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Cinema_success_insights

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mbarriola96 Advanced analysis of movies 5 days ago

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Final Project Submission

Please fill out:

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- Student pace: self paced
- Scheduled project review date/time:
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1. Overview

The project entails performing exploratory data analysis (EDA) on current box office trends to guide the newly established movie studio of your company in creating profitable films. We will collect and analyze data on film genres, budgets, revenues, and ratings to uncover what types of films resonate with audiences and yield high returns. The analysis will result in actionable insights regarding film characteristics such as genre, production budget, and release timing, providing a strategic blueprint for the studio's success in the competitive landscape of film production. The final deliverable will be a concise report with recommendations for the types of films to produce, supported by data-driven evidence.

2. Business Understanding

Our business goal is to establish a data-driven foundation for our new film studio's production strategy by answering three critical questions:

1. Which movie genre yields the highest ROI?
2. What is the relationship between a movie's run-time and its ROI and production costs?
3. How does a director's involvement correlate with a movie's ROI and production costs?

By investigating these areas, we aim to identify profitable genres, optimal film lengths, and directors whose past work indicates a likelihood of future success. These insights will inform our decision-making process in greenlighting new film projects, ensuring that our investments are aligned with market trends and have a higher probability of financial success.

3. Data Understanding

3.1 Data Description

Drawing from a rich dataset aggregated from:

- Box Office Mojo
- IMDB
- Rotten Tomatoes
- TheMovieDB
- The Numbers

Our analysis targets three pivotal questions to carve out a strategic niche for our new movie studio. By exploring which movie genres yield the highest ROI, the relationship between a film's runtime and its financial metrics, and the impact of directorial involvement on a movie's success, we aim to uncover actionable insights. This investigation is set to guide our studio in selecting film projects that align with proven market successes, optimizing for genres, runtimes, and directorial choices that historical data suggests are most lucrative. The outcome of this focused analysis will inform our decision-making process, ensuring that our investments capitalize on trends that offer the greatest potential for financial return. This streamlined approach positions our studio to effectively compete in the dynamic film industry landscape, leveraging data-driven strategies to achieve commercial and critical success.

3.2 Import Necessary Libraries

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import sqlite3
```

In [3]:

```
pd.set_option('display.max_columns', 500)
```

3.3 Define global variables

In [4]:

```
INPUT_PATH_bom_movie_gross = "C:\\Users\\Usuario\\Desktop\\FlatIron\\DataScier
INPUT_PATH_tmdb_movies = "C:\\Users\\Usuario\\Desktop\\FlatIron\\DataScience_F
INPUT_PATH_tn_movie_budgets = "C:\\Users\\Usuario\\Desktop\\FlatIron\\DataScie
INPUT_PATH_rt_movie_info = "C:\\Users\\Usuario\\Desktop\\FlatIron\\DataScience
INPUT_PATH_rt_reviews = "C:\\Users\\Usuario\\Desktop\\FlatIron\\DataScience_Fl
```

3.4 Functions

In [5]:

```
#This function is going to get the genre name from the genre id
def get_genre_from_id(genre_ids):
    """
    Converts a list of genre IDs into their corresponding genre names.

    Parameters:
    genre_ids (list): A list of integers representing genre IDs.

    Returns:
    list: A list of strings where each string is the genre name associated wit
    """
    return [genre_id_dictionary[genre_id] for genre_id in genre_ids]
```

3.5 Code

3.5.1 Bom Movie Gross csv

In [6]:

```
df_bom = pd.read_csv(INPUT_PATH_bom_movie_gross, encoding="latin-1")
df_bom
```

Out[6]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

In [7]:

```
(df_bom.isnull().sum()/len(df_bom))*100
```

Out[7]:
```
title              0.000000
studio             0.147623
domestic_gross     0.826690
foreign_gross     39.858282
year               0.000000
dtype: float64
```

In [8]:
```
df_bom.duplicated().sum()
```

Out[8]:
```
0
```

Bom Movie Gross dataset contains 3387 movies and includes 5 columns of datapoints on each movie. Another noticeable detail is that foreign_gross contains almost 40% of NaNs

3.5.2 Tmdb Movies csv

In [9]:
```
df_tmdb = pd.read_csv(INPUT_PATH_tmdb_movies, encoding="latin-1", index_col=0)
df_tmdb
```

Out[9]:

	genre_ids	id	original_language	original_title	popularity	release_date
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16
...	...	...	...	...	...	...
26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13
26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01
26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01
26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22
26516	[53, 27]	309885	en	The Church	0.600	2018-10-05

26517 rows × 9 columns

In [10]:
```
(df_tmdb.isnull().sum()/len(df_tmdb))*100
```

Out[10]:
```
genre_ids            0.0
id                   0.0
original_language    0.0
original_title       0.0
popularity           0.0
release_date         0.0
title                0.0
vote_average         0.0
vote_count           0.0
dtype: float64
```

In [11]:
```
df_tmdb.duplicated().sum()
```

Out[11]:
```
1020
```

In [12]:
```
duplicates_df_tmdb = df_tmdb[df_tmdb.duplicated(keep=False)].sort_values('id')
duplicates_df_tmdb
```

Out[12]:

	genre_ids	id	original_language	original_title	popularity	release_d
20626	[16, 10751, 14]	129	ja	åƒã¨åƒå°‹ã®ç¥žéš ã —	32.043	2002-09
14173	[16, 10751, 14]	129	ja	åƒã¨åƒå°‹ã®ç¥žéš ã —	32.043	2002-09
43	[35, 10749]	239	en	Some Like It Hot	14.200	1959-03
24000	[35, 10749]	239	en	Some Like It Hot	14.200	1959-03
20639	[28, 53, 878]	280	en	Terminator 2: Judgment Day	24.604	1991-07
...	...	...	...	...	...	
17071	[27]	560717	en	Requiem	0.600	2015-01
23685	[35]	564441	en	Adopting Trouble	0.600	2016-04
20461	[35]	564441	en	Adopting Trouble	0.600	2016-04
23785	[99]	573013	en	Harvested Alive - 10 Years of	0.600	2016-11

23785	[99]	572012	en	10 Years of Investigations	0.600	2016-11
20569	[99]	572012	en	Harvested Alive - 10 Years of Investigations	0.600	2016-11

2016 rows × 9 columns

In [13]:

```
df_tmdb.drop_duplicates(inplace=True)
df_tmdb
```

Out[13]:

	genre_ids	id	original_language	original_title	popularity	release_date
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16
...	...	...	...	...	...	...
26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13
26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01
26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01
26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22
26516	[53, 27]	309885	en	The Church	0.600	2018-10-05

25497 rows × 9 columns

Tmdb movies dataset contains 25497 movies and includes 9 columns of datapoints on each movie. There are no NaNs in any of the columns. We proceeded to drop all the duplicated registrations.

3.5.3 Tn movie budgets csv

In [14]:
```
df_tn = pd.read_csv(INPUT_PATH_tn_movie_budgets, encoding="latin-1")
df_tn
```

Out[14]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gro
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,2
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,8
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,3
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,9
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,7
...	...	...	...	...	...	
5777	78	Dec 31, 2018	Red 11	$7,000	$0	
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,4
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,3
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,0

5782 rows × 6 columns

In [15]:
```
(df_tn.isnull().sum()/len(df_tn))*100
```

Out[15]:
```
id                   0.0
release_date         0.0
movie                0.0
production_budget    0.0
domestic_gross       0.0
worldwide_gross      0.0
dtype: float64
```

In [16]:
```
df_tn.duplicated().sum()
```

Out[16]: 0

Tn movie budget dataset contains 5782 movies and includes 6 columns of datapoints on each movie. There are no NaNs in any of the columns and there are no duplicates.

3.5.4 Rt movie information tsv

In [17]:
```
df_rt_movie = pd.read_csv(INPUT_PATH_rt_movie_info, delimiter = '\t', encoding
df_rt_movie
```

Out[17]:

	id	synopsis	rating	genre	director	writer	theater_date
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN
...	...	...	...	...	...	...	...
1555	1996	Forget terrorists or hijackers -- there's a ha...	R	Action and Adventure|Horror|Mystery and Suspense	NaN	NaN	Aug 18, 2006
1556	1997	The popular Saturday Night Live...	PG	Comedy|Science...	Steve	Terry Turner|Tom Davis|Dan...	Jul 23, 1993

1556	1997	Night Live sketch was exp...	PG	Fiction and Fantasy	Barron	Aykroyd| Bonnie Turner	Jul 23, 1993
1557	1998	Based on a novel by Richard Powell, when the l...	G	Classics|Comedy|Drama|Musical and Performing Arts	Gordon Douglas	NaN	Jan 1, 1962
1558	1999	The Sandlot is a coming-of-age story about a g...	PG	Comedy|Drama|Kids and Family|Sports and Fitness	David Mickey Evans	David Mickey Evans|Robert Gunter	Apr 1, 1993
1559	2000	Suspended from the force, Paris cop Hubert is ...	R	Action and Adventure|Art House and Internation...	NaN	Luc Besson	Sep 27, 2001

1560 rows × 12 columns

In [18]:
```
(df_rt_movie.isnull().sum()/len(df_rt_movie))*100
```

Out[18]:
```
id               0.000000
synopsis         3.974359
rating           0.192308
genre            0.512821
director        12.756410
writer          28.782051
theater_date    23.012821
dvd_date        23.012821
currency        78.205128
box_office      78.205128
runtime          1.923077
studio          68.333333
dtype: float64
```

In [19]:
```
df_rt_movie.duplicated().sum()
```

Out[19]:
```
0
```

Rt movie information dataset contains 1560 movies and includes 12 columns of datapoints on each movie. There is a high percentage of NaNs in currency, box_office and studio. There are no duplicates.

3.5.5 Rt reviews tsv

In [20]:
```
df_rt_reviews = pd.read_csv(INPUT_PATH_rt_reviews, delimiter = '\t', encoding=
```

```
df_rt_reviews
```

Out[20]:

	id	review	rating	fresh	critic	top_critic	publisher
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro
1	3	It's an allegory in search of a meaning that n...	NaN	rotten	Annalee Newitz	0	io9.com
2	3	... life lived in a bubble in financial dealin...	NaN	fresh	Sean Axmaker	0	Stream on Demand
3	3	Continuing along a line introduced in last yea...	NaN	fresh	Daniel Kasman	0	MUBI
4	3	... a perverse twist on neorealism...	NaN	fresh	NaN	0	Cinema Scope
...	...	...	...	...	...	...	...
54427	2000	The real charm of this trifle is the deadpan c...	NaN	fresh	Laura Sinagra	1	Village Voice
54428	2000	NaN	1/5	rotten	Michael Szymanski	0	Zap2it.com
54429	2000	NaN	2/5	rotten	Emanuel Levy	0	EmanuelLevy.Com
54430	2000	NaN	2.5/5	rotten	Christopher Null	0	Filmcritic.com
54431	2000	NaN	3/5	fresh	Nicolas Lacroix	0	Showbizz.net

54432 rows × 8 columns

In [21]:

```
(df_rt_reviews.isnull().sum()/len(df_rt_reviews))*100
```

Out[21]:

```
id             0.000000
review        10.220091
rating        24.832819
```

```
fresh          0.000000
critic         5.000735
top_critic     0.000000
publisher      0.567681
date           0.000000
dtype: float64
```

In [22]:

```python
df_rt_reviews.duplicated().sum()
```

Out[22]: 9

In [23]:

```python
duplicates_df_5_rt_reviews = df_rt_reviews[df_rt_reviews.duplicated(keep=False
duplicates_df_5_rt_reviews
```

Out[23]:

	id	review	rating	fresh	critic	top_critic	publisher	date
8128	304	Friends With Kids is a smart, witty and potty-...	NaN	fresh	NaN	0	Liverpool Echo	June 29, 2012
8129	304	Friends With Kids is a smart, witty and potty-...	NaN	fresh	NaN	0	Liverpool Echo	June 29, 2012
14574	581	NaN	4.5/5	fresh	NaN	0	Film Threat	December 6, 2005
14575	581	NaN	4.5/5	fresh	NaN	0	Film Threat	December 6, 2005
26225	1055	NaN	4/5	fresh	NaN	0	Film Threat	December 6, 2005
26226	1055	NaN	4/5	fresh	NaN	0	Film Threat	December 6, 2005
35161	1368	NaN	2/5	rotten	NaN	0	Film Threat	December 6, 2005
35162	1368	NaN	2/5	rotten	NaN	0	Film Threat	December 6, 2005
35165	1368	NaN	2/5	rotten	NaN	0	Film Threat	December 8, 2002
35166	1368	NaN	2/5	rotten	NaN	0	Film Threat	December 8, 2002
40566	1535	NaN	2/5	rotten	NaN	0	Film Threat	December 6, 2005
40567	1535	NaN	2/5	rotten	NaN	0	Film Threat	December 6, 2005
		This tired,						

42369	1598	neutered action thriller won't cau...	2/5	rotten	NaN	0	Empire Magazine	November 14, 2008
42381	1598	This tired, neutered action thriller won't cau...	2/5	rotten	NaN	0	Empire Magazine	November 14, 2008
49486	1843	NaN	0.5/5	rotten	NaN	0	Film Threat	December 6, 2005
49487	1843	NaN	0.5/5	rotten	NaN	0	Film Threat	December 6, 2005
49491	1843	NaN	0.5/5	rotten	NaN	0	Film Threat	December 8, 2002
49492	1843	NaN	0.5/5	rotten	NaN	0	Film Threat	December 8, 2002

Rt reviews dataset contains 54432 movies and includes 8 columns of datapoints on each movie. There is a low percentage of NaNs in review, and rating.

There are 9 duplicated rows.

3.5.6 IM sqlite3

In [24]:

```
route_db = r"C:\\Users\\Usuario\\Desktop\\FlatIron\\DataScience_FlatIron_Curso

conn = sqlite3.connect(route_db)
df_im_movie_basics = pd.read_sql_query("SELECT * FROM MOVIE_BASICS", conn)

df_im_movie_basics
```

Out[24]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biog
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Co
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,D
...	...	...	...	...	...	

146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	[
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	[

146144 rows × 6 columns

In [25]:
```
(df_im_movie_basics.isnull().sum()/len(df_im_movie_basics))*100
```

Out[25]:
```
movie_id            0.000000
primary_title       0.000000
original_title      0.014369
start_year          0.000000
runtime_minutes    21.717621
genres              3.700460
dtype: float64
```

3.5.7 First Question: Which genre has a higher ROI?

To be able to answer this question we would have to combine Tmdb Movies and Tn movie budgets We would be unable to extract the information of the ROI for each genre from IM because it does not have information about revenues

Let's start looking at df_tmdb

In [26]:
```
df_tmdb
```

Out[26]:

	genre_ids	id	original_language	original_title	popularity	release_date
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07

3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16
...	...	...	...	...	...	...
26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13
26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01
26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01
26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22
26516	[53, 27]	309885	en	The Church	0.600	2018-10-05

25497 rows × 9 columns

We are going to analyze all the films regarless of the original language they are in. Also, we are going to drop the unnecessary columns from the tmdb dataset

In [27]:

```
df_tmdb_updated = df_tmdb.drop(['original_title','original_language','vote_ave
df_tmdb_updated
```

Out[27]:

	genre_ids	id	title
0	[12, 14, 10751]	12444	Harry Potter and the Deathly Hallows: Part 1
1	[14, 12, 16, 10751]	10191	How to Train Your Dragon
2	[12, 28, 878]	10138	Iron Man 2
3	[16, 35, 10751]	862	Toy Story
4	[28, 878, 12]	27205	Inception
...	...	...	...
26512	[27, 18]	488143	Laboratory Conditions
26513	[18, 53]	485975	_EXHIBIT_84xxx_
26514	[14, 28, 12]	381231	The Last One
26515	[10751, 12, 28]	366854	Trailer Made
26516	[53, 27]	309885	The Church

25497 rows × 3 columns

If we look at the column 'genre_ids' one can see that there is a list of them for each movie. One would think that it's because a movie can have multiple genres movie. One would think that it's because a movie can have multiple genres.

To make sense of the genre_ids, we found a logical value for each genre_id in the TMDB website: https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee

In [28]:
```
TMDB_dictionary = {
'Action' : 28,
'Adventure' : 12,
'Animation' : 16,
'Comedy' : 35,
'Crime' : 80,
'Documentary' : 99,
'Drama' : 18,
'Family' : 10751,
'Fantasy' : 14,
'History' : 36,
'Horror' : 27,
'Music' : 10402,
'Mystery' : 9648,
'Romance' : 10749,
'Science Fiction' : 878,
'TV Movie' : 10770,
'Thriller' : 53,
'War' : 10752,
'Western' : 37
}

genre_id_dictionary = {value:key for key,value in TMDB_dictionary.items()}
```

We are going to create another column in the dataset that contains the list of genres that each id corresponds to

In [29]:
```
#We first need to convert genre_ids column from a string to a list
df_tmdb_updated['genre_ids'] = df_tmdb_updated['genre_ids'].apply(lambda x: ev
```

In [30]:
```
df_tmdb_updated['genre_name'] = df_tmdb_updated['genre_ids'].map(lambda x: get
df_tmdb_updated
```

Out[30]:

	genre_ids	id	title	genre_name
0	[12, 14, 10751]	12444	Harry Potter and the Deathly Hallows: Part 1	[Adventure, Fantasy, Family]
1	[14, 12, 16, 10751]	10191	How to Train Your Dragon	[Fantasy, Adventure, Animation, Family]
2	[12, 28, 878]	10138	Iron Man 2	[Adventure, Action, Science Fiction]
3	[16, 35, 10751]	862	Toy Story	[Animation, Comedy, Family]
4	[28, 878, 12]	27205	Inception	[Action, Science Fiction, Adventure]

...	...	...	...	...
26512	[27, 18]	488143	Laboratory Conditions	[Horror, Drama]
26513	[18, 53]	485975	_EXHIBIT_84xxx_	[Drama, Thriller]
26514	[14, 28, 12]	381231	The Last One	[Fantasy, Action, Adventure]
26515	[10751, 12, 28]	366854	Trailer Made	[Family, Adventure, Action]
26516	[53, 27]	309885	The Church	[Thriller, Horror]

25497 rows × 4 columns

Given that we now have the genre names we have no need of the genre_ids, so we will proceed to drop the genre_ids column. Also, we are going to explode all the genres of each title.

In [31]:

```
df_tmdb_updated = df_tmdb_updated.explode('genre_name')
df_tmdb_updated.drop('genre_ids', axis=1, inplace=True)
```

Now let's look at df_tn dataset

In [32]:

```
df_tn
```

Out[32]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gro
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,2
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,8
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,3
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,9
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,7
...	...	...	...	...	...	
5777	78	Dec 31, 2018	Red 11	$7,000	$0	

5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,4
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,3
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,0

5782 rows × 6 columns

Let's try to see which columns from df_tmdb and df_tn are related to each other

In [33]:
```
df_tmdb_updated[df_tmdb_updated['title'].str.contains('Avatar')]
```

Out[33]:

	id	title	genre_name
6	19995	Avatar	Action
6	19995	Avatar	Adventure
6	19995	Avatar	Fantasy
6	19995	Avatar	Science Fiction
1831	278698	Avatar Spirits	NaN
3387	79582	Aliens vs. Avatars	Science Fiction
3387	79582	Aliens vs. Avatars	Horror
3387	79582	Aliens vs. Avatars	Thriller
23157	460441	Avatar Flight of Passage	Adventure
23157	460441	Avatar Flight of Passage	Family

In [34]:
```
df_tn[df_tn['movie'].str.contains('Avatar')]
```

Out[34]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279

We can see that the columns id don't match and the only possible option for both datasets to be joined is by joinin 'title' from df_tmdb_updated with 'movie' from df_tn

Looking at the im dataset, we have information about the genres but there is no information about financial costs or revenues. What we will do is join by the movies name and then carry on the process to try to find the ROI for each genre.

Now, we will drop unnecessary columns and calculate the ROI values for each movie in the df_tn

In the context of movie finances, "worldwide gross" typically includes the "domestic gross". With that in mind, I am going to calculate the ROI column

In [35]:
```
df_tn.drop(['id','release_date','domestic_gross'], axis=1, inplace=True)
```

In [36]:
```
# Convert the currency strings to integers
df_tn['production_budget'] = df_tn['production_budget'].replace('[\$,]', '', r
df_tn['worldwide_gross'] = df_tn['worldwide_gross'].replace('[\$,]', '', regex
```

In [37]:
```
df_tn[df_tn['production_budget']==0]
```

Out[37]:

movie	production_budget	worldwide_gross

In [38]:
```
df_tn['ROI_%'] = round(((df_tn['worldwide_gross']-df_tn['production_budget'])
df_tn
```

Out[38]:

	movie	production_budget	worldwide_gross	ROI_%
0	Avatar	425000000.0	2.776345e+09	553.26
1	Pirates of the Caribbean: On Stranger Tides	410600000.0	1.045664e+09	154.67
2	Dark Phoenix	350000000.0	1.497624e+08	-57.21
3	Avengers: Age of Ultron	330600000.0	1.403014e+09	324.38
4	Star Wars Ep. VIII: The Last Jedi	317000000.0	1.316722e+09	315.37
...	...	...	...	...
5777	Red 11	7000.0	0.000000e+00	-100.00
5778	Following	6000.0	2.404950e+05	3908.25
5779	Return to the Land of Wonders	5000.0	1.338000e+03	-73.24
5780	A Plague So Pleasant	1400.0	0.000000e+00	-100.00
5781	My Date With Drew	1100.0	1.810410e+05	16358.27

5782 rows × 4 columns

Let's now join df_tmdb_updated and df_tn

In [39]:
```
# We will first have to rename the column 'movie' to 'title' so that we can su
df_tn.rename({'movie':'title'},inplace=True,axis=1)
```

In [40]:
```
df_question1 = df_tmdb_updated.merge(df_tn, on='title', how='inner')
df_question1
```

Out[40]:

	id	title	genre_name	production_budget	worldwide_gross	ROI_9
0	10191	How to Train Your Dragon	Fantasy	165000000.0	494870992.0	199.9
1	10191	How to Train Your Dragon	Adventure	165000000.0	494870992.0	199.9
2	10191	How to Train Your Dragon	Animation	165000000.0	494870992.0	199.9
3	10191	How to Train Your Dragon	Family	165000000.0	494870992.0	199.9
4	10138	Iron Man 2	Adventure	170000000.0	621156389.0	265.3
...	...	...	...	...	...	
5234	509306	The Box	Music	25000000.0	34356760.0	37.4
5235	546674	Enough	Comedy	38000000.0	50970660.0	34.1
5236	546674	Enough	Animation	38000000.0	50970660.0	34.1
5237	513161	Undiscovered	NaN	9000000.0	1069318.0	-88.1
5238	514492	Jaws	Animation	12000000.0	470700000.0	3822.5

5239 rows × 6 columns

In [41]:
```
df_question1['title'].nunique()
```

Out[41]: 1924

In [42]:
```
df_question1.groupby('genre_name').count().sort_values('id', ascending=False)
```

Out[42]:

	id	title	production_budget	worldwide_gross	ROI_%
genre_name					
Drama	992	992	992	992	992
Comedy	622	622	622	622	622
Thriller	599	599	599	599	599
Action	517	517	517	517	517
Adventure	334	334	334	334	334

Horror	303	303	303	303	303
Crime	269	269	269	269	269
Romance	261	261	261	261	261
Science Fiction	251	251	251	251	251
Family	209	209	209	209	209
Fantasy	208	208	208	208	208
Mystery	164	164	164	164	164
Animation	136	136	136	136	136
Documentary	88	88	88	88	88
History	77	77	77	77	77
Music	56	56	56	56	56
War	53	53	53	53	53
Western	26	26	26	26	26
TV Movie	10	10	10	10	10

We are going to disregard all the genres that have less than 100 records to try to get solid conclusions

In [43]:

```
# df_question1 = df_question1[~df_question1['genre_name'].isin(['Documentary',
```

In [44]:

```
# df_question1_results = df_question1.groupby('genre_name').mean()[['ROI_%']].
# df_question1_results
```

In [45]:

```
# plt.figure(figsize=(18, 8))  # Set the figure size

# bar_plot = sns.barplot(
#     x='genre_name',  # Set genre_name on the y-axis
#     y='ROI_%',       # Set ROI_% on the x-axis
#     data=df_question1_results,
#     palette='muted',  # Color palette
#     ci=None           # Disable confidence interval
# )

# # Set title and labels for axes
# plt.title('ROI by Genre')
# plt.ylabel('Return on Investment (%)')
# plt.xlabel('Genre')

# # Show the plot
# plt.show()
```

As we can see there is an evident high ROI with the Horror movies.

Let's consider looking at the df_im_movie_basics dataset to see if we can get a larger quantity of movies and thus get more reliable results

In [46]:
```
df_tn.rename({'title':'primary_title'},inplace=True,axis=1)
```

In [47]:
```
df_im_movie_basics
```

Out[47]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biog
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Co
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,D
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	[
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	[

146144 rows × 6 columns

Let's drop potential duplicates of df_im_movie_basics

In [48]:
```
df_im_movie_basics.drop_duplicates(subset=['primary_title'], inplace=True)
```

In [49]:

```
df_im_movie_basics['genres'] = df_im_movie_basics['genres'].str.split(',')
```

In [50]:

```
df_im_movie_basics = df_im_movie_basics.explode('genres')
df_im_movie_basics
```

Out[50]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	gen
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Act
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Cri
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Dra
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biograp
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Dra
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Dra
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Document
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Come
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	Nc
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Document

218557 rows × 6 columns

In [51]:

```
df_question1 = df_im_movie_basics.merge(df_tn, on='primary_title', how='inner'
df_question1
```

Out[51]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0249516	Foodfight!	Foodfight!	2012	91.0	Actior
1	tt0249516	Foodfight!	Foodfight!	2012	91.0	Animatior
2	tt0249516	Foodfight!	Foodfight!	2012	91.0	Comedy
3	tt0293429	Mortal Kombat	Mortal Kombat	2021	NaN	Actior

4	tt0293429	Mortal Kombat	Mortal Kombat	2021	NaN	Adventure
...	...	...	...	...	...	..
5450	tt9805168	Traitor	Traitor	2015	110.0	Action
5451	tt9805168	Traitor	Traitor	2015	110.0	Drama
5452	tt9805168	Traitor	Traitor	2015	110.0	Romance
5453	tt9844102	Ray	Ray	2018	111.0	Crime
5454	tt9893078	Sublime	Sublime	2019	NaN	Documentary

5455 rows × 9 columns

Given that we have more movies in the merging of df_tn with df_im_movie_basics than in the merging of df_tn with df_tmdb (by 2000 approximately), we will consider the df_im_movie_basics dataset

In [52]:

```
df_question1['original_title'].nunique()
```

Out[52]: 2309

In [53]:

```
df_question1.groupby('genres').count().sort_values('movie_id', ascending=False
```

Out[53]:

genres	movie_id	primary_title	original_title	start_year	runtime_minutes	proc
Drama	1147	1147	1147	1147	1081	
Comedy	665	665	665	665	643	
Action	560	560	560	560	529	
Adventure	426	426	426	426	410	
Thriller	392	392	392	392	373	
Crime	311	311	311	311	300	
Horror	288	288	288	288	275	
Romance	267	267	267	267	256	
Documentary	189	189	189	189	178	
Biography	179	179	179	179	178	
Sci-Fi	176	176	176	176	172	
Mystery	174	174	174	174	167	
Fantasy	154	154	154	154	149	

Fantasy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Family	135	135	135	135	128
Animation	122	122	122	122	116
Music	66	66	66	66	63
History	63	63	63	63	63
Sport	50	50	50	50	46
War	31	31	31	31	29
Musical	18	18	18	18	14
Western	16	16	16	16	14
News	1	1	1	1	1

We are going to disregard all the genres that have less than 150 records to try to get solid conclusions

In [54]:

```
df_question1 = df_question1[~df_question1['genres'].isin(['Family','Animation'
```

In [55]:

```
df_question1_results = df_question1.groupby('genres').mean()[['ROI_%']].sort_v
df_question1_results
```

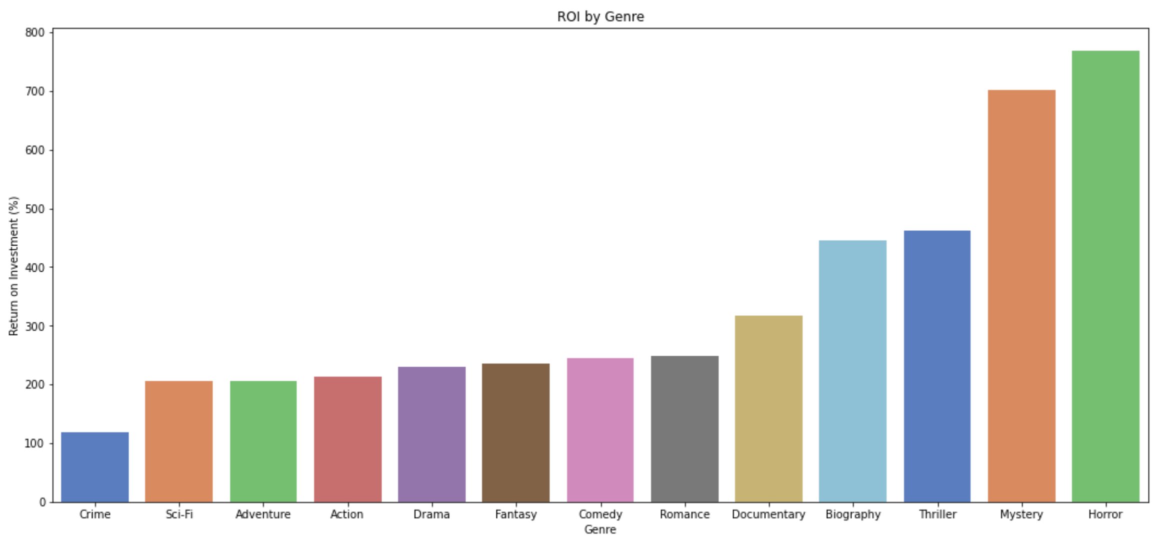
Out[55]:

	genres	ROI_%
0	Crime	119.298971
1	Sci-Fi	205.257557
2	Adventure	205.808357
3	Action	212.421946
4	Drama	229.395798
5	Fantasy	236.153506
6	Comedy	245.242827
7	Romance	248.701199
8	Documentary	317.799894
9	Biography	445.263352
10	Thriller	462.887526
11	Mystery	702.271897
12	Horror	769.228264

In [56]:

```
plt.figure(figsize=(18, 8))  # Set the figure size
```

```
plt.figure(figsize=(15, 8))  # Set the figure size

bar_plot = sns.barplot(
    x='genres',  # Set genre_name on the y-axis
    y='ROI_%',      # Set ROI_% on the x-axis
    data=df_question1_results,
    palette='muted',  # Color palette
    ci=None           # Disable confidence interval
)

# Set title and labels for axes
plt.title('ROI by Genre')
plt.ylabel('Return on Investment (%)')
plt.xlabel('Genre')

# Show the plot
plt.show()
```



As we can see there is an evident high ROI with the Horror and Mystery because they have more than 700% in ROI.

3.5.8 Second Question: Study the relationship of run-time with ROI and Production Cost

Let's look at IM dataset

We look at the table movie_basics of the im dataset as it contains information about the run-times

In [57]:

```
route_db = r"C:\\Users\\Usuario\\Desktop\\FlatIron\\DataScience_FlatIron_Curso

conn = sqlite3.connect(route_db)
df_im_movie_basics = pd.read_sql_query("SELECT * FROM MOVIE_BASICS", conn)

df_im_movie_basics
```

Out[57]:

movie_id	primary_title	original_title	start_year	runtime_minutes

0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biog
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Co
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,D
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	[
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	[

146144 rows × 6 columns

Let's start by droping columns that we're not going to need.

In [58]:

```
drop_list = ['genres','start_year','original_title']
df_im_movie_basics_updated = df_im_movie_basics.drop(drop_list, axis=1)
df_im_movie_basics_updated
```

Out[58]:

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

...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	123.0
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	NaN
146141	tt9916706	Dankyavar Danka	NaN
146142	tt9916730	6 Gunn	116.0
146143	tt9916754	Chico Albuquerque - Revelações	NaN

146144 rows × 3 columns

Let's drop duplicated movies

In [59]:
```
df_im_movie_basics_updated.drop_duplicates(['primary_title'], inplace=True)
```

Let's look at the NaN values of the column runtime_minutes

In [60]:
```
(df_im_movie_basics_updated['runtime_minutes'].isna().sum()/len(df_im_movie_ba
```

Out[60]:
```
21.660015727083653
```

We decide to drop the NaN rows

In [61]:
```
df_im_movie_basics_updated = df_im_movie_basics_updated[df_im_movie_basics_upd
df_im_movie_basics_updated
```

Out[61]:

	movie_id	primary_title	runtime_minutes
0	tt0063540	Sunghursh	175.0
1	tt0066787	One Day Before the Rainy Season	114.0
2	tt0069049	The Other Side of the Wind	122.0
4	tt0100275	The Wandering Soap Opera	80.0
5	tt0111414	A Thin Life	75.0
...	...	...	...
146133	tt9916132	The Mystery of a Buryat Lama	94.0
146136	tt9916186	Illenau - die Geschichte einer ehemaligen Heil...	84.0
146137	tt9916190	Safeguard	90.0
146139	tt9916538	Kuambil Lagi Hatiku	123.0
146142	tt9916730	6 Gunn	116.0

106598 rows × 3 columns

In [62]:
```
bins = [0,90,120,float('inf')]
df_im_movie_basics_updated['runtime_minutes'] = pd.cut(df_im_movie_basics_upda
df_im_movie_basics_updated
```

```
<ipython-input-62-d846936a5a81>: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/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_im_movie_basics_updated['runtime_minutes'] = pd.cut(df_im_movie_basics_upd
ated['runtime_minutes'],labels=['short','medium','long'],bins=bins,right=False)
```

Out[62]:

	movie_id	primary_title	runtime_minutes
0	tt0063540	Sunghursh	long
1	tt0066787	One Day Before the Rainy Season	medium
2	tt0069049	The Other Side of the Wind	long
4	tt0100275	The Wandering Soap Opera	short
5	tt0111414	A Thin Life	short
...	...	...	...
146133	tt9916132	The Mystery of a Buryat Lama	medium
146136	tt9916186	Illenau - die Geschichte einer ehemaligen Heil...	short
146137	tt9916190	Safeguard	medium
146139	tt9916538	Kuambil Lagi Hatiku	long
146142	tt9916730	6 Gunn	medium

106598 rows × 3 columns

We are going to do the merge of df_im_movie_basics_updated with df_tn.

In [63]:
```
df_tn
```

Out[63]:

	primary_title	production_budget	worldwide_gross	ROI_%
0	Avatar	425000000.0	2.776345e+09	553.26
1	Pirates of the Caribbean: On Stranger Tides	410600000.0	1.045664e+09	154.67
2	Dark Phoenix	350000000.0	1.497624e+08	-57.21
3	Avengers: Age of Ultron	330600000.0	1.403014e+09	324.38
4	Star Wars Ep. VIII: The Last Jedi	317000000.0	1.316722e+09	315.37
...	...	...	...	...

5777	Red 11	7000.0	0.000000e+00	-100.00
5778	Following	6000.0	2.404950e+05	3908.25
5779	Return to the Land of Wonders	5000.0	1.338000e+03	-73.24
5780	A Plague So Pleasant	1400.0	0.000000e+00	-100.00
5781	My Date With Drew	1100.0	1.810410e+05	16358.27

5782 rows × 4 columns

In [64]:

```
df_question2 = df_im_movie_basics_updated.merge(df_tn, on='primary_title', how
df_question2
```

Out[64]:

	movie_id	primary_title	runtime_minutes	production_budget	worldwide_gross
0	tt0249516	Foodfight!	medium	45000000.0	73706.0
1	tt0326592	The Overnight	short	200000.0	1165996.0
2	tt0337692	On the Road	long	25000000.0	9313302.0
3	tt0359950	The Secret Life of Walter Mitty	medium	91000000.0	187861183.0
4	tt0365907	A Walk Among the Tombstones	medium	28000000.0	62108587.0
...	...	...	...	...	...
2191	tt9275702	Salvador	short	4500000.0	1500000.0
2192	tt9313936	Stay Alive	short	20000000.0	23187506.0
2193	tt9607270	The Blue Bird	short	1200000.0	887000.0
2194	tt9805168	Traitor	medium	22000000.0	27882226.0
2195	tt9844102	Ray	medium	40000000.0	124823094.0

2196 rows × 6 columns

Let's do a count by groupby in runtime_minutes to see what the distribution is of each runtime_minutes group

In [65]:

```
df_question2.groupby('runtime_minutes').count()
```

Out[65]:

	movie_id	primary_title	production_budget	worldwide_gross	ROI_%
runtime_minutes					

short	477	477	477	477	477
medium	1334	1334	1334	1334	1334
long	385	385	385	385	385

Now, we will calculate the mean of production_budget and ROI_% for each movie

In [66]:

```
df_question2_result = df_question2.groupby('runtime_minutes').agg({'productior
df_question2_result
```

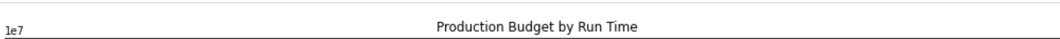
Out[66]:

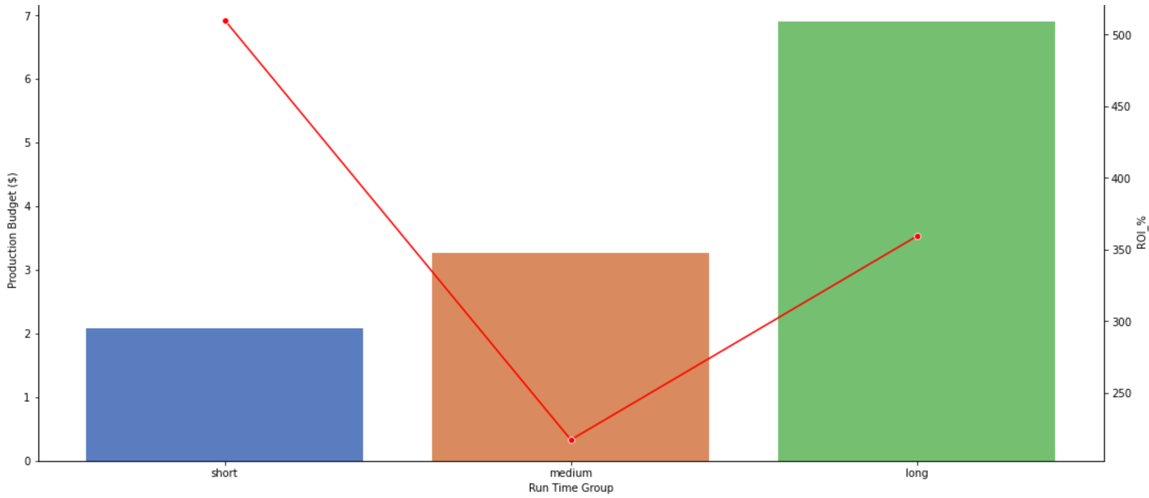
	runtime_minutes	production_budget	ROI_%
0	short	2.078161e+07	510.192013
1	medium	3.272034e+07	217.293778
2	long	6.910003e+07	359.420987

We will now do a representation of each metric

In [67]:

```
plt.figure(figsize=(18, 8))  # Set the figure size

bar_plot = sns.barplot(
    x='runtime_minutes',
    y='production_budget',
    data=df_question2_result,
    palette='muted',  # Color palette
    ci=None           # Disable confidence interval
)

# Set title and labels for axes
plt.title('Production Budget by Run Time')
plt.ylabel('Production Budget ($)')
plt.xlabel('Run Time Group')

ax2 = plt.twinx()

# Let's create a second plot with a line graph that shows the ROI_%
line_plot = sns.lineplot(
    x='runtime_minutes',
    y='ROI_%',
    data=df_question2_result,
    color='red',  # Line color
    marker='o',   # Marker style
    sort=False,   # Avoids sorting to keep the order of the x-axis
    ax=ax2        # Plot against the secondary y-axis
)


# Show the plot
plt.show()
```





With the graph above, we've reached the conclusion that the short films (ie those that have a run_time less than 90 minutes) are very interesting to invest on as they have the highest ROI_% and the shortest production budgets

3.5.9 Third Question: Study the relationship of director with ROI and Production Cost

To be able to answer the third question we're going to need the following tables of IM: movie_ratings, movie_basics, directors, and persons

In [68]:

```
query = """

SELECT p.person_id, p.primary_name, d.movie_id, mb.primary_title, mr.averagera
FROM MOVIE_RATINGS AS mr
INNER JOIN MOVIE_BASICS AS mb
USING (movie_id)
INNER JOIN DIRECTORS AS d
USING (movie_id)
INNER JOIN PERSONS AS p
USING (person_id)


"""
route_db = r"C:\\Users\\Usuario\\Desktop\\FlatIron\\DataScience_FlatIron_Curso

conn = sqlite3.connect(route_db)
df_im = pd.read_sql_query(query, conn)

df_im
```

Out[68]:

	person_id	primary_name	movie_id	primary_title	averagerating	numvot
0	nm8353804	Sukh Sanghera	tt10356526	Laiye Je Yaarian	8.3	
1	nm8353804	Sukh Sanghera	tt10356526	Laiye Je Yaarian	8.3	

2	nm9250842	Caolan Robertson	tt10384606	Borderless	8.9	5
3	nm9932562	George Llewelyn-John	tt10384606	Borderless	8.9	5
4	nm1915232	Marcel Grant	tt1042974	Just Inès	6.4	
...	...	...	...	...	...	
181382	nm0849465	Gorô Taniguchi	tt9844256	Code Geass: Lelouch of the Rebellion - Glorifi...	7.5	
181383	nm0849465	Gorô Taniguchi	tt9844256	Code Geass: Lelouch of the Rebellion - Glorifi...	7.5	
181384	nm1272773	Prachya Pinkaew	tt9851050	Sisters	4.7	
181385	nm0001206	Abel Ferrara	tt9886934	The Projectionist	7.0	
181386	nm10529107	Naveen Nanjundan	tt9894098	Sathru	6.3	1

181387 rows × 6 columns

Let's start by looking at potential duplicates

In [69]:

```
df_im.duplicated().sum()
```

Out[69]: 95357

We proceed to drop them

In [70]:

```
df_im.drop_duplicates(inplace=True)
df_im
```

Out[70]:

	person_id	primary_name	movie_id	primary_title	averagerating	numvot
0	nm8353804	Sukh Sanghera	tt10356526	Laiye Je Yaarian	8.3	
2	nm9250842	Caolan Robertson	tt10384606	Borderless	8.9	5
3	nm9932562	George Llewelyn-John	tt10384606	Borderless	8.9	5
4	nm1915232	Marcel Grant	tt1042974	Just Inès	6.4	
				The Legend		

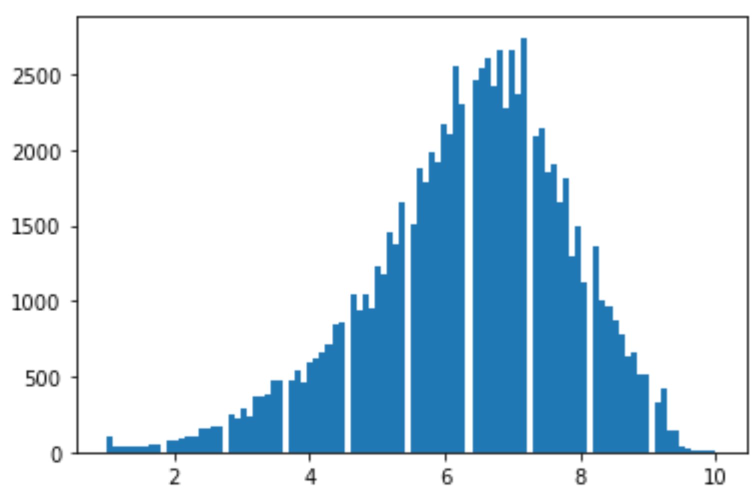
5	nm0001317	Renny Harlin	tt1043726	The Legend of Hercules	4.2	503
...	...	...	...	...	...	
181381	nm3828616	Alexandru Mavrodineanu	tt9805820	Caisa	8.1	
181382	nm0849465	Gorô Taniguchi	tt9844256	Code Geass: Lelouch of the Rebellion - Glorifi...	7.5	
181384	nm1272773	Prachya Pinkaew	tt9851050	Sisters	4.7	
181385	nm0001206	Abel Ferrara	tt9886934	The Projectionist	7.0	
181386	nm10529107	Naveen Nanjundan	tt9894098	Sathru	6.3	1

86030 rows × 6 columns

We would like to see the distribution of averagerating

In [71]:

```
plt.hist(df_im['averagerating'], bins=100);
```



We will now look at the distribution of numvotes

In [72]:

```
df_im.describe()
```

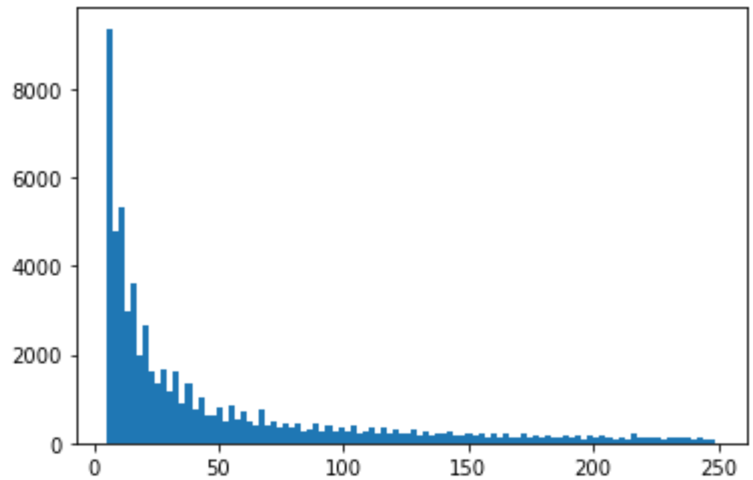
Out[72]:

	averagerating	numvotes
count	86030.000000	8.603000e+04
mean	6.340112	3.370315e+03
std	1.475066	2.945046e+04

min	1.000000	5.000000e+00
25%	5.500000	1.400000e+01
50%	6.500000	4.700000e+01
75%	7.400000	2.640000e+02
max	10.000000	1.841066e+06

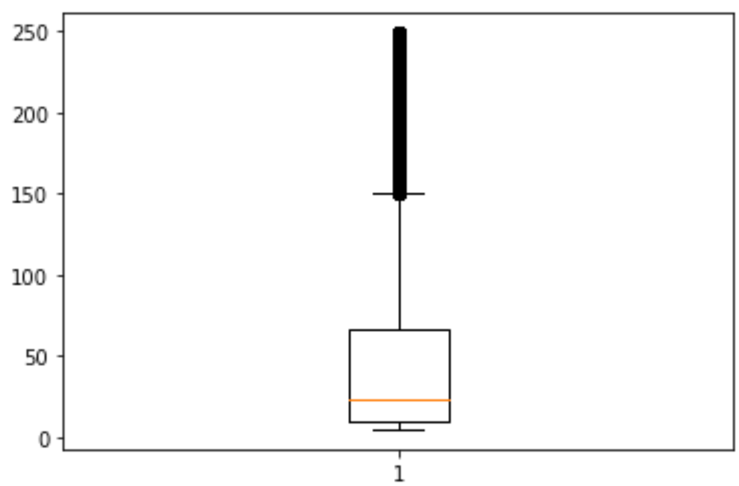
In [73]:

```
plt.hist(df_im[df_im['numvotes']<250]['numvotes'], bins=100);
```



In [74]:

```
plt.boxplot(df_im[df_im['numvotes']<250]['numvotes']);
```



We will carry on by on by eliminating outliers. For that we've decided to disregard anything under the 10% percentile and over the 90% percentile

In [75]:

```
max_value = np.percentile(df_im['numvotes'], 90)
max_value
```

Out[75]: 1494.0

In [76]:
```
min_value = np.percentile(df_im['numvotes'], 10)
min_value
```

Out[76]: 7.0

In [77]:
```
df_im = df_im[df_im['numvotes'].between(min_value, max_value)]
df_im
```

Out[77]:

	person_id	primary_name	movie_id	primary_title	averagerating	numvot
0	nm8353804	Sukh Sanghera	tt10356526	Laiye Je Yaarian	8.3	
2	nm9250842	Caolan Robertson	tt10384606	Borderless	8.9	5
3	nm9932562	George Llewelyn-John	tt10384606	Borderless	8.9	5
4	nm1915232	Marcel Grant	tt1042974	Just Inès	6.4	
9	nm1926349	Carlos M. Barros	tt1060240	Até Onde?	6.5	
...	...	...	...	...	...	
181380	nm8393857	Alwa Ritsila	tt9783738	Bangkok Dark Tales	7.4	
181381	nm3828616	Alexandru Mavrodineanu	tt9805820	Caisa	8.1	
181382	nm0849465	Gorô Taniguchi	tt9844256	Code Geass: Lelouch of the Rebellion - Glorifi...	7.5	
181384	nm1272773	Prachya Pinkaew	tt9851050	Sisters	4.7	
181386	nm10529107	Naveen Nanjundan	tt9894098	Sathru	6.3	1

70988 rows × 6 columns

Let's look again at the distribution of numvotes

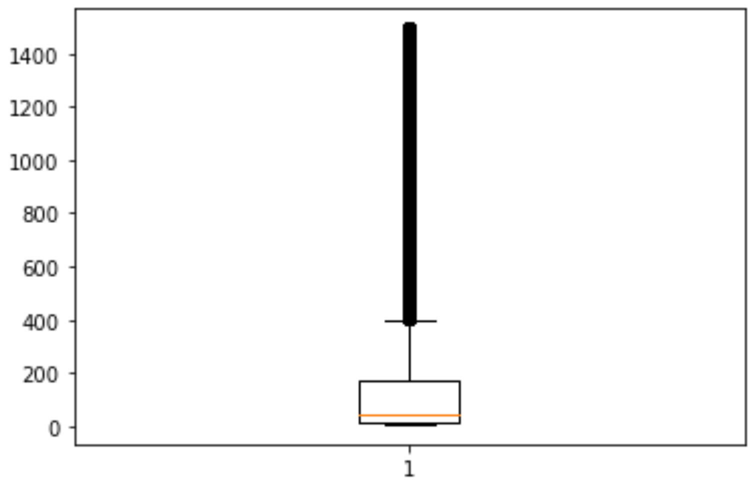
In [78]:
```
df_im.describe()
```

Out[78]:

	averagerating	numvotes
count	70988.000000	70988.000000
mean	6.295291	162.141630

std	1.497798	269.656327
min	1.000000	7.000000
25%	5.400000	16.000000
50%	6.500000	44.000000
75%	7.300000	170.000000
max	10.000000	1494.000000

In [79]:
```
plt.boxplot(df_im['numvotes']);
```



As can be seen there is still a considerable number of outliers. However, we disregard eliminating again registrations as we would consider it necessary to have a large number of registrations

Now let's check if there are NaN of the column averagerating and numvotes

In [80]:
```
df_im['averagerating'].isna().any()
```

Out[80]: False

In [81]:
```
df_im['numvotes'].isna().any()
```

Out[81]: False

We will now proceed to group by director and carry on the analysis

In [82]:
```
df_im
```

Out[82]:

	person_id	primary_name	movie_id	primary_title	averagerating	numvot
0	nm8353804	Sukh Sanghera	tt10356526	Laiye Je Yaarian	8.3	

2	nm9250842	Caolan Robertson	tt10384606	Borderless	8.9	5
3	nm9932562	George Llewelyn-John	tt10384606	Borderless	8.9	5
4	nm1915232	Marcel Grant	tt1042974	Just Inès	6.4	
9	nm1926349	Carlos M. Barros	tt1060240	Até Onde?	6.5	
...	...	...	...	...	...	
181380	nm8393857	Alwa Ritsila	tt9783738	Bangkok Dark Tales	7.4	
181381	nm3828616	Alexandru Mavrodineanu	tt9805820	Caisa	8.1	
181382	nm0849465	Gorô Taniguchi	tt9844256	Code Geass: Lelouch of the Rebellion - Glorifi...	7.5	
181384	nm1272773	Prachya Pinkaew	tt9851050	Sisters	4.7	
181386	nm10529107	Naveen Nanjundan	tt9894098	Sathru	6.3	1

70988 rows × 6 columns

In [83]:

```
df_im.groupby('primary_name').count().sort_values('numvotes', ascending=False)
```

Out[83]:

primary_name	person_id	movie_id	primary_title	averagerating	numvotes
Sergey A.	39	39	39	39	39
Nayato Fio Nuala	34	34	34	34	34
Larry Rosen	34	34	34	34	34
Dustin Ferguson	30	30	30	30	30
Paul T.T. Easter	28	28	28	28	28
...	...	...	...	...	...
Ivan Hurzeler	1	1	1	1	1
Ivan Kavanagh	1	1	1	1	1
Ivan Kitaev	1	1	1	1	1
Ivan Kraljevic	1	1	1	1	1

Þórdur Bragi Jónsson	1	1	1	1	1

49277 rows × 5 columns

In [84]:

```
counts = df_im.groupby('primary_name')['person_id'].count()
```

We will only consider directors who have done at least 4 movies

In [85]:

```
filtered_names = counts[counts>=4].index
```

In [86]:

```
df_im = df_im[df_im['primary_name'].isin(filtered_names)]
df_im
```

Out[86]:

	person_id	primary_name	movie_id	primary_title	averagerating	numvotes
85	nm2310557	Andrey Iskanov	tt1323962	Andrey Iskanov's Ingression	5.1	101
143	nm0135724	Antonio Capuano	tt1438493	Dark Love	6.3	86
144	nm1564826	David Verbeek	tt1443518	R U There	5.5	297
148	nm1494245	Omar Shargawi	tt1450750	My Father from Haifa	8.6	27
190	nm0084819	Claus Bjerre	tt1512893	Father of Four - In Japanese Mode	3.4	212
...	...	...	...	...	...	...
181351	nm3406099	Donatas Ulvydas	tt9575726	Ir visi ju vyrai	7.7	161
181353	nm2418217	Gilles Perret	tt9576110	J'veux du soleil	6.8	65
181359	nm2209378	Lu Zhang	tt9619016	Fukuoka	7.0	27
181371	nm4070848	Meng Zhang	tt9690762	On the Balcony	5.6	37
181382	nm0849465	Gorô Taniguchi	tt9844256	Code Geass: Lelouch of the Rebellion - Glorifi...	7.5	24

11392 rows × 6 columns

Now we're going to look at the averagerating of each director

In [87]:
```
df_averagerating_director = df_im.groupby('primary_name').agg({'averagerating'
df_averagerating_director
```

Out[87]:

primary_name	averagerating
Nuo Wang	9.100000
Yasmine Asha	8.940000
Steve Ravic	8.883333
Zheng Zhou	8.825000
Ian Cranston	8.800000
...	...
Eldar Bogunov	1.342857
Chihiro Ikeda	1.285714
Keiko Tsuruoka	1.216667
Andrey Gromov	1.114286
Satoru Hirohara	1.080000

2019 rows × 1 columns

Now we have to merge df_im with df_tn so as to be able to see per director their average rating, their average production_budget, ROI_%

In [88]:
```
df_tn
```

Out[88]:

	primary_title	production_budget	worldwide_gross	ROI_%
0	Avatar	425000000.0	2.776345e+09	553.26
1	Pirates of the Caribbean: On Stranger Tides	410600000.0	1.045664e+09	154.67
2	Dark Phoenix	350000000.0	1.497624e+08	-57.21
3	Avengers: Age of Ultron	330600000.0	1.403014e+09	324.38
4	Star Wars Ep. VIII: The Last Jedi	317000000.0	1.316722e+09	315.37
...	...	...	...	...
5777	Red 11	7000.0	0.000000e+00	-100.00
5778	Following	6000.0	2.404950e+05	3908.25

5779	Return to the Land of Wonders	5000.0	1.338000e+03	-73.24
5780	A Plague So Pleasant	1400.0	0.000000e+00	-100.00
5781	My Date With Drew	1100.0	1.810410e+05	16358.27

5782 rows × 4 columns

In [89]:

```python
df_question3 = df_im.merge(df_tn, on='primary_title', how='inner')
df_question3
```

Out[89]:

	person_id	primary_name	movie_id	primary_title	averagerating	numvotes
0	nm3620652	Aly Muritiba	tt7467324	Rust	6.6	377
1	nm0000929	Corbin Bernsen	tt1360826	Rust	5.6	404
2	nm0300880	Daniele Gaglianone	tt1833781	Rust	6.1	412
3	nm5619726	Joe Lujan	tt3490320	Rust	6.1	22
4	nm4110102	Raja Chanda	tt10300662	Kidnap	7.5	26
...	...	...	...	...	...	...
199	nm0139337	Fred Carpenter	tt1653203	Jesse	4.9	96
200	nm3147876	Sang-woo Lee	tt4036590	Speed	5.9	9
201	nm1757671	Robert Conway	tt5607782	The Covenant	5.2	1359
202	nm0104487	Larry Brand	tt2387589	The Girl on the Train	4.4	819
203	nm3231736	Marcel Walz	tt2554700	Plastic	2.5	54

204 rows × 9 columns

Let's check for NaN values

In [90]:

```python
df_question3.isnull().any()
```

Out[90]:

```
person_id          False
primary_name       False
movie_id           False
primary_title      False
averagerating      False
numvotes           False
production_budget  False
worldwide_gross    False
ROI_%              False
dtype: bool
```

Now let's group by director and see their averagerating, average production_budget and average ROI_%

In [91]:

```
df_question3_result = df_question3.groupby('primary_name').agg({'averagerating
df_question3_result
```

Out[91]:

primary_name	averagerating	production_budget	ROI_%
Daniel Beard	8.8	90000000.0	-88.28
Tim Van Someren	8.7	10000000.0	-78.20
Aashiq Abu	8.6	75000000.0	-59.16
Brett Sullivan	8.5	5000000.0	2085.07
Larry Rosen	8.3	23000000.0	-18.90
...	...	...	...
Mark Steven Grove	2.8	20000000.0	79.21
Rob Hawk	2.7	20000000.0	-100.00
Steven M. Smith	2.6	1000000.0	1698.50
Michael Crum	2.4	4357373.0	-72.46
Justin Price	2.1	18000000.0	-100.00

181 rows × 3 columns

Let's filter out the directors that have a negative ROI_%

In [92]:

```
df_question3_result = df_question3_result[df_question3_result['ROI_%']>0]
df_question3_result
```

Out[92]:

primary_name	averagerating	production_budget	ROI_%
Brett Sullivan	8.5	5000000.0	2085.070
Jeremy Herrin	8.1	14000000.0	41.630
Robert Delamere	8.1	32100000.0	230.540
Hanung Bramantyo	8.0	7500000.0	712.625
Nawapol Thamrongrattanarit	8.0	37500000.0	35.060
...	...	...	...
Daniel Armstrong	3.5	400000.0	190.500

Vince D'Amato	3.4	20000000.0	1126.520
Maurice Smith	3.0	35000000.0	147.570
Mark Steven Grove	2.8	20000000.0	79.210
Steven M. Smith	2.6	1000000.0	1698.500

89 rows × 3 columns

In [93]:

```
fig, ax1 = plt.subplots(figsize=(22, 10))

# Plot the 'production_budget' as a bar plot
ax1.bar(df_question3_result.index, df_question3_result['production_budget'], l

# Create the secondary axis for the 'ROI_%'
ax2 = ax1.twinx()

# Plot the 'ROI_%' as a line plot
ax2.plot(df_question3_result.index, df_question3_result['ROI_%'], label='ROI %

# Plot the 'averagerating' as another line plot
ax3 = ax1.twinx()
# Offset the second y-axis to the right
ax3.spines['right'].set_position(('outward', 60))
ax3.plot(df_question3_result.index, df_question3_result['averagerating'], labe

# Set the labels and titles
ax1.set_xlabel('Director')
ax1.set_ylabel('Production Budget ($)', color='blue')
ax2.set_ylabel('ROI %', color='red')
ax3.set_ylabel('Average Rating', color='green')

# Set the x-axis category labels (if necessary)
ax1.set_xticklabels(df_question3_result.index, rotation=90)

# Add legends
ax1.legend(loc='upper left')
ax2.legend(loc='upper right')
ax3.legend(loc='center right')

# Show the plot
plt.title('Production Budget, ROI%, and Average Rating for Each Director')
plt.tight_layout()  # Adjust the layout to make room for the x-axis labels
plt.show()
```

```
<ipython-input-93-326b5474f18b>:25: UserWarning: FixedFormatter should only be
used together with FixedLocator
  ax1.set_xticklabels(df_question3_result.index, rotation=90)
```