Final Project Submission

Please fill out:

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- Student pace: FULL TIME
- Scheduled project review date/time:
- Instructor name: ANTONNY MUIKO
- Blog post URL:

Business Problem

Voice of Kenya now sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable insights that the head of your company's new movie studio can use to help decide what type of films to create.

Business Understanding

The business problem presented by Voice of Kenya is to establish their own movie studio to compete within the movie market both locally and globally. For Voice of Kenya to succed in this business, some questions needs answers:

- Are movies really profitable, do they really make money
- What kind of the movie genre will be the most successful
- What is the budget of producing a movie from start to airing
- Who are my competitor and how established are they in the market

Answering this questions will help the Voice of Kenya to make decisions

Data Understanding

After carefully analysising the data provided in relation to the business problem and the business understanding question. I have selected the following datasets together with the columns that will be used in each particular dataset. The primary key is movie_title

1. im.db.zip(movie_basic i.e movie_title and genres)
2. tn.movie_budgets.csv.gz(movie_title, production_budget, domestic_gross, worldwide_gross)
3. bom.movie_gross.csv.gz(movie_title, studio)

Data preparation

The three dataset will go through sanity check first thats is data cleaning, it includes:

1. Converting some columns that are are supposed to be numerical i.e production_budget, domestic_gross_y, worldwide_gross from object dtype to float dtype
2. Check the null or missing values and fill them, and drop where need be
3. Check and drop duplicates
4. Check and drop outliers

After the sanity check then i will merge the datasets 2 by 2 i.e will merge two datasets, then i will take the merged dataset and merge with the third dataset to have one dataset.

```
import pandas as pd
import sqlite3
import numpy as np
import seaborn as sns
import sklearn as sk
import statsmodels.api as sm
import scipy.stats as stats
import matplotlib.pyplot as plt
%matplotlib inline

import zipfile

# define the files path to extract and save the file after extract
zip_path = "zippedData/im.db.zip"
idmb_unzip = "zippedData/unzip idmb"
# unzip the datafile
with zipfile.ZipFile(zip_path, "r") as zip_ref:
    zip_ref.extractall(idmb_unzip)

# connecting our database
conn = sqlite3.connect("zippedData/unzip idmb/im.db")
# retriving our tables
movie_basics = pd.read_sql_query("SELECT* FROM movie_basics", conn)
movie_ratings = pd.read_sql_query("SELECT* FROM movie_ratings", conn)
# closing the connection


# connecting our datasets
# in the movie basic table i just need two columns the genre and
primary title
conn = sqlite3.connect("zippedData/unzip idmb/im.db")
q = """
SELECT
    primary_title,
    genres
FROM movie_basics;
"""
idmb_unzip = pd.read_sql(q, conn)

# cheking the info our movie basic column
idmb_unzip.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 2 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   primary_title  146144 non-null  object
 1   genres         140736 non-null  object
dtypes: object(2)
memory usage: 2.2+ MB
```

Data analysis

1. Checking missing values drop them or fill them
2. Checking for duplicates
3. Checking for outliers but in this dataset we have object dtype so we will ommit checking the outliers

```
# checking of null values
idmb_unzip.isna().sum()

primary_title      0
genres          5408
dtype: int64

# our dataset contains 5408 missing values. This is a very small
percentage so we can drop the missing value rows
idmb_unzip1= idmb_unzip.dropna()
idmb_unzip1

                                          primary_title
genres
0                                            Sunghursh
Action,Crime,Drama
1                      One Day Before the Rainy Season
Biography,Drama
2                          The Other Side of the Wind
Drama
3                                      Sabse Bada Sukh
Comedy,Drama
4                            The Wandering Soap Opera
Comedy,Drama,Fantasy
...                                                ...
...
146138                             The Secret of China
Adventure,History,War
146139                             Kuambil Lagi Hatiku
Drama
146140  Rodolpho Teóphilo - O Legado de um Pioneiro
Documentary
146141                                  Dankyavar Danka
```

```
Comedy
146143                Chico Albuquerque - Revelações
Documentary

[140736 rows x 2 columns]

# confirming if our dataset contains any missing value
idmb_unzip1.isna().sum()

primary_title    0
genres           0
dtype: int64

# Lets check for duplicates
idmb_unzip1.duplicated().sum()

1612

# the dataset contains 1612 duplicates we drop them keeping first
cleaned_imdb = idmb_unzip1.drop_duplicates()
cleaned_imdb

                                      primary_title
genres
0                                         Sunghursh
Action,Crime,Drama
1                   One Day Before the Rainy Season
Biography,Drama
2                        The Other Side of the Wind
Drama
3                                   Sabse Bada Sukh
Comedy,Drama
4                          The Wandering Soap Opera
Comedy,Drama,Fantasy
...                                             ...
...
146138                          The Secret of China
Adventure,History,War
146139                          Kuambil Lagi Hatiku
Drama
146140  Rodolpho Teóphilo - O Legado de um Pioneiro
Documentary
146141                              Dankyavar Danka
Comedy
146143                Chico Albuquerque - Revelações
Documentary

[139124 rows x 2 columns]

# confirming duplicates
cleaned_imdb.duplicated().sum()
```

```
0
```

Our imdb dataset is clean with a new name as cleaned_imdb now we work for our csv data that bom.movie_gross.csv. we start by reading it

```
bom_movie = pd.read_csv("zippedData/bom.movie_gross.csv")
bom_movie.head()
```

```
                                         title studio  domestic_gross
\
0                                  Toy Story 3     BV     415000000.0

1                   Alice in Wonderland (2010)     BV     334200000.0

2  Harry Potter and the Deathly Hallows Part 1     WB     296000000.0

3                                    Inception     WB     292600000.0

4                          Shrek Forever After   P/DW     238700000.0


  foreign_gross  year
0     652000000  2010
1     691300000  2010
2     664300000  2010
3     535700000  2010
4     513900000  2010
```

```
# checking how our dataset looks like
bom_movie.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
```

Data analysis

1. First we will convert the foreign_gross from object dtype to float dtype
2. Check the null or missing values and fill them, and drop where need be
3. Check and drop duplicates
4. Check and drop outliers

```python
#checking the colums
bom_movie.columns
```

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

```python
# we need the foreign gross column in as a float dtype. we need to
convert it from object to float dtype
bom_movie['foreign_gross'] =
bom_movie['foreign_gross'].str.replace(',', '').astype(float)
```

```python
bom_movie.describe()
```

	domestic_gross	foreign_gross	year
count	3.359000e+03	2.037000e+03	3387.000000
mean	2.874585e+07	7.487281e+07	2013.958075
std	6.698250e+07	1.374106e+08	2.478141
min	1.000000e+02	6.000000e+02	2010.000000
25%	1.200000e+05	3.700000e+06	2012.000000
50%	1.400000e+06	1.870000e+07	2014.000000
75%	2.790000e+07	7.490000e+07	2016.000000
max	9.367000e+08	9.605000e+08	2018.000000

```python
# checking for missing values
bom_movie.isna().sum()
```

```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

```python
# The number of missing values in foreign _gross is a huge percentage
to be dropped
# We calculate the mean value and use it to fill the missing values
mean_value = bom_movie['foreign_gross'].mean()
mean_value
```

```
74872810.15046637
```

```python
# Filling the missing values using the mean
bom_movie['foreign_gross'] =
bom_movie['foreign_gross'].fillna(mean_value)
```

```python
# We calculate the mean value and use it to fill the missing values
mean_value = bom_movie['domestic_gross'].mean()
mean_value
```

```
28745845.06698422
```

```
#Filling the missing values using the mean
bom_movie['domestic_gross'] =
bom_movie['domestic_gross'].fillna(mean_value)

# dropping miss values in studio
bom_movie1 = bom_movie.dropna(subset=['studio'])
bom_movie1

                                            title      studio
domestic_gross  \
0                                     Toy Story 3          BV
415000000.0
1                      Alice in Wonderland (2010)          BV
334200000.0
2     Harry Potter and the Deathly Hallows Part 1          WB
296000000.0
3                                       Inception          WB
292600000.0
4                             Shrek Forever After        P/DW
238700000.0
...                                           ...         ...
...
3382                                    The Quake       Magn.
6200.0
3383                  Edward II (2018 re-release)          FM
4800.0
3384                                     El Pacto        Sony
2500.0
3385                                     The Swan  Synergetic
2400.0
3386                          An Actor Prepares       Grav.
1700.0

      foreign_gross  year
0      6.520000e+08  2010
1      6.913000e+08  2010
2      6.643000e+08  2010
3      5.357000e+08  2010
4      5.139000e+08  2010
...             ...   ...
3382   7.487281e+07  2018
3383   7.487281e+07  2018
3384   7.487281e+07  2018
3385   7.487281e+07  2018
3386   7.487281e+07  2018

