Final Project Submission

Please fill out:

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- Student pace: self paced / part time / full time: FULL TIME
- Scheduled project review date/time:
- Instructor name:
- Blog post URL: https://ndirangusdatachronicles.blogspot.com/2023/03/my-maiden-project-as-data-scientist.html (https://ndirangusdatachronicles.blogspot.com/2023/03/my-maiden-project-as-data-scientist.html)

Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don’t know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable insights that the head of Microsoft's new movie studio can use to help decide what type of films to create.

Bussiness Understanding

As a data scientist analyzing the movie industry, my business understanding is that the movie industry is a complex ecosystem that involves various stakeholders, including studios, production companies, distributors, exhibitors, and audiences. The success of a movie depends on several factors, including the quality of the script, the star power of the actors, the marketing campaign, the release date, and the competition from other movies. Certain genres tend to perform better than others. For example, action and adventure films tend to perform well at the box office, while documentaries and foreign language films may have limited appeal to mainstream audiences.

To analyze the movie industry, we need to gather data from various sources, including box office data, social media data, audience surveys, and critical reviews. We can use data analysis techniques such as regression analysis, clustering, and sentiment analysis to identify patterns and insights from the data.

To overcome these challenges, we need to use a combination of quantitative and qualitative analysis techniques and incorporate domain knowledge and expertise. By understanding the movie industry's complexities and using data-driven insights, we can help studios and production companies make informed decisions about which movies to produce, how to market them, and when to release them, ultimately leading to more successful movies and a more profitable industry.

Data Understanding

The datasets used in this notebook are listed below.

1. im.db
2. tn.movie_budgets.csv

Importing Libraries and Modules

In [1]:
```
#import modules & libraries
import pandas as pd
import numpy as np
import csv
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Understanding our ' im.db' movie data set

In [2]:
```
import os
import sqlite3
import pandas as pd
```

In [3]:
```
imdb_path = os.path.join('im.db')

# Open up a connection
conn = sqlite3.connect(imdb_path)
# Initialize a cursor
cursor = conn.cursor()
```

In [4]:
```
# lets get a dropdown list of the tables in this database
table_name_query = """SELECT name
                      AS 'Table Names'
                      FROM sqlite_master
                      WHERE type='table';"""

pd.read_sql(table_name_query, conn)
```

Out[4]:

	Table Names
0	movie_basics
1	directors
2	known_for
3	movie_akas
4	movie_ratings
5	persons
6	principals
7	writers

lets explore the tables and see the first five rows on each table

In [5]:
```
# exploring movie_basics table
q = ("""
SELECT *
FROM movie_basics
;

""")

pd.read_sql(q, conn).head()
```

Out[5]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [6]:
```
# exploring movie_ratings table
q = ("""
SELECT *
FROM movie_ratings
;

""")

pd.read_sql(q, conn).head()
```

Out[6]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21

In [7]:
```
# exploring directors table
q = ("""
SELECT *
FROM directors
;

""")

pd.read_sql(q, conn).head()
```

Out[7]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0462036	nm1940585
2	tt0835418	nm0151540
3	tt0835418	nm0151540
4	tt0878654	nm0089502

In [8]:
```
# exploring known_for table
q = ("""
SELECT *
FROM known_for
;

""")

pd.read_sql(q, conn).head()
```

Out[8]:

	person_id	movie_id
0	nm0061671	tt0837562
1	nm0061671	tt2398241
2	nm0061671	tt0844471
3	nm0061671	tt0118553
4	nm0061865	tt0896534

In [9]:
```
# exploring movie_akas table
q = ("""
SELECT *
FROM movie_akas

""")

pd.read_sql(q, conn).head()
```

Out[9]:

	movie_id	ordering	title	region	language	types	attributes	is_original_title
0	tt0369610	10	Джурасик свят	BG	bg	None	None	0.0
1	tt0369610	11	Jurashikku warudo	JP	None	imdbDisplay	None	0.0
2	tt0369610	12	Jurassic World: O Mundo dos Dinossauros	BR	None	imdbDisplay	None	0.0
3	tt0369610	13	O Mundo dos Dinossauros	BR	None	None	short title	0.0
4	tt0369610	14	Jurassic World	FR	None	imdbDisplay	None	0.0

In [10]:
```
# exploring persons table
q= ("""
SELECT *
FROM persons

""")

pd.read_sql(q, conn).head()
```

Out[10]:

	person_id	primary_name	birth_year	death_year	primary_professio
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,produce
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_departme
2	nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,write
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_departme
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_decorat

In [11]:
```
# exploring principals table
q = ("""
SELECT *
FROM principals

""")

pd.read_sql(q, conn).head()
```

Out[11]:

	movie_id	ordering	person_id	category	job	characters
0	tt0111414	1	nm0246005	actor	None	["The Man"]
1	tt0111414	2	nm0398271	director	None	None
2	tt0111414	3	nm3739909	producer	producer	None
3	tt0323808	10	nm0059247	editor	None	None
4	tt0323808	1	nm3579312	actress	None	["Beth Boothby"]

In [12]:
```
# exploring writers table
q= ("""
SELECT *
FROM writers

""")

pd.read_sql(q, conn).head()
```

Out[12]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0438973	nm0175726
2	tt0438973	nm1802864
3	tt0462036	nm1940585
4	tt0835418	nm0310087

now you can get a feel of the type of data in this database

Understanding our 'tn.movie_budgets.csv' Dataset

In [13]:
```
# lets load the csv file and ouput the the first five rows
movie_budgets_df = pd.read_csv('tn.movie_budgets.csv')
movie_budgets_df.head()
```

Out[13]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [14]:
```
#lets get a list of columns in this dataframe
movie_budgets_df.columns
```

Out[14]:
```
Index(['id', 'release_date', 'movie', 'production_budget', 'domestic_gross',
       'worldwide_gross'],
      dtype='object')
```

In [15]:
```
# summary of the dataframe
movie_budgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

Data Preparation

Preparing the movie budgets data

In [16]:
```
# lets find out the number of null values in this dataframe
movie_budgets_df.isna().sum()
```

Out[16]:
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

It seems there are no null values in this data

In [17]:
```
#lets check the column datatypes
movie_budgets_df.dtypes
```

Out[17]:
```
id                    int64
release_date         object
movie                object
production_budget    object
domestic_gross       object
worldwide_gross      object
dtype: object
```

All columns in this dataset are string(str) datatype.We need to change the production_budget, domestic_gross,worldwide_gross to integer (int) datatype

In [18]:
```
# Lets remove the dollar sign from the production_budget, worldwide_gross, domest
movie_budgets_df["production_budget"] = movie_budgets_df["production_budget"].rep
movie_budgets_df["worldwide_gross"] = movie_budgets_df["worldwide_gross"].replace
movie_budgets_df["domestic_gross"] = movie_budgets_df["domestic_gross"].replace('
movie_budgets_df.head()
```

Out[18]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09

To make the release date column useful, we need to get the years by parsing the last four digits in every row in the column

In [19]:
```
#Lets get the release year of the movies by extracting the last 4 characters of t
movie_budgets_df['release_date'] = movie_budgets_df['release_date'].str[-4:]
movie_budgets_df.head()
```

Out[19]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	2009	Avatar	425000000.0	760507625.0	2.776345e+09
1	2	2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09
2	3	2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08
3	4	2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09
4	5	2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09

Data Analysis

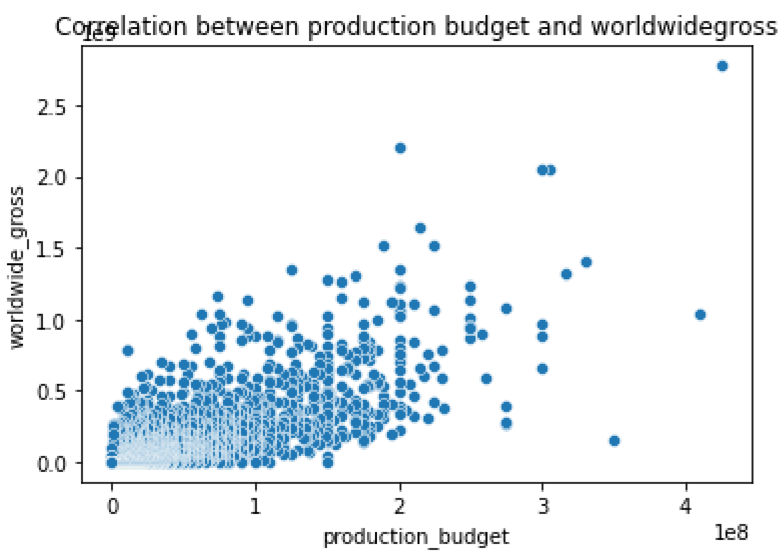
Analysing data from the movie_budgets_df data

In [20]:
```
# statistical measures
movie_budgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5782 non-null   int64  
 1   release_date       5782 non-null   object 
 2   movie              5782 non-null   object 
 3   production_budget  5782 non-null   float64
 4   domestic_gross     5782 non-null   float64
 5   worldwide_gross    5782 non-null   float64
dtypes: float64(3), int64(1), object(2)
memory usage: 271.2+ KB
```

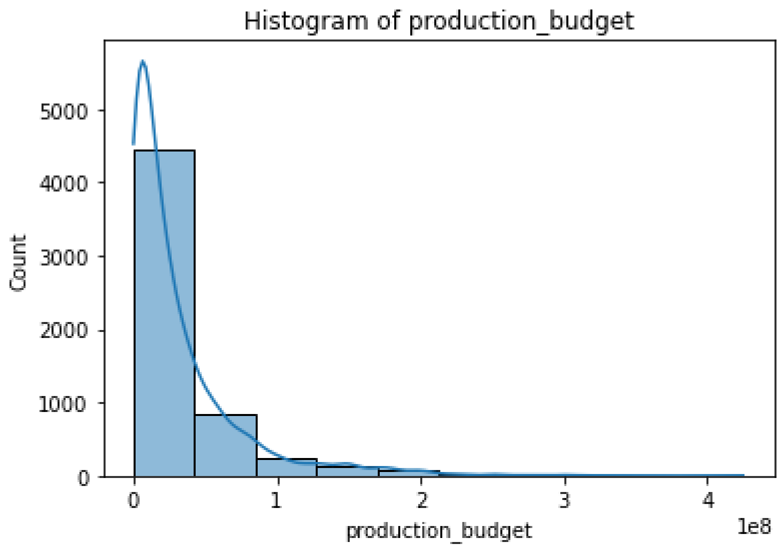
In [21]:
```
# correlation between runtime and ratings
sns.scatterplot(x='production_budget', y='worldwide_gross', data=movie_budgets_df
```

Out[21]:
```
[Text(0.5, 1.0, 'Correlation between production budget and worldwidegross')]
```



There is a positive relationship between production budget and worldwide gross

In [22]:
```
# Plot histogram with Seaborn
sns.histplot(data=movie_budgets_df, x='production_budget', bins=10, kde=True)

# Set plot title and labels
plt.title('Histogram of production_budget')
plt.xlabel('production_budget')
plt.ylabel('Count')

# Show the plot
plt.show()
```



The number of movies increases as the production budget increases

In [23]:
```
#What is the total worldwide_gross for each release_year
df1=movie_budgets_df.groupby('release_date')['worldwide_gross'].sum()
df1
```

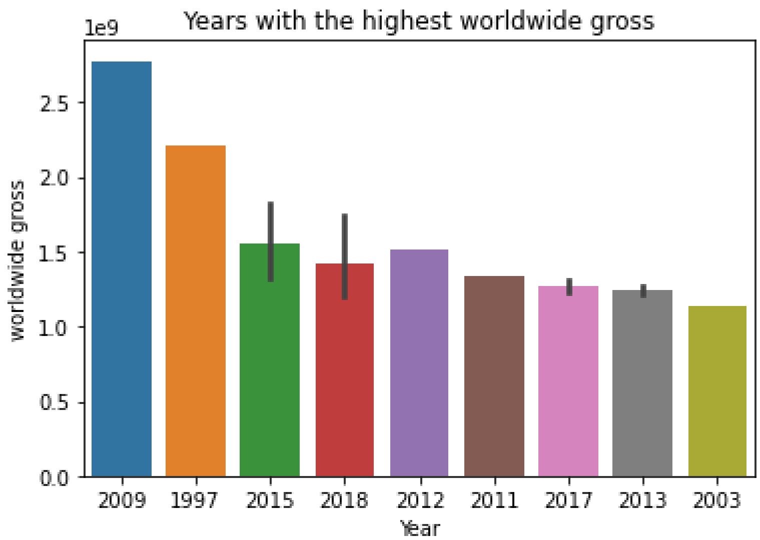
Out[23]:
```
release_date
1915    1.100000e+07
1916    8.000000e+06
1920    3.000000e+06
1925    3.100000e+07
1927    0.000000e+00
            ...
2016    2.876815e+10
2017    2.842963e+10
2018    2.609444e+10
2019    6.676825e+09
2020    0.000000e+00
Name: worldwide_gross, Length: 96, dtype: float64
```

In [24]:
```
#What are the top 10 movies based on movie_budgets
df6=movie_budgets_df.nlargest (n=20, columns='worldwide_gross')
df6
```

Out[24]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	2009	Avatar	425000000.0	760507625.0	2.776345e+09
42	43	1997	Titanic	200000000.0	659363944.0	2.208208e+09
5	6	2015	Star Wars Ep. VII: The Force Awakens	306000000.0	936662225.0	2.053311e+09
6	7	2018	Avengers: Infinity War	300000000.0	678815482.0	2.048134e+09
33	34	2015	Jurassic World	215000000.0	652270625.0	1.648855e+09
66	67	2015	Furious 7	190000000.0	353007020.0	1.518723e+09
26	27	2012	The Avengers	225000000.0	623279547.0	1.517936e+09
3	4	2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09
41	42	2018	Black Panther	200000000.0	700059566.0	1.348258e+09
260	61	2011	Harry Potter and the Deathly Hallows: Part II	125000000.0	381193157.0	1.341693e+09
4	5	2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09
112	13	2018	Jurassic World: Fallen Kingdom	170000000.0	417719760.0	1.305773e+09
155	56	2013	Frozen	150000000.0	400738009.0	1.272470e+09
134	35	2017	Beauty and the Beast	160000000.0	504014165.0	1.259200e+09
43	44	2018	Incredibles 2	200000000.0	608581744.0	1.242521e+09
22	23	2017	The Fate of the Furious	250000000.0	225764765.0	1.234846e+09
47	48	2013	Iron Man 3	200000000.0	408992272.0	1.215392e+09
672	73	2015	Minions	74000000.0	336045770.0	1.160336e+09
135	36	2018	Aquaman	160000000.0	335061807.0	1.146895e+09
425	26	2003	The Lord of the Rings: The Return of the King	94000000.0	377845905.0	1.141403e+09

In [25]:
```
#lets plot a bar chart using Seaborn for the years with the highest worldwide gro
sns.barplot(x='release_date', y='worldwide_gross', data=df6)
plt.title('Years with the highest worldwide gross')
plt.xlabel('Year')
plt.ylabel('worldwide gross')
plt.show()
```



There is no correlation between year of movie release and worldwide gross.

Analysing data from the "im.db" dataset

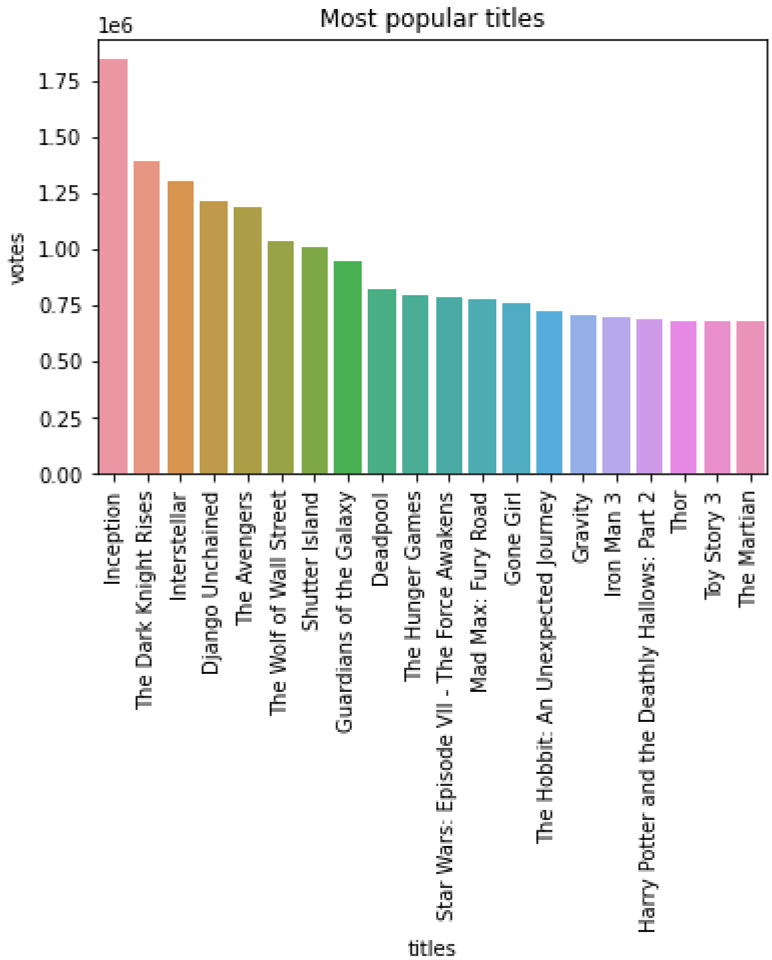
In [26]:

```python
# Most popular titles
q =("""
SELECT mb.primary_title, SUM(mr.numvotes) votes
FROM movie_basics mb
JOIN movie_ratings mr
ON mb.movie_id=mr.movie_id
GROUP BY 1
ORDER BY 2 DESC
;
""")

df1 = pd.read_sql(q, conn).head(20)
df1
```

Out[26]:

	primary_title	votes
0	Inception	1841066
1	The Dark Knight Rises	1387769
2	Interstellar	1299334
3	Django Unchained	1211405
4	The Avengers	1183655
5	The Wolf of Wall Street	1035358
6	Shutter Island	1005960
7	Guardians of the Galaxy	948394
8	Deadpool	820847
9	The Hunger Games	795227
10	Star Wars: Episode VII - The Force Awakens	784780
11	Mad Max: Fury Road	780910
12	Gone Girl	761592
13	The Hobbit: An Unexpected Journey	719629
14	Gravity	710018
15	Iron Man 3	692794
16	Harry Potter and the Deathly Hallows: Part 2	691835
17	Thor	683264
18	Toy Story 3	682218
19	The Martian	680116

In [27]:
```
# let's plot most popular titles
sns.barplot(x = 'primary_title',
            y = 'votes',
            data = df1)
plt.xticks(rotation=90)
plt.title('Most popular titles')
plt.xlabel('titles')
plt.show()
```



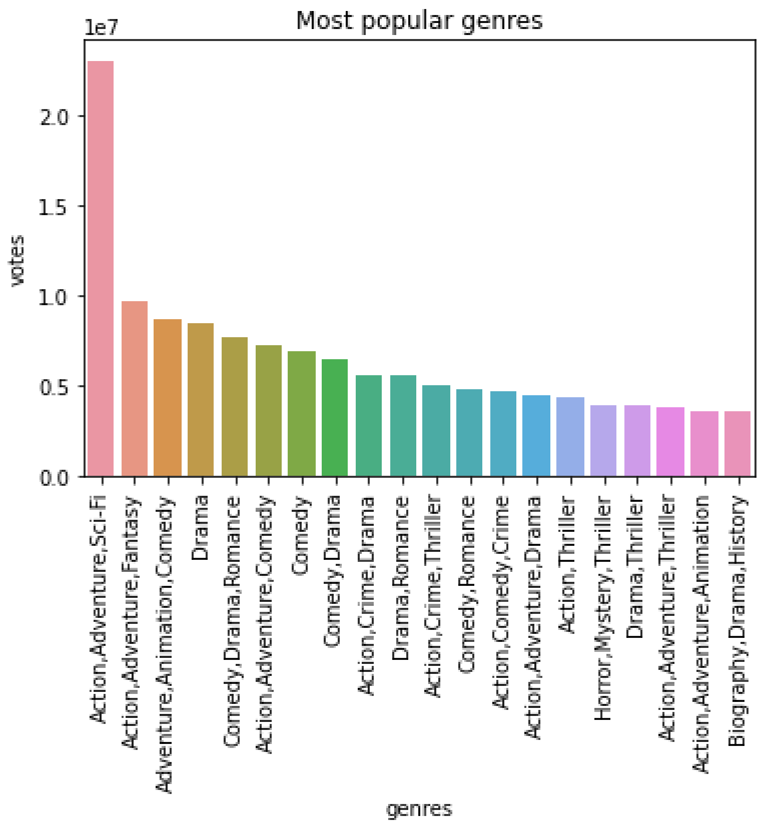
Movie sequels are very popular. They make a majority in this list

In [28]:
```
# Most popular genres
q =("""
SELECT mb.genres, SUM(mr.numvotes) votes
FROM movie_basics mb
JOIN movie_ratings mr
ON mb.movie_id=mr.movie_id
GROUP BY 1
ORDER BY 2 DESC
;
""")

df2 = pd.read_sql(q, conn).head(20)
df2
```

Out[28]:

	genres	votes
0	Action,Adventure,Sci-Fi	23023248
1	Action,Adventure,Fantasy	9658883
2	Adventure,Animation,Comedy	8687435
3	Drama	8395521
4	Comedy,Drama,Romance	7665463
5	Action,Adventure,Comedy	7256686
6	Comedy	6832037
7	Comedy,Drama	6462839
8	Action,Crime,Drama	5563553
9	Drama,Romance	5542760
10	Action,Crime,Thriller	4940335
11	Comedy,Romance	4752398
12	Action,Comedy,Crime	4686559
13	Action,Adventure,Drama	4485443
14	Action,Thriller	4284464
15	Horror,Mystery,Thriller	3902882
16	Drama,Thriller	3879354
17	Action,Adventure,Thriller	3748240
18	Action,Adventure,Animation	3570543
19	Biography,Drama,History	3502843

In [29]:
```
# let's plot most popular genres
sns.barplot(x = 'genres',
            y = 'votes',
            data = df2)
plt.xticks(rotation=90)
plt.title('Most popular genres')
plt.xlabel('genres')
plt.show()
```



A combo of Action, Adventure and Sci-Fi are significantly more popular than other genres

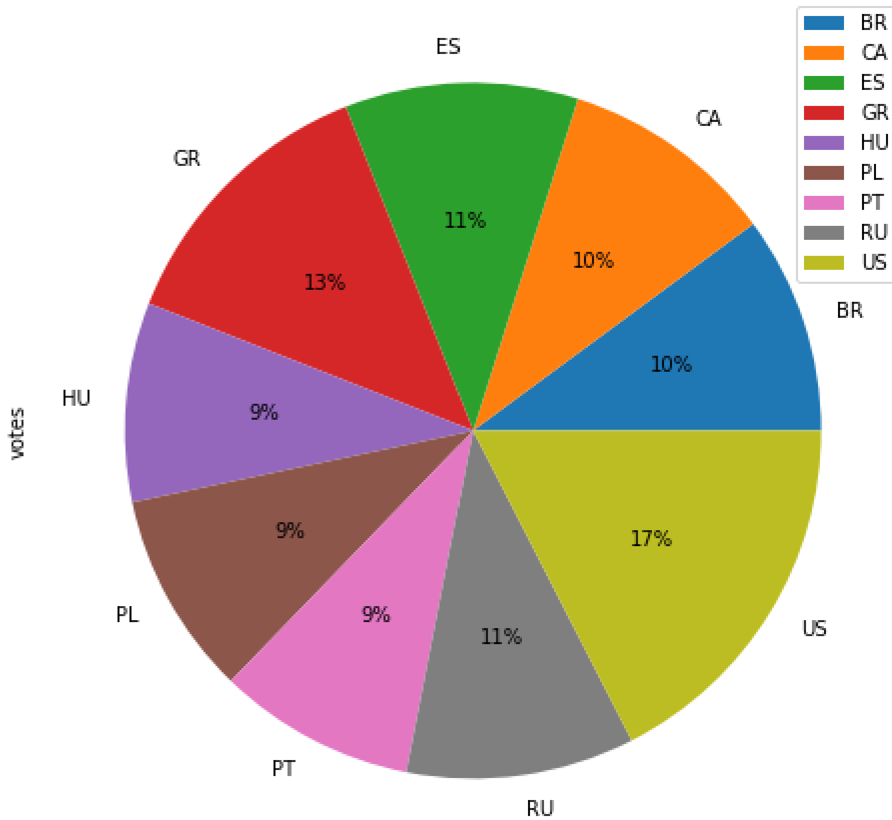
In [30]:
```
# Most popular regions
q =("""
SELECT ma.region, SUM(mr.numvotes) votes
FROM movie_akas ma
JOIN movie_ratings mr
ON ma.movie_id=mr.movie_id
GROUP BY 1
ORDER BY 2 DESC
LIMIT 10
;
""")

df3 = df_region_votes = pd.read_sql(q, conn)
df3
```

Out[30]:

	region	votes
0	US	418957631
1	GR	314020162
2	None	282537288
3	ES	259269856
4	RU	253657614
5	BR	242543329
6	CA	240139452
7	PL	227107093
8	HU	221576907
9	PT	219949216

In [31]:
```
df3.groupby(['region']).sum().plot(kind='pie', y='votes',  autopct='%1.0f%%', fig
```

Out[31]: <AxesSubplot:ylabel='votes'>



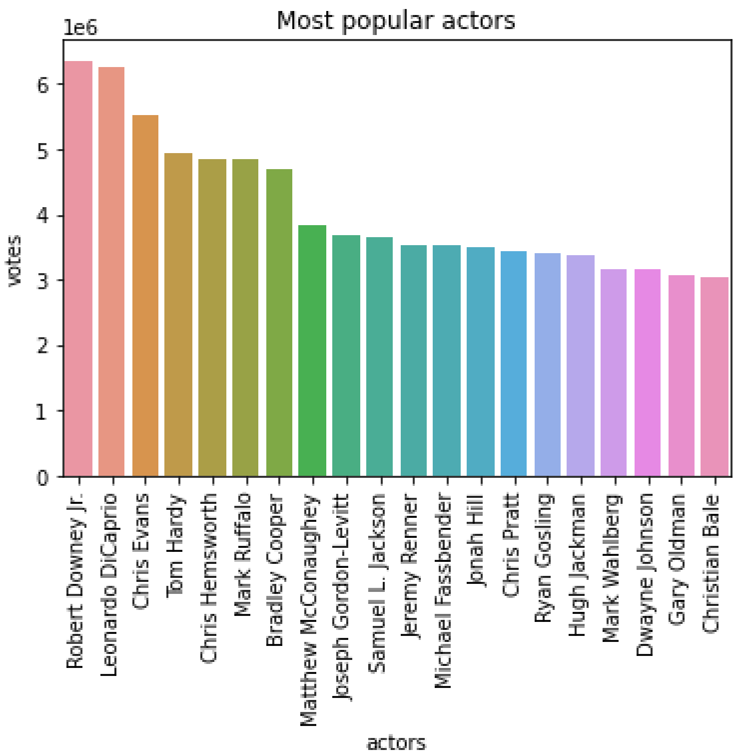
US is the clear leader with 17 % of the market among the top 10 regions, followed by GR with 13% and then a tie at 10% by CA and BR

In [32]:
```
# Most popular actors
q =("""
SELECT ps.primary_name, SUM(mr.numvotes) votes
FROM movie_ratings mr
JOIN principals pr
ON pr.movie_id=mr.movie_id
JOIN persons ps
ON pr.person_id=ps.person_id
WHERE pr.category = "actor"
GROUP BY 1
ORDER BY 2 DESC
;
""")

df4 = pd.read_sql(q, conn).head(20)
df4
```

Out[32]:

	primary_name	votes
0	Robert Downey Jr.	6356093
1	Leonardo DiCaprio	6273640
2	Chris Evans	5508229
3	Tom Hardy	4943284
4	Chris Hemsworth	4848874
5	Mark Ruffalo	4832689
6	Bradley Cooper	4692529
7	Matthew McConaughey	3844585
8	Joseph Gordon-Levitt	3675514
9	Samuel L. Jackson	3640518
10	Jeremy Renner	3535615
11	Michael Fassbender	3513828
12	Jonah Hill	3482202
13	Chris Pratt	3438850
14	Ryan Gosling	3405836
15	Hugh Jackman	3376938
16	Mark Wahlberg	3159282
17	Dwayne Johnson	3153317
18	Gary Oldman	3079611
19	Christian Bale	3032252

In [33]:
```
# let's find most popular actors
sns.barplot(x = 'primary_name',
            y = 'votes',
            data = df4)
plt.xticks(rotation=90)
plt.title('Most popular actors')
plt.xlabel('actors')
plt.show()
```



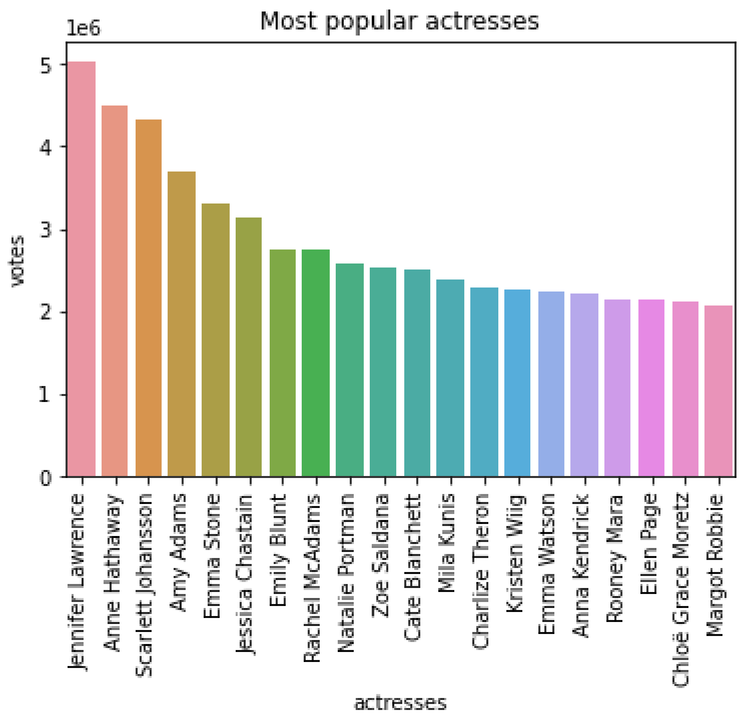
Robert Downey Jr leads the pack, followed closely by Leonardo DiCaprio, then Chris Evans and other popular movie actors

In [34]:
```
# Most popular actresses
q =("""
SELECT ps.primary_name, SUM(mr.numvotes) votes
FROM movie_ratings mr
JOIN principals pr
ON pr.movie_id=mr.movie_id
JOIN persons ps
ON pr.person_id=ps.person_id
WHERE pr.category = "actress"
GROUP BY 1
ORDER BY 2 DESC
;
""")

df5=pd.read_sql(q, conn).head(20)
df5
```

Out[34]:

	primary_name	votes
0	Jennifer Lawrence	5029088
1	Anne Hathaway	4499568
2	Scarlett Johansson	4333717
3	Amy Adams	3691471
4	Emma Stone	3311500
5	Jessica Chastain	3142822
6	Emily Blunt	2757259
7	Rachel McAdams	2734084
8	Natalie Portman	2579298
9	Zoe Saldana	2526790
10	Cate Blanchett	2491619
11	Mila Kunis	2384037
12	Charlize Theron	2274138
13	Kristen Wiig	2251693
14	Emma Watson	2233022
15	Anna Kendrick	2203846
16	Rooney Mara	2149792
17	Ellen Page	2133586
18	Chloë Grace Moretz	2106604
19	Margot Robbie	2062222

In [35]:
```
# let's find most popular actresses
sns.barplot(x = 'primary_name',
            y = 'votes',
            data = df5)
plt.xticks(rotation=90)
plt.title('Most popular actresses')
plt.xlabel('actresses')
plt.show()
```



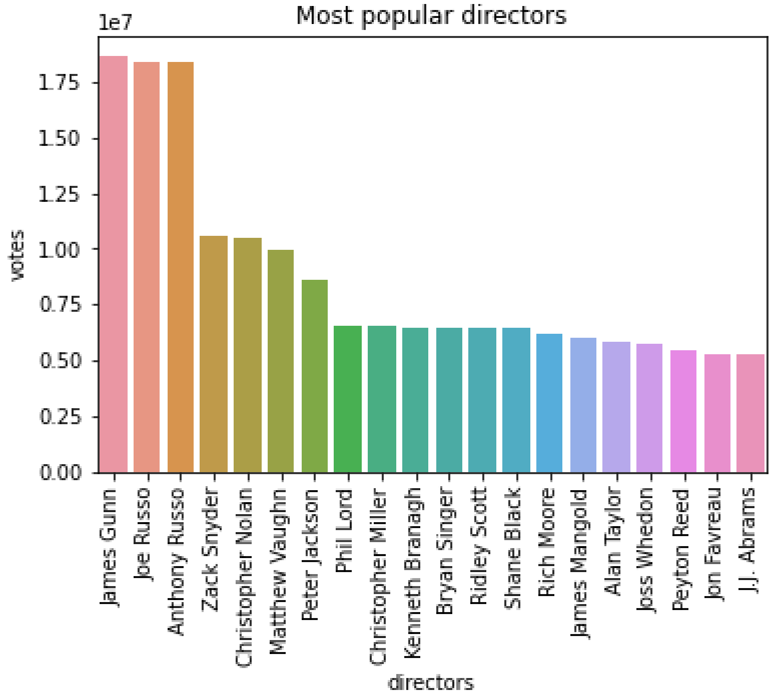
Jennifer Lawrence leads the pack, followed by Anne Hathaway and Scarlett Johansson and other popular actresses

In [36]:
```
# Most popular directors
q =("""
SELECT ps.primary_name, SUM(mr.numvotes) votes
FROM movie_ratings mr
JOIN directors dr
ON dr.movie_id=mr.movie_id
JOIN persons ps
ON dr.person_id=ps.person_id
GROUP BY 1
ORDER BY 2 DESC
LIMIT 20
;
""")

df6 = pd.read_sql(q, conn)
df6
```

Out[36]:

	primary_name	votes
0	James Gunn	18640459
1	Joe Russo	18421688
2	Anthony Russo	18421593
3	Zack Snyder	10576977
4	Christopher Nolan	10457390
5	Matthew Vaughn	9962120
6	Peter Jackson	8634677
7	Phil Lord	6565719
8	Christopher Miller	6565719
9	Kenneth Branagh	6454844
10	Bryan Singer	6423171
11	Ridley Scott	6411206
12	Shane Black	6402578
13	Rich Moore	6164592
14	James Mangold	6014842
15	Alan Taylor	5807424
16	Joss Whedon	5726110
17	Peyton Reed	5460683
18	Jon Favreau	5314585
19	J.J. Abrams	5241835

In [37]:
```
# let's find most popular directors
sns.barplot(x = 'primary_name',
            y = 'votes',
            data = df6)
plt.xticks(rotation=90)
plt.title('Most popular directors')
plt.xlabel('directors')
plt.show()
```



Three directors, James Gunn, Joe Russo and Anthony Russo lead significantly followed by other popular directors

In [38]:
```
# What is the relationship between runtime and popularity
q =("""
SELECT mb.runtime_minutes, mr.numvotes
FROM movie_ratings mr
JOIN movie_basics mb
ON mb.movie_id=mr.movie_id
;
""")

df7 = pd.read_sql(q, conn)
df7
```

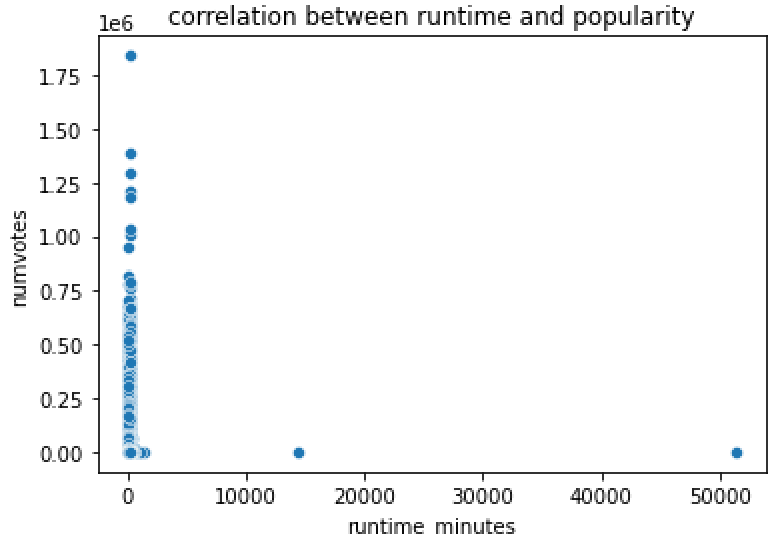
Out[38]:

	runtime_minutes	numvotes
0	117.0	31
1	87.0	559
2	90.0	20
3	99.0	50352
4	73.0	21
...	...	...
73851	84.0	25
73852	120.0	24
73853	NaN	14
73854	81.0	5
73855	129.0	128

73856 rows × 2 columns

In [39]:
```
# what is the correlation between runtime and popularity
sns.scatterplot(x='runtime_minutes', y='numvotes', data=df7).set(title='correlati
```

Out[39]: [Text(0.5, 1.0, 'correlation between runtime and popularity')]



there is no correlation between runtime and popularity of movies

In [40]:
```
# What is the relationship between ratings and popularity
q =("""
SELECT mr.averagerating, mr.numvotes
FROM movie_ratings mr
;
""")

df8 = pd.read_sql(q, conn)
df8
```

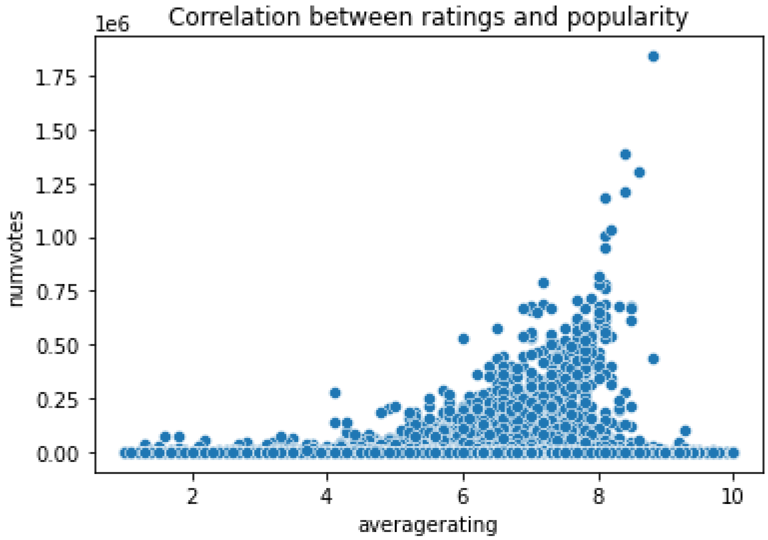
Out[40]:

	averagerating	numvotes
0	8.3	31
1	8.9	559
2	6.4	20
3	4.2	50352
4	6.5	21
...	...	...
73851	8.1	25
73852	7.5	24
73853	4.7	14
73854	7.0	5
73855	6.3	128

73856 rows × 2 columns

In [41]:
```
# what is the correlation between ratings and popularity
sns.scatterplot(x='averagerating', y='numvotes', data=df8).set(title='Correlatior
```

Out[41]:
```
[Text(0.5, 1.0, 'Correlation between ratings and popularity')]
```



There is a positive relationship between movie ratings and popularity.

Summary

In this project, we analyzed data related to the movie industry to gain insights into the revenue and popularity of different genres. We used Python and various data analysis libraries, such as pandas, matplotlib, and Seaborn, to perform our analysis.

We started by exploring and cleaning our dataset to ensure that the data was in a usable format. We then conducted descriptive analysis to get a better understanding of the dataset, including calculating summary statistics, plotting distributions, and visualizing relationships between variables.

Our analysis revealed that the Action genre was the most profitable genre, followed by Drama and Comedy. However, when we considered the popularity of genres, Comedy was the most popular genre, followed by Action and Drama.

We also discovered that there was a positive correlation between the budget and revenue of movies, indicating that higher-budget movies tended to earn more revenue. Additionally, we found that the runtime of movies had little impact on their revenue.

In conclusion, our analysis provides valuable insights into the movie industry, which can be used by stakeholders, such as movie producers and investors, to make more informed decisions. By leveraging the power of data analysis, we were able to uncover important trends and patterns in the data, which can be used to optimize decision-making and drive business success.