genre_profitability

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1 Movie Genre Profitability for Microsoft

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1.1 Overview

I conduct an analysis of the profitability of different movie genres in relation to production budget for Microsoft. Microsoft wants to enter the movie business and develop original content. They will have to decide which genres they wish to invest in early on, since different genres have different production requirements. I conclude that Microsoft should invest in horror for low-budget productions and animation for high-budget productions. Horror has the strongest correlation with return on investment (ROI) of any genre, overall. I further conclude that Microsoft should stay away from drama, action, and crime movies because these are negatively correlated with ROI. Finally, I recommend that Microsoft keep their movie budgets under $250M, because ROI sharply declines after that point.

1.2 Business Problem

Microsoft has decided to enter the movie business and create original material. They want to know what kinds of movies are currently profitable, and they want concrete, actionable, insights.

In my analysis, I attempt to answer the following questions for Microsoft:

1. What genres have the strongest correlation with worldwide return on investment?
2. How does budget affect these correlations?

3. Are high or low-budget films more profitable?

1.2.1 Why Genre?

Different film genres have different markets and different production needs. Some genres are more popular than others, and some cost more to produce. Each genre requires a specialized creative team comprised of actors, writers, set designers, and more. Choosing which genres to invest in is one of the most fundamental early decisions Microsoft will have to make.

1.2.2 Why Correlation?

Correlation—and in particular the Pearson correlation coefficient—is a measure of the strength of the linear relationship between two variables. I focus on correlation because I am interested in the relationships between variables, not simply their central tendencies. Correlation measures something deeper than measures of central tendency, like median or mean. With regard to categorical variables like genres, correlation takes into account what is happening both when a genre is present and when it is absent. For example, if non-crime movies make more money than crime movies, that is captured by the negative correlation between crime and profit. The median profit of crime movies tells you nothing about how they compare with non-crime movies.

1.2.3 Why Return on Investment?

I focus on return on investment (ROI) as a measure of profitability because it takes budget into account. A low-budget movie may not generate as much profit as a high-budget movie, but it might still be more profitable (in a sense) because it generated more profit *relative* to the initial investment. Measuring profit only reveals investment opportunities with high upfront cost. Microsoft might, for example, want to invest in a large number of low-cost films rather than a small number of expensive films, as this strategy would be lower-risk.

1.3 Data Understanding

I use data from two sources in my analysis: The Numbers and the Internet Movie Database (IMDb). IMDb is an expansive and easily accessible source of movie data which, most importantly, includes genre labels for thousands of films. IMDb lacks financial data, however, so I am forced to rely on The Numbers.

[1]:
```
import os
import unidecode
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from matplotlib import ticker
import seaborn as sns

import utils
import cleaning
import plotting

%matplotlib inline
```

```
sns.set(font_scale=1.25, style='darkgrid', palette='deep')
pd.options.display.float_format = '{:,.2f}'.format
```

1.3.1 The Numbers

My financial data comes from a website called "The Numbers" which has a healthy collection of production budget and revenue data. The Numbers is owned by Nash Information Services, a movie industry research and consulting firm. The most important columns for my analysis are `production_budget`, `domestic_gross`, and `worldwide_gross`. I use these columns later to calculate profit and return on investment (ROI).

The table includes 5782 observations.

[2]:
```
tn = pd.read_csv(os.path.join('zipped_data', 'tn.movie_budgets.csv.gz'),
                 parse_dates=['release_date'])
tn.head()
```

[2]:
```
   id release_date                                        movie  \
0   1   2009-12-18                                       Avatar
1   2   2011-05-20  Pirates of the Caribbean: On Stranger Tides
2   3   2019-06-07                                 Dark Phoenix
3   4   2015-05-01                      Avengers: Age of Ultron
4   5   2017-12-15            Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross worldwide_gross
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
2      $350,000,000    $42,762,350    $149,762,350
3      $330,600,000   $459,005,868  $1,403,013,963
4      $317,000,000   $620,181,382  $1,316,721,747
```

[3]:
```
tn.info()
```

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

1.3.2 Internet Movie Database

My genre data comes from IMDb, a subsidiary of Amazon which is a well known source of movie information. Naturally, the most important column for my analysis will be `genres`. I later use this column to compute Pearson correlations between genres and different financial statistics.

This table is much larger than `tn`, with 146,144 observations.

[4]:
```
imdb = pd.read_csv(os.path.join('zipped_data', 'imdb.title.basics.csv.gz'))
imdb.head()
```

[4]:
```
      tconst                    primary_title              original_title  \
0  tt0063540                        Sunghursh                   Sunghursh
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela Errante

   start_year  runtime_minutes                genres
0        2013           175.00    Action,Crime,Drama
1        2019           114.00       Biography,Drama
2        2018           122.00                 Drama
3        2018              nan          Comedy,Drama
4        2017            80.00  Comedy,Drama,Fantasy
```

[5]:
```
imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   tconst           146144 non-null  object
 1   primary_title    146144 non-null  object
 2   original_title   146123 non-null  object
 3   start_year       146144 non-null  int64
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

1.4 Data Preparation

I first process `tn` by trimming the timeframe down to the last decade and calculating financial statistics. I inspect the distributions of all of the financial statistics in order to get a feel for the dataset and check for outliers. I find that there are many extreme values, but that these extreme values are legitimate data points. I then merge `tn` with `imdb` along the year and title fields. It is a crude and inefficient merge, but as there are no shared unique identifiers between the datasets, it is the best I can do. Many titles are lost, but enough remain to conduct my analysis.

See the steps I take below for the specifics on how I cleaned the data, which fields I dropped, and which fields I created.

1.4.1 The Numbers

I start by replacing the incorrect `id` column with a column of genuinely unique ID numbers. I also create a `release_year` column, because it will come in handy later when merging tables.

```
[6]: del tn['id']
tn.insert(0, 'tn_id', np.arange(tn.shape[0]) + 1)
tn.insert(2, 'release_year', tn['release_date'].dt.year)
tn.head()
```

```
[6]:    tn_id release_date  release_year  \
0      1   2009-12-18          2009
1      2   2011-05-20          2011
2      3   2019-06-07          2019
3      4   2015-05-01          2015
4      5   2017-12-15          2017

                                         movie production_budget  \
0                                       Avatar      $425,000,000
1  Pirates of the Caribbean: On Stranger Tides      $410,600,000
2                                 Dark Phoenix      $350,000,000
3                      Avengers: Age of Ultron      $330,600,000
4            Star Wars Ep. VIII: The Last Jedi      $317,000,000

  domestic_gross worldwide_gross
0   $760,507,625  $2,776,345,279
1   $241,063,875  $1,045,663,875
2    $42,762,350    $149,762,350
3   $459,005,868  $1,403,013,963
4   $620,181,382  $1,316,721,747
```

I coerce the titles to ASCII to avoid problems with graph labeling.

```
[7]: tn['movie'] = tn.loc[:, 'movie'].map(unidecode.unidecode)
```

The columns `production_budget`, `domestic gross`, and `worldwide gross` are in string format, so I remove the extraneous symbols and convert them to `np.float64`.

```
[8]: money_cols = ['production_budget', 'domestic_gross', 'worldwide_gross']
tn[money_cols] = (tn.loc[:, money_cols]
                    .apply(cleaning.process_strings)
                    .apply(lambda x: x.astype('float64')))
tn.sort_values('worldwide_gross').head()
```

```
[8]:       tn_id release_date  release_year  \
5037   5038   2019-04-23          2019
```

```
3975   3976   2015-05-15          2015
4627   4628   2011-06-28          2011
4628   4629   2013-01-29          2013
3947   3948   2019-06-21          2019

                                          movie  production_budget  \
5037  Living Dark: The Story of Ted the Caver       1,750,000.00
3975                             Pound of Flesh       7,500,000.00
4627                                       2:13       3,500,000.00
4628  Batman: The Dark Knight Returns, Part 2       3,500,000.00
3947                             Burn Your Maps       8,000,000.00

      domestic_gross  worldwide_gross
5037            0.00             0.00
3975            0.00             0.00
4627            0.00             0.00
4628            0.00             0.00
3947            0.00             0.00
```

These 0 values for `domestic_gross` and `worldwide_gross` look very suspicious. Some of these 0s are for Netflix original productions such as *Bright* and *The Ridiculous 6*. Obviously those should not be counted as massive commercial failures simply because they were not released in theaters. Other 0s are for movies like *PLAYMOBIL*, which other sources report as generating revenue. Still other 0s are for movies which were released only domestically or only abroad.

[9]:
```
tn.query('(domestic_gross == 0) & (worldwide_gross == 0)').head()
```

[9]:
```
     tn_id release_date  release_year             movie  production_budget  \
194    195   2020-12-31          2020          Moonfall     150,000,000.00
479    480   2017-12-13          2017            Bright      90,000,000.00
480    481   2019-12-31          2019  Army of the Dead      90,000,000.00
535    536   2020-02-21          2020  Call of the Wild      82,000,000.00
670    671   2019-08-30          2019         PLAYMOBIL      75,000,000.00

     domestic_gross  worldwide_gross
194            0.00             0.00
479            0.00             0.00
480            0.00             0.00
535            0.00             0.00
670            0.00             0.00
```

I remove any rows where the domestic or worldwide gross is 0, since nearly every 0 is a null value or error.

[10]:
```
tn = tn.loc[tn.query('(domestic_gross > 0) & (worldwide_gross > 0)').index]
tn.sort_values('worldwide_gross').head()
```

[10]:

```
      tn_id release_date  release_year                              movie  \
5770   5771   2008-08-14          2008  The Rise and Fall of Miss Thang
5518   5519   2005-10-13          2005                    The Dark Hours
5769   5770   1996-04-01          1996                              Bang
5466   5467   2018-05-11          2018                      Higher Power
5027   5028   1993-01-01          1993           Ed and his Dead Mother

      production_budget  domestic_gross  worldwide_gross
5770          10,000.00          401.00           401.00
5518         400,000.00          423.00           423.00
5769          10,000.00          527.00           527.00
5466         500,000.00          528.00           528.00
5027       1,800,000.00          673.00           673.00
```

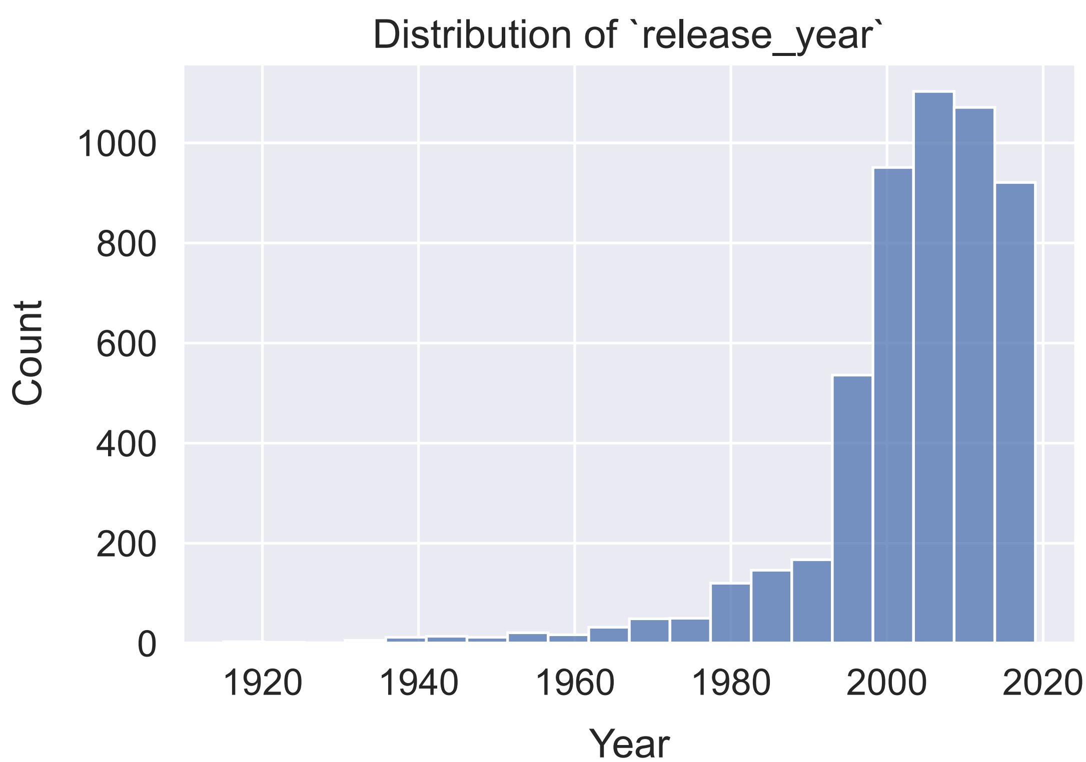
Looks like the data extends back in time much farther than I want.

[11]:

```python
ax = sns.histplot(data=tn, x='release_year', bins=20, palette='deep')
ax.set_title('Distribution of `release_year`')
ax.set_xlabel('Year', labelpad=10)
ax.set_ylabel('Count', labelpad=10)
```

[11]:

```
Text(0, 0.5, 'Count')
```



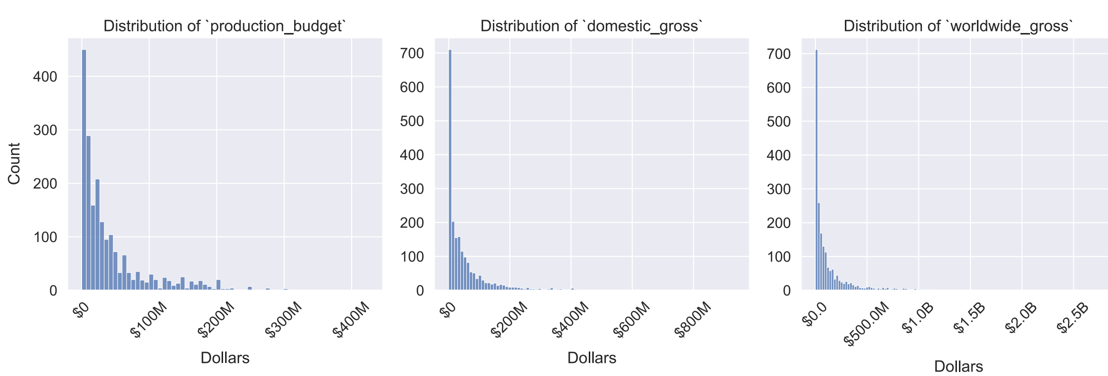
I drop everything earlier than 2009 because I'm only interested in data that's relevant to current box office performance. 2020 was a particularly bad year because of the COVID-19 pandemic, so I leave that out as well.

[12]:
```
tn = tn.loc[tn.query('(release_year <= 2019) & (release_year >= 2009)').index]
tn.sort_values('release_date').head()
```

[12]:
```
      tn_id release_date  release_year               movie  production_budget  \
2934   2935   2009-01-09          2009          The Unborn      16,000,000.00
4318   4319   2009-01-09          2009  Not Easily Broken       5,000,000.00
1880   1881   2009-01-09          2009          Bride Wars      30,000,000.00
1164   1165   2009-01-16          2009            Defiance      50,000,000.00
2736   2737   2009-01-16          2009           Notorious      19,000,000.00

      domestic_gross  worldwide_gross
2934   42,670,410.00    78,208,812.00
4318   10,572,742.00    10,732,909.00
1880   58,715,510.00   115,150,424.00
1164   28,644,813.00    52,987,754.00
2736   36,843,682.00    44,972,183.00
```

Looks like all of the basic money distributions are very right-skewed, which is not surprising. I expect there to be many more small films than big films, financially-speaking.

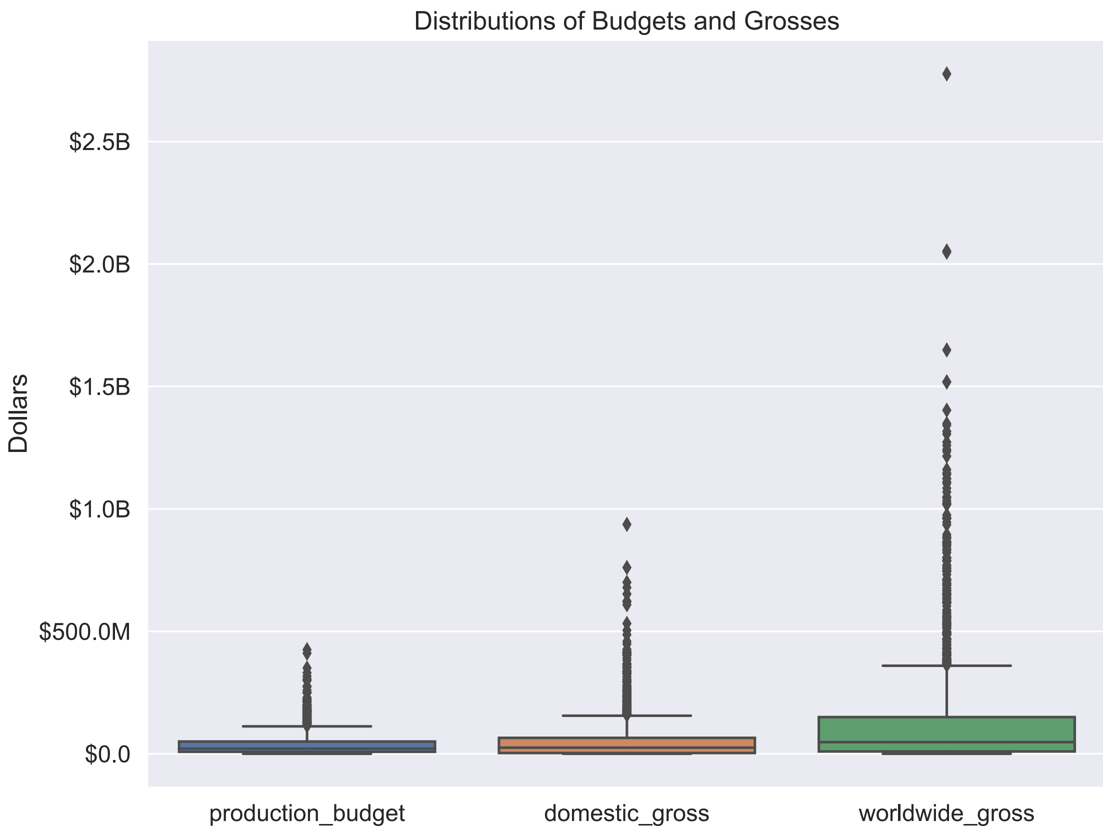
[13]:
```
axs = plotting.multi_hist(tn, include=money_cols, xlabel='Dollars',␣
 ↪palette='deep')
for ax in axs:
    ax.xaxis.set_major_formatter(plotting.big_money_formatter())
    for tick in ax.get_xticklabels():
        tick.set_rotation(45)
axs[2].xaxis.set_major_formatter(plotting.big_money_formatter(1))
plt.tight_layout()
```



These box plots indicate that there are many extreme values in the dataset. The data points beyond the upper whiskers are not truly outliers in this case. *Avatar* really does have a worldwide gross of

2.8 billion dollars. There is not a good scientific reason to altar or remove these values.

[14]:
```
fix, ax = plt.subplots(figsize=(10, 8))
ax = sns.boxplot(data=tn[money_cols],
                 ax=ax,
                palette='deep')
ax.set_title('Distributions of Budgets and Grosses')
ax.set_ylabel('Dollars')
ax.yaxis.set_major_formatter(plotting.big_money_formatter(1))
```



Financial Calculations I calculate domestic and worldwide profit by subtracting `production_budget` from each respective gross column.

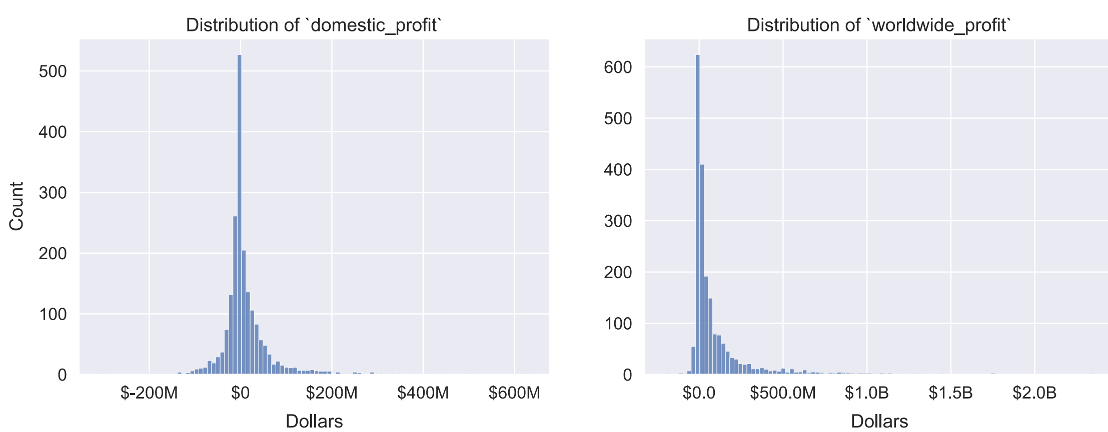
[15]:
```
tn['worldwide_profit'] = tn.eval('worldwide_gross - production_budget')
tn['domestic_profit'] = tn.eval('domestic_gross - production_budget')
tn.sort_values('worldwide_profit', ascending=False).head()
```

[15]:
```
   tn_id release_date  release_year                          movie  \
0      1   2009-12-18          2009                         Avatar
6      7   2018-04-27          2018         Avengers: Infinity War
5      6   2015-12-18          2015  Star Wars Ep. VII: The Force Awakens
```

```
33     34   2015-06-12          2015                          Jurassic World
66     67   2015-04-03          2015                               Furious 7

    production_budget  domestic_gross  worldwide_gross  worldwide_profit  \
0      425,000,000.00  760,507,625.00 2,776,345,279.00  2,351,345,279.00
6      300,000,000.00  678,815,482.00 2,048,134,200.00  1,748,134,200.00
5      306,000,000.00  936,662,225.00 2,053,311,220.00  1,747,311,220.00
33     215,000,000.00  652,270,625.00 1,648,854,864.00  1,433,854,864.00
66     190,000,000.00  353,007,020.00 1,518,722,794.00  1,328,722,794.00

    domestic_profit
0    335,507,625.00
6    378,815,482.00
5    630,662,225.00
33   437,270,625.00
66   163,007,020.00
```

The distribution of `domestic_profit` is almost symmetrical around 0, although it is still right-skewed overall. The distribution of `worldwide_profit` is even more right-skewed. In both distributions the positive skew indicates that there are more winners than losers. This is unsurprising, since production companies strive to generate profit.

[16]:
```
axs = plotting.multi_hist(tn,
                          include=['domestic_profit', 'worldwide_profit'],
                          xlabel='Dollars',
                          bins=100)
axs[0].xaxis.set_major_formatter(plotting.big_money_formatter())
axs[1].xaxis.set_major_formatter(plotting.big_money_formatter(1))
```



I calculate the percent return on investment (ROI) by dividing profit by budget and multiplying by 100. The sorted result is… ominous…

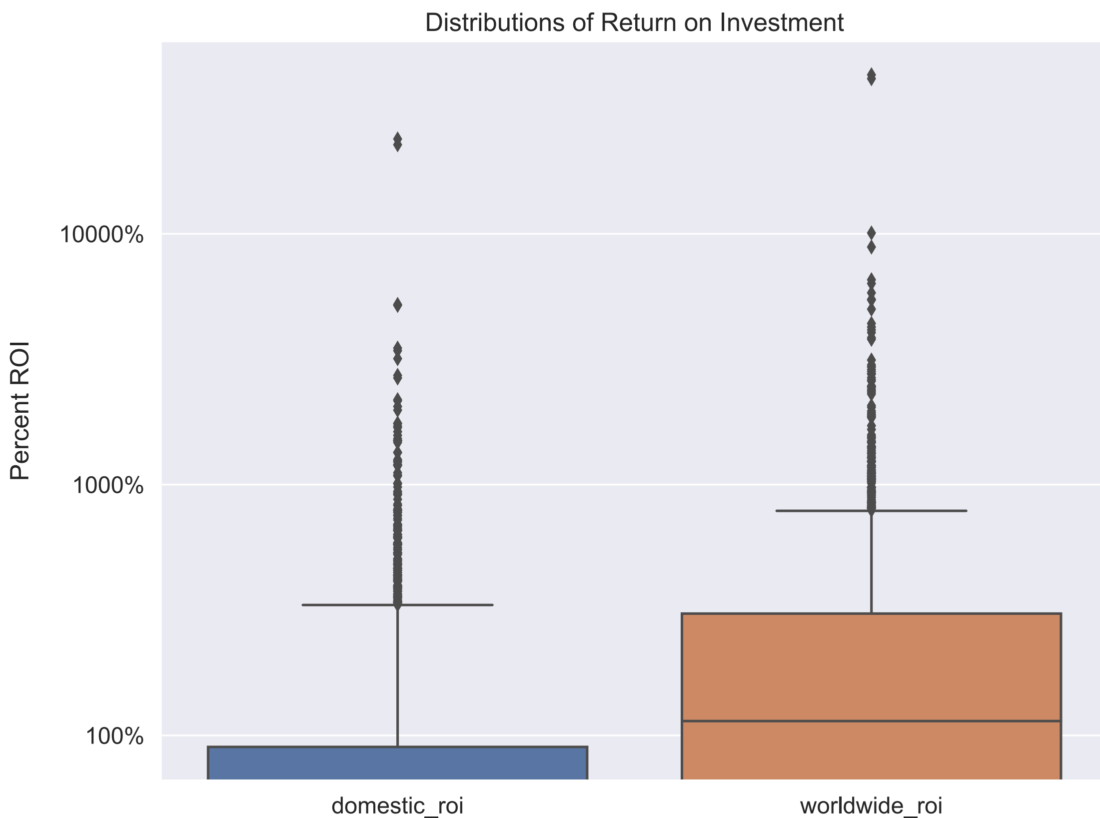
[17]:
```
tn['worldwide_roi'] = tn.eval('(worldwide_profit / production_budget) * 100')
tn['domestic_roi'] = tn.eval('(domestic_profit / production_budget) * 100')
tn.sort_values('worldwide_roi', ascending=False).head()
```

[17]:
```
      tn_id release_date  release_year                movie  \
5492   5493   2009-09-25          2009  Paranormal Activity
5679   5680   2015-07-10          2015          The Gallows
5211   5212   2012-01-06          2012      The Devil Inside
5459   5460   2009-04-23          2009                 Home
5062   5063   2011-04-01          2011            Insidious

      production_budget  domestic_gross  worldwide_gross  worldwide_profit  \
5492         450,000.00  107,918,810.00   194,183,034.00    193,733,034.00
5679         100,000.00   22,764,410.00    41,656,474.00     41,556,474.00
5211       1,000,000.00   53,262,945.00   101,759,490.00    100,759,490.00
5459         500,000.00       15,433.00    44,793,168.00     44,293,168.00
5062       1,500,000.00   54,009,150.00    99,870,886.00     98,370,886.00

      domestic_profit  worldwide_roi  domestic_roi
5492   107,468,810.00      43,051.79     23,881.96
5679    22,664,410.00      41,556.47     22,664.41
5211    52,262,945.00      10,075.95      5,226.29
5459      -484,567.00       8,858.63        -96.91
5062    52,509,150.00       6,558.06      3,500.61
```

The following is a box plot of `domestic_roi` and `worldwide_roi` plotted on a logarithmic scale. Interestingly, `domestic_roi` is heavily clustered under 100%, whereas the upper quartile of `worldwide_roi` is much higher. This is probably because production companies focus on the worldwide market nowadays.

There are a number of extreme values beyond the upper whiskers, but as you can see in the previous cell, these are just extremely successful horror movies. There is not a good scientific reason to altar or remove these data points.

[18]:
```
fix, ax = plt.subplots(figsize=(10, 8))
ax = sns.boxplot(data=tn[['domestic_roi', 'worldwide_roi']],
                 ax=ax,
                 palette='deep')
ax.set_title('Distributions of Return on Investment')
ax.set_ylabel('Percent ROI', labelpad=15)
ax.set_yscale('log')
ax.yaxis.set_major_formatter(ticker.PercentFormatter())
```



Looks like there are some duplicate titles under `movie`, but those rows turn out to be acceptable.

[19]:
```
cleaning.info(tn)
```

[19]:
```
                    dup  dup_%  nan  nan_%
tn_id                 0   0.00    0   0.00
release_date       1329  66.72    0   0.00
release_year       1981  99.45    0   0.00
movie                 4   0.20    0   0.00
production_budget  1687  84.69    0   0.00
domestic_gross        0   0.00    0   0.00
worldwide_gross       0   0.00    0   0.00
worldwide_profit      0   0.00    0   0.00
domestic_profit       0   0.00    0   0.00
worldwide_roi         1   0.05    0   0.00
domestic_roi          1   0.05    0   0.00
```

[20]:
```
tn[tn[['movie']].duplicated(keep=False)].sort_values('movie')
```

[20]:
```
      tn_id release_date  release_year      movie  production_budget  \
2140   2141   2009-12-04          2009   Brothers      26,000,000.00
```

```
3307   3308   2015-08-14          2015    Brothers      13,000,000.00
243     244   2015-03-27          2015        Home     130,000,000.00
5459   5460   2009-04-23          2009        Home         500,000.00
38       39   2010-05-14          2010   Robin Hood    210,000,000.00
408     409   2018-11-21          2018   Robin Hood     99,000,000.00
5009   5010   2010-04-09          2010   The Square      1,900,000.00
5099   5100   2013-10-25          2013   The Square      1,500,000.00

      domestic_gross  worldwide_gross  worldwide_profit  domestic_profit  \
2140   28,544,157.00    45,043,870.00     19,043,870.00     2,544,157.00
3307      656,688.00    17,856,688.00      4,856,688.00   -12,343,312.00
243   177,397,510.00   385,997,896.00    255,997,896.00    47,397,510.00
5459       15,433.00    44,793,168.00     44,293,168.00      -484,567.00
38    105,487,148.00   322,459,006.00    112,459,006.00  -104,512,852.00
408    30,824,628.00    84,747,441.00    -14,252,559.00   -68,175,372.00
5009      406,216.00       740,932.00     -1,159,068.00    -1,493,784.00
5099      124,244.00       176,262.00     -1,323,738.00    -1,375,756.00

      worldwide_roi  domestic_roi
2140          73.25          9.79
3307          37.36        -94.95
243          196.92         36.46
5459       8,858.63        -96.91
38            53.55        -49.77
408          -14.40        -68.86
5009         -61.00        -78.62
5099         -88.25        -91.72
```

Time to save the data and move on.

[21]:
```python
tn.to_json(os.path.join('clean_data', 'tn.profit.json'))
```

1.4.2 Internet Movie Database

After taking a look at my cleaning report, I can see that there are a number of duplicates under `primary_title` and many null values under `runtime_minutes`. I deal with the duplicates first, and later drop the `runtime_minutes` column altogether.

[22]:
```python
cleaning.info(imdb)
```

[22]:

	dup	dup_%	nan	nan_%
runtime_minutes	145776	99.75	31739	21.72
genres	145058	99.26	5408	3.70
original_title	8370	5.73	21	0.01
tconst	0	0.00	0	0.00
primary_title	10073	6.89	0	0.00
start_year	146125	99.99	0	0.00

These duplicates are indeed going to be a problem.

[23]:
```python
imdb[imdb[['primary_title', 'original_title', 'start_year']
          ].duplicated(keep=False)].sort_values('primary_title')
```

[23]:
```
           tconst                        primary_title  \
103890  tt6085916                            (aguirre)
106201  tt6214664                            (aguirre)
129962  tt8032828             100 Milioni di bracciate
129979  tt8034014             100 Milioni di bracciate
20394   tt1855110                                  180
…             …                                    …
66990   tt3815124  Ângelo de Sousa - Tudo o Que Sou Capaz
66992   tt3815128  Ângelo de Sousa - Tudo o Que Sou Capaz
66995   tt3815134  Ângelo de Sousa - Tudo o Que Sou Capaz
92592   tt5352034                             Çagrilan
109103  tt6412726                             Çagrilan

                                original_title  start_year  runtime_minutes  \
103890                               (aguirre)        2016            97.00
106201                               (aguirre)        2016            98.00
129962                100 Milioni di bracciate        2017              nan
129979                100 Milioni di bracciate        2017              nan
20394                                      180        2011           121.00
…                                            …         …               …
66990   Ângelo de Sousa - Tudo o Que Sou Capaz        2010            60.00
66992   Ângelo de Sousa - Tudo o Que Sou Capaz        2010            60.00
66995   Ângelo de Sousa - Tudo o Que Sou Capaz        2010            60.00
92592                                 Çagrilan        2016            85.00
109103                                Çagrilan        2016              nan

                              genres
103890         Biography,Documentary
106201  Biography,Comedy,Documentary
129962                     Biography
129979                     Biography
20394                  Drama,Romance
…                              …
66990          Biography,Documentary
66992          Biography,Documentary
66995          Biography,Documentary
92592                         Horror
109103                           NaN

[3031 rows x 6 columns]
```

I drop rows with duplicates across `primary_title`, `original_title`, and `start_year`.

[24]:
```python
imdb.drop_duplicates(
    subset=['primary_title', 'original_title', 'start_year'], inplace=True)
```

Next I preprocess the titles of both `imdb` and `tn` in preparation for the merge. Since these tables do not share a unique identifier, I have to merge them using the year and title fields.

My string processing function makes all characters lowercase, removes punctuation, and translates Unicode characters to ASCII.

[25]:
```
imdb['clean_title'] = cleaning.process_strings(imdb.loc[:, 'primary_title'])
tn = tn.assign(clean_title=cleaning.process_strings(tn['movie']))
```

For the sake of consistency, I coerce the `imdb` titles to ASCII like I did with those of `tn`.

[26]:
```
imdb['primary_title'] = imdb.loc[:, 'primary_title'].map(unidecode.unidecode)
```

I merge the tables crudely along the year and title fields. While this merge is sufficient for my analysis, it is inefficient. Some movies are lost in translation because their titles do not match character-for-character between tables.

[27]:
```
imdb = pd.merge(imdb,
                tn,
                how='inner',
                left_on=['start_year', 'clean_title'],
                right_on=['release_year', 'clean_title'])
display(imdb.shape)
imdb.head()
```

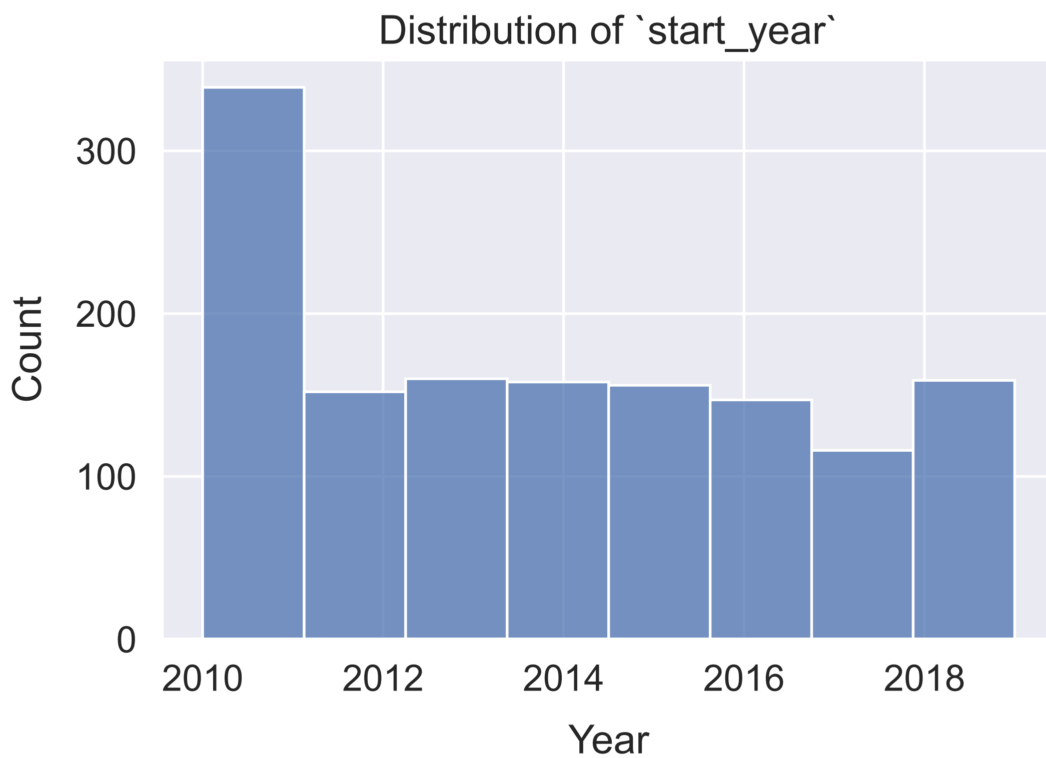
```
(1387, 18)
```

[27]:
```
      tconst                    primary_title  \
0  tt0359950  The Secret Life of Walter Mitty
1  tt0365907      A Walk Among the Tombstones
2  tt0369610                   Jurassic World
3  tt0376136                    The Rum Diary
4  tt0383010                The Three Stooges

                    original_title  start_year  runtime_minutes  \
0  The Secret Life of Walter Mitty        2013           114.00
1      A Walk Among the Tombstones        2014           114.00
2                   Jurassic World        2015           124.00
3                    The Rum Diary        2011           119.00
4                The Three Stooges        2012            92.00

                    genres                      clean_title  tn_id  \
0   Adventure,Comedy,Drama  the secret life of walter mitty    437
1       Action,Crime,Drama      a walk among the tombstones   2067
2  Action,Adventure,Sci-Fi                   jurassic world     34
3             Comedy,Drama                    the rum diary   1316
4            Comedy,Family                the three stooges   1904

  release_date  release_year                            movie  \
0   2013-12-25          2013  The Secret Life of Walter Mitty
```

```
1   2014-09-19          2014      A Walk Among the Tombstones
2   2015-06-12          2015                   Jurassic World
3   2011-10-28          2011                    The Rum Diary
4   2012-04-13          2012                 The Three Stooges

   production_budget  domestic_gross  worldwide_gross  worldwide_profit  \
0      91,000,000.00   58,236,838.00   187,861,183.00     96,861,183.00
1      28,000,000.00   26,017,685.00    62,108,587.00     34,108,587.00
2     215,000,000.00  652,270,625.00 1,648,854,864.00  1,433,854,864.00
3      45,000,000.00   13,109,815.00    21,544,732.00    -23,455,268.00
4      30,000,000.00   44,338,224.00    54,052,249.00     24,052,249.00

   domestic_profit  worldwide_roi  domestic_roi
0   -32,763,162.00         106.44        -36.00
1    -1,982,315.00         121.82         -7.08
2   437,270,625.00         666.91        203.38
3   -31,890,185.00         -52.12        -70.87
4    14,338,224.00          80.17         47.79
```

Looks like the `start_year` range is appropriate. There is a large spike around 2010, which is not ideal. Unfortunately, I am working with a pretty small dataset at this point (~1400 observations), so I am reluctant to discard these early years.

[28]:
```
ax = sns.histplot(imdb, x='start_year', bins=8, palette='deep')
ax.set_title('Distribution of `start_year`')
ax.set_xlabel('Year', labelpad=10)
ax.yaxis.labelpad = 10
```



Next I drop all irrelevant or extraneous columns and check again for nulls and duplicates.

[29]:
```
imdb.drop(columns=['start_year', 'release_year', 'clean_title',
          'movie', 'original_title', 'runtime_minutes'], inplace=True)
```

[30]:
```
cleaning.info(imdb)
```

[30]:

	dup	dup_%	nan	nan_%
tconst	0	0.00	0	0.00
primary_title	15	1.08	0	0.00
genres	1171	84.43	0	0.00
tn_id	14	1.01	0	0.00
release_date	820	59.12	0	0.00
production_budget	1146	82.62	0	0.00
domestic_gross	14	1.01	0	0.00
worldwide_gross	14	1.01	0	0.00
worldwide_profit	14	1.01	0	0.00
domestic_profit	14	1.01	0	0.00
worldwide_roi	15	1.08	0	0.00
domestic_roi	15	1.08	0	0.00

Everything looks to be in order, but I need to convert the `genres` column from `string` to `list` in order to pull apart the individual genre labels.

[31]:
```python
imdb['genres'] = imdb.loc[:, 'genres'].str.split(',')
imdb[['genres']]
```

[31]:
```
                               genres
0      [Adventure, Comedy, Drama]
1          [Action, Crime, Drama]
2     [Action, Adventure, Sci-Fi]
3                 [Comedy, Drama]
4                [Comedy, Family]
…                             …
1382           [Horror, Thriller]
1383     [Crime, Drama, Thriller]
1384     [Drama, Horror, Mystery]
1385                [Documentary]
1386           [Biography, Drama]

[1387 rows x 1 columns]
```

I ensure that there aren't any duplicates or nulls and then inspect the distribution.

[32]:
```python
imdb['genres'] = imdb.loc[:, 'genres'].map(lambda x: list({y for y in x if y}))
imdb.explode('genres')['genres'].value_counts()
```

[32]:
```
Drama          671
Comedy         488
Action         421
Adventure      345
Thriller       235
Crime          214
Romance        183
Horror         150
Sci-Fi         129
Biography      129
Fantasy        120
Mystery        115
Animation      100
Family          87
Music           50
History         39
Documentary     35
Sport           32
War             17
Western         10
Musical          9
Name: genres, dtype: int64
```

Inspecting the movies in the "Music" genre reveals that they are in fact musicals. I collapse these two labels into "Musical".

[33]:
```
imdb.explode('genres').query('genres == "Music"').head()
```

[33]:
```
        tconst  primary_title genres  tn_id release_date  production_budget  \
30   tt0475290  Hail, Caesar!  Music   2422   2016-02-05      22,000,000.00
128  tt1017451   The Runaways  Music   3757   2010-03-19       9,500,000.00
152  tt1068242       Footloose  Music   2339   2011-10-14      24,000,000.00
170  tt1126591       Burlesque  Music   1024   2010-11-24      55,000,000.00
195  tt1193631     Step Up 3D  Music   1909   2010-08-06      30,000,000.00

     domestic_gross  worldwide_gross  worldwide_profit  domestic_profit  \
30    30,080,225.00    64,160,680.00     42,160,680.00     8,080,225.00
128    3,573,673.00     5,278,632.00     -4,221,368.00    -5,926,327.00
152   51,802,742.00    62,989,834.00     38,989,834.00    27,802,742.00
170   39,440,655.00    90,552,675.00     35,552,675.00   -15,559,345.00
195   42,400,223.00   165,889,117.00    135,889,117.00    12,400,223.00

     worldwide_roi  domestic_roi
30          191.64         36.73
128         -44.44        -62.38
152         162.46        115.84
170          64.64        -28.29
195         452.96         41.33
```

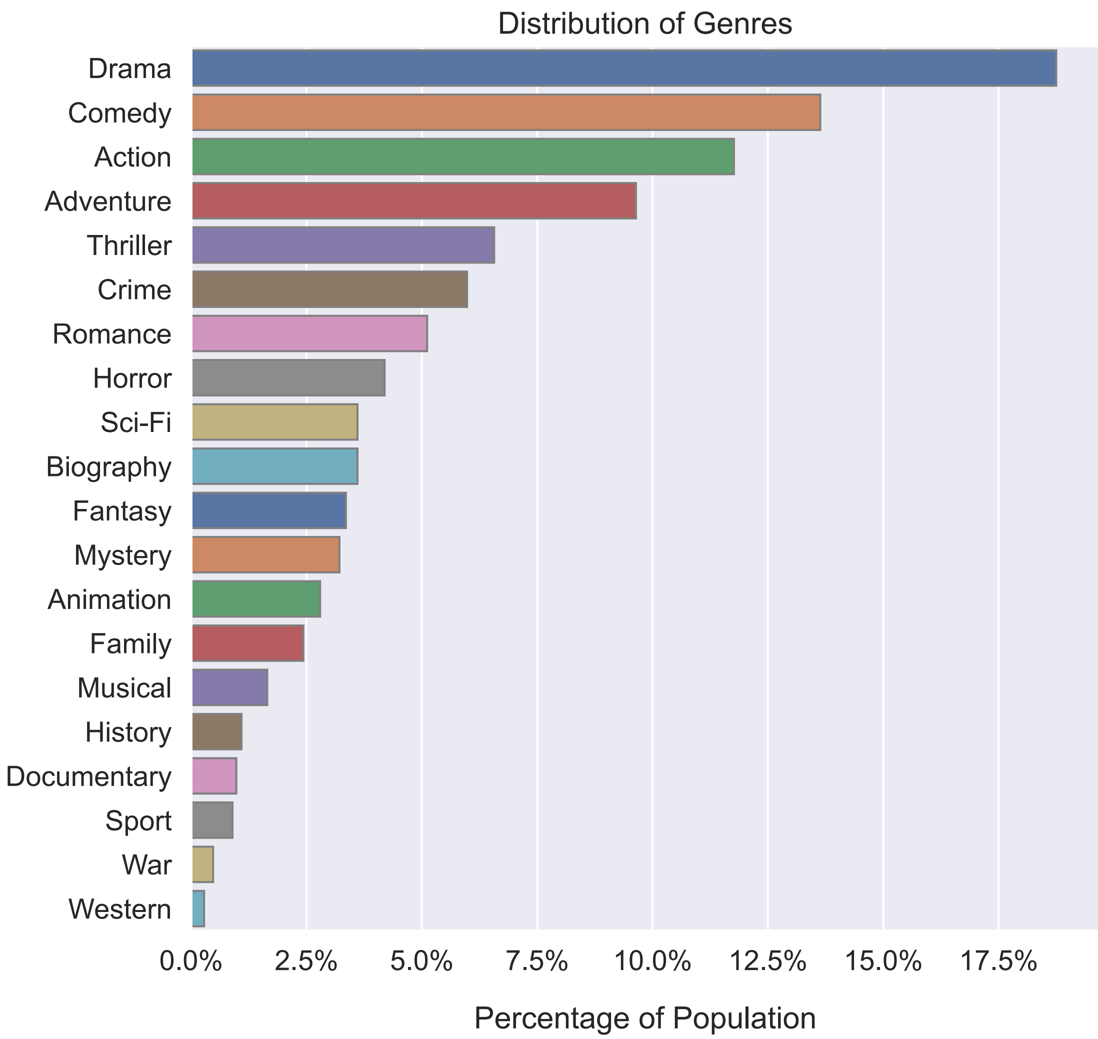
[34]:
```
imdb['genres'] = utils.map_list_likes(
    imdb['genres'], lambda x: 'Musical' if x == 'Music' else x)
imdb.explode('genres')['genres'].value_counts()
```

[34]:
```
Drama          671
Comedy         488
Action         421
Adventure      345
Thriller       235
Crime          214
Romance        183
Horror         150
Sci-Fi         129
Biography      129
Fantasy        120
Mystery        115
Animation      100
Family          87
Musical         59
History         39
Documentary     35
Sport           32
War             17
Western         10
```

```
Name: genres, dtype: int64
```

Here is the final genre distribution chart. I choose to keep low-frequency genres like “War” and “Western” unless they prove disruptive.

[35]:
```
genre_counts = imdb.explode(
    'genres')['genres'].value_counts(normalize=True)
fig, ax = plt.subplots(figsize=(8, 8))
ax = sns.barplot(x=genre_counts.values,
                 y=genre_counts.index,
                 ec='gray',
                 ax=ax,
                 palette='deep')
ax.set_title('Distribution of Genres')
ax.set_xlabel('Percentage of Population', labelpad=15)
ax.xaxis.set_major_formatter(ticker.PercentFormatter(xmax=1))
```



Time to save the data and move on.

```
[36]: imdb.to_json(os.path.join('clean_data', 'imdb.tn.basics.json'))
```

1.5 Data Modeling

1.5.1 Crosstab

I begin by creating a movie-per-movie genre frequency table. Since no genre can occur more than once per movie, the frequencies can be interpreted as binary truth values. Now I can compute correlations between genres and financial outcomes.

```
[37]: combos = pd.crosstab(imdb.explode('genres')['tconst'], imdb.
       ↪explode('genres')['genres'])
      combos = combos.astype(np.bool_)
      combos = combos.sort_index(axis=1).sort_index(axis=0)
      combos.to_json(os.path.join('precomputed', 'genre_combos.json'))
      combos.head()
```

```
[37]: genres     Action  Adventure  Animation  Biography  Comedy  Crime  \
      tconst
      tt0359950   False       True      False      False    True  False
      tt0365907    True      False      False      False   False   True
      tt0369610    True       True      False      False   False  False
      tt0376136   False      False      False      False    True  False
      tt0383010   False      False      False      False    True  False

      genres     Documentary  Drama  Family  Fantasy  History  Horror  Musical  \
      tconst
      tt0359950        False   True   False    False    False   False    False
      tt0365907        False   True   False    False    False   False    False
      tt0369610        False  False   False    False    False   False    False
      tt0376136        False   True   False    False    False   False    False
      tt0383010        False  False    True    False    False   False    False

      genres     Mystery  Romance  Sci-Fi  Sport  Thriller    War  Western
      tconst
      tt0359950    False    False   False  False     False  False    False
      tt0365907    False    False   False  False     False  False    False
      tt0369610    False    False    True  False     False  False    False
      tt0376136    False    False   False  False     False  False    False
      tt0383010    False    False   False  False     False  False    False
```

I set the index of `imdb` to `tconst` for the upcoming computations. I need to use these unique IDs to relate the rows of `imdb` to the rows of `combos`.

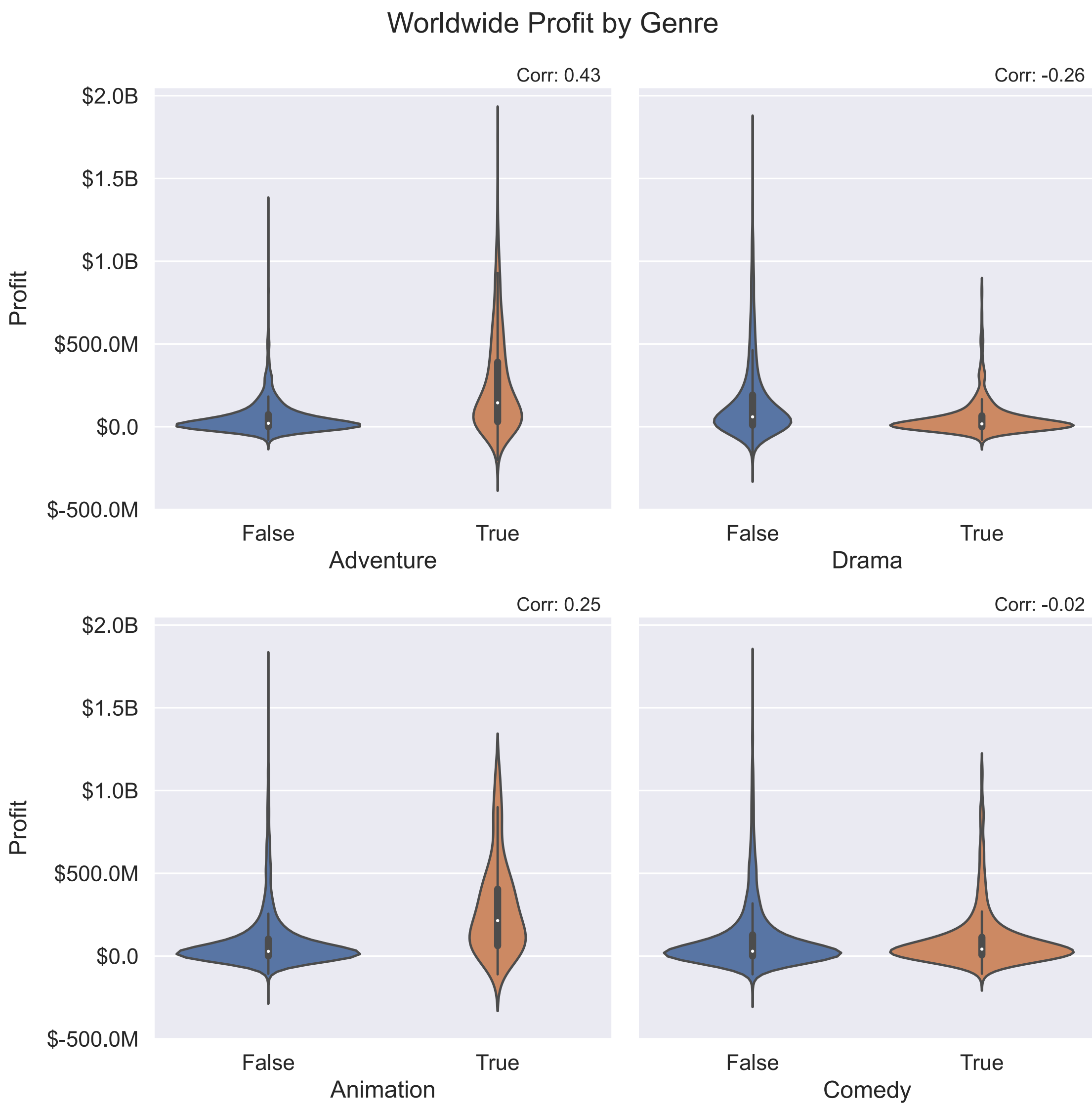
```
[38]: imdb.set_index('tconst', inplace=True)
```

1.5.2 Calculating Correlation

The **Pearson correlation coefficient** is a measure of the degree to which the relationship between two variables resembles a linear relationship. But it's hard to understand intuitively how genre could have anything approaching a linear relationship with, say, profit. What does that even mean?

It all makes good sense if you consider the following violin plots. The blobs indicate the location and density of the points in the distribution. Notice that genres which are positively correlated with profit have a fat violin on `False` and a narrow violin on `True`. Notice that genres which are negatively correlated with profit have a fat violin on `True` and a narrow violin on `False`. And finally, notice that genres with no correlation with profit have two fat violins.

[39]:
```
axs = plotting.boolean_violinplots(
        combos,
        imdb['worldwide_profit'],
        suptitle='Worldwide Profit by Genre',
        include=['Adventure', 'Drama', 'Animation', 'Comedy'],
        ylabel='Profit',
        figsize=(10, 10),
        palette='deep',
        saturation=0.75)
for ax in axs.flat:
        ax.yaxis.set_major_formatter(plotting.big_money_formatter(1))
plt.tight_layout()
```

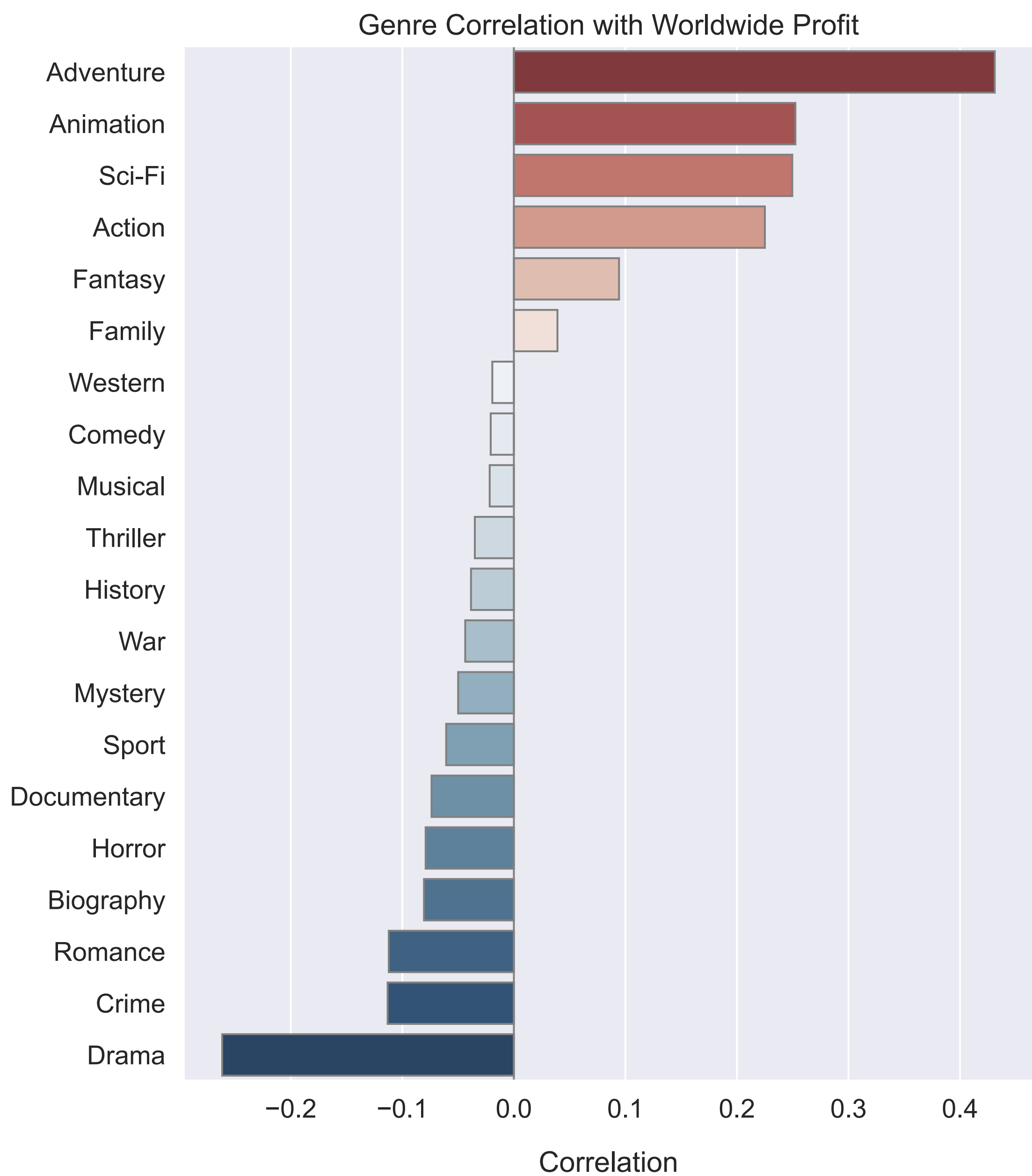


1.5.3 Correlation with Profit

Here are the correlations between each genre and worldwide profit. Notice that the frontrunners are adventure, animation, sci-fi, and action. Also notice that drama has the strongest negative correlation. This is an interesting result.

[40]:
```
ax = plotting.cat_correlation(combos, imdb['worldwide_profit'])
ax.set_title('Genre Correlation with Worldwide Profit')
ax.set_ylabel(None)
```

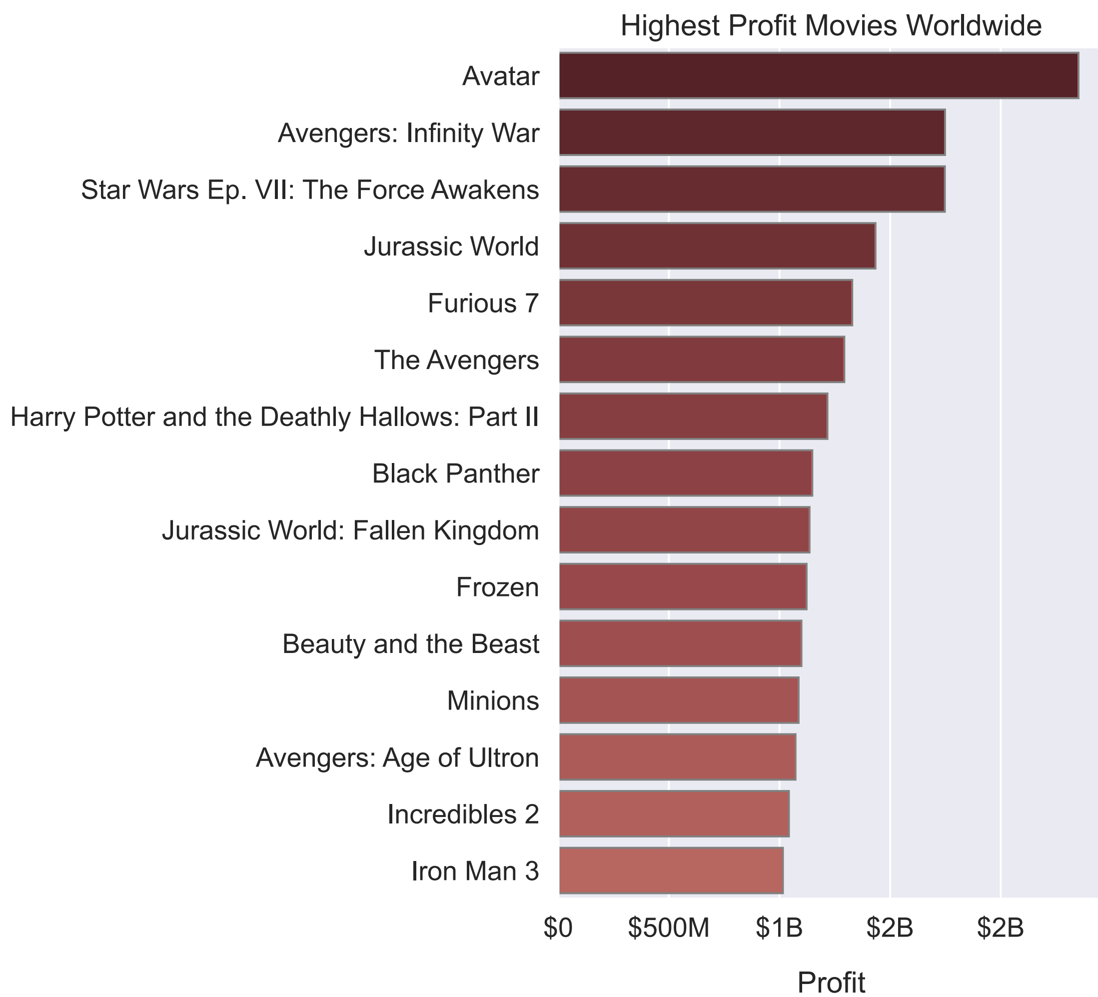
[40]:
```
Text(0, 0.5, '')
```



As a sanity check, I plot the movies with the highest worldwide profit from `tn`. Many adventure and sci-fi titles show up: *Avatar*, *The Avengers*, *Star Wars*, *Jurassic World*. There are also several animated films: *Frozen*, *Beauty and the Beast*, *Minions*, *Incredibles 2*. Looks like the correlation numbers make sense.

[41]:
```
reds = sns.color_palette('Reds_r', 40, desat=0.6)
ax = plotting.topn_ranking(tn,
                           'movie',
                           'worldwide_profit',
```

```
                                15,
                                figsize=(5, 8),
                                palette=reds)
ax.set_title('Highest Profit Movies Worldwide')
ax.set_ylabel(None)
ax.set_xlabel('Profit', labelpad=15)
ax.xaxis.set_major_formatter(plotting.big_money_formatter())
```

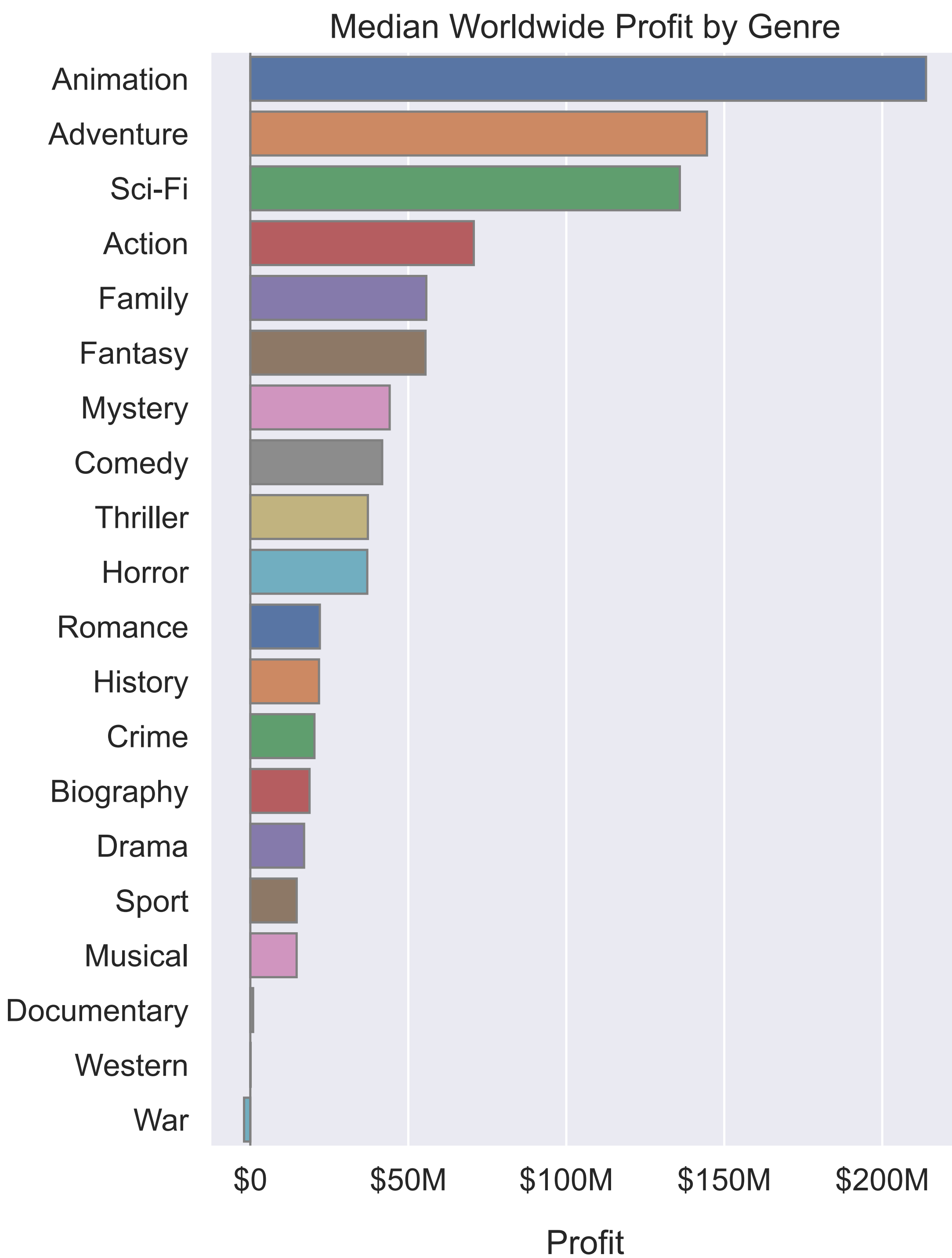


Why not look at things from yet another angle to gain some perspective?

[42]:
```
world_financials = imdb.explode('genres').groupby('genres').median()
world_financials = world_financials.filter(like='worldwide').reset_index()
ax = plotting.topn_ranking(world_financials, 'genres', 'worldwide_profit', 20,␣
↪palette='deep', figsize=(6, 9))
ax.set_title('Median Worldwide Profit by Genre')
ax.set_ylabel(None)
```

```
ax.set_xlabel('Profit', labelpad=15)
ax.xaxis.set_major_formatter(plotting.big_money_formatter())
ax.axvline(x=0, color='gray', lw=1)
```

[42]: <matplotlib.lines.Line2D at 0x20eeb6b5e20>



1.5.4 Correlation with ROI

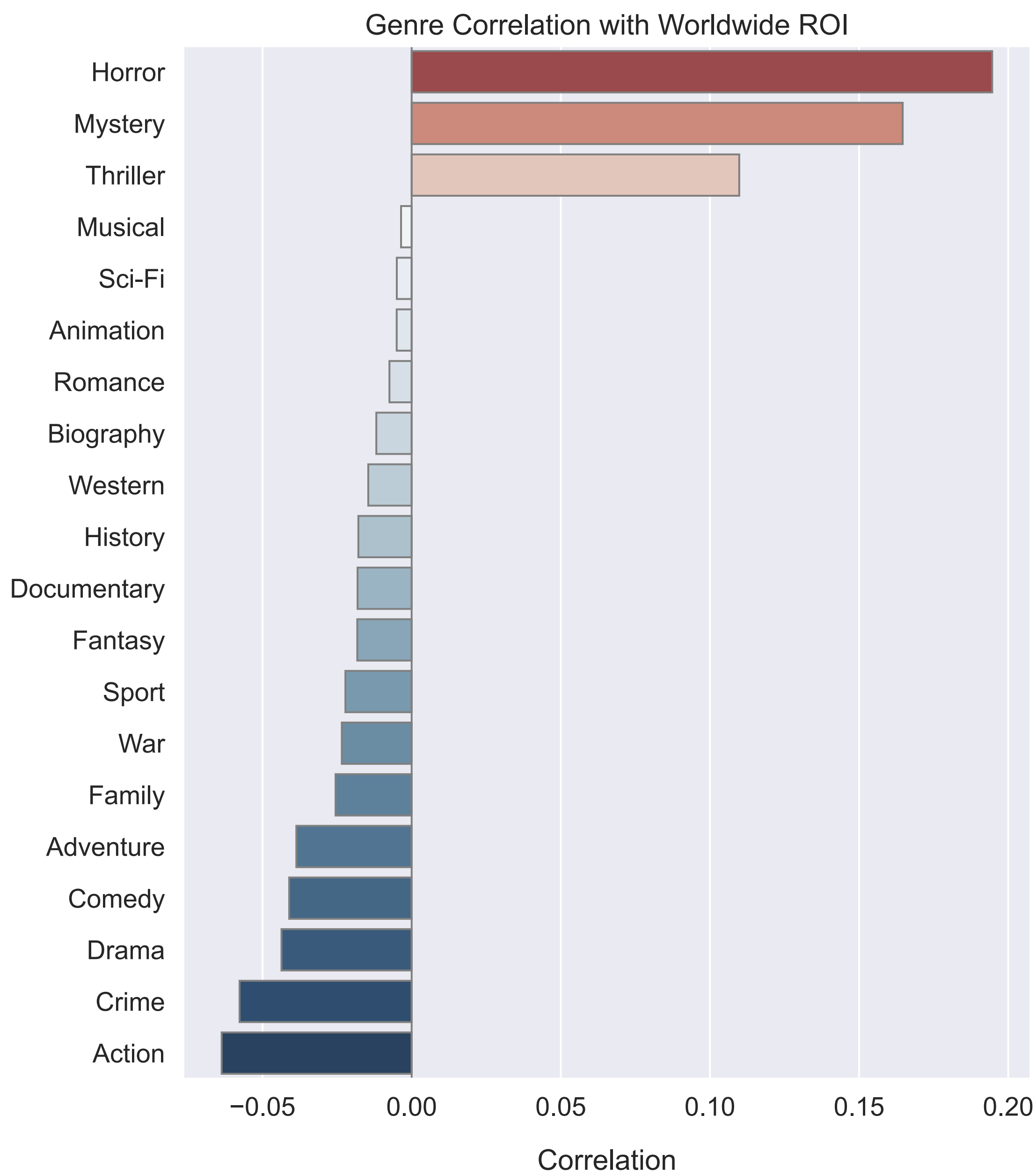
The correlations with worldwide ROI are strikingly different from those with profit. Horror? Mystery? Thriller? These all had a weak negative correlation with worldwide profit. Why are they suddenly the only positive values?

Here's my conjecture: it's because ROI places heavy weight on budget, and top-earning horror films are often very low-budget. A low-budget film can generate revenue which is exponentially higher than its budget. A high-budget film will have a hard time doing that.

Horror movies have a reputation for being low-budget. *Paranormal Activity*, for example, is well-known for its low budget. *The Blair Witch Project* is another obvious example, since it's just a shaky-cam movie with a bunch of kids in the woods. Nonetheless, both of these movies were highly successful at the box office.

[43]:
```
ax = plotting.cat_correlation(combos, imdb['worldwide_roi'])
ax.set_title('Genre Correlation with Worldwide ROI')
ax.set_ylabel(None)
ax.set_xlabel('Correlation', labelpad=15)
```

[43]:
```
Text(0.5, 0, 'Correlation')
```

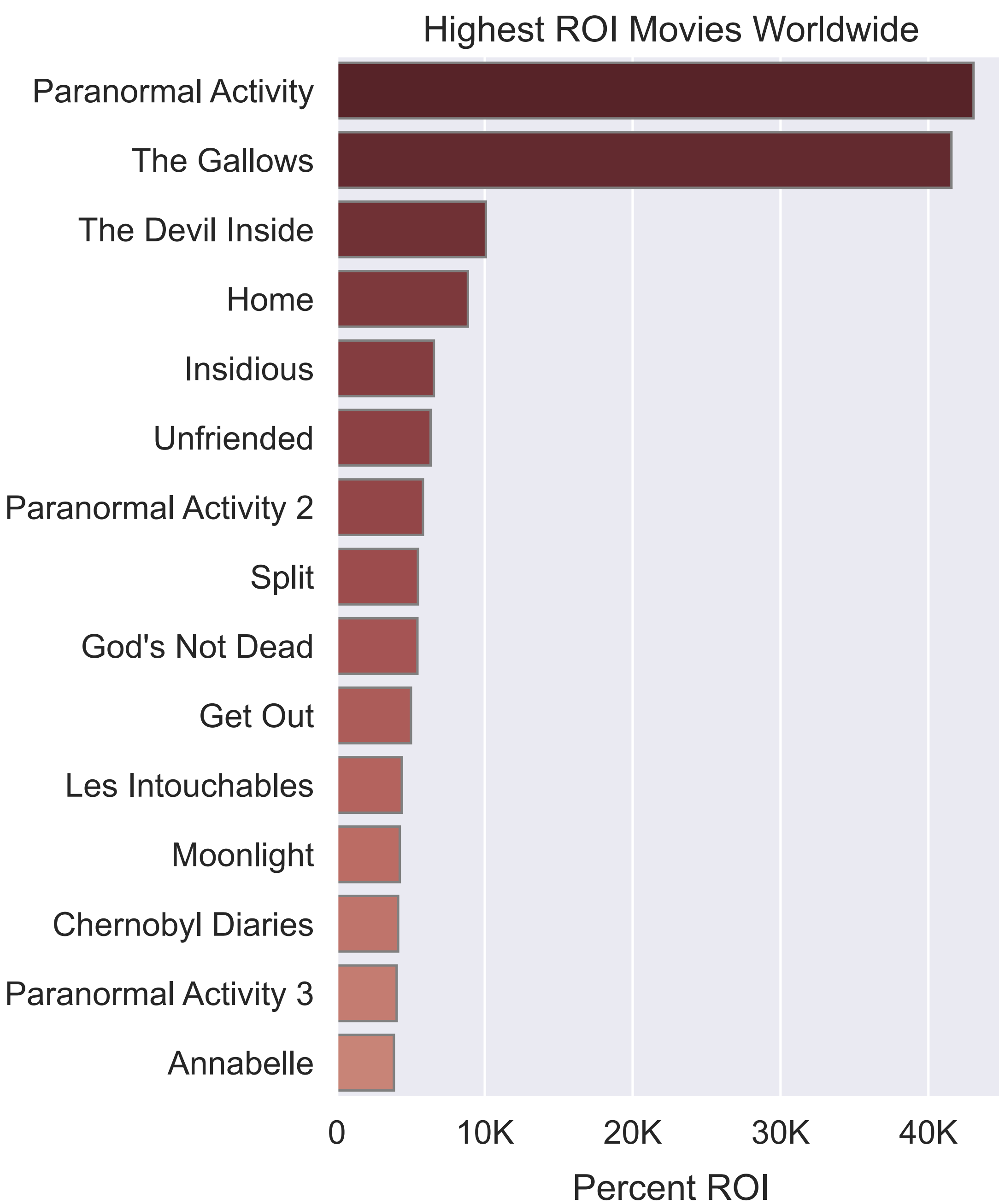


Another sanity check: the highest ROI movies worldwide from `tn`. Nearly all of them are horror titles.

[44]:
```
tn.replace('Godas Not Dead', 'God\'s Not Dead', inplace=True)
reds = sns.color_palette('Reds_r', 30, desat=0.6)
ax = plotting.topn_ranking(tn,
                           'movie',
                           'worldwide_roi',
                           15,
```

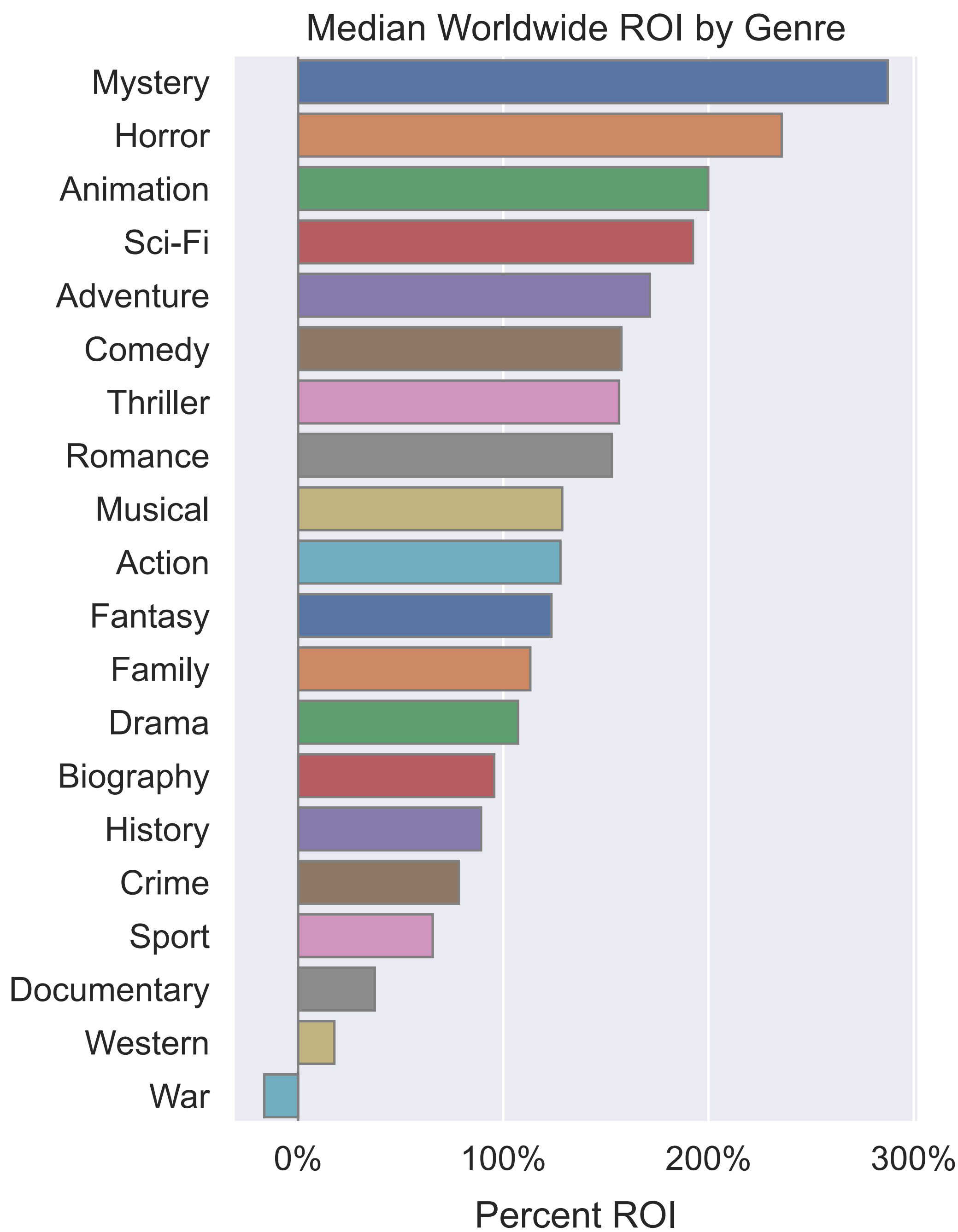
```
                            figsize=(5, 8),
                            palette=reds)
ax.xaxis.set_major_formatter(plotting.big_number_formatter())
ax.set_title('Highest ROI Movies Worldwide')
ax.set_xlabel('Percent ROI', labelpad=10)
ax.set_ylabel(None)
```

[44]: Text(0, 0.5, '')



Another perspective:

[45]:
```
ax = plotting.topn_ranking(world_financials, 'genres', 'worldwide_roi', 24,␣
↪palette='deep')
ax.axvline(x=0, color='gray', lw=1)
ax.set_title('Median Worldwide ROI by Genre')
ax.set_ylabel(None)
ax.set_xlabel('Percent ROI', labelpad=10)
ax.xaxis.set_major_formatter(ticker.PercentFormatter())
```



1.5.5 Effects of Budget

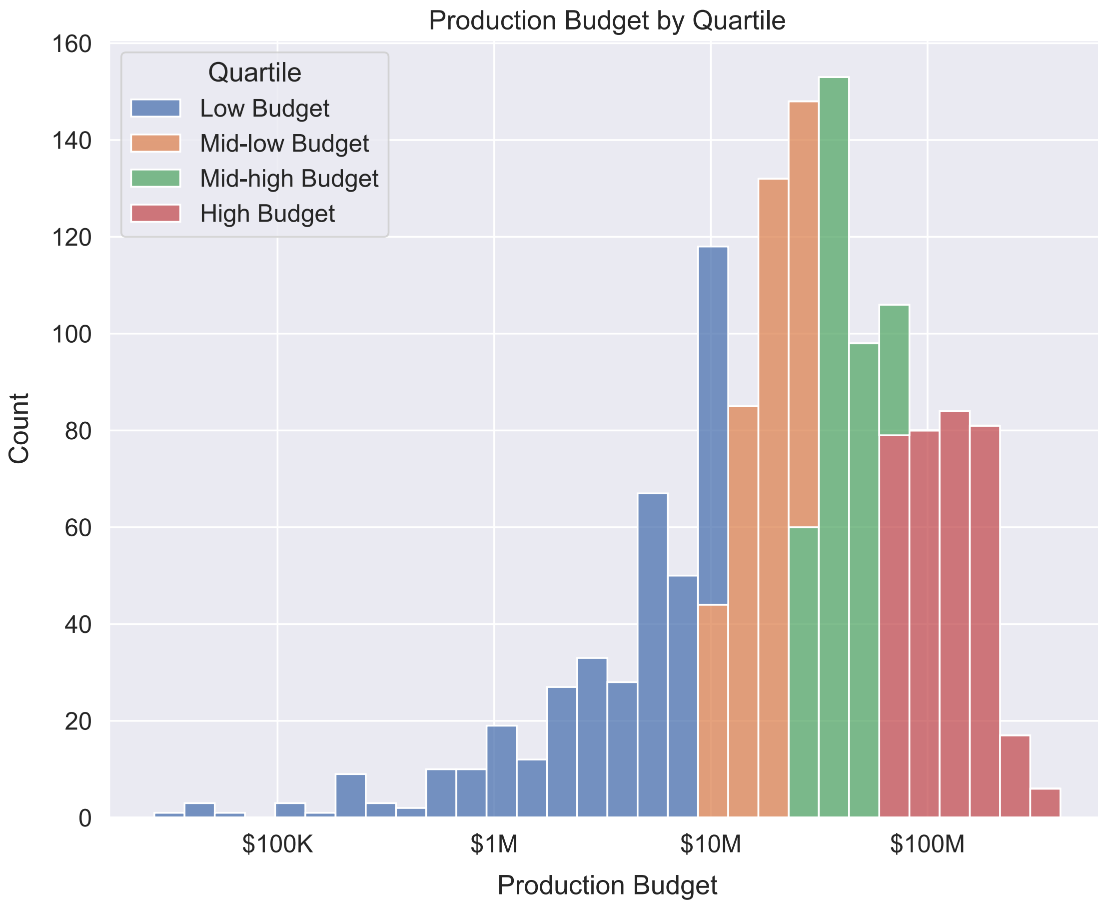
Next, I partition the movies by budget quartile. "Low Budget" refers to the lower quartile (25th percentile) and below. "High Budget" refers to the upper quartile (75th percentile) and above. I want to plot the genre-ROI-correlations for low-budget films alongside those for high-budget films.

[46]:
```
quartile_labels = ['Low Budget', 'Mid-low Budget',
                   'Mid-high Budget', 'High Budget']
imdb['budget_quartile'] = pd.qcut(
    imdb['production_budget'], 4, quartile_labels)
quartile_intervals = pd.qcut(imdb['production_budget'], 4).dtype.categories
world_roi_by_budget = combos.groupby(
    imdb['budget_quartile']).corrwith(imdb['worldwide_roi'])
world_roi_by_budget
```

[46]:
```
genres           Action  Adventure  Animation  Biography  Comedy  Crime  \
budget_quartile
Low Budget        -0.05      -0.04      -0.02      -0.03   -0.08  -0.06
Mid-low Budget    -0.11      -0.04      -0.01       0.05    0.04  -0.13
Mid-high Budget   -0.02      -0.04      -0.02      -0.02   -0.03  -0.12
High Budget       -0.15       0.15       0.25       0.01    0.14  -0.07

genres           Documentary  Drama  Family  Fantasy  History  Horror  \
budget_quartile
Low Budget             -0.05  -0.12   -0.04     0.00    -0.03    0.25
Mid-low Budget          0.00   0.02    0.00    -0.01     0.01    0.10
Mid-high Budget        -0.05  -0.04   -0.04    -0.06    -0.01    0.02
High Budget            -0.02  -0.12   -0.03    -0.07    -0.02   -0.10

genres           Musical  Mystery  Romance  Sci-Fi  Sport  Thriller   War  \
budget_quartile
Low Budget         -0.04     0.23    -0.04   -0.01  -0.03      0.18 -0.03
Mid-low Budget      0.03     0.04     0.02    0.04  -0.05      0.05 -0.08
Mid-high Budget     0.19     0.03     0.11    0.04  -0.01      0.10 -0.06
High Budget         0.09    -0.02    -0.11    0.09  -0.05     -0.05 -0.03

genres           Western
budget_quartile
Low Budget         -0.02
Mid-low Budget     -0.04
Mid-high Budget     0.02
High Budget        -0.03
```

[47]:
```
fig, ax = plt.subplots(figsize=(10, 8))
ax = sns.histplot(data=imdb,
                  x='production_budget',
                  hue='budget_quartile',
                  ax=ax,
                  log_scale=True,
                  multiple='stack',
                  palette='deep')
ax.xaxis.set_major_formatter(plotting.big_money_formatter())
ax.get_legend().set_title('Quartile')
```

```
ax.set_title('Production Budget by Quartile')
ax.set_xlabel('Production Budget', labelpad=10)
ax.set_ylabel('Count', labelpad=10)
ax.xaxis.set_major_locator(ticker.LogLocator(subs=[1.0]))
```



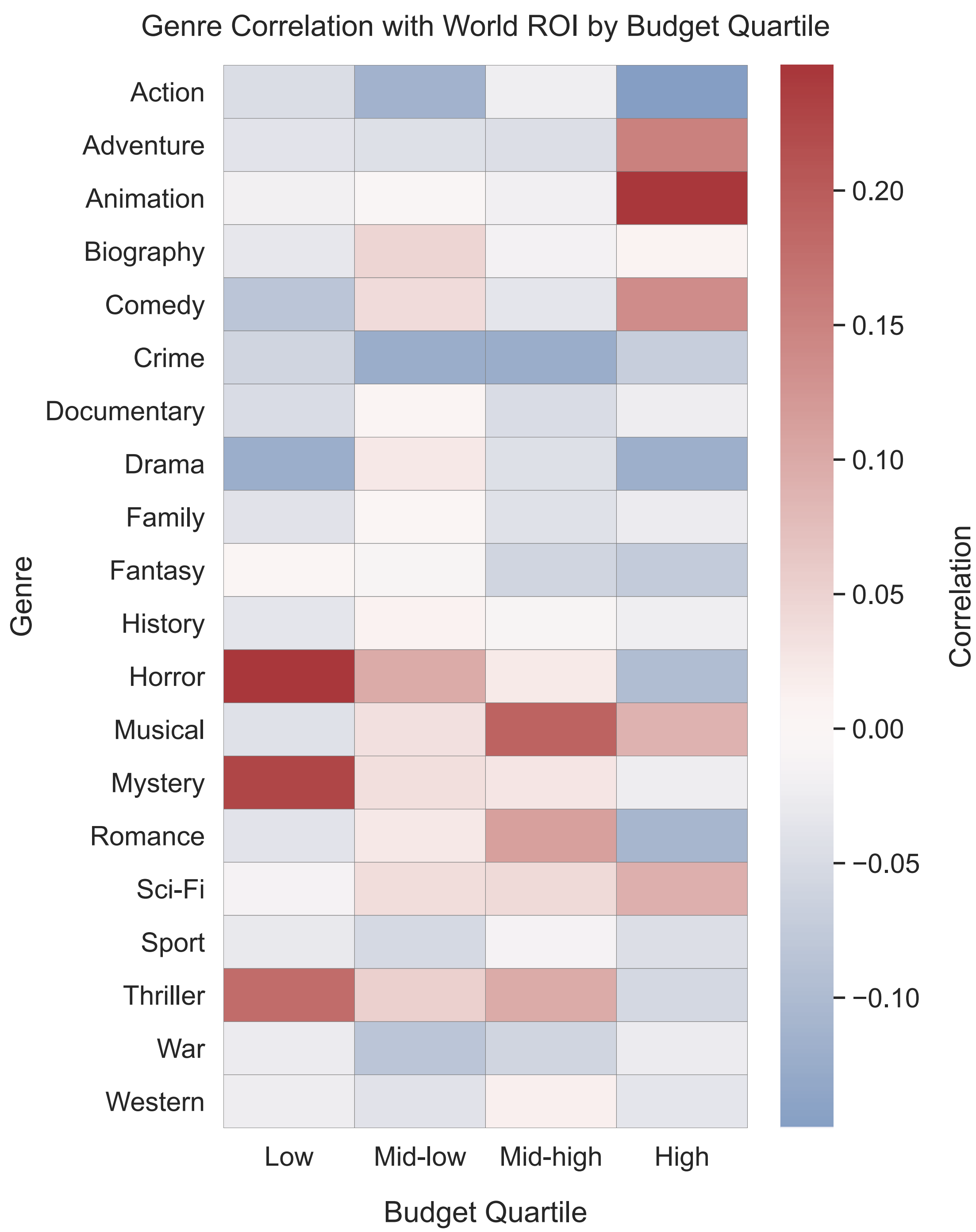
Here's a heatmap of correlations computed separately by budget quartile. Looks like evidence supporting my conjecture that top-earning horror films are often very low-budget, and that low-budget movies are capable of achieving very high ROI.

Interestingly animation, and not adventure, is the frontrunner for high-budget films. Adventure, which led in correlation with worldwide profit, is now in second place.

The correlation scores for the midrange quartiles are lower, but you can see that horror and thriller are still at the top of the mix for mid-low budget films. It's notable that musical and romance movies lead the way for mid-high budget films. These genres definitely go together.

[48]:
```
fig, ax = plt.subplots(figsize=(6,10))
short_quarts = ['Low', 'Mid-low', 'Mid-high', 'High']
ax = sns.heatmap(world_roi_by_budget.T,
                ax=ax,
```

```
                xticklabels=short_quarts,
                cmap='vlag',
                center=0,
                linewidths=0.25,
                linecolor='gray')
ax.set_xlabel('Budget Quartile', labelpad=15)
ax.set_ylabel('Genre')
ax.set_title('Genre Correlation with World ROI by Budget Quartile', pad=15)
ax.collections[0].colorbar.set_label('Correlation', labelpad=15)
```



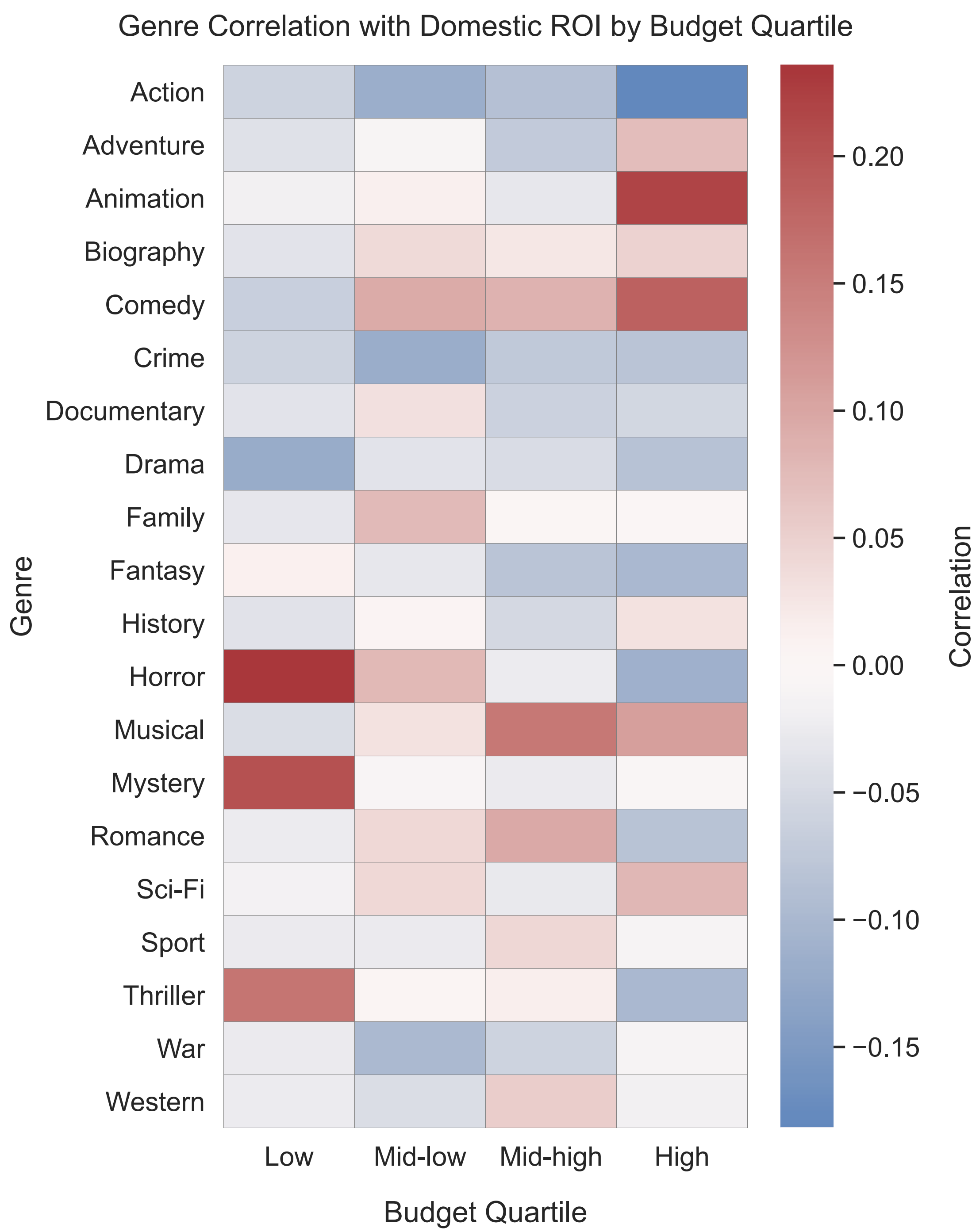
I perform the same calculations for domestic ROI. The results are similar, with some small differences. Notably, Comedy has risen in score for everything but low-budget films.

[49]:
```
domestic_roi_by_budget = combos.groupby(
    imdb['budget_quartile']).corrwith(imdb['domestic_roi'])
```

```python
domestic_roi_by_budget
```

[49]:
```
genres            Action  Adventure  Animation  Biography  Comedy  Crime  \
budget_quartile
Low Budget         -0.06      -0.04      -0.02      -0.04   -0.07  -0.06
Mid-low Budget     -0.12      -0.01       0.01       0.04    0.09  -0.12
Mid-high Budget    -0.09      -0.07      -0.03       0.02    0.08  -0.07
High Budget        -0.18       0.07       0.22       0.05    0.19  -0.08

genres            Documentary  Drama  Family  Fantasy  History  Horror  \
budget_quartile
Low Budget              -0.04  -0.12   -0.03     0.01    -0.04    0.24
Mid-low Budget           0.03  -0.04    0.08    -0.03     0.01    0.08
Mid-high Budget         -0.06  -0.05    0.00    -0.08    -0.05   -0.02
High Budget             -0.05  -0.08   -0.00    -0.10     0.03   -0.11

genres            Musical  Mystery  Romance  Sci-Fi  Sport  Thriller   War  \
budget_quartile
Low Budget          -0.05     0.21    -0.03   -0.01  -0.03      0.16 -0.03
Mid-low Budget       0.03    -0.01     0.04    0.04  -0.03      0.00 -0.10
Mid-high Budget      0.16    -0.03     0.10   -0.03   0.04      0.02 -0.06
High Budget          0.11    -0.00    -0.08    0.08  -0.01     -0.10 -0.01

genres            Western
budget_quartile
Low Budget          -0.02
Mid-low Budget      -0.05
Mid-high Budget      0.05
High Budget         -0.02
```

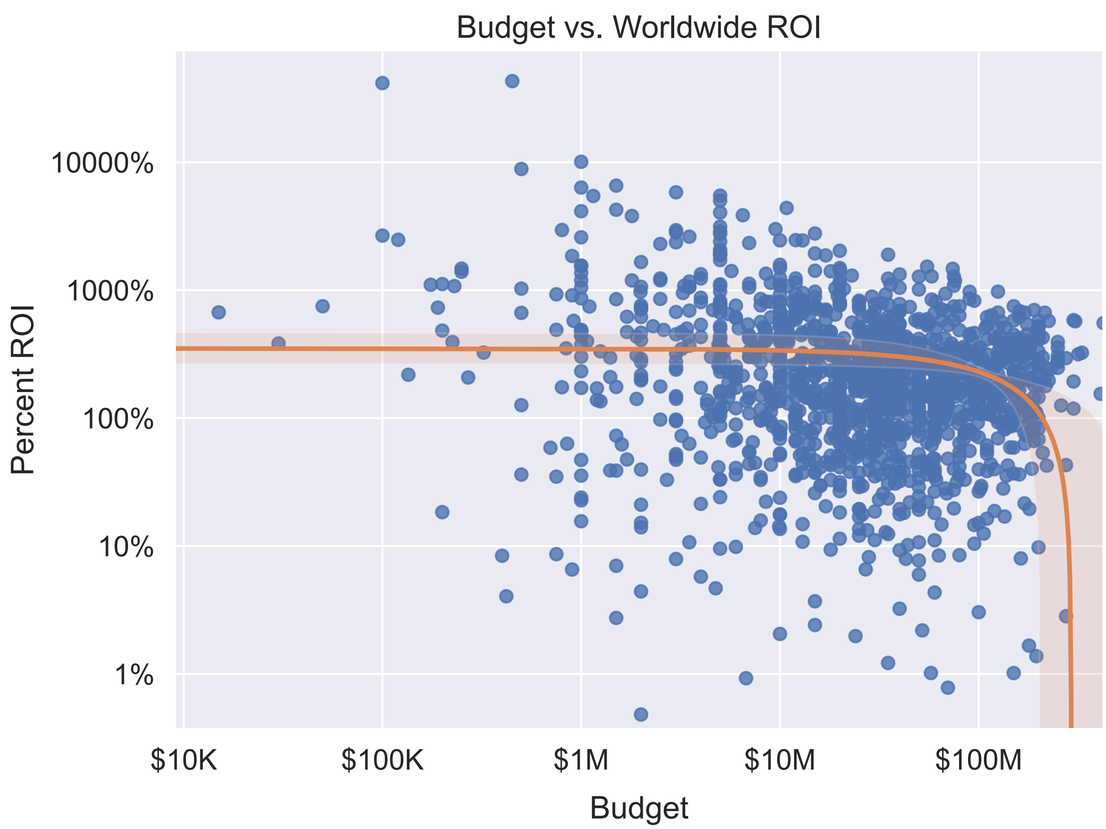
[50]:
```python
fig, ax = plt.subplots(figsize=(6,10))
ax = sns.heatmap(domestic_roi_by_budget.T,
                 ax=ax,
                 xticklabels=short_quarts,
                 cmap='vlag',
                 center=0,
                 linewidths=0.25,
                 linecolor='gray')
ax.set_xlabel('Budget Quartile', labelpad=15)
ax.set_ylabel('Genre')
ax.set_title('Genre Correlation with Domestic ROI by Budget Quartile', pad=15)
ax.collections[0].colorbar.set_label('Correlation', labelpad=15)
```



1.5.6 Budget Independently?

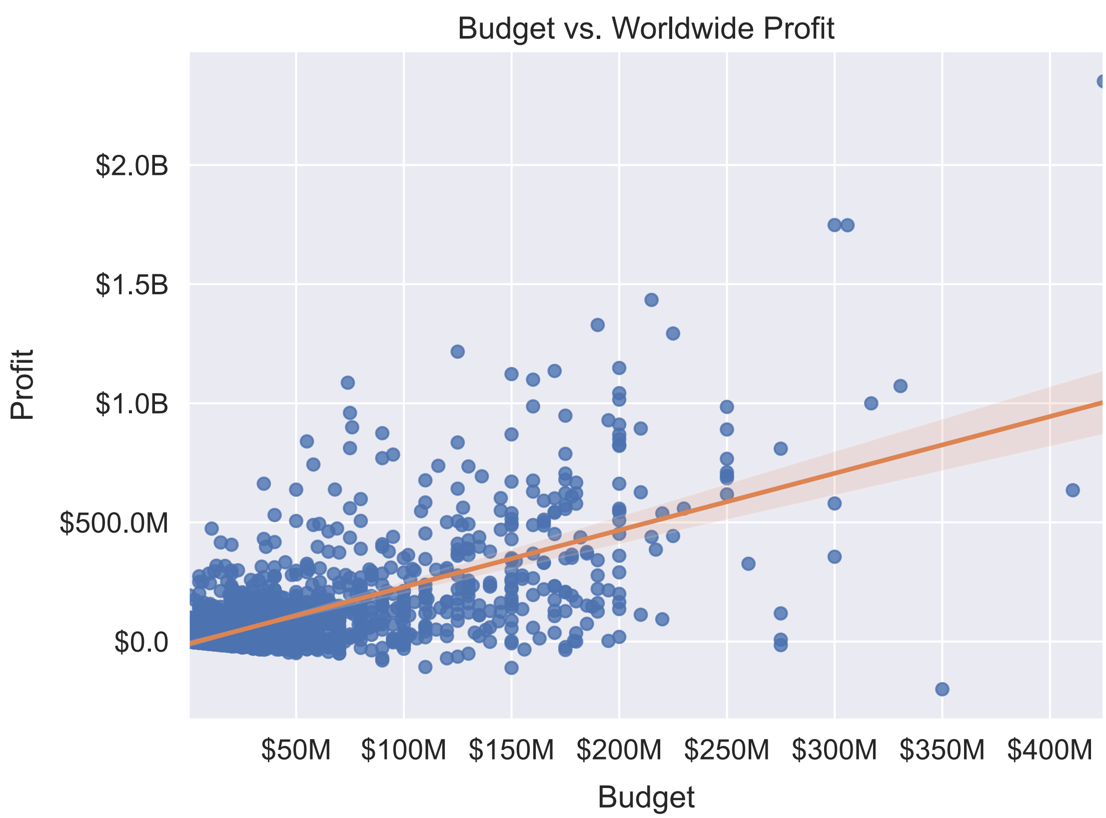
Do low-budget movies simply have higher ROI in general than high-budget movies? No. Having a low-budget makes it possible to achieve an extremely high ROI percentage, but it is not generally correlated with ROI. The following scatterplot with a regression line shows that the relationship between budget and ROI is flat up until the high end of budget, where it falls off. This drop at the end makes sense, since having a high budget makes it difficult to achieve a decent ROI percentage. Note that the confidence interval goes wide at the end, indicating that in reality the dropoff might not be quite so abrupt.

[51]:
```
fig, ax = plt.subplots(figsize=(8, 6))
deeps = sns.color_palette('deep', n_colors=2)
ax = sns.regplot(data=tn, x='production_budget', y='worldwide_roi', ax=ax,␣
 ↪color=deeps[0], line_kws={'color': deeps[1]})
ax.set_xscale('log')
ax.set_yscale('log')
ax.set_title('Budget vs. Worldwide ROI')
ax.set_ylabel('Percent ROI', labelpad=5)
ax.set_xlabel('Budget', labelpad=10)
ax.yaxis.set_major_formatter(ticker.PercentFormatter())
ax.xaxis.set_major_formatter(plotting.big_money_formatter())
```



It also makes sense that profit would have a positive linear relationship with budget. If you spend more you make more, but that doesn't mean you make more relative to how much you spent.

[52]:
```
fig, ax = plt.subplots(figsize=(8, 6))
deeps = sns.color_palette('deep', n_colors=2)
ax = sns.regplot(data=tn, x='production_budget', y='worldwide_profit', ax=ax,␣
 ↪color=deeps[0], line_kws={'color': deeps[1]})
ax.set_xscale('linear')
ax.set_yscale('linear')
ax.set_title('Budget vs. Worldwide Profit')
ax.set_ylabel('Profit', labelpad=10)
ax.set_xlabel('Budget', labelpad=10)
ax.yaxis.set_major_formatter(plotting.big_money_formatter(1))
ax.xaxis.set_major_formatter(plotting.big_money_formatter())
```



1.6 Conclusions

For high-budget productions, go with animation. Animation has by far the strongest correlation (nearly 0.25) with ROI for high-budget films. The next best score is adventure, which is nearly 0.1 lower.

For low-budget productions, go with horror. Nothing beats horror movies in terms of ROI, both overall and for low-budget films. The only other options are mystery and thriller, which both go along with horror anyway.

Stay away from drama, action, and crime. Drama, action, and crime consistently show up in the negative on correlation with ROI. This means that movies achieve higher ROI when they are not drama, action, or crime. While it's possible to have success with these genres, they are the worst choices from an investment standpoint.

Keep your movie budgets under $250M. ROI has almost no correlation with budget, but seems to decline sharply after $250M. This is where risk suddenly overtakes reward.

1.7 Evaluation

My analysis provides some useful insights for Microsoft, but there is much more work to be done. For one, making a successful movie is much more complicated than choosing a genre. There are numerous other factors to consider, such as cast and crew.

Furthermore, I conducted my analysis with a very limited dataset of around 1,400 observations. Many movies were lost in the merge between `imdb` and `tn` because these tables had no unique identifiers in common. The merge could be improved by using fuzzy string matching or another sophisticated process for dirty merging. The ideal situation would be to find a source of data which provides both genre labels and finances.

Nonetheless, I am very confident in the finding that horror movies have the highest ROI. That was a very robust and striking pattern in the data. I am fairly confident in my other findings relating to the business recommendations, but I would like to conduct further research.