Investigate_a_Dataset

December 19, 2022

1 Project: Investigate a Dataset - TMDb movie data

1.1 Table of Contents

Introduction

1.1.1 Dataset Description

We are working with the TMDb movie dataset that contains at least 10.000 values of movie data released all over the years. When we talk about movies details, we refer to the atributtes included in the dataset as follows:

- id
- imdb_id
- popularity
- budget
- revenue
- original_title
- cast
- homepage
- director
- tagline
- keywords
- overview
- runtime
- genres
- production_companies
- release_date
- vote_count
- vote_average
- release_year
- budget_adj
- revenue_ adj

Looking at these attributes, it could be important to give some brief explanation of some of them, such as: * vote_count: stands for number of votes given to a movie * vote_average: stands for the average of vote classification given from the vote count * budget_adj: stands for the budget of the associated movie in terms of 2010 dollars, accounting for inflation over time. * revenue_adj: stands for the reveue of the associated movie in terms of 2010 dollars, accounting for inflation over time.

1.1.2 Question(s) for Analysis

The present report is planned to answer the following questions during the analysis course:

1. Which genre of movie tends to be more appreciated (in terms of voting)?
2. Has nowadays movies been well received by people comparing to old movies?
3. What is the best month of the year used to release the movie?
4. Ranking of the best production companies from year to year on TMDb. By how much?
5. Does long runtime movies are more expensive to produce compared to short runtime movies?
6. Which genre of movie trends to be more expensive to produce?
7. Which movie director directed the prodution of movies (more than one) that became popular in relation to others, in the most recent year in the dataset?

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

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

```
Requirement already up-to-date: pandas in /opt/conda/lib/python3.6/site-packages (1.1.5)
Requirement already satisfied, skipping upgrade: numpy>=1.15.4 in /opt/conda/lib/python3.6/site-
Requirement already satisfied, skipping upgrade: python-dateutil>=2.7.3 in /opt/conda/lib/python
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

For this process, it is necessary to explore the general properties of the dataset, the way that it can lead us to decide what actions can be done to turn the dataset into a clean and accurate one for analysis.

```
In [3]: df = pd.read_csv('tmdb-movies.csv')
```

In [4]:
```
df.head()
```

Out[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

                 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]
```

- Show the dimentions of the dataset.

In [5]:
```
df.shape
```

Out[5]:
```
(10866, 21)
```

- Show the data type of each column in the dataset.

In [6]:
```
df.dtypes
```

Out[6]:
```
id                        int64
imdb_id                  object
popularity              float64
budget                    int64
revenue                   int64
original_title           object
cast                     object
homepage                 object
director                 object
tagline                  object
keywords                 object
overview                 object
runtime                   int64
genres                   object
production_companies     object
release_date             object
vote_count                int64
vote_average            float64
release_year              int64
budget_adj              float64
```

```
revenue_adj            float64
dtype: object
```

- Show the number of not null values in each column, so as their data types, in the dataset.

```
In [7]: 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
```

- Show the number of null values in each column.

```
In [8]: df.isnull().sum()
```

```
Out[8]: 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
```

- Show how many duplicated rows are in the dataset.

```
In [9]: sum(df.duplicated())
```

```
Out[9]: 1
```

- Show how many unique values are in each column in the dataset.

```
In [10]: df.nunique()
```

```
Out[10]: id                      10865
         imdb_id                 10855
         popularity              10814
         budget                    557
         revenue                  4702
         original_title          10571
         cast                    10719
         homepage                 2896
         director                 5067
         tagline                  7997
         keywords                 8804
         overview                10847
         runtime                   247
         genres                   2039
         production_companies     7445
         release_date             5909
         vote_count               1289
         vote_average               72
         release_year               56
         budget_adj               2614
         revenue_adj              4840
         dtype: int64
```

- Show some statistic results of all numerical columns in the dataset.

```
In [11]: df.describe()
```

```
Out[11]:                   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

From the investigation of the data above and based on the questions to analyse, the following cleaning steps are going to be taken:

- Budget : transform to float
- Revenue : transform to float

```
In [12]: df['budget'] = df['budget'].astype(float) # Change the budget data type to float
```

```
In [13]: df['revenue'] = df['revenue'].astype(float) # Change the revenue data type to float
```

- Release date: transform to date

```
In [14]: def arrange_date(x):
             if (int(x[2]) > 20):
                 x[2] = x[2].replace(x[2], '19'+x[2])
             else:
                 x[2] = x[2].replace(x[2], '20'+x[2])
             if (int(x[1]) < 10):
                 x[1] = x[1].replace(x[1], '0'+x[1])
             if (int(x[0]) < 10):
                 x[0] = x[0].replace(x[0], '0'+x[0])
             x = x[0]+x[1]+x[2]
             return x
```

In [15]:
```
df['release_date'] = df['release_date'].apply(lambda x: x.split('/')) # Calls a functio

df['release_date'] = df['release_date'].apply(lambda x: arrange_date(x)) # Calls the fu

df['release_date'] = pd.to_datetime(df['release_date'], format='%m%d%Y') #Format the da
```

- There is one duplicated arrow, so it can be dropped as follows.

In [16]:
```
df = df.drop_duplicates()

sum(df.duplicated())
```

Out[16]:
```
0
```

- There are various null rows in some columns of String data type, but there is no need to fill any value in them, due to the description of each of column, turning difficult to preview what type of value could fill the columns. Fortunatelly, those columns are "Tagline", "Keywords", "Overview" and "homepage" that are not needed for the analysis. So they can be dropped as follows.

In [17]:
```
df.drop(['tagline', 'keywords', 'overview', 'homepage'], axis = 1, inplace = True) # dr
```

- Beside these columns, there are columns like cast, genre and production_companies that will be used to answer the questions. Therefore, having null values in them will not help to make the analysis. So, the null values in these columns will be dropped so as the rows that contains these null values.

In [18]:
```
df.dropna(inplace = True) # drop rows with any null values in the dataset
df.isnull().sum()
```

Out[18]:
```
id                      0
imdb_id                 0
popularity              0
budget                  0
revenue                 0
original_title          0
cast                    0
director                0
runtime                 0
genres                  0
production_companies    0
release_date            0
vote_count              0
vote_average            0
release_year            0
budget_adj              0
revenue_adj             0
dtype: int64
```

- Genres and Production_Companies columns have multiple values that were separated with '|' in each row. turning difficult to make some of the analisys needed. It will be necessary to trim each column value as follows.
- Based in the questions defined above, it will be created two separated datasets (that contains the rows with the '|' character in 'genre' and 'production_companies' columns). One of the dataframes will contain the 'genres' column trimmed, and other the 'production_companies' column trimmed for later analysis.

In [19]:
```
g_df = df[df['genres'].str.contains('|')] # dataframe containing multiple genre values
p_df = df[df['production_companies'].str.contains('|')] # dataframe containing multiple
```

In [20]:
```
print(g_df.shape)
print(p_df.shape)
```

```
(9770, 17)
(9770, 17)
```

```
- As the results above, it is clear that all the columns contais 9770 rows as the cleaned datafr

- There's a function that will help us trim and separate each value in the rows of a determinate
```

In [21]:
```
def split_values(x, i, df, column):
    ind = df[df[column] == x].index.values # gets the index of the row
    x = x.split('|')  # split the multiple values in each row of the column
    if (i == 0):
        return x[i]
    elif (i < len(x)):
        return x[i]   # check if the row has any value in the index i after splitting
    else:
        df.drop(ind)  # drop the row that contain values trimmed in other dataframe in
```

```
- For separating values in 'genre' column, it will be needed hybrid dataframes. We will use the
```

In [22]:
```
g1_df = g_df.copy()
g2_df = g_df.copy()
g1_df['genres'] = g_df['genres'].apply(lambda x: split_values(x, 0, g_df, 'genres'))
g2_df['genres'] = g_df['genres'].apply(lambda x: split_values(x, 1, g_df, 'genres'))
```

```
- Having the two hybrid dataframes with the first and second value of each row in genre column,
```

In [23]:
```
g_df = pd.concat([g1_df, g2_df])
g_df
```

Out[23]:

	id	imdb_id	popularity	budget	revenue	\
0	135397	tt0369610	32.985763	150000000.0	1.513529e+09	
1	76341	tt1392190	28.419936	150000000.0	3.784364e+08	
2	262500	tt2908446	13.112507	110000000.0	2.952382e+08	
3	140607	tt2488496	11.173104	200000000.0	2.068178e+09	

```
4      168259  tt2820852    9.335014  190000000.0  1.506249e+09
...       ...        ...         ...          ...           ...
10861      21  tt0060371    0.080598          0.0  0.000000e+00
10862   20379  tt0060472    0.065543          0.0  0.000000e+00
10863   39768  tt0060161    0.065141          0.0  0.000000e+00
10864   21449  tt0061177    0.064317          0.0  0.000000e+00
10865   22293  tt0060666    0.035919      19000.0  0.000000e+00

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

       runtime     genres                               production_companies  \
0          124     Action  Universal Studios|Amblin Entertainment|Legenda...
1          120     Action  Village Roadshow Pictures|Kennedy Miller Produ...
2          119  Adventure  Summit Entertainment|Mandeville Films|Red Wago...
3          136     Action          Lucasfilm|Truenorth Productions|Bad Robot
4          137     Action  Universal Pictures|Original Film|Media Rights ...
...        ...        ...                                                ...
10861       95       None                                  Bruce Brown Films
10862      176  Adventure  Cherokee Productions|Joel Productions|Douglas ...
10863       94     Comedy                                            Mosfilm
10864       80     Comedy                             Benedict Pictures Corp.
10865       74       None                                          Norm-Iris

      release_date  vote_count  vote_average  release_year    budget_adj  \
```

```
0      2015-06-09       5562          6.5          2015  1.379999e+08
1      2015-05-13       6185          7.1          2015  1.379999e+08
2      2015-03-18       2480          6.3          2015  1.012000e+08
3      2015-12-15       5292          7.5          2015  1.839999e+08
4      2015-04-01       2947          7.3          2015  1.747999e+08
...           ...        ...          ...           ...           ...
10861  1966-06-15         11          7.4          1966  0.000000e+00
10862  1966-12-21         20          5.7          1966  0.000000e+00
10863  1966-01-01         11          6.5          1966  0.000000e+00
10864  1966-11-02         22          5.4          1966  0.000000e+00
10865  1966-11-15         15          1.5          1966  1.276423e+05

        revenue_adj
0      1.392446e+09
1      3.481613e+08
2      2.716190e+08
3      1.902723e+09
4      1.385749e+09
...             ...
10861  0.000000e+00
10862  0.000000e+00
10863  0.000000e+00
10864  0.000000e+00
10865  0.000000e+00

[19540 rows x 17 columns]
```

- For each 'production_companies' row we will use in maximum first two values as sample:

```
In [24]: p1_df = p_df.copy()
         p2_df = p_df.copy()
         p1_df['production_companies'] = p_df['production_companies'].apply(lambda x: split_valu
         p2_df['production_companies'] = p_df['production_companies'].apply(lambda x: split_valu
```

- Finally, the hybrid dataframes will be joined as follows.

```
In [25]: p_df = pd.concat([p1_df, p2_df])
         p_df
```

```
Out[25]:            id    imdb_id  popularity       budget       revenue  \
         0      135397  tt0369610   32.985763  150000000.0  1.513529e+09
         1       76341  tt1392190   28.419936  150000000.0  3.784364e+08
         2      262500  tt2908446   13.112507  110000000.0  2.952382e+08
         3      140607  tt2488496   11.173104  200000000.0  2.068178e+09
         4      168259  tt2820852    9.335014  190000000.0  1.506249e+09
         ...       ...        ...         ...          ...           ...
         10861      21  tt0060371    0.080598          0.0  0.000000e+00
         10862   20379  tt0060472    0.065543          0.0  0.000000e+00
         10863   39768  tt0060161    0.065141          0.0  0.000000e+00
```

```
10864   21449  tt0061177    0.064317          0.0  0.000000e+00
10865   22293  tt0060666    0.035919      19000.0  0.000000e+00

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

       runtime                                     genres  \
0          124  Action|Adventure|Science Fiction|Thriller
1          120  Action|Adventure|Science Fiction|Thriller
2          119         Adventure|Science Fiction|Thriller
3          136   Action|Adventure|Science Fiction|Fantasy
4          137                      Action|Crime|Thriller
...        ...                                        ...
10861       95                                Documentary
10862      176                     Action|Adventure|Drama
10863       94                             Mystery|Comedy
10864       80                              Action|Comedy
10865       74                                     Horror

          production_companies release_date  vote_count  vote_average  \
0            Universal Studios   2015-06-09        5562           6.5
1      Village Roadshow Pictures   2015-05-13        6185           7.1
2         Summit Entertainment   2015-03-18        2480           6.3
3                   Lucasfilm   2015-12-15        5292           7.5
4           Universal Pictures   2015-04-01        2947           7.3
```

```
...                              ...          ...           ...           ...
10861                           None   1966-06-15            11           7.4
10862               Joel Productions   1966-12-21            20           5.7
10863                           None   1966-01-01            11           6.5
10864                           None   1966-11-02            22           5.4
10865                           None   1966-11-15            15           1.5

       release_year    budget_adj   revenue_adj
0              2015  1.379999e+08  1.392446e+09
1              2015  1.379999e+08  3.481613e+08
2              2015  1.012000e+08  2.716190e+08
3              2015  1.839999e+08  1.902723e+09
4              2015  1.747999e+08  1.385749e+09
...             ...           ...           ...
10861          1966  0.000000e+00  0.000000e+00
10862          1966  0.000000e+00  0.000000e+00
10863          1966  0.000000e+00  0.000000e+00
10864          1966  0.000000e+00  0.000000e+00
10865          1966  1.276423e+05  0.000000e+00

[19540 rows x 17 columns]
```

- It was noted that 'budget' and 'revenue' columns do not have null values but have values represented as '0.0', that can be described as null. It is show below:

In [26]:
```python
df[df['revenue'] == 0.0]
```

Out[26]:
```
           id    imdb_id  popularity     budget  revenue  \
48     265208  tt2231253    2.932340 30000000.0      0.0
67     334074  tt3247714    2.331636 20000000.0      0.0
74     347096  tt3478232    2.165433        0.0      0.0
75     308369  tt2582496    2.141506        0.0      0.0
92     370687  tt3608646    1.876037        0.0      0.0
...       ...        ...         ...        ...      ...
10861      21  tt0060371    0.080598        0.0      0.0
10862   20379  tt0060472    0.065543        0.0      0.0
10863   39768  tt0060161    0.065141        0.0      0.0
10864   21449  tt0061177    0.064317        0.0      0.0
10865   22293  tt0060666    0.035919    19000.0      0.0

                     original_title  \
48                        Wild Card
67                         Survivor
74             Mythica: The Darkspore
75     Me and Earl and the Dying Girl
92           Mythica: The Necromancer
...                             ...
10861              The Endless Summer
```

```
10862                   Grand Prix
10863          Beregis Avtomobilya
10864         What's Up, Tiger Lily?
10865       Manos: The Hands of Fate

                                                    cast             director  \
48     Jason Statham|Michael Angarano|Milo Ventimigli...           Simon West
67     Pierce Brosnan|Milla Jovovich|Dylan McDermott|...        James McTeigue
74     Melanie Stone|Kevin Sorbo|Adam Johnson|Jake St...         Anne K. Black
75     Thomas Mann|RJ Cyler|Olivia Cooke|Connie Britt...  Alfonso Gomez-Rejon
92     Melanie Stone|Adam Johnson|Kevin Sorbo|Nicola ...         A. Todd Smith
...                                                  ...                  ...
10861  Michael Hynson|Robert August|Lord 'Tally Ho' B...          Bruce Brown
10862  James Garner|Eva Marie Saint|Yves Montand|Tosh...   John Frankenheimer
10863  Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...       Eldar Ryazanov
10864  Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...          Woody Allen
10865  Harold P. Warren|Tom Neyman|John Reynolds|Dian...     Harold P. Warren

       runtime                    genres  \
48          92      Thriller|Crime|Drama
67          96     Crime|Thriller|Action
74         108  Action|Adventure|Fantasy
75         105              Comedy|Drama
92           0  Fantasy|Action|Adventure
...        ...                       ...
10861       95               Documentary
10862      176    Action|Adventure|Drama
10863       94            Mystery|Comedy
10864       80             Action|Comedy
10865       74                    Horror

