Final Project Submission

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- Student pace: full time
- Scheduled project review date/time:
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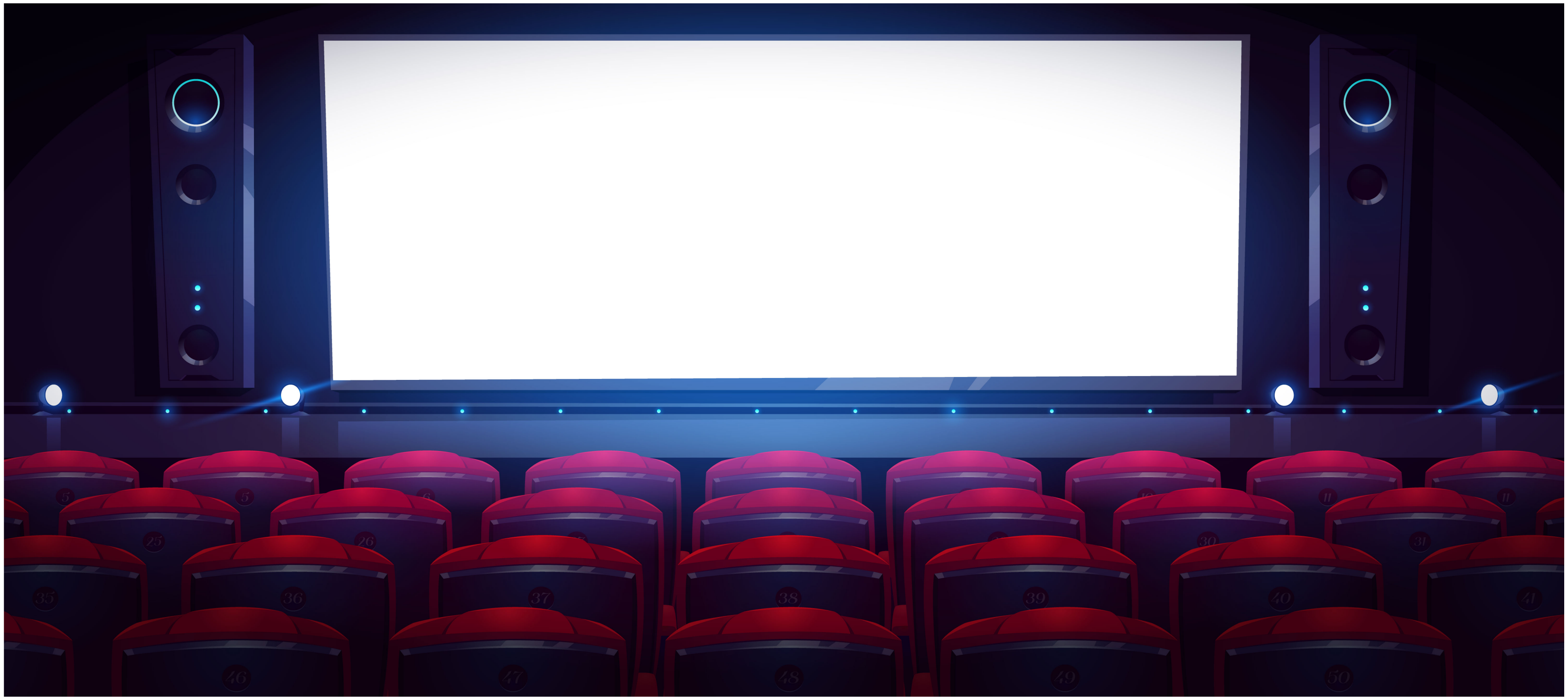
- Blog post URL:



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.

Microsoft Movies & TV

MICROSOFT MOVIES

Areas of focus:

> * movie generes.
> * profitability of success based on seasonality of releases.
> * profitabilty of movie franchise/film series.

3 The imports

3.1 Packages and Libraries

In [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
```

In [2]:

```python
# 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
```

In [3]:

```python
# 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
```

In [4]:

```python
# to see dataframe better
pd.set_option('display.max_columns', 50)
```

3.2 Frequently used fuctions

In [5]:

```python
# Number formatter
def format_number(data_value, index):
    if data_value >= 1_000_000_000:
        formatter = '${:1.1f}B'.format(data_value*0.000_000_001)
    elif data_value >= 1_000_000:
        formatter = '${:1.0f}M'.format(data_value*0.000_001)
    else:
        formatter = '${:1.0f}K'.format(data_value*0.001)
    return formatter
```

In [6]:

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

In [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
```

In [8]:

```python
initialize_scraping_and_API = False
```

4 The Data

- IMDb (https://www.imdb.com/) 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 (https://www.boxofficemojo.com/) is also a part of IMDb.com, Inc., providing indepth financial informations among other metrics.
- TMDb (https://www.themoviedb.org/) 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 (https://datasets.imdbws.com) from downloadables, and scraping using selenium (https://www.selenium.dev/) . Additional data collected from TMDb using API (https://www.themoviedb.org/documentation/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 (https://datasets.imdbws.com/title.basics.tsv.gz)](https://datasets.imdbws.com/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 (https://sites.google.com/a/chromium.org/chromedriver/downloads)](https://sites.google.com/a/chromium.org/chromedriver/downloads).

In [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)
```

```python
        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
```

In [10]:

```python
# 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)
```

In [11]:

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

In [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

In [13]:

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

In [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']
```

In [15]:

```
if initialize_scraping_and_API is True:
    tmdb.API_KEY = api_key
```

In [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"])
```

In [17]:

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

In [18]:

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

In [19]:

```
# empty df to store results
if initialize_scraping_and_API is True:
    df = pd.DataFrame()
```

In [20]:

```python
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
```

In [21]:

```python
if initialize_scraping_and_API is True:
    df = df.reset_index()
```

In [22]:

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

In [23]:

```python
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

In [24]:

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

```
Wall time: 17.7 s
```

5.1.2 inspecting

In [25]:

```python
df_1.head(3)
```

	tconst	titleType	primaryTitle	originalTitle	isAdult	startYear	endYear	runtimeMinutes	genres
0	tt0000001	short	Carmencita	Carmencita	0	1894	\N	1	Documentary,Short
1	tt0000002	short	Le clown et ses chiens	Le clown et ses chiens	0	1892	\N	5	Animation,Short
2	tt0000003	short	Pauvre Pierrot	Pauvre Pierrot	0	1892	\N	4	Animation,Comedy,Romance

In [26]:

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

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

5.1.3 cleaning

In [27]:

```python
%%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
```

	tconst	primaryTitle	originalTitle	startYear	runtimeMinutes	genres
0	tt0000502	Bohemios	Bohemios	1905	100	NoInfo
1	tt0000574	The Story of the Kelly Gang	The Story of the Kelly Gang	1906	70	Action,Adventure,Biography
2	tt0000615	Robbery Under Arms	Robbery Under Arms	1907	NaN	Drama
3	tt0000630	Hamlet	Amleto	1908	NaN	Drama
4	tt0000675	Don Quijote	Don Quijote	1908	NaN	Drama
...	...	...	...	...	...	...
490999	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	57	Documentary
491000	tt9916680	De la ilusión al desconcierto: cine colombiano...	De la ilusión al desconcierto: cine colombiano...	2007	100	Documentary
491001	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
491002	tt9916730	6 Gunn	6 Gunn	2017	116	NoInfo
491003	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	49	Documentary

491004 rows × 6 columns

splitting genere

In [28]:

```python
%%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)
# 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: 28 ms
```

```
['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']
```

In [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: 2.42 s
```

In [30]:

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

In [31]:

```
# enforcing dtypes
movie_main_df = movie_main_df.convert_dtypes()
```

In [32]:

```
movie_main_df.shape
```

```
(491004, 35)
```

In [33]:

```python
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
```

In [34]:

```python
movie_main_df.describe()
```

	tconst	primaryTitle	originalTitle	startYear	runtimeMinutes	genres	NoInfo	Action	Adventure	Biography	Drama	Fantasy	Comedy	War	Documentary
count	491004	491004	491004	491004	348729	491004	491004	491004	491004	491004	491004	491004	491004	491004	491004
unique	491004	435498	444525	133	470	1317	2	2	2	2	2	2	2	2	2
top	tt0010975	Mother	Home	2017	90	Drama	False	False	False	False	False	False	False	False	False
freq	1	40	36	17755	23507	90267	424787	450544	468879	478159	309787	480389	404506	483095	393223

In [35]:

```python
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')
```

In [36]:

```python
movie_main_df['startYear'].sort_values().unique()
```

```
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.

In [37]:

```python
# 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)]
```

In [38]:

```python
movie_main_df_sliced.describe()
```

	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

In [39]:

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

In [40]:

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

In [41]:

```python
movie_main_df_sliced
```

	tconst	primaryTitle	originalTitle	startYear	runtimeMinutes	genres	NoInfo	Action	Adventure	Biography	Drama	Fantasy	Comedy	War
5089	tt0011216	Spanish Fiesta	La fête espagnole	2019	67	Drama	False	False	False	False	True	False	False	False
5560	tt0011801	Tötet nicht mehr	Tötet nicht mehr	2019	0	Action,Crime	False	True	False	False	False	False	False	False
9809	tt0016906	Frivolinas	Frivolinas	2014	80	Comedy,Musical	False	False	False	False	False	False	True	False
45545	tt0062336	El Tango del Viudo y Su Espejo Deformante	El Tango del Viudo y Su Espejo Deformante	2020	70	Drama	False	False	False	False	True	False	False	False
50362	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122	Drama	False	False	False	False	True	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
490995	tt9916270	Il talento del calabrone	Il talento del calabrone	2020	84	Thriller	False	False	False	False	False	False	False	False
490996	tt9916362	Coven	Akelarre	2020	90	Adventure,Drama,History	False	False	True	False	True	False	False	False
490997	tt9916428	The Secret of China	Hong xing zhao yao Zhong guo	2019	0	Adventure,History,War	False	False	True	False	False	False	False	True
490998	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123	Drama	False	False	False	False	True	False	False	False
491002	tt9916730	6 Gunn	6 Gunn	2017	116	NoInfo	True	False	False	False	False	False	False	False

84546 rows × 35 columns

In [42]:

```python
movie_main_df_sliced.to_csv('./Data/movie_main_df_sliced.csv',index = False)
```

5.2 Merging all sources

In [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

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

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

	tconst	primaryTitle	originalTitle	startYear	runtimeMinutes	genres	NoInfo	Action	Adventure	Biography	Drama	Fantasy	Comedy	War	D
0	tt0011216	Spanish Fiesta	La fête espagnole	2019	67	Drama	False	False	False	False	True	False	False	False	Fa
1	tt0011801	Tötet nicht mehr	Tötet nicht mehr	2019	0	Action,Crime	False	True	False	False	False	False	False	False	Fa
2	tt0016906	Frivolinas	Frivolinas	2014	80	Comedy,Musical	False	False	False	False	False	False	True	False	Fa
3	tt0062336	El Tango del Viudo y Su Espejo Deformante	El Tango del Viudo y Su Espejo Deformante	2020	70	Drama	False	False	False	False	True	False	False	False	Fa
4	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122	Drama	False	False	False	False	True	False	False	False	Fa
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
84541	tt9916270	Il talento del calabrone	Il talento del calabrone	2020	84	Thriller	False	False	False	False	False	False	False	False	Fa
84542	tt9916362	Coven	Akelarre	2020	90	Adventure,Drama,History	False	False	True	False	True	False	False	False	Fa
84543	tt9916428	The Secret of China	Hong xing zhao yao Zhong guo	2019	0	Adventure,History,War	False	False	True	False	False	False	False	True	Fa
84544	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123	Drama	False	False	False	False	True	False	False	False	Fa
84545	tt9916730	6 Gunn	6 Gunn	2017	116	NoInfo	True	False	False	False	False	False	False	False	Fa

84546 rows × 42 columns

prepping for merge 2

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

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

```
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')
```

In [48]:

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

In [49]:

```
tmdb_df_reduced = tmdb_df[filter_list]
```

merge 2

In [50]:

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

In [51]:

```
df = merge_2.copy()
```

In [52]:

```
df.columns
```

```
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

In [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

In [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
```

In [55]:

```
df.describe()
```

	startYear	year	runtimeMinutes	budget	revenue	world_collection	int_collection	dom_collection	popularity	vote_average	vote_count
count	44353.000000	13351.000000	44353.000000	4.435300e+04	4.435300e+04	1.335100e+04	1.264600e+04	3.289000e+03	44353.000000	44353.000000	44353.000000
mean	2017.107704	2016.916411	88.849976	1.462749e+06	4.188408e+06	1.722414e+07	1.279721e+07	2.060086e+07	5.966112	3.952096	101.957252
std	2.025922	1.846724	36.046684	1.175852e+07	4.898516e+07	9.106972e+07	6.373112e+07	6.311116e+07	40.339807	3.108509	742.014378
min	2014.000000	2014.000000	0.000000	0.000000e+00	0.000000e+00	2.000000e+00	2.000000e+00	4.900000e+01	0.000000	0.000000	0.000000
25%	2015.000000	2015.000000	81.000000	0.000000e+00	0.000000e+00	3.873450e+04	4.289450e+04	3.447100e+04	0.600000	0.000000	0.000000
50%	2017.000000	2017.000000	92.000000	0.000000e+00	0.000000e+00	3.877660e+05	4.062780e+05	3.423700e+05	1.513000	5.000000	2.000000
75%	2019.000000	2018.000000	106.000000	0.000000e+00	0.000000e+00	3.320476e+06	3.206889e+06	8.106986e+06	5.705000	6.400000	10.000000
max	2021.000000	2021.000000	1260.000000	3.560000e+08	2.797801e+09	2.797501e+09	1.939128e+09	9.366622e+08	5227.005000	10.000000	25252.000000

In [56]:

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

```
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.

In [57]:

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

```
True     31002
False    13351
Name: world_collection, dtype: int64
```

In [58]:

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

```
False    44003
True       350
dtype: int64
```

In [59]:

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

In [60]:

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

In [61]:

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

In [62]:

```
df
```

	tconst	imdb_code	imdb_id	primaryTitle	originalTitle	name	title	startYear	year	release_date	runtimeMinutes	budget	revenue	world_collection
5	tt0100275	tt0100275	tt0100275	The Wandering Soap Opera	La Telenovela Errante	The Wandering Soap Opera	The Wandering Soap Opera	2017	2017.0	2017-08-10	80	0	0	3.624000e+03
22	tt0315642	tt0315642	tt0315642	Wazir	Wazir	Wazir	Wazir	2016	2016.0	2016-01-07	103	5200000	9200000	5.633588e+06
26	tt0331314	tt0331314	tt0331314	Bunyan and Babe	Bunyan and Babe	Bunyan and Babe	Bunyan and Babe	2017	2017.0	2017-01-12	84	0	0	7.206000e+04
32	tt0365907	tt0365907	tt0365907	A Walk Among the Tombstones	A Walk Among the Tombstones	A Walk Among the Tombstones	A Walk Among the Tombstones	2014	2014.0	2014-09-18	114	28000000	53181600	5.883438e+07
33	tt0369610	tt0369610	tt0369610	Jurassic World	Jurassic World	Jurassic World	Jurassic World	2015	2015.0	2015-06-06	124	150000000	1671713208	1.670516e+09
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
44331	tt9908390	tt9908390	tt9908390	Le lion	Le lion	Le lion	The Lion	2020	2020.0	2020-01-29	95	0	0	3.507711e+06
44333	tt9908960	tt9908960	tt9908960	Pliusas	Pliusas	Pliusas	Pliusas	2018	2018.0	2018-09-07	90	0	0	7.463700e+04
44339	tt9911196	tt9911196	tt9911196	The Marriage Escape	De beentjes van Sint-Hildegard	The Marriage Escape	The Marriage Escape	2020	2020.0	2020-02-10	103	0	0	7.760946e+06
44347	tt9914942	tt9914942	tt9914942	La vida sense la Sara Amat	La vida sense la Sara Amat	La vida sense la Sara Amat	La vida sense la Sara Amat	2019	2019.0	2019-07-12	74	0	0	5.979400e+04
44352	tt9916428	tt9916428	tt9916428	The Secret of China	Hong xing zhao yao Zhong guo	The Secret of China	The Secret of China	2019	2019.0	2019-08-08	0	0	0	4.408165e+06

13701 rows × 46 columns

In [63]:

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

In [64]:
```python
# redundent data droping
drop_list = [
    'tconst', 'imdb_code', 'index','name', 'title', 'year', 'revenue', 'url'
]
```

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

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

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

dealing with nested data

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

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

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

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

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

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

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

In [74]:
```python
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)
```

In [75]:

```python
#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)
```

In [76]:

```python
pro = pd.DataFrame.from_dict(temp_li)
```

In [77]:

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

In [78]:

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

In [79]:

```python
df_final = pd.merge(df, pro_1, left_on='imdb_id', right_on='imdb_id')
```

- touchup

In [80]:

```
1 df_final.head(4)
```

	imdb_id	primaryTitle	originalTitle	startYear	release_date	runtimeMinutes	budget	world_collection	int_collection	dom_collection	production_companies	popularity
0	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	2017-08-10	80	0	3624.0	NaN	3624.0	[{'id': 96241, 'logo_path': None, 'name': 'Poe...	1.400
1	tt0315642	Wazir	Wazir	2016	2016-01-07	103	5200000	9200000.0	4509543.0	1124045.0	[{'id': 12865, 'logo_path': None, 'name': 'Get...	5.191
2	tt0331314	Bunyan and Babe	Bunyan and Babe	2017	2017-01-12	84	0	72060.0	72060.0	NaN	[{'id': 87468, 'logo_path': None, 'name': 'Too...	20.049
3	tt0365907	A Walk Among the Tombstones	A Walk Among the Tombstones	2014	2014-09-18	114	28000000	58834384.0	32526784.0	26307600.0	[{'id': 39043, 'logo_path': None, 'name': 'Tra...	34.302

In [81]:

```
1 df_final.columns
```

```
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')
```

In [82]:

```
1 df_final=df_final.drop(columns='production_companies')
```

In [83]:
```
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'
]
```

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

In [85]:
```
df_final
```

	imdb_id	primaryTitle	originalTitle	startYear	release_date	runtimeMinutes	budget	world_collection	int_collection	dom_collection	popularity	vote_average	v
0	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	2017-08-10	80	0	3.624000e+03	NaN	3624.0	1.400	6.5	9
1	tt0315642	Wazir	Wazir	2016	2016-01-07	103	5200000	9.200000e+06	4.509543e+06	1124045.0	5.191	6.6	9
2	tt0331314	Bunyan and Babe	Bunyan and Babe	2017	2017-01-12	84	0	7.206000e+04	7.206000e+04	NaN	20.049	6.2	1

In [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

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

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

In [89]:

```python
main_df=main_df[~main_df.release_date.isna()]
```

In [90]:

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

```
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.

In [91]:

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

In [92]:

```python
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
```

In [93]:

```python
main_df.describe()
```

	startYear	runtimeMinutes	budget	world_collection	int_collection	dom_collection	popularity	vote_average	vote_count	release_year
count	11779.000000	11779.000000	1.177900e+04	1.177900e+04	1.092400e+04	2.765000e+03	11779.000000	11779.000000	11779.000000	11779.000000
mean	2017.283895	100.864080	4.205773e+06	1.681113e+07	1.246981e+07	2.061955e+07	10.595399	5.553162	284.940233	2017.374989
std	1.561950	28.732314	2.011748e+07	9.159840e+07	6.418805e+07	6.528838e+07	41.142722	2.258754	1241.668467	1.564721
min	2014.000000	0.000000	0.000000e+00	1.000000e+00	2.000000e+00	4.900000e+01	0.000000	0.000000	0.000000	2015.000000
25%	2016.000000	90.000000	0.000000e+00	3.603400e+04	3.774625e+04	3.667600e+04	1.279500	5.100000	3.000000	2016.000000
50%	2017.000000	100.000000	0.000000e+00	3.732710e+05	3.666200e+05	3.379070e+05	3.148000	6.100000	14.000000	2017.000000
75%	2019.000000	114.000000	0.000000e+00	3.255714e+06	2.972528e+06	7.743794e+06	8.796000	6.900000	78.000000	2019.000000
max	2021.000000	808.000000	3.560000e+08	2.797801e+09	1.939128e+09	9.366622e+08	2103.518000	10.000000	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.

In [94]:

```python
main_df.shape
```

```
(11779, 18)
```

In [95]:

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

In [96]:

```python
main_df.shape
```

```
(2081, 18)
```

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

In [97]:

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

In [98]:

```python
main_df.shape
```

```
(1113, 18)
```

In [99]:

```python
main_df.columns
```

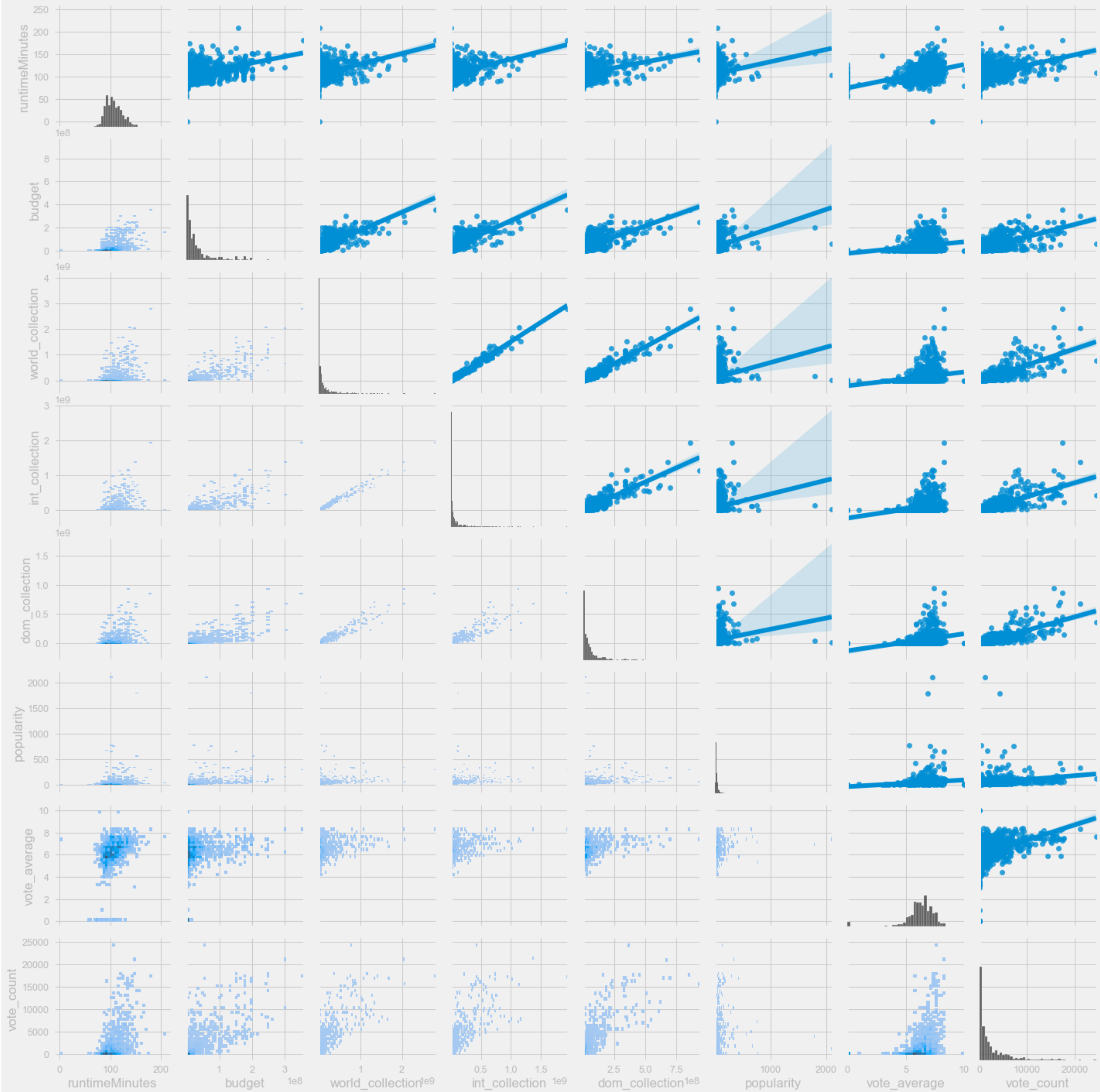
```
Index(['imdb_id', 'primaryTitle', 'originalTitle', 'startYear', 'release_date',
       'runtimeMinutes', 'budget', 'world_collection', 'int_collection',
       'dom_collection', 'popularity', 'vote_average', 'vote_count',
       'production_comp', 'original_language', 'belongs_to_collection.name',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

In [100]:

```
list_for_pairplot = ['release_date',
        'runtimeMinutes', 'budget', 'world_collection', 'int_collection',
        'dom_collection', 'popularity', 'vote_average', 'vote_count',
        'belongs_to_collection.name']
```

In [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)
```


runtimeMinutes
budget
world_collection
int_collection
dom_collection
popularity
vote_average
vote_count
1e8
1e9
1e8

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.

$$\text{ROI (\%)} = \frac{\text{Total Revenue - Total Cost}}{\text{Total Cost}} \times 100$$

5.4.1.1 Return on investment in $ value

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

5.4.1.2 Return on investment in percentage,

expressed in full, not in decimal

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

5.5 Final Check to see that everything is in place

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

```
(1113, 20)
```

In [105]:

```
1main_df.head()
```

	imdb_id	primaryTitle	originalTitle	startYear	release_date	runtimeMinutes	budget	world_collection	int_collection	dom_collection	popularity	vote_average	vote
4	tt0369610	Jurassic World	Jurassic World	2015	2015-06-06	124	150000000	1.671713e+09	1.018131e+09	652385625.0	63.489	6.6	1659
6	tt0385887	Motherless Brooklyn	Motherless Brooklyn	2019	2019-10-31	144	26000000	1.847774e+07	9.200000e+06	9277736.0	75.020	6.8	842
11	tt0437086	Alita: Battle Angel	Alita: Battle Angel	2019	2019-01-31	122	170000000	4.049805e+08	3.191423e+08	85838210.0	175.798	7.2	6343
12	tt0441881	Danger Close	Danger Close: The Battle of Long Tan	2019	2019-08-08	118	23934823	2.088085e+06	2.088085e+06	NaN	112.552	6.8	148
14	tt0443533	The History of Love	The History of Love	2016	2016-11-09	134	20000000	4.922720e+05	4.922720e+05	NaN	5.406	6.4	63

In [106]:

```
1main_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
```

In [107]:

```
main_df.describe()
```

	startYear	runtimeMinutes	budget	world_collection	int_collection	dom_collection	popularity	vote_average	vote_count	release_year	ROI	ROI_perce
count	1113.000000	1113.000000	1.113000e+03	1.113000e+03	1.039000e+03	8.820000e+02	1113.000000	1113.000000	1113.000000	1113.000000	1.113000e+03	1113.00000
mean	2016.993711	107.323450	3.841841e+07	1.271450e+08	8.259442e+07	6.207522e+07	43.486649	6.261995	2338.715184	2017.052111	8.872658e+07	296.570055
std	1.532899	17.613393	5.251428e+07	2.613752e+08	1.761494e+08	1.039024e+08	103.773946	1.246853	3332.521354	1.522309	2.226630e+08	1647.22041
min	2014.000000	0.000000	5.000000e+03	5.470000e+02	5.470000e+02	1.377000e+03	0.600000	0.000000	0.000000	2015.000000	-1.510000e+08	-99.981875
25%	2016.000000	94.000000	6.000000e+06	2.084628e+06	1.177836e+06	5.622565e+06	13.550000	5.800000	266.000000	2016.000000	-3.898454e+06	-69.544079
50%	2017.000000	105.000000	1.900000e+07	2.935520e+07	1.424425e+07	2.740507e+07	22.168000	6.400000	1020.000000	2017.000000	8.197072e+06	63.263233
75%	2018.000000	118.000000	4.000000e+07	1.195200e+08	6.891399e+07	6.725403e+07	41.249000	7.000000	3038.000000	2018.000000	7.501105e+07	296.521358
max	2020.000000	209.000000	3.560000e+08	2.797801e+09	1.939128e+09	9.366622e+08	2103.518000	10.000000	24543.000000	2020.000000	2.441801e+09	42864.4100

> if only want to focus on profitable movies

In [108]:

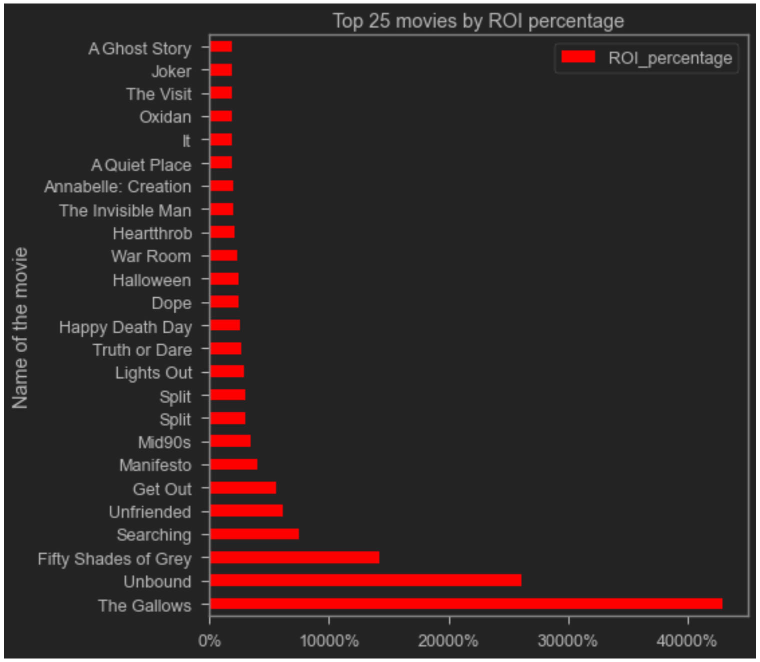
```
# main_df = main_df[main_df.ROI>0]
```

6 Exploratory data analysis

6.1 EDA - top movie by return %

In [109]:

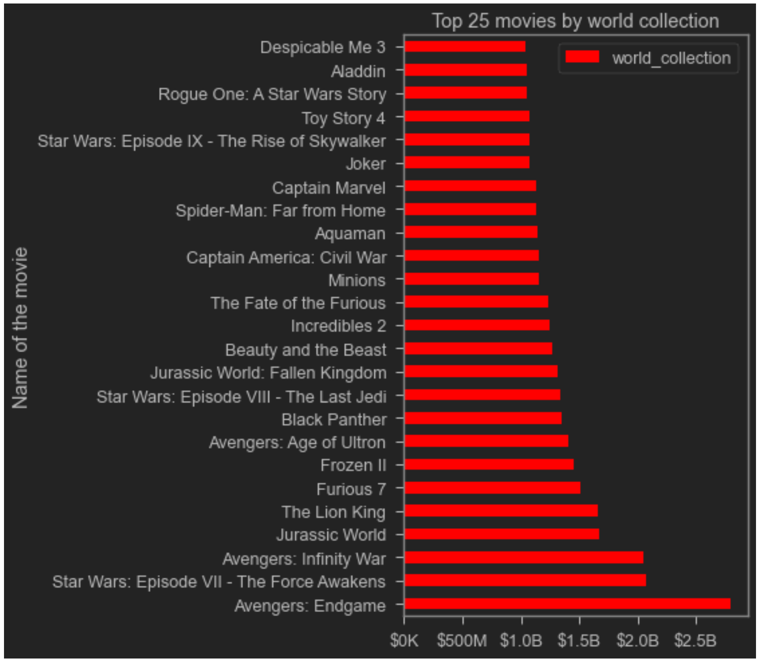
```
ax = main_df.sort_values(by='ROI_percentage',
                         ascending=False).head(25).plot(kind='barh',
                                                        x='primaryTitle',
                                                        y='ROI_percentage',
                                                        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

In [110]:

```
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

In [111]:

```python
studio_df = main_df.copy()
```

In [112]:

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

In [113]:

```python
studio_df_fig = studio_df.explode('production_comp_exp')
```

In [114]:

```python
studio_df_fig.head(3)
```

	imdb_id	primaryTitle	originalTitle	startYear	release_date	runtimeMinutes	budget	world_collection	int_collection	dom_collection	popularity	vote_average	vote
4	tt0369610	Jurassic World	Jurassic World	2015	2015-06-06	124	150000000	1.671713e+09	1.018131e+09	652385625.0	63.489	6.6	1659
4	tt0369610	Jurassic World	Jurassic World	2015	2015-06-06	124	150000000	1.671713e+09	1.018131e+09	652385625.0	63.489	6.6	1659
4	tt0369610	Jurassic World	Jurassic World	2015	2015-06-06	124	150000000	1.671713e+09	1.018131e+09	652385625.0	63.489	6.6	1659

In [115]:

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

In [116]:

```python
# 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)]
```

In [117]:

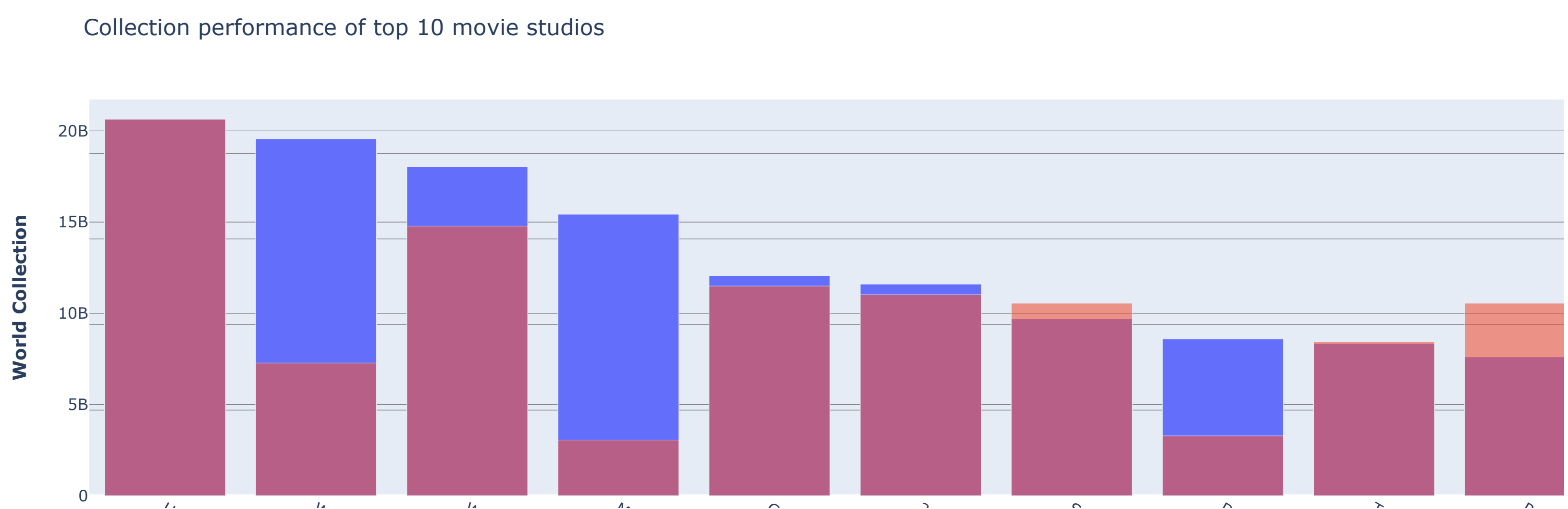
```python
# Total worldwide $ collection by top 20 studios
studio_df_fig_1 = studio_df_fig.groupby(
    by='production_comp_exp').agg('sum').sort_values(by='world_collection',
                                                     ascending=False)[:20]
# Total releases by top 20 studios
studio_df_fig_2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

In [118]:

```python
# 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')
```

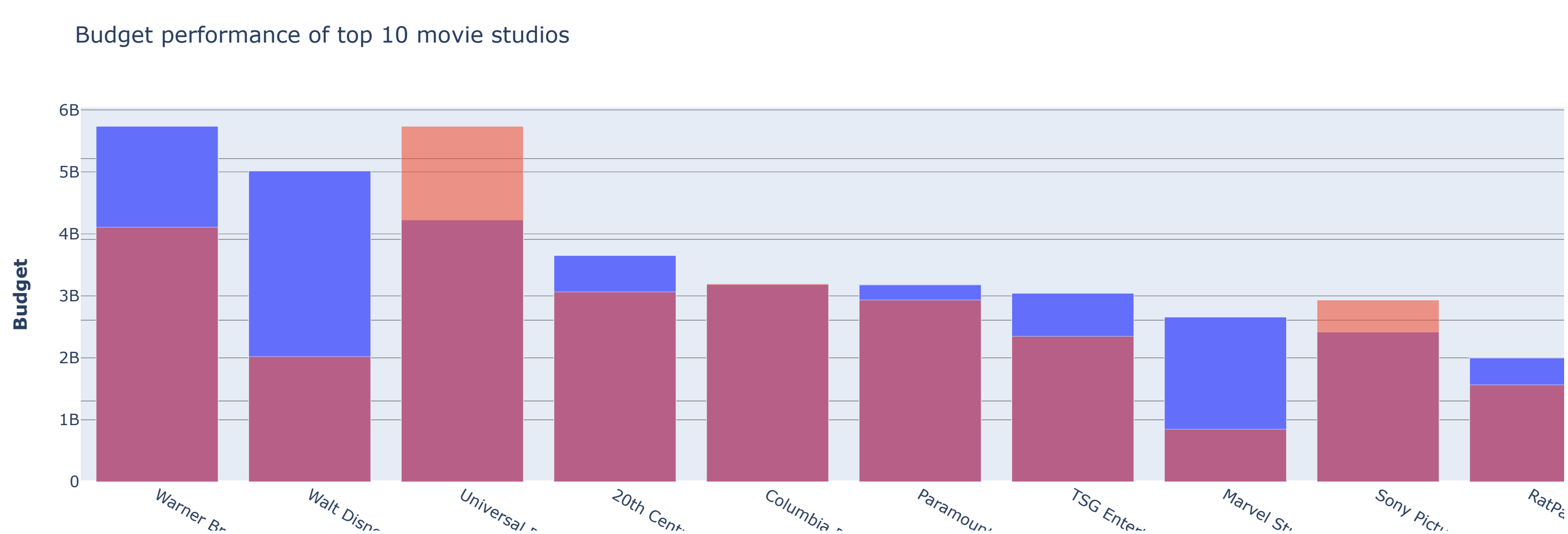
In [119]:

```python
## 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()
```



In [120]:

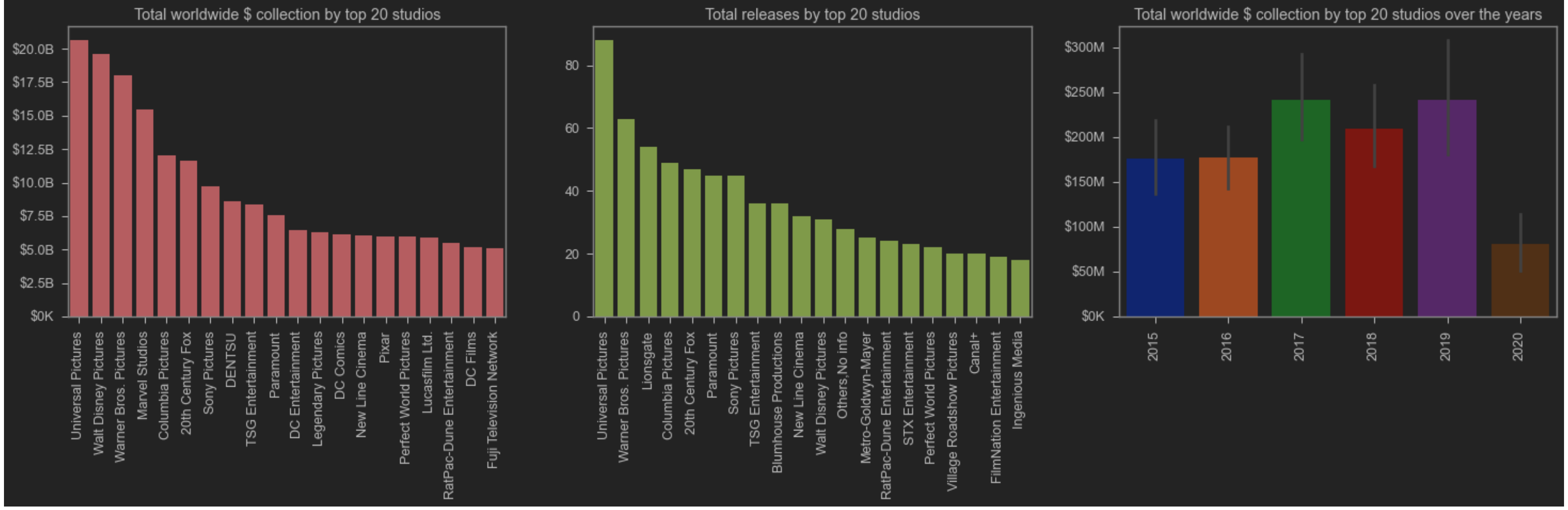
```python
## from https://plotly.com/python/multiple-axes/ ##official plotly how to instructions
fig = make_subplots(specs=[[{"secondary_y": True}]])
# Add traces
fig.add_trace(
    go.Bar(x=studio_df_fig_merged_1.production_comp_exp[:10],
           y=studio_df_fig_merged_1.budget_x[:10],
           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.

In [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

In [122]:

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

In [123]:

```
corr_df = main_df[corelattion_filter_list]
```

In [124]:

```
corr_df_matrix = corr_df.corr()
```

In [125]:

```
corr_df_matrix.style.background_gradient()
```

	startYear	runtimeMinutes	budget	world_collection	int_collection	dom_collection	popularity	vote_average	vote_count
startYear	1.000000	-0.003422	0.053363	0.024102	0.035525	0.040447	0.260186	0.054454	-0.065041
runtimeMinutes	-0.003422	1.000000	0.426111	0.349988	0.351262	0.328371	0.159567	0.368076	0.439491
budget	0.053363	0.426111	1.000000	0.783042	0.787109	0.716023	0.321358	0.237517	0.675298
world_collection	0.024102	0.349988	0.783042	1.000000	0.986302	0.955519	0.236664	0.256312	0.791444
int_collection	0.035525	0.351262	0.787109	0.986302	1.000000	0.892850	0.237610	0.277242	0.763741
dom_collection	0.040447	0.328371	0.716023	0.955519	0.892850	1.000000	0.201020	0.267886	0.773461
popularity	0.260186	0.159567	0.321358	0.236664	0.237610	0.201020	1.000000	0.156417	0.241333
vote_average	0.054454	0.368076	0.237517	0.256312	0.277242	0.267886	0.156417	1.000000	0.366568
vote_count	-0.065041	0.439491	0.675298	0.791444	0.763741	0.773461	0.241333	0.366568	1.000000

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

```
Positive correlations:
          index                          feature_combo  correlation
0     31  int_collection and world_collection     0.986302
1     32  dom_collection and world_collection     0.955519
2     41    int_collection and dom_collection     0.892850
3     35      vote_count and world_collection     0.791444
4     22          int_collection and budget     0.787109
5     21        budget and world_collection     0.783042
6     53        dom_collection and vote_count     0.773461
7     44        int_collection and vote_count     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        startYear and vote_count    -0.065041
1      1    runtimeMinutes and startYear    -0.003422
2      3  startYear and world_collection     0.024102
3      4    int_collection and startYear     0.035525
4      5    dom_collection and startYear     0.040447
5      2            startYear and budget     0.053363
6     18            budget and startYear     0.053363
7      7      vote_average and startYear     0.054454
8     61     vote_average and popularity     0.156417
9     15   runtimeMinutes and popularity     0.159567
```

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

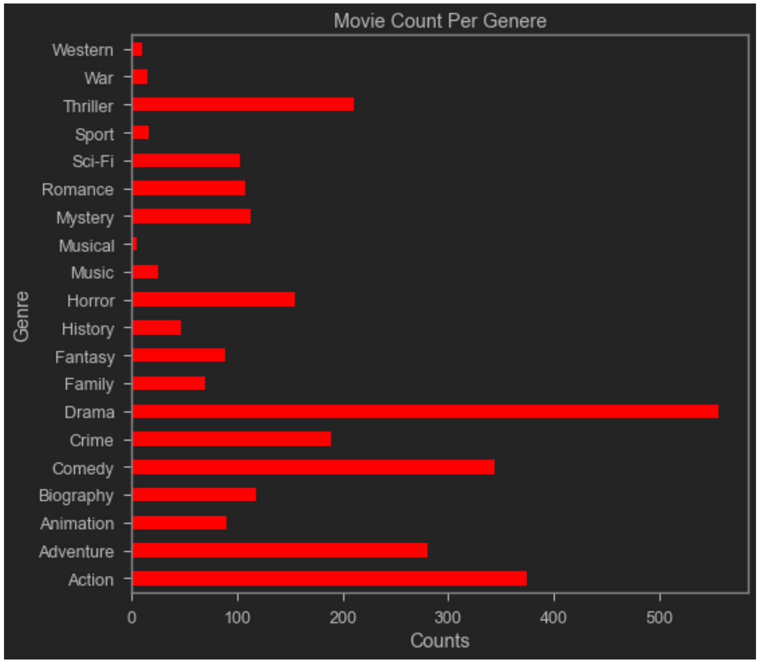
In [127]:
```
genere_df = main_df.copy()
```

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

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

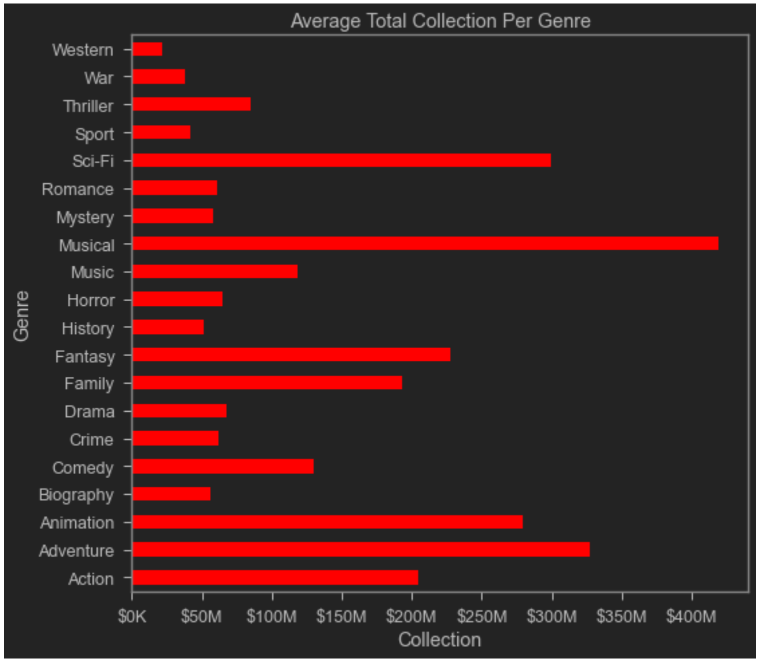
In [130]:

```python
# 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()
```



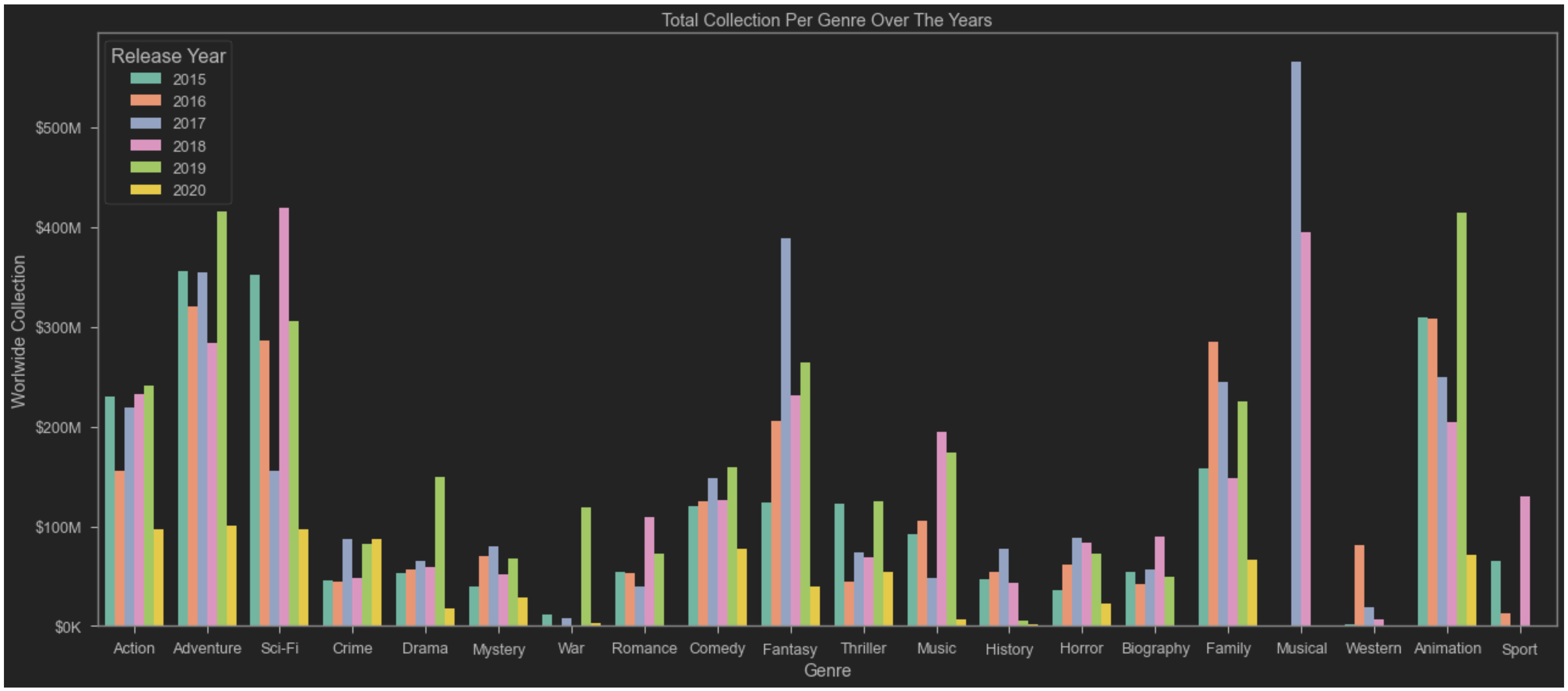
In [131]:

```
# 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()
```



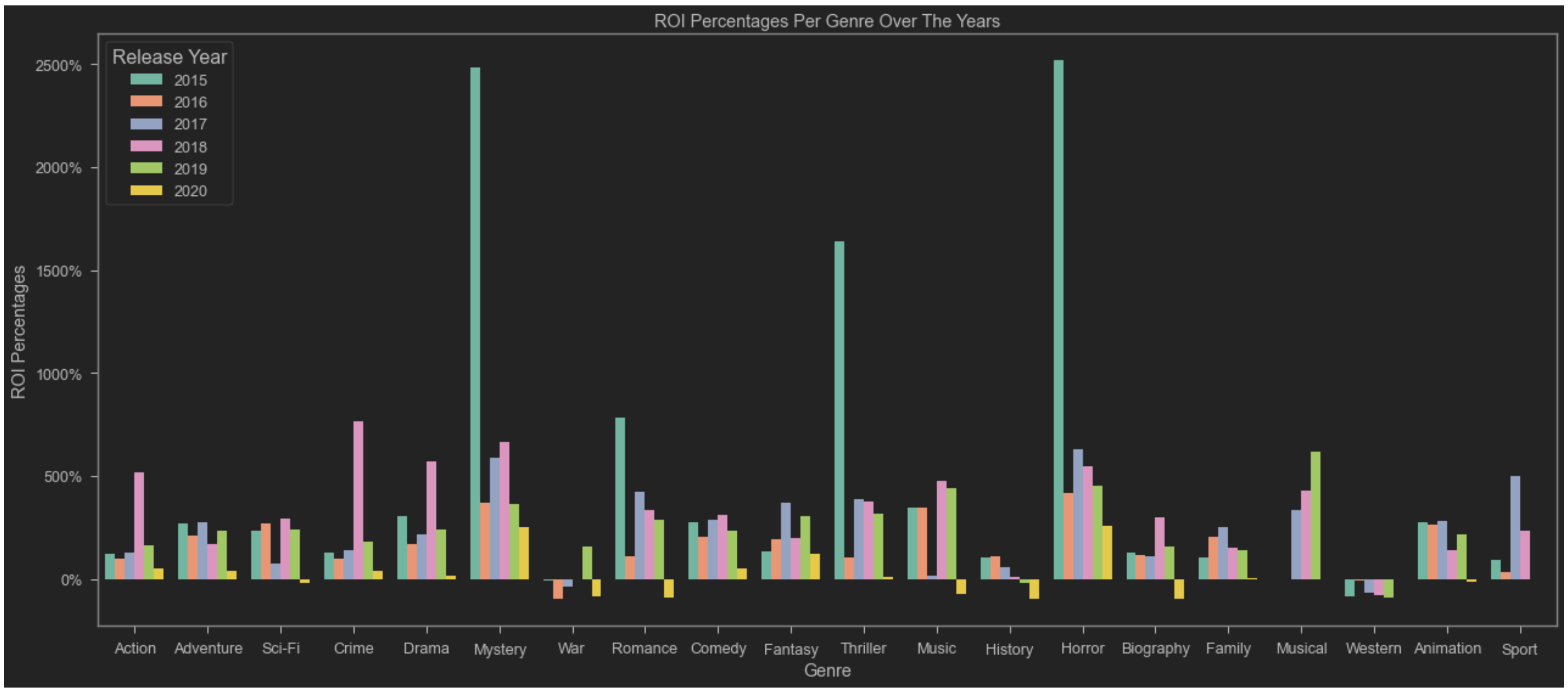
In [132]:

```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()
```



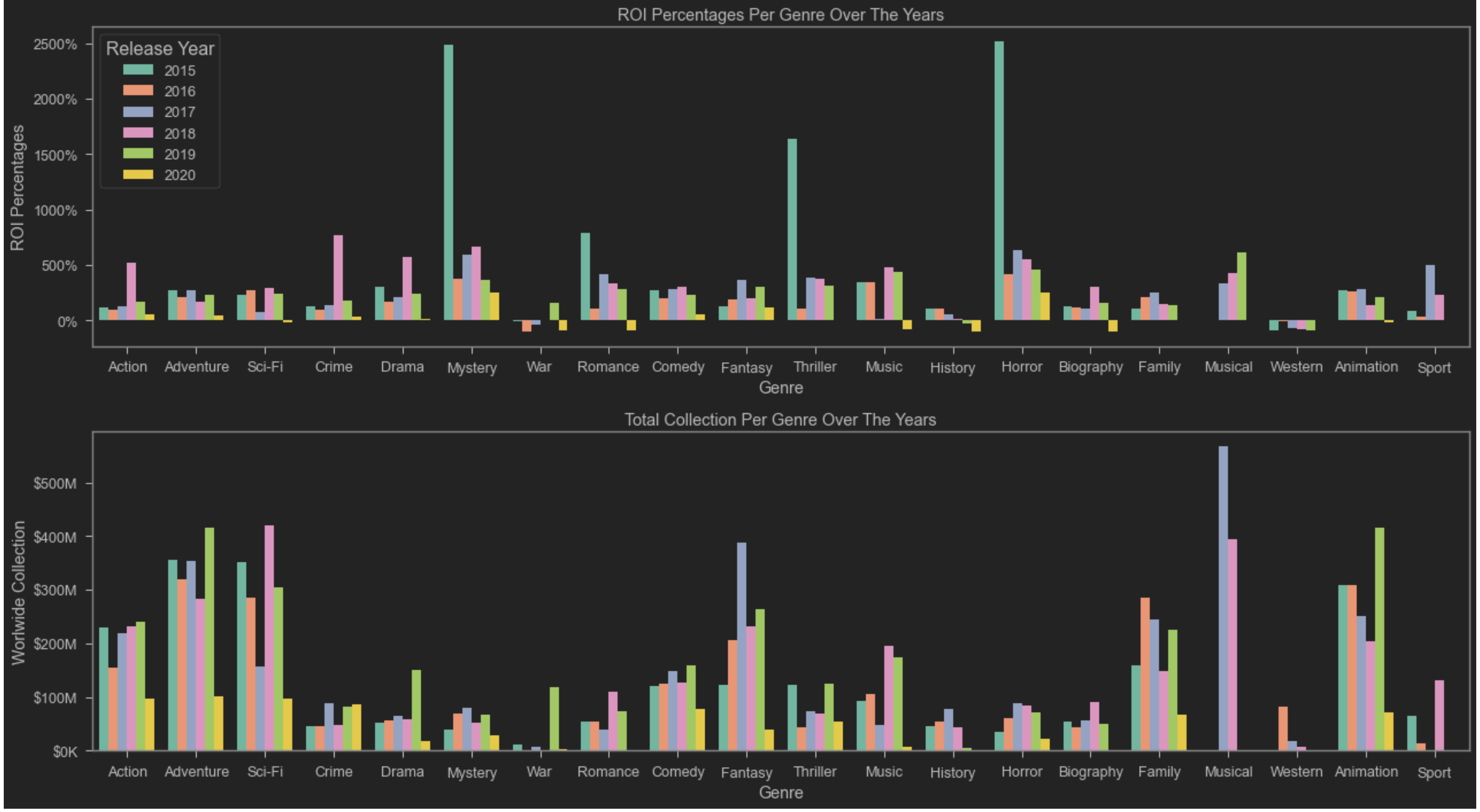
In [133]:

```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='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()
```



In [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

In [135]:

```
timing_df = main_df.copy()
```

In [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 (https://en.wikipedia.org/wiki/Dump_months)](https://en.wikipedia.org/wiki/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

In [137]:

```python
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)
```

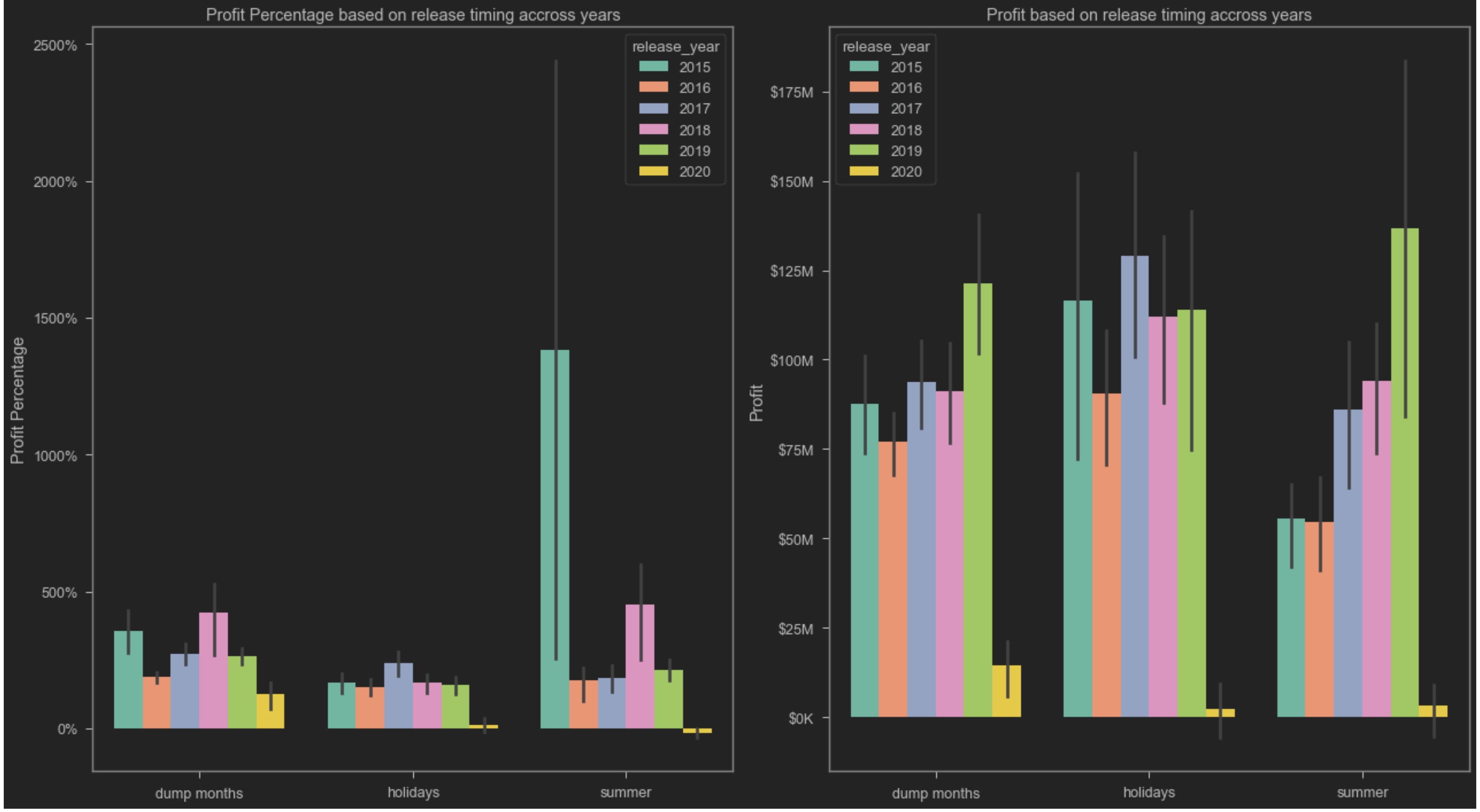
In [138]:

```python
timing_df.head(3)
```

	imdb_id	primaryTitle	originalTitle	startYear	release_date	runtimeMinutes	budget	world_collection	int_collection	dom_collection	popularity	vote_average	vote
4	tt0369610	Jurassic World	Jurassic World	2015	2015-06-06	124	150000000	1.671713e+09	1.018131e+09	652385625.0	63.489	6.6	1659
6	tt0385887	Motherless Brooklyn	Motherless Brooklyn	2019	2019-10-31	144	26000000	1.847774e+07	9.200000e+06	9277736.0	75.020	6.8	842
11	tt0437086	Alita: Battle Angel	Alita: Battle Angel	2019	2019-01-31	122	170000000	4.049805e+08	3.191423e+08	85838210.0	175.798	7.2	6343

In [139]:

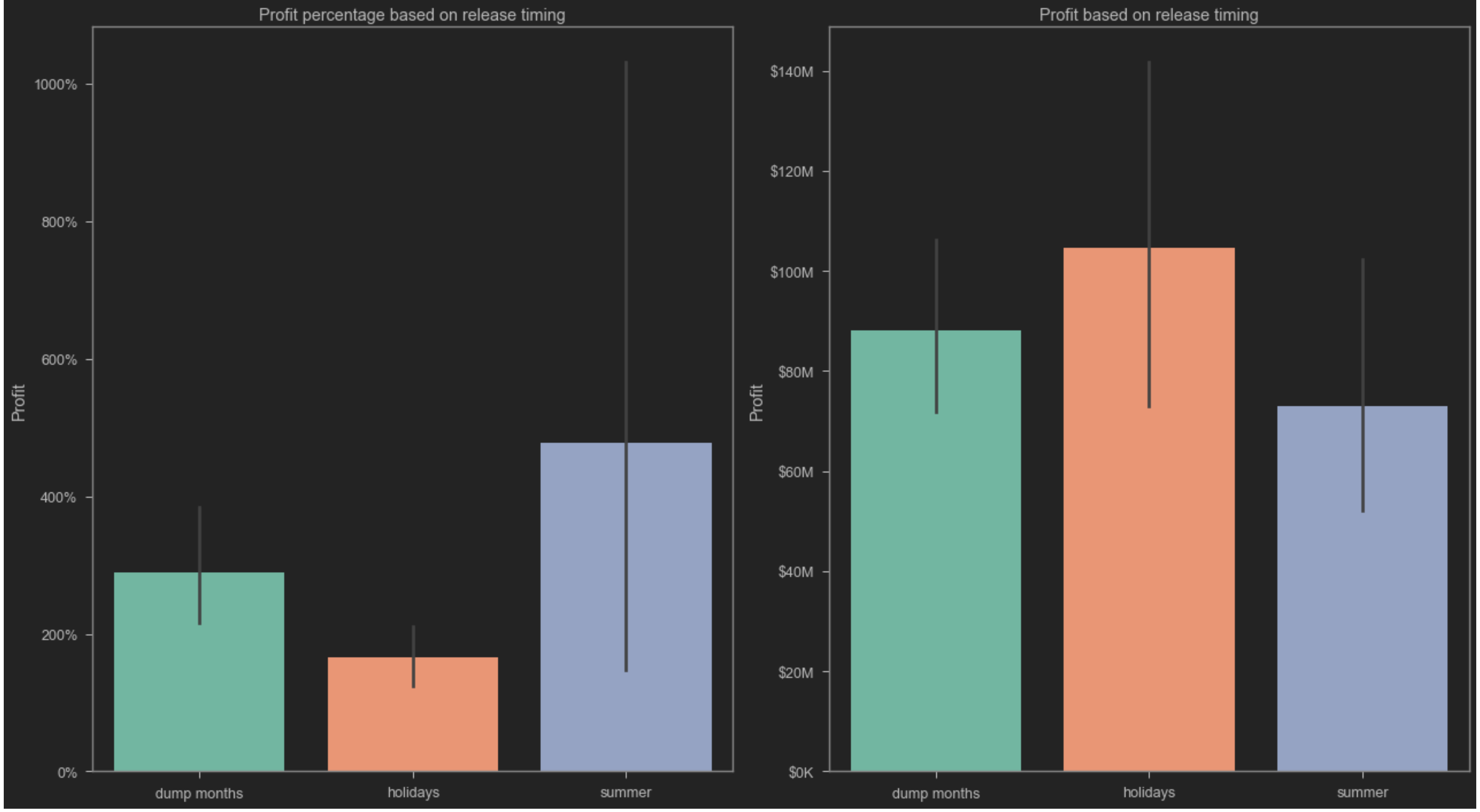
```
plt.figure(figsize=(18, 10))
plt.subplot(1, 2, 1)
sns.barplot(data=timing_df,
            x='release_timing',
            y='ROI_percentage',
            hue='release_year',palette='Set2',
            ci=50).yaxis.set_major_formatter(format_add_percentage)
plt.title('Profit Percentage based on release 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.

In [140]:

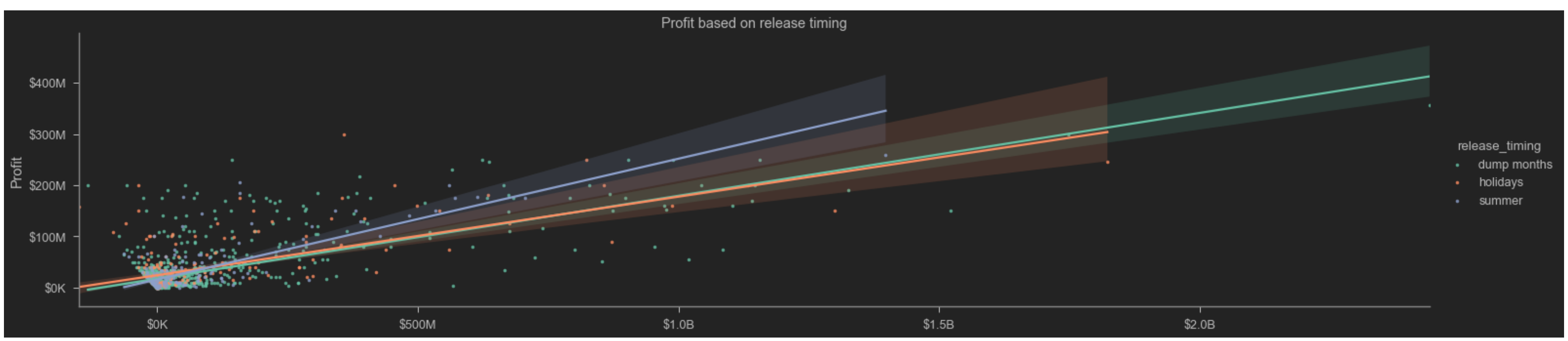
```
plt.figure(figsize=(18, 10))
plt.subplot(1, 2, 2)
sns.barplot(data=timing_df, x='release_timing', y='ROI',
            palette='Set2').yaxis.set_major_formatter(format_number)
plt.title('Profit based on release timing')
plt.ylabel('Profit')
plt.xlabel("")
plt.tight_layout()

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()
```

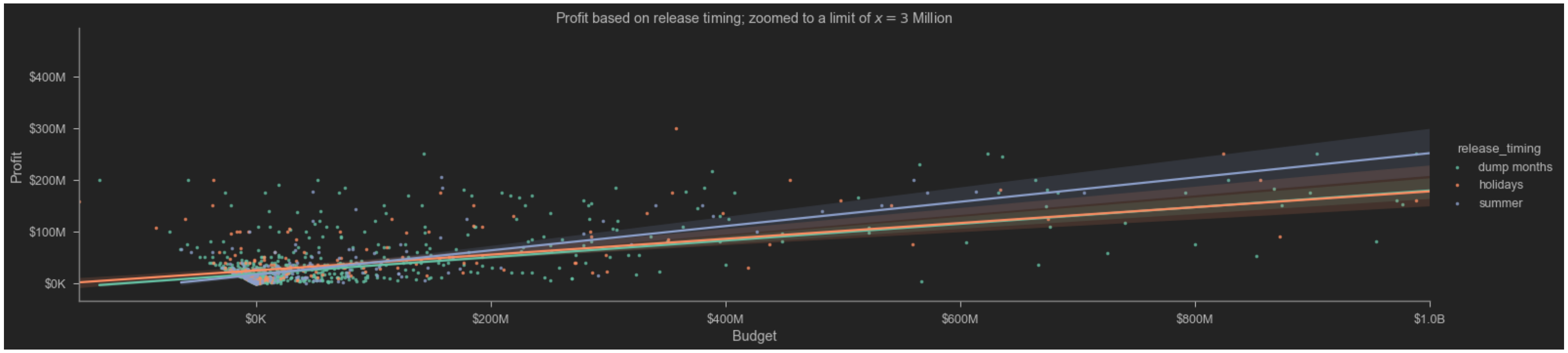


Movies released in holidays earn consistent returns but costs more. Summer is more dollar generating and volatile in a good way, on a uptrend.

In [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()
```



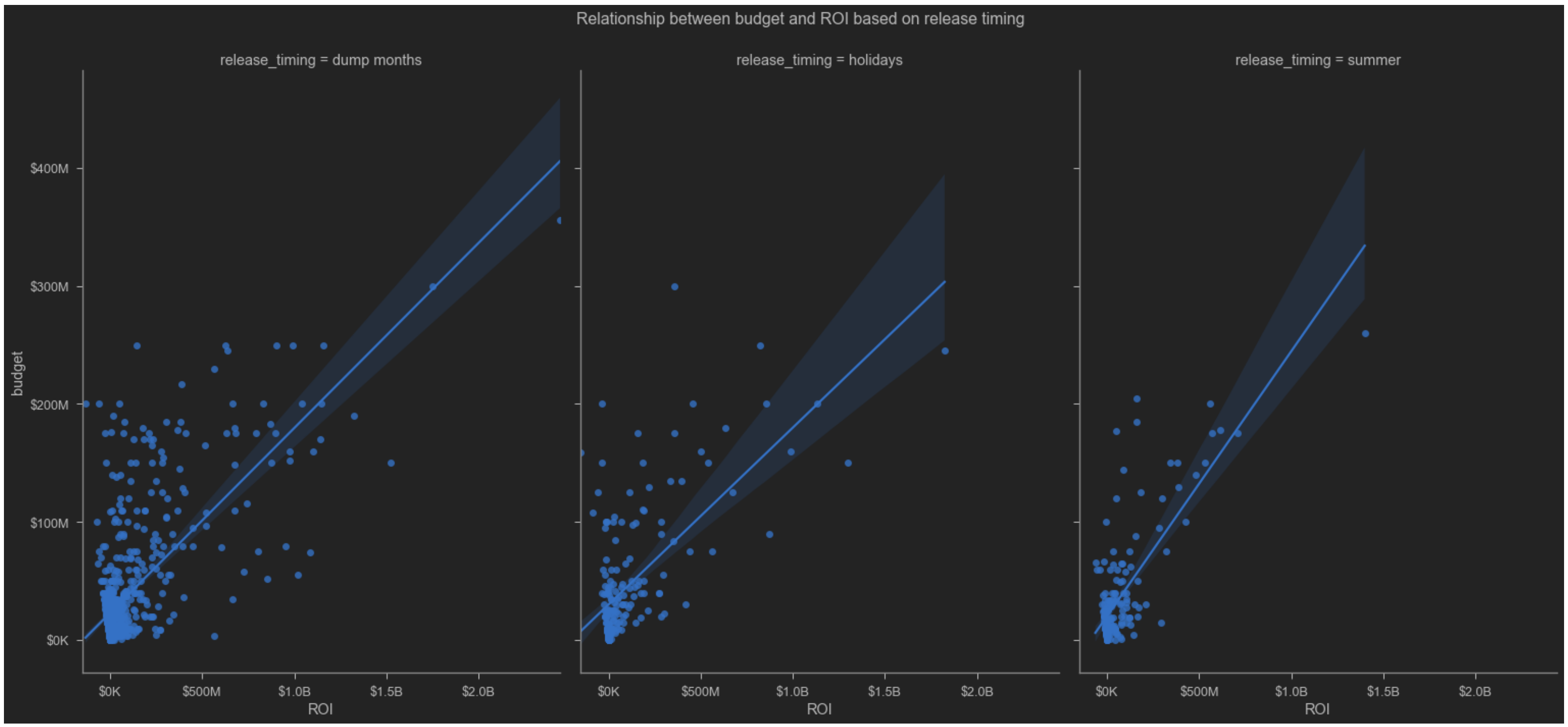


Profit based on release timing; zoomed to a limit of x = 3 Million
Profit
$400M
$300M
$200M
$100M
$0K
$0K
$200M
$400M
$600M
$800M
$1.0B
Budget
release_timing
dump months
holidays
summer

In [142]:

```python
# 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')
```

```
Text(0.5, 0.98, 'Relationship between budget and ROI based on release timing')
```

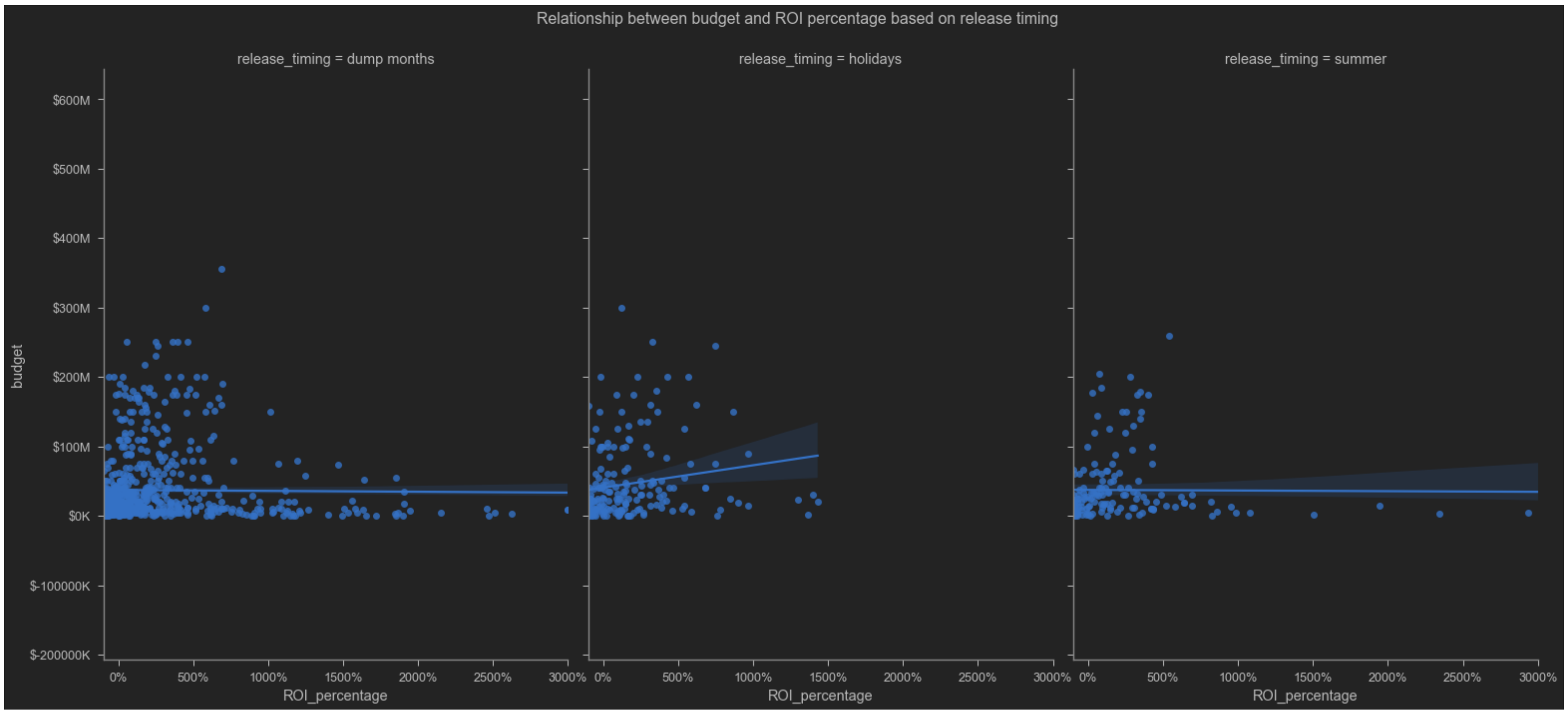


Producing movies for summer release is more costly, but return is steeper. Number of movies beyond 500 million is more frequent as well as observation counts are higher for holidays release, and the line is flatter meaning less costly to produce. Holidays season is the better option.

In [143]:

```python
# 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')
```

```
Text(0.5, 0.98, 'Relationship between budget and ROI percentage based on release timing')
```

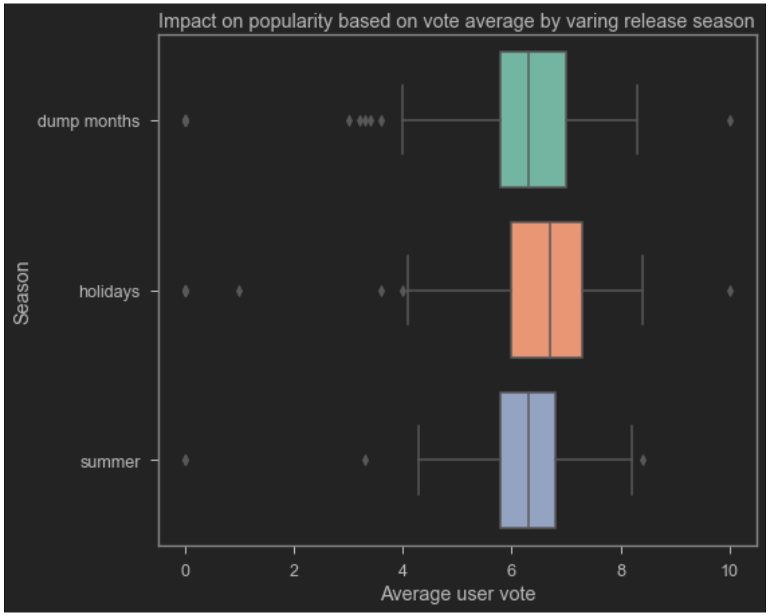


summer has the best earning potential. But line is steeper for holidays, confirming the point made on the previous graph.

In [144]:

```python
# 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")
```

```
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

In [145]:

```python
# getting a copy of main_df
franchaise_df_main = main_df.copy()
```

In [146]:

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

In [147]:

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

In [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.

In [149]:

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

In [150]:

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

In [151]:

```python
# formatting
format_dict = {
    'ROI': '${0:,.0f}',
    'budget': '${0:,.0f}',
    'ROI_percentage': '{:.2f}%'
}
# performance of movies that are part of a franchise
franchise_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')
```

	ROI_percentage	ROI	budget
belongs_to_collection			
The Gallows Collection	42864.41%	$42,864,410	$100,000
Searching Collection	7446.20%	$74,462,037	$1,000,000
Fifty Shades Collection	5115.27%	$403,622,827	$38,000,000
Unfriended Collection	3845.35%	$38,453,538	$1,000,000
Lights Out Collection	2938.14%	$143,968,835	$4,900,000
Halloween Collection	2456.15%	$245,614,941	$10,000,000
A Quiet Place Collection	1905.61%	$323,952,971	$17,000,000
Children of the Corn Collection	1721.12%	$13,768,989	$800,000
Escape Room - Collection	1630.13%	$146,712,077	$9,000,000
Happy Death Day Collection	1565.97%	$88,139,709	$6,900,000
屏住呼吸（系列）	1506.54%	$149,147,649	$9,900,000
Minions Collection	1466.82%	$1,085,444,662	$74,000,000
It Collection	1335.45%	$635,875,764	$57,000,000
Annabelle Collection	1307.14%	$246,384,238	$22,500,000
Insidious Collection	1304.35%	$130,434,738	$10,000,000
Despicable Me Collection	1193.50%	$954,800,131	$80,000,000
The Purge Collection	1020.08%	$116,322,071	$11,500,000
Call Me by Your Name Collection	947.22%	$37,888,660	$4,000,000
Deadpool Collection	932.53%	$700,732,819	$84,000,000
Saw Collection	929.53%	$92,952,888	$10,000,000

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.

7.3.1.1 which genre to franchise

In [152]:

```python
print('On an average films that are part of a franchise earn {:.2f}% return.'.
      format(franchise_df.ROI_percentage.mean()))
```

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

In [153]:

```python
# joining and filtering using SQL statements
list_of_franchise_df0 = sqldf("""SELECT
            DISTINCT belongs_to_collection,
            a.ROI AS 'ROI', b.world_collection,
            b.genres
        FROM franchise_df AS a
        JOIN franchise_df AS b
        USING(belongs_to_collection);""")

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

list_of_franchise_df0[~list_of_franchise_df0.belongs_to_collection.
                       duplicated()].sort_values(
                           by='ROI',
                           ascending=False)[:15].style.background_gradient(
                               cmap='bwr').hide_index().format(format_dict)
```

belongs_to_collection	ROI	world_collection	genres
Star Wars Collection	$1,823,455,919	$1,074,144,248	Action,Adventure,Fantasy
Jurassic Park Collection	$1,521,713,208	$1,310,464,680	Action,Adventure,Sci-Fi
The Lion King (Reboot) Collection	$1,397,870,986	$1,657,870,986	Adventure,Animation,Drama
The Fast and the Furious Collection	$1,325,255,622	$1,238,764,765	Action,Adventure,Crime
Frozen Collection	$1,300,026,933	$1,450,026,933	Adventure,Animation,Comedy
The Avengers Collection	$1,155,403,694	$1,405,403,694	Action,Adventure,Sci-Fi
Black Panther Collection	$1,147,597,973	$1,347,597,973	Action,Adventure,Sci-Fi
Minions Collection	$1,085,444,662	$1,159,444,662	Adventure,Animation,Comedy
The Incredibles Collection	$1,043,089,244	$1,243,089,244	Action,Adventure,Animation
Aquaman Collection	$988,485,886	$1,148,485,886	Action,Adventure,Fantasy
Captain Marvel Collection	$976,462,972	$1,128,462,972	Action,Adventure,Sci-Fi
Despicable Me Collection	$954,800,131	$1,034,800,131	Adventure,Animation,Comedy
Captain America Collection	$903,561,649	$1,153,561,649	Action,Adventure,Sci-Fi
Toy Story Collection	$898,394,593	$1,073,394,593	Adventure,Animation,Comedy
Jumanji Collection	$872,174,450	$800,059,707	Action,Adventure,Comedy

Observation: None of them fall into a single genre.

In [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);""")
```

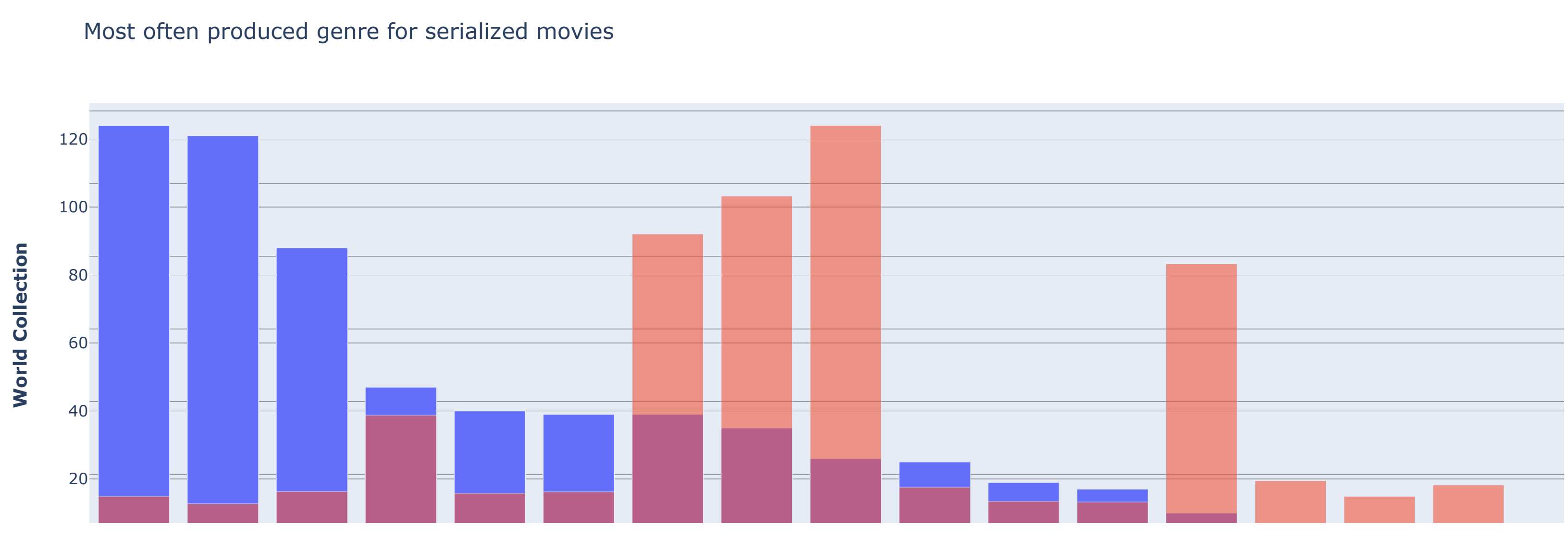
In [155]:

```
# 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')
```

	genres_exp	ROI% count	ROI% mean
0	Adventure	124	349.019417
1	Action	121	297.557482
2	Comedy	88	381.703050
3	Drama	47	906.836685
4	Animation	40	369.577146
5	Sci-Fi	39	379.531594
6	Horror	39	2153.693791
7	Thriller	35	2414.741535
8	Mystery	26	2900.197396
9	Crime	25	411.506582
10	Fantasy	19	314.229739
11	Family	17	309.154043
12	Romance	10	1948.204978
13	Music	4	456.125992
14	Sport	2	348.766674
15	Musical	1	426.755804
16	Biography	1	100.663038

In [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>World Collection</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

In [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.
```

In [158]:

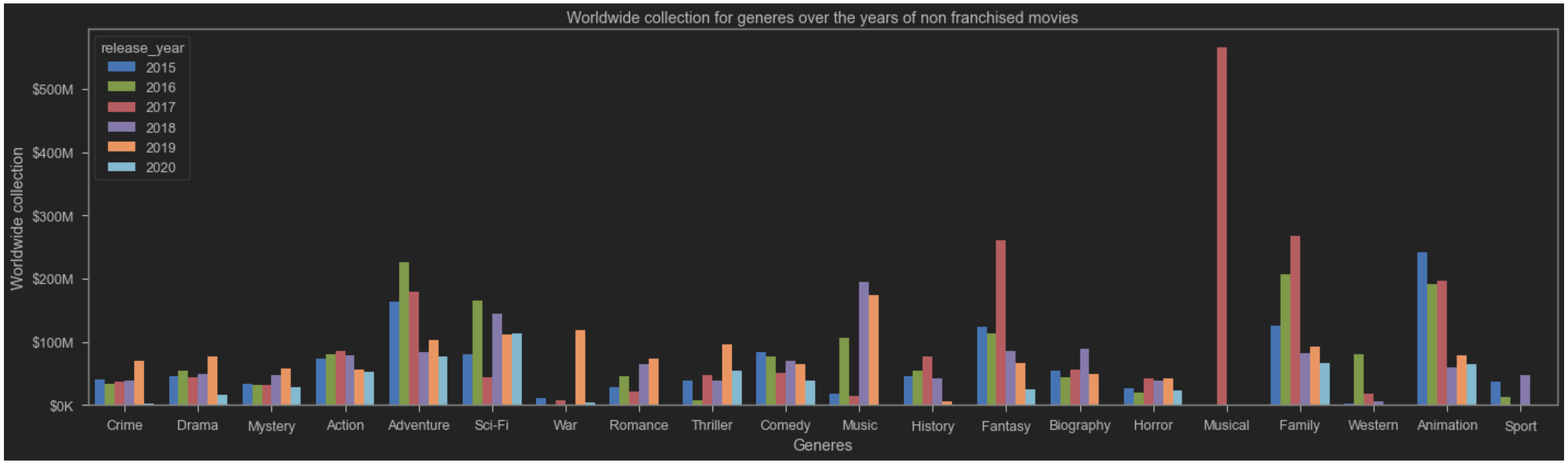
```
non_franchaise_df.loc[:, 'genres_exp'] = non_franchaise_df.genres.map(
    lambda x: x.split(','))
```

In [159]:

```
non_franchaise_df = non_franchaise_df.explode('genres_exp')
```

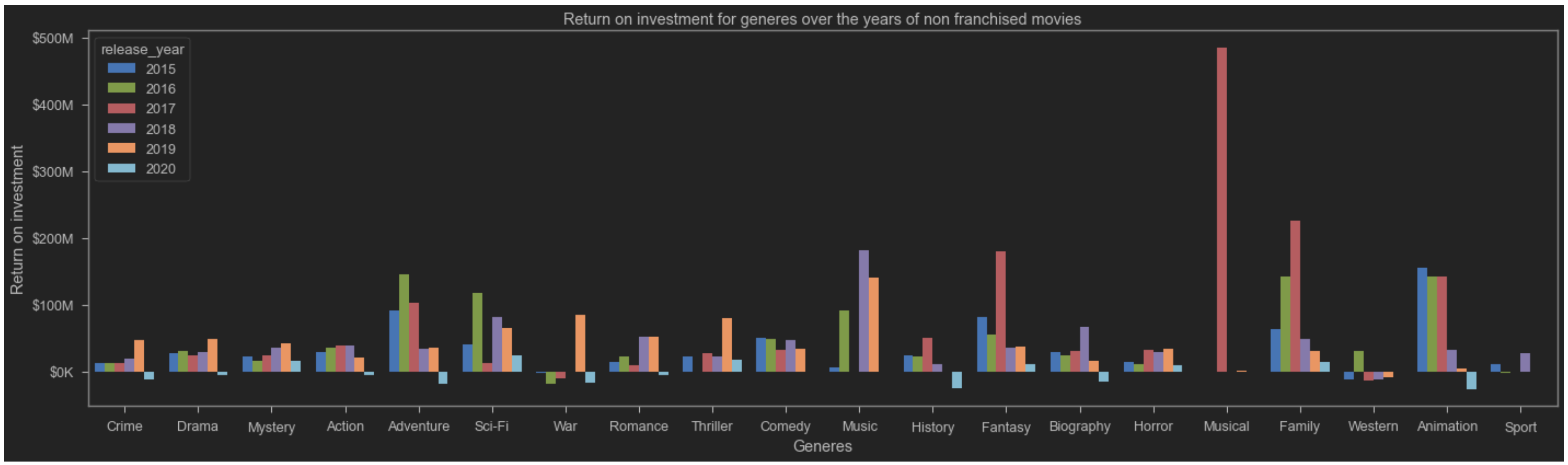
In [160]:

```
# 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()
```



In [161]:

```python
# 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 franchaise info in to a boolean arrey

In [162]:

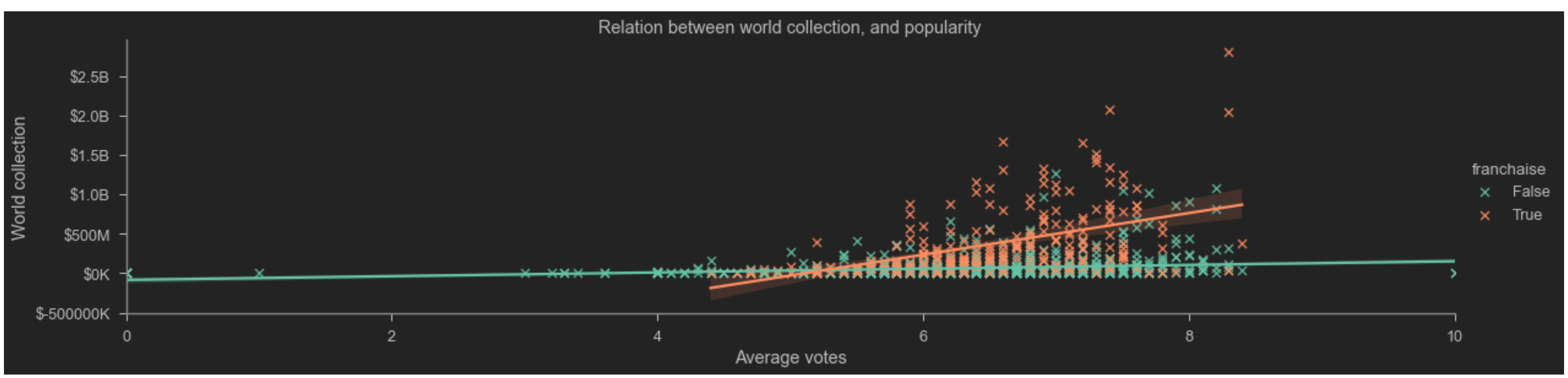
```python
franchise_df_main.loc[~main_df['belongs_to_collection.name'].isna(),
                      'franchaise'] = True
```

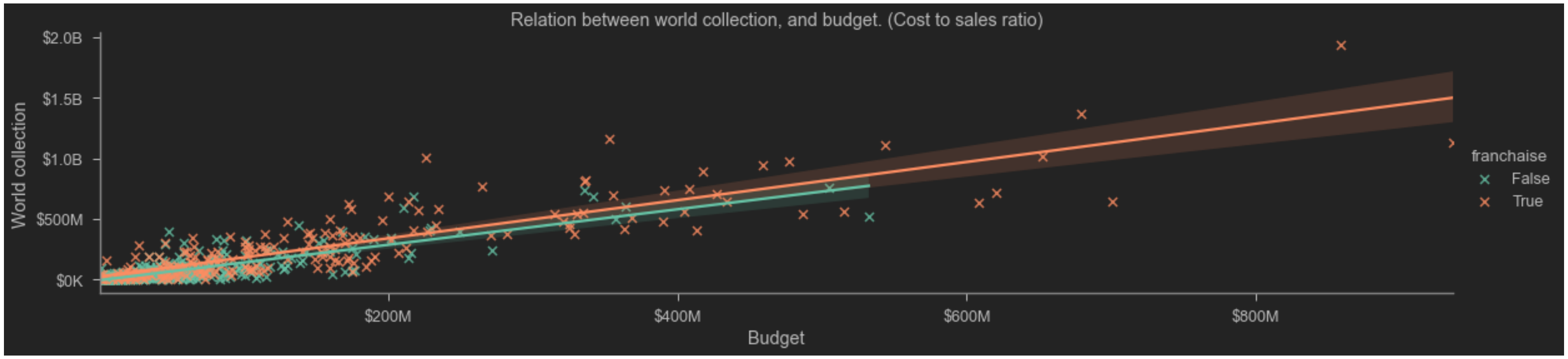
In [163]:

```python
franchise_df_main.loc[main_df['belongs_to_collection.name'].isna(),
                      'franchaise'] = False
```

In [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()
```

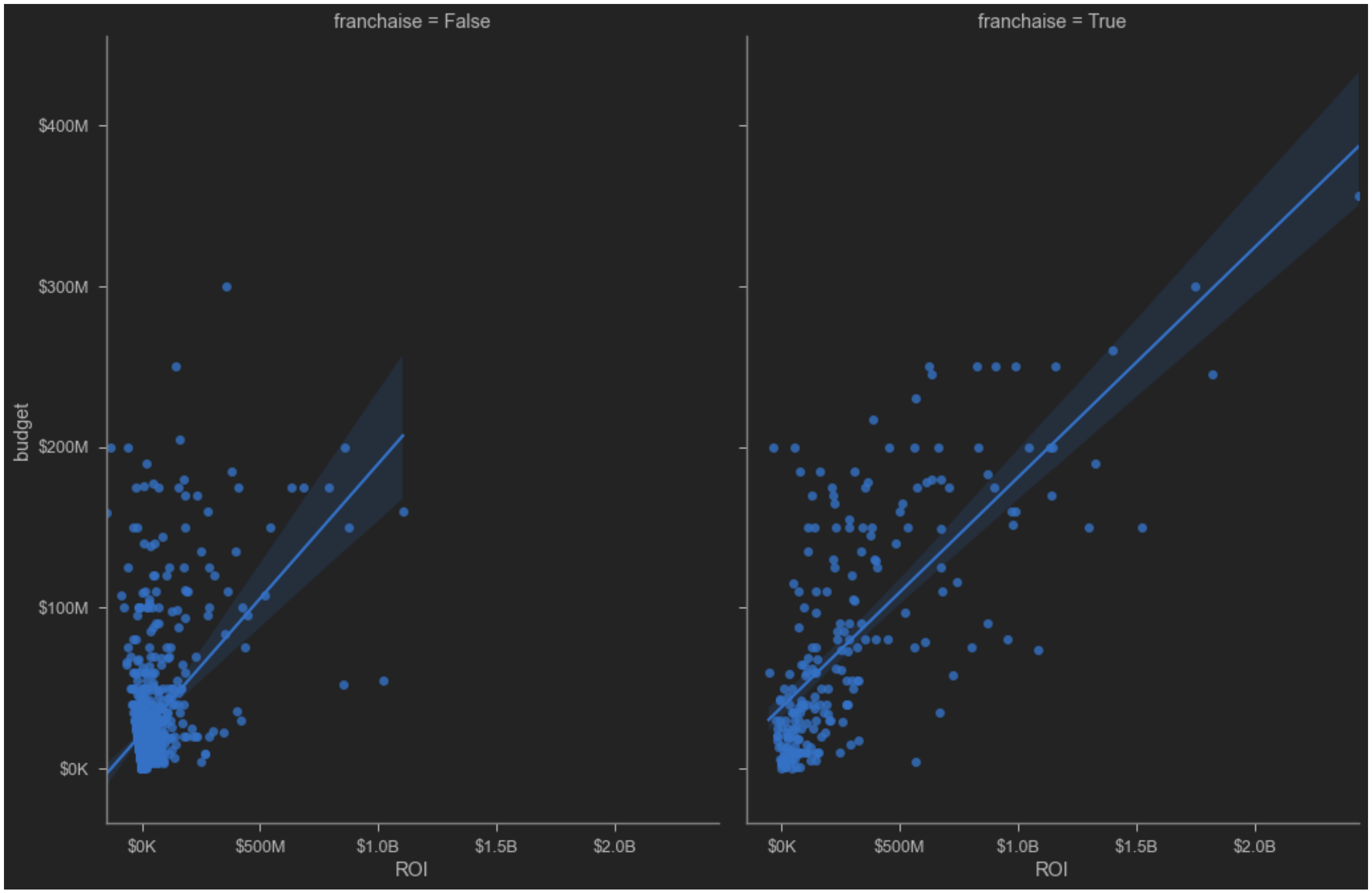




	Franchised movies are often more popular with greater success in international market.

In [165]:

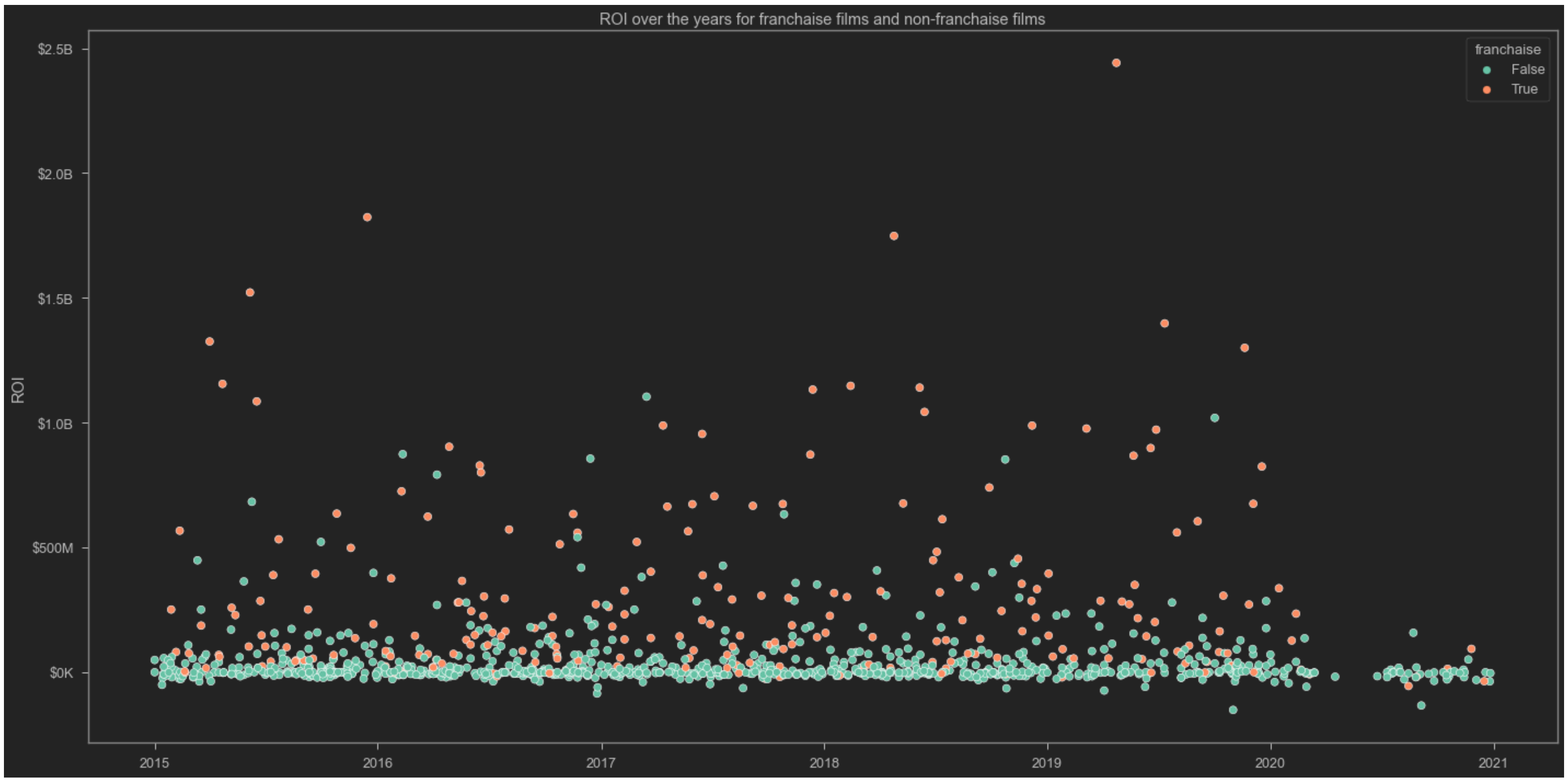
```python
g = sns.FacetGrid(
    franchaise_df_main, col='franchaise',
    height=10, aspect=.7, palette='Set2')
g.map(sns.regplot, 'ROI', 'budget')
for ax in g.axes.flat:
    ax.yaxis.set_major_formatter(format_number)
    ax.xaxis.set_major_formatter(format_number)
g.fig.subplots_adjust(top=0.9)
#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



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

In [166]:

```python
# ROI over the years for franchise films and non-franchise films
plt.figure(figsize=(20, 10))
sns.scatterplot(x='release_date',
                y='ROI',
                hue='franchise',
                data=franchise_df_main,
                palette='Set2',
                legend='brief').yaxis.set_major_formatter(format_number)
plt.title('ROI over the years for franchise films and non-franchise 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 (./student.ipynb) or review this presentation (./presentation.pdf).

11 Appendix

11.1 Most produced genre combo

In [167]:

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

In [168]:

```
combo_genre=combo_genre.corr()
combo_genre.style.background_gradient(cmap='PuRd')
```

	Action	Adventure	Biography	Drama	Fantasy	Comedy	War	Crime	Romance	Family	History	Sci-Fi	Thriller	Western	Sport	Mystery	H
Action	1.000000	0.234557	-0.039696	-0.155409	0.021305	-0.134239	0.007438	0.184287	-0.124091	-0.082017	0.012833	0.119460	0.087795	-0.003914	-0.014039	-0.065094	-
Adventure	0.234557	1.000000	-0.032004	-0.191267	0.096487	-0.008579	-0.034706	-0.047212	-0.109738	0.157636	-0.041994	0.055559	-0.091786	0.000736	-0.030389	-0.057172	-
Biography	-0.039696	-0.032004	1.000000	0.132731	-0.040755	-0.121452	0.024546	0.013829	-0.048016	-0.034802	0.203732	-0.038157	-0.069462	-0.008145	0.076512	-0.053194	-
Drama	-0.155409	-0.191267	0.132731	1.000000	-0.066611	-0.290930	0.063189	0.023217	0.038453	-0.103478	0.117032	-0.076056	-0.111885	0.019962	0.037100	-0.009435	-
Fantasy	0.021305	0.096487	-0.040755	-0.066611	1.000000	-0.016738	-0.020963	-0.058588	-0.019053	0.072728	-0.040150	0.008284	-0.063046	-0.007915	-0.023789	0.013609	0
Comedy	-0.134239	-0.008579	-0.121452	-0.290930	-0.016738	1.000000	-0.080062	-0.109071	0.107414	0.008391	-0.114813	-0.090470	-0.248184	-0.034028	-0.027722	-0.148315	-
War	0.007438	-0.034706	0.024546	0.063189	-0.020963	-0.080062	1.000000	-0.039289	-0.019791	-0.023206	0.118629	-0.017206	-0.025188	0.002384	-0.014776	-0.022964	-
Crime	0.184287	-0.047212	0.013829	0.023217	-0.058588	-0.109071	-0.039289	1.000000	-0.114093	-0.073954	-0.046635	-0.048057	0.136428	0.006373	-0.037173	0.082603	-
Romance	-0.124091	-0.109738	-0.048016	0.038453	-0.019053	0.107414	-0.019791	-0.114093	1.000000	-0.063814	-0.031822	-0.042308	-0.115350	-0.017523	-0.024942	-0.068354	-
Family	-0.082017	0.157636	-0.034802	-0.103478	0.072728	0.008391	-0.023206	-0.073954	-0.063814	1.000000	-0.031871	-0.023233	-0.094161	-0.010673	0.010173	-0.058735	-
History	0.012833	-0.041994	0.203732	0.117032	-0.040150	-0.114813	0.118629	-0.046635	-0.031822	-0.031871	1.000000	-0.028010	-0.053683	-0.005363	0.006565	-0.036475	-
Sci-Fi	0.119460	0.055559	-0.038157	-0.076056	0.008284	-0.090470	-0.017206	-0.048057	-0.042308	-0.023233	-0.028010	1.000000	0.043575	-0.010579	-0.017144	0.040065	0
Thriller	0.087795	-0.091786	-0.069462	-0.111885	-0.063046	-0.248184	-0.025188	0.136428	-0.115350	-0.094161	-0.053683	0.043575	1.000000	0.011551	-0.043187	0.176246	0
Western	-0.003914	0.000736	-0.008145	0.019962	-0.007915	-0.034028	0.002384	0.006373	-0.017523	-0.010673	-0.005363	-0.010579	0.011551	1.000000	0.002428	-0.015553	-
Sport	-0.014039	-0.030389	0.076512	0.037100	-0.023789	-0.027722	-0.014776	-0.037173	-0.024942	0.010173	0.006565	-0.017144	-0.043187	0.002428	1.000000	-0.030591	-
Mystery	-0.065094	-0.057172	-0.053194	-0.009435	0.013609	-0.148315	-0.022964	0.082603	-0.068354	-0.058735	-0.036475	0.040065	0.176246	-0.015553	-0.030591	1.000000	0
Horror	-0.052483	-0.071896	-0.065236	-0.184330	0.054360	-0.150491	-0.030458	-0.059221	-0.105189	-0.076032	-0.056715	0.075418	0.199766	-0.005981	-0.036922	0.242051	1
Music	-0.067461	-0.041102	0.054277	0.025775	-0.005686	-0.007963	-0.010543	-0.052291	0.022317	-0.004684	-0.014798	-0.029989	-0.057237	-0.003808	-0.017649	-0.033203	-
Animation	0.060473	0.353164	-0.036639	-0.203516	0.028996	-0.012312	-0.027168	-0.071642	-0.087790	0.140764	-0.039954	0.014958	-0.090670	-0.015114	-0.005959	-0.057700	-
Musical	-0.033499	-0.017786	-0.014353	-0.028121	0.000515	-0.007671	-0.005422	-0.030310	0.015053	0.010627	-0.001970	-0.016579	-0.032767	0.006416	-0.005377	-0.021159	-

In [169]:

```
correlation_top_bottom(combo_genre)
```

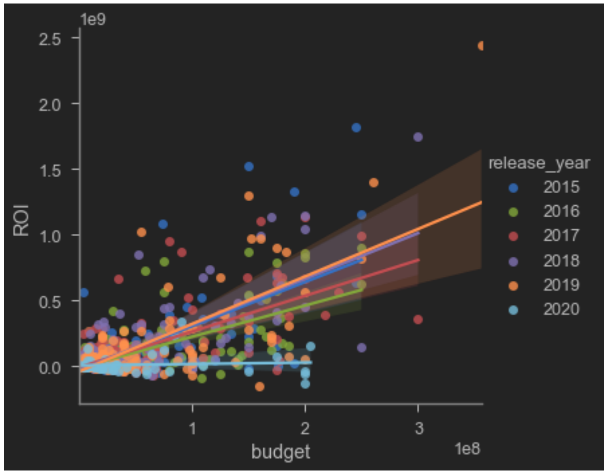
```
Positive correlations:
          index           feature_combo  correlation
0    359        Music and Musical     0.552813
1     38  Animation and Adventure     0.353164
2    316       Mystery and Horror     0.242051
3      1     Action and Adventure     0.234557
4     50    History and Biography     0.203732
5    256      Thriller and Horror     0.199766
6      7         Crime and Action     0.184287
7    255     Mystery and Thriller     0.176246
8     29     Family and Adventure     0.157636
9    198     Animation and Family     0.140764

 ----------------------------------------------------------------------
       Negative correlations:
          index        feature_combo  correlation
0     65      Comedy and Drama    -0.290930
1    112  Comedy and Thriller    -0.248184
2     78   Animation and Drama    -0.203516
3     23  Drama and Adventure    -0.191267
4     76      Drama and Horror    -0.184330
5      3      Action and Drama    -0.155409
6    116     Comedy and Horror    -0.150491
7    115    Mystery and Comedy    -0.148315
8      5     Comedy and Action    -0.134239
9      8    Romance and Action    -0.124091
```

11.2 Variability of profitability on different metrics

11.2.1 budget vs profitability

In [170]:

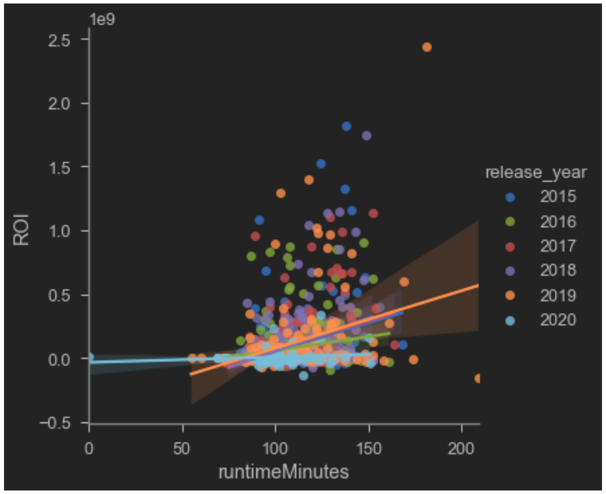
```
sns.lmplot(data=main_df, x='budget', y='ROI',hue='release_year')
plt.show()
```



11.2.2 runtime on profitability

In [171]:

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



11.2.3 user rating on profitability

In [172]:

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