Microsoft Studio Project

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- **Blog post URL: [https://github.com/S-Kagwi/dsc-phase-1-project-v2-4.git (https://github.com/S-Kagwi/dsc-phase-1-project-v2-4.git)](https://github.com/S-Kagwi/dsc-phase-1-project-v2-4.git)**

Business Problem

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

Project Overview

For this project, we will use exploratory data analysis to generate insights for a business stakeholder. The data used was obtained from three renowned movie websites:

Box Office Mojo (https://www.boxofficemojo.com/ (https://www.boxofficemojo.com/)) - bom.movie_gross.csv

IMDB (https://www.imdb.com/ (https://www.imdb.com/)) - im.db

The Numbers (https://www.the-numbers.com/)- (https://www.the-numbers.com/)-) tn.movie_budgets.csv

According to the provided datasets, there are different metrics that can be used to gauge the perfomance of a movie. In this analysis, we shall use the following metrics:

Movie Ratings

Return on Investment

Domestic Gross Revenue

Worldwide Gross Revenue

Number of Votes

We start by importing librararies that we will use for data preparation and analysis.

In [1]:
```
#pandas for data analysis
import pandas as pd

#NumPy for numerical analysis
import numpy as np

# matplotlib and Seaborn for data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Sqlite3 for database management
import sqlite3
```

1. Bom Movie CSV Dataset

Data Understanding

In [2]:
```
#we first load the given dataset and view the data
bom_movie = pd.read_csv("bom.movie_gross.csv")
bom_movie
```

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
...	...	...	...	...	...
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 [3]:
```
#we check the shape of the data
bom_movie.shape
```

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

In [4]:
```
#We use bom_movie.info to get a concise summary of the dataframe.
bom_movie.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]:
```
#We use .describe() to calculate the basic summary statistics for each (
bom_movie.describe()
```

Out[5]:

	domestic_gross	year
count	3.359000e+03	3387.000000
mean	2.874585e+07	2013.958075
std	6.698250e+07	2.478141
min	1.000000e+02	2010.000000
25%	1.200000e+05	2012.000000
50%	1.400000e+06	2014.000000
75%	2.790000e+07	2016.000000
max	9.367000e+08	2018.000000

Data Cleaning

In [6]:
```
#we check the column labels of the Dataframe
bom_movie.columns
```

Out[6]:
```
Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year'],
dtype='object')
```

In [7]:
```
#we check for duplicated values
bom_movie.duplicated().sum()
```

Out[7]:
```
0
```

In [8]:
```
#we check for any missing data values
bom_movie.isna().any()
```

Out[8]:
```
title             False
studio             True
domestic_gross     True
foreign_gross      True
year              False
dtype: bool
```

In [9]:
```
bom_movie.isna().sum()
```

Out[9]:
```
title               0
studio              5
domestic_gross     28
foreign_gross    1350
year                0
dtype: int64
```

We discover that the 'studio', 'domestic_gross' and 'foreign gross' columns have missing data.

In [10]:
```
#We drop the 'foreign gross' column due to alot of missing data.
bom_movie.drop("foreign_gross", axis=1, inplace=True)
```

In [11]:
```
#We replace the missing values in the domestic gross column with the mea
mean_bom = bom_movie['domestic_gross'].mean()
bom_movie['domestic_gross'].fillna(mean_bom, inplace = True)
```

In [12]:
```
#We replace the missing values in the studio column with the mode value
mode_bom = bom_movie['studio'].mode()[0]
bom_movie['studio'].fillna(mode_bom, inplace = True)
```

In [13]:
```
domestic_gross_ = bom_movie.groupby('studio')["domestic_gross"].sum()
domestic_gross_.sort_values(ascending = False).head()
```

Out[13]:
```
studio
BV      1.841903e+10
Uni.    1.290239e+10
WB      1.216805e+10
Fox     1.094950e+10
Sony    8.488429e+09
Name: domestic_gross, dtype: float64
```

In [14]:
```
#we check the summarised data to confirm our changes
bom_movie.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3387 non-null   object 
 2   domestic_gross  3387 non-null   float64
 3   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(2)
memory usage: 106.0+ KB
```

Data Analysis and Visualization

In [15]:
```
bom_movie['studio'].value_counts().head(10)
```

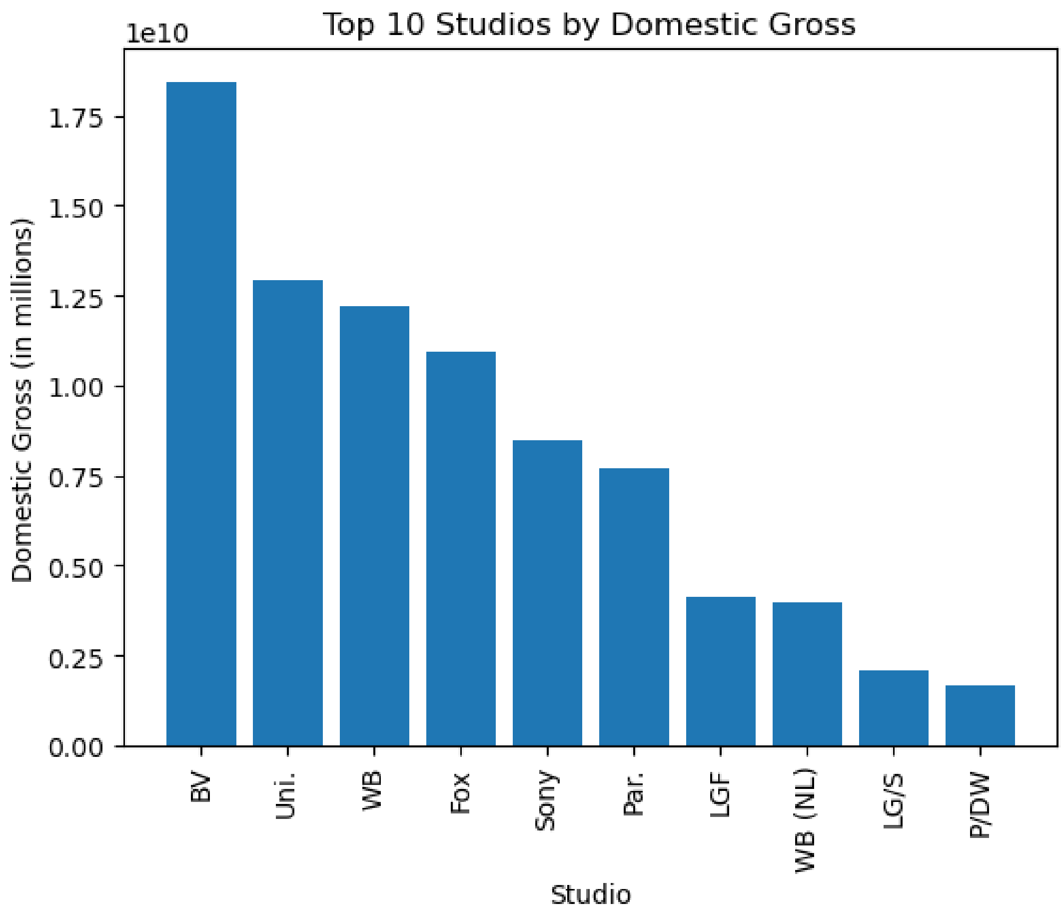
Out[15]:
```
IFC      171
Uni.     147
WB       140
Fox      136
Magn.    136
SPC      123
Sony     110
BV       106
LGF      103
Par.     101
Name: studio, dtype: int64
```

Bar Graph

We plot a bar graph that shows the Top 10 studios based on the domestic gross income.

In [16]:
```
studio_data = bom_movie.groupby('studio')['domestic_gross'].sum().sort_
top_10_studios = studio_data[:10]
```

In [17]:
```
top_10_studios = studio_data[:10]
plt.bar(top_10_studios.index, top_10_studios.values)
plt.xticks(rotation=90)
plt.xlabel('Studio')
plt.ylabel('Domestic Gross (in millions)')
plt.title('Top 10 Studios by Domestic Gross')
plt.show()
```



Based on the above graph, we can conclude that BV Studios produced movies that had the highest total domestic revenue. We then did a value counts test to see whether BV Studios produced most of the movies, which could then have lead to it having the highest total revenues. However, we found out that IFC produced the highest number of movies, and BV Studios ranked 8th in terms of number of movies produced.

We can advise Microsoft to patner with BV Studios in their movie production. This is because BV Studios generated the highest revenue from movies produced, therefore, patnering with them would likely lead to high revenue income from the movies.

2. TN MOVIE BUDGETS FILE

Data Understanding

In [18]:
```
#we first load the given dataset and view the data
movie_budgets = pd.read_csv("tn.movie_budgets.csv")
movie_budgets
```

Out[18]:

	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
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

5782 rows × 6 columns

In [19]:
```
#we check the shape of the data
movie_budgets.shape
```

Out[19]: (5782, 6)

This data has 5782 rows and 6 columns.

In [20]:
```
#we check a summary of the data
movie_budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

This dataset contains data in the float, interger and object types.

Data Cleaning

In [21]:
```
#we check for any duplicated values
movie_budgets.duplicated().sum()
```

Out[21]:
```
0
```

In [22]:
```
#we check for any missing values
movie_budgets.isna().sum()
```

Out[22]:
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

There are no duplicated rows in the data set.

In [23]:

```
#we convert production_budget, domestic_gross and worldwide_gross colum
#we then remove the dollar signs ($) and commas from the values

movie_budgets['production_budget'] = movie_budgets['production_budget']
movie_budgets['domestic_gross'] = movie_budgets['domestic_gross'].str.r
movie_budgets['worldwide_gross'] = movie_budgets['worldwide_gross'].str
movie_budgets
```

```
C:\Users\Grey 1\AppData\Local\Temp\ipykernel_11272\1377922522.py:4: Fu
tureWarning: The default value of regex will change from True to False
in a future version. In addition, single character regular expressions
will *not* be treated as literal strings when regex=True.
  movie_budgets['production_budget'] = movie_budgets['production_budge
t'].str.replace('$', '').str.replace(',', '').astype(float)
C:\Users\Grey 1\AppData\Local\Temp\ipykernel_11272\1377922522.py:5: Fu
tureWarning: The default value of regex will change from True to False
in a future version. In addition, single character regular expressions
will *not* be treated as literal strings when regex=True.
  movie_budgets['domestic_gross'] = movie_budgets['domestic_gross'].st
r.replace('$', '').str.replace(',', '').astype(float)
C:\Users\Grey 1\AppData\Local\Temp\ipykernel_11272\1377922522.py:6: Fu
tureWarning: The default value of regex will change from True to False
in a future version. In addition, single character regular expressions
will *not* be treated as literal strings when regex=True.
  movie_budgets['worldwide_gross'] = movie_budgets['worldwide_gross'].
str.replace('$', '').str.replace(',', '').astype(float)
```

Out[23]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000.0	0.0	0.000000e+00
5778	79	Apr 2, 1999	Following	6000.0	48482.0	2.404950e+05
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000.0	1338.0	1.338000e+03
5780	81	Sep 29, 2015	A Plague So Pleasant	1400.0	0.0	0.000000e+00
5781	82	Aug 5, 2005	My Date With Drew	1100.0	181041.0	1.810410e+05

5782 rows × 6 columns

In [24]:

```
#we then verify that the values in the production_budget, domestic_gros
movie_budgets.dtypes
```

Out[24]:

```
id                    int64
release_date         object
movie                object
production_budget   float64
domestic_gross      float64
worldwide_gross     float64
dtype: object
```

The three highlighted columns likely represent the production budget and revenue figures for each movie, which can be used for financial analysis.

In [25]:
```
#we preview our data again
movie_budgets.head()
```

Out[25]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09

As seen above, the values in the release_date column are float data type. We have to convert in order to use the data.

In [26]:
```
movie_budgets['release_date'] = pd.to_datetime(movie_budgets['release_d
movie_budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   float64
 4   domestic_gross     5782 non-null   float64
 5   worldwide_gross    5782 non-null   float64
dtypes: datetime64[ns](1), float64(3), int64(1), object(1)
memory usage: 271.2+ KB
```

In [27]:

```python
movie_budgets['year'] = movie_budgets['release_date'].dt.year
movie_budgets['month'] = movie_budgets['release_date'].dt.month
movie_budgets['day'] = movie_budgets['release_date'].dt.day

#we print the updated dataframe
print(movie_budgets)
```

```
      id release_date                                        movie  \
0      1   2009-12-18                                       Avatar
1      2   2011-05-20  Pirates of the Caribbean: On Stranger Tides
2      3   2019-06-07                                 Dark Phoenix
3      4   2015-05-01                      Avengers: Age of Ultron
4      5   2017-12-15            Star Wars Ep. VIII: The Last Jedi
...   ..          ...                                          ...
5777  78   2018-12-31                                       Red 11
5778  79   1999-04-02                                    Following
5779  80   2005-07-13                Return to the Land of Wonders
5780  81   2015-09-29                         A Plague So Pleasant
5781  82   2005-08-05                            My Date With Drew

      production_budget  domestic_gross  worldwide_gross  year  month  
day
0           425000000.0     760507625.0     2.776345e+09  2009     12
18
1           410600000.0     241063875.0     1.045664e+09  2011      5
20
2           350000000.0      42762350.0     1.497624e+08  2019      6
7
3           330600000.0     459005868.0     1.403014e+09  2015      5
1
4           317000000.0     620181382.0     1.316722e+09  2017     12
15
...                 ...             ...              ...   ...    ...
...
5777             7000.0             0.0     0.000000e+00  2018     12
31
5778             6000.0         48482.0     2.404950e+05  1999      4
2
5779             5000.0          1338.0     1.338000e+03  2005      7
13
5780             1400.0             0.0     0.000000e+00  2015      9
29
5781             1100.0        181041.0     1.810410e+05  2005      8
5

[5782 rows x 9 columns]
```

In [28]:
```
#We check updated information of the dataset to see the changes that we
movie_budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   float64
 4   domestic_gross     5782 non-null   float64
 5   worldwide_gross    5782 non-null   float64
 6   year               5782 non-null   int64
 7   month              5782 non-null   int64
 8   day                5782 non-null   int64
dtypes: datetime64[ns](1), float64(3), int64(4), object(1)
memory usage: 406.7+ KB
```

In [29]:
```
#we check summary statistics data
movie_budgets.describe()
```

Out[29]:

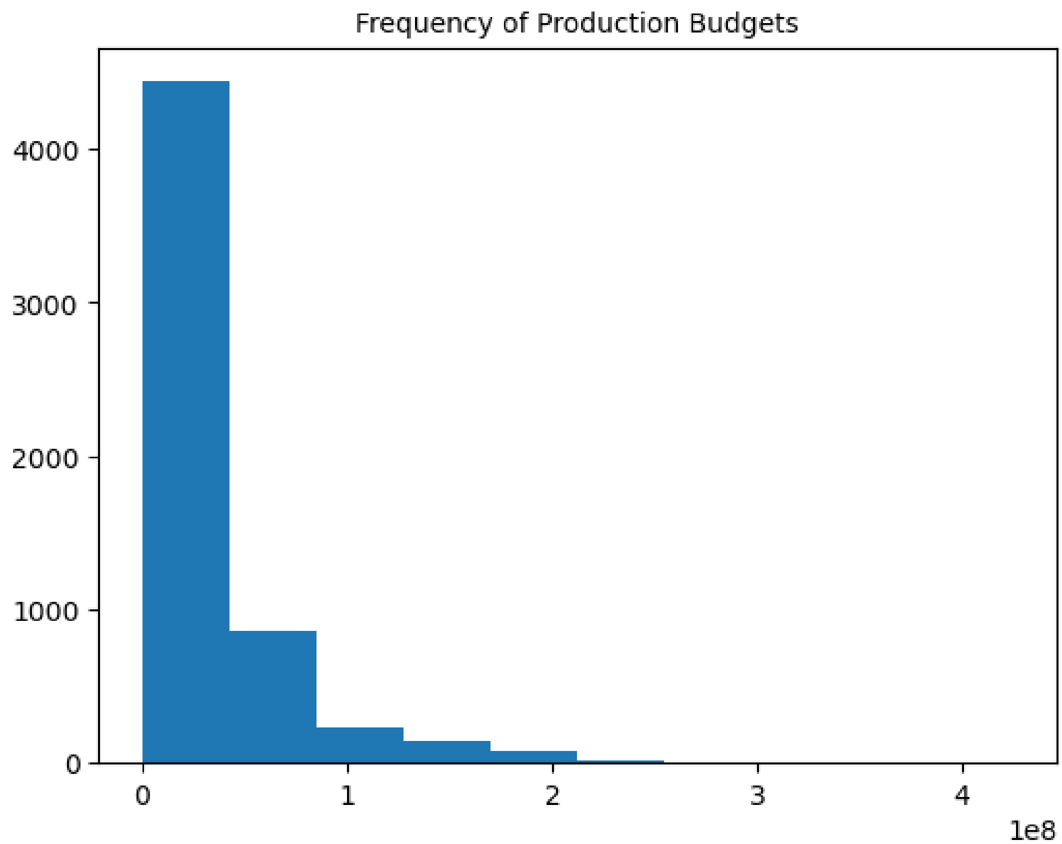
	id	production_budget	domestic_gross	worldwide_gross	year
count	5782.000000	5.782000e+03	5.782000e+03	5.782000e+03	5782.000000
mean	50.372363	3.158776e+07	4.187333e+07	9.148746e+07	2003.967139
std	28.821076	4.181208e+07	6.824060e+07	1.747200e+08	12.724386
min	1.000000	1.100000e+03	0.000000e+00	0.000000e+00	1915.000000
25%	25.000000	5.000000e+06	1.429534e+06	4.125415e+06	2000.000000
50%	50.000000	1.700000e+07	1.722594e+07	2.798445e+07	2007.000000
75%	75.000000	4.000000e+07	5.234866e+07	9.764584e+07	2012.000000
max	100.000000	4.250000e+08	9.366622e+08	2.776345e+09	2020.000000

Data Analysis and Visualization

Histogram

In [30]:

```
#we check the frequency of production budget for movies
plt.hist(movie_budgets['production_budget'], bins = 10);
plt.title("Frequency of Production Budgets", fontsize=10)
plt.show()
```



The histogram above shows us that that the frequency of the movie production budget is skewed to the left. As we can see, majority of the production budget lies between 1,000,000 and 100,000,000. We can use this information to give an guidance to Microsoft Studio on the projected budget range for their movies.

Correlation

We check for whether there exists a relationship between the production budget and the worldwide gross revenue of a movie.

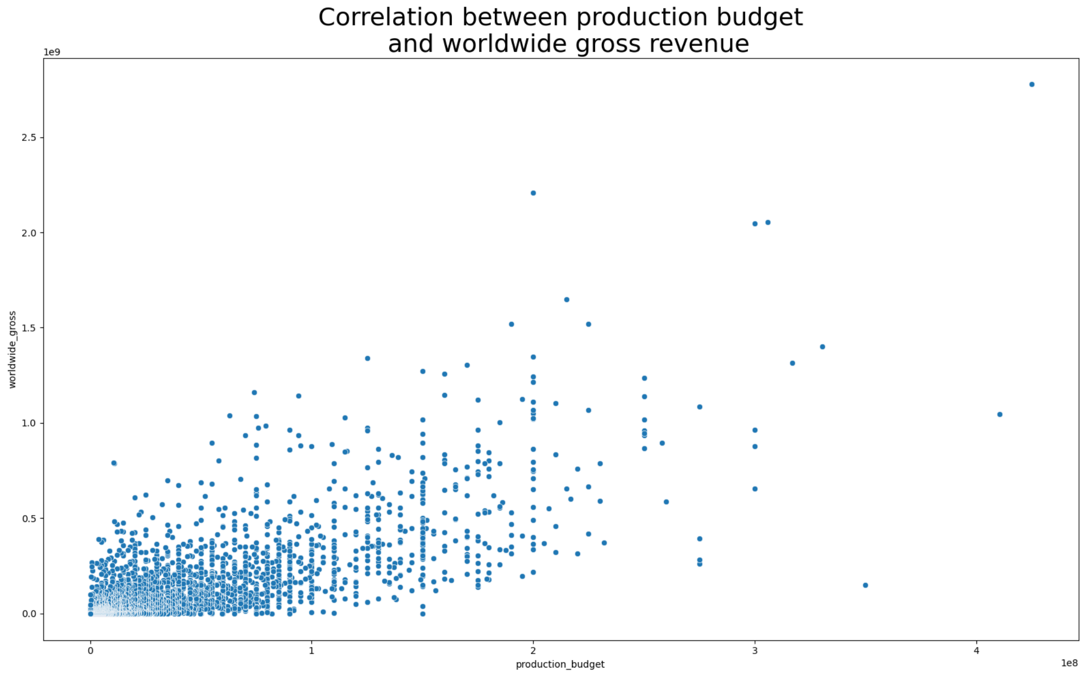
In [31]:

```
correlation_pr_ww = round(movie_budgets['production_budget'].corr(movie_
print("The correlation between production budget and worldwide gross rev
```

```
The correlation between production budget and worldwide gross revenue
is: 0.75
```

We plot the correlation in a scatter plot.

In [32]:
```
plt.figure(figsize=(16, 10))
sns.scatterplot(x='production_budget', y='worldwide_gross', data = movi
plt.title("Correlation between production budget\n  and worldwide gross
plt.tight_layout()
plt.show()
```



Based on the scatter plot, we can see a strong relationship between the production budget and the worldwide gross revenue. It shows that movies with higher production budgets tend to have higher worldwide gross revenue. We can confirm this by looking at the Pearson correlation coefficient (0.75). We see that it is closer to +1, therefore confirming that there is indeed a strong relationship between the production budget and the worldwide gross revenue generated by a movie. We can advise Microsoft Studios to consider increasing their production budget as this will likely incease their worldwide gross revenue.

Return on Investment

We calculate the return on investment,which is a simple ratio that divides the net profit (or loss) from an investment by its cost. Because it is expressed as a percentage, you can compare the effectiveness or profitability of different investment choices. We check the return on investment of movies, according to the month that they were released.

In [33]:

```
#calculating and creating a new column in the dataframe named 'Return o
movie_budgets['return_on_investment'] = ((movie_budgets['worldwide_gros
movie_budgets.head()
```

Out[33]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	ye
0	1	2009-12-18	Avatar	425000000.0	760507625.0	2.776345e+09	20
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	20
2	3	2019-06-07	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	20
3	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	20
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	20

In [34]:

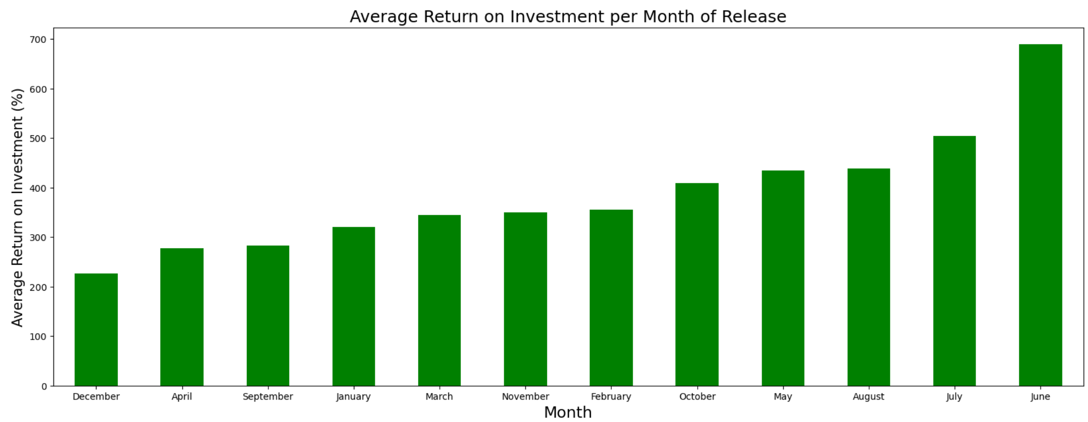
```
# Create a new column that contains the month that the movies were rele
release_time = movie_budgets.copy()

release_time['release_month'] = release_time["release_date"].dt.strftim
# we preview the updated DataFrame
release_time.head(10)
```

Out[34]:

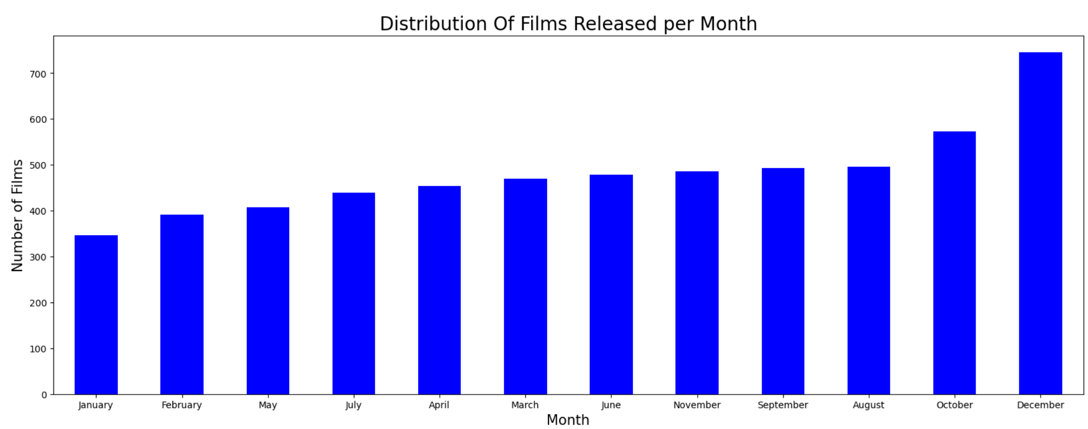
	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	y
0	1	2009-12-18	Avatar	425000000.0	760507625.0	2.776345e+09	2
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	2
2	3	2019-06-07	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	2
3	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	2
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	2
5	6	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000.0	936662225.0	2.053311e+09	2
6	7	2018-04-27	Avengers: Infinity War	300000000.0	678815482.0	2.048134e+09	2
7	8	2007-05-24	Pirates of the Caribbean: At Worldâ s End	300000000.0	309420425.0	9.634204e+08	2
8	9	2017-11-17	Justice League	300000000.0	229024295.0	6.559452e+08	2
9	10	2015-11-06	Spectre	300000000.0	200074175.0	8.796209e+08	2

In [35]:
```
# Create a plot that shows average return on investment by month
fig, ax = plt.subplots(figsize=(20,7))
release_time.groupby('release_month')['return_on_investment'].mean().so
ax.set_xlabel('Month', fontsize=17)
plt.xticks(rotation=0)
ax.set_ylabel('Average Return on Investment (%)', fontsize=15)
ax.set_title('Average Return on Investment per Month of Release', fonts
```



Although there is a positive correlation between production budget and worldwide gross revenue, it is important to examine the return on investment (ROI) of a movie. We then further examine the return on investment of a movies, based on the month that they were produced. Based on our analysis of the ROI by month produced, we would recommend that Microsoft release their movie during the months of June and July, especially July. This is because it is during these months that they can generate the highest returns on their investment in the movie.

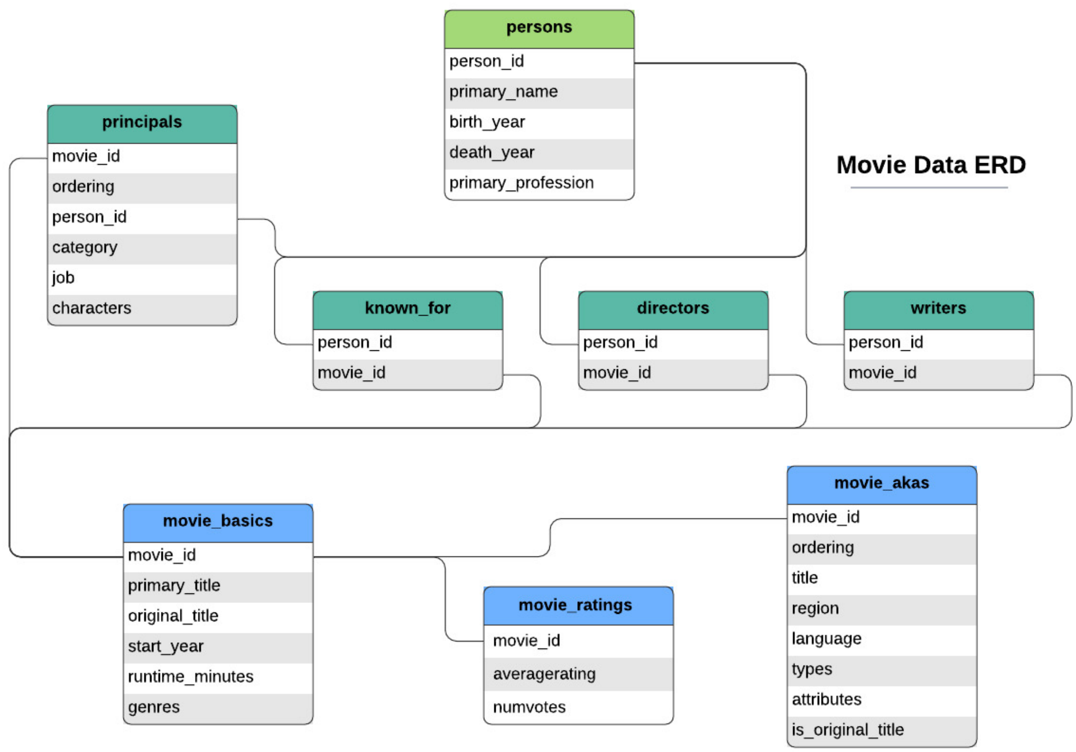
In [36]:
```
# Create a plot that shows the number of films released each month
fig, ax = plt.subplots(figsize=(20,7))
release_time.groupby('release_month')['movie'].count().sort_values().pl
ax.set_xlabel('Month', fontsize=15)
plt.xticks(rotation=0)
ax.set_ylabel('Number of Films', fontsize=15)
ax.set_title('Distribution Of Films Released per Month', fontsize=20);
```



We observe that the month of December had the highest number of movies produced, followed by October. Howerver, this did not translate to the highest return on investment, as seen in the earlier graph.

3. IMDB file

The ERD (Entity Relation Diagram) for this database is shown below:



Data Understanding

In [37]:
```
#connect to the database
conn = sqlite3.connect("im.db")
```

In [38]:

```
#import data from the movie_basics table
imdb_basics = pd.read_sql("""
SELECT *
FROM movie_basics
""", conn)
imdb_basics
```

Out[38]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crim
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biograpl
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	Come
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Doc
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Doc

146144 rows × 6 columns

In [39]:
```
imdb_basics.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
```

The table contains object, float and integer as data types.

In [40]:
```
#import data from the movie_ratings table
imdb_ratings = pd.read_sql("""
SELECT *
FROM movie_ratings
""", conn)
imdb_ratings
```

Out[40]:

	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
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

In [41]:

```
imdb_ratings.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
```

The table contains object, float and integer as data types.

In [42]:
```
#We then join the two tables using a unique identifier (movie_id) that 
imdb = pd.read_sql("""
SELECT *
FROM movie_basics
JOIN movie_ratings
USING(movie_id);
""", conn)
imdb
```

Out[42]:

	movie_id	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,
...	...	...	...	...	...	
73851	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.0	Docu
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.0	Drama
73853	tt9914642	Albatross	Albatross	2017	NaN	Docu
73854	tt9914942	La vida sense la Sara Amat	La vida sense la Sara Amat	2019	NaN	
73855	tt9916160	Drømmeland	Drømmeland	2019	72.0	Docu

73856 rows × 8 columns

In [43]:
```
#We use info() to get a concise summary of the dataframe
imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         73856 non-null  object 
 1   primary_title    73856 non-null  object 
 2   original_title   73856 non-null  object 
 3   start_year       73856 non-null  int64  
 4   runtime_minutes  66236 non-null  float64
 5   genres           73052 non-null  object 
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  int64  
dtypes: float64(2), int64(2), object(4)
memory usage: 4.5+ MB
```

The joined table contains object, float and integer as data types.

Data Preparation

In [44]:
```
#we check for missing values in the data
imdb.isna().sum()
```

Out[44]:
```
movie_id              0
primary_title         0
original_title        0
start_year            0
runtime_minutes    7620
genres              804
averagerating         0
numvotes              0
dtype: int64
```

This means that the data set has 7,620 missing values in the runtime_minutes column and 804 missing values in the genres column.

In [45]:
```
#we check for any duplicated rows
imdb.duplicated().sum()
```

Out[45]:
```
0
```

There are no duplicated rows in the data.

In [46]:
```
#Since the 'genre' column is categorical data, we replace the missing v
imdb['genres'].mode()[0]
```

Out[46]: 'Drama'

In [47]:
```
#we confirm that drama is the mode of the 'genre' column
imdb['genres'].value_counts()
```

Out[47]:
```
Drama                         11612
Documentary                   10313
Comedy                         5613
Horror                         2692
Comedy,Drama                   2617
                              ...
Sport,Thriller                    1
Comedy,Sport,Western              1
Action,Music                      1
Comedy,Sci-Fi,Western             1
Documentary,Family,Sci-Fi         1
Name: genres, Length: 923, dtype: int64
```

In [48]:
```
#We replace the missing values in the genres column with the most-occur
#We define a variable then run

imdb_mode = imdb['genres'].mode()[0]
imdb['genres'].fillna('imdb_mode', inplace = True)
```

In [49]:
```
#replace the missing values in the runtime_minutes column with the mean
#define a variable then run

imdb_mean = imdb['runtime_minutes'].mean()
imdb['runtime_minutes'].fillna('imdb_mean', inplace = True)
```

In [50]:

```
#check a summary of the data to confirm the changes
imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie_id         73856 non-null  object 
 1   primary_title    73856 non-null  object 
 2   original_title   73856 non-null  object 
 3   start_year       73856 non-null  int64  
 4   runtime_minutes  73856 non-null  object 
 5   genres           73856 non-null  object 
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  int64  
dtypes: float64(1), int64(2), object(5)
memory usage: 4.5+ MB
```

In [51]:

```
#we check again for any missing data
imdb.isna().sum()
```

Out[51]:

```
movie_id           0
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
averagerating      0
numvotes           0
dtype: int64
```

Data Analysis and Visualization

In [52]:

```
im_db = pd.read_sql("""
                  SELECT primary_title, start_year, genres, averagerati
                  FROM movie_basics AS MB
                  JOIN movie_ratings AS MR
                   ON MB.movie_id = MR.movie_id
                   WHERE numvotes > 1000000 AND averagerating BETWEEN 6
                   ORDER BY numvotes DESC
                   limit 50;
                  """, conn)
```

In [53]:
```
genres_sorted_mean = pd.DataFrame(im_db.groupby("genres")["numvotes"].m
genres_sorted_mean
```

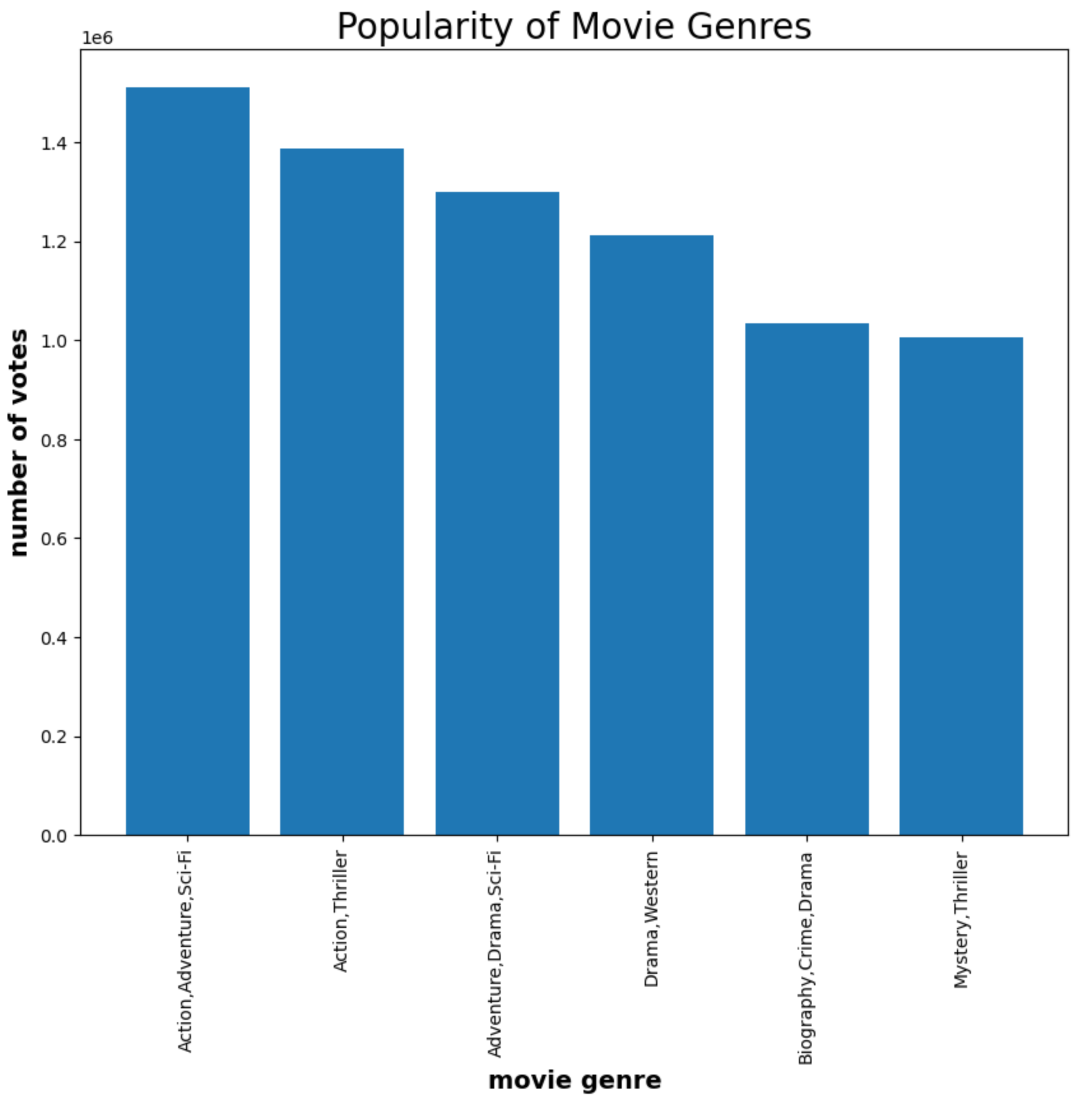
Out[53]:

genres	numvotes
Action,Adventure,Sci-Fi	1512360.5
Action,Thriller	1387769.0
Adventure,Drama,Sci-Fi	1299334.0
Drama,Western	1211405.0
Biography,Crime,Drama	1035358.0
Mystery,Thriller	1005960.0

Bar Graph

We plot a bar graph to determine the most popular movie genres based on the number of votes that they received.

In [54]:
```
plt.figure(figsize=(10, 8))
plt.xticks(rotation=90, fontsize=10)
y = genres_sorted_mean["numvotes"]
plt.xlabel("movie genre", fontsize=14, fontweight='bold')
plt.ylabel("number of votes", fontsize =14, fontweight= 'bold')
plt.title('Popularity of Movie Genres', fontsize=20);
plt.bar(y.index, y.values);
```



The bar graph above shows us the combination of the most popular movie genres based on the number of votes they received.The graph can be useful in identifying which movie genres are more popular among users, which can be helpful in making decisions related to marketing and distribution of movies. We can therefore recommend that Micosoft Studios produce a movie with the combination of Action, Adventure and Sci-Fi. This will likely make the movie very popular.

Findings

This analysis leads us to the following findings and recommendations for the upcoming Microsoft Studios:

1. BV Studios had the highest revenues generated by movies produced. Microsoft Studios should consider patnering with them.
2. Movies with a combination of Action, Adventure and Sci-Fi genres were the most popular. Microsoft should produce a movie with this combination of genres.
3. Releasing movies in June and July would likely lead to the highest return on investment by the movie. Microsoft Studios should relase movies in June especially.
4. A majority of production budgets lies between 1,000,000$and 100,000,000$. This should be the projected budget for the movie.
5. The production budget of a movie has a strong impact on the gross revenue generated by the movie. Notwithstanding no.4 above, Microsoft Studios should consider inceasing their production budget.
6. December has the highest number of movies released.