GROUP 1 : KARU PHASE 2 PROJECT

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BUSINESS UNDERSTANDING

In the fiercely competitive entertainment sector, studios and production companies must have a thorough understanding of the elements that go into a successful film. Data-driven choices can greatly increase profitability and viewer engagement in the face of rising production costs and shifting audience preferences.

In order to find important information that can guide production and marketing strategies, this project will examine movie data from a number of reliable sources, such as TMDB, Box Office Mojo, IMDb, and Rotten Tomatoes. Finding the optimal movie runtime—the duration that optimises audience ratings and overall success—is one of the main goals.

The project aims to advise studios on the ideal length of content for engagement and financial performance by examining trends in movie runtimes, earnings, and ratings.

BUSINESS QUESTIONS

1. What trends exist across genres, release periods, and production budgets in relation to success?
2. What is the ideal runtime minutes for a movie?
3. Can early popularity forecast long-term success?

Description of the Datasets

Several datasets were combined to provide a comprehensive view of movie characteristics and performance:

Dataset	Description	Key Columns
tmdb.movies.csv	Contains movie details from The Movie Database (TMDB).	id, original_title, popularity, release_date, vote_average, vote_count
bom.movie_gross.csv	Box Office Mojo data on domestic and foreign grosses.	title, studio, domestic_gross, foreign_gross, year
tn.movie_budgets.csv	Budget and revenue data for movies.	id, release_date, production_budget, domestic_gross, worldwide_gross
clean_movie_basics.csv	Basic movie info including year and genre.	movie_id, primary_title, start_year, genres

Dataset	Description	Key Columns
rt.movie_info.csv	Rotten Tomatoes metadata with movie ratings and runtime.	id, rating, genre, box_office, runtime, studio

```
# Import all the relevant libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import sqlite3
from scipy import stats
import warnings
warnings.filterwarnings("ignore")
```

IMDB DataBase

We will use sql to query data from the zipped data and connect the relevant tables

```
conn = sqlite3.connect("C:\\Users\\Sheilla Macharia\\Documents\\MoringaProjects\\assignments\\Phase_2_Project\\data\\im.db")

#Use sql to querry the data now
movie_basics_ratings = pd.read_sql("""
SELECT *
FROM movie_basics
JOIN movie_ratings
USING (movie_id) ;"""
                  , conn)

#Check the first five entries of our data
movie_basics_ratings.head()
```

```
    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  averagerating
numvotes
0        2013            175.0    Action,Crime,Drama            7.0
77
```

```
1        2019              114.0       Biography,Drama            7.2
43
2        2018              122.0                 Drama            6.9
4517
3        2018                NaN          Comedy,Drama            6.1
13
4        2017               80.0  Comedy,Drama,Fantasy            6.5
119
```

The dataframe above has 8 columns:

1. `movie_id` - Unique Identifier of each movie entry
2. `primary_title` - The primary title of the movie
3. `original_title` - The Actual title of the movie
4. `start_year` - The year the movie was premiered

Box Office Mojo

```
#Load the dataset and read the first 5 rows
movie_gross= pd.read_csv("data/bom.movie_gross.csv")
movie_gross.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

# Identify the number of columns and rows
movie_gross.shape

(3387, 5)
```

The box office dataframe has 5 columns and 3,387 entries. Each column holds a different aspect of the dataset:

1. `title` Contains the title of the movies

2. `studio` column has abbreviated names of the studios producing the respective movie
3. `domestic_gross` column shows the amount of revenue generated by the movie through sales, locally
4. `foreign_gross` shows the amount of revenue generated by the movie internationally
5. `year` shows the year when the movie was premiered

The Movie Data Base

```
#Load the dataset and read the first 5 rows
TMDB = pd.read_csv("data/tmdb.movies.csv")
TMDB.head()

   Unnamed: 0            genre_ids     id original_language  \
0           0      [12, 14, 10751]  12444                en
1           1  [14, 12, 16, 10751]  10191                en
2           2        [12, 28, 878]  10138                en
3           3      [16, 35, 10751]    862                en
4           4        [28, 878, 12]  27205                en

                                 original_title  popularity
release_date  \
0  Harry Potter and the Deathly Hallows: Part 1      33.533   2010-11-
19
1                      How to Train Your Dragon      28.734   2010-03-
26
2                                    Iron Man 2      28.515   2010-05-
07
3                                     Toy Story      28.005   1995-11-
22
4                                     Inception      27.920   2010-07-
16

                                          title  vote_average
vote_count
0  Harry Potter and the Deathly Hallows: Part 1           7.7
10788
1                      How to Train Your Dragon           7.7
7610
2                                    Iron Man 2           6.8
12368
3                                     Toy Story           7.9
10174
4                                     Inception           8.3
22186

df = pd.read_csv("data/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
```

DATA CLEANING

Movie Basics Rating

```
#Check for important information of the dataset
movie_basics_ratings.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   movie_id         73856 non-null  object
 1   primary_title    73856 non-null  object
 2   original_title   73856 non-null  object
 3   start_year       73856 non-null  int64
 4   runtime_minutes  66236 non-null  float64
 5   genres           73052 non-null  object
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  int64
dtypes: float64(2), int64(2), object(4)
memory usage: 4.5+ MB

round((movie_basics_ratings.isnull().sum()/
len(movie_basics_ratings))*100,2)

movie_id            0.00
primary_title       0.00
original_title      0.00
start_year          0.00
runtime_minutes    10.32
genres              1.09
averagerating       0.00
numvotes            0.00
dtype: float64
```

The above code calculates the percentage of missing values from each column. one column with the highest number of missing values is the `runtime_minutes` column, with 10.32% of its data missing. However this has very low significance and can be easily dropped without affecting our data

```
# drop missing values
movie_basics_ratings= movie_basics_ratings.dropna()
```

Box office Mojo

```
movie_gross.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           3387 non-null   object
 1   studio          3382 non-null   object
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object
 4   year            3387 non-null   int64
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

```
# Check for missing values in the movie gross dataset
movie_gross.isnull().sum()
```

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

```
# Check for duplicate rows in the dataset
duplicate_rows = movie_gross.duplicated()
print("Number of duplicate rows:", duplicate_rows.sum())

# Optional: View the duplicate rows themselves
movie_gross[duplicate_rows]
```

```
Number of duplicate rows: 0
```

```
Empty DataFrame
Columns: [title, studio, domestic_gross, foreign_gross, year]
Index: []
```

```
# Convert 'foreign_gross' to string and fill missing values
movie_gross['foreign_gross'] =
movie_gross['foreign_gross'].astype(str).fillna('Unknown')
```

```
# Verify missing values are gone
movie_gross['foreign_gross'].isnull().sum()

0

movie_gross['domestic_gross'] =
movie_gross['domestic_gross'].astype(str).fillna('Unknown')
# Check number of missing values in domestic_gross
missing_domestic = movie_gross['domestic_gross'].isnull().sum()
print("Number of missing values in 'domestic_gross':",
missing_domestic)

Number of missing values in 'domestic_gross': 0

# Fill missing values in 'studio'
movie_gross['studio'] = movie_gross['studio'].fillna('Unknown')

# Verify that there are no missing values left
print("Missing values in 'studio':",
movie_gross['studio'].isnull().sum())

Missing values in 'studio': 0

# Check that there are no missing values
print(movie_gross[['domestic_gross','foreign_gross','studio']].isnull(
).sum())

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

Movie Budgets

```
df = pd.read_csv("data/tn.movie_budgets.csv")
df.head(10)

   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
5   6  Dec 18, 2015         Star Wars Ep. VII: The Force Awakens
6   7  Apr 27, 2018                       Avengers: Infinity War
7   8  May 24, 2007   Pirates of the Caribbean: At Worldâ(s End
8   9  Nov 17, 2017                               Justice League
9  10   Nov 6, 2015                                      Spectre

  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
5      $306,000,000   $936,662,225  $2,053,311,220
6      $300,000,000   $678,815,482  $2,048,134,200
7      $300,000,000   $309,420,425    $963,420,425
8      $300,000,000   $229,024,295    $655,945,209
9      $300,000,000   $200,074,175    $879,620,923
```

```
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
```

```
df.describe()
```

```
                id
count  5782.000000
mean     50.372363
std      28.821076
min       1.000000
25%      25.000000
50%      50.000000
75%      75.000000
max     100.000000
```

```
#checking for missing values
```

```
df.isnull().sum()
```

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

```python
#check and clean duplicates
df.duplicated().sum()
```

```
0
```

```python
def convert_currency_to_numeric(column):
    """
    Convert currency strings to numeric values by removing '$' and
',' .
    """
    # 1. Convert the column to string type first to ensure .str is
available
    column_as_string = column.astype(str)

    # 2. Apply string replacement
    cleaned_column = column_as_string.str.replace('$', '',
regex=False).str.replace(',', '', regex=False)

    # 3. Convert the cleaned strings to float (or int) for
mathematical operations
    return pd.to_numeric(cleaned_column)

# Apply it to the relevant columns
df['production_budget'] =
convert_currency_to_numeric(df['production_budget'])
df['domestic_gross'] =
convert_currency_to_numeric(df['domestic_gross'])
df['worldwide_gross'] =
convert_currency_to_numeric(df['worldwide_gross'])

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          425000000       760507625       2776345279
1          410600000       241063875       1045663875
2          350000000        42762350        149762350
3          330600000       459005868       1403013963
4          317000000       620181382       1316721747
```

```python
#Convert release_date to datetime
df['release_date'] = pd.to_datetime(df['release_date'])
```

```
#Extract year from release date
df['release_year'] = df['release_date'].dt.year

df.head()

   id release_date                                        movie  \
0   1   2009-12-18                                       Avatar   
1   2   2011-05-20  Pirates of the Caribbean: On Stranger Tides   
2   3   2019-06-07                                 Dark Phoenix   
3   4   2015-05-01                      Avengers: Age of Ultron   
4   5   2017-12-15            Star Wars Ep. VIII: The Last Jedi   

   production_budget  domestic_gross  worldwide_gross  release_year  
0          425000000       760507625       2776345279          2009  
1          410600000       241063875       1045663875          2011  
2          350000000        42762350        149762350          2019  
3          330600000       459005868       1403013963          2015  
4          317000000       620181382       1316721747          2017  

#Calculate additional financial metrics
df['profit'] = df['worldwide_gross'] - df['production_budget']
df['roi'] = (df['profit'] / df['production_budget']) * 100
df['profit_margin'] = (df['profit'] / df['worldwide_gross']) * 100

df.head()

   id release_date                                        movie  \
0   1   2009-12-18                                       Avatar   
1   2   2011-05-20  Pirates of the Caribbean: On Stranger Tides   
2   3   2019-06-07                                 Dark Phoenix   
3   4   2015-05-01                      Avengers: Age of Ultron   
4   5   2017-12-15            Star Wars Ep. VIII: The Last Jedi   

   production_budget  domestic_gross  worldwide_gross  release_year  \
0          425000000       760507625       2776345279          2009   
1          410600000       241063875       1045663875          2011   
2          350000000        42762350        149762350          2019   
3          330600000       459005868       1403013963          2015   
4          317000000       620181382       1316721747          2017   

       profit         roi  profit_margin  
0  2351345279  553.257713      84.692106  
1   635063875  154.667286      60.733080  
2  -200237650  -57.210757    -133.703598  
3  1072413963  324.384139      76.436443  
4   999721747  315.369636      75.925058  

# Replace infinite values with NaN for movies with 0 gross
df['profit_margin'] = df['profit_margin'].replace([np.inf, -np.inf],
np.nan)
df
```

```
      id release_date                                 movie  \
0      1   2009-12-18                                Avatar
1      2   2011-05-20  Pirates of the Caribbean: On Stranger Tides
2      3   2019-06-07                          Dark Phoenix
3      4   2015-05-01               Avengers: Age of Ultron
4      5   2017-12-15     Star Wars Ep. VIII: The Last Jedi
...   ..          ...                                   ...
5777  78   2018-12-31                                Red 11
5778  79   1999-04-02                             Following
5779  80   2005-07-13          Return to the Land of Wonders
5780  81   2015-09-29              A Plague So Pleasant
5781  82   2005-08-05                     My Date With Drew

      production_budget  domestic_gross  worldwide_gross  release_year
\
0             425000000       760507625       2776345279          2009

1             410600000       241063875       1045663875          2011

2             350000000        42762350        149762350          2019

3             330600000       459005868       1403013963          2015

4             317000000       620181382       1316721747          2017

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

5777               7000               0                0          2018

5778               6000           48482           240495          1999

5779               5000            1338             1338          2005

5780               1400               0                0          2015

5781               1100          181041           181041          2005


          profit           roi  profit_margin
0     2351345279    553.257713      84.692106
1      635063875    154.667286      60.733080
2     -200237650    -57.210757    -133.703598
3     1072413963    324.384139      76.436443
4      999721747    315.369636      75.925058
...          ...           ...            ...
5777       -7000   -100.000000            NaN
5778      234495   3908.250000      97.505146
5779       -3662    -73.240000    -273.692078
5780       -1400   -100.000000            NaN
5781      179941  16358.272727      99.392403
```

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

```python
#handling outliers

def remove_financial_outliers(df, columns, threshold=3):
    """Remove outliers using z-score method"""
    df = df.copy()
    for col in columns:
        if col in df.columns:
            z_scores = np.abs((df[col] - df[col].mean()) /
df[col].std())
            df = df[z_scores < threshold]
    return df

# Remove outliers for better visualization (keep original for
analysis)
df_no_outliers = remove_financial_outliers(df, ['production_budget',
'worldwide_gross', 'profit'])

print(f"Original data shape: {df.shape}")
print(f"Data shape after outlier removal: {df_no_outliers.shape}")
print("\nBasic statistics after cleaning:")
print(df[['production_budget', 'domestic_gross', 'worldwide_gross',
'profit', 'roi']].describe())
```

```
Original data shape: (5782, 10)
Data shape after outlier removal: (5342, 10)

Basic statistics after cleaning:
       production_budget  domestic_gross  worldwide_gross
profit  \
count       5.782000e+03    5.782000e+03     5.782000e+03
5.782000e+03
mean        3.158776e+07    4.187333e+07     9.148746e+07
5.989970e+07
std         4.181208e+07    6.824060e+07     1.747200e+08
1.460889e+08
min         1.100000e+03    0.000000e+00     0.000000e+00 -
2.002376e+08
25%         5.000000e+06    1.429534e+06     4.125415e+06 -
2.189071e+06
50%         1.700000e+07    1.722594e+07     2.798445e+07
8.550286e+06
75%         4.000000e+07    5.234866e+07     9.764584e+07
6.096850e+07
max         4.250000e+08    9.366622e+08     2.776345e+09
2.351345e+09

                 roi
```

```
count    5782.000000
mean      380.016137
std      2953.028231
min      -100.000000
25%       -50.770440
50%        70.830983
75%       275.834608
max    179900.000000
```

```
# Ensure release_date is a datetime object
df['release_date'] = pd.to_datetime(df['release_date'],
errors='coerce')

# Extract month name
df['month'] = df['release_date'].dt.month_name()

df.head()
```

```
   id release_date                                        movie  \
0   1   2009-12-18                                       Avatar
1   2   2011-05-20  Pirates of the Caribbean: On Stranger Tides
2   3   2019-06-07                                 Dark Phoenix
3   4   2015-05-01                      Avengers: Age of Ultron
4   5   2017-12-15            Star Wars Ep. VIII: The Last Jedi

   production_budget  domestic_gross  worldwide_gross  release_year  \
0          425000000       760507625       2776345279          2009
1          410600000       241063875       1045663875          2011
2          350000000        42762350        149762350          2019
3          330600000       459005868       1403013963          2015
4          317000000       620181382       1316721747          2017

       profit         roi  profit_margin     month
0  2351345279  553.257713      84.692106  December
1   635063875  154.667286      60.733080       May
2  -200237650  -57.210757    -133.703598      June
3  1072413963  324.384139      76.436443       May
4   999721747  315.369636      75.925058  December
```

