Phase 1 Project

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Overview

This project is an opportunity to apply the concepts and techniques I have learned in Phase 1 and apply it using real world data. Through data analysis, this report will generate 3 key insights that will aid in the decision making of Microsoft's new movie studio. It is important to communicate visually and provide context to help Microsoft understand the large amount of data that is available to them. Finally, I will provide a recommendation based on the analysis I have generated.

Business Problem

Microsoft is exploring options to expand the services they provide. Given the success of other large corporate competitors in the video content space, Microsoft have decided to open their own movie studio. Given the lack of experience in an industry dominated by well-established brands, it is important to identify key metrics that Microsoft can build upon. A strong understanding of these metrics will help the studio choose a direction for success.

An important aspect for any business entering into a new industry is building an identity. What can Microsoft implement to differentiate themselves from their competitors? I have broken it down into 3 overarching directions.

- Playing The Numbers - Maximise viewership by building upon genres that are trending
- Familiar Faces - Audiences will be attracted to people that have had long term success in the industry
- Stories Are Our Strength - Success is defined by being critically acclaimed and it begins with stories

For the purposes of this project, I will focus on insights regarding Playing The Numbers.

Data Understanding

The data being used for this analysis have been gathered from well-known websites IMDb, Rotten Tomatoes and TMDB. Each website collects a large amount of information regarding movies in their own way including financial data, review scores and genre. Casting a wide net of data sets will provide a balanced insight, reflective of a big population given the size of the movie industry.

In [1]:

```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# For data visualisation
import matplotlib.ticker as mtick

%matplotlib inline
```

In [2]:

```
# I imported all data sets available to check their relevance towards helping me explore my insights
df_titlebasics = pd.read_csv('zippedData/imdb.title.basics.csv.gz')
df_titlebasics.head()
```

Out[2]:

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

In [3]:

```
df_titleratings = pd.read_csv('zippedData/imdb.title.ratings.csv.gz')
df_titleratings.head()
```

Out[3]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21

In [4]:

```
df_namebasics = pd.read_csv('zippedData/imdb.name.basics.csv.gz')
df_namebasics.head()
```

Out[4]:

	nconst	primary_name	birth_year	death_year	primary_profession	known_for_titles
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,producer	tt0837562,tt2398241,tt0844471,tt0118553
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_department	tt0896534,tt6791238,tt0287072,tt1682940
2	nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,writer	tt1470654,tt0363631,tt0104030,tt0102898
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_department	tt0114371,tt2004304,tt1618448,tt1224387
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_decorator	tt0452644,tt0452692,tt3458030,tt2178256

In [5]:

```
df_titleakas = pd.read_csv('zippedData/imdb.title.akas.csv.gz')
df_titleakas.head()
```

Out[5]:

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

In [6]:

```
df_titlecrew = pd.read_csv('zippedData/imdb.title.crew.csv.gz')
df_titlecrew.head()
```

Out[6]:

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

In [7]:

```
df_movieinfo = pd.read_csv('zippedData/rt.movie_info.tsv.gz', sep='\t')
df_movieinfo.head()
```

Out[7]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_office	runtime	studio
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN	104 minutes	NaN
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012	Jan 1, 2013	$	600,000	108 minutes	Entertainment One
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	Apr 18, 2000	NaN	NaN	116 minutes	NaN
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	Aug 27, 1997	NaN	NaN	128 minutes	NaN
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	NaN	NaN	NaN	200 minutes	NaN

In [8]:

```
df_reviews = pd.read_csv('zippedData/rt.reviews.tsv.gz', sep='\t', encoding='latin-1')
df_reviews.head()
```

Out[8]:

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

In [9]:

```
df_tmdbmovies = pd.read_csv('zippedData/tmdb.movies.csv.gz')
df_tmdbmovies.head()
```

Out[9]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186

In [10]:

```
df_moviebudget = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')
df_moviebudget.head()
```

Out[10]:

	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

These are my comments from a quick overview of the data sets imported

Recommended:
df_titlebasics - title, genre, runtime. Contains tconst
df_titleratings - ratings - contains tconst
df_moviegross - title, gross, studio

Relevant:
df_titlecrew - find out what director did what movie. See if director has high grossing/high rating movies. Contains tconst
df_titleprincipal - column with job type. Contains tconst and nconst
df_movieinfo - box office/director/genre could be useful. Contains id
df_reviews - reviews by critics. Contains id
df_tmdbmovies - ratings. Could use movie titles with vote count above mean/median
df_moviebudget - budget with gross. Contains id

Not relevant:
df_namebasics - people worked on the movies
df_titleakas - movie by native country

Data Preparation

Insight 1

A simple and great insight to start off with would be to explore which genre had the highest gross. The underlying concept here is that high gross sales equates to more people have viewed that genre of movie.

In [11]:

```
df_moviebudget.head()
```

Out[11]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [12]:

```
# Remove unnecessary strings so it can be converted to an integer for calculation

df_moviebudget[df_moviebudget.columns[3:6]] = df_moviebudget[df_moviebudget.columns[3:6]].replace('[\#&^$@,]', '',regex=True)
```

In [13]:

```
df_moviebudget = df_moviebudget.set_index('movie')
df_moviebudget.head()
```

Out[13]:

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

In [14]:

```
df_titlebasics = df_titlebasics.set_index('primary_title')
df_titlebasics.head()
```

Out[14]:

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

In [15]:

```
# I chose df_titlebasics to be on the left because it is the larger data set
# It should have a higher chance of yielding more movies that overlap

df_titlebasics_df_moviebudget = df_moviebudget.join(df_titlebasics, how='left')
df_titlebasics_df_moviebudget.head()
```

Out[15]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genr
#Horror	16	Nov 20, 2015	1500000	0	0	tt3526286	#Horror	2015.0	101.0	Crime,Drama,Hor
(500) Days of Summer	55	Jul 17, 2009	7500000	32425665	34439060	NaN	NaN	NaN	NaN	N
10 Cloverfield Lane	54	Mar 11, 2016	5000000	72082999	108286422	tt1179933	10 Cloverfield Lane	2016.0	103.0	Drama,Horror,Myst
10 Days in a Madhouse	48	Nov 11, 2015	12000000	14616	14616	tt3453052	10 Days in a Madhouse	2015.0	111.0	Drai
10 Things I Hate About You	63	Mar 31, 1999	13000000	38177966	60413950	NaN	NaN	NaN	NaN	N

In [16]:

```
# I want to add a new column to calculate foreign_gross
# This requires changing data types

df_titlebasics_df_moviebudget['domestic_gross'] = df_titlebasics_df_moviebudget['domestic_gross'].astype(int)
```

In [17]:

```
df_titlebasics_df_moviebudget['worldwide_gross'] = df_titlebasics_df_moviebudget['worldwide_gross'].astype(float)
```

In [18]:

```
df_titlebasics_df_moviebudget['foreign_gross'] = df_titlebasics_df_moviebudget['worldwide_gross'] - df_titlebasics_df_moviebudget['domest
df_titlebasics_df_moviebudget.head()
```

Out[18]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genr
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Crime,Drama,Hor
(500) Days of Summer	55	Jul 17, 2009	7500000	32425665	34439060.0	NaN	NaN	NaN	NaN	N
10 Cloverfield Lane	54	Mar 11, 2016	5000000	72082999	108286422.0	tt1179933	10 Cloverfield Lane	2016.0	103.0	Drama,Horror,Myst
10 Days in a Madhouse	48	Nov 11, 2015	12000000	14616	14616.0	tt3453052	10 Days in a Madhouse	2015.0	111.0	Drai
10 Things I Hate About You	63	Mar 31, 1999	13000000	38177966	60413950.0	NaN	NaN	NaN	NaN	N

Insight 2

A studio pouring a large budget into a movie project does not neccessarily equate to high gross sales in the box office. For Microsoft's newest studio, a reasonable budget is an important consideration. In the scenario of a movie flopping in these early stages would hurt Microsoft's reputation both in the short and long term.

In [19]:

```
df_titlebasics_df_moviebudget['production_budget'] = df_titlebasics_df_moviebudget['production_budget'].astype(int)
```

In [20]:

```
df_titlebasics_df_moviebudget.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7221 entries, #Horror to é�·æ±�ä¸�è�� (CJ7)
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 7221 non-null   int64  
 1   release_date       7221 non-null   object 
 2   production_budget  7221 non-null   int32  
 3   domestic_gross     7221 non-null   int32  
 4   worldwide_gross    7221 non-null   float64
 5   tconst             3815 non-null   object 
 6   original_title     3814 non-null   object 
 7   start_year         3815 non-null   float64
 8   runtime_minutes    3328 non-null   float64
 9   genres             3743 non-null   object 
 10  foreign_gross      7221 non-null   float64
dtypes: float64(4), int32(2), int64(1), object(4)
memory usage: 620.6+ KB
```

In [21]:

```
df_titlebasics_df_moviebudget.head()
```

Out[21]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genr
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Crime,Drama,Hor
(500) Days of Summer	55	Jul 17, 2009	7500000	32425665	34439060.0	NaN	NaN	NaN	NaN	N
10 Cloverfield Lane	54	Mar 11, 2016	5000000	72082999	108286422.0	tt1179933	10 Cloverfield Lane	2016.0	103.0	Drama,Horror,Myst
10 Days in a Madhouse	48	Nov 11, 2015	12000000	14616	14616.0	tt3453052	10 Days in a Madhouse	2015.0	111.0	Dra
10 Things I Hate About You	63	Mar 31, 1999	13000000	38177966	60413950.0	NaN	NaN	NaN	NaN	N

In [22]:

```
# Calculating profit after the budget and adding a new column

df_titlebasics_df_moviebudget['profit'] = df_titlebasics_df_moviebudget['worldwide_gross'] - df_titlebasics_df_moviebudget['production_bu
```

In [23]:

```
# Checking if changed are applied

df_titlebasics_df_moviebudget.head()
```

Out[23]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genr
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Crime,Drama,Hor
(500) Days of Summer	55	Jul 17, 2009	7500000	32425665	34439060.0	NaN	NaN	NaN	NaN	N
10 Cloverfield Lane	54	Mar 11, 2016	5000000	72082999	108286422.0	tt1179933	10 Cloverfield Lane	2016.0	103.0	Drama,Horror,Myst
10 Days in a Madhouse	48	Nov 11, 2015	12000000	14616	14616.0	tt3453052	10 Days in a Madhouse	2015.0	111.0	Dra
10 Things I Hate About You	63	Mar 31, 1999	13000000	38177966	60413950.0	NaN	NaN	NaN	NaN	N

In [24]:

```
# Calculating percentage of profit made and adding a new column
df_titlebasics_df_moviebudget['profit_percentage'] = df_titlebasics_df_moviebudget['profit'] / df_titlebasics_df_moviebudget['production_
```

In [25]:

```
# Checking if changed are applied

df_titlebasics_df_moviebudget.head()
```

Out[25]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genr
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Crime,Drama,Hor
(500) Days of Summer	55	Jul 17, 2009	7500000	32425665	34439060.0	NaN	NaN	NaN	NaN	N
10 Cloverfield Lane	54	Mar 11, 2016	5000000	72082999	108286422.0	tt1179933	10 Cloverfield Lane	2016.0	103.0	Drama,Horror,Myst
10 Days in a Madhouse	48	Nov 11, 2015	12000000	14616	14616.0	tt3453052	10 Days in a Madhouse	2015.0	111.0	Dra
10 Things I Hate About You	63	Mar 31, 1999	13000000	38177966	60413950.0	NaN	NaN	NaN	NaN	N

Insight 3

One of the many attributes that moviegoers look for to make the decision to watch a movie is its rating. As the studio produces more movies, maintaining high quality will become a challenge so the studio must focus on well performing genres for long term sustained success.

In [26]:

```
df_tmdbmovies = df_tmdbmovies.set_index('original_title')
df_tmdbmovies.head()
```

Out[26]:

	Unnamed: 0	genre_ids	id	original_language	popularity	release_date	title	vote_average	vote_count
original_title									
Harry Potter and the Deathly Hallows: Part 1	0	[12, 14, 10751]	12444	en	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788
How to Train Your Dragon	1	[14, 12, 16, 10751]	10191	en	28.734	2010-03-26	How to Train Your Dragon	7.7	7610
Iron Man 2	2	[12, 28, 878]	10138	en	28.515	2010-05-07	Iron Man 2	6.8	12368
Toy Story	3	[16, 35, 10751]	862	en	28.005	1995-11-22	Toy Story	7.9	10174
Inception	4	[28, 878, 12]	27205	en	27.920	2010-07-16	Inception	8.3	22186

In [27]:

```
# Since a large data frame has been previously defined, I will join on top of that

df_tbmb_df_tmdbmovies = df_titlebasics_df_moviebudget.join(df_tmdbmovies, how='left', rsuffix='-tmdb')
df_tbmb_df_tmdbmovies.head()
```

Out[27]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genr
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Crime,Drama,Hor
(500) Days of Summer	55	Jul 17, 2009	7500000	32425665	34439060.0	NaN	NaN	NaN	NaN	N
10 Cloverfield Lane	54	Mar 11, 2016	5000000	72082999	108286422.0	tt1179933	10 Cloverfield Lane	2016.0	103.0	Drama,Horror,Myst
10 Days in a Madhouse	48	Nov 11, 2015	12000000	14616	14616.0	tt3453052	10 Days in a Madhouse	2015.0	111.0	Dra
10 Things I Hate About You	63	Mar 31, 1999	13000000	38177966	60413950.0	NaN	NaN	NaN	NaN	N

5 rows × 22 columns

In [28]:

```
# The final step before modeling is to separate by genre

# For reference, I will use .tail() to check if split and explode are
# applied to xXx movie. Contains Action,Adventure,Thriller
df_tbmb_df_tmdbmovies.tail()
```

Out[28]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	
mother!	59	Sep 15, 2017	30000000	17800004	42531076.0	NaN	NaN	NaN	NaN	
xXx	98	Aug 9, 2002	70000000	141930000	267200000.0	NaN	NaN	NaN	NaN	
xXx: Return of Xander Cage	15	Jan 20, 2017	85000000	44898413	345033359.0	tt1293847	xXx: Return of Xander Cage	2017.0	107.0	Action,Advent
Ã l'intÃ©rieur	57	Apr 15, 2008	3000000	0	895932.0	NaN	NaN	NaN	NaN	
é□·æ±□ä¸□è□□ (CJ7)	2	Mar 7, 2008	20000000	206678	47300771.0	NaN	NaN	NaN	NaN	

5 rows × 22 columns

In [29]:

```
df_tbmb_df_tmdbmovies['genres'] = df_tbmb_df_tmdbmovies['genres'].str.split(',')
df_tbmb_df_tmdbmovies.tail()
```

Out[29]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genres	..
mother!	59	Sep 15, 2017	30000000	17800004	42531076.0	NaN	NaN	NaN	NaN	NaN	..
xXx	98	Aug 9, 2002	70000000	141930000	267200000.0	NaN	NaN	NaN	NaN	NaN	..
xXx: Return of Xander Cage	15	Jan 20, 2017	85000000	44898413	345033359.0	tt1293847	xXx: Return of Xander Cage	2017.0	107.0	[Action, Adventure, Thriller]	..
Ã l'intÃ©rieur	57	Apr 15, 2008	3000000	0	895932.0	NaN	NaN	NaN	NaN	NaN	..
é□·æ±□ä¸□è□□ (CJ7)	2	Mar 7, 2008	20000000	206678	47300771.0	NaN	NaN	NaN	NaN	NaN	..

5 rows × 22 columns

In [30]:

```
df_tbmb_df_tmdbmovies = df_tbmb_df_tmdbmovies.explode('genres')
df_tbmb_df_tmdbmovies.tail()
```

Out[30]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genres	...
xXx: Return of Xander Cage	15	Jan 20, 2017	85000000	44898413	345033359.0	tt1293847	xXx: Return of Xander Cage	2017.0	107.0	Action	...
xXx: Return of Xander Cage	15	Jan 20, 2017	85000000	44898413	345033359.0	tt1293847	xXx: Return of Xander Cage	2017.0	107.0	Adventure	...
xXx: Return of Xander Cage	15	Jan 20, 2017	85000000	44898413	345033359.0	tt1293847	xXx: Return of Xander Cage	2017.0	107.0	Thriller	...
Ã l'intÃ©rieur	57	Apr 15, 2008	3000000	0	895932.0	NaN	NaN	NaN	NaN	NaN	...
é□·æ±□ä¸□è□□ (CJ7)	2	Mar 7, 2008	20000000	206678	47300771.0	NaN	NaN	NaN	NaN	NaN	...

5 rows × 22 columns

Data Modeling

In [31]:

```
# Start with the data frame I will be referencing

df_tbmb_df_tmdbmovies.head()
```

Out[31]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genres	...	profit
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Crime	...	
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Drama	...	
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Horror	...	
(500) Days of Summer	55	Jul 17, 2009	7500000	32425665	34439060.0	NaN	NaN	NaN	NaN	NaN	...	
10 Cloverfield Lane	54	Mar 11, 2016	5000000	72082999	108286422.0	tt1179933	10 Cloverfield Lane	2016.0	103.0	Drama	...	

5 rows × 22 columns

Insight 1

The first insight I will model is the highest grossing genre. This will provide an idea of the volume of people that view each type of genre.

In [32]:

```
gross_genre = df_tbmb_df_tmdbmovies.groupby(df_tbmb_df_tmdbmovies['genres']).agg({'worldwide_gross':'sum', 'domestic_gross':'sum', 'forei
gross_genre
```

Out[32]:

genres	worldwide_gross	domestic_gross	foreign_gross
Action	1.482122e+11	5.636668e+10	9.184554e+10
Adventure	1.630503e+11	5.914995e+10	1.039004e+11
Animation	5.662180e+10	2.123028e+10	3.539152e+10
Biography	2.717552e+10	1.281712e+10	1.435840e+10
Comedy	1.035196e+11	4.660139e+10	5.691816e+10
Crime	3.151545e+10	1.467775e+10	1.683770e+10
Documentary	6.556069e+10	2.955705e+10	3.600365e+10
Drama	1.633956e+11	7.604289e+10	8.735271e+10
Family	4.901667e+10	2.080457e+10	2.821209e+10
Fantasy	5.711860e+10	2.195935e+10	3.515925e+10
History	1.430736e+10	6.502390e+09	7.804974e+09
Horror	3.592640e+10	1.607506e+10	1.985134e+10
Music	6.488494e+09	3.024473e+09	3.464021e+09
Musical	1.305955e+10	5.839628e+09	7.219918e+09
Mystery	2.110961e+10	9.719143e+09	1.139046e+10
News	3.994074e+08	1.142925e+08	2.851149e+08
Reality-TV	0.000000e+00	0.000000e+00	0.000000e+00
Romance	3.471908e+10	1.596668e+10	1.875240e+10
Sci-Fi	5.900949e+10	2.252333e+10	3.648616e+10
Sport	9.611044e+09	4.682471e+09	4.928574e+09
Thriller	6.240137e+10	2.579448e+10	3.660690e+10
War	5.256075e+09	2.253595e+09	3.002480e+09
Western	1.497562e+09	7.803097e+08	7.172522e+08

In [33]:

```python
# The sum totals will be difficult to visualise so I will divide by 10^9 to bring the scale to billions

gross_genre[['worldwide_gross', 'domestic_gross', 'foreign_gross']] = gross_genre[['worldwide_gross', 'domestic_gross', 'foreign_gross']]
gross_genre
```

Out[33]:

genres	worldwide_gross	domestic_gross	foreign_gross
Action	148.212221	56.366683	91.845538
Adventure	163.050335	59.149946	103.900388
Animation	56.621798	21.230277	35.391521
Biography	27.175516	12.817115	14.358401
Comedy	103.519551	46.601392	56.918158
Crime	31.515450	14.677753	16.837697
Documentary	65.560692	29.557046	36.003646
Drama	163.395607	76.042892	87.352714
Family	49.016667	20.804575	28.212092
Fantasy	57.118598	21.959353	35.159245
History	14.307364	6.502390	7.804974
Horror	35.926396	16.075055	19.851341
Music	6.488494	3.024473	3.464021
Musical	13.059545	5.839628	7.219918
Mystery	21.109605	9.719143	11.390462
News	0.399407	0.114292	0.285115
Reality-TV	0.000000	0.000000	0.000000
Romance	34.719081	15.966681	18.752400
Sci-Fi	59.009489	22.523332	36.486158
Sport	9.611044	4.682471	4.928574
Thriller	62.401374	25.794478	36.606897
War	5.256075	2.253595	3.002480
Western	1.497562	0.780310	0.717252

In [34]:

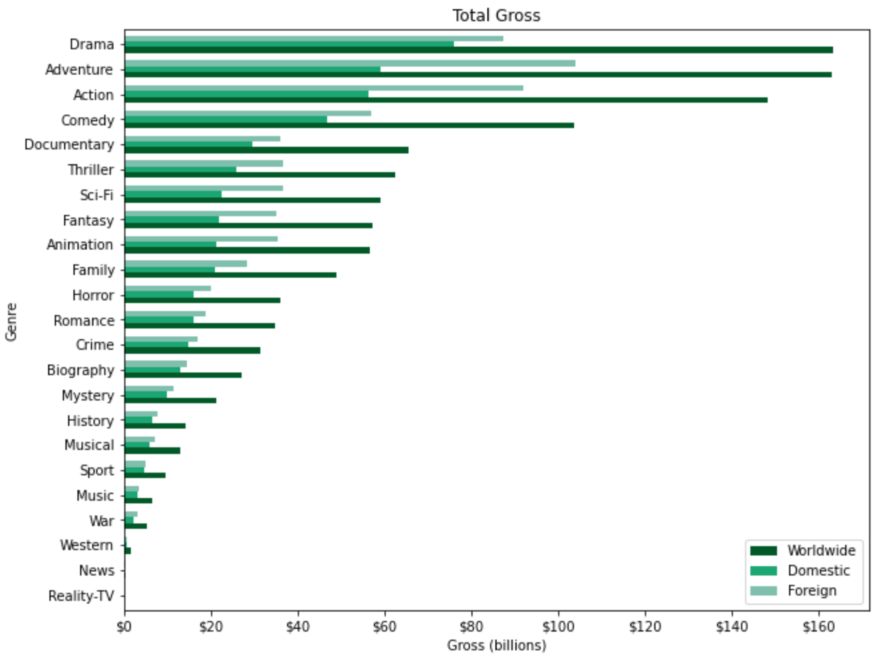
```python
# I will sort by descending order for easier visualisation

gross_genre = gross_genre.sort_values('worldwide_gross', ascending=True)
gross_genre
```

Out[34]:

genres	worldwide_gross	domestic_gross	foreign_gross
Reality-TV	0.000000	0.000000	0.000000
News	0.399407	0.114292	0.285115
Western	1.497562	0.780310	0.717252
War	5.256075	2.253595	3.002480
Music	6.488494	3.024473	3.464021
Sport	9.611044	4.682471	4.928574
Musical	13.059545	5.839628	7.219918
History	14.307364	6.502390	7.804974
Mystery	21.109605	9.719143	11.390462
Biography	27.175516	12.817115	14.358401
Crime	31.515450	14.677753	16.837697
Romance	34.719081	15.966681	18.752400
Horror	35.926396	16.075055	19.851341
Family	49.016667	20.804575	28.212092
Animation	56.621798	21.230277	35.391521
Fantasy	57.118598	21.959353	35.159245
Sci-Fi	59.009489	22.523332	36.486158
Thriller	62.401374	25.794478	36.606897
Documentary	65.560692	29.557046	36.003646
Comedy	103.519551	46.601392	56.918158
Action	148.212221	56.366683	91.845538
Adventure	163.050335	59.149946	103.900388
Drama	163.395607	76.042892	87.352714

In [35]:

```
plt.rcParams['figure.figsize'] = (10,8)

color = ['#025928', '#1CA673', '#80BFAD']

ax = gross_genre.plot(kind='barh', width=0.7, color=color, align='center')

ax.set_title("Total Gross")
ax.set_xlabel('Gross (billions)')
ax.set_ylabel('Genre')

fmt = '${x:,.0f}'
tick = mtick.StrMethodFormatter(fmt)
ax.xaxis.set_major_formatter(tick)

ax.legend(['Worldwide', 'Domestic', 'Foreign'], loc=4)

plt.savefig("Visualisations/gross_genre.png", bbox_inches='tight')

plt.show();
```



Insight 2

The second insight I will model is which genre is the most profitable. This will be based on the percentage of profit made per genre and average amount of profit per genre.

In [36]:

```
profit_percentage_genre = df_tbmb_df_tmdbmovies.groupby(df_tbmb_df_tmdbmovies['genres'], as_index=False).agg({'profit_percentage':'mean'}
profit_percentage_genre
```

Out[36]:

	genres	profit_percentage
0	Action	298.185008
1	Adventure	274.470511
2	Animation	822.403617
3	Biography	603.661885
4	Comedy	336.166994
5	Crime	161.654953
6	Documentary	989.446250
7	Drama	479.231386
8	Family	1047.049246
9	Fantasy	568.555823
10	History	931.405463
11	Horror	746.623388
12	Music	296.751475
13	Musical	913.771101
14	Mystery	537.369042
15	News	62.075071
16	Reality-TV	-100.000000
17	Romance	616.272556
18	Sci-Fi	203.158951
19	Sport	644.938320
20	Thriller	526.718168
21	War	771.352204
22	Western	24.428566

In [37]:

```
profit_avg_genre = df_tbmb_df_tmdbmovies.groupby(df_tbmb_df_tmdbmovies['genres'], as_index=False).agg({'profit':'mean'})
profit_avg_genre
```

Out[37]:

	genres	profit
0	Action	1.124031e+08
1	Adventure	1.944395e+08
2	Animation	1.993639e+08
3	Biography	4.887478e+07
4	Comedy	7.210473e+07
5	Crime	3.765710e+07
6	Documentary	5.283761e+07
7	Drama	4.090176e+07
8	Family	1.207971e+08
9	Fantasy	1.709568e+08
10	History	5.577777e+07
11	Horror	4.649644e+07
12	Music	4.552106e+07
13	Musical	2.392621e+08
14	Mystery	4.633308e+07
15	News	2.208677e+07
16	Reality-TV	-1.000000e+06
17	Romance	4.993981e+07
18	Sci-Fi	1.539206e+08
19	Sport	6.878288e+07
20	Thriller	5.027935e+07
21	War	3.959838e+07
22	Western	1.803489e+07

In [38]:

```python
# Again I will change the scale to millions

profit_avg_genre[['profit']] = profit_avg_genre[['profit']].applymap(lambda x: x / 10**6)
profit_avg_genre
```

Out[38]:

	genres	profit
0	Action	112.403094
1	Adventure	194.439547
2	Animation	199.363920
3	Biography	48.874782
4	Comedy	72.104728
5	Crime	37.657102
6	Documentary	52.837610
7	Drama	40.901760
8	Family	120.797131
9	Fantasy	170.956831
10	History	55.777773
11	Horror	46.496440
12	Music	45.521058
13	Musical	239.262087
14	Mystery	46.333083
15	News	22.086768
16	Reality-TV	-1.000000
17	Romance	49.939805
18	Sci-Fi	153.920604
19	Sport	68.782877
20	Thriller	50.279345
21	War	39.598379
22	Western	18.034892

In [39]:

```
# Not sure why but without resetting the index for both data frames, I am unable to plot

profit_percentage_genre.reset_index()
```

Out[39]:

	index	genres	profit_percentage
0	0	Action	298.185008
1	1	Adventure	274.470511
2	2	Animation	822.403617
3	3	Biography	603.661885
4	4	Comedy	336.166994
5	5	Crime	161.654953
6	6	Documentary	989.446250
7	7	Drama	479.231386
8	8	Family	1047.049246
9	9	Fantasy	568.555823
10	10	History	931.405463
11	11	Horror	746.623388
12	12	Music	296.751475
13	13	Musical	913.771101
14	14	Mystery	537.369042
15	15	News	62.075071
16	16	Reality-TV	-100.000000
17	17	Romance	616.272556
18	18	Sci-Fi	203.158951
19	19	Sport	644.938320
20	20	Thriller	526.718168
21	21	War	771.352204
22	22	Western	24.428566

In [40]:

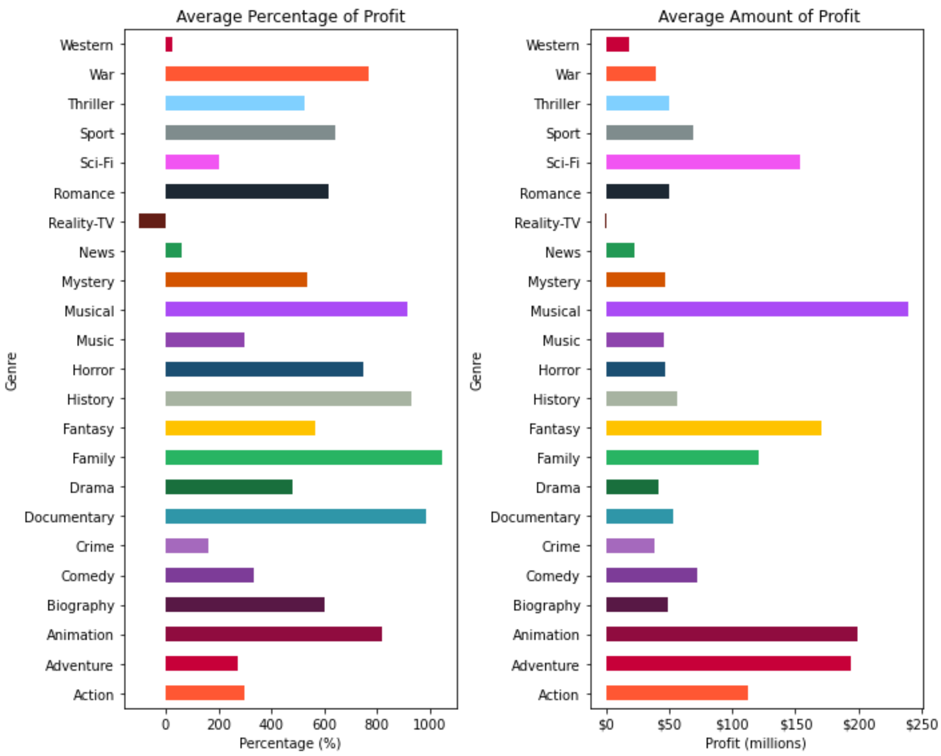
```
profit_avg_genre.reset_index()
```

Out[40]:

	index	genres	profit
0	0	Action	112.403094
1	1	Adventure	194.439547
2	2	Animation	199.363920
3	3	Biography	48.874782
4	4	Comedy	72.104728
5	5	Crime	37.657102
6	6	Documentary	52.837610
7	7	Drama	40.901760
8	8	Family	120.797131
9	9	Fantasy	170.956831
10	10	History	55.777773
11	11	Horror	46.496440
12	12	Music	45.521058
13	13	Musical	239.262087
14	14	Mystery	46.333083
15	15	News	22.086768
16	16	Reality-TV	-1.000000
17	17	Romance	49.939805
18	18	Sci-Fi	153.920604
19	19	Sport	68.782877
20	20	Thriller	50.279345
21	21	War	39.598379
22	22	Western	18.034892

In [41]:

```
colors = ['#FF5733', '#C70039', '#900C3F', '#581845', '#7D3C98', '#A569BD', '#2F96A8', '#196F3D', '#28B463', '#FFC300', '#A7B3A1', '#1B4F7

plt.rcParams['figure.figsize'] = (10,8)

fig, (ax1, ax2) = plt.subplots(1, 2)
fig.set_tight_layout(True)

profit_percentage_genre.plot(x='genres', y='profit_percentage', kind='barh', ax=ax1, color=colors)
profit_avg_genre.plot(x='genres', y='profit', kind='barh', ax=ax2, color=colors)

ax1.set_title("Average Percentage of Profit")
ax1.set_xlabel("Percentage (%)")
ax1.set_ylabel("Genre")
ax1.legend().remove()

ax2.set_title(" Average Amount of Profit")
ax2.set_xlabel("Profit (millions)")
ax2.set_ylabel("Genre")
ax2.legend().remove()

fmt = '${x:,.0f}'
tick = mtick.StrMethodFormatter(fmt)
ax2.xaxis.set_major_formatter(tick)

plt.savefig("Visualisations/profit_ptc_avg.png", bbox_inches='tight')

plt.show();
```



Insight 3

For my final insight I will model the average rating versus the average gross. I chose average gross instead of average profit because it encompasses all expenses involved in producing a movie.

For example a high budget movie may also get a high rating but not earn high profits.

In [42]:

```python
# Beginning with my original data frame

df_tbmb_df_tmdbmovies.head()
```

Out[42]:

	id	release_date	production_budget	domestic_gross	worldwide_gross	tconst	original_title	start_year	runtime_minutes	genres	...	profit
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Crime	...	
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Drama	...	
#Horror	16	Nov 20, 2015	1500000	0	0.0	tt3526286	#Horror	2015.0	101.0	Horror	...	
(500) Days of Summer	55	Jul 17, 2009	7500000	32425665	34439060.0	NaN	NaN	NaN	NaN	NaN	...	
10 Cloverfield Lane	54	Mar 11, 2016	5000000	72082999	108286422.0	tt1179933	10 Cloverfield Lane	2016.0	103.0	Drama	...	

5 rows × 22 columns

In [43]:

```python
avg_rating_gross = df_tbmb_df_tmdbmovies.groupby(df_tbmb_df_tmdbmovies['genres'], as_index=False).agg({'worldwide_gross':'mean', 'vote_ave
avg_rating_gross
```

Out[43]:

	genres	worldwide_gross	vote_average
0	Action	1.737541e+08	6.001493
1	Adventure	2.801552e+08	6.232475
2	Animation	2.735353e+08	6.230387
3	Biography	7.633572e+07	6.485304
4	Comedy	1.053098e+08	6.141310
5	Crime	6.444877e+07	6.073086
6	Documentary	8.341055e+07	6.084355
7	Drama	6.601843e+07	6.292326
8	Family	1.684422e+08	6.150207
9	Fantasy	2.360273e+08	6.087619
10	History	9.475075e+07	6.478986
11	Horror	6.665380e+07	5.693023
12	Music	6.007865e+07	6.450000
13	Musical	2.839032e+08	6.731429
14	Mystery	6.921182e+07	6.010672
15	News	5.705820e+07	6.140000
16	Reality-TV	0.000000e+00	6.400000
17	Romance	7.173364e+07	6.318932
18	Sci-Fi	2.161520e+08	6.102155
19	Sport	9.241389e+07	6.387356
20	Thriller	7.790434e+07	5.900000
21	War	6.826072e+07	6.230303
22	Western	5.164006e+07	5.883333

In [44]:

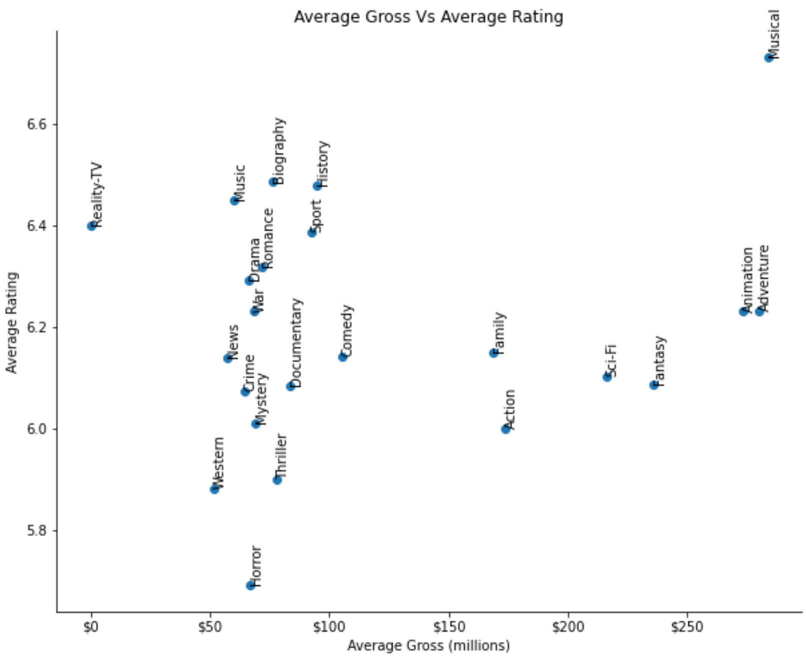
```
# Again to bring units into a nice scale
avg_rating_gross[['worldwide_gross']] = avg_rating_gross[['worldwide_gross']].applymap(lambda x: x / 10**6)
avg_rating_gross
```

Out[44]:

	genres	worldwide_gross	vote_average
0	Action	173.754070	6.001493
1	Adventure	280.155214	6.232475
2	Animation	273.535255	6.230387
3	Biography	76.335720	6.485304
4	Comedy	105.309817	6.141310
5	Crime	64.448773	6.073086
6	Documentary	83.410549	6.084355
7	Drama	66.018427	6.292326
8	Family	168.442154	6.150207
9	Fantasy	236.027265	6.087619
10	History	94.750753	6.478986
11	Horror	66.653796	5.693023
12	Music	60.078651	6.450000
13	Musical	283.903157	6.731429
14	Mystery	69.211821	6.010672
15	News	57.058196	6.140000
16	Reality-TV	0.000000	6.400000
17	Romance	71.733638	6.318932
18	Sci-Fi	216.151976	6.102155
19	Sport	92.413886	6.387356
20	Thriller	77.904338	5.900000
21	War	68.260716	6.230303
22	Western	51.640064	5.883333

In [45]:

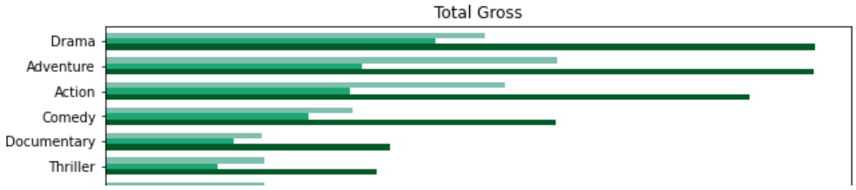
```
plt.rcParams['figure.figsize'] = (10,8)

fig, ax = plt.subplots()

ax.scatter(avg_rating_gross['worldwide_gross'], avg_rating_gross['vote_average'])

# To make genre appear on the scatter plot. Easier to interpret versus a legend
for i, txt in enumerate(avg_rating_gross['genres']):
    ax.text(avg_rating_gross['worldwide_gross'][i], avg_rating_gross['vote_average'][i], txt, rotation=90, va='bottom')

ax.set_title("Average Gross Vs Average Rating")
ax.set_xlabel('Average Gross (millions)')
ax.set_ylabel('Average Rating')

fmt = '${x:,.0f}'
tick = mtick.StrMethodFormatter(fmt)
ax.xaxis.set_major_formatter(tick)

ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

plt.savefig("Visualisations/avg_rating_gross.png", bbox_inches='tight')

plt.show();
```



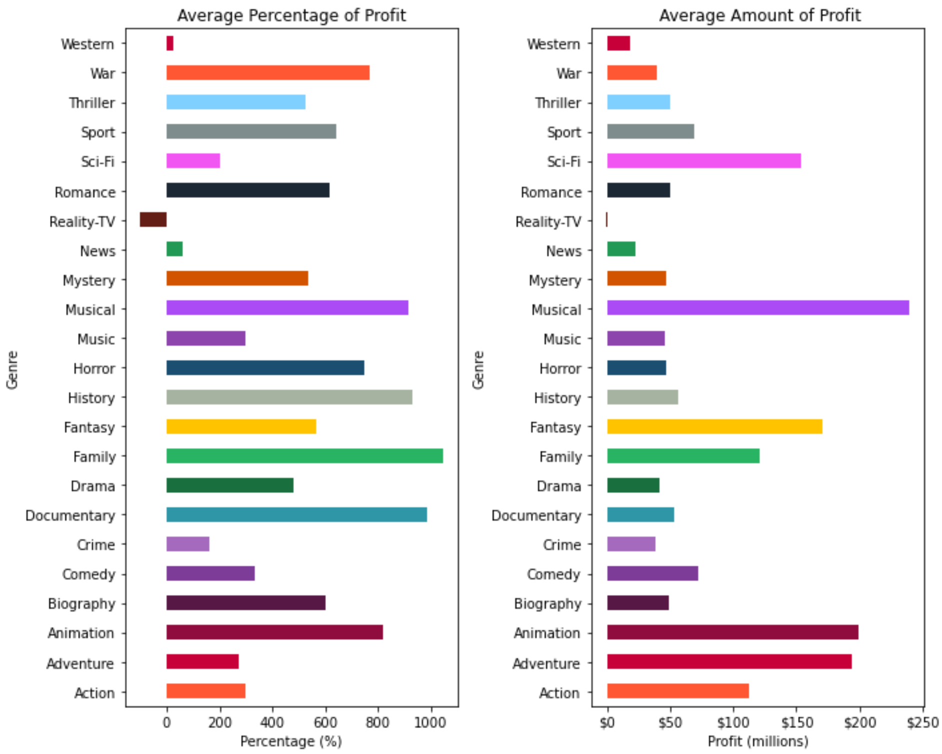
Evaluation

For my evaluation, I want to identify the top 3 performing genres for each insight. This will help the studio identify key genres to focus on and hopefully identify a common well performing genre across all insights

Insight 1



Insight 2



Budget plays a big part in the production of a movie. Ideally, Microsoft would not like to pour funds into a movie that could end up making a net loss. In order to identify, I modelled two graphs to identify the relationshop between budget and the profitability for each genre.

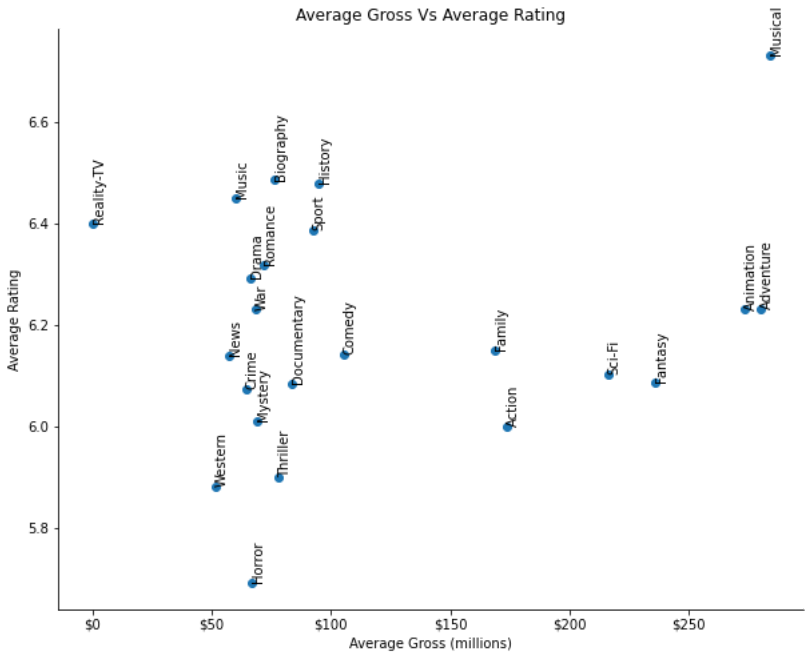
The Average Percentage of Profit graph indicates each genres ability to generate profit based on their budget. For example, if an action movie had a budget of $1 million, it would be able to produce 300% of profit which equates to $3 million. Therefore, a genre like musicals with a higher percentage can have a lower budget to reach the same profit.

However, the Average Percentage of Profit could be misleading if it is not seen in context with the Average Amount of Profit graph. This graph shows how much profit each genre actually made. A genre may have a high percentage to yield a high profit, as we can see in this graph as well as the Total Gross graph, that is not the case in physical sales.

For the Average Percentage of Profit graph, the top 3 genres are **Family, Documentary and Musical**. In general, these movies usually have a lower budget compared to other genres.

For the Average Amount of Profit graph, the top 3 genres are **Musical, Animation and Adventure**. Both the Musical and Animation genre are able to take advantage of their ability to make profit and generate high profit.

Insight 3



One way to support the strong sales displayed in the Top Gross graph and generate long term success is through ratings. Audiences will use ratings as part of their decision making for watching a movie. Generating well rated movies could generate new/repeat viewers (meaning more gross/profit). The Average Gross Vs Average Rating graph helps identify which genres do both well and the top 3 are **Musicals, Adventure and Animation**.

Conclusions

These are the top performers for each insight

- Insight 1: Drama, Adventure and Action
- Insight 2: Family, Documentary and Musical and Musical, Animation and Adventure
- Insight 3: Musicals, Adventure and Animation

Based on these results, it is my recommendation that Microsoft's newest studio focus on releasing an **Adventure** movie. Although it requires a higher budget to yield a higher profit, it is still able to reach those high marks based on the gross sales. A middle of the pack genre rating but again, its ability to generate a high gross makes this a solid direction moving forward.

A surprising and well performing genre is musicals. Its total gross sales are in the bottom third but has great potential to generate profit and rate very well with audiences. If the studio is able to generate enough popularity for a musical movie, it could do very well.

Genres to avoid would be war and westerns. They do not perform well in any insight and are era specific. They most likely appeal to a smaller size of the wider audience.

For further exploration, I would like to explore the strength of covariance and correlation between the insights I have generated. It would provide a deeper context and allow the studio to be more confident in the direction they choose. When the studio makes a decision on a genre, the next insight to explore would be when in the year it would be best to release it.

Furthermore, given the extensive amount of data available, I would like to explore the other 2 overarching directions I mentioned at the beginning of this project, Familar Faces and Stories Are Our Strength. Actors, directors and story all play a part in the production of a movie and I would like to explore how that relates to gross sales, budget and ratings.