Final Project Submission

Please fill out:

- Student name: Group 4
- Student pace: part time
- Scheduled project review date/time: 1/02/26
- Instructor name: Bonface Manyara
- Blog post URL:

MICROSOFT DEBUT STUDIO ANALYSIS

Overview

In this project,exploratory data analysis is applied to the movie industry dataset to provide data-driven insights for a business stakeholder. Microsoft plans to launch a new movie studio but lacks experience in film production.This analysis helps examine movie performances,audience reception,and genre trends across existing films to identify patterns associated with commercial success.The results intend to help Microsoft in decision making on the types of movies they should prioritize producing.

Business Problem

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

Objectives

- Analyze movie industry data from mutiple sources: IMDB, The Numbers and Box Office Movies.
- Identify trends of movie performances.
- Determine key factors associated with high grossing films.
- Provide data-driven recommendations to Microsoft studios.

Key Business Questions

1. Which movie genres generate the highest and lowest box office revenue?
2. How does production budget relate to box office performance?
3. Do movies with higher ratings perform better financially?
4. What characteristics are common among the highest-grossing films?

5. Which factors should Microsoft prioritize when deciding what type of films to produce?

6. Which movie genres type are being produced the most?

Deliverables

- Cleaned and enriched datasets from four sources(Imdb.title ratings,Imdb.title.basics,movie_gross, Tn.movie_budget,).
- Data visualizations illustrating the trend of movie genres, movie ratings, gross income, budget.
- Features with strongest positive and negative correlations.
- A well-documented jupyter notebook with data cleaning, exploratory data, visualizations, and interpretations.
- A PowerPoint presentation to the stakeholder to illustrate the business value projection.

Final Goal

To provide Microsoft with data which will help them decide on what types of movies to produce to ensure their studio is both profitable and competitive.

Import Libraries

In [227…

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
%matplotlib inline
```

Loading Dataframe

In [228…

```
basic_df = pd.read_csv(r'C:\Users\Sylvia\moringa_labs\ms_movie_analysis\Microsoft-Movies-Analysis\unzippedData\title.
rating_df = pd.read_csv(r'C:\Users\Sylvia\moringa_labs\ms_movie_analysis\Microsoft-Movies-Analysis\unzippedData\title
```

```
gross_df = pd.read_csv(r'C:\Users\Sylvia\moringa_labs\ms_movie_analysis\Microsoft-Movies-Analysis\unzippedData\bom.mo
tn_budget_df = pd.read_csv(r'C:\Users\Sylvia\moringa_labs\ms_movie_analysis\Microsoft-Movies-Analysis\unzippedData\tr
```

Data Understanding

Basic.csv dataset

We are getting to understand our dataset by knowing the datatypes,percentages of null values and presence of duplicates

In [229…

```
basic_df.info()
basic_df.duplicated().value_counts()
basic_df.isnull().sum()* 100/len(basic_df)
print(f"The dataset has {basic_df.shape[0]} rows and {basic_df.shape[1]} columns")
basic_df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   tconst           146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
The dataset has 146144 rows and 6 columns
```

Out[229…

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

Rating.csv dataset

In [230…

```
print(f"The dataset has {rating_df.shape[0]} rows and {rating_df.shape[1]} columns")
rating_df.info()
rating_df.isnull().sum()* 100/len(rating_df)
rating_df.duplicated().value_counts()
rating_df.head()
```

```
The dataset has 73856 rows and 3 columns
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   tconst         73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

Out[230…

	tconst	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

Gross.csv dataset

In [231…

```
print(f"The dataset has {gross_df.shape[0]} rows and {gross_df.shape[1]} columns")
gross_df.info()
gross_df.duplicated().value_counts()
gross_df.isnull().sum()* 100/len(gross_df)
gross_df.head()
```

```
The dataset has 3387 rows and 5 columns
<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
```

Out[231…

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

Tn.movie budget csv

In [232…

```
print(f"The dataset has {tn_budget_df.shape[0]} rows and {tn_budget_df.shape[1]} columns")
tn_budget_df.info()
tn_budget_df.duplicated().value_counts()
tn_budget_df.isnull().sum()* 100/len(tn_budget_df)
tn_budget_df.head()
```

```
The dataset has 5782 rows and 6 columns
<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
```

Out[232…

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

Making a copy of the dataset

In [233…

```
basic_df2=basic_df.copy()
rating_df2=rating_df.copy()
gross_df2=gross_df.copy()
tn_budget_df2=tn_budget_df.copy()
```

Data Preparation

Cleaning the data for basic_df2. Drop the original_title since its repetitive and renaming the 'primary_title' to 'movie_title'.

In [234…

```
basic_df2.drop(columns=['original_title'],inplace=True)
basic_df2.rename({'primary_title':'movie_title'}, axis=1, inplace=True)
```

```
basic_df2.head()
```

Out[234…

	tconst	movie_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy

Replacing nan values in 'runtime_minutes' with mode for basic_df2

In [235…

```
basic_df2['runtime_minutes'].mode()
basic_df2['runtime_minutes'].fillna(90, inplace=True)
basic_df2.head()
```

Out[235…

	tconst	movie_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	2018	90.0	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy

Spiltting 'genres' to find the dominant genre for categorical visualization.

In [236…

```
basic_df2['genres'] = basic_df['genres'].str.split(',',expand=True)
#Fill nan values with 'unknown'
basic_df2['genres'].fillna('Unknown',inplace=True)
basic_df2.head()
```

Out[236…

	tconst	movie_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	2013	175.0	Action
1	tt0066787	One Day Before the Rainy Season	2019	114.0	Biography
2	tt0069049	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	2018	90.0	Comedy
4	tt0100275	The Wandering Soap Opera	2017	80.0	Comedy

Changing data type from float to int for runtime_minutes

In [237…

```
basic_df2= basic_df2.astype({'runtime_minutes':'int'})
#basic_df2['runtime_minutes']= basic_df2['runtime_minutes'].astype('int32')-alternative way
#check data types
basic_df2.dtypes
```

Out[237…

```
tconst              object
movie_title         object
start_year           int64
runtime_minutes      int32
genres              object
dtype: object
```

Cleaning the dataset for gross_df2

Changing data type of foreign gross to inter

In [238…

```
gross_df2['foreign_gross']= pd.to_numeric(gross_df['foreign_gross'].str.replace(',', '', regex=True))
 #gross_df['foreign_gross'] = pd.to_numeric(gross_df['foreign_gross'].str.replace(',', '', regex=True))
gross_df2.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   float64
 4   year            3387 non-null   int64  
dtypes: float64(2), int64(1), object(2)
memory usage: 132.4+ KB
```

Dropping nan values and filling

In [239…
```
gross_df2.dropna(axis=0,subset=['domestic_gross','foreign_gross'],inplace=True)
#Fill nan in studio with 'Unknown'
gross_df2['studio'].fillna('Unknown',inplace=True)
#Check shape after dropping
gross_df2.shape
```

Out[239…
```
(2009, 5)
```

Checking Nan values %.

In [240…
```
gross_df2.isnull().sum()* 100/len(gross_df)
```

Out[240…
```
title             0.0
studio            0.0
domestic_gross    0.0
foreign_gross     0.0
year              0.0
dtype: float64
```

Reset the indexing of the dataset

In [241…
```
gross_df2.reset_index(drop=True,inplace=True)
gross_df2.head()
```

Out[241…

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

Cleaning dataset of tn.moviebudgets

Lets change the number datatypes of domestic,budget production and worldwide gross

In [242…

```
tn_budget_df2['domestic_gross'] = tn_budget_df2['domestic_gross'].str.replace(r"[$,]", "", regex=True).astype(int)
tn_budget_df2['production_budget'] = tn_budget_df2['production_budget'].str.replace(r"[$,]", "", regex=True).astype(i
tn_budget_df2["worldwide_gross"] = pd.to_numeric(tn_budget_df2["worldwide_gross"].str.replace(r"[$,]", "", regex=True

tn_budget_df2.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   int32 
 4   domestic_gross     5782 non-null   int32 
 5   worldwide_gross    5782 non-null   int64 
dtypes: int32(2), int64(2), object(2)
memory usage: 226.0+ KB
```

Separate release date to month,year for better visualization

In [243…

```
tn_budget_df2['release_month'] = tn_budget_df2['release_date'].str.split(' ').str[0]
tn_budget_df2['release_year'] = tn_budget_df2['release_date'].str.split(' ').str[-1]
```

```
tn_budget_df2 = tn_budget_df2.drop(columns='release_date', axis=0)
tn_budget_df2.head()
```

Out[243…

	id	movie	production_budget	domestic_gross	worldwide_gross	release_month	release_year
0	1	Avatar	425000000	760507625	2776345279	Dec	2009
1	2	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	May	2011
2	3	Dark Phoenix	350000000	42762350	149762350	Jun	2019
3	4	Avengers: Age of Ultron	330600000	459005868	1403013963	May	2015
4	5	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	Dec	2017

Changing Index. Make the id the index.

In [244…

```
tn_budget_df2.set_index('id', inplace=True)
tn_budget_df2.head()
```

Out[244…

	movie	production_budget	domestic_gross	worldwide_gross	release_month	release_year
id						
1	Avatar	425000000	760507625	2776345279	Dec	2009
2	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	May	2011
3	Dark Phoenix	350000000	42762350	149762350	Jun	2019
4	Avengers: Age of Ultron	330600000	459005868	1403013963	May	2015
5	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	Dec	2017

Merge Tables

Lets join basic_df2 and rating_df2 using inner join

In [245…

```
movie_df= pd.merge(basic_df2, rating_df2, how='inner', on='tconst')
movie_df.head()
```

Out[245…

	tconst	movie_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	tt0063540	Sunghursh	2013	175	Action	7.0	77
1	tt0066787	One Day Before the Rainy Season	2019	114	Biography	7.2	43
2	tt0069049	The Other Side of the Wind	2018	122	Drama	6.9	4517
3	tt0069204	Sabse Bada Sukh	2018	90	Comedy	6.1	13
4	tt0100275	The Wandering Soap Opera	2017	80	Comedy	6.5	119

Get an overview of our new movie_df

In [246…

```
movie_df.info()
movie_df.shape
movie_df.duplicated().value_counts()
movie_df.isnull().sum()*100/len(movie_df)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 73855
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           73856 non-null  object 
 1   movie_title      73856 non-null  object 
 2   start_year       73856 non-null  int64  
 3   runtime_minutes  73856 non-null  int32  
 4   genres           73856 non-null  object 
 5   averagerating    73856 non-null  float64
 6   numvotes         73856 non-null  int64  
dtypes: float64(1), int32(1), int64(2), object(3)
memory usage: 4.2+ MB
```

Out[246…

```
tconst            0.0
movie_title       0.0
start_year        0.0
runtime_minutes   0.0
genres            0.0
averagerating     0.0
numvotes          0.0
dtype: float64
```

Merge movies_df to tn_budget to show how rating affects production budget and gross incomes.

In [247…

```
rating_gross_df = pd.merge(movie_df, tn_budget_df2, how='inner', left_on='movie_title', right_on='movie')
rating_gross_df.info()
rating_gross_df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2875 entries, 0 to 2874
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   tconst             2875 non-null   object 
 1   movie_title        2875 non-null   object 
 2   start_year         2875 non-null   int64  
 3   runtime_minutes    2875 non-null   int32  
 4   genres             2875 non-null   object 
 5   averagerating      2875 non-null   float64
 6   numvotes           2875 non-null   int64  
 7   movie              2875 non-null   object 
 8   production_budget  2875 non-null   int32  
 9   domestic_gross     2875 non-null   int32  
 10  worldwide_gross    2875 non-null   int64  
 11  release_month      2875 non-null   object 
 12  release_year       2875 non-null   object 
dtypes: float64(1), int32(3), int64(3), object(6)
memory usage: 280.8+ KB
```

Out[247…

	tconst	movie_title	start_year	runtime_minutes	genres	averagerating	numvotes	movie	production_budget	dom
0	tt0249516	Foodfight!	2012	91	Action	1.9	8248	Foodfight!	45000000	
1	tt0326592	The Overnight	2010	88	Unknown	7.5	24	The Overnight	200000	
2	tt3844362	The Overnight	2015	79	Comedy	6.1	14828	The Overnight	200000	
3	tt0337692	On the Road	2012	124	Adventure	6.1	37886	On the Road	25000000	
4	tt4339118	On the Road	2014	89	Drama	6.0	6	On the Road	25000000	

In [248…

```
#clean the df:
rating_gross_df.drop(columns=['movie_title', 'numvotes', 'release_year','release_month', 'movie', 'start_year'], inpl
rating_gross_df.reset_index()
rating_gross_df.head()
```

Out[248…

	tconst	runtime_minutes	genres	averagerating	production_budget	domestic_gross	worldwide_gross
0	tt0249516	91	Action	1.9	45000000	0	73706
1	tt0326592	88	Unknown	7.5	200000	1109808	1165996
2	tt3844362	79	Comedy	6.1	200000	1109808	1165996
3	tt0337692	124	Adventure	6.1	25000000	720828	9313302
4	tt4339118	89	Drama	6.0	25000000	720828	9313302

Overall Statistics for movie_df,gross_df2 and tn_budget_df2

In [ ]:

```
movie_df.describe()
# movie_df.describe(include ='all') #inclusive of categorial data
```

Out[ ]:

	tconst	movie_title	start_year	runtime_minutes	genres	averagerating	numvotes
count	73856	73856	73856.000000	73856.000000	73856	73856.000000	7.385600e+04
unique	73856	69993	NaN	NaN	26	NaN	NaN
top	tt1210166	The Return	NaN	NaN	Drama	NaN	NaN
freq	1	11	NaN	NaN	18572	NaN	NaN
mean	NaN	NaN	2014.276132	94.173865	NaN	6.332729	3.523662e+03
std	NaN	NaN	2.614807	197.526503	NaN	1.474978	3.029402e+04
min	NaN	NaN	2010.000000	3.000000	NaN	1.000000	5.000000e+00
25%	NaN	NaN	2012.000000	83.000000	NaN	5.500000	1.400000e+01
50%	NaN	NaN	2014.000000	90.000000	NaN	6.500000	4.900000e+01
75%	NaN	NaN	2016.000000	101.000000	NaN	7.400000	2.820000e+02
max	NaN	NaN	2019.000000	51420.000000	NaN	10.000000	1.841066e+06

The average runtime for this dataset is 94 minutes though we have an outlier at 51420. Drama is the most common genre while the average rating is 6.3.

In [251…

```
gross_df2.describe()
```

Out[251…

	domestic_gross	foreign_gross	year
count	2.009000e+03	2.009000e+03	2009.000000
mean	4.697311e+07	7.571822e+07	2013.503235
std	8.159966e+07	1.381296e+08	2.598481
min	4.000000e+02	6.000000e+02	2010.000000
25%	6.650000e+05	3.900000e+06	2011.000000
50%	1.650000e+07	1.930000e+07	2013.000000
75%	5.600000e+07	7.590000e+07	2016.000000
max	9.367000e+08	9.605000e+08	2018.000000

On average, movies earned about $47milliondomesticallyand76$ million internationally. Although they vary from a few hundred dollars to over $900 million. Half of the movies gross way below the mean meaning a few of the major blockbusters highly contribute to the mean.

In [252…

```
tn_budget_df2.describe()
```

Out[252…

	production_budget	domestic_gross	worldwide_gross
count	5.782000e+03	5.782000e+03	5.782000e+03
mean	3.158776e+07	4.187333e+07	9.148746e+07
std	4.181208e+07	6.824060e+07	1.747200e+08
min	1.100000e+03	0.000000e+00	0.000000e+00
25%	5.000000e+06	1.429534e+06	4.125415e+06
50%	1.700000e+07	1.722594e+07	2.798445e+07
75%	4.000000e+07	5.234866e+07	9.764584e+07
max	4.250000e+08	9.366622e+08	2.776345e+09

With 5,782 movies. The average production budget is about $31.6million, while average domestic and worldwide grosses are 41.9$ million and $91.5 million respectively.

Feature Engineering

Let's get ROI to observe profit in relation to the production budget. A -negative roi means loss.

In [253…

```
tn_budget_df2['roi']=(tn_budget_df2['domestic_gross']-tn_budget_df2['production_budget'])/tn_budget_df2['production_b
tn_budget_df2.head()

#calculate profit
tn_budget_df2['profit']=tn_budget_df2['domestic_gross']-tn_budget_df2['production_budget']
tn_budget_df2.head()
```

Out[253…

id	movie	production_budget	domestic_gross	worldwide_gross	release_month	release_year	roi	profit
1	Avatar	425000000	760507625	2776345279	Dec	2009	78.942971	335507625
2	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	May	2011	-41.289850	-169536125
3	Dark Phoenix	350000000	42762350	149762350	Jun	2019	-87.782186	-307237650
4	Avengers: Age of Ultron	330600000	459005868	1403013963	May	2015	38.840250	128405868
5	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	Dec	2017	95.640815	303181382

Data Analysis

Correlation Analysis

In [254...
```
correlation_matrix = tn_budget_df2.corr()
correlation_matrix
```

Out[254...

	production_budget	domestic_gross	worldwide_gross	roi	profit
production_budget	1.000000	0.685682	0.748306	-0.048022	0.099742
domestic_gross	0.685682	1.000000	0.938853	0.034693	0.792663
worldwide_gross	0.748306	0.938853	1.000000	0.011918	0.656626
roi	-0.048022	0.034693	0.011918	1.000000	0.087646
profit	0.099742	0.792663	0.656626	0.087646	1.000000

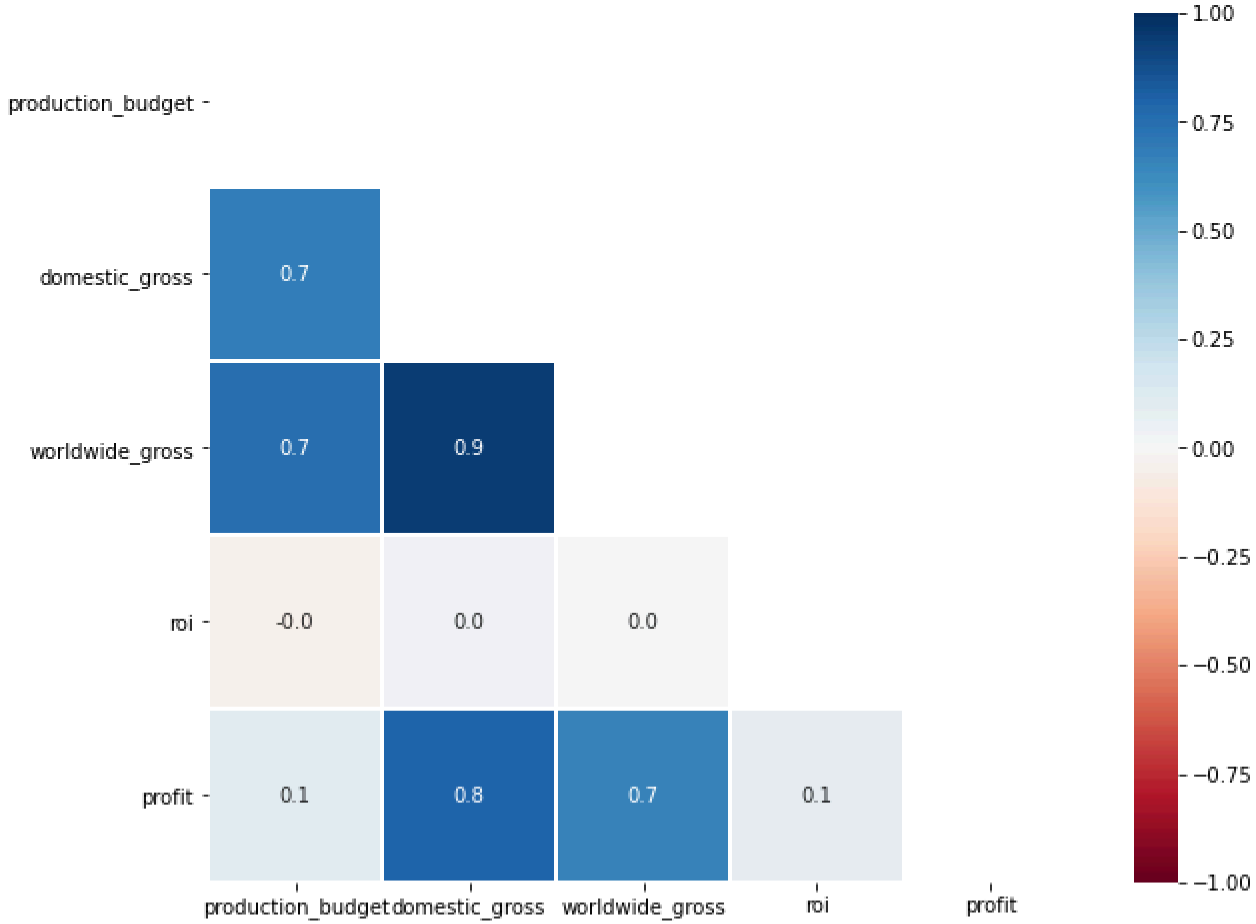
In [255...
```
# flattern correlation
sorted_pairs= correlation_matrix.stack()
sorted_pairs.head(50)

# filter and view only strong correlations
strong_pairs = sorted_pairs[(abs(sorted_pairs) > 0.5) & (sorted_pairs < 1)].drop_duplicates().sort_values(ascending=F
strong_pairs
```

Out[255...
```
domestic_gross     worldwide_gross    0.938853
                   profit             0.792663
production_budget  worldwide_gross    0.748306
                   domestic_gross     0.685682
worldwide_gross    profit             0.656626
dtype: float64
```

Visualize the Correlation Matrix

In [256...
```
plt.figure(figsize=(10,8))
my_mask=np.triu(np.ones_like(correlation_matrix,dtype=bool))
sns.heatmap(correlation_matrix,annot=True,fmt=".1f",
   cmap='RdBu', vmin=-1 ,vmax=1,cbar=True,square=True,linewidths=0.3, mask=my_mask)
```

Out[256...
```
<AxesSubplot:>
```



Observation:

From our tn_budget table, we establish that worldwide_gross has a positive relationship with domestic gross while roi does not have a relatioship; positive or strong with

the other factors. That means if Microsft movies gross well in the domestic market, they will equally do well with the rest of the world. The local consumption does lead

the way.

Correlation between profit and total gross

In [257…

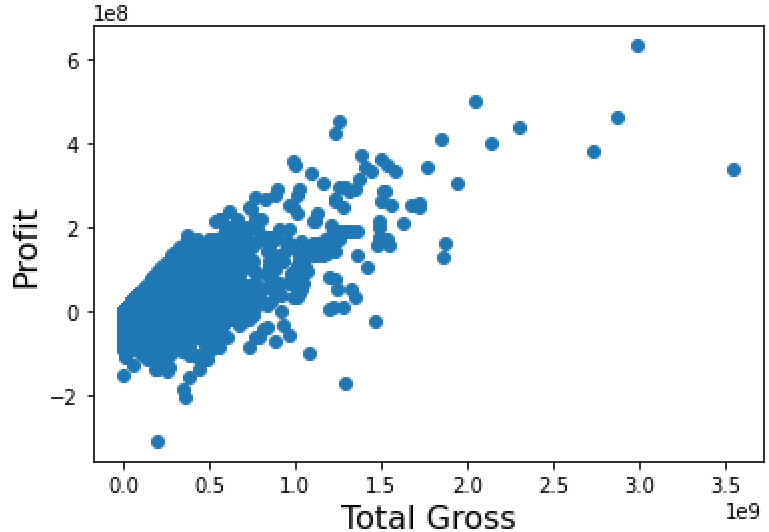
```
# create total gross
tn_budget_df2['total_gross'] = tn_budget_df2['domestic_gross'] + tn_budget_df2['worldwide_gross']
tn_budget_df2.head()
```

Out[257…

	movie	production_budget	domestic_gross	worldwide_gross	release_month	release_year	roi	profit	total_
id									
1	Avatar	425000000	760507625	2776345279	Dec	2009	78.942971	335507625	35368
2	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	May	2011	-41.289850	-169536125	12867
3	Dark Phoenix	350000000	42762350	149762350	Jun	2019	-87.782186	-307237650	1925
4	Avengers: Age of Ultron	330600000	459005868	1403013963	May	2015	38.840250	128405868	18620
5	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	Dec	2017	95.640815	303181382	19369

In [258…

```
fig, ax=plt.subplots()

ax.scatter(tn_budget_df2['total_gross'], tn_budget_df2['profit'])

ax.set_xlabel('Total Gross', fontsize=16)
ax.set_ylabel('Profit', fontsize=16)
plt.show()
```

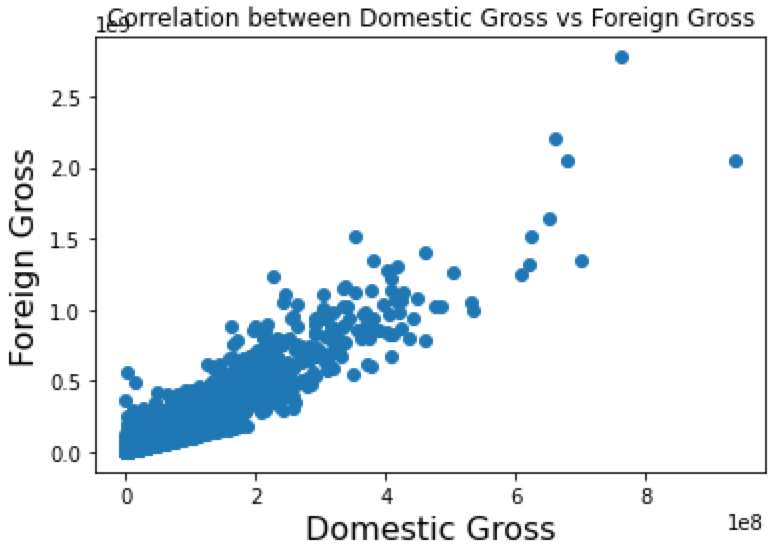


Total gross has a positive relationship with profit. Implying the higher the gross income the higher the profits as well.

Correlation between domestic and foreign gross.

In [259…

```
fig, ax= plt.subplots()

ax.scatter(tn_budget_df2['domestic_gross'],tn_budget_df2['worldwide_gross'])

ax.set_xlabel('Domestic Gross', fontsize =16)
ax.set_ylabel('Foreign Gross', fontsize = 16)
ax.set_title('Correlation between Domestic Gross vs Foreign Gross')
plt.show()
```



Observation:

We see these two: foreign gross vs worldwide gross and total gross vs profit does have a close positive correlation, so the numbers do translate to making profits. Hence

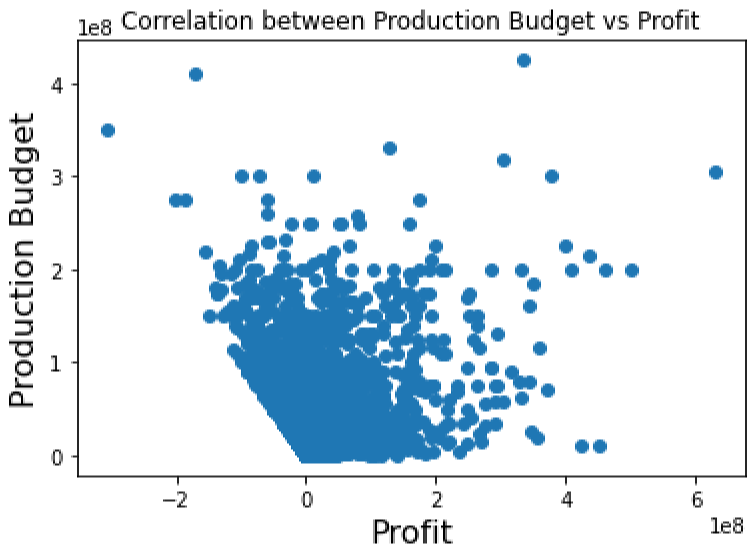
grossing well does mean the production budget is recouped and a good profit margin is achieved and doing well in domestic markets does imply doing well in the rest of the

world too.

Correlation between production budget and profit

In [260…

```
fig, ax= plt.subplots()

ax.scatter(tn_budget_df2['profit'],tn_budget_df2['production_budget'])

ax.set_xlabel('Profit', fontsize =16)
ax.set_ylabel('Production Budget', fontsize = 16)
ax.set_title('Correlation between Production Budget vs Profit')
plt.show()
```



Observation:

The production budget has a weak negative correlation with profit. Splurging on production does

not necessarily translate to making profits. Hence we need to balance the

cost of production with the quality of film produced i.e a better storyline over a very

expensive set for instance.

Visualize dataset

In [261…

```
# movie_df.head()
# top10_len = movie_df.sort_values(by='averagerating', ascending=False).head(10)
# top10_len
```

In [262…

```
genre_stats = movie_df.groupby('genres').agg(avg_rating=('averagerating', 'mean'),avg_runtime=('runtime_minutes', 'me
top10_genres = genre_stats.sort_values(by='avg_rating', ascending=False).head(10)
top10_genres = top10_genres.drop('Unknown')
top10_genres
```

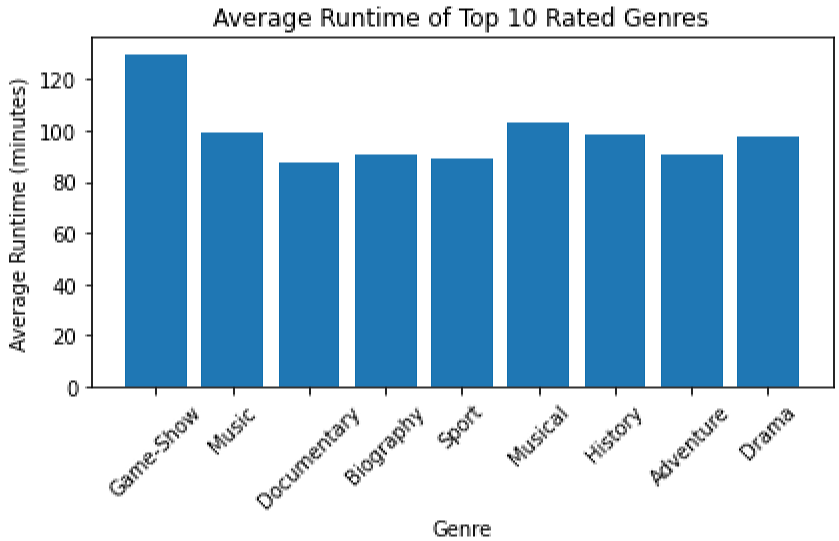
Out[262…

genres	avg_rating	avg_runtime
Game-Show	9.000000	130.000000
Music	7.506771	99.057292
Documentary	7.316595	87.215370
Biography	7.174512	90.530149
Sport	6.944944	89.314607
Musical	6.637255	103.339869
History	6.413235	98.838235
Adventure	6.386710	90.691448
Drama	6.370563	97.440663

Average running time of top rated genres

In [263…

```
# top10_genres['avg_runtime'].plot(kind='bar',figsize=(10,6))
plt.bar(top10_genres.index,top10_genres['avg_runtime'])
plt.title('Average Runtime of Top 10 Rated Genres')
plt.xlabel('Genre')
plt.ylabel('Average Runtime (minutes)')
plt.xticks(rotation=45)

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



Observation:

The average runtime for the top rated genres falls between 90-130 minutes. Besides game show,

the highest rated genre, the rest show the sweetspot for average runtime is

about 90 minutes runtime. Beyond that could be too long to keep the audience.

Year With Highest Domestic Average Revenue from gross table

In [264…

```
gross_df2.head()
```

Out[264...

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

In [265...

```
gross_df2.groupby('year')['domestic_gross'].mean().sort_values(ascending=False)
```

Out[265...

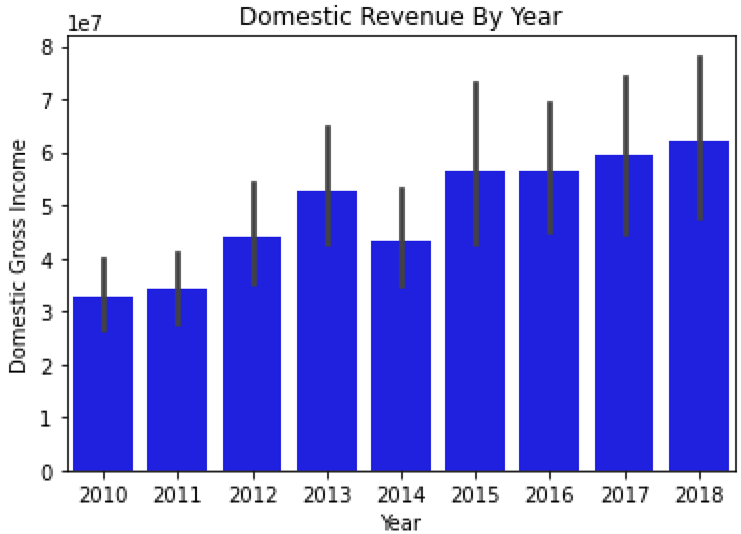
```
year
2018    6.222173e+07
2017    5.941676e+07
2016    5.661299e+07
2015    5.655194e+07
2013    5.279425e+07
2012    4.402413e+07
2014    4.336745e+07
2011    3.407478e+07
2010    3.285708e+07
Name: domestic_gross, dtype: float64
```

In [282...

