Final Project Submission

Please fill out:

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INTRODUCTION

Microsoft is interested in venturing into the world of original movie content and has recently set up a new movie studio. However, as they don't have any prior experience in this field, they require guidance in selecting the right types of films to produce.

To address this issue, I will analyze data on the current box office trends and interpret the insights to advise Microsoft on the types of movies that are performing well and why. This will enable them to make informed decisions on what movies to create in their new studio.

OBJECTIVE

Objective:

To identify the types of films that are currently performing best at the box office and provide actionable insights for Microsoft to make informed decisions about the types of films they should create.

Steps to be undertaken:

> Load all relevant data sets.

> Examine the data to ensure it has been loaded correctly, checking the size, data types, and any missing values.

> Clean the data by removing irrelevant columns or rows, renaming columns, handling missing values, and correcting any errors.

> Merge the relevant data sets to create a master data set.

> Use data analysis to explore the data, looking for trends, patterns, and relationships between variables.

> Use data visualization to present the data in a clear and meaningful way.

> Draw conclusions from the analysis and provide recommendations based on findings.

> Communicate the findings and recommendations to the Microsoft team.

In [401…

```
# Your code here - remember to use markdown cells for comments as well!
import pandas as pd
import numpy as np
import seaborn as sns
import sqlite3
import matplotlib.pyplot as plt
%matplotlib inline

import warnings

warnings.filterwarnings("ignore")
```

In [402…
```
#Opening and Exploring the Data, size

bom_df = pd.read_csv('Data/bom.movie_gross.csv')
bom_df
```

Out[402…

	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
...	...	...	...	...	...
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

3387 rows × 5 columns

In [403…
```
#  Identifying which columns have missing data and determining how to handle

bom_df.isna().sum()
```

Out[403…
```
title               0
studio              5
domestic_gross     28
foreign_gross    1350
year                0
dtype: int64
```

In [404…
```
# Identifing how the datatypes are related to missing data.

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 [405…
```
# Examine the domestic gross data

bom_df.describe().astype(int)
```

Out[405…

	domestic_gross	year
count	3359	3387
mean	28745845	2013
std	66982498	2
min	100	2010
25%	120000	2012
50%	1400000	2014
75%	27900000	2016

max	936700000	2018

In [406…
```
# Examine the year 2010 for the top five trends.

bom_df_2010 = bom_df[(bom_df['year'] == 2010)]

#drop missing data

bom_df_2010 = bom_df_2010.dropna()
```

In [407…
```
# Examine domestic gross for 2010

bom_df_2010.describe().astype(int)
```

Out[407…

	domestic_gross	year
count	308	308
mean	32963448	2010
std	60668552	0
min	800	2010
25%	280250	2010
50%	4000000	2010
75%	40400000	2010
max	415000000	2010

By calculating both the mean and median, we get a sense of the central tendency of the domestic gross box office distribution for films released in 2010. In this case the mean and median are close in value, suggesting that the distribution is roughly symmetrical, with no strong outliers.

In [408…
```
#Identify year 2010 domestic gross mean and median to understand the perform

print("Domestic 2010 gross box office mean",
      bom_df_2010['domestic_gross'].mean())

print("Domestic 2010 gross box office median",
      bom_df_2010['domestic_gross'].median())
```

```
Domestic 2010 gross box office mean 32963448.373376623
Domestic 2010 gross box office median 4000000.0
```

Examine another year to compare with 2010. Here I pick 2018 to see difference over greater time period.

In [409…
```
bom_df_2018 = bom_df[(bom_df['year'] == 2018)]

bom_df_2018.dropna()
```

Out[409…

	title	studio	domestic_gross	foreign_gross	year
3079	Avengers: Infinity War	BV	678800000.0	1,369.5	2018
3080	Black Panther	BV	700100000.0	646900000	2018
3081	Jurassic World: Fallen Kingdom	Uni.	417700000.0	891800000	2018
3082	Incredibles 2	BV	608600000.0	634200000	2018
3083	Aquaman	WB	335100000.0	812700000	2018
…	…	…	…	…	…
3275	I Still See You	LGF	1400.0	1500000	2018
3286	The Catcher Was a Spy	IFC	725000.0	229000	2018
3309	Time Freak	Grindstone	10000.0	256000	2018

3342	Reign of Judges: Title of Liberty - Concept Short	Darin Southa	93200.0	5200	2018
3353	Antonio Lopez 1970: Sex Fashion & Disco	FM	43200.0	30000	2018

173 rows × 5 columns

Here we are getting the statistical summary of the numerical columns in the dataframe bom_df_2018, and then converting the results to integer type. Thereafter we generate a summation of the data of the numbes in columns.

In [410…
```
bom_df_2018.describe().astype(int)
```

Out[410…

	domestic_gross	year
count	308	308
mean	36010421	2018
std	85733961	0
min	1300	2018
25%	175250	2018
50%	2700000	2018
75%	35950000	2018
max	700100000	2018

Identify year 2018 domestic gross mean and median. Compare to 2010 mean and median. This code helps to provide useful summary statistics for the domestic_gross column and help give an idea of the typical box office performance of movies released in 2018. The results therefore suggests that there were some movies that performed exceptionally well and brought up the mean, while most movies had lower domestic gross earnings.

In [411…
```
print("Domestic 2018 gross box office mean",
      bom_df_2018['domestic_gross'].mean())

print("Domestic 2018 gross box office median",
      bom_df_2018['domestic_gross'].median())
```

```
Domestic 2018 gross box office mean 36010421.75
Domestic 2018 gross box office median 2700000.0
```

Exploring the Second Dataset

In [412…
```
mov_budgets_df =  pd.read_csv('Data/tn.movie_budgets.csv')
mov_budgets_df
```

Out[412…

	id	release_date	movie	production_budget	domestic_gross	worldwide_gro
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,2
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,8
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,3
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,9
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,7

...	...	...	...	...	...	
5777	78	Dec 31, 2018	Red 11	$7,000	$0	
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,4
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,3
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,(

5782 rows × 6 columns

In [413…
```
mov_budgets_df[:10]
```

Out[413…

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	$306,000,000	$936,662,225	$2,053,311,220
6	7	Apr 27, 2018	Avengers: Infinity War	$300,000,000	$678,815,482	$2,048,134,200
7	8	May 24, 2007	Pirates of the Caribbean: At Worldâ€™s End	$300,000,000	$309,420,425	$963,420,425
8	9	Nov 17, 2017	Justice League	$300,000,000	$229,024,295	$655,945,209
9	10	Nov 6, 2015	Spectre	$300,000,000	$200,074,175	$879,620,923

In [414…
```
mov_budgets_df.tail()
```

Out[414…

	id	release_date	movie	production_budget	domestic_gross	worldwide_gros
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,49
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,33
5780	81	Sep 29, 2015	A Plague So	$1,400	$0	$

5780	81	Sep 29, 2015	Pleasant	$1,400	$0	$
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,04

In [415…
```
#represents the number of rows and columns
mov_budgets_df.shape
```

Out[415… (5782, 6)

In [416…
```
#Identify any missing data
mov_budgets_df.isna().sum()
```

Out[416…
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

In [417…
```
mov_budgets_df.info()
```

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

Exploring the Third Data Set

In [418…
```
conn = sqlite3.connect('Data/im.db')
pd.read_sql("""SELECT *
                    FROM movie_ratings;""", conn)
```

Out[418…

	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
…	…	…	…
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

73856 rows × 3 columns

In [419…
```
movie_ratings_df.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
```

This code reads in all the columns from the movie_basics table in the im.db database using SQL query and saves the resulting DataFrame in the variable movie_basics_df.

In [420…

```
# Identify data for movie_basics

movie_basics_df = pd.read_sql("""SELECT * FROM movie_basics;""", conn)

movie_basics_df
```

Out[420…

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biog
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Co
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,D
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	

146144 rows × 6 columns

In [421…

```
movie_basics_df.head(10)
```

Out[421…

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,(
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biog
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Co
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Dr
5	tt0111414	A Thin Life	A Thin Life	2018	75.0	

6	tt0112502	Bigfoot	Bigfoot	2017	NaN	H
7	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Anima
8	tt0139613	O Silêncio	O Silêncio	2012	NaN	Docume
9	tt0144449	Nema aviona za Zagreb	Nema aviona za Zagreb	2012	82.0	

In [422…
```
movie_basics_df.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 [ ]:
```
```

In [423…
```
# Examine and identify data types for movie_akas table

movie_akas_df = pd.read_sql("""SELECT * FROM movie_akas;""", conn)

movie_akas_df.head()
```

Out[423…

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

In [424…
```
movie_akas_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 331703 entries, 0 to 331702
Data columns (total 8 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   movie_id           331703 non-null  object 
 1   ordering           331703 non-null  int64  
 2   title              331703 non-null  object 
 3   region             278410 non-null  object 
 4   language           41715 non-null   object 
 5   types              168447 non-null  object 
 6   attributes         14925 non-null   object 
 7   is_original_title  331678 non-null  float64
dtypes: float64(1), int64(1), object(6)
memory usage: 20.2+ MB
```

In [425…
```
# Merge individual imdb tables into one dataframe using movie_id

imdb_df = pd.merge(pd.merge(
    movie_basics_df, movie_ratings_df,on='movie_id'),
```

```
    movie_akas_df, on='movie_id').drop_duplicates(subset = 'movie_id')

imdb_df = imdb_df.reset_index(drop = True)

imdb_df
```

Out[425…

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	A
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Com
...	...	...	...	...	...	
69572	tt9899860	Watching This Movie Is a Crime	Didan in film jorm ast	2019	100.0	
69573	tt9899880	Columbus	Columbus	2018	85.0	
69574	tt9903952	BADMEN with a good behavior	BADMEN with a good behavior	2018	87.0	
69575	tt9905462	Pengalila	Pengalila	2019	111.0	
69576	tt9911774	Padmavyuhathile Abhimanyu	Padmavyuhathile Abhimanyu	2019	130.0	

69577 rows × 15 columns

In [426…

```
imdb_df.isna().sum()
```

Out[426…

```
movie_id                0
primary_title           0
original_title          0
start_year              0
runtime_minutes      6747
genres                640
averagerating           0
numvotes                0
ordering                0
title                   0
region              11444
language            63871
types               45395
attributes          67562
is_original_title       0
dtype: int64
```

Merge DataFames

In [427…

```
All_movies_df = pd.merge(bom_df, movie_budgets_df, left_on='title', right_on

All_movies_df.columns
```

Out[427…

```
Index(['title', 'studio', 'domestic_gross_x', 'foreign_gross', 'year', 'id',
       'release_date', 'movie', 'production_budget', 'domestic_gross_y',
       'worldwide_gross'],
      dtype='object')
```

In [428…

```
#drop column 'movie', keep 'title' as the primary key

All_movies_df.drop('movie', axis=1, inplace=True)
```

In [429…

```
All_movies_df.head()
```

Out[429…

	title	studio	domestic_gross_x	foreign_gross	year	id	release_date	product
0	Toy Story 3	BV	415000000.0	652000000	2010	47	Jun 18, 2010	$
1	Inception	WB	292600000.0	535700000	2010	38	Jul 16, 2010	$
2	Shrek Forever After	P/DW	238700000.0	513900000	2010	27	May 21, 2010	$
3	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010	53	Jun 30, 2010	$
4	Iron Man 2	Par.	312400000.0	311500000	2010	15	May 7, 2010	$

In [433…

```
# Drop following columns: 'id', 'ordering', 'language', 'types',
# 'attributes', 'is_original-title'

Merged_df.drop(['id', 'ordering_x', 'language_y', 'types_x',
                'attributes_x', 'is_original_title_x', 'region_x', 'start_yea
               axis=1, inplace = True)
```

In [431…

```
Merged_df.columns
```

Out[431…

```
Index(['title_x', 'studio', 'domestic_gross_x', 'foreign_gross', 'year', 'i
d',
       'release_date', 'production_budget', 'domestic_gross_y',
       'worldwide_gross', 'movie_id_x', 'primary_title_x', 'original_title_
x',
       'start_year_x', 'runtime_minutes_x', 'genres_x', 'averagerating_x',
       'numvotes_x', 'ordering_x', 'title_y', 'region_x', 'language_x',
       'types_x', 'attributes_x', 'is_original_title_x', 'movie_id_y',
       'primary_title_y', 'original_title_y', 'start_year_y',
       'runtime_minutes_y', 'genres_y', 'averagerating_y', 'numvotes_y',
       'ordering_y', 'title', 'region_y', 'language_y', 'types_y',
       'attributes_y', 'is_original_title_y'],
      dtype='object')
```

In [434…

```
#Cleaning the Data

Merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2108 entries, 0 to 2107
Data columns (total 32 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   title_x              2108 non-null   object
 1   studio               2108 non-null   object
 2   domestic_gross_x     2107 non-null   float64
 3   foreign_gross        1772 non-null   object
 4   year                 2108 non-null   int64
 5   release_date         2108 non-null   object
 6   production_budget    2108 non-null   object
 7   domestic_gross_y     2108 non-null   object
 8   worldwide_gross      2108 non-null   object
 9   movie_id_x           2108 non-null   object
 10  primary_title_x      2108 non-null   object
 11  original_title_x     2108 non-null   object
 12  start_year_x         2108 non-null   int64
 13  runtime_minutes_x    2032 non-null   float64
 14  genres_x             2089 non-null   object
 15  averagerating_x      2108 non-null   float64
 16  numvotes_x           2108 non-null   int64
 17  title_y              2108 non-null   object
 18  language_x           253 non-null    object
 19  movie_id_y           2108 non-null   object
 20  primary_title_y      2108 non-null   object
 21  original_title_y     2108 non-null   object
 22  runtime_minutes_y    2032 non-null   float64
 23  genres_y             2089 non-null   object
 24  averagerating_y      2108 non-null   float64
 25  numvotes_y           2108 non-null   int64
```

```
 26  ordering_y           2108 non-null   int64
 27  title                2108 non-null   object
 28  region_y             1904 non-null   object
 29  types_y              1283 non-null   object
 30  attributes_y         75 non-null     object
 31  is_original_title_y  2108 non-null   float64
dtypes: float64(6), int64(5), object(21)
memory usage: 543.5+ KB
```

In [435…

```
#Looking for missing data

Merged_df.isna().sum()
```

Out[435…

```
title_x                   0
studio                    0
domestic_gross_x          1
foreign_gross           336
year                      0
release_date              0
production_budget         0
domestic_gross_y          0
worldwide_gross           0
movie_id_x                0
primary_title_x           0
original_title_x          0
start_year_x              0
runtime_minutes_x        76
genres_x                 19
averagerating_x           0
numvotes_x                0
title_y                   0
language_x             1855
movie_id_y                0
primary_title_y           0
original_title_y          0
runtime_minutes_y        76
genres_y                 19
averagerating_y           0
numvotes_y                0
ordering_y                0
title                     0
region_y                204
types_y                 825
attributes_y           2033
is_original_title_y       0
dtype: int64
```

In [437…

```
Merged_df.drop(['ordering_y', 'language_x', 'types_y',
                'attributes_y', 'is_original_title_y', 'region_y', 'start_yea
               axis=1, inplace = True)
```

In [144…

```
Merged_df
```

Out[144…

	title_x	studio	domestic_gross_x	foreign_gross	year	release_date	producti
0	Toy Story 3	BV	415000000.0	652000000	2010	Jun 18, 2010	$2
1	Inception	WB	292600000.0	535700000	2010	Jul 16, 2010	$1
2	Shrek Forever After	P/DW	238700000.0	513900000	2010	May 21, 2010	$1
3	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010	Jun 30, 2010	$
4	Iron Man 2	Par.	312400000.0	311500000	2010	May 7, 2010	$1
…	…	…	…	…	…	…	
1393	Gotti	VE	4300000.0	NaN	2018	Jun 15, 2018	$
	Bilal: A New						

1394	...Breed of Hero	VE	491000.0	1700000	2018	Feb 2, 2018	$
1395	Mandy	RLJ	1200000.0	NaN	2018	Sep 14, 2018	
1396	Mandy	RLJ	1200000.0	NaN	2018	Sep 14, 2018	
1397	Lean on Pete	A24	1200000.0	NaN	2018	Apr 6, 2018	

1398 rows × 17 columns

In [439…
```
#Keep title_x and drop duplicate column movie titles

Merged_df.drop(['title_y', 'primary_title_x', 'original_title_x'], axis=1, i
```

In [441…
```
#drop 'movie_id', use Major_df index for new id

Merged_df.drop(['movie_id_y'], axis = 1, inplace = True)
```

In [443…
```
Merged_df.columns
```

Out[443…
```
Index(['title_x', 'studio', 'domestic_gross_x', 'foreign_gross', 'year',
       'release_date', 'production_budget', 'domestic_gross_y',
       'worldwide_gross', 'movie_id_x', 'runtime_minutes_x', 'genres_x',
       'averagerating_x', 'numvotes_x', 'primary_title_y', 'original_title_
y',
       'runtime_minutes_y', 'genres_y', 'averagerating_y', 'numvotes_y',
       'title'],
      dtype='object')
```

In [444…
```
Merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2108 entries, 0 to 2107
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   title_x            2108 non-null   object 
 1   studio             2108 non-null   object 
 2   domestic_gross_x   2107 non-null   float64
 3   foreign_gross      1772 non-null   object 
 4   year               2108 non-null   int64  
 5   release_date       2108 non-null   object 
 6   production_budget  2108 non-null   object 
 7   domestic_gross_y   2108 non-null   object 
 8   worldwide_gross    2108 non-null   object 
 9   movie_id_x         2108 non-null   object 
 10  runtime_minutes_x  2032 non-null   float64
 11  genres_x           2089 non-null   object 
 12  averagerating_x    2108 non-null   float64
 13  numvotes_x         2108 non-null   int64  
 14  primary_title_y    2108 non-null   object 
 15  original_title_y   2108 non-null   object 
 16  runtime_minutes_y  2032 non-null   float64
 17  genres_y           2089 non-null   object 
 18  averagerating_y    2108 non-null   float64
 19  numvotes_y         2108 non-null   int64  
 20  title              2108 non-null   object 
dtypes: float64(5), int64(3), object(13)
memory usage: 362.3+ KB
```

In [445…
```
#convert production budget to integer datatype

Merged_df["production_budget"] = Merged_df["production_budget"].replace(
    "[$,]", "", regex=True).astype(int)
```

In [446…
```
#convert domestic gross and worldwide gross to integer datatype
Merged_df["domestic_gross_y"] = Merged_df["domestic_gross_y"].replace(
    "[$,]", "", regex=True).astype(int)

Merged_df["worldwide_gross"] = Merged_df["worldwide_gross"].replace(
    "[$,]", "", regex=True).astype(int)
```

In [447…
```
# Ascertain data types for further exploration
Merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2108 entries, 0 to 2107
Data columns (total 21 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   title_x             2108 non-null   object 
 1   studio              2108 non-null   object 
 2   domestic_gross_x    2107 non-null   float64
 3   foreign_gross       1772 non-null   object 
 4   year                2108 non-null   int64  
 5   release_date        2108 non-null   object 
 6   production_budget   2108 non-null   int64  
 7   domestic_gross_y    2108 non-null   int64  
 8   worldwide_gross     2108 non-null   int64  
 9   movie_id_x          2108 non-null   object 
 10  runtime_minutes_x   2032 non-null   float64
 11  genres_x            2089 non-null   object 
 12  averagerating_x     2108 non-null   float64
 13  numvotes_x          2108 non-null   int64  
 14  primary_title_y     2108 non-null   object 
 15  original_title_y    2108 non-null   object 
 16  runtime_minutes_y   2032 non-null   float64
 17  genres_y            2089 non-null   object 
 18  averagerating_y     2108 non-null   float64
 19  numvotes_y          2108 non-null   int64  
 20  title               2108 non-null   object 
dtypes: float64(5), int64(6), object(10)
memory usage: 362.3+ KB
```

In [450…
```
#Examine the summary data on runtime_minutes_x,

Merged_df['runtime_minutes_x'].describe()
```

Out[450…
```
count    2032.000000
mean      104.995079
std        20.914211
min         3.000000
25%        92.000000
50%       103.000000
75%       117.000000
max       192.000000
Name: runtime_minutes_x, dtype: float64
```

In [453…
```
#Use median to replace missing data in runtime_minutes

Merged_df['runtime_minutes_x'] = Merged_df['runtime_minutes_x'].fillna(
    Merged_df['runtime_minutes_x'].median())
```

In [456…
```
# Looking at the issing values in the 'genres_x' column of the DataFrame 'Me
#This modifies the original DataFrame in place.

Merged_df['genres_x'] = Merged_df['genres_x'].fillna('missing')
```

In [457…
```
# Ensure all missing data is accounted for.

Merged_df.isna().sum()
```

Out[457…
```
title_x                0
studio                 0
domestic_gross_x       1
foreign_gross        336
year                   0
release_date           0
production_budget      0
domestic_gross_y       0
worldwide_gross        0
movie_id_x             0
runtime_minutes_x      0
genres_x               0
averagerating_x        0
numvotes_x             0
```

```
primary_title_y        0
original_title_y       0
runtime_minutes_y     76
genres_y              19
averagerating_y        0
numvotes_y             0
title                  0
dtype: int64
```

In [459…
```
#convert release date into month released only

Merged_df['release_date'].dtypes
```

Out[459… `dtype('O')`

In [460…
```
#convert the 'release_date' column to a datetime data type.

Merged_df['release_date'] = pd.to_datetime(Merged_df['release_date'])

Merged_df['release_date'].head()
```

Out[460…
```
0   2010-06-18
1   2010-07-16
2   2010-05-21
3   2010-06-30
4   2010-05-07
Name: release_date, dtype: datetime64[ns]
```

In [461…
```
# Create a month released column by month name and month number.

Merged_df['month_released'] = pd.to_datetime(Merged_df['release_date']).dt.m

Merged_df['month_num'] = pd.to_datetime(Merged_df['release_date']).dt.month

Merged_df.columns
```

Out[461…
```
Index(['title_x', 'studio', 'domestic_gross_x', 'foreign_gross', 'year',
       'release_date', 'production_budget', 'domestic_gross_y',
       'worldwide_gross', 'movie_id_x', 'runtime_minutes_x', 'genres_x',
       'averagerating_x', 'numvotes_x', 'primary_title_y', 'original_title_
y',
       'runtime_minutes_y', 'genres_y', 'averagerating_y', 'numvotes_y',
       'title', 'month_released', 'month_num'],
      dtype='object')
```

In [462…
```
# Drop release date and keep months released now.

Merged_df.drop(['release_date'], axis = 1, inplace = True)
```

In [463…
```
Merged_df.columns
```

Out[463…
```
Index(['title_x', 'studio', 'domestic_gross_x', 'foreign_gross', 'year',
       'production_budget', 'domestic_gross_y', 'worldwide_gross',
       'movie_id_x', 'runtime_minutes_x', 'genres_x', 'averagerating_x',
       'numvotes_x', 'primary_title_y', 'original_title_y',
       'runtime_minutes_y', 'genres_y', 'averagerating_y', 'numvotes_y',
       'title', 'month_released', 'month_num'],
      dtype='object')
```

In [464…
```
Merged_df.rename(columns = {'title_x': 'Movie_Title',
                            'domestic_gross_y': 'domestic_gross'}, inplace = 

print(Merged_df.columns)
```

```
Index(['Movie_Title', 'studio', 'domestic_gross_x', 'foreign_gross', 'year',
       'production_budget', 'domestic_gross', 'worldwide_gross', 'movie_id_x',
       'runtime_minutes_x', 'genres_x', 'averagerating_x', 'numvotes_x',
       'primary_title_y', 'original_title_y', 'runtime_minutes_y', 'genres_y',
       'averagerating_y', 'numvotes_y', 'title', 'month_released',
       'month_num'],
      dtype='object')
```

In [465…
```
#simply the difference between the worldwide gross and the domestic gross
```

```
Merged_df['foreign_gross'] = Merged_df['worldwide_gross'] - Merged_df['domes

Merged_df['foreign_gross'].head()
```

Out[465…
```
0    653874642
1    542948447
2    517507886
3    405571077
4    308723058
Name: foreign_gross, dtype: int64
```

In [466…
```
#Show the movie titles and their corresponding production percentages in the

Merged_df['production_percent'] = (Merged_df['production_budget'] /
                                   Merged_df['worldwide_gross'])* 100

Merged_df[['Movie_Title', 'production_percent']].head()
```

Out[466…

	Movie_Title	production_percent
0	Toy Story 3	18.711183
1	Inception	19.149645
2	Shrek Forever After	21.818336
3	The Twilight Saga: Eclipse	9.630325
4	Iron Man 2	27.368309

In [467…
```
Merged_df
```

Out[467…

	Movie_Title	studio	domestic_gross_x	foreign_gross	year	production_budget
0	Toy Story 3	BV	415000000.0	653874642	2010	200000000
1	Inception	WB	292600000.0	542948447	2010	160000000
2	Shrek Forever After	P/DW	238700000.0	517507886	2010	165000000
3	The Twilight Saga: Eclipse	Sum.	300500000.0	405571077	2010	68000000
4	Iron Man 2	Par.	312400000.0	308723058	2010	170000000
...	...	...	...	...	...	...
2103	Mandy	RLJ	1200000.0	213131	2018	6000000
2104	Mandy	RLJ	1200000.0	213131	2018	6000000
2105	Mandy	RLJ	1200000.0	213131	2018	6000000
2106	Mandy	RLJ	1200000.0	213131	2018	6000000
2107	Lean on Pete	A24	1200000.0	1291971	2018	8000000

2108 rows × 23 columns

In [468…
```
# removing resulting duplicate entries in the 'Movie_Title' column.

Merged_df = Merged_df.drop_duplicates(subset= 'Movie_Title', keep="first", i
```

Data Analysis

Here I would like to narrow my focus on the questions of what is the best performing movies, and look at the data related to production costs and identify relationship to

movies, and look at the data related to production costs and identify relationship to domestic revenue and worldwide revenue. Consider whether the median cost to produce a movies has changed over times. Identify key movie attributes that may lead to box office success.

In [469…

```
#Sort dataframe by worldwide gross

Merged_df = Merged_df.sort_values(by = 'worldwide_gross', ascending = False,
                                  ignore_index = True)

Merged_df.head()
```

Out[469…

	Movie_Title	studio	domestic_gross_x	foreign_gross	year	production_budget	dor
0	Avengers: Infinity War	BV	678800000.0	1369318718	2018	300000000	
1	Jurassic World	Uni.	652300000.0	996584239	2015	215000000	
2	Furious 7	Uni.	353000000.0	1165715774	2015	190000000	
3	Avengers: Age of Ultron	BV	459000000.0	944008095	2015	330600000	
4	Black Panther	BV	700100000.0	648198658	2018	200000000	

5 rows × 23 columns

In [470…

```
# slices the data to keep only the first 1000 rows.

Merged_df = Merged_df[:1000]
```

In [471…

```
#Identify top 50 films of each year

df_2010 = Merged_df[Merged_df['year'] == 2010][:50]

df_2011 = Merged_df[Merged_df['year'] == 2011][:50]

df_2012 = Merged_df[Merged_df['year'] == 2012][:50]

df_2013 = Merged_df[Merged_df['year'] == 2013][:50]

df_2014 = Merged_df[Merged_df['year'] == 2014][:50]

df_2015 = Merged_df[Merged_df['year'] == 2015][:50]

df_2016 = Merged_df[Merged_df['year'] == 2016][:50]

df_2017 = Merged_df[Merged_df['year'] == 2017][:50]

df_2018 = Merged_df[Merged_df['year'] == 2018][:50]

# Concatenate each movie year dataframe into one dataframe

top_df = pd.concat([df_2010, df_2011, df_2012, df_2013,
          df_2014, df_2015, df_2016, df_2017,
          df_2018])

top_df = top_df.reset_index(drop = True)
```

In [478…

```
# Sort top 50 movies of each year by worldwide gross revenue

top_df = top_df.sort_values(by = 'worldwide_gross', ascending = False,
                                  ignore_index = True)

# Compare top 50 from each year to overall Merged_df

top_df.describe().astype(int)
```

Out[478…

	domestic_gross_x	foreign_gross	year	production_budget	domestic_gross	wo

count	450	450	450	450	450
mean	131524074	221350670	2014	93217777	132092268
std	105787307	204594244	2	67813267	105363308
min	25400	16100000	2010	3000000	8178001
25%	62525000	80887642	2012	40000000	63573607
50%	100200000	140218880	2014	75000000	100269433
75%	162950000	291295377	2016	140000000	162946882
max	700100000	1369318718	2018	410600000	700059566

In [479…

```
Merged_df.describe().astype(int)
```

Out[479…

	domestic_gross_x	foreign_gross	year	production_budget	domestic_gross	wo
count	1000	1000	1000	1000	1000	
mean	72688777	111094440	2013	55175687	73003308	
std	89708864	170136094	2	58847075	89614462	
min	1000	0	2010	100000	0	
25%	18250000	14720873	2012	15000000	18483036	
50%	42650000	42931359	2014	35000000	42901464	
75%	88725000	121575026	2016	70000000	89144532	
max	700100000	1369318718	2018	410600000	700059566	

In [480…

```
# Print median of production costs Top 50 per year and # Compare top 50 from


print("The median production cost for Merged_df is USD",
      Merged_df['production_budget'].median())
print("The median production cost for top_df is USD",
      top_df['production_budget'].median())

# Domestic gross median compare

print("The median domestic gross for Merged_df is USD",
      Merged_df['domestic_gross'].median())
print("The median domestic_gross for top_df is USD",
      top_df['domestic_gross'].median())

# Worldwide gross compare

print("The median worldwide gross for Merged_df is USD",
      Merged_df['worldwide_gross'].median())
print("The median worldwide gross for top_df is USD",
      top_df['worldwide_gross'].median())
```

```
The median production cost for Merged_df is USD 35000000.0
The median production cost for top_df is USD 75000000.0
The median domestic gross for Merged_df is USD 42901464.5
The median domestic_gross for top_df is USD 100269433.5
The median worldwide gross for Merged_df is USD 88891097.0
The median worldwide gross for top_df is USD 238949263.0
```

In [481…

```
# Identify the skewness of the dataset for the top 50 films per year.

print("The mean production costs for top_df is USD",
      int(round(top_df['production_budget'].mean())))

print("The mean worldwide gross for top_df is USD",
      int(round(top_df['domestic_gross'].mean())))
```

```
The mean production costs for top_df is USD 93217778
The mean worldwide gross for top_df is USD 132092268
```

In [482…

```
#Analysis

top_df[:5]
```

Out[482…

	Movie_Title	studio	domestic_gross_x	foreign_gross	year	production_budget	dor
0	Avengers: Infinity War	BV	678800000.0	1369318718	2018	300000000	
1	Jurassic World	Uni.	652300000.0	996584239	2015	215000000	
2	Furious 7	Uni.	353000000.0	1165715774	2015	190000000	
3	Avengers: Age of Ultron	BV	459000000.0	944008095	2015	330600000	
4	Black Panther	BV	700100000.0	648198658	2018	200000000	

5 rows × 23 columns

In [486…

```
Merged_df.query("74000000 < production_budget < 76000000")
```

Out[486…

	Movie_Title	studio	domestic_gross_x	foreign_gross	year	production_budget	d
20	Despicable Me 3	Uni.	264600000.0	770103450	2017	75000000	
29	The Secret Life of Pets	Uni.	368400000.0	518366204	2016	75000000	
70	Sing	Uni.	270400000.0	364125744	2016	75000000	
151	Now You See Me	LG/S	117700000.0	225045211	2013	75000000	
199	Grown Ups	Sony	162000000.0	110222244	2010	75000000	
244	Inferno	Sony	34300000.0	185175793	2016	75000000	
259	Immortals	Rela.	83500000.0	128058418	2011	75000000	
471	Killers	LGF	47100000.0	48512786	2010	75000000	
497	Sucker Punch	WB	36400000.0	53365887	2011	75000000	

9 rows × 23 columns

In [487…

```
Merged_df.query("100000000 < domestic_gross < 101000000")
```

Out[487…

	Movie_Title	studio	domestic_gross_x	foreign_gross	year	production_budget	d
119	Kingsman: The Golden Circle	Fox	100200000.0	308568858	2017	104000000	
134	Fifty Shades Freed	Uni.	100400000.0	270942859	2018	55000000	
136	Edge of Tomorrow	WB	100200000.0	270335000	2014	178000000	
251	Bad Teacher	Sony	100300000.0	115156141	2011	19000000	
258	Due Date	WB	100500000.0	111200000	2010	65000000	
267	Yogi Bear	WB	100200000.0	104528679	2010	80000000	
268	Arrival	Par.	100500000.0	102581755	2016	47000000	
375	A Wrinkle in Time	BV	100500000.0	32923274	2018	103000000	

time

8 rows × 23 columns

In [488…
```
# Identify most popular months for movie releases for top_50

top_df['month_released'].value_counts()
```

Out[488…
```
November     59
July         57
December     55
June         48
May          40
October      37
February     31
March        31
August       26
September    25
April        22
January      19
Name: month_released, dtype: int64
```

In [490…
```
top_df['genres_y'].value_counts()
```

Out[490…
```
Adventure,Animation,Comedy    51
Action,Adventure,Sci-Fi       41
Action,Adventure,Fantasy      23
Action,Adventure,Drama        14
Action,Adventure,Comedy       13
                              ..
Action,Adventure,Western       1
Adventure,Drama,Western        1
Action,Comedy                  1
Horror,Sci-Fi,Thriller         1
Horror,Romance,Thriller        1
Name: genres_y, Length: 114, dtype: int64
```

In [492…
```
top_df['runtime_minutes_y'].describe().astype(int)
```

Out[492…
```
count    447
mean     114
std       19
min       50
25%       99
50%      112
75%      127
max      180
Name: runtime_minutes_y, dtype: int64
```

In [494…
```
print(top_df["averagerating_y"].median())
print(Merged_df["averagerating_y"].median())
```

```
6.65
6.5
```

SUMMARY DATA ANALYSIS

In summary, the most popular months for releasing a top 50 film are November, December, June, and July. The median runtime for these films is 114 minutes with a maximum runtime of 180 minutes. Action, adventure, and western films are common in the top 50. There is not much difference in ratings between top 50 films and the overall dataset.

The new dataframe, which includes the top 50 films of each year, shows that the median cost for these films is USD 75 million, which is significantly higher than the original dataframe's median cost of USD 35 million. Additionally, the worldwide revenue median for the top 50 films is USD 240 million compared to all films at under USD 90 million. The median payment for a top 50 film is 26% of gross revenue, but the range can be as high as 17-39%. The majority of top 50 films range between 99-127 minutes and are often action and adventure films. The cost of a film does not necessarily affect the ratings.

However, the dataset only considers films from 2010 to 2018 and does not account for any changes to the movie industry. Therefore, future analyses may need to consider a more comprehensive understanding of movie attributes and revenue.

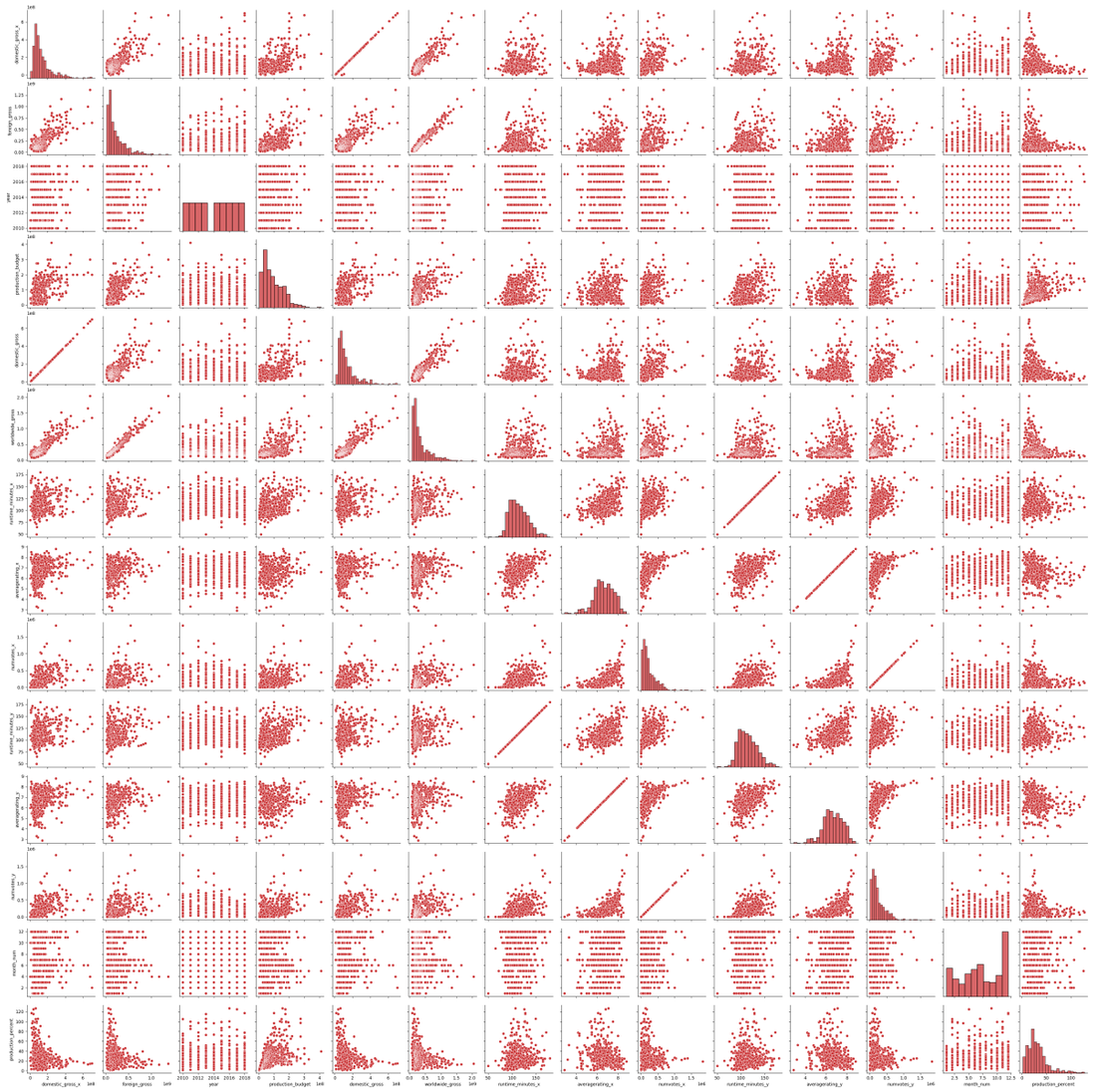
Data Visualisation

In [495…

```
import matplotlib.pyplot as plt
%matplotlib inline
```

In [496…

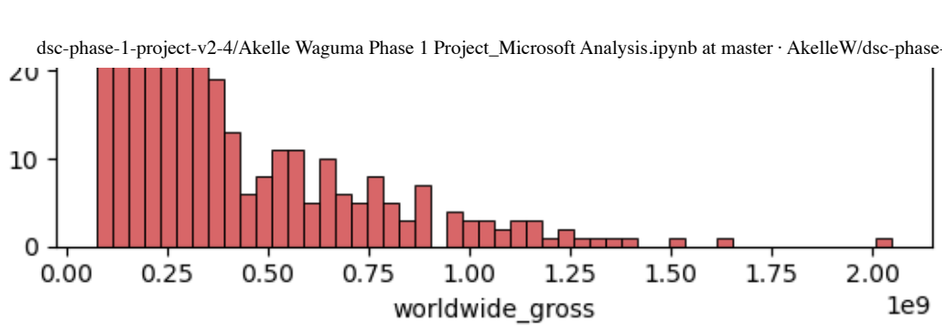
```
sns.pairplot(top_df)

plt.show()
```



In [501…

```
# creates a histogram of the 'worldwide_gross' column, with 50 bins to group
#This line plots the distribution of the total box office revenue earned by

sns.histplot(top_df, x = 'worldwide_gross', bins = 50)
```

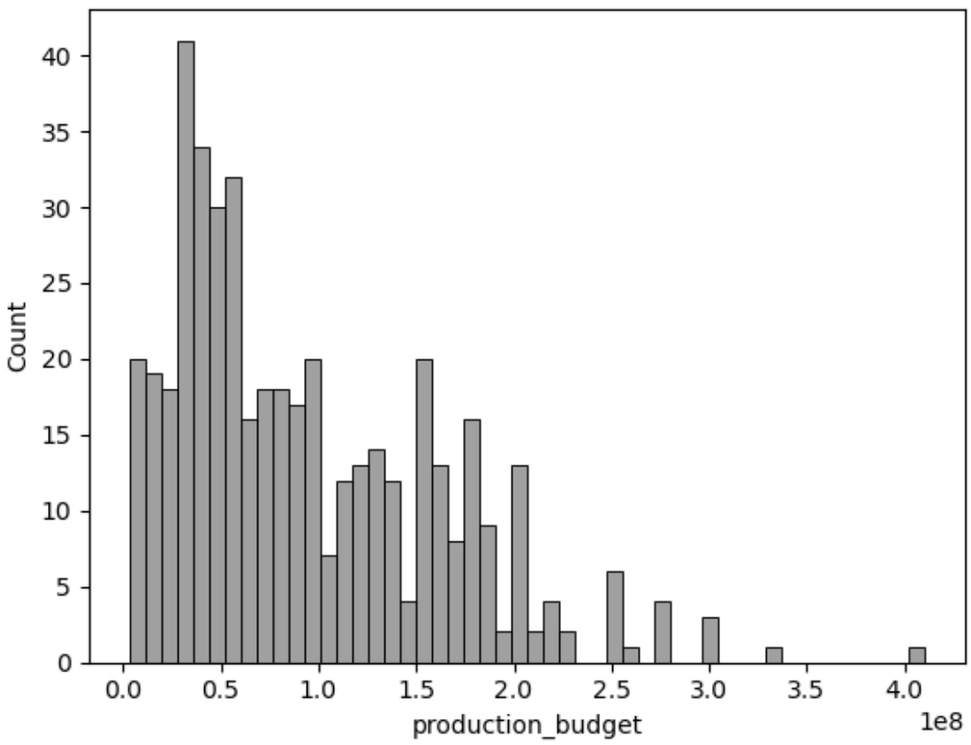
Out[501… <AxesSubplot:xlabel='worldwide_gross', ylabel='Count'>



In [500…

```
#The second line creates a histogram of the 'production_budget' column, also
#This line plots the distribution of the production costs for the top 50 fil

sns.histplot(top_df, x = 'production_budget', bins = 50, color = 'grey')
```

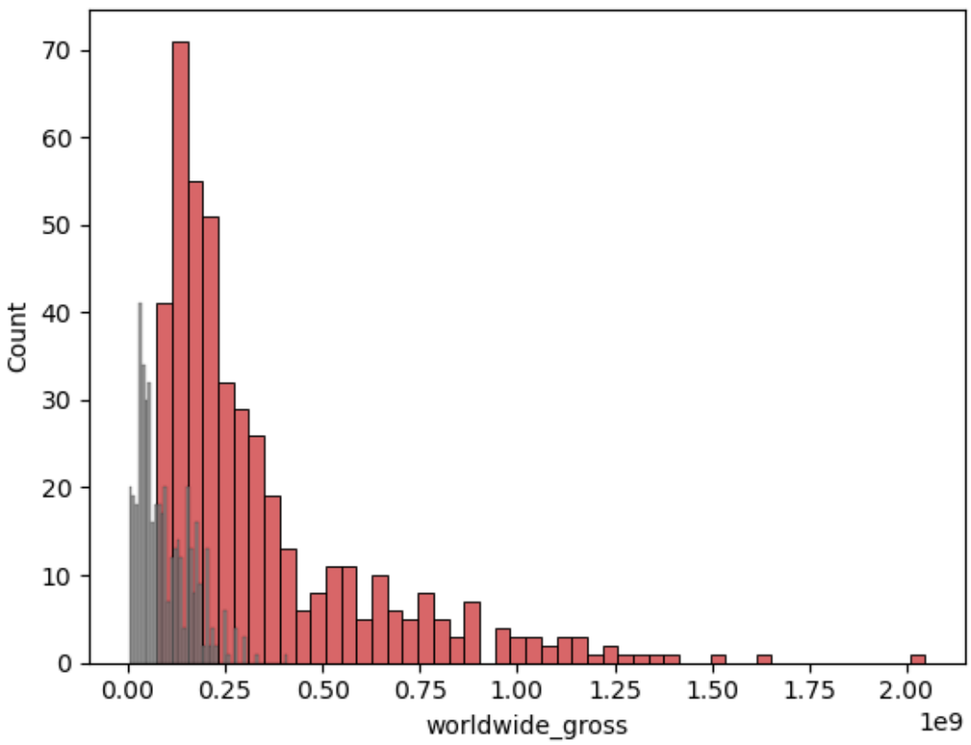
Out[500… <AxesSubplot:xlabel='production_budget', ylabel='Count'>



In [502…

```
sns.histplot(top_df, x = 'worldwide_gross', bins = 50)
sns.histplot(top_df, x = 'production_budget', bins = 50, color = 'grey')
```

Out[502… <AxesSubplot:xlabel='worldwide_gross', ylabel='Count'>



In [503…

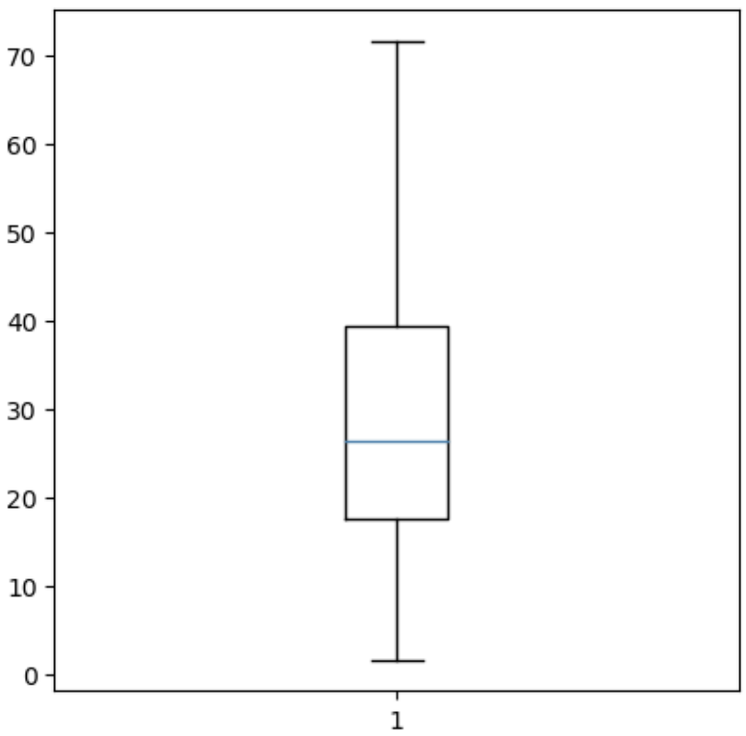
```
#Find the median and mean percentage production cost.
```

```
print("The median percentage of production costs for all films is",
      int(round(top_df["production_percent"].median())), "percent.")

print("The mean percentage of production costs for all films is",
      int(round(top_df["production_percent"].mean())), "percent.")
```

```
The median percentage of production costs for all films is 26 percent.
The mean percentage of production costs for all films is 32 percent.
```

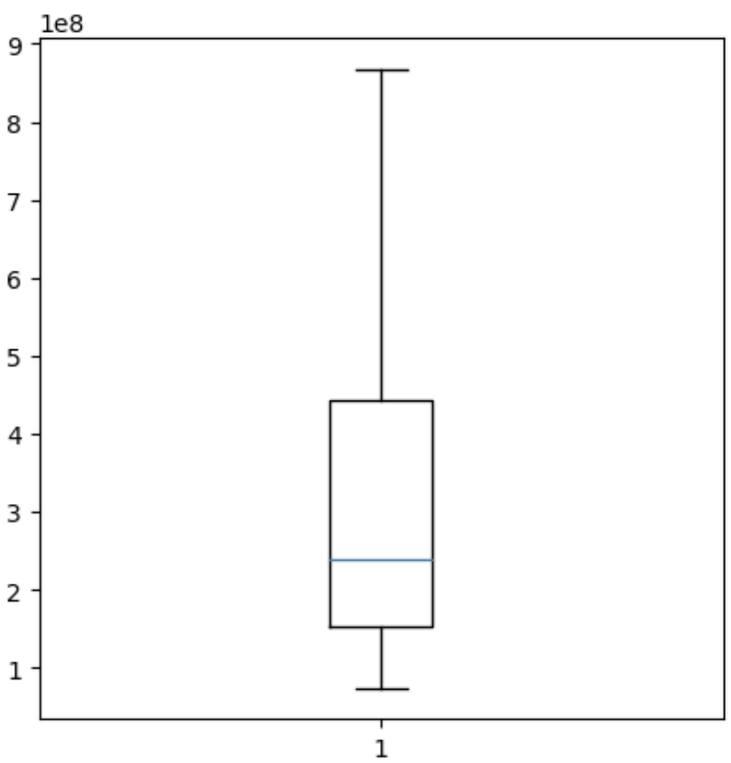
In [505…

```
fig, ax = plt.subplots(figsize=(5, 5))
plt.boxplot(top_df['production_percent'], showfliers = False);
```



In [504…

```
# Examine worldwide revenue median and ranges

fig, ax = plt.subplots(figsize=(5, 5))
plt.boxplot(top_df['worldwide_gross'], showfliers = False);
```



In [506…

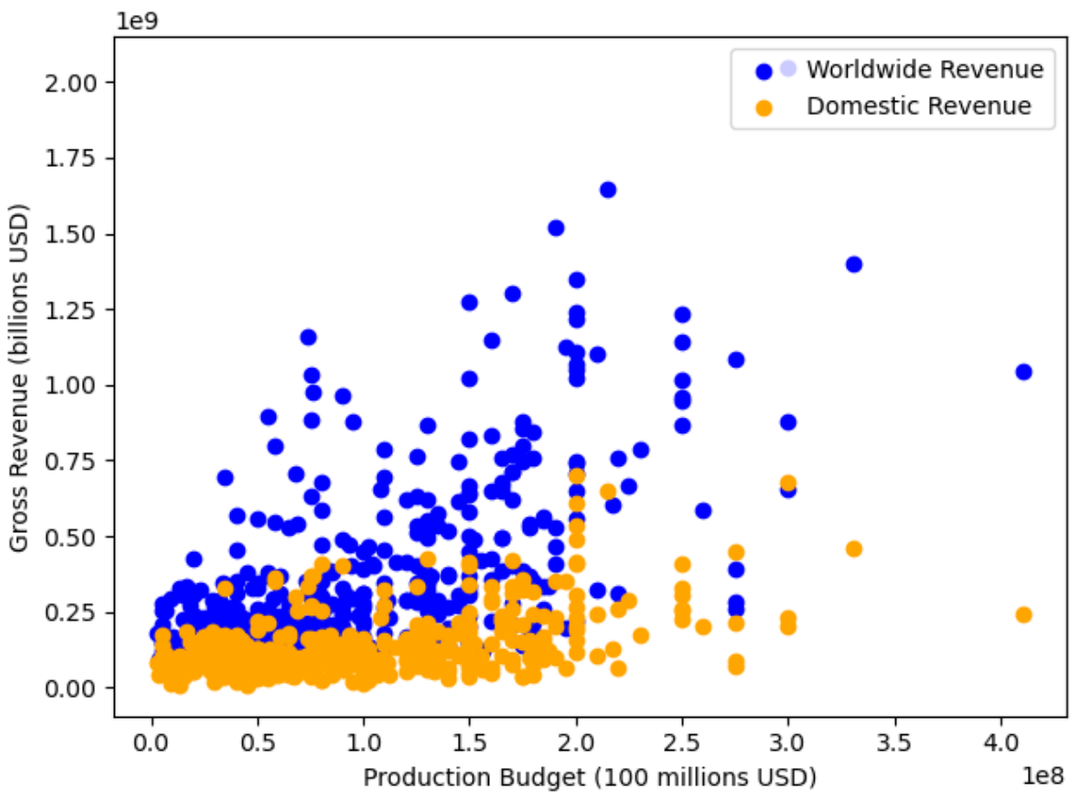
```
# Create reference stat dataframe of costs and gross

top_df[['production_budget', 'domestic_gross', 'worldwide_gross',
        'production_percent']].describe().astype(int)
```

Out[506…

	production_budget	domestic_gross	worldwide_gross	production_percent
count	450	450	450	450
mean	93217777	132092268	353442938	31
std	67813267	105363308	294687399	21
min	3000000	8178001	73866088	1
25%	40000000	63573607	153155012	17
50%	75000000	100269433	238949263	26
75%	140000000	162946882	443582754	39
max	410600000	700059566	2048134200	127

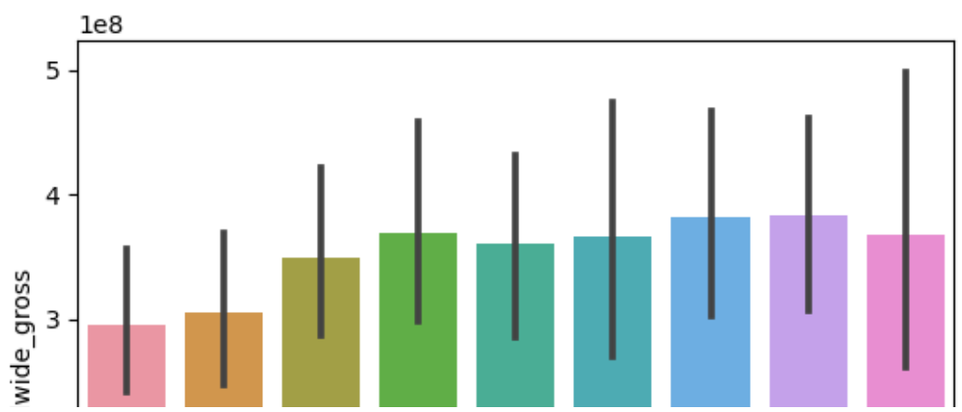
In [318…

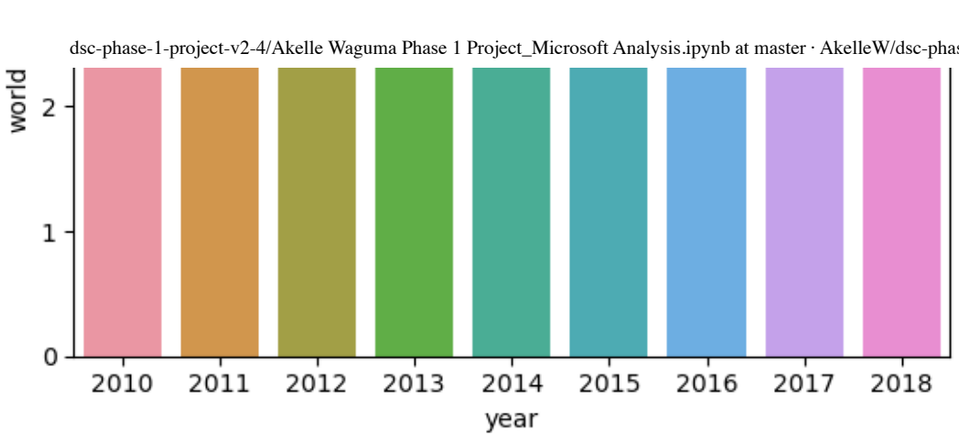
```
fig, ax = plt.subplots()

ax.scatter(top_df['production_budget'], top_df['worldwide_gross'],
           c ='blue')
ax.scatter(top_df['production_budget'], top_df['domestic_gross'],
           c ='orange')


ax.set_xlabel('Production Budget (100 millions USD)')
ax.set_ylabel('Gross Revenue (billions USD)')



ax.legend(['Worldwide Revenue', 'Domestic Revenue'], loc='upper right')
plt.tight_layout()
```



In [507…

```
sns.barplot(x ='year', y = 'worldwide_gross', data = top_df);
```

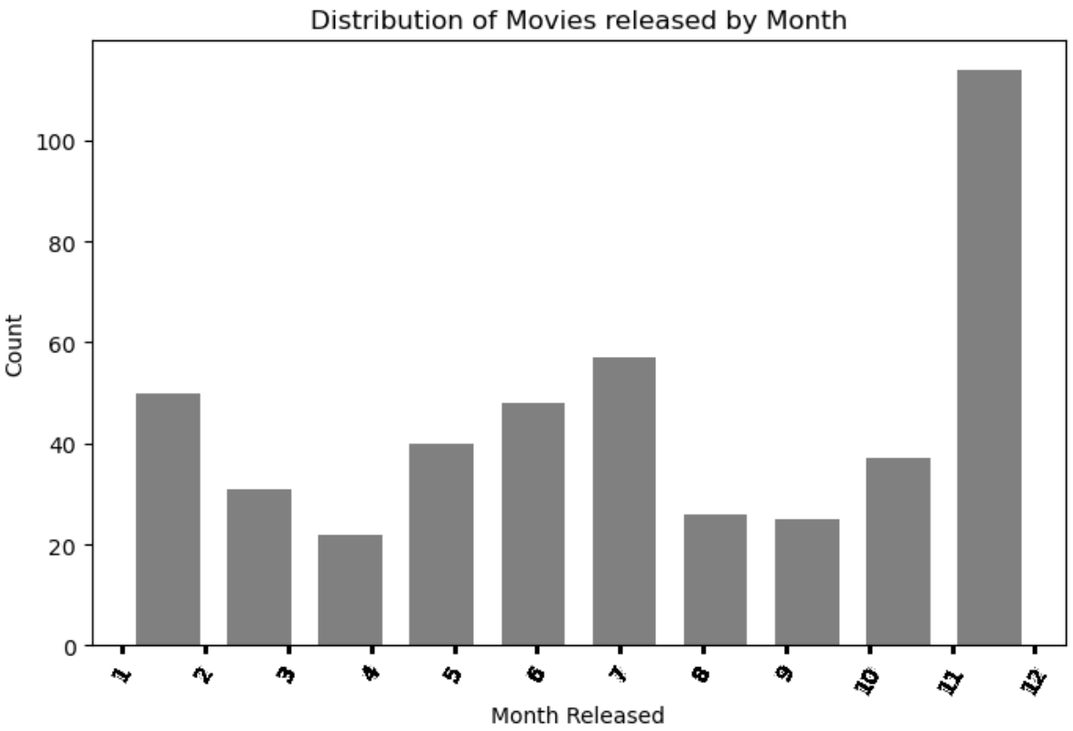




In [508…
```
top_df.columns
```

Out[508…
```
Index(['Movie_Title', 'studio', 'domestic_gross_x', 'foreign_gross', 'year',
       'production_budget', 'domestic_gross', 'worldwide_gross', 'movie_id_
x',
       'runtime_minutes_x', 'genres_x', 'averagerating_x', 'numvotes_x',
       'primary_title_y', 'original_title_y', 'runtime_minutes_y', 'genres_
y',
       'averagerating_y', 'numvotes_y', 'title', 'month_released', 'month_nu
m',
       'production_percent'],
      dtype='object')
```

In [510…
```
#Show histogram for which month films are released

fig, ax = plt.subplots(figsize = (8, 5))
ax.hist(top_df['month_num'], color='grey', rwidth = 0.7)
ax.set_xlabel('Month Released');
ax.set_ylabel('Count')
ax.set_title('Distribution of Movies released by Month')
plt.xticks(Merged_df['month_num'],
                  rotation=60);
```



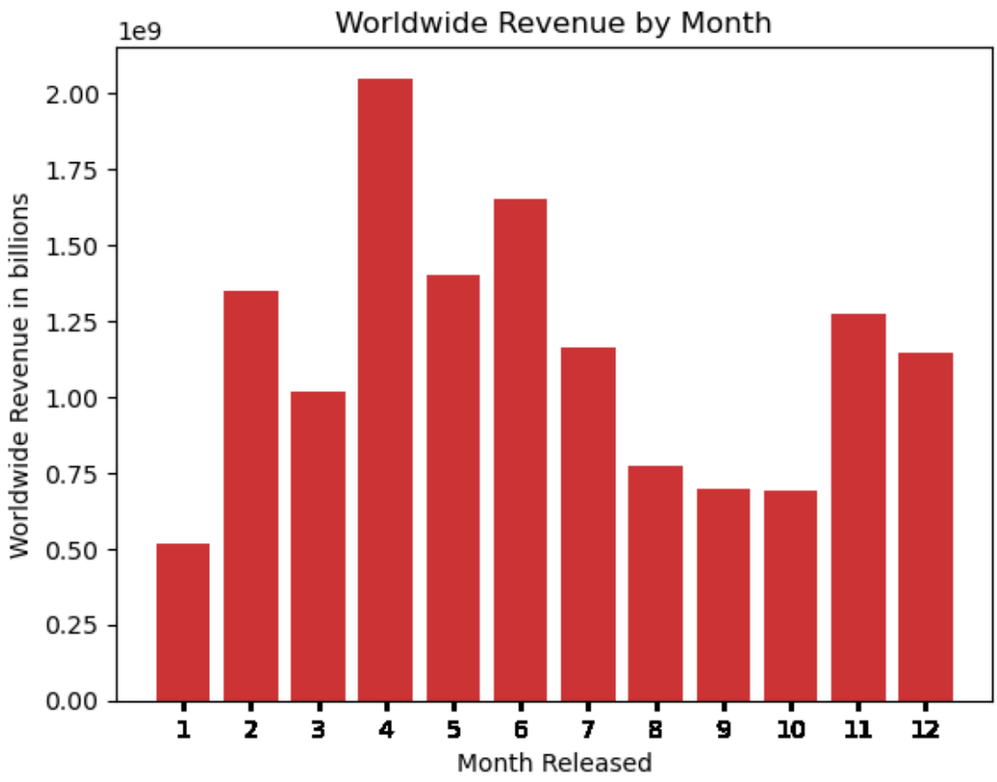
In [511…
```
top_df['month_released'].value_counts()
```

Out[511…
```
November     59
July         57
December     55
June         48
May          40
October      37
February     31
March        31
August       26
September    25
April        22
January      19
```

```
January      19
Name: month_released, dtype: int64
```

In [512…

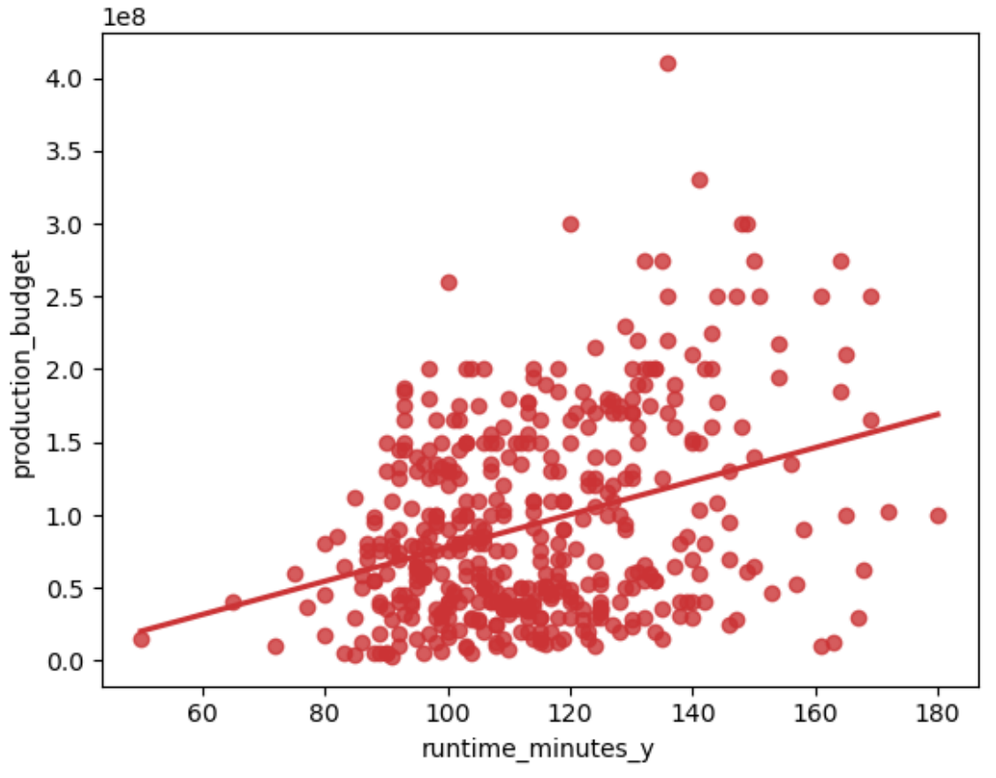
```
# Examine month released and their relationship to revenue.
fig, ax = plt.subplots()

plt.bar(top_df['month_num'], top_df['worldwide_gross'])

ax.set_xlabel('Month Released');
ax.set_ylabel('Worldwide Revenue in billions')
ax.set_title('Worldwide Revenue by Month')
plt.xticks(Merged_df['month_num']);
```



Visual Summary on Movie Release

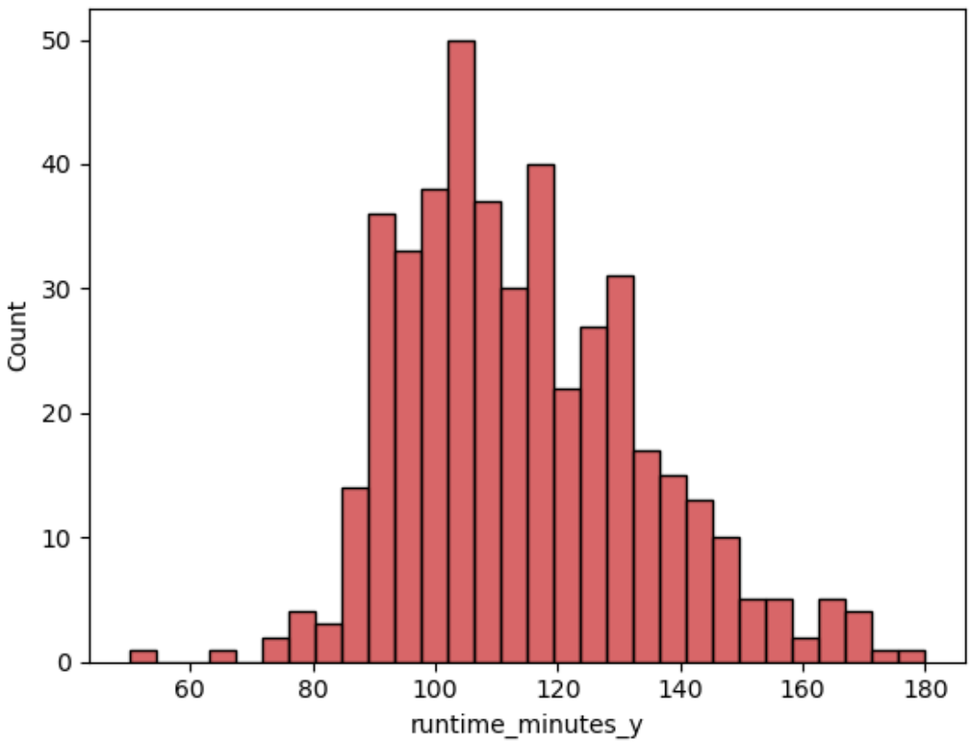
In [514…

```
# Examine relationship between runtime minutes and production budget in 100 
sns.regplot(x = "runtime_minutes_y",
            y = "production_budget",
            ci = None,
            data = top_df);
```



In [515…

```
#Identify the peak movie runtime, use histogram

sns.histplot(top_df, x = 'runtime_minutes_y', bins = 30);
```



In [516…

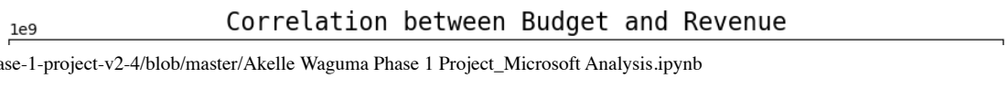
```
top_df.describe().astype(int)
```

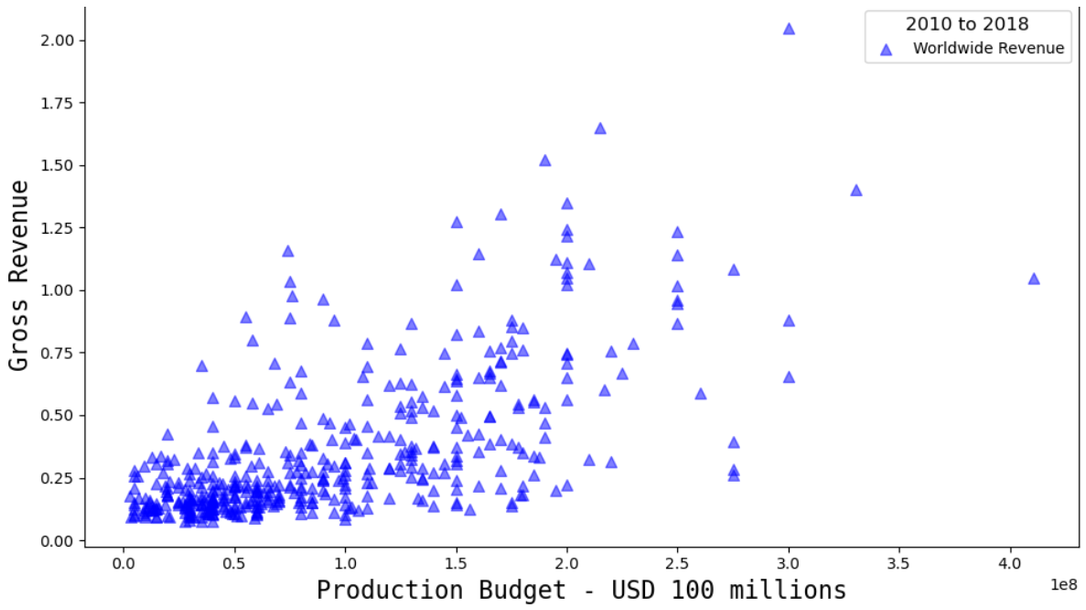
Out[516…

	domestic_gross_x	foreign_gross	year	production_budget	domestic_gross	wo
count	450	450	450	450	450	
mean	131524074	221350670	2014	93217777	132092268	
std	105787307	204594244	2	67813267	105363308	
min	25400	16100000	2010	3000000	8178001	
25%	62525000	80887642	2012	40000000	63573607	
50%	100200000	140218880	2014	75000000	100269433	
75%	162950000	291295377	2016	140000000	162946882	
max	700100000	1369318718	2018	410600000	700059566	

In [517…

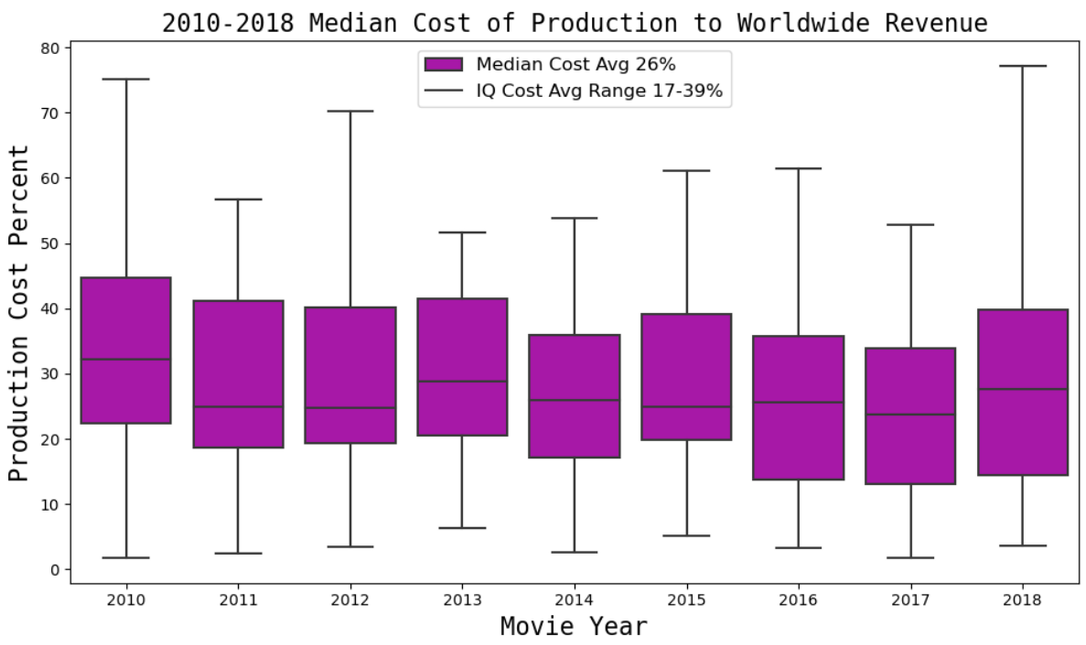
```
# Show relationship between production costs and revenue. Use scatterplot to

fig, ax = plt.subplots(figsize=(10,6))


ax.scatter(top_df['production_budget'], top_df['worldwide_gross'],
           c ='blue',
           alpha=0.5,
           s=50,
           marker='^')



#set labels
plt.xlabel('Production Budget - USD 100 millions', size=16, family='monospac
plt.ylabel('Gross Revenue', size=16, family='monospace')
plt.title('Correlation between Budget and Revenue', size=16,
          family='monospace', weight=500)


# Create Legend
ax.legend(['Worldwide Revenue', 'Domestic Revenue'], title = '2010 to 2018',
          title_fontsize = "12",loc='upper right')

plt.tight_layout();
```





In [518…

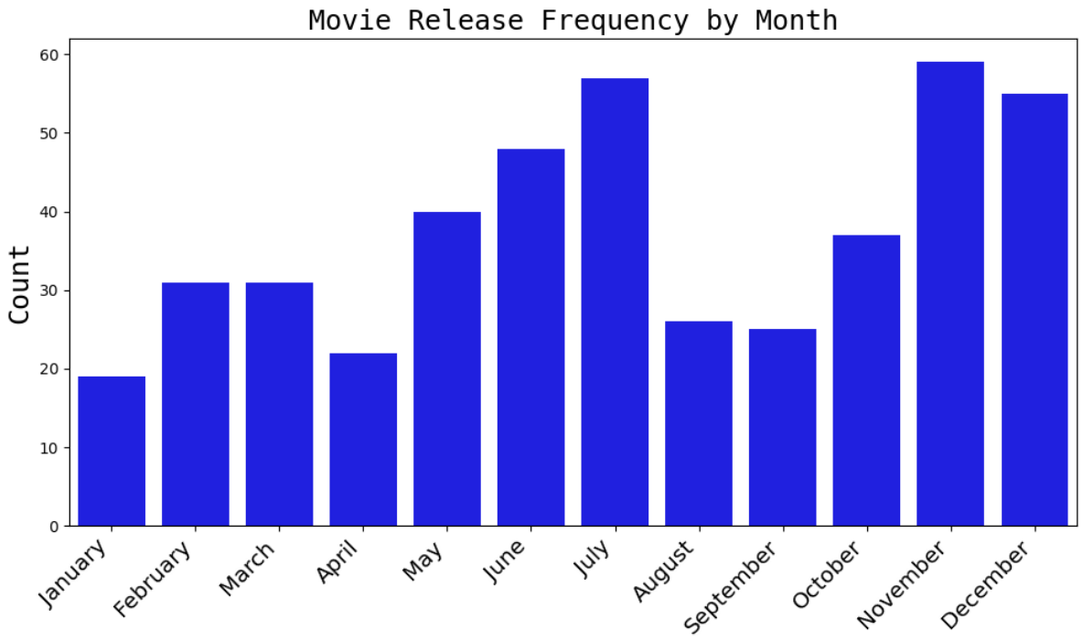
```
# Show the median and interquartile range of production budget percentages o

sns.set_palette("Set1", 8, .75)

plt.figure(figsize=(10,6))

box = sns.boxplot(x = top_df['year'], y = top_df['production_percent'],
                  showfliers = False, color = 'm')


# Add labels and title

plt.xlabel('Movie Year', size=16, family='monospace', weight=500)
plt.ylabel('Production Cost Percent', size=16, family='monospace')
plt.title('2010-2018 Median Cost of Production to Worldwide Revenue', size=1
          family='monospace', weight=500)

# Add text box labeling median, IQ range for all years

plt.legend(['Median Cost Avg 26%', 'IQ Cost Avg Range 17-39%'], fontsize = "
           loc='upper center')


plt.tight_layout();
```



In [331…

```
# Show most common months for movie release.


plt.figure(figsize=(10,6))


sns.countplot(x ='month_released', data = top_df, order = ['January', 'Febru
                                                           'March', 'April'
                                                           'June', 'July',
```

```
                                                                'September', 'Oc
                                                                'November', 'Dec
                color = 'b')

plt.xticks(
    rotation=45,
    horizontalalignment='right',
    fontweight='light',
    fontsize='x-large'
)

#Set Title and Axes Labels

plt.xlabel(None)
plt.ylabel('Count', size=18, family='monospace')
plt.title('Movie Release Frequency by Month', size=18, family='monospace', w

plt.tight_layout();
```



In [521…

```
# Create one more visualization for runtime minutes
plt.figure(figsize=(10,6))

sns.histplot(x ='runtime_minutes_y', data = top_df, bins = 30, color = 'slat

plt.xticks(
    rotation=60,
    horizontalalignment='right',
    fontweight='light',
    fontsize='x-large'
)

# Display median vertical line

plt.axvline(x=top_df.runtime_minutes_y.median(),
            color='grey')

# Label the axes

plt.xlabel('Runtime Minutes', size=16, family='monospace', weight=500)
plt.ylabel('Count', size=16, family='monospace')
plt.title('Movie Runtime in Minutes - Frequency Distribution', size=18,
          family='monospace', weight=500)

# Add detail

plt.legend(['Median: 112 Minutes', 'IQ Range: 99 to 127 Minutes'], title = '
          title_fontsize = "12",loc='center right')

plt.tight_layout();
```