Movie Data Analysis

The purpose of this project is to analyze data from a variety of sources to create a slate of content produced by a new company entering the video streaming marketplace. For the sake of this project, I am assuming I am pitching this project to Microsoft Studios, a fictional film studio.

The Data

The data used for the project was pulled from these various sources:

- IMDB - The International Movie Database
- TMDB - The Movie Database
- Movie Production Budget and Box Office Gross Data

This project is unconcerned with critical failures, but rather what makes a recipe for success? Therefore, I will only focus on data from films with the highest audience vote counts on both IMDB and TMDB, to avoid massive outliers.

What Makes a Streaming Company Succesful?

This is the major question at the heart of this project. Any new streaming service will need a mixture of both original and licensed content covering a multitude of genres and styles. Because of this, unless the company is targeting a niche market, all original content should try to reach as broad an audience as possible. Therefore this project will ask the following questions:

- Does Production Budget affect Popularity?
- What Genres of film are most popular? Are the best financial investment? Have the highest quality?
- What actors, producers, directors and writers should you hire to create this content?

This project will answer all of the above with recommendations for a new streaming service. Below you will find the initial packages installed to help with this analysis as well as the import of data from the file 'zippedData' in the GitHub Repository.

In [1]:
```
# Import required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
# Import all data files.
professional_names_df = pd.read_csv('zippedData/imdb.name.basics.csv.gz')
title_key_df = pd.read_csv('zippedData/imdb.title.akas.csv.gz')
imdb_genres_df = pd.read_csv('zippedData/imdb.title.basics.csv.gz')
crew_df = pd.read_csv('zippedData/imdb.title.principals.csv.gz')
imdb_ratings_df = pd.read_csv('zippedData/imdb.title.ratings.csv.gz')
tmdb_df = pd.read_csv('zippedData/tmdb.movies.csv.gz')
budget_df = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')
```

Functions

Data Cleaning

The following functions are used to clean the initial dataframes imported from the data files. The most important function is clean_title that acts as the primary key to join movies. Movie titles can take many different forms so, in order to join dataframes using the name as the key we need to reduce the title to its simplest parts (i.e. removing punction or extraneous dates) and then we need to add the year because movies of the same title do exist, but tend to not get released in the same annual period.

In [3]:
```
def clean_title(title):

    '''
    Takes a string and normalizes it by removing excess symbols that could be ambiguous
    Also removes any dates attached to titles. These will be added back in during data cleaning.
    '''

    c_title = ''
    l_title = title.lower()

    word_list = l_title.split()

    for word in word_list:
        if word[0] == '(':
            break
        else:
            word = word.replace('?','')
            word = word.replace('/','')
            word = word.replace('!','')
            word = word.replace('—','')
            word = word.replace('-','')
            word = word.replace('&','and')
            word = word.replace('ep.','episode')
            word = word.replace(':','')
            word = word.replace(',','')
            word = word.replace('.','')
            word = word.replace("'","")
            word = word.replace("`",'')

            c_title += word.title()

    return c_title
```

```
In [4]: def separate_values(string):
            '''
            Splits any string by a comma and then returns a list of values
            '''
            if type(string) == str:
                value_list = string.split(',')
            else:
                return string

            return value_list
```

```
In [5]: def clean_money(string):
            '''
            Takes money objects and turns it into a float
            '''
            if type(string) == str:
                answer = string.replace('$','')
                answer = answer.replace(',','')
                answer = float(answer)
            else:
                return string
            return answer
```

Visualization Functions

These are used to aggregate and demonstrate data trends in the final dataframes of the project. Each one is designed to call multiple dataframes as well as a single column in question (each of which is an important metric from the following list: Return on Investment in Dollars, Return on Investment in percentage of production budget, TMDB popularity and TMDB Quality.

In [6]:
```
def genre_counts(dataframe,column):
    '''
    Takes in a dataframe and a column. Orders the DF by the values in the column in question, cuts in
down
    to the top 100 entries. Counts how many of the movies have each genre and then plots a horizontal
    bar graph to show top genres by the column metric.
    '''
    df = dataframe.sort_values(by=[column],ascending=False)
    df = df.iloc[:100]
    df = pd.DataFrame(df[list(genre_set)].sum())
    df.columns = ['count']
    df.sort_values(by='count',ascending=False,inplace=True)
    plt.figure(figsize=(7,7))
    x_values = list(df['count'])
    y_values = list(df.index)
    plt.title(f'Genres ordered by {column}')
    plt.xlabel('Number of Movies')
    plt.ylabel('Genres')
    return sns.barplot(y=y_values,x=x_values, data=df, orient='h');
```

In [7]:
```
def top_crew(dataframe,column):
    '''
    Takes a crew dataframe dictionary and finds the mean of the column metric in question and then pl
ots a bar graph
    of the top fifty entries
    '''
    name = dataframe['name']
    df = dataframe['df'].groupby(by=dataframe['df']['primary_name']).mean().sort_values(by=f'{column}
',ascending=False)
    df = df.iloc[:20]
    plt.figure(figsize=(5,10))
    x_values = list(df[f'{column}'])
    y_values = list(df.index)
    plt.title(f'{name} by {column}')
    return sns.barplot(x = x_values, y = y_values, data = df)
```

Functions for Data Export

This final function produces a list of the top thirty actors, directors, producers and screenwriters based on a desired metric. The output is a simple table that can be easily exported into excel.

In [8]:
```
def create_top_df(list_of_dfs,column_name):

    '''
    Takes in a list of dataframe dictionaries of the format {'df':dataframe,'name':'name of datafram
e'} as well as
    a column in question. It will produce a dataframe of the top thirty Actors, Directors, Producers
 and Writers of
    that particular metric.
    '''

    final_list = []

    for dataframe in list_of_dfs:
        name = dataframe['name']
        df = dataframe['df'].groupby(by=dataframe['df']['primary_name']).mean().sort_values(by=f'{col
umn_name}',ascending=False)
        df = df.iloc[:30]
        df.reset_index(inplace=True)
        df = df.loc[:, ['primary_name']]
        df.rename(columns={'primary_name':f'{name}'},inplace=True)
        final_list.append(df)

    final_df = final_list[0].join(final_list[1:])
    final_df.rename_axis(f"By {column_name.title()}",inplace = True)
    return final_df
```

Data Cleaning

The following cells are the code that joins all requisite data into a single dataframe called 'super_vote_df'. This dataframe includes data covering genre, popularity, production budget, return on investment, and critical quality. It also adds columns to indicate which genres the film belongs to.

In [9]:
```
# Creates the IMDB table to add to other tables. Includes title_id for merging as well as genres
imdb_genres_df.rename(columns={'tconst':'title_id'},inplace=True)
imdb_df = title_key_df.merge(imdb_genres_df,how='left',on='title_id')
imdb_df = imdb_df.loc[:,['title_id','title','primary_title','start_year','runtime_minutes','genres']]
imdb_df['clean_title'] = imdb_df.title.map(lambda x: clean_title(x))

#Renames columns to clean. Splits genres into a list that can be parsed later.
imdb_df.rename(columns={'start_year':'year','runtime_minutes':'runtime'},inplace=True) #Change year i
nto string?
imdb_df['clean_title'] = imdb_df['clean_title'] + " " + imdb_df['year'].astype(str)
```

In [10]:
```
#Joins budget table with IMDB t-const - Goes from 5782 records to 4069
budget_df.rename(columns={'movie':'title'},inplace=True)
budget_df['year'] = budget_df.release_date.map(lambda x: x.split()[-1])
budget_df['clean_title'] = budget_df.title.map(lambda x: clean_title(x))
budget_df['clean_title'] = budget_df['clean_title'] + ' ' + budget_df['year'].astype(str)

budget_tconst_df = budget_df.merge(imdb_df, how='left',on='clean_title')
budget_tconst_df.drop_duplicates(inplace=True)
budget_tconst_df.drop(columns=['title_y','year_y'],inplace = True)
budget_tconst_df.rename(columns={'title_x':'title','year_x':'year'},inplace=True)
# budget_tconst_df.drop_duplicates(subset='title_id',inplace = True)

#Turns money columns into floats from objects
budget_tconst_df['production_budget'] = budget_tconst_df.production_budget.map(lambda x: clean_money(
x))
budget_tconst_df['domestic_gross'] = budget_tconst_df.domestic_gross.map(lambda x: clean_money(x))
budget_tconst_df['worldwide_gross'] = budget_tconst_df.worldwide_gross.map(lambda x: clean_money(x))
final_budget_df = budget_tconst_df
```

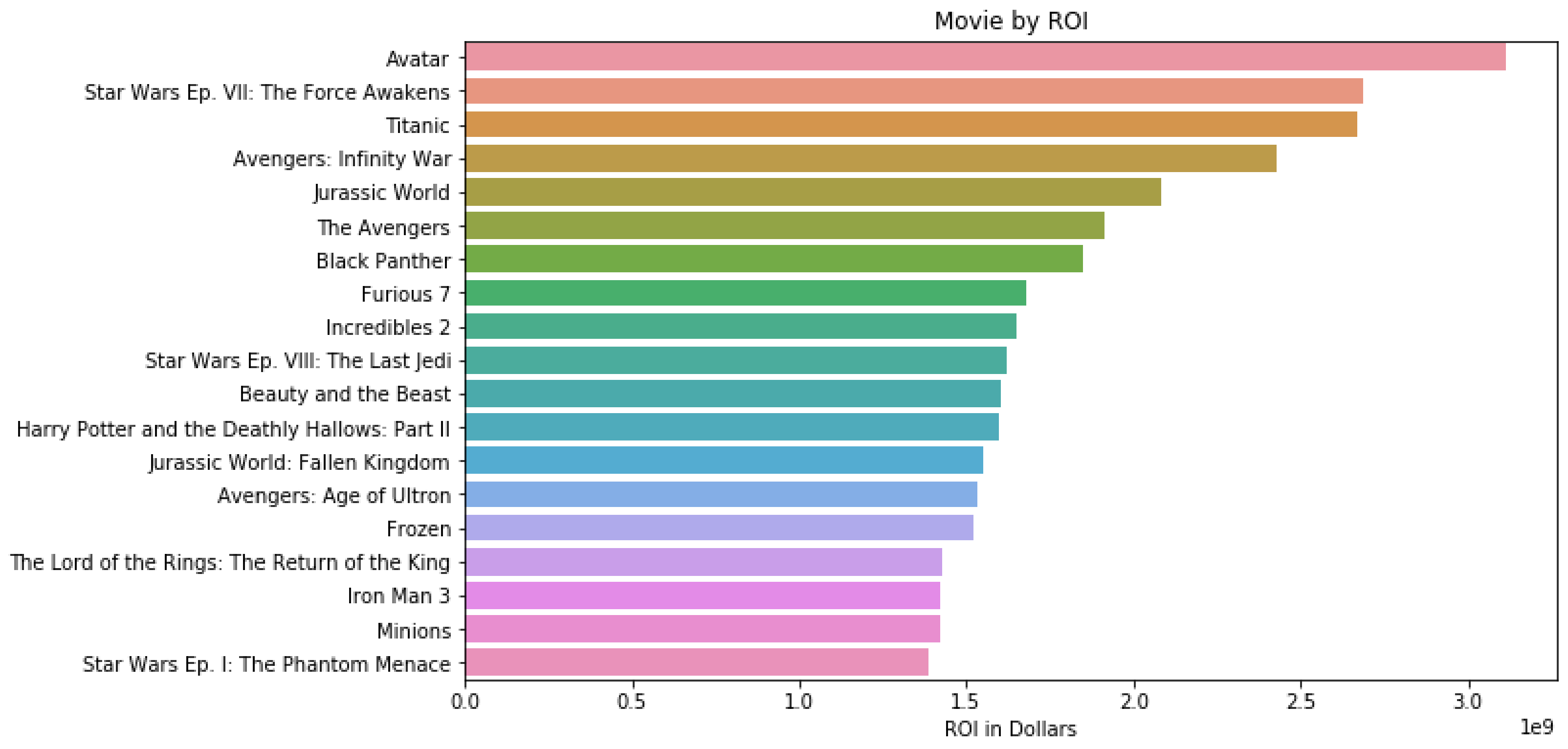
Return on Investment

I chose Return on Investment as one of the major metrics for a few reasons. For a film to gain the most possible profit it would require the necessary intersection of quality filmmaking as well as general popularity. Looking only at box office gross could be deeply misguided as the film 'Dark Phoenix' outperformed the film 'The Blair Witch Project' by a few million, but because 'Dark Phoenix cost over 200 million dollars to make, it lost a substantial amount of money while, as you will see, The Blair Witch Project is the second most successful film of all time when considering Return on Investment as a percentage of the original budget.

Why?

For streaming movies, it is difficult to measure the value a single film brings to a streaming service's portfolio because no streaming company publishes their viewing data. However, general popularity of a film is a good indicator of an audience's interest in paying more money for another streaming service. ROI is the best monetary indicator of popularity.

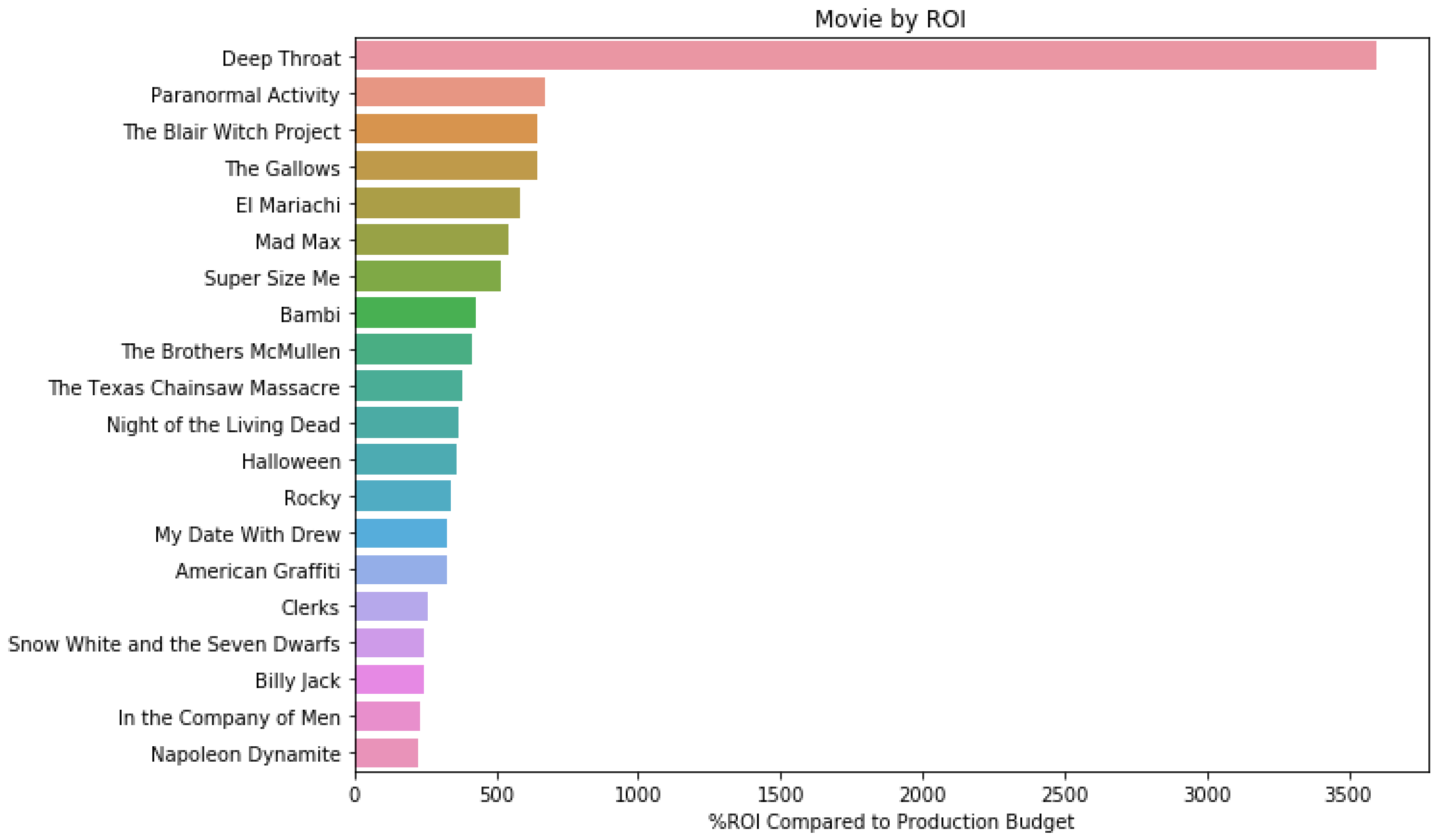
In [11]:
```
#Creates an ROI column for films and creates a column with a boolean value based on whether or not i
t's profitable
final_budget_df['ROI'] = final_budget_df['worldwide_gross'] + final_budget_df['domestic_gross'] - fin
al_budget_df['production_budget']
final_budget_df['ROI%'] = final_budget_df['ROI']/final_budget_df['production_budget']
budget_ROI_df = final_budget_df.sort_values(by='ROI',ascending=False)
budget_ROI_df['Profitable'] = budget_ROI_df.ROI.map(lambda x: x>0)


x_values = list(budget_ROI_df.title[:20])
y_values = list(budget_ROI_df.ROI[:20])

plt.figure(figsize=(10,6))
sns.barplot(y=x_values, x=y_values, data = final_budget_df, orient='h')
plt.xlabel('ROI in Dollars')
plt.title('Movie by ROI');
plt.savefig('movie_roi.png')
```



Already we can see that the movies that create the most profit tend to be big budget action adventure movies. Avatar, famously the most expensive movie of all time, is also the most profitable (a bold bet). However, we can see some interesting patterns that emerge when we consider other metrics.

Return on Investment as a Percentage

In [12]:
```
final_budget_df['ROI%'] = final_budget_df['ROI']/final_budget_df['production_budget']
budget_ROI_df = budget_ROI_df.sort_values(by='ROI%',ascending=False)

x_values = list(budget_ROI_df.title[:20])
y_values = list(budget_ROI_df['ROI%'][:20])

plt.figure(figsize=(10,7))
sns.barplot(y=x_values, x=y_values, data = final_budget_df, orient='h')
plt.xlabel('%ROI Compared to Production Budget')
plt.title('Movie by ROI');
```



When we divide the ROI of a movie by its original budget, we find a completely different and fascinating list of films. Instead of being large budget action films, they are cheaper, smaller horror movies (if we ignore the obvious outlier of 'Deep Throat'). Avatar, while record breakingly successful, made back 100% of its budget in profits. Comoparably, Paranormal Activity made over 600% of its budget.

Why is this important?

Any streaming service needs a breadth of content. Spending all of your money on a second Avatar would be unwise. Cheaper movies can also be popular, though that is not always the case. Some small budget movies can find massive popularity and essential cult status.

More Data Cleaning

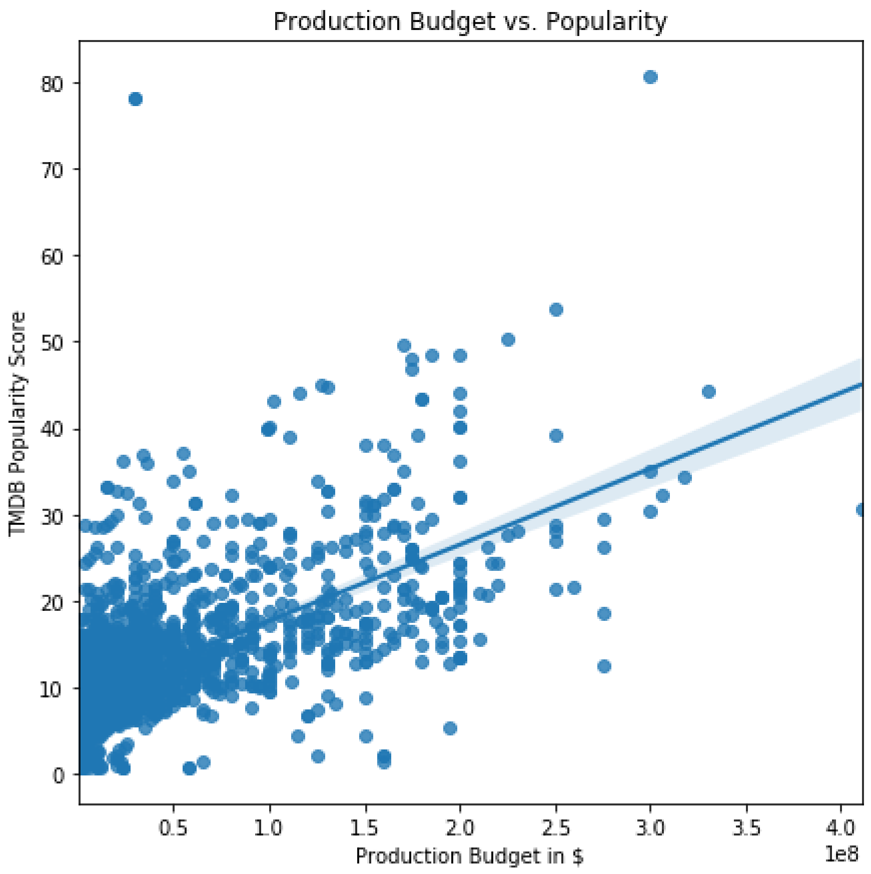
Below I combine popularity data with financial data to see if audience reactions match the money behind the movie.

In [13]:
```
#Joins the TMDB table, which includes information regarding popularity by film.
tmdb_df['clean_title'] = tmdb_df.title.map(lambda x: clean_title(x))
tmdb_df['year'] = tmdb_df.release_date.map(lambda x: x.split('-')[0])
tmdb_df['clean_title'] = tmdb_df['clean_title'] + ' ' + tmdb_df['year'].astype(str)

tmdb_tconst_df = tmdb_df.merge(imdb_df,how='inner',on='clean_title')
tmdb_tconst_df.drop_duplicates(subset='title_id',inplace=True)
tmdb_clean_df = tmdb_tconst_df.loc[:, ['popularity','vote_average','vote_count','clean_title','title_
id']]
```

In [14]:
```
#Creates Super_df that contains ROI, popularity, IMDB rating and vote counts.
imdb_ratings_df.rename(columns={'tconst':'title_id'},inplace=True)
super_df = budget_ROI_df.merge(tmdb_clean_df,how='left',on='title_id')
super_df = super_df.merge(imdb_ratings_df,how='left',on='title_id')
super_df.drop(columns=['clean_title_y'],inplace=True)
```

Question 1 - What is the Relationship between Budget and Popularity?

In [15]:
```
#Creates Linear Regression showing relationship between production budget and popularity
plt.figure(figsize=(7,7))

sns.regplot(x=super_df.production_budget, y=super_df.popularity, data=super_df)
plt.title('Production Budget vs. Popularity');
plt.xlabel('Production Budget in $')
plt.ylabel('TMDB Popularity Score');
```



This is a linear regression charting the relationship between production budget (in dollars) and TMDB popularity score. As you can see there is a positive, linear relationship between the two metrics. This makes sense, as marketing is a large part of the Production Budget. Also, popular actors tend to require more money and, for many years, most films are sold on the talent on screen, hence the higher cost.

Interestingly, there is a vertical cluster at the 200 Million Dollar range. 200M has become the standard budget for a summer blockbuster movie, so you can see the popularity of those films varies wildly.

Question 2 - What Genres Should We Focus On?

The easiest way to identify most movies is by their genre. Genres are both an artistic style as well as a marketing tool. Of the films analyzed, the genres were assigned by IMDB, and most films have multiple genres. This section seeks to ask the following questions:

1. What genre(s) produce the greatest ROI?
2. What genre(s) produce the greatest ROI%?
3. What genre(s) have the highest critical praise?
4. What genre(s) are the most popular?

While similar, all three questions encourage a very different style of content that could increase the success of a new streaming company. But first, more data cleaning

In [16]:
```
#Creates list of genres from the IMDB dataframes
genre_list = list(super_df.genres)
genre_list2 = []

#iterates through the list and adds the genres to a set to get a set of unique values
for item in genre_list:
    if type(item) == str:
        new_list = item.split(',')
        for genre in new_list:
            genre_list2.append(genre)

genre_set = set(genre_list2)
```

In [17]:
```
# drops 36 films that do not have genres
super_df.dropna(subset=['genres'],inplace=True)
```

In [18]:
```
# creates a column for each genre populated with a boolean value if it is in the genre list for that
 movie.
for genre in list(genre_set):
    super_df[f'{genre}'] = super_df.genres.map(lambda x: genre in x)
```

In [19]:
```
# Used this to figure out 25% quartile
super_df.vote_count.describe()
```

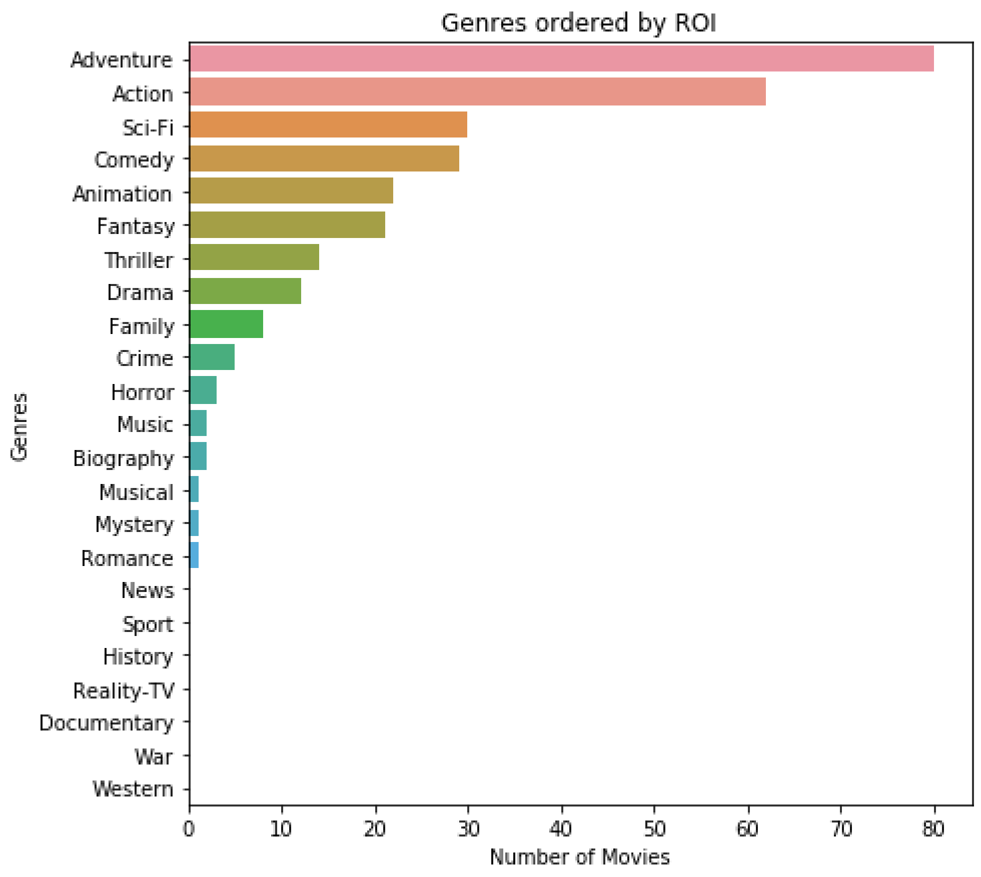
Out[19]:
```
count     1682.000000
mean      2175.905470
std       2894.528106
min          1.000000
25%        307.750000
50%       1078.000000
75%       2813.250000
max      22186.000000
Name: vote_count, dtype: float64
```

In [20]:
```
# Creates a version of the super_df but with only movies having both more than 500 IMDB votes and 200
00 TMDB votes
super_df.rename(columns={'vote_average':'IMDB Quality','averagerating':'TMDB Quality','clean_title_x'
:'clean_title'},inplace=True)
super_vote_df = super_df.loc[(super_df.vote_count > 500) & (super_df.numvotes > 20000)]
```

Genre by Return on Investment

As you can see, Action/Adventure movies tend to return the highest profits. These are going to be the blockbuster films of the streaming service. An action/adventure science fiction film, like any of the Marvel movies, or The Matrix, have proven to be massively popular with audiences, hence their profitable nature

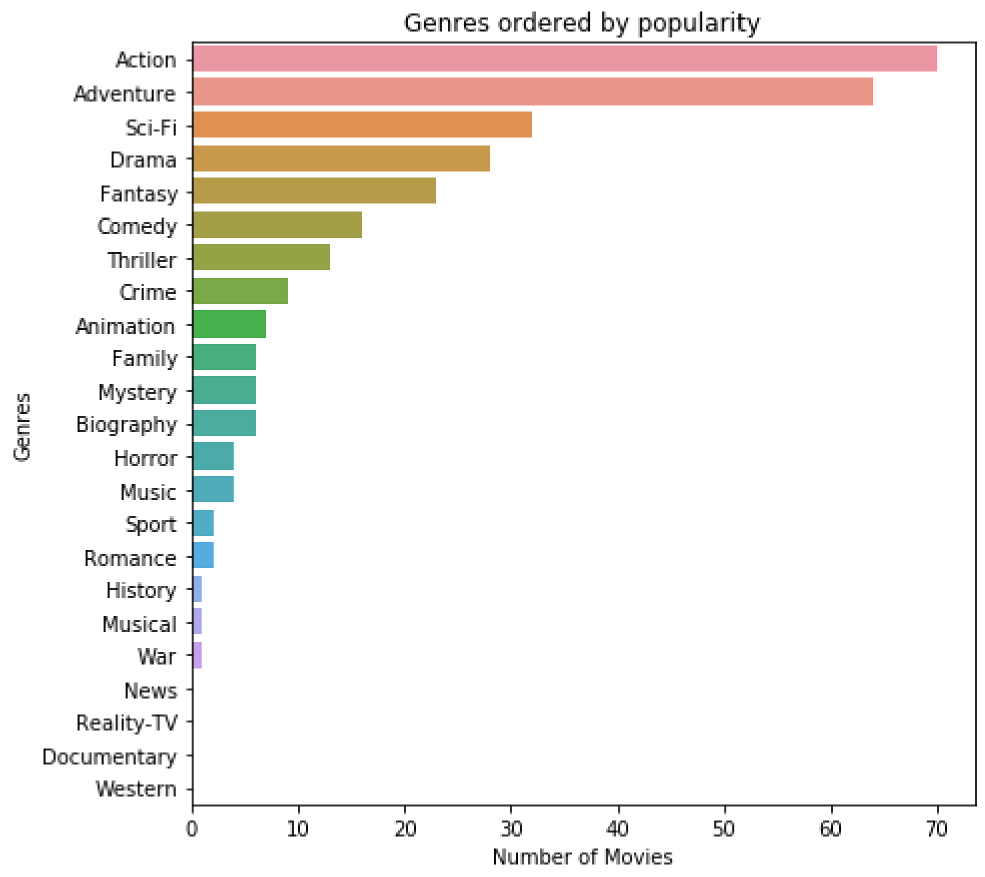
In [21]:
```
genre_counts(super_vote_df,'ROI');
```



Genre by Popularity

Using the TMDB popularity score, we can see that the most popular genres are also the most profitable. Comedies tend to not be as popular as, say, dramas in this category, but Science Fiction Action/Adventure is still the genre combination that will draw the greatest audience.

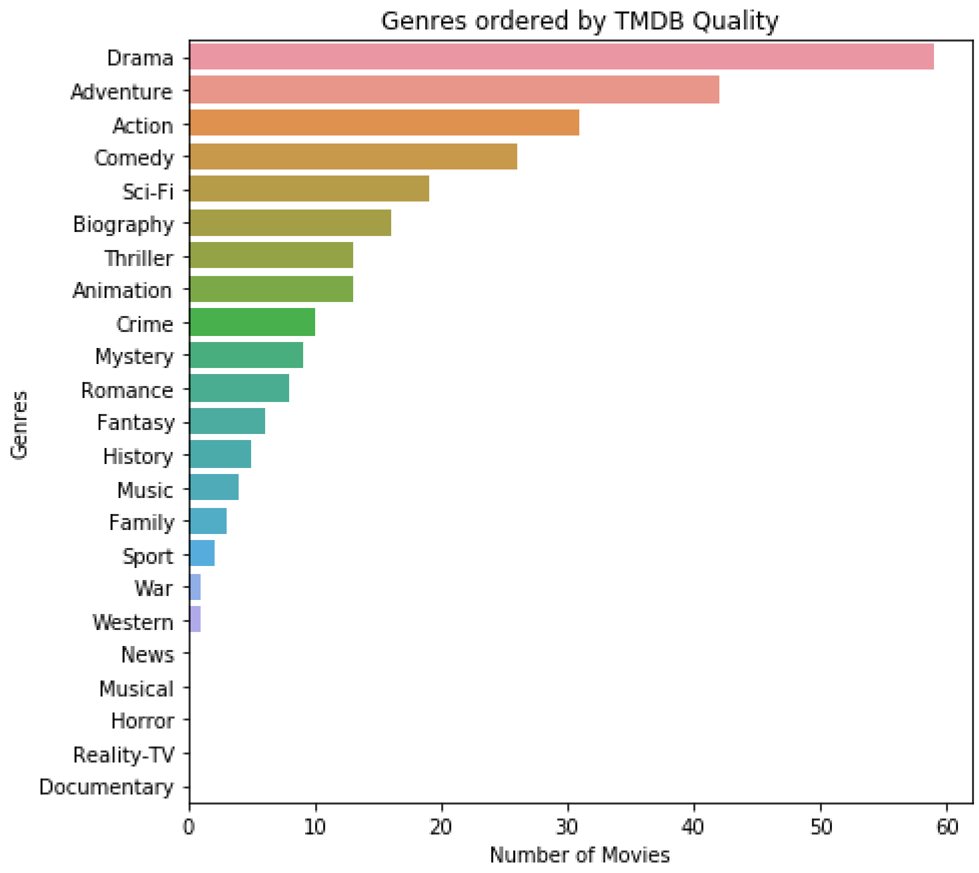
In [22]:
```
genre_counts(super_vote_df,'popularity');
```



Genre by Quality

Movies are sometimes described a 'prestige' meaning that, while they might not sell the most tickets at the movieplex, they stand in good ground with critics. A streaming service should have a fair share of blockbuster popular titles, but it should also have so genuine quality work as well. While Action/Adventures still rank high on this metric, Drama is the most important genre to woo critics.

In [23]:
```
genre_counts(super_vote_df,'TMDB Quality');
```

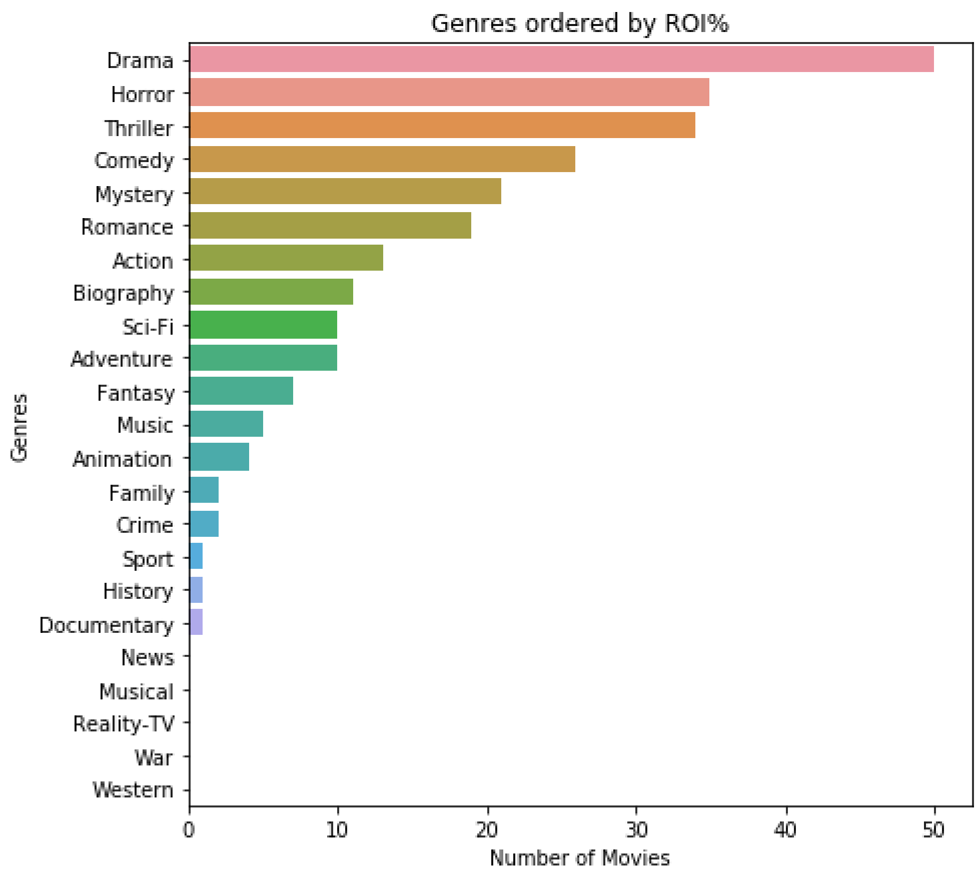


Genre by ROI%

Below you see genres ordered by how successful a movie was against its original budget. These films have the greatest difference between their production budget and their popularity. Films like these should require very little money, comparatively, but could draw large audiences. Similar to 'Quality', Dramas are the highest rated here. This makes sense because most 'Oscar' films tend to have low budgets (compared to, say, the Fast and the Furious films) and high cultural value because they have been nominated for awards.

We can also see that Horror and Thriller are the next two genres. These films tend to be audience pleasers and can be made extremely cheaply. The Blair Witch Project was the 2nd most successful film of all time until Paranormal Activity, a similarly cheap and effective horror film, took its place.

```
In [24]: genre_counts(super_vote_df,'ROI%');
```



Question 3 - Who should we hire?

The success of any movie is determined by the creative team behind it. In general, the most marketable people working on a film are the following:

1. Actors
2. Directors
3. Writers
4. Producers

Every one of these roles is essential to the final product. Actors draw crowds and a fanbase. Directors are in charge of the artistic vision of the piece. Writers have to tell a complete and efficient story. And producers have to put it all together in a package that people love.

Below you will see my data cleaning to join actors, directors, producers and writers onto each movie in the Super_Vote_Df.

In [25]:
```
# Adds Actors, Directors, Writers and Producers to the super_vote DataFrame
crew_df.rename(columns={'tconst':'title_id'},inplace=True)

crew_df = crew_df.loc[(crew_df.category == 'actor') | (crew_df.category == 'actress') | (crew_df.cate
gory == 'producer') | (crew_df.category == 'writer') | (crew_df.category == 'director')]
crew_df = crew_df.merge(professional_names_df, how='left', on='nconst')

crew_df.drop(columns=[
        'characters',
        'job',
        'nconst',
        'ordering',
        'birth_year',
        'death_year',
        'primary_profession',
        'known_for_titles'
    ],inplace=True)

super_crew_df = super_vote_df.merge(crew_df,how='left',on='title_id')
```

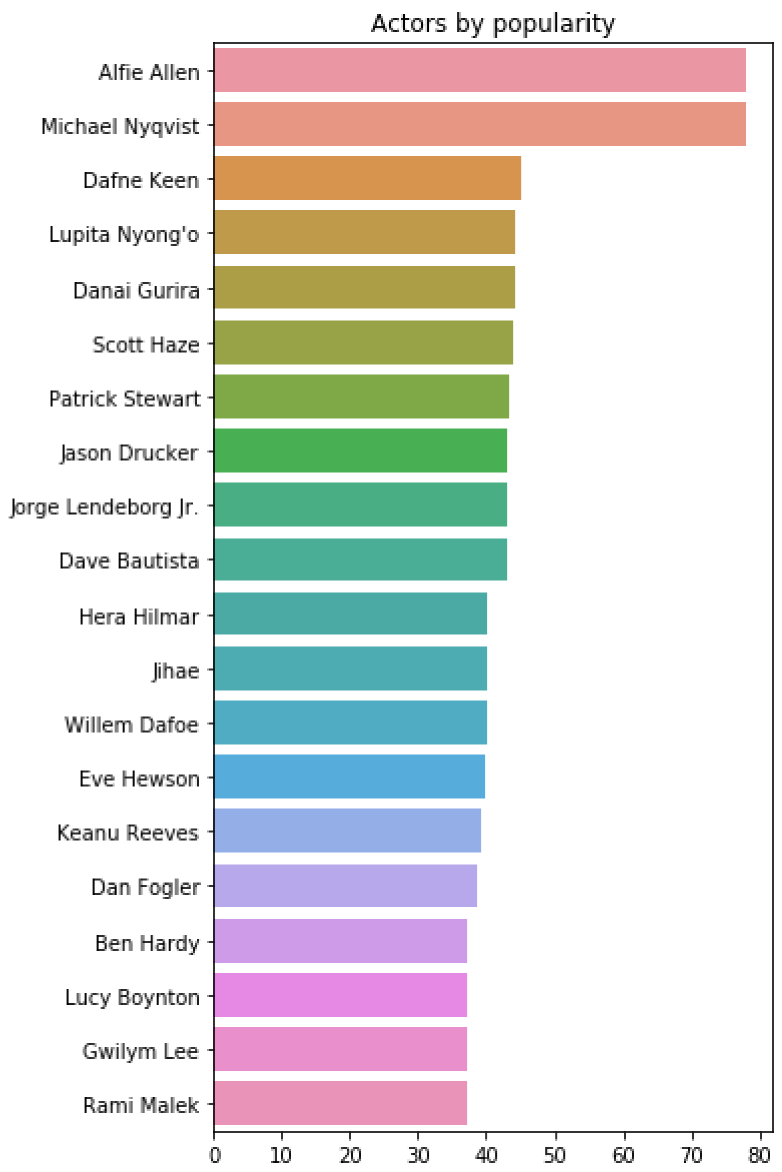
In [26]:
```
#Creates different dataframes for each of the major crew types for further analysis. Treats actors an
d actresses equally
actors = super_crew_df.loc[(super_crew_df.category == 'actor') | (super_crew_df.category == 'actress'
)]
directors = super_crew_df.loc[super_crew_df.category == 'director']
writers = super_crew_df.loc[super_crew_df.category == 'writer']
producers = super_crew_df.loc[super_crew_df.category == 'producer']
```

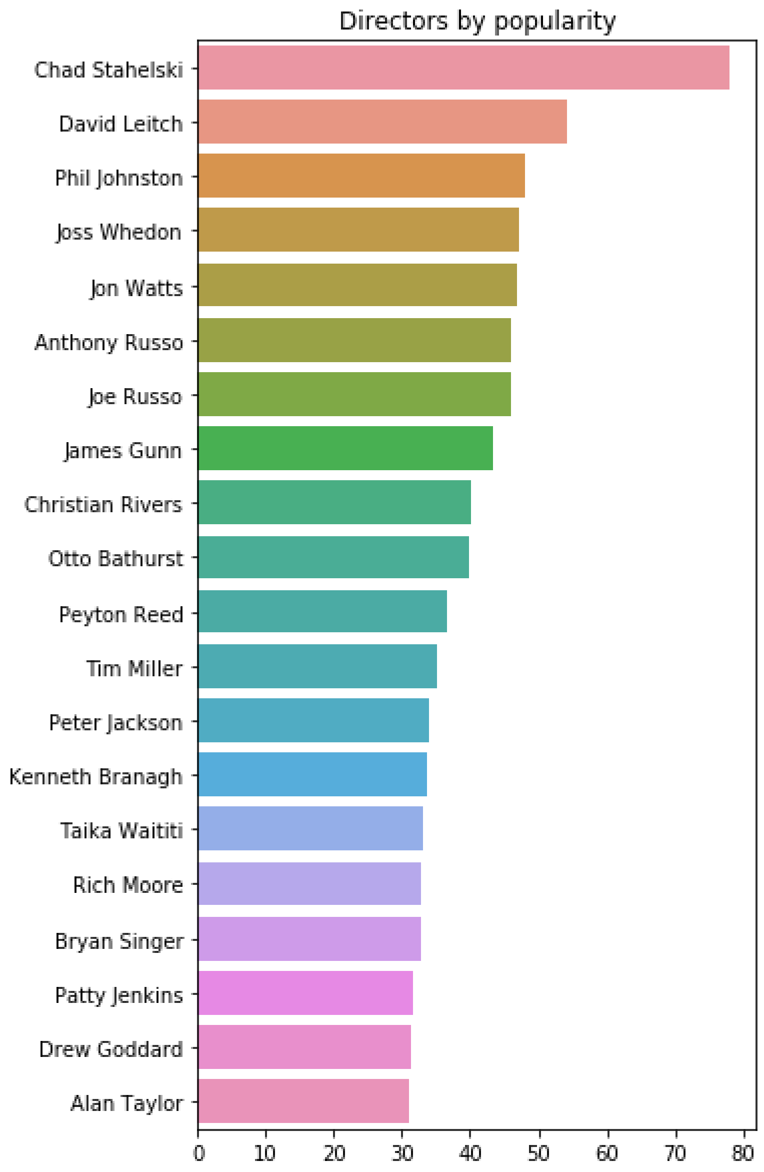
In [27]:
```
# Creates a list of dictionaries used in the create_top_df function.

df_list = [
    {'df':actors,'name':'Actors'},
    {'df': directors, 'name': 'Directors'},
    {'df': writers,'name':'Writers'},
    {'df': producers,'name':'Producers'}
]
```

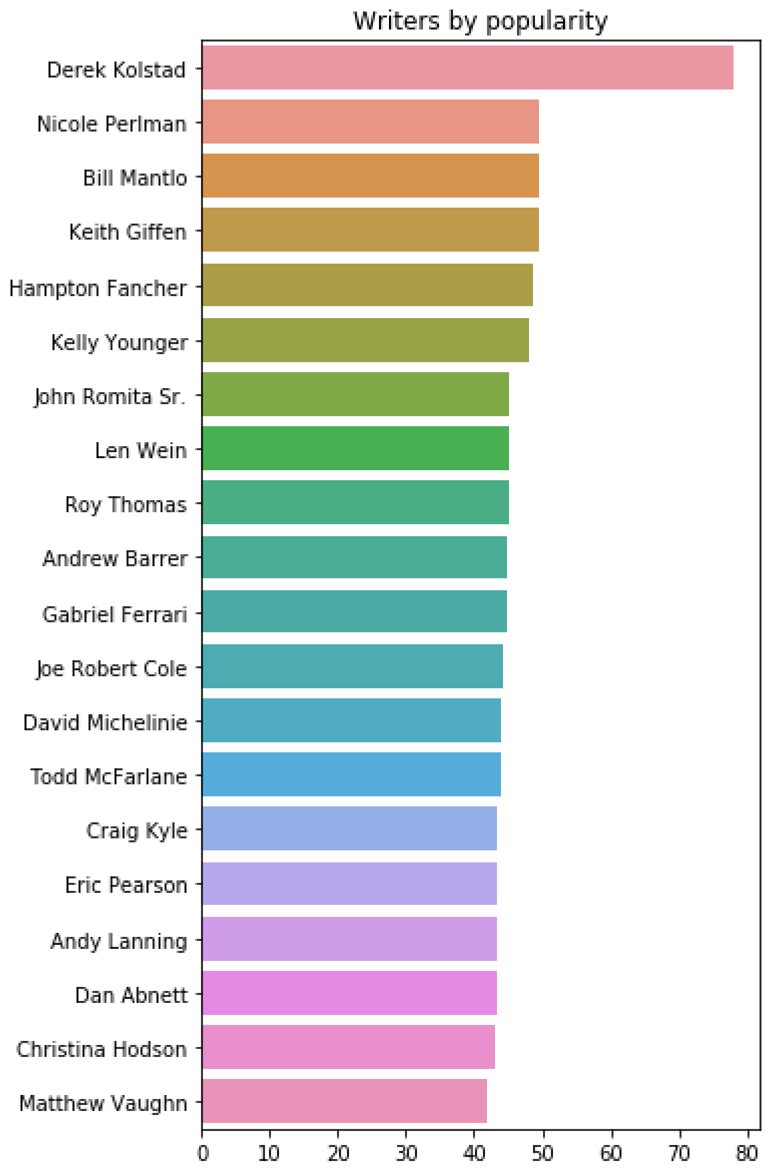
Crew By Popularity

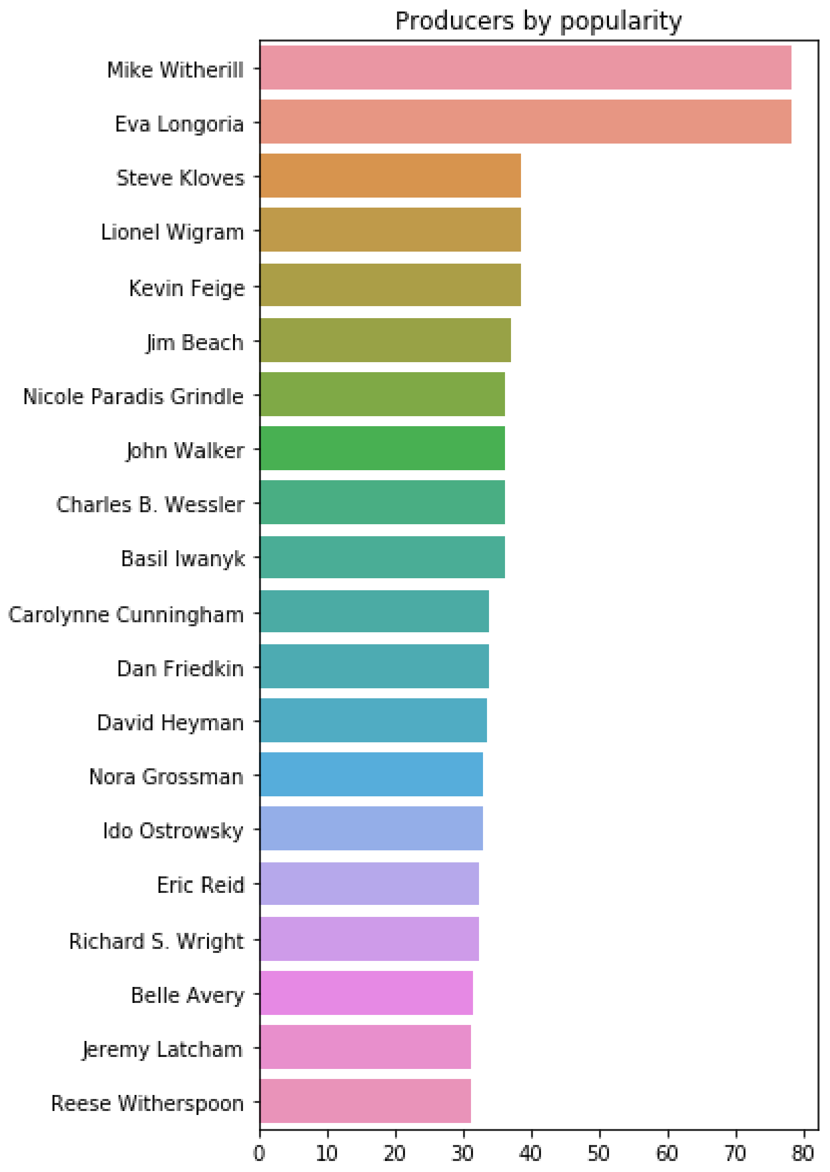
The follow charts are created by taking the mean of each actor's career using the movies in super_vote_df. Some big name actors can be in one or two very popular films, but have some flops too. Below are the actors, directors, writers and producers who have worked on the most popular films during their entire career.

In [28]:
```
column = 'popularity'

for i in range(len(df_list)):
    top_crew(df_list[i],f'{column}');
```


Actors by popularity
Alfie Allen
Michael Nyqvist
Dafne Keen
Lupita Nyong'o
Danai Gurira
Scott Haze
Patrick Stewart
Jason Drucker
Jorge Lendeborg Jr.
Dave Bautista
Hera Hilmar
Jihae
Willem Dafoe
Eve Hewson
Keanu Reeves
Dan Fogler
Ben Hardy
Lucy Boynton
Gwilym Lee
Rami Malek
0
10
20
30
40
50
60
70
80

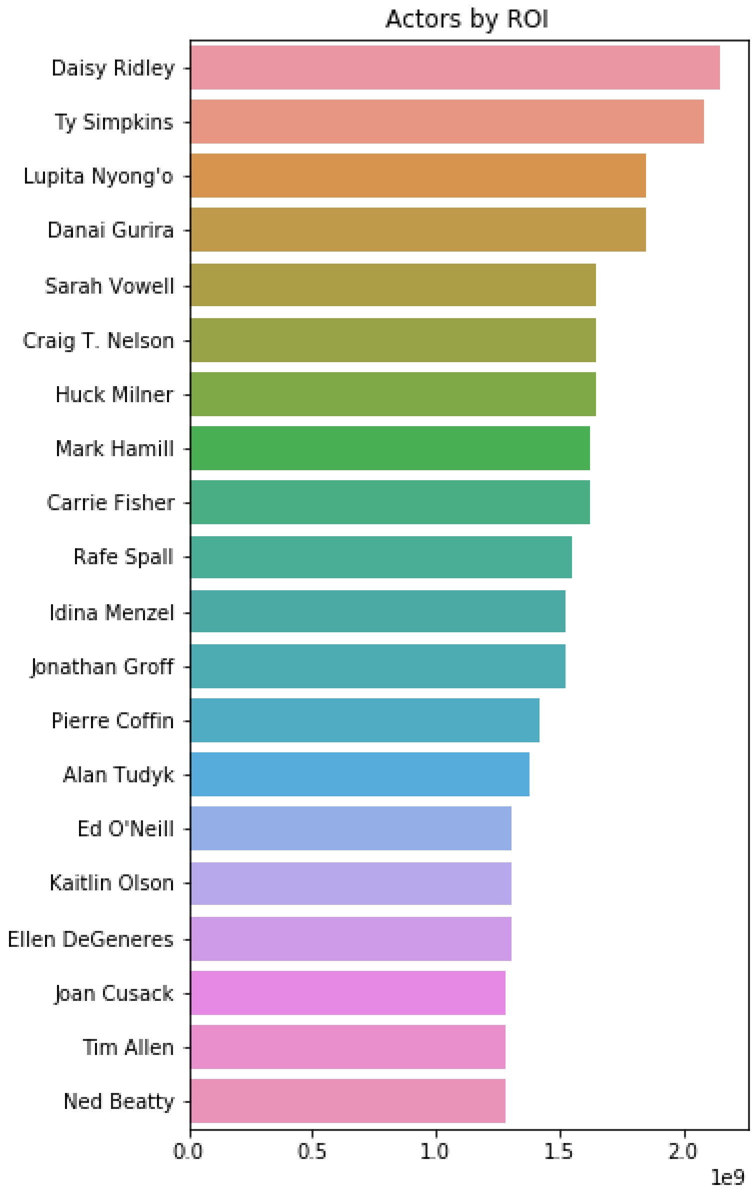

Directors by popularity
Chad Stahelski
David Leitch
Phil Johnston
Joss Whedon
Jon Watts
Anthony Russo
Joe Russo
James Gunn
Christian Rivers
Otto Bathurst
Peyton Reed
Tim Miller
Peter Jackson
Kenneth Branagh
Taika Waititi
Rich Moore
Bryan Singer
Patty Jenkins
Drew Goddard
Alan Taylor
0
10
20
30
40
50
60
70
80

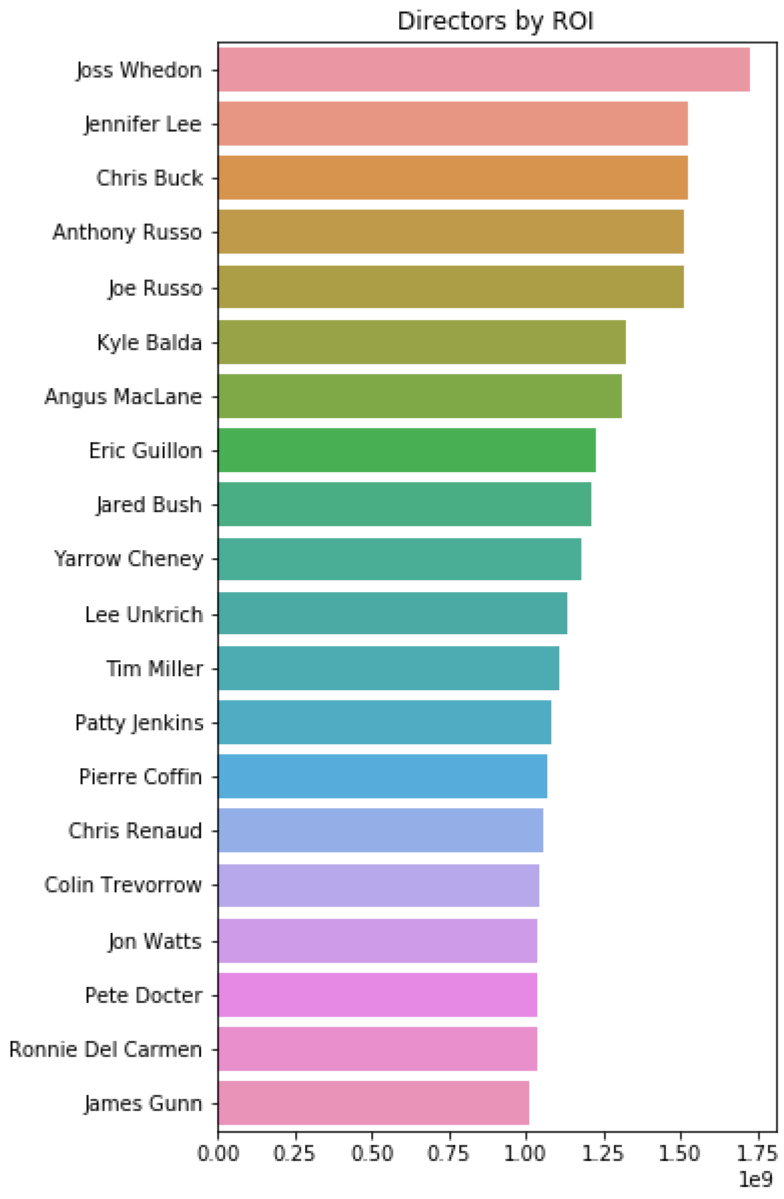

Writers by popularity
Derek Kolstad
Nicole Perlman
Bill Mantlo
Keith Giffen
Hampton Fancher
Kelly Younger
John Romita Sr.
Len Wein
Roy Thomas
Andrew Barrer
Gabriel Ferrari
Joe Robert Cole
David Michelinie
Todd McFarlane
Craig Kyle
Eric Pearson
Andy Lanning
Dan Abnett
Christina Hodson
Matthew Vaughn
0
10
20
30
40
50
60
70
80

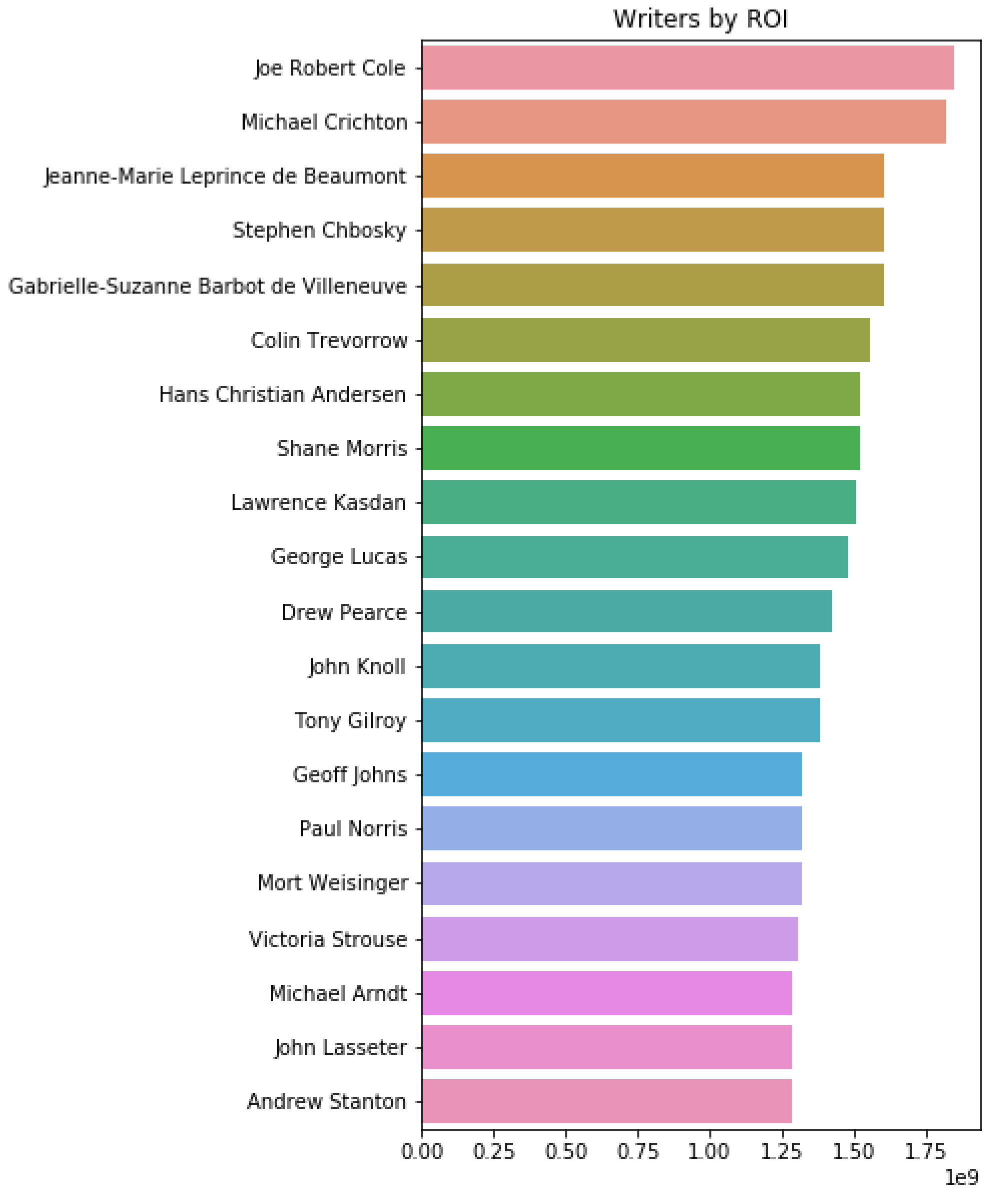


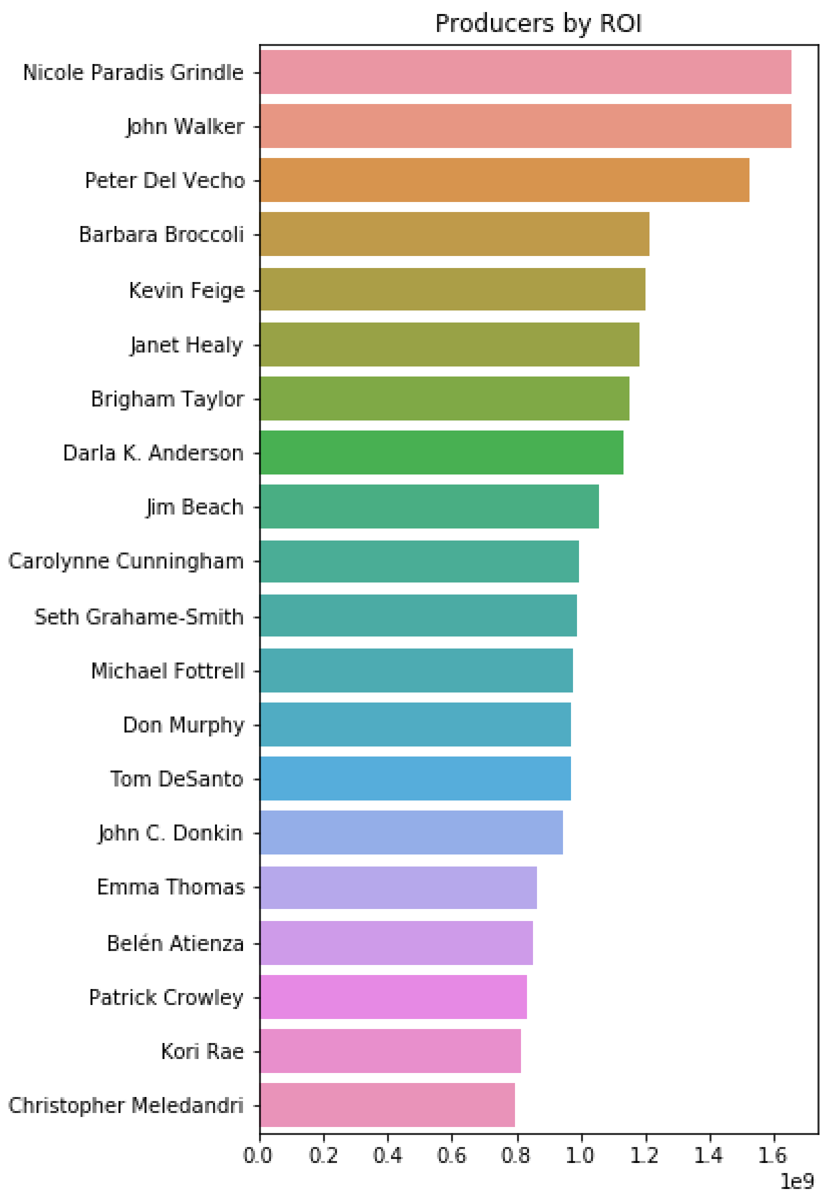
Crew by Return on Investment

In [29]:
```
column = 'ROI'

for i in range(len(df_list)):
    top_crew(df_list[i],f'{column}');
```


Actors by ROI
Daisy Ridley
Ty Simpkins
Lupita Nyong'o
Danai Gurira
Sarah Vowell
Craig T. Nelson
Huck Milner
Mark Hamill
Carrie Fisher
Rafe Spall
Idina Menzel
Jonathan Groff
Pierre Coffin
Alan Tudyk
Ed O'Neill
Kaitlin Olson
Ellen DeGeneres
Joan Cusack
Tim Allen
Ned Beatty
0.0
0.5
1.0
1.5
2.0
1e9

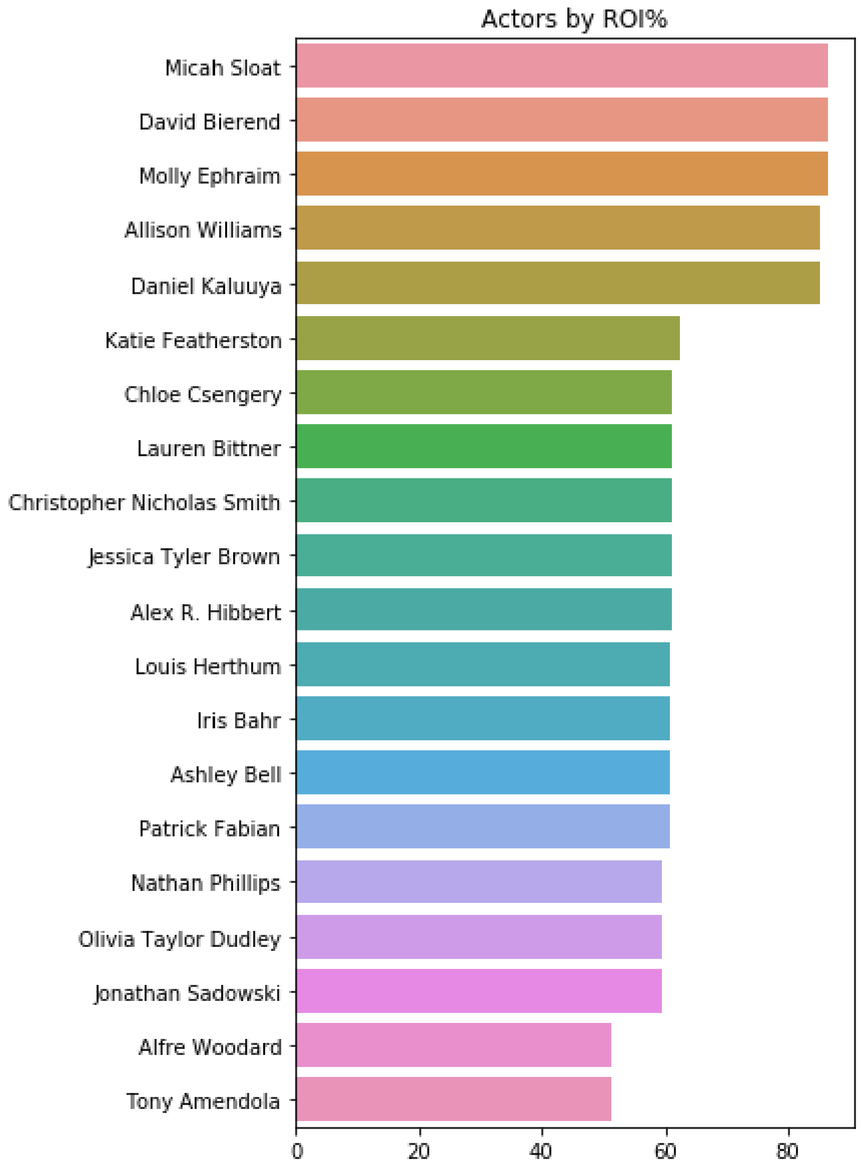

Directors by ROI
Joss Whedon
Jennifer Lee
Chris Buck
Anthony Russo
Joe Russo
Kyle Balda
Angus MacLane
Eric Guillon
Jared Bush
Yarrow Cheney
Lee Unkrich
Tim Miller
Patty Jenkins
Pierre Coffin
Chris Renaud
Colin Trevorrow
Jon Watts
Pete Docter
Ronnie Del Carmen
James Gunn
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e9

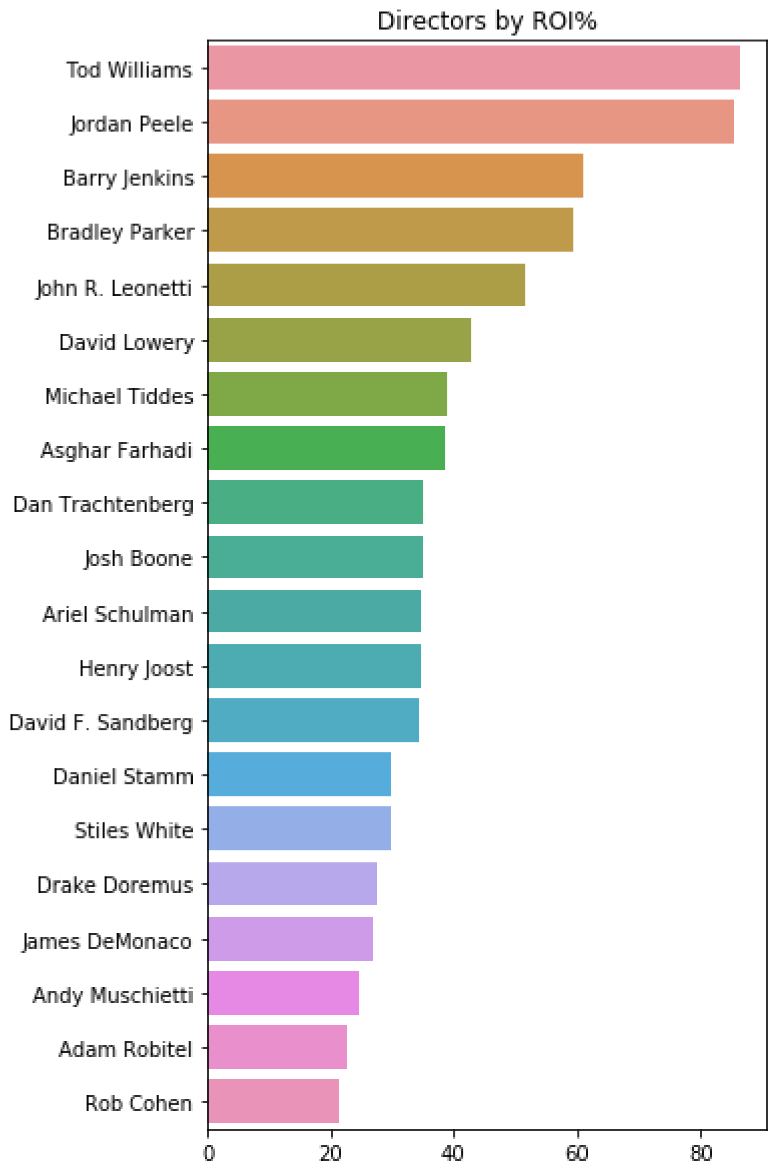

Writers by ROI
Joe Robert Cole
Michael Crichton
Jeanne-Marie Leprince de Beaumont
Stephen Chbosky
Gabrielle-Suzanne Barbot de Villeneuve
Colin Trevorrow
Hans Christian Andersen
Shane Morris
Lawrence Kasdan
George Lucas
Drew Pearce
John Knoll
Tony Gilroy
Geoff Johns
Paul Norris
Mort Weisinger
Victoria Strouse
Michael Arndt
John Lasseter
Andrew Stanton
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e9

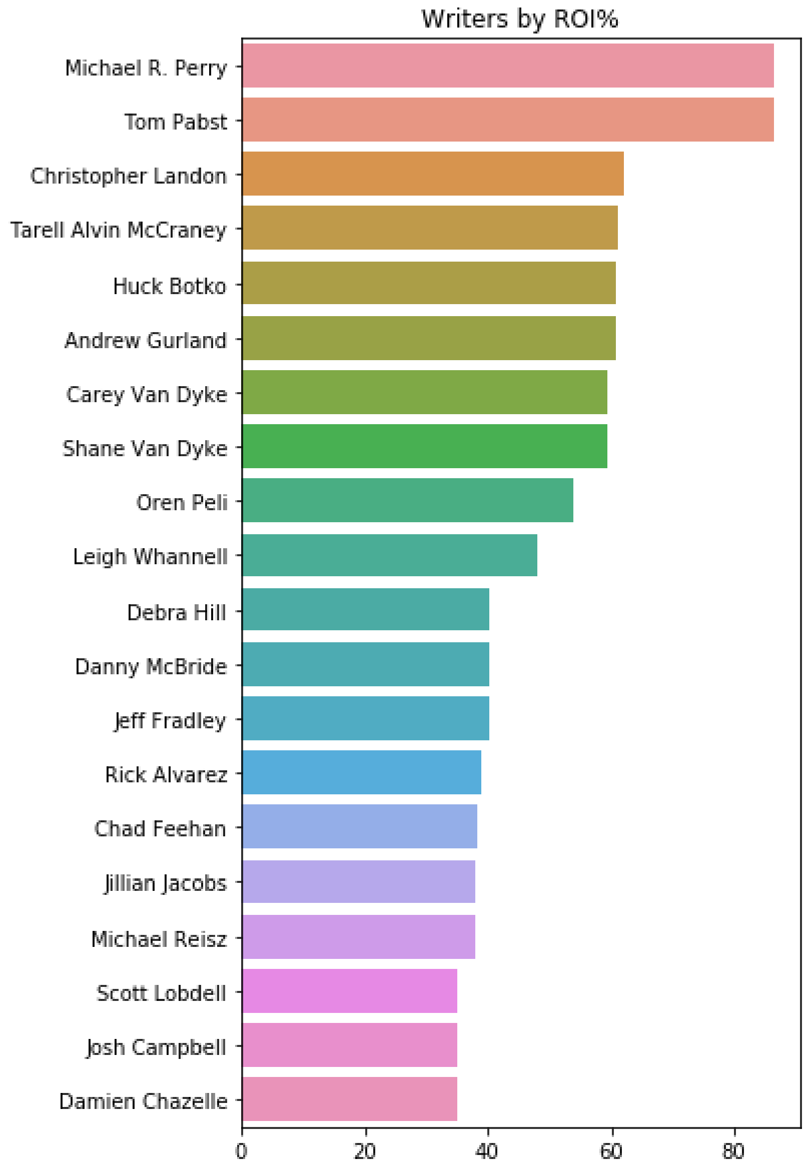

Producers by ROI
Nicole Paradis Grindle
John Walker
Peter Del Vecho
Barbara Broccoli
Kevin Feige
Janet Healy
Brigham Taylor
Darla K. Anderson
Jim Beach
Carolynne Cunningham
Seth Grahame-Smith
Michael Fottrell
Don Murphy
Tom DeSanto
John C. Donkin
Emma Thomas
Belén Atienza
Patrick Crowley
Kori Rae
Christopher Meledandri
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1e9

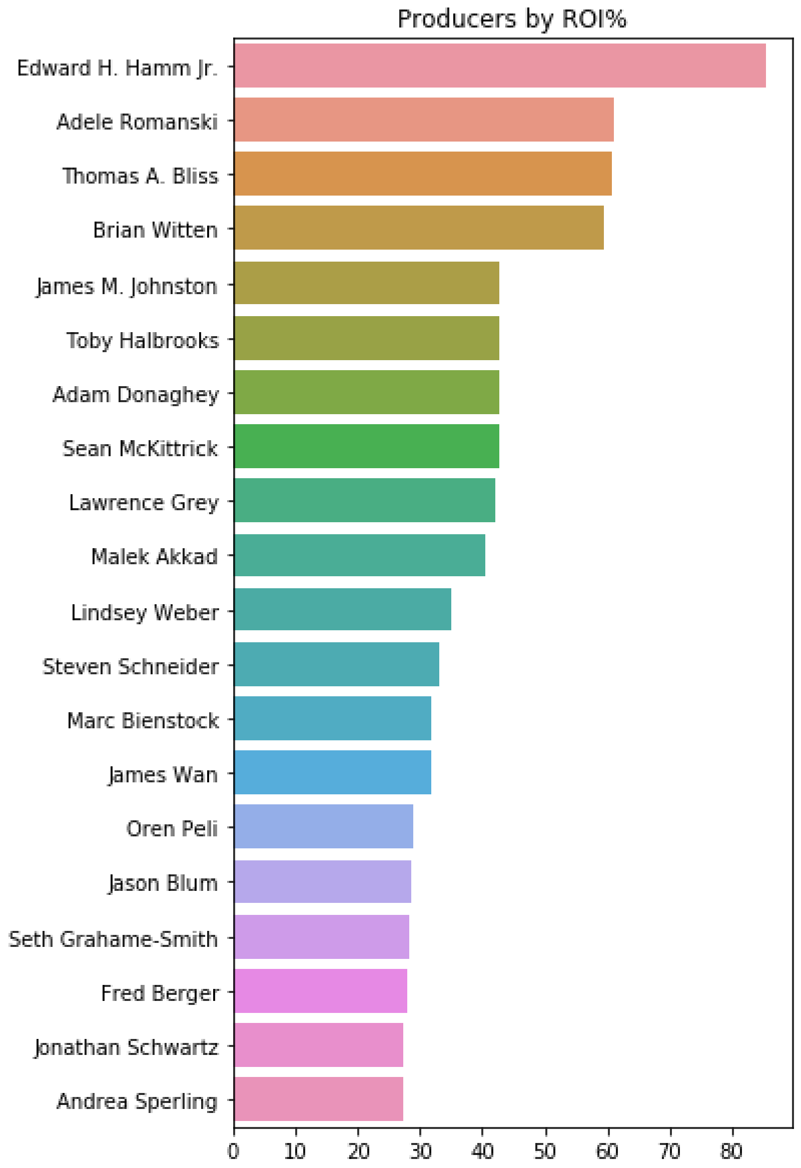
Crew by ROI%

In [30]:
```
column = 'ROI%'

for i in range(len(df_list)):
    top_crew(df_list[i],f'{column}');
```


Actors by ROI%
Micah Sloat
David Bierend
Molly Ephraim
Allison Williams
Daniel Kaluuya
Katie Featherston
Chloe Csengery
Lauren Bittner
Christopher Nicholas Smith
Jessica Tyler Brown
Alex R. Hibbert
Louis Herthum
Iris Bahr
Ashley Bell
Patrick Fabian
Nathan Phillips
Olivia Taylor Dudley
Jonathan Sadowski
Alfre Woodard
Tony Amendola
0
20
40
60
80

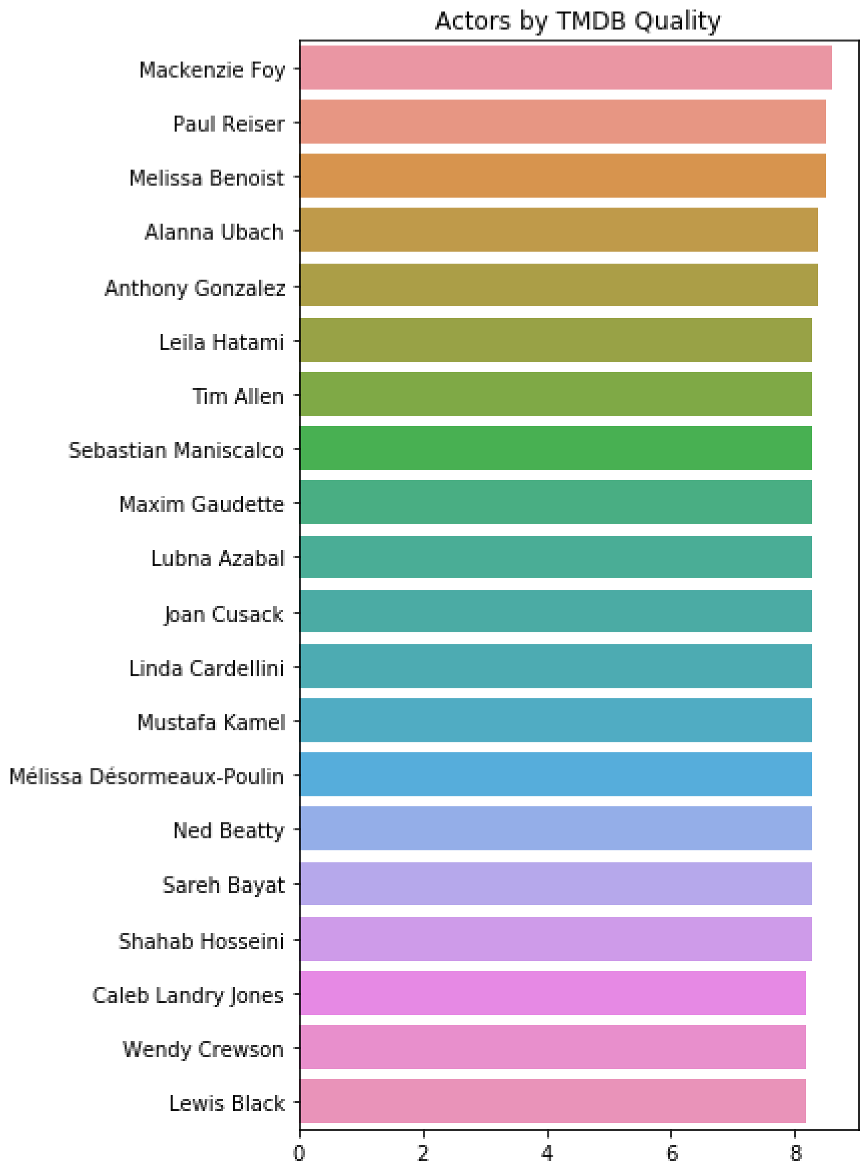

Directors by ROI%
Tod Williams
Jordan Peele
Barry Jenkins
Bradley Parker
John R. Leonetti
David Lowery
Michael Tiddes
Asghar Farhadi
Dan Trachtenberg
Josh Boone
Ariel Schulman
Henry Joost
David F. Sandberg
Daniel Stamm
Stiles White
Drake Doremus
James DeMonaco
Andy Muschietti
Adam Robitel
Rob Cohen
0
20
40
60
80

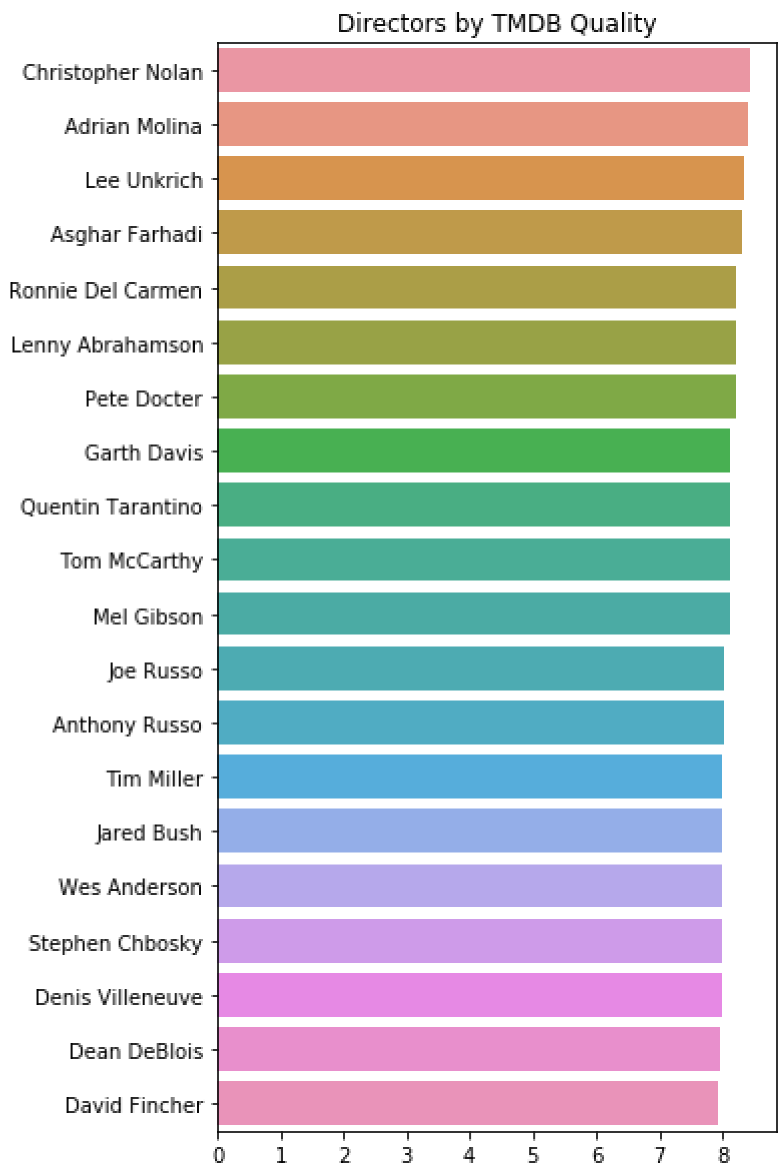

Writers by ROI%
Michael R. Perry
Tom Pabst
Christopher Landon
Tarell Alvin McCraney
Huck Botko
Andrew Gurland
Carey Van Dyke
Shane Van Dyke
Oren Peli
Leigh Whannell
Debra Hill
Danny McBride
Jeff Fradley
Rick Alvarez
Chad Feehan
Jillian Jacobs
Michael Reisz
Scott Lobdell
Josh Campbell
Damien Chazelle
0
20
40
60
80

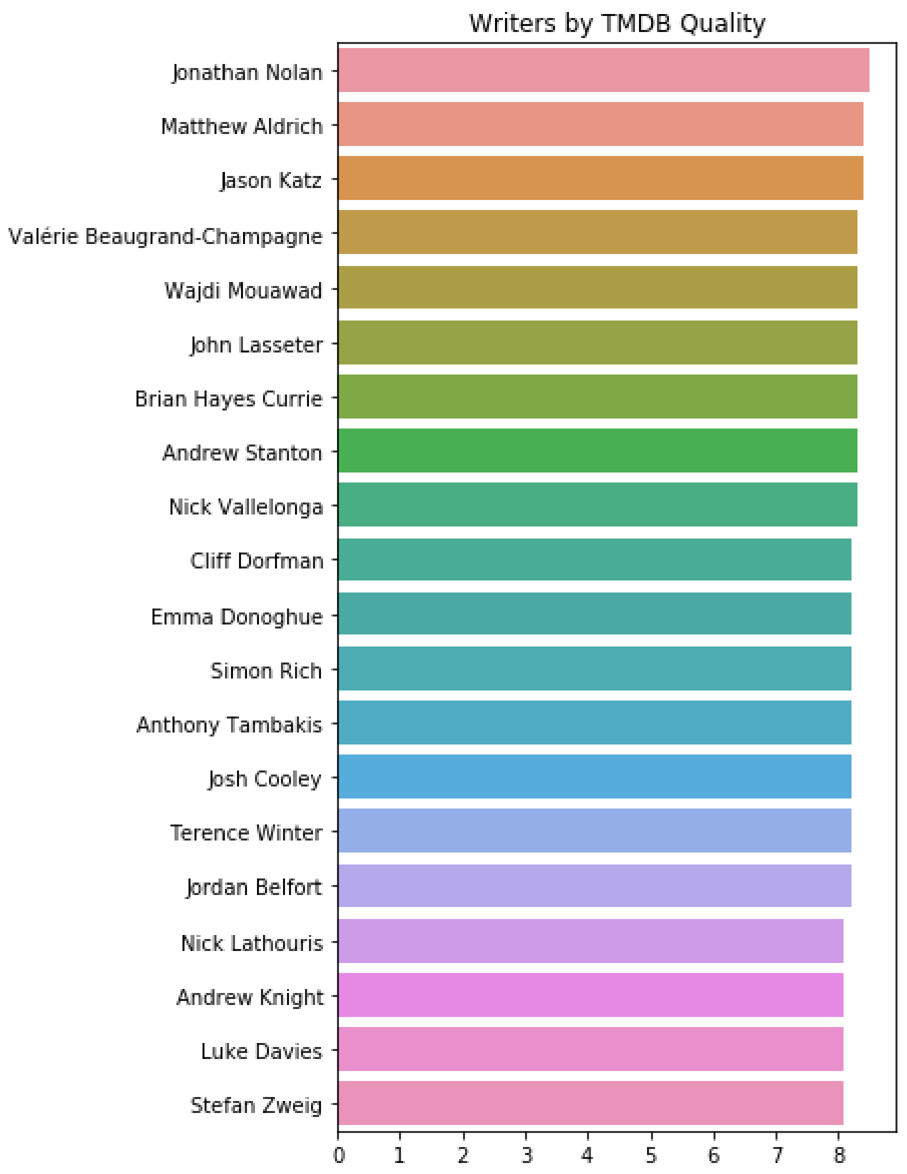


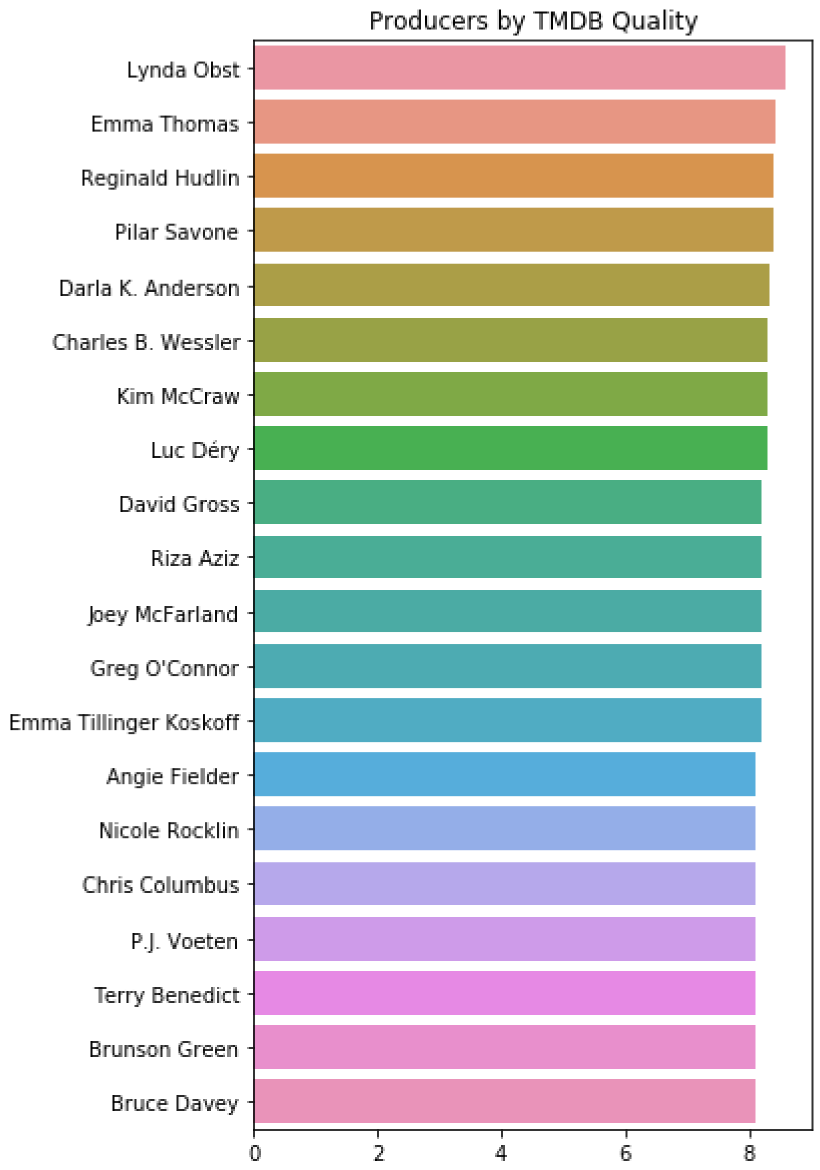
Crew by TMDB Quality

In [31]:
```
column = 'TMDB Quality'

for i in range(len(df_list)):
    top_crew(df_list[i],f'{column}');
```


Actors by TMDB Quality
Mackenzie Foy
Paul Reiser
Melissa Benoist
Alanna Ubach
Anthony Gonzalez
Leila Hatami
Tim Allen
Sebastian Maniscalco
Maxim Gaudette
Lubna Azabal
Joan Cusack
Linda Cardellini
Mustafa Kamel
Mélissa Désormeaux-Poulin
Ned Beatty
Sareh Bayat
Shahab Hosseini
Caleb Landry Jones
Wendy Crewson
Lewis Black
0
2
4
6
8


Directors by TMDB Quality
Christopher Nolan
Adrian Molina
Lee Unkrich
Asghar Farhadi
Ronnie Del Carmen
Lenny Abrahamson
Pete Docter
Garth Davis
Quentin Tarantino
Tom McCarthy
Mel Gibson
Joe Russo
Anthony Russo
Tim Miller
Jared Bush
Wes Anderson
Stephen Chbosky
Denis Villeneuve
Dean DeBlois
David Fincher
0
1
2
3
4
5
6
7
8


Writers by TMDB Quality
Jonathan Nolan
Matthew Aldrich
Jason Katz
Valérie Beaugrand-Champagne
Wajdi Mouawad
John Lasseter
Brian Hayes Currie
Andrew Stanton
Nick Vallelonga
Cliff Dorfman
Emma Donoghue
Simon Rich
Anthony Tambakis
Josh Cooley
Terence Winter
Jordan Belfort
Nick Lathouris
Andrew Knight
Luke Davies
Stefan Zweig
0
1
2
3
4
5
6
7
8


Producers by TMDB Quality
Lynda Obst
Emma Thomas
Reginald Hudlin
Pilar Savone
Darla K. Anderson
Charles B. Wessler
Kim McCraw
Luc Déry
David Gross
Riza Aziz
Joey McFarland
Greg O'Connor
Emma Tillinger Koskoff
Angie Fielder
Nicole Rocklin
Chris Columbus
P.J. Voeten
Terry Benedict
Brunson Green
Bruce Davey
0
2
4
6
8

Conclusions and Exporting the Data

Below you will find the data that was visualization above expanded on and ordered into Dataframes for export into other file formats. For each of the following categories, these are the top 30 artists that you should hire to maximize each metric. While many of the names might seem obscure, these tend to be seasoned veterans in the industry who have worked on some of the most successful films and franchises of all time.

It is clear that any successful streaming service has a wealth of content when it goes live, both original creations and licensed films from other studios. The following conclusions will address each metric we have analyzed and give suggestions for production.

Conclusion Number 1 - Popularity

First and foremost, movies need to be popular if they expect to make a mark on the streaming market. From the genre analysis, the most popular movies tend to:

- Be Action/Adventure Science Fiction Movies
- Have a high budget (typically greater than 200 million dollars)

Below is a list of directors, actors, producers and writers who have proven to create popular work. Examples of content like this include:

- Stranger Things (Netflix)
- Jack Ryan (Amazon)
- Game of Thrones (HBO)

```
In [32]: create_top_df(df_list,'popularity')
```

Out[32]:

By Popularity	Actors	Directors	Writers	Producers
0	Alfie Allen	Chad Stahelski	Derek Kolstad	Mike Witherill
1	Michael Nyqvist	David Leitch	Nicole Perlman	Eva Longoria
2	Dafne Keen	Phil Johnston	Bill Mantlo	Steve Kloves
3	Lupita Nyong'o	Joss Whedon	Keith Giffen	Lionel Wigram
4	Danai Gurira	Jon Watts	Hampton Fancher	Kevin Feige
5	Scott Haze	Anthony Russo	Kelly Younger	Jim Beach
6	Patrick Stewart	Joe Russo	John Romita Sr.	Nicole Paradis Grindle
7	Jason Drucker	James Gunn	Len Wein	John Walker
8	Jorge Lendeborg Jr.	Christian Rivers	Roy Thomas	Charles B. Wessler
9	Dave Bautista	Otto Bathurst	Andrew Barrer	Basil Iwanyk
10	Hera Hilmar	Peyton Reed	Gabriel Ferrari	Carolynne Cunningham
11	Jihae	Tim Miller	Joe Robert Cole	Dan Friedkin
12	Willem Dafoe	Peter Jackson	David Michelinie	David Heyman
13	Eve Hewson	Kenneth Branagh	Todd McFarlane	Nora Grossman
14	Keanu Reeves	Taika Waititi	Craig Kyle	Ido Ostrowsky
15	Dan Fogler	Rich Moore	Eric Pearson	Eric Reid
16	Ben Hardy	Bryan Singer	Andy Lanning	Richard S. Wright
17	Lucy Boynton	Patty Jenkins	Dan Abnett	Belle Avery
18	Gwilym Lee	Drew Goddard	Christina Hodson	Jeremy Latcham
19	Rami Malek	Alan Taylor	Matthew Vaughn	Reese Witherspoon
20	Morena Baccarin	David Yates	Jim Starlin	Dan Farah
21	Scott Adsit	Steven S. DeKnight	Steve Englehart	Cale Boyter
22	Ryan Potter	Stefano Sollima	Steve Gan	Deborah Forte
23	Jamie Chung	Jordan Vogt-Roberts	Zak Penn	Riza Aziz

	Actors	Directors	Writers	Producers
By Popularity				
24	Sarah Vowell	Gary Shore	Philip Reeve	Joey McFarland
25	Craig T. Nelson	Yorgos Lanthimos	Peter Jackson	Emma Tillinger Koskoff
26	Huck Milner	Travis Knight	David James Kelly	Simon Emanuel
27	Linda Cardellini	Gerard McMurray	Ben Chandler	Lee Magiday
28	Sebastian Maniscalco	Brad Bird	Christopher L. Yost	Ceci Dempsey
29	Ian McKellen	Espen Sandberg	Michael Dougherty	Lynda Obst

Conclusion 2 - Return on Investment with a Small Budget

Some of the most popular films of all time were also surprisingly cheap. While action adventure films will be the service's big ticket property, the studio should also focus resources on making popular small budget films. These films should be from one or many of the following genres:

- Drama
- Horror
- Thriller

Below you will find the top thirty writers, actors, directors and producers based on their career's return on investment as a percentage of initial production budget.

Examples of these films include:

- Get Out
- Roma (Netflix)

In [33]:
```
create_top_df(df_list,'ROI%')
```

Out[33]:

By Roi%	Actors	Directors	Writers	Producers
0	Micah Sloat	Tod Williams	Michael R. Perry	Edward H. Hamm Jr.
1	David Bierend	Jordan Peele	Tom Pabst	Adele Romanski
2	Molly Ephraim	Barry Jenkins	Christopher Landon	Thomas A. Bliss
3	Allison Williams	Bradley Parker	Tarell Alvin McCraney	Brian Witten
4	Daniel Kaluuya	John R. Leonetti	Huck Botko	James M. Johnston
5	Katie Featherston	David Lowery	Andrew Gurland	Toby Halbrooks
6	Chloe Csengery	Michael Tiddes	Carey Van Dyke	Adam Donaghey
7	Lauren Bittner	Asghar Farhadi	Shane Van Dyke	Sean McKittrick
8	Christopher Nicholas Smith	Dan Trachtenberg	Oren Peli	Lawrence Grey
9	Jessica Tyler Brown	Josh Boone	Leigh Whannell	Malek Akkad
10	Alex R. Hibbert	Ariel Schulman	Debra Hill	Lindsey Weber
11	Louis Herthum	Henry Joost	Danny McBride	Steven Schneider
12	Iris Bahr	David F. Sandberg	Jeff Fradley	Marc Bienstock
13	Ashley Bell	Daniel Stamm	Rick Alvarez	James Wan
14	Patrick Fabian	Stiles White	Chad Feehan	Oren Peli
15	Nathan Phillips	Drake Doremus	Jillian Jacobs	Jason Blum
16	Olivia Taylor Dudley	James DeMonaco	Michael Reisz	Seth Grahame-Smith
17	Jonathan Sadowski	Andy Muschietti	Scott Lobdell	Fred Berger
18	Alfre Woodard	Adam Robitel	Josh Campbell	Jonathan Schwartz
19	Tony Amendola	Rob Cohen	Damien Chazelle	Andrea Sperling
20	Ward Horton	Jeff Wadlow	Matthew Stuecken	Sébastien K. Lemercier
21	Adelaide Kane	Christopher Landon	Mark Heyman	Jamie Patricof
22	Max Burkholder	James Wan	Andres Heinz	Brad Fuller
23	Barbara Hershey	Tim Miller	Gary Dauberman	Tony DeRosa-Grund

By Roi%	Actors	Directors	Writers	Producers
24	Fred Dalton Thompson	Benh Zeitlin	Scott Beck	Benny Medina
25	Juliet Rylance	Michael Showalter	Bryan Woods	Andrew Form
26	Bradley Whitford	Kyle Balda	Cary Joji Fukunaga	Jordan Horowitz
27	McColm Cephas Jr.	Sam Taylor-Johnson	Chase Palmer	Gary Gilbert
28	Kenneisha Thompson	Ryan Coogler	Ben York Jones	Nora Grossman
29	Maria Bello	Eric Guillon	John Green	Ido Ostrowsky

Conclusion 3 - Prestige Films

The last category is one that rounds out a healthy slate of films is prestige movies (typically dramas). These movies and shows tend to garner the most attention from movie critics and award shows.

Below you will find the top thirty writers, actors, directors and producers based on their career's perceived quality by the viewing audience.

Examples include:

- Transparent (Amazon)
- House of Cards (Netflix)
- Big Little Lies (HBO)

In [34]:
```
create_top_df(df_list, 'TMDB Quality')
```

Out[34]:

	Actors	Directors	Writers	Producers
By Tmdb Quality				
0	Mackenzie Foy	Christopher Nolan	Jonathan Nolan	Lynda Obst
1	Paul Reiser	Adrian Molina	Matthew Aldrich	Emma Thomas
2	Melissa Benoist	Lee Unkrich	Jason Katz	Reginald Hudlin
3	Alanna Ubach	Asghar Farhadi	Valérie Beaugrand-Champagne	Pilar Savone
4	Anthony Gonzalez	Ronnie Del Carmen	Wajdi Mouawad	Darla K. Anderson
5	Leila Hatami	Lenny Abrahamson	John Lasseter	Charles B. Wessler
6	Tim Allen	Pete Docter	Brian Hayes Currie	Kim McCraw
7	Sebastian Maniscalco	Garth Davis	Andrew Stanton	Luc Déry
8	Maxim Gaudette	Quentin Tarantino	Nick Vallelonga	David Gross
9	Lubna Azabal	Tom McCarthy	Cliff Dorfman	Riza Aziz
10	Joan Cusack	Mel Gibson	Emma Donoghue	Joey McFarland
11	Linda Cardellini	Joe Russo	Simon Rich	Greg O'Connor
12	Mustafa Kamel	Anthony Russo	Anthony Tambakis	Emma Tillinger Koskoff
13	Mélissa Désormeaux-Poulin	Tim Miller	Josh Cooley	Angie Fielder
14	Ned Beatty	Jared Bush	Terence Winter	Nicole Rocklin
15	Sareh Bayat	Wes Anderson	Jordan Belfort	Chris Columbus
16	Shahab Hosseini	Stephen Chbosky	Nick Lathouris	P.J. Voeten
17	Caleb Landry Jones	Denis Villeneuve	Andrew Knight	Terry Benedict
18	Wendy Crewson	Dean DeBlois	Luke Davies	Brunson Green
19	Lewis Black	David Fincher	Stefan Zweig	Bruce Davey
20	Jennifer Morrison	Taika Waititi	Saroo Brierley	Paul Currie
21	Sean Bridgers	Dan Gilroy	Len Wein	Doug Mitchell
22	Sunny Pawar	Michael Haneke	Keith Giffen	Adam Kolbrenner
23	F. Murray Abraham	Ang Lee	Brendan McCarthy	Andrew Eaton

By Tmdb Quality	Actors	Directors	Writers	Producers
24	Michael Kenneth Williams	Byron Howard	Solomon Northup	Kira Davis
25	Mathieu Amalric	Michel Hazanavicius	Nicole Perlman	Blye Pagon Faust
26	Dafne Keen	Alejandro G. Iñárritu	Robert Schenkkan	Reese Witherspoon
27	Patrick Stewart	James Gunn	Roy Thomas	Fred Berger
28	Izabela Vidovic	Damien Chazelle	Hugo Guinness	Rachel Winter
29	Jenny Slate	Kenneth Lonergan	Adam F. Goldberg	Ido Ostrowsky

Areas of Further Study

My next goal is to attempt to analyze current streaming libraries on each service's platform to determine what percentage of their overall content offering belongs to the categories listed above. I'm also interested in trying to determine the success of certain tv shows based on the number of seasons it receives from the studio and how much their budget increases season over season. Data on streaming success is notorious difficult to ascertain, but we can draw conclusions about audience numbers based on how willing major streaming studios are to throw money at an intellectual property.

```
In [ ]:
```