```
sns.barplot(x='year',y='domestic_gross',data=gross_df2, color="#0000FF")
plt.xlabel('Year')
plt.ylabel('Domestic Gross Income')
plt.title("Domestic Revenue By Year")
plt.show
```

Out[282...

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



Observations:

Except for 2014, the gross revenue has been on a steady rise over the years; implying the industry keeps growing hence investing has a good promise of growth of the

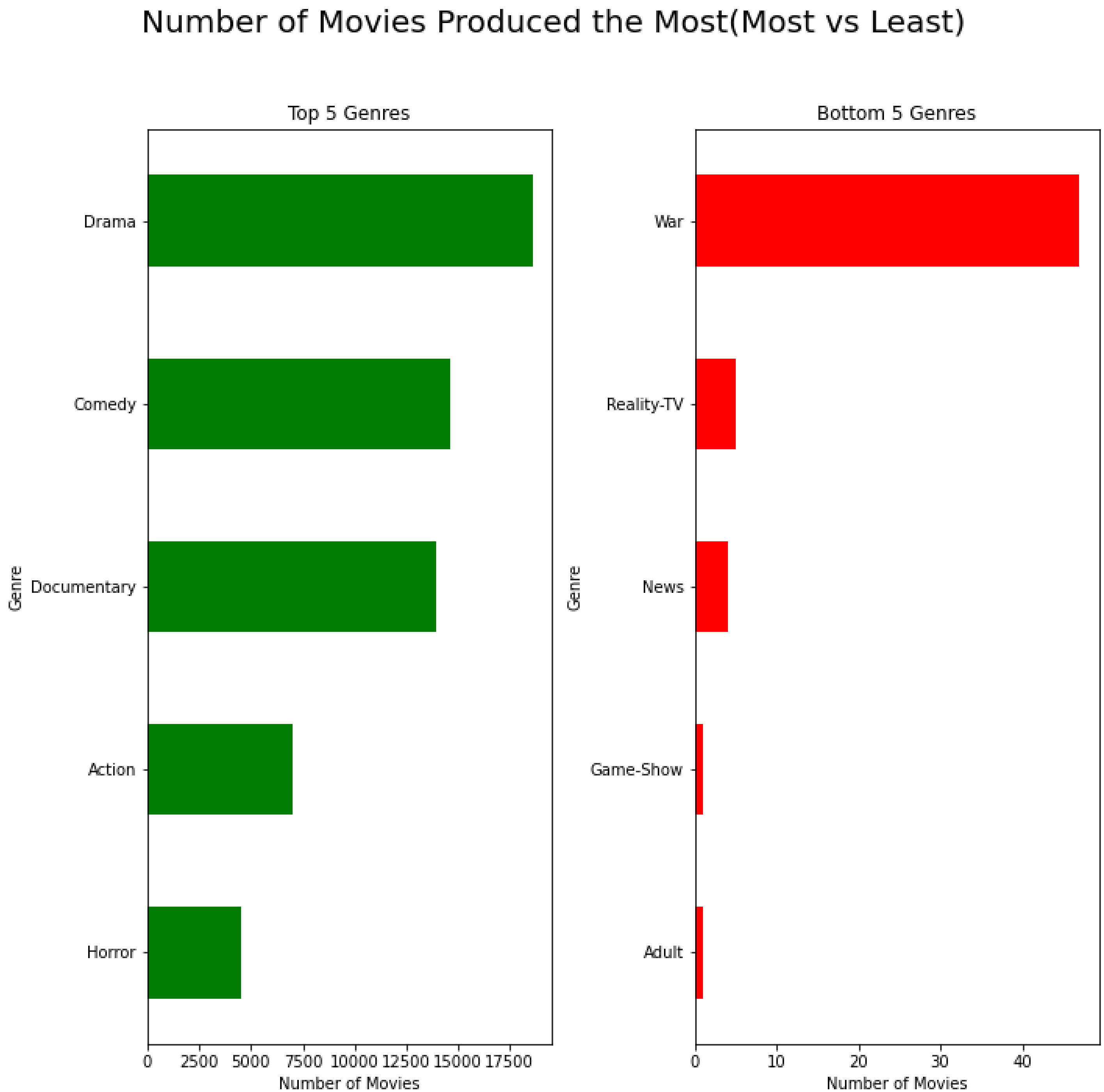
investment. Microsoft should indeed invest in the movie industry to take part in te growth it promises.

Genres that has movies getting produced the most vs ones that are produced the least.

In [267…

```
movie_df['genres'].unique()
genre_counts= movie_df['genres'].value_counts() #drama has most count
top_genres = genre_counts.head(5).sort_values(ascending=True)
bottom_genres = genre_counts.tail(5).sort_values(ascending=True)

fig, axes = plt.subplots(1, 2, figsize=(10,10))
#Most movies
top_genres.plot(kind='barh', ax=axes[0], color='green')
axes[0].set_title('Top 5 Genres')
axes[0].set_xlabel('Number of Movies')
axes[0].set_ylabel('Genre')

#Least movies
```

```
bottom_genres.plot(kind='barh', ax=axes[1], color='red')
axes[1].set_title('Bottom 5 Genres')
axes[1].set_xlabel('Number of Movies')
axes[1].set_ylabel('Genre')

# Main title
fig.suptitle('Number of Movies Produced the Most(Most vs Least)', fontsize=20)

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```


Number of Movies Produced the Most(Most vs Least)
Top 5 Genres
Drama
Comedy
Documentary
Action
Horror
Genre
0
2500
5000
7500
10000
12500
15000
17500
Number of Movies
Bottom 5 Genres
War
Reality-TV
News
Game-Show
Adult
Genre
0
10
20
30
40
Number of Movies

Observation:

In terms of the most produced movies, the drama and comedy do take a lead, although they did

not take a lead in the well rated categories as earlier seen. On the contrary,

game-show that is among the least produced genre was the best rated. Microsoft is now presented

with the decision on whether to choose what is most produced or best rated

categories. We shall investigate if the rating influences the money for us to make a data

driven decision.

Analyze and visualize based on subsets from average_rating. Create a rating categorization of 'Below Average',

'Average', 'Above Average'.

In [268...

```
# create total gross
rating_gross_df['total_gross'] = rating_gross_df['domestic_gross'] +rating_gross_df['worldwide_gross']
```

In [269...

```
#categorize ratinginto 3 categories
def categorize(averagerating):
    if averagerating < 5:
        return 'Below Average'
    if averagerating < 8:
        return 'Average'
    if averagerating > 7:
        return 'Above Average'

rating_gross_df['Rating Category'] = rating_gross_df['averagerating'].apply(categorize)

rating_gross_df.head()
```

Out[269…

	tconst	runtime_minutes	genres	averagerating	production_budget	domestic_gross	worldwide_gross	total_gross	R Cat
0	tt0249516	91	Action	1.9	45000000	0	73706	73706	Av
1	tt0326592	88	Unknown	7.5	200000	1109808	1165996	2275804	Av
2	tt3844362	79	Comedy	6.1	200000	1109808	1165996	2275804	Av
3	tt0337692	124	Adventure	6.1	25000000	720828	9313302	10034130	Av
4	tt4339118	89	Drama	6.0	25000000	720828	9313302	10034130	Av

- Create dfs for each category

In [270…

```
below_avg_df = rating_gross_df[rating_gross_df['Rating Category']=='Below Average']
above_avg_df = rating_gross_df[rating_gross_df['Rating Category']=='Above Average']
avg_df = rating_gross_df[rating_gross_df['Rating Category']=='Average']
above_avg_df.head()
```

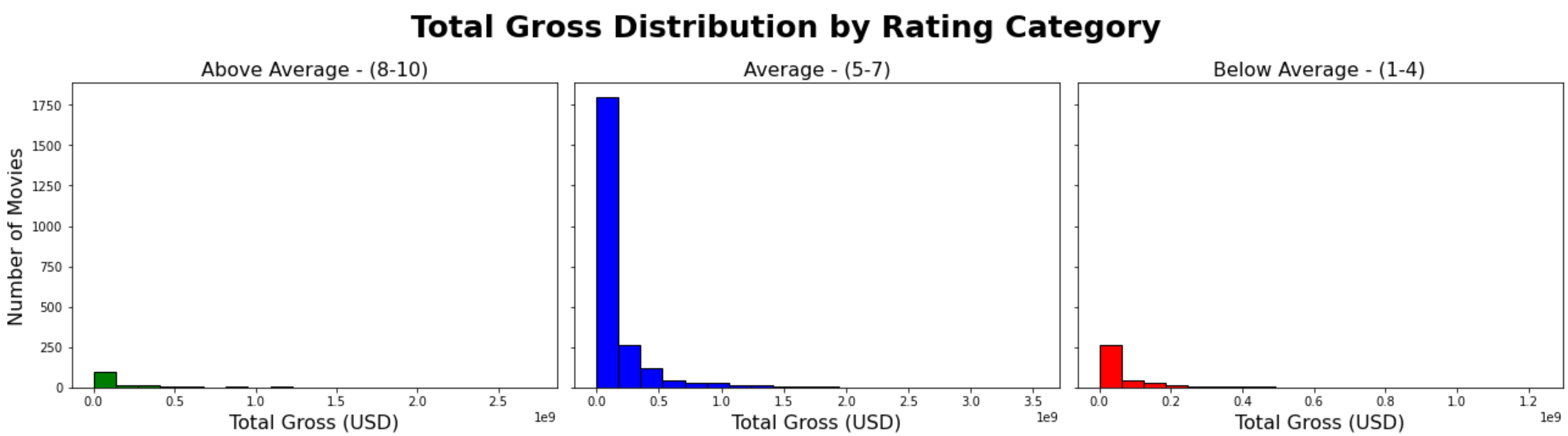
Out[270…

	tconst	runtime_minutes	genres	averagerating	production_budget	domestic_gross	worldwide_gross	total_gross
20	tt0435761	103	Adventure	8.3	200000000	415004880	1068879522	1483884402
48	tt9906218	84	Documentary	8.1	95000000	81562942	165720921	247283863
69	tt0770802	102	Documentary	8.5	4000000	2672413	5966671	8639084
78	tt0790636	117	Biography	8.0	5000000	27298285	60611845	87910130
101	tt0816692	169	Adventure	8.6	165000000	188017894	666379375	854397269

- Plot hists for gross and another to see production budget

In [271…

```
fig, axes = plt.subplots(1, 3, figsize=(18,5), sharey=True)

# Above Average
axes[0].hist(above_avg_df['total_gross'], bins=20, color='green', edgecolor='black')
axes[0].set_title('Above Average - (8-10)', fontsize=16)
axes[0].set_xlabel('Total Gross (USD)', fontsize=16)
axes[0].set_ylabel('Number of Movies',fontsize=16)

# Average
axes[1].hist(avg_df['total_gross'], bins=20, color='blue', edgecolor='black')
axes[1].set_title('Average - (5-7)', fontsize=16)
axes[1].set_xlabel('Total Gross (USD)', fontsize=16)

# Below Average
axes[2].hist(below_avg_df['total_gross'], bins=20, color='red', edgecolor='black')
axes[2].set_title('Below Average - (1-4)', fontsize=16)
axes[2].set_xlabel('Total Gross (USD)', fontsize=16)

fig.suptitle('Total Gross Distribution by Rating Category', fontsize=25, fontweight='bold')
plt.tight_layout()
plt.show()
```



Observation:

We now see that a high rating does not really mean the movie will gross highly. In fact it is

the averagely rated movies that gross the highest while poorly rated movies

gross more than highly rated. Therefore in terms of bringing back the money, rating is not a

good indicator. We therefore choose the data driven decision that the most

produced movies as earlier seen are a better indication on what side of industry to venture

into.

Studio Perfomance Analysis in both foreign and domestic markets.

In [273…

```
gross_df2.info()
gross_df2.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2009 entries, 0 to 2008
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           2009 non-null   object 
 1   studio          2009 non-null   object 
 2   domestic_gross  2009 non-null   float64
 3   foreign_gross   2009 non-null   float64
 4   year            2009 non-null   int64  
dtypes: float64(2), int64(1), object(2)
memory usage: 78.6+ KB
```

Out[273…

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

- Create domestic and foreign dfs. Let's have a clean df to analyze on.

In [274…

```
#create domestic df:drop foreign gross
domestic_gross_df = gross_df2.drop(columns='foreign_gross')
domestic_gross_df['studio'].fillna('Unknown', inplace=True)

domestic_gross_df.dropna(inplace=True,subset=['domestic_gross'])
domestic_gross_df.reset_index(drop=True, inplace=True)
domestic_gross_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2009 entries, 0 to 2008
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           2009 non-null   object 
 1   studio          2009 non-null   object 
 2   domestic_gross  2009 non-null   float64
 3   year            2009 non-null   int64  
dtypes: float64(1), int64(1), object(2)
memory usage: 62.9+ KB
```

In [275…

```
#create foreign df:drop domestic column and Nan values
foreign_gross_df = gross_df2.drop(columns='domestic_gross')
foreign_gross_df['studio'].fillna('Unknown', inplace=True)

foreign_gross_df.dropna(inplace=True,subset=['foreign_gross'])
```

```
foreign_gross_df.reset_index(drop=True, inplace=True)
foreign_gross_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2009 entries, 0 to 2008
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   title          2009 non-null   object 
 1   studio         2009 non-null   object 
 2   foreign_gross  2009 non-null   float64
 3   year           2009 non-null   int64  
dtypes: float64(1), int64(1), object(2)
memory usage: 62.9+ KB
```

- Find the studio perfomance by checking how much they gross in domestic vs foreign markets.

In [276…

```
#domestic markets
studio_domestic_gross = domestic_gross_df.groupby('studio')['domestic_gross'].sum()
studio_domestic_gross = studio_domestic_gross.sort_values(ascending=False)
studio_domestic_gross.describe()
```

Out[276…

```
count    1.730000e+02
mean     5.454855e+08
std      2.284412e+09
min      8.000000e+02
25%      1.880000e+05
50%      2.000000e+06
75%      2.690000e+07
max      1.839653e+10
Name: domestic_gross, dtype: float64
```

In [277…

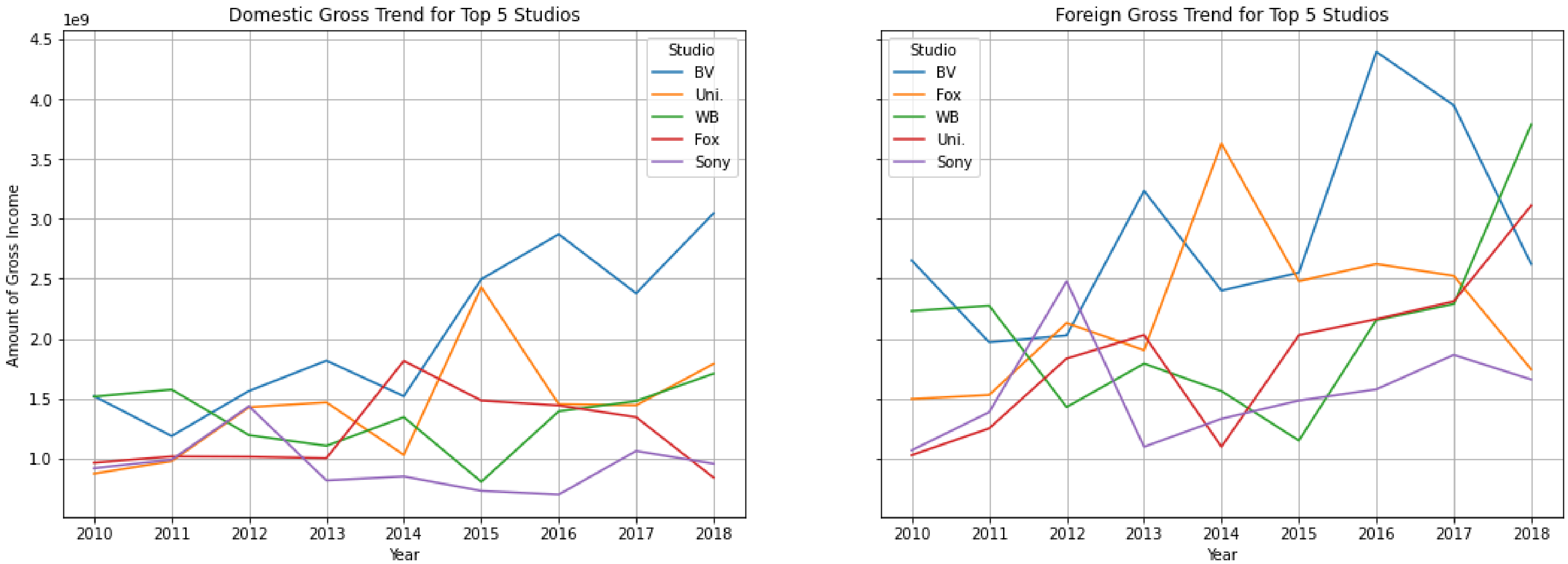
```
# foreign markets
studio_foreign_gross = foreign_gross_df.groupby('studio')['foreign_gross'].sum()
studio_foreign_gross = studio_foreign_gross.sort_values(ascending=False)
studio_foreign_gross.describe()
```

Out[277…

```
count    1.730000e+02
mean     8.792942e+08
std      3.425321e+09
min      5.200000e+03
25%      1.800000e+06
50%      1.788800e+07
75%      1.215000e+08
max      2.579385e+10
Name: foreign_gross, dtype: float64
```

In [278…

```
fig, axes = plt.subplots(1,2, figsize=(18,6), sharey=True)
#add domestic trend
domestic_studio_year = domestic_gross_df.groupby(['year', 'studio'])['domestic_gross'].sum().unstack()

domestic_top_studios = domestic_gross_df.groupby('studio')['domestic_gross'].sum().sort_values(ascending=False).head(
domestic_studio_year[domestic_top_studios].plot(ax=axes[0])

axes[0].set_xlabel('Year')
axes[0].set_ylabel('Amount of Gross Income')
axes[0].set_title('Domestic Gross Trend for Top 5 Studios')
axes[0].legend(title='Studio')
axes[0].grid(True)

#add foreign trend

foreign_studio_year = foreign_gross_df.groupby(['year', 'studio'])['foreign_gross'].sum().unstack()

foreign_top_studios = foreign_gross_df.groupby('studio')['foreign_gross'].sum().sort_values(ascending=False).head(5).
foreign_studio_year[foreign_top_studios].plot(ax=axes[1])
axes[1].set_xlabel('Year')
axes[1].set_ylabel('Amount of Gross Income')
axes[1].set_title('Foreign Gross Trend for Top 5 Studios')
axes[1].legend(title='Studio')


plt.grid(True)
plt.show()
```



Observation:

Over the years, BV seems to have been leading the pack for the most part especially from 2015.

Important to note is that WB has had a more downward trajectory and could be used a case study as well on wha to do/ avoid.