Recommender Project

July 22, 2019

0.1 Executive summary

This project is about creating movie recommender system. Dataset used is 10 million MovieLens.

0.2 About the MovieLens dataset

This data set contains 10000054 ratings and 95580 tags applied to 10681 movies by 71567 users of the online movie recommender service MovieLens.

0.3 Ratings Data File Structure

All ratings are contained in the file ratings.dat. Each line of this file represents one rating of one movie by one user, and has the following format:

UserID::MovieID::Rating::Timestamp

The lines within this file are ordered first by UserID, then, within user, by MovieID.

Ratings are made on a 5-star scale, with half-star increments.

Timestamps represent seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

0.4 Movies Data File Structure

Movie information is contained in the file movies.dat. Each line of this file represents one movie, and has the following format:

MovieID::Title::Genres

MovieID is the real MovieLens id.

Movie titles, by policy, should be entered identically to those found in IMDB, including year of release. However, they are entered manually, so errors and inconsistencies may exist.

Genres are a pipe-separated list, and are selected from the following:

Action
Adventure
Animation
Children's
Comedy
Crime
Documentary
Drama
Fantasy
Film-Noir

Horror
Musical
Mystery
Romance
Sci-Fi
Thriller
War
Western

0.5 Methods/Analysis section

The data science process starts with business requirements that is to get to know the project purpose and what problems it is trying to solve. A dataset is chosen, it will go through the process of exploration, cleaning, feature engineering and feature selection to determine which independant variables are suitable. I will use several machine learning models to test and compare before deciding on the final model.

0.6 Import Libraries

In [132]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("white")
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.preprocessing import MinMaxScaler
from math import sqrt

import tensorflow.keras
from keras.models import Sequential
from keras.layers import Dense

from surprise import SVD
from surprise import Dataset
from surprise import Reader
from surprise import accuracy
from surprise.model_selection import cross_validate
from surprise.model_selection import train_test_split

import warnings
warnings.filterwarnings("ignore")
```

0.7 Explore Ratings.csv file

```
In [2]: ratedata = pd.read_csv('ratings.csv')

In [3]: ratedata.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000054 entries, 0 to 10000053
Data columns (total 4 columns):
UserID       int64
MovieID      int64
Rating       float64
Timestamp    int64
dtypes: float64(1), int64(3)
memory usage: 305.2 MB


In [4]: ratedata.head()

Out[4]:    UserID  MovieID  Rating   Timestamp
        0    7856      110     4.0   950462253
        1    7868      110     4.0   946858664
        2    7890      110     4.0   916652734
        3    7926      110     4.0  1217555133
        4    7936      110     4.0   946869728

In [5]: ratedata.tail()

Out[5]:           UserID  MovieID  Rating   Timestamp
        10000049   67571     3662     1.0   980710189
        10000050   67572      810     1.0  1047948824
        10000051   67572      899     1.0  1047949707
        10000052   67572     1722     1.0  1047948868
        10000053   67572     5255     1.0  1047948895

In [6]: ratedata.describe()

Out[6]:             UserID       MovieID        Rating     Timestamp
        count  1.000005e+07  1.000005e+07  1.000005e+07  1.000005e+07
        mean   3.586986e+04  4.120291e+03  3.512422e+00  1.032606e+09
        std    2.058534e+04  8.938402e+03  1.060418e+00  1.159640e+08
        min    1.000000e+00  1.000000e+00  5.000000e-01  7.896520e+08
        25%    1.812300e+04  6.480000e+02  3.000000e+00  9.467659e+08
        50%    3.574050e+04  1.834000e+03  4.000000e+00  1.035476e+09
        75%    5.360800e+04  3.624000e+03  4.000000e+00  1.126749e+09
        max    7.156700e+04  6.513300e+04  5.000000e+00  1.231132e+09

In [7]: ratedata['Rating'].mean()  #Mean ratings

Out[7]: 3.512421932921562
```

In [8]: ratedata['MovieID'].value_counts()

```
Out[8]: 296      34864
        356      34457
        593      33668
        480      32631
        318      31126
        110      29154
        457      28951
        589      28948
        260      28566
        150      27035
        592      26996
        1        26449
        780      26042
        590      25912
        527      25777
        380      25381
        1210     25098
        32       24397
        50       24037
        608      23794
        377      23748
        588      23531
        2571     23229
        1196     23091
        47       22521
        2858     22120
        1198     21803
        1270     21247
        648      21085
        344      21014
                 ...
        61862        1
        59680        1
        61913        1
        63806        1
        61948        1
        61970        1
        63688        1
        3583         1
        63662        1
        59625        1
        58520        1
        3561         1
        53833        1
        60494        1
        50477        1
```

```
62063        1
64652        1
45707        1
6189         1
55324        1
48374        1
58595        1
4820         1
5565         1
33140        1
64754        1
62237        1
7452         1
6085         1
27740        1
Name: MovieID, Length: 10677, dtype: int64
```

In [9]:
```
ratedata['MovieID'].nunique()
```

Out[9]:
```
10677
```

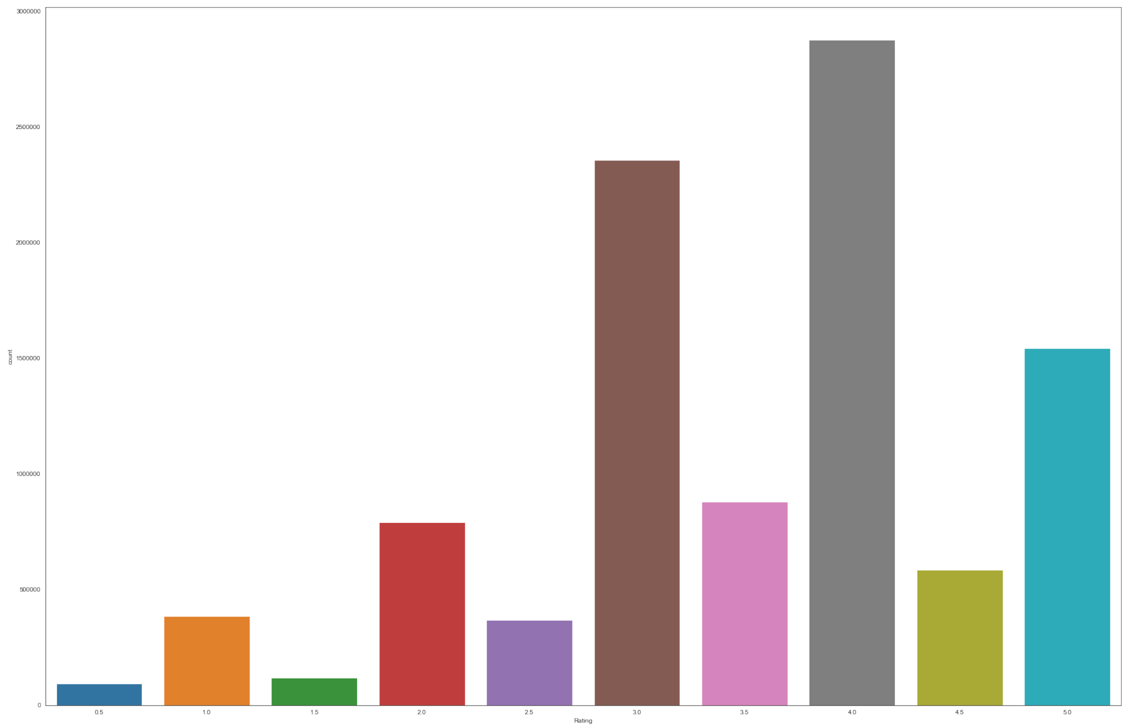
In [10]:
```
ratedata['UserID'].nunique()
```

Out[10]:
```
69878
```

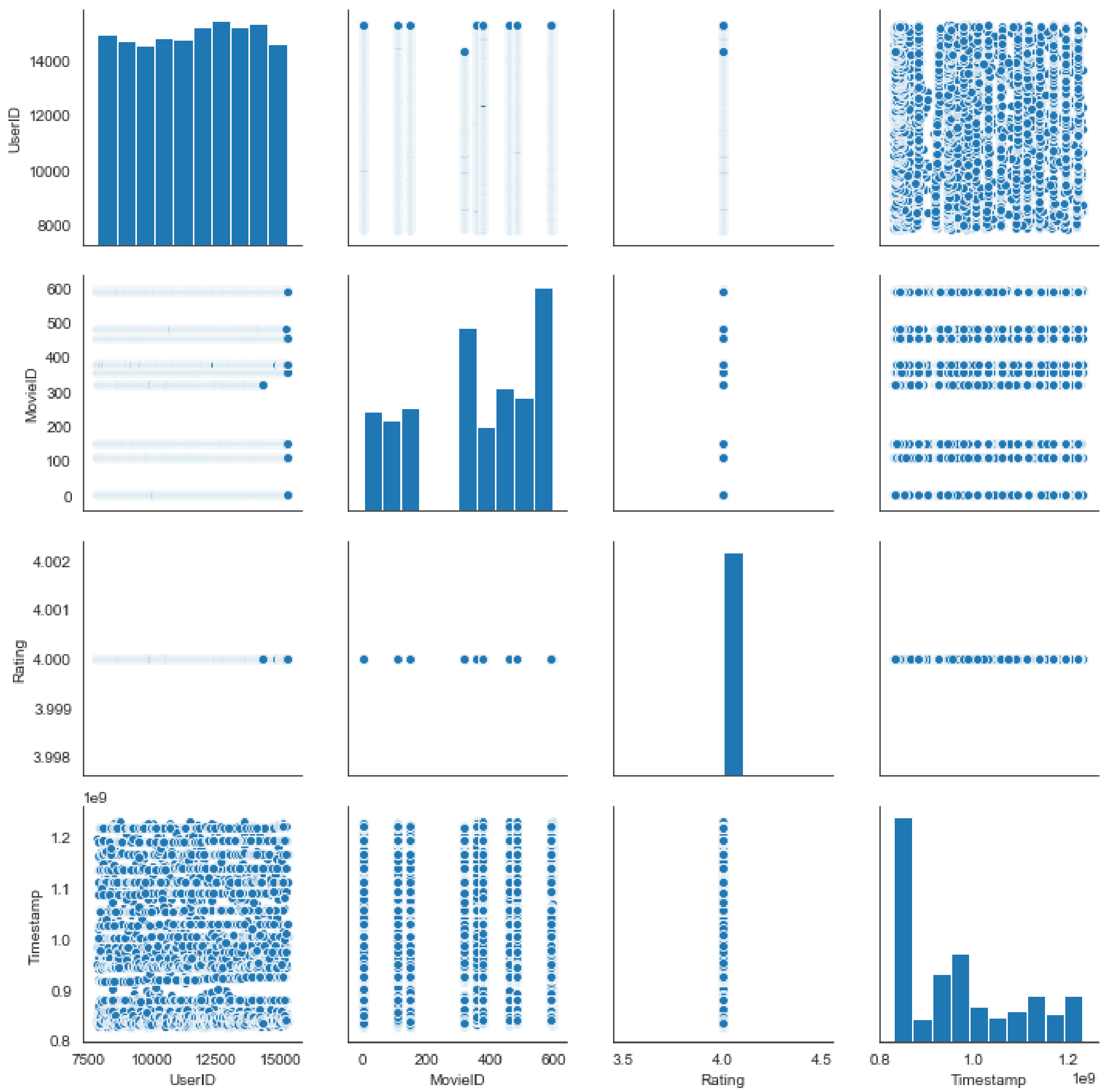
In [11]:
```
#plt.figure(figsize=(30, 20))
#ratedata.plot(x='MovieID',y='Rating',kind='hist') #Rating 4 is the highest countx='M
```

In [12]:
```
plt.figure(figsize=(30, 20))
sns.countplot(x=ratedata['Rating'])
#True or False: In general, half star ratings are less common than whole star ratings
```

Out[12]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x177765fdf98>
```




```
In [13]: #plt.figure(figsize=(30, 20))
         #sns.countplot(x=ratedata['UserID'])

In [14]: ratedata = ratedata[:10000]   #segment first 10k rows

In [15]: sns.pairplot(ratedata)

Out[15]: <seaborn.axisgrid.PairGrid at 0x17709bcf1d0>
```



0.8 Explore movies.csv file

```
In [16]: moviedata = pd.read_csv('movies.csv')
```

```
In [17]: moviedata.head()
```

```
Out[17]:    MovieID                               Title  Genre
         0       14                       Nixon (1995)  Drama
         1       26                     Othello (1995)  Drama
         2       27                Now and Then (1995)  Drama
         3       31            Dangerous Minds (1995)  Drama
         4       40  Cry, the Beloved Country (1995)  Drama
```

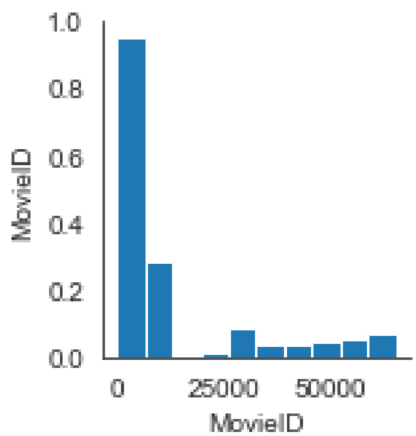
```
In [18]: moviedata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10681 entries, 0 to 10680
Data columns (total 3 columns):
MovieID    10681 non-null int64
Title      10681 non-null object
Genre      10681 non-null object
dtypes: int64(1), object(2)
memory usage: 250.4+ KB
```

In [19]:
```
#plt.figure(figsize=(30, 20))
#sns.countplot(x=moviedata['Genre'])
```

In [20]:
```
sns.pairplot(moviedata)
```

Out[20]: <seaborn.axisgrid.PairGrid at 0x1770a10c240>



0.9 Explore edx.csv file

In [22]:
```
df = pd.read_csv("edx.csv")
```

In [23]:
```
df = df[['userId','movieId','rating','timestamp','title','genres']]
```

In [24]:
```
df.head()
```

Out[24]:

	userId	movieId	rating	timestamp	title \
0	1	122	5.0	838985046	Boomerang (1992)
1	1	185	5.0	838983525	Net, The (1995)
2	1	292	5.0	838983421	Outbreak (1995)
3	1	316	5.0	838983392	Stargate (1994)
4	1	329	5.0	838983392	Star Trek: Generations (1994)

```
                          genres
0                 Comedy|Romance
1          Action|Crime|Thriller
2   Action|Drama|Sci-Fi|Thriller
3        Action|Adventure|Sci-Fi
4  Action|Adventure|Drama|Sci-Fi
```

In [25]: df.describe()

```
Out[25]:
             userId       movieId        rating     timestamp
count  9.000055e+06  9.000055e+06  9.000055e+06  9.000055e+06
mean   3.586982e+04  4.121702e+03  3.512465e+00  1.032616e+09
std    2.058525e+04  8.942108e+03  1.060331e+00  1.159668e+08
min    1.000000e+00  1.000000e+00  5.000000e-01  7.896520e+08
25%    1.812400e+04  6.480000e+02  3.000000e+00  9.467683e+08
50%    3.573800e+04  1.834000e+03  4.000000e+00  1.035494e+09
75%    5.360700e+04  3.626000e+03  4.000000e+00  1.126751e+09
max    7.156700e+04  6.513300e+04  5.000000e+00  1.231132e+09
```

In [26]: df.info() #How many rows and columns are there in the edx dataset?

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9000055 entries, 0 to 9000054
Data columns (total 6 columns):
userId       int64
movieId      int64
rating       float64
timestamp    int64
title        object
genres       object
dtypes: float64(1), int64(3), object(2)
memory usage: 412.0+ MB
```

In [27]: df.isnull().sum() #Any NULL values?

```
Out[27]: userId       0
         movieId      0
         rating       0
         timestamp    0
         title        0
         genres       0
         dtype: int64
```

In [28]: df.isna().sum() #Any NaN values?

```
Out[28]: userId       0
         movieId      0
         rating       0
```

```
timestamp    0
title        0
genres       0
dtype: int64
```

In [29]:
```
#Every genre is separated by a | so we simply have to call the split function on |
df['genres'] = df.genres.str.split('|')
```

In [30]:
```
df.head()
```

Out[30]:
```
   userId  movieId  rating  timestamp                          title  \
0       1      122     5.0  838985046               Boomerang (1992)
1       1      185     5.0  838983525                Net, The (1995)
2       1      292     5.0  838983421                Outbreak (1995)
3       1      316     5.0  838983392                Stargate (1994)
4       1      329     5.0  838983392  Star Trek: Generations (1994)

                                genres
0                    [Comedy, Romance]
1            [Action, Crime, Thriller]
2  [Action, Drama, Sci-Fi, Thriller]
3          [Action, Adventure, Sci-Fi]
4  [Action, Adventure, Drama, Sci-Fi]
```

In [31]:
```
#How many movie ratings are in each of the following genres in the edx dataset?
genredf = pd.DataFrame(df.genres.tolist(), columns=['genre1','genre2','genre3','genre
```

In [32]:
```
genredf.head()
```

Out[32]:
```
   genre1     genre2    genre3    genre4 genre5 genre6 genre7 genre8
0  Comedy    Romance      None      None   None   None   None   None
1  Action      Crime  Thriller      None   None   None   None   None
2  Action      Drama    Sci-Fi  Thriller   None   None   None   None
3  Action  Adventure    Sci-Fi      None   None   None   None   None
4  Action  Adventure     Drama    Sci-Fi   None   None   None   None
```

In [33]:
```
genredf.tail()
```

Out[33]:
```
              genre1    genre2   genre3 genre4 genre5 genre6 genre7 genre8
9000050     Children    Comedy     None   None   None   None   None   None
9000051  Documentary      None     None   None   None   None   None   None
9000052       Comedy   Musical  Western   None   None   None   None   None
9000053  Documentary      None     None   None   None   None   None   None
9000054        Drama  Thriller     None   None   None   None   None   None
```

In [34]:
```
genredf['genre1'].value_counts()
```

Out[34]:
```
Action                    2560545
Comedy                    2437260
```

```
Drama                   1741668
Adventure                753650
Crime                    529521
Horror                   233074
Animation                218123
Children                 181217
Thriller                  94718
Documentary               80966
Sci-Fi                    50254
Mystery                   30536
Fantasy                   26080
Musical                   16264
Film-Noir                 15811
Western                   15300
Romance                   12733
War                        2314
IMAX                         14
(no genres listed)            7
Name: genre1, dtype: int64
```

```
In [35]: genredf['genre2'].value_counts()
```

```
Out[35]: Drama          1614736
         Adventure      1155242
         Romance         791222
         Comedy          612298
         Crime           602588
         Thriller        439793
         Sci-Fi          363458
         Children        339272
         Horror          331407
         Mystery         252348
         Animation       216570
         Fantasy         171412
         War             146064
         Musical         124894
         Film-Noir        47280
         Western          37052
         Documentary      12043
         IMAX              1807
         Name: genre2, dtype: int64
```

```
In [36]: genredf['genre3'].value_counts()
```

```
Out[36]: Thriller       924972
         Sci-Fi         663697
         Romance        657358
         Fantasy        466980
         Drama          451995
```

```
Comedy         325239
War            237791
Children       208398
Mystery        205883
Crime          134792
Western         93272
Horror          85487
Musical         81495
Film-Noir       49814
Animation       32475
IMAX             2006
Documentary        57
Name: genre3, dtype: int64
```

In [37]:
```
genredf['genre4'].value_counts()
```

Out[37]:
```
Thriller     657340
Sci-Fi       207951
Fantasy      171520
Romance      161946
Comedy       157813
Musical      144526
War          113785
Drama         88295
Mystery       57636
Crime         49795
Western       37723
Horror        33736
Children       9107
Film-Noir      5636
IMAX           3738
Name: genre4, dtype: int64
```

In [38]:
```
genredf['genre5'].value_counts()
```

Out[38]:
```
Thriller    189898
Fantasy      76774
Musical      64550
Romance      61109
Sci-Fi       45338
Drama        13433
Crime        11019
Mystery      10599
War           9351
Comedy        8320
Horror        7525
Western        702
IMAX           550
Name: genre5, dtype: int64
```

```
In [39]: genredf['genre6'].value_counts()

Out[39]: Romance     27217
         Thriller    18922
         Fantasy     12871
         Sci-Fi      10229
         Western      5345
         War          1842
         Musical      1351
         Horror        256
         IMAX           66
         Name: genre6, dtype: int64

In [40]: genredf['genre7'].value_counts()

Out[40]: Mystery    11330
         Romance      515
         Sci-Fi       256
         Name: genre7, dtype: int64

In [41]: genredf['genre8'].value_counts()

Out[41]: Thriller    256
         Name: genre8, dtype: int64
```

Added each genre section to get total sum for each movie genre

```
In [42]: df['rating'].value_counts() #How many zeros were given as ratings in the edx dataset

Out[42]: 4.0    2588430
         3.0    2121240
         5.0    1390114
         3.5     791624
         2.0     711422
         4.5     526736
         1.0     345679
         2.5     333010
         1.5     106426
         0.5      85374
         Name: rating, dtype: int64

In [43]: df['movieId'].nunique()  #How many different movies are in the edx dataset?

Out[43]: 10677

In [44]: df['userId'].nunique() #How many different users are in the edx dataset?

Out[44]: 69878

In [45]: df['genres']
```

```
Out[45]: 0                                          [Comedy, Romance]
         1                                 [Action, Crime, Thriller]
         2                         [Action, Drama, Sci-Fi, Thriller]
         3                               [Action, Adventure, Sci-Fi]
         4                        [Action, Adventure, Drama, Sci-Fi]
         5                               [Children, Comedy, Fantasy]
         6                             [Comedy, Drama, Romance, War]
         7                             [Adventure, Children, Romance]
         8          [Adventure, Animation, Children, Drama, Musical]
         9                                          [Action, Comedy]
         10                              [Action, Romance, Thriller]
         11                        [Action, Comedy, Crime, Thriller]
         12                                    [Action, Comedy, War]
         13                                                 [Comedy]
         14                                 [Comedy, Drama, Romance]
         15        [Adventure, Animation, Children, Comedy, Musical]
         16                                         [Action, Sci-Fi]
         17           [Animation, Children, Drama, Fantasy, Musical]
         18                                    [Animation, Children]
         19                                     [Action, Drama, War]
         20                              [Action, Adventure, Sci-Fi]
         21                                       [Action, Thriller]
         22                                 [Comedy, Drama, Romance]
         23                              [Adventure, Drama, Western]
         24                   [Action, Adventure, Mystery, Thriller]
         25                                                 [Comedy]
         26                            [Action, Adventure, Thriller]
         27                   [Action, Adventure, Romance, Thriller]
         28                         [Action, Adventure, Sci-Fi, War]
         29                                [Action, Drama, Thriller]
                                         ...
         9000025                                    [Drama, Romance]
         9000026   [Adventure, Fantasy, Film-Noir, Sci-Fi, Thriller]
         9000027                           [Action, Crime, Thriller]
         9000028                           [Action, Crime, Thriller]
         9000029                   [Crime, Drama, Mystery, Thriller]
         9000030                           [Action, Drama, Thriller]
         9000031                           [Drama, Sci-Fi, Thriller]
         9000032          [Action, Crime, Mystery, Sci-Fi, Thriller]
         9000033                 [Action, Romance, Sci-Fi, Thriller]
         9000034                 [Animation, Children, Fantasy, War]
         9000035                                            [Horror]
         9000036                                            [Horror]
         9000037                                            [Horror]
         9000038                                            [Horror]
         9000039                                            [Horror]
         9000040                           [Comedy, Sci-Fi, Western]
         9000041                                [Action, Drama, War]
```

```
9000042                                    [Horror, Thriller]
9000043                   [Action, Crime, Mystery, Thriller]
9000044    [Adventure, Animation, Children, Comedy, Fantasy]
9000045                          [Horror, Mystery, Thriller]
9000046                                   [Children, Comedy]
9000047                                              [Drama]
9000048                           [Action, Horror, Thriller]
9000049                                              [Drama]
9000050                                   [Children, Comedy]
9000051                                        [Documentary]
9000052                           [Comedy, Musical, Western]
9000053                                        [Documentary]
9000054                                    [Drama, Thriller]
Name: genres, Length: 9000055, dtype: object
```

In [46]:
```
#df.apply(pd.value_counts)
```

In [47]:
```
df['genres'].value_counts() #How many movie ratings are in each of the following genr
```

Out[47]:
```
[Drama]                                          733296
[Comedy]                                         700889
[Comedy, Romance]                                365468
[Comedy, Drama]                                  323637
[Comedy, Drama, Romance]                         261425
[Drama, Romance]                                 259355
[Action, Adventure, Sci-Fi]                      219938
[Action, Adventure, Thriller]                    149091
[Drama, Thriller]                                145373
[Crime, Drama]                                   137387
[Drama, War]                                     111029
[Crime, Drama, Thriller]                         106101
[Action, Adventure, Sci-Fi, Thriller]            105144
[Action, Crime, Thriller]                        102259
[Action, Drama, War]                              99183
[Action, Thriller]                                96535
[Action, Sci-Fi, Thriller]                        95280
[Thriller]                                        94662
[Horror, Thriller]                                75000
[Comedy, Crime]                                   73286
[Action, Adventure, Fantasy]                      71176
[Documentary]                                     70041
[Horror]                                          68738
[Action, Adventure]                               68688
[Action, Crime, Drama, Thriller]                  65183
[Children, Comedy]                                63483
[Drama, Mystery, Thriller]                        61069
[Comedy, Crime, Drama]                            59071
[Action, Comedy]                                  51289
```

```
[Adventure, Drama]                                        51227
                                                          ...
[Animation, IMAX, Sci-Fi]                                     7
[Action, Romance, Western]                                    7
[Adventure, Comedy, Drama, Fantasy, Mystery, Sci-Fi]          7
[(no genres listed)]                                          7
[Fantasy, Horror, Sci-Fi]                                     6
[Comedy, Fantasy, Mystery, Sci-Fi]                            6
[Action, Adventure, Fantasy, Horror, Romance]                 6
[Adventure, Comedy, Fantasy, Romance]                         6
[Adventure, Comedy, Horror, Romance]                          6
[Action, Adventure, Romance, War]                             6
[Crime, Drama, Film-Noir, Romance]                            5
[Adventure, Horror, Romance, Sci-Fi]                          5
[Fantasy, Mystery, Western]                                   5
[Comedy, Drama, Horror, Sci-Fi]                               5
[Horror, Romance, Thriller]                                   4
[Animation, Documentary, War]                                 4
[Drama, Musical, Thriller]                                    4
[Action, Drama, Horror, Sci-Fi]                               4
[Crime, Documentary]                                          4
[Adventure, Animation, Musical, Sci-Fi]                       4
[Action, Adventure, Animation, Comedy, Sci-Fi]                3
[Horror, War, Western]                                        3
[Fantasy, Mystery, Sci-Fi, War]                               2
[Documentary, Romance]                                        2
[Drama, Horror, Mystery, Sci-Fi, Thriller]                    2
[Action, Animation, Comedy, Horror]                           2
[Crime, Drama, Horror, Sci-Fi]                                2
[Adventure, Fantasy, Film-Noir, Mystery, Sci-Fi]              2
[Action, War, Western]                                        2
[Adventure, Mystery]                                          2
Name: genres, Length: 797, dtype: int64
```

```
In [48]: df['title'].value_counts() #Which movie has the greatest number of ratings?
```

```
Out[48]: Pulp Fiction (1994)                                                       3136
Forrest Gump (1994)                                                       3107
Silence of the Lambs, The (1991)                                          3038
Jurassic Park (1993)                                                      2936
Shawshank Redemption, The (1994)                                          2801
Braveheart (1995)                                                         2621
Fugitive, The (1993)                                                      2599
Terminator 2: Judgment Day (1991)                                         2598
Star Wars: Episode IV - A New Hope (a.k.a. Star Wars) (1977)              2567
Apollo 13 (1995)                                                          2428
Batman (1989)                                                             2427
Toy Story (1995)                                                          2379
```

```
Independence Day (a.k.a. ID4) (1996)                                               2344
Dances with Wolves (1990)                                                          2336
Schindler's List (1993)                                                            2319
True Lies (1994)                                                                   2282
Star Wars: Episode VI - Return of the Jedi (1983)                                  2258
12 Monkeys (Twelve Monkeys) (1995)                                                 2189
Usual Suspects, The (1995)                                                         2164
Fargo (1996)                                                                       2139
Speed (1994)                                                                       2136
Aladdin (1992)                                                                     2117
Matrix, The (1999)                                                                 2090
Star Wars: Episode V - The Empire Strikes Back (1980)                              2072
Seven (a.k.a. Se7en) (1995)                                                        2031
American Beauty (1999)                                                             1995
Raiders of the Lost Ark (Indiana Jones and the Raiders of the Lost Ark) (1981)     1967
Back to the Future (1985)                                                          1903
Mission: Impossible (1996)                                                         1899
Ace Ventura: Pet Detective (1994)                                                  1895
                                                                                   ...

Dog Day (Canicule) (1984)
1, 2, 3, Sun (Un, deuz, trois, soleil) (1993)
Fists in the Pocket (I Pugni in tasca) (1965)
Dischord (2001)
Rockin' in the Rockies (1945)
Sun Shines Bright, The (1953)
Love (2005)
Stone Angel, The (2007)
Small Cuts (Petites coupures) (2003)
When Time Ran Out... (a.k.a. The Day the World Ended) (1980)
Young Unknowns, The (2000)
Bellissima (1951)
Once in the Life (2000)
Flu Bird Horror (2008)
Accused (Anklaget) (2005)
Fallout (1998)
Neil Young: Human Highway (1982)
Zona Zamfirova (2002)
Dog Run (1996)
Flandres (2006)
David Holzman's Diary (1967)
Symbiopsychotaxiplasm: Take One (1968)
Confessions of a Superhero (2007)
Splinter (2008)
Vinci (2004)
Where A Good Man Goes (Joi gin a long) (1999)
Stacy's Knights (1982)
Battle of Russia, The (Why We Fight, 5) (1943)
Hundred and One Nights, A (Cent et une nuits de Simon Cinéma, Les) (1995)
```

```
Cruel Story of Youth (Seishun zankoku monogatari) (1960)
Name: title, Length: 10676, dtype: int64
```

```
In [49]: df['rating'].value_counts() #What are the five most given ratings in order from most
```

```
Out[49]: 4.0    2588430
         3.0    2121240
         5.0    1390114
         3.5     791624
         2.0     711422
         4.5     526736
         1.0     345679
         2.5     333010
         1.5     106426
         0.5      85374
         Name: rating, dtype: int64
```

```
In [50]: #df.to_csv('new.csv',index=False)  #Save updated and cleaned csv
```

0.10 Import cleaned dataset for visualization

```
In [2]: df1 = pd.read_csv('new.csv')
```

```
In [3]: df1.head()
```

```
Out[3]:    userId  movieId  rating  timestamp                          title  \
        0       1      122     5.0  838985046               Boomerang (1992)
        1       1      185     5.0  838983525                Net, The (1995)
        2       1      292     5.0  838983421                Outbreak (1995)
        3       1      316     5.0  838983392                Stargate (1994)
        4       1      329     5.0  838983392  Star Trek: Generations (1994)

                                  genres
        0                 Comedy|Romance
        1          Action|Crime|Thriller
        2   Action|Drama|Sci-Fi|Thriller
        3        Action|Adventure|Sci-Fi
        4  Action|Adventure|Drama|Sci-Fi
```

```
In [4]: df1.tail()
```

```
Out[4]:          userId  movieId  rating   timestamp                          title  \
        9000050   32620    33140     3.5  1173562747           Down and Derby (2005)
        9000051   40976    61913     3.0  1227767528             Africa addio (1966)
        9000052   59269    63141     2.0  1226443318  Rockin' in the Rockies (1945)
        9000053   60713     4820     2.0  1119156754    Won't Anybody Listen? (2000)
        9000054   64621    39429     2.5  1201248182                  Confess (2005)

                                  genres
```

```
9000050         Children|Comedy
9000051             Documentary
9000052   Comedy|Musical|Western
9000053             Documentary
9000054          Drama|Thriller
```

In [5]:
```
df1 = df1[:500000] #Due to laptop hardware limitation, segment only first 500000 rows
```

In [6]:
```
df1.head()
```

Out[6]:
```
   userId  movieId  rating  timestamp                          title  \
0       1      122     5.0  838985046               Boomerang (1992)
1       1      185     5.0  838983525                Net, The (1995)
2       1      292     5.0  838983421                Outbreak (1995)
3       1      316     5.0  838983392                Stargate (1994)
4       1      329     5.0  838983392  Star Trek: Generations (1994)

                         genres
0                Comedy|Romance
1         Action|Crime|Thriller
2  Action|Drama|Sci-Fi|Thriller
3       Action|Adventure|Sci-Fi
4 Action|Adventure|Drama|Sci-Fi
```

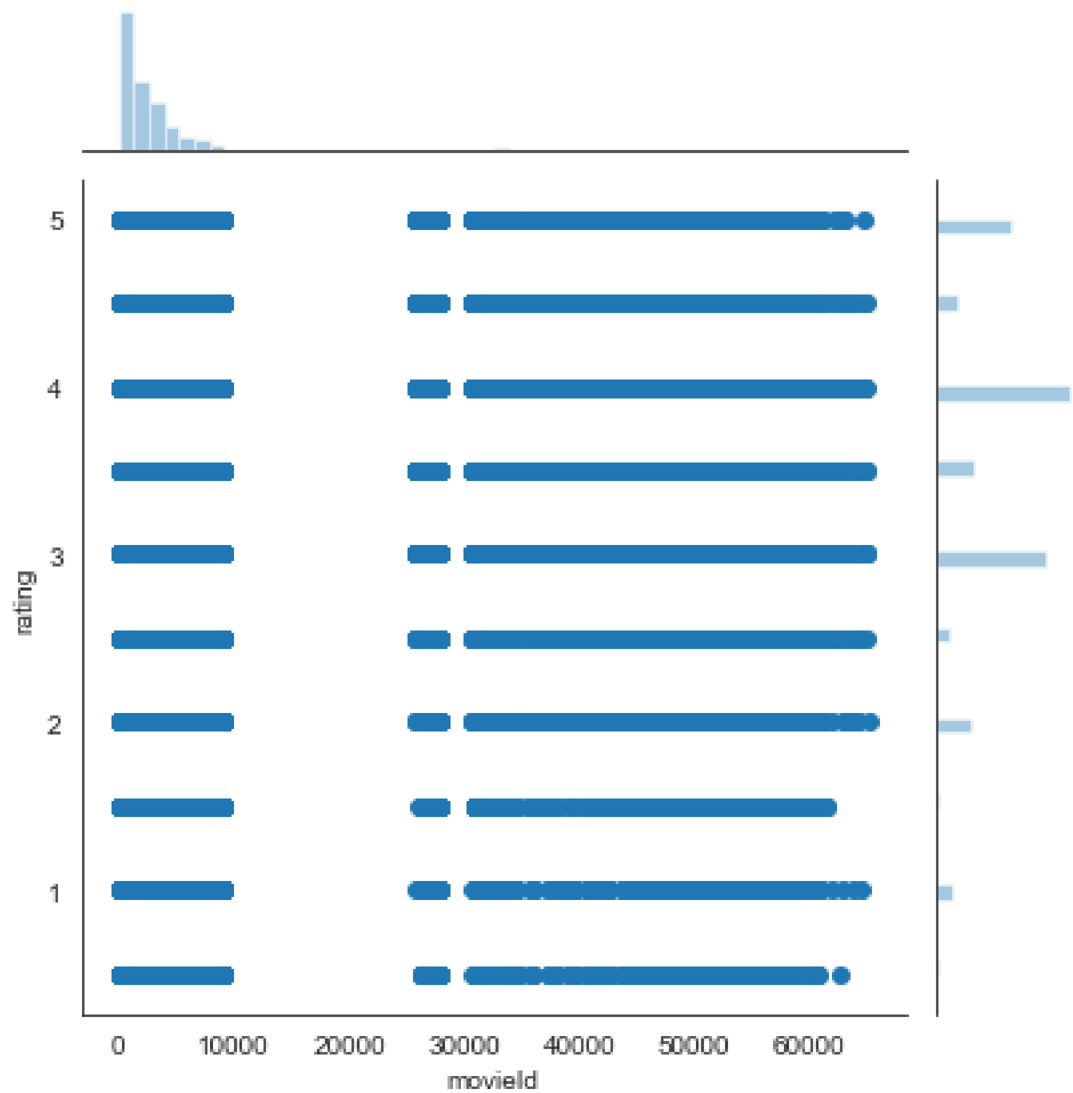
In [7]:
```
df1.tail()
```

Out[7]:
```
        userId  movieId  rating   timestamp  \
499995    4237      999     4.0  1051824541
499996    4237     1027     3.0  1051722378
499997    4237     1037     3.0  1051722360
499998    4237     1136     4.0  1051726606
499999    4237     1196     4.0  1051726645

                                                    title  \
499995                           2 Days in the Valley (1996)
499996                  Robin Hood: Prince of Thieves (1991)
499997                              Lawnmower Man, The (1992)
499998                Monty Python and the Holy Grail (1975)
499999  Star Wars: Episode V - The Empire Strikes Back...

                              genres
499995               Crime|Film-Noir
499996               Adventure|Drama
499997  Action|Horror|Sci-Fi|Thriller
499998                        Comedy
499999       Action|Adventure|Sci-Fi
```

In [8]:
```
plt.figure(figsize=(30, 20))
sns.jointplot(x='movieId',y='rating',data=df1)
```

Out[8]: <seaborn.axisgrid.JointGrid at 0x2ac90424ac8>

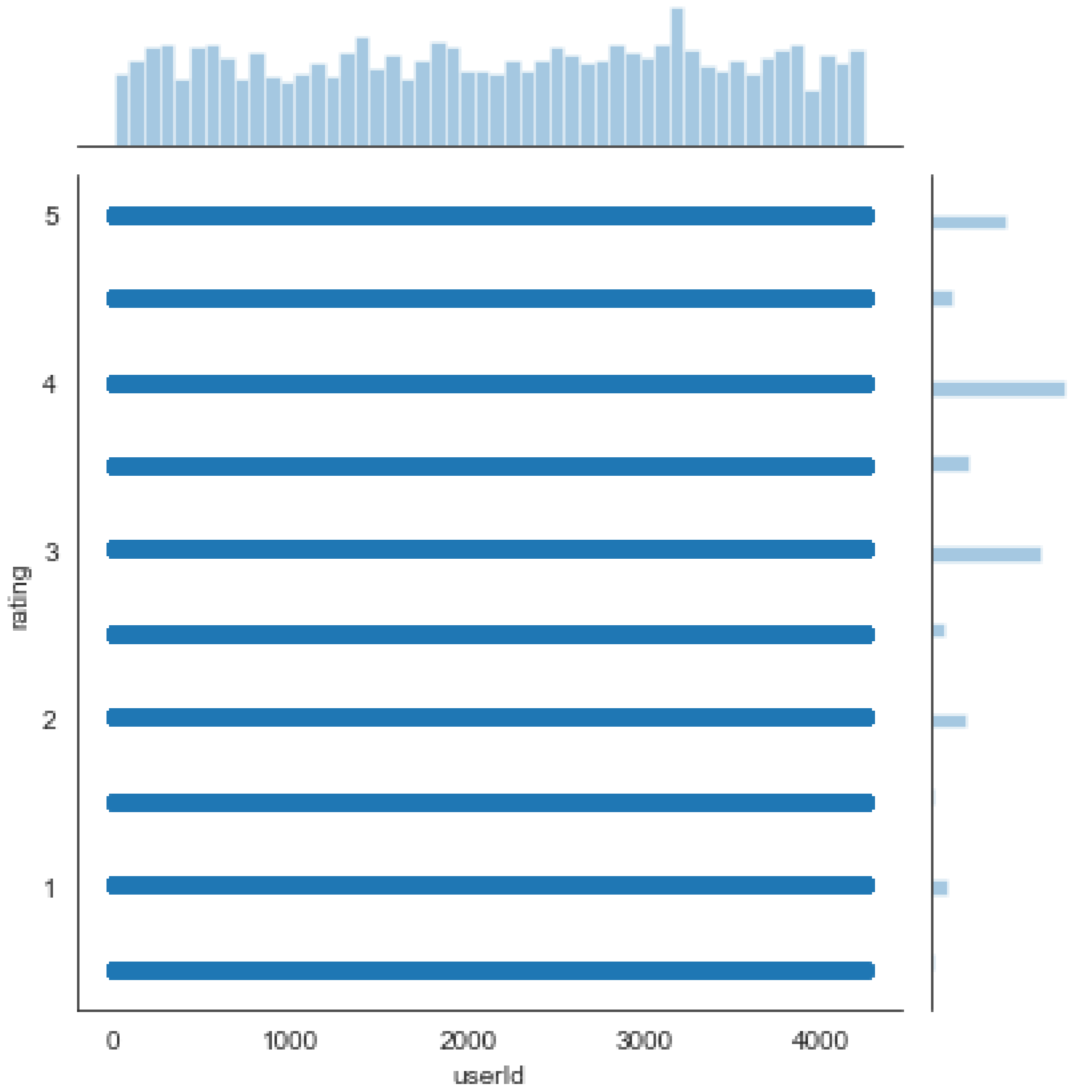
<Figure size 2160x1440 with 0 Axes>




```
In [9]: plt.figure(figsize=(30, 20))
        sns.jointplot(x='userId',y='rating',data=df1)
```

Out[9]: <seaborn.axisgrid.JointGrid at 0x2ac80465cf8>

<Figure size 2160x1440 with 0 Axes>




```
In [10]: df1.drop('timestamp', axis=1, inplace=True)

In [11]: df1.drop('title', axis=1, inplace=True)

In [12]: df1.drop('genres', axis=1, inplace=True)

In [13]: df1.drop('movieId', axis=1, inplace=True)

In [14]: df1.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500000 entries, 0 to 499999
Data columns (total 2 columns):
userId    500000 non-null int64
```

```
rating    500000 non-null float64
dtypes: float64(1), int64(1)
memory usage: 7.6 MB
```

```
In [15]: df1.head()
```

```
Out[15]:    userId  rating
         0       1     5.0
         1       1     5.0
         2       1     5.0
         3       1     5.0
         4       1     5.0
```

```
In [16]: #sns.lmplot(x='userId',y='rating',data=df1)
```

0.11 Simple Linear Regression

```
In [35]: y = df1[['rating']]  #Target variable
```

```
In [36]: y.head()
```

```
Out[36]:    rating
         0     5.0
         1     5.0
         2     5.0
         3     5.0
         4     5.0
```

```
In [37]: X = df1[['userId']]
```

```
In [39]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=
```

```
In [40]: X_train
```

```
Out[40]:        userId
         226114    1947
         435187    3691
         294452    2566
         427864    3635
         188822    1645
         176419    1537
         225346    1938
         105703     902
         205951    1805
         213194    1860
         233523    2023
         310101    2697
         445876    3793
```

494289	4198
189569	1654
123634	1090
18090	171
215206	1870
205519	1805
436150	3699
416632	3519
273200	2398
10055	103
113432	984
459232	3864
477655	4056
184627	1605
230346	1988
404848	3418
232014	2006
...	...
235796	2045
103355	885
267455	2339
199041	1751
252709	2204
327069	2834
194027	1709
321879	2798
262913	2303
64820	545
329365	2852
41090	340
278167	2434
191335	1677
175203	1532
388468	3281
374871	3181
87498	744
430410	3646
475602	4038
137337	1224
54886	469
207892	1825
110268	950
119879	1057
259178	2264
365838	3133
131932	1174
146867	1304
121958	1075

```
[350000 rows x 1 columns]
```

In [41]:
```
X_test
```

Out[41]:

	userId
104241	886
199676	1755
140199	1256
132814	1177
408697	3448
163280	1427
215758	1874
442316	3762
6940	70
382310	3222
472236	4014
309086	2690
230672	1988
209236	1842
102953	878
419699	3545
81780	678
274641	2408
133794	1186
230532	1988
305856	2659
194411	1711
173647	1516
76146	634
452804	3817
119495	1050
3749	37
158067	1398
423413	3592
255715	2233
...	...
215680	1874
25789	215
447644	3795
150974	1336
314216	2729
185469	1617
29367	254
338448	2920
167032	1459
65215	547
96498	820

```
458099    3853
76268      634
78956      654
52542      450
481308    4087
168084    1468
448719    3806
405381    3423
471414    4007
182870    1586
266604    2330
10882      112
174077    1520
136868    1224
424065    3595
149852    1331
491538    4177
37263      303
84268      708

[150000 rows x 1 columns]
```

In [42]:
```
X_train.shape
```

Out[42]:
```
(350000, 1)
```

In [43]:
```
X_test.shape
```

Out[43]:
```
(150000, 1)
```

In [44]:
```
regressor = LinearRegression(fit_intercept=True)
```

In [45]:
```
regressor.fit(X_train,y_train)
```

Out[45]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [46]:
```
print('Linear Model Coefficient (m): ', regressor.coef_)
print('Linear Model Coefficient (b): ', regressor.intercept_)
```

```
Linear Model Coefficient (m):  [[-2.83553837e-05]]
Linear Model Coefficient (b):  [3.59152806]
```

In [47]:
```
y_predict = regressor.predict(X_test)
```

In [48]:
```
mean_squared_error(y_test, y_predict)
```

Out[48]:
```
1.1212803971204748
```

```
In [49]: rms = sqrt(mean_squared_error(y_test, y_predict))
         print("Root Mean Square value is:b ", rms)
```

```
Root Mean Square value is:b  1.0589052824122065
```

```
In [50]: print(y_predict) #Predicted results
```

```
[[3.56640519]
 [3.54176436]
 [3.5559137 ]
 ...
 [3.47308762]
 [3.58293638]
 [3.57145245]]
```

0.12 Multiple Linear Regression

```
In [51]: df2 = pd.read_csv('new.csv')

In [52]: df2 = df2[:500000] #Due to laptop hardware limitation, segment only first 500000 rows

In [53]: df2.tail()
```

```
Out[53]:         userId  movieId  rating   timestamp  \
         499995    4237      999     4.0  1051824541
         499996    4237     1027     3.0  1051722378
         499997    4237     1037     3.0  1051722360
         499998    4237     1136     4.0  1051726606
         499999    4237     1196     4.0  1051726645

                                                    title  \
         499995                        2 Days in the Valley (1996)
         499996                 Robin Hood: Prince of Thieves (1991)
         499997                             Lawnmower Man, The (1992)
         499998               Monty Python and the Holy Grail (1975)
         499999  Star Wars: Episode V - The Empire Strikes Back...

                                       genres
         499995                  Crime|Film-Noir
         499996                  Adventure|Drama
         499997  Action|Horror|Sci-Fi|Thriller
         499998                           Comedy
         499999        Action|Adventure|Sci-Fi
```

```
In [54]: df2.drop('timestamp', axis=1, inplace=True)
         df2.drop('title', axis=1, inplace=True)
         df2.drop('genres', axis=1, inplace=True)
```

```
In [55]: df2.head()
```

```
Out[55]:    userId  movieId  rating
         0       1      122     5.0
         1       1      185     5.0
         2       1      292     5.0
         3       1      316     5.0
         4       1      329     5.0
```

```
In [56]: y = df2['rating']

In [57]: X = df2[['userId', 'movieId']]

In [58]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state

In [59]: X_train.shape

Out[59]: (400000, 2)

In [60]: X_test.shape

Out[60]: (100000, 2)

In [61]: regressor2 = LinearRegression(fit_intercept=True)

In [62]: regressor2.fit(X_train, y_train)

Out[62]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)

In [63]: print('Linear Model Coefficients (m)', regressor2.coef_)
         print('Linear Model Coefficients (b)', regressor2.intercept_)

Linear Model Coefficients (m) [-2.85413157e-05 -7.57854535e-07]
Linear Model Coefficients (b) 3.594964440683402


In [64]: y_predict = regressor2.predict(X_test)

In [65]: y_predict

Out[65]: array([3.56750103, 3.54341708, 3.55728027, ..., 3.55252973, 3.57742356,
                3.53431723])

In [66]: plt.figure(figsize=(30,20))
         plt.scatter(y_test, y_predict, color = 'r')
         plt.title('Multiple Linear Regression Predictions')

Out[66]: Text(0.5, 1.0, 'Multiple Linear Regression Predictions')
```

In [67]:
```
rms = sqrt(mean_squared_error(y_test, y_predict))
print("Root Mean Square value is:b ", rms)
```

```
Root Mean Square value is:b  1.0602279810330444
```

In [68]:
```
r2 = r2_score(y_test, y_predict)
print("R2 score is: ", r2)
```

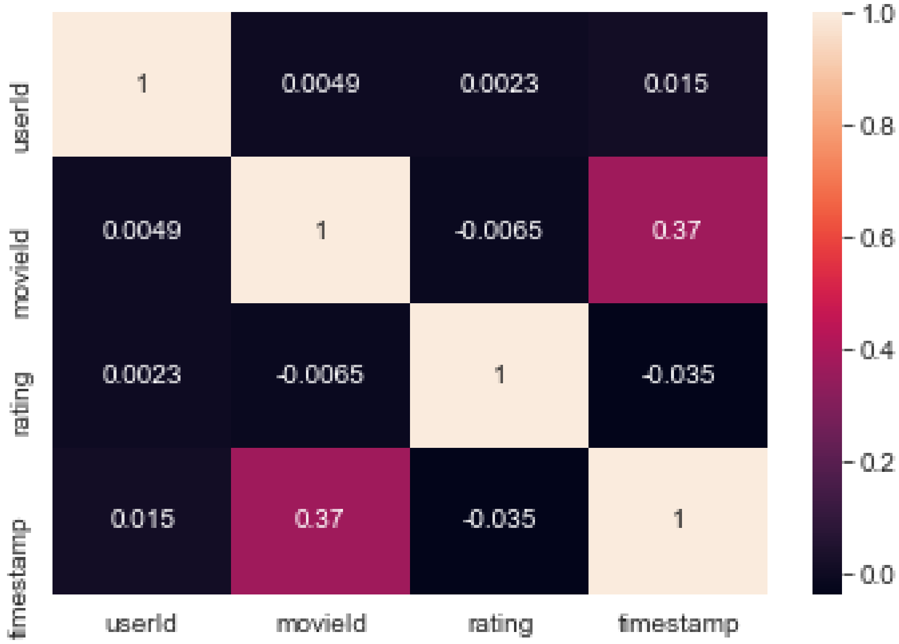
```
R2 score is:  0.0010416484456293729
```

0.13 Artificial Neural Network

In [69]:
```
df3 = pd.read_csv('new.csv')
```

In [70]:
```
sns.heatmap(df3.corr(),annot=True)
```

Out[70]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2ac8279e4e0>
```




```
In [71]: df3 = df3[:500000] #Due to laptop hardware limitation, segment only first 500000 rows

In [72]: df3.head()

Out[72]:    userId  movieId  rating  timestamp                            title  \
         0       1      122     5.0  838985046                Boomerang (1992)
         1       1      185     5.0  838983525                 Net, The (1995)
         2       1      292     5.0  838983421                 Outbreak (1995)
         3       1      316     5.0  838983392                 Stargate (1994)
         4       1      329     5.0  838983392  Star Trek: Generations (1994)

                                  genres
         0                Comedy|Romance
         1         Action|Crime|Thriller
         2   Action|Drama|Sci-Fi|Thriller
         3       Action|Adventure|Sci-Fi
         4  Action|Adventure|Drama|Sci-Fi

In [73]: df3.drop('timestamp', axis=1, inplace=True)
         df3.drop('title', axis=1, inplace=True)
         df3.drop('genres', axis=1, inplace=True)

In [74]: X = df3[['userId','movieId']]

In [75]: y = df3[['rating']]

In [76]: X.shape
```

Out[76]: (500000, 2)

In [77]: y.shape

Out[77]: (500000, 1)

In [78]:
```
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
```

In [79]: X_scaled.shape

Out[79]: (500000, 2)

In [80]:
```
y = y.values.reshape(-1,1)
```

In [81]:
```
y_scaled = scaler.fit_transform(y)
```

In [82]: y_scaled

Out[82]:
```
array([[1.        ],
       [1.        ],
       [1.        ],
       ...,
       [0.55555556],
       [0.77777778],
       [0.77777778]])
```

In [83]: y_scaled.shape

Out[83]: (500000, 1)

In [84]:
```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_scaled, test_size = 0
```

In [85]: X_train.shape

Out[85]: (400000, 2)

In [86]: X_test.shape

Out[86]: (100000, 2)

In [88]:
```
model = Sequential()
model.add(Dense(50, input_dim = 2, activation='relu'))
model.add(Dense(50, activation='relu'))
model.add(Dense(1, activation = 'linear'))
```

In [89]:
```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 50)                150
_________________________________________________________________
dense_5 (Dense)              (None, 50)                2550
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 51
=================================================================
Total params: 2,751
Trainable params: 2,751
Non-trainable params: 0
_________________________________________________________________
```

```
In [91]: model.compile(optimizer='Adam', loss='mean_squared_error')
```

```
In [92]: epochs_hist = model.fit(X_train, y_train, epochs = 50, batch_size = 50, validation_spl
```

```
W0722 09:47:54.198905  7084 deprecation_wrapper.py:119] From C:\ProgramData\Anaconda3\lib\site

W0722 09:47:54.277045  7084 deprecation_wrapper.py:119] From C:\ProgramData\Anaconda3\lib\site



Train on 320000 samples, validate on 80000 samples
Epoch 1/50
320000/320000 [==============================] - 6s 20us/step - loss: 0.0568 - val_loss: 0.054
Epoch 2/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0555 - val_loss: 0.054
Epoch 3/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0554 - val_loss: 0.055
Epoch 4/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0554 - val_loss: 0.054
Epoch 5/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0554 - val_loss: 0.054
Epoch 6/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0554 - val_loss: 0.055
Epoch 7/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0553 - val_loss: 0.054
Epoch 8/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0553 - val_loss: 0.054
Epoch 9/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0553 - val_loss: 0.054
Epoch 10/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0552 - val_loss: 0.054
Epoch 11/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0550 - val_loss: 0.054
Epoch 12/50
```

```
320000/320000 [==============================] - 6s 19us/step - loss: 0.0549 - val_loss: 0.0544
Epoch 13/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0548 - val_loss: 0.0542
Epoch 14/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0548 - val_loss: 0.0542
Epoch 15/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0547 - val_loss: 0.0540
Epoch 16/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0547 - val_loss: 0.0540
Epoch 17/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0547 - val_loss: 0.0540
Epoch 18/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0547 - val_loss: 0.0541
Epoch 19/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0547 - val_loss: 0.0540
Epoch 20/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0539
Epoch 21/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0540
Epoch 22/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0539
Epoch 23/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0544
Epoch 24/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0539
Epoch 25/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0539
Epoch 26/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0540
Epoch 27/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0543
Epoch 28/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0539
Epoch 29/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0546 - val_loss: 0.0539
Epoch 30/50
320000/320000 [==============================] - 6s 17us/step - loss: 0.0545 - val_loss: 0.0541
Epoch 31/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0545 - val_loss: 0.0539
Epoch 32/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0545 - val_loss: 0.0538
Epoch 33/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0544 - val_loss: 0.0537
Epoch 34/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0537
Epoch 35/50
320000/320000 [==============================] - 6s 18us/step - loss: 0.0544 - val_loss: 0.0539
Epoch 36/50
```

```
320000/320000 [==============================] - 6s 17us/step - loss: 0.0544 - val_loss: 0.0539
Epoch 37/50
320000/320000 [==============================] - 6s 20us/step - loss: 0.0544 - val_loss: 0.0538
Epoch 38/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0538
Epoch 39/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0538
Epoch 40/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0537
Epoch 41/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0537
Epoch 42/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0538
Epoch 43/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0537
Epoch 44/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0537
Epoch 45/50
320000/320000 [==============================] - 6s 20us/step - loss: 0.0544 - val_loss: 0.0538
Epoch 46/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0539
Epoch 47/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0544 - val_loss: 0.0538
Epoch 48/50
320000/320000 [==============================] - 6s 19us/step - loss: 0.0543 - val_loss: 0.0537
Epoch 49/50
320000/320000 [==============================] - 6s 20us/step - loss: 0.0543 - val_loss: 0.0538
Epoch 50/50
320000/320000 [==============================] - 7s 21us/step - loss: 0.0544 - val_loss: 0.0537
```

In [93]:
```
y_predict = model.predict(X_test)
```

In [94]:
```
y_predict
```

Out[94]:
```
array([[0.6715395 ],
       [0.7123352 ],
       [0.71521664],
       ...,
       [0.6784505 ],
       [0.67522854],
       [0.64636934]], dtype=float32)
```

In [95]:
```
#Unscale back
y_predict_orig = scaler.inverse_transform(y_predict)
y_test_orig = scaler.inverse_transform(y_test)
```

In [96]:
```
y_predict_orig
```

```
Out[96]: array([[3.5219276],
               [3.7055085],
               [3.7184749],
               ...,
               [3.5530274],
               [3.5385284],
               [3.408662 ]], dtype=float32)
```

```
In [97]: rms = sqrt(mean_squared_error(y_test_orig, y_predict_orig))
         print("Root Mean Square value is: ", rms)
```

```
Root Mean Square value is:  1.0465580834637223
```

```
In [98]: r2 = r2_score(y_test_orig, y_predict_orig)
         print("R2 score is: ", r2)
```

```
R2 score is:  0.02235936331211219
```

0.14 Simple Recommender System - Recommending Similar Movies

```
In [99]: df4 = pd.read_csv('new.csv')
```

```
In [100]: df4.head()
```

```
Out[100]:    userId  movieId  rating  timestamp                          title  \
          0       1      122     5.0  838985046               Boomerang (1992)
          1       1      185     5.0  838983525                Net, The (1995)
          2       1      292     5.0  838983421                Outbreak (1995)
          3       1      316     5.0  838983392                Stargate (1994)
          4       1      329     5.0  838983392  Star Trek: Generations (1994)

                                    genres
          0                 Comedy|Romance
          1          Action|Crime|Thriller
          2  Action|Drama|Sci-Fi|Thriller
          3        Action|Adventure|Sci-Fi
          4  Action|Adventure|Drama|Sci-Fi
```

```
In [101]: df4 = df4[:500000] #Due to laptop hardware limitation, segment only first 500000 row
```

```
In [102]: df4.shape
```

```
Out[102]: (500000, 6)
```

```
In [103]: df4.drop('timestamp', axis=1, inplace=True)
          df4.drop('genres', axis=1, inplace=True)
```

```
In [104]: df4.head()
```

```
Out[104]:    userId  movieId  rating                          title
          0       1      122     5.0               Boomerang (1992)
          1       1      185     5.0                Net, The (1995)
          2       1      292     5.0                Outbreak (1995)
          3       1      316     5.0                Stargate (1994)
          4       1      329     5.0  Star Trek: Generations (1994)
```

```
In [105]: df4.groupby('title')['rating'].describe()
```

```
Out[105]:                                                       count      mean  \
          title
          'Round Midnight (1986)                                  4.0  3.625000
          'Til There Was You (1997)                              25.0  2.880000
          'burbs, The (1989)                                     87.0  2.931034
          'night Mother (1986)                                   11.0  3.272727
          *batteries not included (1987)                         43.0  3.127907
          ...All the Marbles (a.k.a. The California Dolls...      2.0  2.750000
          ...And God Created Woman (Et Dieu... créa la fe...      2.0  3.500000
          ...And God Spoke (1993)                                 3.0  4.000000
          ...And Justice for All (1979)                          29.0  3.862069
          1-900 (06) (1994)                                       4.0  4.000000
          10 (1979)                                              12.0  2.750000
          10 Items or Less (2006)                                 7.0  3.214286
          10 Rillington Place (1971)                              7.0  3.714286
          10 Things I Hate About You (1999)                     301.0  3.431894
          10 to Midnight (1983)                                   3.0  3.833333
          10,000 B.C. (2008)                                     16.0  2.875000
          100 Girls (2000)                                        2.0  2.750000
          1000 Eyes of Dr. Mabuse, The (Tausend Augen des...      2.0  4.000000
          101 Dalmatians (1996)                                 234.0  3.262821
          101 Reykjavik (101 Reykjavík) (2000)                   11.0  3.818182
          102 Dalmatians (2000)                                  20.0  2.275000
          10th Victim, The (La Decima Vittima) (1965)             3.0  3.166667
          11'09"01 - September 11 (2002)                          3.0  3.666667
          11:14 (2003)                                            9.0  3.777778
          12 Angry Men (1957)                                   276.0  4.268116
          12 Monkeys (Twelve Monkeys) (1995)                   1309.0  3.915202
          13 Ghosts (1960)                                       25.0  2.780000
          13 Going on 30 (2004)                                  53.0  3.198113
          13 Rue Madeleine (1947)                                 3.0  4.166667
          13 Tzameti (2005)                                       3.0  3.833333
          ...                                                     ...       ...
          Zatoichi (Zatôichi) (2003)                             33.0  3.560606
          Zazie dans le métro (1960)                              1.0  3.000000
          Zebrahead (1992)                                        2.0  3.250000
          Zed & Two Noughts, A (1985)                             9.0  4.222222
          Zeitgeist: The Movie (2007)                             2.0  3.250000
          Zelary (2003)                                           4.0  4.125000
```

```
Zelig (1983)                                        23.0  3.869565
Zentropa (Europa) (1991)                             9.0  3.777778
Zero Effect (1998)                                  82.0  3.664634
Zero Kelvin (Kjærlighetens kjøtere) (1995)           2.0  4.500000
Zero for Conduct (Zéro de conduite) (1933)           1.0  5.000000
Zeus and Roxanne (1997)                              7.0  2.285714
Ziggy Stardust and the Spiders from Mars (1973)      3.0  2.333333
Zodiac (2007)                                       62.0  3.782258
Zombie (a.k.a. Zombie 2: The Dead Are Among Us)...   2.0  4.000000
Zombie Holocaust (a.k.a. Doctor Butcher M.D.) (...   2.0  2.000000
Zombie Lake (Le Lac des morts vivants) (1981)        1.0  3.500000
Zombie Strippers! (2008)                             1.0  1.000000
Zoolander (2001)                                   185.0  3.291892
Zoom (2006)                                          3.0  1.833333
Zoot Suit (1981)                                     1.0  3.500000
Zorba the Greek (Alexis Zorbas) (1964)               9.0  3.666667
Zorro, the Gay Blade (1981)                          6.0  2.250000
Zulu (1964)                                         18.0  4.194444
Zus & Zo (2001)                                      1.0  3.000000
[Rec] (2007)                                         1.0  3.500000
eXistenZ (1999)                                    135.0  3.351852
loudQUIETloud: A Film About the Pixies (2006)        1.0  4.000000
xXx: State of the Union (2005)                      11.0  2.136364
Âge d'or, L' (1930)                                  2.0  4.250000

                                                        std  min    25%  \
title
'Round Midnight (1986)                             0.750000  3.0  3.000
'Til There Was You (1997)                          1.013246  1.0  2.000
'burbs, The (1989)                                 0.893036  1.0  2.000
'night Mother (1986)                               1.103713  2.0  2.500
*batteries not included (1987)                     0.945497  1.0  2.500
...All the Marbles (a.k.a. The California Dolls... 1.060660  2.0  2.375
...And God Created Woman (Et Dieu... créa la fe... 0.707107  3.0  3.250
...And God Spoke (1993)                            1.000000  3.0  3.500
...And Justice for All (1979)                      0.895390  2.0  3.500
1-900 (06) (1994)                                  1.154701  3.0  3.000
10 (1979)                                          0.839372  1.0  2.375
10 Items or Less (2006)                            0.809174  2.5  2.500
10 Rillington Place (1971)                         0.859125  2.5  3.250
10 Things I Hate About You (1999)                  0.965840  0.5  3.000
10 to Midnight (1983)                              1.258306  2.5  3.250
10,000 B.C. (2008)                                 1.040833  1.0  2.375
100 Girls (2000)                                   1.060660  2.0  2.375
1000 Eyes of Dr. Mabuse, The (Tausend Augen des... 0.707107  3.5  3.750
101 Dalmatians (1996)                              1.058557  0.5  3.000
101 Reykjavik (101 Reykjavík) (2000)               0.513455  2.5  3.750
102 Dalmatians (2000)                              0.938574  0.5  2.000
```

10th Victim, The (La Decima Vittima) (1965)	0.288675	3.0	3.000
11'09"01 - September 11 (2002)	1.258306	2.5	3.000
11:14 (2003)	0.666667	3.0	3.000
12 Angry Men (1957)	0.706231	1.0	4.000
12 Monkeys (Twelve Monkeys) (1995)	0.870686	1.0	3.000
13 Ghosts (1960)	1.021437	0.5	2.000
13 Going on 30 (2004)	0.911147	1.0	2.500
13 Rue Madeleine (1947)	0.288675	4.0	4.000
13 Tzameti (2005)	0.577350	3.5	3.500
...	...	...	...
Zatoichi (Zatôichi) (2003)	0.872833	1.5	3.000
Zazie dans le métro (1960)	NaN	3.0	3.000
Zebrahead (1992)	0.353553	3.0	3.125
Zed & Two Noughts, A (1985)	0.794949	3.0	4.000
Zeitgeist: The Movie (2007)	1.060660	2.5	2.875
Zelary (2003)	0.478714	3.5	3.875
Zelig (1983)	0.726408	2.0	3.500
Zentropa (Europa) (1991)	0.565194	3.0	3.500
Zero Effect (1998)	1.077419	1.0	3.000
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.707107	4.0	4.250
Zero for Conduct (Zéro de conduite) (1933)	NaN	5.0	5.000
Zeus and Roxanne (1997)	1.112697	1.0	1.500
Ziggy Stardust and the Spiders from Mars (1973)	0.763763	1.5	2.000
Zodiac (2007)	0.656749	1.5	3.500
Zombie (a.k.a. Zombie 2: The Dead Are Among Us)...	0.000000	4.0	4.000
Zombie Holocaust (a.k.a. Doctor Butcher M.D.) (...	2.121320	0.5	1.250
Zombie Lake (Le Lac des morts vivants) (1981)	NaN	3.5	3.500
Zombie Strippers! (2008)	NaN	1.0	1.000
Zoolander (2001)	1.006063	1.0	3.000
Zoom (2006)	1.040833	1.0	1.250
Zoot Suit (1981)	NaN	3.5	3.500
Zorba the Greek (Alexis Zorbas) (1964)	1.250000	1.5	3.000
Zorro, the Gay Blade (1981)	1.369306	0.5	1.250
Zulu (1964)	0.730409	2.5	4.000
Zus & Zo (2001)	NaN	3.0	3.000
[Rec] (2007)	NaN	3.5	3.500
eXistenZ (1999)	1.084274	0.5	3.000
loudQUIETloud: A Film About the Pixies (2006)	NaN	4.0	4.000
xXx: State of the Union (2005)	1.074498	1.0	1.500
Âge d'or, L' (1930)	1.060660	3.5	3.875

	50%	75%	max
title			
'Round Midnight (1986)	3.50	4.125	4.5
'Til There Was You (1997)	3.00	4.000	4.0
'burbs, The (1989)	3.00	3.750	5.0
'night Mother (1986)	3.00	4.000	5.0
*batteries not included (1987)	3.00	3.500	5.0

...All the Marbles (a.k.a. The California Dolls...	2.75	3.125	3.5
...And God Created Woman (Et Dieu... créa la fe...	3.50	3.750	4.0
...And God Spoke (1993)	4.00	4.500	5.0
...And Justice for All (1979)	4.00	4.000	5.0
1-900 (06) (1994)	4.00	5.000	5.0
10 (1979)	2.75	3.500	4.0
10 Items or Less (2006)	3.00	3.750	4.5
10 Rillington Place (1971)	4.00	4.250	4.5
10 Things I Hate About You (1999)	3.50	4.000	5.0
10 to Midnight (1983)	4.00	4.500	5.0
10,000 B.C. (2008)	3.00	3.625	4.5
100 Girls (2000)	2.75	3.125	3.5
1000 Eyes of Dr. Mabuse, The (Tausend Augen des...	4.00	4.250	4.5
101 Dalmatians (1996)	3.00	4.000	5.0
101 Reykjavik (101 Reykjavík) (2000)	4.00	4.000	4.5
102 Dalmatians (2000)	2.00	3.000	4.0
10th Victim, The (La Decima Vittima) (1965)	3.00	3.250	3.5
11'09"01 - September 11 (2002)	3.50	4.250	5.0
11:14 (2003)	4.00	4.000	5.0
12 Angry Men (1957)	4.00	5.000	5.0
12 Monkeys (Twelve Monkeys) (1995)	4.00	4.500	5.0
13 Ghosts (1960)	3.00	3.500	4.5
13 Going on 30 (2004)	3.00	4.000	5.0
13 Rue Madeleine (1947)	4.00	4.250	4.5
13 Tzameti (2005)	3.50	4.000	4.5
...	...	...	...
Zatoichi (Zatôichi) (2003)	3.50	4.000	5.0
Zazie dans le métro (1960)	3.00	3.000	3.0
Zebrahead (1992)	3.25	3.375	3.5
Zed & Two Noughts, A (1985)	4.50	5.000	5.0
Zeitgeist: The Movie (2007)	3.25	3.625	4.0
Zelary (2003)	4.25	4.500	4.5
Zelig (1983)	4.00	4.500	5.0
Zentropa (Europa) (1991)	3.50	4.000	5.0
Zero Effect (1998)	4.00	4.500	5.0
Zero Kelvin (Kjærlighetens kjøtere) (1995)	4.50	4.750	5.0
Zero for Conduct (Zéro de conduite) (1933)	5.00	5.000	5.0
Zeus and Roxanne (1997)	2.00	3.000	4.0
Ziggy Stardust and the Spiders from Mars (1973)	2.50	2.750	3.0
Zodiac (2007)	4.00	4.000	5.0
Zombie (a.k.a. Zombie 2: The Dead Are Among Us)...	4.00	4.000	4.0
Zombie Holocaust (a.k.a. Doctor Butcher M.D.) (...	2.00	2.750	3.5
Zombie Lake (Le Lac des morts vivants) (1981)	3.50	3.500	3.5
Zombie Strippers! (2008)	1.00	1.000	1.0
Zoolander (2001)	3.50	4.000	5.0
Zoom (2006)	1.50	2.250	3.0
Zoot Suit (1981)	3.50	3.500	3.5
Zorba the Greek (Alexis Zorbas) (1964)	4.00	4.500	5.0

```
Zorro, the Gay Blade (1981)                          2.25  3.250  4.0
Zulu (1964)                                          4.25  4.875  5.0
Zus & Zo (2001)                                      3.00  3.000  3.0
[Rec] (2007)                                         3.50  3.500  3.5
eXistenZ (1999)                                      3.50  4.000  5.0
loudQUIETloud: A Film About the Pixies (2006)        4.00  4.000  4.0
xXx: State of the Union (2005)                       2.00  2.500  4.0
Âge d'or, L' (1930)                                  4.25  4.625  5.0

[8897 rows x 8 columns]
```

In [106]:
```python
ratings_df_mean = df4.groupby('title')['rating'].describe()['mean']
```

In [107]:
```python
ratings_df_mean   #Average mean ratings for each movie
```

Out[107]:
```
title
'Round Midnight (1986)                                                  3.625000
'Til There Was You (1997)                                               2.880000
'burbs, The (1989)                                                      2.931034
'night Mother (1986)                                                    3.272727
*batteries not included (1987)                                          3.127907
...All the Marbles (a.k.a. The California Dolls) (1981)                 2.750000
...And God Created Woman (Et Dieu... créa la femme) (1956)              3.500000
...And God Spoke (1993)                                                 4.000000
...And Justice for All (1979)                                           3.862069
1-900 (06) (1994)                                                       4.000000
10 (1979)                                                               2.750000
10 Items or Less (2006)                                                 3.214286
10 Rillington Place (1971)                                              3.714286
10 Things I Hate About You (1999)                                       3.431894
10 to Midnight (1983)                                                   3.833333
10,000 B.C. (2008)                                                      2.875000
100 Girls (2000)                                                        2.750000
1000 Eyes of Dr. Mabuse, The (Tausend Augen des Dr. Mabuse, Die) (1960)    4.000000
101 Dalmatians (1996)                                                   3.262821
101 Reykjavik (101 Reykjavík) (2000)                                    3.818182
102 Dalmatians (2000)                                                   2.275000
10th Victim, The (La Decima Vittima) (1965)                             3.166667
11'09"01 - September 11 (2002)                                          3.666667
11:14 (2003)                                                            3.777778
12 Angry Men (1957)                                                     4.268116
12 Monkeys (Twelve Monkeys) (1995)                                      3.915202
13 Ghosts (1960)                                                        2.780000
13 Going on 30 (2004)                                                   3.198113
13 Rue Madeleine (1947)                                                 4.166667
13 Tzameti (2005)                                                       3.833333
                                                                          ...
Zatoichi (Zatôichi) (2003)                                              3.560606
```

```
Zazie dans le métro (1960)                                        3.000000
Zebrahead (1992)                                                  3.250000
Zed & Two Noughts, A (1985)                                       4.222222
Zeitgeist: The Movie (2007)                                       3.250000
Zelary (2003)                                                     4.125000
Zelig (1983)                                                      3.869565
Zentropa (Europa) (1991)                                          3.777778
Zero Effect (1998)                                                3.664634
Zero Kelvin (Kjærlighetens kjøtere) (1995)                        4.500000
Zero for Conduct (Zéro de conduite) (1933)                        5.000000
Zeus and Roxanne (1997)                                           2.285714
Ziggy Stardust and the Spiders from Mars (1973)                   2.333333
Zodiac (2007)                                                     3.782258
Zombie (a.k.a. Zombie 2: The Dead Are Among Us) (Zombi 2) (1979)  4.000000
Zombie Holocaust (a.k.a. Doctor Butcher M.D.) (Zombi Holocaust) (1980)  2.000000
Zombie Lake (Le Lac des morts vivants) (1981)                     3.500000
Zombie Strippers! (2008)                                          1.000000
Zoolander (2001)                                                  3.291892
Zoom (2006)                                                       1.833333
Zoot Suit (1981)                                                  3.500000
Zorba the Greek (Alexis Zorbas) (1964)                            3.666667
Zorro, the Gay Blade (1981)                                       2.250000
Zulu (1964)                                                       4.194444
Zus & Zo (2001)                                                   3.000000
[Rec] (2007)                                                      3.500000
eXistenZ (1999)                                                   3.351852
loudQUIETloud: A Film About the Pixies (2006)                     4.000000
xXx: State of the Union (2005)                                    2.136364
Âge d'or, L' (1930)                                               4.250000
Name: mean, Length: 8897, dtype: float64
```

In [108]:
```
ratings_df_count = df4.groupby('title')['rating'].describe()['count']
```

In [109]:
```
ratings_df_count #no of ratings for each movie
```

Out[109]:
```
title
'Round Midnight (1986)                                               4.0
'Til There Was You (1997)                                           25.0
'burbs, The (1989)                                                  87.0
'night Mother (1986)                                                11.0
*batteries not included (1987)                                      43.0
...All the Marbles (a.k.a. The California Dolls) (1981)              2.0
...And God Created Woman (Et Dieu... créa la femme) (1956)           2.0
...And God Spoke (1993)                                              3.0
...And Justice for All (1979)                                       29.0
1-900 (06) (1994)                                                    4.0
10 (1979)                                                           12.0
10 Items or Less (2006)                                              7.0
```

10 Rillington Place (1971)	7.0
10 Things I Hate About You (1999)	301.0
10 to Midnight (1983)	3.0
10,000 B.C. (2008)	16.0
100 Girls (2000)	2.0
1000 Eyes of Dr. Mabuse, The (Tausend Augen des Dr. Mabuse, Die) (1960)	2.0
101 Dalmatians (1996)	234.0
101 Reykjavik (101 Reykjavík) (2000)	11.0
102 Dalmatians (2000)	20.0
10th Victim, The (La Decima Vittima) (1965)	3.0
11'09"01 - September 11 (2002)	3.0
11:14 (2003)	9.0
12 Angry Men (1957)	276.0
12 Monkeys (Twelve Monkeys) (1995)	1309.0
13 Ghosts (1960)	25.0
13 Going on 30 (2004)	53.0
13 Rue Madeleine (1947)	3.0
13 Tzameti (2005)	3.0
	...
Zatoichi (Zatôichi) (2003)	33.0
Zazie dans le métro (1960)	1.0
Zebrahead (1992)	2.0
Zed & Two Noughts, A (1985)	9.0
Zeitgeist: The Movie (2007)	2.0
Zelary (2003)	4.0
Zelig (1983)	23.0
Zentropa (Europa) (1991)	9.0
Zero Effect (1998)	82.0
Zero Kelvin (Kjærlighetens kjøtere) (1995)	2.0
Zero for Conduct (Zéro de conduite) (1933)	1.0
Zeus and Roxanne (1997)	7.0
Ziggy Stardust and the Spiders from Mars (1973)	3.0
Zodiac (2007)	62.0
Zombie (a.k.a. Zombie 2: The Dead Are Among Us) (Zombi 2) (1979)	2.0
Zombie Holocaust (a.k.a. Doctor Butcher M.D.) (Zombi Holocaust) (1980)	2.0
Zombie Lake (Le Lac des morts vivants) (1981)	1.0
Zombie Strippers! (2008)	1.0
Zoolander (2001)	185.0
Zoom (2006)	3.0
Zoot Suit (1981)	1.0
Zorba the Greek (Alexis Zorbas) (1964)	9.0
Zorro, the Gay Blade (1981)	6.0
Zulu (1964)	18.0
Zus & Zo (2001)	1.0
[Rec] (2007)	1.0
eXistenZ (1999)	135.0
loudQUIETloud: A Film About the Pixies (2006)	1.0
xXx: State of the Union (2005)	11.0

```
Âge d'or, L' (1930)                                                2.0
Name: count, Length: 8897, dtype: float64
```

In [110]:
```
ratings_mean_count_df = pd.concat([ratings_df_count, ratings_df_mean], axis = 1)
```

In [111]:
```
ratings_mean_count_df
```

Out[111]:
```
                                                    count      mean
title
'Round Midnight (1986)                                4.0  3.625000
'Til There Was You (1997)                            25.0  2.880000
'burbs, The (1989)                                   87.0  2.931034
'night Mother (1986)                                 11.0  3.272727
*batteries not included (1987)                       43.0  3.127907
...All the Marbles (a.k.a. The California Dolls...    2.0  2.750000
...And God Created Woman (Et Dieu... créa la fe...    2.0  3.500000
...And God Spoke (1993)                               3.0  4.000000
...And Justice for All (1979)                        29.0  3.862069
1-900 (06) (1994)                                     4.0  4.000000
10 (1979)                                            12.0  2.750000
10 Items or Less (2006)                               7.0  3.214286
10 Rillington Place (1971)                            7.0  3.714286
10 Things I Hate About You (1999)                   301.0  3.431894
10 to Midnight (1983)                                 3.0  3.833333
10,000 B.C. (2008)                                   16.0  2.875000
100 Girls (2000)                                      2.0  2.750000
1000 Eyes of Dr. Mabuse, The (Tausend Augen des...    2.0  4.000000
101 Dalmatians (1996)                               234.0  3.262821
101 Reykjavik (101 Reykjavík) (2000)                 11.0  3.818182
102 Dalmatians (2000)                                20.0  2.275000
10th Victim, The (La Decima Vittima) (1965)           3.0  3.166667
11'09"01 - September 11 (2002)                        3.0  3.666667
11:14 (2003)                                          9.0  3.777778
12 Angry Men (1957)                                 276.0  4.268116
12 Monkeys (Twelve Monkeys) (1995)                 1309.0  3.915202
13 Ghosts (1960)                                     25.0  2.780000
13 Going on 30 (2004)                                53.0  3.198113
13 Rue Madeleine (1947)                               3.0  4.166667
13 Tzameti (2005)                                     3.0  3.833333
...                                                   ...       ...
Zatoichi (Zatôichi) (2003)                           33.0  3.560606
Zazie dans le métro (1960)                            1.0  3.000000
Zebrahead (1992)                                      2.0  3.250000
Zed & Two Noughts, A (1985)                           9.0  4.222222
Zeitgeist: The Movie (2007)                           2.0  3.250000
Zelary (2003)                                         4.0  4.125000
Zelig (1983)                                         23.0  3.869565
Zentropa (Europa) (1991)                              9.0  3.777778
```

```
Zero Effect (1998)                                      82.0  3.664634
Zero Kelvin (Kjærlighetens kjøtere) (1995)               2.0  4.500000
Zero for Conduct (Zéro de conduite) (1933)               1.0  5.000000
Zeus and Roxanne (1997)                                  7.0  2.285714
Ziggy Stardust and the Spiders from Mars (1973)          3.0  2.333333
Zodiac (2007)                                           62.0  3.782258
Zombie (a.k.a. Zombie 2: The Dead Are Among Us)...       2.0  4.000000
Zombie Holocaust (a.k.a. Doctor Butcher M.D.) (...       2.0  2.000000
Zombie Lake (Le Lac des morts vivants) (1981)            1.0  3.500000
Zombie Strippers! (2008)                                 1.0  1.000000
Zoolander (2001)                                       185.0  3.291892
Zoom (2006)                                              3.0  1.833333
Zoot Suit (1981)                                         1.0  3.500000
Zorba the Greek (Alexis Zorbas) (1964)                   9.0  3.666667
Zorro, the Gay Blade (1981)                              6.0  2.250000
Zulu (1964)                                             18.0  4.194444
Zus & Zo (2001)                                          1.0  3.000000
[Rec] (2007)                                             1.0  3.500000
eXistenZ (1999)                                        135.0  3.351852
loudQUIETloud: A Film About the Pixies (2006)            1.0  4.000000
xXx: State of the Union (2005)                          11.0  2.136364
Âge d'or, L' (1930)                                      2.0  4.250000

[8897 rows x 2 columns]
```

In [112]:
```
ratings_mean_count_df.reset_index()
```

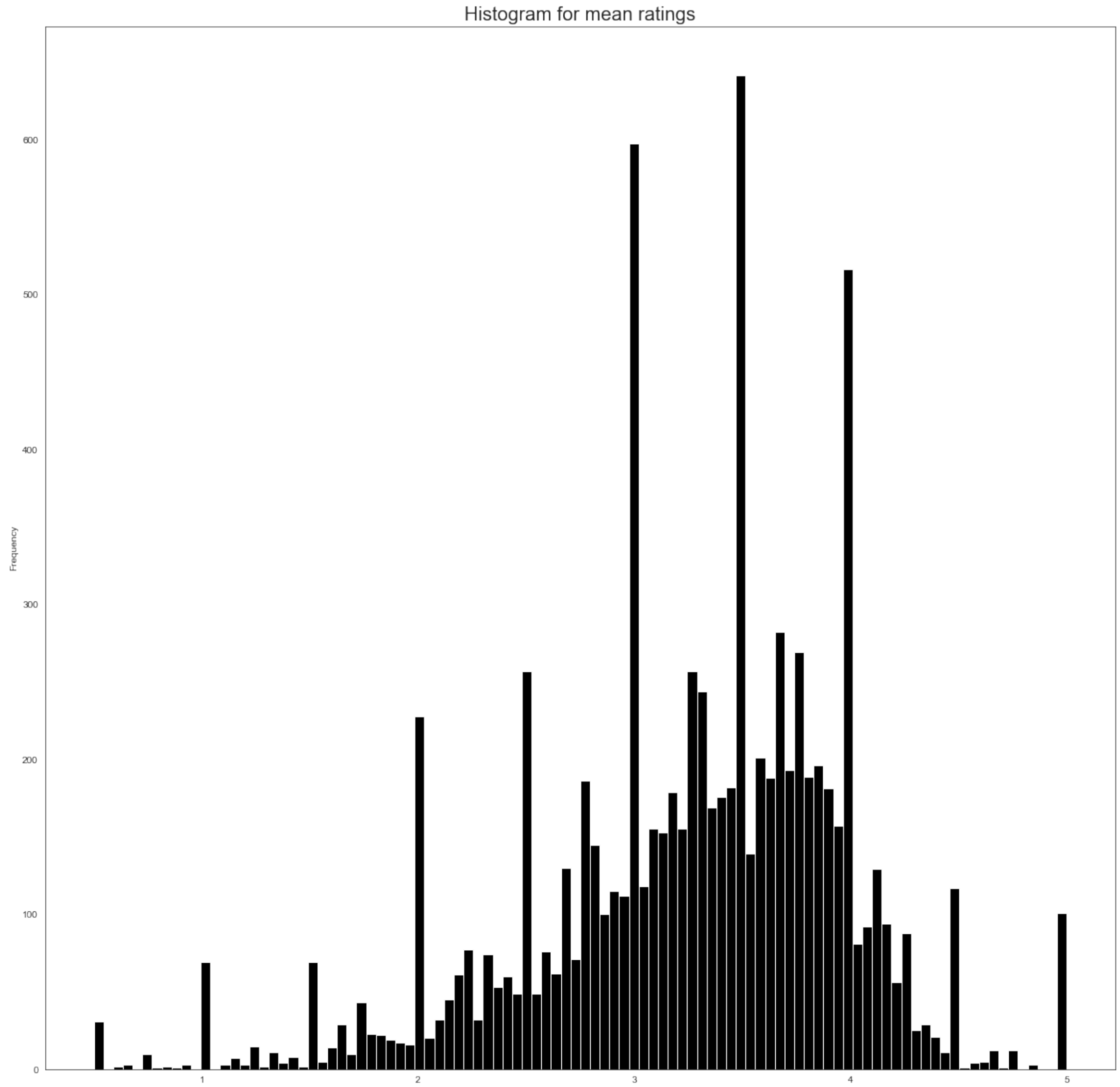
Out[112]:

	title	count	mean
0	'Round Midnight (1986)	4.0	3.625000
1	'Til There Was You (1997)	25.0	2.880000
2	'burbs, The (1989)	87.0	2.931034
3	'night Mother (1986)	11.0	3.272727
4	*batteries not included (1987)	43.0	3.127907
5	...All the Marbles (a.k.a. The California Doll...	2.0	2.750000
6	...And God Created Woman (Et Dieu... créa la f...	2.0	3.500000
7	...And God Spoke (1993)	3.0	4.000000
8	...And Justice for All (1979)	29.0	3.862069
9	1-900 (06) (1994)	4.0	4.000000
10	10 (1979)	12.0	2.750000
11	10 Items or Less (2006)	7.0	3.214286
12	10 Rillington Place (1971)	7.0	3.714286
13	10 Things I Hate About You (1999)	301.0	3.431894
14	10 to Midnight (1983)	3.0	3.833333
15	10,000 B.C. (2008)	16.0	2.875000
16	100 Girls (2000)	2.0	2.750000
17	1000 Eyes of Dr. Mabuse, The (Tausend Augen de...	2.0	4.000000
18	101 Dalmatians (1996)	234.0	3.262821
19	101 Reykjavik (101 Reykjavík) (2000)	11.0	3.818182

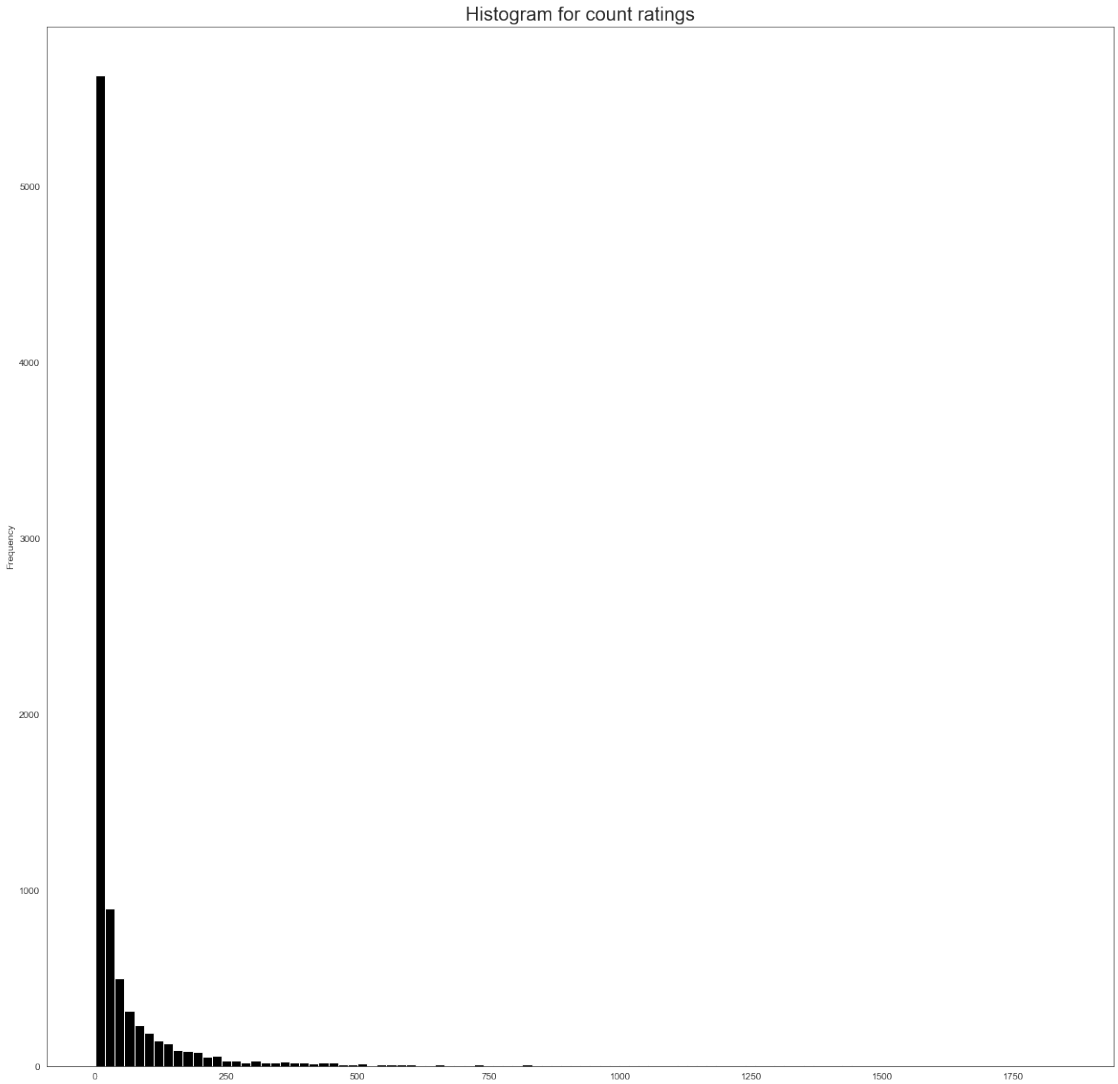
```
20                                 102 Dalmatians (2000)    20.0  2.275000
21             10th Victim, The (La Decima Vittima) (1965)     3.0  3.166667
22                      11'09"01 - September 11 (2002)     3.0  3.666667
23                                      11:14 (2003)     9.0  3.777778
24                               12 Angry Men (1957)   276.0  4.268116
25                 12 Monkeys (Twelve Monkeys) (1995)  1309.0  3.915202
26                                 13 Ghosts (1960)    25.0  2.780000
27                             13 Going on 30 (2004)    53.0  3.198113
28                           13 Rue Madeleine (1947)     3.0  4.166667
29                                 13 Tzameti (2005)     3.0  3.833333
...                                              ...     ...       ...
8867                       Zatoichi (Zatôichi) (2003)    33.0  3.560606
8868                       Zazie dans le métro (1960)     1.0  3.000000
8869                                 Zebrahead (1992)     2.0  3.250000
8870                       Zed & Two Noughts, A (1985)     9.0  4.222222
8871                       Zeitgeist: The Movie (2007)     2.0  3.250000
8872                                    Zelary (2003)     4.0  4.125000
8873                                     Zelig (1983)    23.0  3.869565
8874                         Zentropa (Europa) (1991)     9.0  3.777778
8875                               Zero Effect (1998)    82.0  3.664634
8876           Zero Kelvin (Kjærlighetens kjøtere) (1995)     2.0  4.500000
8877           Zero for Conduct (Zéro de conduite) (1933)     1.0  5.000000
8878                          Zeus and Roxanne (1997)     7.0  2.285714
8879      Ziggy Stardust and the Spiders from Mars (1973)     3.0  2.333333
8880                                    Zodiac (2007)    62.0  3.782258
8881  Zombie (a.k.a. Zombie 2: The Dead Are Among Us...     2.0  4.000000
8882  Zombie Holocaust (a.k.a. Doctor Butcher M.D.) ...     2.0  2.000000
8883      Zombie Lake (Le Lac des morts vivants) (1981)     1.0  3.500000
8884                        Zombie Strippers! (2008)     1.0  1.000000
8885                                 Zoolander (2001)   185.0  3.291892
8886                                      Zoom (2006)     3.0  1.833333
8887                                 Zoot Suit (1981)     1.0  3.500000
8888             Zorba the Greek (Alexis Zorbas) (1964)     9.0  3.666667
8889                        Zorro, the Gay Blade (1981)     6.0  2.250000
8890                                      Zulu (1964)    18.0  4.194444
8891                                  Zus & Zo (2001)     1.0  3.000000
8892                                     [Rec] (2007)     1.0  3.500000
8893                                  eXistenZ (1999)   135.0  3.351852
8894      loudQUIETloud: A Film About the Pixies (2006)     1.0  4.000000
8895                      xXx: State of the Union (2005)    11.0  2.136364
8896                               Âge d'or, L' (1930)     2.0  4.250000

[8897 rows x 3 columns]
```

In [113]:
```python
plt.figure(figsize=(20,20))
ratings_mean_count_df['mean'].plot(bins=100, kind='hist', color = 'black')
plt.title("Histogram for mean ratings", fontsize=20)
```

Out[113]:
```
Text(0.5, 1.0, 'Histogram for mean ratings')
```




```
In [114]: plt.figure(figsize=(20,20))
          ratings_mean_count_df['count'].plot(bins=100, kind='hist', color = 'black')
          plt.title("Histogram for count ratings", fontsize=20)

Out[114]: Text(0.5, 1.0, 'Histogram for count ratings')
```




```
In [115]: ratings_mean_count_df[ratings_mean_count_df['mean'] == 5]  #Low counts for highest r
```

Out[115]:

title	count	mean
Anna (1996)	1.0	5.0
Ay, Carmela! (¡Ay, Carmela!) (1990)	1.0	5.0
Ball of Fire (1941)	1.0	5.0
Battling Butler (1926)	2.0	5.0
Big Clock, The (1948)	1.0	5.0
Blue Kite, The (Lan feng zheng) (1993)	1.0	5.0
Breathing Room (1996)	1.0	5.0
Brother of Sleep (Schlafes Bruder) (1995)	1.0	5.0
California Split (1974)	1.0	5.0
Chase, The (1966)	1.0	5.0

Children Underground (2000)	1.0	5.0
Critical Care (1997)	1.0	5.0
Crows and Sparrows (Wuya yu maque) (1949)	2.0	5.0
Dancemaker (1998)	2.0	5.0
Day the Sun Turned Cold, The (Tianguo niezi) (1...	2.0	5.0
Dear Jesse (1997)	1.0	5.0
Different for Girls (1996)	1.0	5.0
Eat a Bowl of Tea (1989)	1.0	5.0
Every Other Weekend (Un week-end sur deux) (1990)	1.0	5.0
Everybody's Famous! (Iedereen beroemd!) (2000)	1.0	5.0
Farmer & Chase (1997)	1.0	5.0
Fidel (2001)	2.0	5.0
Flying Deuces, The (1939)	1.0	5.0
Foolish Wives (1922)	1.0	5.0
For Ever Mozart (1996)	1.0	5.0
Forbidden Christ, The (Il Cristo proibito) (1950)	1.0	5.0
Gabbeh (1996)	3.0	5.0
Hippie Revolution, The (1996)	1.0	5.0
Hot Pursuit (1987)	1.0	5.0
Human Condition I, The (Ningen no joken I) (1959)	1.0	5.0
...	...	...
San Francisco (1936)	1.0	5.0
Saragossa Manuscript, The (Rekopis znaleziony w...	1.0	5.0
Seven Chances (1925)	2.0	5.0
Seventh Heaven (Septième ciel, Le) (1997)	1.0	5.0
Sexual Life of the Belgians, The (La Vie sexuel...	2.0	5.0
Shadow of Angels (Schatten der Engel) (1976)	2.0	5.0
Simple-Minded Murder, The (Enfaldige mördaren, ...	1.0	5.0
Small Wonders (1995)	1.0	5.0
Snake in the Eagle's Shadow (Se ying diu sau) (...	1.0	5.0
Something for Everyone (1970)	1.0	5.0
Song of Freedom (1936)	1.0	5.0
Source, The (1999)	1.0	5.0
Special Day, A (Una Giornata Particolare) (1977)	1.0	5.0
Starter for 10 (2006)	1.0	5.0
Steamboat Bill, Jr. (1928)	2.0	5.0
Sweet Nothing (1996)	2.0	5.0
Tabu: A Story of the South Seas (1931)	1.0	5.0
Tashunga (1995)	1.0	5.0
Tibet: Cry of the Snow Lion (2002)	1.0	5.0
Too Much Sleep (1997)	1.0	5.0
Up the Yangtze (2007)	1.0	5.0
Vive L'Amour (Aiqing wansui) (1994)	1.0	5.0
War Dance (2007)	1.0	5.0
Who's Singin' Over There? (a.k.a. Who Sings Ove...	1.0	5.0
Woman of Paris, A (1923)	1.0	5.0
Word, The (Ordet) (1955)	1.0	5.0
Wuthering Heights (1970)	2.0	5.0

```
Yes (2004)                                           1.0   5.0
Yol (1982)                                           2.0   5.0
Zero for Conduct (Zéro de conduite) (1933)           1.0   5.0

[101 rows x 2 columns]
```

In [116]:
```python
ratings_mean_count_df.sort_values('count', ascending = False).head(100) #Top 100 has
```

Out[116]:
```
                                                     count      mean
title
Silence of the Lambs, The (1991)                    1849.0  4.247431
Pulp Fiction (1994)                                 1793.0  4.144172
Forrest Gump (1994)                                 1740.0  4.013793
Jurassic Park (1993)                                1621.0  3.677051
Shawshank Redemption, The (1994)                    1598.0  4.485294
Star Wars: Episode IV - A New Hope (a.k.a. Star...  1524.0  4.267388
Braveheart (1995)                                   1486.0  4.117766
Fugitive, The (1993)                                1439.0  4.026060
Terminator 2: Judgment Day (1991)                   1433.0  3.959525
Toy Story (1995)                                    1430.0  3.952797
Independence Day (a.k.a. ID4) (1996)                1409.0  3.430092
Batman (1989)                                       1380.0  3.397101
Schindler's List (1993)                             1358.0  4.358616
Apollo 13 (1995)                                    1356.0  3.902286
Star Wars: Episode VI - Return of the Jedi (1983)   1333.0  4.051763
Fargo (1996)                                        1319.0  4.131918
12 Monkeys (Twelve Monkeys) (1995)                  1309.0  3.915202
True Lies (1994)                                    1301.0  3.551115
Dances with Wolves (1990)                           1295.0  3.735135
Usual Suspects, The (1995)                          1255.0  4.413147
Aladdin (1992)                                      1242.0  3.679147
Star Wars: Episode V - The Empire Strikes Back ...  1229.0  4.213588
Matrix, The (1999)                                  1182.0  4.216159
American Beauty (1999)                              1181.0  4.234547
Mission: Impossible (1996)                          1153.0  3.431917
Speed (1994)                                        1153.0  3.486990
Seven (a.k.a. Se7en) (1995)                         1115.0  4.025561
Raiders of the Lost Ark (Indiana Jones and the ...  1110.0  4.266216
Back to the Future (1985)                           1110.0  3.864865
Ace Ventura: Pet Detective (1994)                   1075.0  3.023256
...                                                    ...       ...
Shakespeare in Love (1998)                           794.0  3.981738
Net, The (1995)                                      791.0  3.135272
L.A. Confidential (1997)                             790.0  4.118354
Firm, The (1993)                                     788.0  3.511421
Clueless (1995)                                      785.0  3.407643
One Flew Over the Cuckoo's Nest (1975)               785.0  4.294268
Cliffhanger (1993)                                   770.0  3.055844
```

```
Crimson Tide (1995)                                    769.0  3.769831
Gladiator (2000)                                       764.0  3.929319
Get Shorty (1995)                                      758.0  3.600264
Broken Arrow (1996)                                    758.0  3.141821
Good Will Hunting (1997)                               752.0  4.089761
Aliens (1986)                                          749.0  4.008011
Austin Powers: The Spy Who Shagged Me (1999)           742.0  3.291779
Birdcage, The (1996)                                   734.0  3.459128
Being John Malkovich (1999)                            733.0  3.972715
While You Were Sleeping (1995)                         733.0  3.452933
Natural Born Killers (1994)                            729.0  3.216049
Lord of the Rings: The Fellowship of the Ring, ...     727.0  4.120358
Jerry Maguire (1996)                                   726.0  3.634298
Leaving Las Vegas (1995)                               725.0  3.628966
Reservoir Dogs (1992)                                  723.0  4.066390
Heat (1995)                                            721.0  3.885576
Clerks (1994)                                          710.0  3.961268
Godfather: Part II, The (1974)                         704.0  4.276989
Goodfellas (1990)                                      695.0  4.189928
Sense and Sensibility (1995)                           689.0  4.049347
Who Framed Roger Rabbit? (1988)                        687.0  3.532023
Fifth Element, The (1997)                              684.0  3.700292
Lord of the Rings: The Two Towers, The (2002)          683.0  4.103953

[100 rows x 2 columns]
```

In [117]:
```python
#Create a matrix consists of each user and what movies they watched
#NaNs means they never watched
userid_movietitle_matrix = df4.pivot_table(index = 'userId', columns = 'title', valu
```

In [118]:
```python
userid_movietitle_matrix
```

Out[118]:
```
title   'Round Midnight (1986)  'Til There Was You (1997)  'burbs, The (1989)  \
userId
1                          NaN                        NaN                 NaN
2                          NaN                        NaN                 NaN
3                          NaN                        NaN                 NaN
4                          NaN                        NaN                 NaN
5                          NaN                        NaN                 NaN
6                          NaN                        NaN                 NaN
7                          NaN                        NaN                 NaN
8                          NaN                        NaN                 4.0
9                          NaN                        NaN                 NaN
10                         NaN                        NaN                 NaN
11                         NaN                        NaN                 NaN
12                         NaN                        NaN                 NaN
13                         NaN                        NaN                 NaN
14                         NaN                        NaN                 NaN
```

16	NaN	NaN	NaN
17	NaN	NaN	NaN
18	NaN	NaN	2.5
19	NaN	NaN	NaN
22	NaN	NaN	NaN
23	NaN	NaN	NaN
24	NaN	NaN	NaN
26	NaN	NaN	NaN
27	NaN	NaN	NaN
28	NaN	NaN	NaN
29	NaN	NaN	NaN
30	NaN	NaN	NaN
33	NaN	NaN	NaN
34	NaN	NaN	NaN
35	NaN	NaN	NaN
36	NaN	NaN	NaN
...	...	...	...
4208	NaN	NaN	NaN
4209	NaN	NaN	NaN
4210	NaN	NaN	NaN
4211	NaN	NaN	NaN
4212	NaN	NaN	NaN
4213	NaN	NaN	NaN
4214	NaN	NaN	NaN
4215	NaN	NaN	NaN
4216	NaN	NaN	NaN
4217	NaN	NaN	NaN
4218	NaN	NaN	NaN
4219	NaN	NaN	NaN
4220	NaN	NaN	3.0
4221	NaN	NaN	NaN
4222	NaN	NaN	NaN
4223	NaN	NaN	NaN
4224	NaN	NaN	NaN
4225	NaN	NaN	NaN
4226	NaN	NaN	NaN
4227	NaN	NaN	NaN
4228	NaN	NaN	NaN
4229	NaN	NaN	NaN
4230	NaN	NaN	NaN
4231	NaN	NaN	NaN
4232	NaN	NaN	NaN
4233	NaN	NaN	NaN
4234	NaN	NaN	NaN
4235	NaN	NaN	NaN
4236	NaN	NaN	NaN
4237	NaN	NaN	NaN

```
title   'night Mother (1986)  *batteries not included (1987)  \
userId
1                        NaN                             NaN
2                        NaN                             NaN
3                        NaN                             NaN
4                        NaN                             NaN
5                        NaN                             NaN
6                        NaN                             NaN
7                        NaN                             NaN
8                        NaN                             3.5
9                        NaN                             NaN
10                       NaN                             NaN
11                       NaN                             NaN
12                       NaN                             NaN
13                       NaN                             NaN
14                       NaN                             NaN
16                       NaN                             NaN
17                       NaN                             NaN
18                       NaN                             NaN
19                       NaN                             NaN
22                       NaN                             NaN
23                       NaN                             NaN
24                       NaN                             NaN
26                       NaN                             NaN
27                       NaN                             NaN
28                       NaN                             NaN
29                       NaN                             NaN
30                       NaN                             NaN
33                       NaN                             NaN
34                       NaN                             NaN
35                       NaN                             NaN
36                       NaN                             NaN
...                      ...                             ...
4208                     NaN                             NaN
4209                     NaN                             NaN
4210                     NaN                             NaN
4211                     NaN                             NaN
4212                     NaN                             NaN
4213                     NaN                             NaN
4214                     NaN                             NaN
4215                     NaN                             NaN
4216                     NaN                             NaN
4217                     NaN                             NaN
4218                     NaN                             NaN
4219                     NaN                             NaN
4220                     NaN                             NaN
4221                     NaN                             NaN
4222                     NaN                             NaN
```

```
4223                    NaN                        NaN
4224                    NaN                        NaN
4225                    NaN                        NaN
4226                    NaN                        NaN
4227                    NaN                        NaN
4228                    NaN                        NaN
4229                    NaN                        NaN
4230                    NaN                        NaN
4231                    NaN                        NaN
4232                    NaN                        NaN
4233                    NaN                        NaN
4234                    NaN                        NaN
4235                    NaN                        NaN
4236                    NaN                        NaN
4237                    NaN                        NaN

title   ...All the Marbles (a.k.a. The California Dolls) (1981)  \
userId
1                                                      NaN
2                                                      NaN
3                                                      NaN
4                                                      NaN
5                                                      NaN
6                                                      NaN
7                                                      NaN
8                                                      NaN
9                                                      NaN
10                                                     NaN
11                                                     NaN
12                                                     NaN
13                                                     NaN
14                                                     NaN
16                                                     NaN
17                                                     NaN
18                                                     NaN
19                                                     NaN
22                                                     NaN
23                                                     NaN
24                                                     NaN
26                                                     NaN
27                                                     NaN
28                                                     NaN
29                                                     NaN
30                                                     NaN
33                                                     NaN
34                                                     NaN
35                                                     NaN
36                                                     NaN
```

```
...                                                      ...
4208                                                     NaN
4209                                                     NaN
4210                                                     NaN
4211                                                     NaN
4212                                                     NaN
4213                                                     NaN
4214                                                     NaN
4215                                                     NaN
4216                                                     NaN
4217                                                     NaN
4218                                                     NaN
4219                                                     NaN
4220                                                     NaN
4221                                                     NaN
4222                                                     NaN
4223                                                     NaN
4224                                                     NaN
4225                                                     NaN
4226                                                     NaN
4227                                                     NaN
4228                                                     NaN
4229                                                     NaN
4230                                                     NaN
4231                                                     NaN
4232                                                     NaN
4233                                                     NaN
4234                                                     NaN
4235                                                     NaN
4236                                                     NaN
4237                                                     NaN

title   ...And God Created Woman (Et Dieu... créa la femme) (1956)  \
userId
1                                                        NaN
2                                                        NaN
3                                                        NaN
4                                                        NaN
5                                                        NaN
6                                                        NaN
7                                                        NaN
8                                                        NaN
9                                                        NaN
10                                                       NaN
11                                                       NaN
12                                                       NaN
13                                                       NaN
14                                                       NaN
```

16	NaN
17	NaN
18	NaN
19	NaN
22	NaN
23	NaN
24	NaN
26	NaN
27	NaN
28	NaN
29	NaN
30	NaN
33	NaN
34	NaN
35	NaN
36	NaN
...	...
4208	NaN
4209	NaN
4210	NaN
4211	NaN
4212	NaN
4213	NaN
4214	NaN
4215	NaN
4216	NaN
4217	NaN
4218	NaN
4219	NaN
4220	NaN
4221	NaN
4222	NaN
4223	NaN
4224	NaN
4225	NaN
4226	NaN
4227	NaN
4228	NaN
4229	NaN
4230	NaN
4231	NaN
4232	NaN
4233	NaN
4234	NaN
4235	NaN
4236	NaN
4237	NaN

```
title   ...And God Spoke (1993)  ...And Justice for All (1979)  \
userId
1                           NaN                            NaN
2                           NaN                            NaN
3                           NaN                            NaN
4                           NaN                            NaN
5                           NaN                            NaN
6                           NaN                            NaN
7                           NaN                            NaN
8                           NaN                            NaN
9                           NaN                            NaN
10                          NaN                            NaN
11                          NaN                            NaN
12                          NaN                            NaN
13                          NaN                            NaN
14                          NaN                            NaN
16                          NaN                            NaN
17                          NaN                            NaN
18                          NaN                            NaN
19                          NaN                            NaN
22                          NaN                            NaN
23                          NaN                            NaN
24                          NaN                            NaN
26                          NaN                            NaN
27                          NaN                            NaN
28                          NaN                            NaN
29                          NaN                            NaN
30                          NaN                            NaN
33                          NaN                            NaN
34                          NaN                            NaN
35                          NaN                            NaN
36                          NaN                            NaN
...                         ...                            ...
4208                        NaN                            NaN
4209                        NaN                            NaN
4210                        NaN                            NaN
4211                        NaN                            NaN
4212                        NaN                            NaN
4213                        NaN                            NaN
4214                        NaN                            NaN
4215                        NaN                            NaN
4216                        NaN                            NaN
4217                        NaN                            NaN
4218                        NaN                            NaN
4219                        NaN                            NaN
4220                        NaN                            NaN
4221                        NaN                            NaN
4222                        NaN                            NaN
```

```
4223                          NaN                            NaN
4224                          NaN                            NaN
4225                          NaN                            NaN
4226                          NaN                            NaN
4227                          NaN                            NaN
4228                          NaN                            NaN
4229                          NaN                            5.0
4230                          NaN                            NaN
4231                          NaN                            NaN
4232                          NaN                            NaN
4233                          NaN                            NaN
4234                          NaN                            NaN
4235                          NaN                            NaN
4236                          NaN                            NaN
4237                          NaN                            NaN

title   1-900 (06) (1994)  ...  Zoot Suit (1981)  \
userId                     ...
1                     NaN  ...               NaN
2                     NaN  ...               NaN
3                     NaN  ...               NaN
4                     NaN  ...               NaN
5                     NaN  ...               NaN
6                     NaN  ...               NaN
7                     NaN  ...               NaN
8                     NaN  ...               NaN
9                     NaN  ...               NaN
10                    NaN  ...               NaN
11                    NaN  ...               NaN
12                    NaN  ...               NaN
13                    NaN  ...               NaN
14                    NaN  ...               NaN
16                    NaN  ...               NaN
17                    NaN  ...               NaN
18                    NaN  ...               NaN
19                    NaN  ...               NaN
22                    NaN  ...               NaN
23                    NaN  ...               NaN
24                    NaN  ...               NaN
26                    NaN  ...               NaN
27                    NaN  ...               NaN
28                    NaN  ...               NaN
29                    NaN  ...               NaN
30                    NaN  ...               NaN
33                    NaN  ...               NaN
34                    NaN  ...               NaN
35                    NaN  ...               NaN
36                    NaN  ...               NaN
```

```
...                ...  ...             ...
4208               NaN  ...             NaN
4209               NaN  ...             NaN
4210               NaN  ...             NaN
4211               NaN  ...             NaN
4212               NaN  ...             NaN
4213               NaN  ...             NaN
4214               NaN  ...             NaN
4215               NaN  ...             NaN
4216               NaN  ...             NaN
4217               NaN  ...             NaN
4218               NaN  ...             NaN
4219               NaN  ...             NaN
4220               NaN  ...             NaN
4221               NaN  ...             NaN
4222               NaN  ...             NaN
4223               NaN  ...             NaN
4224               NaN  ...             NaN
4225               NaN  ...             NaN
4226               NaN  ...             NaN
4227               NaN  ...             NaN
4228               NaN  ...             NaN
4229               NaN  ...             NaN
4230               NaN  ...             NaN
4231               NaN  ...             NaN
4232               NaN  ...             NaN
4233               NaN  ...             NaN
4234               NaN  ...             NaN
4235               NaN  ...             NaN
4236               NaN  ...             NaN
4237               NaN  ...             NaN

title   Zorba the Greek (Alexis Zorbas) (1964)  Zorro, the Gay Blade (1981)  \
userId
1                                          NaN                          NaN
2                                          NaN                          NaN
3                                          NaN                          NaN
4                                          NaN                          NaN
5                                          NaN                          NaN
6                                          NaN                          NaN
7                                          NaN                          NaN
8                                          NaN                          NaN
9                                          NaN                          NaN
10                                         NaN                          NaN
11                                         NaN                          NaN
12                                         NaN                          NaN
13                                         NaN                          NaN
14                                         NaN                          NaN
```

16	NaN	NaN
17	NaN	NaN
18	NaN	NaN
19	NaN	NaN
22	NaN	NaN
23	NaN	NaN
24	NaN	NaN
26	NaN	NaN
27	NaN	NaN
28	NaN	NaN
29	NaN	NaN
30	NaN	NaN
33	NaN	NaN
34	NaN	NaN
35	NaN	NaN
36	NaN	NaN
...	...	...
4208	NaN	NaN
4209	NaN	NaN
4210	NaN	NaN
4211	NaN	NaN
4212	NaN	NaN
4213	NaN	NaN
4214	NaN	NaN
4215	NaN	NaN
4216	NaN	NaN
4217	NaN	NaN
4218	NaN	NaN
4219	NaN	NaN
4220	NaN	NaN
4221	NaN	NaN
4222	NaN	NaN
4223	NaN	NaN
4224	NaN	NaN
4225	NaN	NaN
4226	NaN	NaN
4227	NaN	NaN
4228	NaN	NaN
4229	NaN	NaN
4230	NaN	NaN
4231	NaN	NaN
4232	NaN	NaN
4233	NaN	NaN
4234	NaN	NaN
4235	NaN	NaN
4236	NaN	NaN
4237	NaN	NaN

```
title   Zulu (1964)  Zus & Zo (2001)  [Rec] (2007)  eXistenZ (1999)  \
userId
1               NaN              NaN           NaN              NaN
2               NaN              NaN           NaN              NaN
3               NaN              NaN           NaN              NaN
4               NaN              NaN           NaN              NaN
5               NaN              NaN           NaN              NaN
6               NaN              NaN           NaN              NaN
7               NaN              NaN           NaN              NaN
8               NaN              NaN           NaN              4.0
9               NaN              NaN           NaN              NaN
10              NaN              NaN           NaN              NaN
11              NaN              NaN           NaN              NaN
12              NaN              NaN           NaN              NaN
13              NaN              NaN           NaN              NaN
14              NaN              NaN           NaN              NaN
16              NaN              NaN           NaN              NaN
17              NaN              NaN           NaN              NaN
18              NaN              NaN           NaN              NaN
19              NaN              NaN           NaN              NaN
22              NaN              NaN           NaN              NaN
23              NaN              NaN           NaN              NaN
24              NaN              NaN           NaN              NaN
26              NaN              NaN           NaN              NaN
27              NaN              NaN           NaN              NaN
28              NaN              NaN           NaN              NaN
29              NaN              NaN           NaN              NaN
30              NaN              NaN           NaN              NaN
33              NaN              NaN           NaN              NaN
34              NaN              NaN           NaN              NaN
35              NaN              NaN           NaN              NaN
36              NaN              NaN           NaN              NaN
...             ...              ...           ...              ...
4208            NaN              NaN           NaN              4.0
4209            NaN              NaN           NaN              NaN
4210            NaN              NaN           NaN              NaN
4211            NaN              NaN           NaN              NaN
4212            NaN              NaN           NaN              NaN
4213            NaN              NaN           NaN              NaN
4214            NaN              NaN           NaN              NaN
4215            NaN              NaN           NaN              NaN
4216            NaN              NaN           NaN              NaN
4217            NaN              NaN           NaN              NaN
4218            NaN              NaN           NaN              NaN
4219            NaN              NaN           NaN              NaN
4220            NaN              NaN           NaN              NaN
4221            NaN              NaN           NaN              NaN
4222            NaN              NaN           NaN              NaN
```

```
4223           NaN              NaN             NaN               NaN
4224           NaN              NaN             NaN               NaN
4225           NaN              NaN             NaN               NaN
4226           NaN              NaN             NaN               NaN
4227           NaN              NaN             NaN               NaN
4228           NaN              NaN             NaN               NaN
4229           NaN              NaN             NaN               2.0
4230           NaN              NaN             NaN               NaN
4231           NaN              NaN             NaN               NaN
4232           NaN              NaN             NaN               NaN
4233           NaN              NaN             NaN               3.5
4234           NaN              NaN             NaN               NaN
4235           NaN              NaN             NaN               NaN
4236           NaN              NaN             NaN               NaN
4237           NaN              NaN             NaN               NaN

title   loudQUIETloud: A Film About the Pixies (2006)  \
userId
1                                                NaN
2                                                NaN
3                                                NaN
4                                                NaN
5                                                NaN
6                                                NaN
7                                                NaN
8                                                NaN
9                                                NaN
10                                               NaN
11                                               NaN
12                                               NaN
13                                               NaN
14                                               NaN
16                                               NaN
17                                               NaN
18                                               NaN
19                                               NaN
22                                               NaN
23                                               NaN
24                                               NaN
26                                               NaN
27                                               NaN
28                                               NaN
29                                               NaN
30                                               NaN
33                                               NaN
34                                               NaN
35                                               NaN
36                                               NaN
```

```
...                                                 ...
4208                                                NaN
4209                                                NaN
4210                                                NaN
4211                                                NaN
4212                                                NaN
4213                                                NaN
4214                                                NaN
4215                                                NaN
4216                                                NaN
4217                                                NaN
4218                                                NaN
4219                                                NaN
4220                                                NaN
4221                                                NaN
4222                                                NaN
4223                                                NaN
4224                                                NaN
4225                                                NaN
4226                                                NaN
4227                                                NaN
4228                                                NaN
4229                                                NaN
4230                                                NaN
4231                                                NaN
4232                                                NaN
4233                                                NaN
4234                                                NaN
4235                                                NaN
4236                                                NaN
4237                                                NaN

title   xXx: State of the Union (2005)  Âge d'or, L' (1930)
userId
1                                  NaN                  NaN
2                                  NaN                  NaN
3                                  NaN                  NaN
4                                  NaN                  NaN
5                                  NaN                  NaN
6                                  NaN                  NaN
7                                  NaN                  NaN
8                                  NaN                  NaN
9                                  NaN                  NaN
10                                 NaN                  NaN
11                                 NaN                  NaN
12                                 NaN                  NaN
13                                 NaN                  NaN
14                                 NaN                  NaN
```

16	NaN	NaN
17	NaN	NaN
18	NaN	NaN
19	NaN	NaN
22	NaN	NaN
23	NaN	NaN
24	NaN	NaN
26	NaN	NaN
27	NaN	NaN
28	NaN	NaN
29	NaN	NaN
30	NaN	NaN
33	NaN	NaN
34	NaN	NaN
35	NaN	NaN
36	NaN	NaN
...	...	...
4208	NaN	NaN
4209	NaN	NaN
4210	NaN	NaN
4211	NaN	NaN
4212	NaN	NaN
4213	NaN	NaN
4214	NaN	NaN
4215	NaN	NaN
4216	NaN	NaN
4217	NaN	NaN
4218	NaN	NaN
4219	NaN	NaN
4220	NaN	NaN
4221	NaN	NaN
4222	NaN	NaN
4223	NaN	NaN
4224	NaN	NaN
4225	NaN	NaN
4226	NaN	NaN
4227	NaN	NaN
4228	NaN	NaN
4229	NaN	NaN
4230	NaN	NaN
4231	NaN	NaN
4232	NaN	NaN
4233	NaN	NaN
4234	NaN	NaN
4235	NaN	NaN
4236	NaN	NaN
4237	NaN	NaN

```
[4089 rows x 8897 columns]
```

In [120]:
```
#userid_movietitle_matrix.sort_values('num of ratings', ascending=False).head(10)
```

In [121]:
```
#Use Forrest Gump as Reference Movie
#Find any movies similar to Forrest Gump
```

In [122]:
```
gump = userid_movietitle_matrix['Forrest Gump (1994)']
```

In [123]:
```
gump.head()
```

Out[123]:
```
userId
1    5.0
2    NaN
3    NaN
4    NaN
5    NaN
Name: Forrest Gump (1994), dtype: float64
```

In [124]:
```
similartogump = userid_movietitle_matrix.corrwith(gump)
```

In [125]:
```
similartogump
```

Out[125]:
```
title
'Round Midnight (1986)                                                  -0.406181
'Til There Was You (1997)                                              -0.124712
'burbs, The (1989)                                                     -0.112154
'night Mother (1986)                                                   -0.186339
*batteries not included (1987)                                          0.584178
...All the Marbles (a.k.a. The California Dolls) (1981)                      NaN
...And God Created Woman (Et Dieu... créa la femme) (1956)                   NaN
...And God Spoke (1993)                                                      NaN
...And Justice for All (1979)                                           0.100536
1-900 (06) (1994)                                                            NaN
10 (1979)                                                              -0.139195
10 Items or Less (2006)                                                 0.427425
10 Rillington Place (1971)                                              0.471056
10 Things I Hate About You (1999)                                       0.001580
10 to Midnight (1983)                                                        NaN
10,000 B.C. (2008)                                                      0.074327
100 Girls (2000)                                                             NaN
1000 Eyes of Dr. Mabuse, The (Tausend Augen des Dr. Mabuse, Die) (1960)   1.000000
101 Dalmatians (1996)                                                   0.237558
101 Reykjavik (101 Reykjavík) (2000)                                    0.060193
102 Dalmatians (2000)                                                   0.545269
10th Victim, The (La Decima Vittima) (1965)                                  NaN
11'09"01 - September 11 (2002)                                               NaN
11:14 (2003)                                                            0.210042
12 Angry Men (1957)                                                    -0.197750
```

```
12 Monkeys (Twelve Monkeys) (1995)                                          0.079745
13 Ghosts (1960)                                                            0.192812
13 Going on 30 (2004)                                                      -0.096015
13 Rue Madeleine (1947)                                                          NaN
13 Tzameti (2005)                                                           0.970725
                                                                              ...
Zatoichi (Zatôichi) (2003)                                                  0.252510
Zazie dans le métro (1960)                                                       NaN
Zebrahead (1992)                                                                 NaN
Zed & Two Noughts, A (1985)                                                 0.118217
Zeitgeist: The Movie (2007)                                                 1.000000
Zelary (2003)                                                              -0.500000
Zelig (1983)                                                                0.453784
Zentropa (Europa) (1991)                                                    0.324443
Zero Effect (1998)                                                          0.099197
Zero Kelvin (Kjærlighetens kjøtere) (1995)                                       NaN
Zero for Conduct (Zéro de conduite) (1933)                                       NaN
Zeus and Roxanne (1997)                                                          NaN
Ziggy Stardust and the Spiders from Mars (1973)                            -0.188982
Zodiac (2007)                                                               0.138765
Zombie (a.k.a. Zombie 2: The Dead Are Among Us) (Zombi 2) (1979)                 NaN
Zombie Holocaust (a.k.a. Doctor Butcher M.D.) (Zombi Holocaust) (1980)           NaN
Zombie Lake (Le Lac des morts vivants) (1981)                                    NaN
Zombie Strippers! (2008)                                                         NaN
Zoolander (2001)                                                           -0.004058
Zoom (2006)                                                                 1.000000
Zoot Suit (1981)                                                                 NaN
Zorba the Greek (Alexis Zorbas) (1964)                                     -0.422577
Zorro, the Gay Blade (1981)                                                 0.000000
Zulu (1964)                                                                 0.195093
Zus & Zo (2001)                                                                  NaN
[Rec] (2007)                                                                     NaN
eXistenZ (1999)                                                             0.119672
loudQUIETloud: A Film About the Pixies (2006)                                    NaN
xXx: State of the Union (2005)                                              0.324199
Âge d'or, L' (1930)                                                              NaN
Length: 8897, dtype: float64
```

In [126]:
```python
#Cleaning up and save into new dataframe
corr_gump = pd.DataFrame(similartogump,columns=['Correlation'])
corr_gump.dropna(inplace=True)
```

In [127]:
```python
corr_gump.head()
```

Out[127]:

title	Correlation
'Round Midnight (1986)	-0.406181
'Til There Was You (1997)	-0.124712

```
'burbs, The (1989)                   -0.112154
'night Mother (1986)                 -0.186339
*batteries not included (1987)        0.584178
```

In [128]:
```
corr_gump.sort_values('Correlation',ascending=False).head(10)
```

Out[128]:
```
                                                    Correlation
title
Swarm, The (1978)                                           1.0
Two Brothers (2004)                                         1.0
Town & Country (2001)                                       1.0
Memphis Belle: A Story of a Flying Fortress, Th...          1.0
Memory of a Killer, The (De Zaak Alzheimer) (2003)          1.0
Me Without You (2001)                                       1.0
Train of Life (Train De Vie) (1998)                         1.0
Man on Wire (2008)                                          1.0
American Me (1992)                                          1.0
Little Vampire, The (2000)                                  1.0
```

In [130]:
```
corr_gump
```

Out[130]:
```
                                                    Correlation
title
'Round Midnight (1986)                                -0.406181
'Til There Was You (1997)                             -0.124712
'burbs, The (1989)                                    -0.112154
'night Mother (1986)                                  -0.186339
*batteries not included (1987)                         0.584178
...And Justice for All (1979)                          0.100536
10 (1979)                                             -0.139195
10 Items or Less (2006)                                0.427425
10 Rillington Place (1971)                             0.471056
10 Things I Hate About You (1999)                      0.001580
10,000 B.C. (2008)                                     0.074327
1000 Eyes of Dr. Mabuse, The (Tausend Augen des...     1.000000
101 Dalmatians (1996)                                  0.237558
101 Reykjavik (101 Reykjavík) (2000)                   0.060193
102 Dalmatians (2000)                                  0.545269
11:14 (2003)                                           0.210042
12 Angry Men (1957)                                   -0.197750
12 Monkeys (Twelve Monkeys) (1995)                     0.079745
13 Ghosts (1960)                                       0.192812
13 Going on 30 (2004)                                 -0.096015
13 Tzameti (2005)                                      0.970725
13th Warrior, The (1999)                               0.066572
1408 (2007)                                           -0.053720
1492: Conquest of Paradise (1992)                     -0.636364
15 Minutes (2001)                                      0.324396
16 Blocks (2006)                                       0.437313
```

```
1776 (1972)                                            0.018510
18 Again! (1988)                                      -0.387911
1941 (1979)                                            0.373002
1969 (1988)                                            0.489898
...                                                         ...
Young Guns II (1990)                                   0.251786
Young Lions, The (1958)                               -1.000000
Young Poisoner's Handbook, The (1995)                 -0.233858
Young Sherlock Holmes (1985)                           0.038832
Young and Innocent (1937)                             -0.276407
Youngblood (1986)                                     -0.230774
Your Friends and Neighbors (1998)                      0.209728
Yours, Mine and Ours (1968)                            1.000000
Yu-Gi-Oh! (2004)                                      -0.215166
Z (1969)                                              -0.175484
Zack and Miri Make a Porno (2008)                     -1.000000
Zapped! (1982)                                         0.596040
Zardoz (1974)                                          0.261360
Zathura (2005)                                         0.166667
Zatoichi (Zatôichi) (2003)                             0.252510
Zed & Two Noughts, A (1985)                            0.118217
Zeitgeist: The Movie (2007)                            1.000000
Zelary (2003)                                         -0.500000
Zelig (1983)                                           0.453784
Zentropa (Europa) (1991)                               0.324443
Zero Effect (1998)                                     0.099197
Ziggy Stardust and the Spiders from Mars (1973)       -0.188982
Zodiac (2007)                                          0.138765
Zoolander (2001)                                      -0.004058
Zoom (2006)                                            1.000000
Zorba the Greek (Alexis Zorbas) (1964)                -0.422577
Zorro, the Gay Blade (1981)                            0.000000
Zulu (1964)                                            0.195093
eXistenZ (1999)                                        0.119672
xXx: State of the Union (2005)                         0.324199

[6625 rows x 1 columns]
```

What the system does is use correlation method to compare to each movie item and select the higher scores to recommend movie to users based from ratings. Example 1000 Eyes of Dr. Mabuse, The (Tausend Augen des Dr. Mabuse, Die) (1960) will be recommended to users who have watched Forrest Gump

0.15 Using scikit Surprise package

```
In [133]: df5 = pd.read_csv('new.csv')
```

```
In [134]: df5.head()
```

```
Out[134]:    userId  movieId  rating  timestamp                          title  \
          0       1      122     5.0  838985046                Boomerang (1992)
          1       1      185     5.0  838983525                 Net, The (1995)
          2       1      292     5.0  838983421                 Outbreak (1995)
          3       1      316     5.0  838983392                 Stargate (1994)
          4       1      329     5.0  838983392  Star Trek: Generations (1994)

                                   genres
          0                  Comedy|Romance
          1           Action|Crime|Thriller
          2   Action|Drama|Sci-Fi|Thriller
          3         Action|Adventure|Sci-Fi
          4  Action|Adventure|Drama|Sci-Fi
```

```
In [135]: df5 = df5[:500000] #Due to laptop hardware limitation, segment only first 500000 row
```

```
In [136]: df5.drop('timestamp', axis=1, inplace=True)
          df5.drop('genres', axis=1, inplace=True)
          df5.drop('title', axis=1, inplace=True)
```

```
In [137]: df5.head()
```

```
Out[137]:    userId  movieId  rating
          0       1      122     5.0
          1       1      185     5.0
          2       1      292     5.0
          3       1      316     5.0
          4       1      329     5.0
```

```
In [138]: reader = Reader()
```

```
In [139]: data = Dataset.load_from_df(df5, reader)
```

```
In [140]: trainset, testset = train_test_split(data, test_size=0.20)
```

```
In [141]: algo = SVD() #Use singular value decomposition (SVD)
```

```
In [142]: algo.fit(trainset)
```

```
Out[142]: <surprise.prediction_algorithms.matrix_factorization.SVD at 0x2ac8882e358>
```

```
In [143]: predictions = algo.test(testset)
```

```
In [144]: predictions
```

```
Out[144]: [Prediction(uid=765, iid=357, r_ui=4.0, est=4.284782686887061, details={'was_impossil
           Prediction(uid=5, iid=780, r_ui=1.0, est=3.086532516915338, details={'was_impossible
           Prediction(uid=2237, iid=1981, r_ui=1.0, est=1.9110216642786226, details={'was_impos
           Prediction(uid=1880, iid=2026, r_ui=3.0, est=3.375961648455713, details={'was_impos
           Prediction(uid=2896, iid=2003, r_ui=5.0, est=4.203649982897146, details={'was_impos
```

```
Prediction(uid=2676, iid=924, r_ui=4.0, est=4.200842382005633, details={'was_impossi
Prediction(uid=2286, iid=112, r_ui=3.0, est=3.633592668343769, details={'was_impossi
Prediction(uid=1470, iid=610, r_ui=5.0, est=3.8767074310343737, details={'was_imposs
Prediction(uid=3200, iid=5060, r_ui=4.0, est=3.8147292737718086, details={'was_impos
Prediction(uid=1294, iid=543, r_ui=2.5, est=2.988190758205171, details={'was_impossi
Prediction(uid=173, iid=378, r_ui=3.0, est=3.407805493728103, details={'was_impossil
Prediction(uid=602, iid=2087, r_ui=3.0, est=3.4646880993811067, details={'was_imposs
Prediction(uid=3022, iid=6502, r_ui=4.5, est=4.356475714382373, details={'was_imposs
Prediction(uid=1096, iid=1485, r_ui=3.5, est=3.3614097612719926, details={'was_impos
Prediction(uid=1495, iid=2019, r_ui=5.0, est=4.875317829349654, details={'was_imposs
Prediction(uid=1887, iid=2470, r_ui=4.0, est=3.657484035144418, details={'was_imposs
Prediction(uid=469, iid=7086, r_ui=5.0, est=4.117999765956063, details={'was_impossi
Prediction(uid=513, iid=1188, r_ui=5.0, est=3.65649985995173, details={'was_impossil
Prediction(uid=3642, iid=2762, r_ui=4.5, est=4.491156314478907, details={'was_imposs
Prediction(uid=2204, iid=3897, r_ui=3.0, est=4.163676410928927, details={'was_imposs
Prediction(uid=1038, iid=316, r_ui=5.0, est=4.852359274248792, details={'was_impossi
Prediction(uid=3412, iid=4642, r_ui=1.0, est=3.7141744354445123, details={'was_impos
Prediction(uid=1578, iid=1610, r_ui=4.0, est=3.633800118752574, details={'was_imposs
Prediction(uid=2944, iid=2443, r_ui=3.0, est=3.6070561795993275, details={'was_impos
Prediction(uid=3022, iid=247, r_ui=5.0, est=4.611167337983919, details={'was_impossi
Prediction(uid=896, iid=231, r_ui=3.0, est=2.598819222734736, details={'was_impossil
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Prediction(uid=3119, iid=1747, r_ui=3.0, est=3.58857741851725, details={'was_impossi
Prediction(uid=4038, iid=11, r_ui=1.0, est=2.657614779412342, details={'was_impossil
Prediction(uid=2619, iid=2, r_ui=4.0, est=3.0672530675311953, details={'was_impossil
Prediction(uid=788, iid=1608, r_ui=3.5, est=4.030115102071293, details={'was_impossi
Prediction(uid=215, iid=22, r_ui=4.0, est=3.8264440855237276, details={'was_impossil
Prediction(uid=1517, iid=592, r_ui=4.0, est=3.1195479666017287, details={'was_imposs
Prediction(uid=662, iid=778, r_ui=5.0, est=4.338146405924915, details={'was_impossil
Prediction(uid=1445, iid=39886, r_ui=2.5, est=2.7273711450205753, details={'was_impo
Prediction(uid=2990, iid=593, r_ui=4.0, est=3.888436057335833, details={'was_impossi
Prediction(uid=3036, iid=111, r_ui=5.0, est=4.2855717446734465, details={'was_imposs
Prediction(uid=2291, iid=2712, r_ui=4.0, est=2.406617512433116, details={'was_imposs
Prediction(uid=2162, iid=778, r_ui=4.5, est=3.5443925054678402, details={'was_imposs
Prediction(uid=2541, iid=248, r_ui=5.0, est=3.025003409043801, details={'was_impossi
Prediction(uid=704, iid=3578, r_ui=5.0, est=4.724659566835102, details={'was_impossi
Prediction(uid=1617, iid=11, r_ui=3.0, est=3.2810528308211824, details={'was_imposs
Prediction(uid=1527, iid=8340, r_ui=4.5, est=4.06109193496852, details={'was_impossi
Prediction(uid=444, iid=3528, r_ui=4.0, est=3.7840424994985518, details={'was_impos
Prediction(uid=3991, iid=3173, r_ui=2.5, est=2.488234369606331, details={'was_imposs
Prediction(uid=660, iid=6365, r_ui=4.5, est=3.022046872246044, details={'was_impossi
Prediction(uid=3061, iid=2011, r_ui=3.0, est=3.502232308497254, details={'was_imposs
Prediction(uid=2513, iid=48780, r_ui=4.0, est=4.439242788831393, details={'was_impos
Prediction(uid=3767, iid=151, r_ui=2.0, est=3.309514918359206, details={'was_impossi
...]
```

```
In [145]: accuracy.rmse(predictions)
```

```
RMSE: 0.8566
```

```
Out[145]: 0.8566228080925143
```

The RMSE value is 0.8566 which is the best of all, hence this model is selected

0.16 Testing the algorithm on validation set

```
In [146]: df6 = pd.read_csv('validation.csv')
```

```
In [147]: df6.shape

Out[147]: (999999, 7)

In [148]: df6.head()

Out[148]:    Unnamed: 0  userId  movieId  rating  timestamp                    title  \
          0           1       1      231     5.0  838983392    Dumb & Dumber (1994)
          1           2       1      480     5.0  838983653   Jurassic Park (1993)
          2           3       1      586     5.0  838984068      Home Alone (1990)
          3           4       2      151     5.0  868246450         Rob Roy (1995)
          4           5       2      858     2.0  868245645  Godfather, The (1972)

                                   genres
          0                        Comedy
          1  Action|Adventure|Sci-Fi|Thriller
          2               Children|Comedy
          3        Action|Drama|Romance|War
          4                   Crime|Drama

In [149]: df6 = df6[['userId','movieId','rating']]

In [150]: df6.head()

Out[150]:    userId  movieId  rating
          0       1      231     5.0
          1       1      480     5.0
          2       1      586     5.0
          3       2      151     3.0
          4       2      858     2.0

In [151]: reader = Reader()

In [152]: data1 = Dataset.load_from_df(df6, reader)

In [153]: trainset, testset = train_test_split(data1, test_size=0.20)

In [154]: algo = SVD()

In [155]: algo.fit(trainset)

Out[155]: <surprise.prediction_algorithms.matrix_factorization.SVD at 0x2acd6f88b70>

In [156]: predictions1 = algo.test(testset)

In [157]: accuracy.rmse(predictions1)

RMSE: 0.9041


Out[157]: 0.904119357934113
```

The RMSE value is 0.9041.

0.17 Results

Simple Linear Regression:1.058 Multiple Linear Regression:1.060 Artificial Neural Network:1.046 Simple Recommender System:Not available Scikit Surprise: 0.9041

0.18 Conclusions

Recommender systems are complex and varied. It requires deep understanding of mathematics. Since machine learning and deep learning are continously improving, we expect new algorithms and new Python libraries that are written to make them perform more better and efficient.