student

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Final Project Submission

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- Blog post URL:

1 Overview

A handful of companies have defined the Hollywood film industry, dominating the US and world markets. They have weathered a world war, and a Great Depression and few moderate ones, innovated wide screen and color technologies, made peace with television, learned to exploit home video and online streaming, and are more powerful than ever before.

Most big corporations are already in this business or exploring feasibility of entry. Most of the major corporations operating only in this industry are thriving.

2 Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies.

I am going to try to figure out what types of films are currently performing better at the box office. I shall recommend some actionable insights based on findings of this analysis, which the head of Microsoft's new movie studio can use to help decide what type of films to create.

Areas of focus:

```
* movie genres.
* probability of success based on seasonality of releases.
* profitability of movie franchise/film series.
```

3 The imports

3.1 Packages and Libraries

[1]:
```
# for web scraping and API calls
from selenium import webdriver
from selenium.webdriver.common.keys import Keys
from selenium.webdriver.support import expected_conditions as EC
from selenium.webdriver.common.by import By
from selenium.webdriver.support.wait import WebDriverWait
import os
import wget
import tmdbsimple as tmdb
```

[2]:
```
# for other parts
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import json
import requests
import time
from pandas.core.common import flatten
from pandasql import sqldf
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import re
import ast
```

[3]:
```
# styling (jupyter-themes must be installed)
## https://github.com/dunovank/jupyter-themes
from jupyterthemes import jtplot
# jt -r # default
jtplot.style(theme='monokai', context='notebook', ticks='True', grid='False')

# jt -t monokai -fs 120 -tfs 120 -nfs 115 -cellw 85% -T -N -kl # my setup
```

[4]:
```
# to see dataframe better
pd.set_option('display.max_columns', 50)
```

3.2 Frequently used fuctions

[5]:
```
# Number formatter
def format_number(data_value, index):
    if data_value >= 1_000_000_000:
        formatter = '${:1.1f}B'.format(data_value*0.000_000_001)
    elif data_value >= 1_000_000:
```

```python
        formatter = '${:1.0f}M'.format(data_value*0.000_001)
    else:
        formatter = '${:1.0f}K'.format(data_value*0.001)
    return formatter
```

[6]:
```python
# % formatter
def format_add_percentage(data_value, index):
    formatter = '{:.0f}%'.format(data_value)
    return formatter
```

[7]:
```python
def correlation_top_bottom(df):
    corr_df_matrix_ = df.unstack().reset_index()
    corr_df_matrix_.columns = ["feature_0", 'feature_1', 'correlation']
    corr_df_matrix_['keep'] = corr_df_matrix_.apply(
        lambda x: False if x['feature_0'] == x['feature_1'] else True, axis=1)
    corr_df_matrix_['feature_combo'] = corr_df_matrix_.apply(
        lambda x: ' and '.join(set(x[['feature_0', 'feature_1']])), axis=1)
    corr_featurs = corr_df_matrix_[corr_df_matrix_.keep][[
        'feature_combo', 'correlation'
    ]].drop_duplicates().sort_values(by='correlation', ascending=False)
    print(
        f'Positive correlations:\n\
        {corr_featurs.head(10).reset_index()}\n\n {"-"*70}\n\
        Negative correlations:\n\
        {corr_featurs.sort_values(by="correlation").head(10).reset_index()}'
    )
```

3.3 API and Scraping control

Set this to `True` to perform scraping and API

```python
initialize_scraping_and_API = True
```

[8]:
```python
initialize_scraping_and_API = False
```

4 The Data

- IMDb or Internet Movie Database was Originally a fan-operated website, now owned and operated by IMDb.com, Inc., a subsidiary of Amazon. This is one of the most reliable sourec for any information related movies in general. It is one of the most comprehensive dataset.
- Box Office Mojo is also a part of IMDb.com, Inc., providing indepth financial informations among other metrics.
- TMDb is a reliable source for movie related information. This is a popular user editable database for movies and TV shows.

Those three were used for sourcing data for the project as those are highly reliable sources without going for any paid service for information.

Data is collected from IMDB website from downloadables, and scraping using selenium . Additional data collected from TMDb using API. Then all of them are merged to create 'main_df', upon which this following analysis is performed.

4.1 From IMDb

4.1.1 Dataset from website

File containing detailed movie info inside title.basics.tsv.gz was downloaded from `https://datasets.imdbws.com/title.basics.tsv.gz`

4.1.2 Scraping using selenium

`pip install selenium`

Download webdriver from here.

[9]:
```
%%time
if initialize_scraping_and_API is True:
    # initializing webdriver
    driver = webdriver.Chrome('C:/Users/tamji/Documents/PATH/chromedriver.exe')
    # connection to webpage
    base_url_string = 'https://www.boxofficemojo.com/year/world/'
    # selecting years to get
    list_of_year = np.arange(2014, 2022, 1)
    # initializing scraping
    print(f'+' * 100)
    # temp files
    file_names_ = []
    file_names_error = []
    # scraping
    for im in list_of_year:
        print(f'Working on: {im}')
        url = f'{base_url_string}{im}/'
        print(f'Getting {im} homepage')
        driver.get(url)
        table = driver.find_element_by_xpath('//*[@id="table"]/div/table[2]')
        item_href = driver.find_elements_by_class_name('a-link-normal')
        print(f'Getting {im} list items')
        item_href = [item.get_property('href') for item in item_href]
        print(f'Sorting what to keep from {im} list items')
        # filter results to target needed links
        text_to_check = 'releasegroup'
        to_keep = []
        to_discard = []
        for i in item_href:
            if text_to_check in i:
                to_keep.append(i)
            else:
```

```
                to_discard.append(i)
        print(f'Preping {im} list items for looping')
        href = to_keep # [:2] is for testing, remove this to get full data
        master_list = []
        error = []
        print(f'{im} list items are looping. Hang in there!')
        for item in href:
            try:
                driver.get(item)
                url = driver.find_element_by_xpath(
                    '//*[@id="title-summary-refiner"]/a').get_property('href')
                name = driver.find_element_by_xpath(
                    '//*[@id="a-page"]/main/div/div[1]/div[1]/div/div/div[2]/h1'
                ).text

                driver.get(url)
                year = driver.find_element_by_xpath(
                    '//*[@id="a-page"]/main/div/div[1]/div[1]/div/div/div[2]/
↪div/h1/span'
                ).text
                worldwide = driver.find_element_by_xpath(
                    '//*[@id="a-page"]/main/div/div[3]/div[1]/div/div[3]/
↪span[2]/span'
                ).text
                international = driver.find_element_by_xpath(
                    '//*[@id="a-page"]/main/div/div[3]/div[1]/div/div[2]/
↪span[2]'
                ).text
                domestic = driver.find_element_by_xpath(
                    '//*[@id="a-page"]/main/div/div[3]/div[1]/div/div[1]/
↪span[2]'
                ).text

                year_cleaned = year.strip('()')
                world_collection = worldwide[1:].replace(",", "")
                international_collection = international[1:].replace(",", "")
                domestic_collection = domestic[1:].replace(",", "")
                imdb_code = url.split('/')[4]

                temp_dict = {
                    'imdb_code': imdb_code,
                    'name': name,
                    'year': year_cleaned,
                    'world_collection': world_collection,
                    'int_collection': international_collection,
                    'dom_collection': domestic_collection,
                    'url': url
```

```
                }
                master_list.append(temp_dict)
            except:
                error.append(item)
                continue

        df = pd.DataFrame(master_list)
        file_name_df = f'{im}.csv'
        df.to_csv(file_name_df, index=False)
        dict_ = {'urls': error}
        file_name_error = f'{im}_error.csv'
        pd.DataFrame(dict_).to_csv(file_name_error, index=False)
        file_names_.append(file_name_df)
        file_names_error.append(file_name_error)
        print(f'Finished working on {im}\n')
        print(f'+' * 100)
    print(f'\n\n\nDONE Looping. Cleanig data!!!')

    combined_csv_data = pd.concat([pd.read_csv(f) for f in file_names_])
    combined_csv_data_error = pd.concat(
        [pd.read_csv(f) for f in file_names_error])

    combined_csv_data.reset_index(inplace=True)
    combined_csv_data_error.reset_index(inplace=True)

    combined_csv_data = combined_csv_data.drop(columns='index')
    combined_csv_data_error = combined_csv_data_error.drop(columns='index')

    combined_csv_data = combined_csv_data.drop_duplicates('imdb_code',
                                                          ignore_index=True)

    file_name_1 = f'{list_of_year[0]}to{list_of_year[-1]}.csv'
    file_name_2 = f'{list_of_year[0]}to{list_of_year[-1]}_error.csv'
    combined_csv_data.to_csv(file_name_1, index=False)
    combined_csv_data_error.to_csv(file_name_2, index=False)

    print(f'\n\n\nDONE!!!')
    print(f'+' * 100)
    print(f'+' * 100)
# leaves temp files behind
```

```
Wall time: 0 ns
```

[10]:

```
# moving major files
if initialize_scraping_and_API is True:
    destination_1 = f'./Data/bom_{file_name_1}'
    destination_2 = f'./Data/temp/{file_name_2}'
```

```
    os.rename(file_name_1,destination_1)
    os.rename(file_name_2,destination_2)
```

[11]:
```
def move_files(file):
    destination = f'./Data/temp/{file}'
    os.rename(file,destination)
```

[12]:
```
# moving temp files
if initialize_scraping_and_API is True:
    if True:
        [move_files(f) for f in file_names_]
        [move_files(f) for f in file_names_error]
        print('Done moving!!')
```

Note: ***repo does not include temp files***

4.2 From TMDb API

[13]:
```
# load json
if initialize_scraping_and_API is True:
    def get_keys(path):
        with open(path) as f:
            return json.load(f)
```

[14]:
```
# api key initialize
if initialize_scraping_and_API is True:
    keys = get_keys("/Users/tamji/.secret/tmdb_api.json")
    api_key = keys['api_key']
```

[15]:
```
if initialize_scraping_and_API is True:
    tmdb.API_KEY = api_key
```

[16]:
```
# movie_main_df_sliced is cleaned beforehand
if initialize_scraping_and_API is True:
    # for matching imdb titles
    movie_titles_df = pd.read_csv(r'./Data/movie_main_df_sliced.csv',
                                  usecols=["tconst"])
```

[17]:
```
# preparing loaded data for use
if initialize_scraping_and_API is True:
    imdb_titles = list(flatten(movie_titles_df.values.tolist()))
```

[18]:
```
# get how much data is incoming
if initialize_scraping_and_API is True:
    len(imdb_titles)
```

[19]:
```
# empty df to store results
if initialize_scraping_and_API is True:
```

```
    df = pd.DataFrame()
```

[20]:
```
if initialize_scraping_and_API is True:
    for imdb_id in imdb_titles:
        try:
            movie = tmdb.Movies(imdb_id)
            response = movie.info()
            df = df.append(pd.json_normalize(movie.info()))
        except:
            pass
```

[21]:
```
if initialize_scraping_and_API is True:
    df = df.reset_index()
```

[22]:
```
if initialize_scraping_and_API is True:
    df = df.drop(columns=['index'])
```

[23]:
```
if initialize_scraping_and_API is True:
    df.to_csv(r'./Data/tmdb_parsd.csv')
```

5 Preparing datasets

5.1 IMDb

5.1.1 loading

[24]:
```
%%time
df_1 = pd.read_csv(r'./Data/data.tsv',
                   delimiter='\t',
                   low_memory=False)
```

```
Wall time: 17.7 s
```

5.1.2 inspecting

[25]:
```
df_1.head(3)
```

[25]:
```
      tconst titleType            primaryTitle           originalTitle  \
0  tt0000001     short              Carmencita              Carmencita
1  tt0000002     short  Le clown et ses chiens  Le clown et ses chiens
2  tt0000003     short          Pauvre Pierrot          Pauvre Pierrot

  isAdult startYear endYear runtimeMinutes                    genres
0       0      1894      \N              1         Documentary,Short
1       0      1892      \N              5           Animation,Short
2       0      1892      \N              4  Animation,Comedy,Romance
```

[26]:
```
df_1['titleType'].value_counts()
```

```
[26]: tvEpisode       5590798
      short            799028
      movie            570678
      video            297824
      tvSeries         203184
      tvMovie          130415
      tvMiniSeries      36270
      tvSpecial         31753
      videoGame         27529
      tvShort            9611
      audiobook             1
      radioSeries           1
      episode               1
      Name: titleType, dtype: int64
```

5.1.3 cleaning

```
[27]: %%time
# slicing to keep only movies
movie_df = df_1[df_1['titleType'] == 'movie']
# droping adult titles
movie_df = movie_df[movie_df['isAdult'] == '0']
# handeling nan values
movie_df.loc[movie_df['runtimeMinutes'] == r'\N', 'runtimeMinutes'] = np.nan
movie_df.loc[movie_df['startYear'] == r'\N', 'startYear'] = np.nan
movie_df.loc[movie_df['genres'] == r'\N', 'genres'] = np.nan
# setting nan genere to NoInfo
movie_df.loc[movie_df['genres'].isna(), 'genres'] = "NoInfo"
# nan value droping for start year
movie_df = movie_df[~movie_df['startYear'].isna()]

movie_df = movie_df.reset_index()
movie_df = movie_df.drop(['index', 'titleType', 'endYear', 'isAdult'], axis=1)

movie_df.to_csv(r'./Data/movie_df.csv', index=False)
movie_df
```

```
Wall time: 2.38 s
```

```
[27]:           tconst                                      primaryTitle  \
      0       tt0000502                                          Bohemios
      1       tt0000574                        The Story of the Kelly Gang
      2       tt0000615                                Robbery Under Arms
      3       tt0000630                                            Hamlet
      4       tt0000675                                       Don Quijote
      …             …                                                 …
      490999  tt9916622        Rodolpho Teóphilo - O Legado de um Pioneiro
      491000  tt9916680  De la ilusión al desconcierto: cine colombiano…
```

```
491001  tt9916706                                  Dankyavar Danka
491002  tt9916730                                            6 Gunn
491003  tt9916754                    Chico Albuquerque - Revelações

                                          originalTitle startYear  \
0                                              Bohemios      1905
1                            The Story of the Kelly Gang      1906
2                                    Robbery Under Arms      1907
3                                                Amleto      1908
4                                           Don Quijote      1908
…                                                   …         …
490999        Rodolpho Teóphilo - O Legado de um Pioneiro      2015
491000  De la ilusión al desconcierto: cine colombiano…      2007
491001                                     Dankyavar Danka      2013
491002                                              6 Gunn      2017
491003                       Chico Albuquerque - Revelações      2013

       runtimeMinutes                      genres
0                 100                      NoInfo
1                  70  Action,Adventure,Biography
2                 NaN                       Drama
3                 NaN                       Drama
4                 NaN                       Drama
…                 …                           …
490999             57                 Documentary
491000            100                 Documentary
491001            NaN                      Comedy
491002            116                      NoInfo
491003             49                 Documentary

[491004 rows x 6 columns]
```

splitting genere

[28]:

```
%%time
# getting preliminary unique list for cleaning
genres = list(movie_df['genres'].unique())
# temp list to store list of splited genre
genre_cleaning_temp = []
# getting list of splited genre
for item in genres:
    # for dealing with nan
    if type(item) is not float:
        # actual spliting
        genre_split = item.split(",")
        # appending
        genre_cleaning_temp.extend(genre_split)
```

```python
# geting unique list
from pandas.core.common import flatten
# flattening temp list
## https://stackoverflow.com/questions/12897374/
↪get-unique-values-from-a-list-in-python by https://stackoverflow.com/users/
↪2062318/todor ##
## https://saralgyaan.com/posts/
↪nested-list-to-list-python-in-just-three-lines-of-code/ ##
genre_cleaning_temp = list(flatten(genre_cleaning_temp))
# unique genre list
unique_genre = list(dict.fromkeys(genre_cleaning_temp))

## overly complicated way, theres much simpler method out in the wild.
unique_genre
```

```
Wall time: 30 ms
```

[28]:
```
['NoInfo',
 'Action',
 'Adventure',
 'Biography',
 'Drama',
 'Fantasy',
 'Comedy',
 'War',
 'Documentary',
 'Crime',
 'Romance',
 'Family',
 'History',
 'Sci-Fi',
 'Thriller',
 'Western',
 'Short',
 'Sport',
 'Mystery',
 'Horror',
 'Music',
 'Animation',
 'Musical',
 'Film-Noir',
 'News',
 'Adult',
 'Reality-TV',
 'Game-Show',
 'Talk-Show']
```

[29]:
```
%%time
#boolian matrix for all genere
movie_genre_df = pd.DataFrame([[(x in y) for x in unique_genre]
                                for y in movie_df['genres']],
                               columns=unique_genre)
```

```
Wall time: 2.43 s
```

[30]:
```
# merging
movie_main_df = pd.concat([movie_df, movie_genre_df], axis=1)
```

[31]:
```
# enforcing dtypes
movie_main_df = movie_main_df.convert_dtypes()
```

[32]:
```
movie_main_df.shape
```

[32]:
```
(491004, 35)
```

[33]:
```
movie_main_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 491004 entries, 0 to 491003
Data columns (total 35 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   tconst          491004 non-null  string
 1   primaryTitle    491004 non-null  string
 2   originalTitle   491004 non-null  string
 3   startYear       491004 non-null  string
 4   runtimeMinutes  348729 non-null  string
 5   genres          491004 non-null  string
 6   NoInfo          491004 non-null  boolean
 7   Action          491004 non-null  boolean
 8   Adventure       491004 non-null  boolean
 9   Biography       491004 non-null  boolean
 10  Drama           491004 non-null  boolean
 11  Fantasy         491004 non-null  boolean
 12  Comedy          491004 non-null  boolean
 13  War             491004 non-null  boolean
 14  Documentary     491004 non-null  boolean
 15  Crime           491004 non-null  boolean
 16  Romance         491004 non-null  boolean
 17  Family          491004 non-null  boolean
 18  History         491004 non-null  boolean
 19  Sci-Fi          491004 non-null  boolean
 20  Thriller        491004 non-null  boolean
 21  Western         491004 non-null  boolean
 22  Short           491004 non-null  boolean
 23  Sport           491004 non-null  boolean
```

```
 24  Mystery         491004 non-null  boolean
 25  Horror          491004 non-null  boolean
 26  Music           491004 non-null  boolean
 27  Animation       491004 non-null  boolean
 28  Musical         491004 non-null  boolean
 29  Film-Noir       491004 non-null  boolean
 30  News            491004 non-null  boolean
 31  Adult           491004 non-null  boolean
 32  Reality-TV      491004 non-null  boolean
 33  Game-Show       491004 non-null  boolean
 34  Talk-Show       491004 non-null  boolean
dtypes: boolean(29), string(6)
memory usage: 49.6 MB
```

[34]:
```
movie_main_df.describe()
```

[34]:
```
            tconst primaryTitle originalTitle startYear runtimeMinutes  \
count       491004       491004        491004    491004         348729
unique      491004       435498        444525       133            470
top     tt13627574       Mother          Home      2017             90
freq             1           40            36     17755          23507

        genres  NoInfo  Action Adventure Biography   Drama Fantasy  Comedy  \
count   491004  491004  491004    491004    491004  491004  491004  491004
unique    1317       2       2         2         2       2       2       2
top      Drama   False   False     False     False   False   False   False
freq     90267  424787  450544    468879    478159  309787  480389  404506

           War Documentary   Crime Romance  Family History  Sci-Fi Thriller  \
count   491004      491004  491004  491004  491004  491004  491004   491004
unique       2           2       2       2       2       2       2        2
top      False       False   False   False   False   False   False    False
freq    483095      393223  461821  451561  476778  479702  482990   463182

       Western   Short   Sport Mystery  Horror   Music Animation Musical  \
count   491004  491004  491004  491004  491004  491004    491004  491004
unique       2       2       2       2       2       2         2       2
top      False   False   False   False   False   False     False   False
freq    484426  490966  485607  478308  467678  472317    484749  482077

       Film-Noir    News   Adult Reality-TV Game-Show Talk-Show
count     491004  491004  491004     491004    491004    491004
unique         2       2       2          2         2         2
top        False   False   False      False     False     False
freq      490222  489618  490968     490625    490989    490894
```

[35]:
```
movie_main_df['startYear'] = movie_main_df['startYear'].astype('int')
movie_main_df['runtimeMinutes'].fillna('0', inplace=True)
movie_main_df['runtimeMinutes'] = movie_main_df['runtimeMinutes'].astype('int')
```

[36]:
```
movie_main_df['startYear'].sort_values().unique()
```

[36]:
```
array([1896, 1897, 1898, 1899, 1900, 1901, 1902, 1903, 1904, 1905, 1906,
       1907, 1908, 1909, 1910, 1911, 1912, 1913, 1914, 1915, 1916, 1917,
       1918, 1919, 1920, 1921, 1922, 1923, 1924, 1925, 1926, 1927, 1928,
       1929, 1930, 1931, 1932, 1933, 1934, 1935, 1936, 1937, 1938, 1939,
       1940, 1941, 1942, 1943, 1944, 1945, 1946, 1947, 1948, 1949, 1950,
       1951, 1952, 1953, 1954, 1955, 1956, 1957, 1958, 1959, 1960, 1961,
       1962, 1963, 1964, 1965, 1966, 1967, 1968, 1969, 1970, 1971, 1972,
       1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 1981, 1982, 1983,
       1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 1993, 1994,
       1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005,
       2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016,
       2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024, 2025, 2026, 2027,
       2028])
```

5.1.4 choosing features

*****Choosing to focus analysis on movies released between 2015 to 2020, where primary spoken language is English.*****

- In my opinion this is the most appropriate time frame to focus, as this gives enough data for analysis and at the same time does not include old info which will not be good representative of the current market situation. As customer/viewer taste and market trends shift over the time.
- Microsoft should focus only on releasing content in English for their kick-off. This gives them enough exposure and get noticed as a big player in the game, as they intend to be. Although they should focus on other territory to explore as there are ample opportunities left untapped. For example, in 2020 China surpassed North America in terms of industry value.
  As Microsoft has business across the globe, this should be relatively straight forward for them.
- I am also choosing not to focus on ultra-low budget movies for this analysis. Microsoft is one of the biggest corporations on earth. They have financial support to go for the big studios.
- I am also not including 'Documentary', 'Short', 'Adult', 'Reality-TV', 'Game-Show', 'Talk-Show', 'News', 'Film-Noir' titles. Those are entirely different class of product to be compared with conventional movies.

[37]:
```
# filtering based on year, keeping one addtional year just to be safe
movie_main_df_sliced = movie_main_df[(movie_main_df['startYear'] >= 2014)
                                     & (movie_main_df['startYear'] <= 2021)]
```

[38]:
```
movie_main_df_sliced.describe()
```

[38]:

	startYear	runtimeMinutes
count	123293.000000	123293.000000
mean	2017.221789	68.234523
std	2.117191	100.801411
min	2014.000000	0.000000
25%	2015.000000	45.000000
50%	2017.000000	80.000000
75%	2019.000000	96.000000
max	2021.000000	28643.000000

[39]:

```
to_drop = [
    'Documentary', 'Short', 'Adult', 'Reality-TV', 'Game-Show', 'Talk-Show',
    'News', 'Film-Noir'
]
```

[40]:

```
for item in to_drop:
    movie_main_df_sliced = movie_main_df_sliced[~movie_main_df_sliced[item].
                                                eq(1)]
```

[41]:

```
movie_main_df_sliced
```

[41]:

	tconst	primaryTitle \
5089	tt0011216	Spanish Fiesta
5560	tt0011801	Tötet nicht mehr
9809	tt0016906	Frivolinas
45545	tt0062336	El Tango del Viudo y Su Espejo Deformante
50362	tt0069049	The Other Side of the Wind
…	…	…
490995	tt9916270	Il talento del calabrone
490996	tt9916362	Coven
490997	tt9916428	The Secret of China
490998	tt9916538	Kuambil Lagi Hatiku
491002	tt9916730	6 Gunn

	originalTitle	startYear	runtimeMinutes \
5089	La fête espagnole	2019	67
5560	Tötet nicht mehr	2019	0
9809	Frivolinas	2014	80
45545	El Tango del Viudo y Su Espejo Deformante	2020	70
50362	The Other Side of the Wind	2018	122
…	…	…	…
490995	Il talento del calabrone	2020	84
490996	Akelarre	2020	90
490997	Hong xing zhao yao Zhong guo	2019	0
490998	Kuambil Lagi Hatiku	2019	123
491002	6 Gunn	2017	116

```
                           genres  NoInfo  Action  Adventure  Biography  Drama  \
5089                        Drama   False   False      False      False   True
5560                 Action,Crime   False    True      False      False  False
9809               Comedy,Musical   False   False      False      False  False
45545                       Drama   False   False      False      False   True
50362                       Drama   False   False      False      False   True
…                               …     …     …        …        …     …
490995                   Thriller   False   False      False      False  False
490996    Adventure,Drama,History   False   False       True      False   True
490997      Adventure,History,War   False   False       True      False  False
490998                      Drama   False   False      False      False   True
491002                     NoInfo    True   False      False      False  False

        Fantasy  Comedy    War  Documentary  Crime  Romance  Family  History  \
5089      False   False  False        False  False    False   False    False
5560      False   False  False        False   True    False   False    False
9809      False    True  False        False  False    False   False    False
45545     False   False  False        False  False    False   False    False
50362     False   False  False        False  False    False   False    False
…           …      …     …            …     …       …      …       …
490995    False   False  False        False  False    False   False    False
490996    False   False  False        False  False    False   False     True
490997    False   False   True        False  False    False   False     True
490998    False   False  False        False  False    False   False    False
491002    False   False  False        False  False    False   False    False

        Sci-Fi  Thriller  Western  Short  Sport  Mystery  Horror  Music  \
5089     False     False    False  False  False    False   False  False
5560     False     False    False  False  False    False   False  False
9809     False     False    False  False  False    False   False   True
45545    False     False    False  False  False    False   False  False
50362    False     False    False  False  False    False   False  False
…          …        …       …      …      …       …      …      …
490995   False      True    False  False  False    False   False  False
490996   False     False    False  False  False    False   False  False
490997   False     False    False  False  False    False   False  False
490998   False     False    False  False  False    False   False  False
491002   False     False    False  False  False    False   False  False

        Animation  Musical  Film-Noir   News  Adult  Reality-TV  Game-Show  \
5089        False    False      False  False  False       False      False
5560        False    False      False  False  False       False      False
9809        False     True      False  False  False       False      False
45545       False    False      False  False  False       False      False
50362       False    False      False  False  False       False      False
…             …       …         …      …      …           …          …
490995      False    False      False  False  False       False      False
```

```
490996      False    False      False  False  False       False      False
490997      False    False      False  False  False       False      False
490998      False    False      False  False  False       False      False
491002      False    False      False  False  False       False      False

        Talk-Show
5089        False
5560        False
9809        False
45545       False
50362       False
…           …
490995      False
490996      False
490997      False
490998      False
491002      False

[84546 rows x 35 columns]
```

[42]:
```python
movie_main_df_sliced.to_csv('./Data/movie_main_df_sliced.csv',index = False)
```

5.2 Merging all sources

[43]:
```python
# loading datasets
imdb_df = pd.read_csv('./Data/movie_main_df_sliced.csv')
bom_df = pd.read_csv('./Data/bom_2014to2021.csv')
tmdb_df = pd.read_csv('./Data/tmdb_parsd.csv')
```

merge_1

[44]:
```python
merge_1 = pd.merge(imdb_df,
                   bom_df,
                   how='left',
                   left_on='tconst',
                   right_on='imdb_code')
```

[45]:
```python
merge_1
```

[45]:
```
          tconst                          primaryTitle  \
0      tt0011216                        Spanish Fiesta
1      tt0011801                      Tötet nicht mehr
2      tt0016906                            Frivolinas
3      tt0062336  El Tango del Viudo y Su Espejo Deformante
4      tt0069049                  The Other Side of the Wind
…          …                                        …
84541  tt9916270                  Il talento del calabrone
84542  tt9916362                                     Coven
```

```
84543  tt9916428                        The Secret of China
84544  tt9916538                        Kuambil Lagi Hatiku
84545  tt9916730                                     6 Gunn

                                originalTitle  startYear  runtimeMinutes  \
0                            La fête espagnole       2019              67
1                             Tötet nicht mehr       2019               0
2                                   Frivolinas       2014              80
3      El Tango del Viudo y Su Espejo Deformante       2020              70
4                   The Other Side of the Wind       2018             122
…                                           …        …               …
84541                  Il talento del calabrone       2020              84
84542                                  Akelarre       2020              90
84543                Hong xing zhao yao Zhong guo      2019               0
84544                         Kuambil Lagi Hatiku       2019             123
84545                                      6 Gunn       2017             116

                          genres  NoInfo  Action  Adventure  Biography  Drama  \
0                          Drama   False   False      False      False   True
1                   Action,Crime   False    True      False      False  False
2                 Comedy,Musical   False   False      False      False  False
3                          Drama   False   False      False      False   True
4                          Drama   False   False      False      False   True
…                            …      …       …          …          …      …
84541                   Thriller   False   False      False      False  False
84542  Adventure,Drama,History   False   False       True      False   True
84543    Adventure,History,War   False   False       True      False  False
84544                      Drama   False   False      False      False   True
84545                     NoInfo    True   False      False      False  False

       Fantasy  Comedy    War  Documentary  Crime  Romance  Family  History  \
0        False   False  False        False  False    False   False    False
1        False   False  False        False   True    False   False    False
2        False    True  False        False  False    False   False    False
3        False   False  False        False  False    False   False    False
4        False   False  False        False  False    False   False    False
…          …       …      …            …      …        …       …        …
84541    False   False  False        False  False    False   False    False
84542    False   False  False        False  False    False   False     True
84543    False   False   True        False  False    False   False     True
84544    False   False  False        False  False    False   False    False
84545    False   False  False        False  False    False   False    False

       Sci-Fi  Thriller  Western  Short  Sport  Mystery  Horror  Music  \
0       False     False    False  False  False    False   False  False
1       False     False    False  False  False    False   False  False
2       False     False    False  False  False    False   False   True
```

```
3       False     False    False  False  False    False   False  False
4       False     False    False  False  False    False   False  False
…       …       …       …      …     …       …      …     …
84541   False      True    False  False  False    False   False  False
84542   False     False    False  False  False    False   False  False
84543   False     False    False  False  False    False   False  False
84544   False     False    False  False  False    False   False  False
84545   False     False    False  False  False    False   False  False

       Animation  Musical  Film-Noir   News  Adult  Reality-TV  Game-Show  \
0          False    False      False  False  False       False      False
1          False    False      False  False  False       False      False
2          False     True      False  False  False       False      False
3          False    False      False  False  False       False      False
4          False    False      False  False  False       False      False
…          …      …        …      …    …      …        …
84541      False    False      False  False  False       False      False
84542      False    False      False  False  False       False      False
84543      False    False      False  False  False       False      False
84544      False    False      False  False  False       False      False
84545      False    False      False  False  False       False      False

       Talk-Show  imdb_code                 name    year  world_collection  \
0          False        NaN                  NaN     NaN               NaN
1          False        NaN                  NaN     NaN               NaN
2          False        NaN                  NaN     NaN               NaN
3          False        NaN                  NaN     NaN               NaN
4          False        NaN                  NaN     NaN               NaN
…          …        …                  …      …              …
84541      False        NaN                  NaN     NaN               NaN
84542      False        NaN                  NaN     NaN               NaN
84543      False  tt9916428  The Secret of China  2019.0         4408165.0
84544      False        NaN                  NaN     NaN               NaN
84545      False        NaN                  NaN     NaN               NaN

       int_collection  dom_collection  \
0                 NaN             NaN
1                 NaN             NaN
2                 NaN             NaN
3                 NaN             NaN
4                 NaN             NaN
…               …             …
84541             NaN             NaN
84542             NaN             NaN
84543       4408165.0             NaN
84544             NaN             NaN
84545             NaN             NaN
```

```
                                                    url
0                                                   NaN
1                                                   NaN
2                                                   NaN
3                                                   NaN
4                                                   NaN
…                                                 …
84541                                               NaN
84542                                               NaN
84543  https://www.boxofficemojo.com/title/tt9916428/…
84544                                               NaN
84545                                               NaN

[84546 rows x 42 columns]
```

prepping for merge 2

[46]:
```
tmdb_df = tmdb_df.drop(tmdb_df.columns[0:4], axis=1)
```

[47]:
```
tmdb_df.columns
```

[47]:
```
Index(['budget', 'genres', 'homepage', 'id', 'imdb_id', 'original_language',
       'original_title', 'overview', 'popularity', 'poster_path',
       'production_companies', 'production_countries', 'release_date',
       'revenue', 'runtime', 'spoken_languages', 'status', 'tagline', 'title',
       'video', 'vote_average', 'vote_count', 'belongs_to_collection.id',
       'belongs_to_collection.name', 'belongs_to_collection.poster_path',
       'belongs_to_collection.backdrop_path'],
      dtype='object')
```

[48]:
```
filter_list = [
    'imdb_id', 'title', 'revenue', 'budget', 'release_date',
    'production_companies', 'popularity', 'vote_average', 'vote_count',
    'overview', 'belongs_to_collection.name', 'original_language'
]
```

[49]:
```
tmdb_df_reduced = tmdb_df[filter_list]
```

merge 2

[50]:
```
merge_2 = pd.merge(merge_1,
                   tmdb_df_reduced,
                   how='inner',
                   left_on='tconst',
                   right_on='imdb_id')
```

[51]:
```
df = merge_2.copy()
```

[52]:
```
df.columns
```

[52]:
```
Index(['tconst', 'primaryTitle', 'originalTitle', 'startYear',
       'runtimeMinutes', 'genres', 'NoInfo', 'Action', 'Adventure',
       'Biography', 'Drama', 'Fantasy', 'Comedy', 'War', 'Documentary',
       'Crime', 'Romance', 'Family', 'History', 'Sci-Fi', 'Thriller',
       'Western', 'Short', 'Sport', 'Mystery', 'Horror', 'Music', 'Animation',
       'Musical', 'Film-Noir', 'News', 'Adult', 'Reality-TV', 'Game-Show',
       'Talk-Show', 'imdb_code', 'name', 'year', 'world_collection',
       'int_collection', 'dom_collection', 'url', 'imdb_id', 'title',
       'revenue', 'budget', 'release_date', 'production_companies',
       'popularity', 'vote_average', 'vote_count', 'overview',
       'belongs_to_collection.name', 'original_language'],
      dtype='object')
```

cleaning

[53]:
```
rearrange = [
    'tconst', 'imdb_code', 'imdb_id', 'primaryTitle', 'originalTitle', 'name',
    'title', 'startYear', 'year', 'release_date', 'runtimeMinutes', 'budget',
    'revenue', 'world_collection', 'int_collection', 'dom_collection',
    'production_companies', 'popularity', 'vote_average', 'vote_count',
    'overview', 'belongs_to_collection.name', 'original_language', 'genres',␣
 ↪'NoInfo', 'Action',
    'Adventure', 'Biography', 'Drama', 'Fantasy', 'Comedy', 'War', 'Crime',
    'Romance', 'Family', 'History', 'Sci-Fi', 'Thriller', 'Western', 'Sport',
    'Mystery', 'Horror', 'Music', 'Animation', 'Musical', 'url'
]
df = df[rearrange]
```

filtering order: 1. financial data 2. year 3. review data

[54]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 44353 entries, 0 to 44352
Data columns (total 46 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   tconst                      44353 non-null  object
 1   imdb_code                   13351 non-null  object
 2   imdb_id                     44353 non-null  object
 3   primaryTitle                44353 non-null  object
 4   originalTitle               44353 non-null  object
 5   name                        13351 non-null  object
 6   title                       44353 non-null  object
 7   startYear                   44353 non-null  int64
 8   year                        13351 non-null  float64
 9   release_date                42437 non-null  object
```

```
 10  runtimeMinutes              44353 non-null  int64
 11  budget                      44353 non-null  int64
 12  revenue                     44353 non-null  int64
 13  world_collection            13351 non-null  float64
 14  int_collection              12646 non-null  float64
 15  dom_collection              3289 non-null   float64
 16  production_companies        44353 non-null  object
 17  popularity                  44353 non-null  float64
 18  vote_average                44353 non-null  float64
 19  vote_count                  44353 non-null  int64
 20  overview                    41041 non-null  object
 21  belongs_to_collection.name  1911 non-null   object
 22  original_language           44353 non-null  object
 23  genres                      44353 non-null  object
 24  NoInfo                      44353 non-null  bool
 25  Action                      44353 non-null  bool
 26  Adventure                   44353 non-null  bool
 27  Biography                   44353 non-null  bool
 28  Drama                       44353 non-null  bool
 29  Fantasy                     44353 non-null  bool
 30  Comedy                      44353 non-null  bool
 31  War                         44353 non-null  bool
 32  Crime                       44353 non-null  bool
 33  Romance                     44353 non-null  bool
 34  Family                      44353 non-null  bool
 35  History                     44353 non-null  bool
 36  Sci-Fi                      44353 non-null  bool
 37  Thriller                    44353 non-null  bool
 38  Western                     44353 non-null  bool
 39  Sport                       44353 non-null  bool
 40  Mystery                     44353 non-null  bool
 41  Horror                      44353 non-null  bool
 42  Music                       44353 non-null  bool
 43  Animation                   44353 non-null  bool
 44  Musical                     44353 non-null  bool
 45  url                         13351 non-null  object
dtypes: bool(21), float64(6), int64(5), object(14)
memory usage: 9.7+ MB
```

[55]:
```
df.describe()
```

[55]:
```
          startYear          year  runtimeMinutes        budget       revenue  \
count  44353.000000  13351.000000    44353.000000  4.435300e+04  4.435300e+04
mean    2017.107704   2016.916411       88.849976  1.462749e+06  4.188408e+06
std        2.025922      1.846724       36.046684  1.175852e+07  4.898516e+07
min     2014.000000   2014.000000        0.000000  0.000000e+00  0.000000e+00
25%     2015.000000   2015.000000       81.000000  0.000000e+00  0.000000e+00
```

```
50%     2017.000000   2017.000000      92.000000  0.000000e+00  0.000000e+00
75%     2019.000000   2018.000000     106.000000  0.000000e+00  0.000000e+00
max     2021.000000   2021.000000    1260.000000  3.560000e+08  2.797801e+09

       world_collection  int_collection  dom_collection    popularity  \
count      1.335100e+04    1.264600e+04    3.289000e+03  44353.000000
mean       1.722414e+07    1.279721e+07    2.060086e+07      5.966112
std        9.106972e+07    6.373112e+07    6.311116e+07     40.339807
min        2.000000e+00    2.000000e+00    4.900000e+01      0.000000
25%        3.873450e+04    4.289450e+04    3.447100e+04      0.600000
50%        3.877660e+05    4.062780e+05    3.423700e+05      1.513000
75%        3.320476e+06    3.206889e+06    8.106986e+06      5.705000
max        2.797501e+09    1.939128e+09    9.366622e+08   5227.005000

       vote_average    vote_count
count  44353.000000  44353.000000
mean       3.952096    101.957252
std        3.108509    742.014378
min        0.000000      0.000000
25%        0.000000      0.000000
50%        5.000000      2.000000
75%        6.400000     10.000000
max       10.000000  25252.000000
```

[56]:
```
df['revenue'].sort_values().value_counts() # null values are stored as 0
```

[56]:
```
0            41364
10000           27
100000          21
1500000         17
500              9
             …
147315           1
15894372         1
42972994         1
117813057        1
158162788        1
Name: revenue, Length: 2721, dtype: int64
```

Choosing greater value among two data sources for revenue, then cleaning noises.

[57]:
```
df['world_collection'].isna().value_counts()
```

[57]:
```
True     31002
False    13351
Name: world_collection, dtype: int64
```

[58]:
```
((df['revenue']!=0)&(df['world_collection'].isna())).value_counts()
```

[58]:
```
False    44003
True       350
dtype: int64
```

[59]:
```
condition_1 = (df['revenue']!=0)
```

[60]:
```
condition_2 = ~df['world_collection'].isna()
```

[61]:
```
df = df[condition_1 | condition_2]
```

[62]:
```
df
```

[62]:
```
          tconst  imdb_code    imdb_id                primaryTitle  \
5      tt0100275  tt0100275  tt0100275     The Wandering Soap Opera
22     tt0315642  tt0315642  tt0315642                        Wazir
26     tt0331314  tt0331314  tt0331314               Bunyan and Babe
32     tt0365907  tt0365907  tt0365907  A Walk Among the Tombstones
33     tt0369610  tt0369610  tt0369610               Jurassic World
…            …          …          …                            …
44331  tt9908390  tt9908390  tt9908390                      Le lion
44333  tt9908960  tt9908960  tt9908960                      Pliusas
44339  tt9911196  tt9911196  tt9911196          The Marriage Escape
44347  tt9914942  tt9914942  tt9914942   La vida sense la Sara Amat
44352  tt9916428  tt9916428  tt9916428          The Secret of China

                     originalTitle                         name  \
5            La Telenovela Errante     The Wandering Soap Opera
22                           Wazir                        Wazir
26                 Bunyan and Babe               Bunyan and Babe
32     A Walk Among the Tombstones  A Walk Among the Tombstones
33                  Jurassic World               Jurassic World
…                                …                            …
44331                      Le lion                      Le lion
44333                      Pliusas                      Pliusas
44339  De beentjes van Sint-Hildegard          The Marriage Escape
44347       La vida sense la Sara Amat   La vida sense la Sara Amat
44352    Hong xing zhao yao Zhong guo          The Secret of China

                             title  startYear    year release_date  \
5         The Wandering Soap Opera       2017  2017.0   2017-08-10
22                           Wazir       2016  2016.0   2016-01-07
26                 Bunyan and Babe       2017  2017.0   2017-01-12
32     A Walk Among the Tombstones       2014  2014.0   2014-09-18
33                  Jurassic World       2015  2015.0   2015-06-06
…                                …          …       …            …
44331                     The Lion       2020  2020.0   2020-01-29
44333                      Pliusas       2018  2018.0   2018-09-07
```

```
44339          The Marriage Escape       2020  2020.0   2020-02-10
44347   La vida sense la Sara Amat       2019  2019.0   2019-07-12
44352          The Secret of China       2019  2019.0   2019-08-08

       runtimeMinutes     budget     revenue  world_collection  \
5                  80          0           0      3.624000e+03
22                103    5200000     9200000      5.633588e+06
26                 84          0           0      7.206000e+04
32                114   28000000    53181600      5.883438e+07
33                124  150000000  1671713208      1.670516e+09
…                   …          …           …               …
44331              95          0           0      3.507711e+06
44333              90          0           0      7.463700e+04
44339             103          0           0      7.760946e+06
44347              74          0           0      5.979400e+04
44352               0          0           0      4.408165e+06

       int_collection  dom_collection  \
5                 NaN          3624.0
22       4.509543e+06       1124045.0
26       7.206000e+04             NaN
32       3.252678e+07      26307600.0
33       1.018131e+09     652385625.0
…                   …               …
44331    3.507711e+06             NaN
44333    7.463700e+04             NaN
44339    7.760946e+06             NaN
44347    5.979400e+04             NaN
44352    4.408165e+06             NaN

                                     production_companies  popularity  \
5      [{'id': 96241, 'logo_path': None, 'name': 'Poe…        1.400
22     [{'id': 12865, 'logo_path': None, 'name': 'Get…        5.191
26     [{'id': 87468, 'logo_path': None, 'name': 'Too…       20.049
32     [{'id': 39043, 'logo_path': None, 'name': 'Tra…       34.302
33     [{'id': 56, 'logo_path': '/cEaxANEisCqeEoRvODv…       63.489
…                                                   …           …
44331  [{'id': 90562, 'logo_path': '/qII3jJQ4S32FgJRl…       57.734
44333                                                []       0.600
44339                                                []       4.372
44347  [{'id': 20786, 'logo_path': None, 'name': "Mas…        1.940
44352                                                []       0.651

       vote_average  vote_count  \
5               6.5           9
22              6.6          90
26              6.2          15
```

```
32              6.3        2129
33              6.6       16595
…             …         …
44331           5.3         101
44333           7.0           1
44339           8.5           8
44347           7.4           5
44352           7.0           1

                                                 overview  \
5      The film revolves around the concept of soap o…
22     'Wazir' is a tale of two unlikely friends, a w…
26     Travis and his sister, Whitney, visit their gr…
32     Private investigator Matthew Scudder is hired …
33     Twenty-two years after the events of Jurassic …
…                                                   …
44331  A psychiatric hospital patient pretends to be …
44333                                                 NaN
44339  Jan has been married to Gedda for 35 years. Ge…
44347  Pep, a 13-year-old boy, is in love with a girl…
44352                                                 NaN

      belongs_to_collection.name original_language  \
5                            NaN                es
22                           NaN                hi
26                           NaN                en
32                           NaN                en
33       Jurassic Park Collection               en
…                          …               …
44331                        NaN                fr
44333                        NaN                lt
44339                        NaN                nl
44347                        NaN                ca
44352                        NaN                zh

                         genres  NoInfo  Action  Adventure  Biography  \
5          Comedy,Drama,Fantasy   False   False      False      False
22           Action,Crime,Drama   False    True      False      False
26     Adventure,Animation,Comedy   False   False       True      False
32           Action,Crime,Drama   False    True      False      False
33        Action,Adventure,Sci-Fi   False    True       True      False
…                           …     …     …         …         …
44331                    Comedy   False   False      False      False
44333                    Comedy   False   False      False      False
44339              Comedy,Drama   False   False      False      False
44347                     Drama   False   False      False      False
44352       Adventure,History,War   False   False       True      False
```

```
       Drama  Fantasy  Comedy    War  Crime  Romance  Family  History  Sci-Fi  \
5       True     True    True  False  False    False   False    False   False
22      True    False   False  False   True    False   False    False   False
26     False    False    True  False  False    False   False    False   False
32      True    False   False  False   True    False   False    False   False
33     False    False   False  False  False    False   False    False    True
…      …      …      …     …    …      …     …      …     …
44331  False    False    True  False  False    False   False    False   False
44333  False    False    True  False  False    False   False    False   False
44339   True    False    True  False  False    False   False    False   False
44347   True    False   False  False  False    False   False    False   False
44352  False    False   False   True  False    False   False     True   False

       Thriller  Western  Sport  Mystery  Horror  Music  Animation  Musical  \
5         False    False  False    False   False  False      False    False
22        False    False  False    False   False  False      False    False
26        False    False  False    False   False  False       True    False
32        False    False  False    False   False  False      False    False
33        False    False  False    False   False  False      False    False
…         …     …    …      …     …    …       …     …
44331     False    False  False    False   False  False      False    False
44333     False    False  False    False   False  False      False    False
44339     False    False  False    False   False  False      False    False
44347     False    False  False    False   False  False      False    False
44352     False    False  False    False   False  False      False    False

                                                     url
5      https://www.boxofficemojo.com/title/tt0100275/…
22     https://www.boxofficemojo.com/title/tt0315642/…
26     https://www.boxofficemojo.com/title/tt0331314/…
32     https://www.boxofficemojo.com/title/tt0365907/…
33     https://www.boxofficemojo.com/title/tt0369610/…
…                                                  …
44331  https://www.boxofficemojo.com/title/tt9908390/…
44333  https://www.boxofficemojo.com/title/tt9908960/…
44339  https://www.boxofficemojo.com/title/tt9911196/…
44347  https://www.boxofficemojo.com/title/tt9914942/…
44352  https://www.boxofficemojo.com/title/tt9916428/…

[13701 rows x 46 columns]
```

[63]:
```
# selecting max value as budget
df.loc[:,['world_collection']] = df[['revenue','world_collection']].max(axis=1)
```

[64]:
```
# redundent data droping
drop_list = [
```

```
    'tconst', 'imdb_code', 'index','name', 'title', 'year', 'revenue', 'url'
]
```

[65]:
```
df = df.reset_index()
```

[66]:
```
df = df.drop(columns=drop_list)
```

[67]:
```
df["release_date"] = pd.to_datetime(df["release_date"])
```

dealing with nested data

[68]:
```
# creating a copy of df
df1 = df.copy()
```

[69]:
```
# getting a slice to work on
df1 = df1[['imdb_id','production_companies']]
```

[70]:
```
df1_dict=df1.to_dict()
```

[71]:
```
df1_dict.keys()
```

[71]:
```
dict_keys(['imdb_id', 'production_companies'])
```

[72]:
```
# https://stackoverflow.com/questions/39807724/
↪extract-python-dictionary-from-string by https://stackoverflow.com/users/
↪3734244/danidee
```

[73]:
```
def get_list(string):
    x = ast.literal_eval(re.search('({.+})', string).group(0))
    return x
```

[74]:
```
temp = [] #store temp dicts
ty = [] #catch errors
for item in df1_dict['production_companies']:
    x = df1_dict['production_companies'][item]
    try:
        temp.append(get_list(x))
    except:
        temp.append(ty)
```

[75]:
```
#lopping through temp dicts and extracting production house name
temp_li = []

for i in temp:
    if type(i) == tuple:
        lli = []
        for y in i:
            lli.append(y['name'])
```

```
            code = ', '.join(lli)
            temp_dict = {
                'production_comp': code,
            }
            temp_li.append(temp_dict)
        elif type(i) == dict:

            code = i['name']
            temp_dict = {
                'production_comp': code,
            }
            temp_li.append(temp_dict)

        elif type(i) == list:

            code = 'Others,No info'
            temp_dict = {
                        'production_comp': code,
                    }
            temp_li.append(temp_dict)
```

[76]:
```
pro = pd.DataFrame.from_dict(temp_li)
```

[77]:
```
pro_1=pd.concat([df1.reset_index(),pro],axis=1)
```

[78]:
```
pro_1=pro_1.drop(axis=1, columns=['index','production_companies'])
```

[79]:
```
df_final = pd.merge(df, pro_1, left_on='imdb_id', right_on='imdb_id')
```

- touchup

[80]:
```
df_final.head(4)
```

[80]:
```
     imdb_id                primaryTitle                originalTitle  \
0  tt0100275     The Wandering Soap Opera        La Telenovela Errante
1  tt0315642                        Wazir                        Wazir
2  tt0331314              Bunyan and Babe              Bunyan and Babe
3  tt0365907  A Walk Among the Tombstones  A Walk Among the Tombstones

   startYear release_date  runtimeMinutes    budget  world_collection  \
0       2017   2017-08-10              80         0            3624.0
1       2016   2016-01-07             103   5200000         9200000.0
2       2017   2017-01-12              84         0           72060.0
3       2014   2014-09-18             114  28000000        58834384.0

   int_collection  dom_collection  \
0             NaN          3624.0
1       4509543.0       1124045.0
```

```
2         72060.0             NaN
3      32526784.0      26307600.0

                               production_companies  popularity  \
0  [{'id': 96241, 'logo_path': None, 'name': 'Poe…       1.400
1  [{'id': 12865, 'logo_path': None, 'name': 'Get…       5.191
2  [{'id': 87468, 'logo_path': None, 'name': 'Too…      20.049
3  [{'id': 39043, 'logo_path': None, 'name': 'Tra…      34.302

   vote_average  vote_count  \
0           6.5           9
1           6.6          90
2           6.2          15
3           6.3        2129

                                            overview  \
0  The film revolves around the concept of soap o…
1  'Wazir' is a tale of two unlikely friends, a w…
2  Travis and his sister, Whitney, visit their gr…
3  Private investigator Matthew Scudder is hired …

  belongs_to_collection.name original_language                      genres  \
0                        NaN                es        Comedy,Drama,Fantasy
1                        NaN                hi          Action,Crime,Drama
2                        NaN                en  Adventure,Animation,Comedy
3                        NaN                en          Action,Crime,Drama

   NoInfo  Action  Adventure  Biography  Drama  Fantasy  Comedy    War  Crime  \
0   False   False      False      False   True     True    True  False  False
1   False    True      False      False   True    False   False  False   True
2   False   False       True      False  False    False    True  False  False
3   False    True      False      False   True    False   False  False   True

   Romance  Family  History  Sci-Fi  Thriller  Western  Sport  Mystery  \
0    False   False    False   False     False    False  False    False
1    False   False    False   False     False    False  False    False
2    False   False    False   False     False    False  False    False
3    False   False    False   False     False    False  False    False

   Horror  Music  Animation  Musical  \
0   False  False      False    False
1   False  False      False    False
2   False  False       True    False
3   False  False      False    False

                               production_comp
0                        Poetastros, Suricato
```

```
1  Getaway Films Private Limited, Vinod Chopra Fi…
2             Toonz Entertainment, Exodus Film Group
3  Traveling Picture Show Company (TPSC), Jersey …
```

[81]:
```python
df_final.columns
```

[81]:
```
Index(['imdb_id', 'primaryTitle', 'originalTitle', 'startYear', 'release_date',
       'runtimeMinutes', 'budget', 'world_collection', 'int_collection',
       'dom_collection', 'production_companies', 'popularity', 'vote_average',
       'vote_count', 'overview', 'belongs_to_collection.name',
       'original_language', 'genres', 'NoInfo', 'Action', 'Adventure',
       'Biography', 'Drama', 'Fantasy', 'Comedy', 'War', 'Crime', 'Romance',
       'Family', 'History', 'Sci-Fi', 'Thriller', 'Western', 'Sport',
       'Mystery', 'Horror', 'Music', 'Animation', 'Musical',
       'production_comp'],
      dtype='object')
```

[82]:
```python
df_final=df_final.drop(columns='production_companies')
```

[83]:
```python
rearrange_ = [
    'imdb_id', 'primaryTitle', 'originalTitle', 'startYear', 'release_date',
       'runtimeMinutes', 'budget', 'world_collection', 'int_collection',
       'dom_collection', 'popularity', 'vote_average',
       'vote_count', 'production_comp',␣
↪'original_language','belongs_to_collection.name',
        'genres', 'NoInfo', 'Action', 'Adventure',
       'Biography', 'Drama', 'Fantasy', 'Comedy', 'War', 'Crime', 'Romance',
       'Family', 'History', 'Sci-Fi', 'Thriller', 'Western', 'Sport',
       'Mystery', 'Horror', 'Music', 'Animation', 'Musical',
       'overview'
]
```

[84]:
```python
df_final = df_final[rearrange_]
```

[85]:
```python
df_final
```

[85]:
```
         imdb_id               primaryTitle                originalTitle  \
0      tt0100275     The Wandering Soap Opera        La Telenovela Errante
1      tt0315642                      Wazir                        Wazir
2      tt0331314             Bunyan and Babe              Bunyan and Babe
3      tt0365907  A Walk Among the Tombstones  A Walk Among the Tombstones
4      tt0369610             Jurassic World               Jurassic World
…            …                          …                            …
13696  tt9908390                    Le lion                      Le lion
13697  tt9908960                    Pliusas                      Pliusas
13698  tt9911196         The Marriage Escape  De beentjes van Sint-Hildegard
13699  tt9914942   La vida sense la Sara Amat     La vida sense la Sara Amat
```

```
13700  tt9916428          The Secret of China    Hong xing zhao yao Zhong guo

       startYear release_date  runtimeMinutes     budget  world_collection  \
0           2017   2017-08-10              80          0      3.624000e+03
1           2016   2016-01-07             103    5200000      9.200000e+06
2           2017   2017-01-12              84          0      7.206000e+04
3           2014   2014-09-18             114   28000000      5.883438e+07
4           2015   2015-06-06             124  150000000      1.671713e+09
…            …          …               …         …                …
13696       2020   2020-01-29              95          0      3.507711e+06
13697       2018   2018-09-07              90          0      7.463700e+04
13698       2020   2020-02-10             103          0      7.760946e+06
13699       2019   2019-07-12              74          0      5.979400e+04
13700       2019   2019-08-08               0          0      4.408165e+06

       int_collection  dom_collection  popularity  vote_average  vote_count  \
0                 NaN          3624.0       1.400           6.5           9
1        4.509543e+06       1124045.0       5.191           6.6          90
2        7.206000e+04             NaN      20.049           6.2          15
3        3.252678e+07      26307600.0      34.302           6.3        2129
4        1.018131e+09     652385625.0      63.489           6.6       16595
…                 …               …          …            …          …
13696    3.507711e+06             NaN      57.734           5.3         101
13697    7.463700e+04             NaN       0.600           7.0           1
13698    7.760946e+06             NaN       4.372           8.5           8
13699    5.979400e+04             NaN       1.940           7.4           5
13700    4.408165e+06             NaN       0.651           7.0           1

                                          production_comp original_language  \
0                                    Poetastros, Suricato                es
1      Getaway Films Private Limited, Vinod Chopra Fi…                hi
2                  Toonz Entertainment, Exodus Film Group                en
3      Traveling Picture Show Company (TPSC), Jersey …                en
4      Amblin Entertainment, Legendary Pictures, Univ…                en
…                                                   …               …
13696  TF1 Studio, Monkey Pack Films, Pathé!, TF1 Fil…                fr
13697                                     Others,No info                lt
13698                                     Others,No info                nl
13699                               Massa d'Or Produccions                ca
13700                                     Others,No info                zh

      belongs_to_collection.name                      genres  NoInfo  Action  \
0                            NaN       Comedy,Drama,Fantasy   False   False
1                            NaN         Action,Crime,Drama   False    True
2                            NaN  Adventure,Animation,Comedy   False   False
3                            NaN         Action,Crime,Drama   False    True
4        Jurassic Park Collection     Action,Adventure,Sci-Fi   False    True
```

```
…                            …                           …      …      …
13696                        NaN                      Comedy  False  False
13697                        NaN                      Comedy  False  False
13698                        NaN                Comedy,Drama  False  False
13699                        NaN                       Drama  False  False
13700                        NaN      Adventure,History,War  False  False

       Adventure  Biography  Drama  Fantasy  Comedy    War  Crime  Romance  \
0          False      False   True     True    True  False  False    False
1          False      False   True    False   False  False   True    False
2           True      False  False    False    True  False  False    False
3          False      False   True    False   False  False   True    False
4           True      False  False    False   False  False  False    False
…             …        …     …       …       …     …      …       …
13696      False      False  False    False    True  False  False    False
13697      False      False  False    False    True  False  False    False
13698      False      False   True    False    True  False  False    False
13699      False      False   True    False   False  False  False    False
13700       True      False  False    False   False   True  False    False

       Family  History  Sci-Fi  Thriller  Western  Sport  Mystery  Horror  \
0       False    False   False     False    False  False    False   False
1       False    False   False     False    False  False    False   False
2       False    False   False     False    False  False    False   False
3       False    False   False     False    False  False    False   False
4       False    False    True     False    False  False    False   False
…         …       …      …        …      …     …        …      …
13696   False    False   False     False    False  False    False   False
13697   False    False   False     False    False  False    False   False
13698   False    False   False     False    False  False    False   False
13699   False    False   False     False    False  False    False   False
13700   False     True   False     False    False  False    False   False

       Music  Animation  Musical  \
0      False      False    False
1      False      False    False
2      False       True    False
3      False      False    False
4      False      False    False
…      …         …        …
13696  False      False    False
13697  False      False    False
13698  False      False    False
13699  False      False    False
13700  False      False    False

                                                overview
```

```
0        The film revolves around the concept of soap o…
1        'Wazir' is a tale of two unlikely friends, a w…
2        Travis and his sister, Whitney, visit their gr…
3        Private investigator Matthew Scudder is hired …
4        Twenty-two years after the events of Jurassic …
…                                                     …
13696    A psychiatric hospital patient pretends to be …
13697                                                  NaN
13698    Jan has been married to Gedda for 35 years. Ge…
13699    Pep, a 13-year-old boy, is in love with a girl…
13700                                                  NaN

[13701 rows x 39 columns]
```

[86]:
```
df_final.to_csv('./Data/main_df.csv', index=False)
```

5.3 Working on main_df

5.3.1 prepping for analysis, furthur cleaning

[87]:
```
main_df_raw = pd.read_csv(r'./Data/main_df.csv',
                          parse_dates=['release_date'],
                          low_memory=False)
```

[88]:
```
main_df=main_df_raw.iloc[:,0:17] #droping boolean columns
```

[89]:
```
main_df=main_df[~main_df.release_date.isna()]
```

[90]:
```
main_df['release_year'] = main_df['release_date'].dt.year
main_df['release_year'].astype('int')
```

[90]:
```
0        2017
1        2016
2        2017
3        2014
4        2015
         …
13696    2020
13697    2018
13698    2020
13699    2019
13700    2019
Name: release_year, Length: 13620, dtype: int32
```

Focusing my analysis from 2015 to end of 2020. Inputs below can be changed to focus any timeframe from 2007 to March 12, 2021. Data is in safe folder inside repo.

[91]:
```
main_df = main_df[(main_df.release_date >= '2015-01-01')
                  & (main_df.release_date <= '2020-12-31')]
```

[92]:
```
main_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11779 entries, 0 to 13700
Data columns (total 18 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   imdb_id                       11779 non-null  object
 1   primaryTitle                  11779 non-null  object
 2   originalTitle                 11779 non-null  object
 3   startYear                     11779 non-null  int64
 4   release_date                  11779 non-null  datetime64[ns]
 5   runtimeMinutes                11779 non-null  int64
 6   budget                        11779 non-null  int64
 7   world_collection              11779 non-null  float64
 8   int_collection                10924 non-null  float64
 9   dom_collection                2765 non-null   float64
 10  popularity                    11779 non-null  float64
 11  vote_average                  11779 non-null  float64
 12  vote_count                    11779 non-null  int64
 13  production_comp               11779 non-null  object
 14  original_language             11779 non-null  object
 15  belongs_to_collection.name    1006 non-null   object
 16  genres                        11779 non-null  object
 17  release_year                  11779 non-null  int64
dtypes: datetime64[ns](1), float64(5), int64(5), object(7)
memory usage: 1.7+ MB
```

[93]:
```
main_df.describe()
```

[93]:
```
          startYear  runtimeMinutes        budget  world_collection  \
count  11779.000000    11779.000000  1.177900e+04      1.177900e+04
mean    2017.283895      100.864080  4.205773e+06      1.681113e+07
std        1.561950       28.732314  2.011748e+07      9.159840e+07
min     2014.000000        0.000000  0.000000e+00      1.000000e+00
25%     2016.000000       90.000000  0.000000e+00      3.603400e+04
50%     2017.000000      100.000000  0.000000e+00      3.732710e+05
75%     2019.000000      114.000000  0.000000e+00      3.255714e+06
max     2021.000000      808.000000  3.560000e+08      2.797801e+09

       int_collection  dom_collection    popularity  vote_average  \
count    1.092400e+04    2.765000e+03  11779.000000  11779.000000
mean     1.246981e+07    2.061955e+07     10.595399      5.553162
std      6.418805e+07    6.528838e+07     41.142722      2.258754
min      2.000000e+00    4.900000e+01      0.000000      0.000000
```

```
25%      3.774625e+04    3.667600e+04      1.279500      5.100000
50%      3.666200e+05    3.379070e+05      3.148000      6.100000
75%      2.972528e+06    7.743794e+06      8.796000      6.900000
max      1.939128e+09    9.366622e+08   2103.518000     10.000000

         vote_count  release_year
count  11779.000000  11779.000000
mean     284.940233   2017.374989
std     1241.668467      1.564721
min        0.000000   2015.000000
25%        3.000000   2016.000000
50%       14.000000   2017.000000
75%       78.000000   2019.000000
max    24543.000000   2020.000000
```

dropping ultra low budget movies along with 0, which means no information. And extremely low budget indicates possible error in data collection. Keeping low budget movies does not exactly match with the goal; finding good investment recommendation for a big company.

[94]:
```python
main_df.shape
```

[94]:
```
(11779, 18)
```

[95]:
```python
main_df = main_df[main_df.budget>=5000]
```

[96]:
```python
main_df.shape
```

[96]:
```
(2081, 18)
```

focusing analysis only on movies where primary spoken language is English. MS should focus on this for the commencement.

[97]:
```python
main_df = main_df[main_df.original_language=='en']
```

[98]:
```python
main_df.shape
```

[98]:
```
(1113, 18)
```

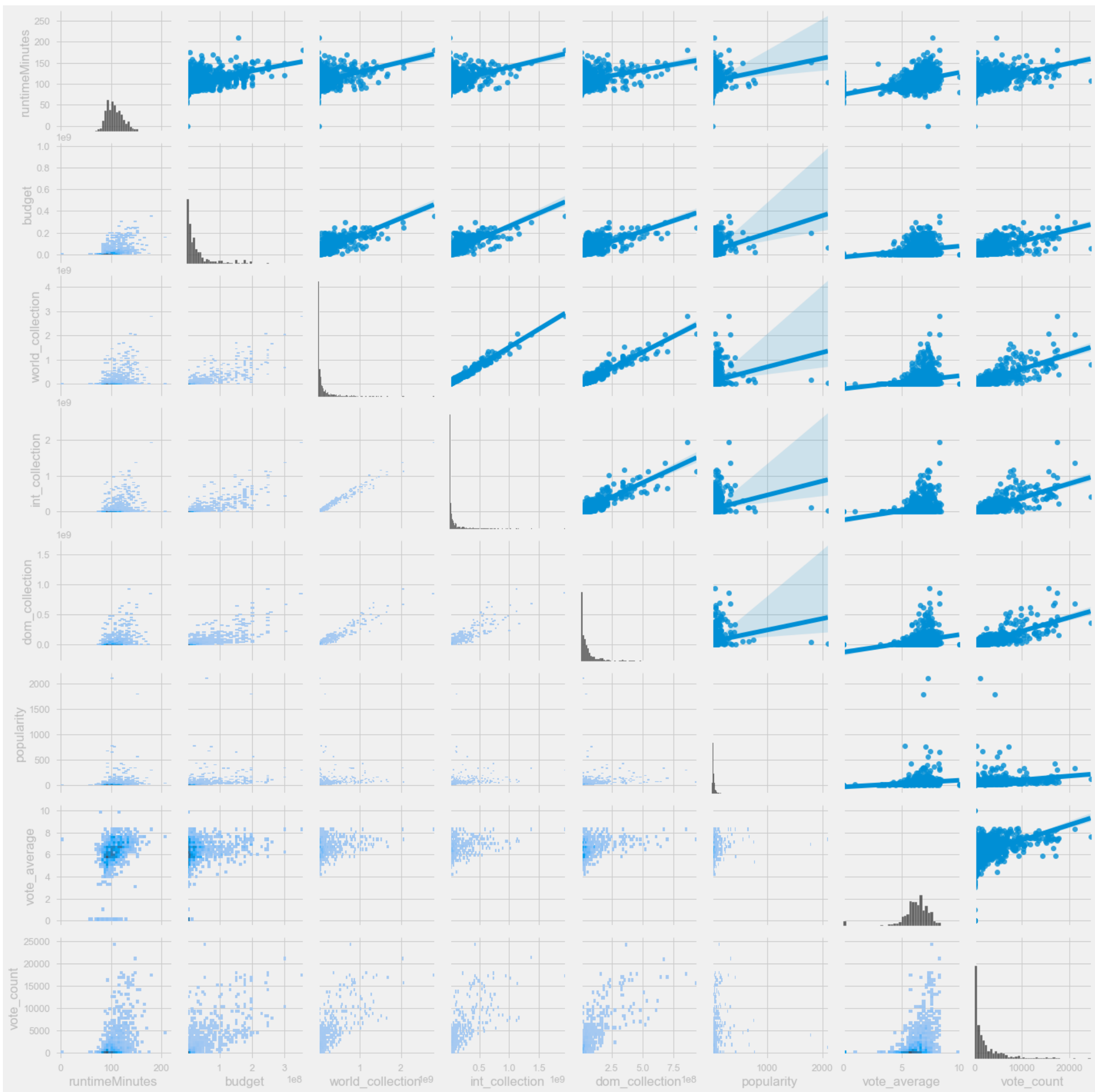
[99]:
```python
main_df.columns
```

[99]:
```
Index(['imdb_id', 'primaryTitle', 'originalTitle', 'startYear', 'release_date',
       'runtimeMinutes', 'budget', 'world_collection', 'int_collection',
       'dom_collection', 'popularity', 'vote_average', 'vote_count',
       'production_comp', 'original_language', 'belongs_to_collection.name',
       'genres', 'release_year'],
      dtype='object')
```

[100]:
```python
list_for_pairplot = ['release_date',
       'runtimeMinutes', 'budget', 'world_collection', 'int_collection',
```

```
    'dom_collection', 'popularity', 'vote_average', 'vote_count',
    'belongs_to_collection.name']
```

[101]:
```
with plt.style.context('fivethirtyeight'):
    g = sns.PairGrid(main_df[list_for_pairplot],layout_pad=.2)
    g.map_diag(sns.histplot)
    g.map_upper(sns.regplot)
    g.map_lower(sns.histplot)
```



No severe anamoly spotted in the graph which warrants further investigation .

5.4 Feature engineering

5.4.1 ROI

Here, budget is the estimetor for cost.

Return on investment in $ value

[102]:
```
main_df['ROI'] = main_df.world_collection - main_df.budget
```

Return on investment in percentage, expressed in full, not in decimal

[103]:
```
main_df['ROI_percentage'] = (main_df.ROI / main_df.budget)*100
```

5.5 Final Check to see that everything is in place

[104]:
```
main_df.shape
```

[104]:
```
(1113, 20)
```

[105]:
```
main_df.head()
```

[105]:
```
      imdb_id         primaryTitle                          originalTitle  \
4   tt0369610        Jurassic World                         Jurassic World
6   tt0385887  Motherless Brooklyn                     Motherless Brooklyn
11  tt0437086  Alita: Battle Angel                     Alita: Battle Angel
12  tt0441881         Danger Close  Danger Close: The Battle of Long Tan
14  tt0443533  The History of Love                     The History of Love

    startYear release_date  runtimeMinutes     budget  world_collection  \
4        2015   2015-06-06             124  150000000      1.671713e+09
6        2019   2019-10-31             144   26000000      1.847774e+07
11       2019   2019-01-31             122  170000000      4.049805e+08
12       2019   2019-08-08             118   23934823      2.088085e+06
14       2016   2016-11-09             134   20000000      4.922720e+05

    int_collection  dom_collection  popularity  vote_average  vote_count  \
4     1.018131e+09     652385625.0      63.489           6.6       16595
6     9.200000e+06       9277736.0      75.020           6.8         842
11    3.191423e+08      85838210.0     175.798           7.2        6343
12    2.088085e+06             NaN     112.552           6.8         148
14    4.922720e+05             NaN       5.406           6.4          63

                                   production_comp original_language  \
4   Amblin Entertainment, Legendary Pictures, Univ…                en
6                          Class 5 Films, MWM Studios                en
11  Troublemaker Studios, Lightstorm Entertainment…                en
12  Red Dune Films, Full Clip Productions, Deeper …                en
14  2.4.7. Films, Oï  Oï  Oï Productions, Caramel …                en

   belongs_to_collection.name                    genres  release_year  \
```

```
4    Jurassic Park Collection  Action,Adventure,Sci-Fi          2015
6                         NaN       Crime,Drama,Mystery          2019
11                        NaN   Action,Adventure,Sci-Fi          2019
12                        NaN           Action,Drama,War          2019
14                        NaN         Drama,Romance,War          2016

             ROI  ROI_percentage
4   1.521713e+09     1014.475472
6  -7.522264e+06      -28.931785
11  2.349805e+08      138.223849
12 -2.184674e+07      -91.275954
14 -1.950773e+07      -97.538640
```

[106]:
```
main_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1113 entries, 4 to 13585
Data columns (total 20 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   imdb_id                   1113 non-null   object
 1   primaryTitle              1113 non-null   object
 2   originalTitle             1113 non-null   object
 3   startYear                 1113 non-null   int64
 4   release_date              1113 non-null   datetime64[ns]
 5   runtimeMinutes            1113 non-null   int64
 6   budget                    1113 non-null   int64
 7   world_collection          1113 non-null   float64
 8   int_collection            1039 non-null   float64
 9   dom_collection            882 non-null    float64
 10  popularity                1113 non-null   float64
 11  vote_average              1113 non-null   float64
 12  vote_count                1113 non-null   int64
 13  production_comp           1113 non-null   object
 14  original_language         1113 non-null   object
 15  belongs_to_collection.name  227 non-null    object
 16  genres                    1113 non-null   object
 17  release_year              1113 non-null   int64
 18  ROI                       1113 non-null   float64
 19  ROI_percentage            1113 non-null   float64
dtypes: datetime64[ns](1), float64(7), int64(5), object(7)
memory usage: 182.6+ KB
```

[107]:
```
main_df.describe()
```

[107]:
```
          startYear  runtimeMinutes        budget  world_collection  \
count  1113.000000     1113.000000  1.113000e+03      1.113000e+03
mean   2016.993711      107.323450  3.841841e+07      1.271450e+08
```

```
std       1.532899       17.613393  5.251428e+07      2.613752e+08
min    2014.000000        0.000000  5.000000e+03      5.470000e+02
25%    2016.000000       94.000000  6.000000e+06      2.084628e+06
50%    2017.000000      105.000000  1.900000e+07      2.935520e+07
75%    2018.000000      118.000000  4.000000e+07      1.195200e+08
max    2020.000000      209.000000  3.560000e+08      2.797801e+09

       int_collection  dom_collection   popularity  vote_average  \
count    1.039000e+03    8.820000e+02  1113.000000   1113.000000
mean     8.259442e+07    6.207522e+07    43.486649      6.261995
std      1.761494e+08    1.039024e+08   103.773946      1.246853
min      5.470000e+02    1.377000e+03     0.600000      0.000000
25%      1.177836e+06    5.622565e+06    13.550000      5.800000
50%      1.424425e+07    2.740507e+07    22.168000      6.400000
75%      6.891399e+07    6.725403e+07    41.249000      7.000000
max      1.939128e+09    9.366622e+08  2103.518000     10.000000

         vote_count  release_year           ROI  ROI_percentage
count   1113.000000   1113.000000  1.113000e+03     1113.000000
mean    2338.715184   2017.052111  8.872658e+07      296.570055
std     3332.521354      1.522309  2.226630e+08     1647.220419
min        0.000000   2015.000000 -1.510000e+08      -99.981875
25%      266.000000   2016.000000 -3.898454e+06      -69.544079
50%     1020.000000   2017.000000  8.197072e+06       63.263233
75%     3038.000000   2018.000000  7.501105e+07      296.521358
max    24543.000000   2020.000000  2.441801e+09    42864.410000
```

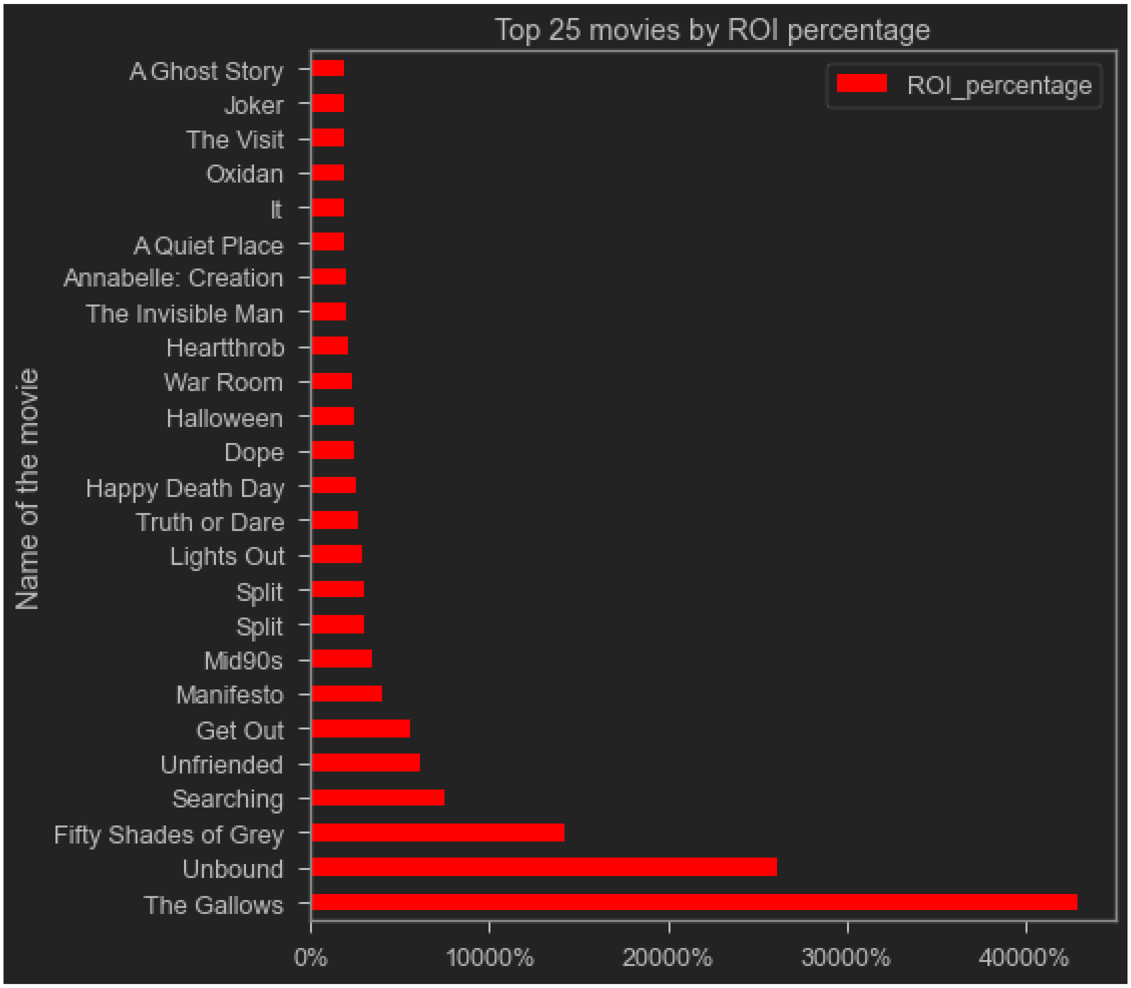
if only want to focus on profitable movies

[108]:
```python
# main_df = main_df[main_df.ROI>0]
```

6 Exploratory data analysis

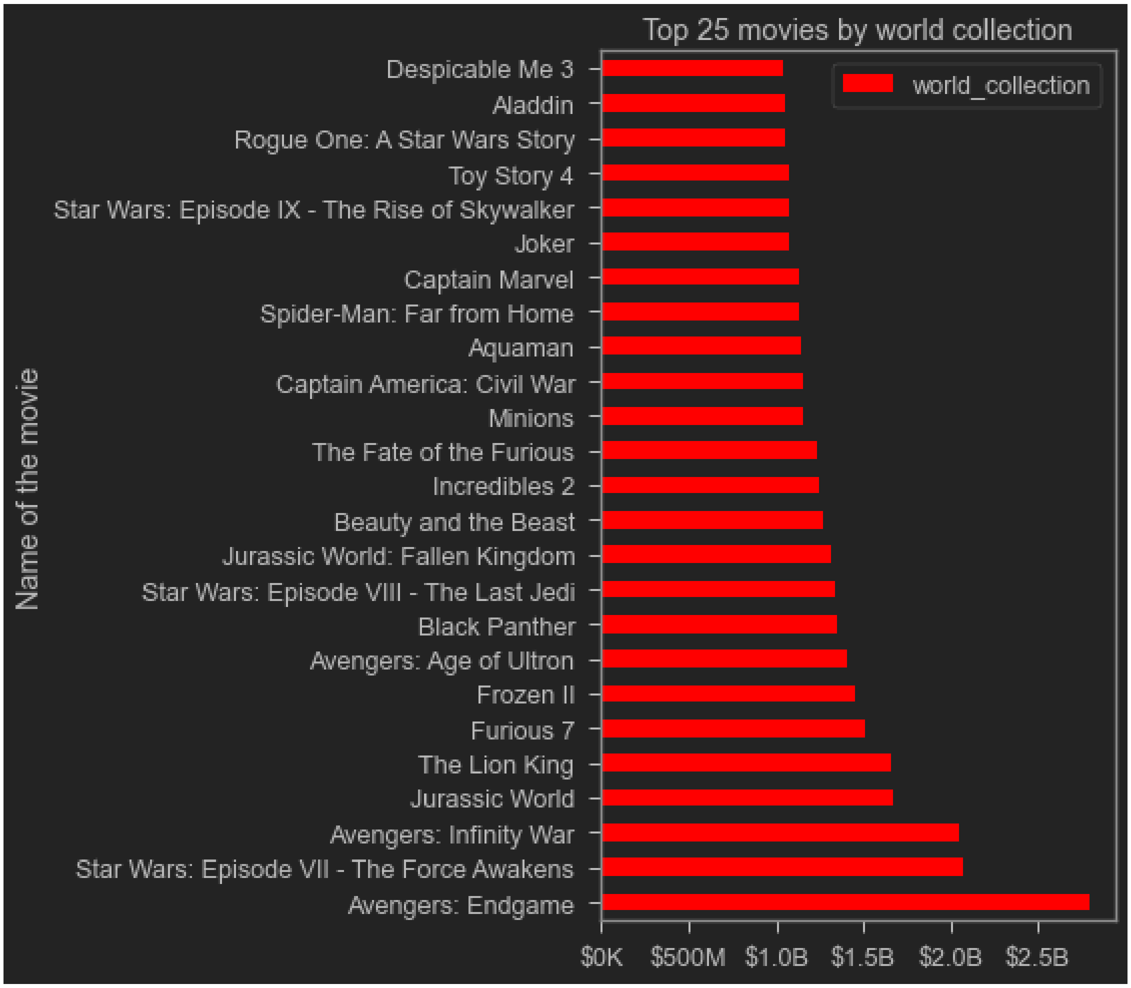
6.1 EDA - top movie by return %

[109]:
```python
ax = main_df.sort_values(by='ROI_percentage',
                         ascending=False).head(25).plot(kind='barh',
                                                        x='primaryTitle',
                                                        y='ROI_percentage',
                                                        color="red")
plt.title('Top 25 movies by ROI percentage')
plt.ylabel('Name of the movie')
plt.tight_layout()
ax.xaxis.set_major_formatter(format_add_percentage)
plt.show()
```



6.2 EDA - top movie by gross profit

[110]:
```python
ax = main_df.sort_values(by='world_collection',
                         ascending=False).head(25).plot(kind='barh',
                                                        x='primaryTitle',
                                                        y='world_collection',
                                                        color="red")

plt.title('Top 25 movies by world collection')
plt.ylabel('Name of the movie')
ax.xaxis.set_major_formatter(format_number)
plt.tight_layout()
plt.show()
```



6.3 EDA - profit by top 20 studio

For competitor analysis and assessing market condition

[111]:
```python
studio_df = main_df.copy()
```

[112]:
```python
studio_df.loc[:, 'production_comp_exp'] = studio_df.production_comp.map(
    lambda x: x.split(', '))
```

[113]:
```python
studio_df_fig = studio_df.explode('production_comp_exp')
```

[114]:
```python
studio_df_fig.head(3)
```

[114]:
```
     imdb_id   primaryTitle   originalTitle  startYear release_date  \
4  tt0369610  Jurassic World  Jurassic World       2015   2015-06-06
4  tt0369610  Jurassic World  Jurassic World       2015   2015-06-06
4  tt0369610  Jurassic World  Jurassic World       2015   2015-06-06
```

```
   runtimeMinutes     budget  world_collection  int_collection  \
4             124  150000000      1.671713e+09    1.018131e+09
4             124  150000000      1.671713e+09    1.018131e+09
4             124  150000000      1.671713e+09    1.018131e+09

   dom_collection  popularity  vote_average  vote_count  \
4     652385625.0      63.489           6.6       16595
4     652385625.0      63.489           6.6       16595
4     652385625.0      63.489           6.6       16595

                                  production_comp original_language  \
4  Amblin Entertainment, Legendary Pictures, Univ…                en
4  Amblin Entertainment, Legendary Pictures, Univ…                en
4  Amblin Entertainment, Legendary Pictures, Univ…                en

  belongs_to_collection.name                   genres  release_year  \
4   Jurassic Park Collection  Action,Adventure,Sci-Fi          2015
4   Jurassic Park Collection  Action,Adventure,Sci-Fi          2015
4   Jurassic Park Collection  Action,Adventure,Sci-Fi          2015

            ROI  ROI_percentage   production_comp_exp
4  1.521713e+09     1014.475472  Amblin Entertainment
4  1.521713e+09     1014.475472    Legendary Pictures
4  1.521713e+09     1014.475472    Universal Pictures
```

[115]:
```
top_production_house_list = list(
    studio_df_fig.production_comp_exp.value_counts().sort_values(
        ascending=False)[:20].index)
```

[116]:
```
# to get Total worldwide $ collection by top 20 studios over the years
studio_df_fig_0 = studio_df_fig[studio_df_fig['production_comp_exp'].isin(
    top_production_house_list)]
```

[117]:
```
# Total worldwide $ collection by top 20 studios
studio_df_fig_1 = studio_df_fig.groupby(
    by='production_comp_exp').agg('sum').sort_values(by='world_collection',
                                                     ascending=False)[:20]
# Total releases by top 20 studios
studio_df_fig_2 = studio_df_fig.groupby(
    by='production_comp_exp').agg('count').sort_values(by='world_collection',
                                                       ascending=False)[:20]
```

[118]:
```
# Collection Performance of top 10 movie studios
studio_df_fig_merged = pd.merge(
    studio_df_fig.groupby(by='production_comp_exp').agg('sum').sort_values(
        by='world_collection',
```

```
        ascending=False)['world_collection'].reset_index(),
    studio_df_fig.groupby(by='production_comp_exp').agg('count').sort_values(
        by='world_collection',
        ascending=False)['world_collection'].reset_index(),
    on='production_comp_exp')
# Budget Performance of top 10 movie studios
studio_df_fig_merged_1 = pd.merge(
    studio_df_fig.groupby(by='production_comp_exp').agg('sum').sort_values(
        by='budget',
        ascending=False)['budget'].reset_index(),
    studio_df_fig.groupby(by='production_comp_exp').agg('count').sort_values(
        by='budget',
        ascending=False)['budget'].reset_index(),
    on='production_comp_exp')
```

[119]:
```
## from https://plotly.com/python/multiple-axes/ ##official plotly how to␣
 ↪instructions
fig = make_subplots(specs=[[{"secondary_y": True}]])
# Add traces
fig.add_trace(
    go.Bar(x=studio_df_fig_merged.production_comp_exp[:10],
           y=studio_df_fig_merged.world_collection_x[:10],
           name="World Collection",
           offset=True),
    secondary_y=False,
)
fig.add_trace(
    go.Bar(x=studio_df_fig_merged.production_comp_exp[:10],
           y=studio_df_fig_merged.world_collection_y[:10],
           name="Movie Released",
           offset=True,
           opacity=.6),
    secondary_y=True,
)
# Add figure title
fig.update_layout(title_text="Collection performance of top 10 movie studios")
# Set x-axis title
fig.update_xaxes(title_text="World Collection")
# Set y-axes titles
fig.update_yaxes(title_text="<b>World Collection</b>", secondary_y=False)
fig.update_yaxes(title_text="<b>Number of Movie Released</b>",
                 secondary_y=True)
fig.show()
```

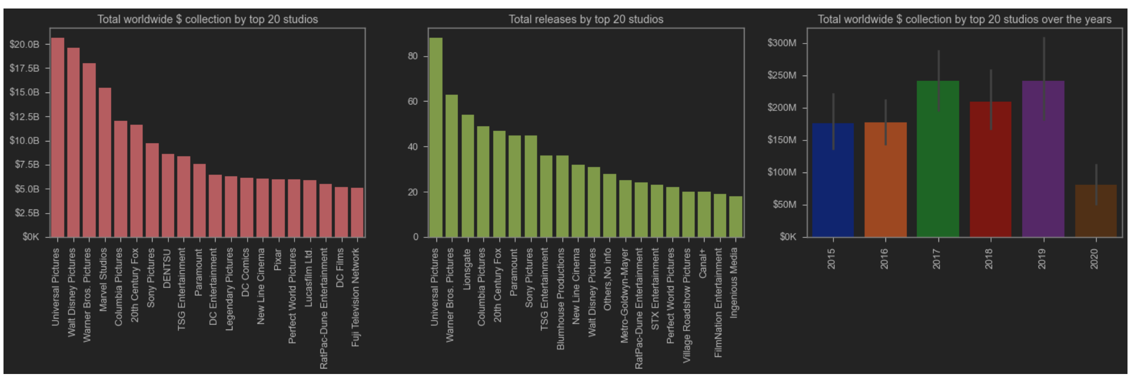
[120]:
```
## from https://plotly.com/python/multiple-axes/ ##official plotly how to␣
 ↪instructions
fig = make_subplots(specs=[[{"secondary_y": True}]])
```

```
# Add traces
fig.add_trace(
    go.Bar(x=studio_df_fig_merged_1.production_comp_exp[:10],
           y=studio_df_fig_merged_1.budget_x[:10],
           name="Budget",
           offset=True),
    secondary_y=False,
)
fig.add_trace(
    go.Bar(x=studio_df_fig_merged_1.production_comp_exp[:10],
           y=studio_df_fig_merged_1.budget_y[:10],
           name="Movie Released",
           offset=True,
           opacity=.6),
    secondary_y=True,
)
# Add figure title
fig.update_layout(title_text="Budget performance of top 10 movie studios")
# Set x-axis title
fig.update_xaxes(title_text="Budget")
# Set y-axes titles
fig.update_yaxes(title_text="<b>Budget</b>", secondary_y=False)
fig.update_yaxes(title_text="<b>Number of Movie Released</b>",
                 secondary_y=True)
fig.show()
```

Marvel Studios and Walt Disney has the best release count to world collection ratio. It took Universal Pictures way more budget to achieve the top spot.

[121]:
```
plt.figure(figsize=(25, 5))
plt.subplot(1, 3, 1)
plt.xticks(rotation='vertical')

plt.title('Total worldwide $ collection by top 20 studios')

sns.barplot(y='world_collection',
            x='production_comp_exp',
            data=studio_df_fig_1.reset_index(),
            color='r').yaxis.set_major_formatter(
                format_number)
plt.xlabel(None)
plt.ylabel(None)


plt.subplot(1, 3, 2)
sns.barplot(y='world_collection',
            x='production_comp_exp',
```

```
            data=studio_df_fig_2.reset_index(),
            color='g').set(xlabel=None, ylabel=None)

plt.xticks(rotation='vertical')

plt.title('Total releases by top 20 studios')

plt.subplot(1, 3, 3)
sns.barplot(data=studio_df_fig_0,
            x='release_year',
            y='world_collection',
            palette='dark').yaxis.set_major_formatter(
                format_number)
plt.title('Total worldwide $ collection by top 20 studios over the years')
plt.xticks(rotation='vertical')
plt.xlabel(None)
plt.ylabel(None)
# plt.tight_layout()
plt.show()
```



One caveat of this graph is that because of the nature of the data, if a movie has multiple studios attached to it then all earnings of it is counted as the studios sole earnings. This is the reason why the mismatch of metrics. All things set aside, from this graph a visual understanding can be achieved about top studios without trying to make sense of the numbers. Turning off ylabels of first two plots can help on that regard.

6.4 EDA - Relation between features

[122]:
```
corelattion_filter_list = ['startYear',
       'runtimeMinutes', 'budget', 'world_collection', 'int_collection',
       'dom_collection', 'popularity', 'vote_average', 'vote_count']
```

[123]:
```
corr_df = main_df[corelattion_filter_list]
```

[124]:
```
corr_df_matrix = corr_df.corr()
```

[125]:
```
corr_df_matrix.style.background_gradient()
```

[125]:
```
<pandas.io.formats.style.Styler at 0x1ff78ff5ee0>
```

[126]:
```
correlation_top_bottom(corr_df_matrix)
```

```
Positive correlations:
      index                        feature_combo  correlation
0     31  world_collection and int_collection     0.986302
1     32  dom_collection and world_collection     0.955519
2     41    dom_collection and int_collection     0.892850
3     35      vote_count and world_collection     0.791444
4     22            budget and int_collection     0.787109
5     21          budget and world_collection     0.783042
6     53        dom_collection and vote_count     0.773461
7     44        vote_count and int_collection     0.763741
8     23            dom_collection and budget     0.716023
9     26                budget and vote_count     0.675298

 ----------------------------------------------------------------------
       Negative correlations:
      index                   feature_combo  correlation
0      8        vote_count and startYear    -0.065041
1      1    runtimeMinutes and startYear    -0.003422
2      3  world_collection and startYear     0.024102
3      4    startYear and int_collection     0.035525
4      5    dom_collection and startYear     0.040447
5      2            budget and startYear     0.053363
6     63      startYear and vote_average     0.054454
7      7      vote_average and startYear     0.054454
8     69     popularity and vote_average     0.156417
9     61     vote_average and popularity     0.156417
```

6.4.1 Findings and observation

From those table it can be observed that world collection, international collection and domestic collection is highly correlated. It is expected as world collection is a dependent variable of the other two. And the later two are highly correlated. This is also expected, as this is indicator of a profitable versus flop movie. Better performing movies has higher popularity as explained by world collection versus vote count, vice versa. High budget movies perform better overseas.

Overall budget is the key for indicating performance both in international and domestic performance and feedback from movie consumers. No other standout correlation was found.

7 Recommendations

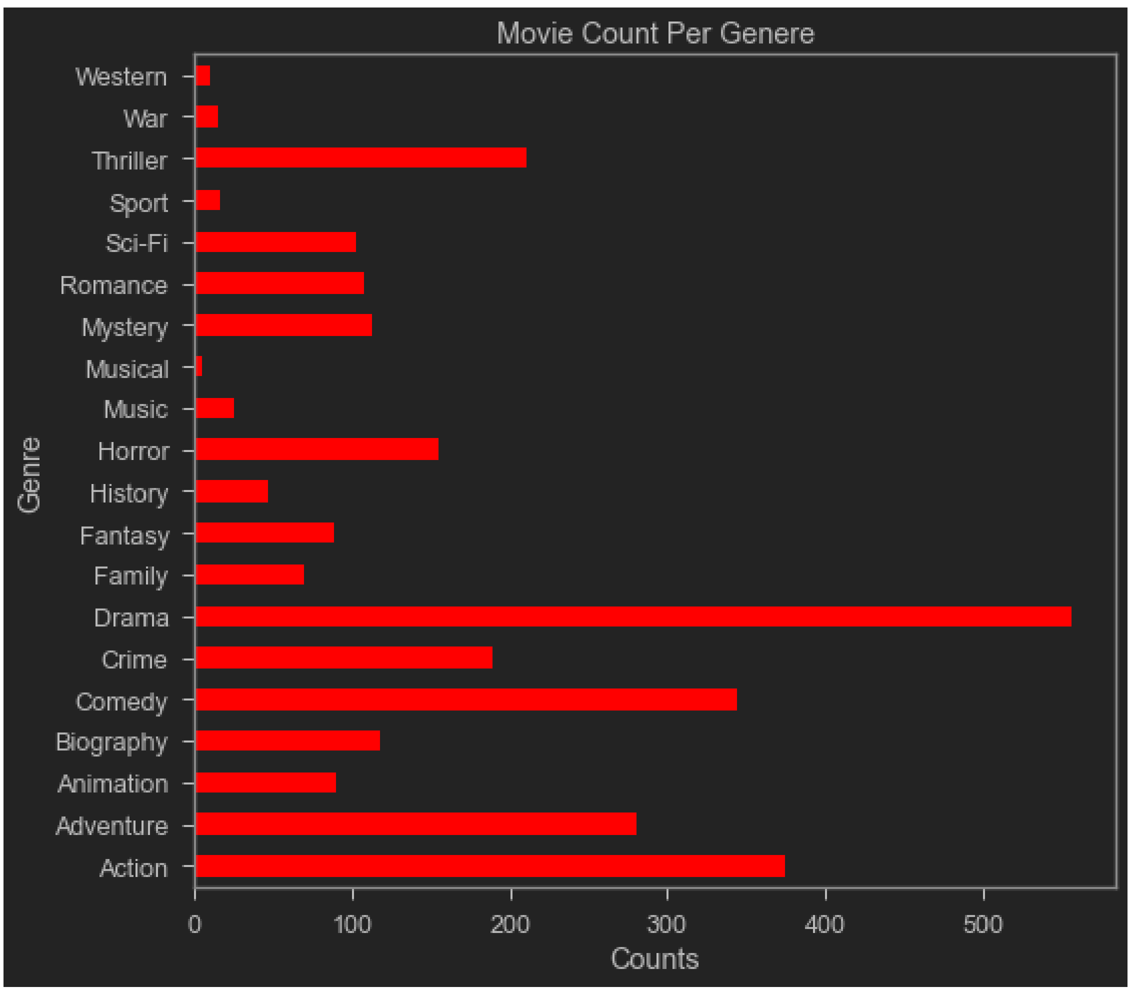
7.1 Which genre of movie to make, explained by top movie per genre

[127]:
```
genere_df = main_df.copy()
```

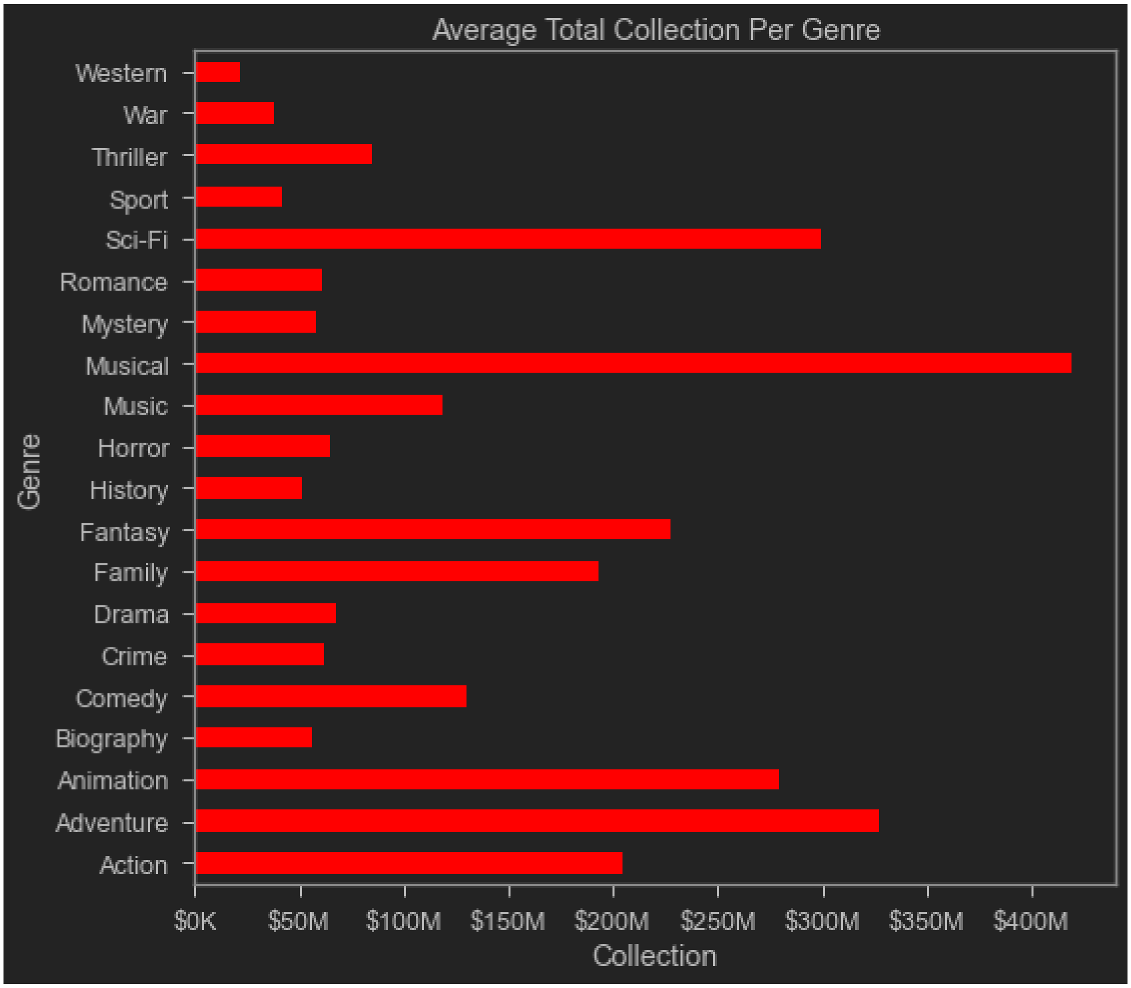
[128]:
```
genere_df.loc[:,'genres_exp'] = genere_df.genres.map(lambda x: x.split(','))
```

[129]:
```
genere_df_fig = genere_df.explode('genres_exp')
```

[130]:
```
# Movie Count Per Genere
genere_df_fig.groupby('genres_exp').count()['imdb_id'].plot(kind='barh',
                                                            color="red")
plt.title('Movie Count Per Genere')
plt.ylabel('Genre')
plt.xlabel('Counts')
plt.tight_layout()
plt.show()
```

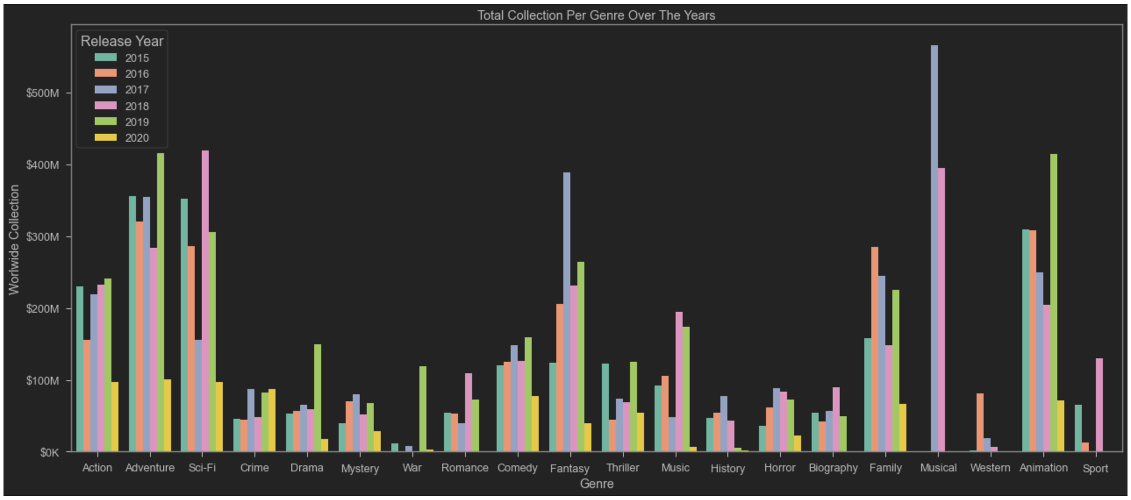


[131]:
```python
# Average Total Collection Per Genere
genere_df_fig.groupby('genres_exp').mean()['world_collection'].plot(
    kind='barh',color="red").xaxis.set_major_formatter(format_number)
plt.title('Average Total Collection Per Genre')
plt.ylabel('Genre')
plt.xlabel('Collection')
plt.tight_layout()
plt.show()
```

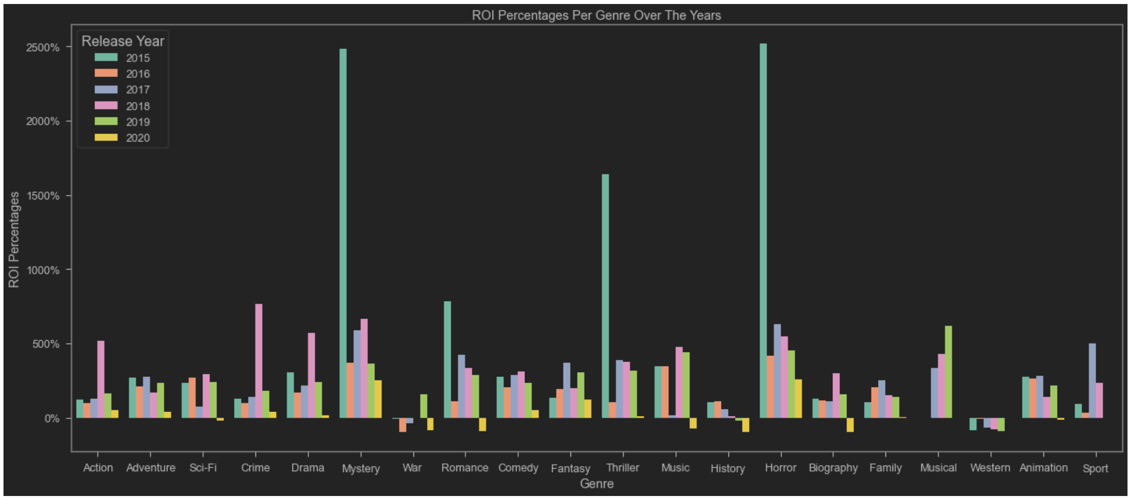


[132]:
```python
# styling
# sns.set_style('ticks')
fig, ax = plt.subplots()
fig.set_size_inches(18, 8)
# plotting
sns.barplot(data=genere_df_fig,
            x='genres_exp',
            y='world_collection',
```

```
            hue='release_year',
            palette='Set2',
            ci=None).yaxis.set_major_formatter(format_number)
plt.title('Total Collection Per Genre Over The Years')
plt.ylabel('Worlwide Collection')
plt.xlabel('Genre')
plt.legend(title='Release Year', title_fontsize='large')
plt.tight_layout()
plt.show()
```



[133]:
```
# styling
# sns.set_style('ticks')
fig, ax = plt.subplots()
fig.set_size_inches(18, 8)
# plotting
sns.barplot(data=genere_df_fig,
            x='genres_exp',
            y='ROI_percentage',
            hue='release_year', palette='Set2',ci=None).yaxis.
↪set_major_formatter(format_add_percentage)
plt.title('ROI Percentages Per Genre Over The Years')
plt.ylabel('ROI Percentages')
plt.xlabel('Genre')
plt.legend(title='Release Year', title_fontsize= 'large')
plt.tight_layout()
plt.show()
```



[134]:
```
plt.figure(figsize=(18, 10))
# plotting
plt.subplot(2, 1, 1)
sns.barplot(data=genere_df_fig,
            x='genres_exp',
            y='ROI_percentage',
            hue='release_year',
            palette='Set2',
            ci=None).yaxis.set_major_formatter(format_add_percentage)
plt.title('ROI Percentages Per Genre Over The Years')
plt.ylabel('ROI Percentages')
plt.xlabel('Genre')
plt.legend(title='Release Year', title_fontsize='large')
plt.tight_layout()

plt.subplot(2, 1, 2)
sns.barplot(data=genere_df_fig,
            x='genres_exp',
            y='world_collection',
            hue='release_year',
            palette='Set2',
            ci=None).yaxis.set_major_formatter(format_number)
plt.title('Total Collection Per Genre Over The Years')
plt.ylabel('Worlwide Collection')
plt.xlabel('Genre')
plt.legend().remove()
plt.tight_layout()

plt.show()
```

2015 was a good year for the industry. Animation has good performance but costly to make, hence lower percentage. Muscial had few good years then fell out of fashion. Action, Adventure, Family, Fantasy has been consistent performers. Horror and Mystery has high return percentage.

7.1.1 Action suggestion

Any one or combination of Action, Adventure, Animation is recommended. Animation and Action has 35% chance for occurring as genre combo. There is no landslide winner here, although this graphs can be used to figure out which one to avoid, for example western and war.

7.2 Best time to release movie

[135]:
```
timing_df = main_df.copy()
```

[136]:
```
timing_df['release_month']=timing_df['release_date'].dt.month
```

- minor feature engineering

Release months are put in three bins based on market analysts opinion.The dump months are what the film community calls the two periods of the year when there are lowered commercial and critical expectations for most new releases from American filmmakers and distributors.

1. January - May: Dump month
2. June - July: Summer
3. August - October: Dump month
4. November - December: Holidays

[137]:
```
timing_df['release_timing'] = pd.cut(
    timing_df['release_month'],
```

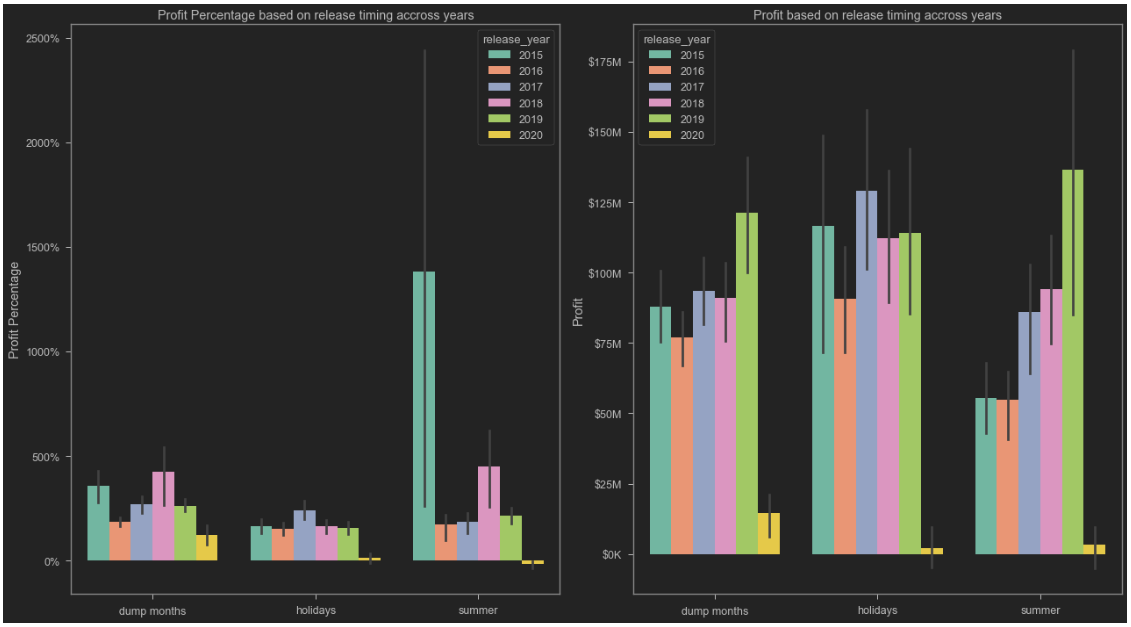
```
    bins=[0, 6, 8, 10, 12],
    labels=['dump months', 'summer', 'dump months', 'holidays'],
    ordered=False)
```

[138]:
```
timing_df.head(3)
```

[138]:
```
      imdb_id        primaryTitle       originalTitle  startYear  \
4   tt0369610      Jurassic World      Jurassic World       2015
6   tt0385887  Motherless Brooklyn  Motherless Brooklyn       2019
11  tt0437086  Alita: Battle Angel  Alita: Battle Angel       2019

   release_date  runtimeMinutes     budget  world_collection  int_collection  \
4    2015-06-06             124  150000000      1.671713e+09    1.018131e+09
6    2019-10-31             144   26000000      1.847774e+07    9.200000e+06
11   2019-01-31             122  170000000      4.049805e+08    3.191423e+08

    dom_collection  popularity  vote_average  vote_count  \
4      652385625.0      63.489           6.6       16595
6        9277736.0      75.020           6.8         842
11      85838210.0     175.798           7.2        6343

                                       production_comp original_language  \
4   Amblin Entertainment, Legendary Pictures, Univ…                en
6                          Class 5 Films, MWM Studios                en
11  Troublemaker Studios, Lightstorm Entertainment…                en

   belongs_to_collection.name                   genres  release_year  \
4     Jurassic Park Collection  Action,Adventure,Sci-Fi          2015
6                          NaN      Crime,Drama,Mystery          2019
11                         NaN  Action,Adventure,Sci-Fi          2019

             ROI  ROI_percentage  release_month release_timing
4   1.521713e+09     1014.475472              6    dump months
6  -7.522264e+06      -28.931785             10    dump months
11  2.349805e+08      138.223849              1    dump months
```

[139]:
```
plt.figure(figsize=(18, 10))
plt.subplot(1, 2, 1)
sns.barplot(data=timing_df,
            x='release_timing',
            y='ROI_percentage',
            hue='release_year',palette='Set2',
            ci=50).yaxis.set_major_formatter(format_add_percentage)
plt.title('Profit Percentage based on release timing accross years')
plt.ylabel('Profit Percentage')
plt.xlabel("")
```

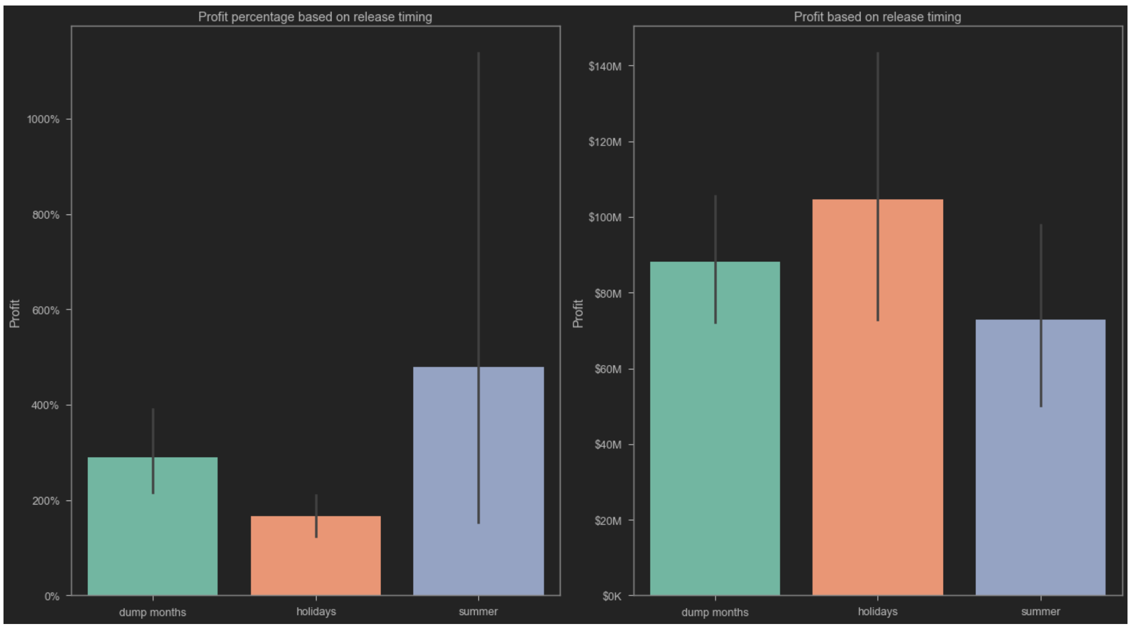
```
plt.subplot(1, 2, 2)
sns.barplot(data=timing_df,
            x='release_timing',
            y='ROI',
            hue='release_year',palette='Set2',
            ci=50).yaxis.set_major_formatter(format_number)
plt.title('Profit based on release timing accross years')
plt.ylabel('Profit')
plt.xlabel("")
plt.tight_layout()

plt.show()
```



2015's Summer was good in terms of percentage return but weirdly did not generate much cash. Releasing movie in the holidays season is the safest bet. But summer is having a consistent raise, except for 2020. 2020's summer was not normal by any means, thus this is expected.

[140]:
```
plt.figure(figsize=(18, 10))
plt.subplot(1, 2, 2)
sns.barplot(data=timing_df, x='release_timing', y='ROI',
            palette='Set2').yaxis.set_major_formatter(format_number)
plt.title('Profit based on release timing')
plt.ylabel('Profit')
plt.xlabel("")
plt.tight_layout()

plt.subplot(1, 2, 1)
```

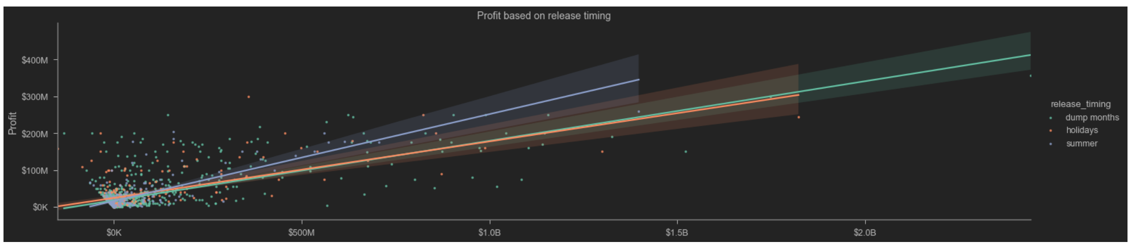
```
sns.barplot(data=timing_df,
            x='release_timing',
            y='ROI_percentage',
            palette='Set2').yaxis.set_major_formatter(format_add_percentage)
plt.title('Profit percentage based on release timing')
plt.ylabel('Profit')
plt.xlabel("")
plt.tight_layout()

plt.show()
```

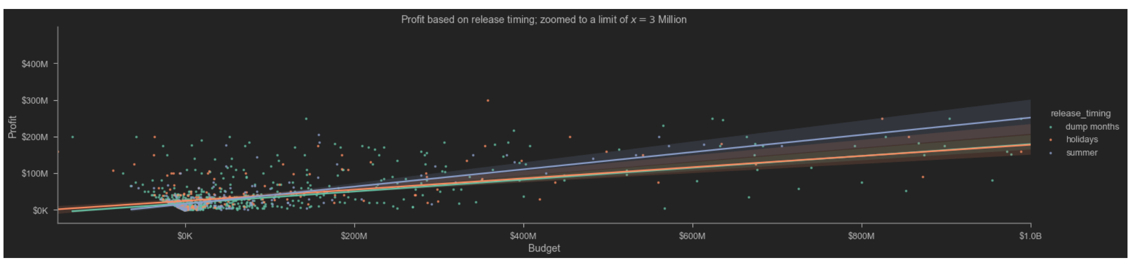


Movies released in holidays earn consistent returns but costs more. Summer is more dollar generating and volatile in a good way, on a uptrend.

[141]:
```
# Profit based on release timing
g = sns.lmplot(data=timing_df,
               x='ROI',
               y='budget',
               hue='release_timing',
               fit_reg=True,
               markers='.',
               aspect=4,palette='Set2',
               robust=True)
for ax in g.axes.flat:
    ax.yaxis.set_major_formatter(format_number)
    ax.xaxis.set_major_formatter(format_number)
plt.title('Profit based on release timing')
```

```
plt.ylabel('Profit')
plt.xlabel("")

g = sns.lmplot(data=timing_df,
               x='ROI',
               y='budget',
               hue='release_timing',
               fit_reg=True,
               markers='.',
               aspect=4,palette='Set2',
               robust=True)
plt.xlim(right=1000000000)
for ax in g.axes.flat:
    ax.yaxis.set_major_formatter(format_number)
    ax.xaxis.set_major_formatter(format_number)
plt.title('Profit based on release timing; zoomed to a limit of $x=3$ Million')
plt.ylabel('Profit')
plt.xlabel("Budget")

plt.show()
```

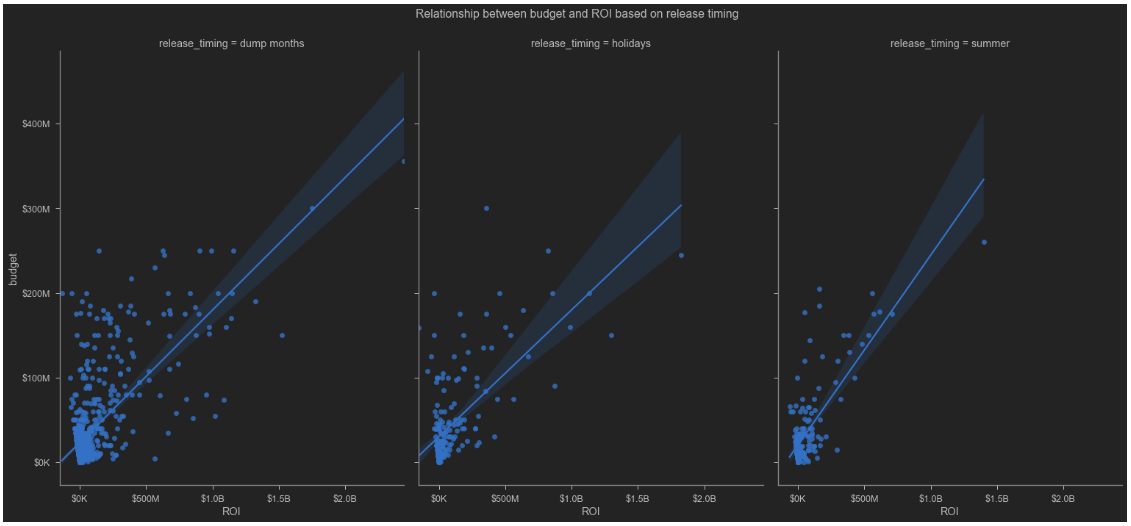




[142]:
```
# Relationship between budget and ROI based on release timing
g = sns.FacetGrid(
   timing_df, col='release_timing',
   height=10, aspect=.7, palette='Set2')
g.map(sns.regplot, 'ROI', 'budget')
for ax in g.axes.flat:
```

```
    ax.yaxis.set_major_formatter(format_number)
    ax.xaxis.set_major_formatter(format_number)
g.fig.subplots_adjust(top=0.9)
g.fig.suptitle('Relationship between budget and ROI based on release timing')
```

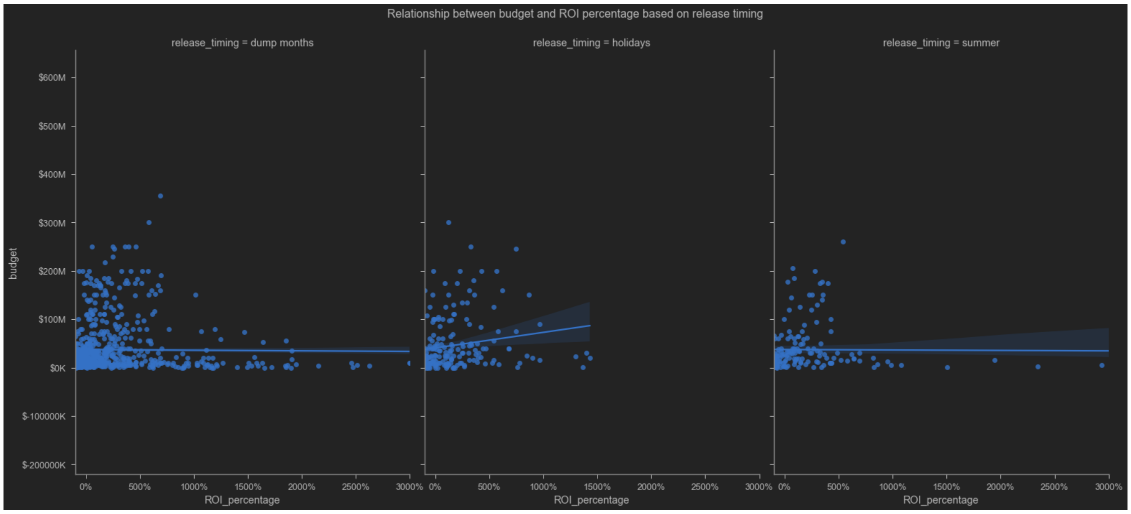
[142]: Text(0.5, 0.98, 'Relationship between budget and ROI based on release timing')



Producing movies for summer release is more costly, but return is steeper. Number of movies beyond 500 million is more frequent as well as observation counts are higher for holidays release, and the line is flatter meaning less costly to produce. Holidays season is the better option.

[143]:
```
# Relationship between budget and ROI based on release timing
g = sns.FacetGrid(
   timing_df, col='release_timing',
   height=10, aspect=.7, palette='Set2')
g.map(sns.regplot, 'ROI_percentage', 'budget')
plt.xlim(right=3000)
for ax in g.axes.flat:
    ax.yaxis.set_major_formatter(format_number)
    ax.xaxis.set_major_formatter(format_add_percentage)
g.fig.subplots_adjust(top=0.9)
g.fig.suptitle('Relationship between budget and ROI percentage based on release␣
 ↪timing')
```

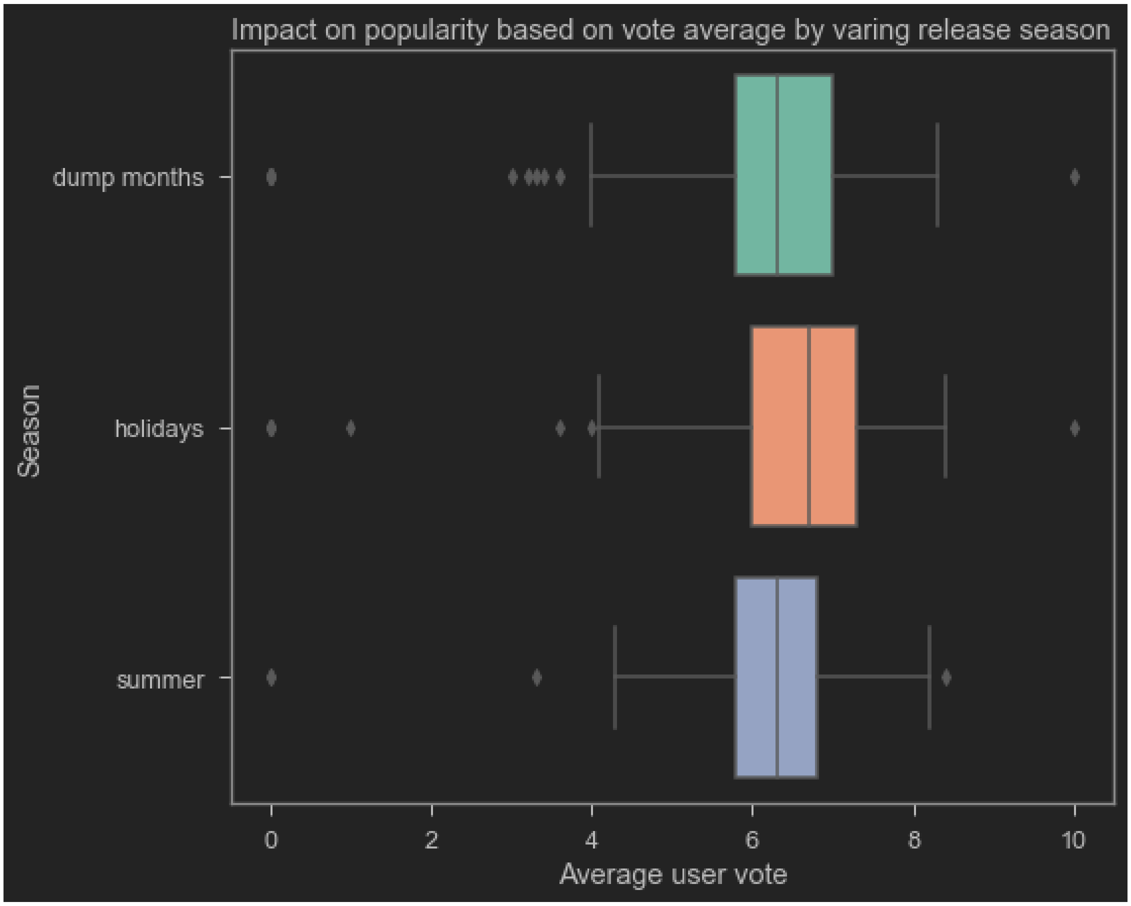
[143]: Text(0.5, 0.98, 'Relationship between budget and ROI percentage based on release timing')



summer has the best earning potential. But line is steeper for holidays, confirming the point made on the previous graph.

[144]:
```
# impact on popularity based on vote average by varing release season
sns.boxplot(x='vote_average', y='release_timing',data=timing_df, palette='Set2')
plt.title('Impact on popularity based on vote average by varing release season')
plt.ylabel('Season')
plt.xlabel("Average user vote")
```

[144]:
```
Text(0.5, 0, 'Average user vote')
```



Holidays movies are more popular and catch people on good mood maybe? Or content is less experimental. Reasoning can not be drawn from this figure but it can be said that holidays movies are more popular, which is good for entering the market with a more favorable impression on people.

7.2.1 Action suggestion

My recommendation is to focus for release schedule in the holidays season. There is higher probability of financial and critical success for movies released in that time frame. It is relatively cheaper to make than the next best option; i.e., Summer.

7.3 Franchise performance analysis leading to recommendation

[145]:
```
# getting a copy of main_df
franchaise_df_main = main_df.copy()
```

[146]:
```
# getting all movies that are part of a franchaise
franchaise_df = franchaise_df_main[~main_df['belongs_to_collection.name'].isna(
)]
```

[147]:
```
# renameing column for use later
franchaise_df = franchaise_df.rename(
    columns={"belongs_to_collection.name": "belongs_to_collection"})
```

[148]:
```
# getting all movies that are not part of a franchaise, yet!
non_franchaise_df = franchaise_df_main[
    main_df['belongs_to_collection.name'].isna()].copy()
```

7.3.1 Franchise info

By franchise I mean serialization of movies either based on a related intellectual property or sharing same cinematic universe.

[149]:
```
# list of unique franchaise names
list_of_franchaise = franchaise_df['belongs_to_collection'].unique()
```

[150]:
```
franchaise_df_ = franchaise_df.groupby('belongs_to_collection').mean(
).ROI_percentage.sort_values(ascending=False).reset_index()
```

[151]:
```
# formatting
format_dict = {
    'ROI': '${0:,.0f}',
    'budget': '${0:,.0f}',
    'ROI_percentage': '{:.2f}%'
}
# performance of movies that are part of a franchaise
franchaise_df.groupby('belongs_to_collection').mean()[[
    'ROI_percentage', 'ROI', 'budget'
]].sort_values(
    by='ROI_percentage',
    ascending=False)[:20].style.format(format_dict).background_gradient(
        cmap='afmhot')
```

[151]:
```
<pandas.io.formats.style.Styler at 0x1ff78ced220>
```

Most franchise earn a lot on their investment. This is expected as there is a reason for film makers to visit same universe several times. More often than not it is because of their proven success record and popularity among movie consumers.

which genre to franchaise

[152]:
```
print('On an average films that are part of a franchaise earn {:.2f}% return.'.
      format(franchaise_df.ROI_percentage.mean()))
```

```
On an average films that are part of a franchaise earn 727.47% return.
```

[153]:
```
# joining and filtering using SQL statements
list_of_franchaise_df0 = sqldf("""SELECT
            DISTINCT belongs_to_collection,
            a.ROI AS 'ROI', b.world_collection,
```

```
            b.genres
        FROM franchaise_df AS a
        JOIN franchaise_df AS b
        USING(belongs_to_collection);""")

format_dict = {'ROI': '${0:,.0f}', 'world_collection': '${0:,.0f}'}

list_of_franchaise_df0[~list_of_franchaise_df0.belongs_to_collection.
                       duplicated()].sort_values(
                           by='ROI',
                           ascending=False)[:15].style.background_gradient(
                               cmap='bwr').hide_index().format(format_dict)
```

[153]: <pandas.io.formats.style.Styler at 0x1ff39d10520>

Observation: None of them fall into a single genre.

[154]:
```
# joining and filtering using SQL statements
list_of_franchaise_df = sqldf(
    """SELECT
            belongs_to_collection,
            a.ROI_percentage AS 'ROI%',
            b.genres
        FROM franchaise_df_ AS a
        JOIN franchaise_df AS b
        USING(belongs_to_collection);""")
```

[155]:
```
# most often produced genre for serialization of movies
list_of_franchaise_df.loc[:, 'genres_exp'] = list_of_franchaise_df.genres.map(
    lambda x: x.split(','))

franchaise_genre = list_of_franchaise_df.explode('genres_exp').groupby(
    'genres_exp').agg(['count', 'mean']).sort_values(by=('ROI%', 'count'),
                                                     ascending=False)
franchaise_genre.columns = [
    " ".join(pair) for pair in franchaise_genre.columns
]
franchaise_genre=franchaise_genre.reset_index()
franchaise_genre.style.background_gradient(cmap='PRGn')
```

[155]: <pandas.io.formats.style.Styler at 0x1ff7b26ecd0>

[156]:
```
## from https://plotly.com/python/multiple-axes/ ##official plotly how to␣
↪instructions
fig = make_subplots(specs=[[{"secondary_y": True}]])
# Add traces
fig.add_trace(
    go.Bar(x=franchaise_genre['genres_exp'],
```

```
            y=franchaise_genre['ROI% count'],
            name="Movies released",
            offset=True),
    secondary_y=False,
)
fig.add_trace(
    go.Bar(x=franchaise_genre['genres_exp'],
            y=franchaise_genre['ROI% mean'],
            name="ROI% mean",
            offset=True,
            opacity=.6),
    secondary_y=True,
)
# Add figure title
fig.update_layout(title_text="Most often produced genre for serialized movies ")
# Set x-axis title
fig.update_xaxes(title_text="Genre")
# Set y-axes titles
fig.update_yaxes(title_text="<b>ROI% mean</b>", secondary_y=False)
fig.update_yaxes(title_text="<b>Number of Movie Released</b>",
                 secondary_y=True)
fig.show()
```

Adventure, Action, Comedy market is saturated. Horror, Thriller, Mystery release count is lower with higher mean return percentage. This recommendation will alter if we look at collection instead of ROI% because those genre requires less budget, so the return percentage is generally higher.

7.3.2 non franchise info

[157]:
```
print(
    'On an average films that are not part of a franchise earn {:.2f}% return.'
    .format(non_franchaise_df.ROI_percentage.mean()))
```

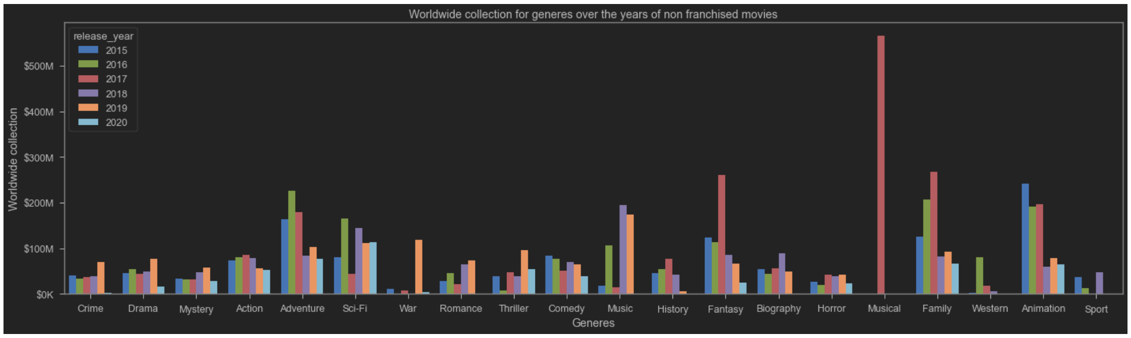
```
On an average films that are not part of a franchise earn 186.17% return.
```

[158]:
```
non_franchaise_df.loc[:, 'genres_exp'] = non_franchaise_df.genres.map(
    lambda x: x.split(','))
```

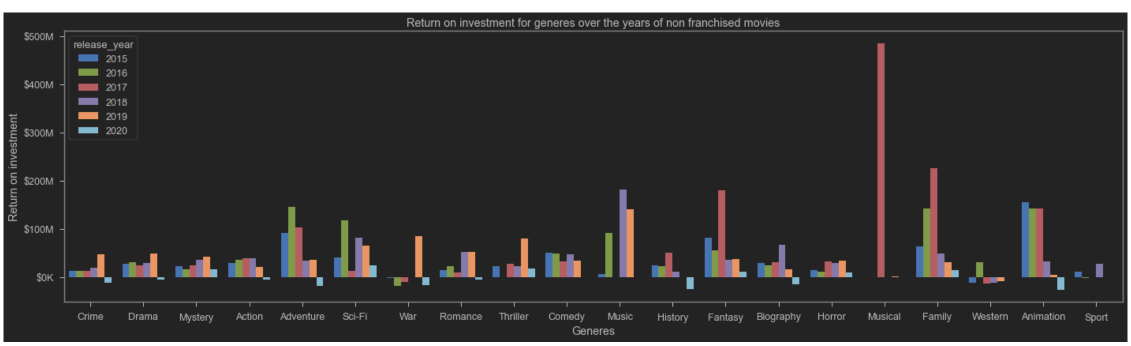
[159]:
```
non_franchaise_df = non_franchaise_df.explode('genres_exp')
```

[160]:
```
# Worldwide collection for generes over the years of non franchised movies
fig, ax = plt.subplots()
fig.set_size_inches(20, 6)
# plotting
sns.barplot(data=non_franchaise_df,
            x='genres_exp',
            y='world_collection',
            hue='release_year',ci=None).yaxis.set_major_formatter(format_number)
```

```
plt.title('Worldwide collection for generes over the years of non franchised␣
↪movies')
plt.ylabel('Worldwide collection')
plt.xlabel("Generes")
plt.tight_layout()

plt.show()
```



[161]:
```
# Return on investment for generes over the years of non franchised movies
fig, ax = plt.subplots()
fig.set_size_inches(20, 6)
# plotting
sns.barplot(data=non_franchaise_df,
            x='genres_exp',
            y='ROI',
            hue='release_year',ci=None).yaxis.set_major_formatter(format_number)
plt.title('Return on investment for generes over the years of non franchised␣
↪movies')
plt.ylabel('Return on investment')
plt.xlabel("Generes")
plt.tight_layout()

plt.show()
```



Non franchised movies are experiencing a hard time in the box office. The general trend is downwards across the board except Crime and Drama and Mystery. Mystery, Sci-Fi and Horror did well in 2020. Those three genres have high correlation.

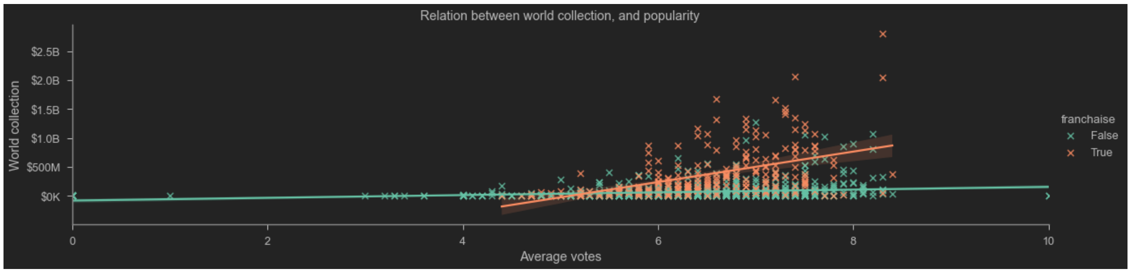
7.3.3 Side by side comparison

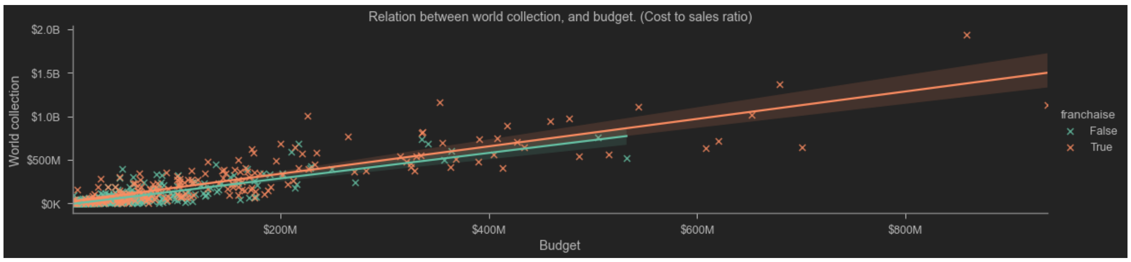
Converting franchise info in to a boolean arrey

[162]:
```
franchaise_df_main.loc[~main_df['belongs_to_collection.name'].isna(),
                       'franchaise'] = True
```

[163]:
```
franchaise_df_main.loc[main_df['belongs_to_collection.name'].isna(),
                       'franchaise'] = False
```

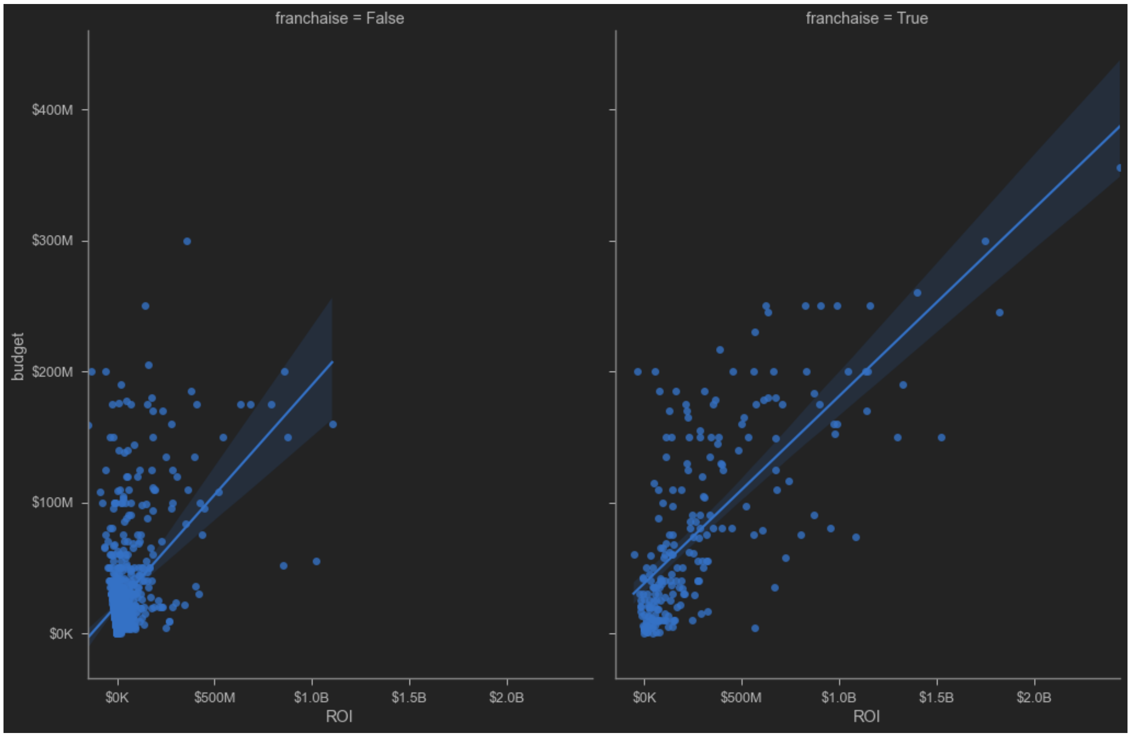
[164]:
```
g = sns.lmplot(data=franchaise_df_main,
               x='vote_average',
               y='world_collection',
               hue='franchaise',
               height=4,
               aspect=4,
               palette='Set2',
               markers='x')
for ax in g.axes.flat:
    ax.yaxis.set_major_formatter(format_number)

plt.title('Relation between world collection, and popularity')
plt.ylabel('World collection')
plt.xlabel("Average votes")

g = sns.lmplot(data=franchaise_df_main,
               x='dom_collection',
               y='int_collection',
               hue='franchaise',
               height=4,
               aspect=4,
               palette='Set2',
               markers='x')
for ax in g.axes.flat:
    ax.yaxis.set_major_formatter(format_number)
    ax.xaxis.set_major_formatter(format_number)
plt.title(
    'Relation between world collection, and budget. (Cost to sales ratio)')
plt.ylabel('World collection')
plt.xlabel("Budget")

plt.show()
```





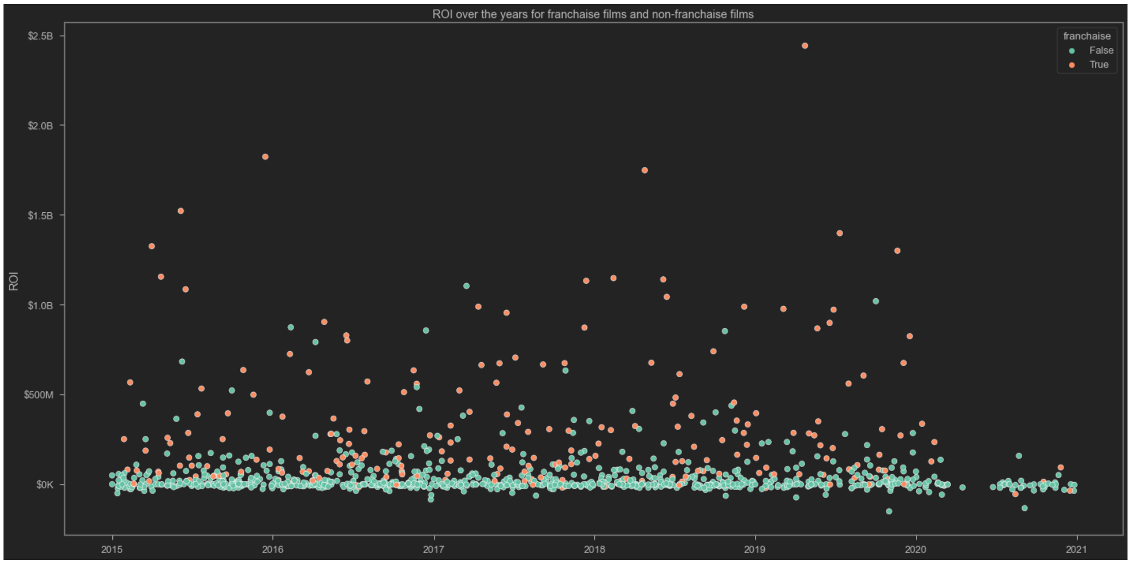
Franchised movies are often more popular with greater success in international market.

[165]:
```
g = sns.FacetGrid(
   franchaise_df_main, col='franchaise',
   height=10, aspect=.7, palette='Set2')
g.map(sns.regplot, 'ROI', 'budget')
for ax in g.axes.flat:
    ax.yaxis.set_major_formatter(format_number)
    ax.xaxis.set_major_formatter(format_number)
g.fig.subplots_adjust(top=0.9)
# g.fig.suptitle('Relationship between budget and ROI based on release timing')
```



Franchised movies require bigger budget bit their return is also significantly higher.

[166]:
```
# ROI over the years for franchaise films and non-franchaise films
plt.figure(figsize=(20, 10))
sns.scatterplot(x='release_date',
                y='ROI',
                hue='franchaise',
                data=franchaise_df_main,
                palette='Set2',
                legend='brief').yaxis.set_major_formatter(format_number)
plt.title('ROI over the years for franchaise films and non-franchaise films')
plt.ylabel('ROI')
plt.xlabel("")
plt.tight_layout()
```



This straightforward time series of box office gross profit of the two categories is the simplest but most layman friendly chart that demonstrate the stark difference between them. Franchised movies are consistently outperforming the other category.

7.3.4 Action suggestion

All the analysis leads towards starting a movie franchise in a shared movie universe. This must be be priority when selecting genre, director and other crew and cast. There must be option for serialization in the future. And for this Horror, Thriller, Mystery and Adventure, Action, Comedy genre should be prioritized. It very rare that a movie falls in only one genre this days.

8 Conclusion

Lets summarize and reiterate: ***1. My recommendation is to focus for release schedule in the*** holidays season***. There is higher probability of financial and critical success for movies released in that time frame. It is relatively cheaper to make than the next best option; i.e., Summer.

2. Any one or combination of ***Action***, ***Adventure***, ***Animation*** is recommended. Animation and Action has 35% chance for occurring as genre combo. There is no landslide winner here, although this graphs can be used to figure out which one to avoid, for example western and war.

3. All the analysis leads towards starting a ***franchise*** in a shared movie universe. This must be be priority when selecting genre, director and other crew and cast. There must be option for serialization in the future. And for this ****Horror, Thriller, Mystery**** or ****Adventure, Action, Comedy**** genre combination should be prioritized.

   It very rare that a movie falls in only one genre this days.

9 Next Steps

Further analyses could yield additional insights to further improve considerations for creating a new movie: ***

- Performance of **other** language movies and markets.
- Focusing on **low budget movies versus high budget movies** performance and rational.
- Movies performance in **home and international market**.
- Recommending **lead director**.
- Recommending **movie cast** classified on genre.
- Focus only on **2020** data and find pattern and trend.

10 For More Information

See the full analysis in the Jupyter Notebook or review this presentation.

11 Appendix

11.1 Most produced genre combo

[167]:
```
combo_genre = main_df_raw.iloc[:,18:-1].copy()
```

[168]:
```
combo_genre=combo_genre.corr()
combo_genre.style.background_gradient(cmap='PuRd')
```

[168]:
```
<pandas.io.formats.style.Styler at 0x1ff793d7220>
```

[169]:
```
correlation_top_bottom(combo_genre)
```

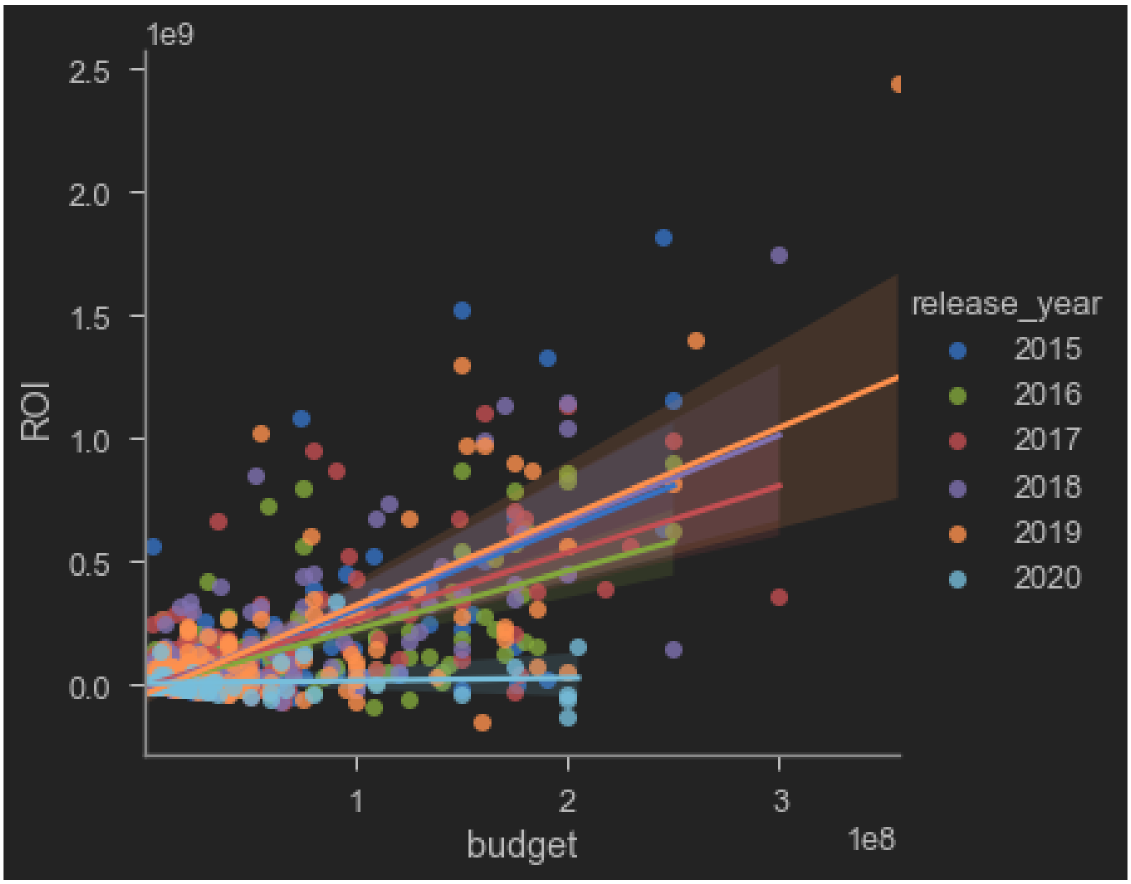
```
Positive correlations:
          index            feature_combo  correlation
0    359        Musical and Music     0.552813
1     38  Animation and Adventure     0.353164
2    316        Mystery and Horror     0.242051
3      1     Action and Adventure     0.234557
4     50     Biography and History     0.203732
5    256       Thriller and Horror     0.199766
6      7          Crime and Action     0.184287
7    140          Action and Crime     0.184287
8    255     Mystery and Thriller     0.176246
9     29     Adventure and Family     0.157636

 --------------------------------------------------------------------

       Negative correlations:
          index        feature_combo  correlation
0     65     Drama and Comedy    -0.290930
1    112  Thriller and Comedy    -0.248184
2     78  Drama and Animation    -0.203516
```

```
3     23  Drama and Adventure    -0.191267
4     76     Drama and Horror    -0.184330
5      3     Drama and Action    -0.155409
6    116    Comedy and Horror    -0.150491
7    115   Mystery and Comedy    -0.148315
8      5    Action and Comedy    -0.134239
9      8   Action and Romance    -0.124091
```

11.2 Variability of profitability on different metrics

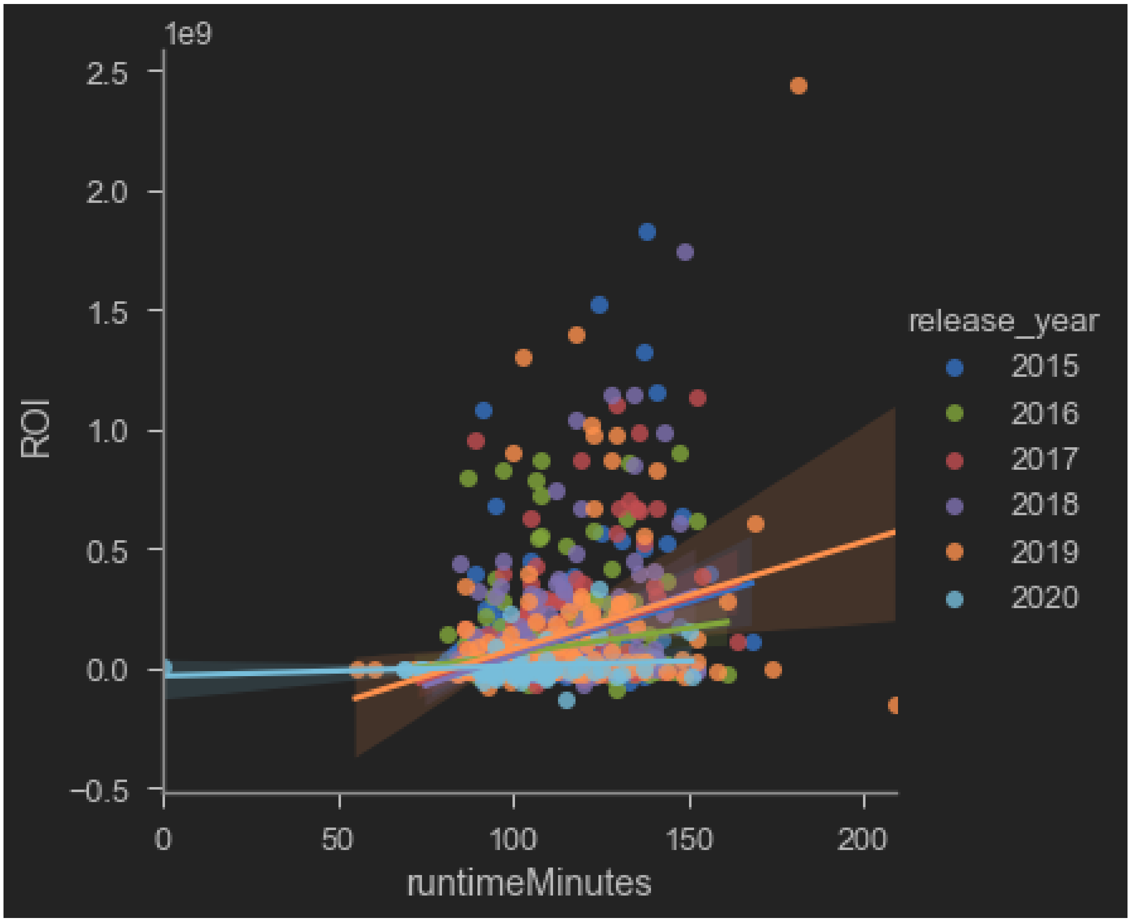
11.2.1 budget vs profitability

[170]:
```
sns.lmplot(data=main_df, x='budget', y='ROI',hue='release_year')
plt.show()
```



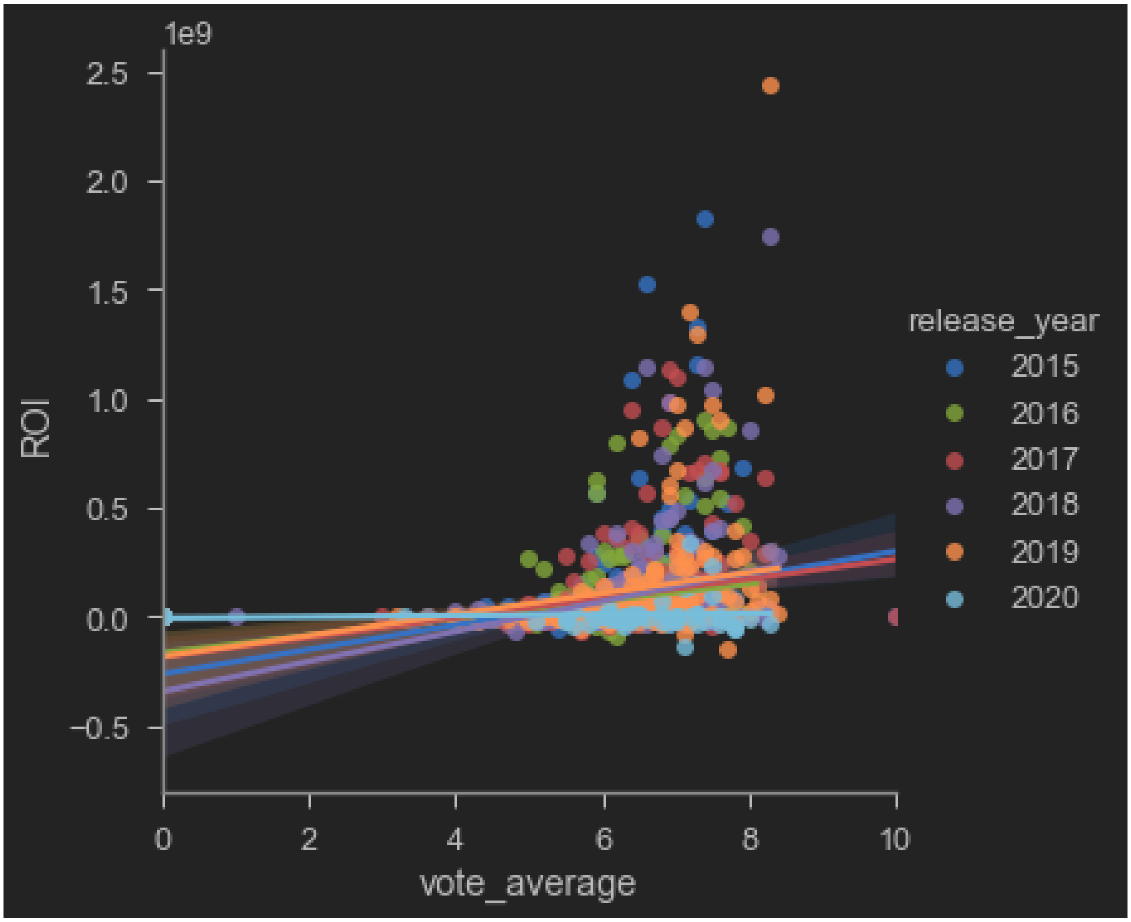
11.2.2 runtime on profitability

[171]:
```
sns.lmplot(data=main_df, x='runtimeMinutes', y='ROI',hue='release_year')
plt.show()
```



11.2.3 user rating on profitability

[172]:
```
sns.lmplot(data=main_df, x='vote_average', y='ROI',hue='release_year')
plt.show()
```


1e9
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
ROI
0
2
4
6
8
10
vote_average
release_year
2015
2016
2017
2018
2019
2020