Final Project Submission

Please fill out:

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- Scheduled project review date/time:
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- Blog post URL:

Project Overview

My task is to use explorative data analysis to analyze the movies dataset and recommend the course of action to be taken by Microsoft corportion

Objectives

1. Ascertain the most popular genre of movies
2. Establish the most popular publisher
3. Ascertain the most popular rating for movies
4. Ascertain the relationship bwtween production budget and profit realized from the movies

Business Understanding

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.

Data Understanding

Before, I start the process of understanding my data, I first import the relevant librares that will enbale me read all my datasets.

These are Pandas,Sqlite and numpy

In [5]:
```
import pandas as pd
import sqlite3
import numpy as np
import warnings
```

The next step is reading and having a feel of the datasets.

I begin with connecting to the database and viewing the tables in the database

im.db

In [79]:

```
conn = sqlite3.connect('im.db') # Establishing connection to the database
data = pd.read_sql_query('SELECT name from sqlite_master where type= "table";'
data
```

Out[79]:

name

bom.movie_gross.csv

In [4]:

```
bomovies_df = pd.read_csv("zippedData/bom.movie_gross.csv.gz") # reading the d
bomovies_df.head(2) # viewing the first two entries
```

Out[4]:

	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

In [ ]:

```
bomovies_df.info() # getting to know the number of entiries and columns and the
```

rt.movie_info.tsv.gz"

In [6]:

```
rt_df = pd.read_csv(("zippedData/rt.movie_info.tsv.gz"),delimiter = "\t") # re
rt_df.head(3) #viewing the first three entries
```

Out[6]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	S
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012	
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	A

In [7]:
```
rt_df.info() #getting to know the number of rows and columns and the datatypes
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            1560 non-null   int64
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: int64(1), object(11)
memory usage: 146.4+ KB
```

rt.reviews.tsv.gz

In [12]:
```
# reading the data and assigning it to rv_df

rv_df = pd.read_csv(("zippedData/rt.reviews.tsv.gz"), delimiter = "\t", encodi

rv_df.tail(3) # viewing the last 3 entries
```

Out[12]:

	id	review	rating	fresh	critic	top_critic	publisher	date
54429	2000	NaN	2/5	rotten	Emanuel Levy	0	EmanuelLevy.Com	July 17, 2005
54430	2000	NaN	2.5/5	rotten	Christopher Null	0	Filmcritic.com	September 7, 2003
54431	2000	NaN	3/5	fresh	Nicolas Lacroix	0	Showbizz.net	November 12, 2002

In [86]:
```
rv_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 33988 entries, 0 to 54424
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          33988 non-null  int64 
 1   review      33988 non-null  object
 2   fresh       33988 non-null  object
 3   critic      33988 non-null  object
 4   top_critic  33988 non-null  int64 
 5   publisher   33988 non-null  object
 6   date        33988 non-null  object
 7   score       33988 non-null  object
 8   outof       27588 non-null  object
dtypes: int64(2), object(7)
memory usage: 2.6+ MB
```

tmdb.movies.csv.gz

In [10]:
```
tmbd_df = pd.read_csv("zippedData/tmdb.movies.csv.gz") # Reading the tmdb data

tmbd_df.head(2) # viewing the first two entries
```

Out[10]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	titl
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harr Potte and th Deathl Hallows Part
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How t Trai You Drago

In [ ]:
```
tmbd_df.info()
```

tn.movie_budgets.csv.gz

In [9]:
```
budgets= pd.read_csv("zippedData/tn.movie_budgets.csv.gz")
budgets.head(2)
```

Out[9]:

	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

In [ ]:
```
budgets.info()
```

Data Preparation

After having a brief overview of the dataset, I started the data prepaation process which invloved cleaning of the data with he following objectives:

1. Deal with the NaNs/ or missing data
2. Ensure that all columns are in the correct datatype
3. Deal with placeholders if any

In the cells taht follow i will conduct data cleaning and ETL for each of the dataset.

bomovies_df

Dealing with missing Values

The first step is to find the proportion of missing values in each of the columns of the bomovies_df

In [13]:
```
bomovies_df.isnull().mean()*100
```

Out[13]:
```
title              0.000000
studio             0.147623
domestic_gross     0.826690
foreign_gross     39.858282
year               0.000000
dtype: float64
```

From the results above, it seems that in the bomovies_df the proportion of missing values for all the columns except the foreign_gross is quite low at less than 1%.

