
War	-0.081951	0.003502	0.075688	-0.014109	0.038446	0.010264	0.135872	0.016647	-0.046114	-0.066539	-0.127101	-0.07
Western	0.003940	0.004114	0.007311	-0.006230	0.038177	0.005924	0.022242	-0.011964	-0.030908	-0.031269	0.007927	-0.04
Gender_F	-0.021626	0.035042	0.019861	0.008895	0.003189	-0.114974	-0.094380	-0.038645	0.017719	0.031662	0.040758	-0.02
Gender_M	0.021626	-0.035042	-0.019861	-0.008895	-0.003189	0.114974	0.094380	0.038645	-0.017719	-0.031662	-0.040758	0.02

*From the above **(Master_DataModiGenrGendr)** correlation matrix "Rating" has some visible correlation with (considered >=0.025)*

- "Age" = 0.0568
- "Timestamp" = -0.0267
- "MovieID" = -0.064
- "Action" = -0.0476
- "Adventure" = -0.037
- "Children's" = -0.0398
- "Comedy" = -0.0396
- "Crime" = 0.033
- "Drama" = 0.123
- "Documentary" = 0.028
- "Film-Noir" = 0.060
- "Horror" = -0.094
- "Sci-Fi" = -0.044
- "War" = 0.076

==

In [44]:
```
# Checking the correlation of the modified "Master_DataModiGenrGendrAge" which affects Rating

Master_DataModiGenrGendrAge.corr()
```

Out[44]:

	MovieID	UserID	Rating	Timestamp	Occupation	Action	Adventure	Animation	Children's	Comedy	Crime	Docu
MovieID	1.000000	-0.017739	-0.064042	0.041632	0.008585	-0.042046	-0.082413	-0.014177	-0.071589	0.061667	-0.061896	-(
UserID	-0.017739	1.000000	0.012303	-0.490383	-0.026698	-0.002023	-0.000683	-0.007665	-0.004862	-0.003651	0.003469	-(
Rating	-0.064042	0.012303	1.000000	-0.026770	0.006753	-0.047633	-0.036718	0.019670	-0.039829	-0.039622	0.033446	(
Timestamp	0.041632	-0.490383	-0.026770	1.000000	0.015646	-0.032990	-0.023252	0.000840	-0.000991	0.006064	-0.009597	(
Occupation	0.008585	-0.026698	0.006753	0.015646	1.000000	0.018347	0.014309	-0.003834	-0.006906	-0.006149	0.002821	-(
Action	-0.042046	-0.002023	-0.047633	-0.032990	0.018347	1.000000	0.374961	-0.110294	-0.141314	-0.268092	0.088519	-(
Adventure	-0.082413	-0.000683	-0.036718	-0.023252	0.014309	0.374961	1.000000	0.004732	0.098283	-0.124960	-0.045924	-(
Animation	-0.014177	-0.007665	0.019670	0.000840	-0.003834	-0.110294	0.004732	1.000000	0.576204	0.018544	-0.062520	-(
Children's	-0.071589	-0.004862	-0.039829	-0.000991	-0.006906	-0.141314	0.098283	0.576204	1.000000	0.058711	-0.081977	-(
Comedy	0.061667	-0.003651	-0.039622	0.006064	-0.006149	-0.268092	-0.124960	0.018544	0.058711	1.000000	-0.078030	-(
Crime	-0.061896	0.003469	0.033446	-0.009597	0.002821	0.088519	-0.045924	-0.062520	-0.081977	-0.078030	1.000000	-(
Documentary	-0.009544	-0.001064	0.028098	0.009029	-0.002689	-0.052565	-0.035109	-0.018991	-0.024901	-0.040697	-0.026243	1
Drama	-0.030856	0.006572	0.122561	0.010374	-0.012326	-0.202415	-0.194570	-0.154479	-0.135707	-0.249840	0.070479	-(
Fantasy	-0.018792	0.002212	-0.023312	-0.011237	0.001299	0.014551	0.227046	0.012025	0.263280	-0.006010	-0.033745	-(
Film-Noir	-0.019655	0.004701	0.060259	-0.008664	0.005246	-0.080288	-0.014178	0.037013	-0.038033	-0.101425	0.136237	-(
Horror	0.057613	-0.001392	-0.094353	-0.007079	0.001439	-0.042733	-0.057256	-0.049730	-0.077099	-0.093064	-0.047899	-(
Musical	-0.059381	-0.000222	0.015643	0.000378	-0.007312	-0.100432	-0.022327	0.335231	0.312567	0.030566	-0.061179	-(
Mystery	-0.028561	0.004334	0.015848	-0.006836	0.002421	-0.054084	-0.043503	-0.042488	-0.052786	-0.105346	0.080093	-(
Romance	-0.118375	0.006834	0.009644	-0.004799	-0.014018	-0.067830	-0.024389	-0.054540	-0.084550	0.112843	-0.073320	-(
Sci-Fi	-0.011747	-0.003283	-0.044487	-0.024150	0.026250	0.319117	0.284190	-0.055526	-0.038844	-0.187079	-0.083730	-(
Thriller	-0.058418	-0.001107	-0.004806	-0.011591	0.008981	0.202756	-0.038423	-0.085713	-0.132642	-0.299501	0.115095	-(
War	-0.081951	0.003502	0.075688	-0.014109	0.010264	0.135872	0.016647	-0.046114	-0.066539	-0.127101	-0.079715	-(
Western	0.003940	0.004114	0.007311	-0.006230	0.005924	0.022242	-0.011964	-0.030908	-0.031269	0.007927	-0.042711	-(
Gender_F	-0.021626	0.035042	0.019861	0.008895	-0.114974	-0.094380	-0.038645	0.017719	0.031662	0.040758	-0.027065	-(
Gender_M	0.021626	-0.035042	-0.019861	-0.008895	0.114974	0.094380	0.038645	-0.017719	-0.031662	-0.040758	0.027065	(
New Age	0.028442	0.033042	0.059047	-0.060244	0.084126	-0.032723	-0.017328	-0.045272	-0.050375	-0.043938	-0.008596	(

