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

```
  Field                  Description
- UserID        Unique identification for each user
- MovieID       Unique identification for each movie
- Rating        User rating for each movie
- Timestamp     Timestamp generated while adding user review
```

- UserIDs range between 1 and 6040
- The MovieIDs range between 1 and 3952
- Ratings are made on a 5-star scale (whole-star ratings only)
- A timestamp is represented in seconds since the epoch is returned by time(2)
- Each user has at least 20 ratings

Users.dat

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

```
  Field                    Description
- UserID         Unique identification for each user
- Genere         Category of each movie
- Age            User’s age
- Occupation     User’s Occupation
- Zip-code       Zip Code for the user’s location
All demographic information is provided voluntarily by the users and is not checked
for accuracy. Only users who have provided demographic information are included in this
data set.
    - Gender is denoted by an "M" for male and "F" for female
    - Age is chosen from the following ranges:

                Value          Description
                  1             "Under 18"
                  18            "18-24"
                  25            "25-34"
                  35            "35-44"
                  45            "45-49"
                  50            "50-55"
                  56            "56+"


    - Occupation is chosen from the following choices:

                Value           Description
                  0          "other" or not specified
                  1          "academic/educator"
                  2          "artist”
                  3          "clerical/admin"
                  4          "college/grad student"
                  5          "customer service"
                  6          "doctor/health care"
                  7          "executive/managerial"
                  8          "farmer"
                  9          "homemaker"
                  10         "K-12 student"
                  11         "lawyer"
                  12         "programmer"
                  13         "retired"
                  14         "sales/marketing"
                  15         "scientist"
                  16         "self-employed"
                  17         "technician/engineer"
                  18         "tradesman/craftsman"
                  19         "unemployed"
                  20         "writer”
```

Movies.dat

Format - MovieID::Title::Genres

```
   Field         Description
  MovieID     Unique identification for each movie
  Title       A title for each movie
  Genres      Category of each movie

- Titles are identical to titles provided by the IMDB (including year of release)
- Genres are pipe-separated and are selected from the following genres:
    Action
    Adventure
    Animation
    Children's
    Comedy
    Crime
    Documentary
    Drama
    Fantasy
    Film-Noir
    Horror
    Musical
    Mystery
    Romance
    Sci-Fi
    Thriller
    War
    Western
- Some MovieIDs do not correspond to a movie due to accidental duplicate entries and/or test ent
ries
- Movies are mostly entered by hand, so errors and inconsistencies may exist
```

In [1]:
```python
# Import necessary header files
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
```

In [2]:
```python
# To ignore warnings
warnings.simplefilter('ignore')
# To display needed number of columns
pd.set_option('display.max_columns',30)
```

Analysis Task 1

```
- Import the Three Datasets
```

In [3]:
```python
# Load ratings.dat file
ratings = pd.read_csv("ratings.dat",sep="::",header=None,names=['UserID','MovieID','Rating','Timestamp'
])
ratings.head()
```

Out[3]:

	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 [4]:
```python
# Load users.dat file
users = pd.read_csv("users.dat",sep="::",header=None,names=['UserID','Gender','Age','Occupation','Zip-c
ode'])
users.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]:
```python
# Load movies.dat file
movies = pd.read_csv("movies.dat",sep="::",header=None,names=['MovieID','Title','Genres'])
movies.head()
```

Out[5]:

	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 [6]:
```python
# Print shape of all three datasets
print("Rating dataset Shape: ",ratings.shape)
print("Users dataset Shape: ",users.shape)
print("Movies dataset Shape: ",movies.shape)
```

```
Rating dataset Shape:  (1000209, 4)
Users dataset Shape:  (6040, 5)
Movies dataset Shape:  (3883, 3)
```

In [ ]:

Analysis Task 2

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

In [7]:
```python
# Merging two dataset movies and ratings on the key MovieID
movie_ratings = pd.merge(movies,ratings,how='inner',on='MovieID')
```

In [8]:
```python
# Merging the third dataset users on the key UserID
df_final = pd.merge(movie_ratings,users,how='inner',on='UserID')
```

In [9]:
```python
# Creating Master data with necessary columns
Master_data = df_final[['MovieID','Title','UserID','Age','Gender','Occupation','Rating']]
```

In [10]:
```python
# Checking for duplicates
Master_data.duplicated().sum()
```

Out[10]: 0

In [11]:
```python
# Master data information
Master_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns (total 7 columns):
 #   Column      Non-Null Count    Dtype
---  ------      --------------    -----
 0   MovieID     1000209 non-null  int64
 1   Title       1000209 non-null  object
 2   UserID      1000209 non-null  int64
 3   Age         1000209 non-null  int64
 4   Gender      1000209 non-null  object
 5   Occupation  1000209 non-null  int64
 6   Rating      1000209 non-null  int64
dtypes: int64(5), object(2)
memory usage: 61.0+ MB
```

In [ ]:

Analysis Task 3

```
- Explore the datasets using visual representations (graphs or tables)
    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
```

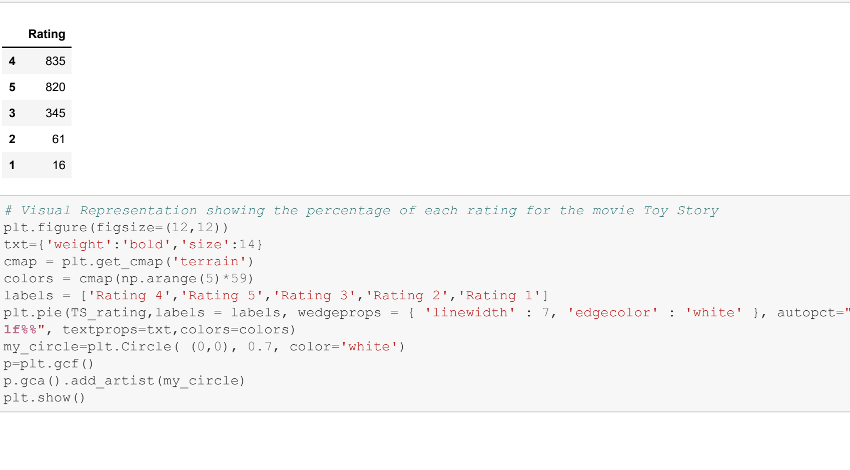
1) Age Distribution

In [12]:
```python
# Finding Age distribution
age_dist = Master_data['Age'].value_counts().to_frame()
age_dist.sort_index(inplace=True)
age_dist
```

Out[12]:

	Age
1	27211
18	183536
25	395556
35	199003
45	83633
50	72490
56	38780

In [13]:
```python
# Visual Representation of the age distribution
plt.figure(figsize=(15,8))
txt = {'weight':'bold'}
sns.set_style("white")
sns.countplot(x='Age',data=Master_data,palette="terrain")
plt.title("User Age Distribution",fontdict=txt)
plt.xlabel("Age (range)",fontdict=txt,labelpad=15)
plt.ylabel("Number of users",fontdict=txt,labelpad=25)
plt.xticks([0,1,2,3,4,5,6],["Under 18","18-24","25-34","35-44","45-49","50-55","56+"],)
for i in range(7):
    plt.annotate(age_dist['Age'].iloc[i],xy=(i-0.2,age_dist['Age'].iloc[i]+5000),size=15)
plt.show()
```



Comments : Most of the users are between the age 25 to 34

In [ ]:

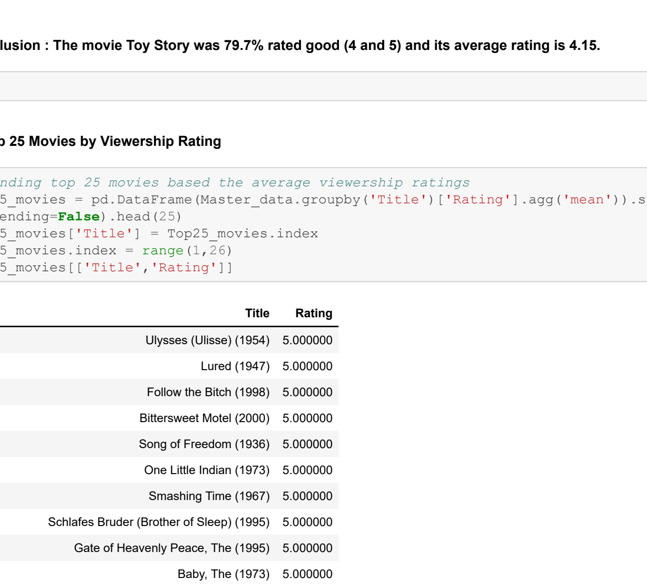
2) User Rating for movie Toy Story

In [14]:
```python
# Finding User rating for the movie Toy Story
Toy_stort_df = Master_data[Master_data['Title'] == "Toy Story (1995)"]
TS_rating = Toy_stort_df['Rating'].value_counts().to_frame()
TS_rating
```

Out[14]:

	Rating
4	835
5	820
3	345
2	61
1	16

In [15]:
```python
# Visual Representation showing the percentage of each rating for the movie Toy Story
plt.figure(figsize=(12,12))
txt={'weight':'bold','size':14}
cmap = plt.get_cmap('terrain')
colors = cmap(np.arange(5)*59)
labels = ['Rating 4','Rating 5','Rating 3','Rating 2','Rating 1']
plt.pie(TS_rating,labels = labels, wedgeprops = { 'linewidth' : 7, 'edgecolor' : 'white' }, autopct="%.
1f%%", textprops=txt,colors=colors)
my_circle=plt.Circle( (0,0), 0.7, color='white')
p=plt.gcf()
p.gca().add_artist(my_circle)
plt.show()
```



In [16]:
```python
# Finding the avearge overall rating
print("Average Rating for the movie Toy Story is {:.2f}".format(Toy_stort_df['Rating'].mean()))
```

```
Average Rating for the movie Toy Story is 4.15
```

Conclusion : The movie Toy Story was 79.7% rated good (4 and 5) and its average rating is 4.15.

In [ ]:

3) Top 25 Movies by Viewership Rating

In [17]:
```python
# Finding top 25 movies based the average viewership ratings
Top25_movies = pd.DataFrame(Master_data.groupby('Title')['Rating'].agg('mean')).sort_values(by='Rating'
,ascending=False).head(25)
Top25_movies['Title'] = Top25_movies.index
Top25_movies.index = range(1,26)
Top25_movies[['Title','Rating']]
```

Out[17]:

	Title	Rating
1	Ulysses (Ulisse) (1954)	5.000000
2	Lured (1947)	5.000000
3	Follow the Bitch (1998)	5.000000
4	Bittersweet Motel (2000)	5.000000
5	Song of Freedom (1936)	5.000000
6	One Little Indian (1973)	5.000000
7	Smashing Time (1967)	5.000000
8	Schlafes Bruder (Brother of Sleep) (1995)	5.000000
9	Gate of Heavenly Peace, The (1995)	5.000000
10	Baby, The (1973)	5.000000
11	I Am Cuba (Soy Cuba/Ya Kuba) (1964)	4.800000
12	Lamerica (1994)	4.750000
13	Apple, The (Sib) (1998)	4.666667
14	Sanjuro (1962)	4.608696
15	Seven Samurai (The Magnificent Seven) (Shichin...	4.560510
16	Shawshank Redemption, The (1994)	4.554558
17	Godfather, The (1972)	4.524966
18	Close Shave, A (1995)	4.520548
19	Usual Suspects, The (1995)	4.517106
20	Schindler's List (1993)	4.510417
21	Wrong Trousers, The (1993)	4.507937
22	Dry Cleaning (Nettoyage à sec) (1997)	4.500000
23	Inheritors, The (Die Siebtelbauern) (1998)	4.500000
24	Mamma Roma (1962)	4.500000
25	Bells, The (1926)	4.500000

Conclusion : Out of top 25 movies first 10 movies has been rated 5 .

In [ ]:

4) User ID = 2696 Rated movies

In [18]:
```python
# Extracting the details of User ID 2696
Userid_2696 = Master_data[Master_data['UserID'] == 2696]
Userid_2696 = Userid_2696.sort_values('Rating',ascending=False,ignore_index=True)
Userid_2696[['MovieID','Title','Rating']]
```

Out[18]:

	MovieID	Title	Rating
0	800	Lone Star (1996)	5
1	1645	Devil's Advocate, The (1997)	4
2	1783	Palmetto (1998)	4
3	1092	Basic Instinct (1992)	4
4	3176	Talented Mr. Ripley, The (1999)	4
5	1258	Shining, The (1980)	4
6	2389	Psycho (1998)	4
7	1892	Perfect Murder, A (1998)	4
8	1617	L.A. Confidential (1997)	4
9	1625	Game, The (1997)	4
10	1805	Wild Things (1998)	4
11	1711	Midnight in the Garden of Good and Evil (1997)	4
12	350	Client, The (1994)	3
13	1589	Cop Land (1997)	3
14	1097	E.T. the Extra-Terrestrial (1982)	3
15	1644	I Know What You Did Last Summer (1997)	2
16	2338	I Still Know What You Did Last Summer (1998)	2
17	1270	Back to the Future (1985)	2
18	2713	Lake Placid (1999)	1
19	3386	JFK (1991)	1

Comments : This user has rated 5 to the movie titled "Lone Star (1996)" and Most of his ratings are 4 .

In [ ]:

Feature Engineering Task 1

```
- Using column 'Genres' , Find out all the unique genres.
```

In [19]:
```python
# Storing Genres column to a variable names genre
genre = df_final['Genres']
genre.head()
```

Out[19]:
```
0             Animation|Children's|Comedy
1     Animation|Children's|Musical|Romance
2                                    Drama
3          Action|Adventure|Fantasy|Sci-Fi
4                                Drama|War
Name: Genres, dtype: object
```

In [20]:
```python
# For loop to store the splitted genre data and append to a list
list1=[]
for row in genre:
    row_list = row.split("|")
    for i in range(len(row_list)):
        list1.append(row_list[i])
```

In [21]:
```python
# Finding unique genres and number of unique genres
unique_genre = list(set(list1))
print(unique_genre)
print()
print("Total Unique Genres : ",len(unique_genre))
```

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

Total Unique Genres :  18
```

In [ ]:

Feature Engineering Task 2

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

In [22]:
```python
# creating a new variable onehotcode to perform onehotencoding
onehotcode = df_final.copy()
onehotcode.head(3)
```

Out[22]:

	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

In [23]:
```python
# Converting categorical variable to numerical variable
dummy = onehotcode['Genres'].str.get_dummies()
dummy.head(3)
```

Out[23]:

	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance
0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
1	0	0	1	1	0	0	0	0	0	0	0	1	0	1
2	0	0	0	0	0	0	0	1	0	0	0	0	0	0

In [24]:
```python
# Merging the final_dataset with newly created onehotcode based on index
final_dataset = pd.merge(onehotcode,dummy,how='inner',left_index=True,right_index=True)
print("Final dataset shape: ",final_dataset.shape)
final_dataset.head(3)
```

```
Final dataset shape:  (1000209, 28)
```

Out[24]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Action	Adven
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	1	10	48067	0	
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351	F	1	10	48067	0	
2	150	Apollo 13 (1995)	Drama	1	5	978301777	F	1	10	48067	0	

In [ ]:

Feature Engineering Task 3

```
- Determine the features affecting the ratings of any particular movie.
```

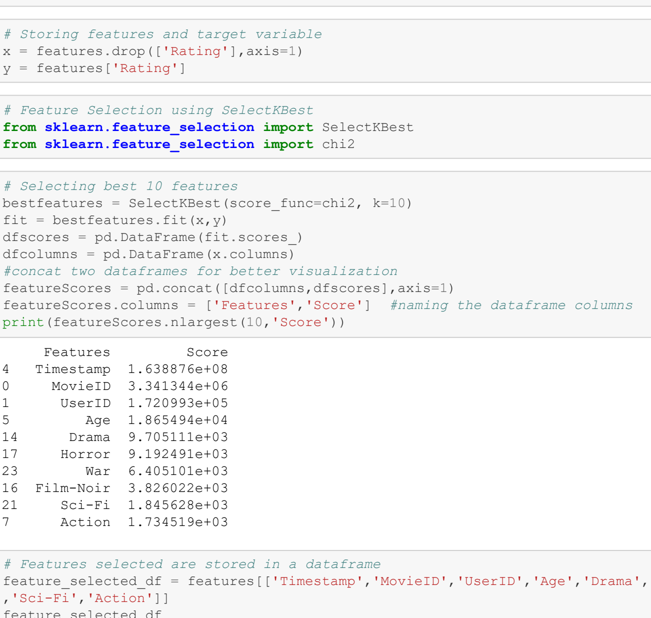
In [25]:
```python
# Converting categorical column "Gender" into numerical column.
gender_dummy = final_dataset['Gender'].str.get_dummies()
```

In [26]:
```python
# Merging the new numerical column to final dataset based on index
final_dataset = pd.merge(final_dataset,gender_dummy,how='inner',left_index=True,right_index=True)
final_dataset.head(3)
```

Out[26]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Action	Adven
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	1	10	48067	0	
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351	F	1	10	48067	0	
2	150	Apollo 13 (1995)	Drama	1	5	978301777	F	1	10	48067	0	

In [27]:
```python
# Creating Heatmap
m = np.ones_like(final_dataset[["MovieID","UserID","Timestamp","Age","F","M","Occupation","Rating"]].co
rr())
m[np.tril_indices_from(m)]=0
sns.set_style("white")
plt.figure(figsize=(12,10))
sns.heatmap(final_dataset[["MovieID","UserID","Timestamp","Age","F","M","Occupation","Rating"]].corr(),
annot=True,cmap="Set3",mask=m)
plt.show()
```



In [28]:
```python
# Creating a new dataframe with only continous data and dummies
features = final_dataset[['MovieID', 'UserID', 'F', 'M', 'Timestamp',
       'Age', 'Occupation', 'Action', 'Adventure', 'Animation',
       "Children's", 'Comedy', 'Crime', 'Documentary', 'Drama', 'Fantasy',
       'Film-Noir', 'Horror', 'Musical', 'Mystery', 'Romance', 'Sci-Fi',
       'Thriller', 'War', 'Western','Rating']]
```

In [29]:
```python
# Storing features and target variable
x = features.drop(['Rating'],axis=1)
y = features['Rating']
```

In [30]:
```python
# Feature Selection using SelectKBest
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
```

In [31]:
```python
# Selecting best 10 features
bestfeatures = SelectKBest(score_func=chi2, k=10)
fit = bestfeatures.fit(x,y)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(x.columns)
#concat two dataframes for better visualization
featureScores = pd.concat([dfcolumns,dfscores],axis=1)
featureScores.columns = ['Features','Score']  #naming the dataframe columns
print(featureScores.nlargest(10,'Score'))
```

```
     Features         Score
4   Timestamp  1.638876e+08
0     MovieID  3.341344e+06
1      UserID  1.720993e+05
5         Age  1.865494e+04
14      Drama  9.705111e+03
17     Horror  9.192491e+03
23        War  6.405101e+03
16  Film-Noir  3.826022e+03
21     Sci-Fi  1.845628e+03
7      Action  1.734519e+03
```

In [32]:
```python
# Features selected are stored in a dataframe
feature_selected_df = features[['Timestamp','MovieID','UserID','Age','Drama','Horror','War','Film-Noir'
,'Sci-Fi','Action']]
feature_selected_df
```

Out[32]:

	Timestamp	MovieID	UserID	Age	Drama	Horror	War	Film-Noir	Sci-Fi	Action
0	978824268	1	1	1	0	0	0	0	0	0
1	978824351	48	1	1	0	0	0	0	0	0
2	978301777	150	1	1	1	0	0	0	0	0
3	978300760	260	1	1	0	0	0	0	1	1
4	978824195	527	1	1	1	0	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...
1000204	958489970	3513	5727	25	1	0	0	0	0	0
1000205	958489970	3535	5727	25	0	1	0	0	0	0
1000206	958489902	3536	5727	25	0	0	0	0	0	0
1000207	958490699	3555	5727	25	0	0	0	0	0	1
1000208	958490171	3578	5727	25	1	0	0	0	0	1

1000209 rows × 10 columns

In [ ]:

Feature Engineering Task 4

```
- Develop an appropriate model to predict the movie ratings
```

In [33]:
```python
# Splitting dataset for training and testing
x_train,x_test,y_train,y_test = train_test_split(feature_selected_df,y,test_size=0.20,random_state=1)
```

In [34]:
```python
# Size of train and test data
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

Out[34]: ((800167, 10), (200042, 10), (800167,), (200042,))

Model 1 - Decision Tree

In [35]:
```python
# Object creation
clf = DecisionTreeClassifier()
# Model Fitting
clf = clf.fit(x_train,y_train)
# Prediction of test data
y_pred = clf.predict(x_test)
print("Decision Tree accuracy: {:.2f}".format(metrics.accuracy_score(y_test, y_pred)))
```

```
Decision Tree accuracy: 0.32
```

In [36]:

```
a = pd.DataFrame()
a['y_test'] = y_test
a['y_pred'] = y_pred
a.head(20)
```

Out[36]:

	y_test	y_pred
630120	4	3
229398	5	5
758377	3	4
159240	5	4
254252	4	3
27168	3	3
196538	3	4
37123	3	2
982048	4	3
994502	2	3
873073	5	3
684013	1	3
852424	4	4
410026	5	5
285794	3	4
141761	4	1
787144	4	4
154218	3	2
162643	5	4
372999	5	5

Model 2 - K-Nearest Neighbours

In [37]:

```
knn = KNeighborsClassifier(n_neighbors = 7).fit(x_train, y_train)
knnaccuracy = knn.score(x_test, y_test)
knn_predictions = knn.predict(x_test)
print("KNN test accuracy: {:.4f}".format(knnaccuracy))
print("KNN train accuracy: {:.4f}".format(knn.score(x_train,y_train)))
```

```
KNN test accuracy: 0.3568
KNN train accuracy: 0.5238
```

Model 3 - Gaussian Naive Bayes

In [38]:

```
gnb = GaussianNB().fit(x_train, y_train)
gnbaccuracy = gnb.score(x_test, y_test)
gnb_predictions = gnb.predict(x_test)
print("GNB test accuracy: {:.4f}".format(gnbaccuracy))
print("GNB train accuracy: {:.4f}".format(gnb.score(x_train,y_train)))
```

```
GNB test accuracy: 0.3485
GNB train accuracy: 0.3470
```

Comparing the accuracy score of all three models , K-Nearest Neighbours has higher accuracy than other models

In [ ]: