Microsoft Movie Analysis

Author: Nurgul Kurbanli kyzy

Project overview

I have been charged with exploring what types of films are currently doing the best at the box office then translating those findings into actionable insights that the head of Microsoft's new movie studio can use to help decide what type of films to create. Based on the datasets available have been found as a successful movie genres are fantasy, mystery and horror that production budget over the 1 million dollars. The most profitable movie directors - Francis Lawrence, Kenneth Branagh, Zack Snyder, and screenwriters - Brian Lynch, Christopher Nolan, Jack Kirby that produced more than 5 movies each. Microsoft can use this analysis to target their genres, movie directors, and screenwriters of their upcoming movie endeavors to earn the highest amount of revenue possible.

Business Problem

Most of the big companies were creating an original video content. Microsoft also wanted to try its hand at this field by creating its own movie studio. Even though they were willing to invest, they were not sure where to start, without having enough knowledge about the movie industry. To help Microsoft, I was instructed to study which types of films are currently showing the best results at the box office, and translate my findings into actionable insights that the head of Microsoft can decide what the content of the studio shoul be. There are many aspects of films that can affect to profitability, having studied them, I based my analysis on three main factors:

- **Movie Genres** (categories that define a movie based on its narrative elements): Which genres of movie content are currently the most successful in terms of their return on investment (ROI)?
- **Movie Directors** (gives a film creative direction by guiding actors through each scene): Who are the top directors from the standpoint of movies profitability?
- **Movie Writers** (writes movie scripts or screenplays): Who are the top screenwriters in terms of the movies' average profit?

I assume that the answers to these questions are one of the main parts of the steps that should be taken into account to create the most cost-effective film in the digital world.

Data Understanding

I used two different movie data sources for my analysis to get the broadest view of the movie industry

- *The Numbers* - film industry data website that tracks box office revenue in a systematic, algorithmic way. The first pre-unfiltered dataset tn_movies is in the format of compressed CSV file. Dataset contains 5782 values for movies' release date, title, production budget, domestic gross, and worldwide gross in dollars.Since most of the column attributes contained numeric values, movies' profit and return on investment has been calculated based on this dataset
- *Internet Movie Database (IMDB)* - website that provides information about millions of films and television programs as well as their cast and crew. The second dataset IMDB is located in a SQLite database. For the purpose of my analysis I eliminated several SQL tables that are peoples (basic information about the people that were involved to the particular movies), directors, writers, movie basics. They all were related to each other throughout the movie_id.

In [1]:
```
# Importing requred packages for my analysis
import pandas as pd
pd.options.display.float_format = '{:.2f}'.format  # pandas display setting to not display sceintific notation
import sqlite3

# Data Visualization packages
import matplotlib.pyplot as plt
%matplotlib inline
```

```
import seaborn as sns
import altair as alt
```

The Numbers Data

In [2]:
```
# reading the csv file
tn_movies = pd.read_csv('./data/tn.movie_budgets.csv.gz')
# getting info for DataFrame
tn_movies.info()
# previewing the DataFrame
tn_movies.head()
```

```
<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
```

Out[2]:

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

Based on the preview the dollar amounts for production budget, domestic and worldwide gross was pulled as an objects (not float/integer). This requires further adjusting in the next stages.

IMDB Data

In [3]:
```
# connceting to SQL file
conn = sqlite3.connect('./data/im.db')
```

In [4]:
```
# reading SQL file
imdb_genres = pd.read_sql('''
 SELECT *
 FROM movie_basics

;''', conn)
```

In [5]:
```
# getting info for DataFrame
imdb_genres.info()

# previewing the DataFrame
imdb_genres.head()
```

```
<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
```

Out[5]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.00	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00	Comedy,Drama,Fantasy

In [6]:
```
# reading sql files
imdb_direc = pd.read_sql('''
 SELECT primary_name, movie_id
 FROM persons
 JOIN directors
 ON persons.person_id = directors.person_id

;''', conn)
```

In [7]:
```
# getting info for DataFrame
imdb_direc.info()

# previewing the DataFrame
imdb_direc.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 291171 entries, 0 to 291170
Data columns (total 2 columns):
 #   Column        Non-Null Count   Dtype 
---  ------        --------------   ----- 
 0   primary_name  291171 non-null  object
 1   movie_id      291171 non-null  object
dtypes: object(2)
memory usage: 4.4+ MB
```

Out[7]:

	primary_name	movie_id
0	Ruel S. Bayani	tt1592569
1	Ruel S. Bayani	tt1592569
2	Ruel S. Bayani	tt1592569
3	Ruel S. Bayani	tt1592569
4	Ruel S. Bayani	tt2057445

In [8]:
```
# reading sql files
imdb_write = pd.read_sql('''
 SELECT primary_name, movie_id
 FROM persons
 JOIN writers
 ON persons.person_id = writers.person_id


;''', conn)
```

In [9]:
```
# getting info for DataFrame
imdb_write.info()

# previewing the DataFrame
imdb_write.head(20)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 255871 entries, 0 to 255870
```

```
Data columns (total 2 columns):
 #   Column        Non-Null Count   Dtype 
---  ------        --------------   ----- 
 0   primary_name  255871 non-null  object
 1   movie_id      255871 non-null  object
dtypes: object(2)
memory usage: 3.9+ MB
```

Out[9]:

	primary_name	movie_id
0	Bryan Beasley	tt3501180
1	Michael Frost Beckner	tt6349302
2	Hava Kohav Beller	tt7701650
3	Joel Bender	tt3790232
4	Joel Bender	tt3790232
5	Doug Benson	tt1975283
6	Joe Berlinger	tt3137552
7	Joe Berlinger	tt6794462
8	Jamie Bernstein	tt4601198
9	Dusty Bias	tt1374996
10	Dusty Bias	tt4794754
11	Claudio Bigagli	tt2299792
12	Miro Bilbrough	tt2012110
13	Fernando Birri	tt1854526
14	Sam Bisbee	tt1651065
15	Sam Bisbee	tt1925466
16	Bob Blagden	tt1712204
17	Maurice Blanchot	tt7781736
18	Maurice Blanchot	tt9173540
19	Maurice Blanchot	tt9173540

Data Preparation

In this step, I will ensure accuracy in the data by cleaning and transforming raw data into a form that can readily and accurately be analyzed.

Data Cleaning

In [10]:
```
# displaying all column names
tn_movies.columns
```

Out[10]:
```
Index(['id', 'release_date', 'movie', 'production_budget', 'domestic_gross',
       'worldwide_gross'],
      dtype='object')
```

In [11]:
```
# dropping unnecessary columns
tn_movies.drop(['id', 'release_date','domestic_gross'], axis=1, inplace=True)
```

In [12]:
```
# renaming the column
tn_movies.rename(columns = {'movie':'title'}, inplace = True)
```

In [13]:
```
# removing dollar signs and commas from dollar amounts
tn_movies['production_budget'] = [str(i).replace("$", "") for i in tn_movies['production_budget']]
tn_movies['production_budget'] = tn_movies['production_budget'].apply(lambda x: str(x).replace(',','') )
# converting dollar amounts from strings into integers
tn_movies['production_budget'] = tn_movies['production_budget'].astype(int)
```

In [14]:
```
# preview the cleaned values
tn_movies['production_budget'].head()
```

Out[14]:
```
0    425000000
1    410600000
2    350000000
3    330600000
4    317000000
Name: production_budget, dtype: int32
```

In [15]:
```
# removing dollar signs and commas from dollar amounts
tn_movies['worldwide_gross'] = [str(i).replace("$", "") for i in tn_movies['worldwide_gross']]
tn_movies['worldwide_gross'] = [str(i).replace(",", "") for i in tn_movies['worldwide_gross']]
# converting dollar amounts from strings into float
tn_movies['worldwide_gross'] = tn_movies['worldwide_gross'].astype(float)
```

In [16]:
```
# preview cleaned bottom values
```

```
tn_movies['worldwide_gross'].tail()
```

Out[16]:
```
5777         0.00
5778    240495.00
5779      1338.00
5780         0.00
5781    181041.00
Name: worldwide_gross, dtype: float64
```

In [17]:
```
# dropping column values that contain 0.0 in it
tn_movies.drop(tn_movies.loc[tn_movies['worldwide_gross']==0.0].index, inplace=True)
```

In [18]:
```
# checking number of duplicate values
imdb_direc.duplicated().sum()
```

Out[18]:
```
127876
```

In [19]:
```
# dropping duplicate values
imdb_direc.drop_duplicates()
```

Out[19]:

	primary_name	movie_id
0	Ruel S. Bayani	tt1592569
4	Ruel S. Bayani	tt2057445
7	Ruel S. Bayani	tt2590280
8	Ruel S. Bayani	tt8421806
10	Bryan Beasley	tt3501180
...	...	...
291164	Zheng Wei	tt8697720
291165	Rama Narayanan	tt8715016
291167	Rama Narayanan	tt8919136
291168	Samir Eshra	tt8717234
291169	Pegasus Envoyé	tt8743182

163295 rows × 2 columns

In [20]:
```
imdb_direc.rename(columns = {'primary_name':'direc_name'}, inplace = True)
```

In [21]:
```
# checking number of duplicate values
imdb_write.duplicated().sum()
```

Out[21]:
```
77763
```

In [22]:
```
# dropping duplicate values
imdb_write.drop_duplicates().head()
```

Out[22]:

	primary_name	movie_id
0	Bryan Beasley	tt3501180
1	Michael Frost Beckner	tt6349302
2	Hava Kohav Beller	tt7701650
3	Joel Bender	tt3790232
5	Doug Benson	tt1975283

In [23]:
```
imdb_write.rename(columns = {'primary_name':'writer_name'}, inplace = True)
```

In [24]:
```
# dropping null values
imdb_write.dropna(subset=['writer_name'],inplace=True)
imdb_write.isnull().sum()
```

Out[24]:
```
writer_name    0
movie_id       0
dtype: int64
```

In [25]:
```
# checking for null values in the DataFrame
imdb_genres.isnull().sum()
```

Out[25]:
```
movie_id               0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres              5408
dtype: int64
```

In [26]:
```
# dropping the null values
imdb_genres.dropna(subset=['genres'], inplace=True)
```

In [27]:
```
imdb_genres.isnull().sum()
```

Out[27]:
```
movie_id               0
primary_title          0
original_title         2
start_year             0
runtime_minutes    28503
genres                 0
dtype: int64
```

In [28]:
```
# dropping unnecessary columns
imdb_genres.drop(['primary_title', 'start_year','runtime_minutes'], axis=1, inplace=True)
```

Data Merging

In [29]:
```
# merging tables based on their movie id key values
direc_genre = pd.merge(imdb_direc, imdb_genres, how="inner", on='movie_id')
direc_genre.head()
```

Out[29]:

	direc_name	movie_id	original_title	genres
0	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance
1	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance
2	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance
3	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance
4	Ruel S. Bayani	tt2057445	No Other Woman	Drama,Romance,Thriller

In [30]:
```
dir_genre_wrt = pd.merge(direc_genre, imdb_write, how="inner", on='movie_id')
dir_genre_wrt
```

Out[30]:

	direc_name	movie_id	original_title	genres	writer_name
0	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance	Henry King Quitain
1	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance	Kriz G. Gazmen
2	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance	Ralph Jacinto Quiblat
3	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance	Camille Andrea Mangampat
4	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance	Henry King Quitain

	direc_name	movie_id	original_title	genres	writer_name
...	...	...	...	...	...
47571101	Abu Iddris	tt8574516	HashTag	Thriller	Abu Iddris
47571102	Tisha Griffith	tt8574866	Black Girl Magic the Documentary	Documentary	Tisha Griffith
47571103	Roberto Farías	tt8274328	Perkin	Drama	Roberto Farías
47571104	Rich Allen	tt8685584	Home Cookin: 5.17.18	Biography,Comedy,Family	Rich Allen
47571105	Samir Eshra	tt8717234	The Shadow Lawyers	Documentary	Samir Eshra

47571106 rows × 5 columns

In [31]:
```
dir_genre_wrt.drop_duplicates(subset='movie_id', keep="first", inplace=True)
dir_genre_wrt
```

Out[31]:

	direc_name	movie_id	original_title	genres	writer_name
0	Ruel S. Bayani	tt1592569	Paano na kaya	Drama,Romance	Henry King Quitain
16	Ruel S. Bayani	tt2057445	No Other Woman	Drama,Romance,Thriller	Ricardo Fernando III
25	Ruel S. Bayani	tt2590280	One More Try	Drama	Xiaoshuai Wang
26	Bryan Beasley	tt3501180	The Quiet Philanthropist: The Edith Gaylord Story	Documentary,History	Bryan Beasley
27	Hans Beimler	tt2098699	Haraka	Drama	Simon Lebsekal
...	...	...	...	...	...
47571101	Abu Iddris	tt8574516	HashTag	Thriller	Abu Iddris
47571102	Tisha Griffith	tt8574866	Black Girl Magic the Documentary	Documentary	Tisha Griffith
47571103	Roberto Farías	tt8274328	Perkin	Drama	Roberto Farías
47571104	Rich Allen	tt8685584	Home Cookin: 5.17.18	Biography,Comedy,Family	Rich Allen
47571105	Samir Eshra	tt8717234	The Shadow Lawyers	Documentary	Samir Eshra

106970 rows × 5 columns

In [32]:
```
# merging tables based on the movies' title
final_df = pd.merge(tn_movies, dir_genre_wrt, how="inner",left_on='title', right_on='original_title')
```

```
final_df.head()
```

Out[32]:

	title	production_budget	worldwide_gross	direc_name	movie_id	original_title	genres	writer_name
0	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875.00	Rob Marshall	tt1298650	Pirates of the Caribbean: On Stranger Tides	Action,Adventure,Fantasy	Terry Rossio
1	Dark Phoenix	350000000	149762350.00	Simon Kinberg	tt6565702	Dark Phoenix	Action,Adventure,Sci-Fi	Jack Kirby
2	Avengers: Age of Ultron	330600000	1403013963.00	Joss Whedon	tt2395427	Avengers: Age of Ultron	Action,Adventure,Sci-Fi	Jack Kirby
3	Avengers: Infinity War	300000000	2048134200.00	Joe Russo	tt4154756	Avengers: Infinity War	Action,Adventure,Sci-Fi	Keith Giffen
4	Justice League	300000000	655945209.00	Zack Snyder	tt0974015	Justice League	Action,Adventure,Fantasy	Bob Kane

In [33]:

```
# splitting values into a list
final_df['genres'] =final_df['genres'].apply(lambda x: x.split(','))
```

In [34]:

```
# dropping unnecessary column
final_df.drop(['original_title'], axis=1, inplace=True)
```

In [35]:

```
# preview the DataFrame
final_df.head()
```

Out[35]:

	title	production_budget	worldwide_gross	direc_name	movie_id	genres	writer_name
0	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875.00	Rob Marshall	tt1298650	[Action, Adventure, Fantasy]	Terry Rossio
1	Dark Phoenix	350000000	149762350.00	Simon Kinberg	tt6565702	[Action, Adventure, Sci-Fi]	Jack Kirby
2	Avengers: Age of Ultron	330600000	1403013963.00	Joss Whedon	tt2395427	[Action, Adventure, Sci-Fi]	Jack Kirby
3	Avengers: Infinity War	300000000	2048134200.00	Joe Russo	tt4154756	[Action, Adventure, Sci-Fi]	Keith Giffen
4	Justice League	300000000	655945209.00	Zack Snyder	tt0974015	[Action, Adventure, Fantasy]	Bob Kane

Feature Engineering

In order to be able to get visual insights about range of the production budgetI decided to devide production budget column into 10 categories in ascending order.

In [36]:
```
# creating new list that containing categorical values

budget_bin=[]
for x in final_df['production_budget']:
    if x>0 and x<1000000:
        budget_bin.append('till_1M')
    elif x< 10000000:
        budget_bin.append('1M_10M')
    elif x< 30000000:
        budget_bin.append ('10M_30M')
    elif x<50000000:
        budget_bin.append ('30M_50M')
    elif x<70000000:
         budget_bin.append ('50M_70M')
    elif x<90000000:
        budget_bin.append ('70M_90M')
    elif x<130000000:
         budget_bin.append ('90M_130M')
    elif  x<150000000:
        budget_bin.append ('130M_150M')
    elif x<170000000:
        budget_bin.append ('150M_170M')
    else:
        budget_bin.append ('over_170M')
```

In [37]:
```
# creating new column
final_df['budget_bins'] = budget_bin
```

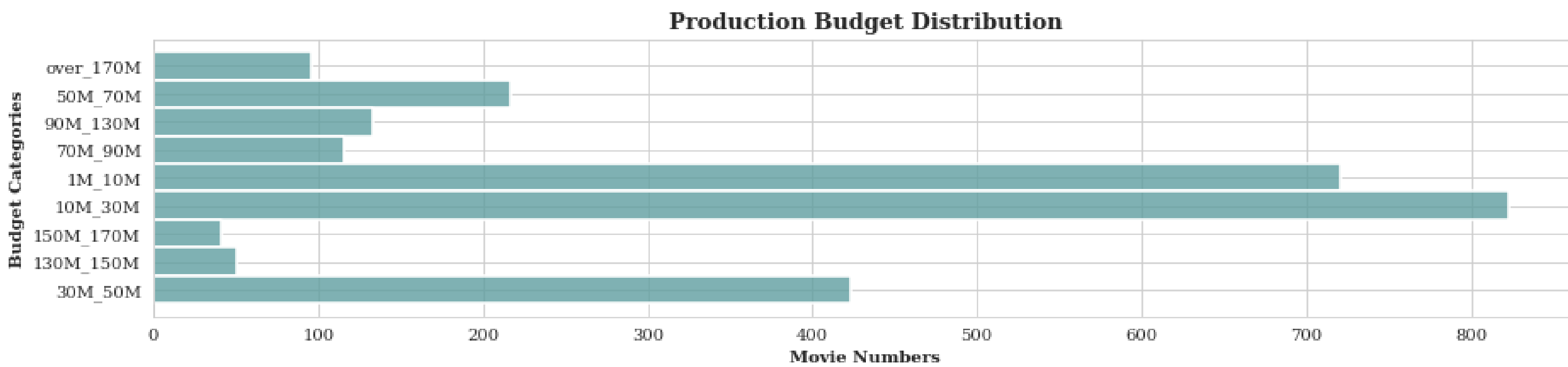
In [76]:
```
# creating barplot
plt.figure(figsize=(15,3))

sns.set_style('whitegrid',{'font.family':'serif', 'font.serif':['Times New Roman']})

ax = sns.histplot(final_df, y='budget_bins', bins=10, multiple="stack", color='cadetblue',alpha=0.8)

plt.title("Production Budget Distribution", fontdict= { 'fontsize': 13, 'fontweight':'bold'})
plt.xlabel("Movie Numbers", fontdict= { 'fontsize': 10, 'fontweight':'bold'})
plt.ylabel("Budget Categories", fontdict= { 'fontsize': 10, 'fontweight':'bold'})
```

```
plt.savefig('./images/fig1.png')
plt.show()
```



Based on the bar graph above I will analyze the movies that production budgets starting from the 1 Million.

In [39]:
```
#drop rows that contain values 'till_1M' in the 'tn_movies'
final_df= final_df[final_df.budget_bins != 'till_1M']
final_df.shape
final_df.tail()
```

Out[39]:

	title	production_budget	worldwide_gross	direc_name	movie_id	genres	writer_name	budget_bins
2633	Special	1000000	26822.00	Ann P Meredith	tt3869446	[Drama]	Ann P Meredith	1M_10M
2634	The Sisterhood of Night	1000000	6870.00	Caryn Waechter	tt1015471	[Drama, Mystery, Thriller]	Marilyn Fu	1M_10M
2635	Heli	1000000	552614.00	Amat Escalante	tt2852376	[Crime, Drama, Romance]	Ayhan Ergürsel	1M_10M
2636	Karachi se Lahore	1000000	17721.00	Wajahat Rauf	tt4590482	[Adventure, Comedy, Family]	Yasir Hussain	1M_10M
2637	American Hero	1000000	26.00	Nick Love	tt4733536	[Action, Comedy, Drama]	Nick Love	1M_10M

Further I will calculate movies' Return on Investment (ROI) by diividing the film's box office earning by the production budget and multiplying the result by 100. The resulting numbers are expressed as a percentage.

In [40]:
```
# calculating the profit and assigning values to new column
final_df['profit'] = final_df['worldwide_gross'] -final_df['production_budget']
```

```
# sorting values in ascending order
final_df.sort_values(by=['profit'],ascending=False)

final_df.head()
```

Out[40]:

	title	production_budget	worldwide_gross	direc_name	movie_id	genres	writer_name	budget_bins	profit
0	Pirates of the Caribbean: On Stranger Tides	410600000	1045663875.00	Rob Marshall	tt1298650	[Action, Adventure, Fantasy]	Terry Rossio	over_170M	635063875.00
1	Dark Phoenix	350000000	149762350.00	Simon Kinberg	tt6565702	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	-200237650.00
2	Avengers: Age of Ultron	330600000	1403013963.00	Joss Whedon	tt2395427	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	1072413963.00
3	Avengers: Infinity War	300000000	2048134200.00	Joe Russo	tt4154756	[Action, Adventure, Sci-Fi]	Keith Giffen	over_170M	1748134200.00
4	Justice League	300000000	655945209.00	Zack Snyder	tt0974015	[Action, Adventure, Fantasy]	Bob Kane	over_170M	355945209.00

In [41]:

```
# calculating Return on Investment and assigning values to new column
final_df['roi'] = (final_df['profit'] / final_df['production_budget'])*100

# sorting values in ascending order
final_df.sort_values(by=['roi'],ascending=False).reset_index()
```

Out[41]:

	index	title	production_budget	worldwide_gross	direc_name	movie_id	genres	writer_name	budget_bins	profit
0	2599	Rocky	1000000	225000000.00	Adnan A. Shaikh	tt9430578	[Action, Drama, Romance]	Vihar Ghag	1M_10M	224000000.00
1	2562	Snow White and the Seven Dwarfs	1488000	184925486.00	Paul Hendy	tt9691476	[Comedy, Drama, Fantasy]	Paul Hendy	1M_10M	183437486.00

	index	title	production_budget	worldwide_gross	direc_name	movie_id	genres	writer_name	budget_bins	profit
2	2600	The Devil Inside	1000000	101759490.00	William Brent Bell	tt1560985	[Horror]	William Brent Bell	1M_10M	100759490.00
3	2601	The Devil Inside	1000000	101759490.00	Joaquin Perea	tt0436230	[Horror, Thriller]	Robert Shaw	1M_10M	100759490.00
4	313	Cinderella	2900000	263591415.00	Kenneth Branagh	tt1661199	[Drama, Family, Fantasy]	Charles Perrault	1M_10M	260691415.00
...	...	...	...	...	...	...	...	...	...	...
2616	2118	Tracker	6500000	3149.00	Ian Sharp	tt1414378	[Action, Adventure, Drama]	Nicolas van Pallandt	1M_10M	-6496851.00
2617	1686	Broken Horses	15000000	3471.00	Vidhu Vinod Chopra	tt2503954	[Action, Crime, Drama]	Vidhu Vinod Chopra	10M_30M	-14996529.00
2618	1994	Skin Trade	9000000	1242.00	Ekachai Uekrongtham	tt1641841	[Action, Crime, Thriller]	Dolph Lundgren	1M_10M	-8998758.00
2619	1995	Skin Trade	9000000	1242.00	Shannon Keith	tt1576702	[Documentary]	Shannon Keith	1M_10M	-8998758.00
2620	2637	American Hero	1000000	26.00	Nick Love	tt4733536	[Action, Comedy, Drama]	Nick Love	1M_10M	-999974.00

2621 rows × 11 columns

In [42]:
```
# dropping unnecessary columns
final_df.drop(['worldwide_gross'], axis=1, inplace=True)
```

In [43]:
```
final_df.head()
```

Out[43]:

	title	production_budget	direc_name	movie_id	genres	writer_name	budget_bins	profit	roi
0	Pirates of the Caribbean: On Stranger Tides	410600000	Rob Marshall	tt1298650	[Action, Adventure, Fantasy]	Terry Rossio	over_170M	635063875.00	154.67

	title	production_budget	direc_name	movie_id	genres	writer_name	budget_bins	profit	roi
1	Dark Phoenix	350000000	Simon Kinberg	tt6565702	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	-200237650.00	-57.21
2	Avengers: Age of Ultron	330600000	Joss Whedon	tt2395427	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	1072413963.00	324.38
3	Avengers: Infinity War	300000000	Joe Russo	tt4154756	[Action, Adventure, Sci-Fi]	Keith Giffen	over_170M	1748134200.00	582.71
4	Justice League	300000000	Zack Snyder	tt0974015	[Action, Adventure, Fantasy]	Bob Kane	over_170M	355945209.00	118.65

To begin with, I will extract genres from the list of films and find the total number of genres of movies. Then I will find the best genres based on their Retorn on Investments.

In [44]:
```
# transforming each element of a list-like to a row
exploded_genres =final_df.explode('genres')
```

In [45]:
```
# returning counts of unique values
exploded_genres['genres'].value_counts()
```

Out[45]:
```
Drama          1315
Comedy          669
Action          591
Thriller        452
Adventure       433
Crime           331
Horror          309
Romance         278
Mystery         195
Biography       189
Documentary     187
Sci-Fi          179
Fantasy         173
Family          148
Animation       126
History          68
Music            64
Sport            51
War              33
Musical          22
Western          19
```

```
News              5
Name: genres, dtype: int64
```

In [46]:
```
# changing musical values into the music
exploded_genres['genres'] = exploded_genres['genres'].str.replace( 'Musical', 'Music')
```

In [47]:
```
# returning new counts of unique values
exploded_genres['genres'].value_counts()
```

Out[47]:
```
Drama          1315
Comedy          669
Action          591
Thriller        452
Adventure       433
Crime           331
Horror          309
Romance         278
Mystery         195
Biography       189
Documentary     187
Sci-Fi          179
Fantasy         173
Family          148
Animation       126
Music            86
History          68
Sport            51
War              33
Western          19
News              5
Name: genres, dtype: int64
```

In [48]:
```
#  splitting the values into groups based on mean
genre_roi = exploded_genres.groupby('genres').mean().reset_index().sort_values('roi', ascending=False)
genre_roi['genres'] =genre_roi['genres'].map(str.upper)
genre_roi
```

Out[48]:

	genres	production_budget	profit	roi
9	FANTASY	70782919.01	150549632.76	566.20
11	HORROR	22127378.64	48977881.39	549.84
13	MYSTERY	25859512.94	54168412.89	473.46
18	THRILLER	31154431.70	58549084.63	332.40

	genres	production_budget	profit	roi
8	FAMILY	55739043.88	131171138.18	332.09
12	MUSIC	21891154.03	82356456.01	327.48
2	ANIMATION	88697448.37	248371031.86	317.39
15	ROMANCE	21695064.75	37415721.19	304.17
17	SPORT	27086274.51	49707760.43	298.63
4	COMEDY	37956354.17	83041435.21	253.51
7	DRAMA	26590688.80	41254909.24	234.99
16	SCI-FI	76603672.47	189691718.88	227.70
0	ACTION	69518985.30	128411447.99	216.93
1	ADVENTURE	95296727.73	215106481.62	202.95
6	DOCUMENTARY	32057860.98	38131305.69	187.37
3	BIOGRAPHY	28175134.81	45242058.33	184.51
19	WAR	26587878.79	39854209.36	146.13
5	CRIME	29984710.26	39306843.47	132.48
10	HISTORY	37164705.88	38135610.74	103.43
20	WESTERN	40705263.16	33730295.79	57.33
14	NEWS	38960000.00	11929191.20	-2.68

In [49]:

```
# selectiong top 15 genres
top_genre = genre_roi.head(15)
top_genre
```

Out[49]:

	genres	production_budget	profit	roi
9	FANTASY	70782919.01	150549632.76	566.20
11	HORROR	22127378.64	48977881.39	549.84
13	MYSTERY	25859512.94	54168412.89	473.46
18	THRILLER	31154431.70	58549084.63	332.40

	genres	production_budget	profit	roi
8	FAMILY	55739043.88	131171138.18	332.09
12	MUSIC	21891154.03	82356456.01	327.48
2	ANIMATION	88697448.37	248371031.86	317.39
15	ROMANCE	21695064.75	37415721.19	304.17
17	SPORT	27086274.51	49707760.43	298.63
4	COMEDY	37956354.17	83041435.21	253.51
7	DRAMA	26590688.80	41254909.24	234.99
16	SCI-FI	76603672.47	189691718.88	227.70
0	ACTION	69518985.30	128411447.99	216.93
1	ADVENTURE	95296727.73	215106481.62	202.95
6	DOCUMENTARY	32057860.98	38131305.69	187.37

Subsequently, I will find the best directors and screenwriters based on their average earned profits from the movies.

In [50]:
```
# row counting and computing mean based on the profit
directors = final_df.groupby('direc_name').agg(['count','mean'])['profit']
```

In [51]:
```
# filtering directors accoring to number of movies that directed
direc_profit= directors[directors['count']>=5].reset_index().sort_values('mean', ascending=False)
direc_profit.rename(columns = {'mean':'mean_profit'}, inplace = True)
direc_profit
```

Out[51]:

	direc_name	count	mean_profit
6	Francis Lawrence	5	404238308.60
23	Zack Snyder	5	294184022.80
10	Kenneth Branagh	5	272373905.60
21	Tim Burton	5	229633372.00
1	Brad Peyton	5	185171680.00
16	Ridley Scott	7	176967321.29

	direc_name	count	mean_profit
11	M. Night Shyamalan	5	176831934.60
13	Paul Feig	5	174341927.80
20	Steven Spielberg	8	164754974.38
8	Jon M. Chu	5	163084695.40
14	Paul W.S. Anderson	5	153293991.00
2	Clint Eastwood	7	135479119.43
4	David O. Russell	5	113364526.00
12	Nicholas Stoller	5	104627034.80
0	Antoine Fuqua	5	98183459.20
7	Jaume Collet-Serra	6	75478617.17
22	Tim Story	6	64289997.17
17	Ron Howard	5	62628345.40
5	Denis Villeneuve	6	57327861.17
19	Steven Soderbergh	6	53204564.50
18	Simon West	5	38949677.20
3	David Gordon Green	7	38463382.29
15	Peter Berg	6	34929965.83
9	Jonathan Levine	5	33089379.40

In [52]:

```
#getting top 15 directors
top_direc = direc_profit.iloc[0:15, :]
top_direc
```

Out[52]:

	direc_name	count	mean_profit
6	Francis Lawrence	5	404238308.60
23	Zack Snyder	5	294184022.80
10	Kenneth Branagh	5	272373905.60

	direc_name	count	mean_profit
21	Tim Burton	5	229633372.00
1	Brad Peyton	5	185171680.00
16	Ridley Scott	7	176967321.29
11	M. Night Shyamalan	5	176831934.60
13	Paul Feig	5	174341927.80
20	Steven Spielberg	8	164754974.38
8	Jon M. Chu	5	163084695.40
14	Paul W.S. Anderson	5	153293991.00
2	Clint Eastwood	7	135479119.43
4	David O. Russell	5	113364526.00
12	Nicholas Stoller	5	104627034.80
0	Antoine Fuqua	5	98183459.20

In [53]:

```
writers = final_df.groupby('writer_name').agg(['count','mean'])['profit']
```

In [54]:

```
wrt_profit= writers[writers['count']>=5].reset_index().sort_values('mean', ascending=False)
wrt_profit.rename(columns = {'mean':'mean_profit'}, inplace = True)
wrt_profit.head()
```

Out[54]:

	writer_name	count	mean_profit
4	Christopher Nolan	5	555836000.40
8	Jack Kirby	16	500108401.88
1	Brian Lynch	5	496416654.60
15	Rhett Reese	5	339379621.60
6	Glenn Berger	5	257048560.40

In [75]:

```
# selecting top 15 rows
top_wrt = wrt_profit.head(15)
top_wrt
```

Out[75]:

	writer_name	count	mean_profit
4	CHRISTOPHER NOLAN	5	555836000.40
8	JACK KIRBY	16	500108401.88
1	BRIAN LYNCH	5	496416654.60
15	RHETT REESE	5	339379621.60
6	GLENN BERGER	5	257048560.40
10	KAY CANNON	5	239729799.00
12	M. NIGHT SHYAMALAN	5	176831934.60
11	LUC BESSON	6	163855194.17
9	JEZ BUTTERWORTH	5	159487483.20
5	DAVID KOEPP	5	152725874.60
3	CHRISTOPHER LANDON	5	131090843.40
0	ADAM MCKAY	7	110635113.57
14	NICHOLAS STOLLER	9	78348911.11
13	MATT MANFREDI	5	68145499.60
7	HOSSEIN AMINI	5	67493934.80

Analysis

Movie Genres

In [77]:

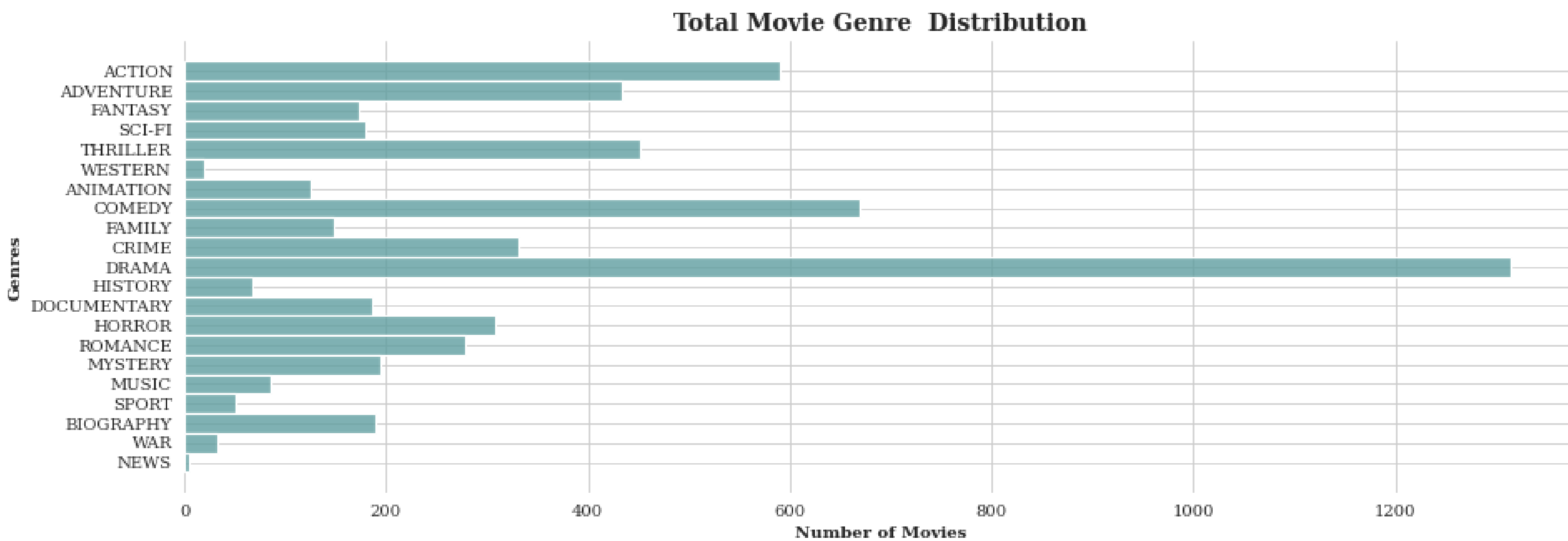
```
# making values uppercase
exploded_genres['genres'] =  exploded_genres['genres'].str.upper()

# Create Plot
plt.figure(figsize=(15,5))

sns.set_style('whitegrid',{'font.family':'serif', 'font.serif':['Times New Roman']})

ax = sns.histplot(exploded_genres, y='genres', bins=10, multiple="stack", color='cadetblue',alpha=0.8)
```

```
plt.title("Total Movie Genre  Distribution", fontdict= { 'fontsize': 14, 'fontweight':'bold'})
plt.xlabel("Number of Movies", fontdict= { 'fontsize': 10, 'fontweight':'bold'})
plt.ylabel("Genres", fontdict= { 'fontsize': 10, 'fontweight':'bold'})
sns.despine(left=True, bottom=True)
#plt.savefig('./images/fig2.png')
plt.show()
```

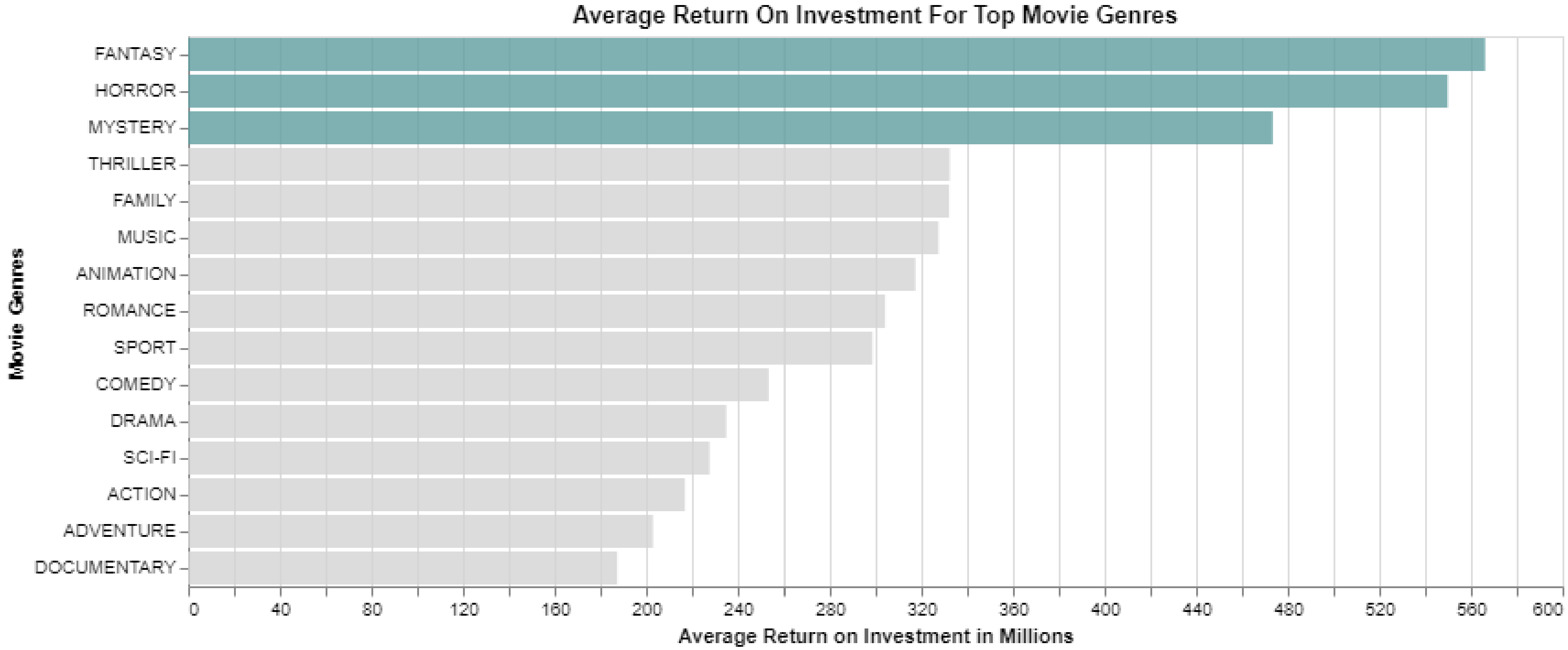


Based on the total amount of the movies produced Drama genre exceeds the rest of the movie genres. Genres comedy and action are the next frequently made movie genres. However, based on the Return on the Investment we can see different movie genres which are fantasy, horror and mystery.

In [57]:
```
# creating plot
alt.Chart(top_genre, title='Average Return On Investment For Top Movie Genres').mark_bar(opacity=0.8).encode(
x=alt.X('roi', title='Average Return on Investment in Millions'),
y=alt.Y('genres', sort='-x', title='Movie Genres'),

# the highlight will be set on the result of a conditional statement
    color=alt.condition(
        alt.datum.roi >= 450,  #this test returns True,
        alt.value('cadetblue'),     # if it is true sets the bar blue
        alt.value('lightgrey')   # and if it's not true it sets the bar grey.
    )
).properties(width=750,height =300)
```

Out[57]:



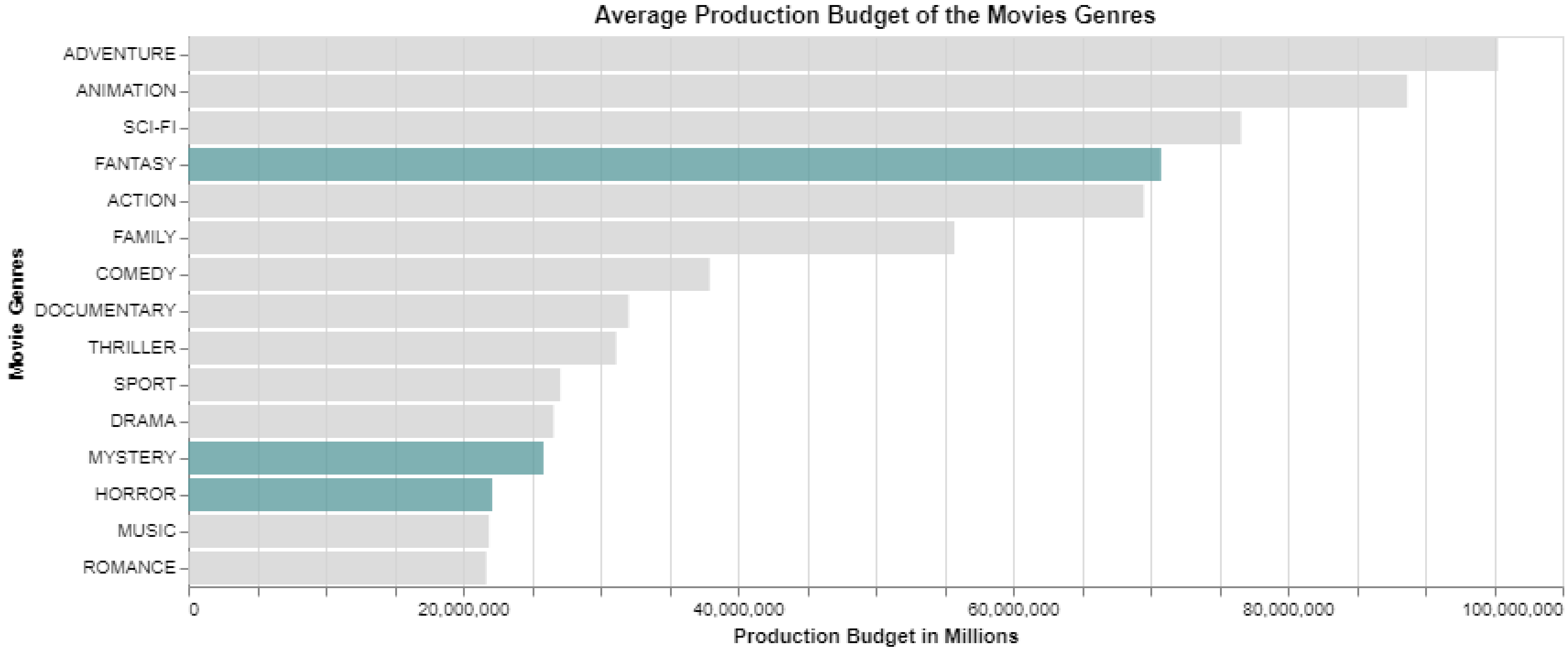
Interestingly, I was attracted to those top genres of films for which a high return on the investment required a smaller production budget, especially horror and mystery, which did not exceed 30 million dollars in production that plotted below

In [58]:

```
# creating plot
alt.Chart(top_genre, title='Average Production Budget of the Movies Genres').mark_bar(opacity=0.8).encode(
x=alt.X('production_budget', title='Production Budget in Millions'),
y=alt.Y('genres', sort='-x', title='Movie Genres'),

# the highlight will be set on the result of a conditional statement
    color=alt.condition(
        alt.datum.roi >= 450,  #this test returns True,
        alt.value('cadetblue'),     # if it is true sets the bar blue
        alt.value('lightgray')   # and if it's not true it sets the bar grey.
    )
).properties(width=750,height =300)
```

Out[58]:



Movie Directors

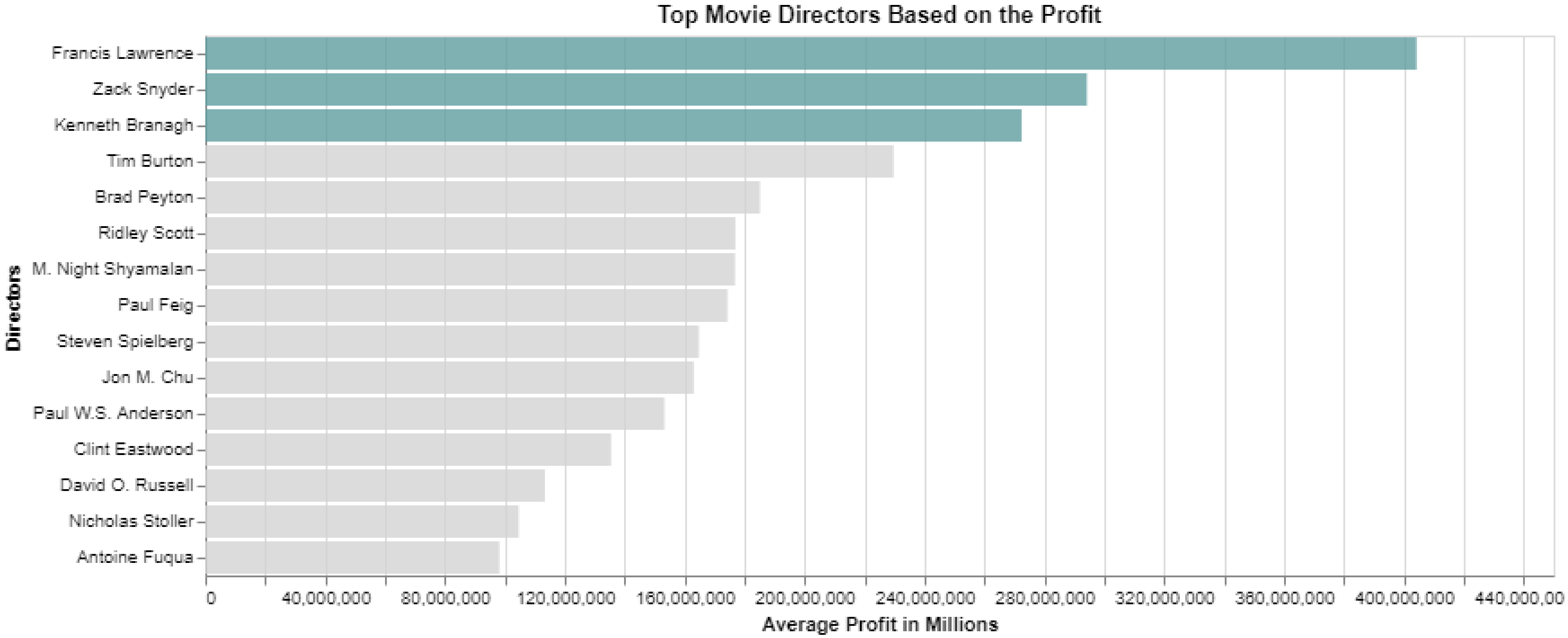
In [59]:

```
# creating plot
alt.Chart(top_direc, title='Top Movie Directors Based on the Profit').mark_bar(opacity=0.8).encode(
x=alt.X('mean_profit', title='Average Profit in Millions'),
y=alt.Y('direc_name', sort='-x', title='Directors'),

    # The highlight will be set on the result of a conditional statement
    color=alt.condition(
        alt.datum.mean_profit > 270000000,  #  setting the condition value,
        alt.value('cadetblue'),     # if the condition is True sets the bar blue
        alt.value('lightgray')   # and if it's not true it sets the bar blue.


    )
).properties(width=750,height=300)
```

Out[59]:



In [60]:
```python
# filtering certain values by rows
d1 = final_df[(final_df['direc_name']=='Francis Lawrence')]
d2 = final_df[(final_df['direc_name']=='Zack Snyder')]
d3 = final_df[(final_df['direc_name']=='Kenneth Branagh')]
```

In [61]:
```python
# cancatinating the tables
final_direc = pd.concat([d1, d2,d3], ignore_index=True, sort=False)
final_direc
```

Out[61]:

	title	production_budget	direc_name	movie_id	genres	writer_name	budget_bins	profit	roi
0	The Hunger Games: Mockingjay - Part 2	160000000	Francis Lawrence	tt1951266	[Action, Adventure, Sci-Fi]	Danny Strong	150M_170M	488986787.00	305.62
1	The Hunger Games: Catching Fire	130000000	Francis Lawrence	tt1951264	[Action, Adventure, Sci-Fi]	Suzanne Collins	130M_150M	734868047.00	565.28

	title	production_budget	direc_name	movie_id	genres	writer_name	budget_bins	profit	roi
2	The Hunger Games: Mockingjay - Part 1	125000000	Francis Lawrence	tt1951265	[Action, Adventure, Sci-Fi]	Danny Strong	90M_130M	641575131.00	513.26
3	Red Sparrow	69000000	Francis Lawrence	tt2873282	[Action, Drama, Thriller]	Justin Haythe	50M_70M	76951861.00	111.52
4	Water for Elephants	38000000	Francis Lawrence	tt1067583	[Drama, Romance]	Richard LaGravenese	30M_50M	78809717.00	207.39
5	Justice League	300000000	Zack Snyder	tt0974015	[Action, Adventure, Fantasy]	Bob Kane	over_170M	355945209.00	118.65
6	Batman v Superman: Dawn of Justice	250000000	Zack Snyder	tt2975590	[Action, Adventure, Fantasy]	Bob Kane	over_170M	617500281.00	247.00
7	Man of Steel	225000000	Zack Snyder	tt0770828	[Action, Adventure, Sci-Fi]	Christopher Nolan	over_170M	442999518.00	196.89
8	Legend of the Guardians: The Owls of Ga'Hoole	100000000	Zack Snyder	tt1219342	[Action, Adventure, Animation]	John Orloff	90M_130M	39716717.00	39.72
9	Sucker Punch	75000000	Zack Snyder	tt0978764	[Action, Adventure, Fantasy]	Steve Shibuya	70M_90M	14758389.00	19.68
10	Thor	150000000	Kenneth Branagh	tt0800369	[Action, Adventure, Fantasy]	Jack Kirby	150M_170M	299326618.00	199.55
11	Cinderella	95000000	Kenneth Branagh	tt1661199	[Drama, Family, Fantasy]	Charles Perrault	90M_130M	439551353.00	462.69
12	Cinderella	2900000	Kenneth Branagh	tt1661199	[Drama, Family, Fantasy]	Charles Perrault	1M_10M	260691415.00	8989.36
13	Jack Ryan: Shadow Recruit	60000000	Kenneth Branagh	tt1205537	[Action, Drama, Thriller]	David Koepp	50M_70M	71377412.00	118.96
14	Murder on the Orient Express	55000000	Kenneth Branagh	tt3402236	[Crime, Drama, Mystery]	Agatha Christie	50M_70M	290922730.00	528.95

In [62]:
```
# grouping the directors based on their movie budgets
direc_budget = final_direc.groupby('direc_name').mean().reset_index().sort_values('production_budget', ascending=False)
direc_budget['direc_name'] = direc_budget['direc_name'].map(str.upper)
direc_budget
```

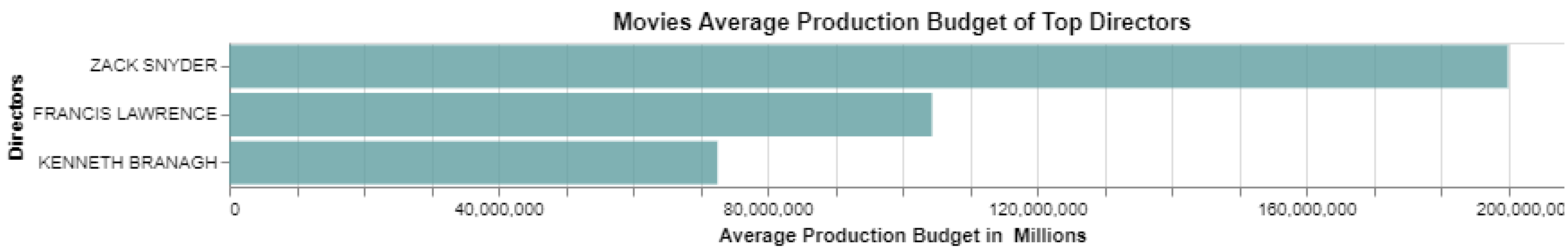
Out[62]:

	direc_name	production_budget	profit	roi
2	ZACK SNYDER	190000000	294184022.80	124.39
0	FRANCIS LAWRENCE	104400000	404238308.60	340.62
1	KENNETH BRANAGH	72580000	272373905.60	2059.90

In [63]:
```
# creating plot
alt.Chart(direc_budget, title='Movies Average Production Budget of Top Directors').mark_bar(opacity=0.8,
                color='cadetblue').encode(
x=alt.X('production_budget', title='Average Production Budget in  Millions'),
y=alt.Y('direc_name', sort='-x', title='Directors'),

).properties(width=750,height =80)
```

Out[63]:



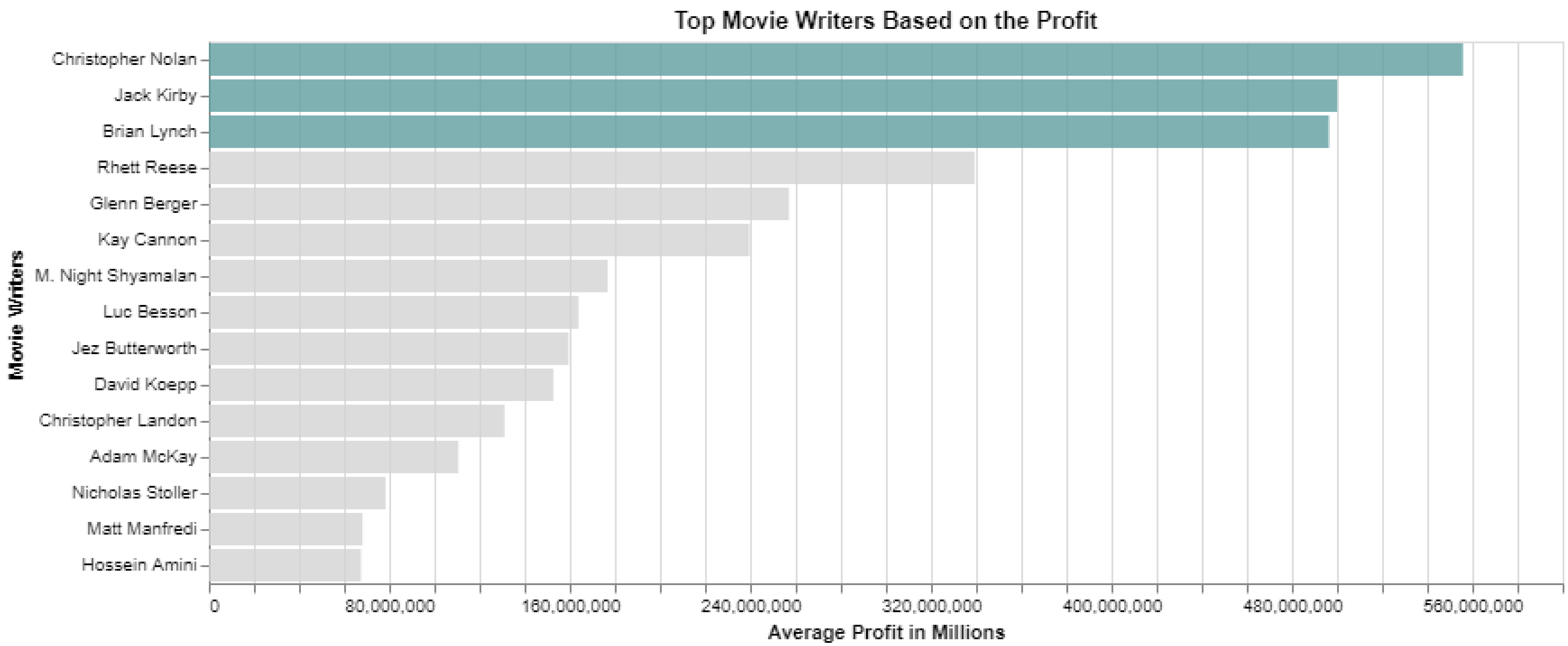
Movie Writers

In [64]:
```
# creating plot
alt.Chart(top_wrt, title='Top Movie Writers Based on the Profit').mark_bar(opacity=0.8).encode(
x=alt.X('mean_profit', title='Average Profit in Millions'),
y=alt.Y('writer_name', sort='-x', title='Movie Writers'),

# the highlight will be set on the result of a conditional statement
    color=alt.condition(
        alt.datum.mean_profit >=400000000,  # setting the condition value
        alt.value('cadetblue'), # if the condition is True sets the bar blue
        alt.value('lightgrey')  # and if it's not True it sets the bar grey.
```

```
    )
).properties(width=750,height =300)
```

Out[64]:



I wanted to further analyze and see the production budget of the films written by Christopher Nolan, Jack Kirby and Brian Lynch.

In [65]:

```
w1 = final_df[(final_df['writer_name']=='Christopher Nolan')]
w2 = final_df[(final_df['writer_name']=='Jack Kirby')]
w3 = final_df[(final_df['writer_name']=='Brian Lynch')]
final_wrt = pd.concat([w1, w2,w3], ignore_index=True, sort=False)
final_wrt
```

Out[65]:

	title	production_budget	direc_name	movie_id	genres	writer_name	budget_bins	profit	roi
0	The Dark Knight Rises	275000000	Christopher Nolan	tt1345836	[Action, Thriller]	Christopher Nolan	over_170M	809439099.00	294.34
1	Man of Steel	225000000	Zack Snyder	tt0770828	[Action, Adventure, Sci-Fi]	Christopher Nolan	over_170M	442999518.00	196.89
2	Interstellar	165000000	Christopher Nolan	tt0816692	[Adventure, Drama, Sci-Fi]	Christopher Nolan	150M_170M	501379375.00	303.87

	title	production_budget	direc_name	movie_id	genres	writer_name	budget_bins	profit	roi
3	Inception	160000000	Christopher Nolan	tt1375666	[Action, Adventure, Sci-Fi]	Christopher Nolan	150M_170M	675524642.00	422.20
4	Dunkirk	150000000	Christopher Nolan	tt5013056	[Action, Drama, History]	Christopher Nolan	150M_170M	349837368.00	233.22
5	Dark Phoenix	350000000	Simon Kinberg	tt6565702	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	-200237650.00	-57.21
6	Avengers: Age of Ultron	330600000	Joss Whedon	tt2395427	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	1072413963.00	324.38
7	Captain America: Civil War	250000000	Joe Russo	tt3498820	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	890069413.00	356.03
8	Black Panther	200000000	Ryan Coogler	tt1825683	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	1148258224.00	574.13
9	X-Men: Days of Future Past	200000000	Bryan Singer	tt1877832	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	547862775.00	273.93
10	Thor: Ragnarok	180000000	Taika Waititi	tt3501632	[Action, Adventure, Comedy]	Jack Kirby	over_170M	666980024.00	370.54
11	X-Men: Apocalypse	178000000	Bryan Singer	tt3385516	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	364537546.00	204.80
12	Spider-Man: Homecoming	175000000	Jon Watts	tt2250912	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	705166350.00	402.95
13	Iron Man 2	170000000	Jon Favreau	tt1228705	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	451156389.00	265.39
14	Captain America: The Winter Soldier	170000000	Joe Russo	tt1843866	[Action, Adventure, Sci-Fi]	Jack Kirby	over_170M	544401889.00	320.24
15	Thor: The Dark World	150000000	Alan Taylor	tt1981115	[Action, Adventure, Fantasy]	Jack Kirby	150M_170M	494602516.00	329.74
16	Thor	150000000	Kenneth Branagh	tt0800369	[Action, Adventure, Fantasy]	Jack Kirby	150M_170M	299326618.00	199.55
17	Captain America: The First Avenger	140000000	Joe Johnston	tt0458339	[Action, Adventure, Sci-Fi]	Jack Kirby	130M_150M	230569776.00	164.69
18	Ant-Man and the Wasp	130000000	Peyton Reed	tt5095030	[Action, Adventure, Comedy]	Jack Kirby	130M_150M	493144660.00	379.34

	title	production_budget	direc_name	movie_id	genres	writer_name	budget_bins	profit	roi
19	Fantastic Four	120000000	Josh Trank	tt1502712	[Action, Adventure, Drama]	Jack Kirby	90M_130M	47849187.00	39.87
20	Fantastic Four	87500000	Josh Trank	tt1502712	[Action, Adventure, Drama]	Jack Kirby	70M_90M	245632750.00	280.72
21	Puss in Boots	130000000	Chris Miller	tt0448694	[Action, Adventure, Animation]	Brian Lynch	130M_150M	424987477.00	326.91
22	The Secret Life of Pets 2	80000000	Chris Renaud	tt5113040	[Adventure, Animation, Comedy]	Brian Lynch	70M_90M	33351496.00	41.69
23	The Secret Life of Pets	75000000	Chris Renaud	tt2709768	[Adventure, Animation, Comedy]	Brian Lynch	70M_90M	811750534.00	1082.33
24	Minions	74000000	Kyle Balda	tt2293640	[Adventure, Animation, Comedy]	Brian Lynch	70M_90M	1086336173.00	1468.02
25	Hop	63000000	Tim Hill	tt1411704	[Adventure, Animation, Comedy]	Brian Lynch	50M_70M	125657593.00	199.46

In [66]:

```
# grouping the writers based on their movie budgets
wrt_budget = final_wrt.groupby('writer_name').mean().reset_index().sort_values('production_budget', ascending=False)
wrt_budget['writer_name'] = wrt_budget['writer_name'].map(str.upper)
wrt_budget
```

Out[66]:

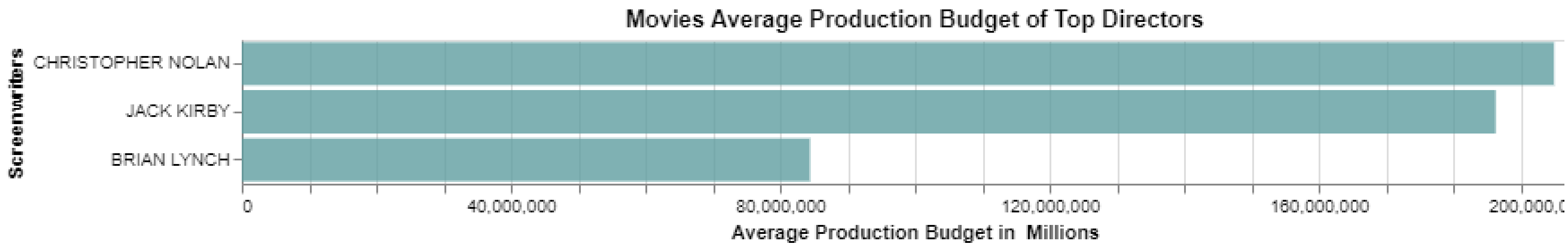
	writer_name	production_budget	profit	roi
1	CHRISTOPHER NOLAN	195000000	555836000.40	290.10
2	JACK KIRBY	186318750	500108401.88	276.82
0	BRIAN LYNCH	84400000	496416654.60	623.68

In [67]:

```
# creating plot
alt.Chart(wrt_budget, title='Movies Average Production Budget of Top Directors').mark_bar(opacity=0.8,
            color='cadetblue').encode(
x=alt.X('production_budget', title='Average Production Budget in  Millions'),
y=alt.Y('writer_name', sort='-x', title='Screenwriters'),
```

```
).properties(width=750,height =80)
```

Out[67]:



Conclusion

The above analysis leads to three recommendations for Microsoft to release a successful film studio :

- Based on Microsoft's investment, I would suggest starting with movie genres with a smaller production budget of about 25 million dolllars which are *mystery* and *horror*, then increasing up to 75 million dollars with the *fantasy* genre. They are the best genres with the greatest return on investments
- For the directing of movies, I would recommend working with *Francis Lawrence* and *Kenneth Branagh* along with an average production volume of 1 million to 105 million. *Zack Snyder* is best suited for films with the highest production budget ove the 170 million.They all are the most profitable directors in the movie industry.
- For the production of a film in average worth up to 85 million dollars, I would recommend *Brian Lynch* as a screenwriter. Whereas, *Christopher Nolan* and *Jack Kirby* are suitable screenwriters for the movies with the higher production budget. They are all the most successful film screenwriters.

Next Steps

- Further analysis could be improved by adding additional data as it becomes available. It could also be expanded upon by determining release times of the movies and other influencing attribute such as actor and actresses.