*From the above **(Master_DataModiGenrGendrAge)** correlation matrix "Rating" has some visible correlation with (considered >=0.025)*

- "New Age" = 0.059 (after LabelEncoding)
- "Timestamp" = -0.0267
- "MovieID" = -0.064
- "Action" = -0.0476
- "Adventure" = -0.037
- "Children's" = -0.0398
- "Comedy" = -0.0396
- "Crime" = 0.033
- "Drama" = 0.123
- "Documentary" = 0.028
- "Film-Noir" = 0.060
- "Horror" = -0.094
- "Sci-Fi" = -0.044
- "War" = 0.076

Looking at the data with 4 defferent correlation matrix, the last matrix with (Master_DataModiGenrGendrAge) gives more information about the features affecting the ratings of a particular movie.

##

4. Develop an appropriate model to predict the movie ratings

Since "Rating" is a discrete variable, so will use classification model. Here KNN model is chosen as "Rating" is multilevel variable.

In [45]:
```
#import required packages
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

# import module for rescaling features and fine tuning model
from sklearn import preprocessing

#import different matrix module for model evaluation
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import roc_auc_score
```

In [46]:
```
#create a feature list with the selected feature
feature_list = ["Rating","New Age","Gender_F","Gender_M","MovieID","Action","Adventure","Children's","Come
dy","Crime","Drama","Documentary","Film-Noir","Horror","Sci-Fi","War",]

# create a clean dataset with the selected features which has good correlation
Master_DataClean = Master_DataModiGenrGendrAge[feature_list]
Master_DataClean.head()
```

Out[46]:

	Rating	New Age	Gender_F	Gender_M	MovieID	Action	Adventure	Children's	Comedy	Crime	Drama	Documentary	Film-Noir	Horror	Sci-Fi	Wa
0	5	0	1	0	1	0	0	1	1	0	0	0	0	0	0	0
1	5	0	1	0	48	0	0	1	0	0	0	0	0	0	0	0
2	5	0	1	0	150	0	0	0	0	0	1	0	0	0	0	0
3	4	0	1	0	260	1	1	0	0	0	0	0	0	0	1	0
4	5	0	1	0	527	0	0	0	0	0	1	0	0	0	0	1

In [47]:
```
Master_DataClean.dtypes
```

Out[47]:
```
Rating          int64
New Age         int64
Gender_F        uint8
Gender_M        uint8
MovieID         int64
Action          int32
Adventure       int32
Children's      int32
Comedy          int32
Crime           int32
Drama           int32
Documentary     int32
Film-Noir       int32
Horror          int32
Sci-Fi          int32
War             int32
dtype: object
```

From the dataset it is evident that "MovieID" are not in a same scale. So we have to scale the features.

In [48]:
```
#create a copy of Selected Feature Data
Master_DataCleanCopy = Master_DataClean.copy()

# create scaler estimator for rescaling feature "MovieID"
scaler = preprocessing.MinMaxScaler()

#select the feature which has to be rescalled
feature_list_1 = feature_list.copy()
feature_list_1.remove("Rating")
feature_list_1 = [feature_list_1]

#scalling the feature vectors
for feature in feature_list_1:
    Master_DataCleanCopy[feature] = scaler.fit_transform(Master_DataCleanCopy[feature])

Master_DataCleanCopy.head()
```

Out[48]:

	Rating	New Age	Gender_F	Gender_M	MovieID	Action	Adventure	Children's	Comedy	Crime	Drama	Documentary	Film-Noir	Horror	Sci-Fi	Wa
0	5	0.0	1.0	0.0	0.000000	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.
1	5	0.0	1.0	0.0	0.011896	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.
2	5	0.0	1.0	0.0	0.037712	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.
3	4	0.0	1.0	0.0	0.065553	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.
4	5	0.0	1.0	0.0	0.133131	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.

In [49]:
```
#view the dataset size
print("Dataset Size: {}".format(Master_DataCleanCopy.shape))

#view the statistics of the dataset
print("Data Statistics : \n",Master_DataCleanCopy.describe())
```

```
Dataset Size: (1000209, 16)
Data Statistics :
             Rating       New Age      Gender_F      Gender_M       MovieID  \
count  1.000209e+06  1.000209e+06  1.000209e+06  1.000209e+06  1.000209e+06
mean   3.581564e+00  4.167994e-01  2.463885e-01  7.536115e-01  4.719159e-01
std    1.117102e+00  2.265423e-01  4.309076e-01  4.309076e-01  2.774084e-01
min    1.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%    3.000000e+00  3.333333e-01  0.000000e+00  1.000000e+00  2.604404e-01
50%    4.000000e+00  3.333333e-01  0.000000e+00  1.000000e+00  4.641863e-01
75%    4.000000e+00  5.000000e-01  0.000000e+00  1.000000e+00  7.008352e-01
max    5.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00

             Action     Adventure    Children's        Comedy         Crime  \
count  1.000209e+06  1.000209e+06  1.000209e+06  1.000209e+06  1.000209e+06
mean   2.574032e-01  1.339250e-01  7.217092e-02  3.565055e-01  7.952438e-02
std    4.372036e-01  3.405719e-01  2.587708e-01  4.789672e-01  2.705556e-01
min    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
50%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
75%    1.000000e+00  0.000000e+00  0.000000e+00  1.000000e+00  0.000000e+00
max    1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00

              Drama   Documentary     Film-Noir        Horror        Sci-Fi  \
count  1.000209e+06  1.000209e+06  1.000209e+06  1.000209e+06  1.000209e+06
mean   3.544549e-01  7.908347e-03  1.825718e-02  7.637004e-02  1.572611e-01
std    4.783481e-01  8.857659e-02  1.338801e-01  2.655894e-01  3.640470e-01
min    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
50%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
75%    1.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
max    1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00

                War
count  1.000209e+06
mean   6.851268e-02
std    2.526237e-01
min    0.000000e+00
25%    0.000000e+00
50%    0.000000e+00
75%    0.000000e+00
max    1.000000e+00
```

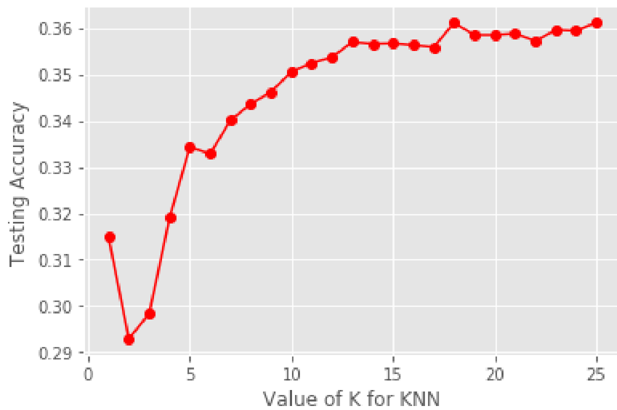
In [50]:
```
# Create the X_feature and Y_target object
X_feature = Master_DataCleanCopy.drop(columns=['Rating'])
Y_target = Master_DataCleanCopy["Rating"]


# Split dataset in Train and Test
# selected 1st 100000 observations(a sample), since the total dataset is huge and take long time to fit an
d predict the model.
X_train, X_test, Y_train, Y_test = train_test_split(X_feature[:100001],Y_target[:100001], random_state=4)

#print the training and testing data set size
print ('Train set:', X_train.shape,  Y_train.shape)
print ('Test set:', X_test.shape,  Y_test.shape)
print ('Main Dataset:', X_feature.shape, Y_target.shape)
```

```
Train set: (75000, 15) (75000,)
Test set: (25001, 15) (25001,)
Main Dataset: (1000209, 15) (1000209,)
```

In [52]:
```
# try K=1 through K=25 and record testing accuracy
k_range = range(1, 26)

# create an empty score[] list
scores = []

# We use a loop through the range 1 to 25
# We append the scores in the dictionary
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, Y_train)
    Y_pred = knn.predict(X_test)
    scores.append(accuracy_score(Y_test, Y_pred))

print(scores)
```

```
[0.31482740690372385, 0.29294828206871726, 0.2983480660773569, 0.3189872405103796, 0.3343066277348906,
0.3328266869325227, 0.3400663973441062, 0.343586256549738, 0.34618615255389784, 0.3505459781608736, 0.35
242590296388143, 0.35366585336586537, 0.35694572217111314, 0.3565457381704732, 0.35666573337066515, 0.35
62657493700252, 0.3558257669693212, 0.3610655573777049, 0.3584656613735451, 0.3584656613735451, 0.358785
64857405704, 0.35714571417143315, 0.359545618175273, 0.359345626174953, 0.3611455541778329]
```

In [53]:
```
# plot the relationship between K and testing accuracy
from matplotlib import style

style.use("ggplot")
plt.plot(k_range, scores,'-or')
plt.xlabel('Value of K for KNN')
plt.ylabel('Testing Accuracy')

plt.show()
```



===

Final KNN model with K=25

In [54]:
```
# create a KNN estimator and pass k=25
k=25
KNN = KNeighborsClassifier(n_neighbors = k).fit(X_train, Y_train)

# Predict test data
Y_pred = KNN.predict(X_test)
```

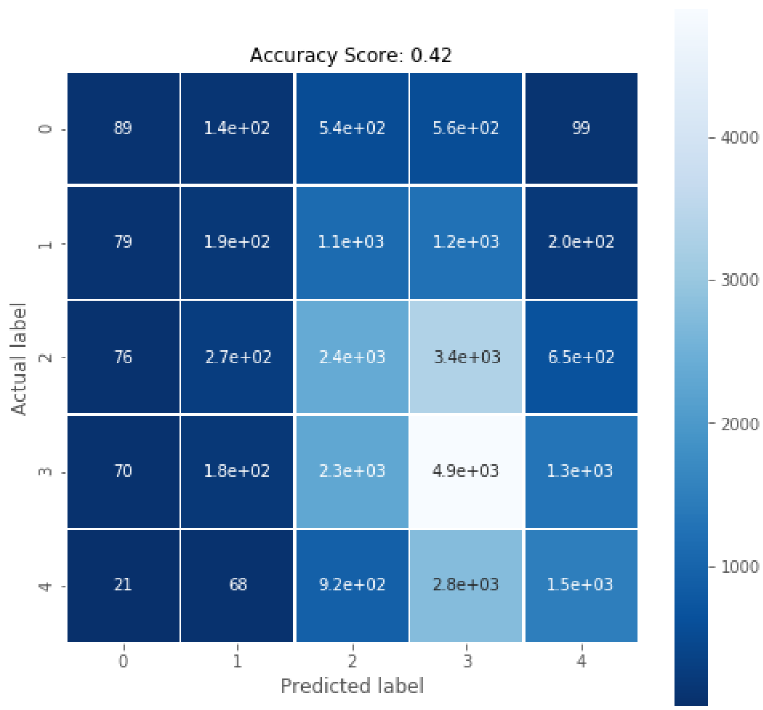
In [55]:
```
# Accuracy Evaluation of train and test data

print("Train set Accuracy: {:.2f}".format(KNN.score(X_train,Y_train)))
print("Test set Accuracy: {:.2f}".format(accuracy_score(Y_test, Y_pred)))
```

```
Train set Accuracy: 0.42
Test set Accuracy: 0.36
```

In [56]:
```
#different accuracy metrix

precision_score = precision_score(Y_test, Y_pred,average='macro')
recall_score = recall_score(Y_test, Y_pred,average='macro')
f1_score = f1_score(Y_test, Y_pred,average='macro')

print( 'Accuracy : {:.2f}'.format(test_score))
print('Precision : {:.2f}'.format(precision_score))
print('Recall: {:.2f}'.format(recall_score))
print('F1: {:.2f}'.format(f1_score))
```

```
Accuracy : 0.36
Precision : 0.32
Recall: 0.26
F1: 0.27
```

In [60]:
```
# predict X_test and analyse the confusion metrics for accuracy testing

from sklearn.metrics import confusion_matrix

CM = confusion_matrix(Y_test, Y_pred)

plt.figure(figsize=(8,8))
sns.heatmap(CM, annot=True, linewidths=.5, square = True, cmap = 'Blues_r')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
title = 'Accuracy Score: {:.2f}'.format(train_score)
plt.title(title, size = 12)
plt.show()
```



In [ ]:

In [ ]: