Microsoft Movie Analysis Summary

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Overview

Microsoft is looking to open up their own movie studio, but don't know anything about movies to know where they should invest their efforts in. This project looks at data from various sources, ranging from IMDB, Rotten Tomatoes, Movie Budgets and gathering additional data from Box Office Mojo to understand the answers to the following questions:

- Which genre has the best ROI
- What movie rating gets the best reviews on rotten tomatoes?
- Should they focus on family friendly or non-family friendly movies?
- How long should the movie last?
- Which month of the year is the best to release a movie, both for overall ROI and best opening weekend sales?

We can see that in the US the best genres to produce for ROI are Horror/Thriller movies due to their low production costs. Afterwards, it is mainly Comedy, Romance & Drama films. When looking at gross revenue, we can see that Action/Adventure/Sci-Fi based movies rank highest. The movie ratings with the best Rotten Tomatoes score is NR, followed by R & PG. Movies should last no longer than 135 minutes and the best months to release movies is January & February for opening weekend % of return. For gross revenue, the best month to release is May/June.

Business Problem

I have been tasked with providing recommendations to Microsoft around what type of movies perform best so they know where to invest their budgets when launching a movie studio to get good returns. In order to do this, I focused on the main questions to be able to answer:

- Which genre has the best ROI
- What movie rating gets the best reviews on rotten tomatoes?
- Should they focus on family friendly or non-family friendly movies?
- How long should the movie last?
- Which month of the year is the best to release a movie, both for overall ROI and best opening weekend sales?

The reason I chose these questions is because, since Microsoft is new to the industry, it is important to focus on understanding the different metrics and measures that revolve around them being able to make money from their films. This is why focusing on ratings, length of movies, genres and month of release are important, as they all factor into overall return on investment. This is important, as movies are very expensive ventures, so unless they have an ulterior motive (to attract a new demographic, target audience for other products) the business should be profit making.

Data Understanding

There are a range of sources being used with the data, these range from rating data both from IMDB and Rotten Tomatoes, production & revenue values from The Numbers movie budgets and opening weekend revenue from Box Office Mojo. Across these different sources we're able to calculate metrics around movie ratings, ROI, time in cinema, genres, runtime which can be used to answer the questions set above.

In [1]:

```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime

%matplotlib inline
from src import boxmojo_scraping as scrap
```

Functions to use

In [2]:

```
def explore_dataframe(dataframe):
    ''' This function is used to explore each
    dataframe to understand it's shape, datatypes
    , if there are missing/null values
    and a few records
    '''
    print(dataframe.shape)
    print(dataframe.info())
    print(dataframe.head())

def generate_primary_key(dataframe):
    '''This function generates a primary key by
    removing all spaces from the movie titles, this will be used
    later in the analysis to join different datasets together'''
    dataframe['key'] = dataframe['movie_title'].replace(" ", "", regex=True)
    return dataframe

def drop_columns(dataframe, columns_to_drop):
    '''This function is used to drop columns from listed dataframes'''
    return dataframe.drop(columns_to_drop, axis=1, inplace=True)

def convert_datatype(dataframe, datatype_dict):
    '''The function takes a dataframe and converts the columns according to an input
    dictionary which includes the column name as key and desired data type as the va
    dataframe = dataframe.astype(datatype_dict)
    return dataframe

def convert_to_datetime(dataframe, column, date_format):
    '''This function takes a dataframe, a specific column and a date format to conve
    a datetime column'''
    dataframe[column] = pd.to_datetime(dataframe[column], format=date_format)
    return dataframe.head()

def agg_rt_func(dataframe):
    '''This function takes a dataframe and creates a series of a dictionary
    used to generate different aggregations specified inside. This will be used on t
    dataset'''
    aggregate_names = {
        'total_count_of_reviews': dataframe['fresh'].count(),
        'total_count_of_fresh_reviews': dataframe[dataframe['fresh'] == 'fresh']['fr
        'total_count_of_critic_reviews': dataframe[dataframe['critic'].notnull()]['f
        'total_count_of_fresh_critic_reviews': dataframe[(dataframe['fresh'] == 'fre
        'total_count_of_top_critic_reviews': dataframe[dataframe['top_critic'] == 1]
        'total_count_of_fresh_top_critic_reviews': dataframe[(dataframe['fresh'] ==
}

    return pd.Series(aggregate_names)
```

Scraping Box Office Mojo Data

In [3]:

```
full_data = []
for year in range(1970, 2020):
    full_data.append(scrap.extract_opening_weekend_data(f"https://www.boxofficemojo.

opening_weekend_rev_movie_df = pd.DataFrame(sum(full_data,[]), columns = ['movie_tit
# We generate a dataframe containing the columns extracted using our web scraping sc
# for movies from 1970 until 2020
```

In [4]:

```
opening_weekend_rev_movie_df['full_release_date'] = opening_weekend_rev_movie_df['re

opening_weekend_rev_movie_df['release_month'] = opening_weekend_rev_movie_df['releas
opening_weekend_rev_movie_df['closing_month'] = opening_weekend_rev_movie_df['closir
# split apart the date fields to extract month names

months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov
month_dict = {month:f"{datetime.strptime(month, '%b').month}" for month in months}
# Creating dictionary to convert month name into month number

opening_weekend_rev_movie_df['release_month'].replace(month_dict, inplace=True)
opening_weekend_rev_movie_df['closing_month'].replace(month_dict, inplace=True)
# Generating month numbers for later transformation

opening_weekend_rev_movie_df[opening_weekend_rev_movie_df['opening_weekend_revenue']
# Exploring null values in opening weekend revenue
```

Out[4]:

```
movie_title                 569
opening_weekend_revenue     603
release_date                603
closing_date                603
year                        603
full_release_date           603
release_month               603
closing_month               603
dtype: int64
```

In [5]:

```
opening_weekend_rev_movie_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7834 entries, 0 to 7833
Data columns (total 8 columns):
 #   Column                   Non-Null Count  Dtype 
---  ------                   --------------  ----- 
 0   movie_title              7677 non-null   object
 1   opening_weekend_revenue  7834 non-null   object
 2   release_date             7834 non-null   object
 3   closing_date             7834 non-null   object
 4   year                     7834 non-null   int64 
 5   full_release_date        7834 non-null   object
 6   release_month            7834 non-null   object
 7   closing_month            7834 non-null   object
dtypes: int64(1), object(7)
memory usage: 489.8+ KB
```

In [6]:

```
opening_weekend_rev_movie_df[opening_weekend_rev_movie_df['closing_date'] == '-'].co
# Currently about half of the records are missing a closing date. Instead of just re
# we will create a separate DataFrame to calculate the portion we can for time in ci
# database for enrichment further down the EDA.
```

Out[6]:

```
movie_title                 3882
opening_weekend_revenue     3969
release_date                3969
closing_date                3969
year                        3969
full_release_date           3969
release_month               3969
closing_month               3969
dtype: int64
```

In [7]:

```
non_empty_closing_date = opening_weekend_rev_movie_df[opening_weekend_rev_movie_df['
non_empty_closing_date['month_diff'] = non_empty_closing_date['closing_month'].astyp
# calculating month_difference to accurately assign closing_date with correct year

non_empty_closing_date['full_closing_date'] = non_empty_closing_date['closing_date']
condition = non_empty_closing_date['month_diff'] < 0.0
non_empty_closing_date.loc[condition, 'full_closing_date'] = non_empty_closing_date[
```

```
<ipython-input-7-4ab68293cc7c>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  non_empty_closing_date['month_diff'] = non_empty_closing_date['closi
ng_month'].astype(int) - non_empty_closing_date['release_month'].astyp
e(int)
<ipython-input-7-4ab68293cc7c>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  non_empty_closing_date['full_closing_date'] = non_empty_closing_date
['closing_date'] + ", " + non_empty_closing_date['year'].astype(str)
/Users/davidboyd/opt/anaconda3/envs/learn-env/lib/python3.8/site-packa
ges/pandas/core/indexing.py:1745: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  isetter(ilocs[0], value)
```

In [8]:

```
non_empty_closing_date.head()
non_empty_closing_date = non_empty_closing_date[non_empty_closing_date['closing_date
# Removing potential leap year closing dates

non_empty_closing_date['release_date_time'] = pd.to_datetime(non_empty_closing_date[
convert_to_datetime(non_empty_closing_date, 'full_closing_date' ,'%b %d, %Y')
# creating datetime datatypes for release_date and closing_date

non_empty_closing_date['time_between_release_and_closing'] = non_empty_closing_date[
# calculates number of days movie was in the cinema

non_empty_closing_date['key'] = non_empty_closing_date['movie_title'].replace(" ", '
opening_weekend_rev_movie_df['key'] = opening_weekend_rev_movie_df['movie_title'].re
# creates key field to enable self joins

full_opening_weekend_rev_movie_df = opening_weekend_rev_movie_df.merge(non_empty_clo
```

In [9]:

```
full_opening_weekend_rev_movie_df.info()
# Complete scraped data dataframe, ready for cleaning
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7838 entries, 0 to 7837
Data columns (total 20 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   movie_title_left                  7677 non-null   object
 1   opening_weekend_revenue_left      7838 non-null   object
 2   release_date_left                 7838 non-null   object
 3   closing_date_left                 7838 non-null   object
 4   year_left                         7838 non-null   int64
 5   full_release_date                 7838 non-null   object
 6   release_month_left                7838 non-null   object
 7   closing_month_left                7838 non-null   object
 8   key                               7677 non-null   object
 9   movie_title_right                 3793 non-null   object
 10  opening_weekend_revenue_right     3867 non-null   object
 11  release_date_right                3867 non-null   object
 12  closing_date_right                3867 non-null   object
 13  year_right                        3867 non-null   float64
 14  release_month_right               3867 non-null   object
 15  closing_month_right               3867 non-null   object
 16  month_diff                        3867 non-null   float64
 17  full_closing_date                 3867 non-null   datetime64[ns]
 18  release_date_time                 3867 non-null   datetime64[ns]
 19  time_between_release_and_closing  3867 non-null   timedelta64[ns]
dtypes: datetime64[ns](2), float64(2), int64(1), object(14), timedelta
64[ns](1)
memory usage: 1.3+ MB
```

Reading in other data sources

In [10]:

```
df_rt_movie_info = pd.read_csv('zippedData/rt.movie_info.tsv.gz', delimiter= '\t')
# contains Rotten Tomatoes movie info

df_rt_reviews = pd.read_csv('zippedData/rt.reviews.tsv.gz', delimiter= '\t', encodir
# contains Rotten Tomatoes movie ratings

df_tn_movie_budgets = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')
df_tn_movie_budgets.rename({'movie':'movie_title'}, axis=1, inplace=True)
# contains production budgets & gross revenues
```

In [11]:

```
from zipfile import ZipFile

with ZipFile('zippedData/im.db.zip', 'r') as zipObj:
   # Extract all the contents of zip file in current directory
   zipObj.extractall('zippedData')
```

In [12]:

```
import sqlite3

conn = sqlite3.connect('zippedData/im.db')

all_data_query = """
WITH base_query AS (
SELECT DISTINCT
m.*
, REPLACE(m.primary_title, " ","") AS key
, p.primary_name AS director_name
, mr.averagerating AS average_rating
, mr.numvotes AS number_of_votes
, row_number() OVER (PARTITION BY REPLACE(m.primary_title, " ","") ORDER BY REPLACE(
FROM movie_basics AS m
LEFT JOIN directors AS d
    ON m.movie_id = d.movie_id
JOIN persons AS p
    ON d.person_id = p.person_id
LEFT JOIN movie_akas AS ma
    ON m.movie_id = ma.movie_id
LEFT JOIN movie_ratings as mr
    ON m.movie_id = mr.movie_id
WHERE ma.region = 'US')

SELECT
*
FROM base_query
WHERE rn = 1
;
"""

df_imdb_data = pd.read_sql(all_data_query, conn)
```

In [13]:

```
df_imdb_data.describe()
df_imdb_data = df_imdb_data[df_imdb_data['runtime_minutes'] < 240]
# removing outliers in dataset with erroneous runtimes
df_imdb_data.describe()
```

Out[13]:

	start_year	runtime_minutes	average_rating	number_of_votes	rn
count	37207.000000	37207.000000	23501.000000	2.350100e+04	37207.0
mean	2013.941086	82.996318	6.226063	9.136092e+03	1.0
std	2.516467	25.903800	1.576156	5.186088e+04	0.0
min	2010.000000	1.000000	1.000000	5.000000e+00	1.0
25%	2012.000000	71.000000	5.200000	1.800000e+01	1.0
50%	2014.000000	86.000000	6.400000	8.200000e+01	1.0
75%	2016.000000	96.000000	7.400000	6.320000e+02	1.0
max	2021.000000	239.000000	10.000000	1.841066e+06	1.0

In [14]:

```
df_imdb_data[df_imdb_data['rn'] != 1]
# Checking no duplicate entries have been made for each movie, otherwise when joinir
# we would start duplicating our data and causing errors
```

Out[14]:

movie_id	primary_title	original_title	start_year	runtime_minutes	genres	key	director_name

Exploring datasets

In [15]:

```
all_dataframes = [df_rt_movie_info, df_rt_reviews, df_tn_movie_budgets, df_imdb_data

for dataframe in all_dataframes:
    explore_dataframe(dataframe)
```

```
(1560, 12)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            1560 non-null   int64 
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: int64(1), object(11)
```

In [16]:

```
for dataframe in all_dataframes:
    try:
        generate_primary_key(dataframe)
    except:
        continue
```

In [17]:

```
df_tn_movie_budgets.head()
# checking primary key field has been added correctly
```

Out[17]:

	id	release_date	movie_title	production_budget	domestic_gross	worldwide_gross	
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279	
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875	Piratesofth
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350	
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963	
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747	

Data Preparation

To prepare the data, each dataset had it's own set of requirements, whether it was drop some columns, as they either didn't have enough data in them, or they weren't relevant to the questions I was trying to answer. Reformat columns and change datatypes from objects to either integers, or datetime. To make the code cleaner, all of the necessary commands were added into a seprate python script to be imported and ran below.

There were some outliers in the IMDB data when it came to the runtime field, these were handled by excluding all values which went above a reasonable figure of 4 hours, as everything else is unrealistic and likely a data entry error.

Dropping unnecessary columns

In [18]:

```
open_weekend_columns_to_drop = ['release_date_left', 'closing_date_left', 'release_m
                              , 'movie_title_right', 'opening_weekend_revenue_right
                              , 'closing_date_right', 'year_right', 'release_month_
                              , 'month_diff', 'release_date_time']
drop_columns(full_opening_weekend_rev_movie_df, open_weekend_columns_to_drop)

drop_columns(df_rt_movie_info, ['synopsis','currency', 'box_office', 'runtime', 'stu

drop_columns(df_rt_reviews, ['review', 'publisher', 'date'])

drop_columns(df_imdb_data, ['original_title'])
```

Data cleaning - The Numbers movie budgets

From exploring the data set, we can see multiple columns that need to be cleaned, first to convert the release date into a datetime format. Then to remove all unnecessary special characters from production budget, domestic gross and worldwide gross to convert into integer values. The code below achieves these steps.

In [19]:

```
convert_to_datetime(df_tn_movie_budgets, 'release_date', '%b %d, %Y')

df_tn_movie_budgets['production_budget'].replace('\W+','',regex=True, inplace=True)
df_tn_movie_budgets['domestic_gross'].replace('\W+','',regex=True, inplace=True)
df_tn_movie_budgets['worldwide_gross'].replace('\W+','',regex=True, inplace=True)
# removing special characters

df_tn_movie_budgets = convert_datatype(df_tn_movie_budgets, {"production_budget":"ir
# converting to integers

df_tn_movie_budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 2   movie_title        5782 non-null   object
 3   production_budget  5782 non-null   int64
 4   domestic_gross     5782 non-null   int64
 5   worldwide_gross    5782 non-null   int64
 6   key                5782 non-null   object
dtypes: datetime64[ns](1), int64(4), object(2)
memory usage: 316.3+ KB
```

Data Cleaning - Scraped data

For the opening weekend revenue dataset that was scraped from the Box Office Mojo site, we need to update release date into a datetime datatype and handle NULL movie titles & opening weekend revenues before converting it into integer values, for later aggregations

In [20]:

```
convert_to_datetime(full_opening_weekend_rev_movie_df, 'full_release_date' ,'%b %d,

full_opening_weekend_rev_movie_df[full_opening_weekend_rev_movie_df['opening_weekenc
# checking to see if there are any null revenue records

full_opening_weekend_rev_movie_df['opening_weekend_revenue_left'] = full_opening_wee
# removing null revenue values to convert datatype

full_opening_weekend_rev_movie_df['opening_weekend_revenue_left'].astype(int)

full_opening_weekend_rev_movie_df.info()
# From the info chart below we can see there are still some missing movie_titles. As
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7838 entries, 0 to 7837
Data columns (total 7 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   movie_title_left                  7677 non-null   object
 1   opening_weekend_revenue_left      7838 non-null   int64
 2   year_left                         7838 non-null   int64
 3   full_release_date                 7838 non-null   datetime64[ns]
 4   key                               7677 non-null   object
 5   full_closing_date                 3867 non-null   datetime64[ns]
 6   time_between_release_and_closing  3867 non-null   timedelta64[ns]
dtypes: datetime64[ns](2), int64(2), object(2), timedelta64[ns](1)
memory usage: 489.9+ KB
```

In [21]:

```
full_opening_weekend_rev_movie_df = full_opening_weekend_rev_movie_df[full_opening_w
full_opening_weekend_rev_movie_df = full_opening_weekend_rev_movie_df[full_opening_w
# ignoring null movie title records

full_opening_weekend_rev_movie_df.info()
# This dataset has now been cleaned of all NULL movie_title values, blank closing_da
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7677 entries, 0 to 7837
Data columns (total 7 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   movie_title_left                  7677 non-null   object
 1   opening_weekend_revenue_left      7677 non-null   int64
 2   year_left                         7677 non-null   int64
 3   full_release_date                 7677 non-null   datetime64[ns]
 4   key                               7677 non-null   object
 5   full_closing_date                 3793 non-null   datetime64[ns]
 6   time_between_release_and_closing  3793 non-null   timedelta64[ns]
dtypes: datetime64[ns](2), int64(2), object(2), timedelta64[ns](1)
memory usage: 479.8+ KB
```

Data Modeling

After the data was cleaned and ready to model, I split the data into two different final datasets, the first being related to the ROI of each movie, this was done through joining the Movie budgets dataset with my opening weekend scraped data. This was then combined with the imdb data to collect features such as genre and director name.

The other dataset focused on our Rotten Tomatoes data and all the reviews related to each movie.

Once the datasets were joined, the next step was doing some feature engineering to create new columns and then create aggregations by Genre, Movie Rating, Director, Writer, Year of release & Month of release. This allowed for the charts below to be created.

Feature engineering - The Numbers movie budgets

To better assist answering the questions about movies, I want to add additional features/columns into the DataFrame, so that I can have a better understanding of what the data represents, the main pieces of information I wish to extract is the domestic/overall ROI each movie has, whether it was a profitable movie or not and what month/year was it released on

In [22]:

```
df_tn_movie_budgets['domestic_%_of_total'] = (df_tn_movie_budgets['domestic_gross']

df_tn_movie_budgets['domestic_ROI'] = (df_tn_movie_budgets['domestic_gross'] / df_tr
df_tn_movie_budgets['overall_ROI'] = (df_tn_movie_budgets['worldwide_gross'] / df_tr
df_tn_movie_budgets['year_of_release'] = df_tn_movie_budgets['release_date'].dt.year
df_tn_movie_budgets['month_of_release'] = df_tn_movie_budgets['release_date'].dt.mor
df_tn_movie_budgets.loc[df_tn_movie_budgets['overall_ROI'] > 0, 'is_profitable'] = 1
df_tn_movie_budgets.loc[df_tn_movie_budgets['overall_ROI'] < 0, 'is_profitable'] = (
# identifies whether the movie was profitable or not

df_tn_movie_budgets.head()

df_tn_movie_budgets = df_tn_movie_budgets.rename(columns={"release_date":"full_relea
# Renaming column for simplicity sake later on to merge with other dataframes
```

Feature Engineering - Rotten Tomatoes Reviews

In [23]:

```
agg_rt_reviews_df = df_rt_reviews.groupby('id').apply(agg_rt_func)
# using pre-defined function to generate aggregate fields per id

agg_rt_reviews_df['overall_rotten_score'] = agg_rt_reviews_df['total_count_of_fresh_
agg_rt_reviews_df['critic_rotten_score'] = agg_rt_reviews_df['total_count_of_fresh_c
agg_rt_reviews_df['top_critic_rotten_score'] = agg_rt_reviews_df['total_count_of_fre
agg_rt_reviews_df['perc_of_total_critic_reviews'] = agg_rt_reviews_df['total_count_c
agg_rt_reviews_df['perc_of_total_top_critic_reviews'] = agg_rt_reviews_df['total_cou
# generating rotten tomatoes score per movie id & % of reviews that are written by c

agg_rt_reviews_df.head()
```

Out[23]:

	total_count_of_reviews	total_count_of_fresh_reviews	total_count_of_critic_reviews	total_count_
id				
3	163	103	160	
5	23	18	21	
6	57	32	52	
8	75	56	69	
10	108	50	104	

In [24]:

```
full_review_data = df_rt_movie_info.merge(agg_rt_reviews_df, how='left', on='id')

full_review_data.rating.unique()
full_review_data['rating'] = full_review_data['rating'].fillna('unknown')
# handling missing rating values

faimly_ratings = ['G', 'PG', 'PG-13']
full_review_data['is_family_friendly'] = np.where(full_review_data['rating'].isin(fa
```

In [25]:

```
aggregate_rating_df = full_review_data.groupby('rating').agg(count_of_movies=('id','
                                                        , avg_overall_rt_score=('overall_rotten_scor
                                                        , avg_critic_rt_score=('critic_rotten_score'
                                                        , avg_perc_critic_rt_reviews=('perc_of_total

# creating aggregation by movie rating
```

Joining Datasets together

Now we have cleaned our isolated data sets, to answer our questions we need to merge some of them together to further enrich what data can be seen about each movie.

In [26]:

```
tn_movie_and_opening = df_tn_movie_budgets.merge(full_opening_weekend_rev_movie_df,

tn_movie_and_opening.info()

imdb_tn_movie_and_opening = tn_movie_and_opening.merge(df_imdb_data, left_on=['key',
# We're left joining with the imdb movie dataset to extract features such as runtime
imdb_tn_movie_and_opening.info()
# we can see only 20% of data matches with imdb
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 0 to 5781
Data columns (total 18 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   id                             5782 non-null   int64
 1   full_release_date              5782 non-null   datetime64[ns]
 2   movie_title                    5782 non-null   object
 3   production_budget              5782 non-null   int64
 4   domestic_gross                 5782 non-null   int64
 5   worldwide_gross                5782 non-null   int64
 6   key                            5782 non-null   object
 7   domestic_%_of_total            5415 non-null   float64
 8   domestic_ROI                   5782 non-null   float64
 9   overall_ROI                    5782 non-null   float64
 10  year_of_release                5782 non-null   int64
 11  month_of_release               5782 non-null   int64
 12  is_profitable                  5782 non-null   float64
 13  movie_title_left               3486 non-null   object
 14  opening_weekend_revenue_left   3486 non-null   float64
 15  year_left                      3486 non-null   float64
 16  full_closing_date              2461 non-null   datetime64[ns]
 17  time_between_release_and_closing  2461 non-null   timedelta64[ns]
dtypes: datetime64[ns](2), float64(6), int64(6), object(3), timedelta6
4[ns](1)
memory usage: 858.3+ KB
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 0 to 5781
Data columns (total 27 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   id                             5782 non-null   int64
 1   full_release_date              5782 non-null   datetime64[ns]
 2   movie_title                    5782 non-null   object
 3   production_budget              5782 non-null   int64
 4   domestic_gross                 5782 non-null   int64
 5   worldwide_gross                5782 non-null   int64
 6   key                            5782 non-null   object
 7   domestic_%_of_total            5415 non-null   float64
 8   domestic_ROI                   5782 non-null   float64
 9   overall_ROI                    5782 non-null   float64
 10  year_of_release                5782 non-null   int64
 11  month_of_release               5782 non-null   int64
 12  is_profitable                  5782 non-null   float64
 13  movie_title_left               3486 non-null   object
 14  opening_weekend_revenue_left   3486 non-null   float64
 15  year_left                      3486 non-null   float64
 16  full_closing_date              2461 non-null   datetime64[ns]
 17  time_between_release_and_closing  2461 non-null   timedelta64[ns]
 18  movie_id                       1247 non-null   object
```

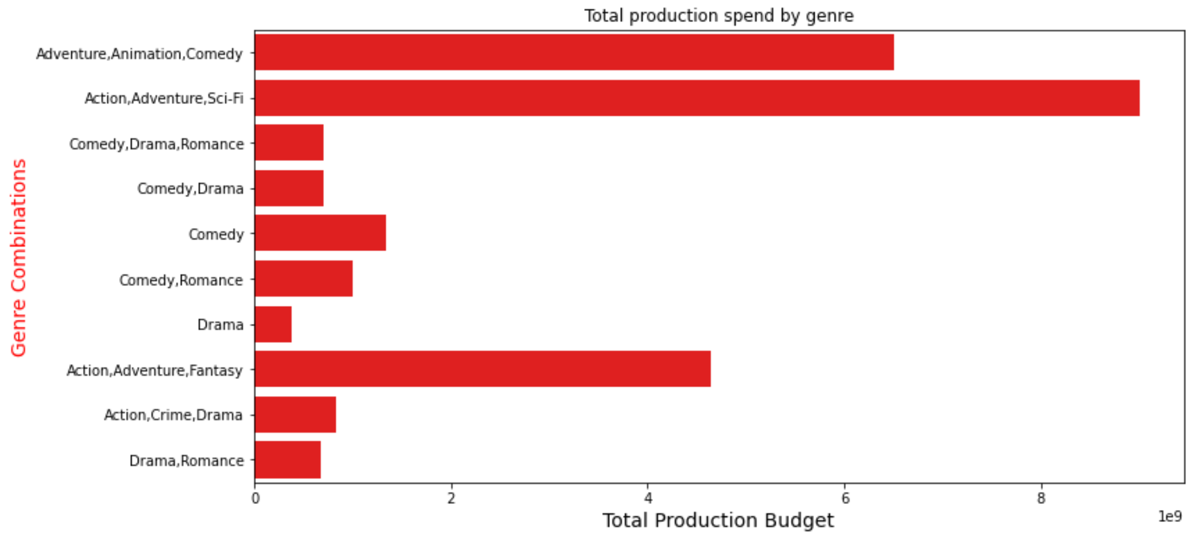
```
 19  primary_title                    1247 non-null   object
 20  start_year                       1247 non-null   float64
 21  runtime_minutes                  1247 non-null   float64
 22  genres                           1247 non-null   object
 23  director_name                    1247 non-null   object
 24  average_rating                   1243 non-null   float64
 25  number_of_votes                  1243 non-null   float64
 26  rn                               1247 non-null   float64
dtypes: datetime64[ns](2), float64(11), int64(6), object(7), timedelta
64[ns](1)
memory usage: 1.2+ MB
```

In [27]:

```
aggregate_genre_df = imdb_tn_movie_and_opening.groupby(['genres']).agg(count_of_movi
                                                        ,total_domestic_gross=('domest
                                                        ,total_opening_weekend_rev=('c
                                                        ,average_imdb_rating=('average
# creating grouped data by genre

aggregate_genre_df['domestic_ROI'] = aggregate_genre_df['total_domestic_gross'] /  a
aggregate_genre_df['overall_ROI'] = aggregate_genre_df['total_worldwide_gross'] / ag
aggregate_genre_df['%_of_domestic_ROI_in_opening_weekend'] = aggregate_genre_df['tot
# calculating ROI and opening weekend contribution by genre

top_10_genre_df = aggregate_genre_df.sort_values(by=['count_of_movies','overall_ROI'
# extracting top 10 genres by ROI
```

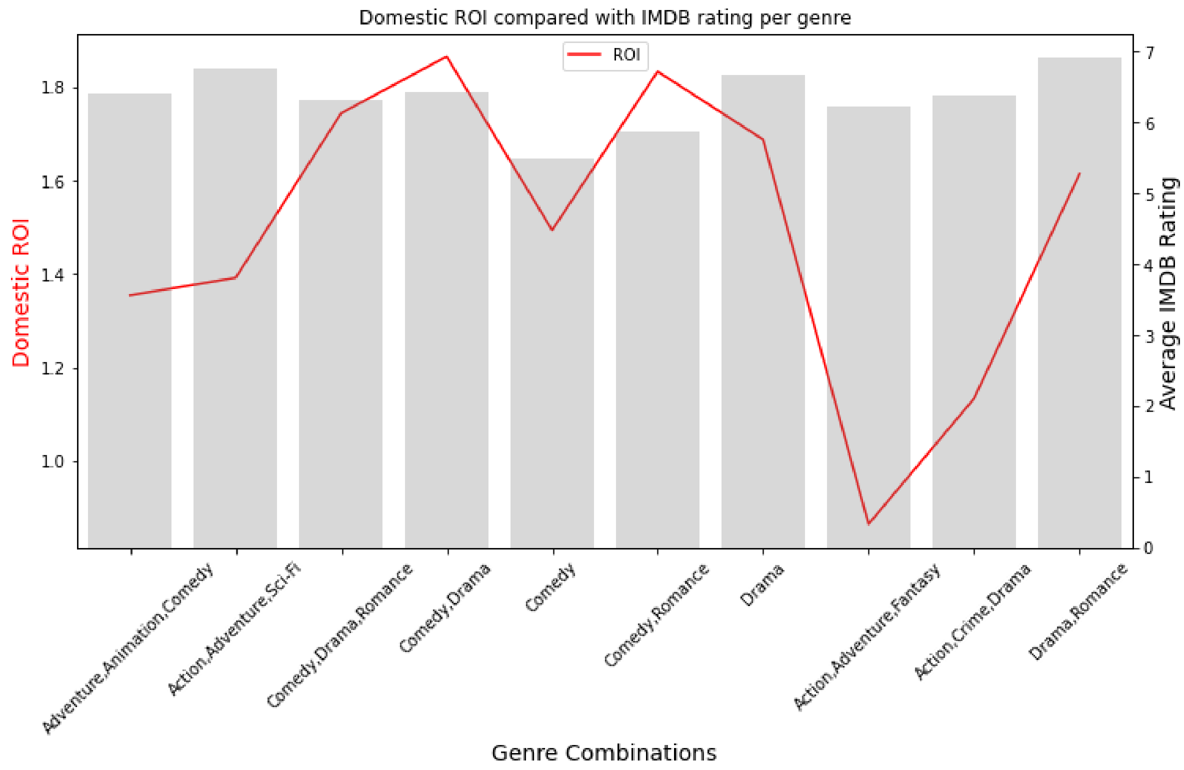
In [28]:

```
fig, ax = plt.subplots(figsize=(12,6))


sns.barplot(data = top_10_genre_df,
        x = 'total_production_budget',
        y = 'genres',
        color="red",
           orient='h')
# set x-axis label
ax.set_xlabel("Total Production Budget", fontsize = 14)
# set y-axis label
ax.set_ylabel("Genre Combinations",
              color="red",
              fontsize=14)
ax.set_title('Total production spend by genre')
plt.show()
```



In [29]:

```
fig, ax = plt.subplots(figsize=(12,6))


sns.lineplot(data = top_10_genre_df,
             x='genres',
             y='domestic_ROI',
        color="red"
            , label='ROI')
# set x-axis label
ax.set_xlabel("Genre Combinations", fontsize = 14)
# set y-axis label
ax.set_ylabel("Domestic ROI",
              color="red",
              fontsize=14)
ax.set_title('Domestic ROI compared with IMDB rating per genre')
plt.legend(loc='upper center')

# twin object for two different y-axis on the sample plot
ax2=ax.twinx()
# make a plot with different y-axis using second axis object
sns.barplot(data = top_10_genre_df, x = 'genres', y = 'average_imdb_rating' , color=
ax2.set_ylabel('Average IMDB Rating',fontsize=14)
ax.tick_params(axis='x', labelrotation=45)
plt.show()
```



In [30]:

```
# Take the profitable films, then understand grouping by year what the average runti
# a movie

runtime_df = imdb_tn_movie_and_opening[(imdb_tn_movie_and_opening['is_profitable'] =
runtime_agg_by_year = runtime_df.groupby('year_of_release')['runtime_minutes'].agg([
runtime_agg_by_year
```

Out[30]:

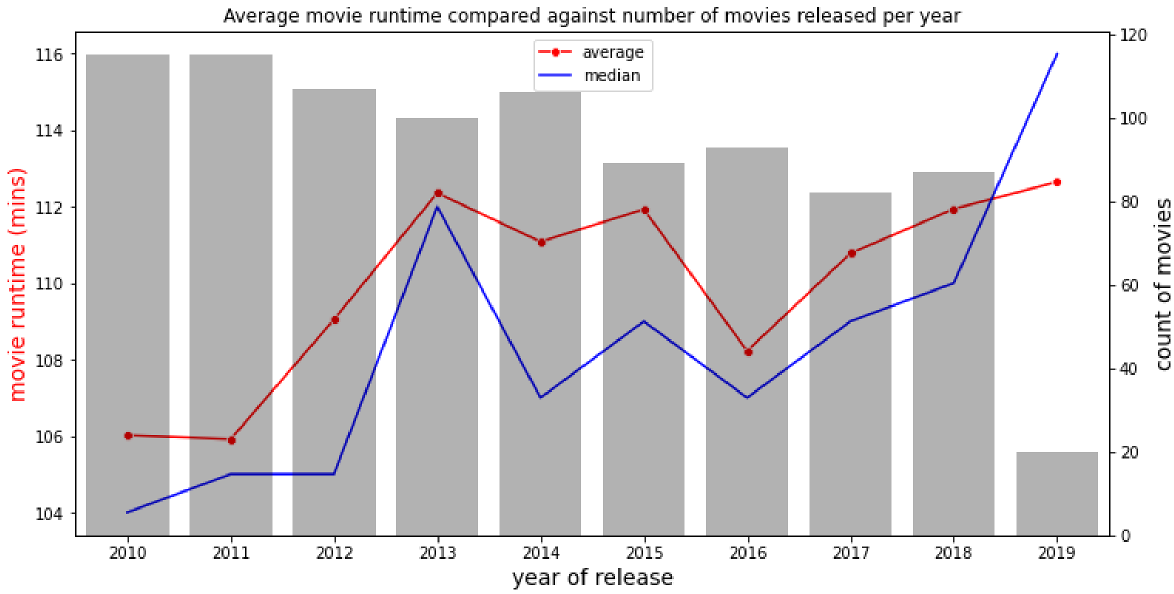
	year_of_release	count	mean	median	max
0	2010	115	106.017391	104.0	148.0
1	2011	115	105.913043	105.0	158.0
2	2012	107	109.046729	105.0	172.0
3	2013	100	112.360000	112.0	180.0
4	2014	106	111.084906	107.0	169.0
5	2015	89	111.932584	109.0	168.0
6	2016	93	108.225806	107.0	161.0
7	2017	82	110.780488	109.0	164.0
8	2018	87	111.942529	110.0	149.0
9	2019	20	112.650000	116.0	133.0

In [31]:

```
# To understand which month to release movies, first we want to take profitable movi
# group by month, taking the sum of production & sum of domestic & worldwide gross

profitable_months_df = imdb_tn_movie_and_opening[imdb_tn_movie_and_opening['is_profi
month_release_agg_df = profitable_months_df.groupby('month_of_release').agg(count_of
                                                        ,total_domestic_gross=('domest
                                                        ,total_opening_weekend_rev=('o
# monthly aggregation for opening weekend, gross revenue and production budget

month_release_agg_df['domestic_ROI'] = month_release_agg_df['total_domestic_gross']
month_release_agg_df['overall_ROI'] = month_release_agg_df['total_worldwide_gross']
# calculating ROI without running into avg of avg error

month_release_agg_df['%_of_domestic_ROI_in_opening_weekend'] = month_release_agg_df[
```

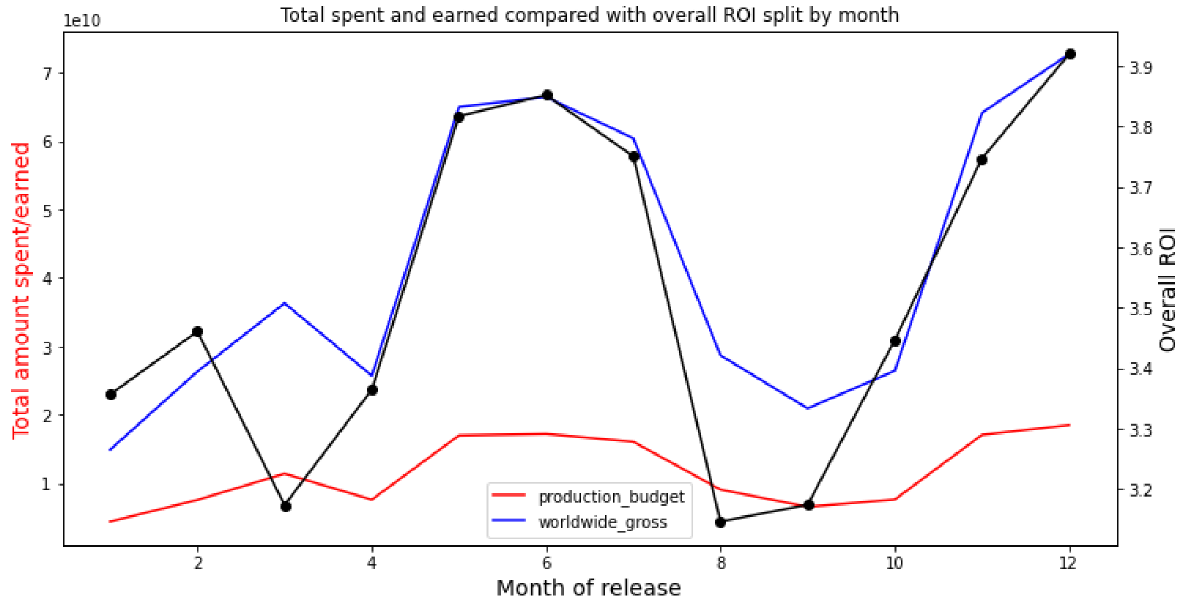
In [32]:

```
fig, ax = plt.subplots(figsize=(12,6))


sns.lineplot(data = runtime_agg_by_year['mean'],
             color="red",
             marker="o",
             label='average')
sns.lineplot(data = runtime_agg_by_year['median'],
             color="blue",
             label='median')
plt.legend(loc='upper center')
# set x-axis label
ax.set_xlabel("year of release", fontsize = 14)
# set y-axis label
ax.set_ylabel("movie runtime (mins)",
              color="red",
              fontsize=14)
ax.set_title('Average movie runtime compared against number of movies released per y

# twin object for two different y-axis on the sample plot
ax2=ax.twinx()
# make a plot with different y-axis using second axis object
sns.barplot(data = runtime_agg_by_year, x = 'year_of_release', y = 'count', color="b
ax2.set_ylabel("count of movies",fontsize=14)
plt.show()
```



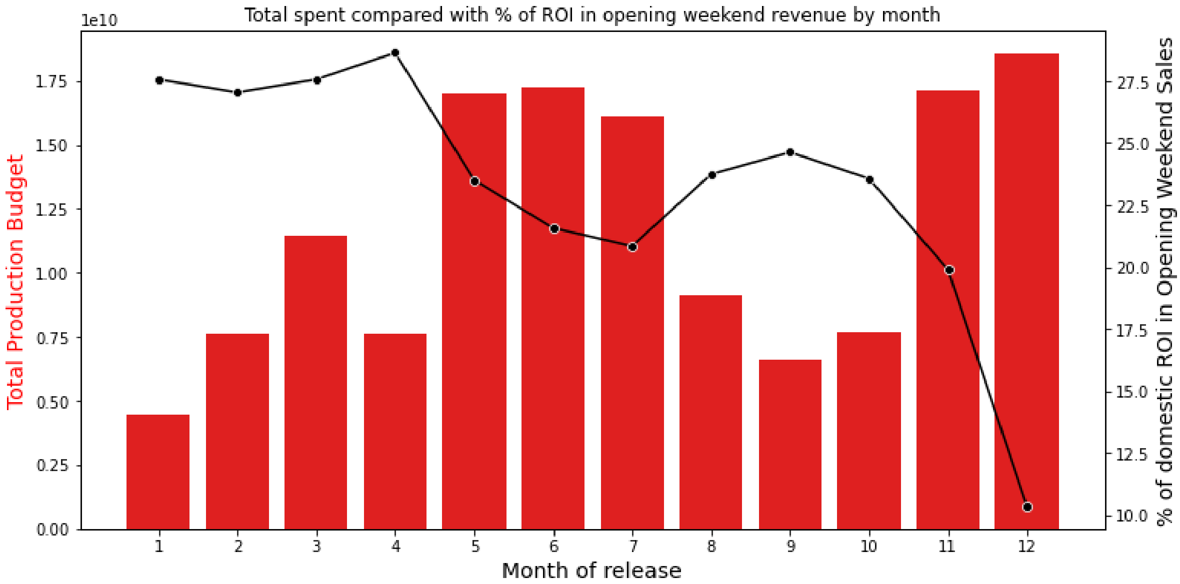
In [33]:

```
x2 = month_release_agg_df['month_of_release']
y2 = month_release_agg_df['total_production_budget']
z2 = month_release_agg_df['total_worldwide_gross']
q2 = month_release_agg_df['overall_ROI']

fig, ax = plt.subplots(figsize=(12,6))


ax.plot(x2,
        y2,
        color="red",
       label='production_budget')
ax.plot(x2,
       z2,
       color='blue',
       label='worldwide_gross')
plt.legend(loc='lower center')
# set x-axis label
ax.set_xlabel("Month of release", fontsize = 14)
# set y-axis label
ax.set_ylabel("Total amount spent/earned",
              color="red",
              fontsize=14)
ax.set_title('Total spent and earned compared with overall ROI split by month')

# twin object for two different y-axis on the sample plot
ax2=ax.twinx()
# make a plot with different y-axis using second axis object
ax2.plot(x2, q2, color="black",marker="o")
ax2.set_ylabel("Overall ROI",fontsize=14)
plt.show()
```



In [34]:

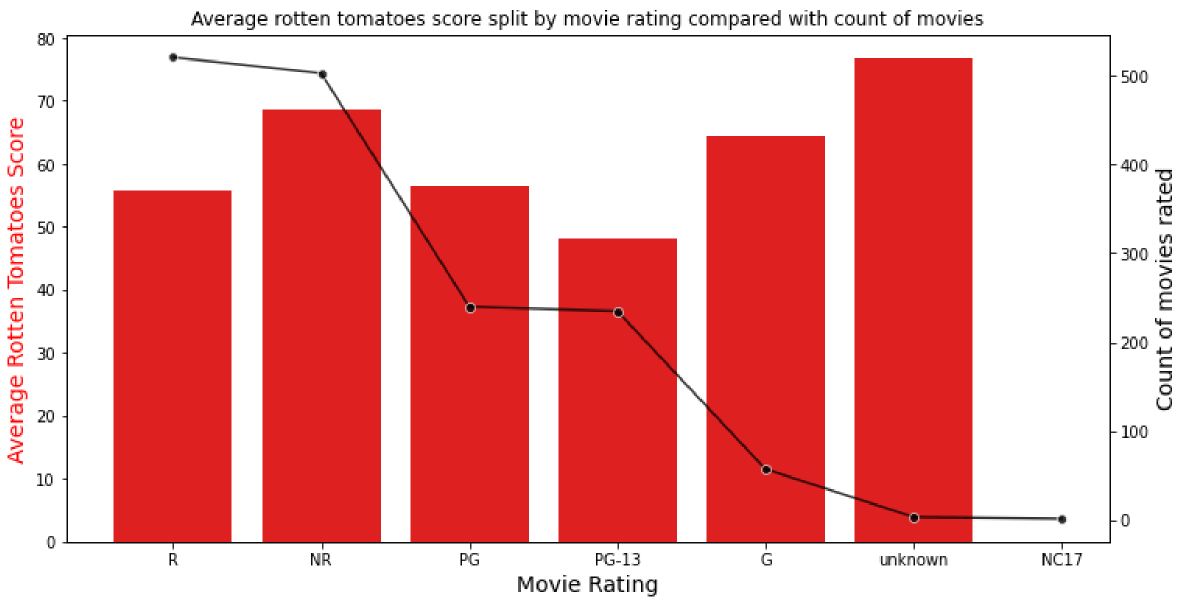
```
fig, ax = plt.subplots(figsize=(12,6))


sns.barplot(data = month_release_agg_df,
        x = 'month_of_release',
        y = 'total_production_budget',
        color="red")
# set x-axis label
ax.set_xlabel("Month of release", fontsize = 14)
# set y-axis label
ax.set_ylabel("Total Production Budget",
              color="red",
              fontsize=14)
ax.set_title('Total spent compared with % of ROI in opening weekend revenue by month

# twin object for two different y-axis on the sample plot
ax2=ax.twinx()
# make a plot with different y-axis using second axis object
sns.lineplot(data = month_release_agg_df['%_of_domestic_ROI_in_opening_weekend'], cc
ax2.set_ylabel("% of domestic ROI in Opening Weekend Sales",fontsize=14)
plt.show()
```



Rotten Tomatoes Data Visualisation

In [35]:

```
fig, ax = plt.subplots(figsize=(12,6))


sns.barplot(data = aggregate_rating_df,
        x='rating',
        y='avg_overall_rt_score',
        color="red")
# set x-axis label
ax.set_xlabel("Movie Rating", fontsize = 14)
# set y-axis label
ax.set_ylabel("Average Rotten Tomatoes Score",
              color="red",
              fontsize=14)
ax.set_title('Average rotten tomatoes score split by movie rating compared with cour

# twin object for two different y-axis on the sample plot
ax2=ax.twinx()
# make a plot with different y-axis using second axis object
sns.lineplot(data=aggregate_rating_df,
           y='count_of_movies',
           x='rating', color="black", marker="o", alpha=0.8)
ax2.set_ylabel("Count of movies rated",fontsize=14)
plt.show()
```



In [36]:

```
full_review_data.groupby('is_family_friendly').agg(count_of_movies=('id','count')
                                                    , avg_overall_rt_score=('overall_rotten_scor
                                                    , avg_critic_rt_score=('critic_rotten_score'

# creating aggregation by family friendly movies
```

Out[36]:

	is_family_friendly	count_of_movies	avg_overall_rt_score	avg_critic_rt_score
0	0	1028	60.499530	60.043011
1	1	532	53.345881	52.606916

In [37]:

```
full_review_data.groupby('director').agg(count_of_movies=('id','count')
                                          , avg_overall_rt_score=('overall_rotten_scor
                                          , avg_critic_rt_score=('critic_rotten_score'

# seeing which directors have the highest ratings
```

Out[37]:

	director	count_of_movies	avg_overall_rt_score	avg_critic_rt_score
1003	Steven Spielberg	10	77.471172	77.166911
172	Clint Eastwood	8	68.476254	68.003735
1100	William Friedkin	4	63.006922	62.231318
1116	Yimou Zhang	4	73.704037	72.240625
869	Ridley Scott	4	70.901329	71.200835
480	Jim Jarmusch	4	64.547423	60.767045
28	Alfred Hitchcock	4	94.601672	95.509693
1111	Woody Allen	4	86.968580	87.648148
124	Bruce Beresford	4	69.567504	64.874157
1096	William Beaudine	4	100.000000	100.000000
181	Curtis Hanson	4	66.631130	66.987179
82	Barry Levinson	4	42.698611	41.403575
550	Joseph Ruben	3	22.747475	21.690821
520	John Landis	3	37.747036	39.473684
225	David Swift	3	63.888889	63.888889

In [38]:

```
full_review_data.groupby('writer').agg(count_of_movies=('id','count')
                                        , avg_overall_rt_score=('overall_rotten_scor
                                        , avg_critic_rt_score=('critic_rotten_score'

# similar to above with writers instead
```

Out[38]:

	writer	count_of_movies	avg_overall_rt_score	avg_critic_rt_score
1059	Woody Allen	4	86.968580	87.648148
492	John Hughes	3	39.270452	37.361586
465	Jim Jarmusch	3	71.777516	70.606061
959	Sylvester Stallone	3	51.937217	47.842208
389	Hong Sang-soo	3	86.666667	85.185185
920	Sidney Sheldon	2	66.666667	66.666667
568	Larry Cohen	2	40.277778	40.277778
257	Don Mancini	2	33.948864	33.518519
772	Peter Morgan	2	45.271498	44.640313
900	Sebastian Gutierrez	2	25.000000	25.000000
951	Steven Zaillian	2	90.484817	90.427998
501	John Patrick Shanley	2	48.611111	54.107143
757	Paul Schrader	2	86.276596	85.494299
751	Paul Laverty	2	89.859438	88.076923
491	John Hodge	2	83.122952	82.982086

Conclusions

Key Findings:

- Movies that aren't family friendly have the higher Rotten Tomatoes score. When broken down deeper we can see this is largely driven from "NR" based movies. The three best rated movie ratings to produce are **G, NR & PG**
- Movies lengths are getting longer over time, make sure to keep your movie **less than 135 minutes** but **over 105-110 minutes**
- The best months to release a movie, varies depending on how quickly you want to get returns. If you care about overall domestic ROI, is June, followed closely by Dec, Jan and Feb. When coupled with what % of sales can be made on the opening weekend, the best two months to release movies on are Jan & Feb, followed by June, due to the massive difference in production budgets.
- In the US, the best ROI genre focuses around **thriller based movies**, due to **low production costs**, in terms of having a large amount of movies with a good domestic ROI, you should focus on Comedy,Drama,Romance based movies.If you also want to consider overall gross, then you should focus on **Action,Adventure,Sci-Fi**.
    - Internationally they should also consider the following genres:

  - **Adventure,Animation,Comedy**
  - **Action,Adventure,Sci-Fi**
  - **Comedy,Romance**
  - **Drama,Thriller**

Limitations:

With the datasets given the limitations occur when trying to connect different data sources together, as there was a loss rate of ***at least 40%*** with each join, meaning the dataset we're able to analyse at the end is only a subset of the data. There were also a lot of other metrics/pieces of relevant information missing that would help enrich the analysis.

Future analysis

- Explore what is the distribution between cinema sales & DVD sales
- Explore what type of movie (animation, etc) drives the best ROI
- See if there is a correlation between rotten tomatoes score & ROI
- What are the most common traits of movies in the top grossing films
- Which countries outside of the US gross the highest % for movies & does it differ by genre? To understand where they should release their movies next & make sure translations are sourced early to increase ROI
- Once defining that G rated movies have the best rating, scrape movie names, directors & writers from that list to get the best performing directors & writers to hire