Final Project Submission

Please fill out:

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- Student pace: Part time
- Scheduled project review date/time: 16/04/2023
- Instructor name: Noah Kandie
- Blog post URL:https://medium.com/@stanleykinyua35/microsoft-movies-studio-prospect-analysis-in-python-db3e528201bb (https://medium.com/@stanleykinyua35/microsoft-movies-studio-prospect-analysis-in-python-db3e528201bb)

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

In [101]:

```
# Importing relevant libraries.

import pandas as pd
import numpy as np
import sqlite3
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures

%matplotlib inline
```

We choose data on the gross sales,the budget, ratings and movie bascis. We are mostly interested in the column gross sales from data gross, the column budget from the data budget, average rating column from the ratings data and the runtime column from the move bascis data.These columns contain the data that we need to compute our analysis.

Journey with me as we dive deeper into the analysis !!

In [5]:

```
# Loading data on gross sales.
gross = pd.read_csv("data/bom.movie_gross.csv")
```

In [6]:
```
# Loading data on movie budget.
budget = pd.read_csv("data/tn.movie_budgets.csv")
```

In [7]:
```
# Loading data on movie ratings.

im_movies = sqlite3.connect("data/im.db")
ratings = pd.read_sql('SELECT * FROM movie_ratings', im_movies)
```

In [8]:
```
#Loading data on movie bascics.

basics = pd.read_sql('SELECT * FROM movie_basics', im_movies)
```

Inspecting the data.

1. Inspecting gross

In [9]:
```
# Loading the first three rows
gross.head(3)
```

Out[9]:

	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

In [10]:
```
# Loading the last three rows
gross.tail(3)
```

Out[10]:

	title	studio	domestic_gross	foreign_gross	year
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 [11]:
```
# Checking a summary of data gross.
# We can see that three columns have missing data. We should have a total
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 [12]:
```
# Checking for the number of rows and columns
# Gross has 5 columns and 3387 rows.
gross.shape
```

Out[12]:
```
(3387, 5)
```

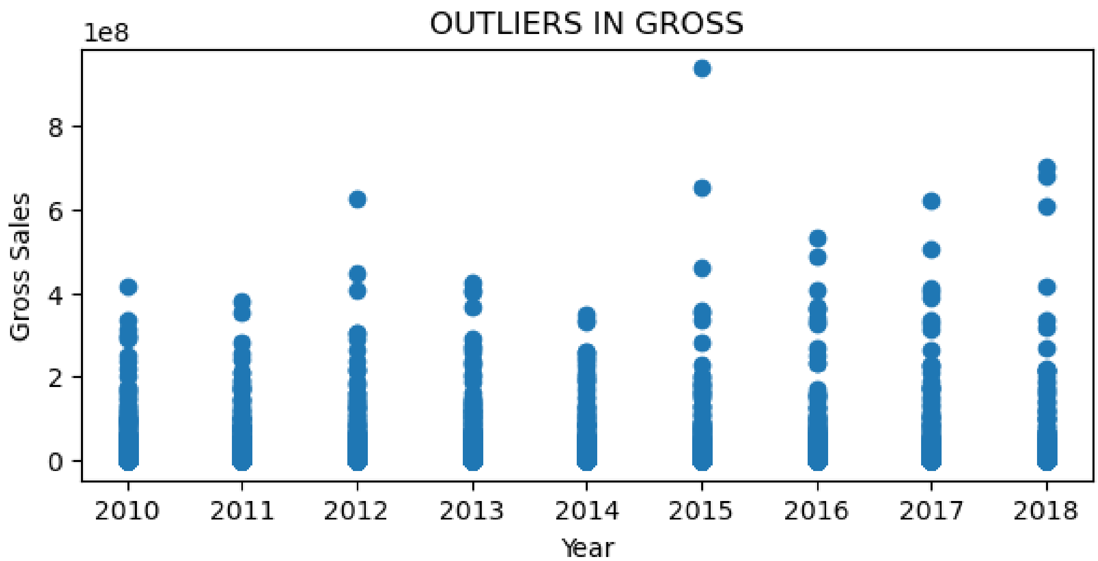
In [13]:
```
#Checking for the number of duplicates in each column
#We see that there no dupilcated entries which means that each movie appea
gross.duplicated().sum()
```

Out[13]:
```
0
```

In [14]:
```
# Checking for the number of null values per column.
# The column foreign_gross has close to has of its values as null values.
gross.isna().sum()
```

Out[14]:
```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

In [15]:
```
# Checking for outliers.
# In the year 2015,there is a movies which grossed way higher than other m

fig, ax = plt.subplots(figsize =(7, 3))

ax.scatter(gross["year"],gross["domestic_gross"])
ax.set_title('OUTLIERS IN GROSS')
ax.set_xlabel('Year')
ax.set_ylabel('Gross Sales')

plt.show()
```



In [16]:
```
# Making a copy of the dataframe to use it avoid making permanent changes
gross_copy = gross.copy()
```

2. Inspecting Budget

In [17]:
```
# Loading the first three rows
budget.head(3)
```

Out[17]:

	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

In [18]:
```
# Loading the last three rows
budget.tail(3)
```

Out[18]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

In [19]:
```
# Checking for the number of rows and columns
# BUdget has 6 columns and 5782 rows.
budget.shape
```

Out[19]:
```
(5782, 6)
```

In [20]:
```
# Checking a summary of data budget.
# We can see that are no missing values. We should have a total of 5782 er
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   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
```

In [21]:
```
#Checking for the number of duplicates in each column
#We see that there no dupilcated entries which means that each movie appea
gross.duplicated().sum()
```

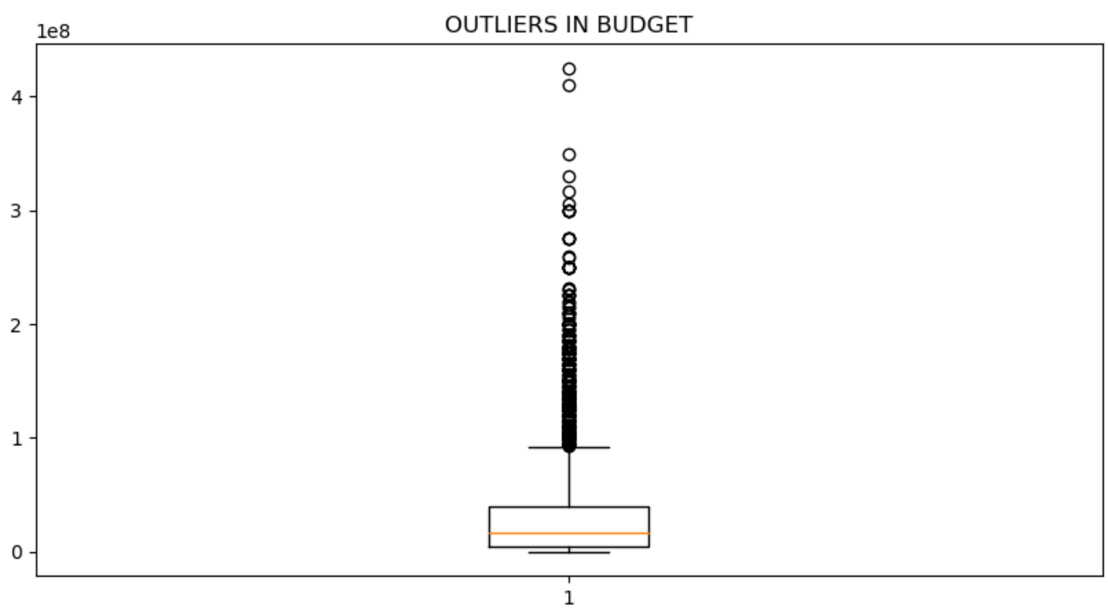
Out[21]:
```
0
```

In [22]:
```
budget["production_budget"] = budget["production_budget"].str.replace("$",

budget['production_budget'].dtype
```

```
C:\Users\Administrator\AppData\Local\Temp\ipykernel_7748\3617633862.py:
1: FutureWarning: The default value of regex will change from True to Fa
lse in a future version. In addition, single character regular expressio
ns will *not* be treated as literal strings when regex=True.
  budget["production_budget"] = budget["production_budget"].str.replace
("$", "").str.replace(",", "").astype(int)
```

Out[22]:
```
dtype('int32')
```

In [23]:
```
# Checking for outliers in budget.
# We see that there are two movies that have an extremely high budget comp

fig, ax = plt.subplots(figsize =(10, 5))

ax.boxplot(budget["production_budget"])
ax.set_title('OUTLIERS IN BUDGET')

plt.show()
```



In [24]:
```
# Making a copy of the dataframe to use it avoid making permanent changes
budget_copy = budget.copy()
```

3. Inspecting Ratings

In [25]:
```
# Loading the first three rows
ratings.head(3)
```

Out[25]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20

In [26]:
```
# Loading the last three rows
ratings.head()
```

Out[26]:

	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 [27]:
```
# Checking a summary of data ratings.
# We can see that are no missing values. We should have a total of 73856
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   movie_id       73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

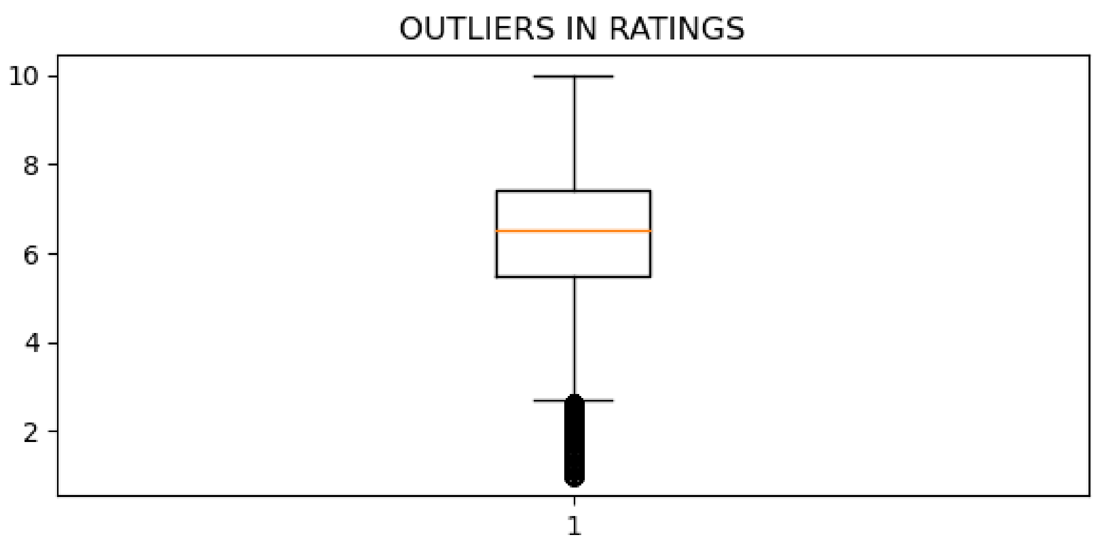
In [28]:
```
# Checking for the number of rows and columns
# Gross has 3 columns and 73856 rows.
ratings.shape
```

Out[28]: (73856, 3)

In [29]:
```
#Checking for the number of duplicates in each column
#We see that there no dupilcated entries which means that each movie appe
ratings.duplicated().sum()
```

Out[29]: 0

In [30]:
```
# Checking for outliers.
# We see in that we have a number of movies have very low rating.

fig, ax = plt.subplots(figsize =(7, 3))

ax.boxplot(ratings["averagerating"])
ax.set_title('OUTLIERS IN RATINGS')

plt.show()
```



In [31]:
```
# Making a copy of the dataframe to use it avoid making permanent changes
ratings_copy = ratings.copy()
```

4. Inspecting Basics.

In [32]:
```
# Loading the first three rows
basics.head(3)
```

Out[32]:

	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

In [33]:
```
# Loading the last three rows
basics.tail(3)
```

Out[33]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
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 [34]:
```
# Checking for the number of rows and columns
# Basics has 6 columns and 146144 rows.

basics.shape
```

Out[34]: (146144, 6)

In [35]:
```
# Checking a summary of data basics.
# The column runtime_minutes has missing values.
#We should have a total of 146144   enntries per column.

basics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

In [36]:
```
#Checking for the number of duplicates in each column
#We see that there no dupilcated entries which means that each movie appea
basics.duplicated().sum()
```

Out[36]: 0

In [37]:

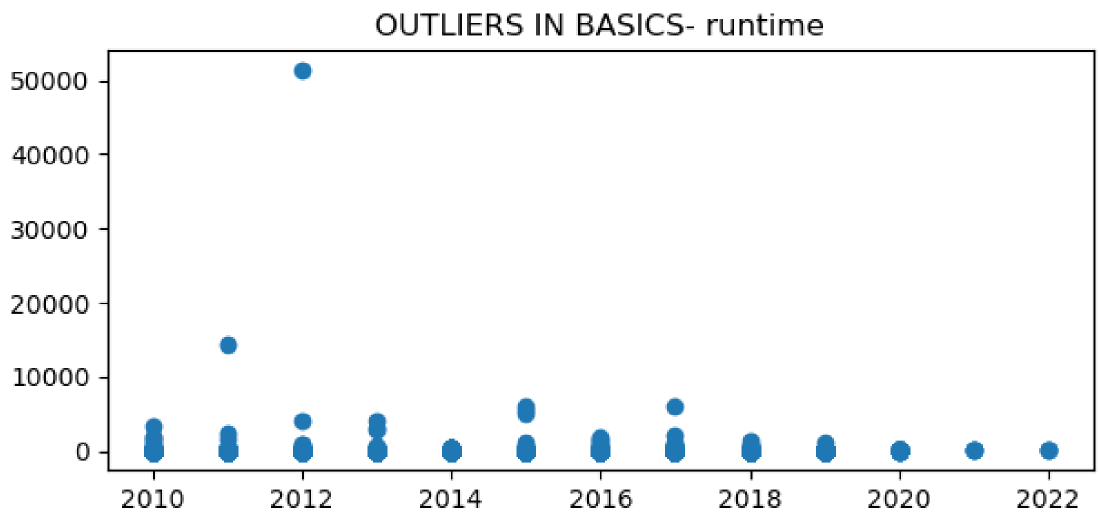
```
# Checking for the number of null values per column.

basics.isna().sum()
```

Out[37]:

```
movie_id               0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres              5408
dtype: int64
```

In [38]:

```
# Checking for outliers.
# We see in that there is a movie in 2012 with an usually long runtime.

fig, ax = plt.subplots(figsize =(7, 3))

ax.scatter(basics["start_year"],basics["runtime_minutes"])
ax.set_title('OUTLIERS IN BASICS- runtime')

plt.show()
```



In [39]:

```
# Making a copy of the dataframe to use it avoid making permanent changes
ratings_copy = ratings.copy()
```

Data Cleaning

Combining the data.

In [40]:
```
# Combining movie basics and movie ratings.
basics_and_ratings = pd.read_sql("""
SELECT *
FROM movie_ratings
JOIN movie_basics
USING (movie_id);
""",im_movies)
```

In [41]:
```
#First three rows.
basics_and_ratings.head(3)
```

Out[41]:

	movie_id	averagerating	numvotes	primary_title	original_title	start_year	runtime_min
0	tt10356526	8.3	31	Laiye Je Yaarian	Laiye Je Yaarian	2019	1
1	tt10384606	8.9	559	Borderless	Borderless	2019	
2	tt1042974	6.4	20	Just Inès	Just Inès	2010	

In [42]:
```
# Last three rows
basics_and_ratings.tail(3)
```

Out[42]:

	movie_id	averagerating	numvotes	primary_title	original_title	start_year	runtime_
73853	tt9851050	4.7	14	Sisters	Sisters	2019	
73854	tt9886934	7.0	5	The Projectionist	The Projectionist	2019	
73855	tt9894098	6.3	128	Sathru	Sathru	2019	

In [43]:
```
#Summary of the combined datasets.
basics_and_ratings.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   averagerating    73856 non-null  float64
 2   numvotes         73856 non-null  int64  
 3   primary_title    73856 non-null  object 
 4   original_title   73856 non-null  object 
 5   start_year       73856 non-null  int64  
 6   runtime_minutes  66236 non-null  float64
 7   genres           73052 non-null  object 
dtypes: float64(2), int64(2), object(4)
memory usage: 4.5+ MB
```

In [44]:
```
# We have eight columns since dataframe basics has 6 and ratings has 3 col
basics_and_ratings.shape
```

Out[44]: (73856, 8)

In [45]:
```
# Renaming the column primary_title to title in dataframe gross.
basics_and_ratings.rename(columns = {'primary_title':'title'}, inplace = T

# Confirming that primary title has been renamed.
basics_and_ratings.head(1)
```

Out[45]:

	movie_id	averagerating	numvotes	title	original_title	start_year	runtime_minutes
0	tt10356526	8.3	31	Laiye Je Yaarian	Laiye Je Yaarian	2019	117.0

In [46]:
```
#Adding data from gross to basics and ratings.
basics_ratings_gross = basics_and_ratings.merge(gross_copy, on='title')
```

In [47]:
```
# Checking the first three elements.
basics_ratings_gross.head(3)
```

Out[47]:

	movie_id	averagerating	numvotes	title	original_title	start_year	runtime_minutes
0	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0
1	tt1171222	5.1	8296	Baggage Claim	Baggage Claim	2013	96.0
2	tt1181840	7.0	5494	Jack and the Cuckoo-Clock Heart	Jack et la mécanique du coeur	2013	94.0

In [48]:
```
# Checking the last three elements.
basics_ratings_gross.tail(3)
```

Out[48]:

	movie_id	averagerating	numvotes	title	original_title	start_year	ru
3024	tt3748512	7.4	4977	Hitchcock/Truffaut	Hitchcock/Truffaut	2015	
3025	tt7008872	7.0	18768	Boy Erased	Boy Erased	2018	
3026	tt7048622	7.7	11168	The Insult	L'insulte	2017	

In [49]:
```
#To check the summary of the table
basics_ratings_gross.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3027 entries, 0 to 3026
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         3027 non-null   object 
 1   averagerating    3027 non-null   float64
 2   numvotes         3027 non-null   int64  
 3   title            3027 non-null   object 
 4   original_title   3027 non-null   object 
 5   start_year       3027 non-null   int64  
 6   runtime_minutes  2980 non-null   float64
 7   genres           3020 non-null   object 
 8   studio           3024 non-null   object 
 9   domestic_gross   3005 non-null   float64
 10  foreign_gross    1832 non-null   object 
 11  year             3027 non-null   int64  
dtypes: float64(3), int64(3), object(6)
memory usage: 307.4+ KB
```

In [50]:
```
# To check the summary of the numeric columns
basics_ratings_gross.describe()
```

Out[50]:

	averagerating	numvotes	start_year	runtime_minutes	domestic_gross	
count	3027.000000	3.027000e+03	3027.000000	2980.000000	3.005000e+03	3027.0(
mean	6.457582	6.170030e+04	2013.783284	107.217114	3.064033e+07	2014.07
std	1.012277	1.255132e+05	2.466955	20.073886	6.671629e+07	2.44
min	1.600000	5.000000e+00	2010.000000	3.000000	1.000000e+02	2010.0(
25%	5.900000	2.117000e+03	2012.000000	94.000000	1.390000e+05	2012.0(
50%	6.600000	1.310900e+04	2014.000000	105.000000	2.000000e+06	2014.0(
75%	7.100000	6.276550e+04	2016.000000	118.000000	3.250000e+07	2016.0(
max	9.200000	1.841066e+06	2019.000000	272.000000	7.001000e+08	2018.0(

In [51]:
```
#Checking duplicated data
# There are no duplicates
basics_ratings_gross.duplicated().sum()
```

Out[51]: 0

In [52]:
```
# Renaming the column primary_title to title
budget_copy.rename(columns = {'movie':'title'}, inplace = True)

#Confirming that renaming was accurate.
budget_copy.head(1)
```

Out[52]:

	id	release_date	title	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	$760,507,625	$2,776,345,279

In [120]:
```
# Adding the budget dataframe to basics_ratings_gross.
combined_movies_data = basics_ratings_gross.merge(budget_copy, on='title')

#The first three elements of combined_movies_data
combined_movies_data.head(3)
```

Out[120]:

	movie_id	averagerating	numvotes	title	original_title	start_year	runtime_minutes
0	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0
1	tt1171222	5.1	8296	Baggage Claim	Baggage Claim	2013	96.0
2	tt1210166	7.6	326657	Moneyball	Moneyball	2011	133.0

In [55]:
```
#The last three elements of combined_movies_data
combined_movies_data.tail(3)
```

Out[55]:

	movie_id	averagerating	numvotes	title	original_title	start_year	runtime_minu
1410	tt2592614	5.6	74979	Resident Evil: The Final Chapter	Resident Evil: The Final Chapter	2016	10
1411	tt2704998	7.0	163279	Game Night	Game Night	2018	10
1412	tt2980210	6.1	36062	A Hologram for the King	A Hologram for the King	2016	9

In [56]:
```
#To check the summary of the table
combined_movies_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1413 entries, 0 to 1412
Data columns (total 17 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   movie_id          1413 non-null   object 
 1   averagerating     1413 non-null   float64
 2   numvotes          1413 non-null   int64  
 3   title             1413 non-null   object 
 4   original_title    1413 non-null   object 
 5   start_year        1413 non-null   int64  
 6   runtime_minutes   1383 non-null   float64
 7   genres            1406 non-null   object 
 8   studio            1413 non-null   object 
 9   domestic_gross_x  1412 non-null   float64
 10  foreign_gross     1215 non-null   object 
 11  year              1413 non-null   int64  
 12  id                1413 non-null   int64  
 13  release_date      1413 non-null   object 
 14  production_budget 1413 non-null   int32  
 15  domestic_gross_y  1413 non-null   object 
 16  worldwide_gross   1413 non-null   object 
dtypes: float64(3), int32(1), int64(4), object(9)
memory usage: 193.2+ KB
```

In [57]:
```
#To check the number of rows and columns
combined_movies_data.shape
```

Out[57]: (1413, 17)

In [58]:
```
# To check the summary of the numeric columns in the combined data.
combined_movies_data.describe()
```

Out[58]:

	averagerating	numvotes	start_year	runtime_minutes	domestic_gross_x	
count	1413.000000	1.413000e+03	1413.000000	1383.000000	1.412000e+03	1413
mean	6.434961	1.133554e+05	2013.644020	107.242950	6.034071e+07	2013
std	1.029822	1.640935e+05	2.531381	19.737869	8.443935e+07	2
min	1.600000	5.000000e+00	2010.000000	3.000000	8.000000e+02	2010
25%	5.900000	1.292600e+04	2011.000000	94.000000	7.175000e+06	2011
50%	6.500000	5.895500e+04	2014.000000	105.000000	3.365000e+07	2014
75%	7.100000	1.377340e+05	2016.000000	118.000000	7.422500e+07	2016
max	9.200000	1.841066e+06	2019.000000	192.000000	7.001000e+08	2018

Duplicated data in the combined data.

In [59]:

```
#Checking duplicated data
# no duplicates,combining the datasets automatically eliminated the duplic
combined_movies_data.duplicated().sum()
```

Out[59]: 0

Missing data.

In [60]:
```
# Defining a function to return percentage of missing values
def missing_values(data):
    #Identify the total missing values per column and sort
    miss = data.isna().sum().sort_values(ascending = False)

    #Calculating percentage of missing values and sorting
    percent_miss = (data.isna().sum()/len(data)).sort_values(ascending = F

    #Store in dataframe
    missing = pd.DataFrame({'Missing values':miss, 'Percentage %':percent_

    return missing

missing_vals = missing_values(combined_movies_data)
missing_vals
```

Out[60]:

	Missing values	Percentage %
foreign_gross	198	14.012739
runtime_minutes	30	2.123142
genres	7	0.495400
domestic_gross_x	1	0.070771
movie_id	0	0.000000
domestic_gross_y	0	0.000000
production_budget	0	0.000000
release_date	0	0.000000
id	0	0.000000
year	0	0.000000
studio	0	0.000000
averagerating	0	0.000000
start_year	0	0.000000
original_title	0	0.000000
title	0	0.000000
numvotes	0	0.000000
worldwide_gross	0	0.000000

In [61]:
```
#Dropping the column foreign_gross 14% missing values with no criteria of
#We will use the worldwide gross for our analysis.

combined_movies_data = combined_movies_data.drop('foreign_gross', axis =
```

In [62]:
```
#confirming the column drop
combined_movies_data.columns
```

Out[62]:
```
Index(['movie_id', 'averagerating', 'numvotes', 'title', 'original_titl
e',
       'start_year', 'runtime_minutes', 'genres', 'studio', 'domestic_gr
oss_x',
       'year', 'id', 'release_date', 'production_budget', 'domestic_gros
s_y',
       'worldwide_gross'],
      dtype='object')
```

In [63]:
```
# Dropping rows in domestic gross and genre (a total of 8 rows).
combined_movies_data = combined_movies_data.dropna(subset=['genres','domes
```

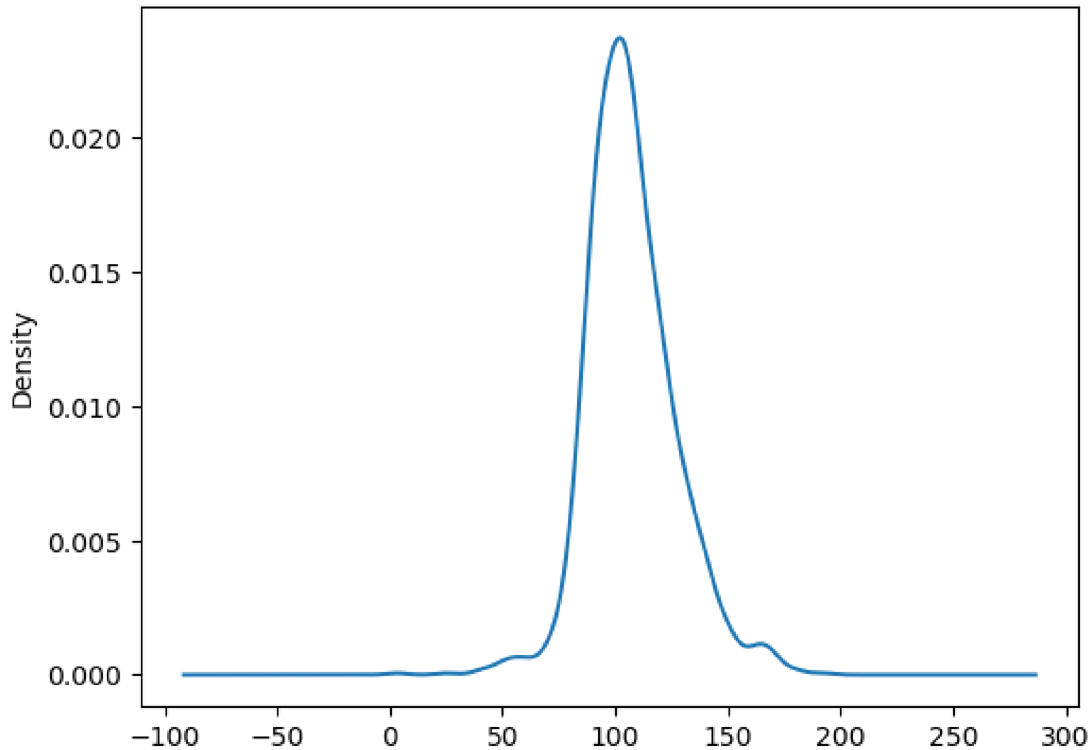
In [64]:
```
# Confirming missing values have been dropped
missing_vals = missing_values(combined_movies_data)
missing_vals
```

Out[64]:

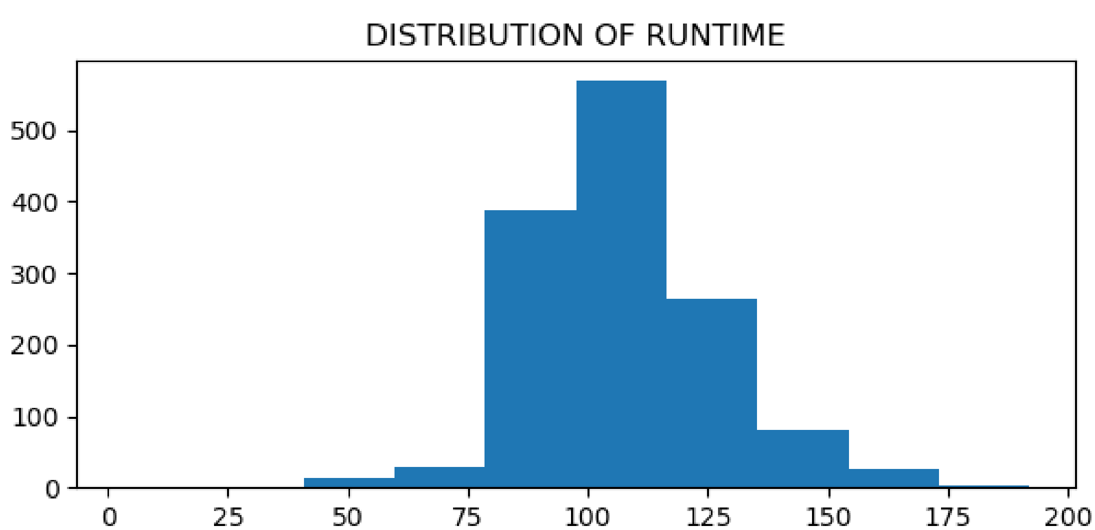
	Missing values	Percentage %
runtime_minutes	27	1.921708
movie_id	0	0.000000
averagerating	0	0.000000
numvotes	0	0.000000
title	0	0.000000
original_title	0	0.000000
start_year	0	0.000000
genres	0	0.000000
studio	0	0.000000
domestic_gross_x	0	0.000000
year	0	0.000000
id	0	0.000000
release_date	0	0.000000
production_budget	0	0.000000
domestic_gross_y	0	0.000000
worldwide_gross	0	0.000000

In [65]:
```
# Distribution of runtime
combined_movies_data['runtime_minutes'].plot(kind='kde')

#Data peaks in the middle.We replace the missing values using the mean.
```

Out[65]: <AxesSubplot:ylabel='Density'>



In [66]:
```
#PLotting a histogram to observe the frequency and disrubution of run time
fig, ax = plt.subplots(figsize =(7, 3))

ax.hist(combined_movies_data['runtime_minutes'])
ax.set_title('DISTRIBUTION OF RUNTIME')

plt.show()
```



In [67]:
```
#Getting the mean.

runtime_mins_mean = combined_movies_data['runtime_minutes'].mean()
runtime_mins_mean
```

Out[67]: 107.30188679245283

In [68]:
```
#Replacing the missing value in with the mean.
combined_movies_data['runtime_minutes'].fillna(value=runtime_mins_mean, ir

#Confirming that all the missing data has been dropped and replaced.
missing_vals = missing_values(combined_movies_data)
missing_vals
```

Out[68]:

	Missing values	Percentage %
movie_id	0	0.0
averagerating	0	0.0
numvotes	0	0.0
title	0	0.0
original_title	0	0.0
start_year	0	0.0
runtime_minutes	0	0.0
genres	0	0.0
studio	0	0.0
domestic_gross_x	0	0.0
year	0	0.0
id	0	0.0
release_date	0	0.0
production_budget	0	0.0
domestic_gross_y	0	0.0
worldwide_gross	0	0.0

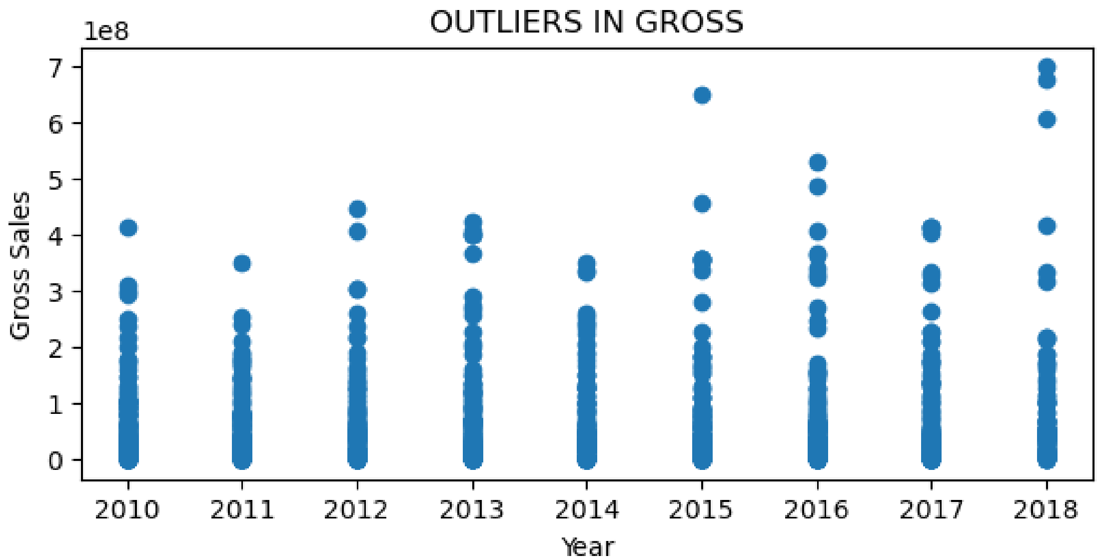
Inspecting Outliers

There are outliers in columns domestic gross, production budget, average ratings and runtime. The next few cells capture an inspection of those outliers before proceeding to analyse the data.

1. Outliers in gross.

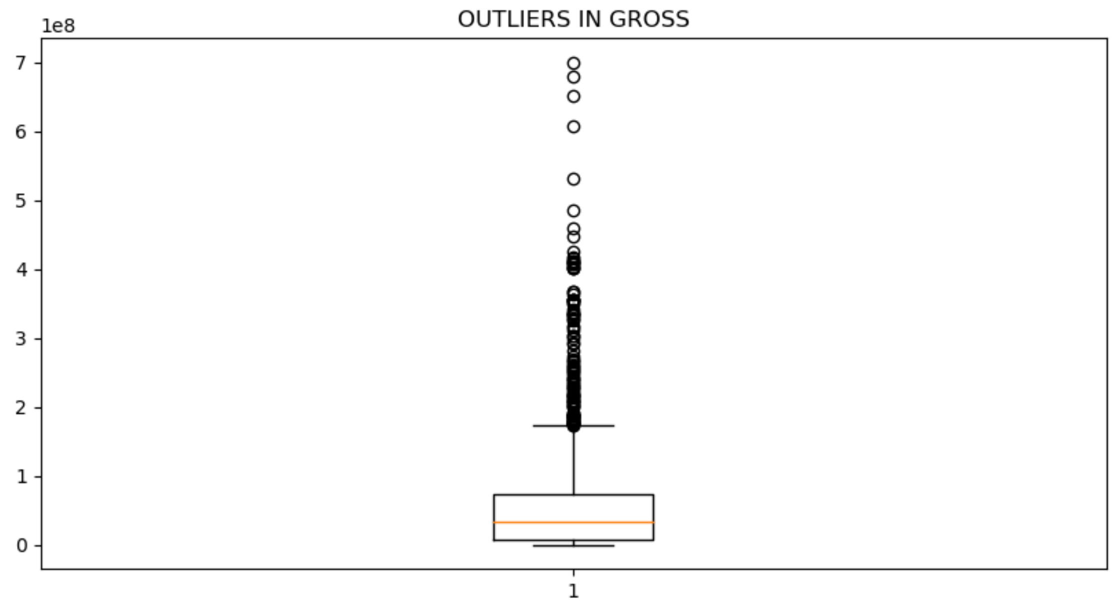
In [69]:

```
fig, ax = plt.subplots(figsize =(7, 3))

ax.scatter(combined_movies_data["year"],combined_movies_data["domestic_gro
ax.set_title('OUTLIERS IN GROSS')
ax.set_xlabel('Year')
ax.set_ylabel('Gross Sales')

plt.show()
```



In [70]:

```
fig, ax = plt.subplots(figsize =(10, 5))

ax.boxplot(combined_movies_data["domestic_gross_x"])
ax.set_title('OUTLIERS IN GROSS')

plt.show()

"""
The outliers should be kept since the parity in gross sales could be due t
difference in the number of times a movies has been watched.For this reasc
having some movies gross way higher than others, does not present an anoma

"""
```



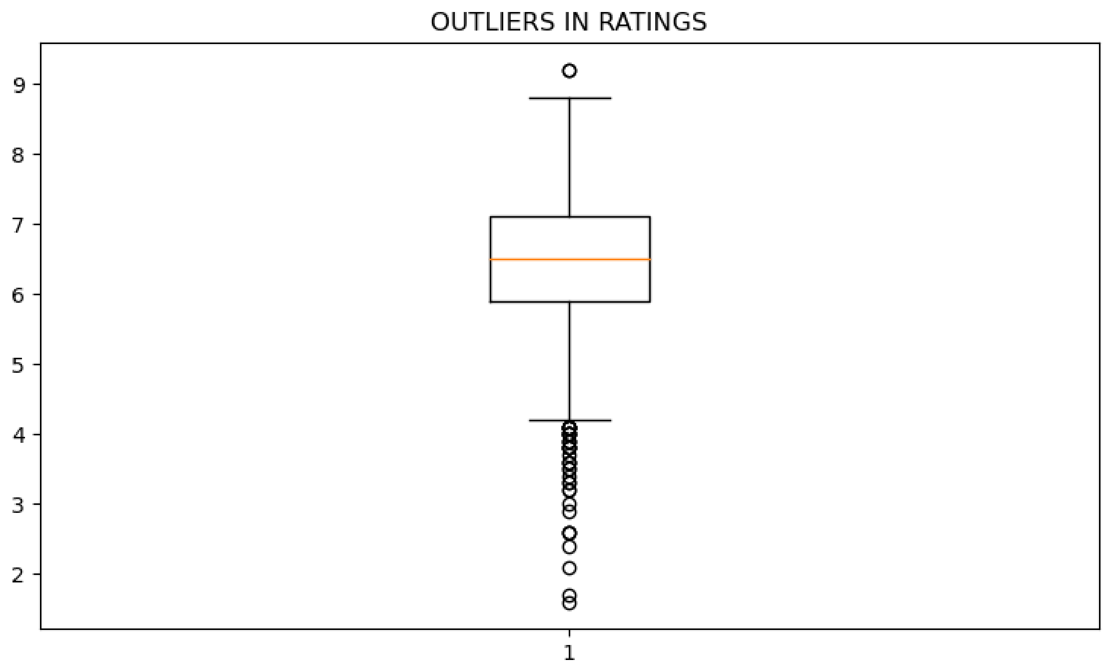
Out[70]:

```
'\nThe outliers should be kept since the parity in gross sales could be
due to a\ndifference in the number of times a movies has been watched.Fo
r this reason, \nhaving some movies gross way higher than others, does n
ot present an anomally for which the points should be removed.\n\n'
```

2. Outliers in Ratings.

In [71]:

```
# Checking for outliers.
# We see in that we have a number of movies have very low rating.

fig, ax = plt.subplots(figsize =(9, 5))

ax.boxplot(combined_movies_data["averagerating"])
ax.set_title('OUTLIERS IN RATINGS')

plt.show()

"""
Many movies have low ratings (below 4) since many points are plotted belov
viewers opinion, I decide to retain the outliers within ratings.

"""
```



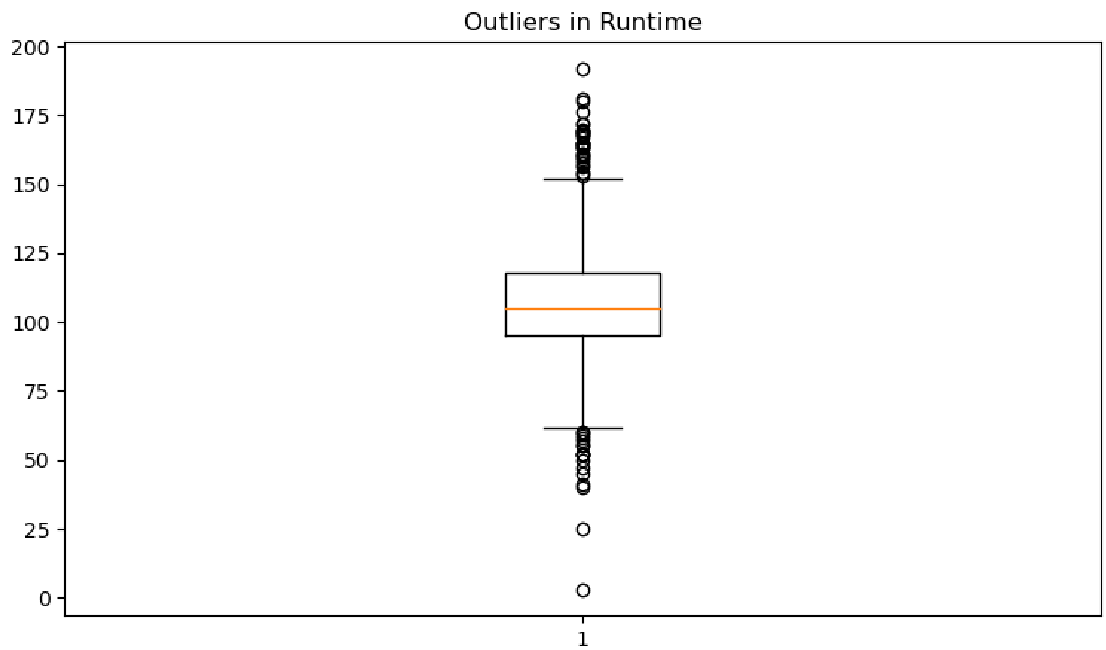
Out[71]:

```
'\nMany movies have low ratings (below 4) since many points are plotted
below the first quartile. There is a movie with an exceptionally high ra
ting. Since  ratings are subjective and highly influenced by the \nviewe
rs opinion, I decide to retain the outliers within ratings.\n\n'
```

3. Outliers in Runtime.

In [72]:

```
fig, ax = plt.subplots(figsize =(9, 5))

ax.boxplot(combined_movies_data["runtime_minutes"])
ax.set_title('Outliers in Runtime')

plt.show()

"""
Outliers to be retained since runtime is greatly influenced by the length

"""
```

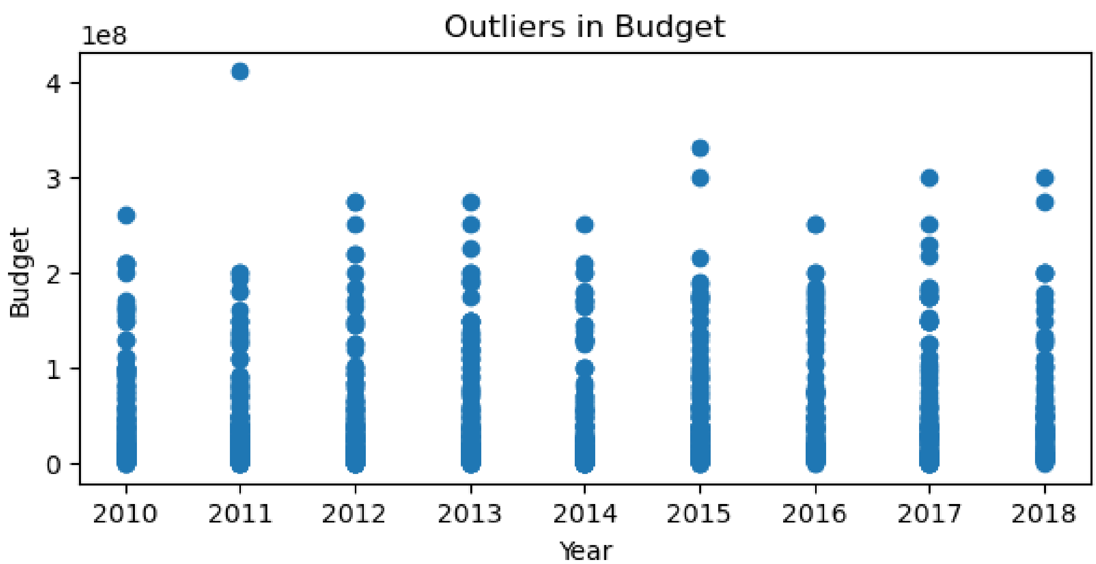


Out[72]:

```
'\nOutliers to be retained since runtime is greatly influenced by the le
ngth of the movie script. \n\n'
```

4. Outliers in Budget.

In [73]:
```
fig, ax = plt.subplots(figsize =(7, 3))

ax.scatter(combined_movies_data["year"],combined_movies_data["production_t
ax.set_title('Outliers in Budget')
ax.set_xlabel('Year')
ax.set_ylabel('Budget')

plt.show()

"""
In 2011 and 2015, there are movies with a very high buddhet compared to th
I retain the outliers in the budget. Budgets vary depending on the length 
"""
```



Out[73]:
```
'\nIn 2011 and 2015, there are movies with a very high buddhet compared
to the rest of the values. The same effect is captured in the plot for o
utliers in gross sales.\nI retain the outliers in the budget. Budgets va
ry depending on the length of the script and type of movie.Also, blockbu
sters tend to have higher marketing budgets than independet movies which
could also be a leading reason in varying budgets. \n'
```

Feature Engineering

Modifying genre

In [74]:

```
# Converting year and start year to date instead of integer.
combined_movies_data.start_year = pd.to_datetime(combined_movies_data.star
combined_movies_data.year = pd.to_datetime(combined_movies_data.year, forr

#Confirming the change.
combined_movies_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1405 entries, 0 to 1412
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   movie_id          1405 non-null   object
 1   averagerating     1405 non-null   float64
 2   numvotes          1405 non-null   int64
 3   title             1405 non-null   object
 4   original_title    1405 non-null   object
 5   start_year        1405 non-null   datetime64[ns]
 6   runtime_minutes   1405 non-null   float64
 7   genres            1405 non-null   object
 8   studio            1405 non-null   object
 9   domestic_gross_x  1405 non-null   float64
 10  year              1405 non-null   datetime64[ns]
 11  id                1405 non-null   int64
 12  release_date      1405 non-null   object
 13  production_budget 1405 non-null   int32
 14  domestic_gross_y  1405 non-null   object
 15  worldwide_gross   1405 non-null   object
dtypes: datetime64[ns](2), float64(3), int32(1), int64(2), object(8)
memory usage: 181.1+ KB
```

In [75]:

```
combined_movies_data_copy = combined_movies_data.copy()
```

In [76]:

```
#seperating the genres and creating columns on each with a count 1 if list
s = combined_movies_data_copy['genres'].str.split(',').explode()
encoder = OneHotEncoder()
encoded = encoder.fit_transform(s.values[:, None])
genres_df = pd.DataFrame(encoded.toarray(), columns=np.ravel(encoder.categ
                .groupby(s.index) \
                .sum()
```

In [77]:
```
genres_df.head()
```

Out[77]:

	Action	Adventure	Animation	Biography	Comedy	Crime	Documentary	Drama	Family
0	1	1	0	0	0	0	0	0	(
1	0	0	0	0	1	0	0	0	(
2	0	0	0	1	0	0	0	1	(
3	0	0	0	0	0	0	0	1	(
4	1	0	0	0	1	1	0	0	(

5 rows × 22 columns

In [78]:
```
# Combining the columns created with the combined movie data dataframe.
combined_movies_data_copy = pd.concat([combined_movies_data, genres_df], a
```

In [79]:
```
# Converting worldwide gross to an integer.

combined_movies_data_copy['worldwide_gross'] = combined_movies_data_copy[
```

```
C:\Users\Administrator\AppData\Local\Temp\ipykernel_7748\415835868.py:3:
FutureWarning: The default value of regex will change from True to False
in a future version. In addition, single character regular expressions w
ill *not* be treated as literal strings when regex=True.
  combined_movies_data_copy['worldwide_gross'] = combined_movies_data_co
py['worldwide_gross'].str.replace('$', '').str.replace(',', '').astype(i
nt)
```

In [80]:
```
#There are 22 more added columns which indicate there are 22 individual ge
combined_movies_data_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1405 entries, 0 to 1412
Data columns (total 38 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           1405 non-null   object
 1   averagerating      1405 non-null   float64
 2   numvotes           1405 non-null   int64
 3   title              1405 non-null   object
 4   original_title     1405 non-null   object
 5   start_year         1405 non-null   datetime64[ns]
 6   runtime_minutes    1405 non-null   float64
 7   genres             1405 non-null   object
 8   studio             1405 non-null   object
 9   domestic_gross_x   1405 non-null   float64
 10  year               1405 non-null   datetime64[ns]
 11  id                 1405 non-null   int64
 12  release_date       1405 non-null   object
 13  production_budget  1405 non-null   int32
 14  domestic_gross_y   1405 non-null   object
 15  worldwide_gross    1405 non-null   int32
 16  Action             1405 non-null   int32
 17  Adventure          1405 non-null   int32
 18  Animation          1405 non-null   int32
 19  Biography          1405 non-null   int32
 20  Comedy             1405 non-null   int32
 21  Crime              1405 non-null   int32
 22  Documentary        1405 non-null   int32
 23  Drama              1405 non-null   int32
 24  Family             1405 non-null   int32
 25  Fantasy            1405 non-null   int32
 26  History            1405 non-null   int32
 27  Horror             1405 non-null   int32
 28  Music              1405 non-null   int32
 29  Musical            1405 non-null   int32
 30  Mystery            1405 non-null   int32
 31  News               1405 non-null   int32
 32  Romance            1405 non-null   int32
 33  Sci-Fi             1405 non-null   int32
 34  Sport              1405 non-null   int32
 35  Thriller           1405 non-null   int32
 36  War                1405 non-null   int32
 37  Western            1405 non-null   int32
dtypes: datetime64[ns](2), float64(3), int32(24), int64(2), object(7)
memory usage: 296.4+ KB
```

In [81]:
```
g profir on the assumption that the budget is equivalent to the total cost
vies_data_copy.loc[:,'Profit'] = combined_movies_data_copy['worldwide_gros
```

In [82]:
```
combined_movies_data_copy.head(1)
```

Out[82]:

	movie_id	averagerating	numvotes	title	original_title	start_year	runtime_minutes
0	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014-01-01	99.0

1 rows × 39 columns

In [83]:
```
type(combined_movies_data_copy)
```

Out[83]:
```
pandas.core.frame.DataFrame
```

Analysis

Questions to answer are:

1. Which is the best rated genre; most profitable genre, genre with highest ratings?
2. What is the correlation between runtime and ratings?
3. What is the correlation between runtime and budget?
4. Which are the studios with the most productions ?

In [84]:
```
# Saving the cleaned data into a csv file
combined_movies_data_copy.to_csv('combined_movies_data_copy.csv',index=Fal
```

In [85]:
```
# Veryfing storage of data by reading the file
combined_movies_data_csv = pd.read_csv('combined_movies_data.csv')
```

Genres

In this part I check for the ranking of genres in relation to profit, budget and ratings.

In [86]:

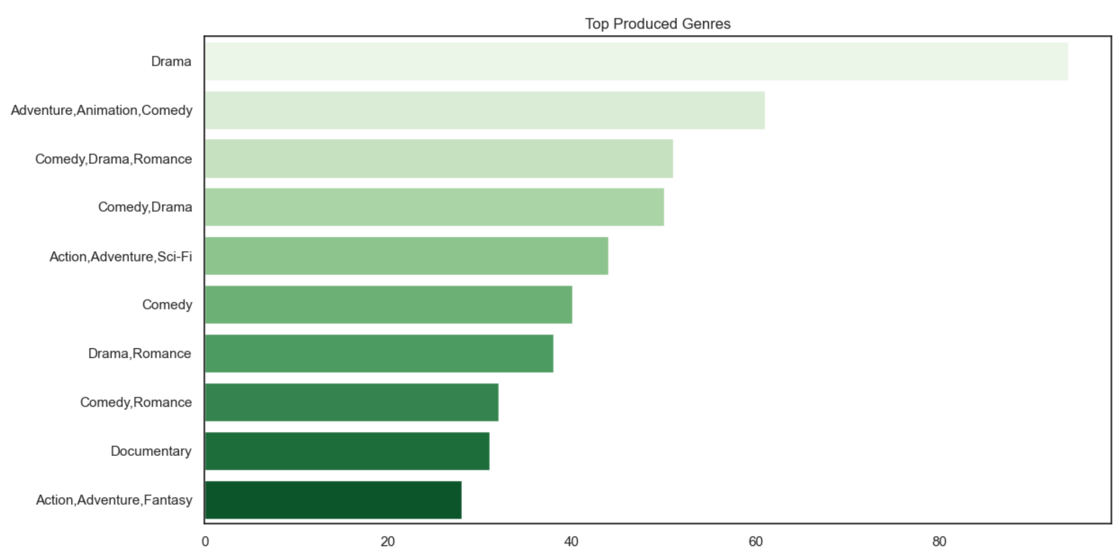
```
#Checking for the most produced genre.

Genres_sorted_frequency = genres_df.sum().sort_values(ascending=False)
Genres_sorted_frequency
```

Out[86]:

```
Drama          729
Comedy         450
Action         384
Adventure      303
Thriller       240
Crime          205
Romance        179
Horror         148
Biography      125
Mystery        111
Sci-Fi         111
Fantasy        102
Animation       90
Family          76
Documentary     49
History         45
Music           40
Sport           30
War             13
Western          8
Musical          6
News             2
dtype: int64
```

In [178]:

```
#Plotting the top produced genres from the dataframe based on the title oj
Genres_plot = combined_movies_data_copy[combined_movies_data_copy.genres
plt.figure(figsize=(13,7))
plt.title('Top Produced Genres')
sns.countplot(y = Genres_plot, order=Genres_plot.value_counts().index[:10]
plt.show()
```



The plot shows the most produced genres. A quick scan shows us that drama is the most featured genres.

Genres and Profit

In [223]:
```
# sort the combined_movies_data_copy by Profit in descending order
sorted_by_profit= combined_movies_data_copy.sort_values(by='Profit', ascen

# extract the Genres column based on the order of the sorted Profit column
top_genres_by_profit = sorted_by_profit['genres']
```

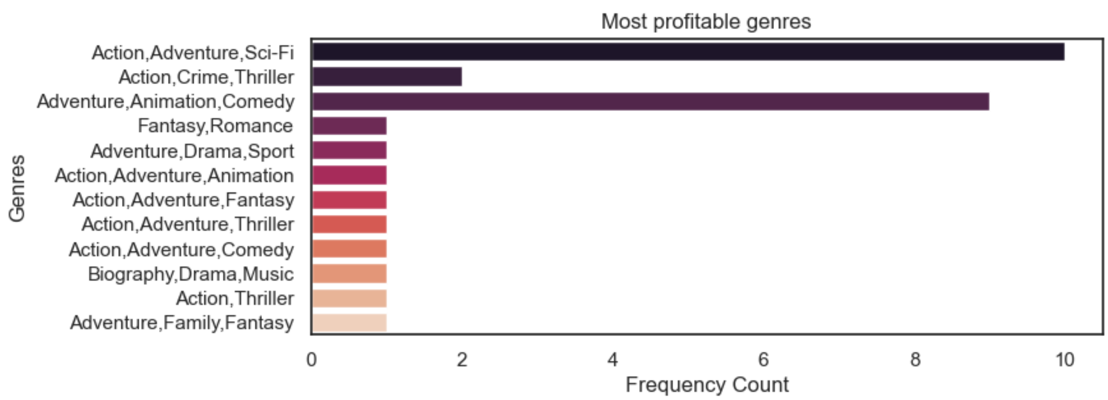
In [234]:
```
#Most profitable genres.
top_genres_by_profit_table = sorted_by_profit.loc[:,['genres','Profit']]
top_genres_by_profit_table.head(20)
```

Out[234]:

	genres	Profit
1395	Action,Adventure,Sci-Fi	1748134200
270	Action,Adventure,Sci-Fi	1433854864
444	Action,Crime,Thriller	1328722794
331	Action,Adventure,Sci-Fi	1148258224
301	Action,Adventure,Sci-Fi	1135772799
516	Adventure,Animation,Comedy	1122469910
515	Fantasy,Romance	1122469910
514	Adventure,Drama,Sport	1122469910
947	Adventure,Animation,Comedy	1086336173
1316	Action,Adventure,Sci-Fi	1072413963
1045	Action,Adventure,Animation	1042520711
656	Action,Adventure,Sci-Fi	1015392272
1096	Action,Adventure,Fantasy	986894640
723	Action,Crime,Thriller	984846267
773	Adventure,Animation,Comedy	959727750
1175	Action,Adventure,Sci-Fi	928790543
1170	Action,Adventure,Thriller	910526981
1250	Adventure,Animation,Comedy	899216835
903	Action,Adventure,Sci-Fi	894039076
1271	Action,Adventure,Sci-Fi	890069413

In [180]:

```
# create a horizontal bar plot of the genre frequencies with higher resolu
sns.set(rc={'figure.figsize':(8,3)}, style='white')
sns.countplot(y=top_genres_by_profit.iloc[:30], palette='rocket')

# set the x-axis label
plt.xlabel('Frequency Count')

# set the y-axis label
plt.ylabel('Genres')

# set the title of the plot
plt.title('Most profitable genres')

# increase the resolution of the plot
plt.savefig('genre_frequencies.png', dpi=300)

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



Action,adventure, Sci-Fi is the genre combination that is most profitable, followed by comedy and animation.

Genres and Budget

In [214]:

```
# sort the combined_movies_data_copy by budget in descending order
sorted_by_budget= combined_movies_data_copy.sort_values(by='production_bud
# extract the Genres column based on the order of the sorted Profit column
top_genres_by_budget = sorted_by_budget['genres']
```

Most costly movie to produce.

In [221]:

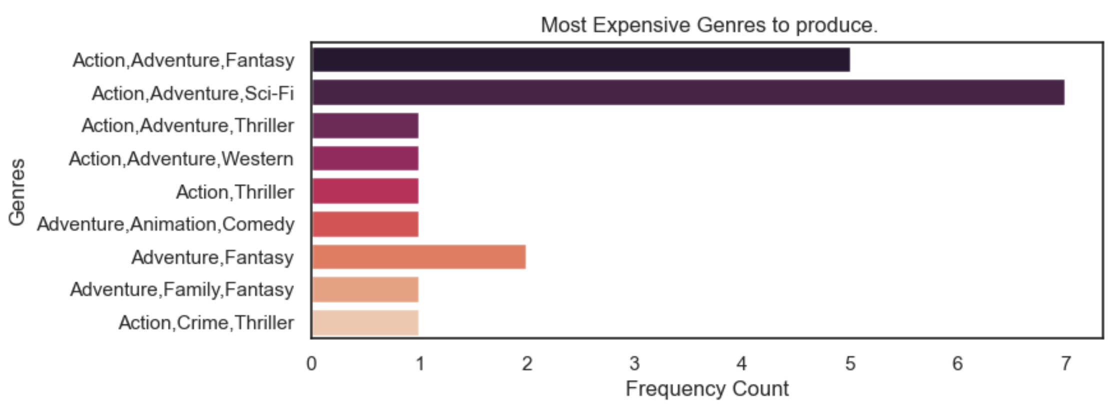
```
#Getting the most costly genre to produce
top_genres_by_budget_table = sorted_by_budget.loc[:,['genres','production_
top_genres_by_budget_table.head()
```

Out[221]:

	genres	production_budget
85	Action,Adventure,Fantasy	410600000
1316	Action,Adventure,Sci-Fi	330600000
877	Action,Adventure,Fantasy	300000000
1079	Action,Adventure,Thriller	300000000
1395	Action,Adventure,Sci-Fi	300000000

In [189]:

```
# create a horizontal bar plot of the genre frequencies with higher resolu
sns.set(rc={'figure.figsize':(8,3)}, style='white')
sns.countplot(y=top_genres_by_budget.head(20), palette='rocket')

# set the x-axis label
plt.xlabel('Frequency Count')

# set the y-axis label
plt.ylabel('Genres')

# set the title of the plot
plt.title(' Most Expensive Genres to produce.')

# increase the resolution of the plot
plt.savefig('genre_frequencies.png', dpi=300)

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



Action adventure movies are the most expensive to produce.

Cheaest Movie to produce

In [222]:

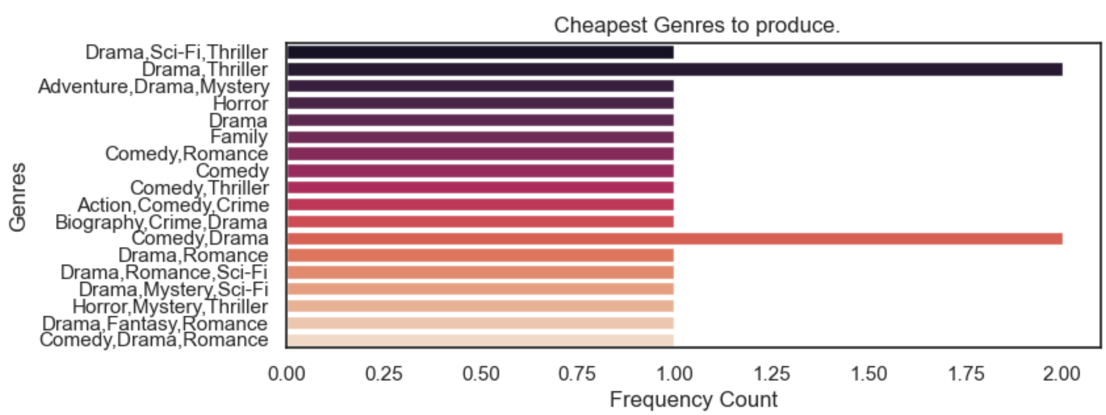
```
#Generate the tail of the gener
top_genres_by_budget_table.tail()
```

Out[222]:

	genres	production_budget
715	Drama,Mystery,Sci-Fi	135000
258	Comedy,Drama	120000
1077	Horror,Mystery,Thriller	100000
782	Drama,Fantasy,Romance	100000
95	Comedy,Drama,Romance	50000

In [197]:

```
# create a horizontal bar plot of the genre frequencies with higher resolu
sns.set(rc={'figure.figsize':(8,3)}, style='white')
sns.countplot(y=top_genres_by_budget.tail(20), palette='rocket')

# set the x-axis label
plt.xlabel('Frequency Count')

# set the y-axis label
plt.ylabel('Genres')

# set the title of the plot
plt.title(' Cheapest Genres to produce.')

# increase the resolution of the plot
plt.savefig('genre_frequencies.png', dpi=300)

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



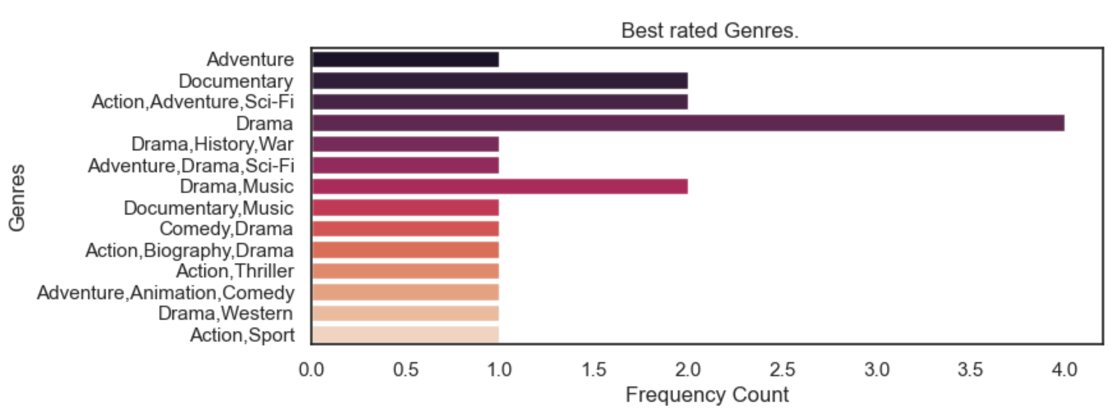
Drama, comedy and thriller movies are the cheapest to produce.

Genres and ratings

In [200]:
```
# sort the combined_movies_data_copy by Ratings in descending order
sorted_by_ratings= combined_movies_data_copy.sort_values(by='averagerating

# extract the Genres column based on the order of the sorted Profit column
top_genres_by_ratings = sorted_by_ratings['genres']

top_genres_by_ratings.head(20).value_counts()
```

Out[200]:
```
Drama                          4
Documentary                    2
Action,Adventure,Sci-Fi        2
Drama,Music                    2
Adventure                      1
Drama,History,War              1
Adventure,Drama,Sci-Fi         1
Documentary,Music              1
Comedy,Drama                   1
Action,Biography,Drama         1
Action,Thriller                1
Adventure,Animation,Comedy     1
Drama,Western                  1
Action,Sport                   1
Name: genres, dtype: int64
```

In [198]:
```
# create a horizontal bar plot of the genre frequencies with higher resolu
sns.set(rc={'figure.figsize':(8,3)}, style='white')
sns.countplot(y=top_genres_by_ratings.head(20), palette='rocket')

# set the x-axis label
plt.xlabel('Frequency Count')

# set the y-axis label
plt.ylabel('Genres')

# set the title of the plot
plt.title(' Best rated Genres.')

# increase the resolution of the plot
plt.savefig('genre_frequencies.png', dpi=300)

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



> Drama is the best rated movie and also cheapest to produce as seen earlier. Action adventure Sci-fi is among best rated movies and also most profitable as seen earlier.

Genre and Runtime

In [232]:

```
# sort the combined_movies_data_copy by budget in descending order
sorted_by_runtime= combined_movies_data_copy.sort_values(by='runtime_minut

# extract the Genres column based on the order of the sorted Profit columr
top_genres_by_runtime = sorted_by_runtime.loc[:, ['genres', 'runtime_minut
top_genres_by_runtime.head(25)
```

Out[232]:

	genres	runtime_minutes
842	Drama,History,War	192.0
873	Documentary	181.0
915	Biography,Crime,Drama	180.0
1195	Drama,Romance	176.0
961	Action,Thriller	172.0
657	Action,Drama,Mystery	172.0
1048	Action,Drama,Sport	170.0
886	Comedy,Drama	169.0
116	Adventure,Family,Fantasy	169.0
652	Adventure,Drama,Sci-Fi	169.0
424	Action,Drama	168.0
1324	Crime,Drama,Mystery	168.0
423	Action,Drama	168.0
1165	Action,Drama	167.0
1232	Drama	165.0
899	Drama,Western	165.0
903	Action,Adventure,Sci-Fi	165.0
31	Action,Thriller	165.0
1052	Drama,Mystery,Sci-Fi	164.0
312	Action,Thriller	164.0
1009	Adventure,Drama,Romance	163.0
337	Action,Comedy,Drama	163.0
484	Adventure,Fantasy	161.0
1013	Action,Biography,Drama	161.0
409	Comedy,Drama,Musical	160.0

A quick scan at the top 15 movies with the highest run time shows that action drama has multiple instances of high runtimes. Action,Adventure,Sci-Fi which is the most profitable appears only once among the top 15 longest movies.

Studios

In [243]:

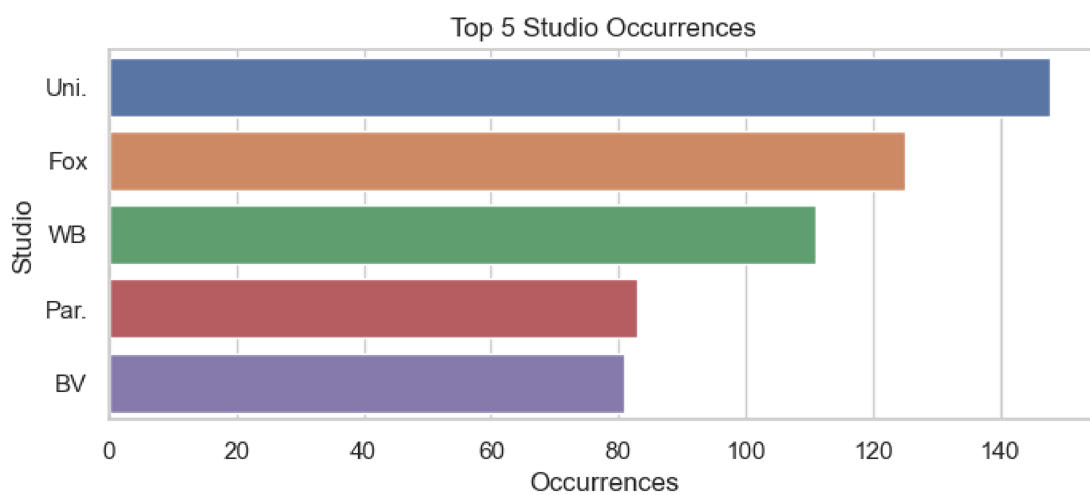
```
#counting the occurence of each studio mention in the dataframe
combined_movies_data_copy.studio.value_counts()

#creating a dictonary to hold the count values
studio_occurrences = combined_movies_data_copy['studio'].value_counts().to
```

In [244]:

```
# convert the dictionary into a pandas dataframe
studio_occurrences = pd.DataFrame.from_dict(studio_occurrences, orient='in

# sort the dataframe in descending order by 'Occurrences' column and slice
top_studios = studio_occurrences.sort_values(by='Occurrences', ascending=F

# create a horizontal bar plot using seaborn
sns.set(style='whitegrid')
ax = sns.barplot(x='Occurrences', y=top_studios.index, data=top_studios)
ax.set(xlabel='Occurrences', ylabel='Studio', title='Top 5 Studio Occurren
```

Out[244]:

```
[Text(0.5, 0, 'Occurrences'),
 Text(0, 0.5, 'Studio'),
 Text(0.5, 1.0, 'Top 5 Studio Occurrences')]
```



Universal studios and Fox studios have produced the most movies.

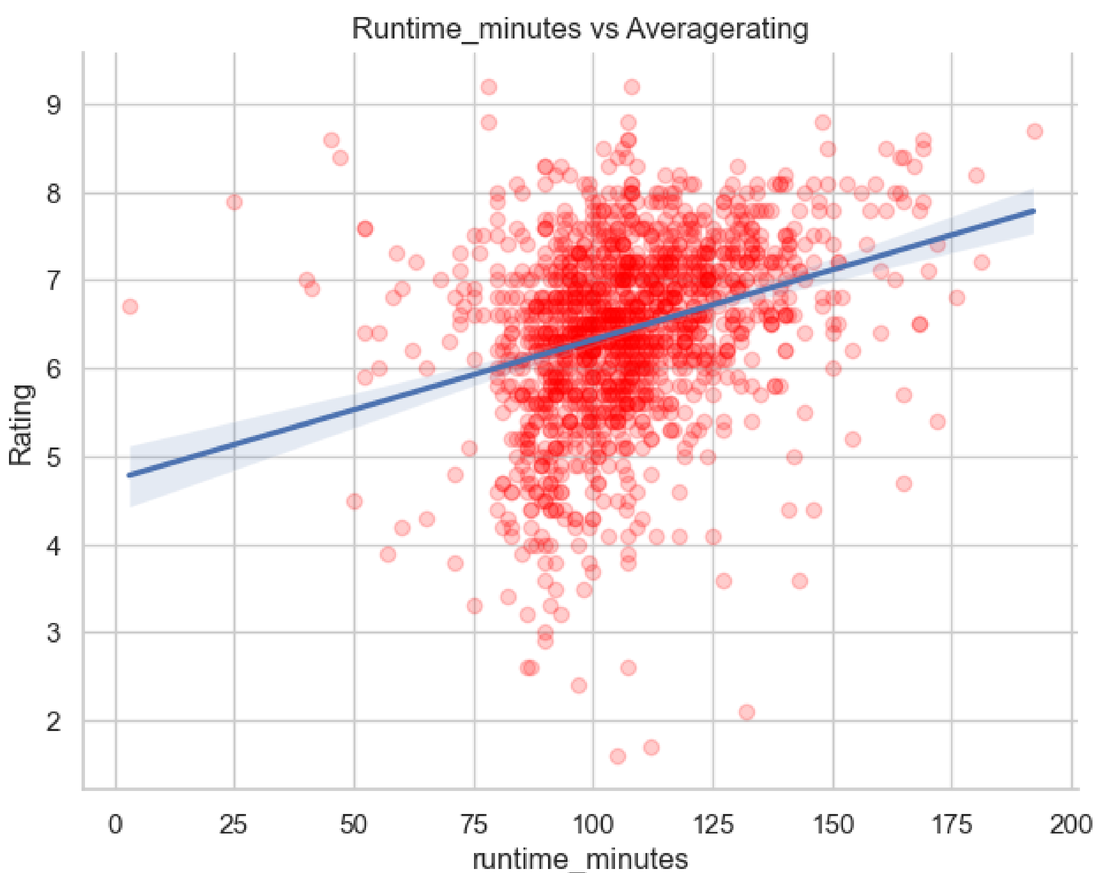
Checking Correlations

Correlation between runtime and ratings.

In [98]:
```
# correlation between Rating and runtime.
cor1 =combined_movies_data_copy[["runtime_minutes","averagerating"]].corr(
print (cor1)
```

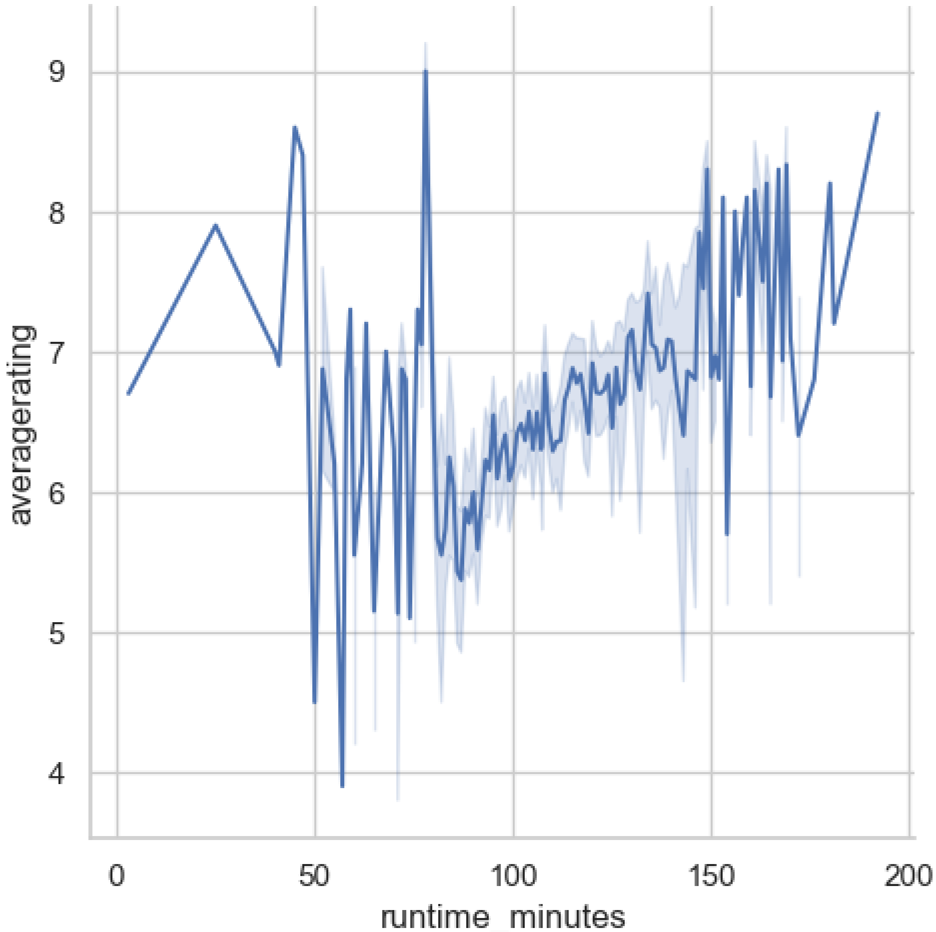
```
                 runtime_minutes  averagerating
runtime_minutes         1.000000       0.301153
averagerating           0.301153       1.000000
```

In [92]:
```
# Plot scatterplot of Runtime_minutes vs Averagerating
sns.lmplot(x="runtime_minutes",
           y="averagerating",
           data= combined_movies_data_copy,
           height = 5,
           aspect=1.3,
           scatter_kws={'alpha':1/5, 'color':'red'},
           palette='Reds')
plt.title('Runtime_minutes vs Averagerating')
plt.xlabel('runtime_minutes')
plt.ylabel('Rating');
```



In [99]:
```
sns.relplot(data= combined_movies_data_copy, x="runtime_minutes", y="avera
```

Out[99]: <seaborn.axisgrid.FacetGrid at 0x1c02dd13b80>



There is weak positive correlation between ratings and runtime. Movies with higher runtimes tend to have higher ratings.The clustered nature of the plot indicates that could be a non-linear relationship between rating and data.

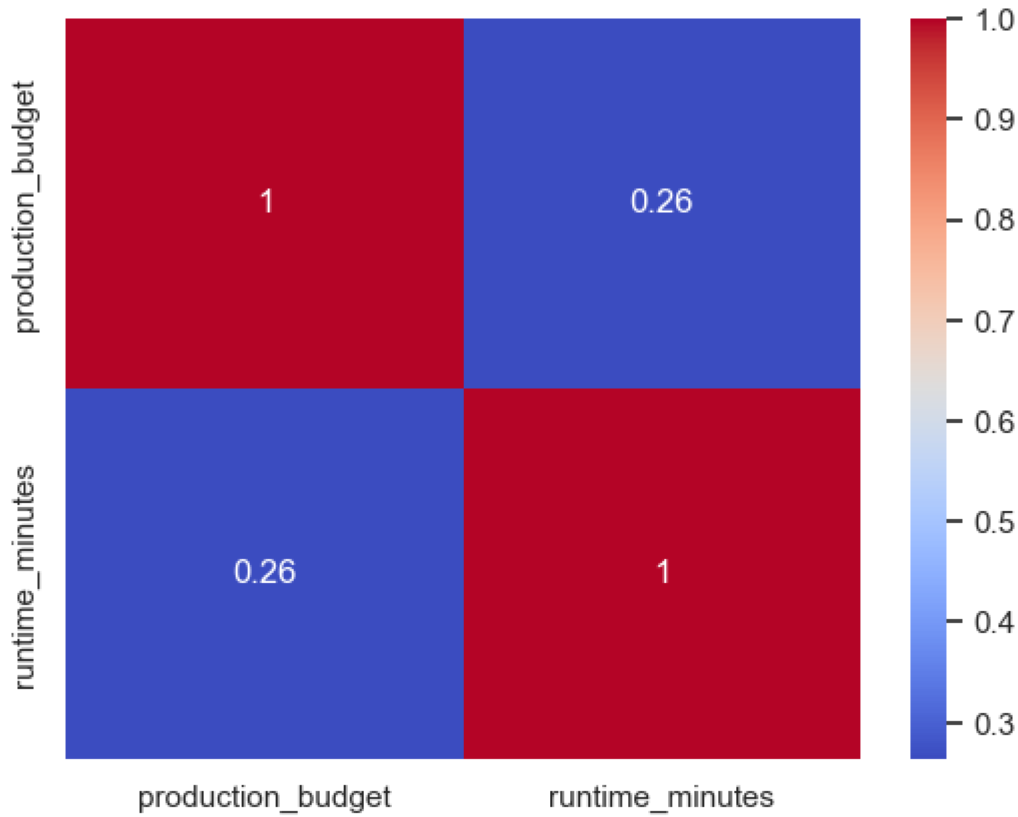
Correlation between runtime and budget.

In [108]:
```
# Correlation between runtime and budget
cor_runtime_budget =combined_movies_data_copy[["production_budget","runtir
print (cor_runtime_budget)
```

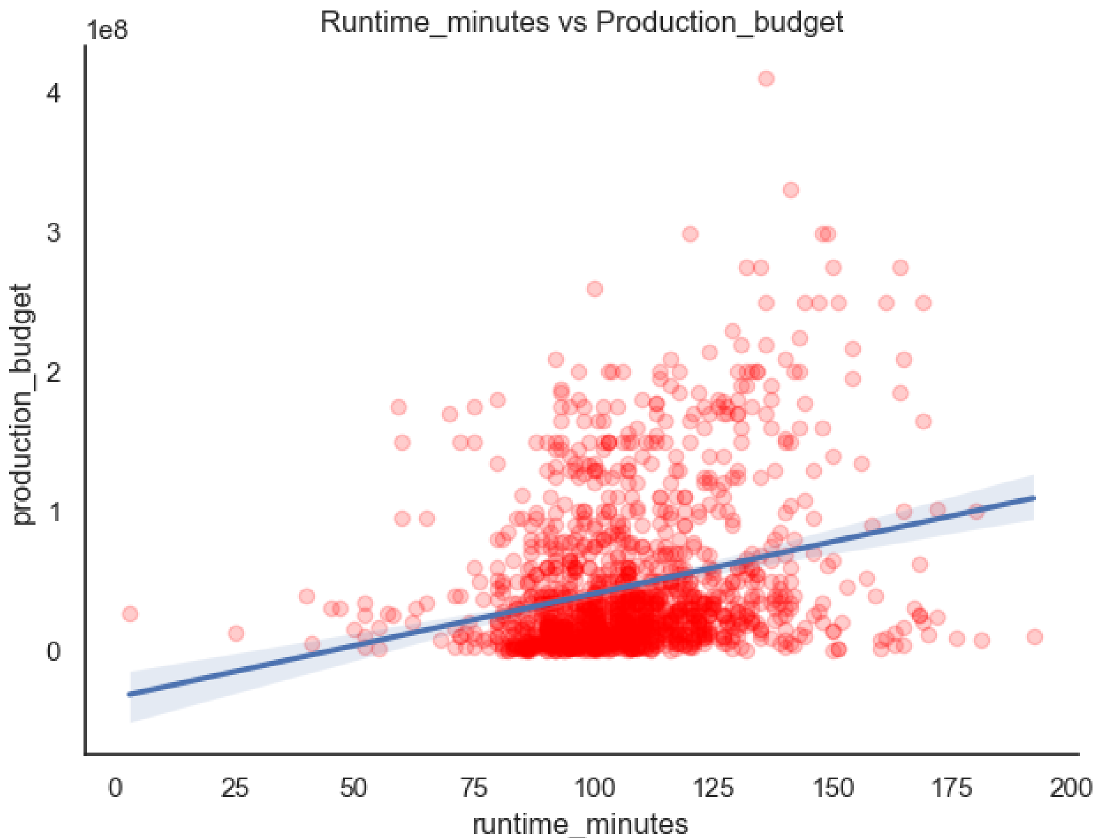
```
                   production_budget  runtime_minutes
production_budget           1.000000         0.264242
runtime_minutes             0.264242         1.000000
```

In [109]:
```
# Calculate the correlation matrix
vars_of_interest = ['production_budget', 'runtime_minutes']
subset_df = combined_movies_data_copy[vars_of_interest]
corr_matrix = subset_df.corr()

# Plot the correlation matrix using a heatmap
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
```

Out[109]: <AxesSubplot:>



In [201]:
```
# Plot scatterplot of Runtime_minutes vs Averagerating
sns.lmplot(x="runtime_minutes",
           y="production_budget",
           data= combined_movies_data_copy,
           height = 5,
           aspect=1.3,
           scatter_kws={'alpha':1/5, 'color':'red'},
           palette='Reds')
plt.title('Runtime_minutes vs Production_budget')
plt.xlabel('runtime_minutes')
plt.ylabel('production_budget');
```



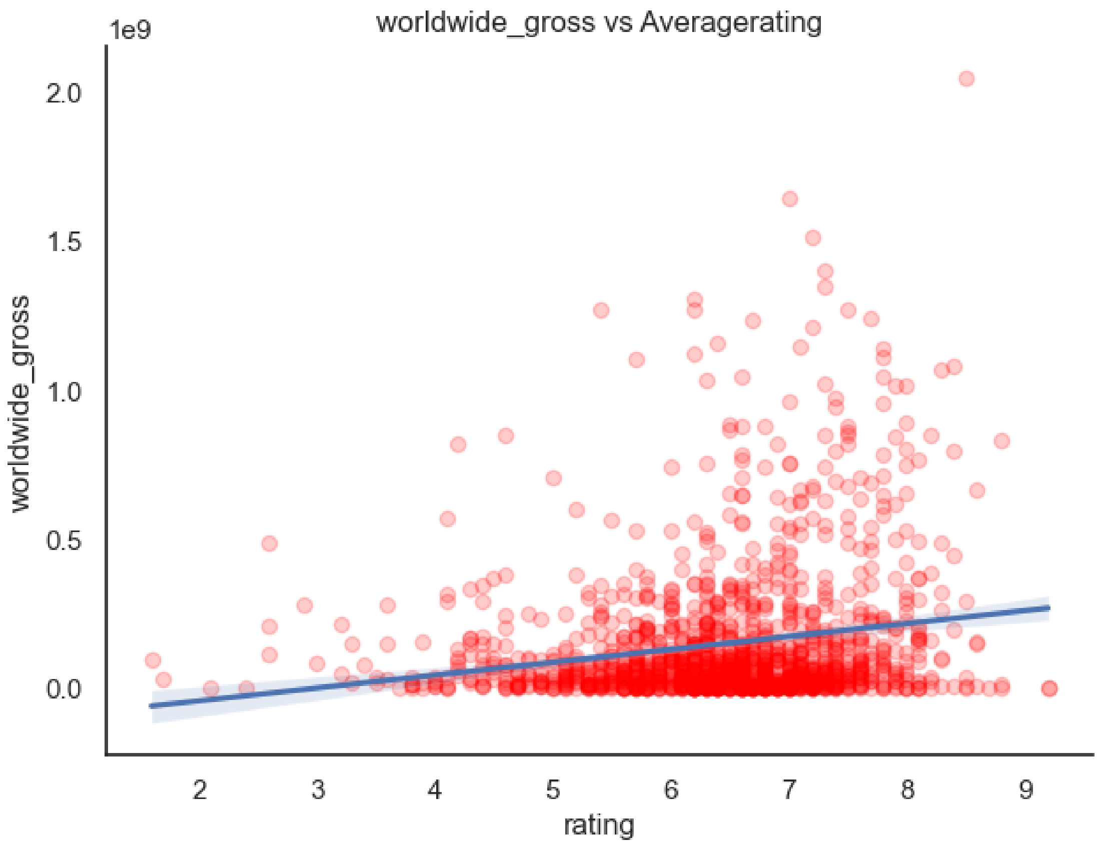
There is a weak positive correlation between budget and runtime. This implies that that as runtime increaes, the budget increases.

Correlation between ratings and worldwide gross sales

In [117]:
```
cor_ratings_gross =combined_movies_data_copy[["averagerating","worldwide_g
print (cor_ratings_gross)
```

```
                 averagerating  worldwide_gross
averagerating         1.000000         0.190962
worldwide_gross       0.190962         1.000000
```

In [202]:
```
# Plot scatterplot of worldwide_gross vs Averagerating
sns.lmplot(x="averagerating",
           y="worldwide_gross",
           data= combined_movies_data_copy,
           height = 5,
           aspect=1.3,
           scatter_kws={'alpha':1/5, 'color':'red'},
           palette='Greens')
plt.title('worldwide_gross vs Averagerating')
plt.xlabel('rating')
plt.ylabel('worldwide_gross');
```



There is a positive correlation between ratings and gross sales. This implies that as ratings increase, the more likely a movie is to make more sales.

Conclusion

From the analysis, the a number of conclusions can be made based on the leading questions.

Which is the best rated genre; most profitable genre, genre with highest ratings?

- The best rated genre is Drama and Action,Adventure,Sci-Fi.
- The most profitable genre is Action,Adventure,Sci-Fi

Which are the most expensive genres and cheapest genres to produce?

- The cateogory of action adventure movies are the most expensive to produce. Action,Adventure,Sci-Fi. being the most expensice action adventure movie to produce
- Drama, comedy and thriller movies are the cheapest to produce.

What is the correlation between runtime and ratings?

- There is weak positive correlation between ratings and runtime.

What is the correlation between runtime and budget.

- There is weak positive correlation between ratings and runtime.

Which are the studios with the most productions ?

- Universal studios and Fox studios have produced the most movies.

Recommendations.

Base on the business problem and the findings, I recommend that:

1.Microsoftstudios can choose to produce either Drama or Action,Adventure,Sci-Fi.

Microsoft studios can start by producing drama movies and variation like darma, comedy, animation since they are cheap to produce and relatively profitable compared to other genres and they have good ratings. After increasing viewership of their movies, Microsoft studios can proceed to produce Action,Adventure,Sci-Fi which is the most profitable but expensive to produce.

2.Microsoft should commission another study to recommend the best distribution channel for its movies. We could not do this since the data was not available.

3.Later on Microsoft studios should consider a study on the market share and how acquiring smaller independent studios would help them grow their market share and viewership.