MovieProject_Notebook

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1 Movie Investigations for Microsoft - Project1

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- Scheduled project review date/time: **May 13, 2023 1pm**
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[1]:
```
from IPython.display import Image
Image(filename='images/filmmaking.jpeg')
```

1.1 Overview

This project analyzes movie data to provide insights and recommendations about the kind of movies Microsoft should make for their new movie studio.

1.2 Business Problem

Microsoft has decided to create a new movie studio, but they need information about what kind of movies are doing best financially. I will be performing exploratory analyses on data from past movies to help Microsoft decide what kind of movies to create.

The process unfolds in this manner:

1. Defining reliable measure(s) for assessing profitability of a movie using `worldwide_gross`, `production_budget` or audience `averageratings`.
2. Looking into various movie characteristics of `genre`, `director`, `release_month` and `runtime_minutes` in relation to profitability.
3. Making suggestions about the kind of movies to be made based on the findings.
   - What genres of movies to make?
   - Which directors to work with?
   - When to release the movie?
   - Which movie length to focus on?

1.3 Data Understanding

I will be using: 1. A dataset from IMDb which involves 4 tables and 140416 Distinct Movies: - movie_basics which involves title, year, runtime, and genre information for each movie. -

movie_ratings which involves average rating. - directors which involves director ID for each movie. - persons which allows us to link director IDs to their names.

The variables representing movie characteristics will be derived from this database.

2. A dataset from The Numbers which involves `production_budget` as well as `worldwide_gross` information of 5698 distinct movies.

The measures for assesing profitability will be mainly derived from this datasheet.

[2]:
```
# Import standard packages
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import matplotlib as mpl
import matplotlib.ticker as mticker
import seaborn as sns
%matplotlib inline
```

Load the IMDB database file (im.db) using SQLite and explore the tables:

[3]:
```
# Read the tables using sqlite
import sqlite3
conn= sqlite3.connect('zippedData/im.db')
```

[4]:
```
# Read the table movie_basics
movie_basics = pd.read_sql("""
SELECT *
FROM movie_basics;
""", conn)
movie_basics.head()
```

[4]:
```
    movie_id                    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            175.0    Action,Crime,Drama
1        2019            114.0       Biography,Drama
2        2018            122.0                 Drama
3        2018              NaN          Comedy,Drama
4        2017             80.0  Comedy,Drama,Fantasy
```

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

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

[6]:
```
movie_basics.nunique()
```

[6]:
```
movie_id           146144
primary_title      136071
original_title     137773
start_year             19
runtime_minutes       367
genres               1085
dtype: int64
```

[7]:
```
movie_basics['primary_title'].duplicated().sum()
# 10073 movie titles are duplicated despite having different movie IDs
```

[7]:
```
10073
```

[8]:
```
movie_basics[movie_basics['primary_title'].duplicated()].head()
```

[8]:
```
        movie_id                primary_title               original_title  \
706   tt10022974                      Nemesis                      Nemesis
948   tt10064536  Untitled Disney Marvel Film  Untitled Disney Marvel Film
949   tt10064558          Untitled Marvel Film         Untitled Marvel Film
1478  tt10127292   Plushtubers: The Apocalypse  Plushtubers: The Apocalypse
1622  tt10148772                    Indemnity                    Indemnity

      start_year  runtime_minutes             genres
706         2019              NaN    Action,Thriller
948         2022              NaN             Action
949         2021              NaN             Action
1478        2019              NaN   Action,Adventure
1622        2018             45.0           Thriller
```

[9]:
```
movie_basics[movie_basics['primary_title'] == 'Nemesis']
# In some cases same movie name was used for different movies/versions.
```

```
[9]:          movie_id primary_title original_title  start_year  runtime_minutes  \
280      tt0800353       Nemesis        Nemesis        2010             83.0
706     tt10022974       Nemesis        Nemesis        2019              NaN
136440   tt8695086       Nemesis        Nemesis        2019             78.0

                  genres
280                Drama
706      Action,Thriller
136440          Thriller
```

```
[10]: movie_basics[movie_basics['primary_title'] == 'Untitled Disney Marvel Film']
# Same movie was repeated with different movie_ids.
```

```
[10]:          movie_id                primary_title               original_title  \
821     tt10042446  Untitled Disney Marvel Film  Untitled Disney Marvel Film
948     tt10064536  Untitled Disney Marvel Film  Untitled Disney Marvel Film
130616   tt8097016  Untitled Disney Marvel Film  Untitled Disney Marvel Film

        start_year  runtime_minutes  genres
821           2022              NaN  Action
948           2022              NaN  Action
130616        2022              NaN  Action
```

ISSUE and SOLUTION: - When the same movie name was used for different movies/versions, we need to take "year" into consideration to tell them apart. - When the same movie was just repeated with different movie_ids, we need to drop those duplicated values.

```
[11]: movie_basics.describe()
```

```
[11]:          start_year  runtime_minutes
count  146144.000000    114405.000000
mean     2014.621798        86.187247
std         2.733583       166.360590
min      2010.000000         1.000000
25%      2012.000000        70.000000
50%      2015.000000        87.000000
75%      2017.000000        99.000000
max      2115.000000     51420.000000
```

```
[12]: print(movie_basics[movie_basics['runtime_minutes'] == 51420])
print(movie_basics[movie_basics['start_year'] == 2115])
# Indeed there is a film with a runtime of 857 hours which is the longest film␣
↪ever made.
# It seems like IMDB is also showing movies that are currently under␣
↪development.
```

```
        movie_id primary_title original_title  start_year  runtime_minutes  \
132389  tt8273150     Logistics      Logistics        2012          51420.0
```

```
                genres
132389  Documentary
        movie_id primary_title original_title  start_year  runtime_minutes  \
89506  tt5174640     100 Years      100 Years        2115              NaN

      genres
89506  Drama
```

Issues to consider about movie_basics: - `movie_id` is the primary key, there are 146.144 movies. - 10073 `primary_title` are duplicated despite having different `movie_id`. - Use `primary_title` instead of `original_title` since it is in English. - Since some movies have multiple `genres`, split the text and assign them to seperate rows.

[13]:
```python
movie_ratings = pd.read_sql("""
SELECT *
FROM movie_ratings;
""", conn)

movie_ratings.head()
```

[13]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21

[14]:
```python
movie_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   movie_id       73856 non-null  object
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

[15]:
```python
# suppress scientific notation output while using .describe()
movie_ratings.describe().apply(lambda x: x.apply('{0:.2f}'.format))
```

[15]:

	averagerating	numvotes
count	73856.00	73856.00
mean	6.33	3523.66
std	1.47	30294.02

```
min             1.00        5.00
25%             5.50       14.00
50%             6.50       49.00
75%             7.40      282.00
max            10.00  1841066.00
```

[16]:
```
movie_ratings['movie_id'].duplicated().sum()
```

[16]:
```
0
```

[17]:
```
movie_ratings[movie_ratings['numvotes']==1841066]
```

[17]:
```
        movie_id  averagerating  numvotes
63498  tt1375666            8.8   1841066
```

[18]:
```
# Inception indeed has been voted for 1841066 times.
movie_basics[movie_basics['movie_id']=='tt1375666']
```

[18]:
```
       movie_id primary_title original_title  start_year  runtime_minutes  \
7066  tt1375666     Inception      Inception        2010            148.0

                    genres
7066  Action,Adventure,Sci-Fi
```

Issues to consider about movie_ratings: - `movie_id` is the primary key, there are 73856 movies, about half the size of movies in movie_basics. - We can use `averagerating` as an indication of how much people like each movie.

[19]:
```
directors = pd.read_sql("""
SELECT *
FROM directors;
""", conn)

directors.head()
```

[19]:
```
    movie_id  person_id
0  tt0285252  nm0899854
1  tt0462036  nm1940585
2  tt0835418  nm0151540
3  tt0835418  nm0151540
4  tt0878654  nm0089502
```

[20]:
```
directors.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 291174 entries, 0 to 291173
Data columns (total 2 columns):
 #   Column     Non-Null Count   Dtype
```

```
---  ------     --------------  -----
 0   movie_id   291174 non-null  object
 1   person_id  291174 non-null  object
dtypes: object(2)
memory usage: 4.4+ MB
```

[21]:
```
directors.nunique()
```

[21]:
```
movie_id     140417
person_id    109253
dtype: int64
```

[22]:
```
print(directors.duplicated().sum())
print(directors['movie_id'].duplicated().sum())
print(directors['person_id'].duplicated().sum())
# There are 127.639 duplicated rows, 150.757 duplicated movies and 181.921␣
↪duplicated persons.
```

```
127639
150757
181921
```

[23]:
```
directors[directors.duplicated()].sort_values(by= 'movie_id').head(10)
```

[23]:

	movie_id	person_id
222428	tt0063540	nm0712540
222429	tt0063540	nm0712540
222430	tt0063540	nm0712540
68345	tt0069049	nm0000080
252268	tt0100275	nm0749914
252267	tt0100275	nm0765384
276830	tt0146592	nm1030585
217424	tt0162942	nm1207262
217423	tt0162942	nm1207262
19674	tt0176694	nm0417757

Issues to consider about directors: - `movie_id` is the primary key, there are 291.174 movies, however about only the half (140.417) are unique entries. - There are 127.639 duplicated rows, 150.757 duplicated movies and 181.921 duplicated persons. - Some of the duplicated `movie ids` and `person ids` are because same director have directed more than 1 movie and some movies probably have multiple directors. - Need to drop the duplicated rows later when looking into factors other than director.

[24]:
```
# In order to extract director name we need persons table.
persons = pd.read_sql("""
SELECT *
FROM persons;
""", conn)
```

```
persons.head()
```

[24]:
```
   person_id       primary_name  birth_year  death_year  \
0  nm0061671  Mary Ellen Bauder         NaN         NaN
1  nm0061865       Joseph Bauer         NaN         NaN
2  nm0062070         Bruce Baum         NaN         NaN
3  nm0062195       Axel Baumann         NaN         NaN
4  nm0062798        Pete Baxter         NaN         NaN

                                  primary_profession
0         miscellaneous,production_manager,producer
1        composer,music_department,sound_department
2                        miscellaneous,actor,writer
3  camera_department,cinematographer,art_department
4  production_designer,art_department,set_decorator
```

[25]:
```
persons.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 606648 entries, 0 to 606647
Data columns (total 5 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   person_id           606648 non-null  object
 1   primary_name        606648 non-null  object
 2   birth_year          82736 non-null   float64
 3   death_year          6783 non-null    float64
 4   primary_profession  555308 non-null  object
dtypes: float64(2), object(3)
memory usage: 23.1+ MB
```

[26]:
```
print(persons['person_id'].duplicated().sum())
print(persons['primary_name'].duplicated().sum())
```

```
0
29445
```

[27]:
```
persons[persons['primary_name'].duplicated()].sort_values(by = 'primary_name').
 ↪head(8)
# Same name has been coded under different person ID's and profession probaby␣
 ↪due to the
# different roles they took in different movies.
```

[27]:
```
        person_id primary_name  birth_year  death_year  \
279631  nm4062141  A. Venkatesh         NaN         NaN
156216  nm1701176  A. Venkatesh         NaN         NaN
```

```
387377  nm8956236  A. Venkatesh         NaN          NaN
436444  nm6758318      A.J. Khan         NaN          NaN
565680  nm7645047      A.K. Azad         NaN          NaN
255710  nm3714249       AJ Perez         NaN          NaN
262683  nm3942577          Aadhi         NaN          NaN
446609  nm6832961          Aadhi         NaN          NaN

                                 primary_profession
279631                        director,actor,writer
156216  cinematographer,camera_department,editor
387377                                     producer
436444                                     producer
565680                     music_department,composer
255710                          producer,writer,actor
262683           actor,music_department,soundtrack
446609                                        actor
```

[28]:
```
persons['primary_profession'].str.contains('director').sum()
```

[28]:
```
146033
```

Issues to consider about persons: - `person_id` is the primary key, there are 606.648 people entries, however only about 146.033 of them are "directors". - We only need `primary_name` information as well as `person_id` to link this table to directors table. - Same name has been coded under different person ID's and profession probably due to different roles in different movies. Therefore there are duplicated entries.

Extract a comprehensive imdb dataframe from the database using 4 tables:

- movie_basics - to get title, year, runtime, and genre information for each movie.
- movie_ratings - to get average rating and number of votes
- directors - to get the director ID information for each movie
- persons - to be able to link the directors to their names

[29]:
```
length_movie_id = [len(x['movie_id']) for x in [movie_basics, movie_ratings,␣
    ↪directors]]
length_movie_id
```

[29]:
```
[146144, 73856, 291174]
```

[30]:
```
# Left join movie_ratings because we want to keep all records regardless they␣
    ↪have a rating.
# Left join directors because we want to keep all records regardless they have␣
    ↪a director.
# Inner join persons because we do NOT want the people who are NOT directors in␣
    ↪the dataset.

imdb = pd.read_sql("""
```

```
SELECT DISTINCT movie_id,
       primary_title,
       start_year,
       runtime_minutes,
       genres,
       averagerating,
       numvotes,
       person_id,
       primary_name as director_name
FROM movie_basics
LEFT JOIN movie_ratings
    USING(movie_id)
LEFT JOIN directors
    USING(movie_id)
JOIN persons
    USING(person_id)
ORDER BY (movie_id)

""", conn)

print(imdb.shape)

imdb.head()
```

```
(163533, 9)
```

[30]:

```
    movie_id                    primary_title  start_year  runtime_minutes  \
0  tt0063540                        Sunghursh        2013            175.0
1  tt0066787  One Day Before the Rainy Season        2019            114.0
2  tt0069049       The Other Side of the Wind        2018            122.0
3  tt0069204                  Sabse Bada Sukh        2018              NaN
4  tt0100275         The Wandering Soap Opera        2017             80.0

                 genres  averagerating  numvotes  person_id  \
0    Action,Crime,Drama            7.0      77.0  nm0712540
1       Biography,Drama            7.2      43.0  nm0002411
2                 Drama            6.9    4517.0  nm0000080
3          Comedy,Drama            6.1      13.0  nm0611531
4  Comedy,Drama,Fantasy            6.5     119.0  nm0749914

          director_name
0   Harnam Singh Rawail
1             Mani Kaul
2          Orson Welles
3  Hrishikesh Mukherjee
4            Raoul Ruiz
```

[31]:
```
imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 163533 entries, 0 to 163532
Data columns (total 9 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   movie_id         163533 non-null  object
 1   primary_title    163533 non-null  object
 2   start_year       163533 non-null  int64
 3   runtime_minutes  130938 non-null  float64
 4   genres           159789 non-null  object
 5   averagerating    86030 non-null   float64
 6   numvotes         86030 non-null   float64
 7   person_id        163533 non-null  object
 8   director_name    163533 non-null  object
dtypes: float64(3), int64(1), object(5)
memory usage: 11.2+ MB
```

[32]:
```
imdb.nunique()
# There are 140,416 unique movie ID's
```

[32]:
```
movie_id           140416
primary_title      131121
start_year             18
runtime_minutes       360
genres               1076
averagerating          91
numvotes             7347
person_id          109251
director_name      106757
dtype: int64
```

[33]:
```
imdb[imdb['primary_title'].duplicated()].head()
```

[33]:
```
     movie_id                         primary_title  start_year  \
5   tt0100275              The Wandering Soap Opera        2017
10  tt0139613                             O Silêncio        2012
24  tt0253093                            Gangavataran        2018
32  tt0283440                       Short Time Heroes        2015
40  tt0312305  Quantum Quest: A Cassini Space Odyssey        2010

    runtime_minutes                genres  averagerating  numvotes  \
5              80.0  Comedy,Drama,Fantasy            6.5     119.0
10              NaN   Documentary,History            NaN       NaN
24            134.0                  None            6.6       8.0
32             45.0                Sci-Fi            6.6      16.0
```

```
40            45.0  Adventure,Animation,Sci-Fi            5.1     287.0

    person_id           director_name
5   nm0765384        Valeria Sarmiento
10  nm0518037        António Loja Neves
24  nm0679610  Dhundiraj Govind Phalke
32  nm1549344             Roman Gonther
40  nm1004541        Harry 'Doc' Kloor
```

[34]:
```python
imdb[imdb['primary_title'] == 'The Wandering Soap Opera']
# Duplications present due to multiple directors
```

[34]:
```
    movie_id             primary_title  start_year  runtime_minutes  \
4  tt0100275  The Wandering Soap Opera        2017             80.0
5  tt0100275  The Wandering Soap Opera        2017             80.0

                 genres  averagerating  numvotes  person_id      director_name
4  Comedy,Drama,Fantasy            6.5     119.0  nm0749914         Raoul Ruiz
5  Comedy,Drama,Fantasy            6.5     119.0  nm0765384  Valeria Sarmiento
```

[35]:
```python
imdb[imdb[['primary_title', 'start_year', 'genres', 'director_name']].
 ↪duplicated()].head()
```

[35]:
```
        movie_id                primary_title  start_year  runtime_minutes  \
1307  tt10095336                 Our Godfather        2019              NaN
1578  tt10127292  Plushtubers: The Apocalypse        2019              NaN
2350  tt10224422                        Olanda        2019            154.0
2403  tt10230042             Rok Sako To Rok Lo        2018              NaN
2421  tt10230622                     Aitebaar        2017             80.0

                genres  averagerating  numvotes   person_id  director_name
1307       Documentary            NaN       NaN   nm2432785   Andrew Meier
1578  Action,Adventure            NaN       NaN  nm10594636 Valarie Holmes
2350       Documentary            NaN       NaN   nm2375939   Bernd Schoch
2403            Comedy            NaN       NaN  nm10641569  Kashif Saleem
2421            Comedy            NaN       NaN  nm10635731  Kashif Saleem
```

[36]:
```python
imdb[imdb['primary_title'] == 'Plushtubers: The Apocalypse']
# Duplications present also due to different movie_ids from the 1st IMDB table.
```

[36]:
```
        movie_id                primary_title  start_year  runtime_minutes  \
1577  tt10127274  Plushtubers: The Apocalypse        2019              NaN
1578  tt10127292  Plushtubers: The Apocalypse        2019              NaN

                genres  averagerating  numvotes   person_id  director_name
1577  Action,Adventure            NaN       NaN  nm10594636 Valarie Holmes
1578  Action,Adventure            NaN       NaN  nm10594636 Valarie Holmes
```

DROP duplicate movies with different IDs: Because the first table from IMDb database included duplicated movies with different movie_ids, find those movies and drop them:

[37]:
```
# Find those cases where only movie_id was different:
to_drop = imdb[imdb[['primary_title', 'start_year', 'genres', 'director_name']].
 ↪duplicated()]
len(to_drop)
```

[37]:
```
369
```

[38]:
```
imdb.drop(to_drop.index, axis=0, inplace=True)
```

[39]:
```
assert(len(imdb[imdb['primary_title'] == 'Plushtubers: The Apocalypse'])==1)
```

Read csv file "bom.movie_gross.csv.gz":

[40]:
```
budgets = pd.read_csv('zippedData/tn.movie_budgets.csv.gz', )
budgets.head()
```

[40]:
```
   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix
3   4   May 1, 2015                      Avengers: Age of Ultron
4   5  Dec 15, 2017            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
```

[41]:
```
budgets.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   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

[42]:
```
budgets['movie'].nunique()
```

[42]:
```
5698
```

[43]:
```
budgets['movie'].duplicated().sum()
```

[43]:
```
84
```

[44]:
```
budgets[budgets['movie'].duplicated()]
```

[44]:
```
        id  release_date                      movie production_budget  \
273     74  May 19, 1998                   Godzilla      $125,000,000
408      9  Nov 21, 2018                 Robin Hood       $99,000,000
484     85   Jul 8, 2005             Fantastic Four       $87,500,000
543     44   May 7, 1999                  The Mummy       $80,000,000
707      8  Jun 13, 1997                   Hercules       $70,000,000
…    …             …                          …                 …
5668    69  Nov 16, 1942                 Cat People          $134,000
5676    77   Oct 1, 1968     Night of the Living Dead          $114,000
5677    78   Feb 8, 1915        The Birth of a Nation          $110,000
5699   100  Aug 30, 1972  The Last House on the Left           $87,000
5718    19  Feb 22, 2008                 The Signal           $50,000

     domestic_gross worldwide_gross
273    $136,314,294    $376,000,000
408     $30,824,628     $84,747,441
484    $154,696,080    $333,132,750
543    $155,385,488    $416,385,488
707     $99,112,101    $250,700,000
…               …               …
5668     $4,000,000      $8,000,000
5676    $12,087,064     $30,087,064
5677    $10,000,000     $11,000,000
5699     $3,100,000      $3,100,000
5718       $251,150        $406,299

[84 rows x 6 columns]
```

[45]:
```
budgets[budgets['movie'] == 'Godzilla']
# Same name but made in different years and so have different financial␣
↪information.
```

[45]:
```
      id  release_date     movie production_budget domestic_gross  \
140   41  May 16, 2014  Godzilla      $160,000,000   $200,676,069
273   74  May 19, 1998  Godzilla      $125,000,000   $136,314,294

    worldwide_gross
```

```
140     $529,076,069
273     $376,000,000
```

Issue: There are 84 movie names duplicated, but the movies are actually differnet movies from different years with different financial information. This will create an issue while merging with IMDB.

Issues to consider about budgets: - `movie` is the key to merge with imdb dataset. - `production_budget`, `domestic_gross`, `worldwide_gross` all coded as a string. Remove the $ sign and covert to integer. - `release_date` coded as a string, convert it to time datatype. - Some movie titles do not match between imdb and budgets datasets. Try to clean/match the movie names as well. - There are also 84 movies sharing a name. So we need to take "year" into consideration to tell them apart.

1.4 Data Preparation

[46]:
```
# create deep copies to clean:
budgets_clean = budgets.copy()
imdb_clean = imdb.copy()
```

Clean the `budgets` dataset:

[47]:
```
# Remove the $ sign and the comma, and convert string into integer.
# Write a function to do this for multiple columns.
def strreplace(df_original,vrbl_list):
    df_modified = df_original.copy()
    for x in vrbl_list:
        df_modified[x] = df_modified[x].str.replace('$','').str.replace(',','').
 ↪astype(int)
    return(df_modified)
```

[48]:
```
budgets_clean = strreplace(budgets_clean, [('production_budget'),␣
 ↪('worldwide_gross'),('domestic_gross')])
budgets_clean.head()
```

[48]:
```
   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix
3   4   May 1, 2015                      Avengers: Age of Ultron
4   5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi

   production_budget  domestic_gross  worldwide_gross
0          425000000       760507625       2776345279
1          410600000       241063875       1045663875
2          350000000        42762350        149762350
3          330600000       459005868       1403013963
4          317000000       620181382       1316721747
```

```
[49]: # Column id is redundant with index
budgets_clean.drop('id', inplace=True, axis=1)
```

```
[50]: # Convert release_date into datetime
budgets_clean['release_date'] = pd.to_datetime(budgets_clean['release_date'])
```

```
[51]: # Extract release year
budgets_clean['release_year'] = budgets_clean['release_date'].dt.year
```

More cleaning to match the movie names between imdb and budget datasets as much as possible:

```
[52]: budgets_clean[budgets_clean['movie'].str.contains('-|:|;')].sample(5)
```

```
[52]:     release_date                                      movie  \
256    2011-11-18  The Twilight Saga: Breaking Dawn, Part 1
2527   2002-02-15            Peter Pan: Return to Neverland
3464   1977-05-25              Star Wars Ep. IV: A New Hope
2305   2018-04-13             Sgt. Stubby: An American Hero
815    2014-08-22              Sin City: A Dame to Kill For

      production_budget  domestic_gross  worldwide_gross  release_year
256           127500000       281287133        689420051          2011
2527           20000000        48430258        109862682          2002
3464           11000000       460998007        786598007          1977
2305           25000000         3054285          3645957          2018
815            65000000        13757804         40650842          2014
```

```
[53]: budgets_clean[budgets_clean['movie'].str.contains('Harry Potter')]
```

```
[53]:    release_date                                         movie  \
19    2009-07-15         Harry Potter and the Half-Blood Prince
157   2007-07-11      Harry Potter and the Order of the Phoenix
158   2005-11-18            Harry Potter and the Goblet of Fire
238   2004-06-04       Harry Potter and the Prisoner of Azkaban
260   2011-07-15  Harry Potter and the Deathly Hallows: Part II
262   2001-11-16         Harry Potter and the Sorcererâ s Stone
263   2010-11-19   Harry Potter and the Deathly Hallows: Part I
363   2002-11-15         Harry Potter and the Chamber of Secrets

     production_budget  domestic_gross  worldwide_gross  release_year
19           250000000       302089278        935213767          2009
157          150000000       292137260        943076457          2007
158          150000000       290201752        897099794          2005
238          130000000       249757726        796907323          2004
260          125000000       381193157       1341693157          2011
262          125000000       317871467        975047606          2001
```

```
263           125000000        296131568        960431568          2010
363           100000000        262233381        879225135          2002
```

[54]:
```python
imdb_clean[imdb_clean['primary_title'].str.contains('Harry Potter')]
```

[54]:
```
         movie_id                                    primary_title  \
505     tt0926084     Harry Potter and the Deathly Hallows: Part 1
5730    tt1201607     Harry Potter and the Deathly Hallows: Part 2
23021   tt1867094                The Seekers Guide to Harry Potter
142709  tt7783322                 Harry Potter: A History of Magic
142710  tt7783322                 Harry Potter: A History of Magic
149455  tt8358970                   The Harry Potter Saga Analyzed
150517  tt8443702  Harry Potter and the Untold Stories of Hogwarts

        start_year  runtime_minutes                     genres  averagerating  \
505           2010            146.0  Adventure,Fantasy,Mystery            7.7
5730          2011            130.0    Adventure,Drama,Fantasy            8.1
23021         2010             75.0                Documentary            3.0
142709        2017             59.0                Documentary            7.2
142710        2017             59.0                Documentary            7.2
149455        2018              NaN                Documentary            NaN
150517        2012             58.0   Adventure,Comedy,Fantasy            NaN

        numvotes  person_id    director_name
505     425530.0  nm0946734      David Yates
5730    691835.0  nm0946734      David Yates
23021       23.0  nm3032813  Philip Gardiner
142709     202.0  nm2901096          Jude Ho
142710     202.0  nm5577200     Alex Harding
149455       NaN  nm4610538    Houston Coley
150517       NaN  nm9297933     Ryan Glista
```

Based on the sample movie names which included Harry Potter series, it seems like there is discrepancy in the way movie names were coded in the two datasets: - Puncutations such as : (some movies include : while some don't etc.) - Roman versus Arabic numerals: (Harry Potter and the Deathly Hallows Part II versus Harry Potter and the Deathly Hallows: Part 2) - In the way Episodes were coded (Ep. versus Episode)

[55]:
```python
# Replace punctuations with empty strings:
budgets_clean['movie'] = budgets_clean['movie'].str.replace(r'[^\w\s]+', '')
imdb_clean['primary_title'] = imdb_clean['primary_title'].str.
↪replace(r'[^\w\s]+', '')

assert(len(budgets_clean[budgets_clean['movie'].str.contains(':')]) == 0)
assert(len(imdb_clean[imdb_clean['primary_title'].str.contains(';')]) == 0)
```

[56]:
```python
# Recode Arabic with Roman numerals because the other way around would replace␣
↪letter I with 1:
# REF: https://stackoverflow.com/questions/6116978/
↪how-to-replace-multiple-substrings-of-a-string
def replace_numerals(var, dic):
    for i, j in dic.items():
        var = var.str.replace(i, j)
    return var
```

[57]:
```python
dic = {'1': 'I', '2': 'II', '3': 'III', '4': 'IV','5': 'V', '6': 'VI', '7':␣
↪'VII','8': 'VII','9': 'IX','10': 'X'}
var = budgets_clean['movie']
budgets_clean['movie'] = replace_numerals(var, dic)

assert(len(budgets_clean[budgets_clean['movie'].str.contains('2|4|8')]) == 0)
```

[58]:
```python
var = imdb_clean['primary_title']
imdb_clean['primary_title'] = replace_numerals(var, dic)

assert(len(imdb_clean[imdb_clean['primary_title'].str.contains('2|4|8')]) == 0)
```

[59]:
```python
# Recode Ep. as Episode:
budgets_clean['movie'] = budgets_clean['movie'].str.replace('Ep.','Episode',␣
↪regex=False)
imdb_clean['primary_title'] = imdb_clean['primary_title'].str.replace('Ep.
↪','Episode', regex=False) # regex=False: Match and extract exact string␣
↪pattern from the text

assert(len(budgets_clean[budgets_clean['movie'].str.contains('Ep.',␣
↪regex=False)]) == 0)
assert(len(imdb_clean[imdb_clean['primary_title'].str.contains('Ep.',␣
↪regex=False)]) == 0)
```

[60]:
```python
# Get the list of the duplicated movies in budgets.
duplicatednames = budgets_clean[budgets_clean['movie'].duplicated()]['movie'].
↪reset_index(drop=True)
duplicatednames = list(duplicatednames)
duplicatednames[:10] # length is 84
```

[60]:
```
['Godzilla',
 'Robin Hood',
 'Fantastic Four',
 'The Mummy',
 'Hercules',
 'Total Recall',
 'The Avengers',
```

```
 'Life',
 'Hellboy',
 'Ghostbusters']
```

[61]:
```
budgets_clean[budgets_clean['movie'] == 'Godzilla']
# The names are duplicated but these are actually different movies from␣
↪different years.
```

[61]:
```
    release_date     movie  production_budget  domestic_gross  \
140   2014-05-16  Godzilla          160000000       200676069
273   1998-05-19  Godzilla          125000000       136314294

     worldwide_gross  release_year
140        529076069          2014
273        376000000          1998
```

[62]:
```
len(imdb_clean[imdb_clean['primary_title'].isin(duplicatednames)])
# There are also 225 movies in the other dataset with the same name.
```

[62]: 225

[63]:
```
# Before adding the year to the name for these specific movies, let's convert␣
↪release year into string
# The function below does not work with str() unless you save the variable as␣
↪string type first.
budgets_clean['release_year'] = budgets_clean['release_year'].astype(str)
```

[64]:
```
# If the movie name is duplicated attach the year next to the name, if not keep␣
↪it the same:
budgets_clean['movie'] = np.where( budgets_clean['movie'].
↪isin(duplicatednames), \
    (budgets_clean['movie'] + ' ' + budgets_clean['release_year']),␣
↪budgets_clean['movie'])

# You need to get a truth value for the condition in np.where()
```

[65]:
```
budgets_clean[budgets_clean['movie'].str.contains('Godzilla')]
# Year was added next to movie name for those duplicated names.
```

[65]:
```
     release_date                        movie  production_budget  \
124    2019-05-31  Godzilla King of the Monsters          170000000
140    2014-05-16                  Godzilla 2014          160000000
273    1998-05-19                  Godzilla 1998          125000000
5223   2000-08-18                 Godzilla II000            1000000

      domestic_gross  worldwide_gross release_year
124         85576941        299276941         2019
```

```
140       200676069      529076069       2014
273       136314294      376000000       1998
5223       10037390       10037390       2000
```

[66]:
```
# Repeat the same step for imdb dataset:
imdb_clean['start_year'] = imdb_clean['start_year'].astype(str)
imdb_clean['primary_title'] = np.where( imdb_clean['primary_title'].
 ↪isin(duplicatednames),\
    (imdb_clean['primary_title'] + ' ' + imdb_clean['start_year']),␣
 ↪imdb_clean['primary_title'])
```

[67]:
```
imdb_clean[imdb_clean['primary_title'].str.contains('Godzilla')].head(2)
```

[67]:
```
        movie_id           primary_title start_year  runtime_minutes  \
354    tt0831387           Godzilla 2014       2014            123.0
1393  tt10106144  The War of Godzilla II       2017             99.0

                        genres  averagerating  numvotes   person_id  \
354   Action,Adventure,Sci-Fi            6.4  350687.0   nm2284484
1393     Action,Comedy,Family            NaN       NaN  nm10537550

       director_name
354   Gareth Edwards
1393            Liam
```

We could not get rid of all discrepancies, but now for example, we will be able to match Godzilla from 2014 in an accurate way while merging. That saved us some more data.

Merge budgets with IMDB to get a master dataset using movie name:

[68]:
```
master = imdb_clean.merge(budgets_clean, left_on='primary_title',␣
 ↪right_on='movie', how='inner')
master.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3930 entries, 0 to 3929
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   movie_id         3930 non-null   object
 1   primary_title    3930 non-null   object
 2   start_year       3930 non-null   object
 3   runtime_minutes  3482 non-null   float64
 4   genres           3891 non-null   object
 5   averagerating    3083 non-null   float64
 6   numvotes         3083 non-null   float64
 7   person_id        3930 non-null   object
 8   director_name    3930 non-null   object
```

```
 9   release_date       3930 non-null   datetime64[ns]
 10  movie              3930 non-null   object
 11  production_budget  3930 non-null   int64
 12  domestic_gross     3930 non-null   int64
 13  worldwide_gross    3930 non-null   int64
 14  release_year       3930 non-null   object
dtypes: datetime64[ns](1), float64(3), int64(3), object(8)
memory usage: 491.2+ KB
```

Clean master dataset:

[69]:
```python
master_clean = master.copy()
```

[70]:
```python
master_clean.drop(['movie', 'person_id', 'start_year'], axis=1, inplace=True)
```

[71]:
```python
master_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3930 entries, 0 to 3929
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           3930 non-null   object
 1   primary_title      3930 non-null   object
 2   runtime_minutes    3482 non-null   float64
 3   genres             3891 non-null   object
 4   averagerating      3083 non-null   float64
 5   numvotes           3083 non-null   float64
 6   director_name      3930 non-null   object
 7   release_date       3930 non-null   datetime64[ns]
 8   production_budget  3930 non-null   int64
 9   domestic_gross     3930 non-null   int64
 10  worldwide_gross    3930 non-null   int64
 11  release_year       3930 non-null   object
dtypes: datetime64[ns](1), float64(3), int64(3), object(5)
memory usage: 399.1+ KB
```

Some movies have missing data on `averagerating`, `runtime_minutes` and `genres`, but we will keep all this data in the master sheet.

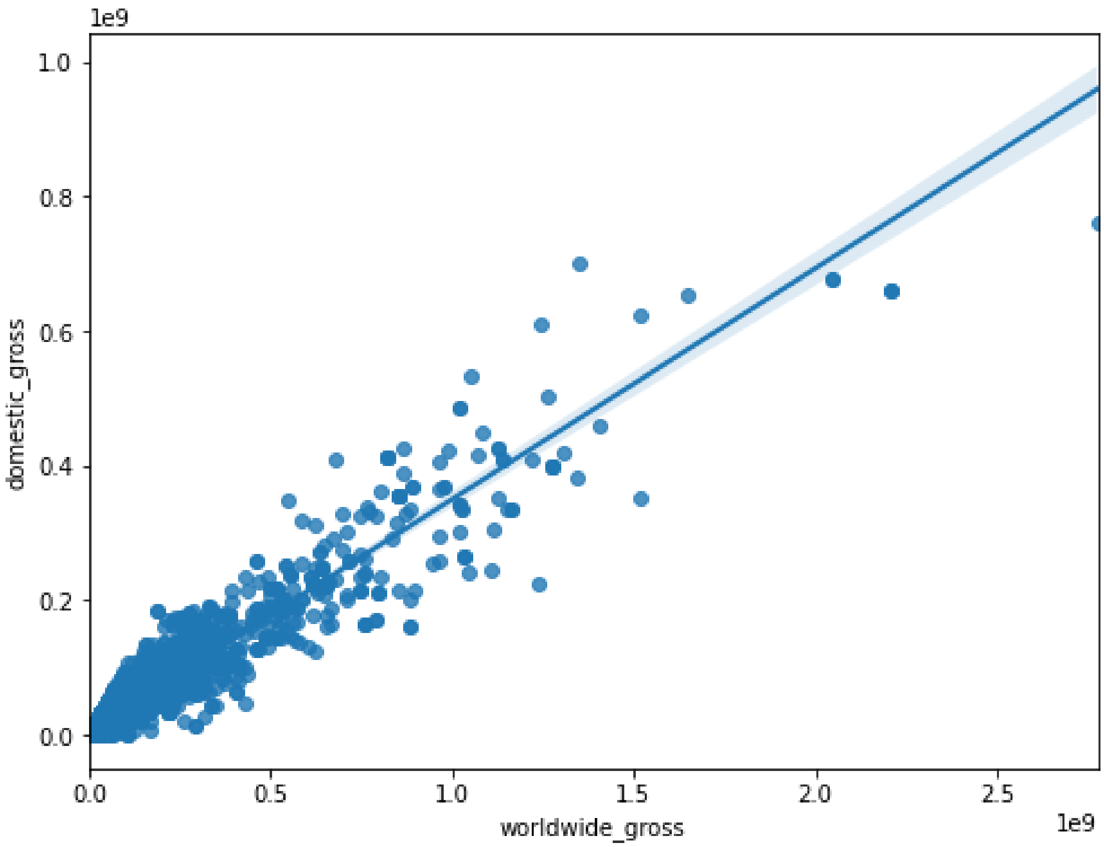
1.5 DATA MODELING

CREATE THE DEPENDENT VARIABLES AND SLICE THE DATA TO ASSESS "PROFITABILITY": Create new columns:

- `profit` to represent profit - calculated by substracting budget from gross.
- `roi'` to represent "return on investment" - calculated by extracting the ratio of profit to the cost.

  - For example a value of 200% ROI means that the profit is twice as much as the cost (or the gross is three times as much as the cost)
- `roi_profit_bins` - SLICE the data into 4 categories based on median profit and ROI values to get more specific roi/profit related insights.
- `budget_bins`- SLICE the data into 4 budget ranges based on quartiles to get more specific budget related answers. ***

[72]:
```
fig, ax1 = plt.subplots(figsize=(8, 6))
sns.regplot(data = master_clean, x ='worldwide_gross', y='domestic_gross',␣
 ↪ax=ax1);

# There is a strong correlation between domestic and worldwide gross
# Let's use "worldwide gross" for calculating profit and roi to get a more␣
 ↪global estimate.
```



[73]:
```
# Create profit and ROI columns:
master_clean['profit'] = master_clean['worldwide_gross'] -␣
 ↪master_clean['production_budget']
master_clean['roi'] = ( (master_clean['worldwide_gross'] -␣
 ↪master_clean['production_budget'])\
```

```
                    / master_clean['production_budget'] )*100
```

[74]:
```
print(master_clean['profit'].median())
print(master_clean['roi'].median())
print(master_clean['production_budget'].quantile(q=(0,.25,.5, .75, 1)))
```

```
6597806.0
49.354005
0.00          1400.0
0.25       4500000.0
0.50      16000000.0
0.75      40000000.0
1.00     425000000.0
Name: production_budget, dtype: float64
```

Create a categorical variable `roi_profit_bins` using the Median values for ROI and PROFIT as cutoff:

- high ROI high profit: > 50% > 6.6 M
- high ROI low profit: > 50% < 6.6 M
- low ROI high profit: < 50% > 6.6 M
- low ROI low profit: < 50% < 6.6 M

[75]:
```
master_clean['roi_bins'] = master_clean['roi'].map(lambda x: '< 50%'\
                                                    if x<=master_clean['roi'].
 ↪median() else ('> 50%'))
master_clean['profit_bins'] = master_clean['profit'].map(lambda x: '< 6.6 M'\
                                                          if␣
 ↪x<=master_clean['profit'].median() else ('> 6.6 M'))
master_clean['roi_profit_bins'] = master_clean['roi_bins'] + ' ' +␣
 ↪master_clean['profit_bins']
```

Create a categorical variable `budget_bins` using the 4 quartiles as cutoff:

- 0-4.5 M (lowest 25% of the data)
- 4.5-16 M (25-50th percentile)
- 16-40 M (50-75th percentile)
- 40-425 M (Top 25% percent)

[76]:
```
master_clean['budget_bins'] = pd.qcut(master_clean['production_budget'], q=4,\
                                      labels=['$0-4.5 M', '$4.5-16 M', '$16-40␣
 ↪M', '$40-425 M'])
```

[77]:
```
master_clean.head()
```

[77]:
```
    movie_id  primary_title  runtime_minutes                     genres  \
0  tt0249516      Foodfight             91.0   Action,Animation,Comedy
1  tt0293429  Mortal Kombat              NaN  Action,Adventure,Fantasy
2  tt0326592  The Overnight             88.0                      None
```

```
3  tt3844362  The Overnight             79.0           Comedy,Mystery
4  tt0337692    On the Road            124.0   Adventure,Drama,Romance

   averagerating  numvotes      director_name release_date  production_budget  \
0            1.9    8248.0  Lawrence Kasanoff   2012-12-31           45000000
1            NaN       NaN      Simon McQuoid   1995-08-18           20000000
2            7.5      24.0     Jed I. Goodman   2015-06-19             200000
3            6.1   14828.0      Patrick Brice   2015-06-19             200000
4            6.1   37886.0      Walter Salles   2013-03-22           25000000

   domestic_gross  worldwide_gross release_year     profit         roi  \
0               0            73706         2012  -44926294  -99.836209
1        70433227        122133227         1995  102133227  510.666135
2         1109808          1165996         2015     965996  482.998000
3         1109808          1165996         2015     965996  482.998000
4          720828          9313302         2013  -15686698  -62.746792

  roi_bins profit_bins roi_profit_bins budget_bins
0    < 50%     < 6.6 M   < 50% < 6.6 M   $40-425 M
1    > 50%     > 6.6 M   > 50% > 6.6 M    $16-40 M
2    > 50%     < 6.6 M   > 50% < 6.6 M   $0-4.5 M
3    > 50%     < 6.6 M   > 50% < 6.6 M   $0-4.5 M
4    < 50%     < 6.6 M   < 50% < 6.6 M    $16-40 M
```

[78]:
```python
len(master_clean['movie_id'])
```

[78]: 3930

[79]:
```python
'''
MASTER dataset included duplicated entries due to multiple directors.
Drop these to create another dataset because
you do not want the same movie repeated for many of your analyses.
'''
master_clean_distinct = master_clean.copy()
```

[80]:
```python
master_clean_distinct['movie_id'].duplicated().sum()
```

[80]: 431

[81]:
```python
master_clean_distinct = master_clean_distinct.
    ↪drop_duplicates(subset='movie_id').reset_index(drop=True)
```

[82]:
```python
assert(master_clean_distinct['movie_id'].duplicated().sum() ==0)
```

[83]:
```python
len(master_clean_distinct['movie_id'])
```

[83]: 3499

[ ]:

```

```

[84]:

```
success_pivot = master_clean_distinct.pivot_table(index=['roi_profit_bins'],
                                                  values=['roi'],
                                                  columns=['budget_bins'],
                                                  aggfunc=['median','count'])
success_pivot = success_pivot.style.format("{:.2f}").
 ↪background_gradient(cmap='Blues', low=0, high=0.75)
success_pivot

#https://towardsdatascience.com/
 ↪adding-style-to-pandas-in-just-a-few-lines-of-code-be942f65b3a5
```

[84]: <pandas.io.formats.style.Styler at 0x7fcc9e65a340>

Table shows that: - Low Roi - Low Profit (Least Successful) movies have more lower budget movies but less loss with higher budgets. - **Low Roi - High Profit** movies are bigger budget movies only - bigger room for more profit. - **High Roi - Low Profit** movies are lower budget movies only - bigger room for more return on investment. - **High Roi - High Profit** (Most Successful) movies have more higher budget movies but ROI gains are more for lower budget movies.

WHAT IS THE RELATIONSHIP BETWEEN PROFIT AND ROI FOR DIFFERENT BUDGETS?

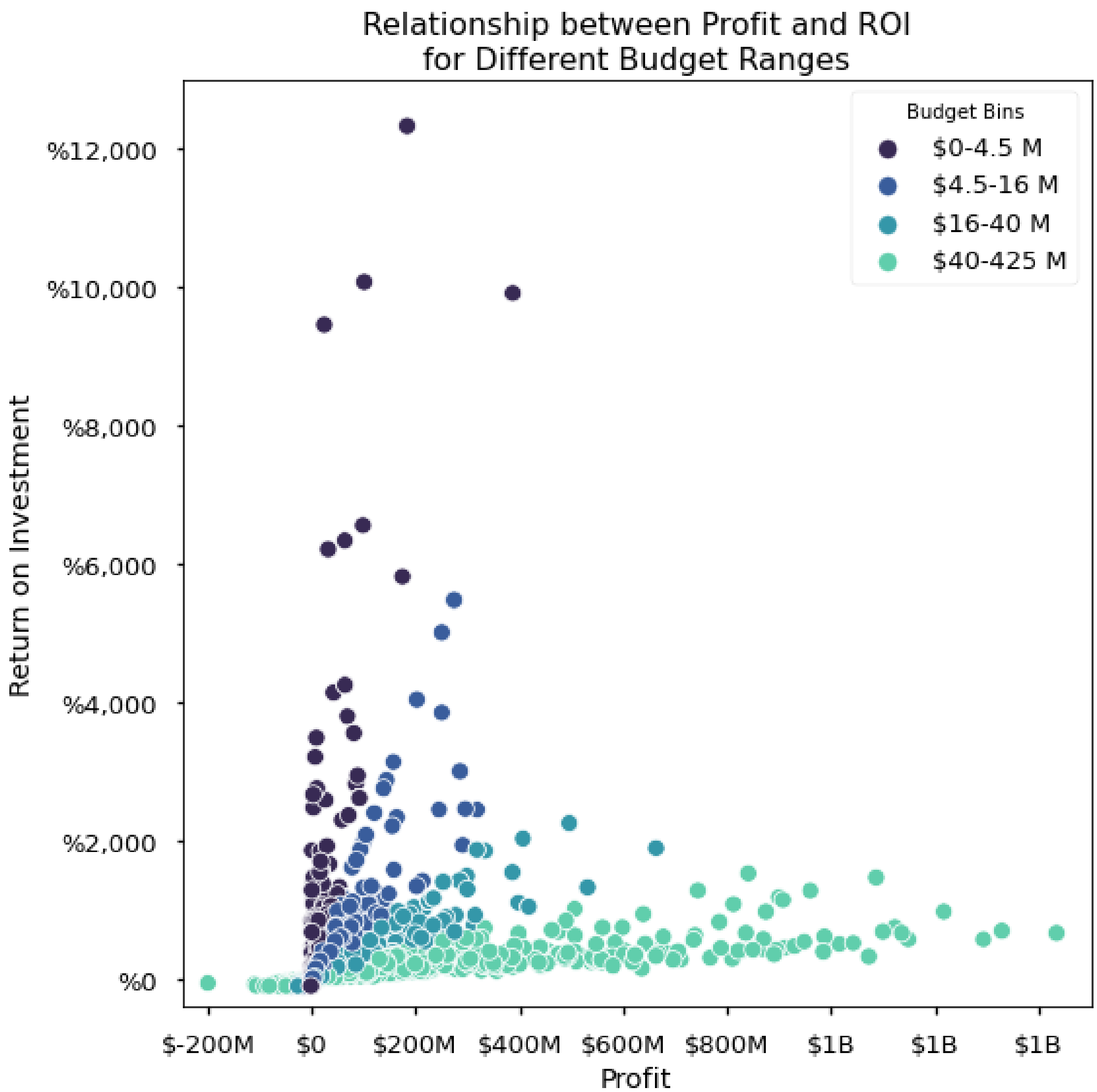
[85]:

```
# Code copied from: https://stackoverflow.com/questions/61330427/
 ↪set-y-axis-in-millions and modified a bit.
# Use the function below to get rid of 1e8s etc on graphs and to format numbers␣
 ↪in thousands, millions, etc in visualizations..:

from matplotlib.ticker import FuncFormatter

def human_format(num, pos):
    magnitude = 0
    while abs(num) >= 1000:
        magnitude += 1
        num /= 1000.0
    return '$%.0f%s' % (num, ['', 'K', 'M', 'B', 'T', 'P'][magnitude])

formatter = FuncFormatter(human_format)
```

[86]:

```
with plt.style.context('seaborn-talk'):
    fig, ax1  = plt.subplots(figsize=(8, 8))
    sns.scatterplot(data=master_clean_distinct, x='profit', y='roi', ax=ax1,␣
 ↪hue='budget_bins', palette = "mako")

    ax1.set_title('Relationship between Profit and ROI\nfor Different Budget␣
 ↪Ranges')
    ax1.set_xlabel("Profit")
```

```
ax1.set_ylabel("Return on Investment")
legends = ax1.get_legend_handles_labels()[0]
ax1.legend(title='Budget Bins')

ax1.set_xlim(-250237650,1500000000) # removing 3 outliers for visualisation
ax1.set_ylim(-400,13000) # removing 3 outliers for visualisation
ax1.xaxis.set_major_formatter(formatter)
ax1.yaxis.set_major_locator(mpl.ticker.MultipleLocator(2000))
ax1.yaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))

fig.tight_layout()
fig.savefig('./images/Scatterplot_RoiProfit.png', dpi=300);
```



- lower than 4.5M Budget : Low profit due to low budget, but high ROI potential.
- higher than 40M Budget: High profit due to high budget, but low ROI potential.

ROI is more meaningful for lower budget movies and profit more meaningful for higher budget movies. Use both measures in your future analyses.

1.5.1 QUESTION1: WHICH MOVIE GENRES ARE MOST PROFITABLE?

[87]:
```
df_genre = master_clean_distinct.copy()
```

[88]:
```
df_genre = df_genre.drop(['runtime_minutes', 'numvotes', 'director_name',
  'release_date'], axis=1)
```

[89]:
```
df_genre.head()
```

[89]:
```
     movie_id  primary_title                     genres  averagerating  \
0  tt0249516      Foodfight   Action,Animation,Comedy            1.9
1  tt0293429  Mortal Kombat  Action,Adventure,Fantasy            NaN
2  tt0326592  The Overnight                      None            7.5
3  tt3844362  The Overnight            Comedy,Mystery            6.1
4  tt0337692    On the Road   Adventure,Drama,Romance            6.1

   production_budget  domestic_gross  worldwide_gross release_year     profit  \
0           45000000               0            73706         2012  -44926294
1           20000000        70433227        122133227         1995  102133227
2             200000         1109808          1165996         2015     965996
3             200000         1109808          1165996         2015     965996
4           25000000          720828          9313302         2013  -15686698

          roi roi_bins profit_bins roi_profit_bins budget_bins
0  -99.836209    < 50%     < 6.6 M   < 50% < 6.6 M   $40-425 M
1  510.666135    > 50%     > 6.6 M   > 50% > 6.6 M    $16-40 M
2  482.998000    > 50%     < 6.6 M   > 50% < 6.6 M    $0-4.5 M
3  482.998000    > 50%     < 6.6 M   > 50% < 6.6 M    $0-4.5 M
4  -62.746792    < 50%     < 6.6 M   < 50% < 6.6 M    $16-40 M
```

[90]:
```
df_genre.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3499 entries, 0 to 3498
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           3499 non-null   object
 1   primary_title      3499 non-null   object
 2   genres             3467 non-null   object
 3   averagerating      2756 non-null   float64
 4   production_budget  3499 non-null   int64
```

```
 5   domestic_gross     3499 non-null   int64
 6   worldwide_gross    3499 non-null   int64
 7   release_year       3499 non-null   object
 8   profit             3499 non-null   int64
 9   roi                3499 non-null   float64
 10  roi_bins           3499 non-null   object
 11  profit_bins        3499 non-null   object
 12  roi_profit_bins    3499 non-null   object
 13  budget_bins        3499 non-null   category
dtypes: category(1), float64(2), int64(4), object(7)
memory usage: 359.1+ KB
```

[91]:
```
# Dropping the 32 rows where Genre is null.
df_genre = df_genre.dropna(subset=['genres']).reset_index(drop=True)
```

Issue: Many movies have **multiple genres**. Seperate them into distict columns to be able to analyze the data:

[92]:
```
# In order to investigate seperate genre categories split the genres seperated␣
↪by commas and expand them into different rows
# df_genre.explode('genres') This function expands to different rows.

df_genre['genres'] = df_genre['genres'].str.split(',')
df_genre = df_genre.explode('genres') # .explode() adds more rows
df_genre.head()
```

[92]:
```
    movie_id primary_title     genres  averagerating  production_budget  \
0  tt0249516     Foodfight     Action            1.9           45000000
0  tt0249516     Foodfight  Animation            1.9           45000000
0  tt0249516     Foodfight     Comedy            1.9           45000000
1  tt0293429  Mortal Kombat     Action            NaN           20000000
1  tt0293429  Mortal Kombat  Adventure            NaN           20000000

   domestic_gross  worldwide_gross release_year     profit        roi  \
0               0            73706         2012  -44926294 -99.836209
0               0            73706         2012  -44926294 -99.836209
0               0            73706         2012  -44926294 -99.836209
1        70433227        122133227         1995  102133227 510.666135
1        70433227        122133227         1995  102133227 510.666135

  roi_bins profit_bins roi_profit_bins budget_bins
0    < 50%     < 6.6 M   < 50% < 6.6 M  $40-425 M
0    < 50%     < 6.6 M   < 50% < 6.6 M  $40-425 M
0    < 50%     < 6.6 M   < 50% < 6.6 M  $40-425 M
1    > 50%     > 6.6 M   > 50% > 6.6 M   $16-40 M
1    > 50%     > 6.6 M   > 50% > 6.6 M   $16-40 M
```

[93]:
```
df_genre.info()
# This gives us 7331 data points to work on.
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7331 entries, 0 to 3466
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   movie_id           7331 non-null   object
 1   primary_title      7331 non-null   object
 2   genres             7331 non-null   object
 3   averagerating      6224 non-null   float64
 4   production_budget  7331 non-null   int64
 5   domestic_gross     7331 non-null   int64
 6   worldwide_gross    7331 non-null   int64
 7   release_year       7331 non-null   object
 8   profit             7331 non-null   int64
 9   roi                7331 non-null   float64
 10  roi_bins           7331 non-null   object
 11  profit_bins        7331 non-null   object
 12  roi_profit_bins    7331 non-null   object
 13  budget_bins        7331 non-null   category
dtypes: category(1), float64(2), int64(4), object(7)
memory usage: 809.2+ KB
```

[94]:
```
df_genre.groupby("genres")['movie_id'].count().sort_values()
```

[94]:
```
genres
Reality-TV        1
News              6
Western          24
Musical          27
War              45
Sport            71
Music            85
History          86
Animation       139
Family          178
Fantasy         178
Sci-Fi          224
Biography       231
Mystery         238
Romance         359
Crime           395
Horror          399
Documentary     419
Adventure       471
```

```
Thriller        570
Action          655
Comedy          839
Drama          1691
Name: movie_id, dtype: int64
```

[95]:
```
# select those genres which produced at least 50 movies to be able to draw␣
 ↪reliable conclusions:
df_genre = df_genre.groupby("genres").filter(lambda x: len(x) > 50)
df_genre.groupby("genres")['movie_id'].count()
```

[95]:
```
genres
Action          655
Adventure       471
Animation       139
Biography       231
Comedy          839
Crime           395
Documentary     419
Drama          1691
Family          178
Fantasy         178
History          86
Horror          399
Music            85
Mystery         238
Romance         359
Sci-Fi          224
Sport            71
Thriller        570
Name: movie_id, dtype: int64
```

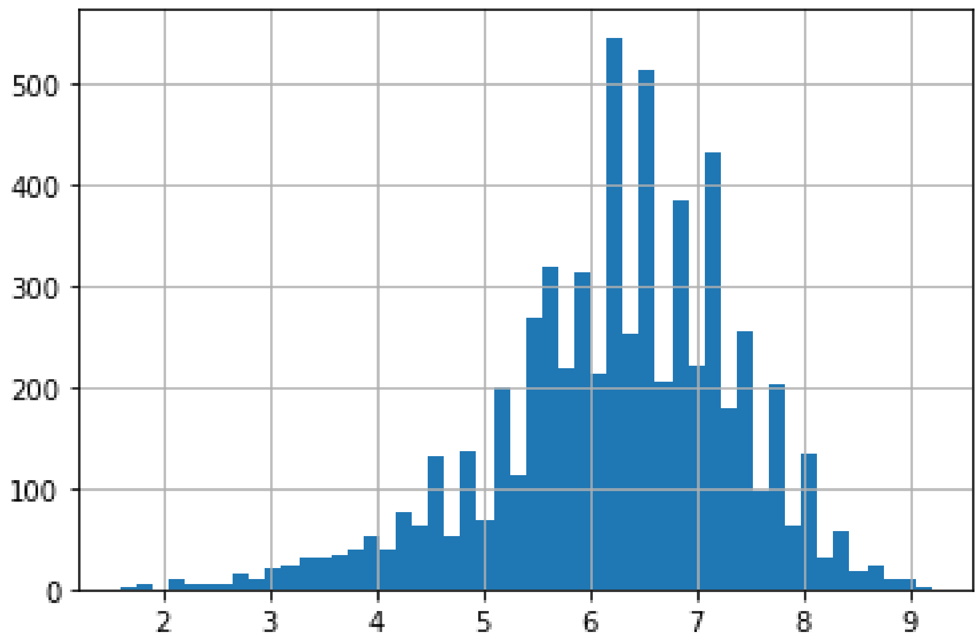
[96]:
```
df_genre.describe().apply(lambda x: x.apply('{0:.0f}'.format))
# The magnitudes are huge, we need format the magnitudes in the visualization
```

[96]:
```
      averagerating production_budget domestic_gross worldwide_gross  \
count          6147              7228           7228            7228
mean              6          36604089       44765988       108939113
std               1          49075690       76203713       209230107
min               2              1400              0               0
25%               6           5000000         538690         2611750
50%               6          18000000       17654912        30628981
75%               7          45000000       53862963       109764978
max               9         425000000      760507625      2776345279

          profit   roi
count       7228  7228
```

```
mean      72335024    269
std      173951843   1357
min     -200237650   -100
25%       -2693352    -65
50%       10023121     59
75%       68729073    253
max     2351345279  41556
```

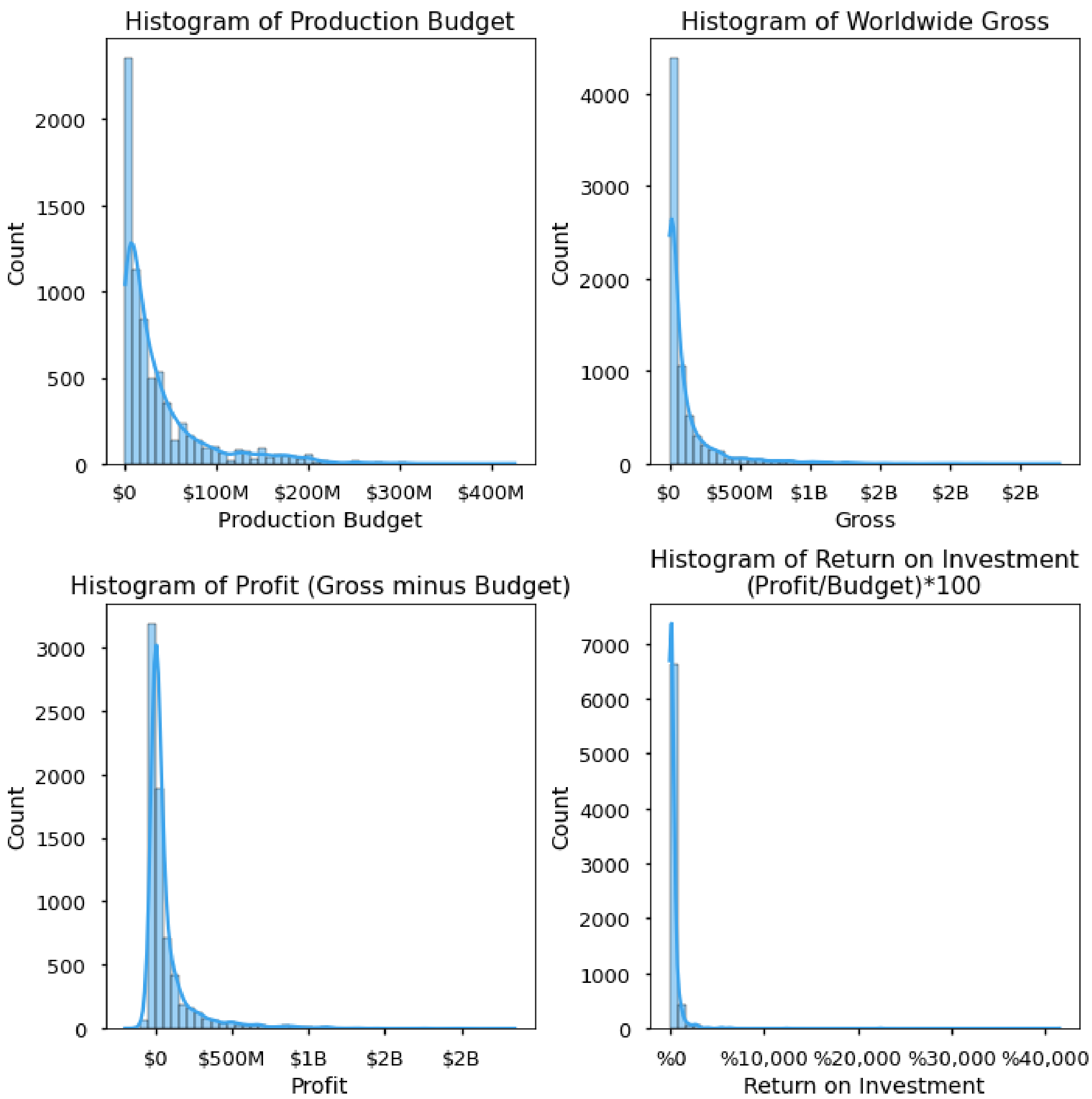
Create histograms to see if the continuous variables are normally distributed or skewed:

```
[97]: df_genre['averagerating'].hist(bins=50);
```



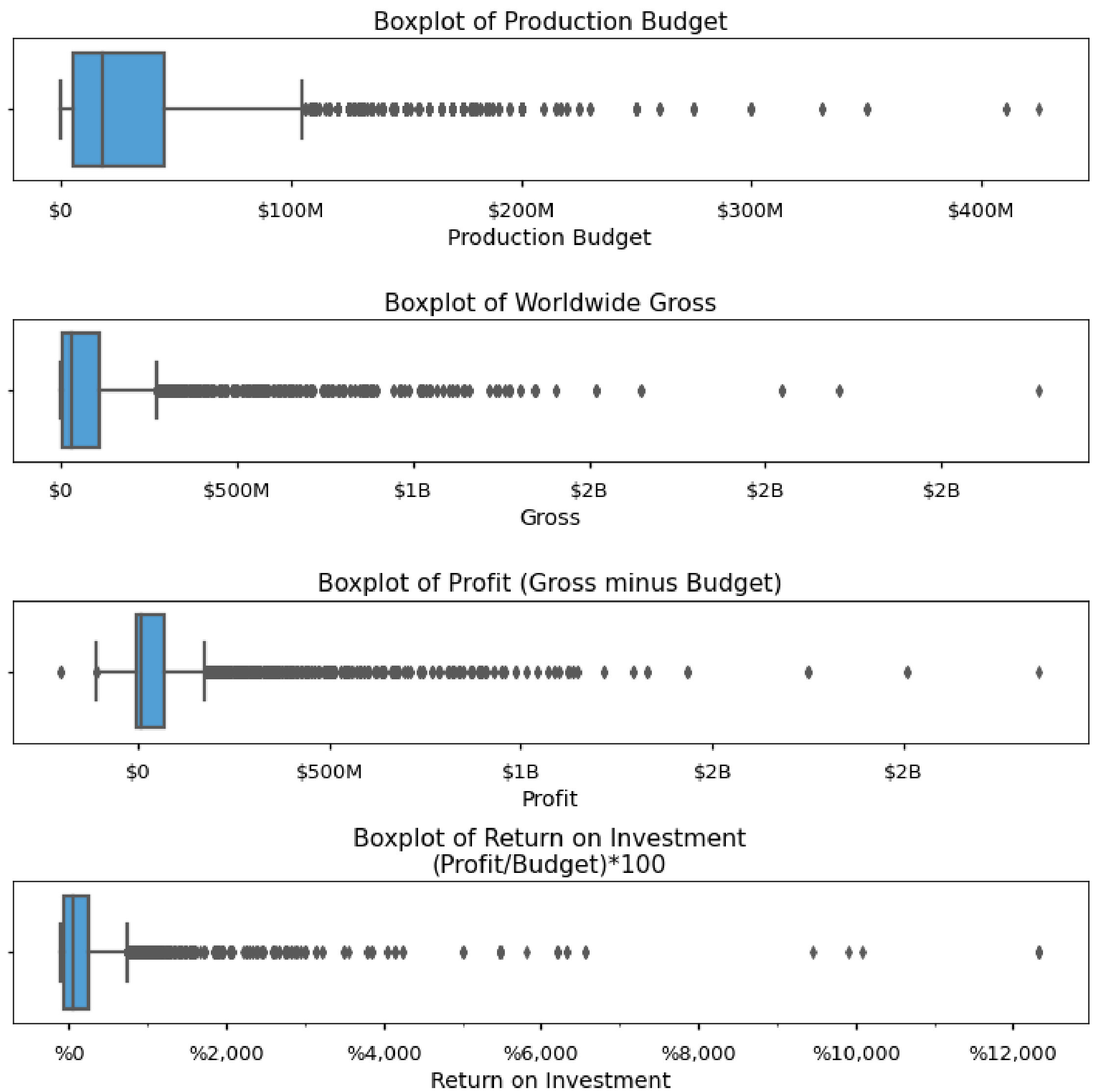

```
[98]: with plt.style.context('seaborn-talk'):
          fig, ( (ax1, ax2),(ax3, ax4))  = plt.subplots(ncols=2, nrows= 2,␣
       ↪figsize=(10, 10))
          base_color = sns.color_palette("husl", 9)[6]

          sns.histplot(x = df_genre['production_budget'], bins = 50, ax=ax1, kde␣
       ↪=True, color =base_color )
          sns.histplot(x = df_genre['worldwide_gross'], bins = 50, ax=ax2, kde =True,␣
       ↪color =base_color )
          sns.histplot(x = df_genre['profit'], bins = 50, ax=ax3, kde =True, color␣
       ↪=base_color )
          sns.histplot(x = df_genre['roi'], bins = 50, ax=ax4, kde =True, color␣
       ↪=base_color )
```

```
    ax1.xaxis.set_major_formatter(formatter)
    ax2.xaxis.set_major_formatter(formatter)
    ax3.xaxis.set_major_formatter(formatter)

    # UserWarning: FixedFormatter should only be used together with FixedLocator
    # Set the locator first before prividing the format:
    ax4.xaxis.set_major_locator(mpl.ticker.MultipleLocator(10000))
    ax4.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}')) #␣
 ↪plt.yticks(rotation=25)

    ax1.set_title('Histogram of Production Budget')
    ax2.set_title('Histogram of Worldwide Gross')
    ax3.set_title('Histogram of Profit (Gross minus Budget)')
    ax4.set_title('Histogram of Return on Investment\n(Profit/Budget)*100')

    ax1.set_xlabel("Production Budget")
    ax2.set_xlabel("Gross")
    ax3.set_xlabel("Profit")
    ax4.set_xlabel("Return on Investment")

    fig.tight_layout();
    fig.savefig('./images/Histograms_DependentMeasures.png', dpi=300);
# All of the variables are highly skewed except average rating.
```



[99]:
```
with plt.style.context('seaborn-talk'):
    fig, ( (ax1), (ax2),(ax3), (ax4))  = plt.subplots(ncols=1, nrows= 4,␣
 ↪figsize=(10, 10))
    base_color = sns.color_palette("husl", 9)[6]

    sns.boxplot(x = df_genre['production_budget'], ax=ax1, color =base_color )
    sns.boxplot(x = df_genre['worldwide_gross'], ax=ax2, color =base_color )
    sns.boxplot(x = df_genre['profit'], ax=ax3, color =base_color )
    sns.boxplot(x = df_genre[df_genre['roi']<20000]['roi'], ax=ax4, color␣
 ↪=base_color )

    ax1.xaxis.set_major_formatter(formatter)
    ax2.xaxis.set_major_formatter(formatter)
```

```
ax3.xaxis.set_major_formatter(formatter)
ax4.xaxis.set_major_locator(mpl.ticker.MultipleLocator(2000))
ax4.xaxis.set_minor_locator(mpl.ticker.MultipleLocator(1000))
ax4.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}')) #␣
↪plt.yticks(rotation=25)

ax1.set_title('Boxplot of Production Budget')
ax2.set_title('Boxplot of Worldwide Gross')
ax3.set_title('Boxplot of Profit (Gross minus Budget)')
ax4.set_title('Boxplot of Return on Investment\n(Profit/Budget)*100')

ax1.set_xlabel("Production Budget")
ax2.set_xlabel("Gross")
ax3.set_xlabel("Profit")
ax4.set_xlabel("Return on Investment")

fig.tight_layout();
fig.savefig('./images/Boxplots_DependentMeasures.png', dpi=300);
```



- All dependent variables are highly skewed except average rating.
- There are many movies with extremely high budget, gross, profit or roi.
- ROI has the highest skew to the right with the most extreme values.

[100]:
```
# Create 4 different dataframes for each specific budget bin to be able to␣
↪visualize them separately:
dfbudgets = []
df_original = master_clean_distinct
q= ['$0-4.5 M','$4.5-16 M','$16-40 M','$40-425 M']
for i in range(0,len(q)):
    dfnew = df_original[df_original['budget_bins'] == q[i]]
    dfbudgets.append(dfnew)
```

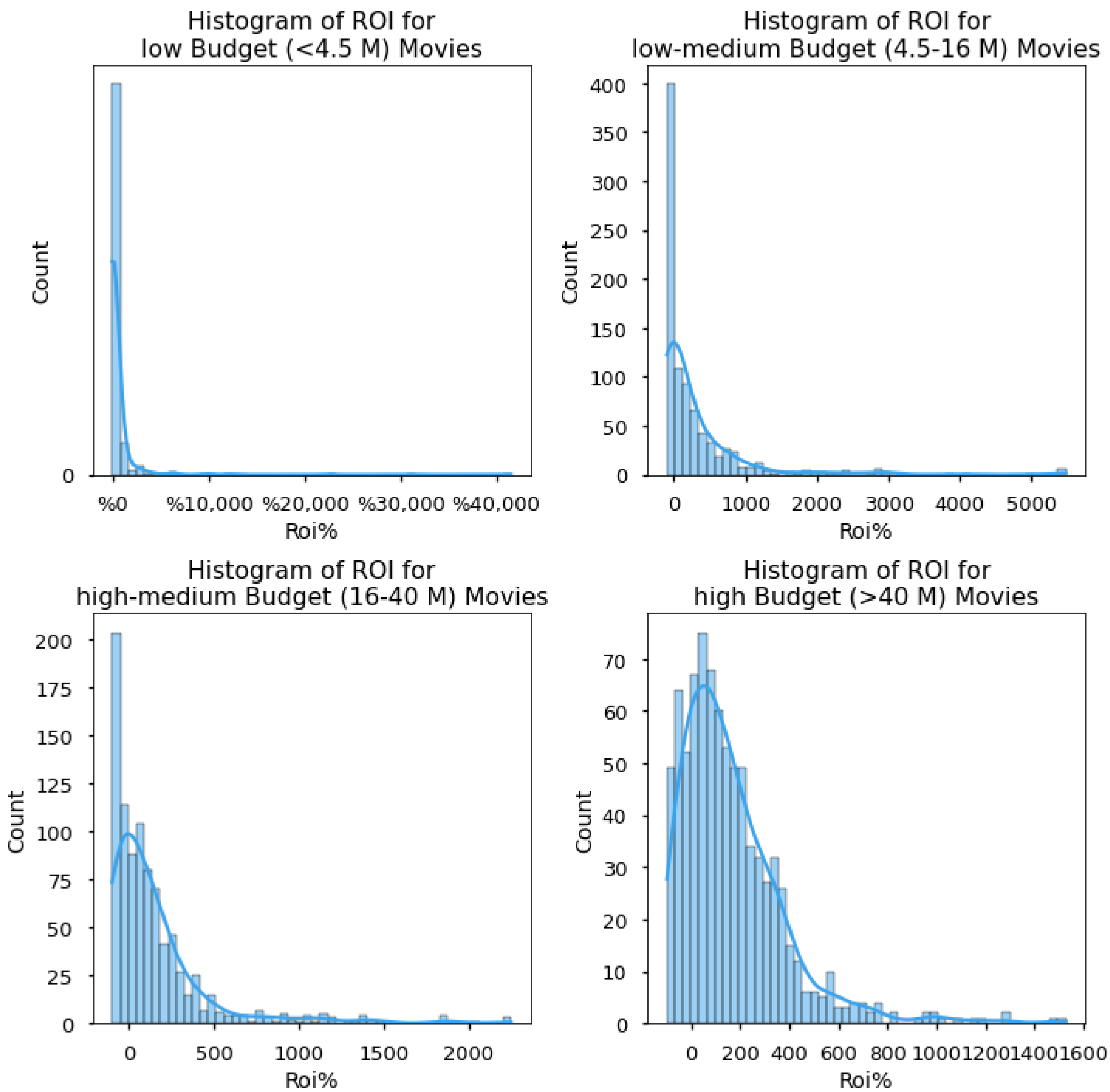
```
print(dfbudgets[0].head(2))
print(dfbudgets[1].head(2))
```

```
    movie_id  primary_title  runtime_minutes          genres  averagerating  \
2  tt0326592  The Overnight             88.0            None            7.5
3  tt3844362  The Overnight             79.0  Comedy,Mystery            6.1

   numvotes   director_name release_date  production_budget  domestic_gross  \
2      24.0  Jed I. Goodman   2015-06-19             200000         1109808
3   14828.0   Patrick Brice   2015-06-19             200000         1109808

   worldwide_gross release_year  profit      roi roi_bins profit_bins  \
2          1165996         2015  965996  482.998    > 50%     < 6.6 M
3          1165996         2015  965996  482.998    > 50%     < 6.6 M

  roi_profit_bins budget_bins
2   > 50% < 6.6 M    $0-4.5 M
3   > 50% < 6.6 M    $0-4.5 M
     movie_id    primary_title  runtime_minutes                   genres  \
20  tt0403935   Action Jackson            144.0          Action,Thriller
23  tt0431021   The Possession             92.0  Horror,Mystery,Thriller

    averagerating  numvotes director_name release_date  production_budget  \
20            3.3    2862.0    Prabhu Deva   1988-02-12            7000000
23            5.9   53649.0   Ole Bornedal   2012-08-31           14000000

    domestic_gross  worldwide_gross release_year    profit         roi  \
20        20257000         20257000         1988  13257000  189.385714
23        49130588         82925064         2012  68925064  492.321886

   roi_bins profit_bins roi_profit_bins budget_bins
20    > 50%     > 6.6 M   > 50% > 6.6 M   $4.5-16 M
23    > 50%     > 6.6 M   > 50% > 6.6 M   $4.5-16 M
```

Based on 4 different budget ranges create different histograms to see if data is still skewed:

[142]:
```
with plt.style.context('seaborn-talk'):
    fig, ( (ax1, ax2),(ax3, ax4) )  = plt.subplots(ncols=2, nrows= 2, figsize=(10, 10))
    base_color = sns.color_palette("husl", 9)[6]

    sns.histplot(x = dfbudgets[0]['roi'], bins = 50, ax=ax1, kde =True, color =base_color )
    sns.histplot(x = dfbudgets[1]['roi'], bins = 50, ax=ax2, kde =True, color =base_color )
    sns.histplot(x = dfbudgets[2]['roi'], bins = 50, ax=ax3, kde =True, color =base_color )
```

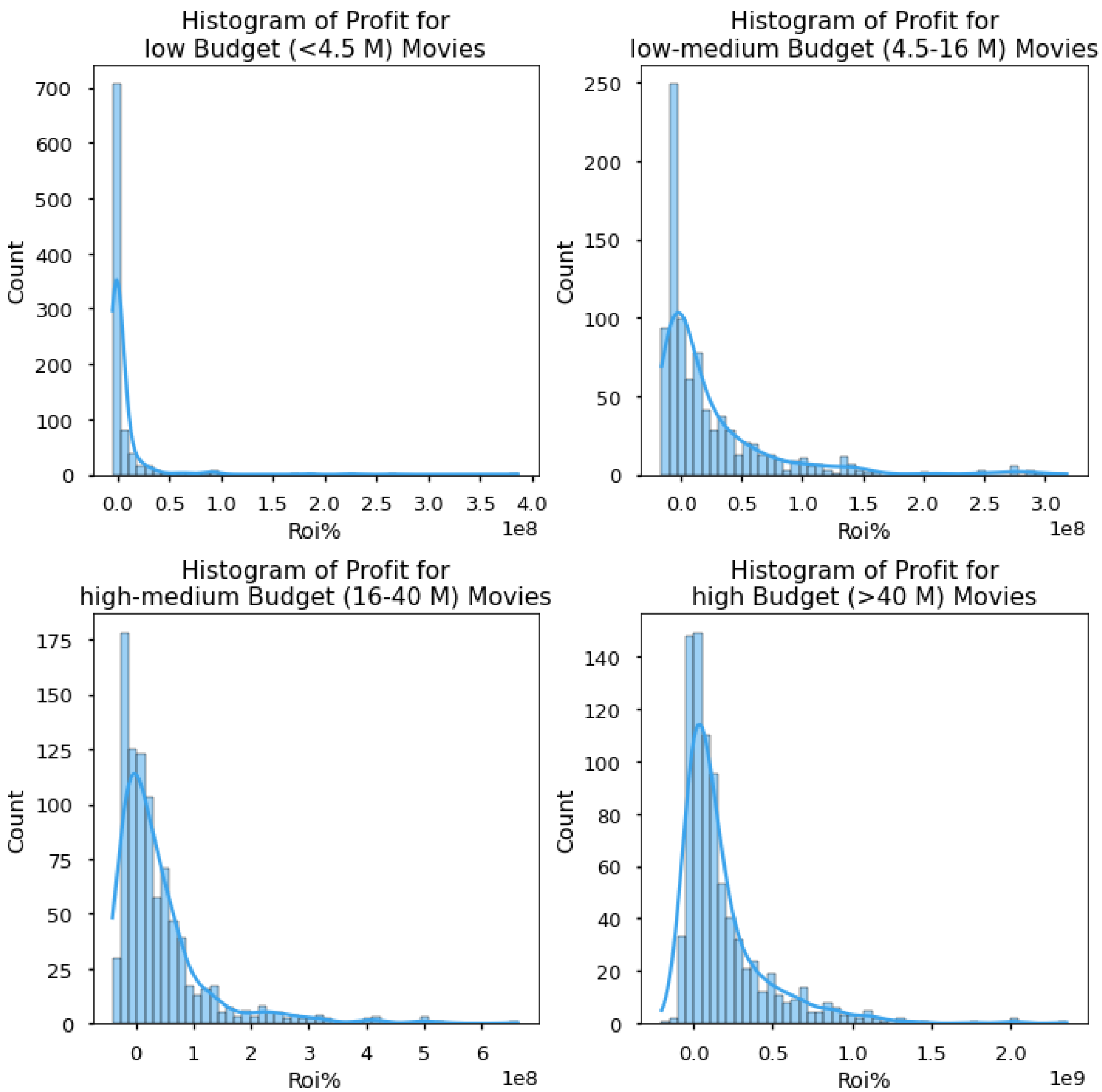
```
    sns.histplot(x = dfbudgets[3]['roi'], bins = 50, ax=ax4, kde =True, color␣
 ↪=base_color )

    ax1.set_title('Histogram of ROI for\nlow Budget (<4.5 M) Movies')
    ax2.set_title('Histogram of ROI for\nlow-medium Budget (4.5-16 M) Movies')
    ax3.set_title('Histogram of ROI for\nhigh-medium Budget (16-40 M) Movies')
    ax4.set_title('Histogram of ROI for\nhigh Budget (>40 M) Movies')

    ax1.xaxis.set_major_formatter(formatter)
    ax1.yaxis.set_major_locator(mpl.ticker.MultipleLocator(2000))
    ax1.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))

    ax1.set_xlabel("Roi%")
    ax2.set_xlabel("Roi%")
    ax3.set_xlabel("Roi%")
    ax4.set_xlabel("Roi%")

    fig.tight_layout();
# Roi distribution is still highly skewed for the low, low-medium and␣
 ↪high-medium
# It is less skewed for high budget movies.
```



[102]:

```
with plt.style.context('seaborn-talk'):
    fig, ( (ax1, ax2),(ax3, ax4) )  = plt.subplots(ncols=2, nrows= 2,␣
↪figsize=(10, 10))
    base_color = sns.color_palette("husl", 9)[6]

    sns.histplot(x = dfbudgets[0]['profit'], bins = 50, ax=ax1, kde =True,␣
↪color =base_color )
    sns.histplot(x = dfbudgets[1]['profit'], bins = 50, ax=ax2, kde =True,␣
↪color =base_color )
    sns.histplot(x = dfbudgets[2]['profit'], bins = 50, ax=ax3, kde =True,␣
↪color =base_color )
    sns.histplot(x = dfbudgets[3]['profit'], bins = 50, ax=ax4, kde =True,␣
↪color =base_color )
```

```
    ax1.set_title('Histogram of Profit for\nlow Budget (<4.5 M) Movies')
    ax2.set_title('Histogram of Profit for\nlow-medium Budget (4.5-16 M)␣
 ↪Movies')
    ax3.set_title('Histogram of Profit for\nhigh-medium Budget (16-40 M)␣
 ↪Movies')
    ax4.set_title('Histogram of Profit for\nhigh Budget (>40 M) Movies')

    ax1.set_xlabel("Roi%")
    ax2.set_xlabel("Roi%")
    ax3.set_xlabel("Roi%")
    ax4.set_xlabel("Roi%")

    fig.tight_layout();

# Profit distribution is highly skewed for the low and low-medium
# It is more normal for high-medium and high in comparison to ROI.
```



[103]:

```
# Create a table with mean/median/count values for roi and profit to use in␣
↪visualisations:
df_genre_table = df_genre.groupby('genres')[['profit', 'roi']].agg(['mean',␣
↪'median','count'])
df_genre_table.reset_index(inplace=True)
df_genre_table
```

[103]:

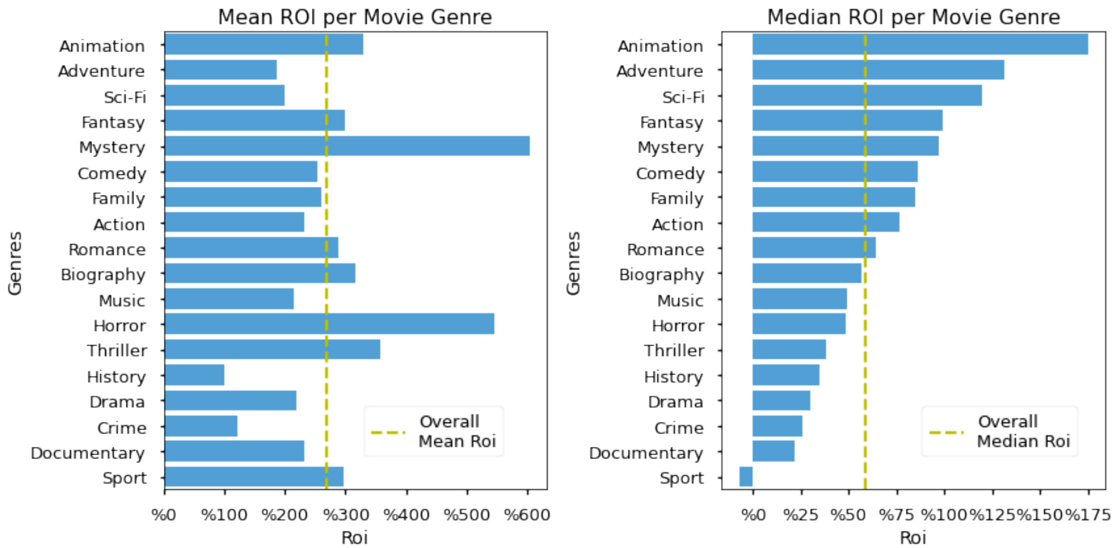
	genres	profit			roi		
		mean	median	count	mean	median	count
0	Action	1.204235e+08	28393687.0	655	231.529534	76.968172	655
1	Adventure	2.047587e+08	71306500.0	471	187.487157	131.278815	471
2	Animation	2.235153e+08	133691277.0	139	328.931906	175.320107	139
3	Biography	4.328547e+07	5910210.0	231	317.408067	56.871648	231

4	Comedy	6.889383e+07	14549338.0	839	253.673775	85.954617	839
5	Crime	3.779599e+07	2599159.0	395	122.835674	25.743070	395
6	Documentary	3.411517e+07	1495262.0	419	233.023250	21.545599	419
7	Drama	3.539827e+07	2511317.0	1691	218.409937	30.260742	1691
8	Family	9.632506e+07	18178226.0	178	259.756893	85.018198	178
9	Fantasy	1.419073e+08	28914614.0	178	298.520219	99.294160	178
10	History	3.693972e+07	4270222.5	86	99.815887	34.596546	86
11	Horror	4.513229e+07	4714370.0	399	545.536431	48.345155	399
12	Music	4.162830e+07	3339868.0	85	214.997588	49.166775	85
13	Mystery	5.134784e+07	14199690.0	238	602.710191	96.989125	238
14	Romance	3.391642e+07	5727536.0	359	288.314537	64.194725	359
15	Sci-Fi	1.652511e+08	24006658.5	224	199.494726	119.611842	224
16	Sport	4.484702e+07	-175000.0	71	297.346925	-7.119100	71
17	Thriller	4.884496e+07	2267819.0	570	356.910132	38.061217	570

[104]:

```python
df_genre_table = df_genre_table.sort_values([('roi','median')], ascending = False)
with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, ((ax1, ax2)) = plt.subplots(ncols=2, figsize=(12, 6))

    sns.barplot(x = df_genre_table['roi','mean'], y= df_genre_table['genres'], ax=ax1, color = base_color)
    sns.barplot(x = df_genre_table['roi','median'], y= df_genre_table['genres'], ax=ax2, color = base_color)

    # Add a line to show the overall mean or median roi values for all movies.
    mean_roi = round(df_genre['roi'].mean())
    median_roi = round(df_genre['roi'].median())

    ax1.axvline(x= mean_roi, ymin=0, ymax=1, color='y', linestyle='--', label = "Overall\nMean Roi")  #label = f"Overall Mean Roi= {mean_roi:,.0f}%"
    ax1.legend(bbox_to_anchor = (0.5, 0.2), loc = 'upper left')
    ax2.axvline(x= median_roi, ymin=0, ymax=1, color='y', linestyle='--', label= "Overall\nMedian Roi")
    ax2.legend(bbox_to_anchor = (0.5, 0.2), loc = 'upper left')

    ax1.xaxis.set_major_locator(mpl.ticker.MultipleLocator(100))
    ax1.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}')) # plt.yticks(rotation=25)
    ax2.xaxis.set_major_locator(mpl.ticker.MultipleLocator(25))
    ax2.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))

    ax1.set_title('Mean ROI per Movie Genre')
    ax2.set_title('Median ROI per Movie Genre')
    ax1.set_xlabel("Roi")
```

```
    ax2.set_xlabel("Roi")
    ax1.set_ylabel("Genres")
    ax2.set_ylabel("Genres")

    fig.tight_layout();
    fig.savefig('./images/Barplot_MeanMedian_Roi.png', dpi=300);
```

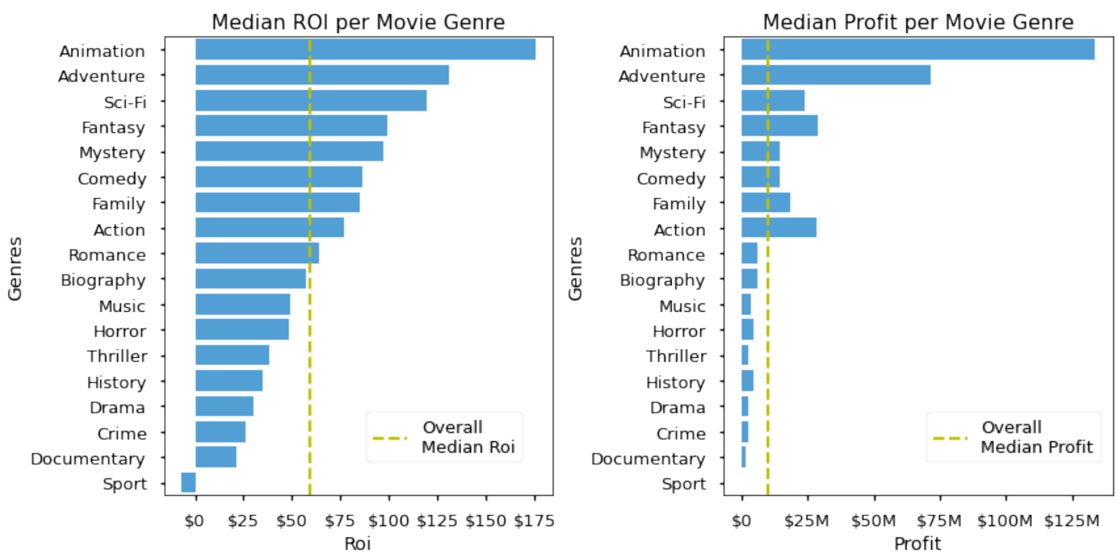


Should we rely on MEAN or MEDIAN?

- The discreancy on the mean versus median roi per genres stem from the outliers present. The value of the mean is distorted by the outliers.
- There are some really low budget but high profit and ROI movies especailly in the Horror and Mysery genres (think of Paranormal Activity or The Blair Witch Project). It would be hard to make a successful Animation or Sci-Fi movie on a low budget.
- We should rely on Median rather than mean since it would give us a more realistic and less risky approach. In reality more movies end up being unsuccessful.

[105]:
```
df_genre_table = df_genre_table.sort_values([('roi','median')], ascending =␣
↪False)

with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, ( (ax1, ax2)) = plt.subplots(ncols=2, figsize=(12, 6))

    sns.barplot(x = df_genre_table['roi','median'], y=␣
↪df_genre_table['genres'],  ax=ax1, color = base_color)
    sns.barplot(x = df_genre_table['profit','median'], y=␣
↪df_genre_table['genres'],  ax=ax2, color = base_color)
```

```
median_roi = round(df_genre['roi'].median())
median_profit = round(df_genre['profit'].median())

ax1.axvline(x= median_roi, ymin=0, ymax=1, color='y', linestyle='--', label␣
↪= "Overall\nMedian Roi")
ax1.legend(bbox_to_anchor = (0.5, 0.2), loc = 'upper left')
ax2.axvline(x= median_profit, ymin=0, ymax=1, color='y', linestyle='--',␣
↪label = "Overall\nMedian Profit")
ax2.legend(bbox_to_anchor = (0.5, 0.2), loc = 'upper left')

ax1.xaxis.set_major_formatter(formatter)
ax2.xaxis.set_major_formatter(formatter)
ax2.xaxis.set_major_locator(mpl.ticker.MultipleLocator(25000000)) # We want␣
↪the ticks a little farther apart

ax1.set_title('Median ROI per Movie Genre')
ax2.set_title('Median Profit per Movie Genre')

ax1.set_xlabel("Roi")
ax2.set_xlabel("Profit")
ax1.set_ylabel("Genres")
ax2.set_ylabel("Genres")

fig.tight_layout();
fig.savefig('./images/Barplot_Median_RoiProfit.png', dpi=300);
```



These graphs more or less overlap, so overall the most profitable two genres are **Animation and**

Adventure.

What **percentage of movies** belong to **high profit & high roi** category in each genre?

Let's also calculate the proportion of high profit & high roi movies in each genre to include into the above summary table:

[106]:
```
proportion_highprofitroi = ((df_genre[df_genre['roi_profit_bins']== '> 50% > 6.
↪6 M']\
                             .groupby('genres')['movie_id'].count())*100)\
                            /(df_genre.groupby('genres')['movie_id'].count())
```

[107]:
```
proportion_highprofitroi = pd.DataFrame(data = proportion_highprofitroi)
proportion_highprofitroi = proportion_highprofitroi.reset_index()
proportion_highprofitroi.rename(columns={'movie_id' : 'proportion'},␣
↪inplace=True)
proportion_highprofitroi.head()
```

[107]:

	genres	proportion
0	Action	53.587786
1	Adventure	64.543524
2	Animation	71.942446
3	Biography	48.051948
4	Comedy	53.277712

[108]:
```
# Adding the proportion array into the tabel with a new column named proportion
# You need to make sure index are the same between the two df.
df_genre_table['proportion'] = proportion_highprofitroi['proportion']
df_genre_table
```

[108]:

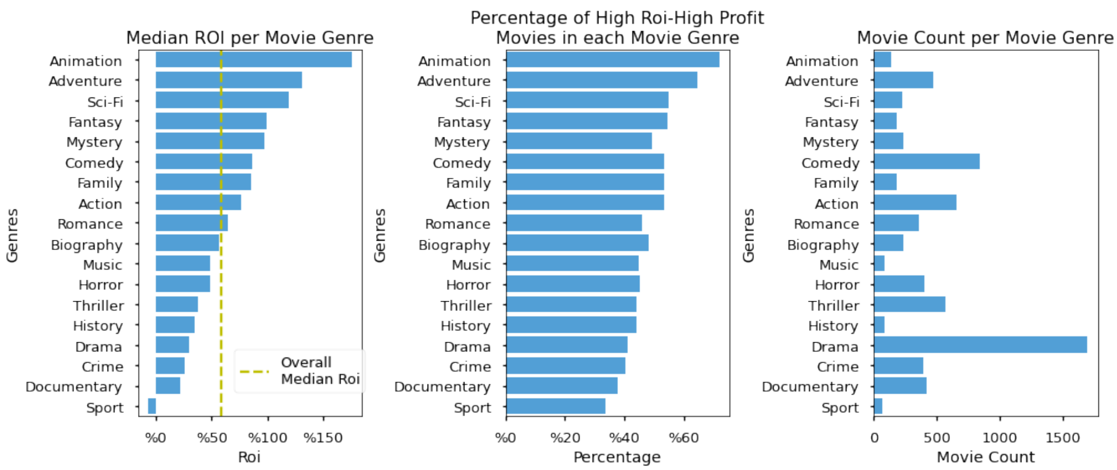
	genres	profit			roi		\
		mean	median	count	mean	median	
2	Animation	2.235153e+08	133691277.0	139	328.931906	175.320107	
1	Adventure	2.047587e+08	71306500.0	471	187.487157	131.278815	
15	Sci-Fi	1.652511e+08	24006658.5	224	199.494726	119.611842	
9	Fantasy	1.419073e+08	28914614.0	178	298.520219	99.294160	
13	Mystery	5.134784e+07	14199690.0	238	602.710191	96.989125	
4	Comedy	6.889383e+07	14549338.0	839	253.673775	85.954617	
8	Family	9.632506e+07	18178226.0	178	259.756893	85.018198	
0	Action	1.204235e+08	28393687.0	655	231.529534	76.968172	
14	Romance	3.391642e+07	5727536.0	359	288.314537	64.194725	
3	Biography	4.328547e+07	5910210.0	231	317.408067	56.871648	
12	Music	4.162830e+07	3339868.0	85	214.997588	49.166775	
11	Horror	4.513229e+07	4714370.0	399	545.536431	48.345155	
17	Thriller	4.884496e+07	2267819.0	570	356.910132	38.061217	
10	History	3.693972e+07	4270222.5	86	99.815887	34.596546	
7	Drama	3.539827e+07	2511317.0	1691	218.409937	30.260742	
5	Crime	3.779599e+07	2599159.0	395	122.835674	25.743070	

```
6   Documentary  3.411517e+07    1495262.0   419  233.023250   21.545599
16        Sport  4.484702e+07    -175000.0    71  297.346925   -7.119100

         proportion
   count
2    139  71.942446
1    471  64.543524
15   224  54.910714
9    178  54.494382
13   238  49.159664
4    839  53.277712
8    178  53.370787
0    655  53.587786
14   359  45.961003
3    231  48.051948
12    85  44.705882
11   399  45.363409
17   570  44.210526
10    86  44.186047
7   1691  41.277351
5    395  40.253165
6    419  37.708831
16    71  33.802817
```

[109]:

```python
df_genre_table = df_genre_table.sort_values([('roi','median')], ascending =␣
  ↪False)
with plt.style.context('seaborn-talk'):
    base_color = sns.color_palette("husl", 9)[6]
    fig, ( (ax1, ax2, ax3) ) = plt.subplots(ncols=3, figsize=(14, 6))

    sns.barplot(x = df_genre_table['roi','median'], y=␣
  ↪df_genre_table['genres'], ax=ax1, color = base_color)
    ax1.axvline(x= df_genre['roi'].median(), ymin=0, ymax=1, color='y',␣
  ↪linestyle='--', label = 'Overall\nMedian Roi')
    ax1.legend(bbox_to_anchor = (0.4, 0.2), loc = 'upper left')

    sns.barplot(x = df_genre_table['proportion'], y= df_genre_table['genres'],␣
  ↪ax=ax2, color = base_color)
    sns.barplot(x = df_genre_table['roi','count'], y= df_genre_table['genres'],␣
  ↪ ax=ax3, color = base_color)

    ax1.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))
    ax2.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))

    ax1.set_title('Median ROI per Movie Genre')
    ax2.set_title('Percentage of High Roi-High Profit\nMovies in each Movie␣
  ↪Genre')
```

```
    ax3.set_title('Movie Count per Movie Genre')

    ax1.set_xlabel("Roi")
    ax2.set_xlabel("Percentage")
    ax3.set_xlabel("Movie Count")

    ax1.set_ylabel("Genres")
    ax2.set_ylabel("Genres")
    ax3.set_ylabel("Genres")

    fig.tight_layout();
    fig.savefig('./images/Barplot_RoiMedianPropCount.png', dpi=300)
```



Overall the most common genre is **drama** however the most profitable genres are **Animation, Adventure, Sci-Fi, and Fantasy** based on ROI and percentage.

Let's make specific inferences for each **budget range** about which movie genres are more profitable?

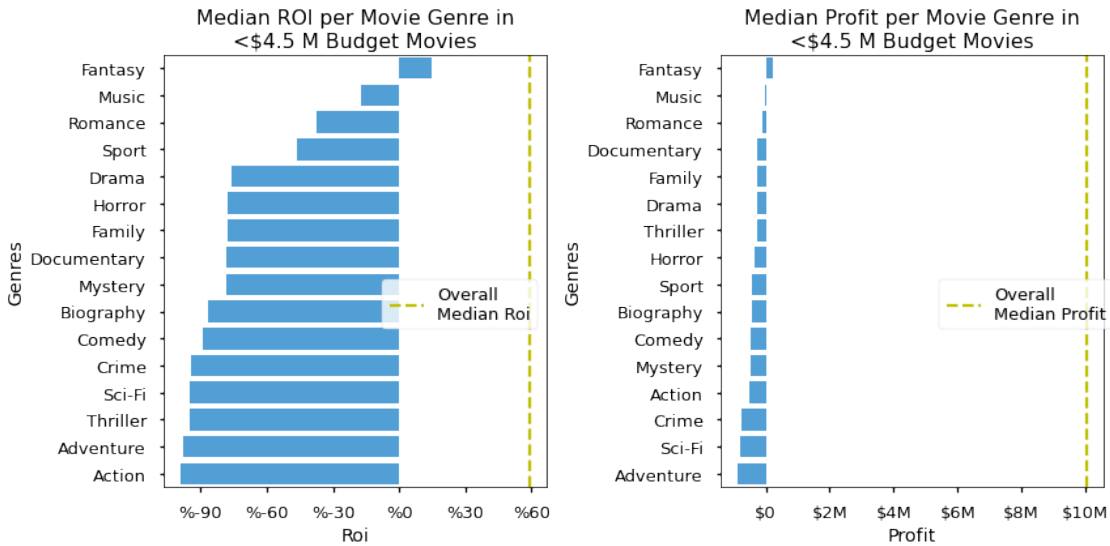
[110]:
```
# Define a function to create separate tables for a variable (e.g. roi) for␣
↪each bin of a different variable (e.g. budget):
def slicing(df_original, q, var):
    dfbudgets_tables = []
    for i in range(0,len(q)):
        dfnew = df_original[df_original['budget_bins'] == q[i]]
        dfnew = dfnew.groupby("genres").filter(lambda x: len(x) >= 20)
        dfnew = pd.DataFrame(dfnew.groupby('genres')[var].median()).
↪reset_index()
        dfbudgets_tables.append(dfnew)
    return dfbudgets_tables
```

[111]:
```
df_original = df_genre
q= ['$0-4.5 M','$4.5-16 M','$16-40 M','$40-425 M']
var = 'roi'
dfbudgets_tables_roi = slicing(df_original, q, var)

df_original = df_genre
q= ['$0-4.5 M','$4.5-16 M','$16-40 M','$40-425 M']
var = 'profit'
dfbudgets_tables_profit = slicing(df_original, q, var)

print(dfbudgets_tables_roi[0].head(2))
print(dfbudgets_tables_profit[3].head(2))
```

```
      genres        roi
0     Action -99.237486
1  Adventure -98.227900
      genres       profit
0     Action  136246291.5
1  Adventure  213500000.0
```

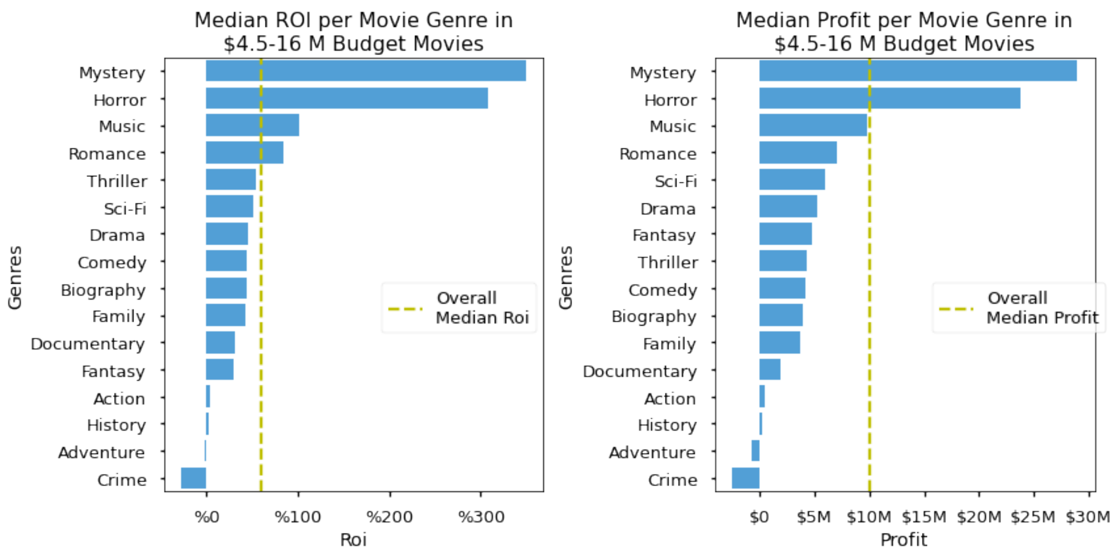
[112]:
```
dfbudgets_tables_roi[0] = dfbudgets_tables_roi[0].sort_values(by=('roi'),␣
↪ascending = False)
dfbudgets_tables_profit[0] = dfbudgets_tables_profit[0].
↪sort_values(by=('profit'), ascending = False)

with plt.style.context('seaborn-talk'):
    fig, ( (ax1, ax2))  = plt.subplots(ncols=2, figsize=(12, 6))
    base_color = sns.color_palette("husl", 9)[6]

    sns.barplot(data = dfbudgets_tables_roi[0], x = 'roi', y= 'genres', ax=ax1,␣
↪color = base_color)
    ax1.axvline(x= df_genre['roi'].median(), ymin=0, ymax=1, color='y',␣
↪linestyle='--', label = 'Overall\nMedian Roi')
    ax1.legend(bbox_to_anchor = (0.55, 0.5), loc = 'upper left')

    sns.barplot(data = dfbudgets_tables_profit[0], x = 'profit', y= 'genres',␣
↪ax=ax2, color = base_color)
    ax2.axvline(x= df_genre['profit'].median(), ymin=0,ymax=1, color='y',␣
↪linestyle='--', label = 'Overall\nMedian Profit')
    ax2.legend(bbox_to_anchor = (0.55, 0.5), loc = 'upper left')

    ax1.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))
    ax1.xaxis.set_major_locator(mpl.ticker.MultipleLocator(30)) # We want the␣
↪ticks a little farther apart
    ax2.xaxis.set_major_formatter(formatter)

    ax1.set_title('Median ROI per Movie Genre in\n<$4.5 M Budget Movies')
```

```
    ax2.set_title('Median Profit per Movie Genre in\n<$4.5 M Budget Movies')

    ax1.set_xlabel("Roi")
    ax2.set_xlabel("Profit")
    ax1.set_ylabel("Genres")
    ax2.set_ylabel("Genres")

    fig.tight_layout();
    fig.savefig('./images/Barplot_RoiProfitbyBudget_1.png', dpi=300);
```



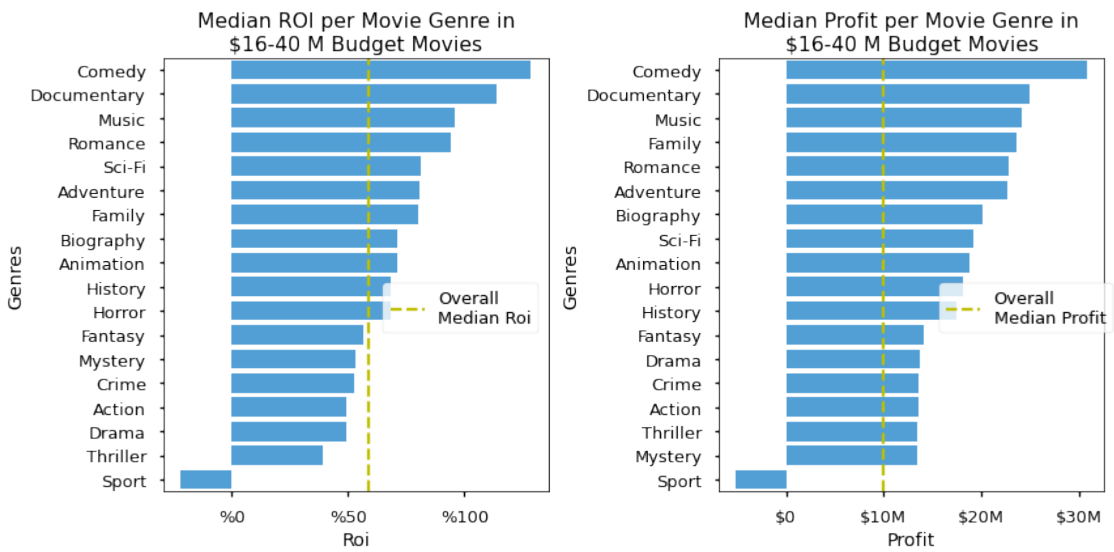
[113]:
```
dfbudgets_tables_roi[1] = dfbudgets_tables_roi[1].sort_values(by=('roi'),␣
↪ascending = False)
dfbudgets_tables_profit[1] = dfbudgets_tables_profit[1].
↪sort_values(by=('profit'), ascending = False)

with plt.style.context('seaborn-talk'):
    fig, ( (ax1, ax2))  = plt.subplots(ncols=2, figsize=(12, 6))
    base_color = sns.color_palette("husl", 9)[6]

    sns.barplot(data = dfbudgets_tables_roi[1], x = 'roi', y= 'genres', ax=ax1,␣
↪color = base_color)
    ax1.axvline(x= df_genre['roi'].median(), ymin=0, ymax=1, color='y',␣
↪linestyle='--', label = 'Overall\nMedian Roi')
    ax1.legend(bbox_to_anchor = (0.55, 0.5), loc = 'upper left')

    sns.barplot(data = dfbudgets_tables_profit[1], x = 'profit', y= 'genres',␣
↪ax=ax2, color = base_color)
```

```
    ax2.axvline(x= df_genre['profit'].median(), ymin=0,ymax=1, color='y',␣
↪linestyle='--', label = 'Overall\nMedian Profit')
    ax2.legend(bbox_to_anchor = (0.55, 0.5), loc = 'upper left')

    ax1.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))
    ax1.xaxis.set_major_locator(mpl.ticker.MultipleLocator(100)) # We want the␣
↪ticks a little farther apart
    ax2.xaxis.set_major_formatter(formatter)

    ax1.set_title('Median ROI per Movie Genre in\n$4.5-16 M Budget Movies')
    ax2.set_title('Median Profit per Movie Genre in\n$4.5-16 M Budget Movies')

    ax1.set_xlabel("Roi")
    ax2.set_xlabel("Profit")
    ax1.set_ylabel("Genres")
    ax2.set_ylabel("Genres")

    fig.tight_layout();
    fig.savefig('./images/Barplot_RoiProfitbyBudget_2.png', dpi=300);
```



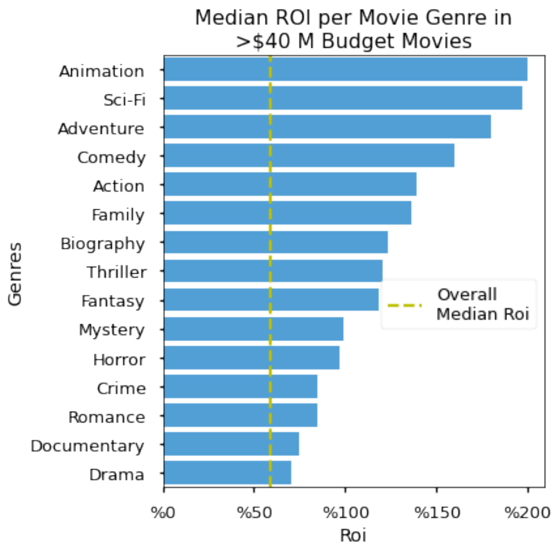
[114]:
```
dfbudgets_tables_roi[2] = dfbudgets_tables_roi[2].sort_values(by=('roi'),␣
↪ascending = False)
dfbudgets_tables_profit[2] = dfbudgets_tables_profit[2].
↪sort_values(by=('profit'), ascending = False)

with plt.style.context('seaborn-talk'):
    fig, ( (ax1, ax2))  = plt.subplots(ncols=2, figsize=(12, 6))
    base_color = sns.color_palette("husl", 9)[6]
```

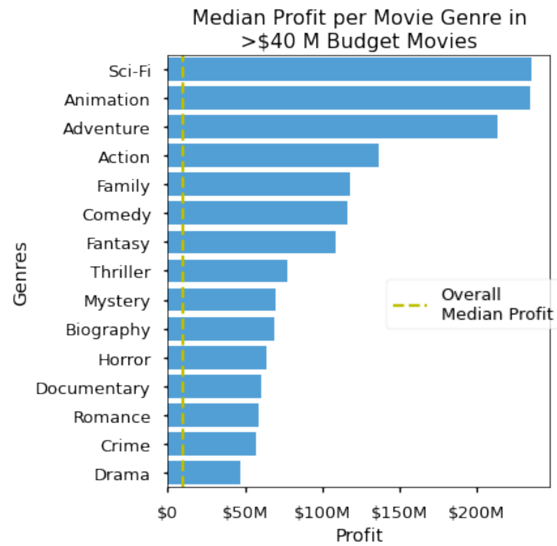
```
sns.barplot(data = dfbudgets_tables_roi[2], x = 'roi', y= 'genres', ax=ax1,␣
↪color = base_color)
ax1.axvline(x= df_genre['roi'].median(), ymin=0, ymax=1, color='y',␣
↪linestyle='--', label = 'Overall\nMedian Roi')
ax1.legend(bbox_to_anchor = (0.55, 0.5), loc = 'upper left')

sns.barplot(data = dfbudgets_tables_profit[2], x = 'profit', y= 'genres',␣
↪ax=ax2, color = base_color)
ax2.axvline(x= df_genre['profit'].median(), ymin=0,ymax=1, color='y',␣
↪linestyle='--', label = 'Overall\nMedian Profit')
ax2.legend(bbox_to_anchor = (0.55, 0.5), loc = 'upper left')

ax1.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))
ax1.xaxis.set_major_locator(mpl.ticker.MultipleLocator(50)) # We want the␣
↪ticks a little farther apart
ax2.xaxis.set_major_formatter(formatter)
ax2.xaxis.set_major_locator(mpl.ticker.MultipleLocator(10000000)) # We want␣
↪the ticks a little farther apart

ax1.set_title('Median ROI per Movie Genre in\n$16-40 M Budget Movies')
ax2.set_title('Median Profit per Movie Genre in\n$16-40 M Budget Movies')

ax1.set_xlabel("Roi")
ax2.set_xlabel("Profit")
ax1.set_ylabel("Genres")
ax2.set_ylabel("Genres")

fig.tight_layout();
fig.savefig('./images/Barplot_RoiProfitbyBudget_3.png', dpi=300);
```



[115]:

```
dfbudgets_tables_roi[3] = dfbudgets_tables_roi[3].sort_values(by=('roi'),␣
↪ascending = False)
dfbudgets_tables_profit[3] = dfbudgets_tables_profit[3].
↪sort_values(by=('profit'), ascending = False)

with plt.style.context('seaborn-talk'):
    fig, ( (ax1, ax2))  = plt.subplots(ncols=2, figsize=(12, 6))
    base_color = sns.color_palette("husl", 9)[6]

    sns.barplot(data = dfbudgets_tables_roi[3], x = 'roi', y= 'genres', ax=ax1,␣
↪color = base_color)
    ax1.axvline(x= df_genre['roi'].median(), ymin=0, ymax=1, color='y',␣
↪linestyle='--', label = 'Overall\nMedian Roi')
    ax1.legend(bbox_to_anchor = (0.55, 0.5), loc = 'upper left')

    sns.barplot(data = dfbudgets_tables_profit[3], x = 'profit', y= 'genres',␣
↪ax=ax2, color = base_color)
    ax2.axvline(x= df_genre['profit'].median(), ymin=0,ymax=1, color='y',␣
↪linestyle='--', label = 'Overall\nMedian Profit')
    ax2.legend(bbox_to_anchor = (0.55, 0.5), loc = 'upper left')

    ax1.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))
    ax1.xaxis.set_major_locator(mpl.ticker.MultipleLocator(50)) # We want the␣
↪ticks a little farther apart
    ax2.xaxis.set_major_formatter(formatter)
    #ax2.xaxis.set_major_locator(mpl.ticker.MultipleLocator(10000000)) # We␣
↪want the ticks a little farther apart

    ax1.set_title('Median ROI per Movie Genre in\n>$40 M Budget Movies')
    ax2.set_title('Median Profit per Movie Genre in\n>$40 M Budget Movies')

    ax1.set_xlabel("Roi")
    ax2.set_xlabel("Profit")
    ax1.set_ylabel("Genres")
    ax2.set_ylabel("Genres")

    fig.tight_layout();
    fig.savefig('./images/Barplot_RoiProfitbyBudget_4.png', dpi=300);
```





Above visualisations show that: - Low budget (<4.5 M) movies do not success in general. Avoid if possible. - 4.5-16 M budget range should invest on **Mystery and Horror** - for which the movies have a high chance of success with around 300% ROI or making a profit three times as much as the cost: about 20-25 M. - 16-40 M budget range can invest on **Comedy** and **Documentary** for about a litte over 100% ROI and 20-25 M profit. - High budget (>40 M) movies should invest on **Animation, Adventure, Sci-Fi** rather than Mystery and Horror. But the Return on investment for these higher budget movies are around 200% - profit is twice as much as the cost - less then what Mystery and Horror would bring in the 4.5-16 M range budget. However since the budget is high profit is also very high in these movies: around 200-250 M.

JUST FOR FUN: WHAT IS THE MOST PROFITABLE MOVIE OF ALL TIMES BASED ON ROI?

[116]:
```
df_genre['roi'].max()
```

[116]:
```
41556.473999999995
```

[117]:
```
df_genre[df_genre['roi'] == 41556.473999999995]
```

[117]:
```
        movie_id primary_title    genres  averagerating  production_budget  \
2277  tt2309260   The Gallows    Horror            4.2             100000
2277  tt2309260   The Gallows   Mystery            4.2             100000
2277  tt2309260   The Gallows  Thriller            4.2             100000

      domestic_gross  worldwide_gross release_year    profit        roi  \
2277        22764410         41656474         2015  41556474  41556.474
2277        22764410         41656474         2015  41556474  41556.474
2277        22764410         41656474         2015  41556474  41556.474

     roi_bins profit_bins roi_profit_bins budget_bins
```

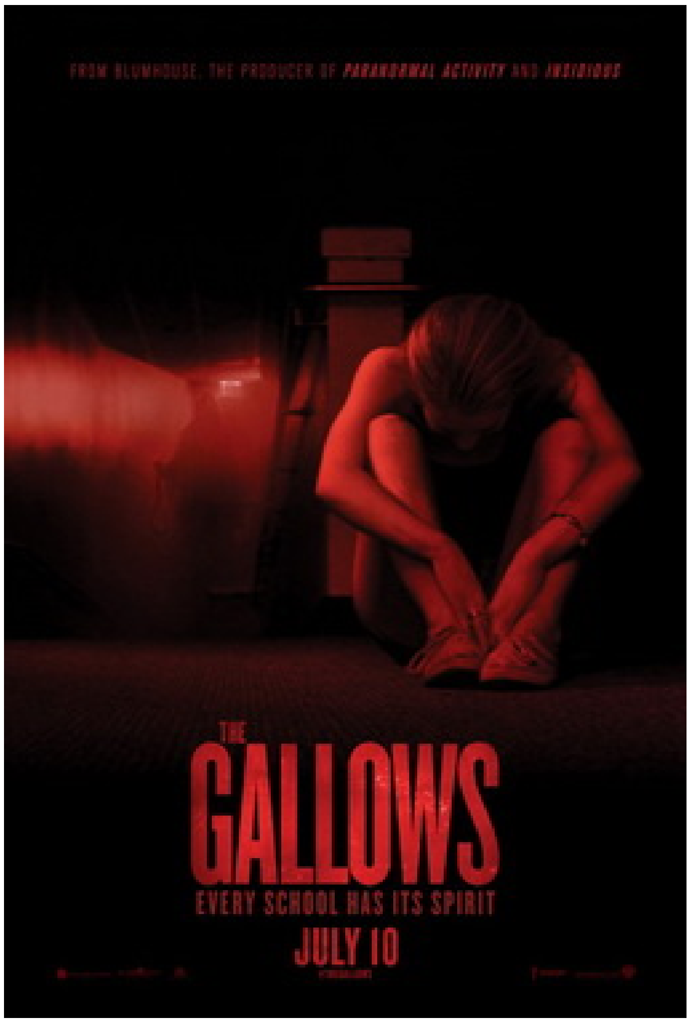
```
2277      > 50%      > 6.6 M    > 50% > 6.6 M     $0-4.5 M
2277      > 50%      > 6.6 M    > 50% > 6.6 M     $0-4.5 M
2277      > 50%      > 6.6 M    > 50% > 6.6 M     $0-4.5 M
```

From wikipedia:

"**The Gallows** was released in the United States by Warner Bros. Pictures and New Line Cinema on July 10, 2015. It was largely disliked by critics and audiences but grossed 43 million dollars worldwide against a 100,000 budget. A sequel, The Gallows Act II, was released in October 2019."

[118]:
```
Image(filename='images/The_Gallows_Poster.jpeg')
```

[118]:



IS THERE A LINK BETWEEN RATING AND ROI?

Can we use movie ratings as a way to assess profitability? Create two ROI bins: Below 0 range which makes zero profit, and over 0 range which makes some profit.

[119]:
```
df_rating_roi = master_clean_distinct.copy()
```

[120]:
```
df_rating_roi['roinegpos'] = pd.cut(df_rating_roi['roi'], bins = [-100, 0,␣
↪20000], labels=['neg', 'pos'])
```

[121]:
```
# Create dataframes for each bin:
dfroibins = []
df_original = df_rating_roi
q= ['neg',  'pos']
for i in range(0,len(q)):
    dfnew = df_original[df_original['roinegpos'] == q[i]]
    dfroibins.append(dfnew)
print(dfroibins[0].head(1))
print(dfroibins[1].head(1))
```

```
    movie_id primary_title  runtime_minutes                   genres  \
0  tt0249516     Foodfight             91.0  Action,Animation,Comedy

   averagerating  numvotes      director_name release_date  production_budget  \
0            1.9    8248.0  Lawrence Kasanoff   2012-12-31           45000000

   domestic_gross  worldwide_gross release_year    profit        roi roi_bins  \
0               0            73706         2012 -44926294 -99.836209    < 50%

  profit_bins roi_profit_bins budget_bins roinegpos
0     < 6.6 M   < 50% < 6.6 M   $40-425 M       neg
    movie_id  primary_title  runtime_minutes                     genres  \
1  tt0293429  Mortal Kombat              NaN  Action,Adventure,Fantasy

   averagerating  numvotes  director_name release_date  production_budget  \
1            NaN       NaN  Simon McQuoid   1995-08-18           20000000

   domestic_gross  worldwide_gross release_year     profit         roi  \
1        70433227        122133227         1995  102133227  510.666135

  roi_bins profit_bins roi_profit_bins budget_bins roinegpos
1    > 50%     > 6.6 M   > 50% > 6.6 M    $16-40 M       pos
```

[122]:
```
dfroibins[1] = dfroibins[1][dfroibins[1]['roi']<20000]
# removing 4 outliers from the high roi graph for visualization purposes.

with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2) = plt.subplots(ncols=2,  figsize=(12, 6))

    base_color = sns.color_palette("husl", 9)[5]
    sns.regplot(data=dfroibins[0], x='averagerating', y='roi', ax=ax1,␣
↪scatter_kws={'alpha':0.6}, color = base_color)
```

```
    sns.regplot(data=dfroibins[1], x='averagerating', y='roi', ax=ax2,␣
↪scatter_kws={'alpha':0.6}, color = base_color)

    ax1.yaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))
    ax2.yaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))

    ax1.set_title('Relationship between Roi and Rating\nin -Roi (no profit)␣
↪Movies')
    ax2.set_title('Relationship between Roi and Rating\nin +Roi (some profit)␣
↪Movies')

    ax1.set_xlabel("Average Rating")
    ax2.set_xlabel("Average Rating")

    ax1.set_ylabel("Roi")
    ax2.set_ylabel("Roi")

    fig.tight_layout();
    fig.savefig('./images/Scatterplot_RatingPerRoi.png', dpi=300);
```

- Ratings could be misleading for assessing movie success.
- Do NOT rely on ratings when assessing a movie's success especially if the movie is making some profit.

1.5.2 QUESTION 2: WHICH DIRECTORS SHOULD YOU WORK WITH?

[123]:
```
df_director = master_clean.copy()
```

[124]:
```
sum(df_director['director_name'].value_counts() == 1 )
# So many directors with just 1 movie. It would be risky to invest on a␣
↪director with just 1 movie.
# Let's not include these directors in the analysis.
```

[124]: 2772

[125]:
```
df_director_small = df_director.groupby('director_name').filter(lambda x:␣
↪len(x) > 3)
# get a subset of the dataset with only those directors with at least 3 movies.
```

[126]:
```
df_director_table = df_director_small.
↪groupby('director_name')[['roi','profit','production_budget']]\
                                                                        ␣
↪    .agg(['mean', 'count'])
df_director_table.reset_index(inplace=True)
df_director_table
```

[126]:
```
        director_name         roi              profit       production_budget  \
                             mean count          mean count              mean
0          Adam McKay  177.256963     4  7.729204e+07     4        59500000.0
1       Antoine Fuqua  167.896770     5  9.818346e+07     5        64400000.0
2   Baltasar Kormákur  179.176662     4  8.102353e+07     4        46500000.0
3         Brad Peyton  198.920731     5  1.851717e+08     5        79800000.0
4        Bryan Singer  501.838024     4  4.387683e+08     4       157000000.0
..                ...         ...   ...           ...   ...               ...
58        Tyler Perry  133.743819     4  2.840940e+07     4        21500000.0
59      V.K. Prakash  126.904153     4  1.772390e+07     4        27875000.0
60         Will Gluck  470.187467     4  1.379407e+08     4        39500000.0
61        Woody Allen  321.858939     4  7.237239e+07     4        21125000.0
62        Zack Snyder  124.386352     5  2.941840e+08     5       190000000.0


   count
0      4
1      5
2      4
3      5
4      4
..   ...
58     4
59     4
60     4
```

```
61      4
62      5

[63 rows x 7 columns]
```

[127]:
```
# Get a subset of the above table sorted from highest ROI, getting only the top␣
↪ten directors
df_director_top_roi = df_director_table.sort_values(by=[('roi','mean')],␣
↪ascending = False).head(10)
df_director_top_roi.reset_index(drop = True, inplace=True)
df_director_top_roi.head()
```

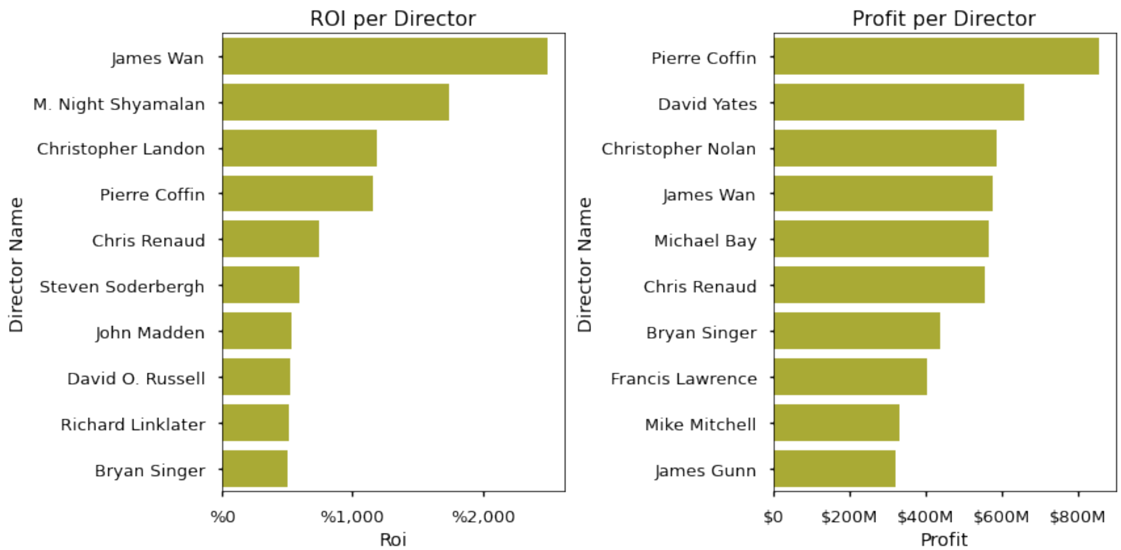
[127]:
```
        director_name          roi              profit          \
                              mean count          mean count
0           James Wan  2500.525402     5  5.737820e+08     5
1  M. Night Shyamalan  1737.194767     5  1.768319e+08     5
2  Christopher Landon  1183.776703     4  6.541237e+07     4
3       Pierre Coffin  1154.617179     4  8.549363e+08     4
4        Chris Renaud   748.708319     4  5.546959e+08     4

  production_budget
               mean count
0        75300000.0     5
1        62000000.0     5
2         8500000.0     4
3        73500000.0     4
4        75000000.0     4
```

[128]:
```
df_director_top_profit = df_director_table.sort_values(by=[('profit','mean')],␣
↪ascending = False).head(10)
df_director_top_profit.reset_index(drop = True, inplace=True)
df_director_top_profit.head()
```

[128]:
```
       director_name          roi              profit       production_budget  \
                             mean count          mean count              mean
0      Pierre Coffin  1154.617179     4  8.549363e+08     4        73500000.0
1        David Yates   461.484729     5  6.591299e+08     5       162000000.0
2  Christopher Nolan   313.408898     4  5.840451e+08     4       187500000.0
3          James Wan  2500.525402     5  5.737820e+08     5        75300000.0
4         Michael Bay   323.116010     4  5.659996e+08     4       162000000.0


  count
0     4
1     5
2     4
3     5
```

4 4

[129]:
```
with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12, 6))
    base_color = sns.color_palette()[8]

    sns.barplot(y= df_director_top_roi['director_name'], x=␣
↪df_director_top_roi['roi', 'mean'], color = base_color, ax=ax1)
    sns.barplot(y= df_director_top_profit['director_name'], x=␣
↪df_director_top_profit['profit', 'mean'],  color = base_color, ax=ax2)

    ax1.xaxis.set_major_locator(mpl.ticker.MultipleLocator(1000))
    ax1.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))
    ax2.xaxis.set_major_formatter(formatter)

    ax1.set_title('ROI per Director')
    ax2.set_title("Profit per Director")

    ax1.set_xlabel("Roi")
    ax2.set_xlabel("Profit")


    ax1.set_ylabel("Director Name")
    ax2.set_ylabel("Director Name")

    fig.tight_layout();
    fig.savefig('./images/Barplot_Directors.png', dpi=300);
```



[130]:
```
def commonnames(list1, list2):
    commonlist = []
    for name in list1:
        if name in list2:
            commonlist.append(name)
    return commonlist
```

[131]:
```
list1 = list(df_director_top_roi['director_name'])
list2 = list(df_director_top_profit['director_name'])
commonnames(list1, list2)
```

[131]:
```
['James Wan', 'Pierre Coffin', 'Chris Renaud', 'Bryan Singer']
```

4 Common Names between the top 10 directors with highest roi and profit - you can invest on these names with trust: **- James Wan - Pierre Coffin - Chris Renaud - Bryan Singer**

For at least 1000% ROI invest on: **- James Wan - M. Night Shayamalan - Christopher Landon - Pierre Coffin**

For at least 550 M profit invest on: **- Pierre Coffin - David Yates - Christopher Nolan - James Wan**

1.5.3 QUESTION 3: WHICH MONTHS ARE THE BEST TO RELEASE A MOVIE?

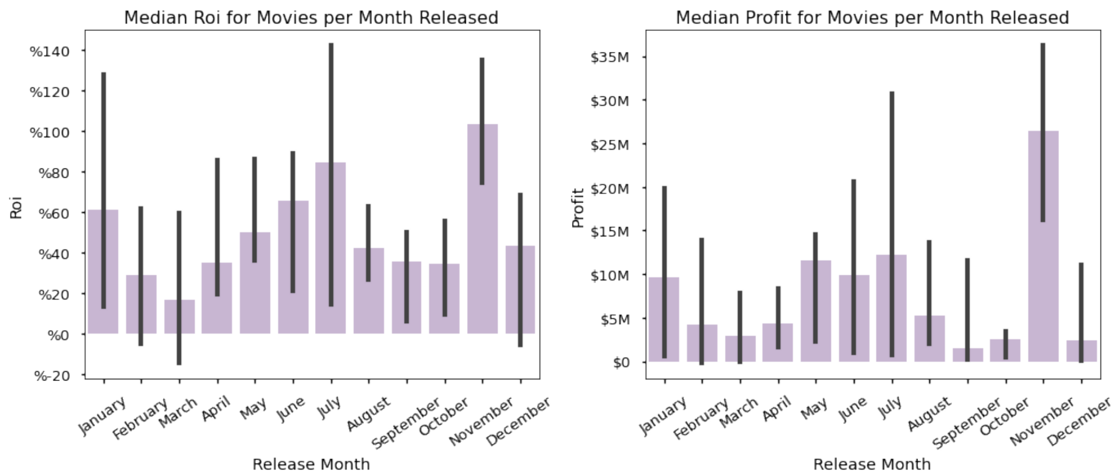
[132]:
```
df_months = master_clean_distinct.copy()
```

[133]:
```
# Extract a new column called release month using the release date.
df_months['release_month'] =  pd.to_datetime(df_months['release_date']).dt.month
```

[134]:
```
# Order the months so they appear in order from January to December:
df_months.sort_values(by='release_month', inplace=True)
```

[135]:
```
with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2) = plt.subplots(figsize=(14,6), ncols=2)
    base_color = sns.color_palette("Paired")[8]

    sns.barplot(data=df_months, x='release_month', y='roi', estimator= np.
 ↪median, ax=ax1,  color = base_color)
    sns.barplot(data=df_months, x='release_month', y='profit', estimator= np.
 ↪median, ax=ax2, color = base_color)

    ax1.set_xticklabels(labels =␣
 ↪['January','February','March','April','May','June',\
                                        ␣
 ↪'July','August','September','October','November','December']\
                                        ,rotation=35)
```

```
ax2.set_xticklabels(labels =␣
↪['January','February','March','April','May','June',\
                                      ␣
↪'July','August','September','October','November','December']\
                                      ,rotation=35)

ax1.yaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))
ax2.yaxis.set_major_formatter(formatter)

ax1.set_title('Median Roi for Movies per Month Released')
ax2.set_title('Median Profit for Movies per Month Released')

ax1.set_xlabel("Release Month")
ax2.set_xlabel("Release Month")

ax1.set_ylabel("Roi")
ax2.set_ylabel("Profit")

fig.tight_layout();
fig.savefig('./images/Barplot_ReleaseMonth.png', dpi=300);
```



- High returns on investment as well as profit occur mostly in the month of **November**. This is the safest month to release a movie due to its lower confidence interval as well. People probably go to more movies in the month of November right before the holiday season kicks in and the temperatures start to drop significantly (in the northern hemisphere).

- Interestingly there is a sharp ***decline*** in ***December*** probably due to the busyness of the holiday season. But **January** - end of holiday season - sees a modest increase again in Roi and Profit.
- **June and July** is also high in ROI and high in profit. With the high temperatures and the

schools being closed people again might be going to the movies more than usual.

1.5.4 QUESTION 4: WHAT IS A GOOD LENGTH TO AIM FOR A MOVIE?

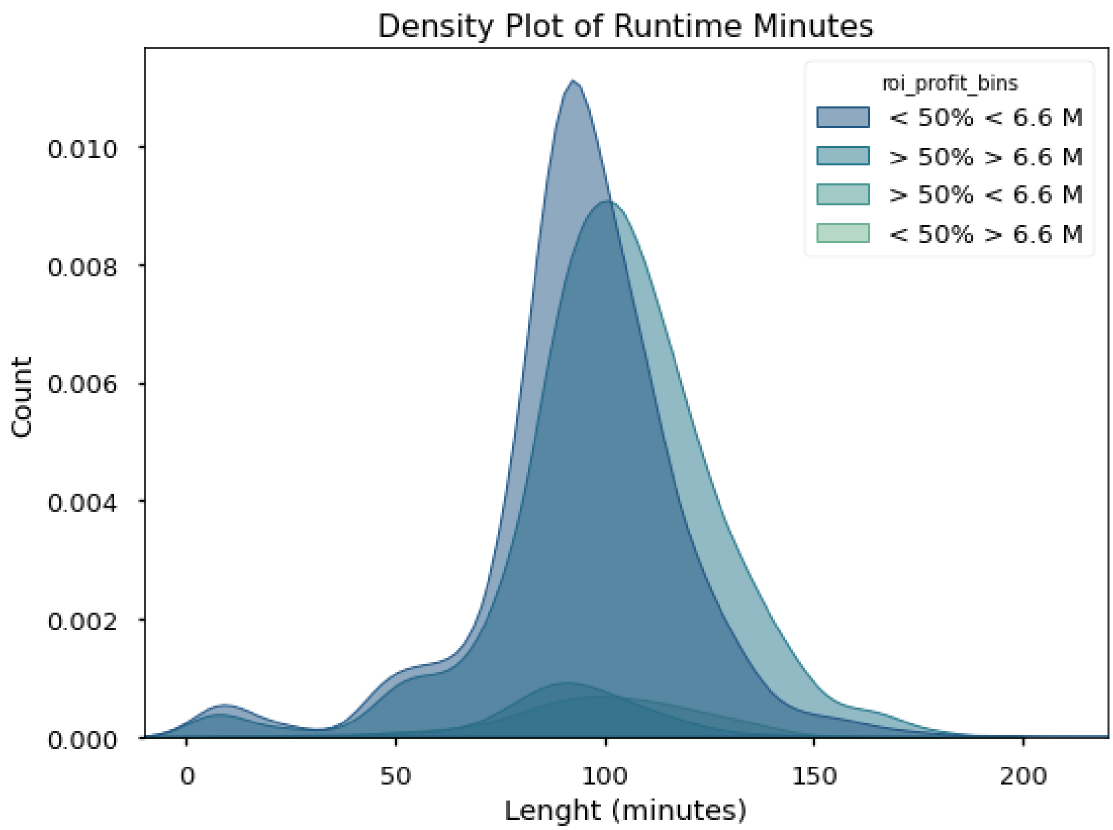
[136]:
```
df_length = master_clean_distinct.copy()
```

[137]:
```
df_length.head()
```

[137]:
```
    movie_id  primary_title  runtime_minutes                    genres  \
0  tt0249516      Foodfight             91.0    Action,Animation,Comedy
1  tt0293429  Mortal Kombat              NaN   Action,Adventure,Fantasy
2  tt0326592  The Overnight             88.0                       None
3  tt3844362  The Overnight             79.0             Comedy,Mystery
4  tt0337692    On the Road            124.0    Adventure,Drama,Romance

   averagerating  numvotes      director_name release_date  production_budget  \
0            1.9    8248.0  Lawrence Kasanoff   2012-12-31           45000000
1            NaN       NaN      Simon McQuoid   1995-08-18           20000000
2            7.5      24.0     Jed I. Goodman   2015-06-19             200000
3            6.1   14828.0      Patrick Brice   2015-06-19             200000
4            6.1   37886.0      Walter Salles   2013-03-22           25000000

   domestic_gross  worldwide_gross release_year     profit         roi  \
0               0            73706         2012  -44926294  -99.836209
1        70433227        122133227         1995  102133227  510.666135
2         1109808          1165996         2015     965996  482.998000
3         1109808          1165996         2015     965996  482.998000
4          720828          9313302         2013  -15686698  -62.746792

  roi_bins profit_bins roi_profit_bins budget_bins
0    < 50%     < 6.6 M   < 50% < 6.6 M   $40-425 M
1    > 50%     > 6.6 M   > 50% > 6.6 M    $16-40 M
2    > 50%     < 6.6 M   > 50% < 6.6 M    $0-4.5 M
3    > 50%     < 6.6 M   > 50% < 6.6 M    $0-4.5 M
4    < 50%     < 6.6 M   < 50% < 6.6 M    $16-40 M
```

[138]:
```
# A kernel density estimate (KDE) plot is a method for visualizing the␣
↪distribution of observations in a dataset, analagous to a histogram. KDE␣
↪represents the data using a continuous probability density curve in one or␣
↪more dimensions.
# https://seaborn.pydata.org/generated/seaborn.kdeplot.html

with plt.style.context('seaborn-talk'):
    fig, ax1  = plt.subplots(figsize=(8, 6))
    sns.kdeplot(data = df_length , x = 'runtime_minutes', hue=␣
↪'roi_profit_bins', ax=ax1,\
                fill=True, alpha=.5, palette="crest_r", linewidth=1)
```

```
    ax1.set_title('Density Plot of Runtime Minutes')
    ax1.set_xlabel("Lenght (minutes)")
    ax1.set_ylabel("Count")
    ax1.set_xlim(-10,220)

    fig.tight_layout();
    fig.savefig('./images/kdeplot_RuntimeMinutes.png', dpi=300);
```



[139]:
```
df_length.groupby('roi_profit_bins')['runtime_minutes'].mean()
```

[139]:
```
roi_profit_bins
< 50% < 6.6 M     94.726182
< 50% > 6.6 M     99.703125
> 50% < 6.6 M     91.801587
> 50% > 6.6 M    102.435237
Name: runtime_minutes, dtype: float64
```

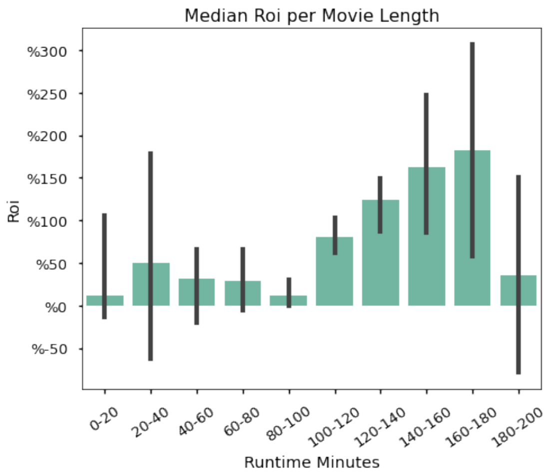
- There is not a strong effect of runtime minutes.
- But higher roi and higher profit movies tend to be slightly longer compared to low roi - low profit movies on average.
- On average a movie in the high roi - high profit bin is **102 minutes** (approximately, 1 hour

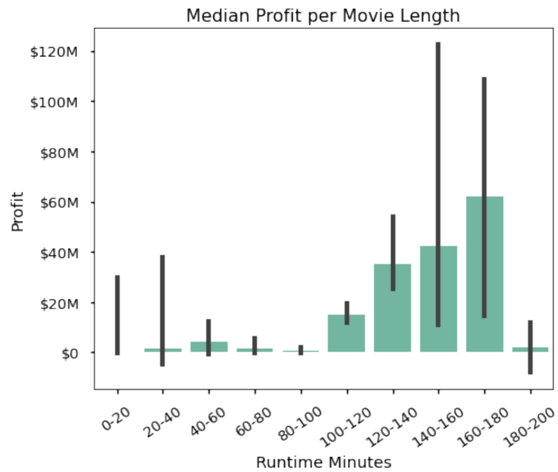
40 minutes) long.

- Let's convert `runtime_minutes` into a categorical variable by binning it.
- Let's limit it at 200 minutes to avoid outliers.

[140]:
```
df_length['runtime_bins'] = pd.cut(df_length['runtime_minutes'],\
                                   bins=list(range(0, 220, 20)),\
 ↪labels=['0-20','20-40','40-60','60-80','80-100',\
 ↪'100-120','120-140','140-160','160-180','180-200'])
```

[141]:
```
with plt.style.context('seaborn-talk'):
    fig,(ax1, ax2) = plt.subplots(figsize=(14,6), ncols=2)
    base_color = sns.color_palette("Set2")[0]
    sns.barplot(data=df_length, x='runtime_bins', y='roi', estimator = np.
 ↪median, ci=95, color = base_color, ax=ax1)
    sns.barplot(data=df_length, x='runtime_bins', y='profit', estimator = np.
 ↪median, ci=95, color = base_color, ax=ax2)

    ax1.yaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('%{x:,.0f}'))
    ax2.yaxis.set_major_formatter(formatter)

    ax1.set_xticklabels(ax1.get_xticklabels(),rotation=35)
    ax2.set_xticklabels(ax2.get_xticklabels(), rotation=35)

    ax1.set_title('Median Roi per Movie Length')
    ax2.set_title('Median Profit per Movie Length')

    ax1.set_xlabel('Runtime Minutes')
    ax2.set_xlabel('Runtime Minutes')

    ax1.set_ylabel('Roi')
    ax2.set_ylabel('Profit')

    fig.tight_layout();
    fig.savefig('./images/Barplot_RuntimeMinutes.png', dpi=300);

# The 95% confidence interval is a range of values that you can be 95%
 ↪confident contains the true mean of the population.
```





- If we focus on roi the least risky lenght interval which would maximize roi is **120-160 min**.
- 160-180 has the potential to bring more roi but it also has the risks of bringing less roi.
- If we focus on profit the least risky lenght interval which would maximaxize profit is **120-140 min**.
- 140-180 has the potential to bring more profit but it also has the risks of bringing less profit.

OVERALL: For the most profit and ROI, target **120-140 min** movie lenght. This is a little over 2 hours.

1.6 Evaluation

There are many reasons why a specific movie becomes successful and there is not one specific recipe. Here I focused on Return on Investment and Profit as means to assess movie profitability.

1.7 Conclusions

Which genre is most profitable?:

- For lower budget movies focus on:
  - **HORROR**
  - **MYSTERY** which can bring a high Return on Invesment.
- For high budget movies focus on:
  - **ANIMATION**
  - **ADVENTURE**
  - **SCI_FI** which can bring a high cash value (profit).

Which directors are most profitable?: For the highest roi and profit, you can invest on these names with trust: - **James Wan** - **Pierre Coffin** - **Chris Renaud** - **Bryan Singer**

Which months are the best to release a movie?:

- Best month to release is: **NOVEMBER**
- If November window is missed then wait until **January** to release. Do **NOT** release in December.
- **June and July** are next best options.

Which movie length should be targeted?

- For the most profit and ROI, target **120-140 min** movie lenght. This is a little over 2 hours.

1.8 Limitations

- Small sample size - due to lack of budget and gross information. API calls or wed scraping?
- Challenging merging: Movie names not coded the same way in different dataset.
- Lots of outlier movies making the statistical analyses more challenging.
- Need more information about Microsoft's allocated budget to be able to make more budget specific suggestions. ***