Final Project Submission

Please fill out:

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- Student pace: Full time
- Scheduled project review date/time: December 10th @ 2:30 PM PST
- Instructor name: Mark Barbour
- Blog post URL:https://medium.com/@namitarana

Movie Industry Analysis for Microsoft

This proposal contains an analysis of various movie data in order to inform executive decision making regarding Microsoft's movie studio who is just about to venture into the movie making business. Specifically, it provides actionable insights with respect to what types of films the studio should focus on creating with the goal of maximizing box office performance. Initial descriptive analysis of box office performance and other movie data shows that box office earnings are related to genre, runtime,rating,release month of the movie and the language preferred by its target audience.

Business Problem:

Microsoft is interested in developing original video content to remain competitive in the tech world by creating a movie studio. This project will examine the movie industry to provide a set of recommendations on where to get started.

Several data sets have been explored, but the following are included in the results:

- Box Office Mojo
- IMDB
- TheMovieDB

Let's import the required libraries:

Questions Our Data Can Answer

- Which Genres are gathering the highest worldwide gross?
- Which languages have generated the maximum reneue: domestically & worldwide?
- Does release month of a movie matter?
- Does votes for a movie count? How does an average_voted movie perform at Box Office?

In [325…
```
#importing the libraries.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Collecting Data:

Importing all the dataset we will be using for this project:

Box Office Mojo:

This dataframe could be useful in determining which movie generated the highest gross earnings and for which year. It can also help us in understanding which studio is producing the movie's with highest gross earnings.

Imdb Data:

For this analysis imdb.title.basics is used which provides data about runtime,genre,original title.

Tmdb Data:

This data can provide us with great insight about which language is the most preferred one by audiences and which language movie has the most voter_count.

In [326…
```
#Import all data files
bom_movie_gross = pd.read_csv('zippedData/bom.movie_gross.csv.gz')
imdb_title_basics = pd.read_csv('zippedData/imdb.title.basics.csv.gz')
tmdb_data = pd.read_csv('zippedData/tmdb.movies.csv.gz')
```

In [327…

```
#bom_movie information
bom_movie_gross.info()
bom_movie_gross.head()
```

```
<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[327…

	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

In [328…

```
#imdb_basics information
imdb_title_basics.info()
imdb_title_basics.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
```

Out[328…

	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

In [329…

```
#tmdb data information
tmdb_data.info()
tmdb_data.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         26517 non-null  int64  
 1   genre_ids          26517 non-null  object 
 2   id                 26517 non-null  int64  
 3   original_language  26517 non-null  object 
 4   original_title     26517 non-null  object 
 5   popularity         26517 non-null  float64
 6   release_date       26517 non-null  object 
 7   title              26517 non-null  object 
 8   vote_average       26517 non-null  float64
 9   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
```

Out[329…

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16

Primary Interest

Our primary interest lies in finding the factors that contribute to high Domestic and worldwide gross I will limit the scope of my analysis to five factors.

- Genre
- Runtime
- Language
- Average_vote count
- Release Month

Data Preparation:

My goal for this step is to merge the datasets into a final datset which I will be using for analysis of the the factors that can help Microsoft in taking the business decisions before investing in the movie industry.

We will start with cleaning the first dataset bom_movie_gross and get it ready to merge:

In [330…

```
# Convert domestic gross value data type to int
#bom_movie_gross['domestic_gross'] = bom_movie_gross['domestic_gross'].fil
bom_movie_gross['foreign_gross'] = bom_movie_gross['foreign_gross'].str.re
bom_movie_gross['foreign_gross'] = bom_movie_gross['foreign_gross'].astype
```

In [331…

```
bom_movie_gross
```

Out[331…

	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
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

In [332…

```
#Replacing the null values in foreign gross with 0:
#as it may have not been released worlwide
bom_movie_gross['foreign_gross'].fillna(0, inplace=True)
bom_movie_gross['domestic_gross'].fillna(0,inplace=True)
```

In [333…

```
display(bom_movie_gross.info())
bom_movie_gross
```

```
<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  3387 non-null   float64
 3   foreign_gross   3387 non-null   float64
 4   year            3387 non-null   int64  
dtypes: float64(2), int64(1), object(2)
memory usage: 132.4+ KB
None
```

Out[333…

	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
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	0.0	2018
3383	Edward II (2018 re-release)	FM	4800.0	0.0	2018
3384	El Pacto	Sony	2500.0	0.0	2018
3385	The Swan	Synergetic	2400.0	0.0	2018
3386	An Actor Prepares	Grav.	1700.0	0.0	2018

3387 rows × 5 columns

Preparing the imdb dataset:

We will be splitting the Imdb datset column genres into discrete genre columns.

In [334…

```
#We will separate the genres column into discrete columns:
imdb_title_basics[['genre_1','genre_2','genre_3']] = imdb_title_basics['ge
imdb_title_basics.head(20)
```

Out[334…

	tconst	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	

3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,I
5	tt0111414	A Thin Life	A Thin Life	2018	75.0	C
6	tt0112502	Bigfoot	Bigfoot	2017	NaN	Horror
7	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,C
8	tt0139613	O Silêncio	O Silêncio	2012	NaN	Documentary,
9	tt0144449	Nema aviona za Zagreb	Nema aviona za Zagreb	2012	82.0	Bic
10	tt0146592	Pál Adrienn	Pál Adrienn	2010	136.0	
11	tt0154039	So Much for Justice!	Oda az igazság	2010	100.0	
12	tt0159369	Cooper and Hemingway: The True Gen	Cooper and Hemingway: The True Gen	2013	180.0	Docur
13	tt0162942	Children of the Green Dragon	A zöld sárkány gyermekei	2010	89.0	
14	tt0170651	T.G.M. - osvoboditel	T.G.M. - osvoboditel	2018	60.0	Docur
15	tt0176694	The Tragedy of Man	Az ember tragédiája	2011	160.0	Animation,Drama,
16	tt0187902	How Huang Fei-hong Rescued the Orphan from the...	How Huang Fei-hong Rescued the Orphan from the...	2011	NaN	
17	tt0192528	Heaven & Hell	Reverse Heaven	2018	104.0	
18	tt0230212	The Final Journey	The Final Journey	2010	120.0	
19	tt0247643	Los pájaros se van con la muerte	Los pájaros se van con la muerte	2011	110.0	Drama,N

In [335…

```
#Drop the genres and tconst column:

imdb_title_basics.isna().sum()
imdb_title_basics.rename(columns={'primary_title': 'title'}, inplace=True)
imdb_title_basics
```

Out[335…

	tconst	title	original_title	start_year	runtime_minutes	g
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,I
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,I
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	I
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,I
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fa
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	I
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Docum
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Co
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Docum

146144 rows × 9 columns

Feature engineering:

Merge the imdb & bom movie gross datasets.

