BEST PERFORMING MOVIES AT THE BOX OFFICE ANALYSIS

OVERVIEW

Microsoft aims to maintain its competitive edge amid the rise of tech giants in the entertainment industry by venturing into a movie studio. Leveraging its expertise in data analytics and cloud technology, Microsoft can collect valuable user data, enabling personalized content recommendations and precise advertising. Additionally, the global appeal of streaming services offers a chance to expand its global presence and enhance brand recognition worldwide.

BUSINESS UNDERSTANDING

Microsoft has ventured into the movie production industry. Being new , they lack expertise on film production among them audience preference and industry patterns. In this project I explore the elements that influence and determine the high box office earnings attained by high performing films. This can be used to inform decisions on which films to create.

OBJECTIVES

- Analyze the budget allocation strategy and its impact on total revenue.
- Analyze the best-performing genres based on total revenue:
- Recommend an Optimized budget strategy enhanced by genre grouping:.
- Assess the influence of popularity and ratings on box office performance

DATA UNDERSTANDING

The movies datasets are from Box Office Mojo, IMDb, Rotten Tomatoes, Rotten Tomatoes Reviews , The MovieDB and The Numbers

In [95]:

```
# Import the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
```

In [96]:

```
# Load the datasets to pandas dataframes
box_office_mojo_df = pd.read_csv("bom.movie_gross.csv")
rotten_tomatoes_df = pd.read_csv("rt.movie_info.tsv",  delimiter='\t')
rt_reviews_df = pd.read_csv("rt.reviews.tsv", delimiter='\t', encoding='ISO-8859-
tmdb_df = pd.read_csv("tmdb.movies.csv", index_col=0)
tn_movie_budgets_df = pd.read_csv("tn.movie_budgets.csv")
```

Previewing The Dataset

Box Office Mojo

The dataset comprises information on a total of 3,387 movies, featuring details such as movie titles, studio names, domestic gross earnings, foreign gross earnings, and release years for each individual film.

In [97]:

```
box_office_mojo_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 [98]:

```
box_office_mojo_df.head()
```

Out[98]:

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

In [99]:

```
box_office_mojo_df.tail()
```

Out[99]:

	title	studio	domestic_gross	foreign_gross	year
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

In [100]:

```
box_office_mojo_df.shape
```

Out[100]:

```
(3387, 5)
```

In [101]:

```
box_office_mojo_df.columns
```

Out[101]:

```
Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'yea
r'], dtype='object')
```

In [102]:

```
box_office_mojo_df["title"].value_counts()
```

Out[102]:

```
Bluebeard                      2
The Sitter                     1
Fists of Legend                1
Learning to Drive              1
Felicite                       1
                              ..
50/50                          1
The House That Jack Built      1
Trumbo (2015)                  1
The Charmer                    1
Tower Heist                    1
Name: title, Length: 3386, dtype: int64
```

In [103]:

```
box_office_mojo_df.duplicated().sum()
```

Out[103]:

```
0
```

In [104]:

```
box_office_mojo_df[box_office_mojo_df["title"] == 'Bluebeard']
```

Out[104]:

	title	studio	domestic_gross	foreign_gross	year
317	Bluebeard	Strand	33500.0	5200	2010
3045	Bluebeard	WGUSA	43100.0	NaN	2017

There are no duplicates. Bluebeard movie appears twice and has been produced by different studios.

In [105]:

```
box_office_mojo_df["studio"].value_counts()
```

Out[105]:

```
IFC      166
Uni.     147
WB       140
Magn.    136
Fox      136
        ...
Swen       1
RME        1
FOAK       1
SEG        1
ELS        1
Name: studio, Length: 257, dtype: int64
```

There are missing values on domestic gross, and foreign gross columns.

In [106]:

```
box_office_mojo_df["domestic_gross"].value_counts()
```

Out[106]:

```
1100000.0      32
1000000.0      30
1300000.0      30
1200000.0      25
1400000.0      23
               ..
68800.0         1
87000000.0      1
739000.0        1
336000000.0     1
727000.0        1
Name: domestic_gross, Length: 1797, dtype: int64
```

In [107]:

```
box_office_mojo_df["foreign_gross"].value_counts()
```

Out[107]:

```
1200000      23
1100000      14
1900000      12
4200000      12
2500000      11
             ..
119000        1
435300000     1
17100000      1
116100000     1
137900000     1
Name: foreign_gross, Length: 1204, dtype: int64
```

In [108]:

```
box_office_mojo_df["year"].value_counts()
```

Out[108]:

```
2015    450
2016    436
2012    400
2011    399
2014    395
2013    350
2010    328
2017    321
2018    308
Name: year, dtype: int64
```

The Numbers Dataset

In [109]:

```
tn_movie_budgets_df.shape
```

Out[109]:

```
(5782, 6)
```

In [110]:

```
tn_movie_budgets_df.info()
```

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

The dataset has no nulls

In [111]:

```
tn_movie_budgets_df.columns
```

Out[111]:

```
Index(['id', 'release_date', 'movie', 'production_budget', 'domestic
_gross',
       'worldwide_gross'],
      dtype='object')
```

In [112]:

```
tn_movie_budgets_df["movie"].value_counts()
```

Out[112]:

```
Home                3
King Kong           3
Halloween           3
Shaft               2
The Island          2
                   ..
Action Point        1
Megamind            1
A Bridge Too Far    1
August              1
The Other Woman     1
Name: movie, Length: 5698, dtype: int64
```

In [113]:

```
tn_movie_budgets_df["release_date"].value_counts()
```

Out[113]:

```
Dec 31, 2014    24
Dec 31, 2015    23
Dec 31, 2010    15
Dec 31, 2008    14
Dec 31, 2013    13
                ..
Jun 14, 1996     1
Feb 5, 1993      1
Mar 18, 1994     1
Mar 1, 2000      1
Oct 21, 1994     1
Name: release_date, Length: 2418, dtype: int64
```

In [114]:

```
tn_movie_budgets_df["production_budget"].value_counts()
```

Out[114]:

```
$20,000,000     231
$10,000,000     212
$30,000,000     177
$15,000,000     173
$25,000,000     171
               ...
$2,850,000        1
$317,000,000      1
$106,000,000      1
$3,450,000        1
$609,000          1
Name: production_budget, Length: 509, dtype: int64
```

In [115]:

```
tn_movie_budgets_df["domestic_gross"].value_counts()
```

Out[115]:

```
$0             548
$8,000,000       9
$7,000,000       7
$2,000,000       7
$10,000,000      6
              ...
$10,915,744      1
$60,323,786      1
$40,363,530      1
$57,924,679      1
$19,438,638      1
Name: domestic_gross, Length: 5164, dtype: int64
```

In [116]:

```
tn_movie_budgets_df["worldwide_gross"].value_counts()
```

Out[116]:

```
$0              367
$8,000,000        9
$7,000,000        6
$2,000,000        6
$9,000,000        4
               ...
$69,792,704       1
$42,227,490       1
$23,661,038       1
$615,461,394      1
$18,250,106       1
Name: worldwide_gross, Length: 5356, dtype: int64
```

There are movies with the same title but are not duplicates.

The Movie Dataset

In [117]:

```
tmdb_df.shape
```

Out[117]:

```
(26517, 9)
```

In [118]:

```
tmdb_df.info()
```

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

There are no null values.

In [119]:

```
tmdb_df["genre_ids"].value_counts()
```

Out[119]:

```
[99]                         3700
[]                           2479
[18]                         2268
[35]                         1660
[27]                         1145
                             ...
[28, 35, 80, 37]                1
[18, 10402, 10749, 35]          1
[80, 28, 18, 10770]             1
[10751, 10749, 35]              1
[27, 53, 9648, 878]             1
Name: genre_ids, Length: 2477, dtype: int64
```

In [120]:

```
tmdb_df["original_language"].value_counts()
```

Out[120]:

```
en    23291
fr      507
es      455
ru      298
ja      265
      ...
yi        1
ps        1
xh        1
nb        1
cr        1
Name: original_language, Length: 76, dtype: int64
```

In [121]:

```
tmdb_df["title"].value_counts()
```

Out[121]:

```
Home                                    7
Eden                                    7
The Box                                 5
Legend                                  5
Aftermath                               5
                                       ..
I Used to Be Darker                     1
Stars in the Park: The Right Now        1
Misdirection: The Horror Comedy         1
Platinum the Dance Movie                1
Breastmilk                              1
Name: title, Length: 24688, dtype: int64
```

In [122]:

```
tmdb_df["release_date"].value_counts()
```

Out[122]:

```
2010-01-01    269
2011-01-01    200
2012-01-01    155
2014-01-01    155
2013-01-01    145
             ...
1980-11-21      1
1998-07-01      1
2015-02-16      1
2009-04-25      1
2007-04-10      1
Name: release_date, Length: 3433, dtype: int64
```

In [123]:

```
tmdb_df["popularity"].value_counts()
```

Out[123]:

```
0.600     7037
1.400      649
0.840      587
0.624      104
0.625       92
          ...
3.742        1
14.749       1
7.924        1
8.414        1
9.060        1
Name: popularity, Length: 7425, dtype: int64
```

IMDb

In [124]:

```
conn = sqlite3.connect("im.db")
```

In [125]:

```
# query = """
#     SELECT primary_title, start_year, runtime_minutes, genres
#     FROM movie_basics
#     WHERE runtime_minutes IS NOT NULL AND genres IS NOT NULL
# """
query2 = """
    SELECT mb.primary_title AS title, mb.start_year, mb.runtime_minutes, mb.genre
    FROM movie_basics mb
    JOIN movie_ratings mv
    ON mb.movie_id = mv.movie_id
    WHERE runtime_minutes IS NOT NULL AND genres IS NOT NULL
"""
# IMDb_df = pd.read_sql(query, conn).isna().any()
IMDb_popularity = pd.read_sql(query2, conn)
IMDb_popularity.head()
```

Out[125]:

	title	start_year	runtime_minutes	genres	rating	votes
0	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
1	One Day Before the Rainy Season	2019	114.0	Biography,Drama	7.2	43
2	The Other Side of the Wind	2018	122.0	Drama	6.9	4517
3	The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy	6.5	119
4	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy	8.1	263

In [126]:

```
# close the connection to the database
conn.close()
```

Data Cleaning

Box Office Mojo

Check and deal with NaN and missing values

In [127]:

```
# Check for NaN values in domestic_gross column
box_office_mojo_df["domestic_gross"].isna().sum()
```

Out[127]:

28

In [128]:

```
# drop the columns with NaN values in domestic_gross column
box_office_mojo_df.dropna(subset=["domestic_gross"], inplace=True)
box_office_mojo_df["foreign_gross"].isna().sum()
```

Out[128]:

```
1350
```

In [129]:

```
# Check for NaN values in foreign_gross column
box_office_mojo_df["foreign_gross"].isna().sum()
```

Out[129]:

```
1350
```

In [130]:

```
# drop the columns with NaN values in foreign_gross column
box_office_mojo_df.dropna(subset=["foreign_gross"], inplace=True)
```

In [131]:

```
box_office_mojo_df["studio"].isna().sum()
```

Out[131]:

```
2
```

In [132]:

```
# There are only two data without studios, we can drop them
box_office_mojo_df.dropna(subset=["studio"], inplace=True)
```

In [133]:

```
# confirm there are no missing values in the dataset
box_office_mojo_df.isna().any()
```

Out[133]:

```
title             False
studio            False
domestic_gross    False
foreign_gross     False
year              False
dtype: bool
```

There are no missing values.

The foreign column should be changed to a float datatype

In [134]:

```
box_office_mojo_df.dtypes
```

Out[134]:

```
title              object
studio             object
domestic_gross    float64
foreign_gross      object
year                int64
dtype: object
```

In [135]:

```
# replace the commas and the change to a float type
box_office_mojo_df["foreign_gross"] = box_office_mojo_df["foreign_gross"].str.rep
box_office_mojo_df.dtypes
```

Out[135]:

```
title              object
studio             object
domestic_gross    float64
foreign_gross     float64
year                int64
dtype: object
```

In [136]:

```
box_office_mojo_df.info()
# The dataset is now clean.
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2007 entries, 0 to 3353
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           2007 non-null   object 
 1   studio          2007 non-null   object 
 2   domestic_gross  2007 non-null   float64
 3   foreign_gross   2007 non-null   float64
 4   year            2007 non-null   int64  
dtypes: float64(2), int64(1), object(2)
memory usage: 94.1+ KB
```

The Numbers

This dataset has no null values but has placeholders in the domestic gross and worldwide gross.

In [137]:

```
# The missing values are denoted by $0
tn_movie_budgets_df["domestic_gross"].value_counts()
```

Out[137]:

```
$0              548
$8,000,000        9
$7,000,000        7
$2,000,000        7
$10,000,000       6
               ...
$10,915,744       1
$60,323,786       1
$40,363,530       1
$57,924,679       1
$19,438,638       1
Name: domestic_gross, Length: 5164, dtype: int64
```

In [138]:

```
# The missing values are denoted by $0
tn_movie_budgets_df["worldwide_gross"].value_counts()
```

Out[138]:

```
$0                367
$8,000,000          9
$7,000,000          6
$2,000,000          6
$9,000,000          4
                 ...
$69,792,704         1
$42,227,490         1
$23,661,038         1
$615,461,394        1
$18,250,106         1
Name: worldwide_gross, Length: 5356, dtype: int64
```

In [139]:

```
# Drop the  rows with $0 in domestic gross and worldwide gross
tn_movie_budgets_df = tn_movie_budgets_df[(tn_movie_budgets_df["domestic_gross"]
```

Change the domestic and worlwide gross columns to float

In [140]:

```
def floating(amount):
    new_amount = None
    if type(amount) == str:
        new_amount = float(amount.strip('$').replace(',',''))
    else:
        new_amount = float(amount)

    return new_amount
tn_movie_budgets_df["domestic_gross"] = tn_movie_budgets_df["domestic_gross"].map
tn_movie_budgets_df["worldwide_gross"] = tn_movie_budgets_df["worldwide_gross"].m
```

Rename the movie and worldwide gross column

In [141]:

