#### **Final Project Submission**

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Blog post URL:

## **Business Understanding**

Movie production is an expensive venture which can lead to serious losses especially when ventured carelessly without adequate knowledge of the video type ,Genre , and amount used in production. Therefore, this project is aimed at helping the head of Microsoft's New Movie Studio study various film types produced by companies that create original film. Reviews and ratings from past movies and tv shows produced will be studied, analysed and visualized. Insights drawn from the study will be used in the decision making of the type of movie to be produced by the upcoming Microsoft's New Movie Studio.

This study focuses mainly to help the stakeholders who are Microsoft get answers to movie genre they should venture in, averange returns to expect, and movie length that attracts most viewers.

## **Data Understanding**

bom.movie.csv This is a CSV file that is found in the file path
 "Data/bom.movie\_gross.csv". Contained in the file is information about various movies
 showing year of production,company of production, and money fetched from local
 market, and foreign market. Original data before cleaning contained 3387 rows and 5
 columns.

Columns present in the file are:

- · title It contains movie names
- studio Contains production studio
- domestic gross Contains money fetched from selling to buyers in the production country
- foreign gross money fetched sales around the world
- year year of production.

```
In [114]: # Your code here - remember to use markdown cells for comments as well
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

i. bom.movie gross.csv

In [115]: # importing the Dataframe and displaying the head
Bom\_Movie = pd.read\_csv('Data/bom.movie\_gross.csv')
Bom\_Movie.head(10)

Out[115]:

	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
5	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010
6	Iron Man 2	Par.	312400000.0	311500000	2010
7	Tangled	BV	200800000.0	391000000	2010
8	Despicable Me	Uni.	251500000.0	291600000	2010
9	How to Train Your Dragon	P/DW	217600000.0	277300000	2010

```
In [116]: # checking for duplicates
Bom_Movie.duplicated().sum()
```

Out[116]: 0

In [117]: # There are no duplicates in the above dataframe.
# Checking for Nan Values and removing if possible.
Bom\_Movie.isna().sum()

From the above we have null values in foreign gross, studio, and domestic gross. Foreign gross, has many misssing values hence will be dropped.

In [118]: # dropping foreign\_gross, year, and title. # year and title will not be very useful in the analysis. Bom\_Movie.drop(['title', 'year', 'foreign\_gross'], axis=1, inplace=Ti

In [119]: # New dataframe Bom Movie

Out[119]:

	studio	domestic_gross
0	BV	415000000.0
1	BV	334200000.0
2	WB	296000000.0
3	WB	292600000.0
4	P/DW	238700000.0
3382	Magn.	6200.0
3383	FM	4800.0
3384	Sony	2500.0
3385	Synergetic	2400.0
3386	Grav.	1700.0

3387 rows × 2 columns

In [120]: Bom Movie.isna().sum()

# From the above we will drop null values present in the studio colum

Out[120]: studio 5 domestic gross 28

dtype: int64

```
In [121]: Bom_Movie.describe()
Out[121]:
                 domestic_gross
            count
                   3.359000e+03
                   2.874585e+07
            mean
             std
                   6.698250e+07
                   1.000000e+02
             min
             25%
                   1.200000e+05
             50%
                   1.400000e+06
             75%
                   2.790000e+07
             max
                   9.367000e+08
In [122]: # Filling missing values in domestic gross
           Bom_Movie['domestic_gross'].fillna(
               Bom Movie['domestic gross'].median(), inplace=True)
In [123]: Bom_Movie.isna().sum()
Out[123]: studio
                              5
           domestic gross
                              0
           dtype: int64
In [124]: Bom_Movie.dropna(inplace=True)
           # confirming there are no missing values.
In [125]:
           Bom_Movie.isna().sum()
Out[125]: studio
                              0
           domestic_gross
                              0
```

dtype: int64

```
# sorting the DataFrame
In [126]:
           Bom Movie New = Bom Movie.groupby('studio')['domestic gross'].mean()
           Bom Movie New = Bom Movie New.sort values(ascending=False).head(10)
           Bom Movie New
Out[126]: studio
           BV
                       1.737644e+08
           P/DW
                      1.682900e+08
           WB (NL)
                      8.879333e+07
           Uni.
                      8.777138e+07
           WB
                      8.691461e+07
                      8.051103e+07
           Fox
           Sony
                      7.691894e+07
                      7.609773e+07
           Par.
           MGM
                      6.666667e+07
                      6.212473e+07
           Sum.
           Name: domestic_gross, dtype: float64
In [127]: # converting the data to a dataframe
           Bom Movie New df1 = pd.DataFrame(Bom Movie New)
           type(Bom Movie New df1)
Out[127]: pandas.core.frame.DataFrame
In [128]: # Data Analysis and Visualization
           # displaying the dataframe
           Bom Movie New df2 = Bom Movie New df1.reset index('studio')
In [129]: Bom_Movie_New_df2
Out[129]:
               studio domestic_gross
           0
                  BV
                       1.737644e+08
                P/DW
                       1.682900e+08
           2 WB (NL)
                       8.879333e+07
           3
                 Uni.
                       8.777138e+07
           4
                 WB
                       8.691461e+07
           5
                 Fox
                       8.051103e+07
                Sony
                       7.691894e+07
           7
                 Par.
                       7.609773e+07
           8
                MGM
                       6.666667e+07
                Sum.
                       6.212473e+07
```

ii. Movie Basics

#### Out[130]:

# Table Names 0 movie\_basics 1 directors 2 known\_for 3 movie\_akas 4 movie\_ratings 5 persons 6 principals 7 writers

# In [131]: # selecting the movie\_basics table db\_data = pd.read\_sql("""SELECT \* FROM movie\_basics""", conn) db\_data.head()

#### Out[131]:

	movie_id	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

```
# checking information of the Movie_basics table for presence of dup
In [132]:
          db data.duplicated().sum()
Out[132]: 0
In [133]: # Checking the tables information
          db data.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 146144 entries, 0 to 146143
          Data columns (total 6 columns):
           #
               Column
                                 Non-Null Count
                                                   Dtype
           - - -
           0
               movie id
                                 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
                                 140736 non-null object
                genres
          dtypes: float64(1), int64(1), object(4)
          memory usage: 6.7+ MB
In [134]:
          # check missing values in the movie_basics table
          db data.isna().sum()
Out[134]: movie id
                                  0
          primary title
                                  0
          original title
                                 21
          start year
                                  0
           runtime_minutes
                              31739
          genres
                               5408
          dtype: int64
          The results above show the presence of missing values in runtime minutes, genres and
          original title.
In [135]: # Droping the title columns in the table above.
          db data.drop('original title', axis=1, inplace=True)
```

In [136]: db\_data

Out[136]:

	movie_id	primary_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
146139	tt9916538	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	2017	116.0	None
146143	tt9916754	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 5 columns

```
In [137]: # Droping the primary title column
          db_data.drop('primary_title', axis=1, inplace=True)
```

To avoid introduction of disturbances in the data, we will drop all the rows that have null values.

In [139]: # new data set's head
db\_data.head(10)

Out[139]:

	movie_id	start_year	runtime_minutes	genres
0	tt0063540	2013	175.0	Action,Crime,Drama
1	tt0066787	2019	114.0	Biography,Drama
2	tt0069049	2018	122.0	Drama
4	tt0100275	2017	80.0	Comedy,Drama,Fantasy
5	tt0111414	2018	75.0	Comedy
7	tt0137204	2017	83.0	Adventure, Animation, Comedy
9	tt0144449	2012	82.0	Biography
10	tt0146592	2010	136.0	Drama
11	tt0154039	2010	100.0	History
12	tt0159369	2013	180.0	Documentary

\*\*\* data analysis \*\*\*

In [140]: # measuring central tendency for the data
db\_data.describe()

Out[140]:

	start_year	runtime_minutes
count	112233.000000	112233.000000
mean	2014.402101	86.261902
std	2.639042	167.895938
min	2010.000000	1.000000
25%	2012.000000	70.000000
50%	2014.000000	87.000000
75%	2017.000000	99.000000
max	2022.000000	51420.000000

From the above description, the averange runtime in minutes is 86 minutes from the 112233 responses available.

iii. Movie\_ Rating

```
In [141]: # Reading the mvie rating column
Movie_Ratingdf = pd.read_sql("""
SELECT *
FROM Movie_ratings;
""", conn)
```

In [142]: # Displaying the head
Movie\_Ratingdf.head(10)

Out[142]:

	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
5	tt1069246	6.2	326
6	tt1094666	7.0	1613
7	tt1130982	6.4	571
8	tt1156528	7.2	265
9	tt1161457	4.2	148

In [143]: # checking the info of the table
Movie\_Ratingdf.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):

# Column Non-Null Count Dtype

0 movie\_id 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

In [144]: # checking presence of repetition
Movie\_Ratingdf.duplicated().sum()

Out[144]: 0

The table above has no repetitions, null values, and missing values. Therefore, since they have almost related columns we join the two tables.

```
In [146]: q ='''SELECT movie_id, original_title, runtime_minutes, genres, avera
FROM movie_basics
    JOIN movie_ratings
    USING(movie_id)
    ;
    imdb = pd.read_sql(q,conn)
```

# **Data Analysis**

i. bom.movie

```
In [147]: # displaying the dataset
Bom_Movie_New_df2
```

#### Out[147]:

	studio	domestic_gross
0	BV	1.737644e+08
1	P/DW	1.682900e+08
2	WB (NL)	8.879333e+07
3	Uni.	8.777138e+07
4	WB	8.691461e+07
5	Fox	8.051103e+07
6	Sony	7.691894e+07
7	Par.	7.609773e+07
8	MGM	6.666667e+07
9	Sum.	6.212473e+07

```
In [148]: # measurements of central tendency for the data
Bom_Movie_New_df2.describe()
```

#### Out[148]:

```
domestic_gross
         1.000000e+01
count
         9.678529e+07
mean
         4.010714e+07
  std
         6.212473e+07
 min
 25%
         7.630303e+07
 50%
         8.371282e+07
 75%
         8.853785e+07
         1.737644e+08
 max
```

```
In [149]: # which movie studio has the highest domestic gross
```

#### Out[149]: studio

BV 1.737644e+08 P/DW 1.682900e+08 WB (NL) 8.879333e+07 8.777138e+07 Uni. WB 8.691461e+07 Fox 8.051103e+07 Sony 7.691894e+07 Par. 7.609773e+07 MGM 6.666667e+07 Sum. 6.212473e+07

Name: domestic gross, dtype: float64

Studio BV has the highest domestic gross of 1.737e+08 followed by P/DW with 1.683e+08

ii. Movie db

In [150]: # data preview
imdb.head()

#### Out[150]:

	movie_id	original_title	runtime_minutes	genres	averagerating	numvotes
0	tt0063540	Sunghursh	175.0	Action,Crime,Drama	7.0	77
1	tt0066787	Ashad Ka Ek Din	114.0	Biography,Drama	7.2	43
2	tt0069049	The Other Side of the Wind	122.0	Drama	6.9	4517
3	tt0069204	Sabse Bada Sukh	NaN	Comedy,Drama	6.1	13
4	tt0100275	La Telenovela Errante	80.0	Comedy,Drama,Fantasy	6.5	119

In [151]: # identifying the movies genres with the highest ratings.
highest\_rate = imdb.averagerating.groupby(imdb['genres']).max()
highest\_ratings = highest\_rate.sort\_values(ascending = False).head(12)
highest\_ratings

#### Out[151]: genres

10.0
10.0
10.0
10.0
10.0
10.0
9.8
9.8
9.8
9.8
9.8
9.7
float64

In [152]: # identifying the movies genres with the highest votes.
highest\_vote = imdb.numvotes.groupby(imdb['genres']).max()
highest\_votes = highest\_vote.sort\_values(ascending = False).head(12)
highest\_votes

#### Out[152]: genres

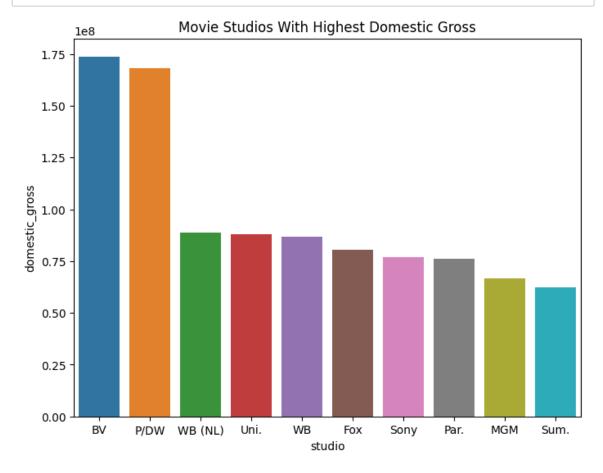
Action, Adventure, Sci-Fi 1841066 Action, Thriller 1387769 Adventure, Drama, Sci-Fi 1299334 Drama, Western 1211405 Biography, Crime, Drama 1035358 Mystery, Thriller 1005960 Action, Adventure, Comedy 948394 Action, Adventure, Fantasy 784780 Drama, Mystery, Thriller 761592 Adventure, Family, Fantasy 719629 Drama, Sci-Fi, Thriller 710018 Adventure, Drama, Fantasy 691835

Name: numvotes, dtype: int64

```
In [153]: #Movies with awesome ratings
          best movie = imdb.averagerating.groupby(imdb['original title']).max()
          best movies = best movie.sort values(ascending = False).head(20)
          best movies
Out[153]: original title
          Renegade
          10.0
          Fly High: Story of the Disc Dog
          10.0
          Calamity Kevin
          10.0
          Atlas Mountain: Barbary Macagues - Childcaring Is the Man's Job
          Ellis Island: The Making of a Master Race in America
          10.0
          Hercule contre Hermès
          10.0
          All Around Us
          10.0
          Pick It Up! - Ska in the '90s
          10.0
          I Was Born Yesterday!
          10.0
          Requiem voor een Boom
          10.0
          Freeing Bernie Baran
          10.0
          Revolution Food
          10.0
          Exteriores: Mulheres Brasileiras na Diplomacia
          10.0
          The Dark Knight: The Ballad of the N Word
          A Dedicated Life: Phoebe Brand Beyond the Group
          10.0
          Dog Days in the Heartland
          10.0
          The Wedding Present: Something Left Behind
          9.9
          Moscow we will lose
          9.9
          LA Foodways
          9.9
          Gini Helida Kathe
          Name: averagerating, dtype: float64
```

```
# identifying the movies runtime minutes with the highest ratings.
In [154]:
          run time = imdb.averagerating.groupby(imdb['runtime minutes']).max()
           run times = run time.sort values(ascending = False).head(15)
           run_times
Out[154]: runtime minutes
          93.0
                    10.0
          129.0
                    10.0
          48.0
                    10.0
          99.0
                    10.0
          31.0
                    10.0
          100.0
                    10.0
          52.0
                    10.0
          65.0
                    10.0
          77.0
                    10.0
          59.0
                    10.0
          70.0
                    10.0
          72.0
                    10.0
          87.0
                     9.9
                     9.9
          51.0
          138.0
                     9.9
          Name: averagerating, dtype: float64
In [155]: # identifying the movies runtime minutes with the highest votes.
           runtimevote = imdb.numvotes.groupby(imdb['runtime minutes']).max()
           runtimevotes= runtimevote.sort values(ascending = False).head(12)
           runtimevotes
Out[155]: runtime_minutes
          148.0
                    1841066
          164.0
                    1387769
          169.0
                    1299334
          165.0
                    1211405
          143.0
                    1183655
          180.0
                    1035358
          138.0
                    1005960
          121.0
                     948394
          108.0
                     820847
          142.0
                     795227
          136.0
                     784780
          120.0
                     780910
          Name: numvotes, dtype: int64
          iv. Data Visualization
In [156]: Bom Movie New df5 = Bom Movie New df2.head(10)
```

In [167]: #Ploting a graph for domestic gross
 plt.figure(figsize=(8,6))
 barplot = sns.barplot(x='studio',y='domestic\_gross', data=Bom\_Movie\_N
 barplot.set(title='Movie Studios With Highest Domestic Gross')
 plt.show()

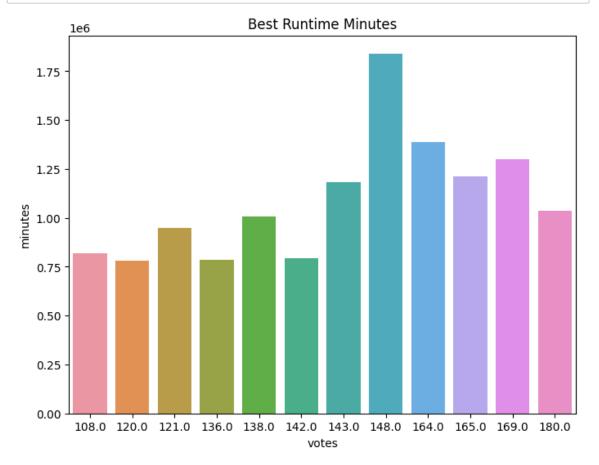


In [158]: # creating a dataframe
 runtimevotes= runtimevotes.rename\_axis('votes')
 runtimevot= runtimevotes.reset\_index(name='minutes')
 runtimevot

#### Out[158]:

	votes	minutes
0	148.0	1841066
1	164.0	1387769
2	169.0	1299334
3	165.0	1211405
4	143.0	1183655
5	180.0	1035358
6	138.0	1005960
7	121.0	948394
8	108.0	820847
9	142.0	795227
10	136.0	784780
11	120.0	780910

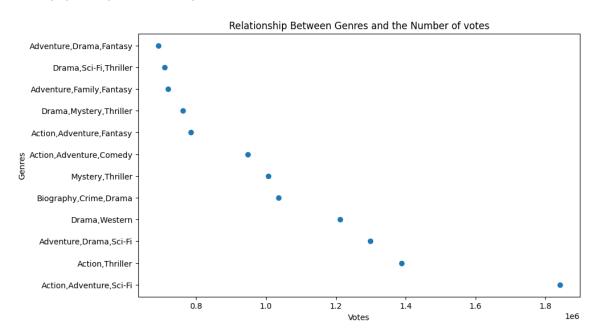
```
In [166]: plt.figure(figsize=(8,6))
    barplot = sns.barplot(x='votes',y='minutes', data=runtimevot)
    barplot.set(title='Best Runtime Minutes')
    plt.show()
```



The highest runtime is at the 148s. This shows that many people prefer to have or watch Videos that range at around that lenghth.

```
In [165]: # investigate the relationship between genres and the number of votes
    scatter_figure, ax = plt.subplots(figsize=(10, 6))
    ax.scatter(highest_votes['votes'], highest_votes['genres'])
    ax.set_title('Relationship Between Genres and the Number of votes')
    ax.set_xlabel('Votes')
    ax.set_ylabel('Genres')
```

Out[165]: Text(0, 0.5, 'Genres')



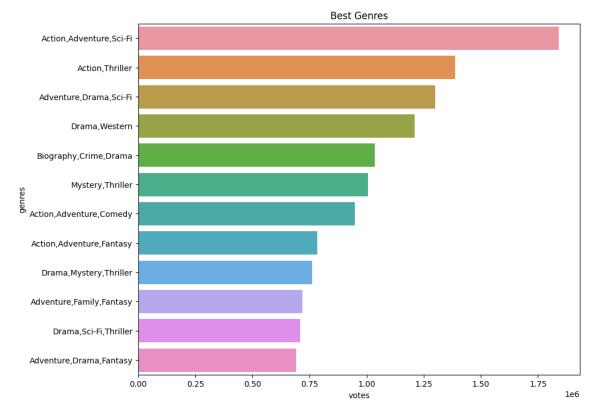
There is a negative relationship between the genre and number of votes.

In [163]: # creating a dataframe
highest\_votes= highest\_votes.rename\_axis('genre')
highest\_votes1= highest\_votes.reset\_index(name='vote')
highest\_votes1

#### Out[163]:

	genres	votes
0	Action,Adventure,Sci-Fi	1841066
1	Action, Thriller	1387769
2	Adventure,Drama,Sci-Fi	1299334
3	Drama,Western	1211405
4	Biography,Crime,Drama	1035358
5	Mystery,Thriller	1005960
6	Action,Adventure,Comedy	948394
7	Action,Adventure,Fantasy	784780
8	Drama, Mystery, Thriller	761592
9	Adventure,Family,Fantasy	719629
10	Drama,Sci-Fi,Thriller	710018
11	Adventure, Drama, Fantasy	691835

```
In [164]: # movie genres with the highest vote.
plt.figure(figsize=(10,8))
barplot = sns.barplot(x='votes',y='genres', data=highest_votes)
barplot.set(title='Best Genres')
plt.show()
```



Action, Adventure, sci-fi have the largest popularity. This makes them the genres to go for as they wiull definitely have a higher return fetched.