Investigate TMDb data

April 10, 2020

1 Project: Investigate TMDb Movie Data

1.1 Table of Contents

Introduction The TMDb dataset we are going to analyze contains information about 10,000 movies collected from the Movie Database, TMDb. It provides details about revenue, budget, votes, cast, production companies among others related to movies that span a period of more than 50 years.

The following questions will be answered as we analyze the data.

What are the Popular Genres From Year to Year

What is the Yearly Revenue Change

What are the properties associated with High Revenue Movies?

Which Director directed Most Of the Top 20 Movies?

Which Actor is Present in Most of the Top 20 Revenue Movies?

Which Production Company produced Most of Top 20 Revenue movies?

What Are 20 The Top Revenue Movies From 1960 to 2015

[1]:
```
# import the necessary packages
import pandas as pd
import numpy as np
import matplotlib.pyplot  as plt
import seaborn as sns

# Initialize seaborn and magic commands
sns.set()
%matplotlib inline
```

Data Wrangling

1.1.1 General Properties

[2]:
```python
# load tmdb-movies csv into a dataframe
movies_df = pd.read_csv('tmdb-movies.csv')

# Examine first 5 rows
movies_df.head(5)
```

[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]
```

[3]:
```python
# check the number of rows and columns
movies_df.shape
```

[3]:
```
(10866, 21)
```

[4]:
```python
# Get a quick statistics of the dataset
movies_df.describe()
```

[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
```

[5]:
```python
# View more details about the dataset
movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10866 non-null  int64
 1   imdb_id               10856 non-null  object
 2   popularity            10866 non-null  float64
 3   budget                10866 non-null  int64
 4   revenue               10866 non-null  int64
 5   original_title        10866 non-null  object
 6   cast                  10790 non-null  object
 7   homepage              2936 non-null   object
 8   director              10822 non-null  object
 9   tagline               8042 non-null   object
 10  keywords              9373 non-null   object
 11  overview              10862 non-null  object
 12  runtime               10866 non-null  int64
 13  genres                10843 non-null  object
 14  production_companies  9836 non-null   object
 15  release_date          10866 non-null  object
 16  vote_count            10866 non-null  int64
 17  vote_average          10866 non-null  float64
 18  release_year          10866 non-null  int64
 19  budget_adj            10866 non-null  float64
 20  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

[6]:
```python
# check the columns with empty values
movies_df.isnull().sum()
```

[6]:
```
id                       0
imdb_id                 10
popularity               0
budget                   0
revenue                  0
```

```
original_title              0
cast                       76
homepage                 7930
director                   44
tagline                  2824
keywords                 1493
overview                    4
runtime                     0
genres                     23
production_companies     1030
release_date                0
vote_count                  0
vote_average                0
release_year                0
budget_adj                  0
revenue_adj                 0
dtype: int64
```

[7]:
```python
# check for number of duplicates
movies_df.duplicated().sum()
```

[7]: 1

1.1.2 Data Cleaning

We observe from our initial checks on our dataset that there are duplicates and some missing values.

We are going to remove the duplicates and replace missing values in the following columns: **cast, director, keywords, genres, production_companies**

We will also drop some columns that will not be relevant to the questions we want to address i.e. **imdb_id, homepage, tagline and overview**

We saw that the **budget, revenue, budget_adj, revenue_adj** columns had a min value of 0.0 which implies some of the rows in these columns had a value of 0.0 which is not desirable for our analysis. These rows will be removed as well.

[8]:
```python
# remove duplicates
movies_df.drop_duplicates(inplace=True)
```

[9]:
```python
# verify duplicates removal
movies_df.duplicated().sum()
```

[9]: 0

[10]:
```python
# confirm the new number of rows
movies_df.shape
```

[10]: (10865, 21)

[11]:
```python
# drop imdb_id, homepage, tagline and overview columns.
movies_df.drop(['imdb_id', 'homepage','tagline', 'overview'], axis=1,␣
 ↪inplace=True )
movies_df.shape
```

[11]: (10865, 17)

[12]:
```python
# remove rows if the budget or revenue or budget_adj or revenue_adj is 0.0
movies_df = movies_df.loc[(movies_df.budget * movies_df.revenue * movies_df.
 ↪budget_adj* movies_df.revenue_adj) != 0]
movies_df.shape
```

[12]: (3854, 17)

[13]:
```python
# fill the missing values in the following columns with the values indicated
# cast = 'no_cast'
# director = 'no_director'
# keywords = 'no_keywords'
# genres = 'no_genres'
# production_companies = 'no_production_companies'

columns_to_fillna = ['cast', 'director', 'keywords', 'genres',␣
 ↪'production_companies']
for column in columns_to_fillna:
    movies_df[column] = movies_df[column].fillna('no_'+column)

# check the number of null values again
movies_df.isnull().sum()
```

[13]:
```
id                      0
popularity              0
budget                  0
revenue                 0
original_title          0
cast                    0
director                0
keywords                0
runtime                 0
genres                  0
production_companies    0
release_date            0
vote_count              0
vote_average            0
release_year            0
budget_adj              0
```

```
revenue_adj           0
dtype: int64
```

Exploratory Data Analysis

1.1.3 Helper Functions To Be used in the Analysis

[14]:
```python
def generate_plot(x_val, y_val, fig_size, title, x_label, y_label):
    """
    This functions takes inputs for a bar graph and produces a plot based on␣
↪the inputs
    """
    plt.subplots(figsize=fig_size)
    sns.barplot(x_val, y_val)
    plt.title(title, fontsize=30)
    plt.xlabel(x_label, fontsize=20)
    plt.ylabel(y_label, fontsize=20);
```

[15]:
```python
def generate_value_and_count(data):
    """
    This functions takes a column and separates the pipe-separated values and␣
↪return a dict of
    the value and the number of times it occurs
    """
    val_list = [val.split('|') for val in data]

    top_val_list = []
    for new_val in val_list:
        for single in new_val:
            top_val_list.append(single)

    # get the value and count of each item in the top_val_list
    val_and_count = dict()
    for i in top_val_list:
        val_and_count[i] = val_and_count.get(i, 0)+1

    return val_and_count
```

Research Question 1 - What are the Popular Genres From Year To Year

I used **vote_average** as the metric for popularity with the understanding that the average votes given to a movies reflects its popularity among consumers

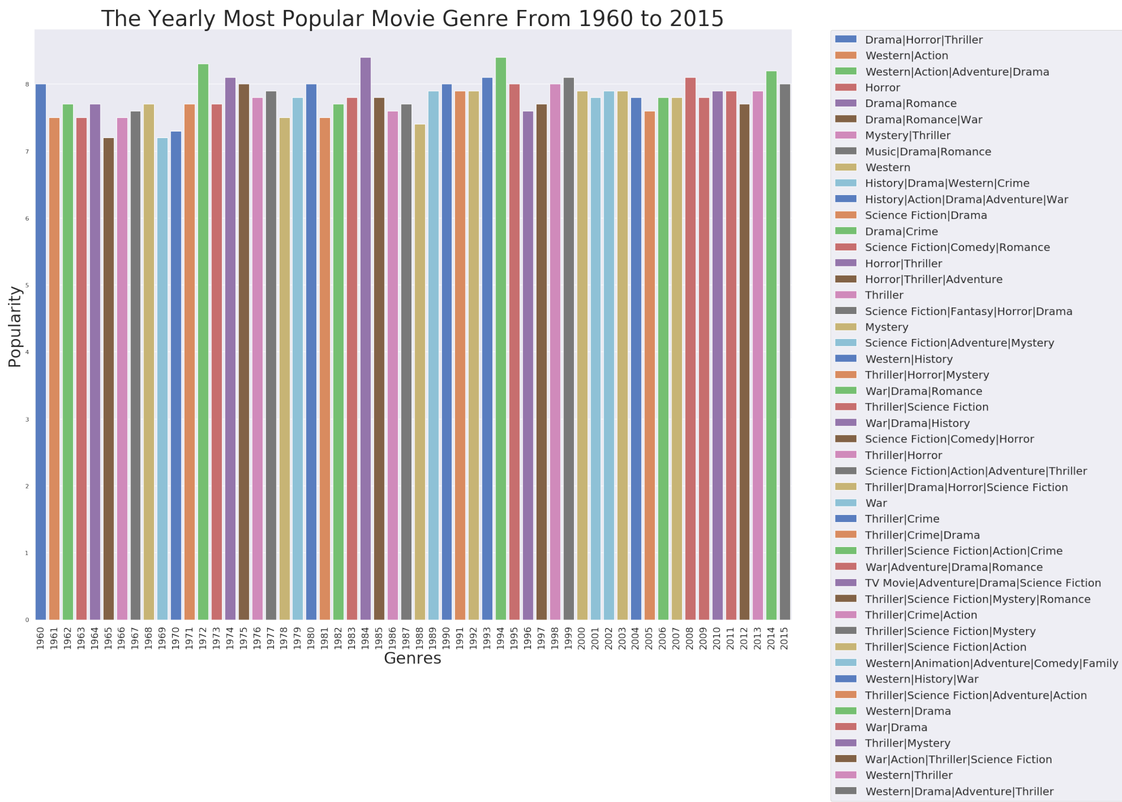
Drama, Western, Romance were the popular genres in the earliest decade.

Western, Drama, Thriller became popular in the most recent.

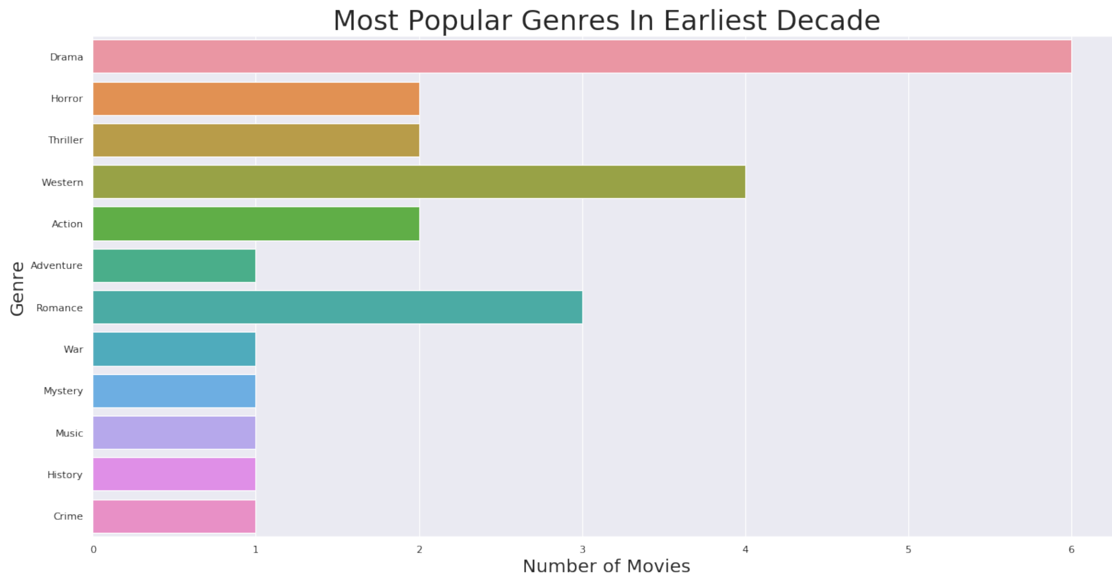
We therefore observe that both Western and Drama genres remained popular in both past and recent times.

The last is a visualization of the various genres associated with the 5 top popular movies for each year

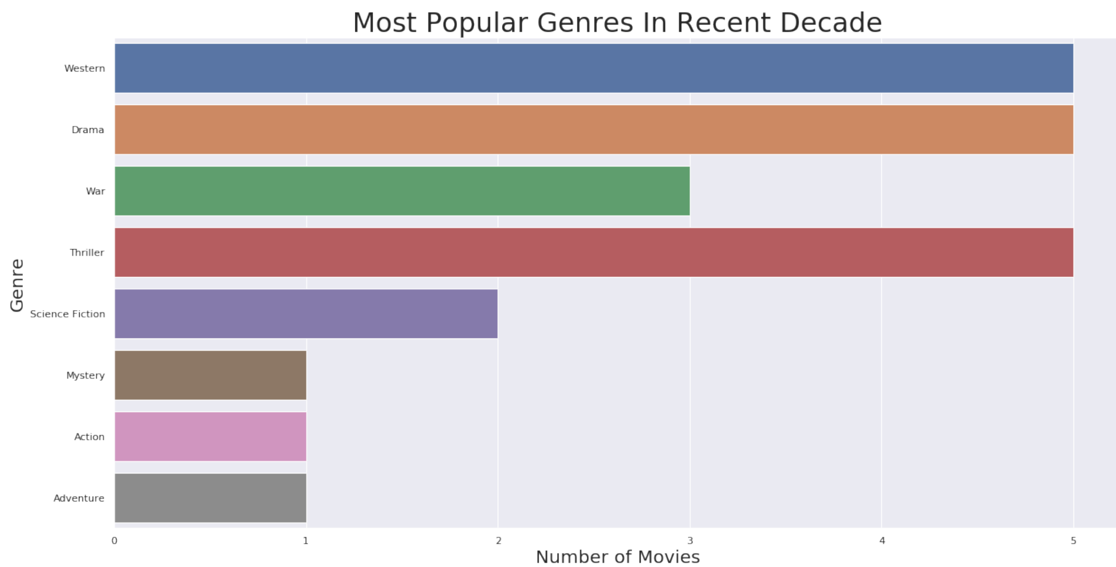
[16]:
```
# Get the Most Popular Genre in Each Release Year
popular_genre_per_year = movies_df.
 ↪groupby(['release_year'])[['vote_average','genres']].max()
plt.subplots(figsize=(25, 20))
graph = sns.barplot(
                    popular_genre_per_year.index,
                    popular_genre_per_year['vote_average'],
                    hue=popular_genre_per_year['genres'],
                    dodge=False,
                    palette='muted',
                   )
graph.set_xticklabels(graph.get_xticklabels(),
                      rotation=90,
                      fontweight='light',fontsize='xx-large'
                     )
graph.axes.set_title("The Yearly Most Popular Movie Genre From 1960 to␣
 ↪2015",fontsize=40)
graph.set_xlabel("Genres",fontsize=30)
graph.set_ylabel("Popularity",fontsize=30);

# Put the legend out of the figure
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.1, prop={'size':␣
 ↪20});
```



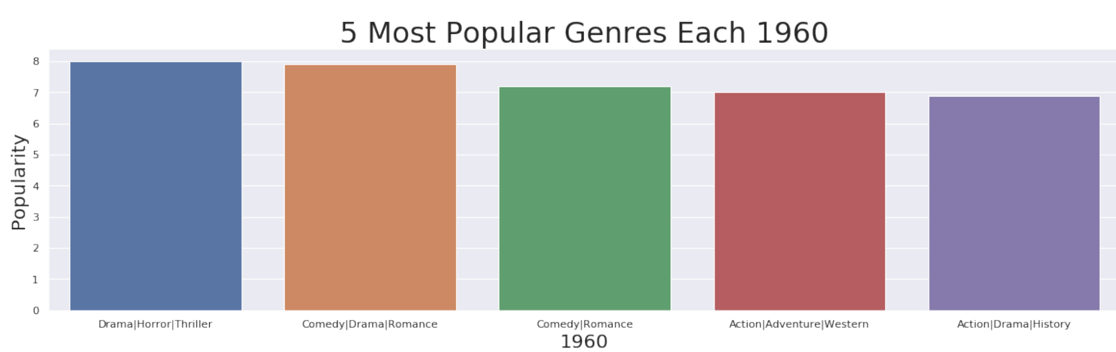
[17]:
```python
# Find the most popular genre in the first earliest decade
earliest_decade = popular_genre_per_year.head(10)['genres']
earliest_decade_genres = generate_value_and_count(data=earliest_decade)
earliest_decade_genres_df = pd.DataFrame.from_dict(earliest_decade_genres,␣
 ↪orient="index")
# Generate the Plot
generate_plot(x_val=earliest_decade_genres_df[0],
              y_val=earliest_decade_genres_df.index,
              fig_size=(20,10),
              title='Most Popular Genres In Earliest Decade',
              x_label='Number of Movies',
              y_label='Genre'
             )
```

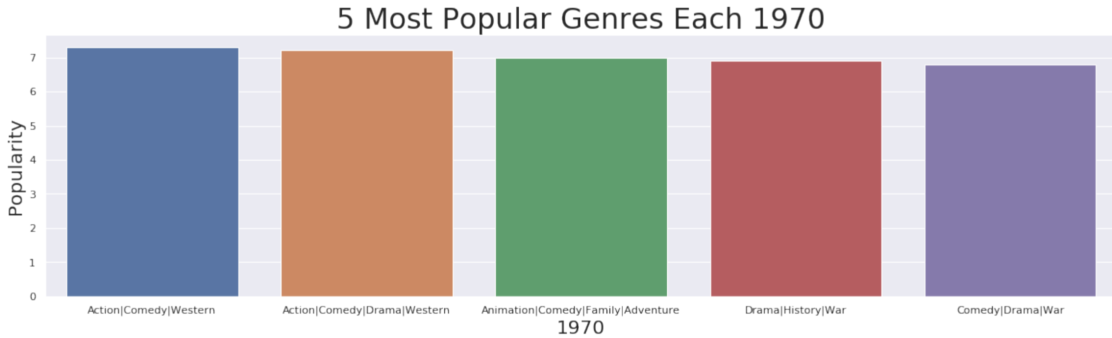


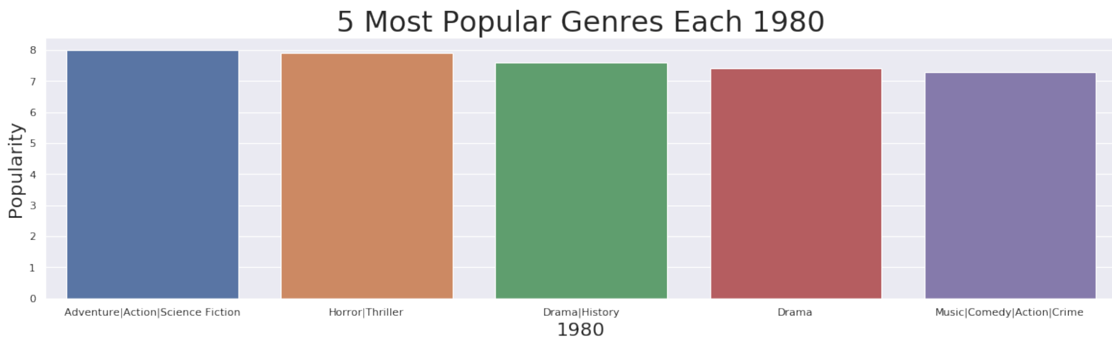
[18]:
```
# Find the most popular genre in the most recent decade
recent_decade = popular_genre_per_year.tail(10)['genres']
recent_decade_genres = generate_value_and_count(data=recent_decade)
recent_decade_genres_df = pd.DataFrame.from_dict(recent_decade_genres,␣
 ↪orient="index")
# Generate the Plot
generate_plot(x_val=recent_decade_genres_df[0],
              y_val=recent_decade_genres_df.index,
              fig_size=(20,10),
              title='Most Popular Genres In Recent Decade',
              x_label='Number of Movies',
              y_label='Genre'
             )
```

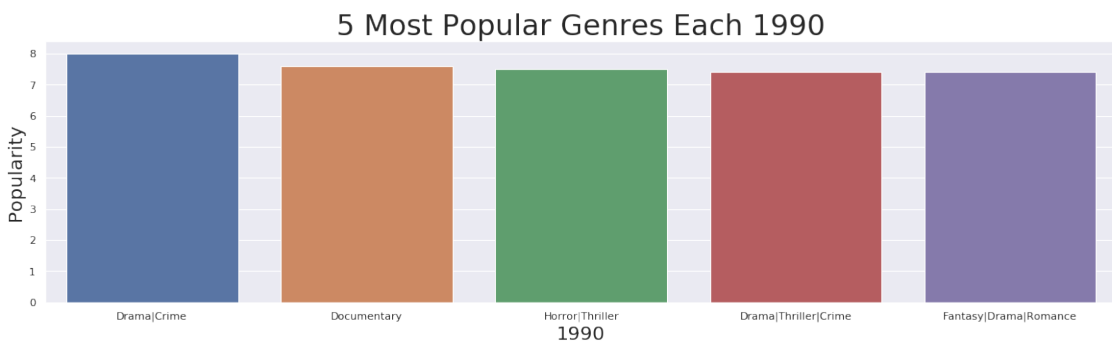


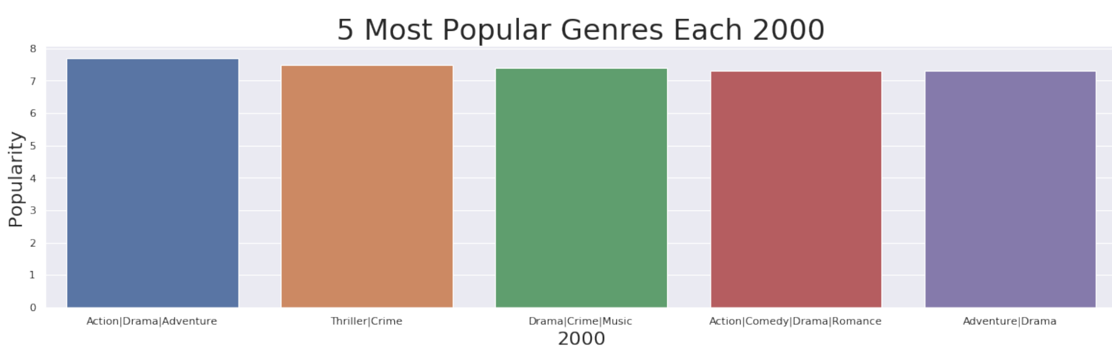
[19]:
```
# Group The Genres by Year and Find the Most Popular Ones in Each Year using␣
↪vote_average as the popularity metric
for year in np.arange(1960,2016, 10): # Interval can be changed if all the␣
↪years need to appear.
    df = movies_df.query('release_year == @year').groupby('genres').mean().
↪sort_values(by=['vote_average'], ascending=False).head(5)
    generate_plot(x_val=df.index,
                  y_val=df['vote_average'],
                  fig_size=(20,5),
                  title=f"5 Most Popular Genres Each {year}",
                  x_label=year,
                  y_label='Popularity'
                 )
```

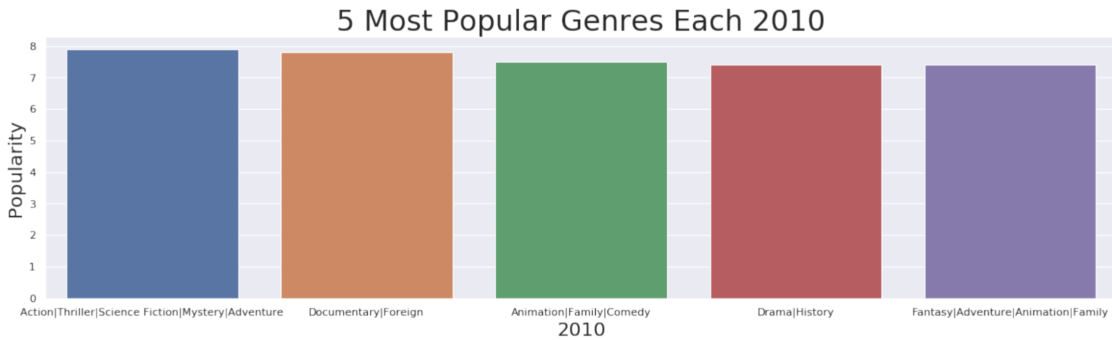



5 Most Popular Genres Each 1970
Popularity
Action|Comedy|Western
Action|Comedy|Drama|Western
Animation|Comedy|Family|Adventure
Drama|History|War
Comedy|Drama|War
1970


5 Most Popular Genres Each 1980
Popularity
Adventure|Action|Science Fiction
Horror|Thriller
Drama|History
Drama
Music|Comedy|Action|Crime
1980


5 Most Popular Genres Each 1990
Popularity
Drama|Crime
Documentary
Horror|Thriller
Drama|Thriller|Crime
Fantasy|Drama|Romance
1990


5 Most Popular Genres Each 2000
Popularity
Action|Drama|Adventure
Thriller|Crime
Drama|Crime|Music
Action|Comedy|Drama|Romance
Adventure|Drama
2000



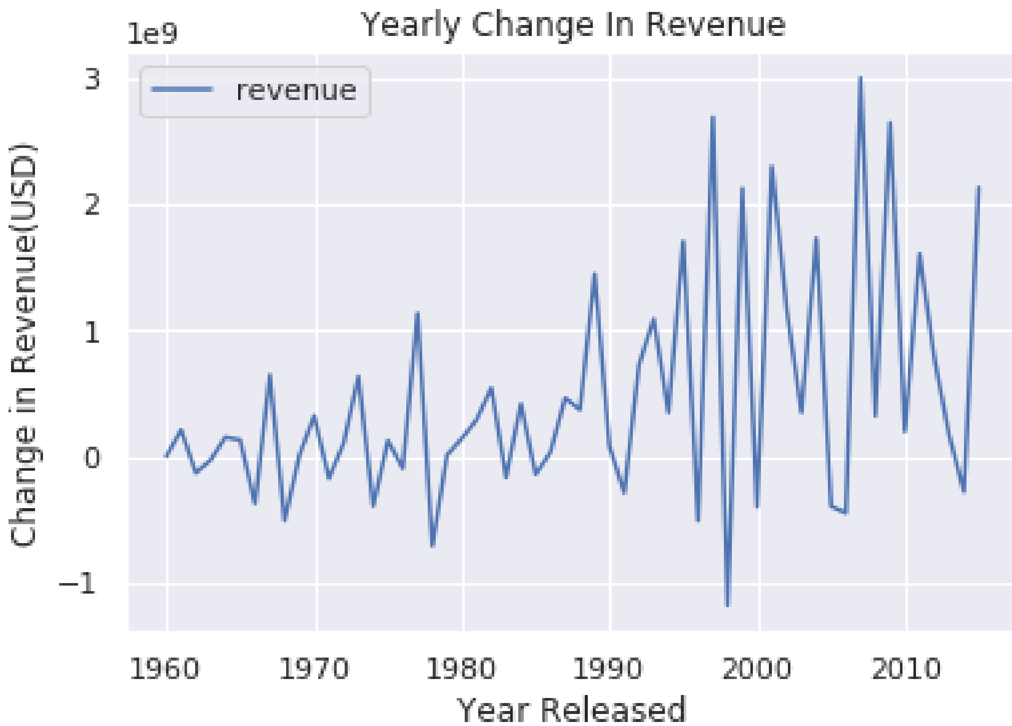
Research Question 2 - What is the Yearly Revenue Change

The change in revenue from year to year does not seem to follow any particular pattern. This could be due to unequal number of movies produced in each year, directly affecting the total sum of revenue generated by year.

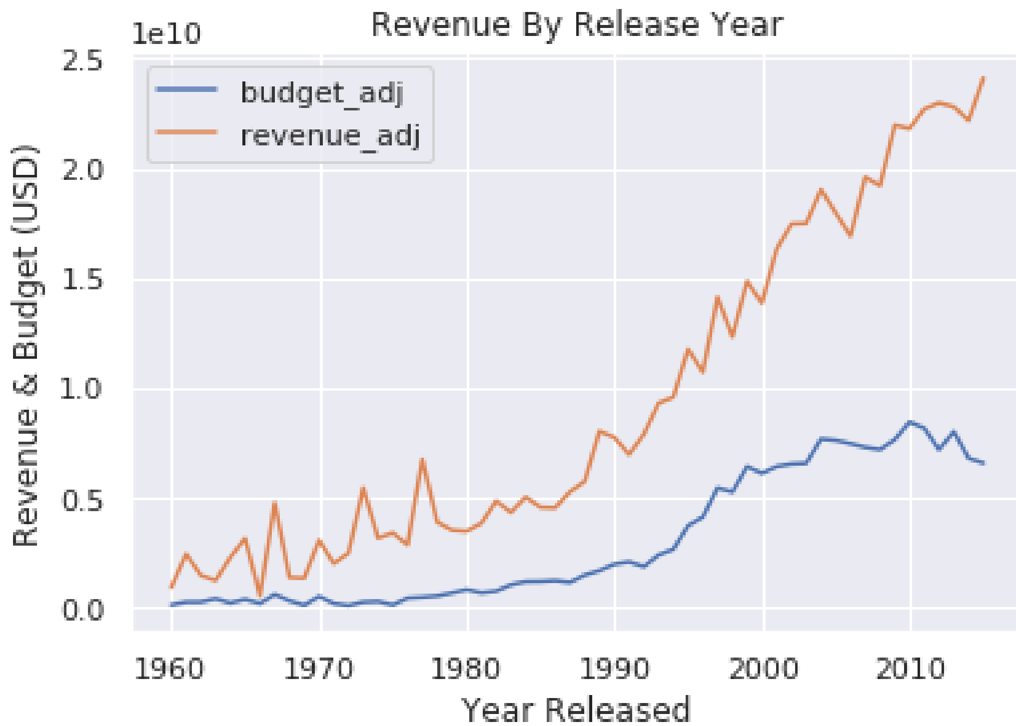
The difference in budget and revenue shows a significant increase in the last decade as captured the dataset. This could be attributed to efficient and improved technologies and distribution channels in recent times.

A movie with a high budget is likely to help in all marketing and sales efforts to boost revenue generated.

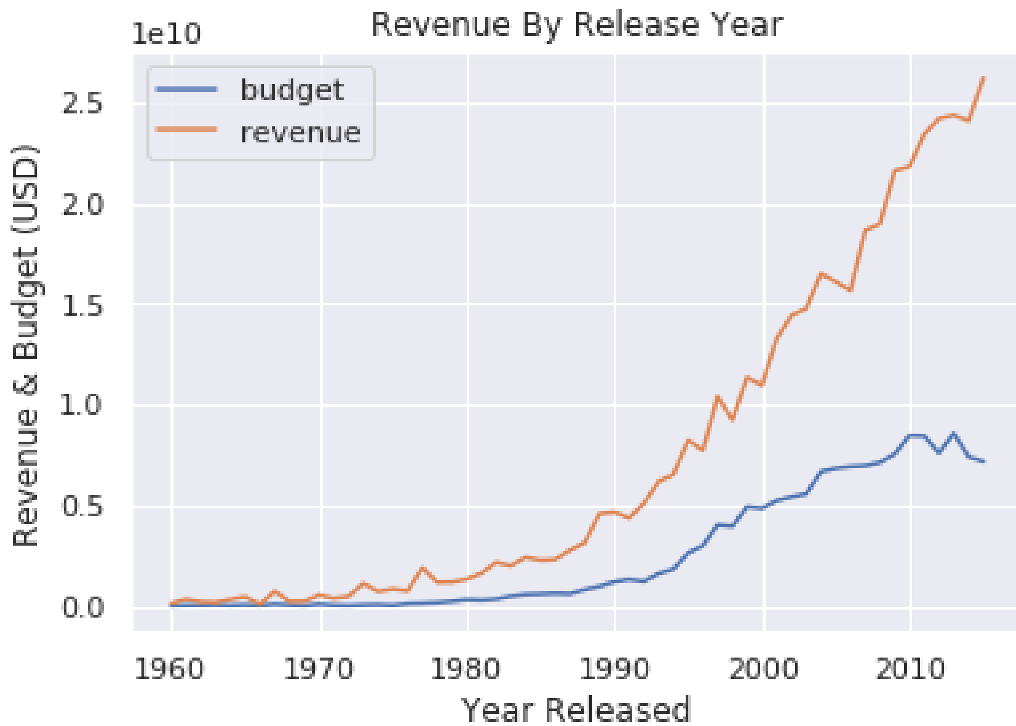
[20]:
```
# Find the Sum of the Various Columns According to the Year the Movies Were Released
yearly_movies_sum = movies_df.groupby('release_year').sum()

# Find The Yearly Change in Revenue
yearly_movies_sum.apply(lambda x:x.diff().fillna(0))[['revenue']].plot()
plt.xlabel('Year Released')
plt.ylabel('Change in Revenue(USD)')
plt.title('Yearly Change In Revenue');
```



[21]:
```
# Compare the Yearly sum for budget_adj and revenue_adj
yearly_movies_sum[['budget_adj', 'revenue_adj']].plot()
plt.xlabel('Year Released')
plt.ylabel('Revenue & Budget (USD)')
plt.title('Revenue By Release Year');
```



[22]:
```
# Compare the Yearly sum for budget and revenue
yearly_movies_sum[['budget', 'revenue']].plot()
plt.xlabel('Year Released')
plt.ylabel('Revenue & Budget (USD)')
plt.title('Revenue By Release Year');
```



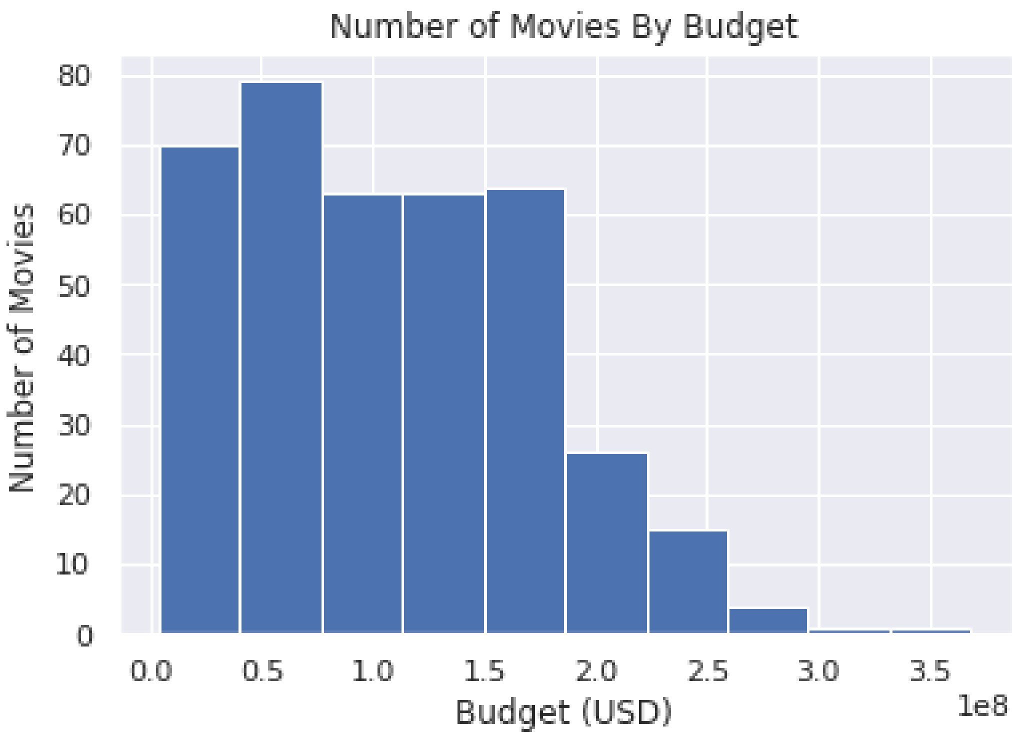
Research Question 3 - What are the properties associated with High Revenue Movies?

I chose movies with a Revenue Greater than the 90th Percentile as High Revenue Movies. I looked at the distribution of the other columns to get a fair idea of the properties associated with the high revenue movies

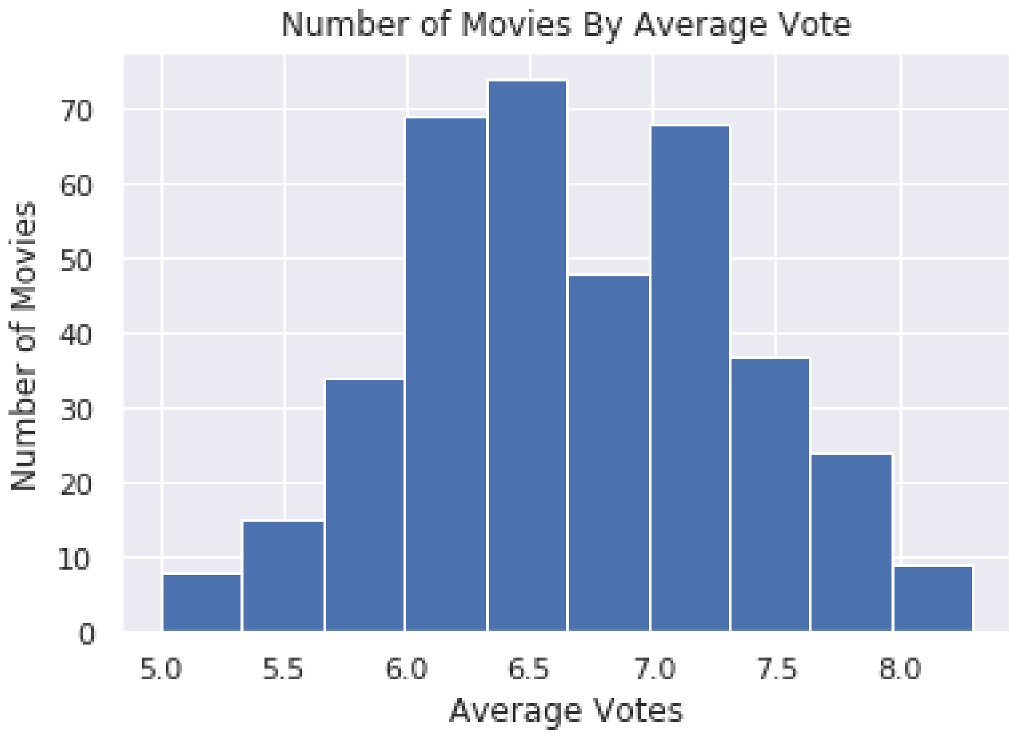
- Budget: Most of them had a budget between 25 Million to 200 Million USD.
- Average Vote: The average vote by consumers was mostly between 6.0 and 7.5 with very few at the 8.0 mark.
- Runtime: Another property worth looking at is how lengthy these high revenue movies were. Most had a runtime between 80mins and 150 mins. We observe that very few lenghty movies are high revenue movies.
- Year of Release: Most of these high revenue movies were also released in the last decade of the year under review, i.e 1960 to 2015.

[23]:
```
# I chose movies with a Revenue Greater than the 90th Percentile as High␣
↪Revenue Movies

# Calculate the 90th Percentile Revenue
ninety_percentile = np.percentile(movies_df['revenue_adj'], 90)

# Filter the movies with movies with revenue greater than 90th Percentile
highest_revenue_movies = movies_df.query('revenue_adj > @ninety_percentile')
```

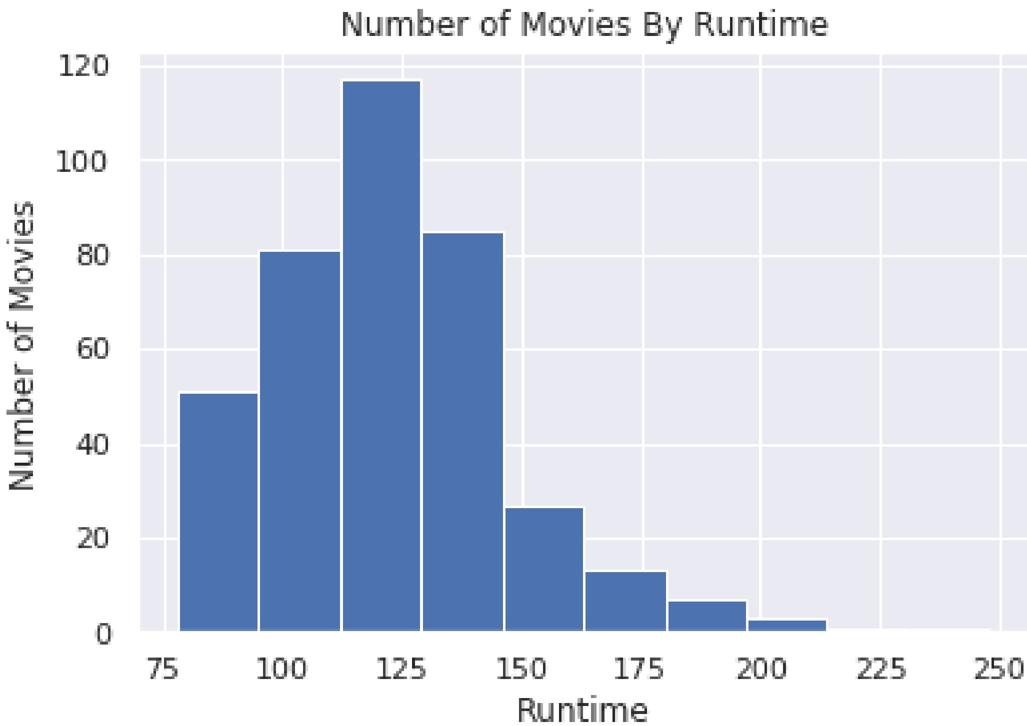
[24]:
```
# Check the Budget for of High Revenue Movies
highest_revenue_movies['budget_adj'].hist()
plt.xlabel('Budget (USD)')
plt.ylabel('Number of Movies')
plt.title('Number of Movies By Budget');
```



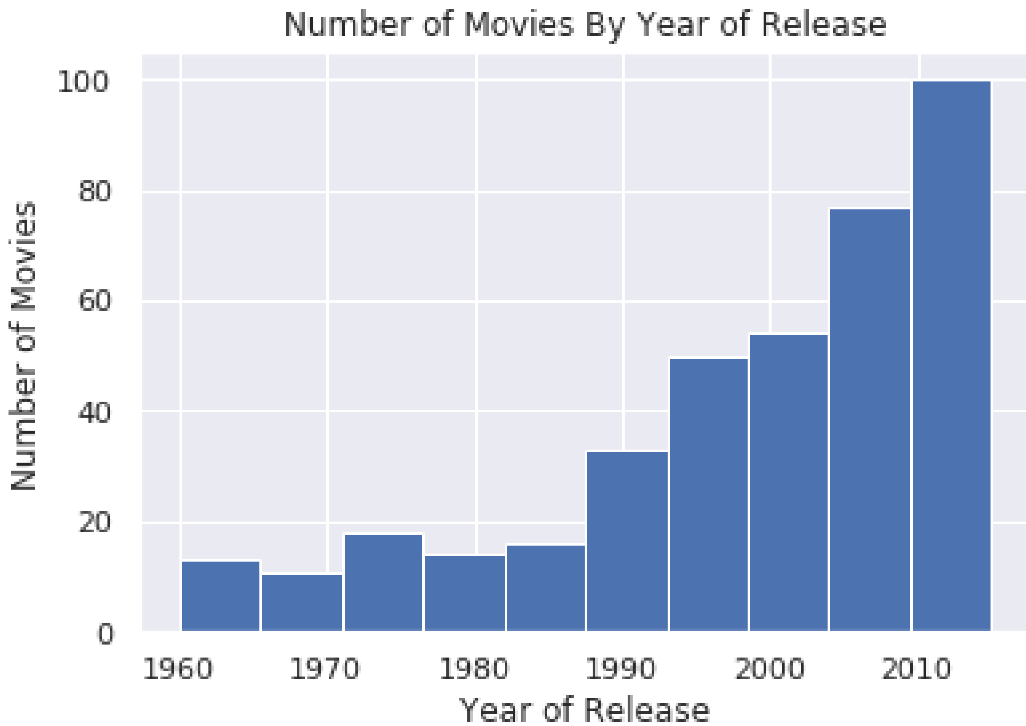
[25]:
```
# Check the Vote Average (Popularity Metric) of High Revenue Movies
highest_revenue_movies['vote_average'].hist()
plt.xlabel('Average Votes')
plt.ylabel('Number of Movies')
plt.title('Number of Movies By Average Vote');
```



[26]:
```
# Check the Runtime of High Revenue Movies - How Long The Movies span
highest_revenue_movies['runtime'].hist()
plt.xlabel('Runtime')
plt.ylabel('Number of Movies')
plt.title('Number of Movies By Runtime');
```



[27]:
```
# Check the Release Year of High Revenue Movies
highest_revenue_movies['release_year'].hist()
plt.xlabel('Year of Release')
plt.ylabel('Number of Movies')
plt.title('Number of Movies By Year of Release');
```



1.1.4 Define Variables to be used in The Next Analysis

[28]:
```
# Find the top 20 revenue movies
top_20_revenue = highest_revenue_movies.sort_values(by=['revenue_adj'],␣
↪ascending=False).head(20)
```

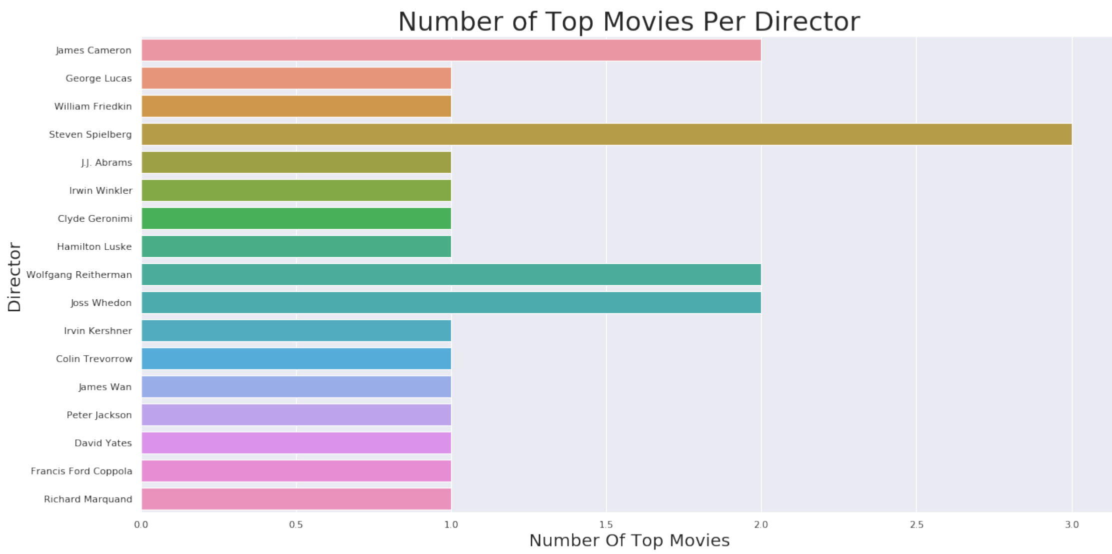
Research Questions 4 - Which Director directed **Most** Of the Top 20 Movies?

We realize that for some movies, they had more than 1 director, directing the movies. I therefore looked at the number of times an individual director, directed or was part of the team that directed a movie.

Steven Spielberg was first, directing 3 top revenue movies, followed **James Cameron, Josh Whedon and Wolfgang Reitherman** with 3 movies each.

[29]:
```
# Find the Director That Featured on Most of the Highest Revenue Movies

director_counts = generate_value_and_count(data=top_20_revenue['director'])
director_count_df = pd.DataFrame.from_dict(director_counts, orient="index")

# Generate the Plot
generate_plot(x_val=director_count_df[0],
              y_val=director_count_df.index,
```

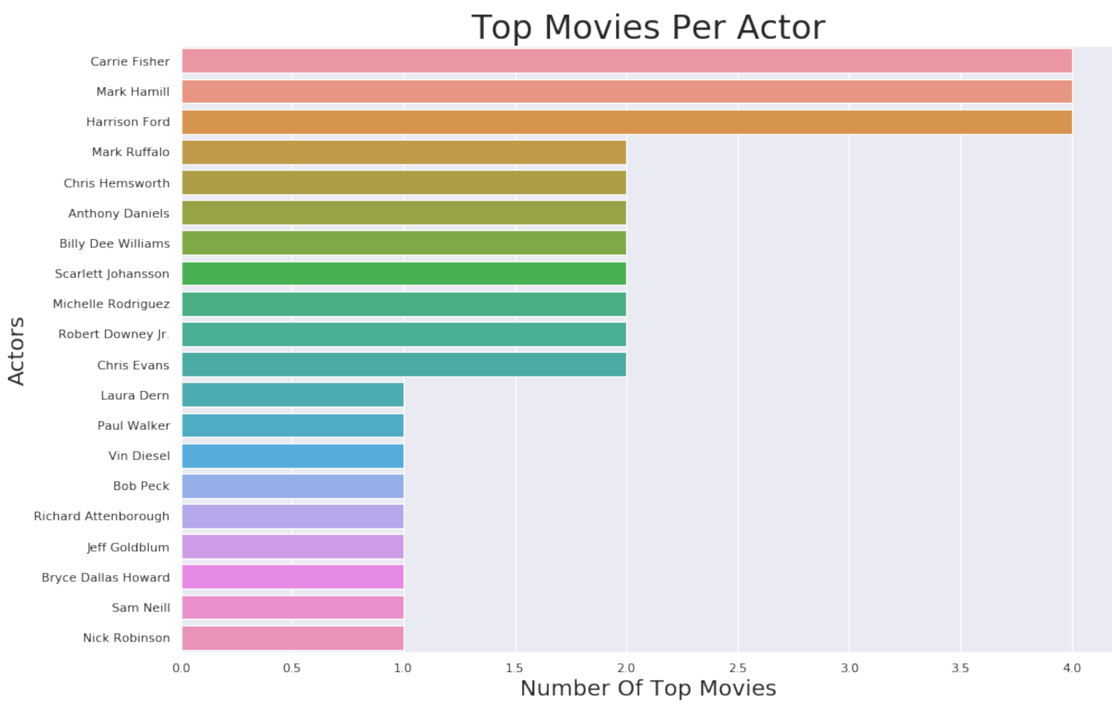
```
              fig_size=(20,10),
              title='Number of Top Movies Per Director',
              x_label='Number Of Top Movies',
              y_label='Director'
             )
```



Research Question 5 - Which Actor is Present in **Most** of the Top 20 Revenue Movies?

Over here we first pick the actors who featured in each of the top 20 revenue movies. We then find the number of movies that all the individual actors featured in. The top 3 who were most present in the top 20 high revenue movies were **Carrie Fisher, Mark Hamill and Harrison Ford**

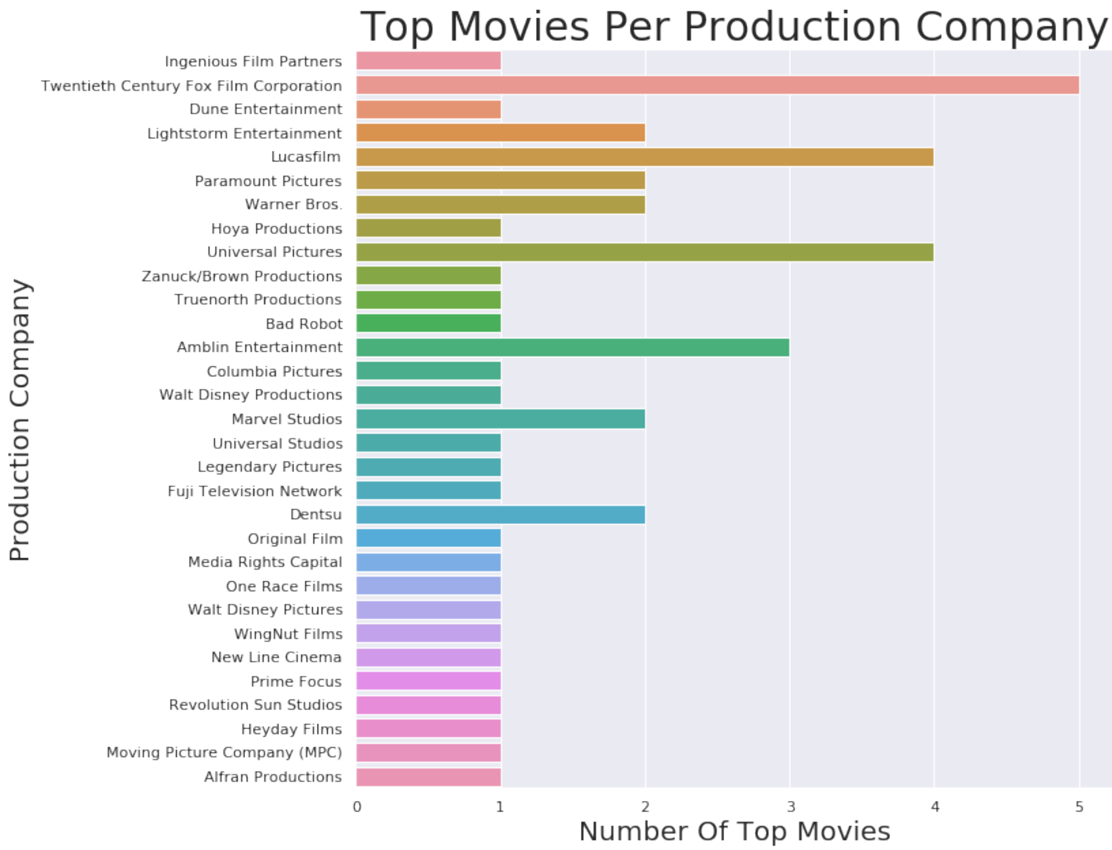
[30]:
```
# Find the Actor That Featured on Most of the Highest Revenue Movies
actor_counts = generate_value_and_count(data=top_20_revenue['cast'])
actor_count_df = pd.DataFrame.from_dict(actor_counts, orient="index").
 ↪sort_values(by=[0], ascending=False).head(20)

# Generate the Plot
generate_plot(x_val=actor_count_df[0],
              y_val=actor_count_df.index,
              fig_size=(15,10),
              title='Top Movies Per Actor',
              x_label='Number Of Top Movies',
              y_label='Actors'
             )
```



Research Question 6 - Which Production Company produced **Most** of the Top 20 Revenue movies?

Twentieth Century Fox Film Corporation was first followed by **Lucas Film and Universal Pictures** as the production companies that produced or were part of the production of the top 20 revenue movies. We used the number of occurences of a production company in all the top 20 revenue movies as the metric for this.

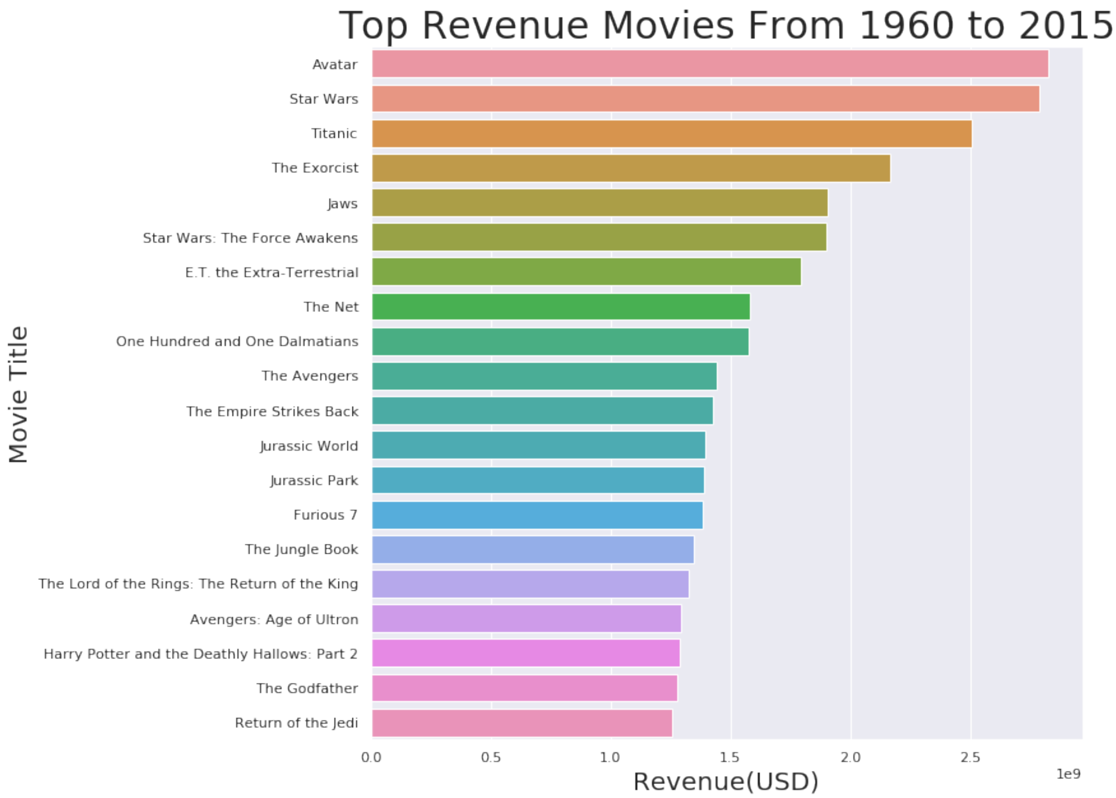
[31]:
```
# Find the Production Company That Featured in Most of the Highest Revenue␣
↪Movies
company_counts =␣
↪generate_value_and_count(data=top_20_revenue['production_companies'])
company_count_df = pd.DataFrame.from_dict(company_counts, orient="index")

# Generate the Plot
generate_plot(x_val=company_count_df[0],
              y_val=company_count_df.index,
              fig_size=(10,10),
              title='Top Movies Per Production Company',
              x_label='Number Of Top Movies',
              y_label='Production Company'
             )
```



Research Question 7 - What Are The Top 20 Revenue Movies From 1960 to 2015?

We found out that **Avatar** is the Highest Revenue Movie from 1960 to 2015

[32]:
```
# Generate plots for highest revenue movies
generate_plot(x_val=top_20_revenue['revenue_adj'],
              y_val=top_20_revenue['original_title'],
              fig_size=(10,10),
              title='Top Revenue Movies From 1960 to 2015',
              x_label='Revenue(USD)',
              y_label='Movie Title'
             )
```



Conclusions

We tried to answer all the questions we asked ourselves at the start of this analysis though we realize that the data that was left after cleaning the data was very small.

The other challenge we observe is the unequal distribution of the number of movies produced each year. It follows that, the comparison among the various years especially in terms of total revevenue generated would not be fair.

This is due to the fact that a lot of the data on revenue was 0 and not desirable and all those corresponding rows had to be dropped. All the observations are therefore tentative.

We observe that: * There has been an increase in revenue in relation to the budget that is set aside for producing the movies over the years. * Avata stood out as the highest revenue movie with the 50+ year period the data spans. * The Drama and Western genres seem to have maintained popularity among consumers over this period.

1.1.5 References

Stackoverflow

Seaborn Documentation

Numpy Documentation