```
#renaming the movie and worlwide gross columns
tn_movie_budgets_df.rename(columns = {'worldwide_gross': 'foreign_gross', 'movie'
```

In [142]:

```
#Getting only the year from the release date, changed to year
tn_movie_budgets_df["release_date"] = tn_movie_budgets_df["release_date"].map(lam
tn_movie_budgets_df.rename(columns={"release_date": "year"}, inplace=True)
```

In [143]:

```
# changing the production budget to float
tn_movie_budgets_df["production_budget"] = tn_movie_budgets_df["production_budget
```

In [144]:

```
tn_movie_budgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5415 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5415 non-null   int64
 1   year               5415 non-null   int64
 2   title              5415 non-null   object
 3   production_budget  5415 non-null   float64
 4   domestic_gross     5415 non-null   float64
 5   foreign_gross      5415 non-null   float64
dtypes: float64(3), int64(2), object(1)
memory usage: 296.1+ KB
```

The movie Dataset

Dealing with nan values

In [145]:

```
# check for duplicated values
tmdb_df[tmdb_df.duplicated(keep=False)]
```

Out[145]:

	genre_ids	id	original_language	original_title	popularity	release_date	titl
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Stor
10	[16, 35, 10751]	863	en	Toy Story 2	22.698	1999-11-24	Toy Story
43	[35, 10749]	239	en	Some Like It Hot	14.200	1959-03-18	Some Lik It Hc
54	[12, 28, 878]	20526	en	TRON: Legacy	13.459	2010-12-10	TRON Legac
56	[35, 16, 10751]	9994	en	The Great Mouse Detective	13.348	1986-07-02	The Grea Mous Detectiv
...	...	...	...	...	...	...	.
26481	[35, 18]	270805	en	Summer League	0.600	2013-03-18	Summe Leagu
26485	[27, 53]	453259	en	Devils in the Darkness	0.600	2013-05-15	Devils i th Darknes
26504	[27, 35, 27]	534282	en	Head	0.600	2015-03-28	Hea
26510	[99]	495045	en	Fail State	0.600	2018-10-19	Fail Stat
26511	[99]	492837	en	Making Filmmakers	0.600	2018-04-07	Makin Filmmaker

2016 rows × 9 columns

In [146]:

```
# investigating more on the duplicates
tmdb_df[tmdb_df["title"] == 'Toy Story']
```

Out[146]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_av
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
2473	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	

In [147]:

```
# dropping the duplicates
tmdb_df.drop_duplicates(inplace=True)
```

In [148]:

```
#checking for any other duplicate
tmdb_df.duplicated().any()
```

Out[148]:

```
False
```

Dropping columns.

In [149]:

```
# drop the genre_ids.A significant number of rows have an empty list.
tmdb_df.drop("genre_ids", axis=1, inplace=True)
```

In [150]:

```
# investigating the original_title and the title
tmdb_df[["original_title", "title"]]

# They have similar values in both. We drop original_title
tmdb_df.drop("original_title", axis=1, inplace=True)
```

In [151]:

```
#drop the vote_average ,vote_count and popularity
# tmdb_df.drop(["vote_average", "vote_count"], axis=1, inplace=True)
```

Change the release date to year

In [152]:

```
tmdb_df.rename(columns={"release_date": "year"}, inplace=True)
tmdb_df["year"] = tmdb_df["year"].map(lambda x: x.split('-')[0])
```

In [153]:

```
tmdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25497 entries, 0 to 26516
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 25497 non-null  int64
 1   original_language  25497 non-null  object
 2   popularity         25497 non-null  float64
 3   year               25497 non-null  object
 4   title              25497 non-null  object
 5   vote_average       25497 non-null  float64
 6   vote_count         25497 non-null  int64
dtypes: float64(2), int64(2), object(3)
memory usage: 1.6+ MB
```

Feature Engineering

Add total revenue column as the sum of domestic gross and foreign gross to the BOM and The Numbers Dataset

In [154]:

```
# creating a total revenue column as the sum of foreign and domestic gross
box_office_mojo_df["total_revenue"] = box_office_mojo_df["domestic_gross"] + box_
box_office_mojo_df.head()
```

Out[154]:

	title	studio	domestic_gross	foreign_gross	year	total_revenue
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1.067000e+09
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010	9.603000e+08
3	Inception	WB	292600000.0	535700000.0	2010	8.283000e+08
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	7.526000e+08

In [155]:

```
tn_movie_budgets_df["total_revenue"] = tn_movie_budgets_df["domestic_gross"] + tn_
tn_movie_budgets_df.head()
```

Out[155]:

	id	year	title	production_budget	domestic_gross	foreign_gross	total_revenue
0	1	2009	Avatar	425000000.0	760507625.0	2.776345e+09	3.536853e+09
1	2	2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	1.286728e+09
2	3	2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	1.925247e+08
3	4	2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	1.862020e+09
4	5	2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	1.936903e+09

Merge The Numbers DataFrame and IMDb data

In [156]:

```
tn_IMDb_df = pd.merge(tn_movie_budgets_df, IMDb_popularity, how='inner', on='titl
tn_IMDb_df.head()
```

Out[156]:

	id	year	title	production_budget	domestic_gross	foreign_gross	total_revenue	sta
0	1	2009	Avatar	425000000.0	760507625.0	2.776345e+09	3.536853e+09	
1	2	2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	1.286728e+09	
2	3	2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	1.925247e+08	
3	4	2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	1.862020e+09	
4	7	2018	Avengers: Infinity War	300000000.0	678815482.0	2.048134e+09	2.726950e+09	

Merging The movie dataset and The numbers dataset

In [157]:

```
tm_tn_df = pd.merge(tmdb_df, tn_movie_budgets_df, how="inner", on="title")
tm_tn_df.head()
```

Out[157]:

	id_x	original_language	popularity	year_x	title	vote_average	vote_count	id_y
0	10191	en	28.734	2010	How to Train Your Dragon	7.7	7610	30
1	10138	en	28.515	2010	Iron Man 2	6.8	12368	15
2	862	en	28.005	1995	Toy Story	7.9	10174	37
3	27205	en	27.920	2010	Inception	8.3	22186	38
4	32657	en	26.691	2010	Percy Jackson & the Olympians: The Lightning T...	6.1	4229	17

Data Analysis

Univariate Analysis

Total Revenue

In [158]:

```
total_revenue_mean = tn_movie_budgets_df["total_revenue"].mean()
f"The average total revenue from making movies is {total_revenue_mean}"
```

Out[158]:

```
'The average total revenue from making movies is 142399275.144229'
```

In [159]:

```
total_revenue_median = tn_movie_budgets_df["total_revenue"].median()
f"The total revenue median is {total_revenue_median}"
```

Out[159]:

```
'The total revenue median is 54200060.0'
```

The total revenue mode

In [160]:

```
total_revenue_mode = tn_movie_budgets_df["total_revenue"].mode()
f"The total revenue mode is {total_revenue_mode}"
total_revenue_mode
```

Out[160]:

```
0    16000000.0
dtype: float64
```

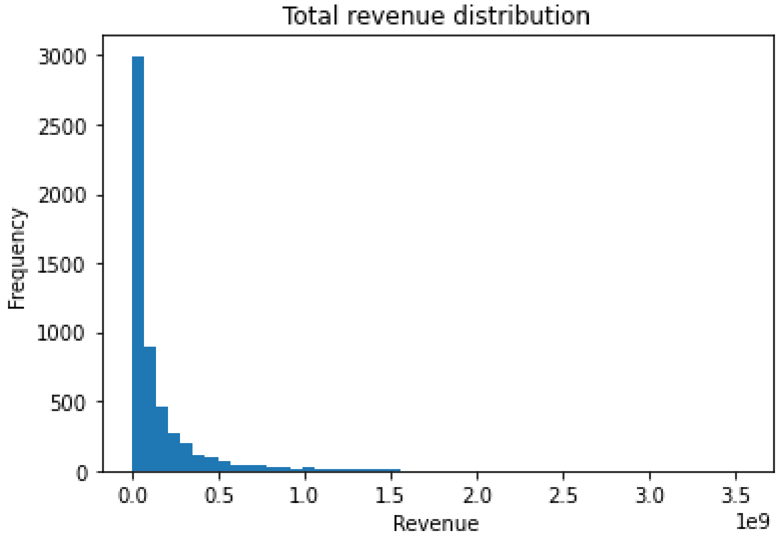
Revenue distribution

In [161]:

```
fig, ax = plt.subplots()
ax.hist(tn_movie_budgets_df["total_revenue"], bins=50)
ax.set_title("Total revenue distribution")
ax.set_ylabel("Frequency")
ax.set_xlabel("Revenue")
# ax.set_ylim(-1000, 6000);
```

Out[161]:

```
Text(0.5, 0, 'Revenue')
```



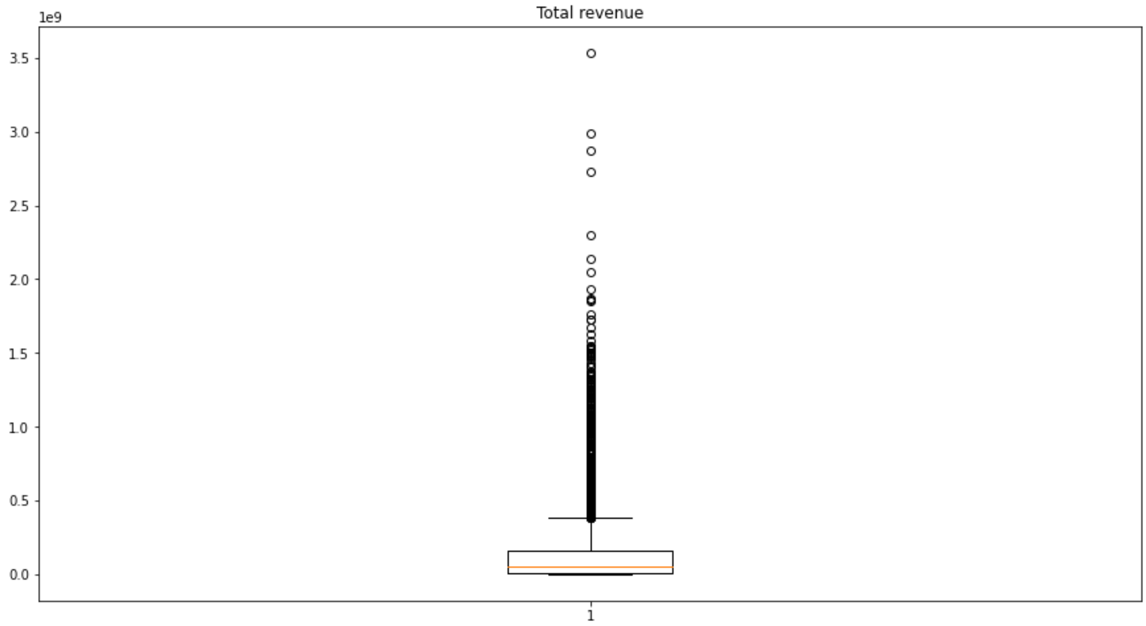
The distribution is positvely skewed. The mean of the data is greater than the median. The mean is pulled towards the right tail while the median is the middle value of the data. This means the outliers of the distribution curve are further out towards the right and closer to the mean on the left

In [162]:

```
fig, ax = plt.subplots(figsize=(15,8))
ax.boxplot(tn_movie_budgets_df["total_revenue"])
ax.set_title("Total revenue")
```

Out[162]:

```
Text(0.5, 1.0, 'Total revenue')
```



In [163]:

```
tn_movie_budgets_df["total_revenue"].quantile([0.25, 0.5, 0.75])
```

Out[163]:

```
0.25     11386162.0
0.50     54200060.0
0.75    161210344.5
Name: total_revenue, dtype: float64
```

Conclusion:
The boxplot and the quartile range confirm that the distribution of the total revenue is positively skewed. Most movies are likely to have a relatively lower total revenue but there are few movies with significantly higher revenue that contribute to the skewness. The movies with the significantly higher revenue are the best performers at the box office.
The median total revenue is `$ 54,200,060` . Movies with revenue higher than `$241,815,516` may be considered outliers.
The wide range between the 25th and 75th percentiles suggests a substantial variability in total revenue. This variability could be attributed to factors such as genre, popularity and production budget.

Production budget

Production budget mean

In [164]:

```
production_budget_mean = tn_movie_budgets_df["production_budget"].mean()
f"The average production budget in  making movies is {production_budget_mean}"
```

Out[164]:

```
'The average production budget in  making movies is 33308006.0853185
58'
```

Production budget median

In [165]:

```
total_revenue_median = tn_movie_budgets_df["production_budget"].median()
f"The production budget median is {total_revenue_median}"
```

Out[165]:

```
'The production budget median is 19000000.0'
```

In [166]:

```
total_revenue_mode = tn_movie_budgets_df["production_budget"].mode()
f"The production budget mode is {total_revenue_mode}"
```

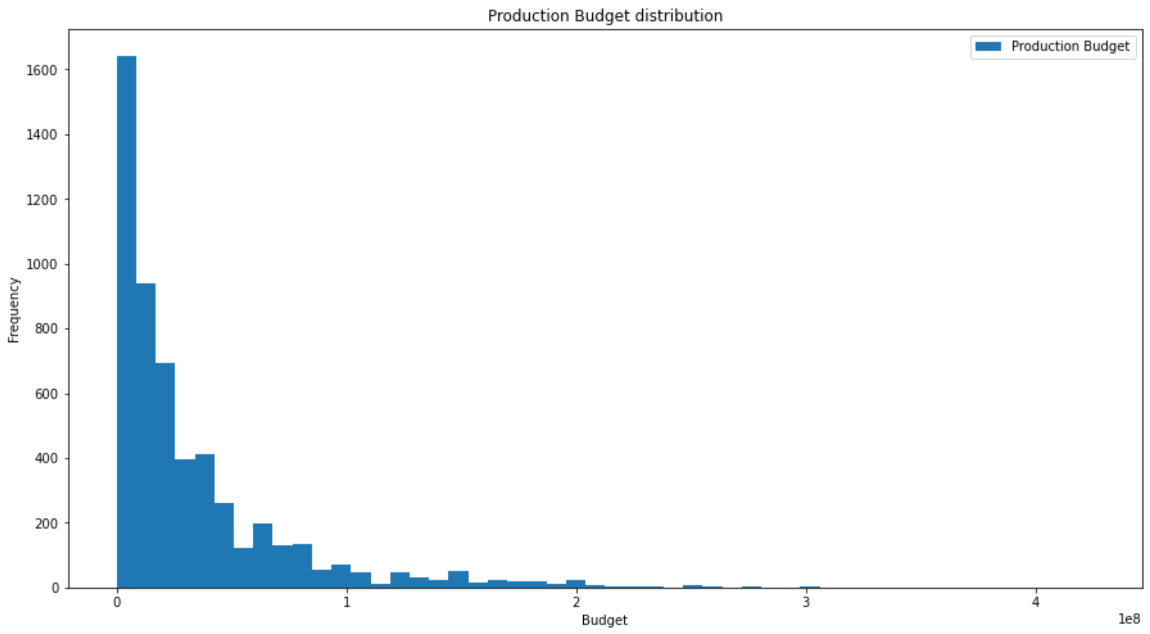
Out[166]:

```
'The production budget mode is 0    20000000.0\ndtype: float64'
```

Production budget Distribution

In [167]:

```
fig, ax = plt.subplots(figsize=(15,8))
ax.hist(tn_movie_budgets_df["production_budget"], bins=50)
ax.legend(["Production Budget"]);
ax.set_title("Production Budget distribution")
ax.set_ylabel("Frequency")
ax.set_xlabel("Budget");
```



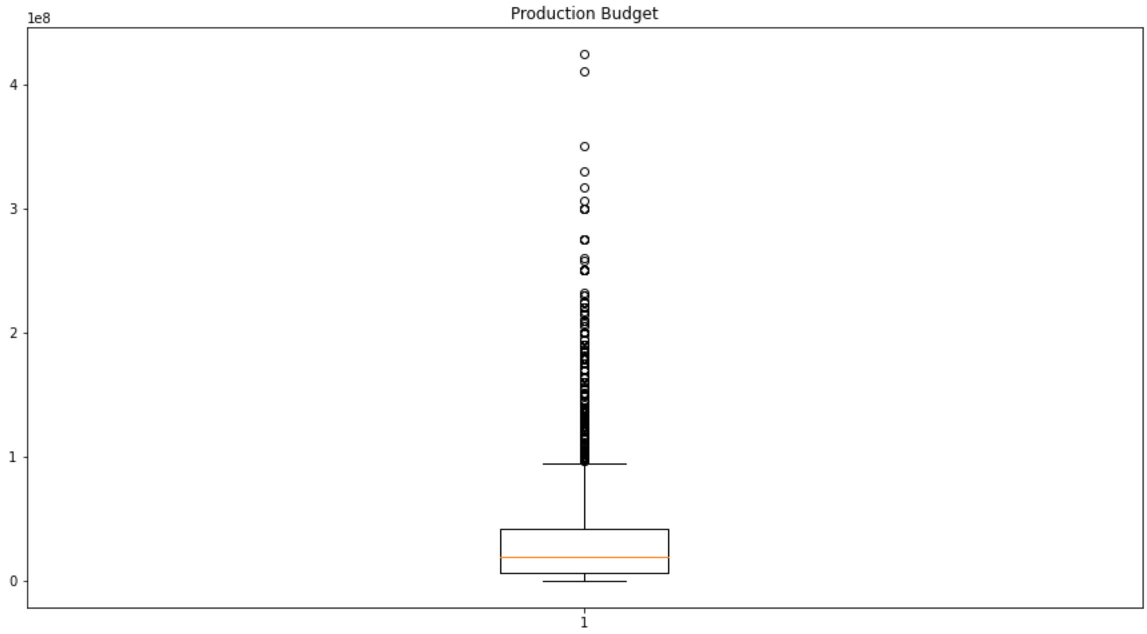
The distribution is positvely skewed. The mean of the data is then greater than the median. The median is the middle value of the data. This means the outliers of the distribution curve are

In [168]:

```
fig, ax = plt.subplots(figsize=(15,8))
ax.boxplot(tn_movie_budgets_df["production_budget"])
ax.set_title("Production Budget")
```

Out[168]:

```
Text(0.5, 1.0, 'Production Budget')
```



In [169]:

```
tn_movie_budgets_df["production_budget"].quantile([0.25, 0.5, 0.75])
```

Out[169]:

```
0.25     6000000.0
0.50    19000000.0
0.75    42000000.0
Name: production_budget, dtype: float64
```

Conclusion:
The box plot confirms that the distribution of the production budget is positively skewed. Most projects are likely to have a relatively lower production budget, but there are a few movies with significantly higher production budgets and that contributes to the skewness.
The median production budget is `$19000000`. Movies with production budgets higher than `$63000000` are considered outliers compared to the majority of the movies and can be influential in skewing the distribution to the right.

Bivariate analysis

How does the production budget affect the total revenue

In [170]:

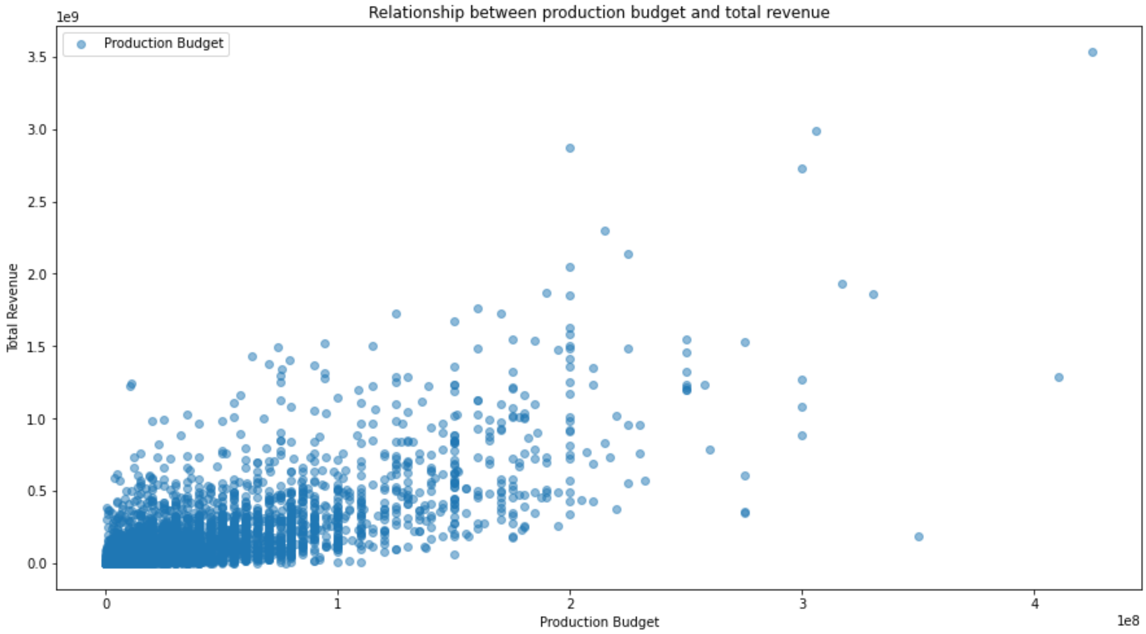
```
#Finding the pearson correlation coefficient(r)
tn_movie_budgets_df["production_budget"].corr(tn_movie_budgets_df["total_revenue"
```

Out[170]:

0.736922079129125

In [171]:

```
#Visualize the relationship between the production budget and the total revenue
fig, ax = plt.subplots(figsize=(15,8))
ax.scatter(tn_movie_budgets_df["production_budget"], tn_movie_budgets_df["total_r
ax.legend(["Production Budget"]);
ax.set_title("Relationship between production budget and total revenue")
ax.set_ylabel("Total Revenue")
ax.set_xlabel("Production Budget");
```



There is a strong positive correlation between production budget and total revenue. As the production budget increases, total revenue tends to increase. However it is not a perfect relationship. Some movies with high budgets may not perform as well as expected and some movies with lower budgets may outperform expectations.

Relationship between IMDb rating and total revenue

We can explore the potential relationship between movie ratings and total revenue in the IMDb dataset by creating a scatter plot, allowing us to visually analyze any correlation between these two variables.

In [172]:

```
# The pearson correlation between  IMDb rating and total revenue
tn_IMDb_df["total_revenue"].corr(tn_IMDb_df["rating"],method ='pearson')
```

Out[172]:

0.16627140240868443

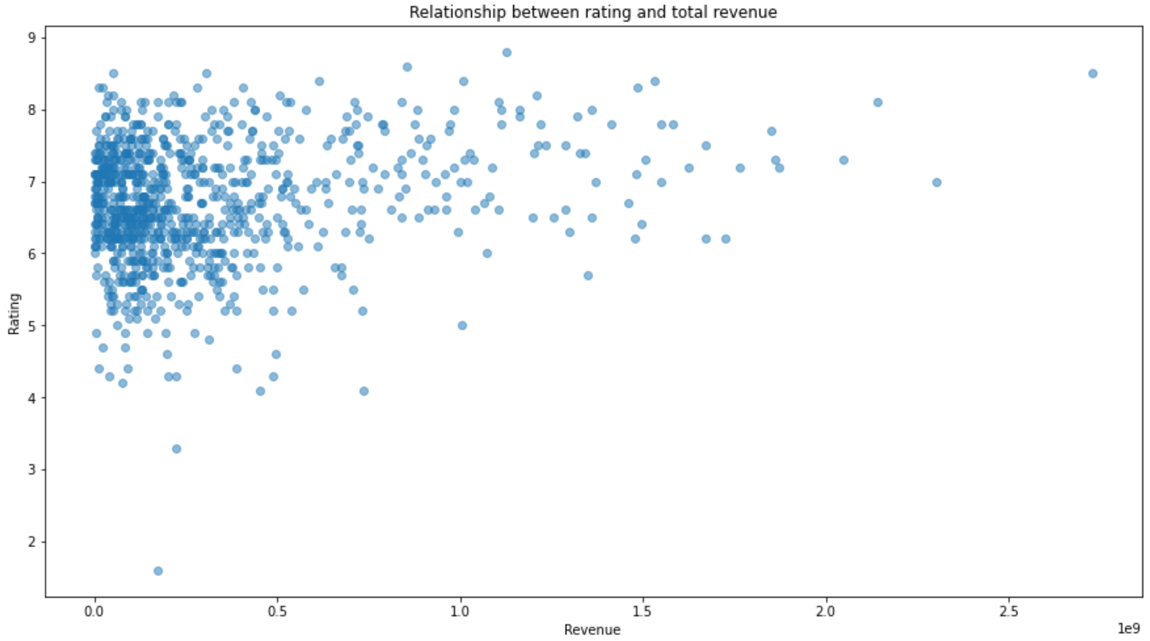
There is a weak positive relationship between total revenue and the IMDb rating

In [173]:

```
# Visualize the relationship betweeb total revenie and  IMDb rating.
tn_IMDb_df_2 = tn_IMDb_df[tn_IMDb_df["votes"] > 50000]
fig, ax = plt.subplots(figsize=(15, 8))
ax.scatter(tn_IMDb_df_2["total_revenue"], tn_IMDb_df_2["rating"], alpha=0.5)
ax.set_title("Relationship between rating and total revenue")
ax.set_xlabel("Revenue")
ax.set_ylabel("Rating")
```

Out[173]:

```
Text(0, 0.5, 'Rating')
```



There is a very weak positive relationship between the IMDb rating and total revenue of the movies. Highly rated movies do not tend to have high revenue. The rating of a movie does not imply a high total revenue.

Relationship between popularity and total revenue

The Movie DB dataset has a column popularity. We could use this column to explore if there is any relationship between the popularity of the movies and the total revenue by each movie

In [174]:

```
# correlation between the popularity and the total revenue of films
tm_tn_df.head()
tm_tn_df["popularity"].corr(tm_tn_df["total_revenue"])
```

Out[174]:

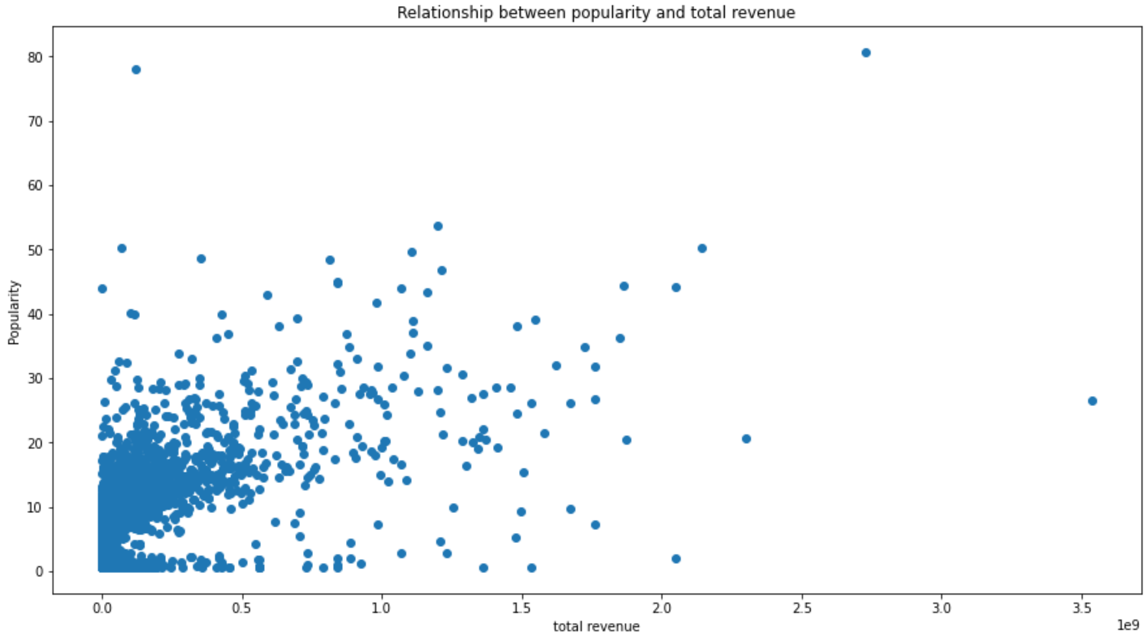
```
0.5407727484863285
```

In [175]:

```
# Visualize the correlation between the popularity and the total revenue
fig, ax = plt.subplots(figsize=(15, 8))
ax.scatter(tm_tn_df["total_revenue"], tm_tn_df["popularity"])
ax.set_title("Relationship between popularity and total revenue")
ax.set_xlabel("total revenue")
ax.set_ylabel("Popularity")
```

Out[175]:

```
Text(0, 0.5, 'Popularity')
```



There is a moderate positive relationship between the popularity of a movie and the total revenues. As the popularity increases, the revenue tends to increase even though moderately.

Grouping movies with genres

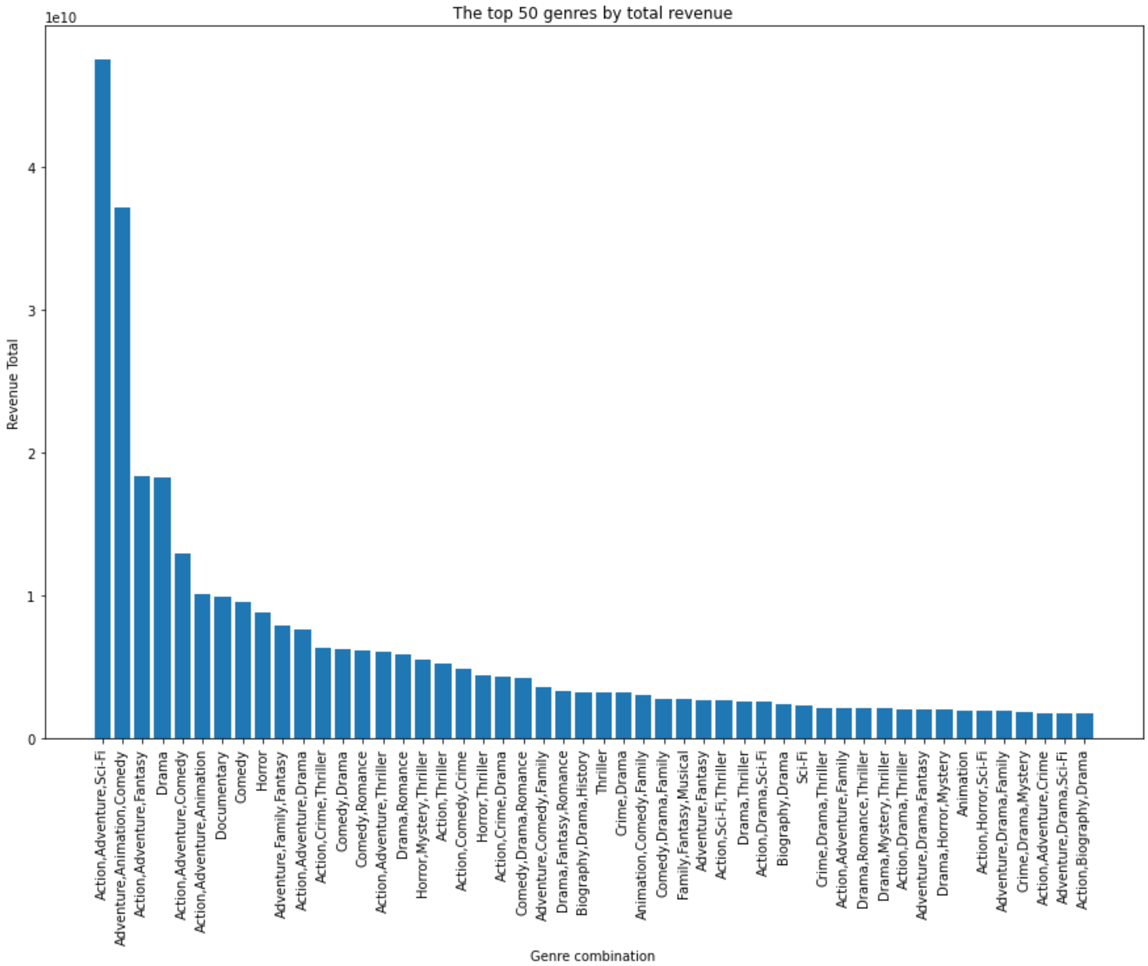
We can get the top 50 genres by the sum of their total revenue.

In [176]:

```
# Group the dataframe by genres.
genre = tn_IMDb_df.groupby("genres").sum()
```

In [177]:

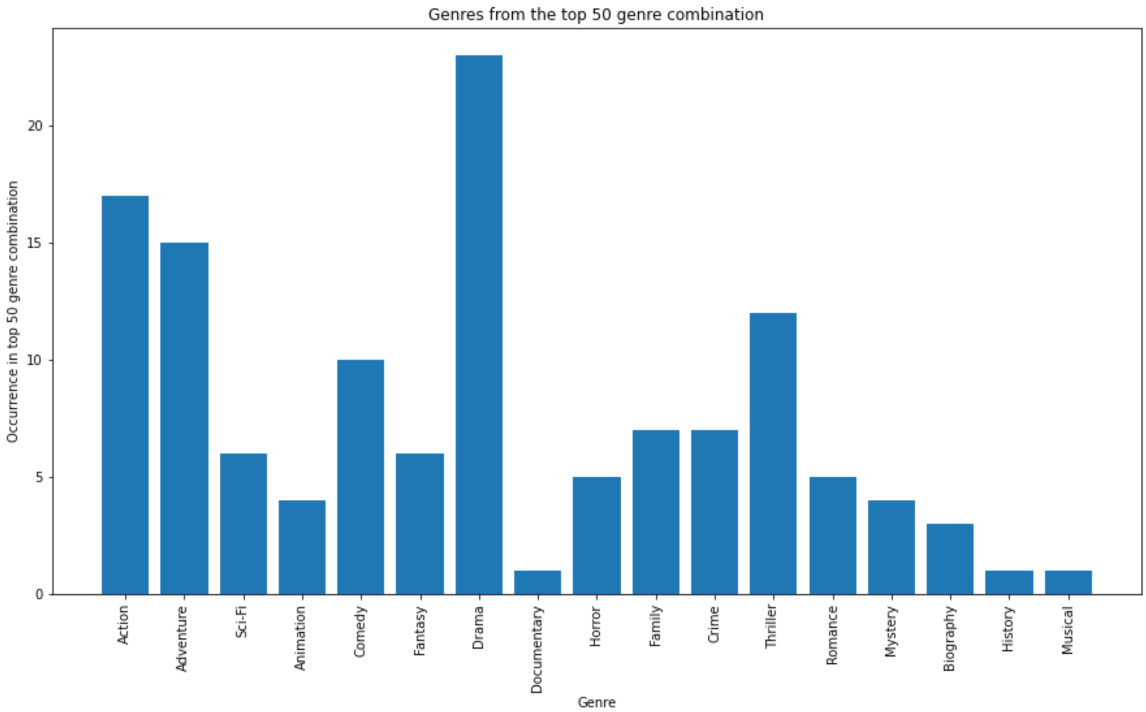
```
# Visualize the top 50 genres by their total revenue.
top_50_revenue_genre = genre.sort_values(by=["total_revenue"], ascending=False)[:
fig, ax = plt.subplots(figsize=(15,10))
ax.bar(top_50_revenue_genre.index, top_50_revenue_genre["total_revenue"])
ax.set_title('The top 50 genres by total revenue')
ax.set_xticks(range(len(top_50_revenue_genre.index)))
ax.set_xticklabels(top_50_revenue_genre.index, rotation=90)
ax.set_xlabel("Genre combination")
ax.set_ylabel("Revenue Total");
```



What genres are in the 50 top genre categories? We have seen the top 50 genre categories, which are made up of different genres. What are the genres that feature in the top 50 genre categories and thow many times do they appear?

In [178]:

