Analyses on IMDb Movie Data

December 19, 2017

Contents

1 Group Information

Group members' ID and name are sorted by alphabetical order of family name.

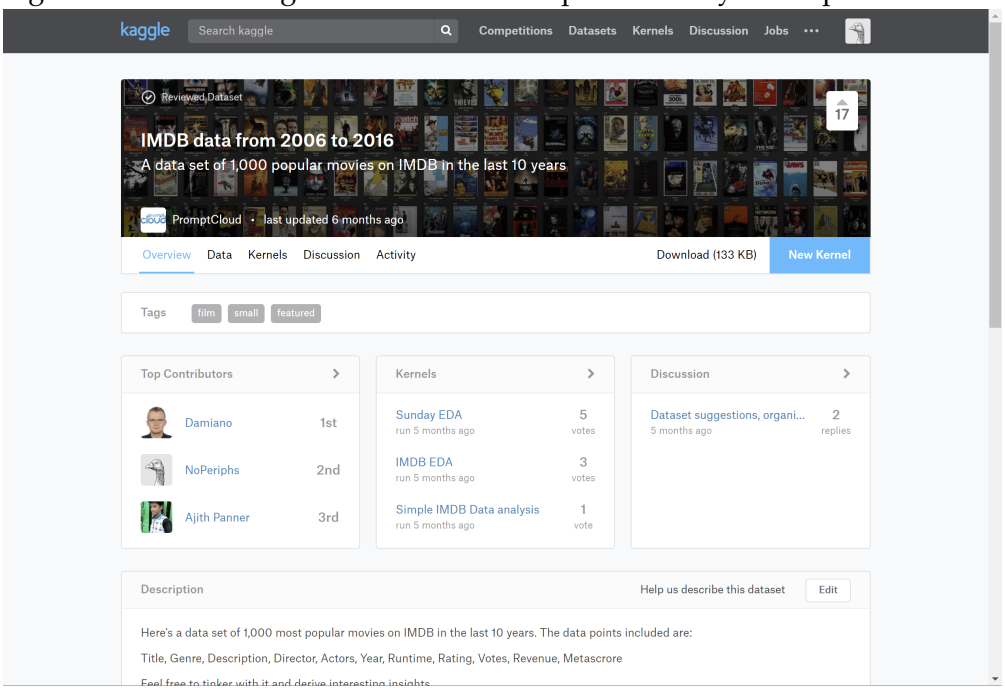
- 1430003004 Yongsheng (Jeff) Fu
- 1430003011 Kedun (Covey) Liu
- 1430003029 Jiaqi (Garfield) Wu
- 1430003030 Kefu (Frank) Wu
- 1430003045 Junru (bill) Zhong

2 Collecting Data

The data comes from Kaggle, which collects data of 1000 movies.

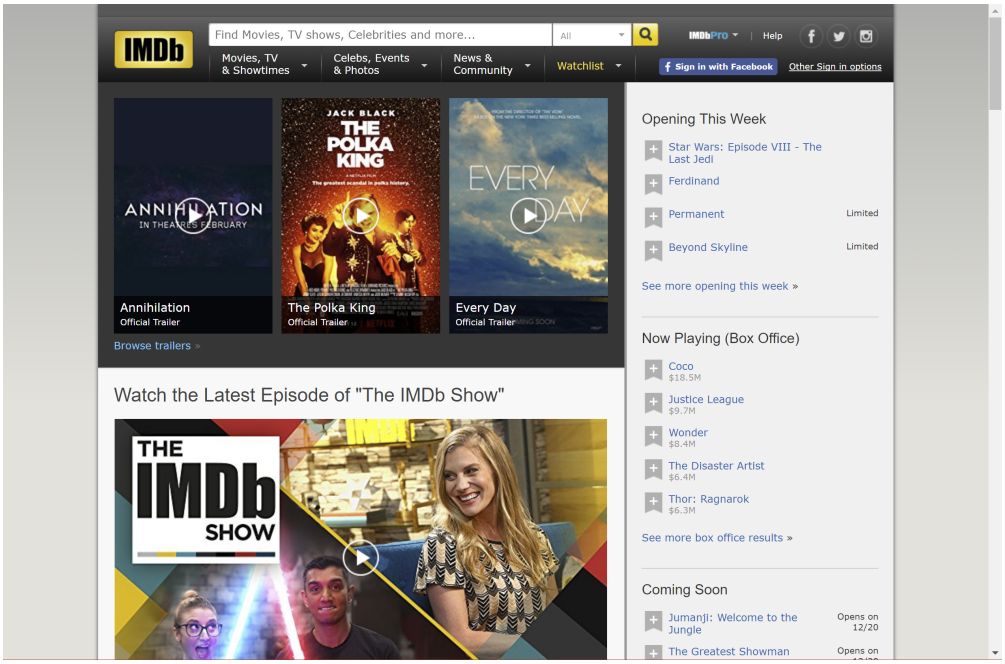
2.1 Kaggle

Kaggle is a platform for predictive modelling and analytics competitions in which statisticians and data miners compete to produce the best models for predicting and describing the datasets uploaded by companies and users.[Wikipedia]

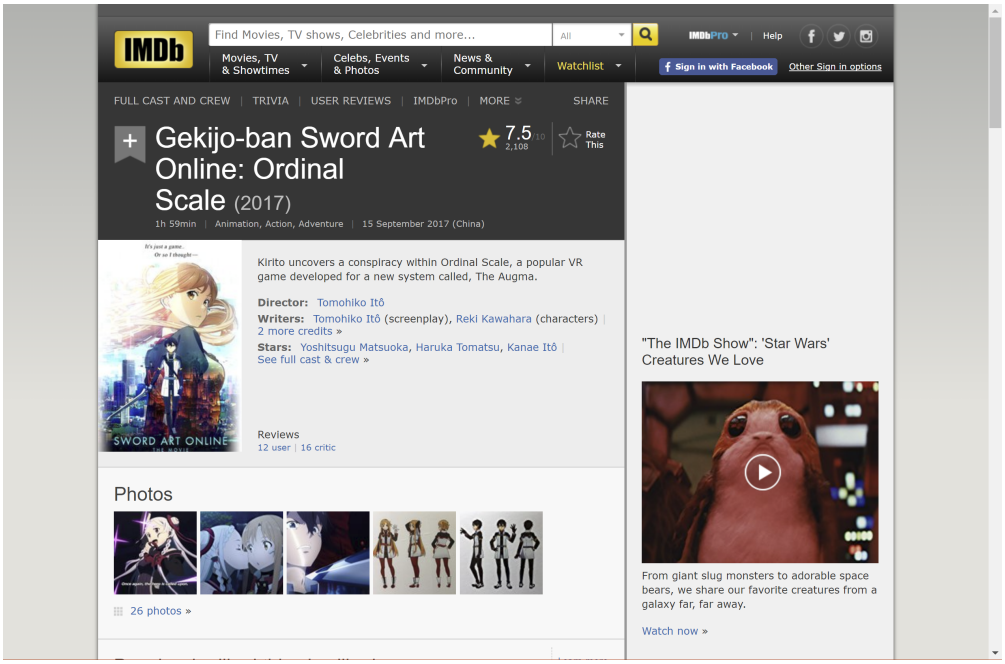


2.2 IMDb

IMDb, formerly known as Internet Movie Database, is an online database of information related to films, television programs and video games, including cast, production crew, fictional characters, biographies, plot summaries, trivia and reviews, operated by IMDb.com, Inc., a subsidiary of Amazon.[Wikipedia]



2.2.1 Movies on IMDb



3 Analyses

Five analyses were brought out by members in the group.

- Directors and Revenue **by Junru (Bill) Zhong**
- Directors and Rating **by Kefu (Frank) Wu**

- Genres and Time **by Yongsheng (Jeff) Fu**
- Rating and Metascore **by Kedun (Covey) Liu**
- Keywords in Films **by Jiaqi (Garfield) Wu**

3.1 Analysis on Directors

This analysis was posted by **Junru (Bill) Zhong**, and the following aims were setted.

- Find out which director earned most.
- Find out the genres of the works of the five-most earned directors.
- Estimate how much each of them will get in their next film.

This analysis was brought by Python with package: pandas

```
In [1]: # Import package
        import pandas as pd
        # Read data
        df = pd.read_csv('../Dataset/IMDB-Movie-Data.csv')
        print(df.head())
```

```
   Rank                    Title                     Genre  \
0     1  Guardians of the Galaxy   Action,Adventure,Sci-Fi
1     2               Prometheus  Adventure,Mystery,Sci-Fi
2     3                    Split           Horror,Thriller
3     4                     Sing   Animation,Comedy,Family
4     5            Suicide Squad  Action,Adventure,Fantasy

                                      Description             Director  \
0  A group of intergalactic criminals are forced ...           James Gunn
1  Following clues to the origin of mankind, a te...         Ridley Scott
2  Three girls are kidnapped by a man with a diag...  M. Night Shyamalan
3  In a city of humanoid animals, a hustling thea...  Christophe Lourdelet
4  A secret government agency recruits some of th...           David Ayer

                                      Actors  Year  Runtime (Minutes)  \
0  Chris Pratt, Vin Diesel, Bradley Cooper, Zoe S...  2014                121
1  Noomi Rapace, Logan Marshall-Green, Michael Fa...  2012                124
2  James McAvoy, Anya Taylor-Joy, Haley Lu Richar...  2016                117
3  Matthew McConaughey,Reese Witherspoon, Seth Ma...  2016                108
4  Will Smith, Jared Leto, Margot Robbie, Viola D...  2016                123

   Rating   Votes  Revenue (Millions)  Metascore
0     8.1  757074              333.13       76.0
1     7.0  485820              126.46       65.0
2     7.3  157606              138.12       62.0
3     7.2   60545              270.32       59.0
4     6.2  393727              325.02       40.0
```

3.1.1 Arranging Data

- Use groupby method provided by pandas, select all directors and their films' revenue.
- Collect this data with the film count and total revenue of their works.
- Drop the data with value of null.

```
In [4]: # List all directors.
        directorList = df.groupby('Director')['Revenue (Millions)'].agg(['sum', 'count']).
        reset_index()
        # Delete invalid data
        directorList = directorList.dropna()
        # Print out result
        print(directorList.head())
```

```
              Director     sum  count
0           Aamir Khan    1.20      1
1  Abdellatif Kechiche    2.20      1
3           Adam McKay  438.14      4
4        Adam Shankman  157.33      2
5         Adam Wingard   21.07      2
```

3.1.2 Sort Data

Sort the data according to the **average revenue** of each film that the directors directed.

- Calculate the average revenue.
- Sort the list.
- Save the first five directors.

```
In [6]: # Get average revenue of each director.
        directorList['avg'] = directorList['sum'] / directorList['count']
        print(directorList.head())
```

```
              Director     sum  count      avg
0           Aamir Khan    1.20      1    1.200
1  Abdellatif Kechiche    2.20      1    2.200
3           Adam McKay  438.14      4  109.535
4        Adam Shankman  157.33      2   78.665
5         Adam Wingard   21.07      2   10.535
```

```
In [7]: # Sorting by revenue, list the first five data.
        firstFive = directorList.sort_values('avg', ascending=False).head()
        print(firstFive)
```

```
            Director      sum  count      avg
261    James Cameron   760.51      1  760.510
```

```
114  Colin Trevorrow   652.18      1  652.180
341      Joss Whedon  1082.27      2  541.135
377      Lee Unkrich   414.98      1  414.980
208        Gary Ross   408.00      1  408.000
```

3.1.3 Genres of Directors' Work

Go back to the original dataset, then match all entries of these directors.

```
In [8]: # Searching their works.
        directorNames = firstFive['Director']
        for directorName in directorNames:
            for index, row in df.iterrows():
                if row['Director'] == directorName:
                    print(row['Director'] + ', ' + row['Genre'] + ', ' + row['Title'])
```

```
James Cameron, Action,Adventure,Fantasy, Avatar
Colin Trevorrow, Action,Adventure,Sci-Fi, Jurassic World
Joss Whedon, Action,Sci-Fi, The Avengers
Joss Whedon, Action,Adventure,Sci-Fi, Avengers: Age of Ultron
Lee Unkrich, Animation,Adventure,Comedy, Toy Story 3
Gary Ross, Adventure,Sci-Fi,Thriller, The Hunger Games
Gary Ross, Action,Biography,Drama, Free State of Jones
```

*One movie from **Gary Ross** was not calculated because there is no revenue data.*

3.1.4 Summary

- In the first five directors, seven of their works were recorded.
- Six of seven films have the genre of **Action**, that means action films are popular.
- Four of seven films have the genre of **Sci-Fi**, this genre is also popular.

3.2 Analysis on Directors by Rating

This analysis was posted by **Kefu (Frank) Wu**, and the following aims were setted.

- Find out which director is praised most by rating,as revenue cannot define how the films are evaluated by the public.
- Find out the genres of the works of the five-most praised directors.
- Estimate the rating that new film may get according to the genres of the film and its director.

This analysis was brought by Python with package: pandas

```
In [3]: # Show origin data
        print(df.head())
```

```
   Rank                    Title                       Genre  \
0     1  Guardians of the Galaxy   Action,Adventure,Sci-Fi
1     2               Prometheus  Adventure,Mystery,Sci-Fi
2     3                    Split           Horror,Thriller
3     4                     Sing   Animation,Comedy,Family
4     5            Suicide Squad  Action,Adventure,Fantasy

                                         Description             Director  \
0  A group of intergalactic criminals are forced ...           James Gunn
1  Following clues to the origin of mankind, a te...          Ridley Scott
2  Three girls are kidnapped by a man with a diag...    M. Night Shyamalan
3  In a city of humanoid animals, a hustling thea...  Christophe Lourdelet
4  A secret government agency recruits some of th...            David Ayer

                                              Actors  Year  Runtime (Minutes)  \
0  Chris Pratt, Vin Diesel, Bradley Cooper, Zoe S...  2014                121
1  Noomi Rapace, Logan Marshall-Green, Michael Fa...  2012                124
2  James McAvoy, Anya Taylor-Joy, Haley Lu Richar...  2016                117
3  Matthew McConaughey,Reese Witherspoon, Seth Ma...  2016                108
4  Will Smith, Jared Leto, Margot Robbie, Viola D...  2016                123

   Rating   Votes  Revenue (Millions)  Metascore
0     8.1  757074              333.13       76.0
1     7.0  485820              126.46       65.0
2     7.3  157606              138.12       62.0
3     7.2   60545              270.32       59.0
4     6.2  393727              325.02       40.0
```

3.2.1 Arranging Data

- Use groupby method provided by pandas, select all directors and their films' rating.
- Collect this data with the film count and sum up the rating of their works.

```
In [4]: # List all directors.
        directorList = df.groupby('Director')['Rating'].agg(['sum', 'count']).reset_index()
        # Print out result
        print(directorList.head())
```

```
              Director   sum  count
0          Aamir Khan   8.5      1
1  Abdellatif Kechiche   7.8      1
2           Adam Leon   6.5      1
3          Adam McKay  28.0      4
4       Adam Shankman  12.6      2
```

3.2.2 Sort Data

Sort the data according to the **average rating** of each film that the directors directed. * Calculate the average rating. * Sort the list. * Save the top five directors that customers praised.

```
In [5]: # Get average rating of each director.
        directorList['avg'] = directorList['sum'] / directorList['count']
        print(directorList.head())
```

```
              Director   sum  count  avg
0           Aamir Khan   8.5      1  8.5
1  Abdellatif Kechiche   7.8      1  7.8
2            Adam Leon   6.5      1  6.5
3           Adam McKay  28.0      4  7.0
4        Adam Shankman  12.6      2  6.3
```

```
In [6]: # Sorting by rating, list the first five data.
        firstFive = directorList.sort_values('avg', ascending=False).head()
        print(firstFive)
```

```
                           Director   sum  count   avg
465                   Nitesh Tiwari   8.8      1  8.80
108                Christopher Nolan  43.4      5  8.68
392                   Makoto Shinkai   8.6      1  8.60
470                  Olivier Nakache   8.6      1  8.60
194  Florian Henckel von Donnersmarck   8.5      1  8.50
```

3.2.3 Genres of Directors' Work

Go back to the original dataset, then match all entries of these directors.

```
In [23]: # Searching their works.
         directorNames = firstFive['Director']
         for directorName in directorNames:
             for index, row in df.iterrows():
                 if row['Director'] == directorName:
                     print(row['Director'] + ': \n\t' + row['Genre'] + ', ' + row['Title'])
```

```
Nitesh Tiwari:
        Action,Biography,Drama, Dangal
Christopher Nolan:
        Adventure,Drama,Sci-Fi, Interstellar
Christopher Nolan:
        Action,Crime,Drama, The Dark Knight
Christopher Nolan:
        Drama,Mystery,Sci-Fi, The Prestige
Christopher Nolan:
```

```
        Action,Adventure,Sci-Fi, Inception
Christopher Nolan:
        Action,Thriller, The Dark Knight Rises
Makoto Shinkai:
        Animation,Drama,Fantasy, Kimi no na wa
Olivier Nakache:
        Biography,Comedy,Drama, The Intouchables
Florian Henckel von Donnersmarck:
        Drama,Thriller, The Lives of Others
```

3.2.4 Summary

- We find out five director that are favored by their audience.
- In the first five directors, nine of their works were recorded.
- Among the directors, Chrostopher Nolan is the only director that can maintain high average rating after producing more than one film.
- In Nolan's five works, there are three of them are action/sci-Fi, which means that Nolan is good at directoring action/sci-Fi film.
- To sum up, we can predict that Chrostopher Nolan's next action/sci-Fi movie will gain a high comment, but for the rest of the top-five directors we cannot predict because there is only one record for each of them.

3.3 Genre's Analysis

The fellowing python code analyze the revenue of each kind of moive in past ten years. We can easily learn what kind of moive is easiest to make money.

```
In [1]: #Import packages

        import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
        import pandas as pd
        import seaborn as sns
        sns.set(style='white', color_codes=True, font_scale=1.25)
        import itertools
```

3.3.1 Load Dataset

First, we read the IMDB dataset csv file, and load it in to a DataFrame. Here are the first 5 row of the dataset.

```
In [2]: #Import the data into a DF and view the first 5 entries

        imdb = pd.read_csv('../Dataset/IMDB-Movie-Data.csv')
        imdb.head()
```

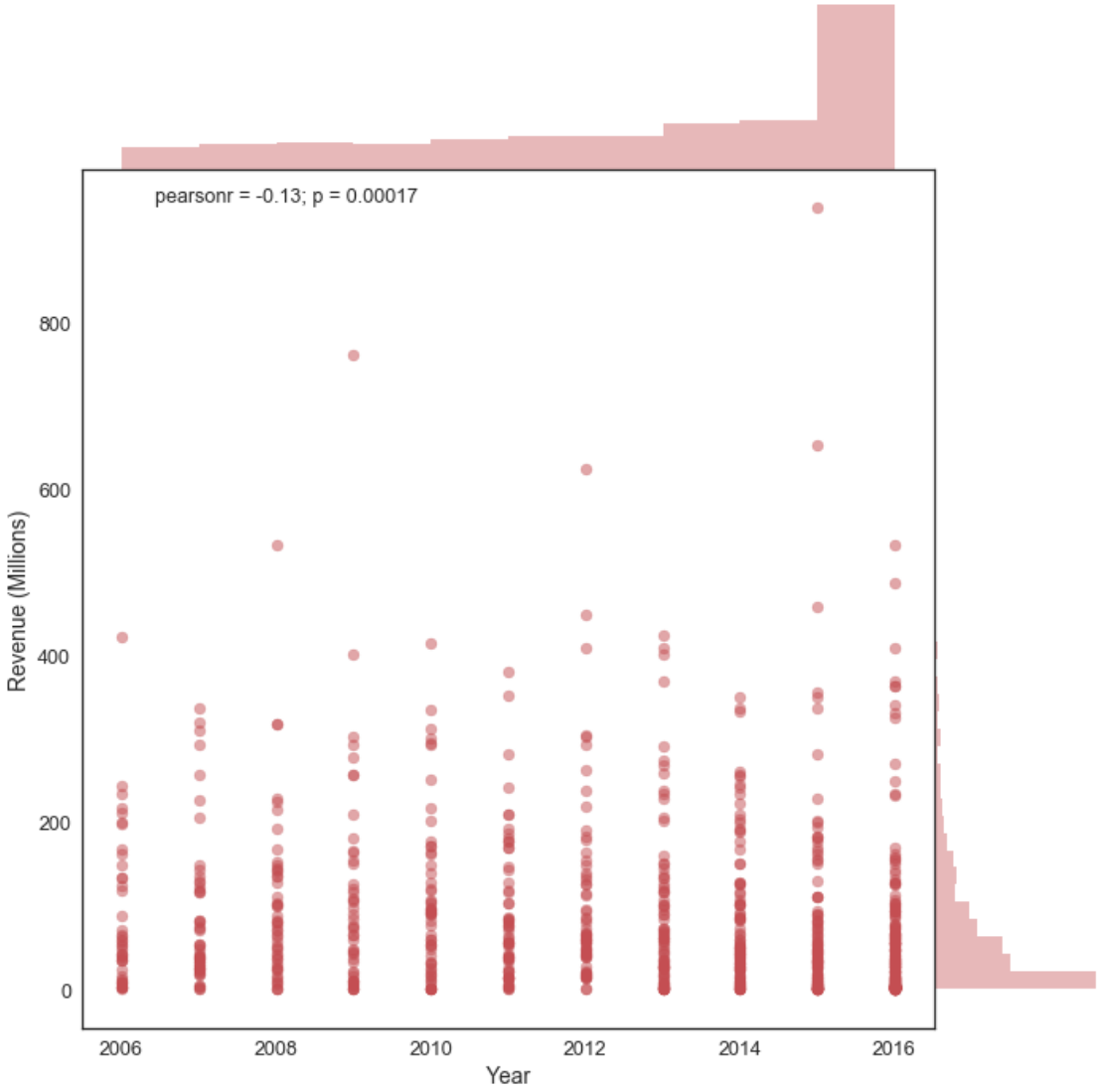
Out[2]:

	Rank	Title	Genre	Description	Director	Actors	Year	Runtime (Minutes)	Rating	Votes	Revenue (Millions)	Metascore
0	1	Guardians of the Galaxy	Action,Adventure,Sci-Fi	A group of intergalactic criminals are forced ...	James Gunn	Chris Pratt, Vin Diesel, Bradley Cooper, Zoe S...	2014	121	8.1	757074	333.13	76.0
1	2	Prometheus	Adventure,Mystery,Sci-Fi	Following clues to the origin of mankind, a te...	Ridley Scott	Noomi Rapace, Logan Marshall-Green, Michael Fa...	2012	124	7.0	485820	126.46	65.0
2	3	Split	Horror,Thriller	Three girls are kidnapped by a man with a diag...	M. Night Shyamalan	James McAvoy, Anya Taylor-Joy, Haley Lu Richar...	2016	117	7.3	157606	138.12	62.0
3	4	Sing	Animation,Comedy,Family	In a city of humanoid animals, a hustling thea...	Christophe Lourdelet	Matthew McConaughey,Reese Witherspoon, Seth Ma...	2016	108	7.2	60545	270.32	59.0
4	5	Suicide Squad	Action,Adventure,Fantasy	A secret government agency recruits some of th...	David Ayer	Will Smith, Jared Leto, Margot Robbie, Viola D...	2016	123	6.2	393727	325.02	40.0

Now, we use above dataset to plot a scatter graph so that we can know the **distribution of moives and their revenue**

In [3]:
```
#Plot the Revenue in recent ten years
sns.jointplot(x='Year', y='Revenue (Millions)', data=imdb,
alpha=0.5, color='r', size=10, space=0)
```

Out[3]:
```
<seaborn.axisgrid.JointGrid at 0x7fa0c64a0f98>
```



As the result shows, we know that more and more file are made in recent year. Besides, the result also shows us that most moive's revenue is less than 200 Millions dollor.

3.3.2 Question

- **What kind of moive are easiest to earn money?**
- **For answering this question, let's divde moive into different genre.**

By using unique() build-in function of pandas package. And record them by iteration, finally we got 20 unique genres. Here are the result.

```
In [4]: #Get unique genres

        unique_genres = imdb['Genre'].unique()
```

```
individual_genres = []
for genre in unique_genres:
    individual_genres.append(genre.split(','))
individual_genres = list(itertools.chain.from_iterable(individual_genres))
individual_genres = set(individual_genres)
individual_genres
```

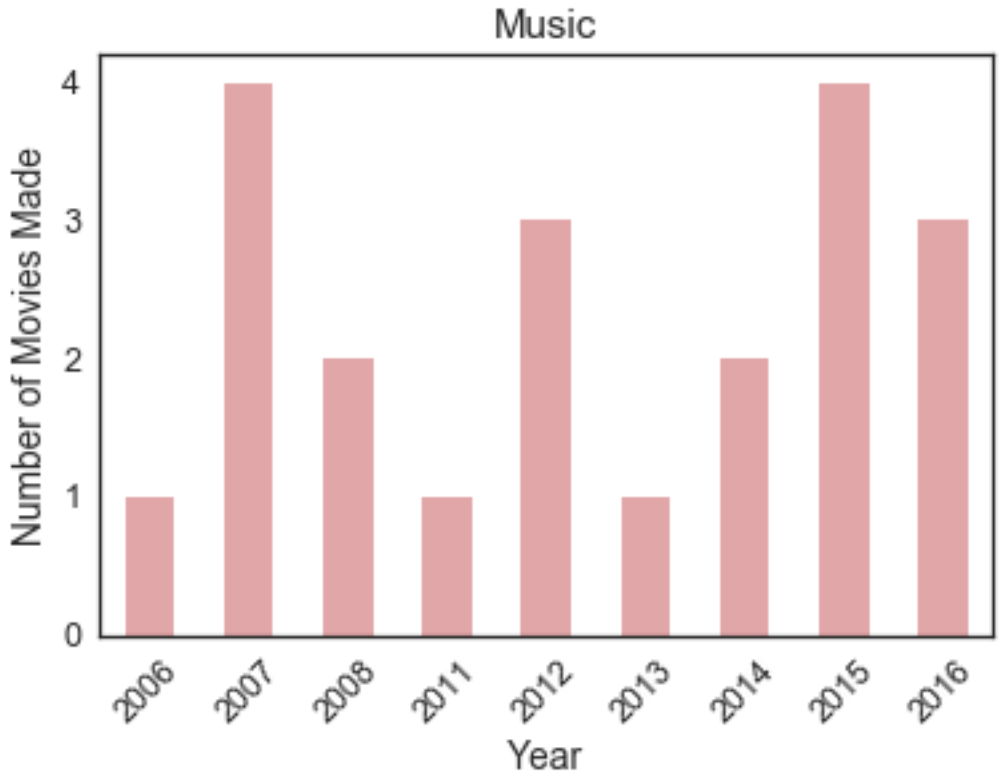
```
Out[4]: {'Action',
 'Adventure',
 'Animation',
 'Biography',
 'Comedy',
 'Crime',
 'Drama',
 'Family',
 'Fantasy',
 'History',
 'Horror',
 'Music',
 'Musical',
 'Mystery',
 'Romance',
 'Sci-Fi',
 'Sport',
 'Thriller',
 'War',
 'Western'}
```

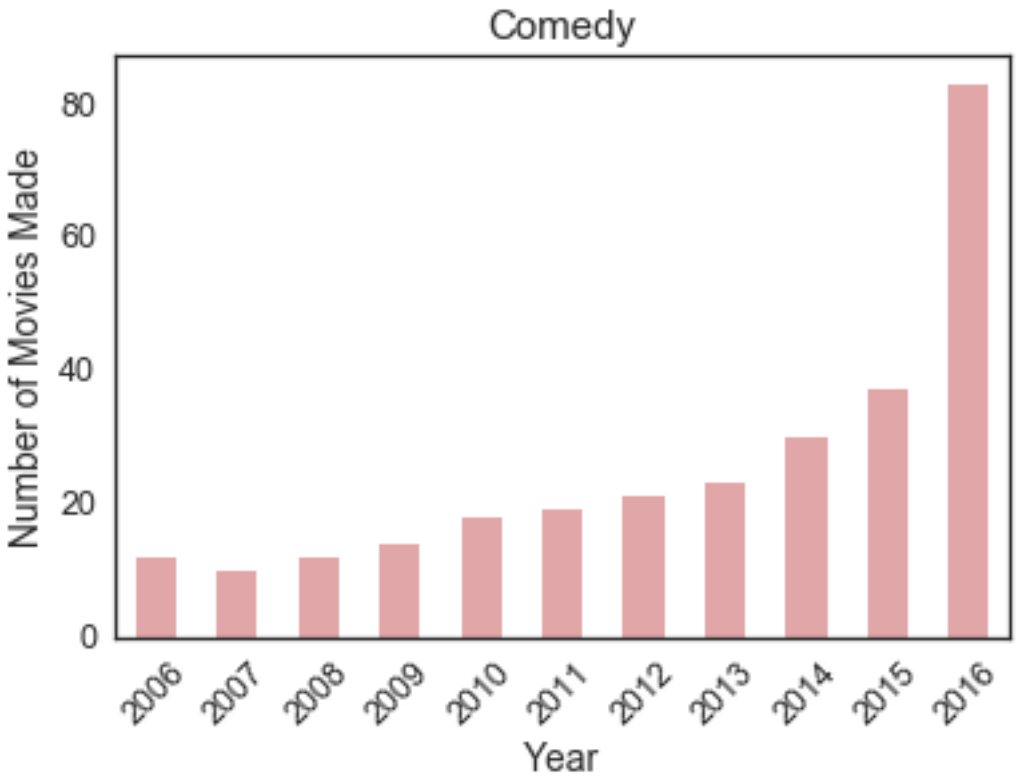
After we get each individual genres. We plot how many films of each genre were made by year onto a bar graph

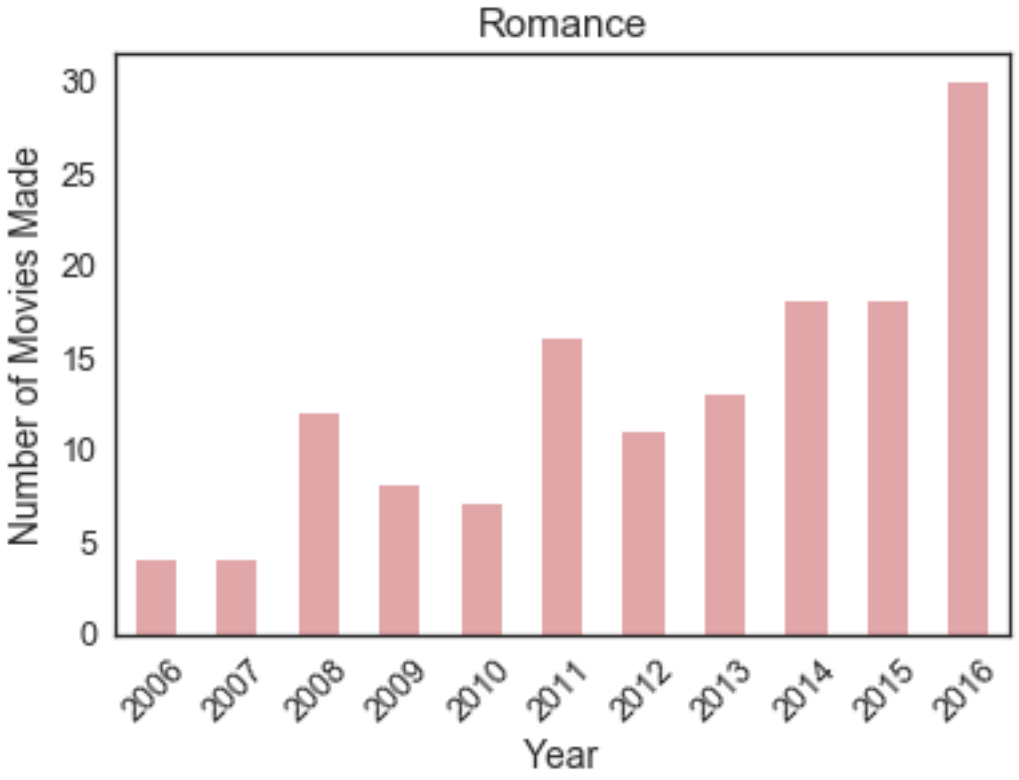
```
In [5]: #Now we can iterate through each genre,
        #counting the number of films that contain that genre
        #then plot how many films of each genre were made by year onto a bar graph

        print('Number of movies in each genre: \n')

        for genre in individual_genres:
            current_genre = imdb['Genre'].str.contains(genre).fillna(False)
            plt.figure()
            plt.xlabel('Year')
            plt.ylabel('Number of Movies Made')
            plt.title(str(genre))
            imdb[current_genre].Year.value_counts().sort_index().
                plot(kind='bar', color='r', alpha=0.5, rot=45)
            print(genre, len(imdb[current_genre]))
```

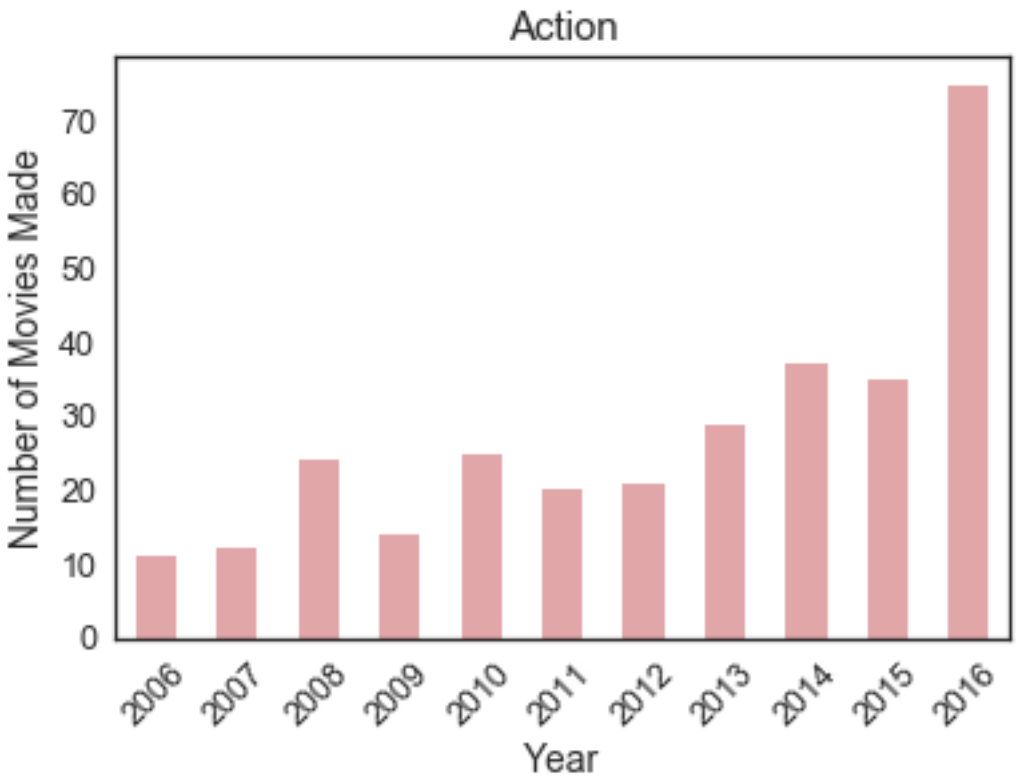
```
Number of movies in each genre:
```

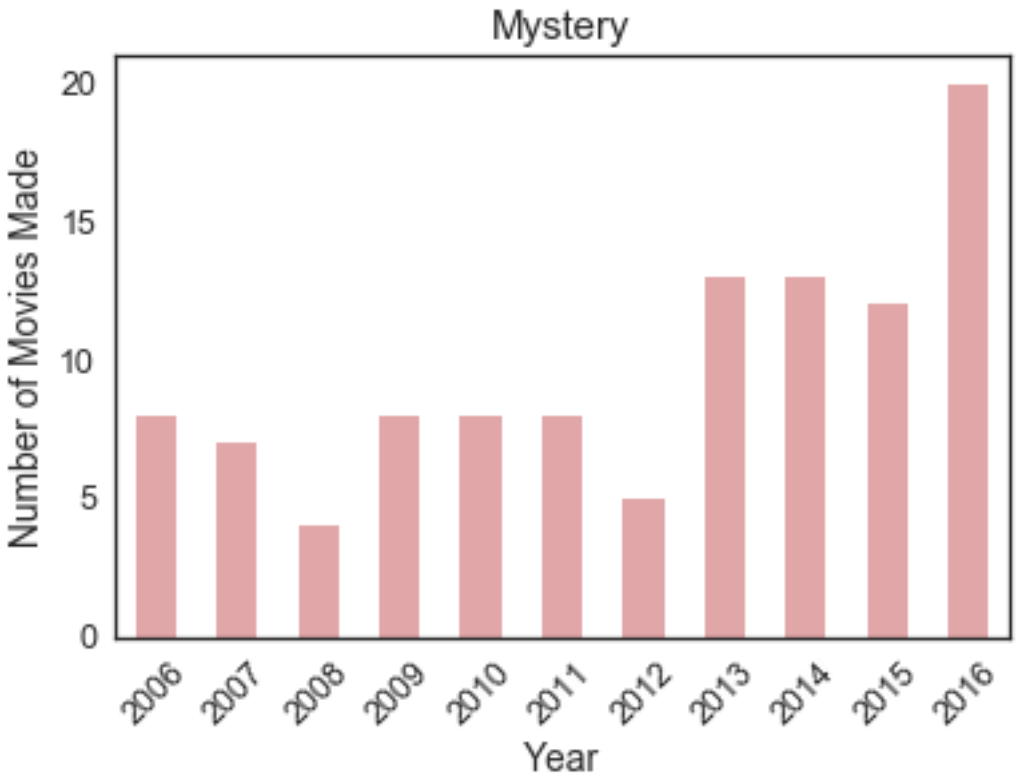
```
Music 21
Comedy 279
Romance 141
Action 303
Mystery 106
Family 51
Drama 513
Biography 81
Sci-Fi 120
History 29
Musical 5
Adventure 259
Thriller 195
Fantasy 101
War 13
Animation 49
Sport 18
Horror 119
Western 7
Crime 150
```

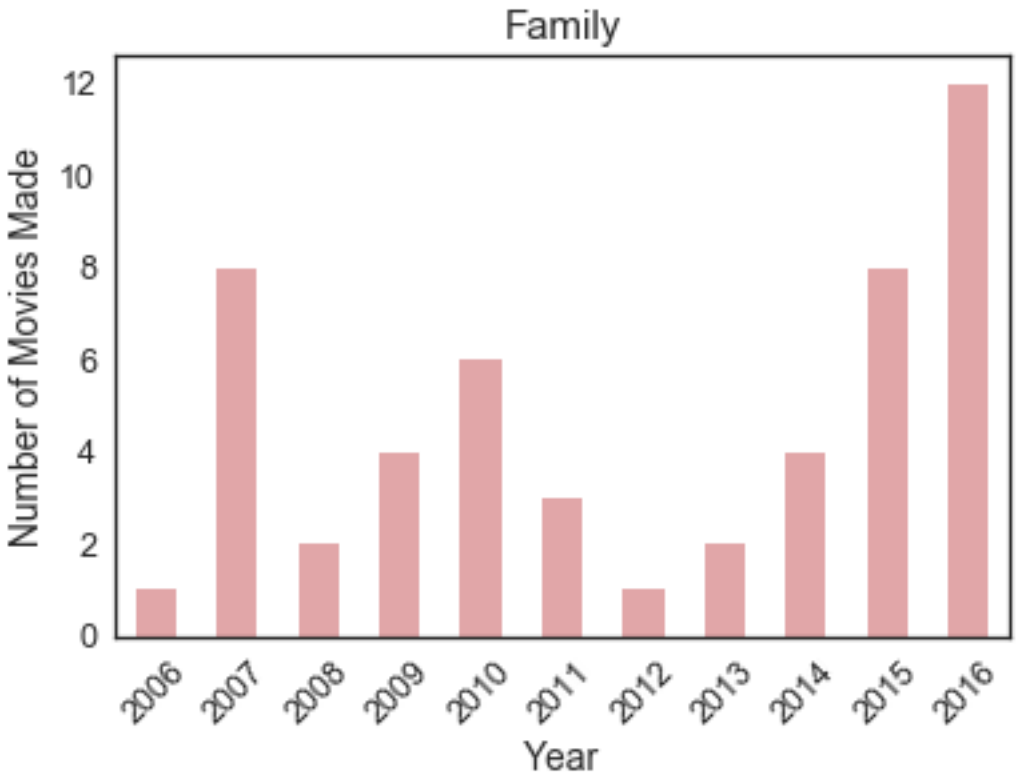


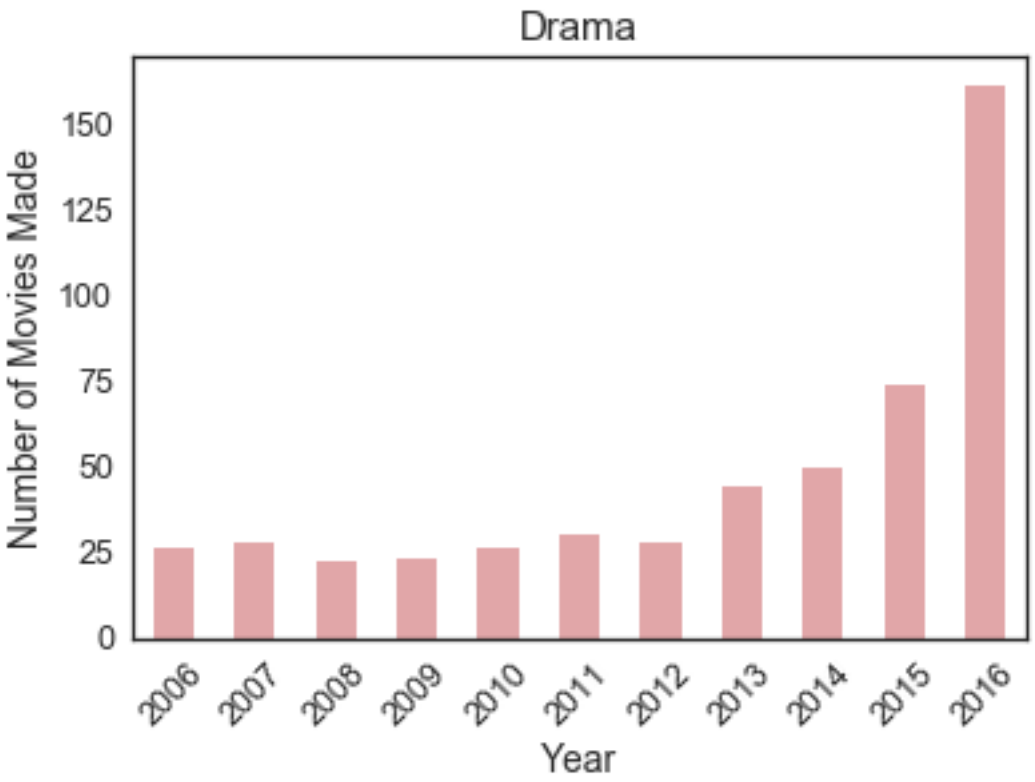

Comedy
Number of Movies Made
0
20
40
60
80
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

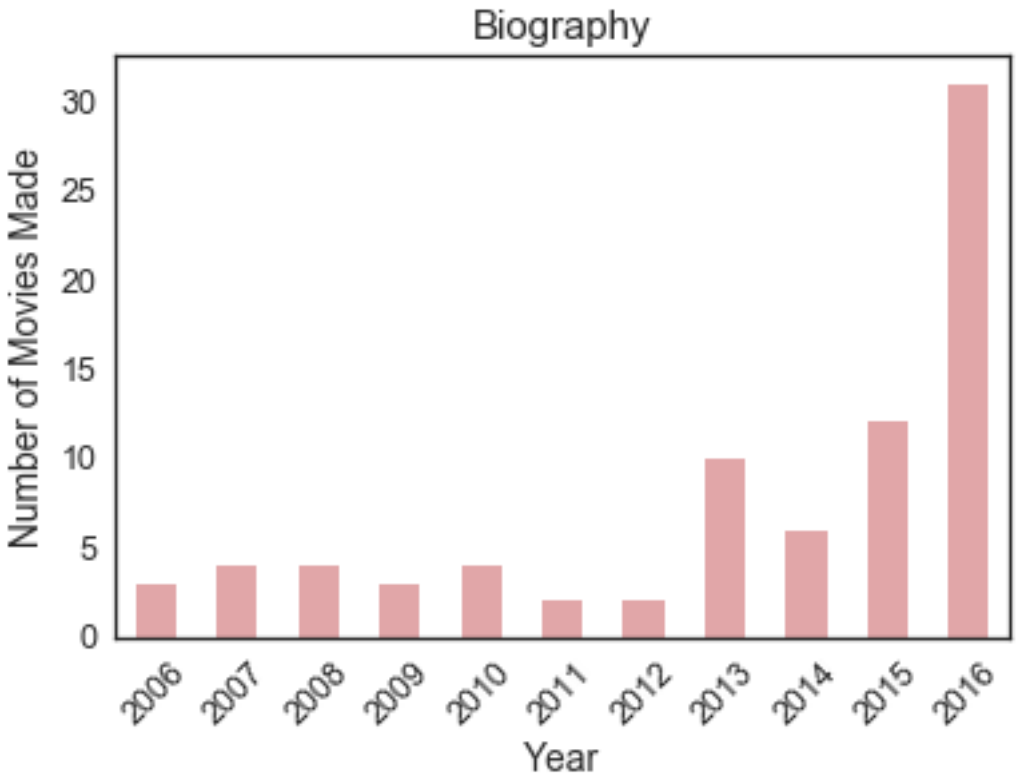

Romance
Number of Movies Made
0
5
10
15
20
25
30
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

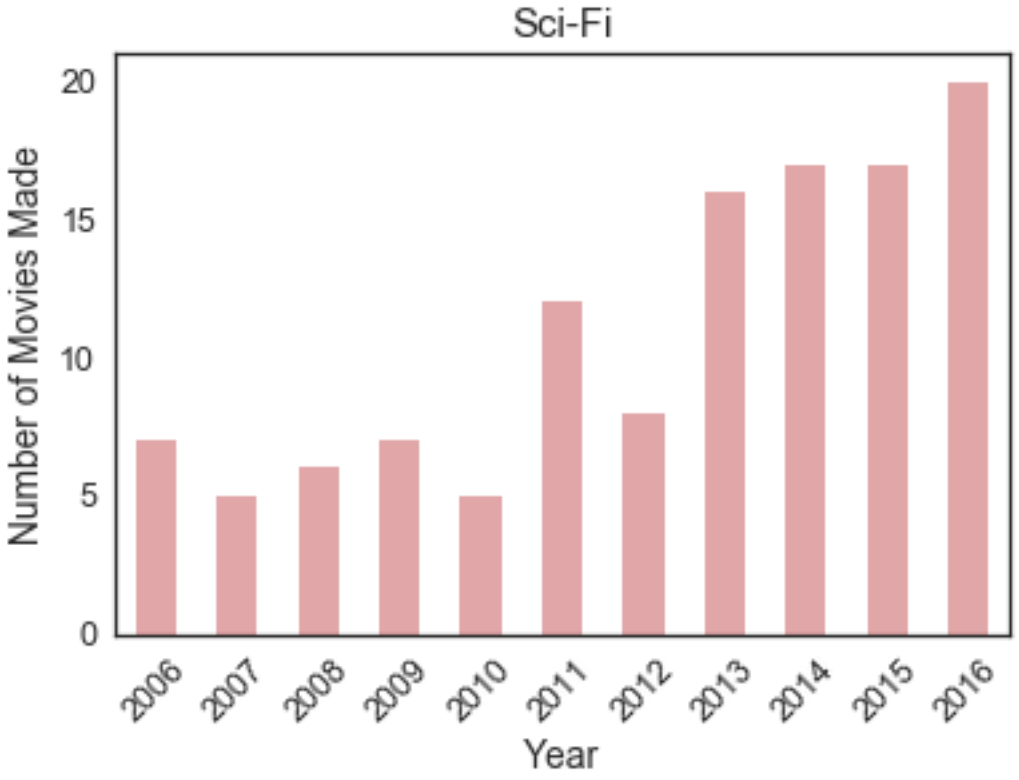

Action
Number of Movies Made
0
10
20
30
40
50
60
70
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

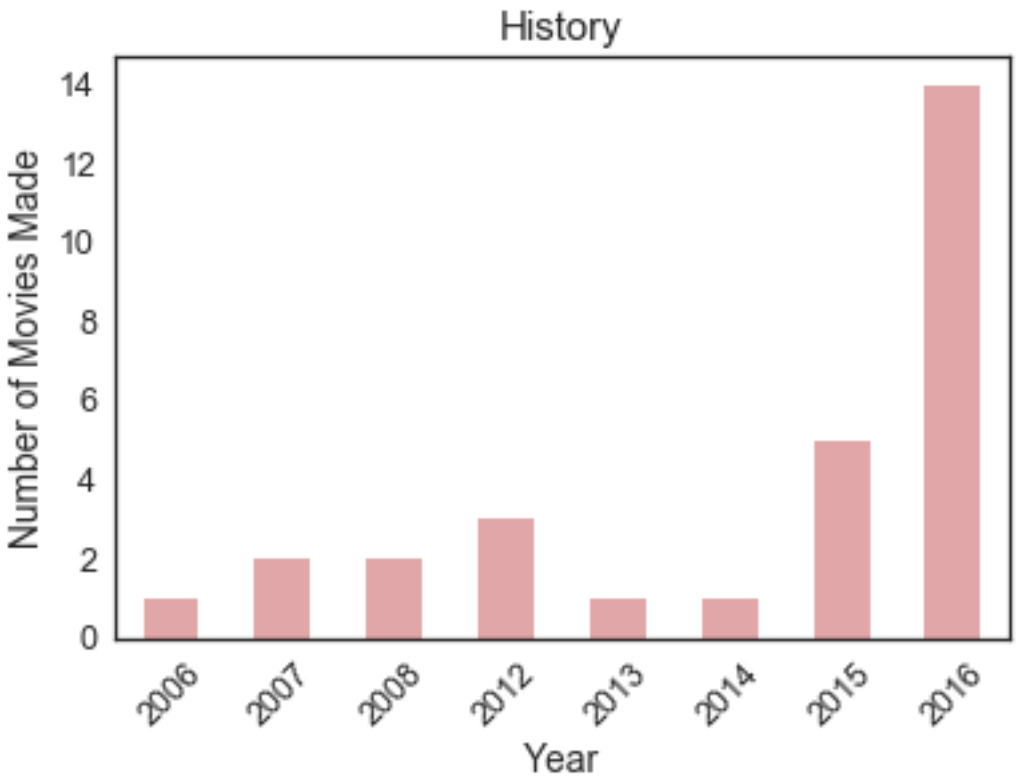

Mystery
Number of Movies Made
0
5
10
15
20
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

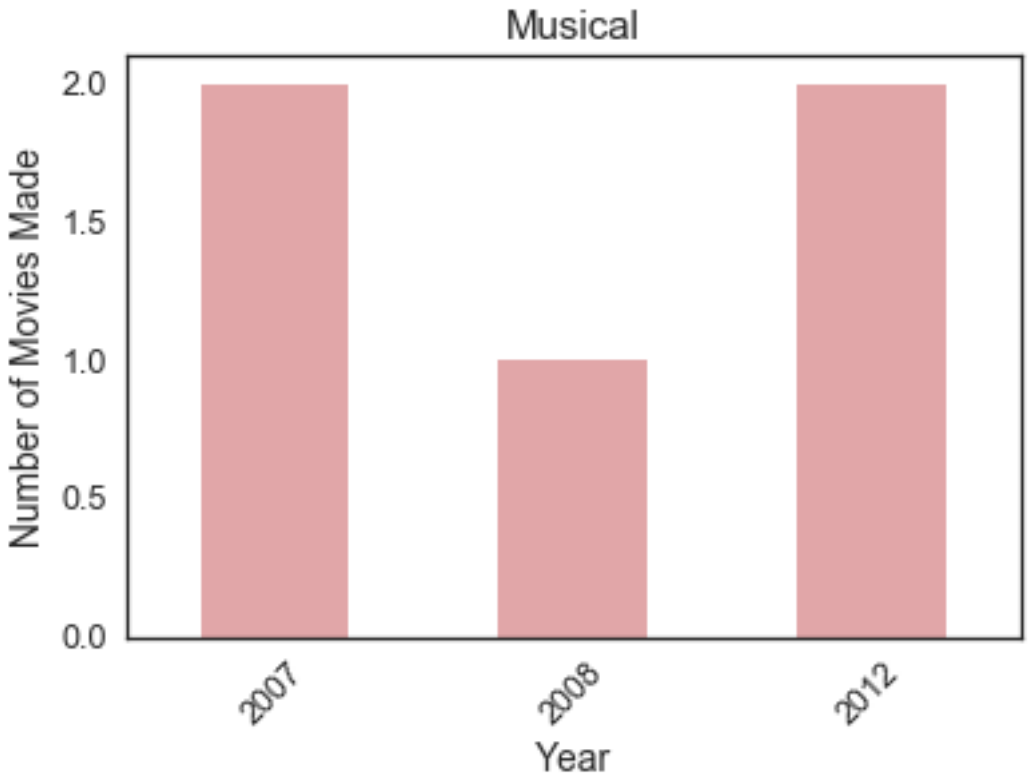

Family
Number of Movies Made
0
2
4
6
8
10
12
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

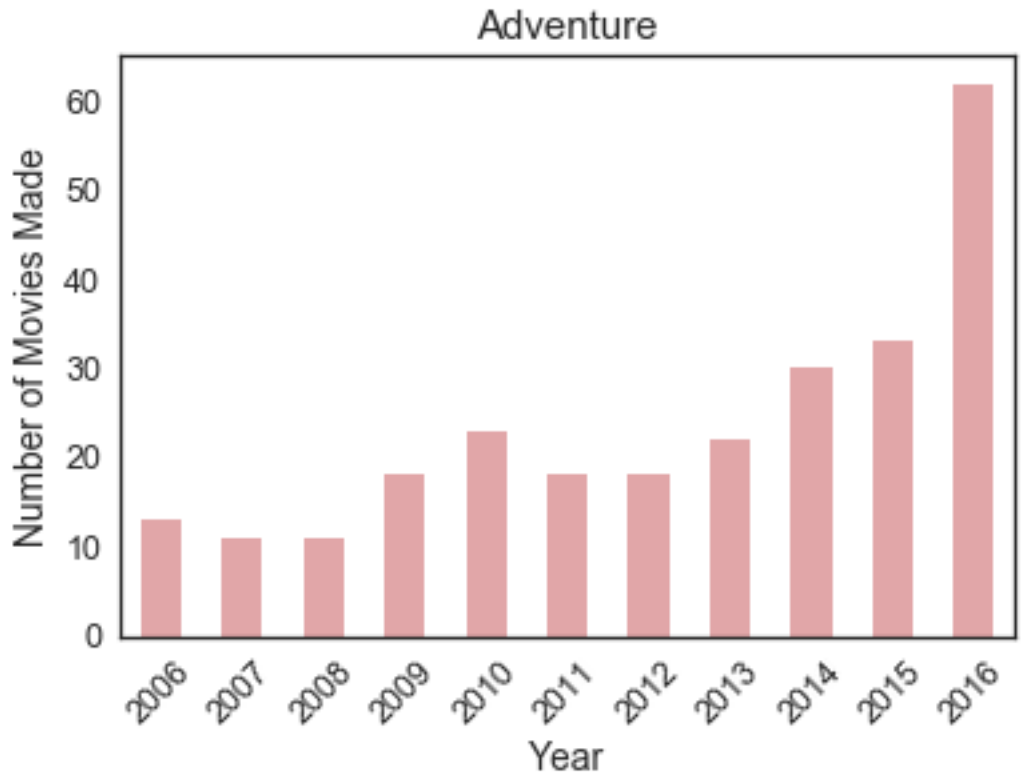

Drama
Number of Movies Made
150
125
100
75
50
25
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

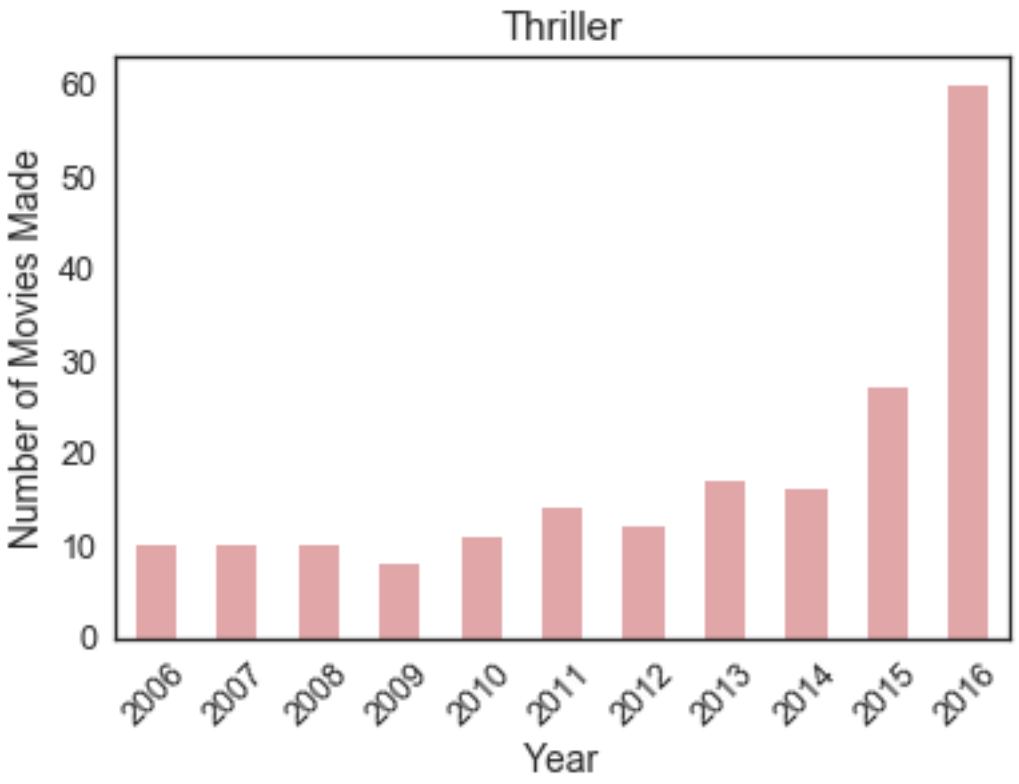

Biography
Number of Movies Made
0
5
10
15
20
25
30
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

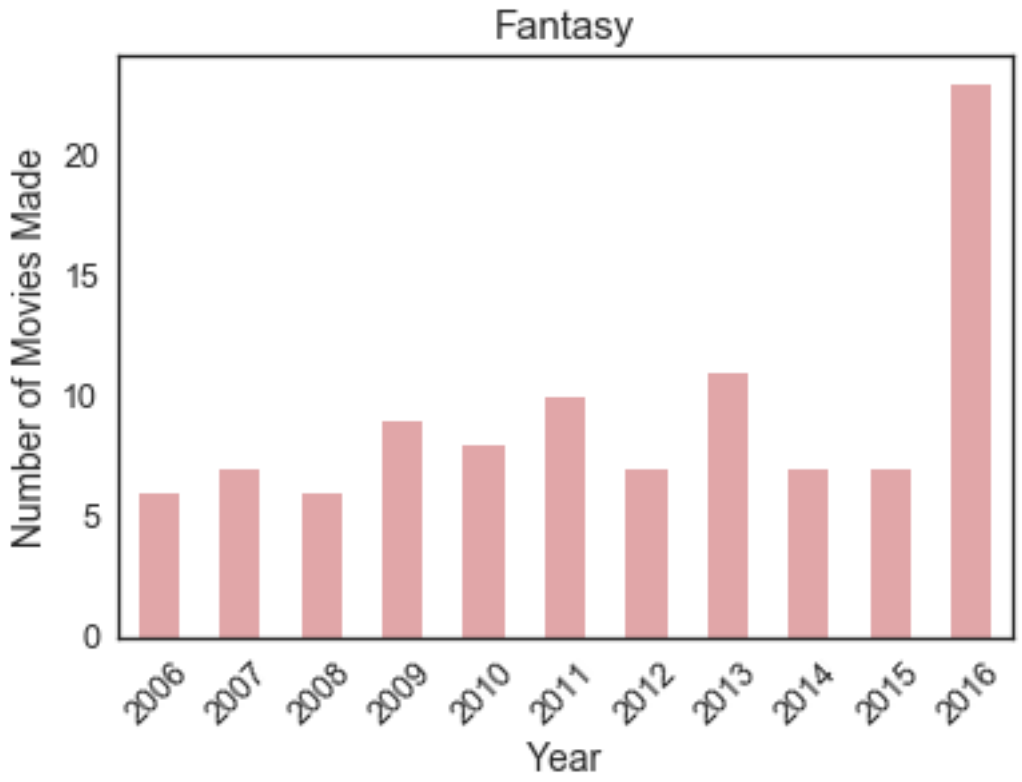

Sci-Fi
Number of Movies Made
0
5
10
15
20
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

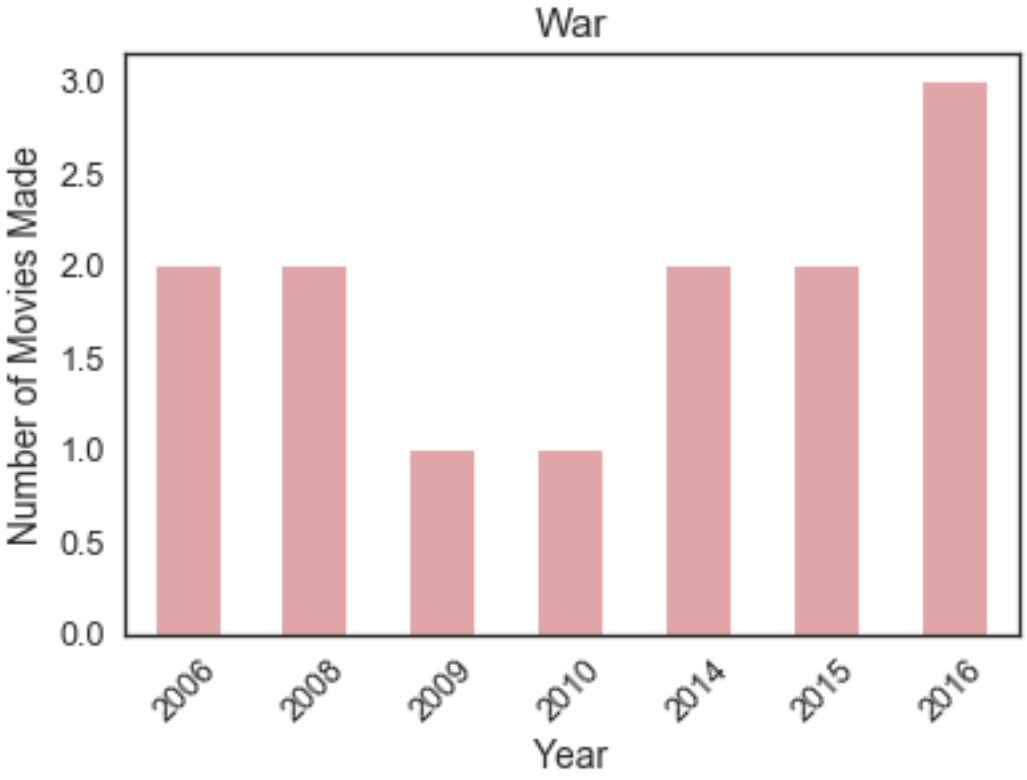

History
Number of Movies Made
0
2
4
6
8
10
12
14
2006
2007
2008
2012
2013
2014
2015
2016
Year

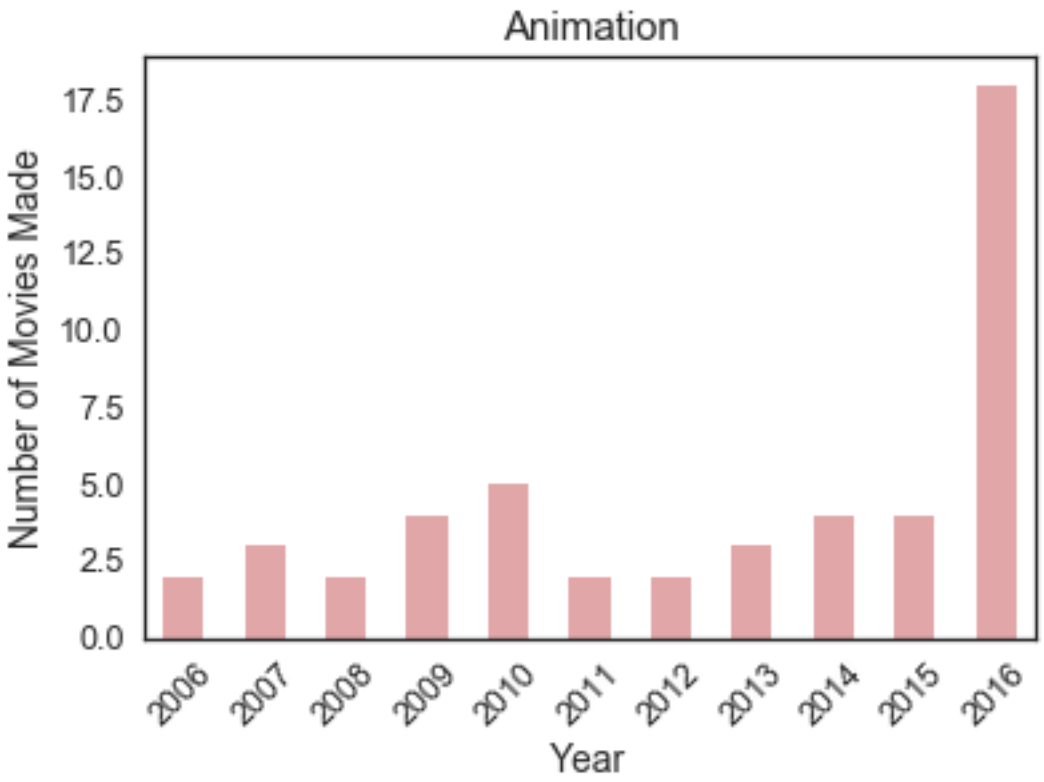

Musical
Number of Movies Made
2.0
1.5
1.0
0.5
0.0
2007
2008
2012
Year

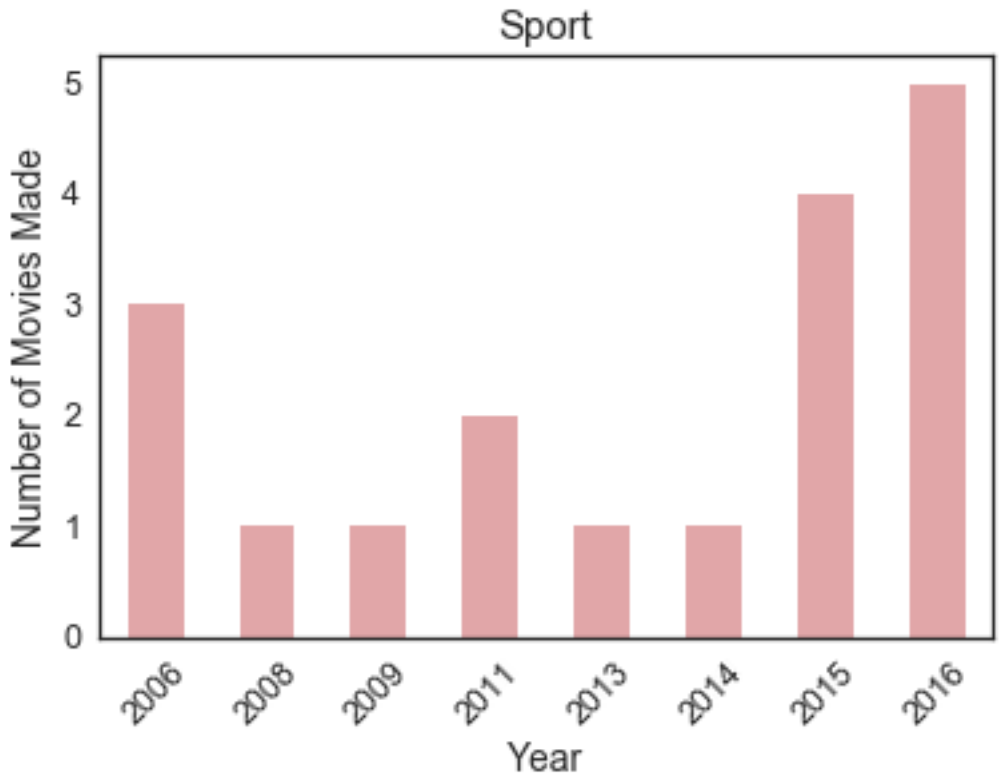

Adventure
Number of Movies Made
60
50
40
30
20
10
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

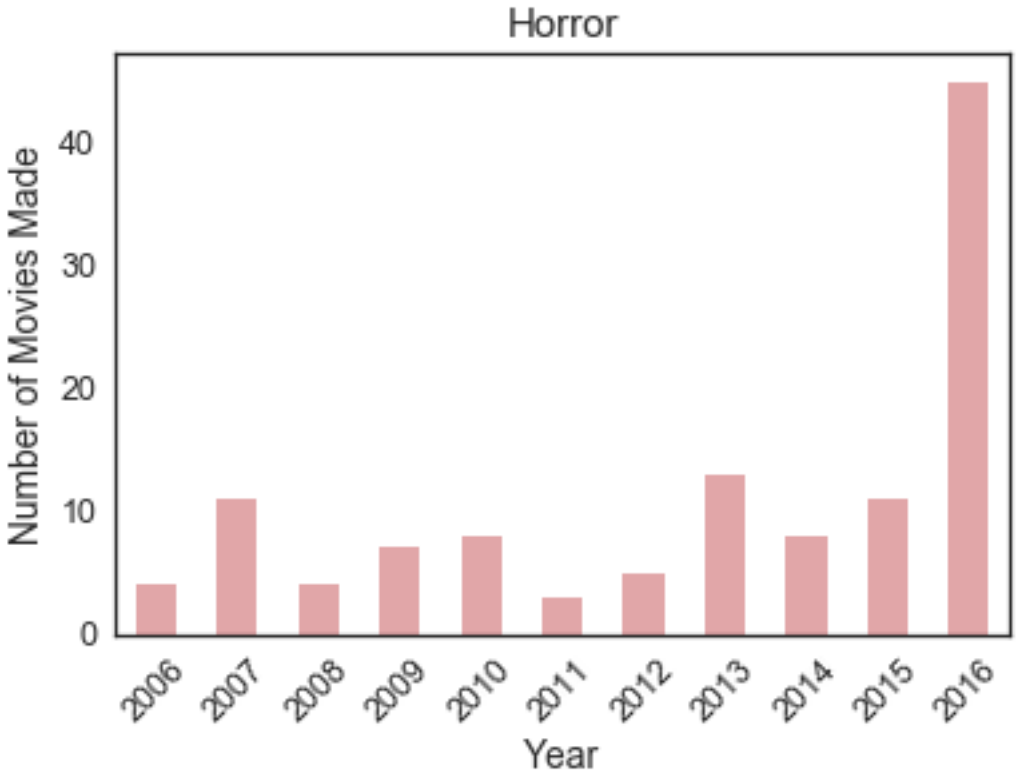

Thriller
Number of Movies Made
0
10
20
30
40
50
60
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

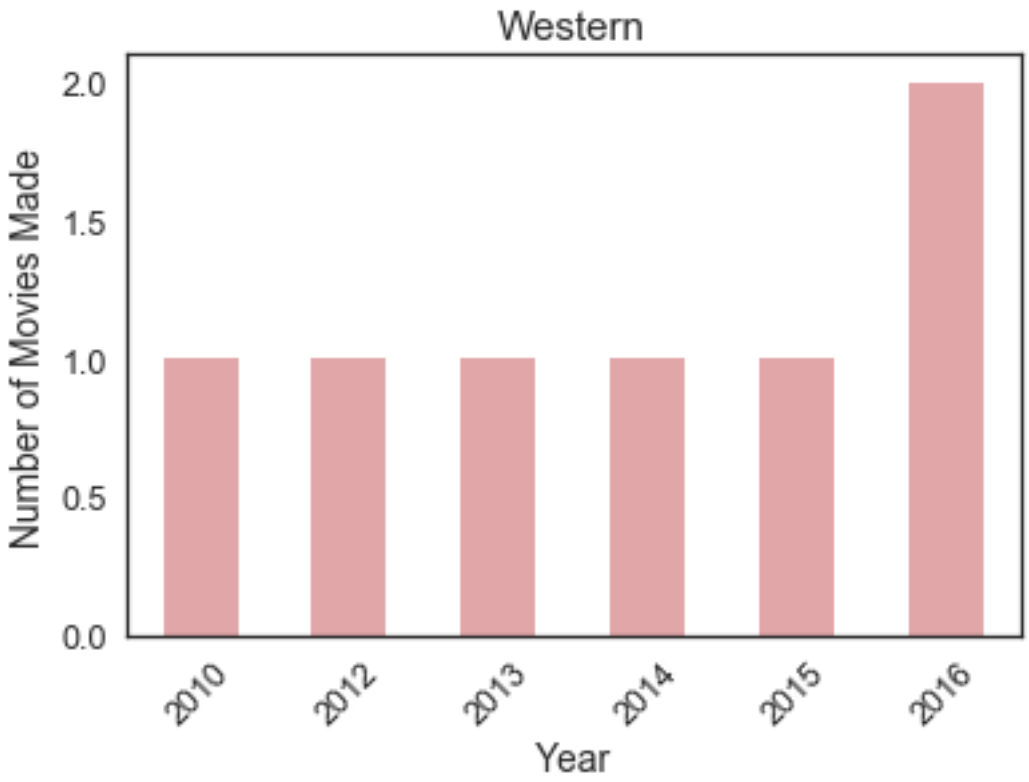

Fantasy
Number of Movies Made
0
5
10
15
20
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

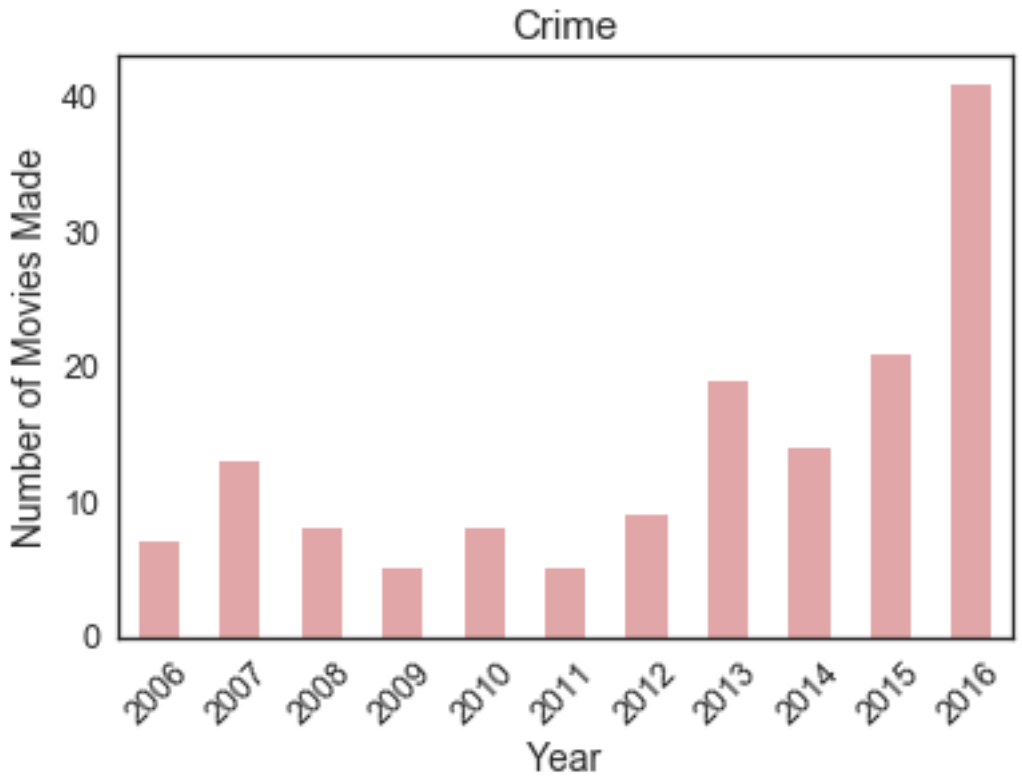

War
Number of Movies Made
0.0
0.5
1.0
1.5
2.0
2.5
3.0
2006
2008
2009
2010
2014
2015
2016
Year


Animation
Number of Movies Made
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year


Sport
Number of Movies Made
0
1
2
3
4
5
2006
2008
2009
2011
2013
2014
2015
2016
Year


Horror
Number of Movies Made
0
10
20
30
40
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year


Western
Number of Movies Made
2.0
1.5
1.0
0.5
0.0
2010
2012
2013
2014
2015
2016
Year



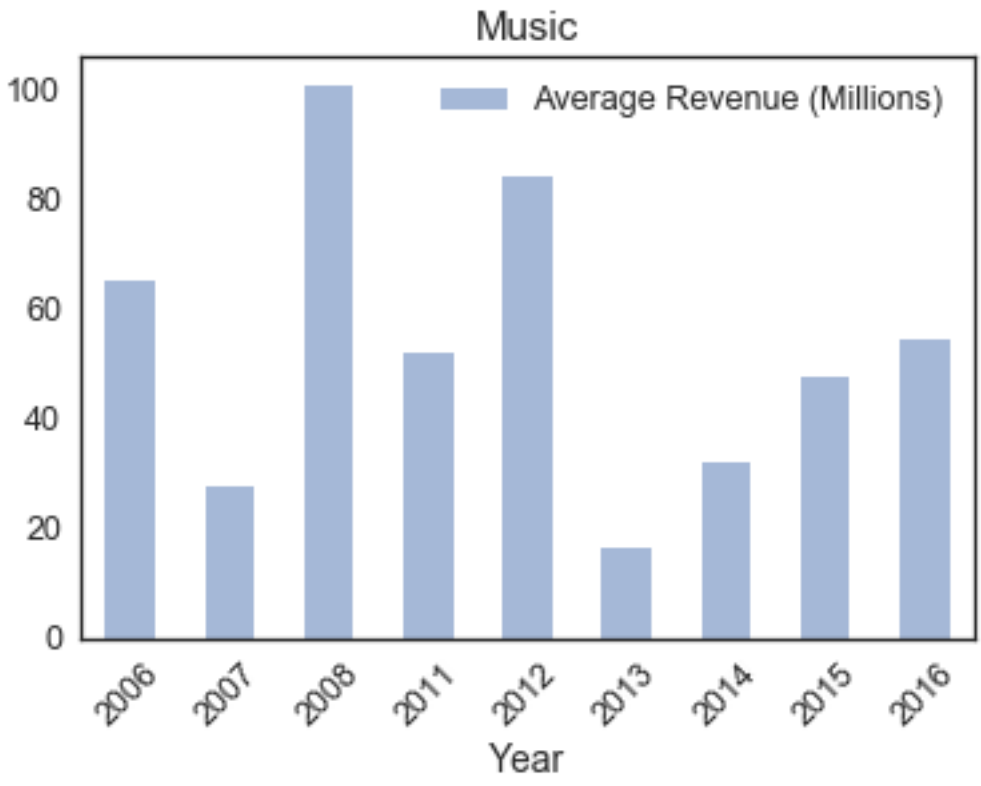
As all bar charts show above. Almost all kinds of moive trend to increasing their production as time going.

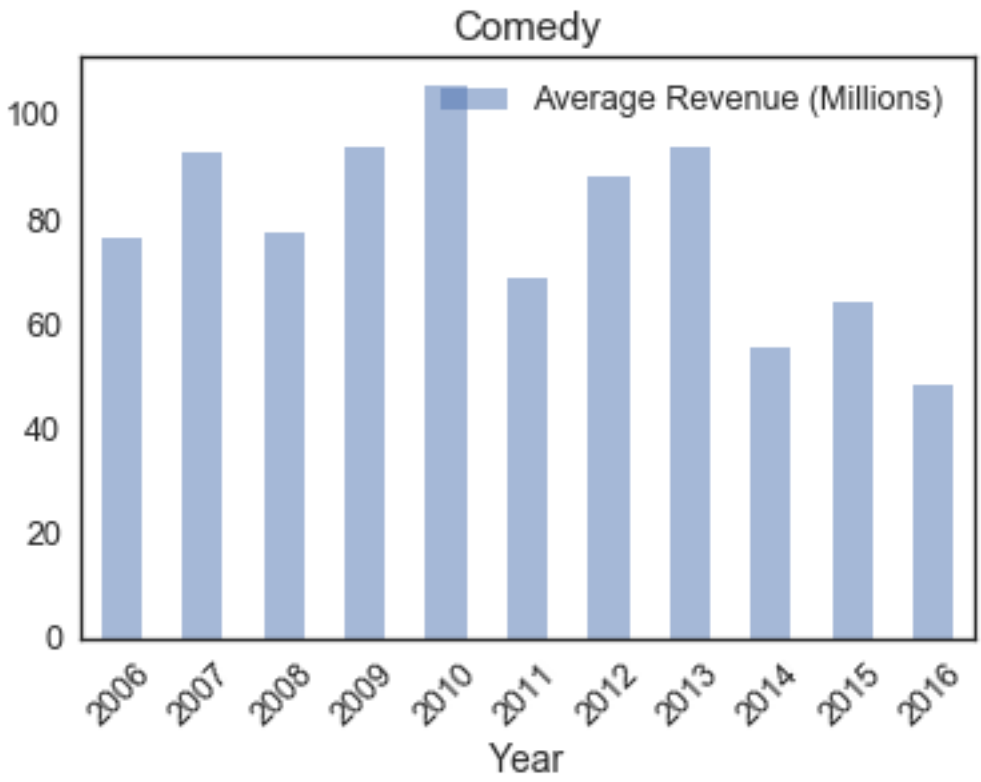
3.3.3 Question

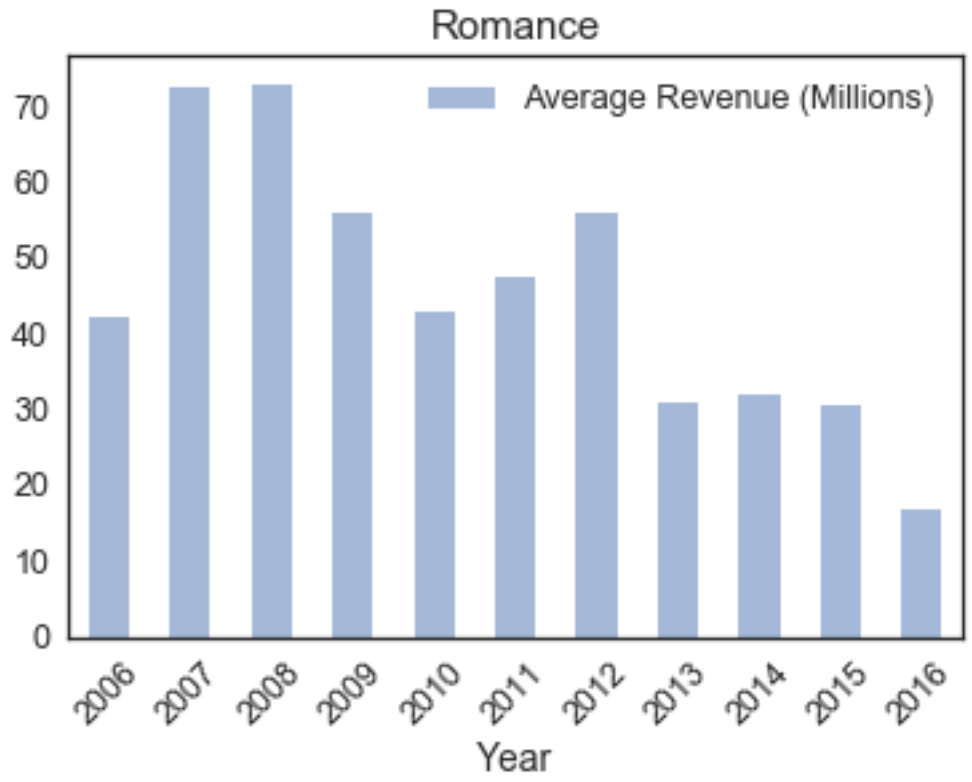
However, does it means all kinds of moive are become easier to make money than before? For answering this question, let's calculate the average revenue of different kind of moives. And sort them by year to draw bar charts.

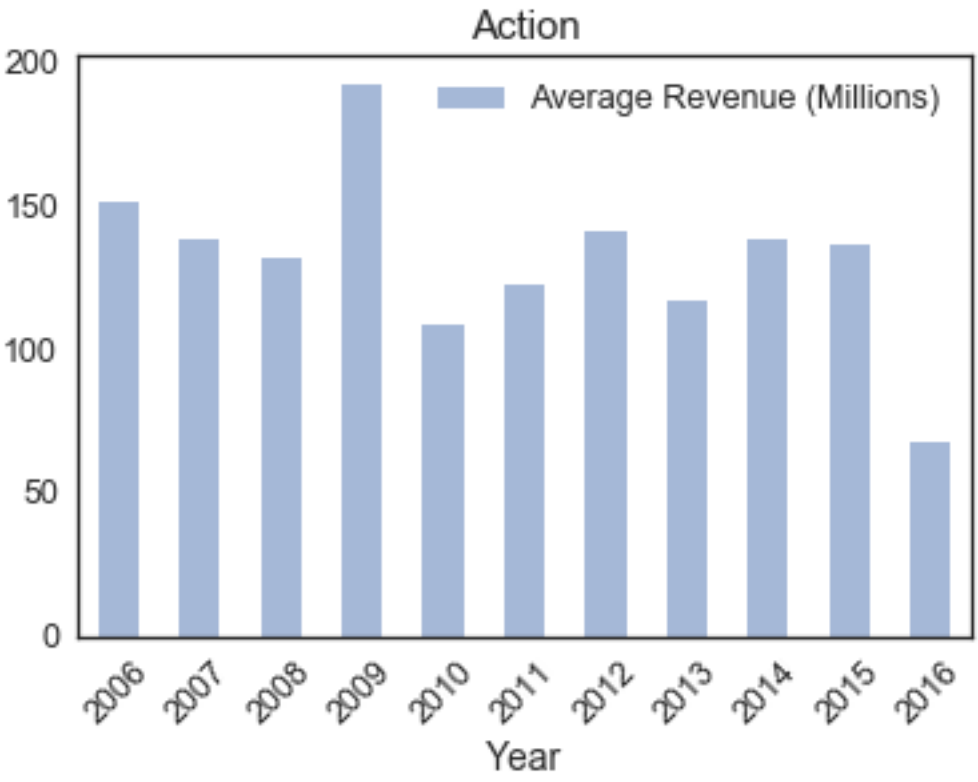
```
In [6]: #Count the average revenue of each genre of film by year

        year={'Year':[2006,2007,2008,2009,2010,2011,2012,2013,2014,2015,2016]}
        YMR=pd.DataFrame(year)
        for genre in individual_genres:
            current_genre = imdb['Genre'].str.contains(genre).fillna(False)
            df = imdb[current_genre]
            genre_revenue=df[['Year','Revenue (Millions)']].fillna(0)
            GR=genre_revenue.groupby('Year')['Revenue (Millions)'].agg(['sum','count
                ']).fillna(0)
            GR['Average Revenue (Millions)']=GR['sum']/GR['count']
            GR.plot(y='Average Revenue (Millions)',kind='bar',
                color='b', alpha=0.5, rot=45,title=genre)
            sum = genre_revenue['Revenue (Millions)'].sum()
```

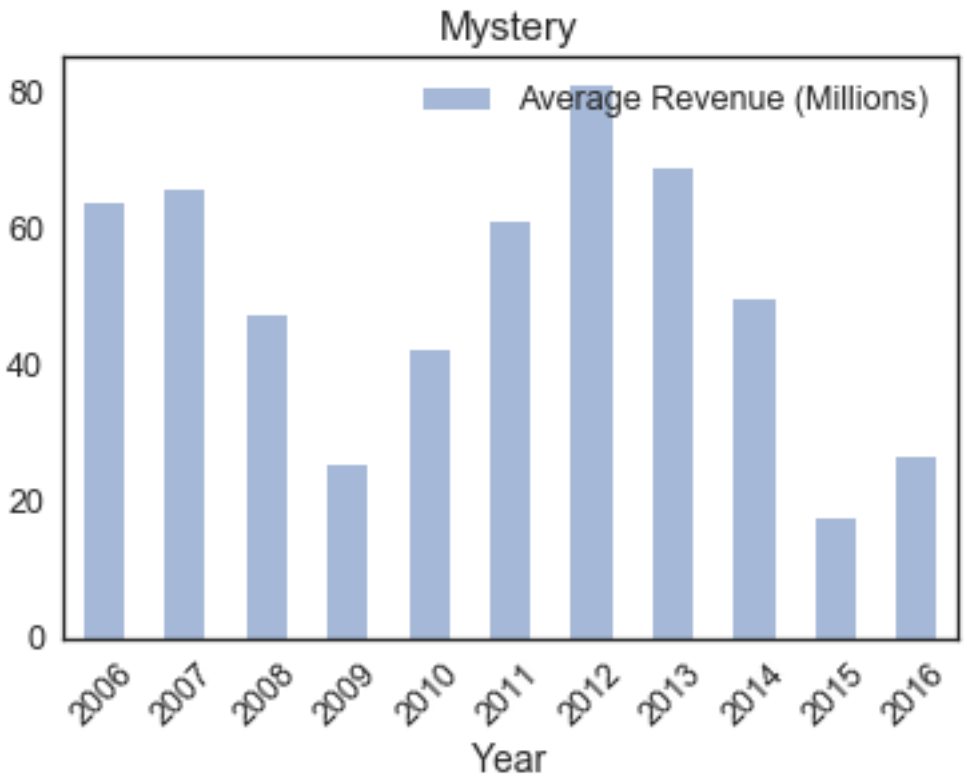
```
count = len(genre_revenue)
AR=GR['Average Revenue (Millions)'].values
if len(AR) == 11:
     YMR[genre]=[AR[0],AR[1],AR[2],AR[3],AR[4],AR[5],AR[6],AR[7],
         AR[8],AR[9],AR[10]]
elif len(AR) == 6:
    YMR[genre]=[np.nan,np.nan,np.nan,np.nan,AR[0],np.nan,
         AR[1],AR[2],AR[3],AR[4],AR[5]]
elif len(AR) ==3:
    YMR[genre]=[np.nan,AR[0],AR[1],np.nan,np.nan,np.nan,
         AR[2],np.nan,np.nan,np.nan,np.nan]
elif len(AR) ==9:
    YMR[genre]=[AR[0],AR[1],AR[2],np.nan,np.nan,
         AR[3],AR[4],AR[5],AR[6],AR[7],AR[8]]
elif len(AR) ==7:
    YMR[genre]=[AR[0],np.nan,AR[1],AR[2],AR[3],np.nan,np.nan,np.nan,
         AR[4],AR[5],AR[6]]
elif len(AR) ==8:
    if genre == 'Western':
        YMR[genre]=[np.nan,np.nan,np.nan,np.nan,AR[0],np.nan,AR[1],
            AR[2],AR[3],AR[4],AR[5]]
    else:
        YMR[genre]=[AR[0],AR[1],AR[2],np.nan,np.nan,np.nan,AR[3],AR[4],
            AR[5],AR[6],AR[7]]
```

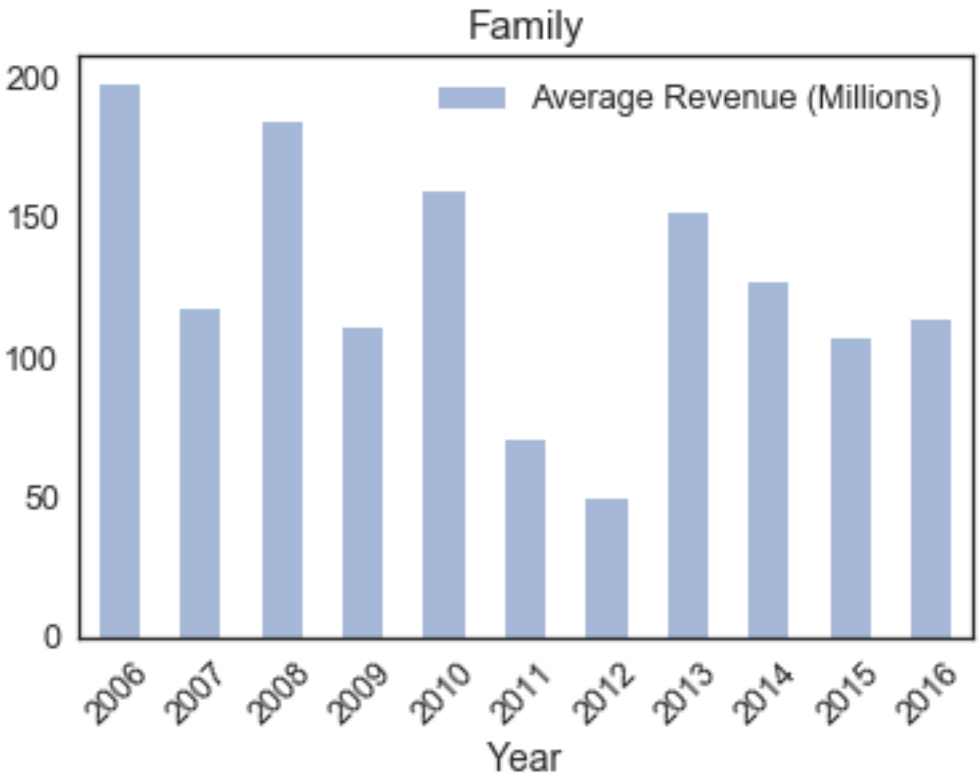


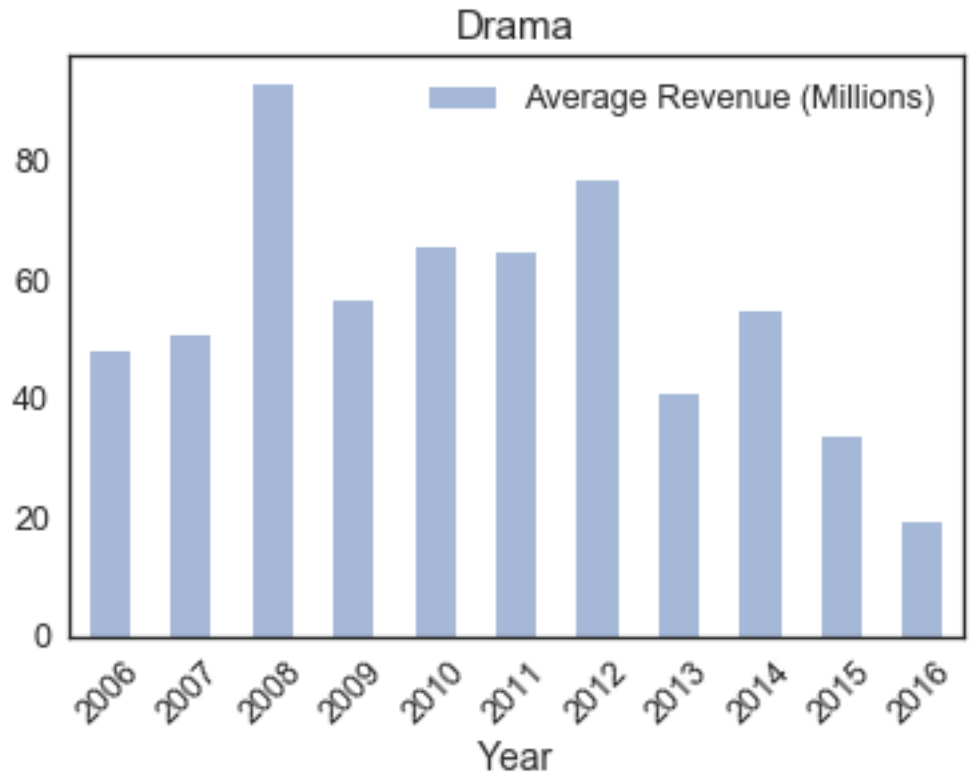

Comedy
Average Revenue (Millions)
100
80
60
40
20
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

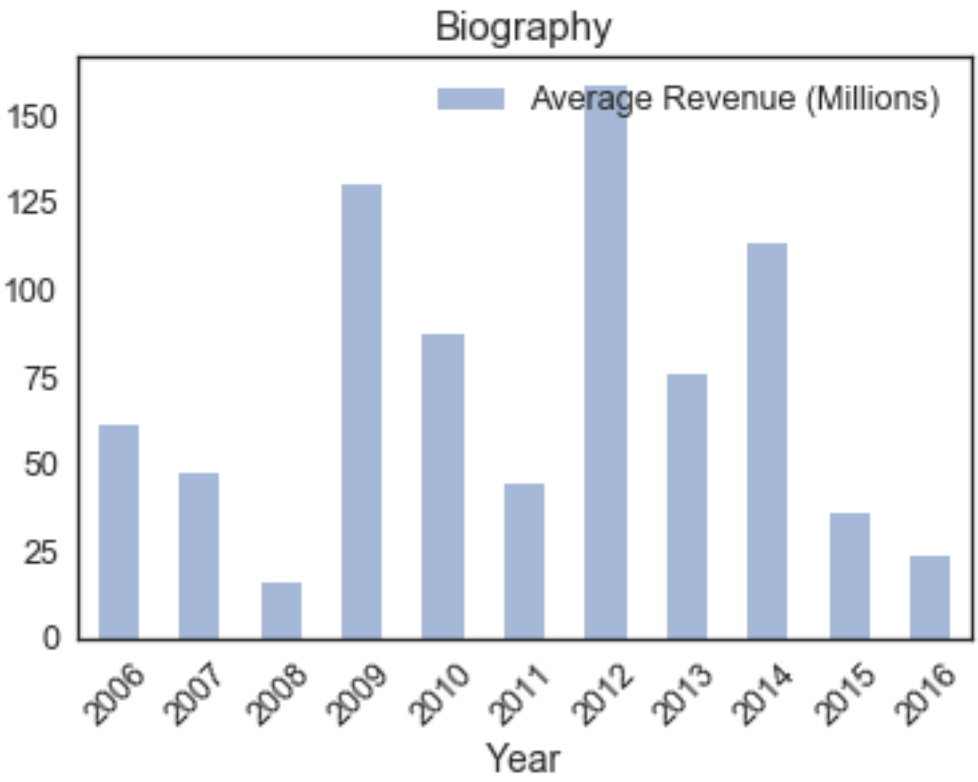

Romance
Average Revenue (Millions)
70
60
50
40
30
20
10
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

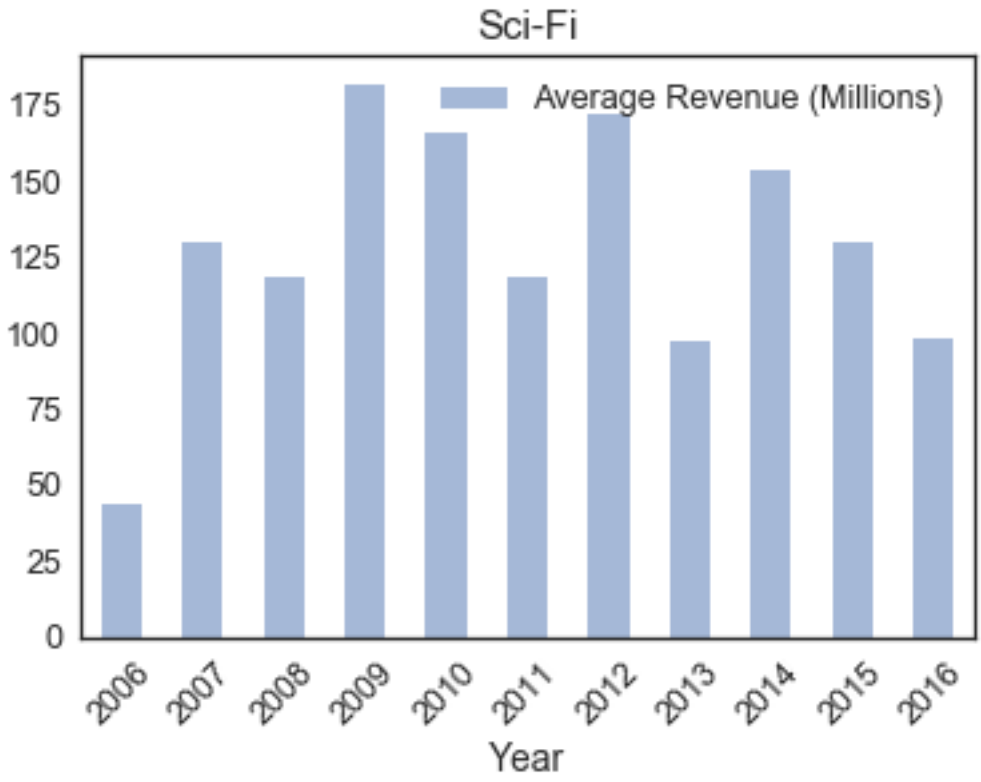

Action
Average Revenue (Millions)
200
150
100
50
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

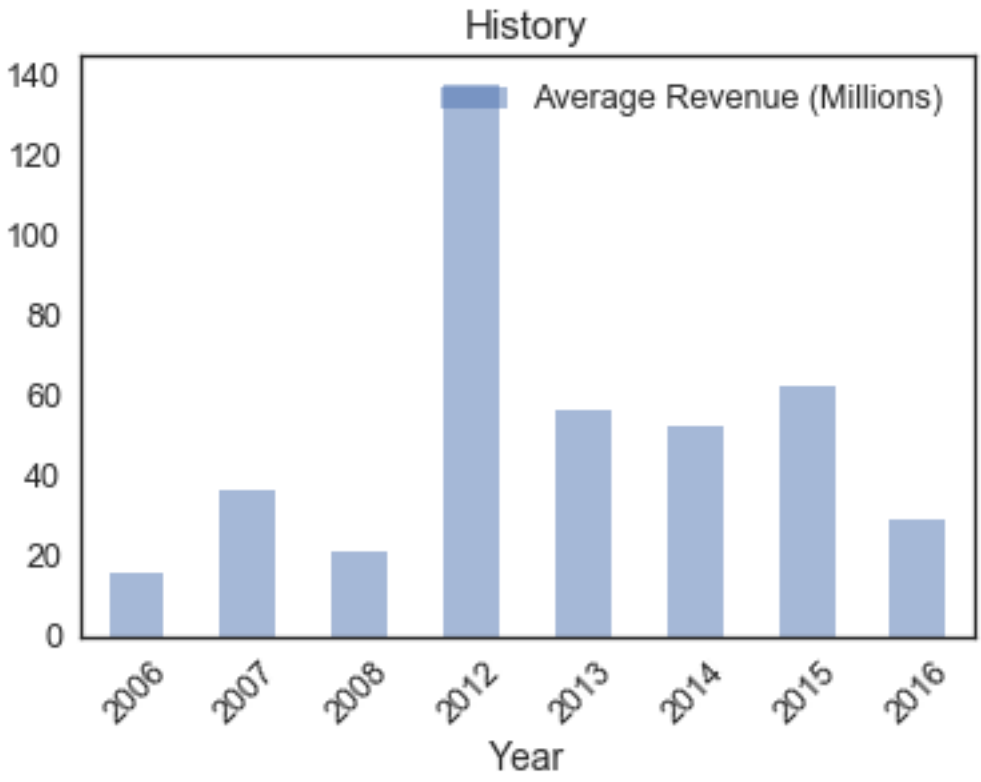

Mystery
Average Revenue (Millions)
80
60
40
20
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

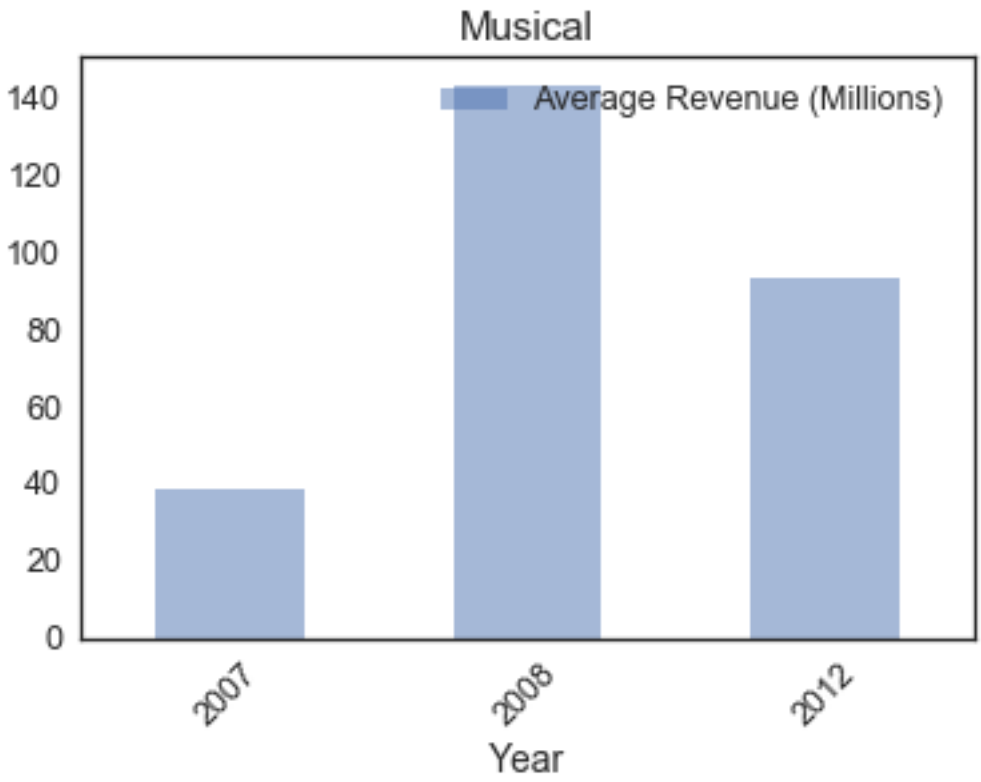

Family
Average Revenue (Millions)
200
150
100
50
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

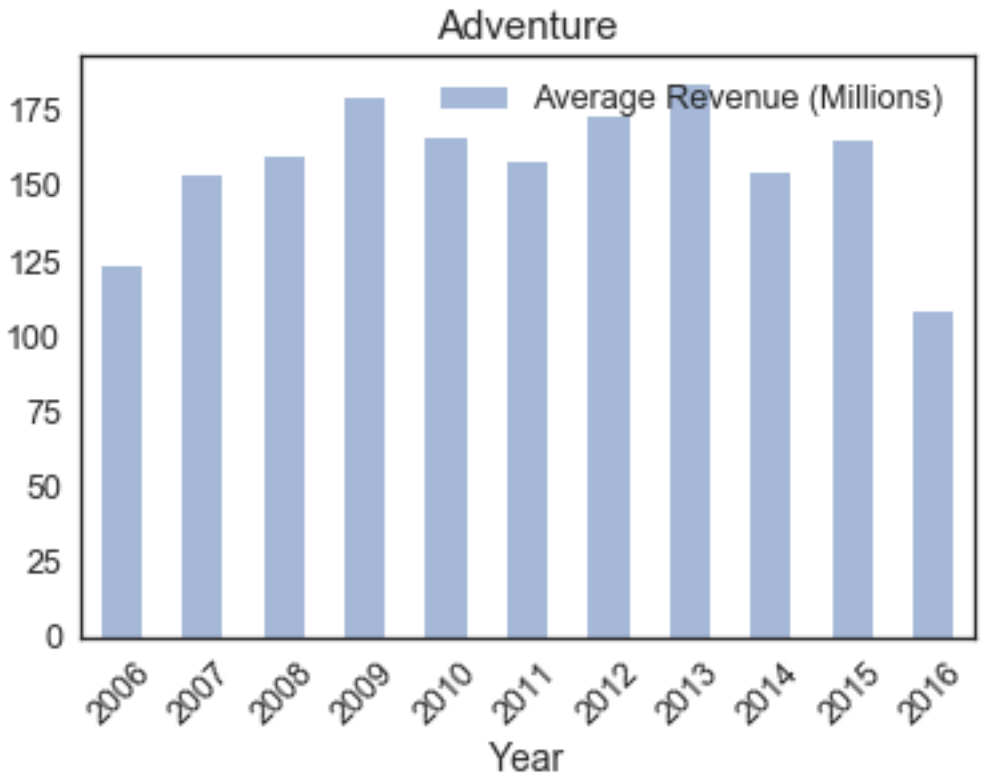

Drama
Average Revenue (Millions)
80
60
40
20
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

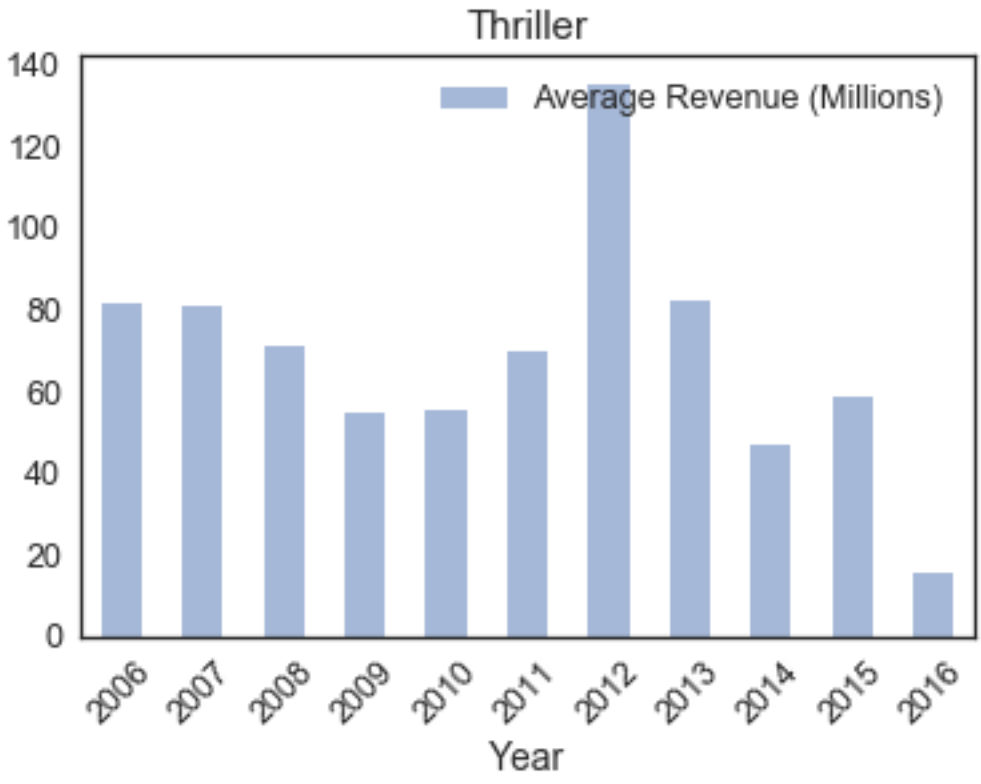

Biography
Average Revenue (Millions)
150
125
100
75
50
25
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

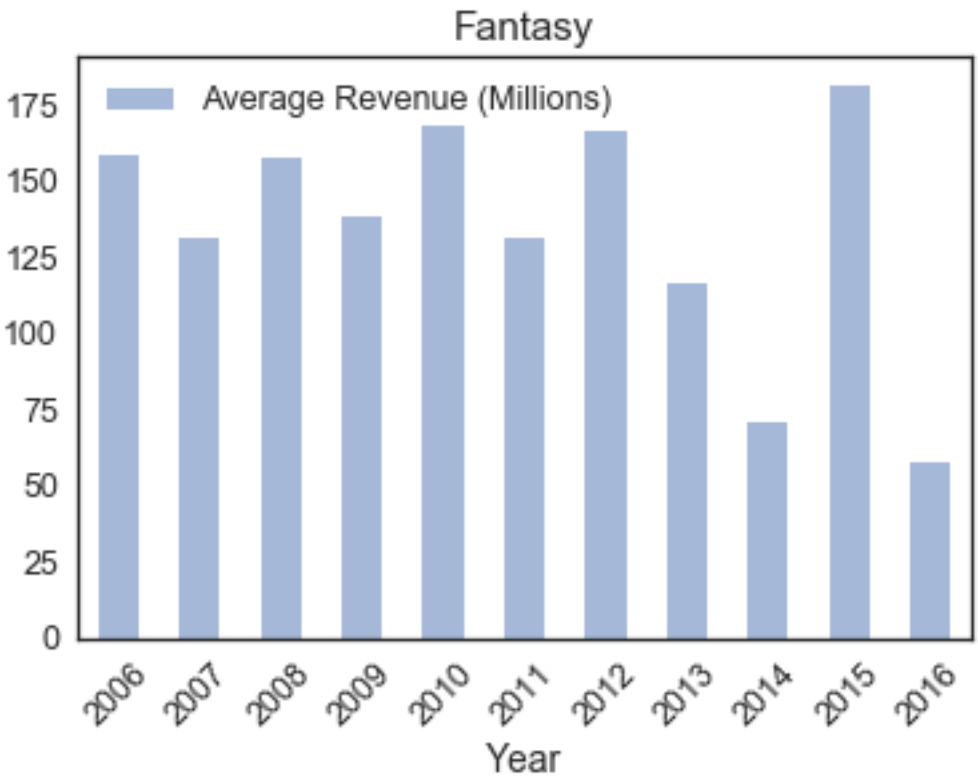

Sci-Fi
Average Revenue (Millions)
175
150
125
100
75
50
25
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

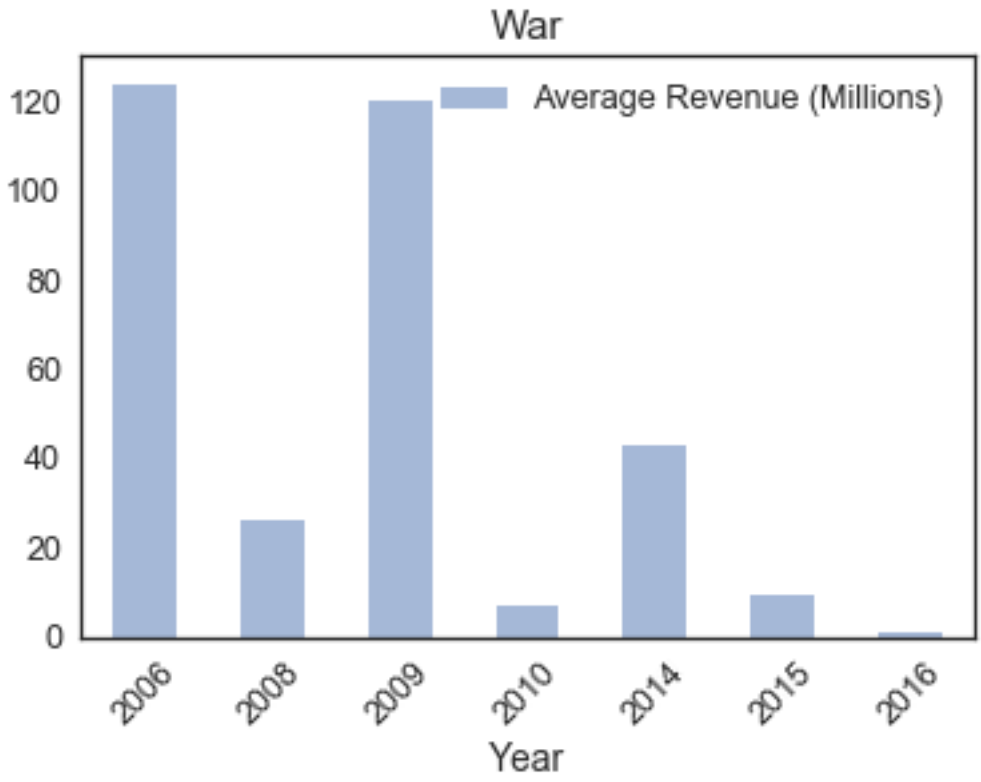

History
Average Revenue (Millions)
140
120
100
80
60
40
20
0
2006
2007
2008
2012
2013
2014
2015
2016
Year

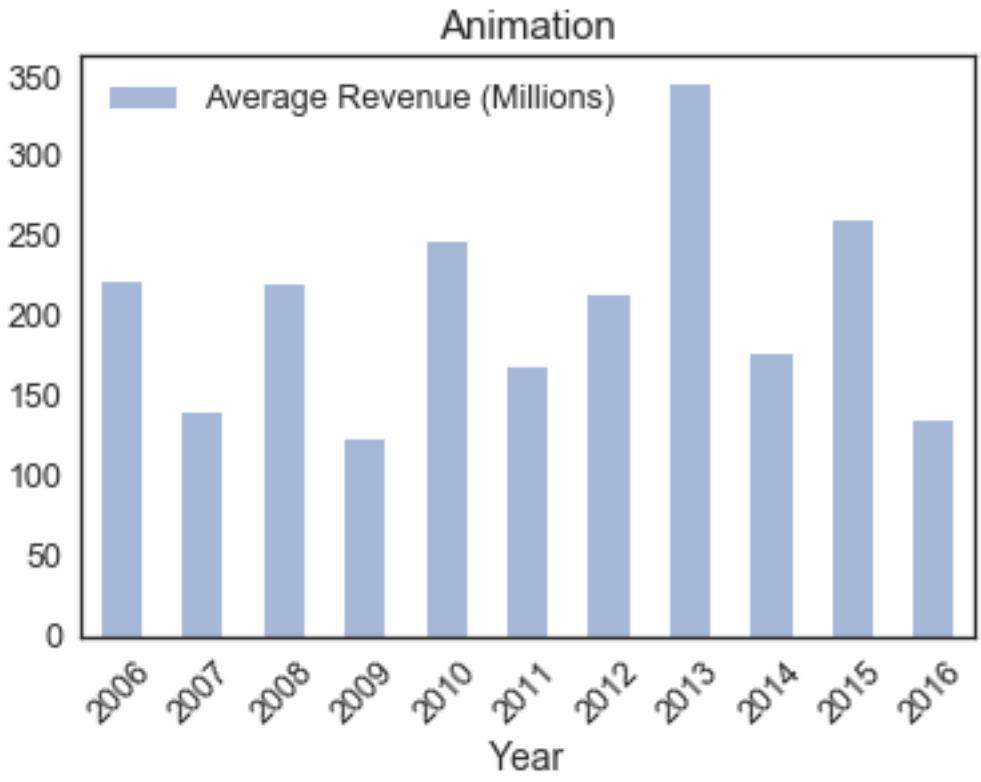

Musical
Average Revenue (Millions)
140
120
100
80
60
40
20
0
2007
2008
2012
Year

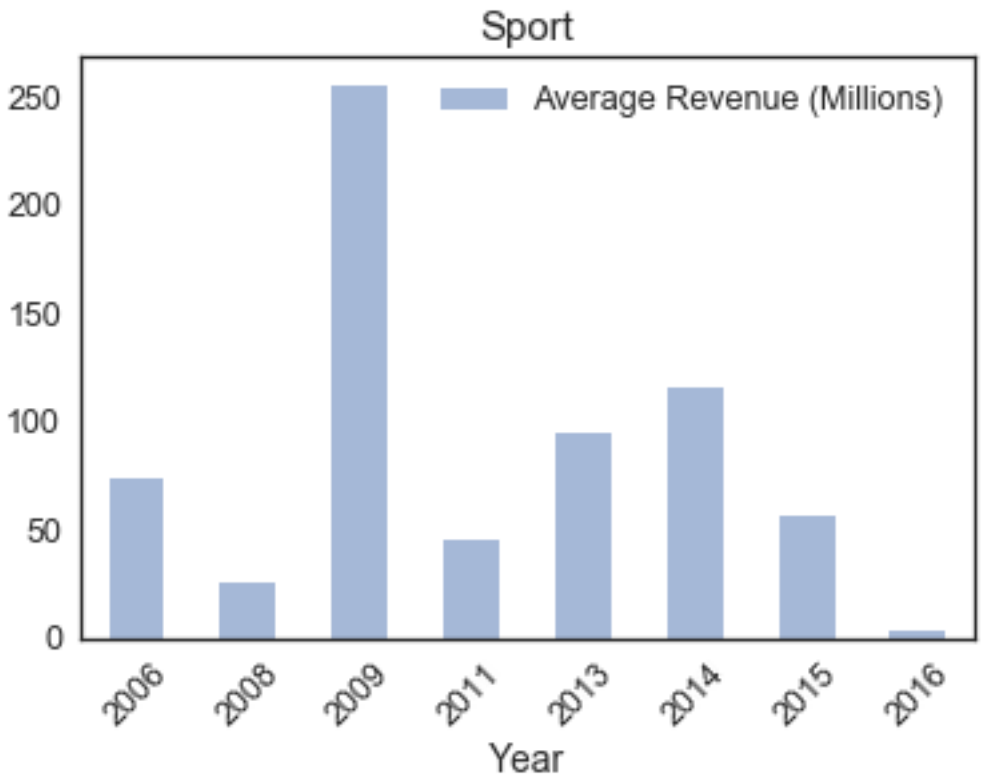

Adventure
Average Revenue (Millions)
175
150
125
100
75
50
25
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

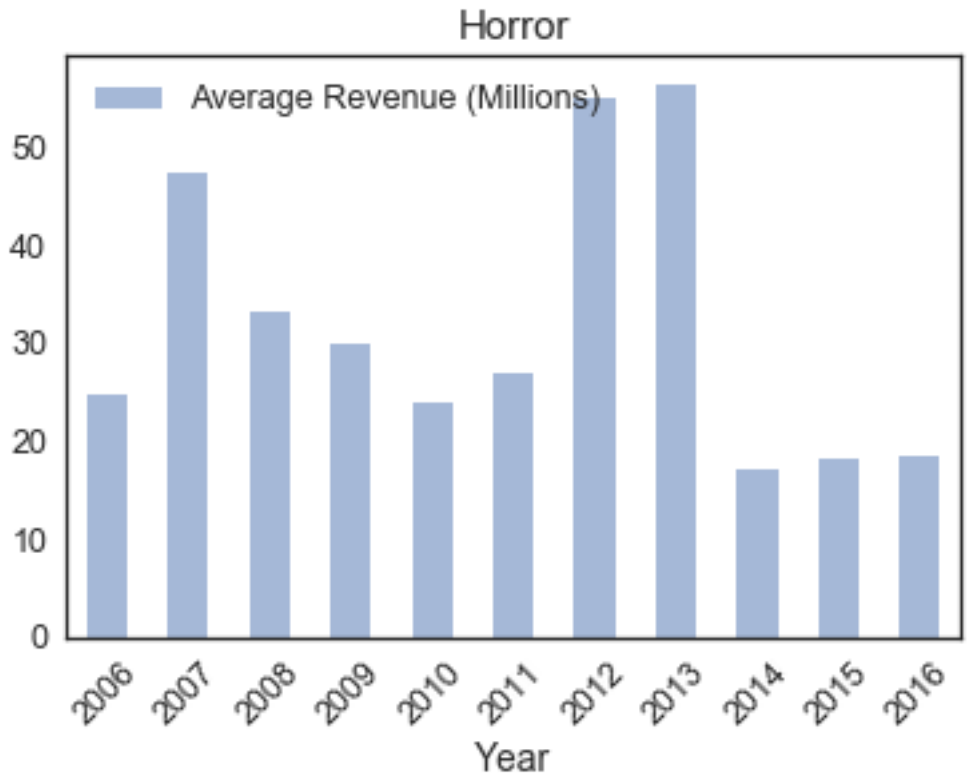

Thriller
Average Revenue (Millions)
140
120
100
80
60
40
20
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

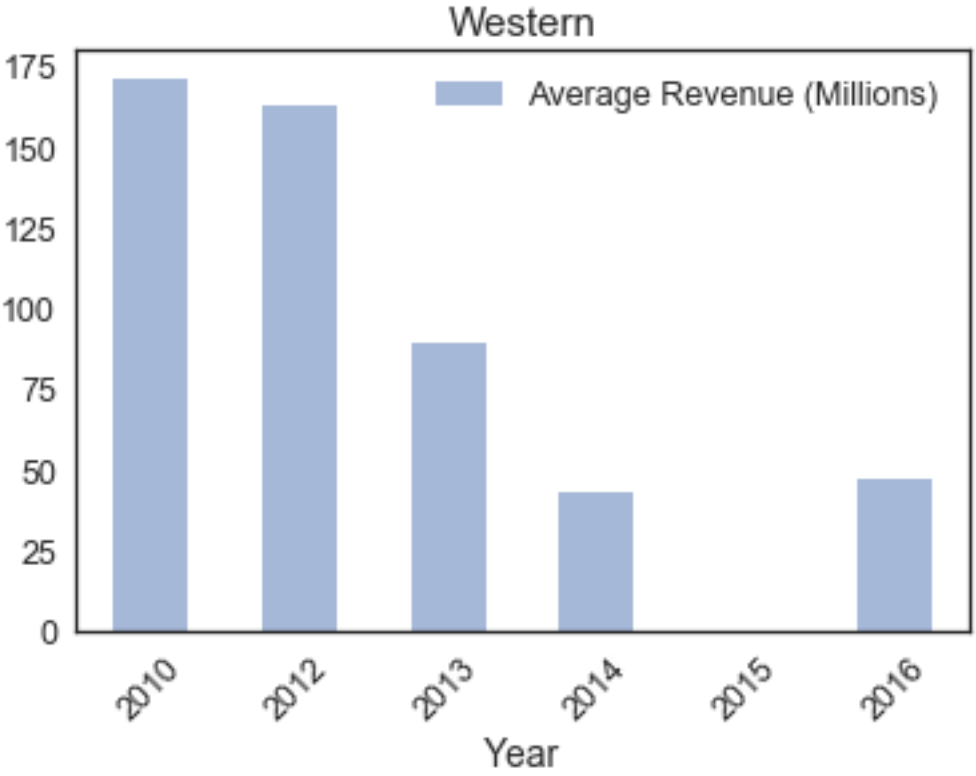

Fantasy
Average Revenue (Millions)
175
150
125
100
75
50
25
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

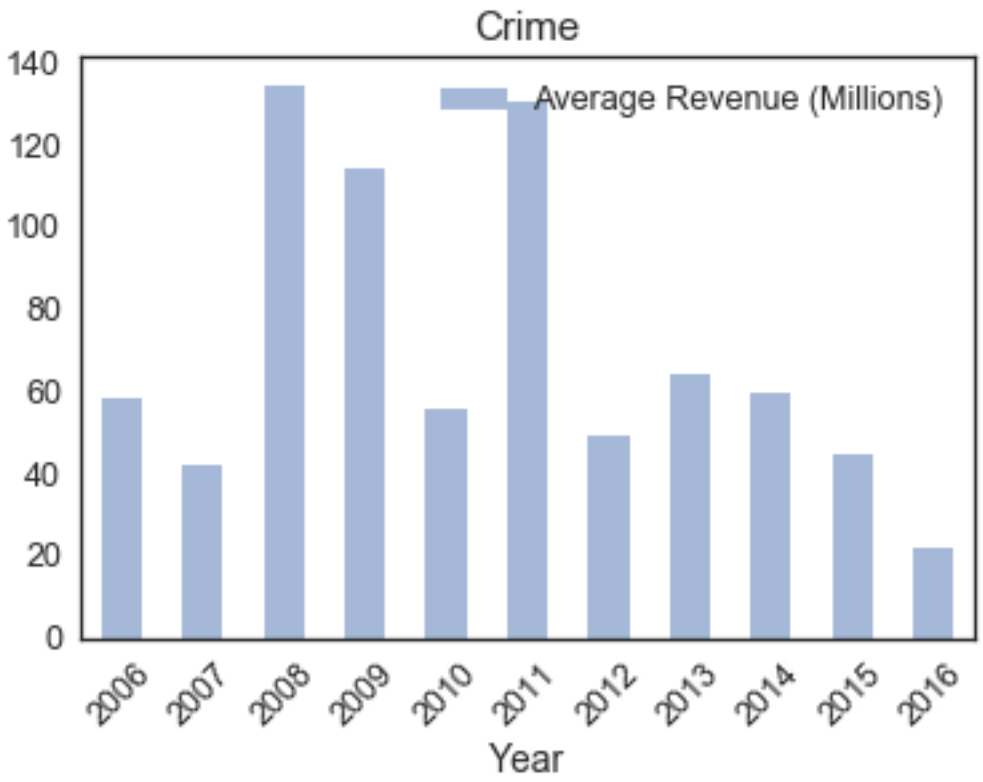

War
Average Revenue (Millions)
120
100
80
60
40
20
0
2006
2008
2009
2010
2014
2015
2016
Year


Animation
Average Revenue (Millions)
350
300
250
200
150
100
50
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year


Sport
Average Revenue (Millions)
250
200
150
100
50
0
2006
2008
2009
2011
2013
2014
2015
2016
Year


Horror
Average Revenue (Millions)
50
40
30
20
10
0
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year


Western
Average Revenue (Millions)
175
150
125
100
75
50
25
0
2010
2012
2013
2014
2015
2016
Year



Above bar charts show us that opposite to the number of moive made. The revenue of each kind of moive is decreasing as time going.
Although the result shows us that moive industry is falling down, we still want to know which genre's moive can make most money.
Here, we get a table of average renvenue of all genres in different years. **(NaN means there have no moive made in that year.)**

```
In [7]: YMR.head(11)
```

Out[7]:

	Year	Music	Comedy	Romance	Action	Mystery	\
0	2006	65.270000	76.336667	42.077500	151.273636	63.836250	
1	2007	27.520000	92.704000	72.525000	138.478333	65.448571	
2	2008	100.855000	77.442500	73.094167	131.270000	47.355000	
3	2009	NaN	93.662857	55.995000	192.460000	25.296250	
4	2010	NaN	105.794444	42.827143	108.455200	41.920000	
5	2011	51.780000	68.814211	47.385625	122.569000	61.068750	
6	2012	84.096667	88.211905	56.084545	140.509524	81.050000	
7	2013	16.170000	93.633043	30.794615	116.272759	68.596154	
8	2014	31.775000	55.254333	31.982222	138.251892	49.429231	
9	2015	47.432500	63.951892	30.486667	136.440571	17.505833	

```
10  2016   54.560000   48.086145  16.657667   67.448533  26.384000

        Family      Drama   Biography      Sci-Fi     ...      Musical  \
0   197.990000  48.170000   61.343333   43.827143     ...          NaN
1   117.103750  50.500000   47.240000  129.854000     ...       38.610
2   183.755000  93.149545   15.692500  118.931667     ...      143.700
3   110.347500  56.290870  129.940000  182.371429     ...          NaN
4   159.753333  65.632692   86.905000  165.740000     ...          NaN
5    70.656667  64.749333   44.395000  118.510000     ...          NaN
6    49.000000  76.583214  159.110000  172.352500     ...       93.645
7   151.730000  40.752273   75.484000   97.255000     ...          NaN
8   127.000000  54.544000  113.780000  153.545294     ...          NaN
9   106.370000  33.529730   36.135833  129.831765     ...          NaN
10  113.081667  19.298086   23.669677   98.070000     ...          NaN

     Adventure    Thriller     Fantasy      War   Animation       Sport  \
0   123.024615   81.673000  158.346667  124.105  221.020000   73.606667
1   153.278182   80.611000  131.707143      NaN  138.770000   24.850000
2   159.570909   71.285000  158.075000   25.875  219.605000  255.950000
3   179.450556   54.971250  138.285556  120.520  123.407500         NaN
4   165.895652   55.117273  168.007500    6.860  246.604000         NaN
5   157.611667   69.570000  131.715000      NaN  167.535000         NaN
6   172.577778  135.587500  166.368571      NaN  213.345000   44.630000
7   184.101818   82.172353  116.452727      NaN  345.760000   95.000000
8   154.687333   46.583125   70.882857   42.855  176.850000  115.600000
9   164.933636   58.363333  181.960000    9.350  259.877500   56.357500
10  107.889677   15.741167   57.406087    0.860  134.296667    2.754000

       Horror  Western       Crime
0   24.682500      NaN   58.191429
1   47.376364      NaN   42.171538
2   33.157500      NaN  134.736250
3   29.895714      NaN  114.250000
4   23.941250   171.03   55.502500
5   26.920000      NaN  130.348000
6   54.896000   162.80   49.362222
7   56.520769    89.29   64.073684
8   17.073750    42.62   59.431429
9   18.185455     0.00   44.389048
10  18.525556    46.69   22.153171

[11 rows x 21 columns]
```

For easier to do operation on this table, we **pop** the column of 'year'. And take its **transformation**.

```
In [8]: YMR.pop('Year')
        YMR.T
```

```
Out[8]:                  0          1          2          3          4   \
```

Music	65.270000	27.520000	100.855000	NaN	NaN
Comedy	76.336667	92.704000	77.442500	93.662857	105.794444
Romance	42.077500	72.525000	73.094167	55.995000	42.827143
Action	151.273636	138.478333	131.270000	192.460000	108.455200
Mystery	63.836250	65.448571	47.355000	25.296250	41.920000
Family	197.990000	117.103750	183.755000	110.347500	159.753333
Drama	48.170000	50.500000	93.149545	56.290870	65.632692
Biography	61.343333	47.240000	15.692500	129.940000	86.905000
Sci-Fi	43.827143	129.854000	118.931667	182.371429	165.740000
History	15.960000	36.635000	21.255000	NaN	NaN
Musical	NaN	38.610000	143.700000	NaN	NaN
Adventure	123.024615	153.278182	159.570909	179.450556	165.895652
Thriller	81.673000	80.611000	71.285000	54.971250	55.117273
Fantasy	158.346667	131.707143	158.075000	138.285556	168.007500
War	124.105000	NaN	25.875000	120.520000	6.860000
Animation	221.020000	138.770000	219.605000	123.407500	246.604000
Sport	73.606667	24.850000	255.950000	NaN	NaN
Horror	24.682500	47.376364	33.157500	29.895714	23.941250
Western	NaN	NaN	NaN	NaN	171.030000
Crime	58.191429	42.171538	134.736250	114.250000	55.502500

	5	6	7	8	9	\
Music	51.780000	84.096667	16.170000	31.775000	47.432500	
Comedy	68.814211	88.211905	93.633043	55.254333	63.951892	
Romance	47.385625	56.084545	30.794615	31.982222	30.486667	
Action	122.569000	140.509524	116.272759	138.251892	136.440571	
Mystery	61.068750	81.050000	68.596154	49.429231	17.505833	
Family	70.656667	49.000000	151.730000	127.000000	106.370000	
Drama	64.749333	76.583214	40.752273	54.544000	33.529730	
Biography	44.395000	159.110000	75.484000	113.780000	36.135833	
Sci-Fi	118.510000	172.352500	97.255000	153.545294	129.831765	
History	NaN	137.980000	56.670000	52.070000	62.456000	
Musical	NaN	93.645000	NaN	NaN	NaN	
Adventure	157.611667	172.577778	184.101818	154.687333	164.933636	
Thriller	69.570000	135.587500	82.172353	46.583125	58.363333	
Fantasy	131.715000	166.368571	116.452727	70.882857	181.960000	
War	NaN	NaN	NaN	42.855000	9.350000	
Animation	167.535000	213.345000	345.760000	176.850000	259.877500	
Sport	NaN	44.630000	95.000000	115.600000	56.357500	
Horror	26.920000	54.896000	56.520769	17.073750	18.185455	
Western	NaN	162.800000	89.290000	42.620000	0.000000	
Crime	130.348000	49.362222	64.073684	59.431429	44.389048	

	10
Music	54.560000
Comedy	48.086145
Romance	16.657667
Action	67.448533

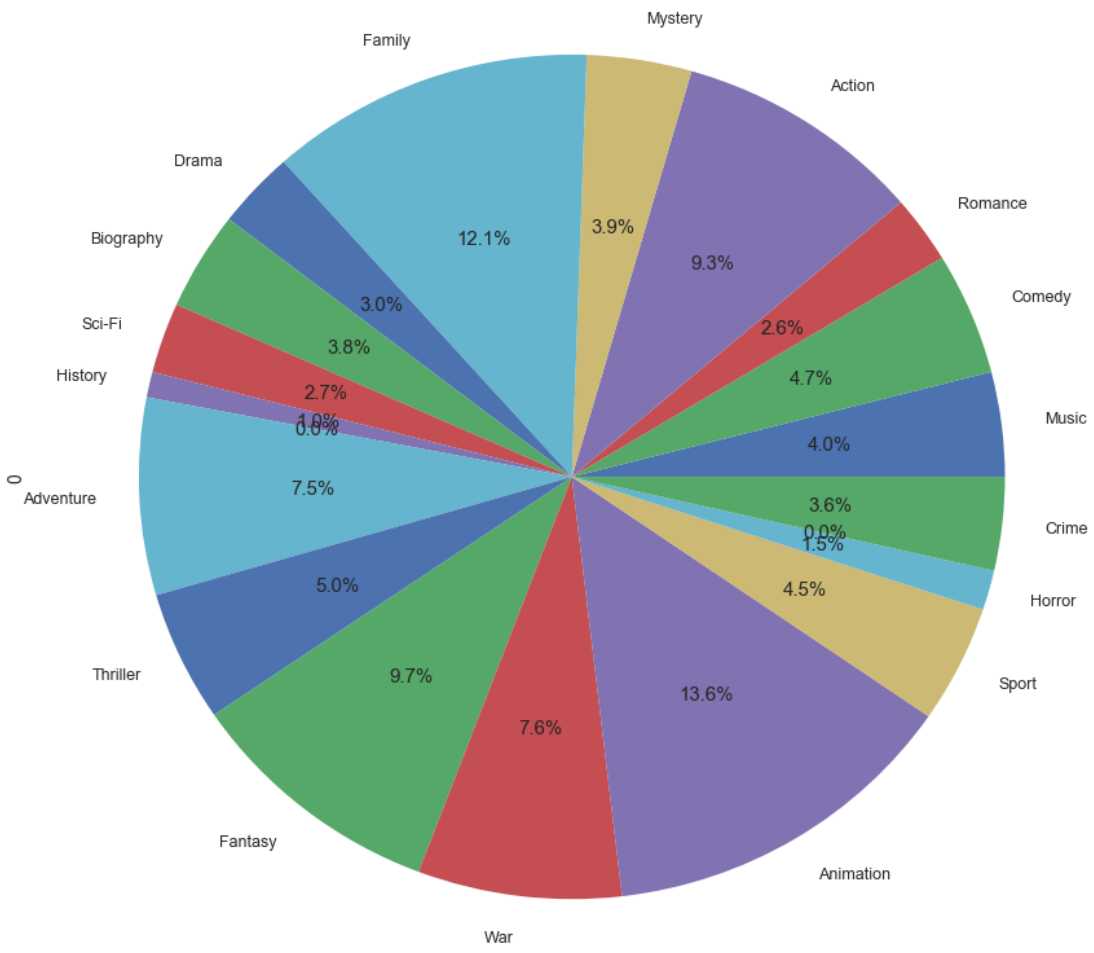
```
Mystery     26.384000
Family     113.081667
Drama       19.298086
Biography   23.669677
Sci-Fi      98.070000
History     29.237143
Musical           NaN
Adventure  107.889677
Thriller    15.741167
Fantasy     57.406087
War          0.860000
Animation  134.296667
Sport        2.754000
Horror      18.525556
Western     46.690000
Crime       22.153171
```

3.3.4 Pie Chart of Average Revenue

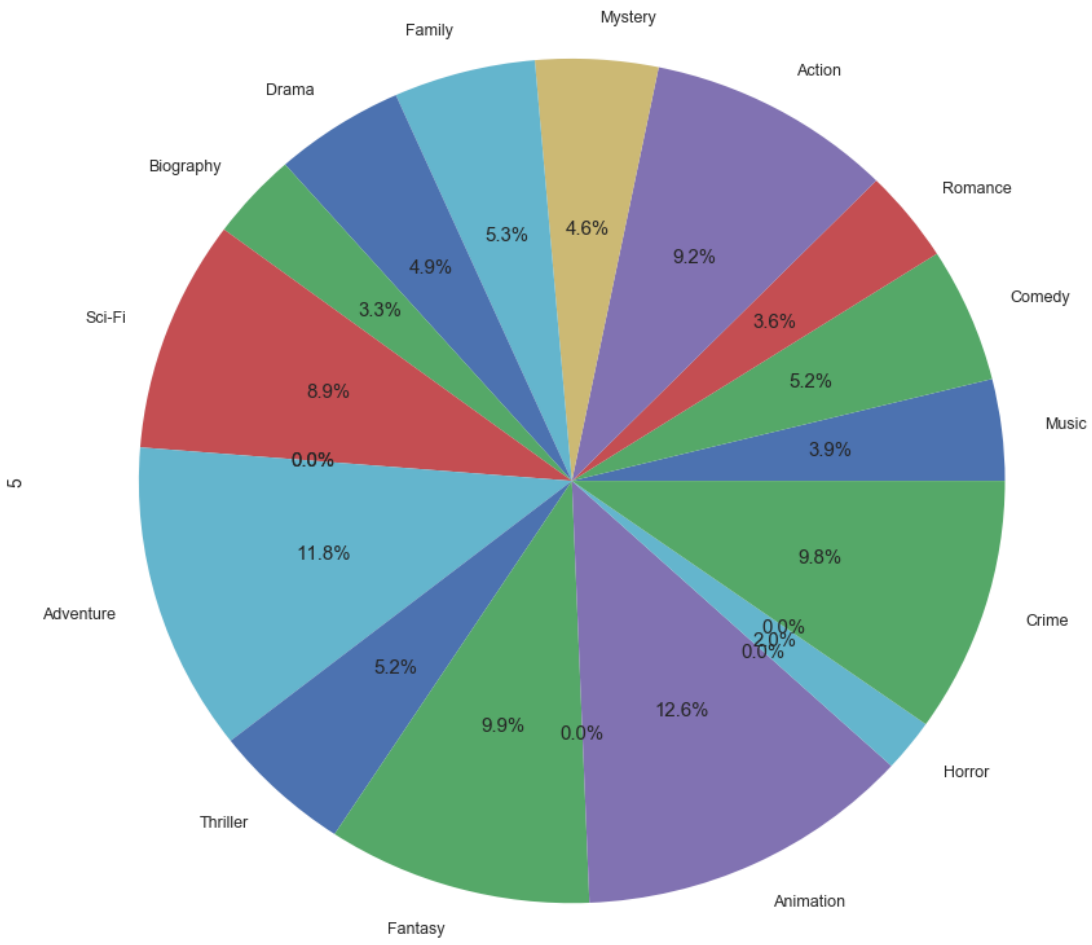
With the new table we get, we can plot pie charts as below. It can directly show the ranking of average revenue to us. Here, I choose three year to draw pie chart.

```
In [9]:  YMR.T[0].plot.pie(subplots=True, figsize=(15, 15),
         autopct='%1.1f%%',title='Average Revenue Percentage in 2006')
```

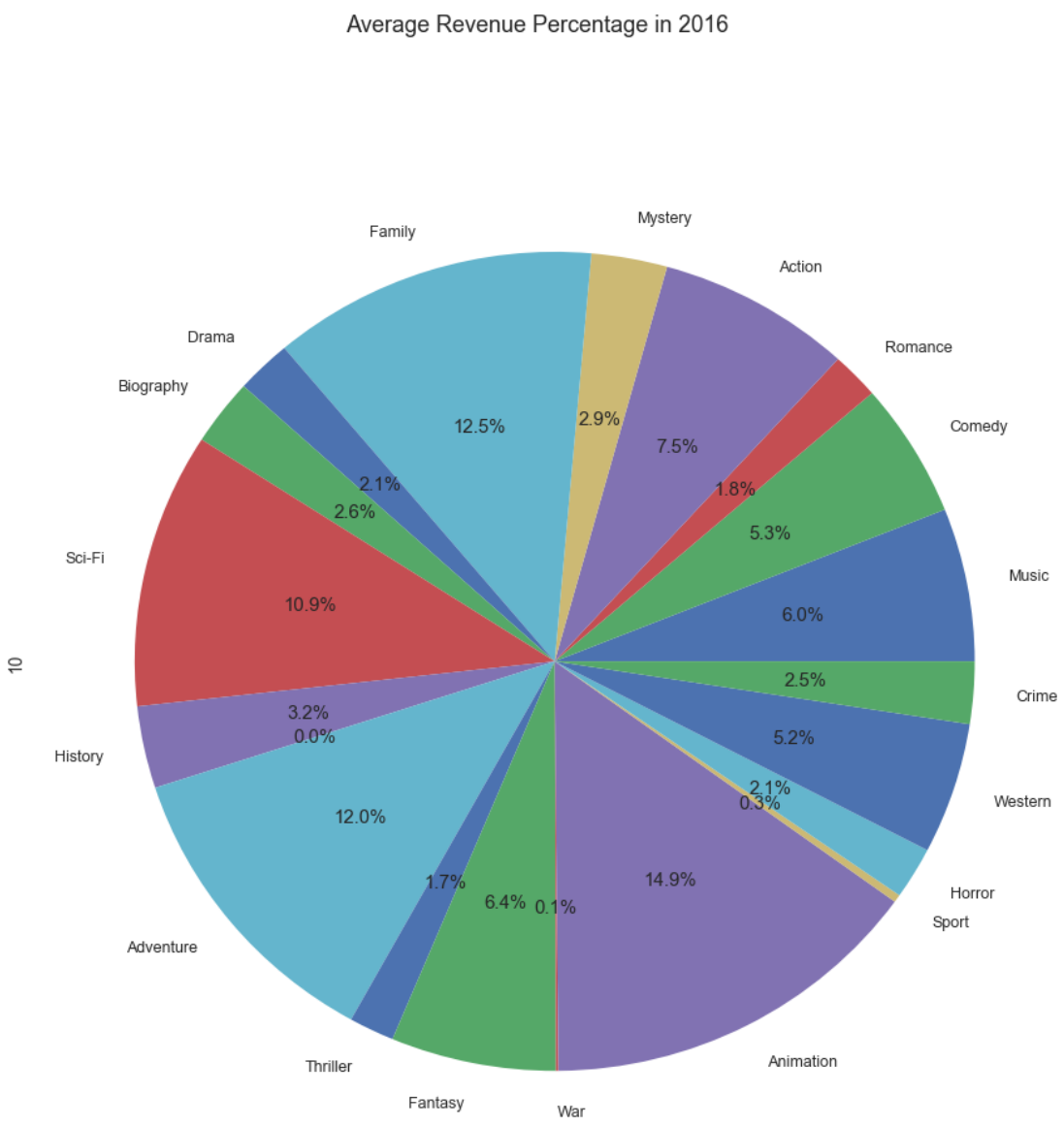
```
Out[9]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x7fa0c62203c8>], dtype=object)
```




```
In [10]: YMR.T[5].plot.pie(subplots=True, figsize=(15, 15),
         autopct='%1.1f%%',title='Average Revenue Percentage in 2011')

Out[10]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x7fa0c31c3630>], dtype=object)
```




```
In [11]: YMR.T[10].plot.pie(subplots=True, figsize=(15, 15),
         autopct='%1.1f%%',title='Average Revenue Percentage in 2016')

Out[11]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x7fa0c311f4e0>], dtype=object)
```



3.3.5 Summary

As above pie chart show, we know that Animation moive is easiest to make money.
Sci-Fi moive are getting easier to earn money than other kinds of movie.
However,the average revenue of all kine of moive are trend to decreasing.
Maybe we need a revolution in moive industry.

3.4 Analysis on Rating and Metascore

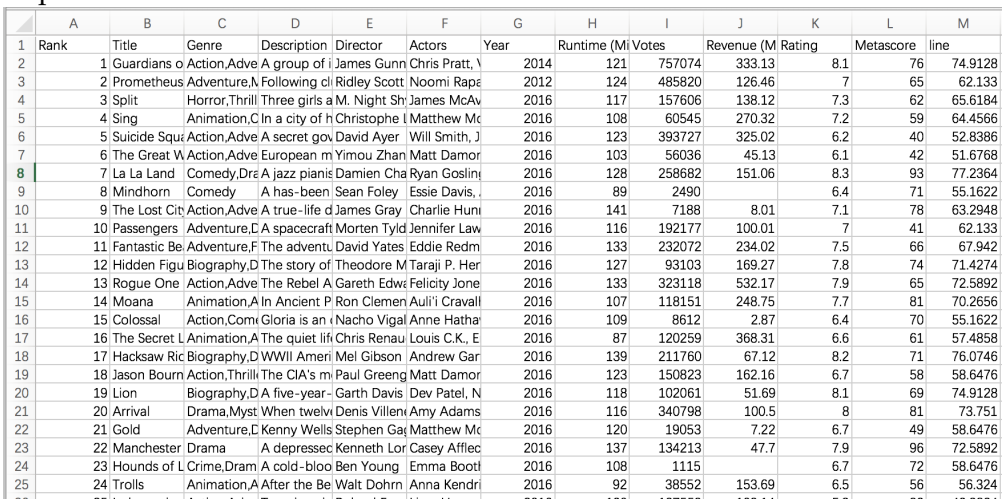
This analysis is provided by Kedun (Covey) Liu, which aims to find out the relationship between metascore and rating.

- The following Excel table analyze the relationship between Rating and MetaScore and find out the outlier.
- We analysis the outlier of what the genre they belong.
- We can finally learn that what kind of movie has the most controversial comment.

This analysis was done by hand in Excel.

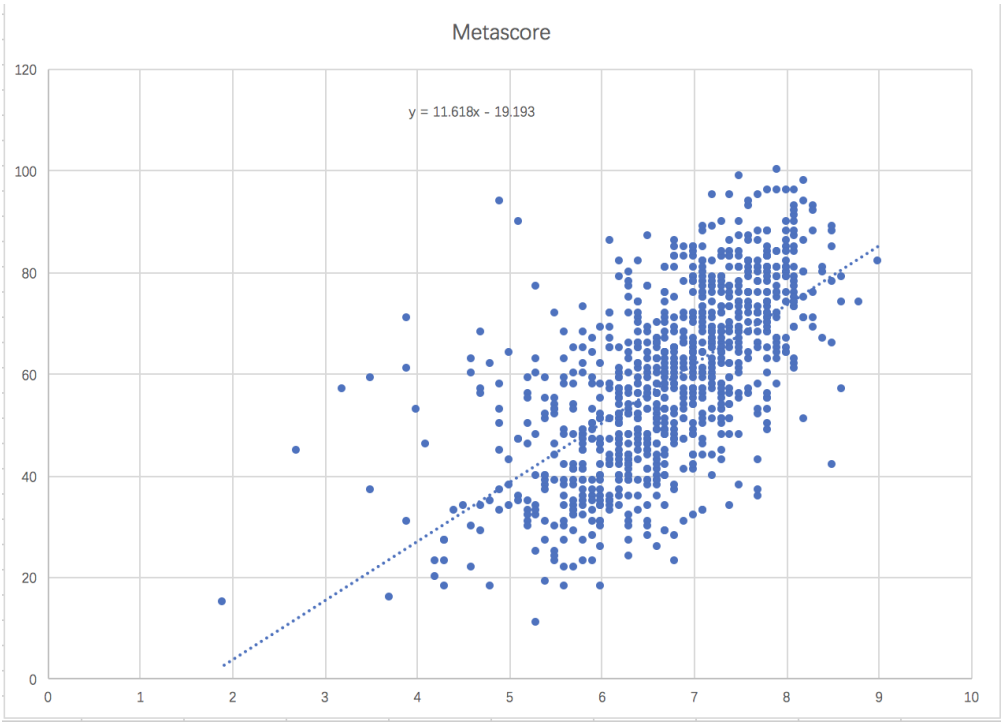
3.4.1 Implementation

Import the data into Excel.



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Rank	Title	Genre	Description	Director	Actors	Year	Runtime (Mi	Votes	Revenue (M	Rating	Metascore	line
2	1	Guardians o	Action,Adve	A group of i	James Gunn	Chris Pratt, V	2014	121	757074	333.13	8.1	76	74.9128
3	2	Prometheus	Adventure,N	Following cl	Ridley Scott	Noomi Rapa	2012	124	485820	126.46	7	65	62.133
4	3	Split	Horror,Thrill	Three girls a	M. Night Sh	James McAv	2016	117	157606	138.12	7.3	62	65.6184
5	4	Sing	Animation,C	In a city of h	Christophe l	Matthew Mc	2016	108	60545	270.32	7.2	59	64.4566
6	5	Suicide Squa	Action,Adve	A secret gov	David Ayer	Will Smith, J	2016	123	393727	325.02	6.2	40	52.8386
7	6	The Great W	Action,Adve	European m	Yimou Zhan	Matt Damor	2016	103	56036	45.13	6.1	42	51.6768
8	7	La La Land	Comedy,Dra	A jazz pianis	Damien Cha	Ryan Goslin	2016	128	258682	151.06	8.3	93	77.2364
9	8	Mindhorn	Comedy	A has-been	Sean Foley	Essie Davis,	2016	89	2490		6.4	71	55.1622
10	9	The Lost Cit	Action,Adve	A true-life d	James Gray	Charlie Hun	2016	141	7188	8.01	7.1	78	63.2948
11	10	Passengers	Adventure,D	A spacecraft	Morten Tyld	Jennifer Law	2016	116	192177	100.01	7	41	62.133
12	11	Fantastic Be	Adventure,F	The adventu	David Yates	Eddie Redm	2016	133	232072	234.02	7.5	66	67.942
13	12	Hidden Figu	Biography,D	The story of	Theodore M	Taraji P. Her	2016	127	93103	169.27	7.8	74	71.4274
14	13	Rogue One	Action,Adve	The Rebel A	Gareth Edw	Felicity Jone	2016	133	323118	532.17	7.9	65	72.5892
15	14	Moana	Animation,A	In Ancient P	Ron Clemen	Auli'i Cravall	2016	107	118151	248.75	7.7	81	70.2656
16	15	Colossal	Action,Com	Gloria is an	Nacho Vigal	Anne Hatha	2016	109	8612	2.87	6.4	70	55.1622
17	16	The Secret L	Animation,A	The quiet lif	Chris Renau	Louis C.K., E	2016	87	120259	368.31	6.6	61	57.4858
18	17	Hacksaw Ric	Biography,D	WWII Ameri	Mel Gibson	Andrew Gar	2016	139	211760	67.12	8.2	71	76.0746
19	18	Jason Bourn	Action,Thrill	The CIA's m	Paul Greeng	Matt Damor	2016	123	150823	162.16	6.7	58	58.6476
20	19	Lion	Biography,D	A five-year-	Garth Davis	Dev Patel, N	2016	118	102061	51.69	8.1	69	74.9128
21	20	Arrival	Drama,Myst	When twelv	Denis Villen	Amy Adams	2016	116	340798	100.5	8	81	73.751
22	21	Gold	Adventure,D	Kenny Wells	Stephen Ga	Matthew Mc	2016	120	19053	7.22	6.7	49	58.6476
23	22	Manchester	Drama	A depressec	Kenneth Lor	Casey Affleo	2016	137	134213	47.7	7.9	96	72.5892
24	23	Hounds of L	Crime,Dram	A cold-bloo	Ben Young	Emma Boot	2016	108	1115		6.7	72	58.6476
25	24	Trolls	Animation,A	After the Be	Walt Dohrn	Anna Kendri	2016	92	38552	153.69	6.5	56	56.324

Then, we remove the line with empty value of MetaScore because in this case, we require the data of MetaScore. After remove, we get 936 valid record.
Then, we user the Excel internal function to draw the scatter diagram of the data and draw the line of **linear regression**

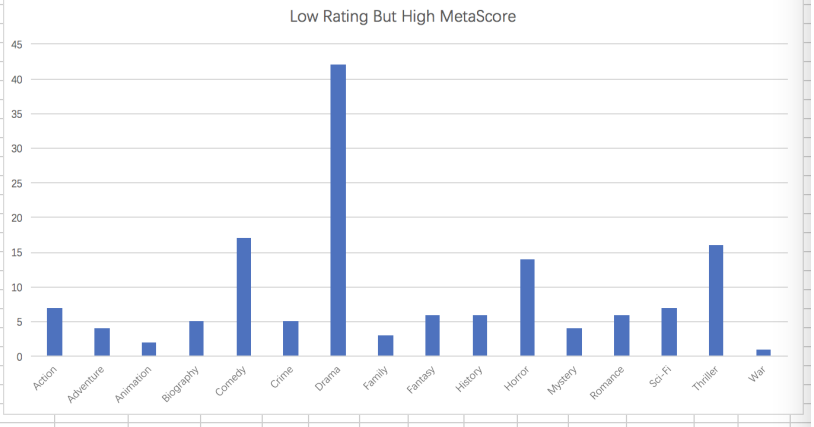


The regression function is `y = 11.618x - 19.193`, where x is rating and y is metascore.
We calculate the absolute value between actual value and linear regression and count the number of record.

mum_diff _abs> 10
420
mum_diff _abs> 15
240
mum_diff _abs> 20
118

We assume that the top 5% and lowest 5% as the outlier.
So, we need to get about 10% of data: 20 is a suitable different.
We first analysis the top 5% (different >20) of the data, which mean "Low Rating but Has High MetaScore". Then we can get:

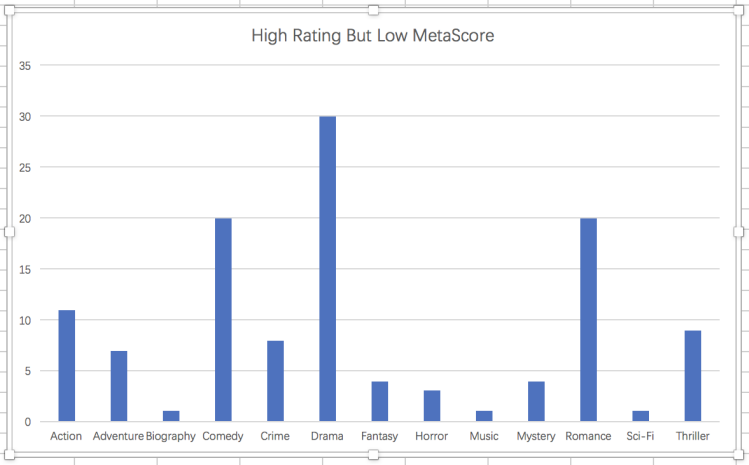
行标签	计数/Genre
Action	7
Adventure	4
Animation	2
Biography	5
Comedy	17
Crime	5
Drama	42
Family	3
Fantasy	6
History	6
Horror	14
Mystery	4
Romance	6
Sci-Fi	7
Thriller	16
War	1
(空白)	
总计	145



We can clear know that Drama is the most common Genre in this case.

Then, we analysis the lowest 5% (different <-20) of the data, which mean "High Rating but Has Low MetaScore". Then we can get:

行标签	计数/Genre
Action	11
Adventure	7
Biography	1
Comedy	20
Crime	8
Drama	30
Fantasy	4
Horror	3
Music	1
Mystery	4
Romance	20
Sci-Fi	1
Thriller	9
(空白)	
总计	119



In this case, we also find that Drama is the most common Genre.

3.4.2 Summary

By analysis the result, we can conclude that Drama Movie has the most controversial comment. Since it has the most gap between Rating and MetaScore. It means the evaluation of Drama Movie is various among people.
For Drama movie, we should carefully consider the Rating and MetaScore, because it has the most possibility that is a stray value.

3.5 Keywords Analyzing

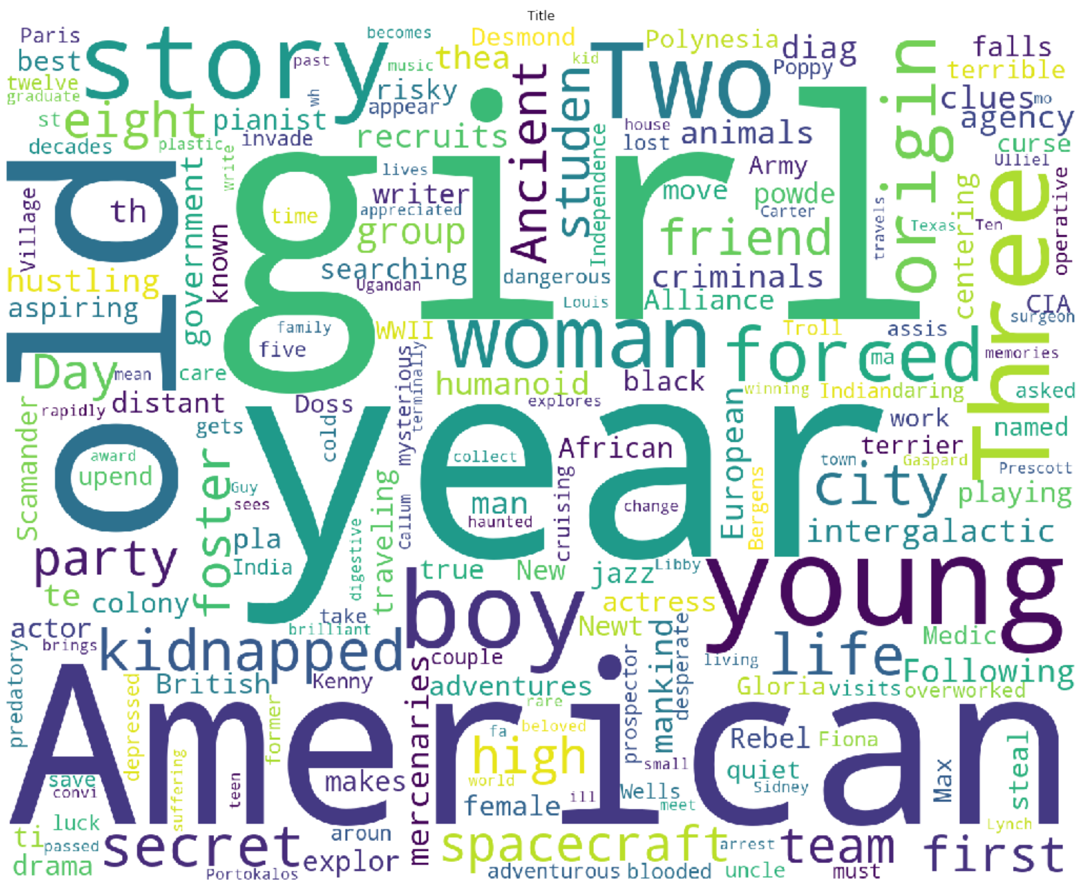
This analysis provided by Jiaqi (Garfield) Wu. By using these data, we can create a word cloud based on the descriptions and to find out the most frequent appeared keyword, and find out why the resulting words are appeared so frequently.

3.5.1 Implementation

Get the keywords

```
In [4]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        %matplotlib inline
        import seaborn as sns
        from os import path
        import matplotlib.pyplot as plt
        import random
        from wordcloud import WordCloud, STOPWORDS
        imdbdata=pd.read_csv('../Dataset/IMDB-Movie-Data.csv')
        text = (str(imdbdata['Description']))
        plt.subplots(figsize=(20,15))
        wordcloud = WordCloud(
```

```
                              stopwords=STOPWORDS,
                              background_color='white',
                              width=1500,
                              height=1200
                             ).generate(text)


plt.imshow(wordcloud)
plt.title('Title')
plt.axis('off')
plt.show()
```



3.5.2 Summary

From the graph, we can get these following keywords:

- Year
- American

- Old
- Young
- Girl

Since most of the 1000 movies are American made, it is not surprising that American will be one of the biggest word in the word cloud. It is interesting that the word "girl" is much bigger than "boy". It shows that people are more interesed in female rather than male. As for the word "year", the reason of why it is so big is that when describing a story, the timeline is always important. So the word "year" appeared frequently in the describtion of movies.

***** This is the end of the report. *****

LaTeX generated by Jupyter @ Anaconda 5.0.1 @ Python 3.6.3, refined by Junru (Bill) Zhong
Last modification: 23:00, December 19, 2017