In [336…

```
#Merged data set of bom_movie_gross & imdb_title_basics
imdb_bom_dataset = pd.merge(imdb_title_basics, bom_movie_gross, on='title'
imdb_bom_dataset
```

Out[336…

	tconst	title	original_title	start_year	runtime_minutes	ge
0	tt0315642	Wazir	Wazir	2016	103.0	Action,Crime,D
1	tt0337692	On the Road	On the Road	2012	124.0	Adventure,Drama,Rom
2	tt2404548	On the Road	On the Road	2011	90.0	D
3	tt3872966	On the Road	On the Road	2013	87.0	Docume
4	tt4339118	On the Road	On the Road	2014	89.0	D
...	...	...	...	...	...	
3361	tt8404272	How Long Will I Love U	Chao shi kong tong ju	2018	101.0	Rom
3362	tt8427036	Helicopter Eela	Helicopter Eela	2018	135.0	D
3363	tt8851262	Spring Fever	Spring Fever	2019	NaN	Comedy,H
3364	tt9078374	Last Letter	Ni hao, Zhihua	2018	114.0	Drama,Rom
3365	tt9151704	Burn the Stage: The Movie	Burn the Stage: The Movie	2018	84.0	Documentary,M

3366 rows × 13 columns

Preparing tmdb dataset

Dropping the genre_ids and orginial column as it doesn't add any value to the data:

In [337…

```
#Dropping the genre_ids:
tmdb_data.drop(columns =['genre_ids','id'], axis = 1,inplace = True)
tmdb_data
```

Out[337…

	Unnamed: 0	original_language	original_title	popularity	release_date	t
0	0	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter the Dea Hallows: Pa
1	1	en	How to Train Your Dragon	28.734	2010-03-26	How to T Your Dra
2	2	en	Iron Man 2	28.515	2010-05-07	Iron Ma
3	3	en	Toy Story	28.005	1995-11-22	Toy St
4	4	en	Inception	27.920	2010-07-16	Incep
...	...	...	...	...	...	
26512	26512	en	Laboratory Conditions	0.600	2018-10-13	Laborat Conditi
26513	26513	en	_EXHIBIT_84xxx_	0.600	2018-05-01	_EXHIBIT_84x
26514	26514	en	The Last One	0.600	2018-10-01	The Last (
26515	26515	en	Trailer Made	0.600	2018-06-22	Trailer M
26516	26516	en	The Church	0.600	2018-10-05	The Chu

26517 rows × 8 columns

Preparing the final dataset:

After merging and cleaning the 2 datasets now I mergerd the imdb_bom_dataset with tmdb_data. This final_movie_dataset will be used for the analysis.

In [338…

```
#Our final dataset
final_movie_dataset = pd.merge( tmdb_data,imdb_bom_dataset)
final_movie_dataset
```

Out[338...

	Unnamed: 0	original_language	original_title	popularity	release_date	title	vote_
0	1	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
1	2	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
2	4	en	Inception	27.920	2010-07-16	Inception	
3	7	en	Toy Story 3	24.445	2010-06-17	Toy Story 3	
4	8	en	Despicable Me	23.673	2010-07-09	Despicable Me	
...	...	...	...	...	...	...	
3193	24778	sv	Unga Astrid	4.734	2018-11-23	Becoming Astrid	
3194	24916	it	Nico, 1988	3.789	2018-07-04	Nico, 1988	
3195	25037	en	Maria by Callas	3.184	2018-11-02	Maria by Callas	
3196	25148	en	Bilal: A New Breed of Hero	2.707	2018-02-02	Bilal: A New Breed of Hero	
3197	25189	es	La Boda de Valentina	2.550	2018-02-09	La Boda de Valentina	

3198 rows × 19 columns

In [339...

```
#Splitting the final_movie_dataset column release_month into 'year','Month
final_movie_dataset[['year','Month','Date']] = final_movie_dataset['release
final_movie_dataset
```

Out[339…

	Unnamed: 0	original_language	original_title	popularity	release_date	title	vote_
0	1	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
1	2	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
2	4	en	Inception	27.920	2010-07-16	Inception	
3	7	en	Toy Story 3	24.445	2010-06-17	Toy Story 3	
4	8	en	Despicable Me	23.673	2010-07-09	Despicable Me	
...	...	...	...	...	...	...	
3193	24778	sv	Unga Astrid	4.734	2018-11-23	Becoming Astrid	
3194	24916	it	Nico, 1988	3.789	2018-07-04	Nico, 1988	
3195	25037	en	Maria by Callas	3.184	2018-11-02	Maria by Callas	
3196	25148	en	Bilal: A New Breed of Hero	2.707	2018-02-02	Bilal: A New Breed of Hero	
3197	25189	es	La Boda de Valentina	2.550	2018-02-09	La Boda de Valentina	

3198 rows × 21 columns

In [340…

```
#Dropping columns: 'tconst', start_year
final_movie_dataset.drop(['tconst','start_year'],axis = 1,inplace = True)
```

In [341…

```
#COnverting month value to respective month name:
import calendar
final_movie_dataset['Month'] = final_movie_dataset['Month'].astype(int)
final_movie_dataset['Month'] = final_movie_dataset['Month'].apply(lambda x
final_movie_dataset
```

Out[341…

	Unnamed: 0	original_language	original_title	popularity	release_date	title	vote_
0	1	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
1	2	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
2	4	en	Inception	27.920	2010-07-16	Inception	
3	7	en	Toy Story 3	24.445	2010-06-17	Toy Story 3	
4	8	en	Despicable Me	23.673	2010-07-09	Despicable Me	
...	...	...	...	...	...	...	
3193	24778	sv	Unga Astrid	4.734	2018-11-23	Becoming Astrid	
3194	24916	it	Nico, 1988	3.789	2018-07-04	Nico, 1988	
3195	25037	en	Maria by Callas	3.184	2018-11-02	Maria by Callas	
3196	25148	en	Bilal: A New Breed of Hero	2.707	2018-02-02	Bilal: A New Breed of Hero	
3197	25189	es	La Boda de Valentina	2.550	2018-02-09	La Boda de Valentina	

3198 rows × 19 columns

Calculating the total Worldwide Gross

Calculate the total worldwide gross by adding the values of domestic & foreign gross.

