Using Data to Support Microsoft's Original Video Content Venture

- Student name: Jacqueline Du Bois
- Student pace: Self paced (Flex)
- Instructor name: Mark Barbour

Overview

This project analyzes available movie data to help Microsoft decide which movie genres might offer the most successful entry into the original content video production market and who they could hire as a director to assist the production.

Business Problem

Microsoft is entertaining the prospects of a new business venture to create original video content. This is the company's first foray into movie production, therefore to help Microsoft to decide how to allocate its available resources, I first identify a method of looking across available measures of popularity, quality, and local market profitability to determine what makes for a successful movie. Upon assembling a set of successful movies using these criteria, I solve the following research questions:

1. Are there particular genres of films that appears frequently within the list of successful movies?
2. Are there directors that are more likely than others to be associated with films in this list?
3. Of the directors who have produced several succesful movies, who would be best equipped to work collaboratively with Microsoft to design a project?

The answers to these questions will define two alternatives Microsoft can choose between to enter the market: either selecting a genre and the best director to direct it, or choosing the most successful director and granting him or her the freedom to work with Microsoft to select the most appropriate subject matter.

Data Understanding

The following publicly available data are used:

- An "IMDb" database containing tables pertaining to basic movie characteristics, ratings, and principle production members.

The IMDb database is valuable in that it permits the matching of movies to their ratings and facilitating insights into whether specific genres are correlated with higher ratings. Likewise, it permits inquiry into the influence of directors, actors, and writers on movie success. IMDb counts itself as "the world's most popular and authoritative source" for visual media information.[1]

- Movie budget data provided by "The Numbers" which in addition to the production budget lists the domestic and global profits for each movies.

The merit of "The Numbers" data is that it allows for insight into the return on investment of a movie. Looking solely at profits may obscure the fact that a movie actually lost money or was dependent on global viewing to break even. "The Numbers" is one of the largest freely-available sources of movie industry information.[2]

1. "IMDB Help Center," IMDb, accessed April 8, 2023, https://help.imdb.com/article/imdb/general-information/what-is-imdb/G836CY29Z4SGNMK5?ref_=helpsect_cons_1_1#.
2. "History," The Numbers, accessed April 8, 2023, https://www.the-numbers.com/about-us.

Assumptions

1. The study is limited to movies that have already been to the box office. Movies yet to debut are eliminated.
2. Ratings are subject to selection bias wherein critics with a strong liking or strong aversion to a movie are more likely to submit a rating. Movies with high numbers of ratings are considered more likely to have been seen and thus more popular.
3. Quality of a film is measured by the ratings received for a given movie.
4. Movies that feature multiple terms to define the genre are best described by the first of those terms.
5. The movie production budget refers only to the monies required to produce the film and do not include marketing.
6. If a movie was able to generate a profit locally, it is deemed financially successful.
7. Monetary amounts are assumed to be in constant dollars to facilitate comparisons between movies made in different years.
8. The director plays a pivotal role in the success of a movie.
9. When more than one director participates on a film, the one who has a lower "order" number in the imdb "principals" table is considered the primary director.
10. A successful movie is determined as having popularity (number of votes), quality (ratings), and profitability (net domestic profits) above the average for all movies assessed.

In [2]:
```
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

IMDB Database Tables

Movie Basics, Ratings, Principals, and Persons tables

In [2]:
```
# Unzip IMDb database file
! unzip zippedData/im.db.zip
```

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

In [3]:
```
# Establish connection to the database file and confirm table schema
conn = sqlite3.connect('im.db')
schema_imdb = pd.read_sql("""SELECT *
                              FROM sqlite_master
                             WHERE type = 'table';
                          """, conn)

print(schema_imdb['sql'][0])
print(schema_imdb['sql'][4])
print(schema_imdb['sql'][5])
print(schema_imdb['sql'][6])
```

```
CREATE TABLE "movie_basics" (
"movie_id" TEXT,
  "primary_title" TEXT,
  "original_title" TEXT,
  "start_year" INTEGER,
  "runtime_minutes" REAL,
  "genres" TEXT
)
CREATE TABLE "movie_ratings" (
"movie_id" TEXT,
  "averagerating" REAL,
  "numvotes" INTEGER
)
CREATE TABLE "persons" (
"person_id" TEXT,
  "primary_name" TEXT,
  "birth_year" REAL,
  "death_year" REAL,
  "primary_profession" TEXT
)
CREATE TABLE "principals" (
"movie_id" TEXT,
  "ordering" INTEGER,
  "person_id" TEXT,
  "category" TEXT,
  "job" TEXT,
  "characters" TEXT
)
```

In [4]:
```
#Characterizing the IMDb "movie_basics" table
imdb_movie_basics = pd.read_sql("""SELECT *
                                    FROM movie_basics;
                                """, conn)

#Confirm data types and missing values
print(imdb_movie_basics.info(),'\n')
```

```python
#Find descriptive statistics for quantitative values
print(imdb_movie_basics.describe())
```

```
<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
None

          start_year  runtime_minutes
count  146144.000000    114405.000000
mean     2014.621798        86.187247
std         2.733583       166.360590
min      2010.000000         1.000000
25%      2012.000000        70.000000
50%      2015.000000        87.000000
75%      2017.000000        99.000000
max      2115.000000     51420.000000
```

In [5]:

```python
#Characterizing the IMDb "movie_ratings" table
imdb_movie_rate = pd.read_sql("""SELECT *
                                    FROM movie_ratings;
                                """, conn)

#Confirm data types and missing values
print(imdb_movie_rate.info(),'\n')

#Find descriptive statistics for quantitative values
print(imdb_movie_rate.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   movie_id       73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
None

       averagerating      numvotes
count   73856.000000  7.385600e+04
mean        6.332729  3.523662e+03
std         1.474978  3.029402e+04
min         1.000000  5.000000e+00
25%         5.500000  1.400000e+01
50%         6.500000  4.900000e+01
75%         7.400000  2.820000e+02
max        10.000000  1.841066e+06
```

In [6]:

```
#Characterizing the IMDB "principals" table
imdb_principals = pd.read_sql("""SELECT *
                                   FROM principals;
                              """, conn)

#Confirm data types and missing values
print(imdb_principals.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1028186 entries, 0 to 1028185
Data columns (total 6 columns):
 #   Column      Non-Null Count    Dtype 
---  ------      --------------    ----- 
 0   movie_id    1028186 non-null  object
 1   ordering    1028186 non-null  int64 
 2   person_id   1028186 non-null  object
 3   category    1028186 non-null  object
 4   job         177684 non-null   object
 5   characters  393360 non-null   object
dtypes: int64(1), object(5)
memory usage: 47.1+ MB
None
```

In [7]:

```
#Characterizing the IMDB "persons" table
imdb_persons = pd.read_sql("""SELECT *
                                FROM persons;
                              """, conn)

#Confirm data types and missing values
print(imdb_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
None
```

"The Numbers"

Movie Production Budget and Gross Earnings Data

In [8]:
```
budget = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')

#View data items and summary of years contained
print(budget.info(),'\n')
print(budget.describe())
```

```
<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
None

                id
count  5782.000000
mean     50.372363
std      28.821076
min       1.000000
25%      25.000000
50%      50.000000
75%      75.000000
max     100.000000
```

Data Preparation

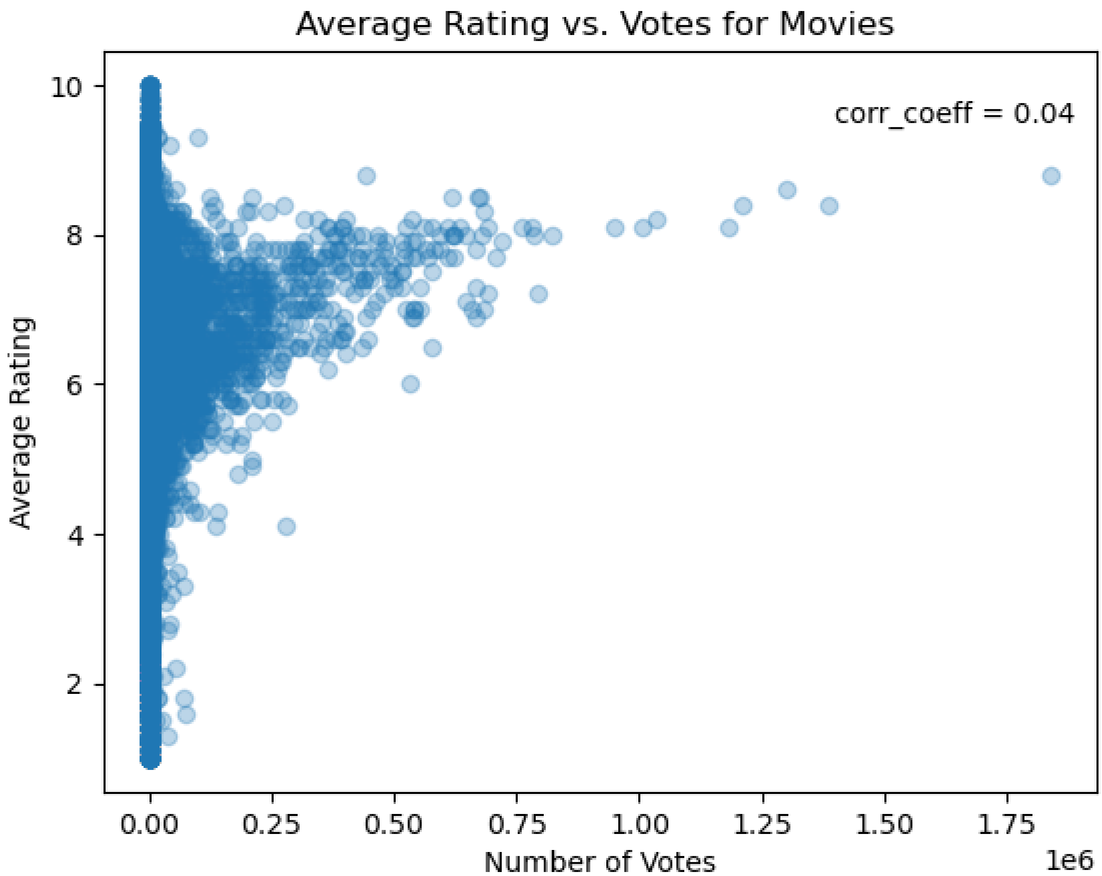
The data preparation step requires first joining the full set of movies represented in the movie_basics table with the movie ratings stored on the movie_ratings table and restricting the year of airing to before 2023. I exclude any movies missing from either file by performing an inner join.

In [9]:
```
#Introduce and join ratings data to movie_basics data
imdb_basics_ratings = pd.read_sql("""SELECT mb.movie_id,
                                            mb.primary_title,
                                            mb.start_year,
                                            mb.genres,
                                            mr.averagerating AS avg_rating,
                                            mr.numvotes
                                       FROM movie_basics AS mb
                                      INNER JOIN movie_ratings AS mr
                                            ON mb.movie_id = mr.movie_id
                                      WHERE mb.start_year < 2023
                                      ORDER BY mr.averagerating DESC;
                                    """, conn)
imdb_basics_ratings.head(10)
imdb_basics_ratings.info()  #73856 rows
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   movie_id       73856 non-null  object
 1   primary_title  73856 non-null  object
 2   start_year     73856 non-null  int64
 3   genres         73052 non-null  object
 4   avg_rating     73856 non-null  float64
 5   numvotes       73856 non-null  int64
dtypes: float64(1), int64(2), object(3)
memory usage: 3.4+ MB
```

To determine whether the number of votes and average rating can be looked at as independent measures, the Pearson correlation coefficient is computed. Here it is positive but extremely small suggesting these two measures of number of votes (popularity) and rating (quality) are independent and can be looked at as measuring different aspects of an audience's response to a film.

In [10]:
```
#Create a scatter plot to check correlation between variables
fig, ax = plt.subplots()
ax.scatter(x = imdb_basics_ratings['numvotes'], y = imdb_basics_ratings['avg_rating'],
ax.set_title('Average Rating vs. Votes for Movies ')
ax.set_xlabel('Number of Votes')
ax.set_ylabel('Average Rating')
rho = 'corr_coeff = {:.2f}'.format(imdb_basics_ratings['avg_rating'].corr(imdb_basics_
ax.text(1.4*10**6,9.5,rho)
plt.savefig("./images/rating_votes_correlation.png", dpi = 150)
plt.show();
```



In [11]:
```
# Generate correlation matrix
imdb_basics_ratings[['avg_rating','numvotes']].corr()
```

Out[11]:

	avg_rating	numvotes
avg_rating	1.000000	0.044478
numvotes	0.044478	1.000000

Next, I format the release date field of the budget data, creating a field "year" that can be used to merge the budget and movie data. This is necessary because of the potential for movies with the same name to be released in different years. The monetary amounts are also converted from strings to integers to compute the net domestic profits.

In [12]:
```
#Create a release year to assist merge with basic movie data
budget['date'] = pd.to_datetime(budget['release_date'])
budget['year'] = budget['date'].dt.year

# Budget data is formatted with a $.  Remove so can perform broadcasting to get net pr
budget['domestic_gross_int'] = budget['domestic_gross'].str.replace('\$|,','', regex =
budget['production_budget_int'] = budget['production_budget'].str.replace('\$|,','', r

budget['net_profit'] = budget['domestic_gross_int'] - budget['production_budget_int']
```

In [13]:
```
# Drop extra columns
local_profits = budget.drop(['id','release_date','domestic_gross','production_budget',
```

```
local_profits = local_profits.sort_values('net_profit', ascending = False)
local_profits.shape   # 5782 rows
```

Out[13]: (5782, 5)

The net domestic profits information is then merged with the movie characteristics and rating information.

In [14]:
```
#Inner join of movie characteristics and budget data
imdb_votesrates_budget = imdb_basics_ratings.merge(local_profits, left_on = ['primary_
                        right_on = ['movie','year'], how = 'inner')

imdb_votesrates_budget.shape  #1498 rows
```

Out[14]: (1498, 11)

In [15]:
```
imdb_votesrates_budget.describe()
```

Out[15]:

	start_year	avg_rating	numvotes	year	domestic_gross_int	production_budget_in
count	1498.000000	1498.000000	1.498000e+03	1498.000000	1.498000e+03	1.498000e+0:
mean	2013.844459	6.288318	1.148142e+05	2013.844459	5.650938e+07	4.483078e+0
std	2.566518	1.071363	1.641172e+05	2.566518	8.491064e+07	5.622902e+0
min	2010.000000	1.600000	5.000000e+00	2010.000000	0.000000e+00	1.500000e+0
25%	2012.000000	5.700000	1.405750e+04	2012.000000	3.243797e+06	8.000000e+0
50%	2014.000000	6.400000	5.843150e+04	2014.000000	2.786025e+07	2.300000e+0
75%	2016.000000	7.000000	1.405365e+05	2016.000000	6.756418e+07	5.500000e+0
max	2019.000000	8.800000	1.841066e+06	2019.000000	7.000596e+08	4.106000e+0

The join leads to a significant loss of movie data and leaves a set wherein the measures of success are more cloely correlated. While it is obvious that more votes cast is associated with more people contributing to the profits of the movie by buying tickets, these results also reflect that movies with high numbers of votes cast tended to receive higher ratings.

In [16]:
```
#Check correlation within the limited set of movies
imdb_votesrates_budget
imdb_votesrates_budget[['avg_rating','numvotes','net_profit']].corr()
```

Out[16]:

	avg_rating	numvotes	net_profit
avg_rating	1.000000	0.481304	0.244327
numvotes	0.481304	1.000000	0.432347
net_profit	0.244327	0.432347	1.000000

The next step is to truncate the dataset to those movies that received above average profits, votes, and ratings. This will create the set of movies deemed most successful on which I will perform the analysis to find the most successful genre of film, the director most likely to support that genre of film's production, and the most successful director overall.

In [25]:
```
# Further subset data to movies with above average values for all three success criter
avg_profit = imdb_votesrates_budget['net_profit'].mean()
avg_votes = imdb_votesrates_budget['numvotes'].mean()
avg_ratings = imdb_votesrates_budget['avg_rating'].mean()

imdb_votesrates_budget_trunc = \
                    imdb_votesrates_budget[(imdb_votesrates_budget['net_profit'] > avg
                                           (imdb_votesrates_budget['avg_rating'] > avg
                                           (imdb_votesrates_budget['numvotes'] > avg_v

imdb_votesrates_budget_trunc.sort_values('numvotes', ascending = False)
```

Out[25]:

	movie_id	primary_title	start_year	genres	avg_rating	numvotes	movie	y
0	tt1375666	Inception	2010	Action,Adventure,Sci-Fi	8.8	1841066	Inception	2
7	tt1345836	The Dark Knight Rises	2012	Action,Thriller	8.4	1387769	The Dark Knight Rises	2
3	tt0816692	Interstellar	2014	Adventure,Drama,Sci-Fi	8.6	1299334	Interstellar	2
9	tt1853728	Django Unchained	2012	Drama,Western	8.4	1211405	Django Unchained	2
27	tt0848228	The Avengers	2012	Action,Adventure,Sci-Fi	8.1	1183655	The Avengers	2
...	...	...	...	...	...	...	...	
730	tt0815236	She's Out of My League	2010	Comedy,Romance	6.4	117245	She's Out of My League	2
180	tt2381111	Brooklyn	2015	Drama,Romance	7.5	117021	Brooklyn	2
269	tt4116284	The Lego Batman Movie	2017	Action,Animation,Comedy	7.3	116433	The Lego Batman Movie	2
154	tt5083738	The Favourite	2018	Biography,Drama,History	7.6	116011	The Favourite	2
376	tt3470600	Sing	2016	Animation,Comedy,Family	7.1	115951	Sing	2

241 rows × 11 columns

The last step is to build a dataset that combines the principal and persons data tables. This will allow me to match the sets of movies to the directors responsible for them.

In [22]:
```
directors =pd.read_sql("""SELECT movie_id, ordering, person_id, primary_name
                          FROM principals
                         INNER JOIN persons
                               USING (person_id)
                         WHERE category = 'director'
```

```
                                ORDER BY movie_id, ordering;
                             """, conn)
directors.head()
```

Out[22]:

	movie_id	ordering	person_id	primary_name
0	tt0063540	5	nm0712540	Harnam Singh Rawail
1	tt0066787	5	nm0002411	Mani Kaul
2	tt0069049	5	nm0000080	Orson Welles
3	tt0069204	5	nm0611531	Hrishikesh Mukherjee
4	tt0100275	5	nm0749914	Raoul Ruiz

In [51]:

```
# Merge in director information with the current set of successful movies
imdb_trunc_directors = imdb_votesrates_budget_trunc.merge(directors, on = 'movie_id',

imdb_trunc_directors_wbudget = imdb_trunc_directors.drop(['year','domestic_gross_int']
imdb_trunc_directors.drop(['year','domestic_gross_int','production_budget_int'], axis

imdb_trunc_directors.sort_values(['movie_id','ordering'], inplace = True)
imdb_trunc_directors.head()
```

Out[51]:

	movie_id	primary_title	start_year	genres	avg_rating	numvotes	movie
185	tt0369610	Jurassic World	2015	Action,Adventure,Sci-Fi	7.0	539338	Jurassic World
8	tt0435761	Toy Story 3	2010	Adventure,Animation,Comedy	8.3	682218	Toy Story 3
118	tt0443272	Lincoln	2012	Biography,Drama,History	7.4	228701	Lincoln
229	tt0448694	Puss in Boots	2011	Action,Adventure,Animation	6.6	133355	Puss in Boots
103	tt0451279	Wonder Woman	2017	Action,Adventure,Fantasy	7.5	487527	Wonder Woman

Because many movies have more than one director, I focus the analysis on the principle director who is assumed to have the lower "ordering" number in the principals table.

In [38]:

```
# Assume the director with the lower "ordering" number is the principal in charge of t
imdb_trunc_directors[imdb_trunc_directors['movie_id'].duplicated()]
imdb_trunc_directors.drop_duplicates(subset=['movie_id'], keep = 'first', inplace = Tr
```

Data Modeling

Identify the most frequently cited genres within the set of successful movies.

To do this, I aggregate the results by genre and try to optimize over 2 or more of the factors of popularity, quality, and net domestic profit. Because some films feature more than one genre code, I assume that it is the first genre listed that is most representative of the film. The distribution of films by genre is printed below.

In [39]:
```
# Maing use of Assumption 4: Split off first mention within genre category to stand or
imdb_votesrates_budget_trunc['first_genre'] = \
                            imdb_votesrates_budget_trunc['genres'].map(lambda x: x.spl
                                                                       if x !=None el


imdb_votesrates_budget_trunc['first_genre'].value_counts()
```

```
C:\Users\jacqu\AppData\Local\Temp\ipykernel_28596\704316776.py:2: SettingWithCopyWarn
ing:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  imdb_votesrates_budget_trunc['first_genre'] = \
```

Out[39]:
```
Action       98
Comedy       32
Adventure    30
Drama        30
Biography    26
Crime        12
Horror        4
Mystery       3
Animation     3
Family        1
Romance       1
Fantasy       1
Name: first_genre, dtype: int64
```

In [55]:
```
# Compute aggregates for the ratings, number of votes, and net profit by genre
aggregate_dict = {'avg_rating':'mean','numvotes':'mean','net_profit':'mean'}
imdb_genre_score = imdb_votesrates_budget_trunc.groupby('first_genre').agg(aggregate_d

print(imdb_genre_score.mean())
print(imdb_genre_score.corr())
imdb_genre_score.sort_values('avg_rating', ascending = False)
```

```
avg_rating    7.263464e+00
numvotes      3.216162e+05
net_profit    9.983850e+07
dtype: float64
            avg_rating  numvotes  net_profit
avg_rating    1.000000  0.606230    0.048291
numvotes      0.606230  1.000000   -0.113402
net_profit    0.048291 -0.113402    1.000000
```

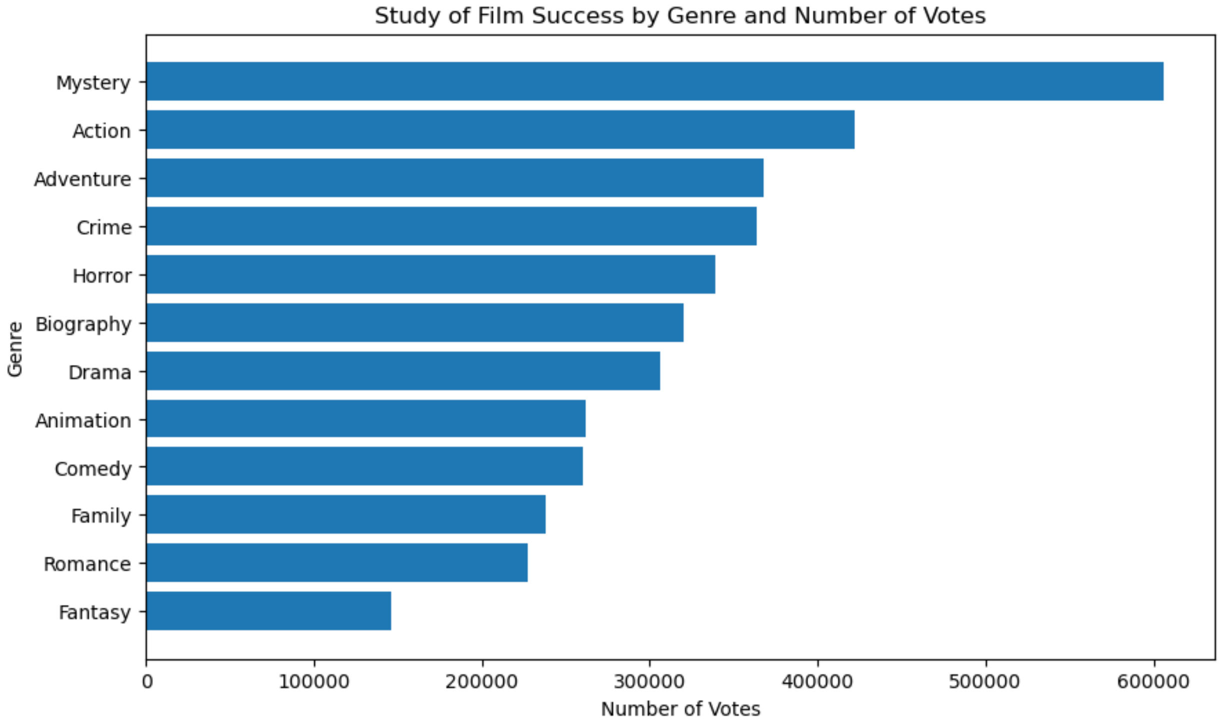
Out[55]:

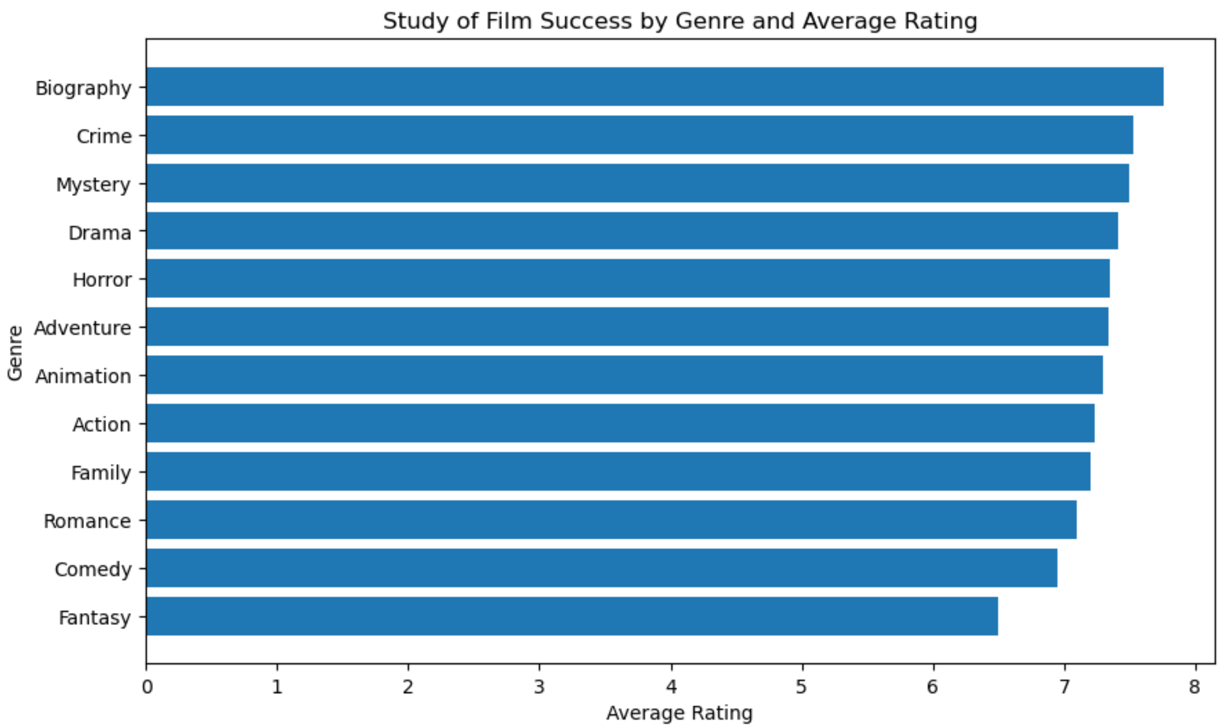
first_genre	avg_rating	numvotes	net_profit
Biography	7.761538	320035.653846	6.010731e+07
Crime	7.525000	364047.583333	3.694070e+07
Mystery	7.500000	606341.666667	5.908886e+07
Drama	7.410000	306217.233333	6.396078e+07
Horror	7.350000	338793.750000	1.565024e+08
Adventure	7.333333	367649.533333	1.139780e+08
Animation	7.300000	261677.666667	1.470520e+08
Action	7.228571	422233.224490	1.063524e+08
Family	7.200000	238325.000000	3.440142e+08
Romance	7.100000	227616.000000	1.229564e+07
Comedy	6.953125	260057.781250	6.052986e+07
Fantasy	6.500000	146399.000000	3.723986e+07

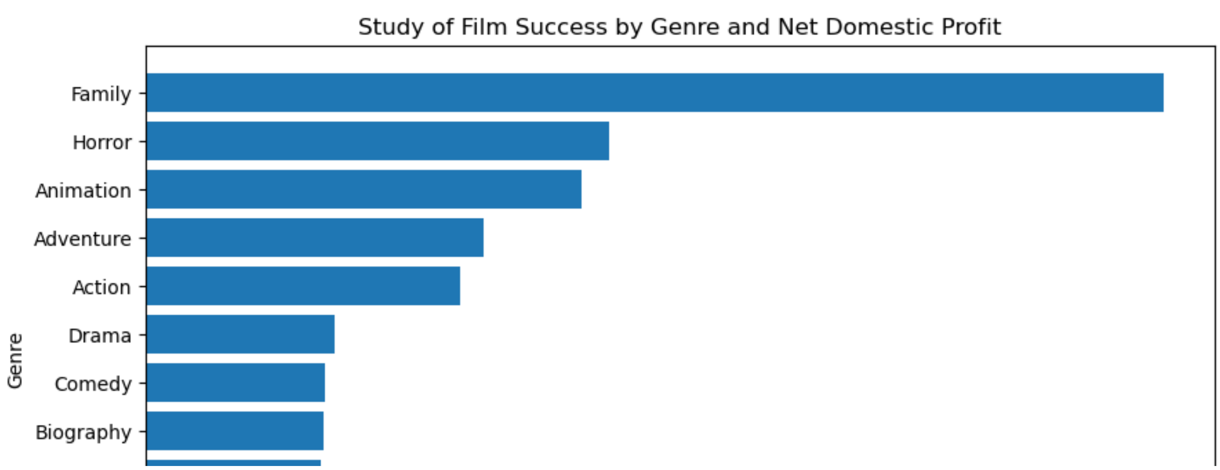
In [57]:

```
#Generate plot of genres by success categories while simultaneously creating lists of
#registering as successful among each of the three sucess categories.

imdb_genre_score = imdb_genre_score.reset_index()

fig, (ax1,ax2,ax3) = plt.subplots(nrows = 3,ncols =1, figsize = (10,20))

imdb_genre_score.sort_values('numvotes', inplace = True)
top_threegenres_1 = imdb_genre_score.iloc[-3:]['first_genre']
top_fourgenres_1 = imdb_genre_score.iloc[-4:]['first_genre']
ax1.barh(y = imdb_genre_score['first_genre'], width = imdb_genre_score['numvotes'])

imdb_genre_score.sort_values('avg_rating', inplace = True)
top_threegenres_2 = imdb_genre_score.iloc[-3:]['first_genre']
top_fourgenres_2 = imdb_genre_score.iloc[-4:]['first_genre']
ax2.barh(y = imdb_genre_score['first_genre'], width = imdb_genre_score['avg_rating'])

imdb_genre_score.sort_values('net_profit', inplace = True)
top_threegenres_3 = imdb_genre_score.iloc[-3:]['first_genre']
top_fourgenres_3 = imdb_genre_score.iloc[-4:]['first_genre']
ax3.barh(y = imdb_genre_score['first_genre'], width = imdb_genre_score['net_profit']);

ax1.set_ylabel('Genre')
ax1.set_xlabel('Number of Votes')
ax1.set_title('Study of Film Success by Genre and Number of Votes')

ax2.set_ylabel('Genre')
ax2.set_xlabel('Average Rating')
ax2.set_title('Study of Film Success by Genre and Average Rating')

ax3.set_ylabel('Genre')
ax3.set_xlabel('Net Domestic Profit')
ax3.set_title('Study of Film Success by Genre and Net Domestic Profit')
```

```
plt.savefig("./images/genre_success_factor.png", dpi = 150)
plt.show();
```


Study of Film Success by Genre and Number of Votes
Mystery
Action
Adventure
Crime
Horror
Biography
Drama
Animation
Comedy
Family
Romance
Fantasy
Genre
0
100000
200000
300000
400000
500000
600000
Number of Votes


Study of Film Success by Genre and Average Rating
Biography
Crime
Mystery
Drama
Horror
Adventure
Animation
Action
Family
Romance
Comedy
Fantasy
Genre
0
1
2
3
4
5
6
7
8
Average Rating


Study of Film Success by Genre and Net Domestic Profit
Family
Horror
Animation
Adventure
Action
Drama
Comedy
Biography
Genre

In [31]:
```
value_threecounts_genre = pd.concat([top_threegenres_1,top_threegenres_2,top_threegenr
top_threegenres_overall_vc = value_threecounts_genre[value_threecounts_genre >= 2]
top_threegenres_overall_names = top_threegenres_overall_vc.index
print(f"Top genre among top three selected from each success category: {top_threegenre

value_fourcounts_genre = pd.concat([top_fourgenres_1,top_fourgenres_2,top_fourgenres_3
top_fourgenres_overall_vc = value_fourcounts_genre[value_fourcounts_genre >= 2]
top_fourgenres_overall_names = top_fourgenres_overall_vc.index
print(f"Top genre among top four selected from each success category: {top_fourgenres_
```

```
Top genre among top three selected from each success category: Index(['Mystery'], dty
pe='object')
Top genre among top four selected from each success category: Index(['Crime', 'Advent
ure', 'Mystery'], dtype='object')
```

The smallest set of genres (3) that maximizes at least two of the categories correlated with success reveals that the Mystery genre may be a place to start. Widening the set to four, I find three genres that optimize at least two of the categories: Mystery, Advernture, and Crime. The average budget for a film of these genres is approximately $132,000,000 for an Adventure film, \$52,300,000 for a Mystery film, and $40,300,000 for a Crime film.

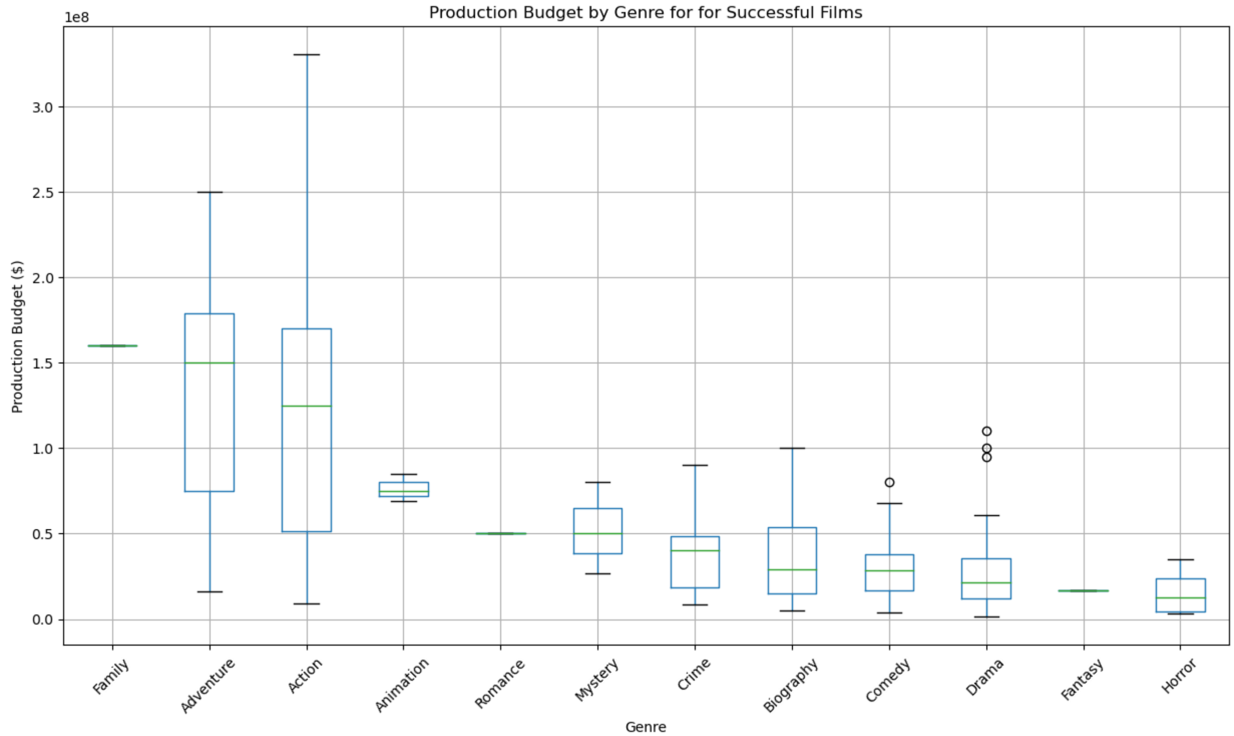
In [90]:
```
aggregate_dict = {'production_budget_int': ['mean','std']}
production_genre_aggregate = imdb_votesrates_budget_trunc.groupby('first_genre').agg(a
production_genre_aggregate.sort_values([('production_budget_int','mean')], ascending =
```

Out[90]:

	production_budget_int	
	mean	std
first_genre		
Family	1.600000e+08	NaN
Adventure	1.318167e+08	6.545444e+07
Action	1.189908e+08	7.208563e+07
Animation	7.633333e+07	8.082904e+06
Mystery	5.233333e+07	2.657693e+07
Romance	5.020000e+07	NaN
Crime	4.029167e+07	2.490022e+07
Biography	3.640385e+07	2.444423e+07
Drama	3.028333e+07	2.826253e+07
Comedy	2.900000e+07	1.858763e+07
Fantasy	1.700000e+07	NaN
Horror	1.575000e+07	1.490805e+07

In [33]:

```
#Boxplot sorting function from https://medium.com/the-barometer/note-to-self-pandas-sc
def boxplot_sorted(df, by, column, rot = 45):
    df2 = pd.DataFrame({col:vals[column] for col, vals in df.groupby(by)})
    meds = df2.median().sort_values(ascending = False)
    return df2[meds.index].boxplot(rot = rot, return_type = "axes", figsize = (15,8))



axes = boxplot_sorted(imdb_votesrates_budget_trunc, by = ['first_genre'], column = 'pr
plt.xlabel('Genre')
plt.ylabel('Production Budget ($)')
#plt.yticks(np.arange(11))
plt.title('Production Budget by Genre for for Successful Films')
plt.savefig("./images/genre_budget.png", dpi = 150)
plt.show();
```

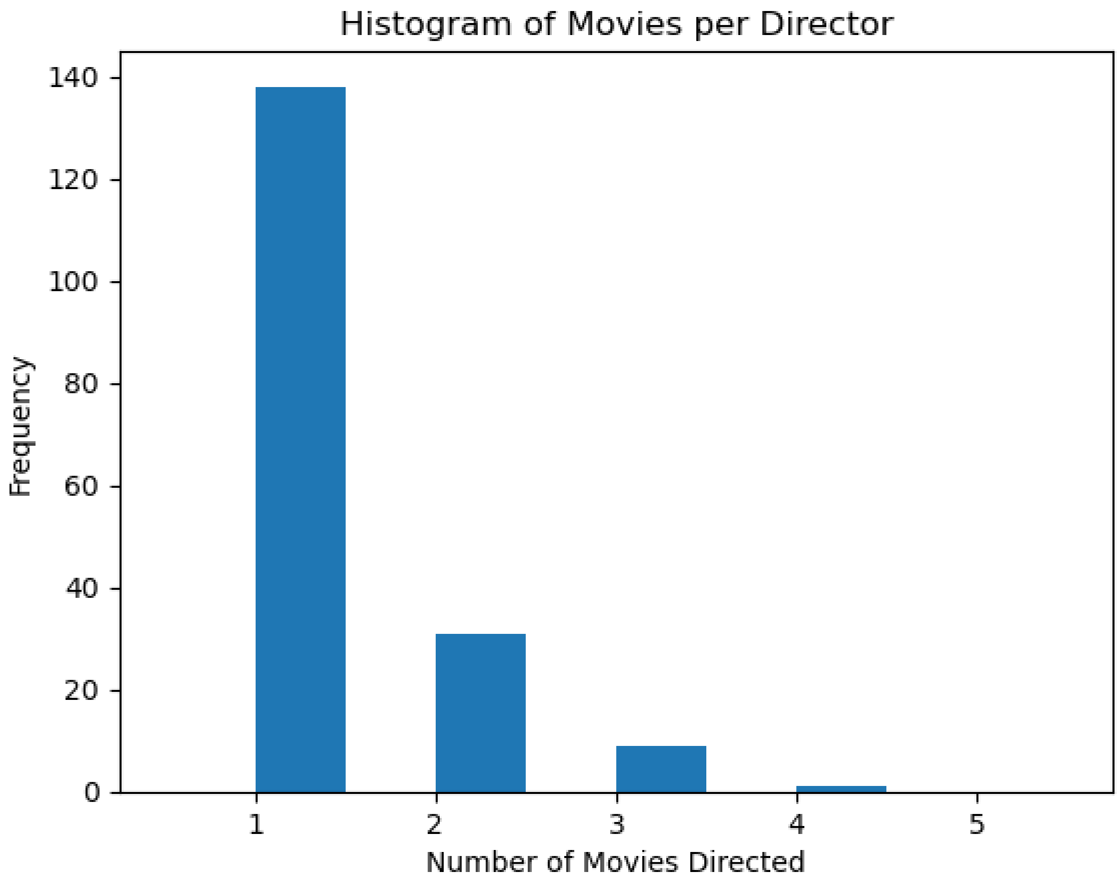


Directors associated with the most successful films' genres

I assert that the more of these films a director has been involved in, the more knowledgeable that person is of the components required to make a successful film. I determine which directors to select based on those represented in the top half of the histogram representing the count of films any given director has produced.

In [32]:
```
# Produce the value counts of films per director in order to find those directors who
# among the list of successful movies

top_directors_vc = imdb_trunc_directors['primary_name'].value_counts()
```

In [33]:
```
# Select the directors represented by the top half of the histogram
fig, ax = plt.subplots()
ax.hist(top_directors_vc, range = [0.5,5.5])
ax.set_title('Histogram of Movies per Director')
ax.set_xlabel('Number of Movies Directed')
ax.set_ylabel('Frequency')
plt.savefig("./images/director_histogram", dpi = 150)
plt.show();
```



In [34]:

```
# Find number of directors making up the top half of the histogram
histpatches = ax.patches
count_half = int(len(histpatches)/2)
freq = [patch.get_height() for patch in histpatches]
top_count = int(sum(freq[-count_half:]))
print(top_count)

# Names of directors making up the top half of the histogram
top_directors_names = top_directors_vc[0:top_count].index
print(top_directors_names)
```

```
10
Index(['Christopher Nolan', 'Adam McKay', 'Phil Lord', 'Francis Lawrence',
       'James Wan', 'Anthony Russo', 'David O. Russell', 'David Fincher',
       'Antoine Fuqua', 'Denis Villeneuve'],
      dtype='object')
```

In [41]:

```
imdb_trunc_directors
```

Out[41]:

	movie_id	primary_title	start_year	genres	avg_rating	numvotes	
185	tt0369610	Jurassic World	2015	Action,Adventure,Sci-Fi	7.0	539338	Jurass
8	tt0435761	Toy Story 3	2010	Adventure,Animation,Comedy	8.3	682218	To
118	tt0443272	Lincoln	2012	Biography,Drama,History	7.4	228701	
229	tt0448694	Puss in Boots	2011	Action,Adventure,Animation	6.6	133355	Puss
103	tt0451279	Wonder Woman	2017	Action,Adventure,Fantasy	7.5	487527	
...	...	...	...	...	...	...	
102	tt6644200	A Quiet Place	2018	Drama,Horror,Sci-Fi	7.6	305031	A Qu
221	tt6823368	Glass	2019	Drama,Sci-Fi,Thriller	6.8	133793	
9	tt6966692	Green Book	2018	Biography,Comedy,Drama	8.3	204972	Gre
117	tt7349662	BlacKkKlansman	2018	Biography,Crime,Drama	7.5	149005	BlacKkK
153	tt7784604	Hereditary	2018	Drama,Horror,Mystery	7.3	151571	H

241 rows × 12 columns

In [42]:

```
# The list of directors with movies in the selected genres and producing the most succ
imdb_trunc_directors['first_genre'] = \
                            imdb_trunc_directors['genres'].map(lambda x: x.split(',')[

imdb_trunc_directors[(imdb_trunc_directors['first_genre'].isin(list(top_fourgenres_ove
                      (imdb_trunc_directors['primary_name'].isin(top_directors_names))]
```

Out[42]:

	movie_id	primary_title	start_year	genres	avg_rating	numvotes	movie	net_
1	tt0816692	Interstellar	2014	Adventure,Drama,Sci-Fi	8.6	1299334	Interstellar	230
18	tt1392214	Prisoners	2013	Crime,Drama,Mystery	8.1	526273	Prisoners	150
54	tt1568346	The Girl with the Dragon Tattoo	2011	Crime,Drama,Mystery	7.8	387580	The Girl with the Dragon Tattoo	125
164	tt1800241	American Hustle	2013	Crime,Drama	7.2	418221	American Hustle	1101

According to this analysis, there are four directors to consider. To produce an Adventure film, the company should consider Christopher Nolan. If they wish to generate a Crime or Mystery the company can select from among David O. Russell, Denis Villeneuve, and David Fincher.

Most successful directors overall

The most successful directors overall will be assessed on how well on average their movies performed according to the metrics of number of votes, average rating, and net domestic profits. Top directors are defined as those producing more than 2 movies among those in the list of successful movies (representing the top half of the histogram).

In [43]:

```
# Isolate the directors to those who appeared in the top director list from the previc
imdb_trunc_top_directors = imdb_trunc_directors[imdb_trunc_directors['primary_name'].i

# Carry over only necessary columns
imdb_cut_top_directors = imdb_trunc_top_directors[['primary_name','avg_rating','numvot

# Aggregate movies by director and sort
imdb_agg_top_directors = imdb_cut_top_directors.groupby('primary_name').mean()
imdb_agg_top_directors.sort_values('avg_rating',ascending = False, inplace = True)
imdb_agg_top_directors
```

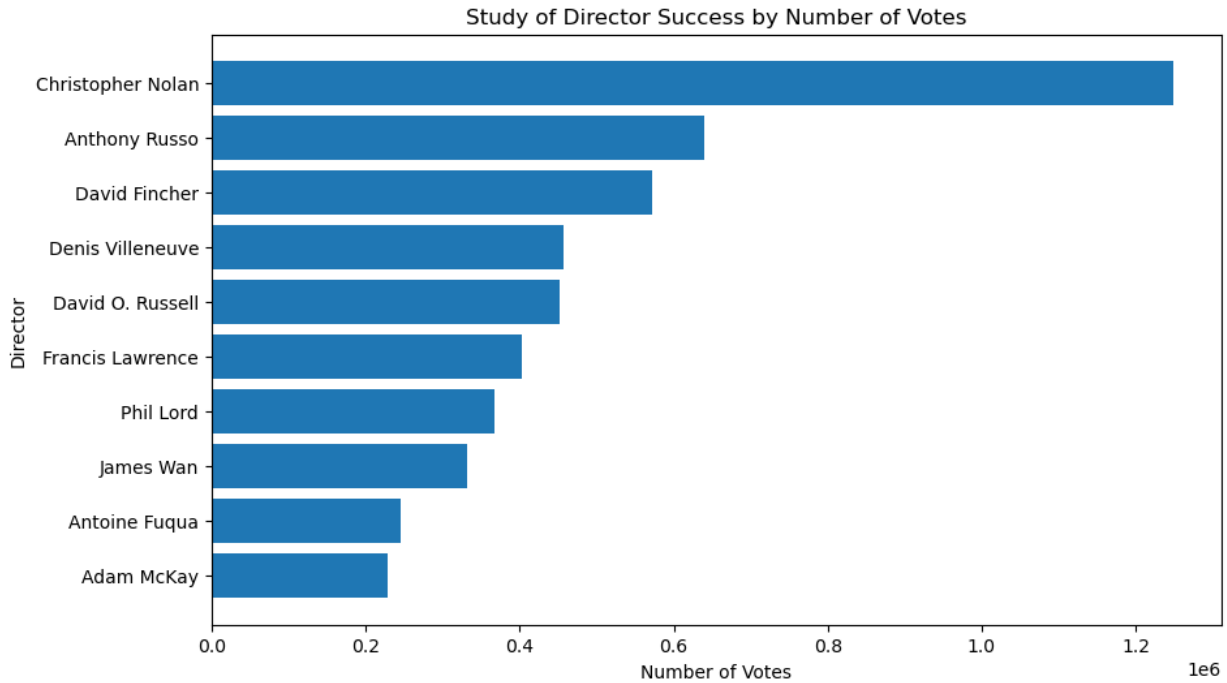
Out[43]:

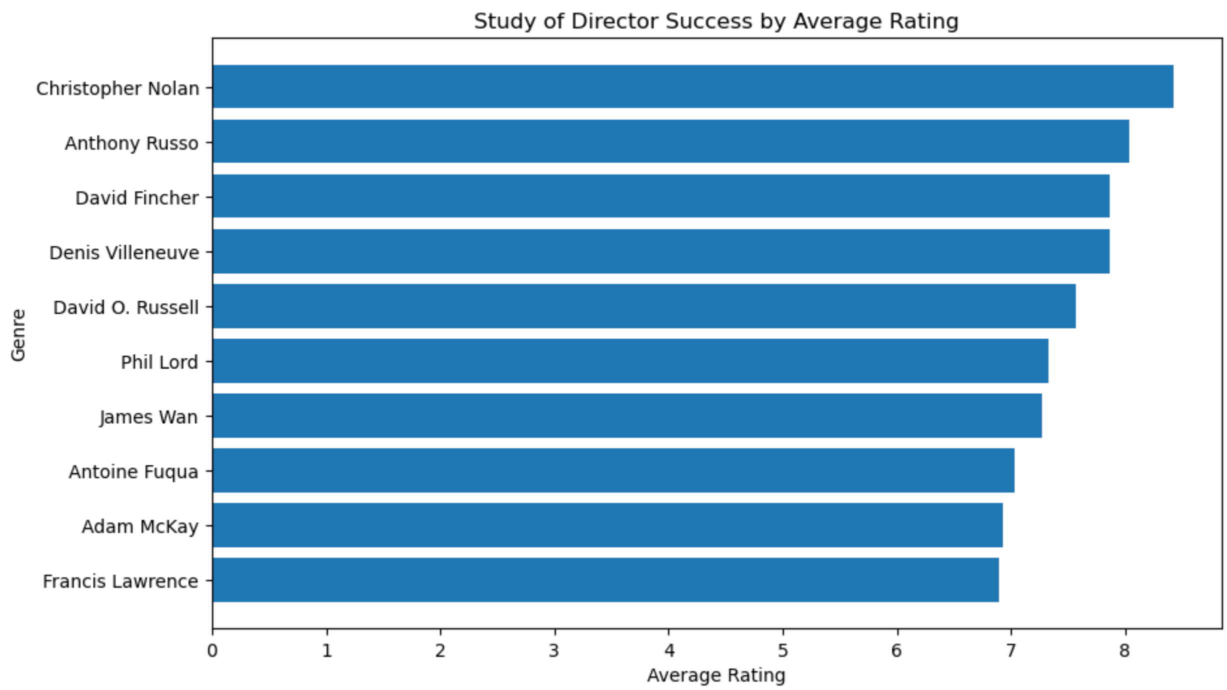
primary_name	avg_rating	numvotes	net_profit
Christopher Nolan	8.425000	1.248687e+06	9.220037e+07
Anthony Russo	8.033333	6.402283e+05	2.088823e+08
David Fincher	7.866667	5.725833e+05	5.874856e+07
Denis Villeneuve	7.866667	4.567680e+05	2.847924e+07
David O. Russell	7.566667	4.519260e+05	1.012759e+08
Phil Lord	7.333333	3.671513e+05	1.453172e+08
James Wan	7.266667	3.318783e+05	1.518230e+08
Antoine Fuqua	7.033333	2.458427e+05	3.262676e+07
Adam McKay	6.933333	2.290023e+05	4.627752e+07
Francis Lawrence	6.900000	4.022963e+05	2.095093e+08

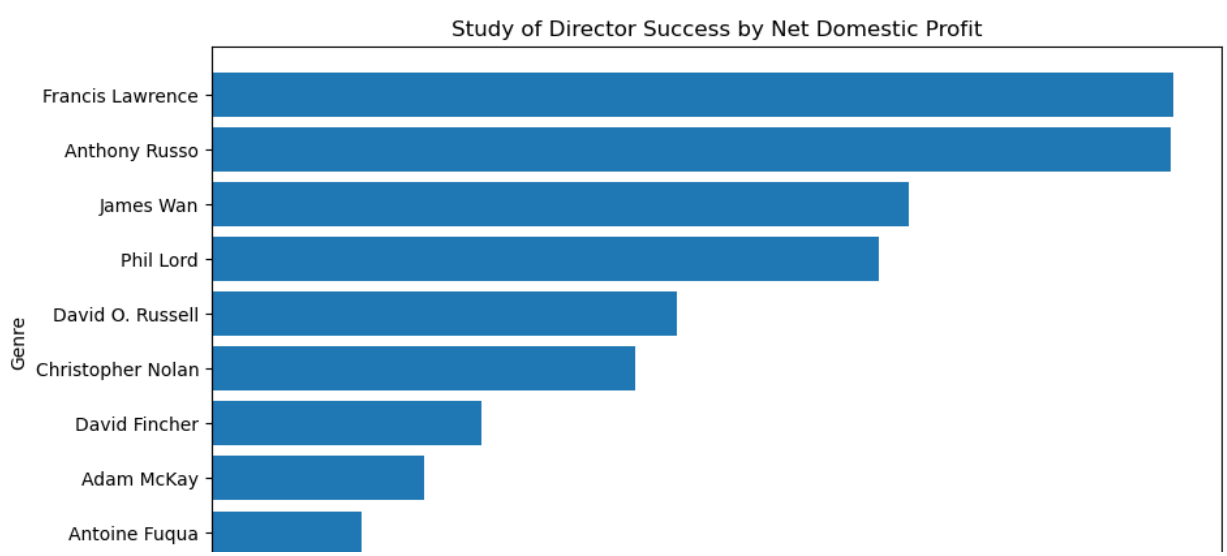
In [46]:

```
imdb_agg_top_directors = imdb_agg_top_directors.reset_index()

fig, (ax1,ax2,ax3) = plt.subplots(nrows = 3,ncols =1, figsize = (10,20))

imdb_agg_top_directors.sort_values('numvotes', inplace = True)
top_three1 = imdb_agg_top_directors.iloc[-3:]['primary_name']
ax1.barh(y = imdb_agg_top_directors['primary_name'], width = imdb_agg_top_directors['r

imdb_agg_top_directors.sort_values('avg_rating', inplace = True)
top_three2 = imdb_agg_top_directors.iloc[-3:]['primary_name']
ax2.barh(y = imdb_agg_top_directors['primary_name'], width = imdb_agg_top_directors['a

imdb_agg_top_directors.sort_values('net_profit', inplace = True)
top_three3 = imdb_agg_top_directors.iloc[-3:]['primary_name']
ax3.barh(y = imdb_agg_top_directors['primary_name'], width = imdb_agg_top_directors['r
```

```python
ax1.set_ylabel('Director')
ax1.set_xlabel('Number of Votes')
ax1.set_title('Study of Director Success by Number of Votes')

ax2.set_ylabel('Genre')
ax2.set_xlabel('Average Rating')
ax2.set_title('Study of Director Success by Average Rating')

ax3.set_ylabel('Genre')
ax3.set_xlabel('Net Domestic Profit')
ax3.set_title('Study of Director Success by Net Domestic Profit')

plt.savefig("./images/director_success.png", dpi = 150)
plt.show();
```


Study of Director Success by Number of Votes
Christopher Nolan
Anthony Russo
David Fincher
Denis Villeneuve
David O. Russell
Francis Lawrence
Phil Lord
James Wan
Antoine Fuqua
Adam McKay
Director
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1e6
Number of Votes


Study of Director Success by Average Rating
Christopher Nolan
Anthony Russo
David Fincher
Denis Villeneuve
David O. Russell
Phil Lord
James Wan
Antoine Fuqua
Adam McKay
Francis Lawrence
Genre
0
1
2
3
4
5
6
7
8
Average Rating


Study of Director Success by Net Domestic Profit
Francis Lawrence
Anthony Russo
James Wan
Phil Lord
David O. Russell
Christopher Nolan
David Fincher
Adam McKay
Antoine Fuqua
Genre

In [47]:

```
#Look at the top three directors with the highest valuation in eqch of the ratings, nu
value_counts_directors = pd.concat([top_three1,top_three2,top_three3]).value_counts()

#Select directors corresponding to the top portion of the list, rounding up if necessa
num_directors = np.ceil(len(value_counts_directors)/2)
top_directors_overall_vc = value_counts_directors.head(int(num_directors))
print(top_directors_overall_vc)

top_directors_overall_names = top_directors_overall_vc.index
```

```
Anthony Russo        3
David Fincher        2
Christopher Nolan    2
Name: primary_name, dtype: int64
```

The director that appears among the top of all three success ratings is Anthony Russo. Additional candidates who appearing in two of the categories are Christopher Nolan and David Fincher.

In [48]:

```
def director_output(dataframe, names):

    """This function takes the database of films + directors and the list of the top
        overall directors and generates their portfolio of movies as a function of
        genre and the success criteria.  This is to assess the diversity of
        their work."""

    for director in names:
        columns = ['movie','numvotes','avg_rating','net_profit','genres']
        output = dataframe.loc[dataframe['primary_name']==director,columns]
        print(director, '\n',pd.DataFrame(output).to_string(justify = 'center'), '\n')
    return()

director_output(imdb_trunc_directors, top_directors_overall_names)
```

```
Anthony Russo
                       movie                   numvotes  avg_rating  net_profit          g
enres
58  Captain America: The Winter Soldier   666252       7.8       89746958  Action,Adv
enture,Sci-Fi
62           Captain America: Civil War   583507       7.8      158084349  Action,Adv
enture,Sci-Fi
2                Avengers: Infinity War   670926       8.5      378815482  Action,Adv
enture,Sci-Fi

David Fincher
                     movie                 numvotes  avg_rating  net_profit          genre
s
70                 The Social Network   568578       7.7       56962694         Biograp
hy,Drama
54  The Girl with the Dragon Tattoo   387580       7.8       12515793     Crime,Dram
a,Mystery
24                          Gone Girl   761592       8.1      106767189  Drama,Mystery,
Thriller

Christopher Nolan
               movie           numvotes  avg_rating  net_profit          genres
1             Interstellar   1299334      8.6       23017894   Adventure,Drama,Sci-Fi
4   The Dark Knight Rises   1387769      8.4      173139099          Action,Thriller
0                Inception   1841066      8.8      132576195  Action,Adventure,Sci-Fi
47                 Dunkirk    466580      7.9       40068280     Action,Drama,History
```

Out[48]:

```
()
```

Evaluation

The first step of the analysis was to determine the factors of success. I used the nominally independent measures provded: Number of Votes (popularity), Average Rating (quality), and Domestic Net Profit (local financial success) to identify a set of "successful" movies.

The analysis used to answer the first question revealed three genres, namely Mystery, Adventure, and Crime. Additional analysis however, revealed an Adventure film's budget could be as high as $200 million which is 4 - 5 times greater than films in the other two genres. This type of expense may pose a risk to Microsoft should the company's first venture yield a smaller than expected profit.

The response to the second question pivoted on finding the smallest set of directors with which to work. While it would have been appropriate to include directors who produced more than median number of films (1 film), doing so would have required additional criteria (e.g. awards) to subset the list to a size Microsoft could easily choose from. Instead, I limited the starting set of directors to those that made up the top half of the histogram and were capable of producing films in the genres surfaced in the analysis that preceded. This analysis suggested Christopher Nolan (highest rating, highest votes), David O'Russell (highest net profit), David Fincher, and David Villeneuve as possible candidates.

Finally, the third question reveals a result that is fairly generalizable -- looking at the top producing directors among the successful films and reviewing their portfolios for measures of success and expressions of diversity of genres. This analysis showed that director Anthony Russo, though successful, has gained reknown for a single type of film -- Action, Adventure, Sci-Fi films -- which may limit the demographic to which Microsoft may wish to appeal and incur financial risk given the large production cost of Action, Adventure films.

Conclusion

This analysis leads to the following three recommendations to support Microsoft's foray into original video content:

If Microsoft decides to approach the venture by focusing on successful film genres, then it is recommended they --

> **Focus on genres associated with the most successful movies and moderate financial risk.** Doing so will limit the broad option space to Mysery and Crime genres.
>
> **Hire the director most capable of realizing the genres associated with the most successful movies.** This limits the field of directors to Denis Villeneuve, David Fincher, and David O. Russell. Christopher Nolan would also be a candidate should the company wish to produce an Adventure film.

If Microsoft prefers to hire the most adept director and work with him to define the scope of the film, it is recommended they --

> **Hire the director that offers the greatest diversity of skill.** This would suggest they consider David Fincher or Christopher Nolan.

Limitations

Limitations of this approach stem from not using all of the listed genres in the analysis. Only the first was used to avoid the complication of double or triple counting the factors pertaining to success.

Future Work

Additional work in this area could include looking at how the presence of different actors affects the different measures of success of a given movie. Likewise, a more rigorous look at the production budget of different film genres or the financial implications of hiring certain actors could help inform Microsoft's venture