Project: TMDb movie data analysis

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Introduction

In this project, I will be analyzing the TMDb movie data set. This data set shows the name of the movies, their genres, budget, profit that they made, the companies that produced those movies, and the year it was released. Through my analysis, I will try to find out trends and answer some questions like:

- Which genres are more popular
- Which genres are more profitable
- Which company make the most profit
- Which movies are the most popular
- Which movies are the most profitable
- What are the profit trend of movies from year to year
- What kinds of properties are associated with movies that have high revenues

Importing needed libraries

In [32]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Data Wrangling

Reading TMDb movies file

In [33]:
```
df = pd.read_csv('tmdb-movies.csv')
df
```

Out[33]:

	id	imdb_id	popularity	budget	revenue	original_title	cast
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...

	id	imdb_id	popularity	budget	revenue	original_title	cast	
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://w
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	I
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	
...	...	...	...	...	...	...	...	
10861	21	tt0060371	0.080598	0	0	The Endless Summer	Michael Hynson|Robert August|Lord 'Tally Ho' B...	
10862	20379	tt0060472	0.065543	0	0	Grand Prix	James Garner|Eva Marie Saint|Yves Montand|Tosh...	
10863	39768	tt0060161	0.065141	0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...	
10864	21449	tt0061177	0.064317	0	0	What's Up, Tiger Lily?	Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...	

	id	imdb_id	popularity	budget	revenue	original_title	cast
10865	22293	tt0060666	0.035919	19000	0	Manos: The Hands of Fate	Harold P. Warren|Tom Neyman|John Reynolds|Dian...

10866 rows × 21 columns

Assessing data

In [34]:
```
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
```

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

Out[4]:

	id	popularity	budget	revenue	runtime	vote_count	vote_avera
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.000000	10866.000
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389748	5.974
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619058	0.935
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000	1.500
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.000000	5.400
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.000000	6.000
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	6.600

	id	popularity	budget	revenue	runtime	vote_count	vote_avera
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	9.200

In [5]:
```
df.duplicated().sum()
```

Out[5]:
```
1
```

In the assessment above I found out the following:

Quality issues:

- The values in the production_companies and genres columns are separated by | character
- Some data are missing
- There is one duplicate
- Some columns are unnecessary

Data Cleaning

Removing the unnecessary columns

In [6]:
```
df.drop(['id', 'imdb_id', 'homepage', 'tagline', 'keywords', 'overview', 'release_date'
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   popularity            10866 non-null  float64
 1   original_title        10866 non-null  object 
 2   cast                  10790 non-null  object 
 3   director              10822 non-null  object 
 4   runtime               10866 non-null  int64  
 5   genres                10843 non-null  object 
 6   production_companies  9836 non-null   object 
 7   vote_count            10866 non-null  int64  
 8   vote_average          10866 non-null  float64
 9   release_year          10866 non-null  int64  
 10  budget_adj            10866 non-null  float64
 11  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(3), object(5)
memory usage: 1018.8+ KB
```

Removing duplicates and the missing values

In [7]:
```
df.dropna(inplace=True)
df.drop_duplicates(inplace = True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9772 entries, 0 to 10865
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   popularity            9772 non-null   float64
 1   original_title        9772 non-null   object 
 2   cast                  9772 non-null   object 
```

```
 3   director              9772 non-null   object 
 4   runtime               9772 non-null   int64  
 5   genres                9772 non-null   object 
 6   production_companies  9772 non-null   object 
 7   vote_count            9772 non-null   int64  
 8   vote_average          9772 non-null   float64
 9   release_year          9772 non-null   int64  
 10  budget_adj            9772 non-null   float64
 11  revenue_adj           9772 non-null   float64
dtypes: float64(4), int64(3), object(5)
memory usage: 992.5+ KB
```

Removing | character from the genres column

In [8]:

```
genre_clean = df.genres.apply(lambda x: pd.value_counts(x.split('|'))).fillna(0)
genre_clean
```

Out[8]:

	Science Fiction	Adventure	Action	Thriller	Fantasy	Crime	Drama	Western	Animation	Family	Con
0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	1.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	
10861	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
10862	0.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
10863	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
10864	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
10865	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

9772 rows × 20 columns

Combining the genres into one table by counting the number of each genre and creating a data frame for it

In [9]:

```
# counting code
genre_count = genre_clean.sum(axis = 0)
# data frame code
genre_df = pd.DataFrame(genre_count, columns=['count'])
genre_df['genre'] = genre_df.index
genre_df
```

