Movielens Case Study

May 3, 2020

0.1 Importing libraries

[1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
```

0.2 Defining Headers

[2]:
```
ratings_header = "UserID::MovieID::Rating::Timestamp".split("::")
users_header = "UserID::Gender::Age::Occupation::Zip-code".split("::")
movies_header = "MovieID::Title::Genres".split("::")
```

0.3 Printing Headers

[3]:
```
print(ratings_header)
print(users_header)
print(movies_header)
```

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

0.4 Step 1 - Importing the data

[4]:
```
movies = pd.read_csv("movies.dat", sep="::", names = movies_header)
users = pd.read_csv("users.dat", sep="::", names = users_header)
ratings = pd.read_csv("ratings.dat", sep="::", names =␣
 ↪ratings_header,parse_dates=["Timestamp"])
```

```
C:\Users\harma\anaconda3\lib\site-packages\ipykernel_launcher.py:1:
ParserWarning: Falling back to the 'python' engine because the 'c' engine does
```

```
not support regex separators (separators > 1 char and different from '\s+' are
interpreted as regex); you can avoid this warning by specifying engine='python'.
  """Entry point for launching an IPython kernel.
C:\Users\harma\anaconda3\lib\site-packages\ipykernel_launcher.py:2:
ParserWarning: Falling back to the 'python' engine because the 'c' engine does
not support regex separators (separators > 1 char and different from '\s+' are
interpreted as regex); you can avoid this warning by specifying engine='python'.

C:\Users\harma\anaconda3\lib\site-packages\ipykernel_launcher.py:3:
ParserWarning: Falling back to the 'python' engine because the 'c' engine does
not support regex separators (separators > 1 char and different from '\s+' are
interpreted as regex); you can avoid this warning by specifying engine='python'.
  This is separate from the ipykernel package so we can avoid doing imports
until
```

0.5 Exploring the data

[5]:
```
movies.head()
```

[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

[6]:
```
users.head()
```

[6]:

	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

[7]:
```
ratings.head()
```

[7]:

	UserID	MovieID	Rating	Timestamp
0	1	1193	5	978300760
1	1	661	3	978302109
2	1	914	3	978301968
3	1	3408	4	978300275
4	1	2355	5	978824291

0.6 Merging the dataset

[8]:
```
movie_and_ratings = pd.merge(movies,ratings,on="MovieID")
```

0.7 Exploring the merged dataset

[9]:
```
movie_and_ratings.head()
```

[9]:

	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

0.8 Step 2 - Merging the dataset into [Master_Data]

[10]:
```
Master_Data = pd.merge(movie_and_ratings,users,on = "UserID")
```

0.9 Exploring the merged dataset - Master_Data

[11]:
```
Master_Data.head()
```

[11]:

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

```
1    1          10    48067
2    1          10    48067
3    1          10    48067
4    1          10    48067
```

0.10 Checking for null values

[12]:
```
Master_Data.isnull().sum()
```

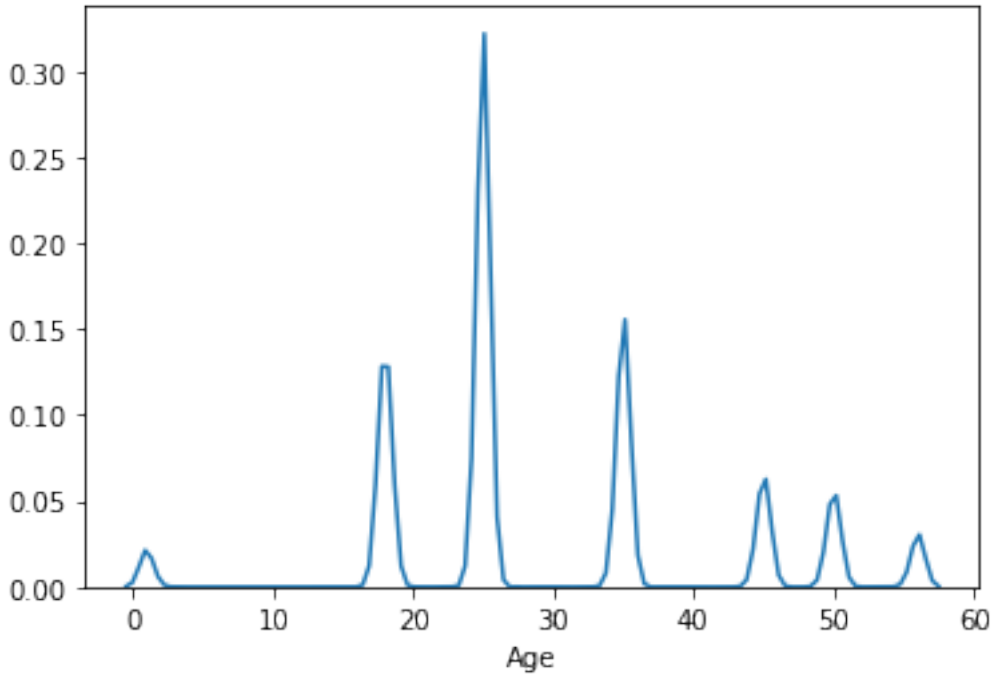
[12]:
```
MovieID       0
Title         0
Genres        0
UserID        0
Rating        0
Timestamp     0
Gender        0
Age           0
Occupation    0
Zip-code      0
dtype: int64
```

0.11 Step 3 - Visual Representation

0.11.1 User Age Distribution

[13]:
```
sns.distplot(Master_Data['Age'], hist=False)
```

[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2599b31c2c8>
```



Comment - User Age Distribution lies mostly 15 years to 60 years as we can observe from the graph

0.11.2 User rating of the movie "Toy Story"

[14]:
```
# Extracting the data needed from the dataset
toy_story = Master_Data[Master_Data["Title"] == "Toy Story (1995)"]
```

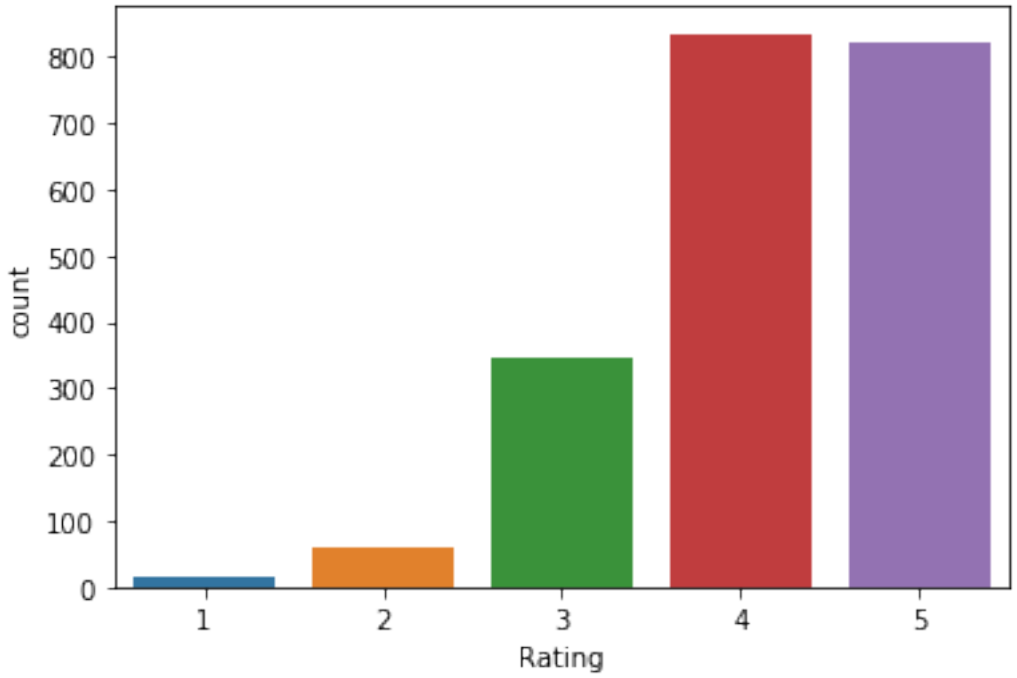
[15]:
```
# Exploring the dataset
toy_story.head()
```

[15]:

	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

[16]:
```
# Ploting the ratings of the toy story movie
sns.countplot("Rating", data = toy_story)
```

[16]: <matplotlib.axes._subplots.AxesSubplot at 0x2599b348388>



Comment - Most user have given either 4 or 5. Very few have given rating of either 1 or 2. There are many who have given a rating of 3 as well. Rating of 4 and 5 have a count of 800 while rating of 3 has a count of near to 400 and rating of 2 has close to 100 and rating of 1 is negligible

0.11.3 Top 25 movies by viewership rating

[17]:
```
# Sorting the dataset on ratings
sorted_rating = Master_Data.sort_values(by = 'Rating', ascending=False)
```

[18]:
```
# Exploring the dataset
sorted_rating.head()
```

[18]:

	MovieID	Title	Genres	UserID	\
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	
489283	2858	American Beauty (1999)	Comedy|Drama	5070	
489259	2599	Election (1999)	Comedy	5070	
489257	2571	Matrix, The (1999)	Action|Sci-Fi|Thriller	5070	
489256	2551	Dead Ringers (1988)	Drama|Thriller	5070	

```
        Rating  Timestamp Gender  Age  Occupation Zip-code
0            5  978824268      F    1          10    48067
489283       5  962466892      M   25           2    55344
489259       5  962467931      M   25           2    55344
489257       5  962468500      M   25           2    55344
489256       5  963746449      M   25           2    55344
```

[19]:
```
# Extracting the movie id and the title from the sorted data
movieid_and_title = sorted_rating[sorted_rating.columns[0:2]]
```

[20]:
```
# Dropping duplicates
movieid_and_title.drop_duplicates(inplace=True)
```

```
C:\Users\harma\anaconda3\lib\site-packages\ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[21]:
```
# Extracting the top 25 movies
top_25 = movieid_and_title['Title'][:25]
```

[22]:
```
# Reseting the index
top_25.reset_index(drop = True,inplace=True)
```

[23]:
```
# Adding 1 to index so that index starts with 1 rather than 0
top_25.index += 1
```

[24]:
```
print(top_25)
```

```
1                        Toy Story (1995)
2                  American Beauty (1999)
3                         Election (1999)
4                      Matrix, The (1999)
5                     Dead Ringers (1988)
6                         Rushmore (1998)
7                   Simple Plan, A (1998)
8              Hands on a Hard Body (1996)
9                     Pleasantville (1998)
10                 Say Anything… (1989)
11                     Beetlejuice (1988)
12                      Roger & Me (1989)
13                      Buffalo 66 (1998)
14                    Out of Sight (1998)
```

```
15                     I Went Down (1997)
16            Opposite of Sex, The (1998)
17               Good Will Hunting (1997)
18    Fast, Cheap & Out of Control (1997)
19                L.A. Confidential (1997)
20                           Contact (1997)
21              Grosse Pointe Blank (1997)
22       Run Lola Run (Lola rennt) (1998)
23                          Dog Park (1998)
24                  Raising Arizona (1987)
25                     Total Recall (1990)
Name: Title, dtype: object
```

Comment - Above is the names of top 25 movies based on viewership rating.

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

[25]:
```
user_id_2696 = Master_Data[Master_Data["UserID"] == 2696][["Title", "Rating"]]
```

[26]:
```
user_id_2696.reset_index(drop = True, inplace = True)
user_id_2696.index += 1
print(user_id_2696)
```

```
                                          Title  Rating
1                              Client, The (1994)       3
2                                Lone Star (1996)       5
3                            Basic Instinct (1992)       4
4                 E.T. the Extra-Terrestrial (1982)       3
5                               Shining, The (1980)       4
6                          Back to the Future (1985)       2
7                                  Cop Land (1997)       3
8                           L.A. Confidential (1997)       4
9                                  Game, The (1997)       4
10           I Know What You Did Last Summer (1997)       2
11                    Devil's Advocate, The (1997)       4
12  Midnight in the Garden of Good and Evil (1997)       4
13                                 Palmetto (1998)       4
14                               Wild Things (1998)       4
15                         Perfect Murder, A (1998)       4
16    I Still Know What You Did Last Summer (1998)       2
17                                   Psycho (1998)       4
18                               Lake Placid (1999)       1
19                  Talented Mr. Ripley, The (1999)       4
20                                     JFK (1991)       1
```

Comment - Above are shown the names of the movie and their corresponding rating given by user id = 2696. Highest rating being of 5 and lowest of 1

0.12 Feature Engineering

0.12.1 Extracting unique genres

[27]:
```
# Extracting genres from the dataset
genres = []
for i in Master_Data["Genres"]:
    temp = i.split("|")
    genres.extend(temp)
```

[28]:
```
# Removing duplicate values
unique_genres = list(set(genres))
```

[29]:
```
# Printing the list of unique genres
print(unique_genres)
```

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

0.12.2 Create a separate column for each genre category with a one-hot encoding

[30]:
```
# Performing one-hot encoding
for i in unique_genres:
    Master_Data[i] = Master_Data["Genres"].str.contains(i) * 1
```

[31]:
```
# Exploring the data
Master_Data.head()
```

[31]:

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

```
4    1          10    48067  …        0          0        0           0

   Drama  Comedy  Romance  Documentary  Fantasy  Film-Noir
0      0       1        0            0        0          0
1      0       0        1            0        0          0
2      1       0        0            0        0          0
3      0       0        0            0        1          0
4      1       0        0            0        0          0

[5 rows x 28 columns]
```

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

[32]:
```
# Label encoding the gender for calculating correlation
Master_Data["Gender"] = Master_Data.Gender.str.replace("F","1")
Master_Data["Gender"] = Master_Data.Gender.str.replace("M","0")
Master_Data["Gender"] = Master_Data.Gender.astype(int)
```

[33]:
```
Master_Data.head()
```

[33]:
```
   MovieID                                     Title  \
0        1                         Toy Story (1995)
1       48                        Pocahontas (1995)
2      150                         Apollo 13 (1995)
3      260  Star Wars: Episode IV - A New Hope (1977)
4      527                   Schindler's List (1993)

                                Genres  UserID  Rating  Timestamp  Gender  \
0           Animation|Children's|Comedy       1       5  978824268       1
1  Animation|Children's|Musical|Romance       1       5  978824351       1
2                                 Drama       1       5  978301777       1
3       Action|Adventure|Fantasy|Sci-Fi       1       4  978300760       1
4                           Drama|War       1       5  978824195       1

   Age  Occupation Zip-code  …  Western  Adventure  Mystery  Children's  \
0    1          10    48067  …        0          0        0           1
1    1          10    48067  …        0          0        0           1
2    1          10    48067  …        0          0        0           0
3    1          10    48067  …        0          1        0           0
4    1          10    48067  …        0          0        0           0

   Drama  Comedy  Romance  Documentary  Fantasy  Film-Noir
0      0       1        0            0        0          0
1      0       0        1            0        0          0
2      1       0        0            0        0          0
3      0       0        0            0        1          0
4      1       0        0            0        0          0
```

```
[5 rows x 28 columns]
```

[34]:
```
# Dropping the genres from dataset as all categories are already included in dataset
Master_Data.drop(['Genres'],inplace=True,axis=1)
Master_Data.head()
```

[34]:

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

```
[5 rows x 27 columns]
```

[35]:
```
# Label encoding age as the prvious values were not consistent
le =  LabelEncoder()
Master_Data['Age'] = le.fit_transform(Master_Data['Age'])
Master_Data['Age'].unique()
```

[35]:
```
array([0, 5, 2, 3, 1, 4, 6], dtype=int64)
```

[36]:
```
# Label encoding MovieID as the prvious values were not consistent
Master_Data["MovieID"] = le.fit_transform(Master_Data['MovieID'])
```

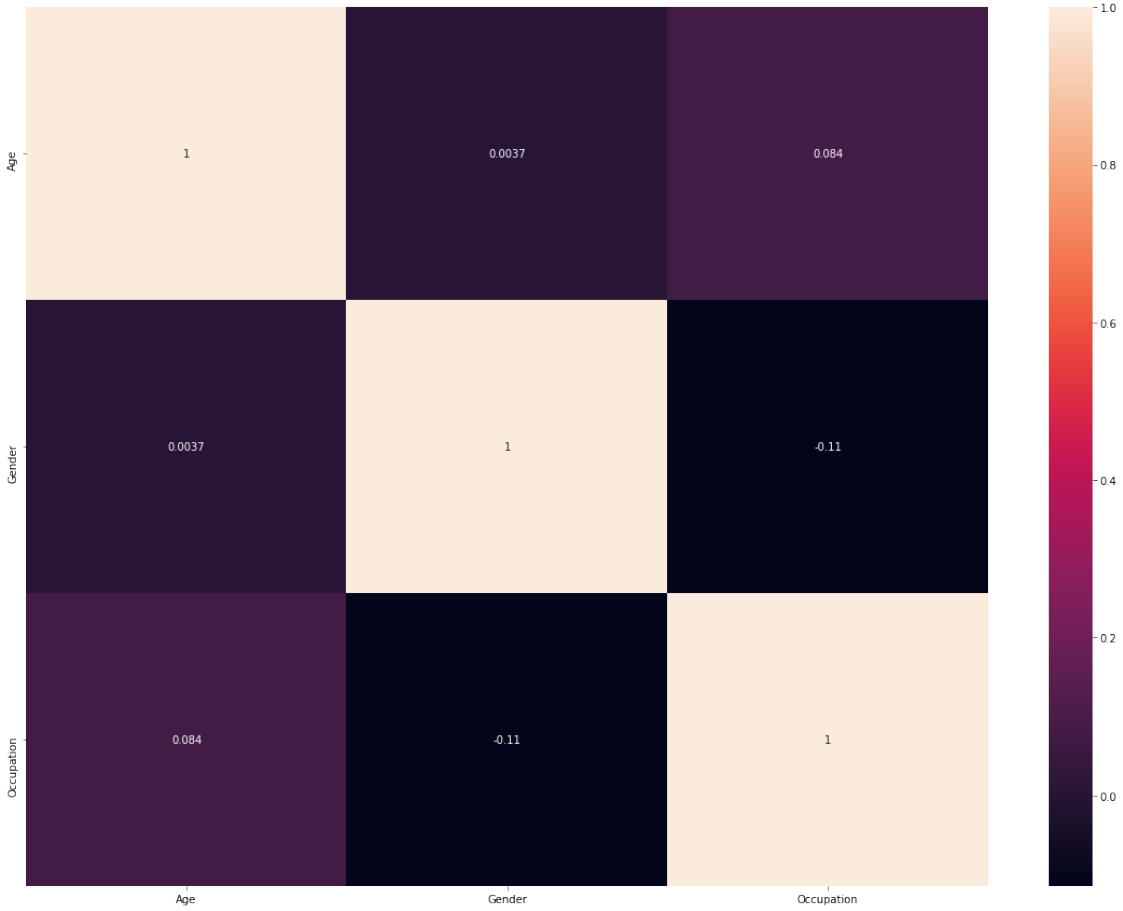
```
Master_Data['MovieID'].unique()
```

[36]:
```
array([   0,   47,  144, …, 1735, 3536, 1654], dtype=int64)
```

[37]:
```
corrMatrix = Master_Data[["Age","Gender", "Occupation"]].corr()
```

[38]:
```
plt.subplots(figsize=(20,15))
sns.heatmap(corrMatrix, annot=True)
```

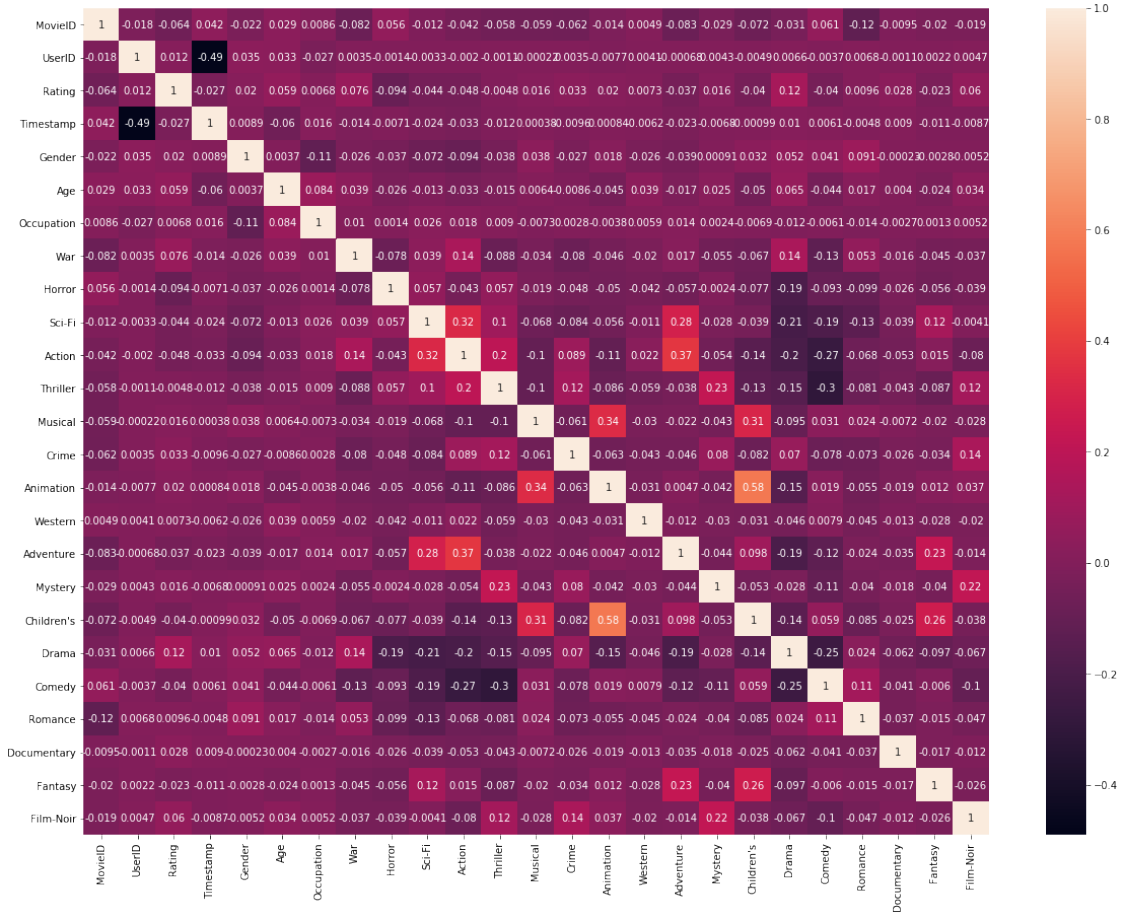
[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2599b36c888>
```



Above we see perfect correlation between diagonal elements because they are being matched with themselves. Here we see Age and Gender are positively correleated but the correlation is very weak. Same could be said for the correlation between Age and Occupation. There is a weak negative correlation between Occupation and gender

[39]:
```
corrMatrix_1 = Master_Data.corr()
plt.subplots(figsize=(20,15))
sns.heatmap(corrMatrix_1, annot=True)
```

[39]: <matplotlib.axes._subplots.AxesSubplot at 0x2599b36d888>



Above we see many correlations.

0.12.4 Develop an appropriate model to predict the movie ratings

[40]:
```
## Dropping columns which are not needed for model building
Master_Data.drop(['UserID','Zip-code','Timestamp','Title'],inplace=True,axis=1)
```

[41]:
```
# Exploring the data
Master_Data.head()
```

[41]:

	MovieID	Rating	Gender	Age	Occupation	War	Horror	Sci-Fi	Action	\
0	0	5	1	0	10	0	0	0	0	
1	47	5	1	0	10	0	0	0	0	
2	144	5	1	0	10	0	0	0	0	
3	253	4	1	0	10	0	0	1	1	
4	513	5	1	0	10	1	0	0	0	

```
   Thriller  …  Western  Adventure  Mystery  Children's  Drama  Comedy  \
0         0  …        0          0        0           1      0       1
1         0  …        0          0        0           1      0       0
2         0  …        0          0        0           0      1       0
3         0  …        0          1        0           0      0       0
4         0  …        0          0        0           0      1       0

   Romance  Documentary  Fantasy  Film-Noir
0        0            0        0          0
1        1            0        0          0
2        0            0        0          0
3        0            0        1          0
4        0            0        0          0

[5 rows x 23 columns]
```

[42]:
```
# Checking the columns of the dataset
Master_Data.columns
```

[42]:
```
Index(['MovieID', 'Rating', 'Gender', 'Age', 'Occupation', 'War', 'Horror',
       'Sci-Fi', 'Action', 'Thriller', 'Musical', 'Crime', 'Animation',
       'Western', 'Adventure', 'Mystery', 'Children's', 'Drama', 'Comedy',
       'Romance', 'Documentary', 'Fantasy', 'Film-Noir'],
      dtype='object')
```

[43]:
```
# Defining input and target variable for the model
x_input = Master_Data[['MovieID', 'Gender', 'Age', 'Occupation', 'Romance',
       'Musical', 'Action', 'Documentary', 'Adventure', 'Drama', 'Thriller',
       'Animation', "Children\'s", 'Horror', 'War', 'Fantasy', 'Mystery',
       'Sci-Fi', 'Crime', 'Film-Noir', 'Comedy', 'Western']]
y_target = Master_Data['Rating']
```

[44]:
```
x_input.head()
```

[44]:
```
   MovieID  Gender  Age  Occupation  Romance  Musical  Action  Documentary  \
0        0       1    0          10        0        0       0            0
1       47       1    0          10        1        1       0            0
2      144       1    0          10        0        0       0            0
3      253       1    0          10        0        0       1            0
4      513       1    0          10        0        0       0            0

   Adventure  Drama  …  Children's  Horror  War  Fantasy  Mystery  Sci-Fi  \
0          0      0  …           1       0    0        0        0       0
1          0      0  …           1       0    0        0        0       0
2          0      1  …           0       0    0        0        0       0
3          1      0  …           0       0    0        1        0       1
```

```
4          0      1  …           0       0    1        0        0       0

   Crime  Film-Noir  Comedy  Western
0      0          0       1        0
1      0          0       0        0
2      0          0       0        0
3      0          0       0        0
4      0          0       0        0

[5 rows x 22 columns]
```

[45]:
```
#Splitting of data into training and testing data
x_train, x_test, y_train, y_test = train_test_split(x_input, y_target,␣
 ↪test_size=0.25)
```

0.12.5 Logistic Regression model

[46]:
```
logReg = LogisticRegression()
logReg.fit(x_train, y_train)
y_pred_logreg = logReg.predict(x_test)
```

```
C:\Users\harma\anaconda3\lib\site-
packages\sklearn\linear_model\_logistic.py:940: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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

[48]:
```
accuracy_score(y_test, y_pred_logreg)
```

[48]:
```
0.34523481022023333
```

0.12.6 Decision Tree model

[49]:
```
decision_tree = DecisionTreeClassifier()
decision_tree.fit(x_train, y_train)
y_pred_decision_tree = decision_tree.predict(x_test)
```

[50]:
```
accuracy_score(y_test,y_pred_decision_tree)
```

[50]:
```
0.3402638640608191
```

0.12.7 Random Forest model

[56]:
```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(x_train, y_train)
y_pred_randforest = random_forest.predict(x_test)
```

[57]:
```
accuracy_score(y_test,y_pred_randforest)
```

[57]:
```
0.3526652349701863
```