                                    production_companies release_date  \
48     Current Entertainment|Lionsgate|Sierra / Affin...   2015-01-14
67     Nu Image Films|Winkler Films|Millennium Films|...   2015-05-21
74                              Arrowstorm Entertainment   2015-06-24
75                                     Indian Paintbrush   2015-06-12
92     Arrowstorm Entertainment|Camera 40 Productions...   2015-12-19
...                                                  ...          ...
10861                                  Bruce Brown Films   1966-06-15
10862  Cherokee Productions|Joel Productions|Douglas ...   1966-12-21
10863                                            Mosfilm   1966-01-01
10864                             Benedict Pictures Corp.   1966-11-02
10865                                          Norm-Iris   1966-11-15

       vote_count  vote_average  release_year    budget_adj  revenue_adj
48            481           5.3          2015  2.759999e+07          0.0
67            280           5.4          2015  1.839999e+07          0.0
74             27           5.1          2015  0.000000e+00          0.0
```

```
75             569          7.7          2015  0.000000e+00          0.0
92              11          5.4          2015  0.000000e+00          0.0
...            ...          ...           ...           ...          ...
10861           11          7.4          1966  0.000000e+00          0.0
10862           20          5.7          1966  0.000000e+00          0.0
10863           11          6.5          1966  0.000000e+00          0.0
10864           22          5.4          1966  0.000000e+00          0.0
10865           15          1.5          1966  1.276423e+05          0.0

[5020 rows x 17 columns]
```

```
- The number of rows containing these values are more than the half of total rows of the cleaned
```

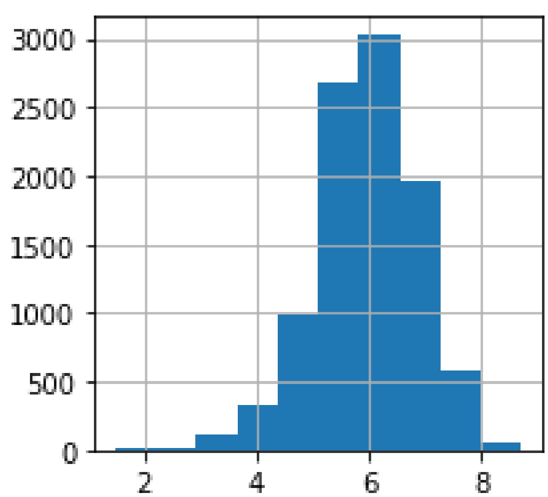
Exploratory Data Analysis
For the research of the questions posed in the Introduction section, it will be computed the relevant statistics to compare and show trends in the visualizations related to the data, based in the questions.

1.1.5 1. Which genre of movie tends to be more appreciated (in terms of voting)?

- We will start the research of this question plotting the histogram for Vote Average distribution.

```
In [27]: df['vote_average'].hist(figsize = (3, 3))
         df['vote_average'].median()
```

```
Out[27]: 6.0
```



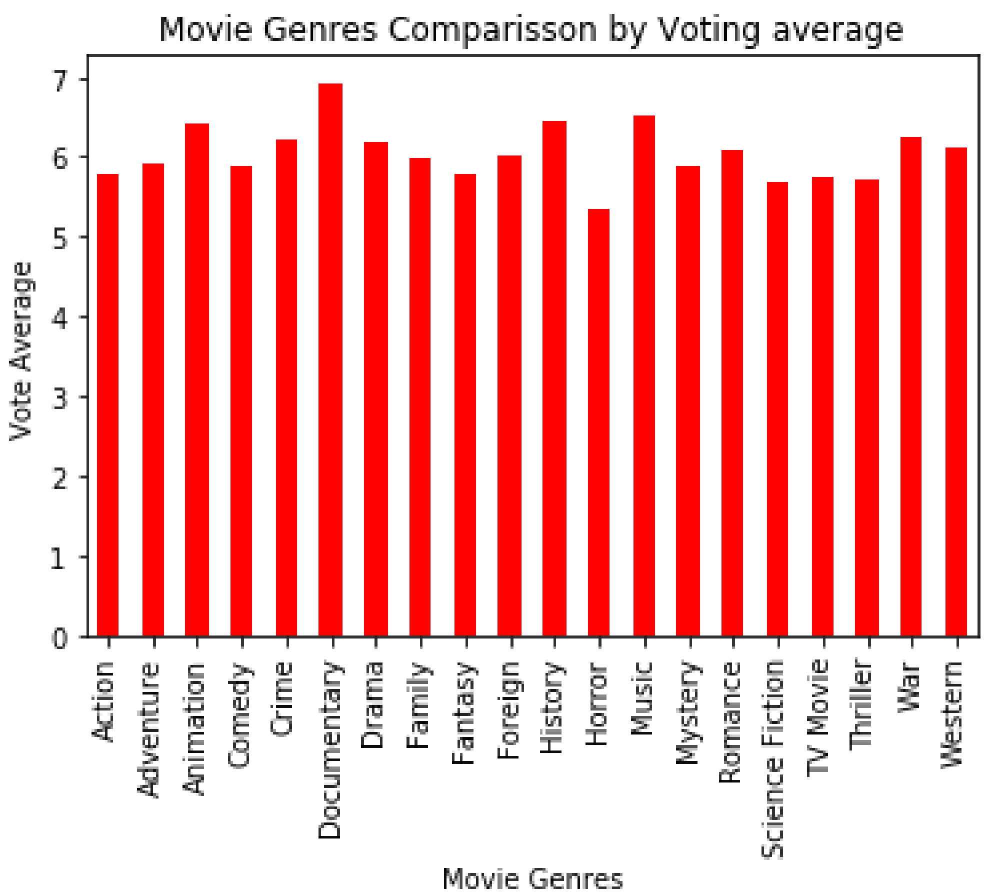
As it is shown above, most of the films tend to have a vote average between 5 to 7 points, and very few of them tend to have more than 8 or less than 4 points as vote.

This plot can lead to the conclusion that the vote average is evenly distributed and not up the sides, stretching across the entire graph. Furthermore, it is balanced toward the center of the frame, with no obvious skew.

- Furthermore, it will be calculated the mean value of vote average in function of each genre of movie using the genre dataframe created, as shown above:

```
In [28]: genre = g_df.groupby(['genres'])['vote_average'].mean()
         genre.plot(kind = 'bar', color = 'red', figsize=(6, 4))
         plt.title('Movie Genres Comparisson by Voting average')
         plt.xlabel('Movie Genres')
         plt.ylabel('Vote Average')
```

```
Out[28]: Text(0,0.5,'Vote Average')
```



The plot results tells that Documentary genre could be the most appreciated by people.

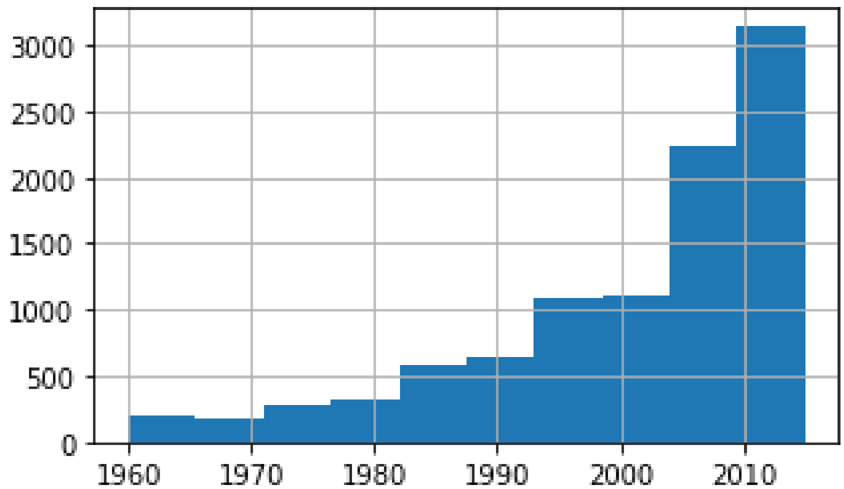
Note: Each movie can have more than one genre and for this analysis where used in maximum only two of those values as sample, because of the number of processes that could be executed in large amount of data generated in spliting phase. With that in mind, the statistical result for this question can be different if we decide to add all the data provided by the dataset.

1.1.6 2. Has nowadays movies been well received by people comparing to old movies?

- We will start the research of this question plotting the histogram for Release year distribution of movies.

```
In [29]: df['release_year'].hist(figsize = (5, 3))
```

```
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7efc85ec5da0>
```

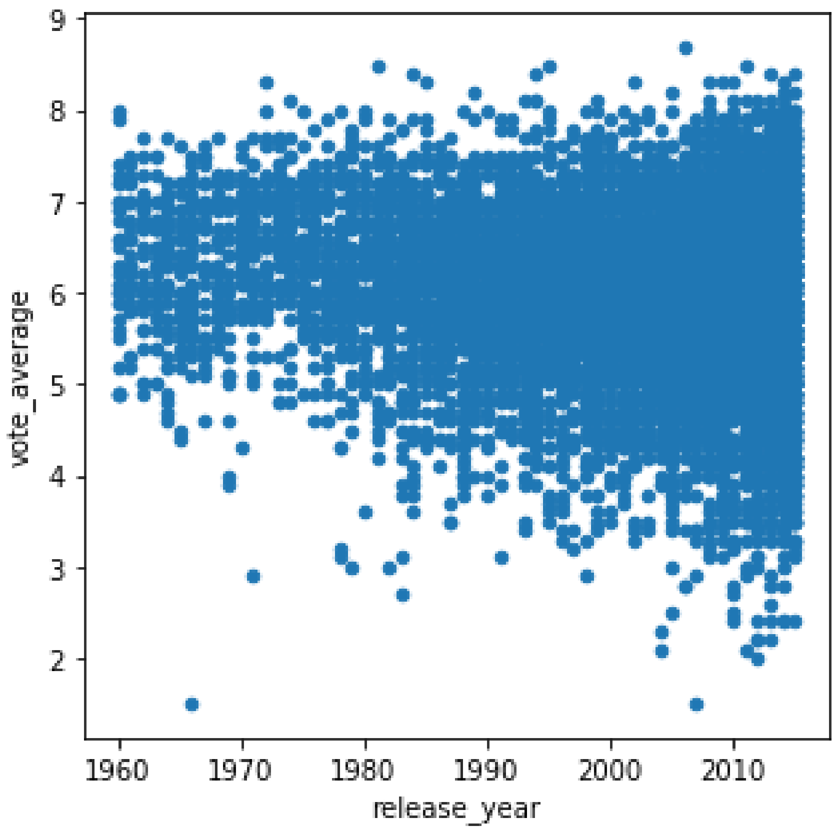


As we can see, the number of movies released every year tends to be larger than the previous year.

- Plotting the Scatterplot of Release Year in Relation to Vote Average.

```
In [30]: df.plot(kind = 'scatter', x = 'release_year', y = 'vote_average', figsize = (5, 5))
```

```
Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x7efc859e2278>
```



This data don't have any kind of pattern, which means that no relationship exists between Release year and Vote average.

- Lastly, for research using the bar plotting, we will define a median first, which function is to separate old movies from modern movies based in the released date. Next step is to define the average vote_average of these two types to compare.

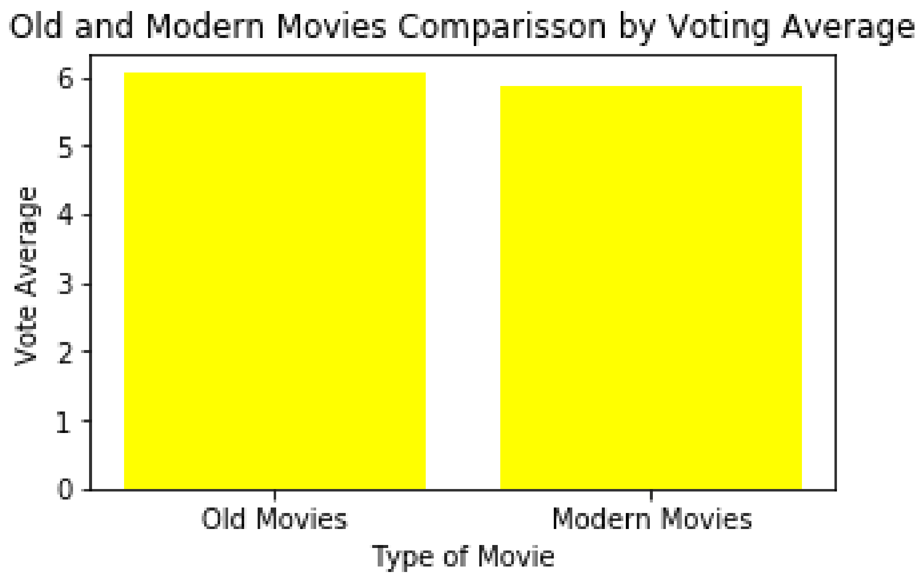
```
In [31]: m = pd.Timestamp(df['release_date'].astype(np.int64).median())
         old_movies = df[df['release_date'] < m]
         old_movies = old_movies['vote_average'].mean()
         modern_movies = df[df['release_date'] >= m]
         modern_movies = modern_movies['vote_average'].mean()
```

Having old movies and modern movies well separated and defined, the results are shown in the plot bar above.

```
In [32]: x = [1 , 2]
         y = [old_movies, modern_movies]
         label = ['Old Movies', 'Modern Movies']
         plt.figure(figsize = (5,3))
         plt.bar(x, y, tick_label = label, color = 'yellow')
         plt.title('Old and Modern Movies Comparisson by Voting Average')
```

```
plt.xlabel('Type of Movie')
plt.ylabel('Vote Average')
```

Out[32]: Text(0,0.5,'Vote Average')



It is shown that old movies are more rated than modern movies. Note that the answer to this question is not limited to only these parameters.

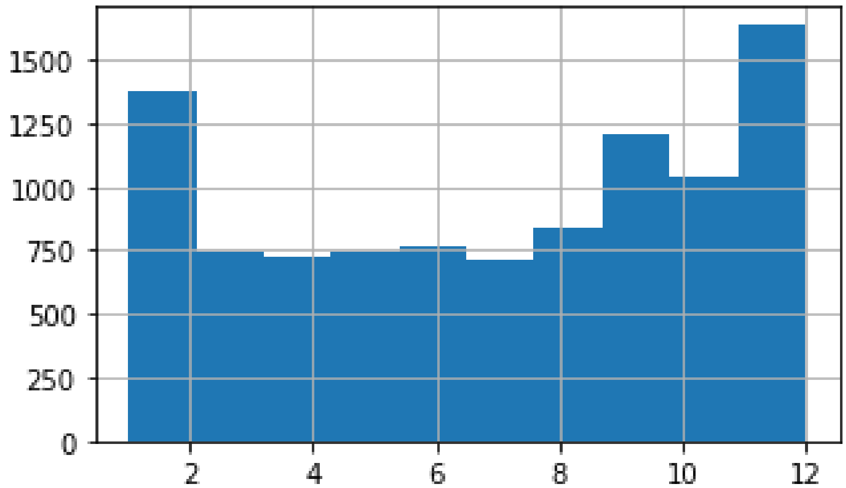
1.1.7 3. What is the best month of the year used to release the movie?

- We will start the research of this question plotting the histogram for Release month distribution of movies.

  Creating a dataframe containing the release month of each movie to help us reseach this question.

```
In [33]: df_months = df.copy()
         df_months['release_month'] = pd.DatetimeIndex(df_months['release_date']).month
         df_months['release_month'].hist(figsize = (5, 3))
```

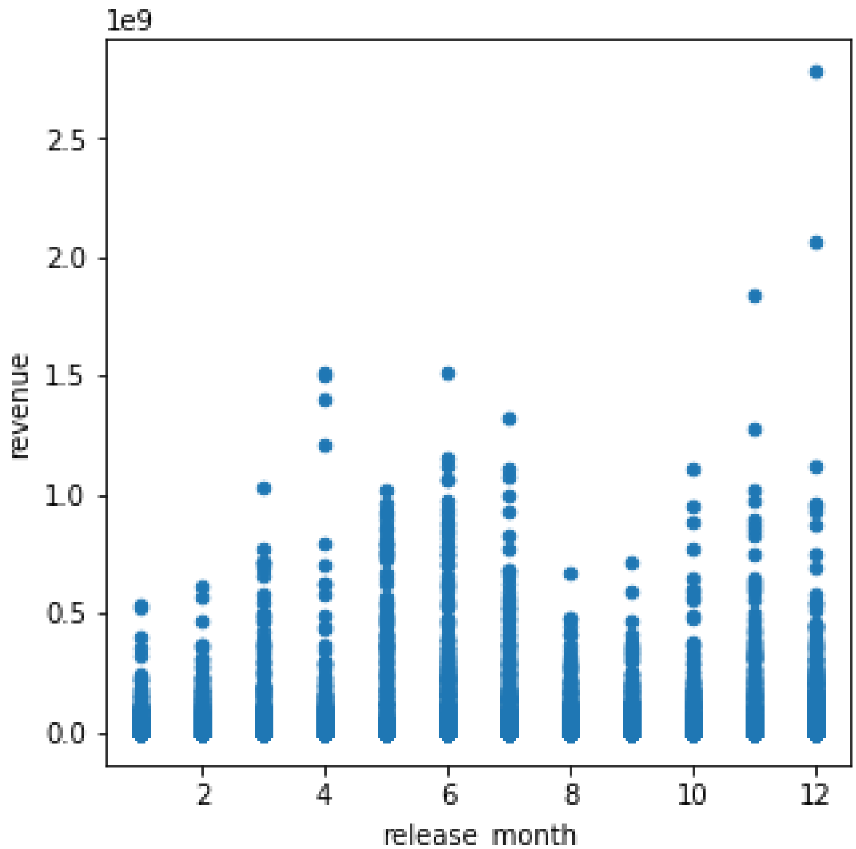
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x7efc85982978>



This shows that most of the movies are released at the end of the year until the beginning of the year (from November to February).

- Plotting the Scatterplot of Release Month in Relation to Revenue.

```
In [34]: df_months.plot(kind = 'scatter', x = 'release_month', y = 'revenue', figsize = (5, 5))

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x7efc858961d0>
```



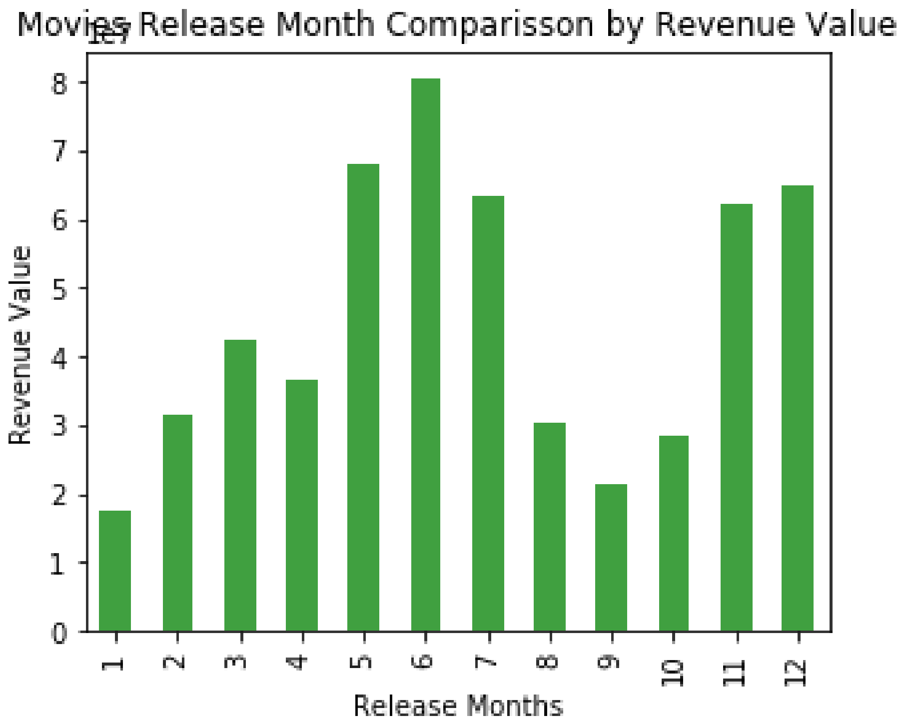
This data don't have any kind of pattern too, which means that no relationship exists between Release month and Revenue.

- To see the bar plot of this question, it will be calculated the mean value of revenue in function of each release month of the movies.

```
In [35]: df_months = df_months.groupby(df_months['release_month'])['revenue'].mean()
```

Having the dataframe for the question defined, there is the plot bar to show the result.

```
In [36]: df_months.plot(kind = 'bar', color = 'green', figsize=(5, 4), alpha = 0.75)
         plt.title('Movies Release Month Comparisson by Revenue Value')
         plt.xlabel('Release Months')
         plt.ylabel('Revenue Value')

Out[36]: Text(0,0.5,'Revenue Value')
```



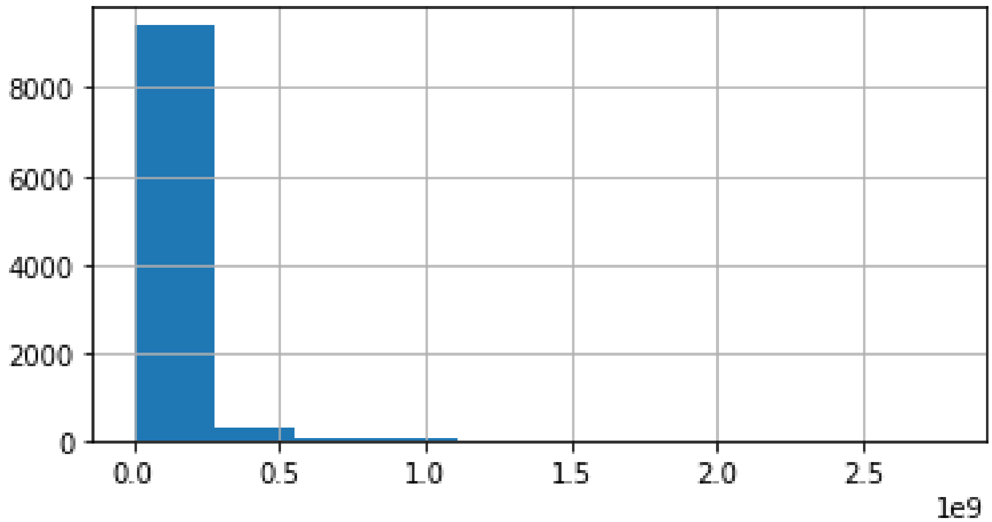
The plot shows that movies released in June month tend to be the ones with more revenue value, followed by movies released in May and December months.

Note: These results are not so trustful due to no correlation existing between these two parameteres seen in the analysis above.

1.1.8 4. Ranking of the best production companies from year to year in TMDb. By how much?

- Plotting the histogram for Revenue distribution of movies.

```
In [37]: df['revenue'].hist(figsize = (6, 3))
         df['revenue'].median()

Out[37]: 0.0
```



The plot shows that the distribution is skewed to the right, which means that most of the movies tend to have less than 250 millions of revenue and few of them more than that.

- For the bar plot, it will be used the production companies dataframe created before, where it will be calculated the mean value of the entire dataframe based in each production company in each year.

```
In [38]: p_df = p_df.groupby(['release_year', 'production_companies']).mean()
```

The next step is to get the labels for our plot, that can be determined by maximum revenue value index (that will be in String form containing the release year and production company together, due to the change of index type made in the step above) in each year

```
In [39]: p_df1 = p_df.groupby(['release_year']).idxmax()
         labels = p_df1.loc[:, 'revenue']
```

That done, we get the maximum revenue value in each year as height(y) of our plot.

The width(x) or number of bars will correspond to the number of index in one of the dataframes.

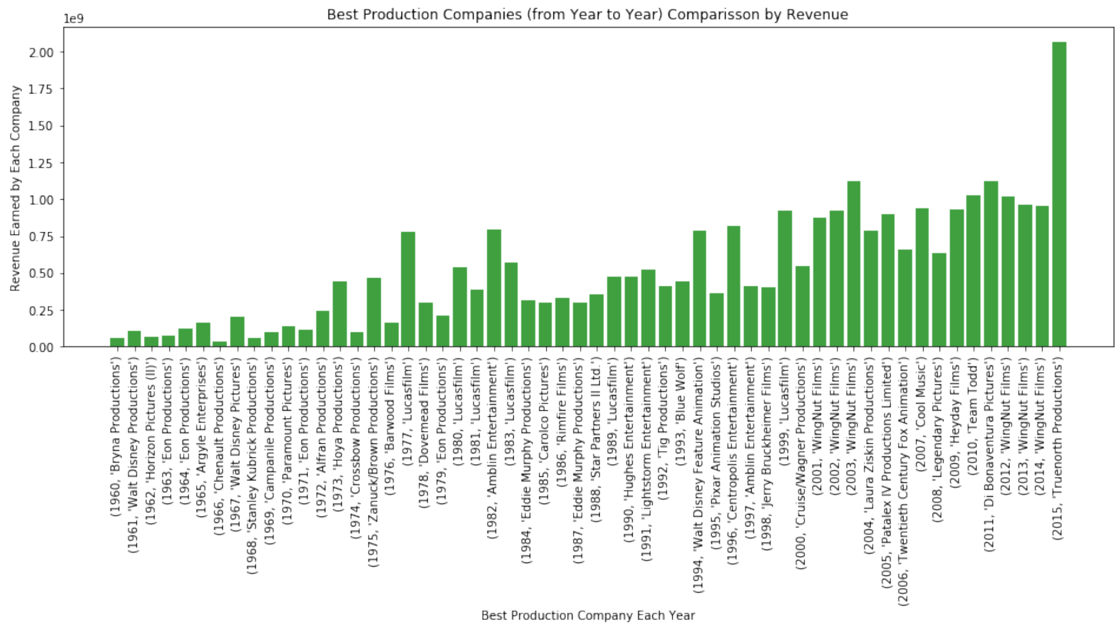
```
In [40]: p_df2 = p_df.groupby(['release_year']).max()
         y = p_df2.loc[:, 'revenue']

         x = p_df2.index.values
```

Finally, the results are above.

```
In [41]: plt.figure(figsize = (16,5))
         plt.bar(x, y, tick_label = labels, alpha = 0.75, color = 'green')
```

```
plt.xticks(rotation = 90)
plt.title('Best Production Companies (from Year to Year) Comparisson by Revenue')
plt.xlabel('Best Production Company Each Year')
plt.ylabel('Revenue Earned by Each Company')
```

Out[41]: Text(0,0.5,'Revenue Earned by Each Company')



Based in this bar plot, the best production company in terms of revenue is the Truenorth Productions that had the highest amount of revenue in 2015 year. Even so, the other production companies shown in the bar plot are the most sucessful in these years too.

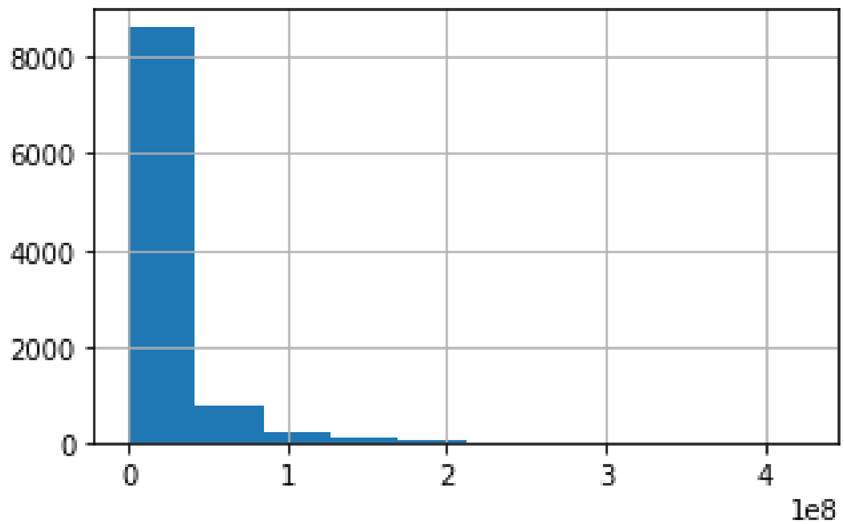
Note: These results can be analysed more precisely and accurately with other more parameters too.

1.1.9 5. Does long runtime movies are more expensive to produce compared to short runtime movies?

- We will start the research of this question plotting the histogram for Budget and Runtime Distribution.

In [42]:
```
df['budget'].hist(figsize = (5, 3))
df['budget'].median()
```

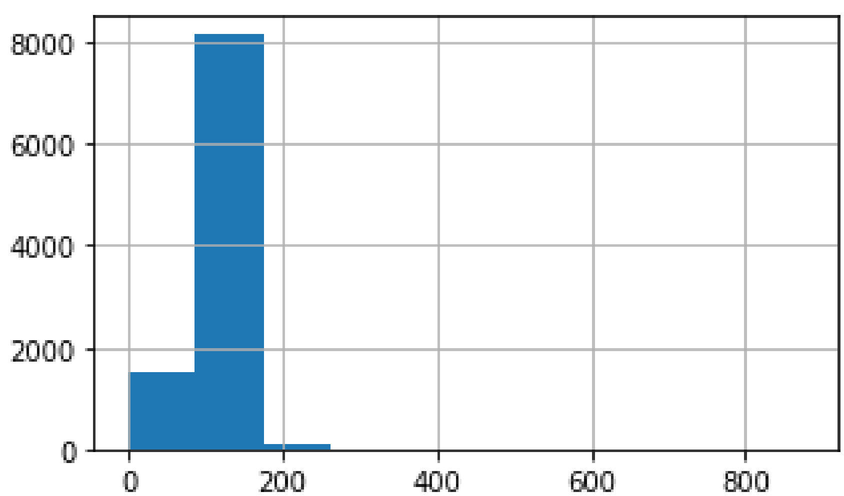
Out[42]: 200000.0



The plot shows that the distribution is skewed to the right, which means that most of the movies tend to have less than 50 millions of budget invested to its production and few of them more than a hundred million.

```
In [43]: df['runtime'].hist(figsize = (5, 3))
         df['runtime'].median()
```

```
Out[43]: 100.0
```

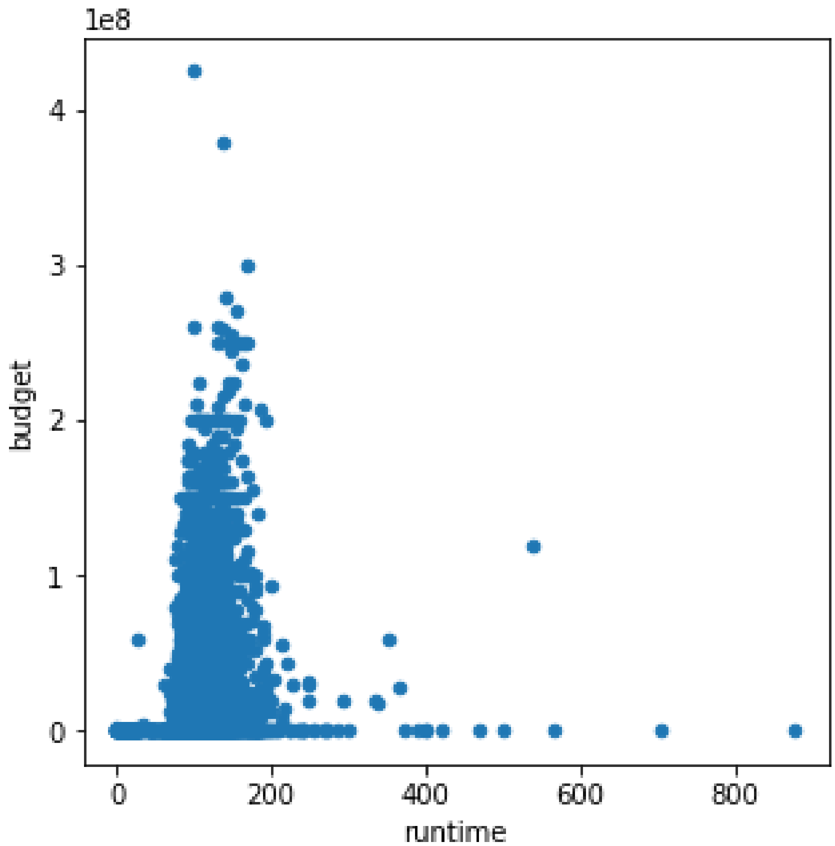


The plot shows that the distribution is skewed to the left, which means that most of the movies tend to have more than 100 runtime minutes and few of them less than 100 minutes.

- Plotting the Scatterplot of Movie Runtime in Relation to Budget.

```
In [44]: df.plot(kind = 'scatter', x = 'runtime', y = 'budget', figsize = (5, 5))
```

```
Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x7efc85394c88>
```



This data don't have any kind of pattern too, which means that no relationship exists between Runtime and Budget.

- Bar plot for the question research.

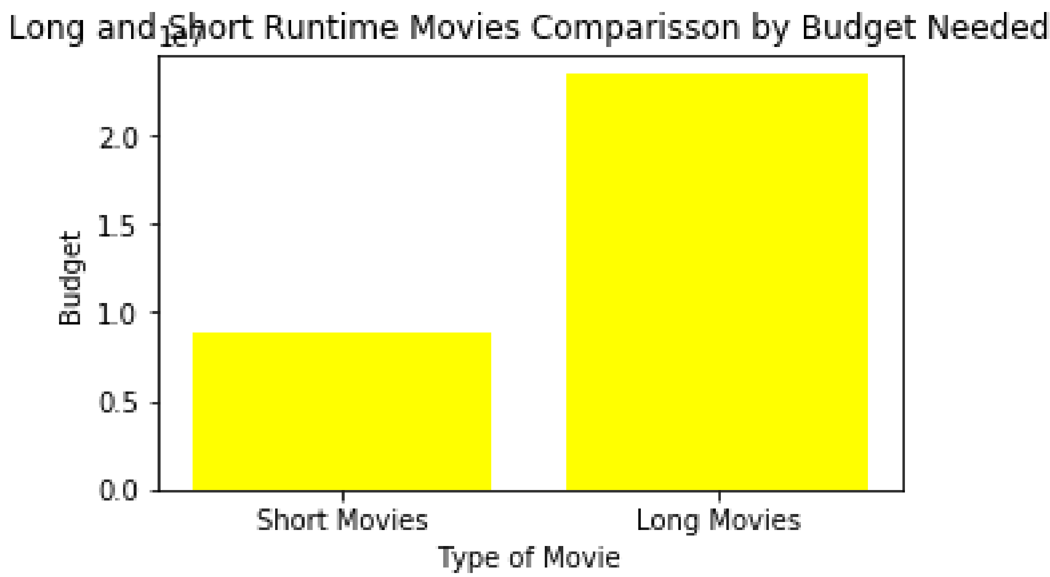
  It will be defined a median first, which function is to separate short runtime movies from long runtime movies based in the runtime median, so as define the average budget of these two types to compare as next step.

```
In [45]: m = df['runtime'].median()
         short_movies = df[df['runtime'] < m]
         short_movies = short_movies['budget'].mean()
         long_movies = df[df['runtime'] >= m]
         long_movies = long_movies['budget'].mean()
```

The answer for the question above.

In [46]:
```
x = [1 , 2]
y = [short_movies, long_movies]
label = ['Short Movies', 'Long Movies']
plt.figure(figsize = (5,3))
plt.bar(x, y, tick_label = label, color = 'yellow')
plt.title('Long and Short Runtime Movies Comparisson by Budget Needed')
plt.xlabel('Type of Movie')
plt.ylabel('Budget')
```

Out[46]: `Text(0,0.5,'Budget')`



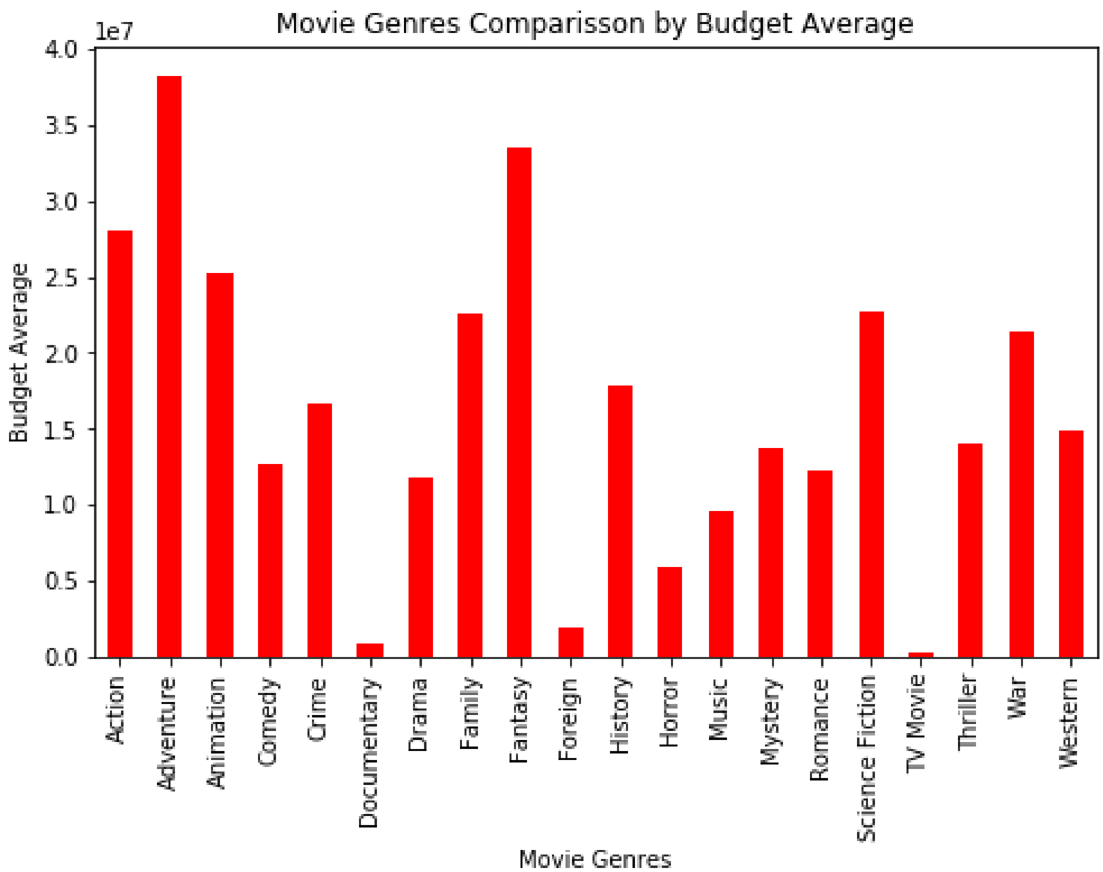
The results above clearly show that long runtime movies can be more expensive to produce.

1.1.10 6. Which genre of movie tends to be more expensive to produce?

To this question, it will be calculated the mean value of budget in function of each genre of movie using the genre dataframe created, as shown above:

In [47]:
```
genre_df = g_df.groupby(['genres'])['budget'].mean()
genre_df.plot(kind = 'bar', color = 'red', figsize=(8, 5))
plt.title('Movie Genres Comparisson by Budget Average')
plt.xlabel('Movie Genres')
plt.ylabel('Budget Average')
```

Out[47]: `Text(0,0.5,'Budget Average')`

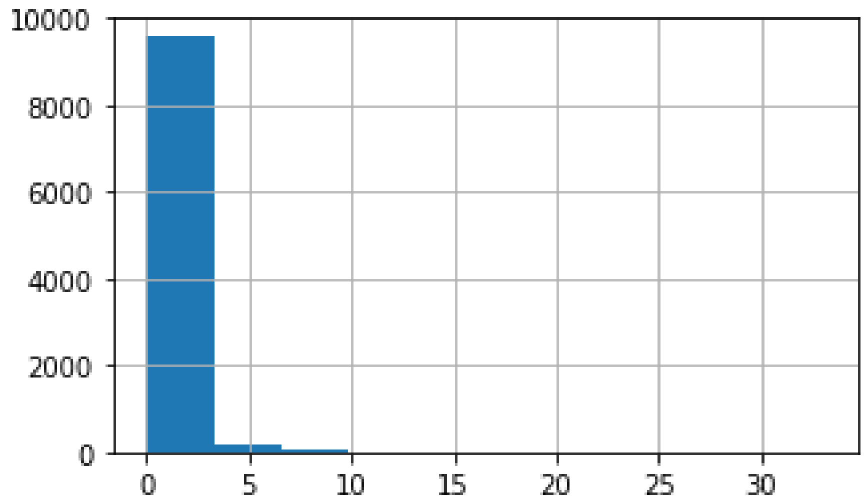


The answer for this question shows that Adventure movies tend to be the most expensive genre to be produced, followed by Fantasy movies.

1.1.11 7. Which movie director directed the prodution of movies (more than one) that became popular in relation to others, in the most recent year in the dataset?

- Histogram plot of Movie Popularity Distribution

```
In [48]: df['popularity'].hist(figsize = (5, 3))
         df['popularity'].median()

Out[48]: 0.41976199999999997
```



The plot shows that the distribution of movie popularity is skewed to the right, which means that most of the movies trend to have less than 0.4 of popularity.

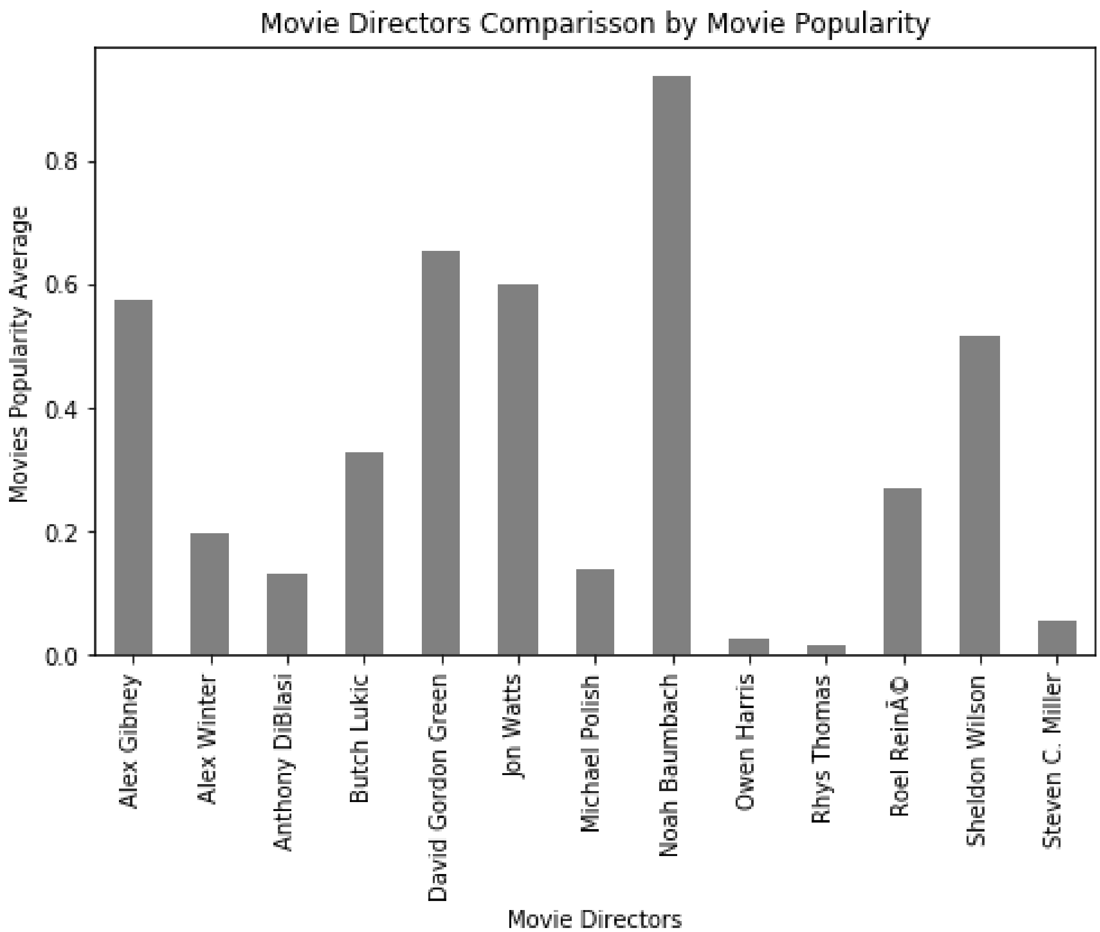
- Bar plot for the question research.

  For this question is going to be defined a dataframe that contains the data of movies released in 2015 year and the directors responsibles for more than one movies in the same year. That done, it will be calculated the average popularity of the movies in function of each director.

```
In [49]: dir_df = df.query('release_year == 2015')
         dir_df = dir_df[dir_df['director'].duplicated()]
         dir_df = dir_df.groupby(['director']).mean()['popularity']
```

  The answer for the question is above.

```
In [50]: dir_df.plot(kind = 'bar', color = 'gray', figsize=(8, 5))
         plt.title('Movie Directors Comparisson by Movie Popularity')
         plt.xlabel('Movie Directors')
         plt.ylabel('Movies Popularity Average')

Out[50]: Text(0,0.5,'Movies Popularity Average')
```



The result tells us that Noah Baumbach was the movie director that produced the most popular movies between directors that produced more than one movie in the 2015 year.

Conclusions

As conclusion of this dataset analysis, it will be organized all the findings based in the questions defined above:

> The Documentary genre could be the most appreciated movie genre. That said, most of the films tend to have a vote average between 5 to 7 points, and very few of them tend to have more than 8 or less than 4 points as vote, making sense because the Documentary movies genres has the vote average almost to 7 points in relation to other movie genres.
>
> Besides the amount of modern movies is larger than the old movies amount, the old movies had way better vote rating in relation to modern movies, but, it does not mean that there is a relationship between the release year of the movie and the vote average of it, because there are still too many modern movies with good rating points compared to old movies, as it is shown in the scatterplot of the question research.
>
> Most of the movies are released at the end of the year until the beginning of the year (from November to February), but most of the movies released in June month tend to

be the ones with more revenue value, followed by movies released in May and December months. Even so, these results are not so trustful due to no correlation existing between the release month and revenue parameteres.

Most of the movies tend to have less than 250 millions of revenue and few of them more than that. That said, the best production company in terms of revenue is the Truenorth Productions that had the highest amount of revenue in 2015 year, which means that it could have been responsible for few movies, but the revenue value was so high that the production company still outstanded.

Most of the movies tend to have less than 50 millions of budget invested to its production and few of them more than a hundred million, so as most of these movies tend to have more than 100 runtime minutes and few of them less than 100 minutes. Regardless the lack of relationship between Runtime and Budget of a movie, long runtime movies can be more expensive to produce. Why? Maybe because these expensive movies are the ones that have more than 100 runtime minutes.

This question can be deeply researched based on other parameters too.

Adventure movies tend to be the most expensive genre to be produced, followed by Fantasy movies.

Lastly, most of the movies trend to have less than 0.4 of popularity, and Noah Baumbach was the movie director that produced the most popular movies between directors that produced more than one movie in the 2015 year (the most recent year included in the dataset).

1.1.12 Limitations

The results can not be so accurate because of the limitation of the number of attributes used, such as genres and production companies of the dataset used to the processes.

The questions were analysed with limited parameters because of the limited scope of analysis, making the results not so accurate and reliable. The statistical result for some questions can be different if we decide to add all the data provided by the dataset.