investigate-a-dataset-TMDb

January 17, 2019

1 Project: TMDb Movie Data Analysis

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Introduction

In this report we work on a data set from TMDb. The data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings, genres, movie budget and movie revenue. In particular we want to understand: 1. Which genres were most popular between 1996 and 2015? 2. What kind of properties are associated with movies that have high revenues?

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

Data Wrangling

1.1.1 Reading Data

```
In [2]: df = pd.read_csv('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]: 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
```

1.1.2 Unuseful Feilds

1. There are some fields which are not relevnat in our analysis like "imdb_id", "original_title", "homepage", "tagline", "keywords" and "overview". We'll drop them in the data cleaning step.

2. The last two fields of "budget_adj" and "revenue_adj" will be used instead of "budget" and "revenue" because they take into account the inflation over the years.

3. 'cast', 'director' and 'production_companies' are not going to be used in our analysis, because there are so many differnt values in them, making it hard to categorize and associate them with other fields.

4. There are two fiels for realease date: "release_date" and " release_year". "release_date" has more detail information which we dont need for our analysis, so we keep" release_year" and drop " release_date".

1.1.3 Missing Values

There are some missing values in 'imdb_id', 'cast', 'homepage', 'director', 'tagline', 'keywords', 'genres' and 'production_companies'. In the previous sectoin, We decided to drop all these fields except "genres". So we just need to take action on "genres" missing values.

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

```
Out[4]:              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 Zero Values

The 25% and 50% values in "budget_adj" and "revenue_adj" columns are zero. So we treat these zero values as missing values and will drop their rows.

```
In [5]: df.query('revenue_adj == 0').id.count()
```

```
Out[5]: 6016
```

```
In [6]: df.query('budget_adj == 0').id.count()
```

```
Out[6]: 5696
```

We treat these zero values as missing values, and drop their rows.

1.2 Data Cleaning

1.2.1 Droping Columns

First we drop the columns we discussed earlier.

```
In [7]: df.drop(['imdb_id', 'budget', 'revenue', 'original_title', 'cast', 'homepage', 'directo
                 'keywords', 'overview', 'production_companies', 'release_date'], axis=1, inpla
```

1.2.2 Check for Duplicates

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

Out[8]: 1

In [9]: df.drop_duplicates(inplace=True)

In [10]: sum(df.duplicated())

Out[10]: 0
```

1.2.3 Droping Missing Values

```
In [11]: df.isnull().sum()

Out[11]: id                0
         popularity        0
         runtime           0
         genres           23
         vote_count        0
         vote_average      0
         release_year      0
         budget_adj        0
         revenue_adj       0
         dtype: int64

In [12]: df.dropna(how='any', inplace=True)

In [13]: df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 10842 entries, 0 to 10865
Data columns (total 9 columns):
id                10842 non-null int64
popularity        10842 non-null float64
runtime           10842 non-null int64
genres            10842 non-null object
vote_count        10842 non-null int64
vote_average      10842 non-null float64
release_year      10842 non-null int64
budget_adj        10842 non-null float64
```

```
revenue_adj     10842 non-null float64
dtypes: float64(4), int64(4), object(1)
memory usage: 847.0+ KB
```

As explained earlier, We drop the rows with zero value for "revenue_adj" or "budget_adj".

```
In [14]: df = df[df.revenue_adj != 0]
         df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4849 entries, 0 to 10848
Data columns (total 9 columns):
id              4849 non-null int64
popularity      4849 non-null float64
runtime         4849 non-null int64
genres          4849 non-null object
vote_count      4849 non-null int64
vote_average    4849 non-null float64
release_year    4849 non-null int64
budget_adj      4849 non-null float64
revenue_adj     4849 non-null float64
dtypes: float64(4), int64(4), object(1)
memory usage: 378.8+ KB
```

```
In [15]: df = df[df.budget_adj != 0]
         df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3854 entries, 0 to 10848
Data columns (total 9 columns):
id              3854 non-null int64
popularity      3854 non-null float64
runtime         3854 non-null int64
genres          3854 non-null object
vote_count      3854 non-null int64
vote_average    3854 non-null float64
release_year    3854 non-null int64
budget_adj      3854 non-null float64
revenue_adj     3854 non-null float64
dtypes: float64(4), int64(4), object(1)
memory usage: 301.1+ KB
```

Exploratory Data Analysis

1.2.4 Q1- Which genres were most popular between 1996 and 2015?

Since this question asks about the movies that were released between 1996 and 2015, we filter our data based on "released_year" field.

```
In [16]: df_20years = df[df.release_year > 1995]
```

```
In [17]: df_20years.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2884 entries, 0 to 9153
Data columns (total 9 columns):
id                2884 non-null int64
popularity        2884 non-null float64
runtime           2884 non-null int64
genres            2884 non-null object
vote_count        2884 non-null int64
vote_average      2884 non-null float64
release_year      2884 non-null int64
budget_adj        2884 non-null float64
revenue_adj       2884 non-null float64
dtypes: float64(4), int64(4), object(1)
memory usage: 225.3+ KB
```

In our data set, "genres" column contains multiple values separated by pipe (|) character. In order to find all genres that exist in our data set, we'll run the following code:

```
In [18]: all_genres = list(set(df_20years.genres.str.cat(sep ="|").split("|")))
         all_genres , len( all_genres)
```

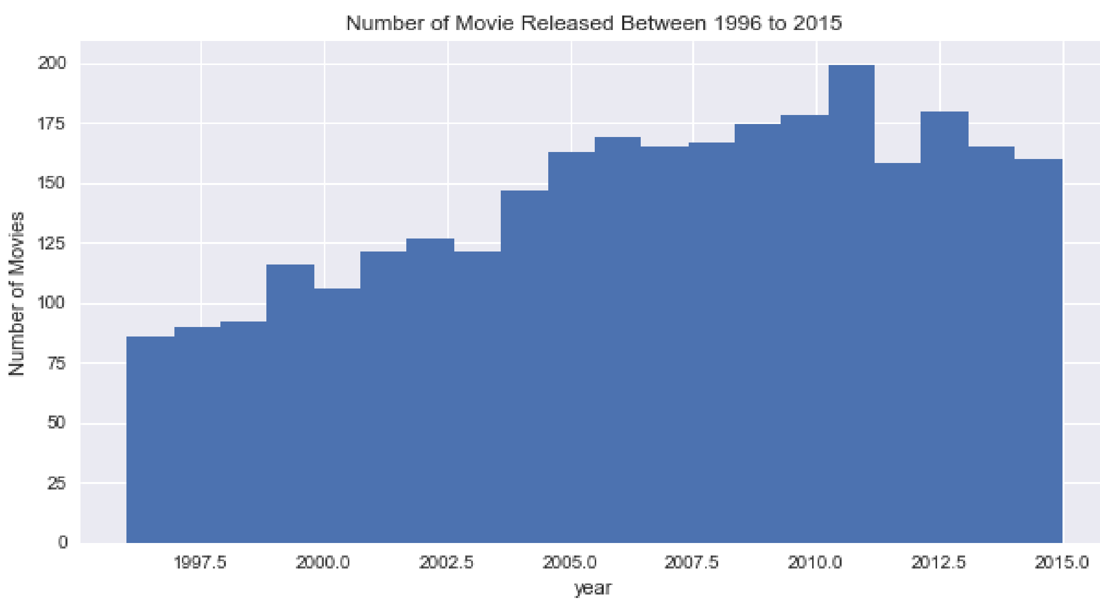
```
Out[18]: (['Music',
           'Comedy',
           'Drama',
           'Fantasy',
           'TV Movie',
           'Horror',
           'War',
           'Mystery',
           'Romance',
           'Animation',
           'Crime',
           'Science Fiction',
           'History',
           'Documentary',
           'Western',
           'Thriller',
           'Foreign',
           'Adventure',
```

```
 'Action',
 'Family'],
20)
```

There are 20 differnt genres in our data set.

1.2.5 Number of movies released from 1996 to 2015

In [19]:
```
plt.figure(figsize=(10, 5))
sns.set()
plt.hist(df_20years['release_year'], bins=20)
plt.xlabel('year')
plt.ylabel('Number of Movies')
plt.title('Number of Movie Released Between 1996 to 2015');
```



As we can see, the number of movies in 2015, is almost twice the number of movies in 1996.

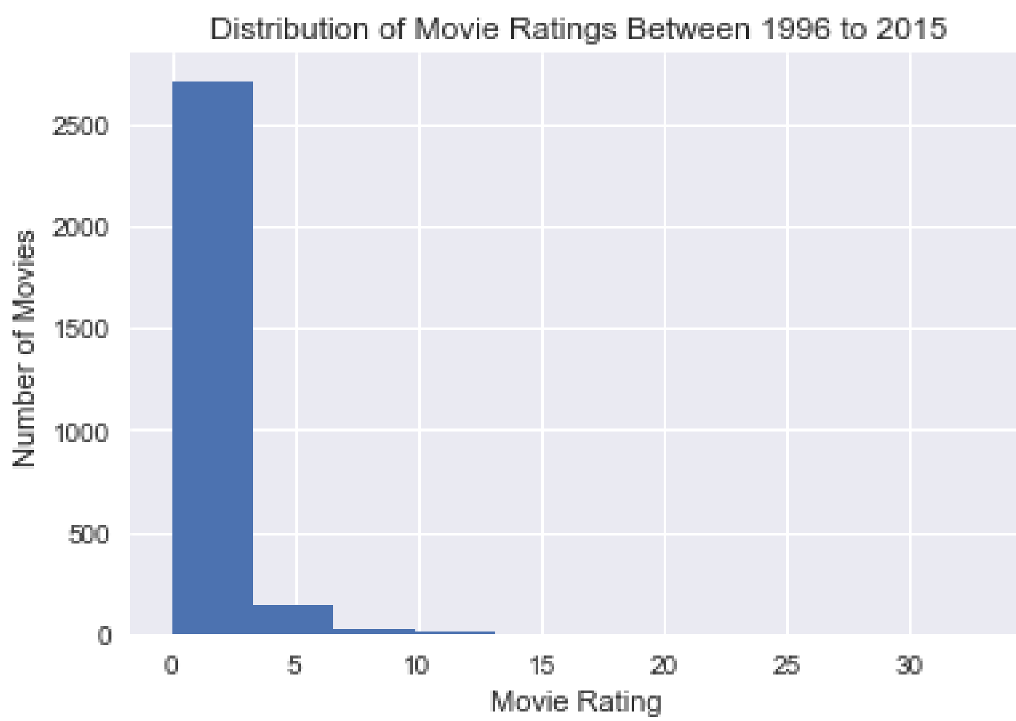
1.2.6 Distribution of popularity between 1996 and 2015:

In [20]:
```
df_20years.describe()
```

Out[20]:
```
                 id   popularity      runtime   vote_count  vote_average  \
count   2884.000000  2884.000000  2884.000000  2884.000000   2884.000000
mean   49999.492025     1.283314   108.489598   601.418169      6.112067
std    74838.071719     1.601480    18.801966   945.451907      0.779351
min       12.000000     0.001117    15.000000    10.000000      2.200000
25%     8487.750000     0.497205    95.000000    85.750000      5.600000
50%    13412.000000     0.876550   105.000000   253.000000      6.100000
75%    58169.250000     1.473959   118.000000   688.250000      6.600000
```

```
max     417859.000000    32.985763   338.000000  9767.000000       8.200000

       release_year    budget_adj    revenue_adj
count   2884.000000  2.884000e+03  2.884000e+03
mean    2006.661928  4.761033e+07  1.277516e+08
std        5.434993  4.827910e+07  2.010761e+08
min     1996.000000  9.693980e-01  2.370705e+00
25%     2002.000000  1.339331e+07  1.614076e+07
50%     2007.000000  3.137941e+07  5.783592e+07
75%     2011.000000  6.691203e+07  1.528228e+08
max     2015.000000  4.250000e+08  2.827124e+09
```

In [21]:
```
plt.hist(df_20years['popularity'])
plt.xlabel('Movie Rating')
plt.ylabel('Number of Movies')
plt.title('Distribution of Movie Ratings Between 1996 to 2015');
```



As we can see the popularity value for most of the movies is less than 3, and the average value for popularity is 1.28.

1.2.7 Number of movies released for diffent genres from 1996 to 2015

We know some movies have multiple genres. In order to do any study per genre, we need to split the rows with multiple genres to several rows; one row per each genre. The result is saved in df_genres data frame.

In [22]:
```
df_genres = (df_20years.drop('genres', axis=1)
             .join
             (
             df_20years.genres
             .str
             .split('|', expand=True)
             .stack()
             .reset_index(drop=True, level=1)
             .rename('genres')
             ))
df_genres.head()
```

Out[22]:

	id	popularity	runtime	vote_count	vote_average	release_year
0	135397	32.985763	124	5562	6.5	2015
0	135397	32.985763	124	5562	6.5	2015
0	135397	32.985763	124	5562	6.5	2015
0	135397	32.985763	124	5562	6.5	2015
1	76341	28.419936	120	6185	7.1	2015

	budget_adj	revenue_adj	genres
0	1.379999e+08	1.392446e+09	Action
0	1.379999e+08	1.392446e+09	Adventure
0	1.379999e+08	1.392446e+09	Science Fiction
0	1.379999e+08	1.392446e+09	Thriller
1	1.379999e+08	3.481613e+08	Action

To find the number of movies were produced in each gener, we'll use the following command:

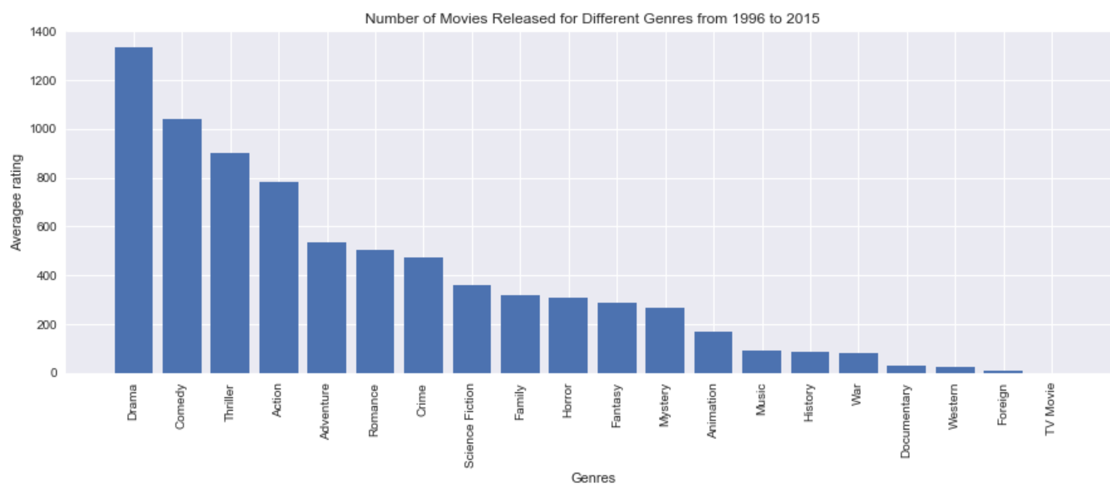
In [23]:
```
movies_in_genres = (df_genres.groupby('genres', as_index=False).id.count()
                                   .sort_values(by='id', ascending=False))

movies_in_genres
```

Out[23]:

	genres	id
6	Drama	1334
3	Comedy	1038
17	Thriller	900
0	Action	782
1	Adventure	534
14	Romance	505
4	Crime	472
15	Science Fiction	359
7	Family	320
11	Horror	309
8	Fantasy	288
13	Mystery	269
2	Animation	169
12	Music	93
10	History	88

```
18              War    79
5       Documentary    31
19          Western    27
9           Foreign     9
16         TV Movie     1
```

```
In [24]: locations = list(range(1,21))
         heights = movies_in_genres.iloc[:, 1]
         lables = movies_in_genres.iloc[:, 0]
         plt.subplots(figsize=(15, 5))
         plt.bar(locations, heights, tick_label=lables)
         plt.title('Number of Movies Released for Different Genres from 1996 to 2015')
         plt.xlabel('Genres')
         plt.ylabel('Averagee rating');
         plt.xticks(rotation=90);
```



As we can see some genres like 'Tv Movie' and 'Foreign' include a very small number of movies in our data set. The genres with the highest number of production are 'Drama', 'Comedy', 'Thriller', 'Action' and 'Adventure'.

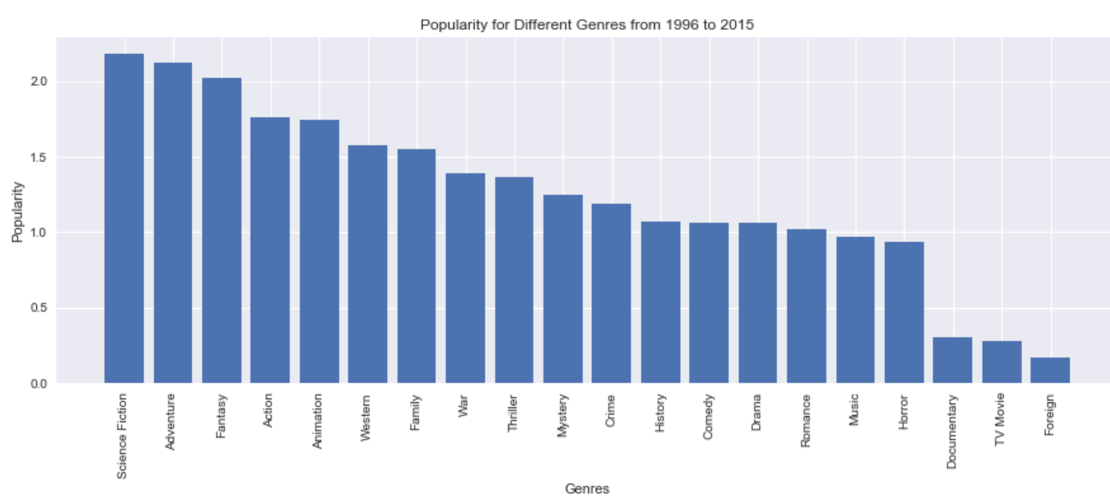
1.2.8 Popularity for different genres from 1996 to 2015

```
In [25]: genre_popularity= (df_genres.groupby('genres', as_index=False)['popularity'].mean()
                                     .sort_values(by='popularity', ascending=False ))

         genre_popularity
```

```
Out[25]:             genres  popularity
         15  Science Fiction    2.182806
         1         Adventure    2.123756
         8           Fantasy    2.025157
         0            Action    1.760900
```

```
2           Animation    1.744508
19            Western    1.575194
7              Family    1.552059
18                War    1.391474
17           Thriller    1.363990
13            Mystery    1.245874
4               Crime    1.186462
10            History    1.070696
3              Comedy    1.064166
6               Drama    1.063308
14            Romance    1.018031
12              Music    0.970286
11             Horror    0.930450
5         Documentary    0.300557
16           TV Movie    0.273628
9             Foreign    0.164174
```

```
In [26]: locations = list(range(1,21))
         heights = genre_popularity.iloc[:, 1]
         lables = genre_popularity.iloc[:, 0]
         plt.subplots(figsize=(15, 5))
         plt.bar(locations, heights, tick_label=lables)
         plt.title('Popularity for Different Genres from 1996 to 2015')
         plt.xlabel('Genres')
         plt.ylabel('Popularity');
         plt.xticks(rotation=90);
```



As we can see 'Science Fiction', 'Adventure', 'Fantasy', 'Action' and 'Animation' had the highest popularity from 1996 to 2015. 'TV Movie' and 'Foreign' genres are the least popular genres and they have the least number of production(we found out in the privious section) in the 20 years of our study.

Now that we've figured out the most popular genres, lets find out the average rating and the trend of popularity for them over these years.

1.2.9 Average rating for the most popular genres

```
In [27]: popular_genres = list(genre_popularity['genres'][:5])
         popular_genres
```

```
Out[27]: ['Science Fiction', 'Adventure', 'Fantasy', 'Action', 'Animation']
```

```
In [28]: df_20years.describe()
```

```
Out[28]:                   id    popularity       runtime    vote_count  vote_average  \
         count    2884.000000  2884.000000  2884.000000  2884.000000   2884.000000
         mean    49999.492025     1.283314   108.489598   601.418169      6.112067
         std     74838.071719     1.601480    18.801966   945.451907      0.779351
         min        12.000000     0.001117    15.000000    10.000000      2.200000
         25%      8487.750000     0.497205    95.000000    85.750000      5.600000
         50%     13412.000000     0.876550   105.000000   253.000000      6.100000
         75%     58169.250000     1.473959   118.000000   688.250000      6.600000
         max    417859.000000    32.985763   338.000000  9767.000000      8.200000

                release_year    budget_adj   revenue_adj
         count   2884.000000  2.884000e+03  2.884000e+03
         mean    2006.661928  4.761033e+07  1.277516e+08
         std        5.434993  4.827910e+07  2.010761e+08
         min     1996.000000  9.693980e-01  2.370705e+00
         25%     2002.000000  1.339331e+07  1.614076e+07
         50%     2007.000000  3.137941e+07  5.783592e+07
         75%     2011.000000  6.691203e+07  1.528228e+08
         max     2015.000000  4.250000e+08  2.827124e+09
```

```
In [29]: popular_genres_rating = (df_genres.query("genres in @popular_genres")
                                           .groupby(['genres'], as_index=False)
                                           .vote_average.mean())
         popular_genres_rating
```

```
Out[29]:             genres  vote_average
         0           Action      5.991049
         1        Adventure      6.079213
         2        Animation      6.335503
         3          Fantasy      6.043056
         4  Science Fiction      6.002228
```

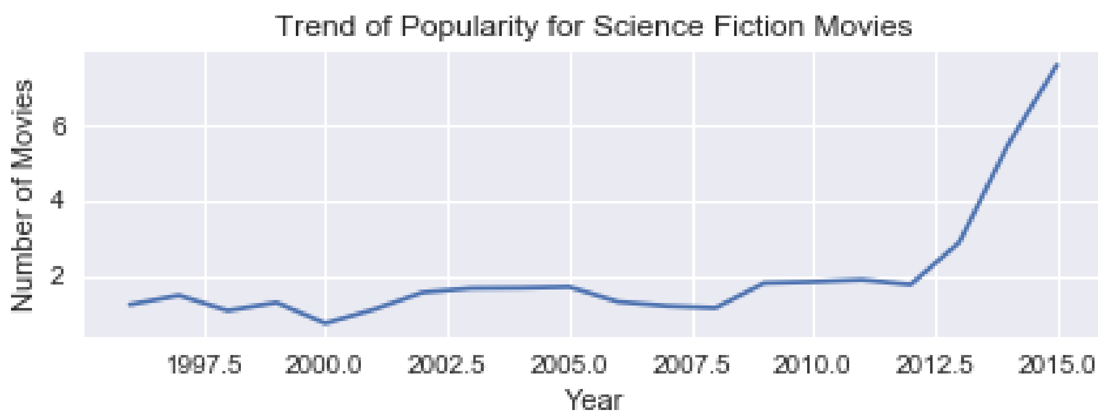
The overall mean value for average rating was '6.11' from 1996 to 2015. Except 'Animation' genre with average rating of '6.33', the other four top popular genres all had a lower value for average voting than the overall mean value.

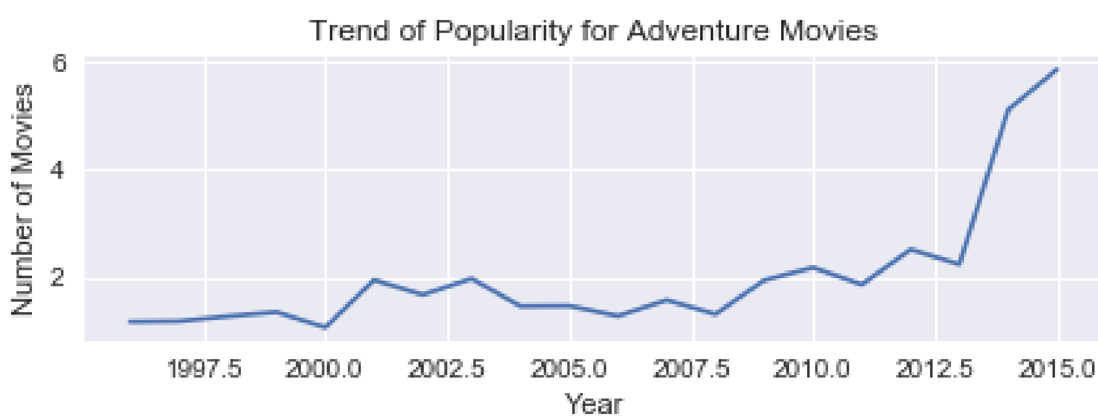
1.2.10 Trend of populairy for most popular genres from 1996 to 2015

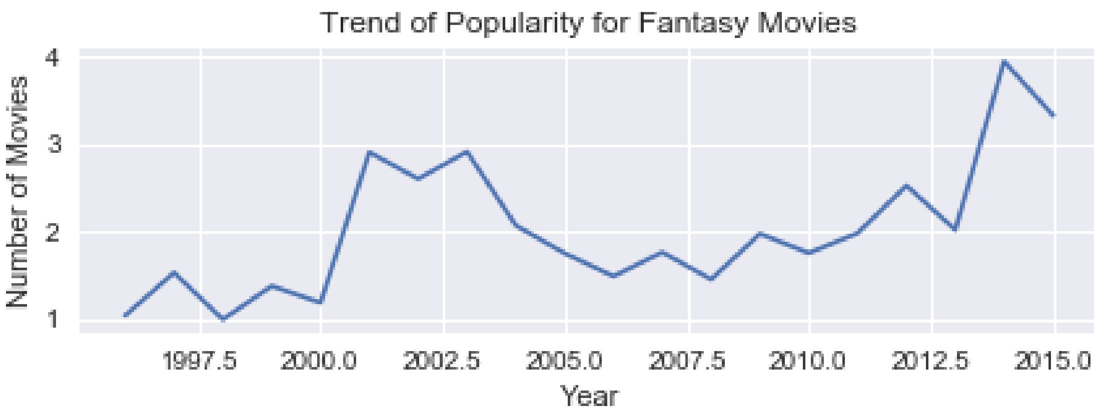
```
In [30]: popular_genres_movies = (df_genres.query("genres in @popular_genres")
                                             .groupby(['genres','release_year'], as_index=False)
                                             .popularity.mean())
```

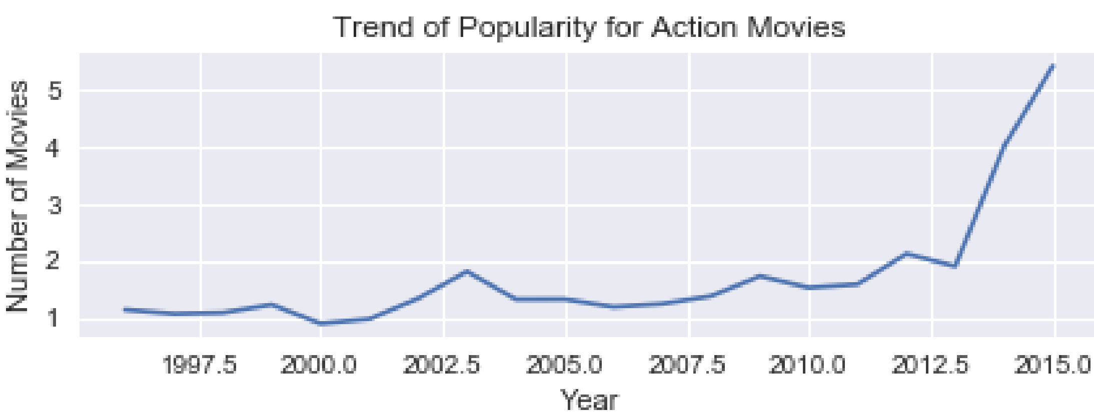
Let's see the reuslts in graphs.

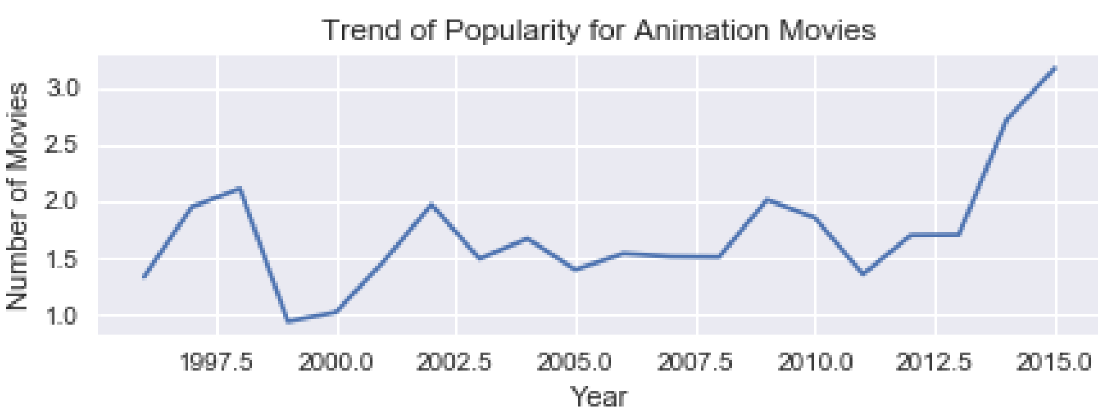
```
In [31]: for i, genre in enumerate(popular_genres):
             df1 = popular_genres_movies[popular_genres_movies.genres == genre]
             plt.figure(figsize=(7, 2))
             plt.title('Trend of Popularity for {} Movies'.format(genre))
             plt.xlabel('Year')
             plt.ylabel('Number of Movies')
             plt.plot(df1['release_year'], df1['popularity'])
             plt.show()
```











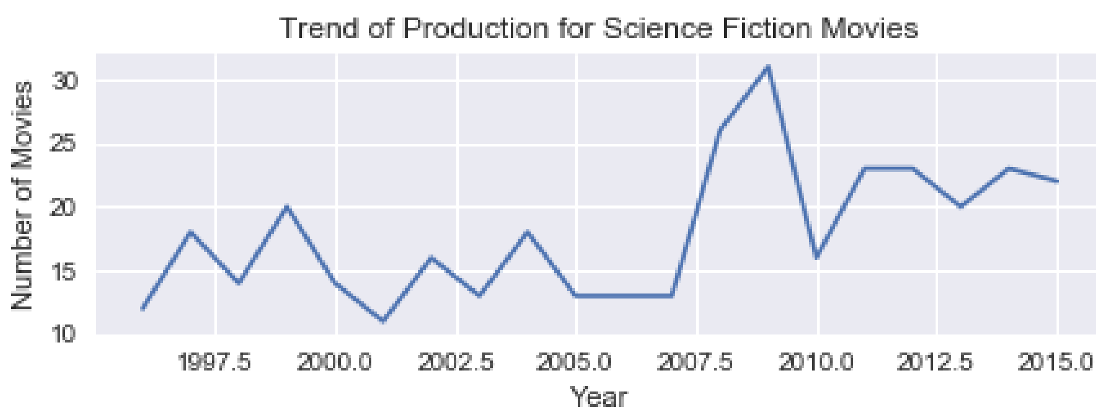
We can see the trend of popularity for the most popular genres has been increased over the 20 years of study. The positive trend is more visilble after 2012. The positive trend is more significant for 'Science Ficion', 'Adventure' and 'Action' genres.

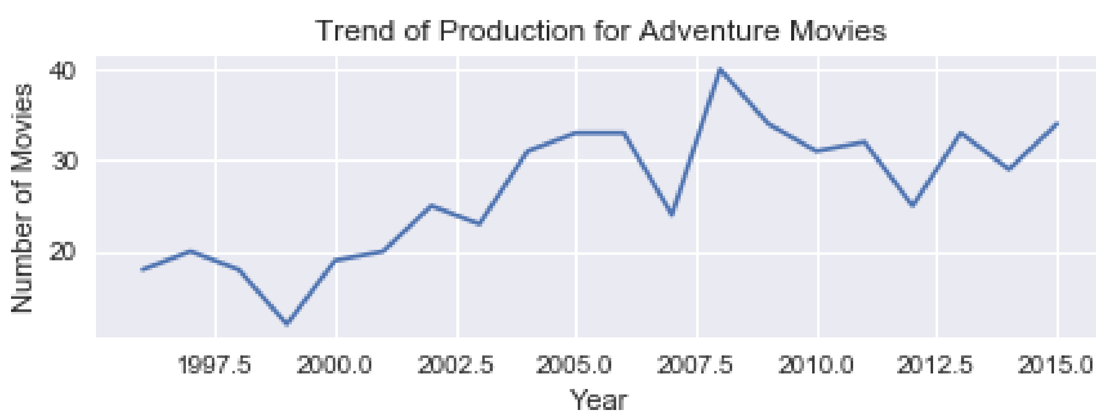
Let's find out how was the trend of movie production for these most popular genres? Did the positvie trend in their popularity have any assosiation with their production?

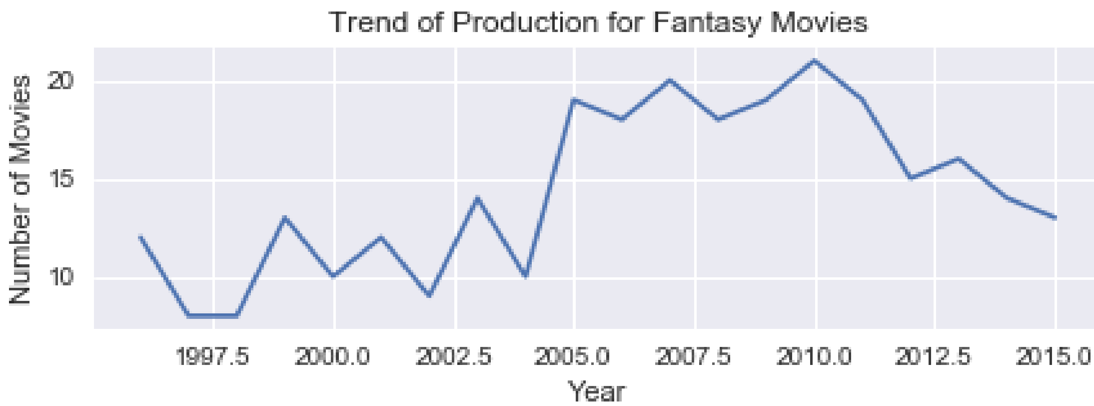
1.2.11 Trend of movie production for most popular genres from 1996 to 2015

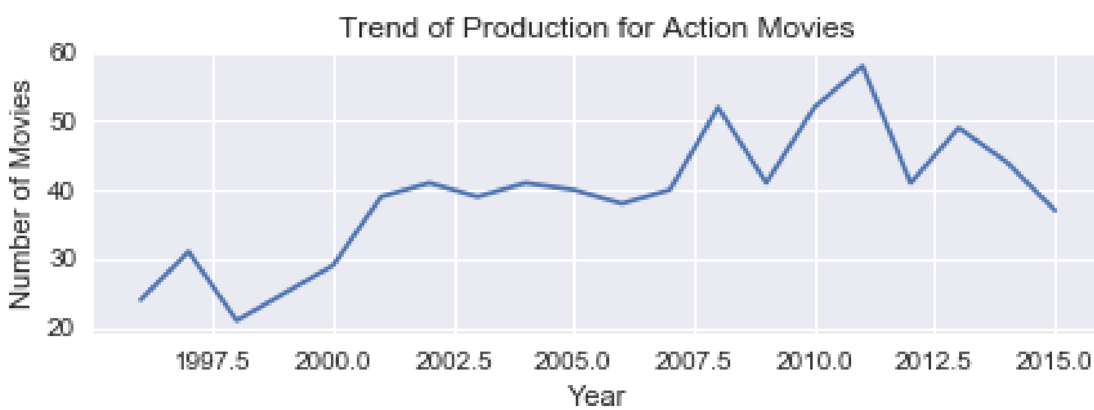
```
In [32]: popular_genres_movies_number = (df_genres.query("genres in @popular_genres")
                                        .groupby(['genres','release_year'], as_index=False)
                                        .id.count())
```

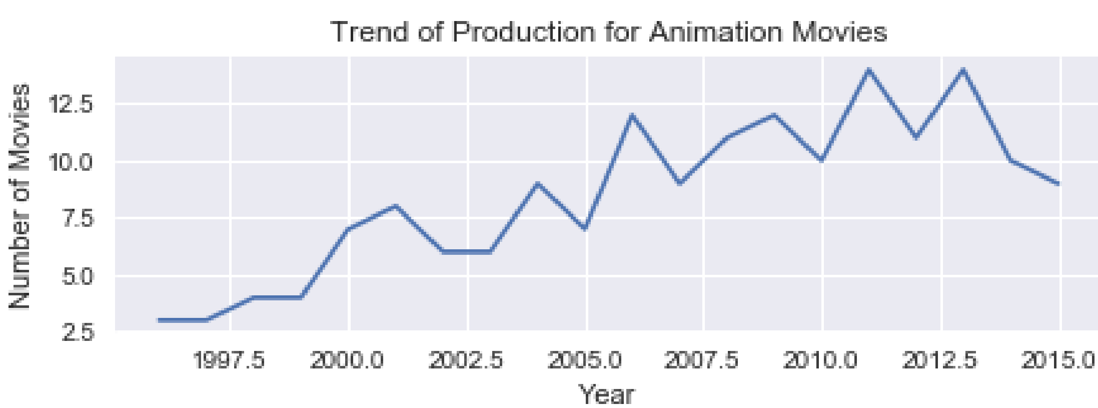
```
In [33]: for i, genre in enumerate(popular_genres):
             df1 = popular_genres_movies_number[popular_genres_movies_number.genres == genre]
             plt.figure(figsize=(7, 2))
             plt.title('Trend of Production for {} Movies'.format(genre))
             plt.xlabel('Year')
             plt.ylabel('Number of Movies')
             plt.plot(df1['release_year'], df1['id'])
             plt.show()
```









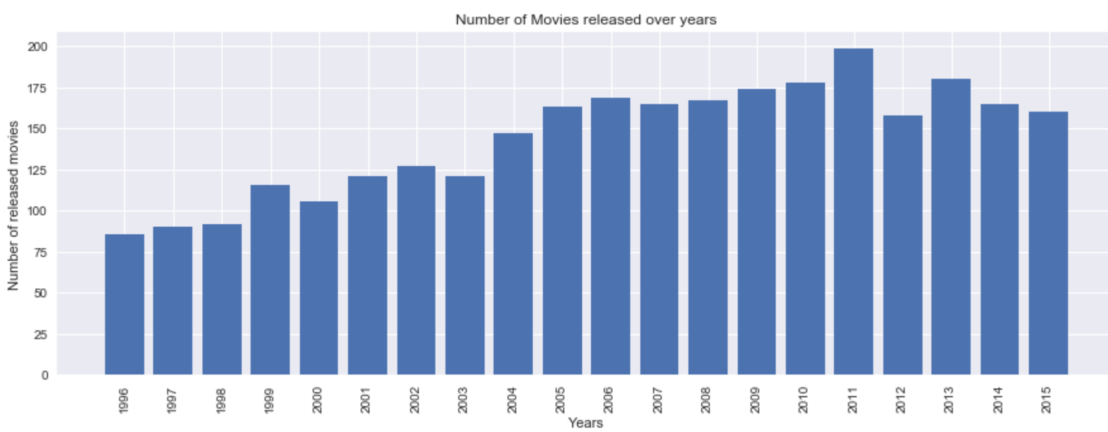


Although we can see that there is an increase in the production of the most popular genres over 20 years, the trend of their production has been negative or none positive after 2012.

1.2.12 Research Q2 : What kind of properties are associated with movies that have high revenues?

To make it possible to use our findings from first question(Reaserch Q1) and make a beeter conclusion, we use the same time period in this question too. We want to see how many movies have been released during the time period of our study.

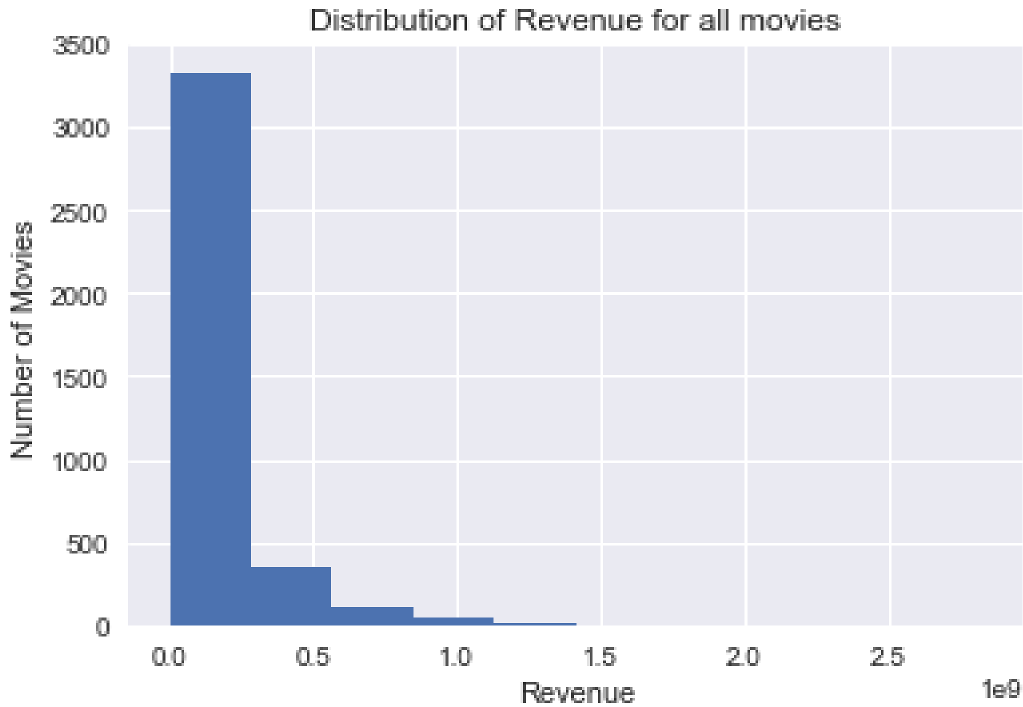
```
In [34]: df1= (df_20years.groupby(['release_year'], as_index=False)['id'].count())

         sns.set()
         locations = list(range(1,21))
         heights = df1.iloc[:, 1]
         lables = df1.iloc[:, 0]
         plt.subplots(figsize=(15, 5))
         plt.bar(locations, heights, tick_label=lables)
         plt.title('Number of Movies released over years')
         plt.xlabel('Years')
         plt.ylabel('Number of released movies');
         plt.xticks(rotation=90);
```



We can see that number of movies have been increased over the years.

To answer our research question, first we need to find high revenue movies. Let's categorzie movies based on some statistics and visulaizations.

```
In [35]: sns.set()
         plt.hist(df['revenue_adj'])
         plt.xlabel('Revenue')
         plt.ylabel('Number of Movies')
         plt.title('Distribution of Revenue for all movies')
         plt.show();
```



In [36]: df_20years.describe()

Out[36]:

```
                  id   popularity      runtime   vote_count  vote_average  \
count    2884.000000  2884.000000  2884.000000  2884.000000   2884.000000
mean    49999.492025     1.283314   108.489598   601.418169      6.112067
std     74838.071719     1.601480    18.801966   945.451907      0.779351
min        12.000000     0.001117    15.000000    10.000000      2.200000
25%      8487.750000     0.497205    95.000000    85.750000      5.600000
50%     13412.000000     0.876550   105.000000   253.000000      6.100000
75%     58169.250000     1.473959   118.000000   688.250000      6.600000
max    417859.000000    32.985763   338.000000  9767.000000      8.200000

       release_year    budget_adj   revenue_adj
count   2884.000000  2.884000e+03  2.884000e+03
mean    2006.661928  4.761033e+07  1.277516e+08
std        5.434993  4.827910e+07  2.010761e+08
min     1996.000000  9.693980e-01  2.370705e+00
25%     2002.000000  1.339331e+07  1.614076e+07
50%     2007.000000  3.137941e+07  5.783592e+07
75%     2011.000000  6.691203e+07  1.528228e+08
max     2015.000000  4.250000e+08  2.827124e+09
```

Based on this statistics, we can divide our movies to high_revenue and low_revenue. In order to do that we consider the top 25 percent of revenue as high_revenue movies and the rest as low_revenue.

```
In [37]: df_20years.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2884 entries, 0 to 9153
Data columns (total 9 columns):
id               2884 non-null int64
popularity       2884 non-null float64
runtime          2884 non-null int64
genres           2884 non-null object
vote_count       2884 non-null int64
vote_average     2884 non-null float64
release_year     2884 non-null int64
budget_adj       2884 non-null float64
revenue_adj      2884 non-null float64
dtypes: float64(4), int64(4), object(1)
memory usage: 305.3+ KB
```

```
In [38]: low_revenue = df_20years[df_20years.revenue_adj < 1.528228e+08]
         high_revenue = df_20years[df_20years.revenue_adj > 1.528228e+08]
```

```
In [39]: high_revenue.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 721 entries, 0 to 9043
Data columns (total 9 columns):
id               721 non-null int64
popularity       721 non-null float64
runtime          721 non-null int64
genres           721 non-null object
vote_count       721 non-null int64
vote_average     721 non-null float64
release_year     721 non-null int64
budget_adj       721 non-null float64
revenue_adj      721 non-null float64
dtypes: float64(4), int64(4), object(1)
memory usage: 56.3+ KB
```

```
In [40]: low_revenue.info()
```

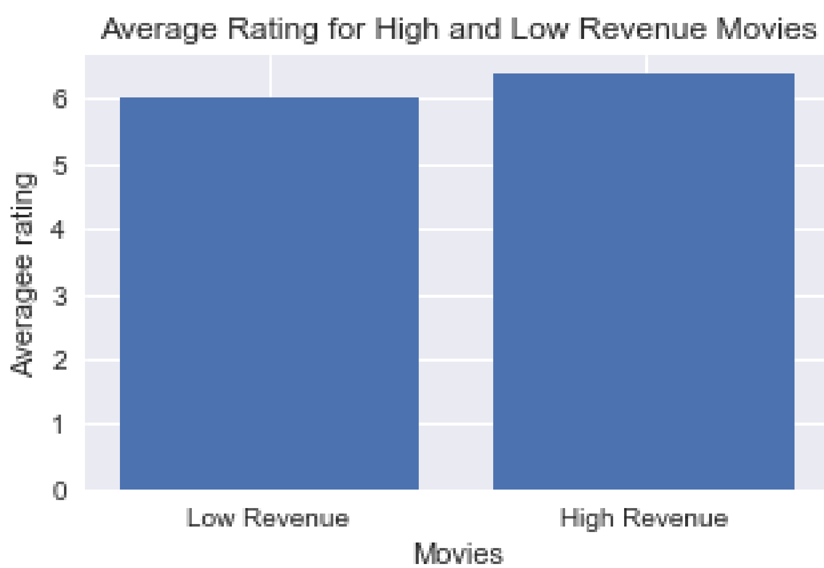
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2163 entries, 12 to 9153
Data columns (total 9 columns):
id               2163 non-null int64
popularity       2163 non-null float64
runtime          2163 non-null int64
genres           2163 non-null object
vote_count       2163 non-null int64
```

```
vote_average    2163 non-null float64
release_year    2163 non-null int64
budget_adj      2163 non-null float64
revenue_adj     2163 non-null float64
dtypes: float64(4), int64(4), object(1)
memory usage: 169.0+ KB
```

```
In [41]: low_revenue_vote = low_revenue['vote_average'].mean()
         high_revenue_vote = high_revenue['vote_average'].mean()
         print(low_revenue_vote, high_revenue_vote)
```

```
6.0293111419324985 6.360332871012483
```

```
In [42]: locations = (1 , 2)
         heights = [low_revenue_vote, high_revenue_vote]
         lables = ('Low Revenue', 'High Revenue')
         plt.subplots(figsize=(5, 3))
         plt.bar(locations, heights, tick_label=lables)
         plt.title('Average Rating for High and Low Revenue Movies')
         plt.xlabel('Movies')
         plt.ylabel('Averagee rating');
```

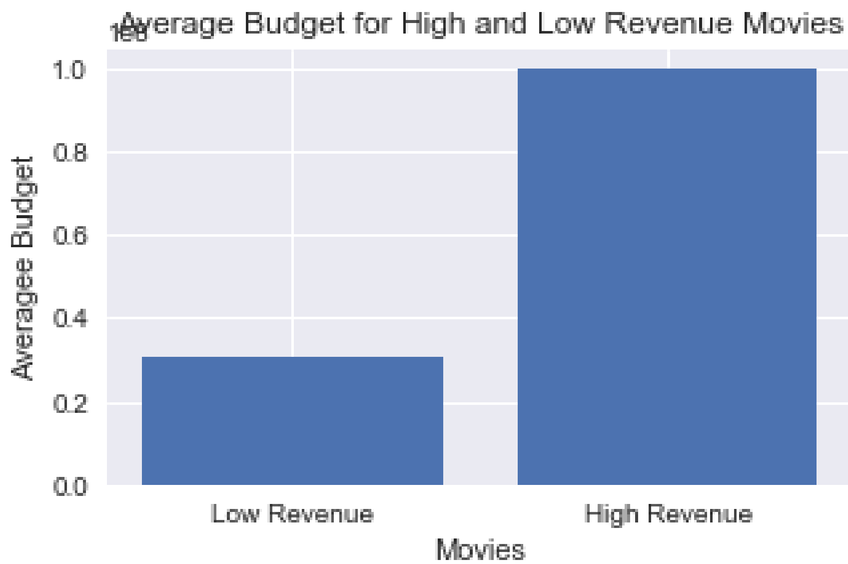


Average rating for high revenue movies is slightly more than low revenue movies.

```
In [43]: low_revenue_budget = low_revenue['budget_adj'].mean()
         high_revenue_budget = high_revenue['budget_adj'].mean()
         print(low_revenue_budget, high_revenue_budget)
```

```
30337834.586533476 99427806.69437586
```

```
In [44]: locations = (1 , 2)
         heights = [low_revenue_budget, high_revenue_budget]
         lables = ('Low Revenue', 'High Revenue')
         plt.subplots(figsize=(5, 3))
         plt.bar(locations, heights, tick_label=lables)
         plt.title('Average Budget for High and Low Revenue Movies')
         plt.xlabel('Movies')
         plt.ylabel('Averagee Budget');
```



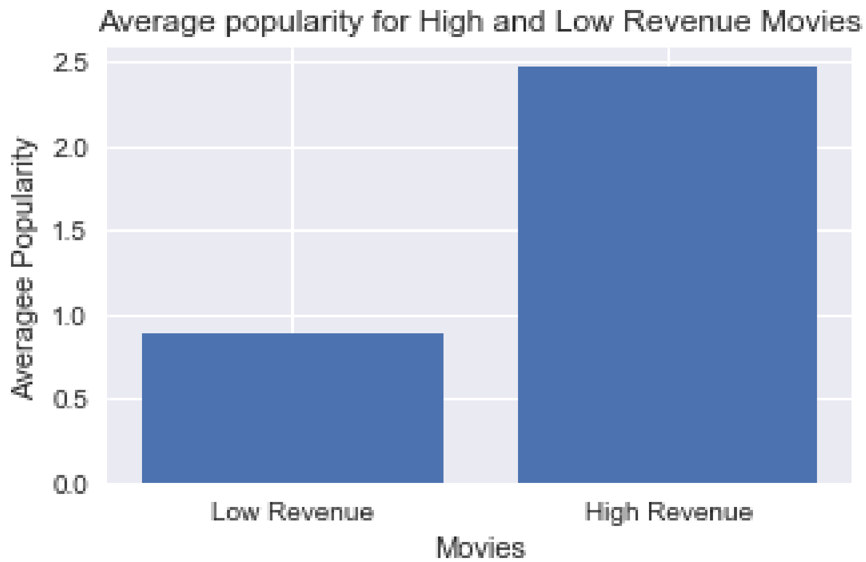
Budget for high revenue movies is 3 times more.

```
In [45]: low_revenue_popularity = low_revenue['popularity'].mean()
         high_revenue_popularity = high_revenue['popularity'].mean()
         print(low_revenue_popularity, high_revenue_popularity)
```

```
0.8895005903837255 2.4647558141470154
```

```
In [46]: locations = (1 , 2)
         heights = [low_revenue_popularity, high_revenue_popularity]
         lables = ('Low Revenue', 'High Revenue')
         plt.subplots(figsize=(5, 3))
         plt.bar(locations, heights, tick_label=lables)
         plt.title('Average popularity for High and Low Revenue Movies')
         plt.xlabel('Movies')
         plt.ylabel('Averagee Popularity')
```

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



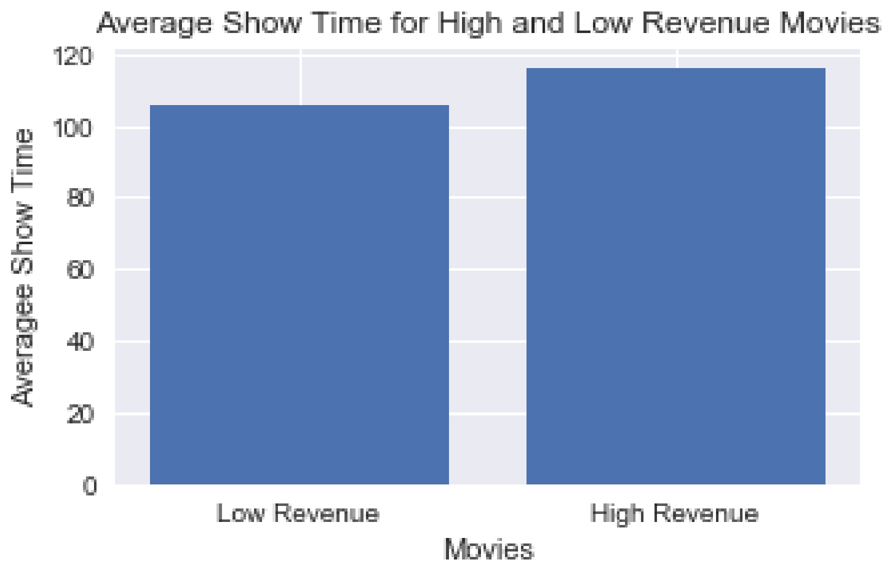
Average popularity for high_revenue movies has been 3 times more than low revenue movies.

```
In [47]: low_revenue_runtime = low_revenue['runtime'].mean()
         high_revenue_runtime = high_revenue['runtime'].mean()
         print(low_revenue_runtime, high_revenue_runtime)
```

```
106.0610263522885 115.7753120665742
```

```
In [48]: locations = (1 , 2)
         heights = [low_revenue_runtime, high_revenue_runtime]
         lables = ('Low Revenue', 'High Revenue')
         plt.subplots(figsize=(5, 3))
         plt.bar(locations, heights, tick_label=lables)
         plt.title('Average Show Time for High and Low Revenue Movies')
         plt.xlabel('Movies')
         plt.ylabel('Averagee Show Time')
```

```
Out[48]: Text(0,0.5,'Averagee Show Time')
```



The average show time for high revenue movies had been 11 minutes longer than low revenue movies.

```
In [49]: high_revenue_genres = (high_revenue.drop('genres', axis=1)
                      .join
                      (
                      high_revenue.genres
                      .str
                      .split('|', expand=True)
                      .stack()
                      .reset_index(drop=True, level=1)
                      .rename('genres')
                      ))
         high_rev_gen_cnt= high_revenue_genres.groupby('genres', as_index = False).id.count()
         high_rev_gen_cnt
```

Out[49]:

	genres	id
0	Action	296
1	Adventure	265
2	Animation	100
3	Comedy	254
4	Crime	99
5	Drama	218
6	Family	152
7	Fantasy	141
8	History	20
9	Horror	41
10	Music	19
11	Mystery	61

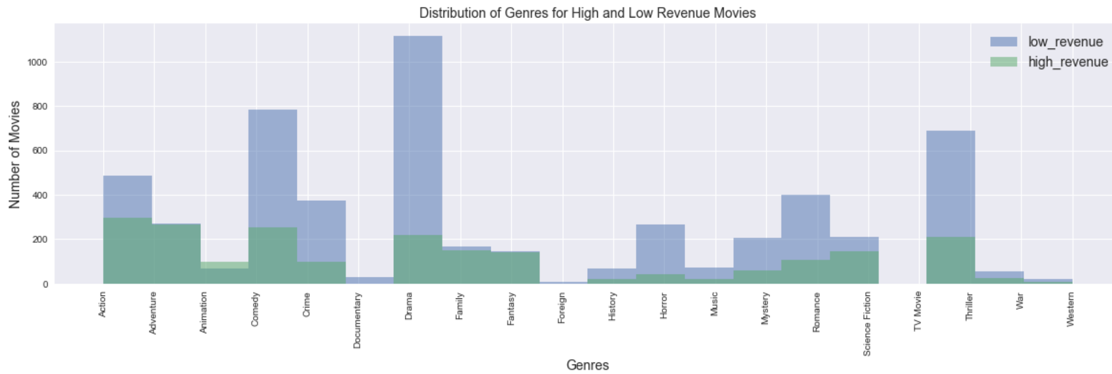
```
12           Romance  107
13   Science Fiction  147
14          Thriller  209
15               War   23
16           Western    7
```

In [50]:
```
low_revenue_genres = (low_revenue.drop('genres', axis=1)
             .join
             (
             low_revenue.genres
             .str
             .split('|', expand=True)
             .stack()
             .reset_index(drop=True, level=1)
             .rename('genres')
             ))
low_rev_gen_cnt= low_revenue_genres.groupby('genres', as_index = False).id.count()
low_rev_gen_cnt
```

Out[50]:
```
             genres    id
0            Action   486
1         Adventure   269
2         Animation    69
3            Comedy   784
4             Crime   373
5       Documentary    31
6             Drama  1116
7            Family   168
8           Fantasy   147
9           Foreign     9
10          History    68
11           Horror   268
12            Music    74
13          Mystery   208
14          Romance   398
15  Science Fiction   212
16         TV Movie     1
17         Thriller   691
18              War    56
19          Western    20
```

In [51]:
```
sns.set()
plt.figure(figsize=(20, 5))
plt.hist( low_revenue_genres['genres'], label='low_revenue', bins = 20, alpha=0.5)
plt.hist( high_revenue_genres['genres'], label='high_revenue', bins=20, alpha=0.5)
plt.xlabel('Genres', fontsize= 14)
plt.ylabel('Number of Movies', fontsize= 14)
plt.title('Distribution of Genres for High and Low Revenue Movies', fontsize= 14)
```

```
plt.xticks(rotation=90);
plt.legend(fontsize=14);
```



looks like 'Animation' was the most succesful, and 'Documnetory' and 'Foreign' were the lease successful genres in terms of revenue. Most of the movies with 'Animation' genre are categorized as high revenue, and all of the movies in 'Documentary' and 'Foreign' genres are categorized as low revenue. We picked top twenty five percent of revenue as high revenue movies, considering that and the above chart, we can say that 'Adventure', 'Fantasy' and 'Family' were more successful in terms of revenue. 'Action' and 'Science fiction' which were among top popular genres in the first research question(Q1), have a high ranking in revenue too.

Conclusions

In this research, we studied the records of movies from Movie Database(TMDb). Dring the data cleaning, we noticed that more than 60% of our movie records have a zero value in revenue or budget fields. We decided to drop the rows with zero value in budget or revenue fields, so we missed almost 60% of our data.

1.2.13 Findings

- 'Science Fiction', 'Adventure', 'Fantasy', 'Action' and 'Animation' were the most popular genres between 1996 and 2015.
- The trend of popularity has been increasing for the most popular genres over the 20 years of our study. After 2012 the positive trend is more significant.
- The trend of movie production has been positive for the most popular genres between 1996 and 2012, then after 2012 it gets stable or negative.
- There was a positive assosiation between movie revenue and these properties: popularity, average rating, movie showtime and movie budget.
- 'Animation' was the most successful genre in terms of revenue, and the average rating for this genre was higher than the overall mean value.
- Although 'Adventure', 'Fantasy', "Family', 'Action' and 'Sience Fiction' were successful genres in terms of popularity and revenue, their average rating was lower than the overall mean value.

```
In [ ]:
```