Investigate_a_Dataset

September 19, 2022

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

## Introduction

1.0.1 Dataset Description

```
* id                    -->       Unique Id for the movie.
* imdb_id               -->       IMDB Id for the movie.
* popularity            -->       Indicates the popularity of the movie. Higher the number, higher
* budget                -->       Budget spent for the movie.
* revenue               -->       Revenue generated by the movie.
* original_title        -->       The title of the movie.
* cast                  -->       These are the cast for the movie separated by '|' symbol.
* homepage              -->       Url for the movie web page.
* director              -->       Director of the movie.
* tagline               -->       Short tagline that comes with the title.
* Keywords              -->       These are the keywords for the movie separated by '|' symbol
* overview              -->       A brief description of the movie plot.
* runtime               -->       Length of the movie in minutes.
* genres                -->       Genre of the movie separated by '|' symbol.
* production_companies-->       Production companies separated by '|' symbol.
* release_date          -->       Date of release of the movie in mm/dd/yy format.
* vote_count            -->       Number of votes for the movie.
* vote_average          -->       Average votes for the movie.
* release_year          -->       Year of release of the movie in yyyy format.
* budget_adj            -->       Adjudsted budget for the movie.
* revenue_adj           -->       Adjusted revenue generated by the movie.
```

1.0.2 Question(s) for Analysis

Research Question 1: Does the budget and revenue have any impact on ratings?

Research Question 2 (Is there any relationship between revenue and the weekend of release? How will this change when we include the popularity?)

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

- Load the data to dataframe

```
In [2]: df = pd.read_csv('Database_TMDb_movie_data/tmdb-movies.csv')
        df.head()
```

```
Out[2]:        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 [3]: #Check the datatypes
        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
```

```
In [4]: df.describe(include='all')
```

```
Out[4]:                    id    imdb_id    popularity        budget       revenue  \
        count    10866.000000      10856  10866.000000  1.086600e+04  1.086600e+04
        unique            NaN      10855           NaN           NaN           NaN
        top               NaN  tt0411951           NaN           NaN           NaN
        freq              NaN          2           NaN           NaN           NaN
        mean     66064.177434        NaN      0.646441  1.462570e+07  3.982332e+07
        std      92130.136561        NaN      1.000185  3.091321e+07  1.170035e+08
        min          5.000000        NaN      0.000065  0.000000e+00  0.000000e+00
        25%      10596.250000        NaN      0.207583  0.000000e+00  0.000000e+00
        50%      20669.000000        NaN      0.383856  0.000000e+00  0.000000e+00
        75%      75610.000000        NaN      0.713817  1.500000e+07  2.400000e+07
        max     417859.000000        NaN     32.985763  4.250000e+08  2.781506e+09

               original_title        cast                           homepage  \
        count           10866       10790                               2936
        unique          10571       10719                               2896
        top            Hamlet  Louis C.K.  http://www.missionimpossible.com/
        freq                4           6                                  4
        mean              NaN         NaN                                NaN
        std               NaN         NaN                                NaN
        min               NaN         NaN                                NaN
        25%               NaN         NaN                                NaN
        50%               NaN         NaN                                NaN
        75%               NaN         NaN                                NaN
        max               NaN         NaN                                NaN

                   director                 tagline      ...                 overview  \
        count         10822                    8042      ...                    10862
        unique         5067                    7997      ...                    10847
        top     Woody Allen  Based on a true story.      ...       No overview found.
        freq             45                       5      ...                       13
        mean            NaN                     NaN      ...                      NaN
        std             NaN                     NaN      ...                      NaN
        min             NaN                     NaN      ...                      NaN
        25%             NaN                     NaN      ...                      NaN
        50%             NaN                     NaN      ...                      NaN
        75%             NaN                     NaN      ...                      NaN
        max             NaN                     NaN      ...                      NaN
```

```
             runtime  genres production_companies release_date    vote_count  \
count   10866.000000   10843                 9836        10866  10866.000000
unique           NaN    2039                 7445         5909           NaN
top              NaN  Comedy   Paramount Pictures       1/1/09           NaN
freq             NaN     712                  156           28           NaN
mean      102.070863     NaN                  NaN          NaN    217.389748
std        31.381405     NaN                  NaN          NaN    575.619058
min         0.000000     NaN                  NaN          NaN     10.000000
25%        90.000000     NaN                  NaN          NaN     17.000000
50%        99.000000     NaN                  NaN          NaN     38.000000
75%       111.000000     NaN                  NaN          NaN    145.750000
max       900.000000     NaN                  NaN          NaN   9767.000000

        vote_average  release_year    budget_adj   revenue_adj
count   10866.000000  10866.000000  1.086600e+04  1.086600e+04
unique           NaN           NaN           NaN           NaN
top              NaN           NaN           NaN           NaN
freq             NaN           NaN           NaN           NaN
mean        5.974922   2001.322658  1.755104e+07  5.136436e+07
std         0.935142     12.812941  3.430616e+07  1.446325e+08
min         1.500000   1960.000000  0.000000e+00  0.000000e+00
25%         5.400000   1995.000000  0.000000e+00  0.000000e+00
50%         6.000000   2006.000000  0.000000e+00  0.000000e+00
75%         6.600000   2011.000000  2.085325e+07  3.369710e+07
max         9.200000   2015.000000  4.250000e+08  2.827124e+09

[11 rows x 21 columns]
```

- Check for duplicate as imdb_id has frequency of 2 even though it is an id column and drop it

```
In [5]: df[df.duplicated()==True]
```

```
Out[5]:         id    imdb_id  popularity    budget  revenue original_title  \
        2090  42194  tt0411951     0.59643  30000000   967000         TEKKEN

                                                           cast homepage  \
        2090  Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...      NaN

                      director              tagline     ...       \
        2090  Dwight H. Little  Survival is no game     ...

                                                       overview runtime  \
        2090  In the year of 2039, after World Wars destroy ...      92

                                                   genres    production_companies  \
        2090  Crime|Drama|Action|Thriller|Science Fiction  Namco|Light Song Films
```

```
             release_date vote_count  vote_average  release_year  budget_adj  \
        2090      3/20/10        110           5.0          2010  30000000.0

              revenue_adj
        2090     967000.0

        [1 rows x 21 columns]
```

```
In [6]: df[df['imdb_id'] == 'tt0411951']
```

```
Out[6]:          id    imdb_id  popularity    budget  revenue original_title  \
        2089  42194  tt0411951     0.59643  30000000   967000         TEKKEN
        2090  42194  tt0411951     0.59643  30000000   967000         TEKKEN

                                                           cast homepage  \
        2089  Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...      NaN
        2090  Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...      NaN

                      director              tagline     ...       \
        2089  Dwight H. Little  Survival is no game     ...
        2090  Dwight H. Little  Survival is no game     ...

                                                       overview runtime  \
        2089  In the year of 2039, after World Wars destroy ...      92
        2090  In the year of 2039, after World Wars destroy ...      92

                                                   genres    production_companies  \
        2089  Crime|Drama|Action|Thriller|Science Fiction  Namco|Light Song Films
        2090  Crime|Drama|Action|Thriller|Science Fiction  Namco|Light Song Films

             release_date vote_count  vote_average  release_year  budget_adj  \
        2089      3/20/10        110           5.0          2010  30000000.0
        2090      3/20/10        110           5.0          2010  30000000.0

              revenue_adj
        2089     967000.0
        2090     967000.0

        [2 rows x 21 columns]
```

```
In [7]: df = df.drop_duplicates()
        df.shape
```

```
Out[7]: (10865, 21)
```

```
In [8]: df.describe(include='all')
```

```
Out[8]:                    id    imdb_id    popularity        budget       revenue  \
        count    10865.000000      10855  10865.000000  1.086500e+04  1.086500e+04
```

```
unique            NaN      10855           NaN           NaN           NaN
top               NaN  tt3277552           NaN           NaN           NaN
freq              NaN          1           NaN           NaN           NaN
mean     66066.374413        NaN      0.646446  1.462429e+07  3.982690e+07
std      92134.091971        NaN      1.000231  3.091428e+07  1.170083e+08
min          5.000000        NaN      0.000065  0.000000e+00  0.000000e+00
25%      10596.000000        NaN      0.207575  0.000000e+00  0.000000e+00
50%      20662.000000        NaN      0.383831  0.000000e+00  0.000000e+00
75%      75612.000000        NaN      0.713857  1.500000e+07  2.400000e+07
max     417859.000000        NaN     32.985763  4.250000e+08  2.781506e+09

       original_title        cast                           homepage  \
count           10865       10789                               2936
unique          10571       10719                               2896
top            Hamlet  Louis C.K.  http://www.missionimpossible.com/
freq                4           6                                  4
mean              NaN         NaN                                NaN
std               NaN         NaN                                NaN
min               NaN         NaN                                NaN
25%               NaN         NaN                                NaN
50%               NaN         NaN                                NaN
75%               NaN         NaN                                NaN
max               NaN         NaN                                NaN

           director                 tagline      ...                  overview  \
count         10821                    8041      ...                     10861
unique         5067                    7997      ...                     10847
top     Woody Allen  Based on a true story.      ...        No overview found.
freq             45                       5      ...                        13
mean            NaN                     NaN      ...                       NaN
std             NaN                     NaN      ...                       NaN
min             NaN                     NaN      ...                       NaN
25%             NaN                     NaN      ...                       NaN
50%             NaN                     NaN      ...                       NaN
75%             NaN                     NaN      ...                       NaN
max             NaN                     NaN      ...                       NaN

             runtime  genres production_companies release_date    vote_count  \
count   10865.000000   10842                 9835        10865  10865.000000
unique           NaN    2039                 7445         5909           NaN
top              NaN  Comedy   Paramount Pictures       1/1/09           NaN
freq             NaN     712                  156           28           NaN
mean      102.071790     NaN                  NaN          NaN    217.399632
std        31.382701     NaN                  NaN          NaN    575.644627
min         0.000000     NaN                  NaN          NaN     10.000000
25%        90.000000     NaN                  NaN          NaN     17.000000
50%        99.000000     NaN                  NaN          NaN     38.000000
75%       111.000000     NaN                  NaN          NaN    146.000000
```

```
max       900.000000     NaN                    NaN          NaN   9767.000000

        vote_average  release_year    budget_adj   revenue_adj
count   10865.000000  10865.000000  1.086500e+04  1.086500e+04
unique           NaN           NaN           NaN           NaN
top              NaN           NaN           NaN           NaN
freq             NaN           NaN           NaN           NaN
mean        5.975012   2001.321859  1.754989e+07  5.136900e+07
std         0.935138     12.813260  3.430753e+07  1.446383e+08
min         1.500000   1960.000000  0.000000e+00  0.000000e+00
25%         5.400000   1995.000000  0.000000e+00  0.000000e+00
50%         6.000000   2006.000000  0.000000e+00  0.000000e+00
75%         6.600000   2011.000000  2.085325e+07  3.370173e+07
max         9.200000   2015.000000  4.250000e+08  2.827124e+09

[11 rows x 21 columns]
```

- Let's consider vote_average as the dependent variable. We shall create another variable called Rating which is binned between 1 to 10 to make it a discrete variable

```
In [9]: df.vote_average.nunique()
```

```
Out[9]: 72
```

```
In [10]: df.vote_average.unique()
```

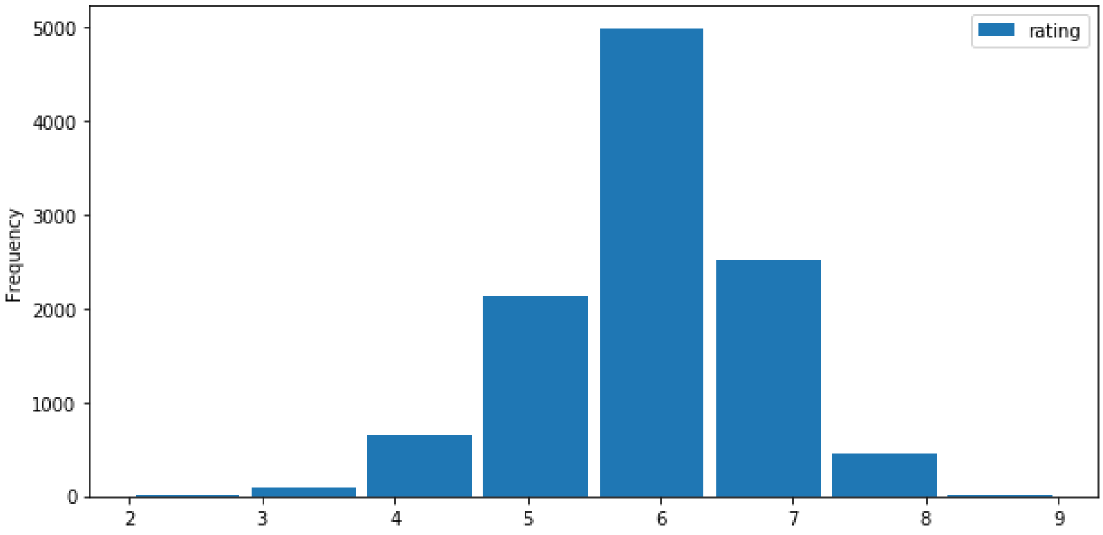
```
Out[10]: array([ 6.5,  7.1,  6.3,  7.5,  7.3,  7.2,  5.8,  7.6,  8. ,  6.2,  5.2,
                 7.4,  6.1,  7. ,  6.8,  5.3,  7.8,  6.4,  6.6,  7.7,  5.6,  6.9,
                 5.9,  6.7,  5.5,  5. ,  4.4,  5.4,  5.1,  4.8,  5.7,  4.1,  3.9,
                 4.5,  6. ,  4.2,  3.6,  4.3,  4.9,  4.7,  4. ,  3.5,  3.8,  3.3,
                 3.7,  4.6,  7.9,  8.2,  2.6,  3.1,  8.9,  3.2,  2.4,  8.4,  3. ,
                 2.8,  3.4,  8.8,  8.1,  8.3,  2.7,  2.5,  2.1,  8.6,  2.9,  8.5,
                 9.2,  2.2,  2. ,  8.7,  2.3,  1.5])
```

- There are 72 values and between 1 and 2 we have only 1.5 and between 9 and 10 we have only 9.2. Rest from 2 to 9 has all values between x.1 to x.9. We will group these values by rounding to nearest rating and creating a new variable called "rating" which will be our dependent variable.

```
In [11]: df['rating'] = df.vote_average.apply(lambda x: round(x))
```

```
In [12]: df.rating.plot(kind='hist',bins=8, legend='rating', rwidth=0.9, figsize=(10, 5))
```

```
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f534ef4f9b0>
```



- Based on the above histogram, there are more movies rated between 5 and 7.

```
In [13]: #Dropping voting_average
         df = df.drop('vote_average', axis=1)
         df.shape
```

```
Out[13]: (10865, 21)
```

1.0.3 Handle null values

```
In [14]: df_null = pd.DataFrame(df.isna().sum())
         df_null = df_null.reset_index()
         df_null.columns = ['column_name', 'null_count']
         df_null = df_null.sort_values(by='null_count', ascending=False)
         df_null = df_null[df_null['null_count'] > 0]
         df_null
```

```
Out[14]:              column_name  null_count
         7               homepage        7929
         9                tagline        2824
         10              keywords        1493
         14  production_companies        1030
         6                   cast          76
         8               director          44
         13                genres          23
         1                imdb_id          10
         11              overview           4
```

Deciding on Homepage's impact on rating

```
In [15]: #Checking homepage data
         df.homepage.nunique()
```

```
Out[15]: 2896
```

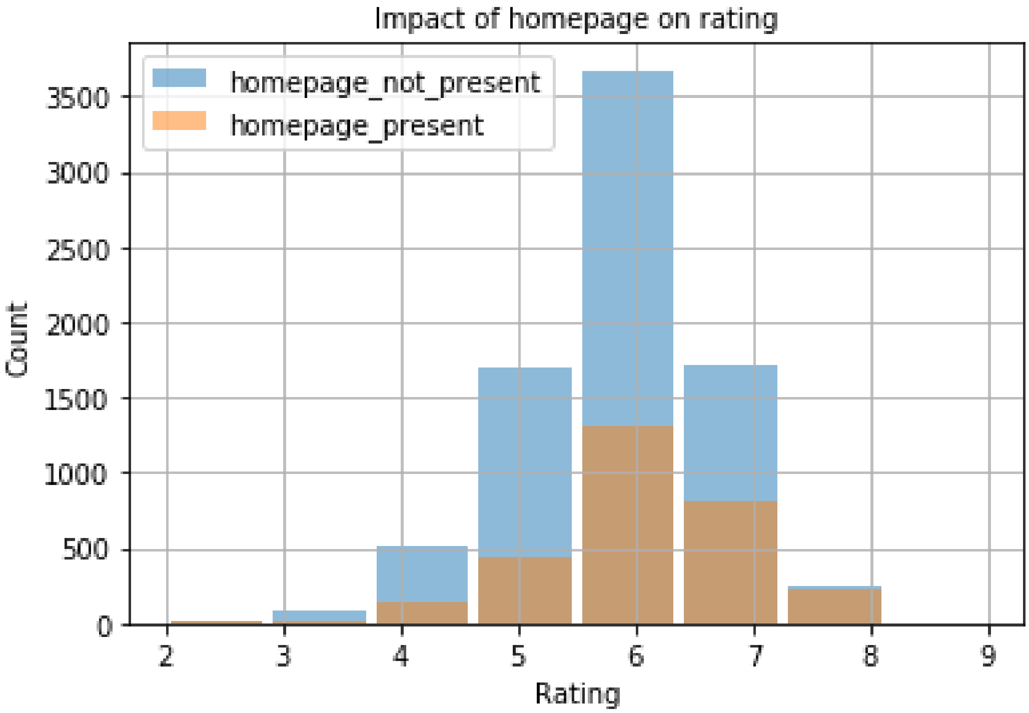
- Out of 2969 homepage urls available, 2896 are unique. Let's check the significance of presence of homepage with the dependent variable rating. Does presence of homepage have any impact on rating?

```
In [16]: df_temp = df.copy()
```

```
In [17]: df_temp['homepage_present'] = df_temp.homepage.isna()==False
```

```
In [18]: homepage_present = df_temp['homepage_present']==True
         homepage_not_present = df_temp['homepage_present']==False
```

```
In [19]: fig, ax = plt.subplots()
         df_temp.rating[homepage_not_present].hist(alpha=0.5, bins=8, rwidth=0.9, label='homepag
         df_temp.rating[homepage_present].hist(alpha=0.5, bins=8,  rwidth=0.9, label='homepage_p
         ax.set_xlabel('Rating')
         ax.set_ylabel('Count')
         ax.set_title('Impact of homepage on rating', fontsize=10)
         plt.legend();
```



- Since the homepage does not have any impact on the rating, we can drop homepage

```
In [20]: df = df.drop('homepage', axis=1)
         df.shape

Out[20]: (10865, 20)
```

Deciding on tag line's impact on rating

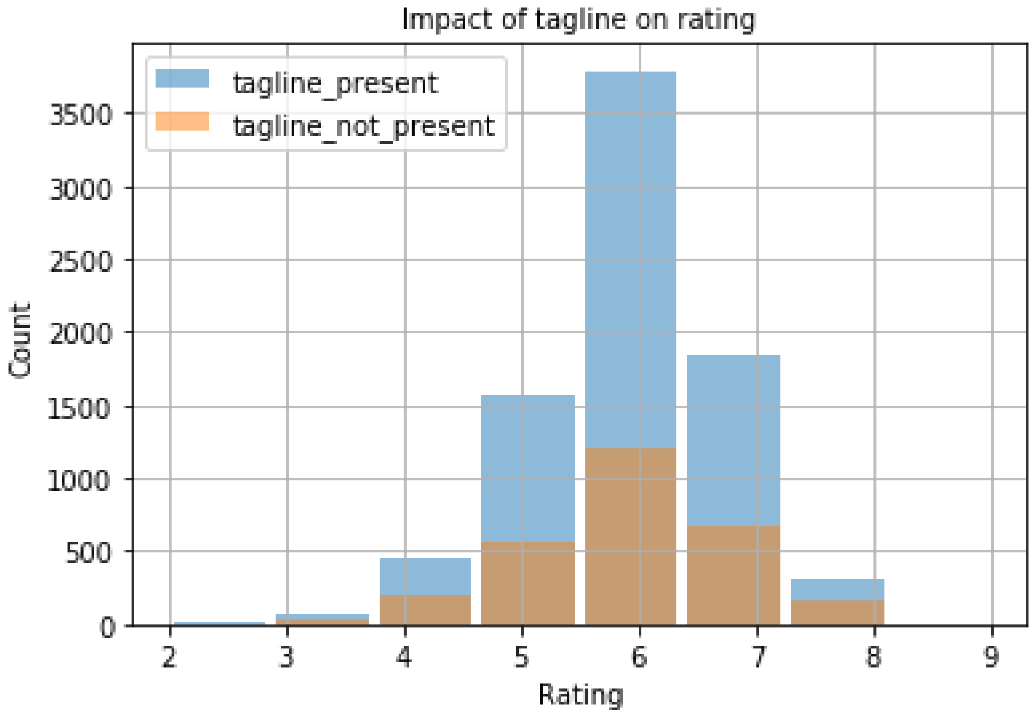
```
In [21]: df_temp.head().tagline

Out[21]: 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
         Name: tagline, dtype: object

In [22]: df_temp['tagline_present'] = df_temp.tagline.isna()==False

In [23]: tagline_present = df_temp['tagline_present']==True
         tagline_not_present = df_temp['tagline_present']==False

In [24]: fig, ax = plt.subplots()
         df_temp.rating[tagline_present].hist(alpha=0.5, bins=8,  rwidth=0.9, label='tagline_pre
         df_temp.rating[tagline_not_present].hist(alpha=0.5, bins=8, rwidth=0.9, label='tagline_
         ax.set_xlabel('Rating')
         ax.set_ylabel('Count')
         ax.set_title('Impact of tagline on rating', fontsize=10)
         plt.legend();
```



- Since the tag line does not have any impact on the rating, we can drop tag line

```
In [25]: df = df.drop('tagline', axis=1)
         df.shape

Out[25]: (10865, 19)
```

Deciding on keywords, production_companies, cast, director, genres, overview

- All these variables are string based and imdb_id is an id column. Hence we can drop these columns

```
In [26]: df = df.drop(['keywords', 'production_companies', 'cast', 'director', 'overview'], axis
         df.shape

Out[26]: (10865, 14)

In [27]: df = df.drop('imdb_id', axis=1)
         df.shape

Out[27]: (10865, 13)

In [28]: df.describe(include='all')

Out[28]:                    id    popularity        budget       revenue  \
         count    10865.000000  10865.000000  1.086500e+04  1.086500e+04
         unique            NaN           NaN           NaN           NaN
         top               NaN           NaN           NaN           NaN
         freq              NaN           NaN           NaN           NaN
         mean     66066.374413      0.646446  1.462429e+07  3.982690e+07
         std      92134.091971      1.000231  3.091428e+07  1.170083e+08
         min          5.000000      0.000065  0.000000e+00  0.000000e+00
         25%      10596.000000      0.207575  0.000000e+00  0.000000e+00
         50%      20662.000000      0.383831  0.000000e+00  0.000000e+00
         75%      75612.000000      0.713857  1.500000e+07  2.400000e+07
         max     417859.000000     32.985763  4.250000e+08  2.781506e+09

                original_title       runtime  genres release_date    vote_count  \
         count           10865  10865.000000   10842        10865  10865.000000
         unique          10571           NaN    2039         5909           NaN
         top            Hamlet           NaN  Comedy       1/1/09           NaN
         freq                4           NaN     712           28           NaN
         mean              NaN    102.071790     NaN          NaN    217.399632
         std               NaN     31.382701     NaN          NaN    575.644627
         min               NaN      0.000000     NaN          NaN     10.000000
         25%               NaN     90.000000     NaN          NaN     17.000000
```

```
50%                 NaN     99.000000     NaN           NaN     38.000000
75%                 NaN    111.000000     NaN           NaN    146.000000
max                 NaN    900.000000     NaN           NaN   9767.000000

        release_year    budget_adj   revenue_adj        rating
count   10865.000000  1.086500e+04  1.086500e+04  10865.000000
unique           NaN           NaN           NaN           NaN
top              NaN           NaN           NaN           NaN
freq             NaN           NaN           NaN           NaN
mean     2001.321859  1.754989e+07  5.136900e+07      5.971008
std        12.813260  3.430753e+07  1.446383e+08      0.973691
min      1960.000000  0.000000e+00  0.000000e+00      2.000000
25%      1995.000000  0.000000e+00  0.000000e+00      5.000000
50%      2006.000000  0.000000e+00  0.000000e+00      6.000000
75%      2011.000000  2.085325e+07  3.370173e+07      7.000000
max      2015.000000  4.250000e+08  2.827124e+09      9.000000
```

- Let's drop the other non-null string variables. Original Title is the other variable to be dropped

```
In [29]: df = df.drop('original_title', axis=1)
         df.shape

Out[29]: (10865, 12)
```

- Let's get the month data from release date

```
In [30]: df['release_date_formatted'] = pd.to_datetime(df['release_date'], format='%m/%d/%y')
         df['month'] = df['release_date_formatted'].dt.month

In [31]: df = df.drop('release_date', axis=1)
         #df = df.drop('release_date_formatted', axis=1)
         df.shape

Out[31]: (10865, 13)

In [32]: df.describe(include='all')

Out[32]:                   id    popularity        budget       revenue       runtime  \
         count   10865.000000  10865.000000  1.086500e+04  1.086500e+04  10865.000000
         unique           NaN           NaN           NaN           NaN           NaN
         top              NaN           NaN           NaN           NaN           NaN
         freq             NaN           NaN           NaN           NaN           NaN
         first            NaN           NaN           NaN           NaN           NaN
         last             NaN           NaN           NaN           NaN           NaN
         mean    66066.374413      0.646446  1.462429e+07  3.982690e+07    102.071790
         std     92134.091971      1.000231  3.091428e+07  1.170083e+08     31.382701
         min         5.000000      0.000065  0.000000e+00  0.000000e+00      0.000000
         25%     10596.000000      0.207575  0.000000e+00  0.000000e+00     90.000000
```

```
50%      20662.000000      0.383831  0.000000e+00  0.000000e+00     99.000000
75%      75612.000000      0.713857  1.500000e+07  2.400000e+07    111.000000
max     417859.000000     32.985763  4.250000e+08  2.781506e+09    900.000000

        genres    vote_count  release_year    budget_adj   revenue_adj  \
count    10842  10865.000000  10865.000000  1.086500e+04  1.086500e+04
unique    2039           NaN           NaN           NaN           NaN
top     Comedy           NaN           NaN           NaN           NaN
freq       712           NaN           NaN           NaN           NaN
first      NaN           NaN           NaN           NaN           NaN
last       NaN           NaN           NaN           NaN           NaN
mean       NaN    217.399632   2001.321859  1.754989e+07  5.136900e+07
std        NaN    575.644627     12.813260  3.430753e+07  1.446383e+08
min        NaN     10.000000   1960.000000  0.000000e+00  0.000000e+00
25%        NaN     17.000000   1995.000000  0.000000e+00  0.000000e+00
50%        NaN     38.000000   2006.000000  0.000000e+00  0.000000e+00
75%        NaN    146.000000   2011.000000  2.085325e+07  3.370173e+07
max        NaN   9767.000000   2015.000000  4.250000e+08  2.827124e+09

              rating release_date_formatted         month
count   10865.000000                  10865  10865.000000
unique           NaN                   5909           NaN
top              NaN    2009-01-01 00:00:00           NaN
freq             NaN                     28           NaN
first            NaN    1969-01-01 00:00:00           NaN
last             NaN    2068-12-22 00:00:00           NaN
mean        5.971008                    NaN      6.827612
std         0.973691                    NaN      3.441764
min         2.000000                    NaN      1.000000
25%         5.000000                    NaN      4.000000
50%         6.000000                    NaN      7.000000
75%         7.000000                    NaN     10.000000
max         9.000000                    NaN     12.000000
```

1.0.4 Research Question 1: Does the budget and revenue have any impact on ratings?

- As we have seen before in the analysis, the ratings are between 2 and 9. The maximum number of movies reveived a 5.5-6.5 rating. And as we moved up or down, the frequency reduced. Let's now check the properties of budget.
- Since budget is is in the order of millions, let's divide the budget variable by one million to standardise the values

```
In [36]: df['budget_adj'] = df['budget_adj']/1000000
```

Let's identify whether all the movies have budget information. We will check the count of movies where the budget is zero and greater than zero.

```
In [37]: df[df['budget_adj'] == 0]['budget_adj'].count()
```

```
Out[37]: 5696
```

Out of 10865 movies, 5696 do not have the budget details. We will check the range of budget of movies

```
In [38]: movies_with_budget = df['budget_adj']>0
         df[movies_with_budget]['budget_adj'].describe()
```

```
Out[38]: count    5.169000e+03
         mean     3.688907e+01
         std      4.196096e+01
         min      9.210911e-07
         25%      8.102293e+00
         50%      2.271505e+01
         75%      5.008384e+01
         max      4.250000e+02
         Name: budget_adj, dtype: float64
```

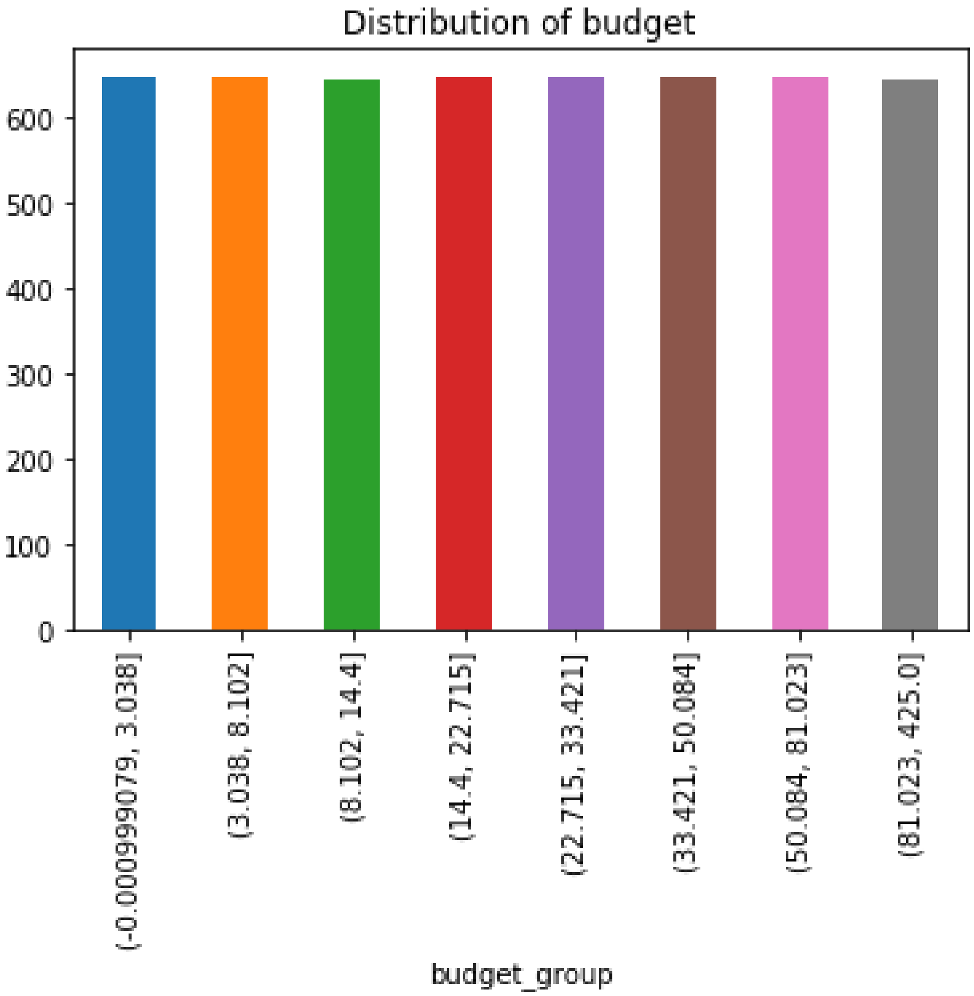
Majority of movies have budget between 6 million to 40 million dollars.

```
In [40]: df['budget_group'] = pd.qcut(df[movies_with_budget]['budget_adj'], 8)
         df[movies_with_budget].groupby(by='budget_group')['budget_group'].count()
```

```
Out[40]: budget_group
         (-0.000999079, 3.038]    648
         (3.038, 8.102]           647
         (8.102, 14.4]            644
         (14.4, 22.715]           646
         (22.715, 33.421]         646
         (33.421, 50.084]         648
         (50.084, 81.023]         647
         (81.023, 425.0]          643
         Name: budget_group, dtype: int64
```

There are: * 648 movies made with budget between 0 and 3 million * 647 movies between 3 and 8.1 million * 644 movies between 8.1 and 14.4 million * 646 movies between 14.4 and 22.7 million * 646 movies between 22.7 and 33.4 million * 648 movies between 33.4 and 50 million * 647 movies between 50 and 81 million * 643 movies between 81 and 425 million

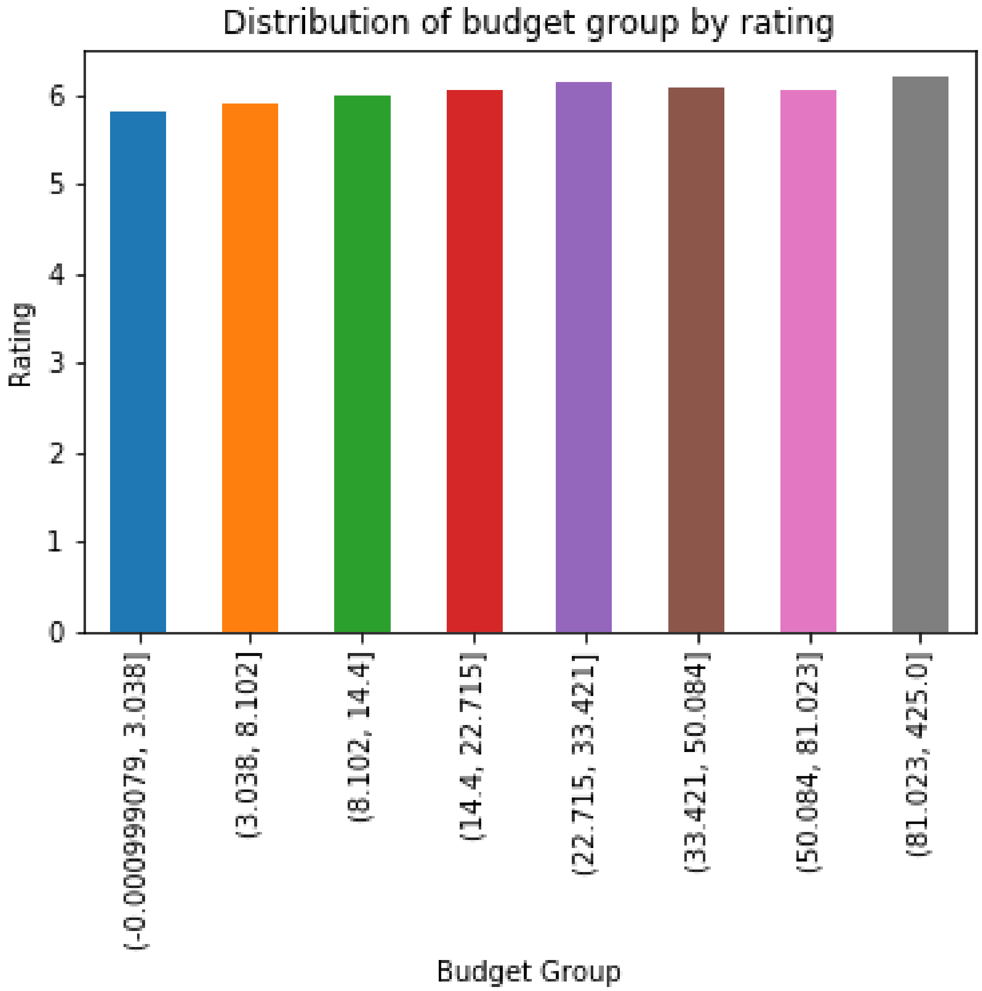
```
In [41]: df[movies_with_budget].groupby(by='budget_group')['budget_group'].count().plot(kind='ba
```



```
In [42]: mean_rating_by_budget_group = df[movies_with_budget].groupby(by='budget_group')['rating
         mean_rating_by_budget_group

Out[42]: budget_group
         (-0.000999079, 3.038]    5.802469
         (3.038, 8.102]           5.914992
         (8.102, 14.4]            6.004658
         (14.4, 22.715]           6.035604
         (22.715, 33.421]         6.126935
         (33.421, 50.084]         6.083333
         (50.084, 81.023]         6.054096
         (81.023, 425.0]          6.185070
         Name: rating, dtype: float64

In [43]: fig, ax = plt.subplots()
         mean_rating_by_budget_group.plot(kind='bar', title='Distribution of budget group by rat
plt.ylabel('Rating')
plt.xlabel('Budget Group');
```



Based on the data selected above, the budget doesn't seem to have any impact on rating. Now let's check the impact of revenue on rating.

- Since revenue is is in the order of millions, let's divide the revenue variable by one million to standardise the values

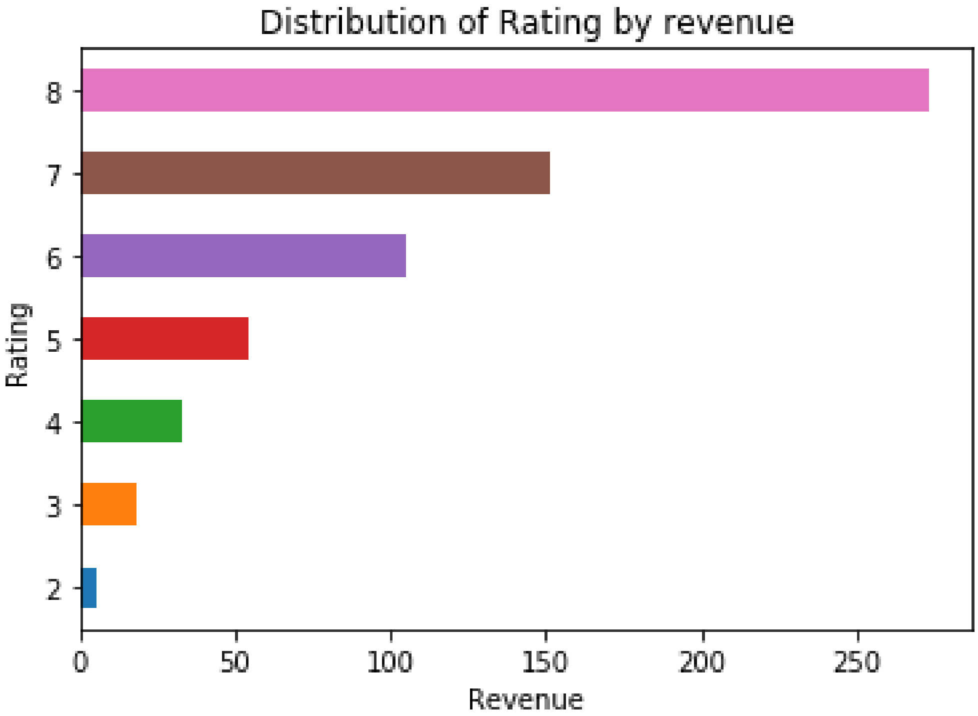
```
In [44]: df['revenue_adj'] = df['revenue_adj']/1000000

In [46]: movies_with_revenue = df['revenue_adj']>0
         mean_rating_by_revenue = df[movies_with_revenue].groupby(by='rating')['revenue_adj'].me
         mean_rating_by_revenue

Out[46]: rating
         2       5.293108
```

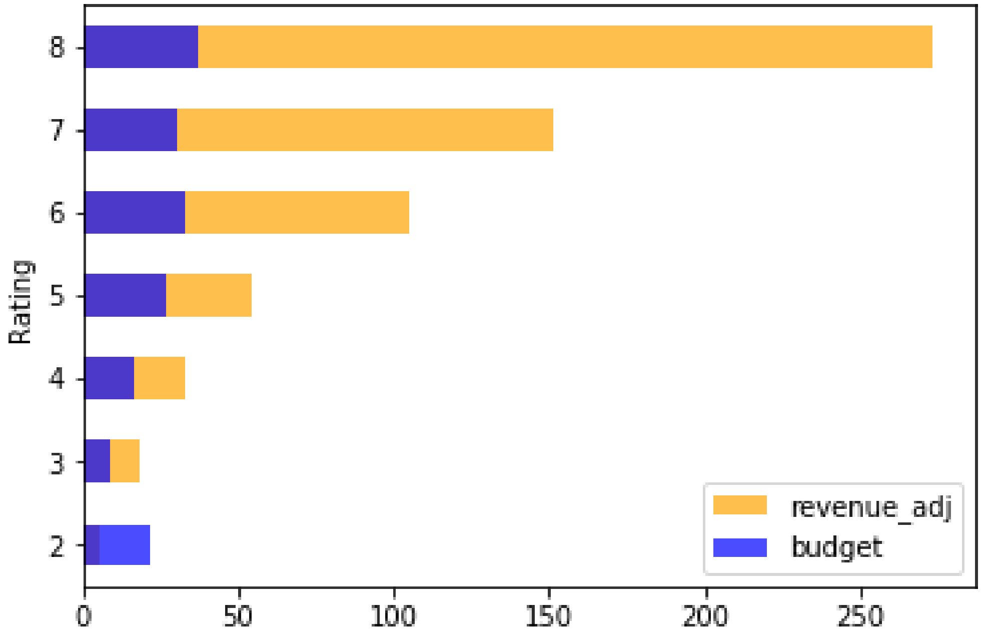
```
3     18.633458
4     32.976966
5     54.299225
6    105.210240
7    151.586754
8    273.738958
Name: revenue_adj, dtype: float64
```

```
In [48]: mean_rating_by_revenue.plot(kind='barh', title='Distribution of Rating by revenue')
         plt.xlabel('Revenue')
         plt.ylabel('Rating');
```



Based on the data selected above, we shall infer that more the rating, more the revenue.

```
In [49]: mean_rating_by_budget = df[movies_with_budget].groupby(by='rating')['budget'].mean()
         mean_rating_by_revenue.plot(kind='barh', legend='Revenue', alpha=0.7, color='orange')
         mean_rating_by_budget.plot(kind='barh', legend='Budget', alpha=0.7, color='blue')
         plt.ylabel('Rating');
```



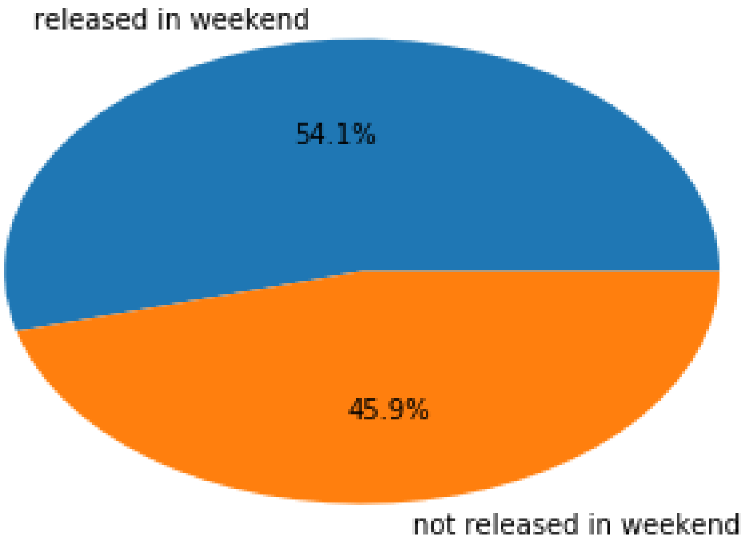
When we compare the budget and revenue against rating, even though the budget for all movies remained almost the same, the revenue increased to a greater extent.

1.0.5 Research Question 2 (Is there any relationship between revenue and the weekend of release? How will this change when we include the popularity?)

Let's get the movies which were released on a Friday which is considered as a weekend release

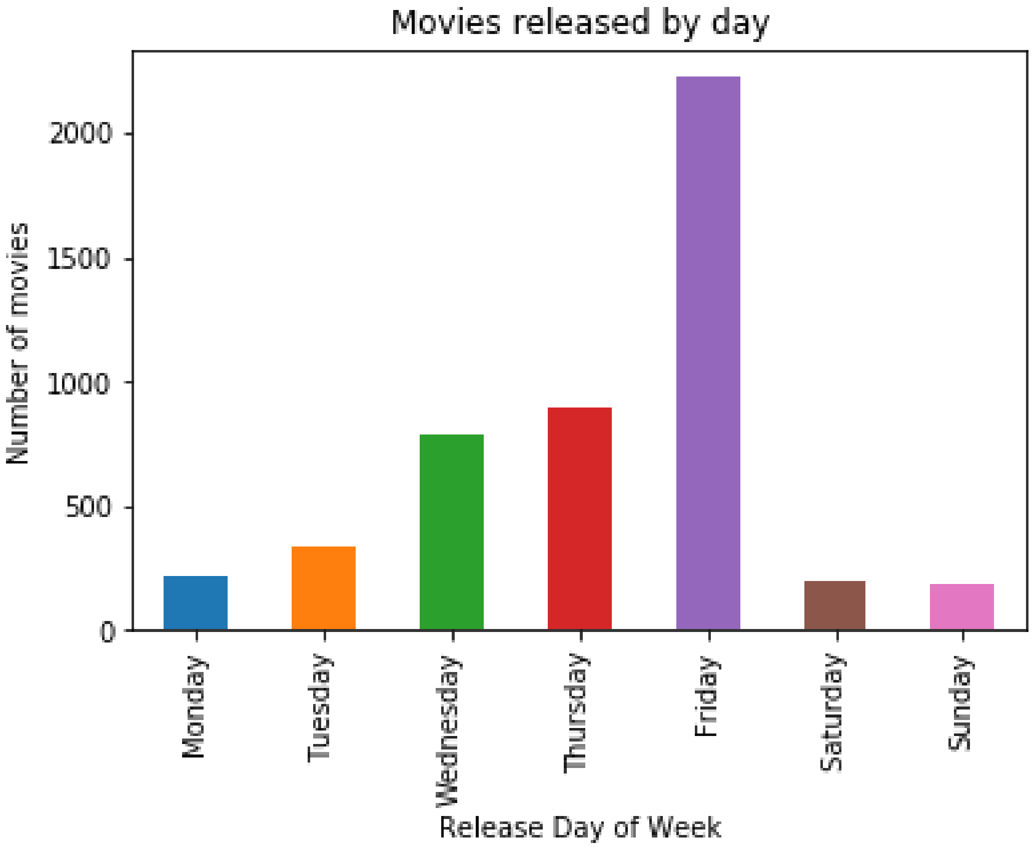
```
In [50]: df['is_weekend_release'] = df['release_date_formatted'].dt.weekday == 4
```

```
In [51]: fig, ax = plt.subplots()
         ax.pie(df[movies_with_revenue]['is_weekend_release'].value_counts(), labels = ['release
         plt.show();
```

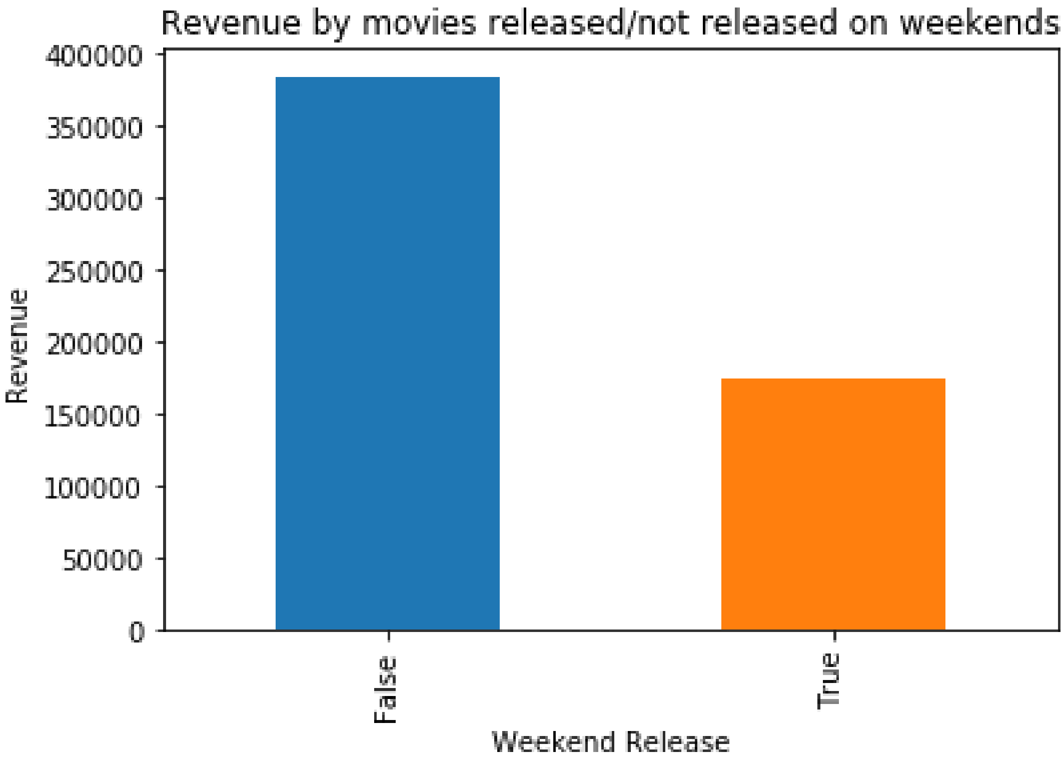


As we can observe 54.1% movies have released on Fridays(weekend release) and 45.9% movies have released on other days.

```
In [52]: weekday = df[movies_with_revenue]['release_date_formatted'].dt.weekday
         fig, ax = plt.subplots()
         df[movies_with_revenue].groupby(weekday)['release_date_formatted'].count().plot('bar')
         ax.set_xlabel('Release Day of Week')
         ax.set_ylabel('Number of movies')
         ax.set_xticklabels(['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',' Saturday',
         plt.title('Movies released by day');
```

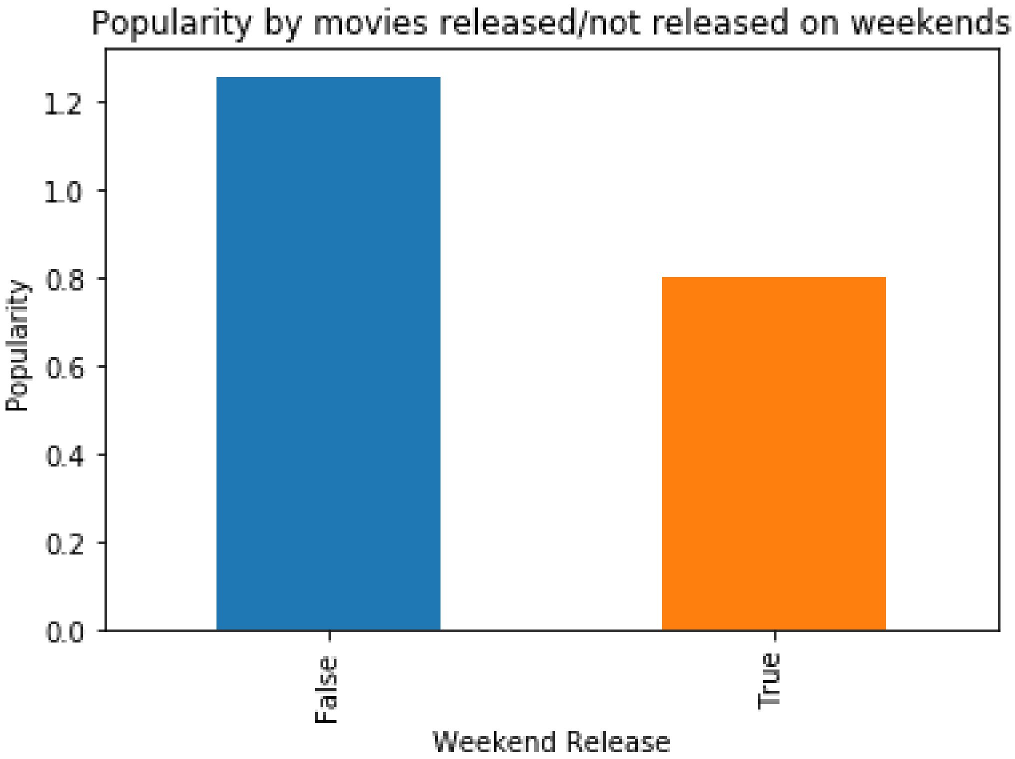


```
In [53]: df[movies_with_revenue].groupby(by='is_weekend_release')['revenue_adj'].sum().plot(kind
         plt.title('Revenue by movies released/not released on weekends')
         plt.xlabel('Weekend Release')
         plt.ylabel('Revenue');
```



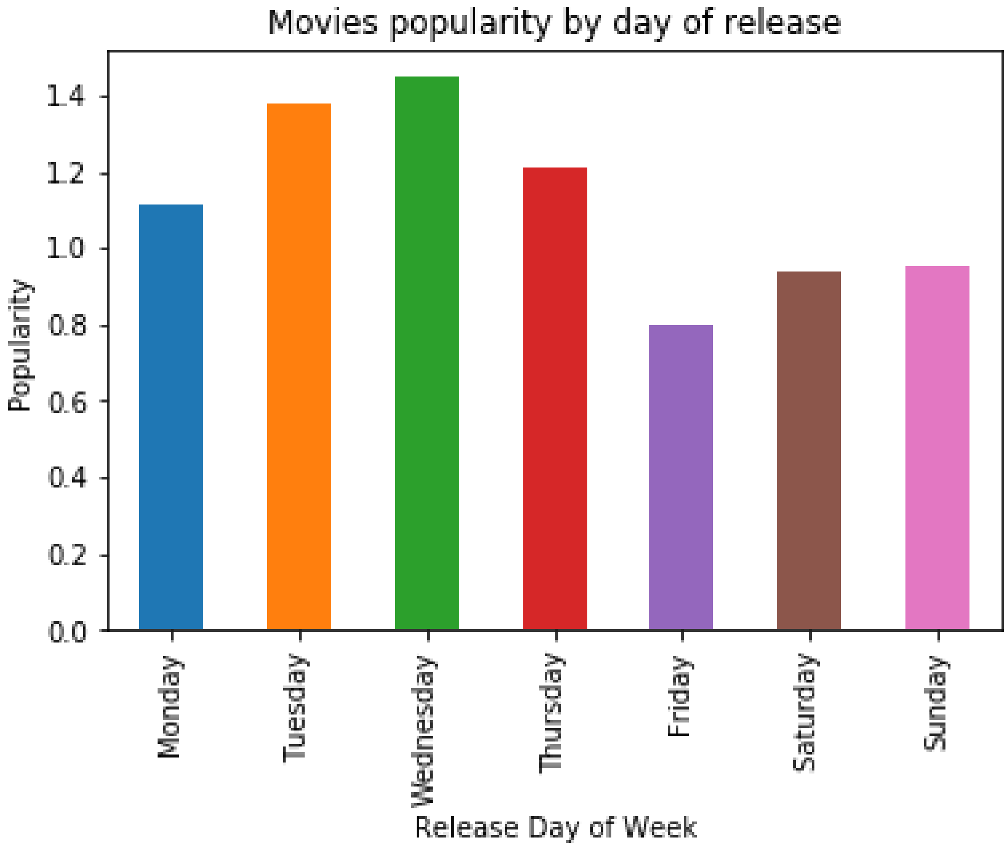
Even though more movies released in weekends, the revenue is more for movies released on weekdays.

```
In [54]: df[movies_with_revenue].groupby(by='is_weekend_release')['popularity'].mean().plot(kind
         plt.title('Popularity by movies released/not released on weekends')
         plt.xlabel('Weekend Release')
         plt.ylabel('Popularity');
```



Even though more movies released in weekends, the popularity is more for movies released on weekdays.

```
In [55]: weekday = df[movies_with_revenue]['release_date_formatted'].dt.weekday
         fig, ax = plt.subplots()
         df[movies_with_revenue].groupby(weekday)['popularity'].mean().plot('bar')
         ax.set_xlabel('Release Day of Week')
         ax.set_ylabel('Popularity')
         ax.set_xticklabels(['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',' Saturday',
         plt.title('Movies popularity by day of release');
```



1.1 Conclusions

- The ratings of the movies in the dataset are between 2 and 9. The maximum number of movies received a 5.5-6.5 rating. And as we moved up or down, the frequency reduced.
- Homepage and tag line do not have any impact on the rating of these movies.
- Majority of the movies in the dataset have budget between 6 million to 40 million dollars.
- Based on the data, the budget doesn't seem to have any impact on the rating, but more the rating more the revenue.
- When we compare the budget and revenue data against rating, even though the budget for all movies remained almost the same, the revenue increased to a greater extent.
- 54.1% movies in this dataset were released on Fridays(weekend release) and 45.9% on other days.
- Even though more movies were released on weekends, the revenue and popularity were more for those released on weekdays.

1.1.1 Limitations

- Around 50% of the movies did not have budget and revenue data and this might have impacted our analysis.

```
In [56]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])

Out[56]: 0
```

Resources

- Pandas Documentation
- Matplotlib Documentation