1 Microsoft Studios Film Profit Analysis

Author: Morgan Didjurgis

1.1 Overview

This project's purpose is to provide recommendations on what type of films perform the best for Microsoft, since they are opening a new movie studio. Analysis of almost 2000 movies made in the US in the last 10 years shows that higher budget films (over $40 million) tend to have higher profits. Among higher budget films, those with certain genres, MPAA ratings, and release months tend to perform better on average.

1.2 Business Problem

Microsoft is seeking recommendations for which type of films they can make in order to have the best chance at maximizing profit. While films are generally risky business ventures, this risk can be reduced by choosing budget sizes, genres, MPAA ratings, and release months that have been shown to have higher success rates.

This project will evaluate:

1) Is budget size correlated with profit?

2) Which genres tend to perform the best?

3) Which MPAA ratings tend to perform the best? I'll also examine which MPAA ratings perform the best within the most profitable genres, since this can be very specific to the type of movie.

4) Do certain release months tend to have higher profits? Does this vary by genre?

1.3 Data Understanding

The data for this project came from multiple online movie databases. The primary source was the IMDB (Internet Movie Database) API with some additional data gathered from Box Office Mojo and TMDB (The Movie Database).

The main variables I intend to use for analysis are worldwide gross, budget, MPAA rating, genre, and release month. Worldwide gross and budget will be used to calculate profit. Budget, MPAA rating, genre, and release month will be used to determine which film characteristics tend to lead to higher profit. MPAA rating, genre, and release month are all categorical, which I will have to keep in mind during the analysis.

- The code for data collection and filtering is contained in 'api_calls.ipynb'. Below is a summary of my process and major decision points.

    1. I started with a list of over 146,000 movies with basic information including IMDB id, title, start year, runtime, and genre. From this list, I filtered out any movies made after 2020 since there were a number of upcoming releases listed.
    2. I used the IMDB ids to query the IMDB API versions endpoint and get country data for these movies. I only kept movies made in the US, since Microsoft is a US based company. I had 49,608 movies after filtering for country of origin.
    3. I then queried the IMDB business endpoint to get worldwide gross and budget data for as many US movies as possible.
    4. Next, I merged the IMDB dataset with data from Box Office Mojo using original titles and filled in budget, domestic gross, and worldwide gross data that was not available on IMDB that this dataset contained.
    5. Using domestic gross and international gross, I was able to estimate worldwide gross for a few movies where that information was not provided directly.
    6. Before making any further queries for other movie information, I filtered the dataset, removing any films without worldwide gross, since this information is crucial to the analysis. I also only included films with a runtime between 45 minutes and 4 hours, since anything outside this range would not be the type of movie I am making recommendations to Microsoft about. After this, I had 4065 movies remaining.
    7. I then queried the IMDB overview endpoint to get MPAA rating and Release Date data. I extracted the month from the release date since I am mostly interested in what month the movie was released.
    8. Lastly, I queried TMDB to find additional information on budget, relase date and MPAA rating for movies missing those values. To do this I isolated films missing any of these values, queried TMDB using the IMDB id to find the matching TMDB id, then queried the TMDB details and release date endpoints.
    9. The data resulting from this process is saved under 'imdb_all_data.csv'

In [98]:
```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

pd.set_option('display.float_format', lambda x: f'{x: ,.2f}')
```

2 Approach

2.1 Data Preparation

Describe and justify the process for preparing the data for analysis.

First, I will standardize the formats for all of the variables, since they were collected from three different databases.

Genres: I converted the strings containing multiple genres into Python lists so that they could later be exploded for easier analysis of genres.

MPAA Rating: I examined all the values in this column and found that a number of the ratings were actually meant for television. Many of these films still had theatrical releases and financial data, so I decided to convert TV ratings to their MPAA equivalent. The maturity content of the film is the most important piece of information from this variable and TV ratings were still a good estimate for this.

Month: I had already pulled release month out of the various release date formats, so these did not have to be cleaned any further.

Since I will mainly be using profit to analyze how sucessful a film was, I decided to drop all rows that did not have budget information. While this meant dropping a large portion of the data, I still had approximately 2000 films and it would allow me to provide better recommendations to Microsoft. Using only worldwide gross could be misleading since high grossing films can have extremely large budgets and low grossing films may have extremely small budgets that still make them fairly profitable.

I also investigated rows with missing genres, MPAA ratings, and months. I found that many of the rows missing this data were actually duplicates that I had not previously identified due to slightly different title information and different IMDB ids. These duplicates had other entries with all the data available, so I decided to drop the rows with missing data.

In [99]:
```
movies=pd.read_csv('student_data/imdb_all_data.csv')
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4065 entries, 0 to 4064
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Unnamed: 0       4065 non-null   int64  
 1   tconst           4065 non-null   object 
 2   original_title   4065 non-null   object 
 3   start_year       4065 non-null   int64  
 4   runtime_minutes  4065 non-null   float64
 5   genres           4063 non-null   object 
 6   budget           2025 non-null   object 
 7   ww_gross         4065 non-null   float64
 8   mpaa_rating      3700 non-null   object 
 9   month            4032 non-null   float64
dtypes: float64(3), int64(2), object(5)
memory usage: 317.7+ KB
```

2.1.1 genres

Check for any variable formatting. Split genres into list of strings. For analysis, I will explode the list of genres.

In [100]:
```
movies['genres'].str.split(',').explode().value_counts()
```

Out[100]:
```
Drama                  1818
Comedy                 1131
Documentary             886
Thriller                600
Action                  598
Horror                  476
Crime                   457
Romance                 450
Adventure               439
Biography               375
Mystery                 272
Sci-Fi                  201
Family                  193
Fantasy                 187
History                 179
Music                   177
Animation               154
Sport                    98
Western                  36
War                      36
News                     33
Musical                  30
['Documentary']           3
['Science Fiction']       1
Name: genres, dtype: int64
```

In [101]:
```
#fix ['Documentary'] and ['Science Fiction']

movies[(movies['genres']=="['Documentary']") |
       (movies['genres']=="['Science Fiction']")]
```

Out[101]:

	Unnamed: 0	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_(
670	670	tt1482889	Jim	2010	101.00	['Science Fiction']	NaN	13,0
3371	3371	tt5515304	Frey: Part I - The Architectural Envoy	2018	65.00	['Documentary']	NaN	2,2
3893	3893	tt7689908	Crime + Punishment	2018	112.00	['Documentary']	NaN	18,6
3894	3894	tt7689956	Chef Flynn	2018	82.00	['Documentary']	NaN	69,5

In [102]:
```
#correct these rows
movies.loc[670,'genres']='Sci-Fi'
movies.loc[[3371,3893,3894],'genres']='Documentary'
```

In [103]:
```
movies['genres'].str.split(',').explode().value_counts()
```

Out[103]:
```
Drama          1818
Comedy         1131
Documentary     889
Thriller        600
Action          598
Horror          476
Crime           457
Romance         450
Adventure       439
Biography       375
Mystery         272
Sci-Fi          202
Family          193
Fantasy         187
History         179
Music           177
Animation       154
Sport            98
Western          36
War              36
News             33
Musical          30
Name: genres, dtype: int64
```

In [104]:
```
#turn genres into list of strings now that formatting is corrected
movies['genres']=movies['genres'].str.split(',')
movies['genres'].head()
```

Out[104]:
```
0        [Action, Animation, Comedy]
1         [Drama, Mystery, Thriller]
2     [Adventure, Animation, Comedy]
3         [Adventure, Comedy, Drama]
4             [Action, Crime, Drama]
Name: genres, dtype: object
```

2.1.2 ratings

Check for any formatting issues

In [105]:
```
movies['mpaa_rating'].value_counts()
```

Out[105]:
```
R            1360
PG-13         850
Not Rated     802
PG            358
Unrated       110
TV-MA          74
G              38
TV-14          37
NR             36
TV-PG          23
TV-G            7
TV-Y            3
NC-17           1
Approved        1
Name: mpaa_rating, dtype: int64
```

1) 'Not Rated' and 'Unrated' are the same, so I will change these all to 'Unrated'.
2) I will explore what 'Approved' means.
3) Explore movies with TV ratings. This analysis is meant for theatrical releases, so movies that were made for TV should not be included.
4) Investigate whether NC-17 movie should be in dataset

In [106]:
```
#Replace 'Not Rated' with 'Unrated'
movies['mpaa_rating']=movies['mpaa_rating'].\
                    where(movies['mpaa_rating']!='Not Rated',other='Unr
movies['mpaa_rating'].value_counts()
```

Out[106]:
```
R           1360
Unrated      912
PG-13        850
PG           358
TV-MA         74
G             38
TV-14         37
NR            36
TV-PG         23
TV-G           7
TV-Y           3
NC-17          1
Approved       1
Name: mpaa_rating, dtype: int64
```

In [107]:
```
movies['mpaa_rating']=movies['mpaa_rating'].\
                    where(movies['mpaa_rating']!='NR',other='Unrated')
```

In [108]:
```
#Investigate 'Approved'
movies[movies['mpaa_rating']=='Approved']
```

Out[108]:

	Unnamed: 0	tconst	original_title	start_year	runtime_minutes	genres	budget	wv
3999	3999	tt8803596	Have It All - The Movie	2018	90.00	[Documentary]	{'amount': 250000.0, 'currency': 'USD'}	197

From filmratings.com/History, films used to be either Approved/Disapproved based on whether they were moral or unmoral under the Hays Code. The current MPAA rating system replaced this in 1968. It does not make sense that a film from 2018 would be rated Approved, so I will change this value to Unrated.

In [109]:
```
#Change value to unrated
movies.loc[3999,'mpaa_rating']='Unrated'
```

In [110]:
```
#Explore movies that are TV-PG
movies[movies['mpaa_rating']=='TV-PG'].head()
```

Out[110]:

	Unnamed: 0	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_g
672	672	tt1482991	Carbon Nation	2010	86.00	[Documentary, Family]	NaN	16,9(
1420	1420	tt1930322	Destiny Road	2012	100.00	[Drama]	NaN	926,11
1577	1577	tt2040398	La Camioneta: The Journey of One American Scho...	2012	71.00	[Documentary]	NaN	18,5
1795	1795	tt2222206	Dear Mr. Watterson	2013	89.00	[Documentary]	NaN	23,8
2020	2020	tt2402114	Forgive - Don't Forget	2018	69.00	[Documentary, History, War]	NaN	128,0(

From digging into the movies on the list, it is clear that many of these movies had theatrical releases. The majority of the movies that I checked have TV ratings that coincide with their MPAA ratings, so I will replace the TV ratings with MPAA ratings, so that they are grouped generally in the correct category for maturity of the content.

In [111]:
```
#Change TV ratings to their MPAA equivalent
new_ratings={'TV-Y':'G','TV-G':'G','TV-PG':'PG','TV-14':'PG-13','TV-MA'
movies['mpaa_rating']=movies['mpaa_rating'].apply(lambda x:
                                                  new_ratings[x] if x in
                                                  new_ratings else x)
movies['mpaa_rating'].value_counts()
```

Out[111]:
```
R          1434
Unrated     949
PG-13       887
PG          381
G            48
NC-17         1
Name: mpaa_rating, dtype: int64
```

In [112]:
```
movies[movies['mpaa_rating']=='NC-17']
```

Out[112]:

	Unnamed: 0	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_g
3919	3919	tt7947150	This One's for the Ladies	2018	82.00	[Documentary]	NaN	13,68

In [113]:
```
#remove this movie- not the kind of material discussed in analysis and
#make much money
movies=movies[movies['mpaa_rating']!='NC-17']
movies['mpaa_rating'].value_counts()
```

Out[113]:
```
R           1434
Unrated      949
PG-13        887
PG           381
G             48
Name: mpaa_rating, dtype: int64
```

In [114]:
```
movies.drop(['Unnamed: 0'],axis=1,inplace=True)
```

In [115]:
```
#movies.to_csv('29SEP_movies.csv')
```

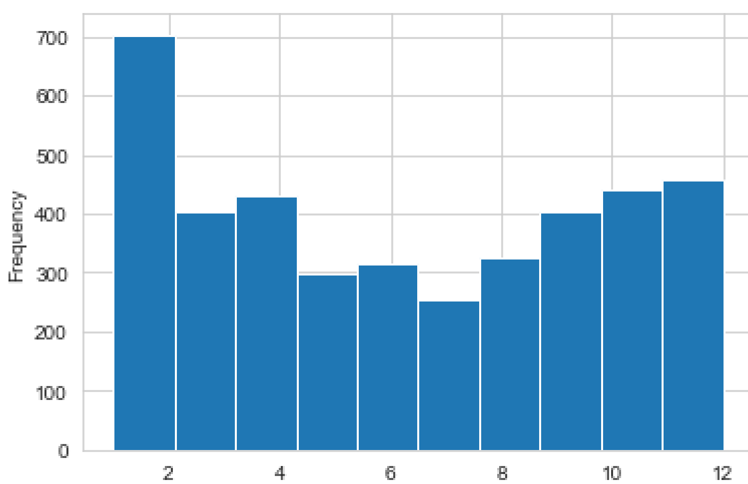
In [116]:
```
movies=pd.read_csv('student_data/29SEP_movies.csv')
movies.drop(['Unnamed: 0'],axis=1,inplace=True)
```

2.1.3 month

Look at distribution of month data and determine how to handle missing values

In [117]:
```
movies['month'].plot(kind='hist')
```

Out[117]: <AxesSubplot:ylabel='Frequency'>



I could fill in the missing month data by using random months with the same distribution as the data, but I don't think this would add to the analysis, since there are only 33/4064 missing values. I will consider dropping these rows after I finish looking at other missing values.

2.1.4 budget

Get all budget data in same format as type float

In [118]:
```
movies[movies['budget'].apply(lambda x: type(x))==str].head()

```

Out[118]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_gross	r
0	tt0249516	Foodfight!	2012	91.00	['Action', 'Animation', 'Comedy']	{'amount': 65000000.0, 'currency': 'USD'}	120,141.00	
1	tt0326965	In My Sleep	2010	104.00	['Drama', 'Mystery', 'Thriller']	{'amount': 1000000.0, 'currency': 'USD'}	30,158.00	
3	tt0359950	The Secret Life of Walter Mitty	2013	114.00	['Adventure', 'Comedy', 'Drama']	{'amount': 90000000, 'currency': 'USD'}	188,133,322.00	
4	tt0365907	A Walk Among the Tombstones	2014	114.00	['Action', 'Crime', 'Drama']	{'amount': 28000000, 'currency': 'USD'}	58,834,384.00	
5	tt0369610	Jurassic World	2015	124.00	['Action', 'Adventure', 'Sci-Fi']	{'amount': 150000000, 'currency': 'USD'}	1,670,516,444.00	

In [119]:
```
def find_dicts(data):
    if type(data)==str:
        if '{' in data:
            return True
        else:
            return False
    else:
        return False

type_bool=movies['budget'].apply(find_dicts)
```

In [120]:
```
def fix_budget(x):
    data=eval(x)
    return data['amount']

movies.loc[type_bool,'budget']=movies.loc[type_bool,
                                          'budget'].apply(fix_budget)
movies['budget'].head(10)
```

Out[120]:
```
0     65,000,000.00
1      1,000,000.00
2               NaN
3     90,000,000.00
4     28,000,000.00
5    150,000,000.00
6      5,000,000.00
7     45,000,000.00
8     30,000,000.00
9    260,000,000.00
Name: budget, dtype: object
```

In [121]:
```
movies['budget']=movies['budget'].astype(float)
```

In [122]:
```
movies['budget'].describe()
```

Out[122]:
```
count          2,025.00
mean      32,090,687.79
std       49,186,123.98
min                0.00
25%        2,000,000.00
50%       12,000,000.00
75%       36,000,000.00
max      356,000,000.00
Name: budget, dtype: float64
```

In [123]:
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4064 entries, 0 to 4063
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           4064 non-null   object 
 1   original_title   4064 non-null   object 
 2   start_year       4064 non-null   int64  
 3   runtime_minutes  4064 non-null   float64
 4   genres           4062 non-null   object 
 5   budget           2025 non-null   float64
 6   ww_gross         4064 non-null   float64
 7   mpaa_rating      3699 non-null   object 
 8   month            4031 non-null   float64
dtypes: float64(4), int64(1), object(4)
memory usage: 285.9+ KB
```

In [124]:
```
#movies.to_csv('30SEP_movies.csv',index=False)
```

In [125]:
```
movies=pd.read_csv('student_data/30SEP_movies.csv')
```

2.1.5 Investigate missing data

For genres, mpaa_rating, month, verify whether there are movies with missing data that we want included in the analysis. Check what the highest values for ww_gross for the movies missing these values.

In [126]:
```
#genres
movies[movies['genres'].isnull()].sort_values('ww_gross',ascending=Fals
```

Out[126]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_gross	mpaa_ratir
2105	tt2504610	The Oscar Nominated Short Films 2010: Live Action	2010	97.00	NaN	nan	1,018,169.00	Na
1082	tt1701997	I'm Still Here	2010	60.00	NaN	nan	569,000.00	Na

In [127]:
```
#mpaa_rating
missing_rating=movies[movies['mpaa_rating'].isnull()].sort_values('ww_g
                                                          ascending=False)
```

In [128]:
```
missing_rating.head()
```

Out[128]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_gros
1623	tt2071483	Inside Out	2011	59.00	['Family']	500,000.00	857,600,000.0(
2847	tt4028068	Wonder Woman	2014	60.00	['Sci-Fi']	15,000.00	821,900,000.0(
2526	tt3300078	The Revenant	2012	80.00	['Horror']	2,000.00	532,900,000.0(
3456	tt5734820	Rio	2017	87.00	['Drama']	nan	484,600,000.0(
2185	tt2614250	Rio	2012	90.00	['Documentary']	250,000.00	484,600,000.0(

In [129]:
```
movies[movies['original_title'].str.contains('Reven')]
```

Out[129]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_g
404	tt1287468	Cats & Dogs: The Revenge of Kitty Galore	2010	82.00	['Action', 'Comedy', 'Family']	85,000,000.00	112,483,76
467	tt1322362	Revenge of the Mekons	2013	95.00	['Documentary']	300,000.00	11,86
584	tt1413496	Revenge of the Electric Car	2011	90.00	['Documentary']	nan	151,27
1015	tt1663202	The Revenant	2015	156.00	['Action', 'Adventure', 'Biography']	135,000,000.00	532,950,50
2526	tt3300078	The Revenant	2012	80.00	['Horror']	2,000.00	532,900,00

In [130]:
```
movies[movies['original_title'].str.contains('Inside Out')]
```

Out[130]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_gros
962	tt1640486	Inside Out	2011	93.00	['Crime', 'Drama']	2,000,000.00	857,600,000.0
1623	tt2071483	Inside Out	2011	59.00	['Family']	500,000.00	857,600,000.0
1666	tt2096673	Inside Out	2015	95.00	['Adventure', 'Animation', 'Comedy']	175,000,000.00	858,848,019.0

It appears that the high-grossing movies without MPAA ratings are actually duplicates with other data errors. It seems like missing ratings could actually be an indicator that the row could have erroneous data. We will drop rows without MPAA rating.

In [131]:
```
movies[movies['month'].isnull()].sort_values('ww_gross',
                                             ascending=False).head(10)
```

Out[131]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_gros
3456	tt5734820	Rio	2017	87.00	['Drama']	nan	484,600,000.0
2185	tt2614250	Rio	2012	90.00	['Documentary']	250,000.00	484,600,000.0
1683	tt2109176	Noah	2011	105.00	['Drama', 'Thriller']	nan	362,599,999.0
1793	tt2221640	Now You See Me	2012	98.00	['Drama', 'Horror', 'Thriller']	nan	351,700,000.0
3713	tt6598256	No Strings Attached	2017	73.00	['Comedy', 'Drama', 'Romance']	nan	149,300,000.0
2022	tt2402731	Unknown	2012	96.00	['Drama']	nan	130,799,999.0
1388	tt1901018	The Visit	2010	50.00	['Thriller']	1,000.00	98,400,000.0
3326	tt5324464	Nerve	2015	62.00	['Documentary', 'History']	nan	85,300,000.0
2056	tt2447982	Abduction	2011	84.00	['Horror', 'Thriller']	nan	82,100,000.0
3175	tt4907156	Widows	2015	79.00	['Comedy']	nan	76,000,000.0

Missing months also seem to indicate multiple missing values and correspond with the movies missing ratings. We'll drop all the rows missing any of these three values.

In [132]:
```
movies=movies[movies['mpaa_rating'].notnull()]
movies=movies[movies['month'].notnull()]
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3696 entries, 0 to 4063
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           3696 non-null   object 
 1   original_title   3696 non-null   object 
 2   start_year       3696 non-null   int64  
 3   runtime_minutes  3696 non-null   float64
 4   genres           3696 non-null   object 
 5   budget           1945 non-null   float64
 6   ww_gross         3696 non-null   float64
 7   mpaa_rating      3696 non-null   object 
 8   month            3696 non-null   float64
dtypes: float64(4), int64(1), object(4)
memory usage: 288.8+ KB
```

In [133]:
```
#movies.to_csv('30SEP_movies_cleaned.csv',index=False)
```

3 Data Analysis

Initially, I examined how worldwide gross related to all the variables, but did not feel like that told the whole story of which movies were most successful, since a company cares about total return on their investment. Next, I tried looking at ROI but I realized that budgets range so much across different films that smaller budget films with huge ROIs were throwing off the results. Even if a film had a relatively small worldwide gross, its ROI could be immense if the budget was extremely small. A company like Microsoft would not be interested in these films that did not gross a large amount since there is so much overhead in operating a studio. Finally, I decided to remove rows without budget data and just focus on profit, since this would be the most valuable variable to analyze for Microsoft's purposes.

```
1. First we will look at budget vs. profit to see in what way they
 are correlated.

2. Then, we will examine which genres have the highest mean/median
 profits. We'll examine the distribution of profit among the top ge
nres to see how many observations there are and in what way they ar
e distributed.

3. Third, we'll look at MPAA rating and Profit and delve into how M
PAA rating is related to profit for individual genres.

4. Next, we'll examine how profit varies by release month for the o
verall dataset and by genre.

5. Last, we'll try to see if there is any value in looking at genr
e, rating, and release month together be finding median profit for
 each grouping of the three variables and by running a linear regre
ssion with statsmodels.
```

3.1 Profit

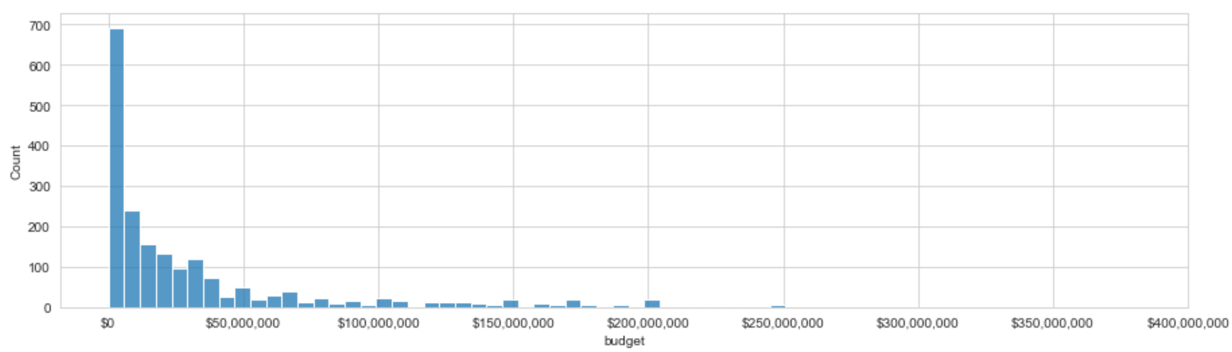
In [134]:

```
#pull out movies with non-null budget
prof_df=movies.copy()
prof_df=prof_df[prof_df['budget'].notnull()]
prof_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1945 entries, 0 to 4053
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   tconst           1945 non-null   object 
 1   original_title   1945 non-null   object 
 2   start_year       1945 non-null   int64  
 3   runtime_minutes  1945 non-null   float64
 4   genres           1945 non-null   object 
 5   budget           1945 non-null   float64
 6   ww_gross         1945 non-null   float64
 7   mpaa_rating      1945 non-null   object 
 8   month            1945 non-null   float64
dtypes: float64(4), int64(1), object(4)
memory usage: 152.0+ KB
```

In [135]:

```
#Examine distribution of budgets using histogram
plt.figure(figsize=(15,4))
sns.set_style('whitegrid')
b=sns.histplot(data=prof_df,x='budget')
ticks=b.get_xticks().tolist()
b.xaxis.set_ticks(ticks[1:])
xlabels=['$'+'{:,.0f}'.format(x) for x in ticks[1:]]
b.set_xticklabels(xlabels);
```

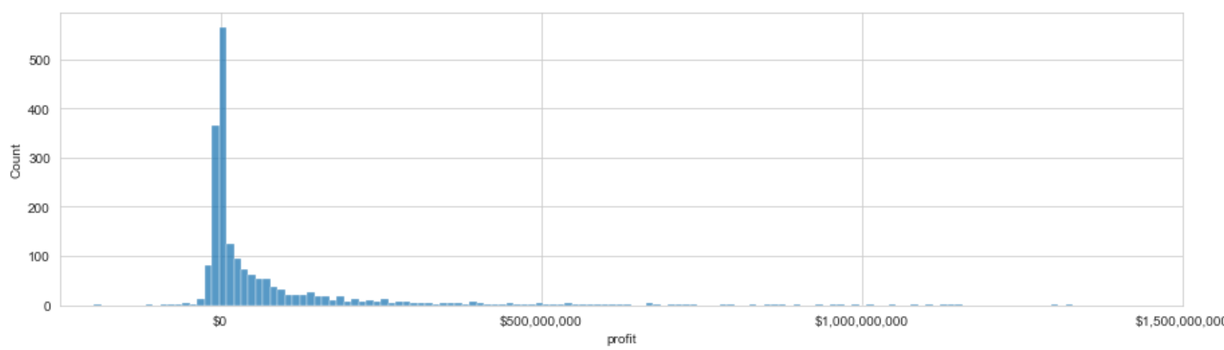


Budgets are right skewed with the mode less than $10 million. Large studios under companies like Microsoft tend to make larger budget films, so there appears to be a large number of smaller budget independent films in the dataset.

In [136]:
```
#Make a profit column (ww_gross - budget)
prof_df['profit']=prof_df['ww_gross']-prof_df['budget']
print(prof_df['profit'].describe())
```

```
count            1,945.00
mean        74,510,158.96
std        183,761,204.79
min       -197,367,417.00
25%         -2,078,248.00
50%          4,042,068.00
75%         69,594,140.00
max      2,441,501,328.00
Name: profit, dtype: float64
```

In [137]:
```
#Show distribution of profit with histogram
plt.figure(figsize=(15,4))
sns.set_style('whitegrid')
b=sns.histplot(data=prof_df,x='profit')
ticks=b.get_xticks().tolist()
b.xaxis.set_ticks(ticks[1:-3])
xlabels=['$'+'{:,.0f}'.format(x) for x in ticks[1:-3]]
b.set_xticklabels(xlabels)
b.set_xlim(-250000000,1500000000);
```

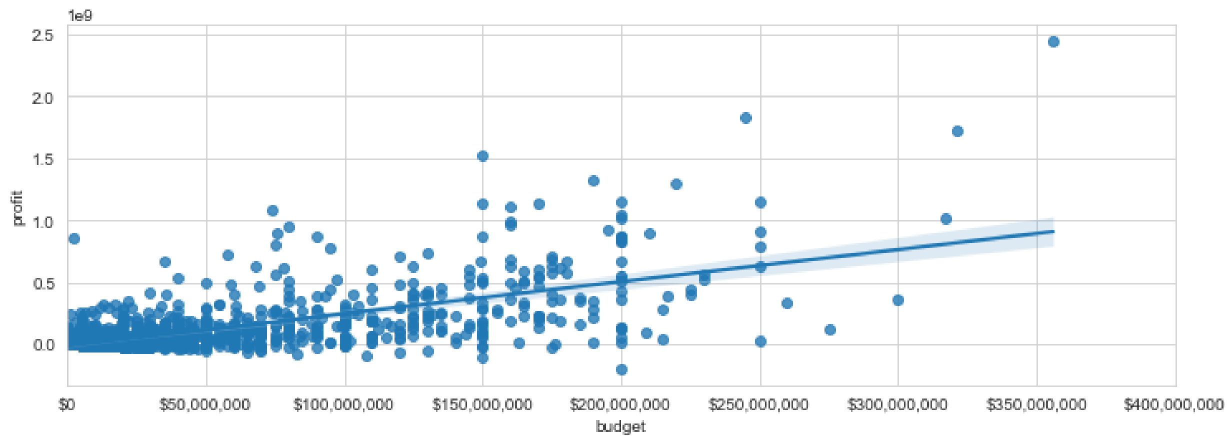


Profit is also right skewed with the majority of movies falling below 250 million USD. There are a few outliers above 1.5 billion USD but the axis was limited to see the majority of movies more clearly.

3.2 Is Budget Correlated with Profit?

Examine if there is a correlation between a movie's budget and its overall profit. Examine for low and high budget films.

In [138]:
```
plt.figure(figsize=(12,4))
pb=sns.regplot(data=prof_df,x='budget',y='profit')
ticks=pb.get_xticks().tolist()
pb.xaxis.set_ticks(ticks)
xlabels=['$'+'{:,.0f}'.format(x) for x in ticks]
pb.set_xticklabels(xlabels);
```



Profit and budget are positively correlated, although it is clear that not all high budget films make a large profit. Since Microsoft is a large company that will have the capital to invest in high budget films that will have a better chance of making a large profit, we will make a column in prof_df that identifies 'high-budget' films so that these can be analyzed separately.

In [139]:
```
#Examine what to call high budget
prof_df['budget'].describe()
```

Out[139]:
```
count          1,945.00
mean      33,378,318.68
std       49,766,651.08
min                0.00
25%        3,000,000.00
50%       13,000,000.00
75%       40,000,000.00
max      356,000,000.00
Name: budget, dtype: float64
```

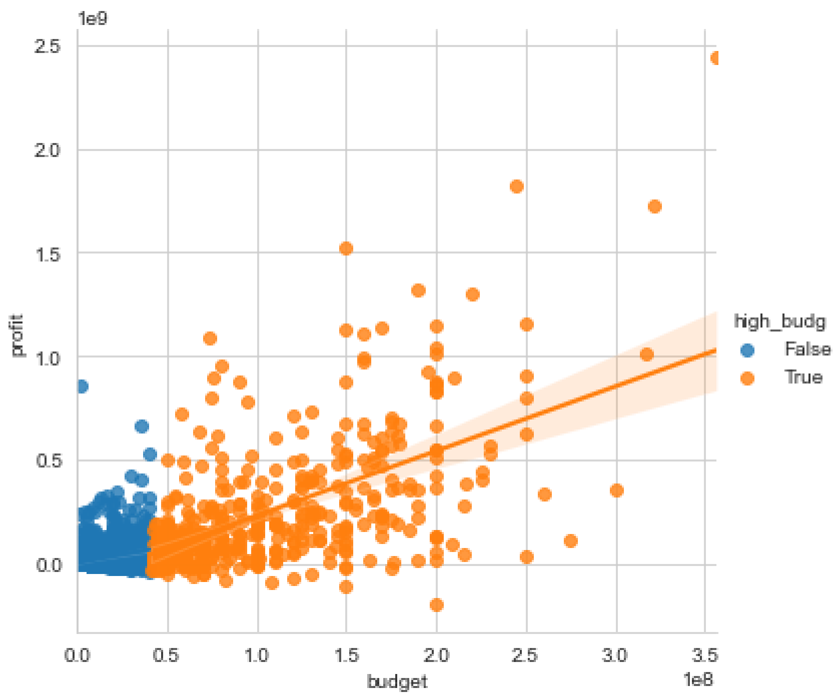
If all films with budgets over 40 million are marked 'high-budget' this will include the most expensive 1/4 of movies. We will use this as the threshold.

In [140]:
```
#create column to identify high budget films, budgets greater than 40,0
#top 1/4 of all budgets

prof_df['high_budg']=prof_df['budget'].apply(lambda x:
                                                  True if x>40000000 else Fa
prof_df['high_budg'].sum()
```

Out[140]:
```
438
```

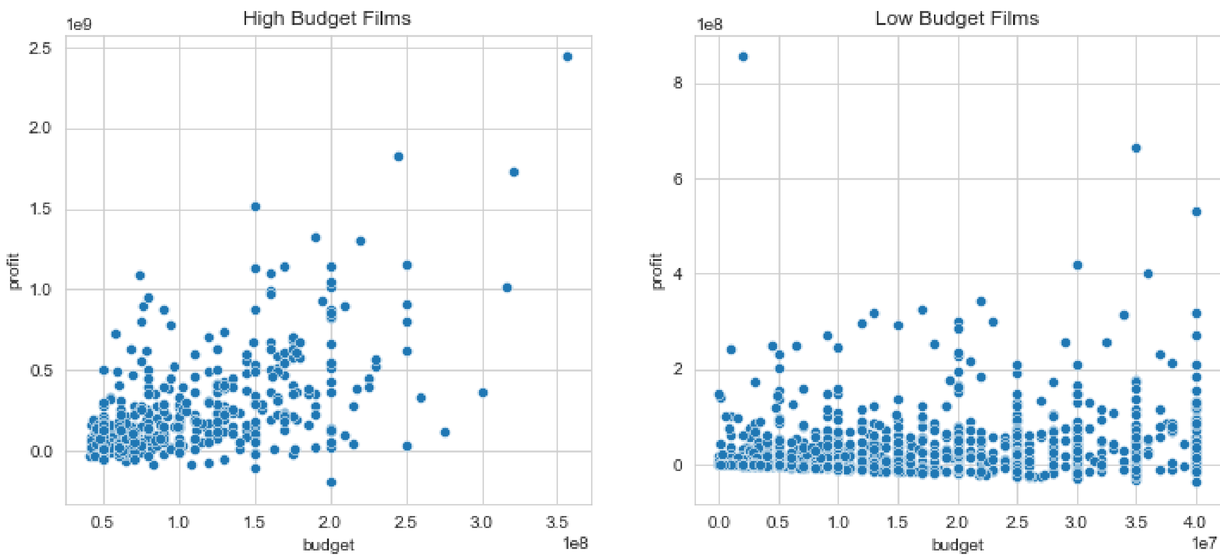
In [141]:
```
#show relplot of budget and profit with distinction of high vs low budg
plt.figure(figsize=(8,4))
sns.lmplot(data=prof_df,x='budget',y='profit',hue='high_budg');
```

```
<Figure size 576x288 with 0 Axes>
```



In [142]:
```
#Separate high and low budget films
high_df=prof_df.query("high_budg==True")
low_df=prof_df.query("high_budg==False")
```

In [143]:
```python
#Plot low budget and high budget separately to see in more detail
fig, ax = plt.subplots(1,2,figsize=(12,5))
sns.scatterplot(data=high_df,x='budget',y='profit',ax=ax[0])
ax[0].set_title('High Budget Films')
sns.scatterplot(data=low_df,x='budget',y='profit',ax=ax[1])
ax[1].set_title('Low Budget Films');


```



In [144]:
```python
#compute correlations between budget and profit
high_corr=high_df['budget'].corr(high_df['profit'])
low_corr=low_df['budget'].corr(low_df['profit'])
print('high budget/profit correlation:v '+str(high_corr))
print('low budget/profit correlation: '+str(low_corr))
```

```
high budget/profit correlation:v 0.5766409472402435
low budget/profit correlation: 0.3181716986049638
```

In [145]:
```python
import statsmodels.api as sm
```

In [146]:

```
#high budget linear regression
x=high_df['budget'].to_list()
x=sm.add_constant(x)
y=high_df['profit'].to_list()
results=sm.OLS(y,x).fit()
print(results.summary2())
```

```
                        Results: Ordinary least squares
==========================================================================
=======
Model:                   OLS                  Adj. R-squared:         0.3
31
Dependent Variable:      y                    AIC:                    181
95.3733
Date:                    2021-10-13 19:48     BIC:                    182
03.5377
No. Observations:        438                  Log-Likelihood:         -90
95.7
Df Model:                1                    F-statistic:            21
7.2
Df Residuals:            436                  Prob (F-statistic):     3.5
3e-40
R-squared:               0.333                Scale:                  6.4
119e+16
--------------------------------------------------------------------------
-------
          Coef.         Std.Err.      t     P>|t|      [0.025         0.9
75]
--------------------------------------------------------------------------
-------
const -83333642.0258 25941423.2496 -3.2124 0.0014 -134319430.2758 -323478
53.7758
x1            3.1208        0.2118 14.7376 0.0000          2.7046
3.5370
--------------------------------------------------------------------------
-------
Omnibus:                 140.621           Durbin-Watson:              1.
663
Prob(Omnibus):           0.000             Jarque-Bera (JB):           57
4.443
Skew:                    1.378             Prob(JB):                   0.
000
Kurtosis:                7.887             Condition No.:              26
2662114
==========================================================================
=======
* The condition number is large (3e+08). This might indicate
strong
multicollinearity or other numerical problems.
```

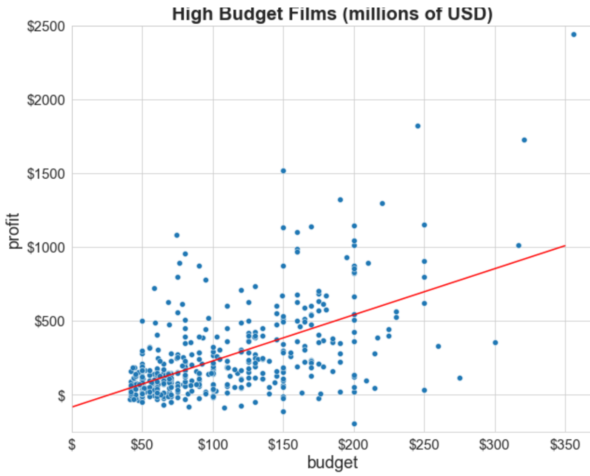
In [147]:

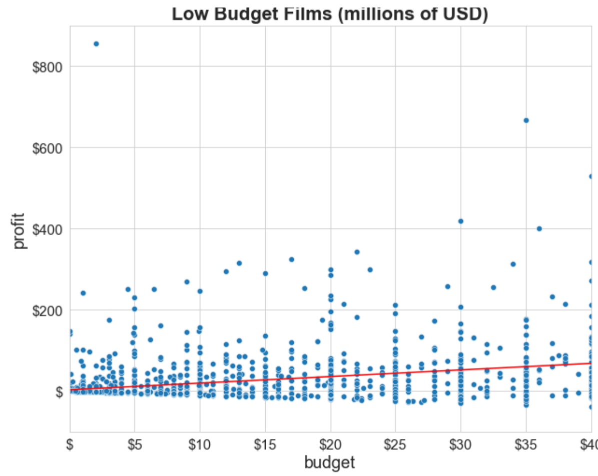
```
#low budget linear regression
x=low_df['budget'].to_list()
x=sm.add_constant(x)
y=low_df['profit'].to_list()
results=sm.OLS(y,x).fit()
print(results.summary2())
```

```
                       Results: Ordinary least squares
==========================================================================
Model:                 OLS                 Adj. R-squared:      0.101
Dependent Variable:    y                   AIC:                 58086.8737
Date:                  2021-10-13 19:48    BIC:                 58097.5095
No. Observations:      1507                Log-Likelihood:      -29041.
Df Model:              1                   F-statistic:         169.5
Df Residuals:          1505                Prob (F-statistic):  8.46e-37
R-squared:             0.101               Scale:               3.2115e+15
--------------------------------------------------------------------------
         Coef.        Std.Err.      t     P>|t|      [0.025       0.975]
--------------------------------------------------------------------------
const 3265661.3233 2054880.8248  1.5892 0.1122 -765072.6743 7296395.3209
x1          1.6255       0.1248 13.0199 0.0000       1.3806       1.8704
--------------------------------------------------------------------------
Omnibus:               1643.862         Durbin-Watson:          1.973
Prob(Omnibus):         0.000            Jarque-Bera (JB):       169301.676
Skew:                  5.249            Prob(JB):               0.000
Kurtosis:              53.853           Condition No.:          23168314
==========================================================================
* The condition number is large (2e+07). This might indicate
strong multicollinearity or other numerical problems.
```

In [148]:

```
#plot scatterplots with correlation line
fig, ax = plt.subplots(1,2,figsize=(22,8))
sns.scatterplot(data=high_df,x='budget',y='profit',ax=ax[0])
#create points for correlation line
x=[0,350000000]
y=[-83330000,((350000000)*3.1208-83330000)]
sns.lineplot(x=x,y=y,ax=ax[0],color='red')

#format x axis into millions of dolalrs
ticks=ax[0].get_xticks().tolist()
ax[0].xaxis.set_ticks(ticks)
xlabels=['$'+'{:.0f}'.format(x)[:-6] for x in ticks]
ax[0].set_xticklabels(xlabels,size=15)
ax[0].set_xlim(0,370000000)
ax[0].set_xlabel('budget',size=18)

#format numbers on y axis into millions of dollars
ticks=ax[0].get_yticks().tolist()
ax[0].yaxis.set_ticks(ticks[1:])
ylabels=['$'+'{:.0f}'.format(y)[:-6] for y in ticks[1:]]
ax[0].set_yticklabels(ylabels,size=15)
ax[0].set_ylim(-250000000,2500000000)
ax[0].set_title('High Budget Films (millions of USD)',fontsize=20,
               fontweight='bold')
ax[0].set_ylabel('profit',size=18)

sns.scatterplot(data=low_df,x='budget',y='profit',ax=ax[1])
x1=[0,40000000]
y1=[3266000,(40000000*1.6255)+3266000]
sns.lineplot(x=x1,y=y1,ax=ax[1],color='red')
ax[1].set_title('Low Budget Films (millions of USD)',fontsize=20,
               fontweight='bold')

#format x axis into millions of dolalrs
ticks=ax[1].get_xticks().tolist()
ax[1].xaxis.set_ticks(ticks)
xlabels=['$'+'{:.0f}'.format(x)[:-6] for x in ticks]
ax[1].set_xticklabels(xlabels,size=15)
ax[1].set_xlim(0,40000000)
ax[1].set_xlabel('budget',size=18)

#format numbers on y axis into millions of dollars
ticks=ax[1].get_yticks().tolist()
ax[1].yaxis.set_ticks(ticks[1:])
ylabels=['$'+'{:.0f}'.format(y)[:-6] for y in ticks[1:]]
ax[1].set_yticklabels(ylabels,size=15)
ax[1].set_ylim(-100000000,900000000)
ax[1].set_ylabel('profit',size=18)

plt.savefig('images/high_low_profit.png',facecolor='w')
```





High budget films (over $40 million) are more positively correlated with higher profits than movies with low budgets (coefficient of 3.12 vs. 1.62). The R-Squared value of this correlation is ~.33, which means it is not an incredibly strong fit. While there is a greater opportunity to make higher profit with a higher budget, it is not guaranteed. We'll examine which genres tend to make higher profits so that we can refine our recommendations to Microsoft.

3.3 Which genres perform best?

Examine which genres tend to make the most profit among high budget films.

3.3.1 Profit across all genres

In [149]:
```
high=high_df.copy()
high['genres']=high['genres'].str.strip('[]').str.split(',')
high['genres']=high['genres'].apply(lambda x: [s.strip() for s in x])
```

In [150]:
```
high['genres']=high['genres'].apply(lambda x: [s.strip("''") for s in x
high_exp=high.explode('genres')
high_exp.head()
```

Out[150]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_gross	mp
0	tt0249516	Foodfight!	2012	91.00	Action	65,000,000.00	120,141.00	
0	tt0249516	Foodfight!	2012	91.00	Animation	65,000,000.00	120,141.00	
0	tt0249516	Foodfight!	2012	91.00	Comedy	65,000,000.00	120,141.00	
3	tt0359950	The Secret Life of Walter Mitty	2013	114.00	Adventure	90,000,000.00	188,133,322.00	
3	tt0359950	The Secret Life of Walter Mitty	2013	114.00	Comedy	90,000,000.00	188,133,322.00	

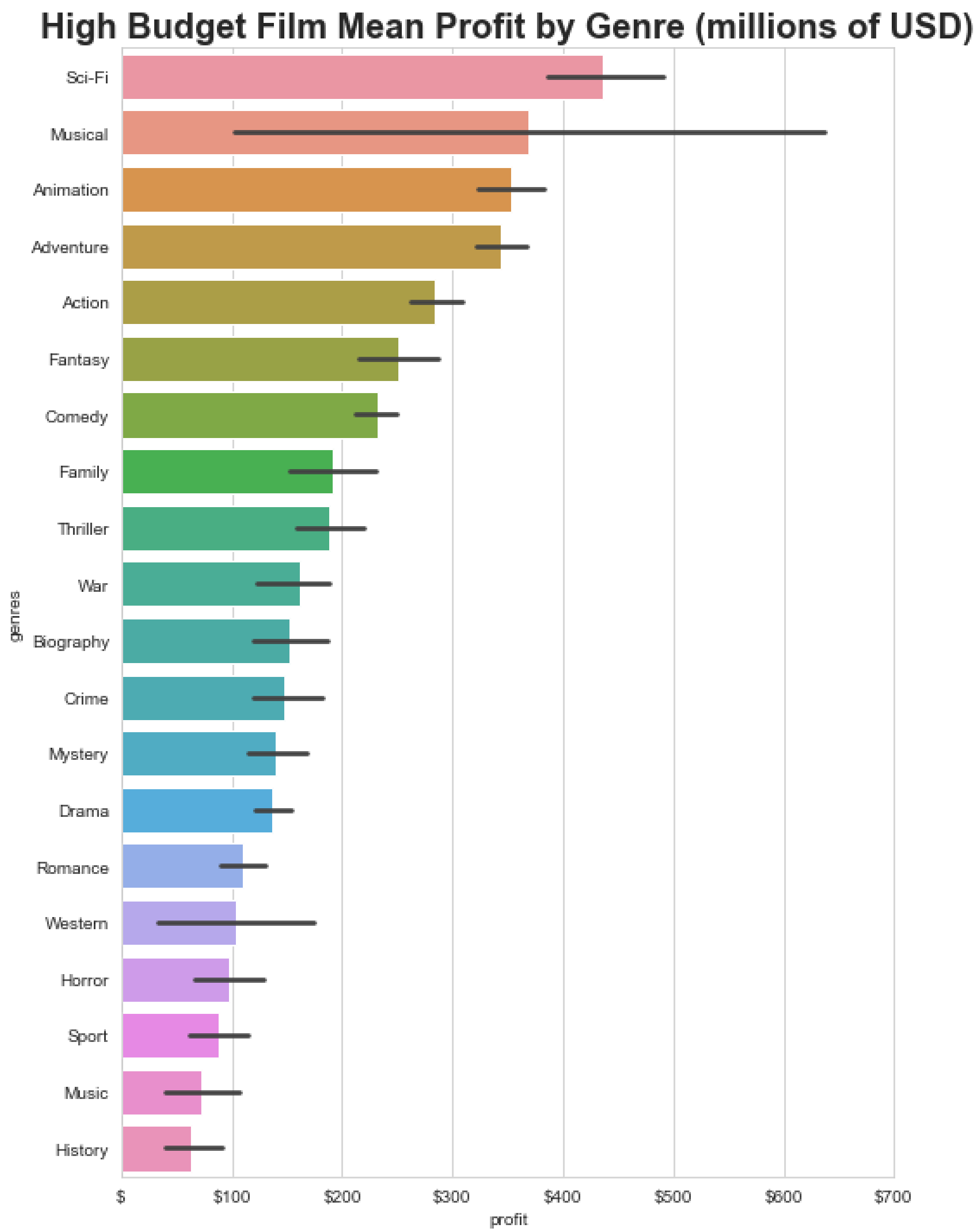
In [151]:
```
high_exp['genres'].value_counts()
```

Out[151]:
```
Adventure    251
Action       247
Comedy       167
Drama        101
Animation     84
Fantasy       77
Sci-Fi        73
Thriller      52
Crime         51
Family        37
Mystery       22
Romance       21
Biography     18
Horror        15
History        9
Sport          4
Western        4
Musical        4
Music          3
War            3
Name: genres, dtype: int64
```

In [152]:
```
#groupby genres and calculate mean profit, then sort to get descending
g_mean_prof=high_exp.groupby('genres'
                        ).mean()['profit'].sort_values(ascending=False)
g_mean_order=g_mean_prof.index
```

In [153]:

```
#plot the mean profit for each genre
plt.figure(figsize=(8,12))
gm=sns.barplot(data=high_exp,x='profit',y='genres',ci=68,order=g_mean_o
#format x axis into millions of dolalrs
ticks=gm.get_xticks().tolist()
gm.xaxis.set_ticks(ticks)
xlabels=['$'+'{:.0f}'.format(x)[:-6] for x in ticks]
gm.set_xticklabels(xlabels)
gm.set_xlim(0,700000000)
gm.set_title('High Budget Film Mean Profit by Genre (millions of USD)',
             fontweight='bold');
```

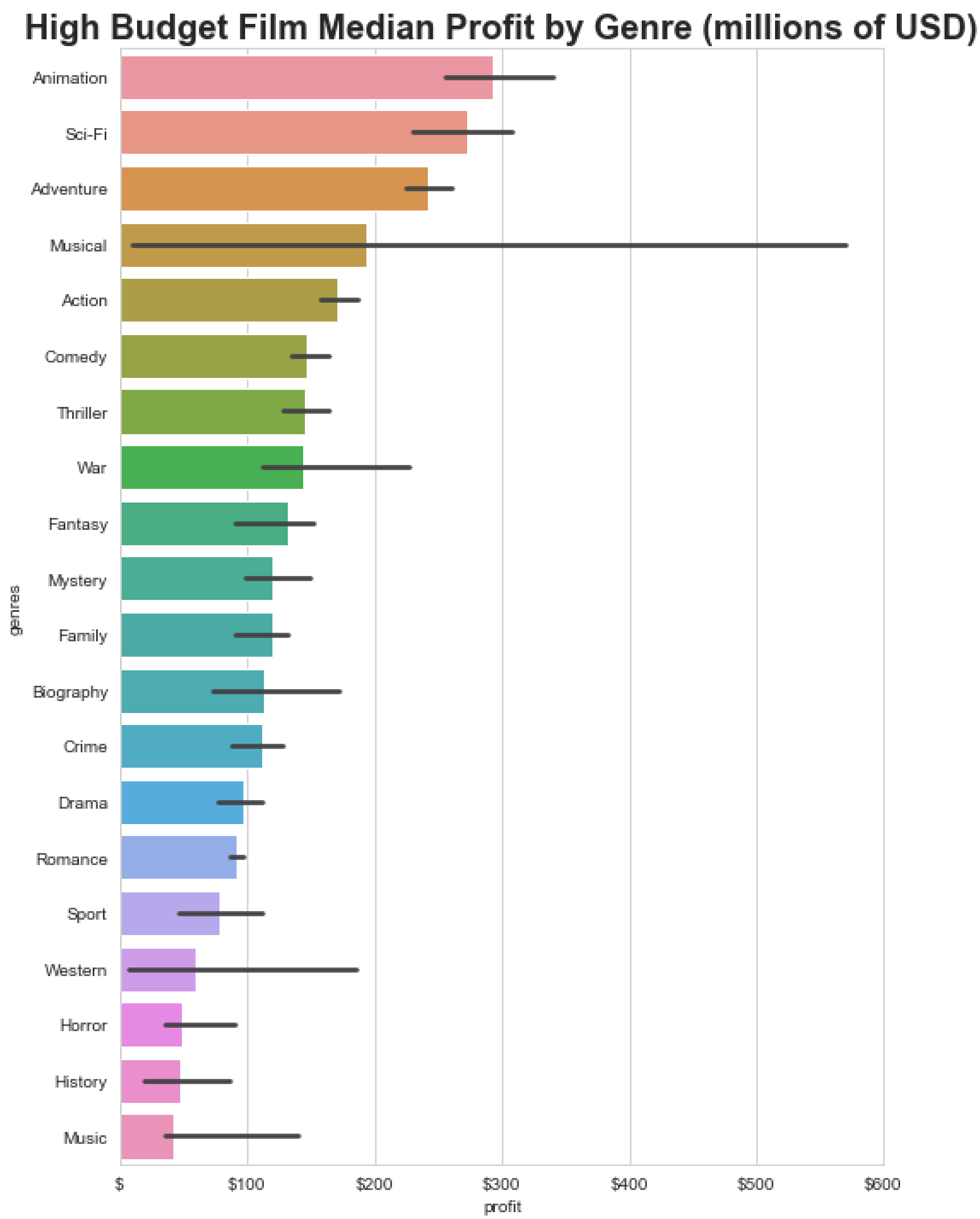


In [154]:

```
#groupby genres and calculate mean profit, then sort to get descending
g_med_prof=high_exp.groupby('genres'
                            ).median()['profit'].sort_values(ascending=Fals
g_med_order=g_med_prof.index
```

In [155]:

```
#plot the mean profit for each genre
plt.figure(figsize=(8,12))
gm=sns.barplot(data=high_exp,x='profit',y='genres',ci=68,estimator=np.m
               order=g_med_order)
#format x axis into millions of dolalrs
ticks=gm.get_xticks().tolist()
gm.xaxis.set_ticks(ticks)
xlabels=['$'+'{:.0f}'.format(x)[:-6] for x in ticks]
gm.set_xticklabels(xlabels)
#gm.set_xlim(0,700000000)
gm.set_title('High Budget Film Median Profit by Genre (millions of USD)
             fontweight='bold')

plt.savefig('images/high_med_prof_genre.png',facecolor='w')
```



The same five genres have both the five highest means and medians. Movies that can be classified as Animation, Sci-Fi, Adventure, Action, and Musical tend to have the highest profit. Of note, the confidence interval for Musicals is very large, so that may be a riskier recommendation. We'll examine the distributions of these five genres in more detail and look at which ratings and release months tend to work best with each genre.

3.3.2 Top Four Genres by Profit

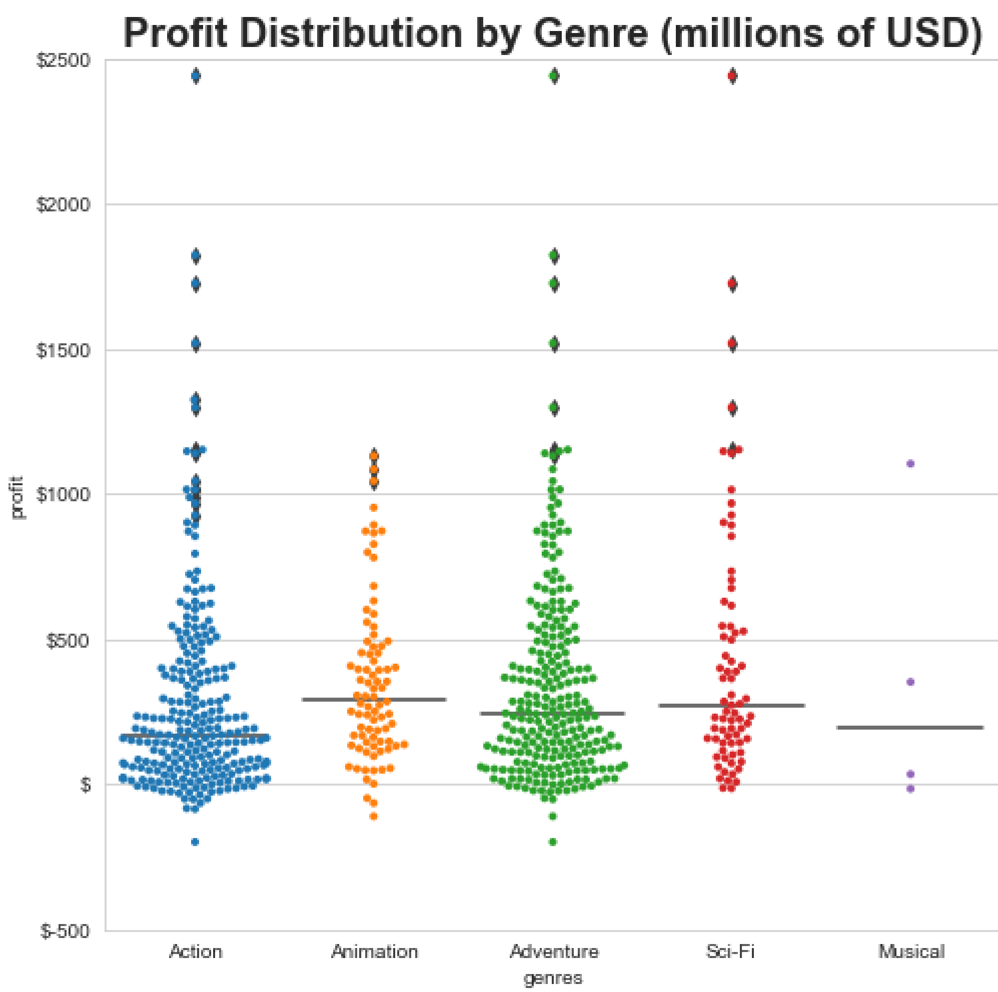
In [156]:
```
q="(genres=='Animation') | (genres=='Action') | (genres=='Sci-Fi') | \
(genres=='Musical') | (genres=='Adventure')"
h=high_exp.copy()
top_5=h.query(q)
top_5.head()
```

Out[156]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_gross
0	tt0249516	Foodfight!	2012	91.00	Action	65,000,000.00	120,141.00
0	tt0249516	Foodfight!	2012	91.00	Animation	65,000,000.00	120,141.00
3	tt0359950	The Secret Life of Walter Mitty	2013	114.00	Adventure	90,000,000.00	188,133,322.00
5	tt0369610	Jurassic World	2015	124.00	Action	150,000,000.00	1,670,516,444.00
5	tt0369610	Jurassic World	2015	124.00	Adventure	150,000,000.00	1,670,516,444.00

In [157]:

```
#plot profit distributions of top 5 genres
plt.figure(figsize=(8,8))
p=sns.swarmplot(data=top_5,x='genres',y='profit',size=4)
sns.boxplot(data=top_5,x='genres',y='profit',showbox=False,
      showcaps=False,whiskerprops={'visible':False})

#format numbers on y axis into millions of dollars
ticks=p.get_yticks().tolist()
p.yaxis.set_ticks(ticks)
ylabels=['$'+'{:.0f}'.format(y)[:-6] for y in ticks]
p.set_yticklabels(ylabels)
p.set_ylim(-500000000,2500000000)
p.set_title('Profit Distribution by Genre (millions of USD)',fontsize=2
           fontweight='bold')

plt.savefig('images/prof_dist_genre.png',facecolor='w')
```



This plot shows that Action and Animation have the largest number of observations. All genres but Musical have right skews, with the majority of films under $500 million profit and a many that have profit close to zero. This does not mean that they are not good choices for genre, it just reflects the risk in making any film. Profit is more likely with these genres, but not guaranteed. We can also see the outliers that make the mean so much higher than the medians. The genre Musical only has 4 observations, which are not enough to make a solid recommendation to Microsoft. We will not include this genre in the analysis of rating and release month.

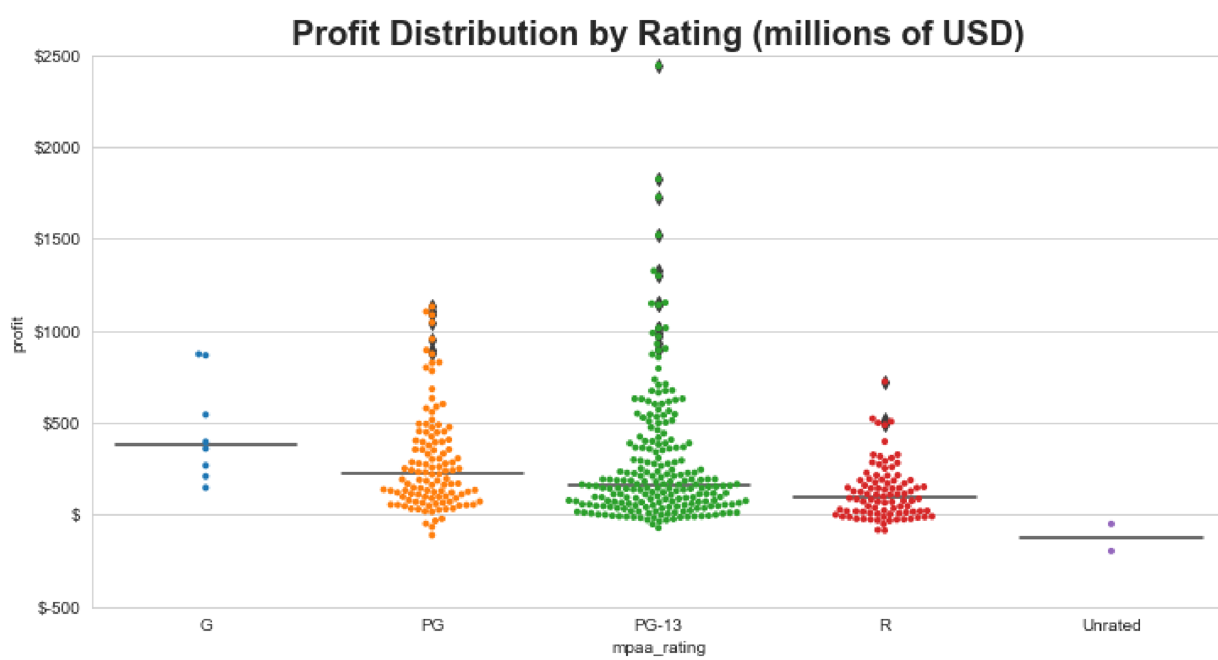
3.4 Which MPAA Ratings perform best?

Examine which MPAA ratings within the top 4 genres tend to have the highest profit.

3.4.1 Profit across MPAA Ratings for all genres

In [158]:

```
#First examine distribution of profit across ratings including all genr
plt.figure(figsize=(12,6))
r=sns.boxplot(data=high_df,x='mpaa_rating',y='profit',showbox=False,
       showcaps=False,whiskerprops={'visible':False},
              order=['G','PG','PG-13','R','Unrated'])
sns.swarmplot(data=high_df,x='mpaa_rating',y='profit',
               order=['G','PG','PG-13','R','Unrated'],size=4)

#format numbers on y axis into millions of dollars
ticks=r.get_yticks().tolist()
r.yaxis.set_ticks(ticks)
ylabels=['$'+'{:.0f}'.format(y)[:-6] for y in ticks]
r.set_yticklabels(ylabels)
r.set_ylim(-500000000,2500000000)
r.set_title('Profit Distribution by Rating (millions of USD)',fontsize=
           fontweight='bold');
```



G movies have the highest median, but the sample size for high budget movies is low. PG has the next highest followed by PG-13 and then R. Since there are only two movies that are unrated, we'll remove them for the genre analysis to make the plots simpler.

All of the top three ratings are right skewed distributions with PG-13 having the highest number of observations and the most high-profit outliers.

3.4.2 Profit across MPAA Ratings in top 4 genres

In [159]:

```
#filter top_5 to remove musicals
q1="(genres=='Animation') | (genres=='Action') | (genres=='Sci-Fi') | \
(genres=='Adventure')"
top_4=top_5.copy().query(q1)
top_4=top_4[top_4['genres']!='Unrated']
top_4.head()
```

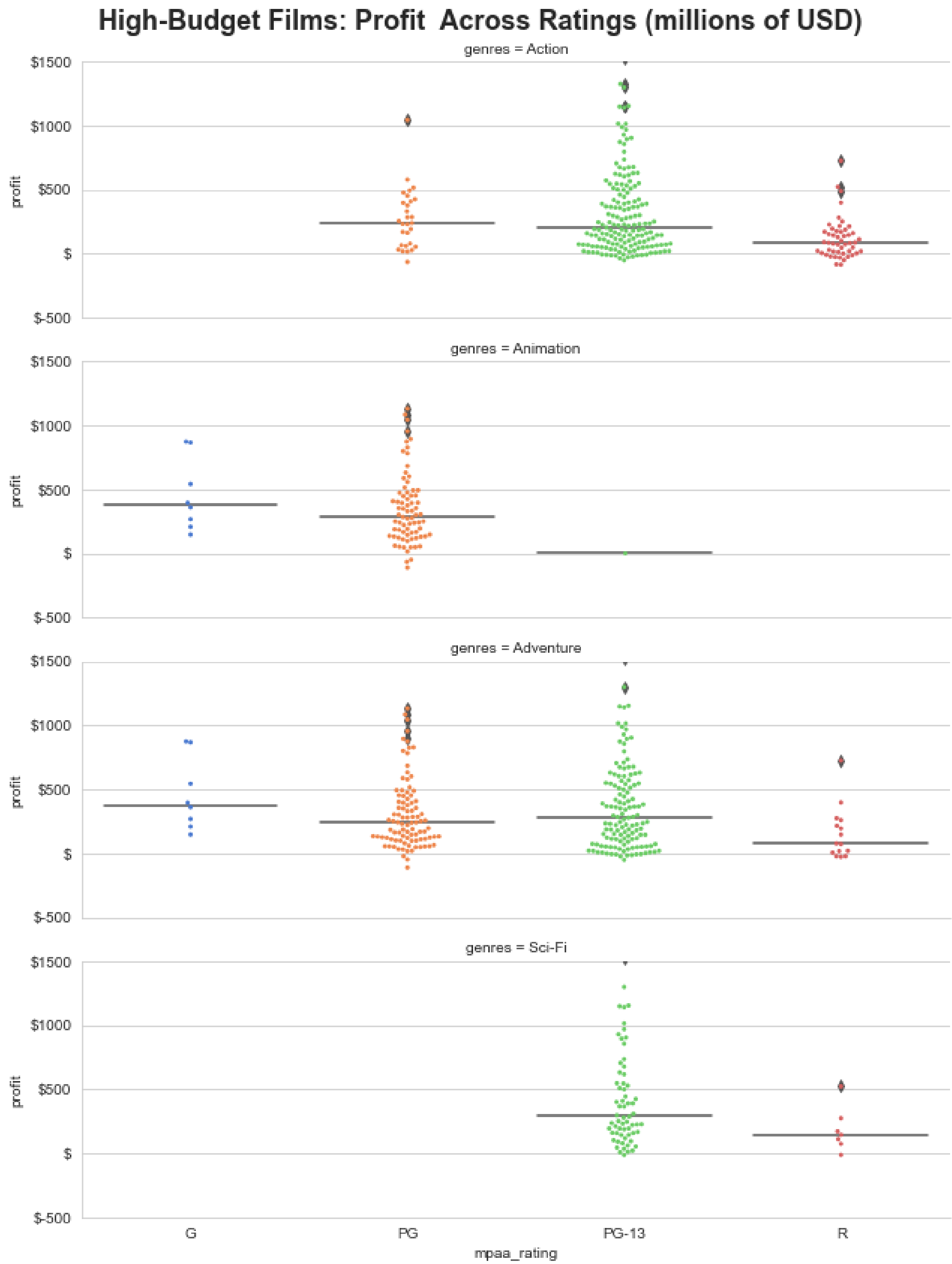
Out[159]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_gross
0	tt0249516	Foodfight!	2012	91.00	Action	65,000,000.00	120,141.00
0	tt0249516	Foodfight!	2012	91.00	Animation	65,000,000.00	120,141.00
3	tt0359950	The Secret Life of Walter Mitty	2013	114.00	Adventure	90,000,000.00	188,133,322.00
5	tt0369610	Jurassic World	2015	124.00	Action	150,000,000.00	1,670,516,444.00
5	tt0369610	Jurassic World	2015	124.00	Adventure	150,000,000.00	1,670,516,444.00

In [160]:

```
plt.figure(figsize=(6,12))

rg=sns.FacetGrid(top_4,row='genres',aspect=3)
rg.map(sns.boxplot, 'mpaa_rating','profit',
       order=['G','PG','PG-13','R'],palette='muted',showbox=False,
      showcaps=False,whiskerprops={'visible':False})
rg.map(sns.swarmplot,'mpaa_rating','profit',
              order=['G','PG','PG-13','R'],size=3,palette='muted')

#fix y-axis to display millions of USD
for ax in rg.axes.flat:
    ticks=ax.get_yticks().tolist()
    ax.yaxis.set_ticks(ticks)
    ylabels=['$'+'{:.0f}'.format(y)[:-6] for y in ticks]
    ax.set_yticklabels(ylabels)
    ax.set_ylim(-500000000,1500000000)


rg.fig.suptitle('High-Budget Films: Profit  Across Ratings (millions of
                fontsize=18,fontweight='bold',va='top',ha='center')
plt.tight_layout()

plt.savefig('images/prof_genre_ratings.png',facecolor='w')
```

```
<Figure size 432x864 with 0 Axes>
```



Action: The majority of Action movies have a PG-13 rating. The median for PG Action movies is slightly higher, but the sample is smaller. Both PG and PG-13 tend to have higher profit than R. Best recommendation would be to make a PG-13 Action movie.

Animation: Almost all of these movies are rated PG. G Animation films can still perform well and have a slightly higher mean, but PG is the best recommendation for this genre.

Adventure: PG and PG-13 films perform well, but PG-13 has a slightly higher median and more high-profit outliers. G has too few observations to make a solid recommendation. PG-13 is the recommended rating level for Adventure.

Sci-Fi: All movies in this genre are either PG-13 or R. PG-13 has a higher median and more observations. The best recommendation for Sci-Fi is PG-13.

3.5 Which release months have the highest profit?

Examine which release months have led to the highest profits for the top 4 genres.

3.5.1 Profit across release months for all genres

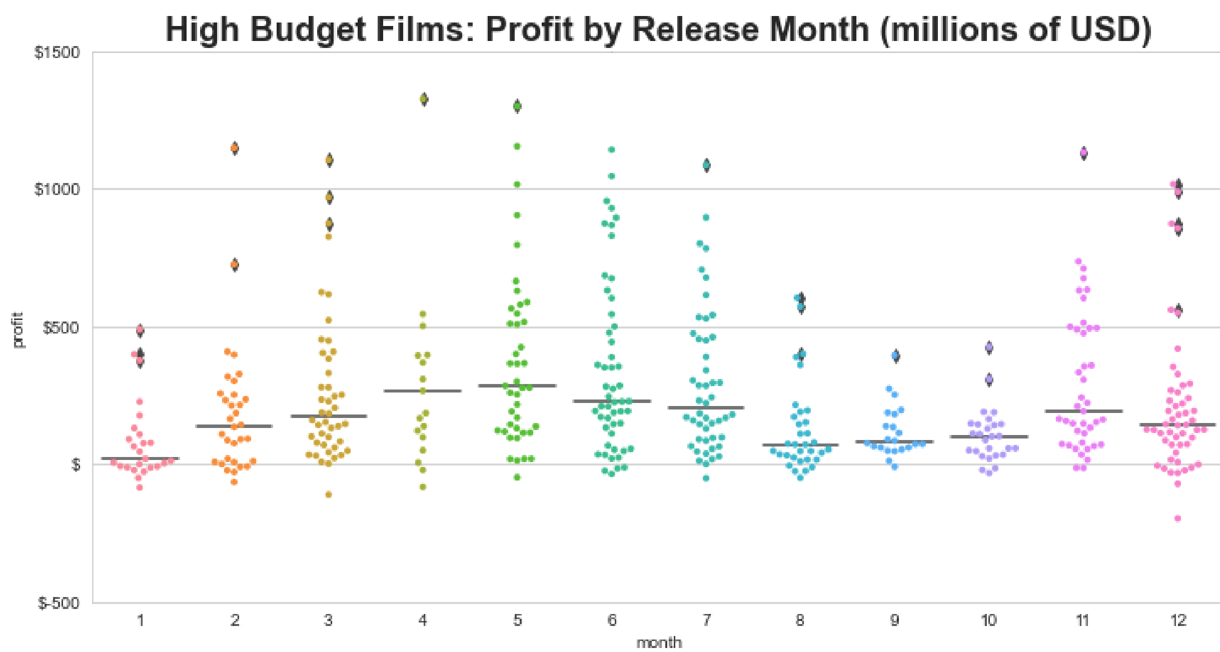
In [161]:
```
high_df.head()
```

Out[161]:

	tconst	original_title	start_year	runtime_minutes	genres	budget	ww_gross
0	tt0249516	Foodfight!	2012	91.00	['Action', 'Animation', 'Comedy']	65,000,000.00	120,141.00
3	tt0359950	The Secret Life of Walter Mitty	2013	114.00	['Adventure', 'Comedy', 'Drama']	90,000,000.00	188,133,322.00
5	tt0369610	Jurassic World	2015	124.00	['Action', 'Adventure', 'Sci-Fi']	150,000,000.00	1,670,516,444.00
7	tt0376136	The Rum Diary	2011	119.00	['Comedy', 'Drama']	45,000,000.00	30,134,958.00
9	tt0398286	Tangled	2010	100.00	['Adventure', 'Animation', 'Comedy']	260,000,000.00	592,462,816.00

In [162]:
```
#turn release months into strings
high['month']=high['month'].apply(lambda x: str(int(x)))
top_4['month']=top_4['month'].apply(lambda x: str(int(x)))
m_order=[str(x) for x in list(range(1,13))]
```

In [163]:
```
#First examine distribution of profit across ratings including all genr
plt.figure(figsize=(12,6))
r=sns.boxplot(data=high,x='month',y='profit',showbox=False,
      showcaps=False,whiskerprops={'visible':False},
             order=m_order)
sns.swarmplot(data=high,x='month',y='profit',
              order=m_order,size=4)

#format numbers on y axis into millions of dollars
ticks=r.get_yticks().tolist()
r.yaxis.set_ticks(ticks)
ylabels=['$'+'{:.0f}'.format(y)[:-6] for y in ticks]
r.set_yticklabels(ylabels)
r.set_ylim(-500000000,1500000000)
r.set_title('High Budget Films: Profit by Release Month (millions of US
           fontweight='bold')

plt.savefig('images/prof_month.png',facecolor='w')
```



Median profit peaks in late Spring/Early Summer and in November. The lowest months are January and August.

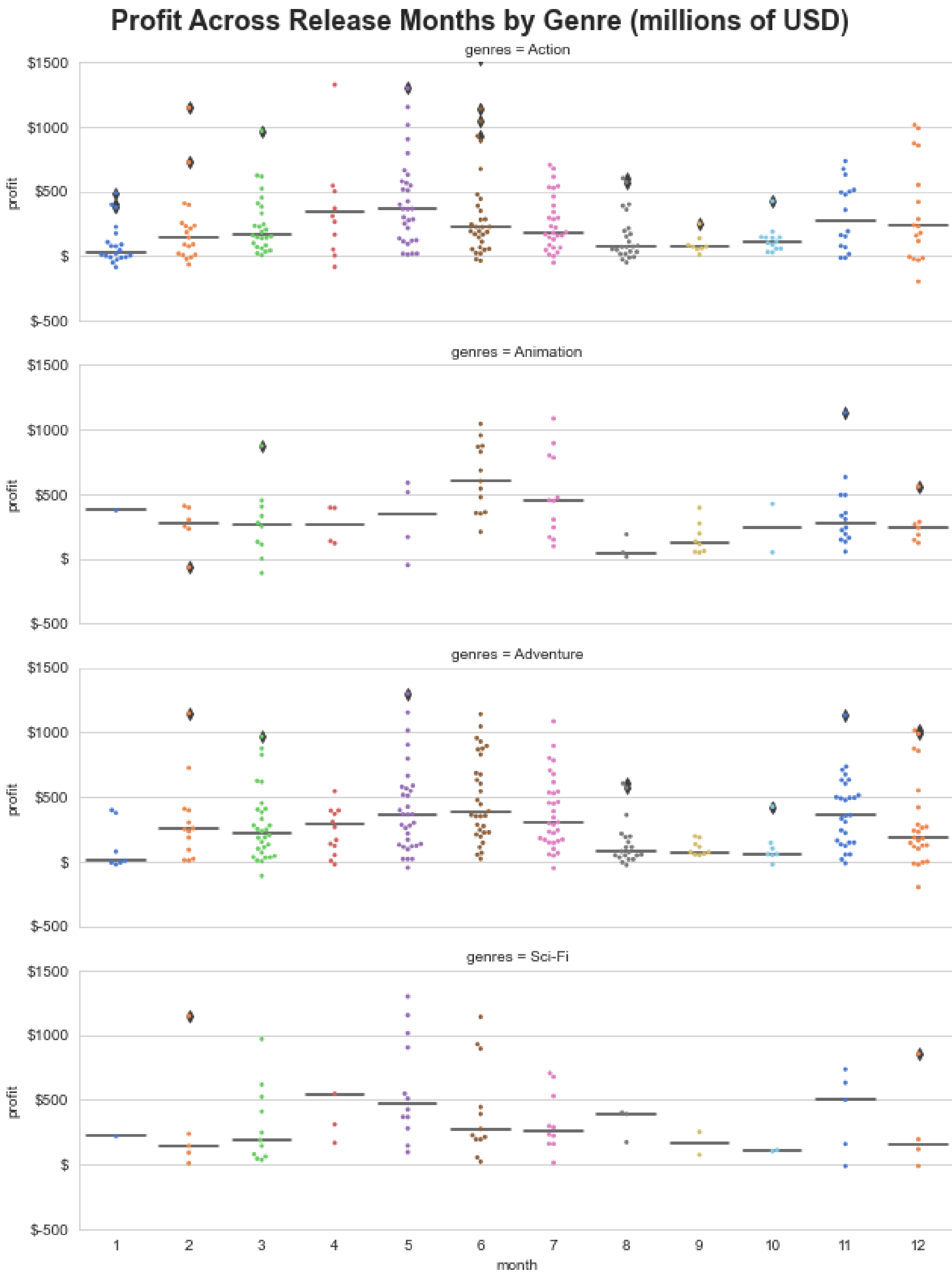
May has the highest median profit followed by April, when relatively fewer high-budget movies have been released, and then June and July when a higher number of high-budget movies are released. November's median is similar to July's.

3.5.2 Profit across release months for top 4 genres

In [164]:

```
#Plot profit by release month across the top 4 genres

plt.figure(figsize=(6,15))

rg=sns.FacetGrid(top_4,row='genres',aspect=3)
rg.map(sns.boxplot, 'month','profit',palette='muted',showbox=False,
      showcaps=False,order=m_order,whiskerprops={'visible':False})
rg.map(sns.swarmplot,'month','profit',size=3,palette='muted',
      order=m_order)

#fix y-axis to display millions of USD
for ax in rg.axes.flat:
    ticks=ax.get_yticks().tolist()
    ax.yaxis.set_ticks(ticks)
    ylabels=['$'+'{:.0f}'.format(y)[:-6] for y in ticks]
    ax.set_yticklabels(ylabels)
    ax.set_ylim(-500000000,1500000000)


rg.fig.suptitle('Profit Across Release Months by Genre (millions of USD
                fontsize=18,fontweight='bold',va='top',ha='center')
plt.tight_layout();
```

```
<Figure size 432x1080 with 0 Axes>
```



Broken down by genre, profit still peaks at similar months to the overall grouping of high budget films in May/June and November.

Animation peaks more in June and not as much in November, so summer releases are a better recommendation for that genre.

Sci-Fi peaks highest in April (few observations) and then in November, although it till has a high median in May.

Adventure also does almost as well in November as it does in May/June.

Action is highest in May and higher in April than June/July. It has a moderate increase in profit in November as well.

3.6 Profit for genre/rating/month groupings

Examine which groupings of genre, rating, and month have the highest median profit.

In [165]:

```
#groupby genres, mpaa rating, and month and calculate median profit
#and count movies in category
all_3_med=high_exp.groupby(['genres','mpaa_rating',
                    'month']).agg({'profit': ['count',
                    'median']}).sort_values(('profit','median'),ascendi
all_3_med.head(20)
```

Out[165]:

			profit	
			count	median
genres	mpaa_rating	month		
Musical	PG	3.00	1	1,104,434,525.00
Fantasy	PG-13	12.00	4	1,002,092,358.00
Thriller	PG-13	4.00	2	913,239,537.00
Action	PG	6.00	2	760,588,523.00
Adventure	R	2.00	1	724,836,791.00
Animation	PG	6.00	8	642,884,646.50
Adventure	PG	6.00	8	642,884,646.50
Sci-Fi	PG-13	4.00	5	544,421,503.00
Comedy	G	6.00	5	543,559,645.00
Adventure	G	6.00	5	543,559,645.00
Animation	G	6.00	5	543,559,645.00
Sci-Fi	R	3.00	1	522,179,950.00
Adventure	PG-13	11.00	11	512,796,076.00
Sci-Fi	PG-13	5.00	11	508,982,323.00
Mystery	R	5.00	1	506,764,305.00
Crime	PG-13	4.00	3	501,137,675.00
Sci-Fi	PG-13	11.00	5	498,344,137.00
Fantasy	PG-13	11.00	6	493,789,608.00
Drama	PG	11.00	1	489,016,565.00
Comedy	PG	6.00	8	477,952,240.50

One has to be careful when examining these results, since some of the groups only have 1 or 2 movies, which means the median says more about the success of an individual movie than a group of movies with the same characteristics. We can see in the top 20 there are quite a few groups with June releases.

3.7 Multiple Regression of genre, MPAA rating, and release month with Profit

In [166]:
```
g_dum=pd.get_dummies(high_exp['genres'],drop_first=True)
mp_dum=pd.get_dummies(high_exp['mpaa_rating'],drop_first=True)
m_dum=pd.get_dummies(high_exp['month'],drop_first=True)
x=pd.concat([g_dum,mp_dum,m_dum],axis=1)
x.head()
```

Out[166]:

	Adventure	Animation	Biography	Comedy	Crime	Drama	Family	Fantasy	History	Horror	...
0	0	0	0	0	0	0	0	0	0	0	...
0	0	1	0	0	0	0	0	0	0	0	...
0	0	0	0	1	0	0	0	0	0	0	...
3	1	0	0	0	0	0	0	0	0	0	...
3	0	0	0	1	0	0	0	0	0	0	...

5 rows × 34 columns

In [167]:
```
x=sm.add_constant(x)
y=high_exp['profit']
```

In [168]:

```
results=sm.OLS(y,x).fit()
results.summary()
```

Out[168]:

OLS Regression Results

Dep. Variable:	profit	**R-squared:**	0.180
Model:	OLS	**Adj. R-squared:**	0.157
Method:	Least Squares	**F-statistic:**	7.825
Date:	Wed, 13 Oct 2021	**Prob (F-statistic):**	1.65e-33
Time:	19:48:34	**Log-Likelihood:**	-25962.
No. Observations:	1243	**AIC:**	5.199e+04
Df Residuals:	1208	**BIC:**	5.217e+04
Df Model:	34		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.524e+08	7.48e+07	3.373	0.001	1.06e+08	3.99e+08
Adventure	2.383e+07	2.69e+07	0.886	0.376	-2.89e+07	7.66e+07
Animation	2.066e+07	4.19e+07	0.493	0.622	-6.15e+07	1.03e+08
Biography	-4.495e+07	7.21e+07	-0.624	0.533	-1.86e+08	9.64e+07
Comedy	-7.563e+07	3.07e+07	-2.465	0.014	-1.36e+08	-1.54e+07
Crime	-8.726e+07	4.56e+07	-1.914	0.056	-1.77e+08	2.19e+06
Drama	-8.739e+07	3.49e+07	-2.502	0.012	-1.56e+08	-1.89e+07
Family	-1.104e+08	5.45e+07	-2.024	0.043	-2.17e+08	-3.4e+06
Fantasy	-3.37e+07	3.79e+07	-0.888	0.375	-1.08e+08	4.07e+07
History	-1.335e+08	9.94e+07	-1.344	0.179	-3.28e+08	6.14e+07
Horror	-9.733e+07	7.77e+07	-1.253	0.210	-2.5e+08	5.5e+07
Music	-2.054e+08	1.69e+08	-1.218	0.223	-5.36e+08	1.25e+08
Musical	2.979e+07	1.46e+08	0.204	0.839	-2.57e+08	3.17e+08
Mystery	-8.937e+07	6.52e+07	-1.370	0.171	-2.17e+08	3.86e+07
Romance	-1.573e+08	6.63e+07	-2.372	0.018	-2.87e+08	-2.72e+07
Sci-Fi	1.109e+08	3.89e+07	2.850	0.004	3.45e+07	1.87e+08
Sport	-1.684e+08	1.47e+08	-1.149	0.251	-4.56e+08	1.19e+08
Thriller	-5.135e+07	4.46e+07	-1.151	0.250	-1.39e+08	3.62e+07
War	-3.884e+07	1.69e+08	-0.230	0.818	-3.7e+08	2.93e+08
Western	-1.263e+08	1.47e+08	-0.861	0.390	-4.14e+08	1.62e+08
PG	-6.141e+07	6.33e+07	-0.970	0.332	-1.86e+08	6.29e+07
PG-13	-7.467e+07	6.41e+07	-1.165	0.244	-2e+08	5.11e+07

R	-1.745e+08	6.67e+07	-2.617	0.009	-3.05e+08	-4.37e+07
Unrated	-4.052e+08	1.36e+08	-2.981	0.003	-6.72e+08	-1.39e+08
2.0	6.729e+07	4.67e+07	1.440	0.150	-2.44e+07	1.59e+08
3.0	1.106e+08	4.41e+07	2.508	0.012	2.41e+07	1.97e+08
4.0	3.239e+08	5.3e+07	6.109	0.000	2.2e+08	4.28e+08
5.0	2.169e+08	4.42e+07	4.905	0.000	1.3e+08	3.04e+08
6.0	2.236e+08	4.34e+07	5.157	0.000	1.39e+08	3.09e+08
7.0	1.421e+08	4.38e+07	3.241	0.001	5.61e+07	2.28e+08
8.0	1.392e+07	4.63e+07	0.301	0.764	-7.69e+07	1.05e+08
9.0	-4.512e+06	5.1e+07	-0.089	0.929	-1.04e+08	9.55e+07
10.0	2.058e+07	4.81e+07	0.428	0.669	-7.37e+07	1.15e+08
11.0	1.504e+08	4.53e+07	3.322	0.001	6.16e+07	2.39e+08
12.0	1.348e+08	4.32e+07	3.119	0.002	5e+07	2.2e+08

Omnibus:	566.797	**Durbin-Watson:**	0.645
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3646.067
Skew:	2.018	**Prob(JB):**	0.00
Kurtosis:	10.356	**Cond. No.**	26.1

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

The R squared for this model is only .18 - for the purposes of this analysis for Microsoft, we already have a good idea of what recommendations we will make. I won't explore performing multiple linear regression on this dataset any further.

4 Evaluation

While this data was not a comprehensive list of all movies made in the US in the last 10 years, it did include most of the large studio movies that would be comparable to what Microsoft would make. Many of the films that were filtered out due to missing data had smaller or unknown budgets and would not have been a part of the high budget group. Therefore, I am reasonably confident that this dataset provided sound information about film performance for Microsoft's purposes.

It is important to note that this was a descriptive analysis based on correlation of certain characteristics with profit. It did not establish clear causation between those characteristics and increased profit. Many films with the recommended characteristics still perform poorly and the quality of the film produced is still important. However, making high-budget films in these categories can give the studio a better chance at success.

There are also other characteristics that can predict performance that are not included in this analysis. Combinations of genres could be examined as well as leading actors, director, script content, and type of storyline.

5 Conclusions

This analysis led to four recommendations for determining what type of films to produce.

1) High budget films (defined as over $40 million in this project) are more positively correlated with profit than low budget films. Since Microsoft is a large company with ample capital, they should invest in higher budget productions.

2) Among high budget films, those which can be classified as Animation, Action, Adventure, or Sci-Fi have higher profits on average. Microsoft should consider making films that fall into one or more of these genres.

3) High-performing MPAA Ratings vary by genre, although overall R-Rated movies tend to have lower profits. Below is a breakdown of recommended MPAA rating for the top four genres:

> -Animation: PG
> -Action: PG-13
> -Adventure: PG-13
> -Sci-Fi: PG-13

4) For high-budget films, profits tend to be higher in late Spring and early Summer (April-July) and in the holiday months (November and December). The month with the highest median profit is May, although this varies slightly by genre. Release dates in either of these peak seasons could give a high-budget film a better chance for success.

5.0.1 Next Steps

More advanced methods could be utilized to create a predictive model for profit. Work has been done on machine learning models that can predict box office income based on characteristics of the film. There are also models that can predict outcomes from a script by using natural language processing to evaluate the storyline, genre, and type of language used. This could allow Microsoft to narrow down profitable films to produce within the overarching categories recommended by this project.