Investigate_a_Dataset

August 8, 2022

1 Project: Investigate a Dataset - [TMDb movie-data]

1.1 Table of Contents

Introduction

1.1.1 Dataset Description

This dataset contains information about around 10000 movies collected from The Movie Database (TMDb) from Kaggle. There is single table which contains 21 columns:

- **id :** The column of unique identifier.
- **imdb_id :** identifier in the movie dtabase.
- **popularity :** Thepopularity of the film.
- **budget :** The budget of the movie.
- **revenue :** The revenue of the movie.
- **original_title :** The movie's title.
- **cast :** The mains characters of the movie.
- **homepage :** The website of the movie.
- **director :** The director of the movie.
- **tagline :** The slogan of the film.
- **keywords :** Some keywords relative to the movie.
- **overview :** A brief summary of the movie.
- **runtime :** The duration in minutes of the movie.
- **genres :** The kind of the movie : romance, police, action ,....
- **production_companies :** The movie production house.
- **release_date :** The date in which the movie has been released.
- **vote_count :** The number of vote.
- **vote_average :** The average note given by the voters.
- **release_year :** The year in which the movie has been released.
- **budget_adj :** The budget of the movie in terms of 2010 dollars, accounting for inflation over time.
- **revenue_adj :** The revenue of the movie in terms of 2010 dollars, accounting for inflation over time.

1.1.2 Question(s) for Analysis

Question 1: Which genres are most popular from year to year ?

Question 2: What kinds of properties are associated with movies that have high revenues ?

Question 3: Which genres of movie make more profit ?

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plot
import seaborn as sns

%matplotlib inline
```

In [2]:
```
# Upgrade pandas to use dataframe.explode() function.
!pip install --upgrade pandas==0.25.0
```

```
Requirement already up-to-date: pandas==0.25.0 in /opt/conda/lib/python3.6/site-packages (0.25.0
Requirement already satisfied, skipping upgrade: python-dateutil>=2.6.1 in /opt/conda/lib/python
Requirement already satisfied, skipping upgrade: numpy>=1.13.3 in /opt/conda/lib/python3.6/site-
Requirement already satisfied, skipping upgrade: pytz>=2017.2 in /opt/conda/lib/python3.6/site-p
Requirement already satisfied, skipping upgrade: six>=1.5 in /opt/conda/lib/python3.6/site-packa
```

Data Wrangling

1.1.3 General Properties

In [3]:
```
# Let's load the data
movie_df = pd.read_csv("tmdb-movies.csv")

#Print the 5 first lines
movie_df.head()
```

Out[3]:
```
       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

                 original_title  \
0                Jurassic World
1            Mad Max: Fury Road
2                     Insurgent
3  Star Wars: The Force Awakens
4                     Furious 7
```

```
                                                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 ...

                                            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

                         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  ...

                                            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

                                      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

                                production_companies release_date vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15       5562
1  Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15       6185
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15       2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15       5292
4  Universal Pictures|Original Film|Media Rights ...       4/1/15       2947

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
3           7.5          2015  1.839999e+08  1.902723e+09
4           7.3          2015  1.747999e+08  1.385749e+09
```

```
[5 rows x 21 columns]
```

```
In [4]: # Let's check the shape of our dataframe
        movie_df.shape
```

```
Out[4]: (10866, 21)
```

Our dataset contains then **10866** rows and **21** columns

```
In [5]: # Type of each columns
        movie_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                      10866 non-null int64
imdb_id                 10856 non-null object
popularity              10866 non-null float64
budget                  10866 non-null int64
revenue                 10866 non-null int64
original_title          10866 non-null object
cast                    10790 non-null object
homepage                2936 non-null object
director                10822 non-null object
tagline                 8042 non-null object
keywords                9373 non-null object
overview                10862 non-null object
runtime                 10866 non-null int64
genres                  10843 non-null object
production_companies    9836 non-null object
release_date            10866 non-null object
vote_count              10866 non-null int64
vote_average            10866 non-null float64
release_year            10866 non-null int64
budget_adj              10866 non-null float64
revenue_adj             10866 non-null float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

We could see that datetime is not in the correct type and that some columns have missing values

```
In [6]: # Stats of our dataset
        movie_df.describe()
```

```
Out[6]:                   id    popularity        budget       revenue       runtime  \
        count   10866.000000  10866.000000  1.086600e+04  1.086600e+04  10866.000000
```

```
mean     66064.177434       0.646441  1.462570e+07  3.982332e+07    102.070863
std      92130.136561       1.000185  3.091321e+07  1.170035e+08     31.381405
min          5.000000       0.000065  0.000000e+00  0.000000e+00      0.000000
25%      10596.250000       0.207583  0.000000e+00  0.000000e+00     90.000000
50%      20669.000000       0.383856  0.000000e+00  0.000000e+00     99.000000
75%      75610.000000       0.713817  1.500000e+07  2.400000e+07    111.000000
max     417859.000000      32.985763  4.250000e+08  2.781506e+09    900.000000

         vote_count  vote_average  release_year    budget_adj   revenue_adj
count  10866.000000  10866.000000  10866.000000  1.086600e+04  1.086600e+04
mean     217.389748      5.974922   2001.322658  1.755104e+07  5.136436e+07
std      575.619058      0.935142     12.812941  3.430616e+07  1.446325e+08
min       10.000000      1.500000   1960.000000  0.000000e+00  0.000000e+00
25%       17.000000      5.400000   1995.000000  0.000000e+00  0.000000e+00
50%       38.000000      6.000000   2006.000000  0.000000e+00  0.000000e+00
75%      145.750000      6.600000   2011.000000  2.085325e+07  3.369710e+07
max     9767.000000      9.200000   2015.000000  4.250000e+08  2.827124e+09
```

1.1.4 Data Cleaning

```
In [7]: # Number of rows duplicated

        sum(movie_df.duplicated())
```

```
Out[7]: 1
```

```
In [8]: # Drop duplicated rows

        movie_df.drop_duplicates(inplace=True)
        movie_df.shape
```

```
Out[8]: (10865, 21)
```

1 row was duplicated, we have droped it and then we have 10865 rows and always 21 columns.

```
In [9]: # Drop useless columns

        movie_df.drop(["imdb_id","homepage", "overview", "tagline", "keywords", "revenue_adj", "
        movie_df.shape
```

```
Out[9]: (10865, 14)
```

Some columns are useless and will not help us or will not be implicated in our investigation through questions we have posed above.

For example imdb_id is useless once id column can be our identifier.

Homepage, overview, keywords, revenue_adj, budget_adj, are not useful for this analysis through the questions we must answer.

We have now 14 columns

```
In [10]: # Correct release_date type
         movie_df["release_date"] = pd.to_datetime(movie_df["release_date"])

         # Let's check
         movie_df.dtypes
```

```
Out[10]: id                               int64
         popularity                     float64
         budget                           int64
         revenue                          int64
         original_title                  object
         cast                            object
         director                        object
         runtime                          int64
         genres                          object
         production_companies            object
         release_date            datetime64[ns]
         vote_count                       int64
         vote_average                   float64
         release_year                     int64
         dtype: object
```

We have corrected release_date value type from object to datetime

```
In [11]: # Drop rows where budget or revenue is 0, surely due to lack of information

         movie_df = movie_df[movie_df["budget"] > 0]
         movie_df = movie_df[movie_df["revenue"] > 0]

         movie_df.shape
```

```
Out[11]: (3854, 14)
```

We have droped all the rows which has 0 as value of budget or revenue, because they represents rows with lack of infromation. Indeed budget or revenue could not be equal to 0

We have now **3854** rows and **14** columns

```
In [12]: # Number of missing values per columns
         movie_df.isna().sum()
```

```
Out[12]: id                      0
         popularity              0
         budget                  0
         revenue                 0
         original_title          0
         cast                    4
         director                1
         runtime                 0
         genres                  0
```

```
production_companies    46
release_date             0
vote_count               0
vote_average             0
release_year             0
dtype: int64
```

```
In [13]: # Drop rows with misssing values

         movie_df.dropna(inplace = True)
         movie_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3805 entries, 0 to 10848
Data columns (total 14 columns):
id                      3805 non-null int64
popularity              3805 non-null float64
budget                  3805 non-null int64
revenue                 3805 non-null int64
original_title          3805 non-null object
cast                    3805 non-null object
director                3805 non-null object
runtime                 3805 non-null int64
genres                  3805 non-null object
production_companies    3805 non-null object
release_date            3805 non-null datetime64[ns]
vote_count              3805 non-null int64
vote_average            3805 non-null float64
release_year            3805 non-null int64
dtypes: datetime64[ns](1), float64(2), int64(6), object(5)
memory usage: 445.9+ KB
```

Some rows have missing values in some columns. We have to delete it to have a better dataset

- The dataset is now cleaned : Missing values, duplicated rows and rows with uncomplete datas have been removed.
- Useless columns which will not serve us in this investigation have been removed
- And uncorrect datas types have been corrected

Let's explore now !
Exploratory Data Analysis

1.1.5 Question 1 : Which genres are most popular from year to year ?

This question takes into account threee features : - Genres - Popularity - Release_year

We will explore and sometimes, visualize single features , after relation between popularity and genres and finally the relation between the three features for answering the question

In [14]:
```
# Split values for genres column
movie_df['genres'] = movie_df['genres'].apply(lambda x: str(x).split('|'))

# Check if values are been well splited to list
movie_df.head(2)
```

Out[14]:
```
       id  popularity     budget     revenue      original_title  \
0  135397   32.985763  150000000  1513528810      Jurassic World
1   76341   28.419936  150000000   378436354  Mad Max: Fury Road

                                                cast          director  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...    George Miller

   runtime                                       genres  \
0      124  [Action, Adventure, Science Fiction, Thriller]
1      120  [Action, Adventure, Science Fiction, Thriller]

                                production_companies release_date  vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
1  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13        6185

   vote_average  release_year
0           6.5          2015
1           7.1          2015
```

In [15]:
```
# Explode values to have one row, one genre
movie_df = movie_df.explode(column="genres")

#New shape for our dataset
movie_df.shape
```

Out[15]:
```
(10180, 14)
```

We have noticed that genres column value are separated by |.

So for a better visualisation, we have splitted each value column so we have for each row a single value of Genre.

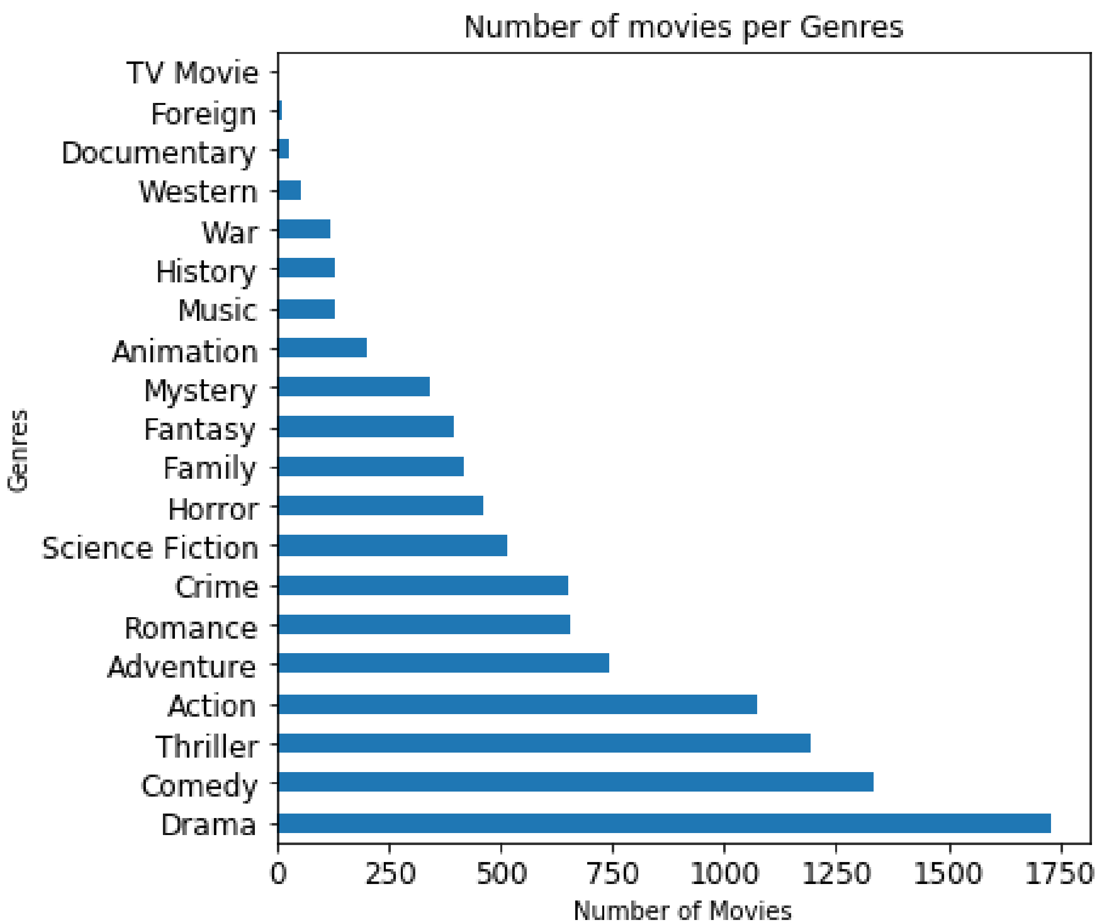
Number of rows naturally increased

In [16]:
```
# Number of movies per genre value
movie_df["genres"].value_counts()
```

Out[16]:
```
Drama              1729
Comedy             1335
Thriller           1194
Action             1076
Adventure           743
Romance             658
Crime               649
```

```
Science Fiction     517
Horror              459
Family              417
Fantasy             395
Mystery             343
Animation           199
Music               131
History             128
War                 119
Western              52
Documentary          26
Foreign               9
TV Movie              1
Name: genres, dtype: int64
```

In [25]:
```
# Visualisation
ax_subplot = movie_df["genres"].value_counts().plot(kind='barh',figsize=(6,6), fontsize
ax_subplot.set_xlabel("Number of Movies");
ax_subplot.set_ylabel("Genres");
```



Above is a visualization fo number of movies produced per each genres value.