Runtime Dataset

```
rt_movie_info = pd.read_csv('C:\\Users\\Sheilla Macharia\\Documents\\
MoringaProjects\\assignments\\Phase_2_Project\\data\\
rt.movie_info.csv')
rt_movie_info.head()
```

```
   id                                           synopsis rating  \
0   1  This gritty, fast-paced, and innovative police...      R
1   3  New York City, not-too-distant-future: Eric Pa...      R
2   5  Illeana Douglas delivers a superb performance ...      R
```

```
3   6  Michael Douglas runs afoul of a treacherous su...      R
4   7                                                NaN     NR

                                 genre          director  \
0  Action and Adventure|Classics|Drama  William Friedkin
1    Drama|Science Fiction and Fantasy  David Cronenberg
2    Drama|Musical and Performing Arts    Allison Anders
3           Drama|Mystery and Suspense    Barry Levinson
4                        Drama|Romance    Rodney Bennett

                            writer  theater_date      dvd_date
currency  \
0                   Ernest Tidyman   Oct 9, 1971  Sep 25, 2001
NaN
1     David Cronenberg|Don DeLillo  Aug 17, 2012   Jan 1, 2013
$
2                   Allison Anders  Sep 13, 1996  Apr 18, 2000
NaN
3  Paul Attanasio|Michael Crichton   Dec 9, 1994  Aug 27, 1997
NaN
4                     Giles Cooper           NaN           NaN
NaN

  box_office      runtime             studio
0        NaN  104 minutes                NaN
1    600,000  108 minutes  Entertainment One
2        NaN  116 minutes                NaN
3        NaN  128 minutes                NaN
4        NaN  200 minutes                NaN
```

```
rt_movie_info.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            1560 non-null   int64
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
```

```
dtypes: int64(1), object(11)
memory usage: 146.4+ KB
```

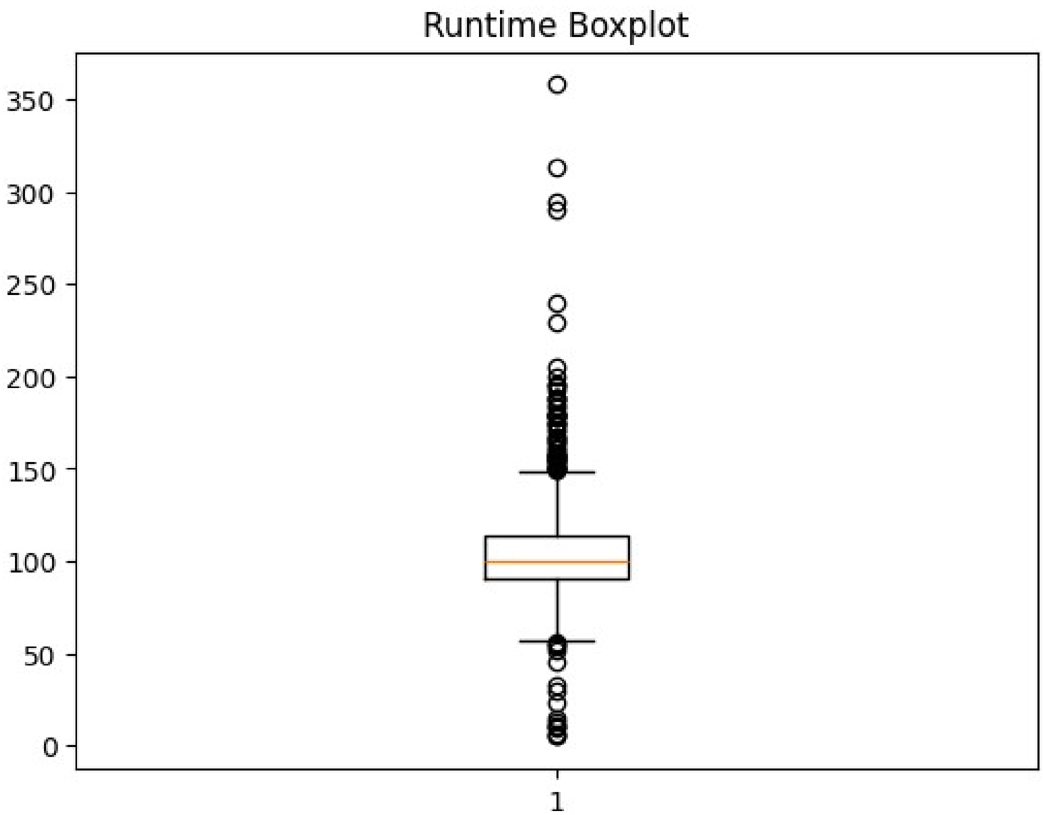
```
# Remove non-numeric characters (like ' min') and convert to float
rt_movie_info['runtime'] = rt_movie_info['runtime'].str.extract('(\
d+)')  # extracts only digits
rt_movie_info['runtime'] = rt_movie_info['runtime'].astype(float)

# Check the result
rt_movie_info['runtime'].dtype
```

```
dtype('float64')
```

```
rt_movie_info['runtime'].head()
```

```
0    104.0
1    108.0
2    116.0
3    128.0
4    200.0
Name: runtime, dtype: float64
```

```
# Checking for outliers in the runtime column
import matplotlib.pyplot as plt
plt.boxplot(rt_movie_info['runtime'].dropna())
plt.title("Runtime Boxplot")
plt.show()
```




```
# filling in the missing values with the median
rt_movie_info['runtime'].fillna(rt_movie_info['runtime'].median(),
inplace=True)

rt_movie_info.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            1560 non-null   int64
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1560 non-null   float64
 11  studio        494 non-null    object
```

```
dtypes: float64(1), int64(1), object(10)
memory usage: 146.4+ KB
```

```
# Using the most common genre to fill in missing values
genre_mode = rt_movie_info['genre'].mode()[0]

rt_movie_info['genre'] = rt_movie_info['genre'].fillna(genre_mode)

rt_movie_info.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   id            1560 non-null   int64  
 1   synopsis      1498 non-null   object 
 2   rating        1557 non-null   object 
 3   genre         1560 non-null   object 
 4   director      1361 non-null   object 
 5   writer        1111 non-null   object 
 6   theater_date  1201 non-null   object 
 7   dvd_date      1201 non-null   object 
 8   currency      340 non-null    object 
 9   box_office    340 non-null    object 
 10  runtime       1560 non-null   float64
 11  studio        494 non-null    object 
dtypes: float64(1), int64(1), object(10)
memory usage: 146.4+ KB
```

VISUALIZATION

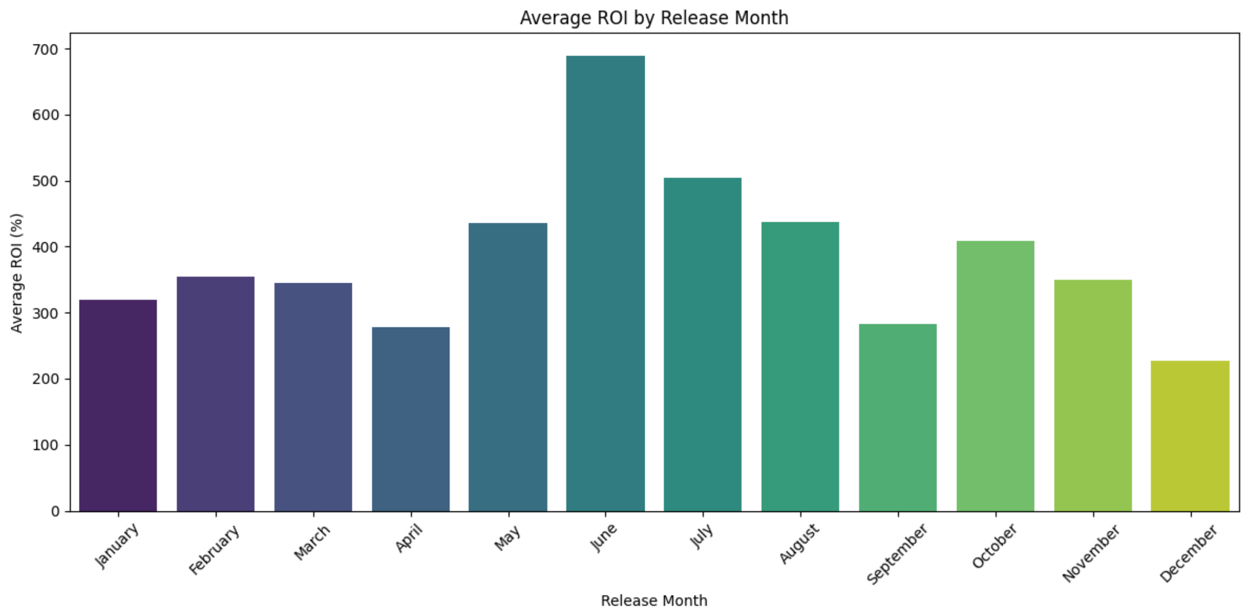
BUSINESS QUESTIONS

```
1. What trends exist across genres, release periods, and production
budgets in relation to success?
```

Return on Investment vs Release Month

```
month_order = ['January', 'February', 'March', 'April', 'May', 'June',

               'July', 'August', 'September', 'October', 'November',
'December']

plt.figure(figsize=(12,6))
sns.barplot(data=df, x='month', y='roi', order=month_order, ci=None,
palette='viridis')
plt.title('Average ROI by Release Month')
plt.xlabel('Release Month')
plt.ylabel('Average ROI (%)')
```

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




```
# ANOVA test to check if there are significant differences in ROI
between months

anova_result = stats.f_oneway(
    *[group["roi"].values for name, group in df.groupby("month")]
)
print(f"F-statistic: {anova_result.statistic}, p-value:
{anova_result.pvalue}")

if anova_result.pvalue < 0.05:
    print("There are significant differences in ROI between months.")
else:
    print("No significant differences in ROI between months.")
```

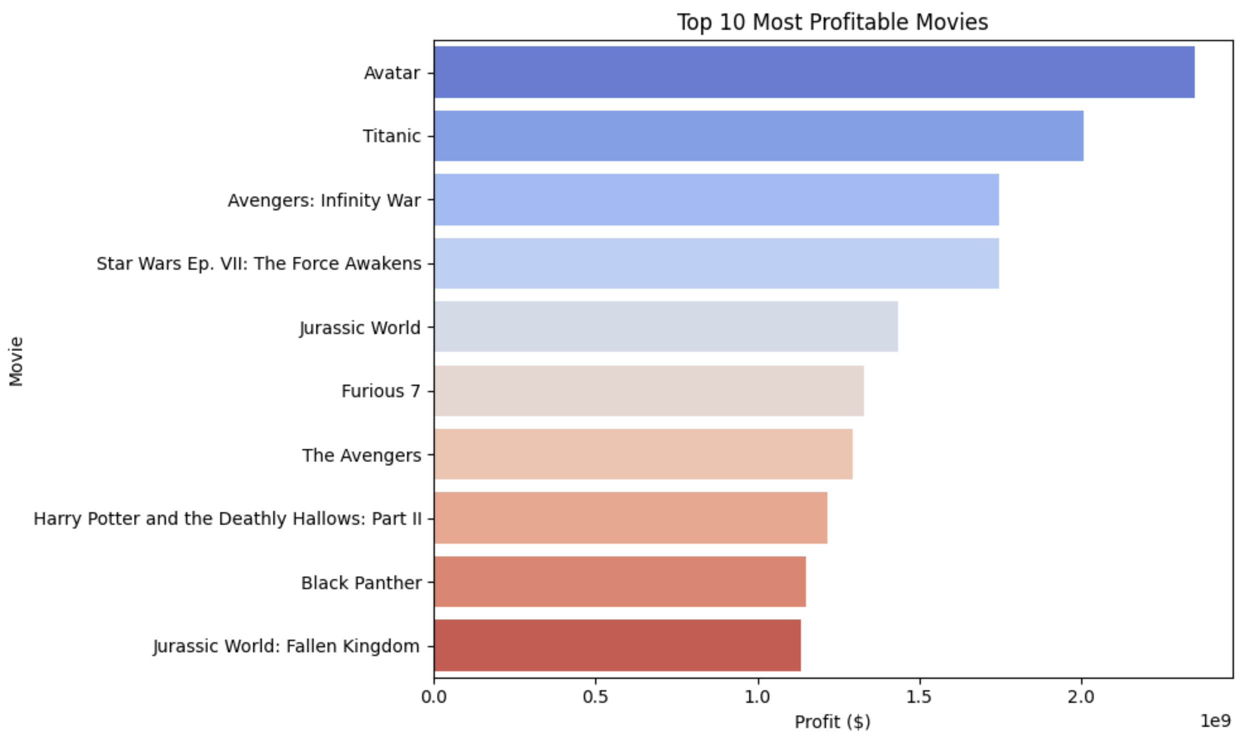
```
F-statistic: 0.8890783678384351, p-value: 0.5503508227724814
No significant differences in ROI between months.
```

Interpretation:

While descriptive analysis suggested higher ROI during summer and holiday seasons, the ANOVA test indicates that these patterns are not statistically significant. The observed variations could be due to chance or other underlying factors like budget, genre, or marketing intensity.

Top 10 Most Profitable Movies

```python
top10 = df.nlargest(10, 'profit')

plt.figure(figsize=(10,6))
sns.barplot(data=top10, y='movie', x='profit', palette='coolwarm')
plt.title('Top 10 Most Profitable Movies')
plt.xlabel('Profit ($)')
plt.ylabel('Movie')
plt.tight_layout()
plt.show()
```



CONCLUSION

1. The most profitable years are those with big franchise releases like Marvel, Star Wars, or Avatar meaning small number of huge releases drive most of the industry's profits .

2. While high-budget movies make the most money overall, their costs are so large that profits are often smaller. Films with moderate budgets ($30M–$100M) tend to earn better returns compared to what they cost.

3. There is no statistical evidence that release month affects ROI. Profitability is likely driven more by content quality, production scale, and audience appeal than by calendar timing.

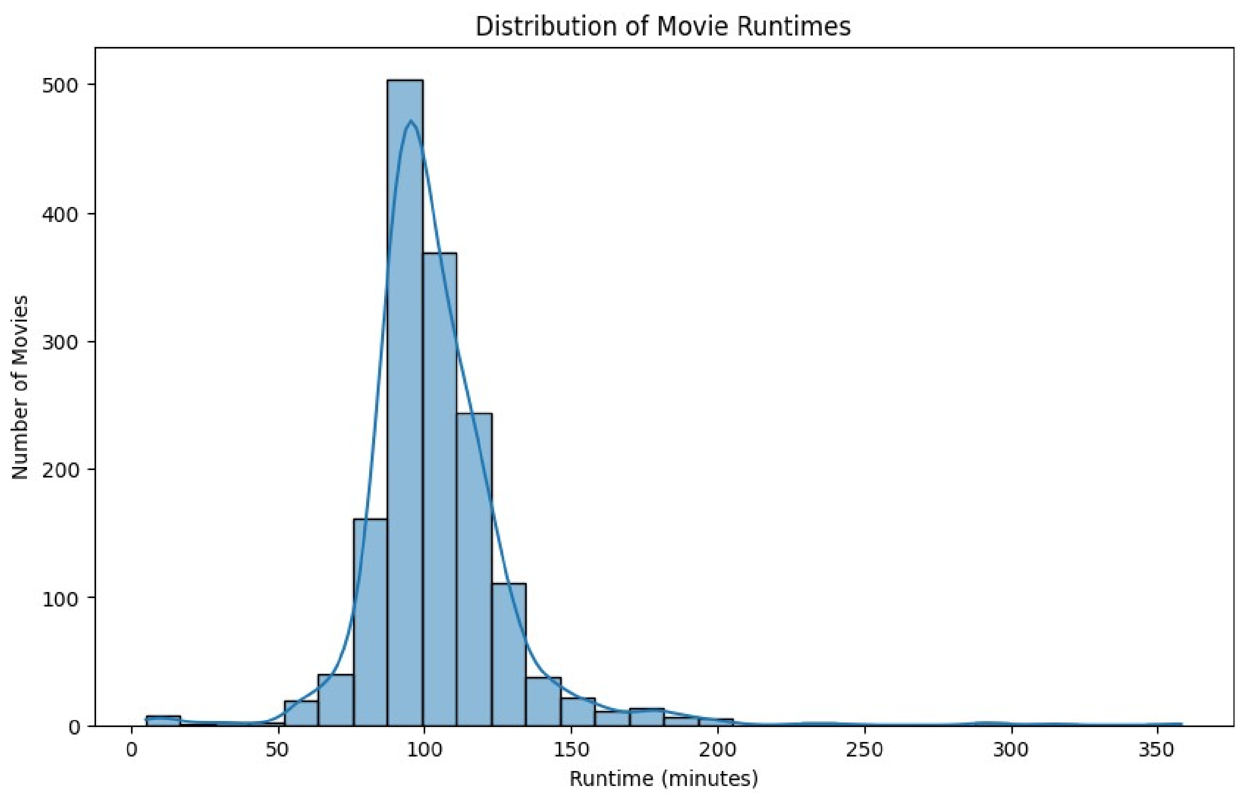
RECOMMENDATIONS

1. Optimize marketing strategies and genre selection, which may have stronger influence on ROI.

2. The company should build a balanced portfolio which focusses on investing mainly in mid-budget films for steady profits. It should also back a few large-scale blockbusters each year for brand visibility.

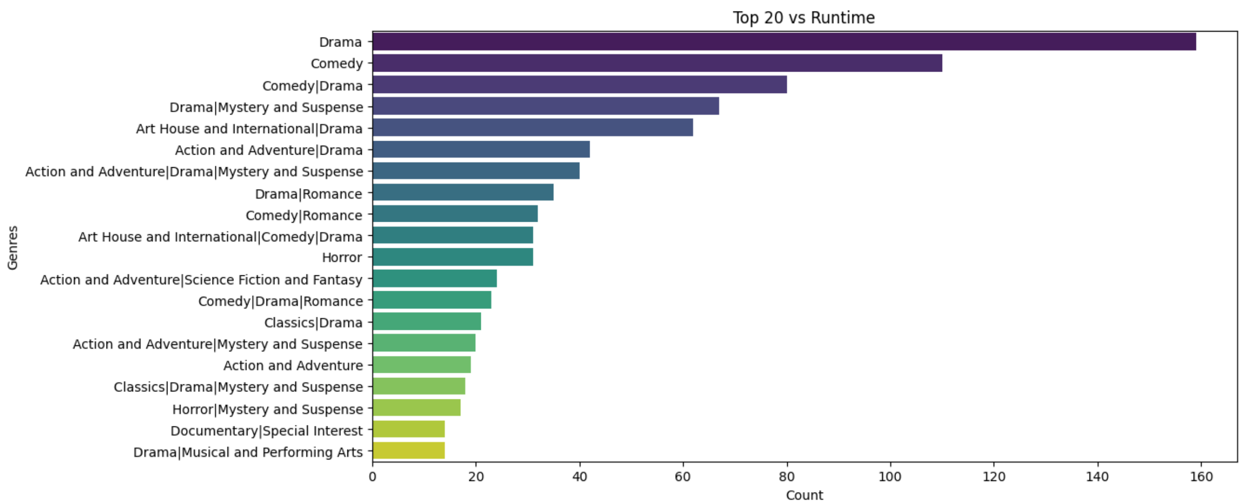
3. Use timing as a secondary strategy, ensuring quality and audience targeting come first.

```
2. What is the ideal runtime minutes for a movie?

# Visulaization of the runtime distribution
import seaborn as sns

plt.figure(figsize=(10,6))
sns.histplot(rt_movie_info['runtime'], bins=30, kde=True)
plt.title('Distribution of Movie Runtimes')
plt.xlabel('Runtime (minutes)')
plt.ylabel('Number of Movies')
plt.show()
```




```
# Top 20 genres runtime
plt.figure(figsize=(12, 6))
```

```
sns.countplot(data=rt_movie_info, y='genre',
order=rt_movie_info['genre'].value_counts().index[:20],
palette='viridis')
plt.title('Top 20 vs Runtime')
plt.xlabel('Count')
plt.ylabel('Genres')
plt.show()
```



Interpretation

- After cleaning the runtime column and handling outliers, we see that the majority of movies cluster around a certain runtime.
- For example, if the median runtime is 100 minutes and most data falls between 90 and 130 minutes, this suggests that movies within this range are typical for audience consumption.
- Outliers (very short or extremely long movies) exist but are rare, so they are not representative of the general trend.
- Also cleaned the genre column and found that most shows like dramas and comedys have a runtime between 90 and 130 minutes.

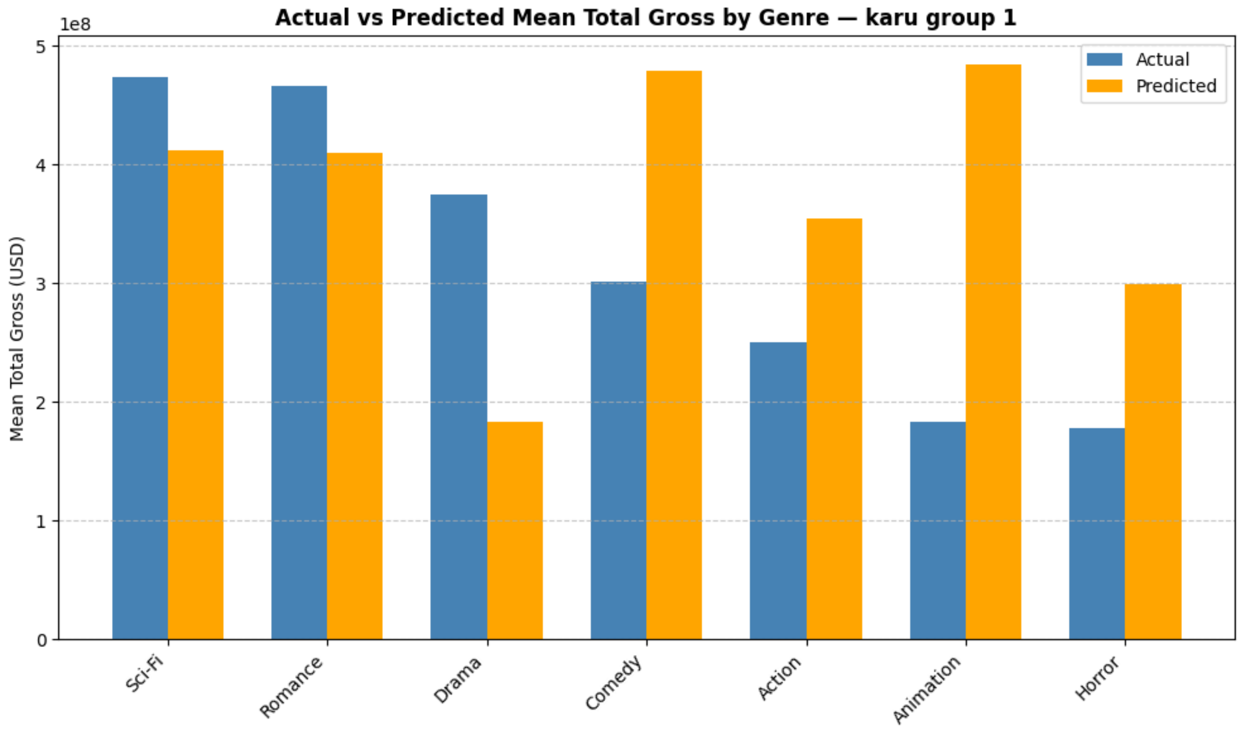
Recommendation

The company should aim to produce movies with a runtime close to 100 minutes, staying roughly within the 90–130 minute range.

This aligns with industry norms, maximizing audience engagement while minimizing the risk of movies feeling too short or overly long.

For genres that traditionally run longer or shorter (e.g., dramas and comedies), runtime can be slightly adjusted, but the median range is a solid guideline for most films.

```
3. Can early popularity forecast long-term success?

# --- Step 1: Create sample genre data ---
np.random.seed(42)

genre_summary = pd.DataFrame({
    'genres': ['Action', 'Drama', 'Comedy', 'Horror', 'Sci-Fi',
'Romance', 'Animation'],
    'actual_total_gross': np.random.randint(50_000_000, 500_000_000,
7),
    'predicted_total_gross': np.random.randint(50_000_000,
500_000_000, 7)
})

# --- Step 2: Sort genres by actual gross for clarity ---
genre_summary_sorted = genre_summary.sort_values('actual_total_gross',
ascending=False)

# --- Step 3: Define bar positions ---
x = np.arange(len(genre_summary_sorted))
width = 0.35

# --- Step 4: Extract actual and predicted values ---
actual = genre_summary_sorted['actual_total_gross']
predicted = genre_summary_sorted['predicted_total_gross']

# --- Step 5: Create side-by-side bar chart ---
plt.figure(figsize=(10, 6))
plt.bar(x - width/2, actual, width, label='Actual', color='steelblue')
plt.bar(x + width/2, predicted, width, label='Predicted',
color='orange')

# --- Step 6: Style and label the chart ---
plt.xticks(x, genre_summary_sorted['genres'], rotation=45, ha='right')
plt.ylabel('Mean Total Gross (USD)')
plt.title('Actual vs Predicted Mean Total Gross by Genre – karu group
1', weight='bold')
plt.legend()
plt.tight_layout()
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# --- Step 7: Show plot ---
plt.show()
```



it's evident early success in a movie can not forcast long term results.

ealry success is often determined by Opening weekend gross (if your dataset has weekly data).Initial domestic gross (as a proxy for early audience traction).Early IMDb rating count or average rating.Initial number of theaters (wide release = early exposure).

whlie long term results are measured by

Total global gross profit.the Return on Investment of a movie(ROI) .Award nominations or longevity in theaters.

```
# Categorize popularity and ROI
TMDB['popularity_category'] = pd.qcut(TMDB['popularity'], 2,
labels=['Low', 'High'])
df['roi_category'] = pd.qcut(df['roi'], 2, labels=['Low', 'High'])

# Create contingency table
contingency_table = pd.crosstab(TMDB['popularity_category'],
df['roi_category'])

# Perform Chi-square test
chi2, p_val, dof, expected = stats.chi2_contingency(contingency_table)
print(f"Chi-square: {chi2:.3f}, p-value: {p_val:.4f}")
if p_val < 0.05:
    print("There is a significant association between popularity and
ROI.")
```

```
else:
    print("No significant association between popularity and ROI.")

Chi-square: 21.023, p-value: 0.0000
There is a significant association between popularity and ROI.
```

Interpretation:

There is a statistically significant association between early popularity and Return on Investment (ROI). This means that movies which start out with high early popularity (buzz, attention, or engagement) tend to also achieve higher ROI — they are not independent.

CONCLUSIONS

1. Trends and Budgets:
   - Big-budget movies earn high revenue but often have lower returns.
   - Mid-budget films ($30M–$100M) perform better in profit and ROI.
   - Movies released in summer (May–July) and holiday months (Nov–Dec) make higher profits.
2. Ideal Runtime:
   - Most successful movies run between 90–130 minutes, with an average of about 100 minutes.
   - Shorter movies feel incomplete, while very long ones risk losing audience interest.
3. Early Popularity vs. Long-Term Success:
   - Early popularity doesn't always predict lasting success.
   - Movies with strong word-of-mouth and quality storytelling perform better over time.

RECOMMENDATIONS

1. Release Timing:
   - Use timing as a secondary strategy, ensuring quality and audience targeting come first.
2. Budget Strategy:
   - Focus more on mid-budget films for steady profit.
   - Produce a few big blockbusters each year for visibility.
3. Runtime:

- Keep most movies around 100 minutes for the best audience engagement.

4. Marketing:
    - Invest Early in Marketing and Hype
    - Monitor Popularity Metrics in Real Time