Machine Learning Assignement 2

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First of all, we import the needed libraries

```
import sklearn
from pathlib import Path
import pandas as pd
import tarfile
import urllib.request
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Then we upload the dataset and print the first rows to see its general form using .head()

```
titles = pd.read_csv(Path("titles.csv"))
titles.head()
```

	id	title	type	description	release_year	age_certification
0	ts300399	Five Came Back: The Reference Films	SHOW	This collection includes 12 World War II-era p...	1945	TV-MA
1	tm84618	Taxi Driver	MOVIE	A mentally unstable Vietnam War veteran works ...	1976	R
2	tm154986	Deliverance	MOVIE	Intent on seeing the Cahulawassee River before...	1972	R
3	tm127384	Monty Python and the Holy Grail	MOVIE	King Arthur, accompanied by his squire, recrui...	1975	PG
4	tm120801	The Dirty Dozen	MOVIE	12 American military prisoners in World War II...	1967	NaN

Here, we change the column type so it uses a numerical variable instead of a string one which isnt as easy to manipulate. If the type is 0 then it is a movie, if it is one then it is a show.

```
# 1 for SHOWS, 0 for MOVIES
titles["type"] = titles["type"].replace(["SHOW"], 1)
titles["type"] = titles["type"].replace(["MOVIE"], 0)
titles = titles.drop(columns = "title")
titles = titles.drop(columns = "description")
titles.head()
```

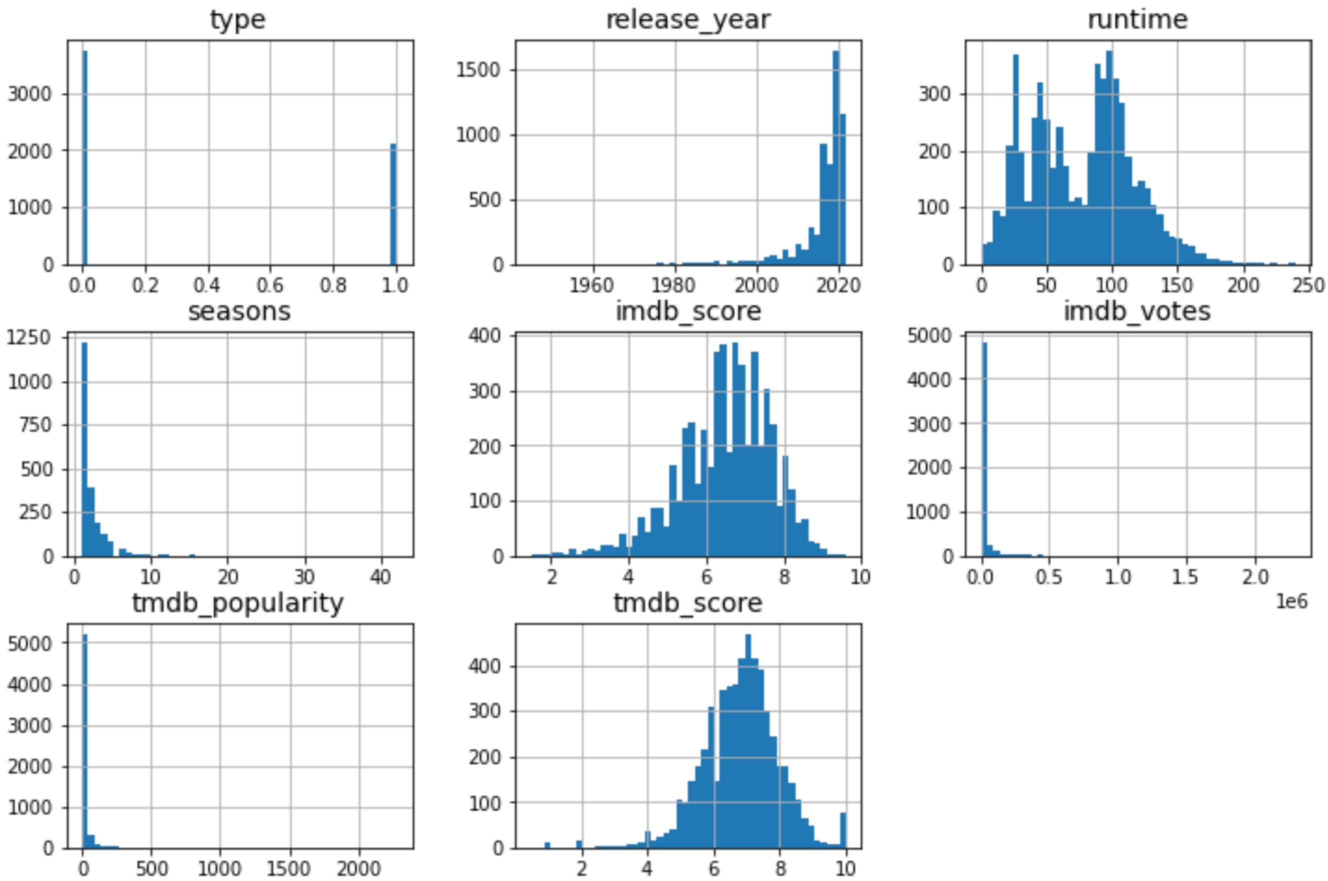
	id	type	release_year	age_certification	runtime	genres	pr
0	ts300399	1	1945	TV-MA	51	['documentation']	
1	tm84618	0	1976	R	114	['drama', 'crime']	
2	tm154986	0	1972	R	109	['drama', 'action', 'thriller', 'european']	
3	tm127384	0	1975	PG	91	['fantasy', 'action', 'comedy']	
4	tm120801	0	1967	NaN	150	['war', 'action']	

Here we use two functions to get more information on the dataset. The function .info will print information about each column, and .column will simply print the name of all of the columns in the dataset

```
titles.info()
titles.columns
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5850 entries, 0 to 5849
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   id                    5850 non-null   object 
 1   type                  5850 non-null   int64  
 2   release_year          5850 non-null   int64  
 3   age_certification     3231 non-null   object 
 4   runtime               5850 non-null   int64  
 5   genres                5850 non-null   object 
 6   production_countries  5850 non-null   object 
 7   seasons               2106 non-null   float64
 8   imdb_id               5447 non-null   object 
 9   imdb_score            5368 non-null   float64
 10  imdb_votes            5352 non-null   float64
 11  tmdb_popularity       5759 non-null   float64
 12  tmdb_score            5539 non-null   float64
dtypes: float64(5), int64(3), object(5)
memory usage: 594.3+ KB
Index(['id', 'type', 'release_year', 'age_certification', 'runtime',
'genres',
       'production_countries', 'seasons', 'imdb_id', 'imdb_score',
       'imdb_votes', 'tmdb_popularity', 'tmdb_score'],
      dtype='object')
```

```
# extra code – the next 5 lines define the default font sizes
plt.rc('font', size=14)
plt.rc('axes', labelsize=14, titlesize=14)
plt.rc('legend', fontsize=14)
plt.rc('xtick', labelsize=10)
plt.rc('ytick', labelsize=10)

titles.hist(bins=50, figsize=(12, 8))

plt.show()
```



```
titles["genres"]
```

```
0                                  ['documentation']
1                                  ['drama', 'crime']
2       ['drama', 'action', 'thriller', 'european']
3                   ['fantasy', 'action', 'comedy']
4                                  ['war', 'action']
                              ...
5845                            ['romance', 'drama']
5846                                       ['drama']
5847                                      ['comedy']
5848                                              []
5849               ['family', 'animation', 'comedy']
Name: genres, Length: 5850, dtype: object
```

Here, the next lines will be use to change the column genre. The database has a column with all the genres of the movie. We want to create one column for each genre, and then put the value on 1 if the genre corresponds to the movie, 0 if it isn't the case.

```
titles["genres"] = titles["genres"].replace(["'"], " ")
titles["genres"] = titles["genres"].replace(["]"], " ")
titles["genres"] = titles["genres"].replace(["["], " ")
print(titles["genres"])
```

```
0                                  ['documentation']
1                                  ['drama', 'crime']
2       ['drama', 'action', 'thriller', 'european']
3                   ['fantasy', 'action', 'comedy']
4                                  ['war', 'action']
                              ...
5845                            ['romance', 'drama']
5846                                       ['drama']
5847                                      ['comedy']
5848                                              []
5849               ['family', 'animation', 'comedy']
Name: genres, Length: 5850, dtype: object
```

Now that we modified the 'genres' column as we wanted, we can split it to get all the different unique genres that appear in the dataset.\

```
titles['genres'] = titles['genres'].str.replace("'","")
titles['genres'] = titles['genres'].str.replace("[","")
titles['genres'] = titles['genres'].str.replace("]","")
titles['genres'] = titles['genres'].str.replace("'","")

print(titles["genres"])
```

```
0                         documentation
1                          drama, crime
2       drama, action, thriller, european
3                 fantasy, action, comedy
4                           war, action
                    ...
5845                     romance, drama
5846                              drama
5847                             comedy
5848
5849            family, animation, comedy
Name: genres, Length: 5850, dtype: object
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: FutureWarni

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: FutureWarni
  This is separate from the ipykernel package so we can avoid doing imports
```

```
distinctTitles = titles['genres'].str.split(",", expand = True)
distinctTitles=distinctTitles[0].unique()
print(distinctTitles)
distinctTitles = np.delete(distinctTitles, 17)
print(distinctTitles)
```

```
['documentation' 'drama' 'fantasy' 'war' 'comedy' 'thriller' 'crime'
 'romance' 'action' 'western' 'history' 'music' 'horror' 'scifi'
 'animation' 'family' 'reality' '' 'sport']
['documentation' 'drama' 'fantasy' 'war' 'comedy' 'thriller' 'crime'
 'romance' 'action' 'western' 'history' 'music' 'horror' 'scifi'
 'animation' 'family' 'reality' 'sport']
```

Now we can add a column for each distinct genre

```
for i in distinctTitles:
  titles.insert(5,i,0, allow_duplicates=False)

print(titles)
```

```
      ...        ...  ...         ...              ...    ...   ...
5845  tm1014599    0         2021              NaN    100     0
5846   tm898842    0         2021              NaN    134     0
```

```
5847  tm1059008     0          2021              NaN       90      0
5848  tm1035612     0          2021            PG-13       37      0
5849   ts271048     1          2021              NaN        7      0

      reality  family  animation  scifi  horror  music  history  western  \
0           0       0          0      0       0      0        0        0
1           0       0          0      0       0      0        0        0
2           0       0          0      0       0      0        0        0
3           0       0          0      0       0      0        0        0
4           0       0          0      0       0      0        0        0
...       ...     ...        ...    ...     ...    ...      ...      ...
5845        0       0          0      0       0      0        0        0
5846        0       0          0      0       0      0        0        0
5847        0       0          0      0       0      0        0        0
5848        0       0          0      0       0      0        0        0
5849        0       0          0      0       0      0        0        0

      action  romance  crime  thriller  comedy  war  fantasy  drama  \
0          0        0      0         0       0    0        0      0
1          0        0      0         0       0    0        0      0
2          0        0      0         0       0    0        0      0
3          0        0      0         0       0    0        0      0
4          0        0      0         0       0    0        0      0
...      ...      ...    ...       ...     ...  ...      ...    ...
5845       0        0      0         0       0    0        0      0
5846       0        0      0         0       0    0        0      0
5847       0        0      0         0       0    0        0      0
5848       0        0      0         0       0    0        0      0
5849       0        0      0         0       0    0        0      0

      documentation                             genres production_countries
0                 0                      documentation               ['US']
1                 0                       drama, crime               ['US']
2                 0  drama, action, thriller, european               ['US']
3                 0            fantasy, action, comedy               ['GB']
4                 0                        war, action         ['GB', 'US']
...             ...                                ...                  ...
5845              0                     romance, drama               ['NG']
5846              0                              drama                   []
5847              0                             comedy               ['CO']
5848              0                                                    ['US']
5849              0          family, animation, comedy                   []

      seasons     imdb_id  imdb_score  imdb_votes  tmdb_popularity  tmdb_sc
0         1.0         NaN         NaN         NaN            0.600
1         NaN   tt0075314         8.2    808582.0           40.965       8.
2         NaN   tt0068473         7.7    107673.0           10.010       7.
3         NaN   tt0071853         8.2    534486.0           15.461       7.
4         NaN   tt0061578         7.7     72662.0           20.398       7.
...       ...         ...         ...         ...              ...
5845      NaN  tt13857480         6.8        45.0            1.466
5846      NaN  tt11803618         7.7       348.0              NaN
5847      NaN  tt14585902         3.8        68.0           26.005       6.
5848      NaN         NaN         NaN         NaN            1.296      10.
```

```
5849      1.0  tt13711094         7.8        18.0             2.289      10.

[5850 rows x 31 columns]
```

```
print(titles.head())
print(titles.columns)
```

```
         id  type  release_year age_certification  runtime  sport  reality
0  ts300399     1          1945             TV-MA       51      0        0
1   tm84618     0          1976                 R      114      0        0
2  tm154986     0          1972                 R      109      0        0
3  tm127384     0          1975                PG       91      0        0
4  tm120801     0          1967               NaN      150      0        0

   family  animation  scifi  horror  music  history  western  action  roman
0       0          0      0       0      0        0        0       0
1       0          0      0       0      0        0        0       0
2       0          0      0       0      0        0        0       0
3       0          0      0       0      0        0        0       0
4       0          0      0       0      0        0        0       0

   crime  thriller  comedy  war  fantasy  drama  documentation  \
0      0         0       0    0        0      0              0
1      0         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

                           genres production_countries  seasons    imdb_
0                   documentation               ['US']      1.0        N
1                    drama, crime               ['US']      NaN  tt00753
2  drama, action, thriller, european               ['US']      NaN  tt00684
3           fantasy, action, comedy               ['GB']      NaN  tt00718
4                      war, action         ['GB', 'US']      NaN  tt00615

   imdb_score  imdb_votes  tmdb_popularity  tmdb_score
0         NaN         NaN            0.600         NaN
1         8.2    808582.0           40.965       8.179
2         7.7    107673.0           10.010       7.300
3         8.2    534486.0           15.461       7.811
4         7.7     72662.0           20.398       7.600
Index(['id', 'type', 'release_year', 'age_certification', 'runtime', 'sport
       'reality', 'family', 'animation', 'scifi', 'horror', 'music', 'histo
       'western', 'action', 'romance', 'crime', 'thriller', 'comedy', 'war'
       'fantasy', 'drama', 'documentation', 'genres', 'production_countries
       'seasons', 'imdb_id', 'imdb_score', 'imdb_votes', 'tmdb_popularity',
       'tmdb_score'],
      dtype='object')
```

Now that we added a column for each genre, we will the column with a 1 whenever this gender appeared in the 'genres' column for this movie.

```
index = 0
for i in titles["genres"]:
  tab = i.split(",")
  for j in tab:
    j = j.strip()
    titles.loc[index, j] = 1
  index +=1
```

Here since the age certification are different labels, we do the same we did for the 'genres' column. We split it and create different columns.

```
# splitting age certification in multiple columns, filled with 0 or 1
unique_certification = titles["age_certification"].unique()

for i in unique_certification:
  titles.insert(5, i, 0, allow_duplicates = False)

index = 0
for i in titles["age_certification"]:
  titles.loc[index, i] = 1
  index += 1
```

Again, we want to split the production_countries column into many columns (one for each county) to make the rest of the task easier. We use the same process, and fill the column with a 1 when the movie was produced in this country, 0 when it wasn't.

```
# splitting production countries into multiple columns, filled with 0 or 1

titles['production_countries'] = titles['production_countries'].str.replace("'",
titles['production_countries'] = titles['production_countries'].str.replace("[",
titles['production_countries'] = titles['production_countries'].str.replace("]",
titles['production_countries'] = titles['production_countries'].str.replace("'",


unique_production_country = titles["production_countries"].str.split(",", expand
unique_production_country = unique_production_country[0].unique()
index = 0
for i in titles["production_countries"]:
  tab = i.split(",")
  for j in tab:
    j = j.strip()
    titles.loc[index, j] = 1
  index +=1


# titles.drop([''], axis =1)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: FutureWarni
  after removing the cwd from sys.path.
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: FutureWarni
  """
/usr/local/lib/python3.7/dist-packages/pandas/core/indexing.py:1684: Perfor
  self.obj[key] = infer_fill_value(value)
```

Now, to study the dataset we decided to divide it into two parts, movies and series. Indeed it is complicated to create models comparing movies and series when they have a completely different structure, don't last nearly as long, ...

We then drop the useless columns from each data frame (like the number of seasons for movies)

```
# splitting the df into 2 distincts : films and series
# series correspond to the rows in titles where seasons is non null
series = titles[titles.seasons >= 1].reset_index()

# films is the entire "titles" DF without the series DF
films = pd.concat([titles, series]).drop_duplicates(keep = False).reset_index()

# we leave seasons from films because it's not relevant
films = films.drop(columns = {"seasons", "type"})

# cleaning float values
for i in unique_certification:
  series[i] = series[i].astype(int)

series["seasons"] = series["seasons"].astype(int)

# removing useless rows from seasons

series = series.drop(columns = {"R", "PG", "PG-13", "G", "NC-17", "type"})
```

Double-cliquez (ou appuyez sur Entrée) pour modifier

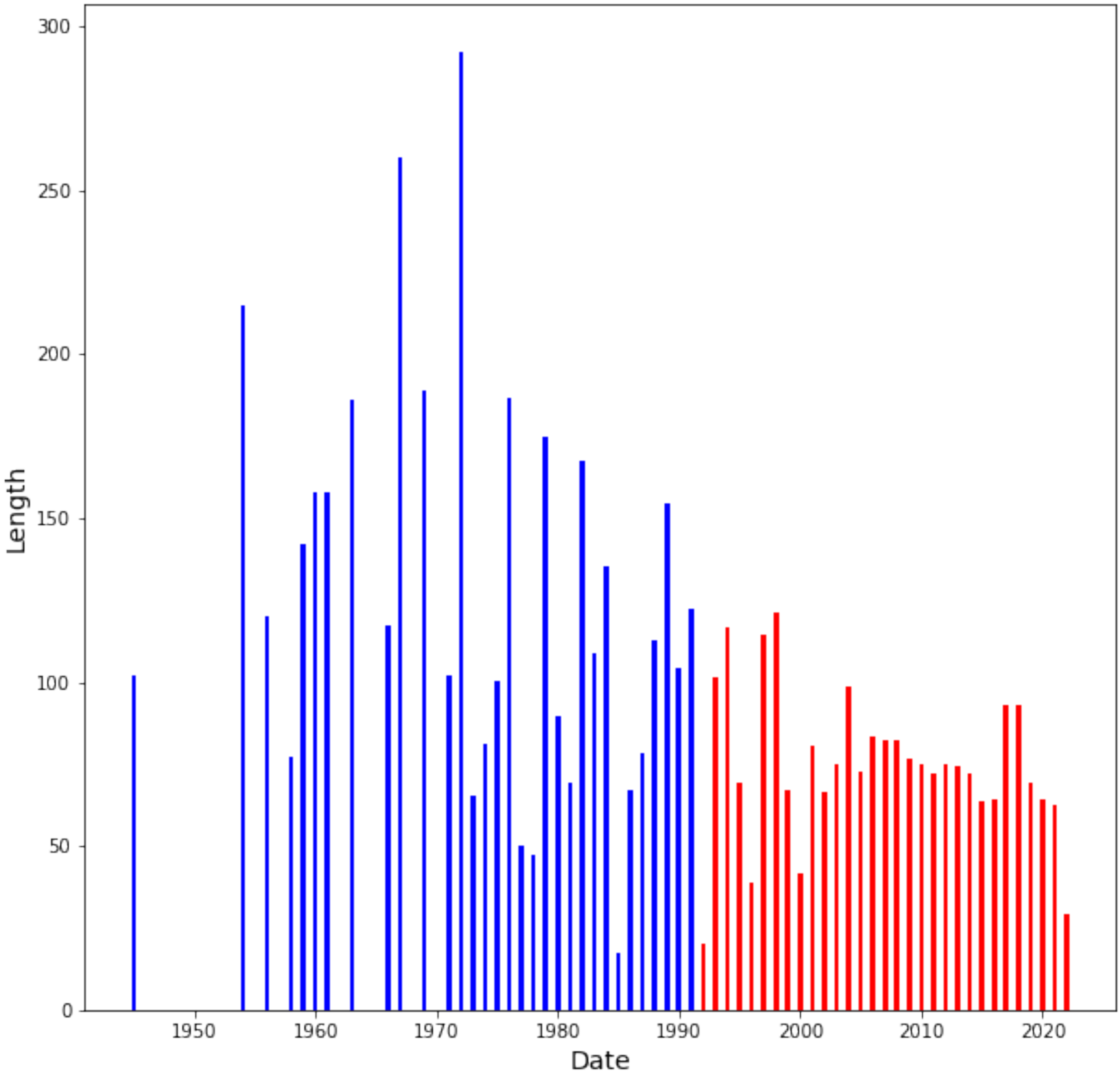
```
pd.set_option('max_columns', None)
pd.set_option('display.max_columns', None)

col_names = []
for i in range(len(films.columns)):
  col_names.append(films.columns[i])
```

Now, we will try to find a correlation between different variables. We will first try to plot some graphe, just bellow will be the link between the length of the movie and the date.

```
# trying to find correlation between release date and duration in films

release_duration_df = films[["release_year", "runtime"]]
release_duration_df.sort_values(by =["release_year"], inplace = True)

average_duration_year = []
unique_year = release_duration_df["release_year"].unique()

## getting the total amount of runtime/year
runtime_year = release_duration_df.groupby(["release_year"]).runtime.sum().reset
```

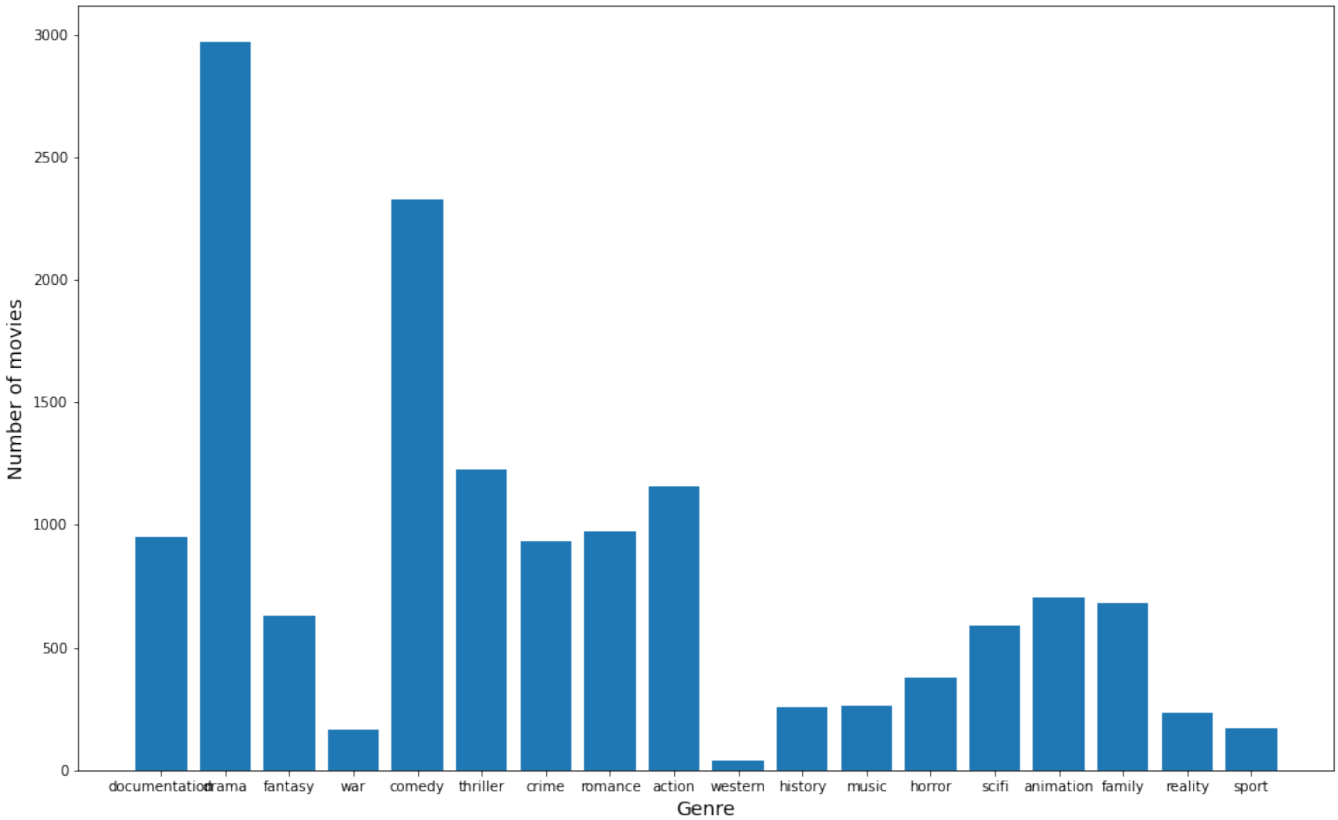
```
# getting this amount in an array
runtimes = []
for i in runtime_year["runtime"]:
  runtimes.append(i)

## getting the number of films/year
film_year = release_duration_df["release_year"].value_counts().reset_index()
film_year.sort_values(by = ["release_year"], inplace = True)

# getting this amount in an array

nb_film_year_array = []
for i in film_year["release_year"]:
  nb_film_year_array.append(i)

count = 0
for i in unique_year:
  mean = runtimes[count] / nb_film_year_array[count]
  average_duration_year.append(mean)
  count += 1

print(average_duration_year)

fig = plt.figure(figsize = (10, 10))
for i in range(len(nb_film_year_array)):
  if(nb_film_year_array[i] >= 10):
    plt.bar(unique_year[i], average_duration_year[i], color= "red", width = 0.4)
  else:
    plt.bar(unique_year[i], average_duration_year[i], color= "blue", width = 0.4

plt.ylabel("Length")
plt.xlabel("Date")
plt.show()

# This plot looks to show us that most recent films has a lower runtime than old
# We have to take care of this because the more older is the film, the less we h
# In blue, we have printed values where the number of films / year is less than
# We see that all the films before the 90's are in this case, making them quite
```

```
/usr/local/lib/python3.7/dist-packages/pandas/util/_decorators.py:311: Sett
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs
  return func(*args, **kwargs)
[102.0, 215.0, 120.0, 77.0, 142.0, 158.0, 158.0, 186.0, 117.0, 260.0, 189.0
```



```
#number of movies by gender
tab=[]
for i in distinctTitles:
  count=0
  for j in range (0, 5849):
    if(titles[i][j]==1):
      count+=1
  tab.append(count)
fig= plt.figure(figsize = (16, 10))
plt.ylabel("Number of movies")
plt.xlabel("Genre")
plt.bar(distinctTitles,tab)
```

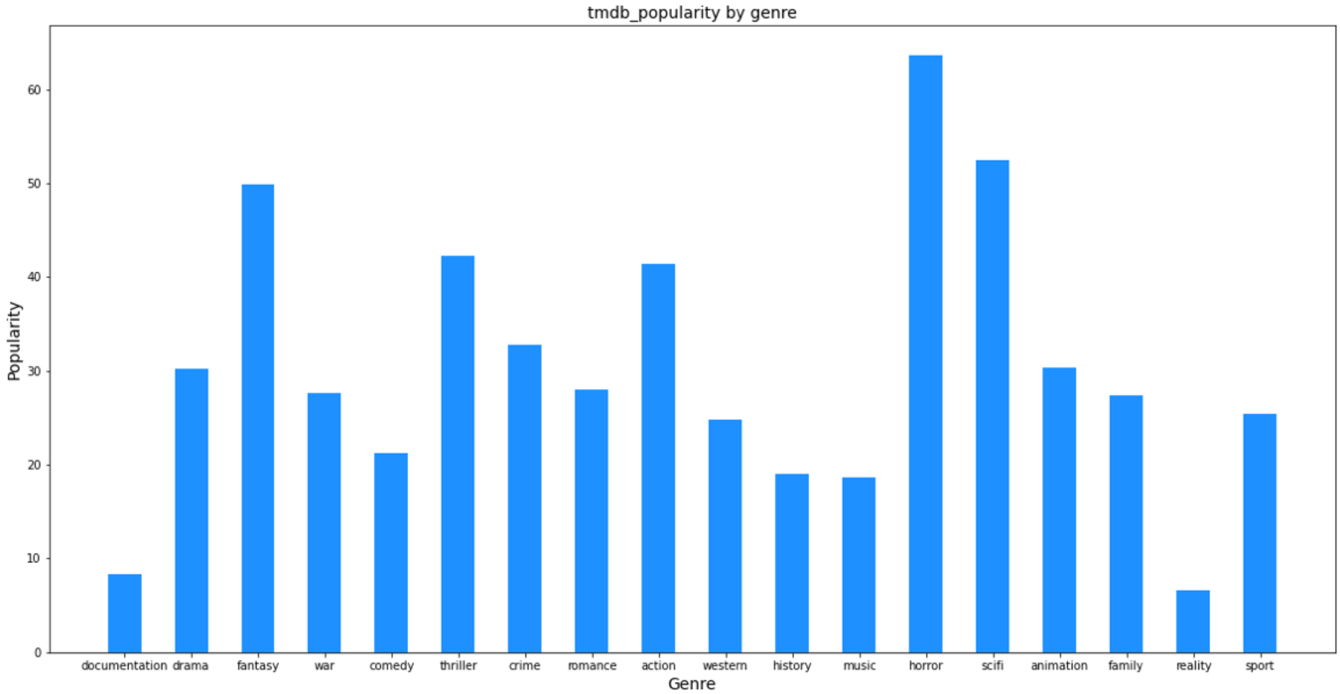
```
<BarContainer object of 18 artists>
```

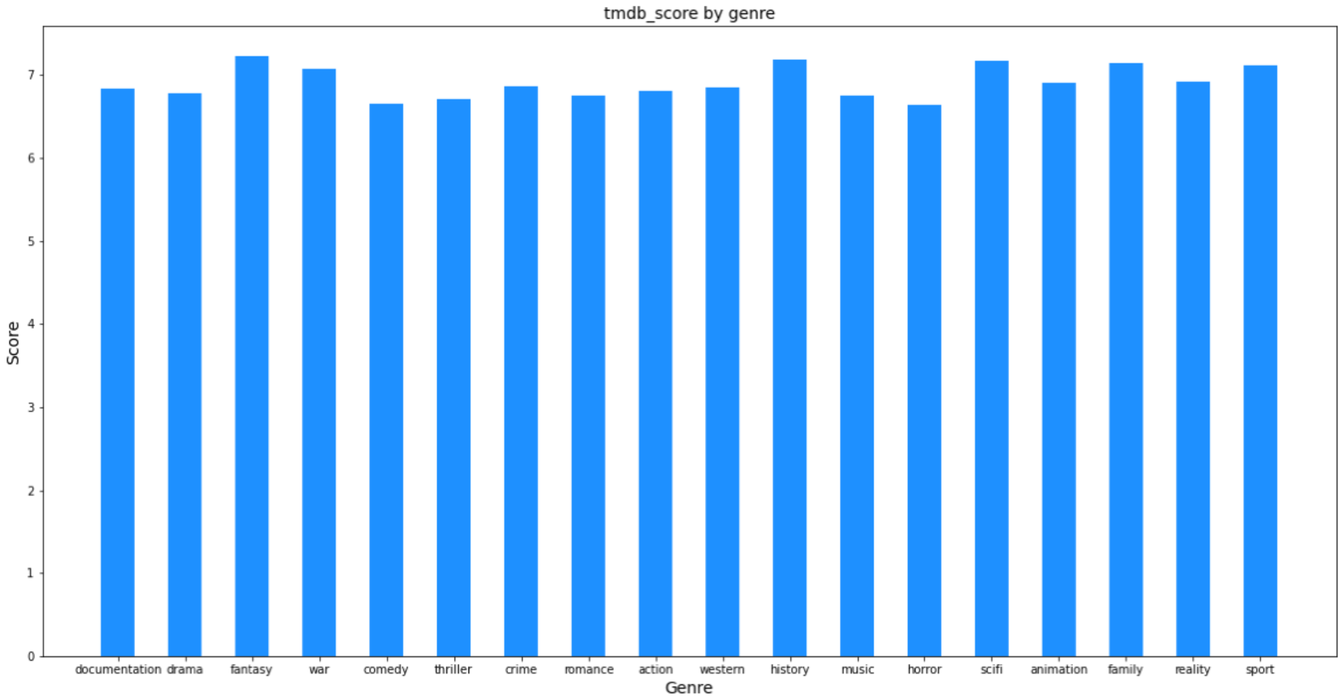


Now we will try to print the tmdb score and popularity depending on the genre of the movie. We can see that the score doesn't seem to vary much depending on the genre. However, we can see that some genre of movies are more popular than others, as exepected. As an example, horror movies are much more popular than documentaries

```
# Trying to find corrolation between genre and score for films for tmdb, and bet
genre_score_df = films[distinctTitles].astype(float)
genre_score_df["tmdb_popularity"] = films["tmdb_popularity"].astype(float)
genre_score_df["tmdb_score"] = films["tmdb_score"].astype(float)
genre_score_df['tmdb_popularity'] = genre_score_df['tmdb_popularity'].fillna(0)
genre_score_df['tmdb_score'] = genre_score_df['tmdb_score'].fillna(0)
genre_score_df["runtime"] = films["runtime"].astype(float)

tab2 = []
fig = plt.figure(figsize = (20, 10))

for col in distinctTitles:
  score = 0
  nb = 0
  for i in genre_score_df.index:
    if genre_score_df.loc[i, col] == 1:
      score += genre_score_df.loc[i, "tmdb_popularity"]
      nb += 1
  mean_score = score/nb
  tab2.append([col, mean_score]) # genre name, mean_score
  plt.bar(col, mean_score, color = "dodgerblue", width = 0.5)

plt.title("tmdb_popularity by genre")
plt.xlabel("Genre")
plt.ylabel("Popularity")
plt.show()

tab2 = []
fig = plt.figure(figsize = (20, 10))

for col in distinctTitles:
  score = 0
  nb = 0
  for i in genre_score_df.index:
    if genre_score_df.loc[i, col] == 1:
      score += genre_score_df.loc[i, "tmdb_score"]
      nb += 1
  mean_score = score/nb
  tab2.append([col, mean_score]) # genre name, mean_score
  plt.bar(col, mean_score, color = "dodgerblue", width = 0.5)
```

```
plt.title("tmdb_score by genre")
plt.xlabel("Genre")
plt.ylabel("Score")
plt.show()
```





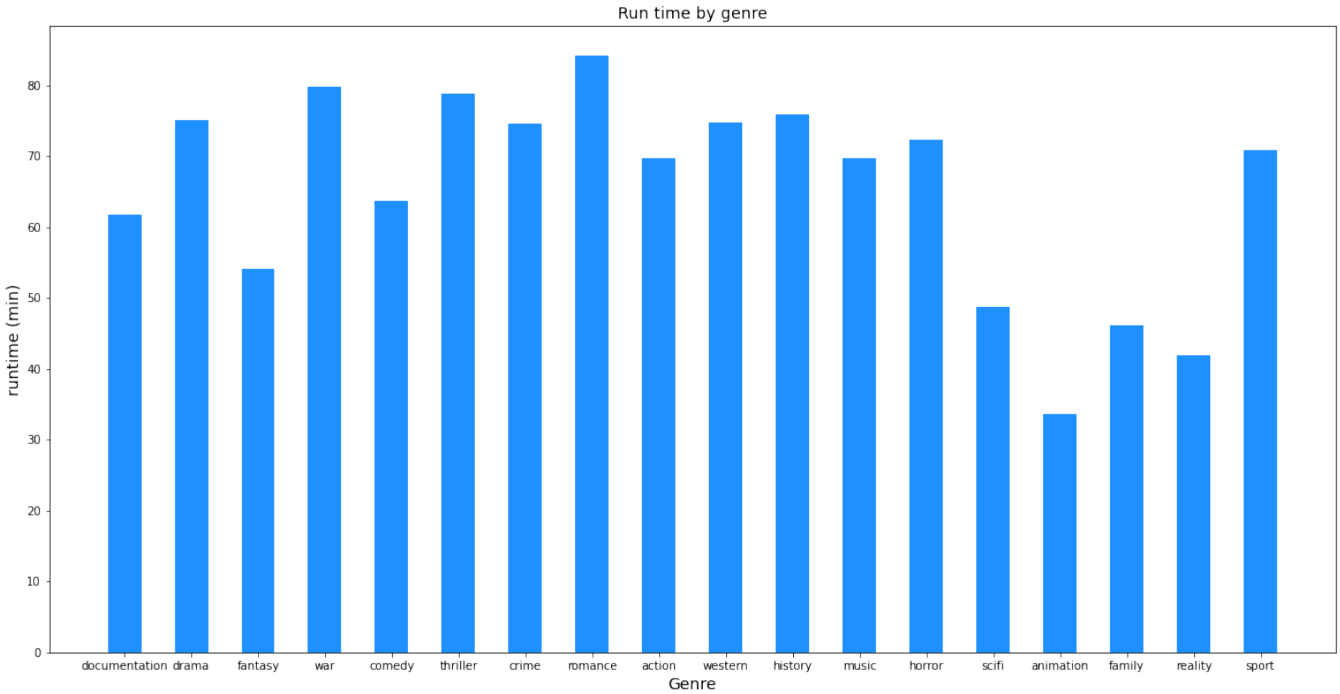
We have printed a barplot showing the mean tmdb_popularity for each kind of genre and another showing the mean tmdb_score for each kind of genre. It attributes to each genres the mean of score/popularity of each film where defined by the genre. If a film is defined by "thriller", "action" and "scifi", it will add to the mean of score/popularity of these genres a new score/popularity value.

- We can see huge disparities between popularity and genre. Some genres, such has documentation, are low compared to fantasy or horror. Some of these values can be explained by the lack of data on some genres.
- Between score and genre, we can see that all the genres has a mean near to 7. It looks that in this dataset, tmdb_scores are almost the same compared to genres.

Here when trying to find correlation between genre and runtime, we find some expected outputs such as a low run time for an animation movie.

```
# showing correlation between genre and runtime (mean)

tab3 = []
fig = plt.figure(figsize = (20, 10))
```

```
for col in distinctTitles:
  score = 0
  nb = 0
  for i in genre_score_df.index:
    if genre_score_df.loc[i, col] == 1:
      score += genre_score_df.loc[i, "runtime"]
      nb += 1
  mean_score = score/nb
  tab3.append([col, mean_score]) # genre name, mean_score
  plt.bar(col, mean_score, color = "dodgerblue", width = 0.5)

plt.title("Run time by genre")
plt.xlabel("Genre")
plt.ylabel("runtime (min)")
plt.show()

# It shows us that some genres, such has animation have a short runtime
# while thrillers, war and romance genres has bigger ones
# It looks relevent compared of what we know about these genres.
```



This piece of code allows to find different correlations between different columns in the dataset. This can give an general idea of the importance of the features, and how we can create links between them to predict the score or the popularity.

```
corrtab = []
for i in films:
  if(np.issubdtype(films[i].dtypes, int) == True | np.issubdtype(films[i].dtypes
    for j in films:
      if(((np.issubdtype(films[j].dtypes, int) == True)| np.issubdtype(films[j].
        corr = films[i].corr(films[j])
        corrtab.append(corr)
        if(corr > 0.10):
```

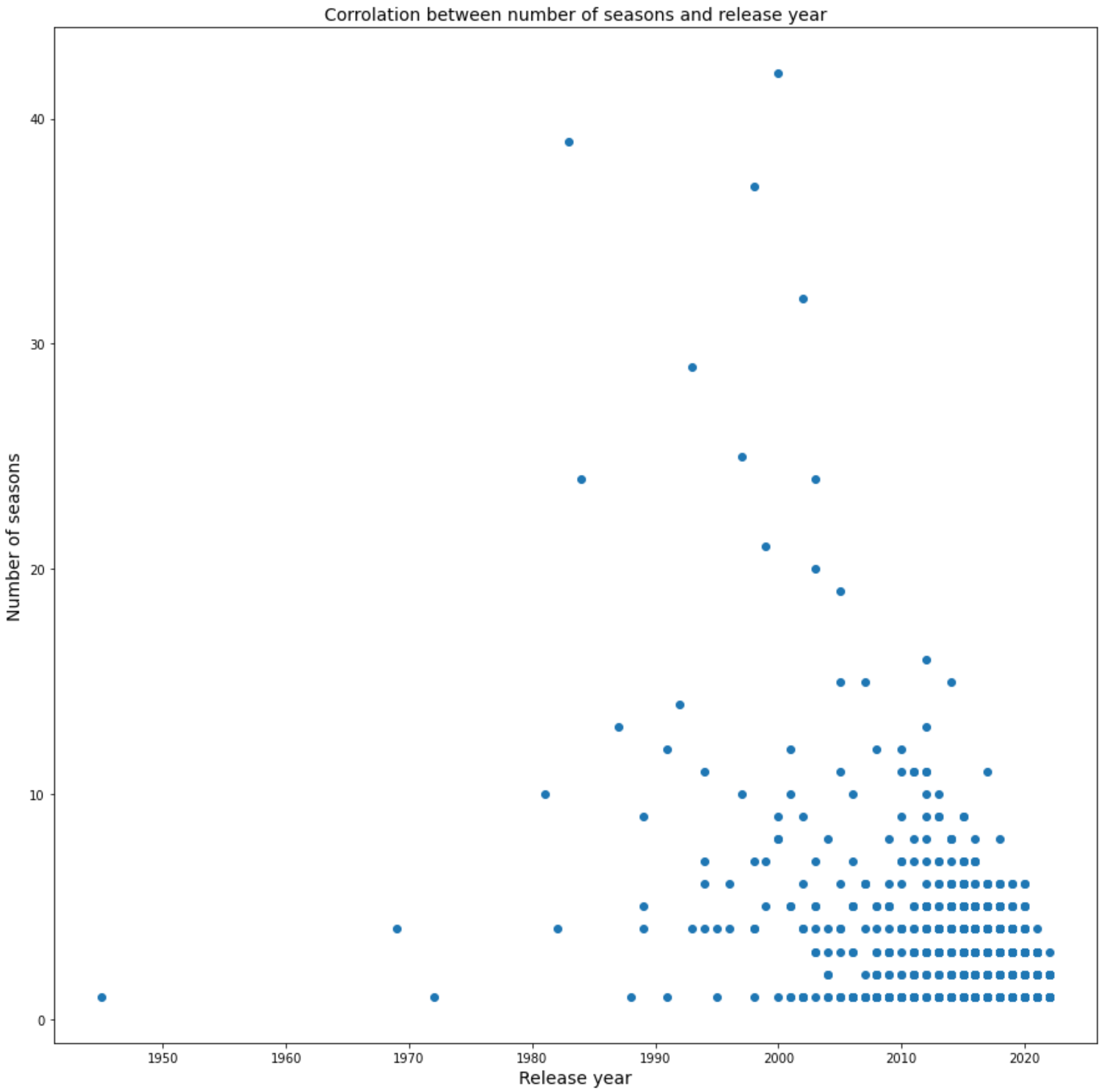
```
        print("Correlation for ", i, " and ", j, " : ", corr)

corrtab.sort(reverse = True)
```

```
Correlation for  scifi  and  fantasy  :  0.4329931172045276
Correlation for  scifi  and  tmdb_popularity  :  0.13104897189009793
Correlation for  scifi  and  tmdb_score  :  0.10784211175204085
Correlation for  horror  and  scifi  :  0.2101908099257621
Correlation for  horror  and  thriller  :  0.32033494467640666
Correlation for  horror  and  fantasy  :  0.19655127171411355
Correlation for  horror  and  tmdb_popularity  :  0.12600677096959595
Correlation for  history  and  war  :  0.27670889499479223
Correlation for  history  and  documentation  :  0.14041955946890516
Correlation for  history  and  imdb_score  :  0.11798579862189999
Correlation for  action  and  TV-Y7  :  0.20158985671953386
Correlation for  action  and  family  :  0.11844413897088028
Correlation for  action  and  animation  :  0.3038817014781834
Correlation for  action  and  scifi  :  0.3568105103693221
Correlation for  action  and  crime  :  0.15559328542076722
Correlation for  action  and  thriller  :  0.23621265007674344
Correlation for  action  and  fantasy  :  0.2914653865904727
Correlation for  action  and  tmdb_popularity  :  0.10846650516950122
Correlation for  romance  and  runtime  :  0.19414439264721425
Correlation for  romance  and  comedy  :  0.15316548796554622
Correlation for  romance  and  drama  :  0.23065510131296016
Correlation for  crime  and  R  :  0.10217770377147542
Correlation for  crime  and  TV-MA  :  0.21698445339601263
Correlation for  crime  and  action  :  0.15559328542076722
Correlation for  crime  and  thriller  :  0.3816434607931516
Correlation for  crime  and  drama  :  0.1698471453503004
Correlation for  thriller  and  runtime  :  0.157489219599009
Correlation for  thriller  and  R  :  0.18075926733618128
Correlation for  thriller  and  TV-MA  :  0.13033472374335148
Correlation for  thriller  and  scifi  :  0.1731890493020356
Correlation for  thriller  and  horror  :  0.32033494467640666
Correlation for  thriller  and  action  :  0.23621265007674347
Correlation for  thriller  and  crime  :  0.3816434607931516
Correlation for  thriller  and  drama  :  0.26762093052300134
Correlation for  thriller  and  imdb_votes  :  0.14872943710726058
Correlation for  thriller  and  tmdb_popularity  :  0.1152986319119266
Correlation for  comedy  and  TV-Y7  :  0.131439372783848
Correlation for  comedy  and  family  :  0.21596612820198308
Correlation for  comedy  and  animation  :  0.14903941622789263
Correlation for  comedy  and  romance  :  0.15316548796554622
Correlation for  war  and  history  :  0.27670889499479223
Correlation for  fantasy  and  TV-Y7  :  0.19418639247026748
Correlation for  fantasy  and  family  :  0.2851706309199075
Correlation for  fantasy  and  animation  :  0.390946285542185
Correlation for  fantasy  and  scifi  :  0.4329931172045276
Correlation for  fantasy  and  horror  :  0.19655127171411357
Correlation for  fantasy  and  action  :  0.2914653865904727
Correlation for  fantasy  and  tmdb_popularity  :  0.11639623979699641
Correlation for  fantasy  and  tmdb_score  :  0.10797893679180419
Correlation for  drama  and  runtime  :  0.22104538833944012
```

```
Correlation for  drama  and  TV-MA  :  0.1275407308697011
Correlation for  drama  and  romance  :  0.2306551013129602
Correlation for  drama  and  crime  :  0.1698471453503004
Correlation for  drama  and  thriller  :  0.26762093052300134
Correlation for  drama  and  imdb_score  :  0.12675155418820036
Correlation for  drama  and  imdb_votes  :  0.10198149964272846
Correlation for  documentation  and  history  :  0.14041955946890516
Correlation for  documentation  and  imdb_score  :  0.15684073198479778
Correlation for  documentation  and  index  :  0.11050341026566436
```

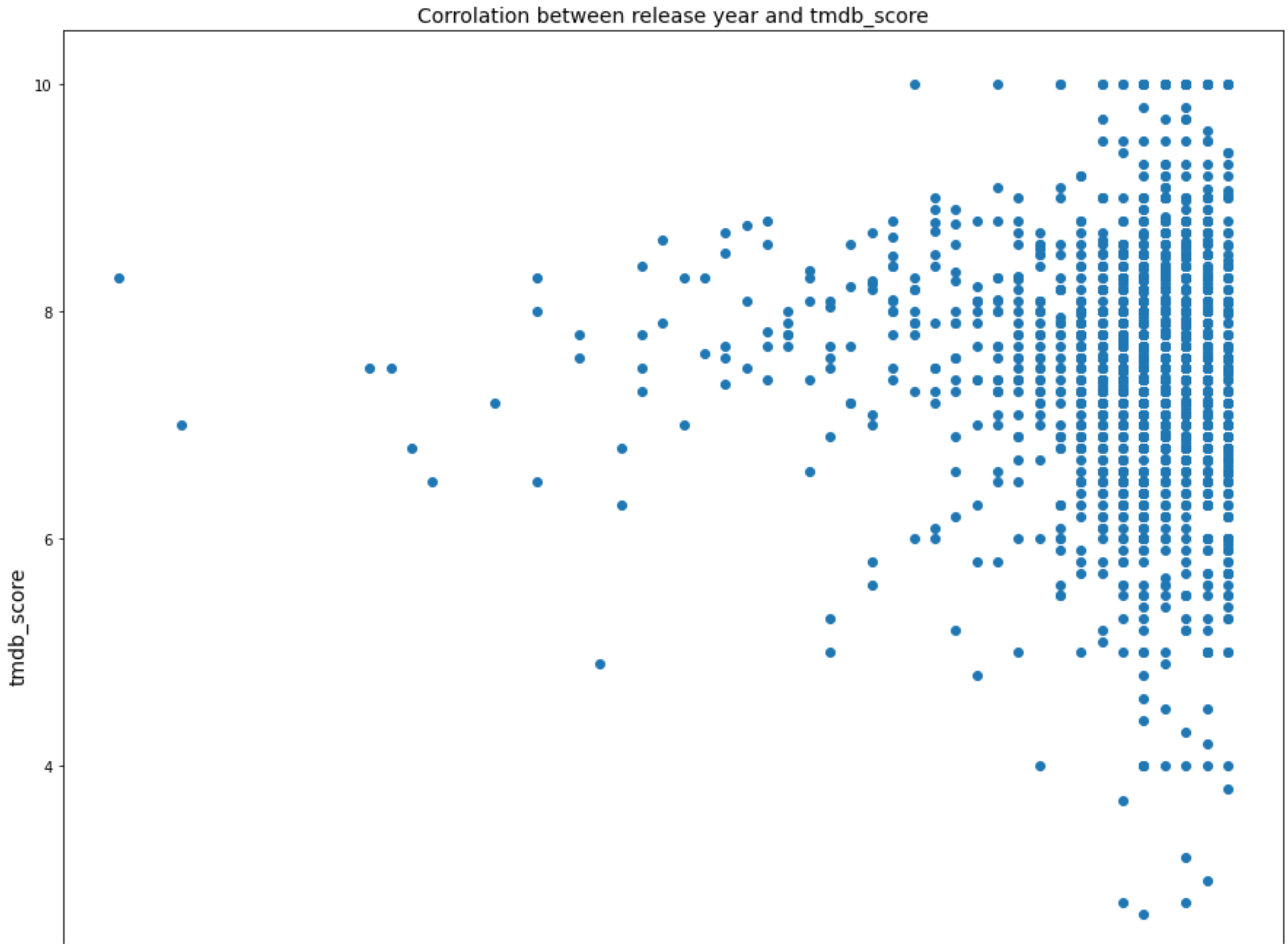
Next, we will try to print some scatter plot of two columns to see if we can find any noticeable correlation. We will also print the actual correlation value between those columns.

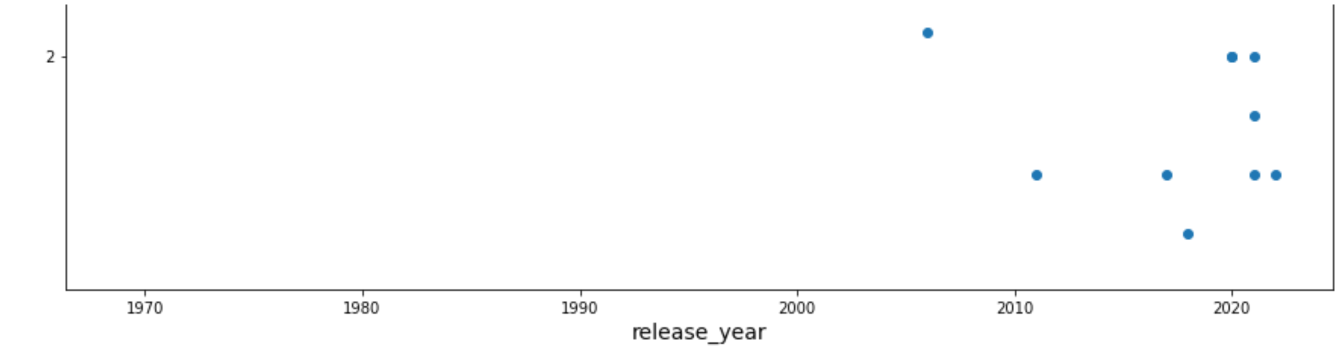
```
#corrolation between number of seasons and release year ?

#print(series.head())
fig = plt.figure(figsize = (15, 15))
plt.scatter(series["release_year"], series["seasons"])
plt.title("Corrolation between number of seasons and release year")
plt.xlabel("Release year")
plt.ylabel("Number of seasons")
plt.show()
corr = series["seasons"].corr(series["release_year"])
print("Correlation is: ", round(corr, 2))
```



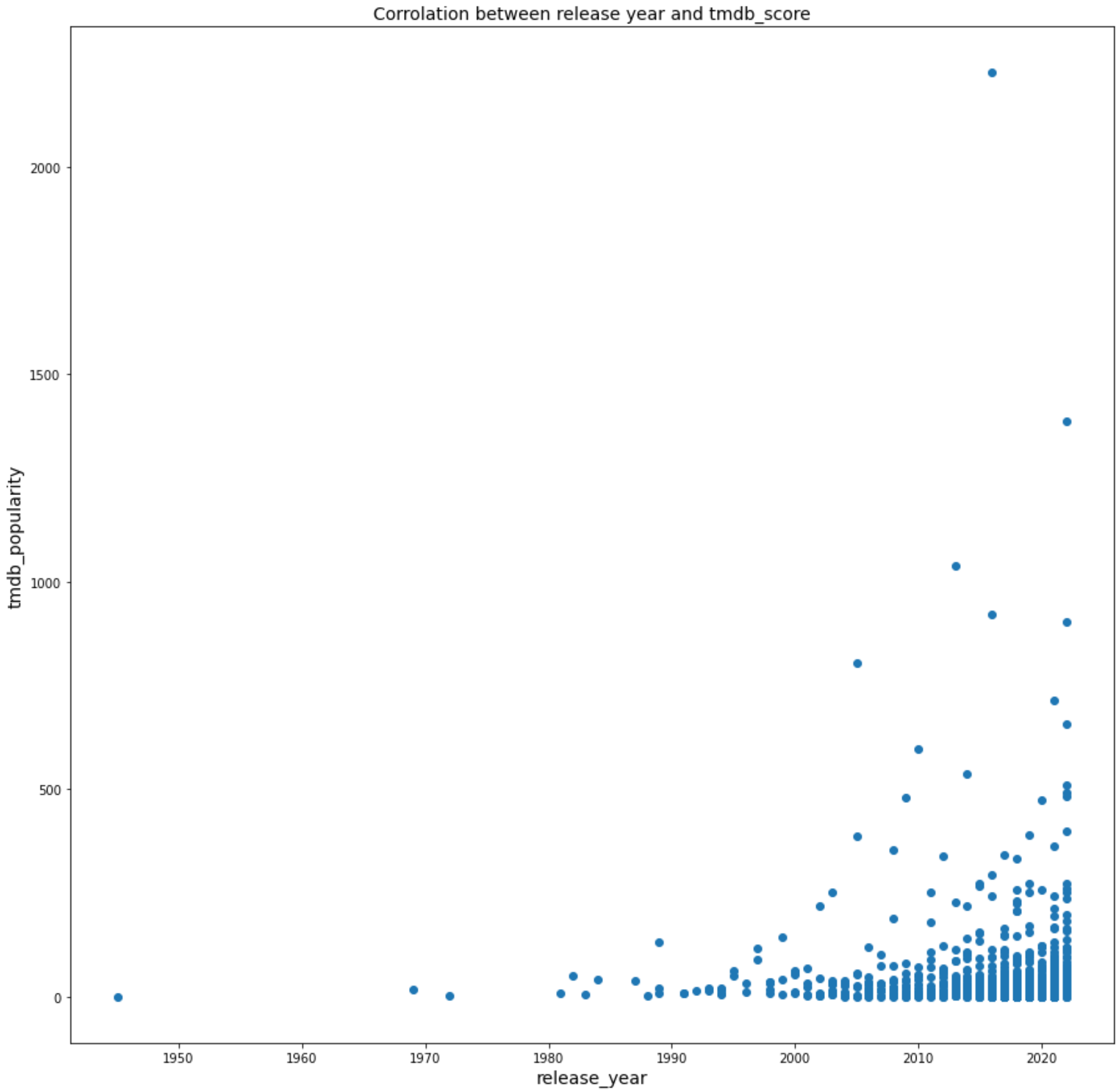

```
Correlation is:  -0.5
```

```
#corrolation between release year and score?

#tmdb_score
fig = plt.figure(figsize = (15, 15))
plt.scatter(series["release_year"],series["tmdb_score"])
plt.title("Corrolation between release year and tmdb_score")
plt.xlabel("release_year")
plt.ylabel("tmdb_score")
plt.show()
corr = series["tmdb_score"].corr(series["release_year"])
print("Correlation is: ", round(corr, 2))

#tmdb_popularity
fig = plt.figure(figsize = (15, 15))
plt.scatter(series["release_year"],series["tmdb_popularity"])
plt.title("Corrolation between release year and tmdb_score")
plt.xlabel("release_year")
plt.ylabel("tmdb_popularity")
plt.show()
corr = series["tmdb_popularity"].corr(series["release_year"])
print("Correlation is: ", round(corr, 2))
print(series["tmdb_popularity"].corr(series["release_year"]))
```





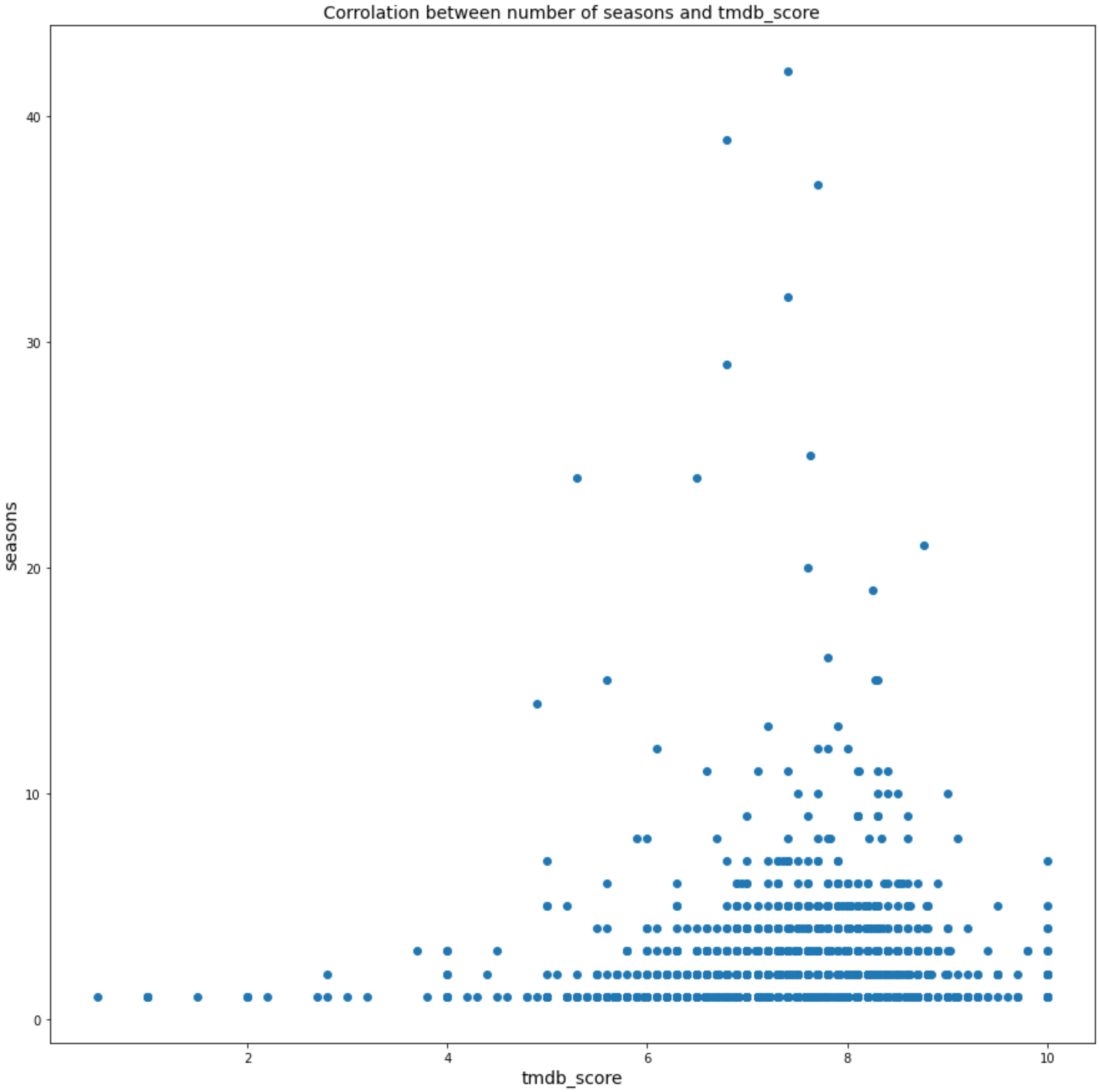

```
Correlation is:  -0.04
```



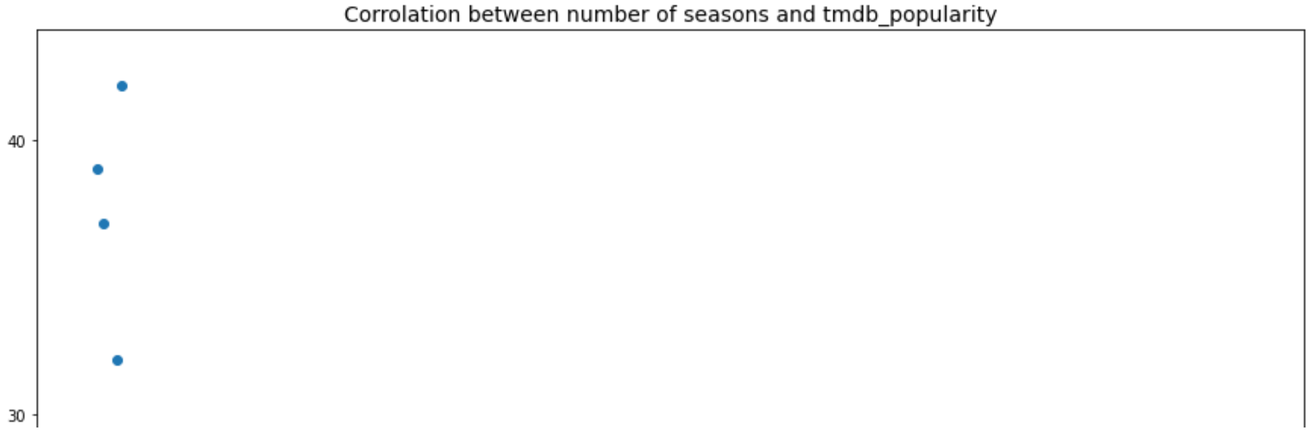

```
Correlation is:  -0.04
-0.04253916468901572
```

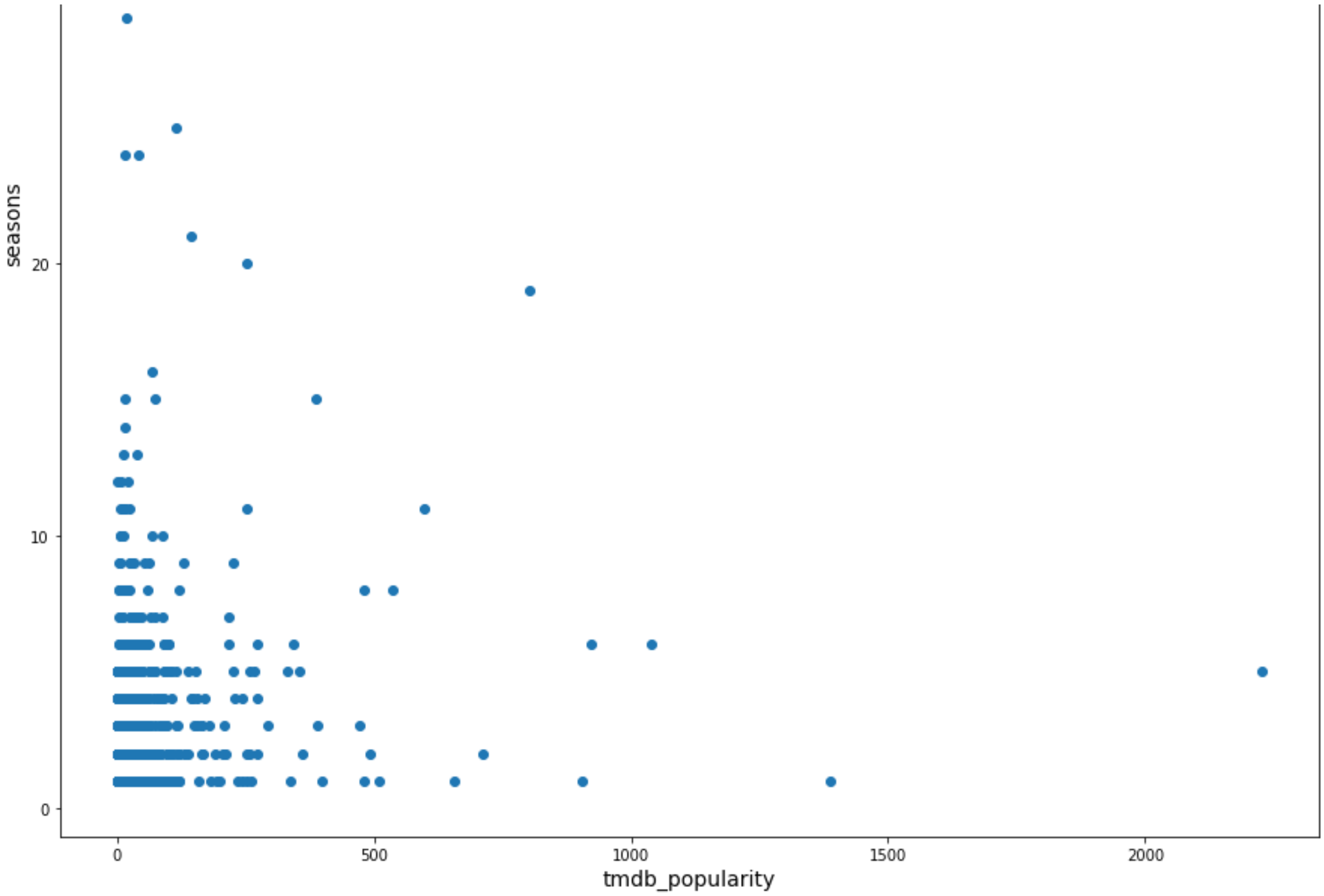
```
#corrolation between number of seasons and score ?

#print(series.head())
fig = plt.figure(figsize = (15, 15))
plt.scatter(series["tmdb_score"],series["seasons"])
plt.title("Corrolation between number of seasons and tmdb_score")
plt.xlabel("tmdb_score")
plt.ylabel("seasons")
plt.show()
corr = series["tmdb_score"].corr(series["seasons"])
print("Correlation tmdb_score/season is: ", round(corr, 2))
print(series["tmdb_score"].corr(series["seasons"]))

#tmdb_popularity

#tmdbpopularity
fig = plt.figure(figsize = (15, 15))
plt.scatter(series["tmdb_popularity"],series["seasons"])
plt.title("Corrolation between number of seasons and tmdb_popularity")
plt.xlabel("tmdb_popularity")
plt.ylabel("seasons")
plt.show()
corr = series["tmdb_popularity"].corr(series["seasons"])
```

```
print("Correlation tmdb_popularity/season is: ", round(corr, 2))
print(series["tmdb_popularity"].corr(series["seasons"]))
```




```
Correlation tmdb_score/season is:  0.04
0.044022846873139614
```

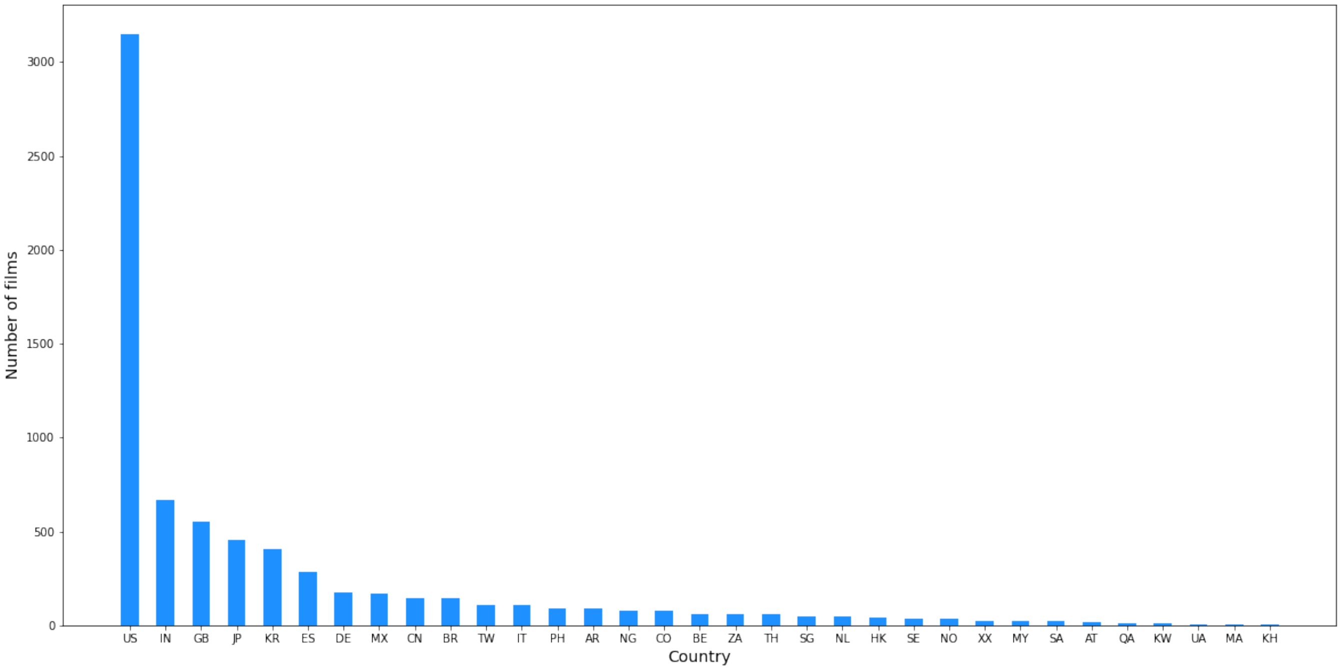





```
Correlation tmdb_popularity/season is:  0.17
0.16805106651455995
```

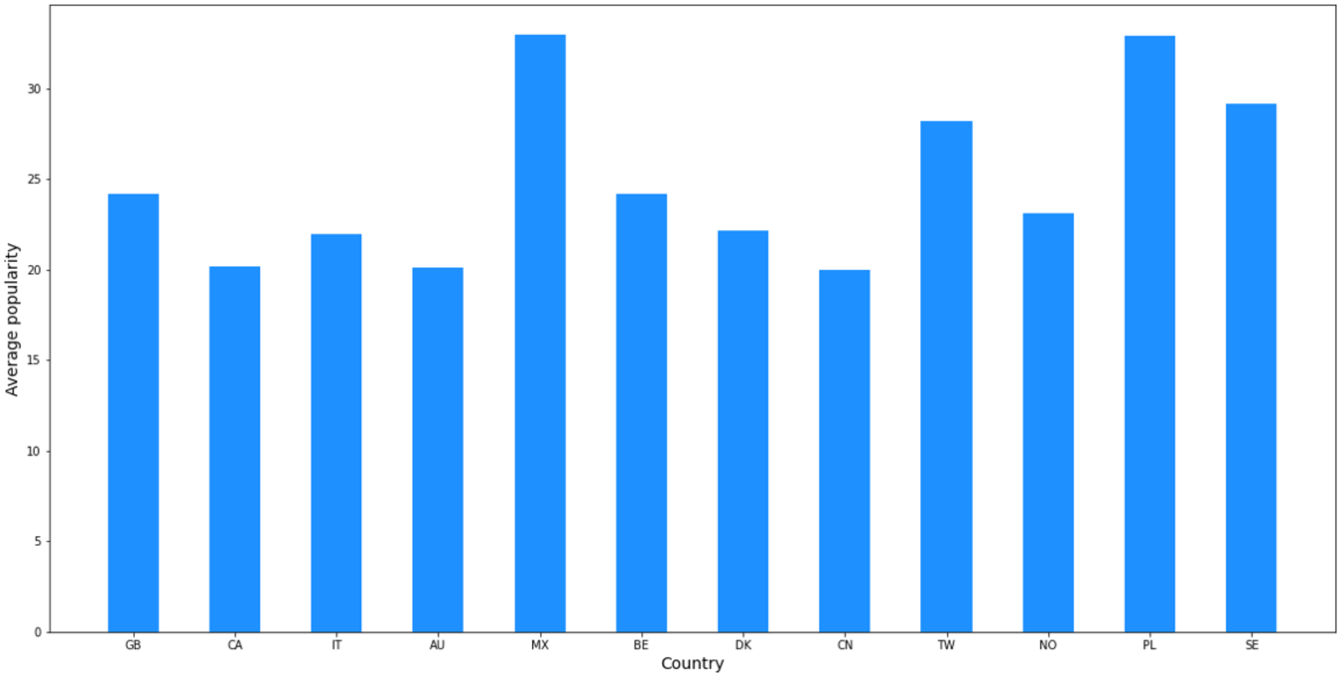
Below, we are trying to display the number of films/country. We will se that the US are mainly dominating, with six times more films than the second : India.

```
# Showing the number films/country of production
fig = plt.figure(figsize = (20, 10))

tab = []
prod_country = []

for i in unique_production_country:
  if i != '':
    value = films[i].sum()
    tab.append(value)
    prod_country.append(i)

my_tab = [[]]

for i in range(len(tab)):
  my_tab.append([tab[i], prod_country[i]])

my_tab.sort(reverse = True)

for i in range(len(unique_production_country) - 1):
  if tab[i] > 30:
    plt.bar(my_tab[i][1], my_tab[i][0], color = "dodgerblue", width = 0.5)

plt.xlabel("Country")
plt.ylabel("Number of films")

plt.show()
```




```
# trying to show the popularity of filmed produced by a country
fig = plt.figure(figsize = (20, 10))
films["tmdb_popularity"] = films["tmdb_popularity"].astype(float)
for col in prod_country:
  score = 0
  nb = 0
  for i in films.index:
    if films.loc[i, col] == 1:
      score += films.loc[i, "tmdb_popularity"]
      nb+=1
  mean = score/nb
  if (mean >= 20) & (nb > 20):
    plt.bar(col, mean, color = "dodgerblue", width = 0.5)
  if(col.strip() == "US"):
    plt.bar(col, mean, color = "red", width = 0.5)
```

```
plt.xlabel("Country")
plt.ylabel("Average popularity")

plt.show()
```



We have printed the mean popularity of films produced by a country. We can see that the US are missing even if they were much important in the previous graph. It looks like our dataset is missing values concerning US popularity.

In the end, we add some trouble finding correlation between different columns. We created a loop that allows to chose the level of correlation we want to get, and when we set the level pretty high we can see that the correlated columns are the age restriction and the type of movie. The correlation found are the one expected (a low limit of age like 7 years old if often correlated with family genre). However, we had trouble finding high correlation between columns and the final score or popularity. The most relevant correlation with the popularity is most certainly the genre. Other than that there are other links like the number of episode for a serie, ... but they are not very important at all. The database is also lacking data for some categories, as an exemple for older movies. In general to build a model able to evaluate the popularity of a movie or a serie, we will need to keep the genre, the date, the length of the movie.

Double-cliquez (ou appuyez sur Entrée) pour modifier