EDA-project1-Edouard Toutounji

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1 EDA - project 1

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Content: - I Loading the libraries and the 3 files into their dataframes - II Understanding the 3 dataframes using info() and describe() methods - III Univariate plots for the attributes : Age, Gender, Occupation , Release Date, Rating - IV Genres popularity over the years - V Top 25 movies with more than 100 ratings - VI Gender Comparison

1.1 I- Loading the libraries and the 3 files into their dataframes

[2]:
```
# Loading the necesseray libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# All the files and the jupyter notebook are on my desktop
```

IMPORTANT: The UserID and MovieID columns syntaxes were UNIFIED

[3]:
```
# Importing the 'u.data' file into dataframe 'ratings'

ratings  = pd.read_csv('u.data', sep = '\t', names= "UserId  MovieId  Rating ␣
 ↪Timestamp".split())
ratings.head()
```

[3]:

	UserId	MovieId	Rating	Timestamp
0	196	242	3	881250949
1	186	302	3	891717742
2	22	377	1	878887116
3	244	51	2	880606923
4	166	346	1	886397596

[4]:
```
# Importing the 'u.item' file into dataframe 'movies'

col_n = ['MovieId' , 'Movie title' , 'Release date' , 'Video release␣
 ↪date',"IMDb URL" ,
```

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

movies = pd.read_csv('u.item',sep = '|',encoding='latin-1',names=col_n)
movies.head()
```

[4]:

```
   MovieId        Movie title Release date  Video release date  \
0        1   Toy Story (1995)  01-Jan-1995                 NaN
1        2   GoldenEye (1995)  01-Jan-1995                 NaN
2        3  Four Rooms (1995)  01-Jan-1995                 NaN
3        4  Get Shorty (1995)  01-Jan-1995                 NaN
4        5     Copycat (1995)  01-Jan-1995                 NaN

                                            IMDb URL  Unknown  Action  \
0  http://us.imdb.com/M/title-exact?Toy%20Story%2…        0       0
1  http://us.imdb.com/M/title-exact?GoldenEye%20(…        0       1
2  http://us.imdb.com/M/title-exact?Four%20Rooms%…        0       0
3  http://us.imdb.com/M/title-exact?Get%20Shorty%…        0       1
4  http://us.imdb.com/M/title-exact?Copycat%20(1995)        0       0

   Adventure  Animation  Children's  …  Fantasy  Film-Noir  Horror  Musical  \
0          0          1           1  …        0          0       0        0
1          1          0           0  …        0          0       0        0
2          0          0           0  …        0          0       0        0
3          0          0           0  …        0          0       0        0
4          0          0           0  …        0          0       0        0

   Mystery  Romance  Sci-Fi  Thriller  War  Western
0        0        0       0         0    0        0
1        0        0       0         1    0        0
2        0        0       0         1    0        0
3        0        0       0         0    0        0
4        0        0       0         1    0        0

[5 rows x 24 columns]
```

[5]:

```
# Importing the 'u.user' file into dataframe 'users'

users  = pd.read_csv('u.user', sep = '|', names= "UserId  Age Gender Occupation␣
↪ Zipcode".split())
users.head()
```

[5]:

```
   UserId  Age Gender  Occupation Zipcode
0       1   24      M  technician   85711
```

```
1         2   53       F        other   94043
2         3   23       M       writer   32067
3         4   24       M   technician   43537
4         5   33       F        other   15213
```

1.2 II - Understanding the 3 dataframes

2.1 Undestanding the 'users' dataframe

[6]:
```python
users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 943 entries, 0 to 942
Data columns (total 5 columns):
UserId        943 non-null int64
Age           943 non-null int64
Gender        943 non-null object
Occupation    943 non-null object
Zipcode       943 non-null object
dtypes: int64(2), object(3)
memory usage: 37.0+ KB
```

[7]:
```python
users.describe()
```

[7]:

	UserId	Age
count	943.000000	943.000000
mean	472.000000	34.051962
std	272.364951	12.192740
min	1.000000	7.000000
25%	236.500000	25.000000
50%	472.000000	31.000000
75%	707.500000	43.000000
max	943.000000	73.000000

2.2 Undestanding the 'movies' dataframe

[8]:
```python
# Aside two columns ['Release date', 'ImDb URL'] , there are no missing values.
# The column ['Video release date'] is just empty .

movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1682 entries, 0 to 1681
Data columns (total 24 columns):
MovieId                 1682 non-null int64
Movie title             1682 non-null object
Release date            1681 non-null object
Video release date      0 non-null float64
IMDb URL                1679 non-null object
```

```
Unknown               1682 non-null int64
Action                1682 non-null int64
Adventure             1682 non-null int64
Animation             1682 non-null int64
Children's            1682 non-null int64
Comedy                1682 non-null int64
Crime                 1682 non-null int64
Documentary           1682 non-null int64
Drama                 1682 non-null int64
Fantasy               1682 non-null int64
Film-Noir             1682 non-null int64
Horror                1682 non-null int64
Musical               1682 non-null int64
Mystery               1682 non-null int64
Romance               1682 non-null int64
Sci-Fi                1682 non-null int64
Thriller              1682 non-null int64
War                   1682 non-null int64
Western               1682 non-null int64
dtypes: float64(1), int64(20), object(3)
memory usage: 315.5+ KB
```

[9]:
```python
movies['Release date']
```

[9]:
```
0        01-Jan-1995
1        01-Jan-1995
2        01-Jan-1995
3        01-Jan-1995
4        01-Jan-1995
            …
1677     06-Feb-1998
1678     06-Feb-1998
1679     01-Jan-1998
1680     01-Jan-1994
1681     08-Mar-1996
Name: Release date, Length: 1682, dtype: object
```

2.3 Undestanding the 'ratings' dataframe

[10]:
```python
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 4 columns):
UserId       100000 non-null int64
MovieId      100000 non-null int64
Rating       100000 non-null int64
Timestamp    100000 non-null int64
dtypes: int64(4)
```

```
memory usage: 3.1 MB
```

[11]:
```
ratings.describe()
```

[11]:

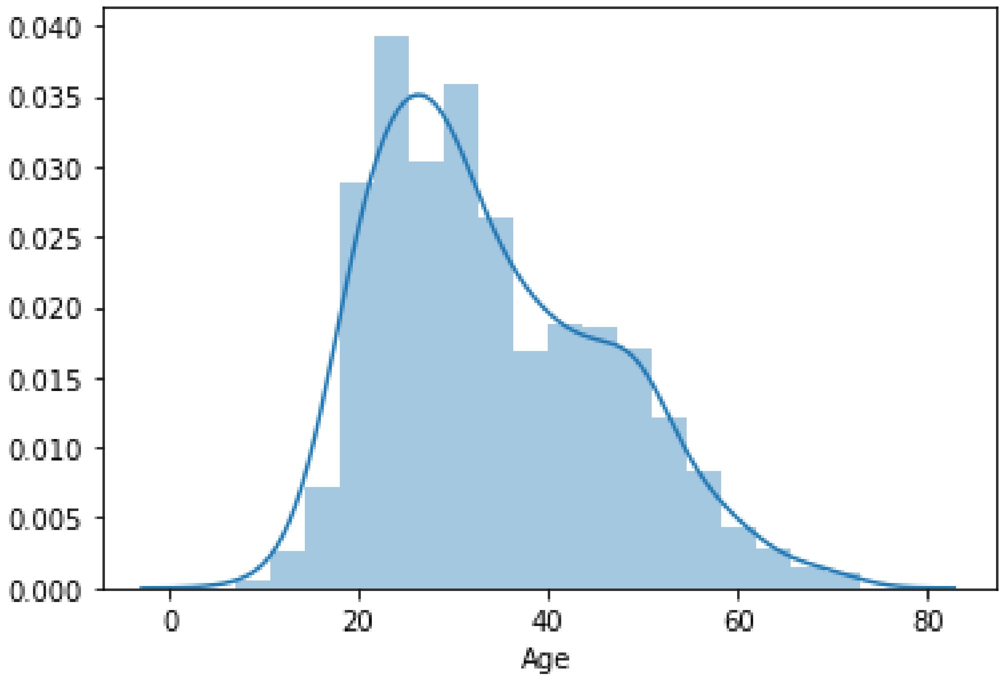
	UserId	MovieId	Rating	Timestamp
count	100000.00000	100000.000000	100000.000000	1.000000e+05
mean	462.48475	425.530130	3.529860	8.835289e+08
std	266.61442	330.798356	1.125674	5.343856e+06
min	1.00000	1.000000	1.000000	8.747247e+08
25%	254.00000	175.000000	3.000000	8.794487e+08
50%	447.00000	322.000000	4.000000	8.828269e+08
75%	682.00000	631.000000	4.000000	8.882600e+08
max	943.00000	1682.000000	5.000000	8.932866e+08

1.3 III - Univariate plots for the attributes

- 'Age'
- 'Gender'
- 'Occupation'
- 'Release date'
- 'Rating'

3.1 Age Distribution

[12]:
```
sns.distplot(users['Age'])
plt.show()
users['Age'].mean()
```



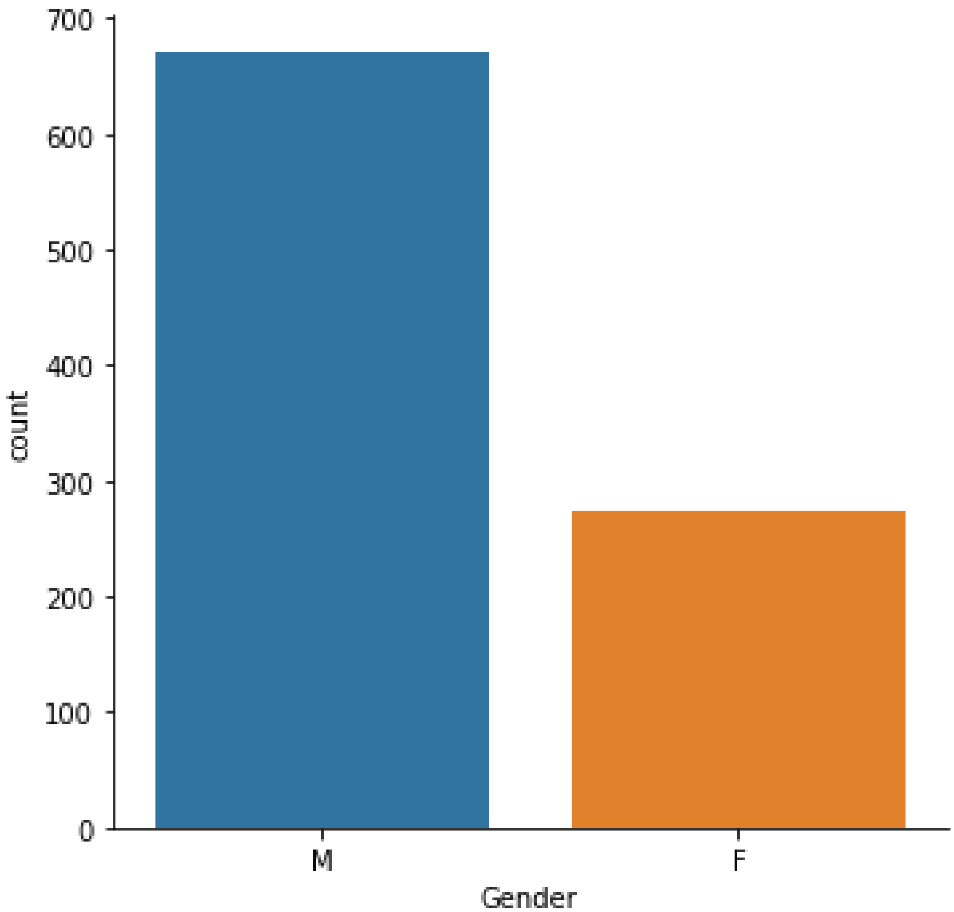
[12]: 34.05196182396607

3.2 Gender Distribution

[13]:
```
users['Gender'].value_counts()
```

[13]:
```
M    670
F    273
Name: Gender, dtype: int64
```

[14]:
```
sns.catplot(x="Gender", kind="count", data=users)
plt.show()
```



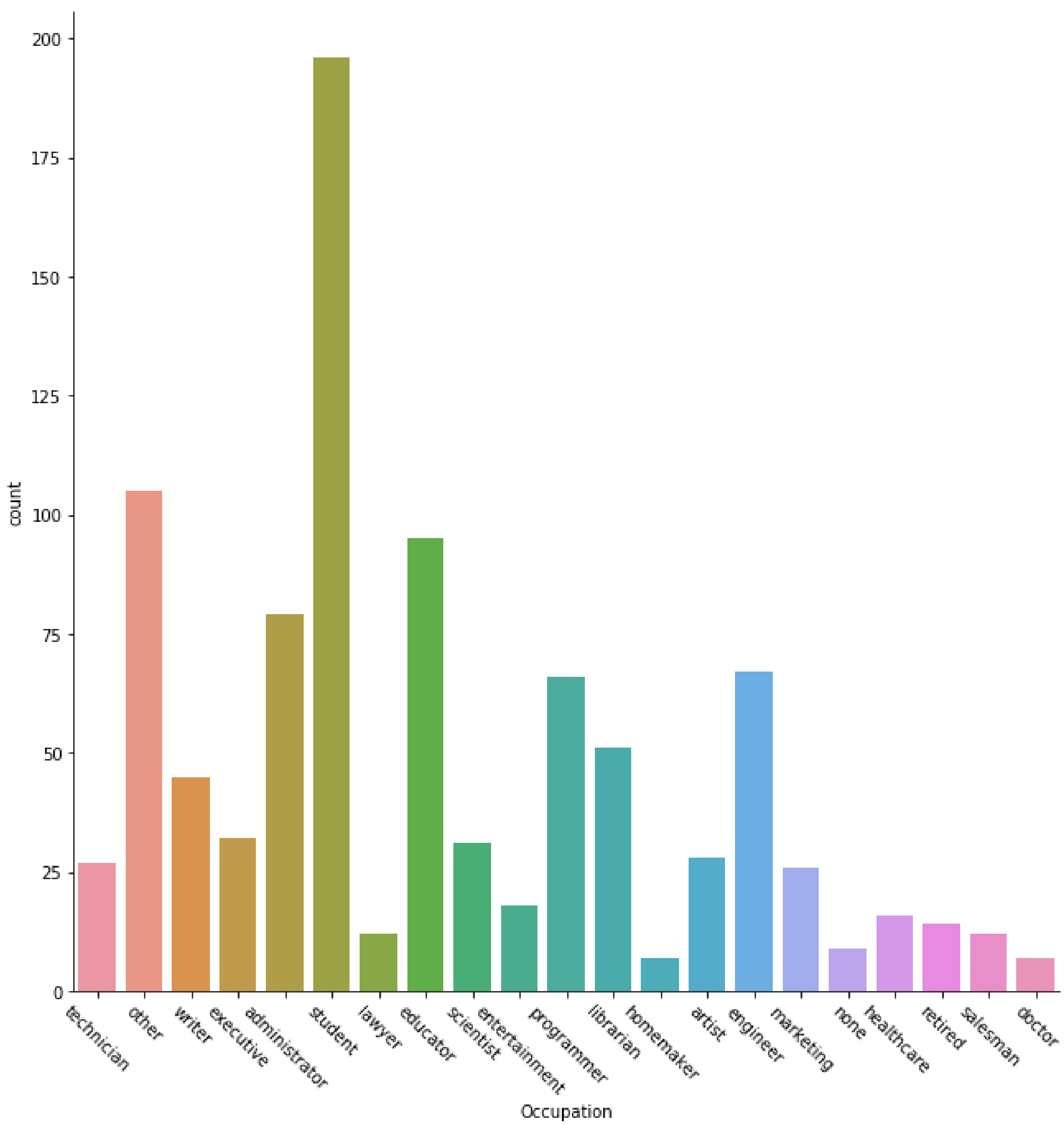
3.3 Occupation Distribution

[15]:
```
users['Occupation'].value_counts()
```

[15]:
```
student          196
other            105
educator          95
administrator     79
engineer          67
programmer        66
librarian         51
writer            45
executive         32
scientist         31
artist            28
technician        27
marketing         26
entertainment     18
```

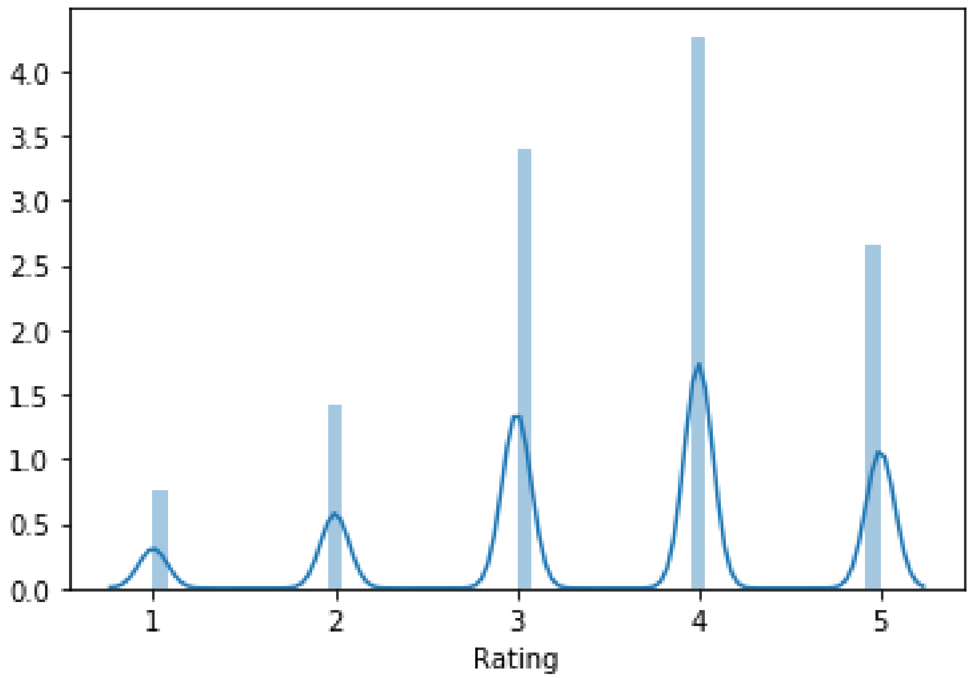
```
healthcare        16
retired           14
lawyer            12
salesman          12
none               9
homemaker          7
doctor             7
Name: Occupation, dtype: int64
```

[21]:
```
sns.catplot(x="Occupation", kind="count", data=users, height=9, aspect=1)
plt.xticks(rotation=-45)
plt.show()
```



3.4 Rating Dstribution

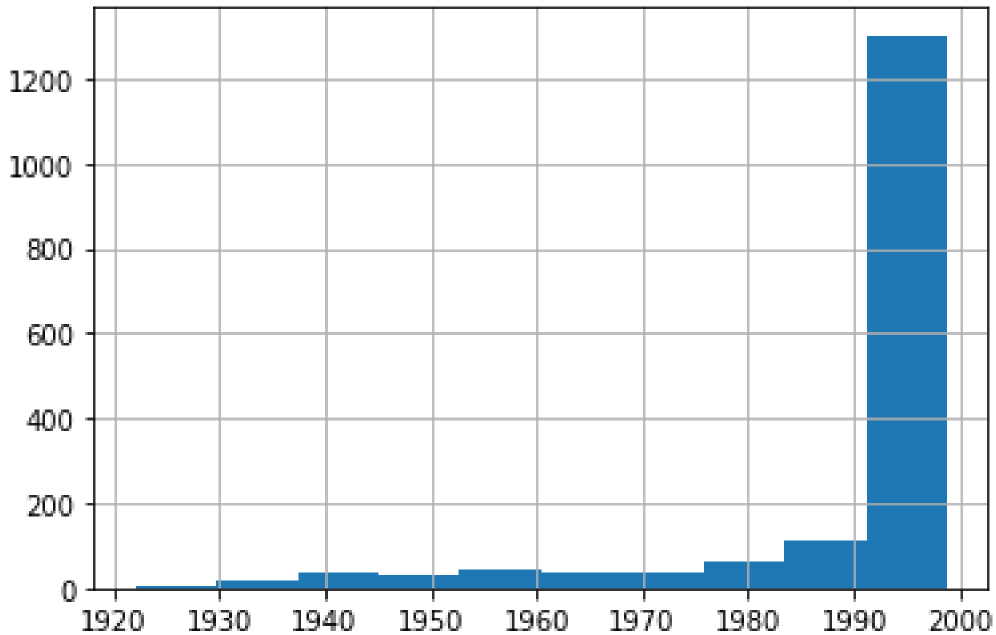
[17]:
```
sns.distplot(ratings["Rating"])
plt.show()
ratings["Rating"].mean()
```



[17]: 3.52986

3.5 Release Date Dstribution

[192]:
```
pd.to_datetime(movies['Release date']).sort_values().hist()
plt.show()
```



1.4 IV - Genres popularity over the years

[93]:
```
# merging the dataframes 'movies' and ' ratings'
DF= pd.merge(movies,ratings,on='MovieId')


# tranform the 'Release date' column to a datetime format so I can reorder it
DF['Date'] = pd.to_datetime(DF['Release date'])
Time_sorted_DF = DF.sort_values(by='Date')
```

[194]:
```
# checking 'Date' column was added at the end
Time_sorted_DF.head(2)
```

[194]:
```
       MovieId                                        Movie title  \
77974      675  Nosferatu (Nosferatu, eine Symphonie des Graue…
77947      675  Nosferatu (Nosferatu, eine Symphonie des Graue…

      Release date  Video release date  \
77974  01-Jan-1922                 NaN
77947  01-Jan-1922                 NaN

                                                IMDb URL  Unknown  Action  \
```

```
77974  http://us.imdb.com/M/title-exact?Nosferatu,%20…        0       0
77947  http://us.imdb.com/M/title-exact?Nosferatu,%20…        0       0

       Adventure  Animation  Children's  …  Mystery  Romance  Sci-Fi  \
77974          0          0           0  …        0        0       0
77947          0          0           0  …        0        0       0

       Thriller  War  Western  UserId  Rating  Timestamp       Date
77974         0    0        0     846       2  883949379 1922-01-01
77947         0    0        0      21       5  874951897 1922-01-01

[2 rows x 28 columns]
```

1.5 Creating time aranged count Series per Genre, so we can plot them later on in one graph

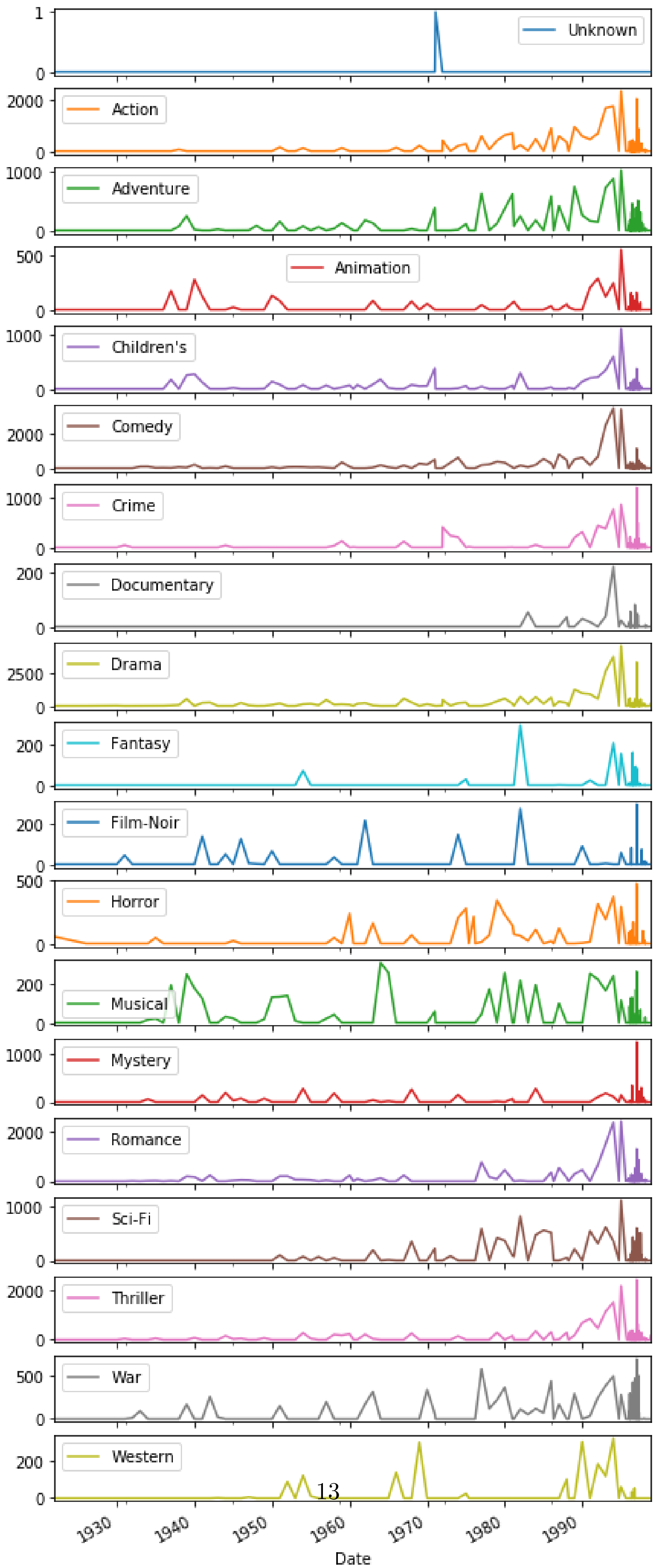
[96]:
```python
Time_sorted_DF.columns
```

[96]:
```
Index(['MovieId', 'Movie title', 'Release date', 'Video release date',
       'IMDb URL', 'Unknown', 'Action', 'Adventure', 'Animation', 'Children's',
       'Comedy', 'Crime', 'Documentary', 'Drama', 'Fantasy', 'Film-Noir',
       'Horror', 'Musical', 'Mystery', 'Romance', 'Sci-Fi', 'Thriller', 'War',
       'Western', 'UserId', 'Rating', 'Timestamp', 'Date'],
      dtype='object')
```

[173]:
```python
# Creating list per genre counts of released movies  over time

Unknown_Time     = Time_sorted_DF.groupby('Date')['Unknown'].sum()
Action_Time      = Time_sorted_DF.groupby('Date')['Action'].sum()
Adventure_Time   = Time_sorted_DF.groupby('Date')['Adventure'].sum()
Animation_Time   = Time_sorted_DF.groupby('Date')['Animation'].sum()
Children_Time    = Time_sorted_DF.groupby('Date')["Children's"].sum()
Comedy_Time      = Time_sorted_DF.groupby('Date')['Comedy'].sum()
Crime_Time       = Time_sorted_DF.groupby('Date')['Crime'].sum()
Documentary_Time = Time_sorted_DF.groupby('Date')['Documentary'].sum()
Drama_Time       = Time_sorted_DF.groupby('Date')['Drama'].sum()
Fantasy_Time     = Time_sorted_DF.groupby('Date')['Fantasy'].sum()
FilmNoir_Time    = Time_sorted_DF.groupby('Date')['Film-Noir'].sum()
Horror_Time      = Time_sorted_DF.groupby('Date')['Horror'].sum()
Musical_Time     = Time_sorted_DF.groupby('Date')['Musical'].sum()
Mystery_Time     = Time_sorted_DF.groupby('Date')['Mystery'].sum()
Romance_Time     = Time_sorted_DF.groupby('Date')['Romance'].sum()
SciFi_Time       = Time_sorted_DF.groupby('Date')['Sci-Fi'].sum()
Thriller_Time    = Time_sorted_DF.groupby('Date')['Thriller'].sum()
War_Time         = Time_sorted_DF.groupby('Date')['War'].sum()
Western_Time     = Time_sorted_DF.groupby('Date')['Western'].sum()
```

[193]:

```
DF_polpularity_Time = pd.concat(
                      [Unknown_Time,   Action_Time,      Adventure_Time,
                       Animation_Time, Children_Time,    Comedy_Time,
                       Crime_Time,     Documentary_Time, Drama_Time,
                       Fantasy_Time,   FilmNoir_Time,    Horror_Time,
                       Musical_Time,   Mystery_Time,     Romance_Time,
                       SciFi_Time,     Thriller_Time,    War_Time,   
 ↪Western_Time  ], axis=1)



DF_polpularity_Time.plot(subplots=True, figsize=(7,20))
plt.show()
```



Unknown
Action
Adventure
Animation
Children's
Comedy
Crime
Documentary
Drama
Fantasy
Film-Noir
Horror
Musical
Mystery
Romance
Sci-Fi
Thriller
War
Western
1930
1940
1950
1960
1970
1980
1990
Date

2 V - Top 25 movies with more than 100 ratings

[247]:
```
DF_Ratings= Time_sorted_DF.groupby('Movie title').size()
```

[248]:
```
DF_Ratings[DF_Ratings>100].sort_values(ascending=False)[:25]
```

[248]:
```
Movie title
Star Wars (1977)                                 583
Contact (1997)                                   509
Fargo (1996)                                     508
Return of the Jedi (1983)                        507
Liar Liar (1997)                                 485
English Patient, The (1996)                      481
Scream (1996)                                    478
Toy Story (1995)                                 452
Air Force One (1997)                             431
Independence Day (ID4) (1996)                    429
Raiders of the Lost Ark (1981)                   420
Godfather, The (1972)                            413
Pulp Fiction (1994)                              394
Twelve Monkeys (1995)                            392
Silence of the Lambs, The (1991)                 390
Jerry Maguire (1996)                             384
Chasing Amy (1997)                               379
Rock, The (1996)                                 378
Empire Strikes Back, The (1980)                  367
Star Trek: First Contact (1996)                  365
Back to the Future (1985)                        350
Titanic (1997)                                   350
Mission: Impossible (1996)                       344
Fugitive, The (1993)                             336
Indiana Jones and the Last Crusade (1989)        331
dtype: int64
```

3 VI - Gender Comparison

[249]:
```
# Merge all three original dataframes

DF1= pd.merge(movies,ratings,on='MovieId')
DF2= pd.merge(DF1,users, on = 'UserId')
```

[250]:
```
# Females gave higher Rating for Drama on average
```

```
pivoted = DF2.pivot_table(index=["Drama"],
                          columns=['Gender'],
                          values='Rating',
                          fill_value=0)
pivoted.head()
```

[250]:

```
Gender         F         M
Drama
0       3.433818  3.422542
1       3.662246  3.696957
```

[243]:

```
# Females gave higher Rating for Romance on average

pivoted = DF2.pivot_table(index=["Romance"],
                          columns=['Gender'],
                          values='Rating',
                          fill_value=0)
pivoted.head()
```

[243]:

```
Gender          F         M
Romance
0        3.494920  3.511845
1        3.655685  3.607072
```

[245]:

```
# Males gave higher Rating for Sci-Fi on average

pivoted = DF2.pivot_table(index=["Sci-Fi"],
                          columns=['Gender'],
                          values='Rating',
                          fill_value=0)
pivoted.head()
```

[245]:

```
Gender         F         M
Sci-Fi
0       3.535329  3.521766
1       3.497908  3.577072
```

NOTE : We did not learn about pivot of tables - the above 3 snippets were from websites that did similar analysis and I tried to adapt it.

I hope subsequent projects are better guided with smaller chuncked steps to guide us through mastery. Thanks.

[ ]: