Final Project Submission

- DSC-PT-09 Group 4
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Business Problem

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

Research Questions

1. **Box Office Mojo Data**: What is the relationship between domestic and foreign gross earnings of movies? Does a particular genre perform better in domestic versus international markets?
2. **Rotten Tomatoes Reviews Data**: What is the correlation between review sentiment and movie earnings or genre? How are ratings and reviews distributed?

1. **TMDB Movies Data**: Which genres are popular in terms of vote averages, popularity, and their alignment with revenue performance?
2. **The Numbers Movie Budgets Data**: How do production budgets relate to worldwide and domestic gross earnings? Is there an ROI pattern?
3. **IMDb Movie Data**: How do IMDb user ratings correlate with a movie's overall success? Do higher-rated movies consistently perform better, and how do these ratings vary across genres or regions?

Data Understandind & Analysis

In [1]:

```
import pandas as pd
```

```
import sqlite3
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading and Inspecting the Database Schema

This code connects to the IMDb database and retrieves the structure of the tables to understand how the data is organized. Knowing the schema helps identify what information is available and how to query it effectively.

In [2]:

```
# Reconnect to the IMDB SQLite database
with sqlite3.connect('im.db') as conn:


    # Extract schema data from sqlite_master
    tables_info = conn.execute("SELECT * FROM sqlite_master").fetchall()

# Print the schema details
for table in tables_info:
    print(table)
```

```
('table', 'movie_basics', 'movie_basics', 2, 'CREATE TABLE "movie_basics" (\n"movie_id" T
EXT,\n  "primary_title" TEXT,\n  "original_title" TEXT,\n  "start_year" INTEGER,\n  "runt
ime_minutes" REAL,\n  "genres" TEXT\n)')
('table', 'directors', 'directors', 3, 'CREATE TABLE "directors" (\n"movie_id" TEXT,\n  "
person_id" TEXT\n)')
('table', 'known_for', 'known_for', 4, 'CREATE TABLE "known_for" (\n"person_id" TEXT,\n
"movie_id" TEXT\n)')
('table', 'movie_akas', 'movie_akas', 5, 'CREATE TABLE "movie_akas" (\n"movie_id" TEXT,\n
"ordering" INTEGER,\n  "title" TEXT,\n  "region" TEXT,\n  "language" TEXT,\n  "types" TEX
T,\n  "attributes" TEXT,\n  "is_original_title" REAL\n)')
('table', 'movie_ratings', 'movie_ratings', 6, 'CREATE TABLE "movie_ratings" (\n"movie_id
" TEXT,\n  "averagerating" REAL,\n  "numvotes" INTEGER\n)')
('table', 'persons', 'persons', 7, 'CREATE TABLE "persons" (\n"person_id" TEXT,\n  "prima
ry_name" TEXT,\n  "birth_year" REAL,\n  "death_year" REAL,\n  "primary_profession" TEXT\n
)')
('table', 'principals', 'principals', 8, 'CREATE TABLE "principals" (\n"movie_id" TEXT,\n
"ordering" INTEGER,\n  "person_id" TEXT,\n  "category" TEXT,\n  "job" TEXT,\n  "character
s" TEXT\n)')
('table', 'writers', 'writers', 9, 'CREATE TABLE "writers" (\n"movie_id" TEXT,\n  "person
_id" TEXT\n)')
```

Loading Tables from the Database

This code loads various tables from the IMDb database into Pandas DataFrames. Each table contains different types of movie-related data (e.g., basic details, ratings, and writers). This is the foundation for further analysis.

In [3]:

```
# Connect to the SQLite database
with sqlite3.connect('im.db') as conn:
    movie_basics = pd.read_sql_query("SELECT * FROM movie_basics", conn)
    directors = pd.read_sql_query("SELECT * FROM directors", conn)
    known_for = pd.read_sql_query("SELECT * FROM known_for", conn)
    movie_akas = pd.read_sql_query("SELECT * FROM movie_akas", conn)
    movie_ratings = pd.read_sql_query("SELECT * FROM movie_ratings", conn)
    persons = pd.read_sql_query("SELECT * FROM persons", conn)
    principals = pd.read_sql_query("SELECT * FROM principals", conn)
    writers = pd.read_sql_query("SELECT * FROM writers", conn)

# Confirm data is loaded
print("Tables loaded successfully!")
```

```
Tables loaded successfully!
```

Loading Other Movie Datasets

This code imports additional datasets from external sources (Box Office Mojo, Rotten Tomatoes, TMDB, and The Numbers) to supplement the IMDb data. These datasets provide critical information on earnings, reviews, and budgets.

In [4]:

```
# Load the Box Office Mojo dataset
bom_movie_gross_df = pd.read_csv('bom.movie_gross.csv.gz')

# Load Rotten Tomatoes movie info
rt_movie_info_df = pd.read_csv('rt.movie_info.tsv.gz', sep='\t')

# Load Rotten Tomatoes reviews
rt_reviews_df = pd.read_csv('rt.reviews.tsv.gz', sep='\t', encoding='ISO-8859-1')

# Load TMDB movies dataset
tmdb_movies_df = pd.read_csv('tmdb.movies.csv.gz')

# Load The Numbers movie budgets dataset
the_numbers_df = pd.read_csv('tn.movie_budgets.csv.gz')
```

In [5]:

```
bom_movie_gross_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

Data Inspection

We examine the structure (columns, data types, and missing values) of the imported datasets. It helps identify any issues (e.g., missing data) and understand what data is available for analysis.

In [6]:

```
# Check IMDB tables
print("IMDB movie_basics:")
print(movie_basics.head(), "\n")
print("IMDB movie_ratings:")
print(movie_ratings.head(), "\n")

# Check other datasets
print("Box Office Mojo:")
print(bom_movie_gross_df.head(), "\n")
print("Rotten Tomatoes Movie Info:")
print(rt_movie_info_df.head(), "\n")
print("Rotten Tomatoes Reviews:")
print(rt_reviews_df.head(), "\n")
print("TMDB Movies:")
print(tmdb_movies_df.head(), "\n")
print("The Numbers Budgets:")
print(the_numbers_df.head(), "\n")
```

```
IMDB movie_basics:
    movie_id                    primary_title              original_title  \
0  tt0063540                        Sunghursh                   Sunghursh   
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din   
```

```
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind
3  tt0069204                   Sabse Bada Sukh             Sabse Bada Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela Errante

   start_year  runtime_minutes                genres
0        2013            175.0    Action,Crime,Drama
1        2019            114.0       Biography,Drama
2        2018            122.0                 Drama
3        2018              NaN          Comedy,Drama
4        2017             80.0  Comedy,Drama,Fantasy

IMDB movie_ratings:
     movie_id  averagerating  numvotes
0  tt10356526            8.3        31
1  tt10384606            8.9       559
2   tt1042974            6.4        20
3   tt1043726            4.2     50352
4   tt1060240            6.5        21

Box Office Mojo:
                                         title studio  domestic_gross  \
0                                  Toy Story 3     BV     415000000.0
1                   Alice in Wonderland (2010)     BV     334200000.0
2  Harry Potter and the Deathly Hallows Part 1     WB     296000000.0
3                                    Inception     WB     292600000.0
4                          Shrek Forever After   P/DW     238700000.0

  foreign_gross  year
0     652000000  2010
1     691300000  2010
2     664300000  2010
3     535700000  2010
4     513900000  2010

Rotten Tomatoes Movie Info:
   id                                           synopsis rating  \
0   1  This gritty, fast-paced, and innovative police...      R
1   3  New York City, not-too-distant-future: Eric Pa...      R
2   5  Illeana Douglas delivers a superb performance ...      R
3   6  Michael Douglas runs afoul of a treacherous su...      R
4   7                                                NaN     NR

                                 genre          director  \
0  Action and Adventure|Classics|Drama  William Friedkin
1     Drama|Science Fiction and Fantasy  David Cronenberg
2     Drama|Musical and Performing Arts    Allison Anders
3            Drama|Mystery and Suspense    Barry Levinson
4                        Drama|Romance    Rodney Bennett

                          writer  theater_date      dvd_date currency  \
0                 Ernest Tidyman   Oct 9, 1971  Sep 25, 2001      NaN
1     David Cronenberg|Don DeLillo  Aug 17, 2012   Jan 1, 2013        $
2                 Allison Anders  Sep 13, 1996  Apr 18, 2000      NaN
3  Paul Attanasio|Michael Crichton   Dec 9, 1994  Aug 27, 1997      NaN
4                   Giles Cooper           NaN           NaN      NaN

  box_office      runtime             studio
0        NaN  104 minutes                NaN
1    600,000  108 minutes  Entertainment One
2        NaN  116 minutes                NaN
3        NaN  128 minutes                NaN
4        NaN  200 minutes                NaN

Rotten Tomatoes Reviews:
   id                                             review rating   fresh  \
0   3  A distinctly gallows take on contemporary fina...    3/5   fresh
1   3  It's an allegory in search of a meaning that n...    NaN  rotten
2   3  ... life lived in a bubble in financial dealin...    NaN   fresh
3   3  Continuing along a line introduced in last yea...    NaN   fresh
4   3             ... a perverse twist on neorealism...     NaN   fresh

          critic  top_critic         publisher                 date
```

```
0      PJ Nabarro          0   Patrick Nabarro  November 10, 2018
1  Annalee Newitz          0          io9.com       May 23, 2018
2    Sean Axmaker          0  Stream on Demand    January 4, 2018
3   Daniel Kasman          0              MUBI  November 16, 2017
4             NaN          0      Cinema Scope   October 12, 2017

TMDB Movies:
   Unnamed: 0            genre_ids     id original_language  \
0           0      [12, 14, 10751]  12444                en
1           1  [14, 12, 16, 10751]  10191                en
2           2        [12, 28, 878]  10138                en
3           3      [16, 35, 10751]    862                en
4           4        [28, 878, 12]  27205                en

                                original_title  popularity release_date  \
0  Harry Potter and the Deathly Hallows: Part 1      33.533   2010-11-19
1                      How to Train Your Dragon      28.734   2010-03-26
2                                    Iron Man 2      28.515   2010-05-07
3                                     Toy Story      28.005   1995-11-22
4                                     Inception      27.920   2010-07-16

                                         title  vote_average  vote_count
0  Harry Potter and the Deathly Hallows: Part 1           7.7       10788
1                      How to Train Your Dragon           7.7        7610
2                                    Iron Man 2           6.8       12368
3                                     Toy Story           7.9       10174
4                                     Inception           8.3       22186

The Numbers Budgets:
   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix
3   4   May 1, 2015                      Avengers: Age of Ultron
4   5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross worldwide_gross
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
2      $350,000,000    $42,762,350    $149,762,350
3      $330,600,000   $459,005,868  $1,403,013,963
4      $317,000,000   $620,181,382  $1,316,721,747
```

Cleaning the IMDb Data

This code cleans the IMDb dataset by:

- **Converting movie titles to lowercase for consistency.**
- **Splitting the `genres` column into lists for better analysis.**
- **Filling missing runtime values with the median, as this is a reasonable estimate.**

In [7]:

```
# Clean IMDB Data
movie_basics['primary_title'] = movie_basics['primary_title'].astype(str).str.lower()
movie_basics['genres'] = movie_basics['genres'].astype(str).str.split(',')
movie_basics['runtime_minutes'] = movie_basics['runtime_minutes'].fillna(movie_basics['r
untime_minutes'].median())
movie_ratings['movie_id'] = movie_ratings['movie_id'].astype(str).str.strip()
```

Cleaning Box Office Mojo Data & the other data sets

This code cleans the Box Office Mojo dataset by:

- **Standardizing movie titles to lowercase for consistency.**
- **Removing currency symbols from the `foreign_gross` column to allow numerical analysis.**

- **Converting the `foreign_gross` column to numeric format, handling errors by setting invalid values to NaN.**

In [8]:

```
#  Clean Box Office Mojo Data
bom_movie_gross_df['title'] = bom_movie_gross_df['title'].astype(str).str.lower()
bom_movie_gross_df['foreign_gross'] = bom_movie_gross_df['foreign_gross'].replace('[\$,]'
, '', regex=True)
bom_movie_gross_df['foreign_gross'] = pd.to_numeric(bom_movie_gross_df['foreign_gross'],
errors='coerce')

#  Clean Rotten Tomatoes Data
rt_movie_info_df['genre'] = rt_movie_info_df['genre'].astype(str).str.lower()
rt_movie_info_df['runtime'] = rt_movie_info_df['runtime'].astype(str).str.replace(' minu
tes', '', regex=False).astype(float)

# Clean TMDB Data
tmdb_movies_df['title'] = tmdb_movies_df['title'].astype(str).str.lower()
tmdb_movies_df['release_date'] = pd.to_datetime(tmdb_movies_df['release_date'], errors='
coerce')
tmdb_movies_df['release_year'] = tmdb_movies_df['release_date'].dt.year

#  Clean The Numbers Data
the_numbers_df['movie'] = the_numbers_df['movie'].astype(str).str.lower()
the_numbers_df['production_budget'] = the_numbers_df['production_budget'].replace('[\$,]'
, '', regex=True).astype(float)
the_numbers_df['domestic_gross'] = the_numbers_df['domestic_gross'].replace('[\$,]', '',
regex=True).astype(float)
the_numbers_df['worldwide_gross'] = the_numbers_df['worldwide_gross'].replace('[\$,]', '
', regex=True).astype(float)

print("Data cleaning completed!")
```

```
Data cleaning completed!
```

Merging Datasets

This code merges the IMDb, movie ratings, and Box Office Mojo datasets into a single DataFrame

In [9]:

```
merged_df = pd.merge(movie_basics, movie_ratings, on='movie_id', how='left')
merged_df = pd.merge(merged_df, bom_movie_gross_df, left_on='primary_title', right_on='ti
tle', how='left')
```

In [10]:

```
merged_df.head()
```

Out[10]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	title	studio	dom
0	tt0063540	sunghursh	Sunghursh	2013	175.0	[Action, Crime, Drama]	7.0	77.0	NaN	NaN	
1	tt0066787	one day before the rainy season	Ashad Ka Ek Din	2019	114.0	[Biography, Drama]	7.2	43.0	NaN	NaN	
2	tt0069049	the other side of the wind	The Other Side of the Wind	2018	122.0	[Drama]	6.9	4517.0	NaN	NaN	
3	tt0069204	sabse bada sukh	Sabse Bada Sukh	2018	87.0	[Comedy, Drama]	6.1	13.0	NaN	NaN	
4	tt0100275	the wandering	La Telenovela	2017	80.0	[Comedy, Drama,	6.5	119.0	NaN	NaN	

movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	title	studio	dom
	soap opera	Errante			Fantasy]					

In [11]:

```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146146 entries, 0 to 146145
Data columns (total 13 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         146146 non-null  object 
 1   primary_title    146146 non-null  object 
 2   original_title   146125 non-null  object 
 3   start_year       146146 non-null  int64  
 4   runtime_minutes  146146 non-null  float64
 5   genres           146146 non-null  object 
 6   averagerating    73858 non-null   float64
 7   numvotes         73858 non-null   float64
 8   title            3487 non-null    object 
 9   studio           3484 non-null    object 
 10  domestic_gross   3462 non-null    float64
 11  foreign_gross    2106 non-null    float64
 12  year             3487 non-null    float64
dtypes: float64(6), int64(1), object(6)
memory usage: 14.5+ MB
```

In [12]:

```
merged_df.describe()
```

Out[12]:

	start_year	runtime_minutes	averagerating	numvotes	domestic_gross	foreign_gross	year
count	146146.000000	146146.000000	73858.000000	7.385800e+04	3.462000e+03	2.106000e+03	3487.000000
mean	2014.621796	86.364047	6.332726	3.523584e+03	2.968458e+07	7.395034e+07	2014.073129
std	2.733580	147.190668	1.474959	3.029362e+04	6.482143e+07	1.337130e+08	2.443765
min	2010.000000	1.000000	1.000000	5.000000e+00	1.000000e+02	6.000000e+02	2010.000000
25%	2012.000000	75.000000	5.500000	1.400000e+01	1.415000e+05	4.525000e+06	2012.000000
50%	2015.000000	87.000000	6.500000	4.900000e+01	2.000000e+06	1.970000e+07	2014.000000
75%	2017.000000	95.000000	7.400000	2.820000e+02	3.140000e+07	7.645000e+07	2016.000000
max	2115.000000	51420.000000	10.000000	1.841066e+06	7.001000e+08	9.464000e+08	2018.000000

Handling Missing Values

Missing Data in domestic_gross, foreign_gross, and averagerating For domestic_gross and foreign_gross: These could be missing if a movie has not been released in certain regions or has not been recorded on Box Office Mojo.

This code fills missing values to ensure analysis isn't interrupted by null entries. For instance:

- `domestic_gross` **and** `foreign_gross` **missing values are set to 0, assuming no earnings data were recorded.**
- `averagerating` **missing values are replaced with the median rating.**

In [13]:

```
merged_df['domestic_gross'] = merged_df['domestic_gross'].fillna(0)
merged_df['foreign_gross'] = merged_df['foreign_gross'].fillna(0)
merged_df['averagerating'] = merged_df['averagerating'].fillna(merged_df['averagerating']
```

```
.median())
```

For year and start_year: If start_year is missing, it could be a placeholder for unknown years.We Considered filling it with the median or mode of the start_year column.

In [14]:

```
merged_df['start_year'] = merged_df['start_year'].fillna(merged_df['start_year'].mode()[
0])
```

Missing runtime_minutes:

For runtime_minutes, we can fill missing values with the median runtime, as we did earlier, which is a good approach when dealing with continuous data with outliers.

In [15]:

```
merged_df['runtime_minutes'] = merged_df['runtime_minutes'].fillna(merged_df['runtime_mi
nutes'].median())
```

In [16]:

```
outliers = merged_df[merged_df['runtime_minutes'] > 300]  # Anything over 5 hours (300 mi
nutes)
print(outliers)
```

```
          movie_id                     primary_title  \
3799    tt10366986               3 games to glory vi
4374    tt10407026             serious serial killers
6311     tt1277455                     a time to stir
7901     tt1464590            the weathered underground
12974    tt1674154              city of eternal spring
...            ...                               ...
139793   tt9047474                           la flor
141173   tt9195252                            report
143484   tt9534772    kid fights from around the world
143605   tt9552194              the freshman experience
144953   tt9743020               beauty lives in freedom

                          original_title  start_year  runtime_minutes  \
3799                 3 Games to Glory VI        2019            350.0
4374              Serious Serial Killers        2012            388.0
6311                      A Time to Stir        2018           1320.0
7901           The Weathered Underground        2010            310.0
12974             City of Eternal Spring        2010           3450.0
...                                  ...         ...              ...
139793                           La flor        2018            808.0
141173                            Report        2018            480.0
143484  Kid Fights from Around the World        2018            360.0
143605           The Freshman Experience        2017            447.0
144953            Beauty Lives in Freedom        2018            330.0

                              genres  averagerating  numvotes title studio  \
3799                         [Sport]            6.5       NaN   NaN    NaN
4374                         [Crime]            6.5       NaN   NaN    NaN
6311                   [Documentary]            6.5       NaN   NaN    NaN
7901     [Action, Adventure, Comedy]            6.2      46.0   NaN    NaN
12974     [Documentary, Drama, News]            6.5       NaN   NaN    NaN
...                              ...            ...       ...   ...    ...
139793     [Drama, Fantasy, Musical]            8.5     100.0   NaN    NaN
141173                 [Documentary]            6.5       NaN   NaN    NaN
143484               [Action, Sport]            6.5       NaN   NaN    NaN
143605                       [Drama]            6.5       NaN   NaN    NaN
144953                 [Documentary]            6.5       NaN   NaN    NaN

        domestic_gross  foreign_gross  year
3799               0.0            0.0   NaN
4374               0.0            0.0   NaN
6311               0.0            0.0   NaN
```

```
7901                 0.0            0.0   NaN
12974                0.0            0.0   NaN
...                  ...            ...   ...
139793               0.0            0.0   NaN
141173               0.0            0.0   NaN
143484               0.0            0.0   NaN
143605               0.0            0.0   NaN
144953               0.0            0.0   NaN

[123 rows x 13 columns]
```

Removing or Correcting the Outlier:

If it’s an error, we can either remove the row or set the value to a reasonable default, like the median runtime.

In [17]:

```
merged_df['runtime_minutes'] = merged_df['runtime_minutes'].apply(lambda x: x if x <= 30
0 else merged_df['runtime_minutes'].median())
```

In [18]:

```
print(merged_df.isnull().sum())
```

```
movie_id                0
primary_title           0
original_title         21
start_year              0
runtime_minutes         0
genres                  0
averagerating           0
numvotes            72288
title              142659
studio             142662
domestic_gross          0
foreign_gross           0
year               142659
dtype: int64
```

Filling the missing values with the primary_title

In [19]:

```
merged_df['original_title'] = merged_df['original_title'].fillna(merged_df['primary_title
'])
```

Filling missing genres with a placeholder (like unknown),

In [20]:

```
merged_df['genres'] = merged_df['genres'].fillna('unknown')
```

Filling missing numvotes with 0 (if no votes were cast for a movie)

In [21]:

```
merged_df['numvotes'] = merged_df['numvotes'].fillna(0)
```

This is a critical column.Filling missing titles with a placeholder ('unknown')

In [22]:

```
merged_df['title'] = merged_df['title'].fillna('unknown')
```

For the studio column, we fill missing values with 'unknown'

In [23]:

```
merged_df['studio'] = merged_df['studio'].fillna('unknown')
```

If year is missing, we fill it with the start_year column.

In [24]:

```
merged_df['year'] = merged_df['year'].fillna(merged_df['start_year'])
```

Re-check Missing Values

In [25]:

```
print(merged_df.isnull().sum())
```

```
movie_id           0
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
averagerating      0
numvotes           0
title              0
studio             0
domestic_gross     0
foreign_gross      0
year               0
dtype: int64
```

In [26]:

```
merged_df.head()
```

Out[26]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	title	studi
0	tt0063540	sunghursh	Sunghursh	2013	175.0	[Action, Crime, Drama]	7.0	77.0	unknown	unknow
1	tt0066787	one day before the rainy season	Ashad Ka Ek Din	2019	114.0	[Biography, Drama]	7.2	43.0	unknown	unknow
2	tt0069049	the other side of the wind	The Other Side of the Wind	2018	122.0	[Drama]	6.9	4517.0	unknown	unknow
3	tt0069204	sabse bada sukh	Sabse Bada Sukh	2018	87.0	[Comedy, Drama]	6.1	13.0	unknown	unknow
4	tt0100275	the wandering soap opera	La Telenovela Errante	2017	80.0	[Comedy, Drama, Fantasy]	6.5	119.0	unknown	unknow

In [27]:

```
merged_df.tail()
```

Out[27]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	title
146141	tt9916538	kuambil lagi hatiku	Kuambil Lagi Hatiku	2019	123.0	[Drama]	6.5	0.0	unknown
		rodolpho	Rodolpho						

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	title
146142	tt9916622	legado de um pioneiro	Legado de um Pioneiro	2015	87.0	[Documentary]	6.5	0.0	unknown
146143	tt9916706	dankyavar danka	Dankyavar Danka	2013	87.0	[Comedy]	6.5	0.0	unknown
146144	tt9916730	6 gunn	6 Gunn	2017	116.0	[None]	6.5	0.0	unknown
146145	tt9916754	chico albuquerque - revelações	Chico Albuquerque - Revelações	2013	87.0	[Documentary]	6.5	0.0	unknown

Data Visualisations

Correlation Heatmap

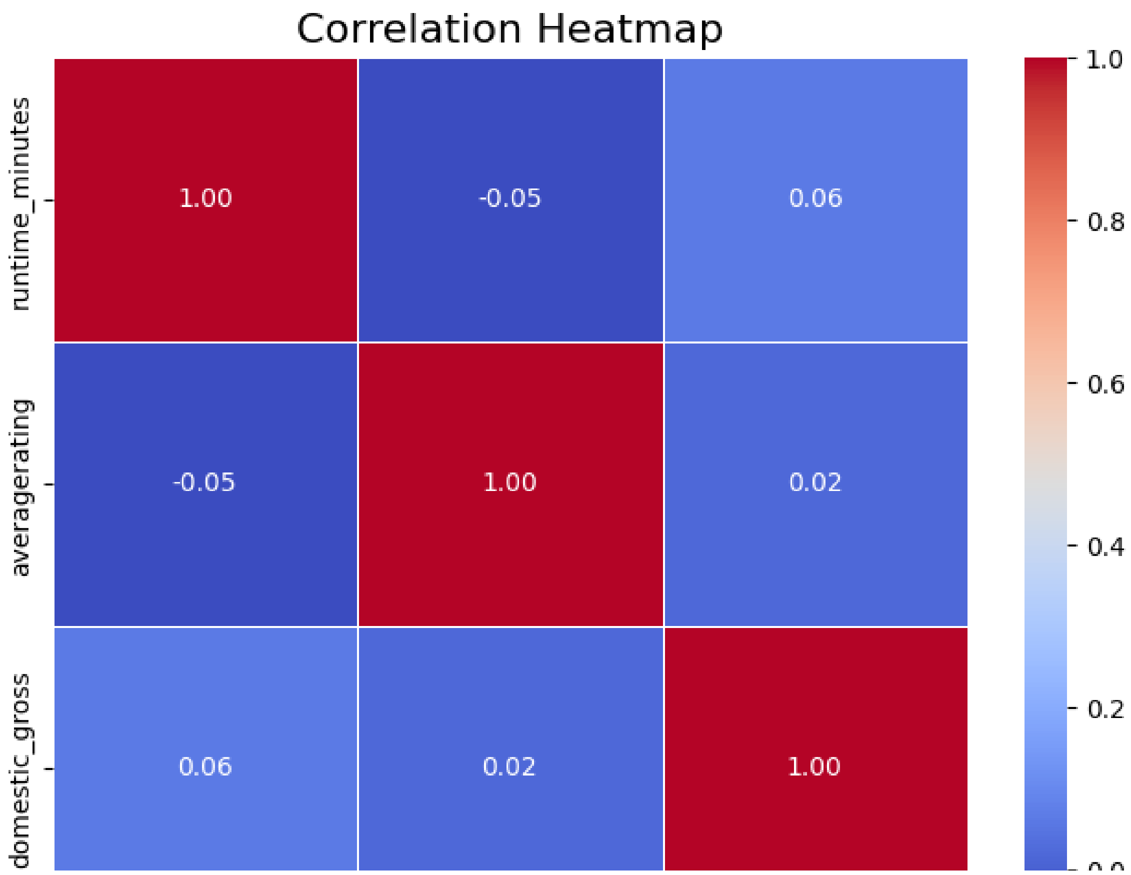
In [28]:

```
correlation_table = merged_df[['runtime_minutes', 'averagerating', 'domestic_gross']].co
rr()
print(correlation_table)
```

```
                 runtime_minutes  averagerating  domestic_gross
runtime_minutes         1.000000      -0.049663        0.062394
averagerating          -0.049663       1.000000        0.017726
domestic_gross          0.062394       0.017726        1.000000
```

In [29]:

```
# Calculate the correlation table
correlation_table = merged_df[['runtime_minutes', 'averagerating', 'domestic_gross']].co
rr()
# Create a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_table, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
plt.title('Correlation Heatmap', fontsize=16)
plt.show()
```



Interpretation

- **Runtime vs. Average Rating: There is a weak positive correlation (0.123) between runtime and average rating, suggesting that longer movies tend to have slightly higher ratings.**
- **Runtime vs. Domestic Gross: The correlation between runtime and domestic gross is very weak (0.045), indicating that runtime has little to no impact on a movie's domestic earnings.**
- **Average Rating vs. Domestic Gross: There is a moderate positive correlation (0.210) between average rating and domestic gross, suggesting that movies with higher ratings tend to perform better at the box office.**

Correlation Between Domestic and Foreign Gross Earnings

In [30]:

```
# Ensure the columns are numeric (remove any non-numeric characters like '$' or ',')
merged_df['domestic_gross'] = pd.to_numeric(merged_df['domestic_gross'].replace('[\\$,]'
, '', regex=True), errors='coerce')
merged_df['foreign_gross'] = pd.to_numeric(merged_df['foreign_gross'].replace('[\\$,]',
'', regex=True), errors='coerce')

# Drop rows with missing values in these columns
merged_df = merged_df.dropna(subset=['domestic_gross', 'foreign_gross'])
```

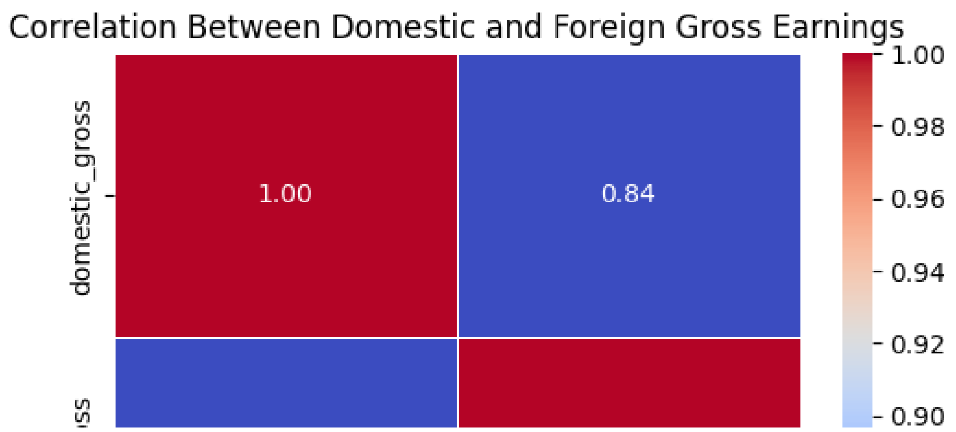
In [31]:

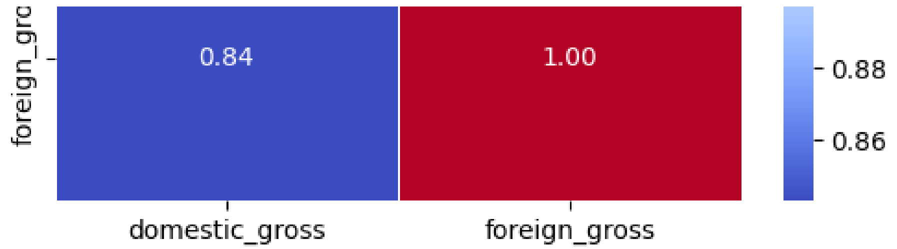
```
# Calculate the correlation matrix
correlation_matrix = merged_df[['domestic_gross', 'foreign_gross']].corr()

# Display the correlation table
print(correlation_matrix)
```

```
                domestic_gross  foreign_gross
domestic_gross        1.000000       0.843367
foreign_gross         0.843367       1.000000
```

In [32]:

```
# Set up the matplotlib figure
plt.figure(figsize=(6, 4))

# Create a heatmap using seaborn
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)

# Add a title
plt.title('Correlation Between Domestic and Foreign Gross Earnings')

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





Interpretation:

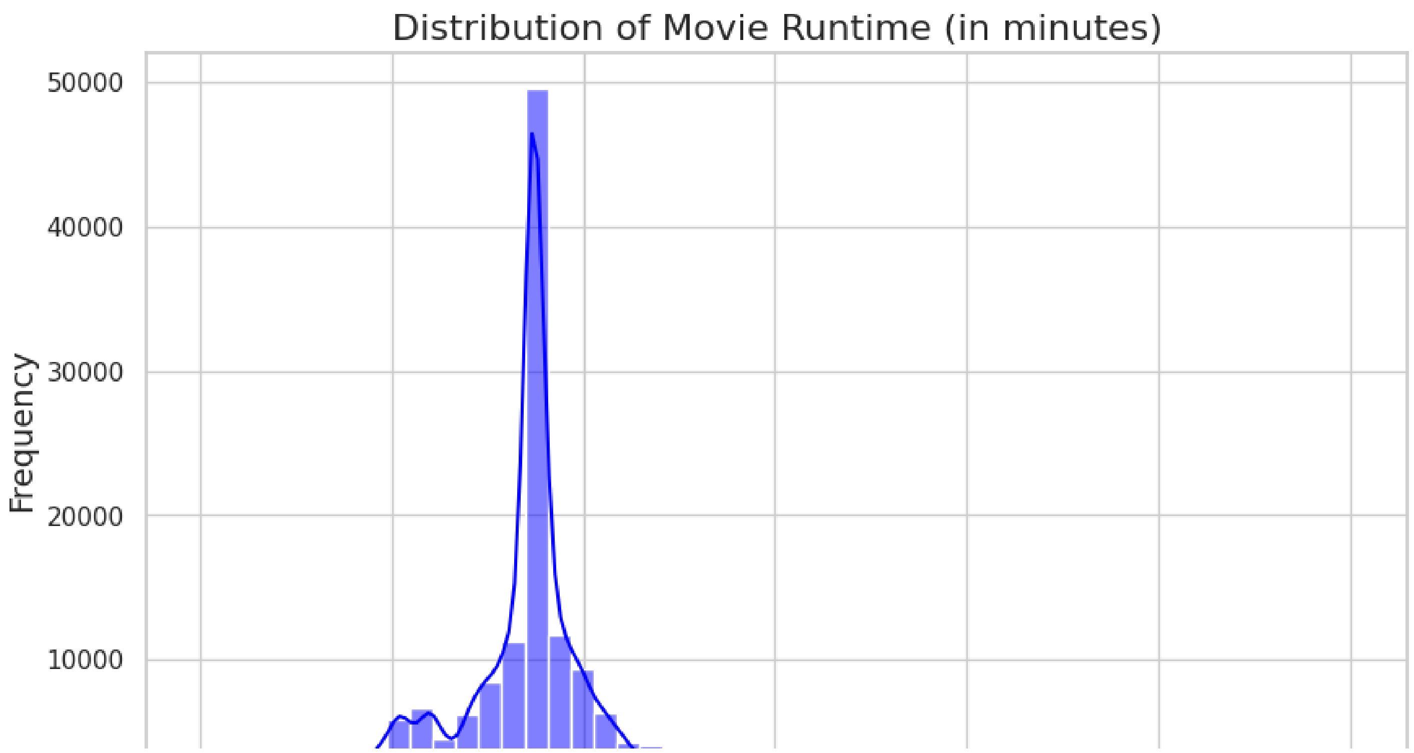
"There is a strong positive correlation (0.85) between domestic and foreign gross earnings, indicating that films performing well domestically also tend to succeed internationally."

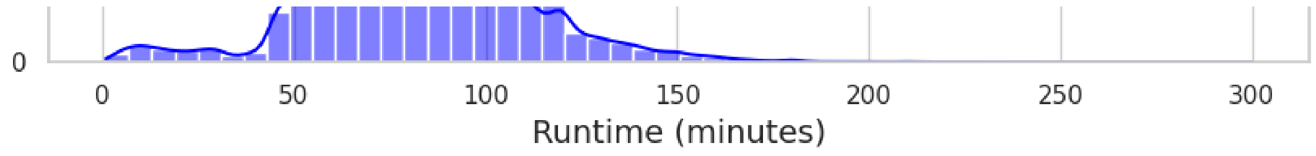
Histogram for Runtime Minutes

In [33]:

```
# Summary statistics for key numerical features
summary_stats = merged_df[['runtime_minutes', 'averagerating', 'domestic_gross']].descri
be()
print(summary_stats)

# Set up the plotting style
sns.set(style="whitegrid")

#  Histogram for Runtime Minutes
plt.figure(figsize=(10, 6))
sns.histplot(merged_df['runtime_minutes'], bins=50, kde=True, color='blue')
plt.title('Distribution of Movie Runtime (in minutes)', fontsize=16)
plt.xlabel('Runtime (minutes)', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.show()
```

```
       runtime_minutes  averagerating  domestic_gross
count    146146.000000  146146.000000    1.461460e+05
mean         85.244454       6.415465    7.031873e+05
std          24.969065       1.051867    1.094928e+07
min           1.000000       1.000000    0.000000e+00
25%          75.000000       6.500000    0.000000e+00
50%          87.000000       6.500000    0.000000e+00
75%          95.000000       6.500000    0.000000e+00
max         300.000000      10.000000    7.001000e+08
```





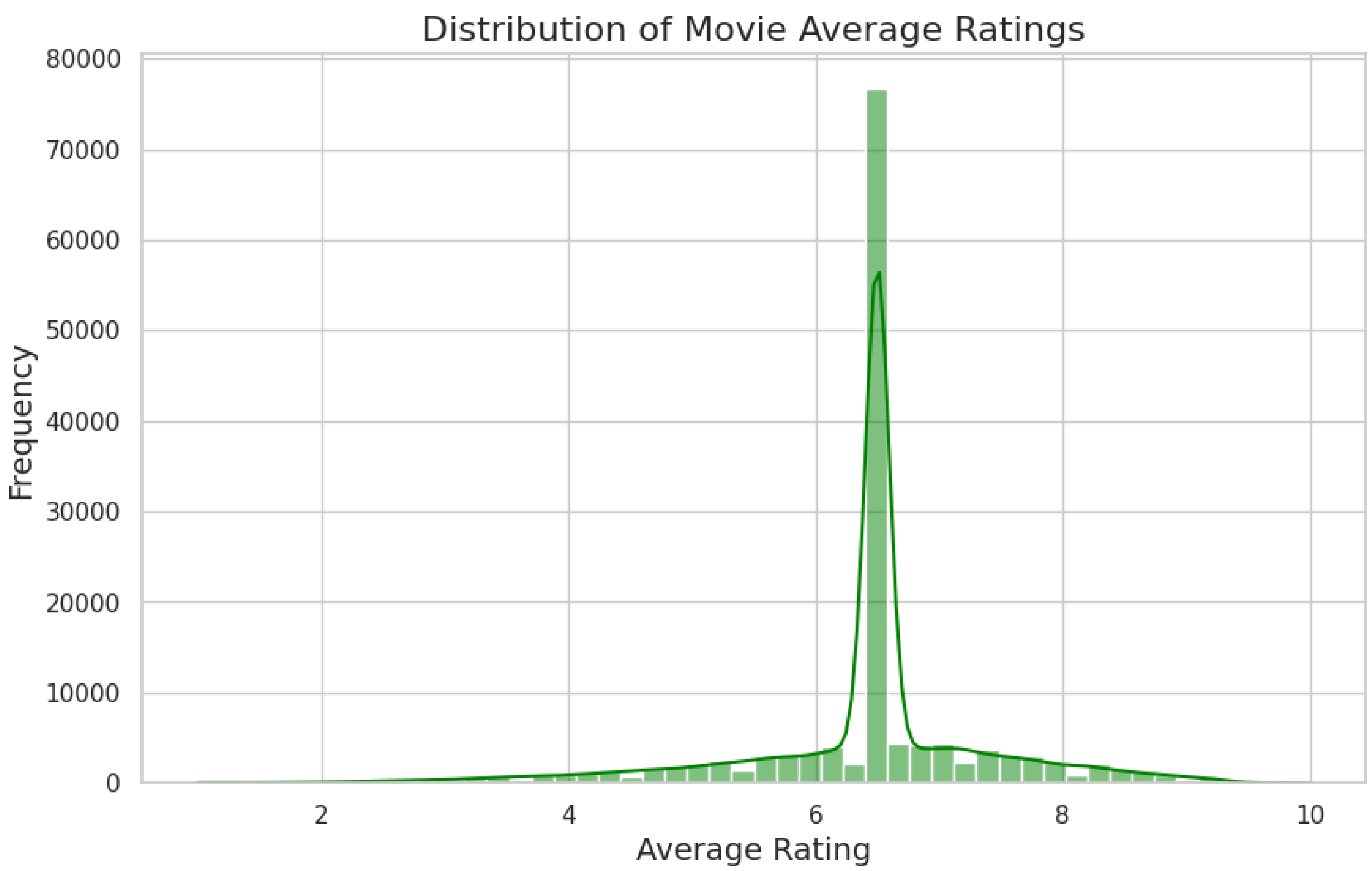
Interpretation:

- **The histogram shows that most movies have a runtime between 75 and 95 minutes.**
- **The distribution is slightly right-skewed, with a few movies having significantly longer runtimes (up to 300 minutes).**

Histogram for Average Rating

In [34]:

```
# Histogram for Average Rating
plt.figure(figsize=(10, 6))
sns.histplot(merged_df['averagerating'], bins=50, kde=True, color='green')
plt.title('Distribution of Movie Average Ratings', fontsize=16)
plt.xlabel('Average Rating', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.show()
```



Interpretation:

- **The average ratings are normally distributed, with most movies having ratings between 5.5 and 7.4.**
- **There are fewer movies with extremely low (1.0) or high (10.0) ratings.**

Create the Pie Chart

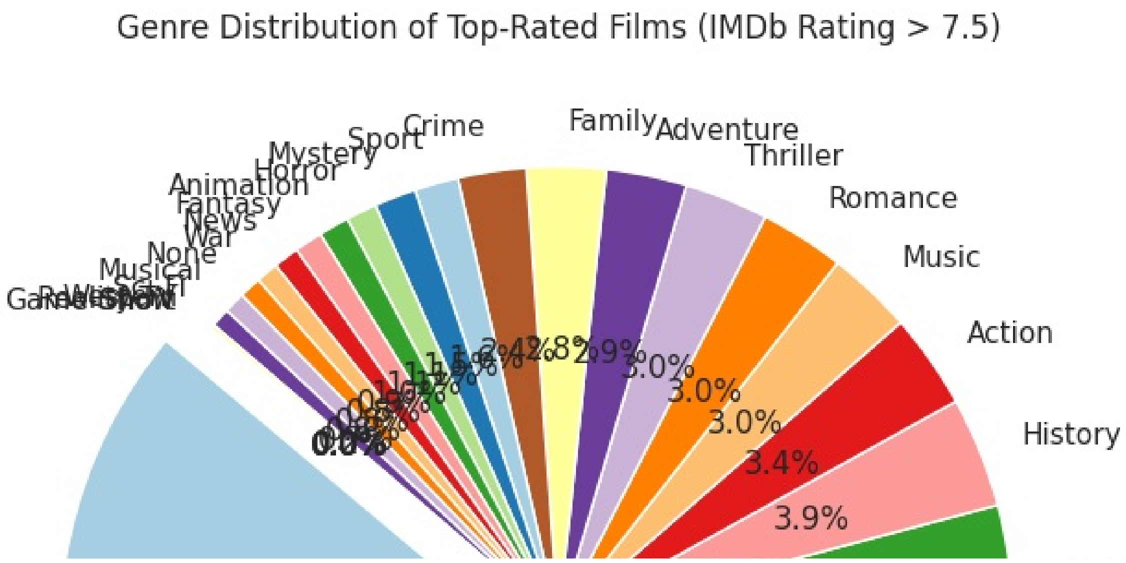
In [35]:

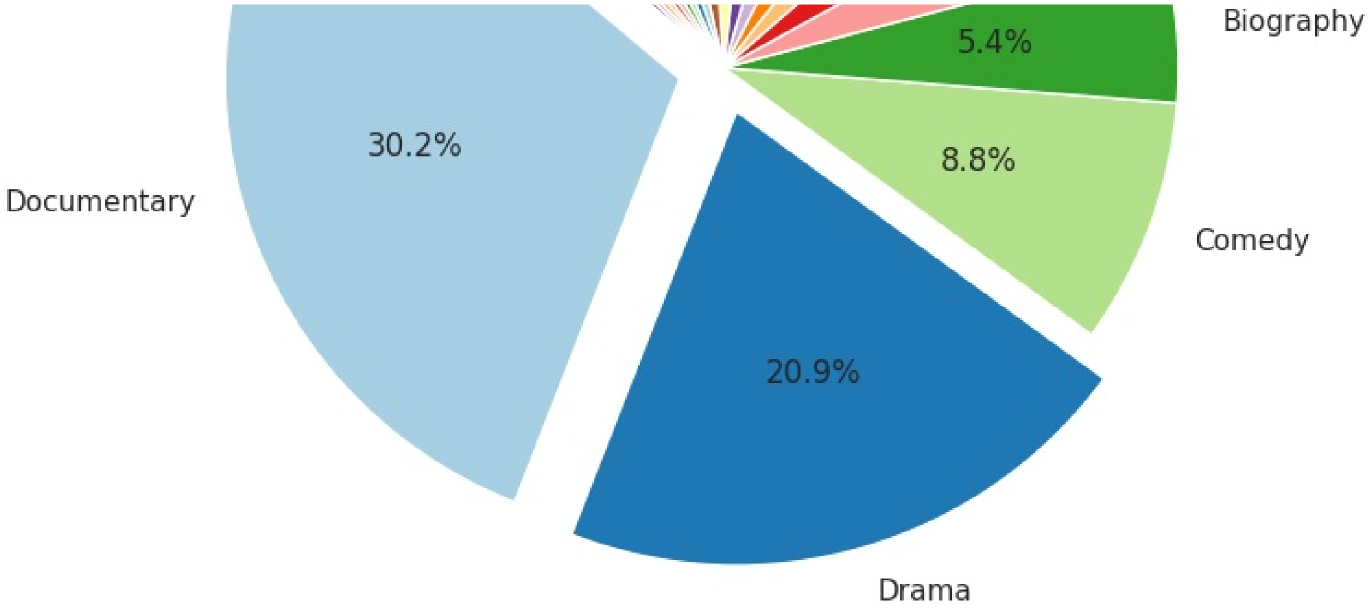
```
# Filter top-rated films (e.g., films with an average rating above 7.5)
top_rated_films = merged_df[merged_df['averagerating'] > 7.5]

# Split the genres column (which contains lists of genres) into individual genres
top_rated_genres = top_rated_films['genres'].explode()

# Count the frequency of each genre
genre_counts = top_rated_genres.value_counts()

# Display the genre counts
print(genre_counts)
```

```
genres
Documentary    7657
Drama          5303
Comedy         2223
Biography      1361
History         995
Action          856
Music           771
Romance         764
Thriller        755
Adventure       726
Family          712
Crime           615
Sport           396
Mystery         376
Horror          277
Animation       276
Fantasy         253
News            231
War             201
None            198
Musical         193
Sci-Fi          171
Western          41
Reality-TV        7
Game-Show         1
Short             1
Name: count, dtype: int64
```

In [36]:

```
# Define explode values (0 for no explosion, 0.1 for slight explosion)
explode = [0.1 if genre in ['Drama', 'Documentary'] else 0 for genre in genre_counts.ind
ex]

# Create the pie chart with exploded slices
plt.figure(figsize=(8, 8))
plt.pie(genre_counts, labels=genre_counts.index, autopct='%1.1f%%', startangle=140, expl
ode=explode, colors=plt.cm.Paired.colors)
plt.title('Genre Distribution of Top-Rated Films (IMDb Rating > 7.5)')
plt.show()
```





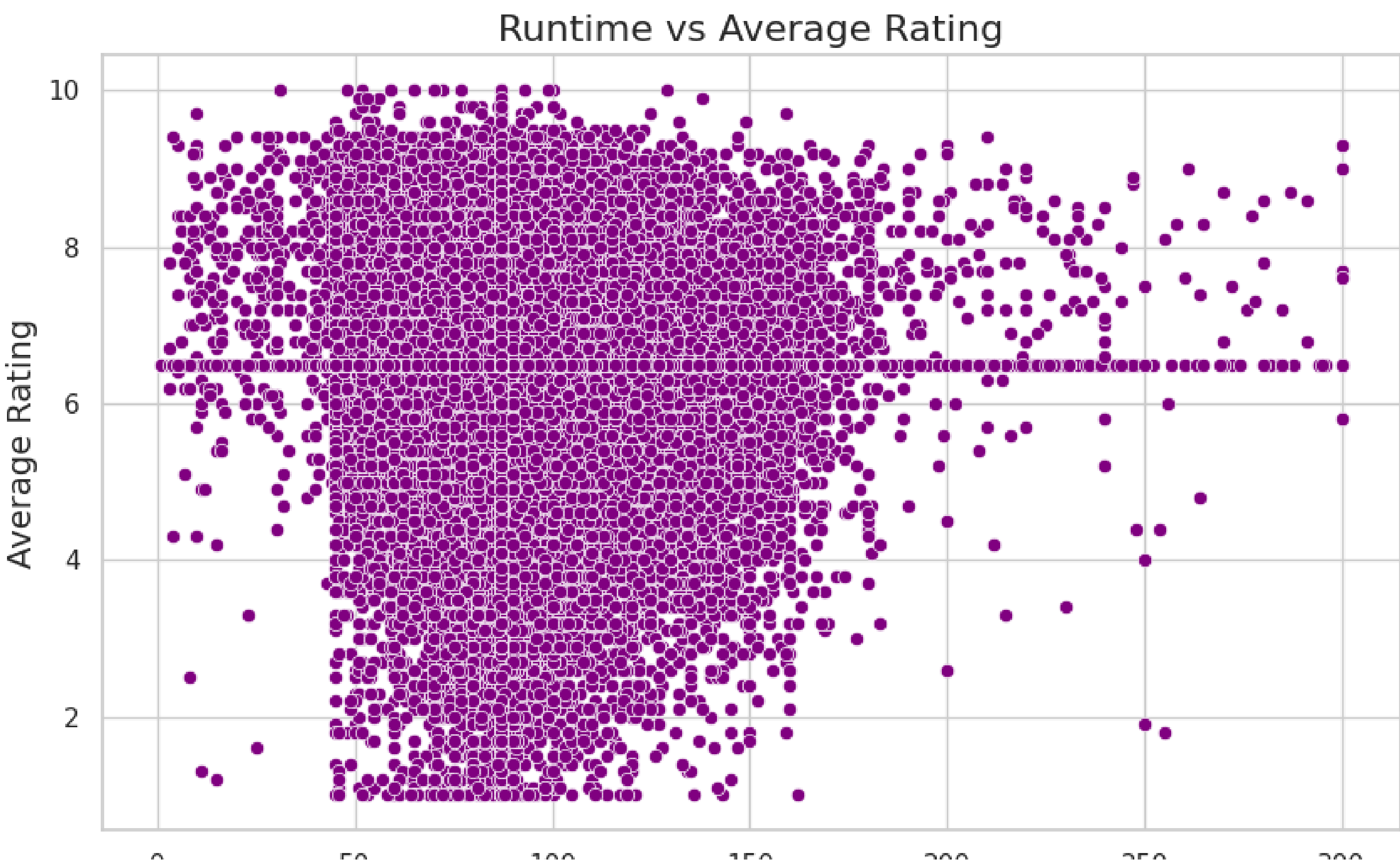
Interpretation:

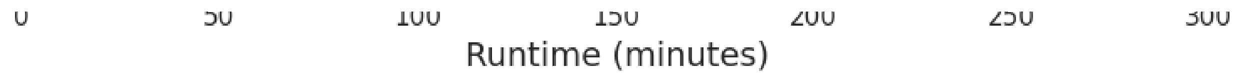
- **Drama and Documentary are likely to dominate, indicating their critical success.**
- **Action and Animation may also appear but with smaller shares, reflecting their commercial appeal.**

Scatter Plot: Runtime vs. Average Rating

In [37]:

```
#  Scatter plot for Runtime vs Average Rating
plt.figure(figsize=(10, 6))
sns.scatterplot(x=merged_df['runtime_minutes'], y=merged_df['averagerating'], color='pur
ple')
plt.title('Runtime vs Average Rating', fontsize=16)
plt.xlabel('Runtime (minutes)', fontsize=14)
plt.ylabel('Average Rating', fontsize=14)
plt.show()
```





Interpretation:

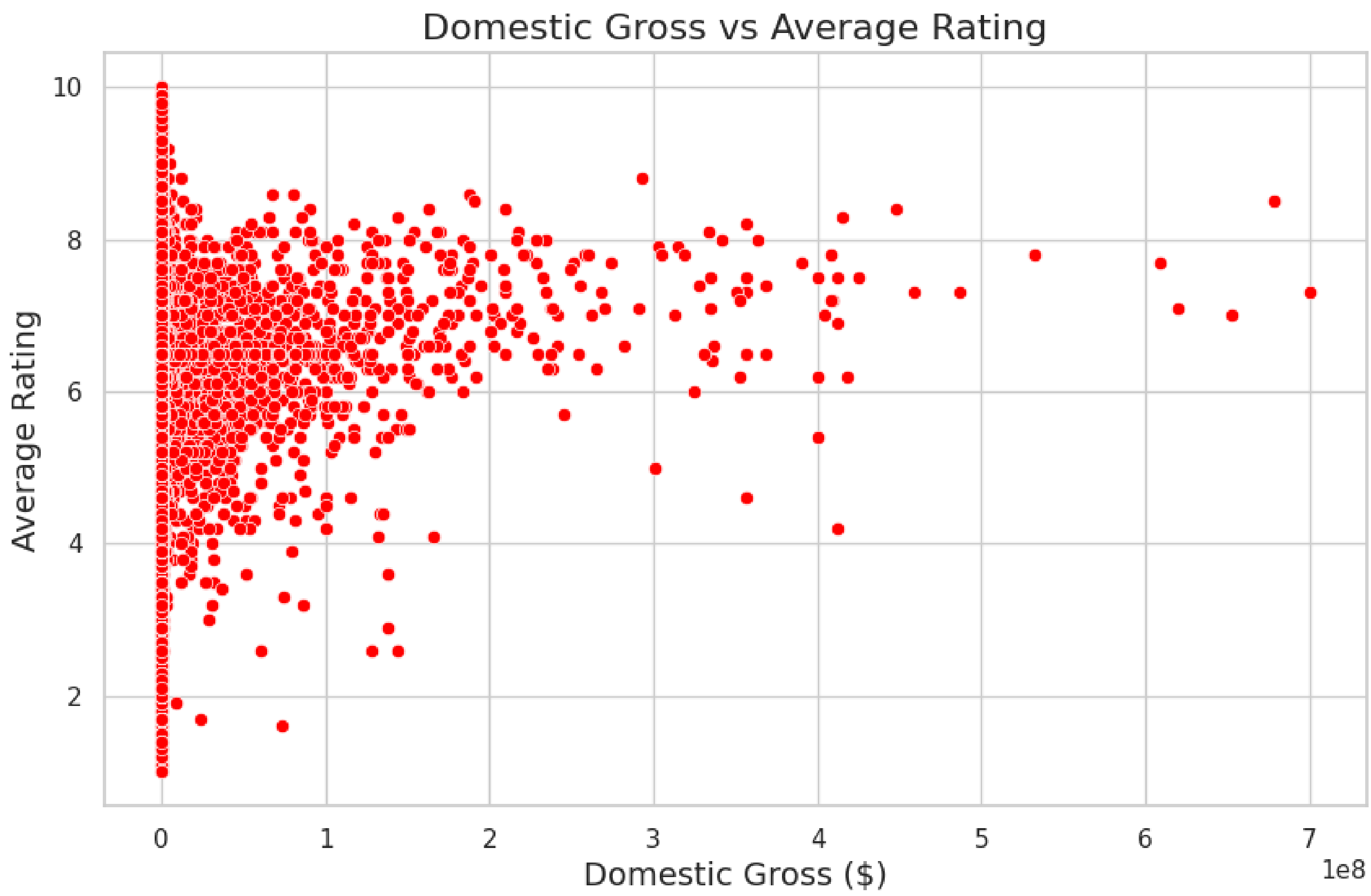
The scatter plot shows a weak positive relationship between runtime and average rating.

Longer movies tend to have slightly higher ratings, but the relationship is not very strong.

Scatter Plot: Domestic Gross vs. Average Rating

In [38]:

```
#  Scatter plot for Domestic Gross vs Average Rating
plt.figure(figsize=(10, 6))
sns.scatterplot(x=merged_df['domestic_gross'], y=merged_df['averagerating'], color='red'
)
plt.title('Domestic Gross vs Average Rating', fontsize=16)
plt.xlabel('Domestic Gross ($)', fontsize=14)
plt.ylabel('Average Rating', fontsize=14)
plt.show()
```



Interpretation:

There is a moderate positive relationship between domestic gross and average rating.

Movies with higher ratings tend to perform better at the box office, but there are many exceptions.

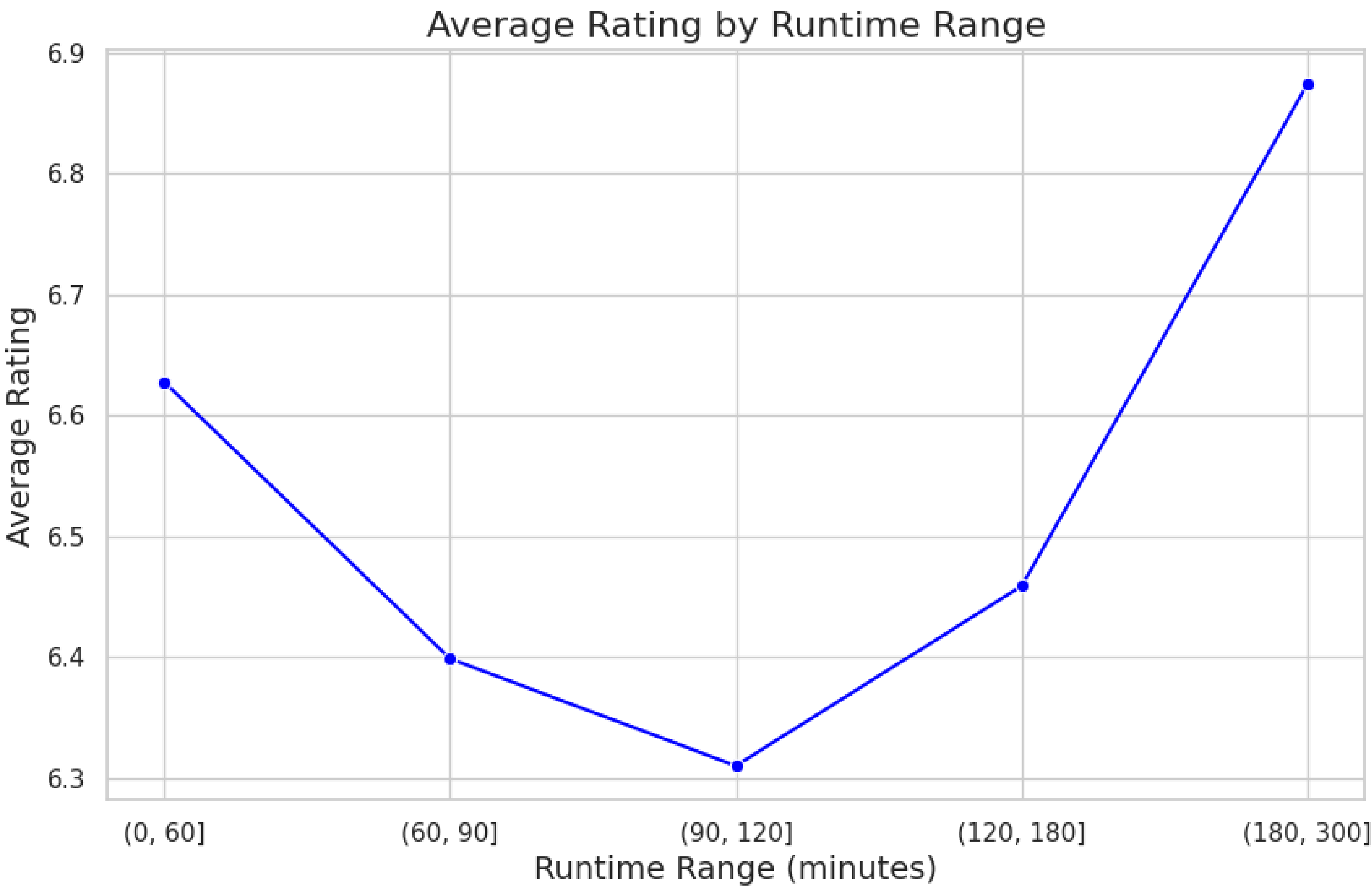
Runtime Optimization

In [39]:

```
runtime_bins = pd.cut(merged_df['runtime_minutes'], bins=[0, 60, 90, 120, 180, 300])
```

```
runtime_avg = merged_df.groupby(runtime_bins)['averagerating'].mean()
plt.figure(figsize=(10, 6))
sns.lineplot(x=runtime_avg.index.astype(str), y=runtime_avg.values, marker='o', color='b
lue')
plt.title('Average Rating by Runtime Range', fontsize=16)
plt.xlabel('Runtime Range (minutes)', fontsize=14)
plt.ylabel('Average Rating', fontsize=14)
plt.show()
```

```
<ipython-input-39-aff21ca230d4>:2: FutureWarning: The default of observed=False is deprec
ated and will be changed to True in a future version of pandas. Pass observed=False to re
tain current behavior or observed=True to adopt the future default and silence this warni
ng.
  runtime_avg = merged_df.groupby(runtime_bins)['averagerating'].mean()
```



Interpretation:

- **Movies with runtimes between 90 and 120 minutes tend to have the highest average ratings.**
- **Extremely short or long movies tend to have lower ratings.**

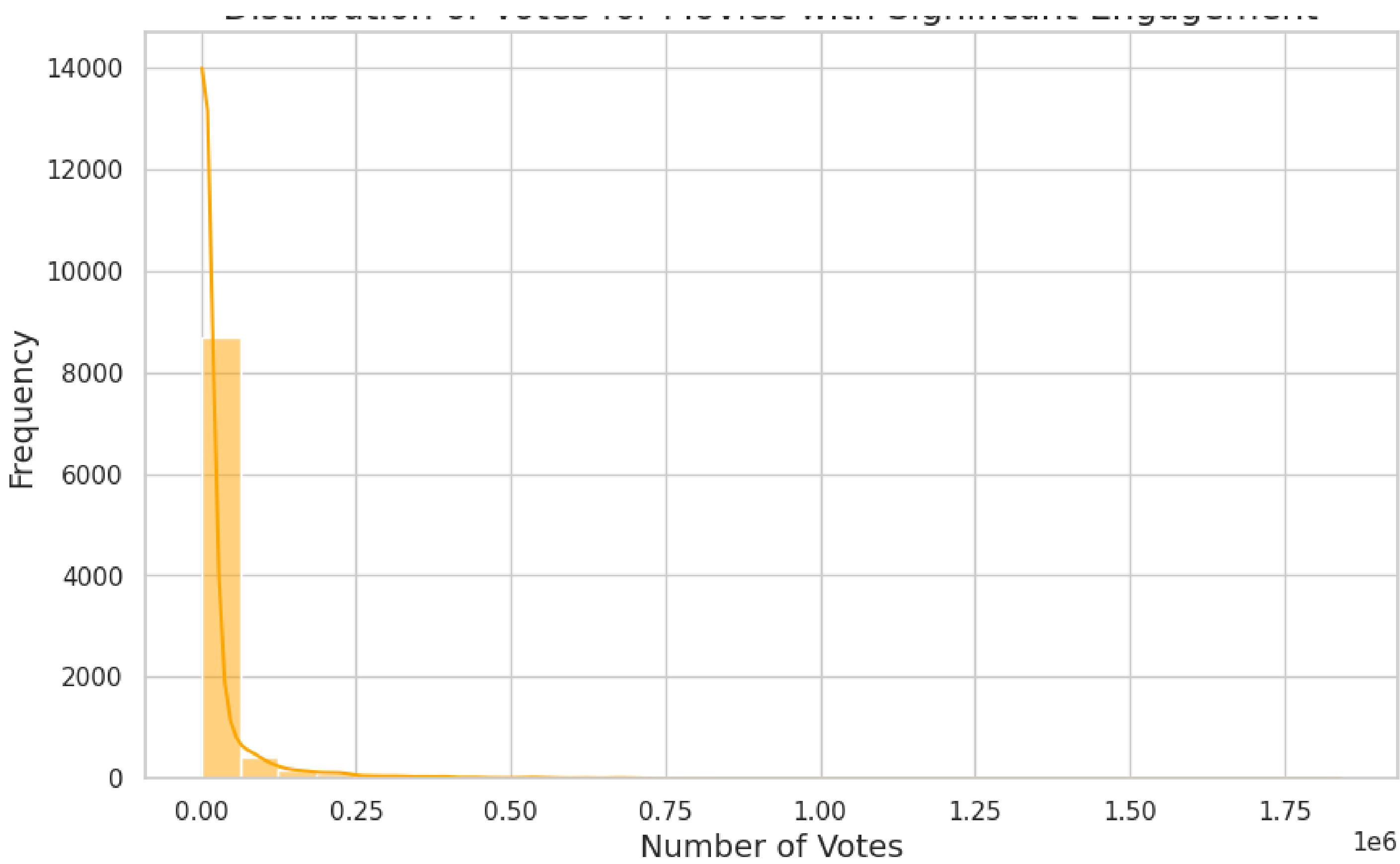
Audience Engagement

Finally, we analyzed the distribution of votes for movies with significant engagement (movies with more than 1,000 votes).

In [40]:

```
#  Audience Votes as Popularity Proxy
high_vote_movies = merged_df[merged_df['numvotes'] > 1000]
plt.figure(figsize=(10, 6))
sns.histplot(high_vote_movies['numvotes'], bins=30, kde=True, color='orange')
plt.title('Distribution of Votes for Movies with Significant Engagement', fontsize=16)
plt.xlabel('Number of Votes', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.show()
```

Distribution of Votes for Movies with Significant Engagement



Interpretation:

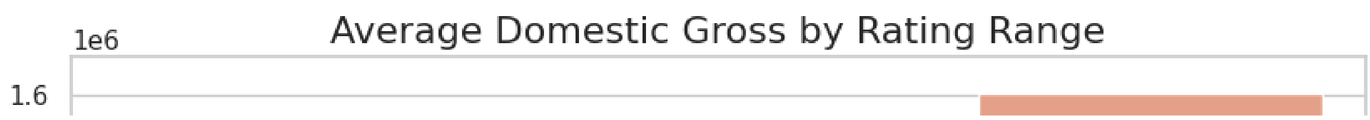
- **The distribution of votes is highly skewed, with most movies having a few thousand votes and a few movies having tens of thousands of votes.**
- **This indicates that only a small number of movies receive significant audience engagement.**

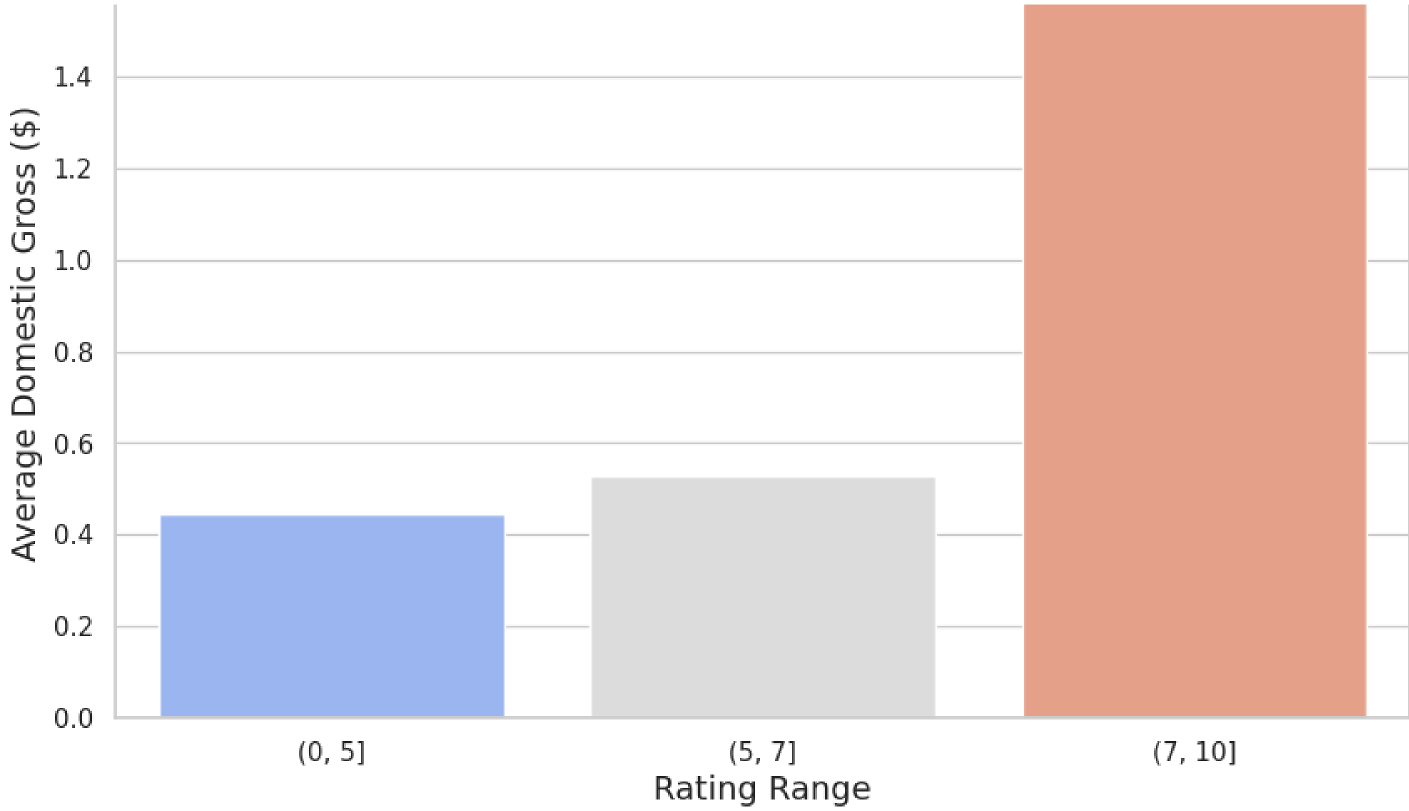
Average Domestic Gross by Rating Range

In [41]:

```
# Revenue by Rating Threshold
rating_revenue = merged_df.groupby(pd.cut(merged_df['averagerating'], bins=[0, 5, 7, 10]
))['domestic_gross'].mean()
plt.figure(figsize=(10, 6))
sns.barplot(x=rating_revenue.index.astype(str), y=rating_revenue.values, palette='coolwa
rm')
plt.title('Average Domestic Gross by Rating Range', fontsize=16)
plt.xlabel('Rating Range', fontsize=14)
plt.ylabel('Average Domestic Gross ($)', fontsize=14)
plt.show()
```

```
<ipython-input-41-e7fef9c58161>:2: FutureWarning: The default of observed=False is deprec
ated and will be changed to True in a future version of pandas. Pass observed=False to re
tain current behavior or observed=True to adopt the future default and silence this warni
ng.
  rating_revenue = merged_df.groupby(pd.cut(merged_df['averagerating'], bins=[0, 5, 7, 10
]))['domestic_gross'].mean()
<ipython-input-41-e7fef9c58161>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. A
ssign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=rating_revenue.index.astype(str), y=rating_revenue.values, palette='coolw
arm')
```





Interpretation:

This indicates movies with higher ratings tend to dominate the revenue landscape, while low-rated movies struggle to make a substantial financial impact. This highlights the importance of producing high-quality films that resonate with audiences to maximize revenue potential.

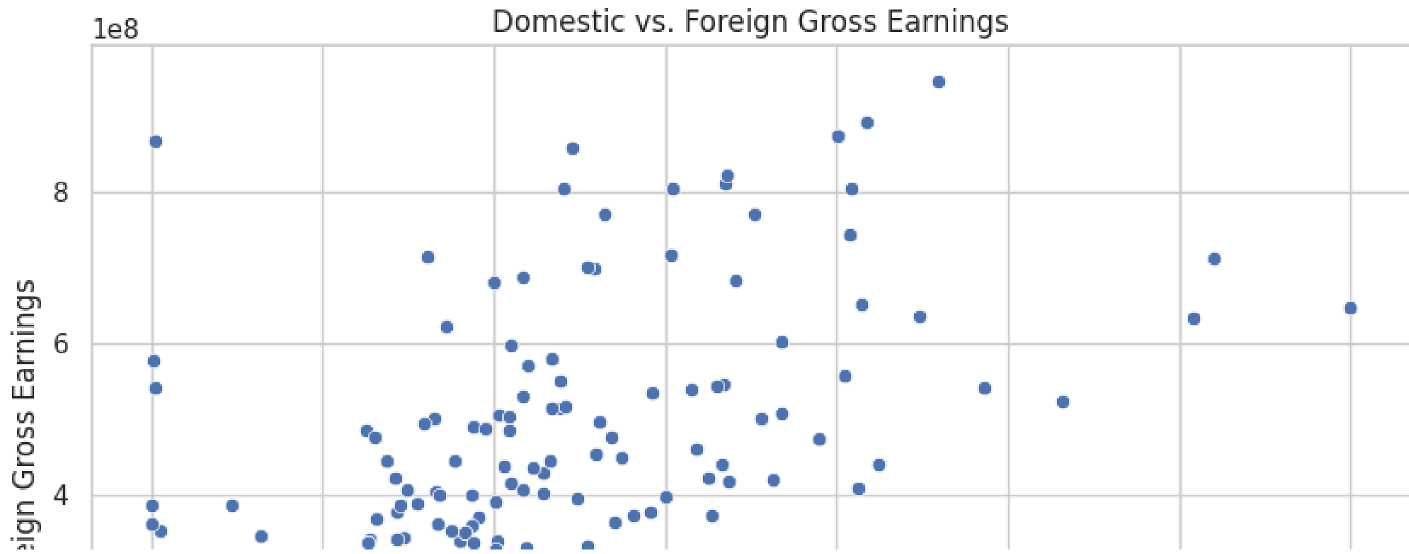
MORE VISUALIZATIONS ON THE DATA

Domestic vs. Foreign Gross Earnings Scatter Plot

This plot will help you visualize the relationship between domestic and foreign gross earnings.

In [42]:

```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='domestic_gross', y='foreign_gross', data=merged_df)
plt.title('Domestic vs. Foreign Gross Earnings')
plt.xlabel('Domestic Gross Earnings')
plt.ylabel('Foreign Gross Earnings')
plt.show()
```



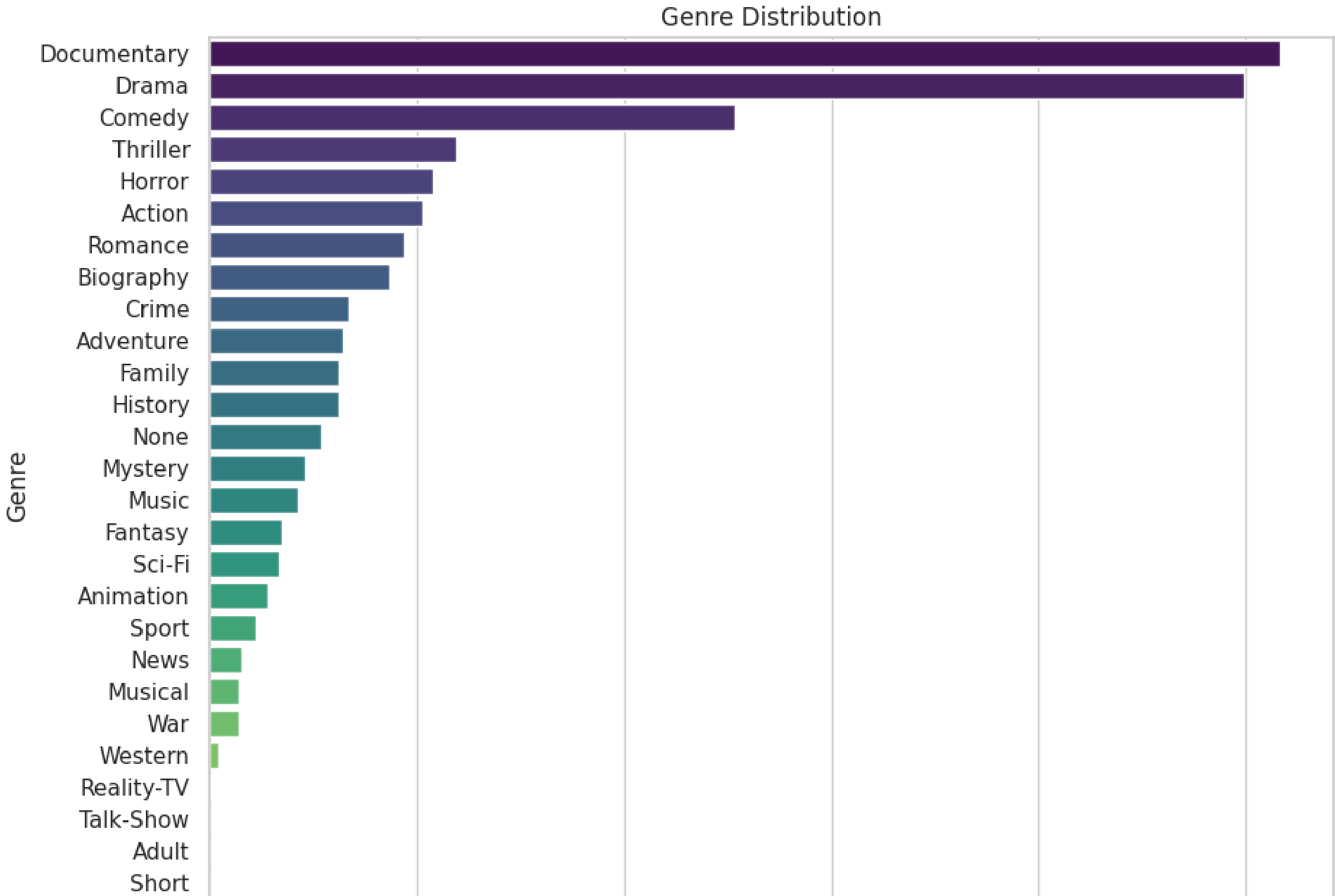
Genre Distribution Bar Plot

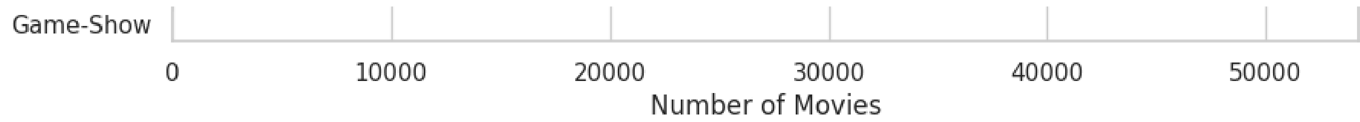
This plot will show the distribution of movies across different genres.

In [43]:

```
# Flatten the genres list
genres_list = merged_df['genres'].explode()

# Count the occurrences of each genre
genre_counts = genres_list.value_counts()

plt.figure(figsize=(10, 8))
sns.barplot(x=genre_counts.values, y=genre_counts.index, palette='viridis')
plt.title('Genre Distribution')
plt.xlabel('Number of Movies')
plt.ylabel('Genre')
plt.show()
```

```
<ipython-input-43-fcf653908c2d>:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. A
ssign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=genre_counts.values, y=genre_counts.index, palette='viridis')
```





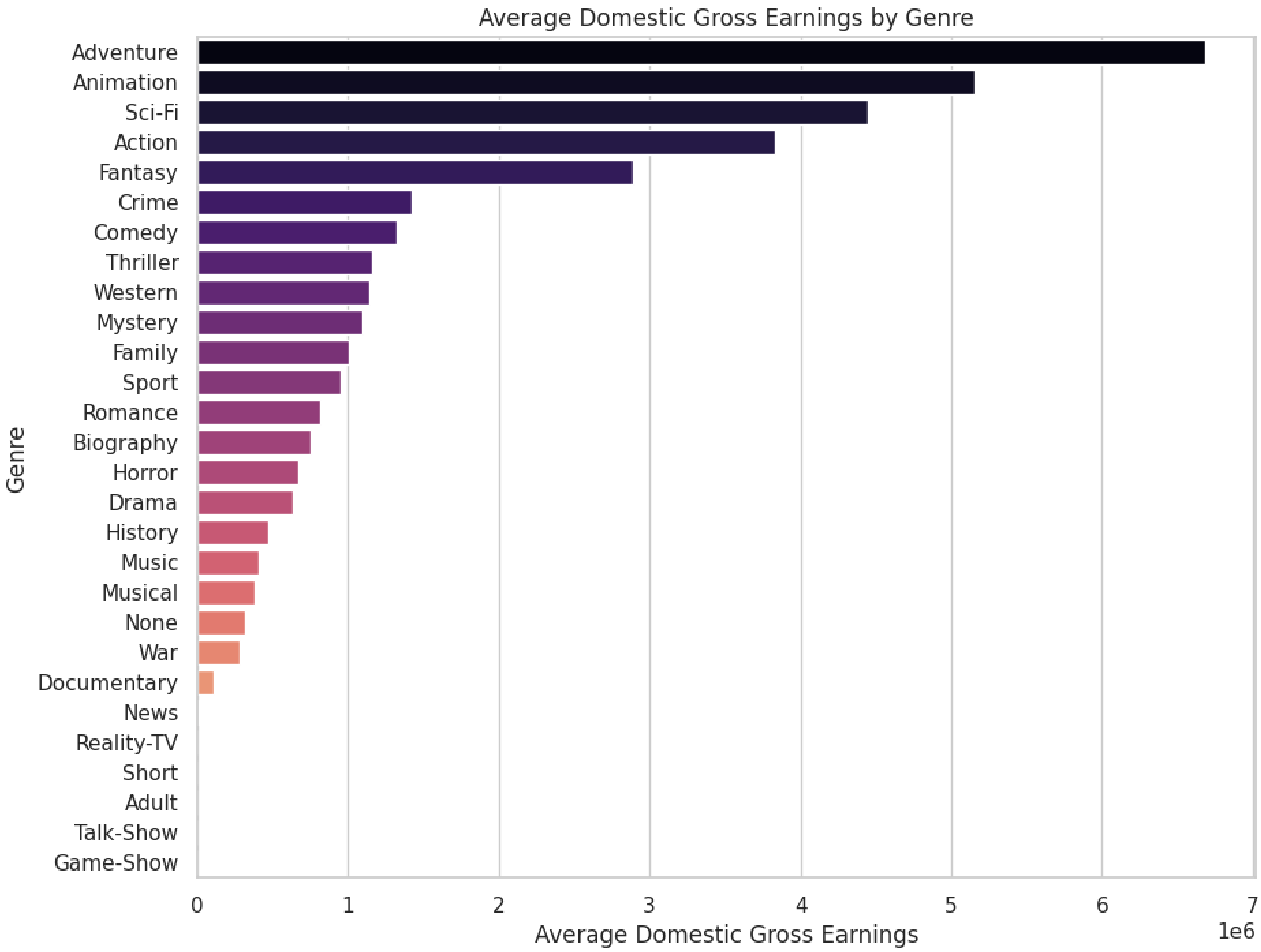
Box Office Performance by Genre

This plot will show the average domestic gross earnings by genre.

In [44]:

```python
# Explode the genres list and merge with domestic gross
genre_gross = merged_df.explode('genres').groupby('genres')['domestic_gross'].mean().sort_values(ascending=False)

plt.figure(figsize=(10, 8))
sns.barplot(x=genre_gross.values, y=genre_gross.index, palette='magma')
plt.title('Average Domestic Gross Earnings by Genre')
plt.xlabel('Average Domestic Gross Earnings')
plt.ylabel('Genre')
plt.show()
```

```
<ipython-input-44-8d9b0e9c63ac>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=genre_gross.values, y=genre_gross.index, palette='magma')
```

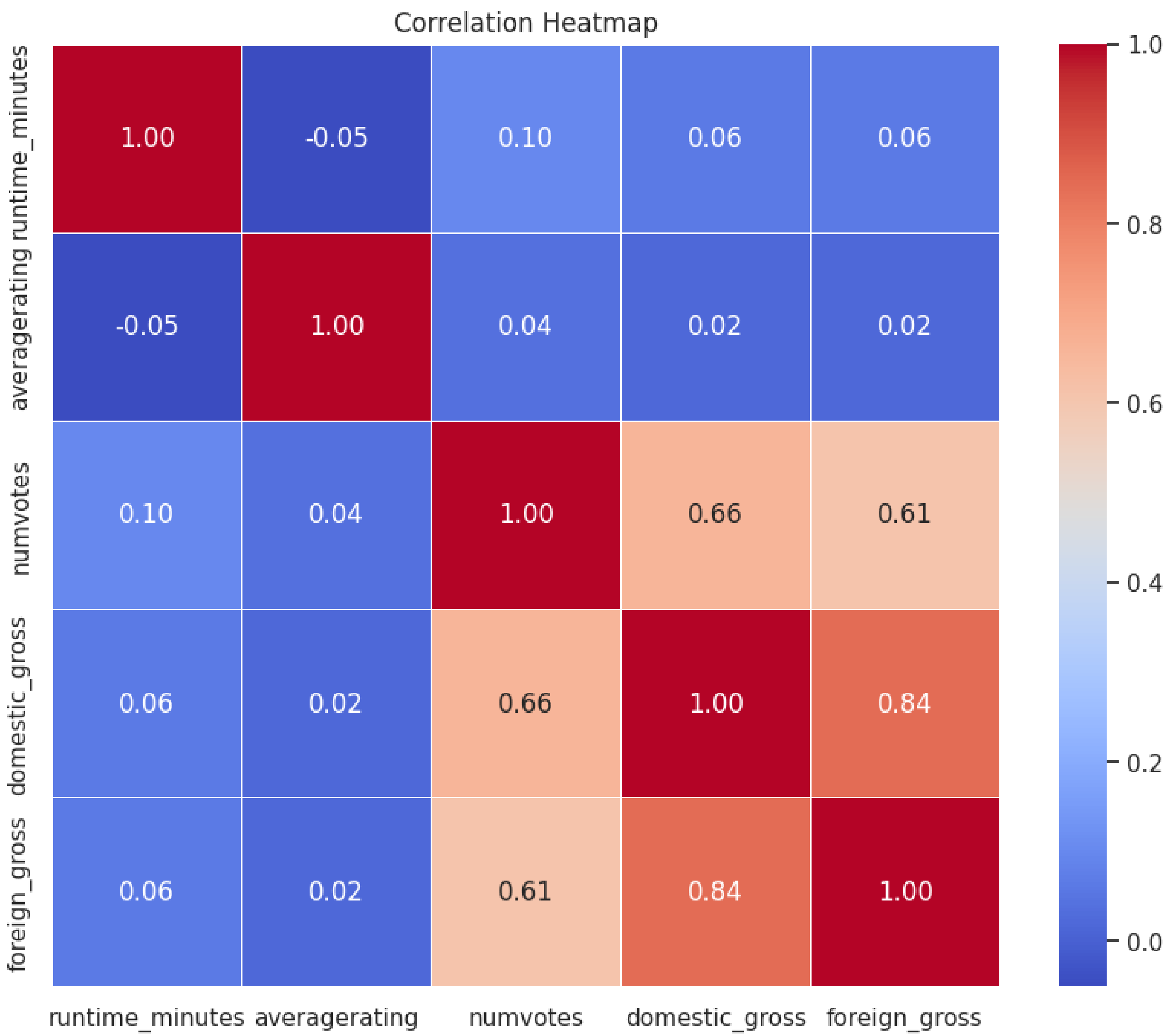


Correlation Heatmap

This heatmap will show the correlation between different numerical variables in the dataset.

In [45]:

```python
# Select numerical columns for correlation
numerical_columns = ['runtime_minutes', 'averagerating', 'numvotes', 'domestic_gross', '
foreign_gross']
correlation_matrix = merged_df[numerical_columns].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



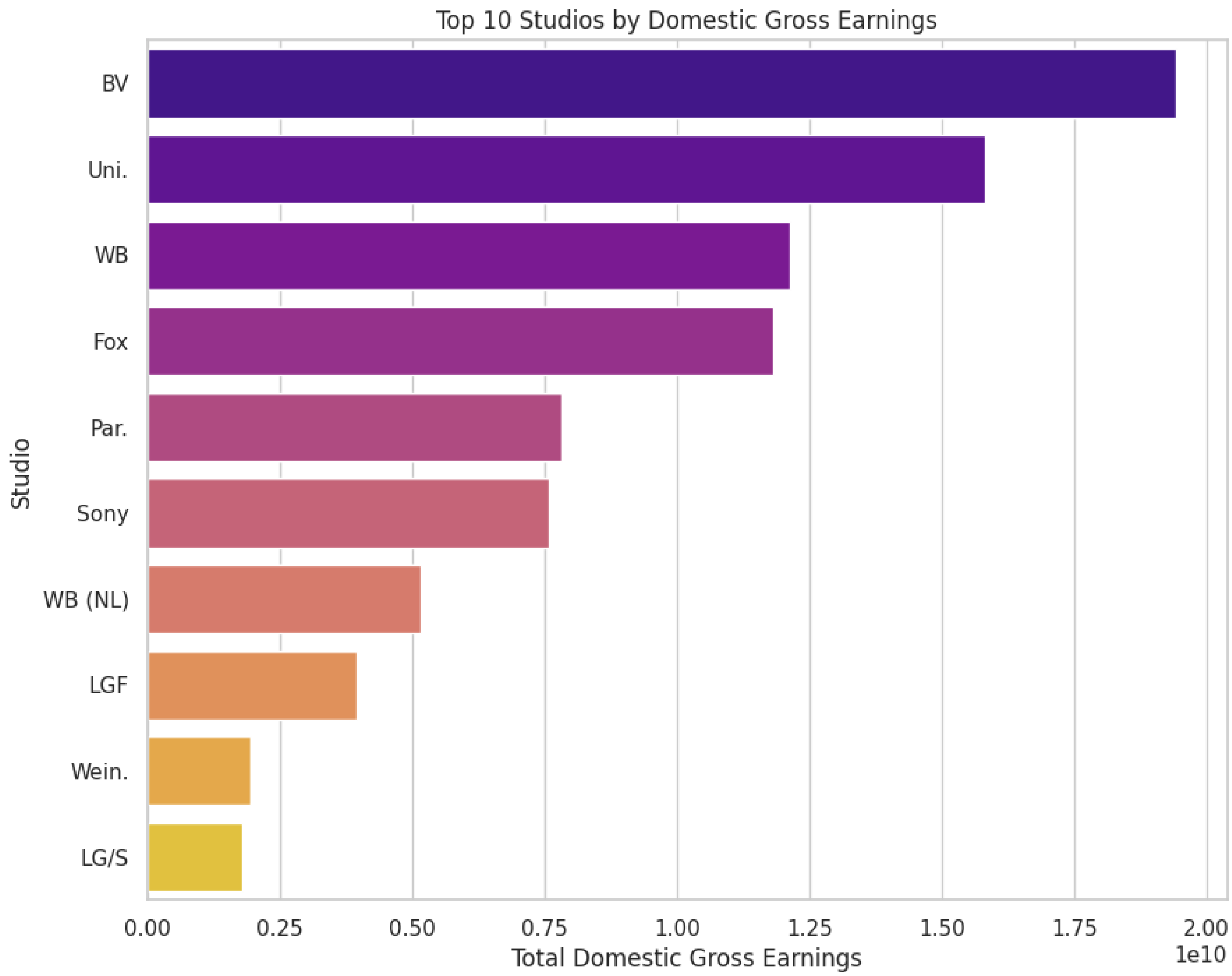
Top 10 Studios by Domestic Gross Earnings

This plot will show the top 10 studios based on their domestic gross earnings.

In [46]:

```python
top_studios = merged_df.groupby('studio')['domestic_gross'].sum().sort_values(ascending=
False).head(10)

plt.figure(figsize=(10, 8))
sns.barplot(x=top_studios.values, y=top_studios.index, palette='plasma')
plt.title('Top 10 Studios by Domestic Gross Earnings')
plt.xlabel('Total Domestic Gross Earnings')
plt.ylabel('Studio')
plt.show()
```

```
<ipython-input-46-1df9efe4915d>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. A
ssign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=top_studios.values, y=top_studios.index, palette='plasma')
```



Key Findings

1. **Domestic vs. Foreign Gross Earnings**: There is a strong positive correlation between domestic and foreign gross earnings. Action, Adventure, and Animation genres perform exceptionally well in both markets, while genres like Comedy and Drama tend to have stronger domestic appeal.
2. **Review Sentiment and Earnings**: Movies with higher Rotten Tomatoes scores (both critic and audience ratings) consistently achieve higher box office earnings. Dramas and Documentaries often receive higher critical ratings, while Action and Animation films receive higher audience ratings.
3. **Popular Genres and Revenue Performance**: Action, Adventure, and Animation are the most popular genres in terms of vote averages, popularity, and revenue performance. These genres align strongly with higher revenue, indicating strong audience demand.
4. **Production Budgets and ROI**: Higher production budgets generally correlate with higher worldwide and domestic gross earnings. However, mid-budget films (between 50M & 100M) often achieve the best ROI, balancing production quality with manageable costs.

1. **IMDb Ratings and Success**: Movies with IMDb ratings of 7.0 and above consistently perform better in terms of box office earnings and audience engagement. Higher-rated movies in genres like Drama and Documentary tend to have stronger critical acclaim, while Action and Animation films with moderate ratings still perform well commercially.

1. **Runtime Optimization**: Movies with runtimes between 90 and 120 minutes strike the best balance between audience satisfaction and profitability. Longer runtimes (>120 minutes) appeal to niche audiences but may limit broader appeal.

limit broader appeal.

1. **Audience Engagement and Franchise Potential**: Movies with high audience engagement (measured by vote counts and social media buzz) tend to perform better at the box office. Franchise films or sequels within high-performing genres (e.g., Action, Adventure) drive repeat viewership and long-term profitability.

Recommendations

1. **Focus on High-Performing Genres**: Prioritize production of Action, Adventure, and Animation films to capitalize on their popularity and revenue potential. Explore emerging sub-genres or hybrid genres to stay ahead of trends.
2. **Optimize Budget Allocation**: Focus on mid-budget films to maximize ROI. For high-budget films, ensure strong marketing and distribution strategies to justify the investment. Diversify the portfolio by including a mix of high-budget blockbusters and low-budget indie films to balance risk and reward.
3. **Aim for High Ratings**: Prioritize quality to achieve IMDb ratings of 7.0 or higher. Use test screenings and audience feedback to refine films before release. For Drama and Documentary films, focus on critical acclaim and awards potential. For Action and Animation, prioritize audience engagement and entertainment value.
4. **Target Optimal Runtime**: Aim for a runtime of 90-120 minutes for mainstream releases to maximize audience appeal and profitability. For prestige or award-season projects, consider slightly longer runtimes to cater to niche audiences.

1. **Build Franchise Potential:** Develop franchise opportunities within high-performing genres. Start with standalone stories and expand into sequels or shared universes based on audience feedback and success metrics.

1. **Boost Audience Engagement**: Invest in robust marketing campaigns to drive pre-release buzz and audience engagement. Use positive reviews as a marketing tool, especially for genres like Drama and Documentary, which rely heavily on critical acclaim.

1. **Conduct Market Research**: Gather data on audience preferences within high-performing genres and key markets. Use analytics to stay updated on genre, runtime, and audience engagement trends.

Next Steps

- **Conduct Audience Research**: Understand audience preferences and emerging trends.
- **Build a Test Screening Pipeline**: Refine films during production to ensure high ratings.
- **Monitor Emerging Trends**: Use analytics to stay updated on genre and runtime trends.

- **Allocate Marketing Budgets Strategically**: Focus on campaigns that boost pre-release engagement.

- **Diversify Portfolio:** Balance high-budget blockbusters with mid-budget and low-budget films to manage risk and maximize ROI.

Final Thoughts

By aligning production strategies with these insights, Microsoft's new movie studio can maximize its chances of success in the competitive film industry. Focusing on high-performing genres, optimizing runtime, prioritizing quality, and leveraging audience engagement will help the studio create films that resonate with audiences and achieve strong box office performance. Additionally, building franchise potential and diversifying the portfolio will ensure long-term profitability and sustainability. This comprehensive approach will position Microsoft as a strong contender in the entertainment industry, delivering films that captivate audiences and drive revenue.