In [342…

```
#calculate the total worldwide gross
final_movie_dataset['worldwide_gross'] = final_movie_dataset['domestic_gros
final_movie_dataset['Average_gross'] = final_movie_dataset['worldwide_gross
final_movie_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3198 entries, 0 to 3197
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         3198 non-null   int64  
 1   original_language  3198 non-null   object 
 2   original_title     3198 non-null   object 
 3   popularity         3198 non-null   float64
 4   release_date       3198 non-null   object 
 5   title              3198 non-null   object 
 6   vote_average       3198 non-null   float64
 7   vote_count         3198 non-null   int64  
 8   runtime_minutes    3010 non-null   float64
 9   genres             3152 non-null   object 
 10  genre_1            3152 non-null   object 
 11  genre_2            2376 non-null   object 
 12  genre_3            1598 non-null   object 
 13  studio             3198 non-null   object 
 14  domestic_gross     3198 non-null   float64
 15  foreign_gross      3198 non-null   float64
 16  year               3198 non-null   object 
 17  Month              3198 non-null   object 
 18  Date               3198 non-null   object 
 19  worldwide_gross    3198 non-null   float64
 20  Average_gross      3198 non-null   float64
dtypes: float64(7), int64(2), object(12)
memory usage: 549.7+ KB
```

Merging Series to compute results.

In [343…

```
#merging the worldwide gross,title, highest worldiwde gross:
final_movie_dataset.info()
final_movie_dataset1 = final_movie_dataset[['genres', 'title','worldwide_g
final_movie_dataset1
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3198 entries, 0 to 3197
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         3198 non-null   int64  
 1   original_language  3198 non-null   object 
 2   original_title     3198 non-null   object 
 3   popularity         3198 non-null   float64
 4   release_date       3198 non-null   object 
 5   title              3198 non-null   object 
 6   vote_average       3198 non-null   float64
 7   vote_count         3198 non-null   int64  
 8   runtime_minutes    3010 non-null   float64
 9   genres             3152 non-null   object 
 10  genre_1            3152 non-null   object 
 11  genre_2            2376 non-null   object 
 12  genre_3            1598 non-null   object 
 13  studio             3198 non-null   object 
 14  domestic_gross     3198 non-null   float64
 15  foreign_gross      3198 non-null   float64
 16  year               3198 non-null   object 
 17  Month              3198 non-null   object 
 18  Date               3198 non-null   object 
 19  worldwide_gross    3198 non-null   float64
 20  Average_gross      3198 non-null   float64
dtypes: float64(7), int64(2), object(12)
memory usage: 549.7+ KB
```

Out[343…

	genres	title	worldwide_gross
0	Action,Adventure,Animation	How to Train Your Dragon	4.949000e+08
1	Action,Adventure,Sci-Fi	Iron Man 2	6.239000e+08
2	Action,Adventure,Sci-Fi	Inception	8.283000e+08
3	Adventure,Animation,Comedy	Toy Story 3	1.067000e+09
4	Animation,Comedy,Family	Despicable Me	5.431000e+08
...	...	...	...
3193	Biography,Drama	Becoming Astrid	1.200000e+05
3194	Biography,Drama,Music	Nico, 1988	7.330000e+04
3195	Biography,Documentary,Music	Maria by Callas	1.300000e+06
3196	Action,Adventure,Animation	Bilal: A New Breed of Hero	2.191000e+06
3197	Comedy,Romance	La Boda de Valentina	2.800000e+06

3198 rows × 3 columns

Getting a list of all genres.

In [344…

```
#Get a list of all the genres:
#By splitting each genre using ',' as the delimiter and stacking the rows (
final_movie_dataset2 = final_movie_dataset.set_index('title').genres.str.sp
final_movie_dataset2.columns = ['title', 'genres']
final_movie_dataset2.head()
```

Out[344…

	title	genres
0	How to Train Your Dragon	Action
1	How to Train Your Dragon	Adventure
2	How to Train Your Dragon	Animation
0	Iron Man 2	Action
1	Iron Man 2	Adventure

Merging the 2 dataframes:

final_movie_dataset1 & final_movie_dataset2

In [345…

```
Genre_popularity = pd.merge( final_movie_dataset1,final_movie_dataset2).dro
Genre_popularity
```

Out[345…

	genres	title	worldwide_gross
0	Comedy	Grown Ups	271400000.0
1	Documentary	Unstoppable	167800000.0
81	Horror	The Town	154000000.0
82	Comedy	Remember Me	56100000.0
84	Thriller	Remember Me	56100000.0
...	...	...	...
3471	Drama	The Bookshop	11500000.0
3472	Drama	The Children Act	17548000.0
3473	Horror	Beast	800000.0
3474	Comedy	An Actor Prepares	1700.0
3475	Drama	What They Had	260000.0

526 rows × 3 columns

Generating Visualizations

Genre generating the highest Worldwide Gross.

In [346…

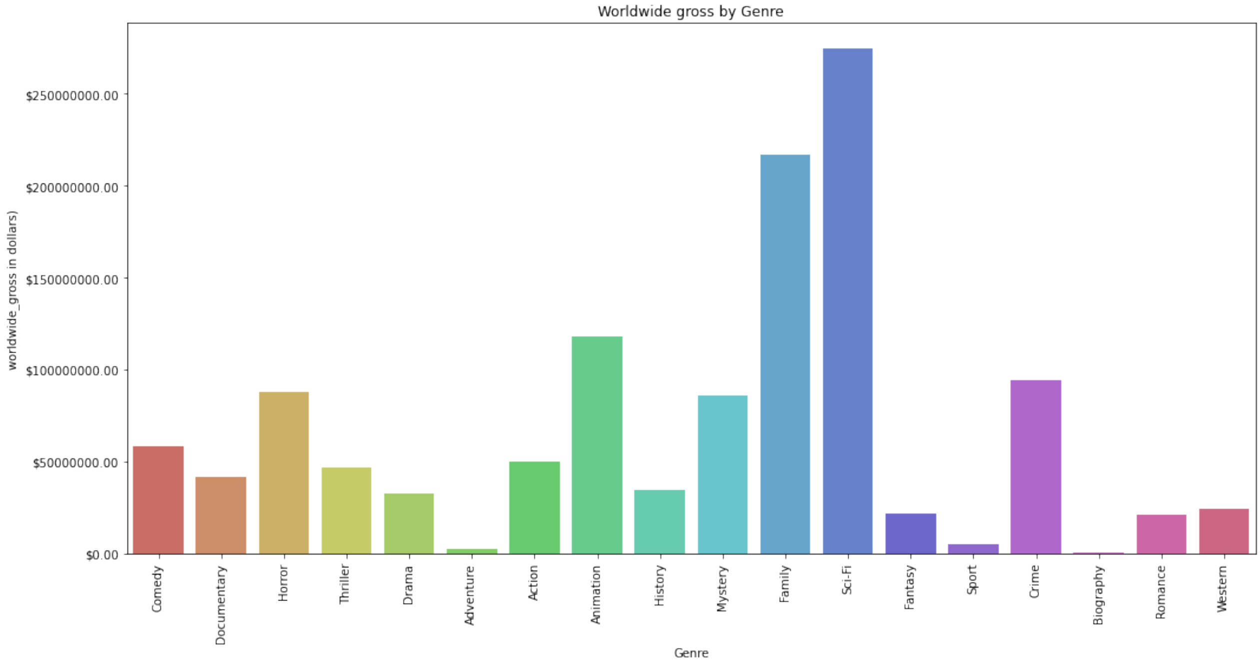
```
#Creating a bar plot to show which Genre is creating the highest worldwide
Genre_popularity_fig, Genre_popularity_ax = plt.subplots(nrows=1, ncols=1,

sns.barplot(ax= Genre_popularity_ax, x='genres', y='worldwide_gross', data=
Genre_popularity_ax.set_xlabel('Genre')
Genre_popularity_ax.set_ylabel('worldwide_gross in dollars)')
Genre_popularity_ax.set_title('Worldwide gross by Genre')
Genre_popularity_ax.yaxis.set_major_formatter('${x:1.2f}')
Genre_popularity_ax.tick_params(axis='x', rotation=90)

plt.tight_layout()

plt.savefig('Images/Genre_popularity_fig.png', dpi=200)

plt.show()
```



Conclusion

- SCi-Fi seems to be gathering the highest worldwide gross.

Creating new dataframes.

In [347…

```
#creating a new dataframe for year
year_df = final_movie_dataset[['year','title']]
year_df
```

Out[347…

	year	title
0	2010	How to Train Your Dragon
1	2010	Iron Man 2
2	2010	Inception
3	2010	Toy Story 3
4	2010	Despicable Me
...	...	...
3193	2018	Becoming Astrid
3194	2018	Nico, 1988
3195	2018	Maria by Callas
3196	2018	Bilal: A New Breed of Hero
3197	2018	La Boda de Valentina

3198 rows × 2 columns

In [348…

```
#Merging the two:
popular_genre = pd.merge(Genre_popularity,year_df,)
popular_genre
```

Out[348…

	genres	title	worldwide_gross	year
0	Comedy	Grown Ups	271400000.0	2010
1	Documentary	Unstoppable	167800000.0	2010
2	Documentary	Unstoppable	167800000.0	2010
3	Documentary	Unstoppable	167800000.0	2010
4	Documentary	Unstoppable	167800000.0	2010
...	...	...	...	...
1927	Horror	Beast	800000.0	2018
1928	Horror	Beast	800000.0	2018
1929	Horror	Beast	800000.0	2018
1930	Comedy	An Actor Prepares	1700.0	2018
1931	Drama	What They Had	260000.0	2018

1932 rows × 4 columns

In [349…

```
#Checking for languagecounts:
final_movie_dataset['original_language'].value_counts().en
```

Out[349… 2862

Language most preferred by audiences Worldwide & Domestic.

Language generating maximum Worldwide Gross.

In [350…

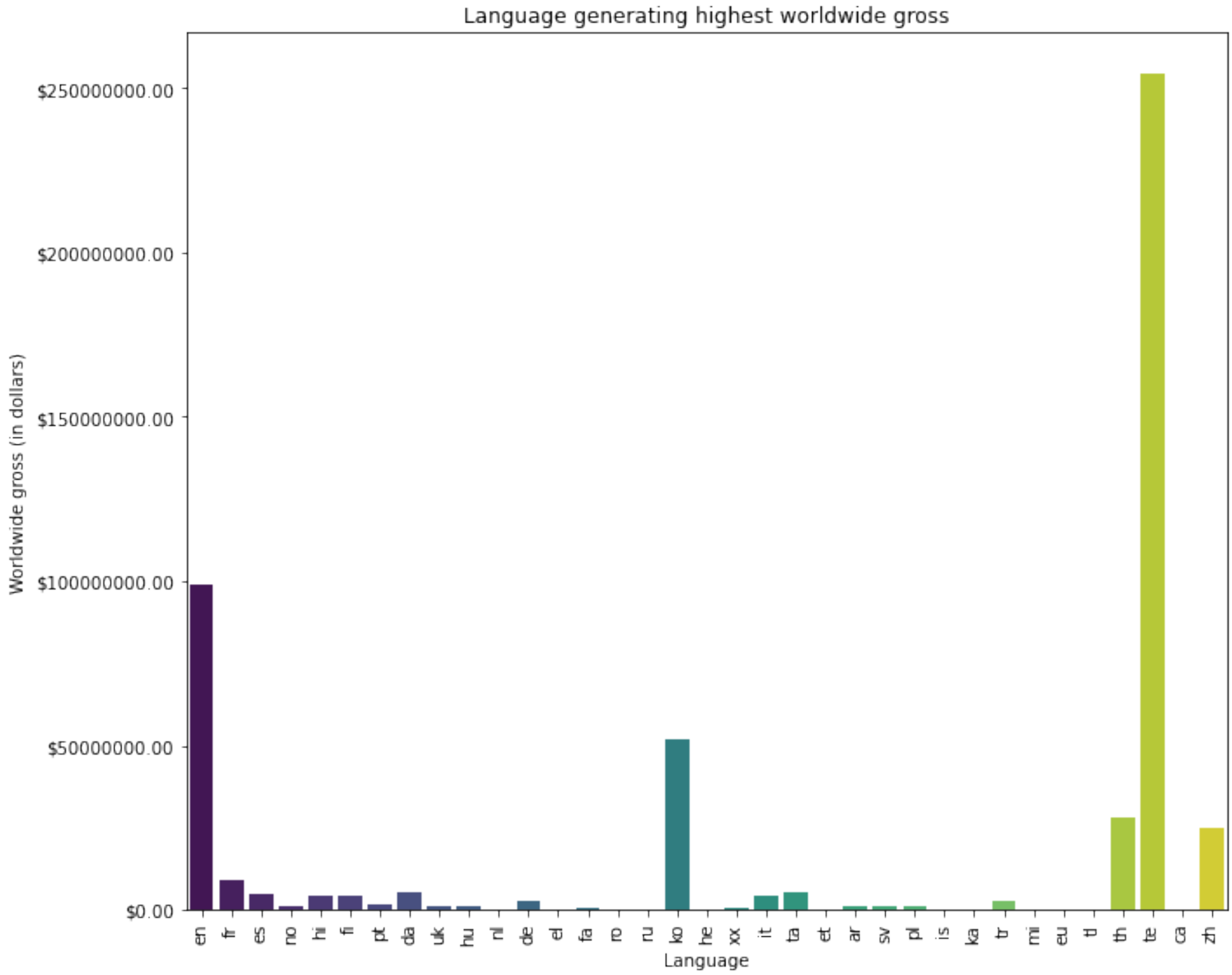
```
#Language generating maximum worldwide gross:
Language_preferred_fig, final_movie_dataset_ax = plt.subplots(nrows=1, ncol

sns.barplot(ax= final_movie_dataset_ax, x='original_language', y='worldwide
final_movie_dataset_ax.set_xlabel('Language')
final_movie_dataset_ax.set_ylabel('Worldwide gross (in dollars)')
final_movie_dataset_ax.set_title('Language generating highest worldwide gro
final_movie_dataset_ax.yaxis.set_major_formatter('${x:1.2f}')
final_movie_dataset_ax.tick_params(axis='x', rotation=90)

plt.tight_layout()

plt.savefig('Images/Language_Worldwide.png', dpi=200)

plt.show()
```



Conclusion:

Language generating maximum WorldWIde Gross is 'te' which stands for 'Telegu'.

Language generating maximum Domestic Gross.

In [351…

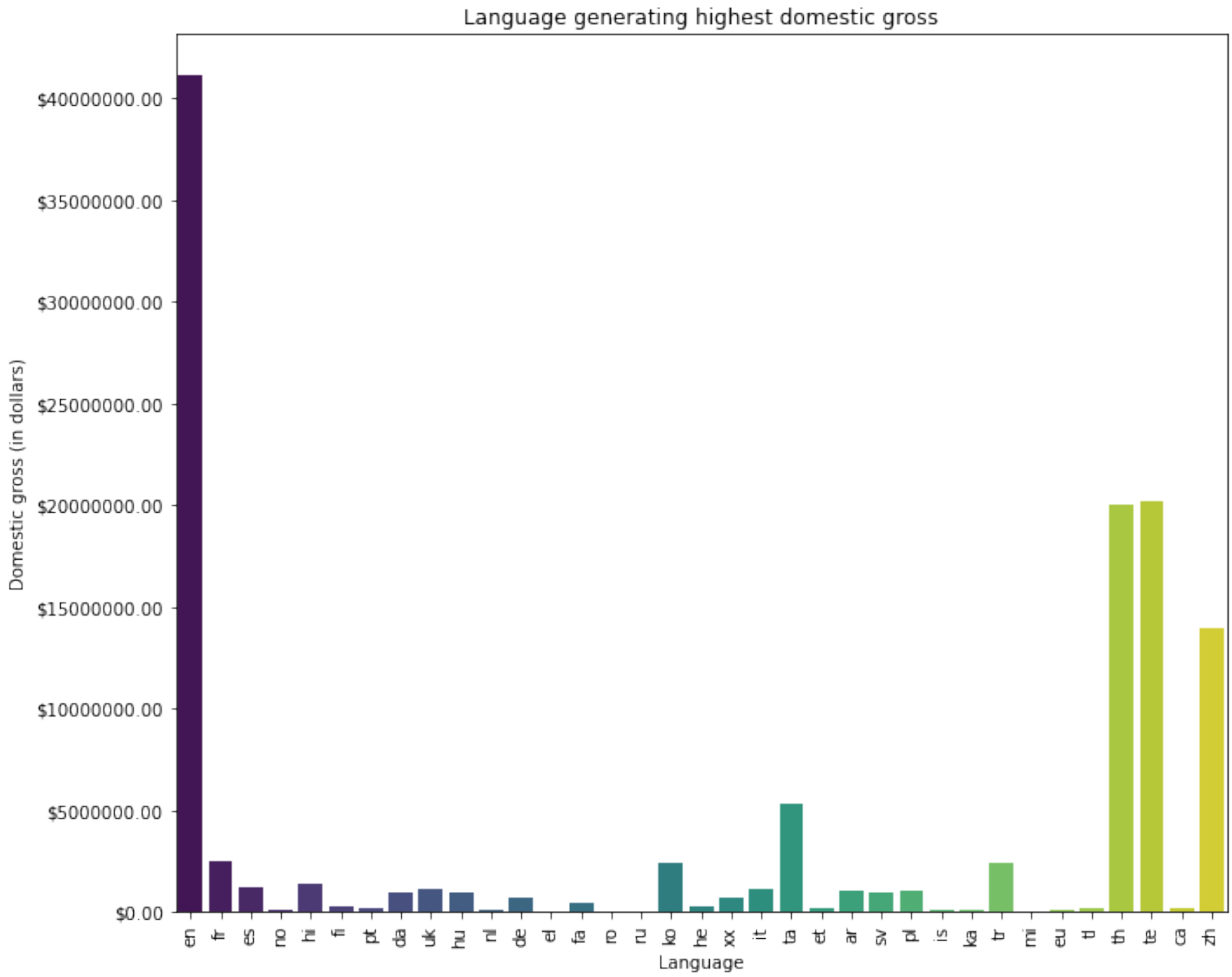
```
#Language generating highest domestic gross:
Language_preferred_fig, final_movie_dataset_ax = plt.subplots(nrows=1, ncol

sns.barplot(ax= final_movie_dataset_ax, x='original_language', y='domestic_
final_movie_dataset_ax.set_xlabel('Language')
final_movie_dataset_ax.set_ylabel('Domestic gross (in dollars)')
final_movie_dataset_ax.set_title('Language generating highest domestic gros
final_movie_dataset_ax.yaxis.set_major_formatter('${x:1.2f}')
final_movie_dataset_ax.tick_params(axis='x', rotation=90)

plt.tight_layout()

plt.savefig('Images/Domestic_gross_language.png', dpi=200)

plt.show()
```



Conclusion:

Language generating maximum Domestic Gross is 'en' which stands for 'English'.

Relationship between runtime of movies and their popularity:

Find how popularity of a movie and it's runtime are related.

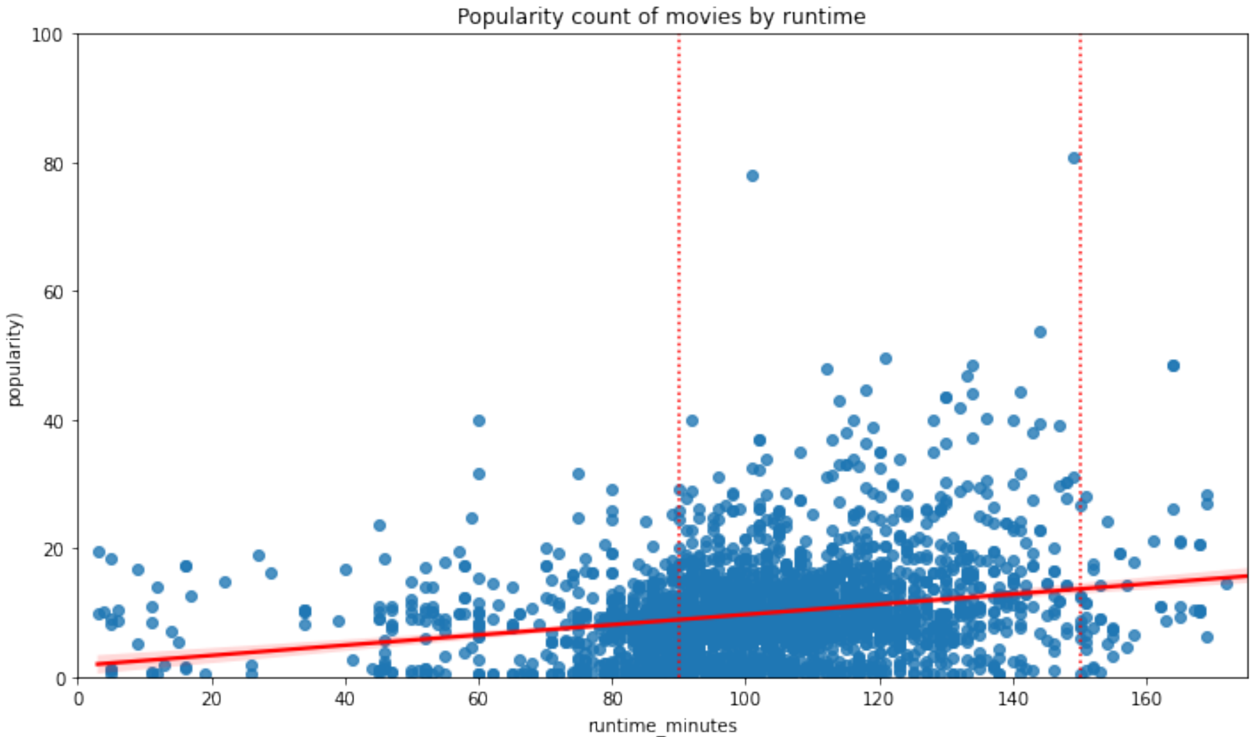
In [352…

```
# Create a scatter plot to visualize the correlation between runtime & popu
fig, ax = plt.subplots(figsize=(10,6))

sns.regplot(ax=ax, x='runtime_minutes', y='popularity', data=final_movie_da
ax.set_xlabel('runtime_minutes')
ax.set_ylabel('popularity)')
ax.set_title('Popularity count of movies by runtime')
ax.set(xlim=(0,175))
ax.set(ylim=(0,100))
ax.axvline(90, color='red', ls=':')
ax.axvline(150, ls=':', color ='red')
plt.tight_layout()

plt.savefig('Images/Popularity count of movies by runtime.png', dpi=150)

plt.show()
```



Conclusion:

There seems to be a close correlation between popularity of a movie and it's runtime. 100-120 seems to be an ideal range.

Most profitable year for the movie industry.

In [353…

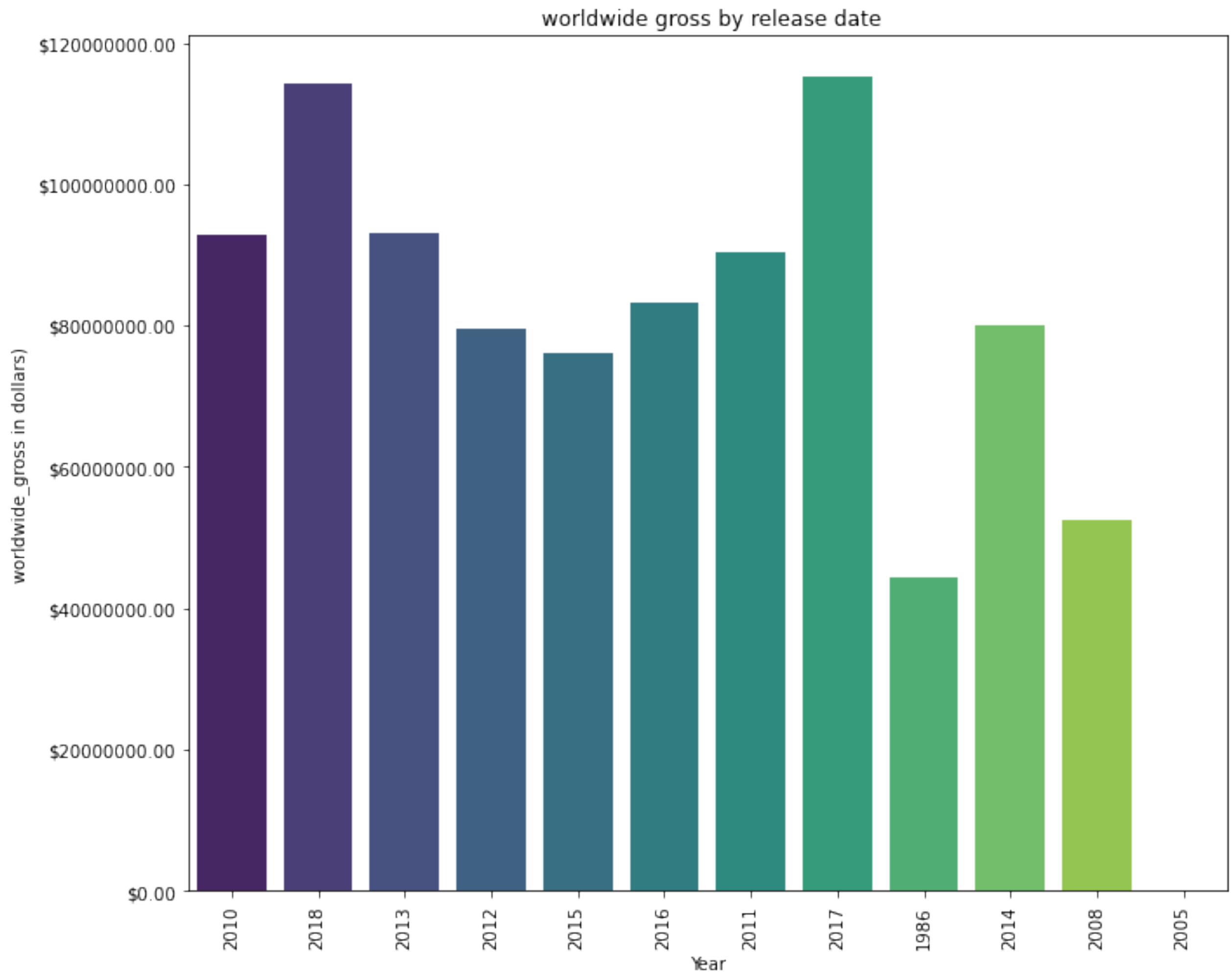
```
#create a bar plot to check which year was the most profitable one
Releasedate_fig, final_movie_dataset_ax = plt.subplots(nrows=1, ncols=1, fi

sns.barplot(ax= final_movie_dataset_ax, x='year', y='worldwide_gross', data
final_movie_dataset_ax.set_xlabel('Year')
final_movie_dataset_ax.set_ylabel('worldwide_gross in dollars)')
final_movie_dataset_ax.set_title(' worldwide gross by release date')
final_movie_dataset_ax.yaxis.set_major_formatter('${x:1.2f}')
final_movie_dataset_ax.tick_params(axis='x', rotation=90)

plt.tight_layout()

plt.savefig('Images/Profitable_Year.png', dpi=200)

plt.show()
```



Conclusion:

The plot above concludes 2017 was the most profitable year for the business.

Release Month that gathers the maximum Worldwide gross.

In [354…

```
#release_month = final_movie_dataset.groupby('Month')[['worldwide_gross']]
#release_month.head()
```

In [355…

```
#Sorting out the months by values.
final_movie_dataset.sort_values(['worldwide_gross'], ascending = False)
release_month = final_movie_dataset.groupby(['Month'])['worldwide_gross'].r
release_month = release_month.reset_index()

release_month
```

Out[355…

	Month	worldwide_gross
0	Apr	5.212346e+07
1	Aug	6.775637e+07
2	Dec	1.050386e+08
3	Feb	9.262619e+07
4	Jan	5.958827e+07
5	Jul	1.255259e+08
6	Jun	1.244365e+08
7	Mar	6.601934e+07
8	May	1.083706e+08
9	Nov	1.415103e+08
10	Oct	4.537215e+07
11	Sep	7.792712e+07

Updating the Month column by names

In [356…

```
#updating cell values to month names instead of numbers
month_names = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Se
month_nums = list(release_month['Month'])
months_dict = dict(zip(month_nums, month_names))
release_month['Month'] = release_month['Month'].map(months_dict)
release_month
```

Out[356…

	Month	worldwide_gross
0	Jan	5.212346e+07
1	Feb	6.775637e+07
2	Mar	1.050386e+08
3	Apr	9.262619e+07
4	May	5.958827e+07
5	Jun	1.255259e+08
6	Jul	1.244365e+08
7	Aug	6.601934e+07
8	Sep	1.083706e+08
9	Oct	1.415103e+08
10	Nov	4.537215e+07
11	Dec	7.792712e+07

In [357…

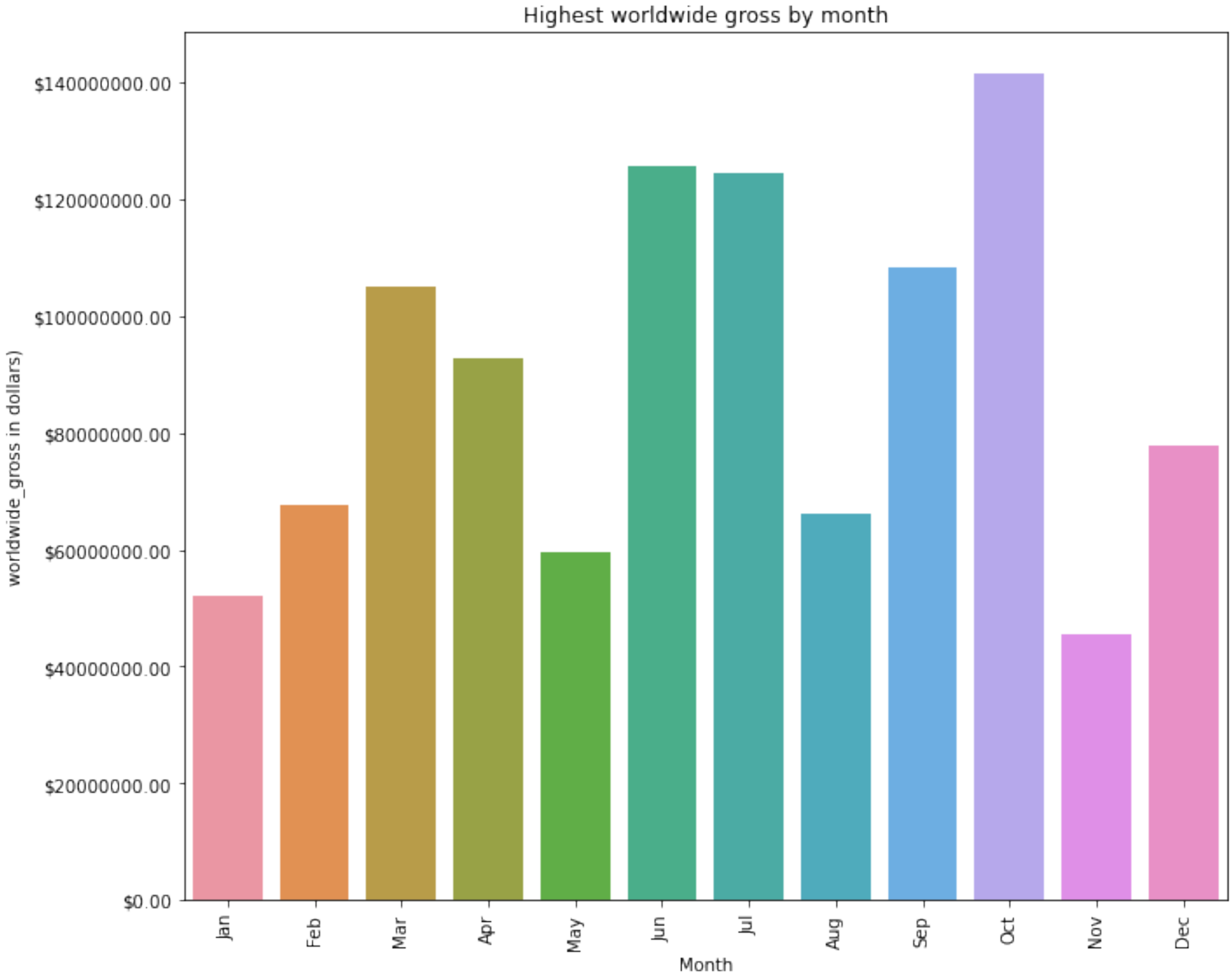
```
#Create a plot to understand which month gathers the maximum Gross earning:
Release_month_fig, release_month_ax = plt.subplots(nrows=1, ncols=1, figsi:

sns.barplot(ax= release_month_ax, x='Month', y='worldwide_gross', data= re]
release_month_ax.set_xlabel('Month')
release_month_ax.set_ylabel('worldwide_gross in dollars)')
release_month_ax.set_title('Highest worldwide gross by month')
release_month_ax.yaxis.set_major_formatter('${x:1.2f}')
release_month_ax.tick_params(axis='x', rotation=90)

plt.tight_layout()

plt.savefig('Images/releasemonth_gross.png', dpi=200)

plt.show()
```



Conclusion:

November is the month that gathers the maximum Worldwide Gross.

Dependency of Worldwide Gross on Average vote count.

In [358…

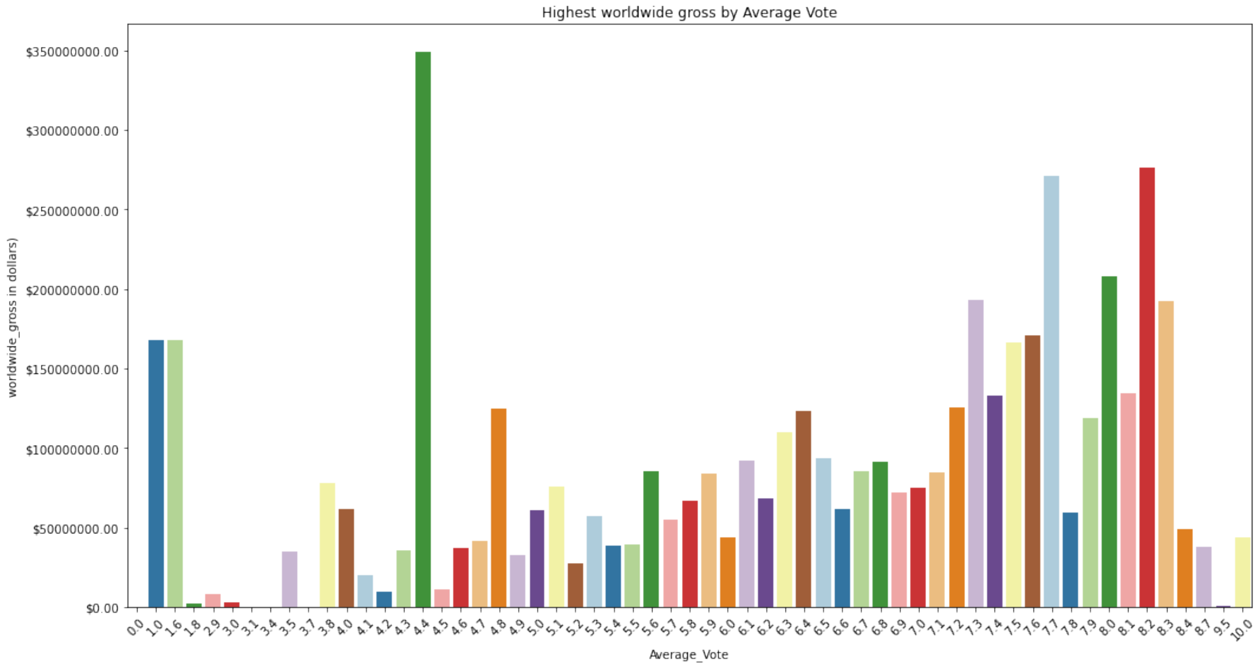
```
Release_month_fig, final_movie_dataset_ax = plt.subplots(nrows=1, ncols=1,

sns.barplot(ax= final_movie_dataset_ax, x='vote_average', y='worldwide_gros
final_movie_dataset_ax.set_xlabel('Average_Vote')
final_movie_dataset_ax.set_ylabel('worldwide_gross in dollars)')
final_movie_dataset_ax.set_title('Highest worldwide gross by Average Vote'
final_movie_dataset_ax.yaxis.set_major_formatter('${x:1.2f}')
final_movie_dataset_ax.tick_params(axis='x', rotation=45)

plt.tight_layout()

plt.savefig('Images/Average_vote.png', dpi=200)

plt.show()
```



Conclusion:

Average_Vote count 4.4 seems to gather maximum Worldwide Gross which concludes that a movie averagely rated also does well.

Evaluation:

This analysis provides five recommendations for Microsoft's new movie studio in order to take calculated business decisions. Knowing the demography of your target audience is crucial,here is the list thatcan be taken into consideration.

- **Make movies of the highest grossing genres.** The movies that could be categorized in the Sci Fi, family & animation, tended to have higher box office earnings. Microsoft should focus on these genres the most.
- **Runtime should not be overlooked.** In general, movies that had longer runtimes also had higher box office earnings.However, once movies surpassed a runtime threshold, box office performance was hampered. Microsoft should focus on making movies within that sweet spot between 100 and 120 minutes.
- **Average vote count for a movie is important**,the above analysis shows even with an average rating the movie can perform well in generating profit.
- **Release Month for a movie everything.** The data showed that the movies released in a particular month tend to have higher box office earnings. Microsoft should prioritize making quality, well reviewed movies that can score at least a 6 on IMDb's scale.
- **Knowing the language preferred by your audience domestically and worldwide.** This plays a pivotal role in deciding how much audience you can gather, which will help the movie make profit.

While the past years of data show that this should be a good recipe for success, one limitation is that we are currently in a global pandemic, which has negatively affected many facets of the global economy. The visualizations above displaying movie gross over time clearly show a rise movie gross till year(2018). However, since movies take quite a bit of time to produce, the expectation is that the market will be trending in the right direction by the time a future movie would be released.

Next Steps

Sourcing more data and conducting further analysis could provide Microsoft more insight on what type of movies to create. Including more data, for example data on movie budgets, distribution location, release date, actors, directors, and more, could provide much more detailed insight into how to make profitable movies.