Movie Data Analysis - Recommendations for Microsoft Movie Studios

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- Scheduled project review date/time: 6/3/2022
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Overview

This project analyzes movie data from movie aggregation websites to create proposals for a hypothetical new Microsoft Movie Studios. The analysis shows that movies which met a budget threshold or released during peak months typically yielded greater profits. Additionally, documentaries were the top-rated genre. Microsoft can leverage these three business insights for producing successful movies.

Buisness Understanding

Our client is a hypothetical new Microsoft Movie Studios. The goal of our analysis is to provide suggestions to help Microsoft decide what kind of movies to produce. We conducted an analysis on movie data to construct three actionable insights that Microsoft can utilize to find success in their movie-making venture.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.patches import Rectangle
```

In [2]:
```
import os
import sqlite3
```

Data Understanding

Our data is stored in a folder named zippedData. The data is sourced from a variety of movie aggregation sites: Box Office Mojo, IMDB, Rotten Tomatoes, TheMovieDB, and The Numbers.

In [3]:
```
import sqlite3
import pandas as pd
import zipfile

# Extract IMDb SQL .db file
with zipfile.ZipFile('./zippedData/im.db.zip') as zipObj:
    # Extract all contents of .zip file into current directory
    zipObj.extractall(path='./zippedData/')

# Create connection to IMDb DB
con = sqlite3.connect('./zippedData/im.db')
```

In [4]:
```
#import data from rt.movie_info.tsv.gz
movie_info = pd.read_csv('./zippedData/rt.movie_info.tsv.gz',sep="\t")
```

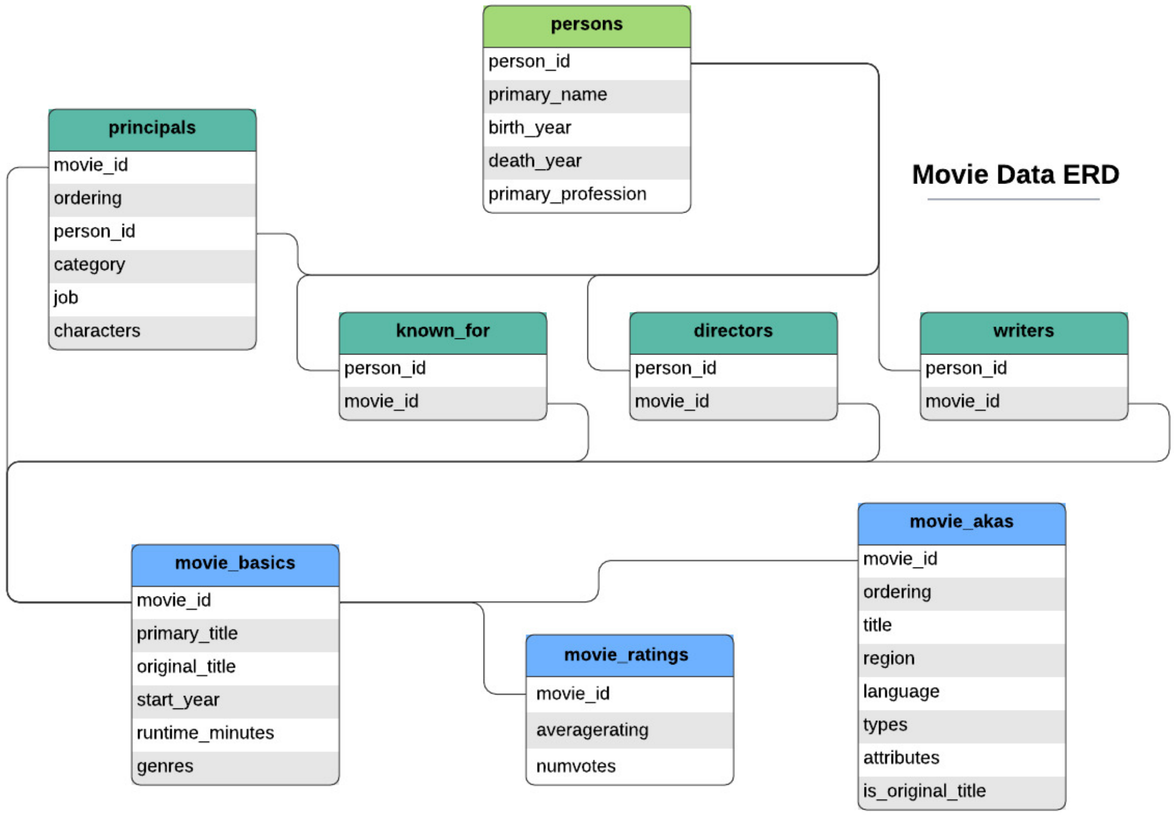
In [5]:
```
#rt.reviews.tsv.gz
reviews = pd.read_csv('./zippedData/rt.reviews.tsv.gz',sep="\t", encoding =
```

In [6]:
```
#bom.movie_gross.csv.gz
movie_gross = pd.read_csv('./zippedData/bom.movie_gross.csv.gz')
```

In [7]:
```
#tmdb.movies.csv.gz
tmdb = pd.read_csv('./zippedData/tmdb.movies.csv.gz')
```

In [8]:
```
#tn.movie_budgets.csv.gz
budgets = pd.read_csv('./zippedData/tn.movie_budgets.csv.gz')
```

One of our datasets is a database from IMDB. The ERD below shows the connections between tables:


Movie Data ERD
persons
person_id
primary_name
birth_year
death_year
primary_profession
principals
movie_id
ordering
person_id
category
job
characters
known_for
person_id
movie_id
directors
person_id
movie_id
writers
person_id
movie_id
movie_basics
movie_id
primary_title
original_title
start_year
runtime_minutes
genres
movie_ratings
movie_id
averagerating
numvotes
movie_akas
movie_id
ordering
title
region
language
types
attributes
is_original_title

In [9]:
```
movie_ratings = """
SELECT *
FROM movie_ratings
"""

pd.read_sql(movie_ratings, con)
```

Out[9]:

	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 [10]:
```
pd.read_sql(movie_ratings, con).describe()
```

Out[10]:

	averagerating	numvotes
count	73856.000000	7.385600e+04
mean	6.332729	3.523662e+03
std	1.474978	3.029402e+04
min	1.000000	5.000000e+00
25%	5.500000	1.400000e+01
50%	6.500000	4.900000e+01
75%	7.400000	2.820000e+02
max	10.000000	1.841066e+06

In [11]:
```
q1 = """
SELECT *
FROM movie_ratings
JOIN movie_basics
    ON movie_ratings.movie_id = movie_basics.movie_id
ORDER BY averagerating DESC

"""

pd.read_sql(q1, con)
```

Out[11]:

	movie_id	averagerating	numvotes	movie_id	primary_title	original_title	start_year	runtim
0	tt5390098	10.0	5	tt5390098	The Paternal Bond: Barbary Macaques	Atlas Mountain: Barbary Macaques - Childcaring...	2015	
1	tt6295832	10.0	5	tt6295832	Requiem voor een Boom	Requiem voor een Boom	2016	
2	tt1770682	10.0	5	tt1770682	Freeing Bernie Baran	Freeing Bernie Baran	2010	
3	tt2632430	10.0	5	tt2632430	Hercule contre Hermès	Hercule contre Hermès	2012	
4	tt8730716	10.0	5	tt8730716	Pick It Up! - Ska in the '90s	Pick It Up! - Ska in the '90s	2019	
...	...	...	...	...	...	...	...	
73851	tt7926296	1.0	17	tt7926296	Nakhodka interneta	Nakhodka interneta	2017	
73852	tt3235258	1.0	510	tt3235258	My First Love	Hatsukoi	2013	
73853	tt7831076	1.0	96	tt7831076	Yes, Sir! 7	Yes, Sir! 7	2016	
73854	tt3262718	1.0	223	tt3262718	Bye Bye Marrano	Bye Bye Marrano	2013	
73855	tt5425998	1.0	20	tt5425998	Cherry Blossoms	Sakura saku	2017	

73856 rows × 9 columns

Joining movie basics and movie ratings tables to be able to compare movie gernes with ratings.

Data Analysis

Here we clean and analyze our data to help make our recomendations.

In [12]:
```
movie_gross.head()
```

Out[12]:

	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 [13]:
```
#Examining movie_gross for nulls
movie_gross.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
```

The data in movie_gross stores foreign_gross as an object data type.

In [14]:
```
#drop rows containing nulls in foreign_gross column
movie_gross_clean= movie_gross.dropna(subset=['foreign_gross'])
```

In [15]:
```
#change foreign_gross into a float type
movie_gross_clean['foreign_gross'] = movie_gross_clean['foreign_gross'].str
movie_gross_clean.head()
```

```
<ipython-input-15-261fdcc9ccea>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  movie_gross_clean['foreign_gross'] = movie_gross_clean['foreign_gros
s'].str.replace(",","").astype(float)
```

Out[15]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000.0	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010
3	Inception	WB	292600000.0	535700000.0	2010
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010

In [16]:
```
#Examining tmdb data for nulls
tmdb.info()
```

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

In [17]:
```python
tmdb.head()
```

Out[17]:

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

In [18]:
```python
#create a new column 'release_month' (string) with just the month
tmdb['release_month'] = tmdb['release_date'].str[5:7]
tmdb.head()
```

Out[18]:

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

In [19]:
```
grouped_tmdb = tmdb.groupby('release_month')
grouped_tmdb.mean()
```

Out[19]:

	Unnamed: 0	id	popularity	vote_average	vote_count
release_month					
01	12421.901980	289163.437101	2.180176	5.866762	65.612388
02	13681.524783	284874.361834	3.352600	5.958240	189.337670
03	14003.534497	289719.502909	3.052933	6.042810	168.189942
04	13902.661341	296493.706937	2.784293	6.117537	120.299299
05	13458.068633	293177.639678	3.123663	6.003539	230.502413
06	13376.954755	293923.416898	3.043683	6.067959	203.485688
07	13026.402261	291002.682846	3.585265	5.883710	304.916223
08	13138.877503	295222.210247	3.580677	5.908539	187.911661
09	13049.484099	296616.382067	3.265490	5.955300	167.389134
10	13201.364415	305666.099835	3.081957	5.913740	155.357496
11	12608.549187	290284.134303	3.459795	6.127459	311.848589
12	13553.141006	311166.230171	3.922681	6.046812	361.810264

In [20]:
```
#examining the popularity statistics
grouped_tmdb['popularity'].describe()
```

Out[20]:

	count	mean	std	min	25%	50%	75%	max
release_month								
01	3132.0	2.180176	2.974335	0.6	0.60000	0.8830	2.17800	28.138
02	1614.0	3.352600	4.304551	0.6	0.62400	1.5130	4.55400	45.253
03	2406.0	3.052933	3.931685	0.6	0.60000	1.4000	3.77100	45.000
04	2566.0	2.784293	3.783140	0.6	0.60000	1.2410	3.25175	80.773
05	1865.0	3.123663	4.683931	0.6	0.60000	1.3470	3.59900	50.289
06	2166.0	3.043683	4.236429	0.6	0.60000	1.3565	3.38750	36.286
07	1504.0	3.585265	4.990946	0.6	0.62875	1.4000	4.77250	46.775
08	1698.0	3.580677	4.426682	0.6	0.60000	1.6020	5.42175	49.606
09	2264.0	3.265490	4.136450	0.6	0.60150	1.4000	4.38850	36.955
10	3035.0	3.081957	4.295220	0.6	0.60000	1.4000	3.81400	78.123
11	2338.0	3.459795	5.257485	0.6	0.60000	1.4000	3.79975	48.508
12	1929.0	3.922681	5.405392	0.6	0.63800	1.5480	5.50600	60.534

In [21]:
```
grouped_tmdb['popularity'].mean()
```

Out[21]:
```
release_month
01    2.180176
02    3.352600
03    3.052933
04    2.784293
05    3.123663
06    3.043683
07    3.585265
08    3.580677
09    3.265490
10    3.081957
11    3.459795
12    3.922681
Name: popularity, dtype: float64
```

In [22]:
```
#looking for nulls in budgets
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
```

In [23]:
```
budgets.head()
#important metrics: domestic_gross, wordwide_gross, production_budget
```

Out[23]:

	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 [24]:
```python
#function to remove the dollar sign and change value from string to a float

def money_string_to_float(df, column_name):
    df[column_name] = df[column_name].str[1:]
    df[column_name] = df[column_name].str.replace(',', '').astype(float)
    return df

money_string_to_float(budgets, "production_budget")
money_string_to_float(budgets, "domestic_gross")
money_string_to_float(budgets, "worldwide_gross")

budgets.head()
#do not run this again (write an exception)
```

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

In [25]:
```python
#create a new column foreign_gross that is the difference between worldwide
budgets['foreign_gross'] = budgets['worldwide_gross'] - budgets['domestic_g
#sort by foreign_gross descending
budgets['foreign_gross'].sort_values(ascending=False)
budgets.head()
```

Out[25]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09	2.015838e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	8.046000e+08
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	1.070000e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	9.440081e+08
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	6.965404e+08

In [26]:
```
#add another column to budgets 'release_month'
budgets['release_month'] = budgets['release_date'].str[0:3]
budgets.tail()
```

Out[26]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gro
5777	78	Dec 31, 2018	Red 11	7000.0	0.0	0.0	0
5778	79	Apr 2, 1999	Following	6000.0	48482.0	240495.0	192013
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000.0	1338.0	1338.0	0
5780	81	Sep 29, 2015	A Plague So Pleasant	1400.0	0.0	0.0	0
5781	82	Aug 5, 2005	My Date With Drew	1100.0	181041.0	181041.0	0

There are some rows with 0's for domestic_gross and worldwide_gross. We dropped these rows to focus on comparing gross between movies.

In [27]:
```
#how many instances of $0 do we have in our gross columns?
gross_zero = budgets[budgets['worldwide_gross'] == 0]
gross_zero.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 367 entries, 194 to 5780
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 367 non-null    int64  
 1   release_date       367 non-null    object 
 2   movie              367 non-null    object 
 3   production_budget  367 non-null    float64
 4   domestic_gross     367 non-null    float64
 5   worldwide_gross    367 non-null    float64
 6   foreign_gross      367 non-null    float64
 7   release_month      367 non-null    object 
dtypes: float64(4), int64(1), object(3)
memory usage: 25.8+ KB
```

In [28]:
```
budgets_clean = budgets.drop(budgets[budgets['worldwide_gross'] == 0].index
budgets_clean.head()
```

Out[28]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09	2.015838e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	8.046000e+08
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	1.070000e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	9.440081e+08
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	6.965404e+08

We grouped our data by 'release_month'.

In [29]:
```python
budgets_month = budgets_clean.groupby('release_month')
budgets_month.mean()
```

Out[29]:

release_month	id	production_budget	domestic_gross	worldwide_gross	foreign_gross
Apr	51.348730	2.479273e+07	2.865379e+07	6.282632e+07	3.417253e+07
Aug	52.344609	2.645859e+07	3.373241e+07	6.394353e+07	3.021112e+07
Dec	50.156200	3.823086e+07	5.530613e+07	1.219991e+08	6.669292e+07
Feb	50.651351	2.919364e+07	3.752039e+07	7.579852e+07	3.827814e+07
Jan	49.591463	2.178006e+07	2.533694e+07	4.926112e+07	2.392418e+07
Jul	49.884434	4.401758e+07	6.301966e+07	1.462830e+08	8.326333e+07
Jun	50.104575	4.484185e+07	6.869623e+07	1.487332e+08	8.003695e+07
Mar	49.822727	3.267950e+07	4.120296e+07	8.613110e+07	4.492814e+07
May	50.358779	4.868485e+07	6.907396e+07	1.680485e+08	9.897459e+07
Nov	49.935622	4.397374e+07	6.067822e+07	1.415674e+08	8.088923e+07
Oct	50.107011	2.137806e+07	2.582041e+07	5.229372e+07	2.647330e+07
Sep	48.381974	2.272352e+07	2.449119e+07	4.939912e+07	2.490793e+07

The data is grouped by month, but we wanted to have this in chronological order. The months are stored as strings of the abbreviated month name. In order to sort the data by chronological release month, we added another column associating the release_month with the number of that month.

In [30]:
```
#create a new column 'month_number'
months_dict = {'Jan':1, 'Feb':2, 'Mar':3, 'Apr':4, 'May':5, 'Jun':6, 'Jul':

month_num_list=[]
for month in budgets_clean['release_month']:
    month_num = months_dict[month]
    month_num_list.append(month_num)
budgets_clean['month_number'] = month_num_list
budgets_clean.head()
```

Out[30]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09	2.015838e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	8.046000e+08
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	1.070000e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	9.440081e+08
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	6.965404e+08

Now we can group the 'budgets' dataframe by 'month_number' and take a look at some aggregation statistics for budget and gross.

In [31]:
```
#group by the month_number
budgets_month = budgets_clean.groupby('month_number')
budgets_month.mean()
```

Out[31]:

month_number	id	production_budget	domestic_gross	worldwide_gross	foreign_gross
1	49.591463	2.178006e+07	2.533694e+07	4.926112e+07	2.392418e+07
2	50.651351	2.919364e+07	3.752039e+07	7.579852e+07	3.827814e+07
3	49.822727	3.267950e+07	4.120296e+07	8.613110e+07	4.492814e+07
4	51.348730	2.479273e+07	2.865379e+07	6.282632e+07	3.417253e+07
5	50.358779	4.868485e+07	6.907396e+07	1.680485e+08	9.897459e+07
6	50.104575	4.484185e+07	6.869623e+07	1.487332e+08	8.003695e+07
7	49.884434	4.401758e+07	6.301966e+07	1.462830e+08	8.326333e+07
8	52.344609	2.645859e+07	3.373241e+07	6.394353e+07	3.021112e+07
9	48.381974	2.272352e+07	2.449119e+07	4.939912e+07	2.490793e+07
10	50.107011	2.137806e+07	2.582041e+07	5.229372e+07	2.647330e+07
11	49.935622	4.397374e+07	6.067822e+07	1.415674e+08	8.088923e+07
12	50.156200	3.823086e+07	5.530613e+07	1.219991e+08	6.669292e+07

Here is some exploration of the gross columns for all three categories: domestic, worldwide, and foreign.

In [32]:
```python
budgets_month['domestic_gross'].describe()
```

Out[32]:

month_number	count	mean	std	min	25%	50%	75%	
1	328.0	2.533694e+07	2.867713e+07	0.0	2380013.00	16204811.0	3.827525e+07	146
2	370.0	3.752039e+07	5.746583e+07	0.0	4050716.75	20267527.5	5.032184e+07	700
3	440.0	4.120296e+07	6.250563e+07	0.0	3484683.75	18733294.5	5.275792e+07	504
4	433.0	2.865379e+07	5.248817e+07	0.0	1224330.00	14249005.0	3.628070e+07	678
5	393.0	6.907396e+07	1.016921e+08	0.0	2956000.00	21540363.0	9.138720e+07	623
6	459.0	6.869623e+07	9.156077e+07	0.0	5007814.00	38311134.0	1.012066e+08	652
7	424.0	6.301966e+07	8.152030e+07	0.0	5768193.50	33034174.5	8.901194e+07	533
8	473.0	3.373241e+07	4.587340e+07	0.0	3100000.00	19184820.0	4.472664e+07	333
9	466.0	2.449119e+07	3.351091e+07	0.0	1490118.00	12799007.0	3.504984e+07	327
10	542.0	2.582041e+07	3.528445e+07	0.0	2051194.00	12851381.0	3.531767e+07	274
11	466.0	6.067822e+07	7.632721e+07	0.0	7552791.00	33223172.5	8.259942e+07	424
12	621.0	5.530613e+07	8.716209e+07	0.0	4002293.00	29807260.0	7.478760e+07	936

In [33]:
```python
budgets_month['worldwide_gross'].describe()
```

Out[33]:

month_number	count	mean	std	min	25%	50%	75%
1	328.0	4.926112e+07	6.691056e+07	673.0	4261841.75	24843762.0	7.068974e+07
2	370.0	7.579852e+07	1.238435e+08	3604.0	7929280.00	37849452.0	8.645606e+07
3	440.0	8.613110e+07	1.552561e+08	3234.0	7282899.00	28711776.5	9.263332e+07
4	433.0	6.282632e+07	1.616966e+08	527.0	4023741.00	22910563.0	6.417045e+07
5	393.0	1.680485e+08	2.595341e+08	528.0	6244618.00	35681080.0	2.550000e+08
6	459.0	1.487332e+08	2.258933e+08	1217.0	9401650.00	54876855.0	2.153745e+08
7	424.0	1.462830e+08	2.192839e+08	1338.0	10764080.75	58978298.0	1.748570e+08
8	473.0	6.394353e+07	9.897115e+07	401.0	5617460.00	26887177.0	8.068118e+07
9	466.0	4.939912e+07	7.634508e+07	1822.0	4244109.25	22336591.0	5.838477e+07
10	542.0	5.229372e+07	8.698372e+07	423.0	5085021.00	19380898.5	6.520677e+07
11	466.0	1.415674e+08	2.065371e+08	176.0	15092938.00	57241389.5	1.699466e+08
12	621.0	1.219991e+08	2.311896e+08	26.0	12803305.00	49628177.0	1.468503e+08

Minimum values of 0 in foreign gross tell us that some movies only had domestic sales.

In [34]:
```
budgets_month['foreign_gross'].describe()
```

Out[34]:

	count	mean	std	min	25%	50%	75%	
month_number								
1	328.0	2.392418e+07	4.849461e+07	0.0	0.00	2709992.0	2.862173e+07	3.74
2	370.0	3.827814e+07	7.601360e+07	0.0	1657.00	8610522.0	4.084868e+07	6.48
3	440.0	4.492814e+07	9.786655e+07	0.0	8789.00	8584576.0	4.200565e+07	7.55
4	433.0	3.417253e+07	1.143279e+08	0.0	0.00	4615682.0	2.700038e+07	1.36
5	393.0	9.897459e+07	1.648751e+08	0.0	47469.00	11999999.0	1.382581e+08	9.44
6	459.0	8.003695e+07	1.422974e+08	0.0	54199.50	13556787.0	1.056281e+08	9.96
7	424.0	8.326333e+07	1.456406e+08	0.0	97116.75	19312855.5	9.546976e+07	9.60
8	473.0	3.021112e+07	5.933793e+07	0.0	0.00	3467655.0	3.433392e+07	4.37
9	466.0	2.490793e+07	4.857892e+07	0.0	12606.00	5310087.0	2.924530e+07	3.69
10	542.0	2.647330e+07	5.695379e+07	0.0	0.00	3664687.5	2.735224e+07	6.40
11	466.0	8.088923e+07	1.385679e+08	0.0	978130.25	24189955.5	9.085373e+07	8.71
12	621.0	6.669292e+07	1.521021e+08	0.0	211411.00	18966379.0	7.660000e+07	2.01

In [35]:
```
#take a look at the budgets_month dataframe with all of our added columns
budgets_month.head()
```

Out[35]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09	2.01583
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	8.0460(
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	1.0700(
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	9.4400ε
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	6.9654(
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000.0	936662225.0	2.053311e+09	1.11664
6	7	Apr 27, 2018	Avengers: Infinity War	300000000.0	678815482.0	2.048134e+09	1.36931

The budgets/gross data encompasses a wide range of years. To hone in on more recent market trends, we limited the release window to the last 25 years. This also reduces the effect of inflation on our analysis.

In [36]:
```
#create a new column 'release_year' that contains the year as an int
#take a look at the data to find the oldest movie and most recent movie
budgets_clean['release_year'] = budgets_clean['release_date'].str[-4:].asty
budgets_clean['release_year'].describe()
```

Out[36]:
```
count    5415.000000
mean     2003.599446
std        12.546965
min      1915.000000
25%      1999.000000
50%      2006.000000
75%      2012.000000
max      2019.000000
Name: release_year, dtype: float64
```

In [37]:
```
budgets_clean = budgets_clean.sort_values('release_year')
budgets_clean
```

Out[37]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gr
5677	78	Feb 8, 1915	The Birth of a Nation	110000.0	10000000.0	11000000.0	100000
5614	15	Dec 24, 1916	20,000 Leagues Under the Sea	200000.0	8000000.0	8000000.0	
5683	84	Sep 17, 1920	Over the Hill to the Poorhouse	100000.0	3000000.0	3000000.0	
4569	70	Dec 30, 1925	Ben-Hur: A Tale of the Christ	3900000.0	9000000.0	9000000.0	
5606	7	Nov 19, 1925	The Big Parade	245000.0	11000000.0	22000000.0	1100000
...	...	...	...	...	...	...	
1176	77	Apr 12, 2019	Hellboy	50000000.0	21903748.0	40725492.0	1882174
3835	36	Jan 16, 2019	Dragon Ball Super: Broly	8500000.0	30376755.0	122747755.0	9237100
496	97	Apr 5, 2019	Shazam!	85000000.0	139606856.0	362899733.0	22329287
3777	78	Feb 13, 2019	Happy Death Day 2U	9000000.0	28051045.0	64179495.0	3612845
2325	26	May 10, 2019	The Professor and the Madman	25000000.0	0.0	5227233.0	522723

5415 rows × 10 columns

The most recent movie released in 2019, and the oldest movie released in 1915. We can subset our 'budgets_clean' dataframe to work with movies from the last 25 years.

In [38]:
```python
#create a subset containing movies released in the last 25 years
budgets_recent = budgets_clean[budgets_clean['release_year'] >= 1997]
budgets_recent.head()
```

Out[38]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gros
3397	98	Aug 6, 1997	Def Jam's How To Be a Player	12000000.0	14010363.0	1.401036e+07	0.000000e+0
4589	90	Aug 13, 1997	The Full Monty	3500000.0	45950122.0	2.612494e+08	2.152993e+0
1135	36	Feb 14, 1997	Absolute Power	50000000.0	50068310.0	5.006831e+07	0.000000e+0
42	43	Dec 19, 1997	Titanic	200000000.0	659363944.0	2.208208e+09	1.548844e+0
1647	48	Sep 19, 1997	In & Out	35000000.0	63826569.0	8.322657e+07	1.940000e+0

With this recent release data subset, we can focus our analysis to provide recommendations based on modern movie productions.

In [39]:
```python
budgets_recent_grouped = budgets_recent.groupby('month_number')
budgets_recent_grouped.mean()
```

Out[39]:

	id	production_budget	domestic_gross	worldwide_gross	foreign_gross	rele
month_number						
1	50.778195	2.485784e+07	2.746353e+07	5.684433e+07	2.938080e+07	200
2	50.498403	3.201040e+07	3.903213e+07	8.234195e+07	4.330982e+07	200
3	50.172775	3.565175e+07	4.183567e+07	9.013388e+07	4.829821e+07	200
4	50.384817	2.672459e+07	3.005665e+07	6.778824e+07	3.773159e+07	200
5	49.414557	5.526434e+07	7.182751e+07	1.806778e+08	1.088503e+08	200
6	50.023188	5.085091e+07	6.800196e+07	1.560863e+08	8.808437e+07	200
7	49.578947	4.829000e+07	6.502817e+07	1.568013e+08	9.177312e+07	200
8	52.733503	2.910880e+07	3.508588e+07	6.919715e+07	3.411127e+07	200
9	48.431373	2.383433e+07	2.408086e+07	5.048054e+07	2.639968e+07	200
10	50.047619	2.249145e+07	2.547916e+07	5.446100e+07	2.898184e+07	200
11	49.137566	4.933140e+07	6.025178e+07	1.482371e+08	8.798533e+07	200
12	49.617108	4.298467e+07	5.620977e+07	1.319811e+08	7.577136e+07	200

In [40]:
```
budgets_recent_grouped.median()
```

Out[40]:

	id	production_budget	domestic_gross	worldwide_gross	foreign_gross	release_y
month_number						
1	48.0	19000000.0	18504178.5	34035337.5	10799881.0	200
2	48.0	22000000.0	22958583.0	43528634.0	13148626.0	200
3	51.0	20000000.0	18626949.0	29437906.0	10216031.5	200
4	51.0	18000000.0	14250917.5	23910786.0	6255147.0	200
5	48.5	21500000.0	21506024.0	38166202.5	14011502.5	200
6	49.0	27000000.0	32267774.0	55443032.0	20110271.0	200
7	49.0	25500000.0	32187940.5	65710949.0	23726380.5	200
8	51.0	20000000.0	19585998.5	32957655.5	7759159.5	200
9	46.0	18000000.0	12295033.0	22903867.0	7075485.5	200
10	52.0	15000000.0	11590500.5	17487358.5	5239077.0	200
11	48.0	28000000.0	31688636.0	58407965.5	26991623.0	200
12	52.0	26000000.0	25317379.0	50363790.0	22628118.0	200

While we are starting to see how gross might relate to release month, we can deepen our analysis by relating gross to the production budget. Dividing the difference of 'worldwide_gross' and 'production_budget' by the 'production_budget' created a Return of Investment (ROI) measure.

In [41]:
```python
budgets_recent['roi'] = (budgets_recent['worldwide_gross'] - budgets_recent
budgets_recent.head()
```

```
<ipython-input-41-ba931a3f6c0c>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  budgets_recent['roi'] = (budgets_recent['worldwide_gross'] - budgets_re
cent['production_budget'])/ budgets_recent['production_budget']
```

Out[41]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gros
3397	98	Aug 6, 1997	Def Jam's How To Be a Player	12000000.0	14010363.0	1.401036e+07	0.000000e+0
4589	90	Aug 13, 1997	The Full Monty	3500000.0	45950122.0	2.612494e+08	2.152993e+0
1135	36	Feb 14, 1997	Absolute Power	50000000.0	50068310.0	5.006831e+07	0.000000e+0
42	43	Dec 19, 1997	Titanic	200000000.0	659363944.0	2.208208e+09	1.548844e+0
1647	48	Sep 19, 1997	In & Out	35000000.0	63826569.0	8.322657e+07	1.940000e+0

In [42]:
```python
budgets_recent_grouped = budgets_recent.groupby('month_number')
budgets_recent_grouped.mean()
```

Out[42]:

month_number	id	production_budget	domestic_gross	worldwide_gross	foreign_gross	rele
1	50.778195	2.485784e+07	2.746353e+07	5.684433e+07	2.938080e+07	200
2	50.498403	3.201040e+07	3.903213e+07	8.234195e+07	4.330982e+07	200
3	50.172775	3.565175e+07	4.183567e+07	9.013388e+07	4.829821e+07	200
4	50.384817	2.672459e+07	3.005665e+07	6.778824e+07	3.773159e+07	200
5	49.414557	5.526434e+07	7.182751e+07	1.806778e+08	1.088503e+08	200
6	50.023188	5.085091e+07	6.800196e+07	1.560863e+08	8.808437e+07	200
7	49.578947	4.829000e+07	6.502817e+07	1.568013e+08	9.177312e+07	200
8	52.733503	2.910880e+07	3.508588e+07	6.919715e+07	3.411127e+07	200
9	48.431373	2.383433e+07	2.408086e+07	5.048054e+07	2.639968e+07	200
10	50.047619	2.249145e+07	2.547916e+07	5.446100e+07	2.898184e+07	200
11	49.137566	4.933140e+07	6.025178e+07	1.482371e+08	8.798533e+07	200
12	49.617108	4.298467e+07	5.620977e+07	1.319811e+08	7.577136e+07	200

In [43]:
```python
budgets_recent_grouped.median()
```

Out[43]:

month_number	id	production_budget	domestic_gross	worldwide_gross	foreign_gross	release_y
1	48.0	19000000.0	18504178.5	34035337.5	10799881.0	200
2	48.0	22000000.0	22958583.0	43528634.0	13148626.0	200
3	51.0	20000000.0	18626949.0	29437906.0	10216031.5	200
4	51.0	18000000.0	14250917.5	23910786.0	6255147.0	200
5	48.5	21500000.0	21506024.0	38166202.5	14011502.5	200
6	49.0	27000000.0	32267774.0	55443032.0	20110271.0	200
7	49.0	25500000.0	32187940.5	65710949.0	23726380.5	200
8	51.0	20000000.0	19585998.5	32957655.5	7759159.5	200
9	46.0	18000000.0	12295033.0	22903867.0	7075485.5	200
10	52.0	15000000.0	11590500.5	17487358.5	5239077.0	200
11	48.0	28000000.0	31688636.0	58407965.5	26991623.0	200
12	52.0	26000000.0	25317379.0	50363790.0	22628118.0	200

In [44]:
```
pd.read_sql(q1, con).describe()
```

Out[44]:

	averagerating	numvotes	start_year	runtime_minutes
count	73856.000000	7.385600e+04	73856.000000	66236.000000
mean	6.332729	3.523662e+03	2014.276132	94.654040
std	1.474978	3.029402e+04	2.614807	208.574111
min	1.000000	5.000000e+00	2010.000000	3.000000
25%	5.500000	1.400000e+01	2012.000000	81.000000
50%	6.500000	4.900000e+01	2014.000000	91.000000
75%	7.400000	2.820000e+02	2016.000000	104.000000
max	10.000000	1.841066e+06	2019.000000	51420.000000

Looking at the mean and median for number of votes. We used this as a way to eliminate movies with so few votes. We utilized the median number of votes to filter (49) due to large range in data. We decided to look at the top 50 and bottom 50 rated films to see which genres were most represented in the highest and lowest rated films.

In [45]:
```
q2 = """
SELECT genres
FROM movie_basics
LEFT JOIN movie_ratings
    ON movie_basics.movie_id = movie_ratings.movie_id
WHERE numvotes > 49
ORDER BY averagerating ASC
LIMIT 50

"""
pd.read_sql(q2, con)

##selecting 50 lowest rated movies with over 49 votes
```

Out[45]:

	genres
0	Drama,Romance
1	Drama
2	Comedy
3	Fantasy,Mystery,Romance
4	Horror
5	Adventure,Animation,Family
6	None
7	Drama
8	Horror
9	Drama
10	Comedy
11	Drama
12	Action,Drama,Horror
13	Drama
14	Adventure
15	Adventure,Biography,Comedy
16	Documentary
17	Family
18	Drama,Family
19	Comedy
20	Comedy,Drama
21	Comedy
22	Romance
23	Drama
24	Drama

	genres
25	Comedy
26	Comedy,Drama
27	Horror
28	Horror
29	Comedy,Drama
30	Comedy,Drama,Romance
31	Comedy,Fantasy
32	Drama
33	Comedy,Drama
34	Drama
35	Comedy
36	Action,Sci-Fi,War
37	Action
38	Documentary
39	Drama
40	Romance
41	Crime,Thriller
42	Comedy,Sci-Fi
43	Romance
44	Comedy,History,Horror
45	Western
46	Comedy
47	Music
48	Adventure,Drama,Romance
49	Comedy,Romance

In [46]:
```
bottom_genres = pd.read_sql(q2, con)
```

In [47]:
```
bottom_genres
```
Out[47]:

	genres
0	Drama,Romance
1	Drama
2	Comedy
3	Fantasy,Mystery,Romance
4	Horror
5	Adventure,Animation,Family
6	None
7	Drama
8	Horror
9	Drama
10	Comedy
11	Drama
12	Action,Drama,Horror
13	Drama
14	Adventure
15	Adventure,Biography,Comedy
16	Documentary
17	Family
18	Drama,Family
19	Comedy
20	Comedy,Drama
21	Comedy
22	Romance
23	Drama
24	Drama
25	Comedy
26	Comedy,Drama
27	Horror
28	Horror
29	Comedy,Drama
30	Comedy,Drama,Romance
31	Comedy,Fantasy
32	Drama

	genres
33	Comedy,Drama
34	Drama
35	Comedy
36	Action,Sci-Fi,War
37	Action
38	Documentary
39	Drama
40	Romance
41	Crime,Thriller
42	Comedy,Sci-Fi
43	Romance
44	Comedy,History,Horror
45	Western
46	Comedy
47	Music
48	Adventure,Drama,Romance
49	Comedy,Romance

In [48]:
```
bottom_genres_split= bottom_genres.genres.str.split(',')
```

Splitting the columns that have multiple genres by "," so that each genre can be counted individually.

In [49]:
```
bottom_genres_split
```

Out[49]:
```
0                  [Drama, Romance]
1                           [Drama]
2                          [Comedy]
3         [Fantasy, Mystery, Romance]
4                          [Horror]
5       [Adventure, Animation, Family]
6                              None
7                           [Drama]
8                          [Horror]
9                           [Drama]
10                         [Comedy]
11                          [Drama]
12             [Action, Drama, Horror]
13                          [Drama]
14                      [Adventure]
15      [Adventure, Biography, Comedy]
16                    [Documentary]
17                         [Family]
18                  [Drama, Family]
19                         [Comedy]
20                  [Comedy, Drama]
21                         [Comedy]
22                        [Romance]
23                          [Drama]
24                          [Drama]
25                         [Comedy]
26                  [Comedy, Drama]
27                         [Horror]
28                         [Horror]
29                  [Comedy, Drama]
30           [Comedy, Drama, Romance]
31                [Comedy, Fantasy]
32                          [Drama]
33                  [Comedy, Drama]
34                          [Drama]
35                         [Comedy]
36               [Action, Sci-Fi, War]
37                         [Action]
38                    [Documentary]
39                          [Drama]
40                        [Romance]
41                [Crime, Thriller]
42                 [Comedy, Sci-Fi]
43                        [Romance]
44          [Comedy, History, Horror]
45                        [Western]
46                         [Comedy]
47                          [Music]
48        [Adventure, Drama, Romance]
49                [Comedy, Romance]
Name: genres, dtype: object
```

In [50]:
```
bottom_genres_split.drop(labels=[6], inplace=True)
```

Dropping the row that does not have a genre listed.

In [51]:
```
bottom_genres_split
```

Out[51]:
```
0                  [Drama, Romance]
1                           [Drama]
2                          [Comedy]
3        [Fantasy, Mystery, Romance]
4                          [Horror]
5      [Adventure, Animation, Family]
7                           [Drama]
8                          [Horror]
9                           [Drama]
10                         [Comedy]
11                          [Drama]
12            [Action, Drama, Horror]
13                          [Drama]
14                      [Adventure]
15     [Adventure, Biography, Comedy]
16                    [Documentary]
17                         [Family]
18                  [Drama, Family]
19                         [Comedy]
20                  [Comedy, Drama]
21                         [Comedy]
22                        [Romance]
23                          [Drama]
24                          [Drama]
25                         [Comedy]
26                  [Comedy, Drama]
27                         [Horror]
28                         [Horror]
29                  [Comedy, Drama]
30         [Comedy, Drama, Romance]
31               [Comedy, Fantasy]
32                          [Drama]
33                  [Comedy, Drama]
34                          [Drama]
35                         [Comedy]
36            [Action, Sci-Fi, War]
37                         [Action]
38                    [Documentary]
39                          [Drama]
40                        [Romance]
41               [Crime, Thriller]
42                 [Comedy, Sci-Fi]
43                        [Romance]
44        [Comedy, History, Horror]
45                        [Western]
46                         [Comedy]
47                          [Music]
48      [Adventure, Drama, Romance]
49               [Comedy, Romance]
Name: genres, dtype: object
```

In [52]:
```
q3 = """
SELECT genres
FROM movie_basics
LEFT JOIN movie_ratings
    ON movie_basics.movie_id = movie_ratings.movie_id
AND numvotes > 49
ORDER BY averagerating DESC
LIMIT 50

"""
pd.read_sql(q3, con)

##selecting 50 highest rated movies with over 49 votes
```

Out[52]:

	genres
0	Drama
1	Comedy,Drama
2	Drama
3	Documentary
4	Adventure,Biography,Documentary
5	Documentary,Drama,Music
6	Biography,Drama,History
7	Drama
8	Comedy,Drama,Family
9	Comedy
10	Action
11	Biography
12	Comedy,Drama,Family
13	Drama,History
14	Documentary,Music
15	Documentary
16	Documentary
17	Drama
18	Documentary
19	Drama
20	Documentary
21	Documentary
22	Comedy,Drama,Musical
23	Documentary
24	Documentary

	genres
25	Documentary
26	Comedy,Drama,Romance
27	Documentary
28	Action,Comedy,Documentary
29	Documentary
30	Documentary
31	Documentary
32	Biography,Crime,Documentary
33	Documentary
34	Documentary,History
35	Documentary
36	Biography,Documentary,Drama
37	Documentary
38	Documentary
39	Adventure,Family
40	Documentary,Music
41	Documentary
42	Documentary,Sport
43	Documentary
44	Documentary
45	Documentary
46	Drama,War
47	Documentary
48	Documentary,Sport
49	Drama

In [53]:
```
top_genres = pd.read_sql(q3, con)
```

In [54]:
```
top_genres_split= top_genres.genres.str.split(',')
```

Splitting the columns that have multiple genres by "," so that each genre can be counted individually.

In [55]:
```
top_genres_split
```

Out[55]:
```
0                               [Drama]
1                       [Comedy, Drama]
2                               [Drama]
3                         [Documentary]
4     [Adventure, Biography, Documentary]
5           [Documentary, Drama, Music]
6           [Biography, Drama, History]
7                               [Drama]
8                [Comedy, Drama, Family]
9                              [Comedy]
10                             [Action]
11                          [Biography]
12               [Comedy, Drama, Family]
13                     [Drama, History]
14                 [Documentary, Music]
15                        [Documentary]
16                        [Documentary]
17                              [Drama]
18                        [Documentary]
19                              [Drama]
20                        [Documentary]
21                        [Documentary]
22              [Comedy, Drama, Musical]
23                        [Documentary]
24                        [Documentary]
25                        [Documentary]
26              [Comedy, Drama, Romance]
27                        [Documentary]
28          [Action, Comedy, Documentary]
29                        [Documentary]
30                        [Documentary]
31                        [Documentary]
32       [Biography, Crime, Documentary]
33                        [Documentary]
34               [Documentary, History]
35                        [Documentary]
36       [Biography, Documentary, Drama]
37                        [Documentary]
38                        [Documentary]
39                  [Adventure, Family]
40                 [Documentary, Music]
41                        [Documentary]
42                 [Documentary, Sport]
43                        [Documentary]
44                        [Documentary]
45                        [Documentary]
46                         [Drama, War]
47                        [Documentary]
48                 [Documentary, Sport]
49                              [Drama]
Name: genres, dtype: object
```

In [56]:
```
def get_genre_counts (genres_split):

    genre_counts = {
        "Documentary": 0,
        "Drama": 0,
        "Music": 0,
        "Comedy": 0,
        "Family" : 0,
        "Romance" : 0,
        "Adventure" : 0,
        "Biography" : 0,
        "History" : 0,
        "Musical" : 0,
        "Sport" : 0,
        "Action" : 0,
        "Fantasy" : 0,
        "Mystery" : 0,
        "Horror" : 0,
        "Animation" : 0,
        "Thriller" : 0,
        "Sci-Fi": 0,
        "Crime": 0,
        "War" : 0,
        "Western" :0,
    }


    for genre in genres_split:
        for item in genre:
            genre_counts[item] +=1
    return genre_counts
```

Created a function that will return the counts of each genre.

In [57]:
```
get_genre_counts (top_genres_split)
```

Out[57]:
```
{'Documentary': 32,
 'Drama': 16,
 'Music': 3,
 'Comedy': 7,
 'Family': 3,
 'Romance': 1,
 'Adventure': 2,
 'Biography': 5,
 'History': 3,
 'Musical': 1,
 'Sport': 2,
 'Action': 2,
 'Fantasy': 0,
 'Mystery': 0,
 'Horror': 0,
 'Animation': 0,
 'Thriller': 0,
 'Sci-Fi': 0,
 'Crime': 1,
 'War': 1,
 'Western': 0}
```

In [58]:
```
get_genre_counts (bottom_genres_split)
```

Out[58]:
```
{'Documentary': 2,
 'Drama': 19,
 'Music': 1,
 'Comedy': 17,
 'Family': 3,
 'Romance': 8,
 'Adventure': 4,
 'Biography': 1,
 'History': 1,
 'Musical': 0,
 'Sport': 0,
 'Action': 3,
 'Fantasy': 2,
 'Mystery': 1,
 'Horror': 6,
 'Animation': 1,
 'Thriller': 1,
 'Sci-Fi': 2,
 'Crime': 1,
 'War': 1,
 'Western': 1}
```

In [59]:
```
top_genre_counts = (get_genre_counts (top_genres_split))
```

In [60]:
```
top_genre_counts_df = pd.DataFrame.from_dict(top_genre_counts, orient='inde
```

In [61]:
```
top_genre_counts_df
```
Out[61]:

	0
Documentary	32
Drama	16
Music	3
Comedy	7
Family	3
Romance	1
Adventure	2
Biography	5
History	3
Musical	1
Sport	2
Action	2
Fantasy	0
Mystery	0
Horror	0
Animation	0
Thriller	0
Sci-Fi	0
Crime	1
War	1
Western	0

In [62]:
```
bottom_genre_counts = (get_genre_counts (bottom_genres_split))
```
In [63]:
```
bottom_genre_counts_df = pd.DataFrame.from_dict(bottom_genre_counts, orient
```

In [64]:
```
bottom_genre_counts_df
```

Out[64]:

	0
Documentary	2
Drama	19
Music	1
Comedy	17
Family	3
Romance	8
Adventure	4
Biography	1
History	1
Musical	0
Sport	0
Action	3
Fantasy	2
Mystery	1
Horror	6
Animation	1
Thriller	1
Sci-Fi	2
Crime	1
War	1
Western	1

In [65]:
```
bottom_genre_counts_df.sort_values([0], ascending=False, inplace=True)
```

Ordering my data frame in descending order so when I graph the data frame, the bars will go in descending order.

In [66]:
```
bottom_genre_counts_df
```

Out[66]:

	0
Drama	19
Comedy	17
Romance	8
Horror	6
Adventure	4
Family	3
Action	3
Documentary	2
Sci-Fi	2
Fantasy	2
War	1
Crime	1
Thriller	1
Animation	1
Western	1
Mystery	1
History	1
Biography	1
Music	1
Musical	0
Sport	0

In [67]:
```
bottom_genre_counts_df = bottom_genre_counts_df.loc[~(bottom_genre_counts_d
```

Removing genres that have a count of "0".

In [68]:
```
bottom_genre_counts_df
```

Out[68]:

	0
Drama	19
Comedy	17
Romance	8
Horror	6
Adventure	4
Family	3
Action	3
Documentary	2
Sci-Fi	2
Fantasy	2
War	1
Crime	1
Thriller	1
Animation	1
Western	1
Mystery	1
History	1
Biography	1
Music	1

In [69]:
```
bottom_genre_counts_df.reset_index(inplace=True)
```

```
In [70]: bottom_genre_counts_df
```

Out[70]:

	index	0
0	Drama	19
1	Comedy	17
2	Romance	8
3	Horror	6
4	Adventure	4
5	Family	3
6	Action	3
7	Documentary	2
8	Sci-Fi	2
9	Fantasy	2
10	War	1
11	Crime	1
12	Thriller	1
13	Animation	1
14	Western	1
15	Mystery	1
16	History	1
17	Biography	1
18	Music	1

```
In [71]: bottom_genre_counts_df = bottom_genre_counts_df.rename(columns={'index': 'G
```

In [72]:
```
bottom_genre_counts_df
```
Out[72]:

	Genre	0
0	Drama	19
1	Comedy	17
2	Romance	8
3	Horror	6
4	Adventure	4
5	Family	3
6	Action	3
7	Documentary	2
8	Sci-Fi	2
9	Fantasy	2
10	War	1
11	Crime	1
12	Thriller	1
13	Animation	1
14	Western	1
15	Mystery	1
16	History	1
17	Biography	1
18	Music	1

In [73]:
```
top_genre_counts_df = top_genre_counts_df.loc[~(top_genre_counts_df==0).all
```

Removing genres that have a count of "0".

In [74]:
```
top_genre_counts_df
```

Out[74]:

	0
Documentary	32
Drama	16
Music	3
Comedy	7
Family	3
Romance	1
Adventure	2
Biography	5
History	3
Musical	1
Sport	2
Action	2
Crime	1
War	1

In [75]:
```
top_genre_counts_df.sort_values([0], ascending=False, inplace=True)
```

```
<ipython-input-75-3d0f4268893c>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  top_genre_counts_df.sort_values([0], ascending=False, inplace=True)
```

Ordering my data frame in descending order so when I graph the data frame, the bars will go in descending order.

In [76]:
```
top_genre_counts_df
```

Out[76]:

	0
Documentary	32
Drama	16
Comedy	7
Biography	5
Music	3
Family	3
History	3
Adventure	2
Sport	2
Action	2
Romance	1
Musical	1
Crime	1
War	1

In [77]:
```
top_genre_counts_df = top_genre_counts_df.reset_index()
```

In [78]:
```
top_genre_counts_df
```

Out[78]:

	index	0
0	Documentary	32
1	Drama	16
2	Comedy	7
3	Biography	5
4	Music	3
5	Family	3
6	History	3
7	Adventure	2
8	Sport	2
9	Action	2
10	Romance	1
11	Musical	1
12	Crime	1
13	War	1

In [79]:
```
top_genre_counts_df = top_genre_counts_df.rename(columns={'index': 'Genre'}
```

In [80]:
```
top_genre_counts_df
```
Out[80]:

	Genre	0
0	Documentary	32
1	Drama	16
2	Comedy	7
3	Biography	5
4	Music	3
5	Family	3
6	History	3
7	Adventure	2
8	Sport	2
9	Action	2
10	Romance	1
11	Musical	1
12	Crime	1
13	War	1

In [81]:
```
bottom_genre_counts_df
```

Out[81]:

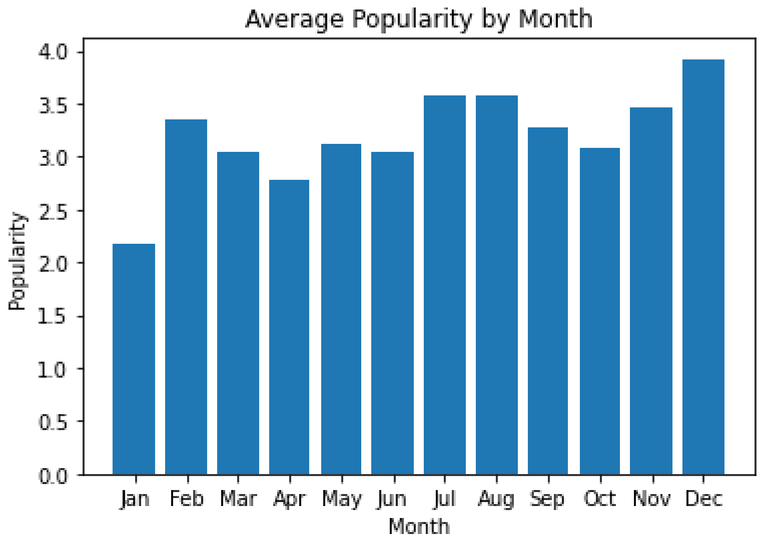
	Genre	0
0	Drama	19
1	Comedy	17
2	Romance	8
3	Horror	6
4	Adventure	4
5	Family	3
6	Action	3
7	Documentary	2
8	Sci-Fi	2
9	Fantasy	2
10	War	1
11	Crime	1
12	Thriller	1
13	Animation	1
14	Western	1
15	Mystery	1
16	History	1
17	Biography	1
18	Music	1

Data Visualizations

Popularity by month

Using the tmdb data, we plotted the popularity score against month to see if any month had more popular movies overall.

In [82]:
```
months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'O

fig, ax = plt.subplots()
ax.bar(months, grouped_tmdb['popularity'].mean())
ax.set_title('Average Popularity by Month')
ax.set_xlabel('Month')
ax.set_ylabel('Popularity');
```



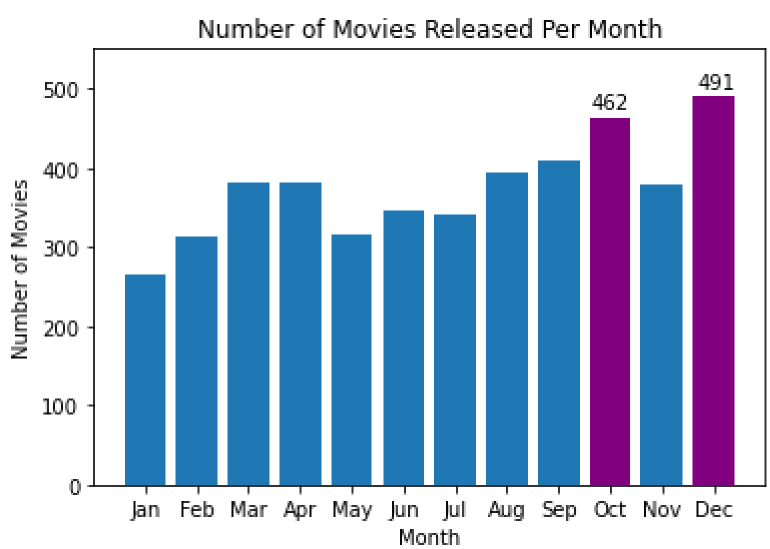
December movies had the highest average popularity score with June's and July's as almost identical runner-ups.

Another aspect to consider for a movie's release month is the quantity of movies released during that month. This can provide some insight into how popular certain months are and how much competition a movie might have during its release.

In [83]:
```
month_count_dict = {'Jan':0, 'Feb':0, 'Mar':0, 'Apr':0, 'May':0, 'Jun':0, '

for month in budgets_recent['release_month']:
    month_count_dict[month] += 1
month_count_dict
```

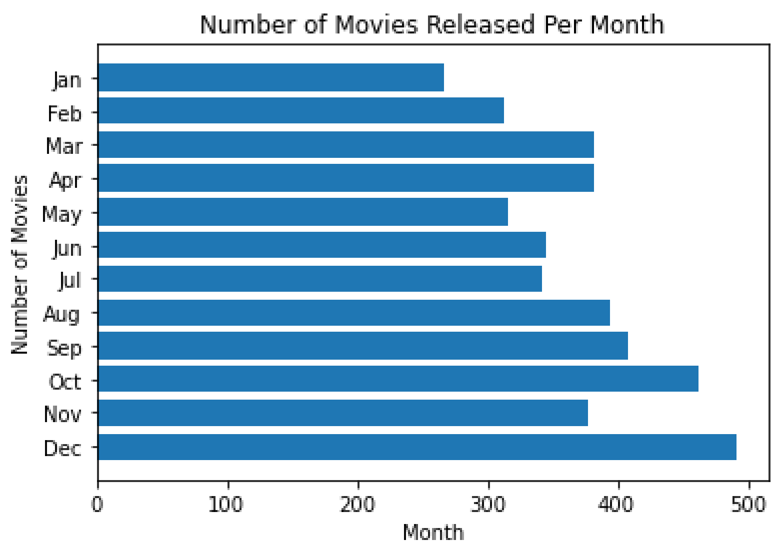
Out[83]:
```
{'Jan': 266,
 'Feb': 313,
 'Mar': 382,
 'Apr': 382,
 'May': 316,
 'Jun': 345,
 'Jul': 342,
 'Aug': 394,
 'Sep': 408,
 'Oct': 462,
 'Nov': 378,
 'Dec': 491}
```

In [84]:
```
fig,ax = plt.subplots()

months_list = list(month_count_dict.keys())
colors = ['purple' if (month == 'Oct' or month =='Dec') else 'tab:blue' for
ax.bar(months_list, month_count_dict.values(), color=colors)
ax.set_title('Number of Movies Released Per Month')
ax.set_xlabel('Month')
ax.set_ylabel("Number of Movies")

ax.set_ylim([0, 550])
plt.annotate('491', (10.70, 500))
plt.annotate('462', (8.65, 475));
```



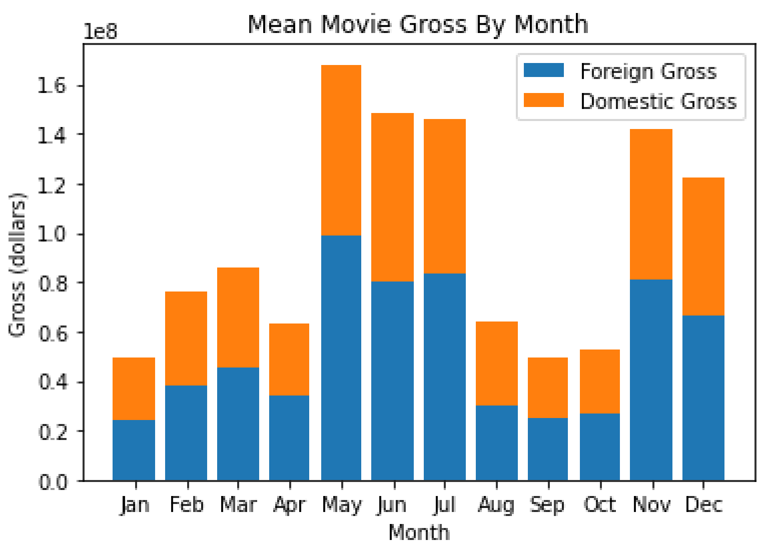
Again, December stands out with the greatest number of movie releases. The other 6 months with the most releases are October, September, August, April, and March.

In [85]:
```
#same data as the graph above, just plotted horizontally
fig,ax = plt.subplots()

months = list(month_count_dict.keys())
movies_count = list(month_count_dict.values())

months.reverse()
movies_count.reverse()

ax.barh(months, movies_count)
ax.set_title('Number of Movies Released Per Month')
ax.set_xlabel('Month')
ax.set_ylabel("Number of Movies");
```



The following stacked bar chart takes our budget/gross dataset and plots the mean gross values grouped by month. A month with a greater mean/median movie gross could indicate more consumers are watching movies during that time.

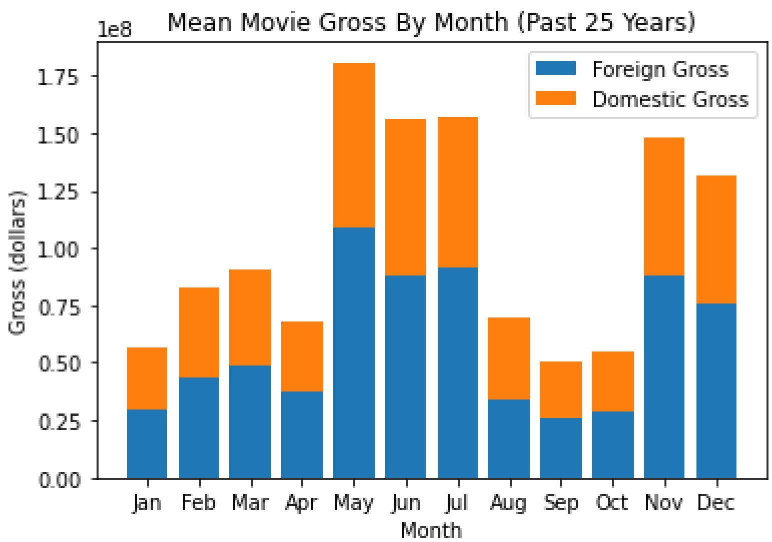
In [86]:
```
#plotting foreign and domestic growth by month as a stacked bar chart
months = list(month_count_dict.keys())

domestic_gross_mean = budgets_month['domestic_gross'].mean()
foreign_gross_mean = budgets_month['foreign_gross'].mean()

fig, ax = plt.subplots()

ax.bar(months, foreign_gross_mean, label='Foreign Gross')
ax.bar(months, domestic_gross_mean, bottom=foreign_gross_mean, label='Domes

ax.set_title("Mean Movie Gross By Month")
ax.set_xlabel("Month")
ax.set_ylabel("Gross (dollars)")

ax.legend();
```



Graphing the same data limited to movies released in the past 25 years revealed similar trends. We focused on the last 25 years to better reflect modern market trends and reduce the effect of inflation.

In [87]:

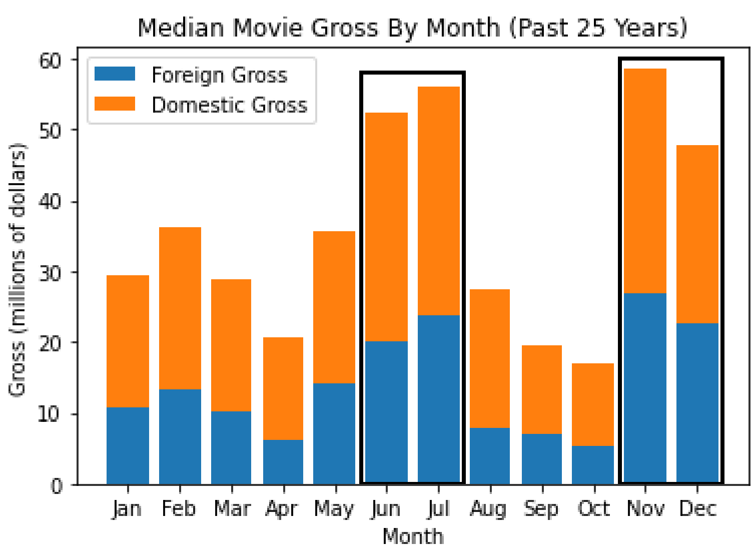
```
domestic_gross_mean = budgets_recent_grouped['domestic_gross'].mean()
foreign_gross_mean = budgets_recent_grouped['foreign_gross'].mean()

fig, ax = plt.subplots()

ax.bar(months, foreign_gross_mean, label='Foreign Gross')
ax.bar(months, domestic_gross_mean, bottom=foreign_gross_mean, label='Domes

ax.set_title("Mean Movie Gross By Month (Past 25 Years)")
ax.set_xlabel("Month")
ax.set_ylabel("Gross (dollars)")

ax.legend();
```



The similarity between the mean and median charts indicates that these measures are weighted heavily by releases from the past 25 years. May had the strongest performing movies, followed closely by June, July, and November. December lagged behind the front-runner months but still stood significantly above the remaining months.

We also graphed the median movie gross grouped by month. Using the median reduces the effect of super-performer movies such as "Avatar". This can give us a better look at how an "average" movie might perform in a given release window.

In [88]:
```
#median movie data from the past 25 years
#plotted as a stacked bar chart of foreign and domestic gross

domestic_gross_median = budgets_recent_grouped['domestic_gross'].median()
foreign_gross_median = budgets_recent_grouped['foreign_gross'].median()

fig, ax = plt.subplots()

ax.bar(months, foreign_gross_median, label='Foreign Gross')
ax.bar(months, domestic_gross_median, bottom=foreign_gross_median, label='D

ax.set_title("Median Movie Gross By Month (Past 25 Years)")
ax.set_xlabel("Month")
ax.set_ylabel("Gross (millions of dollars)")

#function to format y-axis out of scientific notation
def format_number(data_value, idx):
    formatter = '{:1.0f}'.format(data_value*0.000001)
    return formatter
plt.yticks(np.arange(0, 70_000_000, 10_000_000))
ax.yaxis.set_major_formatter(format_number)

ax.add_patch(Rectangle((9.5, 0), width=2, height=60_000_000,fill=False, lw=
ax.add_patch(Rectangle((4.5, 0), width=2, height=58_000_000, fill=False, lw

ax.legend();
```

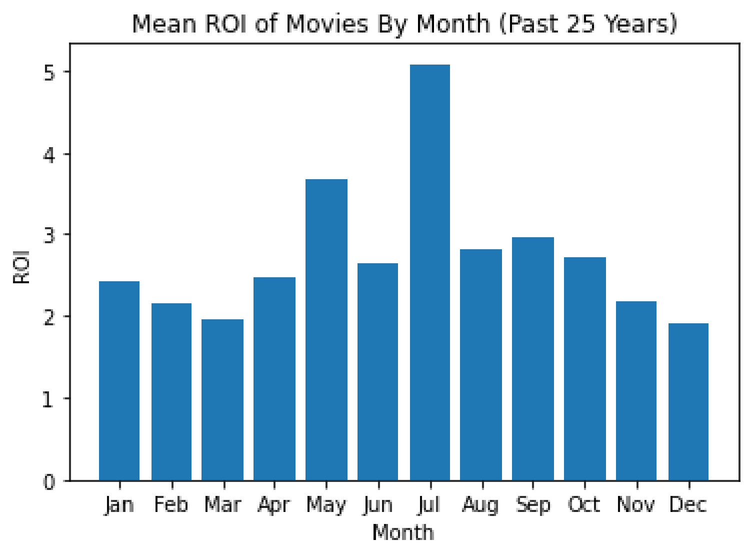


June, July, November, and December also had high mean gross, a trend reflected by the median gross as well. Based on this analysis, we could say that movies releasing in these 4 months generally experienced the best gross performance.

May was the most strongly affected by using the median instead of the mean. This indicates that May had some outlier movies with high gross. The median could be a better metric for a fledgling movie studio.

Now that we've looked at trends in gross data, we added in budget as another variable for consideration. Return on investment (ROI) here was calculated as the difference between gross and budget, divided by the budget. This provided a ratio of movie profits versus movie costs. Similarly to the gross plots, the mean and median ROI for movies grouped by release month were plotted.

In [89]:
```
roi_mean = budgets_recent_grouped['roi'].mean()

fig, ax = plt.subplots()

ax.bar(months, roi_mean)

ax.set_title("Mean ROI of Movies By Month (Past 25 Years)")
ax.set_xlabel("Month")
ax.set_ylabel("ROI");
```

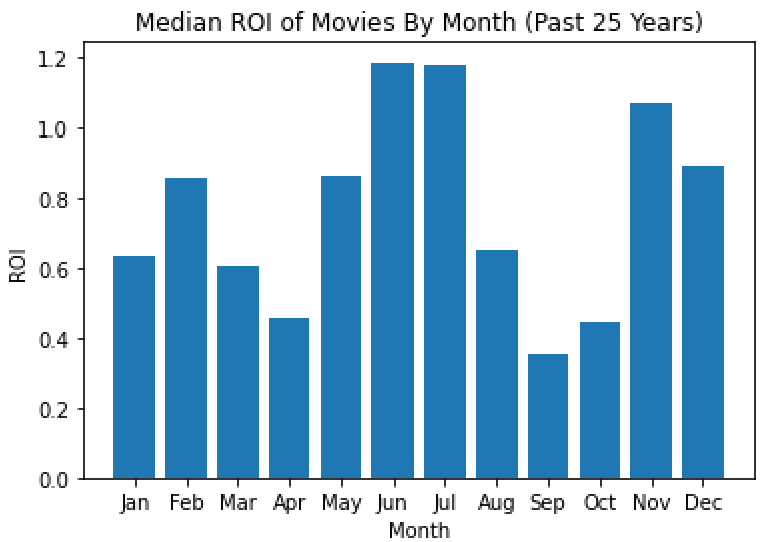


July stands out above the rest with a mean ROI of 5.07. The month with the second greatest mean ROI is May at 3.68.

After plotting the median ROI of movies against their release month, we saw how ROI is greatly affected by overperformers.

In [90]:

```
roi_median = budgets_recent_grouped['roi'].median()

fig, ax = plt.subplots()

ax.bar(months, roi_median)

ax.set_title("Median ROI of Movies By Month (Past 25 Years)")
ax.set_xlabel("Month")
ax.set_ylabel("ROI");
```



The greatest median ROI of movies based on month was 1.18, lower than any value of the mean ROIs. The difference between the means and medians reflects how uncertain the movie market is. Movies that excel can return great profits but are not the norm. Only three months had median ROIs that surpassed the break-even ratio of 1.0. Here we see the best performing months match those highlighted in our median gross by month analysis. June, July, November, and December return as the best performers.

After our analysis of movies based on their release months, we concluded that there are clear months in which movies displayed better financial performance.

Budget

To better narrow down our data we only took data from movies with a budget between 50 million and 250 million.

In [91]:
```
budgets_fix = budgets_clean.query('50000000 <= production_budget <= 2500000
budgets_fix
```

Out[91]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gr
988	89	Dec 15, 1978	Superman	55000000.0	134218018.0	300200000.0	16598198
1048	49	Jun 19, 1981	Superman II	54000000.0	108185706.0	108185706.0	
695	96	Jun 22, 1988	Who Framed Roger Rabbit?	70000000.0	154112492.0	351500000.0	19738750
958	59	May 25, 1988	Rambo III	58000000.0	53715611.0	188715611.0	13500000
722	23	Aug 9, 1989	The Abyss	70000000.0	54243125.0	54243125.0	
...	...	...	...	...	...	...	
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000.0	85576941.0	299276941.0	21370000
619	20	Jan 22, 2019	Renegades	77500000.0	0.0	1521672.0	152167
580	81	Jun 7, 2019	The Secret Life of Pets 2	80000000.0	63795655.0	113351496.0	495558
1176	77	Apr 12, 2019	Hellboy	50000000.0	21903748.0	40725492.0	188217
496	97	Apr 5, 2019	Shazam!	85000000.0	139606856.0	362899733.0	22329287

1181 rows × 10 columns

We wanted to seperate the data by years so as to show the change of trends between production budget and gross revenues for both old movies before 2005 and newer movies 2005 onwards.

In [92]:
```
budgets_new = budgets_fix[budgets_fix['release_year'] >= 2005]
budgets_new
```

Out[92]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gr
532	33	May 27, 2005	The Longest Yard	82000000.0	158119460.0	191558505.0	3343904
550	51	Mar 11, 2005	Robots	80000000.0	128200012.0	260700012.0	1325000(
1151	52	Jun 10, 2005	The Adventures of Sharkboy and Lavagirl in 3-D	50000000.0	39177684.0	69425966.0	3024828
581	82	Jun 24, 2005	Bewitched	80000000.0	63313159.0	131159306.0	6784614
585	86	Oct 28, 2005	The Legend of Zorro	80000000.0	45575336.0	141475336.0	959000(
...	...	...	...	...	...	...	
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000.0	85576941.0	299276941.0	2137000(
619	20	Jan 22, 2019	Renegades	77500000.0	0.0	1521672.0	152167
580	81	Jun 7, 2019	The Secret Life of Pets 2	80000000.0	63795655.0	113351496.0	4955584
1176	77	Apr 12, 2019	Hellboy	50000000.0	21903748.0	40725492.0	1882174
496	97	Apr 5, 2019	Shazam!	85000000.0	139606856.0	362899733.0	2232928

738 rows × 10 columns

In [93]:
```
budgets_old = budgets_fix[budgets_fix['release_year'] < 2005]
budgets_old
```

Out[93]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_grc
988	89	Dec 15, 1978	Superman	55000000.0	134218018.0	300200000.0	16598198
1048	49	Jun 19, 1981	Superman II	54000000.0	108185706.0	108185706.0	(
695	96	Jun 22, 1988	Who Framed Roger Rabbit?	70000000.0	154112492.0	351500000.0	19738750
958	59	May 25, 1988	Rambo III	58000000.0	53715611.0	188715611.0	13500000
722	23	Aug 9, 1989	The Abyss	70000000.0	54243125.0	54243125.0	(
...	...	...	...	...	...	...	
657	58	Dec 17, 2004	Spanglish	75000000.0	42044321.0	54344321.0	1230000
326	27	Dec 17, 2004	The Aviator	110000000.0	102608827.0	208370892.0	10576206
269	70	May 28, 2004	The Day After Tomorrow	125000000.0	186740799.0	556319450.0	36957865
340	41	Jun 16, 2004	Around the World in 80 Days	110000000.0	24004159.0	72004159.0	4800000
336	37	Apr 2, 2004	Home on the Range	110000000.0	50026353.0	76482461.0	2645610

443 rows × 10 columns

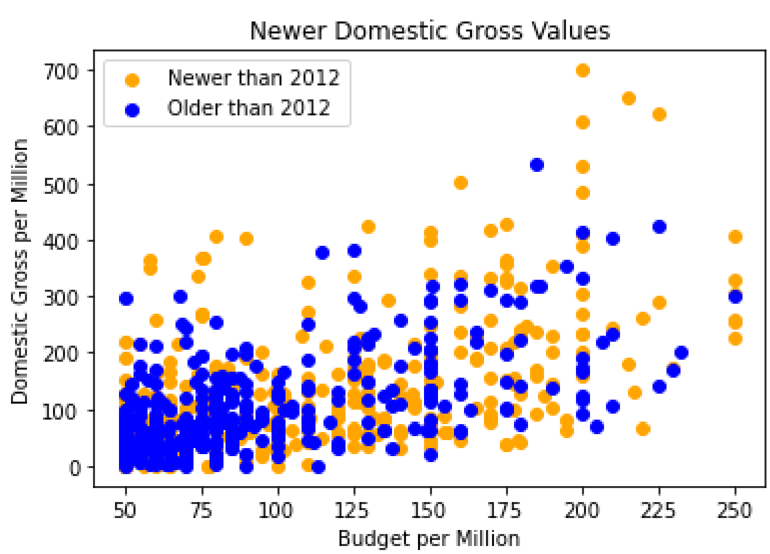
In [94]:
```
#making sure that everything looks correct
budgets_fix.describe()
```

Out[94]:

	id	production_budget	domestic_gross	worldwide_gross	foreign_gross	month_nun
count	1181.000000	1.181000e+03	1.181000e+03	1.181000e+03	1.181000e+03	1181.00
mean	50.752752	9.291470e+07	1.081847e+08	2.699648e+08	1.617802e+08	7.14
std	28.784262	4.402178e+07	9.728462e+07	2.639911e+08	1.777321e+08	3.36
min	1.000000	5.000000e+07	0.000000e+00	5.162790e+05	0.000000e+00	1.00
25%	26.000000	6.000000e+07	4.147610e+07	8.989593e+07	4.194300e+07	5.00
50%	51.000000	7.900000e+07	7.812020e+07	1.833534e+08	1.032547e+08	7.00
75%	76.000000	1.120000e+08	1.404647e+08	3.515000e+08	2.139614e+08	11.00
max	100.000000	2.500000e+08	7.000596e+08	2.208208e+09	1.548844e+09	12.00

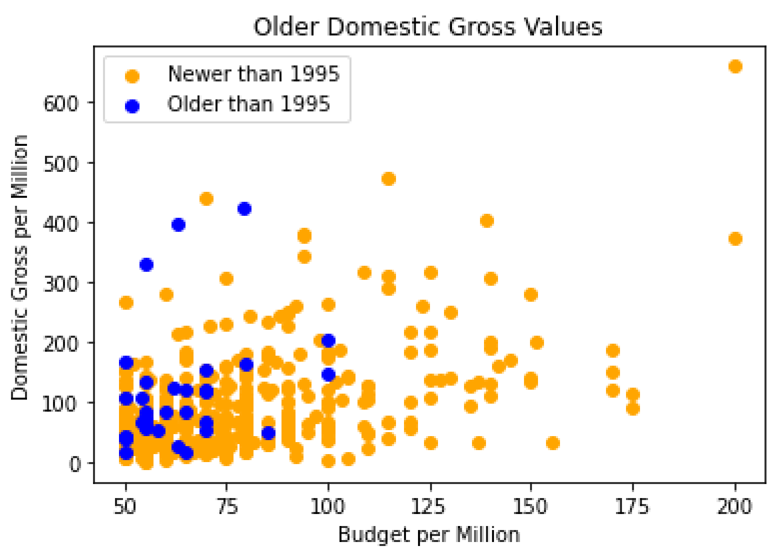
We wanted to show the relationship between new domestic gross and production budgets. To do that we first formatted the data so that the x and y scales werent based off exponenents by running a formatter and changing the x and y ticks to be more accurate to the data being shown. Then we plotted a scatter plot with the x value being budget and y value being gross. We added a third element to the scatter plot to further seperate the data, movies that were newer than 2012 were colored orange and anything before was colored blue. The domestic values wont be presented because they dont get our point across as well as worldwide gross.

In [95]:
```
new_domestic, ax = plt.subplots()

x = budgets_new['production_budget']
y = budgets_new['domestic_gross']

plt.title('Newer Domestic Gross Values')
plt.xlabel('Budget per Million')
plt.ylabel('Domestic Gross per Million')

def format_number(data_value, idx):
    formatter = '{:1.0f}'.format(data_value*0.000001)
    return formatter

def format_numbery(data_value, idx):
    formatter = '{:1.0f}'.format(data_value*0.000001)
    return formatter

plt.xticks(np.arange(0,250_000_001, 25_000_000))
ax.xaxis.set_major_formatter(format_number)

plt.yticks(np.arange(0,2_000_000_001, 100_000_000))
ax.yaxis.set_major_formatter(format_numbery)

ax.scatter(x[budgets_new['release_year'] >= 2012], y[budgets_new['release_y
ax.scatter(x[budgets_new['release_year'] < 2012], y[budgets_new['release_ye

ax.legend()
plt.savefig('new_domestic.png', dpi = 400)
```



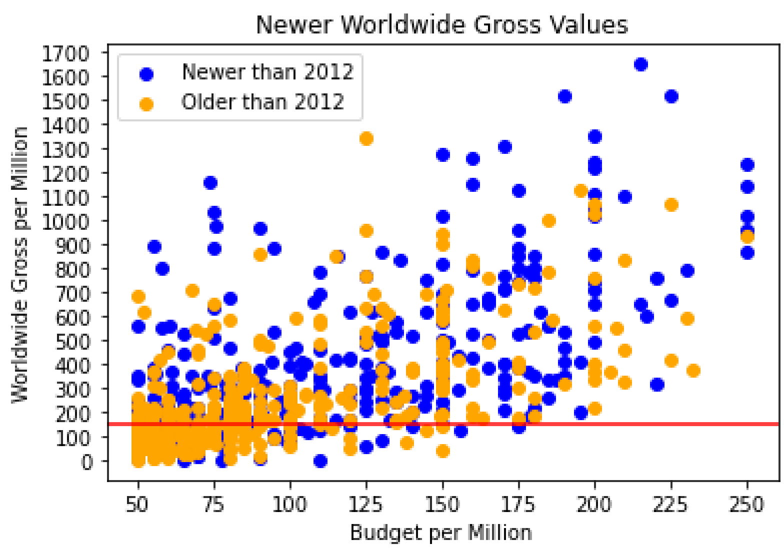
Same concept as the above graph except this is working with older movies, and the color seperation is before and after 1995.

In [96]:
```
old_domestic, ax = plt.subplots()

plt.title('Older Domestic Gross Values')
plt.xlabel('Budget per Million')
plt.ylabel('Domestic Gross per Million')

plt.xticks(np.arange(0,250_000_001, 25_000_000))
ax.xaxis.set_major_formatter(format_number)

plt.yticks(np.arange(0,2_000_000_001, 100_000_000))
ax.yaxis.set_major_formatter(format_numbery)

x = budgets_old['production_budget']
y = budgets_old['domestic_gross']

ax.scatter(x[budgets_old['release_year'] >= 1995], y[budgets_old['release_y
ax.scatter(x[budgets_old['release_year'] < 1995], y[budgets_old['release_ye

ax.legend()
plt.savefig('old_domestic.png', dpi = 400)
```

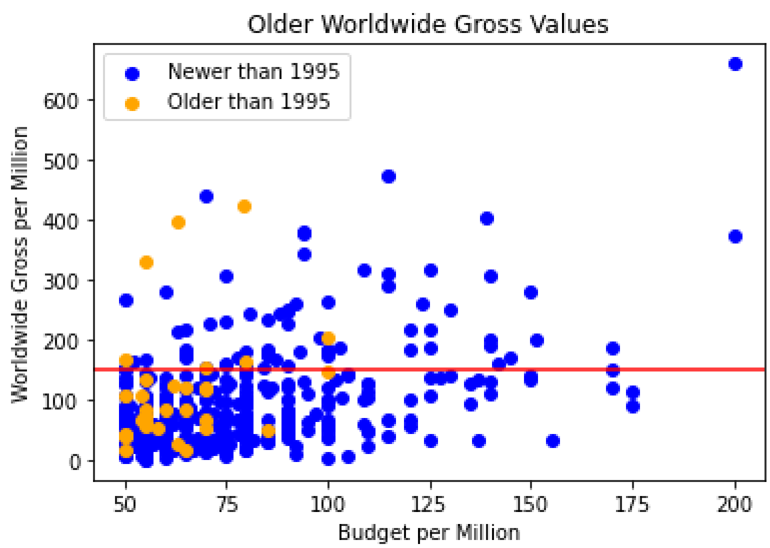


Similar to the above graphs but we are now working with worldwide gross instead of domestic gross. For the next two graphs, which we will be focusing my presentation about, we made a line to show the fact that many movies past the 150 million budget mark far make more profit than budget so their ROI is much more profitable the more they spend.

In [97]:
```
new_worldwide, ax = plt.subplots()

plt.title('Newer Worldwide Gross Values')
plt.xlabel('Budget per Million')
plt.ylabel('Worldwide Gross per Million')

plt.xticks(np.arange(0,250_000_001, 25_000_000))
ax.xaxis.set_major_formatter(format_number)

plt.yticks(np.arange(0,2_000_000_001, 100_000_000))
ax.yaxis.set_major_formatter(format_numbery)

plt.axhline(y = 150_000_000, color = 'r', linestyle = '-')

x = budgets_new['production_budget']
y = budgets_new['worldwide_gross']

ax.scatter(x[budgets_new['release_year'] >= 2012], y[budgets_new['release_y
ax.scatter(x[budgets_new['release_year'] < 2012], y[budgets_new['release_ye

ax.legend()
plt.savefig('new_worldwide.png', dpi = 400)
```



In [98]:
```
old_worldwide, ax = plt.subplots()

plt.title('Older Worldwide Gross Values')
plt.xlabel('Budget per Million')
plt.ylabel('Worldwide Gross per Million')

plt.xticks(np.arange(0,250_000_001, 25_000_000))
ax.xaxis.set_major_formatter(format_number)

plt.yticks(np.arange(0,2_000_000_001, 100_000_000))
ax.yaxis.set_major_formatter(format_numbery)

plt.axhline(y = 150_000_000, color = 'r', linestyle = '-')

x = budgets_old['production_budget']
y = budgets_old['domestic_gross']

ax.scatter(x[budgets_old['release_year'] >= 1995], y[budgets_old['release_y
ax.scatter(x[budgets_old['release_year'] < 1995], y[budgets_old['release_ye

ax.legend()
plt.savefig('old_worldwide.png', dpi = 400)
```



For the next two lines of code we wanted to show examples that could be good starting points for Microsoft if they did want to a documentary style films, while not necessarily full documentarys these two films are dramatizations of documentary biographies and could be relevant if Microsoft wanted to do a similar style for a documentary about Bill Gates or tech culture. To show this we first isolated the two movies into seperate variables and then made even further variables in which we would use to make seperations within my bar graph below. We ended up not using the Steve Jobs data for presentation

In [99]:
```
sj = budgets_clean[budgets_clean['movie'] == "Steve Jobs"]
sj_budget = sj['production_budget']
sj_domestic = sj['domestic_gross']
sj_world = sj['worldwide_gross']
sj
```

Out[99]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gross
1959	60	Oct 9, 2015	Steve Jobs	30000000.0	17766658.0	35579007.0	17812349.0

I wanted to clean up the data in sn specifically so that i could use that data for a clear side by side bar chart

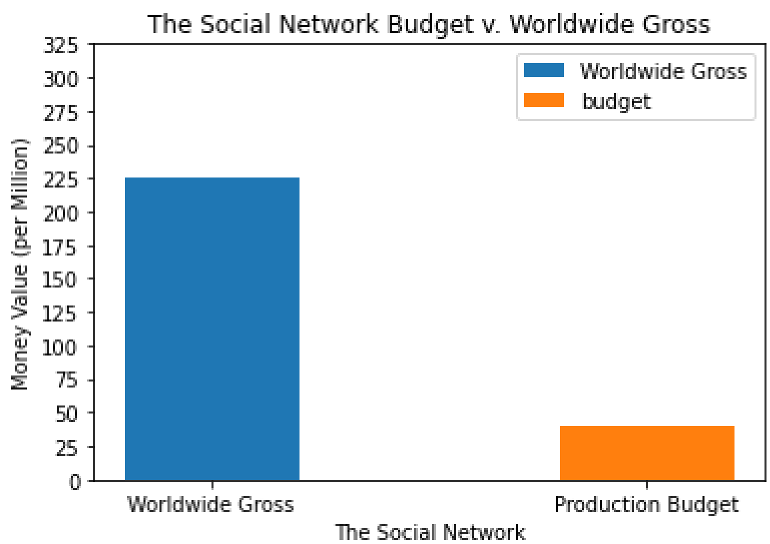
In [100]:
```
sn = budgets[budgets['movie'] == "The Social Network"]
sn
```

Out[100]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	foreign_gros
1390	91	Oct 1, 2010	The Social Network	40000000.0	96962694.0	224922135.0	127959441.

In order to achieve this comparison i first made the variable The Social Network. After setting the x variable i assigned a stacked bar chart for each and used the seperated variables within the data for each statistic i was looking at within the movie to show a clean bar chart which illustrated the budget and worldwide gross for the movie. A legend to show what each color represents helps differentiate.

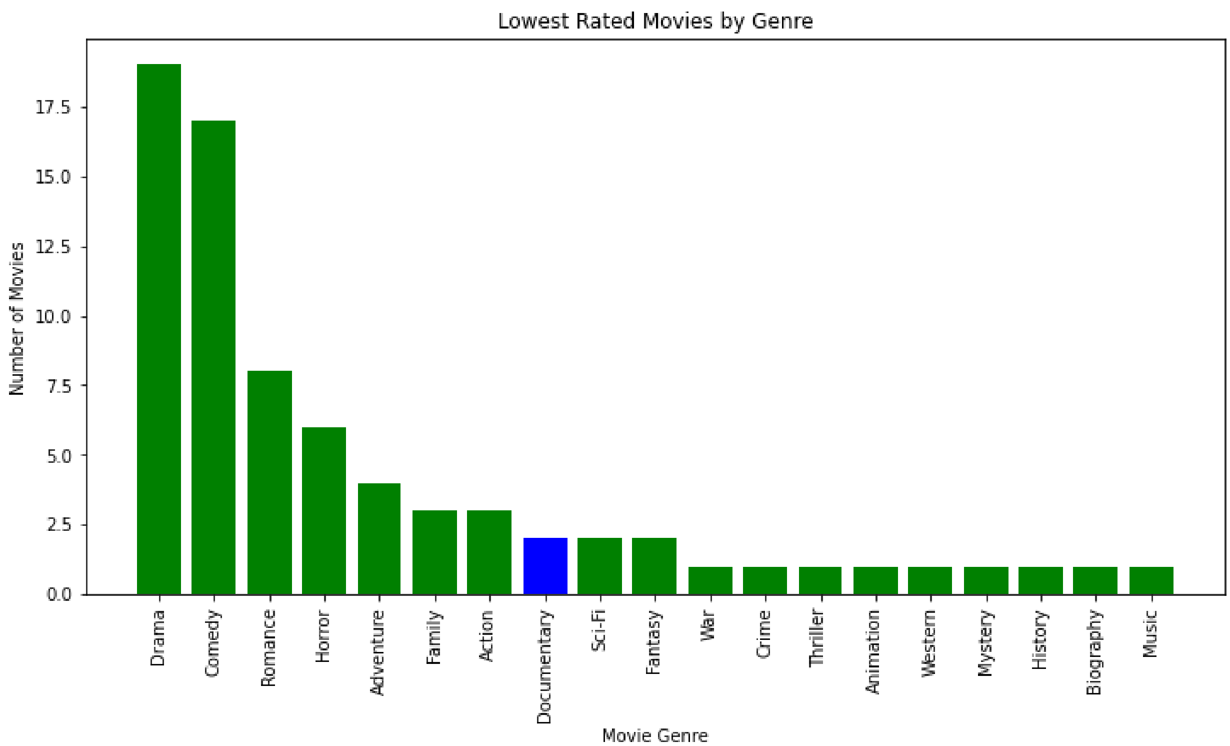
In [101]:
```
x = ['Worldwide Gross']
x2 = ['Production Budget']

Tech_movies, ax = plt.subplots()
width = .8

ax.bar(x, sn['worldwide_gross'], width=0.4, label = 'Worldwide Gross')
ax.bar(x2, sn['production_budget'], width=0.4, label = 'budget')


ax.legend()
plt.yticks(np.arange(0,325_000_001, 25_000_000))
ax.yaxis.set_major_formatter(format_numbery)

plt.title('The Social Network Budget v. Worldwide Gross');
plt.xlabel('The Social Network');
plt.ylabel('Money Value (per Million)');
plt.savefig('Tech_movies.png', dpi = 400)
```



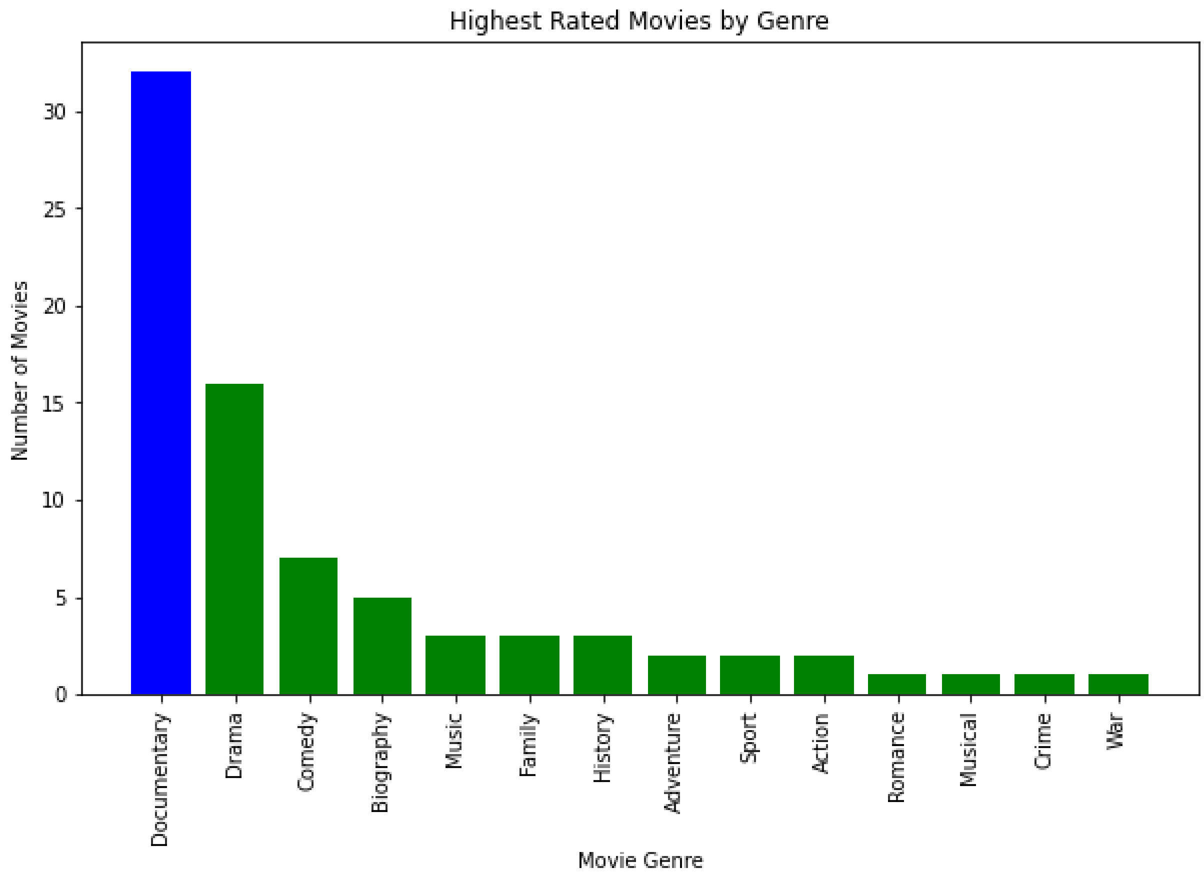
Genre Popularity

To visualize the highest rated films by genre, we plotted the movie counts for the 50 top rated movies to show that Documentary was the genre with the highest movie count. We also plotted the movie countws for the 50 lowest reated movies to show that Documentaries were not as common in the lowest rated movies.

In [102]:
```
fig, ax = plt.subplots(figsize=(12,6))

ax.bar(x=bottom_genre_counts_df['Genre'], height=bottom_genre_counts_df[0],
plt.xticks(rotation = 90)
plt.title('Lowest Rated Movies by Genre')
plt.xlabel('Movie Genre')
plt.ylabel('Number of Movies');

plt.savefig('lowest_genre_graph.png', bbox_inches = "tight", dpi=300)
```



```
In [103]: fig, ax = plt.subplots(figsize=(10, 6))

          ax.bar(x=top_genre_counts_df['Genre'], height=top_genre_counts_df[0], color
          plt.xticks(rotation = 90)
          plt.title('Highest Rated Movies by Genre')
          plt.xlabel('Movie Genre')
          plt.ylabel('Number of Movies');

          plt.savefig('highest_genre_graph.png', bbox_inches = "tight", dpi=300)
```



Conclusion

We developed three recommendations from our analysis for Microsoft Movie Studios:

- **Release films in peak months:** Microsoft Movie Studios should consider releasing movies in June, July, November, and December to optimize movie profits.
- **Allocate a budget of 150 to 200 million dollars:** Since movies with a budget over 150 million dollars displayed a greater return-on-investment, Microsoft Movie Studios should invest within the recommended budget range.
- **Focus on documentaries:** Our analysis found that the documentary genre has the most top rated movies. Microsoft Movie Studios should prioritize documentaries as a safe choice for movie genre.

Next Steps

Here are other ideas to explore for future analysis:

- **Streaming Platforms vs Movie Theaters:** Streaming services are becoming increasingly popular. Further analysis can focus specifically on movies released through streaming services.
- **Investigate success of film adaptations:** Microsoft has many properties that could be adapted to movies. Analysis on adaptation success could help Microsoft leverage those properties.