Microsoft Studios

Designing Data-Driven Recommendations

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Overview

This project analyzes four movie databases to generate business recommendations for Microsoft's new movie studio.

The project highlights three key insights based on the analysis:

- Movie genres
- Franchises & movie sequels
- Studio acquisition

Business Problem

Microsoft has seen that many big companies are creating original video content and they wish to tap into this market. They have decided to create a movie studio but don't have any knowledge about creating movies. The purpose of this project is to make actionable insights to Microsoft based upon what movies are doing the best at the box office. The findings of the project will help Microsoft understand what types of movies to create as well as suggest other business strategies to support content creation.

Key questions:

- Which films in the past decade have made the most profit?
- What are the genres of these films?
- How does franchised and sequel movies perform?
- What can we learn from other production studios?
- Would it be cost-effective to acquire a smaller, already established studio?

In [1]:
```
## Import libraries ##
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
from matplotlib.patches import Rectangle
from matplotlib.pyplot import figure
import seaborn as sns
%matplotlib inline
```

In [2]:
```
## Import datasets ##

# Aisha's datasets: Rotten Tomatoes
df_rt_movie_info = pd.read_csv('data/rt.movie_info.tsv.gz',sep='\t')
df_rt_reviews = pd.read_csv('data/rt.reviews.tsv.gz',sep='\t',encoding='lat

# Adonis's dataset: Box Office Mojo
df_gross = pd.read_csv("data/bom.movie_gross.csv.gz")

# Angela's dataset: The Numbers
mb = pd.read_csv('data/tn.movie_budgets.csv.gz')

# Deja's dataset: TMDB
movie_type = pd.read_csv('data/tmdb.movies.csv.gz')

# James's datasets: IMDB
title_ratings = pd.read_csv('data/imdb.title.ratings.csv.gz')
title_basics = pd.read_csv('data/imdb.title.basics.csv.gz')
title_akas = pd.read_csv('data/imdb.title.akas.csv.gz')
```

Angela's Data Preparation & Analysis:

In [3]:
```
## Preliminary analysis
## Check datatypes and look for any missing values
display(mb.head())
display(mb.info())
```

	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

```
<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
```

```
None
```

Observations and Insights:

- There are 5782 total entries with 0 missing values.
- The release date column is the object datatype and should be changed to the datetime datatype.
- The production budget, domestic gross, and worldwide gross columns are also object datatypes and should be changed to integer.

In [4]:
```
## Change release_date to datetime
mb['release_date'] = pd.to_datetime(mb['release_date'])

## Change production_budget, domestic_gross, and worldwide_gross to integer

mb['production_budget'] = mb['production_budget'].str.replace( ',' , '')
mb['production_budget'] = mb['production_budget'].str.replace( '$' , '')
mb['production_budget'] = pd.to_numeric(mb['production_budget'])

mb['domestic_gross'] = mb['domestic_gross'].str.replace( ',' , '')
mb['domestic_gross'] = mb['domestic_gross'].str.replace( '$' , '')
mb['domestic_gross'] = pd.to_numeric(mb['domestic_gross'])

mb['worldwide_gross'] = mb['worldwide_gross'].str.replace( ',' , '')
mb['worldwide_gross'] = mb['worldwide_gross'].str.replace( '$' , '')
mb['worldwide_gross'] = pd.to_numeric(mb['worldwide_gross'])


## Check that all changes have been correctly made
mb.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   datetime64[ns]
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   int64
 4   domestic_gross     5782 non-null   int64
 5   worldwide_gross    5782 non-null   int64
dtypes: datetime64[ns](1), int64(4), object(1)
memory usage: 271.2+ KB
```

In [5]:
```
## Remove rows with release_date before 2010 to focus on analyzing data fro

mb = mb[(mb['release_date']) >= '2010-01-01']

display(mb.head(30))
display(mb.tail(30))
```

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	2019-06-07	Dark Phoenix	350000000	42762350	149762350
3	4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747
5	6	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220
6	7	2018-04-27	Avengers: Infinity War	300000000	678815482	2048134200
8	9	2017-11-17	Justice League	300000000	229024295	655945209
9	10	2015-11-06	Spectre	300000000	200074175	879620923
10	11	2012-07-20	The Dark Knight Rises	275000000	448139099	1084439099

Observations & Insights:

- There are a lot of gross values that are 0. They also tend to correlate with movies with very small production budgets.
- Upon investigation, these films are usually independently made and don't apply to a large corporation like Microsoft.

In [6]:
```python
## Create two new columns for domestic profit and worldwide profit
## Remove rows with negative profits

mb['domestic_profit'] = (mb['domestic_gross'] - mb['production_budget'])
mb['worldwide_profit'] = (mb['worldwide_gross'] - mb['production_budget'])
mb.head(30)
```

Out[6]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	domestic_
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	-1695
2	3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	-3072
3	4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	1284
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	3031
5	6	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220	6306
6	7	2018-04-27	Avengers: Infinity War	300000000	678815482	2048134200	3788
8	9	2017-11-17	Justice League	300000000	229024295	655945209	-709
9	10	2015-11-06	Spectre	300000000	200074175	879620923	-999
10	11	2012-07-20	The Dark Knight Rises	275000000	448139099	1084439099	1731
11	12	2018-05-25	Solo: A Star Wars Story	275000000	213767512	393151347	-612
12	13	2013-07-02	The Lone Ranger	275000000	89302115	260002115	-1856
13	14	2012-03-09	John Carter	275000000	73058679	282778100	-2019
14	15	2010-11-24	Tangled	260000000	200821936	586477240	-591
16	17	2016-05-06	Captain America: Civil War	250000000	408084349	1140069413	1580
17	18	2016-03-25	Batman v Superman: Dawn of Justice	250000000	330360194	867500281	803
18	19	2012-12-14	The Hobbit: An Unexpected Journey	250000000	303003568	1017003568	530
20	21	2013-12-13	The Hobbit: The Desolation of Smaug	250000000	258366855	960366855	83

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	domestic_
21	22	2014-12-17	The Hobbit: The Battle of the Five Armies	250000000	255119788	945577621	51
22	23	2017-04-14	The Fate of the Furious	250000000	225764765	1234846267	-242
24	25	2017-05-26	Pirates of the Caribbean: Dead Men Tell No Tales	230000000	172558876	788241137	-574
26	27	2012-05-04	The Avengers	225000000	623279547	1517935897	3982
28	29	2013-06-14	Man of Steel	225000000	291045518	667999518	660
30	31	2012-07-03	The Amazing Spider-Man	220000000	262030663	757890267	420
31	32	2012-05-18	Battleship	220000000	65233400	313477717	-1547
32	33	2017-06-21	Transformers: The Last Knight	217000000	130168683	602893340	-868
33	34	2015-06-12	Jurassic World	215000000	652270625	1648854864	4372
34	35	2012-05-25	Men in Black 3	215000000	179020854	654213485	-359
36	37	2014-06-27	Transformers: Age of Extinction	210000000	245439076	1104039076	354
38	39	2010-05-14	Robin Hood	210000000	105487148	322459006	-1045
41	42	2018-02-16	Black Panther	200000000	700059566	1348258224	5000

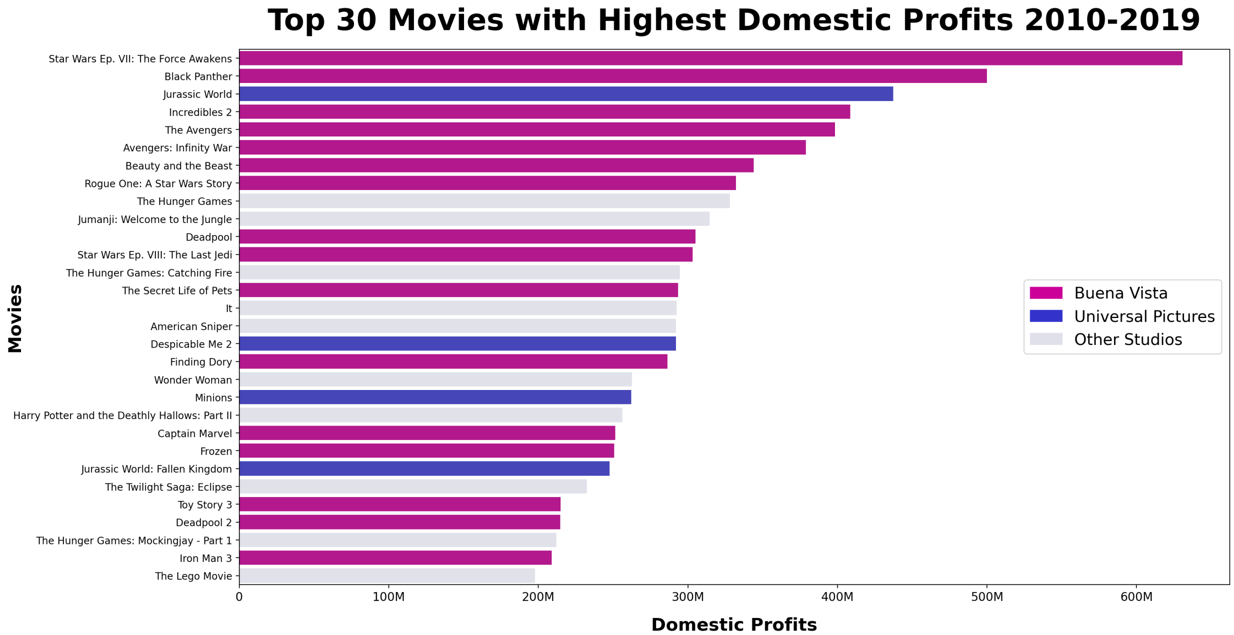
Observations & Insights:

- There are films that are box office bombs such as Dark Phoenix, The Lone Ranger, and Pirates of the Caribbean: On Strangers Tides. Their production budgets overshadowed their box office revenues.

In [7]:

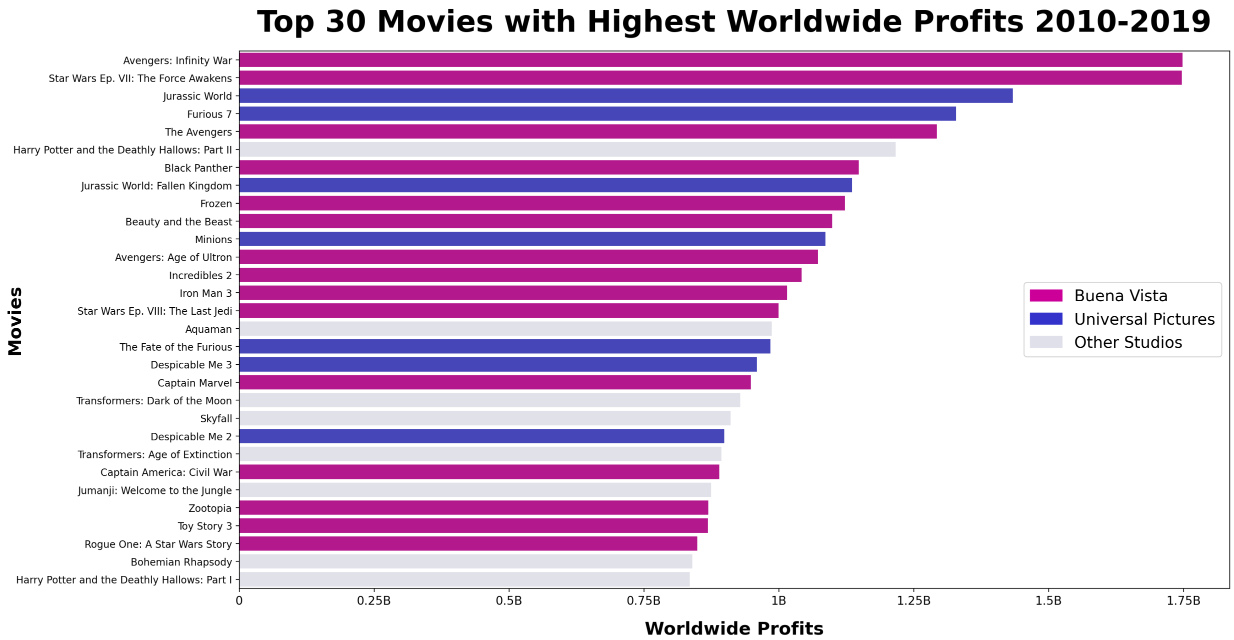
```
## Sort by highest domestic profits

mb_dp = mb.sort_values(by=['domestic_profit'], ascending=False)
mb_dp.reset_index(inplace=True)

## Sort by highest worldwide profits

mb_wp = mb.sort_values(by=['worldwide_profit'], ascending=False)
mb_wp.reset_index(inplace=True)
```

In [8]:
```
## Bar chart of Top 30 Movies with Highest Domestic Profits

fig, ax = plt.subplots(figsize=(18,10), dpi=200)

x1 = mb_dp['movie'][0:30]
y1 = mb_dp['domestic_profit'][0:30]


# Buena Vista is MAGENTA
# Universal Pictures is VIOLET
ax = sns.barplot(x=y1, y=x1,
                 palette=["#cc0099"
                          if x=='Star Wars Ep. VII: The Force Awakens'
                          or x=='Black Panther'
                          or x=='Incredibles 2'
                          or x=='The Avengers'
                          or x=='Avengers: Infinity War'
                          or x=='Beauty and the Beast'
                          or x=='Rogue One: A Star Wars Story'
                          or x=='Deadpool'
                          or x=='Star Wars Ep. VIII: The Last Jedi'
                          or x=='The Secret Life of Pets'
                          or x=='Finding Dory'
                          or x=='Captain Marvel'
                          or x=='Frozen'
                          or x=='Toy Story 3'
                          or x=='Deadpool 2'
                          or x=='Iron Man 3'
                          else '#3333cc'
                          if x=='Jurassic World'
                          or x=='Furious 7'
                          or x=='Jurassic World: Fallen Kingdom'
                          or x=='Minions'
                          or x=='Despicable Me 2'
                          else '#e0e0eb' for x in mb_dp['movie']])

ax.set_xlabel('Domestic Profits', fontsize=18, fontweight='bold', labelpad=
ax.set_ylabel('Movies', fontsize=18, fontweight='bold', labelpad=(-10))
ax.set_title('Top 30 Movies with Highest Domestic Profits 2010-2019', fonts

plt.xticks(ticks=[0,100000000,200000000,300000000,400000000,500000000,60000
           labels=['0','100M', '200M', '300M', '400M', '500M', '600M'], fon
plt.yticks(fontsize=10)

bv_label = mpatches.Patch(color='#cc0099', label='Buena Vista')
up_label = mpatches.Patch(color='#3333cc', label='Universal Pictures')
other_label = mpatches.Patch(color='#e0e0eb', label='Other Studios')
ax.legend(handles=[bv_label, up_label, other_label], loc='center right', pr
```

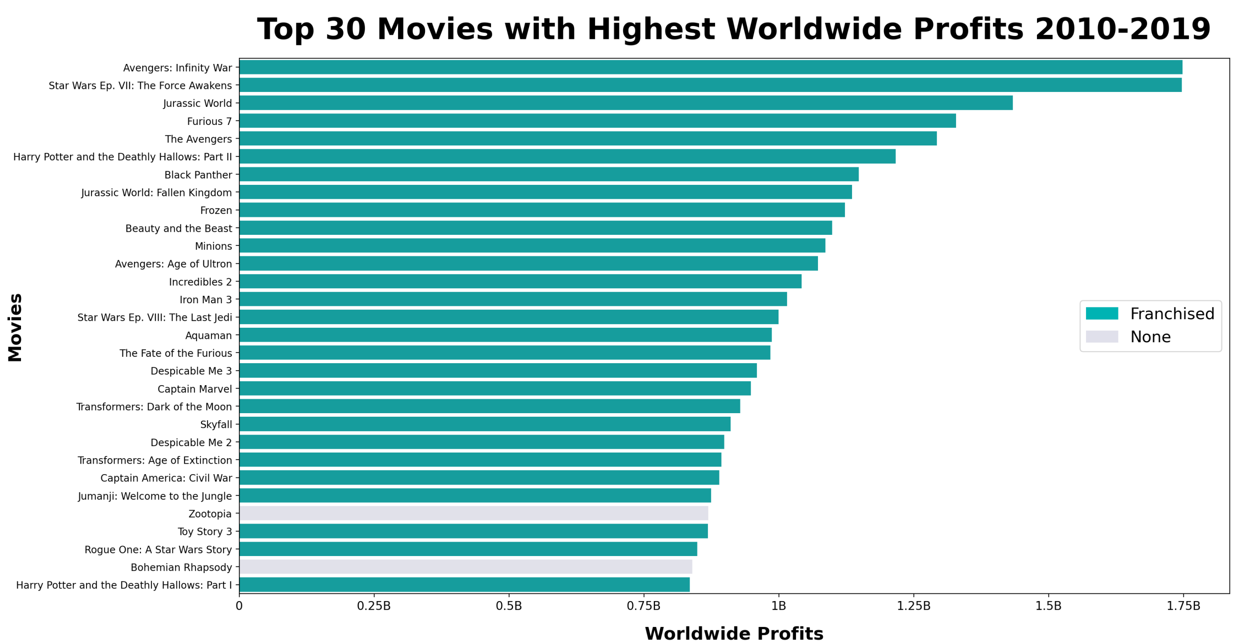

Top 30 Movies with Highest Domestic Profits 2010-2019
Star Wars Ep. VII: The Force Awakens
Black Panther
Jurassic World
Incredibles 2
The Avengers
Avengers: Infinity War
Beauty and the Beast
Rogue One: A Star Wars Story
The Hunger Games
Jumanji: Welcome to the Jungle
Deadpool
Star Wars Ep. VIII: The Last Jedi
The Hunger Games: Catching Fire
The Secret Life of Pets
It
American Sniper
Despicable Me 2
Finding Dory
Wonder Woman
Minions
Harry Potter and the Deathly Hallows: Part II
Captain Marvel
Frozen
Jurassic World: Fallen Kingdom
The Twilight Saga: Eclipse
Toy Story 3
Deadpool 2
The Hunger Games: Mockingjay - Part 1
Iron Man 3
The Lego Movie
Movies
0
100M
200M
300M
400M
500M
600M
Domestic Profits
Buena Vista
Universal Pictures
Other Studios

In [9]:
```
## Bar chart of Top 30 Movies with Highest Worldwide Profits

fig, ax = plt.subplots(figsize=(18,10), dpi=200)

x2 = mb_wp['movie'][0:30]
y2 = mb_wp['worldwide_profit'][0:30]


# Buena Vista is MAGENTA
# Universal Pictures is VIOLET
ax = sns.barplot(x=y2, y=x2,
                 palette=["#cc0099"
                          if x=='Star Wars Ep. VII: The Force Awakens'
                          or x=='Black Panther'
                          or x=='Incredibles 2'
                          or x=='The Avengers'
                          or x=='Avengers: Infinity War'
                          or x=='Beauty and the Beast'
                          or x=='Rogue One: A Star Wars Story'
                          or x=='Deadpool'
                          or x=='Star Wars Ep. VIII: The Last Jedi'
                          or x=='The Secret Life of Pets'
                          or x=='Finding Dory'
                          or x=='Captain Marvel'
                          or x=='Frozen'
                          or x=='Toy Story 3'
                          or x=='Deadpool 2'
                          or x=='Iron Man 3'
                          or x=='Frozen'
                          or x=='Beauty and the Beast'
                          or x=='Stars Wars Ep. VIII: The Last Jedi'
                          or x=='Captain Marvel'
                          or x=='Zootopia'
                          or x=='Avengers: Age of Ultron'
                          or x=='Captain America: Civil War'
                          else '#3333cc'
                          if x=='Jurassic World'
                          or x=='Furious 7'
                          or x=='Jurassic World: Fallen Kingdom'
                          or x=='Minions'
                          or x=='Despicable Me 2'
                          or x=='The Fate of the Furious'
                          or x=='Despicable Me 3'
                          else '#e0e0eb' for x in mb_wp['movie']])

ax.set_xlabel('Worldwide Profits', fontsize=18, fontweight='bold', labelpad
ax.set_ylabel('Movies', fontsize=18, fontweight='bold', labelpad=(-10))
ax.set_title('Top 30 Movies with Highest Worldwide Profits 2010-2019', font

plt.xticks(ticks=[0,0.25e9,0.5e9,0.75e9,1e9,1.25e9,1.5e9,1.75e9],
           labels=['0', '0.25B', '0.5B', '0.75B', '1B', '1.25B', '1.5B', '1
plt.yticks(fontsize=10)

bv_label = mpatches.Patch(color='#cc0099', label='Buena Vista')
up_label = mpatches.Patch(color='#3333cc', label='Universal Pictures')
other_label = mpatches.Patch(color='#e0e0eb', label='Other Studios')
```

```
ax.legend(handles=[bv_label, up_label, other_label], loc='center right', pr
```



In [10]:
```
## Bar chart of Top 30 Movies with Highest Worldwide Profits

fig, ax = plt.subplots(figsize=(18,10), dpi=200)

x2 = mb_wp['movie'][0:30]
y2 = mb_wp['worldwide_profit'][0:30]


ax = sns.barplot(x=y2, y=x2,
                 palette=["#e0e0eb"
                          if x=='Bohemian Rhapsody'
                          or x=='Zootopia'
                          else '#00b3b3' for x in mb_wp['movie']])

ax.set_xlabel('Worldwide Profits', fontsize=18, fontweight='bold', labelpad
ax.set_ylabel('Movies', fontsize=18, fontweight='bold', labelpad=(-10))
ax.set_title('Top 30 Movies with Highest Worldwide Profits 2010-2019', font

plt.xticks(ticks=[0,0.25e9,0.5e9,0.75e9,1e9,1.25e9,1.5e9,1.75e9],
           labels=['0', '0.25B', '0.5B', '0.75B', '1B', '1.25B', '1.5B', '1
plt.yticks(fontsize=10)

fr_label = mpatches.Patch(color='#00b3b3', label='Franchised')
none_label = mpatches.Patch(color='#e0e0eb', label='None')
ax.legend(handles=[fr_label, none_label], loc='center right', prop={'size':
```



Final Observations & Insights:

- The 10 movies with highest domestic profits from 2010-mid2019 are ***Star Wars Ep. VII: The Force Awakens, Black Panther, Jurassic World, Incredibles 2, The Avengers, Avengers: Infinity War, Beauty and the Beast, Rogue One: A Star Wars Story, The Hunger Games, and Jumanji: Welcome to the Jungle.***
- The 10 movies with highest worldwide profits from 2010-mid2019 are ***Avengers: Infinity War, Star Wars Ep. VII: The Force Awakens, Jurassic World, Furious 7, The Avengers, Harry***

Potter and the Deathly Hallows: Part II, Black Panther, Jurassic World: Fallen Kingdom, Frozen, and Beauty and the Beast.
- The most frequently occuring genres of the Top 30 films are ***Sci-fi, Action, Adventure, and Animation***, with most of them having a subgenre of ***Superhero.***
- The majority of these films are part of the ***Marvel*** or ***Star Wars*** franchises.
- There has also been a huge focus on revitalizing or reimagining classics such as ***Jurassic Park, James Bond, and Jumanji.***
- Many financially successful films are sequels such as ***Star Wars Ep. VII, Avengers: Infinity War, Furious 7, Harry Potter and the Deathly Hallows: Parts I & II, and Incredibles 2***

Aisha's Data Preparation & Analysis:

In [11]:
```
df_rt_movie_info.head(3)
```

Out[11]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_d
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 2
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	Ja 2
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	Apr 2

In [12]:
```
## Remove the month and day from the theater_date and create a new column w
df_rt_movie_info['new_theater_date'] = df_rt_movie_info.theater_date.str[-4
```

In [13]:
```
## Convert the values in the 'new_theater_date' column from strings to inte
df_rt_movie_info['new_theater_date'] = df_rt_movie_info['new_theater_date']
```

In [14]:
```
df_rt_movie_info['studio'].isna().value_counts()
```

Out[14]:
```
True     1066
False     494
Name: studio, dtype: int64
```

Observations & Insights

- There are 494 out of 1560 rows that have a missing studio value

In [15]:
```
## All the studios listed
df_rt_movie_info['studio'].value_counts().head()
```

Out[15]:
```
Universal Pictures        35
Paramount Pictures        27
20th Century Fox          26
Sony Pictures Classics    22
Warner Bros. Pictures     21
Name: studio, dtype: int64
```

In [16]:
```
df_rt_reviews[df_rt_reviews['rating'].isna()]
```

Out[16]:

	id	review	rating	fresh	critic	top_critic	publisher	date
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
...	...	...	...	...	...	...	...	...
54409	2000	A lightweight, uneven action comedy that freel...	NaN	rotten	Daniel Eagan	0	Film Journal International	October 5, 2002
54417	2000	The funny thing is, I didn't mind all this con...	NaN	fresh	Andrew Sarris	1	Observer	October 2, 2002
54425	2000	Despite Besson's high-profile name being Wasab...	NaN	fresh	Andy Klein	0	New Times	September 26, 2002
54426	2000	The film lapses too often into sugary sentimen...	NaN	rotten	Paul Malcolm	1	L.A. Weekly	September 26, 2002
54427	2000	The real charm of this trifle is the deadpan c...	NaN	fresh	Laura Sinagra	1	Village Voice	September 24, 2002

13517 rows × 8 columns

In [17]:
```
## Remove all rows that have a null value in the 'rating' column
df_rt_reviews = df_rt_reviews[df_rt_reviews['rating'].notna()]
df_rt_reviews.shape
```

Out[17]:
```
(40915, 8)
```

In [18]:
```
df_rt_reviews.loc[df_rt_reviews ['rating'] == 'T']
```

Out[18]:

	id	review	rating	fresh	critic	top_critic	publisher	date
47013	1765	upposed to be a horror-comedy film, but it's n...	T	rotten	Jeff Vice	0	Deseret News (Salt Lake City)	January 1, 2000

In [19]:
```
## Split the "rating" column into two separate columns, separating them on
df_rt_reviews[['fn','sn']] = df_rt_reviews['rating'].str.split('/',expand=T
```

In [20]:
```
## Replace the null values in the 'sn'(second number) with number 1. The ro
# only if the corresponding 'rating' column has a letter rating.
df_rt_reviews['sn'] = df_rt_reviews.sn.apply(lambda x: x if not pd.isnull(x

## Replace the letter ratings with the appropriate percentages
# The letter ratings are: A+, A, A-, B+, B, B-, C+, C, C-, D+, D, D-, F+, F
# A+ gets 1, A gets 93.34, A- gets 86.68
# B+ gets 80.02, B gets 73.36, B- gets 66.7,
# C+ gets 60.04, C gets 53.38, C- gets 46.72
# D+ gets 40.06, D gets 33.4, D- gets 26.74
# F+ gets 20.08, F gets 13.42, F- gets 6.66
df_rt_reviews['fn'] = df_rt_reviews['fn'].replace(
    ['A+','A','A-','B+','B','B-','C+','C','C-','D+','D','D-','F+','F','F-']
    [1,0.9334,0.8668,0.8002,0.7336,0.667,0.6004,0.5338,0.4672,0.4006,0.334,
```

In [21]:
```
## Delete a row with an outlier value in the 'fn' column which is giving an
# when trying to convert all string values into numeric values
df_rt_reviews = df_rt_reviews[df_rt_reviews.fn != 'N']
df_rt_reviews = df_rt_reviews[df_rt_reviews.fn != 'R']
df_rt_reviews = df_rt_reviews[df_rt_reviews.fn != '1-5']
df_rt_reviews = df_rt_reviews[df_rt_reviews.fn != 'T']
df_rt_reviews = df_rt_reviews[df_rt_reviews.fn != '3 1']

## Convert all string values in the 'fn' and 'sn' columns into numeric valu
df_rt_reviews['fn'] = df_rt_reviews['fn'].apply(pd.to_numeric)
df_rt_reviews['sn'] = df_rt_reviews['sn'].apply(pd.to_numeric)

df_rt_reviews['new_rating'] = df_rt_reviews.apply(lambda row: row.fn/row.sn

## Delete rows that have a new_rating value higher than 1
df_rt_reviews = df_rt_reviews[df_rt_reviews.new_rating <=1]
```

In [22]:
```
df_rt_reviews.head()
```

Out[22]:

	id	review	rating	fresh	critic	top_critic	publisher	date	fn	sn	n
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018	3.0000	5	
6	3	Quickly grows repetitive and tiresome, meander...	C	rotten	Eric D. Snider	0	EricDSnider.com	July 17, 2013	0.5338	1	
7	3	Cronenberg is not a director to be daunted by ...	2/5	rotten	Matt Kelemen	0	Las Vegas CityLife	April 21, 2013	2.0000	5	
11	3	While not one of Cronenberg's stronger films, ...	B-	fresh	Emanuel Levy	0	EmanuelLevy.Com	February 3, 2013	0.6670	1	
12	3	Robert Pattinson works mighty hard to make Cos...	2/4	rotten	Christian Toto	0	Big Hollywood	January 15, 2013	2.0000	4	

In [23]:
```
## Create a new dataset with only 'id' and 'new_rating' columns of the 'df_
# so we can merge it later on with the 'df_rt_movie_info' dataset.
new_rt_reviews = pd.DataFrame(zip(df_rt_reviews.id, df_rt_reviews.new_ratin

## Rename the columns back to original names
new_rt_reviews.rename(columns={0: 'id', 1: 'rating'}, inplace=True)

new_rt_movie_info = pd.DataFrame(zip(df_rt_movie_info.id,
                                     df_rt_movie_info.genre,
                                     df_rt_movie_info.runtime,
                                     df_rt_movie_info.new_theater_date))
```

In [24]:
```
# Rename the columns back to original names
new_rt_movie_info.rename(columns={0: 'id', 1: 'genres', 2: 'runtime', 3: 'r
```

In [25]:
```
# Left join the new_rt_movie_info to new_rt_reviews
merged_datasets = pd.merge(new_rt_reviews,new_rt_movie_info,on='id',how='le
```

In [26]:
```
## First step in splitting the genres of each row into separate rows for ea
## Create a list out of each genres string such as this: 'Action and Advent
merged_datasets['genres']=merged_datasets['genres'].str.split('|')

## Second step in splitting the genres of each row into separate rows for e
merged_datasets = merged_datasets.explode('genres')

# Get rid of text characters in the 'runtime' column
merged_datasets['runtime'] = merged_datasets['runtime'].str.replace(' minut

# Convert the 'runtime' column's string values into floats
merged_datasets['runtime'] = pd.to_numeric(merged_datasets['runtime'])

merged_datasets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 88969 entries, 0 to 40284
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   id            88969 non-null  int64  
 1   rating        88969 non-null  float64
 2   genres        88896 non-null  object 
 3   runtime       87648 non-null  float64
 4   release_year  87190 non-null  float64
dtypes: float64(3), int64(1), object(1)
memory usage: 4.1+ MB
```

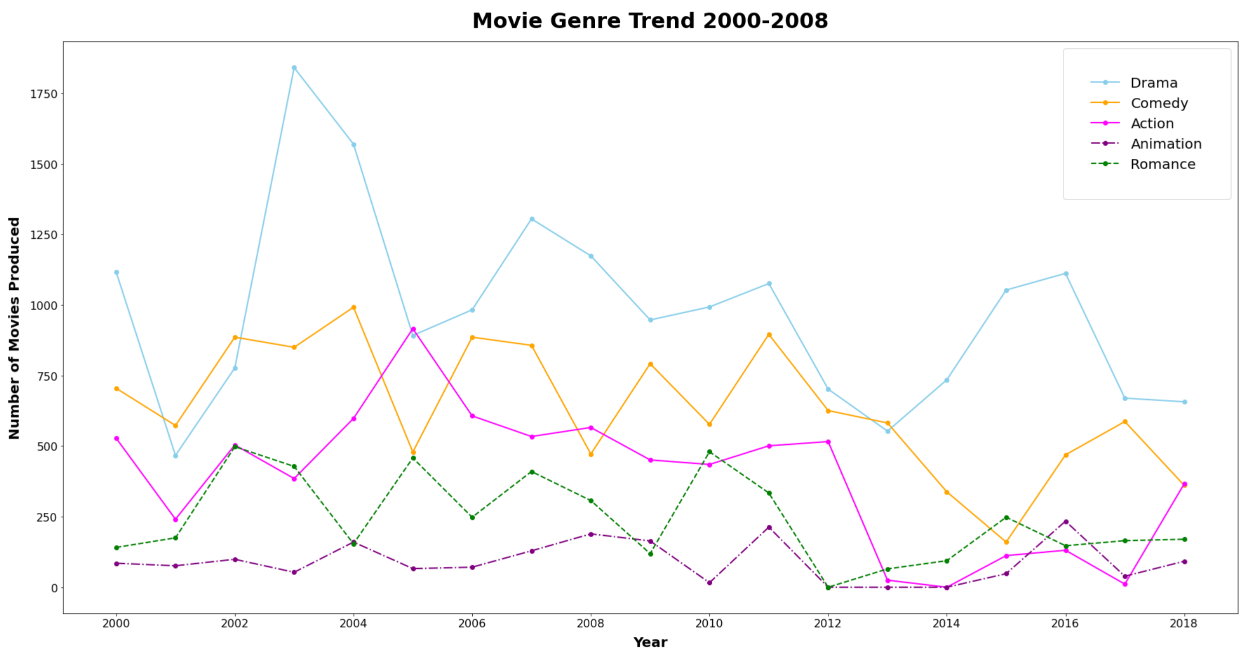
In [27]:
```
## Explore movie genre trends over the years
merged_datasets['genres'].value_counts()
merged_datasets = merged_datasets[merged_datasets['release_year']>1999]
merged_datasets['release_year'].value_counts()
merged_datasets_drama = merged_datasets[merged_datasets['genres']=='Drama']
merged_datasets_comedy = merged_datasets[merged_datasets['genres']=='Comedy
merged_datasets_action_adv= merged_datasets[merged_datasets['genres']=='Act
merged_datasets_animation= merged_datasets[merged_datasets['genres']=='Anim
merged_datasets_romance= merged_datasets[merged_datasets['genres']=='Romanc
```

In [28]:
```
## Make separate dataframes by value counts in each genre
df_drama = merged_datasets_drama.groupby('release_year')['genres'].value_co
df_comedy = merged_datasets_comedy.groupby('release_year')['genres'].value_
df_action_adv = merged_datasets_action_adv.groupby('release_year')['genres'
df_animation = merged_datasets_animation.groupby('release_year')['genres'].
df_romance = merged_datasets_romance.groupby('release_year')['genres'].valu
```

In [29]:
```
## Convert dataframes to lists
mylist_drama = df_drama.to_list()
mylist_comedy = df_comedy.to_list()
mylist_action_adv = df_action_adv.to_list()
mylist_action_adv = [528,241,504,385,598,916,607,534,566,451,435,501,516,25
mylist_animation = df_animation.to_list()
mylist_animation = [85, 76, 99, 53, 160, 66, 71, 129, 189, 164, 16, 213,0,0
mylist_romance = df_romance.to_list()
mylist_romance = [141,175,498,428,154,458,248,410,307,119,480,334,0,65,94,2
```

In [30]:
```
years_list = list(range(2000,2019))
```

In [31]:
```
## Plot
plt.figure(figsize=(30, 15))
plt.plot(years_list, mylist_drama, marker='o',
         color='skyblue', linewidth=2, linestyle='solid', label="Drama")
plt.plot(years_list, mylist_comedy, marker='o',
         color='orange', linewidth=2, linestyle='solid', label="Comedy")
plt.plot(years_list, mylist_action_adv, marker='o',
         color='fuchsia', linewidth=2, linestyle='solid', label="Action")
plt.plot(years_list, mylist_animation, marker='o',
         color='purple', linewidth=2, linestyle='dashdot', label="Animation
plt.plot(years_list, mylist_romance, marker='o',
         color='green', linewidth=2, linestyle='dashed', label="Romance")
plt.legend(borderpad = 2, prop={"size":20})
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.locator_params(axis="x", nbins=10)
plt.title("Movie Genre Trend 2000-2008", fontsize=30, fontweight='bold', pa
plt.xlabel("Year", fontsize=20, fontweight='bold', labelpad=10)
plt.ylabel("Number of Movies Produced", fontsize=20, fontweight='bold', lab
```



In [32]:
```
merged_datasets['genres'].value_counts()
```

Out[32]:
```
Drama                            18624
Comedy                           12088
Action and Adventure              7427
Mystery and Suspense              6439
Romance                           4641
Science Fiction and Fantasy       3722
Kids and Family                   2690
Horror                            2381
Art House and International       2250
Animation                         1734
Musical and Performing Arts       1051
Documentary                        650
Western                            578
Special Interest                   450
Sports and Fitness                 257
Classics                           238
Television                         132
Faith and Spirituality             127
Anime and Manga                     18
Name: genres, dtype: int64
```

Observations & Insights:

- The last four genre categories are too low in numbers compared to other movie genres.
- We think it is best to remove them from our dataset.

In [33]:
```
## Create a list of genres that are not statistically significant
not_significant_genres_list = ['Anime and Manga',
                               'Gay and Lesbian',
                               'Cult Movies',
                               'Faith and Spirituality',
                               'Television',
                               'Sports and Fitness',
                               'Documentary',
                               'Western',
                               'Special Interest']
```

In [34]:
```
## Delete the not statistically insignificant genres from the dataset and c
new_merged_datasets = merged_datasets[~merged_datasets.genres.isin(not_sign
```

In [35]:
```
## Find the mean of runtime for each genre
average_runtime_per_genre = new_merged_datasets.groupby('genres', as_index=

## Rename the 'runtime' column into the 'mean_runtime'
average_runtime_per_genre.rename(columns={'runtime': 'mean_runtime'}, inpla

average_runtime_per_genre
```

Out[35]:

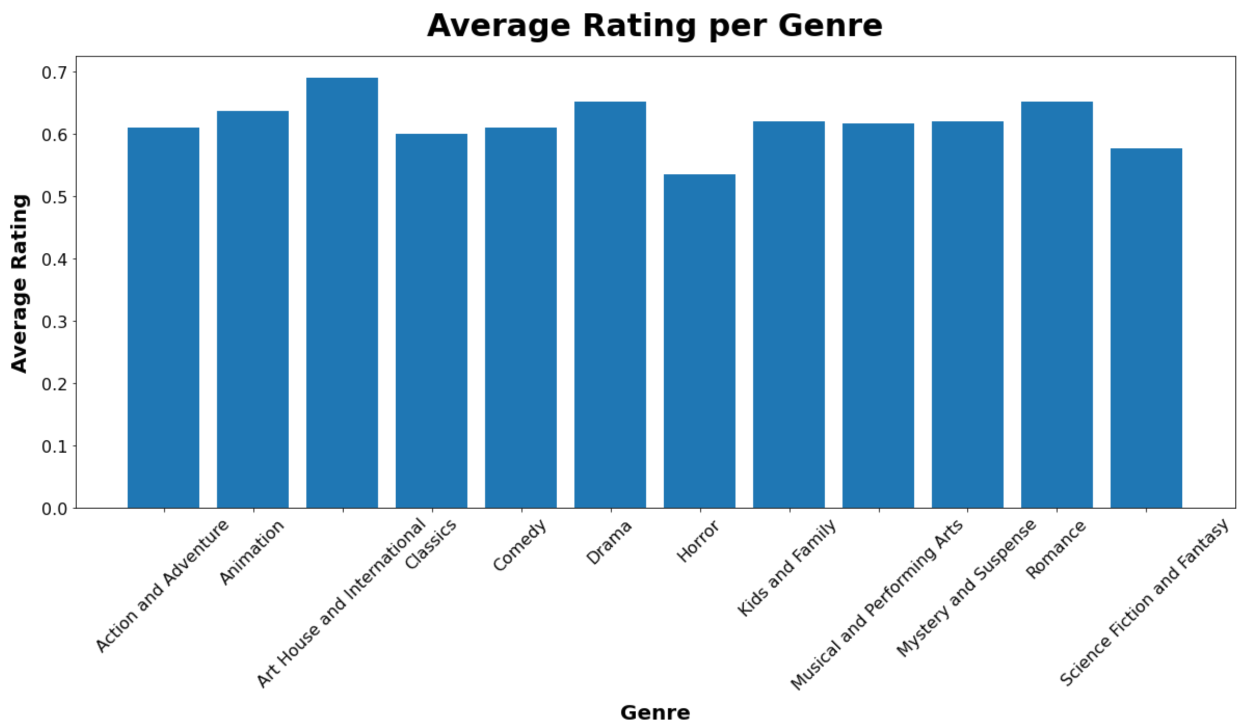
	genres	mean_runtime
0	Action and Adventure	112.473344
1	Animation	94.171280
2	Art House and International	111.512444
3	Classics	176.436975
4	Comedy	102.869470
5	Drama	113.574733
6	Horror	101.153846
7	Kids and Family	100.543093
8	Musical and Performing Arts	110.934348
9	Mystery and Suspense	111.593186
10	Romance	112.731308
11	Science Fiction and Fantasy	114.850601

In [36]:
```
# Find the mean of the ratings for each genre
average_rating_per_genre = new_merged_datasets.groupby('genres', as_index=F

## Rename the "rating" column into the 'mean_rating'
average_rating_per_genre.rename(columns={'rating': 'mean_rating'}, inplace=

average_rating_per_genre
```

Out[36]:

	genres	mean_rating
0	Action and Adventure	0.610588
1	Animation	0.636965
2	Art House and International	0.690348
3	Classics	0.600697
4	Comedy	0.610432
5	Drama	0.652974
6	Horror	0.535693
7	Kids and Family	0.620816
8	Musical and Performing Arts	0.616709
9	Mystery and Suspense	0.620616
10	Romance	0.652658
11	Science Fiction and Fantasy	0.577216

In [37]:
```
## Plot
fig, ax1 = plt.subplots(figsize = (20,8))
x1 = average_rating_per_genre['genres']
y1 = average_rating_per_genre['mean_rating']
ax1.bar(x1,y1)
ax1.set_title('Average Rating per Genre', fontsize=30, fontweight='bold', p
ax1.set_xlabel('Genre', fontsize=20, fontweight='bold', labelpad=10)
ax1.set_ylabel('Average Rating', fontsize=20, fontweight='bold', labelpad=1
plt.xticks(rotation = 45, fontsize=16)
plt.yticks(fontsize=16);
```



Observations & Insights:

The 4 genres that have the highest average ratings:
- Romance
- Art House and International
- Drama
- Mystery and Suspense

In [38]:
```
# Create a list of the four genres with the highest rating
four_genres_list = ['Romance','Art House and International','Drama','Myster

# Create a dataset with only the four genres with the highest ratings
highest_rating_genres_dataset = merged_datasets[merged_datasets.genres.isin

highest_rating_genres_dataset['genres'].value_counts()
```

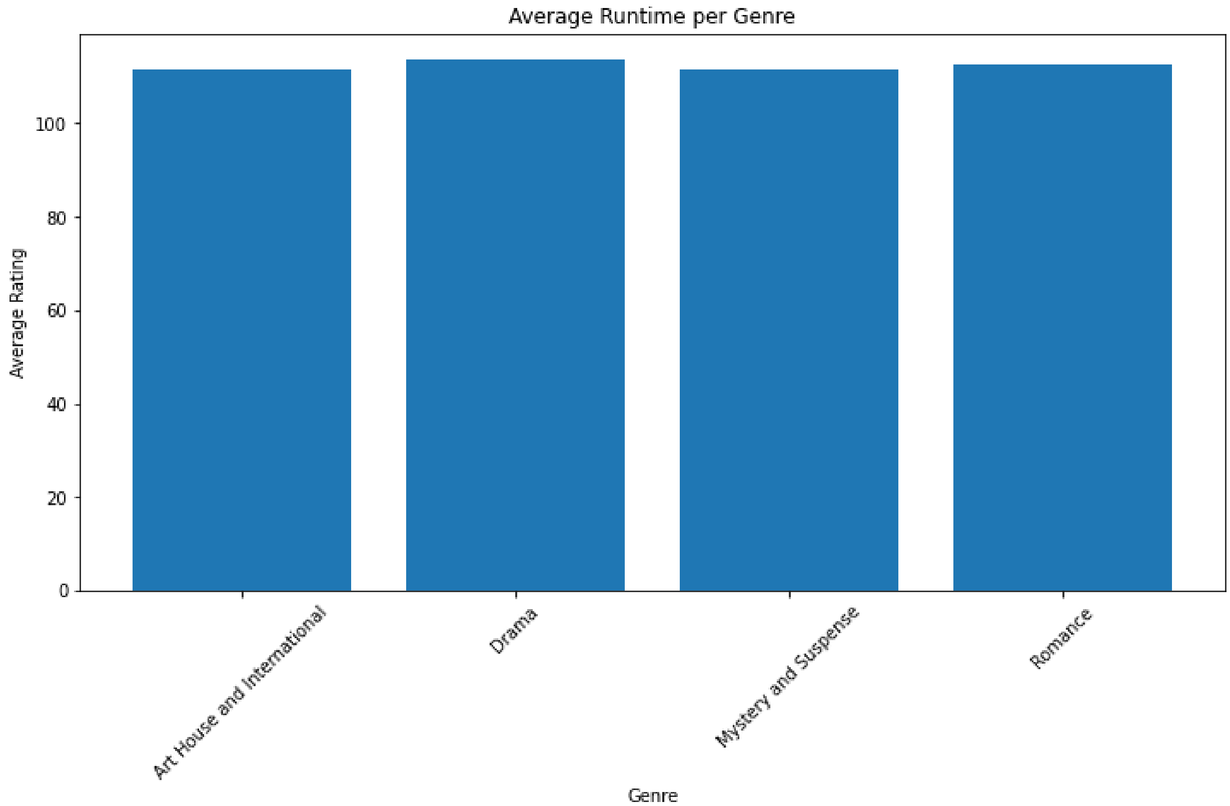
Out[38]:
```
Drama                          18624
Mystery and Suspense            6439
Romance                         4641
Art House and International     2250
Name: genres, dtype: int64
```

In [39]:
```
# The mean of runtime for the four highest rated genres
highest_rating_genres_dataset['runtime'].mean()

# Standard deviation from the mean for the four highest rated genres
highest_rating_genres_dataset['runtime'].std()

# Average runtime for each of the four highest rating genres
avg_runtime_high_rating_genres = highest_rating_genres_dataset.groupby('gen

# Rename the 'runtime' column of the new dataset into the "mean_runtime"
avg_runtime_high_rating_genres.rename(columns={'runtime': 'mean_runtime'},

avg_runtime_high_rating_genres
```

Out[39]:

	genres	mean_runtime
0	Art House and International	111.512444
1	Drama	113.574733
2	Mystery and Suspense	111.593186
3	Romance	112.731308

In [40]:
```
## Plot
fig, ax2 = plt.subplots(figsize = (12,6))
x2 = avg_runtime_high_rating_genres['genres']
y2 = avg_runtime_high_rating_genres['mean_runtime']
ax2.bar(x2,y2)
ax2.set_title('Average Runtime per Genre')
ax2.set_xlabel('Genre')
ax2.set_ylabel('Average Rating')
plt.xticks(rotation = 45);
```



Adonis's Data Preparation & Analysis

In [41]:
```
df_gross.head()
```

Out[41]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

In [42]:
```
## Find null values
df_gross['domestic_gross'].isnull().value_counts()
```

Out[42]:
```
False    3359
True       28
Name: domestic_gross, dtype: int64
```

In [43]:
```
df_gross['foreign_gross'].isnull().value_counts()
```

Out[43]:
```
False    2037
True     1350
Name: foreign_gross, dtype: int64
```

In [44]:
```
df_gross.info()
```

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

In [45]:
```
## Remove commas from values & convert to numeric
df_gross['foreign_gross'] = df_gross['foreign_gross'].str.replace(',', '')
df_gross['foreign_gross'] = pd.to_numeric(df_gross['foreign_gross'])
df_gross['foreign_gross'].head()
```

Out[45]:
```
0    652000000.0
1    691300000.0
2    664300000.0
3    535700000.0
4    513900000.0
Name: foreign_gross, dtype: float64
```

In [46]:
```
## Remove null values from columns
df_gross.dropna(subset=['studio', 'domestic_gross', 'foreign_gross'], inpla
df_gross.shape
```

Out[46]:
```
(2007, 5)
```

In [47]:
```
## Verification of null value deletion
df_gross.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2007 entries, 0 to 3353
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           2007 non-null   object
 1   studio          2007 non-null   object
 2   domestic_gross  2007 non-null   float64
 3   foreign_gross   2007 non-null   float64
 4   year            2007 non-null   int64
dtypes: float64(2), int64(1), object(2)
memory usage: 94.1+ KB
```

Observations & Insights:

- Do the studios that produce the most movies have the highest gross values?

In [48]:
```
## Top 10 studios with the most movies
df_gross['studio'].value_counts()[:10]
```

Out[48]:
```
Uni.     144
Fox      134
WB       130
Sony     105
BV       104
Par.      94
LGF       87
Wein.     69
IFC       68
SPC       59
Name: studio, dtype: int64
```

In [49]:
```
x = list(df_gross['studio'].value_counts()[:10].index)
x
```

Out[49]:
```
['Uni.', 'Fox', 'WB', 'Sony', 'BV', 'Par.', 'LGF', 'Wein.', 'IFC', 'SPC']
```

In [50]:
```
## Top 10 studios domestic gross
dfm2 = df_gross.groupby(['studio']).domestic_gross.sum().reset_index().sort
d = dfm2[dfm2['studio'].isin(x)]
```

Observations & Insights:

- Data analysis will focus on domestic and foreign gross for titles and studios.

In [51]:
```
## Total gross for each film
df_gross['total_gross'] = df_gross['domestic_gross'] + df_gross['foreign_gr
df_gross.head()
```

Out[51]:

	title	studio	domestic_gross	foreign_gross	year	total_gross
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1.067000e+09
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010	9.603000e+08
3	Inception	WB	292600000.0	535700000.0	2010	8.283000e+08
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	7.526000e+08

In [52]:
```
## Sort by domestic gross
f = df_gross.sort_values(by='domestic_gross', ascending=False)
f.head()
```

Out[52]:

	title	studio	domestic_gross	foreign_gross	year	total_gross
1872	Star Wars: The Force Awakens	BV	936700000.0	1131.6	2015	9.367011e+08
3080	Black Panther	BV	700100000.0	646900000.0	2018	1.347000e+09
3079	Avengers: Infinity War	BV	678800000.0	1369.5	2018	6.788014e+08
1873	Jurassic World	Uni.	652300000.0	1019.4	2015	6.523010e+08
727	Marvel's The Avengers	BV	623400000.0	895500000.0	2012	1.518900e+09

Observations & Insights:

- Some foreign gross values seem wrong for blockbuster films. Are there more?

In [53]:
```
## Sort df on foreign gross
g = df_gross.sort_values(by='foreign_gross', ascending=False)
g.head(20)
```

Out[53]:

	title	studio	domestic_gross	foreign_gross	year	total_gross
328	Harry Potter and the Deathly Hallows Part 2	WB	381000000.0	960500000.0	2011	1.341500e+09
1875	Avengers: Age of Ultron	BV	459000000.0	946400000.0	2015	1.405400e+09
727	Marvel's The Avengers	BV	623400000.0	895500000.0	2012	1.518900e+09
3081	Jurassic World: Fallen Kingdom	Uni.	417700000.0	891800000.0	2018	1.309500e+09
1127	Frozen	BV	400700000.0	875700000.0	2013	1.276400e+09
2764	Wolf Warrior 2	HC	2700000.0	867600000.0	2017	8.703000e+08
1477	Transformers: Age of Extinction	Par.	245400000.0	858600000.0	2014	1.104000e+09
1876	Minions	Uni.	336000000.0	823400000.0	2015	1.159400e+09
3083	Aquaman	WB	335100000.0	812700000.0	2018	1.147800e+09
1128	Iron Man 3	BV	409000000.0	805800000.0	2013	1.214800e+09
330	Pirates of the Caribbean: On Stranger Tides	BV	241100000.0	804600000.0	2011	1.045700e+09
728	Skyfall	Sony	304400000.0	804200000.0	2012	1.108600e+09
329	Transformers: Dark of the Moon	P/DW	352400000.0	771400000.0	2011	1.123800e+09
2761	Despicable Me 3	Uni.	264600000.0	770200000.0	2017	1.034800e+09
2759	Beauty and the Beast (2017)	BV	504000000.0	759500000.0	2017	1.263500e+09
2322	Captain America: Civil War	BV	408100000.0	745200000.0	2016	1.153300e+09
730	The Hobbit: An Unexpected Journey	WB (NL)	303000000.0	718100000.0	2012	1.021100e+09
731	Ice Age: Continental Drift	Fox	161300000.0	715900000.0	2012	8.772000e+08
2758	Star Wars: The Last Jedi	BV	620200000.0	712400000.0	2017	1.332600e+09
1478	The Hobbit: The Battle of the Five Armies	WB (NL)	255100000.0	700900000.0	2014	9.560000e+08

In [54]:
```
## Check for more misreported foreign gross
g.tail(20)
```

Out[54]:

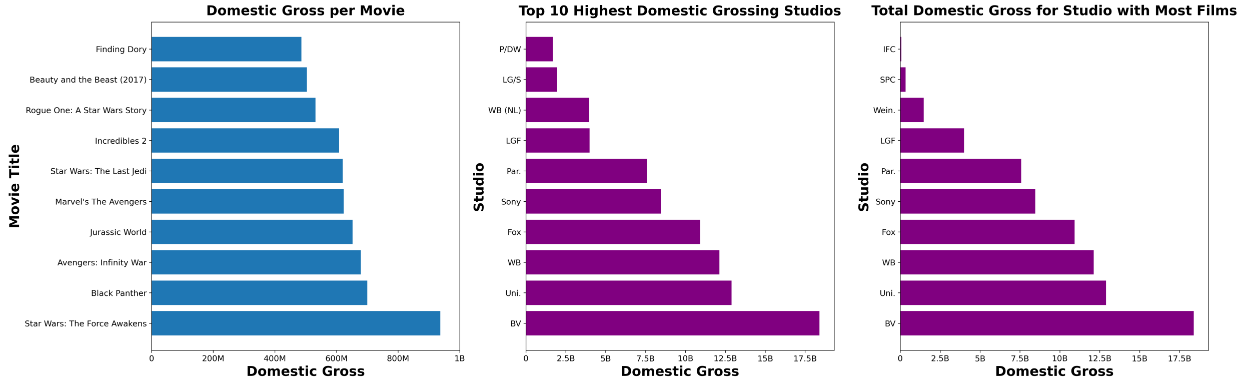
	title	studio	domestic_gross	foreign_gross	year	total_gross
187	Waiting for "Superman"	ParV	6400000.0	9300.0	2010	6409300.0
2696	Troublemakers: The Story of Land Art	FRun	29500.0	9100.0	2016	38600.0
300	Saint John of Las Vegas	IVP	103000.0	9100.0	2010	112100.0
279	Karthik Calling Karthik	Eros	286000.0	7100.0	2010	293100.0
305	Enemies of the People	ICir	73200.0	6400.0	2010	79600.0
320	Nenette	Kino	18000.0	5400.0	2010	23400.0
3342	Reign of Judges: Title of Liberty - Concept Short	Darin Southa	93200.0	5200.0	2018	98400.0
317	Bluebeard	Strand	33500.0	5200.0	2010	38700.0
715	Aurora	CGld	5700.0	5100.0	2011	10800.0
266	The Extra Man	Magn.	453000.0	4500.0	2010	457500.0
304	Waking Sleeping Beauty	BV	80700.0	4200.0	2010	84900.0
290	Client 9: The Rise and Fall of Eliot Spitzer	Magn.	189000.0	3500.0	2010	192500.0
316	The Red Baron	Mont.	37200.0	3100.0	2010	40300.0
3079	Avengers: Infinity War	BV	678800000.0	1369.5	2018	678801369.5
1874	Furious 7	Uni.	353000000.0	1163.0	2015	353001163.0
1872	Star Wars: The Force Awakens	BV	936700000.0	1131.6	2015	936701131.6
1873	Jurassic World	Uni.	652300000.0	1019.4	2015	652301019.4
2760	The Fate of the Furious	Uni.	226000000.0	1010.0	2017	226001010.0
721	To Die Like a Man	Strand	4000.0	900.0	2011	4900.0
921	Chasing Mavericks	Fox	6000000.0	600.0	2012	6000600.0

Observations & Insights:

- Foreign gross values for some blockbusters are misreported.
- Analysis will focus on domestic markets, as foreign gross values cannot be verified/trusted.

In [55]:
```
## Plots

# Domestic gross per title
fig, (ax1, ax2, ax3) = plt.subplots(ncols=3, figsize=(25,8), dpi=300)

x1 = f['title'][:10]
y1 = f['domestic_gross'][:10]
ax1.barh(x1, y1)
ax1.set_xticks([0,200000000, 400000000, 600000000, 800000000, 1000000000])
ax1.set_xticklabels(['0','200M', '400M', '600M', '800M', '1B'], fontsize=12
ax1.set_yticklabels(labels=f.title[:10], fontsize=12)
ax1.set_xlabel("Domestic Gross", fontsize=20, fontweight='bold')
ax1.set_ylabel("Movie Title", fontsize=20, fontweight='bold')
ax1.set_title("Domestic Gross per Movie", fontsize=20, fontweight='bold', p


# Domestic gross per studio
dfm3 = df_gross.groupby(['studio']).domestic_gross.sum().reset_index().sort
    by='domestic_gross', ascending=False)

x2 = dfm3.studio[:10]
y2 = dfm3.domestic_gross[:10]
ax2.barh(x2, y2, color='purple')
ax2.set_xticks([0,2500000000, 5000000000, 7500000000, 10000000000, 12500000
ax2.set_xticklabels(['0','2.5B', '5B', '7.5B', '10B', '12.5B', '15B', '17.5
ax2.set_yticklabels(labels=dfm3.studio[:10], fontsize=12)
ax2.set_xlabel('Domestic Gross', fontsize=20, fontweight='bold')
ax2.set_ylabel('Studio', fontsize=20, fontweight='bold')
ax2.set_title('Top 10 Highest Domestic Grossing Studios', fontsize=20, font

# Domestic gross for studios with most films
x = ['Uni.', 'Fox', 'WB', 'Sony', 'BV', 'Par.', 'LGF', 'Wein.', 'IFC', 'SPC

x3 = d['studio']
y3 = d['domestic_gross']
ax3.barh(x3, y3, color='purple')
ax3.set_xticks([0,2500000000, 5000000000, 7500000000, 10000000000, 12500000
ax3.set_xticklabels(['0','2.5B', '5B', '7.5B', '10B', '12.5B', '15B', '17.5
ax3.set_yticklabels(labels=d.studio, fontsize=12)
ax3.set_xlabel("Domestic Gross", fontsize=20, fontweight='bold')
ax3.set_ylabel("Studio", fontsize=20, fontweight='bold')
ax3.set_title('Total Domestic Gross for Studio with Most Films', fontsize=2

fig.tight_layout();
```

```
<ipython-input-55-5144d49cfd9c>:11: UserWarning: FixedFormatter should on
ly be used together with FixedLocator
  ax1.set_yticklabels(labels=f.title[:10], fontsize=12)
<ipython-input-55-5144d49cfd9c>:26: UserWarning: FixedFormatter should on
ly be used together with FixedLocator
  ax2.set_yticklabels(labels=dfm3.studio[:10], fontsize=12)
<ipython-input-55-5144d49cfd9c>:39: UserWarning: FixedFormatter should on
ly be used together with FixedLocator
  ax3.set_yticklabels(labels=d.studio, fontsize=12)
```



Observations & Insights:

- Most of these studios are subsidiaries of a parent company.
- Should Microsoft acquire studios for its content production?

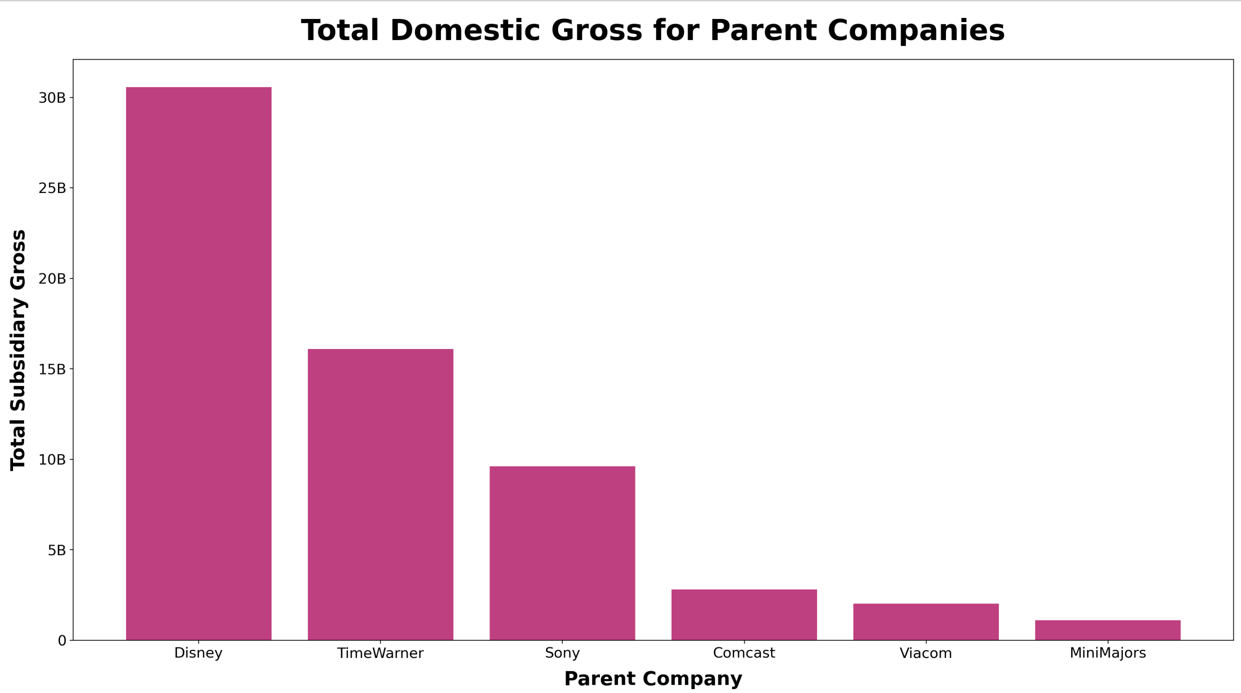
In [56]:
```
## List of unique studios. Used to create sample list for parent companies
df_gross['studio'].unique()
```

Out[56]:
```
array(['BV', 'WB', 'P/DW', 'Sum.', 'Par.', 'Uni.', 'Fox', 'Wein.', 'Son
y',
       'FoxS', 'SGem', 'WB (NL)', 'LGF', 'MBox', 'CL', 'W/Dim.', 'CBS',
       'Focus', 'MGM', 'Over.', 'Mira.', 'IFC', 'CJ', 'NM', 'SPC', 'Par
V',
       'Gold.', 'JS', 'RAtt.', 'Magn.', 'Free', '3D', 'UTV', 'Rela.',
       'Zeit.', 'Anch.', 'PDA', 'Lorb.', 'App.', 'Drft.', 'Osci.', 'IW',
       'Rog.', 'Eros', 'Relbig.', 'Viv.', 'Hann.', 'Strand', 'NGE',
       'Scre.', 'Kino', 'Abr.', 'CZ', 'ATO', 'First', 'GK', 'FInd.',
       'NFC', 'TFC', 'Pala.', 'Imag.', 'NAV', 'Arth.', 'CLS', 'Mont.',
       'Olive', 'CGld', 'FOAK', 'IVP', 'Yash', 'ICir', 'WOW', 'FM', 'FD',
       'Vari.', 'TriS', 'ORF', 'IM', 'Elev.', 'Cohen', 'NeoC', 'Jan.',
       'MNE', 'Trib.', 'Vita.', 'Rocket', 'OMNI/FSR', 'KKM', 'Argo.',
       'Libre', 'FRun', 'P4', 'KC', 'MPFT', 'Icar.', 'AGF', 'NYer',
       'LG/S', 'WHE', 'WGUSA', 'MPI', 'RTWC', 'FIP', 'RF', 'KL', 'ArcEn
t',
       'PalUni', 'EpicPics', 'EOne', 'AF', 'LD', 'TFA', 'WAMCR', 'PM&E',
       'A24', 'Distrib.', 'Imax', 'PH', 'Da.', 'E1', 'Shout!', 'SV', 'C
E',
       'VPD', 'KE', 'Outs', 'HTR', 'DR', 'Ampl.', 'CP', 'BGP', 'Crnth',
       'LGP', 'EC', 'FUN', 'STX', 'BG', 'PFR', 'BST', 'FCW', 'U/P', 'UH
E',
       'FR', 'Orch.', 'PBS', 'ITL', 'AR', 'JBG', 'BH Tilt', 'Zee', 'HC',
       'GrtIndia', 'PNT', 'Neon', 'Good Deed', 'ParC', 'Amazon', 'BBC',
       'Affirm', 'Annapurna', 'MOM', 'Studio 8', 'Global Road',
       'Trafalgar', 'ENTMP', 'Greenwich', 'Spanglish', 'Blue Fox',
       'Aviron', 'VE', 'Grindstone', 'Darin Southa'], dtype=object)
```

In [57]:
```
## Sample list of studios owned by parent companies
Disney = ['BV', 'Fox', 'FoxS', 'W/Dim.']
Comcast = ['Uni', 'P/DW', 'Focus']
TimeWarner = ['WB', 'WB (NL)']
Viacom = ['CBS', 'P/DW', 'Mira', 'ParV']
Sony = ['SPC', 'Sony', 'TriS']
MiniMajors = ['RAtt.', 'Rela.']
```

In [58]:
```
## Simplified DFs to calculate total domestic gross from studios
Disney_df = dfm2[dfm2['studio'].isin(Disney)]
Comcast_df = dfm2[dfm2['studio'].isin(Comcast)]
TimeWarner_df = dfm2[dfm2['studio'].isin(TimeWarner)]
Viacom_df = dfm2[dfm2['studio'].isin(Viacom)]
Sony_df = dfm2[dfm2['studio'].isin(Sony)]
Mini_df = dfm2[dfm2['studio'].isin(MiniMajors)]
```

In [59]:
```
## Plot of total domestic gross per parent company (hard coded)
fig, ax = plt.subplots(figsize=(18,10), dpi=200)

n = ['Disney', 'TimeWarner', 'Sony', 'Comcast', 'Viacom', 'MiniMajors']
m = [Disney_df['domestic_gross'].sum(), TimeWarner_df['domestic_gross'].sum
     Sony_df['domestic_gross'].sum(), Comcast_df['domestic_gross'].sum(),
     Viacom_df['domestic_gross'].sum(),  Mini_df['domestic_gross'].sum()]

plt.bar(n, m, color='#bf4080')
plt.xticks(ticks=n, labels=n, fontsize=15)
plt.yticks(ticks=[0,5000000000, 10000000000, 15000000000, 20000000000, 2500
           labels=['0','5B', '10B', '15B', '20B', '25B', '30B'], fontsize=1
ax.set_xlabel("Parent Company", fontsize=20, fontweight='bold', labelpad=10
ax.set_ylabel("Total Subsidiary Gross", fontsize=20, fontweight='bold', lab
ax.set_title("Total Domestic Gross for Parent Companies", fontsize=30, font

plt.tight_layout()
```



Final Observations & Insights

- Owning multiple studios that produce content yields incredible profits domestically. Microsoft should seek to acquire multiple production studios to create varied content.
- The highest grossing films are all franchises (Marvel, Jurassic Park, Star Wars, etc). It is highly recommended that any action films made be based upon Microsoft franchises to avoid licensure/copyright fees.

Deja's Data Preparation & Analysis

In [60]:
```
# Display dataframe
display(movie_type)
display(movie_type.info())
```

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16
...	...	...	...	...	...	...	...
26512	26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13
26513	26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01
26514	26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01
26515	26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22
26516	26516	[53, 27]	309885	en	The Church	0.600	2018-10-05

26517 rows × 10 columns

```
<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
```

None

Observations & Insights:

- There are 26517 total entries with 0 missing values.
- The vote count needs to be reduced to a more relevant number and discard outliers like 1.
- Genre IDs need to be translated into genre names.
- There are lots of foreign films, and we are currently only interested in English-language films.
- There are duplicate titles.

In [61]:
```
# Show when movies were released
movie_type.sort_values(by='release_date', ascending=False)
```

Out[61]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	
26057	26057	[27, 80, 80, 80, 80, 80, 80]	570704	en	Murdery Christmas	0.840	2020-12-25	Mu Chris
24265	24265	[10749, 18]	428836	en	Ophelia	8.715	2019-06-28	O
24892	24892	[99]	541577	en	This Changes Everything	3.955	2019-06-28	Cha Every
24819	24819	[18]	481880	en	Trial by Fire	4.480	2019-05-17	Tr
24297	24297	[18]	415085	en	All Creatures Here Below	8.316	2019-05-17	Crea E
...	...	...	...	...	...	...	...	
11192	11192	[18, 36, 10749]	887	en	The Best Years of Our Lives	9.647	1946-12-25	The Ye Our
26345	26345	[]	316707	en	How Walt Disney Cartoons Are Made	0.600	1939-01-19	How D Car Are
3580	3580	[35, 18, 10749]	263768	fr	Le Bonheur	1.653	1936-02-27	Bo
21758	21758	[27, 53]	43148	en	The Vampire Bat	2.292	1933-01-21	Va
14335	14335	[18, 10752]	143	en	All Quiet on the Western Front	9.583	1930-04-29	All c We

26517 rows × 10 columns

In [62]:
```
## Filter for movies in English
movie_type = movie_type.loc[movie_type['original_language'] == "en"]

## Condense data to get most voted on movies
movie_type_data = movie_type.loc[movie_type['vote_count'] >= 10000]
```

In [63]:
```
movie_type_data["genre_ids"].iloc[0]
```

Out[63]:
```
'[12, 14, 10751]'
```

In [64]:
```
## Separate genre ids with multiple values
movie_type_data.genre_ids = movie_type_data.genre_ids.map(lambda x:eval(x))
```

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/pandas/core/gen
eric.py:5168: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  self[name] = value
```

In [65]:
```
movie_type_data = movie_type_data.explode("genre_ids")
```

In [66]:
```
## Filter out genres with few votes
movie_type_data= movie_type_data.loc[movie_type_data['genre_ids'] <= 878]
movie_type_data
```

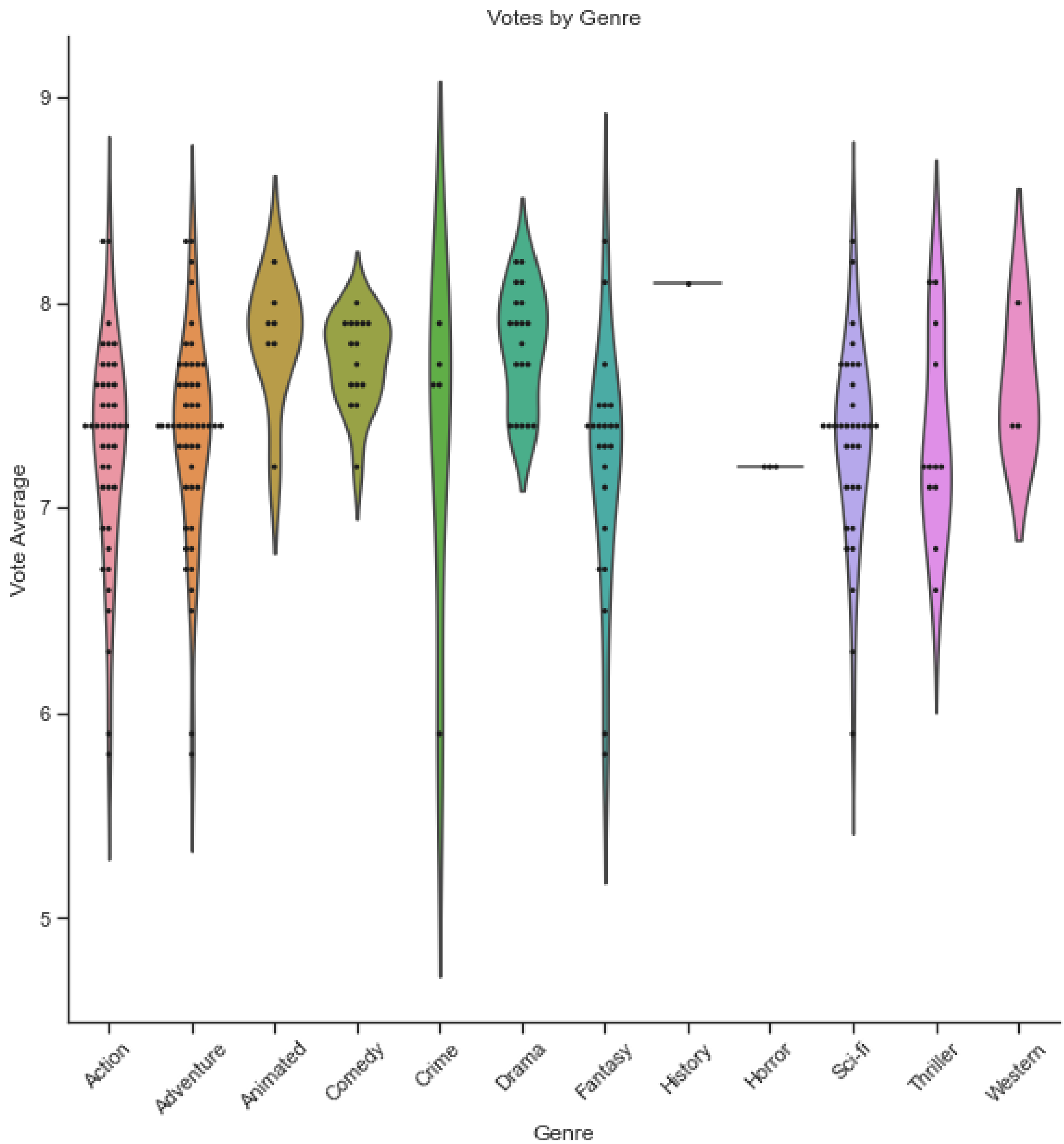
Out[66]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	
0	0	12	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	H P an De Hall P
0	0	14	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	H P an De Hall P
2	2	12	10138	en	Iron Man 2	28.515	2010-05-07	Iron
2	2	28	10138	en	Iron Man 2	28.515	2010-05-07	Iron
2	2	878	10138	en	Iron Man 2	28.515	2010-05-07	Iron
...	...	...	...	...	...	...	...	
23819	23819	12	284053	en	Thor: Ragnarok	43.450	2017-11-03	- Ragr
23819	23819	35	284053	en	Thor: Ragnarok	43.450	2017-11-03	- Ragr
23819	23819	14	284053	en	Thor: Ragnarok	43.450	2017-11-03	- Ragr
24005	24005	27	346364	en	It	13.966	2017-09-08	
24005	24005	53	346364	en	It	13.966	2017-09-08	

212 rows × 10 columns

In [67]:
```
movie_type_data["genre_ids"].replace(
    {12: "Adventure",
     14: "Fantasy",
     16: "Animated",
     18: "Drama",
     27: "Horror",
     28: "Action",
     35: "Comedy",
     36: "History",
     37: "Western",
     53: "Thriller",
     80: "Crime",
     878: "Sci-fi"}, inplace=True)
```

In [68]:
```
## Create a violin plot to display the relationship between vote averages a
sns.set_theme(style="ticks", color_codes=True)
g = sns.catplot(x=movie_type_data["genre_ids"].astype("category"),
                y="vote_average",
                kind="violin", height=8,
                inner=None,
                data=movie_type_data)
sns.swarmplot(x=movie_type_data["genre_ids"].astype("category"), y="vote_av
              color="k", size=3, data=movie_type_data, ax=g.ax)
g.set_xticklabels(rotation=45)
g.ax.set_title("Votes by Genre")
g.ax.set_ylabel("Vote Average")
g.ax.set_xlabel("Genre");
```



Final Observations & Insights:

- This graph shows the correlation between the average ratings.

- Movies were given by genre. While genres can overlap, the focus of resources should be towards action, adventure, fantasy, sci-fi, comedy and crime movies.
- Crime has the highest rating, but the other 5 categories have higher volumes of consumer interaction.

James's Data Preparation & Analysis

In [69]:
```
## Display dataframes
display(title_ratings)
display(title_basics)
display(title_akas)
```

	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
...	...	...	...
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

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

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 6 columns

	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
...	...	...	...	...	...	...	...	...
331698	tt9827784	2	Sayonara kuchibiru	NaN	NaN	original	NaN	1.0
331699	tt9827784	3	Farewell Song	XWW	en	imdbDisplay	NaN	0.0
331700	tt9880178	1	La atención	NaN	NaN	original	NaN	1.0
331701	tt9880178	2	La atención	ES	NaN	NaN	NaN	0.0
331702	tt9880178	3	The Attention	XWW	en	imdbDisplay	NaN	0.0

331703 rows × 8 columns

In [70]:
```
## Set tconst as index for joining 3 separate dataframes
title_ratings.set_index('tconst', inplace = True)
title_basics.set_index('tconst', inplace =True)

## Rename title_id to tconst to join this data frame into our main data fra
title_akas.rename(columns={'title_id':'tconst'}, inplace=True)
title_akas.set_index('tconst', inplace=True)

## Complete first join between title_ratings and title_basics
merged1 = title_ratings.join(title_basics, on='tconst', how='inner')

## Complete second join between the above result and title_akas
imdb_data = merged1.join(title_akas, on='tconst', how='inner')

## Since there are lots of missing data and irrelevant data, the data is fi
imdb_US_movie = imdb_data[imdb_data['region'] == 'US'].copy()

## Sort in descending order
imdb_US_movie = imdb_US_movie.sort_values(by=['numvotes'], ascending=False)

## Drop all duplicate titles from the dataframe
imdb_US_movie = imdb_US_movie.drop_duplicates(subset=['original_title'], ke

## Filter out irrelevant columns in our dataframe
## Set the index to title
imdb_US_movie = imdb_US_movie.set_index('primary_title').copy()
imdb_US_movie = imdb_US_movie[['averagerating', 'numvotes', 'start_year', '
imdb_US_movie.head()
```

Out[70]:

primary_title	averagerating	numvotes	start_year	runtime_minutes	genres
Inception	8.8	1841066	2010	148.0	Action,Adventure,Sci-Fi
The Dark Knight Rises	8.4	1387769	2012	164.0	Action,Thriller
Interstellar	8.6	1299334	2014	169.0	Adventure,Drama,Sci-Fi
Django Unchained	8.4	1211405	2012	165.0	Drama,Western
The Avengers	8.1	1183655	2012	143.0	Action,Adventure,Sci-Fi

In [71]:
```
mean = imdb_US_movie['numvotes'].mean()
median = imdb_US_movie['numvotes'].median()
print(f'mean is {mean} and median is {median}')
```

```
mean is 8626.783681653427 and median is 67.0
```

Observations & Insights:

- The mean vote counts is significantly larger than the median. This means the data is extremely skewed right.
- Therefore we will use the upper quantiles of this data since movies with lower ratings are not significant in our analysis

In [72]:
```
## We will consider top 10 and top 1 percent of the data by vote counts
ten_percentile = imdb_US_movie['numvotes'].quantile(.90)
one_percentile = imdb_US_movie['numvotes'].quantile(.99)

print("top 10 percentile:", round(ten_percentile))
print("top 1 percentile:", round(one_percentile))
```

```
top 10 percentile: 5795.0
top 1 percentile: 223993.0
```

In [73]:
```
## Movies filtered based on the top 10 percentile of vote counts
top_10_percent = imdb_US_movie[(imdb_US_movie['numvotes']>=5795)].reset_ind

## Divide up multiple genres for a single movie into a separate row
top_10_percent.loc[:,('genres')] = top_10_percent.loc[:,('genres')].str.spl
top_10 = top_10_percent.explode('genres')

## Filter out top 5 genres of movie counts within the 10 percentile
genres_count_10_percent = pd.DataFrame(top_10['genres'].value_counts())
genres_count_10_percent = genres_count_10_percent.head()

## Create a table with average number of votes for top five movie genre cou
genres_avgvotes_10 = pd.DataFrame(top_10.groupby('genres')['numvotes'].mean
genres_avgvotes_10 = genres_avgvotes_10.reset_index()
genres_avgvotes_10 = genres_avgvotes_10[genres_avgvotes_10['genres'].isin([
genres_avgvotes_10.set_index('genres', inplace=True)

## Join the movie counts and average number of votes by genre
top10 = genres_count_10_percent.join(genres_avgvotes_10)
top10.rename(columns={'genres':'movie counts'}, inplace=True)
top10 = top10.reset_index().rename(columns={'index':'movie genre'})
top10
```

Out[73]:

	movie genre	movie counts	numvotes
0	Drama	1356	68484.173304
1	Comedy	898	68912.766147
2	Action	694	131380.325648
3	Thriller	497	78318.523139
4	Adventure	475	169220.597895

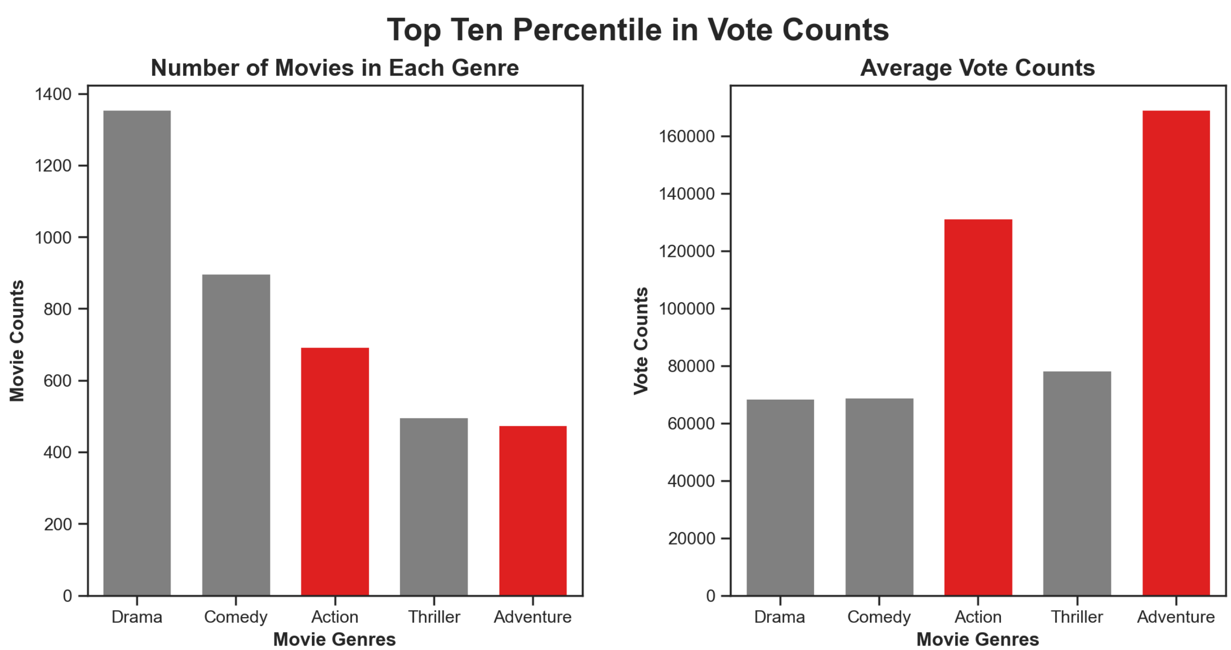
In [74]:

```
## Repeat all the steps above to gather top 1 percentile of number of votes
top_1_percent = imdb_US_movie[(imdb_US_movie['numvotes']>=223993)].reset_in
top_1_percent.loc[:,('genres')] = top_1_percent.loc[:,('genres')].str.split
top_1 = top_1_percent.explode('genres')
genres_count_1percent = pd.DataFrame(top_1['genres'].value_counts())
genres_count_1 = genres_count_1percent.head()
genres_avgvotes_1 = pd.DataFrame(top_1.groupby('genres')['numvotes'].mean()
genres_avgvotes_1 = genres_avgvotes_1.reset_index()
genres_avgvotes_1 = genres_avgvotes_1[genres_avgvotes_1['genres'].isin(['Dr
genres_avgvotes_1.set_index('genres', inplace=True)
top1 = genres_count_1.join(genres_avgvotes_1)
top1.rename(columns={'genres':'movie counts'}, inplace=True)
top1 = top1.reset_index().rename(columns={'index':'movie genre'})
top1
```

Out[74]:

	movie genre	movie counts	numvotes
0	Action	137	420961.715328
1	Adventure	127	443631.188976
2	Drama	98	407722.265306
3	Sci-Fi	64	490730.984375
4	Comedy	59	386693.762712

In [75]:
```
## Two separate bar graphs of top 1 percentile(number of votes) movie genre

def change_width(ax, new_value) :
    for patch in ax.patches :
        current_width = patch.get_width()
        diff = current_width - new_value
        patch.set_width(new_value)
        patch.set_x(patch.get_x() + diff * .5)

fig, (ax1, ax2) = plt.subplots(figsize=(13,6), ncols=2, dpi=200)

x=top10['movie genre']
y=top10['movie counts']
y1=top10['numvotes']
clrs=['grey' if (x != 'Action' and x != 'Adventure') else 'red' for x in x]

sns.barplot(x=x, y=y, palette=clrs, ax=ax1)
ax1.set_title('Number of Movies in Each Genre', fontweight='bold', fontsize
ax1.set_xlabel('Movie Genres', fontweight='bold', fontsize=12)
ax1.set_ylabel('Movie Counts', fontweight='bold', fontsize=12)
change_width(ax1, 0.7)

sns.barplot(x=x, y=y1, palette=clrs, ax=ax2)
ax2.set_title('Average Vote Counts', fontweight='bold', fontsize=15)
ax2.set_xlabel('Movie Genres', fontweight='bold', fontsize=12)
ax2.set_ylabel('Vote Counts', fontweight='bold', fontsize=12);
change_width(ax2, 0.7)

plt.subplots_adjust(wspace=.3)

fig.suptitle("Top Ten Percentile in Vote Counts", fontweight='bold', fontsi
```

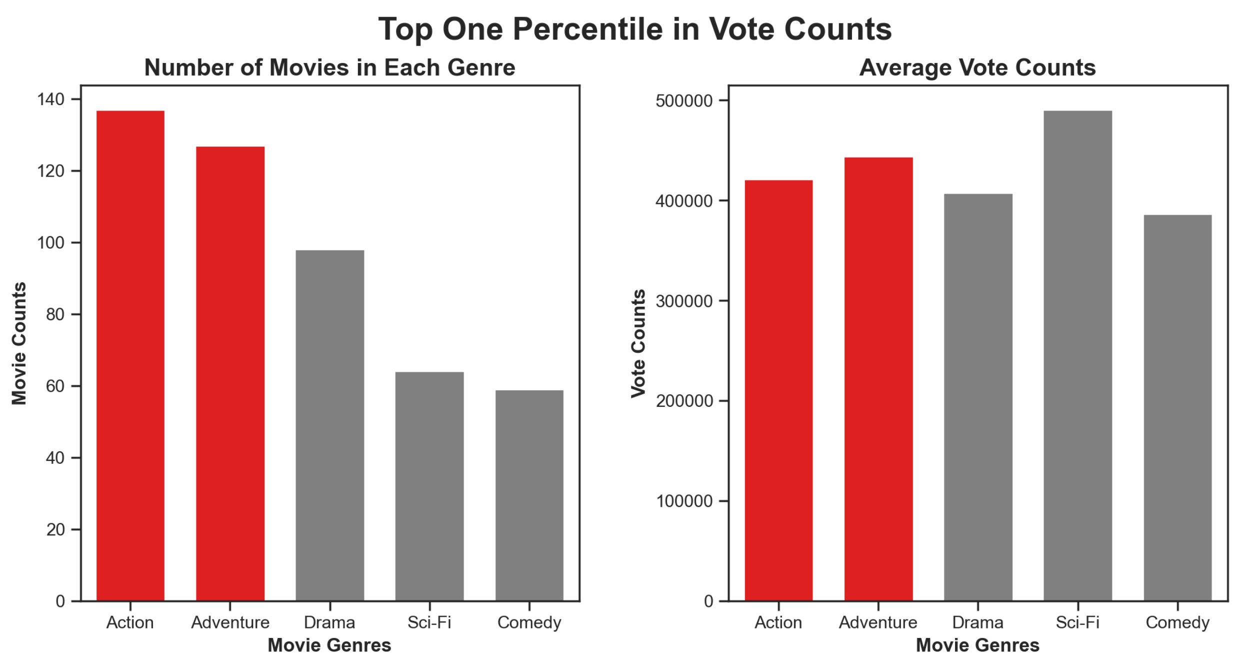


Observations & Insights:

- From the IMDB dataset, we have extracted the top ten quantiles of the movie rating vote counts.

- Although drama and comedy movies are more prevalent in the top ten quantiles, action and adventure movies have much higher average vote counts.
- This indicates that as we move up to the higher quantile in vote counts, the number of action and adventure movies grows.

In [76]:
```
## Two separate bar graphs of top 1 percentile(number of votes) movie genre

def change_width(ax, new_value) :
    for patch in ax.patches :
        current_width = patch.get_width()
        diff = current_width - new_value
        patch.set_width(new_value)
        patch.set_x(patch.get_x() + diff * .5)

fig, (ax1, ax2) = plt.subplots(figsize=(13,6), ncols=2, dpi=200)

xx=top1['movie genre']
yy=top1['movie counts']
y2=top1['numvotes']
clrs=['grey' if (x != 'Action' and x != 'Adventure') else 'red' for x in to

sns.barplot(x=xx, y=yy, palette=clrs, ax=ax1)
ax1.set_title('Number of Movies in Each Genre', fontweight='bold', fontsize
ax1.set_xlabel('Movie Genres', fontweight='bold', fontsize=12)
ax1.set_ylabel('Movie Counts', fontweight='bold', fontsize=12)
change_width(ax1, 0.7)

sns.barplot(x=xx, y=y2, palette=clrs, ax=ax2)
ax2.set_title('Average Vote Counts', fontweight='bold', fontsize=15)
ax2.set_xlabel('Movie Genres', fontweight='bold', fontsize=12)
ax2.set_ylabel('Vote Counts', fontweight='bold', fontsize=12);
change_width(ax2, 0.7)

plt.subplots_adjust(wspace=.3)

fig.suptitle("Top One Percentile in Vote Counts", fontweight='bold', fontsi
```



Final Observations & Insights:

- As seen in the previous graph, this top one quantile visualization confirms that as we move up to datas in the higher quantile, number of action and adventure movies increases.

- Despite the fact that all the movies here in this data were in the top one percentile, adventure and action movies had second and third most average vote counts.

Conclusions

From these insights, we can conclude the following:

- The majority of blockbuster films are established franchises or properties. Movies created by Microsoft should follow this trend.
- The largest production studios are all under parent companies. Microsoft should acquire at least one additional studio to increase production rates and gross earning potential.
- The data suggests that content production be focused upon the Drama, Comedy, Action, Sci-fi, and animated genres.