In [1016]:
```
#Import the libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import sqlite3
import json
import requests
import time
from bs4 import BeautifulSoup
import re
```

In [1017]:
```
#genre_dict line is to map the document with genre ID numbers but not numbers.
df_budget=pd.read_csv('tn.movie_budgets.csv.gz')
genre_dict = {"genres":[{"id":28,"name":"Action"},{"id":12,"name":"Adventure"},{"id":16,"name":"An
df_ratings=pd.read_csv('imdb.title.ratings.csv.gz')
df_basics=pd.read_csv('imdb.title.basics.csv.gz')
df_gross=pd.read_csv('bom.movie_gross.csv.gz')
df_name_basics=pd.read_csv('imdb.name.basics.csv.gz')
df_title_akas=pd.read_csv('imdb.title.akas.csv.gz')
df_TMDB=pd.read_csv('TMDB_cleaned.csv')
df_writers=pd.read_csv('Writersb.csv')
```

Code

Q: What are the Top Rated and Most Rated Films We decided that aside from financial metrics like gross revenues, another importa success metric is quality. User ratings is one of the ways we have defined quality, and we examined the average ratings of films on IMDB.com. One of the reasons we chose this source is that it had a large number of users contributing ratings to films. We also con user ratings on The Movie Database webiste (TMDb) but decided not to use this data due to the comparatively lower number of use ratings per film. Of course the number of ratings can also be an important metric and we use it here as a rough proxy for film popula Note that this analysis was limited to English language films.

Importing Packages and Files

In [1441]:
```
pd.set_option('display.max_columns', 45)
pd.set_option('display.max_rows', 100)
Full = pd.read_csv("df_7.csv")
```

Understanding the Data Frame First step is to understand the size, columns, and types of data that are contained in the dataframe. dataframe is one that was the product of several merges, as I was originally planning to use some of the user rating data from TNDb some from IMDB. We needed to get user ratings, movie names, and genres all into one dataframe from 2 different files. This datafra started with about 14K rows.

In [1442]:
```
print(Full.shape)
print(Full.dtypes)
Full.head()
```

```
(14219, 39)
tconst              object
averagerating      float64
numvotes             int64
primary_title       object
original_title      object
start_year           int64
runtime_minutes    float64
genres              object
Animation            int64
Sport                int64
Mystery              int64
Action               int64
Comedy               int64
Documentary          int64
Romance              int64
News                 int64
War                  int64
Horror               int64
Fantasy              int64
Family               int64
Music                int64
Musical              int64
Sci-Fi               int64
History              int64
Biography            int64
Thriller             int64
Crime                int64
Adventure            int64
Drama                int64
id                   int64
release_date        object
title               object
vote_average       float64
vote_count           int64
Year                 int64
category            object
primary_name        object
birth_year         float64
death_year         float64
dtype: object
```

Out[1442]:

	tconst	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	genres	Animation
0	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy	0
1	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy	0
2	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy	0
3	tt1094666	7.0	1613	The Hammer	Hamill	2010	108.0	Biography,Drama,Sport	0
4	tt1094666	7.0	1613	The Hammer	Hamill	2010	108.0	Biography,Drama,Sport	0

EDA First I took a look at some descriptive statistics and then tried a few visualizations to better see the central tendency and distrib of some of the key data (average ratings and number of ratings). Note that this helped me decide to proceed with just the IMDB data provided a better data set. Another advantage of using the IMDB data set is that they claim to have a weighted average score that h filter out ballot stuffing. The below just shows the steps for the IMDB data set.

In [1443]:
```
Full.averagerating.nunique()
```
Out[1443]:
```
85
```

In [1444]:
```
Full.averagerating.isna().sum()
```
Out[1444]:
```
0
```

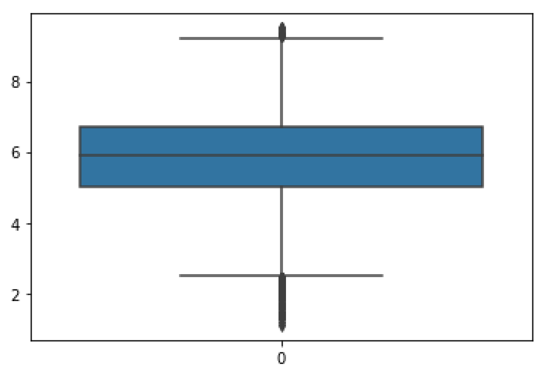
In [1445]:
```
Full.averagerating.describe()
```
Out[1445]:
```
count    14219.000000
mean         5.797173
std          1.324626
min          1.100000
25%          5.000000
50%          5.900000
75%          6.700000
max          9.500000
Name: averagerating, dtype: float64
```

In [1446]:
```
Full.numvotes.nunique()
```
Out[1446]:
```
4030
```

In [1447]:
```
Full.numvotes.isna().sum()
```
Out[1447]:
```
0
```

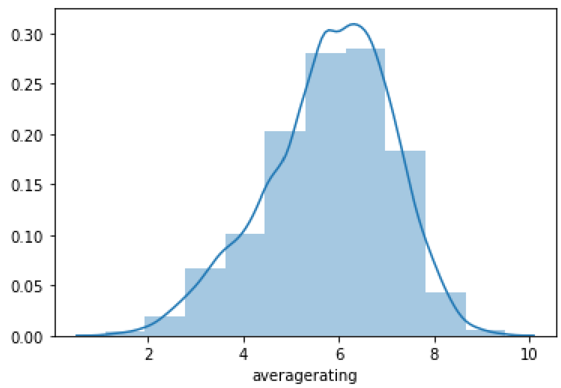
In [1448]:
```
Full.numvotes.describe().astype(int)
```
Out[1448]:
```
count      14219
mean       38723
std       104064
min            5
25%          198
50%         1403
75%        17596
max      1387769
Name: numvotes, dtype: int64
```

In [1449]:
```
# Visualize the average ratings a little bit: as a box plot (median of 6 and more outliers on the
boxplot = sns.boxplot(data=Full['averagerating'])
boxplot
```
Out[1449]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x16b1245b0>
```



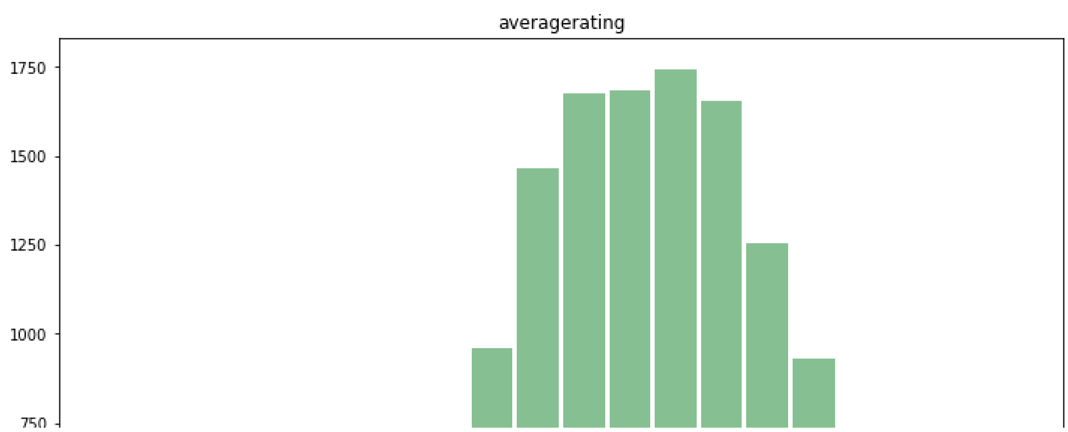
In [1450]:
```
# Visualize this a little bit: as distribution plot (a fairly normal distribution; slight skew to
distplot = sns.distplot(a=Full["averagerating"], bins=10)
distplot
```

Out[1450]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x190442880>
```



In [1451]:
```
# Trying a different method of histogram as a comparison and to familiarize with different librari
Full.hist(column='averagerating', bins=20, grid=False, figsize=(12,8), color='#86bf91', zorder=2,
```

Out[1451]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x15d3c4370>]],
      dtype=object)
```



Initial df Pruning Next step is to cut down the df (from 39 to 5 columns) to make it easier to see and work with. These steps includec

1. Cut the df down to size for analysis of average rating and number of ratings
2. Limited the release date of the movies to a 5 year period (2013 to 2018)
3. Cut out movies with a low number of ratings (based on the IQR)
4. Drop duplicate movies in the df (based on similaries in all columns)
5. Sort primarily on average rating and secondarily on number of ratings.

In [1452]:
```
# Removing unnecesary columns
Ratings = Full[['Year', 'primary_title', 'genres', 'averagerating', 'numvotes']]
Ratings.head()
```

Out[1452]:

	Year	primary_title	genres	averagerating	numvotes
0	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352
1	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352
2	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352
3	2010	The Hammer	Biography,Drama,Sport	7.0	1613
4	2010	The Hammer	Biography,Drama,Sport	7.0	1613

In [1453]:
```
Ratings.Year.value_counts().sort_index()
```

Out[1453]:
```
2010    1082
2011    1382
2012    1280
2013    1734
2014    1697
2015    1862
2016    1851
2017    1793
2018    1538
Name: Year, dtype: int64
```

In [1454]:
```
# Limit the Years to a 5-year period: 2013 - 2018
Ratingsb = Ratings.loc[Ratings.Year >= 2013]
print(Ratingsb.shape)
Ratingsb.head()
```

```
(10475, 5)
```

Out[1454]:

	Year	primary_title	genres	averagerating	numvotes
0	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352
1	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352
2	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352
26	2015	Paradox	Sci-Fi,Thriller	4.6	495
27	2015	Paradox	Sci-Fi,Thriller	4.6	495

In [1455]:
```
# Do an initial sort of ratings and numvotes
Ratingsb.sort_values(['averagerating','numvotes'], ascending=[False, False])
Ratingsb.head()
```

Out[1455]:

	Year	primary_title	genres	averagerating	numvotes
0	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352
1	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352
2	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352
26	2015	Paradox	Sci-Fi,Thriller	4.6	495
27	2015	Paradox	Sci-Fi,Thriller	4.6	495

In [1456]:
```
# Data above is odd.. why a bunch of documentaries?
# Lets look at just descending order for numvotes - as a gauge of popularity?
Ratingsc= Ratingsb.sort_values(['numvotes'], ascending=False)
Ratingsc.head()
```

Out[1456]:

	Year	primary_title	genres	averagerating	numvotes
6130	2014	Interstellar	Adventure,Drama,Sci-Fi	8.6	1299334
8954	2013	The Wolf of Wall Street	Biography,Crime,Drama	8.2	1035358
8955	2013	The Wolf of Wall Street	Biography,Crime,Drama	8.2	1035358
6339	2014	Guardians of the Galaxy	Action,Adventure,Comedy	8.1	948394
6342	2014	Guardians of the Galaxy	Action,Adventure,Comedy	8.1	948394

In [1457]:
```
# Ok, that helps... so now let me try and get rid of duplicates...see what that will do, before cc
Ratingsc.primary_title.duplicated().sum()
```

Out[1457]: 5483

In [1458]:
```
# Ok, I will get rid of duplicates on the whole df
Ratingsd = Ratingsc.drop_duplicates(keep='first')
Ratingsd.head()
```

Out[1458]:

	Year	primary_title	genres	averagerating	numvotes
6130	2014	Interstellar	Adventure,Drama,Sci-Fi	8.6	1299334
8954	2013	The Wolf of Wall Street	Biography,Crime,Drama	8.2	1035358
6339	2014	Guardians of the Galaxy	Action,Adventure,Comedy	8.1	948394
12453	2016	Deadpool	Action,Adventure,Comedy	8.0	820847
1133	2015	Mad Max: Fury Road	Action,Adventure,Sci-Fi	8.1	780910

Getting data ready for vizualization Not sure if this was necessary, seemed that I needed a small df to indicate how many things sho in the plot. There is likely a way to select the number of rows to plot... but time was up.

In [1459]:
```
# Need to get data in shape for plotting...by cutting it down to 20 rows.
Ratingse = Ratingsd.iloc[0:20, :]
Ratingse.head()
```

Out[1459]:

	Year	primary_title	genres	averagerating	numvotes
6130	2014	Interstellar	Adventure,Drama,Sci-Fi	8.6	1299334
8954	2013	The Wolf of Wall Street	Biography,Crime,Drama	8.2	1035358
6339	2014	Guardians of the Galaxy	Action,Adventure,Comedy	8.1	948394
12453	2016	Deadpool	Action,Adventure,Comedy	8.0	820847
1133	2015	Mad Max: Fury Road	Action,Adventure,Sci-Fi	8.1	780910

In [1460]:
```
# Changing the axis for plotting... saw an example of this in a video and assumed it would make th
Ratingse.set_index('primary_title', inplace=True)
Ratingse.head()
```

Out[1460]:

	Year	genres	averagerating	numvotes
primary_title				
Interstellar	2014	Adventure,Drama,Sci-Fi	8.6	1299334
The Wolf of Wall Street	2013	Biography,Crime,Drama	8.2	1035358
Guardians of the Galaxy	2014	Action,Adventure,Comedy	8.1	948394
Deadpool	2016	Action,Adventure,Comedy	8.0	820847
Mad Max: Fury Road	2015	Action,Adventure,Sci-Fi	8.1	780910

Getting a second plotting df ready I created a second df for the second part of the question... which movies have the highest averag customer rating. Similar steps were followed to limit the number of rows, column sorting, and getting rid of low number of votes to ir sorting.

In [1461]:
```
# 3rd approach to filter out lower values... this time it worked.
Ratings_high = Ratingsd.loc[Ratingsd.numvotes >= 17596]
Ratings_high.head()
```

Out[1461]:

	Year	primary_title	genres	averagerating	numvotes
6130	2014	Interstellar	Adventure,Drama,Sci-Fi	8.6	1299334
8954	2013	The Wolf of Wall Street	Biography,Crime,Drama	8.2	1035358
6339	2014	Guardians of the Galaxy	Action,Adventure,Comedy	8.1	948394
12453	2016	Deadpool	Action,Adventure,Comedy	8.0	820847
1133	2015	Mad Max: Fury Road	Action,Adventure,Sci-Fi	8.1	780910

In [1462]:
```
Ratings_high.shape
```

Out[1462]:
```
(959, 5)
```

In [1463]:
```
# Now to sort it on my 2 columns.
Ratings_high.sort_values(['averagerating','numvotes'], ascending=[False, False], inplace=True)
Ratings_high.head()
```

```
<ipython-input-1463-8dec1eb3548c>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/inde
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/ind
g.html#returning-a-view-versus-a-copy)
  Ratings_high.sort_values(['averagerating','numvotes'], ascending=[False, False], inplace=True)
```

Out[1463]:

	Year	primary_title	genres	averagerating	numvotes
6130	2014	Interstellar	Adventure,Drama,Sci-Fi	8.6	1299334
13968	2018	Avengers: Infinity War	Action,Adventure,Sci-Fi	8.5	670926
7861	2018	Spider-Man: Into the Spider-Verse	Action,Adventure,Animation	8.5	210869
8098	2017	Coco	Adventure,Animation,Comedy	8.4	277194
2737	2014	The Hunt	Drama	8.3	242765

In [1464]:
```
# Need to get data in shape for plotting...limit rows
Ratings_high2 = Ratings_high.iloc[0:20, :]
Ratings_high2.head()
```

Out[1464]:

	Year	primary_title	genres	averagerating	numvotes
6130	2014	Interstellar	Adventure,Drama,Sci-Fi	8.6	1299334
13968	2018	Avengers: Infinity War	Action,Adventure,Sci-Fi	8.5	670926
7861	2018	Spider-Man: Into the Spider-Verse	Action,Adventure,Animation	8.5	210869
8098	2017	Coco	Adventure,Animation,Comedy	8.4	277194
2737	2014	The Hunt	Drama	8.3	242765

In [1465]:
```
# Changing the axis for plotting
Ratings_high2.set_index('primary_title', inplace=True)
Ratings_high2.head()
```

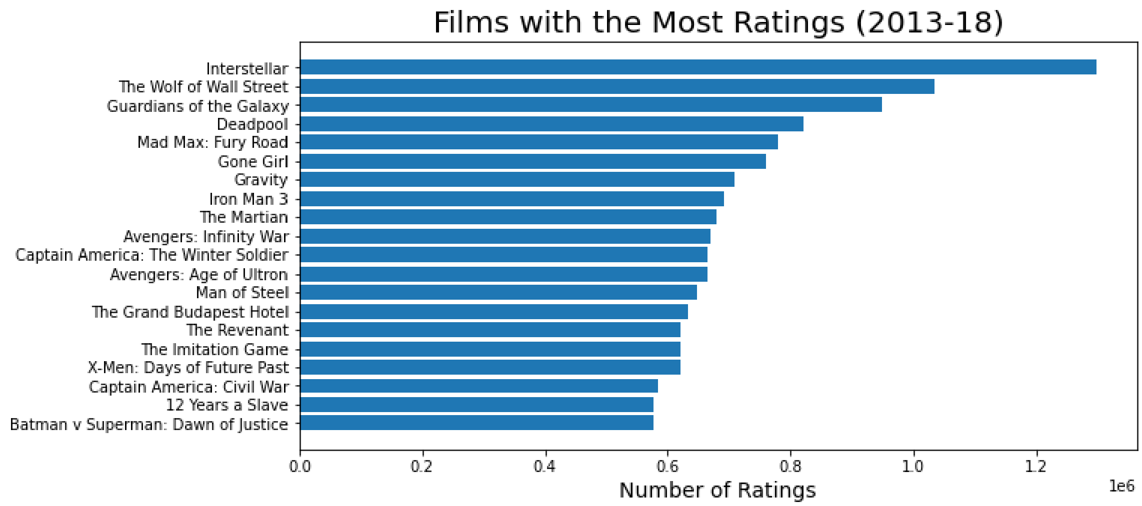
Out[1465]:

	Year	genres	averagerating	numvotes
primary_title				
Interstellar	2014	Adventure,Drama,Sci-Fi	8.6	1299334
Avengers: Infinity War	2018	Action,Adventure,Sci-Fi	8.5	670926
Spider-Man: Into the Spider-Verse	2018	Action,Adventure,Animation	8.5	210869
Coco	2017	Adventure,Animation,Comedy	8.4	277194
The Hunt	2014	Drama	8.3	242765

Creating Visualizations for Presesntation After considerable exploration and trying out both Seaborn and MatPlotLib, we found a for that did the basics. We worked together to ensure that we had similar dimensions and style for our presentation.

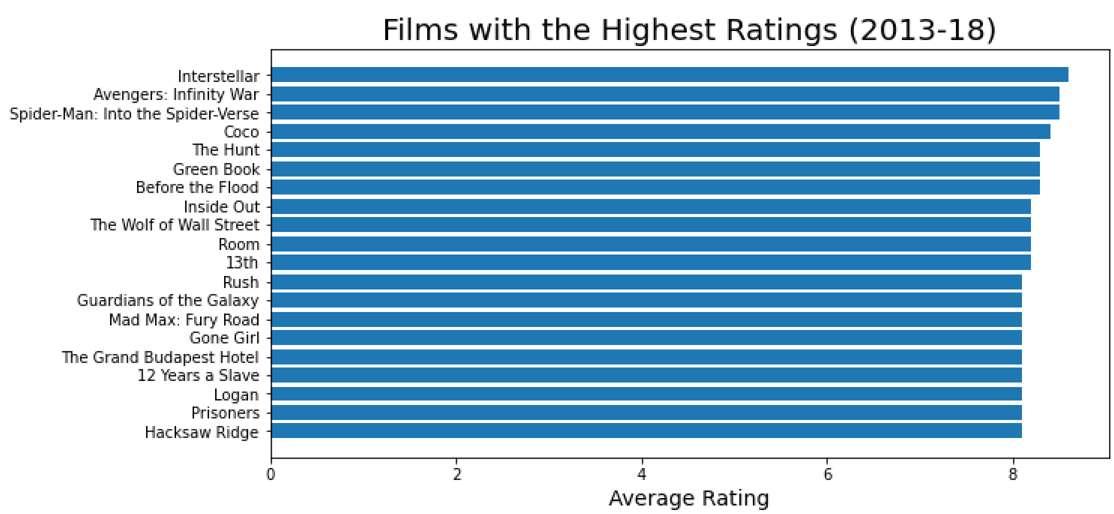
In [1466]:
```
Ratingse= Ratingse.sort_values('numvotes')
fig, ax = plt.subplots(figsize=(10, 5))

ax.barh(Ratingse.index, Ratingse['numvotes'])
ax.set_title('Films with the Most Ratings (2013-18)', fontsize=20)
ax.set_xlabel('Number of Ratings', fontsize=14)
plt.show()
```



In [1467]:
```
Ratings_high2= Ratings_high2.sort_values('averagerating')
fig, ax = plt.subplots(figsize=(10, 5))

ax.barh(Ratings_high2.index, Ratings_high2['averagerating'])
ax.set_title('Films with the Highest Ratings (2013-18)', fontsize=20)
ax.set_xlabel('Average Rating', fontsize=14)
plt.show()
```



Based on the visualizations above, as well as the data frames, we make the following conclusions:

1. I have determined and displayed the 20 films with the highest average user rating on IMDB. All of these films have an average ra 8.1 or higher (up to 8.6). This is on a 10-point scale.
2. I have determined and displayed the 20 films with the most user ratings on IMDB. These films range in number of votes from 57 to a high of 1,299,334. This measure can be thought of as a form of popularity.
3. 8 of the films appear on both of these Top 20 lists, indicating they are BOTH top rated and very popular. Interstellar is at the top both lists, by quite a bit.
4. Inital investigation shows that slightly different genres of film appear in each list. The Top Rated films are more likely Dramas(11) Adventure(8), Action(6), Biography(5) or Comedy(5). Wheras many of the Top Popular films are Adventure(15), Action(12), Sci-Fi(and Drama(7).
5. These lists of the Top 20 in Quality and Popluarity provides a starting point for disecting what makes these films a success whic help our clients re-use elements that lead to this form of success.

Next, we will be observing the writers behind some of the top films in our dataset.

Q: Who Are the Writers for Top Grossing Films? We believe that good writers are key to creating a succesful film. We wanted to find who some of the writers are for the most succesful films. I decided to start by defining success by the finacial measure of domestic So my goals was to get to a listing of writers for the Top 20 Films (based on domestic gross). We would then provide this list to our c as writers they should approach to collaborate on future projects.

In [1468]:
```
pd.set_option('display.max_columns', 55)
pd.set_option('display.max_rows', 200)
```

In [1470]:
```
Full2 = pd.read_csv("df_8.csv")
```

Understanding the Data Frame We want to make sure I understand the size, columns, and types of data that are contained in the dataframe. This dataframe is one that was the product of several merges, as we needed to get writers names, movie names, and fin all into one dataframe from 3 different files.

In [1472]:
```
print(Full2.shape)
print(Full2.dtypes)
Full2.head()
```

```
(6884, 80)
tconst                object
averagerating_x      float64
numvotes_x             int64
primary_title_x       object
original_title_x      object
start_year_x           int64
runtime_minutes_x    float64
genres_x              object
Animation_x            int64
Sport_x                int64
Mystery_x              int64
Action_x               int64
Comedy_x               int64
Documentary_x          int64
Romance_x              int64
News_x                 int64
War_x                  int64
Horror_x               int64
Fantasy_x              int64
Family_x               int64
Music_x                int64
Musical_x              int64
Sci-Fi_x               int64
History_x              int64
Biography_x            int64
Thriller_x             int64
Crime_x                int64
Adventure_x            int64
Drama_x                int64
id                     int64
release_date          object
title_x               object
vote_average_x       float64
vote_count_x           int64
Year_x                 int64
category              object
primary_name          object
birth_year           float64
death_year           float64
id_x                   int64
release_date_x        object
movie                 object
production_budget    float64
domestic_gross       float64
worldwide_gross       object
profit               float64
id_y                   int64
release_date_y        object
title_y               object
vote_average_y       float64
vote_count_y           int64
Year_y                 int64
averagerating_y      float64
numvotes_y             int64
primary_title_y       object
original_title_y      object
start_year_y           int64
runtime_minutes_y    float64
genres_y              object
Animation_y            int64
Sport_y                int64
Mystery_y              int64
Action_y               int64
Comedy_y               int64
Documentary_y          int64
Romance_y              int64
News_y                 int64
War_y                  int64
Horror_y               int64
Fantasy_y              int64
Family_y               int64
```

```
Music_y                int64
Musical_y              int64
Sci-Fi_y               int64
History_y              int64
Biography_y            int64
Thriller_y             int64
Crime_y                int64
Adventure_y            int64
Drama_y                int64
dtype: object
```

Out[1472]:

	tconst	averagerating_x	numvotes_x	primary_title_x	original_title_x	start_year_x	runtime_minutes_x	genres_x
0	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy
1	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy
2	tt1043726	4.2	50352	The Legend of Hercules	The Legend of Hercules	2014	99.0	Action,Adventure,Fantasy
3	tt1094666	7.0	1613	The Hammer	Hamill	2010	108.0	Biography,Drama,Sport
4	tt1094666	7.0	1613	The Hammer	Hamill	2010	108.0	Biography,Drama,Sport

5 rows × 80 columns

EDA We counducted some EDA on domestic gross to better understand that data. This is placed in the appendix.

Initial df Pruning I realized that the merges had created a MONSTER dataframe so first step was to cut it down to the columns I thou might need; then to limit the films to a 5-year period; and also wanted to remove writers who had a death date listed (as not very hel reccomend dead writers for our client to work with).

In [1473]:

```
# Cutting down to just columns needed
Writers = Full2[['Year_x', 'primary_title_x', 'genres_x', 'averagerating_x', 'numvotes_x','product
Writers.head()
```

Out[1473]:

	Year_x	primary_title_x	genres_x	averagerating_x	numvotes_x	production_budget	domestic_gross	profit	c
0	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352	70000000.0	18848538.0	-51151462.0	
1	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352	70000000.0	18848538.0	-51151462.0	
2	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352	70000000.0	18848538.0	-51151462.0	
3	2010	The Hammer	Biography,Drama,Sport	7.0	1613	850000.0	442638.0	-407362.0	
4	2010	The Hammer	Biography,Drama,Sport	7.0	1613	850000.0	442638.0	-407362.0	

In [1474]:

```
Writers.shape
```

Out[1474]:

```
(6884, 12)
```

In [1475]:

```
Writers.Year_x.value_counts().sort_index()
```

Out[1475]:

```
2010     662
2011     586
2012     503
2013     697
2014     755
2015    1268
2016    1106
2017     790
2018     517
Name: Year_x, dtype: int64
```

In [1476]:
```
# Limit the Years to a 5-year period: 2013 - 2018
Writersb = Writers.loc[Writers.Year_x >= 2013]
print(Writersb.shape)
Writersb.head()
```

(5133, 12)

Out[1476]:

	Year_x	primary_title_x	genres_x	averagerating_x	numvotes_x	production_budget	domestic_gross	profit
0	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352	70000000.0	18848538.0	-51151462.0
1	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352	70000000.0	18848538.0	-51151462.0
2	2014	The Legend of Hercules	Action,Adventure,Fantasy	4.2	50352	70000000.0	18848538.0	-51151462.0
20	2013	The Adventurer: The Curse of the Midas Box	Adventure,Family,Fantasy	5.4	5257	25000000.0	0.0	-25000000.0
21	2013	The Adventurer: The Curse of the Midas Box	Adventure,Family,Fantasy	5.4	5257	25000000.0	0.0	-25000000.0

In [1478]:
```
# Checking to see what type of duplication of rows exist. Yes, a lot of duplicates,
# but that is okay, as there are multiple writers per movie.
Writersb.duplicated().sum()
```

Out[1478]: 2491

In [1479]:
```
Writersb.isna().sum()
```

Out[1479]:
```
Year_x                0
primary_title_x       0
genres_x              0
averagerating_x       0
numvotes_x            0
production_budget     0
domestic_gross        0
profit                0
category              0
primary_name          0
birth_year         3095
death_year         4814
dtype: int64
```

In [1480]:
```
# Removing films with a domestic gross of $0
Writersd = Writersb.loc[Writersb.domestic_gross != 0.0]
```

In [1481]:
```
Writersd.shape
```

Out[1481]: (4257, 12)

In [1482]:
```
# Sort on domestic gross - this is our primary delector for top writers
Writerse= Writersd.sort_values(['domestic_gross'], ascending=False)
Writerse.head()
```

Out[1482]:

	Year_x	primary_title_x	genres_x	averagerating_x	numvotes_x	production_budget	domestic_gross	profit	c
1732	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	
1733	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	
1730	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	
1729	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	
1728	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	

Refining the df for Visualization We tended to go back and forth between slicing down the df for better visualizion and refing to make had the correct data (sort order, deduplication, etc). When we got stuck, we tried to forge ahead on something else. We wanted the to have only the data I was going to list or plot and only the two or three columns I needed to answer the question

In [1483]:
```
# Need to get data in shape for plotting...limit rows to cover the top 20 grossing films
Writersg = Writerse.iloc[0:150, :]
Writersg.head()
```

Out[1483]:

	Year_x	primary_title_x	genres_x	averagerating_x	numvotes_x	production_budget	domestic_gross	profit	c
1732	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	
1733	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	
1730	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	
1729	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	
1728	2018	Black Panther	Action,Adventure,Sci-Fi	7.3	516148	200000000.0	700059566.0	500059566.0	

In [1484]:
```
# Simplify the df down to only necessary columns
Writersh = Writersg[['primary_title_x','domestic_gross','primary_name','death_year']]
Writersh.head()
```

Out[1484]:

	primary_title_x	domestic_gross	primary_name	death_year
1732	Black Panther	700059566.0	Joe Robert Cole	NaN
1733	Black Panther	700059566.0	Joe Robert Cole	NaN
1730	Black Panther	700059566.0	Stan Lee	2018.0
1729	Black Panther	700059566.0	Jack Kirby	1994.0
1728	Black Panther	700059566.0	Jack Kirby	1994.0

In [1486]:
```
Writersh.dtypes
```

Out[1486]:
```
primary_title_x     object
domestic_gross     float64
primary_name        object
death_year         float64
dtype: object
```

In [1487]:
```
Writersh.shape
```

Out[1487]:
```
(150, 4)
```

In [1488]:
```
# After some experimentation, was finally able to get rid of writers who had a death year listed.
# Q: Have seen the pink band several times now, is it better to reassign to a variable rather than
Writersh.drop(Writersh[Writersh['death_year'] < 2019].index, inplace = True)
Writersh.head()
```

```
/opt/anaconda3/lib/python3.8/site-packages/pandas/core/frame.py:3990: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/inde
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/ind
g.html#returning-a-view-versus-a-copy)
  return super().drop(
```

Out[1488]:

	primary_title_x	domestic_gross	primary_name	death_year
1732	Black Panther	700059566.0	Joe Robert Cole	NaN
1733	Black Panther	700059566.0	Joe Robert Cole	NaN
6835	Avengers: Infinity War	678815482.0	Christopher Markus	NaN
6836	Avengers: Infinity War	678815482.0	Stephen McFeely	NaN
1466	Jurassic World	652270625.0	Amanda Silver	NaN

In [1489]:
```
# We always like to verify that a change actually worked, and what it did to the number of rows.
Writersh.shape
```
Out[1489]: (110, 4)

In [1490]:
```
Writersh.tail()
```
Out[1490]:

	primary_title_x	domestic_gross	primary_name	death_year
6264	Deadpool	363070709.0	Paul Wernick	NaN
4085	Inside Out	356461711.0	Brian Stewart	NaN
4089	Inside Out	356461711.0	Dylan Schaffer	NaN
4090	Inside Out	356461711.0	Dylan Schaffer	NaN
4082	Inside Out	356461711.0	Michael Arndt	NaN

In [1491]:
```
# Finally time to drop the rows that actually appear to be duplicates.
# Want to drop those that are duplicated in BOTH title and name
Writersi = Writersh.drop_duplicates(subset=['primary_title_x', 'primary_name'], keep='first')
Writersi.head()
```
Out[1491]:

	primary_title_x	domestic_gross	primary_name	death_year
1732	Black Panther	700059566.0	Joe Robert Cole	NaN
6835	Avengers: Infinity War	678815482.0	Christopher Markus	NaN
6836	Avengers: Infinity War	678815482.0	Stephen McFeely	NaN
1466	Jurassic World	652270625.0	Amanda Silver	NaN
1467	Jurassic World	652270625.0	Derek Connolly	NaN

In [1492]:
```
Writersi.shape
```
Out[1492]: (52, 4)

In [1493]:
```
# Yep, this is pretty much my answer right here. The top 20 grossing films and associated writers.
Writersi.head()
```
Out[1493]:

	primary_title_x	domestic_gross	primary_name	death_year
1732	Black Panther	700059566.0	Joe Robert Cole	NaN
6835	Avengers: Infinity War	678815482.0	Christopher Markus	NaN
6836	Avengers: Infinity War	678815482.0	Stephen McFeely	NaN
1466	Jurassic World	652270625.0	Amanda Silver	NaN
1467	Jurassic World	652270625.0	Derek Connolly	NaN

In [1494]:
```
Writersi.primary_name.nunique()
```
Out[1494]: 46

Conclusions Examining the final dataframe (a listing of the 20 Top Grossing films from 2013-18...based on domestic gross):

We have an associated list of 46 writers (try collaborating with these writers) There are 6 of these writers who have worked on 2 of tl films (perhaps really focus on these 6) Most of films in this list have multiple writers (from 2 to 5 writers per film) These films are not t Rated nor Most Rated, only 2 of these films appear in our other analysis. Note that the average rating for these films ranges from 8.5

In [1495]:
```
# Simplify the df down to even fewer columns.
Writersj = Writersi[['primary_title_x','primary_name']]
Writersj.head()
```

Out[1495]:

	primary_title_x	primary_name
1732	Black Panther	Joe Robert Cole
6835	Avengers: Infinity War	Christopher Markus
6836	Avengers: Infinity War	Stephen McFeely
1466	Jurassic World	Amanda Silver
1467	Jurassic World	Derek Connolly

In [1496]:
```
# Set index to movie name (as this may make it easier to read and help for plotting)
# I realize I should rename the columns to make them clearer.
Writersj.set_index('primary_title_x', inplace=True)
Writersj.head()
```

Out[1496]:

	primary_name
primary_title_x	
Black Panther	Joe Robert Cole
Avengers: Infinity War	Christopher Markus
Avengers: Infinity War	Stephen McFeely
Jurassic World	Amanda Silver
Jurassic World	Derek Connolly

In [1497]:
```
Writersj.shape
```

Out[1497]:
```
(52, 1)
```

In [1498]:
```
# Sort on the writer names will help show duplicates on writers names and movies they worked on
# Ideally would sort on last name.
Writersj.sort_values(['primary_name'], ascending=True, inplace=True)
Writersj.head()
```

```
<ipython-input-1498-a0d601d10713>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/inde
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/ind
g.html#returning-a-view-versus-a-copy)
  Writersj.sort_values(['primary_name'], ascending=True, inplace=True)
```

Out[1498]:

	primary_name
primary_title_x	
Wonder Woman	Allan Heinberg
Jurassic World	Amanda Silver
The Jungle Book	Billy Frolick
The Jungle Book	Bob Hilgenberg
Finding Dory	Bob Peterson

Creating Visualizations for Presesntation We ran out of time to figure out if there were good formatting options for Tables in our visua libraries, so we decided to export the dataframes as csv, in hopes of working with them in Powerpoint or a spreadsheet. Will try and include an image of the final product if time permits.

In [1500]:
```
# Export these lists as CSV files to format in another program.
#Writersj.to_csv (r'/Users/markp/Desktop/writers_movies.csv', index = True, header=True)
#Writersi.to_csv (r'/Users/markp/Desktop/writers_movies_gross.csv', index = False, header=True)
```

In [1501]:
```
from IPython.display import Image
Image(filename = "download.png", width = 600, height = 300)
```

Out[1501]:

Writers on Top Grossing Films (2013-18)

Allan Heinberg	Dylan Schaffer	Linda Woolverton
Amanda Silver	Gary Scott Thompson	Michael Arndt
Billy Frolick	Erik Sommers	Paul Wernick
Bob Hilgenberg	Evan Spiliotopoulos	Rhett Reese
Bob Peterson	Gary Whitta	Rick Jaffa
Brian Lynch	George Lucas	Rob Muir
Brian Stewart	Jason Fuchs	Sandra Vo-Anh
Chris McKenna	Jeff Pinkner	Scott Rosenberg
Chris Moran	Jessica J. Herrera	Shane Morris
Chris Van Allsburg	Jim Starlin	Simon Beaufoy
Chris Weitz	Joe Robert Cole	Stephen Chbosky
Christopher Markus	John Knoll	Stephen McFeely
Cinco Paul	Justin Marks	Suzanne Collins
Colin Trevorrow	Ka Yee Yim	Tony Gilroy
Derek Connolly	Ken Daurio	Victoria Strouse
Drew Pearce	Larry Lieber	Zack Snyder

In [1503]:
```
Image(filename = "Top-Writers-Films.png", width = 600, height = 300)
```

Out[1503]:

In [1022]:
```
df_ratings_basics=df_ratings.merge(df_basics)
df_ratings_basics.sort_values(by='numvotes',ascending=False)
```

Out[1022]:

	tconst	averagerating	numvotes	primary_title	original_title	start_year	runtime_minutes	g
63498	tt1375666	8.8	1841066	Inception	Inception	2010	148.0	Action,Adventure
8738	tt1345836	8.4	1387769	The Dark Knight Rises	The Dark Knight Rises	2012	164.0	Action,
24920	tt0816692	8.6	1299334	Interstellar	Interstellar	2014	169.0	Adventure,Drama
38058	tt1853728	8.4	1211405	Django Unchained	Django Unchained	2012	165.0	Drama,W
48221	tt0848228	8.1	1183655	The Avengers	The Avengers	2012	143.0	Action,Adventure
...	...	...	...	...	...	...	...	
39180	tt8050582	8.0	5	Jackal Stories	Cuentos de chacales	2017	70.0	Docum
33886	tt6449270	4.0	5	Chu lian wei man	Chu lian wei man	2013	105.0	Drama,Ro
22243	tt3819584	7.6	5	De onderkoning: strijd om de grondwet	De onderkoning: strijd om de grondwet	2014	51.0	
49605	tt2136926	5.8	5	Fools	Fools	2011	77.0	Action,Comedy
32411	tt2056595	8.8	5	Hayseeds and Scalawags	Hayseeds and Scalawags	2011	76.0	Comedy,Drama,Ro

73856 rows × 8 columns

In [1025]:
```
#genres=[]
#for f in df_ratings_basics:
#    for g in f.strip('[]').split(','):
#        if not g in genres:
#            genres.append(g)
```

In [1026]:
```
#genres=set(list(map(lambda x: x.strip(' '),genres)))
```

In [1027]:
```
#for g in genres:
#    df_ratings_basics[g]=df_ratings_basics.apply(lambda x: g in x)
```

In [1029]:
```
#Generating a list of all genres
#genres = set()
#for genre_string in df_ratings_basics['genres']:
#   genre_list = genre_string.split(',')
#   for genre in genre_list:
#       genres.add(genre)
#genres = list(genres)
#Made these comments after running this (do not want this to happen every time we run this cell).
```

In [1031]:
```
#for g in genres:
#    df_ratings_basics_new[g]=df_ratings_basics_new['genres'].apply(lambda x: g in x)
```

In [1032]:
```
df_topdf_ratings_basics_new[['Animation', 'Sport', 'Mystery', 'Action', 'Comedy', 'Documentary', '
```

In [1035]:
```
df_ratings_basics_new=df_ratings_basics.dropna(subset=['genres'])
```

In [1296]:

```
#We do not want null values. This will help us address them (decided null runtime values were acce
#since those are unrelated to our analysis and recommendations).
df_ratings_basics_new.isna().sum()
```

Out[1296]:

```
tconst              0
averagerating       0
numvotes            0
primary_title       0
original_title      0
start_year          0
runtime_minutes  7332
genres              0
Animation           0
Sport               0
Mystery             0
Action              0
Comedy              0
Documentary         0
Romance             0
News                0
War                 0
Horror              0
Fantasy             0
Family              0
Music               0
Musical             0
Sci-Fi              0
History             0
Biography           0
Thriller            0
Crime               0
Adventure           0
Drama               0
dtype: int64
```

In [1038]:

```
df_basics.head(100).sort_values('genres',ascending=False)
#How to deal with comma-separated genres and break those apart. Use different columns?
#Create 3 columns? Analysis on top genres/studios/writers would be helpful.
```

Out[1038]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
32	tt0293069	Dark Blood	Dark Blood	2012	86.0	Thriller
29	tt0283440	Short Time Heroes	Kurzzeithelden	2015	45.0	Sci-Fi
6	tt0112502	Bigfoot	Bigfoot	2017	NaN	Horror,Thriller
97	tt0431021	The Possession	The Possession	2012	92.0	Horror,Mystery,Thriller
51	tt0339736	The Evil Within	The Evil Within	2017	98.0	Horror
...	...	...	...	...	...	...
22	tt0253093	Gangavataran	Gangavataran	2018	134.0	NaN
35	tt0306058	Second Coming	Second Coming	2012	95.0	NaN
40	tt0326592	The Overnight	The Overnight	2010	88.0	NaN
44	tt0330811	Regret Not Speaking	Regret Not Speaking	2011	NaN	NaN
45	tt0330987	Tiden är en dröm, del 2	Tiden är en dröm, del 2	2014	109.0	NaN

100 rows × 6 columns

In [1039]:
```
df_gross_basics=df_basics.merge(df_gross, left_on='primary_title',right_on='title')
df_gross_basics.sort_values(['domestic_gross'], ascending=False)
```

Out[1039]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	title	studio	domestic_gro
1528	tt1825683	Black Panther	Black Panther	2018	134.0	Action,Adventure,Sci-Fi	Black Panther	BV	70010000(
2876	tt4154756	Avengers: Infinity War	Avengers: Infinity War	2018	149.0	Action,Adventure,Sci-Fi	Avengers: Infinity War	BV	67880000(
9	tt0369610	Jurassic World	Jurassic World	2015	124.0	Action,Adventure,Sci-Fi	Jurassic World	Uni.	65230000(
2283	tt2527336	Star Wars: The Last Jedi	Star Wars: Episode VIII - The Last Jedi	2017	152.0	Action,Adventure,Fantasy	Star Wars: The Last Jedi	BV	62020000(
2703	tt3606756	Incredibles 2	Incredibles 2	2018	118.0	Action,Adventure,Animation	Incredibles 2	BV	60860000(
...	...	...	...	...	...	...	...	...	
2083	tt2300975	Jessabelle	Jessabelle	2014	90.0	Horror,Thriller	Jessabelle	LGF	Na
2322	tt2594078	Viral	Viral	2013	95.0	Comedy,Horror,Thriller	Viral	W/Dim.	Na
2323	tt2597892	Viral	Viral	2016	85.0	Drama,Horror,Sci-Fi	Viral	W/Dim.	Na
2324	tt3892200	Viral	Viral	2015	NaN	Horror	Viral	W/Dim.	Na
3224	tt6108090	Secret Superstar	Secret Superstar	2017	150.0	Drama,Music	Secret Superstar	NaN	Na

3366 rows × 11 columns

In [1168]:
```
#Convert domestic gross into a number format so that we can do arithmetic with it.
df_budget['domestic_gross'] = df_budget['domestic_gross'].replace({'\$': '', ',': ''}, regex=True)
```

In [1167]:
```
df_budget.head()
```

Out[1167]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	profit
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	$2,776,345,279	335507625.0
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	$1,045,663,875	-169536125.0
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	$149,762,350	-307237650.0
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	$1,403,013,963	128405868.0
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	$1,316,721,747	303181382.0

In [1044]:
```
#We need to get everything into a format that allows us to do arithmetic.
#Specifically, we are looking to subtract production budget from domestic gross to find the profit
df_budget['production_budget'] = df_budget['production_budget'].replace({'\$': '', ',': ''}, regex
```

In [1045]:
```
df_budget['profit'] = df_budget['domestic_gross'] - df_budget['production_budget']
```

In [1046]:
```
df_budget.sort_values('profit',ascending=False)
```

Out[1046]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	profit
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000.0	936662225.0	$2,053,311,220	630662225.0
41	42	Feb 16, 2018	Black Panther	200000000.0	700059566.0	$1,348,258,224	500059566.0
42	43	Dec 19, 1997	Titanic	200000000.0	659363944.0	$2,208,208,395	459363944.0
3464	65	May 25, 1977	Star Wars Ep. IV: A New Hope	11000000.0	460998007.0	$786,598,007	449998007.0
33	34	Jun 12, 2015	Jurassic World	215000000.0	652270625.0	$1,648,854,864	437270625.0
...	...	...	...	...	...	...	...
31	32	May 18, 2012	Battleship	220000000.0	65233400.0	$313,477,717	-154766600.0
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	$1,045,663,875	-169536125.0
12	13	Jul 2, 2013	The Lone Ranger	275000000.0	89302115.0	$260,002,115	-185697885.0
13	14	Mar 9, 2012	John Carter	275000000.0	73058679.0	$282,778,100	-201941321.0
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	$149,762,350	-307237650.0

5782 rows × 7 columns

In [1048]:
```
#df_budget_TMDB=df_budget.merge(df_TMDB, left_on='movie',right_on='title')
#Merging the budget and TMDB tables on the movie titles to get the information we need in one data
df_budget_TMDB.sort_values(['vote_count'], ascending=False)
```

Out[1048]:

	id_x	release_date_x	movie	production_budget	domestic_gross	worldwide_gross	profit	id_y	release_date_y
117	38	Jul 16, 2010	Inception	160000000.0	292576195.0	$835,524,642	132576195.0	27205	2010-07-16
484	56	Feb 12, 2016	Deadpool	58000000.0	363070709.0	$801,025,593	305070709.0	293660	2016-02-12
20	35	Aug 14, 1998	The Avengers	60000000.0	23385416.0	$48,585,416	-36614584.0	24428	2012-05-04
19	27	May 4, 2012	The Avengers	225000000.0	623279547.0	$1,517,935,897	398279547.0	24428	2012-05-04
110	32	Nov 5, 2014	Interstellar	165000000.0	188017894.0	$666,379,375	23017894.0	157336	2014-11-05
...	...	...	...	...	...	...	...	...	...
1968	43	Apr 7, 2006	Simon	1300000.0	4055.0	$1,738,663	-1295945.0	259712	2017-02-01
1966	35	May 22, 2009	The Girlfriend Experience	1300000.0	695840.0	$1,005,840	-604160.0	496053	2014-10-05
1965	28	Dec 31, 2014	House at the End of the Drive	1400000.0	0.0	$0	-1400000.0	280381	2014-01-11
1067	43	Jul 27, 2016	Nerve	20000000.0	38583626.0	$70,652,284	18583626.0	455240	2011-12-07
621	63	Oct 2, 1992	Hero	42000000.0	19487173.0	$66,787,173	-22512827.0	452590	2014-04-17

2188 rows × 13 columns

In [1096]:
```
df_profit_genre=df_budget_TMDB.merge(df_ratings_basics_new,left_on='movie',right_on='primary_title
```

In [1319]:
```
df_profit_genre_ranked=df_profit_genre.sort_values('profit',ascending=False)
```

Trying to make a master table with all columns we need. We would also like to ensure the lack of duplicate records.

In [1161]:
```
df_9.tconst.duplicated().sum()
```

Out[1161]: 2721

In [1162]:
```
df_9b = df_9.drop_duplicates(keep='first', subset='tconst')
```

Looking for correlations between average rating and various variables such as genre and domestic gross. As we expect, one of the strongest positive correlations is between average rating and domestic gross.

In [1438]:
```
df_9b.corr()['averagerating'].sort_values(ascending=False).head(10)
```

Out[1438]:
```
averagerating        1.000000
vote_average         0.616414
numvotes             0.433461
vote_count           0.377074
runtime_minutes      0.344690
domestic_gross       0.274010
profit               0.208912
Biography            0.207274
Drama                0.204670
production_budget    0.199099
Name: averagerating, dtype: float64
```

In [1175]:
```
df_ratings_basics_new.sum(axis = 0, skipna = True)
```

Out[1175]:
```
tconst             tt10356526tt10384606tt1042974tt1043726tt106024...
averagerating                                                 462487
numvotes                                                   260223835
primary_title      Laiye Je YaarianBorderlessJust InèsThe Legend ...
original_title     Laiye Je YaarianBorderlessJust InèsThe Legend ...
start_year                                                 147147287
runtime_minutes                                          6.22580e+06
genres             RomanceDocumentaryDramaAction,Adventure,Fantas...
Animation                                                       1743
Sport                                                           1179
Mystery                                                         3039
Action                                                          6988
Comedy                                                         17290
Documentary                                                    17753
Romance                                                         6589
News                                                             579
War                                                              853
Horror                                                          7674
Fantasy                                                         2126
Family                                                          3412
Music                                                           2644
Musical                                                          721
Sci-Fi                                                          2206
History                                                         2825
Biography                                                       3809
Thriller                                                        8217
Crime                                                           4611
Adventure                                                       3817
Drama                                                          30788
dtype: object
```

In [1176]:
```
#Our work is not done, as we do not want to leave duplicate records in. More cleaning is required.
df_ratings_basics_nodups = df_ratings_basics_new.drop_duplicates(keep='first', subset='tconst')
```

In [1178]:
```
df_profit_analysis=df_budget_TMDB.merge(df_ratings_basics_nodups,left_on='movie',right_on='primary
```

In [1211]:
```
#Looking for the top 20 grossing films since 2013.
df_top20=df_profit_analysis.sort_values('domestic_gross',ascending=False)
```

In [1286]:
```
df_top20.head(3)
```

Out[1286]:

	id_x	release_date_x	movie	production_budget	domestic_gross	worldwide_gross	profit	id_y	release_date_y	
46	42	2018-02-16	Black Panther	200000000.0	700059566.0	$1,348,258,224	500059566.0	86841	2011-01-18	P
2	7	2018-04-27	Avengers: Infinity War	300000000.0	678815482.0	$2,048,134,200	378815482.0	299536	2018-04-27	Ave I
25	34	2015-06-12	Jurassic World	215000000.0	652270625.0	$1,648,854,864	437270625.0	135397	2015-06-12	Ju

3 rows × 42 columns

In [1221]:
```
#Getting rid of duplicates
df_top20.drop_duplicates(keep='first', subset='id_x', inplace=True)
```

In [1318]:
```
#Converted all release dates into a date format (originally were text format.)
#This format conversion allows us to filtering out dates from before 2013.
df_top20['release_date_x']=pd.to_datetime(df_top20.release_date_x)
```

In [1298]:
```
#Finalizing our list of the top 20 grossing films.
df_top20b = df_top20.loc[df_top20.Year >= 2013]
```

In [1291]:
```
df_top20c=df_top20b.head(20)
```

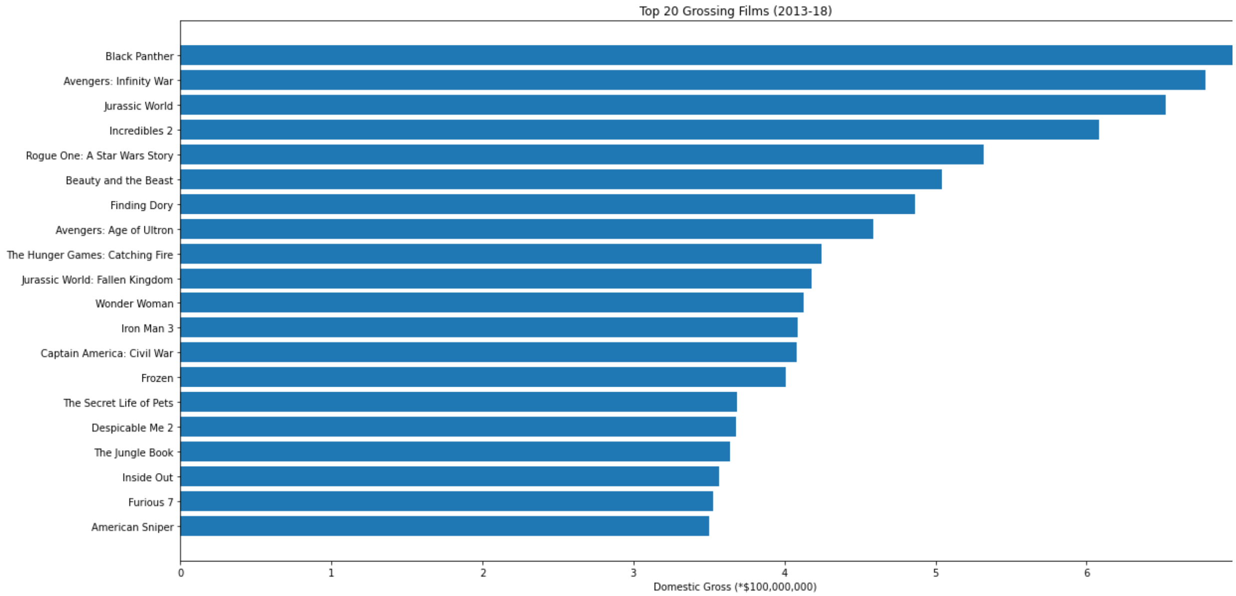
In [1292]:
```
#As we want, here are the top 20 grossing films.
#Please note that to test that only the top 20 were kept, we inserted a number
#greater than 20 in .head().
df_top20c.head(25)
```

Out[1292]:

	id_x	release_date_x	movie	production_budget	domestic_gross	worldwide_gross	profit	id_y	release_date_y	
46	42	2018-02-16	Black Panther	200000000.0	700059566.0	$1,348,258,224	500059566.0	86841	2011-01-18	
2	7	2018-04-27	Avengers: Infinity War	300000000.0	678815482.0	$2,048,134,200	378815482.0	299536	2018-04-27	Ir
25	34	2015-06-12	Jurassic World	215000000.0	652270625.0	$1,648,854,864	437270625.0	135397	2015-06-12	
48	44	2018-06-15	Incredibles 2	200000000.0	608581744.0	$1,242,520,711	408581744.0	260513	2018-06-15	Ir
50	45	2016-12-16	Rogue One: A Star Wars Story	200000000.0	532177324.0	$1,049,102,856	332177324.0	330459	2016-12-16	
139	35	2017-03-17	Beauty and the Beast	160000000.0	504014165.0	$1,259,199,706	344014165.0	10020	2012-01-13	
51	46	2016-06-17	Finding Dory	200000000.0	486295561.0	$1,021,215,193	286295561.0	127380	2016-06-17	
1	4	2015-05-01	Avengers: Age of Ultron	330600000.0	459005868.0	$1,403,013,963	128405868.0	99861	2015-05-01	
217	38	2013-11-22	The Hunger Games: Catching Fire	130000000.0	424668047.0	$864,868,047	294668047.0	101299	2013-11-22	
121	13	2018-06-22	Jurassic World: Fallen Kingdom	170000000.0	417719760.0	$1,305,772,799	247719760.0	351286	2018-06-22	
166	55	2017-06-02	Wonder Woman	150000000.0	412563408.0	$821,133,378	262563408.0	297762	2017-06-02	
53	48	2013-05-03	Iron Man 3	200000000.0	408992272.0	$1,215,392,272	208992272.0	68721	2013-05-03	Ir
12	17	2016-05-06	Captain America: Civil War	250000000.0	408084349.0	$1,140,069,413	158084349.0	271110	2016-05-06	
170	56	2013-11-22	Frozen	150000000.0	400738009.0	$1,272,469,910	250738009.0	109445	2013-11-27	
578	26	2016-07-08	The Secret Life of Pets	75000000.0	368384330.0	$886,750,534	293384330.0	328111	2016-07-08	T
577	22	2013-07-03	Despicable Me 2	76000000.0	368065385.0	$975,216,835	292065385.0	93456	2013-07-03	D
100	97	2016-04-15	The Jungle Book	175000000.0	364001123.0	$962,854,547	189001123.0	278927	2016-04-15	T
104	98	2015-06-19	Inside Out	175000000.0	356461711.0	$854,235,992	181461711.0	70877	2011-09-27	I
74	67	2015-04-03	Furious 7	190000000.0	353007020.0	$1,518,722,794	163007020.0	168259	2015-04-03	
728	57	2014-12-25	American Sniper	58000000.0	350126372.0	$547,326,372	292126372.0	190859	2014-12-25	

20 rows × 42 columns

In [1435]:
```
#And now, putting the top 20 grossing films in bar graph form.
df_top20c = df_top20c.sort_values('domestic_gross')
fig, ax = plt.subplots(figsize=(20, 10))
ax.barh(df_top20c['movie'],df_top20c['domestic_gross'])
ax.set_title('Top 20 Grossing Films (2013-18)')
ax.set_xlabel('Domestic Gross (*$100,000,000)')
plt.show()
```



In [1253]:
```
#Next, we are finding the movie genres that are created most often.
df_profit_analysis.sum(axis = 0, skipna = True)
```

Out[1253]:
```
id_x                                                             158641
release_date_x       May 20, 2011May 1, 2015Apr 27, 2018Nov 17, 201...
movie                Pirates of the Caribbean: On Stranger TidesAve...
production_budget                                           1.11464e+11
domestic_gross                                              1.43871e+11
worldwide_gross      $1,045,663,875$1,403,013,963$2,048,134,200$655...
profit                                                      3.24074e+10
id_y                                                          737709424
release_date_y       2011-05-202015-05-012018-04-272017-11-172017-1...
title                Pirates of the Caribbean: On Stranger TidesAve...
vote_average                                                    18950.4
vote_count                                                      4561888
Year                                                            6209176
tconst               tt1298650tt2395427tt4154756tt0974015tt0974015t...
averagerating                                                   19390.9
numvotes                                                      224708512
primary_title        Pirates of the Caribbean: On Stranger TidesAve...
original_title       Pirates of the Caribbean: On Stranger TidesAve...
start_year                                                      6208971
runtime_minutes                                                  306738
genres               Action,Adventure,FantasyAction,Adventure,Sci-F...
Animation                                                           153
Sport                                                                76
Mystery                                                             231
Action                                                              662
Comedy                                                              767
Documentary                                                         185
Romance                                                             349
News                                                                  3
War                                                                  38
Horror                                                              404
Fantasy                                                             190
Family                                                              138
Music                                                                89
Musical                                                              22
Sci-Fi                                                              214
History                                                              81
Biography                                                           223
Thriller                                                            609
Crime                                                               391
Adventure                                                           481
Drama                                                              1686
dtype: object
```

In [1264]:
```
df_profit_analysis_filter = df_profit_analysis.filter(['Animation', 'Sport', 'Mystery', 'Action',
```

In [1267]:
```
df_profit_analysis_sum=df_profit_analysis_filter.sum()
```

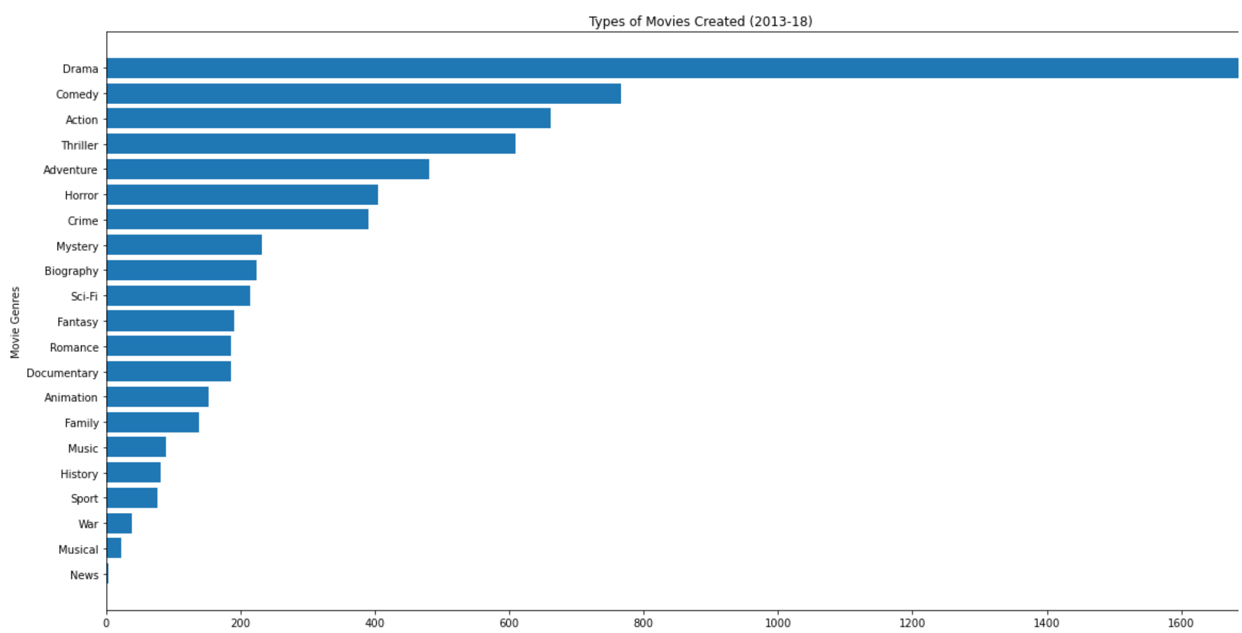
In [1277]:
```
df_profit_analysis_sum.head(21)
```

Out[1277]:
```
Animation        153
Sport             76
Mystery          231
Action           662
Comedy           767
Documentary      185
Romance          349
News               3
War               38
Horror           404
Fantasy          190
Family           138
Music             89
Musical           22
Sci-Fi           214
History           81
Biography        223
Thriller         609
Crime            391
Adventure        481
Drama           1686
dtype: int64
```

In [1383]:
```
genredata = [['Animation', 153], ['Sport', 76], ['Mystery', 231],['Action',662],['Comedy',767],['D
```

In [1384]:
```
df_genredata = pd.DataFrame(genredata, columns = ['Genre', 'Quantity'])
```

In [1436]:
```
#Finally, this will put the most frequently created movie genres in bar graph form.
df_genredata = df_genredata.sort_values('Quantity')
fig, ax = plt.subplots(figsize=(20, 10))
ax.barh(df_genredata['Genre'],df_genredata['Quantity'])
ax.set_title('Types of Movies Created (2013-18)')
ax.set_xlabel('Number of Movies')
ax.set_ylabel('Movie Genres')
plt.show()
```



Dramas are the most frequent type of movie created by a wide margin. As a result, it will be more difficult to stand out against other companies. While it is acceptable to produce these, we recommend diversifying and not relying on dramas as the main source of re

In [1303]:
```python
df_profit_analysis2.head()
```

Out[1303]:

	id_x	release_date_x	movie	production_budget	domestic_gross	worldwide_gross	profit	id_y	release_date_y	
1	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	$1,403,013,963	128405868.0	99861	2015-05-01	Aven A U
2	7	Apr 27, 2018	Avengers: Infinity War	300000000.0	678815482.0	$2,048,134,200	378815482.0	299536	2018-04-27	Aven In
3	9	Nov 17, 2017	Justice League	300000000.0	229024295.0	$655,945,209	-70975705.0	141052	2017-11-17	Ju Le
5	10	Nov 6, 2015	Spectre	300000000.0	200074175.0	$879,620,923	-99925825.0	206647	2015-11-06	Sp
8	12	May 25, 2018	Solo: A Star Wars Story	275000000.0	213767512.0	$393,151,347	-61232488.0	348350	2018-05-25	Sc Star

5 rows × 42 columns

In [1255]:
```python
#We need to filter out movies from before 2013.
df_profit_analysis2=df_profit_analysis.loc[df_profit_analysis.Year >= 2013]
```

In [1256]:
```python
df_profit_analysis2.head()
```

Out[1256]:

	id_x	release_date_x	movie	production_budget	domestic_gross	worldwide_gross	profit	id_y	release_date_y	
1	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	$1,403,013,963	128405868.0	99861	2015-05-01	Aven A U
2	7	Apr 27, 2018	Avengers: Infinity War	300000000.0	678815482.0	$2,048,134,200	378815482.0	299536	2018-04-27	Aven In
3	9	Nov 17, 2017	Justice League	300000000.0	229024295.0	$655,945,209	-70975705.0	141052	2017-11-17	Ju Le
4	9	Nov 17, 2017	Justice League	300000000.0	229024295.0	$655,945,209	-70975705.0	141052	2017-11-17	Ju Le
5	10	Nov 6, 2015	Spectre	300000000.0	200074175.0	$879,620,923	-99925825.0	206647	2015-11-06	Sp

5 rows × 42 columns

In [1257]:
```python
#Dropping duplicates.
df_profit_analysis2.drop_duplicates(keep='first',subset='id_y',inplace=True)
```

```
<ipython-input-1257-891536fc50b4>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/inde
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/ind
g.html#returning-a-view-versus-a-copy)
  df_profit_analysis2.drop_duplicates(keep='first',subset='id_y',inplace=True)
```

In [1294]:
```
#Making sure that our updated table no longer has duplicates and releases from before 2013.
df_profit_analysis2.head(10)
```

Out[1294]:

	id_x	release_date_x	movie	production_budget	domestic_gross	worldwide_gross	profit	id_y	release_date_y
1	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	$1,403,013,963	128405868.0	99861	2015-05-01
2	7	Apr 27, 2018	Avengers: Infinity War	300000000.0	678815482.0	$2,048,134,200	378815482.0	299536	2018-04-27
3	9	Nov 17, 2017	Justice League	300000000.0	229024295.0	$655,945,209	-70975705.0	141052	2017-11-17
5	10	Nov 6, 2015	Spectre	300000000.0	200074175.0	$879,620,923	-99925825.0	206647	2015-11-06
8	12	May 25, 2018	Solo: A Star Wars Story	275000000.0	213767512.0	$393,151,347	-61232488.0	348350	2018-05-25
9	13	Jul 2, 2013	The Lone Ranger	275000000.0	89302115.0	$260,002,115	-185697885.0	57201	2013-07-03
12	17	May 6, 2016	Captain America: Civil War	250000000.0	408084349.0	$1,140,069,413	158084349.0	271110	2016-05-06
13	18	Mar 25, 2016	Batman v Superman: Dawn of Justice	250000000.0	330360194.0	$867,500,281	80360194.0	209112	2016-03-25
15	21	Dec 13, 2013	The Hobbit: The Desolation of Smaug	250000000.0	258366855.0	$960,366,855	8366855.0	57158	2013-12-13
16	22	Dec 17, 2014	The Hobbit: The Battle of the Five Armies	250000000.0	255119788.0	$945,577,621	5119788.0	122917	2014-12-17

10 rows × 42 columns

In [1330]:
```
#Now, we will make a visual for how much revenue the average film of each genre generates at the b
#Specifically, we will be graphing the 21 genres based on average domestic gross.
genre_means=[df_profit_analysis2.groupby(genre).mean() for genre in genres]
means_df=pd.DataFrame
genres = list(genres)
```

In [1380]:
```
genre_means[20]
```

Out[1380]:

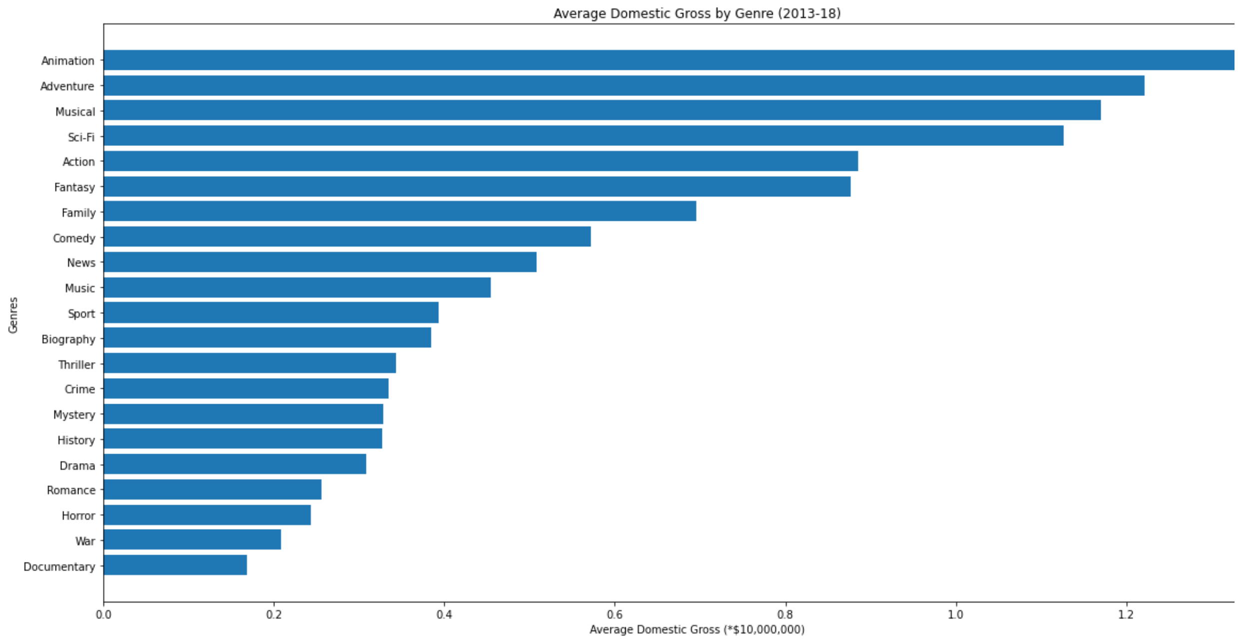
		id_x	production_budget	domestic_gross	profit	id_y	vote_average	vote_count	Year
Drama									
	0	51.909091	5.459634e+07	7.196465e+07	1.736831e+07	268537.895623	5.954209	2224.880471	2015.215488
	1	50.694268	2.590876e+07	3.084340e+07	4.934633e+06	292611.635350	6.419108	1401.479299	2015.191083

2 rows × 32 columns

In [1382]:
```
domestic_gross_genre_data = [['Animation', 1.327373e+08], ['Sport', 3.933974e+07], ['Mystery', 3.2
```

In [1386]:
```
df_domestic_gross_genre_data = pd.DataFrame(domestic_gross_genre_data, columns = ['Genre', 'Averag
```

In [1437]:
```
#And now, putting the top 20 grossing films in bar graph form.
df_domestic_gross_genre_data = df_domestic_gross_genre_data.sort_values('Average domestic gross')
fig, ax = plt.subplots(figsize=(20, 10))
ax.barh(df_domestic_gross_genre_data['Genre'],df_domestic_gross_genre_data['Average domestic gross
ax.set_title('Average Domestic Gross by Genre (2013-18)')
ax.set_xlabel('Average Domestic Gross (*$10,000,000)')
ax.set_ylabel('Genres')
plt.show()
```



Based on this information, there is a ton of potenial for animation and adventure movies. By contrast, dramas are more difficult to su with, as they do not produce as good of results at the box office on average. Also, with how many dramas are being made, it is relat difficult to make ones that stick out from the crowd.

With all of our analysis in mind, we have some recommendations for Microsoft as it enters this market. To summarize, we recommer while dramas are highly rated and have a lot of potential, they do not average as much as most genres at the box office, and it is dif stand out from the many others being made. Instead, consider focusing on genres like animations and adventure films, which have a average gross in a field that are not oversaturated with competition. In addition, sci-fi's numbers are also promising, and those films fit in very nicely with Microsoft's brand. Exploring niche genres and becoming a leader for sci-fi films would be a practical goal for Microsoft. As for writers, it is best to work with those having a proven track record. With the right writers, Microsoft could stand out genre, even the crowded drama genre.

It is also worth noting that financials are just one measure of success. If Microsoft wishes to go after quality rather than gross, then c can be a good choice as are lesser earning genres like documentaries and biographies.

A long-term recommendation that goes beyond the scope of our project relates to diversity. There is an opportunity for Microsoft to leader in diversity and inclusion by encouraging the production of niche genres and working with women and African American write other creators. Recruiting the top writers from underrepesented demographics could go a long way and serve as a way to attract audiences.