```
# Get the top genres and the frequency of their occurrence.
def best_genres(arr):
    """
    Returns the genres that make up the genre 50 categories and their occurrence.
    """
    genre_occurrence = {}
    for genre_combination in arr:
        for each_genre in genre_combination.split(','):
            if each_genre in genre_occurrence:
                genre_occurrence[each_genre] += 1
            else:
                genre_occurrence[each_genre] = 1
    return genre_occurrence
data = best_genres(top_50_revenue_genre.index)
df = pd.DataFrame.from_dict(data, orient='index')
fig, ax = plt.subplots(figsize=(15,8))
ax.bar(df.index, df[0])
ax.set_xticks(range(len(df.index)))
ax.set_xticklabels(df.index, rotation=90)
ax.set_title("Genres from the top 50 genre combination")
ax.set_xlabel("Genre")
ax.set_ylabel("Occurrence in top 50 genre combination");
```



The above graph shows us the top genres. Drama genre occurs most, 23 times in the top 50 genre categories. Documentary, History and Musical genres occur only once in the top 50 genre categories.

How do production budget and total revenue correlate in the top 50 genre combinations.

In [179]:

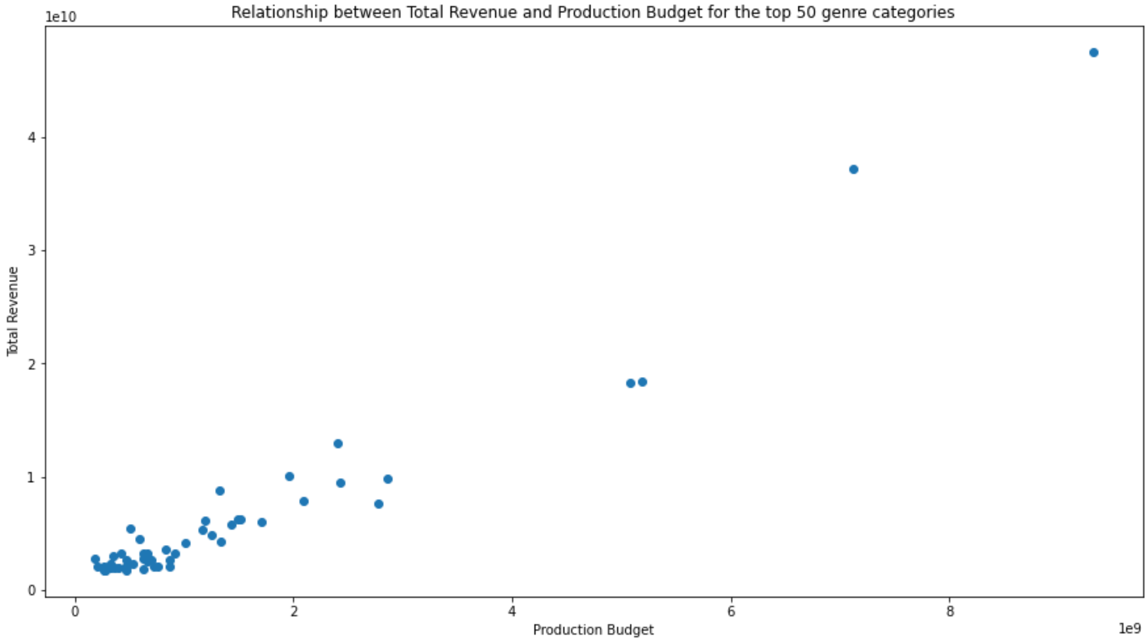
```
# Pearson correlation between the production budget and total revenue for the top
top_50_revenue_genre["production_budget"].corr(top_50_revenue_genre["total_revenu
```

Out[179]:

```
0.9713874658448312
```

In [180]:

```
# Visualize the relationship between the production budget and total revenue for
fig, ax = plt.subplots(figsize=(15,8))
ax.scatter(top_50_revenue_genre["production_budget"], top_50_revenue_genre["total_
ax.set_title("Relationship between Total Revenue and Production Budget for the to
ax.set_xlabel("Production Budget")
ax.set_ylabel("Total Revenue");
```



There is a high positive between the production budget and the total revenue. The relationship here is stronger than when movies are not grouped. As the production budget increases, the total revenue increases.

Recomendations

Production Budget

Budget Allocation Strategy - Allocate budgets strategically based on the observed positive correlation. Consider allocating resources to high-budget productions that have the potential generate substantial revenue. However be selective and base your decision on other factors such as genre analysis as the correlation is not perfect.

Genres

Genre Prioritization - Focus resources and efforts on genres that have consistently performed well in terms of total revenue, the genres in the top 50 genre categories. Direct more resources, both financial and creative to projects within these high revenue genres.

Budget optimization Strategy - Given the strong correlation between budget and revenue in the top genres, consider allocating budgets strategically to projects with these genres to maximise returns.

Risk Management - A near perfect relationship indicates a lower level of risk in budget allocation for these genres. It suggests well funded project in the top genres are likely to yield more positive returns.

Popularity

Popularity driven marketing - Invest in effective marketing strategies that enhance the popularity of movies. Engage with the target audience through strategies like promotions, social media and interactive campaigns to boost anticipation and interest.

Ratings

Quality vs Commercial Appeal - While high IMdb ratings are important for prestige and reputation, recognize that ratings do not correlate with revenue. Diversify your movie portfolio to include high rated projects as well as commercially driven projects

Next steps

Cast - Further analysis could be carried out to analyse if there is any relationship between the cast of a movie and its revenue. Do the A tier directors and actors have any correlation to the total revenue of a film?

Genres Trend - What is the genre trend over the years? What are the genres that are trendung now? What are the emerging genres?