However for foreign gross, the missing value percentage is almost 40%. I assumed that the missing values in foreign_gross means that the movies were sold domestically and did not reach the international market hence their revenue from the international market is 0. Therefore, I replace the missing values in the foreign_gross column by 0.

I also replaced missing values in domestic_gross column with zero since i assummed that these movies did not sell in the domestic market

The codes below replaces the Nans with 0 in the columns domestic_gross and foreign_gross respectively.

In [14]:
```
bomovies_df["domestic_gross"].fillna(0, inplace= True) # replaces all NANs in t
bomovies_df["foreign_gross"].fillna(0, inplace= True) # replaces all NANs in th
```

In [15]:
```
bomovies_df.isna().mean() # Check if the Nulls have disappeared.
```

Out[15]:
```
title             0.000000
studio            0.001476
domestic_gross    0.000000
foreign_gross     0.000000
year              0.000000
dtype: float64
```

For the studio column I replaced the missing values with the mode, which is the most occuring studio.

To find the most occuring studio I used the following code:

In [16]:
```
bomovies_df["studio"].value_counts().nlargest(1) # Checking for the most commo
```

Out[16]:
```
IFC    166
Name: studio, dtype: int64
```

Since IFC is the most common studio, i replaced the missing values in the studio column with it

In [17]:
```
bomovies_df["studio"].fillna("IFC",inplace=True) # replacing missing values in
bomovies_df.isna().mean() # checking if the nulls have disappeared
```

Out[17]:
```
title             0.0
studio            0.0
domestic_gross    0.0
foreign_gross     0.0
year              0.0
dtype: float64
```

I have now dealt with the missing values in the bomovies_df succesfully.

Converting to the appropriate column datatypes

However, i I realized domestic-gross and foreign gross and year are in the wrong datatype and therefore i cast them to the correct datatype

In [20]:
```
bomovies_df = bomovies_df = bomovies_df.astype({"domestic_gross": int})
```

In [21]:
```
bomovies_df.info() # checking column datatypes have converted succesfull
```

```
<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          3387 non-null   object
 2   domestic_gross  3387 non-null   int32 
 3   foreign_gross   3387 non-null   object
 4   year            3387 non-null   int64 
dtypes: int32(1), int64(1), object(3)
memory usage: 119.2+ KB
```

rt_df

Dealing with missing values in rt_df

In [22]:
```
rt_df.isna().mean()*100 # First find the proportion of missing  values in rt_d
```

Out[22]:
```
id               0.000000
synopsis         3.974359
rating           0.192308
genre            0.512821
director        12.756410
writer          28.782051
theater_date    23.012821
dvd_date        23.012821
currency        78.205128
box_office      78.205128
runtime          1.923077
studio          68.333333
dtype: float64
```

Dealing with the nulls;

In the dataframe rt_df, i realized that only to columns would be important for my analysis. These are the genre and rating columns. I sliced them from the main datframe as follows:

In [80]:
```
rt_df = rt_df[["genre", "rating"]] # to  slice relevant columns from the rt_df
rt_df.head(2)
```

Out[80]:

	genre	rating
0	Action and Adventure|Classics|Drama	R
1	Drama|Science Fiction and Fantasy	R

I then dealt with the missing values by droppping the rows that had missing values in the column

In [24]:
```
rt_df = rt_df.dropna()
```

In [25]:
```
rt_df.isna().mean()*100
```

Out[25]:
```
genre     0.0
rating    0.0
dtype: float64
```

rv_df

Deal with the missing values by dropping all null vlaues in the rows

In [26]:
```
rv_df.dropna(inplace =True) # dropping rows with missing values
```

In [27]:
```
rv_df.isnull().mean()*100 # checking if the nulls have disappeared.
```

Out[27]:
```
id            0.0
review        0.0
rating        0.0
fresh         0.0
critic        0.0
top_critic    0.0
publisher     0.0
date          0.0
dtype: float64
```

The ratings column in the rt_reviews (rv_df) can be split into two columns so that we can be able to standardize ratings of all the enries throough feature engineering. The next cell splits the rating column ito two and displays them as separate columns

In [ ]:
```

```

In [28]:
```
new = rv_df["rating"].str.split(pat ="/", n = 1, expand=True) # splitting the 
rv_df["score"] = new[0]
rv_df["outof"] = new[1]
rv_df.drop(columns = ["rating"], inplace = True)
rv_df
```

Out[28]:

	id	review	fresh	critic	top_critic	publisher	date	score	outof
0	3	A distinctly gallows take on contemporary fina...	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018	3	5
6	3	Quickly grows repetitive and tiresome, meander...	rotten	Eric D. Snider	0	EricDSnider.com	July 17, 2013	C	None
7	3	Cronenberg is not a director to be daunted by ...	rotten	Matt Kelemen	0	Las Vegas CityLife	April 21, 2013	2	5
11	3	While not one of Cronenberg's stronger films, ...	fresh	Emanuel Levy	0	EmanuelLevy.Com	February 3, 2013	B-	None
12	3	Robert Pattinson works mighty hard to make Cos...	rotten	Christian Toto	0	Big Hollywood	January 15, 2013	2	4
...	...	...	...	...	...	...	...	...	...
54419	2000	Sleek, shallow, but frequently amusing.	fresh	Gene Seymour	1	Newsday	September 27, 2002	2.5	4
54420	2000	The spaniel-eyed Jean Reno infuses Hubert with...	fresh	Megan Turner	1	New York Post	September 27, 2002	3	4
54421	2000	Manages to be somewhat well-acted, not badly a...	rotten	Bob Strauss	0	Los Angeles Daily News	September 27, 2002	1.5	4
54422	2000	Arguably the best script that Besson has writt...	fresh	Wade Major	0	Boxoffice Magazine	September 27, 2002	3.5	5
54424	2000	Dawdles and drags when it should pop; it doesn...	rotten	Manohla Dargis	1	Los Angeles Times	September 26, 2002	1.5	5

33988 rows × 9 columns

In [ ]:

Before I standardize the ratings, i willl first convert the column types from string to integer to allow for mathematical computation.

In [ ]:

tmbd_df

Check fo missing values

In [81]:
```
tmbd_df.isna().mean()*100 # checking proportion of missing values
```

Out[81]:
```
Unnamed: 0           0.0
genre_ids            0.0
id                   0.0
original_language    0.0
original_title       0.0
popularity           0.0
release_date         0.0
title                0.0
vote_average         0.0
vote_count           0.0
dtype: float64
```

Perfect! This data has no any missing value.

In [30]:
```
tmbd_df["genre_ids"].value_counts() # check for  unique values of Genre_ids
```

Out[30]:
```
[99]                          3700
[]                            2479
[18]                          2268
[35]                          1660
[27]                          1145
                              ...
[37, 12]                         1
[10752, 878]                     1
[28, 53, 10749, 18, 35]          1
[99, 80, 53, 36]                 1
[10751, 12, 28]                  1
Name: genre_ids, Length: 2477, dtype: int64
```

In [ ]:

budgets_df

Check for missing values

In [ ]:
```
budgets.isna().mean()*100  #checks for percentage of missing values.
```

The budgets_df is also complete!

Since the domestic_gross,Production_budget and Worldwide_gross columns are strings, we needto convet them to inerger to faciltate feature engineering to make the data more insightful.

In [31]:
```
#The codes below convert  the columns with the $ sign into interger to facilit

budgets['domestic_gross'] = budgets['domestic_gross'].apply(lambda x: int(''.j
budgets['production_budget'] = budgets['production_budget'].apply(lambda x: in
budgets["worldwide_gross"] = budgets['worldwide_gross'].apply(lambda x: int(''
```

Perfect! since we have our budget and gross columns as intergers, it is possibe to create new profit columns. Pofit is the difference between productioin cost and gross revenue

In [32]:
```
budgets["Domestic_profit"] = budgets["domestic_gross"]- budgets["production_bu
```

In [33]:
```
budgets["worldwide_profit"] = budgets["worldwide_gross"]-budgets["production_b
budgets.info()  # checkig if  we have the correct datatypes
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 8 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   int64 
 4   domestic_gross     5782 non-null   int64 
 5   worldwide_gross    5782 non-null   int64 
 6   Domestic_profit    5782 non-null   int64 
 7   worldwide_profit   5782 non-null   int64 
dtypes: int64(6), object(2)
memory usage: 361.5+ KB
```

Data Analysis

After prepaing the data and making sure that it is not dirty, I delved into data analysis. In thi section i will try to make sense of the data. I will ty to merge datasets to come up with more insightful analysis and to create a story that microsoft would definitely buy in.

My Data Analysis will focus on Establishing the following:

1. Which is the most popular genre of movies
2. Which is the most popular studio
3. Which rating is most prefered
4. wh

Most popular Genre of Movies

From the rt_ movies dataset I can establish the top 5 genres of movies

In [34]:
```
rt_df.genre.value_counts().nlargest(5)
```

Out[34]:
```
Drama                                    151
Comedy                                   110
Comedy|Drama                              80
Drama|Mystery and Suspense                67
Art House and International|Drama         62
Name: genre, dtype: int64
```

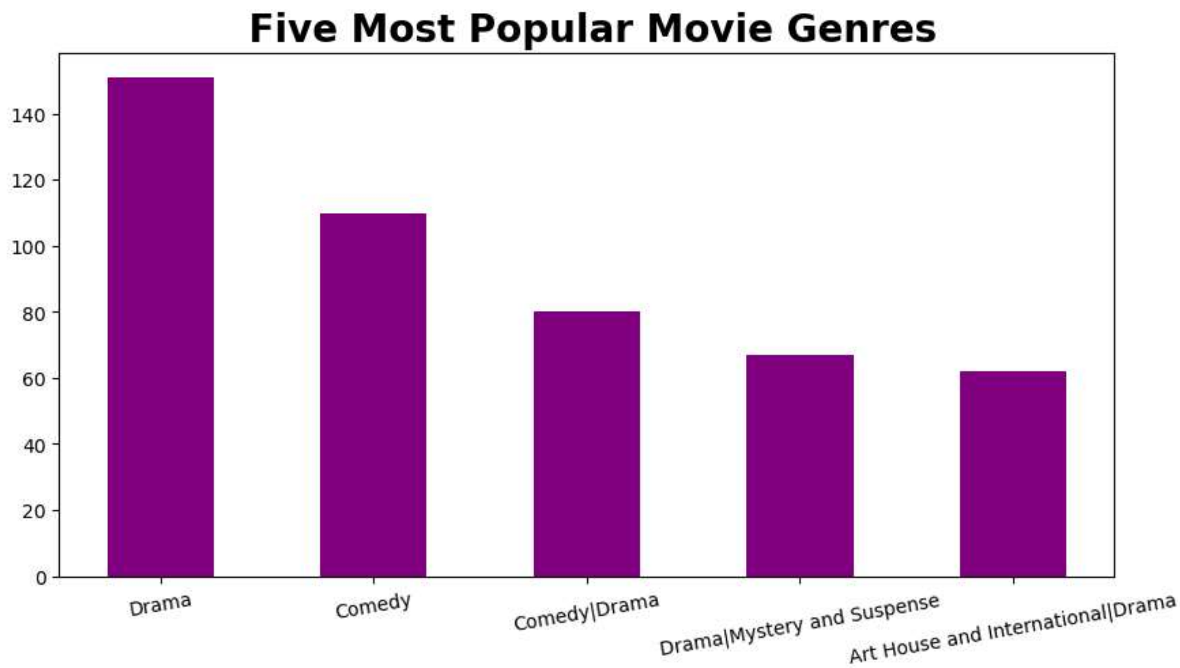
From the above code, the most popular genre of movies is Drama, followed by Comedy, then comedy|Drama and so on... This can be better presetnteed in the visualization below:

In [35]:
```

import matplotlib.pyplot as plt # Importing the library neccesaty to create vi
%matplotlib inline
import seaborn as sns
```

In [36]:
```
# Getting the X and Y  values
x = rt_df["genre"].value_counts().head().index.tolist()
y = list(rt_df["genre"].value_counts().nlargest(5))
```

In [37]:
```
# Ploting  Most popular  Genres and their frequencies
fig,ax = plt.subplots(figsize = (10,5))
plt.bar(x, y, color = "Purple", width = 0.5)
plt.xticks(rotation = 10);
plt.title(" Five Most Popular Movie Genres", fontsize = 20, fontweight = "bold
```



Most Popular studio

I can be able to find the most popular studio from the bomovies _df

In [ ]:
```
rt_df["rating"].value_counts()
```

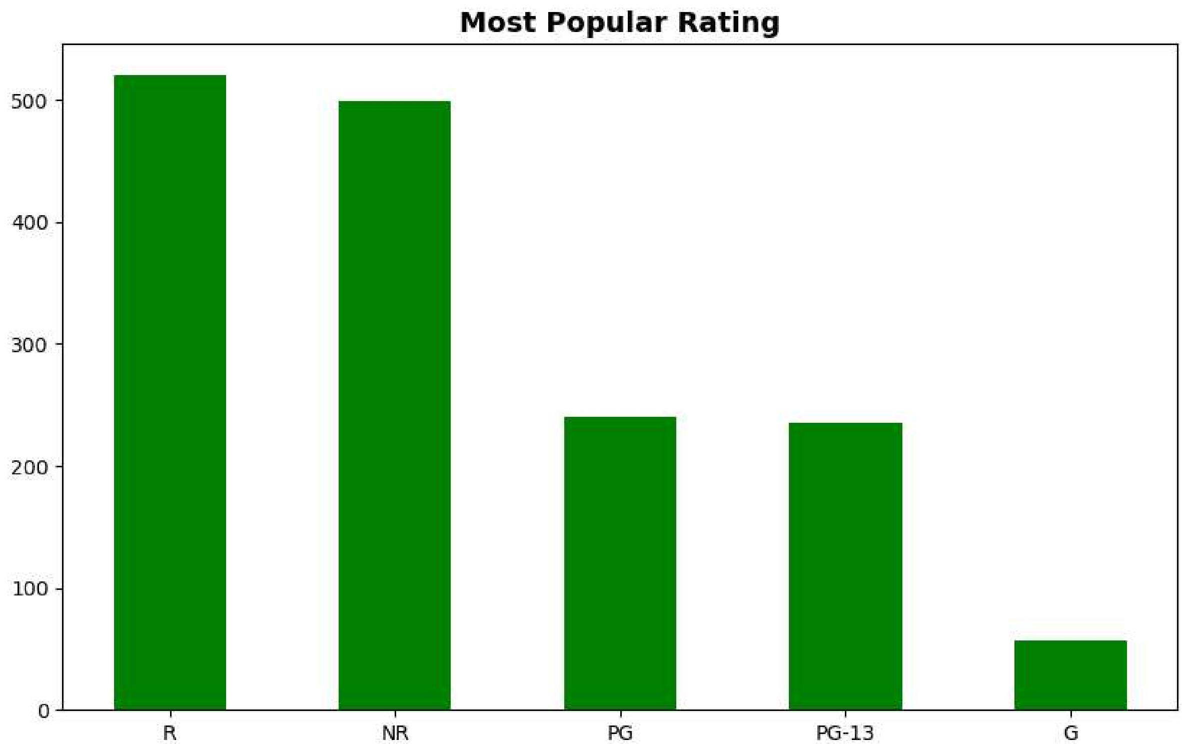
These can be visually presented as:

In [38]:
```
rating= rt_df["rating"].value_counts().head().index.tolist()
frequency=list(rt_df["rating"].value_counts().nlargest(5))
```

In [39]:
```
fig, ax = plt.subplots(figsize= (10,6))

plt.bar(rating, frequency, color = "green", width =0.5); # plotting ratings an

plt.title("Most Popular Rating", fontsize = 14, fontweight = "bold");
```



Most Popular Rating

Is There a Relationship Bewteen Movie Prodcuction Budget and Profits Realised

Inorder to ascertain whether production budget affects profitability, I calculated correlation betweem production budget and profit realised domestically and worldwide

In [40]:
```
budgets.corr()
```

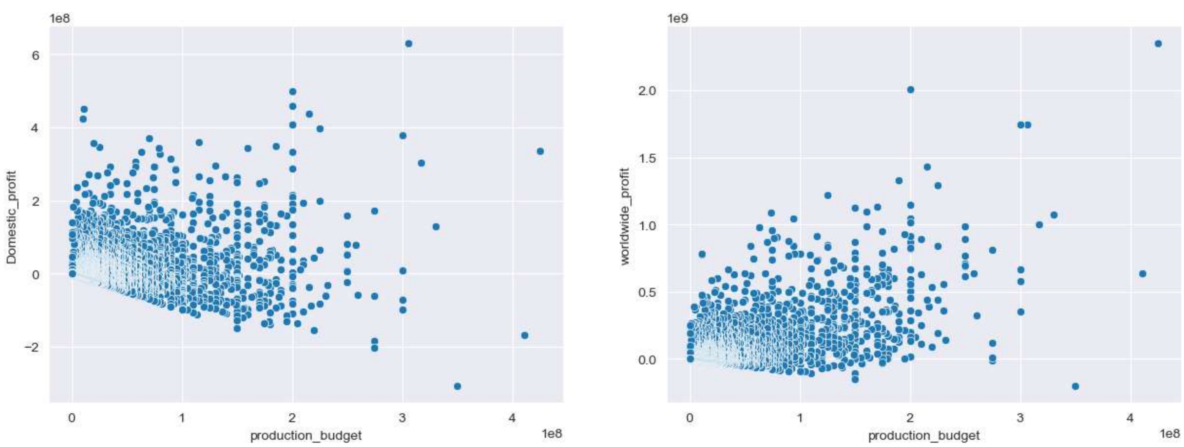
```
C:\Users\user\AppData\Local\Temp\ipykernel_10264\2354375143.py:1: FutureWarni
ng: The default value of numeric_only in DataFrame.corr is deprecated. In a f
uture version, it will default to False. Select only valid columns or specify
the value of numeric_only to silence this warning.
  budgets.corr()
```

Out[40]:

	id	production_budget	domestic_gross	worldwide_gross	Domestic_pr
id	1.000000	-0.035278	0.008255	-0.009422	0.0408
production_budget	-0.035278	1.000000	0.685682	0.748306	0.0997
domestic_gross	0.008255	0.685682	1.000000	0.938853	0.7926
worldwide_gross	-0.009422	0.748306	0.938853	1.000000	0.6566
Domestic_profit	0.040832	0.099742	0.792663	0.656626	1.0000
worldwide_profit	-0.001172	0.608752	0.926605	0.981811	0.7567

In the correlation matrix above, The correlation between Production budget and worldwide_profit is positive and higgher than that between prodcution budget and domestic profit. Below is scatter plot showing the relationsip

In [82]:
```
sns.set_style("darkgrid")
fig, axes = plt.subplots(1,2,figsize= (15,5))
sns.scatterplot(x= budgets["production_budget"], y =budgets["Domestic_profit"]
sns.scatterplot(x= budgets["production_budget"], y =budgets["worldwide_profit"
```



In [ ]:
```
sns.set_style("darkgrid")
fig, axes = plt.subplots(1,2,figsize= (15,5))
sns.scatterplot(x= budgets["production_budget"], y =budgets["domestic_gross"],
sns.scatterplot(x= budgets["production_budget"], y =budgets["worldwide_gross"]
```

Most Popular Genre_ids

In [84]:
```
# grouping by genre-ids and aggregating by max()

grouped1= tmbd_df.groupby(["genre_ids"]).max().sort_values(by="popularity", as
grouped1.head()
```

Out[84]:

	Unnamed: 0	id	original_language	original_title	popularity	release_date	ti
genre_ids							
[12, 28, 14]	24034	522417	zh	奇门遁甲	80.773	2018-10-23	T Thousa Faces Dur
[28, 53]	26399	569869	th	우는 남자	78.123	2018-12-20	Your Mc
[28, 12, 16, 878, 35]	23812	324857	en	Spider-Man: Into the Spider-Verse	60.534	2018-12-14	Spider-Ma Into t Spid Ver
[28, 12, 14]	24318	525135	zh	西游记之孙悟空三打白骨精	53.783	2018-12-21	Warcr
[878, 28, 12]	24924	521323	en	Wastelander	50.289	2018-02-02	Wastelanc

Popularity By Language

In [85]:
```
# Grouping by  Original _language
grouped = tmbd_df.groupby(["original_language"]).sum().sort_values(by="popular
grouped.head()
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_10264\4174702788.py:2: FutureWarni
ng: The default value of numeric_only in DataFrameGroupBy.sum is deprecated.
In a future version, numeric_only will default to False. Either specify numer
ic_only or select only columns which should be valid for the function.
  grouped = tmbd_df.groupby(["original_language"]).sum().sort_values(by="popu
larity", ascending= False)
```

Out[85]:

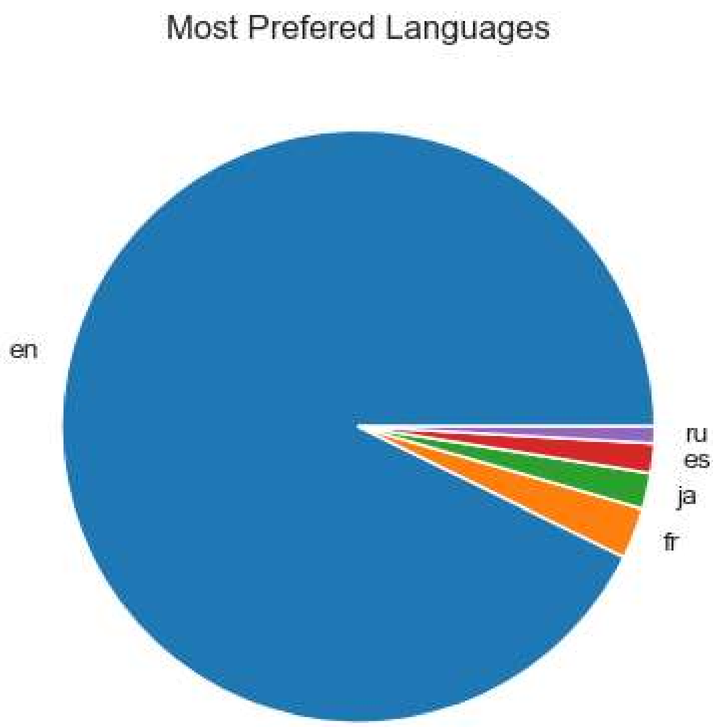
	Unnamed: 0	id	popularity	vote_average	vote_count
original_language					
en	312028215	7005029780	71895.155	138662.0	4874990
fr	5744495	118048030	2155.574	3130.8	75337
ja	3769256	70813222	1513.434	1809.1	54774
es	6070196	127264882	1257.725	2874.3	29396
ru	2859417	64494601	708.220	1579.4	4901

In [63]:
```
language =  ["en","fr","ja","es", "ru"]
Popularity= [71896,2155,1513,1257,708]
```

In [60]:
```
grouped["popularity"].head()
```

Out[60]:
```
original_language
en    71895.155
fr     2155.574
ja     1513.434
es     1257.725
ru      708.220
Name: popularity, dtype: float64
```

In [72]:
```
fig,ax = plt.subplots()
plt.pie(Popularity, labels = language)
plt.title("Most Prefered Languages");
```



Merging Datasets

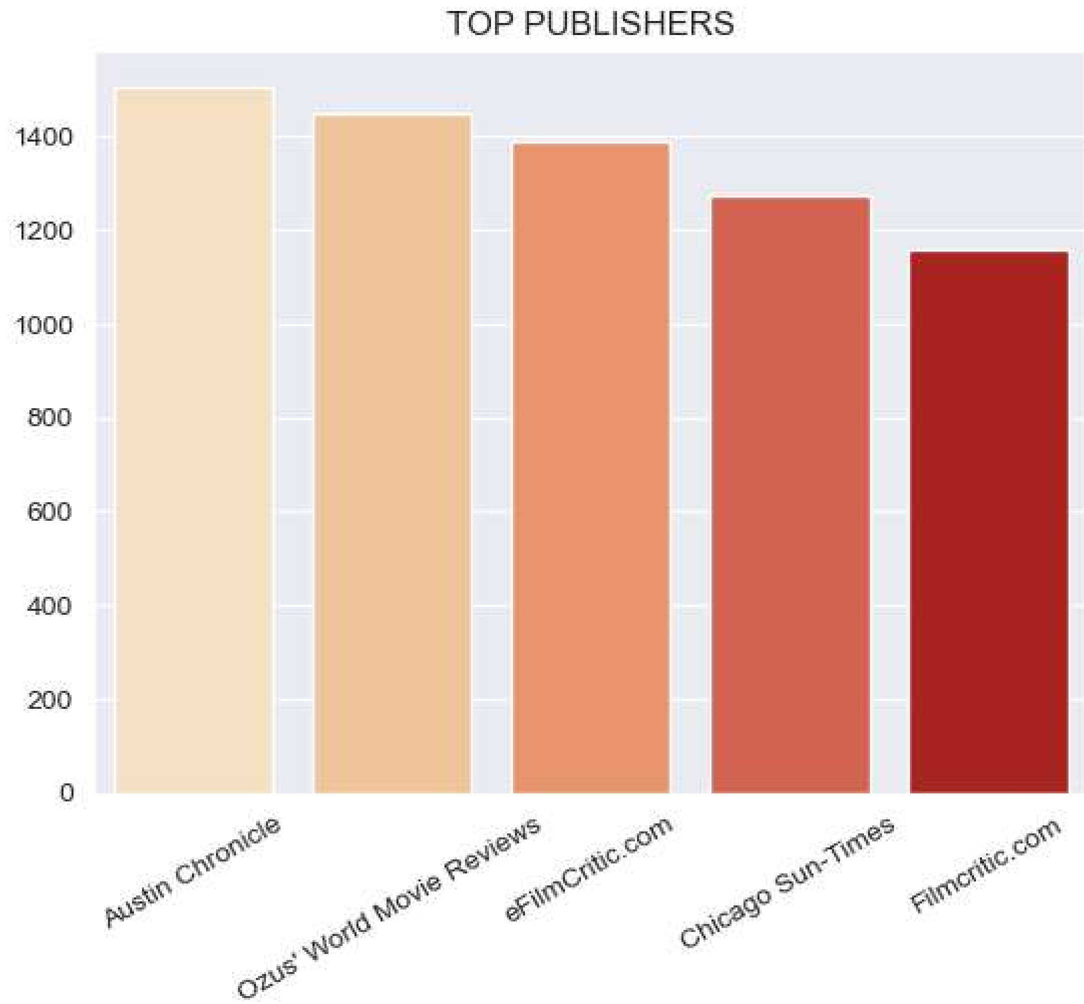
In [83]:
```
Merged_df= pd.merge(rv_df, budgets) #Merging datasets with common columns
Merged_df.head()
```

Out[83]:

	id	review	fresh	critic	top_critic	publisher	date	score	outof	release_date
0	3	A distinctly gallows take on contemporary fina...	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018	3	5	Jun 7, 2019
1	3	A distinctly gallows take on contemporary fina...	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018	3	5	Nov 21, 2018
2	3	A distinctly gallows take on contemporary fina...	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018	3	5	Apr 8, 2005
3	3	A distinctly gallows take on contemporary fina...	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018	3	5	Oct 5, 2018
4	3	A distinctly gallows take on contemporary fina...	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018	3	5	Feb 18, 2005

In [ ]:

In [77]:
```
publisher= Merged_df["publisher"].value_counts().head().index.tolist()
frequncy=list(Merged_df["publisher"].value_counts().nlargest(5))
sns.barplot(x=publisher, y = frequncy, data = Merged_df, palette='OrRd')
plt.xticks(rotation = 30);
plt.title("TOP PUBLISHERS");
```



Summary

The Visualizations above inform how microsoft will begin their movie-Production journey. With the insights we can be sure that Microsoft wil get it right in data analysis

In [ ]: