Group One Final Notebook

Import all necessary Libraries

In [1]:
```
# Importing relevant libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
%matplotlib inline
import scipy.stats as stats
from math import sqrt
```

In [2]:
```
tmdb = pd.read_csv("data/zippedData/tmdb.movies.csv.gz")
tmdb.head()
```

Out[2]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title
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

In [3]:
```
tn_budgets = pd.read_csv("data/zippedData/tn.movie_budgets.csv.gz")
tn_budgets.head()
```

Out[3]:

	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

To clean this dataframe, the only things to do would be convert production_budget, domestic_gross, and worldwide_gross to integer data types and change release_date to datetime data type.

Data Cleaning

In [4]:

```
# change release_date column from str to datetime
tn_budgets['release_date'] = pd.to_datetime(tn_budgets['release_date'])

# cleaning the production_budget column of dollar signs and commas and chan
tn_budgets['production_budget'] = tn_budgets['production_budget'].str.repla
tn_budgets['production_budget'] = tn_budgets['production_budget'].str.repla
tn_budgets = tn_budgets.astype({'production_budget': 'int64'})

# cleaning the domestic_gross column of dollar signs and commas and changin
tn_budgets['domestic_gross'] = tn_budgets['domestic_gross'].str.replace('$'
tn_budgets['domestic_gross'] = tn_budgets['domestic_gross'].str.replace(','
tn_budgets = tn_budgets.astype({'domestic_gross': 'int64'})

# cleaning the worldwide_gross column of dollar signs and commas and changi
tn_budgets['worldwide_gross'] = tn_budgets['worldwide_gross'].str.replace('
tn_budgets['worldwide_gross'] = tn_budgets['worldwide_gross'].str.replace('
tn_budgets = tn_budgets.astype({'worldwide_gross': 'int64'})

# Find the net revenue and assigning the values to the new column named Net
tn_budgets['Net Revenue'] = tn_budgets['worldwide_gross'] - tn_budgets['pro
tn_budgets.describe()
```

Out[4]:

	id	production_budget	domestic_gross	worldwide_gross	Net Revenue
count	5782.000000	5.782000e+03	5.782000e+03	5.782000e+03	5.782000e+03
mean	50.372363	3.158776e+07	4.187333e+07	9.148746e+07	5.989970e+07
std	28.821076	4.181208e+07	6.824060e+07	1.747200e+08	1.460889e+08
min	1.000000	1.100000e+03	0.000000e+00	0.000000e+00	-2.002376e+08
25%	25.000000	5.000000e+06	1.429534e+06	4.125415e+06	-2.189071e+06
50%	50.000000	1.700000e+07	1.722594e+07	2.798445e+07	8.550286e+06
75%	75.000000	4.000000e+07	5.234866e+07	9.764584e+07	6.096850e+07
max	100.000000	4.250000e+08	9.366622e+08	2.776345e+09	2.351345e+09

Genre Analysis

In [5]:
```
genre_df = pd.merge(tmdb, tn_budgets, left_on=['title'], right_on=['movie']
genre_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2385 entries, 0 to 2384
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         2385 non-null   int64
 1   genre_ids          2385 non-null   object
 2   id_x               2385 non-null   int64
 3   original_language  2385 non-null   object
 4   original_title     2385 non-null   object
 5   popularity         2385 non-null   float64
 6   release_date_x     2385 non-null   object
 7   title              2385 non-null   object
 8   vote_average       2385 non-null   float64
 9   vote_count         2385 non-null   int64
 10  id_y               2385 non-null   int64
 11  release_date_y     2385 non-null   datetime64[ns]
 12  movie              2385 non-null   object
 13  production_budget  2385 non-null   int64
 14  domestic_gross     2385 non-null   int64
 15  worldwide_gross    2385 non-null   int64
 16  Net Revenue        2385 non-null   int64
dtypes: datetime64[ns](1), float64(2), int64(8), object(6)
memory usage: 335.4+ KB
```

We see that we have shrunk the dataset to 2385 but believe that to be sufficient enough to conduct further analysis.

In [6]:
```
genre_df
```

Out[6]:

	Unnamed: 0	genre_ids	id_x	original_language	original_title	popularity	release_date_x	
0	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	Ho Yo
1	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	I
2	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	
3	2473	[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	
...	...	...	...	...	...	...	...	
2380	26323	[]	509316	en	The Box	0.600	2018-03-04	
2381	26425	[10402]	509306	en	The Box	0.600	2018-03-04	
2382	26092	[35, 16]	546674	en	Enough	0.719	2018-03-22	
2383	26322	[]	513161	en	Undiscovered	0.600	2018-04-07	Und
2384	26508	[16]	514492	en	Jaws	0.600	2018-05-29	

2385 rows × 17 columns

In [7]:
```
# We notice some duplicates and choose to remove those.
genre_df = genre_df[genre_df['title'] != 'Home']
genre_df = genre_df.drop_duplicates(subset='title')
```

In [8]:
```
genre_df
```

Out[8]:

	Unnamed: 0	genre_ids	id_x	original_language	original_title	popularity	release_date_x	
0	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	Ho Yo
1	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Ir
2	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	
5	5	[12, 14, 10751]	32657	en	Percy Jackson & the Olympians: The Lightning T...	26.691	2010-02-11	O The
...	...	...	...	...	...	...	...	
2376	25825	[28, 878]	448764	en	Molly	1.400	2018-09-25	
2377	26040	[]	509314	en	The Box	0.840	2018-03-04	
2382	26092	[35, 16]	546674	en	Enough	0.719	2018-03-22	
2383	26322	[]	513161	en	Undiscovered	0.600	2018-04-07	Und
2384	26508	[16]	514492	en	Jaws	0.600	2018-05-29	

1923 rows × 17 columns

We are ultimately left with 1923 rows in the dataset which we still believe to be ok.

We decide we want our target variable to be Net Revenue, so we subtract production budget from worldwide gross. We make the assumption that in order to produce the movie, all of the production budget was used and ONLY the production budget. In other words, no more and no less than the production budget was spent in the creation of a movie.

In [9]:
```
genre_df['Net Revenue'] = genre_df['worldwide_gross'] - genre_df['productio
genre_df.head()
```

Out[9]:

	Unnamed: 0	genre_ids	id_x	original_language	original_title	popularity	release_date_x	titl
0	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How t Train You Drago
1	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man
2	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Stor
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inceptio
5	5	[12, 14, 10751]	32657	en	Percy Jackson & the Olympians: The Lightning T...	26.691	2010-02-11	Perc Jackson th Olympians Th Lightnin T.

In [10]:
```
# We realize the genre codes are in long strings. We remove the brackets an

genre_df['genre_ids'] = genre_df['genre_ids'].str.replace("[", "")
genre_df['genre_ids'] = genre_df['genre_ids'].str.replace("]", "")
genre_df['genre_ids'] = genre_df['genre_ids'].str.replace(",", "")
genre_df['genre_ids'] = genre_df['genre_ids'].apply(lambda x: x.split(" "))
genre_df['genre_ids'][0]
```

Out[10]: ['14', '12', '16', '10751']

We found a key on the TMDB website that says what genre each number code relate to. Below we use a for loop to change them in the dataframe.

In [11]:
```
for lst in genre_df['genre_ids']:
    for i in range(len(lst)):
            if lst[i] == '12':
                lst[i] = 'Adventure'
            elif lst[i] == '14':
                lst[i] = 'Fantasy'
            elif lst[i] == '28':
                lst[i] = 'Action'
            elif lst[i] == '16':
                lst[i] = 'Animation'
            elif lst[i] == '35':
                lst[i] = 'Comedy'
            elif lst[i] == '80':
                lst[i] = 'Crime'
            elif lst[i] == '99':
                lst[i] = 'Documentary'
            elif lst[i] == '18':
                lst[i] = 'Drama'
            elif lst[i] == '10751':
                lst[i] = 'Family'
            elif lst[i] == '36':
                lst[i] = 'History'
            elif lst[i] == '27':
                lst[i] = 'Horror'
            elif lst[i] == '10402':
                lst[i] = 'Music'
            elif lst[i] == '9648':
                lst[i] = 'Mystery'
            elif lst[i] == '10749':
                lst[i] = 'Romance'
            elif lst[i] == '878':
                lst[i] = 'SciFi'
            elif lst[i] == '10770':
                lst[i] = 'TV Movie'
            elif lst[i] == '53':
                lst[i] = 'Thriller'
            elif lst[i] == '10752':
                lst[i] = 'War'
            elif lst[i] == '37':
                lst[i] = 'Western'
```

In [12]:
```
genre_df
```

Out[12]:

	Unnamed: 0	genre_ids	id_x	original_language	original_title	popularity	release_date_x	
0	1	[Fantasy, Adventure, Animation, Family]	10191	en	How to Train Your Dragon	28.734	2010-03-26	H Y
1	2	[Adventure, Action, SciFi]	10138	en	Iron Man 2	28.515	2010-05-07	
2	3	[Animation, Comedy, Family]	862	en	Toy Story	28.005	1995-11-22	
4	4	[Action, SciFi, Adventure]	27205	en	Inception	27.920	2010-07-16	
5	5	[Adventure, Fantasy, Family]	32657	en	Percy Jackson & the Olympians: The Lightning T...	26.691	2010-02-11	(Th
...	...	...	...	...	...	...	...	
2376	25825	[Action, SciFi]	448764	en	Molly	1.400	2018-09-25	
2377	26040	[]	509314	en	The Box	0.840	2018-03-04	
2382	26092	[Comedy, Animation]	546674	en	Enough	0.719	2018-03-22	
2383	26322	[]	513161	en	Undiscovered	0.600	2018-04-07	Un
2384	26508	[Animation]	514492	en	Jaws	0.600	2018-05-29	

1923 rows × 17 columns

To make the genre column easier to analyze, we use the .explode() function to create a unique row for each genre in the list. For instance, if a movie has 4 genres listed then it will now have 4 rows, each with a different one of the listed genres.

In [13]:
```
genre_df_exploded = genre_df.explode('genre_ids')

#remove rows with empty genres
genre_df_exploded = genre_df_exploded[genre_df_exploded['genre_ids'] != '']
```

We can now use groupby to find the average net revenue by genre. Note, if a movie has multiple rows, its revenue will be considered in multiple categories.

In [14]:
```
average_group = genre_df_exploded.groupby(['genre_ids'])['Net Revenue'].mea
average_group
```

Out[14]:

	genre_ids	Net Revenue
0	Animation	2.439302e+08
1	Adventure	2.421081e+08
2	Fantasy	2.058034e+08
3	Family	1.920874e+08
4	SciFi	1.782768e+08
5	Action	1.589646e+08
6	Comedy	8.484031e+07
7	Thriller	6.275487e+07
8	Crime	6.079877e+07
9	Music	5.508409e+07
10	War	5.469261e+07
11	Mystery	5.270099e+07
12	Romance	5.111473e+07
13	Drama	4.583196e+07
14	Western	4.506243e+07
15	Horror	4.048204e+07
16	History	3.560990e+07
17	Documentary	3.013668e+07
18	TV Movie	2.918712e+07

In [15]:
```
#groupby genre on count
count_group = genre_df_exploded.groupby('genre_ids')['Net Revenue'].count()
count_group
```

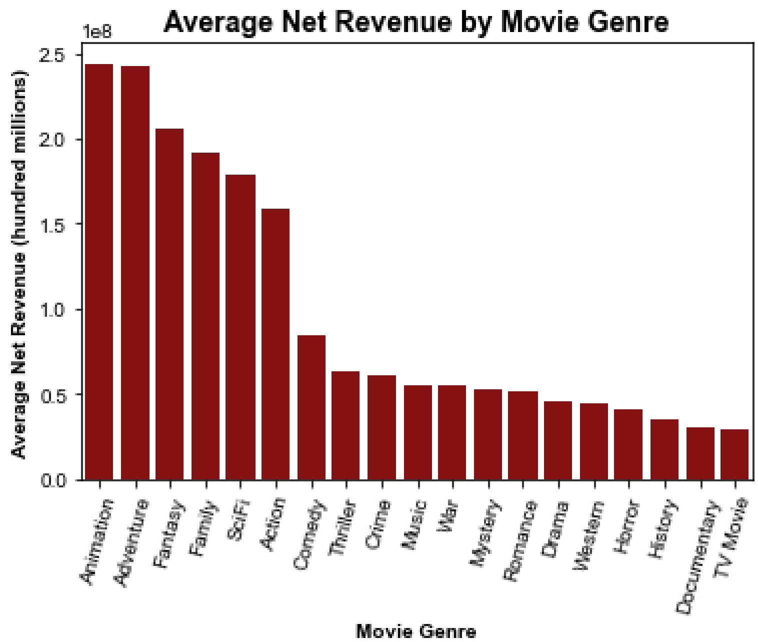
Out[15]:

	genre_ids	Net Revenue
0	Drama	872
1	Comedy	584
2	Thriller	518
3	Action	472
4	Adventure	298
5	Horror	258
6	Crime	241
7	Romance	233
8	SciFi	217
9	Family	187
10	Fantasy	178
11	Mystery	139
12	Animation	123
13	History	70
14	Documentary	69
15	War	47
16	Music	47
17	Western	24
18	TV Movie	10

Final Plot

In [16]:

```
#average net revenue by movie genre
ax = sns.barplot(data=average_group, x='genre_ids', y='Net Revenue', color=
ax.set_xticklabels(ax.get_xticklabels(), rotation=75);
ax.set_title('Average Net Revenue by Movie Genre', fontsize = 14, weight =
ax.set_ylabel('Average Net Revenue (hundred millions)', weight='bold')
ax.set_xlabel('Movie Genre', weight='bold');
sns.set_style('whitegrid')
```



Studio Analysis

In [17]:
```
bom = pd.read_csv('data/zippedData/bom.movie_gross.csv.gz')
bom
```

Out[17]:

	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
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

Cleaning Studio columns to remove duplicates

In [18]:
```
bom['studio'].unique()
bom['studio'] = bom['studio'].str.strip('()')
bom['studio'] = bom['studio'].str.strip('(NL')
bom['studio'] = bom['studio'].str.strip()
bom['studio'] = bom['studio'].str.strip()
bom['studio'] = bom['studio'].str.replace('BV','Walt Disney')
bom['studio'] = bom['studio'].str.replace('P/DW','Pixar')
bom['studio'] = bom['studio'].str.replace('Uni.','Universial')
bom['studio'] = bom['studio'].str.replace('Par.','Paramount')
bom['studio'] = bom['studio'].str.strip()
```

Feature Creation create year column & Join Merge Bom & Tn_budgets

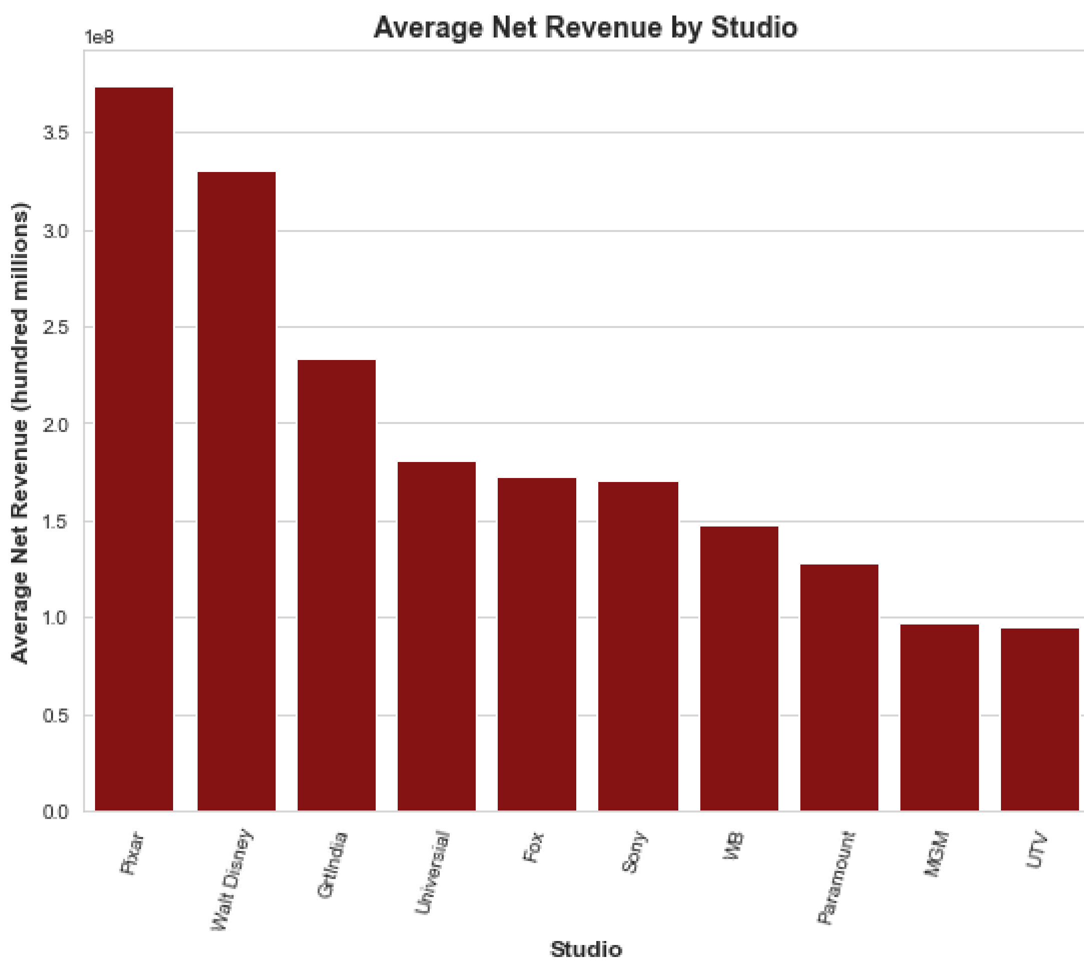
In [19]:
```
## Adding a year column
tn_budgets['year'] =  pd.DatetimeIndex(tn_budgets['release_date']).year
### Merging bom dataframe and Tn budgets
bom_budgets = pd.merge(tn_budgets, bom[['studio','title', 'year']],left_on=
### Creating a column called net that calculates the difference between wor
bom_budgets['net'] = bom_budgets['worldwide_gross'] - bom_budgets['producti
```

Groups by studio and find the top ten Studio by net profit

In [20]:
```
#Reduces the amount of digits displayed
pd.set_option('display.float_format', lambda x: '%.3f' % x)
net_studio = bom_budgets.groupby("studio")['net'].mean().to_frame(name = 'a
top10_studio = net_studio.sort_values(by=['average_net'], ascending= False,
```

Bargraph of top ten studio by Average net revenue

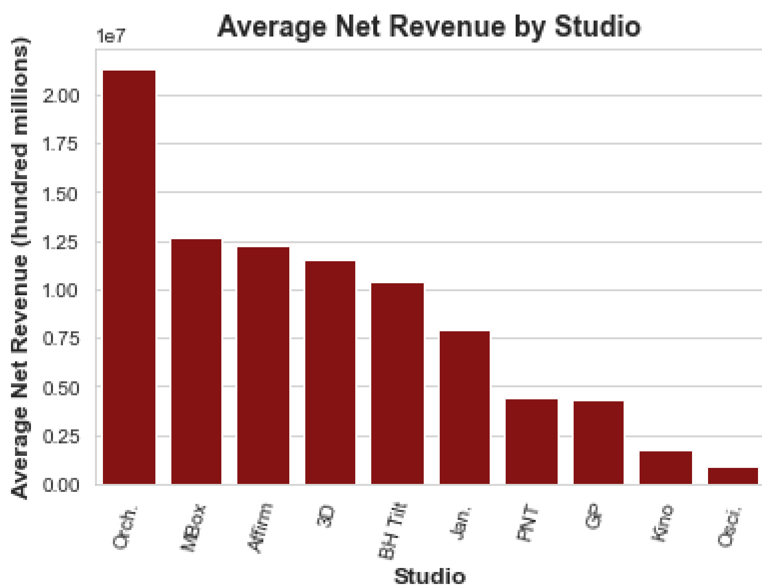
In [21]:
```
sns.set_style("whitegrid")
#setting figure size
plt.figure(figsize =(9,7))
#creating bar plot
ax_studio = sns.barplot(data=top10_studio, x='studio', y='average_net',colo
#setting title and axis names
ax_studio.set_title('Average Net Revenue by Studio', fontsize = 14, weight
ax_studio.set_ylabel('Average Net Revenue (hundred millions)', fontsize = 1
ax_studio.set_xlabel('Studio', fontsize = 12, weight = 'bold')
ax_studio.set_xticklabels(ax_studio.get_xticklabels(), rotation=75);
plt.show()
```



Bar Graph of top ten studios whose production cost is in the 25th interquartile range

In [22]:
```
#grouping by studios by production cost
studio_cost = bom_budgets.groupby("studio")['production_budget'].mean().to_
#creating_quartiles to find what inter quartile ranges of cost
studio_cost_qt = studio_cost['average_cost'].quantile([0.25, 0.5, 0.75])
# Selecting only studios in the 25th quartile or lower
low_budget_studios = studio_cost[studio_cost['average_cost'] <= 6407142.857
list_low = list(low_budget_studios['studio'])
low_cost_studios = bom_budgets[bom_budgets['studio'] == 'Viv' ]
#looping through a the list of every studio that is in the 25th quartile an
for i in list_low:
    low_cost_studios = bom_budgets[bom_budgets['studio'] ==  i].append(low_
pd.set_option('display.float_format', lambda x: '%.3f' % x)
low_net_studio = low_cost_studios.groupby("studio")['net'].mean().to_frame(
top10_low = low_net_studio.sort_values(by=['average_net'], ascending= False
```

In [23]:
```
sns.set_style("whitegrid")
#creating bar plot
ax_studio_low = sns.barplot(data=top10_low, x='studio', y='average_net',col
#setting figure size
plt.figure(figsize =(9,7))
#setting title and axis names
ax_studio_low.set_title('Average Net Revenue by Studio', fontsize = 14, wei
ax_studio_low.set_ylabel('Average Net Revenue (hundred millions)', fontsize
ax_studio_low.set_xlabel('Studio', fontsize = 12, weight = 'bold')
ax_studio_low.set_xticklabels(ax_studio_low.get_xticklabels(), rotation=75)
plt.show()
```




```
<Figure size 648x504 with 0 Axes>
```

Release Date Analysis

Hypothesis

Alternative hypothesis is that movies released in the summer season will generate a higher net revenue than the population average

H_a = μ<M

Null hypothesis is that movies released in the summer season will not generate a higher net revenue than population average

H_0 = $\mu \geq M$

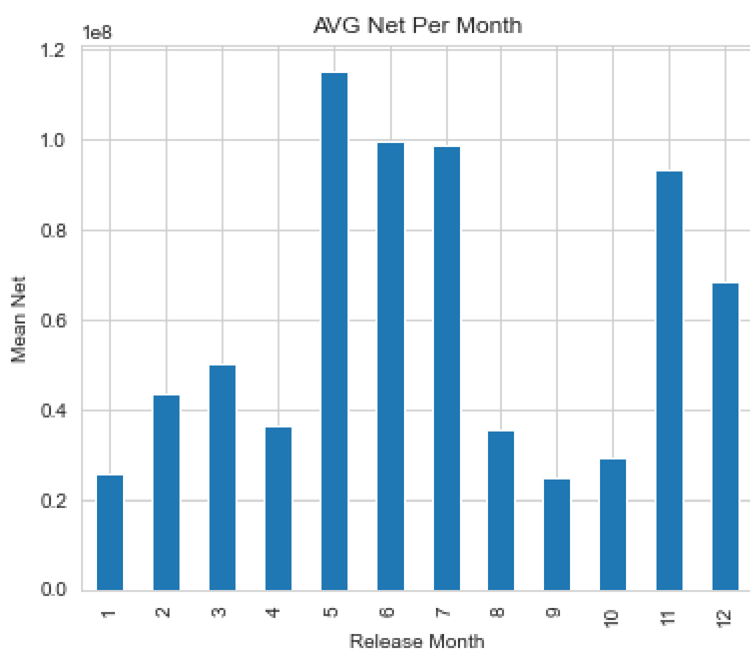
In [24]:
```
# Taking month out of release date and creating new column with the values
tn_budgets["release_month"] = tn_budgets["release_date"].dt.month

# Creating a variable that groups the release_month and Net Revenue columns
by_month = tn_budgets.groupby("release_month")["Net Revenue"].mean()
```

Map average gross revenue by month

In [25]:
```
# Plotting the data from by_month into a bar graph
by_month.plot(kind='bar', title='AVG Net Per Month', ylabel='Mean Net',
        xlabel='Release Month', figsize=(6, 5))
```

Out[25]:
```
<AxesSubplot:title={'center':'AVG Net Per Month'}, xlabel='Release Mont
h', ylabel='Mean Net'>
```



From this chart we notice that movies released in summer generate a higher Net Revenue

In [26]:
```
# Create dictionary to assign month to season to properly evaluate the data
season_month = {
            12:'Winter', 1:'Winter', 2:'Winter',
            3:'Spring', 4:'Spring', 5:'Spring',
            6:'Summer', 7:'Summer', 8:'Summer',
            9:'Fall', 10:'Fall', 11:'Fall'}

# map through data and create new column with movie release season
tn_budgets['release_season'] = tn_budgets["release_month"].map(season_month
tn_budgets.sort_values(by=["release_season"])
by_season = tn_budgets.groupby("release_season")["Net Revenue"].mean().rese
```

In [27]:
```
# Create new dataframe that groups the release_season and Net Revenue colum
season_mean = tn_budgets.groupby("release_season")["Net Revenue"].mean().re
season_mean
```

Out[27]:

	release_season	Net Revenue
0	Fall	47803627.875
1	Spring	65128830.067
2	Summer	76676469.389
3	Winter	51863328.816

In [28]:
```
season_count = tn_budgets.groupby("release_season")["Net Revenue"].count().
season_count
```

Out[28]:

	release_season	Net Revenue
0	Fall	1552
1	Spring	1331
2	Summer	1415
3	Winter	1484

In [29]:
```
import scipy.stats as stats
from math import sqrt
x_bar = season_mean["Net Revenue"][2] # sample mean of summer
n = season_count["Net Revenue"][2] # number of sample inputs
sigma = tn_budgets["Net Revenue"].std() # sd of all inputs
mu = tn_budgets["Net Revenue"].mean() # all inputs mean

z_value = (x_bar - mu)/(sigma/sqrt(n))
z_value
```

Out[29]: 4.319856231441833

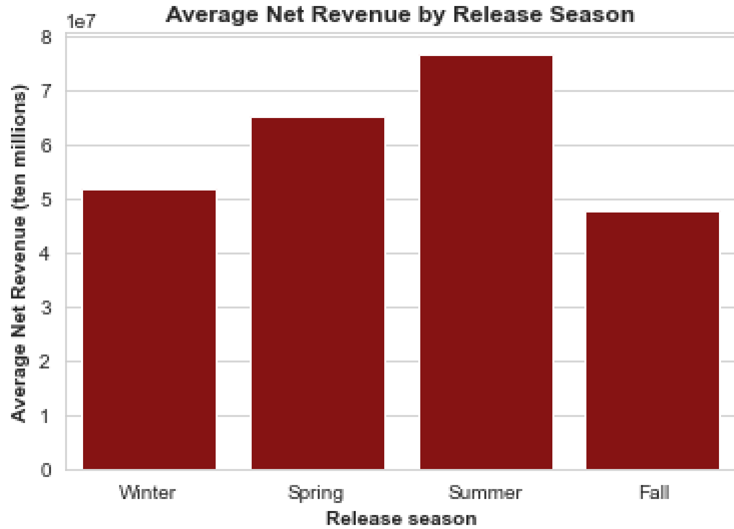
In [30]:
```
p_value = stats.norm.sf(z_value)
print('p_value = 0.0000078065311787312228')
p_value
```

```
p_value = 0.0000078065311787312228
```

Out[30]:
```
7.806544209520419e-06
```

In [31]:
```
# Plot out the by_season variable that allows us to evaluate average net re
ax = sns.barplot(data=by_season, x='release_season', y='Net Revenue', color
ax.set_xticklabels(ax.get_xticklabels());
ax.set_title('Average Net Revenue by Release Season', fontsize=12, weight='
ax.set_ylabel('Average Net Revenue (ten millions)', weight='bold')
ax.set_xlabel('Release season', weight='bold')
```

Out[31]:
```
Text(0.5, 0, 'Release season')
```



Conclusion

alpha = .05

z score = 4.319

p score = 0.0000078065311787312228

After running the z score and p score, we can reject the null hypothesis with 99.9 percent confidence