Microsoft Movie Analysis

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Data Understanding

In [1]:

```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from glob import glob
import os
%matplotlib inline
```

In [2]:

```
csv_files = glob("./data/zippedData/*.csv.gz")
csv_files
```

Out[2]:

```
['./data/zippedData/imdb.title.crew.csv.gz',
 './data/zippedData/tmdb.movies.csv.gz',
 './data/zippedData/imdb.title.akas.csv.gz',
 './data/zippedData/imdb.title.ratings.csv.gz',
 './data/zippedData/imdb.name.basics.csv.gz',
 './data/zippedData/imdb.title.basics.csv.gz',
 './data/zippedData/tn.movie_budgets.csv.gz',
 './data/zippedData/bom.movie_gross.csv.gz',
 './data/zippedData/imdb.title.principals.csv.gz']
```

In [3]:

```
csv_files_dict = {}
for filename in csv_files:
    filename_cleaned = os.path.basename(filename).replace(".csv", "").replace(".", "_")
    filename_df = pd.read_csv(filename, index_col=0)
    csv_files_dict[filename_cleaned] = filename_df
```

In [4]:

```
csv_files_dict.keys()
```

Out[4]:

```
dict_keys(['imdb_title_crew_gz', 'tmdb_movies_gz', 'imdb_title_akas_gz', 'imdb_title_ratings_gz',
'imdb_name_basics_gz', 'imdb_title_basics_gz', 'tn_movie_budgets_gz', 'bom_movie_gross_gz',
'imdb_title_principals_gz'])
```

Movies (TMDB)

In [5]:

```
movies_df = csv_files_dict['tmdb_movies_gz']
type(movies_df)
```

Out[5]:

```
pandas.core.frame.DataFrame
```

In [6]:

```
movies_df.shape
```

Out[6]:

```
(26517, 9)
```

In [7]:

```
movies_df.head()
```

Out[7]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
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	[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	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186

In [8]:

```
movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26517 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   genre_ids          26517 non-null  object 
 1   id                 26517 non-null  int64  
 2   original_language  26517 non-null  object 
 3   original_title     26517 non-null  object 
 4   popularity         26517 non-null  float64
 5   release_date       26517 non-null  object 
 6   title              26517 non-null  object 
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 2.0+ MB
```

Contains TMDB rating and popularity info along with other details for various movies.

Observations: Everything looks to be formatted well except for release_date, which should be cast to date-time. Would be interesting to use popularity or rating info as a heatmap.

Title AKAs (IMDB)

In [9]:

```
title_akas_df = csv_files_dict['imdb_title_akas_gz']
type(movies_df)
```

Out[9]:

```
pandas.core.frame.DataFrame
```

In [10]:

```
title_akas_df.shape
```

Out[10]:

```
(331703, 7)
```

In [11]:

```
title_akas_df.head()
```

Out[11]:

	ordering	title	region	language	types	attributes	is_original_title
title_id							
tt0369610	10	Джурасик свят	BG	bg	NaN	NaN	0.0
tt0369610	11	Jurashikku warudo	JP	NaN	imdbDisplay	NaN	0.0
tt0369610	12	Jurassic World: O Mundo dos Dinossauros	BR	NaN	imdbDisplay	NaN	0.0
tt0369610	13	O Mundo dos Dinossauros	BR	NaN	NaN	short title	0.0
tt0369610	14	Jurassic World	FR	NaN	imdbDisplay	NaN	0.0

In [12]:

```
title_akas_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 331703 entries, tt0369610 to tt9880178
Data columns (total 7 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   ordering           331703 non-null  int64  
 1   title              331703 non-null  object 
 2   region             278410 non-null  object 
 3   language           41715 non-null   object 
 4   types              168447 non-null  object 
 5   attributes         14925 non-null   object 
 6   is_original_title  331678 non-null  float64
dtypes: float64(1), int64(1), object(5)
memory usage: 20.2+ MB
```

Shows alternative titles and the regions associated for those titles. If an aka is original title, it is marked accordingly in is_original_title

Observations: lots of missing values, but dtypes look correct

Title Basics (IMBD)

In [13]:

```
title_basics_df = csv_files_dict['imdb_title_basics_gz']
type(title_basics_df)
```

Out[13]:

```
pandas.core.frame.DataFrame
```

In [14]:

```
title_basics_df.shape
```

Out[14]:

```
(146144, 5)
```

In [15]:

```
title_basics_df.head()
```

Out[15]:

tconst	primary_title	original_title	start_year	runtime_minutes	genres
tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [16]:

```
title_basics_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 146144 entries, tt0063540 to tt9916754
Data columns (total 5 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   primary_title    146144 non-null  object 
 1   original_title   146123 non-null  object 
 2   start_year       146144 non-null  int64  
 3   runtime_minutes  114405 non-null  float64
 4   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(3)
memory usage: 6.7+ MB
```

title_basics_df contains basic information about various movie titles from IMDB. "tconst" is an alphanumeric unique identifier for titles in IMDB's datasets. Descriptions for all columns in IMDB datasets can be found here: https://www.imdb.com/interfaces/.

Observations:

- Some missing values for original_title (not much of a problem), runtime_minutes, and genres.
- genres is a string array, with "," separation

Questions:

- Any relationship between runtime and performance at the box office?
- Any relationship between genre and performance (are some genres more popular)?

Title Ratings (IMDB)

In [17]:

```
title_ratings_df = csv_files_dict['imdb_title_ratings_gz']
type(title_ratings_df)
```

Out[17]:

```
pandas.core.frame.DataFrame
```

In [18]:

```
title_ratings_df.shape
```

Out[18]:

```
(73856, 2)
```

In [19]:

```
title_ratings_df.head()
```

Out[19]:

tconst	averagerating	numvotes
tt10356526	8.3	31
tt10384606	8.9	559
tt1042974	6.4	20
tt1043726	4.2	50352
tt1060240	6.5	21

In [20]:

```
title_ratings_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 73856 entries, tt10356526 to tt9894098
Data columns (total 2 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   averagerating  73856 non-null  float64
 1   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1)
memory usage: 1.7+ MB
```

From IMDB. This dataset contains IMDB ratings (weighted average of individual user ratings) and the number of votes for each title, identified by "tconst".

Observations: dataset looks rather complete. Some titles have way more votes, affecting the reliability of "averagerating".

Questions: Are IMDB ratings correlated with box office performance? What about the number of individual votes? More people may be likely to review more popular (high-grossing) films, regardless of what rating they submit.

Title Crew (IMDB)

In [21]:

```
title_crew_df = csv_files_dict['imdb_title_crew_gz']
type(title_crew_df)
```

Out[21]:

```
pandas.core.frame.DataFrame
```

In [22]:

```
title_crew_df.shape
```

Out[22]:

```
(146144, 2)
```

In [23]:

```
title_crew_df.head()
```

Out[23]:

tconst	directors	writers
tt0285252	nm0899854	nm0899854
tt0438973	NaN	nm0175726,nm1802864
tt0462036	nm1940585	nm1940585
tt0835418	nm0151540	nm0310087,nm0841532
tt0878654	nm0089502,nm2291498,nm2292011	nm0284943

In [24]:

```
title_crew_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 146144 entries, tt0285252 to tt9010172
Data columns (total 2 columns):
 #   Column     Non-Null Count   Dtype 
---  ------     --------------   ----- 
 0   directors  140417 non-null  object
 1   writers    110261 non-null  object
dtypes: object(2)
memory usage: 3.3+ MB
```

From IMDB. Shows directors and writers associated with each title. Some missing values for directors and/or writers for some titles.

Observations:

- Directors and writers are denoted by nconsts (alphanumeric unique identifier for a name/person). I would need another dataset to find the names associated with each ncost.
- directors and writers columns contain string arrays

Questions: Should Microsoft consider working with some directors/writers over others?

Title Principals (IMDB)

In [25]:

```
title_principals_df = csv_files_dict['imdb_title_principals_gz']
type(title_principals_df)
```

Out[25]:

```
pandas.core.frame.DataFrame
```

In [26]:

```
title_principals_df.shape
```

Out[26]:

```
(1028186, 5)
```

In [27]:

```
title_principals_df.head()
```

Out[27]:

tconst	ordering	nconst	category	job	characters
tt0111414	1	nm0246005	actor	NaN	["The Man"]
tt0111414	2	nm0398271	director	NaN	NaN
tt0111414	3	nm3739909	producer	producer	NaN
tt0323808	10	nm0059247	editor	NaN	NaN
tt0323808	1	nm3579312	actress	NaN	["Beth Boothby"]

In [28]:

```
title_principals_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1028186 entries, tt0111414 to tt9692684
Data columns (total 5 columns):
 #   Column      Non-Null Count    Dtype
---  ------      --------------    -----
 0   ordering    1028186 non-null  int64
 1   nconst      1028186 non-null  object
 2   category    1028186 non-null  object
 3   job         177684 non-null   object
 4   characters  393360 non-null   object
dtypes: int64(1), object(4)
memory usage: 47.1+ MB
```

Name Basics (IMDB)

In [29]:

```
name_basics_df = csv_files_dict['imdb_name_basics_gz']
type(name_basics_df)
```

Out[29]:

```
pandas.core.frame.DataFrame
```

In [30]:

```
name_basics_df.shape
```

Out[30]:

```
(606648, 5)
```

In [31]:

```
name_basics_df.head()
```

Out[31]:

nconst	primary_name	birth_year	death_year	primary_profession	known_for_titles
nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,producer	tt0837562,tt2398241,tt0844471,tt0118553
nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_department	tt0896534,tt6791238,tt0287072,tt1682940
nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,writer	tt1470654,tt0363631,tt0104030,tt0102898
nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_department	tt0114371,tt2004304,tt1618448,tt1224387
nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_decorator	tt0452644,tt0452692,tt3458030,tt2178256

In [32]:

```
name_basics_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 606648 entries, nm0061671 to nm9993380
Data columns (total 5 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   primary_name        606648 non-null  object
 1   birth_year          82736 non-null   float64
 2   death_year          6783 non-null    float64
 3   primary_profession  555308 non-null  object
 4   known_for_titles    576444 non-null  object
dtypes: float64(2), object(3)
memory usage: 27.8+ MB
```

From IMDB. Shows basic info for people in the business, ordered by nconst.

We can use this to look up the name (and other background info) of a director or writer who works on a high-performing film

Observations:

- Some missing values. I know I won't be interested in people who have died (those who have a non-null entry for death_year.
- more string arrays. May nor may not need to deal with these

Movie Gross (BOM)

In [33]:

```
movie_gross_df = csv_files_dict['bom_movie_gross_gz']
type(movie_gross_df)
```

Out[33]:

```
pandas.core.frame.DataFrame
```

In [34]:

```
movie_gross_df.shape
```

Out[34]:

```
(3387, 4)
```

In [35]:

```
movie_gross_df.head()
```

Out[35]:

title	studio	domestic_gross	foreign_gross	year
Toy Story 3	BV	415000000.0	652000000	2010
Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
Inception	WB	292600000.0	535700000	2010
Shrek Forever After	P/DW	238700000.0	513900000	2010

In [36]:

```
movie_gross_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3387 entries, Toy Story 3 to An Actor Prepares
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   studio          3382 non-null   object 
 1   domestic_gross  3359 non-null   float64
 2   foreign_gross   2037 non-null   object 
 3   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(2)
memory usage: 132.3+ KB
```

From Box Office Mojo. This dataset shoes foreign and domestic gross information for different titles.

Observations:

- foreign_gross datatype is object while domestic_gross is type float. Change foreign_gross to type float or int.
- movie_gross_df also contains studio information, which could also be a predictor for movie success.

Movie Budgets (The Numbers)

In [37]:

```
movie_budgets_df = csv_files_dict['tn_movie_budgets_gz']
type(movie_budgets_df)
```

Out[37]:

```
pandas.core.frame.DataFrame
```

In [38]:

```
movie_budgets_df.shape
```

Out[38]:

```
(5782, 5)
```

In [39]:

```
movie_budgets_df.head()
```

Out[39]:

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

In [40]:

```
movie_budgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   release_date       5782 non-null   object
 1   movie              5782 non-null   object
 2   production_budget  5782 non-null   object
 3   domestic_gross     5782 non-null   object
 4   worldwide_gross    5782 non-null   object
dtypes: object(5)
memory usage: 271.0+ KB
```

From The Numbers.

Observations:

- release_date is dtype object. Possibly convert to date-time format.
- Gross figures are also objects, and should be converted to type int or float

Question 1: How much money should you spend to make a successful movie?

Clean Data

Clean data and create new variables to enhance analysis. Should adjust for inflation in order to work with the monetary data.

Check for duplicates

In [41]:

```
movie_budgets_df.duplicated().value_counts()
```

Out[41]:

```
False    5782
dtype: int64
```

No duplicate entries

Check null values and most common values

In [42]:

```
movie_budgets_df.isna().sum()
```

Out[42]:

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

No missing values in any columns

In [43]:

```
for col in movie_budgets_df:
    print(col)
    print(movie_budgets_df[col].value_counts(normalize=True))
    print("==========================================================")
```

```
release_date
Dec 31, 2014    0.004151
Dec 31, 2015    0.003978
Dec 31, 2010    0.002594
Dec 31, 2008    0.002421
Dec 31, 2009    0.002248
                  ...
Dec 31, 1996    0.000173
Apr 12, 2019    0.000173
Dec 14, 1957    0.000173
Apr 7, 2004     0.000173
Dec 17, 2008    0.000173
Name: release_date, Length: 2418, dtype: float64
==========================================================
movie
Home                    0.000519
Halloween               0.000519
King Kong               0.000519
The Ten Commandments    0.000346
RoboCop                 0.000346
                            ...
Heartbreakers           0.000173
The Kingdom             0.000173
One True Thing          0.000173
Jumper                  0.000173
O Menino e o Mundo      0.000173
Name: movie, Length: 5698, dtype: float64
==========================================================
production_budget
$20,000,000     0.039952
$10,000,000     0.036666
$30,000,000     0.030612
$15,000,000     0.029920
$25,000,000     0.029575
                  ...
$6,750,000      0.000173
$111,000,000    0.000173
$10,750,000     0.000173
$210,000        0.000173
$71,500,000     0.000173
Name: production_budget, Length: 509, dtype: float64
==========================================================
domestic_gross
$0              0.094777
$8,000,000      0.001557
$7,000,000      0.001211
$2,000,000      0.001211
$10,000,000     0.001038
                  ...
$7,100,000      0.000173
$30,564,825     0.000173
$34,416,893     0.000173
$84,185,387     0.000173
$106,885,658    0.000173
Name: domestic_gross, Length: 5164, dtype: float64
==========================================================
worldwide_gross
$0              0.063473
$8,000,000      0.001557
$7,000,000      0.001038
$2,000,000      0.001038
$9,000,000      0.000692
                  ...
$263,502,914    0.000173
$49,800,000     0.000173
$71,000,000     0.000173
$27,053,815     0.000173
$47,407,635     0.000173
Name: worldwide_gross, Length: 5356, dtype: float64
==========================================================
```

9.4% of movies have no domestic_gross, 6.3% of movies have no worldwide_gross. This data is either missing or the movies were never released

Change dtypes and reformat monetary data

In [44]:

In [45]:

```
# function for changing money columns to int types
def convert_amt_to_int(df, col):
    df[col] = df[col].str.replace("$", "").str.replace(",", "").astype(int)
    return df
```

In [45]:

```
money_cols = ['production_budget', 'domestic_gross', 'worldwide_gross']

for col in money_cols:
    movie_budgets_df = convert_amt_to_int(movie_budgets_df, col)
```

In [46]:

```
movie_budgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   release_date       5782 non-null   object
 1   movie              5782 non-null   object
 2   production_budget  5782 non-null   int64 
 3   domestic_gross     5782 non-null   int64 
 4   worldwide_gross    5782 non-null   int64 
dtypes: int64(3), object(2)
memory usage: 271.0+ KB
```

In [47]:

```
movie_budgets_df.head()
```

Out[47]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747

In [48]:

```
movie_budgets_df['release_date'] = pd.to_datetime(movie_budgets_df['release_date'])
movie_budgets_df.head()
```

Out[48]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
1	2009-12-18	Avatar	425000000	760507625	2776345279
2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
3	2019-06-07	Dark Phoenix	350000000	42762350	149762350
4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963
5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747

Account for inflation

We are adjusting for inflation because we are dealing with historical monetary data.

In [49]:

```
import cpi
```

In [50]:

```
cpi.update()
```

In [51]:

```
movie_budgets_df['release_year'] = movie_budgets_df['release_date'].dt.year
movie_budgets_df.head()
```

Out[51]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year
1	2009-12-18	Avatar	425000000	760507625	2776345279	2009
2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011
3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019
4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015
5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017

In [52]:

```
movie_budgets_df.reset_index(inplace=True)
```

In [53]:

```
budgets_to_2018 = movie_budgets_df[movie_budgets_df['release_year'] < 2019].copy()
```

In [54]:

```
budgets_to_2018['budget_adjusted'] = budgets_to_2018.apply(lambda x: cpi.inflate(x.production_budget, x.r
budgets_to_2018['dgross_adjusted'] = budgets_to_2018.apply(lambda x: cpi.inflate(x.domestic_gross, x.rele
budgets_to_2018['wwgross_adjusted'] = budgets_to_2018.apply(lambda x: cpi.inflate(x.worldwide_gross, x.re
```

In [55]:

```
#movie_budgets_df['budget_adjusted'] = movie_budgets_df.apply(lambda x: cpi.inflate(x.production_budget,
#movie_budgets_df['dgross_adjusted'] = movie_budgets_df.apply(lambda x: cpi.inflate(x.domestic_gross, x.
#movie_budgets_df['wwgross_adjusted'] = movie_budgets_df.apply(lambda x: cpi.inflate(x.worldwide_gross,
```

In [56]:

```
budgets_after_2018 = movie_budgets_df[movie_budgets_df['release_year'] <= 2019].copy()
```

In [57]:

```
budgets_after_2018['budget_adjusted'] = budgets_after_2018['production_budget']
budgets_after_2018['dgross_adjusted'] = budgets_after_2018['domestic_gross']
budgets_after_2018['wwgross_adjusted'] = budgets_after_2018['worldwide_gross']
```

In [58]:

```
movie_budgets_df = pd.concat([budgets_to_2018, budgets_after_2018], axis=0)
```

EDA

Calculate ROI

In [59]:

```
movie_budgets_df['roi'] = (movie_budgets_df['wwgross_adjusted'] - movie_budgets_df['budget_adjusted']) /
movie_budgets_df['domestic_roi'] = (movie_budgets_df['dgross_adjusted'] - movie_budgets_df['budget_adjust
```

In [60]:

```
movie_budgets_df.head()
```

Out[60]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year	budget_adjusted	dgross_adjusted	wwgross_ad
0	1	2009-12-18	Avatar	425000000	760507625	2776345279	2009	5.127072e+08	9.174536e+08	3.34930
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011	4.724294e+08	2.773640e+08	1.20312
3	4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015	3.609991e+08	5.012120e+08	1.53202
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017	3.347058e+08	6.548212e+08	1.39026
5	6	2015-12-18	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220	2015	3.341371e+08	1.022789e+09	2.24211

In [61]:

```
movie_budgets_df.shape
```

Out[61]:

```
(11491, 12)
```

In [62]:

```
movie_budgets_df = movie_budgets_df.sort_values(by='roi', ascending=False)
movie_budgets_df.head()
```

Out[62]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year	budget_adjusted	dgross_adjusted	wwgro
5745	46	1972-06-30	Deep Throat	25000	45000000	45000000	1972	25000.000000	4.500000e+07	4.5
5745	46	1972-06-30	Deep Throat	25000	45000000	45000000	1972	154791.267943	2.786243e+08	2.7
5613	14	1980-03-21	Mad Max	200000	8750000	99750000	1980	200000.000000	8.750000e+06	9.9
5613	14	1980-03-21	Mad Max	200000	8750000	99750000	1980	628182.038835	2.748296e+07	3.1
5492	93	2009-09-25	Paranormal Activity	450000	107918810	194183034	2009	542866.498553	1.301900e+08	2.3

In [63]:

```
movie_budgets_df.reset_index(inplace=True)
```

In [64]:

```
budgets_adjusted_df = movie_budgets_df.drop(['production_budget', 'domestic_gross', 'worldwide_gross', 'i
budgets_adjusted_df.head()
```

Out[64]:

	index	release_date	movie	release_year	budget_adjusted	dgross_adjusted	wwgross_adjusted	roi	domestic_roi
0	5745	1972-06-30	Deep Throat	1972	25000.000000	4.500000e+07	4.500000e+07	1799.000000	1799.000000
1	5745	1972-06-30	Deep Throat	1972	154791.267943	2.786243e+08	2.786243e+08	1799.000000	1799.000000
2	5613	1980-03-21	Mad Max	1980	200000.000000	8.750000e+06	9.975000e+07	497.750000	42.750000
3	5613	1980-03-21	Mad Max	1980	628182.038835	2.748296e+07	3.133058e+08	497.750000	42.750000
4	5492	2009-09-25	Paranormal Activity	2009	542866.498553	1.301900e+08	2.342566e+08	430.517853	238.819578

In [65]:

```
budgets_adjusted_df.isna().sum()
```

Out[65]:

```
index               0
release_date        0
movie               0
release_year        0
budget_adjusted     0
dgross_adjusted     0
wwgross_adjusted    0
roi                 0
domestic_roi        0
dtype: int64
```

No duplicates in inflation-adjusted dataframe

Create budget classes

In [66]:

```
budgets_adjusted_df['budget_adjusted'].describe()
```

Out[66]:

```
count    1.149100e+04
mean     3.699914e+07
std      4.700373e+07
min      1.100000e+03
25%      6.000000e+06
50%      2.000000e+07
75%      4.838919e+07
max      5.127072e+08
Name: budget_adjusted, dtype: float64
```

Distribution of budgets is right_skewed

In [67]:

```
budgets_adjusted_df['budget_range'] = pd.qcut(budgets_adjusted_df['budget_adjusted'], q=4, precision=0)
budgets_adjusted_df.head()
```

Out[67]:

	index	release_date	movie	release_year	budget_adjusted	dgross_adjusted	wwgross_adjusted	roi	domestic_roi	budget_range
0	5745	1972-06-30	Deep Throat	1972	25000.000000	4.500000e+07	4.500000e+07	1799.000000	1799.000000	(1099.0, 6000000.0]
1	5745	1972-06-30	Deep Throat	1972	154791.267943	2.786243e+08	2.786243e+08	1799.000000	1799.000000	(1099.0, 6000000.0]
2	5613	1980-03-21	Mad Max	1980	200000.000000	8.750000e+06	9.975000e+07	497.750000	42.750000	(1099.0, 6000000.0]
3	5613	1980-03-21	Mad Max	1980	628182.038835	2.748296e+07	3.133058e+08	497.750000	42.750000	(1099.0, 6000000.0]
4	5492	2009-09-25	Paranormal Activity	2009	542866.498553	1.301900e+08	2.342566e+08	430.517853	238.819578	(1099.0, 6000000.0]

In [68]:

```
budgets_adjusted_df['budget_range'].value_counts()
```

Out[68]:

```
(1099.0, 6000000.0]          2924
(6000000.0, 20000000.0]      2881
(48389193.0, 512707249.0]    2873
(20000000.0, 48389193.0]     2813
Name: budget_range, dtype: int64
```

We have roughly the same number of entries in each bin

- Low Budget: 1,000 - 7,800,000
- Low Medium Budget: 7.8 - 24 million
- High Medium Budget: 24 - 58 million
- High Budget: 58 million + (up to 513 million)

In [69]:

```
bin_labels = ['Low', 'Low Medium', 'High Medium', 'High']

budgets_adjusted_df['budget_class'] = pd.qcut(budgets_adjusted_df['budget_adjusted'], q=[0, 0.25, 0.5, 0.
budgets_adjusted_df.head()
```

Out[69]:

	index	release_date	movie	release_year	budget_adjusted	dgross_adjusted	wwgross_adjusted	roi	domestic_roi	budget_range
0	5745	1972-06-30	Deep Throat	1972	25000.000000	4.500000e+07	4.500000e+07	1799.000000	1799.000000	(1099.0, 6000000.0]
1	5745	1972-06-30	Deep Throat	1972	154791.267943	2.786243e+08	2.786243e+08	1799.000000	1799.000000	(1099.0, 6000000.0]
2	5613	1980-03-21	Mad Max	1980	200000.000000	8.750000e+06	9.975000e+07	497.750000	42.750000	(1099.0, 6000000.0]
3	5613	1980-03-21	Mad Max	1980	628182.038835	2.748296e+07	3.133058e+08	497.750000	42.750000	(1099.0, 6000000.0]
4	5492	2009-09-25	Paranormal Activity	2009	542866.498553	1.301900e+08	2.342566e+08	430.517853	238.819578	(1099.0, 6000000.0]

Add profit column(s)

Calculating budget-gross difference

In [70]:

```
budgets_adjusted_df['budget_gross_diff'] = budgets_adjusted_df['wwgross_adjusted'] - budgets_adjusted_df[
budgets_adjusted_df['domestic_profit'] = budgets_adjusted_df['dgross_adjusted'] - budgets_adjusted_df['bu
```

In [71]:

```
budgets_adjusted_df.rename(columns = {'budget_adjusted':'budget', 'dgross_adjusted':'domestic_gross', 'ww
```

In [72]:

```
budgets_adjusted_df.head()
```

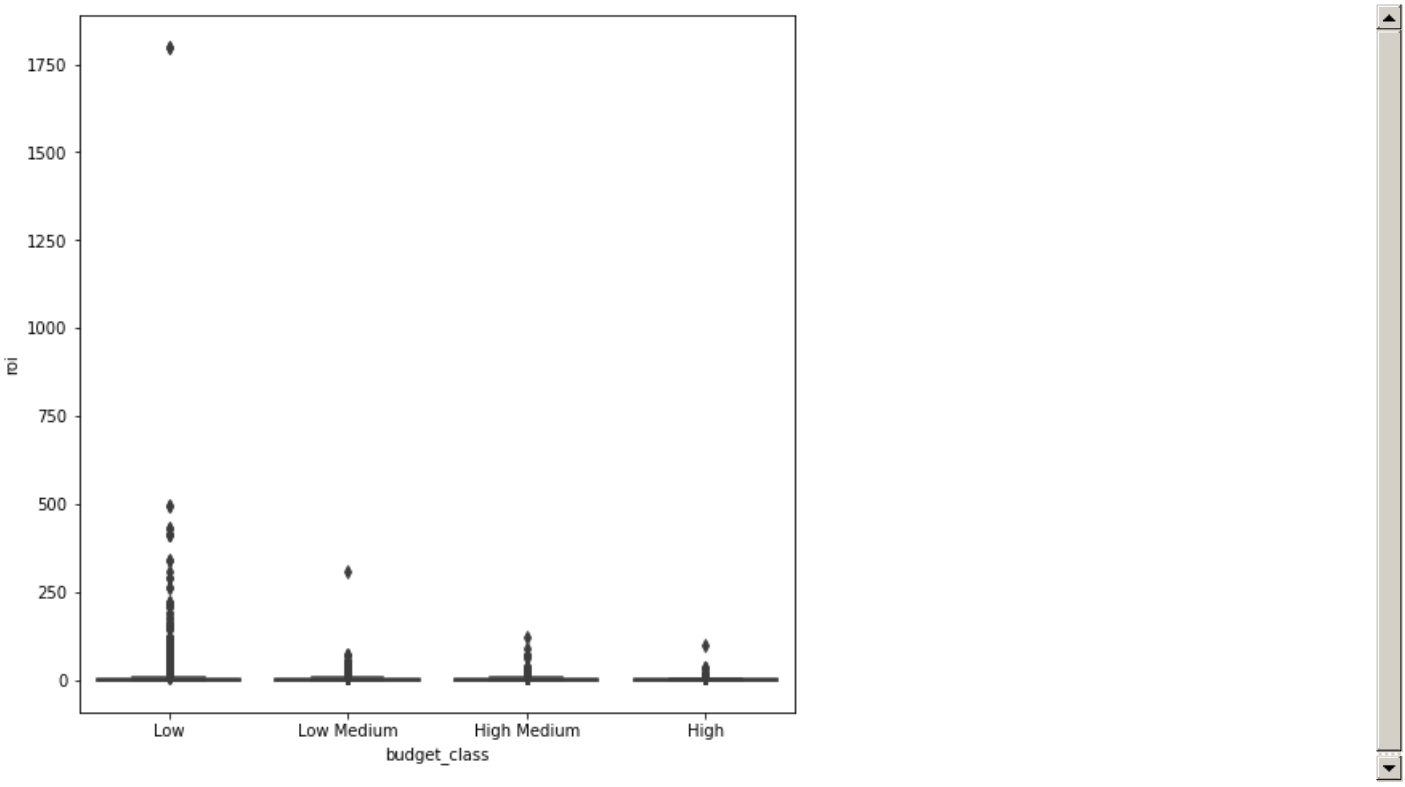
Out[72]:

	index	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	bu
0	5745	1972-06-30	Deep Throat	1972	25000.000000	4.500000e+07	4.500000e+07	1799.000000	1799.000000	(1099.0, 6000000.0]	
1	5745	1972-06-30	Deep Throat	1972	154791.267943	2.786243e+08	2.786243e+08	1799.000000	1799.000000	(1099.0, 6000000.0]	
2	5613	1980-03-21	Mad Max	1980	200000.000000	8.750000e+06	9.975000e+07	497.750000	42.750000	(1099.0, 6000000.0]	
3	5613	1980-03-21	Mad Max	1980	628182.038835	2.748296e+07	3.133058e+08	497.750000	42.750000	(1099.0, 6000000.0]	
4	5492	2009-09-25	Paranormal Activity	2009	542866.498553	1.301900e+08	2.342566e+08	430.517853	238.819578	(1099.0, 6000000.0]	

Preliminary Visualization

In [73]:

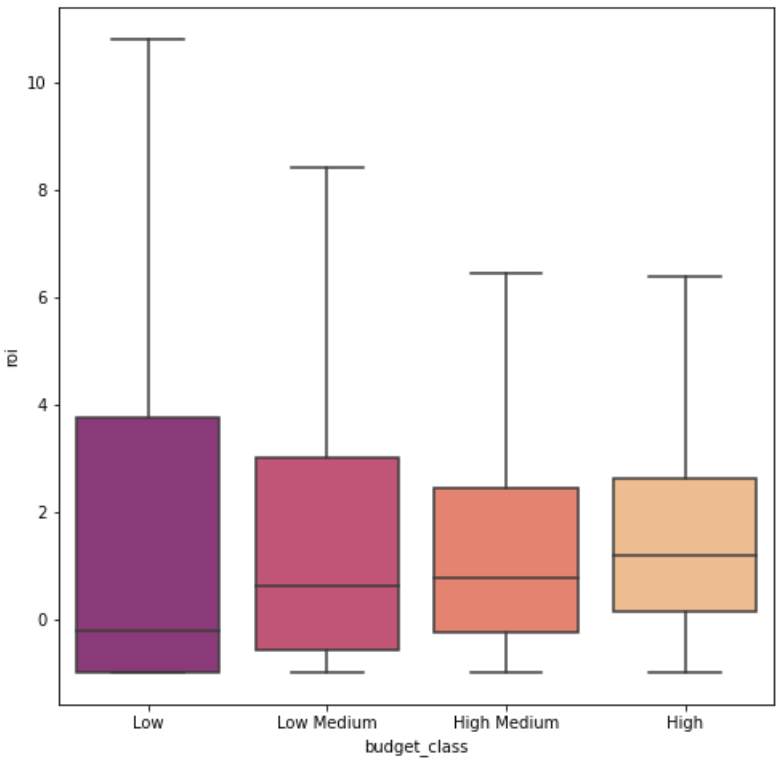
```
plt.figure(figsize=(8,8))
sns.boxplot(x='budget_class', y='roi', data=budgets_adjusted_df);
```



Lots of outliers per budget class for ROI. The Low budget class contains the most outliers

In [74]:

```
plt.figure(figsize=(8,8))
clrs = ['#982d80', '#d3436e', '#f8765c', '#febb81']
sns.boxplot(x='budget_class', y='roi', data=budgets_adjusted_df, showfliers=False, palette=clrs);
```



Same plot without outliers

Inspect and address outliers

Inspecting ROI outliers first. Calculations use the IQR method.

In [75]:

```
budgets_adjusted_df = budgets_adjusted_df.sort_values(by='roi', ascending=True)

Q1 = np.quantile(budgets_adjusted_df['roi'],0.25)
Q3 = np.quantile(budgets_adjusted_df['roi'],0.75)
IQR = Q3 - Q1
IQR
```

Out[75]:

```
3.2653807091919194
```

In [76]:

```
lower_lim = Q1 - (1.5*IQR)
upper_lim = Q3 + (1.5*IQR)
```

In [77]:

```
outliers_low = (budgets_adjusted_df['roi'] < lower_lim)
outliers_high = (budgets_adjusted_df['roi'] > upper_lim)
outlier_df = budgets_adjusted_df[outliers_low | outliers_high]
outlier_df.head()
```

Out[77]:

	index	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	budget
983	1344	1999-05-28	Notting Hill	1999	4.200000e+07	1.160897e+08	3.637281e+08	7.660192	1.764040	(20000000.0, 48389193.0]	High M
984	1344	1999-05-28	Notting Hill	1999	6.524647e+07	1.803439e+08	5.650470e+08	7.660192	1.764040	(48389193.0, 512707249.0]	
982	4781	1959-03-29	Some Like it Hot	1959	2.564851e+07	2.223462e+08	2.225200e+08	7.675749	7.668973	(20000000.0, 48389193.0]	High M
981	4781	1959-03-29	Some Like it Hot	1959	2.883848e+06	2.500000e+07	2.501954e+07	7.675749	7.668973	(1099.0, 6000000.0]	
980	631	2006-03-31	Ice Age: The Meltdown	2006	9.628385e+07	2.507625e+08	8.368983e+08	7.691990	1.604408	(48389193.0, 512707249.0]	

In [78]:

```
outlier_df['budget_class'].value_counts(normalize=True)
```

Out[78]:

```
Low            0.487310
Low Medium     0.269036
High Medium    0.153299
High           0.090355
Name: budget_class, dtype: float64
```

In [79]:

```
no_roi_outliers = budgets_adjusted_df[~(outliers_low | outliers_high)]
```

Most of the outliers for ROI happen to be Low and Low-Medium budget films (1000-7,800,000 and 7,800,000-24,000,000 respectively). I saw this in my preliminary boxplot. Now to examine profit outliers:

In [80]:

```
budgets_adjusted_df = budgets_adjusted_df.sort_values(by='profit', ascending=True)

Q1 = np.quantile(budgets_adjusted_df['profit'],0.25)
Q3 = np.quantile(budgets_adjusted_df['profit'],0.75)
IQR = Q3 - Q1

lower_lim = Q1 - (1.5*IQR)
upper_lim = Q3 + (1.5*IQR)

outliers_low = (budgets_adjusted_df['profit'] < lower_lim)
outliers_high = (budgets_adjusted_df['profit'] > upper_lim)
profit_outlier_df = budgets_adjusted_df[outliers_low | outliers_high]
profit_outlier_df.head()
```

Out[80]:

	index	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	buc
8803	2	2019-06-07	Dark Phoenix	2019	3.500000e+08	4.276235e+07	1.497624e+08	-0.572108	-0.877822	(48389193.0, 512707249.0]	
10943	2327	1970-01-01	Waterloo	1970	1.667597e+08	0.000000e+00	0.000000e+00	-1.000000	-1.000000	(48389193.0, 512707249.0]	
9887	352	2001-04-27	Town & Country	2001	1.534453e+08	9.809464e+06	1.514690e+07	-0.901288	-0.936072	(48389193.0, 512707249.0]	
10025	404	2002-08-16	The Adventures of Pluto Nash	2002	1.438638e+08	6.345980e+06	1.020713e+07	-0.929050	-0.955889	(48389193.0, 512707249.0]	
9974	1333	1980-11-19	Heaven's Gate	1980	1.382000e+08	1.094397e+07	1.094457e+07	-0.920806	-0.920811	(48389193.0, 512707249.0]	

In [81]:

```
profit_outlier_df.sort_values(by='profit', ascending=False)
```

Out[81]:

	index	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	l
57	4567	1939-12-15	Gone with the Wind	1939	7.261604e+07	3.699330e+09	7.271382e+09	99.134665	49.943710	(48389193.0, 512707249.0]	
12	5346	1942-08-13	Bambi	1942	1.362330e+07	1.632208e+09	4.255297e+09	311.354312	118.810023	(6000000.0, 20000000.0]	
78	3464	1977-05-25	Star Wars Ep. IV: A New Hope	1977	4.697889e+07	1.968834e+09	3.359410e+09	70.508910	40.908910	(20000000.0, 48389193.0]	
36	5117	1937-12-21	Snow White and the Seven Dwarfs	1937	2.674380e+07	3.323663e+09	3.323663e+09	123.277880	123.277880	(20000000.0, 48389193.0]	
702	42	1997-12-19	Titanic	1997	3.225059e+08	1.063244e+09	3.560801e+09	10.041042	2.296820	(48389193.0, 512707249.0]	
...	...	...	...	...	...	...	...	...	...	...	
9974	1333	1980-11-19	Heaven's Gate	1980	1.382000e+08	1.094397e+07	1.094457e+07	-0.920806	-0.920811	(48389193.0, 512707249.0]	
10025	404	2002-08-16	The Adventures of Pluto Nash	2002	1.438638e+08	6.345980e+06	1.020713e+07	-0.929050	-0.955889	(48389193.0, 512707249.0]	
9887	352	2001-04-27	Town & Country	2001	1.534453e+08	9.809464e+06	1.514690e+07	-0.901288	-0.936072	(48389193.0, 512707249.0]	
10943	2327	1970-01-01	Waterloo	1970	1.667597e+08	0.000000e+00	0.000000e+00	-1.000000	-1.000000	(48389193.0, 512707249.0]	
8803	2	2019-06-07	Dark Phoenix	2019	3.500000e+08	4.276235e+07	1.497624e+08	-0.572108	-0.877822	(48389193.0, 512707249.0]	

1342 rows × 13 columns

In [82]:

```
profit_outlier_df['budget_class'].value_counts(normalize=True)
```

Out[82]:

```
High           0.725037
High Medium    0.173621
Low Medium     0.077496
Low            0.023845
Name: budget_class, dtype: float64
```

In [83]:

```
profit_outlier_df.groupby('budget_class').mean()
```

Out[83]:

	index	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	profit	domestic_pr
budget_class									
Low	4943.750000	1984.437500	3.425048e+06	1.833037e+08	3.270556e+08	209.756112	132.631138	3.236306e+08	1.798786e
Low Medium	3461.980769	1995.394231	1.425764e+07	1.832396e+08	3.703483e+08	27.442540	13.224603	3.560907e+08	1.689820e
High Medium	2399.309013	1996.476395	3.457087e+07	2.461760e+08	4.469761e+08	12.444151	6.441327	4.124052e+08	2.116051e
High	610.759507	2005.421377	1.320084e+08	2.474337e+08	6.205105e+08	4.282092	1.219803	4.885021e+08	1.154252e

In [84]:

```
profit_outlier_df.groupby('budget_class').std()
```

Out[84]:

budget_class	index	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	profit	domestic_prof
Low	579.299967	27.626469	2.011151e+06	1.546607e+08	1.796733e+08	322.751215	312.791584	1.792134e+08	1.543330e+(
Low Medium	753.992828	17.157420	4.121518e+06	1.789110e+08	4.034298e+08	30.976690	14.432035	4.035080e+08	1.791561e+(
High Medium	956.914599	16.769497	7.612963e+06	3.088870e+08	4.105341e+08	12.915339	10.045939	4.100790e+08	3.087476e+(
High	726.940829	11.782635	6.466245e+07	1.899445e+08	4.207328e+08	4.461794	2.409619	3.973757e+08	1.860483e+(

Profit outliers disproportionately come from high budget films. The average budgets of these films don't seem to be on the higher ends of their respective categories. That is, it is not necessarily the extremely high budget films (budget outliers) that lead to outliers in profit.

In [85]:

```
no_profit_outliers = budgets_adjusted_df[~(outliers_low | outliers_high)]
no_profit_outliers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10149 entries, 9397 to 753
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   index            10149 non-null  int64
 1   release_date     10149 non-null  datetime64[ns]
 2   movie            10149 non-null  object
 3   release_year     10149 non-null  int64
 4   budget           10149 non-null  float64
 5   domestic_gross   10149 non-null  float64
 6   worldwide_gross  10149 non-null  float64
 7   roi              10149 non-null  float64
 8   domestic_roi     10149 non-null  float64
 9   budget_range     10149 non-null  category
 10  budget_class     10149 non-null  category
 11  profit           10149 non-null  float64
 12  domestic_profit  10149 non-null  float64
dtypes: category(2), datetime64[ns](1), float64(7), int64(2), object(1)
memory usage: 971.7+ KB
```

Visualization

In [86]:

```
from matplotlib import ticker
```

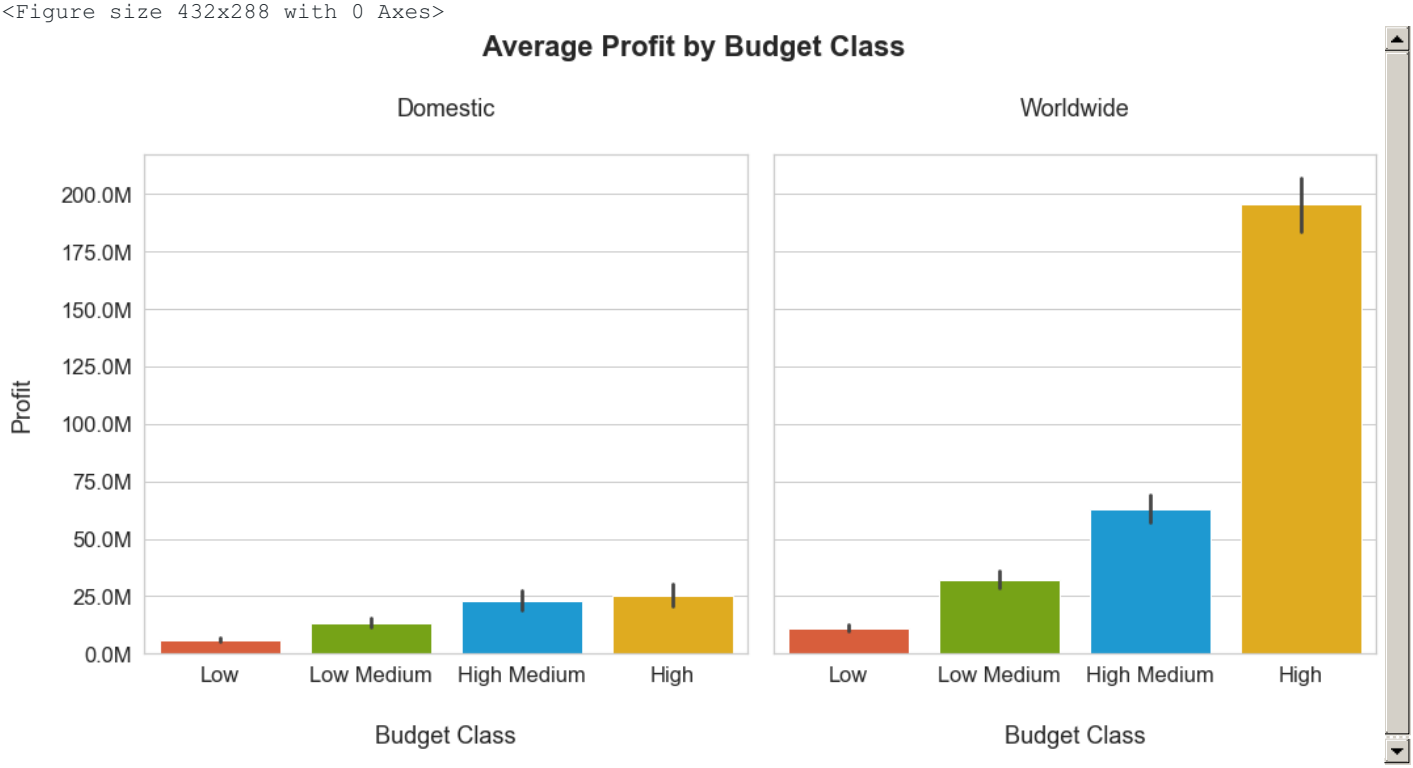
In [87]:

```
clrs = ['#f25022', '#7fba00', '#00a4ef', '#ffb900', '#737373']
sns.set_palette(clrs)
```

In [88]:

```
sns.set_theme(font_scale=1.5)
sns.set_style('whitegrid')
sns.despine()

fig,axes = plt.subplots(1,2, figsize=(15,8), sharey=True)
fig.suptitle('Average Profit by Budget Class', fontweight='bold')

sns.barplot(x='budget_class', y='domestic_profit', data=budgets_adjusted_df, palette=clrs, ax=axes[0])
axes[0].set_title('Domestic', pad=30)
axes[0].set_xlabel('Budget Class', labelpad=30)
axes[0].set_ylabel('Profit', labelpad=20)
axes[0].yaxis.get_major_formatter().set_scientific(False)
axes[0].yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.1f}'.format(x/1000000) + 'M'))

sns.barplot(x='budget_class', y='profit', data=budgets_adjusted_df, palette=clrs, ax=axes[1])
axes[1].set_title('Worldwide', pad=30)
axes[1].set_xlabel('Budget Class', labelpad=30)
axes[1].set_ylabel('')
fig.tight_layout()
plt.savefig('Profit_BudgetClass', dpi=300);
```

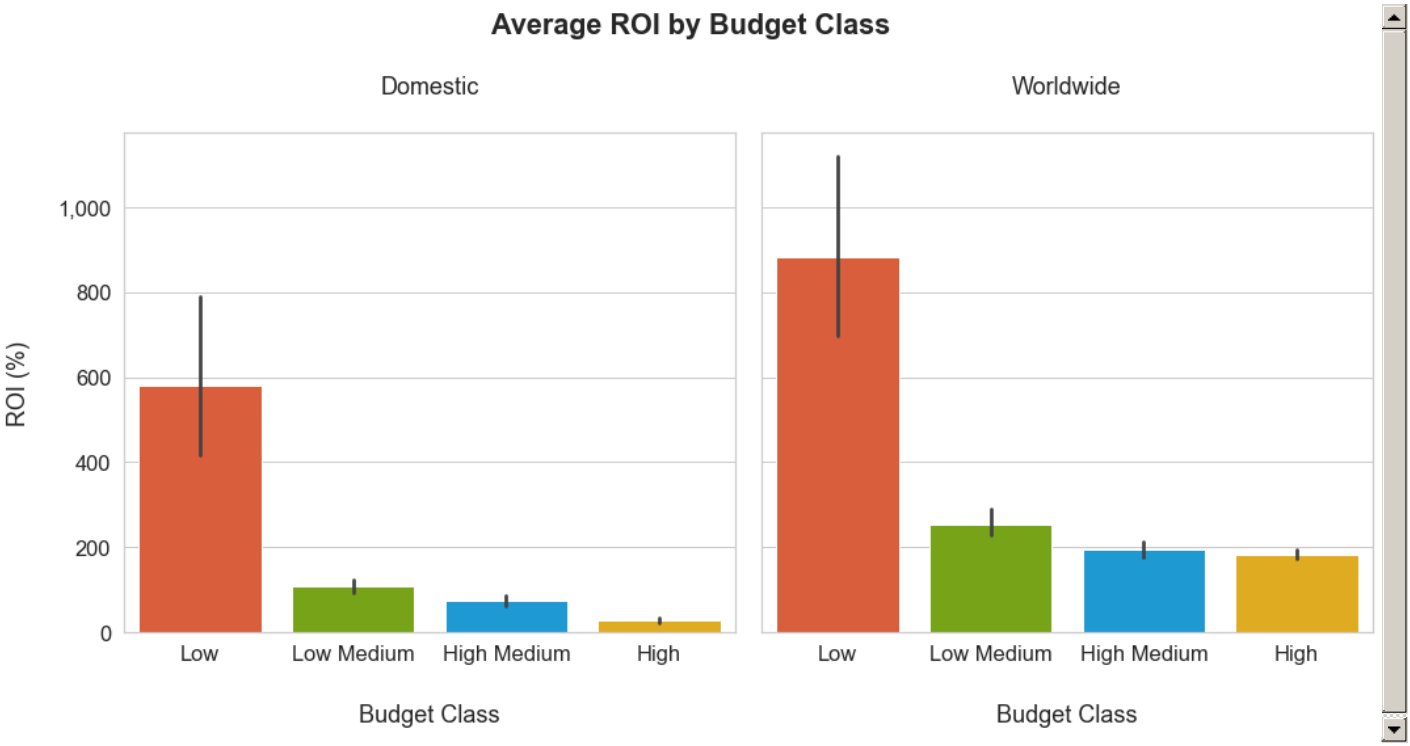
```
<Figure size 432x288 with 0 Axes>
```



High medium budget films (24-58 million) lead to greater profits domestically, while high budget films (58 million +) yield greater profits on average worldwide.

In [89]:

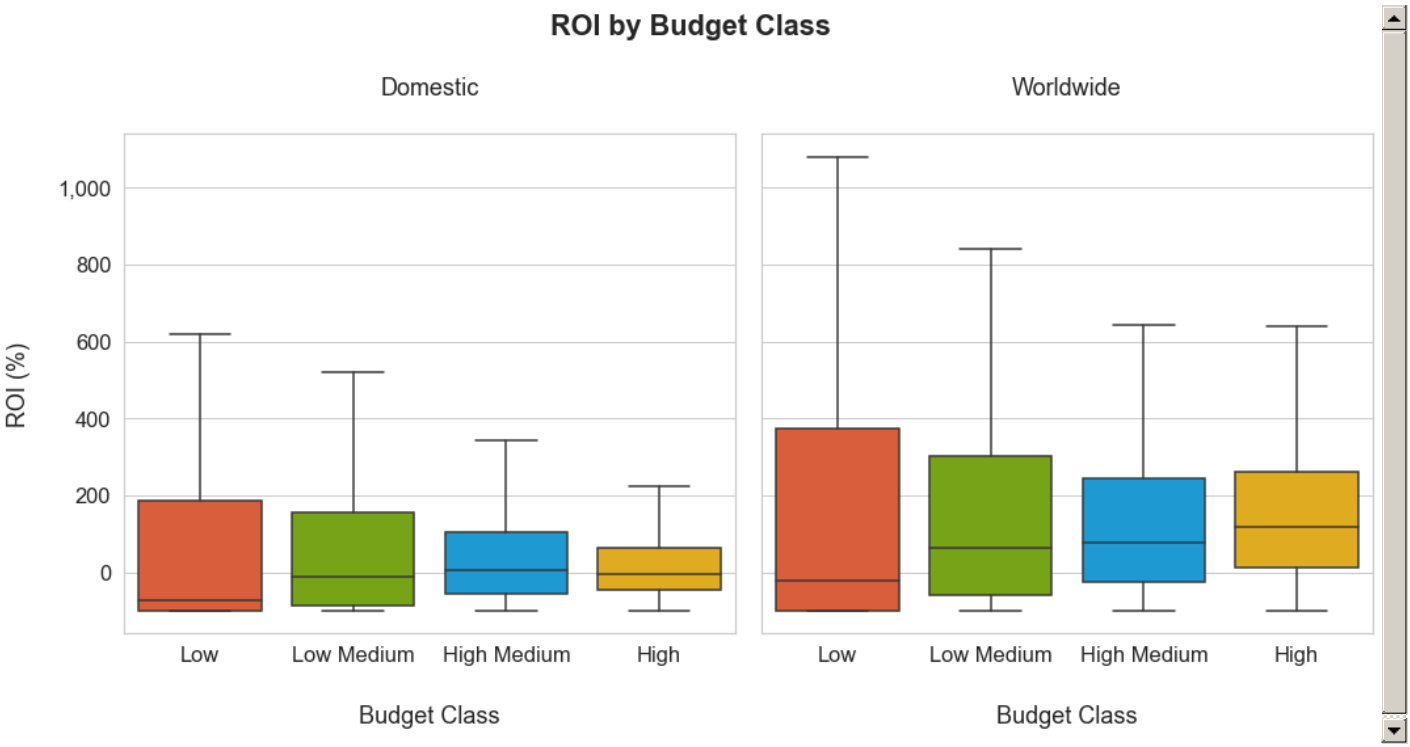
```
fig, axes = plt.subplots(1, 2, figsize=(15, 8), sharey=True)
fig.suptitle('Average ROI by Budget Class', fontweight='bold')

sns.barplot(x='budget_class', y='domestic_roi', data=budgets_adjusted_df, palette=clrs, ax=axes[0])
axes[0].set_title('Domestic', pad=30)
axes[0].set_xlabel('Budget Class', labelpad=30)
axes[0].set_ylabel('ROI (%)', labelpad=20)
axes[0].yaxis.get_major_formatter().set_scientific(False)
axes[0].yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.0f}'.format(x*100)))


sns.barplot(x='budget_class', y='roi', data=budgets_adjusted_df, palette=clrs, ax=axes[1])
axes[1].set_title('Worldwide', pad=30)
axes[1].set_xlabel('Budget Class', labelpad=30)
axes[1].set_ylabel('')
fig.tight_layout()
plt.savefig('ROI_BudgetClass', dpi=300);
```



Low budget films (1,000 - 7,800,000) yield have the highest ROI on average. But we can see by the error bars that this data is quite spread out. In my preliminary visualization, we saw that low budget films have the most outliers and the greatest spread (which makes sense, given the small sizes of these budgets). A boxplot may be more useful.

In [90]:

```
fig, axes = plt.subplots(1, 2, figsize=(15, 8), sharey=True)
fig.suptitle('ROI by Budget Class', fontweight='bold')

sns.boxplot(x='budget_class', y='domestic_roi', data=budgets_adjusted_df, showfliers=False,
            palette=clrs, ax=axes[0])
axes[0].set_title('Domestic', pad=30)
axes[0].set_xlabel('Budget Class', labelpad=30)
axes[0].set_ylabel('ROI (%)', labelpad=20)
axes[0].yaxis.get_major_formatter().set_scientific(False)
axes[0].yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.0f}'.format(x*100)))


sns.boxplot(x='budget_class', y='roi', data=budgets_adjusted_df, showfliers=False,
            palette=clrs, ax=axes[1])
axes[1].set_title('Worldwide', pad=30)
axes[1].set_xlabel('Budget Class', labelpad=30)
axes[1].set_ylabel('')
fig.tight_layout()
plt.savefig('ROI_BudgetClass_Boxplot', dpi=300);
```



At first glance, low budget films have the highest average return on investment, but the spread of the data is much larger. With outliers removed from the boxplots above, we see that the median domestic and worldwide ROI values are actually lower than those of the other budget categories. Meanwhile, there is a generally positive trend between budget size and profit. In general, there is potential to see higher ROIs from lower budget films, but this is not guaranteed. Higher budget films will make the most money on average. After taking these visualizations into consideration, the sweetspot for this seems to be the High Medium budget category (24-58 million), especially for domestic releases. For worldwide releases, Microsoft should consider spending upwards of 58 million if they want larger profits. Therefore, I recommend spending in the high medium range first, then high budget range in the future.

In [91]:

```
clrs
```

Out[91]:

```
['#f25022', '#7fba00', '#00a4ef', '#ffb900', '#737373']
```

In [92]:

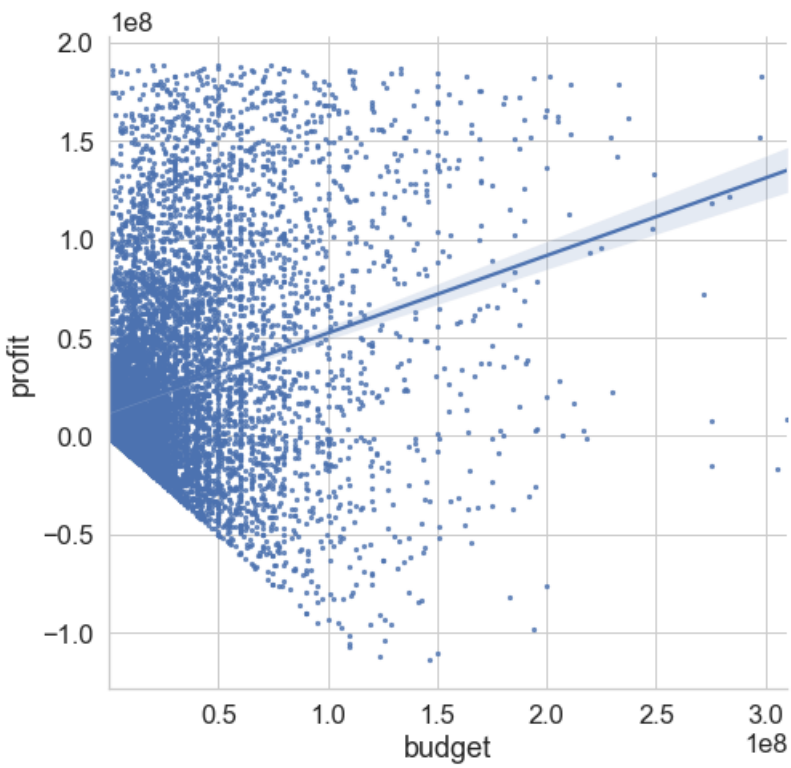
```
plt.figure(figsize=(10,8))
ax = sns.regplot(x='budget', y='profit', data=budgets_adjusted_df[budgets_adjusted_df['budget'] <= 500000
                 color='#f25022' , scatter_kws={"s": 15})
plt.title('Profit v. Budget', fontweight='bold', pad=30)
plt.xlabel('Budget', labelpad=20)
plt.ylabel('Profit', labelpad=20)

ax.yaxis.get_major_formatter().set_scientific(False)
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.1f}'.format(x/1000000) + 'M'))

ax.xaxis.get_major_formatter().set_scientific(False)
```

```
ax.xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.1f}'.format(x/1000000) + 'M'))
plt.tight_layout()
plt.savefig('Profit_Budget', dpi=300);
```

Other correlation plots, removing ROI and profit outliers

In [93]:

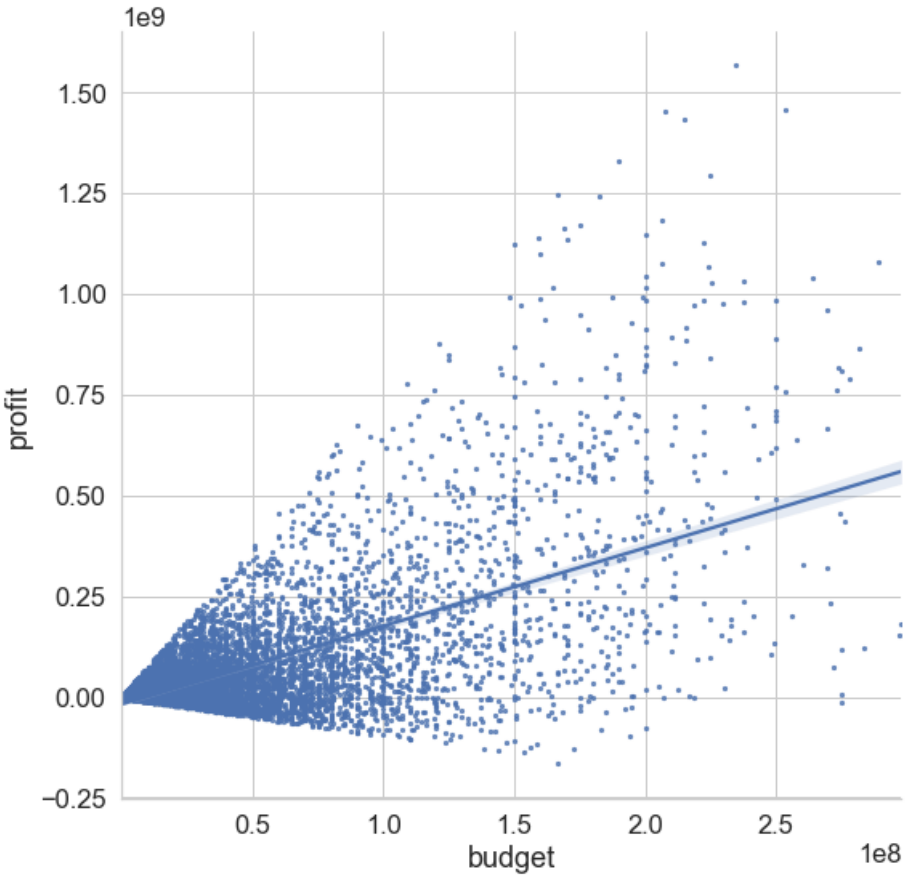
```
sns.lmplot(x='budget', y='profit', data=no_profit_outliers[:], scatter_kws={"s": 5}, height=7);
```



Scatter plot of all data. We can see that there are some budget outliers off to the right of the plot

In [94]:

```
sns.lmplot(x='budget', y='profit', data=no_roi_outliers[no_roi_outliers['budget'] < 300000000],
           scatter_kws={"s": 5}, height=8);
```



Bonus visualization

I'd like a scatterplot with rating as a colormap. Need to clean movies_df first.

In [95]:

```
movies_df.head()
```

Out[95]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
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	[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	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186

In [96]:

```
movies_df.shape
```

Out[96]:

```
(26517, 9)
```

In [97]:

```
movies_df['release_date'] = pd.to_datetime(movies_df['release_date'])
movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26517 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   genre_ids          26517 non-null  object
 1   id                 26517 non-null  int64
 2   original_language  26517 non-null  object
 3   original_title     26517 non-null  object
 4   popularity         26517 non-null  float64
 5   release_date       26517 non-null  datetime64[ns]
 6   title              26517 non-null  object
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64
dtypes: datetime64[ns](1), float64(2), int64(2), object(4)
memory usage: 2.0+ MB
```

There might be slightly different release dates between two dataframes, so let's join on release year instead

In [98]:

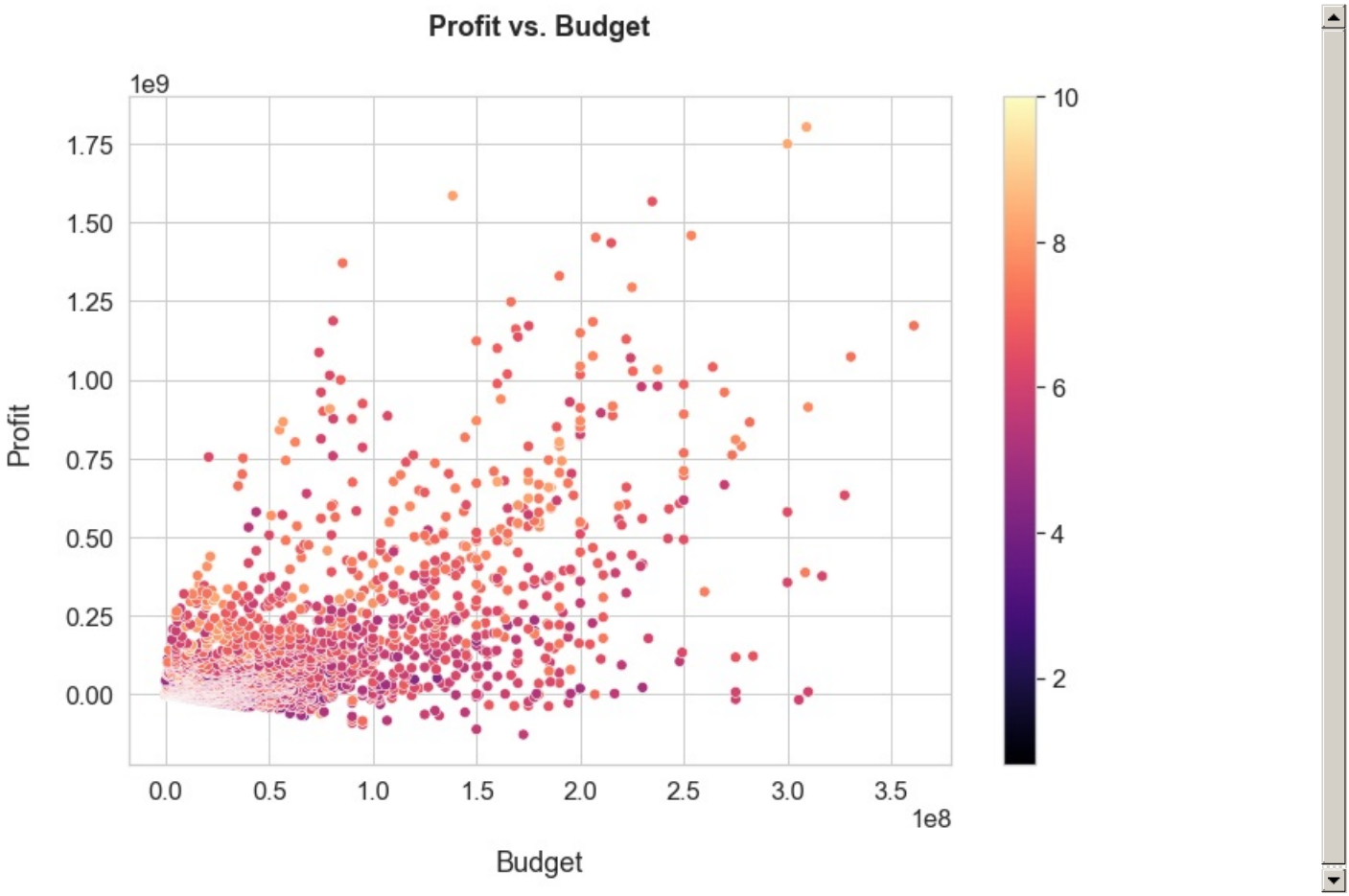
```
movies_df['release_year'] = movies_df['release_date'].dt.year
```

In [99]:

```
budgets_ratings_df = pd.merge(budgets_adjusted_df, movies_df, left_on=['movie', 'release_year'],
                              right_on=['original_title', 'release_year'])
```

In [100]:

```
plt.figure(figsize=(12,8))
ax = sns.scatterplot(x='budget', y='profit', data=budgets_ratings_df[budgets_ratings_df['budget'] < 40000(
                     s=50, hue='vote_average', palette='magma')
plt.title('Profit vs. Budget', fontweight='bold', pad=40, fontsize=18)
plt.xlabel('Budget', labelpad=30)
plt.ylabel('Profit', labelpad=20)
norm = plt.Normalize(budgets_ratings_df['vote_average'].min(), budgets_ratings_df['vote_average'].max())
sm = plt.cm.ScalarMappable(cmap='magma', norm=norm)

ax.get_legend().remove()
ax.figure.colorbar(sm);
```



Clean up budget dataframe for other analyses

I want to exclude the low budget category, which produces most of the ROI outliers, as well as films bade before 2010. I am keeping profit outliers

In [101]:

```
budgets_adjusted_df.head()
```

Out[101]:

	index	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	buc
8803	2	2019-06-07	Dark Phoenix	2019	3.500000e+08	4.276235e+07	1.497624e+08	-0.572108	-0.877822	(48389193.0, 512707249.0]	
10943	2327	1970-01-01	Waterloo	1970	1.667597e+08	0.000000e+00	0.000000e+00	-1.000000	-1.000000	(48389193.0, 512707249.0]	
9887	352	2001-04-27	Town & Country	2001	1.534453e+08	9.809464e+06	1.514690e+07	-0.901288	-0.936072	(48389193.0, 512707249.0]	
10025	404	2002-08-16	The Adventures of Pluto Nash	2002	1.438638e+08	6.345980e+06	1.020713e+07	-0.929050	-0.955889	(48389193.0, 512707249.0]	
9974	1333	1980-11-19	Heaven's Gate	1980	1.382000e+08	1.094397e+07	1.094457e+07	-0.920806	-0.920811	(48389193.0, 512707249.0]	

In [102]:

```
budgets_adjusted_df.shape
```

Out[102]:

```
(11491, 13)
```

In [103]:

```
budgets_adjusted_df = budgets_adjusted_df.loc[~(budgets_adjusted_df['budget_class']=='Low')]
budgets_adjusted_df = budgets_adjusted_df[budgets_adjusted_df['release_year'] >= 2000]
budgets_adjusted_df.shape
```

Out[103]:

```
(6410, 13)
```

In [104]:

```
budgets_adjusted_df.reset_index(inplace=True)
budgets_adjusted_df = budgets_adjusted_df.drop('index', axis=1)
budgets_adjusted_df.head()
```

Out[104]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	budge
0	8803	2019-06-07	Dark Phoenix	2019	3.500000e+08	4.276235e+07	1.497624e+08	-0.572108	-0.877822	(48389193.0, 512707249.0]	
1	9887	2001-04-27	Town & Country	2001	1.534453e+08	9.809464e+06	1.514690e+07	-0.901288	-0.936072	(48389193.0, 512707249.0]	
2	10025	2002-08-16	The Adventures of Pluto Nash	2002	1.438638e+08	6.345980e+06	1.020713e+07	-0.929050	-0.955889	(48389193.0, 512707249.0]	
3	9276	2011-03-11	Mars Needs Moms	2011	1.725875e+08	2.461414e+07	4.550528e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	
4	9275	2011-03-11	Mars Needs Moms	2011	1.500000e+08	2.139276e+07	3.954976e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	

Question 2: When to release a movie?

Get month name and month number

In [105]:

```
budgets_adjusted_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6410 entries, 0 to 6409
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   level_0          6410 non-null   int64
 1   release_date     6410 non-null   datetime64[ns]
 2   movie            6410 non-null   object
 3   release_year     6410 non-null   int64
 4   budget           6410 non-null   float64
 5   domestic_gross   6410 non-null   float64
 6   worldwide_gross  6410 non-null   float64
 7   roi              6410 non-null   float64
 8   domestic_roi     6410 non-null   float64
 9   budget_range     6410 non-null   category
 10  budget_class     6410 non-null   category
 11  profit           6410 non-null   float64
 12  domestic_profit  6410 non-null   float64
dtypes: category(2), datetime64[ns](1), float64(7), int64(2), object(1)
memory usage: 563.9+ KB
```

In [106]:

```
months_df = budgets_adjusted_df.copy()
months_df['month'] = months_df['release_date'].dt.month_name()
months_df['month_no'] = months_df['release_date'].dt.month

months_df.head()
```

Out[106]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	budge
0	8803	2019-06-07	Dark Phoenix	2019	3.500000e+08	4.276235e+07	1.497624e+08	-0.572108	-0.877822	(48389193.0, 512707249.0]	
1	9887	2001-04-27	Town & Country	2001	1.534453e+08	9.809464e+06	1.514690e+07	-0.901288	-0.936072	(48389193.0, 512707249.0]	
2	10025	2002-08-16	The Adventures of Pluto Nash	2002	1.438638e+08	6.345980e+06	1.020713e+07	-0.929050	-0.955889	(48389193.0, 512707249.0]	
3	9276	2011-03-11	Mars Needs Moms	2011	1.725875e+08	2.461414e+07	4.550528e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	
4	9275	2011-03-11	Mars Needs Moms	2011	1.500000e+08	2.139276e+07	3.954976e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	

In [107]:

```
months_grouped = months_df.groupby(['month_no', 'month']).mean()
```

In [108]:

```
months_grouped
```

Out[108]:

month_no	month	level_0	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	profit	dome
1	January	5424.262467	2009.687664	3.343733e+07	3.713698e+07	7.730724e+07	1.734188	0.450388	4.386991e+07	3.6
2	February	5536.170526	2009.160000	4.181815e+07	5.092696e+07	1.072284e+08	1.668786	0.408797	6.541026e+07	9.1
3	March	5690.527985	2008.916045	5.093658e+07	5.800538e+07	1.261046e+08	1.299152	0.223114	7.516801e+07	7.0
4	April	5947.662188	2008.589251	3.897530e+07	4.301098e+07	9.700815e+07	1.268824	0.212702	5.803285e+07	4.0
5	May	5207.913440	2009.234624	7.992699e+07	1.029342e+08	2.603477e+08	2.046394	0.288317	1.804207e+08	2.3
6	June	5166.907598	2009.069815	7.094094e+07	9.461683e+07	2.196052e+08	2.063257	0.484574	1.486642e+08	2.3
7	July	4880.371179	2008.958515	7.182923e+07	9.289714e+07	2.293545e+08	2.186993	0.454330	1.575253e+08	2.1
8	August	5650.644689	2008.597070	4.156193e+07	4.938651e+07	9.836658e+07	1.501281	0.330855	5.680465e+07	7.8
9	September	6095.869718	2008.855634	3.446636e+07	3.198859e+07	6.842437e+07	1.101147	0.048607	3.395802e+07	-2.4
10	October	6039.207856	2008.644845	3.237111e+07	3.598538e+07	7.758079e+07	1.586550	0.323468	4.520968e+07	3.6
11	November	5204.425957	2009.412646	6.218787e+07	7.560958e+07	1.884997e+08	2.122445	0.340671	1.263118e+08	1.3
12	December	5531.013977	2008.691233	5.465652e+07	6.851931e+07	1.627710e+08	1.768012	0.230694	1.081145e+08	1.3

In [109]:

```
months_grouped.reset_index(inplace=True)
months_grouped.head()
```

Out[109]:

	month_no	month	level_0	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	profit	dom
0	1	January	5424.262467	2009.687664	3.343733e+07	3.713698e+07	7.730724e+07	1.734188	0.450388	4.386991e+07	3.(
1	2	February	5536.170526	2009.160000	4.181815e+07	5.092696e+07	1.072284e+08	1.668786	0.408797	6.541026e+07	9.1
2	3	March	5690.527985	2008.916045	5.093658e+07	5.800538e+07	1.261046e+08	1.299152	0.223114	7.516801e+07	7.(
3	4	April	5947.662188	2008.589251	3.897530e+07	4.301098e+07	9.700815e+07	1.268824	0.212702	5.803285e+07	4.(
4	5	May	5207.913440	2009.234624	7.992699e+07	1.029342e+08	2.603477e+08	2.046394	0.288317	1.804207e+08	2.1

Visualization

In [110]:

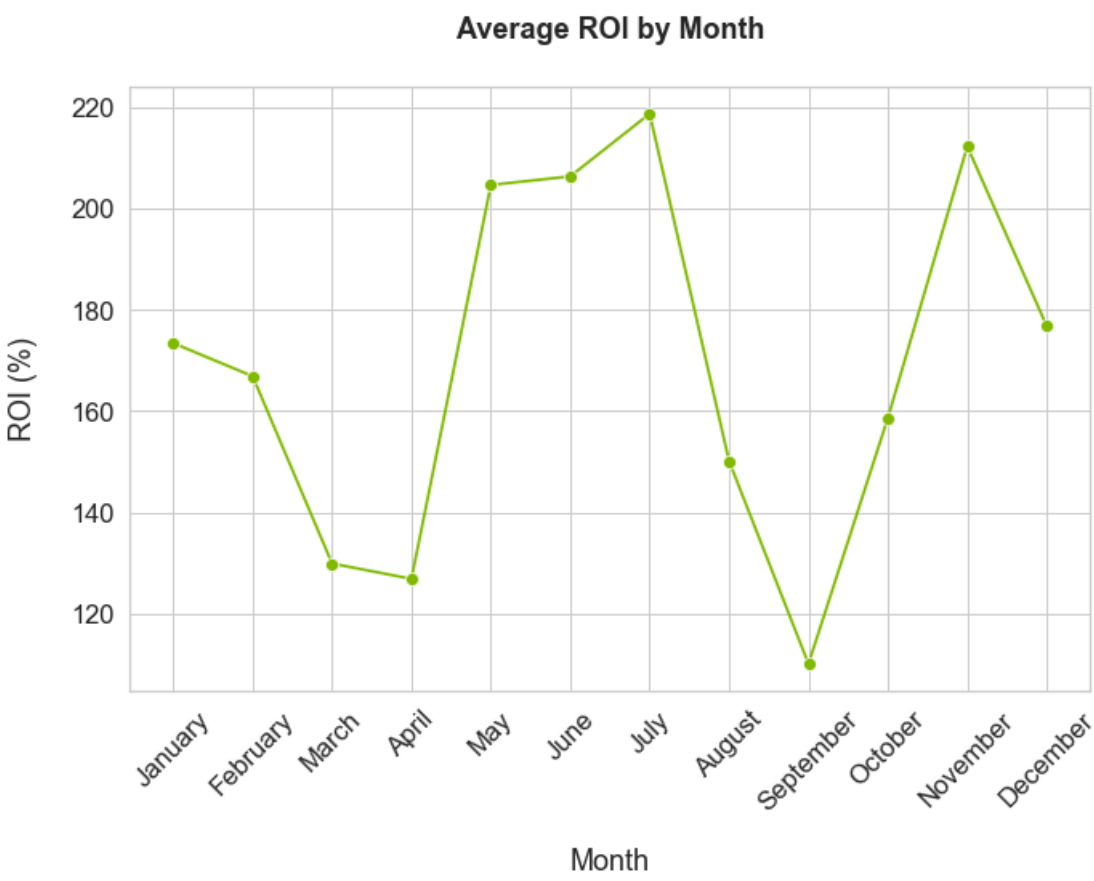
```
clrs
```

Out[110]:

```
['#f25022', '#7fba00', '#00a4ef', '#ffb900', '#737373']
```

In [111]:

```
plt.figure(figsize=(10,8))

ax = sns.lineplot(x='month', y='roi', data=months_grouped, color='#7fba00', marker='o',
                  markersize=8, linewidth=1.75)
plt.title('Average ROI by Month', fontweight='bold', pad=30)
plt.xlabel('Month', labelpad=20)
plt.ylabel('ROI (%)', labelpad=20)
plt.xticks(rotation=45)

ax.yaxis.get_major_formatter().set_scientific(False)
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.0f}'.format(x*100)))
plt.tight_layout()
plt.savefig('ROI_Month', dpi=300);
```



Over the years, the best months for releasing a movie appear to be the summer months of May-June (with peak profits in May) as well as November-December

Question 3: What genres have the highest ROI?

Clean data

In [112]:

```
title_basics_df.head()
```

Out[112]:

tconst	primary_title	original_title	start_year	runtime_minutes	genres
tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [113]:

```
title_basics_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 146144 entries, tt0063540 to tt9916754
Data columns (total 5 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   primary_title    146144 non-null  object 
 1   original_title   146123 non-null  object 
 2   start_year       146144 non-null  int64  
 3   runtime_minutes  114405 non-null  float64
 4   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(3)
memory usage: 6.7+ MB
```

In [114]:

```
for col in title_basics_df:
    print(col)
```

```
    print(title_basics_df[col].value_counts(normalize=True))
    print("=====================================================")
```

```
primary_title
Home                                              0.000164
Broken                                            0.000137
The Return                                        0.000137
Homecoming                                        0.000109
Alone                                             0.000109
                                                    ...
The Invisible Friend                              0.000007
BuzzKill                                          0.000007
Skapandet av Shadowgames                          0.000007
Killing the Messenger: The Deadly Cost of News    0.000007
The Taste of Betel Nut                            0.000007
Name: primary_title, Length: 136071, dtype: float64
=====================================================
original_title
Broken                                     0.000130
Home                                       0.000123
The Return                                 0.000116
Homecoming                                 0.000089
Freedom                                    0.000089
                                               ...
One Table Two Elephants                    0.000007
Tío Yim                                    0.000007
Møllehave: Hellere forrykt end forgæves    0.000007
Seven in Heaven                            0.000007
Bam-seom-hae-jeok-dan seo-ul bul-ba-da     0.000007
Name: original_title, Length: 137773, dtype: float64
=====================================================
start_year
2017    0.119772
2016    0.118185
2018    0.115290
2015    0.111144
2014    0.106669
2013    0.100647
2012    0.094338
2011    0.088269
2010    0.081078
2019    0.057334
2020    0.006411
2021    0.000568
2022    0.000219
2023    0.000034
2024    0.000014
2027    0.000007
2026    0.000007
2025    0.000007
2115    0.000007
Name: start_year, dtype: float64
=====================================================
runtime_minutes
90.0     0.062331
80.0     0.030820
85.0     0.025480
100.0    0.023268
95.0     0.022280
           ...
382.0    0.000009
724.0    0.000009
808.0    0.000009
287.0    0.000009
540.0    0.000009
Name: runtime_minutes, Length: 367, dtype: float64
=====================================================
genres
Documentary                  0.228691
Drama                        0.152669
Comedy                       0.065207
Horror                       0.031065
Comedy,Drama                 0.025004
                               ...
Adventure,Biography,Family   0.000007
Drama,Game-Show,Thriller     0.000007
Fantasy,War                  0.000007
Animation,History,Musical    0.000007
```

```
Animation,History,Musical      0.000007
Documentary,News,Western       0.000007
Name: genres, Length: 1085, dtype: float64
==================================================
```

2115 must be a placeholder value for missing start year data.

Check for and inspect duplicates

In [115]:

```
title_basics_df.duplicated().value_counts()
```

Out[115]:

```
False    146022
True        122
dtype: int64
```

In [116]:

```
title_basics_df[title_basics_df.duplicated(keep=False)].sort_values(by='primary_title')
```

Out[116]:

tconst	primary_title	original_title	start_year	runtime_minutes	genres
tt8032828	100 Milioni di bracciate	100 Milioni di bracciate	2017	NaN	Biography
tt8034014	100 Milioni di bracciate	100 Milioni di bracciate	2017	NaN	Biography
tt9660588	3. Elma	3. Elma	2014	65.0	Drama
tt9653930	3. Elma	3. Elma	2014	65.0	Drama
tt9773302	3. Elma	3. Elma	2014	65.0	Drama
...	...	...	...	...	...
tt3815130	Ângelo de Sousa - Tudo o Que Sou Capaz	Ângelo de Sousa - Tudo o Que Sou Capaz	2010	60.0	Biography,Documentary
tt3815132	Ângelo de Sousa - Tudo o Que Sou Capaz	Ângelo de Sousa - Tudo o Que Sou Capaz	2010	60.0	Biography,Documentary
tt3815134	Ângelo de Sousa - Tudo o Que Sou Capaz	Ângelo de Sousa - Tudo o Que Sou Capaz	2010	60.0	Biography,Documentary
tt3815122	Ângelo de Sousa - Tudo o Que Sou Capaz	Ângelo de Sousa - Tudo o Que Sou Capaz	2010	60.0	Biography,Documentary
tt3815128	Ângelo de Sousa - Tudo o Que Sou Capaz	Ângelo de Sousa - Tudo o Que Sou Capaz	2010	60.0	Biography,Documentary

230 rows × 5 columns

Duplicate titles seem to have different tconst values. Keep all entries for now, as we may need options for tconst values as we merge this dataframe with others

In [117]:

```
title_basics_df['start_year'] = title_basics_df['start_year'].astype(int)
title_basics_df.reset_index(inplace=True)
```

EDA

Merge title basics with movie budgets

Connect genre info to monetary info for films with highest roi

In [118]:

```
# Sort by most profitable movies
sorted_df = budgets_adjusted_df.sort_values(by='roi', ascending=False)
top100_df = sorted_df[:100]
top100_df.head()
```

Out[118]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range
6149	75	2002-04-19	My Big Fat Greek Wedding	2002	7.193191e+06	3.473422e+08	5.393311e+08	73.978007	47.287642	(6000000.0, 20000000.0]
6101	130	2012-05-25	Les Intouchables	2012	1.080000e+07	1.318228e+07	4.848730e+08	43.895652	0.220582	(6000000.0, 20000000.0]
6154	131	2012-05-25	Les Intouchables	2012	1.217435e+07	1.485979e+07	5.465756e+08	43.895652	0.220582	(6000000.0, 20000000.0]
5736	148	2014-10-03	Annabelle	2014	6.500000e+06	8.427381e+07	2.568629e+08	38.517372	11.965202	(6000000.0, 20000000.0]
5792	149	2014-10-03	Annabelle	2014	7.106108e+06	9.213212e+07	2.808147e+08	38.517372	11.965202	(6000000.0, 20000000.0]

In [119]:

```
movie_details_df = pd.merge(top100_df, title_basics_df, left_on = ['movie', 'release_year'],
                            right_on=['primary_title', 'start_year'], how='left')
```

In [120]:

```
movie_details_df.shape
```

Out[120]:

```
(100, 19)
```

In [121]:

```
movie_details_df.isna().sum()
```

Out[121]:

```
level_0             0
release_date        0
movie               0
release_year        0
budget              0
domestic_gross      0
worldwide_gross     0
roi                 0
domestic_roi        0
budget_range        0
budget_class        0
profit              0
domestic_profit     0
tconst             54
primary_title      54
original_title     54
start_year         54
runtime_minutes    54
genres             54
dtype: int64
```

In [122]:

```
movie_details_df.duplicated().value_counts()
```

Out[122]:

```
False    100
dtype: int64
```

No duplicates in our left-joined frame, but we should drop rows without genre information. We are losing some data here.

In [123]:

```
movie_details_df.dropna(inplace=True)
```

Create separate columns for each genre

In [124]:

```
movie_details_df['genres'] = movie_details_df['genres'].astype(str)
movie_details_df['genres'] = movie_details_df['genres'].apply(lambda x: x.split(",") if x else x)
```

In [125]:

```
movie_details_df.head()
```

Out[125]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	budg
3	148	2014-10-03	Annabelle	2014	6.500000e+06	8.427381e+07	2.568629e+08	38.517372	11.965202	(6000000.0, 20000000.0]	Low
4	149	2014-10-03	Annabelle	2014	7.106108e+06	9.213212e+07	2.808147e+08	38.517372	11.965202	(6000000.0, 20000000.0]	Low
8	196	2016-12-21	Dangal	2016	9.500000e+06	1.239176e+07	2.946546e+08	30.016276	0.304396	(6000000.0, 20000000.0]	Low
9	197	2016-12-21	Dangal	2016	1.024430e+07	1.336263e+07	3.177401e+08	30.016276	0.304396	(6000000.0, 20000000.0]	Low
15	250	2014-06-06	The Fault in Our Stars	2014	1.311897e+07	1.365164e+08	3.358093e+08	24.597236	9.406029	(6000000.0, 20000000.0]	Low

In [126]:

```
all_genres = set()
for genres in movie_details_df['genres']:
    if genres:
        all_genres.update(genres)

all_genres
```

Out[126]:

```
{'Action',
 'Adventure',
 'Animation',
 'Biography',
 'Comedy',
 'Crime',
 'Drama',
 'Family',
 'Horror',
 'Music',
 'Mystery',
 'Romance',
 'Sci-Fi',
 'Thriller'}
```

In [127]:

```
# add cols with zeros for all genres. Will modify entries to 1 if film is of that genre
for genre in all_genres:
    movie_details_df[genre] = np.zeros(shape=movie_details_df.shape[0])

movie_details_df.head()
```

Out[127]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	...	H
3	148	2014-10-03	Annabelle	2014	6.500000e+06	8.427381e+07	2.568629e+08	38.517372	11.965202	(6000000.0, 20000000.0]	...	
4	149	2014-10-03	Annabelle	2014	7.106108e+06	9.213212e+07	2.808147e+08	38.517372	11.965202	(6000000.0, 20000000.0]	...	
8	196	2016-12-21	Dangal	2016	9.500000e+06	1.239176e+07	2.946546e+08	30.016276	0.304396	(6000000.0, 20000000.0]	...	
9	197	2016-12-21	Dangal	2016	1.024430e+07	1.336263e+07	3.177401e+08	30.016276	0.304396	(6000000.0, 20000000.0]	...	
15	250	2014-06-06	The Fault in Our Stars	2014	1.311897e+07	1.365164e+08	3.358093e+08	24.597236	9.406029	(6000000.0, 20000000.0]	...	

5 rows × 33 columns

In [128]:

```
for index, row in movie_details_df.iterrows():
    if row['genres']:
```

```
        for genre in row['genres']:
            movie_details_df.loc[index, genre] = 1

movie_details_df.head()
```

Out[128]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	...	h
3	148	2014-10-03	Annabelle	2014	6.500000e+06	8.427381e+07	2.568629e+08	38.517372	11.965202	(6000000.0, 20000000.0]	...	
4	149	2014-10-03	Annabelle	2014	7.106108e+06	9.213212e+07	2.808147e+08	38.517372	11.965202	(6000000.0, 20000000.0]	...	
8	196	2016-12-21	Dangal	2016	9.500000e+06	1.239176e+07	2.946546e+08	30.016276	0.304396	(6000000.0, 20000000.0]	...	
9	197	2016-12-21	Dangal	2016	1.024430e+07	1.336263e+07	3.177401e+08	30.016276	0.304396	(6000000.0, 20000000.0]	...	
15	250	2014-06-06	The Fault in Our Stars	2014	1.311897e+07	1.365164e+08	3.358093e+08	24.597236	9.406029	(6000000.0, 20000000.0]	...	

5 rows × 33 columns

In [129]:

```
#checking the counts for all different genres
for col in movie_details_df:
    print(f'Viewing values in col: {col}')
    print(f'Top values:\n{movie_details_df[col].value_counts()}')
```

```
Viewing values in col: level_0
Top values:
255    1
334    1
409    1
408    1
149    1
148    1
446    1
521    1
465    1
464    1
335    1
269    1
254    1
268    1
520    1
329    1
328    1
519    1
568    1
197    1
196    1
321    1
522    1
447    1
461    1
541    1
253    1
252    1
251    1
250    1
313    1
312    1
542    1
567    1
437    1
436    1
456    1
496    1
495    1
429    1
428    1
457    1
506    1
```

```
505    1
460    1
320    1
Name: level_0, dtype: int64
Viewing values in col: release_date
Top values:
2014-05-09    2
2014-10-03    2
2018-11-02    2
2017-08-11    2
2018-04-06    2
2017-06-30    2
2016-02-12    2
2014-06-06    2
2014-11-28    2
2017-11-17    2
2015-07-10    2
2010-12-03    2
2015-02-13    2
2017-09-08    2
2013-07-19    2
2016-12-21    2
2018-01-05    2
2016-12-09    2
2018-11-16    2
2012-06-29    2
2017-11-10    2
2018-10-19    2
2013-07-03    2
Name: release_date, dtype: int64
Viewing values in col: movie
Top values:
Magic Mike                                    2
Three Billboards Outside Ebbing, Missouri     2
Deadpool                                      2
Halloween                                     2
Insidious: The Last Key                       2
Minions                                       2
Despicable Me 2                               2
La La Land                                    2
Bohemian Rhapsody                             2
Black Swan                                    2
The Conjuring                                 2
The Fault in Our Stars                        2
A Quiet Place                                 2
Neighbors                                     2
Annabelle                                     2
Annabelle: Creation                           2
The Imitation Game                            2
Despicable Me 3                               2
Fifty Shades of Grey                          2
It                                            2
Wonder                                        2
Dangal                                        2
Green Book                                    2
Name: movie, dtype: int64
Viewing values in col: release_year
Top values:
2018    10
2017    10
2014     8
2016     6
2015     4
2013     4
2012     2
2010     2
Name: release_year, dtype: int64
Viewing values in col: budget
Top values:
2.000000e+07    3
1.500000e+07    2
1.030680e+07    2
1.000000e+07    2
1.200000e+07    2
2.111709e+07    1
7.400000e+07    1
6.500000e+06    1
```

```
2.156695e+07    1
7.500000e+07    1
1.267025e+07    1
3.695490e+07    1
1.542972e+07    1
2.221964e+07    1
1.583781e+07    1
4.367805e+07    1
1.967845e+07    1
1.639871e+07    1
1.800000e+07    1
4.000000e+07    1
9.500000e+06    1
5.800000e+07    1
8.080439e+07    1
3.500000e+07    1
1.024430e+07    1
5.500000e+07    1
7.000000e+06    1
5.668741e+07    1
7.918907e+07    1
1.700000e+07    1
7.600000e+07    1
1.300000e+07    1
7.106108e+06    1
1.311897e+07    1
7.890785e+06    1
6.254417e+07    1
2.300000e+07    1
8.443462e+07    1
1.752156e+07    1
2.370564e+07    1
Name: budget, dtype: int64
Viewing values in col: domestic_gross
Top values:
1.069547e+08    1
3.669456e+08    1
1.937930e+08    1
1.336263e+07    1
1.239176e+07    1
8.427381e+07    1
9.962232e+07    1
3.360458e+08    1
1.629403e+08    1
3.915165e+08    1
1.374001e+08    1
1.248724e+08    1
1.269447e+08    1
1.640820e+08    1
1.077945e+08    1
1.814465e+08    1
2.163033e+08    1
1.880244e+08    1
1.365164e+08    1
5.451374e+07    1
1.661672e+08    1
1.137216e+08    1
1.020922e+08    1
2.646243e+08    1
1.593420e+08    1
3.680654e+08    1
3.274817e+08    1
1.398192e+08    1
1.324228e+08    1
1.526491e+08    1
3.630707e+08    1
5.755857e+07    1
2.229396e+08    1
8.508017e+07    1
3.457730e+08    1
6.774533e+07    1
9.112514e+07    1
4.089140e+08    1
1.642307e+08    1
6.982377e+07    1
9.213212e+07    1
1.281932e+08    1
```

```
1.500868e+08    1
8.769044e+07    1
1.511018e+08    1
2.794047e+08    1
Name: domestic_gross, dtype: int64
Viewing values in col: worldwide_gross
Top values:
3.071668e+08    1
1.160336e+09    1
1.705498e+08    1
4.597548e+08    1
3.312667e+08    1
3.180001e+08    1
1.267030e+09    1
3.447855e+08    1
6.974580e+08    1
9.224436e+08    1
1.601919e+08    1
1.730363e+08    1
3.532924e+08    1
2.962093e+08    1
4.263512e+08    1
2.277405e+08    1
3.177401e+08    1
2.946546e+08    1
1.678856e+08    1
2.808147e+08    1
1.691393e+08    1
6.235021e+08    1
3.931810e+08    1
3.358093e+08    1
8.949853e+08    1
1.092522e+09    1
3.319145e+08    1
8.637841e+08    1
1.922531e+08    1
2.549007e+08    1
2.709444e+08    1
1.083448e+09    1
2.489767e+08    1
3.345223e+08    1
7.364140e+08    1
3.224419e+08    1
5.709981e+08    1
2.627211e+08    1
3.220344e+08    1
1.034728e+09    1
8.010256e+08    1
2.568629e+08    1
3.216182e+08    1
9.752168e+08    1
3.053849e+08    1
3.046047e+08    1
Name: worldwide_gross, dtype: int64
Viewing values in col: roi
Top values:
38.517372    2
18.677782    2
14.900007    2
11.831800    2
14.052468    2
14.182698    2
12.349326    2
12.810786    2
20.317558    2
14.230236    1
24.482055    1
24.482055    1
13.274953    1
14.680219    1
12.796370    1
13.001497    1
12.796370    1
13.001497    1
19.358991    1
13.274953    1
30.016276    1
```

```
14.230236    1
30.016276    1
24.490067    1
18.927371    1
24.597236    1
15.272461    1
15.272461    1
24.597236    1
15.788559    1
23.364250    1
23.364250    1
15.788559    1
24.490067    1
18.927371    1
14.680219    1
19.358991    1
Name: roi, dtype: int64
Viewing values in col: domestic_roi
Top values:
10.060257    2
15.245939    2
3.154181     2
3.542812     2
9.406029     2
11.965202    2
5.259840     2
2.528324     2
7.338156     2
5.806147     2
5.870007     1
6.555090     1
6.555090     1
3.842966     1
2.932788     1
2.932788     1
5.774533     1
8.356621     1
8.356621     1
2.699138     1
5.870007     1
5.621140     1
5.621140     1
0.304396     1
3.842966     1
14.934202    1
5.075010     1
5.075010     1
3.541159     1
7.227283     1
3.541159     1
7.227283     1
5.774533     1
0.304396     1
14.934201    1
2.699138     1
Name: domestic_roi, dtype: int64
Viewing values in col: budget_range
Top values:
(6000000.0, 20000000.0]      27
(48389193.0, 512707249.0]    10
(20000000.0, 48389193.0]      9
(1099.0, 6000000.0]           0
Name: budget_range, dtype: int64
Viewing values in col: budget_class
Top values:
Low Medium     27
High           10
High Medium     9
Low             0
Name: budget_class, dtype: int64
Viewing values in col: profit
Top values:
1.013333e+09    1
1.635498e+08    1
9.597278e+08    1
3.066041e+08    1
3.272639e+08    1
```

```
2.765308e+08    1
1.627295e+08    1
2.980001e+08    1
5.798240e+08    1
2.529444e+08    1
6.624580e+08    1
2.127405e+08    1
5.309981e+08    1
3.074958e+08    1
2.851546e+08    1
2.524143e+08    1
8.399853e+08    1
7.430256e+08    1
1.086336e+09    1
1.564691e+08    1
8.657562e+08    1
6.994591e+08    1
3.005011e+08    1
2.449007e+08    1
1.843623e+08    1
2.325779e+08    1
8.992168e+08    1
2.503629e+08    1
3.082089e+08    1
4.381878e+08    1
1.186226e+09    1
4.063512e+08    1
2.903849e+08    1
9.990136e+08    1
2.990344e+08    1
2.846047e+08    1
2.951668e+08    1
3.310727e+08    1
8.012400e+08    1
3.182667e+08    1
3.226904e+08    1
2.737086e+08    1
1.578856e+08    1
1.481919e+08    1
3.777512e+08    1
3.175223e+08    1
Name: profit, dtype: int64
Viewing values in col: domestic_profit
Top values:
5.774533e+07    1
1.233974e+08    1
2.891761e+06    1
8.709220e+07    1
1.539239e+08    1
1.128724e+08    1
1.762714e+08    1
4.251374e+07    1
1.261672e+08    1
6.208017e+07    1
1.304294e+08    1
3.244793e+08    1
1.174001e+08    1
1.613033e+08    1
5.951697e+07    1
4.488831e+07    1
1.413733e+08    1
1.493420e+08    1
8.322361e+07    1
9.395468e+07    1
1.124228e+08    1
3.088181e+08    1
1.662521e+08    1
1.115150e+08    1
1.710244e+08    1
1.203024e+08    1
8.502601e+07    1
1.377685e+08    1
3.050707e+08    1
1.320868e+08    1
7.777381e+07    1
9.195667e+07    1
2.924817e+08    1
```

```
3.289723e+08    1
2.620458e+08    1
1.187021e+08    1
1.896243e+08    1
1.444035e+08    1
2.002156e+08    1
2.920654e+08    1
1.311018e+08    1
7.612514e+07    1
2.861412e+08    1
6.398480e+07    1
1.067216e+08    1
3.118324e+06    1
Name: domestic_profit, dtype: int64
Viewing values in col: tconst
Top values:
tt0947798    2
tt6644200    2
tt5074352    2
tt5726086    2
tt3469046    2
tt1396484    2
tt3783958    2
tt2543472    2
tt6966692    2
tt3322940    2
tt1690953    2
tt1915581    2
tt1431045    2
tt2004420    2
tt2084970    2
tt1727824    2
tt1457767    2
tt1502407    2
tt2322441    2
tt2582846    2
tt2293640    2
tt5027774    2
tt5140878    2
Name: tconst, dtype: int64
Viewing values in col: primary_title
Top values:
Magic Mike                                    2
Three Billboards Outside Ebbing, Missouri     2
Deadpool                                      2
Halloween                                     2
Insidious: The Last Key                       2
Minions                                       2
Despicable Me 2                               2
La La Land                                    2
Bohemian Rhapsody                             2
Black Swan                                    2
The Conjuring                                 2
The Fault in Our Stars                        2
A Quiet Place                                 2
Neighbors                                     2
Annabelle                                     2
Annabelle: Creation                           2
The Imitation Game                            2
Despicable Me 3                               2
Fifty Shades of Grey                          2
It                                            2
Wonder                                        2
Dangal                                        2
Green Book                                    2
Name: primary_title, dtype: int64
Viewing values in col: original_title
Top values:
Magic Mike                                    2
Three Billboards Outside Ebbing, Missouri     2
Deadpool                                      2
Halloween                                     2
Insidious: The Last Key                       2
Minions                                       2
Despicable Me 2                               2
La La Land                                    2
Bohemian Rhapsody                             2
```

```
Black Swan                                  2
The Conjuring                               2
The Fault in Our Stars                      2
A Quiet Place                               2
Neighbors                                   2
Annabelle                                   2
Annabelle: Creation                         2
The Imitation Game                          2
Despicable Me 3                             2
Fifty Shades of Grey                        2
It                                          2
Wonder                                      2
Dangal                                      2
Green Book                                  2
Name: original_title, dtype: int64
Viewing values in col: start_year
Top values:
2017.0    10
2018.0    10
2014.0     8
2016.0     6
2015.0     4
2013.0     4
2012.0     2
2010.0     2
Name: start_year, dtype: int64
Viewing values in col: runtime_minutes
Top values:
108.0    4
98.0     2
115.0    2
161.0    2
126.0    2
106.0    2
110.0    2
128.0    2
109.0    2
135.0    2
90.0     2
103.0    2
134.0    2
112.0    2
91.0     2
113.0    2
114.0    2
97.0     2
125.0    2
130.0    2
89.0     2
99.0     2
Name: runtime_minutes, dtype: int64
Viewing values in col: genres
Top values:
[Horror, Mystery, Thriller]       8
[Adventure, Animation, Comedy]    6
[Horror, Thriller]                4
[Drama, Horror, Sci-Fi]           2
[Comedy, Drama]                   2
[Drama, Family]                   2
[Drama, Romance]                  2
[Action, Adventure, Comedy]       2
[Biography, Drama, Music]         2
[Crime, Drama]                    2
[Drama, Thriller]                 2
[Biography, Drama, Thriller]      2
[Comedy, Drama, Music]            2
[Comedy]                          2
[Action, Biography, Drama]        2
[Drama, Romance, Thriller]        2
[Biography, Comedy, Drama]        2
Name: genres, dtype: int64
Viewing values in col: Drama
Top values:
1.0    24
0.0    22
Name: Drama, dtype: int64
Viewing values in col: Romance
```

```
Top values:
0.0    42
1.0     4
Name: Romance, dtype: int64
Viewing values in col: Family
Top values:
0.0    44
1.0     2
Name: Family, dtype: int64
Viewing values in col: Mystery
Top values:
0.0    38
1.0     8
Name: Mystery, dtype: int64
Viewing values in col: Horror
Top values:
0.0    32
1.0    14
Name: Horror, dtype: int64
Viewing values in col: Music
Top values:
0.0    42
1.0     4
Name: Music, dtype: int64
Viewing values in col: Animation
Top values:
0.0    40
1.0     6
Name: Animation, dtype: int64
Viewing values in col: Adventure
Top values:
0.0    38
1.0     8
Name: Adventure, dtype: int64
Viewing values in col: Action
Top values:
0.0    42
1.0     4
Name: Action, dtype: int64
Viewing values in col: Thriller
Top values:
0.0    28
1.0    18
Name: Thriller, dtype: int64
Viewing values in col: Sci-Fi
Top values:
0.0    44
1.0     2
Name: Sci-Fi, dtype: int64
Viewing values in col: Comedy
Top values:
0.0    30
1.0    16
Name: Comedy, dtype: int64
Viewing values in col: Crime
Top values:
0.0    44
1.0     2
Name: Crime, dtype: int64
Viewing values in col: Biography
Top values:
0.0    38
1.0     8
Name: Biography, dtype: int64
```

Create dictionary for genres and mean ROI

In [130]:

```
movie_details_df.groupby(by='Crime').mean()
```

Out[130]:

	level_0	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	profit	domestic_profit	st
Crime										
0.0	380.818182	2015.454545	2.967595e+07	1.769302e+08	4.920752e+08	18.616864	6.522655	4.623993e+08	1.472542e+08	201
1.0	541.500000	2017.000000	1.233513e+07	5.603615e+07	1.646656e+08	12.349326	3.542812	1.523305e+08	4.370103e+07	201

2 rows × 24 columns

In [131]:

```
roi = {}
for genre in all_genres:
    grouped = movie_details_df.groupby(by=''.join(genre)).mean()
    roi[genre] = grouped.iloc[1]['roi']
```

In [132]:

```
roi.items()
```

Out[132]:

```
dict_items([('Drama', 18.647193913280493), ('Romance', 18.936094345833336), ('Family', 14.2302356), ('Mys
tery', 22.141232289423076), ('Horror', 21.522878342935638), ('Music', 17.795009456818182), ('Animation',
13.102796338193455), ('Adventure', 13.029793775196815), ('Action', 21.41353083257713), ('Thriller', 20.43
57856749186), ('Sci-Fi', 18.677782), ('Comedy', 15.356868656175875), ('Crime', 12.34932625),
('Biography', 18.118232805935786)])
```

In [133]:

```
roi = dict(sorted(roi.items(), key = lambda item: item[1], reverse=True))
roi
```

Out[133]:

```
{'Mystery': 22.141232289423076,
 'Horror': 21.522878342935638,
 'Action': 21.41353083257713,
 'Thriller': 20.4357856749186,
 'Romance': 18.936094345833336,
 'Sci-Fi': 18.677782,
 'Drama': 18.647193913280493,
 'Biography': 18.118232805935786,
 'Music': 17.795009456818182,
 'Comedy': 15.356868656175875,
 'Family': 14.2302356,
 'Animation': 13.102796338193455,
 'Adventure': 13.029793775196815,
 'Crime': 12.34932625}
```

Visualization

Average ROI for genres of top films

In [134]:

```
roi.values()
```

Out[134]:

```
dict_values([22.141232289423076, 21.522878342935638, 21.41353083257713, 20.4357856749186,
18.936094345833336, 18.677782, 18.647193913280493, 18.118232805935786, 17.795009456818182,
15.356868656175875, 14.2302356, 13.102796338193455, 13.029793775196815, 12.34932625])
```

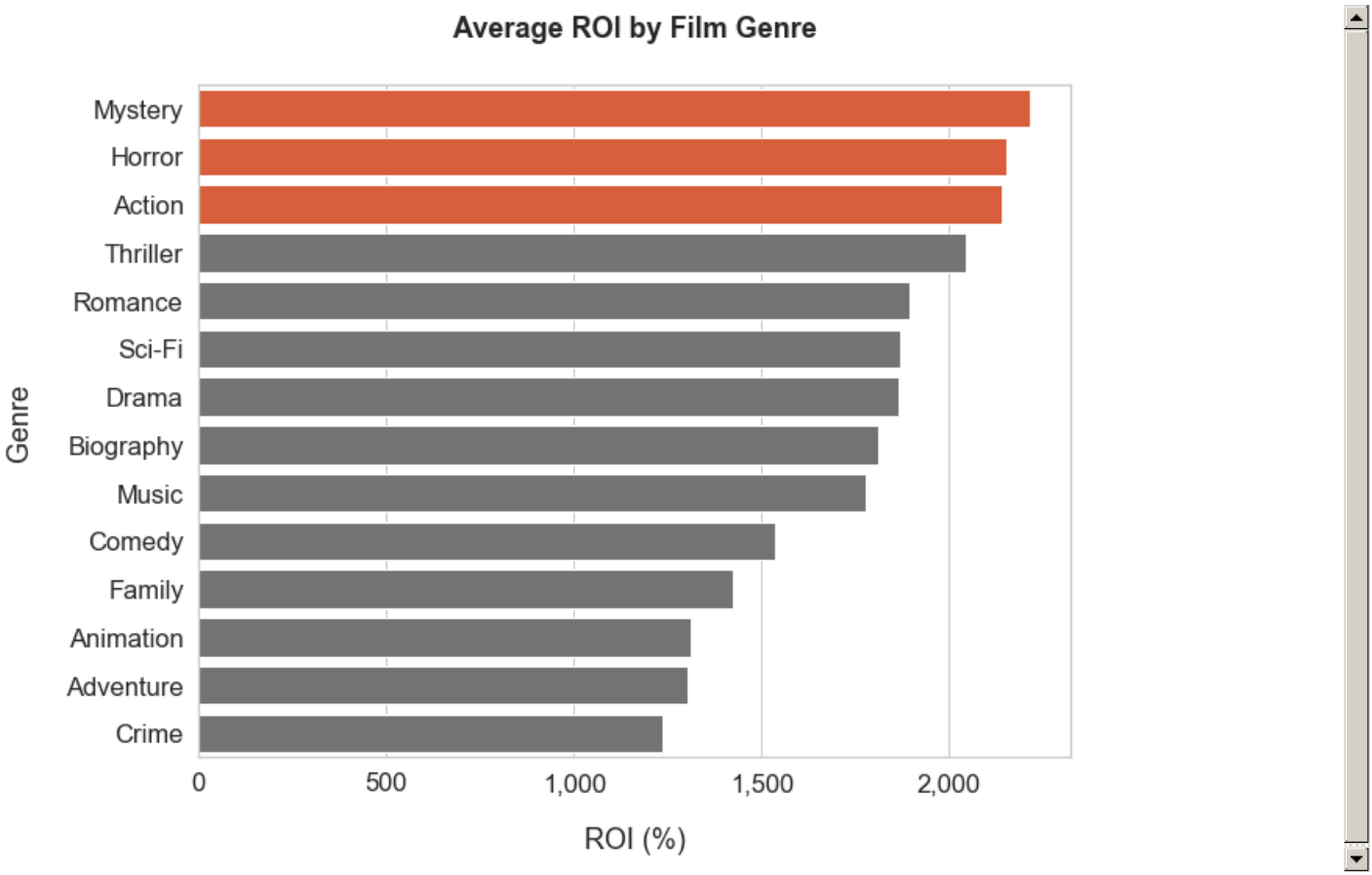
In [135]:

```
key = list(roi.keys())
value= list(roi.values())
```

In [136]:

```
top3_genres = value[:3]

plt.figure(figsize=(10,8))

bar_colors = ['#f25022' if (x in top3_genres) else '#737373' for x in roi.values() ]

ax = sns.barplot(x = list(roi.values()), y = list(roi.keys()), palette=bar_colors)
plt.xlabel("ROI (%)", labelpad=20)
plt.ylabel("Genre", labelpad=20)
plt.title('Average ROI by Film Genre', fontweight='bold', pad=30)

ax.xaxis.get_major_formatter().set_scientific(False)
ax.xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.0f}'.format(x*100)))
```

```
plt.tight_layout()
plt.savefig('ROI_Genre', dpi=300);
```



Question 4-1: Which actors bring the most value to a movie?

Clean data

Drop the dead

Microsoft can't hire anyone who is deceased

In [137]:

```
name_basics_df = name_basics_df[name_basics_df['death_year'].isnull()]
name_basics_df.head()
```

Out[137]:

nconst	primary_name	birth_year	death_year	primary_profession	known_for_titles
nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,producer	tt0837562,tt2398241,tt0844471,tt0118553
nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_department	tt0896534,tt6791238,tt0287072,tt1682940
nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,writer	tt1470654,tt0363631,tt0104030,tt0102898
nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_department	tt0114371,tt2004304,tt1618448,tt1224387
nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_decorator	tt0452644,tt0452692,tt3458030,tt2178256

In [138]:

```
name_basics_df.shape
```

Out[138]:

```
(599865, 5)
```

In [139]:

```
name_basics_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 599865 entries, nm0061671 to nm9993380
Data columns (total 5 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   primary_name       599865 non-null  object 
 1   birth_year         76464 non-null   float64
 2   death_year         0 non-null       float64
 3   primary_profession 549317 non-null  object 
 4   known_for_titles   569766 non-null  object 
dtypes: float64(2), object(3)
memory usage: 27.5+ MB
```

EDA

Merge principals & name basics

Links nconst to names of people. Find actors (includes actresses) and directors for top-performing films.

In [140]:

```
title_principals_df.head()
```

Out[140]:

tconst	ordering	nconst	category	job	characters
tt0111414	1	nm0246005	actor	NaN	["The Man"]
tt0111414	2	nm0398271	director	NaN	NaN
tt0111414	3	nm3739909	producer	producer	NaN
tt0323808	10	nm0059247	editor	NaN	NaN
tt0323808	1	nm3579312	actress	NaN	["Beth Boothby"]

In [141]:

```
title_principals_df.shape
```

Out[141]:

```
(1028186, 5)
```

In [142]:

```
name_basics_df.reset_index(inplace=True)
title_principals_df.reset_index(inplace=True)
```

In [143]:

```
principal_info_df = pd.merge(title_principals_df, name_basics_df, on='nconst', how='left')
principal_info_df.head(10)
```

Out[143]:

	tconst	ordering	nconst	category	job	characters	primary_name	birth_year	death_year	primary_profess
0	tt0111414	1	nm0246005	actor	NaN	["The Man"]	Tommy Dysart	NaN	NaN	ac
1	tt0111414	2	nm0398271	director	NaN	NaN	Frank Howson	1952.0	NaN	actor,writer,produ
2	tt0111414	3	nm3739909	producer	producer	NaN	Barry Porter-Robinson	NaN	NaN	producer,art_departm
3	tt0323808	10	nm0059247	editor	NaN	NaN	Sean Barton	1944.0	NaN	editor,editorial_department,assistant_direc
4	tt0323808	1	nm3579312	actress	NaN	["Beth Boothby"]	Brittania Nicol	NaN	NaN	actress,soundtr
5	tt0323808	2	nm2694680	actor	NaN	["Steve Thomson"]	Henry Garrett	NaN	NaN	ac
6	tt0323808	3	nm0574615	actor	NaN	["Sir Lachlan Morrison"]	Graham McTavish	1961.0	NaN	actor,soundtrack,direc
7	tt0323808	4	nm0502652	actress	NaN	["Lady Delia Morrison"]	Jacqueline Leonard	1967.0	NaN	actr
8	tt0323808	5	nm0362736	director	NaN	NaN	NaN	NaN	NaN	N
9	tt0323808	6	nm0811056	producer	producer	NaN	Peter Snell	1938.0	NaN	producer,soundtrack,execu

In [144]:

```
principal_info_df[principal_info_df.duplicated(keep=False)]
```

Out[144]:

	tconst	ordering	nconst	category	job	characters	primary_name	birth_year	death_year	primary_profession	known_for_titles

no duplicates

In [145]:

```
principal_info_df.shape
```

Out[145]:

```
(1028186, 11)
```

In [146]:

```
principal_info_df.isna().sum()
```

Out[146]:

```
tconst                     0
ordering                   0
nconst                     0
category                   0
job                   850502
characters            634826
primary_name           12117
birth_year            805118
death_year           1028186
primary_profession     64811
known_for_titles       42470
dtype: int64
```

Lots of missing values in "job." More reliable to look at category to discern role in a specific title

In [147]:

```
principal_info_df['category'].value_counts()
```

Out[147]:

```
actor                 256718
director              146393
actress               146208
producer              113724
cinematographer        80091
composer               77063
writer                 74357
self                   65424
editor                 55512
production_designer     9373
archive_footage         3307
archive_sound             16
Name: category, dtype: int64
```

In [148]:

```
principal_info_df = principal_info_df.drop(['job', 'death_year', 'known_for_titles', 'ordering'], axis=1)
principal_info_df.head()
```

Out[148]:

	tconst	nconst	category	characters	primary_name	birth_year	primary_profession
0	tt0111414	nm0246005	actor	["The Man"]	Tommy Dysart	NaN	actor
1	tt0111414	nm0398271	director	NaN	Frank Howson	1952.0	actor,writer,producer
2	tt0111414	nm3739909	producer	NaN	Barry Porter-Robinson	NaN	producer,art_department
3	tt0323808	nm0059247	editor	NaN	Sean Barton	1944.0	editor,editorial_department,assistant_director
4	tt0323808	nm3579312	actress	["Beth Boothby"]	Brittania Nicol	NaN	actress,soundtrack

Create separate dataframes for actors and directors

In [149]:

```
actors_info_df = principal_info_df[(principal_info_df['category']=='actor') | (principal_info_df['categor
actors_info_df.reset_index(inplace=True)
actors_info_df.head()
```

Out[149]:

	index	tconst	nconst	category	characters	primary_name	birth_year	primary_profession
0	0	tt0111414	nm0246005	actor	["The Man"]	Tommy Dysart	NaN	actor
1	4	tt0323808	nm3579312	actress	["Beth Boothby"]	Brittania Nicol	NaN	actress,soundtrack
2	5	tt0323808	nm2694680	actor	["Steve Thomson"]	Henry Garrett	NaN	actor
3	6	tt0323808	nm0574615	actor	["Sir Lachlan Morrison"]	Graham McTavish	1961.0	actor,soundtrack,director
4	7	tt0323808	nm0502652	actress	["Lady Delia Morrison"]	Jacqueline Leonard	1967.0	actress

In [150]:

```
director_info_df = principal_info_df[principal_info_df['category']=='director']
director_info_df.reset_index(inplace=True)
director_info_df.head()
```

Out[150]:

	index	tconst	nconst	category	characters	primary_name	birth_year	primary_profession
0	1	tt0111414	nm0398271	director	NaN	Frank Howson	1952.0	actor,writer,producer
1	8	tt0323808	nm0362736	director	NaN	NaN	NaN	NaN
2	18	tt0417610	nm1145057	director	NaN	Alejandro Chomski	1968.0	director,writer,producer
3	28	tt0469152	nm0707738	director	NaN	Alyssa R. Bennett	1960.0	producer,director,actress
4	35	tt0473032	nm0776090	director	NaN	J. Neil Schulman	1953.0	actor,writer,soundtrack

Merge movie budgets with title basics

We can match principal info to boxoffice performance using tconst. Must merge the movie budgets to title info first, as the budgets table does not contain a tconst column. This merge was performed in the previous question, but only with the top 100 films from `budgets_adjusted_df`.

In [151]:

```
budgets_adjusted_df.head()
```

Out[151]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	budge
0	8803	2019-06-07	Dark Phoenix	2019	3.500000e+08	4.276235e+07	1.497624e+08	-0.572108	-0.877822	(48389193.0, 512707249.0]	
1	9887	2001-04-27	Town & Country	2001	1.534453e+08	9.809464e+06	1.514690e+07	-0.901288	-0.936072	(48389193.0, 512707249.0]	
2	10025	2002-08-16	The Adventures of Pluto Nash	2002	1.438638e+08	6.345980e+06	1.020713e+07	-0.929050	-0.955889	(48389193.0, 512707249.0]	
3	9276	2011-03-11	Mars Needs Moms	2011	1.725875e+08	2.461414e+07	4.550528e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	
4	9275	2011-03-11	Mars Needs Moms	2011	1.500000e+08	2.139276e+07	3.954976e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	

In [152]:

```
budgets_adjusted_df.shape
```

Out[152]:

```
(6410, 13)
```

In [153]:

```
title_basics_df.head()
```

Out[153]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [154]:

```
title_basics_df.shape
```

Out[154]:

```
(146144, 6)
```

In [155]:

```
movie_details_df2 = pd.merge(budgets_adjusted_df, title_basics_df, right_on = ['primary_title', 'start_ye
                             left_on=['movie', 'release_year'], how='left')
movie_details_df2.head()
```

Out[155]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	budge
0	8803	2019-06-07	Dark Phoenix	2019	3.500000e+08	4.276235e+07	1.497624e+08	-0.572108	-0.877822	(48389193.0, 512707249.0]	
1	9887	2001-04-27	Town & Country	2001	1.534453e+08	9.809464e+06	1.514690e+07	-0.901288	-0.936072	(48389193.0, 512707249.0]	
2	10025	2002-08-16	The Adventures of Pluto Nash	2002	1.438638e+08	6.345980e+06	1.020713e+07	-0.929050	-0.955889	(48389193.0, 512707249.0]	
3	9276	2011-03-11	Mars Needs Moms	2011	1.725875e+08	2.461414e+07	4.550528e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	
4	9275	2011-03-11	Mars Needs Moms	2011	1.500000e+08	2.139276e+07	3.954976e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	

In [156]:

```
movie_details_df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6492 entries, 0 to 6491
Data columns (total 19 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   level_0          6492 non-null   int64
 1   release_date     6492 non-null   datetime64[ns]
 2   movie            6492 non-null   object
 3   release_year     6492 non-null   int64
 4   budget           6492 non-null   float64
 5   domestic_gross   6492 non-null   float64
 6   worldwide_gross  6492 non-null   float64
 7   roi              6492 non-null   float64
 8   domestic_roi     6492 non-null   float64
 9   budget_range     6492 non-null   category
 10  budget_class     6492 non-null   category
 11  profit           6492 non-null   float64
 12  domestic_profit  6492 non-null   float64
 13  tconst           2350 non-null   object
 14  primary_title    2350 non-null   object
 15  original_title   2350 non-null   object
 16  start_year       2350 non-null   float64
 17  runtime_minutes  2323 non-null   float64
 18  genres           2344 non-null   object
dtypes: category(2), datetime64[ns](1), float64(9), int64(2), object(5)
memory usage: 926.2+ KB
```

In [157]:

```
movie_details_df2 = movie_details_df2.drop(['primary_title', 'original_title',
                                            'start_year', 'genres'], axis=1)
```

In [158]:

```
movie_details_df2[movie_details_df2.duplicated(keep=False)].sort_values(by='movie')
```

Out[158]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	budget_class	profit	do

Merge actor info to budget/profit info

In [159]:

```
actors_info_df.head()
```

Out[159]:

	index	tconst	nconst	category	characters	primary_name	birth_year	primary_profession
0	0	tt0111414	nm0246005	actor	["The Man"]	Tommy Dysart	NaN	actor
1	4	tt0323808	nm3579312	actress	["Beth Boothby"]	Brittania Nicol	NaN	actress,soundtrack
2	5	tt0323808	nm2694680	actor	["Steve Thomson"]	Henry Garrett	NaN	actor
3	6	tt0323808	nm0574615	actor	["Sir Lachlan Morrison"]	Graham McTavish	1961.0	actor,soundtrack,director
4	7	tt0323808	nm0502652	actress	["Lady Delia Morrison"]	Jacqueline Leonard	1967.0	actress

In [160]:

```
actors_info_df.shape
```

Out[160]:

```
(402926, 8)
```

In [161]:

```
actors_budgets_df = pd.merge(actors_info_df, movie_details_df2, on='tconst', how='left')
actors_budgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 407448 entries, 0 to 407447
Data columns (total 22 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   index               407448 non-null  int64
 1   tconst              407448 non-null  object
 2   nconst              407448 non-null  object
 3   category            407448 non-null  object
 4   characters          329524 non-null  object
 5   primary_name        403601 non-null  object
 6   birth_year          128614 non-null  float64
 7   primary_profession  385706 non-null  object
 8   level_0             9264 non-null    float64
 9   release_date        9264 non-null    datetime64[ns]
 10  movie               9264 non-null    object
 11  release_year        9264 non-null    float64
 12  budget              9264 non-null    float64
 13  domestic_gross      9264 non-null    float64
 14  worldwide_gross     9264 non-null    float64
 15  roi                 9264 non-null    float64
 16  domestic_roi        9264 non-null    float64
 17  budget_range        9264 non-null    category
 18  budget_class        9264 non-null    category
 19  profit              9264 non-null    float64
 20  domestic_profit     9264 non-null    float64
 21  runtime_minutes     9168 non-null    float64
dtypes: category(2), datetime64[ns](1), float64(11), int64(1), object(7)
memory usage: 66.1+ MB
```

Filter for actors who have appeared in more than 5 films

In [162]:

```
# Finding cutoff through trial and error
actors_budgets_df['primary_name'].value_counts().head(8650)
```

Out[162]:

```
Eric Roberts            147
Brahmanandam            126
Prakash Raj              79
Tom Sizemore             71
Mihir Das                71
                        ...
David Denman              6
Eva Josefíková            5
Eric Warrington           5
Iain De Caestecker        5
Andrius Bialobzeskis      5
Name: primary_name, Length: 8650, dtype: int64
```

In [163]:

```
#Filter for actors that have appeared in more than 5 films
actor_list = actors_budgets_df['primary_name'].value_counts().index[:8646].tolist()
```

In [164]:

```
mask = actors_budgets_df['primary_name'].isin(actor_list)
```

In [165]:

```
actors_filtered_df = actors_budgets_df[mask]
```

Filter for top genre

In [166]:

```
top_genres = ['Mystery']
```

In [167]:

```
title_basics_df.head()
```

Out[167]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [168]:

```
subset = title_basics_df[['tconst', 'genres']]
subset = subset.dropna(axis=0, subset=['genres'])
```

In [169]:

```
mask = subset['genres'].str.contains('|'.join(top_genres))
title_genres = subset[mask]
```

In [170]:

```
actors_filtered_genres = pd.merge(actors_filtered_df, title_genres, on='tconst',
                                  how='inner')
```

In [171]:

```
actors_filtered_genres
```

Out[171]:

	index	tconst	nconst	category	characters	primary_name	birth_year	primary_profession	level_0	release_date	...	dc
0	48	tt0477302	nm0000158	actor	["Thomas Schell"]	Tom Hanks	1956.0	producer,actor,soundtrack	NaN	NaT	...	
1	49	tt0477302	nm0000113	actress	["Linda Schell"]	Sandra Bullock	1964.0	producer,actress,soundtrack	NaN	NaT	...	
2	50	tt0477302	nm0001884	actor	["The Renter"]	Max von Sydow	1929.0	actor,soundtrack,director	NaN	NaT	...	
3	726	tt1078591	nm0523344	actress	["Raeanne"]	Lynn Lowry	1947.0	actress,writer,producer	NaN	NaT	...	
4	727	tt1078591	nm1594672	actor	["Sage"]	Peter Stickles	1976.0	actor,miscellaneous,producer	NaN	NaT	...	
...	...	...	...	...	...	...	...	...	...	...	...	
4450	1025705	tt7172308	nm1795232	actor	["Kuldip Patwal"]	Deepak Dobriyal	NaN	actor	NaN	NaT	...	
4451	1025706	tt7172308	nm3761132	actor	["Lawyer Parduman Shahpuri"]	Gulshan Devaiah	NaN	actor	NaN	NaT	...	
4452	1025707	tt7172308	nm0784025	actress	["Simrat Chadha"]	Raima Sen	1979.0	actress	NaN	NaT	...	
4453	1025708	tt7172308	nm0196375	actor	["CM Varun Chadha"]	Parvin Dabas	1974.0	actor,director,writer	NaN	NaT	...	
4454	1025744	tt7201192	nm6018266	actor	NaN	Daniel Mansfield	NaN	actor,producer,director	NaN	NaT	...	

4455 rows × 23 columns

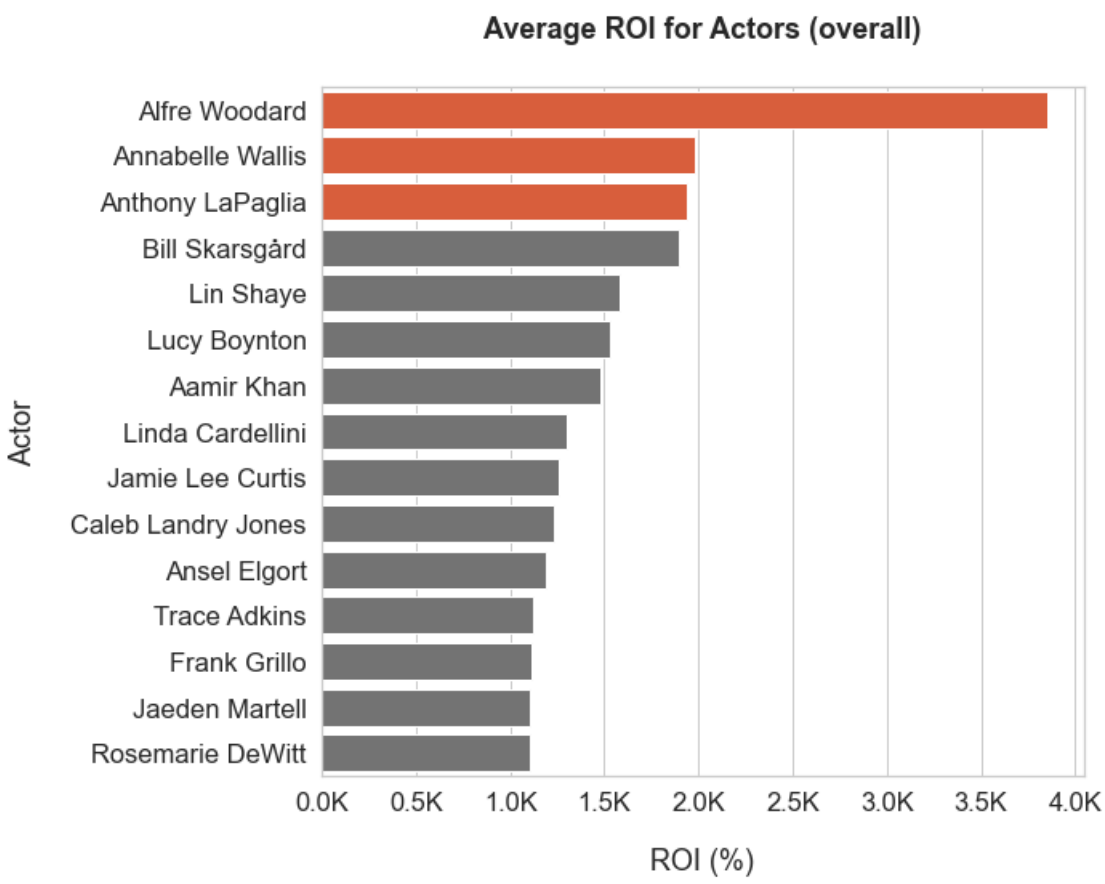
Visualization

In [172]:

```
actors_grouped = actors_filtered_df.groupby('primary_name').mean()
actors_grouped = actors_grouped.sort_values(by='roi', ascending=False)
actors_grouped.reset_index(inplace=True)
```

In [173]:

```
labels = list(actors_grouped['primary_name'][:15])
values = list(actors_grouped['roi'][:15])
top3_values = values[:3]

clrs = ['#f25022' if (x in top3_values) else '#737373' for x in values]

plt.figure(figsize=(10,8))
ax = sns.barplot(x=values, y=labels, palette=clrs)
plt.title('Average ROI for Actors (overall)',
          fontweight='bold', pad=30)
plt.xlabel('ROI (%)', labelpad=20)
plt.ylabel('Actor', labelpad=20)

ax.xaxis.get_major_formatter().set_scientific(False)
#ax.xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.0f}'.format(x/1000000) + 'M'))
ax.xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.1f}'.format(x/10) + 'K'))
plt.tight_layout()
plt.savefig('ROI_Actor', dpi=300);
```

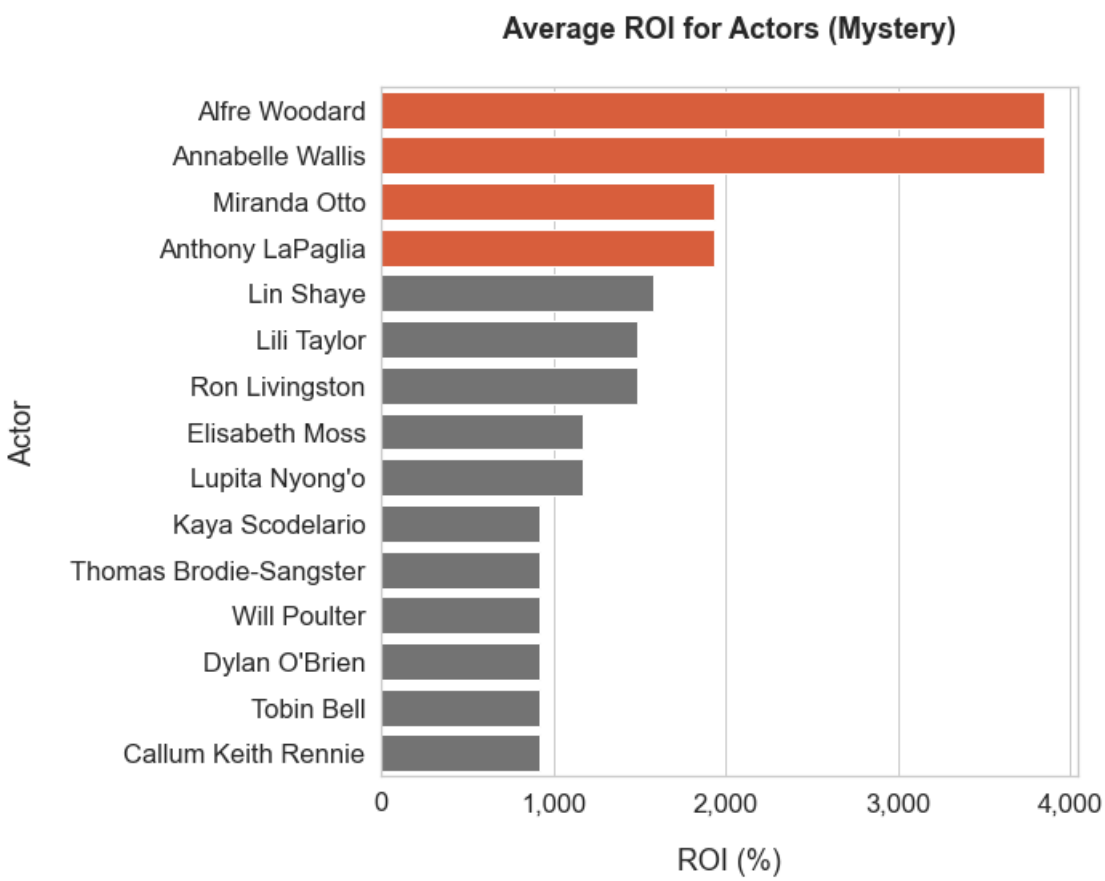


In [174]:

```
actors_genres_grouped = actors_filtered_genres.groupby('primary_name').mean()
actors_genres_grouped = actors_genres_grouped.sort_values(by='roi', ascending=False)
actors_genres_grouped.reset_index(inplace=True)
```

In [175]:

```
labels = list(actors_genres_grouped['primary_name'][:15])
values = list(actors_genres_grouped['roi'][:15])
top3_values = values[:3]

clrs = ['#f25022' if (x in top3_values) else '#737373' for x in values]

plt.figure(figsize=(10,8))
ax = sns.barplot(x=values, y=labels, palette=clrs)
plt.title('Average ROI for Actors (Mystery)',
          fontweight='bold', pad=30)
plt.xlabel('ROI (%)', labelpad=20)
plt.ylabel('Actor', labelpad=20)

ax.xaxis.get_major_formatter().set_scientific(False)
ax.xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.0f}'.format(x*100)))

plt.tight_layout()
plt.savefig('ROI_Actor_Genre', dpi=300);
```



Question 4-2: Which directors bring the most value to a movie?

Merge director info to budget/profit info

In [176]:

```
director_info_df.head()
```

Out[176]:

	index	tconst	nconst	category	characters	primary_name	birth_year	primary_profession
0	1	tt0111414	nm0398271	director	NaN	Frank Howson	1952.0	actor,writer,producer
1	8	tt0323808	nm0362736	director	NaN	NaN	NaN	NaN
2	18	tt0417610	nm1145057	director	NaN	Alejandro Chomski	1968.0	director,writer,producer
3	28	tt0469152	nm0707738	director	NaN	Alyssa R. Bennett	1960.0	producer,director,actress
4	35	tt0473032	nm0776090	director	NaN	J. Neil Schulman	1953.0	actor,writer,soundtrack

In [177]:

```
director_info_df.shape
```

Out[177]:

```
(146393, 8)
```

In [178]:

```
movie_details_df2.head()
```

Out[178]:

	level_0	release_date	movie	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	budget_range	budge
0	8803	2019-06-07	Dark Phoenix	2019	3.500000e+08	4.276235e+07	1.497624e+08	-0.572108	-0.877822	(48389193.0, 512707249.0]	
1	9887	2001-04-27	Town & Country	2001	1.534453e+08	9.809464e+06	1.514690e+07	-0.901288	-0.936072	(48389193.0, 512707249.0]	
2	10025	2002-08-16	The Adventures of Pluto Nash	2002	1.438638e+08	6.345980e+06	1.020713e+07	-0.929050	-0.955889	(48389193.0, 512707249.0]	
3	9276	2011-03-11	Mars Needs Moms	2011	1.725875e+08	2.461414e+07	4.550528e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	
4	9275	2011-03-11	Mars Needs Moms	2011	1.500000e+08	2.139276e+07	3.954976e+07	-0.736335	-0.857382	(48389193.0, 512707249.0]	

In [179]:

```
movie_details_df2.shape
```

Out[179]:

```
(6492, 15)
```

In [180]:

```
director_budgets_df = pd.merge(director_info_df, movie_details_df2, on='tconst', how='left')
director_budgets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 147605 entries, 0 to 147604
Data columns (total 22 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   index               147605 non-null  int64
 1   tconst              147605 non-null  object
 2   nconst              147605 non-null  object
 3   category            147605 non-null  object
 4   characters          0 non-null       object
 5   primary_name        146744 non-null  object
 6   birth_year          29903 non-null   float64
 7   primary_profession  146157 non-null  object
 8   level_0             2482 non-null    float64
 9   release_date        2482 non-null    datetime64[ns]
 10  movie               2482 non-null    object
 11  release_year        2482 non-null    float64
 12  budget              2482 non-null    float64
 13  domestic_gross      2482 non-null    float64
 14  worldwide_gross     2482 non-null    float64
 15  roi                 2482 non-null    float64
 16  domestic_roi        2482 non-null    float64
 17  budget_range        2482 non-null    category
 18  budget_class        2482 non-null    category
 19  profit              2482 non-null    float64
 20  domestic_profit     2482 non-null    float64
 21  runtime_minutes     2455 non-null    float64
dtypes: category(2), datetime64[ns](1), float64(11), int64(1), object(7)
memory usage: 23.9+ MB
```

Filter for directors who have directed more than 5 films

In [181]:

```
director_budgets_df['primary_name'].value_counts().head(1675)
```

Out[181]:

```
Rajiv Chilaka              49
Stephan Düfel              48
Graeme Duane               45
Claudio Costa              42
Nayato Fio Nuala           41
                           ..
Takayuki Shibasaki          6
Dennis Bots                 6
Tamae Garateguy             6
Renee S. Warren Peoples     6
Humberto Rosa               5
Name: primary_name, Length: 1675, dtype: int64
```

In [182]:

```
#Filter for directors who have directed more than 5 films
director_list = director_budgets_df['primary_name'].value_counts().index[:1674].tolist()
```

In [183]:

```
mask = director_budgets_df['primary_name'].isin(director_list)
director_filtered_df = director_budgets_df[mask]
```

In [184]:

```
directors_grouped = director_filtered_df.groupby('primary_name').mean()
directors_grouped = directors_grouped.sort_values(by='roi', ascending=False)
directors_grouped.head()
```

Out[184]:

primary_name	index	birth_year	level_0	release_year	budget	domestic_gross	worldwide_gross	roi	domestic_roi	
John R. Leonetti	574505.500000	1956.0	2713.0	2015.500000	9.569090e+06	5.145194e+07	1.464859e+08	19.736909	6.078497	1.36
Kyle Balda	369057.333333	1971.0	484.0	2016.000000	7.724837e+07	3.117551e+08	1.138654e+09	13.738294	3.034742	1.06
James DeMonaco	453180.666667	1969.0	613.0	2015.000000	9.905676e+06	7.851895e+07	1.199462e+08	11.122119	6.927819	1.10
Pierre Coffin	204932.000000	1967.0	743.5	2013.333333	7.758665e+07	3.118408e+08	8.957363e+08	10.501490	3.005473	8.18
James Wan	369982.400000	1977.0	944.5	2015.333333	1.274332e+08	2.848210e+08	1.029560e+09	9.353792	2.607358	9.02

Filter for top genre

In [185]:

```
directors_filtered_genres = pd.merge(director_filtered_df, title_genres, on='tconst',
                                     how='inner')
```

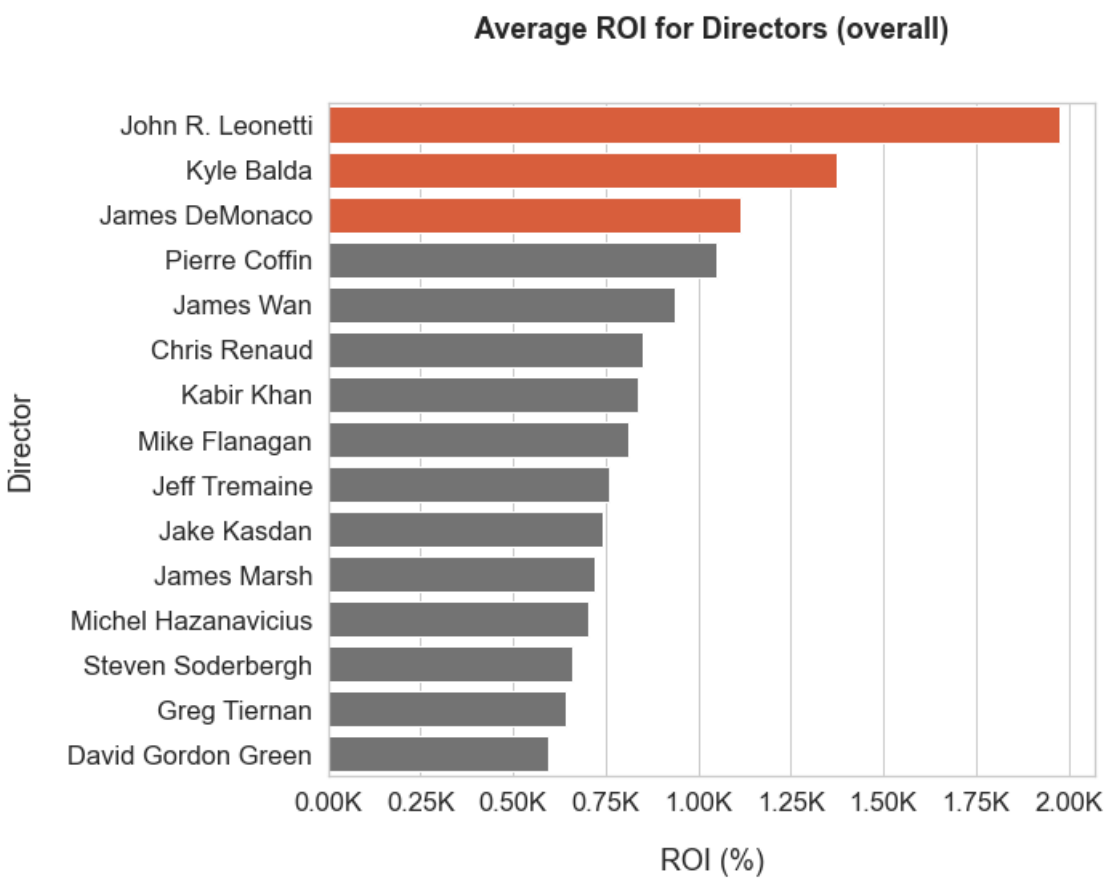
Visualization

In [186]:

```
directors_grouped.reset_index(inplace=True)
```

In [187]:

```
labels = list(directors_grouped['primary_name'][:15])
values = list(directors_grouped['roi'][:15])
top3_values = values[:3]

clrs = ['#f25022' if (x in top3_values) else '#737373' for x in values]

plt.figure(figsize=(10,8))
ax = sns.barplot(x=values, y=labels, palette=clrs)
plt.title('Average ROI for Directors (overall)',
          fontweight='bold', pad=40);
plt.xlabel('ROI (%)', labelpad=20)
plt.ylabel('Director', labelpad=20)

ax.xaxis.get_major_formatter().set_scientific(False)
ax.xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.2f}'.format(x/10) + 'K'))

plt.tight_layout()
plt.savefig('ROI_Director', dpi=300);
```

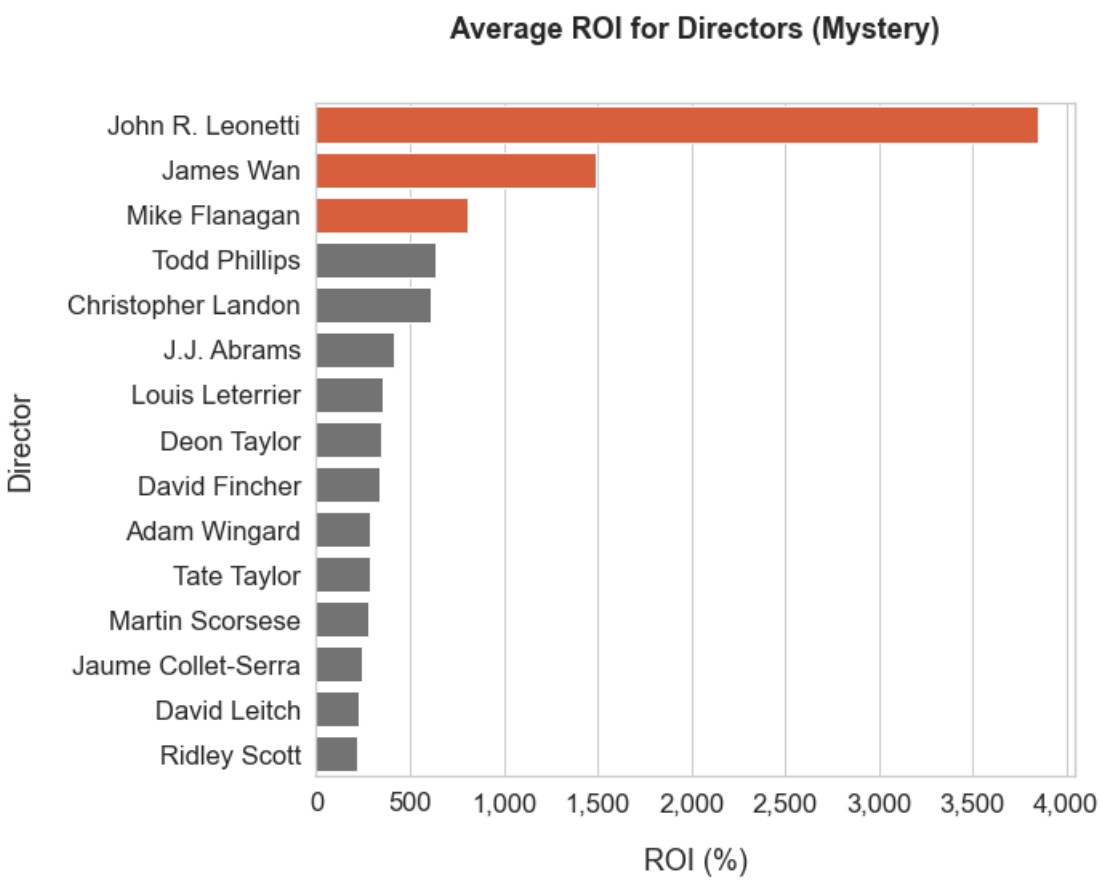


In [188]:

```
directors_genres_grouped = directors_filtered_genres.groupby('primary_name').mean()
directors_genres_grouped = directors_genres_grouped.sort_values(by='roi', ascending=False)
directors_genres_grouped.reset_index(inplace=True)
```

In [189]:

```
labels = list(directors_genres_grouped['primary_name'][:15])
values = list(directors_genres_grouped['roi'][:15])
top3_values = values[:3]

clrs = ['#f25022' if (x in top3_values) else '#737373' for x in values]

plt.figure(figsize=(10,8))
ax = sns.barplot(x=values, y=labels, palette=clrs)
plt.title('Average ROI for Directors (Mystery)',
          fontweight='bold', pad=40);
plt.xlabel('ROI (%)', labelpad=20)
plt.ylabel('Director', labelpad=20)

ax.xaxis.get_major_formatter().set_scientific(False)
ax.xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.0f}'.format(x*100)))

plt.tight_layout()
plt.savefig('ROI_Director_Genre', dpi=300);
```


Average ROI for Directors (Mystery)
John R. Leonetti
James Wan
Mike Flanagan
Todd Phillips
Christopher Landon
J.J. Abrams
Louis Leterrier
Deon Taylor
David Fincher
Adam Wingard
Tate Taylor
Martin Scorsese
Jaume Collet-Serra
David Leitch
Ridley Scott
Director
0
500
1,000
1,500
2,000
2,500
3,000
3,500
4,000
ROI (%)

In [ ]: