Studio-Afrik

Overview

With the increasing trend of big studios creating original video content, Studio-Afrik has decided to establish a new movie studio. However, we currently lack expertise in movie production. To ensure our new venture's success, it is crucial to to carry out data analysis from historical data. We can derive actionable insights to guide the head of Studio-Afrik in making informed decisions about the types of films to produce.

Business Understanding

Studio-Afrik aims to enter the movie production industry by establishing its new movie studio. The primary goal is to create original video content that resonates with audiences and performs well at the box office, leveraging the current trend among big companies.

To ensure the success in this new indurstry, it is crucial to understand the types of films that are currently performing best. This involves analyzing market trends, audience preferences, and the financial performance of various genres and film types.

Data Understanding

Imports & Data

The code cell below contain libraries that are essential in this project analysis.

```python
# Perfom data manipulation and analysis.
import pandas as pd

# Perfoming mathematical calculations.
import numpy as np

# The two libraries below will aid in creating visualizations.
import matplotlib.pyplot as plt
import seaborn as sns

# Library for linear
import scipy.stats as stats

# This library helps in accessing our relational database.
import sqlite3

# Code below imports all code in the custom_func file
from custom_code import *
```

Working with available data

I. **Relational Database**

1. im.db

II. **CSV FILES**

1. tn.movie_budgets.csv

1. IMDB

This dataset comprises of multiple tables containing information about movies. The tables of interest are: movie_basics and movie_ratings.

The movie_basics table includes movie titles, release year, and genres. The movie_ratings table includes average movie rating and number of votes. The primary key for both tables is movie_id which will help in joining the two tables.

Here, I am creating a Connection to the relational database from im.db using module sqlite3.

```
path = "Data/im.db"
conn = sqlite3.connect(path)
```

Display all the tables in the imdb database

```
query = """
SELECT name
FROM sqlite_master
    WHERE type = 'table';
"""
# print tables in the sql database
imdb_tables = pd.read_sql(query, conn)
```

In order to start using our data, you will have to view information from tables I find relevant to complete this analysis.

Movie Ratings table

```
query = """
SELECT *
FROM movie_ratings;
"""

movie_ratings = pd.read_sql(query, conn)
movie_ratings.head()
```

	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
```

Movie Basics table

```
query = """
SELECT *
FROM movie_basics;
"""

movie_basics= pd.read_sql(query, conn)
movie_basics.head(5)

    movie_id                    primary_title
original_title  \
0  tt0063540                        Sunghursh
Sunghursh
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek
Din
2  tt0069049       The Other Side of the Wind  The Other Side of the
Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada
Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela
Errante

   start_year  runtime_minutes                genres
0        2013            175.0    Action,Crime,Drama
1        2019            114.0       Biography,Drama
2        2018            122.0                 Drama
3        2018              NaN          Comedy,Drama
4        2017             80.0  Comedy,Drama,Fantasy
```

Director Names

JOIN persons table and directors table

```
query = """
SELECT DISTINCT d.movie_id, d.person_id AS director_id, p.primary_name
AS director_name
FROM persons AS p
    INNER JOIN directors AS d
        USING(person_id);
"""

director_data = pd.read_sql(query, conn)
director_data

         movie_id director_id   director_name
0       tt1592569   nm0062879  Ruel S. Bayani
```

```
1       tt2057445   nm0062879  Ruel S. Bayani
2       tt2590280   nm0062879  Ruel S. Bayani
3       tt8421806   nm0062879  Ruel S. Bayani
4       tt3501180   nm0064023   Bryan Beasley
...           ...         ...             ...
163528  tt8697720   nm9971456       Zheng Wei
163529  tt8715016   nm9980896  Rama Narayanan
163530  tt8919136   nm9980896  Rama Narayanan
163531  tt8717234   nm9981679     Samir Eshra
163532  tt8743182   nm9993380  Pegasus Envoyé

[163533 rows x 3 columns]
```

2. tn.movie_budgets.csv

This dataset contain financial information about each movie in their dataset. The columns production budget, domestic gross and worldwide gross describes how much was spent during production and its return after production in each movie.

It will also help us calculate the foreign gross and net profit based on domestic,foreign and total profit.

```
finance_df = pd.read_csv("Data/tn.movie_budgets.csv")
display(finance_df.head())
# Check if our dataset contains missing values
display(finance_df.info())

   id release_date                                        movie  \
0   1    18-Dec-09                                       Avatar
1   2    20-May-11  Pirates of the Caribbean: On Stranger Tides
2   3     7-Jun-19                                 Dark Phoenix
3   4     1-May-15                      Avengers: Age of Ultron
4   5    15-Dec-17            Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross  worldwide_gross
0      $425,000,000   $760,507,625   $2,776,345,279
1      $410,600,000   $241,063,875   $1,045,663,875
2      $350,000,000    $42,762,350     $149,762,350
3      $330,600,000   $459,005,868   $1,403,013,963
4      $317,000,000   $620,181,382   $1,316,721,747

<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

None
```

Data Analysis & Preparation

Transforming raw data from the above datasets into a format that can be easily and effectively used for analysis.

Relational Database - IMDB

merge movie basics table with movie ratings table from imdb to get more detailed information about movies.

```
movie_details = movie_basics.merge(movie_ratings, how="inner",
left_on="movie_id", right_on="movie_id")

movie_details

        movie_id                    primary_title
original_title  \
0      tt0063540                        Sunghursh
Sunghursh
1      tt0066787  One Day Before the Rainy Season             Ashad Ka
Ek Din
2      tt0069049       The Other Side of the Wind  The Other Side of
the Wind
3      tt0069204                  Sabse Bada Sukh             Sabse
Bada Sukh
4      tt0100275         The Wandering Soap Opera       La Telenovela
Errante
...          ...                              ...
...
73851  tt9913084                Diabolik sono io            Diabolik
sono io
73852  tt9914286                Sokagin Çocuklari           Sokagin
Çocuklari
73853  tt9914642                        Albatross
Albatross
73854  tt9914942       La vida sense la Sara Amat  La vida sense la
Sara Amat
73855  tt9916160                       Drømmeland
Drømmeland

       start_year  runtime_minutes                genres
averagerating  \
0            2013            175.0    Action,Crime,Drama
```

```
7.0
1             2019            114.0       Biography,Drama
7.2
2             2018            122.0                 Drama
6.9
3             2018              NaN          Comedy,Drama
6.1
4             2017             80.0  Comedy,Drama,Fantasy
6.5
...            ...              ...                   ...              ..
.
73851         2019             75.0           Documentary
6.2
73852         2019             98.0          Drama,Family
8.7
73853         2017              NaN           Documentary
8.5
73854         2019              NaN                  None
6.6
73855         2019             72.0           Documentary
6.5

       numvotes
0            77
1            43
2          4517
3            13
4           119
...         ...
73851         6
73852       136
73853         8
73854         5
73855        11

[73856 rows x 8 columns]

# Renaming columns in the movie details dataframe
movie_details.rename(columns={"primary_title": "title",
"runtime_minutes": "duration", "genres": "genre", "averagerating":
"rating", "numvotes": "votes"}, inplace=True)

# Display more information about the data
movie_details.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
```

```
 0   movie_id        73856 non-null  object
 1   title           73856 non-null  object
 2   original_title  73856 non-null  object
 3   start_year      73856 non-null  int64
 4   duration        66236 non-null  float64
 5   genre           73052 non-null  object
 6   rating          73856 non-null  float64
 7   votes           73856 non-null  int64
dtypes: float64(2), int64(2), object(4)
memory usage: 5.1+ MB
```

Dealing with missing values in movie_details dataframe

```
# check for missing values
movie_details.isna().sum()

movie_id             0
title                0
original_title       0
start_year           0
duration          7620
genre              804
rating               0
votes                0
dtype: int64

# Drop all missing values in column genre
movie_details = movie_details.dropna(subset = ["genre"])

# fill all missing values in duration with the mean of its column
movie_details.loc[:,
"duration"].fillna(value=round(movie_details["duration"].mean()),
inplace=True)

movie_details = movie_details.reset_index(drop=True)

c:\Users\user\anaconda3\envs\learn-env\lib\site-packages\pandas\core\
series.py:4517: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  return super().fillna(

# Check if there is any existing missing values
movie_details.isna().sum()

movie_id          0
title             0
```

```
original_title    0
start_year        0
duration          0
genre             0
rating            0
votes             0
dtype: int64

# Preview count of how many movies produced per yearly
yearly_movie_count = movie_details.groupby("start_year")
['movie_id'].count()
yearly_movie_count

start_year
2010    6701
2011    7274
2012    7602
2013    7905
2014    8269
2015    8405
2016    8613
2017    8638
2018    7476
2019    2169
Name: movie_id, dtype: int64

# Navigation through the genre column and only keeping the first genre
where multiple genres describes a single movie

movie_details['genre'] = movie_details.loc[:,
'genre'].str.split(',').apply(lambda x: x[0]).reset_index(drop=True)

movie_details

        movie_id                           title
original_title  \
0      tt0063540                       Sunghursh
Sunghursh
1      tt0066787  One Day Before the Rainy Season             Ashad Ka
Ek Din
2      tt0069049      The Other Side of the Wind  The Other Side of
the Wind
3      tt0069204                 Sabse Bada Sukh             Sabse
Bada Sukh
4      tt0100275        The Wandering Soap Opera       La Telenovela
Errante
...          ...                             ...
...
73047  tt9913056                    Swarm Season                Swarm
Season
```

```
73048  tt9913084                 Diabolik sono io            Diabolik
sono io
73049  tt9914286                Sokagin Çocuklari           Sokagin
Çocuklari
73050  tt9914642                        Albatross
Albatross
73051  tt9916160                       Drømmeland
Drømmeland

       start_year  duration        genre  rating  votes
0            2013     175.0       Action     7.0     77
1            2019     114.0    Biography     7.2     43
2            2018     122.0        Drama     6.9   4517
3            2018      95.0       Comedy     6.1     13
4            2017      80.0       Comedy     6.5    119
...           ...       ...          ...     ...    ...
73047        2019      86.0  Documentary     6.2      5
73048        2019      75.0  Documentary     6.2      6
73049        2019      98.0        Drama     8.7    136
73050        2017      95.0  Documentary     8.5      8
73051        2019      72.0  Documentary     6.5     11

[73052 rows x 8 columns]
```

```
# convert year into a string so as to perform aggregate functions on
the movie details dataframe.
movie_details['start_year'] = movie_details['start_year'].astype(str)

# convert rating into an integer so as to perform aggregate functions
on the movie details dataframe.
movie_details['rating'] = movie_details['rating'].astype(int)

# display information
movie_details.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73052 entries, 0 to 73051
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   movie_id        73052 non-null  object
 1   title           73052 non-null  object
 2   original_title  73052 non-null  object
 3   start_year      73052 non-null  object
 4   duration        73052 non-null  float64
 5   genre           73052 non-null  object
 6   rating          73052 non-null  int32
 7   votes           73052 non-null  int64
dtypes: float64(1), int32(1), int64(1), object(5)
memory usage: 4.2+ MB
```

Aggregate functions

```
# Group by genre and calculate the mean of ratings and votes
movie_avg_rating_genre = movie_details.groupby('genre')[["rating",
"votes", "duration"]].mean().sort_values(by='rating', ascending=False)
movie_avg_rating_genre = movie_avg_rating_genre.round({"rating": 1,
"votes": 0, "duration": 0})
movie_avg_rating_genre
```

	rating	votes	duration
genre			
Game-Show	9.0	7.0	130.0
Music	7.0	223.0	100.0
Documentary	6.9	213.0	88.0
Biography	6.7	5186.0	91.0
Sport	6.5	59.0	90.0
Musical	6.2	142.0	105.0
History	6.0	94.0	100.0
Adventure	5.9	10420.0	91.0
Drama	5.9	2199.0	98.0
Animation	5.8	2026.0	84.0
Crime	5.7	5287.0	97.0
Mystery	5.7	5496.0	97.0
War	5.6	118.0	95.0
Romance	5.6	594.0	106.0
Family	5.6	511.0	92.0
Comedy	5.6	2733.0	97.0
Action	5.4	14476.0	103.0
Thriller	5.3	295.0	95.0
Fantasy	5.2	1409.0	92.0
Reality-TV	5.2	23.0	119.0
News	5.0	11.0	97.0
Sci-Fi	4.9	670.0	90.0
Western	4.6	208.0	91.0
Horror	4.4	2369.0	88.0
Adult	2.0	128.0	120.0

```
# Number of movies per genre
movie_avg_rating_genre['movies_per_genre'] =
movie_details.groupby('genre')['movie_id'].count()
movie_avg_rating_genre
```

	rating	votes	duration	movies_per_genre
genre				
Game-Show	9.0	7.0	130.0	1
Music	7.0	223.0	100.0	192
Documentary	6.9	213.0	88.0	13962
Biography	6.7	5186.0	91.0	3433
Sport	6.5	59.0	90.0	89
Musical	6.2	142.0	105.0	153

```
History          6.0     94.0     100.0                 136
Adventure        5.9  10420.0      91.0                2596
Drama            5.9   2199.0      98.0               18572
Animation        5.8   2026.0      84.0                 962
Crime            5.7   5287.0      97.0                2494
Mystery          5.7   5496.0      97.0                 433
War              5.6    118.0      95.0                  47
Romance          5.6    594.0     106.0                 786
Family           5.6    511.0      92.0                 604
Comedy           5.6   2733.0      97.0               14649
Action           5.4  14476.0     103.0                6988
Thriller         5.3    295.0      95.0                1563
Fantasy          5.2   1409.0      92.0                 429
Reality-TV       5.2     23.0     119.0                   5
News             5.0     11.0      97.0                   4
Sci-Fi           4.9    670.0      90.0                 388
Western          4.6    208.0      91.0                  75
Horror           4.4   2369.0      88.0                4490
Adult            2.0    128.0     120.0                   1
```

```
movie_avg_rating_genre.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 25 entries, Game-Show to Adult
Data columns (total 4 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   rating            25 non-null     float64
 1   votes             25 non-null     float64
 2   duration          25 non-null     float64
 3   movies_per_genre  25 non-null     int64
dtypes: float64(3), int64(1)
memory usage: 1000.0+ bytes
```

```
# agg of columns above
display(movie_avg_rating_genre["rating"].median())

display(movie_avg_rating_genre["votes"].median())

display(movie_avg_rating_genre["duration"].median())
```

```
5.6

511.0

97.0
```

Filter Genre by count

```
# filtering out genres that have a count less than 500
filter_movie_avg_rating_genre =
movie_avg_rating_genre.loc[movie_avg_rating_genre['movies_per_genre']
> 500 ]
filter_movie_avg_rating_genre.sort_values(by="movies_per_genre")
```

```
             rating    votes  duration  movies_per_genre
genre
Family          5.6    511.0      92.0               604
Romance         5.6    594.0     106.0               786
Animation       5.8   2026.0      84.0               962
Thriller        5.3    295.0      95.0              1563
Crime           5.7   5287.0      97.0              2494
Adventure       5.9  10420.0      91.0              2596
Biography       6.7   5186.0      91.0              3433
Horror          4.4   2369.0      88.0              4490
Action          5.4  14476.0     103.0              6988
Documentary     6.9    213.0      88.0             13962
Comedy          5.6   2733.0      97.0             14649
Drama           5.9   2199.0      98.0             18572
```

Merge movie details dataframe with director data dataframe to get all the information about movies produced.

The Movie details dataframe contains data about movie id, title, year, time, genres, ratings, votes and the director data dataframe contains information about movie id, director name

```
movie_infor = movie_details.merge(director_data, how="inner",
left_on="movie_id", right_on="movie_id")

movie_infor
```

```
        movie_id                            title
original_title  \
0      tt0063540                        Sunghursh
Sunghursh
1      tt0066787  One Day Before the Rainy Season             Ashad Ka
Ek Din
2      tt0069049       The Other Side of the Wind  The Other Side of
the Wind
3      tt0069204                  Sabse Bada Sukh             Sabse
Bada Sukh
4      tt0100275         The Wandering Soap Opera       La Telenovela
Errante
...          ...                              ...
...
85227  tt9913056                     Swarm Season                Swarm
Season
85228  tt9913084                 Diabolik sono io             Diabolik
```

```
sono io
85229  tt9914286                Sokagin Çocuklari           Sokagin
Çocuklari
85230  tt9914642                        Albatross
Albatross
85231  tt9916160                       Drømmeland
Drømmeland

      start_year  duration        genre  rating  votes director_id  \
0           2013     175.0       Action       7     77   nm0712540
1           2019     114.0    Biography       7     43   nm0002411
2           2018     122.0        Drama       6   4517   nm0000080
3           2018      95.0       Comedy       6     13   nm0611531
4           2017      80.0       Comedy       6    119   nm0749914
...          ...       ...          ...     ...    ...         ...
85227       2019      86.0  Documentary       6      5   nm1502645
85228       2019      75.0  Documentary       6      6   nm0812850
85229       2019      98.0        Drama       8    136   nm4394529
85230       2017      95.0  Documentary       8      8   nm5300859
85231       2019      72.0  Documentary       6     11   nm5684093

              director_name
0       Harnam Singh Rawail
1                 Mani Kaul
2              Orson Welles
3      Hrishikesh Mukherjee
4                Raoul Ruiz
...                     ...
85227       Sarah Christman
85228       Giancarlo Soldi
85229      Ahmet Faik Akinci
85230          Chris Jordan
85231     Joost van der Wiel

[85232 rows x 10 columns]
```

Drop unnecessary columns from the above dataframe

```
movie_infor.drop(columns="original_title", inplace=True)

movie_infor

        movie_id                            title start_year  duration
\
0      tt0063540                        Sunghursh       2013     175.0

1      tt0066787  One Day Before the Rainy Season       2019     114.0

2      tt0069049        The Other Side of the Wind       2018     122.0
```

```
3      tt0069204                    Sabse Bada Sukh      2018      95.0

4      tt0100275          The Wandering Soap Opera       2017      80.0

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

85227  tt9913056                      Swarm Season       2019      86.0

85228  tt9913084                   Diabolik sono io      2019      75.0

85229  tt9914286                 Sokagin Çocuklari       2019      98.0

85230  tt9914642                         Albatross       2019      95.0

85231  tt9916160                        Drømmeland       2019      72.0


             genre  rating  votes director_id          director_name
0           Action       7     77   nm0712540    Harnam Singh Rawail
1        Biography       7     43   nm0002411              Mani Kaul
2            Drama       6   4517   nm0000080           Orson Welles
3           Comedy       6     13   nm0611531  Hrishikesh Mukherjee
4           Comedy       6    119   nm0749914             Raoul Ruiz
...            ...     ...    ...         ...                    ...
85227  Documentary       6      5   nm1502645        Sarah Christman
85228  Documentary       6      6   nm0812850        Giancarlo Soldi
85229        Drama       8    136   nm4394529      Ahmet Faik Akinci
85230  Documentary       8      8   nm5300859           Chris Jordan
85231  Documentary       6     11   nm5684093      Joost van der Wiel

[85232 rows x 9 columns]
```

Top directors according to movie rating.

```
director_movie_infor = movie_infor.groupby('director_name')[['rating',
'votes']].mean().sort_values(by="rating", ascending=False)
director_movie_infor

                        rating  votes
director_name
Masahiro Hayakawa         10.0    5.0
Chad Carpenter            10.0    5.0
Stephen Peek              10.0   20.0
Tristan David Luciotti    10.0    6.0
Emre Oran                 10.0    6.0
...                        ...    ...
Aliakbar Campwala          1.0  347.0
Charlie Chu                1.0   67.0
Ferda Gelendost            1.0   14.0
Vitali Pavlov              1.0    8.0
```

```
Smita Maroo                      1.0   415.0

[56277 rows x 2 columns]

# mean of votes grouped by directors.
director_movie_infor['votes'].mean()

2106.3387304768107

director_movie_infor_rating_per_votings =
director_movie_infor.loc[director_movie_infor['votes'] >
director_movie_infor['votes'].mean() ]

director_movie_infor_rating_per_votings

                        rating    votes
director_name
Donavon Warren             9.0  17308.0
Mari Selvaraj              9.0   4854.0
Anjana Krishnakumar        9.0   9629.0
Chathra Weeraman           9.0   6509.0
Amitabh Reza Chowdhury     9.0  18470.0
...                        ...      ...
Jianxin Huang              2.0   5538.0
Olya Schechter             1.0   3426.0
James Nguyen               1.0  11537.0
Gökhan Gök                 1.0  36986.0
Celal Çimen                1.0  26723.0

[3704 rows x 2 columns]
```

CSV File

Dealing with data from the csv datasets.

tn.movie_budgets.csv The tn.movie_budgets.csv dataset contain data about finances in the movie indurstry. The data available includes production budget, domestic gross, worldwide gross that will help us calculate the foreign gross and the net profit based on domestic, foreign and worldwide film production.

```
finance_df

      id release_date                                        movie  \
0      1    18-Dec-09                                       Avatar
1      2    20-May-11  Pirates of the Caribbean: On Stranger Tides
2      3     7-Jun-19                                 Dark Phoenix
3      4     1-May-15                      Avengers: Age of Ultron
4      5    15-Dec-17            Star Wars Ep. VIII: The Last Jedi
...   ..          ...                                          ...
5777  78    31-Dec-18                                       Red 11
5778  79     2-Apr-99                                    Following
```

```
5779  80    13-Jul-05                Return to the Land of Wonders
5780  81    29-Sep-15                         A Plague So Pleasant
5781  82     5-Aug-05                            My Date With Drew

     production_budget domestic_gross  worldwide_gross
0         $425,000,000   $760,507,625   $2,776,345,279
1         $410,600,000   $241,063,875   $1,045,663,875
2         $350,000,000    $42,762,350     $149,762,350
3         $330,600,000   $459,005,868   $1,403,013,963
4         $317,000,000   $620,181,382   $1,316,721,747
...                ...            ...              ...
5777            $7,000             $0               $0
5778            $6,000        $48,482         $240,495
5779            $5,000         $1,338           $1,338
5780            $1,400             $0               $0
5781            $1,100       $181,041         $181,041

[5782 rows x 6 columns]
```

Before performing any calculations, we need to ensure we are dealing with numbers by checking the data type. In this dataset, the columns with finace data need to be cleaned.

The function call below helps convert production budget, domestic gross, worldwide gross into intergers and remove any unnecessary string punctuations.

```
# columns to apply in my function
my_finance_columns = ["domestic_gross", "production_budget",
"worldwide_gross"]

# imported function from custom_func.py
finance_col(finance_df, my_finance_columns)

# finance gross
finance_df["foreign_gross"] = finance_df["worldwide_gross"] -
finance_df["domestic_gross"]

# domestic profit
finance_df["domestic_profit"] = finance_df["domestic_gross"] -
finance_df["production_budget"]

# foreign profit
finance_df["foreign_profit"] = finance_df["foreign_gross"] -
finance_df["production_budget"]

# net profit
finance_df["net_profit"] = finance_df["worldwide_gross"] -
finance_df["production_budget"]

finance_df
```

```
      id release_date                                         movie  \
0      1    18-Dec-09                                        Avatar
1      2    20-May-11  Pirates of the Caribbean: On Stranger Tides
2      3     7-Jun-19                                  Dark Phoenix
3      4     1-May-15                       Avengers: Age of Ultron
4      5    15-Dec-17             Star Wars Ep. VIII: The Last Jedi
...   ..          ...                                           ...
5777  78    31-Dec-18                                        Red 11
5778  79     2-Apr-99                                     Following
5779  80    13-Jul-05                 Return to the Land of Wonders
5780  81    29-Sep-15                          A Plague So Pleasant
5781  82     5-Aug-05                             My Date With Drew

      production_budget  domestic_gross  worldwide_gross
foreign_gross  \
0             425000000       760507625       2776345279
2015837654
1             410600000       241063875       1045663875
804600000
2             350000000        42762350        149762350
107000000
3             330600000       459005868       1403013963
944008095
4             317000000       620181382       1316721747
696540365
...                 ...             ...              ...             ..
.
5777               7000               0                0
0
5778               6000           48482           240495
192013
5779               5000            1338             1338
0
5780               1400               0                0
0
5781               1100          181041           181041
0

      domestic_profit  foreign_profit  net_profit
0           335507625      1590837654  2351345279
1          -169536125       394000000   635063875
2          -307237650      -243000000  -200237650
3           128405868       613408095  1072413963
4           303181382       379540365   999721747
...               ...             ...         ...
5777            -7000           -7000       -7000
5778            42482          186013      234495
5779            -3662           -5000       -3662
5780            -1400           -1400       -1400
5781           179941           -1100      179941
```

```
[5782 rows x 10 columns]
```

Drop columns that will not be applied in my analysis.

```
finance_df.drop(columns="release_date", inplace=True)
finance_df

      id                                        movie
production_budget  \
0      1                                       Avatar
425000000
1      2  Pirates of the Caribbean: On Stranger Tides
410600000
2      3                                 Dark Phoenix
350000000
3      4                      Avengers: Age of Ultron
330600000
4      5            Star Wars Ep. VIII: The Last Jedi
317000000
...   ..                                          ...                .
..
5777  78                                       Red 11
7000
5778  79                                    Following
6000
5779  80                 Return to the Land of Wonders
5000
5780  81                         A Plague So Pleasant
1400
5781  82                            My Date With Drew
1100

      domestic_gross  worldwide_gross  foreign_gross  domestic_profit
\
0          760507625       2776345279     2015837654        335507625

1          241063875       1045663875      804600000       -169536125

2           42762350        149762350      107000000       -307237650

3          459005868       1403013963      944008095        128405868

4          620181382       1316721747      696540365        303181382

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

5777               0                0              0            -7000

5778           48482           240495         192013            42482
```

```
5779              1338              1338              0              -3662

5780                 0                 0              0              -1400

5781            181041            181041              0             179941


      foreign_profit  net_profit
0         1590837654  2351345279
1          394000000   635063875
2         -243000000  -200237650
3          613408095  1072413963
4          379540365   999721747
...              ...         ...
5777           -7000       -7000
5778          186013      234495
5779           -5000       -3662
5780           -1400       -1400
5781           -1100      179941

[5782 rows x 9 columns]
```

```
display(finance_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 9 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   id                  5782 non-null   int64
 1   movie               5782 non-null   object
 2   production_budget   5782 non-null   int64
 3   domestic_gross      5782 non-null   int64
 4   worldwide_gross     5782 non-null   int64
 5   foreign_gross       5782 non-null   int64
 6   domestic_profit     5782 non-null   int64
 7   foreign_profit      5782 non-null   int64
 8   net_profit          5782 non-null   int64
dtypes: int64(8), object(1)
memory usage: 406.7+ KB

None
```

```
finance_df.isna().sum()
```

```
id                    0
movie                 0
production_budget     0
domestic_gross        0
worldwide_gross       0
foreign_gross         0
```

```
domestic_profit      0
foreign_profit       0
net_profit           0
dtype: int64
```

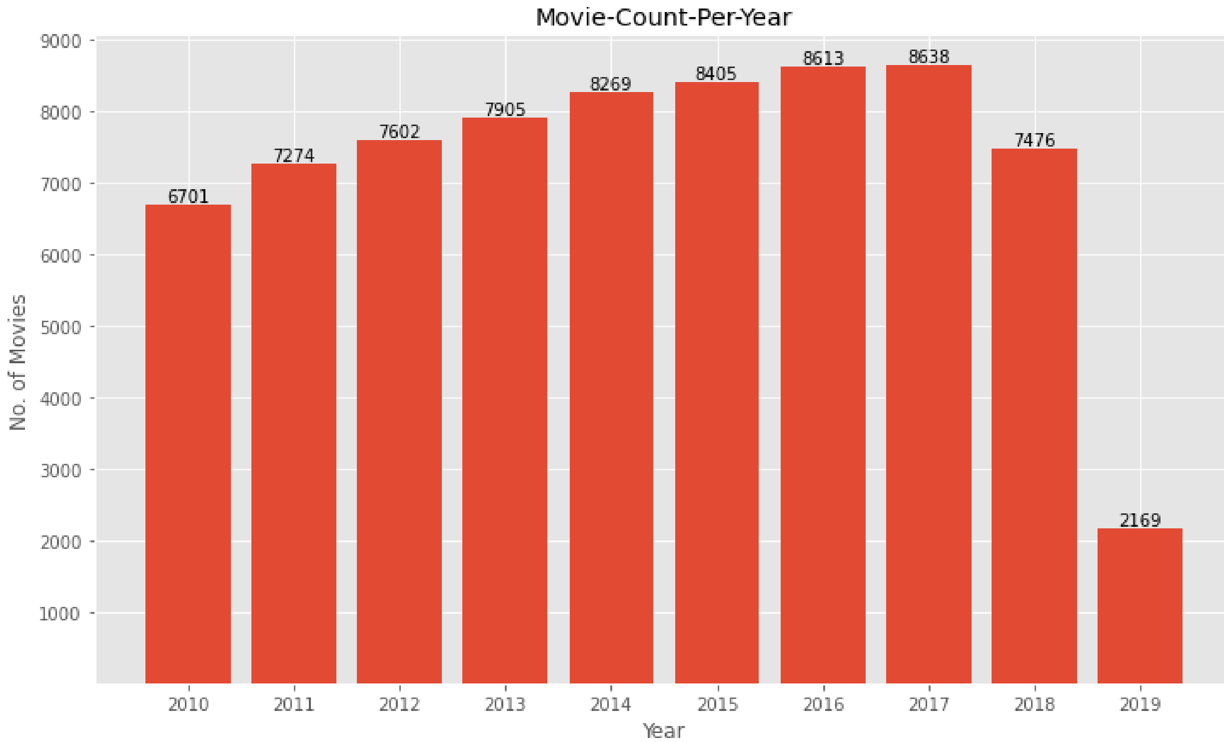
Data Visualization

In this section, I will create reasonable insights from my analysed data and determine what to consider for our Studio-Afrik start-up.

Number of movies produced per year.

The plot below shows the total number of movies in every year from the dataset.

```
# Data to visualize
plt.style.use('ggplot')

x = yearly_movie_count.sort_values(ascending=False).index
y = yearly_movie_count.sort_values(ascending=False).values

fig, ax = plt.subplots(figsize=(12,7))

# labelling my chart
ax.set(
    title = "Movie-Count-Per-Year",
    xlabel = "Year",
    ylabel = "No. of Movies",
    # customised ticks
    yticks = [(value * 10**3) for value in np.arange(1,10,1)],
    xticks = [ time for time in x]
)

# plot
bars = ax.bar(x, y)

for bar in bars:
    height = bar.get_height()
    ax.text(
        bar.get_x() + bar.get_width() / 2,  # X coordinate
        height,                             # Y coordinate
        f'{height}',                        # Text label
        ha='center',                        # Horizontal alignment
        va='bottom'                         # Vertical alignment
    )


plt.show()
```

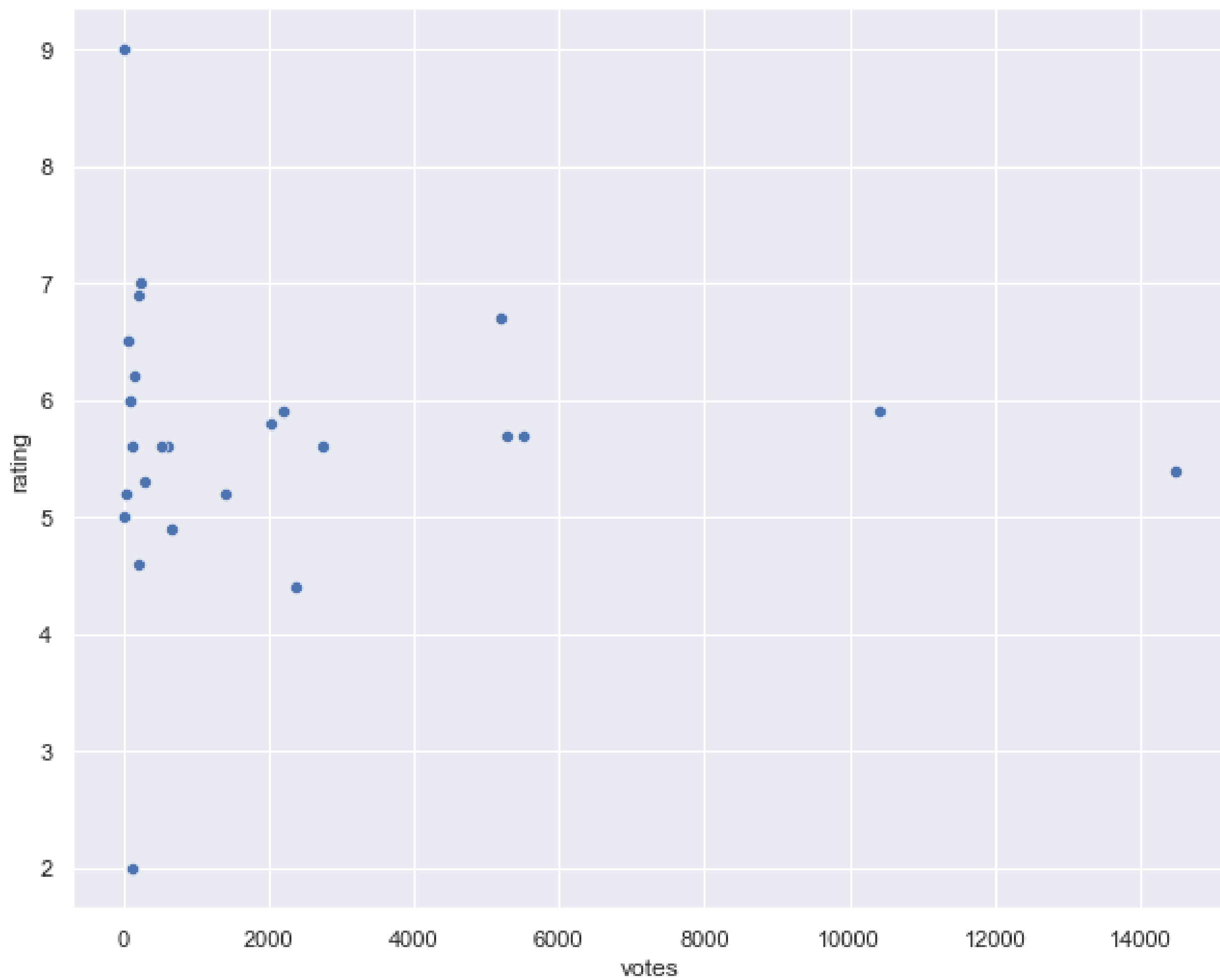


Display the average rating vs votes in each genre.

NB: Movie genre should not be picked according to the rating alone, because the visualization below shows high ratings appear in movies that had low votes

Therefore, rating should be considered in regards to votes

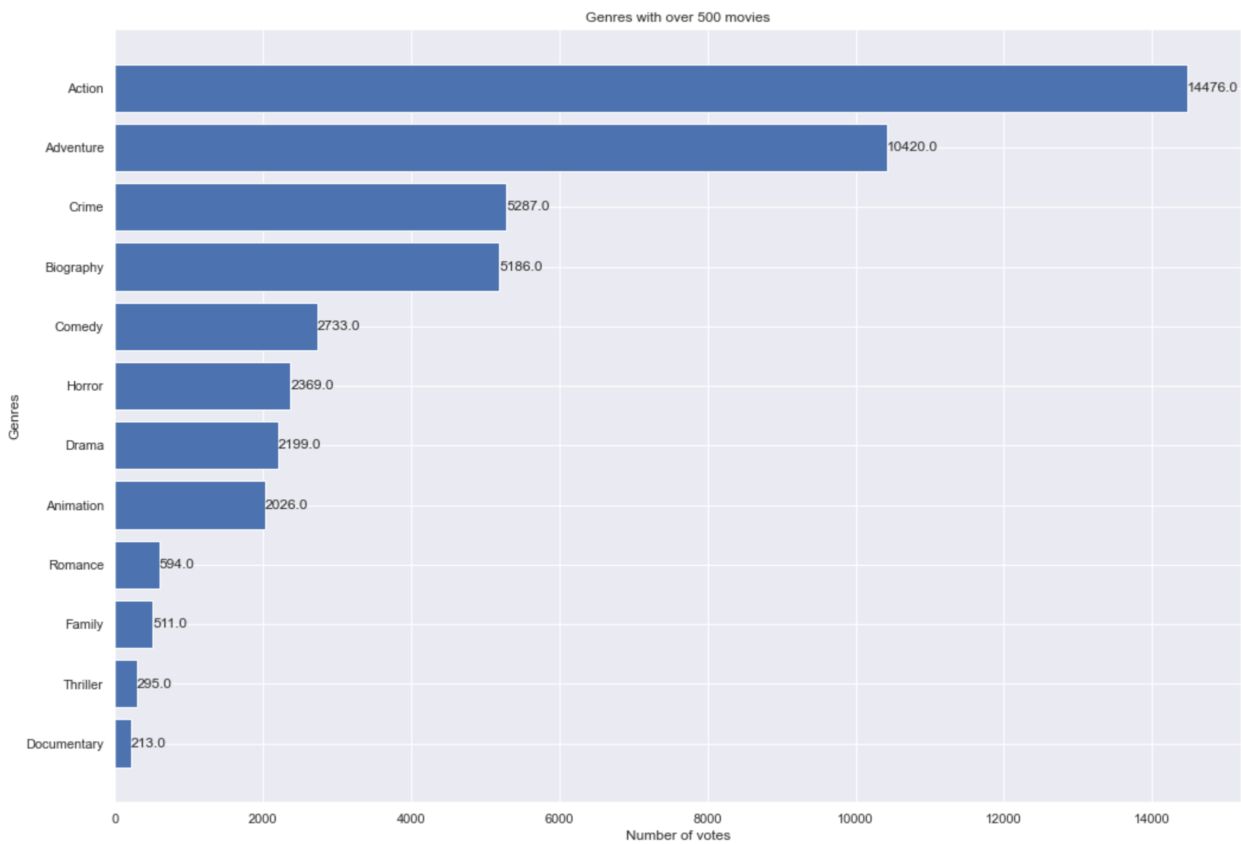
```
# why it is not a good idea to consider ratings without counter
checking number of votes

sns.set_theme(style="darkgrid")
fig, ax =  plt.subplots(figsize=(10,8))
sns.scatterplot(data=movie_avg_rating_genre, x="votes", y="rating")
plt.show

<function matplotlib.pyplot.show(close=None, block=None)>
```



Top genre with over 500 movies

```
sns.set_theme(style="darkgrid")
fig, ax =  plt.subplots(figsize=(17,12))
x = filter_movie_avg_rating_genre.sort_values(by="votes",
ascending=True).index
y = filter_movie_avg_rating_genre.sort_values(by="votes",
ascending=True)["votes"]

# labels
ax.set(
    title = "Genres with over 500 movies",
    xlabel = "Number of votes",
    ylabel = "Genres"
)

bars = ax.barh(x, y)

for bar in bars:
    width = bar.get_width()
```

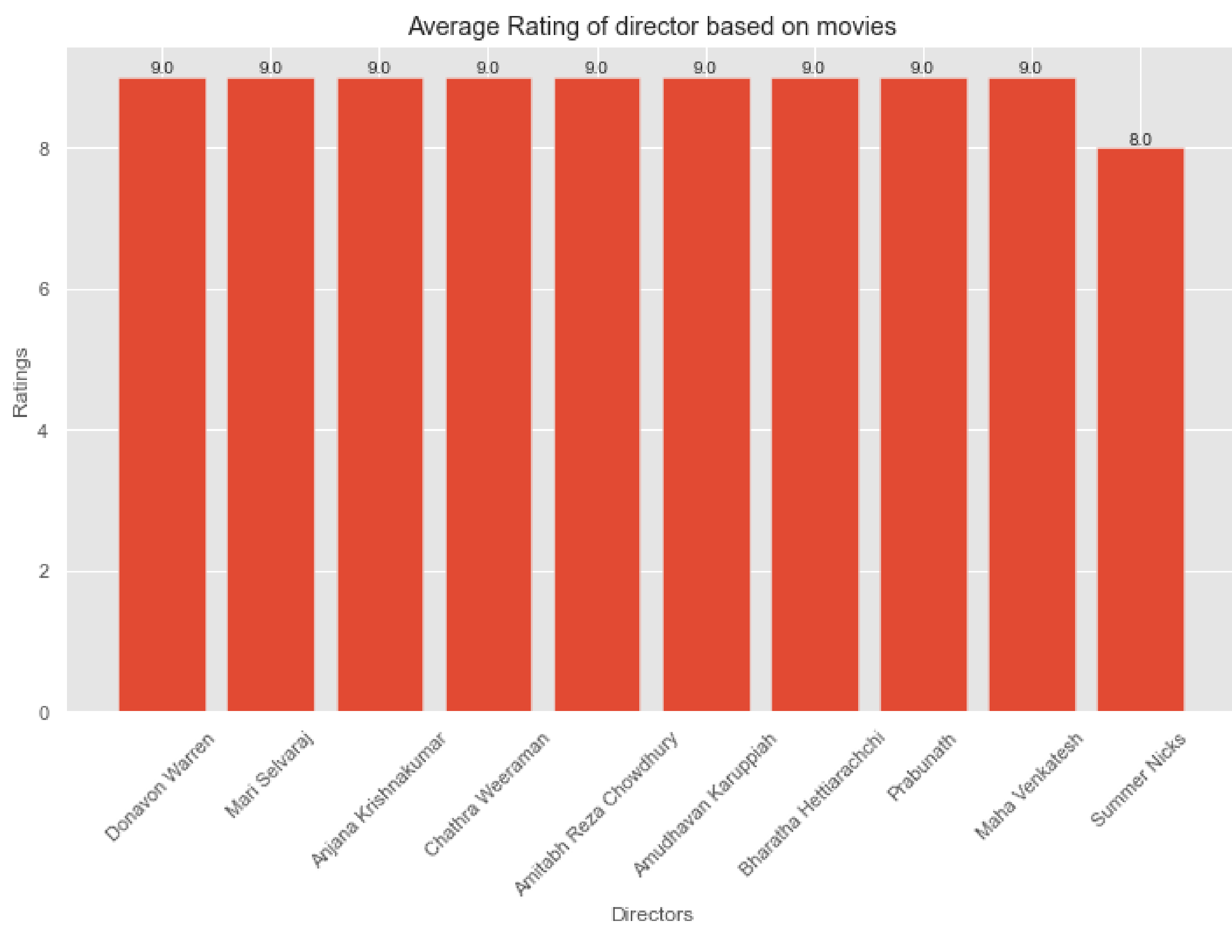
```
    ax.text(width, bar.get_y() + bar.get_height()/2, f'{width}',
va='center')


plt.show()
```



Directors to hire based on average movie ratings with average votes above the mean of votes.

```
# Data to visualize
plt.style.use('ggplot')

x = director_movie_infor_rating_per_votings.iloc[0:10].index
y = director_movie_infor_rating_per_votings.iloc[0:10]['rating']

fig, ax = plt.subplots(figsize=(12,7))

# labelling my chart
ax.set(
    title = "Average Rating of director based on movies",
    xlabel = "Directors",
    ylabel = "Ratings",
    # customised ticks
    # yticks = [(value * 10**3) for value in np.arange(1,10,1)],
```

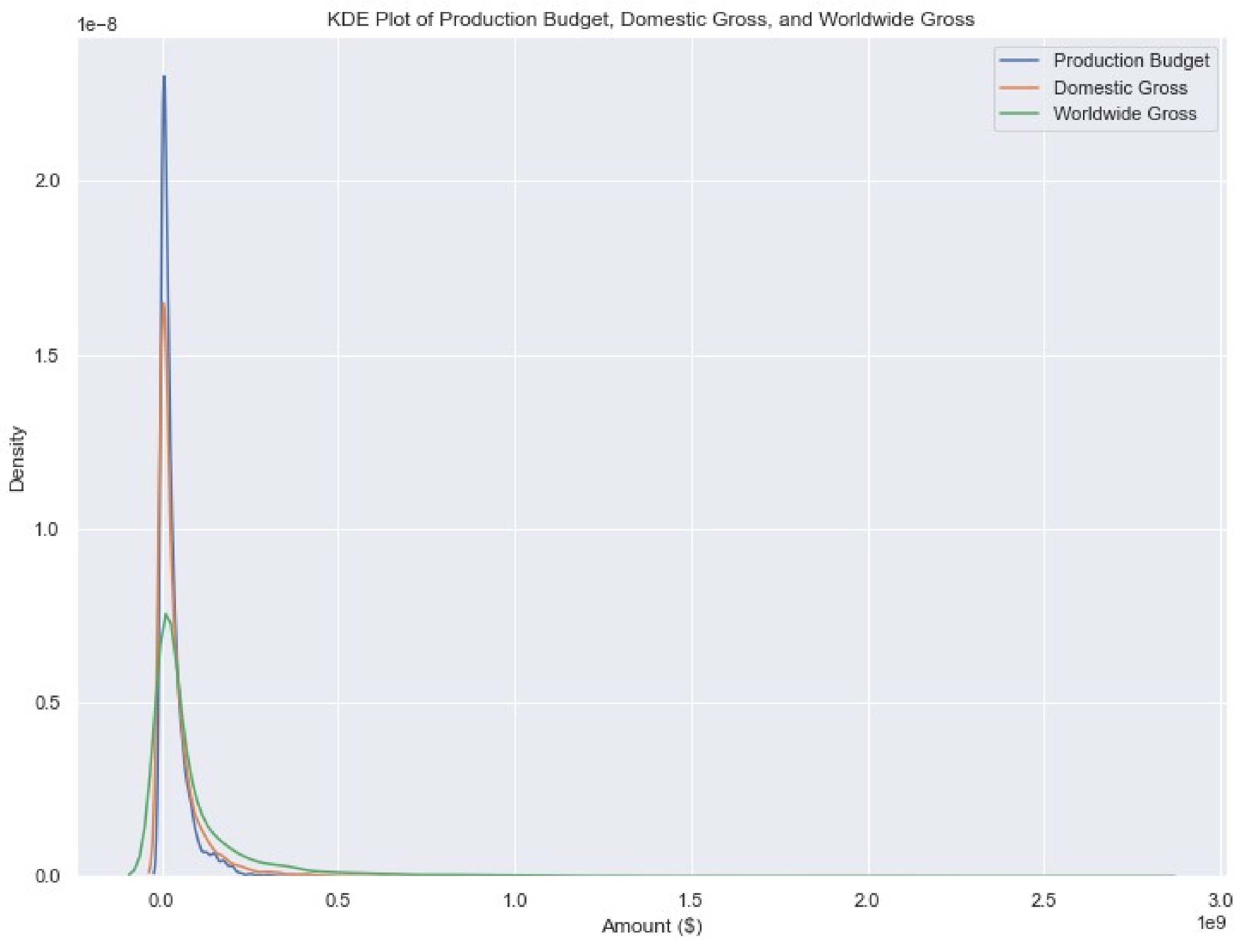
```
    # xticks = [ time for time in x]
)

# plot
bars = ax.bar(x, y)

for bar in bars:
    height = bar.get_height()
    ax.text(
        bar.get_x() + bar.get_width() / 2,  # X coordinate
        height,                             # Y coordinate
        f'{height}',                        # Text label
        ha='center',                        # Horizontal alignment
        va='bottom'                         # Vertical alignment
    )

plt.xticks(rotation=45)
plt.show()
```



Multivariate Analysis

The plot below is skewed indicating that our data contains outliers.

```
# kde plot of 'production_budget', 'domestic_gross', 'worldwide_gross'
# Create a figure and axis object
sns.set_theme(style="darkgrid")
fig, ax = plt.subplots(figsize=(12,9))

# Plot the KDE for each column
sns.kdeplot(data=finance_df, x='production_budget', ax=ax,
label='Production Budget')
sns.kdeplot(data=finance_df, x='domestic_gross', ax=ax,
label='Domestic Gross')
sns.kdeplot(data=finance_df, x='worldwide_gross', ax=ax,
label='Worldwide Gross')

# Set the title and labels
ax.set_title('KDE Plot of Production Budget, Domestic Gross, and
Worldwide Gross')
ax.set_xlabel('Amount ($)')
ax.set_ylabel('Density')

# Show the legend
ax.legend()

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



Investments & High ROI

```
studio_roi = movie_details.merge(finance_df, how="inner",
left_on="title", right_on="movie")
studio_roi

       movie_id                             title  \
0     tt0249516                        Foodfight!
1     tt0337692                       On the Road
2     tt4339118                       On the Road
3     tt5647250                       On the Road
4     tt0359950  The Secret Life of Walter Mitty
...         ...                               ...
2862  tt8680254                       Richard III
2863  tt8824064                            Heroes
2864  tt8976772                              Push
2865  tt9024106                         Unplanned
2866  tt9248762                     The Terrorist

                       original_title start_year  duration
genre  \
0                          Foodfight!       2012      91.0
```

```
Action
1                          On the Road       2012     124.0
Adventure
2                          On the Road       2014      89.0
Drama
3                          On the Road       2016     121.0
Drama
4     The Secret Life of Walter Mitty       2013     114.0
Adventure
...                                ...        ...       ...            ..
.
2862                       Richard III       2016      95.0
Drama
2863                            Heroes       2019      88.0
Documentary
2864                              Push       2019      92.0
Documentary
2865                         Unplanned       2019     106.0
Biography
2866                     The Terrorist       2018      95.0
Thriller

      rating   votes  id                             movie
production_budget  \
0          1    8248  26                        Foodfight!
45000000
1          6   37886  17                       On the Road
25000000
2          6       6  17                       On the Road
25000000
3          5     127  17                       On the Road
25000000
4          7  275300  37  The Secret Life of Walter Mitty
91000000
...      ...     ...  ..                               ...
...
2862       9      28  65                       Richard III
9200000
2863       7       7  12                            Heroes
400000
2864       7      33  70                              Push
38000000
2865       6    5945  33                         Unplanned
6000000
2866       6       6  48                     The Terrorist
25000

      domestic_gross  worldwide_gross  foreign_gross  domestic_profit
\
```

```
0                    0           73706        73706     -45000000
1               720828         9313302      8592474     -24279172
2               720828         9313302      8592474     -24279172
3               720828         9313302      8592474     -24279172
4             58236838       187861183    129624345     -32763162
...                ...             ...          ...           ...
2862           2684904         4199334      1514430      -6515096
2863            655538          655538            0        255538
2864          31811527        49678401     17866874      -6188473
2865          18107621        18107621            0      12107621
2866            195043          195043            0        170043

      foreign_profit  net_profit
0          -44926294   -44926294
1          -16407526   -15686698
2          -16407526   -15686698
3          -16407526   -15686698
4           38624345    96861183
...              ...         ...
2862        -7685570    -5000666
2863         -400000      255538
2864       -20133126    11678401
2865        -6000000    12107621
2866          -25000      170043

[2867 rows x 17 columns]
```

```
studio_roi.drop(columns=["original_title", "id", "movie"],
inplace=True)
studio_roi.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2867 entries, 0 to 2866
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           2867 non-null   object
 1   title              2867 non-null   object
 2   start_year         2867 non-null   object
 3   duration           2867 non-null   float64
```

```
 4   genre                2867 non-null   object
 5   rating               2867 non-null   int32
 6   votes                2867 non-null   int64
 7   production_budget    2867 non-null   int64
 8   domestic_gross       2867 non-null   int64
 9   worldwide_gross      2867 non-null   int64
 10  foreign_gross        2867 non-null   int64
 11  domestic_profit      2867 non-null   int64
 12  foreign_profit       2867 non-null   int64
 13  net_profit           2867 non-null   int64
dtypes: float64(1), int32(1), int64(8), object(4)
memory usage: 324.8+ KB
```

```
# check for missing values
studio_roi.isna().sum()
```

```
movie_id             0
title                0
start_year           0
duration             0
genre                0
rating               0
votes                0
production_budget    0
domestic_gross       0
worldwide_gross      0
foreign_gross        0
domestic_profit      0
foreign_profit       0
net_profit           0
dtype: int64
```

Group the studio_roi dataframe by genre and plot net profit vs production budget to observe linearity between the data.

```
studio_roi_by_genre = studio_roi.groupby('genre')
[["production_budget", "worldwide_gross", "foreign_gross",
"domestic_gross","foreign_profit","domestic_profit","net_profit"]].mea
n().sort_values(by="net_profit", ascending=False)
studio_roi_by_genre
```

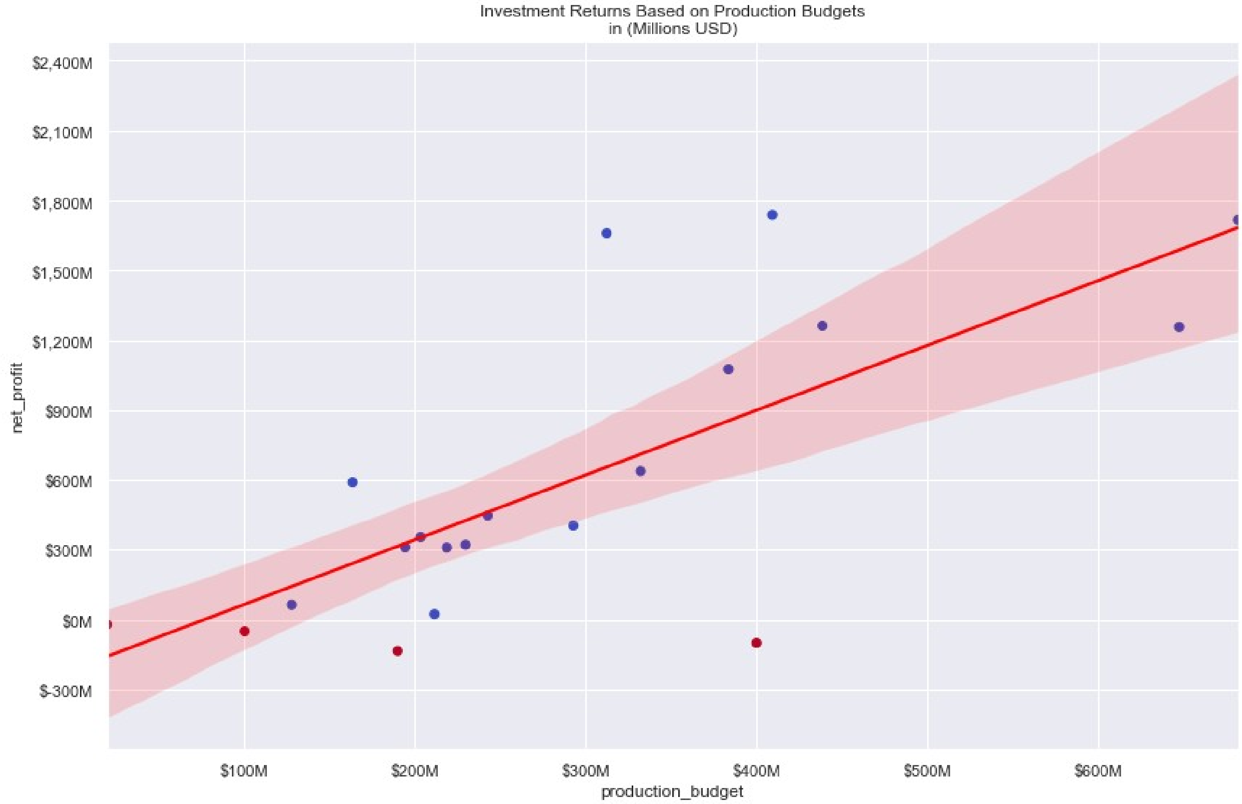
```
             production_budget  worldwide_gross  foreign_gross  \
genre
Fantasy           4.092500e+07     2.147509e+08   1.414200e+08
Adventure         6.817763e+07     2.398441e+08   1.529084e+08
Family            3.123262e+07     1.971572e+08   1.060152e+08
Animation         4.385157e+07     1.700755e+08   9.893777e+07
Action            6.472846e+07     1.904540e+08   1.195223e+08
Sci-Fi            3.836000e+07     1.459656e+08   7.625957e+07
Mystery           3.321500e+07     9.710790e+07   5.084519e+07
```

```
Horror              1.636488e+07      7.549052e+07   4.166628e+07
Biography           2.427259e+07      6.908652e+07   3.487363e+07
Thriller            2.928053e+07      6.981514e+07   4.109927e+07
Comedy              2.034669e+07      5.598395e+07   2.539617e+07
Documentary         2.297327e+07      5.526057e+07   2.729473e+07
Drama               1.944040e+07      5.063247e+07   2.645354e+07
Crime               2.187272e+07      5.296999e+07   2.823440e+07
Musical             1.280000e+07      1.934830e+07   7.400000e+06
Romance             2.115938e+07      2.371941e+07   9.333949e+06
Western             2.000000e+06      7.818100e+04   6.918100e+04
Music               1.005000e+07      5.232365e+06   3.081470e+06
War                 4.000000e+07      3.019910e+07   0.000000e+00
Sport               1.900000e+07      5.745503e+06   4.349490e+05

             domestic_gross  foreign_profit  domestic_profit
net_profit
genre

Fantasy       7.333090e+07    1.004950e+08     3.240590e+07
1.738259e+08
Adventure     8.693569e+07    8.473078e+07     1.875806e+07
1.716665e+08
Family        9.114204e+07    7.478253e+07     5.990942e+07
1.659246e+08
Animation     7.113769e+07    5.508620e+07     2.728612e+07
1.262239e+08
Action        7.093171e+07    5.479387e+07     6.203254e+06
1.257256e+08
Sci-Fi        6.970608e+07    3.789957e+07     3.134608e+07
1.076056e+08
Mystery       4.626272e+07    1.763019e+07     1.304772e+07
6.389290e+07
Horror        3.382424e+07    2.530140e+07     1.745935e+07
5.912563e+07
Biography     3.421289e+07    1.060104e+07     9.940293e+06
4.481392e+07
Thriller      2.871587e+07    1.181874e+07    -5.646550e+05
4.053461e+07
Comedy        3.058779e+07    5.049477e+06     1.024110e+07
3.563726e+07
Documentary   2.796584e+07    4.321470e+06     4.992574e+06
3.228731e+07
Drama         2.417893e+07    7.013146e+06     4.738534e+06
3.119208e+07
Crime         2.473559e+07    6.361675e+06     2.862873e+06
3.109727e+07
Musical       1.194830e+07   -5.400000e+06    -8.517050e+05
6.548295e+06
Romance       1.438547e+07   -1.182543e+07    -6.773909e+06
```

```
2.560039e+06
Western          9.000000e+03   -1.930819e+06    -1.991000e+06 -
1.921819e+06
Music            2.150896e+06   -6.968530e+06    -7.899104e+06 -
4.817635e+06
War              3.019910e+07   -4.000000e+07    -9.800895e+06 -
9.800895e+06
Sport            5.310554e+06   -1.856505e+07    -1.368945e+07 -
1.325450e+07
```

Linear regression model for production model vs net_profit

```
fig, ax = plt.subplots(figsize=(14, 9))

x = studio_roi_by_genre['production_budget']
y = studio_roi_by_genre['net_profit']
ax.scatter(
    x=x,
    y=y,
    c=np.sign(y),
    cmap=plt.cm.coolwarm.reversed()
)

_x_ticks = [value * 10**6 for value in range(10,350+1,10)]
_y_ticks = [value * 10**6 for value in range(-30,1750+1,30)]
ax.set(
    title="Investment Returns Based on Production Budgets\nin
(Millions USD)",
    xlabel="Production Budget",
    ylabel="Net Profit",
    xticks=_x_ticks,
    xticklabels = [f'${int(value/100000):,}M' for value in _x_ticks],
    yticks=_y_ticks,
    yticklabels = [f'${int(value/100000):,}M' for value in _y_ticks],
)

sns.regplot(x='production_budget', y='net_profit',
data=studio_roi_by_genre, scatter=False, color='red')
plt.show()
```




```
# fig, ax = plt.subplots(figsize=(14, 9))

# x = studio_roi_by_genre['production_budget']
# y = studio_roi_by_genre['net_profit']
# ax.scatter(
#     x=x,
#     y=y,
#     c=np.sign(y),
#     cmap=plt.cm.coolwarm.reversed()
# )

# _x_ticks = [value * 10**6 for value in range(10,350+1,10)]
# _y_ticks = [value * 10**6 for value in range(-30,1750+1,30)]
# ax.set(
#     title="Investment Returns Based on Production Budgets\nin
(Millions USD)",
#     xlabel="Production Budget",
#     ylabel="Net Profit",
#     xticks=_x_ticks,
#     xticklabels = [f'${int(value/100000):,}M' for value in
_x_ticks],
#     yticks=_y_ticks,
#     yticklabels = [f'${int(value/100000):,}M' for value in
_y_ticks],
# )
```

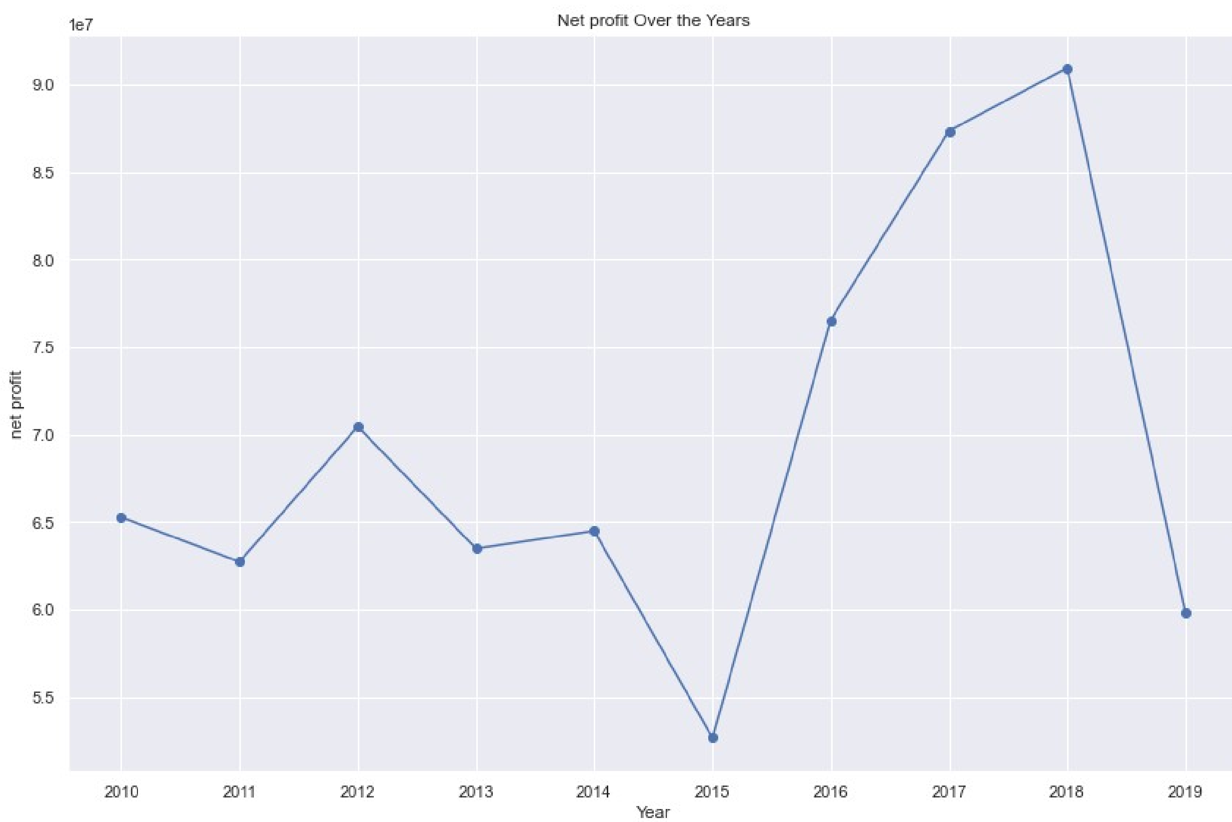
```
# z = np.polyfit(x, y, 2)
# p = np.poly1d(z)

# ax.plot(x,p(x),"r--")
# plt.xticks(fontsize=14, rotation=0)
# plt.yticks(fontsize=14, rotation=0)
# plt.rc('font', size = 25)
# '';
```

Find the average net profit achieved in each year in our dataset

```
studio_roi_by_year = studio_roi.groupby('start_year')
[["production_budget", "worldwide_gross", "foreign_gross",
"domestic_gross","foreign_profit","domestic_profit","net_profit"]].mea
n()
studio_roi_by_year
```

```
            production_budget  worldwide_gross  foreign_gross
domestic_gross  \
start_year

2010             3.389267e+07     9.915976e+07   5.606330e+07
4.309645e+07
2011             3.516761e+07     9.789789e+07   5.837459e+07
3.952330e+07
2012             3.425390e+07     1.047078e+08   6.227616e+07
4.243160e+07
2013             3.432303e+07     9.781125e+07   5.651543e+07
4.129581e+07
2014             2.937504e+07     9.386530e+07   5.444474e+07
3.942055e+07
2015             2.795641e+07     8.062794e+07   4.687885e+07
3.374909e+07
2016             3.603538e+07     1.125813e+08   6.402047e+07
4.856080e+07
2017             4.151334e+07     1.288640e+08   7.772757e+07
5.113639e+07
2018             3.806005e+07     1.290080e+08   7.456274e+07
5.444531e+07
2019             4.512681e+07     1.049705e+08   5.756508e+07
4.740540e+07

            foreign_profit  domestic_profit    net_profit
start_year
2010          2.217063e+07     9.203784e+06  6.526709e+07
2011          2.320698e+07     4.355696e+06  6.273028e+07
2012          2.802226e+07     8.177698e+06  7.045385e+07
2013          2.219240e+07     6.972785e+06  6.348822e+07
2014          2.506970e+07     1.004551e+07  6.449026e+07
```

```
2015          1.892244e+07     5.792676e+06  5.267153e+07
2016          2.798509e+07     1.252542e+07  7.654589e+07
2017          3.621423e+07     9.623049e+06  8.735062e+07
2018          3.650269e+07     1.638526e+07  9.094800e+07
2019          1.243828e+07     2.278591e+06  5.984367e+07

plt.figure(figsize=(12, 8))
plt.plot(studio_roi_by_year.index, studio_roi_by_year["net_profit"],
marker='o', linestyle='-', color='b')

# Adding titles and labels
plt.title('Net profit Over the Years')
plt.xlabel('Year')
plt.ylabel('net profit')
plt.grid(True)
plt.tight_layout()

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



Recommendations

Genre

Studio-Afrik should consider picking top rated genres with highest number of votes. Our analysis indicates a genre can have a high average rating due to low votes. Therefore, they should venture into Action, Adventure, Crime, Biography, comedy which are the top five rated genres considering they have high number of votes.

Directors to higher

Studio-Afrik should focus on attracting renowned and respected directors to elevate film quality and enhance audience ratings, which will ultimately generate greater revenue and create lasting impact in the film industry.

The top ten directors with average movie rating based on votes above mean of votes are: 'Donavon Warren', 'Mari Selvaraj', 'Anjana Krishnakumar', 'Chathra Weeraman', 'Amitabh Reza Chowdhury', 'Amudhavan Karuppiah','Bharatha Hettiarachchi', 'Prabunath', 'Maha Venkatesh' and 'Summer Nicks'

Invest in production budget

From our analysis above, we observe that investmenting in production budget has a positive return on the net profit. Our data shows a positive linear relationship between production budget and net profit.