Microsoft Original Video Content

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Overview

This project analyzes the success of movies based on data gathered from multiple sources: https://www.imdb.com/ (https://www.imdb.com/), https://www.the-numbers.com/ (https://www.the-numbers.com/), and https://www.boxofficemojo.com/ (https://www.boxofficemojo.com/). We've come to the conclusion that genre type, the production budget, and the director play a most noticable role in profits. While it is important to get a good rating, we've found that it is not as important when trying to build capital.

Business Problem

Microsoft is planning on expanding their company developing an original content studio. We believe it best to start with a comprehensive understanding of the current market. Doing so will allow for the best opportunity for success, longevity, and great content.

We've created bar charts and scatter plots that have been a useful practice while coming to our conclusions. Doing so has allowed us to gain an understanding of trends and specific methods we can use to bring in profits. The information we are displaying is from 2012 to 2019.

Data Understanding

In [1]:
```
# Import linraries and modules

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
```

In [2]:
```
#Access IMDB data through sqlite3

# Connect to sqlite3
conn = sqlite3.connect('data/im.db')

# Query and join IMDB tables movie_basics, movie_ratings and director informa

df_imdb = pd.read_sql("""
    SELECT *
    FROM
    movie_basics AS mb
        LEFT JOIN movie_ratings AS mr
            ON mb.movie_id = mr.movie_id
        LEFT JOIN
            (SELECT *
            FROM directors GROUP BY movie_id) AS dr
            ON mb.movie_id = dr.movie_id
        LEFT JOIN persons AS ps
            ON dr.person_id = ps.person_id
""", conn)
```

In [3]:
```
# Import The Numbers dataset
df_tn = pd.read_csv('data/tn.movie_budgets.csv')
```

In [4]:
```
# Import The Numbers dataset
df_bom = pd.read_csv('data/bom.movie_gross.csv')
```

In [5]:
```
df_imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 16 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   movie_id            146144 non-null  object 
 1   primary_title       146144 non-null  object 
 2   original_title      146123 non-null  object 
 3   start_year          146144 non-null  int64  
 4   runtime_minutes     114405 non-null  float64
 5   genres              140736 non-null  object 
 6   movie_id            73856 non-null   object 
 7   averagerating       73856 non-null   float64
 8   numvotes            73856 non-null   float64
 9   movie_id            140417 non-null  object 
 10  person_id           140417 non-null  object 
 11  person_id           140416 non-null  object 
 12  primary_name        140416 non-null  object 
 13  birth_year          30609 non-null   float64
 14  death_year          856 non-null     float64
 15  primary_profession  139887 non-null  object 
dtypes: float64(5), int64(1), object(10)
memory usage: 17.8+ MB
```

In [6]:
```
df_tn.info()
```

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

In [7]:
```
df_bom.info()
```

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

Data Preperation

Data Cleaning

IMDB Cleaning

In [8]:
```
# Split genres from IMDB data into spereate columns
df_imdb[['Genre_1','Genre_2', 'Genre_3']] = df_imdb["genres"].str.split(",",e

# Add colum of avrage rating relative to mean of overall average rating
df_imdb['rating_relative_to_avg'] = df_imdb['averagerating'] - df_imdb['avera


# Create dataframe of counts of genres
# Count genres by column
df_gen_cnt = df_imdb[['Genre_1', 'Genre_2', 'Genre_3']].apply(pd.Series.value
# Make NaNs 0
df_gen_cnt = df_gen_cnt.fillna(0)

# Get total count per genre and add to total counts column
df_gen_cnt['total_gen_cnt'] = df_gen_cnt['Genre_1'] + df_gen_cnt['Genre_2'] +

# Create a datafram of genre combinations and their averagerating
df_genres = df_imdb.loc[:, ["Genre_1","Genre_2","Genre_3", "averagerating", "

# A dataframe of genre value counts
df_gen_cnt = df_imdb[['Genre_1', 'Genre_2', 'Genre_3']].apply(pd.Series.value
df_gen_cnt = df_gen_cnt.fillna(0)
df_gen_cnt['total_gen_cnt'] = df_gen_cnt['Genre_1'] + df_gen_cnt['Genre_2'] +
df_genres = df_genres.dropna(subset=['averagerating'])
```

In [9]:
```
df_gen_cnt
```

Out[9]:

	Genre_1	Genre_2	Genre_3	total_gen_cnt
Action	10335	0.0	0.0	10335.0
Adult	23	2.0	0.0	25.0
Adventure	4760	1705.0	0.0	6465.0
Animation	1839	763.0	197.0	2799.0
Biography	8021	656.0	45.0	8722.0
Comedy	21514	3092.0	706.0	25312.0
Crime	3919	2369.0	465.0	6753.0
Documentary	41609	8737.0	1294.0	51640.0
Drama	31343	14559.0	3981.0	49883.0
Family	1108	2980.0	2139.0	6227.0
Fantasy	905	1512.0	1099.0	3516.0
Game-Show	3	1.0	0.0	4.0
History	468	3046.0	2711.0	6225.0
Horror	6650	3110.0	1045.0	10805.0
Music	741	2082.0	1491.0	4314.0
Musical	423	524.0	483.0	1430.0
Mystery	866	2247.0	1546.0	4659.0
News	17	706.0	828.0	1551.0
Reality-TV	54	22.0	22.0	98.0
Romance	1555	4417.0	3400.0	9372.0
Sci-Fi	851	1204.0	1310.0	3365.0
Short	1	6.0	4.0	11.0
Sport	363	985.0	886.0	2234.0
Talk-Show	39	11.0	0.0	50.0
Thriller	3055	4036.0	4792.0	11883.0
War	132	471.0	802.0	1405.0
Western	142	135.0	190.0	467.0

In [10]:
```
#Top 50 movies by rating with at least 100,000 votes and released no later th
df_top50_rat = df_imdb[(df_imdb['numvotes'] >= 100000) & (df_imdb['start_year
```

TN Cleaning

In [11]:
```
# Remove non-numerical characters from strings that will be converted to nume
df_tn['production_budget'] = df_tn['production_budget'].str.replace(",","")
df_tn['production_budget'] = df_tn['production_budget'].str.replace("$","")

df_tn['worldwide_gross'] = df_tn['worldwide_gross'].str.replace(",","")
df_tn['worldwide_gross'] = df_tn['worldwide_gross'].str.replace("$","")

df_tn['domestic_gross'] = df_tn['worldwide_gross'].str.replace(",","")
df_tn['domestic_gross'] = df_tn['worldwide_gross'].str.replace("$","")
```

In [12]:
```
# Convert strings representing money values to numeric
df_tn['worldwide_gross'] = df_tn['worldwide_gross'].astype('int64')
df_tn['production_budget'] = df_tn['production_budget'].astype('int64')
df_tn['domestic_gross'] = df_tn['domestic_gross'].astype('int64')
```

In [13]:
```
# Convert the data type of the 'release_date' column to a date
df_tn['release_date'] = pd.to_datetime(df_tn['release_date'],format="%b %d, %

# Add a new columns 'year'
df_tn['release_year'] = df_tn['release_date'].dt.year

# Create key column movie + year
df_tn['release_year'] = df_tn['release_year'].astype(str)
df_tn['mov_yr_key'] = df_tn['movie'] + "-" + df_tn['release_year']
```

In [14]:
```
# Create a column of wordwide profit by sibtracting production budget from wo
df_tn['worldwide_profit'] = df_tn['worldwide_gross'] - df_tn['production_budg
```

BOM

In [15]:
```
# # Remove non-numerical characters from strings that will be converted to nu
df_bom['foreign_gross'] = df_bom['foreign_gross'].str.replace(",","")

# Convert strings representing money values to numeric
df_bom['foreign_gross'] = df_bom['foreign_gross'].astype(float)

# Create a column of total gross by adding together foreign gross and domesit
df_bom['total_gross'] = df_bom['foreign_gross'] + df_bom['domestic_gross']
```

Data Merging

Before merging the datasets, we created new column in both the IMDB and TN datasets 'mov_yr_key' a conbination of the title and year string columns of each data set.

We originally tried merging on only columns that contained the movei titles, however, the same title can apply to multiple movies, causing data mixup. As an example, when we first merged the dataframes, the left dataframe row with data on James Cameron's 2009 "Avatar" was merged with Atsushi Wada's 2011 movie by the same name from the right dataframe.

In [16]:
```
df_imdb['year_str'] = df_imdb['start_year'].astype(str)
df_imdb['mov_yr_key'] = df_imdb['primary_title'] + "-" + df_imdb['year_str']
```

In [17]:
```
# Merge the imdb and tn datasets on 'mov_yr_key'
df_tn_imdb = df_tn.merge(df_imdb,how='inner',left_on='mov_yr_key', right_on='
```

To focus on recent trend and successes in the indiustry, we will focus on movies made no older than 2012.

In [18]:
```
# Create filtered dataFrame of merged data to only include movies made since
df_tn_imdb_filt_year = df_tn_imdb[df_imdb['start_year'] >= 2012]

# Create filtered dataFrame of merged data to only include movies made since
#and made a worldwide profit of at least $50,000,000
df_tn_imdb_filt_year_5hunthou = df_tn_imdb_filt_year[df_tn_imdb_filt_year['wo

# Create filtered dataFrame of merged data to only include movies with at lea
df_tn_imdb_filt = df_tn_imdb[(df_tn_imdb['numvotes'] >= 100000) & (df_imdb['s
df_bom_filt = df_bom[df_bom['year'] >= 2012]
```

```
<ipython-input-18-c1ded018ef5d>:2: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  df_tn_imdb_filt_year = df_tn_imdb[df_imdb['start_year'] >= 2012]
<ipython-input-18-c1ded018ef5d>:9: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  df_tn_imdb_filt = df_tn_imdb[(df_tn_imdb['numvotes'] >= 100000) & (df_imd
b['start_year'] >= 2012)]
```

Analysis

Average User Rating on IMDB

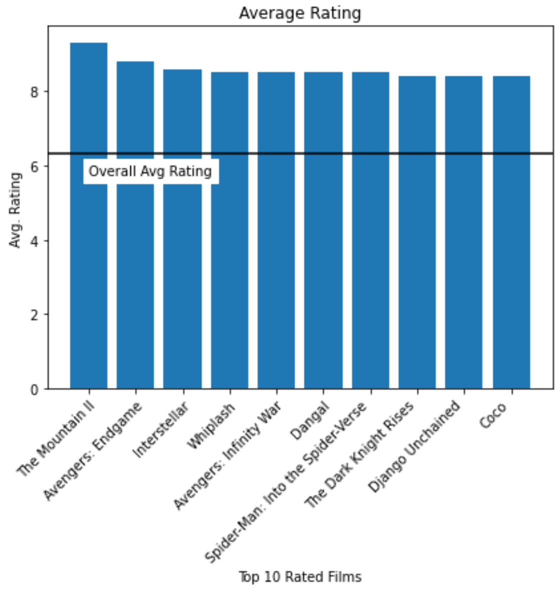
To start to understand the data and movie related data in general, we first looked at the average IMDB user rating for top rated films. We then wanted to see if there was a relation between number of votes and avg rating, to see if more popular (measured by number of votes) or less popular movies had an advantage in recieving high average ratings. Next, we checked on a relationship between average rating and profit. Does an higher average score on IMDB incrrease the likelihood of higher profit?

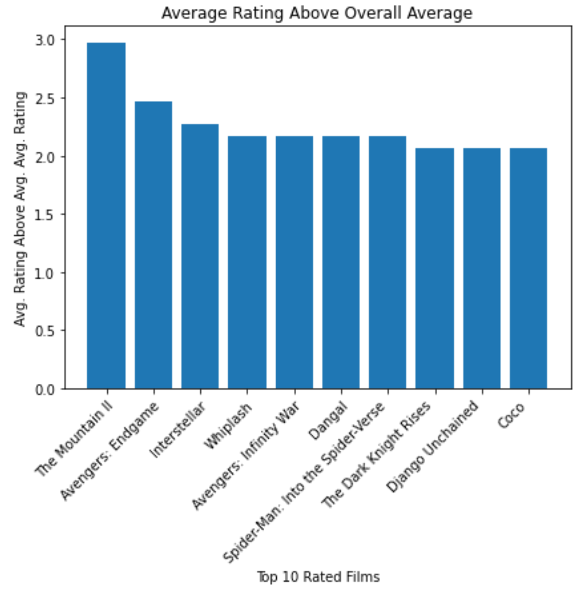
In [19]:

```
# Viz of Top 10 movies by rating with at least 100,000 votes and released no
df_top10_rat = df_top50_rat[0:10]

fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=(15,5))

x1 = df_top10_rat['primary_title']
y1 = df_top10_rat['averagerating']

x2 = df_top10_rat['primary_title']
y2 = df_top10_rat['rating_relative_to_avg']

ax1.axhline(6.332729, c="black")
ax1.text(0,5.75,"Overall Avg Rating", backgroundcolor="White")

ax1.set_xticklabels(x1, rotation=45, ha = 'right', rotation_mode = 'anchor')
ax2.set_xticklabels(x2, rotation=45, ha = 'right', rotation_mode = 'anchor')

ax1.set_xlabel("Top 10 Rated Films")
ax1.set_ylabel("Avg. Rating")

ax2.set_xlabel("Top 10 Rated Films")
ax2.set_ylabel("Avg. Rating Above Avg. Avg. Rating")

ax1.set_title("Average Rating")
ax2.set_title("Average Rating Above Overall Average")

ax1.bar(x1,y1)
ax2.bar(x2,y2)

plt.savefig('../images/avg_rat_bmov', bbox_inches='tight')
```

```
<ipython-input-19-efc2e5935fa8>:15: UserWarning: FixedFormatter should only
be used together with FixedLocator
  ax1.set_xticklabels(x1, rotation=45, ha = 'right', rotation_mode = 'ancho
r')
<ipython-input-19-efc2e5935fa8>:16: UserWarning: FixedFormatter should only
be used together with FixedLocator
  ax2.set_xticklabels(x2, rotation=45, ha = 'right', rotation_mode = 'ancho
r')

---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
<ipython-input-19-efc2e5935fa8> in <module>
     28 ax2.bar(x2,y2)
     29
---> 30 plt.savefig('../images/avg_rat_bmov', bbox_inches='tight')

~\anaconda3\envs\learn-env\lib\site-packages\matplotlib\pyplot.py in savefi
g(*args, **kwargs)
    841 def savefig(*args, **kwargs):
    842     fig = gcf()
--> 843     res = fig.savefig(*args, **kwargs)
    844     fig.canvas.draw_idle()   # need this if 'transparent=True' to r
eset colors
    845     return res

~\anaconda3\envs\learn-env\lib\site-packages\matplotlib\figure.py in savefi
```

```
g(self, fname, transparent, **kwargs)
   2309                 patch.set_edgecolor('none')
   2310 
-> 2311         self.canvas.print_figure(fname, **kwargs)
   2312 
   2313         if transparent:

~\anaconda3\envs\learn-env\lib\site-packages\matplotlib\backend_bases.py in
print_figure(self, filename, dpi, facecolor, edgecolor, orientation, forma
t, bbox_inches, pad_inches, bbox_extra_artists, backend, **kwargs)
   2208 
   2209             try:
-> 2210                 result = print_method(
   2211                     filename,
   2212                     dpi=dpi,

~\anaconda3\envs\learn-env\lib\site-packages\matplotlib\backend_bases.py in
wrapper(*args, **kwargs)
   1637             kwargs.pop(arg)
   1638 
-> 1639         return func(*args, **kwargs)
   1640 
   1641     return wrapper

~\anaconda3\envs\learn-env\lib\site-packages\matplotlib\backends\backend_ag
g.py in print_png(self, filename_or_obj, metadata, pil_kwargs, *args)
    508         """
    509         FigureCanvasAgg.draw(self)
--> 510         mpl.image.imsave(
    511             filename_or_obj, self.buffer_rgba(), format="png", orig
in="upper",
    512             dpi=self.figure.dpi, metadata=metadata, pil_kwargs=pil_
kwargs)

~\anaconda3\envs\learn-env\lib\site-packages\matplotlib\image.py in imsave
(fname, arr, vmin, vmax, cmap, format, origin, dpi, metadata, pil_kwargs)
   1599         pil_kwargs.setdefault("format", format)
   1600         pil_kwargs.setdefault("dpi", (dpi, dpi))
-> 1601         image.save(fname, **pil_kwargs)
   1602 
   1603 

~\anaconda3\envs\learn-env\lib\site-packages\PIL\Image.py in save(self, fp,
format, **params)
   2146                 fp = builtins.open(filename, "r+b")
   2147             else:
-> 2148                 fp = builtins.open(filename, "w+b")
   2149 
   2150         try:

FileNotFoundError: [Errno 2] No such file or directory: '../images/avg_rat_
bmov.png'
```





In [ ]:

```
# Viz of comparison of number of votes and average rating

fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=(15,5))

x1 = df_imdb['averagerating']
y1 = df_imdb['numvotes']/1000

x2 = df_top50_rat['averagerating']
y2 = df_top50_rat['numvotes']/1000


ax1.set_xlabel("Average Rating")
ax1.set_ylabel("Number of Votes (thousands)")
ax1.set_title("Average Rating by Number of Votes")

ax2.set_xlabel("Average Rating")
ax2.set_ylabel("Number of Votes (thousands)")
ax2.set_title("Average Rating by Number of Votes for Top 50 Rated")

ax1.scatter(x1,y1)
ax2.scatter(x2,y2)
```

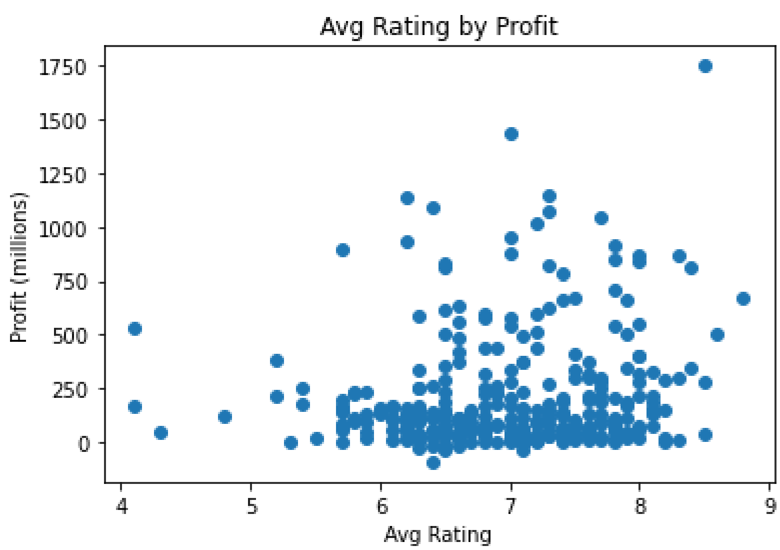
In [20]:

```
# Get correlation average rating and number of votes
df_tn_imdb_filt['averagerating'].corr(df_tn_imdb_filt['numvotes'])
```

Out[20]: 0.49613474170077504

In [21]:
```
# Vizualize Average Rating by Profit
fig, ax = plt.subplots()

x = df_tn_imdb_filt['averagerating']
y = df_tn_imdb_filt['worldwide_profit']/1000000

ax.set_xlabel("Avg Rating")
ax.set_ylabel("Profit (millions)")
ax.set_title("Avg Rating by Profit")



ax.scatter(x,y)
```

Out[21]: <matplotlib.collections.PathCollection at 0x2b3d21565b0>



In [22]:
```
# Get correlation average rating and worldwide profit
df_tn_imdb_filt['averagerating'].corr(df_tn_imdb_filt['worldwide_profit'])
```

Out[22]: 0.14375206103201144

Average rating does not have a strong correlation to profit, and therefor we only use it as a measure of possible "industry credit" and not for a successful finacial indicator.

Studios to Hire From

Microsoft will need to staff the new movie studio with successful and experienced persons. We identified the top movie studios since 2012 by movies made and total gross to create a list of the studios where Microsoft should look to hire from.

In [23]:
```
# Group by studio and examine largest sums of total gross
df_bom_filt.groupby('studio').sum().sort_values('total_gross', ascending=Fals
```

Out[23]:

studio	domestic_gross	foreign_gross	year	total_gross
BV	1.570240e+10	2.117251e+10	157157	3.686251e+10
Fox	8.967700e+09	1.702962e+10	209547	2.597232e+10
Uni.	1.105189e+10	1.457537e+10	235767	2.561691e+10
WB	9.073773e+09	1.416202e+10	209564	2.319382e+10
Sony	6.550983e+09	1.149014e+10	175332	1.804092e+10
...	...	...	...	...
Gaatri	8.980000e+05	0.000000e+00	2016	0.000000e+00
Fathom	1.144700e+07	0.000000e+00	20177	0.000000e+00
FOR	1.020000e+04	0.000000e+00	2015	0.000000e+00
FEF	6.130000e+05	0.000000e+00	2013	0.000000e+00
Jampa	2.670000e+04	0.000000e+00	2016	0.000000e+00

219 rows × 4 columns

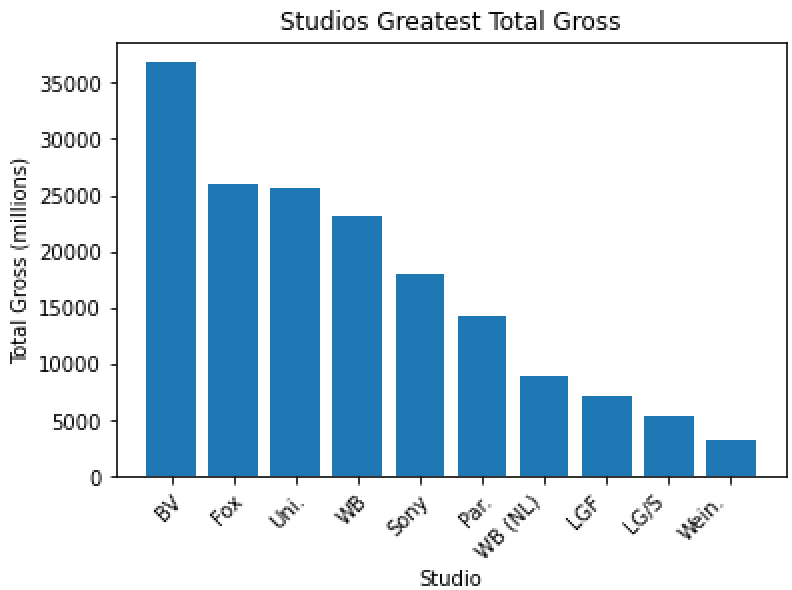
In [24]:
```
# Select the top 10 studios by sum of total gross and save to a variable
top10_stud_filt = df_bom_filt.groupby('studio').sum().sort_values('total_gros
top10_stud_filt
```

Out[24]:

studio	domestic_gross	foreign_gross	year	total_gross
BV	1.570240e+10	2.117251e+10	157157	3.686251e+10
Fox	8.967700e+09	1.702962e+10	209547	2.597232e+10
Uni.	1.105189e+10	1.457537e+10	235767	2.561691e+10
WB	9.073773e+09	1.416202e+10	209564	2.319382e+10
Sony	6.550983e+09	1.149014e+10	175332	1.804092e+10
Par.	5.298605e+09	9.049485e+09	159185	1.424340e+10
WB (NL)	3.416300e+09	5.567200e+09	72549	8.962900e+09
LGF	3.427902e+09	3.811285e+09	161198	7.106475e+09
LG/S	2.078200e+09	3.353724e+09	82599	5.318924e+09
Wein.	1.242996e+09	2.063821e+09	122850	3.266239e+09

In [27]:

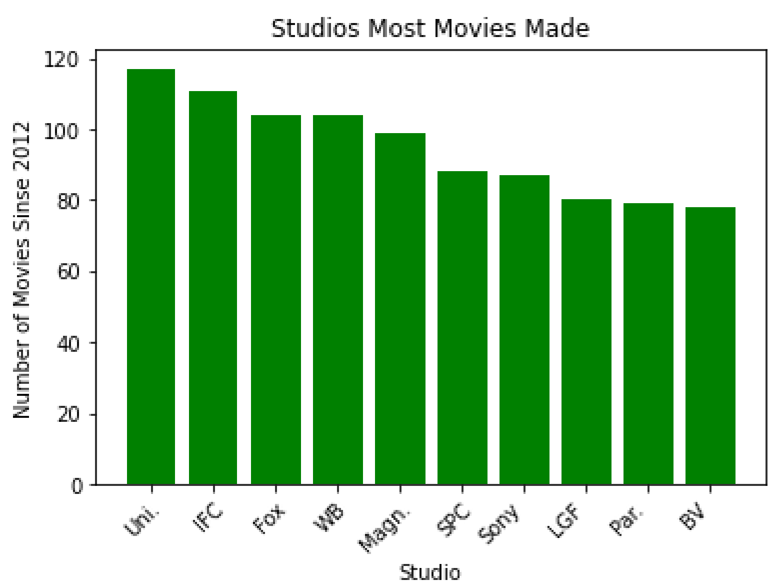
```
# Vizualize top 10 studios by sum of total gross since 2012
fig, ax = plt.subplots()

x = top10_stud_filt.index
y = top10_stud_filt['total_gross']/1000000

ax.set_xlabel("Studio")
ax.set_ylabel("Total Gross (millions)")
ax.set_title("Studios Greatest Total Gross")

ha = ['right', 'center', 'left']

plt.xticks(rotation=45, ha = 'right', rotation_mode = 'anchor')

ax.bar(x,y)

plt.savefig('images/top_studios_filt_gross.png', bbox_inches='tight')
```



In [28]:
```
# Select the top 10 studios by number of movies released
stud_top_num_mov = df_bom_filt.value_counts(subset='studio')[:10]
stud_top_num_mov
```

Out[28]:
```
studio
Uni.     117
IFC      111
Fox      104
WB       104
Magn.     99
SPC       88
Sony      87
LGF       80
Par.      79
BV        78
dtype: int64
```

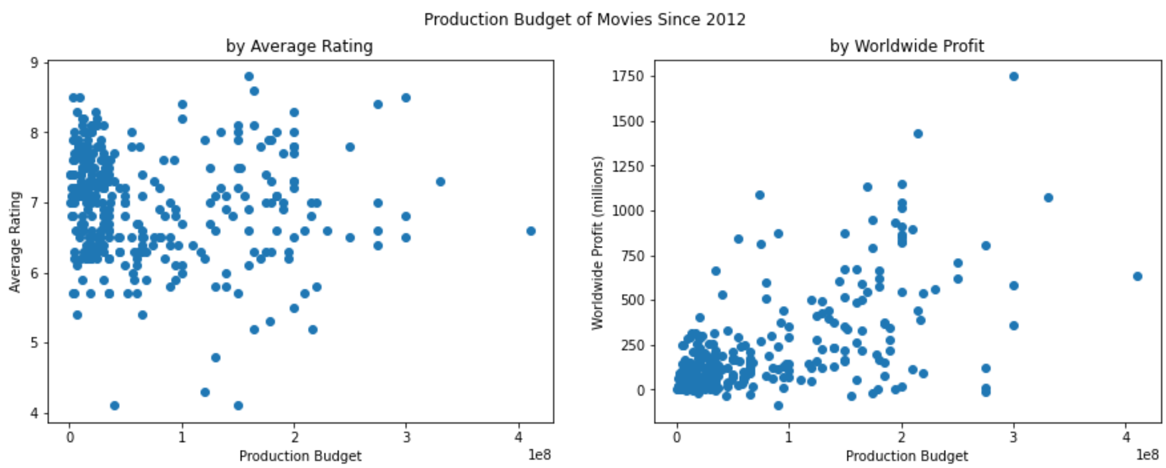
In [30]:
```
# Vizualize top 10 studios by number of movies released
fig, ax = plt.subplots()

x = stud_top_num_mov.index
y = stud_top_num_mov.values

ax.set_xlabel("Studio")
ax.set_ylabel("Number of Movies Sinse 2012")
ax.set_title("Studios Most Movies Made")

ha = ['right', 'center', 'left']

plt.xticks(rotation=45, ha = 'right', rotation_mode = 'anchor')

ax.bar(x,y, color="green")
plt.savefig('images/top_studios_filt_num_movs', bbox_inches='tight')
```



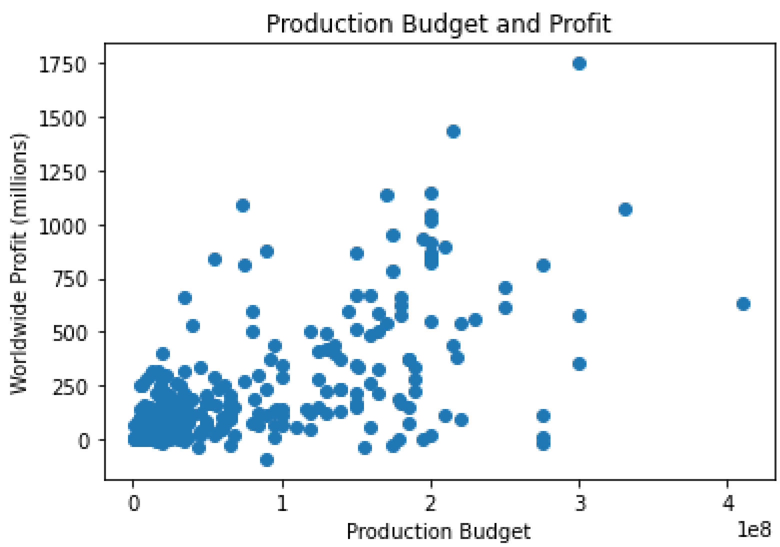
Allocation of Budget

Microsoft will need to knwo how much budget to allocate to it's new movies. We looked at the relationship between production budget and average rating and worldwide profit.

In [31]:
```
# Vizualize produciton budget vs average rating & production budget vs worldw
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=(15,5))

plt.suptitle("Production Budget of Movies Since 2012")

x1 = df_tn_imdb_filt['production_budget']
y1 = df_tn_imdb_filt['averagerating']

x2 = df_tn_imdb_filt['production_budget']
y2 = df_tn_imdb_filt['worldwide_profit']/1000000


ax1.set_xlabel("Production Budget")
ax1.set_ylabel("Average Rating")
ax1.set_title("by Average Rating")

ax2.set_xlabel("Production Budget")
ax2.set_ylabel("Worldwide Profit (millions)")
ax2.set_title("by Worldwide Profit")

ax1.scatter(x1, y1)
ax2.scatter(x2, y2)

plt.savefig('images/bud_filt_avgrat_wwprofit', bbox_inches='tight')
```



In [32]:
```
# Singling out production budget vs worldwide profit since 2012
fig, ax = plt.subplots()

x = df_tn_imdb_filt['production_budget']
y = df_tn_imdb_filt['worldwide_profit']/1000000


ax.set_xlabel("Production Budget")
ax.set_ylabel("Worldwide Profit (millions)")
ax.set_title("Production Budget and Profit")

ax.scatter(x, y)

plt.savefig('images/bud_filt_wwprofit', bbox_inches='tight')
```



In [33]:
```
# Get correlation of produciton budget vand average rating
df_tn_imdb_filt['production_budget'].corr(df_tn_imdb_filt['averagerating'])
```

Out[33]: -0.09842752224249707

In [34]:
```
# Get correlation of production budget and worldwide profit
df_tn_imdb_filt['production_budget'].corr(df_tn_imdb_filt['worldwide_profit']
```

Out[34]: 0.6237389744636805

In [35]:
```
# Get all time correlation of produciton budget vand average rating
df_tn_imdb['production_budget'].corr(df_tn_imdb['averagerating'])
```

Out[35]: 0.2225609389897727

In [36]:
```
# Get all time correlation of production budget and worldwide profit
df_tn_imdb['production_budget'].corr(df_tn_imdb['worldwide_profit'])
```

Out[36]: 0.6622588394897604

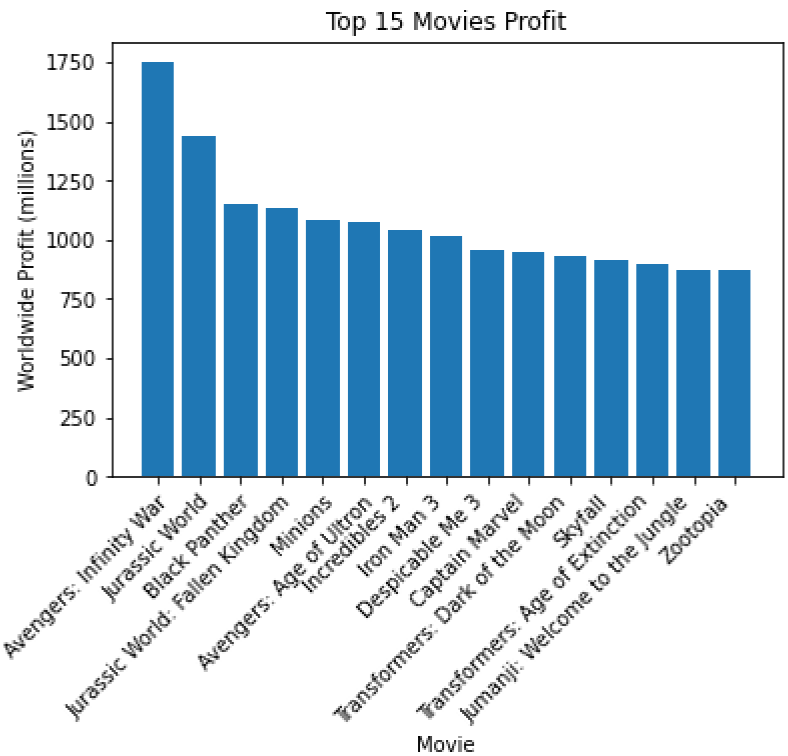
In [37]:
```
# Mean Budget for films since 2012 that made at least 50,000,000 in profit wo
df_tn_imdb_filt_year_5hunthou['production_budget'].mean()
```

Out[37]: 69161538.46153846

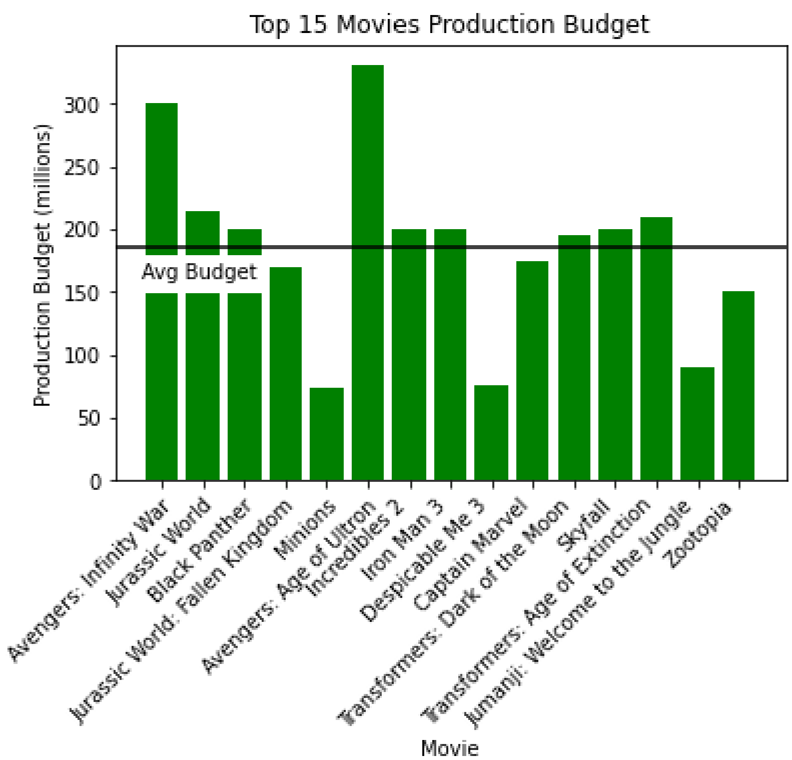
In [38]:
```
# Filter data to find the top movies by worldwide profit since 2012
top15_movs_profit = df_tn_imdb_filt_year.groupby('primary_title').mean().sort
```

In [39]:
```
# Find the average production budget of the top 15 films
top15_movs_profit_avg_probud = top15_movs_profit['production_budget'].mean()
```

In [40]:
```
fig, ax = plt.subplots()

x = top15_movs_profit.index
y = top15_movs_profit['worldwide_profit']/1000000

ha = ['right', 'center', 'left']

plt.xticks(rotation=45, ha = 'right', rotation_mode = 'anchor')

ax.set_xlabel('Movie')
ax.set_ylabel('Worldwide Profit (millions)')
ax.set_title('Top 15 Movies Profit')

ax.bar(x,y)

plt.savefig('images/top_profit_movies_budget_profit', bbox_inches='tight')
```



In [42]:
```
fig, ax = plt.subplots()

x = top15_movs_profit.index
y = top15_movs_profit['production_budget']/1000000

ax.axhline(top15_movs_profit_avg_probud/1000000, c="black")
ax.text(-.5,160,"Avg Budget", backgroundcolor="White")

ha = ['right', 'center', 'left']

plt.xticks(rotation=45, ha = 'right', rotation_mode = 'anchor')

ax.set_xlabel('Movie')
ax.set_ylabel('Production Budget (millions)')
ax.set_title('Top 15 Movies Production Budget')

ax.bar(x,y, color="green")

plt.savefig('images/top_profit_movies_budget', bbox_inches='tight', dpi=500)
```



Successful Genre Combinations

After hiring staff and allocating budget, the new studio will need to knwo what kinds of movies to make and focus on. We used the data of genre combinations to see what kinds of movies performed best. Future analysis should break down generes combinatiosn into their single genres and their success.

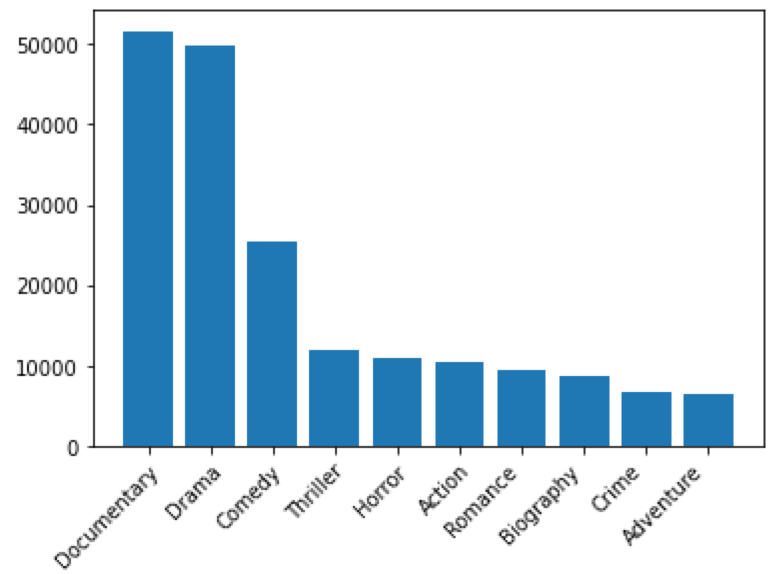
In [43]:
```
# Looking at the top 10 rated genre combinations with > 100000 votes since 20
df_top10_gen_comb_rat = df_genres[(df_genres['numvotes'] >= 100000) & (df_ger
df_top10_gen_comb_rat
```

Out[43]:

Genre_1	Genre_2	Genre_3	averagerating	numvotes	start_year
Action	**Drama**	**War**	8.450	241280.50	2015.00
Animation	**Drama**	**Fantasy**	8.400	134084.00	2016.00
Adventure	**Drama**	**Sci-Fi**	8.300	989725.00	2014.50
Comedy	**Drama**	**Thriller**	8.100	151123.00	2014.00
		Fantasy	8.000	200574.00	2013.50
Biography	**Drama**	**Music**	8.000	345466.00	2018.00
Action	**Biography**	**Drama**	7.850	291407.75	2014.00
Drama	**Music**	**Romance**	7.800	249245.00	2018.00
	Mystery	**Sci-Fi**	7.775	385403.75	2015.25
Biography	**Drama**	**Thriller**	7.700	415517.00	2013.75

In [44]:
```
# Viz of genre counts
top10_gen_cnt = df_gen_cnt.sort_values('total_gen_cnt', ascending=False)[0:10

fig, ax = plt.subplots()

x = top10_gen_cnt.index
y = top10_gen_cnt['total_gen_cnt']

ha = ['right', 'center', 'left']

plt.xticks(rotation=45, ha = "right", rotation_mode = 'anchor')

ax.bar(x,y)
```

Out[44]: <BarContainer object of 10 artists>



In [45]:
```
df_com_yr_sr_rat = df_tn_imdb_filt_year.sort_values('averagerating', ascendir
top_gen_s_2012 = df_com_yr_sr_rat.loc[:,['genres', 'averagerating', 'worldwic
top_gen_s_2012['genres'] = top_gen_s_2012['genres'].str.replace(',', ' - ')
top_gen_s_2012_grp = top_gen_s_2012.groupby('genres').mean()
```

In [46]:
```
top10_gen_s2012_brat = top_gen_s_2012_grp.sort_values('averagerating', ascenc
top10_gen_s2012_brat
```

Out[46]:

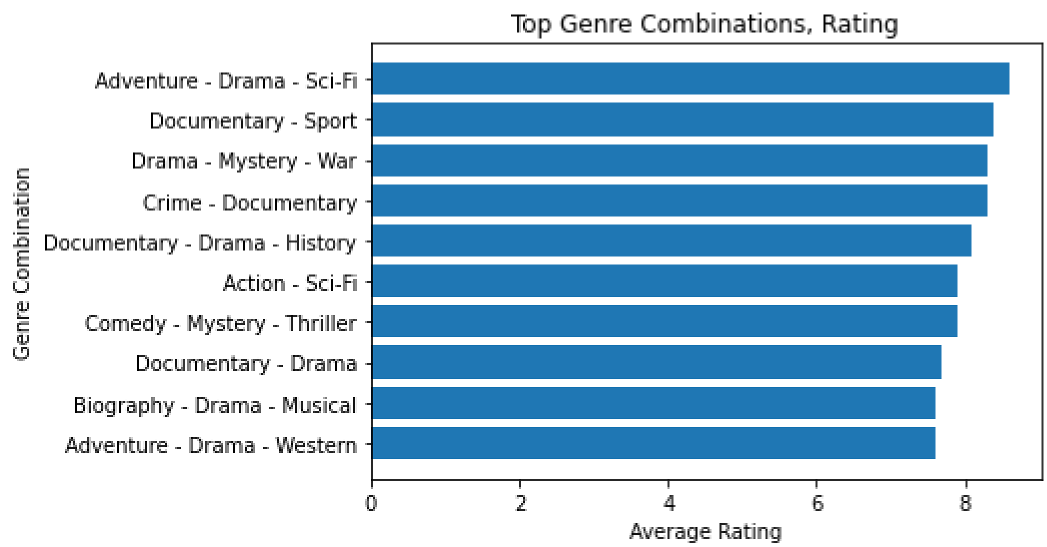
genres	averagerating	worldwide_gross
Adventure - Drama - Sci-Fi	8.6	666379375.0
Documentary - Sport	8.4	314444.0
Drama - Mystery - War	8.3	16038343.0
Crime - Documentary	8.3	7799257.0
Documentary - Drama - History	8.1	176262.0
Action - Sci-Fi	7.9	370541256.0
Comedy - Mystery - Thriller	7.9	0.0
Documentary - Drama	7.7	0.0
Biography - Drama - Musical	7.6	386665550.0
Adventure - Drama - Western	7.6	252276928.0

In [47]:
```
top10_gen_s2012_bwrgr = top_gen_s_2012_grp.sort_values('worldwide_gross', asc
top10_gen_s2012_bwrgr
```

Out[47]:

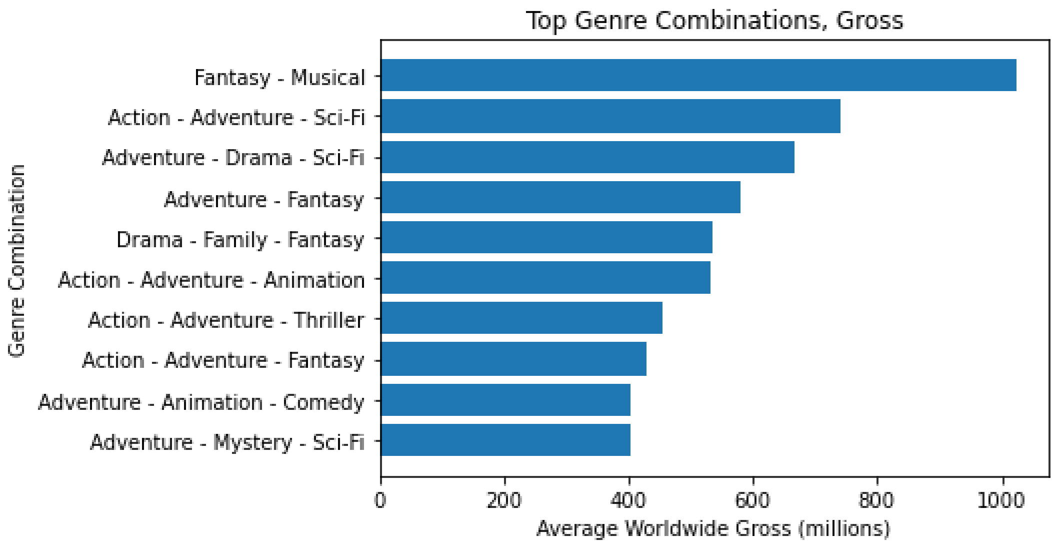
genres	averagerating	worldwide_gross
Fantasy - Musical	6.500000	1.025491e+09
Action - Adventure - Sci-Fi	6.703333	7.405735e+08
Adventure - Drama - Sci-Fi	8.600000	6.663794e+08
Adventure - Fantasy	7.050000	5.790272e+08
Drama - Family - Fantasy	6.900000	5.345514e+08
Action - Adventure - Animation	7.212500	5.310212e+08
Action - Adventure - Thriller	6.342857	4.540020e+08
Action - Adventure - Fantasy	6.250000	4.303633e+08
Adventure - Animation - Comedy	6.390000	4.027423e+08
Adventure - Mystery - Sci-Fi	7.000000	4.024483e+08

In [49]:
```
fig, ax = plt.subplots()

x = top10_gen_s2012_brat.index
y = top10_gen_s2012_brat['averagerating']

ax.set_xlabel("Average Rating")
ax.set_ylabel("Genre Combination")
ax.set_title("Top Genre Combinations, Rating")

plt.gca().invert_yaxis()

ax.barh(x,y)
plt.savefig('images/top_gen_s_2012_b_avg_rat', bbox_inches='tight')
```



In [51]:

```
fig, ax = plt.subplots()

x = top10_gen_s2012_bwrgr.index
y = top10_gen_s2012_bwrgr['worldwide_gross']/1000000

ax.set_xlabel("Average Worldwide Gross (millions)")
ax.set_ylabel("Genre Combination")
ax.set_title("Top Genre Combinations, Gross")

plt.gca().invert_yaxis()

ax.barh(x,y)
plt.savefig('images/top_gen_s_2012_b_avg_wwgr', bbox_inches='tight')
```

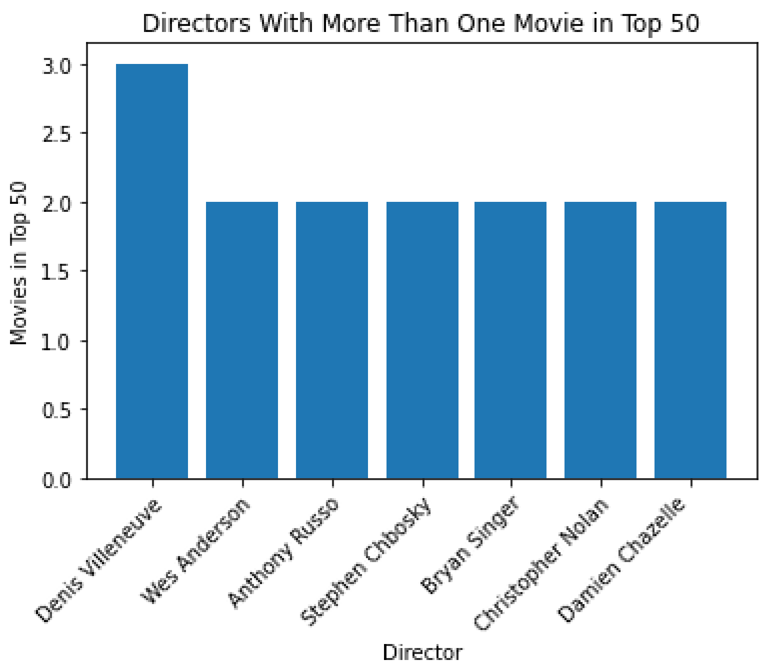


Directors to Work With

In addition to the most successful genres, we looked into the most succesfull directors since 2012 so Microsoft will know who to build relationships with and hire onto movies. We looked at director success through the lenses of being in the top 50 user rated movies (for industry acceptance and awareness) and average profit per movie.

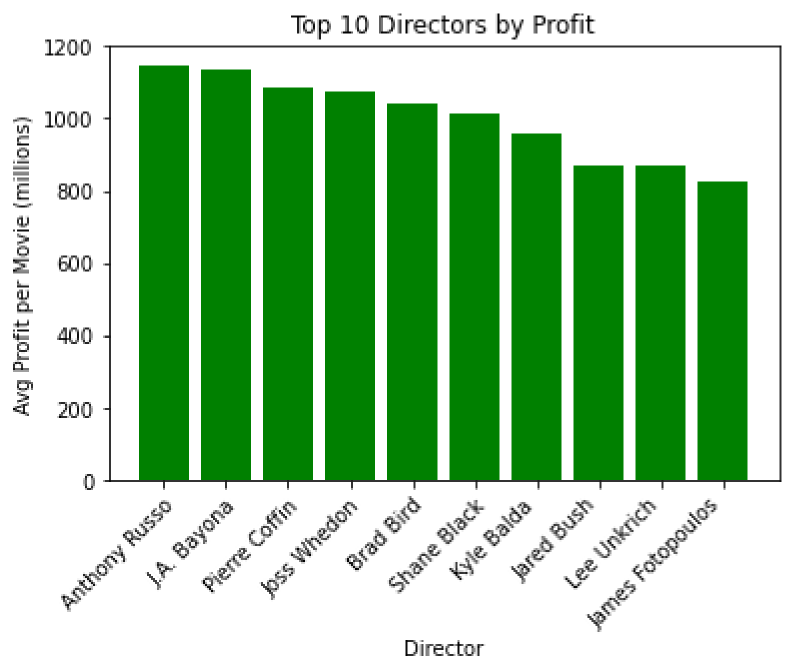
In [52]:

```
# Viz of the directors who have more than one film in the top 50 rated movies

# Create a series of directors who have more than one film in the top 50 rate
dir_mul_top50 = df_top50_rat.value_counts('primary_name')[0:7]

fig, ax = plt.subplots()

x = dir_mul_top50.index
y = dir_mul_top50.values

ha = ['right', 'center', 'left']

plt.xticks(rotation=45, ha = 'right', rotation_mode = 'anchor')

ax.set_xlabel('Director')
ax.set_ylabel('Movies in Top 50')
ax.set_title('Directors With More Than One Movie in Top 50')

ax.bar(x,y)
plt.savefig('images/top_studios_all_data', bbox_inches='tight')
```



In [53]:
```
# Filter data to find the top ten directors by total profit since 2012 who's
top10_dirs_profit = df_tn_imdb_filt_year.groupby('primary_name').mean().sort_
```

In [54]:
```
# Vizualize top 10 directors by average worldwide profit per movie
fig, ax = plt.subplots()

x = top10_dirs_profit.index
y = top10_dirs_profit['worldwide_profit']/1000000

ax.set_xlabel("Director")
ax.set_ylabel("Avg Profit per Movie (millions)")
ax.set_title("Top 10 Directors by Profit")

ha = ['right', 'center', 'left']
plt.xticks(rotation=45, ha = 'right', rotation_mode = 'anchor')

ax.bar(x,y, color="green")
plt.savefig('images/top_dirs_profit_s_2012', bbox_inches='tight')
```



Nest Steps

- Analyze **individual genres** and their success.
- Break down **budget allocation suggestion by film type**.
- Find the **reviewers that are the best indication of a movie that will perform** well and what elements of a movie impact their review.
- **Subset foreign audiences** and where the biggest rpofts are made.

In [ ]: