Final Project Submission

Please fill out:

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- Student pace: Flex
- Scheduled project review date/time:
- Instructor name: Morgan Jones
- Blog post URL:

Phase 1 Project

In this hypothetical scenario, Microsoft wants to start a movie studio and has asked me to look at historical movie data to try to determine what works and what does not.

The two metrics I will use to measure success are profit and viewer ratings. Microsoft is going to want their new studio to be profitable, so my recommendations will be based on what has made movies profitable in the past. In addition to making money, I want to make sure that the new studio's movies are well-received, particularly the first few releases, because a positive first impression will make people more likely to want to see future movies. That is why I am also looking at trends for movies with both high and low ratings.

The three main factors I will look at are budget, genre, and star-power. Budget: Microsoft will want to know how much capital to invest into the new studio in order to realistically make a large profit.

Genre: I will look through movies released in the US market to determine which genres tend to make the most money and receive the highest praise.

Star-power: I want to determine if having recognizable actors/directors involved in a movie affects profit or ratings. This is the most challenging factor to tease out of the data because I need to come up with a metric for how much "star-power" a person has as a function of time throughout their career.

Data Exploration

I am going to start by just reading in the data and seeing what info is included.

In [1]:
```
import pandas as pd
```

In [2]:
```
#Define a path to where all the data is kept
dir_path = 'C:/Users/david/Documents/Flatiron/phase_1/Phase1-Microsoft-I
```

Box Office Mojo

The Box Office Mojo data includes title, studio, domestic and foreign gross, and the year. The data only dates back to 2010.

In [3]:
```
#Box Office Mojo
df = pd.read_csv(dir_path+'Data/bom.movie_gross.csv')
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

In [5]:
```
df.head(10)
```

Out[5]:

	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
5	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010
6	Iron Man 2	Par.	312400000.0	311500000	2010
7	Tangled	BV	200800000.0	391000000	2010
8	Despicable Me	Uni.	251500000.0	291600000	2010
9	How to Train Your Dragon	P/DW	217600000.0	277300000	2010

In [6]:
```
df.year.min()
```

Out[6]:
```
2010
```

Rotten Tomatoes Information

This dataset includes information about genre, rating, director, writer, release date, box office, runtime, and studio. Strangely, it doesn't actually include the title of the movie. I will look to see if that is in a different dataset.

In [7]:
```
#Rotten Tomatoes Information
df = pd.read_csv(dir_path+'Data/rt.movie_info.tsv',sep='\t')
```

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            1560 non-null   int64 
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: int64(1), object(11)
memory usage: 146.4+ KB
```

In [9]:

```
df.head(10)
```

Out[9]:

	id	synopsis	rating	genre	director	writer	theater
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	A
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	S
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	
5	8	The year is 1942. As the Allies unite overseas...	PG	Drama|Kids and Family	Jay Russell	Gail Gilchriest	Mar 3
6	10	Some cast and crew from NBC's highly acclaimed...	PG-13	Comedy	Jake Kasdan	Mike White	Jan 11
7	13	Stewart Kane, an Irishman living in the Austra...	R	Drama	Ray Lawrence	Raymond Carver|Beatrix Christian	Apr 27
8	14	"Love Ranch" is a bittersweet love story that ...	R	Drama	Taylor Hackford	Mark Jacobson	Jun 30
9	15	When a diamond expedition in the Congo is lost...	PG-13	Action and Adventure|Mystery and Suspense|Scie...	Frank Marshall	John Patrick Shanley	Jun 9

Rotten Tomatoes Reviews

This dataset includes reviews of each movie. Again, the movie title is not included. The ID allows for this dataset to be joined with the previous Rotten Tomatoes dataset which also does not contain movie titles. Based on my current plans, I do not expect to use this dataset.

In [10]:
```
#Rotten Tomatoes Reviews
df = pd.read_csv(dir_path+'Data/rt.reviews.tsv', sep='\t', encoding = '
```

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54432 entries, 0 to 54431
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          54432 non-null  int64 
 1   review      48869 non-null  object
 2   rating      40915 non-null  object
 3   fresh       54432 non-null  object
 4   critic      51710 non-null  object
 5   top_critic  54432 non-null  int64 
 6   publisher   54123 non-null  object
 7   date        54432 non-null  object
dtypes: int64(2), object(6)
memory usage: 3.3+ MB
```

In [12]:
```
df.head(10)
```

Out[12]:

	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
5	3	... Cronenberg's Cosmopolis expresses somethin...	NaN	fresh	Michelle Orange	0	Capital New York	September 11, 2017
6	3	Quickly grows repetitive and tiresome, meander...	C	rotten	Eric D. Snider	0	EricDSnider.com	July 17, 2013
7	3	Cronenberg is not a director to be daunted by ...	2/5	rotten	Matt Kelemen	0	Las Vegas CityLife	April 21, 2013
8	3	Cronenberg's cold, exacting precision and emot...	NaN	fresh	Sean Axmaker	0	Parallax View	March 24, 2013
9	3	Over and above its topical urgency or the bit ...	NaN	fresh	Kong Rithdee	0	Bangkok Post	March 4, 2013

TheMovieDB

This dataset contains genre, title, popularity, release date, vote average, and vote count. I will need to do a little research to figure out how some of these columns are calculated. What is popularity? Does more votes automatically mean the movie was well received?

After looking into the data more closely, some movies show up multiple times with identical information. I am not sure why, but if I use this dataset, I should try to remove the duplicates. There are a little over 1000 duplicates.

Popularity: I looked this up and it seems like popularity is just a measure of how much people are engaging with the movie on the website. It also looks like something that changes day-to-day, so chances are the popularity score in the table is just from the day the data was pulled. I do not actually think popularity is a useful metric for my analysis.

I tried merging this dataset with the dataset from TheNumbers because I wanted to see how hard it would be. What I found is that a little fewer than 100 movies couldn't be crosslisted by title, and when I checked the titles to see why, it actually turns out TheMovieDB data just doesn't have many of them (including big releases). I think this is just because of when the data was pulled. For example, Captain Marvel is not in this dataset, but there is currently a webpage for it on TheMovieDB. This does make me less likely to utilize this dataset. That is

In [13]:
```
#TheMovieDB
df = pd.read_csv(dir_path+'Data/tmdb.movies.csv')
```

In [14]:
```
df.info()
```

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

In [15]:
```
df.drop_duplicates(subset='id').info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25497 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         25497 non-null  int64  
 1   genre_ids          25497 non-null  object 
 2   id                 25497 non-null  int64  
 3   original_language  25497 non-null  object 
 4   original_title     25497 non-null  object 
 5   popularity         25497 non-null  float64
 6   release_date       25497 non-null  object 
 7   title              25497 non-null  object 
 8   vote_average       25497 non-null  float64
 9   vote_count         25497 non-null  int64  
dtypes: float64(2), int64(3), object(5)
memory usage: 2.1+ MB
```

The Numbers

This dataset includes release date, title, budget, and both domestic and worldwide gross. Production budget is one of the things I want to use in my analysis, so I will use this dataset.

In [16]:
```
#The Numbers
df = pd.read_csv(dir_path+'Data/tn.movie_budgets.csv')
```

In [17]:
```
df.info()
```

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

In [18]:
```
df.head(10)
```

Out[18]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	$306,000,000	$936,662,225	$2,053,311,220
6	7	Apr 27, 2018	Avengers: Infinity War	$300,000,000	$678,815,482	$2,048,134,200
7	8	May 24, 2007	Pirates of the Caribbean: At Worldâ□□s End	$300,000,000	$309,420,425	$963,420,425
8	9	Nov 17, 2017	Justice League	$300,000,000	$229,024,295	$655,945,209
9	10	Nov 6, 2015	Spectre	$300,000,000	$200,074,175	$879,620,923

IMDB

There are 8 tables in this database:

1. persons: This includes 606,648 people, but many are from the distant past or they are not known to the American movie audience. I will want to only keep those who are featured in major movies released in the US.
2. principals: This lists the principal actors and directors of each movie.
3. known_for: I looked up what this means specifically, and it only includes 4 movies per person. This is not particularly helpful for what I want to do.
4. directors: Lists the movies directed by each person.
5. writers: Lists the movies written by each person.
6. movie_basics: For each movie, it lists the title, year, and genres. I will want to filter the 146,144 movies down to just major movies released in the US.

7. movie_ratings: Lists average rating of each movie and the number of votes. I do not know where the ratings are coming from (are they professional critics or just user ratings). My guess is that it has to just be user ratings because some movies have hundreds of thousands of votes.
8. movie_akas: Is the only table that includes the regions in which the movies were released. This will be needed to find movies released in the US.

In [19]:
```
import sqlite3
```

In [20]:
```
#IMDB
conn = sqlite3.connect(dir_path+'im.db/im.db')
```

In [21]:
```
pd.read_sql("""
SELECT *
  FROM persons;
""", conn)
```

Out[21]:

	person_id	primary_name	birth_year	death_year	
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,productio
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_departme
2	nm0062070	Bruce Baum	NaN	NaN	misce
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematogra
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_depa
...	...	...	...	...	
606643	nm9990381	Susan Grobes	NaN	NaN	
606644	nm9990690	Joo Yeon So	NaN	NaN	
606645	nm9991320	Madeline Smith	NaN	NaN	
606646	nm9991786	Michelle Modigliani	NaN	NaN	
606647	nm9993380	Pegasus Envoyé	NaN	NaN	

606648 rows × 5 columns

In [22]:

```
pd.read_sql("""
SELECT *
  FROM movie_basics;
""", conn)
```

Out[22]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crim
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biograpl
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Come
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Doc
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Doc

146144 rows × 6 columns

In [23]:
```
pd.read_sql("""
SELECT *
  FROM movie_ratings;
""", conn)
```

Out[23]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

Budget

Plan: Only one of the datasets includes information on budget (The Numbers). This dataset includes 5782 rows. This is far fewer than the total number of movies listed on TheNumbers.com, which makes me think this has already been filtered to some extent. I will first see what kind of movies are included in the dataset.

In [24]:
```
df = pd.read_csv(dir_path+'Data/tn.movie_budgets.csv')
```

In [25]:
```
#The release date is not formatted as a date datatype, so I convert it.
df.release_date = pd.to_datetime(df.release_date, format = '%b %d, %Y')
```

In [26]:
```
#I want to be able to treat the monetary columns as numbers instead of 
#I also make it so they are measured in millions of dollars
df.production_budget = df.production_budget.replace('[\$,]', '', regex=
df.domestic_gross = df.domestic_gross.replace('[\$,]', '', regex=True).
df.worldwide_gross = df.worldwide_gross.replace('[\$,]', '', regex=True
```

In [27]:
```
df.sort_values(by='release_date').head(10)
```

Out[27]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
5677	78	1915-02-08	The Birth of a Nation	0.110000	10.0	11.000
5523	24	1916-09-05	Intolerance	0.385907	0.0	0.000
5614	15	1916-12-24	20,000 Leagues Under the Sea	0.200000	8.0	8.000
5683	84	1920-09-17	Over the Hill to the Poorhouse	0.100000	3.0	3.000
5606	7	1925-11-19	The Big Parade	0.245000	11.0	22.000
4569	70	1925-12-30	Ben-Hur: A Tale of the Christ	3.900000	9.0	9.000
4984	85	1927-08-12	Wings	2.000000	0.0	0.000
5524	25	1929-02-01	The Broadway Melody	0.379000	2.8	4.358
4559	60	1930-11-15	Hell's Angels	4.000000	0.0	0.000
5423	24	1931-12-26	Mata Hari	0.558000	0.9	0.900

The earliest movie in the database was released in 1915. That is pretty cool, but I do not think movies from many decades ago are going to help find trends among the modern movie industry. I am going to only include movies in the last 30 years (back to 1993). This still includes most of the data (5103 movies).

I also notice that some movies have a domestic and/or worldwide gross that is equal to 0 dollars. I looked into one example (Bright) and the webpage for Bright on TheNumbers.com does not show a gross of 0, but instead just a dash. I think this means 0 is just a placeholder from an unknown amount. Ignoring movies with unknown domestic_gross leaves 4580 movies.

In [28]:
```
df[df.release_date > '1993-01-01'][df.domestic_gross > 0].sort_values(b
```

```
<ipython-input-28-66b5b7912ea5>:1: UserWarning: Boolean Series key wil
l be reindexed to match DataFrame index.
  df[df.release_date > '1993-01-01'][df.domestic_gross > 0].sort_value
s(by = 'release_date', ascending = False)
```

Out[28]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gros
341	42	2019-06-14	Men in Black: International	110.0	3.100000	3.10000
1997	98	2019-06-14	Shaft	30.0	0.600000	0.60000
4534	35	2019-06-07	Late Night	4.0	0.246305	0.24630
2	3	2019-06-07	Dark Phoenix	350.0	42.762350	149.76235
580	81	2019-06-07	The Secret Life of Pets 2	80.0	63.795655	113.35149
...	...	...	...	...	...	.
4741	42	1993-02-12	Dead Alive	3.0	0.242623	0.24262
3264	65	1993-02-05	Loaded Weapon 1	13.0	27.979399	27.97939
4929	30	1993-01-29	Nemesis	2.0	2.001124	2.00112
3064	65	1993-01-15	Nowhere to Run	15.0	22.189039	52.18903
1801	2	1993-01-15	Alive	32.0	36.299670	36.29967

4580 rows × 6 columns

In [29]:
```
#I am going to create a new column called profit. This will just be wor
df['profit'] = df.worldwide_gross - df.production_budget
```

In [30]:
```
#Make a new DataFrame that only includes movies since 1993 and actually
df_93_hasgross = df[df.release_date > '1993-01-01'][df.domestic_gross >
```

```
<ipython-input-30-81a7709466f8>:2: UserWarning: Boolean Series key wil
l be reindexed to match DataFrame index.
  df_93_hasgross = df[df.release_date > '1993-01-01'][df.domestic_gros
s > 0]
```

In [31]:
```
df_93_hasgross.sort_values(by = 'profit', ascending = False)
```

Out[31]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	2009-12-18	Avatar	425.0	760.507625	2776.345279
42	43	1997-12-19	Titanic	200.0	659.363944	2208.208395
6	7	2018-04-27	Avengers: Infinity War	300.0	678.815482	2048.134200
5	6	2015-12-18	Star Wars Ep. VII: The Force Awakens	306.0	936.662225	2053.311220
33	34	2015-06-12	Jurassic World	215.0	652.270625	1648.854864
...	...	...	...	...	...	...
404	5	2002-08-16	The Adventures of Pluto Nash	100.0	4.411102	7.094995
352	53	2001-04-27	Town & Country	105.0	6.712451	10.364769
341	42	2019-06-14	Men in Black: International	110.0	3.100000	3.100000
193	94	2011-03-11	Mars Needs Moms	150.0	21.392758	39.549758
2	3	2019-06-07	Dark Phoenix	350.0	42.762350	149.762350

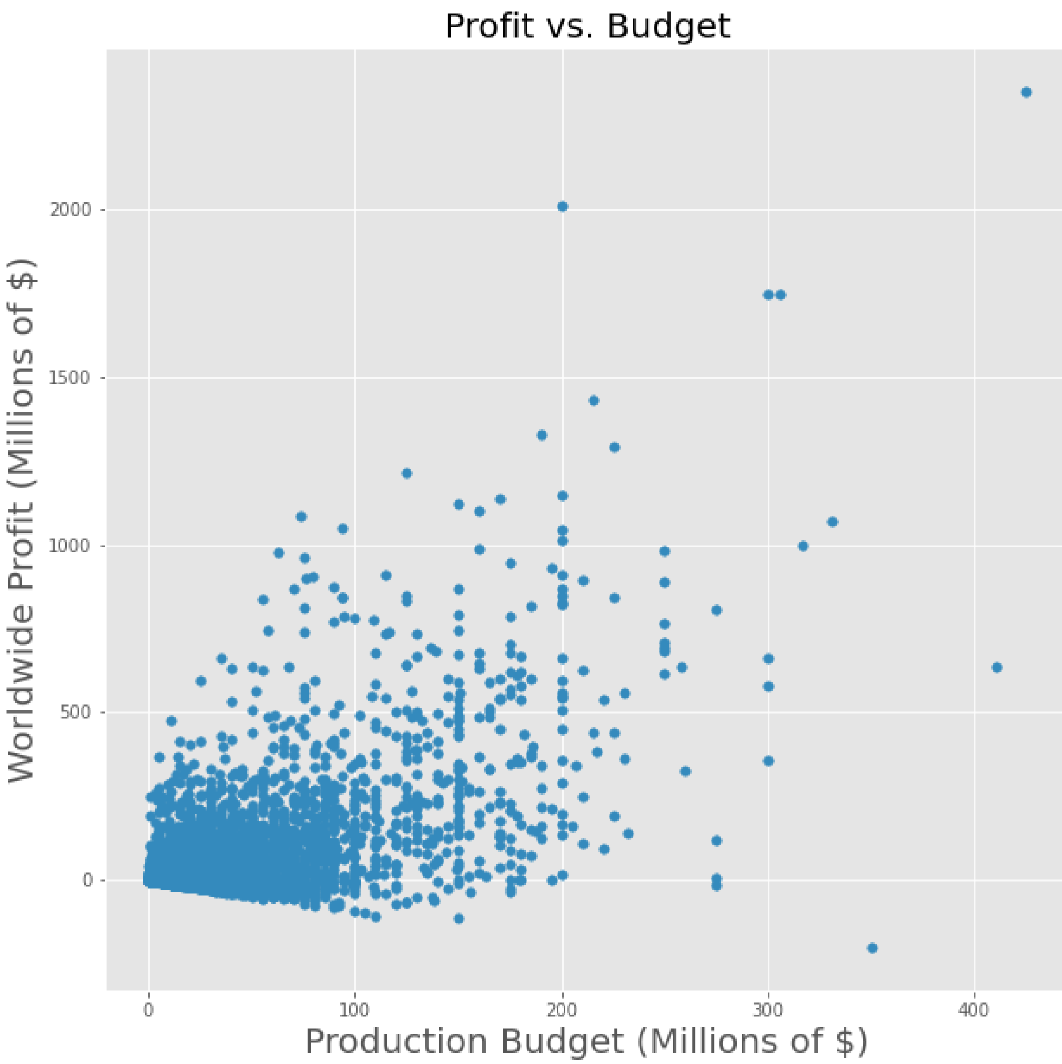
4580 rows × 7 columns

In [32]:
```
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
plt.rcParams['figure.figsize'] = (10, 10)
plt.style.use('ggplot')
```

In [33]:

```
ax = df_93_hasgross.plot('production_budget', 'profit', kind = 'scatter
ax.set_xlabel('Production Budget (Millions of $)', fontsize = 20)
ax.set_ylabel('Worldwide Profit (Millions of $)', fontsize = 20)
ax.set_title('Profit vs. Budget', fontsize = 20)
```

Out[33]: Text(0.5, 1.0, 'Profit vs. Budget')



In [34]:

```
#I am dividing the movies into 10 groups based on their production budg
#This is being added to the table as budget_range
groups, edges = pd.qcut(df_93_hasgross.production_budget,q=10, retbins=

df_93_hasgross['budget_range'] = groups
```

In [35]:
```
#Determine what percentage of movies were profitable in each budget rang
df_93_hasgross['Profitable?'] = df_93_hasgross.profit > 0
df_grouped_by_budget = df_93_hasgross.groupby('budget_range').mean()
df_93_hasgross.groupby('budget_range').mean()
```

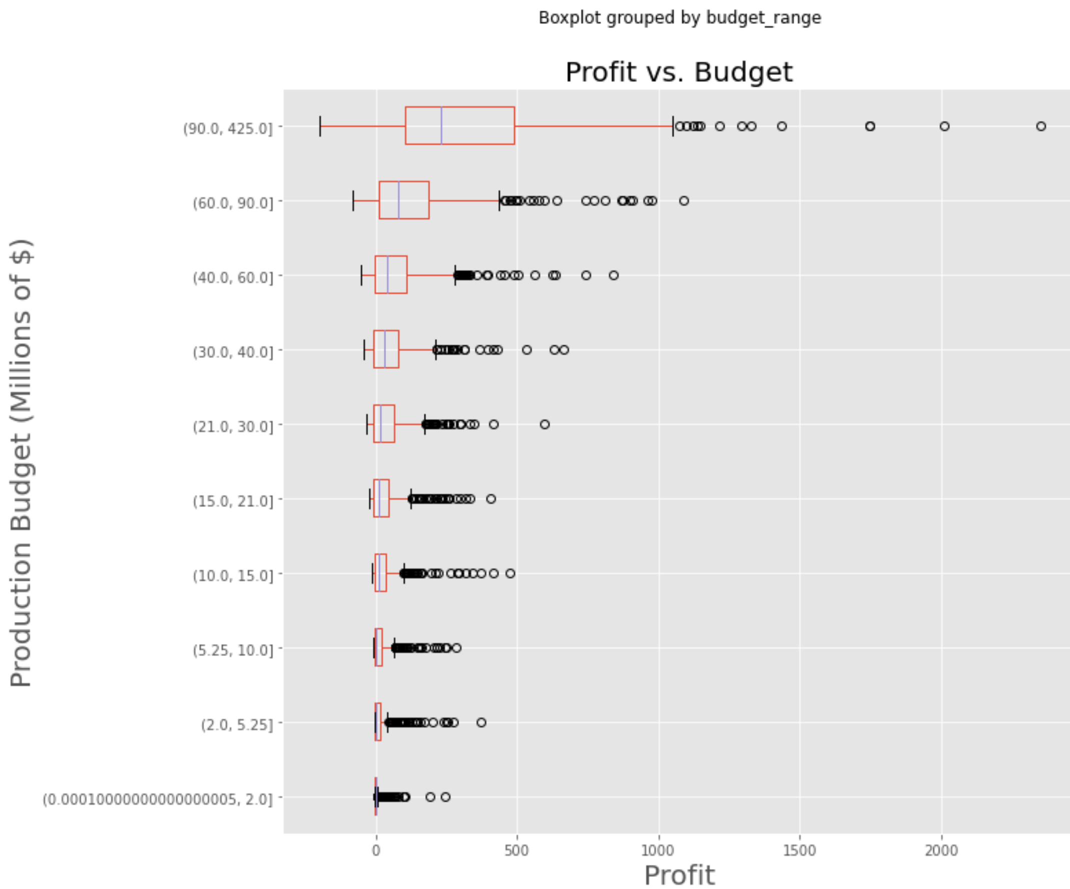
Out[35]:

budget_range	id	production_budget	domestic_gross	worldwide_gro
(0.00010000000000000005, 2.0]	51.486381	0.941134	3.371635	5.9800
(2.0, 5.25]	46.819307	3.909761	10.541414	20.0609
(5.25, 10.0]	50.174242	8.216687	13.898224	25.1084
(10.0, 15.0]	48.898585	13.284434	21.566826	41.4142
(15.0, 21.0]	52.804545	18.775966	28.304959	50.7945
(21.0, 30.0]	51.162617	26.575009	38.498903	68.5418
(30.0, 40.0]	51.063415	36.815488	46.323991	88.4582
(40.0, 60.0]	51.502000	51.821826	59.320215	122.1574
(60.0, 90.0]	50.612821	75.864997	90.945888	205.6056
(90.0, 425.0]	47.685057	148.327816	171.138472	473.2674

In [36]:

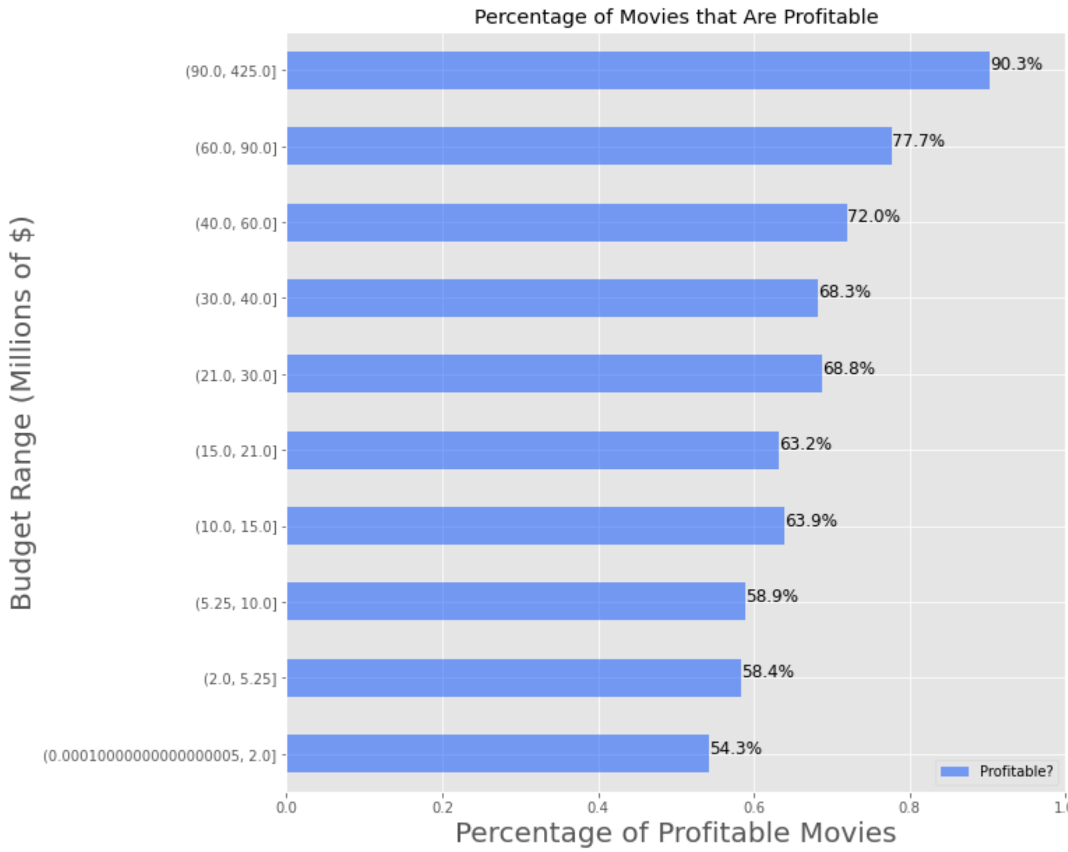
```
# Make a figure with boxplots for each range of budget
ax = df_93_hasgross.boxplot(column = 'profit', by = 'budget_range', ver
ax.set_xlabel('Profit', fontsize = 20)
ax.set_ylabel('Production Budget (Millions of $)', fontsize = 20)
ax.set_title('Profit vs. Budget', fontsize = 20)
```

Out[36]: Text(0.5, 1.0, 'Profit vs. Budget')



In [37]:

```
# This plot shows the percentage of movies that are profitable within e
ax = df_grouped_by_budget.plot(y = 'Profitable?', kind='barh', color=(0
ax.set_xlim((0,1))
ax.set_xlabel('Percentage of Profitable Movies', fontsize = 20)
ax.set_ylabel('Budget Range (Millions of $)', fontsize = 20)
for i,perc in enumerate(df_grouped_by_budget['Profitable?']):
    ax.text(perc, i, f"{round(100*perc,1)}%", fontsize = 12)
```



Conclusions about budget

The plot shows that the higher the budget, the higher the profit tends to be. Importantly, as the budget increases, the probability of making a profit increases. Movies with budgets exceeding 90 million made money about 90% of the time while movies with budgets between 60 and 90 million only made money about 78% of the time.

Spending lots of money does not guarantee a big payday. Just look at Dark Phoenix. That movie had a budget of 350 million and it lost 200 million. We need to make sure that we spend the money wisely. That is what the other recommendations will help us do.

Data Cleaning

The IMDB dataset, which has the most information, has unique IDs for each movie. Unfortunately, those IDs can only be used to merge tables within the dataset, not with other non-IMDB datasets. I can try using movie titles to combine, but that leads to issues because some movies were released under multiple different titles. There are three other issues when trying to merge

1. The merge method is case sensitive. This is the easiest to fix because I can just make all the titles lower case.
2. In the TheNumbers data, the original csv document with the data has some strange artifacts in place of special characters. Characters like apostrophes, dashes, ellipses, and accented letters do not show up correctly. There are a small enough number of these (less than 100) that they can be fixed manually.
3. The hardest problem to fix is just that some titles differ slightly. For example, a movie

In [38]:
```
df_basics = pd.read_sql("""
SELECT *
  FROM movie_basics;
""", conn)
```

In [39]:
```
#The IMDB data starts at 2010
df_basics.start_year.min()
```

Out[39]:
```
2010
```

In [40]:
```
#I am reading in the TheNumbers data again, but this time the version tl
#I perform some of the same alterations to the columns, but this time, :
df = pd.read_csv(dir_path+'Data/tn.movie_budgets_clean.csv')
df.release_date = pd.to_datetime(df.release_date, format = '%b %d, %Y')
df.production_budget = df.production_budget.replace('[\$,]', '', regex='
df.domestic_gross = df.domestic_gross.replace('[\$,]', '', regex=True).
df.worldwide_gross = df.worldwide_gross.replace('[\$,]', '', regex=True
df['profit'] = df.worldwide_gross - df.production_budget
df_10_hasgross = df[df.release_date >= '2010-01-01'][df.domestic_gross
```

```
<ipython-input-40-7609ece1c8fa>:9: UserWarning: Boolean Series key wil
l be reindexed to match DataFrame index.
  df_10_hasgross = df[df.release_date >= '2010-01-01'][df.domestic_gro
ss > 0]
```

In [41]:
```
#Change the titles so it is all lower case. This will help when merging
df_basics['primary_title'] = df_basics['primary_title'].str.lower()
df_10_hasgross['movie'] = df_10_hasgross['movie'].str.lower()
```

In [42]:
```
#Merge the data from TheNumbers with the IMDB basics table
df_merge = df_10_hasgross.merge(df_basics, left_on = 'movie', right_on
```

In [43]:
```
#This is a list of all the movies in the TheNumbers data that I couldn't
#This is mostly a list of foreign movies or low budget movies.
#I had to manually change quite a few movie titles so they would match,
df_merge[df_merge.primary_title.isna()]
```

Out[43]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
400	2	2010-04-22	oceans	80.000	19.422319	86.78753(
450	49	2010-05-28	agora	70.000	0.619423	38.99229:
488	20	2015-09-04	tian jiang xiong shi	65.000	0.074070	122.51987
497	42	2016-02-19	mei ren yu	60.720	3.229457	554.51667
538	51	2016-02-05	xi you ji zhi sun wu kong san da bai gu jing	60.000	0.709982	194.05850
...	...	...	...	...	...	..
2383	39	2010-06-25	kynodontas	0.323	0.110248	1.37340
2385	53	2012-11-09	nothing but a man	0.300	0.017241	0.01724
2430	31	2010-03-12	the exploding girl	0.040	0.025572	0.02557
2433	41	2010-10-15	down terrace	0.030	0.009812	0.00981
2437	61	2010-04-02	breaking upwards	0.015	0.115592	0.11559

127 rows × 13 columns

In [44]:

```
#The total number of rows in the merged table is 2439.
#However, when I use drop duplicates on the movie title, there are only
#This means there are a lot of duplicates.
#This can happen because multiple different movies in the IMDB dataset 
#I need to remove the duplicates
df_merge.drop_duplicates(subset = 'movie')
```

Out[44]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	2	2011-05-20	pirates of the caribbean: on stranger tides	410.600	241.063875	1045.663875
1	3	2019-06-07	dark phoenix	350.000	42.762350	149.762350
2	4	2015-05-01	avengers: age of ultron	330.600	459.005868	1403.013963
3	5	2017-12-15	star wars: the last jedi	317.000	620.181382	1316.721747
4	6	2015-12-18	star wars: episode vii - the force awakens	306.000	936.662225	2053.311220
...	...	...	...	...	...	...
2432	38	2016-03-18	krisha	0.030	0.144822	0.144822
2433	41	2010-10-15	down terrace	0.030	0.009812	0.009812
2434	45	2017-01-27	emily	0.027	0.003547	0.003547
2437	61	2010-04-02	breaking upwards	0.015	0.115592	0.115592
2438	73	2012-01-13	newlyweds	0.009	0.004584	0.004584

1785 rows × 13 columns

In [45]:
```
#Get value counts of the movie titles to see what titles are being dupl
df_merge.movie.value_counts()
```

Out[45]:
```
home                24
brothers            13
the gift            13
the promise         10
robin hood          10
                    ..
j. edgar             1
trainwreck           1
le petit nicolas     1
top spin             1
the finest hours     1
Name: movie, Length: 1785, dtype: int64
```

In [46]:
```
#I can fix the duplicates by just going through the list and seeing whi
#I made the matches by looking at the release date and start year as we
#I used the actual IMDB pages for each movie to double check the matche
df_merge[df_merge.movie == 'robin hood']
```

Out[46]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
28	39	2010-05-14	robin hood	210.0	105.487148	322.459006	112
29	39	2010-05-14	robin hood	210.0	105.487148	322.459006	112
30	39	2010-05-14	robin hood	210.0	105.487148	322.459006	112
31	39	2010-05-14	robin hood	210.0	105.487148	322.459006	112
32	39	2010-05-14	robin hood	210.0	105.487148	322.459006	112
309	9	2018-11-21	robin hood	99.0	30.824628	84.747441	-14
310	9	2018-11-21	robin hood	99.0	30.824628	84.747441	-14
311	9	2018-11-21	robin hood	99.0	30.824628	84.747441	-14
312	9	2018-11-21	robin hood	99.0	30.824628	84.747441	-14
313	9	2018-11-21	robin hood	99.0	30.824628	84.747441	-14

In [47]:
```
#This is a new CSV file I made that stores the movie_id that matches ea
df_dup_remover = pd.read_csv(dir_path + 'Data/duplicate_remover.csv')
```

In [48]:
```
df_dup_remover
```

Out[48]:

	movie	movie_id
0	home	tt2224026
1	brothers	tt3802576
2	the gift	tt4178092
3	the promise	tt4776998
4	silence	tt0490215
...	...	...
289	burlesque	tt1126591
290	flight	tt1907668
291	elysium	tt1535108
292	don't breathe	tt4160708
293	the last stand	tt1549920

294 rows × 2 columns

In [49]:
```
#I am going to loop over each movie in df_dup_remover and drop rows tha
for movie, movie_id in zip(df_dup_remover.movie, df_dup_remover.movie_i
    if movie_id == 'remove': #Some movies did not actually match up wit
        df_merge.drop(df_merge.index[df_merge.movie == movie], inplace
    if movie != 'robin hood': #There are two robin hood movies, so I wi
        df_merge.drop(df_merge.index[(df_merge.movie == movie) & (df_me
```

In [50]:
```
#There are two movies called robin hood that match a movie from the IMD
#I need to treat these cases separately because the code above would ju
df_merge.drop(df_merge.index[(df_merge.movie == 'robin hood') & (df_mer
df_merge.drop(df_merge.index[(df_merge.movie == 'robin hood') & (df_mer
#There are two movies called the square, but only one of them matches.
df_merge.drop(df_merge.index[(df_merge.movie == 'the square') & (df_mer
```

In [51]:
```
#Now, the combined data should not include any duplicates
df_merge.movie.value_counts()
```

Out[51]:
```
robin hood                              2
barbecue                                1
evil dead                               1
shame                                   1
night at the museum: secret of the tomb 1
                                       ..
jupiter ascending                       1
resident evil: afterlife                1
50 to 1                                 1
les herbes folles                       1
the finest hours                        1
Name: movie, Length: 1783, dtype: int64
```

Now there are no repeats in the dataset. Just so I don't have to rerun the cells above every time I restart the kernel, I am going to save this DataFrame as a CSV file.

In [52]:
```
#Select the cells I want to keep (I am excluding redundant cells)
df_merge = df_merge[['release_date', 'movie', 'production_budget', 'dom
```

In [53]:
```
df_merge.to_csv(dir_path + 'Data/TheNumbers_IMDB_Merge.csv')
```

Genres

Using the movies that are listed in both TheNumbers and the IMDB datasets, I will look at how the genre is related to both the profit and the rating.

In [54]:
```
df_merge = pd.read_csv(dir_path + 'Data/TheNumbers_IMDB_Merge.csv')
```

In [55]:
```
#Convert release date to datetime
df_merge.release_date = pd.to_datetime(df.release_date, format = '%b %d
```

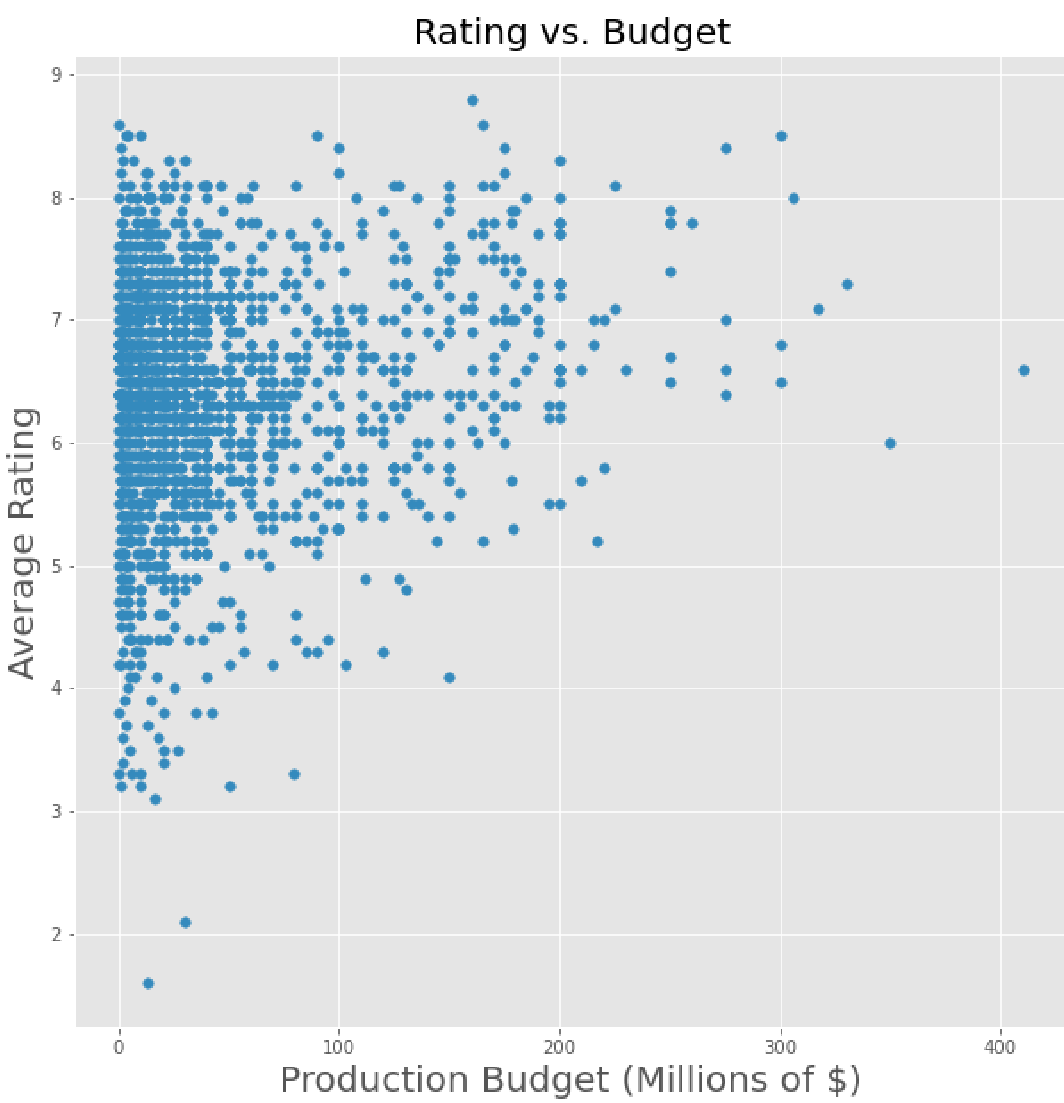
In [56]:
```
df_ratings = pd.read_sql("""
SELECT *
  FROM movie_ratings;
""", conn)
```

In [57]:
```
df_merge = df_merge.merge(df_ratings, left_on = 'movie_id', right_on =
```

In [58]:
```
#Make it so the genres are all lower case
df_merge['genres'] = df_merge['genres'].str.lower()
```

In [59]:
```
#I also looked at Rating vs. Budget
#It seems that very high budget movies have a higher floor than low budg
ax = df_merge.plot('production_budget', 'averagerating', kind = 'scatte
ax.set_xlabel('Production Budget (Millions of $)', fontsize = 20)
ax.set_ylabel('Average Rating', fontsize = 20)
ax.set_title('Rating vs. Budget', fontsize = 20)
```

Out[59]: Text(0.5, 1.0, 'Rating vs. Budget')



In [60]:

```
#The IMDB data lists multiple genres per movie as as single string separ
#I want to get a list of unique genres so I can look at each genre separ
#I found a nice snippet of code from https://medium.com/analytics-vidhya
from sklearn.feature_extraction.text import CountVectorizer

temp = df_merge.genres.dropna()
vec = CountVectorizer(token_pattern='(?u)\\b[\\w-]+\\b', analyzer='word
unique_genres =  vec.get_feature_names()
unique_genres
```

Out[60]:

```
['action',
 'adventure',
 'animation',
 'biography',
 'comedy',
 'crime',
 'documentary',
 'drama',
 'family',
 'fantasy',
 'history',
 'horror',
 'music',
 'musical',
 'mystery',
 'romance',
 'sci-fi',
 'sport',
 'thriller',
 'war',
 'western']
```

In [61]:
```
#Find the average rating of each genre and sort the genres by that avera
avg = []
for genre in unique_genres:
    genre_avg = df_merge[df_merge.genres.str.contains(genre)].averagera
    avg.append(genre_avg)

avg
```

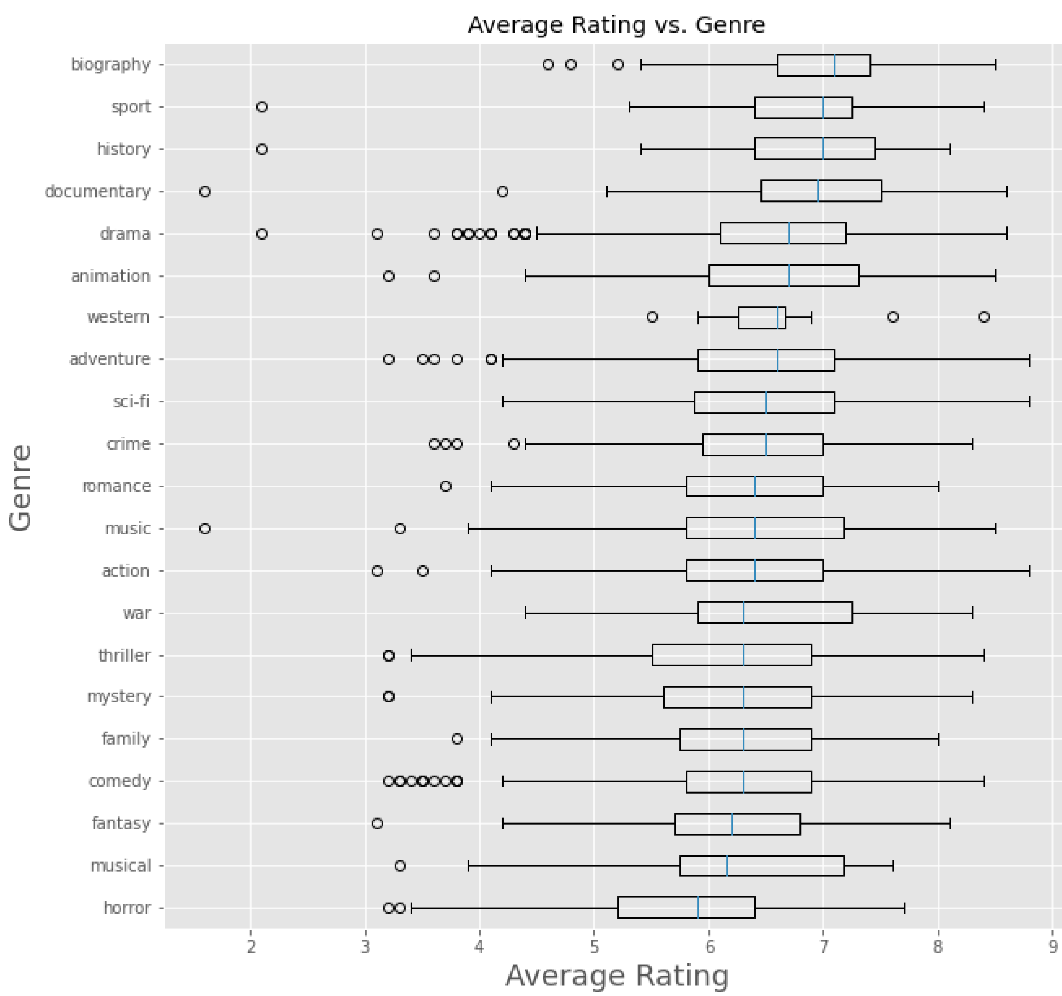
Out[61]:
```
[6.4,
 6.6,
 6.7,
 7.1,
 6.3,
 6.5,
 6.95,
 6.7,
 6.3,
 6.2,
 7.0,
 5.9,
 6.4,
 6.15,
 6.3,
 6.4,
 6.5,
 7.0,
 6.3,
 6.3,
 6.6]
```

In [62]:
```
avg_and_genres = sorted(list(zip(avg,unique_genres)))
sorted_genres = [avg_and_genres[i][1] for i in range(len(avg_and_genres
sorted_genres
```

Out[62]:
```
['horror',
 'musical',
 'fantasy',
 'comedy',
 'family',
 'mystery',
 'thriller',
 'war',
 'action',
 'music',
 'romance',
 'crime',
 'sci-fi',
 'adventure',
 'western',
 'animation',
 'drama',
 'documentary',
 'history',
 'sport',
 'biography']
```

In [63]:
```
#Average rating vs. genre
fig, ax = plt.subplots(figsize = (10,10))

n=0
for genre in sorted_genres:
    #df_sub = df_merge[(df_merge.genres.str.contains(genre)) & (df_merge
    df_sub = df_merge[df_merge.genres.str.contains(genre)]
    ax.boxplot(df_sub.averagerating, vert = False, positions = [n], wid
    n = n + 1
ax.set_yticklabels(sorted_genres)
ax.set_title('Average Rating vs. Genre')
ax.set_xlabel('Average Rating', fontsize = 18)
ax.set_ylabel('Genre', fontsize = 18)
```

Out[63]: Text(0, 0.5, 'Genre')



In terms of rating, it seems like people enjoy true stories because the highest rated genres are biography, history, and documentary. Sports movies are also quite high. Some of these movies are also based on true stories. The worst rated are horror, musical, fantasy, and comedy.

The truth is that the movies have a wide range of ratings and you can have a highly rated horror movie or a low-rated biography.

Now to see how the genres compare financially.

In [64]:

```
#Find the average profit of each genre and sort the genres by that avera
avg = []
for genre in unique_genres:
    genre_avg = df_merge[df_merge.genres.str.contains(genre)].profit.mea
    avg.append(genre_avg)

avg
```

Out[64]:

```
[69.59089,
 132.98126100000002,
 166.56231200000002,
 16.0067175,
 31.887901500000005,
 13.844132,
 0.38636800000000004,
 12.141616999999998,
 55.462444500000004,
 53.461527,
 8.099931,
 30.74923,
 9.1696265,
 16.878986499999996,
 36.824065999999995,
 16.649645000000003,
 110.0982585,
 7.3621764999999995,
 33.866088000000005,
 -1.315295,
 -1.185188]
```

In [65]:

```
avg_and_genres = sorted(list(zip(avg,unique_genres)))
sorted_genres = [avg_and_genres[i][1] for i in range(len(avg_and_genres
sorted_genres
```

Out[65]:

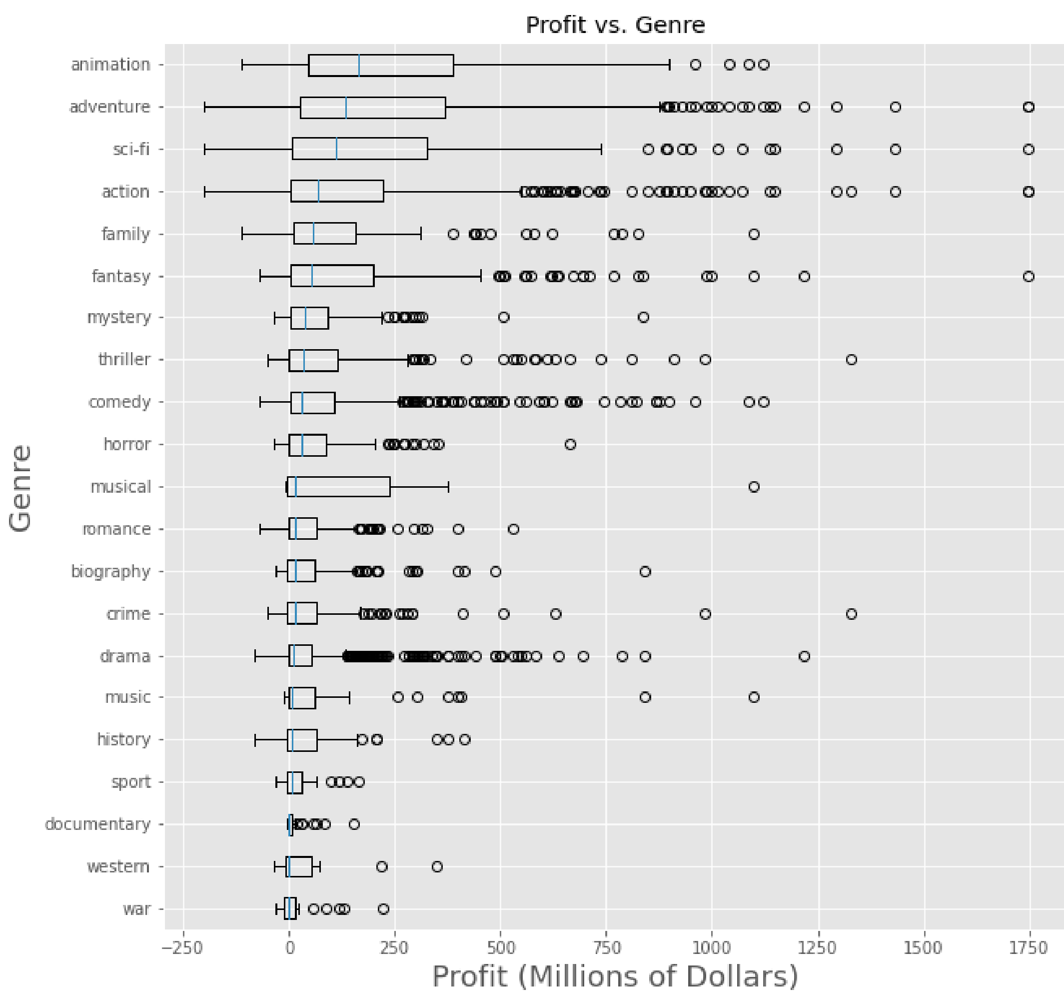
```
['war',
 'western',
 'documentary',
 'sport',
 'history',
 'music',
 'drama',
 'crime',
 'biography',
 'romance',
 'musical',
 'horror',
 'comedy',
 'thriller',
 'mystery',
 'fantasy',
 'family',
 'action',
 'sci-fi',
 'adventure',
 'animation']
```

In [66]:

```
#Profit vs. genre
fig, ax = plt.subplots(figsize = (10,10))

n=0
for genre in sorted_genres:
    #df_sub = df_merge[(df_merge.genres.str.contains(genre)) & (df_merge
    df_sub = df_merge[df_merge.genres.str.contains(genre)]
    ax.boxplot(df_sub.profit, vert = False, positions = [n], widths = 0
    n = n + 1
ax.set_yticklabels(sorted_genres)
ax.set_title('Profit vs. Genre')
ax.set_xlabel('Profit (Millions of Dollars)', fontsize = 18)
ax.set_ylabel('Genre', fontsize = 18)
```

Out[66]:

```
Text(0, 0.5, 'Genre')
```



People love their documentaries, but that doesn't mean those movies make money. Documentaries, biographies, and history movies are near the bottom in profits. The most profitable movies are animated movies, adventure movies, and sci-fi. The average is higher due to a small number of very successful movies. Inception, Interstellar, and Avengers: Infinity War all fall in the adventure and sci-fi genres. They are the bigger outliers to the right. However, the adventure and sci-fi genres do still have some of the highest MEDIAN profits, showing that it is not just a matter of the box office hits skewing the data.

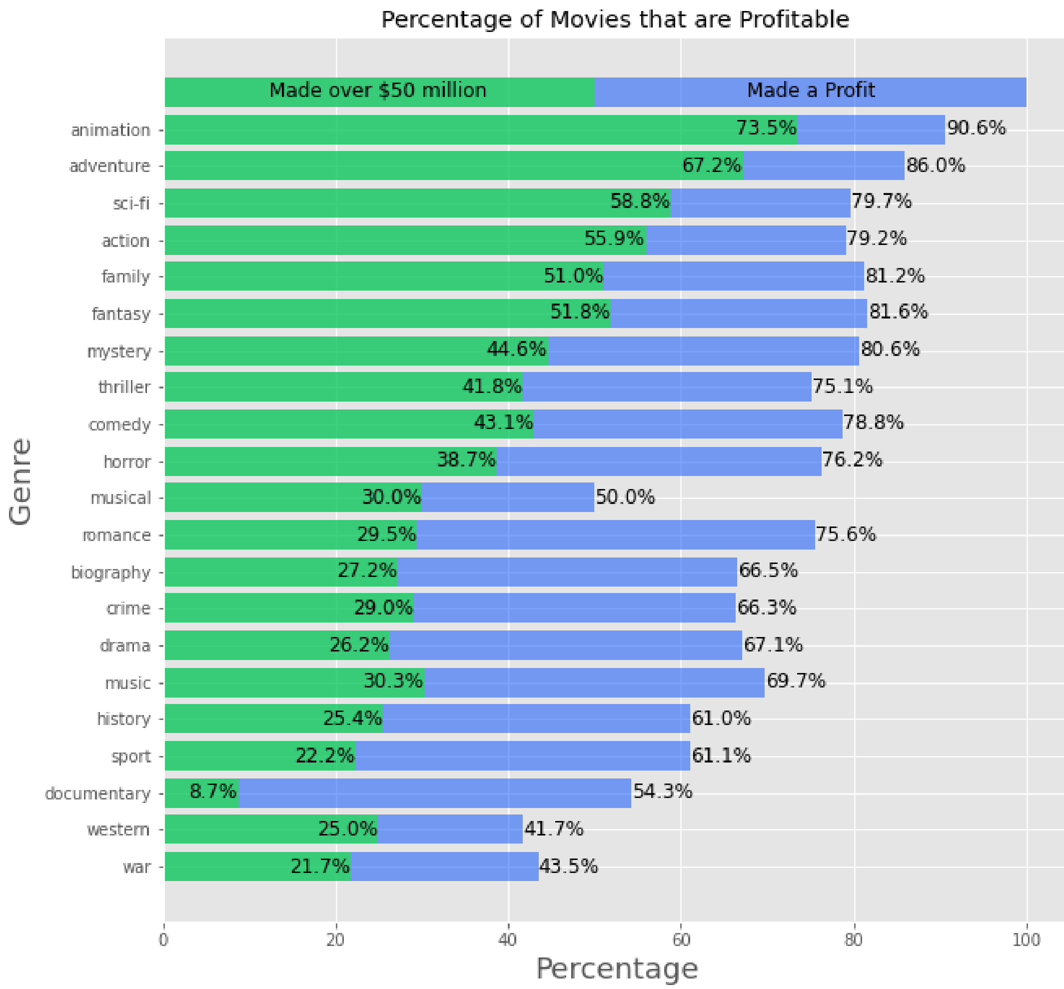
This does not necessarily mean I recommend making only animated sci-fi, adventure movies. Most of the genres include multiple highly profitable movies (the only genres that do not include at least one movie with a profit of 500 million dollars are horror, western, history, romance, sport, war, and documentary). These genres are probably not what we should aim for if we want to make a major profit.

Idea to do: Make a horizontal bar plot showing probability of making profit and probability of making big profit (over 100 million dollars)

In [67]:
```
#Percentage of movies that are profitable within each genre
fig, ax = plt.subplots(figsize = (10,10))

n=0
for genre in sorted_genres:
    df_sub = df_merge[df_merge.genres.str.contains(genre)]
    perc = 100 * len(df_sub[df_sub.profit > 0.0]) / len(df_sub)
    ax.barh(width = perc, height = 0.8, y = n, color = (0.0, 0.3, 1, 0.
    ax.text(perc, n, f"{round(perc,1)}%", fontsize = 12, horizontalalig

    perc = 100 * len(df_sub[df_sub.profit > 50.0]) / len(df_sub)
    ax.barh(width = perc, height = 0.8, y = n, color = (0.0, 1, 0, 0.5)
    ax.text(perc, n, f"{round(perc,1)}%", fontsize = 12, horizontalalig

    n = n + 1

ax.barh(width = 100, height = 0.8, y = n, color = (0.0 , 0.3 , 1, 0.5))
ax.barh(width = 50, height = 0.8, y = n, color = (0.0, 1, 0.0, 0.5))
ax.text(25, n, "Made over $50 million", fontsize = 12, horizontalalignm
ax.text(75, n, "Made a Profit", fontsize = 12, horizontalalignment = 'c

ax.set_yticklabels(sorted_genres)
ax.set_yticks(range(len(sorted_genres)))
ax.set_title('Percentage of Movies that are Profitable')
ax.set_xlabel('Percentage', fontsize = 18)
ax.set_ylabel('Genre', fontsize = 18)
```

```
<ipython-input-67-33097a5fd156>:22: UserWarning: FixedFormatter should
only be used together with FixedLocator
  ax.set_yticklabels(sorted_genres)
```

Out[67]:
```
Text(0, 0.5, 'Genre')
```



Genre Conclusion:

While a wide variety of genres are capable of earning large profits and high ratings, the most successful genres are animation, adventure, sci-fi, and action. Movies in the war, western, and sports genres are not as successful. Documentaries are very popular (high ratings), but don't typically make much money.

Star Power

Next, I will look at how the profit and ratings of movies are affected by the people who make those movies. This will be the hardest to code. Plan: For each movie, create a "star power" rating. I will look at the principal people involved in each movie, then I will count how many movies those people have previously done. I can also require that those movies had a certain level of success (profit above 50 million). To do this, I will need to loop through each movie and find the people associated with that movie (using the principals table). Then, I will sum up all of the movies those people have PREVIOUSLY done to get the star power rating.

PROBLEM: If the movies in my main dataset start in 2010, then this limits what I can do with this star power metric. This means movies released prior to 2010 will not contribute to the star power rating.

How to fix it: I can specifically look at movies from the last 6 years and use star power since 2010. This should still work pretty well because more recent starring roles are probably more influential than ones from decades ago.

In [68]:
```
conn = sqlite3.connect(dir_path+'im.db/im.db')
```

In [69]:
```
# Read in the principals table from IMDB
# I want to do this separately for actors/actresses and directors (I cou
df_actors = pd.read_sql("""
SELECT movie_id, person_id, category
  FROM principals
  WHERE category IN ('actor', 'actress')
;
""", conn)

# Directors
df_directors = pd.read_sql("""
SELECT movie_id, person_id, category
  FROM principals
  WHERE category IN ('director')
;
""", conn)
```

In [70]:
```
#Create a new column for actor/actress star power
df_merge['act_star_power'] = 0.0
df_merge['dir_star_power'] = 0.0
```

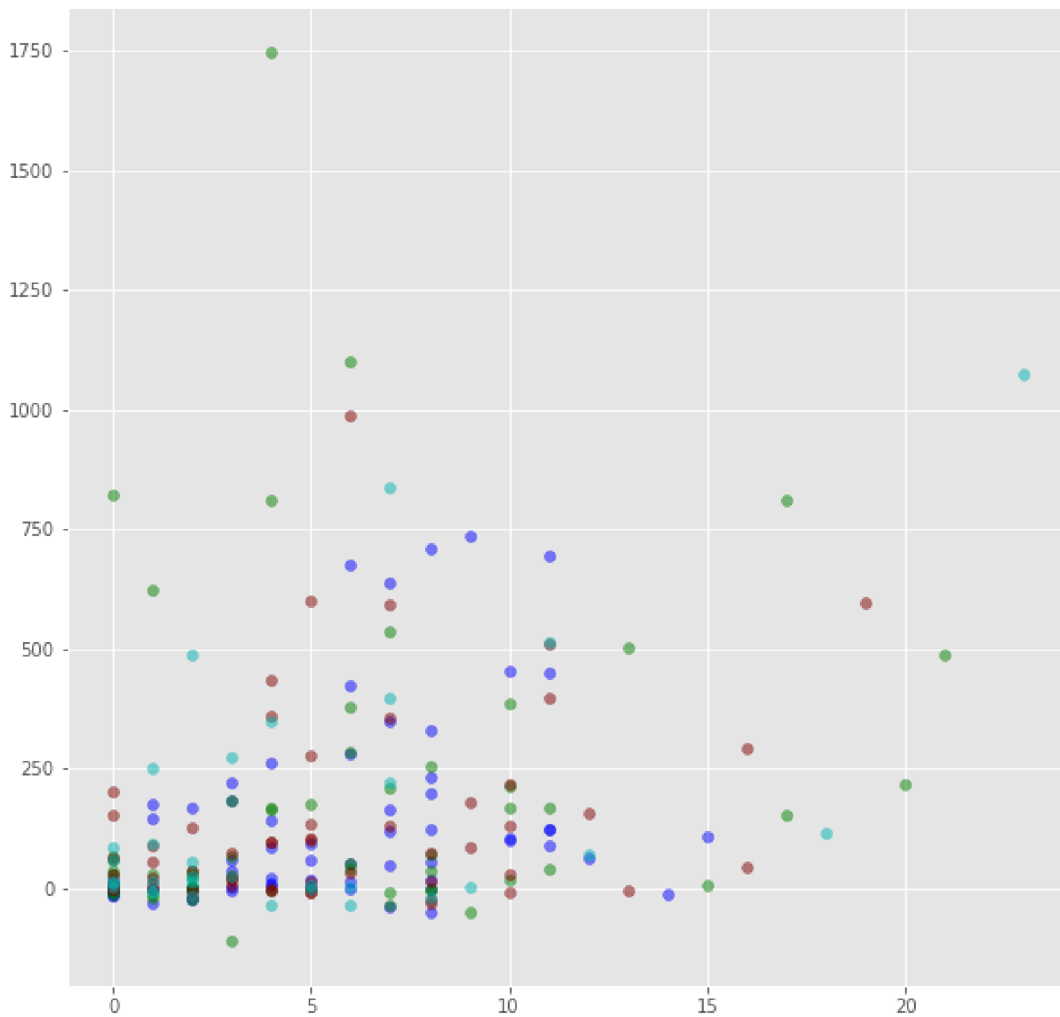
In [71]:
```
# This is for actors/actresses only
# Loop over movies. I will go ahead and measure the star power for every
# movies in the analysis.
star_power_list = []
for mov_id in df_merge.movie_id:
    release_date = df_merge[df_merge.movie_id == mov_id].release_date
    person_ids = list(df_actors[df_actors.movie_id == mov_id].person_id
    df_mov_with_same_people = df_actors[df_actors.person_id.isin(person_

    star_power_list.append(len(df_mov_with_same_people[(df_mov_with_same
                                                        (df_mov_with_same

df_merge['act_star_power'] = star_power_list
```

In [72]:

```
# This is for directors only
# Loop over movies. I will go ahead and measure the star power for every
# movies in the analysis.
star_power_list = []
for mov_id in df_merge.movie_id:
    release_date = df_merge[df_merge.movie_id == mov_id].release_date
    person_ids = list(df_directors[df_directors.movie_id == mov_id].pers
    df_mov_with_same_people = df_directors[df_directors.person_id.isin(p

    star_power_list.append(len(df_mov_with_same_people[(df_mov_with_same
                                                        (df_mov_with_same

df_merge['dir_star_power'] = star_power_list
```

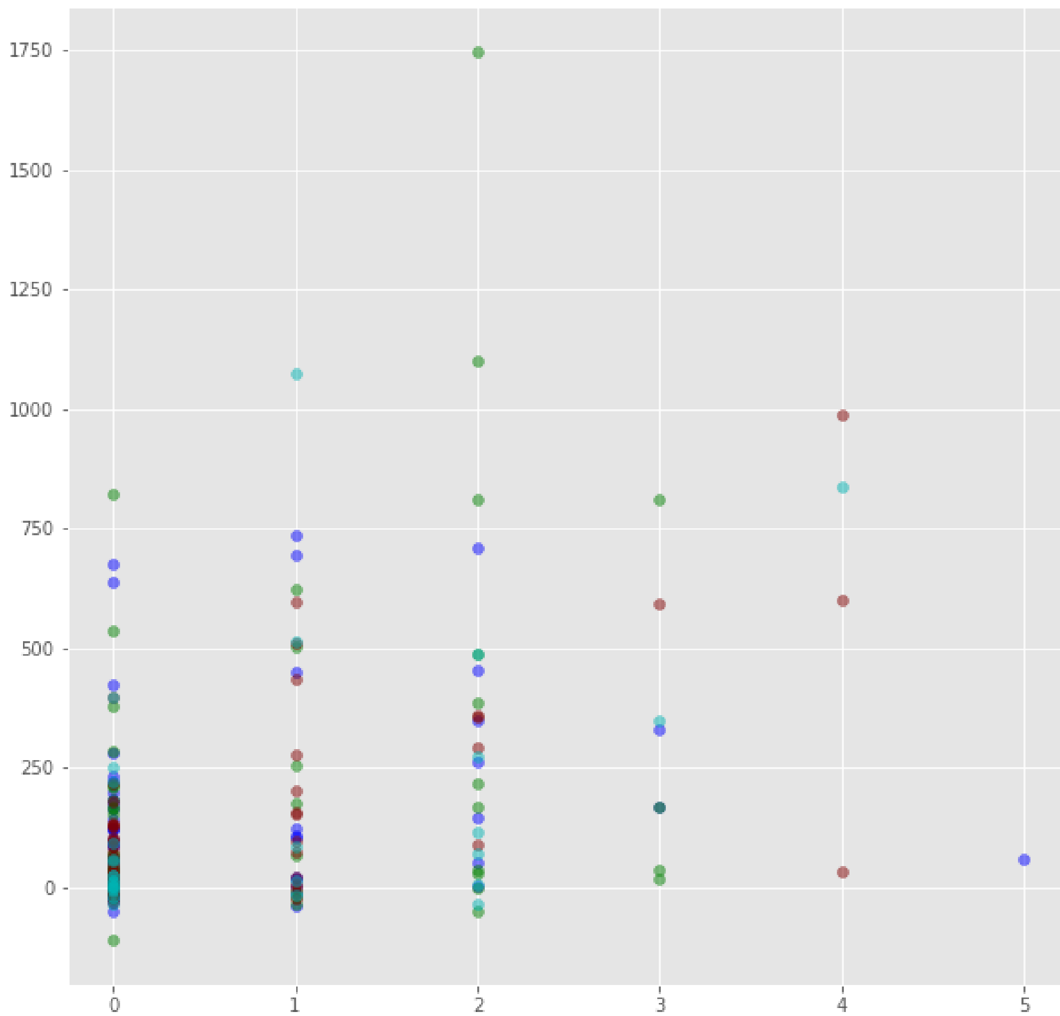
In [73]:
```
#Make a plot of actor star power for movies since 2016
#Each year has a separate color.
fig, ax = plt.subplots(figsize = (10,10))

df_year = df_merge[(df_merge.release_date > '2016-01-01') & (df_merge.r
ax.scatter(x = df_year.act_star_power, y = df_year.profit, color = (0,0

df_year = df_merge[(df_merge.release_date > '2017-01-01') & (df_merge.r
ax.scatter(x = df_year.act_star_power, y = df_year.profit, color = (0.0

df_year = df_merge[(df_merge.release_date > '2018-01-01') & (df_merge.r
ax.scatter(x = df_year.act_star_power, y = df_year.profit, color = (0.5

df_year = df_merge[(df_merge.release_date > '2019-01-01') & (df_merge.r
ax.scatter(x = df_year.act_star_power, y = df_year.profit, color = (0.0
```

Out[73]: <matplotlib.collections.PathCollection at 0x21fb52b9c70>



In [74]:
```
#Plot of director star power
fig, ax = plt.subplots(figsize = (10,10))

df_year = df_merge[(df_merge.release_date > '2016-01-01') & (df_merge.r
ax.scatter(x = df_year.dir_star_power, y = df_year.profit, color = (0,0

df_year = df_merge[(df_merge.release_date > '2017-01-01') & (df_merge.r
ax.scatter(x = df_year.dir_star_power, y = df_year.profit, color = (0.0

df_year = df_merge[(df_merge.release_date > '2018-01-01') & (df_merge.r
ax.scatter(x = df_year.dir_star_power, y = df_year.profit, color = (0.5

df_year = df_merge[(df_merge.release_date > '2019-01-01') & (df_merge.r
ax.scatter(x = df_year.dir_star_power, y = df_year.profit, color = (0.0
```

Out[74]: <matplotlib.collections.PathCollection at 0x21fd4864430>

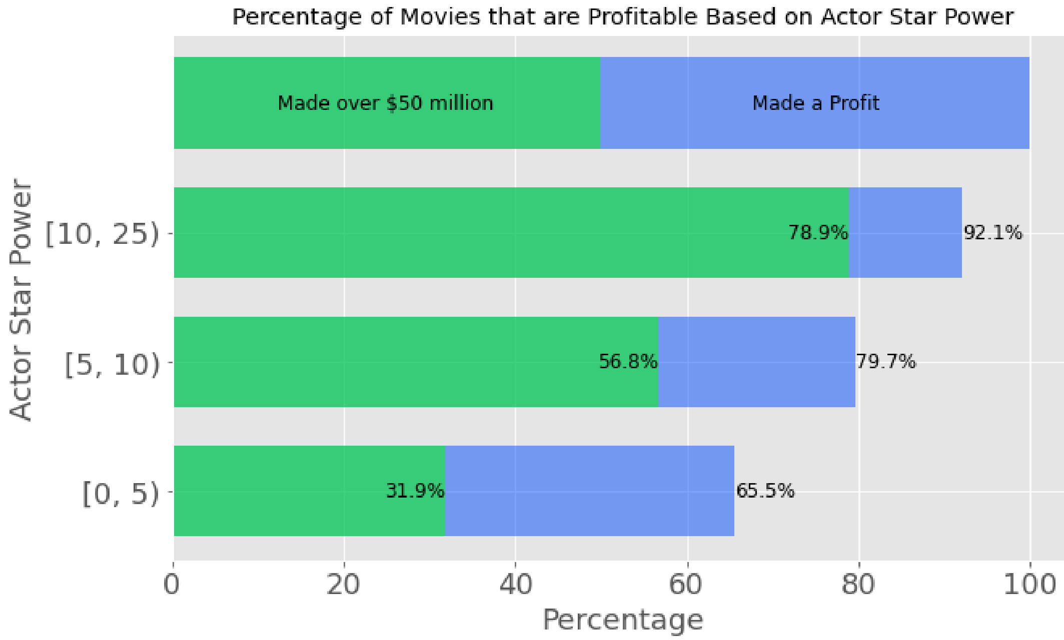


In [75]:
```
# Make a new DateFrame that only includes movies since 2016
# The reason for doing this is because movies prior to that won't have v
df_cut = df_merge[df_merge.release_date > '2016-01-01']
```

In [76]:
```
#Percentage of movies that are profitable based on actor/actress star po
fig, ax = plt.subplots(figsize = (10,6))

star_power_bins = [0,5,10,25]

for n in range(3):
    perc = 100 * len(df_cut[(df_cut.act_star_power >= star_power_bins[n
                        & (df_cut.profit > 0.0)]) / \
        len(df_cut[(df_cut.act_star_power >= star_power_bins[n]) & (df_

    ax.barh(width = perc, height = 0.7, y = n, color = (0.0, 0.3, 1.0, 
    ax.text(perc, n, f"{round(perc,1)}%", fontsize = 12, horizontalalig

    perc = 100 * len(df_cut[(df_cut.act_star_power >= star_power_bins[n
                        & (df_cut.profit > 50.0)]) / \
        len(df_cut[(df_cut.act_star_power >= star_power_bins[n]) & (df_

    ax.barh(width = perc, height = 0.7, y = n, color = (0.0, 1, 0.0, 0.
    ax.text(perc, n, f"{round(perc,1)}%", fontsize = 12, horizontalalig

n = n + 1
ax.barh(width = 100, height = 0.7, y = n, color = (0.0 , 0.3 , 1, 0.5))
ax.barh(width = 50, height = 0.7, y = n, color = (0.0, 1, 0.0, 0.5))
ax.text(25, n, "Made over $50 million", fontsize = 12, horizontalalignm
ax.text(75, n, "Made a Profit", fontsize = 12, horizontalalignment = 'c

ax.set_yticklabels([f"[{star_power_bins[n]}, {star_power_bins[n+1]})" f
ax.set_xticklabels(np.arange(0,120,20),fontsize = 18)
ax.set_yticks(range(3))
ax.set_title('Percentage of Movies that are Profitable Based on Actor S
ax.set_xlabel('Percentage', fontsize = 18)
ax.set_ylabel('Actor Star Power', fontsize = 18)
```

```
<ipython-input-76-582b1f3e90fc>:27: UserWarning: FixedFormatter should
only be used together with FixedLocator
  ax.set_yticklabels([f"[{star_power_bins[n]}, {star_power_bins[n+
1]})" for n in range(3)], fontsize = 18)
<ipython-input-76-582b1f3e90fc>:28: UserWarning: FixedFormatter should
only be used together with FixedLocator
  ax.set_xticklabels(np.arange(0,120,20),fontsize = 18)
```

Out[76]:
```
Text(0, 0.5, 'Actor Star Power')
```



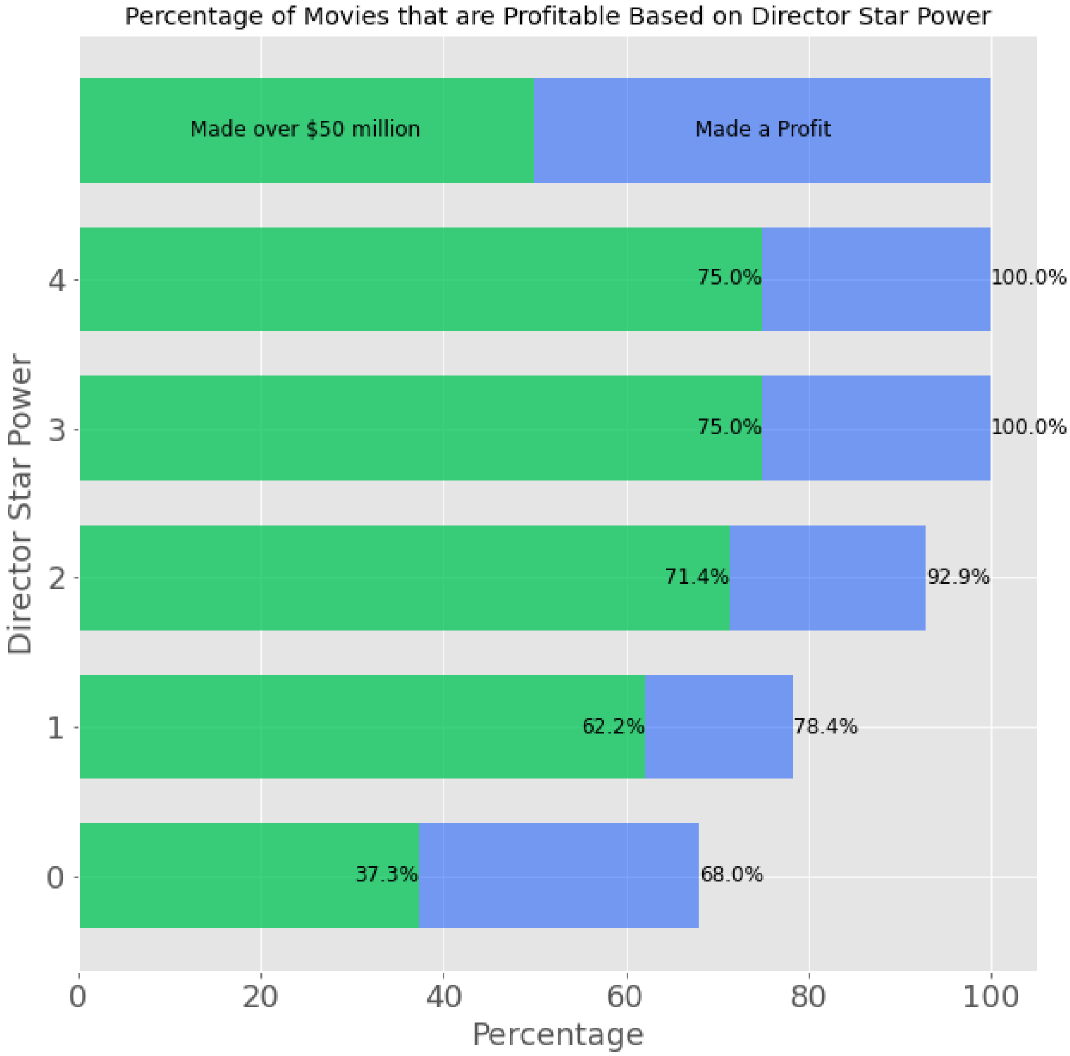
Percentage of Movies that are Profitable Based on Actor Star Power
Made over $50 million
Made a Profit
Actor Star Power
[10, 25)
[5, 10)
[0, 5)
78.9%
92.1%
56.8%
79.7%
31.9%
65.5%
0
20
40
60
80
100
Percentage

In [77]:

```
#Percentage of movies that are profitable based on director star power
fig, ax = plt.subplots(figsize = (10,10))

star_power_bins = [0,1,2,3,4,5,6]

for n in range(5):
    perc = 100 * len(df_cut[(df_cut.dir_star_power >= star_power_bins[n
                     & (df_cut.profit > 0.0)]) / \
        len(df_cut[(df_cut.dir_star_power >= star_power_bins[n]) & (df_

    ax.barh(width = perc, height = 0.7, y = n, color = (0.0, 0.3, 1.0, (
    ax.text(perc, n, f"{round(perc,1)}%", fontsize = 12, horizontalalig

    perc = 100 * len(df_cut[(df_cut.dir_star_power >= star_power_bins[n
                     & (df_cut.profit > 50.0)]) / \
        len(df_cut[(df_cut.dir_star_power >= star_power_bins[n]) & (df_

    ax.barh(width = perc, height = 0.7, y = n, color = (0.0, 1, 0.0, 0.
    ax.text(perc, n, f"{round(perc,1)}%", fontsize = 12, horizontalalig

n = n + 1
ax.barh(width = 100, height = 0.7, y = n, color = (0.0 , 0.3 , 1, 0.5))
ax.barh(width = 50, height = 0.7, y = n, color = (0.0, 1, 0.0, 0.5))
ax.text(25, n, "Made over $50 million", fontsize = 12, horizontalalignm
ax.text(75, n, "Made a Profit", fontsize = 12, horizontalalignment = 'c

ax.set_yticklabels(range(5), fontsize = 18)
ax.set_xticklabels(np.arange(0,120,20),fontsize = 18)
ax.set_yticks(range(5))
ax.set_title('Percentage of Movies that are Profitable Based on Director
ax.set_xlabel('Percentage', fontsize = 18)
ax.set_ylabel('Director Star Power', fontsize = 18)
```

```
<ipython-input-77-b9d7c6393af7>:27: UserWarning: FixedFormatter should
only be used together with FixedLocator
  ax.set_yticklabels(range(5), fontsize = 18)
<ipython-input-77-b9d7c6393af7>:28: UserWarning: FixedFormatter should
only be used together with FixedLocator
  ax.set_xticklabels(np.arange(0,120,20),fontsize = 18)
```

Out[77]: Text(0, 0.5, 'Director Star Power')



Casting/Directing Conclusions

Hiring actors/actresses and directors who have previously been involved in successful, profitable movies does seem to be correlated with future success. This could be because those people are talented and are therefore more likely to help create a good movie. It could also be because having big, recognizable names attached to a movie helps get more attention on that movie so that people will go see it, regardless of its actual quality. It is easier to sell a movie starring Tom Hanks then a movie starring John Whoever, even if Mr. Whoever is very talented.