Final Project Submission

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- **Student pace: Full time**
- **Scheduled project review date/time: 11/20/2022**
- **Instructor name: Mark Tiba**
- **Blog post URL:**

1. Introduction

1.1 Overview

The main goal of the project is to come up with insights to help Microsoft start and excel in the movie business.We will use exploratory data analysis to come up with actionable insights to help decide what type of films Microsoft should create.

1.2 Objectives

1.2.1 General objectives

Explore and analyze the types of films that are currently doing the best at the box office and using the findings to help decide the types of films to create

1.2.2 Specific objectives

i. Loading datasets into pandas
ii. Retrieving data from a DataFrame
iii. Data preparation annd cleaning
iv. Exploratory analysis
v. Data visualization

1.3 Questions to answer

The analysis below should be able to answer the following questions:

1. What are the popular genres in the box office?

2. What are the most popular studios with high world-wide gross?
3. Does popularity affect the worldwide gross?
4. Does budget affect revenue?
5. Does rating affect revenue?
6. Does popularity affect the rating?
7. Does the runtime minutes affect the ratings?
8. Does runtime minutes affect the popularity?

2. Data Understanding

2.1 The Data

The datasets are stored in the 'zippedData' folder which were sourced from:

- Box Office MojoLinks
  - bom.movie_gross.csv
- IMDBLinks
  - im.db
- Rotten TomatoesLinks
  - rt.movie_info.tsv
- TheMovieDBLinks
  - tmdb.movies.csv
- The Numbers
  - tn.movie_budgets.csv

2.2 Importing the relevant libraries

Begin by importing pandas, numpy, csv with their aliases

In [2]:
```
# Your code here - remember to use markdown cells for comments as well!
#importing libraries
import pandas as pd
import sqlite3
import csv
import numpy as np
from datetime import datetime
```

In [3]:
```
#importing data visualisation tools
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Loading the datasets

To load the data use:

- movies_budget = pd.read_csv('zippedData/tn.movie_budgets.csv')
- movies_gross = pd.read_csv('zippedData/bom.movie_gross.csv')
- tmd = pd.read_csv('zippedData/tmdb.movies.csv',index_col=0)
- reviews = pd.read_csv('zippedData/rt.reviews.tsv', delimiter='\t',encoding='unicode_escape')
- conn = sqlite3.connect('zippedData/im.db')
- movie_info = pd.read_csv('zippedData/rt.movie_info.tsv', delimiter ='\t', encoding='unicode_escape')

2.3 Exploring the datasets

2.3.1 The Numbers dataset

The Numbers dataset gives us information on the budget and returns.

In [4]:

```
#Load the data from tn.movie_budgets.csv into a dataframe
movies_budget = pd.read_csv('zippedData/tn.movie_budgets.csv')

#Cast to numeric data type
movies_budget['production_budget'] = movies_budget['production_budget'].replace('
movies_budget['domestic_gross'] = movies_budget['domestic_gross'].replace('[^.0-9
movies_budget['worldwide_gross'] = movies_budget['worldwide_gross'].replace('[^.0
movies_budget.head(5)
```

Out[4]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507648.0	2.776345e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063872.0	1.045664e+09
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762352.0	1.497624e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005856.0	1.403014e+09
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181376.0	1.316722e+09

The production budget, domestic gross, and worldwide gross are then cast to float type for mathematical manipulation.

In [5]:

```
movies_budget.shape
```

Out[5]: (5782, 6)

In [6]:
```
movies_budget.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   float32
 4   domestic_gross     5782 non-null   float32
 5   worldwide_gross    5782 non-null   float64
dtypes: float32(2), float64(1), int64(1), object(2)
memory usage: 226.0+ KB
```

In [7]:
```
movies_budget.isna().sum()
```

Out[7]:
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

The movie budget Data frame has 5,782 rows and 6 columns namely: id,release_date, movie, production_budget, domestic gross and worldwide_gross. The data types are as float,object and int. The are no null values.

Finding out the movies budget, first we get the international gross by subtracting the domestic gross from the woorldwide gross

In [8]:
```
#getting the international gross
movies_budget['international_gross'] = movies_budget['worldwide_gross'] - movies_
cols = list(movies_budget.columns)

movies_budget.head(10)
```

Out[8]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	international
0	1	Dec 18, 2009	Avatar	425000000.0	760507648.0	2.776345e+09	2.0158
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063872.0	1.045664e+09	8.0460
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762352.0	1.497624e+08	1.0700
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005856.0	1.403014e+09	9.4400
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181376.0	1.316722e+09	6.9654
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000.0	936662208.0	2.053311e+09	1.1166
6	7	Apr 27, 2018	Avengers: Infinity War	300000000.0	678815488.0	2.048134e+09	1.3693
7	8	May 24, 2007	Pirates of the Caribbean: At Worldâ s End	300000000.0	309420416.0	9.634204e+08	6.5400
8	9	Nov 17, 2017	Justice League	300000000.0	229024288.0	6.559452e+08	4.2692
9	10	Nov 6, 2015	Spectre	300000000.0	200074176.0	8.796209e+08	6.7954

The release date is an object, in order to filter the years convert to date time type.

In [9]:
```
#converting object to dateTime
movies_budget['release_date'] = pd.to_datetime(movies_budget['release_date'], err
movies_budget['year'] = movies_budget['release_date'].dt.strftime('%Y')
movies_budget.head(10)
```

Out[9]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	international
0	1	2009-12-18	Avatar	425000000.0	760507648.0	2.776345e+09	2.0158
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063872.0	1.045664e+09	8.0460
2	3	2019-06-07	Dark Phoenix	350000000.0	42762352.0	1.497624e+08	1.0700
3	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005856.0	1.403014e+09	9.4400
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181376.0	1.316722e+09	6.9654
5	6	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000.0	936662208.0	2.053311e+09	1.1166
6	7	2018-04-27	Avengers: Infinity War	300000000.0	678815488.0	2.048134e+09	1.3693
7	8	2007-05-24	Pirates of the Caribbean: At Worldâ s End	300000000.0	309420416.0	9.634204e+08	6.5400
8	9	2017-11-17	Justice League	300000000.0	229024288.0	6.559452e+08	4.2692
9	10	2015-11-06	Spectre	300000000.0	200074176.0	8.796209e+08	6.7954

In [10]:
```
movies_budget.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   id                   5782 non-null   int64
 1   release_date         5782 non-null   datetime64[ns]
 2   movie                5782 non-null   object
 3   production_budget    5782 non-null   float32
 4   domestic_gross       5782 non-null   float32
 5   worldwide_gross      5782 non-null   float64
 6   international_gross  5782 non-null   float64
 7   year                 5782 non-null   object
dtypes: datetime64[ns](1), float32(2), float64(2), int64(1), object(2)
memory usage: 316.3+ KB
```

Filtering the Data

Here we will drop the rows without the values for the domestic, international and worldwide gross.

In [11]:
```
movies_budget.sort_values('worldwide_gross')
```

Out[11]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	internatior
5037	38	2019-04-23	Living Dark: The Story of Ted the Caver	1750000.0	0.0	0.000000e+00	0.00
3975	76	2015-05-15	Pound of Flesh	7500000.0	0.0	0.000000e+00	0.00
4627	28	2011-06-28	2:13	3500000.0	0.0	0.000000e+00	0.00
4628	29	2013-01-29	Batman: The Dark Knight Returns, Part 2	3500000.0	0.0	0.000000e+00	0.00
3947	48	2019-06-21	Burn Your Maps	8000000.0	0.0	0.000000e+00	0.00
...	...	...	...	...	...	...	
33	34	2015-06-12	Jurassic World	215000000.0	652270656.0	1.648855e+09	9.96
6	7	2018-04-27	Avengers: Infinity War	300000000.0	678815488.0	2.048134e+09	1.36
5	6	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000.0	936662208.0	2.053311e+09	1.11
42	43	1997-12-19	Titanic	200000000.0	659363968.0	2.208208e+09	1.54
0	1	2009-12-18	Avatar	425000000.0	760507648.0	2.776345e+09	2.01

5782 rows × 8 columns

In [12]:
```
#drop all all rows without the gross values
movies_budget_drop = movies_budget[(movies_budget['domestic_gross'] == 0) & (movi
```

In [13]:
```
movies_budget.drop(movies_budget_drop.index, axis=0, inplace=True)
movies_budget.head(5)
```

Out[13]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	international_
0	1	2009-12-18	Avatar	425000000.0	760507648.0	2.776345e+09	2.01583
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063872.0	1.045664e+09	8.04600
2	3	2019-06-07	Dark Phoenix	350000000.0	42762352.0	1.497624e+08	1.07000
3	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005856.0	1.403014e+09	9.44008
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181376.0	1.316722e+09	6.96540

In order to have relevant budgeting information, filter the years to get only the data from 2011

In [14]:
```
#convert from object to string
movies_budget['year'] = movies_budget['year'].astype(int)
```

In [15]:
```
#drop rows which are not between the years 2015 and 2022
drop_=  movies_budget[(movies_budget['year'] <= 2014)]
movies_budget.drop(drop_.index, axis=0, inplace=True)
movies_budget.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 797 entries, 2 to 5748
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   id                   797 non-null    int64
 1   release_date         797 non-null    datetime64[ns]
 2   movie                797 non-null    object
 3   production_budget    797 non-null    float32
 4   domestic_gross       797 non-null    float32
 5   worldwide_gross      797 non-null    float64
 6   international_gross  797 non-null    float64
 7   year                 797 non-null    int32
dtypes: datetime64[ns](1), float32(2), float64(2), int32(1), int64(1), object
(1)
memory usage: 46.7+ KB
```

In [16]:
```
movies_budget['year'].value_counts()
```

Out[16]:
```
2015    242
2016    204
2017    162
2018    140
2019     49
Name: year, dtype: int64
```

In [17]:
```
movies_budget.describe()
```

Out[17]:

	id	production_budget	domestic_gross	worldwide_gross	international_gross	
count	797.000000	797.0	797.0	7.970000e+02	7.970000e+02	797.
mean	50.634881	44454288.0	57354036.0	1.477667e+08	9.041263e+07	2016.
std	29.339221	57002492.0	98196584.0	2.607258e+08	1.710463e+08	1.
min	1.000000	25000.0	0.0	2.600000e+01	-1.000000e+00	2015.
25%	25.000000	8000000.0	3000342.0	8.200000e+06	2.053330e+06	2015.
50%	50.000000	22000000.0	24431472.0	4.517374e+07	1.928622e+07	2016.
75%	78.000000	55000000.0	63859436.0	1.594876e+08	9.237100e+07	2017.
max	100.000000	350000000.0	936662208.0	2.053311e+09	1.369319e+09	2019.

Finding the percentage profits of the movies based on the production budget and the world wide gross.

In [18]:
```
movies_budget['profit/loss'] = (movies_budget['worldwide_gross'] - movies_budget[
movies_budget['profit/loss'] = movies_budget['profit/loss'].astype(int)
movies_budget['profit/loss'].tail()
```

Out[18]:
```
5701    -66201
5719    -41626
5737    114822
5744    -23453
5748    464792
Name: profit/loss, dtype: int32
```

In [19]:
```
movies_budget.shape
```

Out[19]:
```
(797, 9)
```

In [20]:
```
movies_budget
```

Out[20]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	internatior
2	3	2019-06-07	Dark Phoenix	350000000.0	42762352.0	1.497624e+08	1.07
3	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005856.0	1.403014e+09	9.44
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181376.0	1.316722e+09	6.96
5	6	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000.0	936662208.0	2.053311e+09	1.11
6	7	2018-04-27	Avengers: Infinity War	300000000.0	678815488.0	2.048134e+09	1.36
...	...	...	...	...	...	...	
5701	2	2015-07-17	Dawn of the Crescent Moon	75000.0	8799.0	8.799000e+03	0.00
5719	20	2015-07-31	Counting	50000.0	8374.0	8.374000e+03	0.00
5737	38	2016-03-18	Krisha	30000.0	144822.0	1.448220e+05	0.00
5744	45	2017-01-27	Emily	27000.0	3547.0	3.547000e+03	0.00
5748	49	2015-09-01	Exeter	25000.0	0.0	4.897920e+05	4.89

797 rows × 9 columns

2.3.2 Box Office Mojo Dataset

The bom dataset gives information on the domestic gross values and the foreign gross.

In [21]:
```
#previewing the second dataset
movies_gross = pd.read_csv('zippedData/bom.movie_gross.csv')
movies_gross.tail(10)
```

Out[21]:

	title	studio	domestic_gross	foreign_gross	year
3377	Let Yourself Go	Men.	12200.0	NaN	2018
3378	Hannah (2018)	PDF	11700.0	NaN	2018
3379	Souvenir	Strand	11400.0	NaN	2018
3380	Furious (Legend of Kolovrat)	CARUSEL	10000.0	NaN	2018
3381	Beauty and the Dogs	Osci.	8900.0	NaN	2018
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

In [22]:
```
#find out the shape of the dataset
movies_gross.shape
```

Out[22]:
```
(3387, 5)
```

In [23]:
```
movies_gross['year'].unique()
```

Out[23]:
```
array([2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018], dtype=int64)
```

In [24]:
```
movies_gross.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

In [25]:
```
movies_gross.isna().sum()
```

Out[25]:
```
title               0
studio              5
domestic_gross     28
foreign_gross    1350
year                0
dtype: int64
```

In [26]:
```
#drop the rows without gross values
movies_gross.dropna(subset=['foreign_gross','domestic_gross'], inplace=True)
movies_gross.isna().sum()
```

Out[26]:
```
title            0
studio           2
domestic_gross   0
foreign_gross    0
year             0
dtype: int64
```

2.3.3 TheMovieDB dataset

The tmdb.movies dataset gives us information on the popularity of a movie with respect to the language.

In [27]:
```
tmd = pd.read_csv('zippedData/tmdb.movies.csv',index_col=0)
tmd.head(5)
```

Out[27]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_avera
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8

In [28]:
```
tmd['original_language'].value_counts().head(5)
```

Out[28]:
```
en    23291
fr      507
es      455
ru      298
ja      265
Name: original_language, dtype: int64
```

In [29]:
```
tmd.shape
```

Out[29]:
```
(26517, 9)
```

The dataset has 26,517 rows and 9 columns

In [30]:
```
tmd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26517 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   genre_ids          26517 non-null  object 
 1   id                 26517 non-null  int64  
 2   original_language  26517 non-null  object 
 3   original_title     26517 non-null  object 
 4   popularity         26517 non-null  float64
 5   release_date       26517 non-null  object 
 6   title              26517 non-null  object 
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 2.0+ MB
```

In [31]:
```
tmd.duplicated().sum()
```

Out[31]:
```
1020
```

In [32]:
```
#drop all duplicate rows based on the titles columns
tmd = tmd.drop_duplicates(subset = ['title','original_title'], keep = 'first')
tmd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 24842 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   genre_ids          24842 non-null  object 
 1   id                 24842 non-null  int64  
 2   original_language  24842 non-null  object 
 3   original_title     24842 non-null  object 
 4   popularity         24842 non-null  float64
 5   release_date       24842 non-null  object 
 6   title              24842 non-null  object 
 7   vote_average       24842 non-null  float64
 8   vote_count         24842 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 1.9+ MB
```

In [33]:
```
tmd.duplicated().sum()
```

Out[33]:
```
0
```

The data has no duplicates

In [34]:
```
tmd['popularity'].max()
```

Out[34]:
```
80.773
```

2.3.4 Rotten tomatoes dataset

In [35]:
```
reviews = pd.read_csv('zippedData/rt.reviews.tsv', delimiter='\t',encoding='unico
reviews.tail(10)
```

Out[35]:

	id	review	rating	fresh	critic	top_critic	publisher	date
54422	2000	Arguably the best script that Besson has writt...	3.5/5	fresh	Wade Major	0	Boxoffice Magazine	September 27, 2002
54423	2000	Despite the title, Wasabi isn't so spicy.	C	rotten	NaN	0	E! Online	September 27, 2002
54424	2000	Dawdles and drags when it should pop; it doesn...	1.5/5	rotten	Manohla Dargis	1	Los Angeles Times	September 26, 2002
54425	2000	Despite Besson's high-profile name being Wasab...	NaN	fresh	Andy Klein	0	New Times	September 26, 2002
54426	2000	The film lapses too often into sugary sentimen...	NaN	rotten	Paul Malcolm	1	L.A. Weekly	September 26, 2002
54427	2000	The real charm of this trifle is the deadpan c...	NaN	fresh	Laura Sinagra	1	Village Voice	September 24, 2002
54428	2000	NaN	1/5	rotten	Michael Szymanski	0	Zap2it.com	September 21, 2005
54429	2000	NaN	2/5	rotten	Emanuel Levy	0	EmanuelLevy.Com	July 17, 2005
54430	2000	NaN	2.5/5	rotten	Christopher Null	0	Filmcritic.com	September 7, 2003
54431	2000	NaN	3/5	fresh	Nicolas Lacroix	0	Showbizz.net	November 12, 2002

In [36]:
```
reviews.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54432 entries, 0 to 54431
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          54432 non-null  int64 
 1   review      48869 non-null  object
 2   rating      40915 non-null  object
 3   fresh       54432 non-null  object
 4   critic      51710 non-null  object
 5   top_critic  54432 non-null  int64 
 6   publisher   54123 non-null  object
 7   date        54432 non-null  object
dtypes: int64(2), object(6)
memory usage: 3.3+ MB
```

In [37]:
```
reviews.isna().sum()
```

Out[37]:
```
id                 0
review          5563
rating         13517
fresh              0
critic          2722
top_critic         0
publisher        309
date               0
dtype: int64
```

In [38]:
```
reviews.duplicated().sum()
```

Out[38]:
```
9
```

In [39]:
```
reviews.dropna(axis=0, inplace = True)
reviews.head(10)
```

Out[39]:

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
6	3	Quickly grows repetitive and tiresome, meander...	C	rotten	Eric D. Snider	0	EricDSnider.com	July 17, 2013
7	3	Cronenberg is not a director to be daunted by ...	2/5	rotten	Matt Kelemen	0	Las Vegas CityLife	April 21, 2013
11	3	While not one of Cronenberg's stronger films, ...	B-	fresh	Emanuel Levy	0	EmanuelLevy.Com	February 3, 2013
12	3	Robert Pattinson works mighty hard to make Cos...	2/4	rotten	Christian Toto	0	Big Hollywood	January 15, 2013
13	3	The anger over the injustice of the financial ...	B	fresh	Robert Roten	0	Laramie Movie Scope	January 7, 2013
14	3	For those who like their Cronenberg thick and ...	3/4	fresh	Marty Mapes	0	Movie Habit	October 20, 2012
15	3	For better or worse - often both - Cosmopolis ...	3/5	fresh	Adam Ross	0	The Aristocrat	September 27, 2012
16	3	For one of the smartest films I've seen in a w...	4/5	fresh	Patrick Kolan	0	Shotgun Cinema	September 26, 2012
17	3	Its major problem is that it's not cinematic.	B	fresh	Dennis Schwartz	0	Ozus' World Movie Reviews	September 25, 2012

From the reviews dataframe it is impossible to get valid data that can be used to draw conclusion on the ratings and the reviews

2.3.5 IMDB dataset

In [40]:
```
conn = sqlite3.connect('zippedData/im.db')
cur = conn.cursor()
```

Find the table names in im.db

In [41]:
```
cur.execute("""SELECT name FROM sqlite_master WHERE type = 'table';""")
# Fetch the result and store it in table_names
table_names = cur.fetchall()
table_names
```

Out[41]:
```
[('movie_basics',),
 ('directors',),
 ('known_for',),
 ('movie_akas',),
 ('movie_ratings',),
 ('persons',),
 ('principals',),
 ('writers',)]
```

Im.db has 8 tables. The movie_ratings and movie_basics are more relevant to our study as they will help gain information on the highly rated genres.

In [42]:
```
moviebasics = pd.read_sql_query("""SELECT *
FROM movie_basics
;""",conn)

moviebasics.tail(10)
```

Out[42]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
146134	tt9916160	Drømmeland	Drømmeland	2019	72.0	Documentary
146135	tt9916170	The Rehearsal	O Ensaio	2019	51.0	Drama
146136	tt9916186	Illenau - die Geschichte einer ehemaligen Heil...	Illenau - die Geschichte einer ehemaligen Heil...	2017	84.0	Documentary
146137	tt9916190	Safeguard	Safeguard	2019	90.0	Drama,Thriller
146138	tt9916428	The Secret of China	The Secret of China	2019	NaN	Adventure,History,War
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	None
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

In [43]:
```
movieratings = pd.read_sql_query("""SELECT *
FROM movie_ratings
;""",conn)

movieratings.tail(10)
```

Out[43]:

	movie_id	averagerating	numvotes
73846	tt9691896	6.3	21
73847	tt9708284	4.9	19
73848	tt9722952	7.0	6
73849	tt9768966	8.6	27
73850	tt9783738	7.4	7
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

In [44]:
```
ratings = pd.read_sql_query("""
SELECT primary_title, movie_id, start_year, runtime_minutes, genres, averageratir
FROM movie_basics
JOIN movie_ratings
    USING(movie_id)
LIMIT 10
;""", conn)

ratings
```

Out[44]:

	primary_title	movie_id	start_year	runtime_minutes	genres	averagerating
0	Sunghursh	tt0063540	2013	175.0	Action,Crime,Drama	7.0
1	One Day Before the Rainy Season	tt0066787	2019	114.0	Biography,Drama	7.2
2	The Other Side of the Wind	tt0069049	2018	122.0	Drama	6.9
3	Sabse Bada Sukh	tt0069204	2018	NaN	Comedy,Drama	6.1
4	The Wandering Soap Opera	tt0100275	2017	80.0	Comedy,Drama,Fantasy	6.5
5	Bigfoot	tt0112502	2017	NaN	Horror,Thriller	4.1
6	Joe Finds Grace	tt0137204	2017	83.0	Adventure,Animation,Comedy	8.1
7	Pál Adrienn	tt0146592	2010	136.0	Drama	6.8
8	So Much for Justice!	tt0154039	2010	100.0	History	4.6
9	Cooper and Hemingway: The True Gen	tt0159369	2013	180.0	Documentary	7.6

In [45]:
```
movie_akas = pd.read_sql_query("""SELECT *
FROM movie_akas
;""",conn)

movie_akas.tail(10)
```

Out[45]:

	movie_id	ordering	title	region	language	types	attributes	is_original_title
331693	tt9726638	3	Qi Tian Da Sheng Huo Yan Shan	CN	yue	imdbDisplay	None	0.0
331694	tt9755806	1	Big Shark	US	None	None	None	0.0
331695	tt9755806	2	Большая Акула	RU	None	None	None	0.0
331696	tt9755806	3	Big Shark	None	None	original	None	1.0
331697	tt9827784	1	Sayonara kuchibiru	JP	None	None	None	0.0
331698	tt9827784	2	Sayonara kuchibiru	None	None	original	None	1.0
331699	tt9827784	3	Farewell Song	XWW	en	imdbDisplay	None	0.0
331700	tt9880178	1	La atención	None	None	original	None	1.0
331701	tt9880178	2	La atención	ES	None	None	None	0.0
331702	tt9880178	3	The Attention	XWW	en	imdbDisplay	None	0.0

In [46]:
```
#find the languages
movie_akas['language'].unique()
movie_akas['language'].value_counts().head(10)
```

Out[46]:
```
en     22895
tr      3847
bg      3609
fr      3576
he      2680
sv       965
cmn      727
fa       482
hi       307
yue      286
Name: language, dtype: int64
```

In [47]:
```
movie_info = pd.read_csv('zippedData/rt.movie_info.tsv', delimiter ='\t', encodir
movie_info
```

Out[47]:

	id	synopsis	rating	genre	director	writer	theater
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	
...	...	...	...	...	...	...	
1555	1996	Forget terrorists or hijackers -- there's a ha...	R	Action and Adventure|Horror|Mystery and Suspense	NaN	NaN	Aug 18
1556	1997	The popular Saturday Night Live sketch was exp...	PG	Comedy|Science Fiction and Fantasy	Steve Barron	Terry Turner|Tom Davis|Dan Aykroyd|Bonnie Turner	Jul 23
1557	1998	Based on a novel by Richard Powell, when the I...	G	Classics|Comedy|Drama|Musical and Performing Arts	Gordon Douglas	NaN	Jan 1
1558	1999	The Sandlot is a coming-of-age story about a g...	PG	Comedy|Drama|Kids and Family|Sports and Fitness	David Mickey Evans	David Mickey Evans|Robert Gunter	Apr 1
1559	2000	Suspended from the force, Paris cop Hubert is ...	R	Action and Adventure|Art House and Internation...	NaN	Luc Besson	Sep 27

1560 rows × 12 columns

In [48]:
```
movie_info.isna().sum()
```

Out[48]:
```
id                 0
synopsis          62
rating             3
genre              8
director         199
writer           449
theater_date     359
dvd_date         359
currency        1220
box_office      1220
runtime           30
studio          1066
dtype: int64
```

In [49]:
```
movie_info.dropna(inplace = True)
```

In [50]:
```
movie_info.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 235 entries, 1 to 1545
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            235 non-null    int64
 1   synopsis      235 non-null    object
 2   rating        235 non-null    object
 3   genre         235 non-null    object
 4   director      235 non-null    object
 5   writer        235 non-null    object
 6   theater_date  235 non-null    object
 7   dvd_date      235 non-null    object
 8   currency      235 non-null    object
 9   box_office    235 non-null    object
 10  runtime       235 non-null    object
 11  studio        235 non-null    object
dtypes: int64(1), object(11)
memory usage: 23.9+ KB
```

In [51]:
```
movie_info.head(10)
```

Out[51]:

	id	synopsis	rating	genre	director	writer	theater_
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17,
6	10	Some cast and crew from NBC's highly acclaimed...	PG-13	Comedy	Jake Kasdan	Mike White	Jan 11,
7	13	Stewart Kane, an Irishman living in the Austra...	R	Drama	Ray Lawrence	Raymond Carver|Beatrix Christian	Apr 27,
15	22	Two-time Academy Award Winner Kevin Spacey giv...	R	Comedy|Drama|Mystery and Suspense	George Hickenlooper	Norman Snider	Dec 17,
18	25	From ancient Japan's most enduring tale, the e...	PG-13	Action and Adventure|Drama|Science Fiction and...	Carl Erik Rinsch	Chris Morgan|Hossein Amini	Dec 25,
19	26	A comic series of short vignettes build on one...	R	Art House and International|Comedy|Drama|Music...	Jim Jarmusch	Jim Jarmusch	Ma
29	41	Ken Loach directs Sweet Sixteen, a gritty dram...	R	Drama	Ken Loach	Paul Laverty	Ma
48	61	Death once again shows he's determined to get ...	R	Action and Adventure|Drama|Horror|Mystery and ...	James Wong	James Wong|Glen Morgan	Feb 10,
61	77	Until he was downsized, affable, amiable Larry...	PG-13	Comedy|Drama	Tom Hanks	Tom Hanks|Nia Vardalos	Jul 1,
69	87	"Mao's Last Dancer" is the inspiring true stor...	PG	Art House and International|Drama|Musical and ...	Bruce Beresford	Jan Sardi	Aug 20,

3. Merging Datasets

In [52]:
```
#renaming the column for merging

movies_gross.rename(columns={'title':'movie'}, inplace=True)
tmd.rename(columns={'original_title':'movie'}, inplace=True)
moviebasics.rename(columns={'original_title':'movie'},inplace=True)
```

In [53]:
```
#merging the movie_budget dataframe and movie_gross

df_budget_and_gross = movies_budget.merge(movies_gross, how = 'inner', on ='movie
```

In [54]:
```
df_budget_and_gross.shape
```

Out[54]:
```
(409, 13)
```

Merging tmd dataframe with the moviebasics table

In [55]:
```
#merge tmd with movie basics to get common languages

popularity_ratings_df = tmd.merge(moviebasics, how = 'inner', on ='movie')
```

In [56]:
```
popularity_ratings_df.shape
```

Out[56]:
```
(17891, 14)
```

In [57]:
```
final_df = pd.merge(df_budget_and_gross,popularity_ratings_df, how = 'inner', on
final_df.head(5)
```

Out[57]:

	id_x	release_date_x	movie	production_budget	domestic_gross_x	worldwide_gross	internat
0	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005856.0	1.403014e+09	9
1	7	2018-04-27	Avengers: Infinity War	300000000.0	678815488.0	2.048134e+09	1
2	9	2017-11-17	Justice League	300000000.0	229024288.0	6.559452e+08	4
3	10	2015-11-06	Spectre	300000000.0	200074176.0	8.796209e+08	6
4	12	2018-05-25	Solo: A Star Wars Story	275000000.0	213767520.0	3.931513e+08	1

5 rows × 26 columns

In [58]:
```
final_df.shape
```

Out[58]:
```
(535, 26)
```

In [59]:
```
#finding the column names
list(final_df.columns)
```

Out[59]:
```
['id_x',
 'release_date_x',
 'movie',
 'production_budget',
 'domestic_gross_x',
 'worldwide_gross',
 'international_gross',
 'year_x',
 'profit/loss',
 'studio',
 'domestic_gross_y',
 'foreign_gross',
 'year_y',
 'genre_ids',
 'id_y',
 'original_language',
 'popularity',
 'release_date_y',
 'title',
 'vote_average',
 'vote_count',
 'movie_id',
 'primary_title',
 'start_year',
 'runtime_minutes',
 'genres']
```

In [60]:
```
# dropping the unnecessary columns

final_df.drop(columns=['id_x', 'release_date_x', 'domestic_gross_x','year_x','dor
final_df.head(5)
```

Out[60]:

	movie	production_budget	worldwide_gross	international_gross	profit/loss	studio	foreign_
0	Avengers: Age of Ultron	330600000.0	1.403014e+09	9.440081e+08	1072413963	BV	9464
1	Avengers: Infinity War	300000000.0	2.048134e+09	1.369319e+09	1748134200	BV	1
2	Justice League	300000000.0	6.559452e+08	4.269209e+08	355945209	WB	4289
3	Spectre	300000000.0	8.796209e+08	6.795467e+08	579620923	Sony	6806
4	Solo: A Star Wars Story	275000000.0	3.931513e+08	1.793838e+08	118151347	BV	1792

In [61]:
```
#lets view the last 10 columns

final_df.tail(10)
```

Out[61]:

	movie	production_budget	worldwide_gross	international_gross	profit/loss	studio	foreig
525	Do You Believe?	2300000.0	14304931.0	1319331.0	12004931	PFR	
526	Do You Believe?	2300000.0	14304931.0	1319331.0	12004931	PFR	
527	Hardcore Henry	2000000.0	17187434.0	7935396.0	15187434	STX	
528	All Saints	2000000.0	5941994.0	139786.0	3941994	Affirm	
529	We Are Your Friends	2000000.0	10153415.0	6561998.0	8153415	WB	
530	Unsane	1500000.0	14244931.0	6554887.0	12744931	BST	
531	Unfriended	1000000.0	64364198.0	31574554.0	63364198	Uni.	3
532	Unfriended: Dark Web	1000000.0	16434588.0	7567843.0	15434588	BH Tilt	
533	Patti Cake$	1000000.0	1471090.0	670942.0	471090	FoxS	
534	The Gallows	100000.0	41656474.0	18892064.0	41556474	WB (NL)	2

The common language is English so we can drop that column

In [62]:
```
final_df.drop(columns=['title','original_language'],inplace=True)
final_df.head(5)
```

Out[62]:

	movie	production_budget	worldwide_gross	international_gross	profit/loss	studio	foreign_
0	Avengers: Age of Ultron	330600000.0	1.403014e+09	9.440081e+08	1072413963	BV	9464
1	Avengers: Infinity War	300000000.0	2.048134e+09	1.369319e+09	1748134200	BV	1
2	Justice League	300000000.0	6.559452e+08	4.269209e+08	355945209	WB	4289
3	Spectre	300000000.0	8.796209e+08	6.795467e+08	579620923	Sony	6806
4	Solo: A Star Wars Story	275000000.0	3.931513e+08	1.793838e+08	118151347	BV	1792

In [63]:
```
final_df.nunique()
```

Out[63]:
```
movie                  388
production_budget      117
worldwide_gross        388
international_gross    388
profit/loss            388
studio                  40
foreign_gross          347
popularity             379
vote_average            43
vote_count             372
runtime_minutes        102
genres                 135
dtype: int64
```

In [64]:
```
# checking for null values

final_df.isna().sum()
```

Out[64]:
```
movie                   0
production_budget       0
worldwide_gross         0
international_gross     0
profit/loss             0
studio                  0
foreign_gross           0
popularity              0
vote_average            0
vote_count              0
runtime_minutes        33
genres                  6
dtype: int64
```

In [65]:
```
# checking for duplicates

final_df.duplicated(['movie']).sum()
```

Out[65]:
```
147
```

In [66]:
```
final_df.drop_duplicates(subset= ['movie'] ,inplace=True)
final_df.shape
```

Out[66]:
```
(388, 12)
```

In [67]:
```
final_df.isna().sum()
```

Out[67]:
```
movie                  0
production_budget      0
worldwide_gross        0
international_gross    0
profit/loss            0
studio                 0
foreign_gross          0
popularity             0
vote_average           0
vote_count             0
runtime_minutes        8
genres                 2
dtype: int64
```

Drop the two rows with null values in the genres column.

In [68]:
```
final_df.dropna(subset = ['genres'],inplace=True)
final_df.isna().sum()
```

Out[68]:
```
movie                  0
production_budget      0
worldwide_gross        0
international_gross    0
profit/loss            0
studio                 0
foreign_gross          0
popularity             0
vote_average           0
vote_count             0
runtime_minutes        6
genres                 0
dtype: int64
```

In [69]:
```
# Exporting this combined dataframe to a csv

final_df.to_csv('Cleaned Microsoft Data.csv')
```

4. Exploratory Data Analysis (EDA)

4.1 What are the popular genres in the box office?

In [70]:
```
popular = final_df.sort_values('popularity', ascending = False)
```

In [71]:
```
# accessing the individual genre element per row

top_genres = [genre.split(',') for genre in popular['genres']]

top_genres
```

Out[71]:
```
[['Action', 'Adventure', 'Sci-Fi'],
 ['Drama', 'Mystery', 'Sci-Fi'],
 ['Adventure', 'Family', 'Fantasy'],
 ['Action', 'Adventure', 'Sci-Fi'],
 ['Action', 'Adventure', 'Comedy'],
 ['Action', 'Adventure', 'Sci-Fi'],
 ['Action', 'Adventure', 'Comedy'],
 ['Action', 'Adventure', 'Sci-Fi'],
 ['Action', 'Adventure', 'Fantasy'],
 ['Action', 'Adventure', 'Sci-Fi'],
 ['Action', 'Adventure', 'Sci-Fi'],
 ['Action', 'Adventure', 'Comedy'],
 ['Action', 'Adventure', 'Fantasy'],
 ['Biography', 'Drama', 'Music'],
 ['Action', 'Adventure', 'Animation'],
 ['Biography', 'Comedy', 'Drama'],
 ['Action', 'Adventure', 'Comedy'],
 ['Action', 'Adventure', 'Sci-Fi'],
 ['Action', 'Adventure', 'Fantasy'],
```

In [72]:
```
# accessing all genre elements in the rows

top_genres_list = [genre_ for element in top_genres  for genre_ in element]

top_genres_list
```

Out[72]:
```
['Action',
 'Adventure',
 'Sci-Fi',
 'Drama',
 'Mystery',
 'Sci-Fi',
 'Adventure',
 'Family',
 'Fantasy',
 'Action',
 'Adventure',
 'Sci-Fi',
 'Action',
 'Adventure',
 'Comedy',
 'Action',
 'Adventure',
 'Sci-Fi',
 'Action',
```

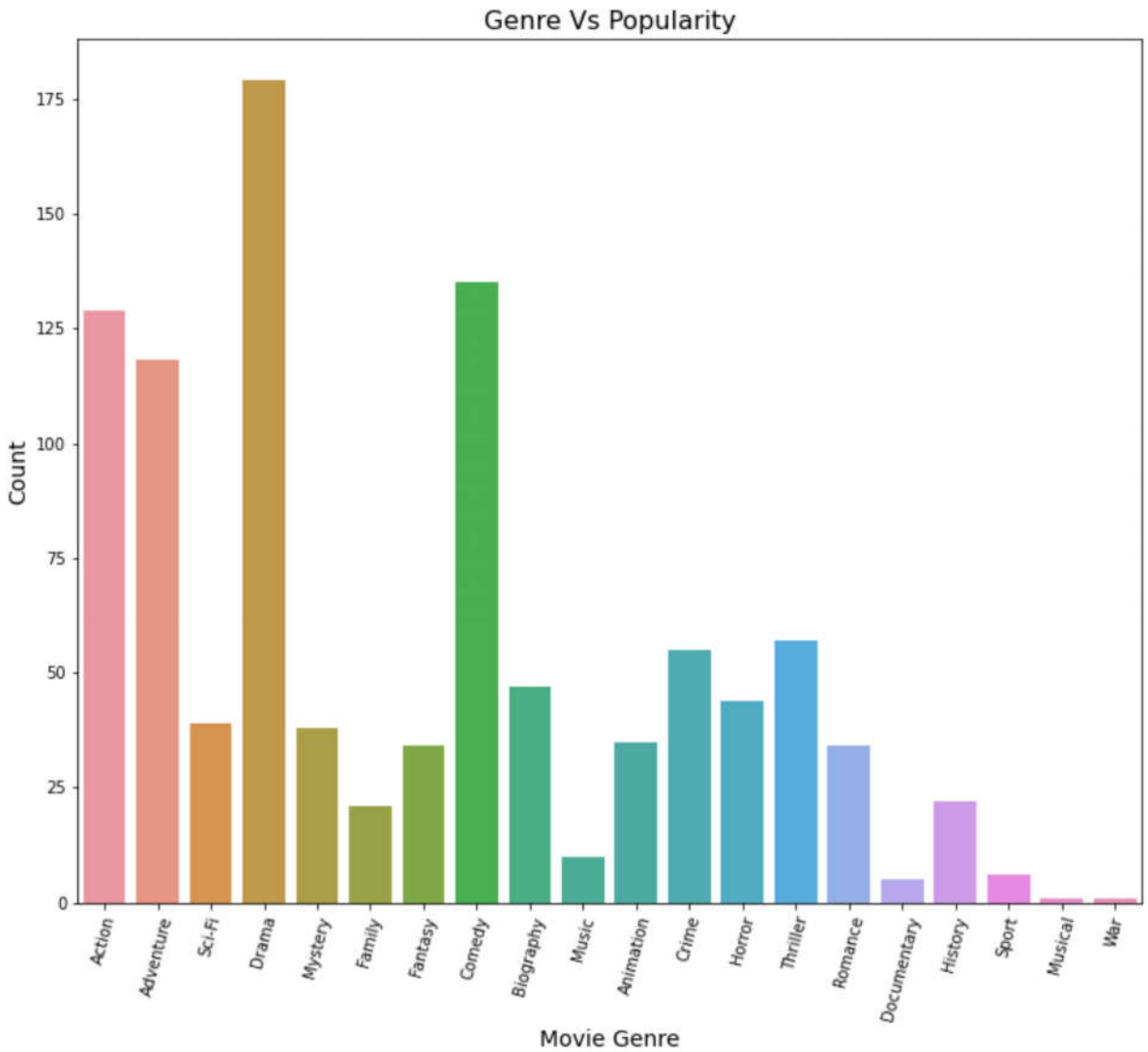
In [73]:
```
# get the unique genres

unique_genres = []

for genre_ in top_genres_list:
    if genre_ not in unique_genres:
        unique_genres.append(genre_)
```

In [74]:
```
# count the number of times the unique genre appeared.
#import Counter
from collections import Counter

count_1 = Counter(top_genres_list)
count_1
```

Out[74]:
```
Counter({'Action': 129,
         'Adventure': 118,
         'Sci-Fi': 39,
         'Drama': 179,
         'Mystery': 38,
         'Family': 21,
         'Fantasy': 34,
         'Comedy': 135,
         'Biography': 47,
         'Music': 10,
         'Animation': 35,
         'Crime': 55,
         'Horror': 44,
         'Thriller': 57,
         'Romance': 34,
         'Documentary': 5,
         'History': 22,
         'Sport': 6,
         'Musical': 1,
         'War': 1})
```

In [75]:
```
# separating the genres and the count

genre = []
count = []

for key, values in count_1.items():
    genre.append(key)
    count.append(values)
```

In [76]:
```
# plotting the data above


fig, ax = plt.subplots(figsize=(12,10))

x = genre
y = count

ax = sns.barplot(x = x, y = y, ax = ax)

ax.set_title('Genre Vs Popularity', fontsize=16)
ax.set_xlabel("Movie Genre",fontsize=14)
ax.set_ylabel("Count", fontsize=14);

ax.set_xticklabels(labels = x, rotation = 75)
fig.savefig('Genres Vs Popularity.png');
```



From the bar graph,we can say that Drama is the most popular Genre in the movie industry as it has the tallest bar.

In [77]:
```
# sorting to find the popular movies per vote_average

movie_ratings = final_df.sort_values(by = ['popularity', 'vote_average'],ascendir
movie_ratings = movie_ratings.sort_values('vote_average',ascending=False).reset_i
```

In [78]:
```
# The highly rated movies

movie_ratings.loc[:,['movie','vote_average','studio']]
```

Out[78]:

	movie	vote_average	studio
0	Avengers: Infinity War	8.3	BV
1	Thor: Ragnarok	7.5	BV
2	Blade Runner 2049	7.4	WB
3	Spider-Man: Homecoming	7.4	Sony
4	Avengers: Age of Ultron	7.3	BV
5	Ant-Man and the Wasp	7.0	BV
6	Fantastic Beasts: The Crimes of Grindelwald	6.9	WB
7	Bumblebee	6.5	Par.
8	X-Men: Apocalypse	6.5	Fox
9	Mortal Engines	6.0	Uni.

In [79]:
```
final_df['studio'].unique()
```

Out[79]:
```
array(['BV', 'WB', 'Sony', 'Uni.', 'Par.', 'STX', 'Fox', 'LGF', 'LG/S',
       'WB (NL)', 'EOne', 'Wein.', 'Focus', 'Annapurna', 'W/Dim.',
       'Studio 8', 'MGM', 'ORF', 'Strand', 'SGem', 'TriS', 'GrtIndia',
       'BST', 'RAtt.', 'VE', 'EC', 'BG', 'Amazon', 'FoxS', 'RTWC',
       'Global Road', 'A24', 'FCW', 'Neon', 'IFC', 'SPC', 'Rela.',
       'Affirm', 'BH Tilt', 'PFR'], dtype=object)
```

4.2 What are the most popular studios with high world-wide gross?

In [80]:
```
# sorting values to find movies with the highest grossing

highest_gross = final_df.sort_values('worldwide_gross', ascending = False).head(1
highest_gross.reset_index(drop=True)
```

Out[80]:

	movie	production_budget	worldwide_gross	international_gross	profit/loss	studio	foreign
0	Avengers: Infinity War	300000000.0	2.048134e+09	1.369319e+09	1748134200	BV	
1	Jurassic World	215000000.0	1.648855e+09	9.965842e+08	1433854864	Uni.	
2	Avengers: Age of Ultron	330600000.0	1.403014e+09	9.440081e+08	1072413963	BV	946
3	Black Panther	200000000.0	1.348258e+09	6.481986e+08	1148258224	BV	646
4	Jurassic World: Fallen Kingdom	170000000.0	1.305773e+09	8.880531e+08	1135772799	Uni.	891
5	Incredibles 2	200000000.0	1.242521e+09	6.339390e+08	1042520711	BV	634
6	The Fate of the Furious	250000000.0	1.234846e+09	1.009081e+09	984846267	Uni.	
7	Minions	74000000.0	1.160336e+09	8.242904e+08	1086336173	Uni.	823
8	Aquaman	160000000.0	1.146895e+09	8.118328e+08	986894640	WB	812
9	Captain America: Civil War	250000000.0	1.140069e+09	7.319851e+08	890069413	BV	745

In [81]:
```
# movies with the highest gross

highest_gross.loc[:,['movie','worldwide_gross']]
```

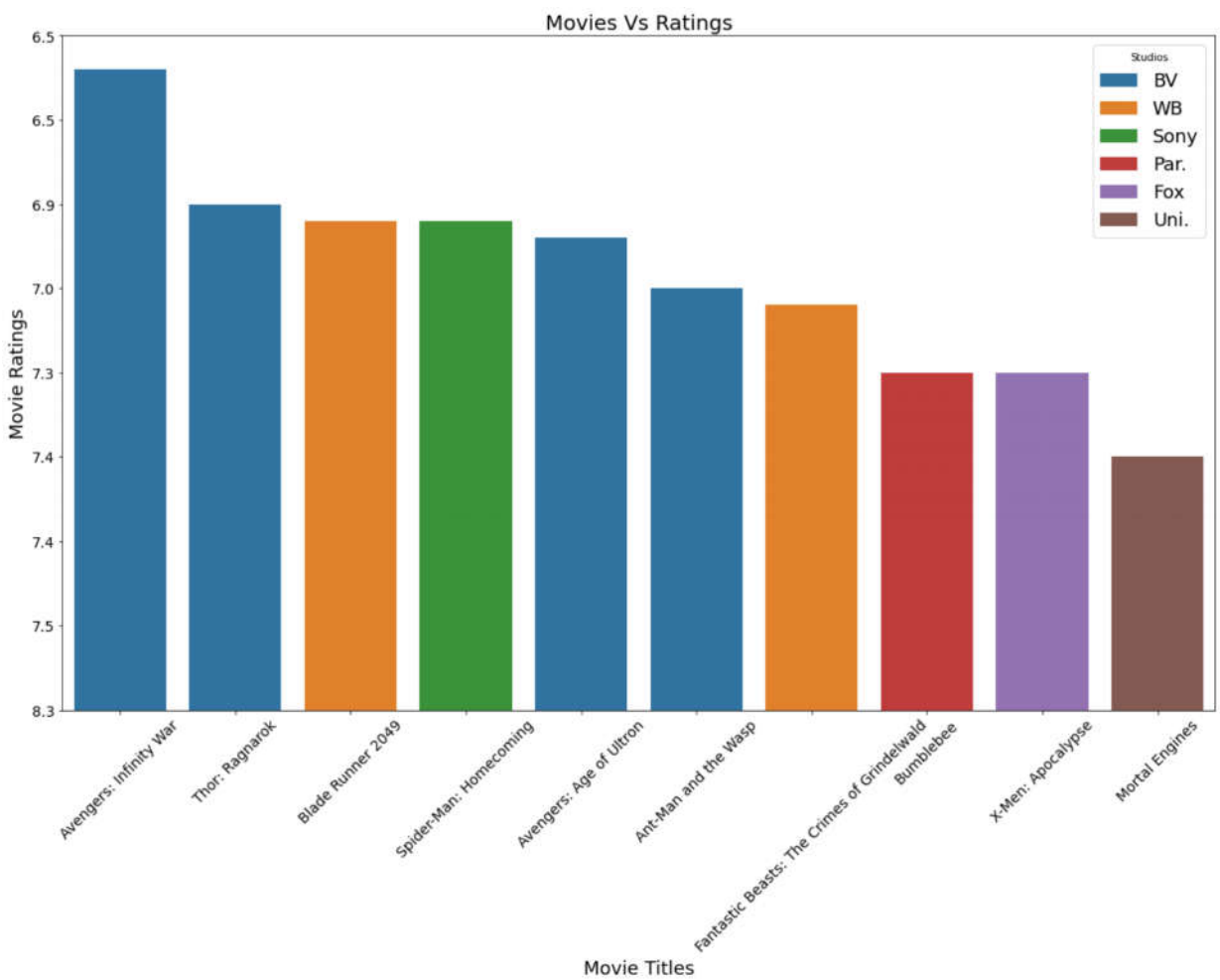
Out[81]:

	movie	worldwide_gross
1	Avengers: Infinity War	2.048134e+09
10	Jurassic World	1.648855e+09
0	Avengers: Age of Ultron	1.403014e+09
11	Black Panther	1.348258e+09
39	Jurassic World: Fallen Kingdom	1.305773e+09
12	Incredibles 2	1.242521e+09
7	The Fate of the Furious	1.234846e+09
117	Minions	1.160336e+09
45	Aquaman	1.146895e+09
5	Captain America: Civil War	1.140069e+09

In [82]:
```
import matplotlib.ticker as mticker
```

In [83]:
```
# plotting the data above

fig, ax1= plt.subplots(figsize=(20,12))

x = list(movie_ratings['movie'].values)
y = movie_ratings['vote_average']

ax1 = sns.barplot(data = movie_ratings, x = 'movie', y = 'vote_average', hue = 's

ax1.set_title('Movies Vs Ratings', fontsize=20)
ax1.set_xlabel("Movie Titles",fontsize=18)
ax1.set_ylabel("Movie Ratings", fontsize=18)
ax1.legend(title='Studios', fontsize=18, loc=1)
ax1.set_xticklabels(labels = x, rotation = 60,fontsize=14)
ax1.set_yticklabels(labels = y,fontsize=14)

ax1.set_xticklabels(labels = x, rotation = 45)
ax1.set_ylim(4.5, 8.5)
fig.savefig('Movies Vs Ratings per studio.png')
```

```
<ipython-input-83-23765b0daa1e>:15: UserWarning: FixedFormatter should only be
used together with FixedLocator
  ax1.set_yticklabels(labels = y,fontsize=14)
```

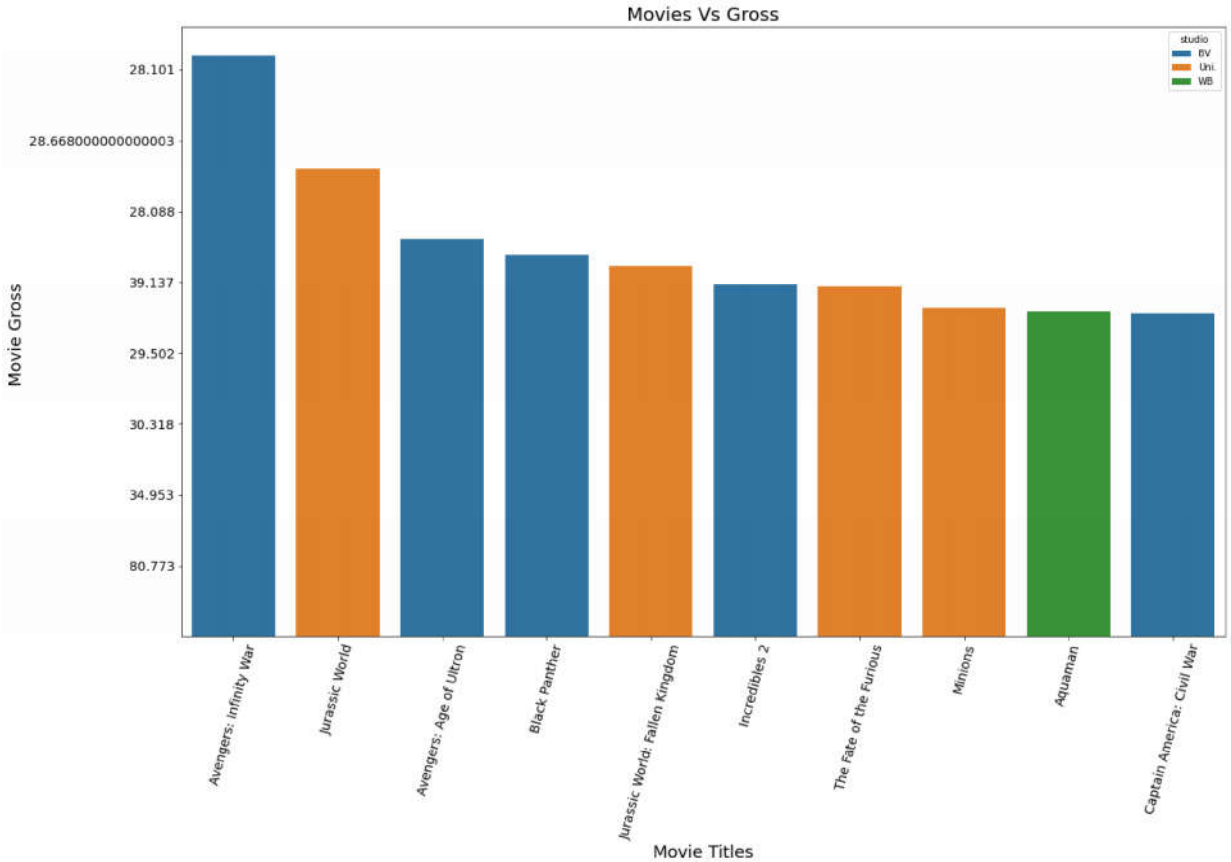


From the bar graph we can see that BV studios has highly rated movies, with the top two movies being Avengers and Thor.

In [94]:

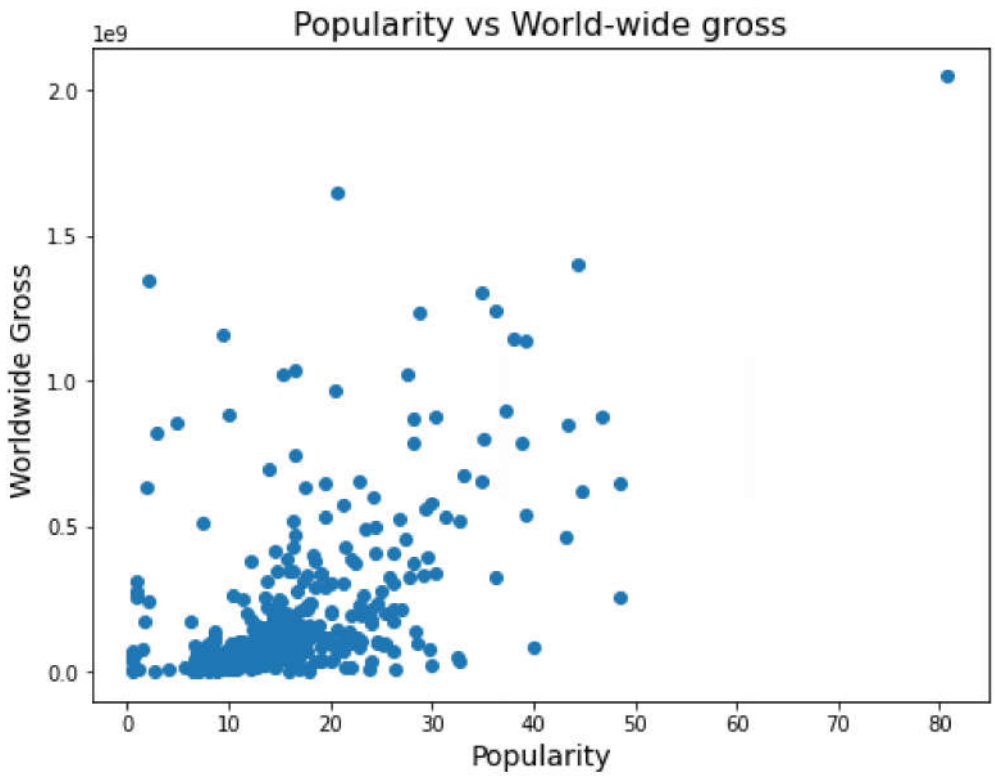
```
fig, ax2= plt.subplots(figsize=(20,12))
ax2 = sns.barplot(data = highest_gross, x = 'movie', y = 'worldwide_gross',hue =

labels = list(highest_gross['movie'])
ax2.set_title('Movies Vs Gross', fontsize=20)
ax2.set_xlabel("Movie Titles",fontsize=18)
ax2.set_ylabel("Movie Gross ", fontsize=18)
ax2.set_ylim(1000)

ax2.set_xticklabels(labels = labels, rotation = 75,fontsize=14)
ax2.set_yticklabels(labels = y,fontsize=14)

fig.savefig('Movies Vs Worldwide gross.png');
```

```
<ipython-input-94-5fc8ff7005f0>:11: UserWarning: FixedFormatter should only be
used together with FixedLocator
  ax2.set_yticklabels(labels = y,fontsize=14)
```



4.3 Does popularity affect the worldwide gross?

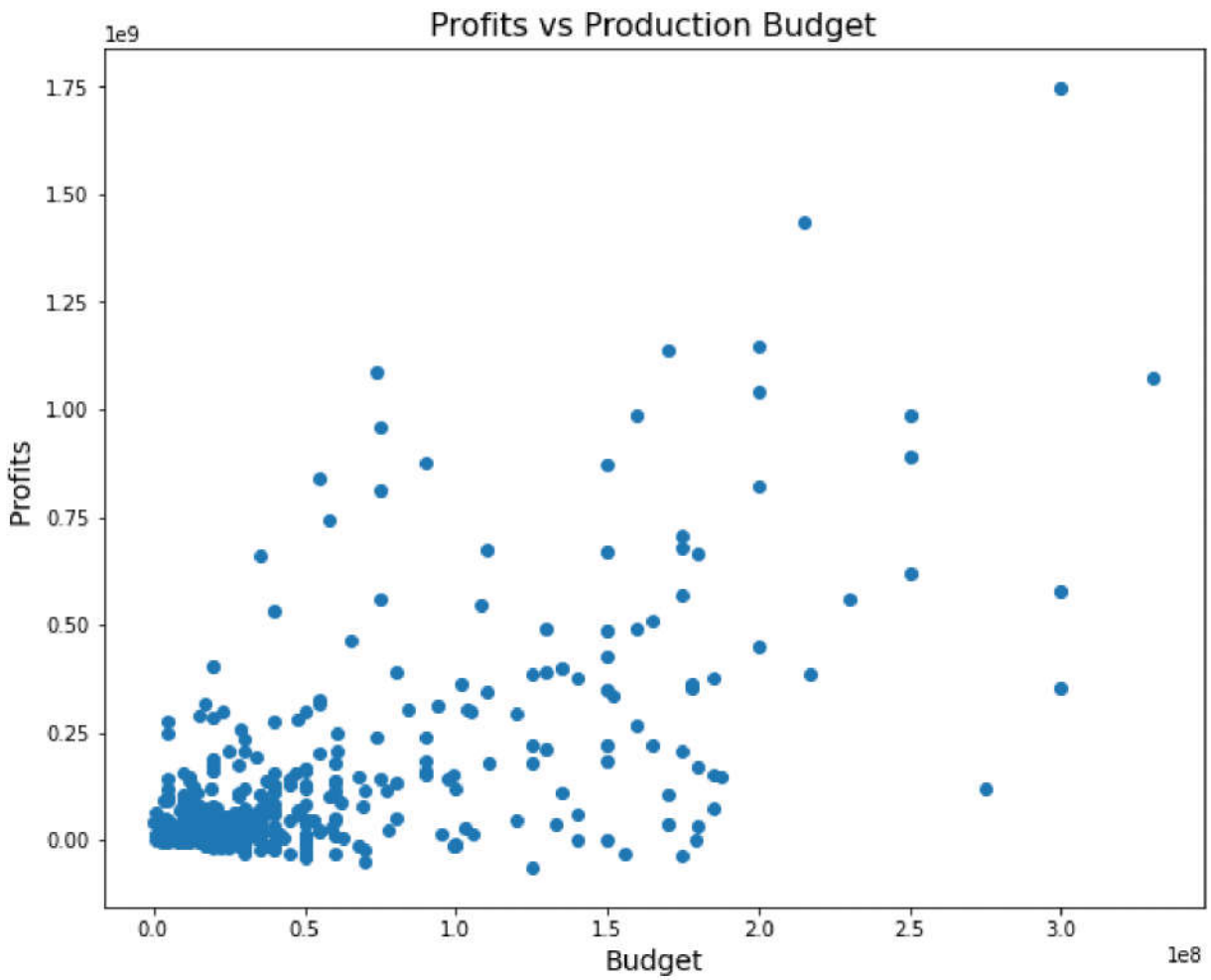
In [85]:
```
# plotting a scatterplot

fig, ax= plt.subplots(figsize=(8,6))

x = final_df['popularity']
y = final_df['worldwide_gross']

ax.scatter(x,y)

ax.set_title('Popularity vs World-wide gross', fontsize=16)
ax.set_xlabel("Popularity",fontsize=14)
ax.set_ylabel("Worldwide Gross ", fontsize=14)
fig.savefig('Popularity vs Worldwide gross.png');
```



The more the popularity the higher the worldwide gross

4.4 Does budget affect revenue?

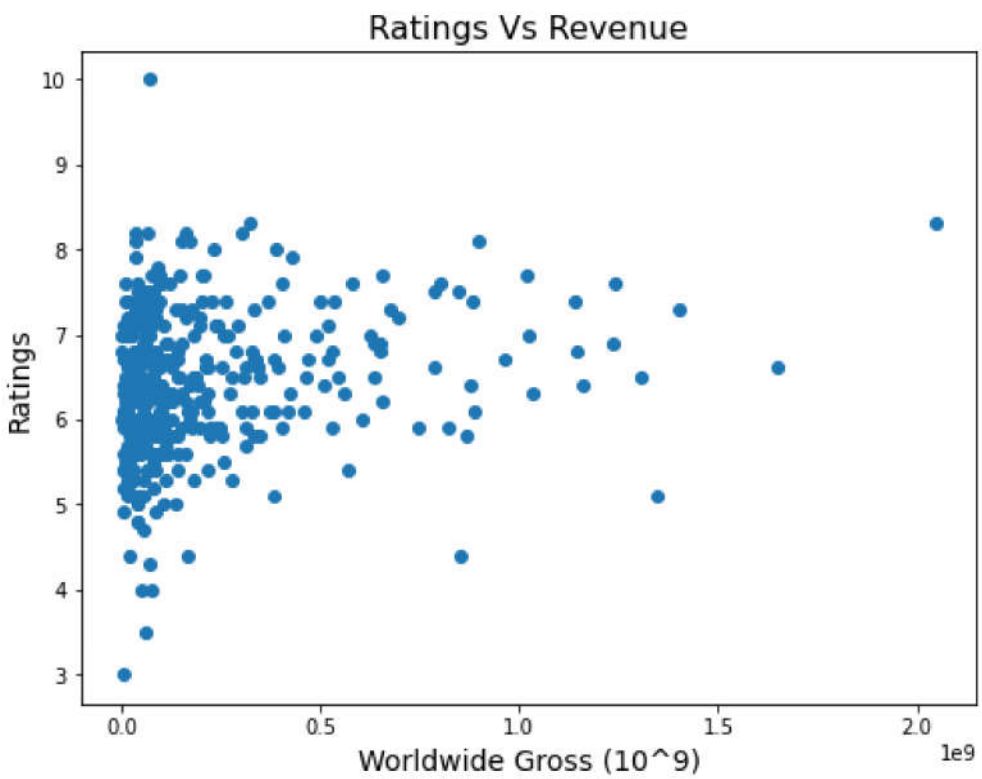
In [86]:
```
# plotting a scatterplot

fig, ax= plt.subplots(figsize=(10,8))

x = final_df['production_budget']
y = final_df['profit/loss']

ax.scatter(x,y)

ax.set_title('Profits vs Production Budget', fontsize=16)
ax.set_xlabel("Budget",fontsize=14)
ax.set_ylabel("Profits ", fontsize=14)
fig.savefig('Budget vs Revenue.png');
```



```
Profits are high where the budget is high. A larger budget results to high
profits.
```

4.5 Does rating affect revenue?

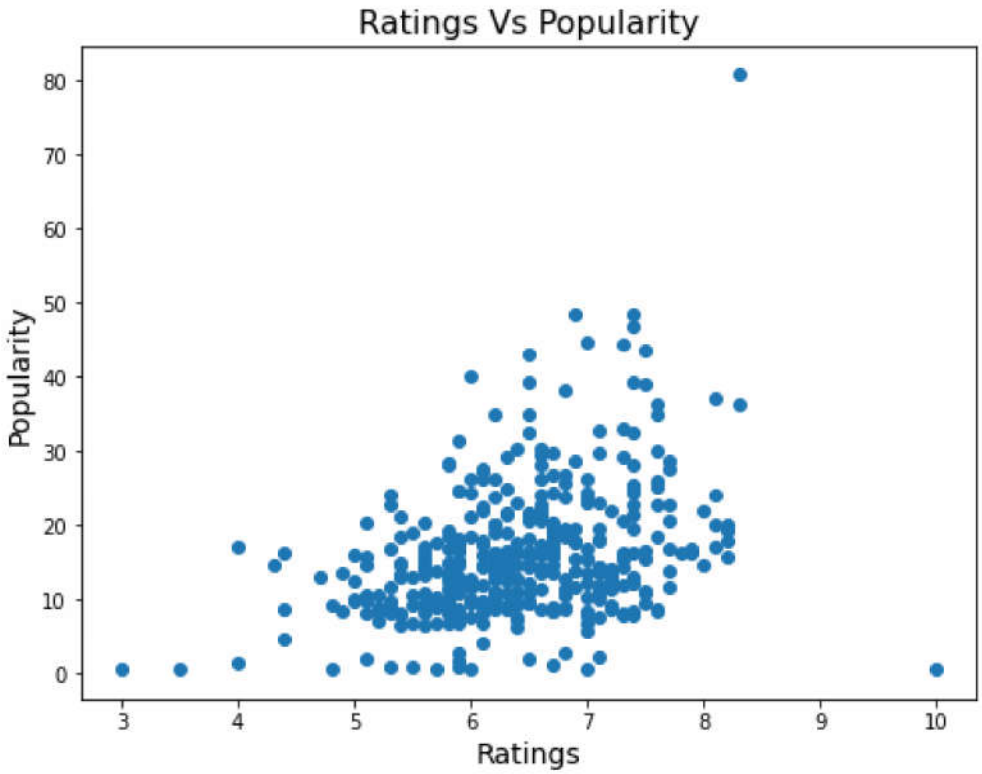
In [95]:
```
# plotting a scatterplot

fig, ax= plt.subplots(figsize=(8,6))

x= final_df['worldwide_gross']
y = final_df['vote_average']

ax.scatter(x,y)

ax.set_title('Ratings Vs Revenue', fontsize=16)
ax.set_ylabel("Ratings",fontsize=14)
ax.set_xlabel("Worldwide Gross (10^9)", fontsize=14)
fig.savefig('Ratings vs Revenue.png');
```



From the above plot, it is possible to deduce that ratings affect revenue. It can be noted that movies with high ratings have a high revenue.

4.6 Does popularity affect the rating?

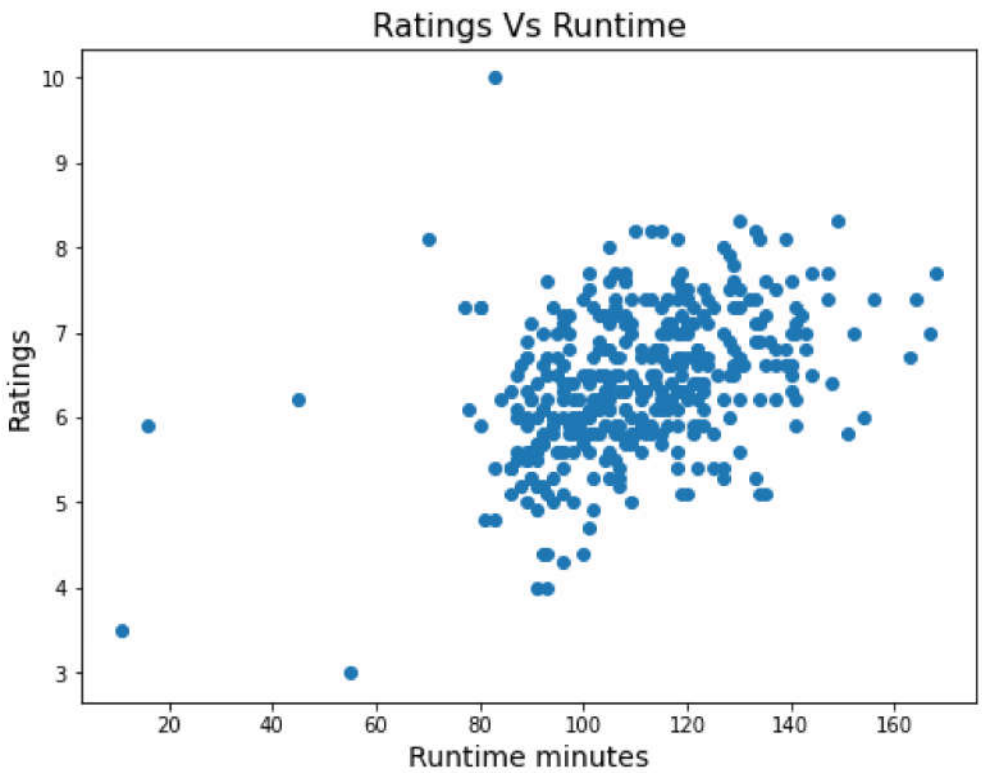
In [88]:
```
# plotting a scatterplot

fig, ax= plt.subplots(figsize=(8,6))

x = final_df['vote_average']
y = final_df['popularity']

ax.scatter(x,y)

ax.set_title('Ratings Vs Popularity', fontsize=16)
ax.set_xlabel("Ratings",fontsize=14)
ax.set_ylabel("Popularity", fontsize=14)
fig.savefig('Ratings vs Popularity.png');
```



The rating of the movie increases with its popularity.

4.7 Does the runtime minutes affect the ratings?

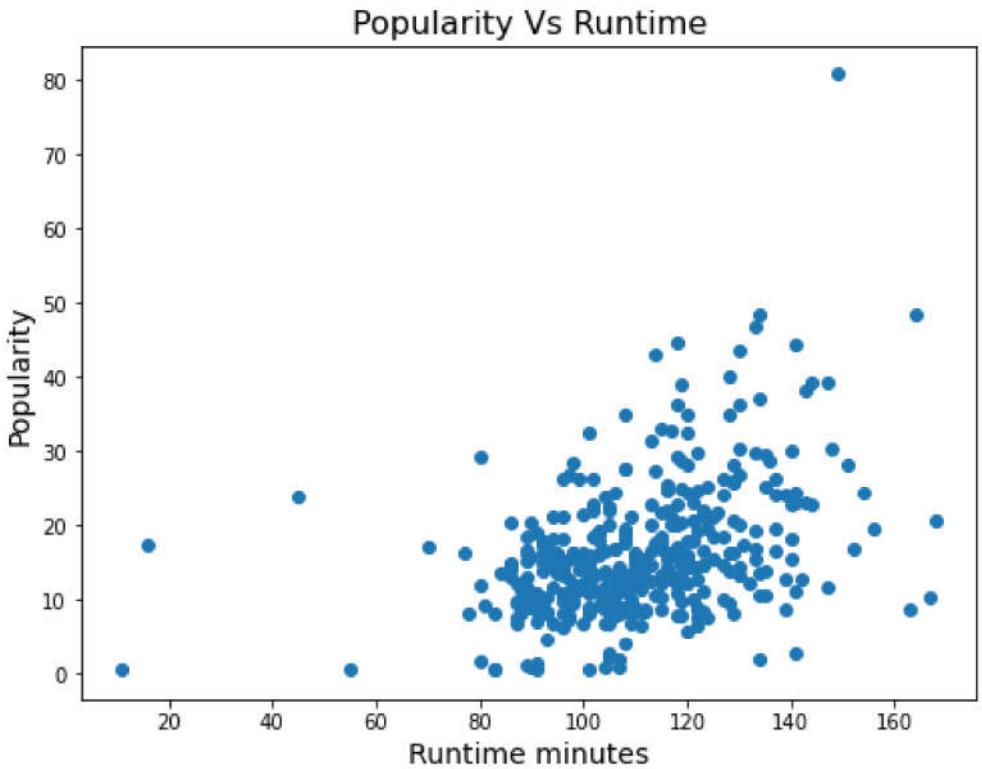
In [89]:
```
# plotting a scatterplot

fig, ax= plt.subplots(figsize=(8,6))

x = final_df['runtime_minutes']
y = final_df['vote_average']

ax.scatter(x,y)

ax.set_title('Ratings Vs Runtime', fontsize=16)
ax.set_ylabel("Ratings",fontsize=14)
ax.set_xlabel("Runtime minutes", fontsize=14)
fig.savefig('Ratings vs Runtime.png');
```



Movies with runtime minutes of about 80 to 140 minutes have higher ratings.

4.8 Does runtime minutes affect the popularity?

In [90]:
```
# plotting a scatterplot

fig, ax= plt.subplots(figsize=(8,6))

x= final_df['runtime_minutes']
y= final_df['popularity']


ax.scatter(x,y)

ax.set_title('Popularity Vs Runtime', fontsize=16)
ax.set_ylabel("Popularity",fontsize=14)
ax.set_xlabel("Runtime minutes", fontsize=14)
fig.savefig('Popularity vs Runtime.png');
```



Movies with runtime minutes of about 80 to 140 minutes have a higher popularity

In [91]:
```
conn.close()
```

5. Conclusion

1. Movies with a high budget make more profits as compared to those with a low budget.
2. High rated movies gross higher, hence high profit margins.

3. Popular movies have high ratings
4. Drama, Comedy and Action genre of movies are the best to venture into since they are the popular genres

6.Recommendation

1. Microsoft should come up with movies that incorporate drama and comedy.
2. Microsoft can benchmark from BV and … since they produce high ranking and grossing movies.
3. Microsoft should come up with a strong marketing strategy since popularity increases the ratings and profits.