1 Microsoft Studios: A New Frontier

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1.1 Overview

Microsoft decided to create a new movie studio to compete with other companies in the space but they are not familiar with the movie industry or what kinds of movies they should be creating for this studio to be successful. Our task was to explore box office data in order to find at least three takeaways from the movie industry for Microsoft to act on.

There are many different factors that go into making a movie "successful". One can argue that the most important metric for a successful movie is the financial data such as revenue and profit. There would not be any business case if the movies did not make any money after all... However, we believe that the public reaction to the movie is almost as important as the financial data, especially for a new company entering this space. A movie may return a profit but if the moviegoers do not like the actual production, this will jeopardize the future success of the studio by hurting their brand, even if the movies they are making may be better in the future. For sustained growth, we believe that providing high quality productions liked by the masses that are profitable is the way forward. With this in mind, we came up with the following metrics: A movie should return at least a 25% profit and should have a higher average rating than 6.5.

In 2009, James Cameron's Avatar changed the movie industry forever. The technologies they developed and used to make CGI elements look as realistic as possible ended up being adopted by many movies and defining the past decade of the movie industry. Keeping this in mind, we believe that the data from 2009-2019 is the most relevant for Microsoft's business case. Therefore we limited our analysis to the past decade (2009-2019). Throughout the analysis we looked at the importance of what genre a movie is, how the production budget may affect the financial success and popularity of the movie as well as exploring whether there was an optimal time to release a movie to capitalize on.

1.2 Data Understanding & Preparation

For our data analysis we explored data from the largest movie databases online. These were namely: Box Office Mojo, IMDb, TMDb, The Numbers (TN) and Rotten Tomatoes. In order to pick which datasets we were going to use, we had to perform an exploratory data analysis (EDA) first. Our EDA began with comparing and contrasting the datasets that were provided to ensure that we kept as many data points as possible after the datasets were filtered and merged. This analysis also allowed us to define the success parameters for a movie: 25% profit and higher than a 6.5 rating. In the end, our analysis used data from IMDb and TN only since we ended up with the most amount of reliable data points with them.

1.2.1 Importing Data

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import os
%matplotlib inline
```

In [2]:

```
folder ='zippedData/'
os.listdir(folder)
```

Out[2]:

```
['bom.movie_gross.csv.gz',
 'imdb.name.basics.csv.gz',
 'imdb.title.akas.csv.gz',
 'imdb.title.basics.csv.gz',
 'imdb.title.crew.csv.gz',
 'imdb.title.principals.csv.gz',
 'imdb.title.ratings.csv.gz',
 'rt.movie_info.tsv.gz',
 'rt.reviews.tsv.gz',
 'tmdb.movies.csv.gz',
 'tn.movie_budgets.csv.gz']
```

In [3]:

```
bom_movie_gross = pd.read_csv(f'{folder}bom.movie_gross.csv.gz')
imdb_name_basics = pd.read_csv(f'{folder}imdb.name.basics.csv.gz')
imdb_title_akas = pd.read_csv(f'{folder}imdb.title.akas.csv.gz')
imdb_title_basics = pd.read_csv(f'{folder}imdb.title.basics.csv.gz')
imdb_title_crew = pd.read_csv(f'{folder}imdb.title.crew.csv.gz')
imdb_title_principals = pd.read_csv(f'{folder}imdb.title.principals.csv.gz')
imdb_title_ratings = pd.read_csv(f'{folder}imdb.title.ratings.csv.gz')
rt_movie_info = pd.read_csv(f'{folder}rt.movie_info.tsv.gz', delimiter='\t')
rt_reviews = pd.read_csv(f'{folder}rt.reviews.tsv.gz', delimiter='\t', encod
tmdb_movies = pd.read_csv(f'{folder}tmdb.movies.csv.gz',index_col=0)
tn_movie_budgets = pd.read_csv(f'{folder}tn.movie_budgets.csv.gz')
```

In [4]:

```
tmdb_movies.head()
```

Out[4]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_avera
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	7
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8

In [5]:

```
tmdb_movies['id'].value_counts()
```

Out[5]:

```
292086    3
463839    3
11976     3
391872    3
416572    3
         ..
356987    1
350846    1
479871    1
500353    1
524288    1
Name: id, Length: 25497, dtype: int64
```

In [6]:

```
tn_movie_budgets.head()
```

Out[6]:

	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 [7]:
```
bom_movie_gross.head()
```

Out[7]:

	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 [8]:
```
imdb_name_basics.head()
```

Out[8]:

	nconst	primary_name	birth_year	death_year	primary_professio
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,produce
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_departme
2	nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,write
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_departme
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_decorat

In [9]:
```
imdb_title_akas.head()
```

Out[9]:

	title_id	ordering	title	region	language	types	attributes	is_original_title
0	tt0369610	10	Джурасик свят	BG	bg	NaN	NaN	0.0
1	tt0369610	11	Jurashikku warudo	JP	NaN	imdbDisplay	NaN	0.0
2	tt0369610	12	Jurassic World: O Mundo dos Dinossauros	BR	NaN	imdbDisplay	NaN	0.0
3	tt0369610	13	O Mundo dos Dinossauros	BR	NaN	NaN	short title	0.0
4	tt0369610	14	Jurassic World	FR	NaN	imdbDisplay	NaN	0.0

In [10]:

```
imdb_title_principals.head()
```

Out[10]:

	tconst	ordering	nconst	category	job	characters
0	tt0111414	1	nm0246005	actor	NaN	["The Man"]
1	tt0111414	2	nm0398271	director	NaN	NaN
2	tt0111414	3	nm3739909	producer	producer	NaN
3	tt0323808	10	nm0059247	editor	NaN	NaN
4	tt0323808	1	nm3579312	actress	NaN	["Beth Boothby"]

In [11]:

```
imdb_title_crew.head()
```

Out[11]:

	tconst	directors	writers
0	tt0285252	nm0899854	nm0899854
1	tt0438973	NaN	nm0175726,nm1802864
2	tt0462036	nm1940585	nm1940585
3	tt0835418	nm0151540	nm0310087,nm0841532
4	tt0878654	nm0089502,nm2291498,nm2292011	nm0284943

In [12]:

```
imdb_title_ratings.head()
```

Out[12]:

	tconst	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

In [13]:
```
rt_movie_info.head()
```

Out[13]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Se
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012	J
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	A
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	Au
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	

In [14]:
```
rt_reviews.head()
```

Out[14]:

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
1	3	It's an allegory in search of a meaning that n...	NaN	rotten	Annalee Newitz	0	io9.com	May 23, 2018
2	3	... life lived in a bubble in financial dealin...	NaN	fresh	Sean Axmaker	0	Stream on Demand	January 4, 2018
3	3	Continuing along a line introduced in last yea...	NaN	fresh	Daniel Kasman	0	MUBI	November 16, 2017
4	3	... a perverse twist on neorealism...	NaN	fresh	NaN	0	Cinema Scope	October 12, 2017

In [15]:

```
tmdb_movies.head()
```

Out[15]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_avera
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	7
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8

In [16]:

```
imdb_title_basics.head()
```

Out[16]:

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

1.2.2 EDA to determine which movie df to use (looking at Sample Size, n)

EDA to figure out which dataframe has most movies for the past decade 2009 on excluding 2020. I excluded 2020 since it was an outlier year due to the pandemic and chose my start year as 2009 since the movie industry changed in a major way after the technology used in Avatar was adopted widely that year.

In [17]:
```
movies_financials = pd.merge(imdb_title_basics, bom_movie_gross, how="left",
movies_financials.isna().sum()
# len(tmdb_movies) #26517
# len(bom_movie_gross) #3387
# len(imdb_title_basics) #146144

```

Out[17]:
```
tconst                  0
primary_title           0
original_title         21
start_year              0
runtime_minutes     31739
genres               5408
title              142780
studio             142783
domestic_gross     142804
foreign_gross      144103
year               142780
dtype: int64
```

In [18]:
```
imdb_title_basics[(imdb_title_basics['start_year']>=2009) &
                  (imdb_title_basics['start_year']!=2020)] #937 rows in 2020

```

Out[18]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi	Kuambil Lagi	2019	123.0	Drama

In [19]:
```
imdb_title_basics['start_year'].min()
```

Out[19]:
```
2010
```

In [20]:
```
imdb_title_basics['start_year'].unique()
```

Out[20]:
```
array([2013, 2019, 2018, 2017, 2012, 2010, 2011, 2015, 2021, 2016, 2014,
       2020, 2022, 2023, 2024, 2026, 2025, 2115, 2027], dtype=int64)
```

```
In [21]: tmdb_movies['release_year'] = tmdb_movies['release_date'].map(lambda x: x[:4
         tmdb_movies['release_year'].dtype
```

```
Out[21]: dtype('O')
```

Changing the release_year column for tmdb movies to integer values so that I can sort by them.

```
In [22]: tmdb_movies['release_year'] = tmdb_movies['release_year'].astype('int64')
         df = tmdb_movies[(tmdb_movies['release_year']>=2009) & (tmdb_movies['release
         df['release_year'].unique()
```

```
Out[22]: array([2010, 2009, 2012, 2011, 2014, 2013, 2015, 2017, 2016, 2018, 2019],
               dtype=int64)
```

```
In [23]: len(df) #26,330
```

```
Out[23]: 26330
```

```
In [24]: df.head()
```

Out[24]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave
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	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	
5	[12, 14, 10751]	32657	en	Percy Jackson & the Olympians: The Lightning T...	26.691	2010-02-11	Percy Jackson & the Olympians: The Lightning T...	

1.2.3 Checking for duplicates

In [25]:

```
df[df.duplicated()]
```

Out[25]:

	genre_ids	id	original_language	original_title	popularity	release_date	title
2536	[12, 28, 878]	20526	en	TRON: Legacy	13.459	2010-12-10	TRON: Legacy
2673	[18, 10749]	46705	en	Blue Valentine	8.994	2010-12-29	Blue Valentine
2717	[35, 18, 14, 27, 9648]	45649	en	Rubber	8.319	2010-09-01	Rubber
2803	[35, 18]	46829	en	Barney's Version	7.357	2011-01-14	Barney's Version
2919	[18]	54602	en	Skateland	5.938	2011-05-13	Skateland
...	...	...	...	...	...	...	...
26481	[35, 18]	270805	en	Summer League	0.600	2013-03-18	Summer League

It looks like there is 1004 rows that are duplicated. I will check a couple id numbers to make sure that the duplicated method is running correctly.

In [26]:

```
df[df['id']==46829]
```

Out[26]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_av
289	[35, 18]	46829	en	Barney's Version	7.357	2011-01-14	Barney's Version	
2803	[35, 18]	46829	en	Barney's Version	7.357	2011-01-14	Barney's Version	

In [27]:

```
df[df['id']==54602]
```

Out[27]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_a
386	[18]	54602	en	Skateland	5.938	2011-05-13	Skateland	
2919	[18]	54602	en	Skateland	5.938	2011-05-13	Skateland	

1.2.4 Dropping duplicates

In [28]:
```
df = df.drop_duplicates(keep='first')
df[df['id']==46829] #spot-checking to make sure that the duplicates have bee
```

Out[28]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave
289	[35, 18]	46829	en	Barney's Version	7.357	2011-01-14	Barney's Version	

1.2.5 Checking for missing/placeholder values

In [29]:
```
df.isna().sum()
```

Out[29]:
```
genre_ids            0
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
title                0
vote_average         0
vote_count           0
release_year         0
dtype: int64
```

In [30]:
```
df[df['title']==None]
```

Out[30]:

genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_

1.2.6 EDA to figure out which financial df to use (looking at Sample Size, n)

In [31]:
```
len(tn_movie_budgets) #5782
# len(bom_movie_gross) #3387
```

Out[31]:
```
5782
```

Even though the amount of data points in the bom_movie_gross is almost half of tn_movie_budgets, depending on the merges I used it still could have resulted in a higher sample size compared to tn_movie budgets so I wanted to test the different merges to see how many data points were remaining.

In [32]:

```
#cleaned tmdb_movies (df) + bom_movie_gross
release_profit = pd.merge(df, bom_movie_gross, how='inner', left_on='title',
len(release_profit)
```

Out[32]:

```
2450
```

In [33]:

```
#cleaned tmdb_movies (df) + tn_movie_budgets
release_profit = pd.merge(df, tn_movie_budgets, how='inner', left_on='title'
len(release_profit)
```

Out[33]:

```
2156
```

Changing the financial information to integers so that I can manipulate them.

In [34]:

```
tn_movie_budgets['worldwide_gross'] = tn_movie_budgets['worldwide_gross'].ma
tn_movie_budgets['worldwide_gross'] = tn_movie_budgets['worldwide_gross'].as
tn_movie_budgets['worldwide_gross'].dtype
```

Out[34]:

```
dtype('int64')
```

Wrote a function to quickly re-apply the above logic and change the financial information to integer values.

In [35]:

```
def convertdollarstoint(df, col):
    df[col] = df[col].map(lambda x: x[1:].replace(',',''))
    df[col] = df[col].astype('int64')
    return df
```

In [36]:

```
convertdollarstoint(df = tn_movie_budgets, col = 'domestic_gross')
```

Out[36]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	620181382	1316721747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	0	0
5778	79	Apr 2, 1999	Following	$6,000	48482	240495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	1338	1338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	0	0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	181041	181041

5782 rows × 6 columns

In [37]:
```
convertdollarstoint(df = tn_movie_budgets, col = 'production_budget')
```

Out[37]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000	0	0
5778	79	Apr 2, 1999	Following	6000	48482	240495
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000	1338	1338
5780	81	Sep 29, 2015	A Plague So Pleasant	1400	0	0
5781	82	Aug 5, 2005	My Date With Drew	1100	181041	181041

5782 rows × 6 columns

In [38]:
```
tn_movie_budgets.head()
```

Out[38]:

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

Creating additional columns for profit and profit %.

In [39]:
```
tn_movie_budgets['profit'] = tn_movie_budgets['worldwide_gross'] - tn_movie_
tn_movie_budgets['profit %'] = (((tn_movie_budgets['worldwide_gross'] - tn_m
                                 /tn_movie_budgets['production_budget'])*100
tn_movie_budgets.head()
```

Out[39]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	profit
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	2351345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	635063875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	-200237650
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	1072413963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	999721747

Creating an additional column to isolate the months for the release date question I'll be exploring.

In [40]:

```
tn_movie_budgets['release_month'] = tn_movie_budgets['release_date'].map(lam
tn_movie_budgets['release_year'] = tn_movie_budgets['release_date'].map(lamb
tn_movie_budgets['release_year'] = tn_movie_budgets['release_year'].astype('
tn_movie_budgets.head()
```

Out[40]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	profit
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	2351345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	635063875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	-200237650
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	1072413963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	999721747

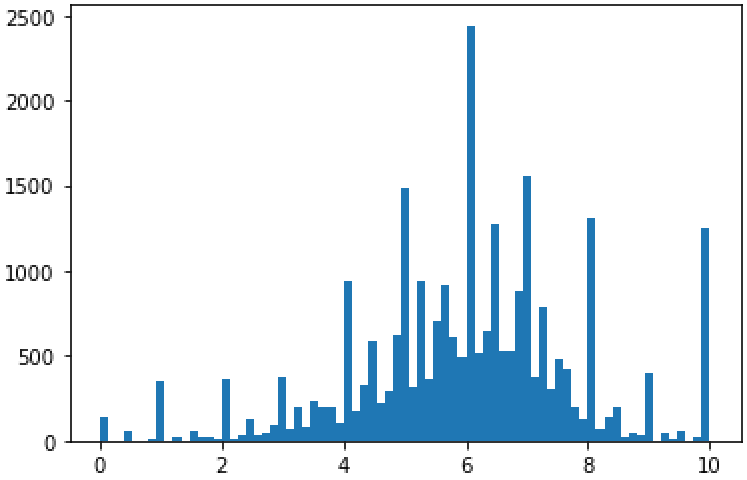
1.2.7 Exploring ratings for movies prior to merge to see distribution of ratings

In [41]:

```
plt.hist(x=tmdb_movies['vote_average'], bins='auto')
plt.show
```

Out[41]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [42]:

```
#quick check to make sure that there are no movies with 0 votes
tmdb_movies[tmdb_movies['vote_count']==0]
```

Out[42]:

genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_

All movies seem to have votes on their ratings which means we can use the vote_average information without having to fill any NaN values.

In [43]:

```
tt = tmdb_movies[tmdb_movies['release_year']>=2009]
tt['vote_average'].agg('mean')
```

Out[43]:

```
5.986039269302343
```

In [44]:

```
tt['vote_average'].agg('median')
```

Out[44]:

```
6.0
```

In [45]:

```
tt['vote_average'].agg('mode')
```

Out[45]:

```
0    6.0
dtype: float64
```

1.2.8 Defining a "successful movie" - larger than x% profit and higher than x rating & Filtering by successful movies.

It seems like the mean, median and mode values for the movie ratings converge to a 6.0 rating. Since Microsoft is just opening up this studio they will want to not only turn a profit but make movies that the public likes. A movie can turn a profit but not be liked by the public. So at the end of the day what will matter is the public opinion of this new studio as well as the profitability for sustained success. Therefore, we are going to be filtering the information by this information as well since we would like the movie to do better than just "average".

In [46]:

```python
tn_movie_budgets['release_year'].unique()
```

Out[46]:

```
array([2009, 2011, 2019, 2015, 2017, 2018, 2007, 2012, 2013, 2010, 2016,
       2014, 2006, 2008, 2005, 1997, 2004, 1999, 1995, 2003, 2001, 2020,
       2002, 1998, 2000, 1991, 1994, 1996, 1993, 1992, 1988, 1990, 1989,
       1978, 1981, 1984, 1982, 1985, 1980, 1963, 1987, 1986, 1983, 1979,
       1977, 1970, 1969, 1976, 1965, 1962, 1964, 1959, 1966, 1974, 1956,
       1975, 1973, 1960, 1967, 1968, 1971, 1951, 1972, 1961, 1946, 1944,
       1953, 1954, 1957, 1952, 1930, 1939, 1925, 1950, 1948, 1958, 1943,
       1940, 1945, 1947, 1938, 1927, 1949, 1955, 1936, 1937, 1941, 1942,
       1933, 1935, 1931, 1916, 1929, 1934, 1915, 1920], dtype=int64)
```

We decided to filter the dataset by the last decade (2009-2019) as the older movies have very little, if at all, meaning to the analysis we will be looking at. The target audiences for the older movies were different and the culture has changed significantly since then. We also think that since Avatar was a very influential movie in terms of the CGI modeling technologies it used that was a good place to start for "modern-day" movies. 2020 was also filtered out since it was an outlier year with the pandemic causing there to be shutdowns of nearly all businesses including movie theaters.

In [47]:

```
tn_filtered = tn_movie_budgets[(tn_movie_budgets['profit %']>=25)&(tn_movie_
                                &(tn_movie_budgets['release_year']<2020)]
tn_filtered
```

Out[47]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	pro
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	23513452
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	6350638
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	10724139
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	9997217
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220	17473112
...	...	...	...	...	...	...	
5685	86	Jul 7, 2017	A Ghost Story	100000	1594798	2769782	26697
5717	18	Nov 12, 2010	Tiny Furniture	50000	391674	424149	3741
5737	38	Mar 18, 2016	Krisha	30000	144822	144822	1148
5748	49	Sep 1, 2015	Exeter	25000	0	489792	4647
5760	61	Apr 2, 2010	Breaking Upwards	15000	115592	115592	1005

1363 rows × 10 columns

In [48]:

```
merged_df = pd.merge(tn_filtered, tmdb_movies, how='left', left_on='movie',
```

In [49]:
```
merged_df.head()
```

Out[49]:

	id_x	release_date_x	movie	production_budget	domestic_gross	worldwide_gross	pr
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	23513452
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	6350638
2	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	10724139
3	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	9997217
4	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220	17473112

In [50]:
```
len(merged_df)
```

Out[50]:
```
1550
```

In [51]:

```
merged_df[merged_df['movie'].duplicated()]
```

Out[51]:

	id_x	release_date_x	movie	production_budget	domestic_gross	worldwide_gross	pr
7	9	Nov 17, 2017	Justice League	300000000	229024295	655945209	355945
9	10	Nov 6, 2015	Spectre	300000000	200074175	879620923	579620
31	39	May 14, 2010	Robin Hood	210000000	105487148	322459006	112459
33	42	Feb 16, 2018	Black Panther	200000000	700059566	1348258224	1148258
36	45	Dec 16, 2016	Rogue One: A Star Wars Story	200000000	532177324	1049102856	849102
...	...	...	...	...	...	...	
1524	60	Apr 23, 2009	Home	500000	15433	44793168	44293
1531	72	Apr 28, 2017	Sleight	250000	3930990	3934450	3684
1535	10	Jul 20, 2012	Burn	225000	1109276	1109276	884
1546	38	Mar 18, 2016	Krisha	30000	144822	144822	114
1547	38	Mar 18, 2016	Krisha	30000	144822	144822	114

189 rows × 20 columns

In [52]:

```
test = merged_df.drop_duplicates(keep='first')
test[test.duplicated()]
```

Out[52]:

id_x	release_date_x	movie	production_budget	domestic_gross	worldwide_gross	profit	profit %

In [53]:

```
len(test)
```

Out[53]: 1446

In [54]:

```
test.isna().sum()
```

Out[54]:

```
id_x                   0
release_date_x         0
movie                  0
production_budget      0
domestic_gross         0
worldwide_gross        0
profit                 0
profit %               0
release_month          0
release_year_x         0
genre_ids            331
id_y                 331
original_language    331
original_title       331
popularity           331
release_date_y       331
title                331
vote_average         331
vote_count           331
release_year_y       331
dtype: int64
```

Since there were 331 data points missing from the above merged tables I decided to try out and see how many missing data the imdb tables merged with tn_movie_budgets would result in.

In [55]:

```
imdb = pd.merge(imdb_title_basics, imdb_title_ratings, left_on='tconst', rig
imdb.head()
```

Out[55]:

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

In [56]:

```
len(imdb)
```

Out[56]:

```
73856
```

In [57]:

```
imdb.loc[imdb['start_year']>2008, 'averagerating']
```

Out[57]:

```
0        7.0
1        7.2
2        6.9
3        6.1
4        6.5
        ... 
73851    6.2
73852    8.7
73853    8.5
73854    6.6
73855    6.5
Name: averagerating, Length: 73856, dtype: float64
```

In [58]:

```
imdb['averagerating'].agg('mean')
```

Out[58]:

```
6.332728552859619
```

In [59]:

```
imdb['averagerating'].agg('median')
```

Out[59]:

```
6.5
```

In [60]:

```
imdb['averagerating'].agg('mode')
```

Out[60]:

```
0    7.0
dtype: float64
```

Per the imdb datasets it seems like the average rating median is at 6.5 compared to the 6.0 shown above.

In [61]:

```
tn_filtered[tn_filtered.duplicated()]
```

Out[61]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	profit	profit %	rele

Since there can be movies with the same title, one way to weed out the duplicates is to use multiple columns for merging. I decided to use the release year as well as the title to ensure that there were no duplicated/inaccurate information in the resulting dataframe.

In [62]:

```
test2 = pd.merge(tn_filtered, imdb, left_on=['movie', 'release_year'], right
```

In [63]:

```
test2[test2.duplicated()]
```

Out[63]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	profit	profit %	rele

In [64]:

```
len(test2)
```

Out[64]:

```
983
```

Since I am testing out the merge between imdb and tn_filtered, I adjusted my success metric of being higher than the median average to 6.5.

In [65]:

```
imdb_tn_filtered = test2[test2['averagerating']>6.5]
```

In [66]:

```
imdb_tn_filtered.isna().sum()
```

Out[66]:

```
id                    0
release_date          0
movie                 0
production_budget     0
domestic_gross        0
worldwide_gross       0
profit                0
profit %              0
release_month         0
release_year          0
tconst                0
primary_title         0
original_title        0
start_year            0
runtime_minutes       2
genres                0
averagerating         0
numvotes              0
dtype: int64
```

Since this merge did not result in as many null values, and I have more of a complete dataframe I decided to use imdb_title_basics, imdb_title_ratings and tn_movie_budgets combination as my main dataframe throughout the analysis.

In [67]:

```
len(imdb_tn_filtered)
```

Out[67]:

```
493
```

In [68]:
```
imdb_tn_filtered.head()
```

Out[68]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	prof
0	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	63506387
1	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	107241396
2	7	Apr 27, 2018	Avengers: Infinity War	300000000	678815482	2048134200	174813420
4	10	Nov 6, 2015	Spectre	300000000	200074175	879620923	57962092
5	11	Jul 20, 2012	The Dark Knight	275000000	448139099	1084439099	80943909

In [69]:
```
#conversion of x and y ticks into millions to clean up the graphs we are goi
from matplotlib.ticker import FuncFormatter

#Source: https://stackoverflow.com/questions/61330427/set-y-axis-in-millions
#The two args are the value and tick position

def millions(x, pos):
    return '%1.0fM' % (x * 1e-6)
formatter = FuncFormatter(millions)
```

1.3 Data Modeling

A movie's success can be definitely affected by its genre, production budget and its release date. People often times look at the genre of a movie before anything else and make a snap decision whether they would like to see it or not. Similarly, a movie's production budget will affect this decision-making process since some movie-goers may want to see movies with higher quality production, better directors and actors etc. compared to indie movies. Lastly, depending on the release month movie-goers may not be able to go to the movies as much due to having to be in school or having to care for their school-aged children during the school year. So for our analysis we decided to take a deeper dive into these three areas to see if there are clear trends that Microsoft may use strategically for their movie creation process.

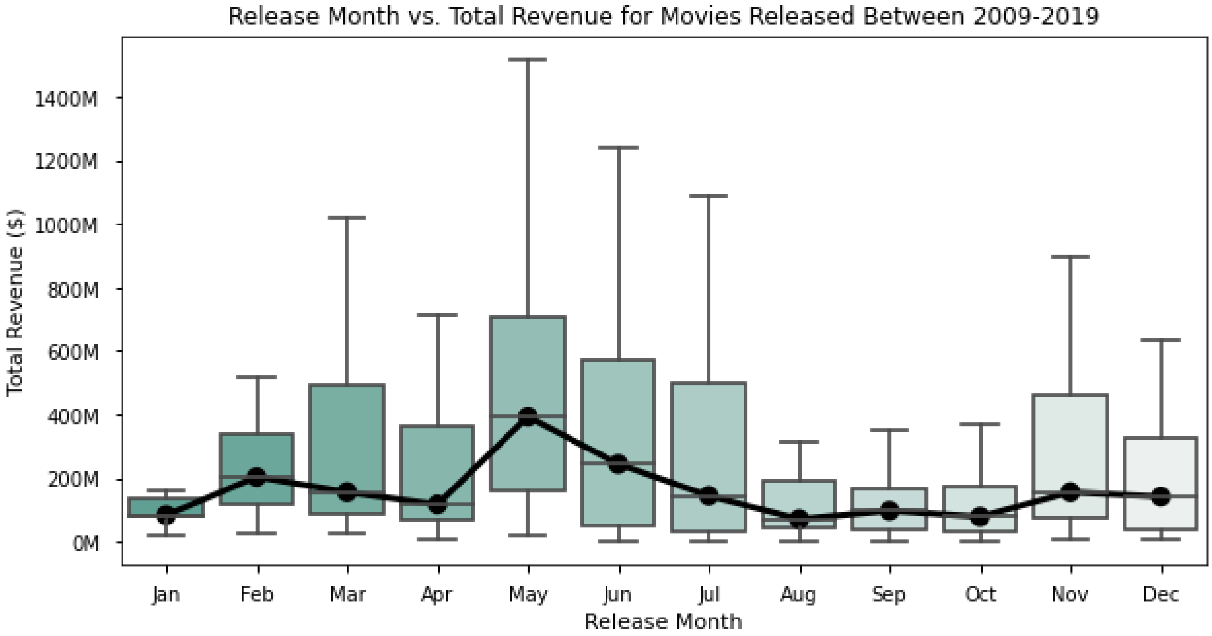
1.3.1 Question 1: How does release date affect a movie's success?

1.3.1.1 Release Month vs. Total Revenue

In [70]:
```
medians = imdb_tn_filtered.groupby('release_month')['worldwide_gross'].media
medians.sort_values(by='worldwide_gross', ascending=False)

order = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct
```

In [71]:
```
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(10,5))
    sns.boxplot(x=imdb_tn_filtered['release_month'], y=imdb_tn_filtered['wor
            showfliers=False, ax=ax, palette="light:#5A9_r")
    sns.pointplot(data=medians, x='release_month', y='worldwide_gross',
                  order=order, ax=ax, color='black')
    ax.set_xlabel('Release Month')
    ax.set_ylabel('Total Revenue ($)')
    ax.set_title('Release Month vs. Total Revenue for Movies Released Betwee
    ax.yaxis.set_major_formatter(formatter);
```



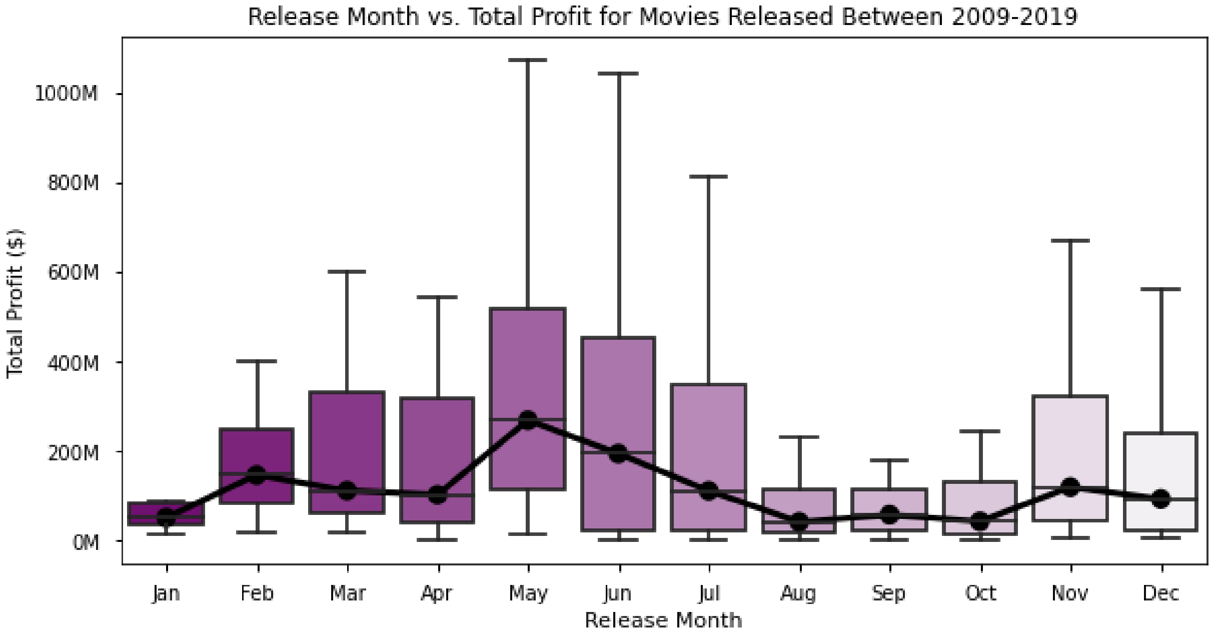
From this graph we can see that historically, the months of May and June were when the most revenue was generated. The black line in this graph represents the median revenue values while the boxplot gives an idea on the spread of the data.

1.3.1.2 Release Month vs. Total Profit

In [72]:
```
medians = imdb_tn_filtered.groupby('release_month')['profit'].median().reset
```

In [73]:

```
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(10,5))
    sns.boxplot(x=imdb_tn_filtered['release_month'], y=imdb_tn_filtered['pro
            order=order, showfliers=False, ax=ax, palette='light:purple_r')
    sns.pointplot(data=medians, x='release_month', y='profit', order=order,
    ax.set_xlabel('Release Month')
    ax.set_ylabel('Total Profit ($)')
    ax.set_title('Release Month vs. Total Profit for Movies Released Between
    ax.yaxis.set_major_formatter(formatter);
```



Similar to the previous graph that shows the release month vs. total revenue, this graph shows a similar trend that suggests the most profitable movies were the ones that were released in May followed closely by June.

1.3.1.3 Our Recommendation for Microsoft

Microsoft should strongly consider releasing their movies in the summer months preferably in May or June. As the school year comes to an end, these months allow for more movie-goers to enjoy the movies in their local theater and this directly translates into maximizing revenue and profit.

1.3.2 Question 2: How does the genre of the movie affect its success?

In [74]:

```
imdb_tn_filtered['genres'] = imdb_tn_filtered['genres'].map(lambda x: x.stri
imdb_tn_filtered.head()
```

```
<ipython-input-74-048b0847e17d>: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-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  imdb_tn_filtered['genres'] = imdb_tn_filtered['genres'].map(lambda x: x.strip
().split(','))
```

Out[74]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	profit
0	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	635063875
1	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	1072413963
2	7	Apr 27, 2018	Avengers: Infinity War	300000000	678815482	2048134200	1748134200
4	10	Nov 6, 2015	Spectre	300000000	200074175	879620923	579620923
5	11	Jul 20, 2012	The Dark Knight Rises	275000000	448139099	1084439099	809439099

I need to check to make sure that one movie doesn't have more than 3 genres at the same time since my code is geared towards that.

In [75]:

```
for x in imdb_tn_filtered['genres']:
    if len(x)>3:
        print(len(x))
```

In [76]:

```
imdb_tn_filtered['genre1'] = imdb_tn_filtered['genres'].map(lambda x: x[0].s
imdb_tn_filtered['genre2'] = imdb_tn_filtered['genres'].map(lambda x: x[1].s
imdb_tn_filtered['genre3'] = imdb_tn_filtered['genres'].map(lambda x: x[2].s
```

```
<ipython-input-76-b72c3f5e9305>: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-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  imdb_tn_filtered['genre1'] = imdb_tn_filtered['genres'].map(lambda x: x[0].st
rip())
<ipython-input-76-b72c3f5e9305>: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-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  imdb_tn_filtered['genre2'] = imdb_tn_filtered['genres'].map(lambda x: x[1].st
rip() if (len(x)>=2) else np.NaN)
<ipython-input-76-b72c3f5e9305>:3: 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-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  imdb_tn_filtered['genre3'] = imdb_tn_filtered['genres'].map(lambda x: x[2].st
rip() if (len(x)==3) else np.NaN)
```

In [77]:

```python
genre1_counts = {}

for genre in imdb_tn_filtered['genre1']:
    if genre not in genre1_counts.keys():
        genre1_counts[genre]=1
    else:
        genre1_counts[genre]+=1

genre2_counts = {}

for genre in imdb_tn_filtered['genre2']:
    if genre not in genre2_counts.keys():
        genre2_counts[genre]=1
    else:
        genre2_counts[genre]+=1

genre3_counts = {}

for genre in imdb_tn_filtered['genre3']:
    if genre not in genre3_counts.keys():
        genre3_counts[genre]=1
    else:
        genre3_counts[genre]+=1

print(genre1_counts, genre2_counts, genre3_counts)
```

```
{'Action': 154, 'Adventure': 65, 'Drama': 92, 'Horror': 8, 'Family': 1, 'Comed
y': 70, 'Biography': 59, 'Crime': 25, 'Animation': 5, 'Mystery': 3, 'Romance':
1, 'Thriller': 1, 'Documentary': 9} {'Adventure': 84, 'Thriller': 18, 'Animatio
n': 36, 'Family': 10, 'Fantasy': 11, 'Crime': 41, 'Romance': 27, 'Mystery': 21,
'Comedy': 39, 'Sci-Fi': 11, 'Drama': 129, nan: 33, 'Western': 1, 'History': 3,
'Biography': 10, 'Sport': 3, 'Horror': 5, 'War': 2, 'Music': 6, 'Documentary':
3} {'Fantasy': 21, 'Sci-Fi': 46, 'Thriller': 52, nan: 139, 'Comedy': 47, 'Dram
a': 58, 'Animation': 14, 'Horror': 3, 'Family': 20, 'Musical': 3, 'History': 1
5, 'Biography': 3, 'Crime': 11, 'Mystery': 11, 'Western': 2, 'War': 3, 'Sport':
11, 'Music': 6, 'Romance': 27, 'Documentary': 1}
```

In [78]:

```python
#code snippet from https://www.geeksforgeeks.org/python-combine-two-dictiona
import itertools
import collections

total_genre = collections.defaultdict(int)
for key, val in itertools.chain(genre1_counts.items(), genre2_counts.items()
    total_genre[key] += val

total_genre
```

Out[78]:

```
defaultdict(int,
            {'Action': 154,
             'Adventure': 149,
             'Drama': 221,
             'Horror': 13,
             'Family': 11,
             'Comedy': 109,
             'Biography': 69,
             'Crime': 66,
             'Animation': 41,
             'Mystery': 24,
             'Romance': 28,
             'Thriller': 19,
             'Documentary': 12,
             'Fantasy': 11,
             'Sci-Fi': 11,
             nan: 33,
             'Western': 1,
             'History': 3,
             'Sport': 3,
             'War': 2,
             'Music': 6})
```

In [79]:

```python
#code snippet from https://www.geeksforgeeks.org/python-combine-two-dictiona
total_genre_counts = collections.defaultdict(int)
for key, val in itertools.chain(total_genre.items(), genre3_counts.items()):
    total_genre_counts[key] += val
total_genre_counts
del total_genre_counts[np.nan]
```

In [80]:

```
#code snippet from https://stackoverflow.com/questions/613183/how-do-i-sort-
total_genre_counts={k: v for k, v in sorted(total_genre_counts.items(), key=
total_genre_counts
```

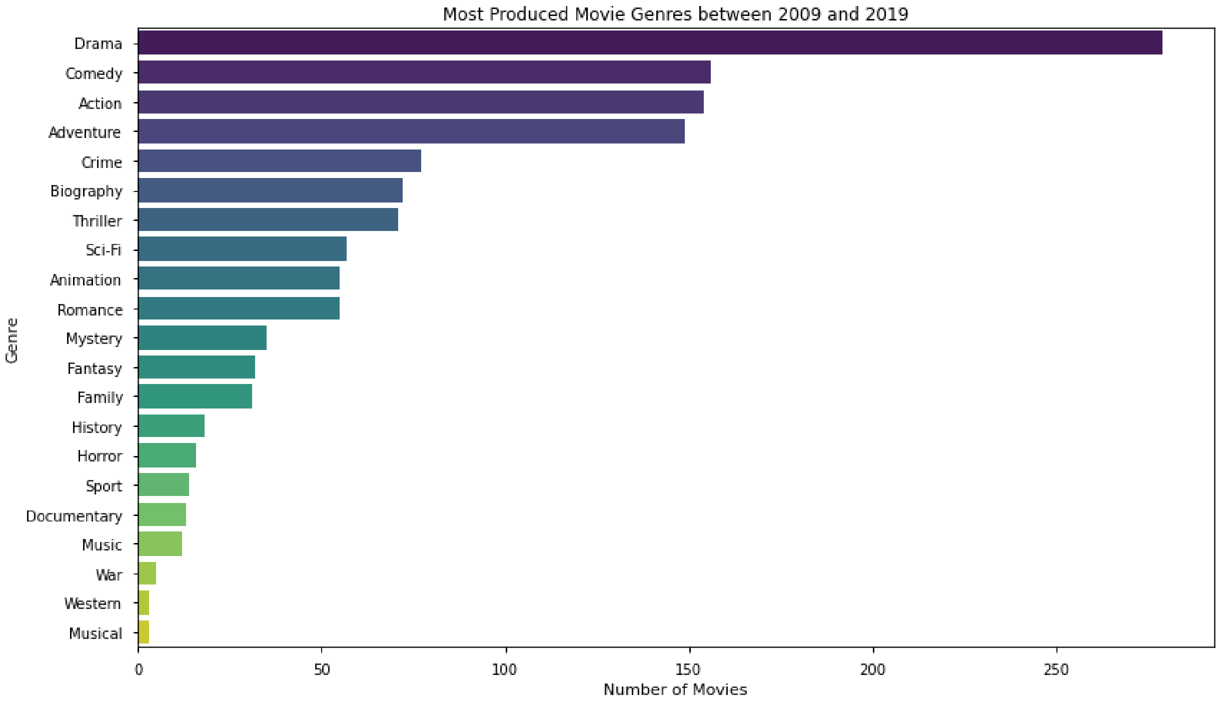
Out[80]:

```
{'Drama': 279,
 'Comedy': 156,
 'Action': 154,
 'Adventure': 149,
 'Crime': 77,
 'Biography': 72,
 'Thriller': 71,
 'Sci-Fi': 57,
 'Animation': 55,
 'Romance': 55,
 'Mystery': 35,
 'Fantasy': 32,
 'Family': 31,
 'History': 18,
 'Horror': 16,
 'Sport': 14,
 'Documentary': 13,
 'Music': 12,
 'War': 5,
 'Western': 3,
 'Musical': 3}
```

1.3.2.1 Most Produced Movie Genres

In [81]:

```
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(12,7))
    sns.barplot(x=list(total_genre_counts.values()), y= list(total_genre_cou
                orient='h', palette='viridis')
    ax.set_xlabel('Number of Movies')
    ax.set_ylabel('Genre')
    ax.set_title('Most Produced Movie Genres between 2009 and 2019')
    plt.tight_layout()
    fig.savefig('images/Most-Produced-Genre.png', transparent=False, facecol
```



As seen above, Drama was by far the most produced genre between 2009 and 2019 followed by Comedy, Action and Adventure.

1.3.2.2 Genre vs. Median Revenue

In [82]:

```
exploded_imdb_tn = imdb_tn_filtered.explode('genres')
exploded_imdb_tn.head()
```

Out[82]:

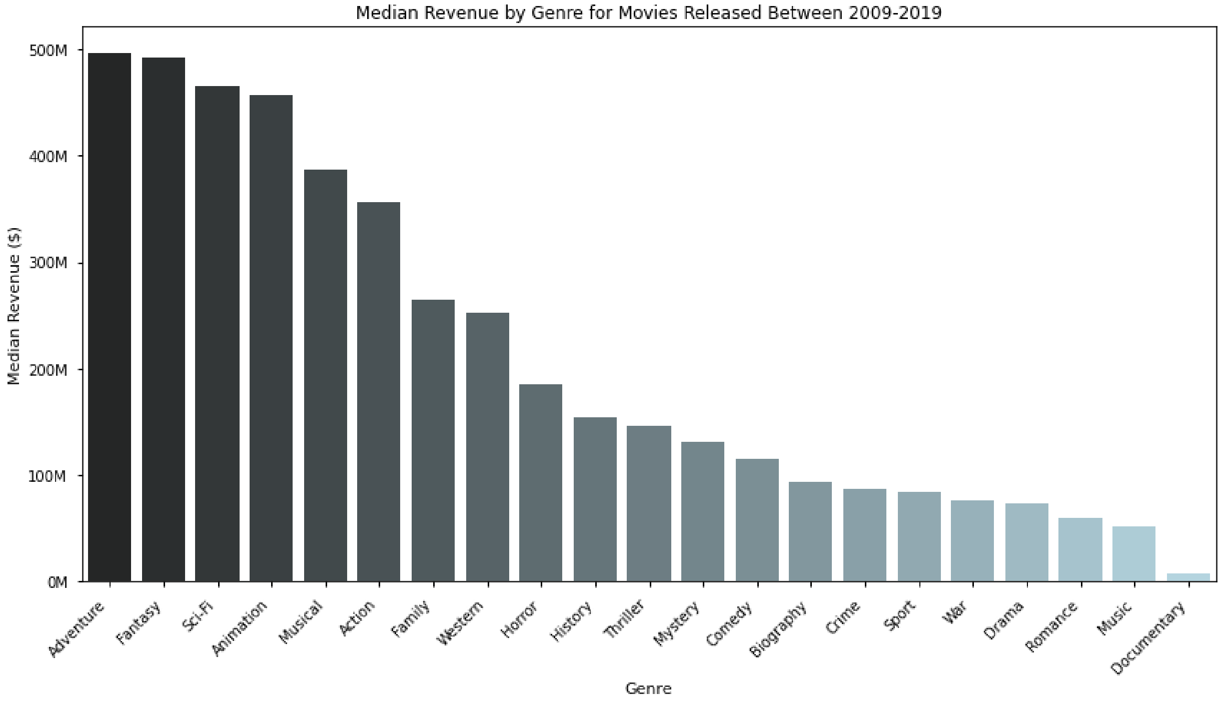
	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	prof
0	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	63506387
0	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	63506387
0	2	May 20, 2011	Pirates of the Caribbean: On	410600000	241063875	1045663875	63506387

In [83]:

```
genre_revenue_order = exploded_imdb_tn.groupby('genres').median()['worldwide_
```

In [84]:

```python
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(12,7))
    sns.barplot(x=exploded_imdb_tn['genres'], y=exploded_imdb_tn['worldwide_
                ci=None, order=genre_revenue_order, palette="dark:lightblue"
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45,ha='right')
    ax.set_ylabel('Median Revenue ($)')
    ax.set_xlabel('Genre')
    ax.set_title('Median Revenue by Genre for Movies Released Between 2009-2
    ax.yaxis.set_major_formatter(formatter)
    plt.tight_layout()
    fig.savefig('images/Rev-Genre.png', transparent=False, facecolor='white'
```



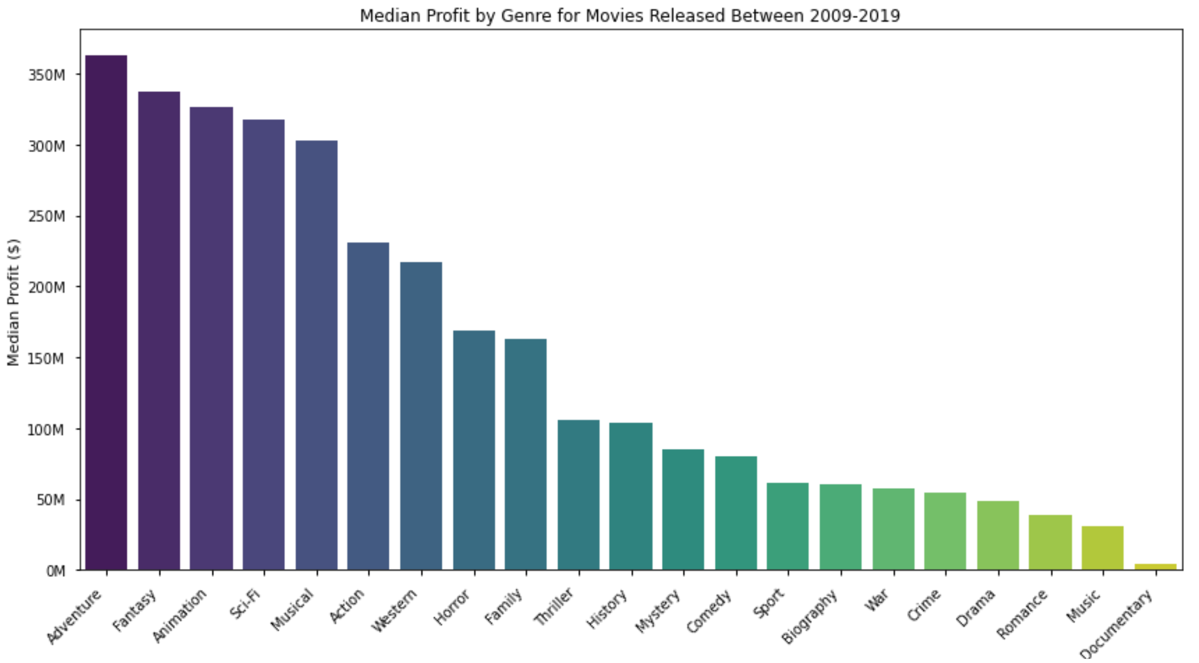
Even though our analysis shows that Drama was the highest produced genre in the past decade, this graph shows us that Drama is not the optimal choice for generating revenue. Here we see that Adventure, Fantasy, Sci-Fi and Animation movies tend to generate more revenue compared to the other genres.

1.3.2.3 Genre vs. Median Profit

In [85]:

```python
genre_profit_order = exploded_imdb_tn.groupby('genres').median()['profit'].s
```

In [86]:
```
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(12,7))
    sns.barplot(x=exploded_imdb_tn['genres'], y=exploded_imdb_tn['profit'],
                ci=None, order=genre_profit_order, palette='viridis')
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45,ha='right')
    ax.set_ylabel('Median Profit ($)')
    ax.set_xlabel('Genre')
    ax.set_title('Median Profit by Genre for Movies Released Between 2009-20
    ax.yaxis.set_major_formatter(formatter)
    plt.tight_layout()
    fig.savefig('images/Prof-Genre.png', transparent=False, facecolor='white
```



Similar to the relationship between genre and revenue, we see that the most profitable genres are Adventure, Fantasy, Animation and Sci-Fi even though they are not the ones most produced.

1.3.2.4 Our Recommendation for Microsoft

As we saw in the past decade, even though Drama was the most produced genre, followed by Comedy, the most profitable and high grossing movies tended to be Adventure, Fantasy, Animation and Sci-Fi movies. This presents a great opportunity for Microsoft. By focusing on these four key genres and incorporating them into their movies, Microsoft can make a great entry into the movie industry, gain popularity and build their brand while also generating the financial returns that they desire.

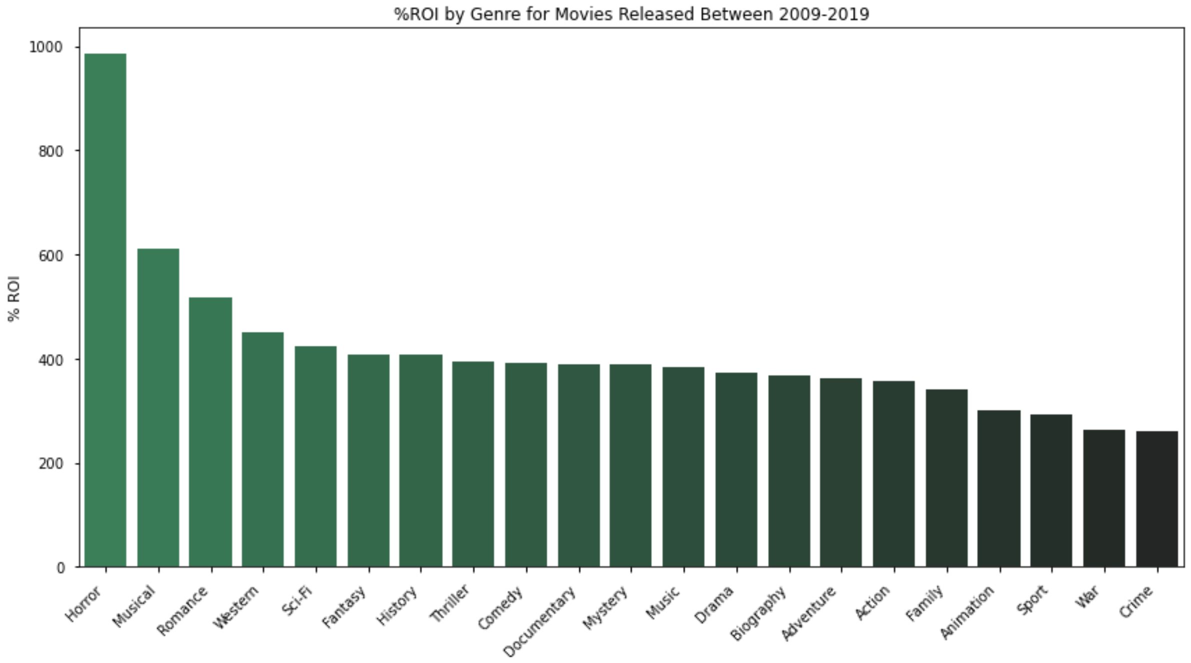
1.3.2.5 Genre vs. % ROI

In [87]:
```
exploded_imdb_tn['ROI %'] = (exploded_imdb_tn['worldwide_gross']/exploded_im
```

In [88]:
```
genre_roi_order = exploded_imdb_tn.groupby('genres').median()['ROI %'].sort_
```

In [89]:

```python
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(12,7))
    sns.barplot(x=exploded_imdb_tn['genres'], y=exploded_imdb_tn['ROI %'], e
                order=genre_roi_order, palette='dark:seagreen_r')
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45,ha='right')
    ax.set_ylabel('% ROI')
    ax.set_xlabel('Genre')
    ax.set_title('%ROI by Genre for Movies Released Between 2009-2019')
    plt.tight_layout()
    fig.savefig('images/ROI-Genre.png', transparent=False, facecolor='white'
```



1.3.2.6 Side Note for Microsoft

If Microsoft's financial targets are more aligned with return on investment (% ROI) rather than pure revenue or profits, then we recommend they produce Horror movies instead. Our analysis showed that Horror had a higher ROI percentage compared to any other genre as can be seen above. This means that a higher return can be achieved compared to what is spent on the production budget.

1.3.3 Question 3: How does the production budget affect a movie's ratings and financial success?

In [90]:
```
a = imdb_tn_filtered
a['ROI %'] = (a['worldwide_gross']/a['production_budget'])*100
```

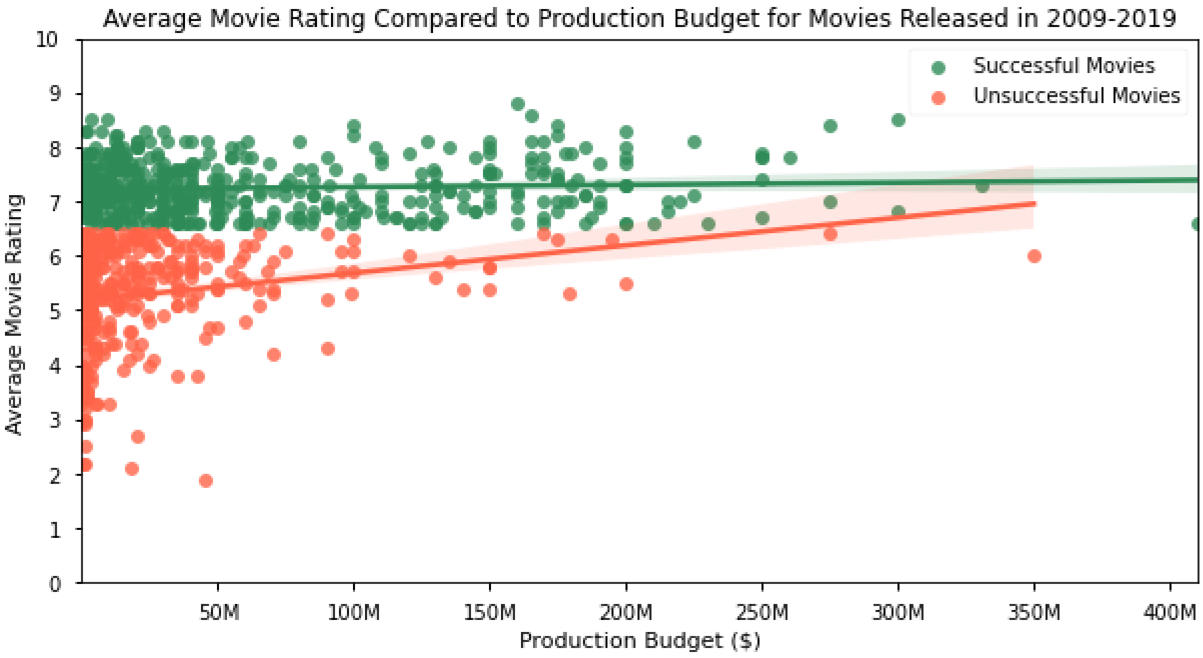
```
<ipython-input-90-5ea35b07874a>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  a['ROI %'] = (a['worldwide_gross']/a['production_budget'])*100
```

In [91]:
```
a = tn_movie_budgets[tn_movie_budgets['release_year']>2008]
b = pd.merge(a, imdb, left_on=['movie', 'release_year'], right_on=['original
```

1.3.3.1 Production Budget vs. Average Movie Rating

In [92]:
```
unsuccessful_df = b[(b['averagerating']<6.5) & (b['profit %']<25)]
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(10,5))
    sns.regplot(data=imdb_tn_filtered, x='production_budget', y='averagerati
                color='seagreen', ax=ax, label='Successful Movies')
    sns.regplot(data=unsuccessful_df, x='production_budget', y='averageratin
                color='tomato', ax=ax, label='Unsuccessful Movies')
    ax.legend()
    ax.set_xlabel('Production Budget ($)')
    ax.set_ylabel('Average Movie Rating')
    ax.set_ylim(0,10)
    ax.set_title('Average Movie Rating Compared to Production Budget for Mov
    ax.xaxis.set_major_formatter(formatter)
    ax.set_yticks(np.arange(0, 11, step=1));
```



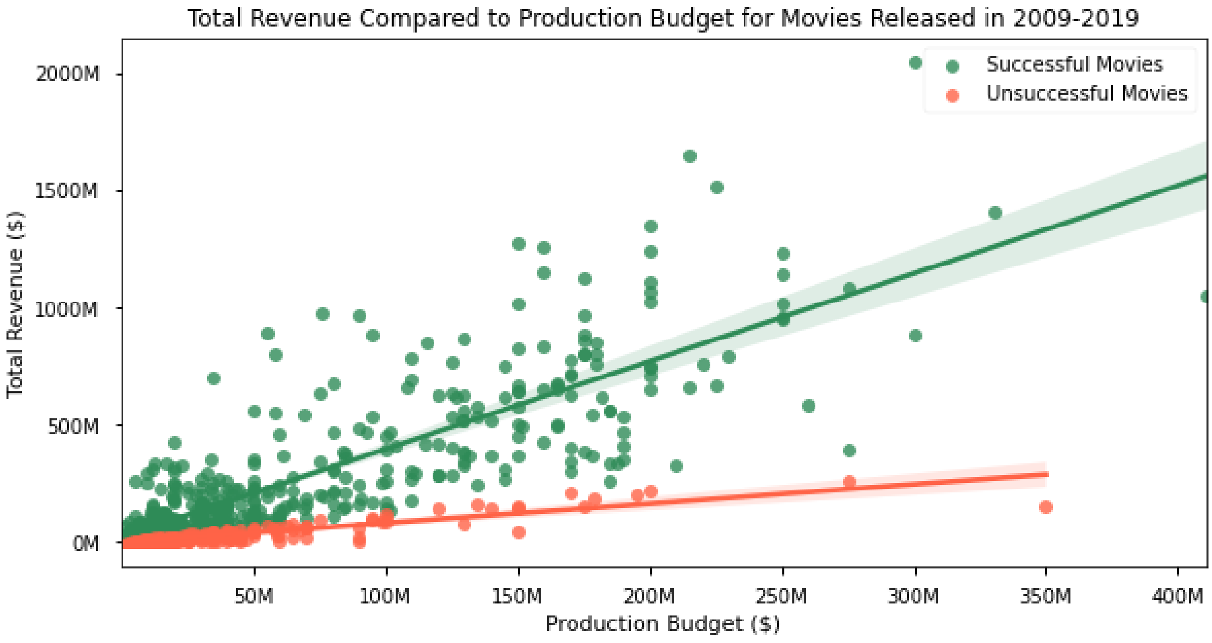
As can be seen from the graph above, the successful movies as we defined them (higher than

25% profit and higher than a 6.5 rating) don't show a clear correlation between the production budget and the movie ratings while unsuccessful movies show a relatively higher correlation, but an overall weak one at that. This relationship debunks the assumption that as more money is spent on the movie, the more it will be liked by cinema fans. The relationship shown suggests that a movie studio does not need to have a high production budget for it to have higher movie ratings.

1.3.3.2 Production Budget vs. Total Revenue

In [93]:

```
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(10,5))
    sns.regplot(x=imdb_tn_filtered['production_budget'], y=imdb_tn_filtered[
                color='seagreen', ax=ax, label='Successful Movies')
    sns.regplot(x=unsuccessful_df['production_budget'], y=unsuccessful_df['w
                color='tomato', ax=ax, label='Unsuccessful Movies')
    ax.legend()
    ax.set_xlabel('Production Budget ($)')
    ax.set_ylabel('Total Revenue ($)')
    ax.set_title('Total Revenue Compared to Production Budget for Movies Rel
    ax.yaxis.set_major_formatter(formatter)
    ax.xaxis.set_major_formatter(formatter);
```

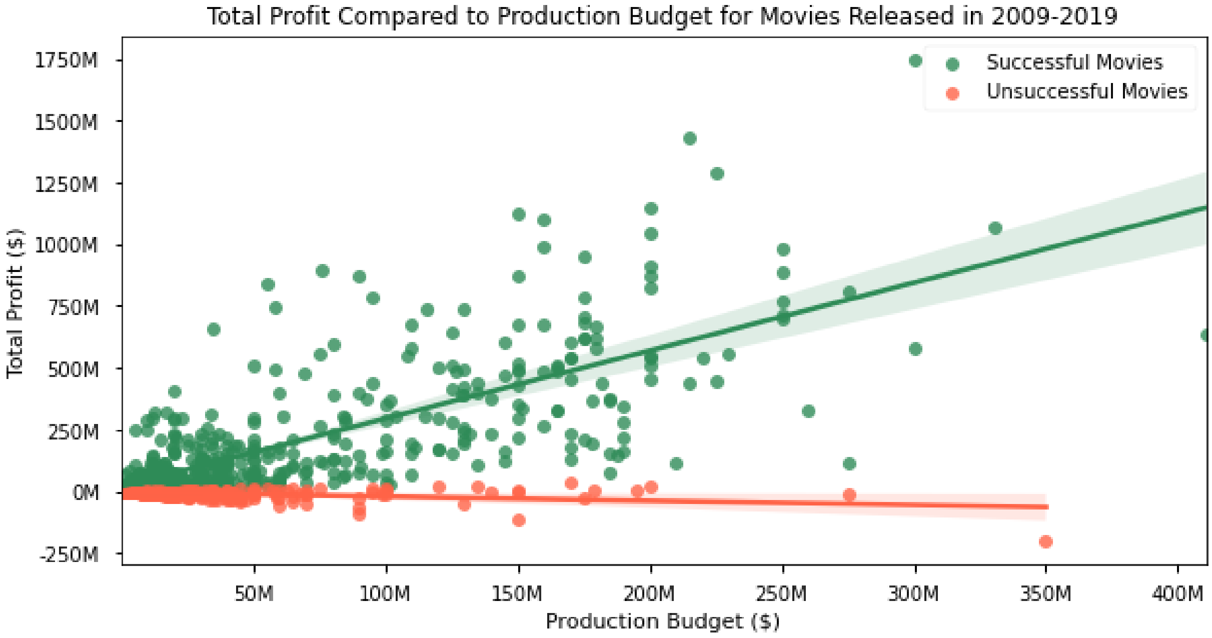


As seen above, the production budget has more of a direct effect on the revenue generated by the movie. This may be due to factors such as having increased marketing budgets, or being able to show the movie in more countries compared to a lower budget production. The difference between the successful and unsuccessful movies in this relationship is also noteworthy. Even with lower quality productions, the revenue tends to increase with the budget but is ultimately stifled potentially due to the overall quality of the production.

1.3.3.3 Production Budget vs. Total Profit

In [94]:

```
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(10,5))
    sns.regplot(x=imdb_tn_filtered['production_budget'], y=imdb_tn_filtered[
                ax=ax, label='Successful Movies')
    sns.regplot(x=unsuccessful_df['production_budget'], y=unsuccessful_df['p
                ax=ax, label='Unsuccessful Movies')
    ax.legend()
    ax.set_xlabel('Production Budget ($)')
    ax.set_ylabel('Total Profit ($)')
    ax.set_title('Total Profit Compared to Production Budget for Movies Rele
    ax.yaxis.set_major_formatter(formatter)
    ax.xaxis.set_major_formatter(formatter);
```



The analysis between total profit and production budget shows a positive correlation for successful movies. As the production budget increases, the total profit amount tends to increase as well. For unsuccessful movies though the story is a little different. As the production budget increases, total profit tends to stay flat or even decrease. This is potentially due to the relationship we explored above between total revenue and production budget. Since the revenue numbers are stifled for unsuccessful movies, the higher the budget gets, the harder it is to turn a profit or even breakeven.

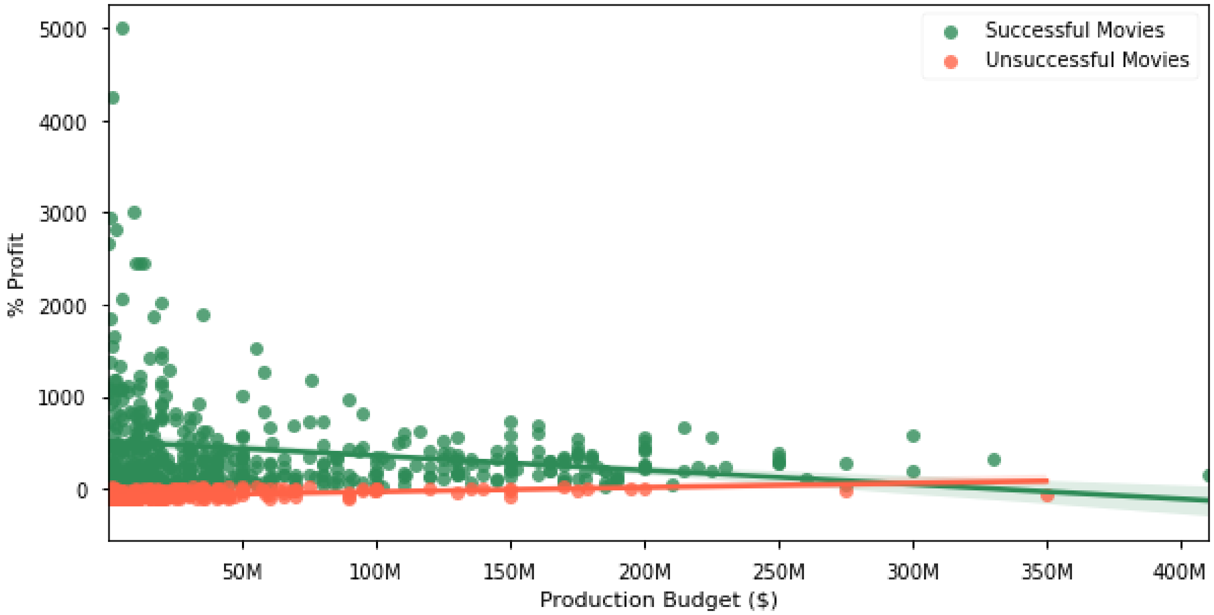
1.3.3.4 Our Recommendation for Microsoft

Our analysis showed that, ultimately, production budget affects revenue and profits pretty strongly while the movie ratings by the general public tend to not change with higher budgets. Microsoft should strategically think about the production budget and decide between the riskier approach or the safer approach. If they are okay with taking a riskier approach, then higher production budgets may return stronger numbers; however, if the movie is not successful, the overall production may lose more money. Either way, we found that having higher budgets don't translate into moviegoers liking the movies better. Therefore, our recommendation would be for Microsoft to build their fanbase prior to producing movies with higher budgets since it is absolutely possible to produce quality movies with lower budgets as can be seen. This will allow for Microsoft Studios to be financially successful and will pave the path for a sustained growth and success.

1.3.3.5 Production Budget vs. Profit %

In [95]:

```
with plt.style.context('seaborn-notebook'):
    fig, ax = plt.subplots(figsize=(10,5))
    sns.regplot(x=imdb_tn_filtered['production_budget'], y=imdb_tn_filtered[
                ax=ax, label='Successful Movies')
    sns.regplot(x=unsuccessful_df['production_budget'], y=unsuccessful_df['p
                ax=ax, label='Unsuccessful Movies')
    ax.legend()
    ax.set_xlabel('Production Budget ($)')
    ax.set_ylabel('% Profit')
    ax.xaxis.set_major_formatter(formatter);
```



The relationship between % profit and production budget is an interesting one. It seems like as production budget increases the % profit decreases. This is potentially due to the movie having to perform even better than lower costing successful movies to offset the high amount of costs associated with the production. This insight can be valuable for Microsoft if their earnings are reported in terms of % profit to shareholders rather than total values.

1.4 Conclusions

Even though the movie industry is a new frontier for Microsoft, it is an exciting industry filled with opportunities. To sum up, our analysis showed the following:

- Movies released in May and June historically performed better compared to other months in terms of revenue and profits.
- Even though the most produced genre for the past decade was Drama, most revenue and profit was generated by Adventure movies followed closely by Fantasy, Animation and Sci-Fi.

- The best genre in terms of % ROI was Horror.
- Higher production budgets don't translate into the public liking those movies more.
- Higher production budgets generated more revenue and profit for successful movies but unsuccessful movies with higher budgets ended up losing more money overall.

Given more time and information about what kinds of movies Microsoft would like to make, we would have wanted to analyze how much the actors, writers and directors affect the success of the movies and what the optimal cast would look like. It would also be fruitful to analyze the data by generations so that Microsoft's marketing team can optimize their efforts for specific generations depending on the target audience of their movies. Furthermore, analyzing the unsuccessful movies in more depth to find common traits among them for Microsoft to avoid would lower the financial risks associated with this industry. Lastly, we would collect more data to improve on the accuracy of these findings.