Movie Data Analysis For Microsoft

Overview

This project analyzes a number of movie datasets as included in the Box Office Mojo, IMDB, Rotten Tomatoes, TheMovieDB, and The Numbers in order to better understand the success of movies within other studios. The goal of this analysis is to then assess and help create business recommendations to present to Microsoft, as they attempt to open and manage their own movie studio.

Business Understanding

The movie dataset that I will present has a variety of metrics that I will use to better explain and extrapolate the potential success of Microsoft Movie Studios. Microsoft may be able to create a movie studio to be both profitable and successful, while also ensuring that they remain competitive in the entertainment landscape. Doing so will allow Microsoft to expand their client base, as well as grow their resources in expanding into a different service than what is already offered. Using the different movie databases as datasets, I will describe different industry patterns, techniques, and cycles to help keep Microsoft competitive in all their services.

Data Understanding

In order to help Microsoft create their movie studio, I have used some of the most established movie datasets available. Every movie has their own subsequent data to inform us about its profitability, success.

Data Manipulation and Analysis with pandas

-Formatting the data

-Cleaning the data

-Exploring the metric that will help us give our recommendation to Microsoft

-Give our recommendation base on our findings

Data Preparation

In [1]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

EDA for bom_movie_gross

In [2]:
```python
#  Creating df for
bom_movie_gross_df = pd.read_csv("zippedData/bom.movie_gross.csv.gz")
bom_movie_gross_df.head()
```

Out[2]:

	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 [3]:
```python
bom_movie_gross_df.shape
```

Out[3]:
```
(3387, 5)
```

In [4]:
```python
bom_movie_gross_df.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   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

In [5]:
```python
#Checking the number of studios
bom_movie_gross_df.studio.value_counts()
```

Out[5]:
```
IFC           166
Uni.          147
WB            140
Fox           136
Magn.         136
             ... 
E1              1
PI              1
ELS             1
PalT            1
Synergetic      1
Name: studio, Length: 257, dtype: int64
```

In [6]:
```
#domestic_gross count
bom_movie_gross_df.domestic_gross.value_counts().sum()
```

Out[6]:
```
3359
```

In [7]:
```
#foreign_gross count
bom_movie_gross_df.foreign_gross.value_counts().sum()
```

Out[7]:
```
2037
```

In [8]:
```
#checking for Nan
bom_movie_gross_df.isna().sum()
```

Out[8]:
```
title               0
studio              5
domestic_gross     28
foreign_gross    1350
year                0
dtype: int64
```

In [9]:
```
#checking the columns
bom_movie_gross_df.columns
```

Out[9]:
```
Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year'], dtype='ob
ject')
```

EDA for tn_movie_budget_df

In [10]:
```
#  Creating df for
tn_movie_budget_df = pd.read_csv("zippedData/tn.movie_budgets.csv.gz")
tn_movie_budget_df.head()
```

Out[10]:

	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

In [11]:
```
tn_movie_budget_df.shape
```

Out[11]:
```
(5782, 6)
```

In [12]:
```python
tn_movie_budget_df.columns
```

Out[12]:
```
Index(['id', 'release_date', 'movie', 'production_budget', 'domestic_gross',
       'worldwide_gross'],
      dtype='object')
```

Data cleaning for the columns

In [13]:
```python
#cleaning for production_budget
tn_movie_budget_df['production_budget'] = tn_movie_budget_df['production_budget']
tn_movie_budget_df['production_budget'] = tn_movie_budget_df['production_budget']
```

In [14]:
```python
tn_movie_budget_df['production_budget'].astype(float)
```

Out[14]:
```
0       425000000.0
1       410600000.0
2       350000000.0
3       330600000.0
4       317000000.0
           ...
5777         7000.0
5778         6000.0
5779         5000.0
5780         1400.0
5781         1100.0
Name: production_budget, Length: 5782, dtype: float64
```

In [15]:
```python
#cleaning for domestic_gross
tn_movie_budget_df['domestic_gross'] = tn_movie_budget_df['domestic_gross'].str.r
tn_movie_budget_df['domestic_gross'] = tn_movie_budget_df['domestic_gross'].str.r
```

In [16]:
```python
tn_movie_budget_df['domestic_gross'].astype(float)
```

Out[16]:
```
0       760507625.0
1       241063875.0
2        42762350.0
3       459005868.0
4       620181382.0
           ...
5777            0.0
5778        48482.0
5779         1338.0
5780            0.0
5781       181041.0
Name: domestic_gross, Length: 5782, dtype: float64
```

In [17]:
```python
#cleaning for worldwide_gross
tn_movie_budget_df['worldwide_gross'] = tn_movie_budget_df['worldwide_gross'].str
tn_movie_budget_df['worldwide_gross'] = tn_movie_budget_df['worldwide_gross'].str
```

In [18]:
```python
tn_movie_budget_df['worldwide_gross'].astype(float)
```

Out[18]:
```
0       2.776345e+09
1       1.045664e+09
2       1.497624e+08
3       1.403014e+09
4       1.316722e+09
            ...
5777    0.000000e+00
5778    2.404950e+05
5779    1.338000e+03
5780    0.000000e+00
5781    1.810410e+05
Name: worldwide_gross, Length: 5782, dtype: float64
```

In [19]:
```python
#checking df after cleaning
tn_movie_budget_df.head()
```

Out[19]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747

In [20]:
```python
# Checking for Nah
tn_movie_budget_df.isna().sum()
```

Out[20]:
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

In [21]:
```python
# Extracting the year and month from the release_date
tn_movie_budget_df['release_date'] = pd.to_datetime(tn_movie_budget_df['release_d
```

In [22]:
```python
tn_movie_budget_df['year'] = tn_movie_budget_df['release_date'].dt.year
```

In [23]:
```
tn_movie_budget_df.dtypes
```

Out[23]:
```
id                            int64
release_date         datetime64[ns]
movie                        object
production_budget            object
domestic_gross               object
worldwide_gross              object
year                          int64
dtype: object
```

In [24]:
```
tn_movie_budget_df['month'] = tn_movie_budget_df['release_date'].dt.month
```

In [25]:
```
tn_movie_budget_df.head()
```

Out[25]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	year	month
0	1	2009-12-18	Avatar	425000000	760507625	2776345279	2009	12
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011	5
2	3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019	6
3	4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015	5
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017	12

In [26]:
```
tn_movie_budget_df.shape
```

Out[26]:
```
(5782, 8)
```

In [27]:
```
tn_movie_budget_df.dtypes
```

Out[27]:
```
id                            int64
release_date         datetime64[ns]
movie                        object
production_budget            object
domestic_gross               object
worldwide_gross              object
year                          int64
month                         int64
dtype: object
```

changing the types of domestic_gross, production_budget, worldwide_gross from Object to int

In [28]:
```python
tn_movie_budget_df['domestic_gross'] = tn_movie_budget_df['domestic_gross'].astyp
```

In [29]:
```python
tn_movie_budget_df['production_budget'] = tn_movie_budget_df['production_budget']
```

In [30]:
```python
tn_movie_budget_df['worldwide_gross'] = tn_movie_budget_df['worldwide_gross'].ast
```

In [31]:
```python
# rechecking the types
tn_movie_budget_df.dtypes
```

Out[31]:
```
id                            int64
release_date         datetime64[ns]
movie                        object
production_budget             int64
domestic_gross                int64
worldwide_gross               int64
year                          int64
month                         int64
dtype: object
```

Feature Engineering

Calculating the ROI (return on investment so I can plot them against some metrics like month of release, Domestic, and Genres

Extracted Month feature, created avg_profit_per_month, ww_profit to better evaluate the ROI in my analysis

In [32]:
```python
#domestic_gross

profit_ret_on_investment = tn_movie_budget_df['domestic_gross']  - tn_movie_budge
```

In [33]:
```python
profit_ret_on_investment
```

Out[33]:
```
0       335507625
1      -169536125
2      -307237650
3       128405868
4       303181382
          ...
5777        -7000
5778        42482
5779        -3662
5780        -1400
5781       179941
Length: 5782, dtype: int64
```

In [34]:
```python
#adding the roi column to our df
tn_movie_budget_df['profit_ret_on_investment'] = tn_movie_budget_df['domestic_gro
```

In [35]:
```python
tn_movie_budget_df.head()
```

Out[35]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	year	month
0	1	2009-12-18	Avatar	425000000	760507625	2776345279	2009	12
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011	5
2	3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019	6
3	4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015	5
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017	12

In [36]:
```python
tn_movie_budget_df.shape
```

Out[36]:
```
(5782, 9)
```

In [37]:
```python
tn_movie_budget_df['month'].value_counts()
```

Out[37]:
```
12    745
10    573
8     496
9     493
11    486
6     479
3     470
4     454
7     440
5     407
2     392
1     347
Name: month, dtype: int64
```

In [38]:
```python
#Domestic mean
avg_profit_per_month = tn_movie_budget_df.groupby('month').mean()['profit_ret_on_
```

In [39]:
```python
#Domestic mean
avg_profit_per_month
```

Out[39]:
```
month
1     3.106128e+06
2     7.368234e+06
3     7.790907e+06
4     3.525568e+06
5     1.956275e+07
6     2.272879e+07
7     1.818188e+07
8     6.612111e+06
9     1.336985e+06
10    4.030837e+06
11    1.558112e+07
12    1.284921e+07
Name: profit_ret_on_investment, dtype: float64
```

In [40]:
```python
#creating a column for the worldwide profit
tn_movie_budget_df['ww_profit'] = tn_movie_budget_df['worldwide_gross']  - tn_mov
```

In [41]:
```python
tn_movie_budget_df.head()
```

Out[41]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	year	month
0	1	2009-12-18	Avatar	425000000	760507625	2776345279	2009	12
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011	5
2	3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019	6
3	4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015	5
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017	12

In [42]:
```python
#finding the mean/avg of the  ww profit(calculating the avg worldwide profit per
avg_ww_profit = tn_movie_budget_df.groupby('month').mean()['ww_profit']
```

In [43]:
```
#Worldwide mean
avg_ww_profit
```

Out[43]:
```
month
1     2.572033e+07
2     4.349811e+07
3     4.985129e+07
4     3.611743e+07
5     1.151328e+08
6     9.942391e+07
7     9.841746e+07
8     3.542232e+07
9     2.488078e+07
10    2.907190e+07
11    9.314157e+07
12    6.844157e+07
Name: ww_profit, dtype: float64
```

SQL Data

The below line should only need to be run once. It unzips the SQL data, since SQLite doesn't work with zipped data.**

The below line should only need to be run once. It unzips the SQL data, since SQLite doesn't work with zipped data.

In [44]:
```
! unzip -n zippedData/im.db.zip
```

```
Archive:  zippedData/im.db.zip
```

In [45]:
```
import sqlite3
```

In [46]:
```
conn = sqlite3.connect("im.db")
```

EDA for movie_basics

In [47]:
```
#im_db_df
movie_basics_df = pd.read_sql("SELECT * FROM movie_basics;", conn)
movie_basics_df.head()
```

Out[47]:

	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

In [48]:
```
movie_basics_df.shape
```

Out[48]:
```
(146144, 6)
```

In [49]:
```
movie_basics_df.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   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

In [50]:
```
movie_basics_df.columns
```

Out[50]:
```
Index(['movie_id', 'primary_title', 'original_title', 'start_year',
       'runtime_minutes', 'genres'],
      dtype='object')
```

In [51]:
```
# crating a new columns
movie_basics_df['genre_list'] = movie_basics_df['genres'].str.split(',')
```

In [52]:
```
tn_movie_budget_df.head()
```

Out[52]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	year	month
0	1	2009-12-18	Avatar	425000000	760507625	2776345279	2009	12
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011	5
2	3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019	6
3	4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015	5
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017	12

In [53]:
```
movie_basics_df.head()
```

Out[53]:

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

Merging Datasets

In [54]:
```
#creating a new table by merging my two df
df_base = pd.merge(movie_basics_df, tn_movie_budget_df, left_on=['primary_title',
```

In [55]:
```
df_base.head()
```

Out[55]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	gen
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	[A Anir Co
1	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	[Adve Co [
2	tt0365907	A Walk Among the Tombstones	A Walk Among the Tombstones	2014	114.0	Action,Crime,Drama	[A [
3	tt0369610	Jurassic World	Jurassic World	2015	124.0	Action,Adventure,Sci-Fi	[A Adve
4	tt0376136	The Rum Diary	The Rum Diary	2011	119.0	Comedy,Drama	[Co [

In [56]:
```
df_base.drop(columns=['genre_list'])
```

Out[56]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	i
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	2
1	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	3
2	tt0365907	A Walk Among the Tombstones	A Walk Among the Tombstones	2014	114.0	Action,Crime,Drama	6
3	tt0369610	Jurassic World	Jurassic World	2015	124.0	Action,Adventure,Sci-Fi	3
4	tt0376136	The Rum Diary	The Rum Diary	2011	119.0	Comedy,Drama	1
...	...	...	...	...	...	...	.
1542	tt8364368	Crawl	Crawl	2019	NaN	Action,Horror,Thriller	1
1543	tt8408152	Detention	Detention	2012	NaN	Horror	4
1544	tt8632862	Fahrenheit 11/9	Fahrenheit 11/9	2018	128.0	Documentary	2
1545	tt8852552	Icarus	Icarus	2010	78.0	Thriller	9
1546	tt9024106	Unplanned	Unplanned	2019	106.0	Biography,Drama	3

1547 rows × 16 columns

In [ ]:

In [57]:
```
#making  a copy of my df_base

df = df_base.copy()
```

In [58]:
```
#using explode() function to separe the genres
df_explode = df.explode('genre_list')
```

In [59]:
```
df_explode.head()
```

Out[59]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	genr
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	A
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	Anin
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	Co
1	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	Adve
1	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	Co

In [60]:
```
df_explode.groupby('genre_list')
```

Out[60]: <pandas.core.groupby.generic.DataFrameGroupBy object at 0x7f89a28b6880>

In [61]:
```
df_explode.shape
```

Out[61]: (3887, 17)

In [62]:
```
df_explode.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3887 entries, 0 to 1546
Data columns (total 17 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   movie_id                  3887 non-null   object
 1   primary_title             3887 non-null   object
 2   original_title            3887 non-null   object
 3   start_year                3887 non-null   int64
 4   runtime_minutes           3846 non-null   float64
 5   genres                    3881 non-null   object
 6   genre_list                3881 non-null   object
 7   id                        3887 non-null   int64
 8   release_date              3887 non-null   datetime64[ns]
 9   movie                     3887 non-null   object
 10  production_budget         3887 non-null   int64
 11  domestic_gross            3887 non-null   int64
 12  worldwide_gross           3887 non-null   int64
 13  year                      3887 non-null   int64
 14  month                     3887 non-null   int64
 15  profit_ret_on_investment  3887 non-null   int64
 16  ww_profit                 3887 non-null   int64
dtypes: datetime64[ns](1), float64(1), int64(9), object(6)
memory usage: 546.6+ KB
```

In [63]:
```
#copy of my df_explode

df = df_explode.copy()
```

In [64]:
```
df.head()
```

Out[64]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	genr
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	/
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	Anin
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	Co
1	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	Adve
1	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	Co

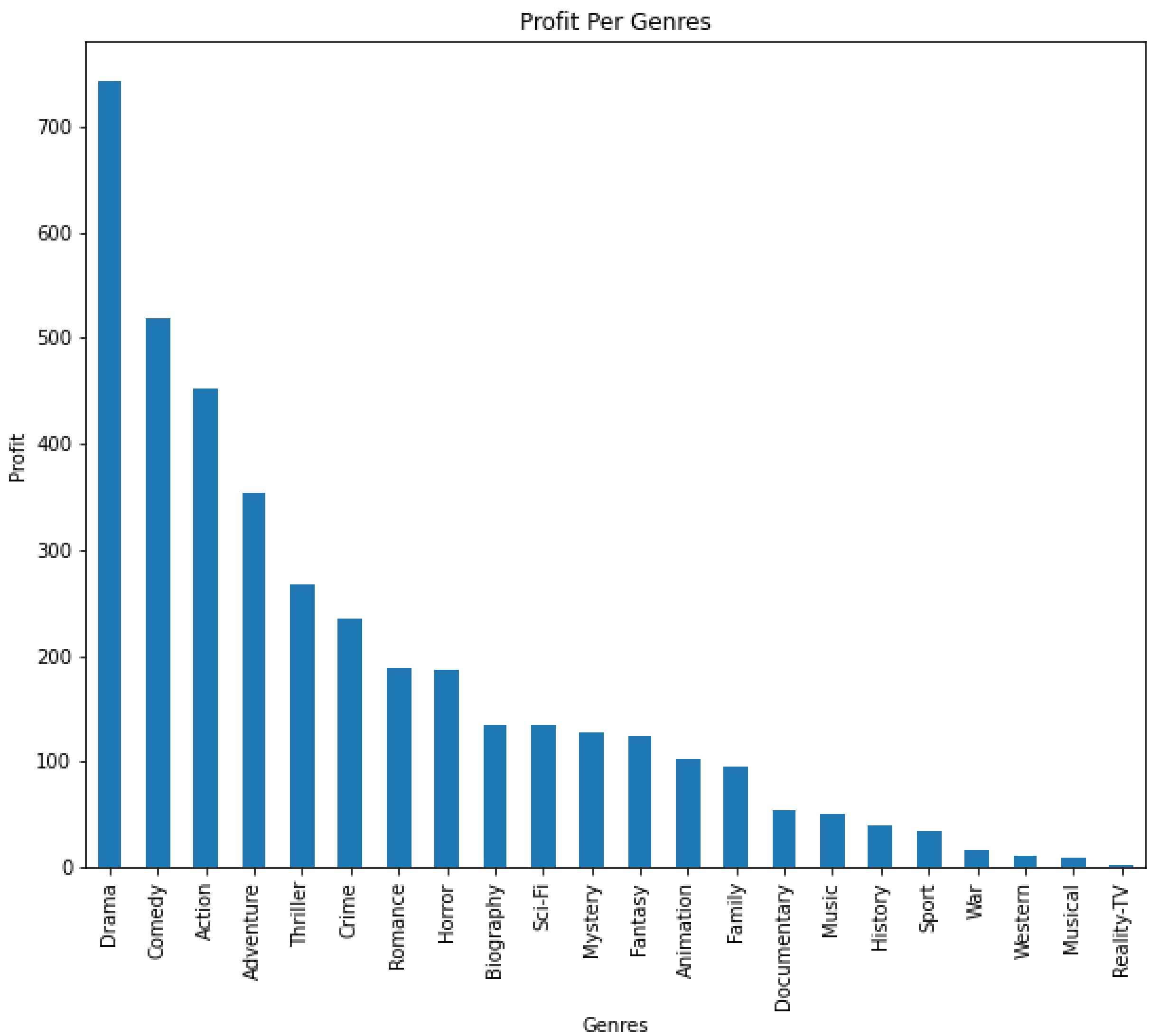
In [65]:
```python
roi_genres_df = df[['genre_list', 'profit_ret_on_investment']]
roi_genres_df.head(25)
```

Out[65]:

	genre_list	profit_ret_on_investment
0	Action	-45000000
0	Animation	-45000000
0	Comedy	-45000000
1	Adventure	-32763162
1	Comedy	-32763162
1	Drama	-32763162
2	Action	-1982315
2	Crime	-1982315
2	Drama	-1982315
3	Action	437270625
3	Adventure	437270625
3	Sci-Fi	437270625
4	Comedy	-31890185
4	Drama	-31890185
5	Comedy	14338224
5	Family	14338224
6	Comedy	-300000
6	Drama	-300000
6	Romance	-300000
7	Adventure	-59178064
7	Animation	-59178064
7	Comedy	-59178064
8	Action	-201941321
8	Adventure	-201941321
8	Sci-Fi	-201941321

Analysis

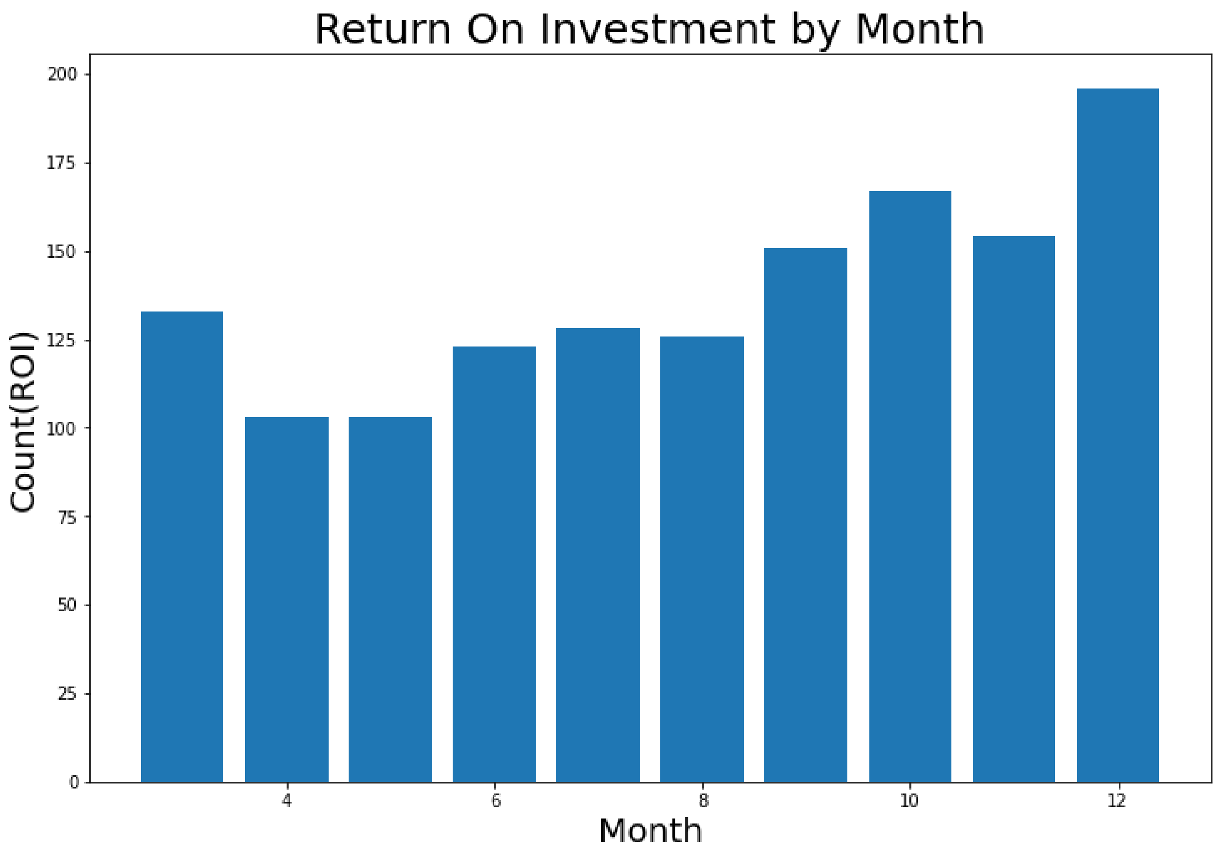
In [66]:
```
#Data for 1st recommendation - Genre with the highest roi
roi_genres_df['genre_list'].value_counts().plot.bar(figsize=(10,8)).set(
    title='Profit Per Genres',
    xlabel='Genres',
    ylabel='Profit'
);
```



In [67]:
```
#Data for my 2nd recommendation
release_month = df_base.groupby('month').count()['profit_ret_on_investment'].sort
```

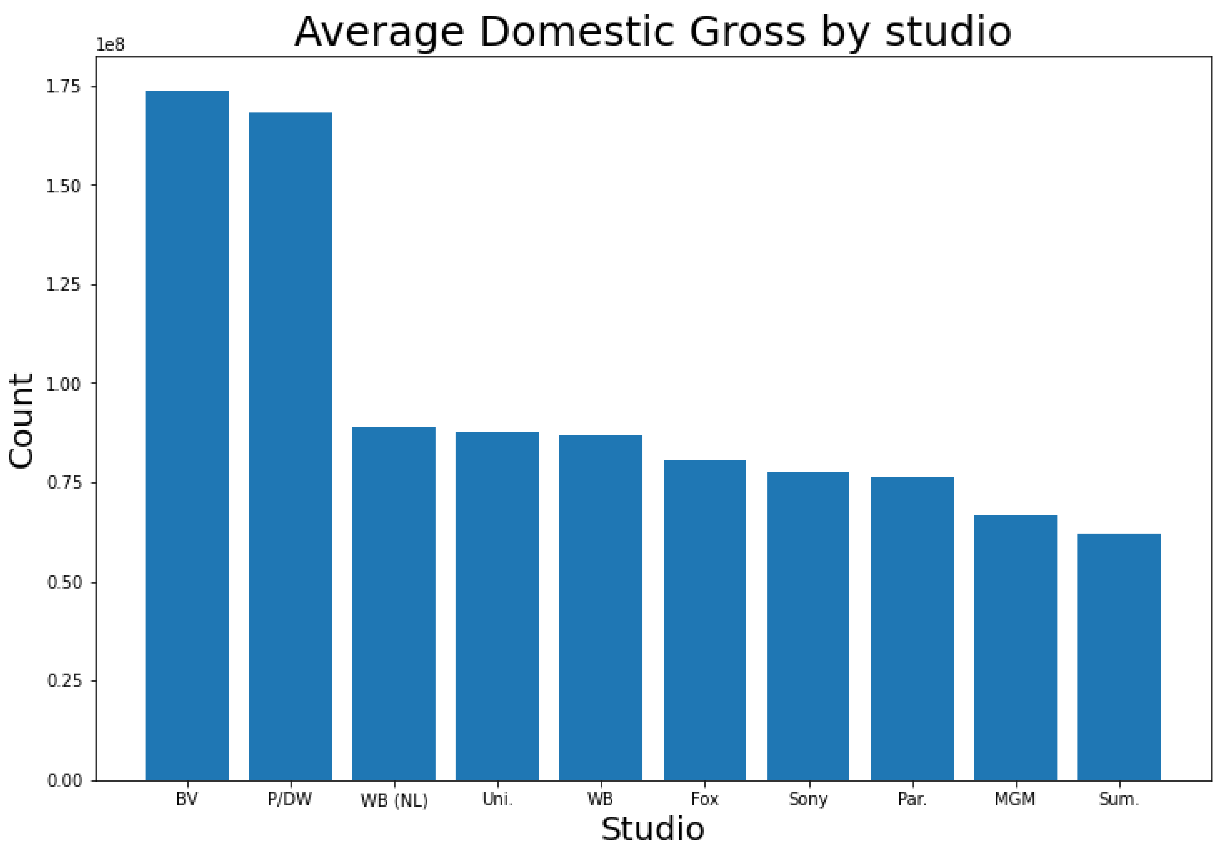
In [68]:
```
fig, ax = plt.subplots(figsize=(12,8))
ax.bar(release_month.index, release_month.values)
plt.title('Return On Investment by Month',  fontsize=25)# release month with high
plt.xlabel('Month', fontsize=20)
plt.ylabel('Count(ROI)', fontsize=20)
ax.set;

#plt.savefig("./images/Return_On_Investment_by_Month.png", dpi=150)
```



In [69]:
```
#Data for my 3rd recommendation
studios = bom_movie_gross_df.groupby('studio').mean()['domestic_gross'].sort_valu
```

In [70]:
```
fig, ax = plt.subplots(figsize=(12,8))
ax.bar(studios.index, studios.values)
plt.title('Average Domestic Gross by studio',  fontsize=25)
plt.xlabel('Studio', fontsize=20)
plt.ylabel('Count', fontsize=20)
ax.set;
```



Recommendations

This analysis leads to three reommendations taht will guide Microsoft Stackholders in creating their Movie studio with better profitability at the sam time satisfy thhis audience.

#1 - Genre with the highest Return On Investment (Profit per genres)

Based on the data in the df_profit_per_genres and the genrelist_df along with the visualization, we recommend that Microsoft focuses on specific genres over others in order to maximize overall profitability. As we can infer, certain genres very clearly perform better in the Box Office, such as Drama and Comedy.

#2 - Strong release timelines both domestically and worldwide (avg_profit_per_month,avg_ww_profit)/Release Month with the highest Return On Investment

The return on investment (ROI) domestically versus worldwide speaks to different patterns. Domestically, the ROI directly draws a line between American culture, holidays, and traditions. From that, we can see that the most profitable months are February, March, August, and October. Respectively, that speaks to Valentine's Day and Black History Month, Women's Month, the end of summertime, and Halloween. Because these are such strong times in American culture, it only makes sense that they create the most amount of profit for studios.

#3 - Best Performing Studio vs Production Budget

Regarding the information amassed above, we can infer that the best performing film studios, Buena Vista Walt Disney, Paramount DreamWorks, and Warner Brothers New Line Cinema have the highest returns due to their budgets. I do believe that Microsoft can compete with these studios as they have a similar capital, therefore is able to bring similar budgets to their films.

Next Steps

Further analyses could yeild addition insights to further inform Microsoft's Studio Efforts such as:

Target international audience

Worldwide, the ROI follows traditional quarterly film release schedules.

- Quarter 1 generally finds post-Holiday movies that are less critically acclaimed. This is usually where we find romance, Black-led, and women-led movies. Because these categories are less emphasized in the foreign markets, they typically don't get much attention outside of the domestic market.

- Quarter 2 is normally seen as Blockbuster season for action movies. The season overall starts with romantic comedies, as the industry exits Q1, and moves into comedies and action movies. Moreover, this is where we predominantly see the superhero season begin, with the more mature films coming in this quarter.

- Quarter 3 more often than not is where the family friendly films come out as this where theatres start to see nore traffic worldwide. This is also peak superhero season as we see more age appropriate content released for the masses. We also see the child friendly comedies phase out and go into more dramatic action movies.

- Quarter 4 sees "Oscars" release season, especially with dramatic films. This is also routinely where and when Holiday movies are released worldwide to align with the holiday season. Occasionally, overflow Blockbusters are released at this time to prevent flooding the theaters with the same type of movies in other quarters.

Quarters 2 through 4 are more likely to have at least one Blockbuster release in order to keep the quarter most profitable.

Create Original Content

- Focus original content on most popular genres
- Find new writers to introduce new voices
- Forgo limits imposed by other studios

Venture into Different Media

- Create television programming
- Open the door for family friendly and childrens content
- Take ownership of least performing genres

In [71]:
```
conn.close()
```

In [ ]:
```

```