JUPITER TEAM MOVIE ANALYSIS PROJECT

Analysis Goals

Our team was tasked by Microsoft to advise their fledgling studio on what types of movies would be the most successful. Our goal in this project is to give recommendations to Microsoft team by performing three in-depth analyses about movie studios, movie genres, and cast & crew. Our collective recommendations can be found at the last section of this report.

The Data

Our data came from a number of sources, as no single database held all of the information required for our analysis.

IMDB - Internet Movie Database - The go-to website for information on all things movies, this served as the primary base for compiling the necessary information. IMDB's size was a double edged sword, its tables often consisting of tens of thousands of rows. This gave us a fantastic number of films and personnel to investigate, but sifting through that much data had its own challenges as well.

TheNumbers.com - For all of IMDB's greatness, it does not provide us with the financial information we wanted to add to our analysis. Thenumbers.com is a website wholly devoted to tracking budgets and revenues for films. The fact that it tracked both was critical, because that allowed us to calculate net profit by adding together foreign and domestic revenue, then subtracting the budget.

TMDB - The Movie Database - This database provided additional ratings, genres, and financial data.

Box Office Mojo - This database was combined with the others to give additional ratings and popularity data.

We will start by importing the libraries needed for perfoming data exploration, analysis, and visualization.

In [1]:

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

%matplotlib inline
```

1. Movie Studios Analysis

Business Recommendation

I'm going to recommend that Microsoft mirror the competition in this industry. The Walt Disney Company purchased 21st Century Fox in 2019 for 71.3 billion, Amazon just recently purchased MGM studios for 8.4 billion, and Warner Media merged with Discovery. Sony Pictures would be a really interesting acquisiton for a tech giant looking to enter the film industry, and I'll show why in this analysis.

1.1. Reading the Data

In [2]:

```
tmdb_data = pd.read_csv('data/tmdb.movies.csv', index_col=0)
bom_data = pd.read_csv('data/bom.movie_gross.csv')
```

In [3]:
```
tmdb_data.head()
```

Out[3]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
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	[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	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186

In [4]:
```
bom_data.head()
```

Out[4]:

	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

1.2. Data Merging & Cleaning

Examining the dataframes above, we can see that they all have a column named title. Let's merge the information on the title column.

In [5]:
```
df_merge = pd.merge(tmdb_data, bom_data, on='title')

#Create new dataframe with the columns we want
new_df = df_merge[['title', 'year', 'studio', 'popularity', 'domestic_gross', 'foreign_gross']].sor
new_df.head()
```

Out[5]:

	title	year	studio	popularity	domestic_gross	foreign_gross
2702	Last Letter	2018	CL	0.600	181000.0	NaN
2555	Mortal Engines	2018	Uni.	40.095	16000000.0	67700000
2566	Ready Player One	2018	WB	30.029	137700000.0	445200000
2565	Mary Poppins Returns	2018	BV	30.419	172000000.0	177600000
2564	The Meg	2018	WB	31.397	145400000.0	384800000

1.2.1. Data Cleaning

Add foreign and domestic profits together to get an international picture of how much each movie has made.

In [6]:
```
# Convert the domestic gross column to a numeric column so it can be added to the foreign gross col
# NaN values.
new_df['domestic_gross'] = pd.to_numeric(new_df['domestic_gross'])
new_df['domestic_gross'] = new_df['domestic_gross'].fillna(0)

# remove commas from foreign gross, convert to a numeric column, and remove all NaN values.
new_df['foreign_gross'].replace(',','', regex=True, inplace=True)
new_df['foreign_gross'] = pd.to_numeric(new_df['foreign_gross'])
new_df['foreign_gross'] = new_df['foreign_gross'].fillna(0)

# Create a new column adding the domestic and foreign gross values together to show each title's to
new_df['total_gross'] = new_df['domestic_gross'] + new_df['foreign_gross']

# Limit results to only the past 10 years (2011)
new_df = new_df.loc[new_df['year'] >= 2011]

# Order our new dataframe by total_gross to view the top grossing films of the last ten years.
new_df = new_df.sort_values(by='total_gross', ascending=False)
new_df
```

Out[6]:

	title	year	studio	popularity	domestic_gross	foreign_gross	total_gross
1622	Avengers: Age of Ultron	2015	BV	44.383	459000000.0	946400000.0	1.405400e+09
608	Black Panther	2018	BV	2.058	700100000.0	646900000.0	1.347000e+09
609	Black Panther	2018	BV	44.140	700100000.0	646900000.0	1.347000e+09
2320	Star Wars: The Last Jedi	2017	BV	34.293	620200000.0	712400000.0	1.332600e+09
2319	Star Wars: The Last Jedi	2017	BV	34.293	620200000.0	712400000.0	1.332600e+09
...	...	...	...	...	...	...	...
1132	Into the White	2013	Magn.	7.072	700.0	0.0	7.000000e+02
555	Death of a Superhero	2012	Trib.	5.158	600.0	0.0	6.000000e+02
2423	2:22	2017	Magn.	11.316	400.0	0.0	4.000000e+02
2251	Satanic	2016	Magn.	6.403	300.0	0.0	3.000000e+02
1152	Storage 24	2013	Magn.	6.441	100.0	0.0	1.000000e+02

2470 rows × 7 columns

Note*

Something to keep in mind is that Disney acquired 21st Century Fox in 2019. The data here from Fox shows movies that were made before 2019, so they are still considered to be made by Fox during the time this data was gathered.

1.3. Data Exploration and Questions

In this step I'll explore the data set and answer these questions:

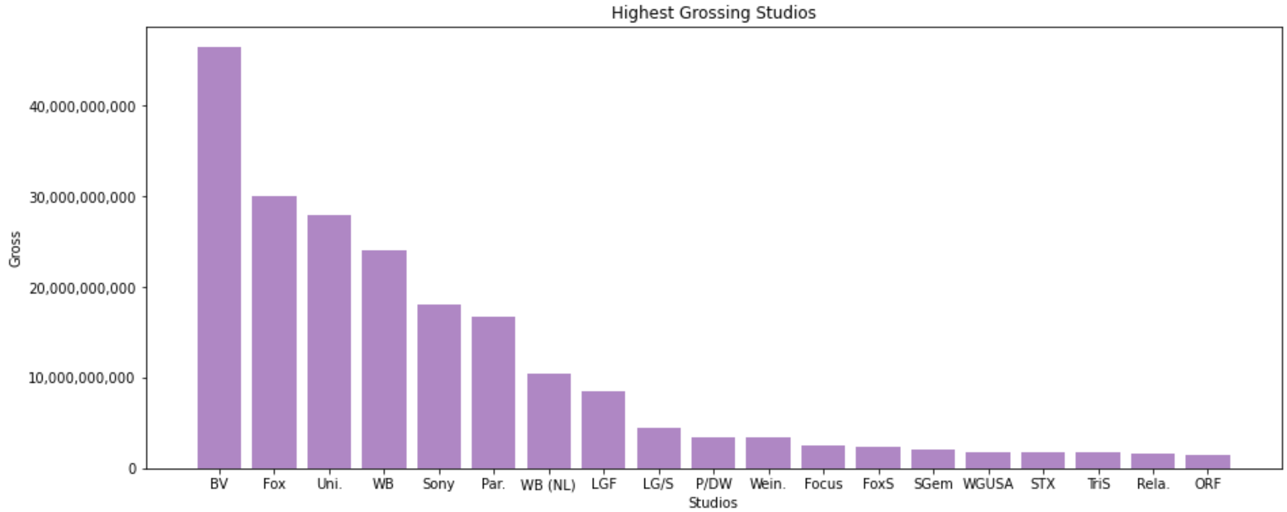
1. Which studios grossed the most money in the past 10 years?
2. Which studios made the most movies in the past 10 years?
3. Which studios made the most popular movies in the last 10 years?

1.3.1. Which studios grossed the most money in the past 10 years?

In [7]:
```
# Create a new data frame with the total_gross as the values and the columns as the studios/
studio_totals = new_df.pivot_table(index=new_df.index, values='total_gross', columns='studio')

# Make a dictionary of all these studios and their total gross, then sort them
# from greatest to least.
# Dictionary of the dataframe from studio_totals
dict_studio_totals = dict(studio_totals.sum(0))

# Find the average of all of the studios total profits
list_studio_values = list(studio_totals.sum(0))
list_studio_index = list(studio_totals.sum(0).index)
avg_list_studio_values = sum(list_studio_values) / len(list_studio_values)

#I want my plot to show studios that had at or above the average total_gross of all films.
dict_studio_totals = dict((k, v) for k, v in dict_studio_totals.items() if v >= avg_list_studio_val

#Now I want to sort my values from greatest to least
dict_studio_totals = {k: v for k, v in sorted(dict_studio_totals.items(), key=lambda item: item[1],
dict_studio_totals
```

Out[7]:
```
{'BV': 46440514631.7,
 'Fox': 30095166596.0,
 'Uni.': 27890183191.4,
 'WB': 24012620999.0,
 'Sony': 18114886498.0,
 'Par.': 16730279696.0,
 'WB (NL)': 10508699999.0,
 'LGF': 8426402400.0,
 'LG/S': 4496523999.0,
 'P/DW': 3420300000.0,
 'Wein.': 3359832697.0,
 'Focus': 2513440000.0,
 'FoxS': 2404889300.0,
 'SGem': 1993187000.0,
 'WGUSA': 1828468400.0,
 'STX': 1733600000.0,
 'TriS': 1711315000.0,
 'Rela.': 1679894000.0,
 'ORF': 1421526999.0}
```

In [8]:
```
#I'll get my x axis from the keys in the dictionary and my height from the values in the dictionary
x = list(dict_studio_totals.keys())
height = list(dict_studio_totals.values())

fig, ax = plt.subplots(figsize=(15,6))

ax.bar(x, height, color='#af87c4')
ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
ax.set_title('Highest Grossing Studios')
ax.set_xlabel('Studios')
ax.set_ylabel('Gross');
```

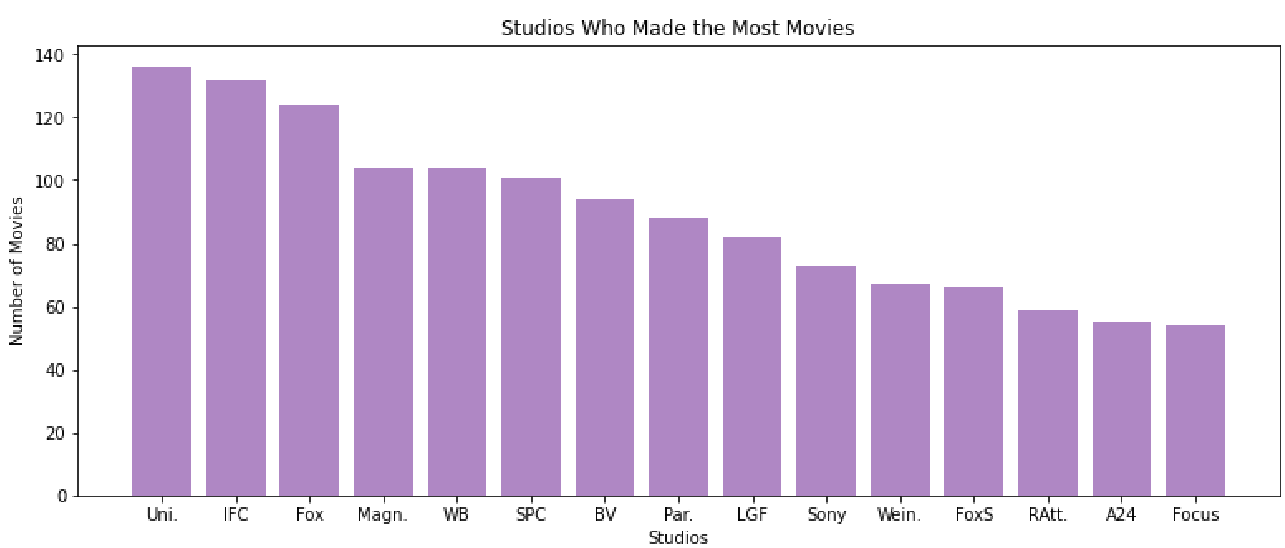


Note*

Disney is represented as BV. Disney appears to gross the most money based on this data.

1.3.2. Which studios made the most movies in the last 10 years?

In [9]:
```
# Show the value counts for each studio that gives us the number of movies each studio made.
studio_counts = new_df['studio'].value_counts()
x = list(studio_counts.index)
y = list(studio_counts.values)

#Let's only show studios that made 50 or more movies.
height = []
for i in y:
    if i >= 50:
        height.append(i)

fig, ax = plt.subplots(figsize=(13,5))

ax.bar(x[0:15], height, color='#af87c4')

ax.set_title('Studios Who Made the Most Movies')
ax.set_xlabel('Studios')
ax.set_ylabel('Number of Movies');
```



Note*

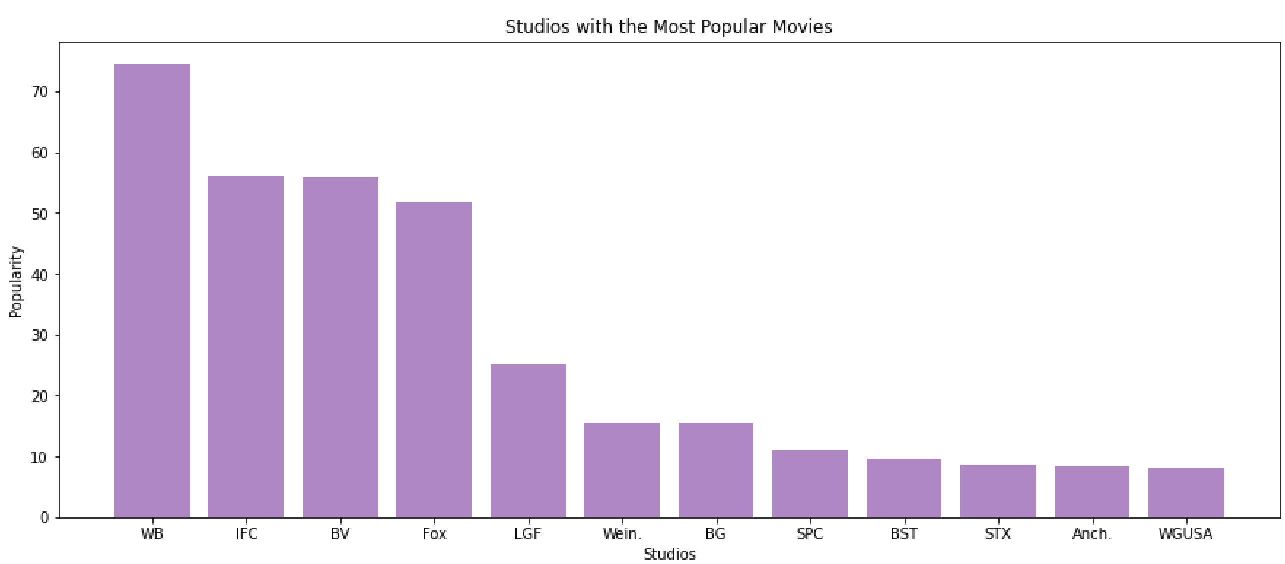
It appears that just because the studio makes a lot of movies, doesn't mean they gross the most money. Even though Disney made the most money, they didn't make the highest quantity of movies.

1.3.3. Which studios made the most popular movies in the last 10 years?

In [10]:
```
# Sort our dataframe to see the most popular movies
popularity_df = new_df.sort_values(by='popularity', ascending=False)

# Create a dataframe that shows the top 50 most popular movies in the last 10 years
popularity_df = popularity_df[['studio', 'title', 'popularity']]
top_pop = popularity_df.pivot_table(index=new_df.index, values='popularity', columns='studio').heac

# Create a dictionary showing the popularity for each studio
dict_top_pop = dict(top_pop.sum(0))

# Now limit those results to see studios that had higher popularity than 8.
dict_top_pop = dict((k, v) for k, v in dict_top_pop.items() if v > 8)

# Sort them from greatest to least
dict_top_pop = {k: v for k, v in sorted(dict_top_pop.items(), key=lambda item: item[1], reverse=Tru
dict_top_pop
```

Out[10]:
```
{'WB': 74.477,
 'IFC': 56.138000000000005,
 'BV': 55.827999999999996,
 'Fox': 51.71600000000001,
 'LGF': 25.131,
 'Wein.': 15.641,
 'BG': 15.521999999999998,
 'SPC': 10.952,
 'BST': 9.486,
 'STX': 8.574,
 'Anch.': 8.322000000000001,
 'WGUSA': 8.16}
```

In [11]:
```
x = list(dict_top_pop.keys())
height = list(dict_top_pop.values())

fig, ax = plt.subplots(figsize=(15,6))

ax.bar(x, height, color='#af87c4')

ax.set_title('Studios with the Most Popular Movies')
ax.set_xlabel('Studios')
ax.set_ylabel('Popularity');
```



1.4. Merging New Data

I'll bring in new data that contains the production budgets so I can calculate net profits and ROI%. I'll clean this data up a bit, as well.

In [12]:
```
#Read in our new data set
tn_data = pd.read_csv('data/tn.movie_budgets.csv')
tn_data = tn_data[['movie', 'production_budget']]

#Clean up this data
#remove the commas from the data so we can convert this column to a numeric column to calculate our
tn_data['production_budget'].replace(',','', regex=True, inplace=True)
#remove the dollar signs.
tn_data['production_budget'].replace({'\$':''}, regex = True, inplace=True)

#rename 'movie' to 'title' for an easier merge since the other data shows 'title' for the movie nam
tn_data = tn_data.rename(columns={"movie": "title"})
tn_data
```

Out[12]:

	title	production_budget
0	Avatar	425000000
1	Pirates of the Caribbean: On Stranger Tides	410600000
2	Dark Phoenix	350000000
3	Avengers: Age of Ultron	330600000
4	Star Wars Ep. VIII: The Last Jedi	317000000
...	...	...
5777	Red 11	7000
5778	Following	6000
5779	Return to the Land of Wonders	5000
5780	A Plague So Pleasant	1400
5781	My Date With Drew	1100

5782 rows × 2 columns

1.4.1. Merge the new data

In [13]:
```
# Merge the new data set on the shared 'title' column.
df_merge = pd.merge(new_df, tn_data, on='title')
df_merge = df_merge[['title', 'studio', 'year', 'total_gross', 'production_budget']]
df_merge['production_budget'] = pd.to_numeric(df_merge['production_budget'])

# Create a new column for net profit and ROI%
df_merge['net_profit'] = df_merge['total_gross'] - df_merge['production_budget']
net_profit_df = df_merge

# ROI = 100(net profit / budget)
net_profit_df['ROI%'] = 100 * (net_profit_df['net_profit'] / net_profit_df['production_budget'])

#Sort them to see the studios with the highest net profit.
net_profit_df.sort_values(by='net_profit', ascending=False, inplace=True)
net_profit_df
```

Out[13]:

	title	studio	year	total_gross	production_budget	net_profit	ROI%
1	Black Panther	BV	2018	1.347000e+09	200000000	1.147000e+09	573.500000

	title	studio	year	total_gross	production_budget	net_profit	ROI%
2	Black Panther	BV	2018	1.347000e+09	200000000	1.147000e+09	573.500000
3	Jurassic World: Fallen Kingdom	Uni.	2018	1.309500e+09	170000000	1.139500e+09	670.294118
4	Frozen	BV	2013	1.276400e+09	150000000	1.126400e+09	750.933333
5	Frozen	BV	2013	1.276400e+09	150000000	1.126400e+09	750.933333
...	...	...	...	...	...	...	...
565	R.I.P.D.	Uni.	2013	7.830000e+07	130000000	-5.170000e+07	-39.769231
624	Monster Trucks	Par.	2017	6.450000e+07	125000000	-6.050000e+07	-48.400000
1208	Evolution	IFC	2016	2.480000e+04	80000000	-7.997520e+07	-99.969000
1209	Evolution	IFC	2016	2.480000e+04	80000000	-7.997520e+07	-99.969000
768	Mars Needs Moms	BV	2011	3.900000e+07	150000000	-1.110000e+08	-74.000000

1224 rows × 7 columns

1.4.2. What studios had the highest net profit?

In [14]:

```
#Created a new table showing the columns as studios and values as their net profits.
studio_profits = net_profit_df.pivot_table(index=df_merge.index, values='net_profit', columns='stud

#Find the average net profit for all the studios. I want to calculate the average to see the studio
#above this amount.
list_studio_profits = list(studio_profits.sum(0))
list_studio_index = list(studio_profits.sum(0).index)
avg_list_studio_profits = sum(list_studio_profits) / len(list_studio_profits)
avg_list_studio_profits

#Make a dictionary of the studio_profits dataframe to get the keys as the studio name and their val
a = dict(studio_profits.sum(0))
net_profit_keys = list(a.keys())
net_profit_values = list(a.values())

#I want to show the studios that had at or above average net profit.
b = dict((k, v) for k, v in a.items() if v >= avg_list_studio_profits)

#Now I want to sort my values from greatest to least and show studios with the highest net profits.
c = {k: v for k, v in sorted(b.items(), key=lambda item: item[1], reverse=True)}
c
```

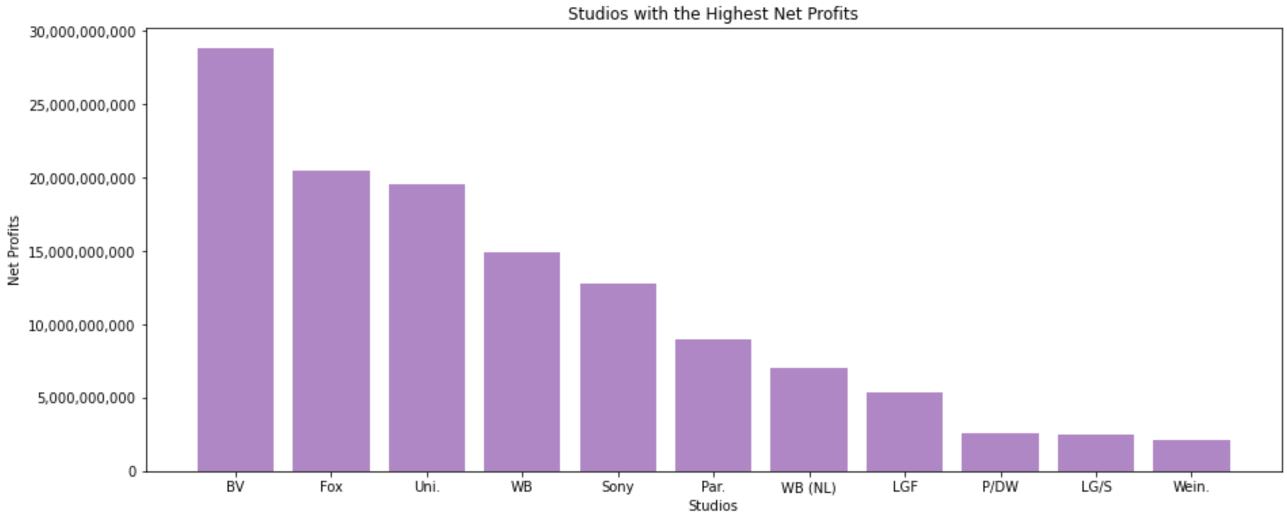
Out[14]:

```
{'BV': 28799801369.5,
 'Fox': 20495033596.0,
 'Uni.': 19510861191.4,
 'WB': 14879520998.0,
 'Sony': 12798499998.0,
 'Par.': 8942766996.0,
 'WB (NL)': 7066199999.0,
 'LGF': 5392518000.0,
 'P/DW': 2615300000.0,
 'LG/S': 2492493999.0,
 'Wein.': 2077783397.0}
```

In [15]:

```
c_keys = list(c.keys())
c_values = list(c.values())

fig, ax = plt.subplots(figsize=(15,6))

ax.bar(x=c_keys, height=c_values, color='#af87c4')
ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
```

```
ax.set_title('Studios with the Highest Net Profits')
ax.set_xlabel('Studios')
ax.set_ylabel('Net Profits');
```



The visualizations for net profit show Disney still has the highest profits.

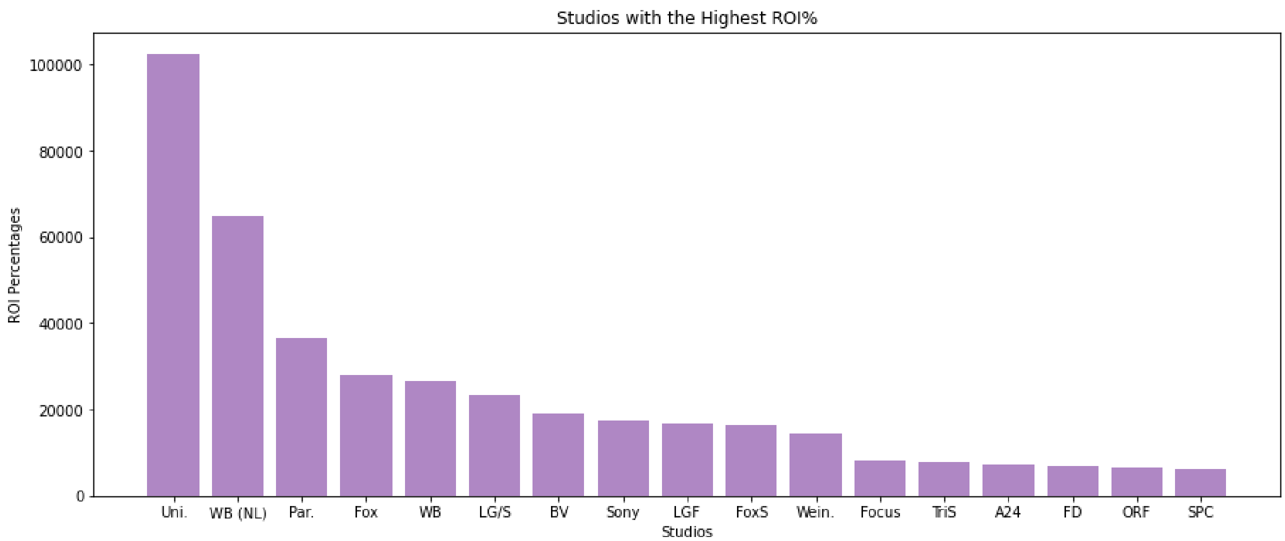
1.4.3. ROI%.

In [16]:
```
# Create a dataframe with each studio's ROI% as a value and the studios as columns
studio_roi_df = net_profit_df.pivot_table(index=df_merge.index, values='ROI%', columns='studio')

# Find the average ROI% so we can look at studios with above average ROI%
list_studio_roi = list(studio_roi_df.sum(0))
list_roi_index = list(studio_roi_df.sum(0).index)
avg_list_studio_roi = sum(list_studio_roi) / len(list_studio_roi)
avg_list_studio_roi

# Create a dictionary showing each studio's ROI%
a = dict(studio_roi_df.sum(0))
studio_roi_df_keys = list(a.keys())
studio_roi_df_values = list(a.values())

#I want to show the studios that had at or above average ROI%.
b = dict((k, v) for k, v in a.items() if v >= avg_list_studio_roi)

#Now I want to sort my values from greatest to least and show studios with the highest ROI%.
c = {k: v for k, v in sorted(b.items(), key=lambda item: item[1], reverse=True)}
c
```

Out[16]:
```
{'Uni.': 102350.77846329947,
 'WB (NL)': 64790.53066726985,
 'Par.': 36643.83359765203,
 'Fox': 27933.836389553227,
 'WB': 26675.473175505667,
 'LG/S': 23352.14995755767,
 'BV': 18953.12201122903,
 'Sony': 17554.63871073789,
 'LGF': 16668.087357812623,
 'FoxS': 16342.791022944726,
 'Wein.': 14395.870932086902,
 'Focus': 8198.029771815489,
 'TriS': 7878.192455828485,
 'A24': 7324.1393665158375,
 'FD': 6934.615873015872,
 'ORF': 6605.56696154593,
 'SPC': 6340.5804291464465}
```

In [17]:
```
#Visualization of each studio's ROI%
fig, ax = plt.subplots(figsize=(15,6))
```

```
x = list(c.keys())
height = list(c.values())

ax.bar(x, height, color='#af87c4')

ax.set_title('Studios with the Highest ROI%')
ax.set_xlabel('Studios')
ax.set_ylabel('ROI Percentages');
```



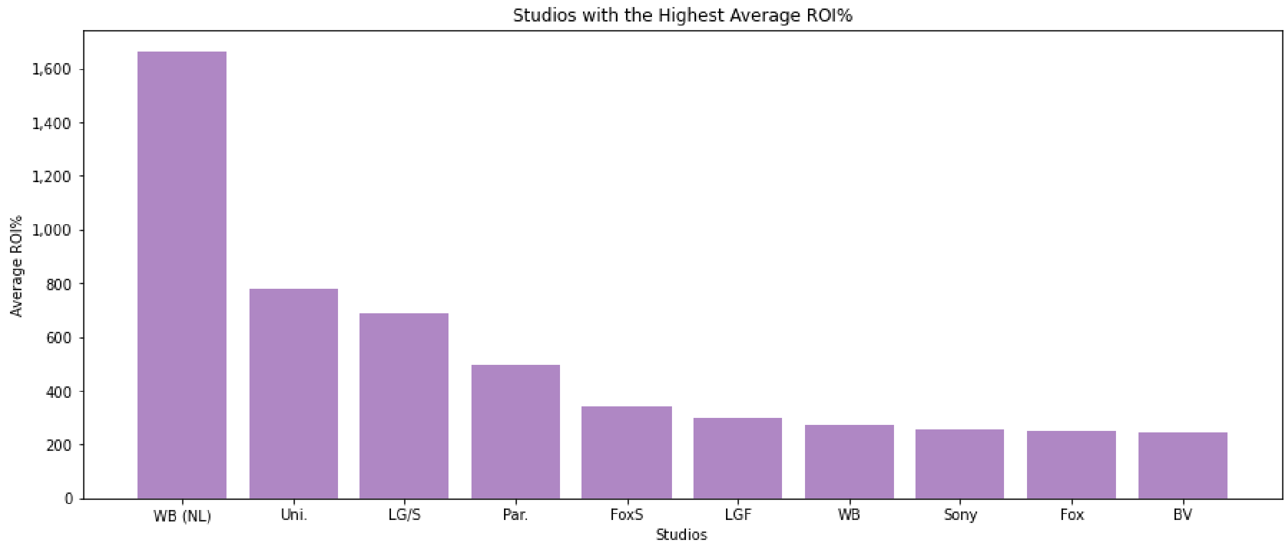
1.5. Exploring the Stats

I'll examine the the average ROI% and average net profits that each studio made for each movie.

In [18]:
```
# Create a dataframe of the stats for studios that had the highest average ROI%
roi_stats = studio_roi_df.describe()[1:4:5]
avg_roi = roi_stats[['Uni.', 'WB (NL)', 'Par.', 'Fox', 'WB', 'LG/S', 'BV', 'Sony', 'LGF', 'FoxS']]

# Create a dictionary where the keys are the studios and the means are the values.
a = dict(avg_roi.sum(0))

# Sort them from greatest to least
a = {k: v for k, v in sorted(a.items(), key=lambda item: item[1], reverse=True)}

# Visualizations for average ROI% of each studio.
x = list(a.keys())
height = list(a.values())

fig, ax = plt.subplots(figsize=(15,6))

ax.bar(x, height, color='#af87c4')
ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
ax.set_title('Studios with the Highest Average ROI%')
ax.set_xlabel('Studios')
ax.set_ylabel('Average ROI%')
a
```

Out[18]:
```
{'WB (NL)': 1661.2956581351243,
 'Uni.': 781.3036523915987,
 'LG/S': 686.8279399281668,
 'Par.': 495.1869405088111,
 'FoxS': 340.4748129780152,
 'LGF': 297.64441710379685,
 'WB': 272.1987058725068,
 'Sony': 258.1564516284985,
```

```
 'Fox': 251.65618368966864,
 'BV': 246.14444170427313}
```

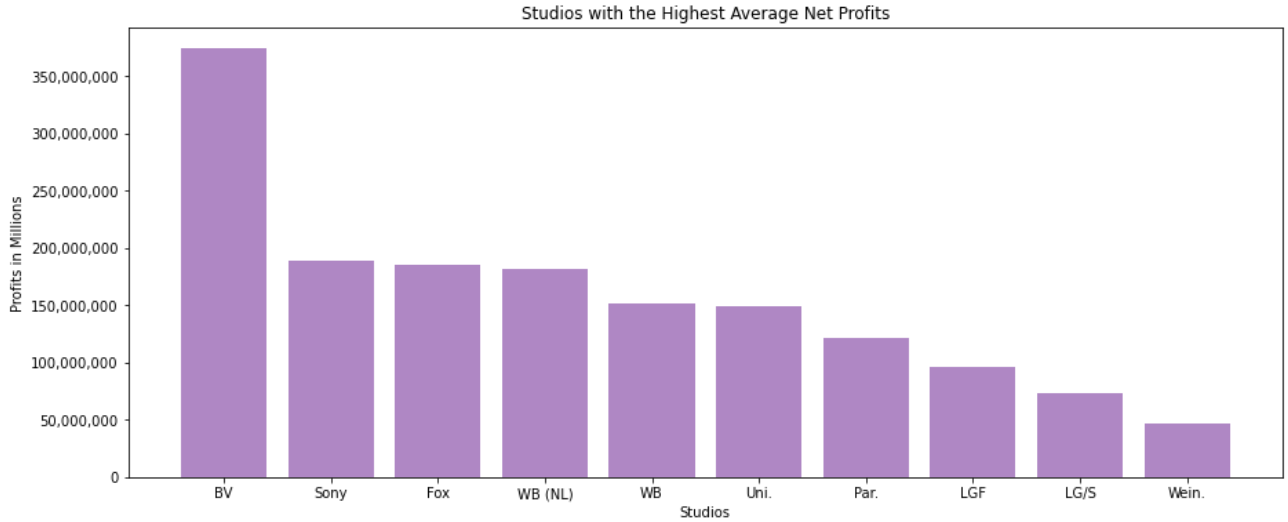


In [19]:

```
# Create a dataframe of the stats for studios that had the highest net profits.
studio_profit_stats = studio_profits.describe()
stats = studio_profit_stats[['BV', 'Fox', 'Uni.', 'WB', 'Sony', 'Par.', 'WB (NL)', 'LGF', 'LG/S', '

# Show the average net profits for each studio in our stats dataframe
mean_np_studios = stats[1:4:5]

# Create a dictionary where the keys are the studios and the means are the values.
d = dict(mean_np_studios.sum(0))

# Sort them from greatest to least
d = {k: v for k, v in sorted(d.items(), key=lambda item: item[1], reverse=True)}

# Visualizations for average net profits of each studio.
x = list(d.keys())
height = list(d.values())

fig, ax = plt.subplots(figsize=(15,6))

ax.bar(x, height, color='#af87c4')
ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
ax.set_title('Studios with the Highest Average Net Profits')
ax.set_xlabel('Studios')
ax.set_ylabel('Profits in Millions')
d
```

Out[19]:

```
{'BV': 374023394.40909094,
 'Sony': 188213235.2647059,
 'Fox': 184639942.3063063,
 'WB (NL)': 181184615.35897437,
 'WB': 151831846.91836736,
 'Uni.': 148937871.69007635,
 'Par.': 120848202.64864865,
 'LGF': 96294964.28571428,
 'LG/S': 73308647.02941176,
 'Wein.': 47222349.93181818}
```



1.6. Recommendations

It appears Sony Pictures has the second highest net profits on average for each film they've made. I'd recommend Microsoft make a bid on Sony Pictures for their new movie studio. Several of the studios sitting at the top of the data alongside Sony Pictures have already been acquired or have merged with larger companies in the last few years. I wouldn't recommend buying Disney because Disney is currently valued over 330 billion dollars according to Yahoo Finance statistics on their market cap (https://finance.yahoo.com/quote/DIS/key-statistics?p=DIS). I wouldn't recommend 21st Century Fox, because Disney acquired them in 2019 for 71.3 billion. I wouldn't recommend Warner Brothers because they merged with Discovery as of this year. I wouldn't recommend Universal because they're owned by Comcast. I wouldn't recommend MGM Studios because they were recently purchased by Amazon for $8.45 billion in May of this year. This leaves Sony Pictures as the dangling cheese for potentially several companies. The data here shows their films are profitable and their average net profits are second to Disney based on this data. I'm also not the first to come to this conclusion. Digging deeper into the questions from this data, I found a Vox article from 2017 with a similar suggestion that "Sony Pictures would make an interesting buy for a tech giant": https://www.vox.com/2017/1/17/14273598/sony-pictures-buy-amazon-alphabet-facebook-apple.

According to this article, it is believed by Vox that Sony Pictures may have been worth about $30 billion in 2017. That would be a cheaper buy than what Disney paid for 21st Century Fox.

Also, Sony Pictures owns the film rights for the Spider-Man movies. The rights for the Spider Man movies are so valuable, Sony won't just give them up. Disney had to write up licensing contracts with Sony Pictures to be able to feature Spider Man in the Marvel Universe. Spider-Man films are some of Sony Pictures highest grossing, collectively grossing over 6 billion. If Microsoft can acquire Sony Pictures, Microsoft could have those rights. More information on this can be found here: https://en.wikipedia.org/wiki/Spider-Man_in_film.

---

2. Movie Genres Analysis

Business Recommendation

One of the business recommendation we are delivering to the Microsoft Studio team will be about choosing best genres for their future movies. Which genre categories have more ratings, and/or popularity will determine our recommendations. For this analysis, we will use IMDB and TMDB data to measure average ratings and popularity, respectively. In this work, we will focus on the analysis of the movies with release year between 2010 and 2019.

In the first part of the analysis, we will investigate average ratings and genre relationship. Secondly, we will use popularity measure to look into each genre. In the final part, we will compare the results from each analysis, and make recommendations accordingly.

2.1. Movie Genres vs. Average Rating Relationship

1.1. Importing the Data

First we need to read IMDB ratings data and IMDB movie basic data files.

In [20]:
```
imdb_title_ratings = pd.read_csv('data/imdb.title.ratings.csv.gz', compression='gzip')
imdb_title_ratings
```

Out[20]:

	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

In [21]:
```
imdb_title_basics = pd.read_csv('data/imdb.title.basics.csv')
imdb_title_basics
```

Out[21]:

	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

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

146144 rows × 6 columns

2.1.2. Preparing Dataframes

Merging Dataframes

Before analyzing the data, we need to construct the desired dataframe from IMDB title basics table and IMDB title ratings table.

First of all, let's start with merging these two datafames by using 'tconst' column in both dataframes, and create a new 'imdb_title_and_ratings' dataframe.

In [22]:
```
imbd_title_and_ratings = pd.merge(imdb_title_ratings, imdb_title_basics, on='tconst')
imbd_title_and_ratings
```

Out[22]:

	tconst	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	
0	tt10356526	8.3	31	Laiye Je Yaarian	Laiye Je Yaarian	2019	117.0	I
1	tt10384606	8.9	559	Borderless	Borderless	2019	87.0	Docu
2	tt1042974	6.4	20	Just Inès	Just Inès	2010	90.0	
3	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventur
4	tt1060240	6.5	21	Até Onde?	Até Onde?	2011	73.0	Myster
...	...	...	...	...	...	...	...	
73851	tt9805820	8.1	25	Caisa	Caisa	2018	84.0	Docu
73852	tt9844256	7.5	24	Code Geass: Lelouch of the Rebellion - Glorifi...	Code Geass: Lelouch of the Rebellion Episode III	2018	120.0	Action,Animat
73853	tt9851050	4.7	14	Sisters	Sisters	2019	NaN	Actic
73854	tt9886934	7.0	5	The Projectionist	The Projectionist	2019	81.0	Docu
73855	tt9894098	6.3	128	Sathru	Sathru	2019	129.0	

73856 rows × 8 columns

When we sort 'imbd_title_and_ratings' dataframe by the 'start_year' column, it is seen that the data contains movies from 2010 to 2019:

In [23]:
```
imbd_title_and_ratings.sort_values(by='start_year', ascending=False)
```

Out[23]:

	tconst	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	
0	tt10356526	8.3	31	Laiye Je Yaarian	Laiye Je Yaarian	2019	117.0	
23991	tt5929354	5.1	18	Out of Sight, Out of Mind	Out of Sight, Out of Mind	2019	131.0	
24002	tt5969180	6.5	1312	I Hate Kids	I Hate Kids	2019	89.0	
24012	tt6032090	8.6	15	Use Me	Use Me	2019	NaN	
24028	tt6081668	7.6	51	Mating	Parningsmarknaden	2019	93.0	
...	...	...	...	...	...	...	...	
36328	tt1754573	8.8	21	Taliya.Date.Com	Taliya.Date.Com	2010	54.0	Biograpl
36325	tt1753960	7.4	67	Israel vs Israel	Israel vs Israel	2010	58.0	
17412	tt1640202	4.3	3706	Çok Filim Hareketler Bunlar	Çok Filim Hareketler Bunlar	2010	134.0	
17411	tt1639457	5.6	11	Indiana Jones und der Speer des Schicksals	Indiana Jones und der Speer des Schicksals	2010	66.0	
7772	tt1773083	6.8	387	The Recipe	Doenjang	2010	107.0	

73856 rows × 8 columns

Now, we need to sort the dataframe from highest to lowest rating movie, and filter out movies with vote numbers less than 500 for respresentation concerns.

In [24]:

```
sorted_df = imbd_title_and_ratings.sort_values(by='averagerating', ascending=False)
sorted_df = sorted_df[sorted_df['numvotes']> 500]
sorted_df
```

Out[24]:

	tconst	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	
73780	tt8718580	9.7	639	Eghantham	Eghantham	2018	125.0	
63149	tt7131622	9.7	5600	Once Upon a Time ... in Hollywood	Once Upon a Time ... in Hollywood	2019	159.0	
3908	tt9680166	9.6	624	Yeh Suhaagraat Impossible	Yeh Suhaagraat Impossible	2019	92.0	
54115	tt4131686	9.6	1339	I Want to Live	I Want to Live	2015	106.0	Adventure,Biogr
19606	tt9343826	9.6	808	Ananthu V/S Nusrath	Ananthu V/S Nusrath	2018	149.0	Cor
...	...	...	...	...	...	...	...	
67090	tt3166658	1.1	502	Kanagawa University of Fine Arts, Office of Fi...	Kanagawa geijutsu daigaku eizou gakka kenkyuus...	2013	70.0	
9532	tt5311054	1.1	710	Browncoats: Independence War	Browncoats: Independence War	2015	98.0	
65791	tt3235258	1.0	510	My First Love	Hatsukoi	2013	82.0	

	tconst	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	
63269	tt7923374	1.0	674	Badang	Badang	2018	105.0	
7893	tt3855260	1.0	520	Yurameku	Yurameku	2014	61.0	Fantasy

13880 rows × 8 columns

Now, we need to split multiple genre names into separate rows by using explode function.

In [25]:
```
sorted_df['genres']= sorted_df['genres'].str.split(",")
sorted_df = sorted_df.explode('genres')
sorted_df
```

Out[25]:

	tconst	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	genres
73780	tt8718580	9.7	639	Eghantham	Eghantham	2018	125.0	Drama
63149	tt7131622	9.7	5600	Once Upon a Time ... in Hollywood	Once Upon a Time ... in Hollywood	2019	159.0	Comedy
63149	tt7131622	9.7	5600	Once Upon a Time ... in Hollywood	Once Upon a Time ... in Hollywood	2019	159.0	Drama
3908	tt9680166	9.6	624	Yeh Suhaagraat Impossible	Yeh Suhaagraat Impossible	2019	92.0	Comedy
54115	tt4131686	9.6	1339	I Want to Live	I Want to Live	2015	106.0	Adventure
...	...	...	...	...	...	...	...	...
63269	tt7923374	1.0	674	Badang	Badang	2018	105.0	Comedy
63269	tt7923374	1.0	674	Badang	Badang	2018	105.0	Fantasy
7893	tt3855260	1.0	520	Yurameku	Yurameku	2014	61.0	Fantasy
7893	tt3855260	1.0	520	Yurameku	Yurameku	2014	61.0	Mystery
7893	tt3855260	1.0	520	Yurameku	Yurameku	2014	61.0	Romance

30007 rows × 8 columns

Genre Counts

In our analysis, we need to compare average ratings with genres.

We can look into the genre types in the 'sorted_df' dataframe, and see number of movie produced in each genre between 2010 and 2019.

In [26]:
```
sorted_df['genres'].value_counts()
```

Out[26]:
```
Drama          7036
Comedy         4315
Action         2556
Thriller       2498
Romance        1883
Horror         1859
Crime          1660
Adventure      1237
Documentary    1221
Mystery         922
Biography       894
```

```
Sci-Fi          698
Fantasy         627
History         536
Animation       492
Family          450
Music           399
Sport           277
War             237
Musical         108
Western          62
News             36
Game-Show         1
Name: genres, dtype: int64
```

We will filter out any genre with less than 50 entries due to respresentation concerns. According to value counts above, we need to filter out all movies with genres as News and Game-Show from this analysis.

In [27]:
```
sorted_df = sorted_df[(sorted_df.genres != 'News') &
                      (sorted_df.genres != 'Game-Show')]
```

In [28]:
```
sorted_df['genres'].value_counts()
```

Out[28]:
```
Drama          7036
Comedy         4315
Action         2556
Thriller       2498
Romance        1883
Horror         1859
Crime          1660
Adventure      1237
Documentary    1221
Mystery         922
Biography       894
Sci-Fi          698
Fantasy         627
History         536
Animation       492
Family          450
Music           399
Sport           277
War             237
Musical         108
Western          62
Name: genres, dtype: int64
```

2.1.3. Grouping Average Ratings by Genres

We will group by genres and calculate average ratings associated with each genre.

In [29]:
```
imdb_mov_rat = sorted_df[['averagerating', 'genres']]
imdb_mov_rat
```

Out[29]:

	averagerating	genres
73780	9.7	Drama
63149	9.7	Comedy
63149	9.7	Drama
3908	9.6	Comedy
54115	9.6	Adventure
...	...	...
63269	1.0	Comedy
63269	1.0	Fantasy

	averagerating	genres
7893	1.0	Fantasy
7893	1.0	Mystery
7893	1.0	Romance

29970 rows × 2 columns

In [30]:
```
imdb_genre_rating_df = imdb_mov_rat.groupby(['genres']).mean().sort_values(by='averagerating', asce
imdb_genre_rating_df
```

Out[30]:

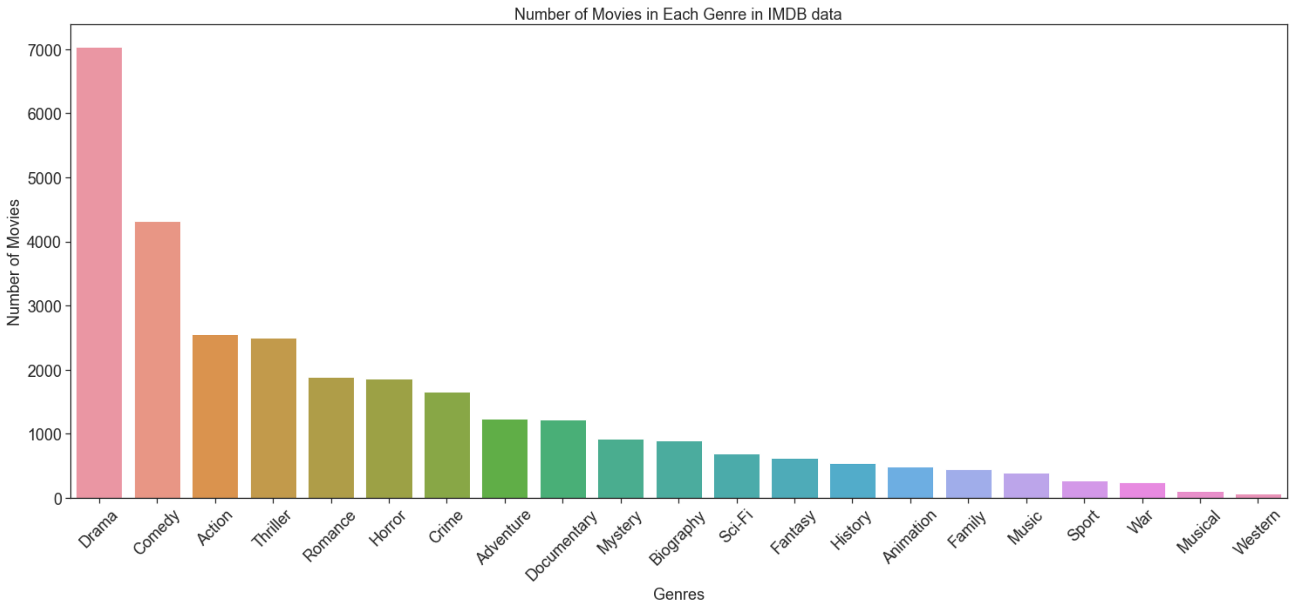
genres	averagerating
Documentary	7.196806
Biography	6.937696
History	6.787313
Sport	6.786643
Music	6.722306
Animation	6.559959
Musical	6.463889
War	6.460759
Drama	6.394912
Family	6.259333
Romance	6.238980
Crime	6.177470
Adventure	6.032336
Comedy	5.980927
Mystery	5.912798
Action	5.852269
Western	5.850000
Fantasy	5.830622
Thriller	5.727822
Sci-Fi	5.467765
Horror	5.062614

2.1.4. Visualization

Number of Movies in Each Genre with IMDB Data

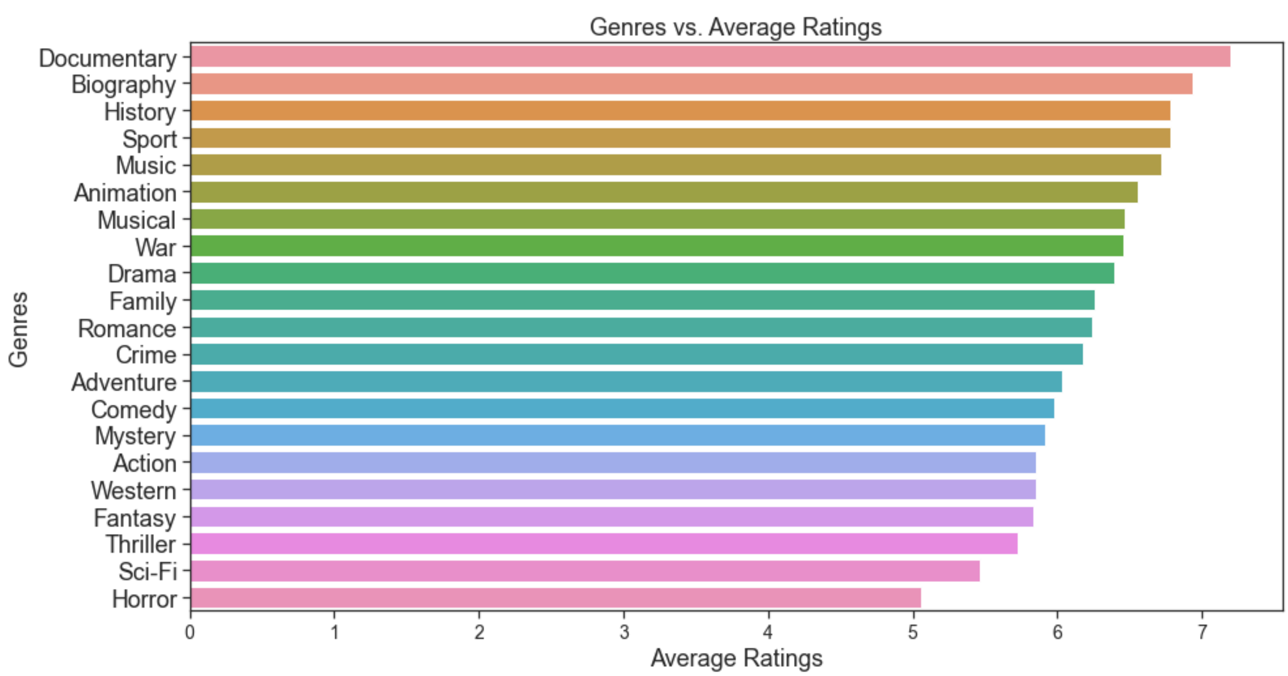
In [31]:
```
sns.set_theme(context='notebook',style="ticks", color_codes=True, palette='deep')
fig, ax = plt.subplots(figsize=(25, 10))
ax = sns.countplot(x="genres", data=sorted_df, order=sorted_df['genres'].value_counts().index)
ax.set_title('Number of Movies in Each Genre in IMDB data',fontsize=18)
ax.set_xlabel('Genres', fontsize=18)
ax.set_ylabel('Number of Movies', fontsize=18);
locs, labels = plt.xticks()
```

```
plt.setp(labels, rotation=45)
plt.xticks(fontsize=18)
plt.yticks(fontsize=18);
```



Genres vs. Average Ratings

In [32]:
```
sns.set_theme(context='notebook',style="ticks", color_codes=True, palette='deep')
fig, ax = plt.subplots(figsize=(15, 8))

ax = sns.barplot(y=imdb_genre_rating_df.index, x ='averagerating', data=imdb_genre_rating_df)
ax.set_title('Genres vs. Average Ratings', fontsize=18)
ax.set_ylabel('Genres', fontsize=18)
ax.set_xlabel('Average Ratings', fontsize=18);
plt.xticks(fontsize=14)
plt.yticks(fontsize=18);
```



If the Microsoft company is concerned about average ratings of their future movie, Documentary, Biography, or History genres are the best options. These categories have very niche group of viewers, not the general audience, but their future movie will probably have better ratings than compared to the other genres.

Now we will look into popularity measure.

2.2. Movie Genres vs. Popularity Relationship

Here we will do analysis according to genres vs popularity measure.

The data we used for this analysis is TMDB movies data stored in in 'tmdb.movies.csv' file.

For the consistency of the analysis, we will focus on movies released between 2010 - 2019.

2.2.1. Importing the Data

In [33]:
```
tmdb = pd.read_csv('data/tmdb.movies.csv')
tmdb
```

Out[33]:

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

26517 rows × 10 columns

2.2.2. Preparing Dataframes

In [34]:
```
tmdb['release_year']=pd.DatetimeIndex(tmdb['release_date']).year
tmdb
```

Out[34]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vo
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	

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

26517 rows × 11 columns

In [35]:
```
tmdb2010_2019= tmdb[(tmdb['release_year']>=2010) & (tmdb['release_year']<2020)]
tmdb2010_2019['release_year'].value_counts()
```

Out[35]:
```
2015    3258
2016    3192
2013    3147
2017    3145
2014    3137
2011    2696
2012    2659
2018    2587
2010    2406
2019      63
Name: release_year, dtype: int64
```

Now, we need to change genre ids into associated genre names. In order to do this we need to define genre id to genre name dictionary to give the key value pairs for each genre type.

In [36]:
```
genre_id_dict = {"28": "Action", "12": "Adventure", "16": "Animation", "35":"Comedy", "80": "Crime'
                 "18": "Drama", "10751": "Family", "14": "Fantasy", "36": "History", "27": "Horror'
                 "9648": "Mystery", "10749": "Romance", "878": "Science Fiction", "10770": "TV Movi
                 "10752": "War", "37": "Western"}
```

In [37]:
```
tmdb2010_2019 = tmdb2010_2019.replace(pd.Series(genre_id_dict).astype(str), regex=True)
tmdb2010_2019
```

Out[37]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	v
0	0	[Adventure, Fantasy, Family]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	v
1	1	[Fantasy, Adventure, Animation, Family]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	2	[Adventure, Action, Science Fiction]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
4	4	[Action, Science Fiction, Adventure]	27205	en	Inception	27.920	2010-07-Animation	Inception	
5	5	[Adventure, Fantasy, Family]	32657	en	Percy Jackson & the Olympians: The Lightning T...	26.691	2010-02-11	Percy Jackson & the Olympians: The Lightning T...	
...	...	...	...	...	...	...	...	...	
26512	26512	[Horror, Drama]	488143	en	Laboratory Conditions	0.600	20Drama-10-13	Laboratory Conditions	
26513	26513	[Drama, Thriller]	485975	en	_EXHIBIT_84xxx_	0.600	20Drama-05-01	_EXHIBIT_84xxx_	
26514	26514	[Fantasy, Action, Adventure]	381231	en	The Last One	0.600	20Drama-10-01	The Last One	
26515	26515	[Family, Adventure, Action]	366854	en	Trailer Made	0.600	20Drama-06-22	Trailer Made	
26516	26516	[Thriller, Horror]	309885	en	The Church	0.600	20Drama-10-05	The Church	

26290 rows × 11 columns

In [38]:
```
tmdb2010_2019['genre_ids']= tmdb2010_2019['genre_ids'].str.strip(" ] [")
```

In [39]:
```
tmdb2010_2019['genre_ids'].value_counts()
```

Out[39]:
```
Documentary                                          3687
                                                     2472
Drama                                                2248
Comedy                                               1653
Horror                                               1139
                                                     ...
Action, Crime, Science Fiction, Thriller, Mystery, Drama    1
Animation, Drama, Mystery, Science Fiction              1
Thriller, Crime, Drama, Romance                         1
Action, Adventure, Animation, Family, Fantasy, Comedy   1
Comedy, Romance, TV Movie, Fantasy                      1
Name: genre_ids, Length: 2452, dtype: int64
```

In [40]:
```
# Here is all the genres with null entries.
tmdb2010_2019[tmdb2010_2019['genre_ids'] == str()]
```

Out[40]:

Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_ave
517	517		31059	ru	Наша Russia: Яйца судьбы	3.867	2010-01-21	Nasha Russia: Yaytsa sudby	
559	559		151316	en	Shrek's Yule Log	3.424	2010-Adventure-07	Shrek's Yule Log	
589	589		75828	en	Erratum	3.154	2010-09-Animation	Erratum	
689	689		150782	en	Bikini Frankenstein	2.625	2010-01-Drama	Bikini Frankenstein	
731	731		200946	en	Weakness	2.451	2010-10-24	Weakness	
...	...	...	...	...	...	...	...	...	
26495	26495		556601	en	Recursion	0.600	20Drama-08-Action	Recursion	
26497	26497		514045	en	The Portuguese Kid	0.600	20Drama-02-Fantasy	The Portuguese Kid	
26498	26498		497839	en	The 23rd Annual Critics' Choice Awards	0.600	20Drama-01-11	The 23rd Annual Critics' Choice Awards	
26500	26500		561932	en	Two	0.600	20Drama-02-04	Two	
26506	26506		561861	en	Eden	0.600	20Drama-11-25	Eden	

2472 rows × 11 columns

In [41]:
```
tmdb2010_2019_clean = tmdb2010_2019[tmdb2010_2019['genre_ids'] != str()]
```

In [42]:
```
tmdb2010_2019_clean['genre_ids'].value_counts()
```

Out[42]:
```
Documentary                         3687
Drama                               2248
Comedy                              1653
Horror                              1139
Thriller                             479
                                    ...
Documentary, Music, History            1
Horror, Adventure                      1
Family, Science Fiction, Comedy        1
War, Documentary, Adventure, History   1
Romance, Fantasy, Family, Drama        1
Name: genre_ids, Length: 2451, dtype: int64
```

In [43]:
```
tmdb2010_2019_clean['genre_ids']= tmdb2010_2019_clean['genre_ids'].str.split(", ")
tmdb_exploded = tmdb2010_2019_clean.explode('genre_ids')
tmdb_exploded
```

```
<ipython-input-43-57175bbb6fc3>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/index
ing.html#returning-a-view-versus-a-copy
  tmdb2010_2019_clean['genre_ids']= tmdb2010_2019_clean['genre_ids'].str.split(", ")
```

Out[43]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_averag
0	0	Adventure	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.
0	0	Fantasy	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.
0	0	Family	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.
1	1	Fantasy	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.
1	1	Adventure	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.
...	...	...	...	...	...	...	...	...	.
26515	26515	Family	366854	en	Trailer Made	0.600	20Drama-06-22	Trailer Made	0.
26515	26515	Adventure	366854	en	Trailer Made	0.600	20Drama-06-22	Trailer Made	0.
26515	26515	Action	366854	en	Trailer Made	0.600	20Drama-06-22	Trailer Made	0.
26516	26516	Thriller	309885	en	The Church	0.600	20Drama-10-05	The Church	0.
26516	26516	Horror	309885	en	The Church	0.600	20Drama-10-05	The Church	0.

44820 rows × 11 columns

In [44]:

```
tmdb_exploded['genre_ids'].value_counts()
```

Out[44]:

```
Drama              8207
Comedy             5597
Documentary        4945
Thriller           4165
Horror             3658
Action             2567
Romance            2294
Science Fiction    1743
Family             1538
Crime              1484
```

```
Animation          1452
Adventure          1368
Music              1251
Mystery            1223
Fantasy            1113
TV Movie           1077
History             611
War                 323
Western             204
Name: genre_ids, dtype: int64
```

In [45]:
```
tmdb_pop_genre = tmdb_exploded[['popularity', 'genre_ids']]
tmdb_pop_genre
```

Out[45]:

	popularity	genre_ids
0	33.533	Adventure
0	33.533	Fantasy
0	33.533	Family
1	28.734	Fantasy
1	28.734	Adventure
...	...	...
26515	0.600	Family
26515	0.600	Adventure
26515	0.600	Action
26516	0.600	Thriller
26516	0.600	Horror

44820 rows × 2 columns

2.2.3. Grouping Popularity by Genres

We will group by genres and calculate average popularity for each genre.

In [46]:
```
tmdb_pop_genre_df= tmdb_pop_genre.groupby(['genre_ids']).mean().sort_values(by='popularity', ascend
tmdb_pop_genre_df
```

Out[46]:

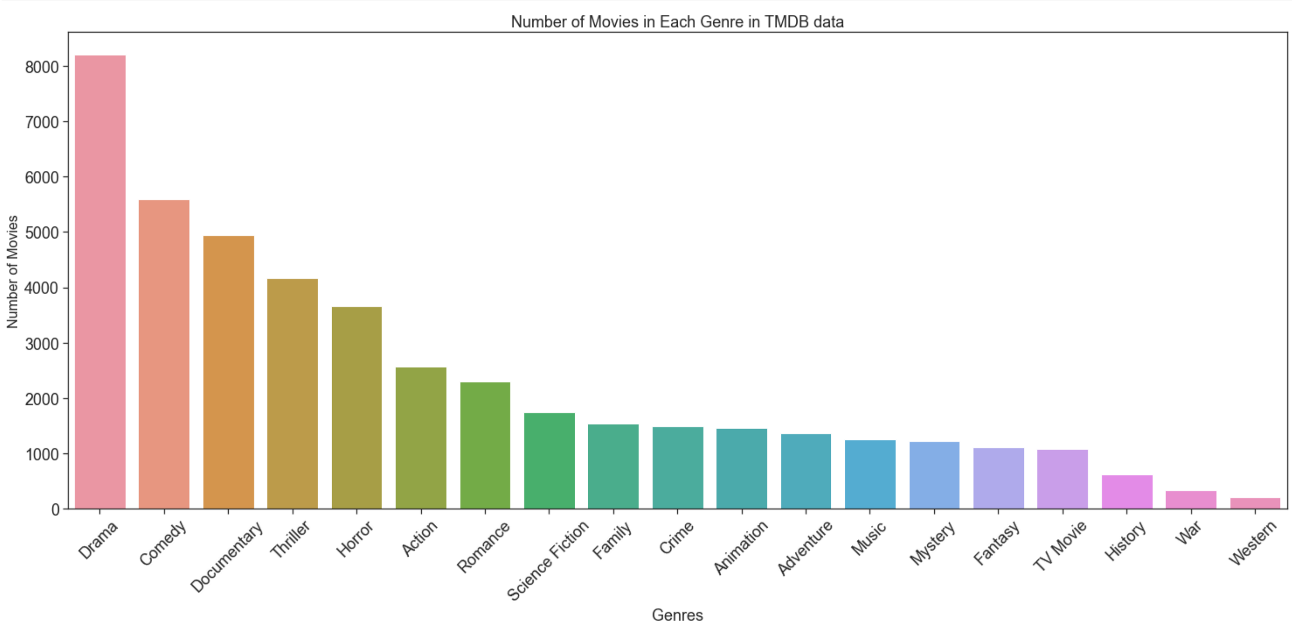
	popularity
genre_ids	
Adventure	7.506921
Action	6.417480
Fantasy	6.287668
Crime	5.360015
Science Fiction	5.167303
War	5.146235
Thriller	4.781564
Mystery	4.739093
Family	4.618991
Animation	4.472171

	popularity
genre_ids	
History	4.282982
Western	4.164294
Romance	4.129854
Drama	3.933752
Comedy	3.819133
Horror	3.220983
TV Movie	2.696560
Music	2.003803
Documentary	1.348641

2.2.4. Visualization

Number of Movies in Each Genre with TMDB data

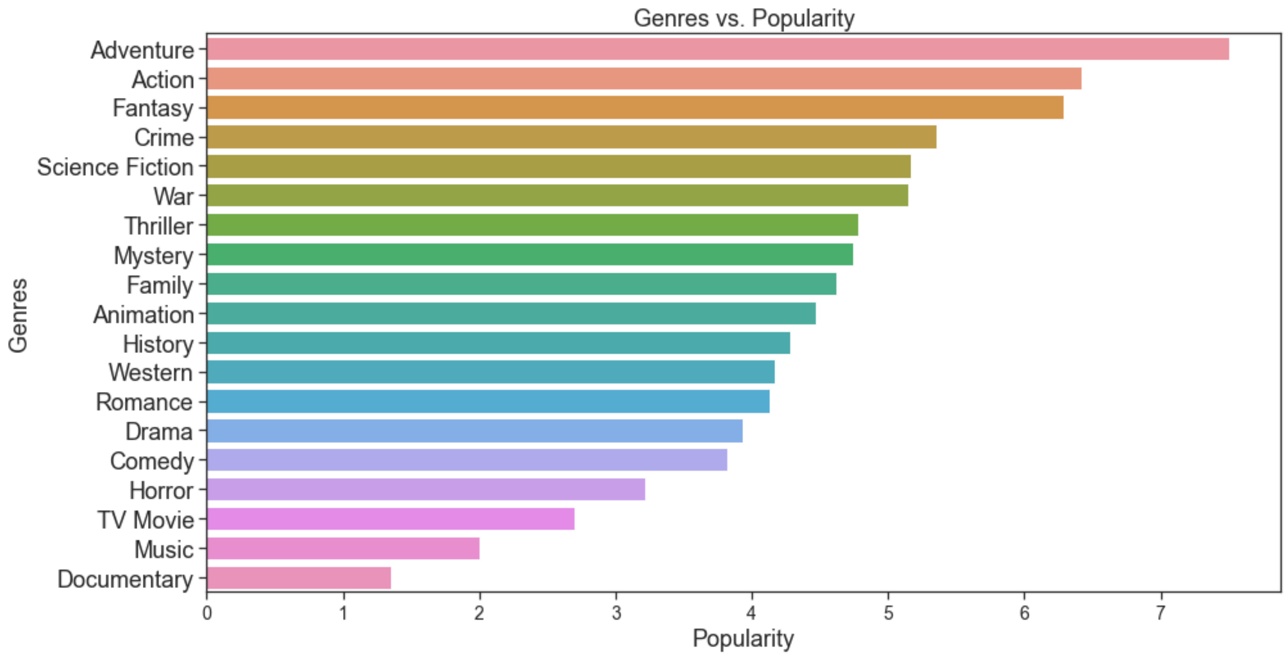
In [47]:
```
sns.set_theme(context='notebook',style="ticks", color_codes=True, palette='deep')
fig, ax = plt.subplots(figsize=(25, 10))
ax = sns.countplot(x="genre_ids", data=tmdb_exploded, order=tmdb_exploded['genre_ids'].value_counts
ax.set_title('Number of Movies in Each Genre in TMDB data',fontsize=18)
ax.set_xlabel('Genres', fontsize=18)
ax.set_ylabel('Number of Movies', fontsize=16);
locs, labels = plt.xticks()
plt.setp(labels, rotation=45)
plt.xticks(fontsize=18)
plt.yticks(fontsize=18);
```



Genres vs. Popularity

In [48]:
```
sns.set_theme(context='notebook',style="ticks", color_codes=True, palette='deep')
fig, ax = plt.subplots(figsize=(15, 8))

ax = sns.barplot(y=tmdb_pop_genre_df.index, x = 'popularity', data=tmdb_pop_genre_df)
ax.set_title('Genres vs. Popularity', fontsize=18)
ax.set_ylabel('Genres', fontsize=18)
```

```
ax.set_xlabel('Popularity', fontsize=18);
plt.xticks(fontsize=14)
plt.yticks(fontsize=18);
```



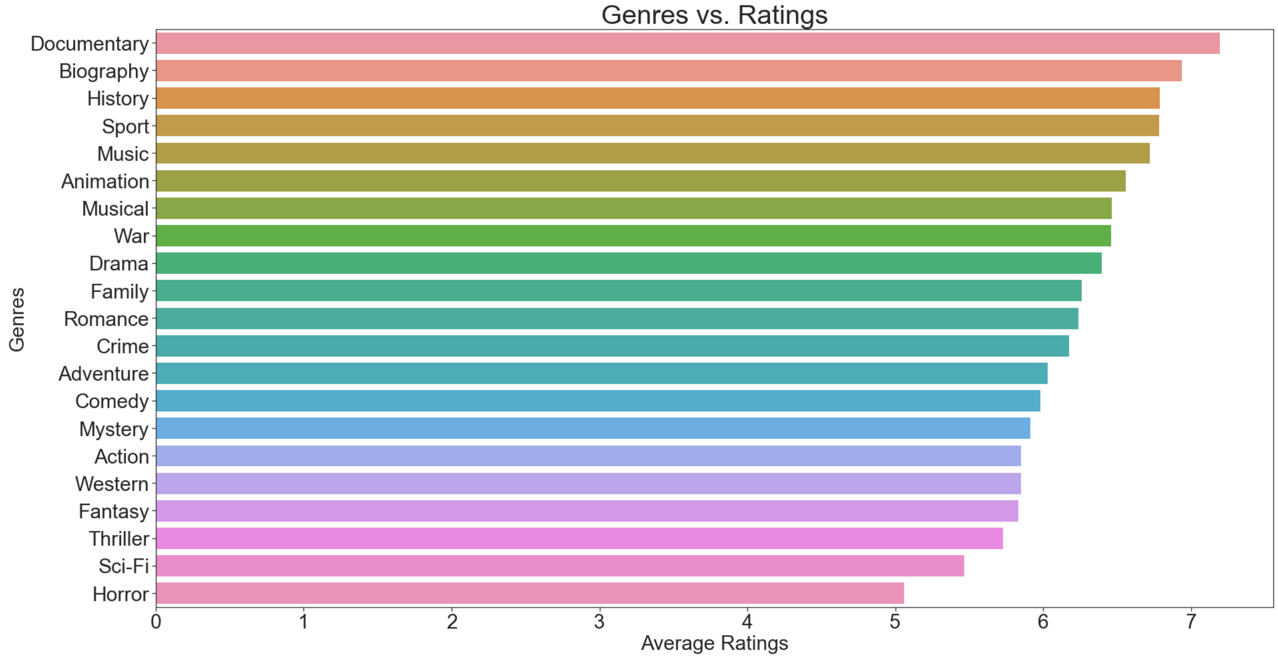
Doing an anlysis with popularity measure gave us different results compared to average reatings measure. According to popularity analysis, Adventure, Action, or Fantasy genres are the best options.

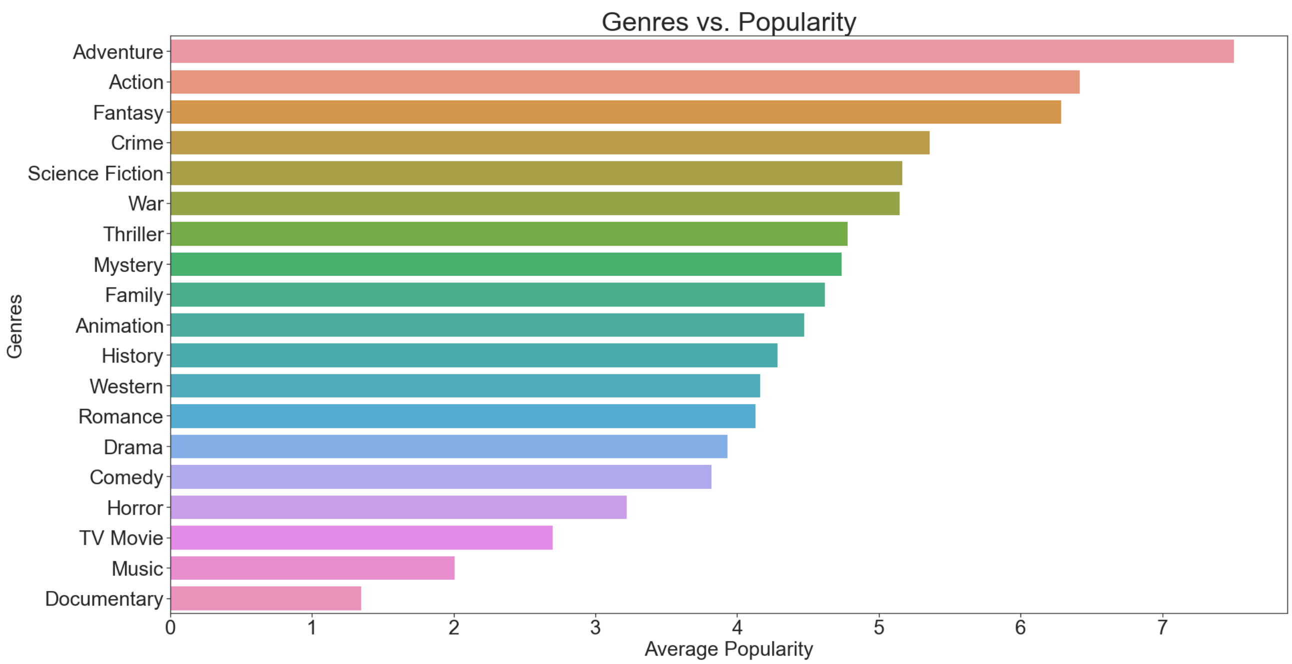
Now, let's put two bar charts together and compare our findings!

2.3. Comparison and Conclusion

In [49]:

```
sns.set_theme(context='notebook',style="ticks", color_codes=True, palette='deep')
figure, axs= plt.subplots(nrows=2, figsize=(30, 35))

sns.barplot(y=imdb_genre_rating_df.index, x ='averagerating', data=imdb_genre_rating_df, ax=axs[0])
sns.barplot(y=tmdb_pop_genre_df.index, x = 'popularity', data=tmdb_pop_genre_df, ax=axs[1])

axs[0].set_title('Genres vs. Ratings', fontsize=40)
axs[0].set_xlabel('Average Ratings', fontsize=30);
axs[0].set_ylabel('Genres', fontsize=30)
axs[0].tick_params(labelsize=30)


axs[1].set_title('Genres vs. Popularity', fontsize=40)
axs[1].set_ylabel('Genres', fontsize=30)
axs[1].set_xlabel('Average Popularity', fontsize=30)
axs[1].tick_params(labelsize=30);
```





According to both analyses, it is seen that there is no straightforward answer for which genre types should be recommended to the Microsoft Studio team.

If the Microsoft team more concerned about the ratings of their future films, producing movies in Documentary, Biography, or History categories will be a better option. These genres have less total movie counts, but they have higher ratings due to their niche audience. However, choosing genre type according to average rating measure cannot guarentee it will be watched by general audience.

On the other hand, if the Microsoft team is more concerned about the popularity of their future films, sticking to Adventure, Action, or Fantasy genres will be a better option. These genres will bring more popularity to their future movies, which can also increase popularity of Microsoft brand itself. These movies reach larger general audience rather than niche group of viewers.

Therefore, we can conclude that choosing the best genre for a future movie depends heavily on the expectation of the Microsoft team. However, as a team we advise Microsoft team to focus on popularity to have more reach for their future films. Popular movies can include cultural diversity, help to create social inclusion, and make long lasting impact on people globally.

For further investigation, we looked into a new measure by combining average ratings with popularity. This new measure can give Microsoft team a new insight by comparing average ratings per popularity for each genre category. The results of this new measure can be found in appendix section.

---

3. Cast and Crew Analysis

Business Recommendation

The business recommendation I will be delivering to the Microsoft Studio team will be ordered lists of the actors and crew members whose movies made the most money over the last ten years, measured by net profit. This is to ensure that once the studio is up and running, the creatives associated with the most profitable films of the last ten years can be hired. This will ensure that Microsoft Studio's investment in personnel is as fruitful as possible.

3.1. Reading the Data

The data used in this analysis comes mostly from IMDB, the go-to online database for information about movies. IMDB is so perfect for this analysis because it painstakingly tracks all the people involved in the making of movies, where many other websites simply track reviews.

The one caveat to this is that IMDB does not track financial data for the films in its database. The revenues and profitability of the last decade's films are at the core of the business insights I will deliver to the Microsoft Studios team. So I will combine IMDB's cast and crew data with movie accounting information from The Numbers, a website wholly devoted to recording movie revenues.

IMDB has a massive catalogue of films, which for us is a double edged sword. While this quantity of information makes for robust analysis, it also enhances the complexity of our process.

In [50]:
```
# Turning the relevant csv files into pandas dataframes we can work with

name_keys = pd.read_csv('data/imdb.name.basics.csv')

title_keys = pd.read_csv('data/imdb.title.akas.csv')

names_to_jobs = pd.read_csv('data/imdb.title.principals.csv')

financials = pd.read_csv('data/tn.movie_budgets.csv')
```

3.2. Preparing our Dataframes

3.2.1. Name Keys

As our dataframes stand right now, they contain unneccessary data, redundant data, and null values.

When examining the first rows of the IMDB dataframes, I noticed that titles and names are often stored as codes instead of plain-text. I realized this is due to the fact that IMDB is a global website, and movies have a global audience, so instead of storing redundant data in every language, they store information under name and title codes. Much of our data preperation will be translating coded names and titles into their plain-text english versions.

name_keys is the first dataframe I will prepare. The label I have chosen for this dataframe is due to the fact that it ties imdb's internal name codes to the real world names of the cast and crew members.

To prepare this dataframe, I will remove any rows where the death_year column is not NaN, as I cant recommend Microsoft Studios attempt to hire the deceased to work on their upcoming projects.

I will then remove all columns except nconst and primary_name, as I am only interested in the values in these two columns.

In [51]:

```
# Here I am removing the 1000 or so columns with a non null value

def stringify(s):
    return str(s)

name_keys['death'] = name_keys['death_year'].map(stringify)

name_keys = name_keys[ name_keys['death'] == 'nan']

# Selecting all the rows with Null values in the death_year column, then selecting the columns I wo

name_keys = name_keys[['nconst', 'primary_name']]

name_keys.head()
```

Out[51]:

	nconst	primary_name
0	nm0061671	Mary Ellen Bauder
1	nm0061865	Joseph Bauer
2	nm0062070	Bruce Baum
3	nm0062195	Axel Baumann
4	nm0062798	Pete Baxter

3.2.2. Title Keys

This dataframe is named title_keys because much like name_keys, it will allow us to tie the english titles of movies to IMDB's internal title code for those movies.

To prepare this dataframe we will select only rows where the region is US, because our financials table has both domestic and international revenue data, so we only need the US titles to access global revenue data.

The last cleaning step to perform is to keep in mind that IMDB does not provide financial data, so we are going to have to merge our IMDB dataframes with our financial dataframe, to facilitate this merge, I will write a function to remove all whitespace, capitalizations, and punctuation in case they differ between the two different dataframes. We can resuse this funciton later on to clean the financials title column in the same way.

Then we will grab only the title_id and title columns, as these will serve as our keys, and none of the other coumns serve our specific analysis goal.

In [52]:

```
# Grabbing the relevant columns
title_keys = title_keys.loc[title_keys['region'] == 'US', ['title_id', 'title']]

# Our title cleaning function
def title_cleaner(string):
    new_string = ''
    alpha = 'abcdefghijklmnopqrstuvwxyz0123456789'
    string = string.lower()
    for i in string:
        if i in alpha:
```

```
            new_string += i
    return new_string

# Creating a new column filled with cleaned titles
title_keys['clean_title'] = title_keys['title'].map(title_cleaner)

# Getting rid of the original title name column
title_keys = title_keys[['title_id','clean_title']]

# Sanity Check
title_keys.head()
```

Out[52]:

	title_id	clean_title
12	tt0369610	jurassicworld3d
20	tt0369610	jurassicworld
21	tt0369610	ebbtide
28	tt0369610	jurassicparkiv
37	tt0369610	jurassicpark4

3.2.3. Names and Jobs

The names_to_jobs dataframe lists movies (as their IMDB title codes) , and the names of people who worked on them (as their IMDB name codes) as well as their role in the production, and character name if they are an actor.

This dataframe will eventually serve as the base for the final combined dataframe we will run our analysis on.

To clean up this dataframe, we will drop rows with NaN values, and select the columns of interest to us, which are tconst, nconst, and category

In [53]:

```
# Removing rows with Null values in essential columns
names_to_jobs.dropna(subset=['tconst', 'nconst', 'category'])

# Selecting only those essential columns
names_to_jobs = names_to_jobs[['tconst', 'nconst', 'category']]

# Sanity check
names_to_jobs.head()
```

Out[53]:

	tconst	nconst	category
0	tt0111414	nm0246005	actor
1	tt0111414	nm0398271	director
2	tt0111414	nm3739909	producer
3	tt0323808	nm0059247	editor
4	tt0323808	nm3579312	actress

3.2.4. The Financials

The final dataframe required is the financials dataframe. This dataframe is critical to our cast and crew analysis because it contains the accounting data we will use to calculate the profit of each movie.

Our team has decided to only look at movies released in the last ten years. We believe this achieves a balance between sample size, and not including movies that are too old to be relevant. To meet this goal I will convert the last 4 elements of the strings in the release_date column to an integer to obtain the year, and filter my dataframe based on the result.

The next issue we need to deal with is turning the numbers, stored as strings, into integers so we can perform arithmetic operations on them. We can achieve this by replacing the $ with nothing, then using the int() function.

I can then subtract the budget from the global box office numbers to calculate net profit.

Finally we will apply our title cleaning function from above, and select only the columns of interest to us.

In [54]:
```
# Defining our string to integer conversion function, to get year as a number
def convert_year(string):
    return int(string[-4:])

# Creating a new column year by applying our conversion function to the 'release date' column
financials['year'] = financials['release_date'].map(convert_year)

# Getting only the rows from the last ten years
financials = financials.loc[ financials['year'] >= 2011 ]

# Defining our function to convert the dolalr amounts stored as strings into integers
def convert_money(string):
    return int(string.replace('$','').replace(',',''))

# Making two new columns to hold our integer money values
financials['budget'] = financials['production_budget'].map(convert_money)
financials['global_gross'] = financials['worldwide_gross'].map(convert_money)

# Making a net profit column
financials['net_profit'] = financials['global_gross'] - financials['budget']

# Creating a clean name column to hold the results of our title cleaning function
financials['clean_name'] = financials['movie'].map(title_cleaner)

# Selecting our shiny new processed columns
financials = financials[['clean_name', 'budget', 'net_profit']]

# Sanity check after all of those changes
financials.head()
```

Out[54]:

	clean_name	budget	net_profit
1	piratesofthecaribbeanonstrangertides	410600000	635063875
2	darkphoenix	350000000	-200237650
3	avengersageofultron	330600000	1072413963
4	starwarsepviiithelastjedi	317000000	999721747
5	starwarsepviitheforceawakens	306000000	1747311220

3.3. Combining our Processed Dataframes

Now that all of our dataframes are better formatted, lets start smashing them together into something more useful. With names_to_jobs as our base structure to build upon, we will combine our dataframes in a series of three merges.

Merge 1 is combining names_to_jobs with name_keys. This will allow us to see the plain text english names of all the people listed in our names_to_jobs dataframe.

Merge 2 is connecting our merge 1 dataframe to title_keys, this translates our IMDB title codes into plain text movie title names.

Merge 3 is combining the merge 2 dataframe, which is all IMDB information with our outside financial data. These two dataframes will be stitched together based on their cleaned and stripped title columns.

Then after looking at the data I noticed that several rows where the title columns were empty, and the financial data was repeating in a very suspicious pattern, so I removed any rows that did not have a title name.

Finally I used drop_duplicates so that our data would not be skewed by repeated rows.

In [55]:

```
# Adding the plain-text names onto our main dataframe
merged = names_to_jobs.merge(name_keys, left_on=['nconst'], right_on=['nconst'])

# Adding the plain-text titles onto our main dataframe
merged_2 = merged.merge(title_keys, left_on=['tconst'], right_on=['title_id'])

# Adding the financial data onto our main dataframe where the seperately cleaned titles match up
merged_3 = merged_2.merge(financials, left_on=['clean_title'], right_on=['clean_name'])

# Removing rows without titles that were exhibiting suspicious activity
cleaned_merged_3 = merged_3.loc[ merged_3['clean_title'] != '']

# Dropping duplicate rows to ensure our net profits are not inflated by counting rows multiple time
cleaned_merged_3 = cleaned_merged_3.drop_duplicates()


# The all important sanity check
cleaned_merged_3.iloc[3000:3005]
```

Out[55]:

	tconst	nconst	category	primary_name	title_id	clean_title	clean_name	budget	net_profit
3145	tt1655460	nm0000098	actress	Jennifer Aniston	tt1655460	wanderlust	wanderlust	32500000	-8340066
3146	tt1655460	nm0748620	actor	Paul Rudd	tt1655460	wanderlust	wanderlust	32500000	-8340066
3147	tt1655460	nm0857620	actor	Justin Theroux	tt1655460	wanderlust	wanderlust	32500000	-8340066
3148	tt1655460	nm0015196	actress	Malin Akerman	tt1655460	wanderlust	wanderlust	32500000	-8340066
3149	tt1655460	nm0547800	writer	Ken Marino	tt1655460	wanderlust	wanderlust	32500000	-8340066

3.4. Grouping by Job Title, Ordering by Performance

Now that we have our final, composite dataframe, we can extract wisdom out of the data. This specific analysis perspective calls for the grouping of rows based on job title, and then ordering the results by sum net profits. What this will provide for us is a collection of lists, telling us in descending order who the most commercially successful directors, producers, actors, actresses, and writers are.

In [56]:

```
# Sorting our final dataframe by the job title 'director', then sorting by descending sum of net pr
directors = cleaned_merged_3.loc[ cleaned_merged_3['category'] == 'director']
directors = directors.groupby(['primary_name']).sum().sort_values(['net_profit'], ascending=False)
directors = directors.iloc[:15, : ]


directors_avg = cleaned_merged_3.loc[ cleaned_merged_3['category'] == 'director']
series = list(directors_avg['net_profit'])


# Repeating the process for producers
producers = cleaned_merged_3.loc[ cleaned_merged_3['category'] == 'producer']
producers = producers.groupby(['primary_name']).sum().sort_values(['net_profit'], ascending=False)
producers = producers.iloc[:15, : ]
```

```
# Repeating the process for actors
actors = cleaned_merged_3.loc[ cleaned_merged_3['category'] == 'actor']
actors = actors.groupby(['primary_name']).sum().sort_values(['net_profit'], ascending=False)
actors = actors.iloc[:15, : ]

# Repeating the process for actresses
actresses = cleaned_merged_3.loc[ cleaned_merged_3['category'] == 'actress']
actresses = actresses.groupby(['primary_name']).sum().sort_values(['net_profit'], ascending=False)
actresses = actresses.iloc[:15, : ]

# Repeating the process for writers
writers = cleaned_merged_3.loc[ cleaned_merged_3['category'] == 'writer']
writers = writers.groupby(['primary_name']).sum().sort_values(['net_profit'], ascending=False)
writers = writers.iloc[:15, : ]

# Sanity check incoming
directors.head()
```

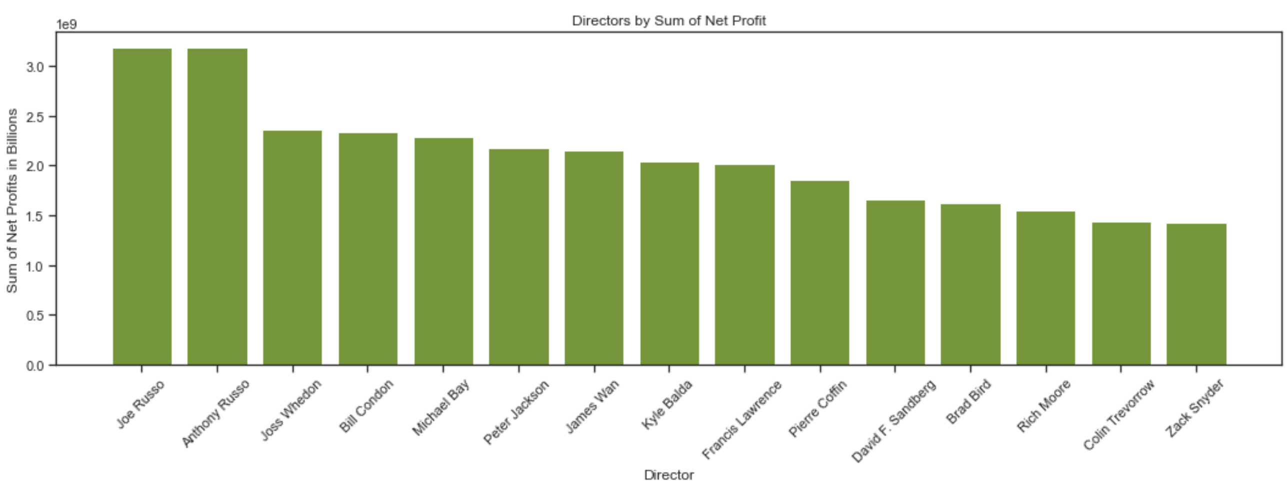
Out[56]:

	budget	net_profit
primary_name		
Joe Russo	720000000	3182605502
Anthony Russo	720000000	3182605502
Joss Whedon	555600000	2365349860
Bill Condon	449700000	2334798666
Michael Bay	698000000	2283409620

3.5. Visualization and Summary

In [57]:

```
crew_recommendations, Directors = plt.subplots(figsize=(18, 5))
plt.xticks(rotation=45)
Directors.bar(directors.index, directors['net_profit'], color='#76963c')
Directors.set_title('Directors by Sum of Net Profit')
Directors.set_xlabel('Director')
Directors.set_ylabel('Sum of Net Profits in Billions')
plt.savefig('directors')
```



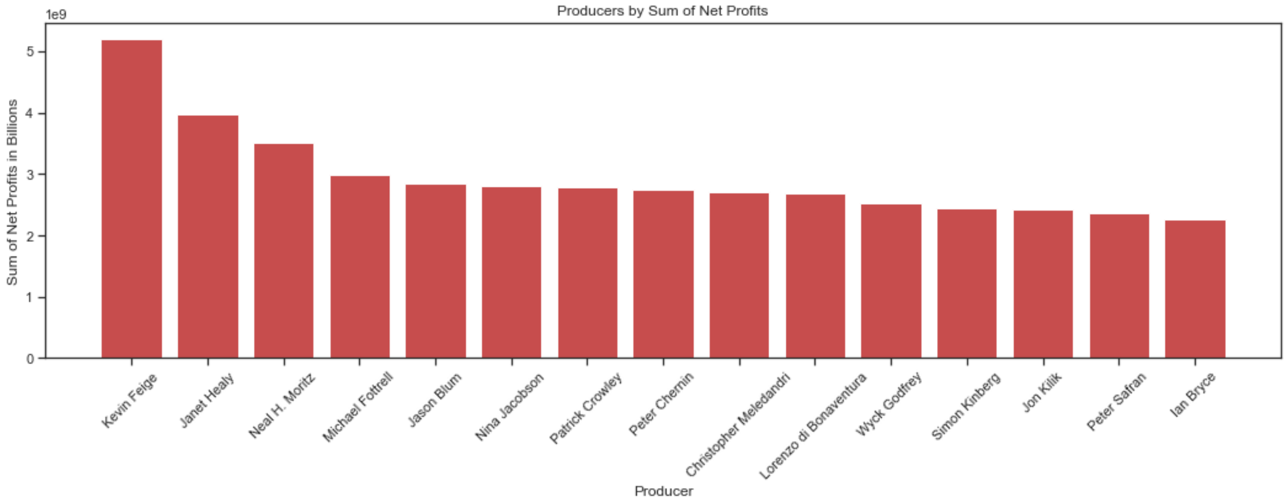
Directors

There is no single variable more influential on the quality of a film than who the director is. Movies often live or die based on if the director is able to deftly compose all of the disparate people and departments into a cohesive narrative. Not only is the quality of the film dependent on the quality of the director, many 'all-star' directors can be a massive draw to a movie, possibly even more than the principal actors.

This list is of extreme value to Microsoft Studios as choosing directors whose films consistently generate profit will be essential in the early stages of the studio's development.

In [58]:

```
crew_recommendations, Producers = plt.subplots(figsize=(18, 5))
plt.xticks(rotation=45)
Producers.bar(producers.index, producers['net_profit'], color='#c74d4d')
Producers.set_title('Producers by Sum of Net Profits')
Producers.set_xlabel('Producer')
Producers.set_ylabel('Sum of Net Profits in Billions')
plt.savefig('producers')
```

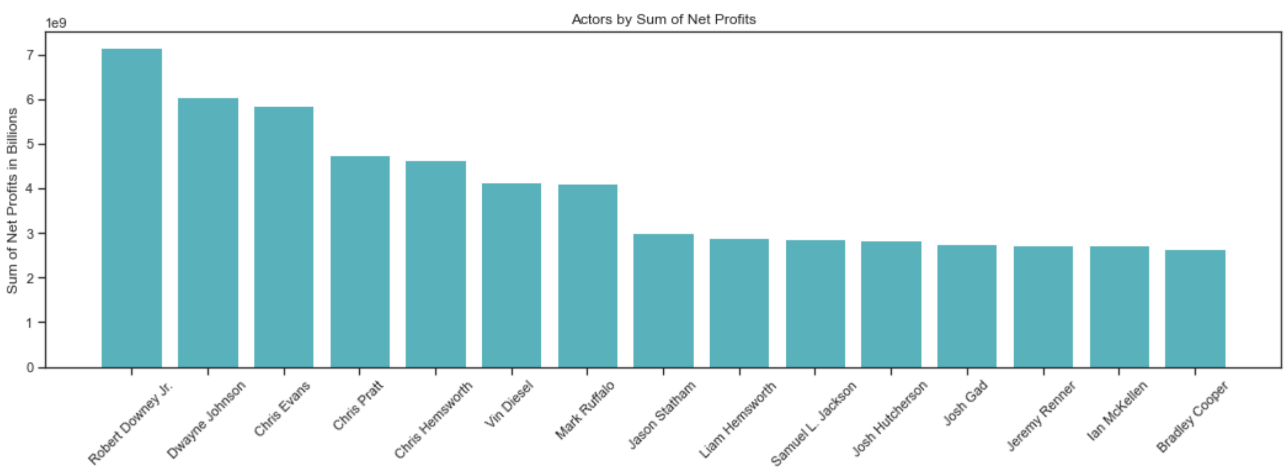


Producers

This list of the top fifteen most profitable producers will give Microsoft Studios a direction on who can provide domain knowledge to the executives chosen to run the studio. Microsoft should reach out to either directly hire, or partner with these producers, as they consistently fund projects that generate high net profits.

In [59]:

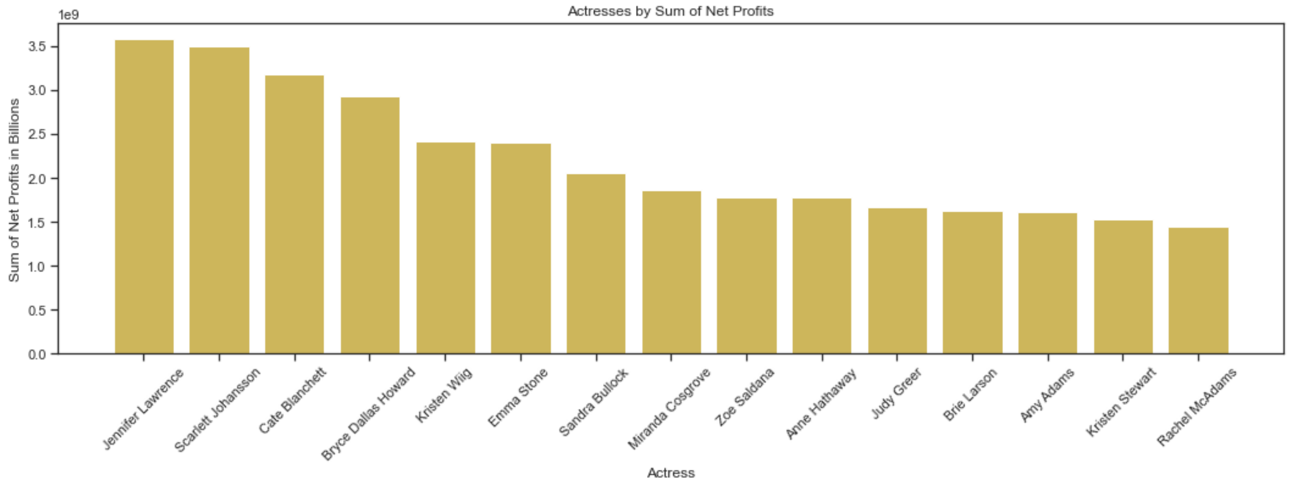
```
crew_recommendations, Actors = plt.subplots(figsize=(18, 5))
plt.xticks(rotation=45)
Actors.bar(actors.index, actors['net_profit'], color='#58b1bb')
Actors.set_title('Actors by Sum of Net Profits')
Actors.set_xlabel('Actor')
Actors.set_ylabel('Sum of Net Profits in Billions')
plt.savefig('actors')
```



Actors

Dominated by stars of Marvel Comic book movies, this list will help point Microsoft Studios towards the actors people know, that will draw in audiences to the Microsoft streaming platform.

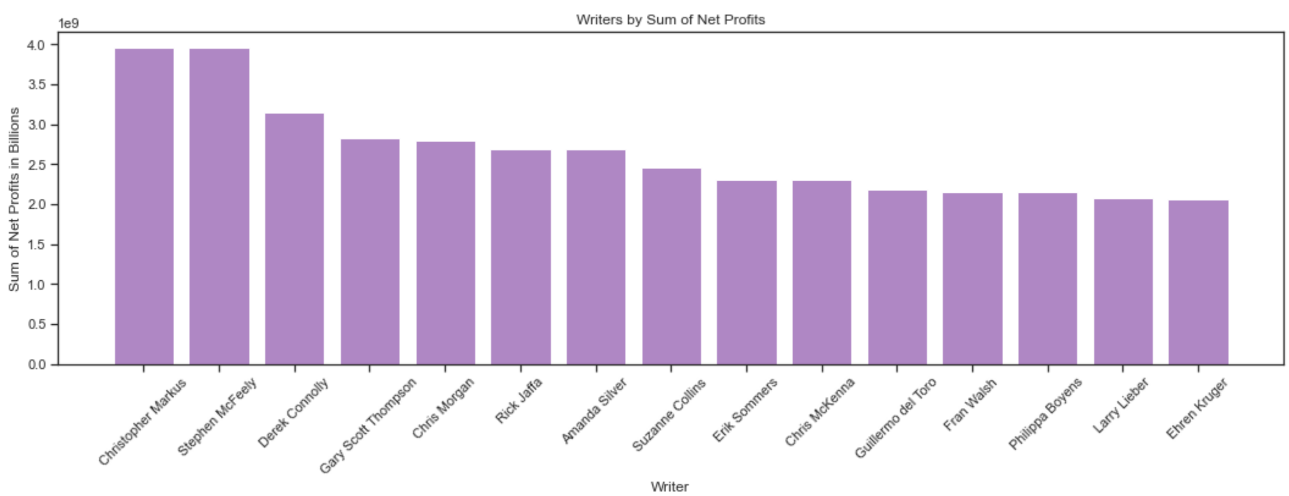
In [60]:
```
crew_recommendations, Actresses = plt.subplots(figsize=(18, 5))
plt.xticks(rotation=45)
Actresses.bar(actresses.index, actresses['net_profit'], color='#cdb65b')
Actresses.set_title('Actresses by Sum of Net Profits')
Actresses.set_xlabel('Actress')
Actresses.set_ylabel('Sum of Net Profits in Billions')
plt.savefig('actresses')
```



Actresses

Just like the Actors table, these 15 actresses should be Microsoft's first point of contact for casting leads in their main projects.

In [61]:
```
crew_recommendations, Writers = plt.subplots(figsize=(18, 5))
plt.xticks(rotation=45)
Writers.bar(writers.index, writers['net_profit'],  color='#af87c4')
Writers.set_title('Writers by Sum of Net Profits')
Writers.set_xlabel('Writer')
Writers.set_ylabel('Sum of Net Profits in Billions')
plt.savefig('writers')
```



Writers

This list is a combination of people who write screenplays for movies, and writers who authored the books that popular films have been based on. This list serves a dual purpose as it both points to those people that can be hired as screenwriters to work on Microsoft's films, and also what kind of books make for good movie adaptations.

General Commentary on Cast & Crew Analysis

The super-elephant in the room has to be addressed. These five lists, in combination with a little domain knowledge, would make it immediately clear that some of the most profitable films of all time, and possibly ever made are modern superhero blockbusters. Eight of the top fifteen actors, four of the top fifteen actresses, the top producer, the top two writers, and the top three directors have all worked on films in, and owe most of their ranking in these charts to, Disney's Marvel Cinematic Universe. DC's competing universe makes a less dramatic, but still highly relevant showing. What this means for Microsoft Studios going forward is that in combination with our other analyses, we highly recommend that Microsoft purchase some popular yet unadapted intellectual properties.

The other obvious feature of this data is the uncomfortable absence of women and people of color in the gender-nuetral lists. The Directors, Producers, and Writers graphics show the discrepency in how often women and POC are hired for these roles. I think this is a massive opportunity for Microsoft Studios to first of all, do their part in righting a societal wrong, but simultaneously having the knock on effect of differentiating themselves from their competitors. Doing this in transparent way would lead to all kinds of free publicity in the form of news stories and articles.

Limitations of this Data

One critical limitaiton of this data, is that it does not account for the billing of the actors and actresses in these high revenue generating movies. For example Josh Gad is a well known actor, but probably could not have a film marketed using solely his name. However this dataset places him above actors like Jeremy Renner, Ian McKellen, and Bradley Cooper, three oscar winning movie stars who could easily have a movie marketed based on their role in the film. This is a smaller issue, as big stars will always in general come out ahead in terms of their movies having the highest net profits, but it's something to consider.

4. Collective Recommendations

Finally, we recommend Microsoft team to:

- Acquire the expertise from a movie studio like Sony Pictures or Lionsgate.
- Focus on genres that are popular, like Adventure, Action, or Fantasy, to have more reach.
- Represent people equally in films through the cast and crew.

Appendix

A.1. Average Ratings per Popularity Measure for Movie Genres

In order to calculate average ratings per popularity, we will use TMDB movies data stored in in 'tmdb.movies.csv' file, and focus on movies with release year between 2010 to 2019. For popularity analysis above, we cleaned the data, filtered out the years which are out of our range, and exploded genre names into seperate rows. For this analysis we will use the same dataframe by focusung on 'popularity', 'vote_average', 'vote_count' and 'genre_ids' columns.

This analysis may give more accurate results if the IMDB dataframe is merged with TMDB dataframe, and then average rating values are used from IMDB dataframe and popularity values are used from TMDB dataframe. This approach is recommended as a next step of genre analysis, but now we will multiply 'vote_average' with 'vote_count' from TMDB dataframe as a proxy for average ratings for this work.

Let's starts recalling the TMDB dataframe from above.

In [62]:
```
tmdb_exploded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 44820 entries, 0 to 26516
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         44820 non-null  int64
 1   genre_ids          44820 non-null  object
 2   id                 44820 non-null  int64
 3   original_language  44820 non-null  object
 4   original_title     44820 non-null  object
 5   popularity         44820 non-null  float64
 6   release_date       44820 non-null  object
 7   title              44820 non-null  object
 8   vote_average       44820 non-null  float64
 9   vote_count         44820 non-null  int64
 10  release_year       44820 non-null  int64
dtypes: float64(2), int64(4), object(5)
memory usage: 5.4+ MB
```

In [63]:
```
ratings_per_popularity = tmdb_exploded[['genre_ids','popularity', 'vote_average', 'vote_count']]
ratings_per_popularity
```

Out[63]:

	genre_ids	popularity	vote_average	vote_count
0	Adventure	33.533	7.7	10788
0	Fantasy	33.533	7.7	10788
0	Family	33.533	7.7	10788
1	Fantasy	28.734	7.7	7610
1	Adventure	28.734	7.7	7610
...	...	...	...	...
26515	Family	0.600	0.0	1
26515	Adventure	0.600	0.0	1
26515	Action	0.600	0.0	1
26516	Thriller	0.600	0.0	1
26516	Horror	0.600	0.0	1

44820 rows × 4 columns

In [64]:
```
ratings_per_popularity = ratings_per_popularity[ratings_per_popularity['vote_count'] >500]
ratings_per_popularity
```

Out[64]:

	genre_ids	popularity	vote_average	vote_count
0	Adventure	33.533	7.7	10788
0	Fantasy	33.533	7.7	10788
0	Family	33.533	7.7	10788
1	Fantasy	28.734	7.7	7610

	genre_ids	popularity	vote_average	vote_count
1	Adventure	28.734	7.7	7610
...	...	...	...	...
24462	Animation	6.868	7.4	721
24462	Fantasy	6.868	7.4	721
24462	Adventure	6.868	7.4	721
24462	Comedy	6.868	7.4	721
24462	Science Fiction	6.868	7.4	721

4335 rows × 4 columns

In [65]:

```
ratings_per_popularity['ratingsum'] = ratings_per_popularity['vote_average']*ratings_per_popularity
ratings_per_popularity
```

```
<ipython-input-65-0389de1aabcc>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/index
ing.html#returning-a-view-versus-a-copy
  ratings_per_popularity['ratingsum'] = ratings_per_popularity['vote_average']*ratings_per_populari
ty['vote_count']
```

Out[65]:

	genre_ids	popularity	vote_average	vote_count	ratingsum
0	Adventure	33.533	7.7	10788	83067.6
0	Fantasy	33.533	7.7	10788	83067.6
0	Family	33.533	7.7	10788	83067.6
1	Fantasy	28.734	7.7	7610	58597.0
1	Adventure	28.734	7.7	7610	58597.0
...	...	...	...	...	...
24462	Animation	6.868	7.4	721	5335.4
24462	Fantasy	6.868	7.4	721	5335.4
24462	Adventure	6.868	7.4	721	5335.4
24462	Comedy	6.868	7.4	721	5335.4
24462	Science Fiction	6.868	7.4	721	5335.4

4335 rows × 5 columns

In [66]:

```
ratings_per_popularity['rating_per_popularity'] = ratings_per_popularity['ratingsum']/ratings_per_p
ratings_per_popularity
```

```
<ipython-input-66-839d81e4aa03>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/index
ing.html#returning-a-view-versus-a-copy
  ratings_per_popularity['rating_per_popularity'] = ratings_per_popularity['ratingsum']/ratings_per
_popularity['popularity']
```

Out[66]:

	genre_ids	popularity	vote_average	vote_count	ratingsum	rating_per_popularity
0	Adventure	33.533	7.7	10788	83067.6	2477.189634

	genre_ids	popularity	vote_average	vote_count	ratingsum	rating_per_popularity
0	Fantasy	33.533	7.7	10788	83067.6	2477.189634
0	Family	33.533	7.7	10788	83067.6	2477.189634
1	Fantasy	28.734	7.7	7610	58597.0	2039.291432
1	Adventure	28.734	7.7	7610	58597.0	2039.291432
...	...	...	...	...	...	...
24462	Animation	6.868	7.4	721	5335.4	776.849156
24462	Fantasy	6.868	7.4	721	5335.4	776.849156
24462	Adventure	6.868	7.4	721	5335.4	776.849156
24462	Comedy	6.868	7.4	721	5335.4	776.849156
24462	Science Fiction	6.868	7.4	721	5335.4	776.849156

4335 rows × 6 columns

In [67]:

```
ratings_per_popularity_df = ratings_per_popularity.groupby(['genre_ids']).mean()
ratings_per_popularity_df
```

Out[67]:

	popularity	vote_average	vote_count	ratingsum	rating_per_popularity
genre_ids					
Action	18.414539	6.381360	3773.403509	25462.415570	1528.288417
Adventure	19.718027	6.530091	4694.224924	32310.188146	1730.804926
Animation	16.168880	6.983803	2734.823944	19563.827465	1219.966236
Comedy	13.494346	6.464370	2220.057087	15068.209252	1096.839656
Crime	14.124996	6.528692	2270.004219	15465.440928	1222.236243
Documentary	9.435400	7.520000	691.600000	5211.800000	594.569798
Drama	12.975031	6.838441	2228.063172	15872.598790	1096.244708
Family	16.427902	6.716763	3049.861272	21381.839306	1261.522877
Fantasy	18.331484	6.476959	3744.631336	25261.359908	1252.258767
History	13.450781	7.030137	2135.150685	15654.823288	1129.048732
Horror	13.016688	6.007317	1790.648780	11267.458537	1003.803634
Music	14.009367	6.936667	1964.233333	14359.220000	882.261452
Mystery	13.813118	6.474534	2259.559006	15248.589441	1000.570950
Romance	12.441300	6.741350	2159.666667	15005.501688	1112.799624
Science Fiction	18.441943	6.450410	4567.008197	31302.035246	1851.856009
TV Movie	12.376000	6.300000	980.857143	6262.542857	519.995231
Thriller	14.379123	6.356324	2176.881423	14456.586957	1026.978400
War	15.792000	6.912821	2931.307692	21232.848718	1105.003396
Western	15.305545	6.581818	3935.590909	28120.372727	1585.119771

In [68]:

```
ratings_per_popularity_df['normalized']= ratings_per_popularity_df['rating_per_popularity']/ratings
ratings_per_popularity_df
```

Out[68]:

genre_ids	popularity	vote_average	vote_count	ratingsum	rating_per_popularity	normalized
Action	18.414539	6.381360	3773.403509	25462.415570	1528.288417	6.877933
Adventure	19.718027	6.530091	4694.224924	32310.188146	1730.804926	7.789342
Animation	16.168880	6.983803	2734.823944	19563.827465	1219.966236	5.490355
Comedy	13.494346	6.464370	2220.057087	15068.209252	1096.839656	4.936235
Crime	14.124996	6.528692	2270.004219	15465.440928	1222.236243	5.500571
Documentary	9.435400	7.520000	691.600000	5211.800000	594.569798	2.675811
Drama	12.975031	6.838441	2228.063172	15872.598790	1096.244708	4.933557
Family	16.427902	6.716763	3049.861272	21381.839306	1261.522877	5.677378
Fantasy	18.331484	6.476959	3744.631336	25261.359908	1252.258767	5.635685
History	13.450781	7.030137	2135.150685	15654.823288	1129.048732	5.081189
Horror	13.016688	6.007317	1790.648780	11267.458537	1003.803634	4.517534
Music	14.009367	6.936667	1964.233333	14359.220000	882.261452	3.970543
Mystery	13.813118	6.474534	2259.559006	15248.589441	1000.570950	4.502985
Romance	12.441300	6.741350	2159.666667	15005.501688	1112.799624	5.008061
Science Fiction	18.441943	6.450410	4567.008197	31302.035246	1851.856009	8.334122
TV Movie	12.376000	6.300000	980.857143	6262.542857	519.995231	2.340195
Thriller	14.379123	6.356324	2176.881423	14456.586957	1026.978400	4.621830
War	15.792000	6.912821	2931.307692	21232.848718	1105.003396	4.972975
Western	15.305545	6.581818	3935.590909	28120.372727	1585.119771	7.133698

In [69]:

```
df_rating_per_popularity = ratings_per_popularity_df.sort_values(by='normalized', ascending =False)
df_rating_per_popularity
```

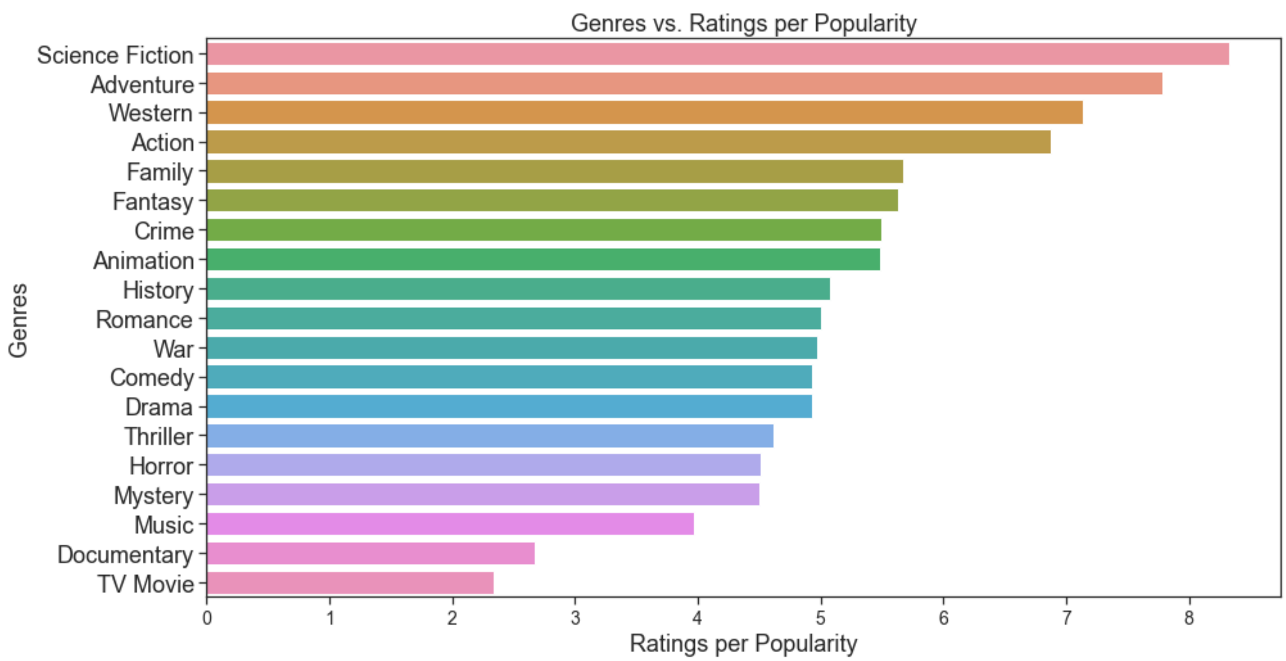
Out[69]:

genre_ids	popularity	vote_average	vote_count	ratingsum	rating_per_popularity	normalized
Science Fiction	18.441943	6.450410	4567.008197	31302.035246	1851.856009	8.334122
Adventure	19.718027	6.530091	4694.224924	32310.188146	1730.804926	7.789342
Western	15.305545	6.581818	3935.590909	28120.372727	1585.119771	7.133698
Action	18.414539	6.381360	3773.403509	25462.415570	1528.288417	6.877933
Family	16.427902	6.716763	3049.861272	21381.839306	1261.522877	5.677378
Fantasy	18.331484	6.476959	3744.631336	25261.359908	1252.258767	5.635685
Crime	14.124996	6.528692	2270.004219	15465.440928	1222.236243	5.500571
Animation	16.168880	6.983803	2734.823944	19563.827465	1219.966236	5.490355
History	13.450781	7.030137	2135.150685	15654.823288	1129.048732	5.081189
Romance	12.441300	6.741350	2159.666667	15005.501688	1112.799624	5.008061
War	15.792000	6.912821	2931.307692	21232.848718	1105.003396	4.972975
Comedy	13.494346	6.464370	2220.057087	15068.209252	1096.839656	4.936235
Drama	12.975031	6.838441	2228.063172	15872.598790	1096.244708	4.933557

genre_ids	popularity	vote_average	vote_count	ratingsum	rating_per_popularity	normalized
Thriller	14.379123	6.356324	2176.881423	14456.586957	1026.978400	4.621830
Horror	13.016688	6.007317	1790.648780	11267.458537	1003.803634	4.517534
Mystery	13.813118	6.474534	2259.559006	15248.589441	1000.570950	4.502985
Music	14.009367	6.936667	1964.233333	14359.220000	882.261452	3.970543
Documentary	9.435400	7.520000	691.600000	5211.800000	594.569798	2.675811
TV Movie	12.376000	6.300000	980.857143	6262.542857	519.995231	2.340195

In [70]:

```
sns.set_theme(context='notebook',style="ticks", color_codes=True, palette='deep')
fig, ax = plt.subplots(figsize=(15, 8))

ax = sns.barplot(y=df_rating_per_popularity.index, x = 'normalized', data=df_rating_per_popularity)
ax.set_title('Genres vs. Ratings per Popularity', fontsize=18)
ax.set_ylabel('Genres', fontsize=18)
ax.set_xlabel('Ratings per Popularity', fontsize=18);
plt.xticks(fontsize=14)
plt.yticks(fontsize=18);
```



This final analysis shows that a future movie with science fiction, adventure, or western genre, or combination of these genres are the best if you are using ratings per popularity measure!

In [ ]: