Phase 2 Final Project Submission

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- Scheduled Project Review: April 1st, 2024
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1. Business Understanding

This data exploratory project focuses on analyzing characteristics of successful movies at the box office to support the company's strategic investment in the movie industry. The goal is to gain valuable insights contributing to movie production success and provide meaningful recommendations to major stakeholders of the investments.
The return on investment (ROI) is used throuout this report as core measurement to compare movies' success. This measurement is simply the ratio between the gross profit and production cost. The use of ROI helps normalize the scales of differences between blockbusters and less-known movies.

2. Data Understanding

The dataset used in this analysis extracted from various different movie sources including IMDb, the Numbers, and TMDB. As these datasets were collected from different sources, they have different formats. While TMDB and the Numbers datasets are compressed as CVS files, the IMDb, the largest dataset among the three, is stored within a SQLite database.
These datasets not only contain movies' information on their cast, production crew, budget, and revenues, etc. but also the public opinions regarding the movies' success such as ratings and votes.

3. Data Preparation

In [1]:
```
#import appropriate libraries for analysis and visualization
import pandas as pd
import sqlite3
import datetime
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import re

%matplotlib inline
```

a. Load Data to Dataframes

In [2]:
```
conn = sqlite3.connect('data\im.db')
df = pd.read_sql('''SELECT title, start_year, runtime_minutes, averagerating, numvotes,
                    primary_name, category FROM
                    (SELECT  * FROM movie_basics LEFT JOIN
                             (SELECT * FROM movie_akas LEFT JOIN movie_ratings USING(movie_id))
                             USING(movie_id)) LEFT JOIN
                             (SELECT movie_id, primary_name, category FROM principals LEFT JOIN
                             persons USING(person_id) WHERE death_year IS NULL) USING(movie_id)
                             ''', conn)

```

In [3]:
```
#Load all csv and tsc files into dataframe
df1 = pd.read_csv('Data/tmdb.movies.csv', parse_dates = ['release_date'], converters={'genre_ids': pd.e
df2 = pd.read_csv('Data/tn.movie_budgets.csv', parse_dates = ['release_date'])

```

b. Cleaning Dataframes

IMDb Dataset

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2928123 entries, 0 to 2928122
Data columns (total 7 columns):
 #   Column           Dtype  
---  ------           -----  
 0   title            object 
 1   start_year       int64  
 2   runtime_minutes  float64
 3   averagerating    float64
 4   numvotes         float64
 5   primary_name     object 
 6   category         object 
dtypes: float64(3), int64(1), object(3)
memory usage: 156.4+ MB
```

In [5]:
```
df.drop_duplicates(inplace = True)
df.isna().sum()
```

```
title             128692
start_year             0
runtime_minutes    243179
averagerating      494112
numvotes           494112
primary_name         1697
category             1313
dtype: int64
```

In [6]:

```
# As I will use this dataset to analyze directors' success, it is best to drop rows that
# have Nan director values
df.dropna(subset=['title','primary_name'], inplace = True)
# fill column runtime_minutes' Nan values with its mode,
#  meanwhile, averagerating and numvotes' Nan values will be filled with 0
runtime = df['runtime_minutes'].mode().values[0]
df.fillna(value = {'runtime_minutes':runtime, 'averagerating':0, 'numvotes':0}, inplace = True)
```

In [7]:

```
df.isna().sum()
```

```
title              0
start_year         0
runtime_minutes    0
averagerating      0
numvotes           0
primary_name       0
category           0
dtype: int64
```

TMDB Dataset

In [8]:

```
#Let's have a overview of the TMDB dataset
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype         
---  ------             --------------  -----         
 0   Unnamed: 0         26517 non-null  int64         
 1   genre_ids          26517 non-null  object        
 2   id                 26517 non-null  int64         
 3   original_language  26517 non-null  object        
 4   original_title     26517 non-null  object        
 5   popularity         26517 non-null  float64       
 6   release_date       26517 non-null  datetime64[ns]
 7   title              26517 non-null  object        
 8   vote_average       26517 non-null  float64       
 9   vote_count         26517 non-null  int64         
dtypes: datetime64[ns](1), float64(2), int64(3), object(4)
memory usage: 2.0+ MB
```

In [9]:

```
#Check the number of Nan values in TMDB dataset
df1.isna().sum()
```

```
Unnamed: 0          0
genre_ids           0
id                  0
original_language   0
original_title      0
popularity          0
release_date        0
title               0
vote_average        0
vote_count          0
dtype: int64
```

In [10]:
```
df1.head()
```

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186

I realize the genres in TMDB dataset are all recorded as id code. I found the actual name for each of genre id from TMDB website and store them in dictionary d. I will split the data stored in column genre_ids into individual columns. If a movie is assigned as that particular genre, the cell in that genre column will show 1, else it will show 0.

In [12]:

```
# Split the genre_ids column into multiple columns and change the genre_ids to identical genres
d = {28: 'Action',
12: 'Adventure',
16: 'Animation',
35: 'Comedy',
80: 'Crime',
99: 'Documentary',
18: 'Drama',
10751: 'Family',
14: 'Fantasy',
36: 'History',
27: 'Horror',
10402: 'Music',
9648: 'Mystery',
10749: 'Romance',
878: 'Science Fiction',
10770: 'TV Movie',
53: 'Thriller',
10752: 'War',
37: 'Western'}
# Split the genre_ids column which is a string type into multiple columns
# if movie contains a certain genre, the movie's genre column will show 1, else 0
genres = np.unique(np.concatenate(np.array(df1['genre_ids'])))
genres = [int(x) for x in genres]
df1[genres] = 0
for i, row in df1.iterrows():
    for g in row['genre_ids']:
        df1.at[i,g] = 1
```

```
29
30 #Change the genre_ids into genres' identical names
31 df1.rename(columns = d, inplace = True)
32 # the genres array now contains the genres identical names, not ids
33 genres = list(d.values())
34
35 # create a new column containing the number of genres associated with the movie
36 df1['genre_len'] = [len(x) for x in df1['genre_ids']]
```

Let's look at the dataset after splitting the genres into individual columns

In [13]:

```
1 df1.head()
```

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186

5 rows × 30 columns

The Numbers Dataset

In [14]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype         
---  ------             --------------  -----         
 0   id                 5782 non-null   int64         
 1   release_date       5782 non-null   datetime64[ns]
 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: datetime64[ns](1), int64(1), object(4)
memory usage: 271.2+ KB
```

In [15]:
```
#Check the number of Nan values in The Numbers dataset
df2.isna().sum()
```

```
id                 0
release_date       0
movie              0
production_budget  0
domestic_gross     0
worldwide_gross    0
dtype: int64
```

I realize all data stored in columns production_budget, domestic_gross and worldwide_gross are under string type. To convert these columns to float type, I need to strip the special character $ out of the string before converting. I also create a new column ROI which stands for return on investment. ROI is calculated as the difference between worldwide_gross and production_budget divided by production_budget.

In [16]:

```
#convert string types columns into float types
df2['production_budget'] = df2['production_budget'].replace('[\$,]', '', regex=True).astype(float)
df2['domestic_gross'] = df2['domestic_gross'].replace('[\$,]', '', regex=True).astype(float)
df2['worldwide_gross'] = df2['worldwide_gross'].replace('[\$,]', '', regex=True).astype(float)

#Create ROI (Return on Investment) column: ROI = (earnings - budget)/budget
df2['ROI'] = (df2['worldwide_gross']-df2['production_budget'])/df2['production_budget']
df2['year'] = pd.DatetimeIndex(df2['release_date']).year
```

Joining TMDB and The Numbers dataset

While TMDB dataset has over 25000 data points of different movies with great features such as genres, popularity, vote average; it is missing gross revenue - one of the crucial features detemining the success of a movie. Such gross revenue information is only carried by the Numbers' dataset. As a result, I joined the two dataset together using their title columns to better understannd how different movies' features contributing to their success.

In [17]:

```
#join dataset from TMDB and The Numbers using their titles. As The Numbers dataset
# have a greater number of data points, I use right join to maximize the data points after the join
df12 =  pd.merge(df1, df2, left_on='original_title', right_on='movie', how='right')
df12.dropna(inplace = True)
# Keep only important columns
keep = ['title','vote_average','vote_count', 'release_date_x','popularity','production_budget','domesti
df12 = df12[keep]

#reset index so that the index shows continuous values rather than the join index
df12.reset_index(inplace=True)
df12.drop(['index'], axis = 1, inplace = True)
df12.drop_duplicates(inplace = True)

#create new column "released_month" which is the month part of "released_date"
df12['release_month'] = pd.DatetimeIndex(df12['release_date_x']).month
```

Joining IMDb and The Numbers dataset

I plan to analyze what are the best directors in terms of both ROI and overall ratings later. While IMDb's dataset contains detail information regarding movies and directors, it does not have any gross revenue or production budget information. Such data can only be found under The Numbers' dataset. Thus, I decide to merge IMDb's and The Numbers' dataset together.

In [18]:

```
# Here I am only interested in movies that have directors' information
df_dir = df[df['category'] == 'director']

# Merging data with a right join
df_dir =  pd.merge(df_dir, df2, left_on=['title','start_year'], right_on=['movie','year'], how='right')
df_dir = df_dir[['title','averagerating','numvotes','primary_name','category',
                 'production_budget','domestic_gross','worldwide_gross','ROI']]
# Create a new column ROI in the joined dataframe
df_dir['ROI'] = (df_dir['worldwide_gross'] - df_dir['production_budget']) /df_dir['production_budget']

df_dir.dropna(inplace = True)
```

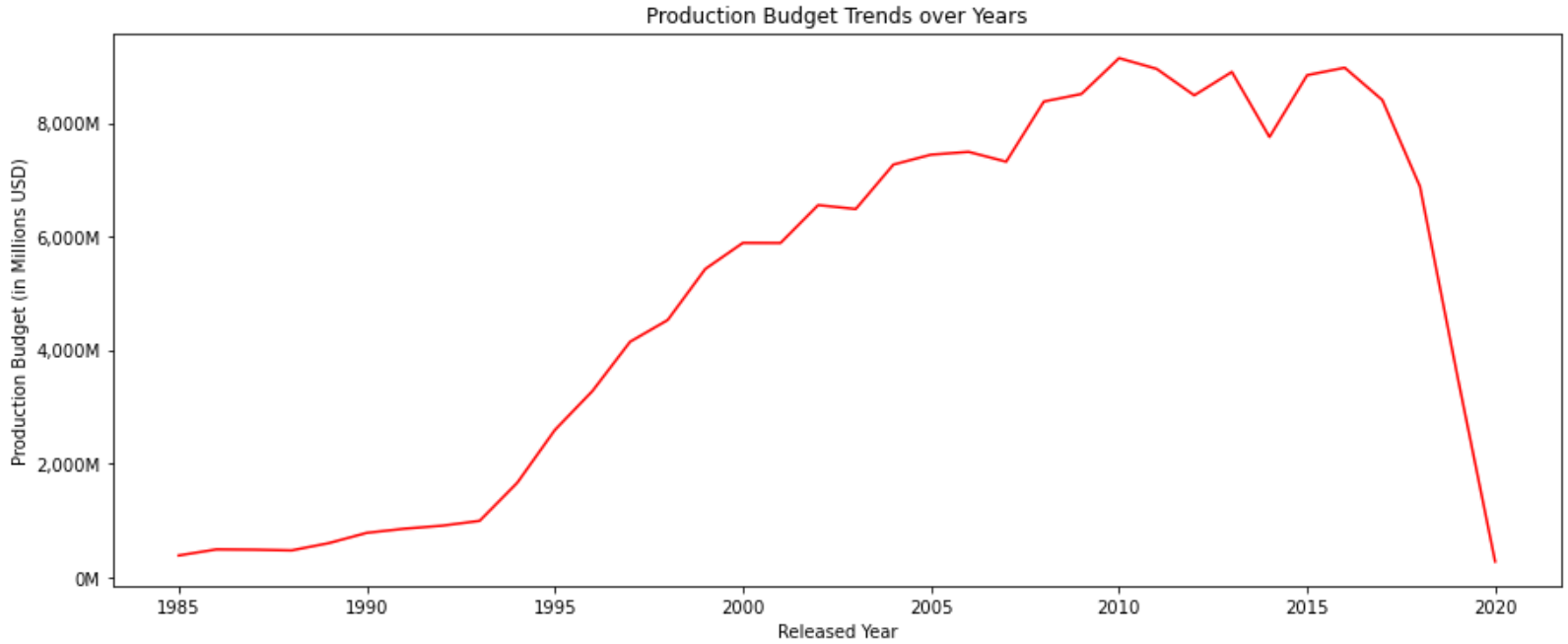
Exploratory Data Analysis

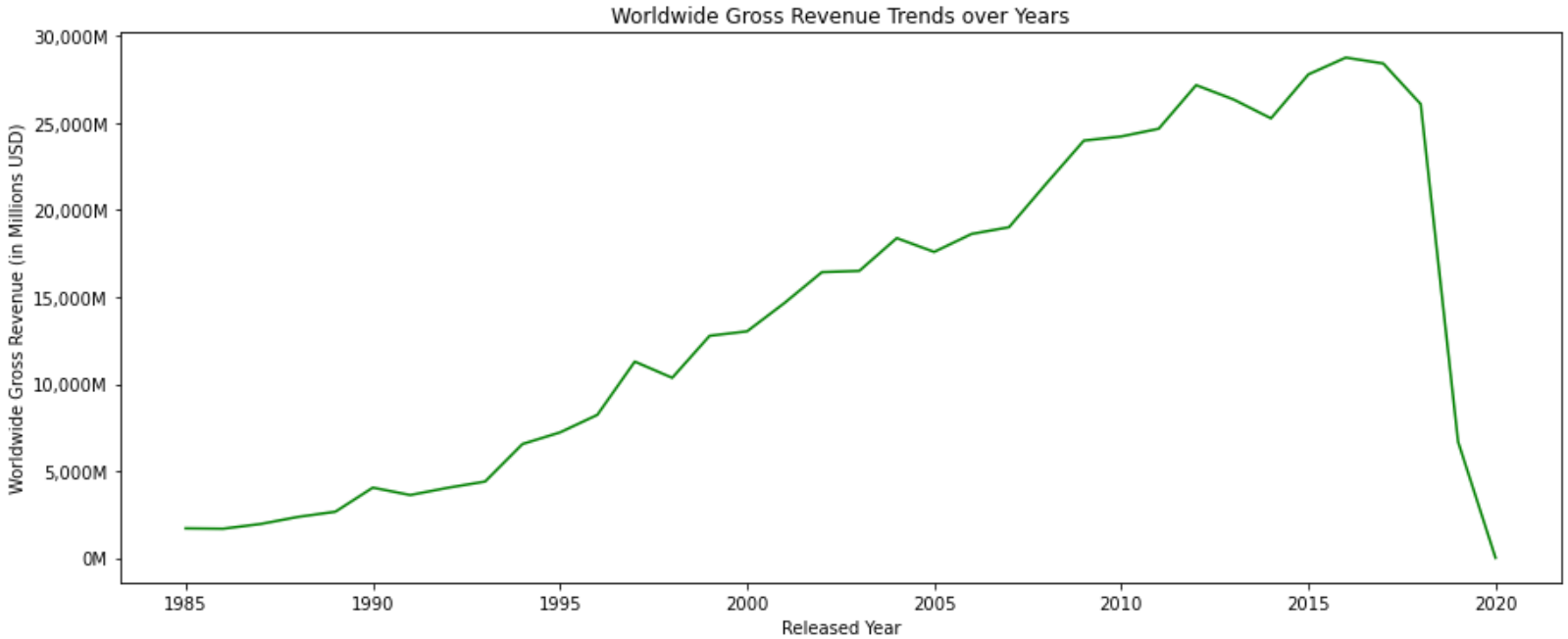
Overview Trends

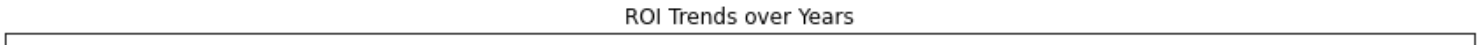
In [19]:

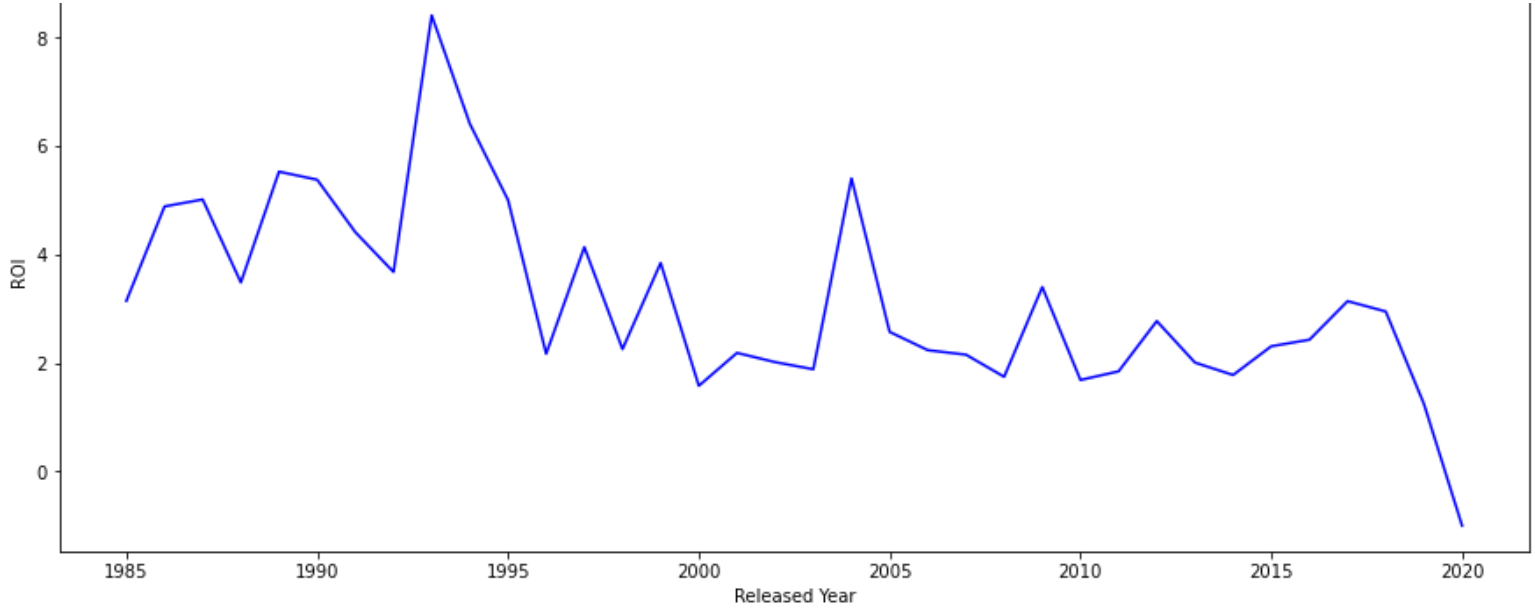
```
df2['year'] = pd.DatetimeIndex(df2['release_date']).year
df_trends = df2[df2['year'] >= 1985]
d_year = df_trends.groupby('year').aggregate({'production_budget':'sum',
                                              'worldwide_gross':'sum','ROI':'mean'})
fig, ((ax1), (ax2), (ax3)) = plt.subplots(figsize = (15,20), nrows = 3)
ax1.plot(d_year.index, d_year.production_budget, color = 'red')
ax1.set_xlabel('Released Year')
ax1.set_ylabel('Production Budget (in Millions USD)')
ax1.set_title('Production Budget Trends over Years')

ax2.plot(d_year.index, d_year.worldwide_gross, color = 'green')
ax2.set_xlabel('Released Year')
ax2.set_ylabel('Worldwide Gross Revenue (in Millions USD)')
ax2.set_title('Worldwide Gross Revenue Trends over Years')

ax3.plot(d_year.index, d_year.ROI, color = 'blue')
ax3.set_xlabel('Released Year')
ax3.set_ylabel('ROI')
ax3.set_title('ROI Trends over Years')

# suppress scientific notation by setting yticklabels
for ax in [ax1, ax2]:
    ylabels = ['{:,.0f}'.format(y) + 'M' for y in ax.get_yticks()/1000000]
    ax.set_yticklabels(ylabels)
plt.show();
```

```
<ipython-input-19-0a7f579d11db>:24: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax.set_yticklabels(ylabels)
```


Production Budget Trends over Years
Production Budget (in Millions USD)
8,000M
6,000M
4,000M
2,000M
0M
1985
1990
1995
2000
2005
2010
2015
2020
Released Year


Worldwide Gross Revenue Trends over Years
Worldwide Gross Revenue (in Millions USD)
30,000M
25,000M
20,000M
15,000M
10,000M
5,000M
0M
1985
1990
1995
2000
2005
2010
2015
2020
Released Year


ROI Trends over Years



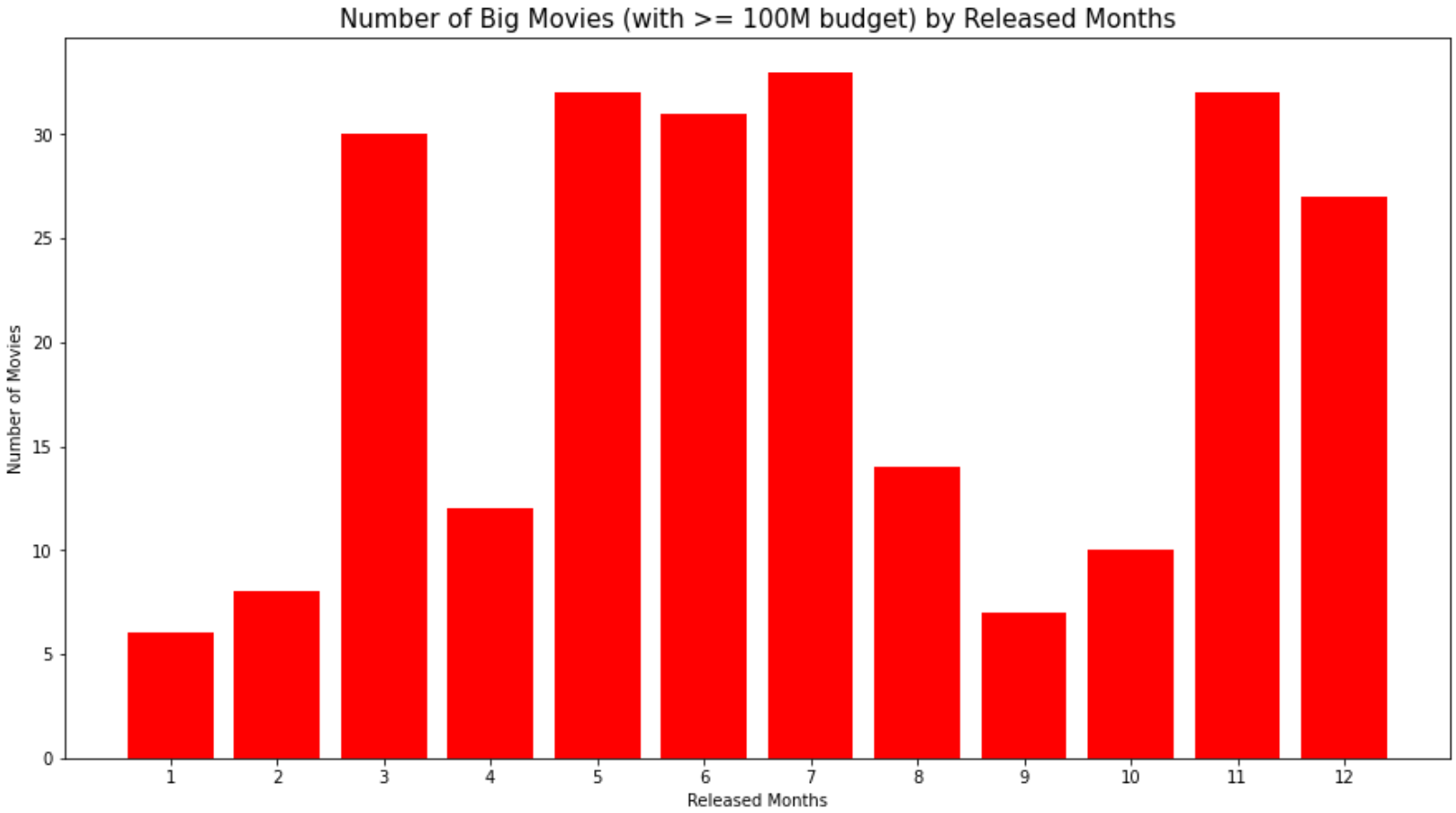
The above charts show that the investment in the movie industry has consistently increased from 1985 - 2018. This consistent investment trend in movie industry also leads to growing worldwide gross revenue for movie production. However, the Covid-19 incident in late 2019 - early 2020 had caused a deep dive in both movie budget production and worldwide gross revenue. An incentive for investors to pour their investment in the movie industry is due to its high ROI. Though ROI is somewhat on a down trend from 1985 - 2020, the yearly average return had been consistently stayed above 200% from 1985 - 2018.

First Recommendation

a. In which month big movies (production budget over 100M) released?

In [20]:

```
# group the joined dataset by release month and filter only those moview with production cost
# more than 100M
big_movies = df12[df12['production_budget'] >= 100000000].groupby('release_month').count()

#Graphing the data
fig, ax = plt.subplots(figsize = (15,8))
plt.bar(x = big_movies.index, height = big_movies['production_budget'], color = 'red')
plt.xticks(range(1,13))
plt.xlabel('Released Months')
plt.ylabel('Number of Movies')
plt.title('Number of Big Movies (with >= 100M budget) by Released Months', fontsize = 15)
plt.show();
```

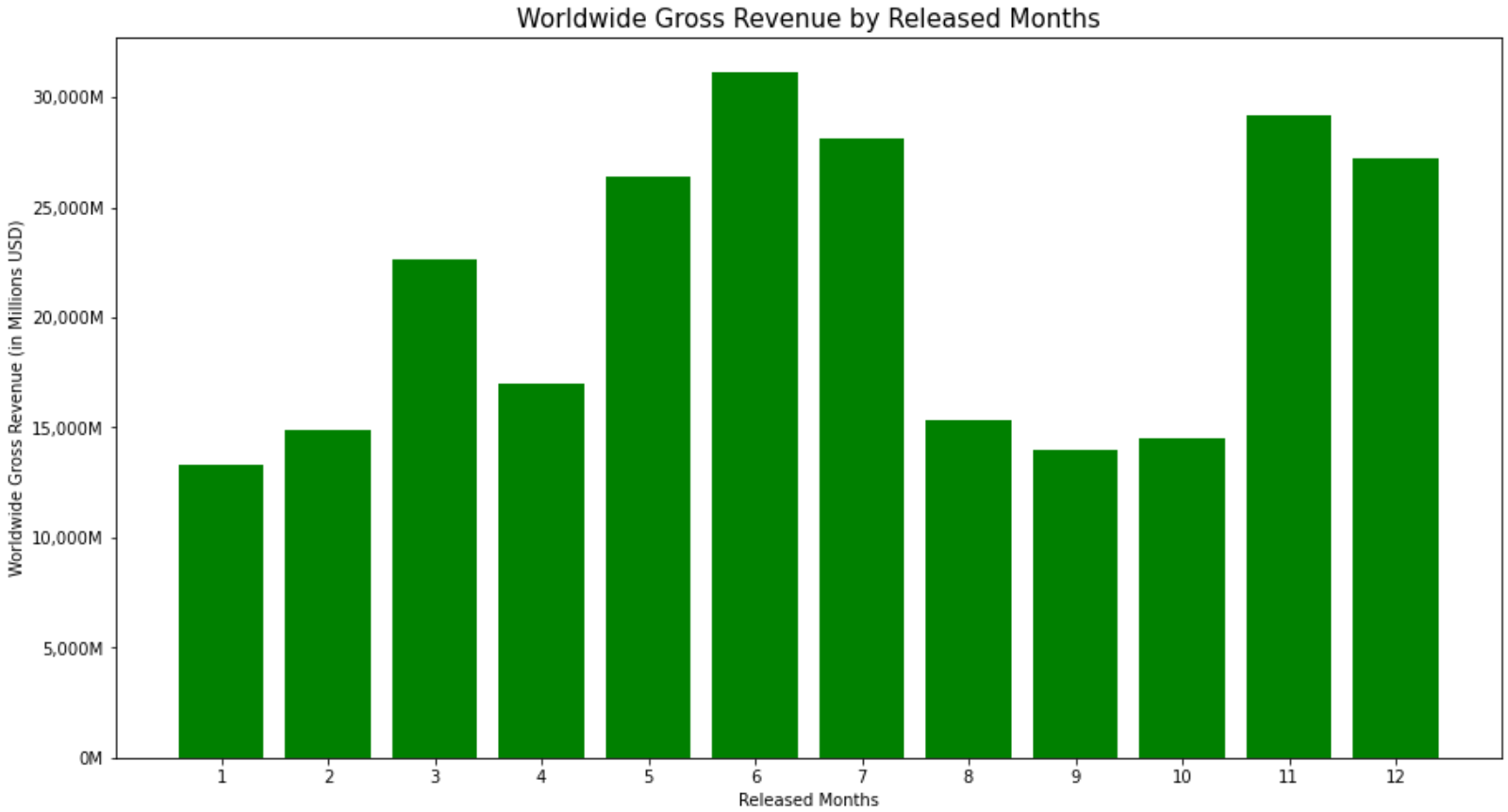


b. In which month do movies hit best gross revenue?

In [21]:

```
# Group the joined dataset by released_month but this time, we want to view worldwide gross revenue
# distributed by released month
release_month = df12.groupby('release_month').sum()

# Graphing the data
fig, ax = plt.subplots(figsize = (15,8))
ax.bar(x = release_month.index, height = release_month['worldwide_gross'], color = 'green')
ax.set_xticks(range(1,13))
ax.set_xlabel('Released Months')
ax.set_ylabel('Worldwide Gross Revenue (in Millions USD)')
ax.set_title('Worldwide Gross Revenue by Released Months', fontsize = 15)
ylabels = ['{:,.0f}'.format(y) + 'M' for y in ax.get_yticks()/1000000]
ax.set_yticklabels(ylabels)
plt.show();
```

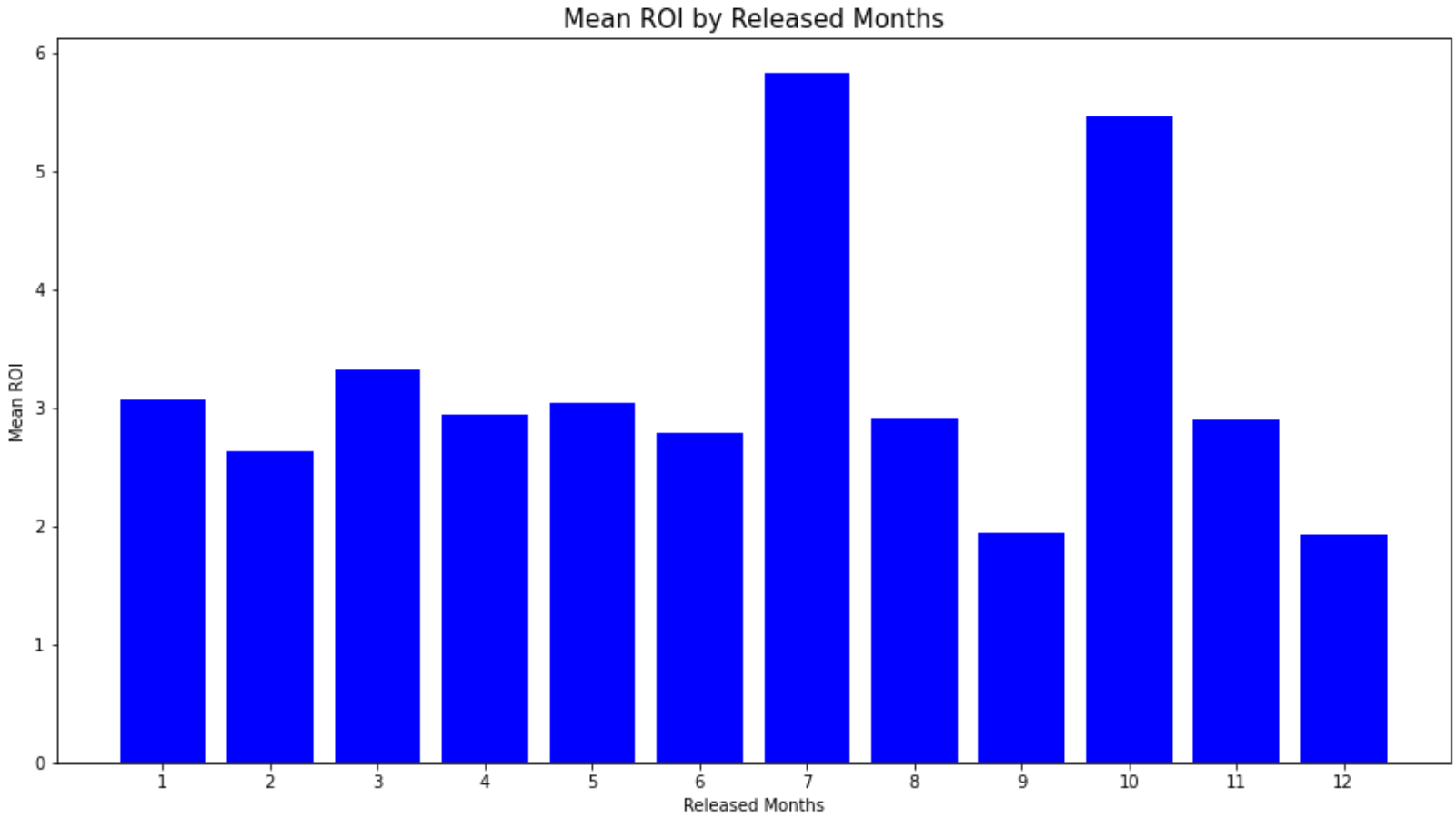
```
<ipython-input-21-1a363bddecbf>:13: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax.set_yticklabels(ylabels)
```



c. In which month do movies achieve best ROI?

In [22]:

```
# Group the joined dataset by released_month, but this time, we want to compare them by mean values
# of the movies' ROI rate
roi_month = df12.groupby('release_month').mean()

# Graphing the data
fig, ax = plt.subplots(figsize = (15,8))
plt.bar(x = roi_month.index, height = roi_month['ROI'], color = 'blue')
plt.xticks(range(1,13))
plt.xlabel('Released Months')
plt.ylabel('Mean ROI')
plt.title('Mean ROI by Released Months', fontsize = 15)
plt.show();
```



With our 12 months analysis, we can realize July and October are the 2 best months in which movies can achieve great ROI for studio producers. On the other hand, we also want to avoid compete directly with the majo movies in the box office (assumed with over 100M budget production). The first and second chart show that mos big movies are often released during summer (Jun - August) and the last two months of the year (November and December). As a result, my first recommendation to the stakeholders is to prioritize releasing movie in October o the year. Not only we can avoid compete directly with major movies, but also have a higher chance of hitting higher ROI rates.

Second Recommendation

a. Which movie genres have the largest production budget?

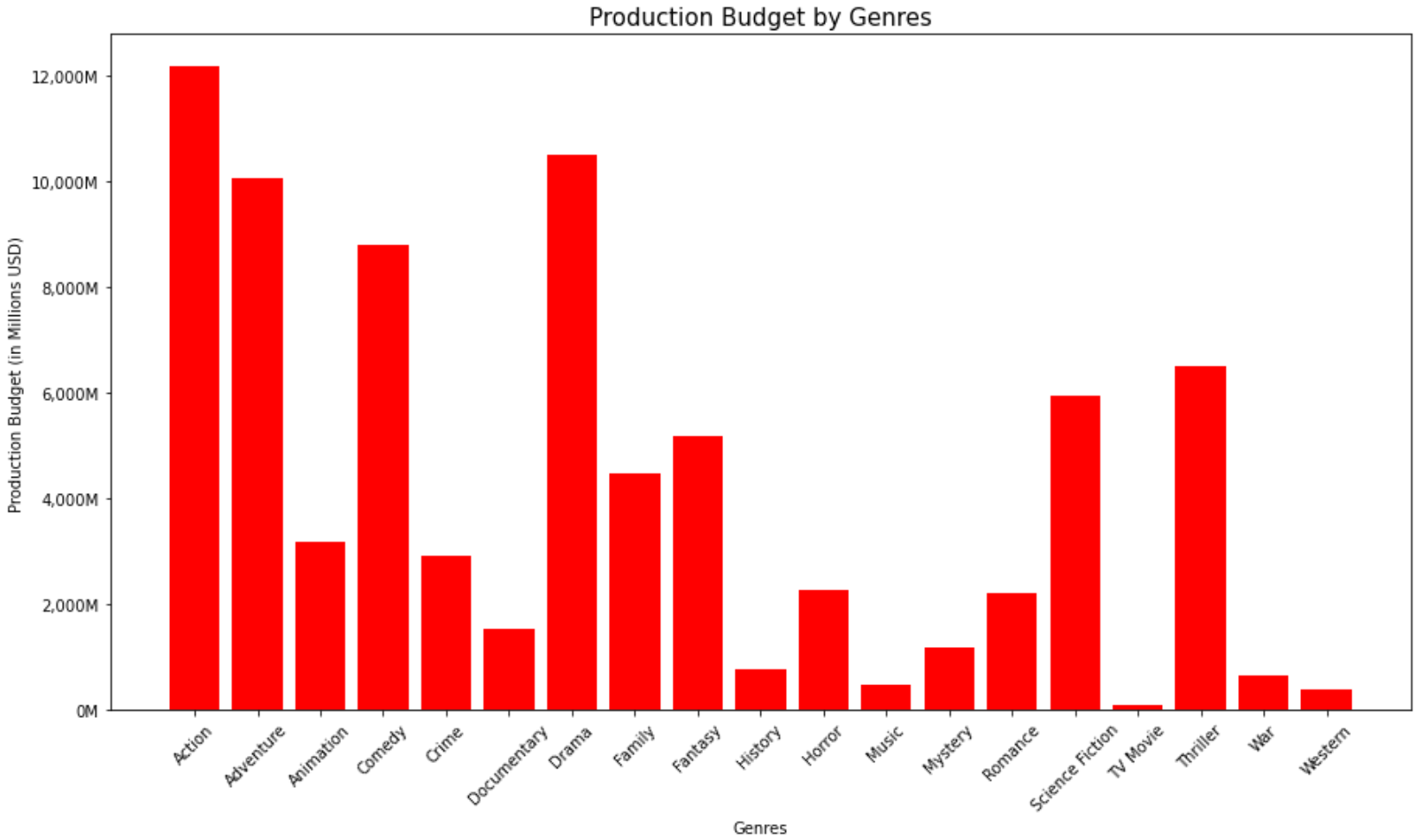
In [23]:

```
#create a new column rev_per_genre
df12['rev_per_genre'] = df12['worldwide_gross'] / df12['genre_len']

# create a new column budget_per_genre
df12['budget_per_genre'] = df12['production_budget'] / df12['genre_len']

# distribute budget per genre and revenue per genre into each of genre column according to movies' genr
gross_rev_genre = df12[genres].multiply(df12['rev_per_genre'], axis = 0)
budget_genre = df12[genres].multiply(df12['budget_per_genre'], axis = 0)

#get the total revenue and budget production associated with each genres
sum_rev_genres = gross_rev_genre.sum(axis = 0)
sum_budget_genres = budget_genre.sum(axis = 0)
# obtain return on investment associated with each genres
roi_genres = round(sum_rev_genres/sum_budget_genres - 1,2)
```

In [24]:

```
# Chart production budget by genres
fig, ax = plt.subplots(figsize = (15,8))
ax.bar(x = sum_budget_genres.index, height = sum_budget_genres.values, color = 'red')
ax.tick_params(axis='x', labelrotation=45)
ax.set_xlabel('Genres')
ax.set_ylabel('Production Budget (in Millions USD)')
ax.set_title('Production Budget by Genres', fontsize = 15)
ylabels = ['{:,.0f}'.format(y) + 'M' for y in ax.get_yticks()/1000000]
ax.set_yticklabels(ylabels)
plt.show();
```

```
<ipython-input-24-b66f968ec4fd>:9: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax.set_yticklabels(ylabels)
```

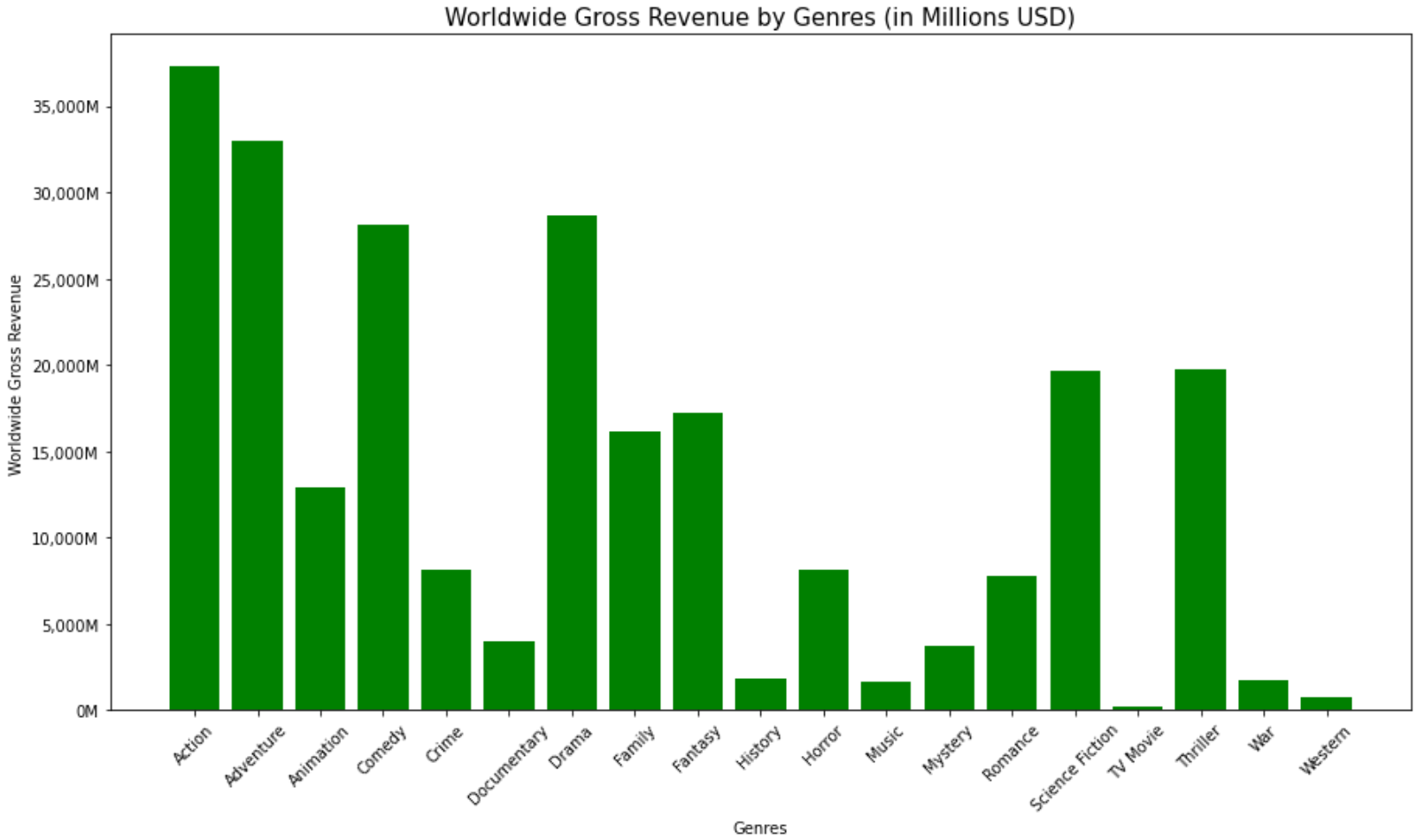


b. Which movie genres have the highest gross revenue?

In [25]:

```
# Chart worldwide gross revenue by genres
fig, ax = plt.subplots(figsize = (15,8))
ax.bar(x = sum_rev_genres.index, height = sum_rev_genres.values, color = 'green')
ax.tick_params(axis='x', labelrotation=45)
ax.set_xlabel('Genres')
ax.set_ylabel('Worldwide Gross Revenue')
ax.set_title('Worldwide Gross Revenue by Genres (in Millions USD)', fontsize = 15)
ylabels = ['{:,.0f}'.format(y) + 'M' for y in ax.get_yticks()/1000000]
ax.set_yticklabels(ylabels)
plt.show();
```

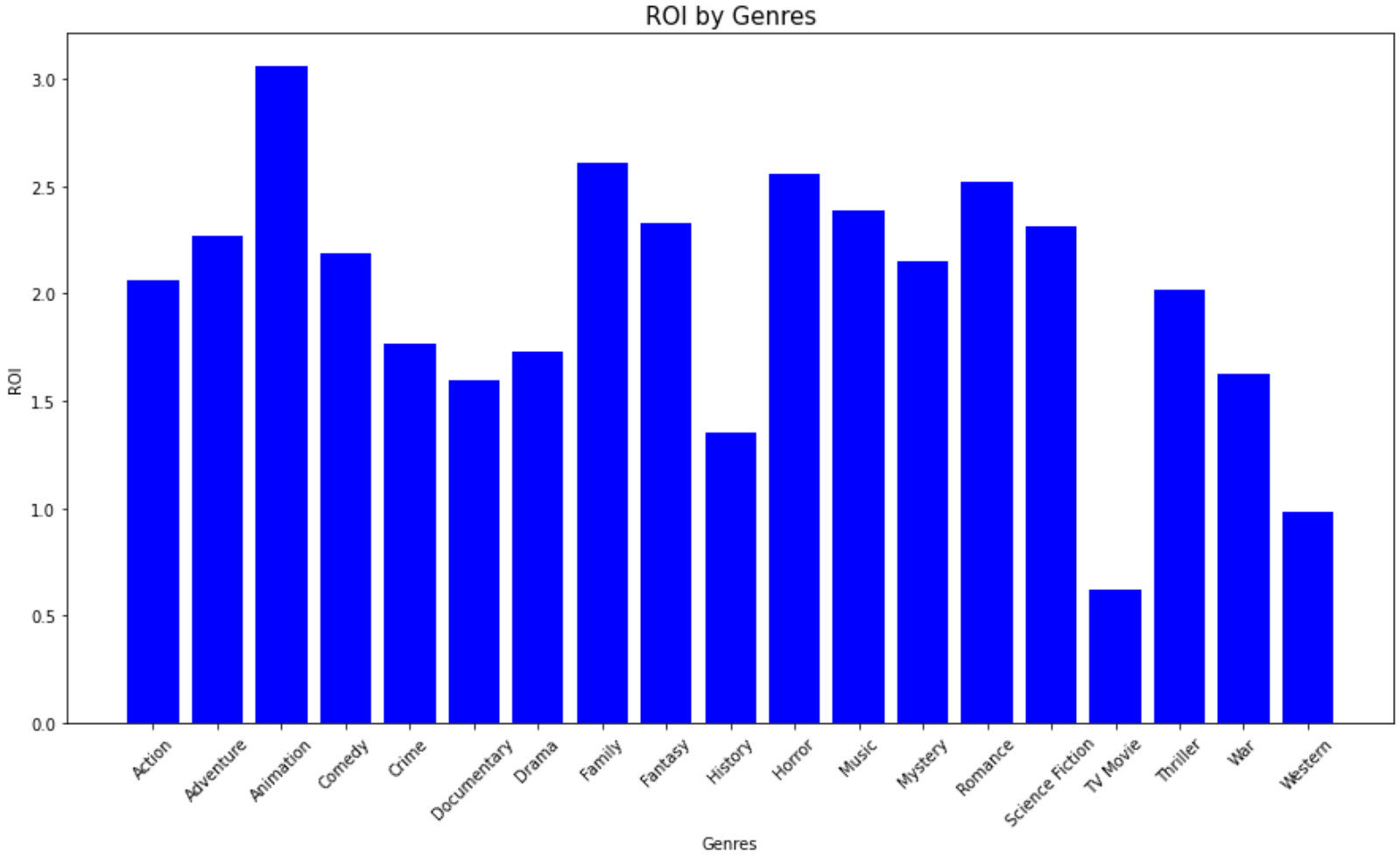
```
<ipython-input-25-011072ee5840>:9: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax.set_yticklabels(ylabels)
```



c. Which movie genres have the highest return on investment (ROI)?

In [26]:

```
# Chart ROI by genres
fig, ax = plt.subplots(figsize = (15,8))
ax.bar(x = roi_genres.index, height = roi_genres.values, color = 'blue')
ax.tick_params(axis='x', labelrotation=45)
ax.set_xlabel('Genres')
ax.set_ylabel('ROI')
ax.set_title('ROI by Genres', fontsize = 15)
plt.show();
```



d. Which movie genres have the highest ROI and lowest ratio between budget and revenue?

In [27]:

```
#Suppressing scientific notations
pd.options.display.float_format = '{:.0f}'.format

#combine the aggregate genres together and turn budget, revenue and ROI into separated columns
g = pd.concat([sum_budget_genres,sum_rev_genres, roi_genres], axis = 1)
g.columns = ['budget','revenue' ,'ROI']
#calculate to see what percentage of budget needed to achieve gross revenue
g['budget/rev'] = g['budget']/g['revenue']*100
# sort values with ROI and revenue as descending while budget as ascending
g.sort_values(by = ['ROI','budget/rev'], ascending = [False, True])[:10]
```

	budget	revenue	ROI	budget/rev
Animation	3173761905	12887223169	3	25
Family	4478295238	16153244216	3	28
Horror	2270333873	8090762134	3	28
Romance	2208368238	7783494817	3	28
Music	472733333	1602741319	2	29
Fantasy	5177499405	17252211819	2	30
Science Fiction	5929398750	19613437008	2	30
Adventure	10062379821	32951920652	2	31
Comedy	8805747744	28091860428	2	31
Mystery	1180781121	3724501544	2	32

My second recommendation is to focus on producing animation, horror, romance, and family movies. The reasor I recommend these genres is due to their general low production cost relative to gross revenue and high ROI rate. As a result, the risk of loss due to high production cost in movie industry will be minimized if stakeholders' studio only invest in the four genres mentioned above, particularly animation.

Third Recommendation

Which directors have the highest ROI and average ratings? (great with both values and movie qualities)

In [28]:

```
# Group the movies' stats by directors
directors_stats = df_dir.groupby(['primary_name']).aggregate({'production_budget':'mean',
                                                              'worldwide_gross':'mean','ROI':'mean',
                                                              'averagerating':'mean','numvotes':'sum',
                                                             'title':'count'})
# Only include directors with at least 3 movies (average in this database) -
# purpose is to exclude one-hit directors and look for consistent performers
directors_stats = directors_stats[directors_stats.title >= 3]

# # Only include directors with at least 6 average rating (quality movies)
directors_stats = directors_stats[directors_stats.averagerating >= 6]

# # Rank directors by their ROI, average rating, and number of votes received for their movies, and
# # only keep top 10
df_d = directors_stats.sort_values(by = ['ROI','averagerating'], ascending = [False,False])[:10]
df_d
```

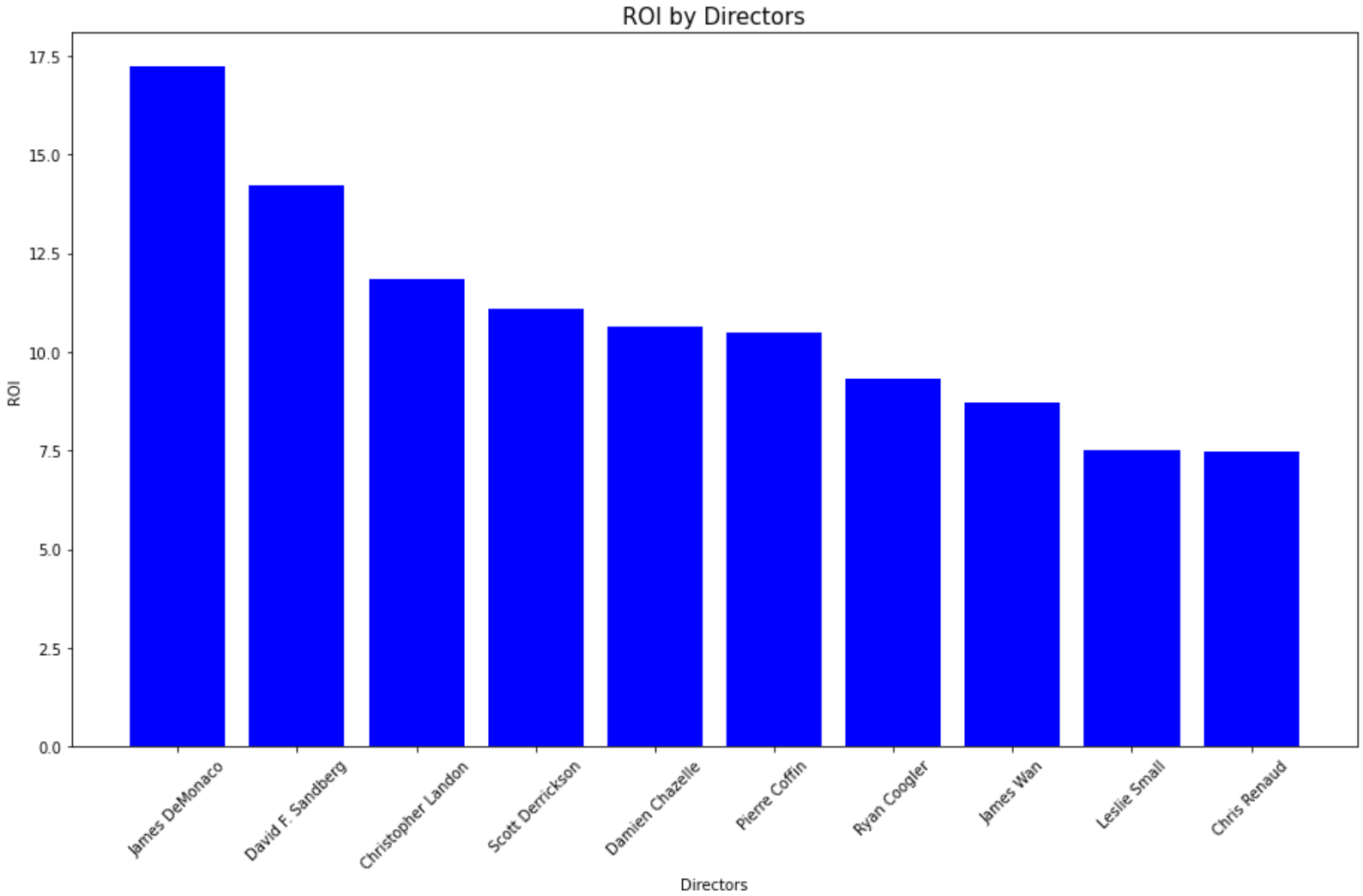
primary_name	production_budget	worldwide_gross	ROI	averagerating	numvotes	title
James DeMonaco	7333333	107105396	17	6	390006	3
David F. Sandberg	70000000	485038164	14	7	409154	4
Christopher Landon	8500000	73912366	12	6	192220	4
Scott Derrickson	66000000	284029664	11	7	776648	3
Damien Chazelle	27766667	190174675	11	8	1172995	3
Pierre Coffin	73333333	851136386	11	7	901321	3
Ryan Coogler	79300000	513125150	9	7	809006	3
James Wan	102500000	823719919	9	7	1190178	4
Leslie Small	4416667	21210245	8	7	21095	3

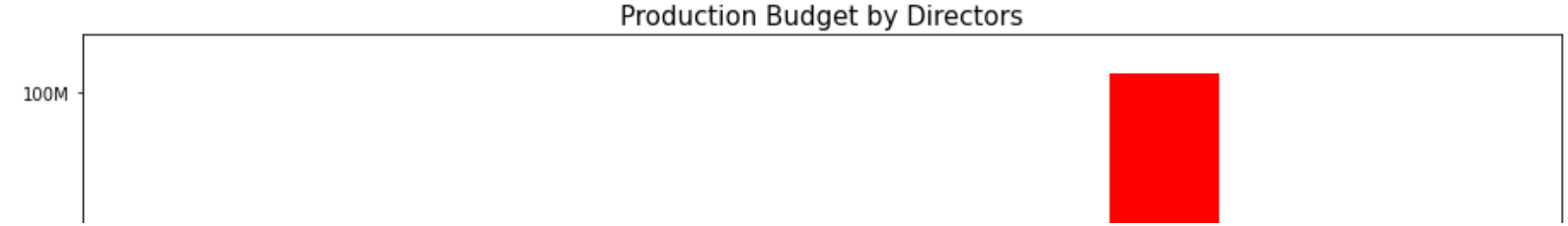
primary_name	production_budget	worldwide_gross	ROI	averagerating	numvotes	title
Chris Renaud	75000000	629695860	7	7	974205	4

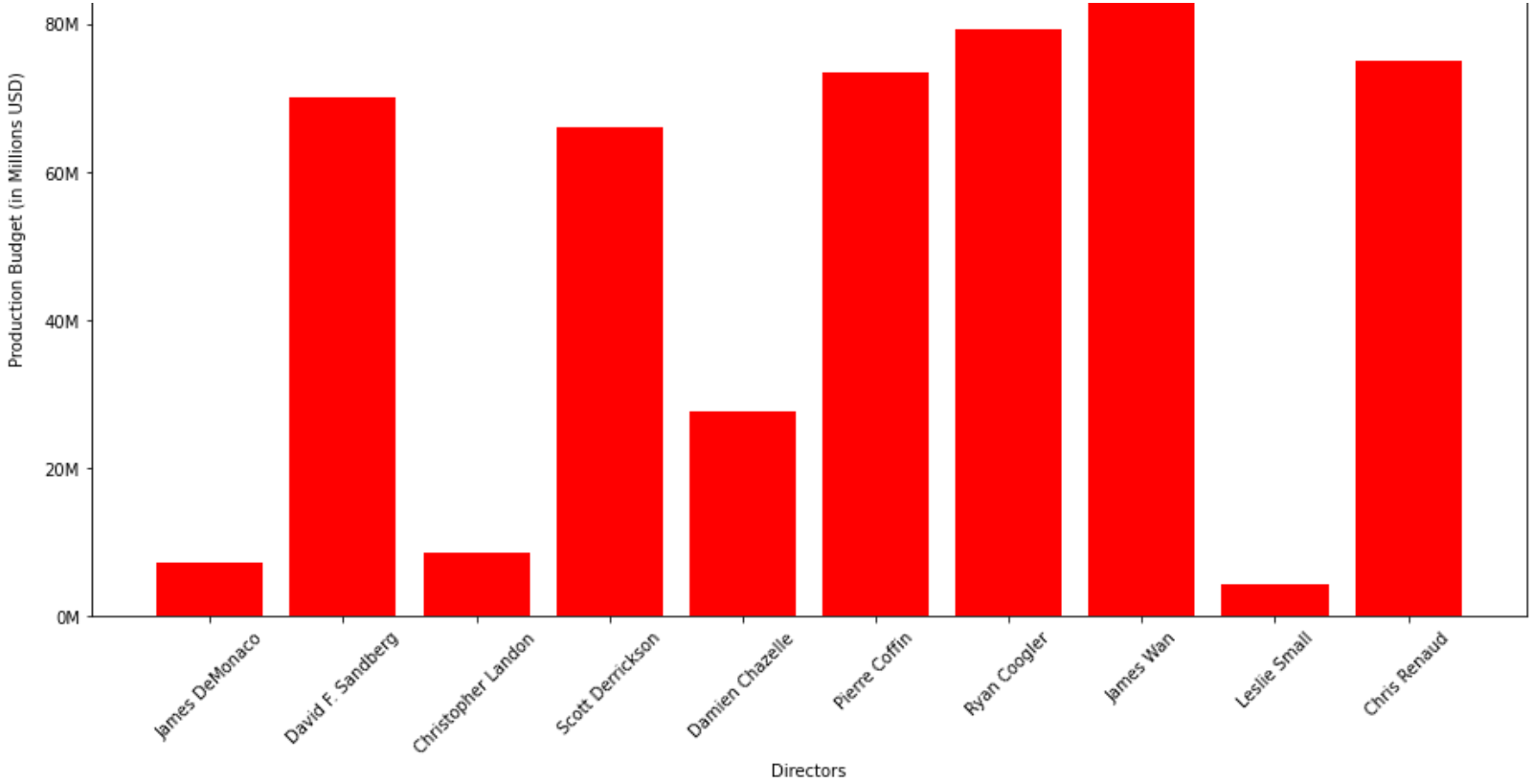
In [29]:

```
# Chart production budget
fig, ((ax1), (ax2)) = plt.subplots(figsize = (15,20), nrows = 2)

ax1.bar(x = df_d.index, height = df_d.ROI, color = 'blue')
ax1.tick_params(axis='x', labelrotation=45)
ax1.set_ylabel('ROI')
ax1.set_xlabel('Directors')
ax1.set_title('ROI by Directors', fontsize = 15)

ax2.bar(x = df_d.index, height = df_d.production_budget, color = 'red')
ax2.tick_params(axis='x', labelrotation=45)
ax2.set_ylabel('Production Budget (in Millions USD)')
ax2.set_xlabel('Directors')
ax2.set_title('Production Budget by Directors', fontsize = 15)
ylabels = ['{:,.0f}'.format(y) + 'M' for y in ax2.get_yticks()/1000000]
ax2.set_yticklabels(ylabels)

# set the spacing between subplots
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.4,
                    hspace=0.4)
plt.show();
```

```
<ipython-input-29-9a5514519ca3>:16: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax2.set_yticklabels(ylabels)
```


ROI by Directors
ROI
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
James DeMonaco
David F. Sandberg
Christopher Landon
Scott Derrickson
Damien Chazelle
Pierre Coffin
Ryan Coogler
James Wan
Leslie Small
Chris Renaud
Directors


Production Budget by Directors
100M



My third recommendation to stakeholder is to select the 3 following directors for studio production:

- James DeMonaco
- Christopher Landon
- Damien Chazelle

According to my analysis, these 3 directors not only achieve consistent good ROI rates with their movies but also awarded with high IMDb's average ratings. Moreover, to achieve such high ROI for their movies, these 3 directors don't need a large production budget. Thus, the investment cost required from the stakeholders' studio for new movies is also lower and the risk of loss will also be minimized.

Summary

Based on our exploratory analysis, there are three recommendations I have for our stakeholders include:

- Prioritize releasing movie in October of the year. Not only we can avoid compete directly with major movies, but also have a higher chance of hitting higher ROI rates.
- Prioritize producing animation, horror, romance, and family movies due to their general low production cost relative to gross revenue and high ROI rate.
- Prioritize inviting James DeMonaco, Christopher Landon, and Damien Chazelle to be the directors of the company's movies. They not only have great experience in the movie industry but also good track record of turning small budget movies into great returns.