Out[9]:

	count	genre
Science Fiction	1136.0	Science Fiction
Adventure	1384.0	Adventure
Action	2235.0	Action
Thriller	2746.0	Thriller

	count	genre
Fantasy	840.0	Fantasy
Crime	1299.0	Crime
Drama	4364.0	Drama
Western	160.0	Western
Animation	617.0	Animation
Family	1095.0	Family
Comedy	3433.0	Comedy
Mystery	773.0	Mystery
Romance	1570.0	Romance
War	258.0	War
History	306.0	History
Music	339.0	Music
Horror	1526.0	Horror
Documentary	317.0	Documentary
TV Movie	132.0	TV Movie
Foreign	120.0	Foreign

Removing | character from the production_companies column

In [10]:
```
companies_cleaned = df.production_companies.apply(lambda x: pd.value_counts(x.split('|'
companies_cleaned
```

Out[10]:

	Legendary Pictures	Universal Studios	Fuji Television Network	Amblin Entertainment	Dentsu	Village Roadshow Pictures	Kennedy Miller Productions	NeoReel	I Ent
0	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	
10861	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
10862	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
10863	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
10864	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
10865	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

9772 rows × 7842 columns

Exploratory Data Analysis

Research Question 1 (Which genres are more popular)

First creating a list

In [11]:
```
genres = list(genre_df.genre)
```

Using the matrix method to calculate the popularity for each genre

In [12]:
```
popularity_calculation = np.matrix(df.popularity) * np.matrix(genre_clean)
```

Creating popularity list

In [13]:
```
genre_popularity_calculation_list = popularity_calculation.tolist()[0]
```

Creating a data frame for genre and popularity

In [14]:
```
genre_popularity = pd.DataFrame({'genre': genres,
                                 'popularity': genre_popularity_calculation_list})
genre_popularity
```

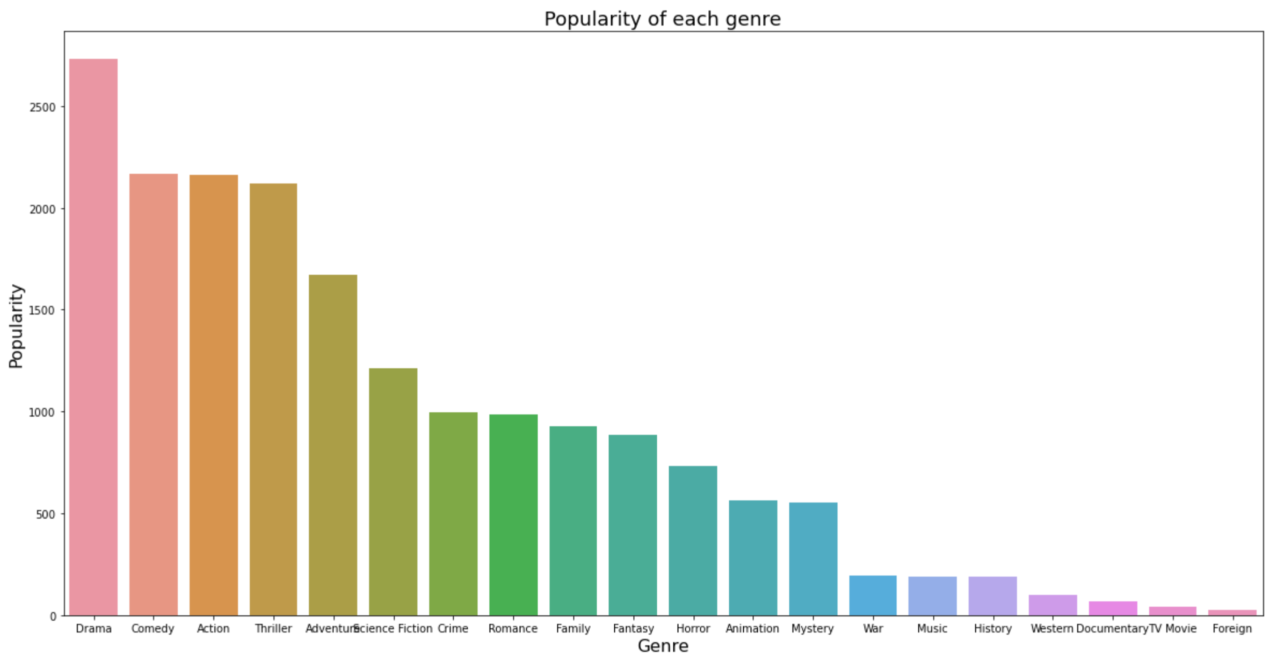
Out[14]:

	genre	popularity
0	Science Fiction	1210.155764
1	Adventure	1673.329036
2	Action	2164.052715
3	Thriller	2120.385441
4	Fantasy	887.300733
5	Crime	996.770934
6	Drama	2731.333255
7	Western	96.728674
8	Animation	564.111643
9	Family	926.881471
10	Comedy	2168.162456
11	Mystery	551.609983
12	Romance	984.669716
13	War	194.216473
14	History	186.506870
15	Music	186.749755
16	Horror	732.795567

	genre	popularity
17	Documentary	68.842029
18	TV Movie	39.053984
19	Foreign	25.126097

Creating a bar chart to demonstrate the popularity of each genre

In [15]:
```
plt.figure(figsize=[20,10])
sns.barplot(data=genre_popularity.sort_values(by='popularity', ascending=False), x='gen
plt.xlabel('Genre', fontsize=16)
plt.ylabel('Popularity', fontsize=16)
plt.title('Popularity of each genre', fontsize=18);
```



- It looks like Drama is the most liked genre by the audience.

Research Question 2 (Which genres are more profitable)

Using the matrix method to calculate the revenue for each genre and creating revenue list

In [16]:
```
revenue_calculation = np.matrix(df.revenue_adj) * np.matrix(genre_clean)
genre_revenue_calculation_list = revenue_calculation.tolist()[0]
```

Creating a data frame for genre and revenue

In [17]:
```
genre_revenue = pd.DataFrame({'genre': genres,
                              'revenue': genre_revenue_calculation_list})
genre_revenue
```

Out[17]:

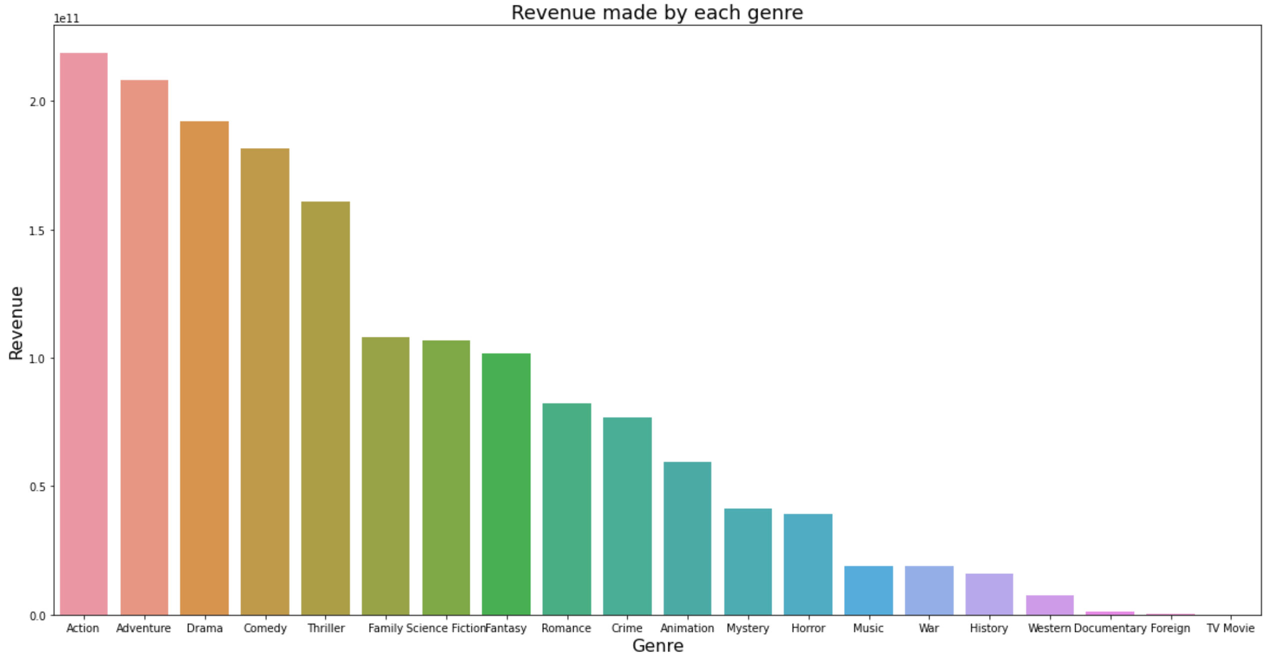
	genre	revenue
0	Science Fiction	1.068414e+11
1	Adventure	2.082414e+11
2	Action	2.186066e+11

	genre	revenue
3	Thriller	1.605913e+11
4	Fantasy	1.018289e+11
5	Crime	7.667539e+10
6	Drama	1.921169e+11
7	Western	7.606709e+09
8	Animation	5.953321e+10
9	Family	1.078018e+11
10	Comedy	1.814423e+11
11	Mystery	4.114336e+10
12	Romance	8.242227e+10
13	War	1.889625e+10
14	History	1.601051e+10
15	Music	1.902425e+10
16	Horror	3.936368e+10
17	Documentary	1.112954e+09
18	TV Movie	5.838910e+07
19	Foreign	2.229048e+08

Creating a bar chart to demonstrate the profitability of each genre

In [18]:

```
plt.figure(figsize=[20,10])
sns.barplot(data=genre_revenue.sort_values(by='revenue', ascending=False), x='genre', y
plt.xlabel('Genre', fontsize=16)
plt.ylabel('Revenue', fontsize=16)
plt.title('Revenue made by each genre', fontsize=18);
```



- Although that Drama is the most popular genre, it looks like Action has more profit which means also that it is watched more by the audience.

Research Question 3 (Which company make the most profit)

Because there were a lot of companies I only took the companies which produced more than 100 movies

Extracting the desired companies

In [19]:
```
top_companies = companies_cleaned.sum()[companies_cleaned.sum()>100].index.tolist()
```

Calling the data

In [20]:
```
companies = companies_cleaned[top_companies]
```

Using the matrix method to calculate the revenue for each company and creating a list

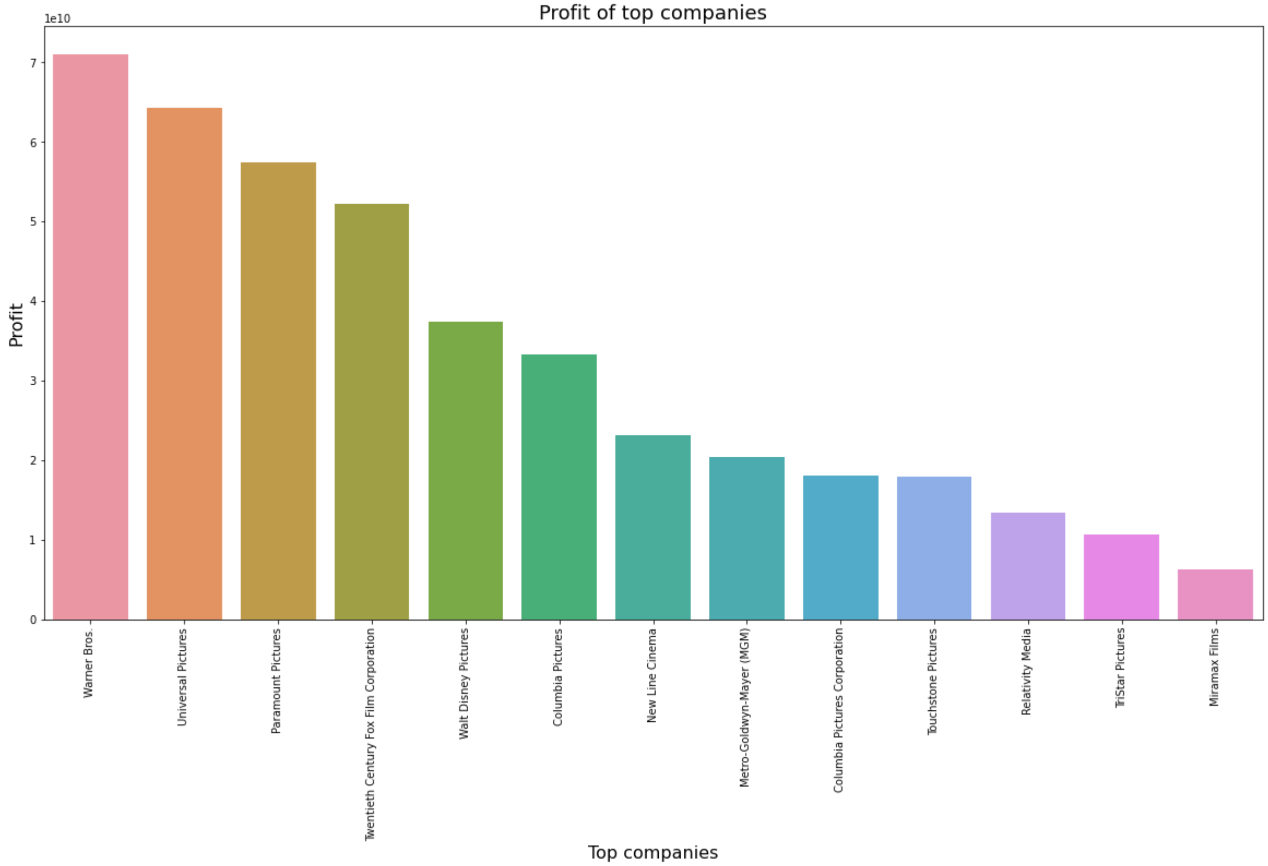
In [21]:
```
companies_revenue_calculation = np.matrix(df.revenue_adj) * np.matrix(companies)
companies_revenue_calculation_list = companies_revenue_calculation.tolist()[0]
```

Creating a data frame for companies and revenue

In [22]:
```
top_companies_profit = pd.DataFrame({'companies': top_companies,
                                     'revenue': companies_revenue_calculation_list})
```

Creating a bar chart to demonstrate the wich companey made the most profit

In [23]:
```
plt.figure(figsize=[20,10])
sns.barplot(data=top_companies_profit.sort_values(by='revenue', ascending=False)[0:15],
plt.xticks(rotation=90)
plt.xlabel('Top companies', fontsize=16)
plt.ylabel('Profit', fontsize=16)
plt.title('Profit of top companies', fontsize=18);
```

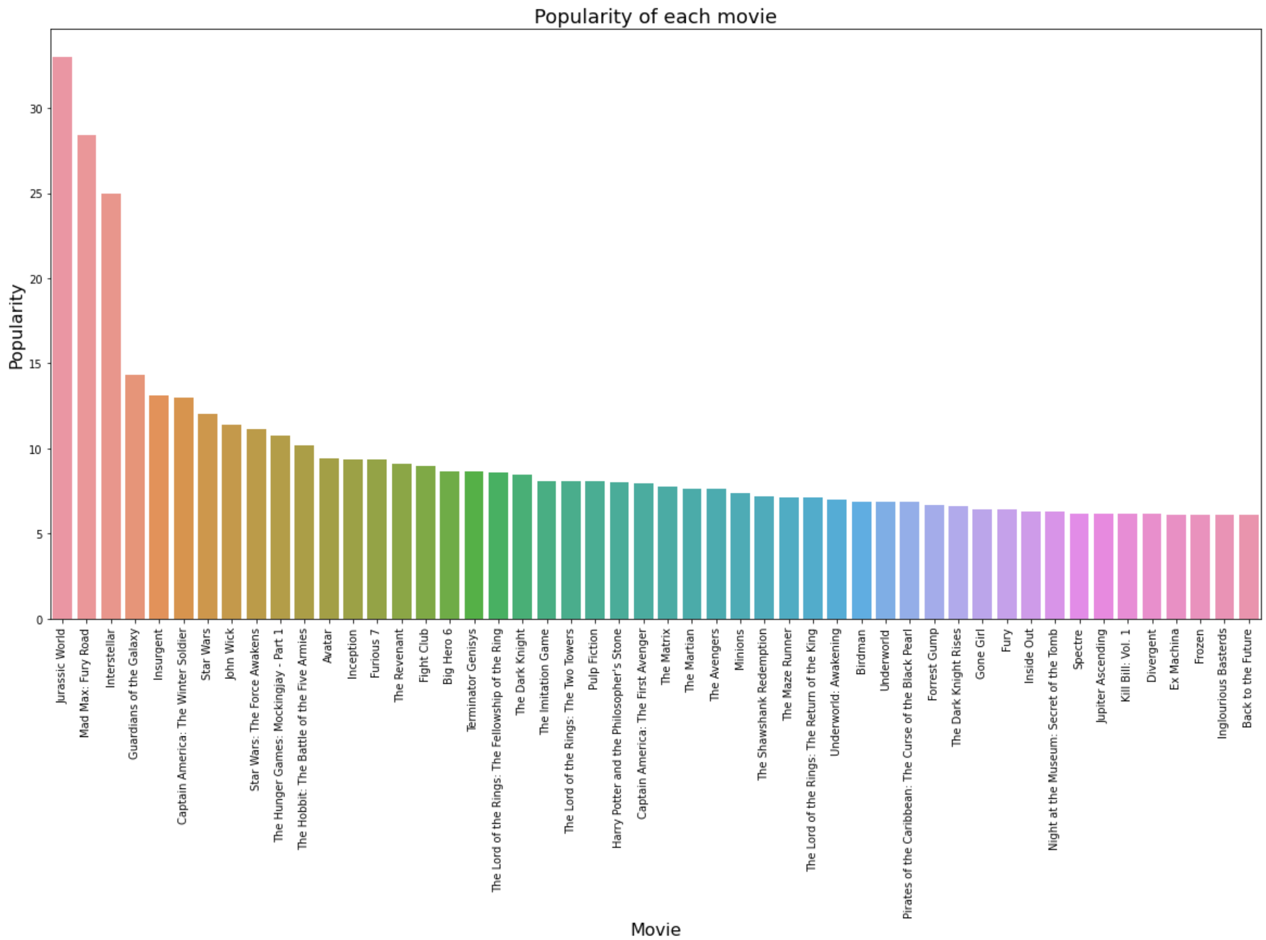


- Warner Bros made the highest profit

Research Question 4 (Which movies are the most popular)

Creating a bar chart to demonstrate which movies are the most popular

In [24]:
```
# calling the needed data
most_popular_movie = df[['original_title', 'popularity']]
# bar chart code
plt.figure(figsize=[20,10])
sns.barplot(data=most_popular_movie.sort_values(by='popularity', ascending=False)[0:50]
plt.xticks(rotation=90)
plt.xlabel('Movie', fontsize=16)
plt.ylabel('Popularity', fontsize=16)
plt.title('Popularity of each movie', fontsize=18);
```

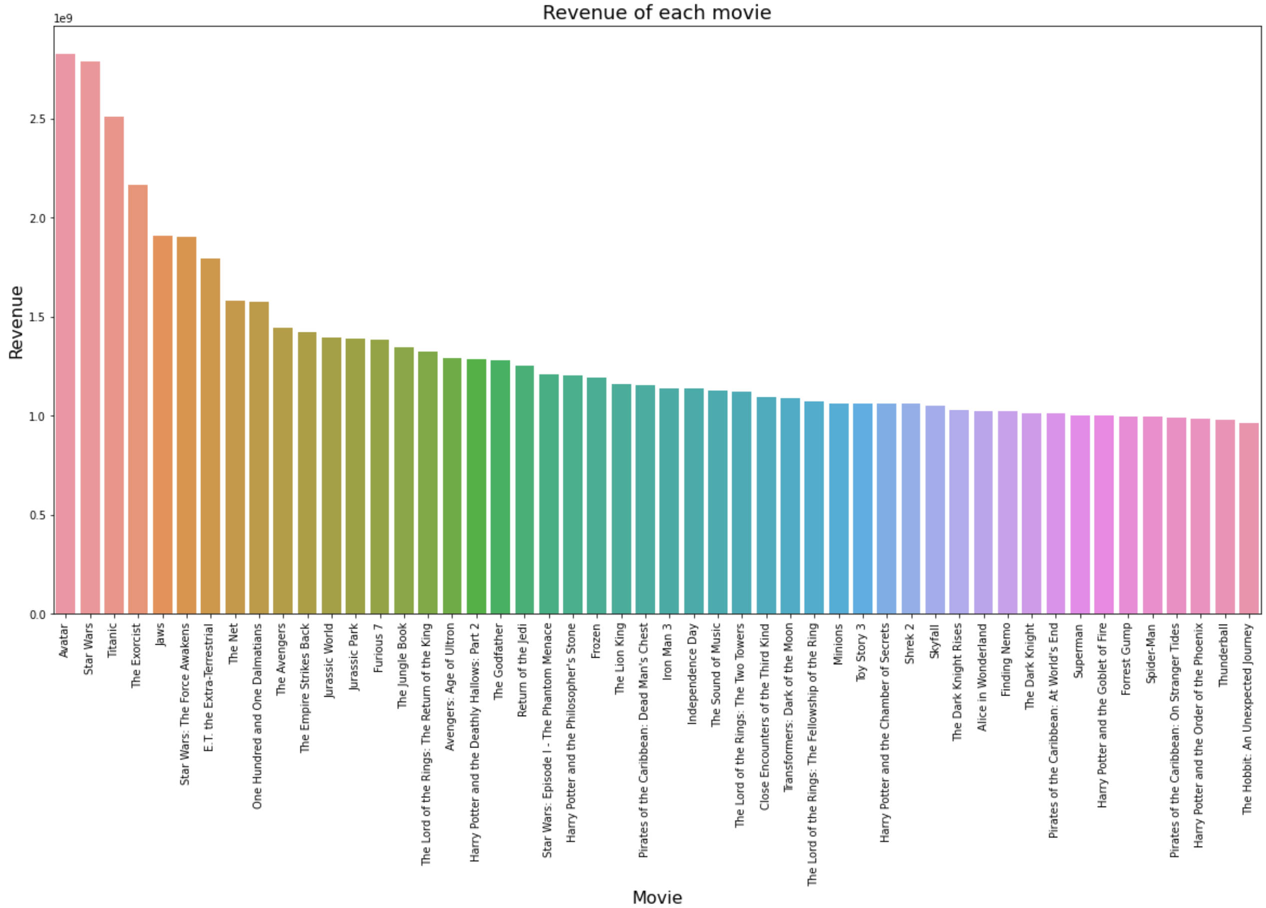


- Jurassic World has the most popularity between all movies.

Research Question 4 (Which movies are the most profitable)

Creating a bar chart to demonstrate the wich movies are the most profitable

In [25]:
```
# calling the data needed
most_profitable_movie = df[['original_title', 'revenue_adj']]
# bar chart code
plt.figure(figsize=[20,10])
sns.barplot(data=most_profitable_movie.sort_values(by='revenue_adj', ascending=False)[0
plt.xticks(rotation=90)
plt.xlabel('Movie', fontsize=16)
plt.ylabel('Revenue', fontsize=16)
plt.title('Revenue of each movie', fontsize=18);
```



- Avatar made the highest profit which also means its has the highest view rates.

Research Question 5 (What are the profit trend of movies from year to year)

Creating a new column that calculates the difference between the revenue and the budget

In [26]:
```
df['profit_or_loss_ammount'] = df['revenue_adj'] - df['budget_adj']
```

Creting a line gragh to show the trend

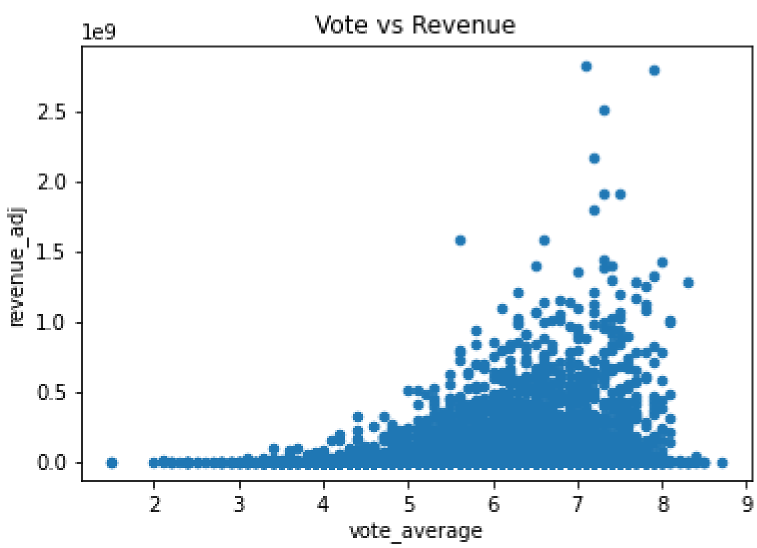
In [27]:
```
df.groupby('release_year')['profit_or_loss_ammount'].sum().plot(kind = 'line', figsize
plt.xlabel('Year', fontsize=16)
plt.ylabel('Profit or Loss ammount', fontsize=16)
plt.title('Profit trend over the years', fontsize=18);
```

- The gragh shows that there is an increase in profit through time.

Research Question 6 (What kinds of properties are associated with movies that have high revenues)

This polt shows the relation between the votes and the revenue

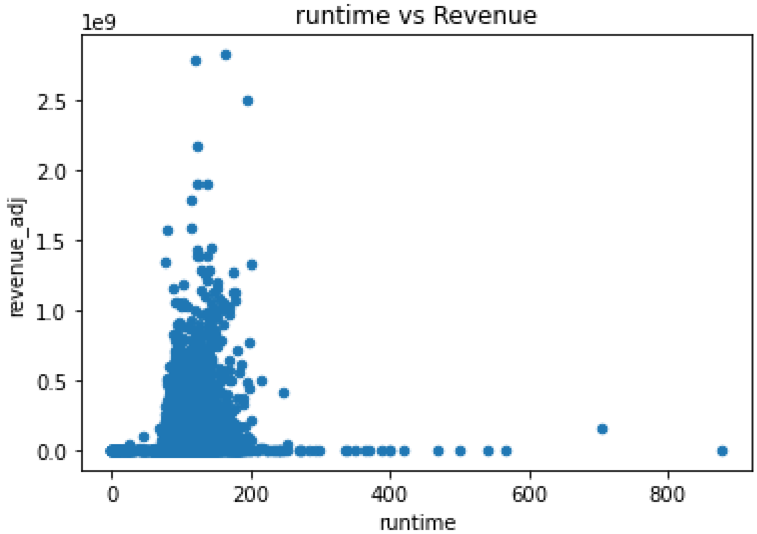
In [28]:
```
df.plot(x='vote_average',y='revenue_adj',kind='scatter')
plt.title('Vote vs Revenue')
plt.show()
```



- The scatter plot shows that there is a positive correlation between the votes and the revenue.

This polt shows the relation between the runtime and the revenue

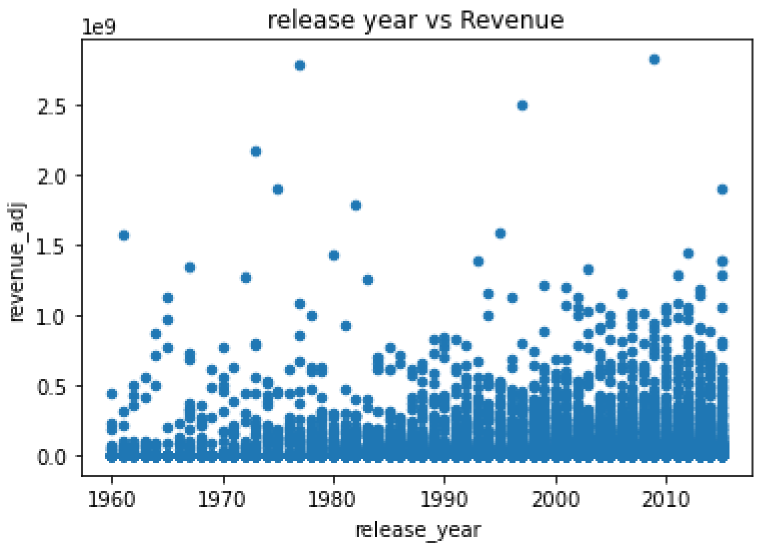
In [29]:
```
df.plot(x='runtime',y='revenue_adj',kind='scatter')
plt.title('runtime vs Revenue')
plt.show()
```



- The scatter plot shows that there is a negative correlation between the runtime and the revenue.

This polt shows the relation between the release year and the revenue

In [31]:
```
df.plot(x='release_year',y='revenue_adj',kind='scatter')
plt.title('release year vs Revenue')
plt.show()
```



- The scatter plot shows that there is a positive correlation between the release year and the revenue.

Conclusions

As demonstrated from the questions and the analysis above I arrived at the following conclusions:

- Drama is the most liked genre that comes on first then Comedy, Action, Thriller with a very small difference between them.

- Although Drama came up first as the most liked genre. Action has the highest revenue then comes Adventure and Drama in third place. Which indicates that Action has the highest view rates.
- The movie industry has a massive amount of production companies, so to be able to find out which were the most profitable ones I had in my analysis only the companies that have more than 100 movies. The most profitable one was Warner Bros, and then came respectively Universal Pictures, Paramount Pictures, 20th Century Fox, Walt Disney Pictures, Columbia Pictures, New Line Cinema, Metro Goldwyn Mayer. It is expected that these companies would come at the top for they are the leading filmmakers, and they know what is popular with the audience.
- The most popular movie was Jurassic World, then came Mad Max Fury Road, then Interstellar. There is a big difference between the first three movies and the rest of the list.
- The most profitable movie was Avatar, the came Star Wars, then Titanic. It also shows that they have the highest view rates.
- I found out that profit increases through the years. Which shows that the film making industry is growing.
- I found out that the more votes the movie gets the highest the revenue, also if the movie runtime is no more than 200 and not very short the highest the revenue it gets. And also with time the profit increases, maybe because more movies were made and technology is better.

In [ ]:

In [ ]:

In [ ]:

In [ ]: