Microsoft Studios Project

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- **Blog post URL:https://github.com/leah-katiwa/dsc-phase-1-project-v2-4.git (https://github.com/leah-katiwa/dsc-phase-1-project-v2-4.git)**

Project Overview

For this project, we will use exploratory data analysis to generate insights for a business stakeholder.

**Following the creation of movie studio, we have been tasked by Microsoft, who have no idea about making films, to identify what makes a film perform well at the box office. After identifying return on investment (RoI) as the primary metric of success, we narrowed down the datasets provided to the top 200 most grossing movies worldwide then calculated the RoI for each. After plotting several scatter and bar plots comparing runtime, production budget, gross revenue, release date, genre, directors, writers, and rating, the analysis identified the following: The best time to release a film is during Summer. Films directed by Kyle Balda, Pierre Coffin, Chris Rennaud, David F. Sandberg, and James Wan perform the best, whereas those Gary Dauberman were the most successful of all the other writers. Lastly we that length of a film, gross revenue and rating, and have no impact on the RoI of a film.

Microsoft Studios

Type *Markdown* and LaTeX: α^2

Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. 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 has decided to enter the original video content scene by creating a new movie studio. However, they don't know anything about creating movies. In order to solve this problem, the analysis shall be centered around answering the following question:

What types of films are currently performing the best at the box office? According to this Holywood Reporter article, we see that the metric used to determine performance of a movie at the box office may vary. Therefore, it is important to clarify that within this analysis, the metric that shall be used to determine the success of a movie will be based on the return on investment (RoI) of the highest grossing films. RoI is an important performance measure used by businesses to evaluate the profitability of an investment or compare the efficiency of a number of different investments.

In order to further understand the types of movies that are currently performing the best at the box office, this analysis will look into the impact following features have on the RoI:

Runtime

Production Budget

Gross Revenue

Release Date

Genre

Directors

Writers

Rating

EDA

In [1]:
```
#we import the libraries that we will need

#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 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 - shows number of rows and columns
bom_movie.shape
```

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

In [4]:
```
#We use bom_movie.info to get a concise summary of the dataframe i.e including
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 column
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 identify for duplicated values
bom_movie.duplicated().sum()
```

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

shows there is no duplicated values

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
```

If there is at least one missing value in a column or row, the corresponding element in the resulting boolean Series is True; otherwise, it is False.

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

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

Observation: 'studio' has 5 missing values, 'domestic_gross' has 28 and 'foreign gross' has 1350 missing values.

In [10]:
```
#We drop the 'foreign gross' column has lots of missing values which may resu
bom_movie.drop("foreign_gross", axis=1, inplace=True)
```

In [11]:
```
#We replace the missing values in the domestic gross column with the mean valu
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)
```

we use mode since is a measure of central tendency that represents the most commonly occurring value in a dataset.

In [13]:
```
#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
```

The studio non-null count now reads 3387 which is the total number of rows -all the missing values have been replaced

In [14]:
```
# we check the frequency of each studio
bom_movie['studio'].value_counts().head(5)
```

Out[14]:
```
IFC      171
Uni.     147
WB       140
Magn.    136
Fox      136
Name: studio, dtype: int64
```

Data Analysis

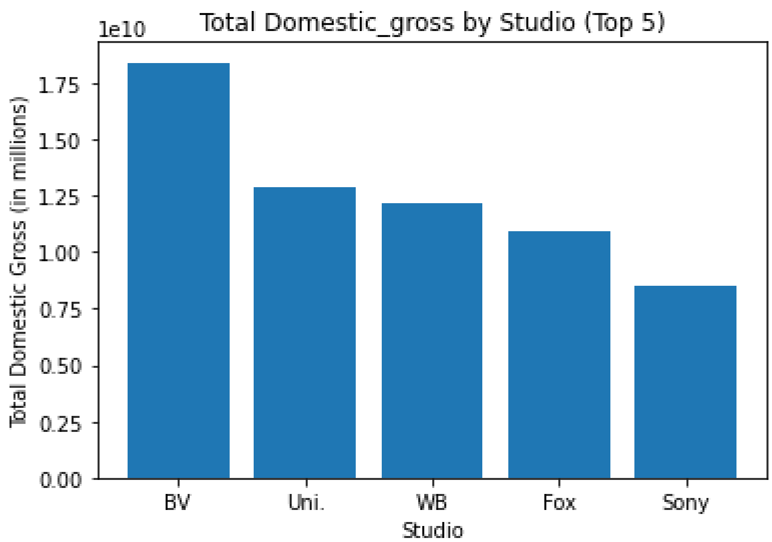
we group studio data with domestic gross to see the performance of each studio within the home country domestic_gross_ = bom_movie.groupby('studio')["domestic_gross"].sum() domestic_gross_.sort_values(ascending = False).head()

In [15]:
```
#we identify the top 10 best selling studios withing the country( consider the
# Order the studios from the one that has the highest domestic gross
bom_movie.sort_values(by='domestic_gross', ascending=False, inplace=True)
domestic_gross_by_studio  = bom_movie.groupby(['studio'])['domestic_gross'].s
domestic_gross_by_studio
```

Out[15]:
```
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
```

Data visualization

In [16]:
```
#Visualizing the first top_10_studios with the highest domestic gross
fig, ax = plt.subplots(figsize=(6, 4))
ax.bar(domestic_gross_by_studio.index, domestic_gross_by_studio.values)

# Set the title and axis labels
ax.set_title('Total Domestic_gross by Studio (Top 5)')
ax.set_xlabel('Studio')
ax.set_ylabel('Total Domestic Gross (in millions)')
plt.show()
```



Observation

**The graph displays the top 5 studios based on their domestic gross in millions. The graph is a bar chart, where the x-axis shows the studios name, and the y-axis shows their domestic gross in millions.From the bar graph it's evident that BV, Uni, WB Studio, Fox, and Sony are the top 5 best performing studios in terms of domestic gross.Microsoft should consider partnering with these established and well successful studios since they already have a substantial fan-base for their products.

2. TN MOVIE BUDGETS FILE

Data Understanding

In [17]:
```
#we load the tn movie dataset and view the data
movie_budgets = pd.read_csv("tn.movie_budgets.csv")
movie_budgets
```

Out[17]:

	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 [18]:
```
#we check the shape of the data to know the number of rows and columns of our
movie_budgets.shape
```

Out[18]:
```
(5782, 6)
```

This data has 5782 rows and 6 columns.

In [19]:
```
#we check a summary of the data i.ethe column names, data types, and the numbe
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 [20]:
```
#we check for any duplicated values
movie_budgets.duplicated().sum()
```

Out[20]:
```
0
```

There is no duplicated values in the dataset

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

Out[21]:
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

There are no missing values rows in the data set.

In [22]:
```
#we convert production_budget, domestic_gross and worldwide_gross columns fro
#we then remove the dollar signs ($) and commas from the values

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

In [23]:
```
#we then verify that the values in the production_budget, domestic_gross and w
movie_budgets.dtypes
```

Out[23]:
```
id                    int64
release_date         object
movie                object
production_budget   float64
domestic_gross      float64
worldwide_gross     float64
dtype: object
```

production_budget,domestic_gross,worldwide_gross are now in float form that is decimal place

In [24]:
```
#we preview our data again
movie_budgets.head()
```

Out[24]:

	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 object data type. We have to convert in order to use the data.

In [25]:
```
# we convert the release date from an object
movie_budgets['release_date'] = pd.to_datetime(movie_budgets['release_date'])
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 [26]:
```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]
```

Now our release date is in form of a datetime not object anymore

In [27]:
```
#We confirm from the above updated dataframe if th of the data to see the cha
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 [28]:
```
#we check summary statistics data
movie_budgets.describe()
```

Out[28]:

	id	production_budget	domestic_gross	worldwide_gross	year	m
count	5782.000000	5.782000e+03	5.782000e+03	5.782000e+03	5782.000000	5782.00
mean	50.372363	3.158776e+07	4.187333e+07	9.148746e+07	2003.967139	7.05
std	28.821076	4.181208e+07	6.824060e+07	1.747200e+08	12.724386	3.48
min	1.000000	1.100000e+03	0.000000e+00	0.000000e+00	1915.000000	1.00
25%	25.000000	5.000000e+06	1.429534e+06	4.125415e+06	2000.000000	4.00
50%	50.000000	1.700000e+07	1.722594e+07	2.798445e+07	2007.000000	7.00
75%	75.000000	4.000000e+07	5.234866e+07	9.764584e+07	2012.000000	10.00
max	100.000000	4.250000e+08	9.366622e+08	2.776345e+09	2020.000000	12.00

Data Analysis

Correlation

To determine whether there is a correlation between the production budget, domestic gross, and worldwide gross variables,perform a correlation analysis to determine if there is a strong, moderate, or weak linear relationship between them.

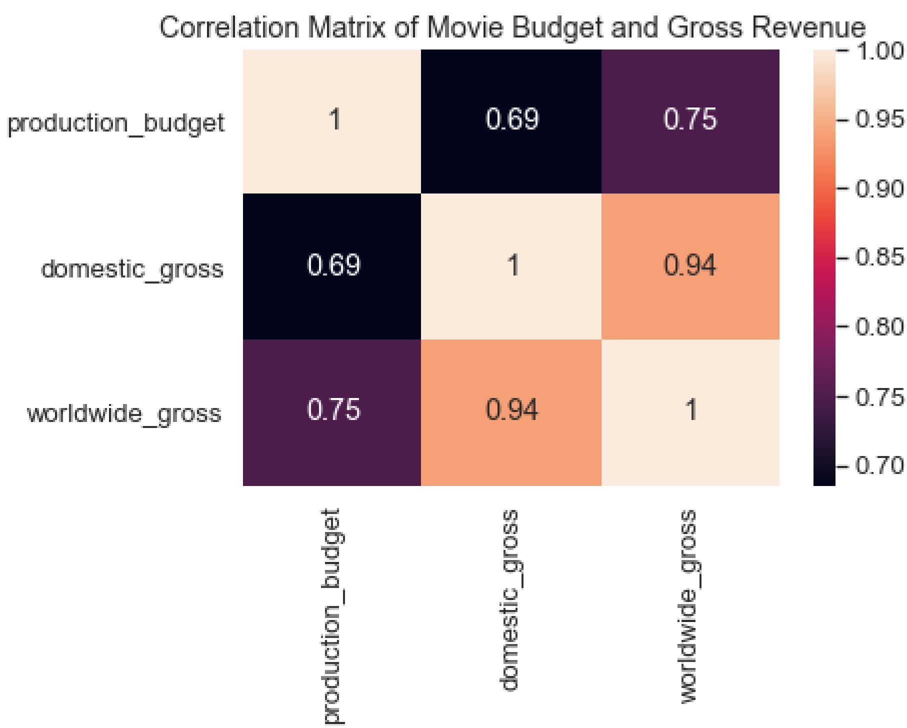
In [29]:
```
# generate a correlation matrix
correlation_matrix = movie_budgets[['production_budget','domestic_gross','wor
correlation_matrix
```

Out[29]:

	production_budget	domestic_gross	worldwide_gross
production_budget	1.000000	0.685682	0.748306
domestic_gross	0.685682	1.000000	0.938853
worldwide_gross	0.748306	0.938853	1.000000

Data Visualization

In [30]:
```
# Plot a heatmap sowing the correlation between these variables
sns.set(font_scale=1.2)
sns.heatmap(correlation_matrix, annot=True)
plt.title('Correlation Matrix of Movie Budget and Gross Revenue')
plt.show()
```



Based on the correlation matrix, there is a strong positive correlation between the production budget both with the domestic and worldwide gross. This means that as the production budget increases, the domestic and worldwide gross also increase. Therefore, if Microsoft wants to generate maximum profits it should consider investing more money in its production budget of its movies. However, it is important to note that correlation alone does not imply causation and therefor other factors also affect the success of a movie.

In [31]:
```
#calculating and creating a new column in the dataframe named Return on Invest
movie_budgets['return_on_investment'] = ((movie_budgets['worldwide_gross'] - 
movie_budgets.head()
```

Out[31]:

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

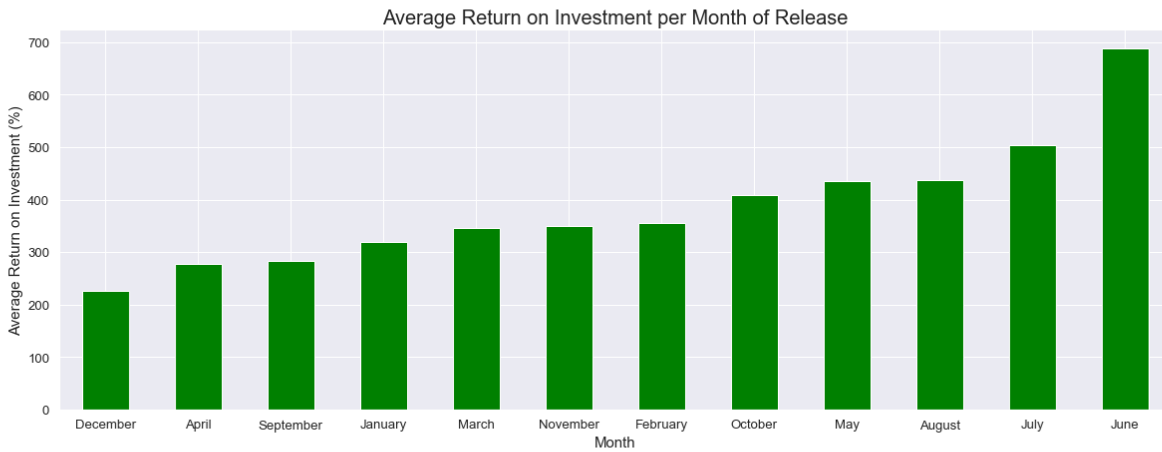
In [32]:
```
# Create a new column that contains the month that the movies were released
release_time = movie_budgets.copy()

release_time['release_month'] = release_time["release_date"].dt.strftime('%B'

release_time.head() # Preview the updated 'release_time_df' DataFrame
```

Out[32]:

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

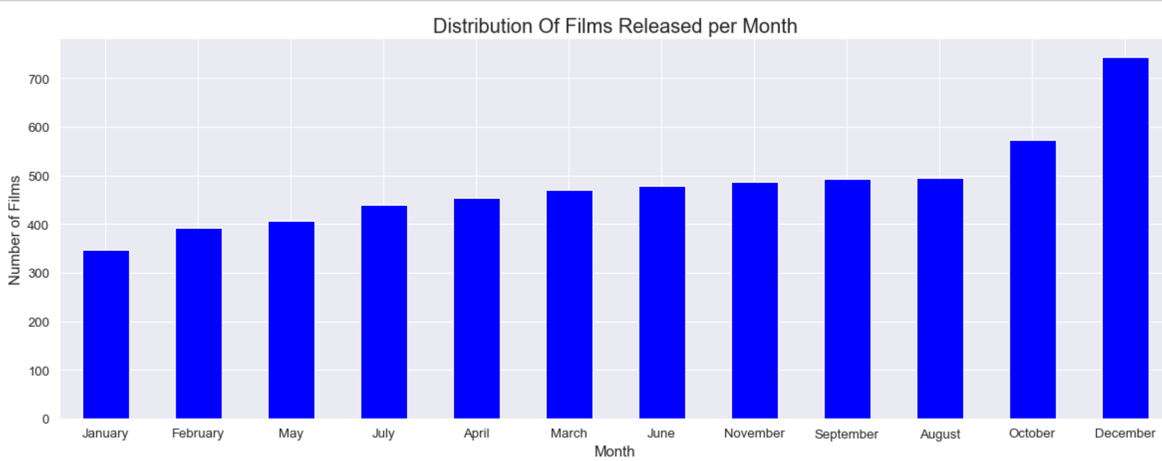
Data Visualization

In [33]:
```
# Create a plot that shows average return on investment (RoI) by month
fig, ax = plt.subplots(figsize=(20,7))
release_time.groupby('release_month')['return_on_investment'].mean().sort_valu
ax.set_xlabel('Month', fontsize=15)
plt.xticks(rotation=0)
ax.set_ylabel('Average Return on Investment (%)', fontsize=15)
ax.set_title('Average Return on Investment per Month of Release', fontsize=20
```



Observation:The highest return on investment for movie release is on june .Microsoft studio should consider releasing their movies on June since its potraying to have the highest return on Investment.

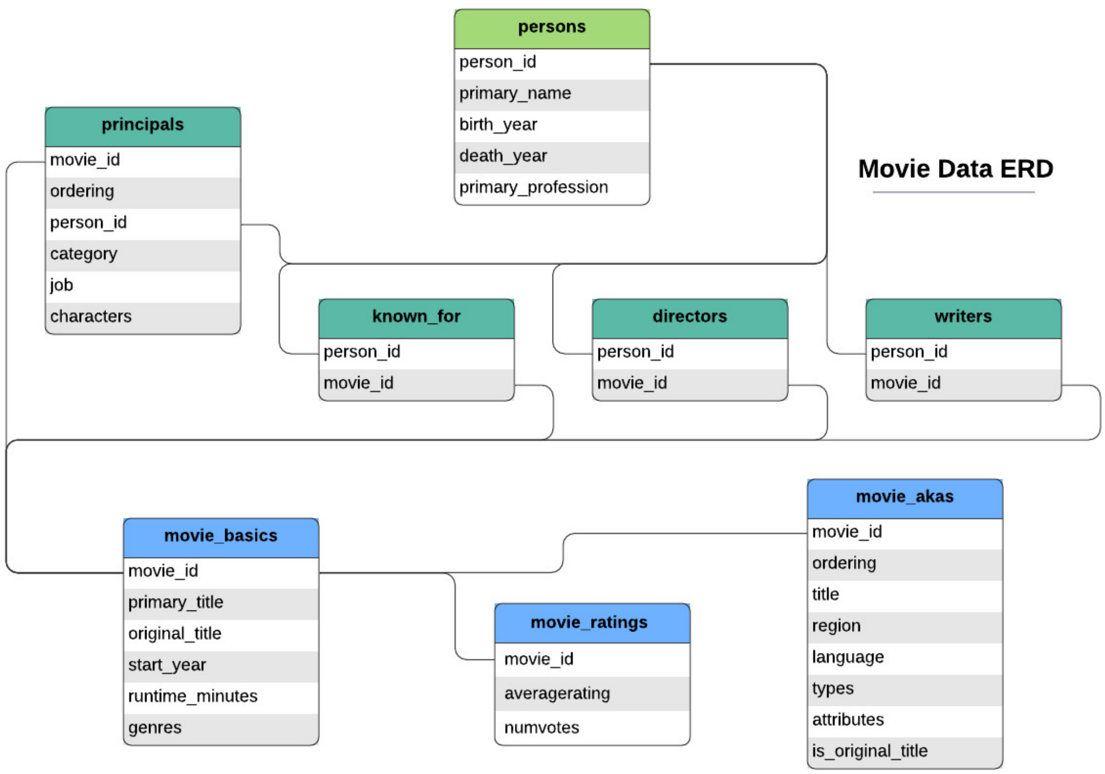
In [34]:
```
# Create a plot that shows the number of films released each month
fig, ax = plt.subplots(figsize=(20,7))
release_time.groupby('release_month')['movie'].count().sort_values().plot(kin
ax.set_xlabel('Month', fontsize=15)
plt.xticks(rotation=0)
ax.set_ylabel('Number of Films', fontsize=15)
ax.set_title('Distribution Of Films Released per Month', fontsize=20);
```



Observation :December has the highest number of films released as shown above therefore microsoft should consider releasing their films during that month but bearing in mind that month of film release has slight effect on the number of films released

3. IMDB file

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



Data Understanding

In [35]:
```
#we connect to the database
conn = sqlite3.connect("im.db")
```

In [36]:
```
#we import data from the movie_basics file.
imdb_basics = pd.read_sql("""
SELECT *
FROM movie_basics
""", conn)
imdb_basics
```

Out[36]:

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

146144 rows × 6 columns

In [37]:
```
#We check concise summary of the dataframe i.e the column names, data types, (
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 [38]:
```
#We import data from the movie_ratings file.
imdb_ratings = pd.read_sql("""
SELECT *
FROM movie_ratings
"""
            ,conn)
imdb_ratings
```

Out[38]:

	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

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

In [39]:
```
#We then join the two movie basics and movie rating using a unique identifier
imdb = pd.read_sql("""
SELECT *
FROM movie_basics
JOIN movie_ratings
USING(movie_id);
""",conn)
imdb.head(20)
```

Out[39]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	geni
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Dra
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Dra
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Dra
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Dra
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fanta
5	tt0112502	Bigfoot	Bigfoot	2017	NaN	Horror,Thri
6	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Come
7	tt0146592	Pál Adrienn	Pál Adrienn	2010	136.0	Dra
8	tt0154039	So Much for Justice!	Oda az igazság	2010	100.0	Hist
9	tt0159369	Cooper and Hemingway: The True Gen	Cooper and Hemingway: The True Gen	2013	180.0	Document
10	tt0162942	Children of the Green Dragon	A zöld sárkány gyermekei	2010	89.0	Dra
11	tt0170651	T.G.M. - osvoboditel	T.G.M. - osvoboditel	2018	60.0	Document
12	tt0176694	The Tragedy of Man	Az ember tragédiája	2011	160.0	Animation,Drama,Hist
13	tt0192528	Heaven & Hell	Reverse Heaven	2018	104.0	Dra
14	tt0230212	The Final Journey	The Final Journey	2010	120.0	Dra
15	tt0247643	Los pájaros se van con la muerte	Los pájaros se van con la muerte	2011	110.0	Drama,Myst
16	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Come
17	tt0250404	Godfather	Godfather	2012	NaN	Crime,Dra
18	tt0253093	Gangavataran	Gangavataran	2018	134.0	Nc
19	tt0255820	Return to Babylon	Return to Babylon	2013	75.0	Biography,Comedy,Dra

In [40]:
```
#We check the concise summary of the dataframe i.e the column names, data typ
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 Cleaning

In [41]:
```
#we check for missing values in the imdb data
imdb.isna().sum()
```

Out[41]:
```
movie_id              0
primary_title         0
original_title        0
start_year            0
runtime_minutes    7620
genres              804
averagerating         0
numvotes              0
dtype: int64
```

runtime_minutes column has 7,620 missing values while genres column has 804 missing values.

In [42]:
```
#we check for any duplicated data
imdb.duplicated().sum()
```

Out[42]:
```
0
```

There are no duplicated data in the rows.

In [43]:
```
# how to confirm the most occuring genre
imdb['genres'].value_counts()
```

Out[43]:
```
Drama                          11612
Documentary                    10313
Comedy                          5613
Horror                          2692
Comedy,Drama                    2617
                               ...
Documentary,Family,Musical         1
Action,Family,Mystery              1
Fantasy,Horror,Romance             1
Action,Adventure,Musical           1
Fantasy,Horror,Western             1
Name: genres, Length: 923, dtype: int64
```

Drama has a frequency of 11612 hence the most occuring genre

In [44]:
```
#Since the 'genre' column is categorical data, we replace the missing values w
imdb['genres'].mode()[0]
```

Out[44]:
```
'Drama'
```

In [45]:
```
#We replace the missing values in the genres column with drama (most occuring

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

In [46]:
```
#we check a summary of the data to check update of our work
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           73856 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
```

In [47]:
```
#we confirm if there is still missing
imdb.isna().sum()
```

Out[47]:
```
movie_id              0
primary_title         0
original_title        0
start_year            0
runtime_minutes    7620
genres                0
averagerating         0
numvotes              0
dtype: int64
```

In [48]:
```
# we replace the missing values in the runtimme_minutes
imdb_mean = imdb['runtime_minutes'].mean()
imdb['runtime_minutes'].fillna('imdb_mean', inplace = True)
```

In [49]:
```
#  we get to confirm our concise summary of our data
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
```

Data Analysis

In [50]:
```
im_db = pd.read_sql("""
                  SELECT primary_title, start_year, genres, averagerating, nu
                  FROM movie_basics AS MB
                  JOIN movie_ratings AS MR
                   ON MB.movie_id = MR.movie_id
                   WHERE numvotes > 1000000 AND averagerating BETWEEN 6.5 AND
                   ORDER BY numvotes DESC
                   limit 50;
                  """, conn)
```

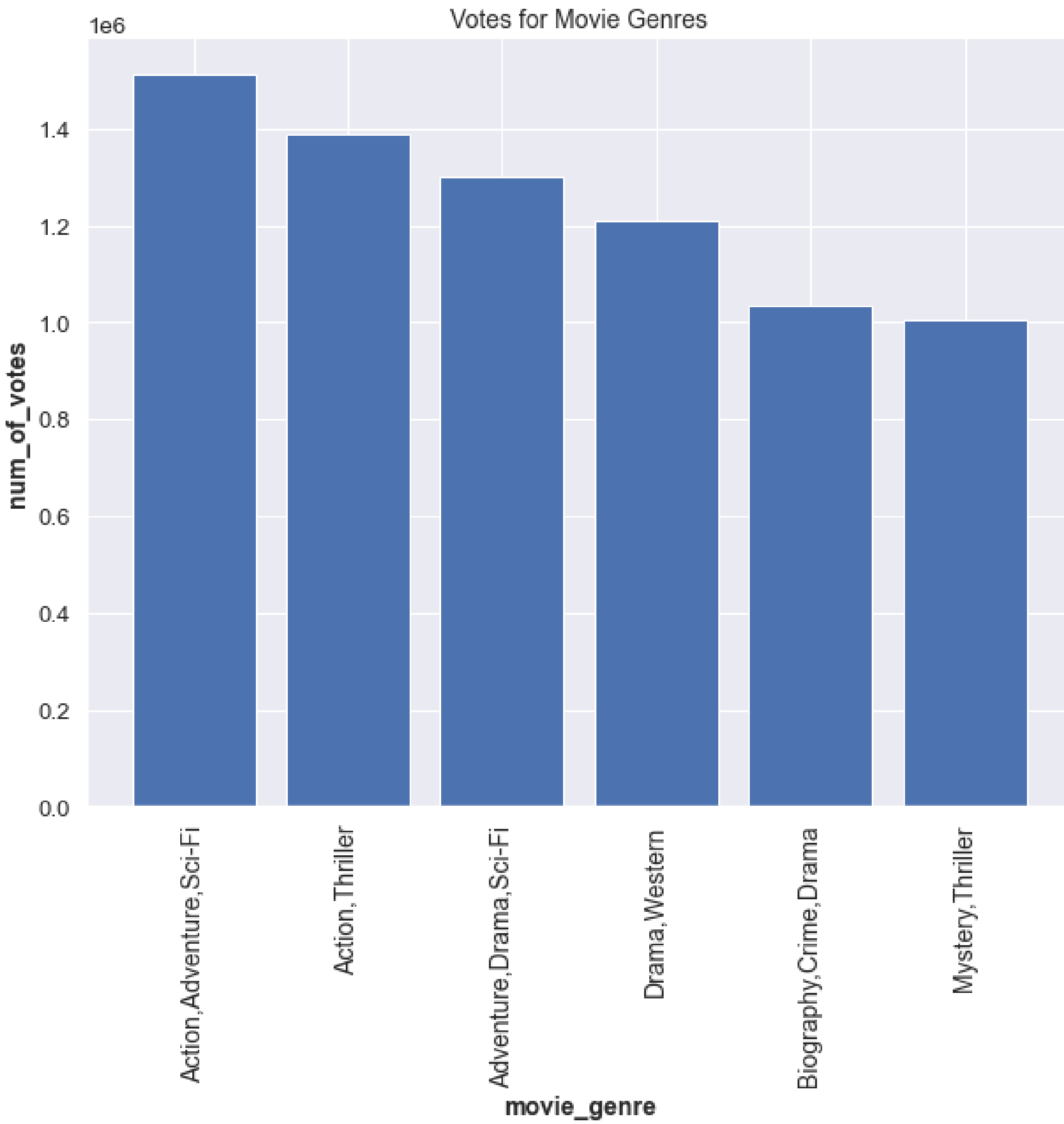
In [51]:
```
mean_of_genres = pd.DataFrame(im_db.groupby("genres")["numvotes"].mean()).sor
mean_of_genres
```

Out[51]:

	numvotes
genres	
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

Data Visualization

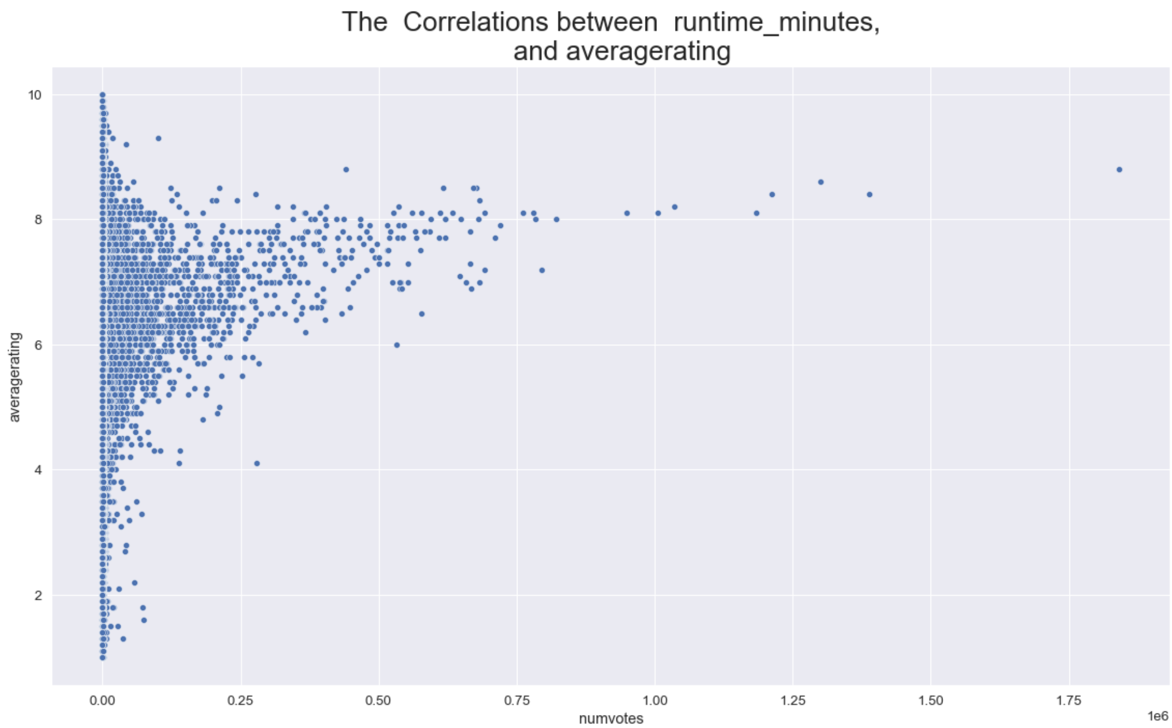
In [52]:
```
#ploting a bar chart to show relationship between number of votes and move gen
plt.figure(figsize=(10, 8))
plt.xticks(rotation=90, fontsize=14)
y = mean_of_genres["numvotes"]
plt.xlabel("movie_genre", fontsize=14, fontweight='bold')
plt.ylabel("num_of_votes", fontsize =14, fontweight= 'bold')
plt.title('Votes for Movie Genres', fontsize=14);
plt.bar(y.index, y.values);
```



Observation:The bar chart above can be used show which movie genre is most populary used hence this is of importance to microsoft in deciding on which movie genre to produce consider the demand in the market.

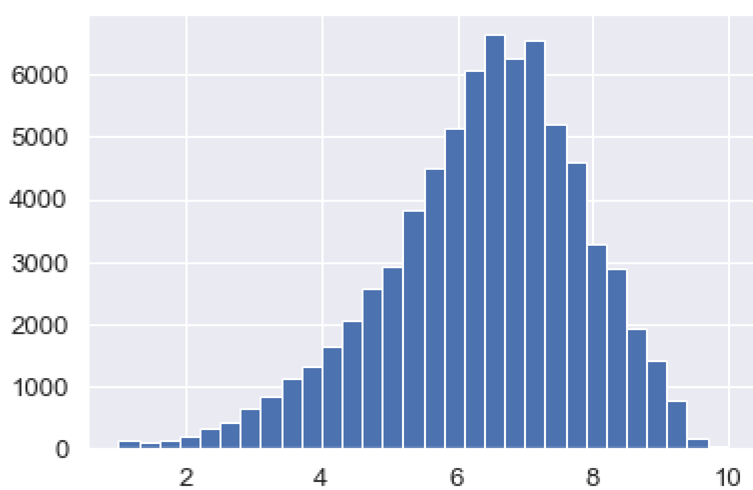
Correlation

In [53]:
```
plt.figure(figsize=(16, 10))
sns.scatterplot(x='numvotes', y='averagerating', data = imdb)
plt.title("The  Correlations between  runtime_minutes,\n   and averagerating")
plt.tight_layout()
plt.show()
```



Observation: The correlation between the runtime and the number of votes is positive but weakly related hence microsoft should note that the runtime and number of votes have small or zero relationship.

In [54]:
```
plt.hist(imdb['averagerating'], bins = 30);
```



Observations:The histogram has 10 bins representing the range of values of 'averagerating' that is it was rated out of 10. The x-axis represents the intervals and the y-axis shows the count of observations that fall within each bin. The distribution of 'averagerating' appears to be slightly skewed to the right, indicating that the majority of the films have a rating of 6-8 on a

RECOMMENDATIONS

```
From the bom data Microsoft should consider working hand in hand with
BV,Uni,Wb,fox and Sony since they are the top 5 studios considering the
domestic gross.By merging with these top studio will give Microsoft a
competitive advantage in the market and this will result to high profit
generation in Microsoft studio.
```

Based on the budget data microsoft should consider having efficient capital as their mean of financing their studio since its evident that in consideration of other factors the higher the production budget the higher the domestic gross and the higher the worldwide gross too.In this movie production industry the quality of the performance is through efficient production budget.

Considering the imdb data Microsft should consider producing Action, Adventureand Sci-Fi movies since they are the most watched genres in the current market hece to be on the safe side it should consider the market scale.This is affect the voting carried out during the research.

NEXT STEP

Microsoft should consider doing further research to identify how different runtimes perform so as to be the best and outrun the other studios.

Microsoft should be careful on their return on investment since quality beats quantity hence producing more films can have less return on investment in the case where the number of films produced were of low quantity and less demanded in the market while the few number of films are of high quality and produced according to the market demand consider supply demand force thhat is producing what is highly demanded

Microsoft should carry a research on how the marketing of their band has positive impact on the return on income in this case advertsing of their released movie film through well established and best selling industry is a bonus to their high return on investment of their quality work examaple work in partnership with Netflix or prime video.

Microsoft should narrow down how different director and specific actors spice up the quality of the movie hence leading to high return on investment