A Movie Data Analysis for Microsoft

Overview

This project analyzes data from the movie industry for the hypothetical client Microsoft (https://www.microsoft.com/en-us/?ql=4). Descriptive analysis of movie genres, directors, and writers provides insight into which genres outperform others and who the top-performing talent are. The primary metric used is profit but other metrics are included as they can provide insight into other factors such as prominence. Should it desire to enter the movie industry, Microsoft can use this analysis to decide which type of movies to invest in and who to hire.

Business Opportunity

Since 2005 when [Microsoft sold its stake in NBC to Comcast (https://www.reuters.com/article/us-msnbc-microsoft-idUSBRE86F04W20120716)](https://www.reuters.com/article/us-msnbc-microsoft-idUSBRE86F04W20120716), it has not had a presence in the movie or cable industry. Instead, it's [acquisitions (https://acquiredby.co/what-companies-does-microsoft-own/)](https://acquiredby.co/what-companies-does-microsoft-own/) have focused on software companies (ex. Intrinsa, Github), social networking sites (ex. LinkedIN), telecommunications (ex. Skype), speech recognition (ex. Tellme Network, Nuance Communications), advertising (ex. aQuantive, Xandr), music (ex. Musiwave), cloud computing (ex. Adallom), machine learning (ex. Equivio), and gaming (ex. Mojang, ZeniMax Media). Its 2022 acquisition of [Activision Blizzard for $68.7 billion (https://theorg.com/insights/what-companies-does-microsoft-own)](https://theorg.com/insights/what-companies-does-microsoft-own) continued its expansion into the gaming industry. While not necessarily its primary purpose, the Activision acquisition gives Microsoft rights to popular video game titles including [Overwatch, Diablo, World of Warcraft, Candy Crush, StarCraft, and Call of Duty (https://news.microsoft.com/2022/01/18/microsoft-to-acquire-activision-blizzard-to-bring-the-joy-and-community-of-gaming-to-everyone-across-every-device/)](https://news.microsoft.com/2022/01/18/microsoft-to-acquire-activision-blizzard-to-bring-the-joy-and-community-of-gaming-to-everyone-across-every-device/). It also expands Microsoft's CGI talent pool. The presence of in-house CGI talent and the rights to popular video game titles puts Microsoft in a position to expand into the movie industry should it choose to do so. Income from movies can help recoup some of the money Microsoft spent on the acquisition of Activision.

The Data Sources

The two sources of data used in this analysis are [IMBD (https://www.imdb.com/search/)](https://www.imdb.com/search/) and [The Numbers (https://www.the-numbers.com/movies/#tab=year)](https://www.the-numbers.com/movies/#tab=year). IMBD is an online searchable database that contains information about a film such as genre, actors, directors, writers, ratings, and "Ways to Watch". The Numbers, on the other hand, includes information about worldwide gross, domestic gross, and budget. These two sites are complimentary as they each have information the other site doesn't have. This analysis will merge these two datasets to provide a more complete overview of the movie industry. IMBD is owned by Amazon and The Numbers is run by the company [Nash Information Services (https://www.nashinfoservices.com/)](https://www.nashinfoservices.com/).

Data Understanding

IMBD is an SQL database comprised of multiple datasets. The ones used in this analysis are movie basics, persons, writers, and directors as these four datasets provide information on movie titles, genres, directors, and writers which are the four main categorical criteria used in this analysis. Runtime minutes, birth year, and death year are stored as floats. Start year is stored as an integer. The rest of the column values are stored as objects.

In [1]:
```
# This imports data from the IMBD database, as well as the pandas and numpy
# libraries.
import pandas as pd
import numpy as np
! unzip -n zippedData/im.db.zip
import sqlite3
conn = sqlite3.connect("im.db")
```

```
Archive:  zippedData/im.db.zip
```

In [2]:
```
# This dataframe will be used for the analysis of genres and joined with other
# SQL datafromes for an analysis of directors and writers.
movie_basics = pd.read_sql("SELECT * FROM movie_basics;", conn)
movie_basics.head()
```

Out[2]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [3]:
```
# Genres has some missing values.  These will need to be dropped.
# There are 146144 movies in the database.
movie_basics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 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 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

In [4]:
```
# The directors dataframe requires the use of the persons
# dataframe in order to return director names.
directors = pd.read_sql("SELECT * FROM directors;", conn)
directors.head()
```

Out[4]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0462036	nm1940585
2	tt0835418	nm0151540
3	tt0835418	nm0151540
4	tt0878654	nm0089502

In [5]:
```
# These values are stored as objects. None are missing.
# There are 291174 directors in the database.
directors.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 291174 entries, 0 to 291173
Data columns (total 2 columns):
 #   Column     Non-Null Count   Dtype 
---  ------     --------------   ----- 
 0   movie_id   291174 non-null  object
 1   person_id  291174 non-null  object
dtypes: object(2)
memory usage: 4.4+ MB
```

In [6]:
```
# The writers dataframe is essentially the same as the directors dataframe,
# the main difference being that is specific to writers.
writers = pd.read_sql("SELECT * FROM writers;", conn)
writers.head()
```

Out[6]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0438973	nm0175726
2	tt0438973	nm1802864
3	tt0462036	nm1940585
4	tt0835418	nm0310087

In [7]:
```
writers.info()  # There are 255873 writers in the database.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 255873 entries, 0 to 255872
Data columns (total 2 columns):
 #   Column     Non-Null Count   Dtype 
---  ------     --------------   ----- 
 0   movie_id   255873 non-null  object
 1   person_id  255873 non-null  object
dtypes: object(2)
memory usage: 3.9+ MB
```

In [8]:
```
# The persons dataframe enables primary names to be added into a dataframe visa
# vi their person_id.
persons = pd.read_sql("SELECT * FROM persons;", conn)
persons.head()
```

Out[8]:

	person_id	primary_name	birth_year	death_year	primary_professio
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,produce
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_departme
2	nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,write
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_departme
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_decorat

In [9]:
```
# Birth year and death year are stored as floats so they don't need to be
# cleaned. There are missing values as everyone should have a birth year.
# There are 606648 total persons in the database.
persons.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 606648 entries, 0 to 606647
Data columns (total 5 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   person_id           606648 non-null  object 
 1   primary_name        606648 non-null  object 
 2   birth_year          82736 non-null   float64
 3   death_year          6783 non-null    float64
 4   primary_profession  555308 non-null  object 
dtypes: float64(2), object(3)
memory usage: 23.1+ MB
```

THE NUMBERS

The Numbers is a CSV file that contains information about release date, movie title, production budget, domestic gross, and worldwide gross. The values of the aforementioned columns are all stored as objects.

In [10]:
```
# This imports data from The Numbers csv file.
tn_movies = pd.read_csv("zippedData/tn.movie_budgets.csv.gz")
tn_movies.head()
```

Out[10]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [11]:
```
# There are 5782 movies in the database.
# Everything except ID is stored as objects.
tn_movies.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
```

Data Preparation

Joining IMBD's SQL Databases

IMBD’s movie basics dataframe has all of the IMBD data necessary for an analysis on genres. In order to create dataframes that contain the IMBD data necessary for an analysis on directors and writers, the directors and writers dataframes need to be joined with the movie basics and persons dataframes.

In [12]:
```
# This joins the movie bascis, directors, and persons dataframes to create an
# IMBD dataframe that will be used in the analysis of directors.
movie_basics_directors = pd.read_sql("""
SELECT *, dr.person_id AS director_id
FROM movie_basics
JOIN directors AS dr
     USING(movie_id)
JOIN persons as pe
    USING(person_id);
""", conn)
movie_basics_directors.head()
```

Out[12]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	person_i
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	nm071254
1	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	nm071254
2	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	nm071254
3	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	nm071254
4	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	nm000241

In [13]:
```
#This does the same thing as above, only using the writers dataframe instead of
# the directors dataframe.
movie_basics_writers = pd.read_sql( """
SELECT *, wr.person_id AS writer_id
FROM movie_basics
JOIN writers as wr
    USING(movie_id)
JOIN persons as pe
    USING(person_id);
""", conn)
movie_basics_writers.head()
```

Out[13]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	person_ic
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	nm002355
1	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	nm034789
2	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	nm119431
3	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	nm139127
4	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	nm000008

Data Cleaning

The genres column has multiple values stored in the same row (Comedy and Drama, for example). This will prove problematic once it comes time to do an analysis of genres. While technically feature engineering, the movie basics dataframe needs to be prepared early on as the explode function utilized will not work once the dataframe is joined with The Numbers dataframe. The genres column also has several movies that don't have genres listed. These rows were dropped.

Both the writers and the directors dataframes have duplicates. This is likely due to other variables included in the database. For example, a director may be listed multiple times due to the fact that there are multiple writers working with him or her. These duplicates were also dropped.

Genres

In [14]:
```
# Several movies have multiple genres listed on the same row.
movie_basics['genres'].value_counts()
```

Out[14]:
```
Documentary                  32185
Drama                        21486
Comedy                        9177
Horror                        4372
Comedy,Drama                  3519
                             ...  
Adventure,Music,Mystery          1
Documentary,Horror,Romance       1
Sport,Thriller                   1
Comedy,Sport,Western             1
Adventure,History,War            1
Name: genres, Length: 1085, dtype: int64
```

In [15]:
```
# The explode function works with lists.  The string split function turns the
# values in the gernes column into lists.
movie_basics['genres_list'] = movie_basics['genres'].str.split(',')
movie_basics.head()
```

Out[15]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	[Ac Cr Dr
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	[Biogra Dr
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	[Dr
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama	[Com Dr
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	[Com Dr Fan

In [16]:
```
#The explode function seperates the genres onto seperate rows. This is being
# saved as a new name.
movie_basics1 = movie_basics.explode('genres_list')
movie_basics1.head()
```

Out[16]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	genres_lis
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	Actior
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	Crim
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	Dram
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	Biograph
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	Dram

In [17]:
```
# The info function reveals we have multiple null values in the genres_list
# that need to be dropped.
movie_basics1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 234958 entries, 0 to 146143
Data columns (total 7 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         234958 non-null  object 
 1   primary_title    234958 non-null  object 
 2   original_title   234937 non-null  object 
 3   start_year       234958 non-null  int64  
 4   runtime_minutes  195904 non-null  float64
 5   genres           229550 non-null  object 
 6   genres_list      229550 non-null  object 
dtypes: float64(1), int64(1), object(5)
memory usage: 14.3+ MB
```

In [18]:
```
# The following function drops the null values in the genres_list column so
# that only movies with listed genres remain.
movie_basics1 = movie_basics1.dropna(subset = ['genres_list'])
movie_basics1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 229550 entries, 0 to 146143
Data columns (total 7 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         229550 non-null  object 
 1   primary_title    229550 non-null  object 
 2   original_title   229548 non-null  object 
 3   start_year       229550 non-null  int64  
 4   runtime_minutes  193732 non-null  float64
 5   genres           229550 non-null  object 
 6   genres_list      229550 non-null  object 
dtypes: float64(1), int64(1), object(5)
memory usage: 14.0+ MB
```

Directors

In [19]:
```
# The function value_counts reveals that many directors are listed more than
# once.
movie_basics_directors['primary_name'].value_counts()
```

Out[19]:
```
Tony Newton          238
Jason Impey          190
Shane Ryan           186
Ruben Rodriguez      181
Sam Mason-Bell       144
                    ... 
Mike King              1
Cristian Piazza        1
Qaisar Sanobar         1
Safdar Hussain         1
Kiran Gawade           1
Name: primary_name, Length: 106757, dtype: int64
```

In [20]:
```
# Anthony Russo is one such director.  All of the duplicated columns have the
# same values so the drop_duplicates function should work to remove multiple
# mentions of his name for the production of the same movie.
movie_basics_directors[movie_basics_directors \
["primary_name"]=="Anthony Russo"].head()
```

Out[20]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	per
37914	tt1843866	Captain America: The Winter Soldier	Captain America: The Winter Soldier	2014	136.0	Action,Adventure,Sci-Fi	nm0
37915	tt1843866	Captain America: The Winter Soldier	Captain America: The Winter Soldier	2014	136.0	Action,Adventure,Sci-Fi	nm0
37916	tt1843866	Captain America: The Winter Soldier	Captain America: The Winter Soldier	2014	136.0	Action,Adventure,Sci-Fi	nm0
37917	tt1843866	Captain America: The Winter Soldier	Captain America: The Winter Soldier	2014	136.0	Action,Adventure,Sci-Fi	nm0
37918	tt1843866	Captain America: The Winter Soldier	Captain America: The Winter Soldier	2014	136.0	Action,Adventure,Sci-Fi	nm0

In [21]:
```
# This removes the duplicates.
movie_basics_directors = movie_basics_directors.drop_duplicates()
```

In [22]:
```
# Now Anthony Russo is only mentioned once per movie he directed.
movie_basics_directors[movie_basics_directors \
["primary_name"]=="Anthony Russo"].head()
```

Out[22]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	pe
37914	tt1843866	Captain America: The Winter Soldier	Captain America: The Winter Soldier	2014	136.0	Action,Adventure,Sci-Fi	nm
125264	tt3498820	Captain America: Civil War	Captain America: Civil War	2016	147.0	Action,Adventure,Sci-Fi	nm
154748	tt4154756	Avengers: Infinity War	Avengers: Infinity War	2018	149.0	Action,Adventure,Sci-Fi	nm
154772	tt4154796	Avengers: Endgame	Avengers: Endgame	2019	181.0	Action,Adventure,Sci-Fi	nm
282341	tt9130508	Cherry	Cherry	2020	NaN	Drama	nm

In [23]:
```
# There are still multiples but this likely due to multiple movie
# productions such as Avengers and Captain America movies in
# the case of Anthony Russo.
movie_basics_directors['primary_name'].value_counts()
```

Out[23]:
```
Omer Pasha          62
Larry Rosen         53
Rajiv Chilaka       49
Stephan Düfel       48
Graeme Duane        45
                    ..
Michael Okum         1
Adam LeHouillier     1
Lori Cholewka        1
Brion Dodson         1
Kiran Gawade         1
Name: primary_name, Length: 106757, dtype: int64
```

Writers

In [24]:
```
# The same problem arises with writers.  For example, William Shakespeare
# is only listed once for Gnomeo & Juliet but twice for Hamlet A.D.D.
# The drop_duplicates should also work for writers.
movie_basics_writers[movie_basics_writers \
["primary_name"] == 'William Shakespeare'].head()
```

Out[24]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genre
122	tt0377981	Gnomeo & Juliet	Gnomeo & Juliet	2011	84.0	Adventure,Animation,Comed
1016	tt0892062	Hamlet A.D.D.	Hamlet A.D.D.	2014	95.0	Animation,Comedy,Fantas
1017	tt0892062	Hamlet A.D.D.	Hamlet A.D.D.	2014	95.0	Animation,Comedy,Fantas
4381	tt10332120	Much Ado About Nothing	Much Ado About Nothing	2019	130.0	Dram
8488	tt1274300	The Tempest	The Tempest	2010	110.0	Comedy,Drama,Fantas

In [25]:
```
movie_basics_writers = movie_basics_writers.drop_duplicates()
```

In [26]:
```
# Now William Shakespeare is now only listed once for the movie Hamlet A.D.D.
movie_basics_writers[movie_basics_writers \
["primary_name"] == 'William Shakespeare'].head()
```

Out[26]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genr
122	tt0377981	Gnomeo & Juliet	Gnomeo & Juliet	2011	84.0	Adventure,Animation,Come
1016	tt0892062	Hamlet A.D.D.	Hamlet A.D.D.	2014	95.0	Animation,Comedy,Fanta
4381	tt10332120	Much Ado About Nothing	Much Ado About Nothing	2019	130.0	Drar
8488	tt1274300	The Tempest	The Tempest	2010	110.0	Comedy,Drama,Fanta
10242	tt1372686	Coriolanus	Coriolanus	2011	123.0	Drama,Thriller,W

THE NUMBERS

The Numbers data were stored as objects. These were converted into floats in order to do numerical analysis. They were also divided by 1,000,000 so that the numbers represent millions of dollars. This makes the data easier to read.

The conversions resulted in columns that were no longer necessary. Those columns were dropped.

There were some movies that had zero dollars of world wide gross. While it is possible for a movie to have zero domestic gross if it is only released internationally, one would expect movies to have at least some world wide gross if it had been released. Inclusion of these values would throw off the data analysis. Thus, they were dropped.

In [27]:
```
# This shows the data is stored as objects.
tn_movies.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 [28]:
```
# The values for columns like production_budget have dollar signs and commas.
# These need to be removed.
tn_movies.head()
```

Out[28]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [29]:
```
# This function strips the dollar signs and commas, and converts the objects
# into floats.
tn_movies['productionbudget'] = tn_movies['production_budget'].apply \
(lambda x: x.replace(',', '').replace('$', '')).astype(float)
tn_movies['domesticgross'] = tn_movies['domestic_gross'].apply \
(lambda x: x.replace(',', '').replace('$', '')).astype(float)
tn_movies['worldwidegross'] = tn_movies['worldwide_gross'].apply \
(lambda x: x.replace(',', '').replace('$', '')).astype(float)
```

In [30]:
```
# This divides the numbers by 1,000,000 so the numbers can repesent
# millions of dollars.
tn_movies = tn_movies.assign(budgetinmil = lambda \
x: (x['productionbudget'] / 1000000))
tn_movies = tn_movies.assign(domesticinmil = lambda  \
x: (x['domesticgross'] / 1000000))
tn_movies = tn_movies.assign(worldwideinmil = lambda  \
x: (x['worldwidegross'] / 1000000))
```

In [31]:
```
# This drops columns that are no longer needed.  It also saves the dataframe
# with a new variable name.
tn_movies1 = tn_movies.drop(['production_budget','domestic_gross',  \
'worldwide_gross','productionbudget', 'domesticgross', 'worldwidegross', \
'id'], axis = 1)
```

In [32]:
```
# There are 367 movies in the dataframe that have 0 dollars of worldwide gross.
# These movies were dropped in order to clean the dataset as it is indicative
# of problems in data collection or some other unknown factor.
tn_movies1[tn_movies1['worldwideinmil'] == 0]
```

Out[32]:

	release_date	movie	budgetinmil	domesticinmil	worldwideinmil
194	Dec 31, 2020	Moonfall	150.0000	0.0	0.0
479	Dec 13, 2017	Bright	90.0000	0.0	0.0
480	Dec 31, 2019	Army of the Dead	90.0000	0.0	0.0
535	Feb 21, 2020	Call of the Wild	82.0000	0.0	0.0
670	Aug 30, 2019	PLAYMOBIL	75.0000	0.0	0.0
...	...	...	...	...	...
5761	Dec 31, 2014	Stories of Our Lives	0.0150	0.0	0.0
5764	Dec 31, 2007	Tin Can Man	0.0120	0.0	0.0
5771	May 19, 2015	Family Motocross	0.0100	0.0	0.0
5777	Dec 31, 2018	Red 11	0.0070	0.0	0.0
5780	Sep 29, 2015	A Plague So Pleasant	0.0014	0.0	0.0

367 rows × 5 columns

In [33]:
```
# This function drops the movies with zero dollars of world wide gross
# found in the dataframe.
tn_movies1 = tn_movies1.drop(tn_movies1[tn_movies1['worldwideinmil'] == 0].index)
```

In [34]:
```
# The dataframe now has 5415 movies as opposed to the orginal 5782.
tn_movies1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5415 entries, 0 to 5781
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   release_date    5415 non-null   object 
 1   movie           5415 non-null   object 
 2   budgetinmil     5415 non-null   float64
 3   domesticinmil   5415 non-null   float64
 4   worldwideinmil  5415 non-null   float64
dtypes: float64(3), object(2)
memory usage: 253.8+ KB
```

In [35]:
```
# The result of the cleaning.
tn_movies1.head()
```

Out[35]:

	release_date	movie	budgetinmil	domesticinmil	worldwideinmil
0	Dec 18, 2009	Avatar	425.0	760.507625	2776.345279
1	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410.6	241.063875	1045.663875
2	Jun 7, 2019	Dark Phoenix	350.0	42.762350	149.762350
3	May 1, 2015	Avengers: Age of Ultron	330.6	459.005868	1403.013963
4	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317.0	620.181382	1316.721747

Merging IMBD and The Numbers Databases

Both the IMBD and The Numbers databases had movies with titles that were duplicated. Most of these are likely remakes. For example, The Numbers database includes both the 2019 version of *Aladdin* as well as the 1992 version. In order to avoid having the wrong data being attached to the wrong movie, two columns were used to merge the IMBD and The Numbers databases, namely the title and the year a movie was released.

In the case of the IMBD database, start_year was already stored as an integer and thus didn’t need to be converted. In the case of The Numbers database, it was necessary to convert the release date into an integer.

A successful merge results in the 2019 data from the Numbers database being joined with the 2019 movie data from the IMBD database. These same merges are done for the directors and writers dataframes.

In [36]:
```
# Sevaral movies in the IMBD database have the same name.
movie_basics['primary_title'].value_counts()
```

Out[36]:
```
Home                                24
The Return                          20
Broken                              20
Homecoming                          16
Alone                               16
                                    ..
Viktor                               1
Hooked to the Silver Screen          1
Anaamika                             1
Blood for Blood                      1
Chico Albuquerque - Revelações       1
Name: primary_title, Length: 136071, dtype: int64
```

In [37]:
```
# The Numbers database also has multiple movies with the same name.
tn_movies['movie'].value_counts()
```

Out[37]:
```
Halloween                              3
Home                                   3
King Kong                              3
Friday the 13th                        2
The Last House on the Left             2
                                      ..
9                                      1
What's the Worst That Could Happen?    1
Entourage                              1
Love and Other Drugs                   1
My Date With Drew                      1
Name: movie, Length: 5698, dtype: int64
```

In [38]:
```
# One such movie is Aladdin.  The IMBD database has both the 2017 and 2019
# Alladin movies.
movie_basics1[movie_basics1['primary_title'] == 'Aladdin']
```

Out[38]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
105015	tt6139732	Aladdin	Aladdin	2019	128.0	Adventure,Comedy,Family
105015	tt6139732	Aladdin	Aladdin	2019	128.0	Adventure,Comedy,Family
105015	tt6139732	Aladdin	Aladdin	2019	128.0	Adventure,Comedy,Family
144696	tt9698912	Aladdin	Aladdin	2017	NaN	Fantasy

In [39]:
```
# The Numbers database also multople Aladdins, namely the 2019 Aladdin and
# the 1992 version.
tn_movies1[tn_movies1['movie'] == 'Aladdin']
```

Out[39]:

	release_date	movie	budgetinmil	domesticinmil	worldwideinmil
80	May 24, 2019	Aladdin	182.0	246.734314	619.234314
2032	Nov 11, 1992	Aladdin	28.0	217.350219	504.050219

In [40]:
```
# The first function in this cell turns the release_date into a datetime
# object so that the year can be extracted.  The second function extacts
# the year and adds it to a new column.
tn_movies1['release_date'] = pd.to_datetime(tn_movies1['release_date'])
tn_movies1['year'] = tn_movies1['release_date'].dt.year
```

In [41]:
```
# The Numbers dataframe now has year listed as an integer.  This column
# can now be used to merge with the IMBD dataframes.
tn_movies1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5415 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   release_date    5415 non-null   datetime64[ns]
 1   movie           5415 non-null   object
 2   budgetinmil     5415 non-null   float64
 3   domesticinmil   5415 non-null   float64
 4   worldwideinmil  5415 non-null   float64
 5   year            5415 non-null   int64
dtypes: datetime64[ns](1), float64(3), int64(1), object(1)
memory usage: 296.1+ KB
```

In [42]:
```
# Multiple merges are being done in this cell.  The first one merges the
# movie_basics1 dataframe with The Numbers datagrame, matching "primary_title"
# with "movie" and "start_year" with "year".  The resulting dataframe is
# stored as the variable proift_movies.  This dataframe will be used to analyze
# genres.  The other two merges do the same thing for the IMBD directors and
# writers dataframes.

profit_movies = pd.merge(movie_basics1, tn_movies1, \
left_on=['primary_title','start_year'], right_on = ['movie','year'])
director_df = pd.merge(movie_basics_directors, tn_movies1, \
left_on=['primary_title','start_year'], right_on = ['movie','year'])
writer_df = pd.merge(movie_basics_writers, tn_movies1, \
left_on=['primary_title','start_year'], right_on = ['movie','year'])
```

In [43]:
```
# This cell reveals that the merge was successful as only the 2019 movie
# was returned, not IMBD's 2017 version or The Numbers 1992 version.

profit_movies[profit_movies['primary_title'] == 'Aladdin']
```

Out[43]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	g
3489	tt6139732	Aladdin	Aladdin	2019	128.0	Adventure,Comedy,Family	
3490	tt6139732	Aladdin	Aladdin	2019	128.0	Adventure,Comedy,Family	
3491	tt6139732	Aladdin	Aladdin	2019	128.0	Adventure,Comedy,Family	

In [44]:
```
# This returns the total number of movies in the dataset - 1365.
len(profit_movies['primary_title'].unique())
```

Out[44]: 1365

Feature Engineering

Profit can be calculated by subtracting the world wide gross by the production budget. Domestic gross is included in world wide gross and thus does not factor into this calculation. Return on investemnt (ROI) can be calculated by dividing the profit by the production budget.

In [45]:
```
# This calcuates profit for the various dataframes and adds it as a new column.

profit_movies['profitinmil'] = profit_movies['worldwideinmil'] - profit_movies \
['budgetinmil']
director_df['profitinmil'] = director_df['worldwideinmil'] - director_df \
['budgetinmil']
writer_df['profitinmil'] = writer_df['worldwideinmil'] - writer_df \
['budgetinmil']
```

In [47]:
```
# This calcuates ROI for the various dataframes and adds it as a new column.
profit_movies['roiinmil'] =  (profit_movies['worldwideinmil'] - profit_movies \
['budgetinmil']) / profit_movies['budgetinmil']
director_df['roiinmil'] = (director_df['worldwideinmil'] - director_df \
['budgetinmil']) / director_df['budgetinmil']
writer_df['roiinmil'] = (writer_df['worldwideinmil'] - writer_df \
['budgetinmil']) / writer_df['budgetinmil']
```

In [48]:
```
# The profit_movies dataframe now has a column for profit and ROI.
profit_movies.head()
```

Out[48]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	genr
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	
1	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	Ani
2	tt0249516	Foodfight!	Foodfight!	2012	91.0	Action,Animation,Comedy	C
3	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	Adv
4	tt0359950	The Secret Life of Walter Mitty	The Secret Life of Walter Mitty	2013	114.0	Adventure,Comedy,Drama	C

Analysis

Genres

According to the data included in the IMBD and The Numbers databases, Animation is the most profitable genre, followed by Musical, Sci-Fi, Adventure, Action, Fantasy, and Family. The Musical genre data needs to be approached with caution as there are only 8 movies in it and there are 50 movies in the Music category which, if included, would significantly bring down the average. The other top categories are represented by significant numbers of movies (98 for Animation, 127 for Sci-Fi, 343 for Adventure, 422 for Action, 119 for Fantasy, and 88 for Family).

Profit is correlated with worldwide and domestic gross (.99). Hence, more profitable movies also tend to be the movies with the most domestic and global prominence. For this reason, profit will be used as the primary metric moving forward as it determines net revenue and approximates domestic and global appeal. The genres with the highest profit also tend to have the highest production costs which shouldn't be an issue for well-capitalized companies but could prove problematic for ones with stricter budgetary constraints.

In general, movies have a mean profit of 111 million, a median of 64 million, and a standard deviation of 89 million dollars. The fact that the median is significantly lower than the mean indicates that several highly profitable movies are bringing up the average of the various genres. This trend is seen in the top 7 genres mentioned earlier as they all have means higher than the medians. High standard deviations for the top 7 genres (ranging from 435 million for Musical to 222 million for Family) are indicative of high variability of profit for movies within these genres.

In [86]:
```
# These are additional libraries that will be used to create data visualizations.

import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')

import warnings
warnings.filterwarnings("ignore")
```

In [50]:
```
# This enables the use of SQL syntax with Pandas dataframes.

!pip install -U pandasql
```

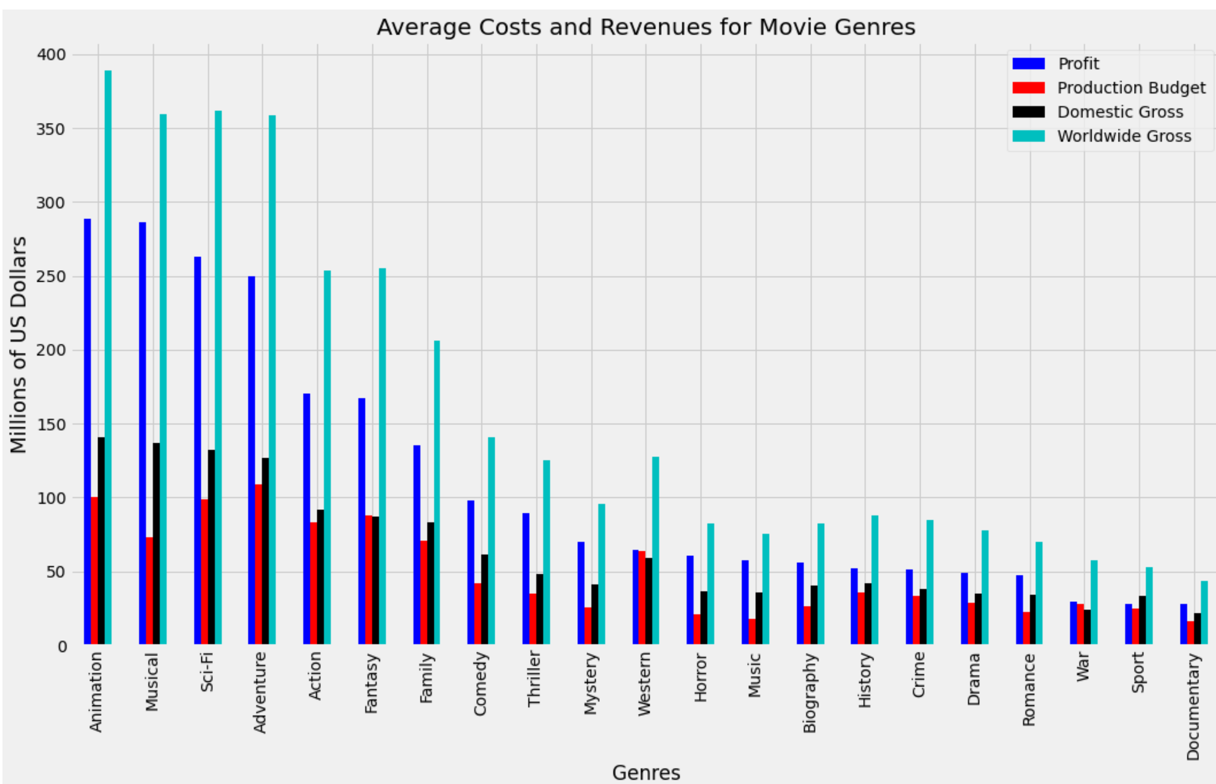
```
Requirement already satisfied: pandasql in c:\users\eincr\anaconda3\lib\site-pa
ckages (0.7.3)
Requirement already satisfied: sqlalchemy in c:\users\eincr\anaconda3\lib\site-
packages (from pandasql) (1.4.22)
Requirement already satisfied: numpy in c:\users\eincr\anaconda3\lib\site-packa
ges (from pandasql) (1.23.1)
Requirement already satisfied: pandas in c:\users\eincr\anaconda3\lib\site-pack
ages (from pandasql) (1.3.4)
Requirement already satisfied: pytz>=2017.3 in c:\users\eincr\anaconda3\lib\sit
e-packages (from pandas->pandasql) (2021.3)
Requirement already satisfied: python-dateutil>=2.7.3 in c:\users\eincr\anacond
a3\lib\site-packages (from pandas->pandasql) (2.8.2)
Requirement already satisfied: six>=1.5 in c:\users\eincr\anaconda3\lib\site-pa
ckages (from python-dateutil>=2.7.3->pandas->pandasql) (1.16.0)
Requirement already satisfied: greenlet!=0.4.17 in c:\users\eincr\anaconda3\lib
\site-packages (from sqlalchemy->pandasql) (1.1.1)
```

In [51]:
```
# This is a function that makes it easier to use SQL syntax.

from pandasql import sqldf
pysqldf = lambda q: sqldf(q, globals())
```

In [52]:
```
# SQL syntax was used to extract genres, profit, budget, domestic gross, and
# worldwide gross from the profit_movies dataframe.  It was grouped by genres
# and ordered by profit.
q = """
SELECT
    genres_list AS Genres,
    AVG(profitinmil) AS AVG_Profit,
    AVG(budgetinmil) AS AVG_Budget,
    AVG(domesticinmil) AS AVG_Dom_Gross,
    AVG(worldwideinmil) AS AVG_WW_Gross
FROM profit_movies
GROUP BY genres_list
ORDER BY AVG_Profit DESC
;
"""
genre_profit = pysqldf(q)
```

In [53]:
```
# The index was reset to Genres.  This makes it easier to create a grouped
# bar plot as the index becomes the x axis.
genre_profit.set_index('Genres', inplace=True)
```

In [54]:
```
# This is the resulting bar plot, with profit descending.  Dark blue was used
# with profit to have it stand out.

genre_profit.plot(kind='bar', figsize=[16,9], color = ['b', 'r', 'k', 'c'])
plt.legend(['Profit', 'Production Budget', 'Domestic Gross', \
'Worldwide Gross'])
plt.title("Average Costs and Revenues for Movie Genres", fontsize=20)
plt.ylabel('Millions of US Dollars', fontsize=18);
```



In [55]:
```
# The correlation between World Wide Gross and ROI is high.
genre_profit["AVG_Profit"].corr(genre_profit["AVG_WW_Gross"])
```

Out[55]:
```
0.993425225588679
```

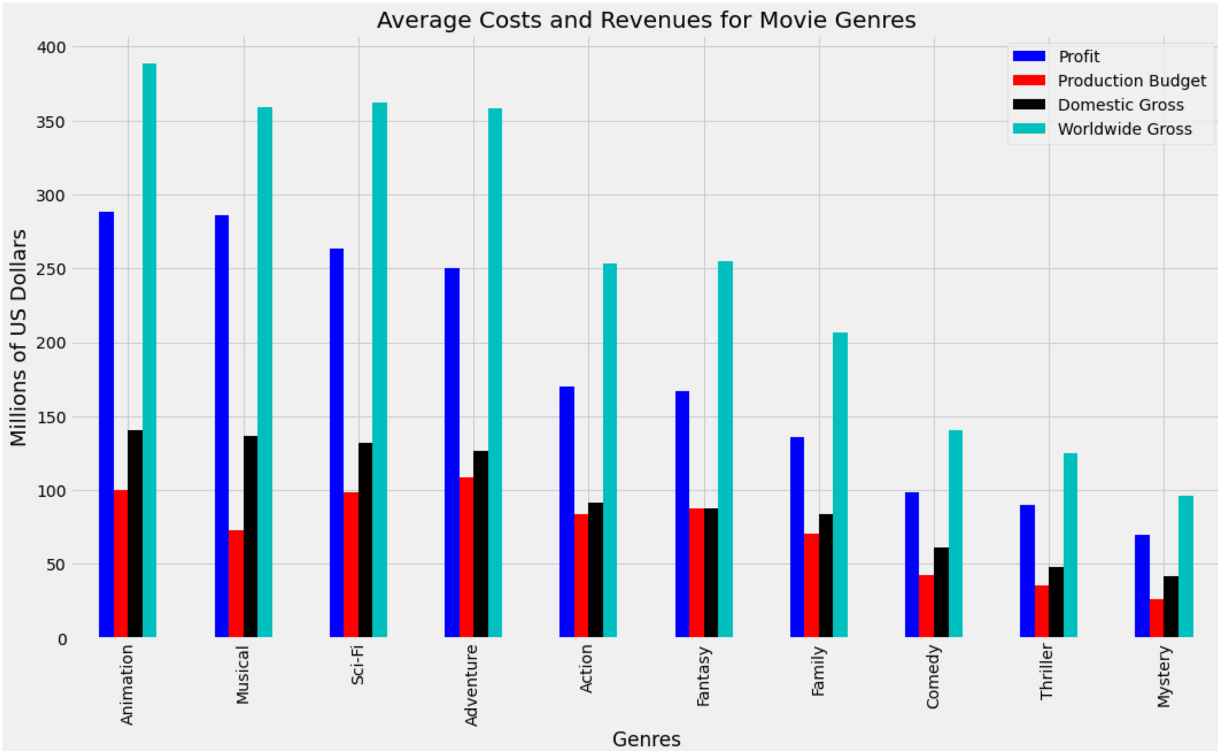
In [56]:
```
# As is the correlation between Domestic Gross and ROI.
genre_profit["AVG_Profit"].corr(genre_profit["AVG_Dom_Gross"])
```

Out[56]:
```
0.9907622235939796
```

In [57]:
```
# This is the same as above, focusing on the top 10
# genres in order to make the chart smaller.
q = """
SELECT
    genres_list AS Genres,
    AVG(profitinmil) AS AVG_Profit,
    AVG(budgetinmil) AS AVG_Budget,
    AVG(domesticinmil) AS AVG_Dom_Gross,
    AVG(worldwideinmil) AS AVG_WW_Gross
FROM profit_movies
GROUP BY genres_list
ORDER BY AVG_Profit DESC
Limit 10
;
"""
genre_profit2 = pysqldf(q)
```

In [58]:
```
genre_profit2.set_index('Genres', inplace=True)
```

In [59]:
```
genre_profit2.plot(kind='bar', figsize=[16,9], color = ['b', 'r', 'k', 'c'])
plt.legend(['Profit', 'Production Budget', 'Domestic Gross', \
'Worldwide Gross'])
plt.title("Average Costs and Revenues for Movie Genres", fontsize=20)
plt.ylabel('Millions of US Dollars', fontsize=18);
```



In [60]:
```
# The describe funcion reveals the number of genres, the mean, the median,
# the standard deviation, and the interquartile range of the dataframe.
genre_profit.describe()
```

Out[60]:

	AVG_Profit	AVG_Budget	AVG_Dom_Gross	AVG_WW_Gross
count	21.000000	21.000000	21.000000	21.000000
mean	111.590755	49.792578	64.321312	161.383333
std	89.422232	31.005644	39.705127	118.101133
min	27.836954	16.093708	21.594357	43.930662
25%	51.354882	26.029090	35.593247	77.772900
50%	64.489819	35.402969	41.921456	96.045168
75%	166.917536	73.112500	87.307723	253.587047
max	288.561604	108.712099	140.702119	388.755481

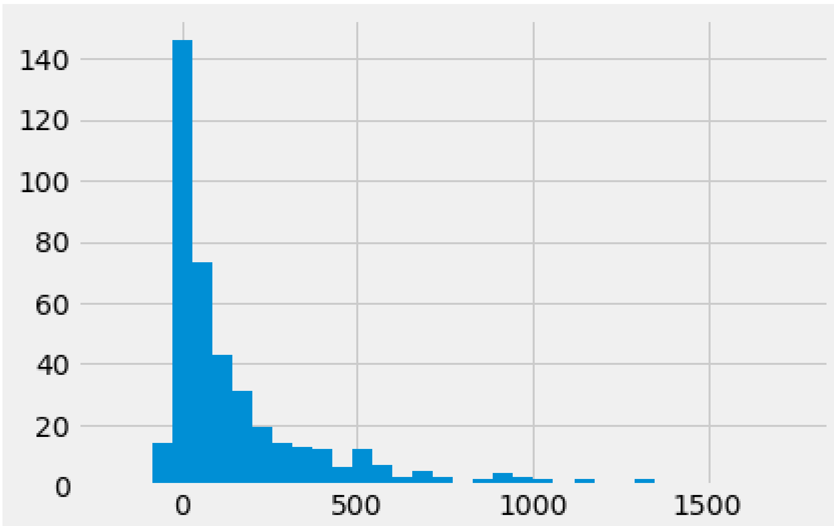
In [61]:
```
# The following function determines the number of movies in the various
# genres, the median, the mean, and the standard deviation. The number
# of movies is particularly important as statistics are improved when
# one has more data.  The fact that the musical genre only has 8 movies
# in it is particularly concerning.  The standard deviation is also
# important as it indicates the likelihood of deviation from the mean.

profit_movies[['genres_list', 'profitinmil']].groupby(['genres_list']).agg \
(['count', 'median', 'mean', 'std'])
```

Out[61]:

	profitinmil			
	count	median	mean	std
genres_list				
Action	422	61.987606	170.186360	266.117287
Adventure	343	135.930148	249.801897	301.271734
Animation	98	213.845751	288.561604	281.277620
Biography	132	18.395522	56.265238	111.424312
Comedy	489	35.129909	98.275525	174.471145
Crime	222	17.371661	51.354882	129.769223
Documentary	48	3.251244	27.836954	64.087666
Drama	687	14.477051	49.335011	101.010972
Family	88	51.927284	135.626479	222.025257
Fantasy	119	49.911903	166.917536	249.370540
History	39	20.044909	52.232883	85.209008
Horror	157	28.985577	60.977703	101.430978
Music	50	12.687654	57.637477	134.894489
Musical	8	39.040070	286.175335	435.774205
Mystery	118	39.117894	70.016077	93.672098
Romance	182	19.210645	47.111438	74.856152
Sci-Fi	127	128.564919	263.055276	348.189022
Sport	33	14.217912	28.272505	45.077416
Thriller	240	34.607332	89.758719	170.667046
War	17	-1.973745	29.517132	69.730024
Western	9	-2.240304	64.489819	131.781607

In [62]:
```
# This confirms that profit is highly skewed in the positive
# direction for the action genre.

action = (profit_movies[profit_movies["genres_list"] == 'Action']['profitinmil'])

action1 = action.values

plt.hist(action1, bins='auto');

from scipy.stats import skew
skew(action1)
```

Out[62]:
```
2.348764891087526
```



Directors

Directors who produced three or more movies were selected in order to filter out one-hit wonders. The two directors with the highest average profit, Joe and Anthony Russo, are brothers who direct their movies together and thus were combined onto a single row. They averaged over 1 billion dollars. David Yates was the lowest of the top ten directors. He averaged over 400 million dollars in profit.

Four of the top ten directors produced movies based off of Marvel Comics and 2 produced movies based off of DC Comics. Of these six directors, several have produced other well-known big-budget films (ex. James Wan - *Furious 7*, Christopher Nolan – *Dunkirk*, and Bryan Singer - *Bohemian Rhapsody*). All of the movies based off of comics fell into the Action category. Most fell into the Adventure category, the Batman movie *The Dark Night Rises* being the sole exception. All but *The Dark Night Rises* and *Aquaman* fell into the Sci-Fi genre.

Two of the directors produced movies based off of popular books - Peter Jackson (*The Hobbit* series) and David Yates (*Fantastic Beasts*). *The Hobbit* and *Fantastic Beasts* fell into Adventure and Fantasy genres and often into the Family genre.

The remaining two directors produced Animated movies. Chris Renaud and Pierre Coffin both produced at least two *Despicable Me* movies. Coffin also produced *Minions* and Renaud also produced The *Secret Life of Pets*.

The average profit of the bottom ten directors with three or more movies ranged from a high of 18 million (Danny Boyle) to a low of -2.0 million (Jeff Nichols). As it is possible that a director could be in the bottom ten due to having a smaller budget and not due to ineffectiveness, a search that took budget into consideration was done to examine this possibility. All of Leslie Small's movies were profitable and he had an average budget of less than 10 million dollars. The rest of the directors in the bottom ten had average budgets greater than 10 million.

In [63]:
```
# SQL syntax was used to extract primary_name, Number_of_Movies,
# AVG_Profit, MAX_Profit, and MIN_Profit from the director dataframe.
# Directors who were deceased were filtered out (although there were none
# in the top ten) and only directors with 3 or more movies were selected.
# The results were grouped by director_id and ordered by average profit.
# The top 11 directors were chosen as Joe and Anthony Russo took up the
# top two spots.

q = """
SELECT
       primary_name AS Name,
       COUNT(movie_id) AS Number_of_Movies,
       AVG(profitinmil) AS AVG_Profit,
       MAX(profitinmil) AS MAX_Profit,
       MIN(profitinmil) AS MIN_Profit
FROM director_df
WHERE death_year IS NULL
GROUP BY director_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_Profit DESC
LIMIT 11
;
"""
top_ten_director = pysqldf(q)
top_ten_director
```

Out[63]:

	Name	Number_of_Movies	AVG_Profit	MAX_Profit	MIN_Profit
0	Joe Russo	3	1060.868501	1748.134200	544.401889
1	Anthony Russo	3	1060.868501	1748.134200	544.401889
2	James Wan	3	871.205858	1328.722794	298.000141
3	Pierre Coffin	4	854.936333	1086.336173	474.464573
4	Peter Jackson	3	724.316015	767.003568	695.577621
5	Christopher Nolan	4	584.045121	809.439099	349.837368
6	Michael Bay	4	565.999563	928.790543	55.275291
7	Chris Renaud	4	554.695860	899.216835	33.351496
8	Bryan Singer	4	438.768316	839.985342	2.687603
9	Ryan Coogler	3	433.825150	1148.258224	16.649645
10	David Yates	3	414.508321	622.402853	168.902025

In [64]:
```
# The name Anthony Russo was changed to Joe and Anthony Russo and the
# row that contained Joe Russo was dropped so that the dataframe didn't
# double-count the Russo brothers for having directed the same movies.

top_ten_director["Name"] = top_ten_director["Name"].str.replace \
('Anthony Russo','Joe and Anthony Russo')
top_ten_director = top_ten_director.drop(0)
top_ten_director
```

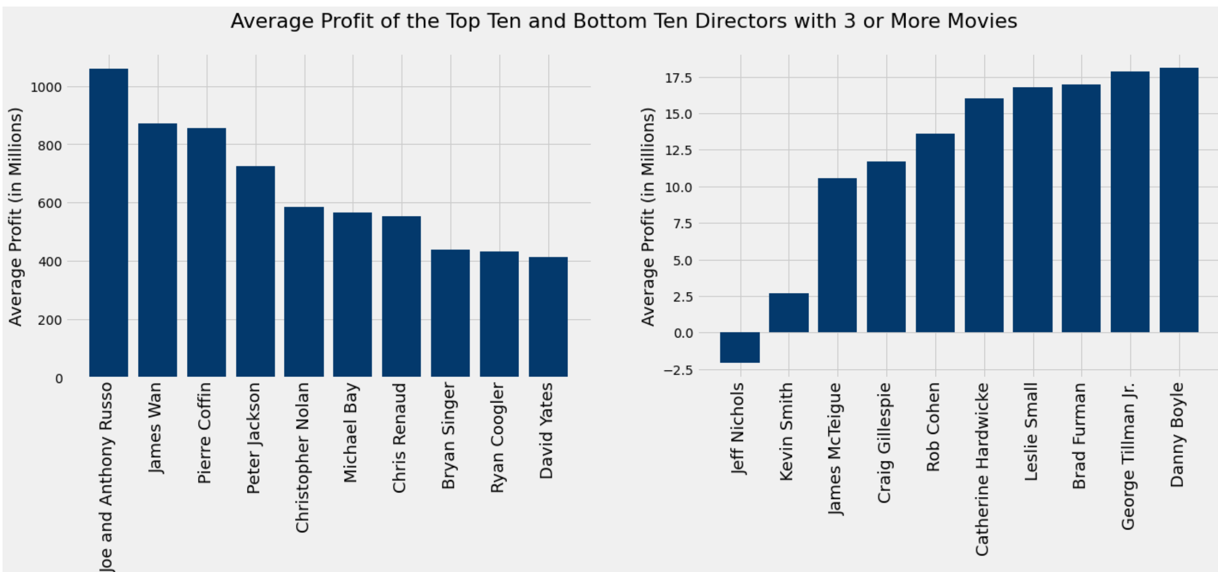
Out[64]:

	Name	Number_of_Movies	AVG_Profit	MAX_Profit	MIN_Profit
1	Joe and Anthony Russo	3	1060.868501	1748.134200	544.401889
2	James Wan	3	871.205858	1328.722794	298.000141
3	Pierre Coffin	4	854.936333	1086.336173	474.464573
4	Peter Jackson	3	724.316015	767.003568	695.577621
5	Christopher Nolan	4	584.045121	809.439099	349.837368
6	Michael Bay	4	565.999563	928.790543	55.275291
7	Chris Renaud	4	554.695860	899.216835	33.351496
8	Bryan Singer	4	438.768316	839.985342	2.687603
9	Ryan Coogler	3	433.825150	1148.258224	16.649645
10	David Yates	3	414.508321	622.402853	168.902025

In [65]:
```
# SQL syntax was also used to extract the bottom ten directors.
# This time only ten were selected as there weren't any directors
# who exclusively worked together on movies.

q = """
SELECT
       primary_name AS Name,
       AVG(profitinmil) AS AVG_Profit,
       MAX(profitinmil) AS MAX_Profit,
       MIN(profitinmil) AS MIN_Profit
FROM director_df
WHERE death_year IS NULL
GROUP BY director_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_Profit
LIMIT 10
;
"""
bottom_ten_director = pysqldf(q)
```

In [66]:
```
# The indexes were reset to Name to make plotting easier.
top_ten_director.set_index('Name', inplace=True)
bottom_ten_director.set_index('Name', inplace=True)
```

In [67]:
```
# Only the Average Progit was selected when making the plots in order
# to make the data visualization easier to understand.  This was
# done for both the top ten and the bottom ten in order to provide
# some insight about the range of the expected values. It should be
# noted that this is the top and bottom ten of the directors with 3
# or movies that are contained within the IMBD and The Numbers
# databases.  Directors who produce less well-known films are likely
# to be excluded due to their absence in the datasets.

plt.figure(figsize=[20,6])
plt.suptitle("Average Profit of the Top Ten and Bottom Ten Directors with 3 or Mo

plt.subplot(1,2,1)
plt.bar(x=top_ten_director.index, height='AVG_Profit',  \
        color = ['#03396c'], data = top_ten_director)
plt.xticks(rotation=90, fontsize=18)
plt.ylabel('Average Profit (in Millions)', fontsize=18)

plt.subplot(1,2,2)
plt.bar(x=bottom_ten_director.index, height='AVG_Profit', \
        color = ['#03396c'], data = bottom_ten_director)
plt.xticks(rotation=90, fontsize=18)
plt.ylabel('Average Profit (in Millions)', fontsize=18);
```



In [88]:
```
# SQL syntax was also used to extract the movies the directors produced
# and the genres that they fell under.  This information is important as
# one should try to hire directors for the type of movies they are knwon
# for.  For example, if one is trying to produce a Scooby-Doo movie and
# wants to target the family audience, one should probably avoid hiring
# Quentin Tarantino. Bryan Singer appears to have had this problem with
# Jack the Giant Slayer as it was considered too dark for families and
# it wasn't particulary targeted to adults.  This being said, Bohemian
# Rhapsody wasn't an X-Men movie and he pulled  that off well.

q = """
SELECT
       primary_name AS Name,
       movie AS Movie,
       genres AS Genre,
       profitinmil as Profit,
       roiinmil AS ROI
FROM director_df
WHERE Name IN ("Anthony Russo", "James Wan",
             "Pierre Coffin", "Peter Jackson",
             "Christopher Nolan", "Michael Bay",
             "Chris Renaud", "Bryan Singer",
             "Ryan Coogler", "David Yates")
Order BY Name
;
"""
movie_name = pysqldf(q)
movie_name
```

Out[88]:

	Name	Movie	Genre	Profit	ROI
0	Anthony Russo	Captain America: The Winter Soldier	Action,Adventure,Sci-Fi	544.401889	3.202364
1	Anthony Russo	Captain America: Civil War	Action,Adventure,Sci-Fi	890.069413	3.560278
2	Anthony Russo	Avengers: Infinity War	Action,Adventure,Sci-Fi	1748.134200	5.827114
3	Bryan Singer	Jack the Giant Slayer	Adventure,Fantasy	2.687603	0.013783
4	Bryan Singer	Bohemian Rhapsody	Biography,Drama,Music	839.985342	15.272461
5	Bryan Singer	X-Men: Days of Future Past	Action,Adventure,Sci-Fi	547.862775	2.739314
6	Bryan Singer	X-Men: Apocalypse	Action,Adventure,Sci-Fi	364.537546	2.047964
7	Chris Renaud	Despicable Me	Animation,Comedy,Family	474.464573	6.876298
8	Chris Renaud	Despicable Me 2	Adventure,Animation,Comedy	899.216835	11.831800
9	Chris Renaud	The Secret Life of Pets	Adventure,Animation,Comedy	811.750534	10.823340
10	Chris Renaud	The Secret Life of Pets 2	Adventure,Animation,Comedy	33.351496	0.416894
11	Christopher Nolan	Interstellar	Adventure,Drama,Sci-Fi	501.379375	3.038663

	Name	Movie	Genre	Profit	ROI
12	Christopher Nolan	The Dark Knight Rises	Action,Thriller	809.439099	2.943415
13	Christopher Nolan	Inception	Action,Adventure,Sci-Fi	675.524642	4.222029
14	Christopher Nolan	Dunkirk	Action,Drama,History	349.837368	2.332249
15	David Yates	The Legend of Tarzan	Action,Adventure,Drama	168.902025	0.938345
16	David Yates	Fantastic Beasts and Where to Find Them	Adventure,Family,Fantasy	622.402853	3.457794
17	David Yates	Fantastic Beasts: The Crimes of Grindelwald	Adventure,Family,Fantasy	452.220086	2.261100
18	James Wan	The Conjuring	Horror,Mystery,Thriller	298.000141	14.900007
19	James Wan	Aquaman	Action,Adventure,Fantasy	986.894640	6.168092
20	James Wan	Furious 7	Action,Crime,Thriller	1328.722794	6.993278
21	Michael Bay	Transformers: Dark of the Moon	Action,Adventure,Sci-Fi	928.790543	4.763028
22	Michael Bay	Pain & Gain	Action,Comedy,Crime	55.275291	2.125973
23	Michael Bay	Transformers: Age of Extinction	Action,Adventure,Sci-Fi	894.039076	4.257329
24	Michael Bay	Transformers: The Last Knight	Action,Adventure,Sci-Fi	385.893340	1.778310
25	Peter Jackson	The Hobbit: An Unexpected Journey	Adventure,Family,Fantasy	767.003568	3.068014
26	Peter Jackson	The Hobbit: The Desolation of Smaug	Adventure,Fantasy	710.366855	2.841467
27	Peter Jackson	The Hobbit: The Battle of the Five Armies	Adventure,Fantasy	695.577621	2.782310
28	Pierre Coffin	Despicable Me	Animation,Comedy,Family	474.464573	6.876298
29	Pierre Coffin	Despicable Me 2	Adventure,Animation,Comedy	899.216835	11.831800
30	Pierre Coffin	Minions	Adventure,Animation,Comedy	1086.336173	14.680219
31	Pierre Coffin	Despicable Me 3	Adventure,Animation,Comedy	959.727750	12.796370
32	Ryan Coogler	Black Panther	Action,Adventure,Sci-Fi	1148.258224	5.741291
33	Ryan Coogler	Fruitvale Station	Biography,Drama,Romance	16.649645	18.499606
34	Ryan Coogler	Creed	Drama,Sport	136.567581	3.691016

In [91]:
```
# Directors with average budgets less than ten million dollars included
# in the bottom ten were extracted in order to more fairly evaluate them.

q = """
SELECT
       primary_name AS Name,
       AVG(budgetinmil) AS AVG_Budget,
       AVG(profitinmil) as AVG_Profit,
       AVG(roiinmil) AS AVG_ROI
FROM director_df
GROUP BY director_id
    HAVING COUNT(movie_id) >= 3 AND AVG_Budget < 10.0 AND AVG_Profit < 18.0
;
"""
bottom_ten_budget_director = pysqldf(q)

bottom_ten_budget_director
```

Out[91]:

	Name	AVG_Budget	AVG_Profit	AVG_ROI
0	Leslie Small	4.416667	16.793578	7.524418

In [70]:
```
# Leslie Small appears to have done alright for what he was trying to do.
# He made profitable movies on smaller budgets.
director_df[director_df["primary_name"] == 'Leslie Small']
```

Out[70]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	pers
868	tt1999192	Kevin Hart: Laugh at My Pain	Kevin Hart: Laugh at My Pain	2011	89.0	Comedy,Documentary	nm08
1104	tt2609912	Kevin Hart: Let Me Explain	Kevin Hart: Let Me Explain	2013	75.0	Comedy,Documentary	nm08
1419	tt4669186	Kevin Hart: What Now?	Kevin Hart: What Now?	2016	96.0	Comedy,Documentary	nm08

Writers

Writers accredited with three or more movies were selected in order to filter out one-hit wonders. Writers who are deceased were filtered out as they can no longer write movies. Don Heck, Joe Simon, and J.R.R. Tolkien had been in the top ten without the filter. Jim Starlin has the highest profit, with an average movie grossing well over 1 billion dollars. Stephen McFeely has the lowest of the top ten, with an average profit of 603 million.

4 of the top writers are either comic book writers or have made screenplays based off of comic books. 3 more have written animated films (Cinco Paul, Ken Daurio, Linda Woolverton). The remaining 3 have written big budget action films (ex. *Jurassic World*, *Furious 7*, *The Hunger Games*).

The average profit of the bottom ten writers ranged from a high of 18 million (Stephen Susco) to a low of -14 million (David Dobkin). A search that took budget into consideration was used to examine the bottom ten. Kevin Smith and Nicole Holofcener both had average budgets less than 10 million. None of Kevin Smith's movies were profitable. On the other hand, all of Nicole Holofcener's movies were.

In [92]:
```
# The same SQL syntax used with the directors dataframe was used with
# the writers dataframe.  In the case of writers, 3 of the top ten were
# deceased prior to being filtered (two of which were asscociated with
# comic books).  It should be noted that if a person's death wasn't
# listed in the IMBD database, then they would still show up as being
# alive with this query which could be an issue for less famous writers
# and directors.  There are multiple writers and directors without birth
# dates in the dataset. Hence, one must double check ones work (and/or drop
# more rows).  Age was intentionally not added as a selecting factor due to
# societal norms, but it should be noted that Larry Lieber is in his 90s and
# is likely retired.

q = """
SELECT
       primary_name AS Name,
       AVG(profitinmil) AS AVG_Profit,
       MAX(profitinmil) AS MAX_Profit,
       MIN(profitinmil) AS MIN_Profit
FROM writer_df
WHERE death_year IS NULL
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_Profit DESC
LIMIT 10
;
"""
top_ten_writer = pysqldf(q)
top_ten_writer
```

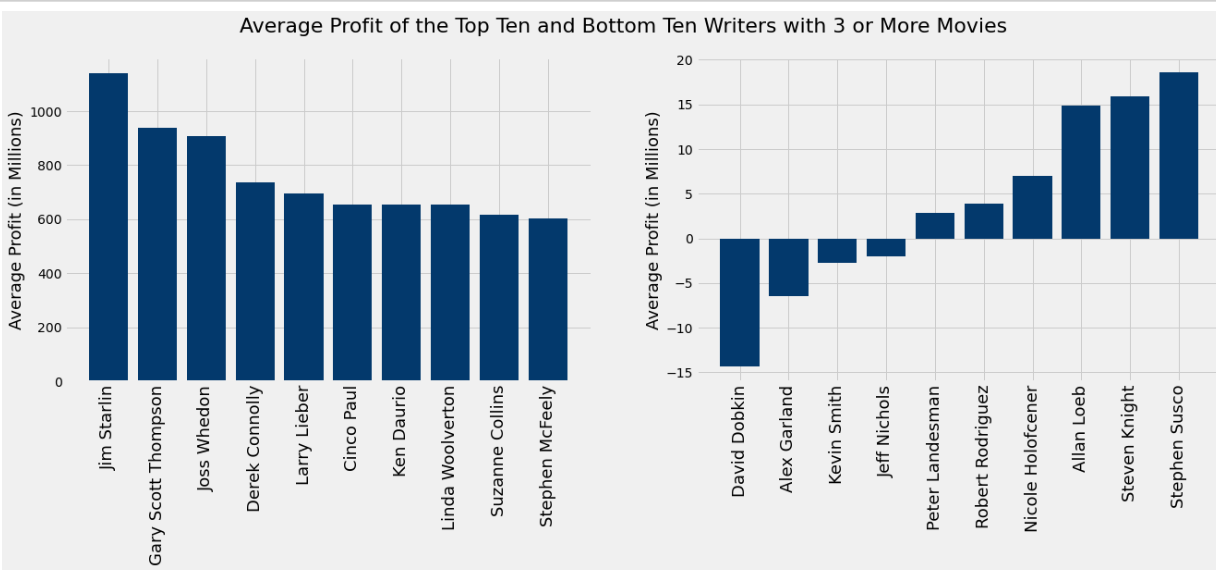
Out[92]:

	Name	AVG_Profit	MAX_Profit	MIN_Profit
0	Jim Starlin	1140.471893	1748.134200	600.867516
1	Gary Scott Thompson	939.577505	1328.722794	505.163454
2	Joss Whedon	907.098356	1292.935897	355.945209
3	Derek Connolly	737.343010	1433.854864	3.672318
4	Larry Lieber	694.699391	1748.134200	299.326618
5	Cinco Paul	654.163457	959.727750	125.657593
6	Ken Daurio	654.163457	959.727750	125.657593
7	Linda Woolverton	652.538916	1099.199706	106.928112
8	Suzanne Collins	615.838336	734.868047	488.986787
9	Stephen McFeely	603.748576	1748.134200	55.275291

In [93]:
```
# Similar to the directors dataframe seen above.
q = """
SELECT
       primary_name AS Name,
       AVG(profitinmil) AS AVG_Profit,
       MAX(profitinmil) AS MAX_Profit,
       MIN(profitinmil) AS MIN_Profit
FROM writer_df
WHERE death_year IS NULL
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_Profit
LIMIT 10
;
"""
bottom_ten_writer = pysqldf(q)
```

In [94]:
```
# Similar to the directors dataframe.
top_ten_writer.set_index('Name', inplace=True)
bottom_ten_writer.set_index('Name', inplace=True)
```

In [95]:
```
# Similar to the directors dataframe.
plt.figure(figsize=[20,6])
plt.suptitle("Average Profit of the Top Ten and Bottom Ten Writers with 3 or More

plt.subplot(1,2,1)
plt.bar(x=top_ten_writer.index, height='AVG_Profit', \
        color = ['#03396c'], data = top_ten_writer)
plt.xticks(rotation=90, fontsize=18)
plt.ylabel('Average Profit (in Millions)', fontsize=18)

plt.subplot(1,2,2)
plt.bar(x=bottom_ten_writer.index, height='AVG_Profit', \
        color = ['#03396c'], data = bottom_ten_writer)
plt.xticks(rotation=90, fontsize=18)
plt.ylabel('Average Profit (in Millions)', fontsize=18);
```



In [96]:
```
# Similar to the directors dataframe.  It shold be noted that the writers
# Cinco Paul and Ken Daurio like to work together, often under the direction
# of Chris Renaud and/or Pierre Coffin.

q = """
SELECT
       primary_name AS Name,
       movie AS Movie,
       genres AS Genre,
       profitinmil as Profit,
       roiinmil AS ROI
FROM writer_df
WHERE Name IN ("Jim Starlin", "Gary Scott Thompson",
              "Joss Whedon", "Derek Connolly",
              "Larry Lieber", "Cinco Paul",
              "Ken Daurio", "Linda Woolverton",
              "Suzanne Collins", "Stephen McFeely")
Order BY Name
;
"""
writer_movie_name = pysqldf(q)
writer_movie_name
```

Out[96]:

	Name	Movie	Genre	Profit	ROI
0	Cinco Paul	Despicable Me	Animation,Comedy,Family	474.464573	6.876298
1	Cinco Paul	Hop	Adventure,Animation,Comedy	125.657593	1.994565
2	Cinco Paul	Despicable Me 2	Adventure,Animation,Comedy	899.216835	11.831800
3	Cinco Paul	The Secret Life of Pets	Adventure,Animation,Comedy	811.750534	10.823340
4	Cinco Paul	Despicable Me 3	Adventure,Animation,Comedy	959.727750	12.796370
5	Derek Connolly	Jurassic World	Action,Adventure,Sci-Fi	1433.854864	6.669092
6	Derek Connolly	Safety Not Guaranteed	Comedy,Drama,Romance	3.672318	4.896424
7	Derek Connolly	Kong: Skull Island	Action,Adventure,Fantasy	376.072059	2.032822
8	Derek Connolly	Jurassic World: Fallen Kingdom	Action,Adventure,Sci-Fi	1135.772799	6.681016
9	Gary Scott Thompson	Fast Five	Action,Crime,Thriller	505.163454	4.041308
10	Gary Scott Thompson	Furious 7	Action,Crime,Thriller	1328.722794	6.993278
11	Gary Scott Thompson	The Fate of the Furious	Action,Crime,Thriller	984.846267	3.939385
12	Jim Starlin	Guardians of the Galaxy	Action,Adventure,Comedy	600.867516	3.534515
13	Jim Starlin	Avengers: Age of Ultron	Action,Adventure,Sci-Fi	1072.413963	3.243841
14	Jim Starlin	Avengers: Infinity War	Action,Adventure,Sci-Fi	1748.134200	5.827114
15	Joss Whedon	The Avengers	Action,Adventure,Sci-Fi	1292.935897	5.746382

	Name	Movie	Genre	Profit	ROI
16	Joss Whedon	Justice League	Action,Adventure,Fantasy	355.945209	1.186484
17	Joss Whedon	Avengers: Age of Ultron	Action,Adventure,Sci-Fi	1072.413963	3.243841
18	Ken Daurio	Despicable Me	Animation,Comedy,Family	474.464573	6.876298
19	Ken Daurio	Hop	Adventure,Animation,Comedy	125.657593	1.994565
20	Ken Daurio	Despicable Me 2	Adventure,Animation,Comedy	899.216835	11.831800
21	Ken Daurio	The Secret Life of Pets	Adventure,Animation,Comedy	811.750534	10.823340
22	Ken Daurio	Despicable Me 3	Adventure,Animation,Comedy	959.727750	12.796370
23	Larry Lieber	Ant-Man	Action,Adventure,Comedy	388.858449	2.991219
24	Larry Lieber	Thor	Action,Adventure,Fantasy	299.326618	1.995511
25	Larry Lieber	Iron Man 2	Action,Adventure,Sci-Fi	451.156389	2.653861
26	Larry Lieber	Iron Man 3	Action,Adventure,Sci-Fi	1015.392272	5.076961
27	Larry Lieber	Thor: The Dark World	Action,Adventure,Fantasy	494.602516	3.297350
28	Larry Lieber	Thor: Ragnarok	Action,Adventure,Comedy	666.980024	3.705445
29	Larry Lieber	Avengers: Infinity War	Action,Adventure,Sci-Fi	1748.134200	5.827114
30	Larry Lieber	Ant-Man and the Wasp	Action,Adventure,Comedy	493.144660	3.793420
31	Linda Woolverton	Alice in Wonderland	Adventure,Family,Fantasy	825.491110	4.127456
32	Linda Woolverton	Maleficent	Action,Adventure,Family	578.536735	3.214093
33	Linda Woolverton	Alice Through the Looking Glass	Adventure,Family,Fantasy	106.928112	0.628989
34	Linda Woolverton	Beauty and the Beast	Family,Fantasy,Musical	1099.199706	6.869998
35	Stephen McFeely	Captain America: The First Avenger	Action,Adventure,Sci-Fi	230.569776	1.646927
36	Stephen McFeely	The Chronicles of Narnia: The Voyage of the Da...	Adventure,Family,Fantasy	263.186950	1.697980
37	Stephen McFeely	Captain America: The Winter Soldier	Action,Adventure,Sci-Fi	544.401889	3.202364
38	Stephen McFeely	Pain & Gain	Action,Comedy,Crime	55.275291	2.125973
39	Stephen McFeely	Thor: The Dark World	Action,Adventure,Fantasy	494.602516	3.297350
40	Stephen McFeely	Captain America: Civil War	Action,Adventure,Sci-Fi	890.069413	3.560278
41	Stephen McFeely	Avengers: Infinity War	Action,Adventure,Sci-Fi	1748.134200	5.827114
42	Suzanne Collins	The Hunger Games	Action,Adventure,Sci-Fi	597.923379	7.474042
43	Suzanne Collins	The Hunger Games: Catching Fire	Action,Adventure,Sci-Fi	734.868047	5.652831
44	Suzanne Collins	The Hunger Games: Mockingjay - Part 1	Action,Adventure,Sci-Fi	641.575131	5.132601

	Name	Movie	Genre	Profit	ROI
45	Suzanne Collins	The Hunger Games: Mockingjay - Part 2	Action,Adventure,Sci-Fi	488.986787	3.056167

In [97]:
```
# Similar to the directors dataframe.
q = """
SELECT
       primary_name AS Name,
       AVG(budgetinmil) AS AVG_Budget,
       AVG(profitinmil) as AVG_Profit,
       AVG(roiinmil) AS AVG_ROI
FROM writer_df
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3 AND AVG_Budget < 10.0 AND AVG_Profit < 18.0
;
"""
bottom_ten_budget_writer = pysqldf(q)

bottom_ten_budget_writer
```

Out[97]:

	Name	AVG_Budget	AVG_Profit	AVG_ROI
0	Kevin Smith	4.0	-2.701964	-0.623442
1	Nicole Holofcener	7.0	6.981338	0.967104

In [77]:
```
# It looks like Kevin Smith deserves to be in the bottom ten.  None of his
# movies are profitable.
writer_df[writer_df["primary_name"] == 'Kevin Smith']
```

Out[77]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	pe
272	tt0873886	Red State	Red State	2011	88.0	Action,Crime,Horror	nm0
2834	tt3099498	Tusk	Tusk	2014	102.0	Comedy,Drama,Horror	nm0
3141	tt3838992	Yoga Hosers	Yoga Hosers	2016	88.0	Action,Comedy,Fantasy	nm0

In [78]:
```
# Nicole Holofcener has been profitable.

writer_df[writer_df["primary_name"] == 'Nicole Holofcener']
```

Out[78]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	p
273	tt0878835	Please Give	Please Give	2010	87.0	Comedy,Drama	nr
2519	tt2390361	Enough Said	Enough Said	2013	93.0	Comedy,Drama,Romance	nr
3316	tt4595882	Can You Ever Forgive Me?	Can You Ever Forgive Me?	2018	106.0	Biography,Comedy,Crime	nr

Conclusions

- **Resist the temptation to make a movie based off of *Call of Duty***
  In general, war movies do not do well. The genres that are best suited for Microsoft are Animation, Sci-Fi, Fantasy, Action, Adventure, and Family. These genres have higher production costs which means smaller companies are less likely to take risks on them due to fear of becoming insolvent. Hence, the only likely competition is with other industry giants. Unless done as an Animated Family film like *Beauty and the Beast*, it is probably best to avoid the Musical genre. There aren't enough movies in the dataset to support the genre's inclusion in the top tier and Musicals don't take advantage of the two main strengths Microsoft has – high market capitalization and in-house CGI talent. *Diablo*, *Overwatch*, *World of Warcraft* and *StarCraft* are Activision titles that have the potential to be turned into movies due to their Sci-Fi, Fantasy, Action, and Adventure elements. [*World of Warcraft* (https://www.imdb.com/video/vi4072453145/?playlistId=tt0803096&ref_=tt_pr_ov_vi)](https://www.imdb.com/video/vi4072453145/?playlistId=tt0803096&ref_=tt_pr_ov_vi) has been produced before (profitably) and a sequel or remake may be a good entry point into the movie space. It would be difficult to pull off, but *Candy Crush* could be turned into an Animated Family movie.

- **Hire top directing talent for that genre**
  For films in the Sci FI / Action / Adventure / Fantasy categories, the Russo brothers, Bryan Singer, Christopher Nolan, David Yates, James Wan, Michael Bay, Peter Jackson, and Ryan Coogler are all top-notch talent. For the Animated / Family categories, Chris Renaud and Pierre Coffin are better choices.

- **Hire top writing talent for that genre**
  For films in the Sci FI / Action / Adventure / Fantasy categories, Jim Starlin, Gary Scott Thompson, Joss Whedon, Derek Connolly, Suzanne Collins and Stephen McFeely are all top-notch talent. Larry Lieber might be able to be hired as a consultant, but the fact he is in his 90s probably precludes him from being the primary writer. For films in the Animated / Family categories, Cinco Paul, Ken Daurio, and Linda Woolverton are better candidates.

Next Steps

- **Investigate the interest level of a *Warcraft* sequel or remake.**
  With a profit of 265 million, the revenue generated by the original movie were average. By comparison, *The Hobbit* films had an average ROI of 724 million despite having similar stylistic elements. Consider bringing in better writing and directing talent as those are possible reasons for its lackluster performance. If it becomes a huge success, it could be turned into a series of moives much like *Jurassic Park* or *Iron Man*.

- **Investigate *Overwatch*.**
  There was an abortive attempt to make *Overwatch* into a Netflix movie or series. Microsoft now owns the rights. Consider using them.

- **Consider creating a movie studio.**
  Microsoft’s in-house CGI talent puts it in a prime position to make Animated films which is the highest grossing genre. CGI is also used in the highly profitable Action, Sci-Fi, Adventure, and Fantasy genres. What Microsoft lacks is access to writing and directing talent. A studio with talent scouts and recruiters from the movie industry could help with that. It would also be helpful with rebranding and marketing. "A movie brought to you by Activision Studios" probably sounds better to most people than "A movie brought to you by Microsoft."

Appendix

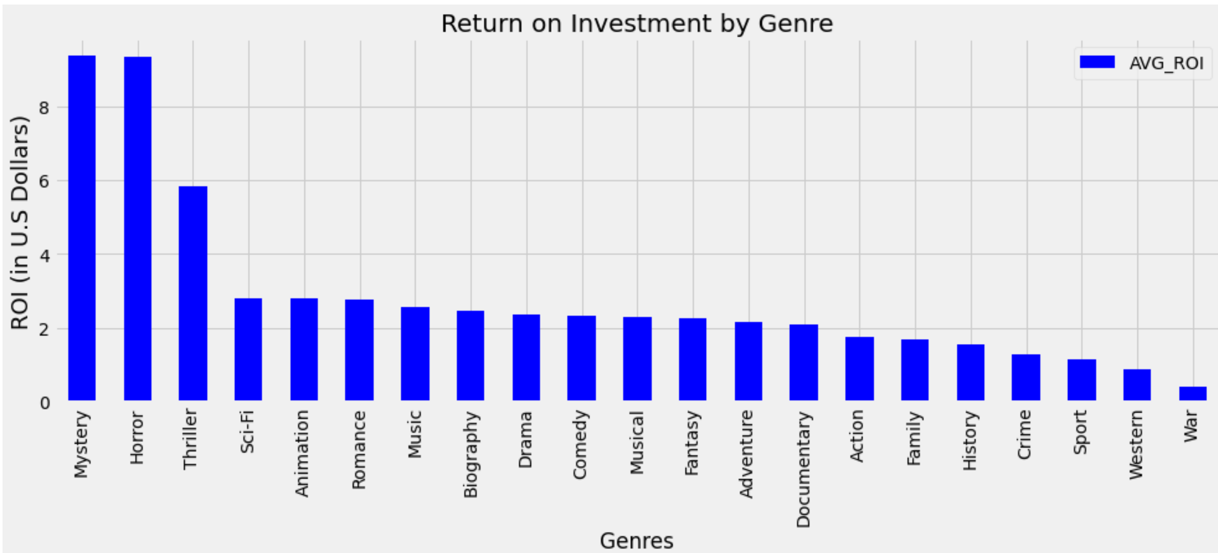
It was necesasary to make certain assumptions and omissions in order to avoid a more cluttered analysis and a potentially confusing summary. Thus, it was decided to include these extras into the appendix.

The primary assumption made in this analysis was to use profit instead of ROI. This was done because it was assumed that a company like Microsoft which can borrow money at extremely low interest rates is more interested in total profit than they are in ROI. However, this may not be the case for them or other companies. Having an ROI analysis is also a good way to evaluate the effectiveness of writers and directors and so one was included in this appendix.

Additionally, a method to evaluate all directors and writers whom have helped create three of movies was devleoped as it is possible that top candidates aren’t available due to demand from other film productions or retirement.

ROI Analysis

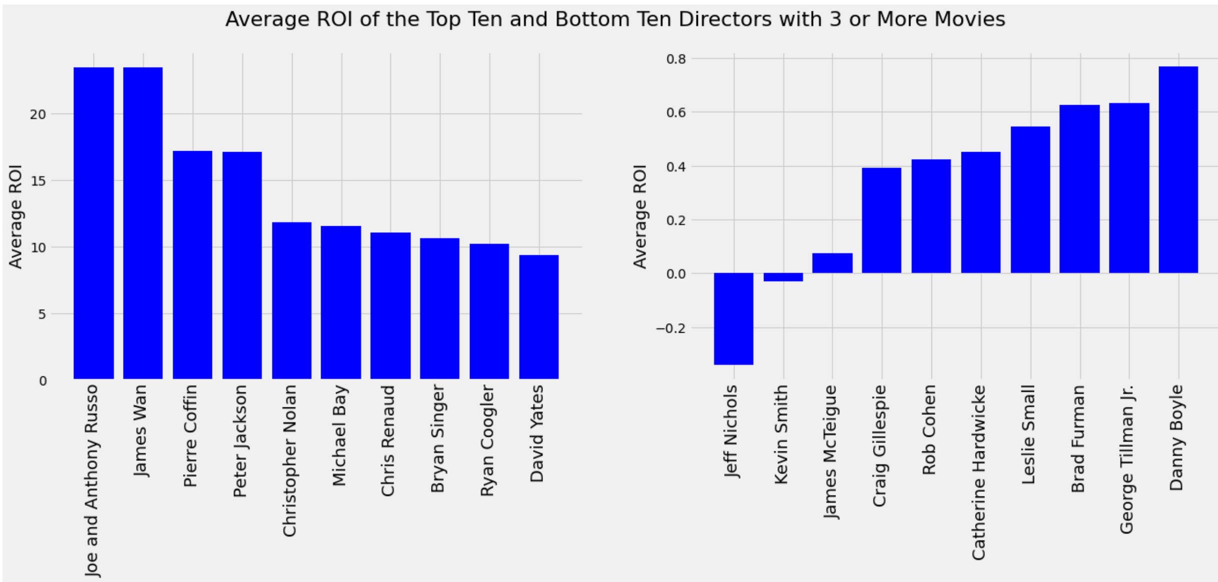
In [101]:
```
# This groups the top genres by ROI which gives us an entirely
# different set of movies as the top contenders.
q = """
SELECT
    genres_list AS Genres,
    AVG(roiinmil) AS AVG_ROI
FROM profit_movies
GROUP BY genres_list
ORDER BY AVG_ROI DESC;
"""
genre_roi = pysqldf(q)
genre_roi.set_index('Genres', inplace=True)

genre_roi.plot(kind='bar', figsize=[15,5], color = ['b'])
plt.title("Return on Investment by Genre", fontsize=20)
plt.ylabel("ROI (in U.S Dollars)", fontsize=18);
```



In [103]:
```
q = """
SELECT
       primary_name AS Name,
       COUNT(movie_id) AS Number_of_Movies,
       AVG(roiinmil) AS AVG_ROI,
       MAX(roiinmil) AS MAX_ROI,
       MIN(roiinmil) AS MIN_ROI
FROM director_df
WHERE death_year IS NULL
GROUP BY director_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_ROI DESC
LIMIT 10
;
"""
ROI_top_ten_director = pysqldf(q)
```

In [104]:
```
q = """
SELECT
       primary_name AS Name,
       COUNT(movie_id) AS Number_of_Movies,
       AVG(roiinmil) AS AVG_ROI,
       MAX(roiinmil) AS MAX_ROI,
       MIN(roiinmil) AS MIN_ROI
FROM director_df
WHERE death_year IS NULL
GROUP BY director_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_ROI
LIMIT 10
;
"""
ROI_bottom_ten_director = pysqldf(q)
```

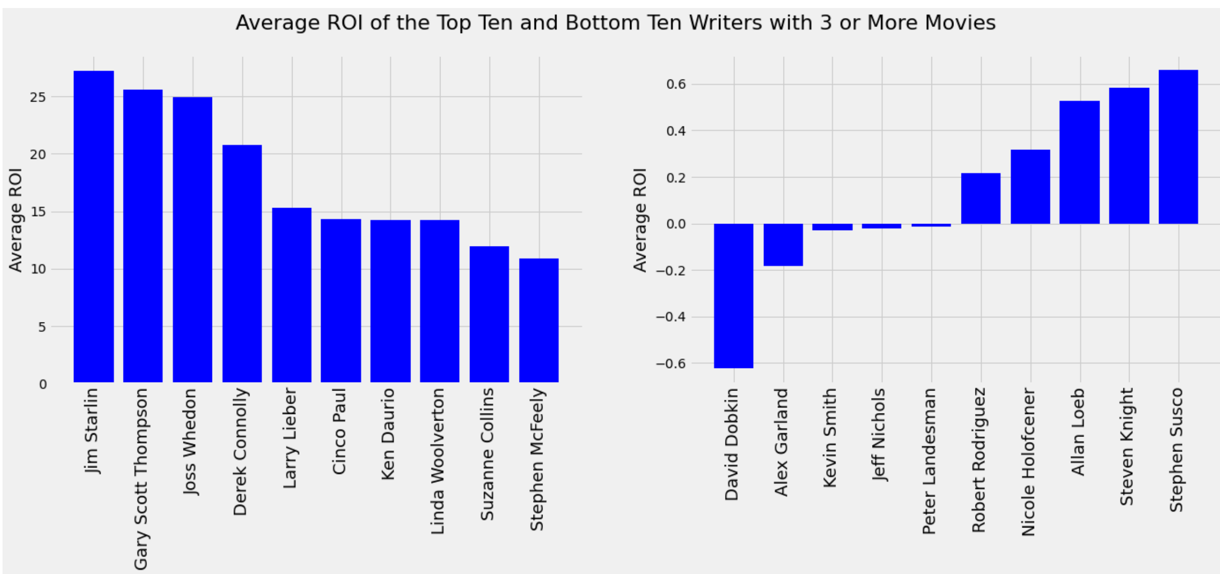
In [106]:
```
plt.figure(figsize=[20,6])
plt.suptitle("Average ROI of the Top Ten and Bottom Ten Directors with 3 or More

plt.subplot(1,2,1)
plt.bar(x=top_ten_director.index, height='AVG_ROI',  \
        color = ['b'], data = ROI_top_ten_director)
plt.xticks(rotation=90, fontsize=18)
plt.ylabel('Average ROI', fontsize=18)

plt.subplot(1,2,2)
plt.bar(x=bottom_ten_director.index, height='AVG_ROI', \
        color = ['b'], data = ROI_bottom_ten_director)
plt.xticks(rotation=90, fontsize=18)
plt.ylabel('Average ROI', fontsize=18);
```



In [108]:
```
q = """
SELECT
       primary_name AS Name,
       COUNT(movie_id) AS Number_of_Movies,
       AVG(roiinmil) AS AVG_ROI,
       MAX(roiinmil) AS MAX_ROI,
       MIN(roiinmil) AS MIN_ROI
FROM writer_df
WHERE death_year IS NULL
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_ROI DESC
LIMIT 10
;
"""
ROI_top_ten_writer = pysqldf(q)
```

In [109]:
```
q = """
SELECT
       primary_name AS Name,
       COUNT(movie_id) AS Number_of_Movies,
       AVG(roiinmil) AS AVG_ROI,
       MAX(roiinmil) AS MAX_ROI,
       MIN(roiinmil) AS MIN_ROI
FROM writer_df
WHERE death_year IS NULL
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_ROI
LIMIT 10
;
"""
ROI_bottom_ten_writer = pysqldf(q)
```

In [110]:
```
plt.figure(figsize=[20,6])
plt.suptitle("Average ROI of the Top Ten and Bottom Ten Writers with 3 or More Mo

plt.subplot(1,2,1)
plt.bar(x=top_ten_writer.index, height='AVG_ROI',  \
        color = ['b'], data = ROI_top_ten_writer)
plt.xticks(rotation=90, fontsize=18)
plt.ylabel('Average ROI', fontsize=18)

plt.subplot(1,2,2)
plt.bar(x=bottom_ten_writer.index, height='AVG_ROI', \
        color = ['b'], data = ROI_bottom_ten_writer)
plt.xticks(rotation=90, fontsize=18)
plt.ylabel('Average ROI', fontsize=18);
```



Analysis of All Writers and Directors with 3 or more Movies

As it is possible that top candidates aren’t available due to demand from other film productions or retirement, the average profit for all directors and writers with 3 or more movies was examined. For directors, the median profit was 124 million dollars and 50% of directors have an average profit between 58 to 271 million dollars. The median proift for the worst film these directors produced was 19 million dollars and the median for the best film was 230 million dollars.

For writers, the median profit was 162 million dollars and 50% of writers have an average profit between 86 to 319 million dollars. The median profit for the worst film these writers produced was 22 million dollars and the median for the best film was 360 million dollars.

Similar analyses were done with ROI. The results can be seen in their respective box plots which can be used as a guide when evaluating talent not in the top ten.

In [121]:
```
q = """
SELECT
       primary_name AS Name,
       MIN(profitinmil) AS MIN_Profit,
       AVG(profitinmil) AS AVG_Profit,
       MAX(profitinmil) AS MAX_Profit
FROM director_df
GROUP BY director_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_Profit DESC
;
"""
director_profit = pysqldf(q)
```

In [112]:
```
director_profit.describe()
```

Out[112]:

	MIN_Profit	AVG_Profit	MAX_Profit
count	124.000000	124.000000	124.000000
mean	55.100668	190.119782	352.457389
std	120.198733	201.393435	332.164721
min	-106.900000	-2.066557	3.898064
25%	-2.097597	58.065475	120.607944
50%	19.173475	124.162351	230.693026
75%	57.964044	271.955655	488.677639
max	695.577621	1060.868501	1748.134200

In [79]:
```
q = """
SELECT
       primary_name AS Name,
       MIN(roiinmil) AS MIN_ROI,
       AVG(roiinmil) AS AVG_ROI,
       MAX(roiinmil) AS MAX_ROI
FROM director_df
GROUP BY director_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_ROI DESC
;
"""
director_roi = pysqldf(q)
```

In [80]:
```
director_roi.describe()
```

Out[80]:

	MIN_ROI	AVG_ROI	MAX_ROI
count	124.000000	124.000000	124.000000
mean	0.896447	3.683003	7.176563
std	1.687337	3.971748	7.470110
min	-0.995408	-0.339812	0.433118
25%	-0.057781	1.434028	3.019733
50%	0.494897	2.539341	4.200667
75%	1.443707	3.873312	7.809481
max	10.851473	23.501394	40.407969

In [113]:
```
q = """
SELECT
       primary_name AS Name,
       MIN(profitinmil) AS MIN_Profit,
       AVG(profitinmil) AS AVG_Profit,
       MAX(profitinmil) AS MAX_Profit
FROM writer_df
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_Profit DESC
;
"""
writer_profit = pysqldf(q)
```

In [114]:
```
writer_profit.describe()
```

Out[114]:

	MIN_Profit	AVG_Profit	MAX_Profit
count	266.000000	266.000000	266.000000
mean	60.890643	239.284260	458.401486
std	113.580089	204.439345	381.606693
min	-200.237650	-14.371499	-3.532394
25%	-1.363294	90.198144	162.673547
50%	27.767444	168.027888	368.645478
75%	79.256571	354.726163	632.049931
max	695.577621	1140.471893	1748.134200

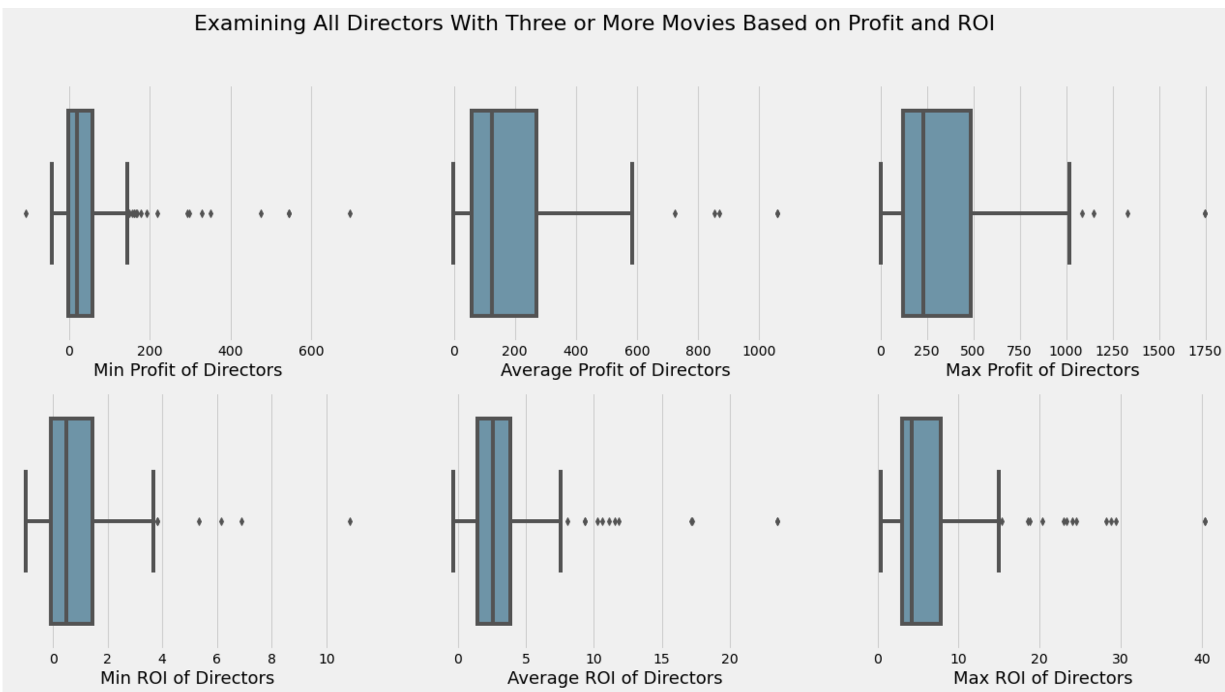
In [115]:
```
# Similar to the directors dataframe.
q = """
SELECT
      primary_name AS Name,
      MIN(roiinmil) AS MIN_ROI,
      AVG(roiinmil) AS AVG_ROI,
      MAX(roiinmil) AS MAX_ROI
FROM writer_df
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_ROI DESC
;
"""
writer_roi = pysqldf(q)
```

In [116]:
```
# Similar to the directors dataframe.
writer_roi.describe()
```

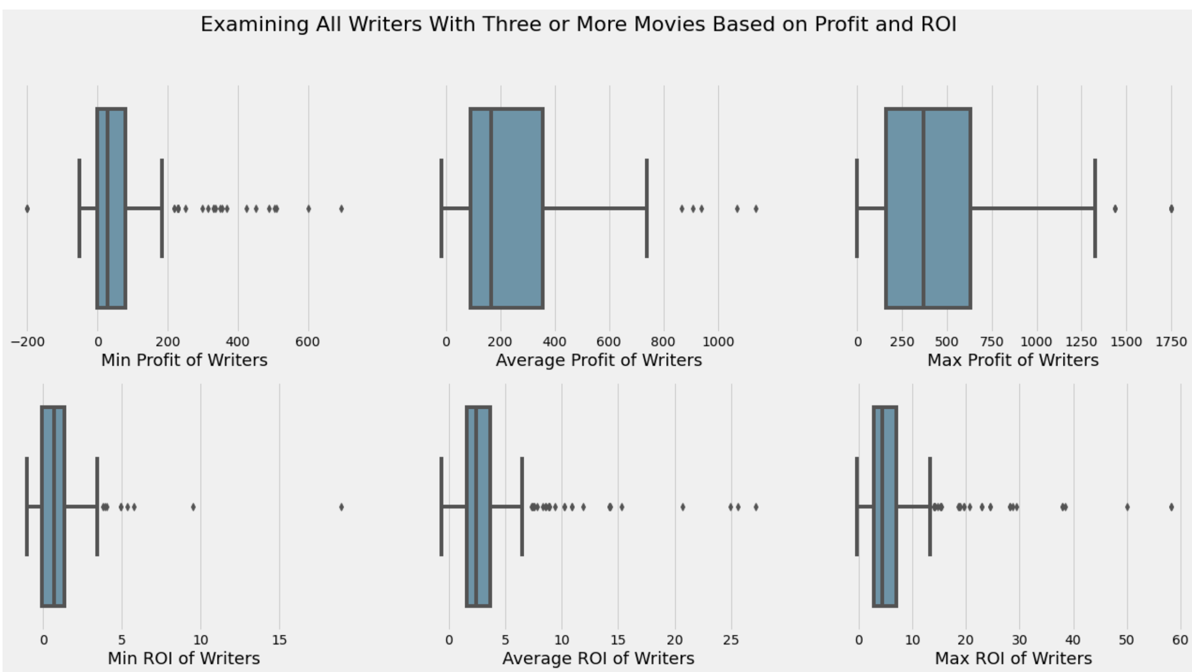
Out[116]:

	MIN_ROI	AVG_ROI	MAX_ROI
count	266.000000	266.000000	266.000000
mean	0.920009	3.440989	6.915378
std	1.696468	3.648380	8.110093
min	-0.998489	-0.623442	-0.370815
25%	-0.047096	1.577183	2.883250
50%	0.732428	2.440873	4.416887
75%	1.371345	3.698911	7.080011
max	18.927371	27.218912	58.170677

In [123]:
```
plt.figure(figsize=[20,10])
plt.suptitle("Examining All Directors With Three or More Movies Based on Profit a

plt.subplot(2,3,1)
sns.boxplot(director_profit.MIN_Profit, color='#6497b1')
plt.xlabel('Min Profit of Directors', fontsize=18)

plt.subplot(2,3,2)
sns.boxplot(director_profit.AVG_Profit, color='#6497b1')
plt.xlabel('Average Profit of Directors', fontsize=18)

plt.subplot(2,3,3)
sns.boxplot(director_profit.MAX_Profit, color='#6497b1')
plt.xlabel('Max Profit of Directors', fontsize=18)

plt.subplot(2,3,4)
sns.boxplot(director_roi.MIN_ROI, color='#6497b1')
plt.xlabel('Min ROI of Directors', fontsize=18)

plt.subplot(2,3,5)
sns.boxplot(director_roi.AVG_ROI, color='#6497b1')
plt.xlabel('Average ROI of Directors', fontsize=18)

plt.subplot(2,3,6)
sns.boxplot(director_roi.MAX_ROI, color='#6497b1')
plt.xlabel('Max ROI of Directors', fontsize=18);
```



In [124]:
```
# These are the resulting box plots formed from the data collected
# from the above SQL queries. Directors is shown above and writers is
# shown below.  The line in the middle of the box represents the median
# and the box itself represents the interquartile range which is where
# 50 percent of the results lie.  Anything outside of the "whiskers" of
# the box plot is considered to be an outlier.  In case you are wonderng
# what that -200 million outlier in the MIN ROI writers dataframe is,
# the answer is X-Men: Dark Phoenix, a movie with a large budget that bombed.


plt.figure(figsize=[20,10])
plt.suptitle("Examining All Writers With Three or More Movies Based on Profit and

plt.subplot(2,3,1)
sns.boxplot(writer_profit.MIN_Profit, color='#6497b1')
plt.xlabel('Min Profit of Writers', fontsize=18);

plt.subplot(2,3,2)
sns.boxplot(writer_profit.AVG_Profit, color='#6497b1')
plt.xlabel('Average Profit of Writers', fontsize=18)

plt.subplot(2,3,3)
sns.boxplot(writer_profit.MAX_Profit, color='#6497b1')
plt.xlabel('Max Profit of Writers', fontsize=18);

plt.subplot(2,3,4)
sns.boxplot(writer_roi.MIN_ROI, color='#6497b1')
plt.xlabel('Min ROI of Writers', fontsize=18);

plt.subplot(2,3,5)
sns.boxplot(writer_roi.AVG_ROI, color='#6497b1')
plt.xlabel('Average ROI of Writers', fontsize=18)

plt.subplot(2,3,6)
sns.boxplot(writer_roi.MAX_ROI, color='#6497b1')
plt.xlabel('Max ROI of Writers', fontsize=18);
```



In [ ]: