Movie_data_analysis_final

June 13, 2022

1 A Movie Data Analysis for Microsoft

1.1 Overview

This project analyzes data from the movie industry for the hypothetical client Microsoft. 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 return on investment (ROI) 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.

1.2 Business Opportunity

Since 2005 when Microsoft sold its stake in NBC to Comcast, it has not had a presence in the movie or cable industry. Instead, it's acquisitions 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 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. 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.

1.3 The Data Sources

The two sources of data used in this analysis are IMBD and The Numbers. 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.

1.4 Data Understanding

IMBD is an SQL database comprised of multiple dataframes. The ones used in this analysis are movie basics, persons, writers, and directors as these four dataframes 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.

[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
```

[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()
```

[2]:
```
    movie_id                    primary_title              original_title  \
0  tt0063540                        Sunghursh                   Sunghursh
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela Errante

   start_year  runtime_minutes                genres
```

```
0        2013            175.0    Action,Crime,Drama
1        2019            114.0       Biography,Drama
2        2018            122.0                 Drama
3        2018              NaN          Comedy,Drama
4        2017             80.0  Comedy,Drama,Fantasy
```

[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
```

[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()
```

[4]:
```
    movie_id  person_id
0  tt0285252  nm0899854
1  tt0462036  nm1940585
2  tt0835418  nm0151540
3  tt0835418  nm0151540
4  tt0878654  nm0089502
```

[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
```

[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()
```

[6]:

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

[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
```

[8]:
```
# The persons dataframe enables primary names to be added into a dataframe visa␣
↪vi their person_id.
# It also cantains information about birth and death year which can be used as␣
↪part of a more in-depth analysis.
persons = pd.read_sql("SELECT * FROM persons;", conn)
persons.head()
```

[8]:
```
   person_id       primary_name  birth_year  death_year  \
0  nm0061671  Mary Ellen Bauder         NaN         NaN
1  nm0061865       Joseph Bauer         NaN         NaN
2  nm0062070         Bruce Baum         NaN         NaN
3  nm0062195       Axel Baumann         NaN         NaN
4  nm0062798        Pete Baxter         NaN         NaN

                                 primary_profession
0        miscellaneous,production_manager,producer
1       composer,music_department,sound_department
2                        miscellaneous,actor,writer
3  camera_department,cinematographer,art_department
```

```
4  production_designer,art_department,set_decorator
```

[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. One might need to drop some rows depending on what
 ↪kind of analysis one is doing.
# 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 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.

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

[10]:
```
   id  release_date                                       movie  \
0   1  Dec 18, 2009                                      Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix
3   4   May 1, 2015                      Avengers: Age of Ultron
4   5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross worldwide_gross
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
2      $350,000,000    $42,762,350    $149,762,350
3      $330,600,000   $459,005,868  $1,403,013,963
4      $317,000,000   $620,181,382  $1,316,721,747
```

```
[11]: # Release date, production budget, domestic gross, and worldwide gross will all␣
      ↪need to be converted into integers or floats
      # in order to do numerical analysis and joins.  There are 5782 movies in the␣
      ↪database.
      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
```

1.5 Data Preparation

1.5.1 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.

```
[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()
```

```
[12]:     movie_id                    primary_title   original_title  start_year  \
      0  tt0063540                        Sunghursh        Sunghursh        2013
      1  tt0063540                        Sunghursh        Sunghursh        2013
      2  tt0063540                        Sunghursh        Sunghursh        2013
      3  tt0063540                        Sunghursh        Sunghursh        2013
      4  tt0066787  One Day Before the Rainy Season  Ashad Ka Ek Din        2019
```

```
   runtime_minutes              genres  person_id          primary_name  \
0            175.0  Action,Crime,Drama  nm0712540  Harnam Singh Rawail
1            175.0  Action,Crime,Drama  nm0712540  Harnam Singh Rawail
2            175.0  Action,Crime,Drama  nm0712540  Harnam Singh Rawail
3            175.0  Action,Crime,Drama  nm0712540  Harnam Singh Rawail
4            114.0     Biography,Drama  nm0002411            Mani Kaul

   birth_year  death_year        primary_profession director_id
0      1921.0      2004.0  director,writer,producer   nm0712540
1      1921.0      2004.0  director,writer,producer   nm0712540
2      1921.0      2004.0  director,writer,producer   nm0712540
3      1921.0      2004.0  director,writer,producer   nm0712540
4      1944.0      2011.0     director,writer,actor   nm0002411
```

[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()
```

[13]:

```
    movie_id              primary_title             original_title  \
0  tt0063540                 Sunghursh                  Sunghursh
1  tt0063540                 Sunghursh                  Sunghursh
2  tt0063540                 Sunghursh                  Sunghursh
3  tt0063540                 Sunghursh                  Sunghursh
4  tt0069049  The Other Side of the Wind  The Other Side of the Wind

   start_year  runtime_minutes              genres  person_id    primary_name  \
0        2013            175.0  Action,Crime,Drama  nm0023551      Abrar Alvi
1        2013            175.0  Action,Crime,Drama  nm0347899          Gulzar
2        2013            175.0  Action,Crime,Drama  nm1194313  Mahasweta Devi
3        2013            175.0  Action,Crime,Drama  nm1391276    Anjana Rawail
4        2018            122.0               Drama  nm0000080    Orson Welles

   birth_year  death_year                      primary_profession  writer_id
0      1927.0      2009.0                   writer,actor,director  nm0023551
1      1936.0         NaN  music_department,writer,soundtrack  nm0347899
2      1926.0      2016.0                                  writer  nm1194313
3         NaN         NaN                writer,costume_designer  nm1391276
4      1915.0      1985.0                   actor,director,writer  nm0000080
```

1.5.2 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

[14]:
```
# The function value_counts reveals that many movies have multiple genres listed␣
↪on the same row.  In order for a movie to be
# counted as Drama and Comendy instead of the genre "Comedy, Drama", the genre␣
↪needs to be seperated onto seperate rows.
movie_basics['genres'].value_counts()
```

[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
```

[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()
```

[15]:
```
    movie_id                    primary_title              original_title  \
0  tt0063540                        Sunghursh                   Sunghursh
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela Errante

   start_year  runtime_minutes                genres              genres_list
0        2013            175.0    Action,Crime,Drama    [Action, Crime, Drama]
1        2019            114.0       Biography,Drama       [Biography, Drama]
2        2018            122.0                 Drama                  [Drama]
```

```
3        2018             NaN          Comedy,Drama           [Comedy, Drama]
4        2017            80.0  Comedy,Drama,Fantasy  [Comedy, Drama, Fantasy]
```

[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()
```

[16]:
```
    movie_id                    primary_title   original_title  start_year  \
0  tt0063540                        Sunghursh        Sunghursh        2013
0  tt0063540                        Sunghursh        Sunghursh        2013
0  tt0063540                        Sunghursh        Sunghursh        2013
1  tt0066787  One Day Before the Rainy Season  Ashad Ka Ek Din        2019
1  tt0066787  One Day Before the Rainy Season  Ashad Ka Ek Din        2019

   runtime_minutes              genres genres_list
0            175.0  Action,Crime,Drama      Action
0            175.0  Action,Crime,Drama       Crime
0            175.0  Action,Crime,Drama       Drama
1            114.0     Biography,Drama   Biography
1            114.0     Biography,Drama       Drama
```

[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
```

[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

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

[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
```

[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()
```

[20]:
```
        movie_id                         primary_title  \
37914  tt1843866  Captain America: The Winter Soldier
37915  tt1843866  Captain America: The Winter Soldier
37916  tt1843866  Captain America: The Winter Soldier
37917  tt1843866  Captain America: The Winter Soldier
37918  tt1843866  Captain America: The Winter Soldier

                            original_title  start_year  runtime_minutes  \
```

```
37914  Captain America: The Winter Soldier       2014            136.0
37915  Captain America: The Winter Soldier       2014            136.0
37916  Captain America: The Winter Soldier       2014            136.0
37917  Captain America: The Winter Soldier       2014            136.0
37918  Captain America: The Winter Soldier       2014            136.0

                        genres  person_id   primary_name  birth_year  \
37914  Action,Adventure,Sci-Fi  nm0751577  Anthony Russo      1970.0
37915  Action,Adventure,Sci-Fi  nm0751577  Anthony Russo      1970.0
37916  Action,Adventure,Sci-Fi  nm0751577  Anthony Russo      1970.0
37917  Action,Adventure,Sci-Fi  nm0751577  Anthony Russo      1970.0
37918  Action,Adventure,Sci-Fi  nm0751577  Anthony Russo      1970.0

       death_year        primary_profession director_id
37914         NaN  producer,director,writer   nm0751577
37915         NaN  producer,director,writer   nm0751577
37916         NaN  producer,director,writer   nm0751577
37917         NaN  producer,director,writer   nm0751577
37918         NaN  producer,director,writer   nm0751577
```

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

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

[22]:
```
         movie_id                        primary_title  \
37914   tt1843866  Captain America: The Winter Soldier
125264  tt3498820           Captain America: Civil War
154748  tt4154756               Avengers: Infinity War
154772  tt4154796                    Avengers: Endgame
282341  tt9130508                               Cherry

                             original_title  start_year  runtime_minutes  \
37914   Captain America: The Winter Soldier        2014            136.0
125264           Captain America: Civil War        2016            147.0
154748               Avengers: Infinity War        2018            149.0
154772                    Avengers: Endgame        2019            181.0
282341                               Cherry        2020              NaN

                         genres  person_id   primary_name  birth_year  \
37914   Action,Adventure,Sci-Fi  nm0751577  Anthony Russo      1970.0
125264  Action,Adventure,Sci-Fi  nm0751577  Anthony Russo      1970.0
154748  Action,Adventure,Sci-Fi  nm0751577  Anthony Russo      1970.0
154772  Action,Adventure,Sci-Fi  nm0751577  Anthony Russo      1970.0
282341                    Drama  nm0751577  Anthony Russo      1970.0
```

```
        death_year        primary_profession  director_id
37914          NaN  producer,director,writer    nm0751577
125264         NaN  producer,director,writer    nm0751577
154748         NaN  producer,director,writer    nm0751577
154772         NaN  producer,director,writer    nm0751577
282341         NaN  producer,director,writer    nm0751577
```

[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()
```

[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

[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()
```

[24]:
```
        movie_id          primary_title         original_title  start_year  \
122    tt0377981         Gnomeo & Juliet        Gnomeo & Juliet        2011
1016   tt0892062            Hamlet A.D.D.          Hamlet A.D.D.        2014
1017   tt0892062            Hamlet A.D.D.          Hamlet A.D.D.        2014
4381  tt10332120  Much Ado About Nothing  Much Ado About Nothing        2019
8488   tt1274300              The Tempest            The Tempest        2010

      runtime_minutes                      genres  person_id  \
122              84.0  Adventure,Animation,Comedy  nm0000636
1016             95.0    Animation,Comedy,Fantasy  nm0000636
1017             95.0    Animation,Comedy,Fantasy  nm0000636
4381            130.0                       Drama  nm0000636
8488            110.0        Comedy,Drama,Fantasy  nm0000636
```

```
            primary_name  birth_year  death_year  \
122   William Shakespeare      1564.0      1616.0
1016  William Shakespeare      1564.0      1616.0
1017  William Shakespeare      1564.0      1616.0
4381  William Shakespeare      1564.0      1616.0
8488  William Shakespeare      1564.0      1616.0

                  primary_profession  writer_id
122   writer,soundtrack,miscellaneous  nm0000636
1016  writer,soundtrack,miscellaneous  nm0000636
1017  writer,soundtrack,miscellaneous  nm0000636
4381  writer,soundtrack,miscellaneous  nm0000636
8488  writer,soundtrack,miscellaneous  nm0000636
```

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

[26]:
```python
# 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()
```

[26]:
```
        movie_id          primary_title         original_title  start_year  \
122    tt0377981         Gnomeo & Juliet        Gnomeo & Juliet        2011
1016   tt0892062          Hamlet A.D.D.          Hamlet A.D.D.        2014
4381   tt10332120  Much Ado About Nothing  Much Ado About Nothing        2019
8488   tt1274300            The Tempest            The Tempest        2010
10242  tt1372686             Coriolanus             Coriolanus        2011

       runtime_minutes                      genres  person_id  \
122               84.0  Adventure,Animation,Comedy  nm0000636
1016              95.0    Animation,Comedy,Fantasy  nm0000636
4381             130.0                       Drama  nm0000636
8488             110.0        Comedy,Drama,Fantasy  nm0000636
10242            123.0          Drama,Thriller,War  nm0000636

              primary_name  birth_year  death_year  \
122    William Shakespeare      1564.0      1616.0
1016   William Shakespeare      1564.0      1616.0
4381   William Shakespeare      1564.0      1616.0
8488   William Shakespeare      1564.0      1616.0
10242  William Shakespeare      1564.0      1616.0

                   primary_profession  writer_id
122    writer,soundtrack,miscellaneous  nm0000636
1016   writer,soundtrack,miscellaneous  nm0000636
4381   writer,soundtrack,miscellaneous  nm0000636
8488   writer,soundtrack,miscellaneous  nm0000636
```

```
10242  writer,soundtrack,miscellaneous  nm0000636
```

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.

[27]:
```python
# 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
```

[28]:
```python
# The values for columns like production_budget have dollar signs and commas. ␣
↪These need to be removed.
tn_movies.head()
```

[28]:
```
   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix
3   4   May 1, 2015                      Avengers: Age of Ultron
4   5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross worldwide_gross
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
```

```
2      $350,000,000    $42,762,350    $149,762,350
3      $330,600,000   $459,005,868  $1,403,013,963
4      $317,000,000   $620,181,382  $1,316,721,747
```

[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)
```

[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))
```

[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)
```

[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]
```

[32]:
```
      release_date                movie  budgetinmil  domesticinmil  \
194   Dec 31, 2020             Moonfall     150.0000            0.0
479   Dec 13, 2017               Bright      90.0000            0.0
480   Dec 31, 2019     Army of the Dead      90.0000            0.0
535   Feb 21, 2020     Call of the Wild      82.0000            0.0
670   Aug 30, 2019            PLAYMOBIL      75.0000            0.0
...            ...                  ...          ...            ...
5761  Dec 31, 2014  Stories of Our Lives      0.0150            0.0
5764  Dec 31, 2007          Tin Can Man       0.0120            0.0
5771  May 19, 2015      Family Motocross      0.0100            0.0
5777  Dec 31, 2018               Red 11       0.0070            0.0
```

```
5780  Sep 29, 2015  A Plague So Pleasant       0.0014            0.0

      worldwideinmil
194              0.0
479              0.0
480              0.0
535              0.0
670              0.0
...              ...
5761             0.0
5764             0.0
5771             0.0
5777             0.0
5780             0.0

[367 rows x 5 columns]
```

[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)
```

[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
```

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

[35]:
```
   release_date                                      movie  budgetinmil  \
0  Dec 18, 2009                                     Avatar        425.0
1  May 20, 2011  Pirates of the Caribbean: On Stranger Tides        410.6
2   Jun 7, 2019                                Dark Phoenix        350.0
3   May 1, 2015                     Avengers: Age of Ultron        330.6
4  Dec 15, 2017           Star Wars Ep. VIII: The Last Jedi        317.0
```

```
   domesticinmil  worldwideinmil
0     760.507625     2776.345279
1     241.063875     1045.663875
2      42.762350      149.762350
3     459.005868     1403.013963
4     620.181382     1316.721747
```

1.5.3 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.

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

[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
```

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

[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
```

[39]:
```
# One such movie is Aladdin.  The IMBD database has both the 2017 and 2019␣
↪Alladin movies.  Please note, the multiple 2019s
# seen is due to the genres being split onto seperate rows, not due to multiple␣
↪2019 movies.  Movies listed in the IMBD database
# tend to be more recent.
movie_basics1[movie_basics1['primary_title'] == 'Aladdin']
```

[39]:
```
         movie_id primary_title original_title  start_year  runtime_minutes  \
105015  tt6139732       Aladdin        Aladdin        2019            128.0
105015  tt6139732       Aladdin        Aladdin        2019            128.0
105015  tt6139732       Aladdin        Aladdin        2019            128.0
144696  tt9698912       Aladdin        Aladdin        2017              NaN

                          genres genres_list
105015  Adventure,Comedy,Family   Adventure
105015  Adventure,Comedy,Family      Comedy
105015  Adventure,Comedy,Family      Family
144696                  Fantasy     Fantasy
```

[40]:
```
# The Numbers database also multople Aladdins, namely the 2019 Aladdin and the␣
↪1992 version.  Movies listed in The Numbers
# database tend to be the more well-known versions.
tn_movies1[tn_movies1['movie'] == 'Aladdin']
```

[40]:
```
      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
```

[41]:
```
# The first function in this cell turns the release_date into a datetime object␣
↪so that the year can be extracted.
# The second function extracts 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
```

[42]:
```
# 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
```

[43]:
```python
# 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
# roi_movies.  This dataframe will be used to analyze genres.  The other two␣
 ↪merges do the same thing for the
# IMBD directors and writers dataframes.

roi_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'])
```

[81]:
```python
# 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.

roi_movies[roi_movies['primary_title'] == 'Aladdin']
```

[81]:
```
        movie_id primary_title original_title  start_year  runtime_minutes  \
3489  tt6139732       Aladdin        Aladdin        2019            128.0
3490  tt6139732       Aladdin        Aladdin        2019            128.0
3491  tt6139732       Aladdin        Aladdin        2019            128.0

                      genres genres_list release_date    movie  budgetinmil  \
3489  Adventure,Comedy,Family   Adventure   2019-05-24  Aladdin        182.0
3490  Adventure,Comedy,Family      Comedy   2019-05-24  Aladdin        182.0
3491  Adventure,Comedy,Family      Family   2019-05-24  Aladdin        182.0

      domesticinmil  worldwideinmil  year    roiinmil
3489     246.734314      619.234314  2019  437.234314
3490     246.734314      619.234314  2019  437.234314
3491     246.734314      619.234314  2019  437.234314
```

[86]:
```
# This returns the total number of movies in the roi dataset - 1365.
len(roi_movies['primary_title'].unique())
```

[86]: 1365

1.5.4 Feature Engineering

Return on Investment (ROI) 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.

[45]:
```
# This calcuates ROI for the various dataframes and adds it as a new column. ␣
↪(This assumes that the movie stuck to
# its production budget and/or the production budget was updated once it ran␣
↪over).

roi_movies['roiinmil'] = roi_movies['worldwideinmil'] - roi_movies['budgetinmil']
director_df['roiinmil'] = director_df['worldwideinmil'] -␣
↪director_df['budgetinmil']
writer_df['roiinmil'] = writer_df['worldwideinmil'] - writer_df['budgetinmil']
```

[78]:
```
# The roi_movies dataframe now has a column for return on investment (roiinmil).
# FYI - The ROI for Foodfight appears to be roughly accurate.  The movie was␣
↪that bad.
roi_movies.head()
```

[78]:
```
    movie_id                   primary_title  \
0  tt0249516                      Foodfight!
1  tt0249516                      Foodfight!
2  tt0249516                      Foodfight!
3  tt0359950  The Secret Life of Walter Mitty
4  tt0359950  The Secret Life of Walter Mitty

                    original_title  start_year  runtime_minutes  \
0                       Foodfight!        2012             91.0
1                       Foodfight!        2012             91.0
2                       Foodfight!        2012             91.0
3  The Secret Life of Walter Mitty        2013            114.0
4  The Secret Life of Walter Mitty        2013            114.0

                    genres genres_list release_date  \
0  Action,Animation,Comedy      Action   2012-12-31
1  Action,Animation,Comedy   Animation   2012-12-31
2  Action,Animation,Comedy      Comedy   2012-12-31
3   Adventure,Comedy,Drama   Adventure   2013-12-25
4   Adventure,Comedy,Drama      Comedy   2013-12-25
```

```
                           movie  budgetinmil  domesticinmil  \
0                     Foodfight!         45.0       0.000000
1                     Foodfight!         45.0       0.000000
2                     Foodfight!         45.0       0.000000
3  The Secret Life of Walter Mitty         91.0      58.236838
4  The Secret Life of Walter Mitty         91.0      58.236838

   worldwideinmil  year   roiinmil
0        0.073706  2012 -44.926294
1        0.073706  2012 -44.926294
2        0.073706  2012 -44.926294
3      187.861183  2013  96.861183
4      187.861183  2013  96.861183
```

1.6 Analysis

1.6.1 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).

ROI 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, ROI will be used as the primary metric moving forward as it determines profit and approximates domestic and global appeal. The genres with the highest ROI 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 ROI 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.

[47]:
```python
# 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")
```

[48]:
```
# This enables the use of SQL syntax with Pandas dataframes.

!pip install -U pandasql
```

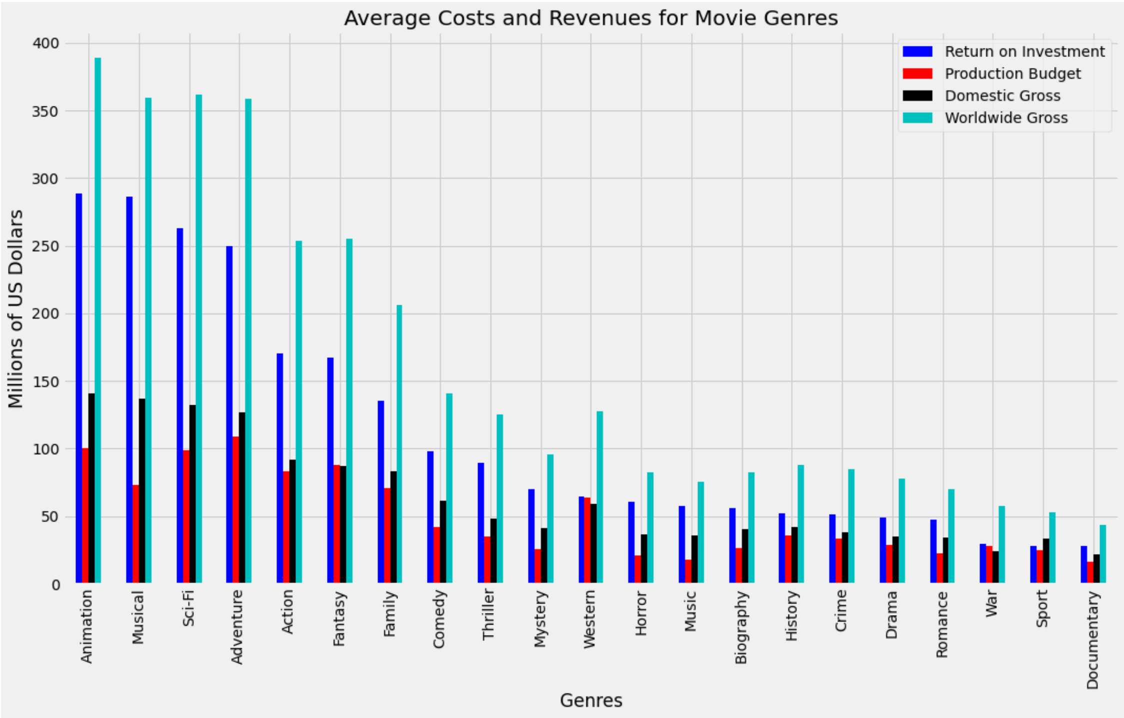
```
Requirement already satisfied: pandasql in c:\users\eincr\anaconda3\lib\site-
packages (0.7.3)
Requirement already satisfied: numpy in c:\users\eincr\anaconda3\lib\site-
packages (from pandasql) (1.20.3)
Requirement already satisfied: pandas in c:\users\eincr\anaconda3\lib\site-
packages (from pandasql) (1.3.4)
Requirement already satisfied: sqlalchemy in c:\users\eincr\anaconda3\lib\site-
packages (from pandasql) (1.4.22)
Requirement already satisfied: pytz>=2017.3 in
c:\users\eincr\anaconda3\lib\site-packages (from pandas->pandasql) (2021.3)
Requirement already satisfied: python-dateutil>=2.7.3 in
c:\users\eincr\anaconda3\lib\site-packages (from pandas->pandasql) (2.8.2)
Requirement already satisfied: six>=1.5 in c:\users\eincr\anaconda3\lib\site-
packages (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)
```

[49]:
```
# This is a function that makes it easier to use SQL syntax.

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

[50]:
```
# SQL syntax was used to extract genres, ROI, budget, domestic gross, and␣
↪worldwide gross from the roi_movies
# dataframe.  It was grouped by genres and ordered by ROI.
q = """
SELECT
    genres_list AS Genres,
    AVG(roiinmil) AS AVG_ROI,
    AVG(budgetinmil) AS AVG_Budget,
    AVG(domesticinmil) AS AVG_Dom_Gross,
    AVG(worldwideinmil) AS AVG_WW_Gross
FROM roi_movies
GROUP BY genres_list
ORDER BY AVG_ROI DESC
;
"""
genre_roi = pysqldf(q)
```

[51]:
```
# The index was reset to Genres.  This makes it easier to create a grouped bar␣
↪plot as the index becomes the x axis.
genre_roi.set_index('Genres', inplace=True)
```

[52]:
```
# This is the resulting bar plot, with ROI descending.  Dark blue was used with␣
↪ROI to have it stand out. ROI was considered to
# be the most important variable as it determines profitability.  The other␣
↪values were kept as one may wish to know likely
# production costs for the various genres which can be revealed through␣
↪production budget, or the amount of domestic and global
# appeal which can be evaluated visa via domestic and worldwide gross,␣
↪respectively.

genre_roi.plot(kind='bar', figsize=[16,9], color = ['b', 'r', 'k', 'c'])
plt.legend(['Return on Investment', '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);
```



[53]:
```
# The correlation between World Wide Gross and ROI is high.
genre_roi["AVG_ROI"].corr(genre_roi["AVG_WW_Gross"])
```

[53]: 0.993425225588679

[54]:
```
# As is the correlation between Domestic Gross and ROI.
genre_roi["AVG_ROI"].corr(genre_roi["AVG_Dom_Gross"])
```

[54]: 0.9907622235939796

[55]:
```python
# The describe funcion reveals the number of genres, the mean, the median, the␣
↪standard deviation, and the
# interquartile range of the dataframe.
genre_roi.describe()
```

[55]:

	AVG_ROI	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

[56]:
```python
# 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.

roi_movies[['genres_list', 'roiinmil']].groupby(['genres_list']).agg(['count',␣
↪'median', 'mean', 'std'])
```

[56]:

	roiinmil			
	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

1.6.2 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 ROI, 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 ROI.

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 ROI 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.

[57]:
```
# SQL syntax was used to extract primary_name, AVG ROI, MAX ROI, and Min ROI␣
↪from the roi_movies 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 ROI.␣
↪ The top 11 directors were chosen as Joe and
# Anthony Russo took up the top two spots.

q = """
SELECT
       primary_name AS Name,
       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 11
;
"""
top_ten_director = pysqldf(q)
top_ten_director
```

[57]:

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

[58]:

```
# 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
```

[58]:

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

[59]:

```
# 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(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
;
"""
bottom_ten_director = pysqldf(q)
```

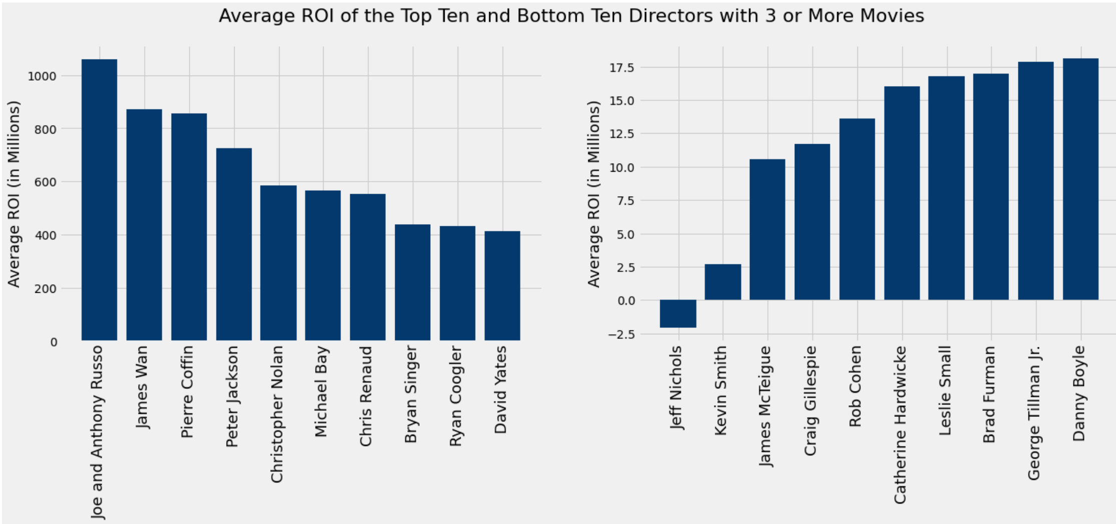
[60]:

```
# 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)
```

[61]:

```
# Only the Average ROI 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 ROI of the Top Ten and Bottom Ten Directors with 3 or More␣
 ↪Movies", size=22)

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

plt.subplot(1,2,2)
plt.bar(x=bottom_ten_director.index, height='AVG_ROI', color = ['#03396c'], data␣
 ↪= bottom_ten_director)
plt.xticks(rotation=90, fontsize=18)
```

```
plt.ylabel('Average ROI (in Millions)', fontsize=18);
```



[89]:
```
# 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,
       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
```

[89]:

```
                 Name                                          Movie  \
0       Anthony Russo          Captain America: The Winter Soldier
1       Anthony Russo                   Captain America: Civil War
2       Anthony Russo                       Avengers: Infinity War
3        Bryan Singer                       Jack the Giant Slayer
4        Bryan Singer                           Bohemian Rhapsody
5        Bryan Singer                  X-Men: Days of Future Past
6        Bryan Singer                          X-Men: Apocalypse
7        Chris Renaud                               Despicable Me
8        Chris Renaud                             Despicable Me 2
9        Chris Renaud                     The Secret Life of Pets
10       Chris Renaud                   The Secret Life of Pets 2
11  Christopher Nolan                                Interstellar
12  Christopher Nolan                       The Dark Knight Rises
13  Christopher Nolan                                   Inception
14  Christopher Nolan                                     Dunkirk
15        David Yates                       The Legend of Tarzan
16        David Yates      Fantastic Beasts and Where to Find Them
17        David Yates  Fantastic Beasts: The Crimes of Grindelwald
18          James Wan                                The Conjuring
19          James Wan                                      Aquaman
20          James Wan                                    Furious 7
21        Michael Bay              Transformers: Dark of the Moon
22        Michael Bay                                  Pain & Gain
23        Michael Bay             Transformers: Age of Extinction
24        Michael Bay                Transformers: The Last Knight
25      Peter Jackson            The Hobbit: An Unexpected Journey
26      Peter Jackson          The Hobbit: The Desolation of Smaug
27      Peter Jackson      The Hobbit: The Battle of the Five Armies
28      Pierre Coffin                               Despicable Me
29      Pierre Coffin                             Despicable Me 2
30      Pierre Coffin                                     Minions
31      Pierre Coffin                             Despicable Me 3
32       Ryan Coogler                               Black Panther
33       Ryan Coogler                           Fruitvale Station
34       Ryan Coogler                                       Creed

                        Genre          ROI
0      Action,Adventure,Sci-Fi   544.401889
1      Action,Adventure,Sci-Fi   890.069413
2      Action,Adventure,Sci-Fi  1748.134200
3            Adventure,Fantasy     2.687603
4        Biography,Drama,Music   839.985342
5      Action,Adventure,Sci-Fi   547.862775
```

```
6      Action,Adventure,Sci-Fi   364.537546
7      Animation,Comedy,Family   474.464573
8   Adventure,Animation,Comedy   899.216835
9   Adventure,Animation,Comedy   811.750534
10  Adventure,Animation,Comedy    33.351496
11       Adventure,Drama,Sci-Fi   501.379375
12              Action,Thriller   809.439099
13      Action,Adventure,Sci-Fi   675.524642
14         Action,Drama,History   349.837368
15       Action,Adventure,Drama   168.902025
16    Adventure,Family,Fantasy   622.402853
17    Adventure,Family,Fantasy   452.220086
18      Horror,Mystery,Thriller   298.000141
19    Action,Adventure,Fantasy   986.894640
20        Action,Crime,Thriller  1328.722794
21      Action,Adventure,Sci-Fi   928.790543
22          Action,Comedy,Crime    55.275291
23      Action,Adventure,Sci-Fi   894.039076
24      Action,Adventure,Sci-Fi   385.893340
25    Adventure,Family,Fantasy   767.003568
26            Adventure,Fantasy   710.366855
27            Adventure,Fantasy   695.577621
28      Animation,Comedy,Family   474.464573
29  Adventure,Animation,Comedy   899.216835
30  Adventure,Animation,Comedy  1086.336173
31  Adventure,Animation,Comedy   959.727750
32      Action,Adventure,Sci-Fi  1148.258224
33      Biography,Drama,Romance    16.649645
34                  Drama,Sport   136.567581
```

[63]:

```
# 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(roiinmil) AS AVG_ROI
FROM director_df
GROUP BY director_id
    HAVING COUNT(movie_id) >= 3 AND AVG_Budget < 10.0 AND AVG_ROI < 18.0
;
"""
bottom_ten_budget_director = pysqldf(q)

bottom_ten_budget_director
```

[63]:
```
           Name  AVG_Budget    AVG_ROI
0  Leslie Small    4.416667  16.793578
```

[64]:
```
# 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']
```

[64]:
```
        movie_id                primary_title                original_title  \
868   tt1999192  Kevin Hart: Laugh at My Pain  Kevin Hart: Laugh at My Pain
1104  tt2609912    Kevin Hart: Let Me Explain    Kevin Hart: Let Me Explain
1419  tt4669186          Kevin Hart: What Now?         Kevin Hart: What Now?

      start_year  runtime_minutes               genres  person_id  \
868         2011             89.0  Comedy,Documentary  nm0806492
1104        2013             75.0  Comedy,Documentary  nm0806492
1419        2016             96.0  Comedy,Documentary  nm0806492

      primary_name  birth_year  death_year        primary_profession  \
868   Leslie Small         NaN         NaN  director,producer,editor
1104  Leslie Small         NaN         NaN  director,producer,editor
1419  Leslie Small         NaN         NaN  director,producer,editor

     director_id release_date                         movie  budgetinmil  \
868    nm0806492   2011-09-09  Kevin Hart: Laugh at My Pain         0.75
1104   nm0806492   2013-07-03    Kevin Hart: Let Me Explain         2.50
1419   nm0806492   2016-10-14         Kevin Hart: What Now?        10.00

      domesticinmil  worldwideinmil  year   roiinmil
868        7.706436        7.712436  2011   6.962436
1104      32.244051       32.327255  2013  29.827255
1419      23.591043       23.591043  2016  13.591043
```

1.6.3 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 ROI, with an average movie grossing well over 1 billion dollars. Stephen McFeely has the lowest of the top ten, with an average ROI 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 ROI 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.

[65]:
```
# 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(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
;
"""
top_ten_writer = pysqldf(q)
top_ten_writer
```

[65]:

	Name	AVG_ROI	MAX_ROI	MIN_ROI
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

[66]:
```
# Similar to the directors dataframe seen above.
q = """
SELECT
```

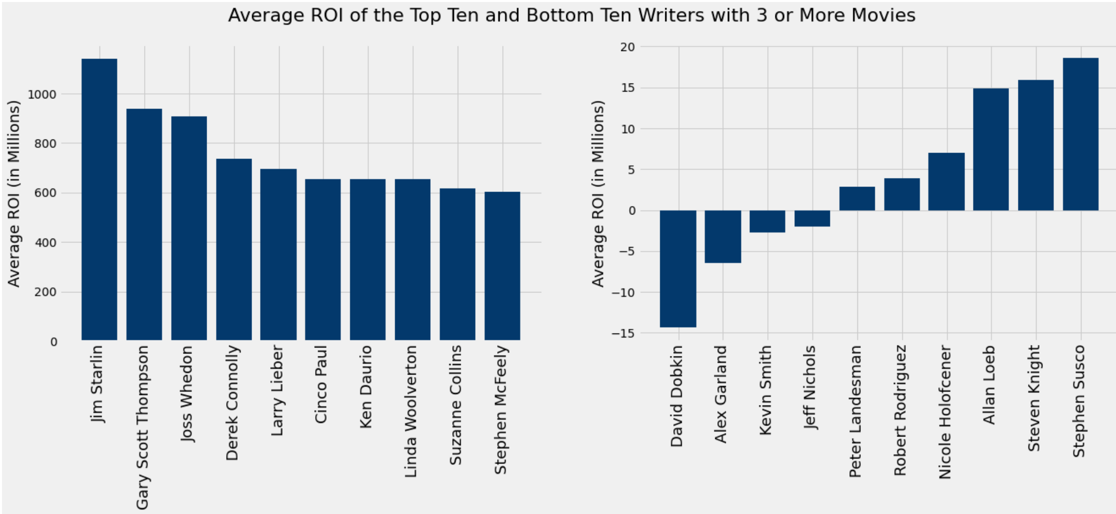
```
       primary_name AS Name,
       AVG(roiinmil) AS AVG_ROI,
       MAX(roiinmil) AS MAX_ROI,
       MIN(roiinmil) AS MIN_ROI
FROM writer_df
WHERE death_year IS NULL
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_ROI
LIMIT 10
;
"""
bottom_ten_writer = pysqldf(q)
```

[67]:

```
# Similar to the directors dataframe.
top_ten_writer.set_index('Name', inplace=True)
bottom_ten_writer.set_index('Name', inplace=True)
```

[68]:

```
# Similar to the directors dataframe.
plt.figure(figsize=[20,6])
plt.suptitle("Average ROI of the Top Ten and Bottom Ten Writers with 3 or More␣
 ↪Movies", size=22)

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

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



[90]:
```python
# 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,
       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
```

[90]:
```
                Name                                          Movie  \
0         Cinco Paul                                   Despicable Me
1         Cinco Paul                                             Hop
2         Cinco Paul                                 Despicable Me 2
3         Cinco Paul                         The Secret Life of Pets
4         Cinco Paul                                 Despicable Me 3
5     Derek Connolly                                  Jurassic World
6     Derek Connolly                          Safety Not Guaranteed
```

7	Derek Connolly	Kong: Skull Island
8	Derek Connolly	Jurassic World: Fallen Kingdom
9	Gary Scott Thompson	Fast Five
10	Gary Scott Thompson	Furious 7
11	Gary Scott Thompson	The Fate of the Furious
12	Jim Starlin	Guardians of the Galaxy
13	Jim Starlin	Avengers: Age of Ultron
14	Jim Starlin	Avengers: Infinity War
15	Joss Whedon	The Avengers
16	Joss Whedon	Justice League
17	Joss Whedon	Avengers: Age of Ultron
18	Ken Daurio	Despicable Me
19	Ken Daurio	Hop
20	Ken Daurio	Despicable Me 2
21	Ken Daurio	The Secret Life of Pets
22	Ken Daurio	Despicable Me 3
23	Larry Lieber	Ant-Man
24	Larry Lieber	Thor
25	Larry Lieber	Iron Man 2
26	Larry Lieber	Iron Man 3
27	Larry Lieber	Thor: The Dark World
28	Larry Lieber	Thor: Ragnarok
29	Larry Lieber	Avengers: Infinity War
30	Larry Lieber	Ant-Man and the Wasp
31	Linda Woolverton	Alice in Wonderland
32	Linda Woolverton	Maleficent
33	Linda Woolverton	Alice Through the Looking Glass
34	Linda Woolverton	Beauty and the Beast
35	Stephen McFeely	Captain America: The First Avenger
36	Stephen McFeely	The Chronicles of Narnia: The Voyage of the Da...
37	Stephen McFeely	Captain America: The Winter Soldier
38	Stephen McFeely	Pain & Gain
39	Stephen McFeely	Thor: The Dark World
40	Stephen McFeely	Captain America: Civil War
41	Stephen McFeely	Avengers: Infinity War
42	Suzanne Collins	The Hunger Games
43	Suzanne Collins	The Hunger Games: Catching Fire
44	Suzanne Collins	The Hunger Games: Mockingjay - Part 1
45	Suzanne Collins	The Hunger Games: Mockingjay - Part 2

	Genre	ROI
0	Animation,Comedy,Family	474.464573
1	Adventure,Animation,Comedy	125.657593
2	Adventure,Animation,Comedy	899.216835
3	Adventure,Animation,Comedy	811.750534
4	Adventure,Animation,Comedy	959.727750
5	Action,Adventure,Sci-Fi	1433.854864

```
6          Comedy,Drama,Romance     3.672318
7      Action,Adventure,Fantasy   376.072059
8       Action,Adventure,Sci-Fi  1135.772799
9         Action,Crime,Thriller   505.163454
10        Action,Crime,Thriller  1328.722794
11        Action,Crime,Thriller   984.846267
12      Action,Adventure,Comedy   600.867516
13      Action,Adventure,Sci-Fi  1072.413963
14      Action,Adventure,Sci-Fi  1748.134200
15      Action,Adventure,Sci-Fi  1292.935897
16     Action,Adventure,Fantasy   355.945209
17      Action,Adventure,Sci-Fi  1072.413963
18      Animation,Comedy,Family   474.464573
19   Adventure,Animation,Comedy   125.657593
20   Adventure,Animation,Comedy   899.216835
21   Adventure,Animation,Comedy   811.750534
22   Adventure,Animation,Comedy   959.727750
23      Action,Adventure,Comedy   388.858449
24     Action,Adventure,Fantasy   299.326618
25      Action,Adventure,Sci-Fi   451.156389
26      Action,Adventure,Sci-Fi  1015.392272
27     Action,Adventure,Fantasy   494.602516
28      Action,Adventure,Comedy   666.980024
29      Action,Adventure,Sci-Fi  1748.134200
30      Action,Adventure,Comedy   493.144660
31     Adventure,Family,Fantasy   825.491110
32      Action,Adventure,Family   578.536735
33     Adventure,Family,Fantasy   106.928112
34       Family,Fantasy,Musical  1099.199706
35      Action,Adventure,Sci-Fi   230.569776
36     Adventure,Family,Fantasy   263.186950
37      Action,Adventure,Sci-Fi   544.401889
38          Action,Comedy,Crime    55.275291
39     Action,Adventure,Fantasy   494.602516
40      Action,Adventure,Sci-Fi   890.069413
41      Action,Adventure,Sci-Fi  1748.134200
42      Action,Adventure,Sci-Fi   597.923379
43      Action,Adventure,Sci-Fi   734.868047
44      Action,Adventure,Sci-Fi   641.575131
45      Action,Adventure,Sci-Fi   488.986787
```

[70]:

```
# Similar to the directors dataframe.
q = """
SELECT
       primary_name AS Name,
       AVG(budgetinmil) AS AVG_Budget,
       AVG(roiinmil) AS AVG_ROI
```

```
FROM writer_df
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3 AND AVG_Budget < 10.0 AND AVG_ROI < 18.0
;
"""
bottom_ten_budget_writer = pysqldf(q)

bottom_ten_budget_writer
```

[70]:

```
                 Name  AVG_Budget   AVG_ROI
0         Kevin Smith         4.0 -2.701964
1  Nicole Holofcener         7.0  6.981338
```

[71]:

```
# 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']
```

[71]:

```
       movie_id primary_title original_title  start_year  runtime_minutes  \
272   tt0873886     Red State      Red State        2011             88.0
2834  tt3099498          Tusk           Tusk        2014            102.0
3141  tt3838992   Yoga Hosers    Yoga Hosers        2016             88.0

                    genres  person_id primary_name  birth_year  death_year  \
272     Action,Crime,Horror  nm0003620  Kevin Smith      1970.0         NaN
2834    Comedy,Drama,Horror  nm0003620  Kevin Smith      1970.0         NaN
3141  Action,Comedy,Fantasy  nm0003620  Kevin Smith      1970.0         NaN

         primary_profession  writer_id release_date        movie  budgetinmil  \
272   producer,writer,actor  nm0003620   2011-09-23    Red State          4.0
2834  producer,writer,actor  nm0003620   2014-09-19         Tusk          3.0
3141  producer,writer,actor  nm0003620   2016-09-02  Yoga Hosers          5.0

      domesticinmil  worldwideinmil  year  roiinmil
272        1.065429        1.983596  2011 -2.016404
2834       1.821983        1.887554  2014 -1.112446
3141       0.000000        0.022958  2016 -4.977042
```

[72]:

```
# Nicole Holofcener has been profitable.

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

[72]:

```
       movie_id             primary_title            original_title  \
273   tt0878835               Please Give               Please Give
2519  tt2390361               Enough Said               Enough Said
3316  tt4595882  Can You Ever Forgive Me?  Can You Ever Forgive Me?

      start_year  runtime_minutes                   genres  person_id  \
```

```
273          2010             87.0             Comedy,Drama  nm0392237
2519         2013             93.0     Comedy,Drama,Romance  nm0392237
3316         2018            106.0   Biography,Comedy,Crime  nm0392237

           primary_name  birth_year  death_year       primary_profession  \
273   Nicole Holofcener      1960.0         NaN  director,writer,actress
2519  Nicole Holofcener      1960.0         NaN  director,writer,actress
3316  Nicole Holofcener      1960.0         NaN  director,writer,actress

      writer_id release_date                      movie  budgetinmil  \
273   nm0392237   2010-04-30                Please Give          3.0
2519  nm0392237   2013-09-18                Enough Said          8.0
3316  nm0392237   2018-10-19  Can You Ever Forgive Me?          10.0

      domesticinmil  worldwideinmil  year   roiinmil
273        4.033574        4.570178  2010   1.570178
2519      17.550872       25.621449  2013  17.621449
3316       8.803865       11.752387  2018   1.752387
```

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 ROI for all directors and writers with 3 or more movies was examined. For directors, the median ROI was 124 million dollars and 50% of directors have an average ROI between 58 to 271 million dollars. The median ROI for the worst film these directors produced was 19 million dollars and the median for the best film was 230 million dollars. One should be cautious hiring any director who has produced a major film that has an ROI of less than 19 million and hasn't produced a film that has an ROI of more than 230 million. On the other hand, directors whose worst film has an ROI of more than 57 million and whose best film has an ROI of more than 488 million are among the top 25th percentile of the directors in this dataset.

For writers, the median ROI was 162 million dollars and 50% of writers have an average ROI between 86 to 319 million dollars. The median ROI for the worst film these writers produced was 22 million dollars and the median for the best film was 360 million dollars. One should be cautious hiring any writer who has produced a film that has an ROI of less than 22 million and hasn't produced a film that has an ROI of more than 360 million. On the other hand, writers whose worst film has an ROI of more than 68 million and whose best film has an ROI of more than 597 million are among the top 25th percentile of the writers in this dataset.

[73]:
```
# This SQL syntax is being used to collect ROI data of all directors with 3 or
↪more movies so it can be plotted
# as a box plot that can be used to help gauge a director's effectiveness.

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)
```

[74]:
```
# These are some of the numbers that will be plotted in the box plot. While␣
 ↪these numbers can be used as a guide, they
# cannot be interpreted as absoulute criteria. For example, based on MIN ROI,␣
 ↪Bryan Singer would be considered
# a poor director based off Jack the Giant Slayer.  His other movies, however,␣
 ↪strongly suggest that this isn't the case.
director_roi.describe()
```

[74]:

	MIN_ROI	AVG_ROI	MAX_ROI
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

[75]:
```
# 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
WHERE death_year IS NULL
GROUP BY writer_id
    HAVING COUNT(movie_id) >= 3
ORDER BY AVG_ROI DESC
;
"""
writer_roi = pysqldf(q)
```

[76]:
```
# Similar to the directors dataframe.
writer_roi.describe()
```

[76]:

	MIN_ROI	AVG_ROI	MAX_ROI
count	249.000000	249.000000	249.000000
mean	50.012844	222.135171	432.159770
std	92.197768	190.918037	355.121472
min	-200.237650	-14.371499	-3.532394
25%	-2.476980	86.332529	154.041804
50%	22.531552	162.042402	360.004754
75%	68.345423	319.625484	597.923379
max	600.867516	1140.471893	1748.134200

[77]:

```
# 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 and Directors With Three or More Movies
↪Based on Return On Investment", size=22)

plt.subplot(2,3,1)
sns.boxplot(director_roi.MIN_ROI, color='#6497b1')
plt.xlabel('Min ROI (in Millions) of Directors', fontsize=18)

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

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

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

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

plt.subplot(2,3,6)
sns.boxplot(writer_roi.MAX_ROI, color='#6497b1')
```

```
plt.xlabel('Max ROI (in Millions) of Writers', fontsize=18);
```

1.7 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* 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. As a rule of thumb, one should be looking for directors whose average ROI is above 271 million dollars and whose worst major film production had an ROI no lower than 19 million. This having been said, there are exceptions to this rule, Bryan Singer being one of them.

- **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. As a rule of thumb, one should be looking for writers whose average ROI is above 319 million dollars and whose worst major film production had an ROI no lower than 22 million. There are also exceptions to this rule, Derek Connolly being one of them.

1.8 Next Steps

- **Investigate the interest level of a *Warcraft* sequel or remake.**
  With an ROI of 265 million, the profits of 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."

[ ]:

```
```