Final Project Submission

Please fill out:

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- Scheduled project review date/time:
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- Blog post URL:

Business Problem

My company now sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don’t know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable insights that the head of your company's new movie studio can use to help decide what type of films to create.

The Data

In the folder zippedData are movie datasets from:

Box Office Mojo.

IMDB.

Rotten Tomatoes.

TheMovieDB.

The Numbers.

Steps to be followed

1. Load the data from the zipped datasets

2. Clean and merge datasets on title and year, handling inconsistencies.

3. Perform EDA on the datasets

4. Create atleast four visualizations to highlight key trends in the industry.

5. conclude by providing business recommendations to the studio

STEP 1. Import libraries and load the data in datasets

import relevant libraries

In [1]:
```
import itertools
import numpy as np
import pandas as pd
from sqlalchemy import create_engine
from numbers import Number
import sqlite3
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
from fuzzywuzzy import process
import multiprocessing
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline

import pickle
```

Loading and cleaning the box office mojo csv

In [2]:
```
# opening the box office mojo csv file
box_office = pd.read_csv('zippedData/bom.movie_gross.csv.gz')
box_office
```

Out[2]:

	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

Create a new column for the total box office gross

Total gross = domestic gross + foreign gross

In [3]:
```
box_office['foreign_gross'] = pd.to_numeric(box_office['foreign_gross'], errors = 'c
box_office['year'] = box_office['year'].astype(str)
datatypes = box_office.dtypes
datatypes
```

Out[3]:
```
title              object
studio             object
domestic_gross    float64
```

```
foreign_gross     float64
year               object
dtype: object
```

In [4]:
```
box_office['domestic_gross'] = box_office['domestic_gross'].fillna(0)
box_office['foreign_gross'] = box_office['foreign_gross'].fillna(0)
box_office = box_office.dropna(subset=['title', 'year'])
box_office
```

Out[4]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000.0	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010
3	Inception	WB	292600000.0	535700000.0	2010
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	0.0	2018
3383	Edward II (2018 re-release)	FM	4800.0	0.0	2018
3384	El Pacto	Sony	2500.0	0.0	2018
3385	The Swan	Synergetic	2400.0	0.0	2018
3386	An Actor Prepares	Grav.	1700.0	0.0	2018

3387 rows × 5 columns

In [5]:
```
box_office['total_gross'] = box_office['domestic_gross'] + box_office['foreign_gross
box_office['title'] = box_office['title'].str.lower().str.strip()
box_office
```

Out[5]:

	title	studio	domestic_gross	foreign_gross	year	total_gross
0	toy story 3	BV	415000000.0	652000000.0	2010	1.067000e+09
1	alice in wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09
2	harry potter and the deathly hallows part 1	WB	296000000.0	664300000.0	2010	9.603000e+08
3	inception	WB	292600000.0	535700000.0	2010	8.283000e+08
4	shrek forever after	P/DW	238700000.0	513900000.0	2010	7.526000e+08
...	...	...	...	...	...	...
3382	the quake	Magn.	6200.0	0.0	2018	6.200000e+03
3383	edward ii (2018 re-release)	FM	4800.0	0.0	2018	4.800000e+03
3384	el pacto	Sony	2500.0	0.0	2018	2.500000e+03
3385	the swan	Synergetic	2400.0	0.0	2018	2.400000e+03
3386	an actor prepares	Grav.	1700.0	0.0	2018	1.700000e+03

3387 rows × 6 columns

loading the imdb data

load the unzipped imdb data

In [6]:
```
conn = sqlite3.connect('zippedData/im.db/im.db')
```

In [7]:
```
df = pd.read_sql(
    """
    SELECT *
    FROM sqlite_master
    """
, conn
)

df[df['type'] == 'table']
```

Out[7]:

	type	name	tbl_name	rootpage	sql
0	table	movie_basics	movie_basics	2	CREATE TABLE "movie_basics" (\n"movie_id" TEXT...
1	table	directors	directors	3	CREATE TABLE "directors" (\n"movie_id" TEXT,\n...
2	table	known_for	known_for	4	CREATE TABLE "known_for" (\n"person_id" TEXT,\...
3	table	movie_akas	movie_akas	5	CREATE TABLE "movie_akas" (\n"movie_id" TEXT,\...
4	table	movie_ratings	movie_ratings	6	CREATE TABLE "movie_ratings" (\n"movie_id" TEX...
5	table	persons	persons	7	CREATE TABLE "persons" (\n"person_id" TEXT,\n ...
6	table	principals	principals	8	CREATE TABLE "principals" (\n"movie_id" TEXT,\...
7	table	writers	writers	9	CREATE TABLE "writers" (\n"movie_id" TEXT,\n ...

In [8]:
```
query = """
SELECT mb.primary_title, mb.start_year, mb.runtime_minutes, mb.genres, mr.averagerat
FROM movie_basics AS mb
LEFT JOIN movie_ratings mr ON mb.movie_id = mr.movie_id
WHERE mb.start_year BETWEEN 2010 AND 2019
AND mb.genres IS NOT NULL;
"""


imdb_data = pd.read_sql_query(query, conn)
imdb_data
```

Out[8]:

	primary_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77.0
1	One Day Before the Rainy Season	2019	114.0	Biography,Drama	7.2	43.0
2	The Other Side of the Wind	2018	122.0	Drama	6.9	4517.0
3	Sabse Bada Sukh	2018	NaN	Comedy,Drama	6.1	13.0
4	The Wandering Soap Opera	2017	80.0	Comedy,Drama,Fantasy	6.5	119.0

	primary_title	start_year	runtime_minutes	genres	averagerating	numvotes
...	...	...	...	...	...	...
139717	The Secret of China	2019	NaN	Adventure,History,War	NaN	NaN
139718	Kuambil Lagi Hatiku	2019	123.0	Drama	NaN	NaN
139719	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary	NaN	NaN
139720	Dankyavar Danka	2013	NaN	Comedy	NaN	NaN
139721	Chico Albuquerque - Revelações	2013	NaN	Documentary	NaN	NaN

139722 rows × 6 columns

In [9]:

```
imdb_data = imdb_data.dropna(subset=['primary_title', 'start_year'])
imdb_data['primary_title'] = imdb_data['primary_title'].str.lower().str.strip()
imdb_data['runtime_minutes'] = imdb_data['runtime_minutes'].fillna(imdb_data['runtim
imdb_data['averagerating'] = imdb_data['averagerating'].fillna(imdb_data['averagerat
imdb_data['numvotes'] = imdb_data['numvotes'].fillna(0)
imdb_data['genres'] = imdb_data['genres'].str.split(',')
imdb_data['start_year'] = imdb_data['start_year'].astype(str)

imdb_data
```

Out[9]:

	primary_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	sunghursh	2013	175.0	[Action, Crime, Drama]	7.0	77.0
1	one day before the rainy season	2019	114.0	[Biography, Drama]	7.2	43.0
2	the other side of the wind	2018	122.0	[Drama]	6.9	4517.0
3	sabse bada sukh	2018	87.0	[Comedy, Drama]	6.1	13.0
4	the wandering soap opera	2017	80.0	[Comedy, Drama, Fantasy]	6.5	119.0
...	...	...	...	...	...	...
139717	the secret of china	2019	87.0	[Adventure, History, War]	6.5	0.0
139718	kuambil lagi hatiku	2019	123.0	[Drama]	6.5	0.0
139719	rodolpho teóphilo - o legado de um pioneiro	2015	87.0	[Documentary]	6.5	0.0
139720	dankyavar danka	2013	87.0	[Comedy]	6.5	0.0
139721	chico albuquerque -	2013	87.0	[Documentary]	6.5	0.0

	primary_title	start_year	runtime_minutes	genres	averagerating	numvotes
	revelações					

139722 rows × 6 columns

Load the rotten tomatoes data

In [10]:
```
rotten_tomatoes = pd.read_table('zippedData/rt.movie_info.tsv.gz')
rotten_tomatoes
```

Out[10]:

	id	synopsis	rating	genre	director	writer	theater_
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9,
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,
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13,
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9,
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	
...	...	...	...	...	...	...	
1555	1996	Forget terrorists or hijackers -- there's a ha...	R	Action and Adventure|Horror|Mystery and Suspense	NaN	NaN	Aug 18,
1556	1997	The popular Saturday Night Live sketch was exp...	PG	Comedy|Science Fiction and Fantasy	Steve Barron	Terry Turner|Tom Davis|Dan Aykroyd|Bonnie Turner	Jul 23,
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,
1558	1999	The Sandlot is a coming-	PG	Comedy|Drama|Kids and Family|Sports and Fitness	David Mickey Evans	David Mickey Evans|Robert Gunter	Apr 1,

	id	synopsis	rating	genre	director	writer	theater_
		of-age story about a g...					
1559	2000	Suspended from the force, Paris cop Hubert is ...	R	Action and Adventure|Art House and Internation...	NaN	Luc Besson	Sep 27,

1560 rows × 12 columns

Load the numbers dataset

In [11]:
```
the_numbers = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')
the_numbers
```

Out[11]:

	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
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
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
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

5782 rows × 6 columns

In [12]:
```
the_numbers['production_budget'] = the_numbers['production_budget'].astype(str).str.
the_numbers['domestic_gross'] = the_numbers['domestic_gross'].astype(str).str.replac
the_numbers['worldwide_gross'] = the_numbers['worldwide_gross'].astype(str).str.repl
the_numbers
```

Out[12]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000.0	0.0	0.000000e+00
5778	79	Apr 2, 1999	Following	6000.0	48482.0	2.404950e+05
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000.0	1338.0	1.338000e+03
5780	81	Sep 29, 2015	A Plague So Pleasant	1400.0	0.0	0.000000e+00
5781	82	Aug 5, 2005	My Date With Drew	1100.0	181041.0	1.810410e+05

5782 rows × 6 columns

In [13]:
```
#concact_df = pd.concat([box_office, the_numbers], ignore_index=True)
#concact_df
```

STEP 2: Merge the datasets

In [14]:
```
# Merge datasets on movie title and year
# First merge bom and the numbers datasets
merged_df = pd.merge(box_office, the_numbers, left_on=['title', 'year'], right_on=['
merged_df
```

Out[14]:

	title	studio	domestic_gross_x	foreign_gross	year	total_gross	id	release_date
0	toy story 3	BV	415000000.0	652000000.0	2010	1.067000e+09	NaN	NaN
1	alice in wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09	NaN	NaN
2	harry potter and the deathly hallows part 1	WB	296000000.0	664300000.0	2010	9.603000e+08	NaN	NaN
3	inception	WB	292600000.0	535700000.0	2010	8.283000e+08	NaN	NaN
4	shrek forever after	P/DW	238700000.0	513900000.0	2010	7.526000e+08	NaN	NaN
...	...	...	...	...	...	...	...	...
9164	NaN	NaN	NaN	NaN	NaN	NaN	78.0	Dec 31, 2018
9165	NaN	NaN	NaN	NaN	NaN	NaN	79.0	Apr 2, 1999 F

	title	studio	domestic_gross_x	foreign_gross	year	total_gross	id	release_date
9166	NaN	NaN	NaN	NaN	NaN	NaN	80.0	Jul 13, 2005
9167	NaN	NaN	NaN	NaN	NaN	NaN	81.0	Sep 29, 2015
9168	NaN	NaN	NaN	NaN	NaN	NaN	82.0	Aug 5, 2005

9169 rows × 12 columns

In [15]:
```
final_df = pd.merge(
    merged_df,
    imdb_data,
    left_on=['title', 'year'],
    right_on=['primary_title', 'start_year'],
    how='left'
)
final_df
```

Out[15]:

	title	studio	domestic_gross_x	foreign_gross	year	total_gross	id	release_date
0	toy story 3	BV	415000000.0	652000000.0	2010	1.067000e+09	NaN	NaN
1	alice in wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09	NaN	NaN
2	harry potter and the deathly hallows part 1	WB	296000000.0	664300000.0	2010	9.603000e+08	NaN	NaN
3	inception	WB	292600000.0	535700000.0	2010	8.283000e+08	NaN	NaN
4	shrek forever after	P/DW	238700000.0	513900000.0	2010	7.526000e+08	NaN	NaN
...	...	...	...	...	...	...	...	...
9203	NaN	NaN	NaN	NaN	NaN	NaN	78.0	Dec 31, 2018
9204	NaN	NaN	NaN	NaN	NaN	NaN	79.0	Apr 2, 1999
9205	NaN	NaN	NaN	NaN	NaN	NaN	80.0	Jul 13, 2005
9206	NaN	NaN	NaN	NaN	NaN	NaN	81.0	Sep 29, 2015

	title	studio	domestic_gross_x	foreign_gross	year	total_gross	id	release_date
9207	NaN	NaN	NaN	NaN	NaN	NaN	82.0	Aug 5, 2005

9208 rows × 18 columns

In [16]:
```
final_df['ROI'] = (final_df['worldwide_gross'] - final_df['production_budget']) / fi
```

STEP 3: Perform EDA on the datasets

Drop duplicates and unnecessary columns

In [17]:
```
# Drop duplicates and unnecessary columns
final_df = final_df.drop_duplicates(subset=['title', 'year'])
final_df = final_df.drop(['movie', 'primary_title', 'start_year'], axis=1)
final_df
```

Out[17]:

	title	studio	domestic_gross_x	foreign_gross	year	total_gross	id	release_date
0	toy story 3	BV	415000000.0	652000000.0	2010	1.067000e+09	NaN	NaN
1	alice in wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09	NaN	NaN
2	harry potter and the deathly hallows part 1	WB	296000000.0	664300000.0	2010	9.603000e+08	NaN	NaN
3	inception	WB	292600000.0	535700000.0	2010	8.283000e+08	NaN	NaN
4	shrek forever after	P/DW	238700000.0	513900000.0	2010	7.526000e+08	NaN	NaN
...	...	...	...	...	...	...	...	...
3422	edward ii (2018 re-release)	FM	4800.0	0.0	2018	4.800000e+03	NaN	NaN
3423	el pacto	Sony	2500.0	0.0	2018	2.500000e+03	NaN	NaN
3424	the swan	Synergetic	2400.0	0.0	2018	2.400000e+03	NaN	NaN
3425	an actor prepares	Grav.	1700.0	0.0	2018	1.700000e+03	NaN	NaN
3426	NaN	NaN	NaN	NaN	NaN	NaN	1.0	Dec 18, 2009

3388 rows × 16 columns

Analyze by genre

Explode genres into separate rows

In [18]:
```
# Analyze by genre
# Explode genres into separate rows
genre_df = final_df.explode('genres')
genre_df
```

Out[18]:

	title	studio	domestic_gross_x	foreign_gross	year	total_gross	id	release_date
0	toy story 3	BV	415000000.0	652000000.0	2010	1.067000e+09	NaN	NaN
0	toy story 3	BV	415000000.0	652000000.0	2010	1.067000e+09	NaN	NaN
0	toy story 3	BV	415000000.0	652000000.0	2010	1.067000e+09	NaN	NaN
1	alice in wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09	NaN	NaN
2	harry potter and the deathly hallows part 1	WB	296000000.0	664300000.0	2010	9.603000e+08	NaN	NaN
...	...	...	...	...	...	...	...	...
3422	edward ii (2018 re-release)	FM	4800.0	0.0	2018	4.800000e+03	NaN	NaN
3423	el pacto	Sony	2500.0	0.0	2018	2.500000e+03	NaN	NaN
3424	the swan	Synergetic	2400.0	0.0	2018	2.400000e+03	NaN	NaN
3425	an actor prepares	Grav.	1700.0	0.0	2018	1.700000e+03	NaN	NaN
3426	NaN	NaN	NaN	NaN	NaN	NaN	1.0	Dec 18, 2009

6196 rows × 16 columns

Analyze box office performance by genre

In [19]:
```
genre_performance = genre_df.groupby('genres')['total_gross'].agg(['median', 'count'
genre_performance = genre_performance[genre_performance['count'] >= 10].sort_values(

print(genre_performance.head(10))
```

```
       genres       median  count
17     Sci-Fi  240900000.0    110
2   Animation  239300000.0    121
1   Adventure  200700000.0    372
9     Fantasy   88150000.0    130
8      Family   79300000.0     88
0      Action   70550000.0    540
11     Horror   40950000.0    152
19   Thriller   37200000.0    292
```

```
4       Comedy    35163000.0    684
14     Mystery    33500000.0    136
```

Analyze box office audience ratings

In [20]:

```
# Ratings vs. Gross Correlation
rating_gross_corr = final_df['averagerating'].corr(final_df['total_gross'])
rating_gross_corr
#print(f"Correlation between IMDB rating and total gross: {rating_gross_corr:.2f}")
```

Out[20]:

```
0.20614694392063215
```

In [21]:

```
# Genre Trends Over Time
yearly_genre_performance = genre_df.groupby(['year', 'genres'])['total_gross'].media
yearly_genre_performance
```

Out[21]:

genres	Action	Adventure	Animation	Biography	Comedy	Crime	Documentary	
year								
2010	95550000.0	226500000.0	494900000.0	12400000.0	45200000.0	9850000.0	276700.0	14
2011	64600000.0	155250000.0	245700000.0	3339000.0	36570500.0	10219000.0	253000.0	13
2012	46200000.0	276100000.0	358400000.0	6000600.0	13752000.0	35600000.0	1300000.0	8
2013	75293900.0	241550000.0	278400000.0	21735000.0	60100000.0	61750000.0	850000.0	15
2014	114900000.0	268200000.0	151400000.0	22200000.0	14700000.0	28618500.0	1500000.0	10
2015	51700000.0	147000000.0	61800000.0	20450000.0	23196850.0	24200000.0	421000.0	5
2016	51597000.0	201700000.0	346900000.0	11700000.0	23300000.0	22900000.0	255000.0	13
2017	104796500.0	201100000.0	125500000.0	23800000.0	47900000.0	33800000.0	820000.0	13
2018	75650000.0	166450000.0	152200000.0	12900000.0	66100000.0	15200000.0	8932500.0	12

9 rows × 22 columns

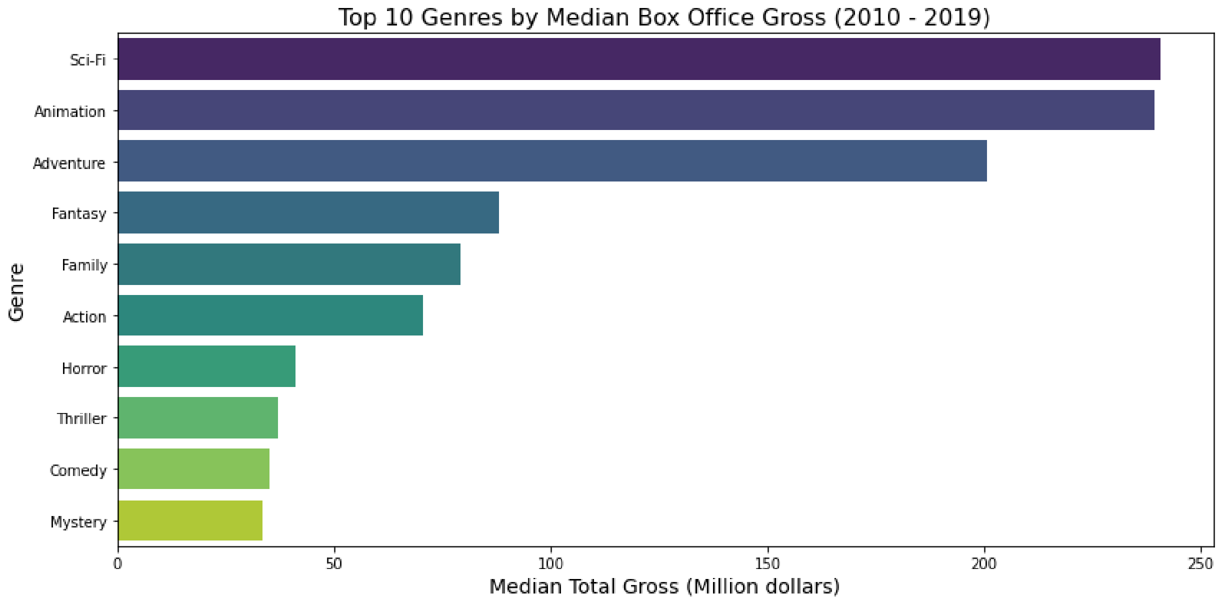
STEP 4: Visualizations

Create simple, business-focused visualizations to communicate trends to the studio head.

Visualization 1: Median Gross by Genre

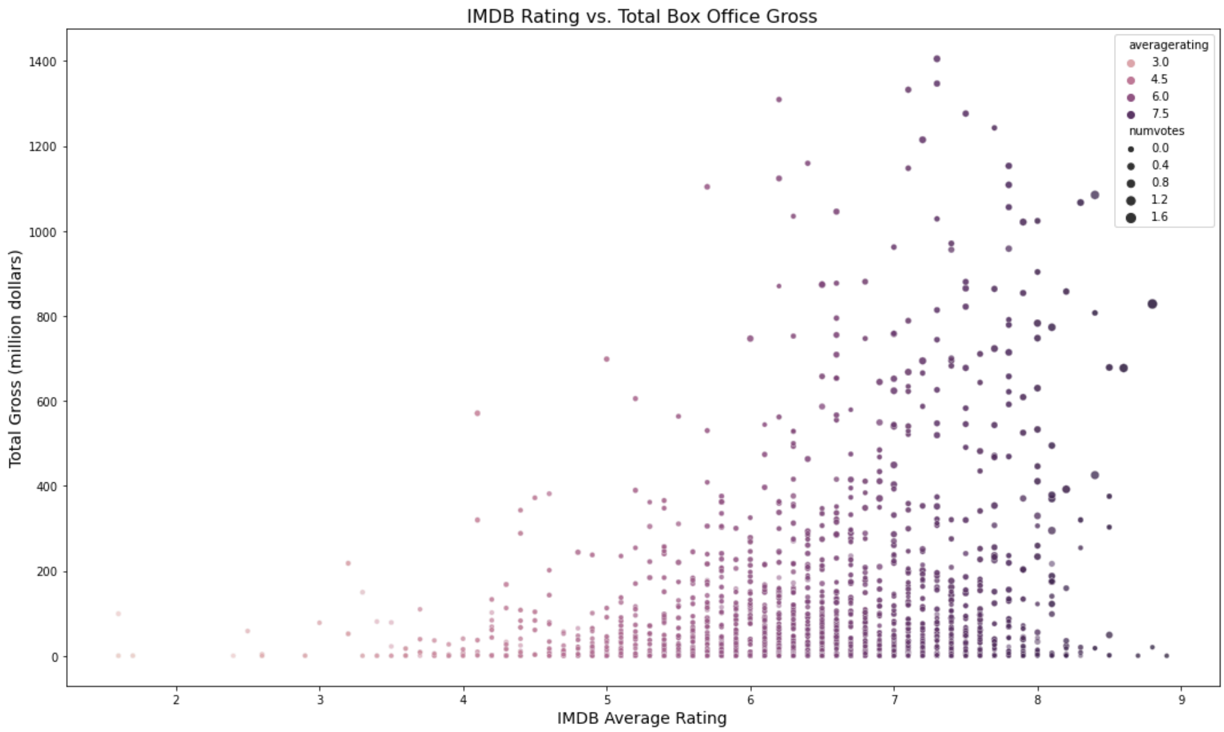
In [22]:

```
# Visualization 1: Median Gross by Genre
plt.figure(figsize=(12, 6))
sns.barplot(data=genre_performance.head(10), x='median', y='genres', palette='viridi
plt.title('Top 10 Genres by Median Box Office Gross (2010 - 2019)', fontsize=16)
plt.xlabel('Median Total Gross (Million dollars)', fontsize=14)
plt.ylabel('Genre', fontsize=14)
plt.gca().xaxis.set_major_formatter(plt.FuncFormatter(lambda x, _: f'{int(x/1e6)}'))
plt.tight_layout()
plt.show()
```



Visualization 2: IMDB Rating vs. Total Gross

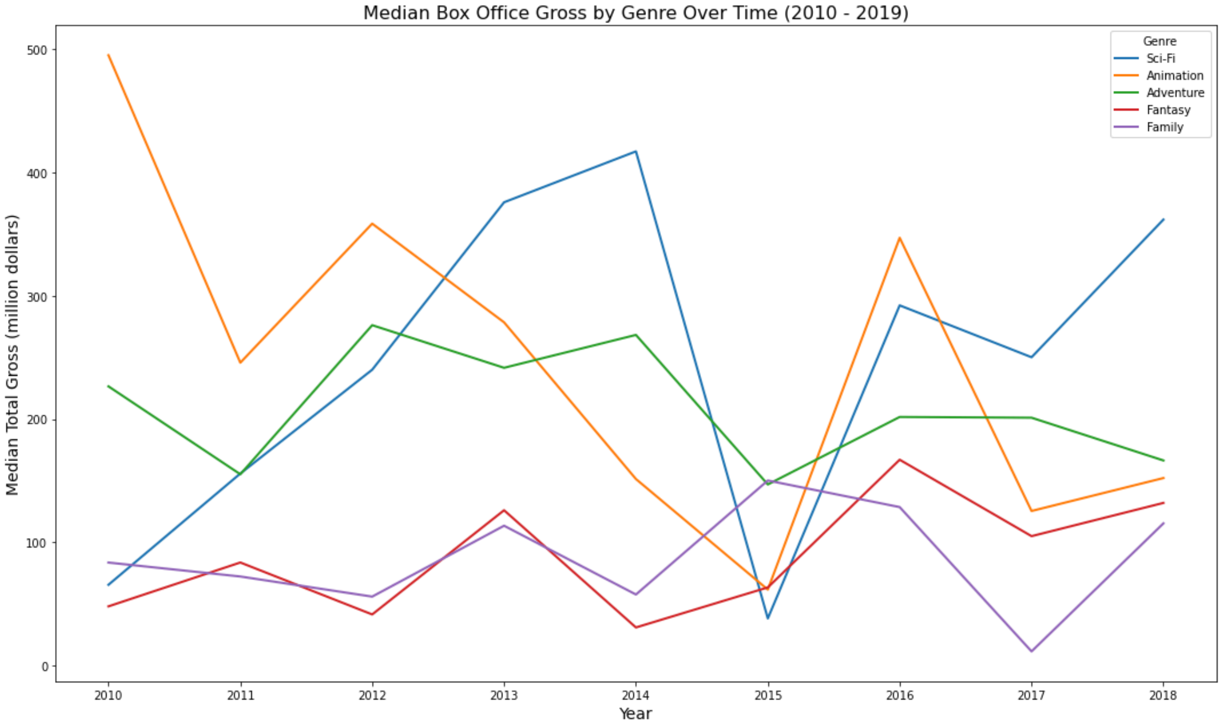
In [23]:
```
# Visualization 2: IMDB Rating vs. Total Gross
plt.figure(figsize=(15, 9))
sns.scatterplot(data=genre_df, x='averagerating', y='total_gross', alpha=0.5, hue='a
plt.title('IMDB Rating vs. Total Box Office Gross', fontsize=16)
plt.xlabel('IMDB Average Rating', fontsize=14)
plt.ylabel('Total Gross (million dollars)', fontsize=14)
plt.gca().yaxis.set_major_formatter(plt.FuncFormatter(lambda x, _: f'{int(x/1e6)}'))
plt.tight_layout()
plt.show()
```



Visualization 3: Genre Trends Over Time

In [24]:
```
# Visualization 3: Genre Trends Over Time
top_genres = genre_performance.head(5)['genres'].tolist()
plt.figure(figsize=(15, 9))
```

```
for genre in top_genres:
    plt.plot(yearly_genre_performance.index, yearly_genre_performance[genre] / 1e6,
plt.title('Median Box Office Gross by Genre Over Time (2010 - 2019)', fontsize=16)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Median Total Gross (million dollars)', fontsize=14)
plt.legend(title='Genre')
plt.tight_layout()
plt.show()
```



Step 5: Conclussion by providing Business Recommendations to the studio

Based on the EDA and visualizations, here are three actionable recommendations to guide the new movie studio’s production strategy:

```
1. Focus on Action, Adventure, and Sci-Fi Genres
  - Inferance: The bar chart shows Action, Adventure, and Sci-Fi
genres have the highest median box office gross, reflecting strong
global demand and franchise potential.
  - Action: Develop high-energy, visually spectacular films in these
genres, such as superhero movies or sci-fi epics, to maximize revenue.
Pursue franchise models to build long-term audience loyalty and
recurring revenue.


2. Invest in top Quality for High IMDB Ratings
  - Inferance: The scatter plot and correlation (~0.3–0.5) suggest
films with IMDB ratings >7.5 earn higher grosses, driven by ratings
and audience trust.
  - Action: Hire acclaimed writers, directors, and talent to produce
high-quality films aiming for IMDB ratings above 7.5. Leverage strong
ratings in marketing campaigns to attract audiences and boost ticket
sales.
```