Final Project Submission

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- Student pace: part time
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- Blog post URL: https://github.com/SteveNdirangu/dsc-phase-1-project-v2-4 (https://github.com/SteveNdirangu/dsc-phase-1-project-v2-4)

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.

This analysis is to help reveal insights for Microsoft's new movie studio.The point of interest is which movies are doing well currently in the box office.

This analysis will focus on ratings and revenue of the movies as the relevant information

1) Importing relevant Libraries

In [166]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sqlite3
import seaborn as sns
%matplotlib inline
```

2) Loading the Datasets

We start with the Sql dataset from IMDB

In [2]:
```
conn = sqlite3.connect("zippedData/im.db")
cur=conn.cursor()
cur.execute("SELECT name FROM sqlite_master WHERE type = 'table';")
tables= cur.fetchall()
tables
```

Out[2]:
```
[('movie_basics',),
 ('directors',),
 ('known_for',),
 ('movie_akas',),
 ('movie_ratings',),
 ('persons',),
 ('principals',),
 ('writers',)]
```

We read the Sql tables we need, and join them to create one dataset

In [3]:
```
imdb_df = pd.read_sql("""SELECT * FROM movie_basics  JOIN movie_ratings USING(movie_id);""", conn)
```

In [4]:
```
bom_df = pd.read_csv("zippedData/bom.movie_gross.csv.gz")
```

In [5]:
```
tn_df = pd.read_csv("zippedData/tn.movie_budgets.csv.gz", index_col=0)
```

3) Cleaning the first Dataset

In [6]:
```
imdb_df.head()
```

Out[6]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	43
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	6.9	4517
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama	6.1	13
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	119

In [7]:
```
imdb_df.columns
```

Out[7]:
```
Index(['movie_id', 'primary_title', 'original_title', 'start_year',
       'runtime_minutes', 'genres', 'averagerating', 'numvotes'],
      dtype='object')
```

In [8]:
```
imdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         73856 non-null  object 
 1   primary_title    73856 non-null  object 
 2   original_title   73856 non-null  object 
 3   start_year       73856 non-null  int64  
 4   runtime_minutes  66236 non-null  float64
 5   genres           73052 non-null  object 
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 4.5+ MB
```

In [9]:
```
imdb_df.describe()
```

Out[9]:

	start_year	runtime_minutes	averagerating	numvotes
count	73856.000000	66236.000000	73856.000000	7.385600e+04
mean	2014.276132	94.654040	6.332729	3.523662e+03
std	2.614807	208.574111	1.474978	3.029402e+04
min	2010.000000	3.000000	1.000000	5.000000e+00
25%	2012.000000	81.000000	5.500000	1.400000e+01
50%	2014.000000	91.000000	6.500000	4.900000e+01
75%	2016.000000	104.000000	7.400000	2.820000e+02
max	2019.000000	51420.000000	10.000000	1.841066e+06

The dataset contains movies since 2010 to 2019

Average runtime is 94 minutes with some outliers for example 51,420 minutes

average ratings are 6.3 and ratings go from 1 to 10

In [10]:
```
dup_vals= imdb_df.duplicated().any().sum()
print("There are {} duplicates in this dataset".format(dup_vals))
```

```
There are 0 duplicates in this dataset
```

In [11]:
```
imdb_df.loc[imdb_df["runtime_minutes"]>180]
```

Out[11]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
60	tt0396123	Den milde smerte	Den milde smerte	2010	280.0	Drama	7.8	6
64	tt0403645	Burnt by the Sun 2	Utomlennye solntsem 2	2010	181.0	Drama,History,War	4.1	3907
260	tt0808447	The Last Pogo Jumps Again	The Last Pogo Jumps Again	2013	200.0	Documentary,Music	9.3	42
776	tt10244756	Ang hupa	Ang hupa	2019	276.0	Sci-Fi	7.2	5
1052	tt1113829	George Harrison: Living in the Material World	George Harrison: Living in the Material World	2011	208.0	Biography,Documentary,Music	8.2	9372
...	...	...	...	...	...	...	...	...
72452	tt9055926	National Theatre Live: King Lear	National Theatre Live: King Lear	2018	227.0	Drama	8.6	135
72572	tt9097864	My Thesis Film: A Thesis Film by Erik Anderson	My Thesis Film: A Thesis Film by Erik Anderson	2018	233.0	Drama	8.4	5
73022	tt9318514	Reason	Vivek	2018	261.0	Documentary	9.0	44
73388	tt9573980	Leaving Neverland	Leaving Neverland	2019	240.0	Documentary	7.1	19632
73653	tt9749570	Heimat Is a Space in Time	Heimat ist ein Raum aus Zeit	2019	218.0	Documentary	7.8	14

243 rows × 8 columns

In [12]:
```
# imdb_df.groupby("genres")["averagerating"].mean().sort_values().tail(20)
```

In [13]:
```
imdb_df.isna().sum()
```

Out[13]:
```
movie_id              0
primary_title         0
original_title        0
start_year            0
runtime_minutes    7620
genres              804
averagerating         0
numvotes              0
dtype: int64
```

In [14]:
```
imdb_df["genres"].fillna("missing", inplace=True)
```

Now to deal with the runtime values that are null

In [15]:
```
imdb_df.dropna(inplace=True)
```

In [16]:
```
imdb_df = imdb_df.rename(columns={'primary_title': 'movie'})
```

In [17]:
```
imdb_df = imdb_df.rename(columns={'start_year': 'year'})
```

In [18]:
```
imdb_df.set_index("movie", inplace=True)
```

In [19]:
```
imdb_df.drop(columns=["movie_id","original_title"], inplace=True)
```

In [20]:
```
imdb_df
```

Out[20]:

movie	year	runtime_minutes	genres	averagerating	numvotes
Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
One Day Before the Rainy Season	2019	114.0	Biography,Drama	7.2	43
The Other Side of the Wind	2018	122.0	Drama	6.9	4517
The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy	6.5	119
Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy	8.1	263
...	...	...	...	...	...
Padmavyuhathile Abhimanyu	2019	130.0	Drama	8.4	365
Swarm Season	2019	86.0	Documentary	6.2	5
Diabolik sono io	2019	75.0	Documentary	6.2	6
Sokagin Çocuklari	2019	98.0	Drama,Family	8.7	136
Drømmeland	2019	72.0	Documentary	6.5	11

66236 rows × 5 columns

4) Cleaning the second Dataset

In [21]:
```
bom_df.head()
```

Out[21]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

In [22]:
```
bom_df.columns
```

Out[22]:
```
Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year'], dtype='object')
```

In [23]:
```
bom_df.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 [24]:
```
bom_df[bom_df["foreign_gross"].isna()]
```

Out[24]:

	title	studio	domestic_gross	foreign_gross	year
222	Flipped	WB	1800000.0	NaN	2010
254	The Polar Express (IMAX re-issue 2010)	WB	673000.0	NaN	2010
267	Tiny Furniture	IFC	392000.0	NaN	2010
269	Grease (Sing-a-Long re-issue)	Par.	366000.0	NaN	2010
280	Last Train Home	Zeit.	288000.0	NaN	2010
...	...	...	...	...	...
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

1350 rows × 5 columns

In [25]:
```
# percentage of missing values in columns
bom_df.isna().sum()/bom_df.shape[0]*100
```

Out[25]:
```
title              0.000000
studio             0.147623
domestic_gross     0.826690
foreign_gross     39.858282
year               0.000000
dtype: float64
```

In [26]:
```
# foreign gross has 39% missing values, we can drop it
bom_df.drop(columns=["foreign_gross"], inplace=True)
```

In [27]:
```
bom_df = bom_df.rename(columns={'title': 'movie'})
```

In [28]:
```
bom_df.set_index("movie", inplace=True)
```

In [29]:
```
bom_df.dropna(inplace=True)
```

In [30]:
```
bom_df
```

Out[30]:

movie	studio	domestic_gross	year
Toy Story 3	BV	415000000.0	2010
Alice in Wonderland (2010)	BV	334200000.0	2010
Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	2010
Inception	WB	292600000.0	2010
Shrek Forever After	P/DW	238700000.0	2010
...	...	...	...
The Quake	Magn.	6200.0	2018
Edward II (2018 re-release)	FM	4800.0	2018
El Pacto	Sony	2500.0	2018
The Swan	Synergetic	2400.0	2018
An Actor Prepares	Grav.	1700.0	2018

3356 rows × 3 columns

5) Cleaning The Third dataset

In [31]:
```
tn_df.head(8)
```

Out[31]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	$306,000,000	$936,662,225	$2,053,311,220
7	Apr 27, 2018	Avengers: Infinity War	$300,000,000	$678,815,482	$2,048,134,200
8	May 24, 2007	Pirates of the Caribbean: At Worldâ□□s End	$300,000,000	$309,420,425	$963,420,425

In [32]:
```
tn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   release_date       5782 non-null   object
 1   movie              5782 non-null   object
 2   production_budget  5782 non-null   object
 3   domestic_gross     5782 non-null   object
 4   worldwide_gross    5782 non-null   object
dtypes: object(5)
memory usage: 271.0+ KB
```

This dataset has no missing values,but the values of money are not in the correct format, so we will change them to the correct type...numerical

We strip the dollar signs and the commas first

In [33]:
```
tn_df['domestic_gross'] = tn_df['domestic_gross'].str.replace('$', '').str.replace(',', '')
tn_df['production_budget'] = tn_df['production_budget'].str.replace('$', '').str.replace(',', '')
tn_df['worldwide_gross'] = tn_df['worldwide_gross'].str.replace('$', '').str.replace(',', '')
```

we then change the type of data for the columns

In [34]:
```
tn_df["domestic_gross"]=pd.to_numeric(tn_df["domestic_gross"])
tn_df["production_budget"]=pd.to_numeric(tn_df["production_budget"])
tn_df["worldwide_gross"]=pd.to_numeric(tn_df["worldwide_gross"])
tn_df['release_date'] = pd.to_datetime(tn_df['release_date'])

tn_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype         
---  ------             --------------  -----         
 0   release_date       5782 non-null   datetime64[ns]
 1   movie              5782 non-null   object        
 2   production_budget  5782 non-null   int64         
 3   domestic_gross     5782 non-null   int64         
 4   worldwide_gross    5782 non-null   int64         
dtypes: datetime64[ns](1), int64(3), object(1)
memory usage: 271.0+ KB
```

Now we can set the movie's name as the index

In [35]:
```
tn_df.set_index("movie", inplace=True)
```

In [36]:
```
tn_df['year'] = tn_df['release_date'].dt.year
```

In [37]:
```
tn_df
```

Out[37]:

movie	release_date	production_budget	domestic_gross	worldwide_gross	year
Avatar	2009-12-18	425000000	760507625	2776345279	2009
Pirates of the Caribbean: On Stranger Tides	2011-05-20	410600000	241063875	1045663875	2011
Dark Phoenix	2019-06-07	350000000	42762350	149762350	2019
Avengers: Age of Ultron	2015-05-01	330600000	459005868	1403013963	2015
Star Wars Ep. VIII: The Last Jedi	2017-12-15	317000000	620181382	1316721747	2017
...	...	...	...	...	...
Red 11	2018-12-31	7000	0	0	2018
Following	1999-04-02	6000	48482	240495	1999
Return to the Land of Wonders	2005-07-13	5000	1338	1338	2005
A Plague So Pleasant	2015-09-29	1400	0	0	2015
My Date With Drew	2005-08-05	1100	181041	181041	2005

5782 rows × 5 columns

6) Combining the Datasets

First, i will reset the index so as to merge

In [51]:
```
imdb_df.reset_index(inplace=True)
bom_df.reset_index(inplace=True)
tn_df.reset_index(inplace=True)
```

Chaining together the merge

In [56]:
```
merged_df = imdb_df.merge(bom_df, on=['movie', 'year']).merge(tn_df, on=['movie', 'year'])
```

In [58]:
```
merged_df
```

Out[58]:

	movie	year	runtime_minutes	genres	averagerating	numvotes	studio	domestic_gross_x	release_date
0	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	7.3	275300	Fox	58200000.0	2013-12-25
1	A Walk Among the Tombstones	2014	114.0	Action,Crime,Drama	6.5	105116	Uni.	26300000.0	2014-09-19
2	Jurassic World	2015	124.0	Action,Adventure,Sci-Fi	7.0	539338	Uni.	652300000.0	2015-06-12
3	The Rum Diary	2011	119.0	Comedy,Drama	6.2	94787	FD	13100000.0	2011-10-28
4	The Three Stooges	2012	92.0	Comedy,Family	5.1	28570	Fox	44300000.0	2012-04-13
...	...	...	...	...	...	...	...	...	...
1034	Paul, Apostle of Christ	2018	108.0	Adventure,Biography,Drama	6.7	5662	Affirm	17600000.0	2018-03-23
1035	Instant Family	2018	118.0	Comedy,Drama	7.4	46728	Par.	67400000.0	2018-11-16
1036	The Great Wall	2017	72.0	Documentary	6.5	24	Uni.	45500000.0	2017-02-17
1037	Hereditary	2018	127.0	Drama,Horror,Mystery	7.3	151571	A24	44100000.0	2018-06-08
1038	The Mule	2018	116.0	Crime,Drama,Thriller	7.1	58955	WB	103800000.0	2018-12-14

1039 rows × 12 columns

In [109]:
```
merged_df.columns
```

Out[109]:
```
Index(['movie', 'year', 'runtime_minutes', 'genres', 'averagerating',
       'numvotes', 'studio', 'domestic_gross_x', 'release_date',
       'production_budget', 'domestic_gross_y', 'worldwide_gross'],
      dtype='object')
```

In [149]:
```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1039 entries, 0 to 1038
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype         
---  ------             --------------  -----         
 0   movie              1039 non-null   object        
 1   year               1039 non-null   int64         
 2   runtime_minutes    1039 non-null   float64       
 3   genres             1039 non-null   object        
 4   averagerating      1039 non-null   float64       
 5   numvotes           1039 non-null   int64         
 6   studio             1039 non-null   object        
 7   domestic_gross_x   1039 non-null   float64       
 8   release_date       1039 non-null   datetime64[ns]
 9   production_budget  1039 non-null   int64         
 10  domestic_gross_y   1039 non-null   int64         
 11  worldwide_gross    1039 non-null   int64         
dtypes: datetime64[ns](1), float64(3), int64(5), object(3)
memory usage: 145.5+ KB
```

Extracting the month so that we can create groupings based on the year, and each month

In [184]:
```
#we create a column for the extracted month
merged_df['month'] = merged_df['release_date'].dt.month
grouped_df = merged_df.groupby(['year', 'month'])["worldwide_gross"].mean()
```

In [181]:
```
merged_df
```

Out[181]:

	movie	year	runtime_minutes	genres	averagerating	numvotes	studio	domestic_gross_x	release_date
0	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	7.3	275300	Fox	58200000.0	2013-12-25
1	A Walk Among the Tombstones	2014	114.0	Action,Crime,Drama	6.5	105116	Uni.	26300000.0	2014-09-19
2	Jurassic World	2015	124.0	Action,Adventure,Sci-Fi	7.0	539338	Uni.	652300000.0	2015-06-12
3	The Rum Diary	2011	119.0	Comedy,Drama	6.2	94787	FD	13100000.0	2011-10-28
4	The Three Stooges	2012	92.0	Comedy,Family	5.1	28570	Fox	44300000.0	2012-04-13
...	...	...	...	...	...	...	...	...	...
1034	Paul, Apostle of Christ	2018	108.0	Adventure,Biography,Drama	6.7	5662	Affirm	17600000.0	2018-03-23
1035	Instant Family	2018	118.0	Comedy,Drama	7.4	46728	Par.	67400000.0	2018-11-16
1036	The Great Wall	2017	72.0	Documentary	6.5	24	Uni.	45500000.0	2017-02-17
1037	Hereditary	2018	127.0	Drama,Horror,Mystery	7.3	151571	A24	44100000.0	2018-06-08
1038	The Mule	2018	116.0	Crime,Drama,Thriller	7.1	58955	WB	103800000.0	2018-12-14

1039 rows × 13 columns

This data now shows each year, and each month, with the mean gross worldwide

In [183]:
```
grouped_df.head(30)
```

Out[183]:

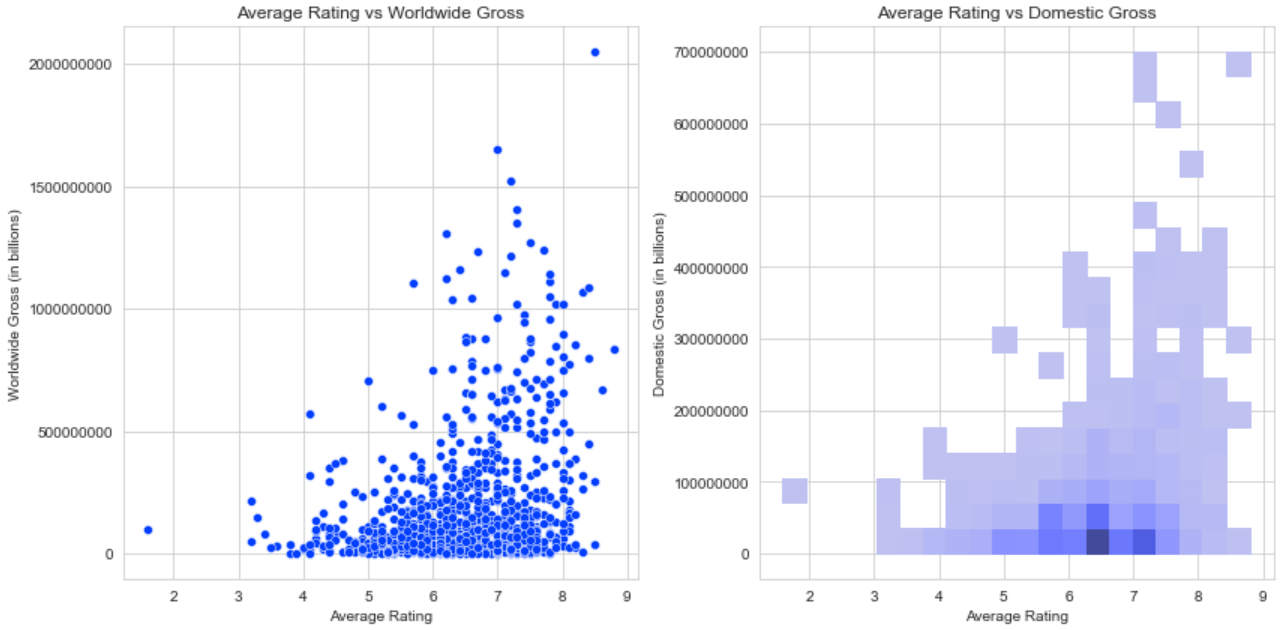
```
year  month
2010  1        6.885591e+07
      2        1.399410e+08
      3        1.012614e+08
      4        4.936259e+07
      5        2.378730e+08
      6        2.233880e+08
      7        2.205927e+08
      8        9.288672e+07
      9        8.209742e+07
      10       4.784011e+07
      11       1.163128e+08
      12       1.249881e+08
2011  1        1.189247e+08
      2        7.267380e+07
      3        9.607406e+07
      4        1.655081e+08
      5        2.880511e+08
      6        3.042299e+08
      7        1.188380e+08
      8        1.013905e+08
      9        4.651884e+07
      10       1.087665e+08
      11       1.051226e+08
      12       1.865594e+08
2012  1        6.626224e+07
      2        1.427703e+08
      3        2.523166e+08
      4        8.493019e+07
      5        1.552604e+08
      6        2.296121e+08
Name: worldwide_gross, dtype: float64
```

check the distribution of the last 5 years' average world wide grosses per month

7) Visualizing the data

Lets check the rating versus the Gross worldwide, and Domestic gross

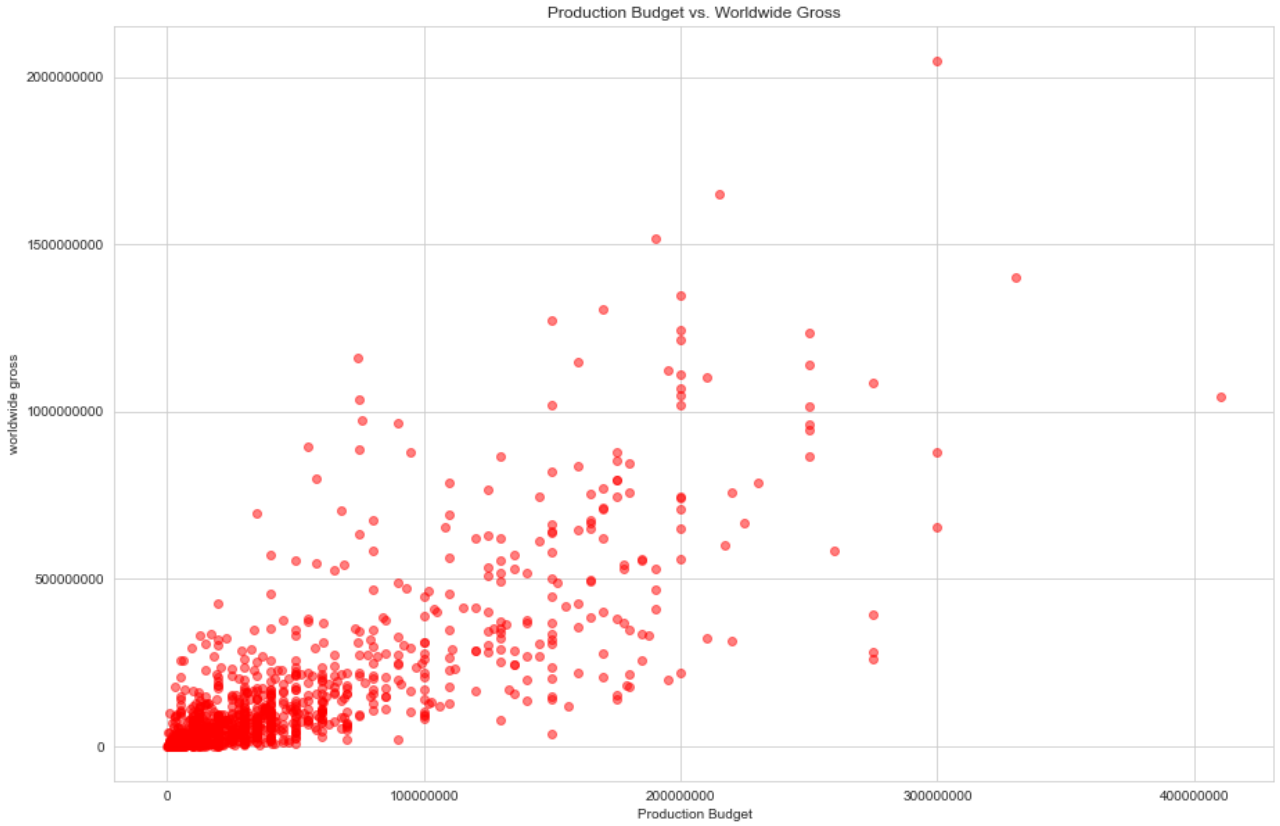
In [123]:
```
# Set figure size
plt.figure(figsize=(12, 6))

# First plot: scatter plot of rating vs worldwide gross
plt.subplot(1, 2, 1)
sns.scatterplot(x='averagerating', y='worldwide_gross', data=merged_df)
plt.title('Average Rating vs Worldwide Gross')
plt.xlabel('Average Rating')
plt.ylabel('Worldwide Gross (in billions)')
plt.ticklabel_format(style='plain', axis='y')

# Second plot: histogram of rating vs domestic gross
plt.subplot(1, 2, 2)
sns.histplot(x='averagerating', y='domestic_gross_y', data=merged_df, bins=20)
plt.title('Average Rating vs Domestic Gross')
plt.xlabel('Average Rating')
plt.ylabel('Domestic Gross (in billions)')
plt.ticklabel_format(style='plain', axis='y')

plt.tight_layout()
plt.show()
```



Similar trends for both

Checking whether Production Budget has a relation with the worldwide gross

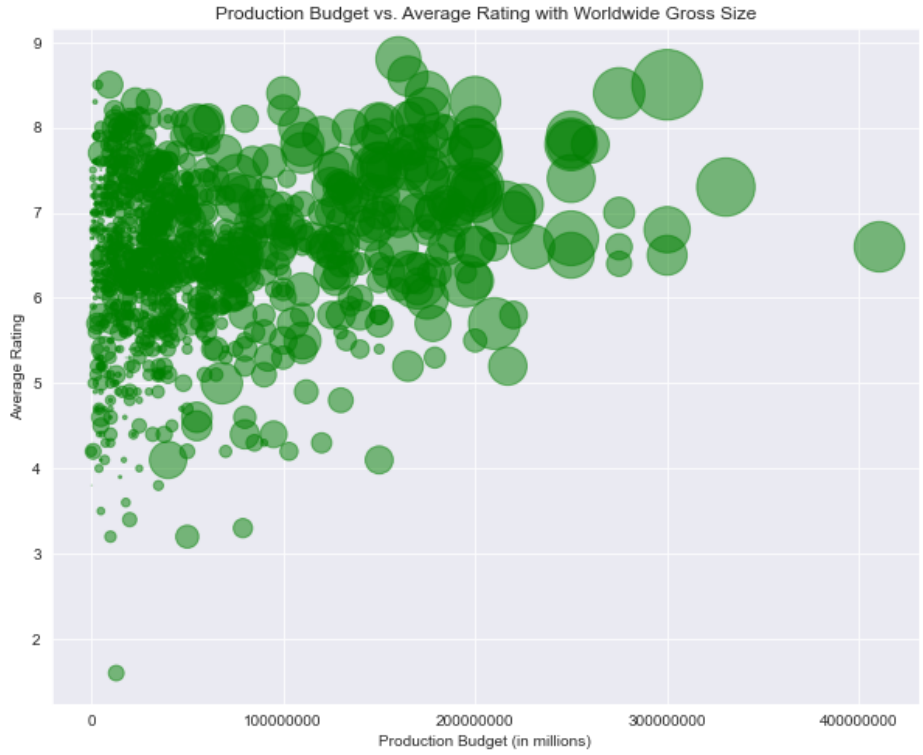
In [135]:
```
plt.figure(figsize=(15,10))
plt.scatter(merged_df['production_budget'], merged_df['worldwide_gross'], alpha=0.5, color="red")
plt.ticklabel_format(style='plain', axis='both')
plt.title('Production Budget vs. Worldwide Gross')
plt.xlabel('Production Budget')
plt.ylabel('worldwide gross')
plt.show()
```



though more expensive movies are rare, the trend is: the more budget, the more gross

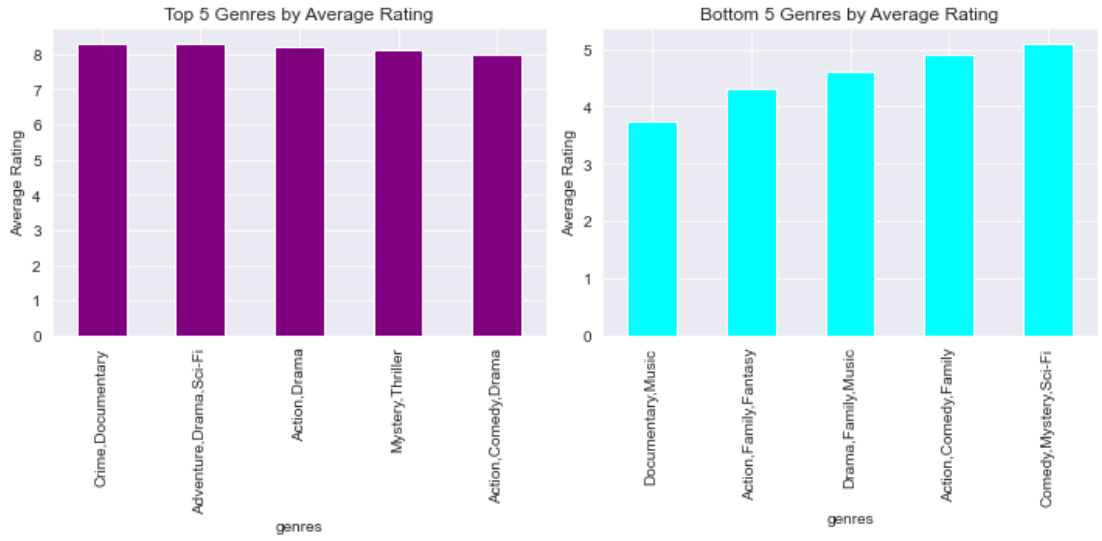
Production Budget versus Average Rating, with worldwide Gross size

In [186]:
```
plt.figure(figsize=(10, 8))
plt.ticklabel_format(style='plain', axis='x')
plt.scatter(merged_df['production_budget'], merged_df['averagerating'], s=merged_df['worldwide_gross']/10000
plt.title('Production Budget vs. Average Rating with Worldwide Gross Size')
plt.xlabel('Production Budget (in millions)')
plt.ylabel('Average Rating')
plt.show()
```

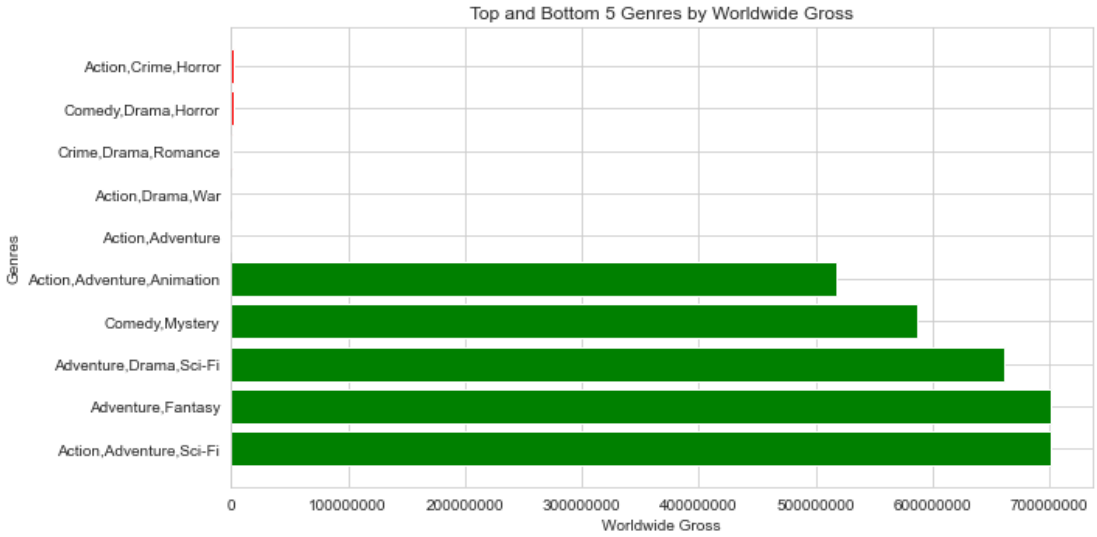


Lets check the Genres that are popular in rating and those with good returns in the box office

In [187]:
```
# Grouping by genre and calculate mean rating
genre_ratings = merged_df.groupby('genres')['averagerating'].mean()

# Sorting by rating and get top/bottom 5 genres
top_genres = genre_ratings.sort_values(ascending=False)[:5]
bottom_genres = genre_ratings.sort_values()[:5]

#bar plot
fig, axes = plt.subplots(ncols=2, figsize=(10, 5))
ax1, ax2 = axes

top_genres.plot(kind='bar', ax=ax1, color="purple")
ax1.set_title('Top 5 Genres by Average Rating')
ax1.set_ylabel('Average Rating')

bottom_genres.plot(kind='bar', ax=ax2, color="cyan")
ax2.set_title('Bottom 5 Genres by Average Rating')
ax2.set_ylabel('Average Rating')

plt.tight_layout()
plt.show()
```



In [134]:
```
genre_gross = merged_df.groupby('genres')['worldwide_gross'].mean()

# Sort the values in descending order and get the top and bottom 5
top5_gross = genre_gross.sort_values(ascending=False)[:5]
bottom5_gross = genre_gross.sort_values()[:5]

# Creating a horizontal bar plot of the top 5 and bottom 5 genres
plt.figure(figsize=(10, 5))
plt.ticklabel_format(style='plain', axis='x')
plt.barh(top5_gross.index, top5_gross.values, color='green')
plt.barh(bottom5_gross.index, bottom5_gross.values, color='red')
plt.title('Top and Bottom 5 Genres by Worldwide Gross')
plt.xlabel('Worldwide Gross')
plt.ylabel('Genres')
plt.tight_layout()
plt.show()
```

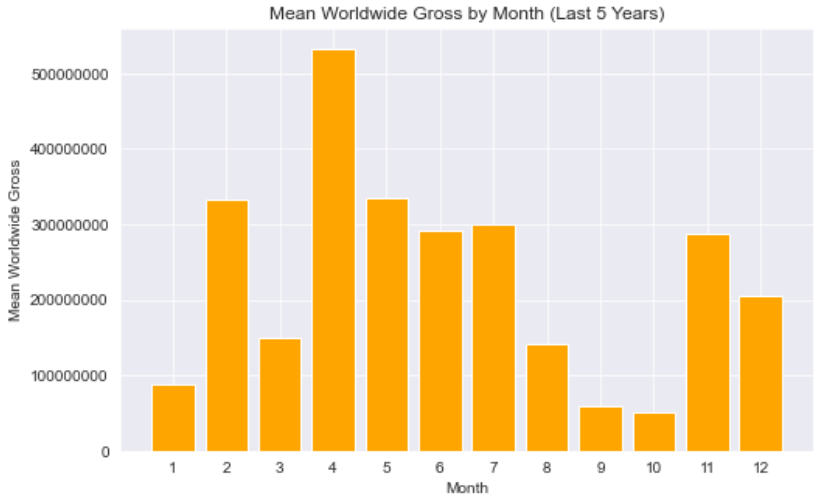


Lets compare rating to runtime

In [148]:
```
# Set plot size
plt.figure(figsize=(12, 7))

# Plot the first graph
plt.subplot(1, 2, 1)
sns.scatterplot(x='runtime_minutes', y='averagerating', data=merged_df)
plt.title('Runtime vs Rating')
plt.ticklabel_format(style='plain', axis='both')
# Plot the second graph
plt.subplot(1, 2, 2)
sns.scatterplot(x='runtime_minutes', y='worldwide_gross', data=merged_df)
plt.title('Runtime vs Worldwide Gross')
plt.ticklabel_format(style='plain', axis='both')
# Display the plot
plt.tight_layout()
plt.show()
```

check the distribution of the last 5 years' average world wide grosses per month

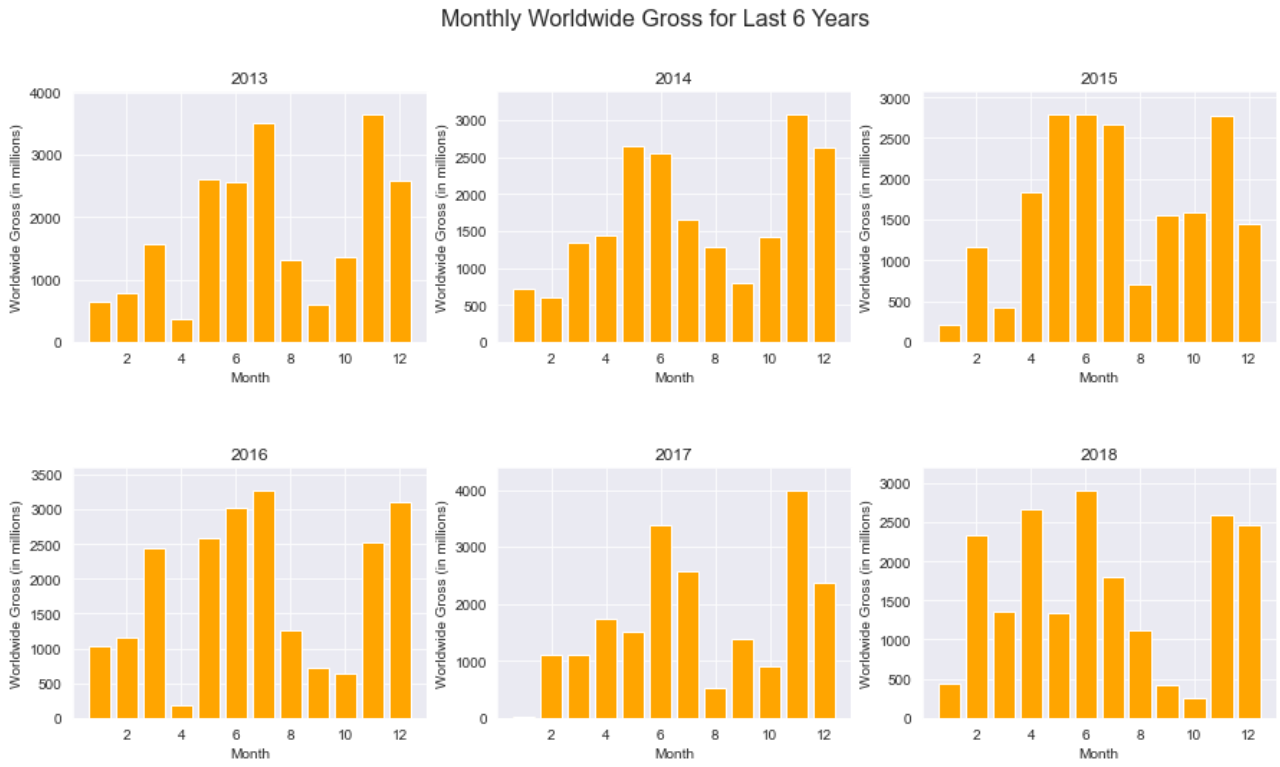
In [170]:
```
# group by year and month
grouped_df = merged_df.groupby([merged_df['release_date'].dt.year.rename('year'), merged_df['release_date'].

# filter last 5 years
last_5_years = grouped_df.filter(lambda x: x['release_date'].dt.year.max() >= 2018)

# calculate mean worldwide gross for each month
monthly_mean_gross = last_5_years.groupby('month')['worldwide_gross'].mean()

# plot the data
plt.figure(figsize=(8,5))
plt.bar(monthly_mean_gross.index, monthly_mean_gross, color="Orange")
plt.title('Mean Worldwide Gross by Month (Last 5 Years)')
plt.xlabel('Month')
plt.ylabel('Mean Worldwide Gross')
plt.xticks(range(1, 13))
plt.ticklabel_format(style='plain', axis='both')
plt.show()
```



Checking per year

In [173]:

```
grouped_df = merged_df.groupby(['year', 'month']).sum().reset_index()

# Get the last 6 years
last_6_years = grouped_df['year'].unique()[-6:]

# Create subplots
fig, axs = plt.subplots(2, 3, figsize=(15, 8))

# Loop through each year and plot the monthly gross
for i, year in enumerate(last_6_years):
    ax = axs[i // 3][i % 3]
    year_df = grouped_df[grouped_df['year'] == year]
    ax.bar(year_df['month'], year_df['worldwide_gross'] / 1000000, color="orange")
    ax.set_title(year)
    ax.set_xlabel('Month')
    ax.set_ylabel('Worldwide Gross (in millions)')
    ax.ticklabel_format(style='plain', axis='y')
    #the limits of y axis are from zero to the maximum gross available, the scale is then made visible
    ax.set_ylim([0, year_df['worldwide_gross'].max() / 1000000 * 1.1])

# Set the overall title
fig.suptitle('Monthly Worldwide Gross for Last 6 Years', fontsize=16)

# Adjust the horizontal spacing between subplots
plt.subplots_adjust(hspace=0.5)

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



Finally, lets see the correlations

In [175]:
```
correlations = merged_df.corr()
correlations["averagerating"].sort_index()
```

Out[175]:
```
averagerating        1.000000
domestic_gross_x     0.292718
domestic_gross_y     0.292750
month                0.252920
numvotes             0.517907
production_budget    0.168339
runtime_minutes      0.406148
worldwide_gross      0.278457
year                 0.024619
Name: averagerating, dtype: float64
```

In [176]:
```
correlations = merged_df.corr()
correlations["production_budget"].sort_index()
```

Out[176]:
```
averagerating        0.168339
domestic_gross_x     0.694491
domestic_gross_y     0.694416
month               -0.041025
numvotes             0.514512
production_budget    1.000000
runtime_minutes      0.337804
worldwide_gross      0.778029
year                 0.053264
Name: production_budget, dtype: float64
```

In [177]:
```
correlations
```

Out[177]:

	year	runtime_minutes	averagerating	numvotes	domestic_gross_x	production_budget	domestic_gross_y	wo
year	1.000000	0.117873	0.024619	-0.092889	0.104557	0.053264	0.104553	
runtime_minutes	0.117873	1.000000	0.406148	0.413304	0.276495	0.337804	0.276426	
averagerating	0.024619	0.406148	1.000000	0.517907	0.292718	0.168339	0.292750	
numvotes	-0.092889	0.413304	0.517907	1.000000	0.637405	0.514512	0.637399	
domestic_gross_x	0.104557	0.276495	0.292718	0.637405	1.000000	0.694491	0.999997	
production_budget	0.053264	0.337804	0.168339	0.514512	0.694491	1.000000	0.694416	
domestic_gross_y	0.104553	0.276426	0.292750	0.637399	0.999997	0.694416	1.000000	
worldwide_gross	0.116616	0.297700	0.278457	0.621866	0.937926	0.778029	0.937880	
month	-0.006038	0.151590	0.252920	0.048037	-0.028107	-0.041025	-0.028061	

Findings

Budget

The production budget has very strong positive correlation with the domestic and worldwide grosses

Average rating

-movies rated higher did much better in the box office,both for domestic and worlwide audiences, and in fact, movies rated lower than 5 did very poor

-curiously, the rating isn't really affected by increased budget, probably due to the fact that many things go into a production

-it would seem the average rating has a weak positive correlation with both domestic and worldwide gross,

Genre

Generally genres dont really affect a rating, but the top 5 that make money worldwide are anything of the "adventure genre" involving scifi, animation and comedy

Runtime

-Rating has a strong positive correlation with the runtime of the movie, but closer investigation shows the dirstibution is clustered within a value range of 80 to 140 minutes

Month of release

Conlusions an Recommendations

1) Mirosoft should invest in the Genres of Adventure, with scifi,comedy,and/or animation, with main projects being of the genre "Adventure,Drama,Scifi" as it gets high reviews as well as high grossing worldwide

2) A high budget in these genres will give better returns worldwide, somewhere above the 100 million mark

3)A runtime of Between 80 minutes and 140 minutes is the most consistent at good ratings

4) Releasing between months 4-6, and at the tail end of the year might also give good worldwide grosses...probably because these are the months in which holidays occur eg easter, christmas