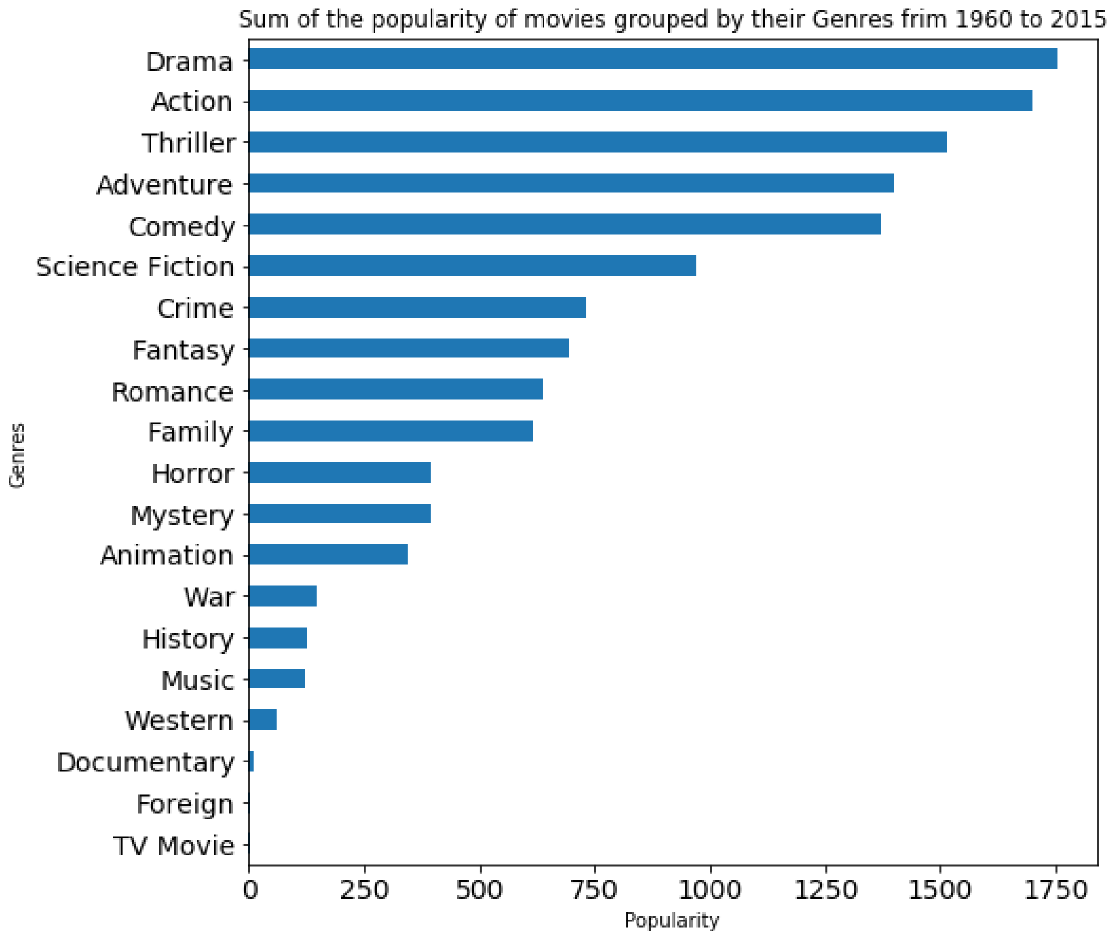
- Drama is the most represented while
- TV Movie and Foreign are the least represented

Let's see now a description for popularity feature

```
In [26]: movie_df["popularity"].describe()
```

```
Out[26]: count    10180.000000
         mean         1.274476
         std          1.613311
         min          0.010335
         25%          0.487399
         50%          0.856329
         75%          1.470711
         max         32.985763
         Name: popularity, dtype: float64
```

```
In [29]: # Visualize genres of movie and the sum of their popularity since 1960 to 2015

         ax = movie_df.groupby("genres")["popularity"].sum().sort_values().plot(kind = 'barh',ti
         ax.set_xlabel("Popularity");
         ax.set_ylabel("Genres");
```



The previous chart show us the popularity of movie per genres since 1960 to 2015 - Drama's movies and action's movie are the most popular films since 1960 - Documentary , Foreign and TV movie are the least popular ones

Now we will see the genres of movies which are more popular over year to year. We'll then consider the release_year feature

In [31]:
```
# Genres with the mean of popularity per year
genres_year_meanPopularity = movie_df.groupby(["genres", "release_year"], as_index=Fals
genres_year_meanPopularity.head()
```

Out[31]:

	genres	release_year	popularity
0	Action	1960	1.504538
1	Action	1961	0.464139
2	Action	1962	1.848380
3	Action	1963	1.357698
4	Action	1964	3.153791

This dataframe present the mean of popularity for each genre for each year since 1960 to 2015

We could stop on this dataframe and try to visualize the relation between those features, but the shape and the form of this dataframe will not permit us to visualize correctly the evolution of the popularity over year to year and find out the genres which are more popular over year to year

In [32]:
```
# List of all values for genres features
allGenres = movie_df["genres"].unique()

# Create a pseudo dataframe with genres as index and year as columns
popular_genres_df = pd.DataFrame(index = allGenres, columns = np.arange(1960, 2016))

#Fill our dataframe with 0 waiting to fill it with the corresponding popularity value
popular_genres_df.fillna(0, inplace=True)
popular_genres_df
```

Out[32]:
```
                 1960  1961  1962  1963  1964  1965  1966  1967  1968  1969  \
Action              0     0     0     0     0     0     0     0     0     0
Adventure           0     0     0     0     0     0     0     0     0     0
Science Fiction     0     0     0     0     0     0     0     0     0     0
Thriller            0     0     0     0     0     0     0     0     0     0
Fantasy             0     0     0     0     0     0     0     0     0     0
Crime               0     0     0     0     0     0     0     0     0     0
Western             0     0     0     0     0     0     0     0     0     0
Drama               0     0     0     0     0     0     0     0     0     0
Family              0     0     0     0     0     0     0     0     0     0
Animation           0     0     0     0     0     0     0     0     0     0
Comedy              0     0     0     0     0     0     0     0     0     0
Mystery             0     0     0     0     0     0     0     0     0     0
Romance             0     0     0     0     0     0     0     0     0     0
War                 0     0     0     0     0     0     0     0     0     0
History             0     0     0     0     0     0     0     0     0     0
Music               0     0     0     0     0     0     0     0     0     0
Horror              0     0     0     0     0     0     0     0     0     0
Documentary         0     0     0     0     0     0     0     0     0     0
Foreign             0     0     0     0     0     0     0     0     0     0
TV Movie            0     0     0     0     0     0     0     0     0     0

                 ...  2006  2007  2008  2009  2010  2011  2012  2013  2014  \
Action           ...     0     0     0     0     0     0     0     0     0
Adventure        ...     0     0     0     0     0     0     0     0     0
Science Fiction  ...     0     0     0     0     0     0     0     0     0
Thriller         ...     0     0     0     0     0     0     0     0     0
Fantasy          ...     0     0     0     0     0     0     0     0     0
Crime            ...     0     0     0     0     0     0     0     0     0
Western          ...     0     0     0     0     0     0     0     0     0
Drama            ...     0     0     0     0     0     0     0     0     0
Family           ...     0     0     0     0     0     0     0     0     0
Animation        ...     0     0     0     0     0     0     0     0     0
Comedy           ...     0     0     0     0     0     0     0     0     0
```

```
Mystery          ...    0     0     0     0     0     0     0     0     0
Romance          ...    0     0     0     0     0     0     0     0     0
War              ...    0     0     0     0     0     0     0     0     0
History          ...    0     0     0     0     0     0     0     0     0
Music            ...    0     0     0     0     0     0     0     0     0
Horror           ...    0     0     0     0     0     0     0     0     0
Documentary      ...    0     0     0     0     0     0     0     0     0
Foreign          ...    0     0     0     0     0     0     0     0     0
TV Movie         ...    0     0     0     0     0     0     0     0     0

                 2015
Action              0
Adventure           0
Science Fiction     0
Thriller            0
Fantasy             0
Crime               0
Western             0
Drama               0
Family              0
Animation           0
Comedy              0
Mystery             0
Romance             0
War                 0
History             0
Music               0
Horror              0
Documentary         0
Foreign             0
TV Movie            0

[20 rows x 56 columns]
```

This form is more adapted for a complete and a better visualization.

Now let's fill each cell with the corresponding value using **genres_year_meanPopularity** dataframe

```
In [33]: for i in allGenres:
             k = 0
             genre_year = genres_year_meanPopularity.query('genres == "{}"'.format(i))["release_
             for j in genre_year:
                 popular_genres_df.loc[i,j] = genres_year_meanPopularity["popularity"][k]
                 k+=1

         popular_genres_df
```

```
Out[33]:                      1960      1961      1962      1963      1964      1965  \
         Action           1.504538  0.464139  1.848380  1.357698  3.153791  1.266311
```

```
Adventure        1.504538  0.464139  1.848380  1.357698  3.153791  1.266311
Science Fiction  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
Thriller         1.504538  0.000000  0.464139  1.848380  1.357698  3.153791
Fantasy          0.000000  0.000000  0.000000  0.000000  1.504538  0.000000
Crime            0.000000  1.504538  0.464139  0.000000  1.848380  0.000000
Western          1.504538  0.464139  1.848380  0.000000  0.000000  0.000000
Drama            1.504538  0.464139  1.848380  1.357698  3.153791  1.266311
Family           0.000000  1.504538  0.000000  0.000000  0.464139  1.848380
Animation        0.000000  1.504538  0.000000  0.000000  0.000000  0.000000
Comedy           1.504538  0.464139  0.000000  1.848380  1.357698  3.153791
Mystery          0.000000  0.000000  0.000000  1.504538  0.464139  0.000000
Romance          1.504538  0.464139  0.000000  1.848380  1.357698  3.153791
War              0.000000  1.504538  0.464139  1.848380  1.357698  3.153791
History          1.504538  0.464139  1.848380  1.357698  0.000000  3.153791
Music            0.000000  1.504538  0.000000  0.000000  0.464139  1.848380
Horror           1.504538  0.464139  0.000000  1.848380  0.000000  0.000000
Documentary      0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
Foreign          0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
TV Movie         0.000000  0.000000  0.000000  0.000000  0.000000  0.000000

                     1966      1967      1968      1969  ...      2006  \
Action           0.347789  1.338467  0.678138  1.778746  ...  1.189849
Adventure        0.347789  1.338467  0.678138  1.778746  ...  1.270305
Science Fiction  1.504538  0.000000  0.464139  0.000000  ...  1.230245
Thriller         1.266311  0.347789  1.338467  0.678138  ...  1.189849
Fantasy          0.000000  0.464139  0.000000  0.000000  ...  0.837698
Crime            0.000000  1.357698  3.153791  1.266311  ...  1.810953
Western          1.357698  0.000000  3.153791  1.266311  ...  1.134663
Drama            0.347789  1.338467  0.678138  1.778746  ...  1.270305
Family           0.000000  1.357698  3.153791  0.000000  ...  1.088277
Animation        0.000000  0.464139  0.000000  0.000000  ...  0.994141
Comedy           0.000000  1.266311  0.000000  0.000000  ...  1.339254
Mystery          1.848380  1.357698  3.153791  0.000000  ...  0.898608
Romance          1.266311  0.347789  1.338467  0.000000  ...  1.810953
War              1.266311  0.347789  1.338467  0.000000  ...  1.141319
History          0.000000  0.000000  1.266311  0.347789  ...  1.070567
Music            0.000000  1.357698  3.153791  0.000000  ...  0.805102
Horror           0.000000  0.000000  1.357698  0.000000  ...  1.088277
Documentary      0.000000  0.000000  0.000000  0.000000  ...  1.338467
Foreign          0.000000  0.000000  0.000000  0.000000  ...  0.000000
TV Movie         0.000000  0.000000  0.000000  0.000000  ...  0.000000

                     2007      2008      2009      2010      2011      2012  \
Action           1.270305  1.445200  1.769773  1.553890  1.588119  2.122119
Adventure        1.445200  1.769773  1.553890  1.588119  2.122119  1.902791
Science Fiction  0.898608  0.977753  1.339254  1.810953  1.352502  1.324182
Thriller         1.270305  1.445200  1.769773  1.553890  1.588119  2.122119
Fantasy          0.935207  1.122515  1.141319  1.070567  1.088277  1.230245
```

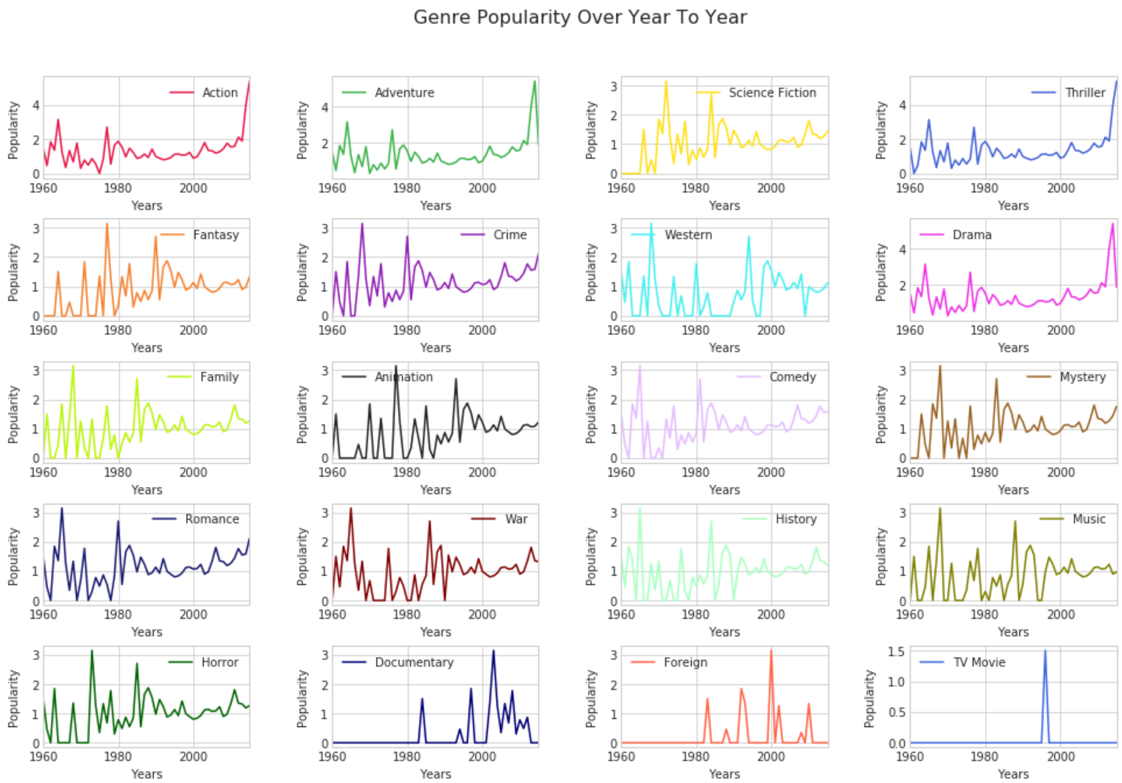
```
Crime            1.352502  1.324182  1.189849  1.270305  1.445200  1.769773
Western          0.929729  1.424568  0.000000  0.994141  0.894390  0.805102
Drama            1.445200  1.769773  1.553890  1.588119  2.122119  1.902791
Family           1.230245  0.898608  0.977753  1.339254  1.810953  1.352502
Animation        0.894390  0.805102  0.837698  0.935207  1.122515  1.141319
Comedy           1.810953  1.352502  1.324182  1.189849  1.270305  1.445200
Mystery          0.977753  1.339254  1.810953  1.352502  1.324182  1.189849
Romance          1.352502  1.324182  1.189849  1.270305  1.445200  1.769773
War              1.070567  1.088277  1.230245  0.898608  0.977753  1.339254
History          1.088277  1.230245  0.898608  0.977753  1.339254  1.810953
Music            0.837698  0.935207  1.122515  1.141319  1.070567  1.088277
Horror           1.230245  0.898608  0.977753  1.339254  1.810953  1.352502
Documentary      0.678138  1.778746  0.300380  0.783304  0.487846  0.871426
Foreign          0.000000  0.347789  0.000000  1.338467  0.000000  0.000000
TV Movie         0.000000  0.000000  0.000000  0.000000  0.000000  0.000000

                     2013      2014      2015
Action           1.902791  4.005362  5.412644
Adventure        4.005362  5.412644  1.872132
Science Fiction  1.189849  1.270305  1.445200
Thriller         1.902791  4.005362  5.412644
Fantasy          0.898608  0.977753  1.339254
Crime            1.553890  1.588119  2.122119
Western          0.837698  0.935207  1.122515
Drama            4.005362  5.412644  1.872132
Family           1.324182  1.189849  1.270305
Animation        1.070567  1.088277  1.230245
Comedy           1.769773  1.553890  1.588119
Mystery          1.270305  1.445200  1.769773
Romance          1.553890  1.588119  2.122119
War              1.810953  1.352502  1.324182
History          1.352502  1.324182  1.189849
Music            1.230245  0.898608  0.977753
Horror           1.324182  1.189849  1.270305
Documentary      0.000000  0.000000  0.000000
Foreign          0.000000  0.000000  0.000000
TV Movie         0.000000  0.000000  0.000000

[20 rows x 56 columns]
```

Now, we're going to visualize for each genre, his evolution over year to year and then find out the genres which are more popular over year to year.

In [41]:
```
# This function will draw a line plot for each genres value.

def draw_line_plot(df, genres, title):
    sns.set_style("whitegrid")
```

```
    # Make a subplot of 5 rows and 4 columns
    fig, ax = plot.subplots(5,4,figsize = (16,10))
    plot.subplots_adjust(left=0.1, bottom=0.1, right=0.9, top=0.9, wspace=0.4, hspace=0

    # Set the title of the subplot.
    fig.suptitle(title,fontsize = 16)

    colors = ['#e6194b', '#3cb44b', '#ffe119', '#4363d8', '#f58231', '#911eb4', '#46f0f
    i=0
    ax_x = 0
    ax_y = 0
    for genre in genres:
        ax_subplot = df.loc["{}".format(genre)].plot(label = "{}".format(genre),color =
        ax_subplot.set_xlabel("Years", labelpad=5)
        ax_subplot.set_ylabel("Popularity", labelpad=10)
        i+=1
        if(ax_y == 3):
            ax_x += 1
            ax_y = 0
        else:
            ax_y+=1
```

```
In [42]: draw_line_plot(popular_genres_df, allGenres, 'Genre Popularity Over Year To Year')
```



- We can see that for Action and **Thriller** movies, the popularity is skyrocketing since 2008. On the other hand, **Drama** and **Adventure** movies are in free fall since 2010.
- **Documentary** type films had almost zero popularity from 1960 until around 1985 before experiencing great popularity in the years 1985-1987, 1995-1998, 2001-2005 but have since 2010 a low popularity which has been around since 2014 0
- Films of the **War**, **History**, **Music**, **Science Fiction**, **Mystery** type have a medium popularity since 2000
- **Romance**, **Comedy** and **Family**, **Crime** type films have seen a slight rise in popularity since around 2000
- **Horror** movie had a great popularity i years 1970 to 1985 and now it is rather medium

To sum up and to answer to the question, The movies that are the most popular on average over year to year are mainly **Action** and **Thriller** movie.

We could add to **Romance**,**Science Fiction**, **Comedy**, **Crime** and **Drama** even if actually Drama's movie popularity is falling.

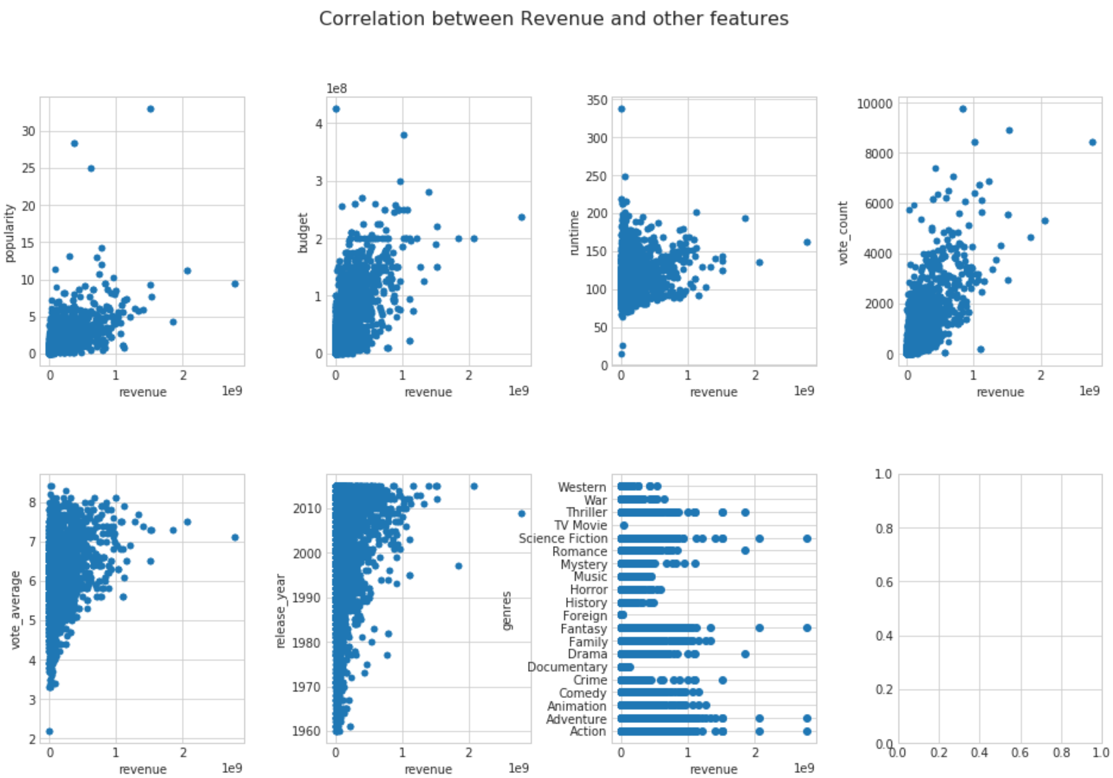
1.1.6 Question 2 What kinds of properties are associated with movies that have high revenues?

We will try to find out the features which have more co-relation with revenue feature

In [43]:
```
# Draw a scatter plot for revenue feature and each other feature


def draw_corr_plot(df, features, title):
    sns.set_style("whitegrid")

    # Make a subplot of two rows and 4 columns.
    fig, ax = plot.subplots(2,4,figsize = (16,10))
    plot.subplots_adjust(right=0.9, wspace=0.4, hspace=0.4)

    # Set the title of the subplot.
    fig.suptitle(title,fontsize = 16)

    ax_x = 0
    ax_y = 0
    for f in features:
        df.plot(x="revenue", y="{}".format(f), kind="scatter", ax = ax[ax_x][ax_y], leg
        if(ax_y == 3):
            ax_x += 1
            ax_y = 0
        else:
            ax_y+=1

    #Draw specially genres scatter plot with revenue because pandas scatter plot lauch
    ax = ax[1][2]
    ax.scatter(movie_df["revenue"], movie_df["genres"])
```

```
        ax.set_xlabel("revenue")
        ax.set_ylabel("genres")
```

```
In [44]: # Let's see the co-relation between features

         draw_corr_plot(movie_df, ['popularity', 'budget','runtime', 'vote_count', 'vote_average
```



We have choosen this kind of chart because, the scatterplot is the most useful graph for displaying the relationship between two variables.

We have choosen to let production_house, director, cast, id, original_title columns after preview the result, we can't get anything good out of it

We could see that features with high correlation with revenue are **budget**, **popularity**, and **vote_count** - Movies with high budget have more revenue - Movies with great popularity have also more revenue except a few ones - Mainly, Movie with high vote_account have also more revenue - Genres of movie which have more revenue are mainly those of Science-Fiction, Action , Adventure and Fantasy

In summary movies with higher budgets have shown to generate higher revenues.

1.1.7 Question 3 : Which genres of movie make more profit

We will fisrtly create another column profit which result from the substract between budget and revenue and after visualize the relation between this new column and the genres of movie

```
In [45]: # Create another column which is the difference between the revenue and the budget

         profit = np.array(movie_df.revenue - movie_df.budget)
```

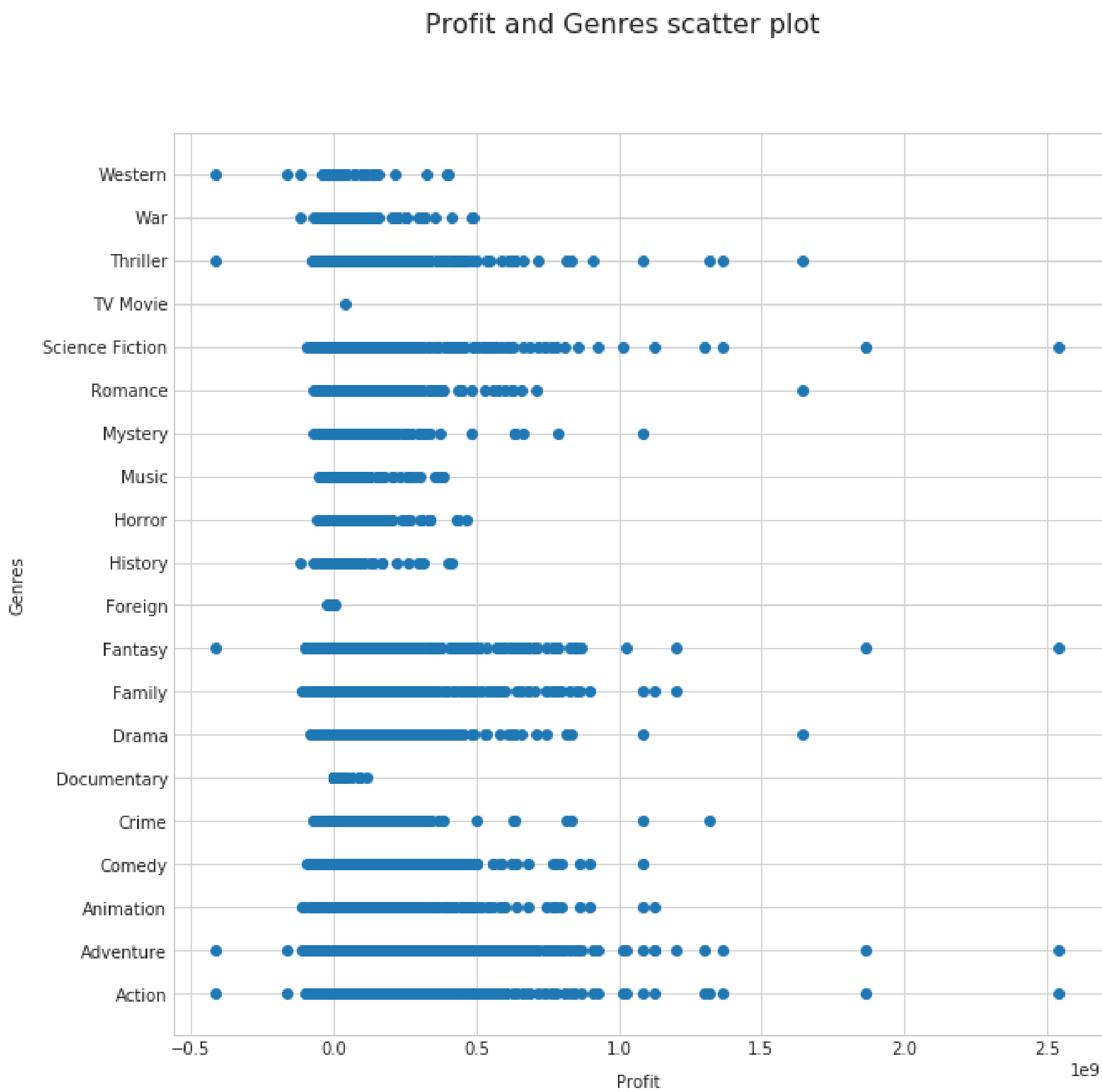
```
In [46]: # Add column to the dataframe
         movie_df["profit"] = profit

         # Let's visualize
         movie_df.head()
```

```
Out[46]:        id  popularity     budget     revenue      original_title  \
         0  135397   32.985763  150000000  1513528810      Jurassic World
         0  135397   32.985763  150000000  1513528810      Jurassic World
         0  135397   32.985763  150000000  1513528810      Jurassic World
         0  135397   32.985763  150000000  1513528810      Jurassic World
         1   76341   28.419936  150000000   378436354  Mad Max: Fury Road

                                                       cast         director  \
         0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow
         0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow
         0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow
         0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow
         1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...    George Miller

            runtime           genres  \
         0      124           Action
         0      124        Adventure
         0      124  Science Fiction
         0      124         Thriller
         1      120           Action

                                         production_companies release_date  vote_count  \
         0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
         0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
         0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
         0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
         1  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13        6185

            vote_average  release_year      profit
         0           6.5          2015  1363528810
         0           6.5          2015  1363528810
         0           6.5          2015  1363528810
         0           6.5          2015  1363528810
         1           7.1          2015   228436354
```

The new column has been added and the corresponding value, filled

```
In [53]: fig, ax = plot.subplots(figsize = (10,10))
```

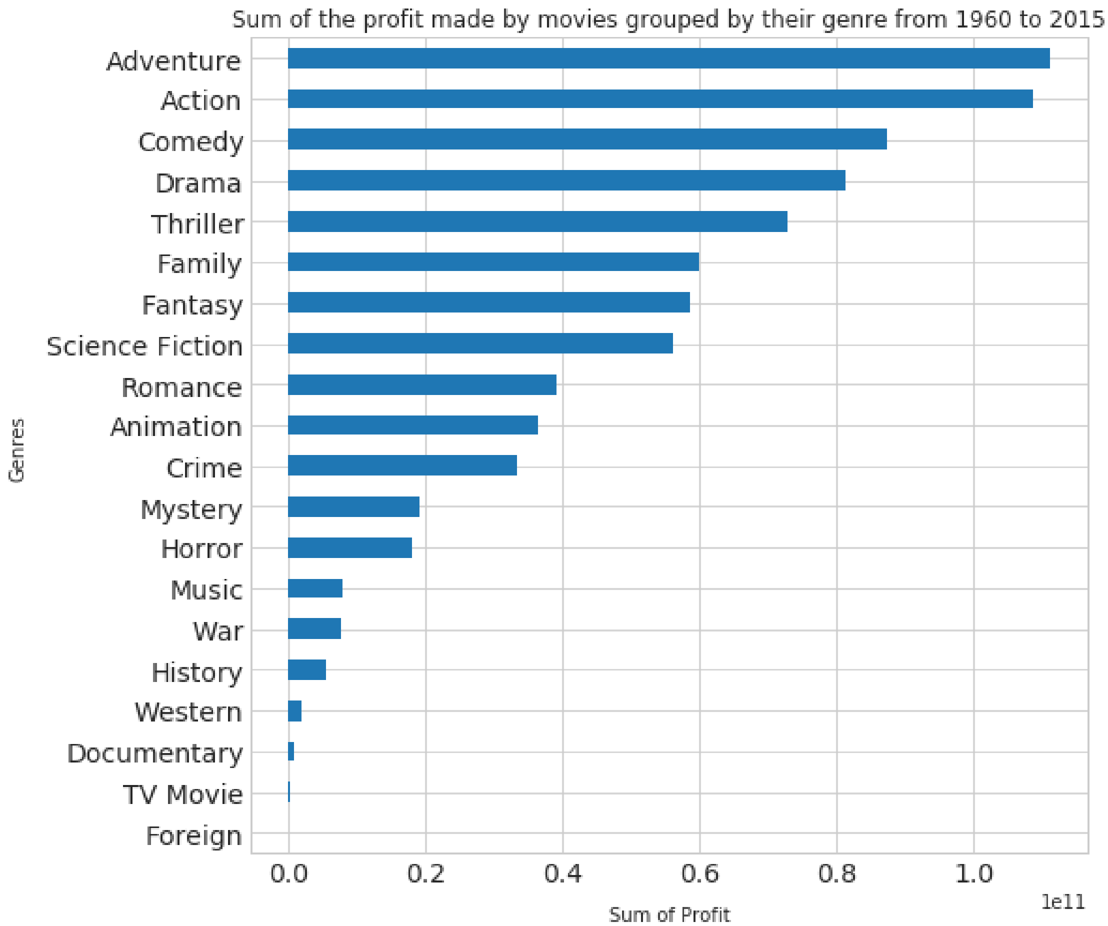
```
fig.suptitle("Profit and Genres scatter plot",fontsize = 16)
ax.scatter(movie_df["profit"], movie_df["genres"]);
plot.xlabel("Profit", labelpad=10);
plot.ylabel("Genres", labelpad=10);
```



Visualization with a scatter chart. Each point represent a movie with its corresponding profit and genre.

Now, let's visualize with a bar chart the sum of profit for the movies grouped by their genres to have a better visualization and for an appropriate conclusion

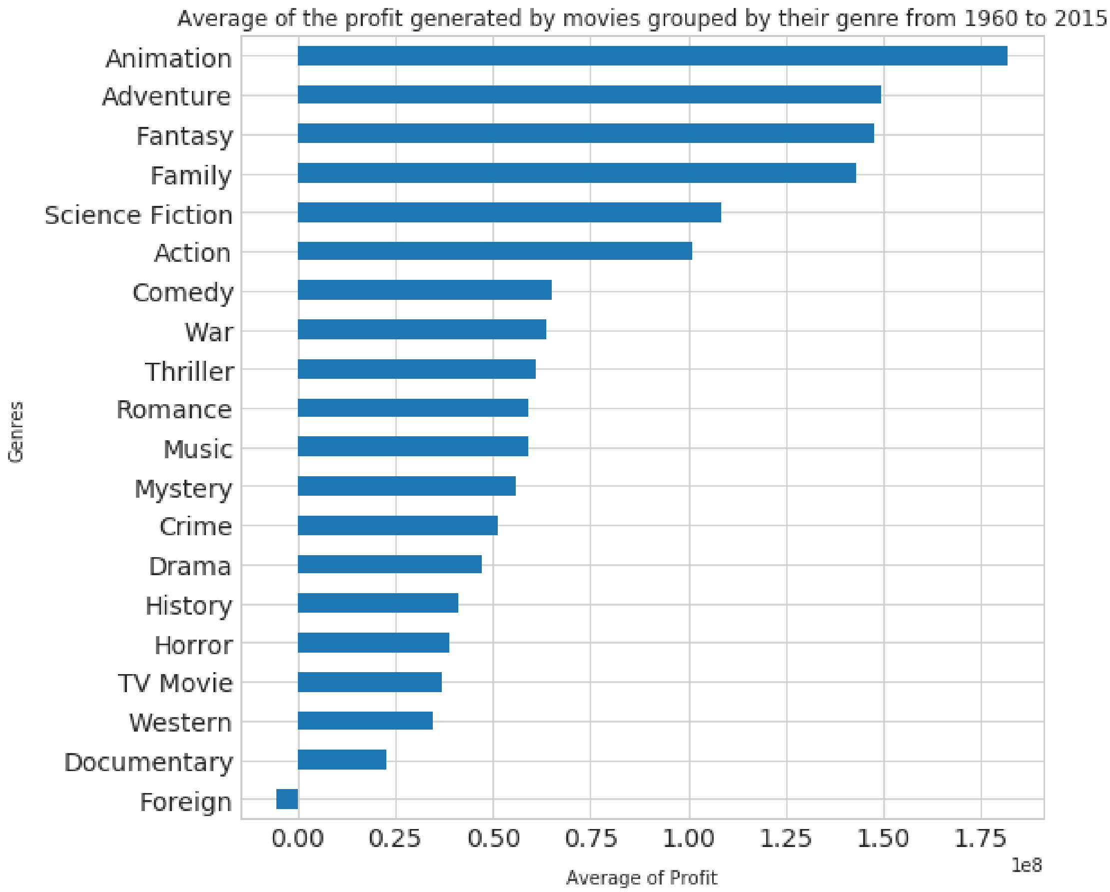
```
In [56]: # Bar chart presenting the total profit per genre of movie
         ax = movie_df.groupby("genres")["profit"].sum().sort_values().plot(kind='barh', title =
         ax.set_xlabel("Sum of Profit", labelpad=10);
         ax.set_ylabel("Genres", labelpad=10);
```



We can see through this visualisation that, in terms of cumulative profits, since 1960, **Adventure** movies have generated more profit, just followed by **Action's** movie.

Let's see now the genre of Movie which have generated in average more profit

```
In [59]: # Bar chart presenting the average profit per genre of movie
         ax = movie_df.groupby("genres")["profit"].mean().sort_values().plot(kind='barh', title
         ax.set_xlabel("Average of Profit", labelpad=10);
         ax.set_ylabel("Genres", labelpad=10);
```



In avearge, **Animation's** Movies generate more profit, folllowed by **Adventure**, **Fantasy** and **Family** movies

Conclusions

1. The movies that are the most popular in average over year to year are mainly **Action** and **Thriller** movies. We could also add **Romance**,**Science Fiction**, **Crime**, **Comedy** and **Drama** movies even if actually Drama's movie popularity is falling. This conclusion is based on the average of popularity from 1960 to 2015.

   We could expand our analyse and do the same work for different aggregations methods ...

2. - Movies with high budget have more revenue
   - Movies with great popularity have also more revenue except a few ones
   - Mainly, Movie with high vote_account have also more revenue
   - Genres of movie which have more revenue are mainly those of Science-Fiction, Action , Adventure and Fantasy In summary movies with higher budgets have shown to generate higher revenues. We could expand our analyse to other features, but the the co-relation is not so high as those of features we have taken into account

3. - Since 1960, by accumulating the profits, Adventure movies have generated more profit, just followed by Action's movie.

- In avearge, Animation's Movies generate more profit, folllowed by Adventure, Fantasy, Family movies from 1960 to 2015

1.2 Limitations

- We were obliged in order to have a very cleaned dataset to remove all rows with zero **budget** or **revenue** which also considerably reduced the size of the data set. If these values are available, this could impact the results obtained in questions 2 and 3
- We were not able to assign a unit of measurement to the **popularity** feature values...this had a little impact on the interpretation of our results
- It is also important to precise that we have use the average of popularity to answer the question 1.Someone else could use another aggregate methods.

```
In [1]: from subprocess import call
        call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])

Out[1]: 0

In [ ]:
```