

Project 1

March 27, 2024

1 Project: Investigate a Dataset (TMD 5000 Movie Dataset)

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Introduction

```
[1]: import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
#import seaborn as sns
pd.options.mode.chained_assignment = None # default='warn'

%matplotlib inline
```

Data Wrangling

1.1.1 General Properties

```
[2]: # loading data ...
df = pd.read_csv('tmdb-movies.csv')
```

```
[3]: # checking info for df ...
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                    10866 non-null  int64
1   imdb_id              10856 non-null  object
2   popularity            10866 non-null  float64
```

```

3  budget                10866 non-null  int64
4  revenue               10866 non-null  int64
5  original_title        10866 non-null  object
6  cast                  10790 non-null  object
7  homepage              2936 non-null   object
8  director              10822 non-null  object
9  tagline                8042 non-null  object
10 keywords              9373 non-null  object
11 overview              10862 non-null  object
12 runtime               10866 non-null  int64
13 genres                10843 non-null  object
14 production_companies  9836 non-null  object
15 release_date          10866 non-null  object
16 vote_count            10866 non-null  int64
17 vote_average          10866 non-null  float64
18 release_year          10866 non-null  int64
19 budget_adj            10866 non-null  float64
20 revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB

```

```

[4]: # viewing the data ...
df

```

```

[4]:
   id  imdb_id  popularity  budget  revenue \
0  135397  tt0369610   32.985763  150000000  1513528810
1    76341  tt1392190   28.419936  150000000   378436354
2   262500  tt2908446   13.112507  110000000   295238201
3   140607  tt2488496   11.173104  200000000  2068178225
4   168259  tt2820852    9.335014  190000000  1506249360
...
10861    21  tt0060371    0.080598         0         0
10862   20379  tt0060472    0.065543         0         0
10863   39768  tt0060161    0.065141         0         0
10864   21449  tt0061177    0.064317         0         0
10865   22293  tt0060666    0.035919    19000         0

   original_title \
0      Jurassic World
1    Mad Max: Fury Road
2      Insurgent
3  Star Wars: The Force Awakens
4      Furious 7
...
10861    The Endless Summer
10862      Grand Prix
10863  Beregis Avtomobilya

```

10864 What's Up, Tiger Lily?
 10865 Manos: The Hands of Fate

cast \

0	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi...
1	Tom Hardy Charlize Theron Hugh Keays-Byrne Nic...
2	Shailene Woodley Theo James Kate Winslet Ansel...
3	Harrison Ford Mark Hamill Carrie Fisher Adam D...
4	Vin Diesel Paul Walker Jason Statham Michelle ...
...	...
10861	Michael Hynson Robert August Lord 'Tally Ho' B...
10862	James Garner Eva Marie Saint Yves Montand Tosh...
10863	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z...
10864	Tatsuya Mihashi Akiko Wakabayashi Mie Hama Joh...
10865	Harold P. Warren Tom Neyman John Reynolds Dian...

	homepage	director \
0	http://www.jurassicworld.com/	Colin Trevorrow
1	http://www.madmaxmovie.com/	George Miller
2	http://www.thedivergentseries.movie/#insurgent	Robert Schwentke
3	http://www.starwars.com/films/star-wars-episod...	J.J. Abrams
4	http://www.furious7.com/	James Wan
...
10861	NaN	Bruce Brown
10862	NaN	John Frankenheimer
10863	NaN	Eldar Ryazanov
10864	NaN	Woody Allen
10865	NaN	Harold P. Warren

tagline ... \

0	The park is open. ...
1	What a Lovely Day. ...
2	One Choice Can Destroy You ...
3	Every generation has a story. ...
4	Vengeance Hits Home ...
...
10861	NaN ...
10862	Cinerama sweeps YOU into a drama of speed and
10863	NaN ...
10864	WOODY ALLEN STRIKES BACK! ...
10865	It's Shocking! It's Beyond Your Imagination! ...

	overview runtime \
0	Twenty-two years after the events of Jurassic ... 124
1	An apocalyptic story set in the furthest reach... 120
2	Beatrice Prior must confront her inner demons ... 119
3	Thirty years after defeating the Galactic Empi... 136

4	Deckard Shaw seeks revenge against Dominic Tor...	137
...
10861	The Endless Summer, by Bruce Brown, is one of ...	95
10862	Grand Prix driver Pete Aron is fired by his te...	176
10863	An insurance agent who moonlights as a carthie...	94
10864	In comic Woody Allen's film debut, he took the...	80
10865	A family gets lost on the road and stumbles up...	74

	genres \
0	Action Adventure Science Fiction Thriller
1	Action Adventure Science Fiction Thriller
2	Adventure Science Fiction Thriller
3	Action Adventure Science Fiction Fantasy
4	Action Crime Thriller
...	...
10861	Documentary
10862	Action Adventure Drama
10863	Mystery Comedy
10864	Action Comedy
10865	Horror

	production_companies	release_date \
0	Universal Studios Amblin Entertainment Legenda...	6/9/15
1	Village Roadshow Pictures Kennedy Miller Produ...	5/13/15
2	Summit Entertainment Mandeville Films Red Wago...	3/18/15
3	Lucasfilm Truenorth Productions Bad Robot	12/15/15
4	Universal Pictures Original Film Media Rights ...	4/1/15
...
10861	Bruce Brown Films	6/15/66
10862	Cherokee Productions Joel Productions Douglas ...	12/21/66
10863	Mosfilm	1/1/66
10864	Benedict Pictures Corp.	11/2/66
10865	Norm-Iris	11/15/66

	vote_count	vote_average	release_year	budget_adj	revenue_adj
0	5562	6.5	2015	1.379999e+08	1.392446e+09
1	6185	7.1	2015	1.379999e+08	3.481613e+08
2	2480	6.3	2015	1.012000e+08	2.716190e+08
3	5292	7.5	2015	1.839999e+08	1.902723e+09
4	2947	7.3	2015	1.747999e+08	1.385749e+09
...
10861	11	7.4	1966	0.000000e+00	0.000000e+00
10862	20	5.7	1966	0.000000e+00	0.000000e+00
10863	11	6.5	1966	0.000000e+00	0.000000e+00
10864	22	5.4	1966	0.000000e+00	0.000000e+00
10865	15	1.5	1966	1.276423e+05	0.000000e+00

[10866 rows x 21 columns]

Now that we have our data, we want to check for NaN values and clean our data ...

```
[5]: # using .isnull() then .sum() to figure out how many NaN values each column
      ↪ contains ...
```

```
df.isnull().sum()
```

```
[5]: id                0
     imdb_id          10
     popularity        0
     budget            0
     revenue           0
     original_title    0
     cast              76
     homepage         7930
     director          44
     tagline          2824
     keywords         1493
     overview          4
     runtime           0
     genres            23
     production_companies 1030
     release_date      0
     vote_count        0
     vote_average      0
     release_year      0
     budget_adj        0
     revenue_adj       0
     dtype: int64
```

We now see:

- imdb_id has 10.
- cast has 76.
- homepage has 7930.
- director has 44.
- tagline has 2824.
- keywords has 1493.
- overview has 4.
- genres has 23.
- production_companies has 1030.

1.1.2 We now ask questions about the data and from there we determine which NaN values to get rid of:

- Which genre was the most common from year to year?
- Does runtime affect the movie's revenues?

1.1.3 Now we choose which NaN values to drop in accordance with our questions:

- Looking at `imdb_id`, we notice that it is just the ids for the movies, which doesn't affect our analysis. Hence, we leave its NaN values.
- Looking at `cast`, it doesn't have an effect either. Like `imdb_id`, we leave its NaN values.
- Looking at `homepage`, it lists the homepages of the movies. We leave its NaN values.
- Looking at `director`, it lists the directors (obviously). We leave its NaN values.
- Looking at `tagline`, it lists the taglines (catchphrases), which aren't important to our analysis. We leave its NaN values.
- Looking at `keywords`, it lists key search words, again, not important to our analysis. We leave its NaN values.
- Looking at `overview`, it lists the summary and main theme of the movie. We leave its NaN values.
- Looking at `genres`, it lists the genres corresponding to the movies, we need those for our questions, so we drop its NaN values.
- Looking at `production_companies`, it lists the companies involved in the production of the movie. We leave its NaN values.

```
[6]: # dropping the rows for 'genre'
df.dropna(subset=['genres'], inplace = True)
# resetting the indices ...
df.reset_index(inplace = True, drop = True)
df
```

```
[6]:
```

	id	imdb_id	popularity	budget	revenue	\
0	135397	tt0369610	32.985763	150000000	1513528810	
1	76341	tt1392190	28.419936	150000000	378436354	
2	262500	tt2908446	13.112507	110000000	295238201	
3	140607	tt2488496	11.173104	200000000	2068178225	
4	168259	tt2820852	9.335014	190000000	1506249360	
...	
10838	21	tt0060371	0.080598	0	0	
10839	20379	tt0060472	0.065543	0	0	
10840	39768	tt0060161	0.065141	0	0	
10841	21449	tt0061177	0.064317	0	0	
10842	22293	tt0060666	0.035919	19000	0	

	original_title	\
0	Jurassic World	
1	Mad Max: Fury Road	
2	Insurgent	
3	Star Wars: The Force Awakens	
4	Furious 7	
...	...	
10838	The Endless Summer	
10839	Grand Prix	
10840	Beregis Avtomobilya	
10841	What's Up, Tiger Lily?	

10842 Manos: The Hands of Fate

```

                                cast \
0      Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1      Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2      Shailene Woodley|Theo James|Kate Winslet|Ansel...
3      Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4      Vin Diesel|Paul Walker|Jason Statham|Michelle ...
...
10838  Michael Hynson|Robert August|Lord 'Tally Ho' B...
10839  James Garner|Eva Marie Saint|Yves Montand|Tosh...
10840  Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...
10841  Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...
10842  Harold P. Warren|Tom Neyman|John Reynolds|Dian...

```

```

                                homepage                    director \
0      http://www.jurassicworld.com/           Colin Trevorrow
1      http://www.madmaxmovie.com/            George Miller
2      http://www.thedivergentseries.movie/#insurgent   Robert Schwentke
3      http://www.starwars.com/films/star-wars-episod...   J.J. Abrams
4      http://www.furious7.com/               James Wan
...
10838  NaN                    Bruce Brown
10839  NaN                    John Frankenheimer
10840  NaN                    Eldar Ryazanov
10841  NaN                    Woody Allen
10842  NaN                    Harold P. Warren

```

```

                                tagline ... \
0      The park is open. ...
1      What a Lovely Day. ...
2      One Choice Can Destroy You ...
3      Every generation has a story. ...
4      Vengeance Hits Home ...
...
10838  NaN ...
10839  Cinerama sweeps YOU into a drama of speed and ... ..
10840  NaN ...
10841  WOODY ALLEN STRIKES BACK! ...
10842  It's Shocking! It's Beyond Your Imagination! ...

```

```

                                overview runtime \
0      Twenty-two years after the events of Jurassic ...    124
1      An apocalyptic story set in the furthest reach...    120
2      Beatrice Prior must confront her inner demons ...    119
3      Thirty years after defeating the Galactic Empi...    136
4      Deckard Shaw seeks revenge against Dominic Tor...    137

```

...	
10838	The Endless Summer, by Bruce Brown, is one of ...	95	
10839	Grand Prix driver Pete Aron is fired by his te...	176	
10840	An insurance agent who moonlights as a carthie...	94	
10841	In comic Woody Allen's film debut, he took the...	80	
10842	A family gets lost on the road and stumbles up...	74	

	genres \
0	Action Adventure Science Fiction Thriller
1	Action Adventure Science Fiction Thriller
2	Adventure Science Fiction Thriller
3	Action Adventure Science Fiction Fantasy
4	Action Crime Thriller

...	...
10838	Documentary
10839	Action Adventure Drama
10840	Mystery Comedy
10841	Action Comedy
10842	Horror

	production_companies	release_date \
0	Universal Studios Amblin Entertainment Legenda...	6/9/15
1	Village Roadshow Pictures Kennedy Miller Produ...	5/13/15
2	Summit Entertainment Mandeville Films Red Wago...	3/18/15
3	Lucasfilm Truenorth Productions Bad Robot	12/15/15
4	Universal Pictures Original Film Media Rights ...	4/1/15

...
10838	Bruce Brown Films	6/15/66
10839	Cherokee Productions Joel Productions Douglas ...	12/21/66
10840	Mosfilm	1/1/66
10841	Benedict Pictures Corp.	11/2/66
10842	Norm-Iris	11/15/66

	vote_count	vote_average	release_year	budget_adj	revenue_adj
0	5562	6.5	2015	1.379999e+08	1.392446e+09
1	6185	7.1	2015	1.379999e+08	3.481613e+08
2	2480	6.3	2015	1.012000e+08	2.716190e+08
3	5292	7.5	2015	1.839999e+08	1.902723e+09
4	2947	7.3	2015	1.747999e+08	1.385749e+09
...
10838	11	7.4	1966	0.000000e+00	0.000000e+00
10839	20	5.7	1966	0.000000e+00	0.000000e+00
10840	11	6.5	1966	0.000000e+00	0.000000e+00
10841	22	5.4	1966	0.000000e+00	0.000000e+00
10842	15	1.5	1966	1.276423e+05	0.000000e+00

[10843 rows x 21 columns]


```
[7]: # running .isnull().sum() again to check ...
df.isnull().sum()
```

```
[7]: id                0
     imdb_id          8
     popularity       0
     budget           0
     revenue          0
     original_title   0
     cast             75
     homepage        7912
     director         42
     tagline         2806
     keywords        1475
     overview         3
     runtime          0
     genres           0
     production_companies 1016
     release_date     0
     vote_count       0
     vote_average     0
     release_year     0
     budget_adj       0
     revenue_adj      0
     dtype: int64
```

1.1.4 We check for duplicates in our dataset ...

```
[8]: df.duplicated().sum()
```

```
[8]: 1
```

```
[9]: # dropping duplicated rows ...
df.drop_duplicates(inplace=True)
df.reset_index(inplace = True, drop = True)
df
```

```
[9]:
```

	id	imdb_id	popularity	budget	revenue \
0	135397	tt0369610	32.985763	150000000	1513528810
1	76341	tt1392190	28.419936	150000000	378436354
2	262500	tt2908446	13.112507	110000000	295238201
3	140607	tt2488496	11.173104	200000000	2068178225
4	168259	tt2820852	9.335014	190000000	1506249360
...
10837	21	tt0060371	0.080598	0	0
10838	20379	tt0060472	0.065543	0	0
10839	39768	tt0060161	0.065141	0	0

10840	21449	tt0061177	0.064317	0	0
10841	22293	tt0060666	0.035919	19000	0

	original_title \
0	Jurassic World
1	Mad Max: Fury Road
2	Insurgent
3	Star Wars: The Force Awakens
4	Furious 7
...	...
10837	The Endless Summer
10838	Grand Prix
10839	Beregis Avtomobilya
10840	What's Up, Tiger Lily?
10841	Manos: The Hands of Fate

	cast \
0	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi...
1	Tom Hardy Charlize Theron Hugh Keays-Byrne Nic...
2	Shailene Woodley Theo James Kate Winslet Ansel...
3	Harrison Ford Mark Hamill Carrie Fisher Adam D...
4	Vin Diesel Paul Walker Jason Statham Michelle ...
...	...
10837	Michael Hynson Robert August Lord 'Tally Ho' B...
10838	James Garner Eva Marie Saint Yves Montand Tosh...
10839	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z...
10840	Tatsuya Mihashi Akiko Wakabayashi Mie Hama Joh...
10841	Harold P. Warren Tom Neyman John Reynolds Dian...

	homepage	director \
0	http://www.jurassicworld.com/	Colin Trevorrow
1	http://www.madmaxmovie.com/	George Miller
2	http://www.thedivergentseries.movie/#insurgent	Robert Schwentke
3	http://www.starwars.com/films/star-wars-episod...	J.J. Abrams
4	http://www.furious7.com/	James Wan
...
10837	NaN	Bruce Brown
10838	NaN	John Frankenheimer
10839	NaN	Eldar Ryazanov
10840	NaN	Woody Allen
10841	NaN	Harold P. Warren

	tagline ... \
0	The park is open. ...
1	What a Lovely Day. ...
2	One Choice Can Destroy You ...
3	Every generation has a story. ...

4	Vengeance Hits Home	...
...
10837		NaN
10838	Cinerama sweeps YOU into a drama of speed and	...
10839		NaN
10840	WOODY ALLEN STRIKES BACK!	...
10841	It's Shocking! It's Beyond Your Imagination!	...

		overview runtime	\
0	Twenty-two years after the events of Jurassic	124	
1	An apocalyptic story set in the furthest reach...	120	
2	Beatrice Prior must confront her inner demons	119	
3	Thirty years after defeating the Galactic Empi...	136	
4	Deckard Shaw seeks revenge against Dominic Tor...	137	
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10837	The Endless Summer, by Bruce Brown, is one of	95	
10838	Grand Prix driver Pete Aron is fired by his te...	176	
10839	An insurance agent who moonlights as a carthie...	94	
10840	In comic Woody Allen's film debut, he took the...	80	
10841	A family gets lost on the road and stumbles up...	74	

	genres	\
0	Action Adventure Science Fiction Thriller	
1	Action Adventure Science Fiction Thriller	
2	Adventure Science Fiction Thriller	
3	Action Adventure Science Fiction Fantasy	
4	Action Crime Thriller	
...	...	
10837	Documentary	
10838	Action Adventure Drama	
10839	Mystery Comedy	
10840	Action Comedy	
10841	Horror	

	production_companies	release_date	\
0	Universal Studios Amblin Entertainment Legenda...	6/9/15	
1	Village Roadshow Pictures Kennedy Miller Produ...	5/13/15	
2	Summit Entertainment Mandeville Films Red Wago...	3/18/15	
3	Lucasfilm Truenorth Productions Bad Robot	12/15/15	
4	Universal Pictures Original Film Media Rights	4/1/15	
...	
10837	Bruce Brown Films	6/15/66	
10838	Cherokee Productions Joel Productions Douglas	12/21/66	
10839	Mosfilm	1/1/66	
10840	Benedict Pictures Corp.	11/2/66	
10841	Norm-Iris	11/15/66	

	vote_count	vote_average	release_year	budget_adj	revenue_adj
0	5562	6.5	2015	1.379999e+08	1.392446e+09
1	6185	7.1	2015	1.379999e+08	3.481613e+08
2	2480	6.3	2015	1.012000e+08	2.716190e+08
3	5292	7.5	2015	1.839999e+08	1.902723e+09
4	2947	7.3	2015	1.747999e+08	1.385749e+09
...
10837	11	7.4	1966	0.000000e+00	0.000000e+00
10838	20	5.7	1966	0.000000e+00	0.000000e+00
10839	11	6.5	1966	0.000000e+00	0.000000e+00
10840	22	5.4	1966	0.000000e+00	0.000000e+00
10841	15	1.5	1966	1.276423e+05	0.000000e+00

[10842 rows x 21 columns]

Exploratory Data Analysis

1.2 Now we answer our first question:

Which genre was the most common from year to year?

First, we notice that genres has pipe-separated values (ie, genre_0|genre_1|genre_2|... |genre_n), so, we would like to separate these values to be able to do operations and answer our question.

One way to do this is to make a series with all the separated genres contained in a list. Once that's over, we want to create a new data frame with columns with the name of each genre, and then place 1 wherever the movie has a genre which is equal to the column's name, and leave a NaN wherever it isn't equal. Then we concatenate our original data frame and this new one.

We may find it helpful to define two functions for this process.

```
[10]: # defining a function to separate all pipe-separated values into a list ...
# col -> column to separate values for
# char -> separating character

def separate_into_series(col, char):
    return df[col].str.split(char)
```

```
[11]: # defining a function to make a new data frame with our series
# rows -> number of rows to iterate on
# col_list -> list containing desired column names (that are also the names we
# filter on)
# d_series -> the series that has the data

def df_new(rows, col_list, d_series):
    df_temp = pd.DataFrame(index = range(0, rows), columns = col_list)
```

```

for i in range(0, rows):
    list_temp = d_series[i]
    for j in col_list:
        for k in range(0, len(list_temp)):
            if list_temp[k] == j:
                df_temp.at[i, j] = 1
return df_temp

```

Now we desire to find what the list of all genres (col_list) is. An approach to this is we could form a dictionary that adds a genre as the key. Then we do `list(dict.keys())` to get a list of all the keys (genres in this case).

We may find it helpful to define this as a function

```

[12]: # defining a function to get the list of columns ...
      # rows -> number of rows to iterate on
      # d_series -> the series that has the data

def col_list(rows, d_series):
    dict_temp = {}
    for i in range(0, rows):
        list_temp = d_series[i]
        for j in range(0, len(list_temp)):
            if not list_temp[j] in dict_temp:
                dict_temp[list_temp[j]] = 1
    return list(dict_temp.keys())

```

Now we are ready to answer our first question:

```

[13]: # first we separate the data into a series ...
      series_1a = separate_into_series('genres', '|')

```

```

[14]: # second we run col_list() to obtain a list of all genres.
      list_1a = col_list(10842, series_1a)

```

```

[15]: # third we create our dataframe ...
      df_1a = df_new(10842, list_1a, series_1a)

```

```

[16]: # we now concatenate df and df_1 ...
      df = pd.concat([df, df_1a], axis = 1)
      df

```

```

[16]:
      id  imdb_id  popularity  budget  revenue \
0    135397  tt0369610    32.985763  150000000  1513528810
1     76341  tt1392190    28.419936  150000000   378436354
2    262500  tt2908446    13.112507  110000000   295238201
3    140607  tt2488496    11.173104  200000000  2068178225
4    168259  tt2820852     9.335014  190000000  1506249360
...     ...     ...     ...     ...     ...

```

10837	21	tt0060371	0.080598	0	0
10838	20379	tt0060472	0.065543	0	0
10839	39768	tt0060161	0.065141	0	0
10840	21449	tt0061177	0.064317	0	0
10841	22293	tt0060666	0.035919	19000	0

		original_title \
0		Jurassic World
1		Mad Max: Fury Road
2		Insurgent
3		Star Wars: The Force Awakens
4		Furious 7
...		...
10837		The Endless Summer
10838		Grand Prix
10839		Beregis Avtomobilya
10840		What's Up, Tiger Lily?
10841		Manos: The Hands of Fate

		cast \
0		Chris Pratt Bryce Dallas Howard Irrfan Khan Vi...
1		Tom Hardy Charlize Theron Hugh Keays-Byrne Nic...
2		Shailene Woodley Theo James Kate Winslet Ansel...
3		Harrison Ford Mark Hamill Carrie Fisher Adam D...
4		Vin Diesel Paul Walker Jason Statham Michelle ...
...		...
10837		Michael Hynson Robert August Lord 'Tally Ho' B...
10838		James Garner Eva Marie Saint Yves Montand Tosh...
10839		Innokentiy Smoktunovskiy Oleg Efremov Georgi Z...
10840		Tatsuya Mihashi Akiko Wakabayashi Mie Hama Joh...
10841		Harold P. Warren Tom Neyman John Reynolds Dian...

		homepage	director \
0		http://www.jurassicworld.com/	Colin Trevorrow
1		http://www.madmaxmovie.com/	George Miller
2		http://www.thedivergentseries.movie/#insurgent	Robert Schwentke
3		http://www.starwars.com/films/star-wars-episod...	J.J. Abrams
4		http://www.furious7.com/	James Wan
...	
10837		NaN	Bruce Brown
10838		NaN	John Frankenheimer
10839		NaN	Eldar Ryazanov
10840		NaN	Woody Allen
10841		NaN	Harold P. Warren

		tagline ... Comedy Mystery \
0		The park is open. ... NaN NaN

1		What a Lovely Day.	...	NaN	NaN
2		One Choice Can Destroy You	...	NaN	NaN
3		Every generation has a story.	...	NaN	NaN
4		Vengeance Hits Home	...	NaN	NaN
...		
10837			NaN	...	NaN
10838	Cinerama sweeps YOU into a drama of speed and	...	NaN	NaN	NaN
10839			NaN	...	1
10840		WOODY ALLEN STRIKES BACK!	...	1	NaN
10841	It's Shocking! It's Beyond Your Imagination!	...	NaN	NaN	NaN

	Romance	War	History	Music	Horror	Documentary	TV Movie	Foreign
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...
10837	NaN	NaN	NaN	NaN	NaN	1	NaN	NaN
10838	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10839	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10840	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10841	NaN	NaN	NaN	NaN	1	NaN	NaN	NaN

[10842 rows x 41 columns]

```
[17]: # we now want to know the range of years, which is simple ...
print(f'Maximum year is {df["release_year"].max()}')
print(f'Minimum year is {df["release_year"].min()}')
# now we create a list with all years in between (including the max and min) ...
list_years = []
for i in range(1960, 2015 + 1):
    list_years.append(i)
```

Maximum year is 2015

Minimum year is 1960

```
[18]: # defining a function ...
# col1 -> column to group by
# col2 -> column to get values for
# list_val -> list of values which match the values of **unique** col1

def df_part(col1, col2, list_val):
    df_temp = pd.DataFrame(df.groupby(col1)[col2].value_counts().
        sort_index(ascending = True))
    list_temp = list(df_temp.index.get_level_values(0))
    dict_temp = {}
```

```

for i in list_val:
    # safety check.
    if i in list_temp:
        dict_temp[i] = df_temp[col2][i][1]
return pd.DataFrame(dict_temp, index = [col2]).T

```

In the following 2 lines of code, we plot all the plots into one cell window. The reader is encouraged to make the window larger for ease of viewing. These plots show the trend of each genre with each passing year. We see that most of the genres follow an increasing trend as we tend to the right side of the graph, only going down a bit at 2015 sometimes.

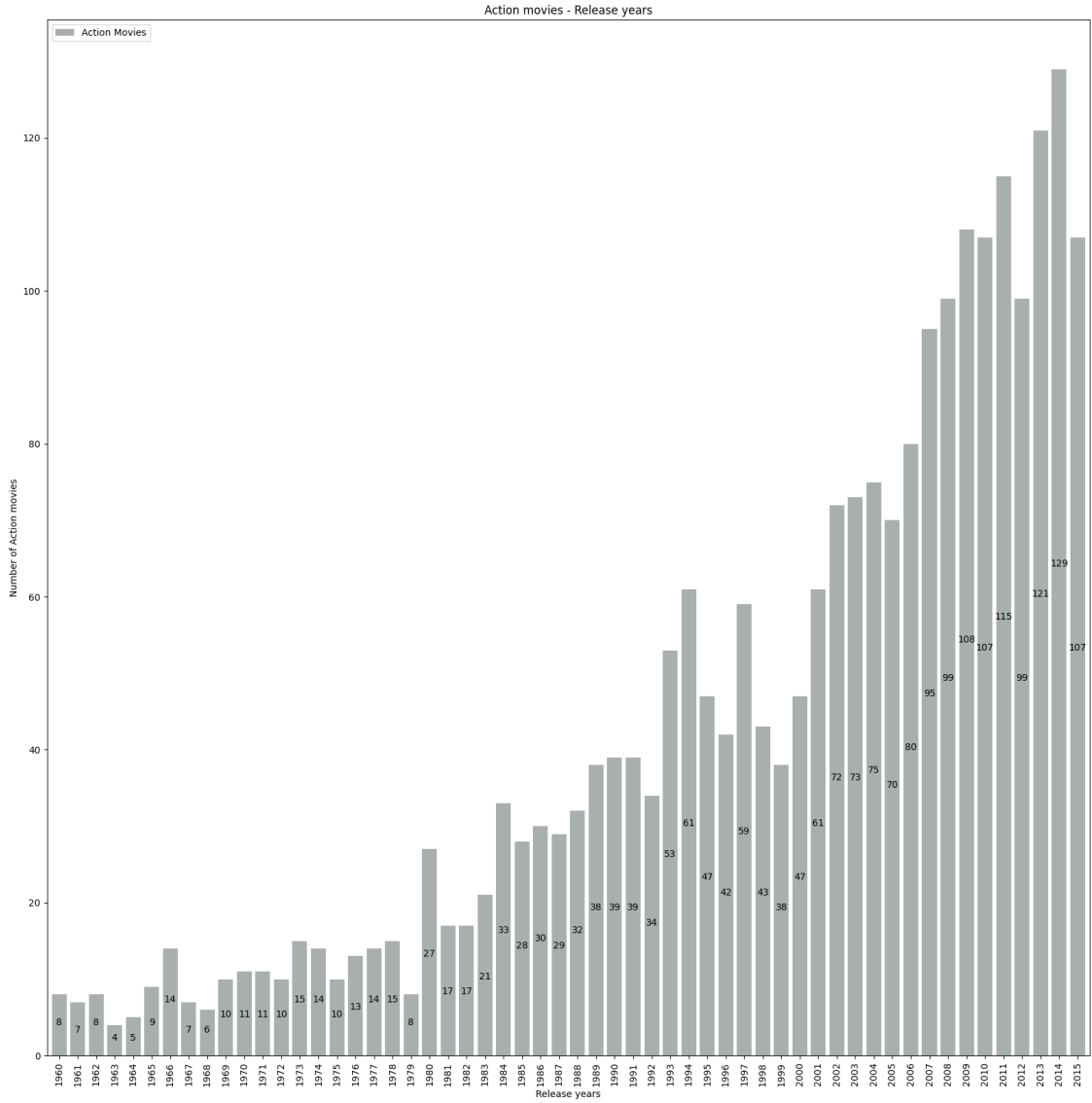
We present our answer for this question in the cell after the following one.

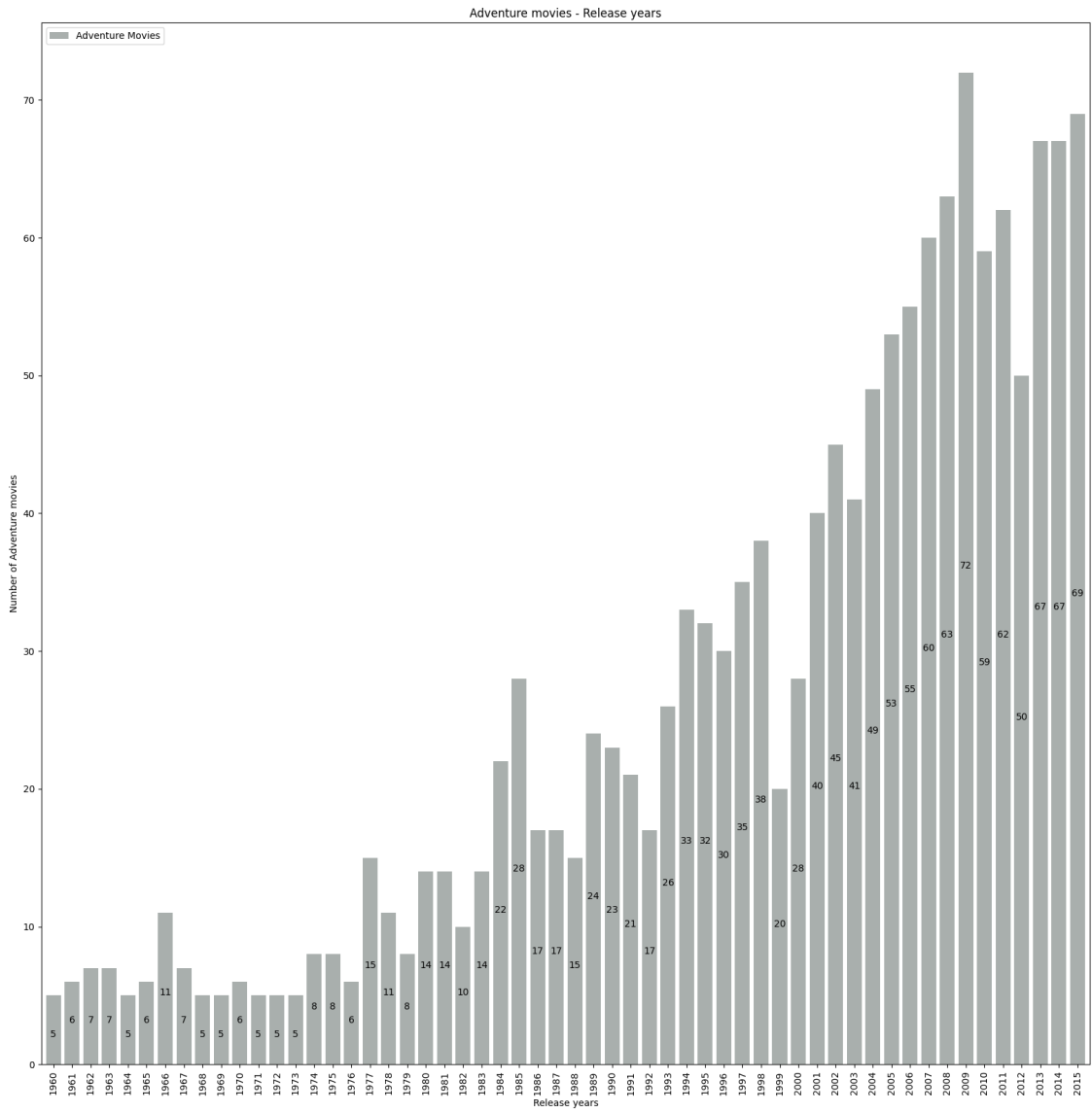
```

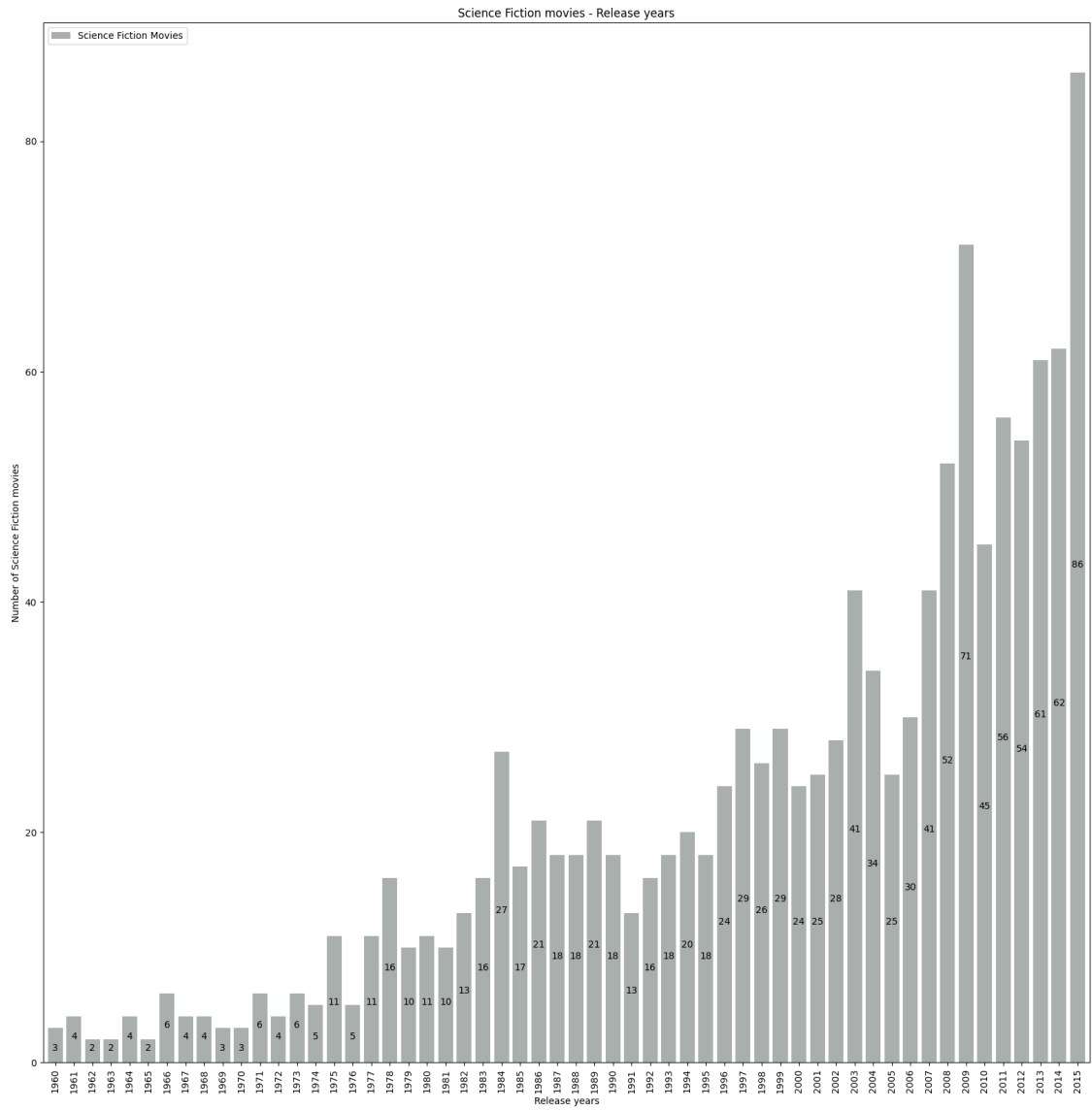
[19]: # this definition of a function is available on: https://www.geeksforgeeks.org/adding-value-labels-on-a-matplotlib-bar-chart/ , I reused it here.
def addlabels(x,y):
    for i in range(len(x)):
        plt.text(i, y[i]//2, y[i], ha = 'center')

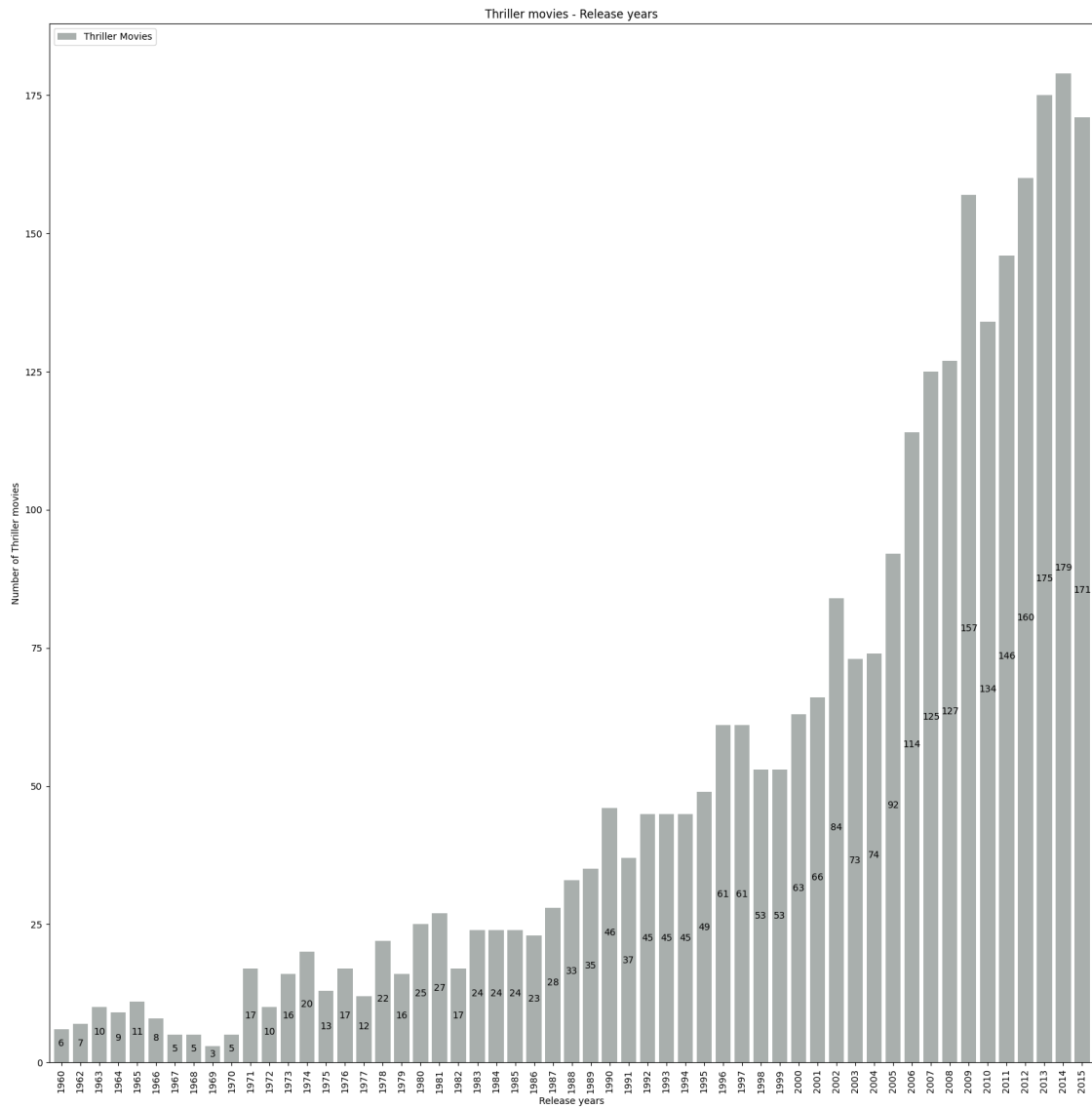
for i in list_1a:
    vals = []
    df_2a = df_part('release_year', i, list_years)
    df_2a.plot(kind = 'bar', figsize = (20, 20), width=0.8, color = (0.166, 0.224, 0.204, 0.4), xlabel = 'Release years', ylabel = f'Number of {i} movies', title = f'{i} movies - Release years')
    plt.legend([f'{i} Movies'], loc = 'upper left')
    # producing a list of values to render in the box plot ...
    for j in list(df_2a[i].index.get_level_values(0)):
        vals.append(df_2a[i][j])
    # adding the values as labels ...
    addlabels(list(df_2a[i].index.get_level_values(0)), vals)

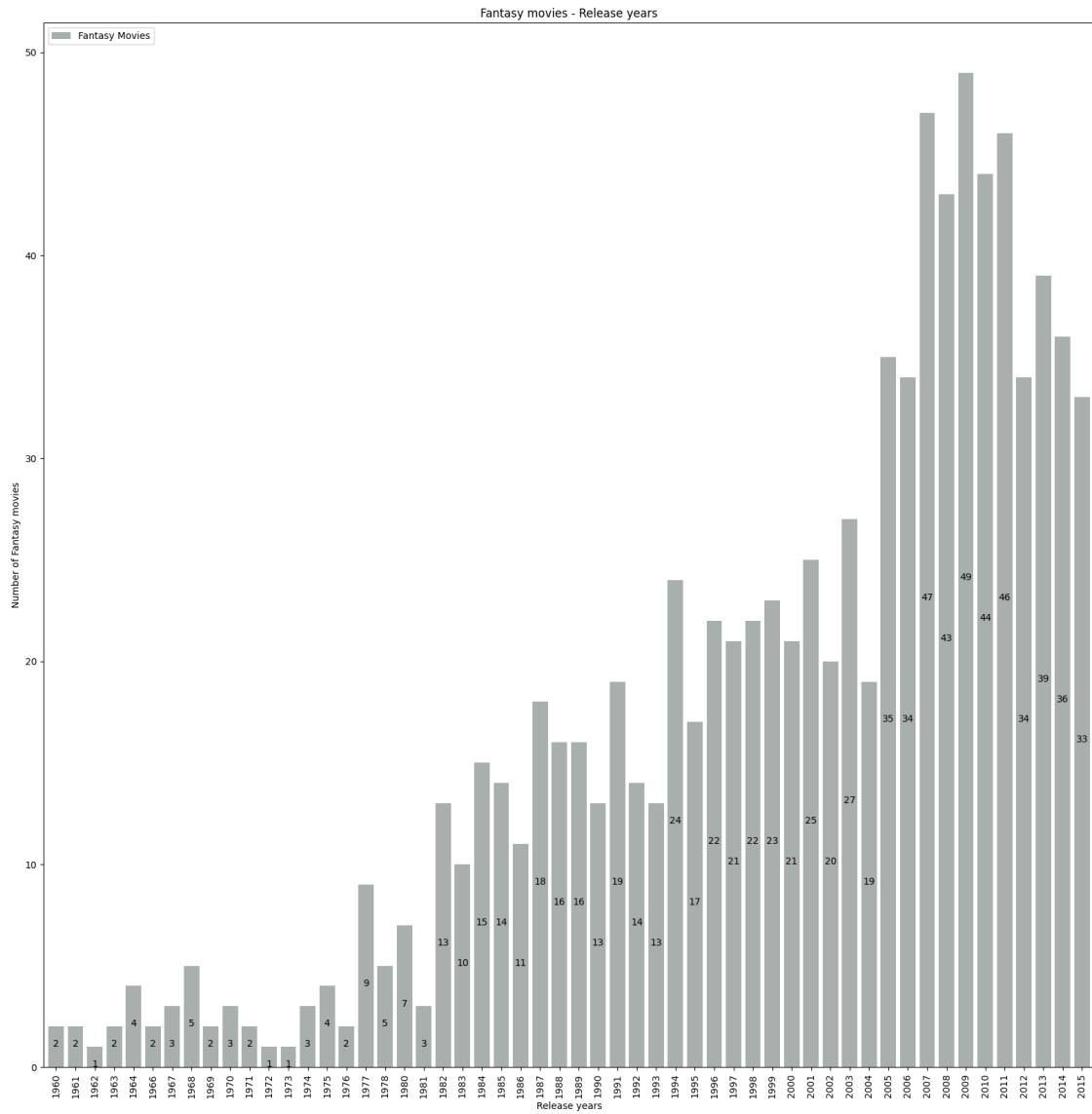
```

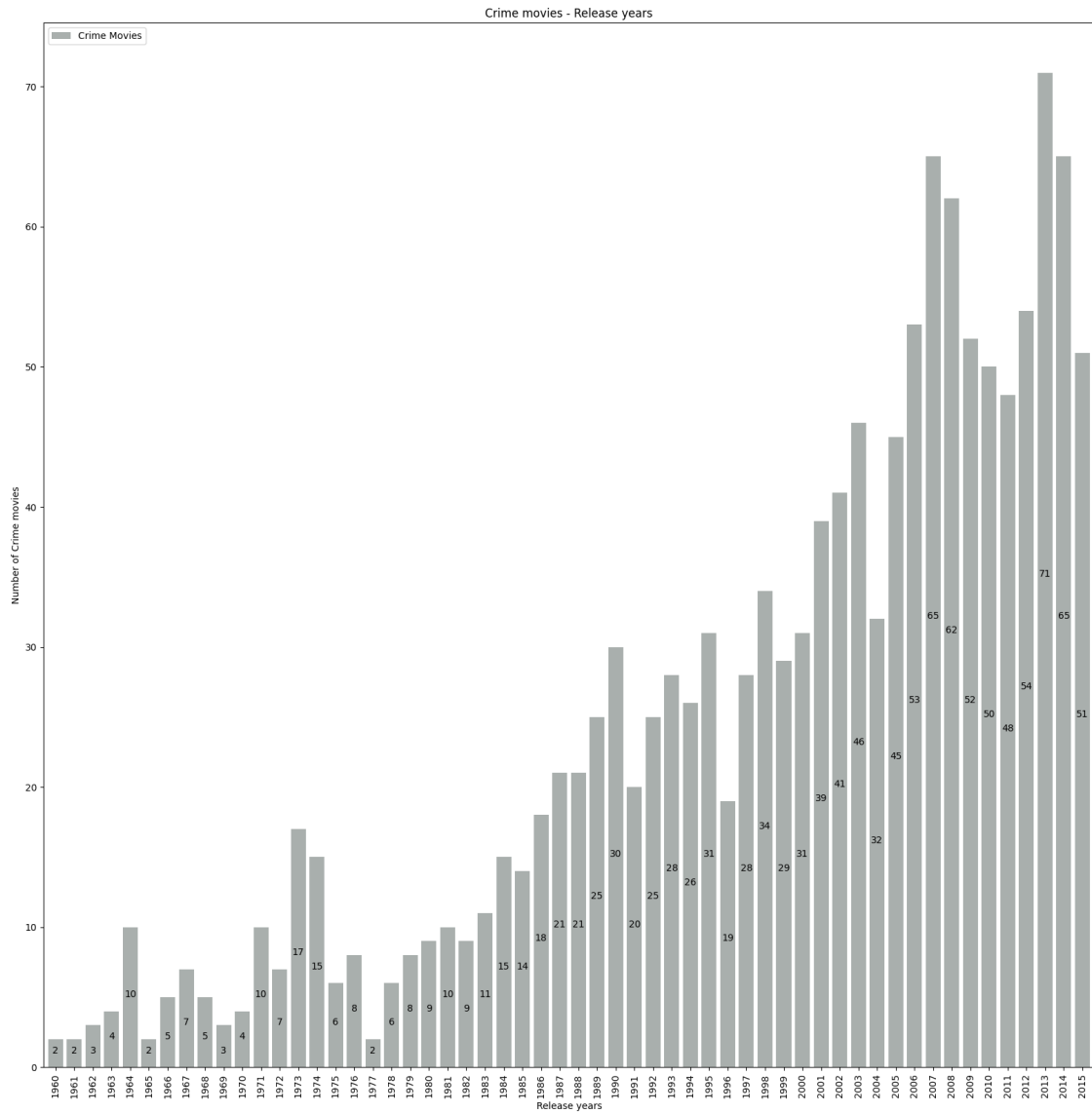



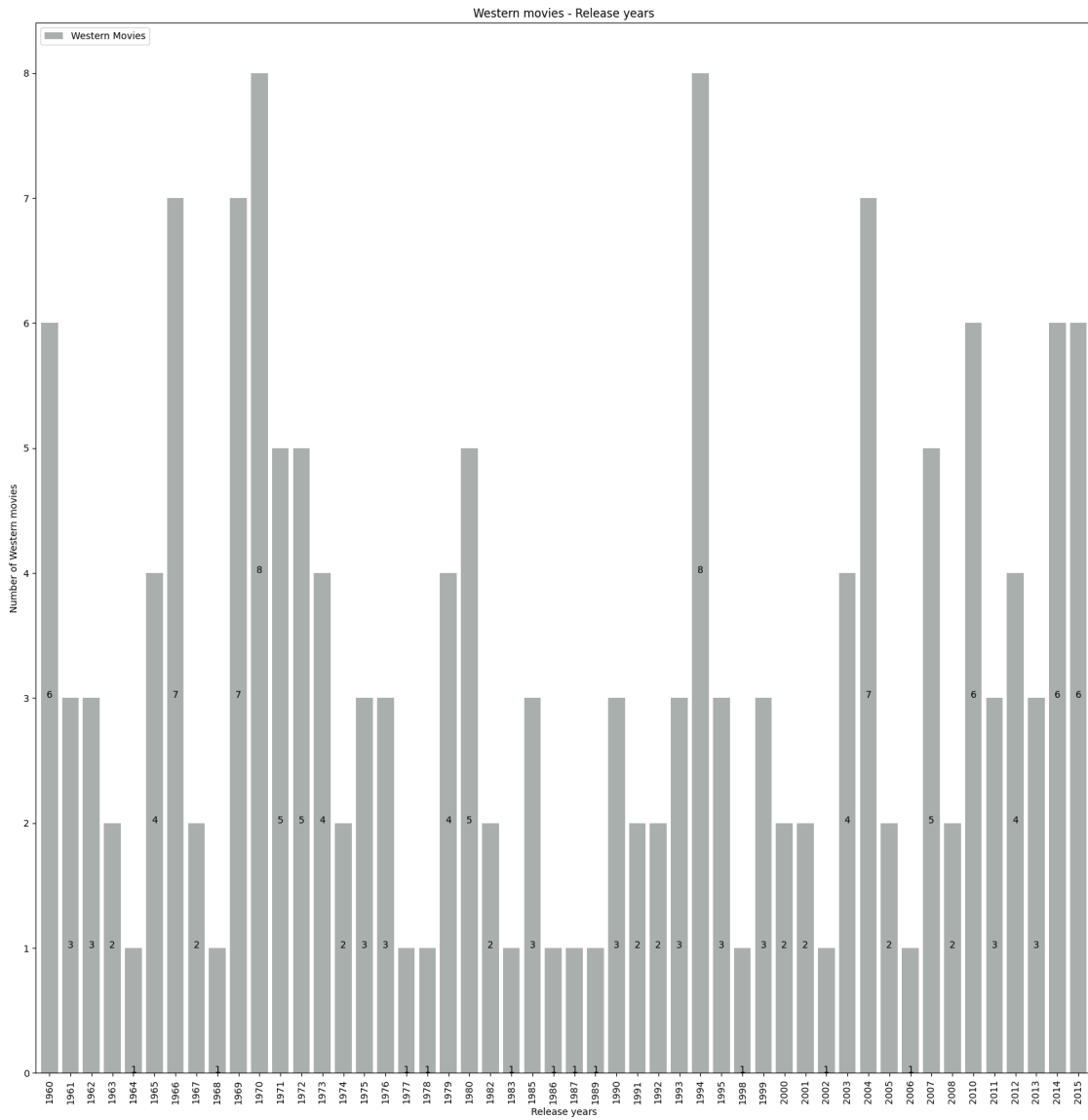


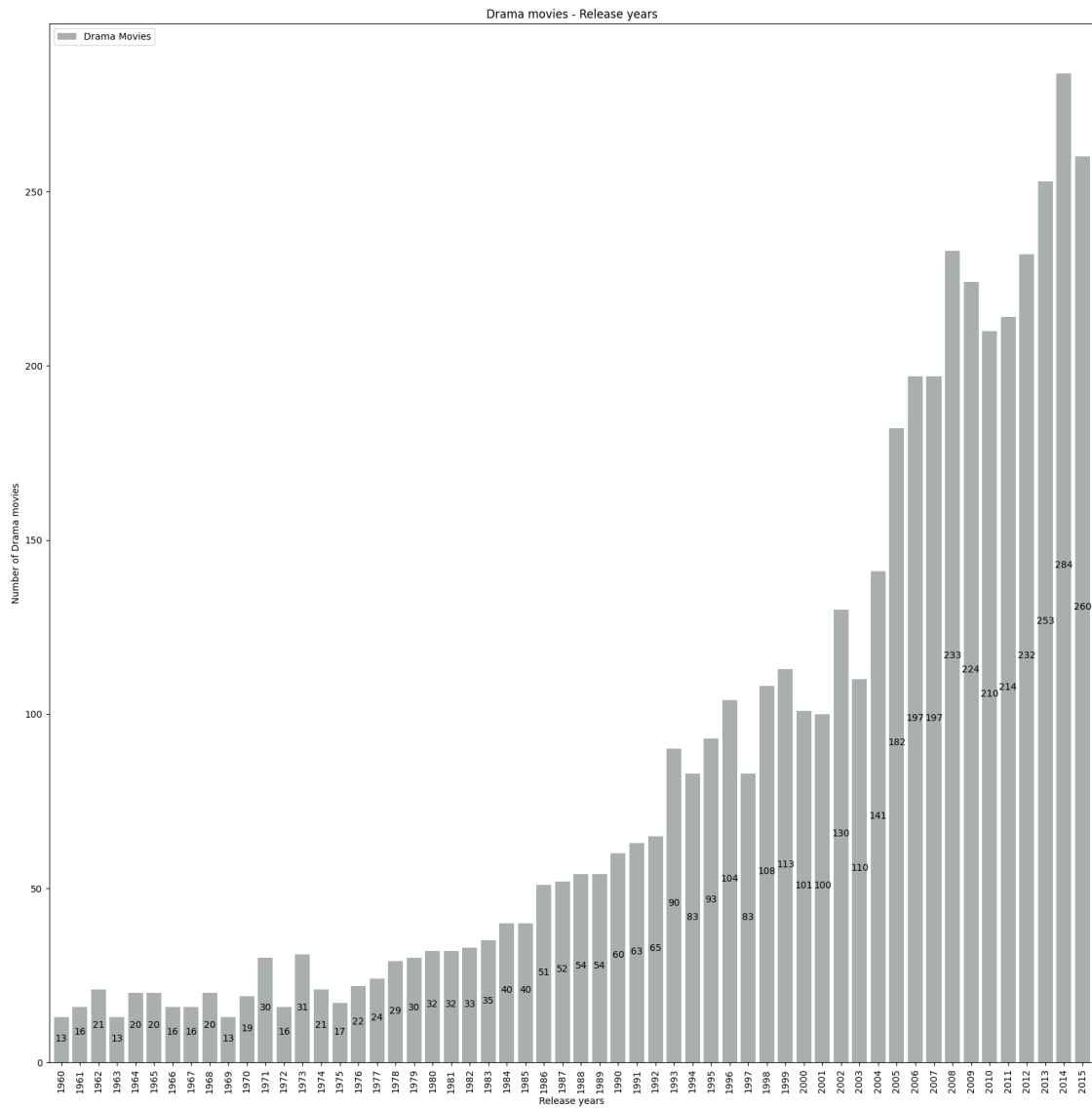


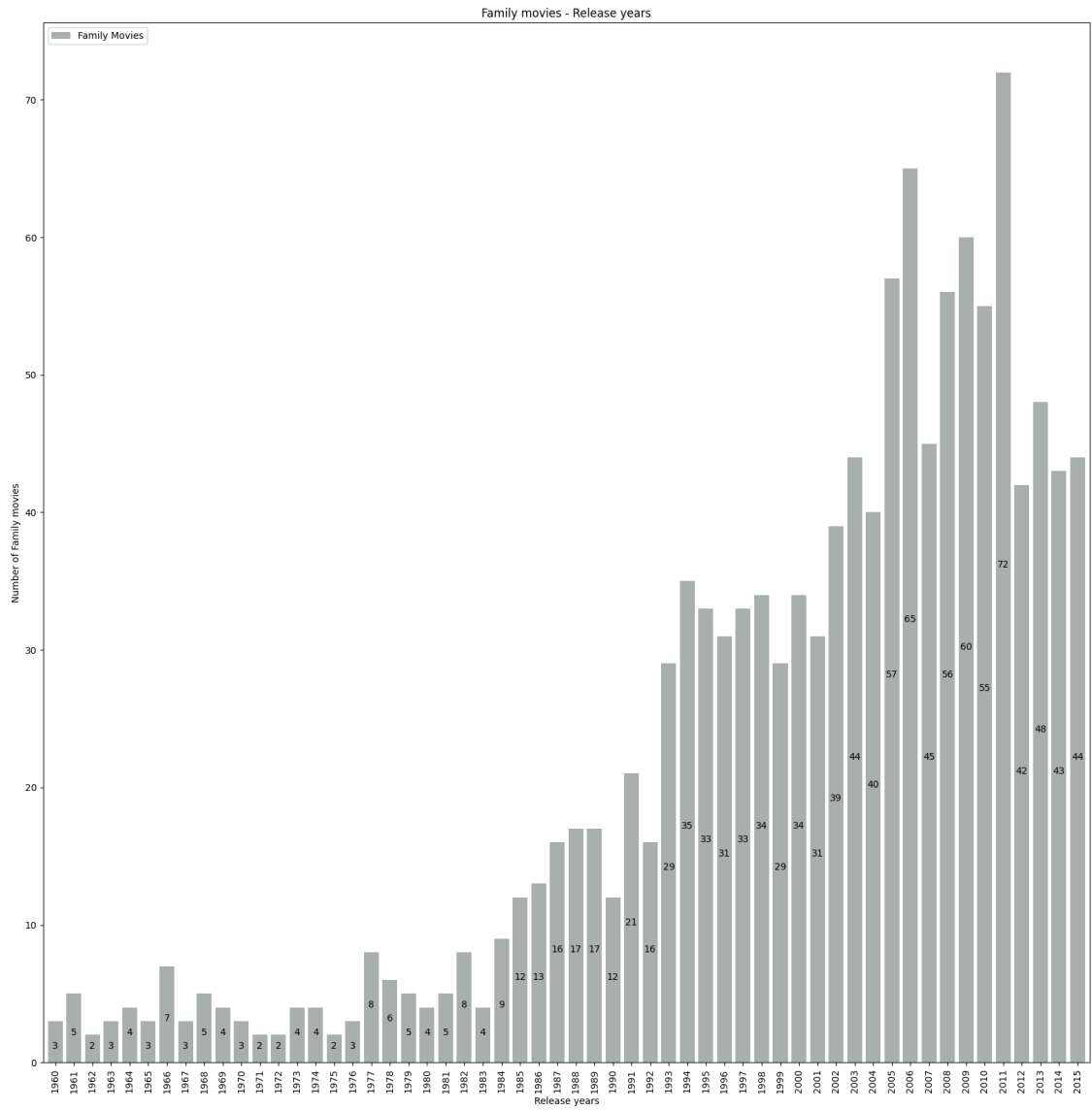


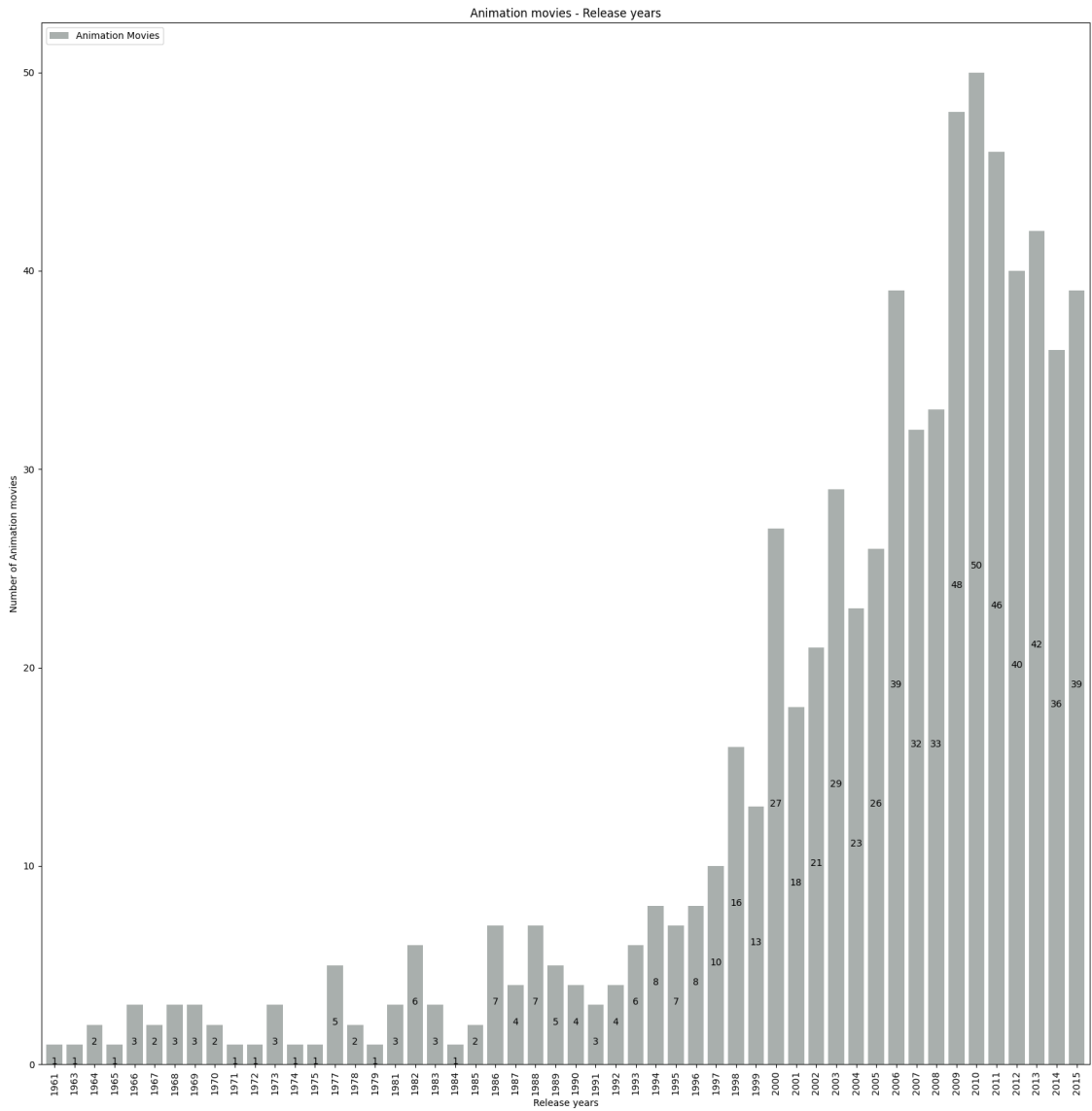


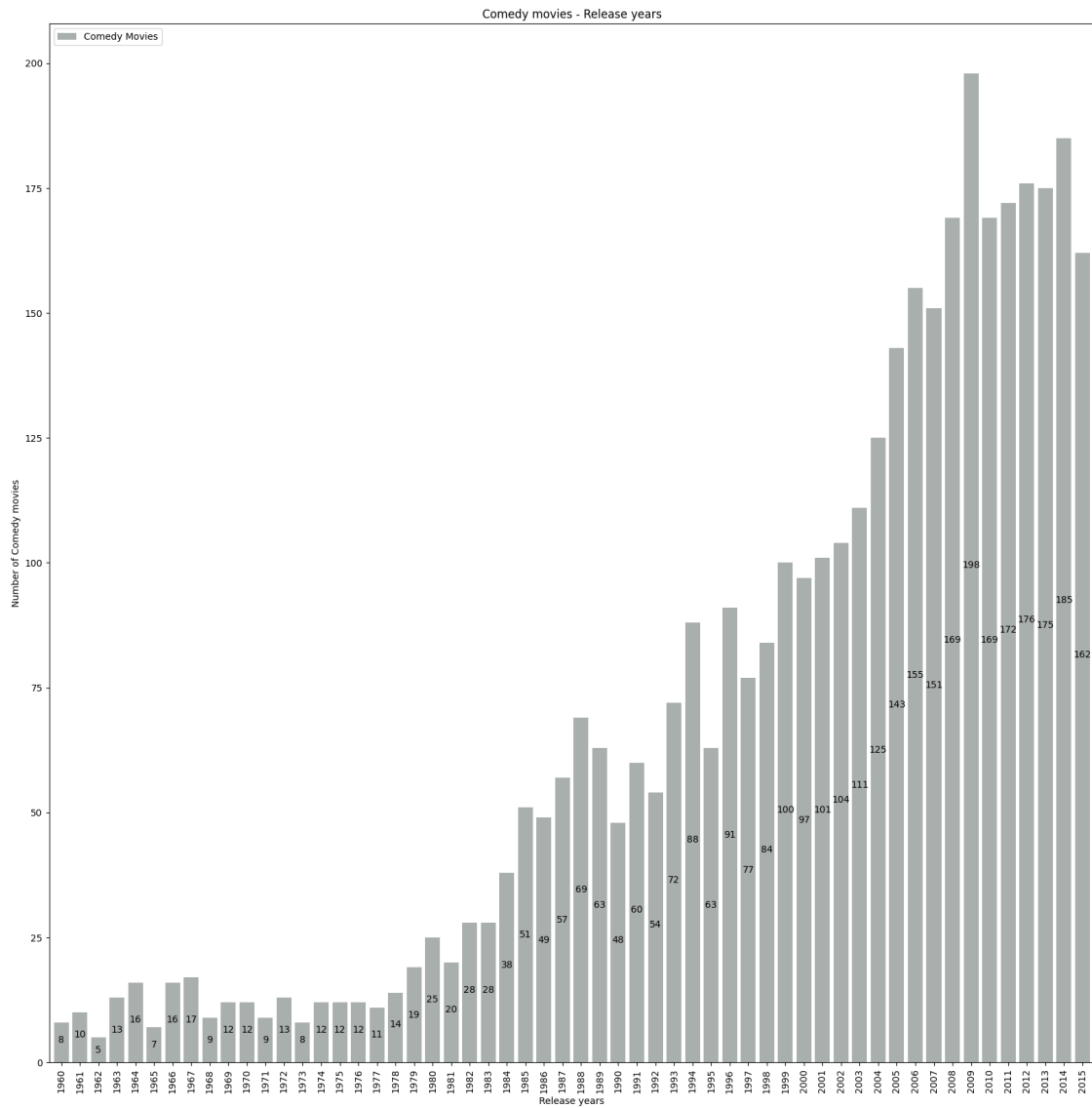


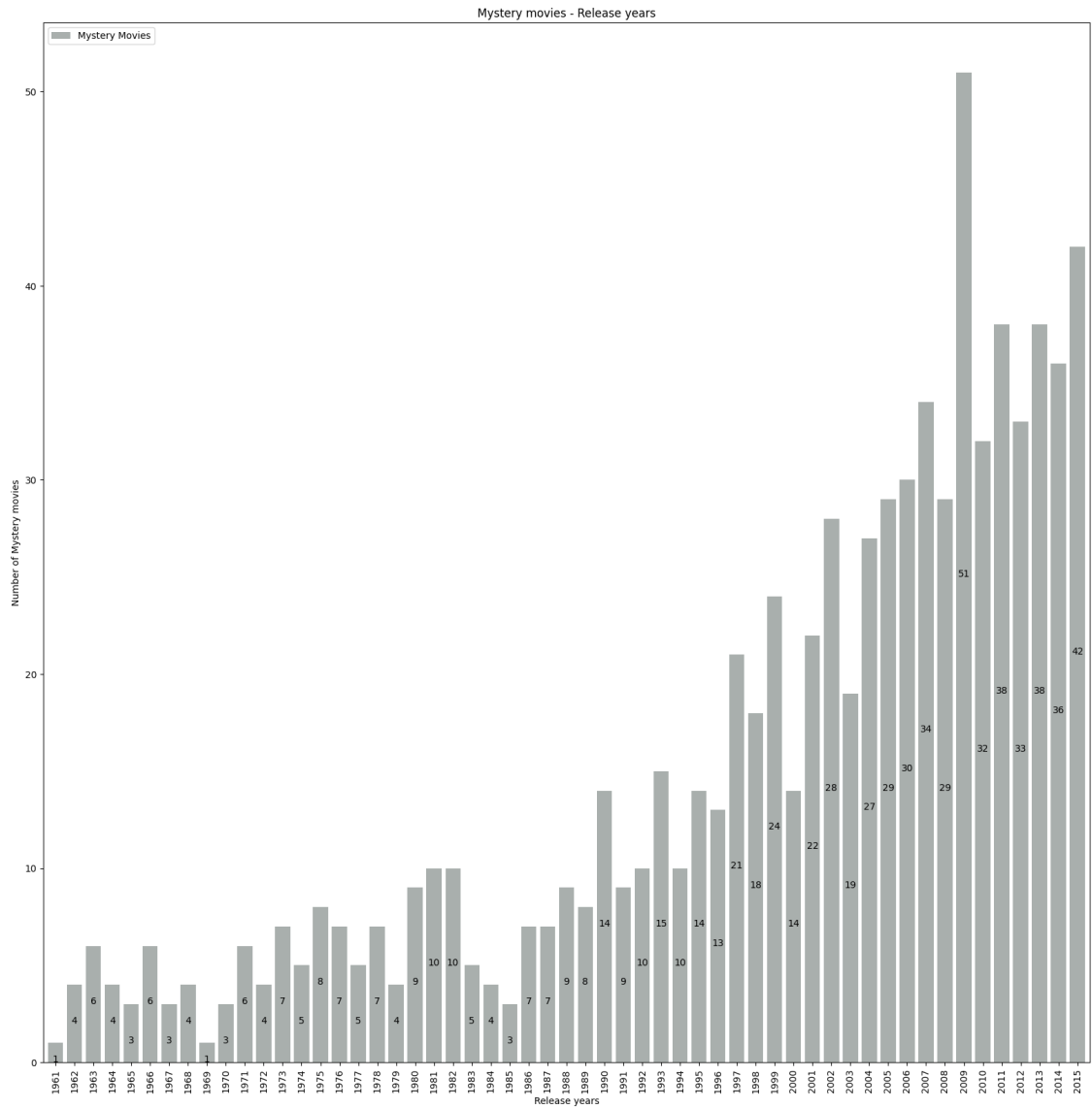


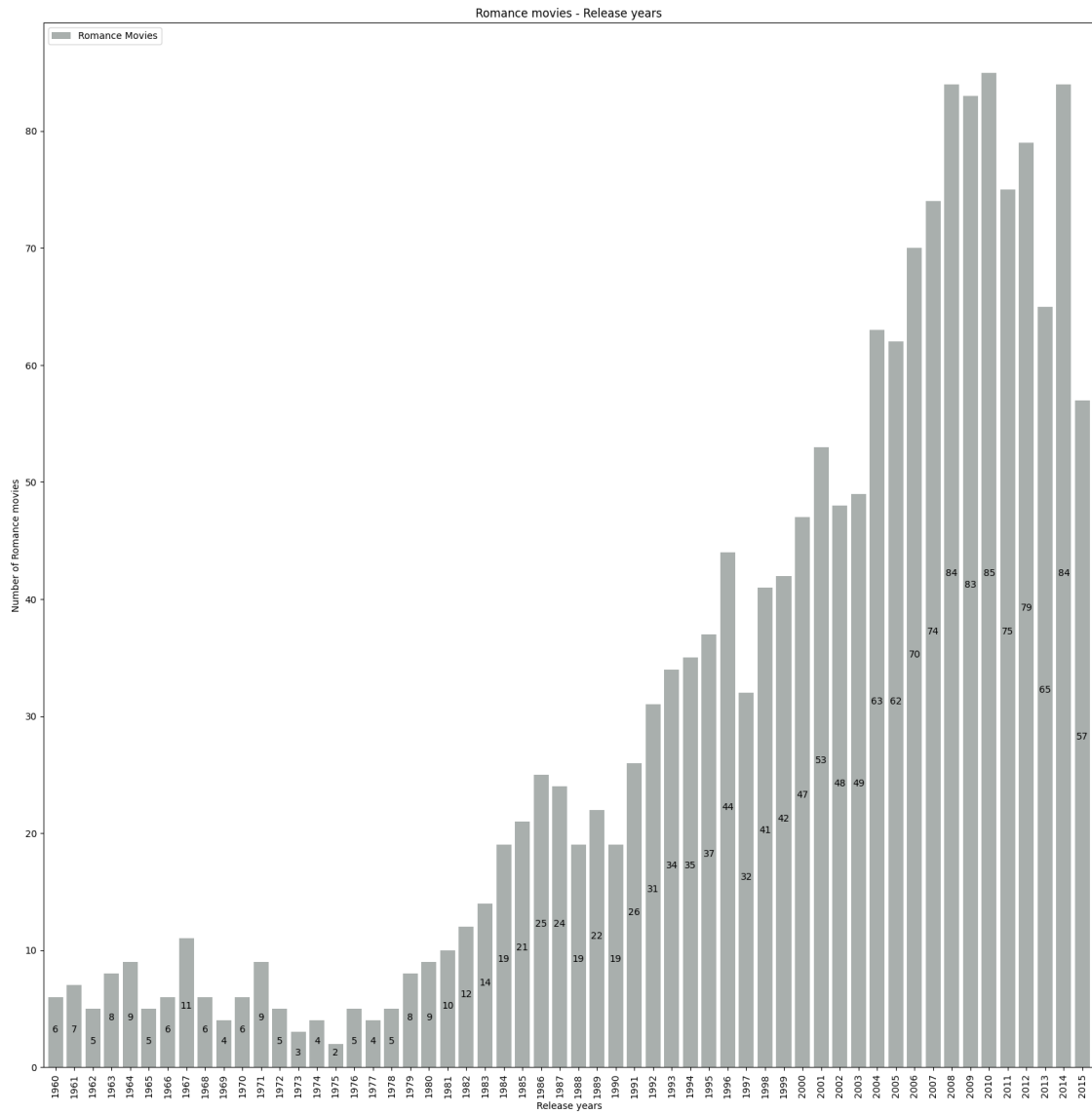


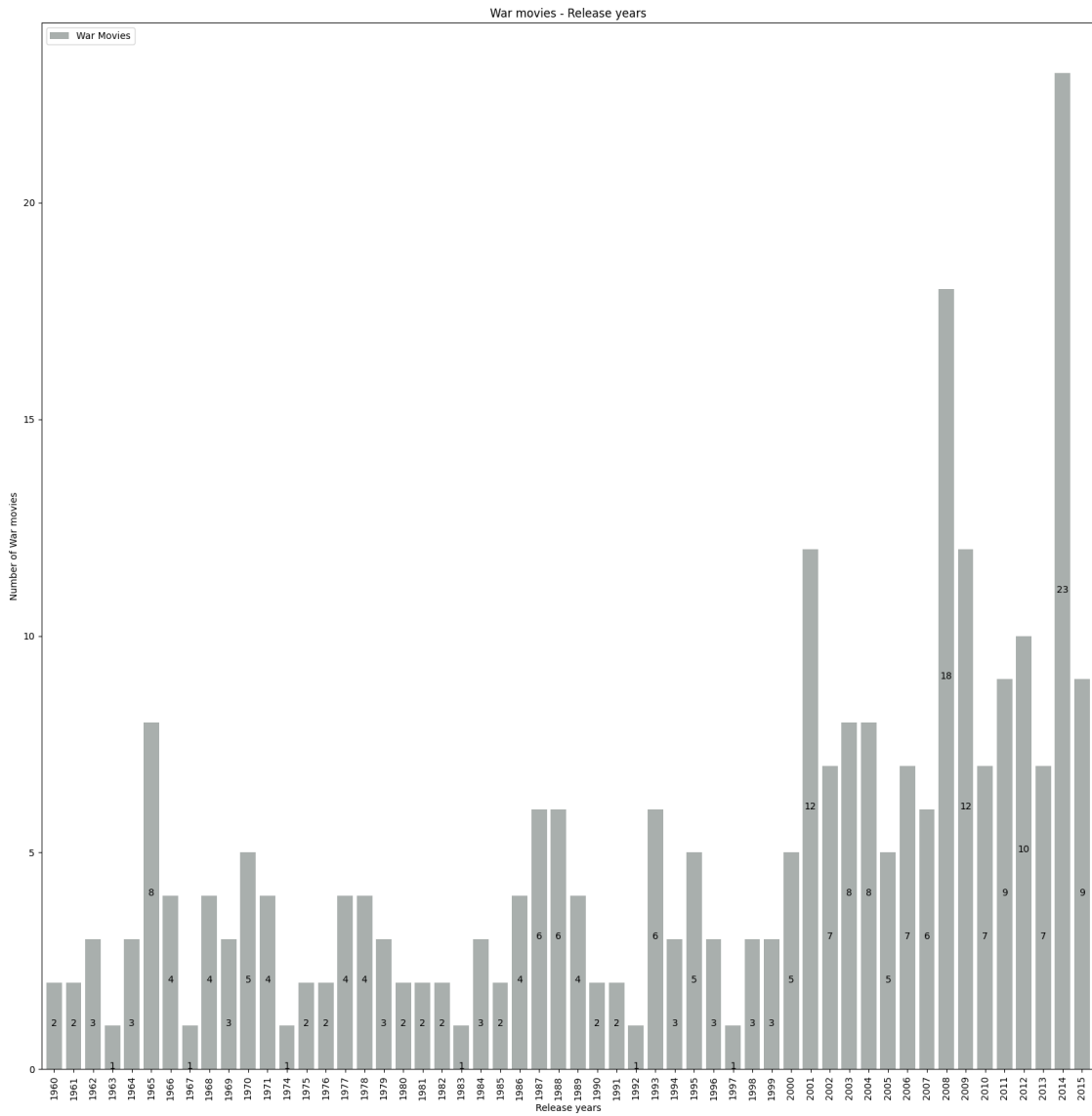


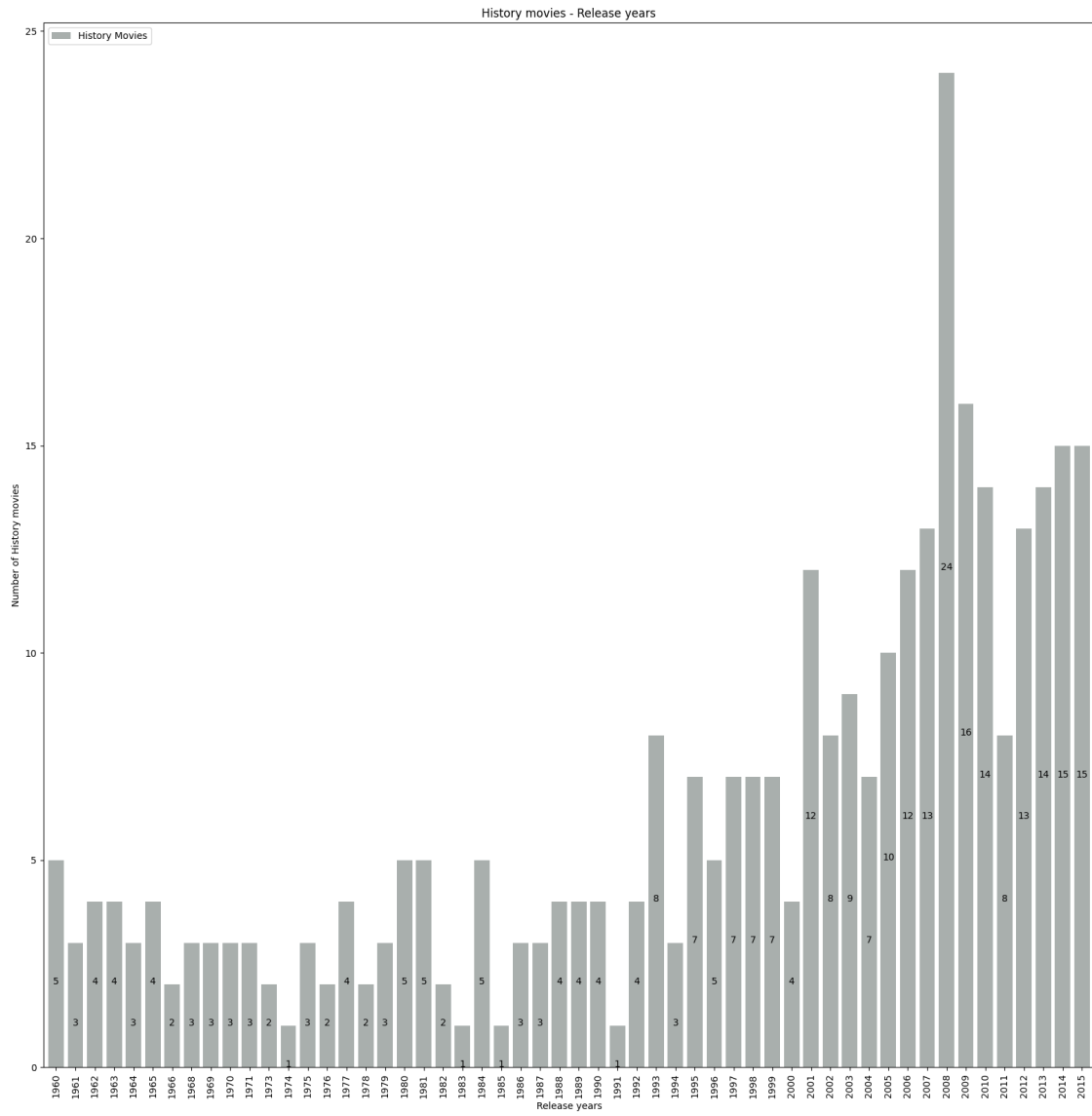


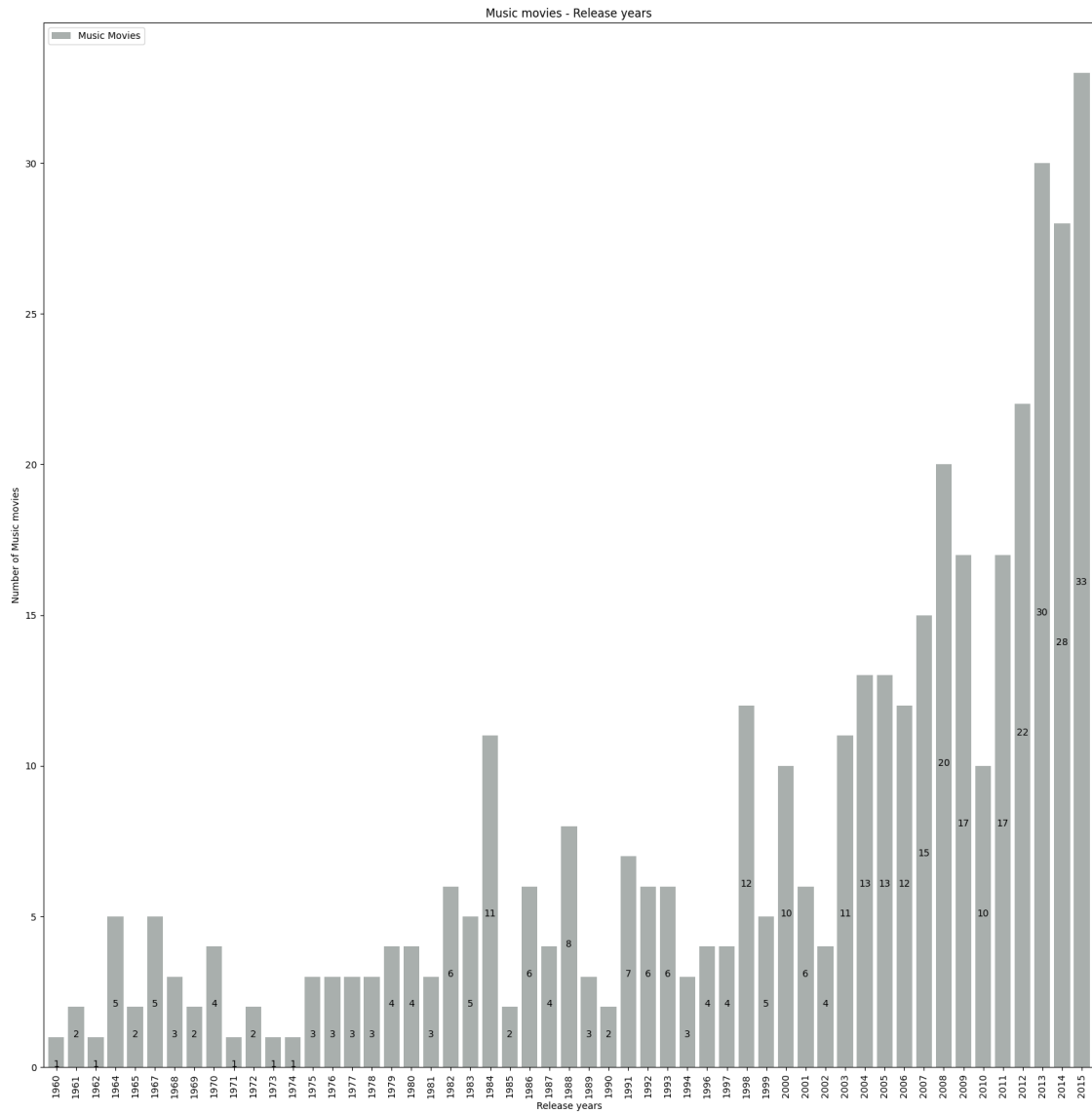


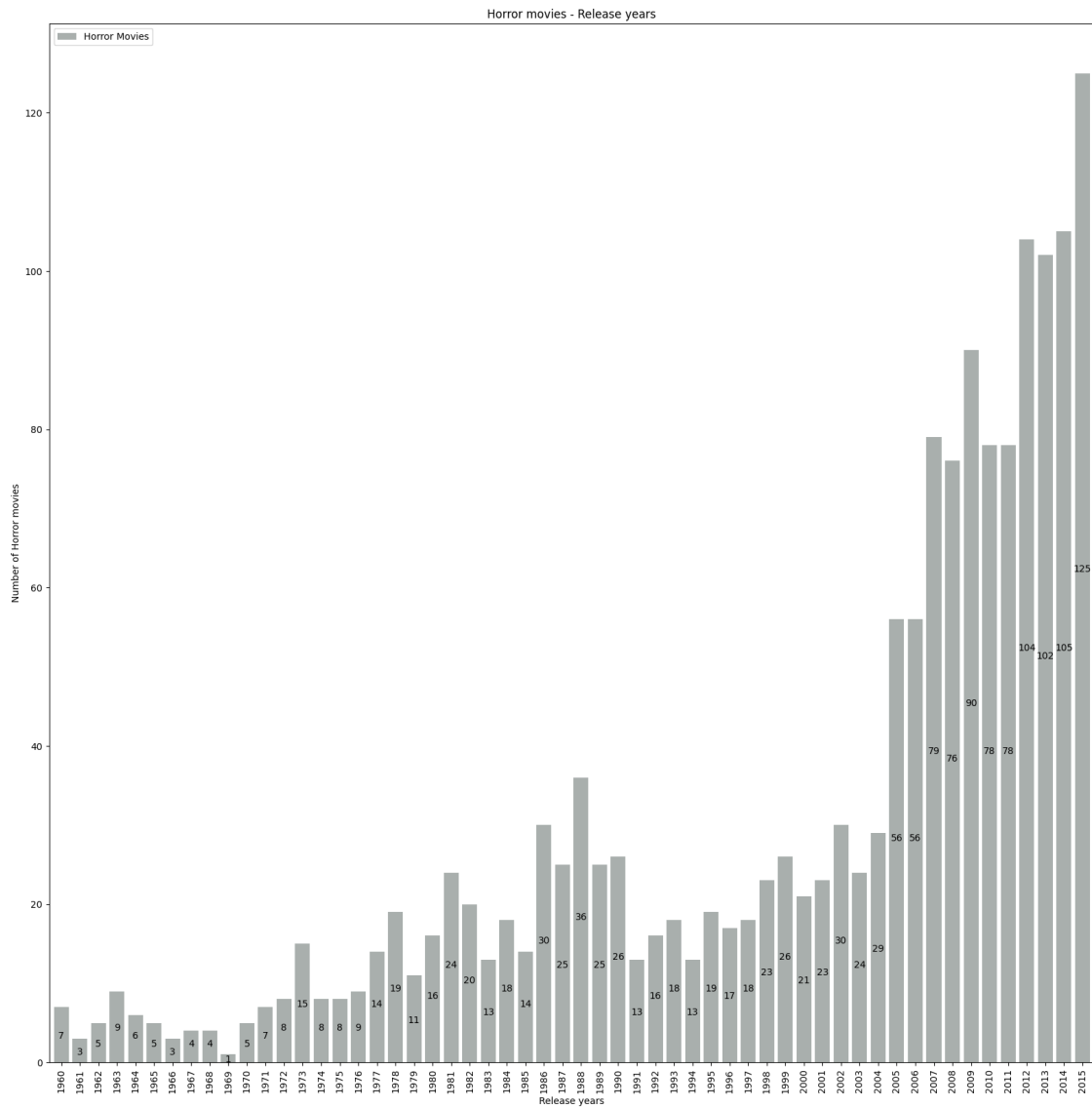


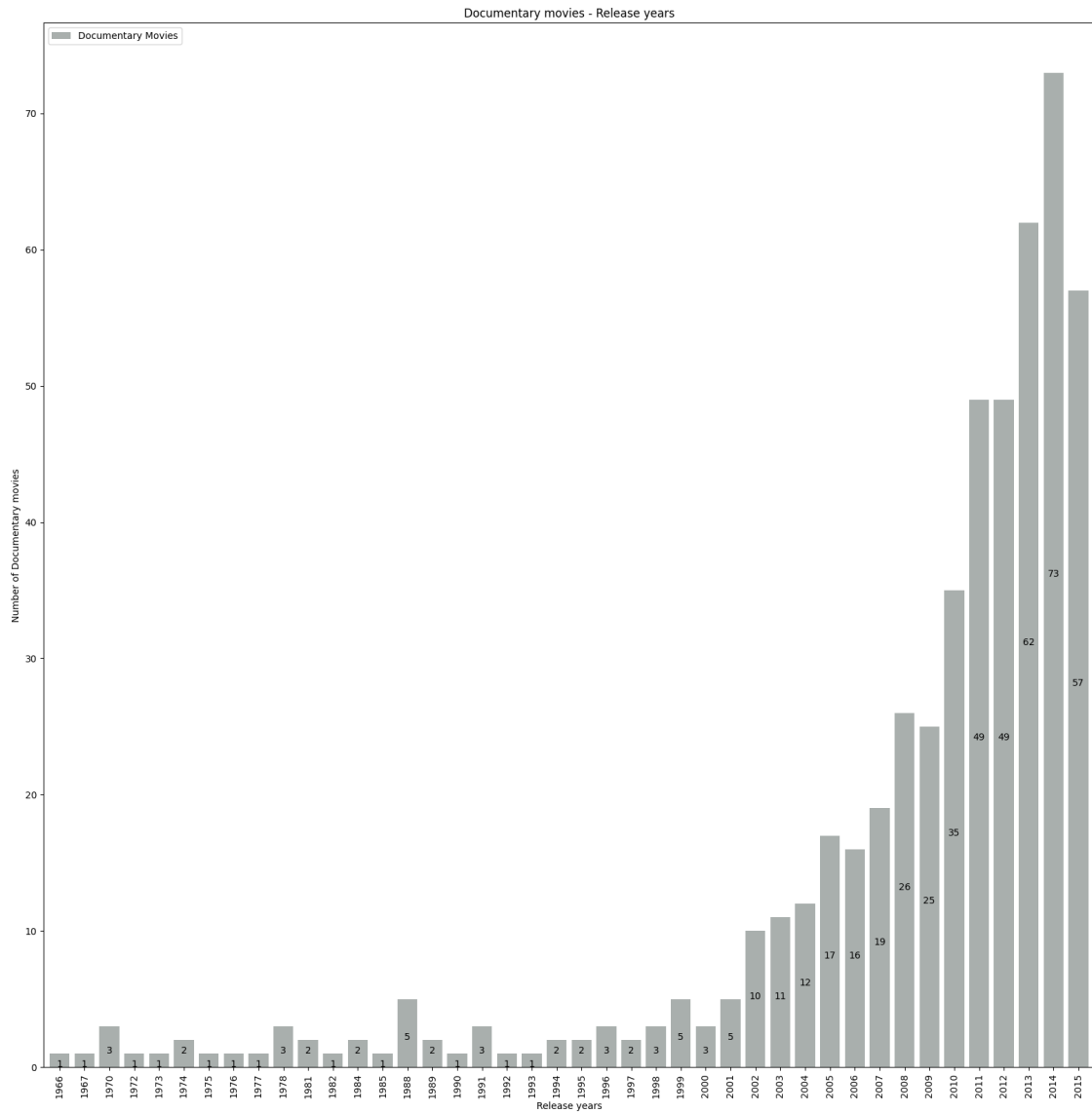


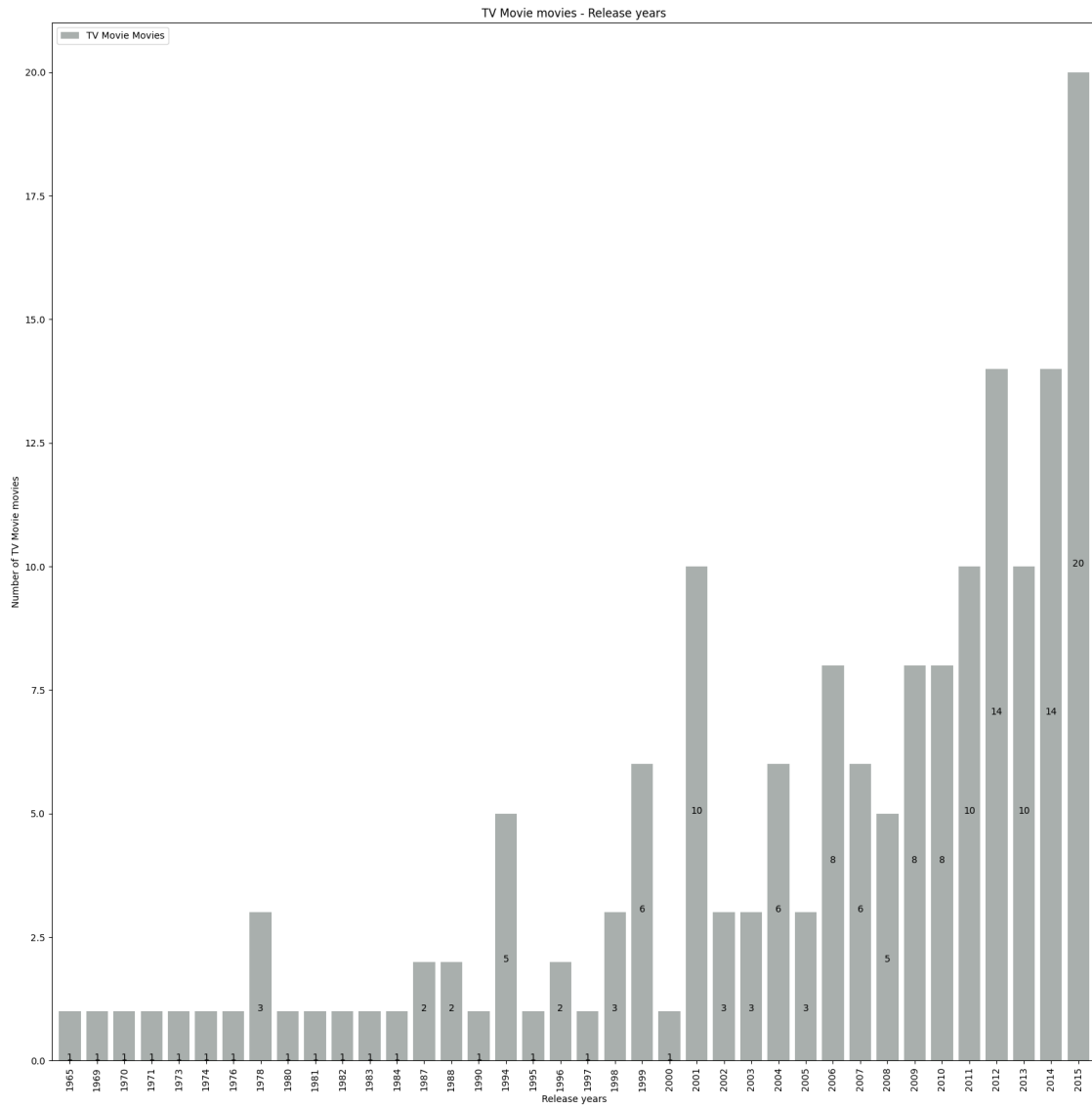


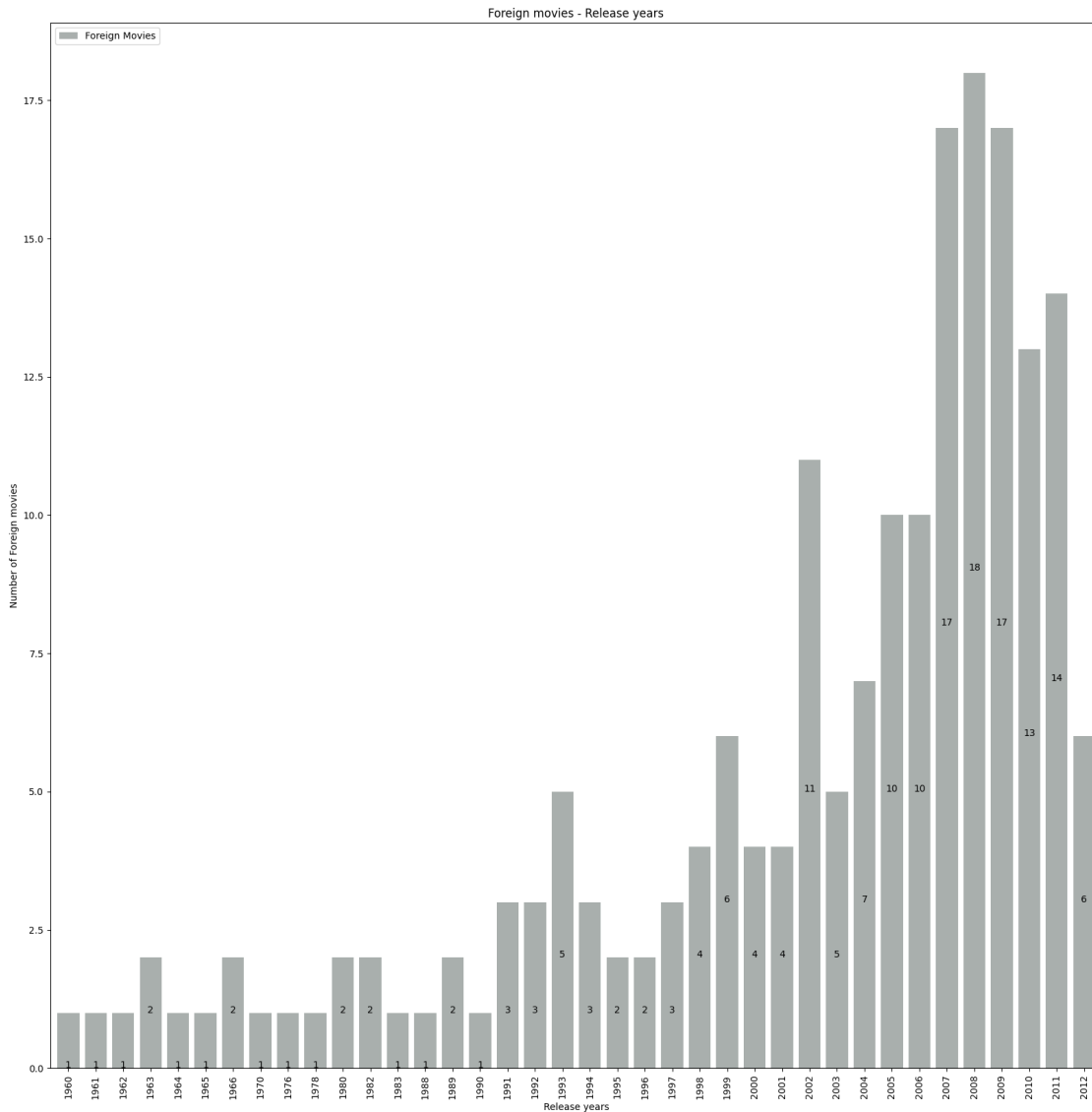












Answer: from the plots we have plotted, we can see that for:

[20]: # here, we print the most popular genre for each year, along with its number.

```
for i in list_years:
    list_compare = []
    dict_compare = {}
    for j in list_1a:
        df_part('release_year', j, list_years)
        if i in list(df_part('release_year', j, list_years)[j].index.
↳get_level_values(0)):
            list_compare.append(df_part('release_year', j, list_years)[j][i])
            dict_compare[j] = df_part('release_year', j, list_years)[j][i]
```

```
# finally, print the following formatted string.
print(f'* For {i}, the most common genre is {str(max(dict_compare,
↳key=dict_compare.get))} of value {str(max(list_compare))}.')
```

```
* For 1960, the most common genre is Drama of value 13.
* For 1961, the most common genre is Drama of value 16.
* For 1962, the most common genre is Drama of value 21.
* For 1963, the most common genre is Drama of value 13.
* For 1964, the most common genre is Drama of value 20.
* For 1965, the most common genre is Drama of value 20.
* For 1966, the most common genre is Drama of value 16.
* For 1967, the most common genre is Comedy of value 17.
* For 1968, the most common genre is Drama of value 20.
* For 1969, the most common genre is Drama of value 13.
* For 1970, the most common genre is Drama of value 19.
* For 1971, the most common genre is Drama of value 30.
* For 1972, the most common genre is Drama of value 16.
* For 1973, the most common genre is Drama of value 31.
* For 1974, the most common genre is Drama of value 21.
* For 1975, the most common genre is Drama of value 17.
* For 1976, the most common genre is Drama of value 22.
* For 1977, the most common genre is Drama of value 24.
* For 1978, the most common genre is Drama of value 29.
* For 1979, the most common genre is Drama of value 30.
* For 1980, the most common genre is Drama of value 32.
* For 1981, the most common genre is Drama of value 32.
* For 1982, the most common genre is Drama of value 33.
* For 1983, the most common genre is Drama of value 35.
* For 1984, the most common genre is Drama of value 40.
* For 1985, the most common genre is Comedy of value 51.
* For 1986, the most common genre is Drama of value 51.
* For 1987, the most common genre is Comedy of value 57.
* For 1988, the most common genre is Comedy of value 69.
* For 1989, the most common genre is Comedy of value 63.
* For 1990, the most common genre is Drama of value 60.
* For 1991, the most common genre is Drama of value 63.
* For 1992, the most common genre is Drama of value 65.
* For 1993, the most common genre is Drama of value 90.
* For 1994, the most common genre is Comedy of value 88.
* For 1995, the most common genre is Drama of value 93.
* For 1996, the most common genre is Drama of value 104.
* For 1997, the most common genre is Drama of value 83.
* For 1998, the most common genre is Drama of value 108.
* For 1999, the most common genre is Drama of value 113.
* For 2000, the most common genre is Drama of value 101.
* For 2001, the most common genre is Comedy of value 101.
* For 2002, the most common genre is Drama of value 130.
* For 2003, the most common genre is Comedy of value 111.
```

```

* For 2004, the most common genre is Drama of value 141.
* For 2005, the most common genre is Drama of value 182.
* For 2006, the most common genre is Drama of value 197.
* For 2007, the most common genre is Drama of value 197.
* For 2008, the most common genre is Drama of value 233.
* For 2009, the most common genre is Drama of value 224.
* For 2010, the most common genre is Drama of value 210.
* For 2011, the most common genre is Drama of value 214.
* For 2012, the most common genre is Drama of value 232.
* For 2013, the most common genre is Drama of value 253.
* For 2014, the most common genre is Drama of value 284.
* For 2015, the most common genre is Drama of value 260.

```

1.2.1 The code above prints the following:

- For 1960, the most common genre is Drama of value 13.
- For 1961, the most common genre is Drama of value 16.
- For 1962, the most common genre is Drama of value 21.
- For 1963, the most common genre is Drama of value 13.
- For 1964, the most common genre is Drama of value 20.
- For 1965, the most common genre is Drama of value 20.
- For 1966, the most common genre is Drama of value 16.
- For 1967, the most common genre is Comedy of value 17.
- For 1968, the most common genre is Drama of value 20.
- For 1969, the most common genre is Drama of value 13.
- For 1970, the most common genre is Drama of value 19.
- For 1971, the most common genre is Drama of value 30.
- For 1972, the most common genre is Drama of value 16.
- For 1973, the most common genre is Drama of value 31.
- For 1974, the most common genre is Drama of value 21.
- For 1975, the most common genre is Drama of value 17.
- For 1976, the most common genre is Drama of value 22.
- For 1977, the most common genre is Drama of value 24.
- For 1978, the most common genre is Drama of value 29.
- For 1979, the most common genre is Drama of value 30.
- For 1980, the most common genre is Drama of value 32.
- For 1981, the most common genre is Drama of value 32.
- For 1982, the most common genre is Drama of value 33.
- For 1983, the most common genre is Drama of value 35.
- For 1984, the most common genre is Drama of value 40.
- For 1985, the most common genre is Comedy of value 51.
- For 1986, the most common genre is Drama of value 51.
- For 1987, the most common genre is Comedy of value 57.
- For 1988, the most common genre is Comedy of value 69.
- For 1989, the most common genre is Comedy of value 63.
- For 1990, the most common genre is Drama of value 60.
- For 1991, the most common genre is Drama of value 63.
- For 1992, the most common genre is Drama of value 65.

- For 1993, the most common genre is Drama of value 90.
- For 1994, the most common genre is Comedy of value 88.
- For 1995, the most common genre is Drama of value 93.
- For 1996, the most common genre is Drama of value 104.
- For 1997, the most common genre is Drama of value 83.
- For 1998, the most common genre is Drama of value 108.
- For 1999, the most common genre is Drama of value 113.
- For 2000, the most common genre is Drama of value 101.
- For 2001, the most common genre is Comedy of value 101.
- For 2002, the most common genre is Drama of value 130.
- For 2003, the most common genre is Comedy of value 111.
- For 2004, the most common genre is Drama of value 141.
- For 2005, the most common genre is Drama of value 182.
- For 2006, the most common genre is Drama of value 197.
- For 2007, the most common genre is Drama of value 197.
- For 2008, the most common genre is Drama of value 233.
- For 2009, the most common genre is Drama of value 224.
- For 2010, the most common genre is Drama of value 210.
- For 2011, the most common genre is Drama of value 214.
- For 2012, the most common genre is Drama of value 232.
- For 2013, the most common genre is Drama of value 253.
- For 2014, the most common genre is Drama of value 284.
- For 2015, the most common genre is Drama of value 260.

We can conclude that Drama is the most common movie genre overall, and has dominated early TV.

Comedy was also a very good competitor from 1985 to around 2003.

We can also conclude that with the rising number of Drama movies over the time interval, we can say that TV has gotten extremely popular and might've reached its peak at 2014 only dropping a bit during 2015.

1.3 Second question:

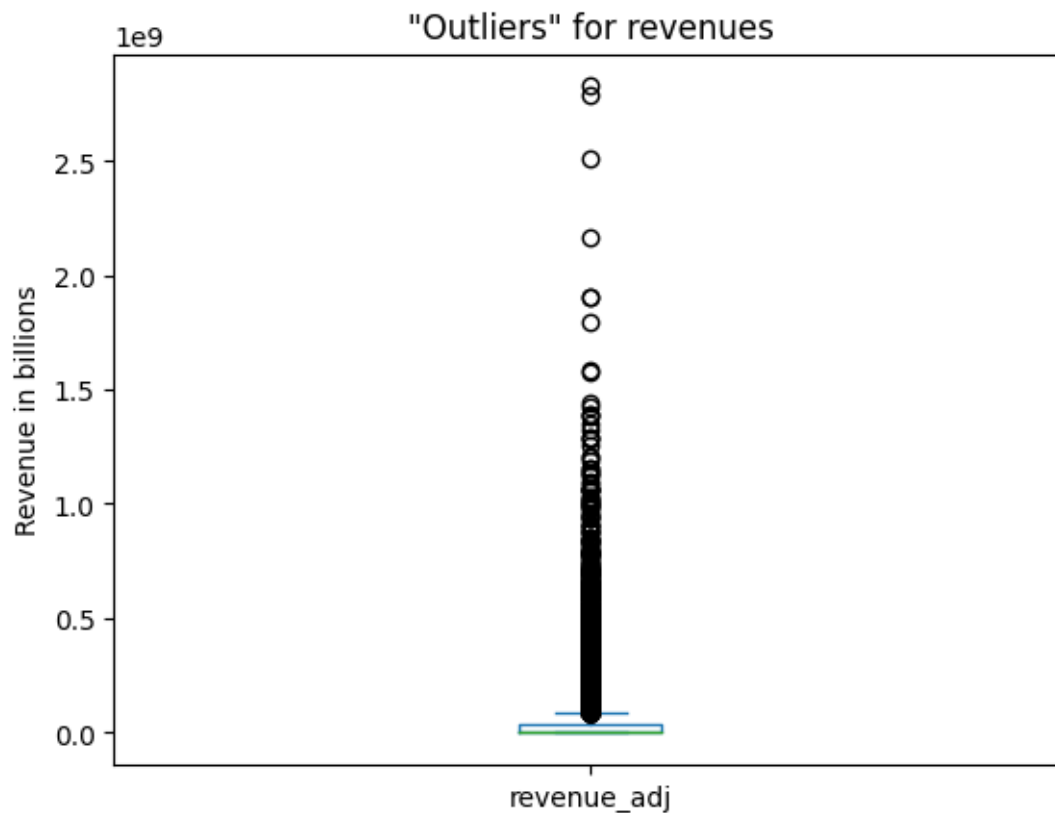
Does runtime affect the movie's revenues?

For this one, we need to isolate our two columns 'runtime' and 'revenue_adj'. Then get the mean for each group of runtime, which will give us a rough idea for our question.

(runtime is measured in minutes and revenue_adj accounts for inflation.)

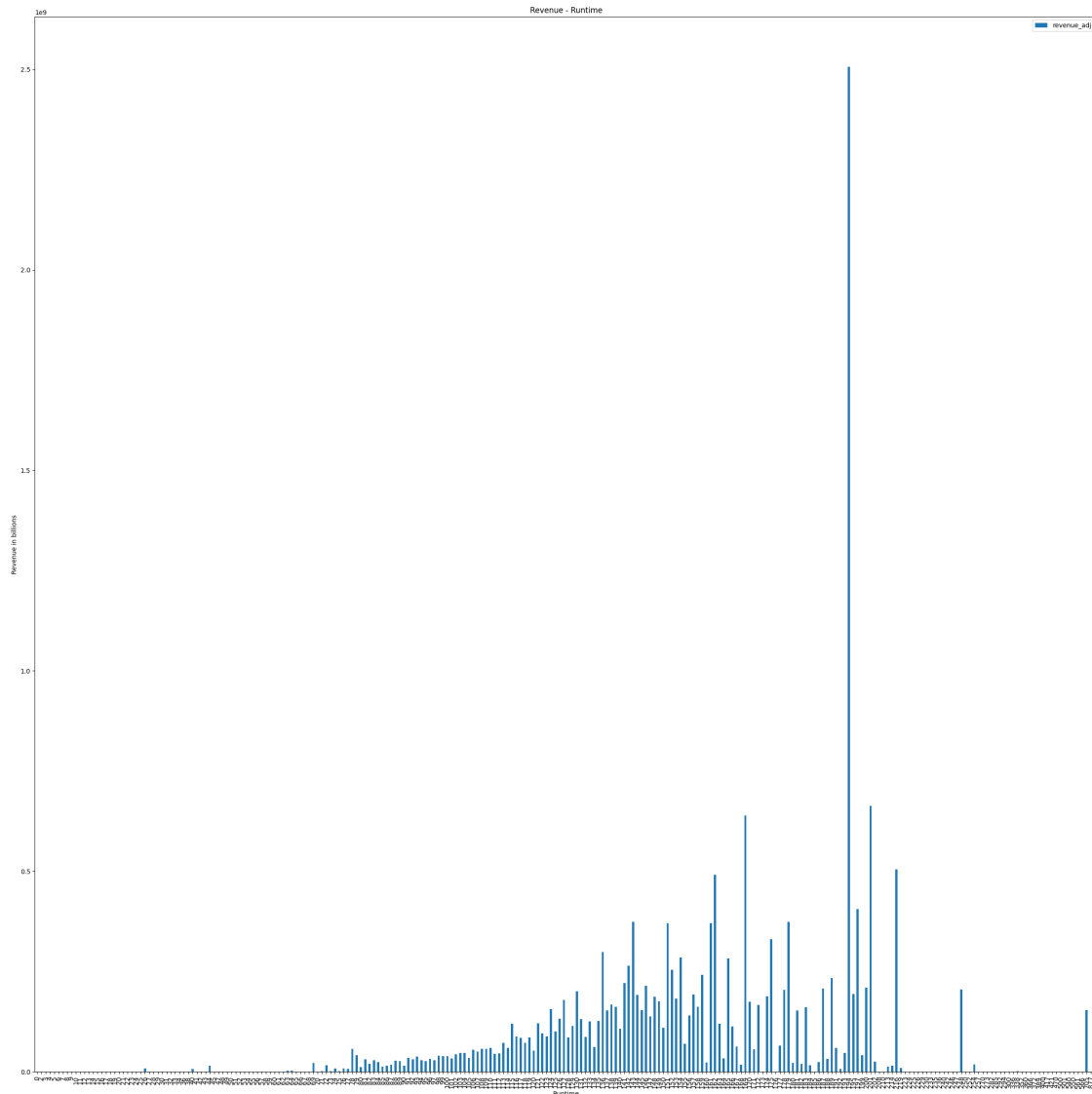
However, let's check for outliers.

```
[21]: df['revenue_adj'].plot(kind = 'box', ylabel = 'Revenue in billions', title = "Outliers for revenues");
```



Apparently most movies flop which gives us a ton of outliers.

```
[22]: # the y-values are measured in billions.
pd.DataFrame(df.groupby('runtime')['revenue_adj'].mean()).plot(kind = 'bar',
    ↳ figsize = (30, 30), xlabel = 'Runtime', ylabel = 'Revenue in billions',
    ↳ title = 'Revenue - Runtime');
```

```
[23]: #identifying what value that large spike (apparent outlier) is ...  
df.groupby('runtime')['revenue_adj'].mean().max()
```

```
[23]: 2506405735.41947
```

Now, this is a very rough plot, many values are plotted on the x-axis and so you don't get a good look at the x-values. However, the plot is very clear, and we'll be making use of this in our answer. First, we see that for values of runtime under a certain value, these movies got almost no revenue, and for above that certain value, we see a very positive correlation between runtime and revenue.

This trend doesn't continue on for long though. Eventually, the revenue approaches zero steadily once again except for a few outliers which I think are probably related

to documentaries and large movie productions that are very hyped up and has a good marketing team.

Now, let's call the values that are at the bounds of the region where there is positive correlation t_a (lower bound) and t_b (upper bound). We see that for values:

- $t < t_a$ we use our observations to quantify this and we get that the revenue $r \rightarrow 0$ (approaches zero).
- $t_a < t < t_b$, the revenue r has a positive correlation and is expected to rise (almost) regularly until t_b .
- $t > t_b$, the revenue r has a negative correlation (which is true for most of the movies in that interval, except a few outliers) and swiftly approaches zero ($r \rightarrow 0$).

We can tell what t_a and t_b are by inspecting the plot, which is definitely hard, but, by inspection:

- t_a is around the 80 mark.
- t_b is around the 152 mark.

1.3.1 So, for optimal revenue, assuming the movie's theme, marketing strategies and whatnot are optimised, your movie's runtime should fall in the (80, 152) minute interval.

Conclusions

1.3.2 Finally, at the end of our two questions, we can conclude that for a movie to be successful it might have two criteria to fill:

- It might have to be a Drama film/movie. Reasoning behind this is most movies and films are of genre 'Drama', we can conclude that most production companies (including very very big ones) produce mostly Drama films.
- And it has to fall in the 80 to 152 minute interval for its runtime. Reasoning behind this is we notice a slight positive correlation between runtime and revenue in our graph/plot, which leads us to think that on average, people are more likely to watch a movie or film if its runtime doesn't exceed 2.53 hours (152 minutes) and doesn't fall beneath 1.3 hours (80 minutes) and ideally is inside that region, not teetering on the edge of it.

1.3.3 That doesn't always mean success for our movie or film, but it does have a slight effect.

1.3.4 We also have to recognise the limitations of this analysis. If we wanted to analyse production companies, you might want to separate them (they're in a pipe-separated format), for which case you would get many many many more values than when we did that to genres, which would take much more time to analyse. We also state that point for analysing directors.

1.3.5 With revenue vs runtime, the plot we produced is very very full of values, which makes it hard to analyse it.