[3382 rows x 5 columns]

bom_movie1.isna().sum()
```

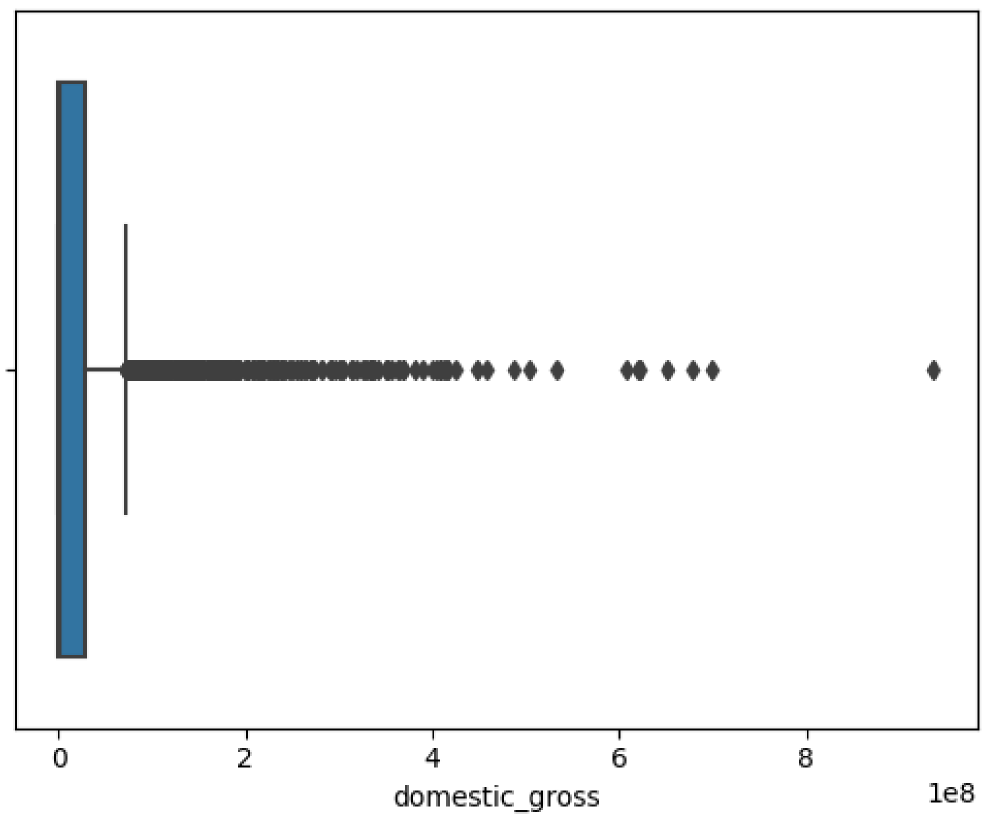
```
title             0
studio            0
domestic_gross    0
foreign_gross     0
year              0
dtype: int64
```

```
# Checking for duplicates, bom_movie1 has no duplicates
bom_movie1.duplicated().sum()
```

```
0
```

```
# Checking for outliers domestic_gross column using the boxplot
sns.boxplot(x = bom_movie1['domestic_gross'])
```

```
<Axes: xlabel='domestic_gross'>
```



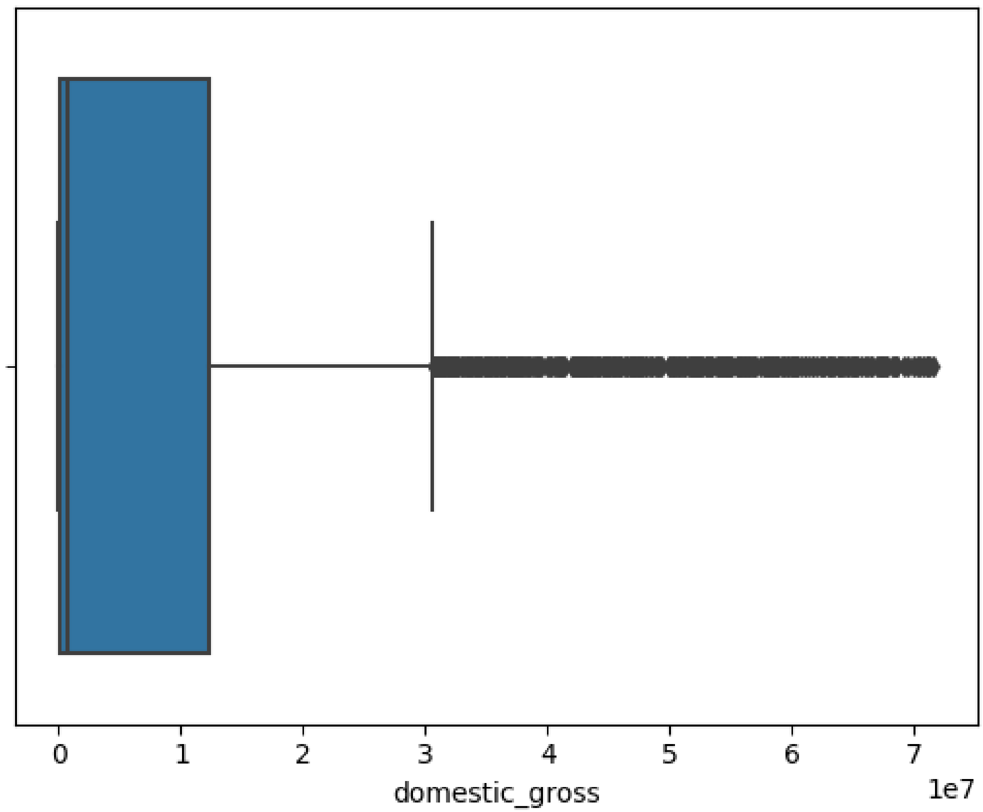

```
# i will use the interquatile range to calculate and filter out outliers
# Calculate the IQR
Q1 = bom_movie1['domestic_gross'].quantile(0.25)
Q3 = bom_movie1['domestic_gross'].quantile(0.75)
IQR = Q3 - Q1
```

```
# Define the bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out outliers
fi_bom_movie = bom_movie1[(bom_movie1['domestic_gross'] >=
lower_bound) & (bom_movie1['domestic_gross'] <= upper_bound)]
fi_bom_movie
```

```
                            title      studio  domestic_gross
foreign_gross  \
21        Resident Evil: Afterlife        SGem      60100000.0
2.401000e+08
25                     The Tourist        Sony      67600000.0
2.107000e+08
30              Gulliver's Travels         Fox      42800000.0
1.946000e+08
34       The Sorcerer's Apprentice          BV      63200000.0
1.521000e+08
44                     Step Up 3-D          BV      42400000.0
1.169000e+08
...                            ...         ...             ...
...
3382                     The Quake       Magn.          6200.0
7.487281e+07
3383   Edward II (2018 re-release)          FM          4800.0
7.487281e+07
3384                      El Pacto        Sony          2500.0
7.487281e+07
3385                      The Swan  Synergetic          2400.0
7.487281e+07
3386             An Actor Prepares       Grav.          1700.0
7.487281e+07

      year
21    2010
25    2010
30    2010
34    2010
44    2010
...    ...
3382  2018
3383  2018
3384  2018
3385  2018
3386  2018

[2984 rows x 5 columns]
```

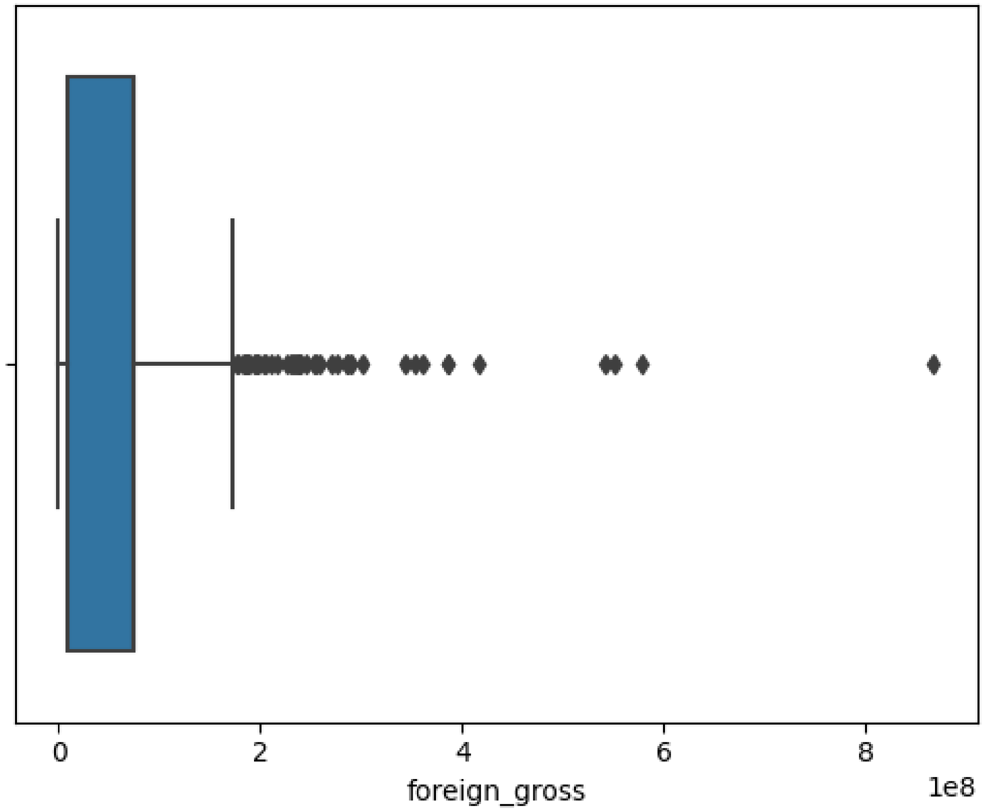
```
# Checking outliers for the domestic_gross column after filtering out,
a way of confirming
sns.boxplot(x = fi_bom_movie ['domestic_gross'])
```

```
<Axes: xlabel='domestic_gross'>
```




```
# Checking out outliers in the foreign_gross column using the boxplot
sns.boxplot(x=fi_bom_movie['foreign_gross'])
```

```
<Axes: xlabel='foreign_gross'>
```



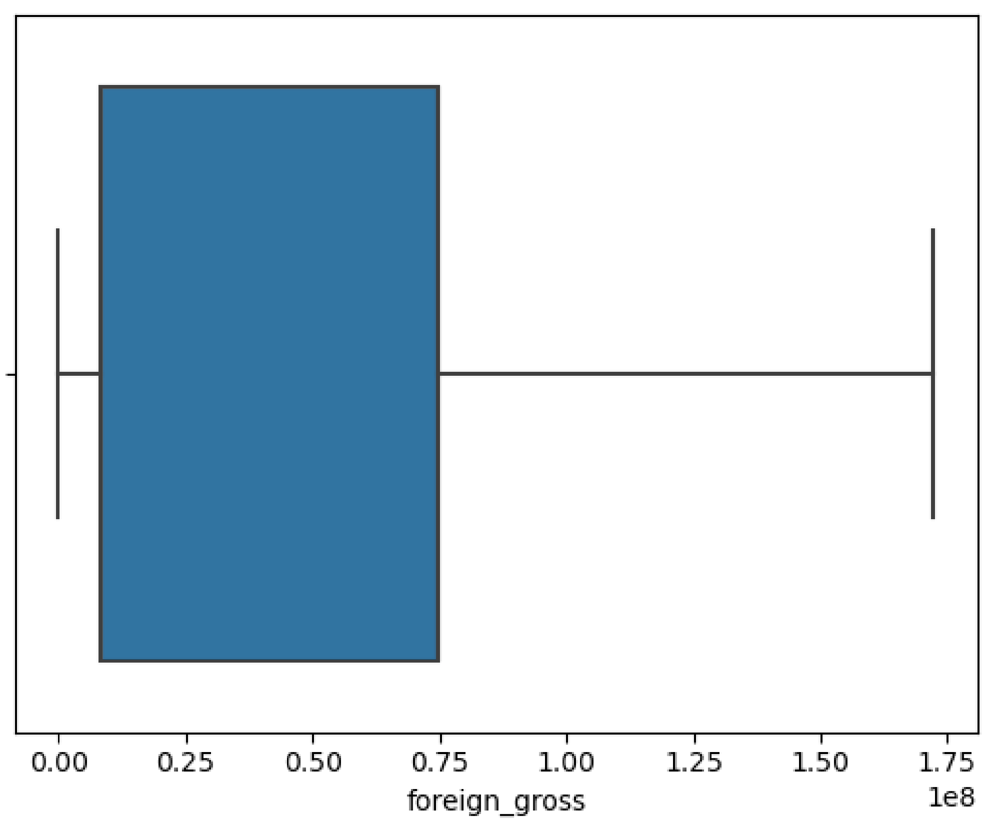

```
# i will use the interquatile range to calculate and filter out
outliers
# Calculate the IQR
Q1 = fi_bom_movie['foreign_gross'].quantile(0.25)
Q3 = fi_bom_movie['foreign_gross'].quantile(0.75)
IQR = Q3 - Q1

# Define the bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out outliers
cleaned_bom_movie = fi_bom_movie[(fi_bom_movie['foreign_gross'] >=
lower_bound) & (fi_bom_movie['foreign_gross'] <= upper_bound)]
cleaned_bom_movie
```

```
                                                title      studio  \
34                            The Sorcerer's Apprentice          BV
44                                        Step Up 3-D          BV
48    Legend of the Guardians: The Owls of Ga'Hoole          WB
49                                        The Wolfman        Uni.
50                                  The Bounty Hunter        Sony
...                                               ...         ...
3382                                        The Quake       Magn.
```

```
3383                     Edward II (2018 re-release)          FM
3384                                        El Pacto        Sony
3385                                        The Swan  Synergetic
3386                               An Actor Prepares       Grav.

      domestic_gross  foreign_gross  year
34        63200000.0   1.521000e+08  2010
44        42400000.0   1.169000e+08  2010
48        55700000.0   8.440000e+07  2010
49        62000000.0   7.780000e+07  2010
50        67099999.0   6.930000e+07  2010
...              ...            ...   ...
3382          6200.0   7.487281e+07  2018
3383          4800.0   7.487281e+07  2018
3384          2500.0   7.487281e+07  2018
3385          2400.0   7.487281e+07  2018
3386          1700.0   7.487281e+07  2018

[2936 rows x 5 columns]
```

```python
# Checking outliers for the foreign_gross column after filtering out, a way of confirming
sns.boxplot(x=cleaned_bom_movie['foreign_gross'])
```

```
<Axes: xlabel='foreign_gross'>
```



```
df = pd.read_csv("zippedData/tn.movie_budgets.csv")
df.head()

   id  release_date                                            movie  \
0   1  Dec 18, 2009                                           Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                     Dark Phoenix
3   4   May 1, 2015                          Avengers: Age of Ultron
4   5  Dec 15, 2017            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

#checking the shape of the datasets it 5782 contains rows and 6
columns
df.shape

(5782, 6)

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
```

Data analysis

1. First we will convert the production_budget, domestic_gross, worldwide_gross from object dtype to float dtype
2. Check the null or missing values and fill them, and drop where need be
3. Check and drop duplicates
4. Check and drop outliers

To convert the production_budget, domestic_gross, worldwide_gross we have to get rid of commas and the dollar signs.The reason been to work with numbers in calculations or data analysis, you need to get rid of these symbols since computers will nottreat them as numbers.

```
# we defined a function
def remove_dollar_sign(x):
    return x.replace('$', '').replace(',', '')

# defined the columns we need to remove sysmbols and commas
remove_columns = ['production_budget', 'domestic_gross',
'worldwide_gross']
# we use for loops to iterate through the columns
for column in remove_columns:
    df[column] = df[column].apply(remove_dollar_sign)

# confirming if our columns contains the signs, good we are okay
df.head(2)
```

```
   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides

  production_budget domestic_gross worldwide_gross
0         425000000      760507625      2776345279
1         410600000      241063875      1045663875
```

```
# first we convert the production_budget, domestic_gross,
worldwide_gross from object dtype to flaat dtype
# converting the production_budget
df['production_budget'] = df['production_budget'].str.replace(',',
'').astype(float)

# converting the domestic_gross
df['domestic_gross'] = df['domestic_gross'].str.replace(',',
'').astype(float)

#converting the worldwide_gross
df['worldwide_gross'] = df['worldwide_gross'].str.replace(',',
'').astype(float)

#succesfully converted to float dtype
df.dtypes
```

```
id                     int64
release_date          object
movie                 object
production_budget    float64
domestic_gross       float64
worldwide_gross      float64
dtype: object
```

```
# checking the stats i.e mean, median, mode, count e.t.c
df.describe()
```

```
                id  production_budget  domestic_gross  worldwide_gross
count  5782.000000       5.782000e+03    5.782000e+03     5.782000e+03
```

mean	50.372363	3.158776e+07	4.187333e+07	9.148746e+07
std	28.821076	4.181208e+07	6.824060e+07	1.747200e+08
min	1.000000	1.100000e+03	0.000000e+00	0.000000e+00
25%	25.000000	5.000000e+06	1.429534e+06	4.125415e+06
50%	50.000000	1.700000e+07	1.722594e+07	2.798445e+07
75%	75.000000	4.000000e+07	5.234866e+07	9.764584e+07
max	100.000000	4.250000e+08	9.366622e+08	2.776345e+09

performing sanity check

```
#checking missing values, drop, or fill them.
df.isna().sum() # our data has no missing values
```

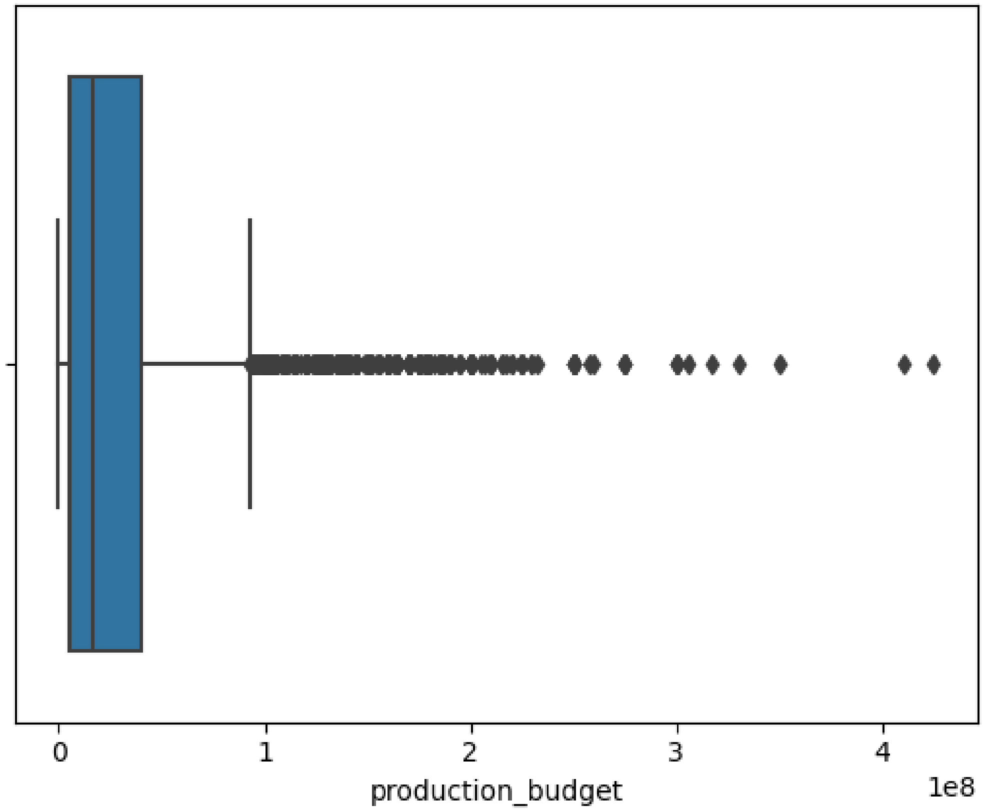
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

```
# checking for duplicates
df.duplicated().sum() # no duplicates
```

```
0
```

```
# checking for outliers using sns library and box plot
sns.boxplot(x =df['production_budget'])
```

```
<Axes: xlabel='production_budget'>
```



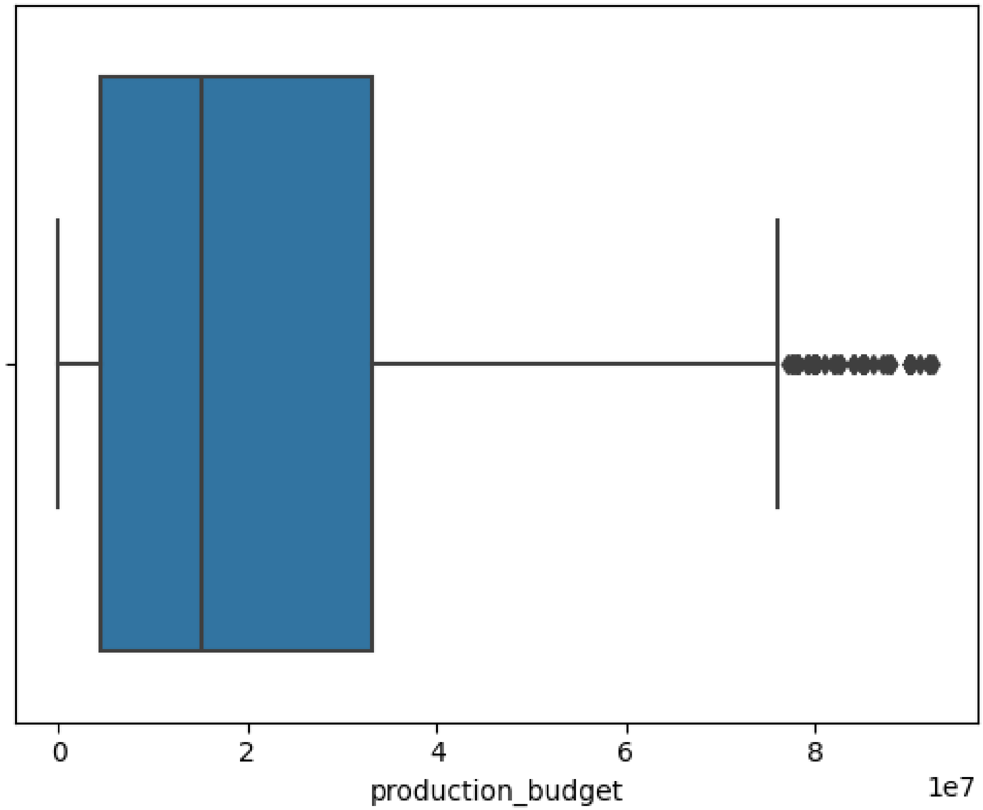

```
# i will use the interquatile range to calculate and filter out
outliers
# Calculate the IQR
Q1 = df['production_budget'].quantile(0.25)
Q3 = df['production_budget'].quantile(0.75)
IQR = Q3 - Q1

# Define the bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out outliers
df1 = df[(df['production_budget'] >= lower_bound) &
(df['production_budget'] <= upper_bound)]
df1
```

```
      id  release_date                          movie
production_budget  \
431   32  Feb 14, 2008      The Spiderwick Chronicles
92500000.0
432   33   Nov 5, 2004               The Incredibles
92000000.0
433   34  Feb 14, 2013         A Good Day to Die Hard
92000000.0
```

```
434   35   Apr 9, 2004                      The Alamo
92000000.0
435   36  Dec 22, 1995               Cutthroat Island
92000000.0
...   ..          ...                             ...                .
..
5777  78  Dec 31, 2018                         Red 11
7000.0
5778  79   Apr 2, 1999                      Following
6000.0
5779  80  Jul 13, 2005  Return to the Land of Wonders
5000.0
5780  81  Sep 29, 2015          A Plague So Pleasant
1400.0
5781  82   Aug 5, 2005               My Date With Drew
1100.0

      domestic_gross  worldwide_gross
431       71195053.0      162839667.0
432      261441092.0      614726752.0
433       67349198.0      304249198.0
434       22406362.0       23911362.0
435       10017322.0       18517322.0
...              ...              ...
5777             0.0              0.0
5778         48482.0         240495.0
5779          1338.0           1338.0
5780             0.0              0.0
5781        181041.0         181041.0

[5351 rows x 6 columns]
```

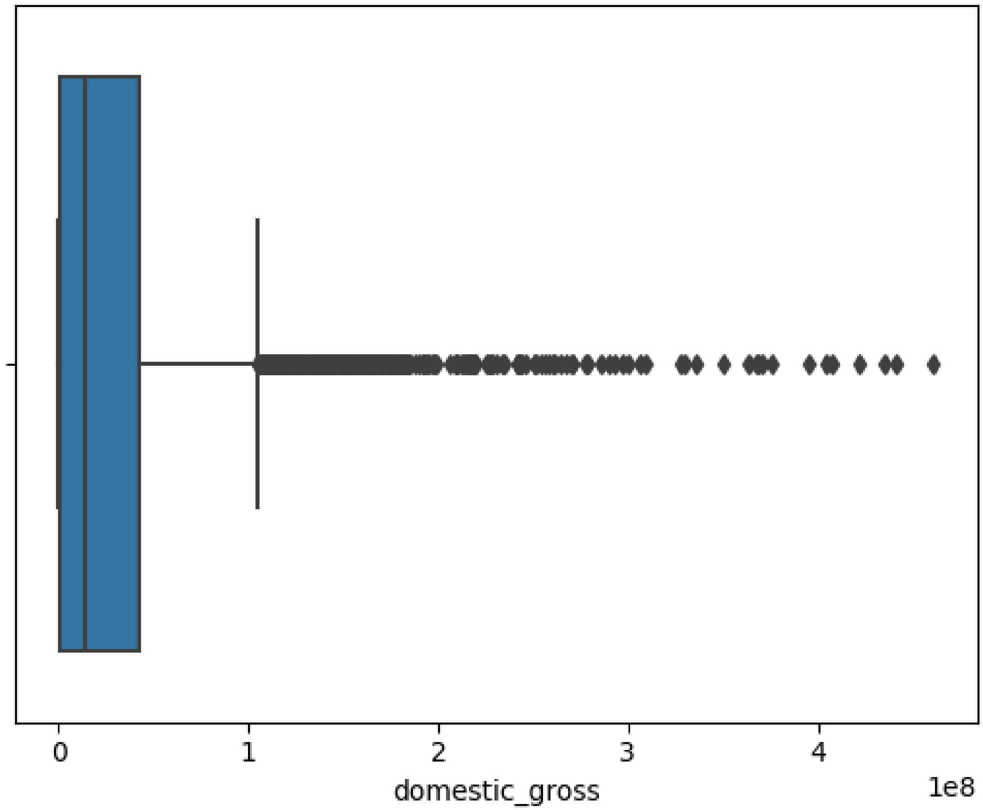
```
sns.boxplot(x =df1['production_budget'])
```

```
<Axes: xlabel='production_budget'>
```




```
sns.boxplot(x =df1['domestic_gross'])
```

```
<Axes: xlabel='domestic_gross'>
```



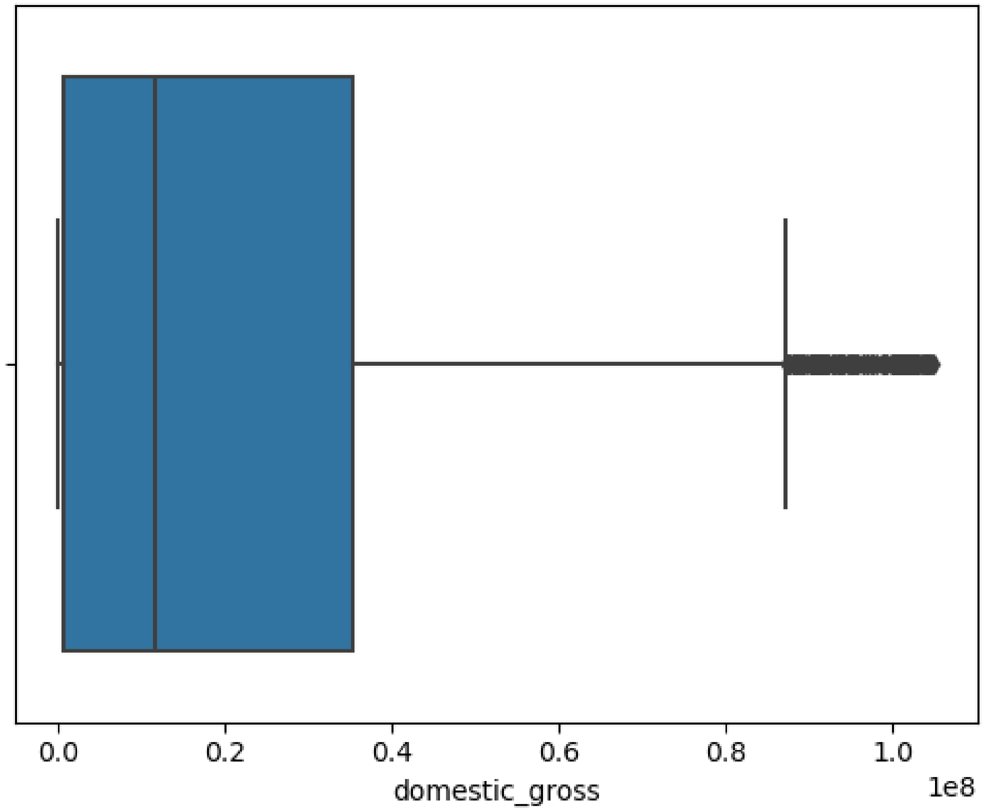

```
# i will use the interquatile range to calculate and filter out
outliers
# Calculate the IQR
Q1 = df1['domestic_gross'].quantile(0.25)
Q3 = df1['domestic_gross'].quantile(0.75)
IQR = Q3 - Q1

# Define the bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out outliers
df2 = df1[(df1['domestic_gross'] >= lower_bound) &
(df1['domestic_gross'] <= upper_bound)]
df2
```

```
      id  release_date                            movie
production_budget  \
431   32  Feb 14, 2008       The Spiderwick Chronicles
92500000.0
433   34  Feb 14, 2013            A Good Day to Die Hard
92000000.0
434   35   Apr 9, 2004                         The Alamo
92000000.0
```

```
435   36  Dec 22, 1995                 Cutthroat Island
92000000.0
436   37  Dec 25, 2013  The Secret Life of Walter Mitty
91000000.0
...   ..           ...                              ...
...
5777  78  Dec 31, 2018                           Red 11
7000.0
5778  79   Apr 2, 1999                        Following
6000.0
5779  80  Jul 13, 2005    Return to the Land of Wonders
5000.0
5780  81  Sep 29, 2015              A Plague So Pleasant
1400.0
5781  82   Aug 5, 2005                 My Date With Drew
1100.0

      domestic_gross  worldwide_gross
431       71195053.0      162839667.0
433       67349198.0      304249198.0
434       22406362.0       23911362.0
435       10017322.0       18517322.0
436       58236838.0      187861183.0
...              ...              ...
5777             0.0              0.0
5778         48482.0         240495.0
5779          1338.0           1338.0
5780             0.0              0.0
5781        181041.0         181041.0

[4994 rows x 6 columns]
```

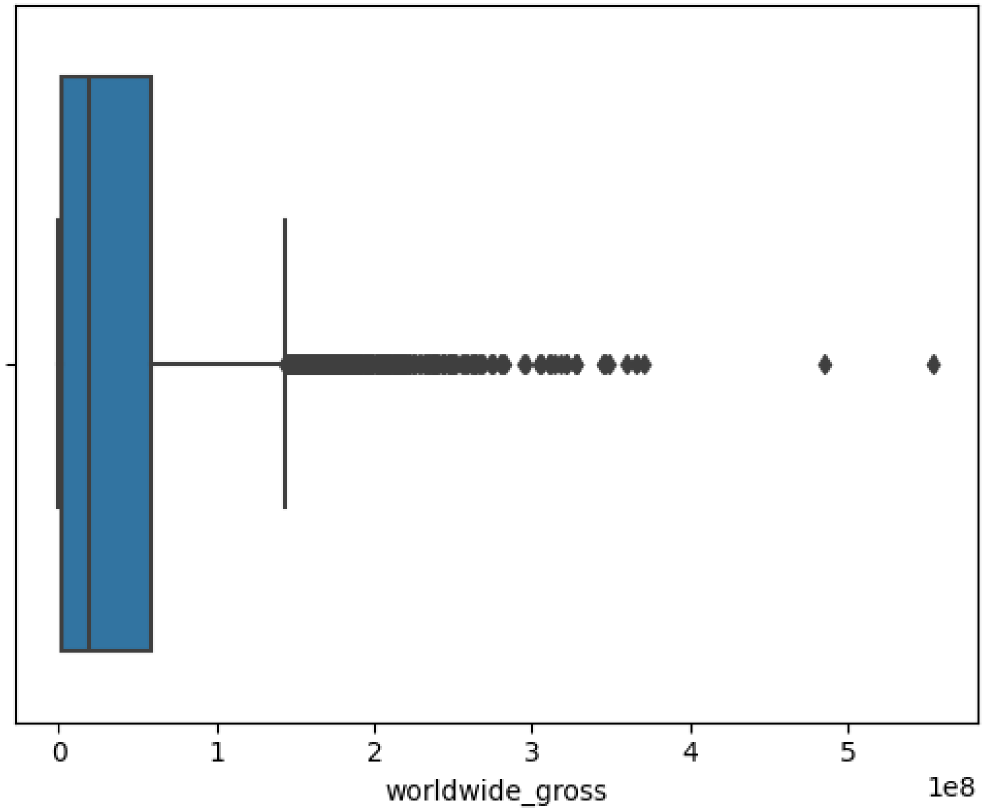
```
sns.boxplot(x =df2['domestic_gross'])
```

```
<Axes: xlabel='domestic_gross'>
```




```
sns.boxplot(x =df2['worldwide_gross'])
```

```
<Axes: xlabel='worldwide_gross'>
```



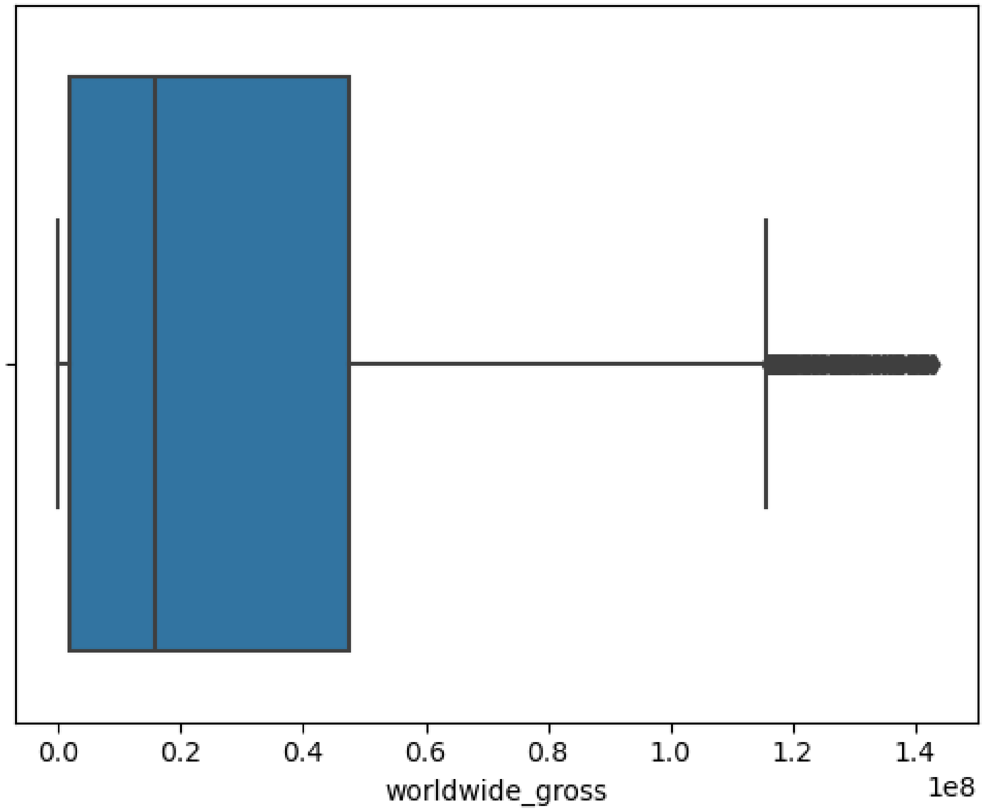

```
# i will use the interquatile range to calculate and filter out
outliers
# Calculate the IQR
Q1 = df2['worldwide_gross'].quantile(0.25)
Q3 = df2['worldwide_gross'].quantile(0.75)
IQR = Q3 - Q1

# Define the bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter out outliers
tn_movie = df2[(df2['worldwide_gross'] >= lower_bound) &
(df2['worldwide_gross'] <= upper_bound)]
tn_movie
```

```
      id  release_date                                   movie
production_budget  \
434   35   Apr 9, 2004                               The Alamo
92000000.0
435   36  Dec 22, 1995                        Cutthroat Island
92000000.0
466   67  Nov 21, 2001                                Spy Game
90000000.0
```

```
468   69  Mar 10, 2000                Mission to Mars
90000000.0
470   71  Dec 17, 1999               Bicentennial Man
90000000.0
...   ..           ...                            ...                .
..
5777  78  Dec 31, 2018                         Red 11
7000.0
5778  79   Apr 2, 1999                      Following
6000.0
5779  80  Jul 13, 2005  Return to the Land of Wonders
5000.0
5780  81  Sep 29, 2015          A Plague So Pleasant
1400.0
5781  82   Aug 5, 2005              My Date With Drew
1100.0

      domestic_gross  worldwide_gross
434       22406362.0       23911362.0
435       10017322.0       18517322.0
466       62362560.0      143049560.0
468       60874615.0      106000000.0
470       58220776.0       87420776.0
...              ...              ...
5777             0.0              0.0
5778         48482.0         240495.0
5779          1338.0           1338.0
5780             0.0              0.0
5781        181041.0         181041.0

[4657 rows x 6 columns]
```

```
sns.boxplot(x =tn_movie['worldwide_gross'])
```

```
<Axes: xlabel='worldwide_gross'>
```



Our dataset is clean and the new name is cleaned_bom_movie

By merging the datasets I will create a consolidated dataset for a better and and not complicated analysis. To ensure data integrity and completeness, I will exclude any records that do not have a match between the datasets, thus eliminating any potential missing values for the features.

1. I will create a unique key thats is a primary key. in the two datasets they have a common column thats contains the title of the movies just that they have different column names. i will rename the column names in both dataset
2. Having a primary key named movie_title i can proceed on merging the two datasets

```
# rename primary title to more readable and understanding column name
cleaned_imdb = cleaned_imdb.rename(columns={'primary_title':
'movie_title'})
cleaned_imdb

                                             movie_title
genres
0                                              Sunghursh
Action,Crime,Drama
1                         One Day Before the Rainy Season
```

```
Biography,Drama
2                             The Other Side of the Wind
Drama
3                                         Sabse Bada Sukh
Comedy,Drama
4                               The Wandering Soap Opera
Comedy,Drama,Fantasy
...                                                  ...
...
146138                              The Secret of China
Adventure,History,War
146139                              Kuambil Lagi Hatiku
Drama
146140  Rodolpho Teóphilo - O Legado de um Pioneiro
Documentary
146141                                  Dankyavar Danka
Comedy
146143                 Chico Albuquerque - Revelações
Documentary

[139124 rows x 2 columns]
```

```
cleaned_imdb.columns
```

```
Index(['movie_title', 'genres'], dtype='object')
```

```
# renaming the title in the bom dataset to movie
cleaned_bom_movie =
cleaned_bom_movie.rename(columns={'title':'movie_title'})
cleaned_bom_movie
```

```
                                         movie_title      studio  \
34                           The Sorcerer's Apprentice          BV
44                                        Step Up 3-D          BV
48    Legend of the Guardians: The Owls of Ga'Hoole          WB
49                                        The Wolfman        Uni.
50                                   The Bounty Hunter        Sony
...                                               ...         ...
3382                                        The Quake       Magn.
3383                       Edward II (2018 re-release)          FM
3384                                         El Pacto        Sony
3385                                         The Swan  Synergetic
3386                                 An Actor Prepares       Grav.

      domestic_gross  foreign_gross  year
34        63200000.0   1.521000e+08  2010
44        42400000.0   1.169000e+08  2010
48        55700000.0   8.440000e+07  2010
49        62000000.0   7.780000e+07  2010
50        67099999.0   6.930000e+07  2010
```

```
...              ...          ...   ...
3382          6200.0   7.487281e+07  2018
3383          4800.0   7.487281e+07  2018
3384          2500.0   7.487281e+07  2018
3385          2400.0   7.487281e+07  2018
3386          1700.0   7.487281e+07  2018

[2936 rows x 5 columns]
```

```
cleaned_bom_movie.columns
```

```
Index(['movie_title', 'studio', 'domestic_gross', 'foreign_gross',
'year'], dtype='object')
```

```
cleaned_tn_movie = tn_movie.rename(columns={'movie': 'movie_title'})
cleaned_tn_movie
```

```
      id  release_date                     movie_title
production_budget  \
434   35   Apr 9, 2004                       The Alamo
92000000.0
435   36  Dec 22, 1995                Cutthroat Island
92000000.0
466   67  Nov 21, 2001                        Spy Game
90000000.0
468   69  Mar 10, 2000                Mission to Mars
90000000.0
470   71  Dec 17, 1999                Bicentennial Man
90000000.0
...   ..           ...                             ...                 .
..
5777  78  Dec 31, 2018                          Red 11
7000.0
5778  79   Apr 2, 1999                       Following
6000.0
5779  80  Jul 13, 2005  Return to the Land of Wonders
5000.0
5780  81  Sep 29, 2015          A Plague So Pleasant
1400.0
5781  82   Aug 5, 2005              My Date With Drew
1100.0

      domestic_gross  worldwide_gross
434       22406362.0       23911362.0
435       10017322.0       18517322.0
466       62362560.0      143049560.0
468       60874615.0      106000000.0
470       58220776.0       87420776.0
...              ...              ...
5777             0.0              0.0
```

```
5778         48482.0         240495.0
5779          1338.0           1338.0
5780             0.0              0.0
5781        181041.0         181041.0

[4657 rows x 6 columns]
```

We will use the merge method to merge cleaned_idmb and cleaned_bom_movie cleaned_tn_movie on movie_title as our primary key using an inner join parameter and we name the merged dataset as movies

```
# Merge tn_mb and bom_movie_gross on movie_title
movies1 = pd.merge(cleaned_imdb,
                  cleaned_bom_movie,
                  on=['movie_title'],
                  how='inner')

# Checking the 5 first rows as well as confirming if our dataset has
merged
movies1.head()

                       movie_title                   genres
studio  \
0                            Wazir       Action,Crime,Drama  Relbig.

1                      On the Road  Adventure,Drama,Romance      IFC

2                      On the Road                    Drama      IFC

3                      On the Road              Documentary      IFC

4  The Secret Life of Walter Mitty   Adventure,Comedy,Drama      Fox


   domestic_gross  foreign_gross  year
0       1100000.0   7.487281e+07  2016
1        744000.0   8.000000e+06  2012
2        744000.0   8.000000e+06  2012
3        744000.0   8.000000e+06  2012
4      58200000.0   1.299000e+08  2013

# Merge movies1 and tn.movie on movie_title
movies2 = pd.merge(movies1,
                  cleaned_tn_movie,
                  on=['movie_title'],
                  how='inner')

movies2.head()

                  movie_title                   genres studio  \
0                 On the Road  Adventure,Drama,Romance    IFC
```

```
1                  On the Road                       Drama    IFC
2                  On the Road                 Documentary    IFC
3  A Walk Among the Tombstones       Action,Crime,Drama   Uni.
4                The Rum Diary                Comedy,Drama     FD

   domestic_gross_x  foreign_gross  year  id  release_date
production_budget  \
0          744000.0      8000000.0  2012  17  Mar 22, 2013
25000000.0
1          744000.0      8000000.0  2012  17  Mar 22, 2013
25000000.0
2          744000.0      8000000.0  2012  17  Mar 22, 2013
25000000.0
3        26300000.0     26900000.0  2014  67  Sep 19, 2014
28000000.0
4        13100000.0     10800000.0  2011  16  Oct 28, 2011
45000000.0

   domestic_gross_y  worldwide_gross
0          720828.0        9313302.0
1          720828.0        9313302.0
2          720828.0        9313302.0
3        26017685.0       62108587.0
4        13109815.0       21544732.0
```

Our dataset has successfully merged but it contains some columns that we will not use so lets drop them they include: domestic_gross_x, foreign_gross, year, id, release_date

```
movies = movies2.drop(['domestic_gross_x', 'foreign_gross', 'id',
'release_date'], axis=1)
movies.head(2)

   movie_title                   genres studio  year
production_budget  \
0  On the Road  Adventure,Drama,Romance    IFC  2012
25000000.0
1  On the Road                    Drama    IFC  2012
25000000.0

   domestic_gross_y  worldwide_gross
0          720828.0        9313302.0
1          720828.0        9313302.0

movies.columns

Index(['movie_title', 'genres', 'studio', 'year', 'production_budget',
       'domestic_gross_y', 'worldwide_gross'],
      dtype='object')

movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1037 entries, 0 to 1036
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   movie_title        1037 non-null   object 
 1   genres             1037 non-null   object 
 2   studio             1037 non-null   object 
 3   year               1037 non-null   int64  
 4   production_budget  1037 non-null   float64
 5   domestic_gross_y   1037 non-null   float64
 6   worldwide_gross    1037 non-null   float64
dtypes: float64(3), int64(1), object(3)
memory usage: 56.8+ KB
```

```
movies.shape
```

```
(1037, 7)
```

Our final dataset is called movies, it is a clean data, note we cleaned the datasets before merging them. Our dataset contains 1037 rows and 6 columns

Data visualization

The aim of starting a business is to make profit, Voice of Kenya want to venture in the movie production business. The question is, is this movie production profitable. Our dataset has two columns i.e domestic_gross_y and worldwide_gross where worldwide_gross is total revenue collected worldwide that means that even the domestic_gross is inclusive

profitability calculation or return on investiment

```
# Removing a film that is multipled genred like the same movie has multiple genre i.e adventure, drama, comedy
movies['genres'] = movies['genres'].str.split(',').str[0].str.strip()
len(movies)
```

```
1037
```

```
# we have 67 duplicates which need dropping
movies.duplicated().sum()
```

```
67
```

```
# drop duplicates this duplicates arised when we splitted our dataset genre which had multiple genre and we kept one
movies_1 = movies.drop_duplicates()
movies_1.duplicated().sum()
```

```
0
```

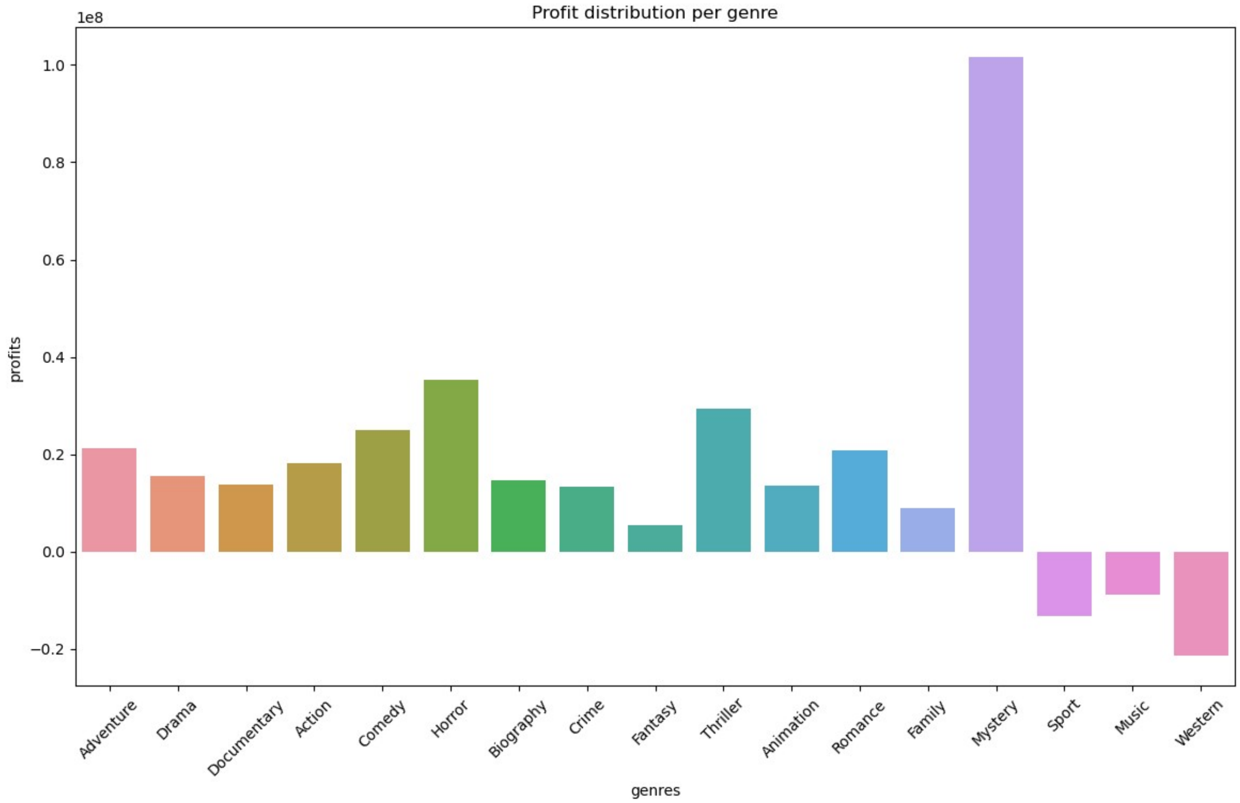
lets calculate the profit distribution per genre and draw a visualization to see which genre is more profitable

```
# calculating profit
movies_1['profits'] = movies_1['worldwide_gross'] -
movies_1['production_budget']
```

```
C:\Users\PC\AppData\Local\Temp\ipykernel_3088\3027505178.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  movies_1['profits'] = movies_1['worldwide_gross'] -
movies_1['production_budget']
```

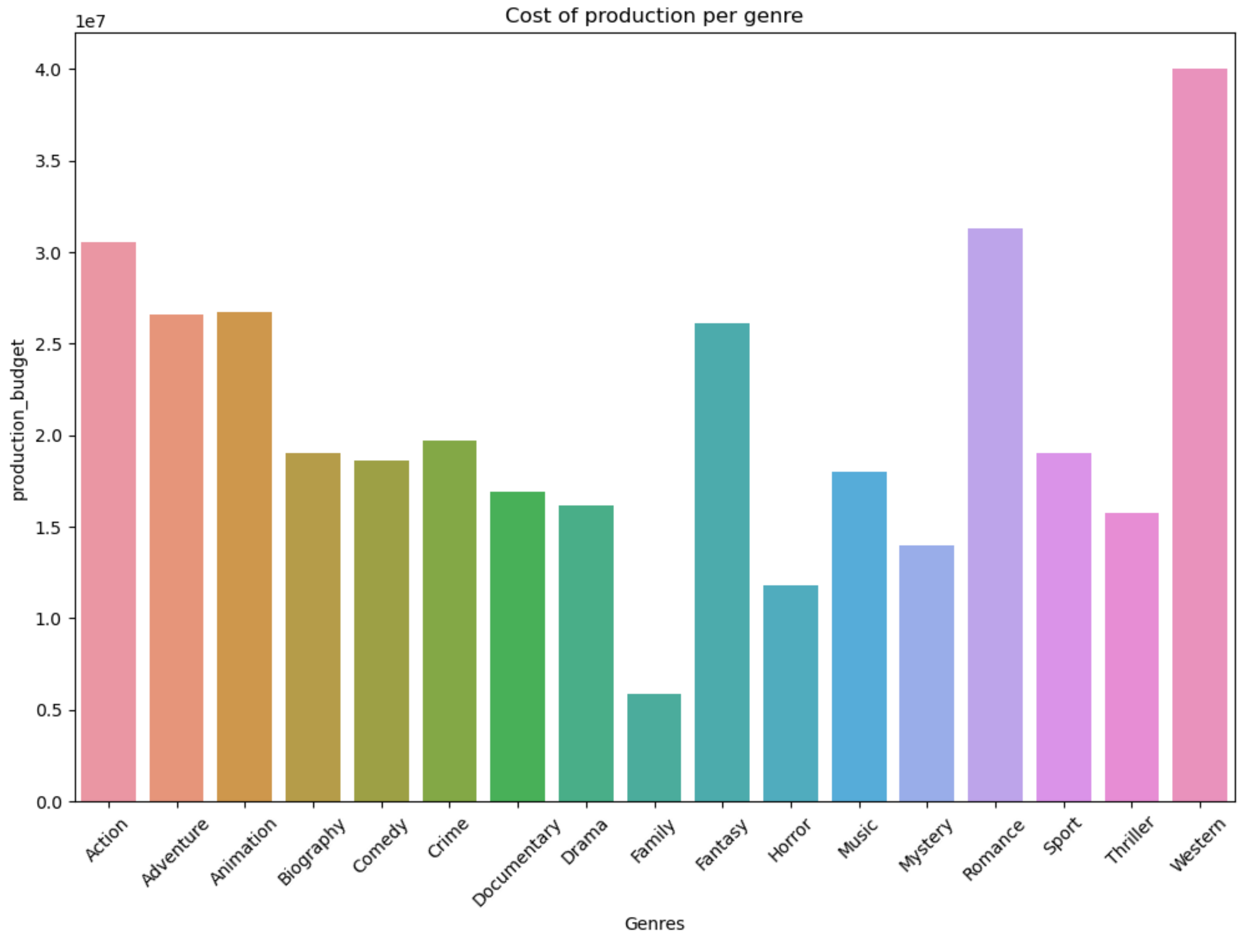
```
# visualizing the distribution of profits
# using bargraph
plt.figure(figsize=(14,8))
sns.barplot(x = 'genres', y = 'profits', data = movies_1 , ci= None)
plt.title('Profit distribution per genre')
plt.xlabel('genres')
plt.xticks(rotation=45 )
plt.ylabel('profits')
```

```
C:\Users\PC\AppData\Local\Temp\ipykernel_3088\3856034616.py:4:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same
effect.

  sns.barplot(x = 'genres', y = 'profits', data = movies_1 , ci= None)

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



Lets do the production of movie budget and the genre. in production the cost differs with the genre for example animation is cheaper compared to adventure.

```
# Calculate the average production per genre
movies_2 = movies_1.groupby('genres')
['production_budget'].mean().reset_index()

# ploting  bargraph
plt.figure(figsize=(12,8))
sns.barplot(x = 'genres', y = 'production_budget', data = movies_2)
plt.title('Cost of production per genre')
plt.xlabel('Genres')
plt.xticks(rotation=45)
plt.ylabel('production_budget')
plt.show()
```



Lets do the production of movie budget and the genre. in production the cost differs with the genre for example animation is cheaper compared to adventure.

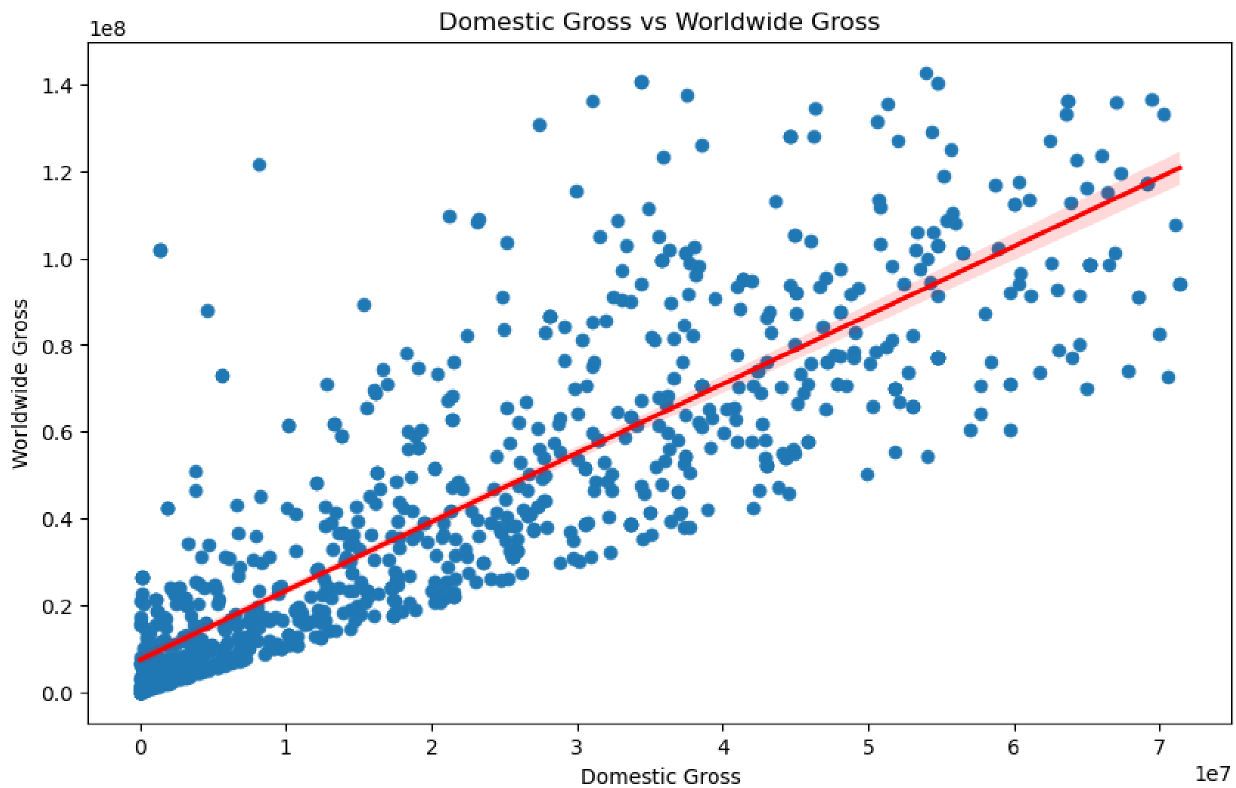
Define X and Y

importing linear regression libraries, we want to see the relationship between the domestic_gross and worldwide gross if they have any relationship

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# performing a simple linear regression
X = movies_1['domestic_gross_y']
y = movies_1['worldwide_gross']
# Add a constant to the independent variable
X = sm.add_constant(X)
# Perform linear regression
model = sm.OLS(y, X).fit()
#summary of the regression
print(model.summary())
```

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:        worldwide_gross   R-squared:
0.731
Model:                            OLS   Adj. R-squared:
0.731
Method:                 Least Squares   F-statistic:
2630.
Date:                Sun, 28 Jul 2024   Prob (F-statistic):
3.11e-278
Time:                        10:44:49   Log-Likelihood:
-17621.
No. Observations:                 970   AIC:
3.525e+04
Df Residuals:                     968   BIC:
3.526e+04
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
==============
                       coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
--------------
const             7.445e+06   8.73e+05      8.526      0.000
5.73e+06    9.16e+06
domestic_gross_y     1.5875      0.031     51.286      0.000
1.527       1.648
==============================================================================
========
Omnibus:                      337.901   Durbin-Watson:
1.624
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1239.045
Skew:                           1.656   Prob(JB):
8.81e-270
Kurtosis:                       7.437   Cond. No.
4.09e+07
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 4.09e+07. This might indicate that
```

```
there are
strong multicollinearity or other numerical problems.

# Scatter plot to visualize the relationshipand a regression plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='domestic_gross_y', y='worldwide_gross',
data=movies_1)
sns.regplot(x='domestic_gross_y', y='worldwide_gross', data=movies_1,
line_kws={'color': 'red'})
plt.title('Domestic Gross vs Worldwide Gross')
plt.xlabel('Domestic Gross')
plt.ylabel('Worldwide Gross')
plt.show()
```



Recommedations

1. Profitable Genre - Voice of kenya should focus more on production of mystery genre movie. This genre has earned about 100m in a period of 8 years. Voice of Kenya should also venture in producing adventure, action, comedy, horror, and thriller films. These genres offer a balance of manageable profitability, making them the most strategic investment for achieving strong and wide market.

2. Cost of production - This is a key aspect. For example producing the western genre is very costly yet it is not profitable at all. In our data it shows that the cost of production of the thriller is not very high but it gives the best profit Based on the

analysis of production costs per genre. Producing Horror, Comedy, and Thriller films, which offer a good balance of moderate production costs and high profitability.

3. Using the linear regression model, it show that there is a positive linear relationship between domestic and worldwide gross. The strong positive linear relationship between Domestic Gross and Worldwide Gross suggests that movies performing well domestically tend to also perform well internationally. Invest in genres and film types that have historically performed well domestically. Focus on marketing strategies to boost domestic performance, as it is a strong predictor of worldwide success

Conclusion

Voice of Kenya should focus on producing Mystery, Adventure, Action, Comedy, Horror, and Thriller films for optimal profitability and market reach. Emphasize cost-effective genres like Thriller, Horror, and Comedy. Leverage the strong positive relationship between domestic and worldwide gross by enhancing domestic performance through strategic marketing. Avoid high-cost, low-profit genres like Western.