Film Data Analysis for Microsoft

Flatiron School Data Science Phase 1 Project

Final Project Submision

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Business Understanding

Microsoft's venture into the film-making industry has prompted a comprehensive analysis of provided datasets to deliver actionable recommendations. Commissioned by Microsoft, our task is to delve into the complexities of the movie industry. Specifically, our goal is to conduct data analysis aimed at uncovering the key factors driving successful box office performance. These insights will serve as a compass, guiding strategic decisions for Microsoft's upcoming movie studio.

The primary stakeholders vested in this analysis are the Board of Directors at Microsoft. Our findings will play a pivotal role in shaping their decision-making processes, aiding in the identification of lucrative film genres, potential directors, and critical success factors for maximizing movie performance.

Beyond the scope of analysis, this project holds immense significance by offering actionable insights that empower Microsoft to curate a portfolio of high-potential movies.

Data Understanding

Data Sources Overview:

The project utilizes the following data files:

There are six data files provided:

Data Source	Data File	Size (in bytes)
Box Office Mojo	bom.movie_gross.csv.gz	53,544
IMDB	im.db.zip	67,149,708
Rotten Tomatoes (movie info)	rt.movie_info.tsv.gz	498,202
Rotten Tomatoes (reviews)	rt.reviews.tsv.gz	3,402,194
The Movie DB	tmdb.movies.csv.gz	827,840

Data Source	Data File	Size (in bytes)
The Numbers	tn.movie_budgets.csv.gz	153,218
Total	6 Files	72,084,706 bytes

- Box Office Mojo (bom.movie_gross.csv.gz)
- IMDB (im.db.zip)
- Rotten Tomatoes - movie information (rt.movie_info.tsv.gz)
- Rotten Tomatoes - reviews (rt.reviews.tsv.gz)
- The Movie DB (tmdb.movies.csv.gz)
- The Numbers (tn.movie_budgets.csv.gz)

Detailed information:

Data File	Size (in bytes)	Shape	Columns	Data Frame ID
bom.movie_gross.csv.gz	53,544	3387, 5	title, studio, domestic_gross, foreign_gross, year	df_mg
im.db	169,443,328	8 tables	* see below	df_1
rt.movie_info.tsv	1,184,685	156, 12	id, synopsis, rating, genre, director, writer, theater_date, dvd_date, currency, box_office, runtime, studio	df_rt_mi
rt.reviews.tsv.gz	3,402,194	54432, 8	id, review, rating, fresh, critic, top_critic, publisher, date	db_reviews

Data File	Size (in bytes)	Shape	Columns	Data Frame ID
tmdb.movies.csv.gz	827,840	26517, 10	Unnamed: 0, genre_ids, id, original_language, original_title, popularity, release_date, title, vote_average, vote_count	db_movies
tn.movie_budgets.csv.gz	153,218	5782, 6	id, release_date, movie, production_budget, domestic_gross, worldwide_gross	db_movie_budgets

IMDB table contents:

Table ID	Name	Shape	Columns	Data Frame ID
0	movie_basics	146144, 6	movie_id, primary_title, original_title, start_year, runtime_minutes, genres	df_mb
1	directors	291174, 2	movie_id, person_id	df_dir
2	known_for	1638260, 2	person_id, movie_id	df_kf
3	movie_akas	331703, 8	movie_id, ordering, title, region, language, types, attributes, is_original_title	df_akas
4	movie_ratings	73856, 3	movie_id, averagerating, numvotes	df_ratings
5	persons	606648	person_id, primary_name, birth_year, death_year,	df_perso

Table ID	Name	Shape	Columns	Data Frame ID
		, 5	primary_profession	ns
6	principals	1028186, 6	movie_id, ordering, person_id, category, job, characters	df_principals
7	writers	255873, 2	movie_id, person_id	df_writers

The information shown above was obtained after opening files and exploring the data. The process follows below:

Opening and Reading Database Files

After importing the necessary Python libraries for the technical presentation, we will now delve into the databases. This initial exploratory step will shed light on the content of the given data. The conclusions of this section have already been presented above, in the tables at the beginning of the "data understanding" section.

As a first step, we use the "dir" command to list our data files and their size.

```
# Let's see that the data is there
! dir Data
```

```
 Volume in drive C is Acer
 Volume Serial Number is B208-A089

 Directory of C:\Users\rafvr\OneDrive\Documents\Flatiron\Phase1\
MovieAnalysis\Data

01/03/2024  08:24 PM    <DIR>          .
01/10/2024  12:58 PM    <DIR>          ..
01/03/2024  01:35 PM            53,544 bom.movie_gross.csv.gz
01/10/2024  12:57 PM       169,443,328 im.db
01/03/2024  07:47 PM        67,149,708 im.db.zip
01/03/2024  07:48 PM           498,202 rt.movie_info.tsv.gz
01/03/2024  07:48 PM         3,402,194 rt.reviews.tsv.gz
01/03/2024  07:48 PM           827,840 tmdb.movies.csv.gz
01/03/2024  07:48 PM           153,218 tn.movie_budgets.csv.gz
               7 File(s)    241,528,034 bytes
               2 Dir(s)  866,056,609,792 bytes free
```

Data Preparation

Notebook shows how and why you prepared your data, including:

- Instructions or code needed to get and prepare the raw data for analysis

- Valid justifications for why the steps you took are appropriate for the problem you are solving

```
# Bringing in the libraries I will use for this project
import pandas as pd           # Data manipulation
import numpy as np            # Numerical computations
import sqlite3                # Database operations
import zipfile                # Handling zip files
import gzip                   # Handling gzip files
import shutil  # For file copying during decompression
import random                 # Random number generation
import matplotlib.pyplot as plt  # Data visualization
import seaborn as sns
import math
import calendar
%matplotlib inline
plt.style.use('ggplot')
```

Now we will unzip the data to make it accessible

```
# unzip the IMDB file
zip_path = 'Data/im.db.zip'  # Path to the ZIP file

# Extract the contents of the ZIP file
with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall('Data')  # Extract to the 'Data' folder

# Proceed with the following files:

# Box Office Mojo
df_mg = pd.read_csv('Data/bom.movie_gross.csv.gz')

# Rotten Tomatoes movie info
file_path = 'Data/rt.movie_info.tsv.gz'
with gzip.open(file_path, 'rb') as f:
    file_content = f.read()
df_rt_mi = pd.read_csv(file_path, sep='\t', encoding='ISO-8859-1')

# Rotten Tomatoes reviews
file_path = 'Data/rt.reviews.tsv.gz'
with gzip.open(file_path, 'rb') as f:
    file_content = f.read()
db_reviews = pd.read_csv(file_path, sep='\t', encoding='ISO-8859-1')

# The Movie DB
file_path = 'Data/tmdb.movies.csv.gz'
db_movies = pd.read_csv(file_path, compression='gzip')

# The Numbers
file_path = 'Data/tn.movie_budgets.csv.gz'
db_movie_budgets = pd.read_csv(file_path, compression='gzip')
```

Since IMdB is an SQL collection of tables, we will open and explore the contents separatedly from the rest of the data

```
# Connecting to the IMDb Database
conn = sqlite3.connect('Data\im.db')  # connects to the file
cursor = conn.cursor() # places the cursor there
```

An SQL database file contains various tables of information. we want to reach into those tables, and then use Python to open and explore them. Let's proceed to read the tables list.

```
db_path = 'Data/im.db'  # Path to the SQLite database file

# Connect to the SQLite database
conn = sqlite3.connect(db_path)

# Create a cursor object to execute SQL queries
cursor = conn.cursor()

# Retrieve the table names
cursor.execute("SELECT name FROM sqlite_master WHERE type='table';")
tables = cursor.fetchall()

# Print the table names
for table in tables:
    print(table[0])

# Close the cursor and connection
# cursor.close() # <--- we don't want this closed yet
# conn.close() # <--- we don't want this closed yet

movie_basics
directors
known_for
movie_akas
movie_ratings
persons
principals
writers
```

There are 8 tables: movie_basics, directors, known_for, movie_akas, movie_ratings, persons, principals, and writers. Let's create dataframes with them.

```
# Reading data from SQL tables into Pandas DataFrames
movie_basics_df = pd.read_sql("""
SELECT *
FROM movie_basics
;""", conn)  # Data from 'movie_basics' table

directors_df = pd.read_sql("""
SELECT *
```

```
FROM directors
;""", conn)  # Data from 'directors' table

known_for_df = pd.read_sql("""
SELECT *
FROM known_for
;""", conn)  # Data from 'known_for' table

movie_akas_df = pd.read_sql("""
SELECT *
FROM movie_akas
;""", conn)  # Data from 'movie_akas' table

movie_ratings_df = pd.read_sql("""
SELECT *
FROM movie_ratings
;""", conn)  # Data from 'movie_ratings' table

persons_df = pd.read_sql("""
SELECT *
FROM persons
;""", conn)  # Data from 'persons' table

principals_df = pd.read_sql("""
SELECT *
FROM principals
;""", conn)  # Data from 'principals' table

writers_df = pd.read_sql("""
SELECT *
FROM writers
;""", conn)  # Data from 'writers' table

# conn.close() <-- we'll keep it open for now
```

Let's take a look at some statistics here:

```
from IPython.display import display, Markdown

# Define a function to display DataFrame description with a title
def display_with_title(df, title):
    display(Markdown(f"**{title} DataFrame:**"))
    display(df.describe())

# Call the display_with_title function for each DataFrame
display_with_title(movie_ratings_df, "Movie Ratings")
display_with_title(movie_basics_df, "Movie Basics")
display_with_title(movie_akas_df, "Movie AKAs")
display_with_title(persons_df, "Persons")
display_with_title(principals_df, "Principals")
```

```
display_with_title(directors_df, "Directors")
display_with_title(known_for_df, "Known For")
display_with_title(writers_df, "Writers")
```

```
<IPython.core.display.Markdown object>
```

```
       averagerating      numvotes
count   73856.000000  7.385600e+04
mean        6.332729  3.523662e+03
std         1.474978  3.029402e+04
min         1.000000  5.000000e+00
25%         5.500000  1.400000e+01
50%         6.500000  4.900000e+01
75%         7.400000  2.820000e+02
max        10.000000  1.841066e+06
```

```
<IPython.core.display.Markdown object>
```

```
          start_year  runtime_minutes
count  146144.000000    114405.000000
mean     2014.621798        86.187247
std         2.733583       166.360590
min      2010.000000         1.000000
25%      2012.000000        70.000000
50%      2015.000000        87.000000
75%      2017.000000        99.000000
max      2115.000000     51420.000000
```

```
<IPython.core.display.Markdown object>
```

```
            ordering  is_original_title
count  331703.000000      331678.000000
mean        5.125872           0.134769
std         6.706664           0.341477
min         1.000000           0.000000
25%         1.000000           0.000000
50%         2.000000           0.000000
75%         6.000000           0.000000
max        61.000000           1.000000
```

```
<IPython.core.display.Markdown object>
```

```
         birth_year   death_year
count  82736.000000  6783.000000
mean    1967.043826  2000.523367
std       22.122190    43.951530
min        1.000000    17.000000
25%     1957.000000  2001.000000
50%     1971.000000  2013.000000
75%     1981.000000  2016.000000
max     2014.000000  2019.000000
```

```
<IPython.core.display.Markdown object>

            ordering
count  1.028186e+06
mean   4.739847e+00
std    2.747446e+00
min    1.000000e+00
25%    2.000000e+00
50%    4.000000e+00
75%    7.000000e+00
max    1.000000e+01

<IPython.core.display.Markdown object>

         movie_id  person_id
count      291174     291174
unique     140417     109253
top     tt4050462  nm6935209
freq         3818        238

<IPython.core.display.Markdown object>

        person_id   movie_id
count     1638260    1638260
unique     576444     514781
top     nm1202937  tt0806910
freq            6        633

<IPython.core.display.Markdown object>

         movie_id  person_id
count      255873     255873
unique     110261     122576
top     tt4050462  nm6935209
freq         3818        543
```

Easier to display in a single table:

DF	Movie Ratings	Movie Ratings	Movie Basics	Movie Basics	Movie AKAs	Movie AKAs	Persons	Persons	Principals
Column	averagerating	numvotes	start_year	runtime_minutes	ordering	is_original_title	birth_year	death_year	ordering
count	73856.000000	7.385600e+04	146144.000000	114405.000000	331703.000000	331678.000000	82736.000000	6783.000000	1.028186e+06
mean	6.332729	3.523662e+03	2014.621798	86.187247	5.125872	0.134769	1967.043826	2000.523367	4.739847e+00
std	1.4749	3.0294	2.7335	166.36	6.706	0.3414	22.122	43.951	2.7474

DF	Movie Ratings	Movie Ratings	Movie Basics	Movie Basics	Movie AKAs	Movie AKAs	Persons	Persons	Principals
	78	02e+04	83	0590	664	77	190	530	46e+00
min	1.000000	5.000000e+00	2010.000000	1.000000	1.000000	0.000000	1.000000	17.000000	1.000000e+00
25%	5.500000	1.400000e+01	2012.000000	70.000000	1.000000	0.000000	1957.000000	2001.000000	2.000000e+00
50%	6.500000	4.900000e+01	2015.000000	87.000000	2.000000	0.000000	1971.000000	2013.000000	4.000000e+00
75%	7.400000	2.820000e+02	2017.000000	99.000000	6.000000	0.000000	1981.000000	2016.000000	7.000000e+00
max	10.000000	1.841066e+06	2115.000000	51420.000000	61.000000	1.000000	2014.000000	2019.000000	1.000000e+01

DF	Directors	Directors	Known For	Known For	Writers	Writers
Column	movie_id	person_id	person_id	movie_id	movie_id	person_id
count	291174	291174	1638260	1638260	255873	255873
unique	140417	109253	576444	514781	110261	122576
top	tt4050462	nm6935209	nm1202937	tt0806910	tt4050462	nm6935209
freq	3818	238	6	633	3818	543

This table provides a clear correspondence between the DataFrame variables (movie_basics_df, directors_df, known_for_df, etc.) and their respective tables in the dataset:

DataFrame	Contains Data File
movie_basics_df	Movie Basics
directors_df	Directors
known_for_df	Known For
movie_akas_df	Movie AKAs
movie_ratings_df	Movie Ratings
persons_df	Persons
principals_df	Principals
writers_df	Writers

Let's now look at their shape, to see how many columns and lines does each table contain.

```
# For further exploration:
```

```python
# assigning short df dataframes

sql = "SELECT * FROM movie_basics"
df_mb = pd.read_sql(sql, conn)

sql = "SELECT * FROM directors"
df_dir = pd.read_sql(sql, conn)

sql = "SELECT * FROM known_for"
df_kf = pd.read_sql(sql, conn)

sql = "SELECT * FROM movie_akas"
df_akas = pd.read_sql(sql, conn)

sql = "SELECT * FROM movie_ratings"
df_ratings = pd.read_sql(sql, conn)

sql = "SELECT * FROM persons"
df_persons = pd.read_sql(sql, conn)

sql = "SELECT * FROM principals"
df_principals = pd.read_sql(sql, conn)

sql = "SELECT * FROM writers"
df_writers = pd.read_sql(sql, conn)

# Define a dictionary to store the table names and their corresponding
dataframes
tables = {
    'movie_basics': df_mb,
    'directors': df_dir,
    'known_for': df_kf,
    'movie_akas': df_akas,
    'movie_ratings': df_ratings,
    'persons': df_persons,
    'principals': df_principals,
    'writers': df_writers
}

# Iterate over the tables and print the table name and shape
for table_name, dataframe in tables.items():
    print(f"Table: {table_name}")
    print(f"Shape: {dataframe.shape}")
    print()
```

```
Table: movie_basics
Shape: (146144, 6)

Table: directors
Shape: (291174, 2)
```

```
Table: known_for
Shape: (1638260, 2)

Table: movie_akas
Shape: (331703, 8)

Table: movie_ratings
Shape: (73856, 3)

Table: persons
Shape: (606648, 5)

Table: principals
Shape: (1028186, 6)

Table: writers
Shape: (255873, 2)
```

Here is the information in tabular form:

Table Name	Rows	Columns
movie_basics	146144	6
directors	291174	2
known_for	1638260	2
movie_akas	331703	8
movie_ratings	73856	3
persons	606648	5
principals	1028186	6
writers	255873	2

In this tabular version, the shape is divided into two columns, "Rows" and "Columns," providing a clearer breakdown of the dimensions for each table.

```python
# Iterate over the tables and print the table name and head of each
dataframe
for table_name, dataframe in tables.items():
    print(f"Table: {table_name}")
    print(dataframe.head())
    print()
```

```
Table: movie_basics
    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

Table: directors
    movie_id  person_id
0  tt0285252  nm0899854
1  tt0462036  nm1940585
2  tt0835418  nm0151540
3  tt0835418  nm0151540
4  tt0878654  nm0089502

Table: known_for
   person_id   movie_id
0  nm0061671  tt0837562
1  nm0061671  tt2398241
2  nm0061671  tt0844471
3  nm0061671  tt0118553
4  nm0061865  tt0896534

Table: movie_akas
    movie_id  ordering                                   title region
\
0  tt0369610        10                           Джурасик свят     BG

1  tt0369610        11                       Jurashikku warudo     JP

2  tt0369610        12  Jurassic World: O Mundo dos Dinossauros     BR

3  tt0369610        13                 O Mundo dos Dinossauros     BR

4  tt0369610        14                          Jurassic World     FR


  language        types   attributes  is_original_title
0       bg         None         None                0.0
1     None  imdbDisplay         None                0.0
2     None  imdbDisplay         None                0.0
3     None         None  short title                0.0
```

```
4     None  imdbDisplay         None                0.0

Table: movie_ratings
     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

Table: persons
   person_id       primary_name  birth_year  death_year  \
0  nm0061671  Mary Ellen Bauder         NaN         NaN
1  nm0061865       Joseph Bauer         NaN         NaN
2  nm0062070         Bruce Baum         NaN         NaN
3  nm0062195       Axel Baumann         NaN         NaN
4  nm0062798        Pete Baxter         NaN         NaN

                                 primary_profession
0         miscellaneous,production_manager,producer
1        composer,music_department,sound_department
2                          miscellaneous,actor,writer
3  camera_department,cinematographer,art_department
4  production_designer,art_department,set_decorator

Table: principals
    movie_id  ordering  person_id  category       job
characters
0  tt0111414         1  nm0246005     actor      None         ["The
Man"]
1  tt0111414         2  nm0398271  director      None
None
2  tt0111414         3  nm3739909  producer  producer
None
3  tt0323808        10  nm0059247    editor      None
None
4  tt0323808         1  nm3579312   actress      None  ["Beth
Boothby"]

Table: writers
    movie_id  person_id
0  tt0285252  nm0899854
1  tt0438973  nm0175726
2  tt0438973  nm1802864
3  tt0462036  nm1940585
4  tt0835418  nm0310087


# Iterate over the tables and print the table name and column titles
of each dataframe
```

```python
for table_name, dataframe in tables.items():
    print(f"Table: {table_name}")
    print(f"Columns: {list(dataframe.columns)}")
    print()
```

```
Table: movie_basics
Columns: ['movie_id', 'primary_title', 'original_title', 'start_year',
'runtime_minutes', 'genres']

Table: directors
Columns: ['movie_id', 'person_id']

Table: known_for
Columns: ['person_id', 'movie_id']

Table: movie_akas
Columns: ['movie_id', 'ordering', 'title', 'region', 'language',
'types', 'attributes', 'is_original_title']

Table: movie_ratings
Columns: ['movie_id', 'averagerating', 'numvotes']

Table: persons
Columns: ['person_id', 'primary_name', 'birth_year', 'death_year',
'primary_profession']

Table: principals
Columns: ['movie_id', 'ordering', 'person_id', 'category', 'job',
'characters']

Table: writers
Columns: ['movie_id', 'person_id']
```

Here's the arranged information in a tabular format:

Table Name	Column Titles
movie_basics	movie_id, primary_title, original_title, start_year, runtime_minutes, genres
directors	movie_id, person_id
known_for	person_id, movie_id
movie_akas	movie_id, ordering, title, region, language, types, attributes, is_original_title
movie_ratings	movie_id, averagerating, numvotes
persons	person_id, primary_name, birth_year, death_year, primary_profession
principals	movie_id, ordering, person_id, category, job, characters
writers	movie_id, person_id

This table provides a clearer representation with each column title listed as a separate column, making it easier to compare the tables and their respective columns. Here "movie_id" and "person_id" listed in the first two columns, and other column titles shifted to the right. Thus we learn what the tables are comparing, and how to put them together if needed for further exploratory analysis.

Table Name	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8
movie_basics	movie_id		primary_title	original_title	start_year	runtime_minutes	genres	
directors	movie_id	person_id						
known_for	movie_id	person_id						
movie_akas	movie_id		ordering	title	region	language	types	attributes
movie_ratings	movie_id		averagerating	numvotes				
persons		person_id	primary_name	birth_year	death_year	primary_profession		
principals	movie_id	person_id	ordering	category	job	characters		
writers	movie_id	person_id						

Frame Mergers

We have frames with part of the information we need for comparative analisys, but we need to put together these pieces in order to have them in one place. We will do a few mergers in order to unify out dfs. The table above will serve as a map for how this will be done.

```
# Merge 'directors' with 'known_for'
merged_directors_known_for = pd.merge(df_dir, df_kf, on='person_id',
how='inner')

# Merge 'directors_known_for' with 'persons'
merged_directors_known_for_persons =
pd.merge(merged_directors_known_for, df_persons, on='person_id',
how='left')

# At this point we encountered a conflict with two "movie_id" columns
# Rename the 'movie_id' columns to resolve naming conflict
```

```
merged_directors_known_for_persons.rename(columns={'movie_id_x':
'movie_id'}, inplace=True)

# Merge 'movie_basics' with 'merged_directors_known_for_persons'
merged_movie_directors_known_for_persons =
pd.merge(df_mb[['primary_title', 'runtime_minutes', 'genres',
'movie_id']], merged_directors_known_for_persons, on='movie_id',
how='inner')

# Drop the 'movie_id_y' column
merged_movie_directors_known_for_persons.drop(columns=['movie_id_y'],
inplace=True)

# Eliminate duplicates
merged_movie_directors_known_for_persons =
merged_movie_directors_known_for_persons.drop_duplicates()

# Merge 'merged_movie_directors_known_for_persons' with
'movie_ratings'
merged_df = pd.merge(merged_movie_directors_known_for_persons,
df_ratings, on='movie_id', how='inner')

# Merge 'merged_df' with 'principals'
merged_df = pd.merge(merged_df, df_principals[['movie_id',
'person_id', 'category']], on='movie_id', how='inner')

# Merge 'merged_df' with 'writers'
merged_df = pd.merge(merged_df, df_writers, on='movie_id',
how='inner')
```

Having merged all those dataframes together, we can now see who directed and/or acted in which film, what genre is the film, what is the film rating, it's runtime, and number of votes. We can also see if the person related to the film is alive or deceased. Let's take a look at our merged dataframe:

```
# Print the final merged DataFrame
merged_df

                      primary_title  runtime_minutes
genres  \
0                         Sunghursh            175.0
Action,Crime,Drama
1                         Sunghursh            175.0
Action,Crime,Drama
2                         Sunghursh            175.0
Action,Crime,Drama
3                         Sunghursh            175.0
Action,Crime,Drama
4                         Sunghursh            175.0
Action,Crime,Drama
```

```
...                              ...              ...
...
15257297  La vida sense la Sara Amat              NaN
None
15257298  La vida sense la Sara Amat              NaN
None
15257299  La vida sense la Sara Amat              NaN
None
15257300  La vida sense la Sara Amat              NaN
None
15257301  La vida sense la Sara Amat              NaN
None

           movie_id person_id_x         primary_name  birth_year
death_year  \
0         tt0063540   nm0712540  Harnam Singh Rawail      1921.0
2004.0
1         tt0063540   nm0712540  Harnam Singh Rawail      1921.0
2004.0
2         tt0063540   nm0712540  Harnam Singh Rawail      1921.0
2004.0
3         tt0063540   nm0712540  Harnam Singh Rawail      1921.0
2004.0
4         tt0063540   nm0712540  Harnam Singh Rawail      1921.0
2004.0
...             ...         ...                  ...         ...
...
15257297  tt9914942   nm1716653            Laura Jou         NaN
NaN
15257298  tt9914942   nm1716653            Laura Jou         NaN
NaN
15257299  tt9914942   nm1716653            Laura Jou         NaN
NaN
15257300  tt9914942   nm1716653            Laura Jou         NaN
NaN
15257301  tt9914942   nm1716653            Laura Jou         NaN
NaN

                      primary_profession  averagerating  numvotes
person_id_y  \
0               director,writer,producer            7.0        77
nm0006210
1               director,writer,producer            7.0        77
nm0006210
2               director,writer,producer            7.0        77
nm0006210
3               director,writer,producer            7.0        77
nm0006210
4               director,writer,producer            7.0        77
```

```
nm0474801
...                                    ...            ...       ...
...
15257297  miscellaneous,actress,director            6.6         5
nm3678448
15257298  miscellaneous,actress,director            6.6         5
nm9361716
15257299  miscellaneous,actress,director            6.6         5
nm9361716
15257300  miscellaneous,actress,director            6.6         5
nm1966322
15257301  miscellaneous,actress,director            6.6         5
nm1966322

                 category  person_id
0                composer  nm0023551
1                composer  nm1194313
2                composer  nm0347899
3                composer  nm1391276
4                   actor  nm0023551
...                   ...        ...
15257297           writer  nm9361716
15257298           writer  nm3678448
15257299           writer  nm9361716
15257300  cinematographer  nm3678448
15257301  cinematographer  nm9361716

[15257302 rows x 14 columns]
```

Data Cleaning

Having put that into a single frame is usefull, but there are obvious duplicates and missing vialues, as well as unnecessary columns. So let's proceed with cleaning our merged database:

```
# Drop 'person_id', 'person_id_x' and 'person_id_y' columns
merged_df.drop(columns=['person_id_x', 'person_id_y', 'person_id'],
inplace=True)

# Drop 'category' column
merged_df.drop(columns=['category'], inplace=True)

# Eliminate duplicates
merged_df = merged_df.drop_duplicates()
```

Now let's take a look:

```
# Print the updated merged DataFrame
merged_df
```

```
                           primary_title  runtime_minutes
genres  \
0                              Sunghursh            175.0
Action,Crime,Drama
40          The Other Side of the Wind            122.0
Drama
60                        Sabse Bada Sukh              NaN
Comedy,Drama
70            The Wandering Soap Opera             80.0
Comedy,Drama,Fantasy
110           The Wandering Soap Opera             80.0
Comedy,Drama,Fantasy
...                                   ...              ...
...
15257225                  Hayatta Olmaz             97.0
Comedy
15257234                Diabolik sono io             75.0
Documentary
15257254               Sokagin Çocuklari             98.0
Drama,Family
15257272                       Albatross              NaN
Documentary
15257286  La vida sense la Sara Amat              NaN
None

           movie_id          primary_name  birth_year  death_year  \
0         tt0063540   Harnam Singh Rawail      1921.0      2004.0
40        tt0069049          Orson Welles      1915.0      1985.0
60        tt0069204  Hrishikesh Mukherjee      1922.0      2006.0
70        tt0100275     Valeria Sarmiento      1948.0         NaN
110       tt0100275            Raoul Ruiz      1941.0      2011.0
...             ...                   ...         ...         ...
15257225  tt9910502          Emre Çaltili         NaN         NaN
15257234  tt9913084      Giancarlo Soldi      1954.0         NaN
15257254  tt9914286     Ahmet Faik Akinci         NaN         NaN
15257272  tt9914642          Chris Jordan         NaN         NaN
15257286  tt9914942             Laura Jou         NaN         NaN

                        primary_profession  averagerating  numvotes
0                director,writer,producer            7.0        77
40                  actor,director,writer            6.9      4517
60                 director,editor,writer            6.1        13
70                 editor,director,writer            6.5       119
110              director,writer,producer            6.5       119
...                                    ...            ...       ...
15257225            actor,director,writer            7.0         9
15257234         director,writer,producer            6.2         6
15257254                  director,writer            8.7       136
15257272           director,writer,editor            8.5         8
15257286  miscellaneous,actress,director            6.6         5
```

```
[73155 rows x 10 columns]
```

We will now clean any rows that do not provide information on runtime, genre, or birth year. Then we will erase from the database directors who have a death year - we will not make recommendations on directors that are no-longer alive.

```
# Drop rows with NaN values in 'runtime_minutes', 'genres', and
'birth_year'
filtered_merged_df = merged_df.dropna(subset=['runtime_minutes',
'genres', 'birth_year'])

# Filter rows where 'birth_year' has a value and 'death_year' is NaN
filtered_merged_df = filtered_merged_df.query("birth_year.notnull()
and death_year.isnull()")

# Reset the index of the DataFrame
filtered_merged_df = filtered_merged_df.reset_index(drop=True)

# Print the modified DataFrame
filtered_merged_df

# Print the filtered DataFrame
filtered_merged_df

                      primary_title  runtime_minutes  \
0          The Wandering Soap Opera             80.0
1                    Joe Finds Grace            83.0
2                        Pál Adrienn           136.0
3       Children of the Green Dragon            89.0
4                 The Tragedy of Man           160.0
...                              ...              ...
20393                  Dulce Familia           101.0
20394      Vosotros sois mi película            98.0
20395           Killing Patient Zero           100.0
20396                      Pengalila           111.0
20397                Diabolik sono io            75.0

                           genres   movie_id       primary_name
birth_year  \
0          Comedy,Drama,Fantasy  tt0100275  Valeria Sarmiento
1948.0
1       Adventure,Animation,Comedy  tt0137204   Anthony Harrison
1961.0
2                            Drama  tt0146592       Ágnes Kocsis
1971.0
3                            Drama  tt0162942     Bence Miklauzic
1970.0
4         Animation,Drama,History  tt0176694  Marcell Jankovics
1941.0
```

```
...                             ...        ...                 ...
...
20393                        Comedy  tt9880982      Nicolás López
1983.0
20394                   Documentary  tt9888844       Carlo Padial
1977.0
20395                   Documentary  tt9896252        Laurie Lynd
1959.0
20396                         Drama  tt9905462      T.V. Chandran
1950.0
20397                   Documentary  tt9913084    Giancarlo Soldi
1954.0

       death_year                     primary_profession  averagerating
\
0             NaN                 editor,director,writer            6.5

1             NaN                 actor,writer,producer             8.1

2             NaN               director,writer,producer            6.8

3             NaN   director,writer,assistant_director             6.9

4             NaN  writer,director,animation_department            7.8

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

20393         NaN               writer,producer,director            4.6

20394         NaN                 writer,director,editor            3.9

20395         NaN               director,writer,producer            8.2

20396         NaN                  director,writer,actor            8.4

20397         NaN               director,writer,producer            6.2


       numvotes
0           119
1           263
2           451
3           120
4           584
...         ...
20393       102
20394       253
20395        13
20396       600
20397         6
```

```
[20398 rows x 10 columns]
```

We have now a clean data frame that lists only living people. It contains information on the movies they made, the runtime length, the average votes and the number of votes - that measure popularity as well as the genre. All these information elements will be relevant to our analisys.

Merger of Other Data Frames

```
# merge 'movie_basics' with 'movie_ratings'
# we're performing a "left" merger
df_im_mgd = pd.merge(df_mb, df_ratings, on='movie_id', how='left')

# Check for duplicates in the df_im_mgd DataFrame
duplicates = df_im_mgd[df_im_mgd.duplicated()]

# Check if there are any duplicates
if duplicates.shape[0] > 0:
    print("Duplicates found in df_im_mgd DataFrame.")
    print(duplicates)
else:
    print("No duplicates found in df_im_mgd DataFrame.")

No duplicates found in df_im_mgd DataFrame.

# Check if the data is clean (e.g., check for null values)
if df_im_mgd.isnull().values.any():
    print("The data contains null values.")
else:
    print("The data does not contain null values.")

The data contains null values.

# Check the number of rows and columns in the DataFrame
num_rows, num_columns = df_im_mgd.shape
print(f"Number of Rows: {num_rows}")
print(f"Number of Columns: {num_columns}")

Number of Rows: 146144
Number of Columns: 8

# Display the first few rows of the DataFrame
print("First few rows of the DataFrame:")
df_im_mgd.head()

First few rows of the DataFrame:

    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
77.0
1        2019            114.0       Biography,Drama            7.2
43.0
2        2018            122.0                 Drama            6.9
4517.0
3        2018              NaN          Comedy,Drama            6.1
13.0
4        2017             80.0  Comedy,Drama,Fantasy            6.5
119.0
```

Having put together the IMDb data from all the tables is now contained in a single dataframe, 'df_im_mgd', and the data is clean and relevant.

```
df_mg.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

df_rt_mi.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

db_reviews.head()

   id                                             review rating
fresh  \
0   3  A distinctly gallows take on contemporary fina...    3/5
fresh
1   3  It's an allegory in search of a meaning that n...    NaN
rotten
2   3  ... life lived in a bubble in financial dealin...    NaN
fresh
3   3  Continuing along a line introduced in last yea...    NaN
fresh
4   3             ... a perverse twist on neorealism...    NaN
fresh

           critic  top_critic         publisher               date
0      PJ Nabarro           0   Patrick Nabarro  November 10, 2018
```

```
1  Annalee Newitz           0           io9.com       May 23, 2018
2    Sean Axmaker           0  Stream on Demand    January 4, 2018
3   Daniel Kasman           0              MUBI  November 16, 2017
4             NaN           0      Cinema Scope   October 12, 2017
```

```
db_movies.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
```

```
db_movie_budgets.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
```

These are the columns in each data frame:

DataFrame	Columns
df_mg	title, studio, domestic_gross, foreign_gross, year
df_rt_mi	id, synopsis, rating, genre, director, writer, theater_date, dvd_date, currency, box_office, runtime, studio
db_reviews	id, review, rating, fresh, critic, top_critic, publisher, date
db_movies	Unnamed: 0, genre_ids, id, original_language, original_title, popularity, release_date, title, vote_average, vote_count
db_movie_budgets	id, release_date, movie, production_budget, domestic_gross, worldwide_gross

Of these, we're going to keep 'df_mg', 'db_movies', 'db_movie_budgets', and merge them into a single data frame. May be analize 'df_rt_mi' separatedly since it has genre informaiton, but lacks movie titles. Discard 'db_reviews' from further analisys, since it lacks title and genre informaiton.

```
# Merge df_mg with db_movies based on the 'title' column
unified_df = pd.merge(df_mg, db_movies, on='title', how='inner')

# Explanation of the code:
# pd.merge() function is used to merge DataFrames df_mg and db_movies
# 'on='title'' specifies the common column to merge on ('title'
column)
# 'how='inner'' performs an inner join, keeping only matching rows
from both DataFrames
```

Now we erase unnecessary columns

```
# List of columns to be eliminated
columns_to_drop = ['Unnamed: 0', 'id', 'original_language',
'original_title']

# Drop the specified columns from unified_df
unified_df = unified_df.drop(columns=columns_to_drop, errors='ignore')

# Display the cleaned DataFrame
unified_df.head()

                        title studio  domestic_gross foreign_gross
year  \
0                 Toy Story 3     BV     415000000.0     652000000
```

```
2010
1                    Inception      WB     292600000.0     535700000
2010
2          Shrek Forever After    P/DW     238700000.0     513900000
2010
3  The Twilight Saga: Eclipse    Sum.     300500000.0     398000000
2010
4                   Iron Man 2    Par.     312400000.0     311500000
2010

                 genre_ids  popularity release_date  vote_average
vote_count
0          [16, 10751, 35]      24.445   2010-06-17           7.7
8340
1            [28, 878, 12]      27.920   2010-07-16           8.3
22186
2  [35, 12, 14, 16, 10751]      15.041   2010-05-16           6.1
3843
3      [12, 14, 18, 10749]      20.340   2010-06-23           6.0
4909
4            [12, 28, 878]      28.515   2010-05-07           6.8
12368

# Merge unified_df with db_movie_budgets based on the 'title' and
'movie' columns
final_df = pd.merge(unified_df, db_movie_budgets, left_on='title',
right_on='movie', how='inner')

# Drop the redundant 'movie' column after merging
final_df.drop('movie', axis=1, inplace=True)

# Drop the 'id' column from final_df
final_df.drop('id', axis=1, inplace=True)

# Display the final merged DataFrame
final_df

                           title studio  domestic_gross_x
foreign_gross  year  \
0                    Toy Story 3     BV       415000000.0
652000000  2010
1                      Inception     WB       292600000.0
535700000  2010
2            Shrek Forever After   P/DW       238700000.0
513900000  2010
3     The Twilight Saga: Eclipse   Sum.       300500000.0
398000000  2010
4                     Iron Man 2   Par.       312400000.0
311500000  2010
...                          ...    ...               ...            ..
```

```
.   ...
1390  Bilal: A New Breed of Hero      VE           491000.0
1700000  2018
1391                         Mandy    RLJ         1200000.0
NaN  2018
1392                         Mandy    RLJ         1200000.0
NaN  2018
1393                  Lean on Pete    A24         1200000.0
NaN  2018
1394                  Lean on Pete    A24         1200000.0
NaN  2018

                    genre_ids  popularity release_date_x  vote_average
\
0              [16, 10751, 35]      24.445     2010-06-17           7.7

1                [28, 878, 12]      27.920     2010-07-16           8.3

2      [35, 12, 14, 16, 10751]      15.041     2010-05-16           6.1

3          [12, 14, 18, 10749]      20.340     2010-06-23           6.0

4                [12, 28, 878]      28.515     2010-05-07           6.8

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

1390              [28, 12, 16]       2.707     2018-02-02           6.8

1391                      [18]       0.600     2016-01-24           3.5

1392    [28, 53, 27, 14, 9648]      16.240     2018-09-13           6.2

1393                  [18, 12]       9.307     2018-04-06           6.9

1394                  [18, 12]       9.307     2018-04-06           6.9


      vote_count release_date_y production_budget domestic_gross_y  \
0           8340   Jun 18, 2010      $200,000,000     $415,004,880
1          22186   Jul 16, 2010      $160,000,000     $292,576,195
2           3843   May 21, 2010      $165,000,000     $238,736,787
3           4909   Jun 30, 2010       $68,000,000     $300,531,751
4          12368    May 7, 2010      $170,000,000     $312,433,331
...          ...            ...               ...              ...
1390          54    Feb 2, 2018       $30,000,000         $490,973
1391           2   Sep 14, 2018        $6,000,000       $1,214,525
1392         618   Sep 14, 2018        $6,000,000       $1,214,525
1393         133    Apr 6, 2018        $8,000,000       $1,163,056
1394         133    Apr 6, 2018        $8,000,000       $1,163,056

     worldwide_gross
```

```
0     $1,068,879,522
1       $835,524,642
2       $756,244,673
3       $706,102,828
4       $621,156,389
...              ...
1390        $648,599
1391      $1,427,656
1392      $1,427,656
1393      $2,455,027
1394      $2,455,027

[1395 rows x 14 columns]
```

```
# Merge filtered_merged_df with final_df based on the 'primary_title'
and 'title' columns
merged_final_df = pd.merge(filtered_merged_df, final_df,
left_on='primary_title', right_on='title', how='inner')

# Display the merged DataFrame
merged_final_df
```

```
                        primary_title  runtime_minutes  \
0                         On the Road            124.0
1     The Secret Life of Walter Mitty            114.0
2         A Walk Among the Tombstones            114.0
3                     Jurassic World            124.0
4                       The Rum Diary            119.0
...                               ...              ...
1274                           Unsane             98.0
1275                       Uncle Drew            103.0
1276                   BlacKkKlansman            135.0
1277          Paul, Apostle of Christ            108.0
1278                              Red             90.0

                          genres   movie_id       primary_name
birth_year  \
0       Adventure,Drama,Romance  tt0337692      Walter Salles
1956.0
1        Adventure,Comedy,Drama  tt0359950        Ben Stiller
1965.0
2            Action,Crime,Drama  tt0365907        Scott Frank
1960.0
3       Action,Adventure,Sci-Fi  tt0369610    Colin Trevorrow
1976.0
4                  Comedy,Drama  tt0376136     Bruce Robinson
1946.0
...                         ...        ...                ...
...
1274       Drama,Horror,Mystery  tt7153766  Steven Soderbergh
```

```
1963.0
1275                Comedy,Sport  tt7334528  Charles Stone III
1966.0
1276      Biography,Crime,Drama  tt7349662          Spike Lee
1957.0
1277  Adventure,Biography,Drama  tt7388562       Andrew Hyatt
1982.0
1278                      Drama  tt8851190   Michael Grandage
1962.0

      death_year                 primary_profession  averagerating
numvotes  \
0            NaN          director,producer,writer            6.1
37886
1            NaN           producer,actor,director            7.3
275300
2            NaN          writer,producer,director            6.5
105116
3            NaN          writer,producer,director            7.0
539338
4            NaN             actor,writer,director            6.2
94787
...          ...                               ...            ...
...
1274         NaN  producer,director,cinematographer            6.4
32049
1275         NaN                    director,actor            5.7
9739
1276         NaN          director,producer,writer            7.5
149005
1277         NaN      miscellaneous,director,writer            6.7
5662
1278         NaN           actor,director,producer            8.1
26

      ...  year           genre_ids  popularity release_date_x
vote_average  \
0     ...  2012            [12, 18]       8.919     2012-12-21
5.6
1     ...  2013    [12, 35, 18, 14]      10.743     2013-12-25
7.1
2     ...  2014  [80, 18, 9648, 53]      19.373     2014-09-19
6.3
3     ...  2015   [28, 12, 878, 53]      20.709     2015-06-12
6.6
4     ...  2011            [18, 35]      12.011     2011-10-27
5.7
...   ...   ...                 ...         ...            ...
...
```

```
1274  ...  2018            [27, 53]      16.316     2018-03-23
6.2
1275  ...  2018                [35]      10.836     2018-06-29
6.5
1276  ...  2018            [80, 18]      25.101     2018-07-30
7.6
1277  ...  2018                [36]      12.005     2018-03-28
7.1
1278  ...  2010                  []       0.600     2014-01-01
5.0

     vote_count  release_date_y production_budget  domestic_gross_y  \
0           518    Mar 22, 2013       $25,000,000          $720,828
1          4859    Dec 25, 2013       $91,000,000       $58,236,838
2          1685    Sep 19, 2014       $28,000,000       $26,017,685
3         14056    Jun 12, 2015      $215,000,000      $652,270,625
4           652    Oct 28, 2011       $45,000,000       $13,109,815
...         ...             ...               ...               ...
1274        667    Mar 23, 2018        $1,500,000        $7,690,044
1275        220    Jun 29, 2018       $18,000,000       $42,469,946
1276       3138    Aug 10, 2018       $15,000,000       $49,275,340
1277         98    Mar 23, 2018        $5,000,000       $17,547,999
1278          1    Oct 15, 2010       $60,000,000       $90,380,162

      worldwide_gross
0          $9,313,302
1        $187,861,183
2         $62,108,587
3      $1,648,854,864
4         $21,544,732
...               ...
1274      $14,244,931
1275      $46,527,161
1276      $93,017,335
1277      $25,529,498
1278     $196,439,693

[1279 rows x 24 columns]
```

We have made a general merger, which is rather a small part of the original data, with only 1279 rows. SInce this is very limited, we will use our two previous mergers, 'filtered_merged_df' from the IMDb tables and 'unified_df' from the selected data frame files. We will also use those earlier mergers wich are more rich in data.

Data Preparation for merged_final_df

```
# Convert columns to numeric values (remove commas and dollar signs)
merged_final_df['worldwide_gross'] =
merged_final_df['worldwide_gross'].str.replace(',',
'').str.replace('$', '').astype(float)
```

```python
merged_final_df['production_budget'] =
merged_final_df['production_budget'].str.replace(',',
'').str.replace('$', '').astype(float)

# Define the desired column order
desired_columns = ['primary_title', 'domestic_gross_y',
'domestic_gross_x', 'foreign_gross', 'worldwide_gross',
'production_budget']

# Get a list of current columns excluding the desired ones
other_columns = [col for col in merged_final_df.columns if col not in
desired_columns]

# Reorder the columns as per the desired order
reordered_columns = desired_columns + other_columns

# Reindex the DataFrame columns
merged_final_df = merged_final_df.reindex(columns=reordered_columns)
```

A bit more cleaning...

```python
# Drop the 'genre_ids' column
merged_final_df.drop(columns='genre_ids', inplace=True)

# Drop the 'domestic_gross_y' column
merged_final_df.drop(columns='domestic_gross_y', inplace=True)

# Rename 'domestic_gross_x' to 'domestic_gross'
merged_final_df.rename(columns={'domestic_gross_x': 'domestic_gross'},
inplace=True)

# Convert 'foreign_gross' to float64
merged_final_df['foreign_gross'] =
merged_final_df['foreign_gross'].replace('[\$,]', '',
regex=True).astype(float)

# Displaying the data types of specific columns
selected_columns = ['domestic_gross', 'foreign_gross',
'worldwide_gross', 'production_budget']
column_types = merged_final_df[selected_columns].dtypes
print(column_types)
```

```
domestic_gross       float64
foreign_gross        float64
worldwide_gross      float64
production_budget    float64
dtype: object
```

```python
# now let's take a look
merged_final_df.head()
```

```
                     primary_title  domestic_gross  foreign_gross  \
0                      On the Road        744000.0      8000000.0
1  The Secret Life of Walter Mitty      58200000.0    129900000.0
2      A Walk Among the Tombstones      26300000.0     26900000.0
3                   Jurassic World     652300000.0         1019.4
4                    The Rum Diary      13100000.0     10800000.0

   worldwide_gross  production_budget  runtime_minutes  \
0     9.313302e+06         25000000.0            124.0
1     1.878612e+08         91000000.0            114.0
2     6.210859e+07         28000000.0            114.0
3     1.648855e+09        215000000.0            124.0
4     2.154473e+07         45000000.0            119.0

                    genres   movie_id     primary_name
birth_year  ...  \
0  Adventure,Drama,Romance  tt0337692    Walter Salles
1956.0  ...
1   Adventure,Comedy,Drama  tt0359950      Ben Stiller
1965.0  ...
2       Action,Crime,Drama  tt0365907      Scott Frank
1960.0  ...
3  Action,Adventure,Sci-Fi  tt0369610  Colin Trevorrow
1976.0  ...
4             Comedy,Drama  tt0376136   Bruce Robinson
1946.0  ...

   averagerating numvotes                             title  studio
year  \
0            6.1    37886                       On the Road     IFC
2012
1            7.3   275300  The Secret Life of Walter Mitty     Fox
2013
2            6.5   105116      A Walk Among the Tombstones    Uni.
2014
3            7.0   539338                    Jurassic World    Uni.
2015
4            6.2    94787                     The Rum Diary      FD
2011

  popularity  release_date_x  vote_average vote_count  release_date_y

0      8.919      2012-12-21           5.6        518    Mar 22, 2013

1     10.743      2013-12-25           7.1       4859    Dec 25, 2013

2     19.373      2014-09-19           6.3       1685    Sep 19, 2014

3     20.709      2015-06-12           6.6      14056    Jun 12, 2015

4     12.011      2011-10-27           5.7        652    Oct 28, 2011
```

```
[5 rows x 22 columns]
```

Exploratory Data Analysis

Notebook promotes three recommendations for choosing films to produce:

- Uses three or more findings from data analyses to support recommendations
- Explains why the findings support the recommendations
- Explains how the recommendations would help the new movie studio succeed

Let's calculate ROI and net profit with these formulas (Source):

Net Profit = Gross Revenue - Budget ROI = (Net Profit / Budget) * 100

```
# Calculate Profit and ROI using correct formulas
merged_final_df['profit'] = merged_final_df['worldwide_gross'] -
merged_final_df['production_budget']
merged_final_df['roi'] = (merged_final_df['profit'] /
merged_final_df['production_budget']) * 100

# Define the desired column order
desired_columns = ['primary_title', 'domestic_gross', 'foreign_gross',
'worldwide_gross', 'production_budget', 'profit', 'roi']

# Get a list of current columns excluding the desired ones
other_columns = [col for col in merged_final_df.columns if col not in
desired_columns]

# Reorder the columns as per the desired order
reordered_columns = desired_columns + other_columns

# Reindex the DataFrame columns
merged_final_df = merged_final_df.reindex(columns=reordered_columns)
merged_final_df.head()
```

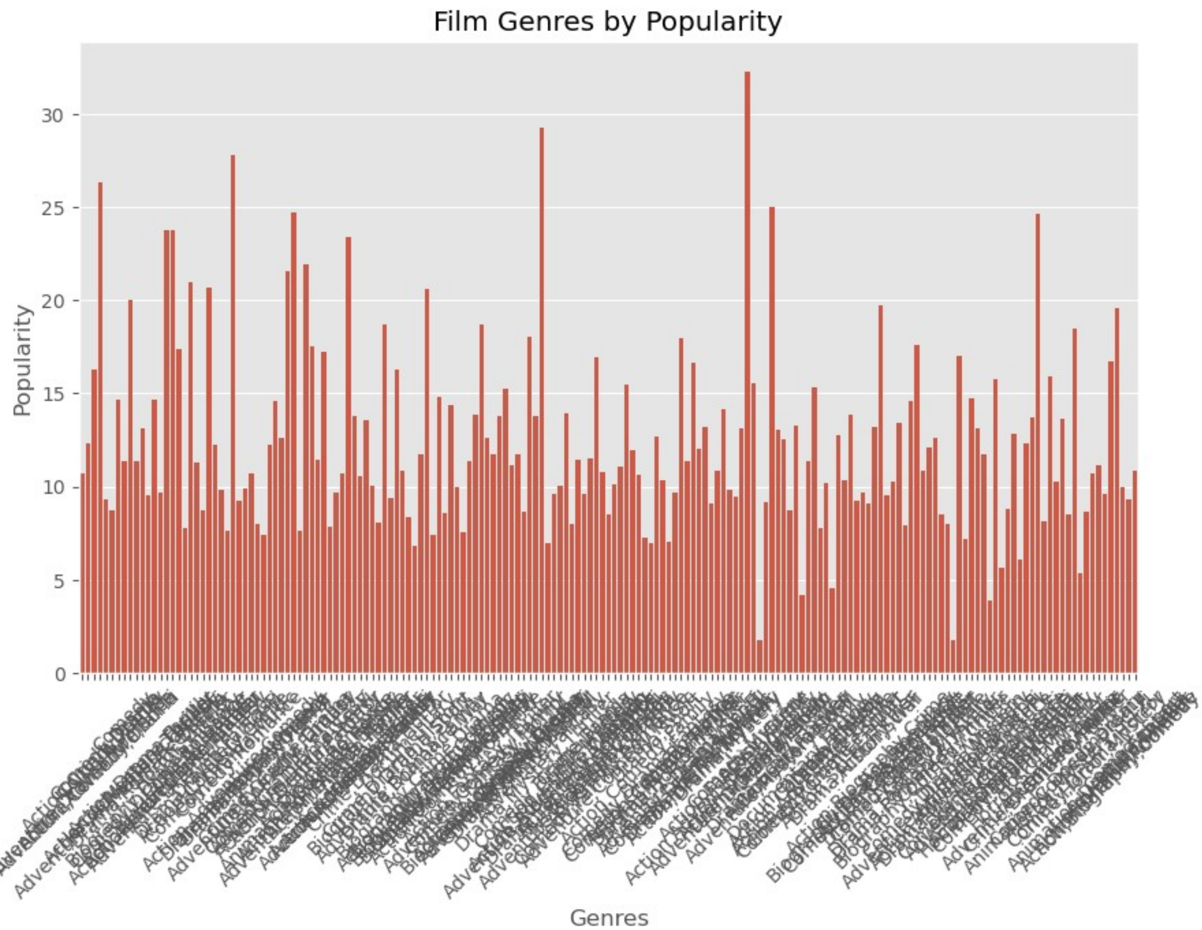
```
                    primary_title  domestic_gross  foreign_gross  \
0                     On the Road        744000.0      8000000.0   
1  The Secret Life of Walter Mitty      58200000.0    129900000.0   
2      A Walk Among the Tombstones      26300000.0     26900000.0   
3                  Jurassic World     652300000.0         1019.4   
4                   The Rum Diary      13100000.0     10800000.0   

   worldwide_gross  production_budget        profit         roi  \
0     9.313302e+06         25000000.0 -1.568670e+07  -62.746792   
1     1.878612e+08         91000000.0  9.686118e+07  106.440860   
2     6.210859e+07         28000000.0  3.410859e+07  121.816382   
3     1.648855e+09        215000000.0  1.433855e+09  666.909239   
```

```
4     2.154473e+07         45000000.0 -2.345527e+07  -52.122818

   runtime_minutes                        genres   movie_id  ...
averagerating  \
0            124.0  Adventure,Drama,Romance  tt0337692  ...
6.1
1            114.0   Adventure,Comedy,Drama  tt0359950  ...
7.3
2            114.0       Action,Crime,Drama  tt0365907  ...
6.5
3            124.0  Action,Adventure,Sci-Fi  tt0369610  ...
7.0
4            119.0             Comedy,Drama  tt0376136  ...
6.2

   numvotes                              title studio  year  popularity
\
0     37886                        On the Road    IFC  2012       8.919

1    275300  The Secret Life of Walter Mitty    Fox  2013      10.743

2    105116      A Walk Among the Tombstones   Uni.  2014      19.373

3    539338                     Jurassic World   Uni.  2015      20.709

4     94787                      The Rum Diary     FD  2011      12.011


  release_date_x vote_average  vote_count  release_date_y
0     2012-12-21          5.6         518    Mar 22, 2013
1     2013-12-25          7.1        4859    Dec 25, 2013
2     2014-09-19          6.3        1685    Sep 19, 2014
3     2015-06-12          6.6       14056    Jun 12, 2015
4     2011-10-27          5.7         652    Oct 28, 2011

[5 rows x 24 columns]
```

Let's explore our data.

```python
# Assuming 'genre' and 'popularity' columns exist in merged_final_df
plt.figure(figsize=(10, 6))
sns.barplot(x='genres', y='popularity', data=merged_final_df, ci=None)
plt.title('Film Genres by Popularity')
plt.xlabel('Genres')
plt.ylabel('Popularity')
plt.xticks(rotation=45)
plt.show()

C:\Users\rafvr\AppData\Local\Temp\ipykernel_22344\1567199818.py:3:
FutureWarning:
```

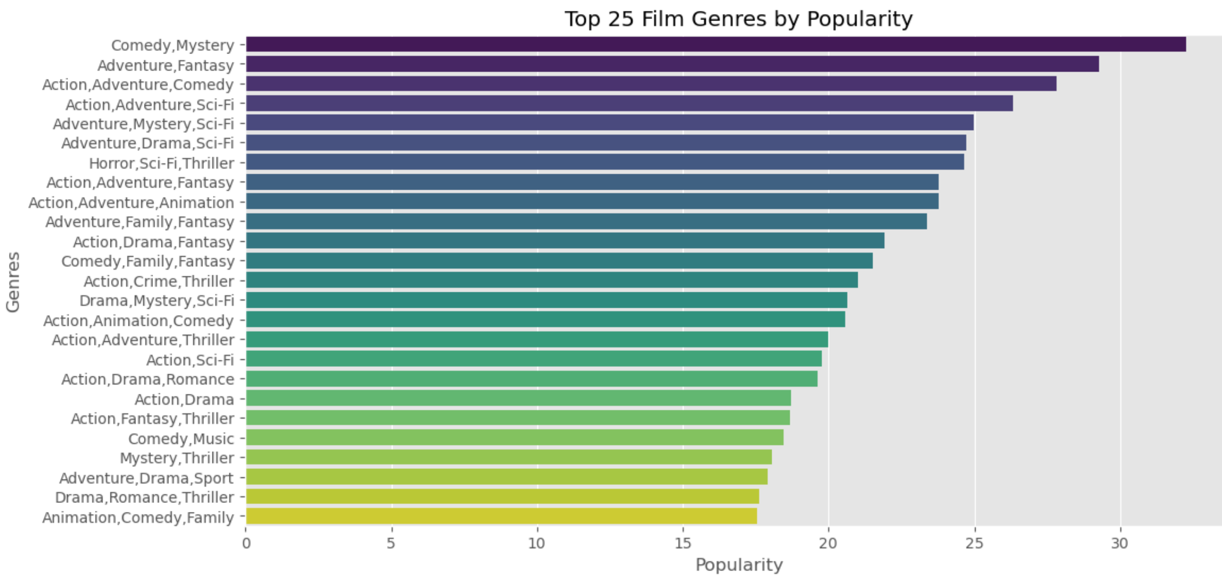
```
The `ci` parameter is deprecated. Use `errorbar=None` for the same
effect.

  sns.barplot(x='genres', y='popularity', data=merged_final_df,
ci=None)
```



Reducing the set to the top 25 most popular films genres.

```
# Assuming 'genres' and 'popularity' columns exist in merged_final_df
top_25_genres = merged_final_df.groupby('genres')
['popularity'].mean().nlargest(25).sort_values(ascending=False)

plt.figure(figsize=(12, 6))
sns.barplot(x=top_25_genres.values, y=top_25_genres.index,
palette='viridis')
plt.title('Top 25 Film Genres by Popularity')
plt.xlabel('Popularity')
plt.ylabel('Genres')
plt.show()
```

```
C:\Users\rafvr\AppData\Local\Temp\ipykernel_22344\1499904627.py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=top_25_genres.values, y=top_25_genres.index, palette='viridis')
```

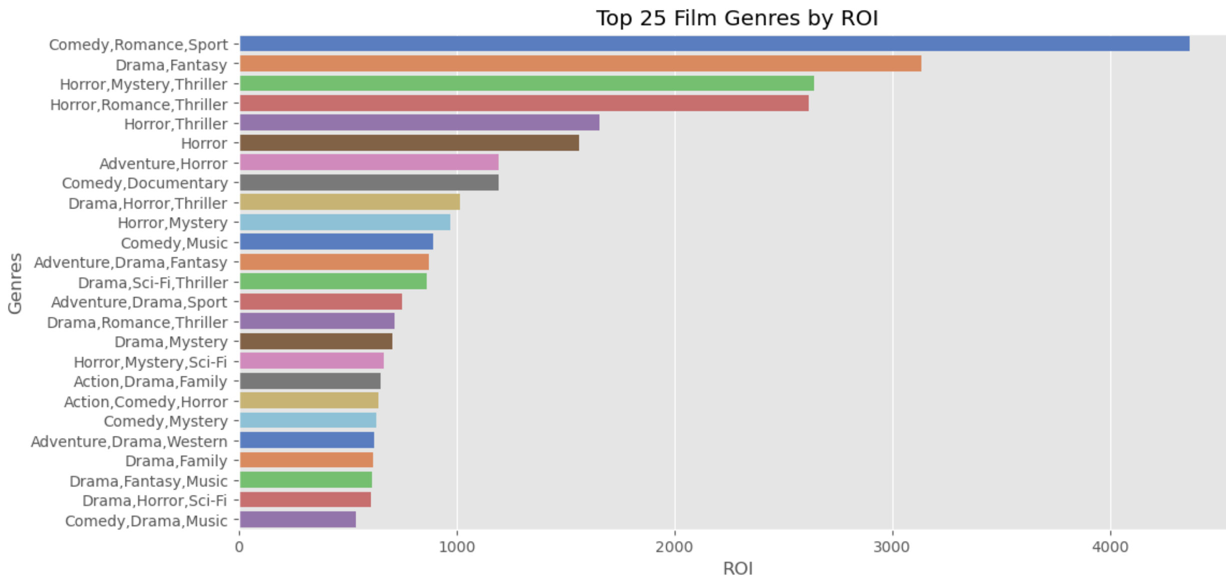


The top 25 best ROI films.

```
# Bar plot to display the top 25 film genres by their mean Return on Investment (ROI)
top_25_genres_roi = merged_final_df.groupby('genres')['roi'].mean().nlargest(25).sort_values(ascending=False)

plt.figure(figsize=(12, 6))
sns.barplot(x=top_25_genres_roi.values, y=top_25_genres_roi.index, palette='muted')
plt.title('Top 25 Film Genres by ROI')
plt.xlabel('ROI')
plt.ylabel('Genres')
plt.show()
```

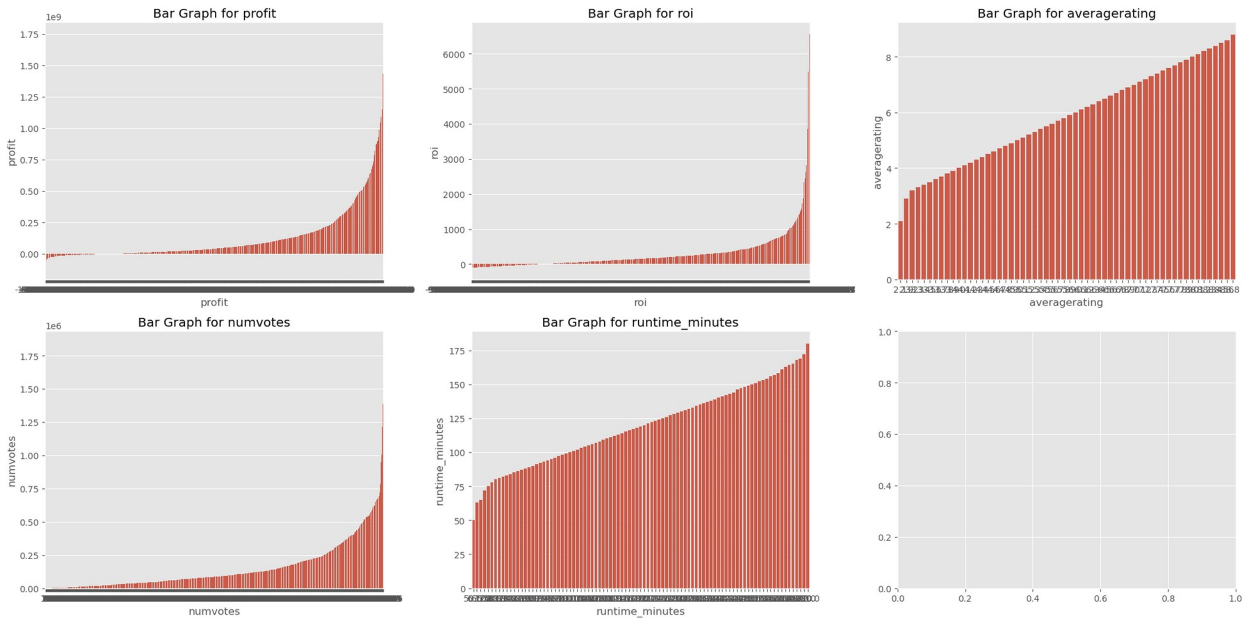
```
C:\Users\rafvr\AppData\Local\Temp\ipykernel_22344\1330475812.py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.
```

```
sns.barplot(x=top_25_genres_roi.values, y=top_25_genres_roi.index,
palette='muted')
```



General data visualization explorations:

```
# Define columns for different plots
bar_columns = ['profit', 'roi', 'averagerating', 'numvotes',
'runtime_minutes']

# Calculate the total number of plots
total_plots = len(bar_columns)
rows = 2  # Set the number of rows to 2 for two rows

# Create a subplot grid
fig, axes = plt.subplots(nrows=rows, ncols=3, figsize=(20, 5 * rows))

# Loop through the columns and create respective plots
for i, col in enumerate(bar_columns):
    sns.barplot(x=col, y=col, data=merged_final_df, ax=axes[i // 3, i
% 3])
    axes[i // 3, i % 3].set_title(f'Bar Graph for {col}')

# Adjust layout
plt.tight_layout()
plt.show()
```



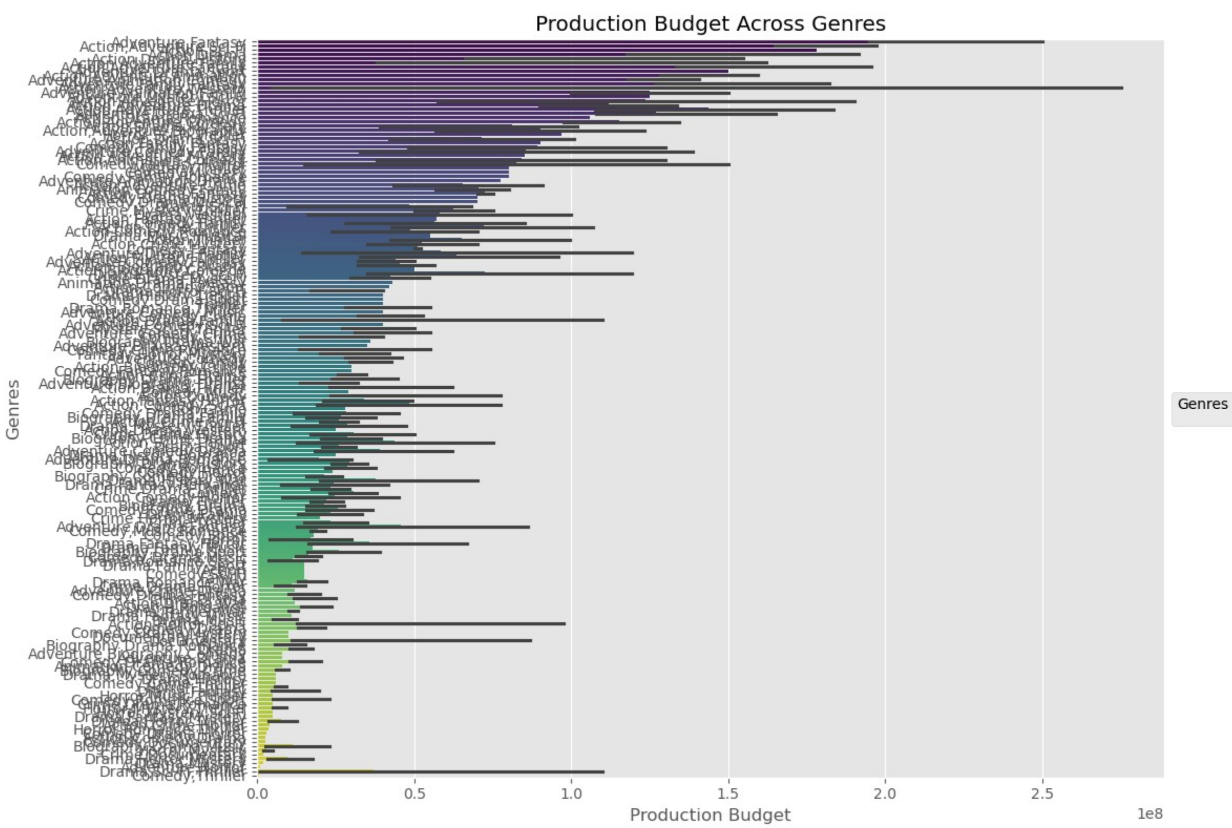

```
# List of columns to plot
columns_to_plot = ['genres', 'studio', 'year', 'popularity',
'release_date_x', 'vote_average', 'vote_count', 'release_date_y']

# Calculate the number of rows needed for subplots
num_rows = (len(columns_to_plot) - 1) // 3 + 1

# Create subplots with proper size
fig, axes = plt.subplots(num_rows, 3, figsize=(15, num_rows * 5))

# Loop through columns and plot
for i, col in enumerate(columns_to_plot):
    row = i // 3
    col_index = i % 3
    sns.countplot(x=merged_final_df[col], data=merged_final_df,
ax=axes[row, col_index])
    axes[row, col_index].set_title(f'Count Plot for {col}')

plt.tight_layout()
plt.show()
```

At this point we would like to visualize budget and consider dividing production costs in budget brackets. This should be useful for stakeholders when deciding how much to invest and posible outcome of investment within such and such limits.

```
# Calculate median production budget for each genre and sort the
genres accordingly
genre_order = merged_final_df.groupby('genres')
['production_budget'].median().sort_values(ascending=False).index

# Set up the figure size
plt.figure(figsize=(12, 8))
```

```python
# Create a bar plot for 'genres' vs 'production_budget' with distinct colors for each genre
sns.barplot(x='production_budget', y='genres', data=merged_final_df, order=genre_order, palette='viridis')
plt.title('Production Budget Across Genres')
plt.xlabel('Production Budget')
plt.ylabel('Genres')

# Show legend
plt.legend(title='Genres', loc='center left', bbox_to_anchor=(1, 0.5))
plt.tight_layout()
plt.show()
```

```
C:\Users\rafvr\AppData\Local\Temp\ipykernel_22344\2950482186.py:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='production_budget', y='genres', data=merged_final_df, order=genre_order, palette='viridis')
No artists with labels found to put in legend.  Note that artists whose label start with an underscore are ignored when legend() is called with no argument.
```

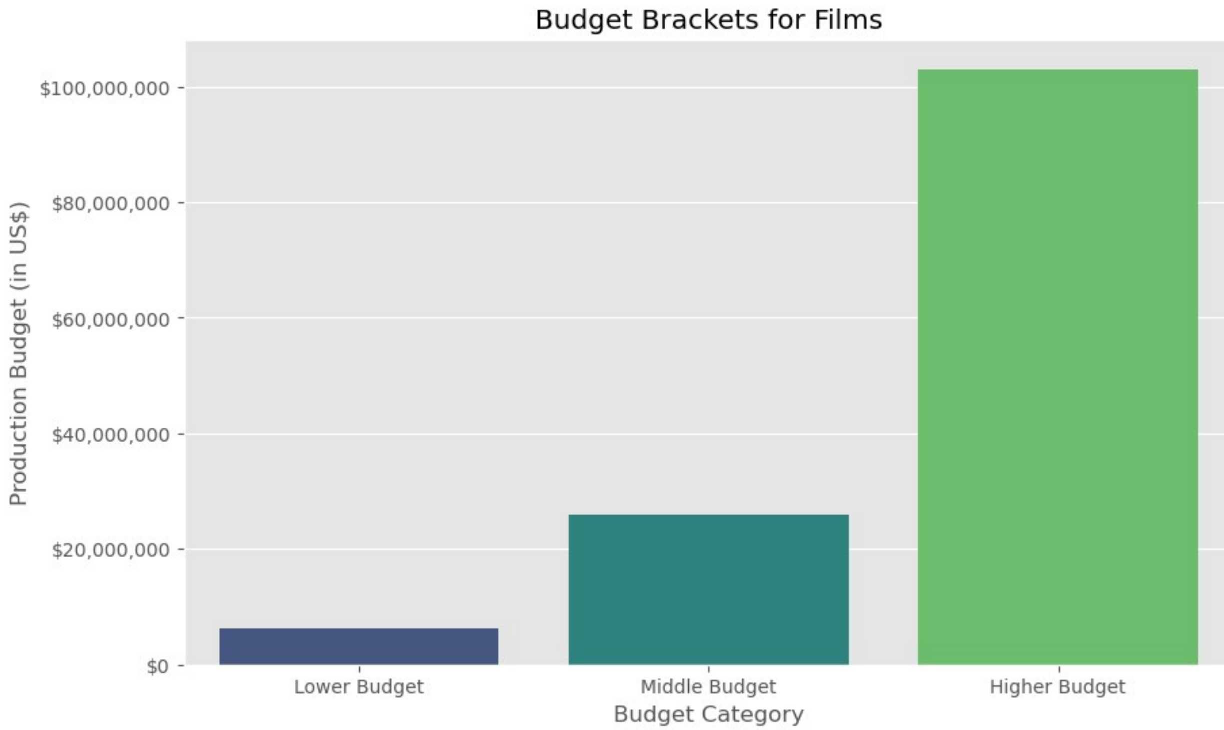


Production Budget Analysis and Categorization

Since we were requested three recommendations, we will strategize production budget in three sections: lower, middle and higher budget brackets.

```
import matplotlib.ticker as ticker

# Calculate quartiles for 'production_budget'
lower_quartile = merged_final_df['production_budget'].quantile(1/3)
upper_quartile = merged_final_df['production_budget'].quantile(2/3)

# Define labels and ranges for the three budget categories
budget_labels = ['Lower Budget', 'Middle Budget', 'Higher Budget']
budget_ranges = [
    (merged_final_df['production_budget'].min(), lower_quartile),
    (lower_quartile, upper_quartile),
    (upper_quartile, merged_final_df['production_budget'].max())
]

# Calculate median values for each budget category
median_values = [merged_final_df[(merged_final_df['production_budget']
>= lower) & (merged_final_df['production_budget'] < upper)]
['production_budget'].median()
                 for lower, upper in budget_ranges]

# Create a bar plot showing the budget ranges for each category
plt.figure(figsize=(10, 6))
ax = sns.barplot(x=budget_labels, y=median_values, palette='viridis')
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, _: '$
{:,.0f}'.format(x)))
plt.title('Budget Brackets for Films')
plt.xlabel('Budget Category')
plt.ylabel('Production Budget (in US$)')
plt.show()
```

```
C:\Users\rafvr\AppData\Local\Temp\ipykernel_22344\203977153.py:21:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  ax = sns.barplot(x=budget_labels, y=median_values,
palette='viridis')
```




```
# Define the quartiles for 'production_budget'
lower_quartile = merged_final_df['production_budget'].quantile(1/3)
upper_quartile = merged_final_df['production_budget'].quantile(2/3)

# Count the number of films and unique genres in each budget bracket
lower_budget_films =
merged_final_df[merged_final_df['production_budget'] < lower_quartile]
middle_budget_films =
merged_final_df[(merged_final_df['production_budget'] >=
lower_quartile) & (merged_final_df['production_budget'] <
upper_quartile)]
higher_budget_films =
merged_final_df[merged_final_df['production_budget'] >=
upper_quartile]

# Create the table data
brackets = ['Lower Budget', 'Middle Budget', 'Higher Budget']
min_amounts = ['$0', f'${lower_quartile:,.0f}', f'$
{upper_quartile:,.0f}']
max_amounts = [f'${lower_quartile:,.0f}', f'${upper_quartile:,.0f}',
'More']
film_counts = [len(lower_budget_films), len(middle_budget_films),
len(higher_budget_films)]

# Print the tabular result
print("Budget Brackets: | Min. Amount(US$) | Max. Amount(US$) | Number
of Films:")
```

```
print("-----------------|------------------|------------------|-------
----------")
for i in range(3):
    print(f"{brackets[i]:<16} | {min_amounts[i]:<18} |
{max_amounts[i]:<16} | {film_counts[i]}")
```

```
Budget Brackets: | Min. Amount(US$) | Max. Amount(US$) | Number of
Films:
-----------------|------------------|------------------|--------------
---
Lower Budget     | $0                 | $15,000,000      | 398
Middle Budget    | $15,000,000        | $50,000,000      | 437
Higher Budget    | $50,000,000        | More             | 444
```

```
print(merged_final_df.columns)
```

```
Index(['primary_title', 'domestic_gross', 'foreign_gross',
'worldwide_gross',
       'production_budget', 'profit', 'roi', 'runtime_minutes',
'genres',
       'movie_id', 'primary_name', 'birth_year', 'death_year',
       'primary_profession', 'averagerating', 'numvotes', 'title',
'studio',
       'year', 'popularity', 'release_date_x', 'vote_average',
'vote_count',
       'release_date_y'],
      dtype='object')
```

Genre Analysis

Having divided the Production Budget per film in three sections, let us now find out the best ROI per film and the genre, for each budget bracket. We will pull the best three films in each category.

```
# Define the quartiles for 'production_budget'
lower_quartile = merged_final_df['production_budget'].quantile(1/3)
upper_quartile = merged_final_df['production_budget'].quantile(2/3)

# Define the budget categories
merged_final_df['budget_category'] =
pd.cut(merged_final_df['production_budget'],
                                           bins=[-np.inf,
lower_quartile, upper_quartile, np.inf],
                                           labels=['Lower Budget',
'Middle Budget', 'Higher Budget'])

# Sort films by ROI within each budget category and get the genres
top_genres_lower = (merged_final_df[merged_final_df['budget_category']
== 'Lower Budget']
```

```
                    .groupby('genres')['roi'].mean()
                    .nlargest(3)
                    .reset_index())
top_genres_middle =
(merged_final_df[merged_final_df['budget_category'] == 'Middle
Budget']
                     .groupby('genres')['roi'].mean()
                     .nlargest(3)
                     .reset_index())
top_genres_higher =
(merged_final_df[merged_final_df['budget_category'] == 'Higher
Budget']
                     .groupby('genres')['roi'].mean()
                     .nlargest(3)
                     .reset_index())

# Display the results
print("Top 3 genres with the best ROI in the Lower Budget:")
print(top_genres_lower)

print("\nTop 3 genres with the best ROI in the Middle Budget:")
print(top_genres_middle)

print("\nTop 3 genres with the best ROI in the Higher Budget:")
print(top_genres_higher)
```

```
Top 3 genres with the best ROI in the Lower Budget:
                 genres          roi
0  Comedy,Romance,Sport  5479.296120
1         Drama,Fantasy  4384.589026
2                Horror  2987.584937

Top 3 genres with the best ROI in the Middle Budget:
                    genres          roi
0  Horror,Mystery,Thriller  1490.000705
1   Action,Sci-Fi,Thriller  1043.769440
2           Comedy,Fantasy  1012.033254

Top 3 genres with the best ROI in the Higher Budget:
                   genres          roi
0   Biography,Drama,Music  1527.246076
1  Action,Biography,Drama   843.666159
2   Adventure,Drama,Sport   748.313273
```

Seasonal Analysis

```
# Display a sample of the columns related to the release date
release_date_cols = ['release_year', 'release_month']
print(merged_final_df[release_date_cols].sample(10))
```

```
------------------------------------------------------------------------
-----
KeyError                                  Traceback (most recent call
last)
Cell In[94], line 3
      1 # Display a sample of the columns related to the release date
      2 release_date_cols = ['release_year', 'release_month']
----> 3 print(merged_final_df[release_date_cols].sample(10))

File ~\anaconda3\lib\site-packages\pandas\core\frame.py:3899, in
DataFrame.__getitem__(self, key)
   3897     if is_iterator(key):
   3898         key = list(key)
-> 3899     indexer = self.columns._get_indexer_strict(key, "columns")
[1]
   3901 # take() does not accept boolean indexers
   3902 if getattr(indexer, "dtype", None) == bool:

File ~\anaconda3\lib\site-packages\pandas\core\indexes\base.py:6115,
in Index._get_indexer_strict(self, key, axis_name)
   6112 else:
   6113     keyarr, indexer, new_indexer =
self._reindex_non_unique(keyarr)
-> 6115 self._raise_if_missing(keyarr, indexer, axis_name)
   6117 keyarr = self.take(indexer)
   6118 if isinstance(key, Index):
   6119     # GH 42790 - Preserve name from an Index

File ~\anaconda3\lib\site-packages\pandas\core\indexes\base.py:6176,
in Index._raise_if_missing(self, key, indexer, axis_name)
   6174     if use_interval_msg:
   6175         key = list(key)
-> 6176     raise KeyError(f"None of [{key}] are in the
[{axis_name}]")
   6178 not_found = list(ensure_index(key)[missing_mask.nonzero()
[0]].unique())
   6179 raise KeyError(f"{not_found} not in index")

KeyError: "None of [Index(['release_year', 'release_month'],
dtype='object')] are in the [columns]"

# Ensure 'release_date_x' column is in datetime format
merged_final_df['release_date_x'] =
pd.to_datetime(merged_final_df['release_date_x'])

# Extract month and year information
merged_final_df['release_month'] =
merged_final_df['release_date_x'].dt.month.astype(int)
merged_final_df['release_year'] =
merged_final_df['release_date_x'].dt.year.astype(int)
```

```python
# Group by month and year, calculate average ROI
average_monthly_roi = merged_final_df.groupby(['release_year',
'release_month'])['roi'].mean().reset_index()

# Visualization: Plotting average ROI against month
plt.figure(figsize=(12, 6))
plt.plot(average_monthly_roi.index, average_monthly_roi['roi'],
marker='o')
plt.xlabel('Month')
plt.ylabel('Average ROI')
plt.title(f'Average ROI per Month from
{merged_final_df["release_date_x"].min().strftime("%b %Y")} to
{merged_final_df["release_date_x"].max().strftime("%b %Y")}')

# Add month-year labels to the x-axis
plt.xticks(ticks=average_monthly_roi.index,
labels=average_monthly_roi['release_year'].astype(str) + '-' +
average_monthly_roi['release_month'].astype(str).str.zfill(2),
rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()

# Extract month and year information
merged_final_df['release_month'] =
merged_final_df['release_date_x'].dt.month.astype(int)
merged_final_df['release_year'] =
merged_final_df['release_date_x'].dt.year.astype(int)

# Group by month and year, calculate average ROI
average_monthly_roi = merged_final_df.groupby(['release_month'])
['roi'].mean().reset_index()

# Visualization: Plotting average ROI against month
plt.figure(figsize=(10, 6))
plt.bar(average_monthly_roi['release_month'],
average_monthly_roi['roi'], color='skyblue')
plt.xlabel('Month')
plt.ylabel('Average ROI')
plt.title('Average ROI per Month (Dec 1968 to Dec 2018)')
plt.xticks(np.arange(1, 13), ['Jan', 'Feb', 'Mar', 'Apr', 'May',
'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.grid(axis='y')
plt.tight_layout()
plt.show()

# Group by month and year, calculate average ROI
average_monthly_roi = merged_final_df.groupby(['release_year',
'release_month', 'budget_category'])['roi'].mean().reset_index()
```

```
# Map month numbers to their names
average_monthly_roi['release_month_name'] =
average_monthly_roi['release_month'].apply(lambda x:
calendar.month_name[x])

# Find the top 3 months with the best average monthly ROI for each
budget bracket
top_months_lower =
(average_monthly_roi[average_monthly_roi['budget_category'] == 'Lower
Budget']
                    .groupby('release_month_name')['roi'].mean()
                    .nlargest(3)
                    .reset_index())
top_months_middle =
(average_monthly_roi[average_monthly_roi['budget_category'] == 'Middle
Budget']
                     .groupby('release_month_name')['roi'].mean()
                     .nlargest(3)
                     .reset_index())
top_months_higher =
(average_monthly_roi[average_monthly_roi['budget_category'] == 'Higher
Budget']
                     .groupby('release_month_name')['roi'].mean()
                     .nlargest(3)
                     .reset_index())

# Display the results
print("Top 3 performing months in terms of average monthly ROI for
Lower Budget:")
print(top_months_lower)

print("\nTop 3 performing months in terms of average monthly ROI for
Middle Budget:")
print(top_months_middle)

print("\nTop 3 performing months in terms of average monthly ROI for
Higher Budget:")
print(top_months_higher)
```

Staff Analysis

```
# Filter the data based on conditions for 'primary_profession'
filtered_df = merged_final_df[
    (merged_final_df['primary_profession'].notnull()) &
    (merged_final_df['birth_year'].notnull()) &
    (merged_final_df['death_year'].isnull())
]

# Display unique values in the 'primary_profession' column
```

```python
unique_professions = filtered_df['primary_profession'].unique()
print("Unique values in 'primary_profession' column:")
print(unique_professions)
```

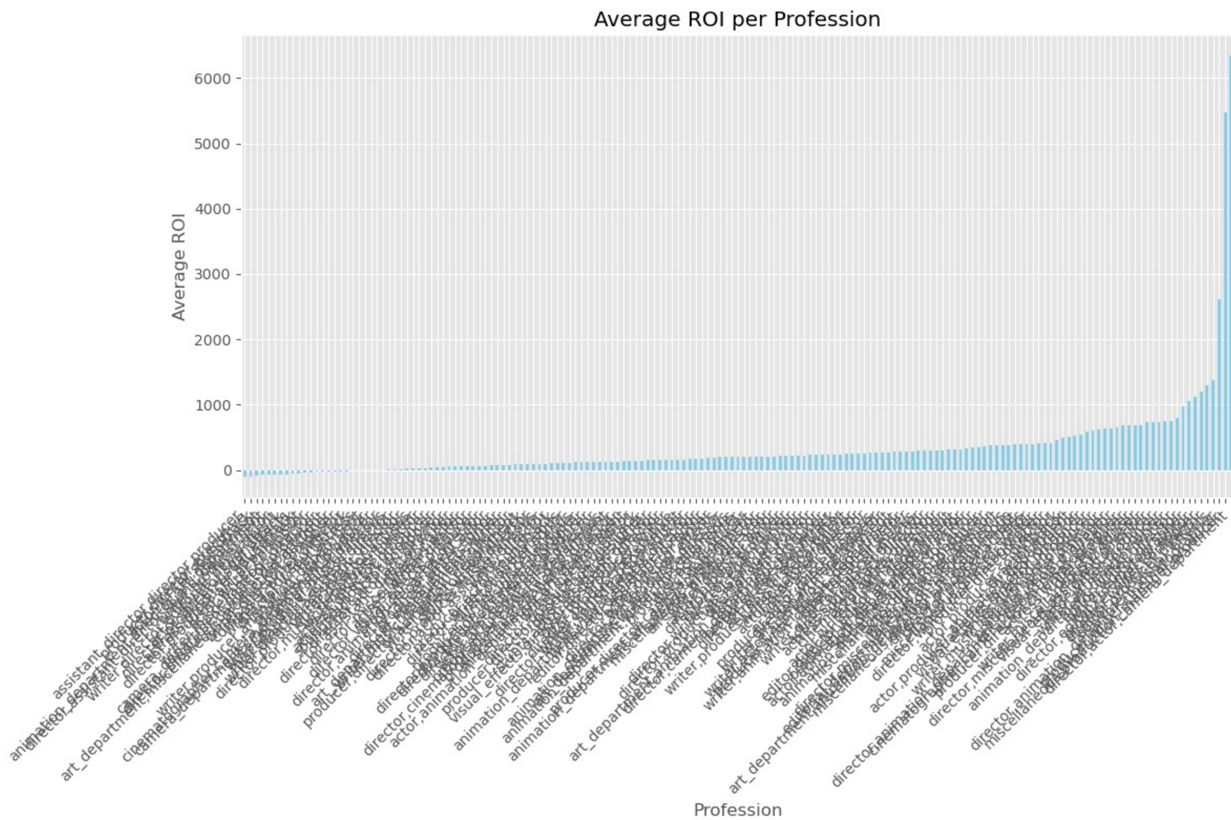
```
Unique values in 'primary_profession' column:
['director,producer,writer' 'producer,actor,director'
 'writer,producer,director' 'actor,writer,director'
 'producer,writer,director' 'actor,art_department,director'
 'animation_department,director,actor' 'writer,actor,producer'
 'producer,director,writer' 'writer,director,producer'
 'producer,director,actor' 'editorial_department,editor,miscellaneous'
 'actor,producer,director' 'actor,animation_department,director'
 'director,writer,producer' 'director,producer,actor'
 'director,visual_effects,producer' 'writer,actor,director'
 'editor,director,editorial_department'
 'director,cinematographer,camera_department'
 'writer,actor,animation_department' 'writer,director,soundtrack'
 'director,actor,producer' 'producer,actor,writer'
 'producer,director,editor' 'director,writer,soundtrack'
 'director,writer,cinematographer' 'director,writer,editor'
 'director,writer,actor' 'actor,director,producer'
'actor,writer,producer'
 'director,writer,assistant_director'
 'producer,director,animation_department' 'producer,writer,actor'
 'director,writer,actress' 'writer,producer,music_department'
 'stunts,writer,director' 'writer,animation_department,director'
 'actor,director,writer' 'producer,director,production_designer'
 'writer,director,editor' 'director,producer,assistant_director'
 'director,producer,miscellaneous' 'writer,producer,miscellaneous'
 'director,miscellaneous,assistant_director'
 'miscellaneous,writer,producer' 'director,producer,editor'
 'director,producer,art_department' 'writer,director'
 'producer,director,miscellaneous' 'producer,miscellaneous,director'
 'writer,director,assistant_director' 'writer,director,actor'
 'director,miscellaneous,producer' 'director,writer,visual_effects'
 'director,producer,cinematographer'
 'animation_department,writer,miscellaneous'
 'art_department,writer,miscellaneous' 'producer,actor,miscellaneous'
 'writer,actress,director' 'camera_department,director,producer'
 'director,writer' 'director,producer,soundtrack'
 'soundtrack,actor,composer' 'producer,writer,miscellaneous'
 'director,production_manager,writer'
 'director,assistant_director,sound_department'
 'director,miscellaneous,writer' 'miscellaneous,director,producer'
 'actor,producer,animation_department'
 'animation_department,art_department,director'
 'visual_effects,director,assistant_director'
 'animation_department,director,art_department'
 'actress,director,producer' 'animation_department,director,writer'
 'writer,miscellaneous,producer' 'actress,producer,director'
```

```
 'actor,producer,writer' 'actor,writer,composer'
 'composer,writer,director' 'director,actor,assistant_director'
 'actor,director,soundtrack' 'director,actor,writer'
 'producer,director,camera_department' 'director,producer,executive'
 'director,producer' 'producer,writer,music_department'
 'actress,director,writer' 'director,visual_effects,writer'
 'editor,director,assistant_director' 'director,actor,art_director'
 'actor,producer,soundtrack' 'director,animation_department,actor'
 'writer,art_department,director' 'writer,editor,director'
 'writer,actor,soundtrack' 'visual_effects,director,writer'
 'director,producer,visual_effects'
 'director,production_designer,producer'
'actor,writer,cinematographer'
 'producer,director,cinematographer' 'soundtrack,director,writer'
 'director,editor,cinematographer' 'writer,miscellaneous,director'
 'visual_effects,editor,director' 'actress,producer,soundtrack'
 'cinematographer,director' 'actress,soundtrack,director'
 'visual_effects,director,producer' 'writer,actress,producer'
 'producer,actor,soundtrack' 'director,camera_department,producer'
 'director,writer,miscellaneous' 'director,assistant_director,writer'
 'art_department,miscellaneous,writer' 'director,editor'
 'writer,music_department,producer' 'writer,director,miscellaneous'
 'director,miscellaneous,art_department' 'writer,art_department,actor'
 'director,actress,writer' 'miscellaneous,actress,director'
 'director,animation_department,production_manager'
 'assistant_director,director,producer'
'director,music_department,writer'
 'director,writer,camera_department'
 'miscellaneous,director,art_department'
'miscellaneous,writer,director'
 'actor,writer,soundtrack'
'cinematographer,camera_department,director'
 'actor,animation_department,art_department'
'director,producer,actress'
 'director,editor,writer'
 'art_department,animation_department,miscellaneous'
 'director,writer,composer' 'producer,writer,cinematographer'
 'director,actor' 'producer,writer,editor'
 'producer,writer,art_department'
 'director,animation_department,visual_effects' 'director'
 'editor,producer,director' 'editor,writer,director'
 'art_department,animation_department,director'
 'camera_department,cinematographer,director'
 'miscellaneous,production_manager,producer' 'writer,producer,actor'
 'stunts,actor,assistant_director' 'actor,soundtrack,producer'
 'writer,music_department,director' 'writer,director,composer'
 'art_department,miscellaneous,production_designer'
 'director,actor,camera_department' 'actress,writer,director'
 'writer,director,actress' 'animation_department,producer,director'
```

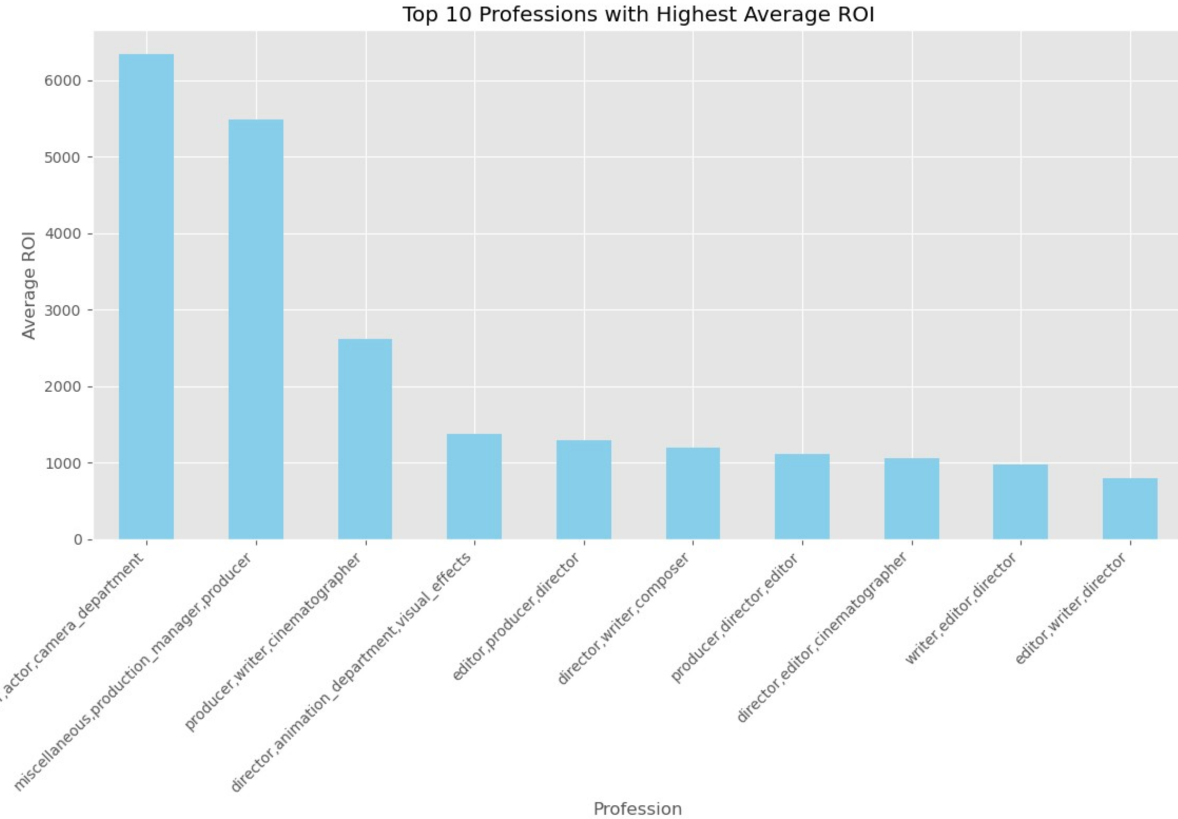
```
 'director,producer,camera_department'
 'cinematographer,camera_department,producer'
 'writer,producer,animation_department' 'producer,director,executive'
 'actress,writer,producer' 'writer,director,editorial_department'
 'writer,soundtrack,producer'
 'animation_department,visual_effects,director'
 'miscellaneous,director,writer']
```

Let's divide the list into individual values. This will make the information shorter and easier to analyze.

```
# Create a new DataFrame to store individual professions
individual_professions = merged_final_df.copy()

# Split values in the 'primary_profession' column by comma and explode
into separate rows
individual_professions['primary_profession'] =
individual_professions['primary_profession'].str.split(',')
individual_professions =
individual_professions.explode('primary_profession')

# Display unique values after splitting the professions
unique_individual_professions =
individual_professions['primary_profession'].unique()
print("Unique individual professions:")
print(unique_individual_professions)

Unique individual professions:
['director' 'producer' 'writer' 'actor' 'art_department'
 'animation_department' 'editorial_department' 'editor'
'miscellaneous'
 'visual_effects' 'cinematographer' 'camera_department' 'soundtrack'
 'assistant_director' 'actress' 'music_department' 'stunts'
 'production_designer' 'composer' 'production_manager'
'sound_department'
 'executive' 'art_director']

# Calculate average ROI per profession
avg_roi_per_profession = merged_final_df.groupby('primary_profession')
['roi'].mean().sort_values()

# Create a bar plot for average ROI per profession
plt.figure(figsize=(12, 8))
avg_roi_per_profession.plot(kind='bar', color='skyblue')
plt.xlabel('Profession')
plt.ylabel('Average ROI')
plt.title('Average ROI per Profession')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```




```
# Calculate average ROI per profession
avg_roi_per_profession = merged_final_df.groupby('primary_profession')
['roi'].mean().sort_values(ascending=False)

# Select top 10 professions with highest average ROI
top_10_avg_roi = avg_roi_per_profession.head(10)

# Create a bar plot for top 10 average ROI per profession
plt.figure(figsize=(12, 8))
top_10_avg_roi.plot(kind='bar', color='skyblue')
plt.xlabel('Profession')
plt.ylabel('Average ROI')
plt.title('Top 10 Professions with Highest Average ROI')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```




```
# Dictionary to store top 3 individuals for each profession within
each budget category
top_individuals_by_budget_profession = {}

for budget_category in ['Lower Budget', 'Middle Budget', 'Higher
Budget']:
    top_individuals_by_budget_profession[budget_category] = {}

    # Filter data for the specific budget category
    budget_category_data =
merged_final_df[merged_final_df['budget_category'] == budget_category]

    # Find the top 3 professions with the highest average ROI for this
budget category
    top_3_professions =
budget_category_data.groupby('primary_profession')
['roi'].mean().nlargest(3).index.tolist()

    for profession in top_3_professions:
        # Filter data for the specific profession
        filtered_data =
budget_category_data[budget_category_data['primary_profession'] ==
profession]
```

```
        # Filter individuals who are alive
        alive_individuals =
filtered_data[(filtered_data['birth_year'].notnull()) &
(filtered_data['death_year'].isnull())]

        # Find the top 3 individuals with the highest ROI for the
profession within the budget category
        top_individuals = alive_individuals.nlargest(3, 'roi')
[['primary_name', 'roi']]

        # Check for duplicate names and include the next best
individual
        unique_individuals =
top_individuals.drop_duplicates(subset=['primary_name'], keep='first')
        if len(unique_individuals) < 3:
            additional_individuals =
alive_individuals[~alive_individuals['primary_name'].isin(unique_indiv
iduals['primary_name'])]
            additional_individuals = additional_individuals.nlargest(3
- len(unique_individuals), 'roi')[['primary_name', 'roi']]
            unique_individuals = pd.concat([unique_individuals,
additional_individuals])
            unique_individuals =
unique_individuals.drop_duplicates(subset=['primary_name'],
keep='first')

        # Store the top individuals in a dictionary
        top_individuals_by_budget_profession[budget_category]
[profession] = unique_individuals.to_dict(orient='records')

# Display the results
for budget_category, professions in
top_individuals_by_budget_profession.items():
    print(f"Top  individuals in top performing professions for
{budget_category}:")
    for profession, individuals in professions.items():
        print(f"\nProfession: {profession}")
        print("Top Individuals:")
        for ind in individuals:
            print(f"Name: {ind['primary_name']}, ROI: {ind['roi']}")
        print("=" * 50)
```

```
Top  individuals in top performing professions for Lower Budget:

Profession: director,actor,camera_department
Top Individuals:
Name: Levan Gabriadze, ROI: 6336.419800000001
==================================================

Profession: miscellaneous,production_manager,producer
```

```
Top Individuals:
Name: Jamie Buckner, ROI: 5479.29612
==================================================

Profession: producer,writer,cinematographer
Top Individuals:
Name: Tom Boyle, ROI: 2617.9241142857145
==================================================
Top  individuals in top performing professions for Middle Budget:

Profession: director,producer,actress
Top Individuals:
Name: Sam Taylor-Johnson, ROI: 1327.4952524999999
==================================================

Profession: writer,music_department,producer
Top Individuals:
Name: Seth MacFarlane, ROI: 1012.0332539999999
==================================================

Profession: actor,producer,animation_department
Top Individuals:
Name: Conrad Vernon, ROI: 643.9171315789474
==================================================
Top  individuals in top performing professions for Higher Budget:

Profession: director,animation_department,visual_effects
Top Individuals:
Name: Kyle Balda, ROI: 1468.0218554054054
==================================================

Profession: animation_department,director,writer
Top Individuals:
Name: Chris Buck, ROI: 748.3132733333333
==================================================

Profession: writer,miscellaneous,producer
Top Individuals:
Name: Jennifer Lee, ROI: 748.3132733333333
Name: Jared Bush, ROI: 579.6197440000001
==================================================
```

Recommendations

Budget Bracket Recommendations:

Lower Budget, Production Budget Range: 1 Million to 15 Million US$

Here are our three recommendations by the criteria of Genre, Season (month) of release, and Staff.

Genre Recommendations	Genre
Best Recommendation	Comedy, Romance, Sport
Second Recommendation	Drama, Fantasy
Third Recommendation	Horror

Seasonal Recommendations	Month
Best Recommendation	February
Second Recommendation	August
Third Recommendation	May

Staff Recommendations	Name
Director, Actor, Camera Department	Levan Gabriadze
Miscellaneous, Production Manager, Producer	Jamie Buckner
Producer, Writer, Cinematographer	Tom Boyle

Middle Budget, Production Budget Range: 15 Million to 50 Million US$

Here are our three recommendations by the criteria of Genre, Season (month) of release, and Staff.

Genre Recommendations	Genre
Best Recommendation	Horror, Mystery, Thriller
Second Recommendation	Action, Sci-Fi, Thriller
Third Recommendation	Comedy, Fantasy

Seasonal Recommendations	Month
Best Recommendation	July
Second Recommendation	November
Third Recommendation	January

Staff Recommendations	Name
Director, Producer, Actress	Sam Taylor-Johnson
Writer, Music Department, Producer	Seth MacFarlane
Actor, Producer, Animation Department	Conrad Vernon

Higher Budget, Production Budget Range: Above 50 Million US$

Genre Recommendations	Genre
Best Recommendation	Biography, Drama, Music
Second Recommendation	Action, Biography, Drama
Third Recommendation	Adventure, Drama, Sport

Seasonal Recommendations	Month
Best Recommendation	April
Second Recommendation	June
Third Recommendation	July

Staff Recommendations	Name
Director, Animation Department, Visual Effects	Kyle Balda
Animation Department, Director, Writer	Chris Buck
Writer, Miscellaneous, Producer	Jennifer Lee, Jared Bush

Conclusions

Our analysis highlights promising trends across different budget brackets in the film industry. From genre preferences and release timings to key professionals, the data unveils actionable insights. These findings offer valuable recommendations for optimizing film production strategies tailored to three budget categories. Our stakeholders have now a starting point to make their investment and production decisions.

Limitations

Our analysis is confined to the provided dataset and lacks consideration of additional factors that might impact future performance. Limited to data up until 2018, potential emerging trends within the past six years remain unexplored. The analysis presents a high-level overview, and a more granular breakdown may enhance accuracy. Furthermore, we haven't adjusted the financial data for present-day inflation rates, which could influence the final outcomes of our calculations.

Next Steps

Future steps for this project involve in-depth exploration of the US and Foreign film markets to better understand their influence on the industry. Acquiring data from the last six years will complement our existing dataset, enabling a comprehensive analysis of recent trends. Additionally, delving deeper into the original, albeit incomplete, datasets may provide valuable insights that were lost during the merging process. These efforts aim to enhance the completeness and relevance of our research, paving the way for a more robust and insightful analysis.