Movie Dataset Analysis

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1. Introduction

Project Description

This project explores a movie dataset that consists of three interconnected tables: **Movies**, **Financial**, and **Audience**.

The goal is to gain insights into various aspects of movies, such as:

- **Duration**
- **Release date**
- **Production company**
- **Financial performance** (revenue, budget, net profit)
- **Audience reception** (votes, popularity)

By analyzing this dataset, we aim to uncover **patterns**, **correlations**, and **trends** that can help in understanding the success factors of movies.

Table Descriptions

1. Movies Table

Contains general details about movies.

- **Id (Primary Key):** Unique identifier for each movie
- **Name:** Title of the movie
- **Duration:** Length of the movie (in minutes)
- **ReleaseDate:** The release date of the movie
- **Actors:** List of actors in the movie
- **ProductionCompany:** Name of the production company
- **Recency:** A measure of how recent the movie is
- **genres:** Kind of the film

2. Financial Table

Contains financial performance data for each movie.

- **Id (Foreign Key):** Links to the Movies table
- **Revenue:** Total revenue generated by the movie
- **Budget:** Total budget allocated to the movie
- **NetProfit:** Calculated as `Revenue - Budget`

3. Audience Table

Contains audience reception and engagement metrics for each movie.

- **Id (Foreign Key):** Links to the Movies table
- **Votes:** Total votes received for the movie

- **VoteCount:** Number of individual vote submissions
- **Popularity:** A score indicating the movie's popularity

2. Importing Required Libraries

In [10]:
```
import os
from IPython.display import display, HTML
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

3. Checking if the dataset is available

In [12]:
```
db_path = r"C:\Users\ehabh\Desktop\new_movies.db"
print(os.path.exists(db_path))  # Should print True if the file exists
```

```
True
```

4. Connectig to the database and showiing the tables

In [14]:
```
# Path to the database
db_path = r"C:\Users\ehabh\Desktop\new_movies.db"

# Establish connection to the database
conn = sqlite3.connect(db_path)

# List of table names
tables = ['Movie', 'Financial', 'Audience']

# Fetch and display data for each table
print("\n")
for table in tables:
    display(HTML(f"<h2 style='color: #1f4e78;'>Showing data from {table} table:</h2>
    query = f"SELECT * FROM {table} LIMIT 10;"  # Adjust the number of rows as neede
    df = pd.read_sql(query, conn)
    display(df)  # In Jupyter Notebook, use display to show data in a more readable
    print("\n")  # Adding a newline for better separation between tables
```

Showing data from Movie table:

	id	Title	runtime	release_date	Actors	production_companies	recency	genr
0	5	Four Rooms	98.0	1995-12-09	Tim Roth-Jennifer Beals-Antonio Banderas-Valer...	Miramax-A Band Apart	19382	Crim Come
1	6	Judgment Night	96.0	1993-10-15	Emilio Estevez-Cuba Gooding Jr.-Denis Leary-St...	JVC-Largo Entertainment	20167	Actio Crim Thril
2	11	Star Wars	121.0	1977-05-25	Mark Hamill-Harrison Ford-Carrie Fisher-Peter ...	Lucasfilm-20th Century Fox	26154	Adventur Actio Scien Ficti
3	12	Finding Nemo	100.0	2003-05-30	Albert Brooks-Ellen DeGeneres-Alexander Gould-...	Pixar	16653	Animatio Fam
4	13	Forrest Gump	142.0	1994-06-23	Tom Hanks-Robin Wright-Gary Sinise-Sally Field...	Paramount-The Steve Tisch Company-Wendy Finerm...	19916	Comec Dram Roman
5	14	American Beauty	69.0	1999-09-15	Kevin Spacey-Annette Bening-Thora Birch-Wes Be...	Jinks/Cohen Company-DreamWorks Pictures	18006	Drar
6	15	Citizen Kane	119.0	1941-04-17	Orson Welles-Joseph Cotten-Dorothy Comingore-R...	Mercury Productions-RKO Radio Pictures	39341	Myster Drar
7	16	Dancer in the Dark	141.0	2000-06-30	Björk-Catherine Deneuve-David Morse-Peter Stor...	Fine Line Features-WDR-Constantin Film-Zentrop...	17717	Dram Crir
8	18	The Fifth Element	126.0	1997-05-02	Bruce Willis-Milla Jovovich-Gary	Gaumont-Buena Vista International-Columbia Pic...	18872	Adventur Fantas Actio Thrille

	id	Title	runtime	release_date	Actors	production_companies	recency	genr
					Oldman-Ian Ho...			Scien Ficti
9	20	My Life Without Me	106.0	2003-03-07	Sarah Polley-Amanda Plummer-Scott Speedman-Mar...	El Deseo-Milestone Productions	16737	Dram Roman

Showing data from Financial table:

	id	revenue	budget	netprofit
0	5	4257354.0	4000000.0	2.573540e+05
1	6	6068469.0	10500000.0	-4.431531e+06
2	11	775398007.0	11000000.0	7.643980e+08
3	12	940335536.0	94000000.0	8.463355e+08
4	13	677387716.0	55000000.0	6.223877e+08
5	14	118765533.66666667	5000000.0	1.137655e+08
6	15	23218000.0	839727.0	2.237827e+07
7	16	40031879.0	12800000.0	2.723188e+07
8	18	263920180.0	90000000.0	1.739202e+08
9	20	12300000.0	2500000.0	9.800000e+06

Showing data from Audience table:

	id	votes	vote_count	popularity
0	5	5.7	2288.0	41.855
1	6	3.8	138.0	5.3125
2	11	8.2	18331.0	96.126
3	12	7.823	17612.0	73.866
4	13	8.48	24667.0	63.502
5	14	2.677	3613.6666666666665	9.770666666666667
6	15	8.022	4775.0	19.9
7	16	7.9	1513.0	17.53
8	18	7.5	9524.0	53.821
9	20	5.852	392.0	32.575

5. Questions and Queries and vesualization for it

5.1. What is the average number of votes for the top 25% most profitable movies?

Relationship Between Profitability and Audience Votes

This analysis investigates the relationship between **profitability** and **audience votes** by calculating the **average number of votes** received by movies in the **top 25% of net profit**.

In [18]:
```
# SQL query to join Audience and Financial tables and select relevant columns
query_1 = """
select a.Votes, a.Popularity, f.NetProfit
from Audience a
join Financial f on a.Id = f.Id;
"""

# Execute the query and store the result in a DataFrame
result_1 = pd.read_sql_query(query_1, conn)
display(result_1)

# Describe the dataset to get statistical summaries
description = result_1.describe()
display(description)

# Calculate the 75th percentile of the 'NetProfit' column
profit_75th = result_1['netprofit'].quantile(0.75)

# Filter the top 25% of movies based on NetProfit
top_25 = result_1[result_1['netprofit'] >= profit_75th]
display(top_25.head())

# Convert 'votes' column to numeric, coercing errors to NaN
top_25.loc[:, 'votes'] = pd.to_numeric(top_25['votes'], errors='coerce')

# Calculate the average number of votes for the top 25% of movies
avg_Votes_top_25 = top_25['votes'].mean()
print(avg_Votes_top_25)
```

	votes	popularity	netprofit
0	5.7	41.855	2.573540e+05
1	3.8	5.3125	-4.431531e+06
2	8.2	96.126	7.643980e+08
3	7.823	73.866	8.463355e+08
4	8.48	63.502	6.223877e+08
...	...	...	...
9277	1.7333333333333334	1.8236666666666668	-9.567989e+04
9278	9.0	0.666	2.750000e+03
9279	3.0	0.8062499999999999	-8.152500e+02
9280	3.85	9.344000000000001	3.565306e+06
9281	3.2875	2.206625	3.775480e+05

9282 rows × 3 columns

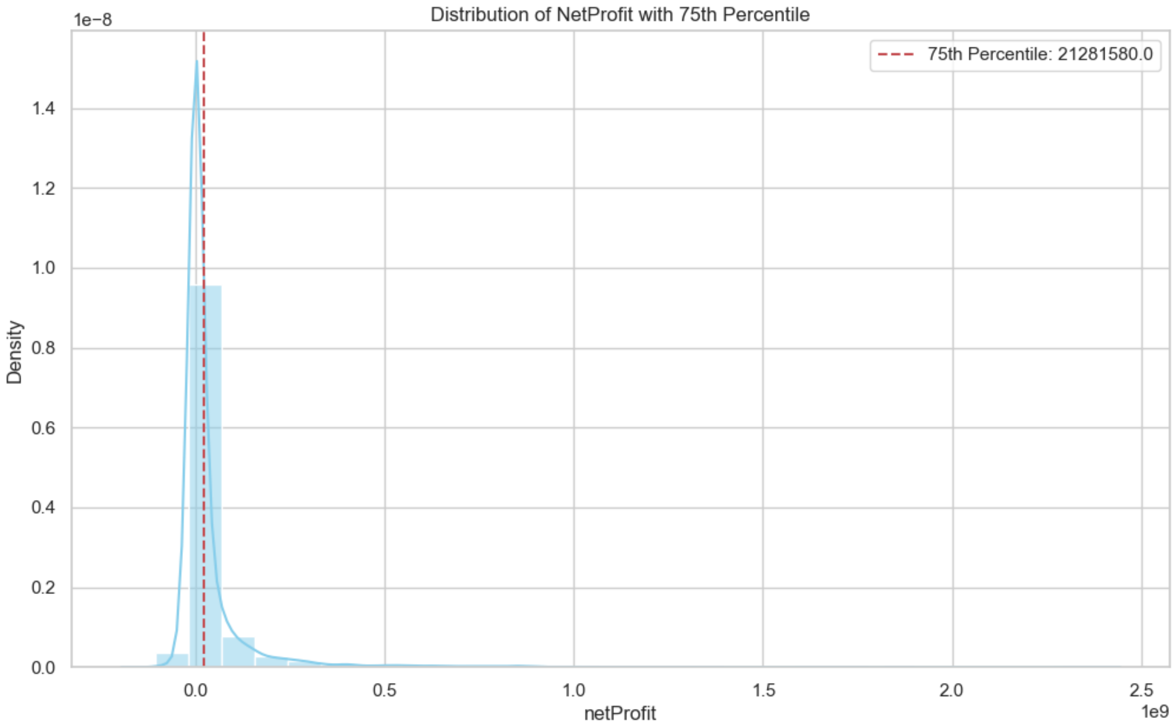
	netprofit
count	9.282000e+03
mean	3.470107e+07
std	1.151217e+08
min	-1.947758e+08
25%	-6.407245e+05
50%	1.485000e+06
75%	2.128158e+07
max	2.443439e+09

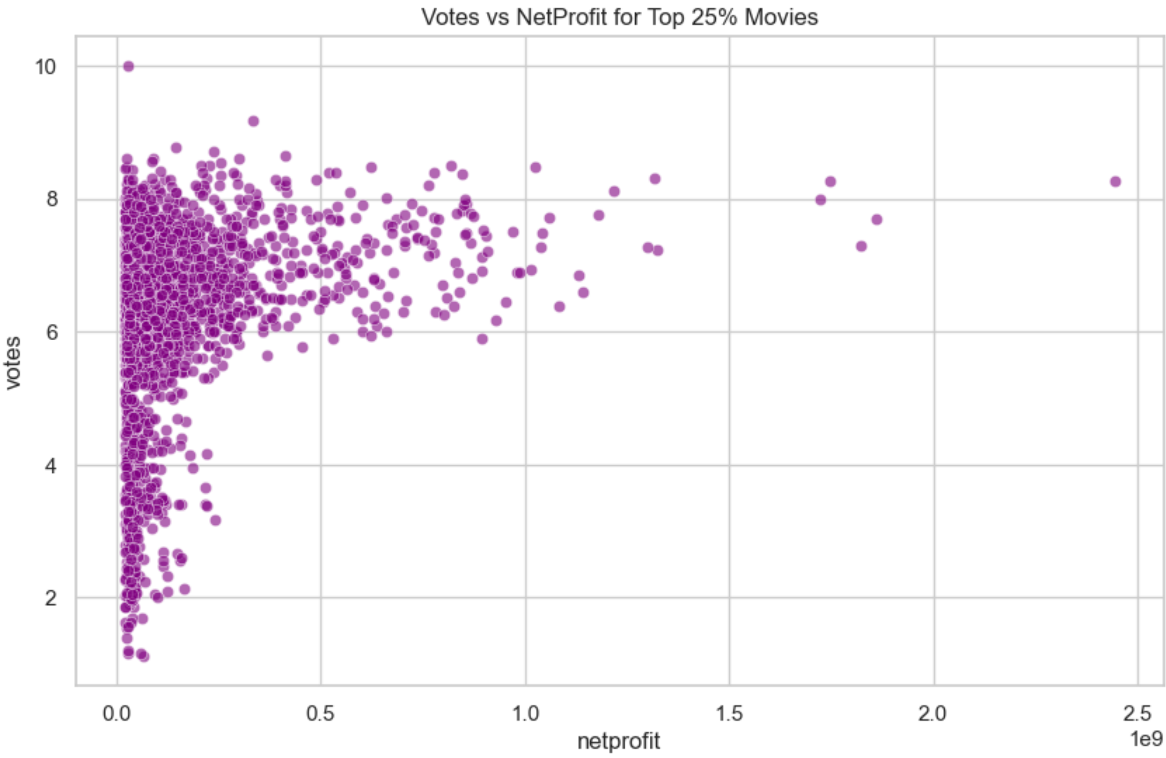
	votes	popularity	netprofit
2	8.2	96.126	7.643980e+08
3	7.823	73.866	8.463355e+08
4	8.48	63.502	6.223877e+08
5	2.677	9.770666666666667	1.137655e+08
6	8.022	19.9	2.237827e+07

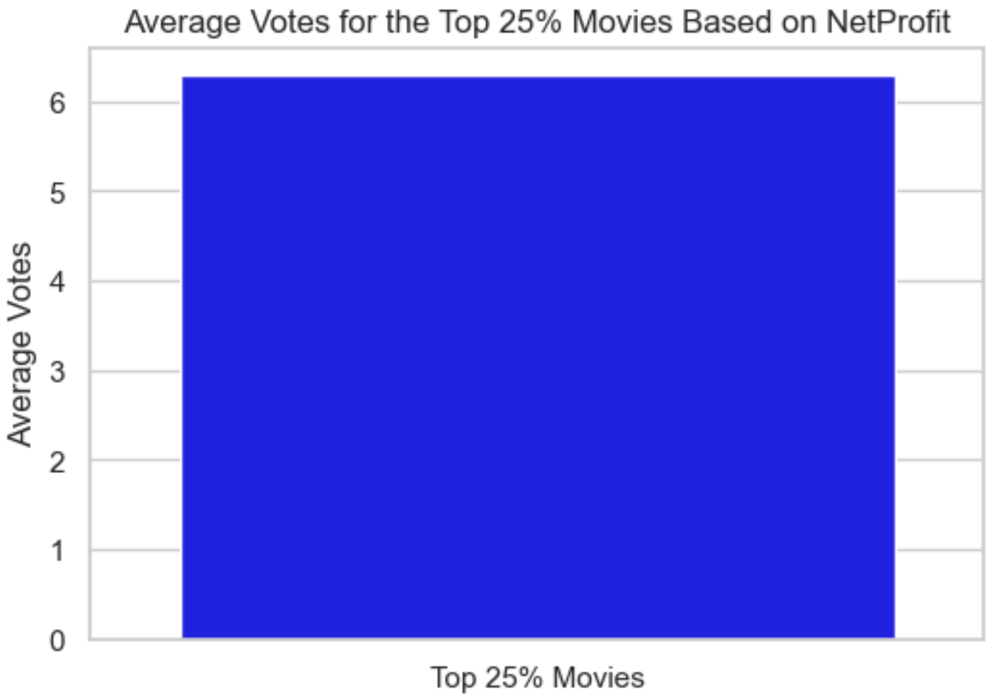
```
6.284805198574009
```

In [19]:
```
# Set the style for the plots
sns.set(style="whitegrid")

# Plot 1: Distribution of 'NetProfit' with the 75th percentile line
plt.figure(figsize=(12, 7))
sns.histplot(result_1['netprofit'], kde=True, bins=30, color='skyblue', stat='densit
plt.axvline(profit_75th, color='r', linestyle='--', label=f'75th Percentile: {profit
plt.title('Distribution of NetProfit with 75th Percentile')
```

```
plt.xlabel('netProfit')
plt.ylabel('Density')
plt.legend()
plt.show()

# Plot 2: Scatter plot of Votes vs NetProfit for Top 25% movies
plt.figure(figsize=(10, 6))
sns.scatterplot(data=top_25, x='netprofit', y='votes', color='purple', alpha=0.6)
plt.title('Votes vs NetProfit for Top 25% Movies')
plt.xlabel('netprofit')
plt.ylabel('votes')
plt.show()

# Plot 3: Average Votes for the Top 25% Movies
plt.figure(figsize=(6, 4))
sns.barplot(x=['Top 25% Movies'], y=[avg_Votes_top_25], color='blue')
plt.title('Average Votes for the Top 25% Movies Based on NetProfit')
plt.ylabel('Average Votes')
plt.show()
```







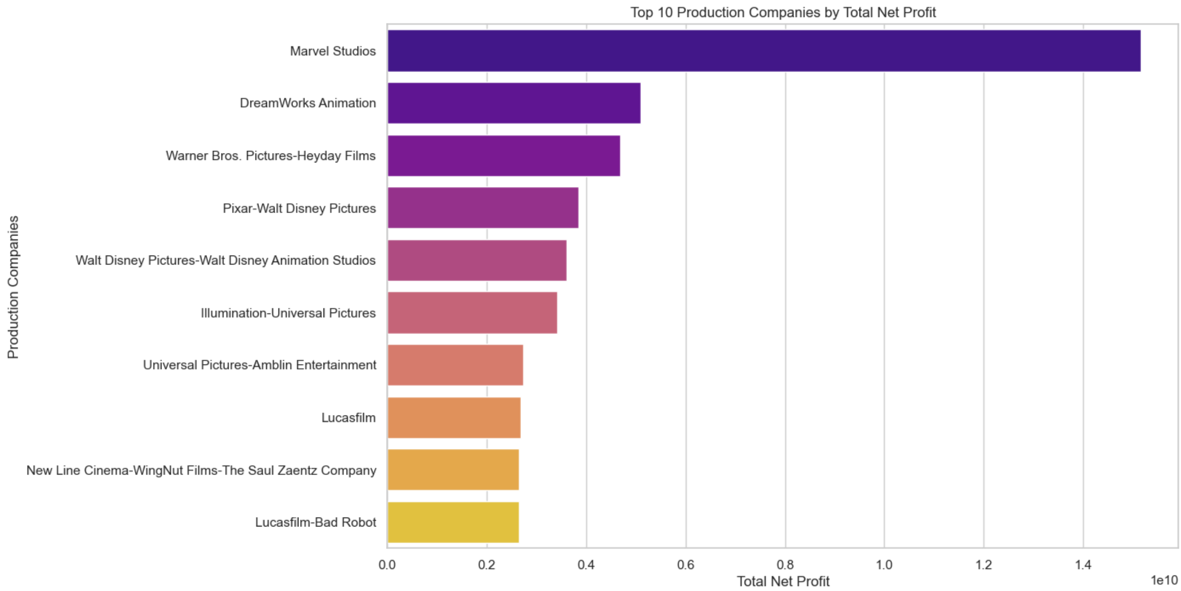
5.2. What is the Top 10 Production Companies by Total Net Profit?

Grouping by Production Company

Grouping by the **Production Company** allows us to analyze the profitability of each company rather than individual films. This means we can compare how profitable different production companies are based on the net profit of the films they produced. It aggregates the data by production company and calculates the total or average profitability for each company.

In [25]:
```
# SQL query to group by production companies and calculate total net profit
query_group_by_company = """
select m.production_companies, sum(f.netprofit) as total_netprofit
from Movie m
join Financial f on m.Id = f.Id
join Audience a on m.Id = a.Id
group by m.production_companies
order by total_netprofit desc
limit 100;
"""

# Execute the query and store the result in a DataFrame
result_group_by_company = pd.read_sql_query(query_group_by_company, conn)
# Display the result
display(result_group_by_company.head(10))

# Set the size of the plot
plt.figure(figsize=(12, 8))

# Plot a bar chart of total net profit by production company
sns.barplot(x='total_netprofit', y='production_companies', data=result_group_by_comp

# Set the labels and title
plt.xlabel('Total Net Profit')
plt.ylabel('Production Companies')
plt.title('Top 10 Production Companies by Total Net Profit')

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

	production_companies	total_netprofit
0	Marvel Studios	1.517090e+10
1	DreamWorks Animation	5.088777e+09
2	Warner Bros. Pictures-Heyday Films	4.684138e+09
3	Pixar-Walt Disney Pictures	3.841730e+09
4	Walt Disney Pictures-Walt Disney Animation Stu...	3.600900e+09
5	Illumination-Universal Pictures	3.423963e+09
6	Universal Pictures-Amblin Entertainment	2.725727e+09
7	Lucasfilm	2.679016e+09
8	New Line Cinema-WingNut Films-The Saul Zaentz ...	2.650545e+09
9	Lucasfilm-Bad Robot	2.647368e+09



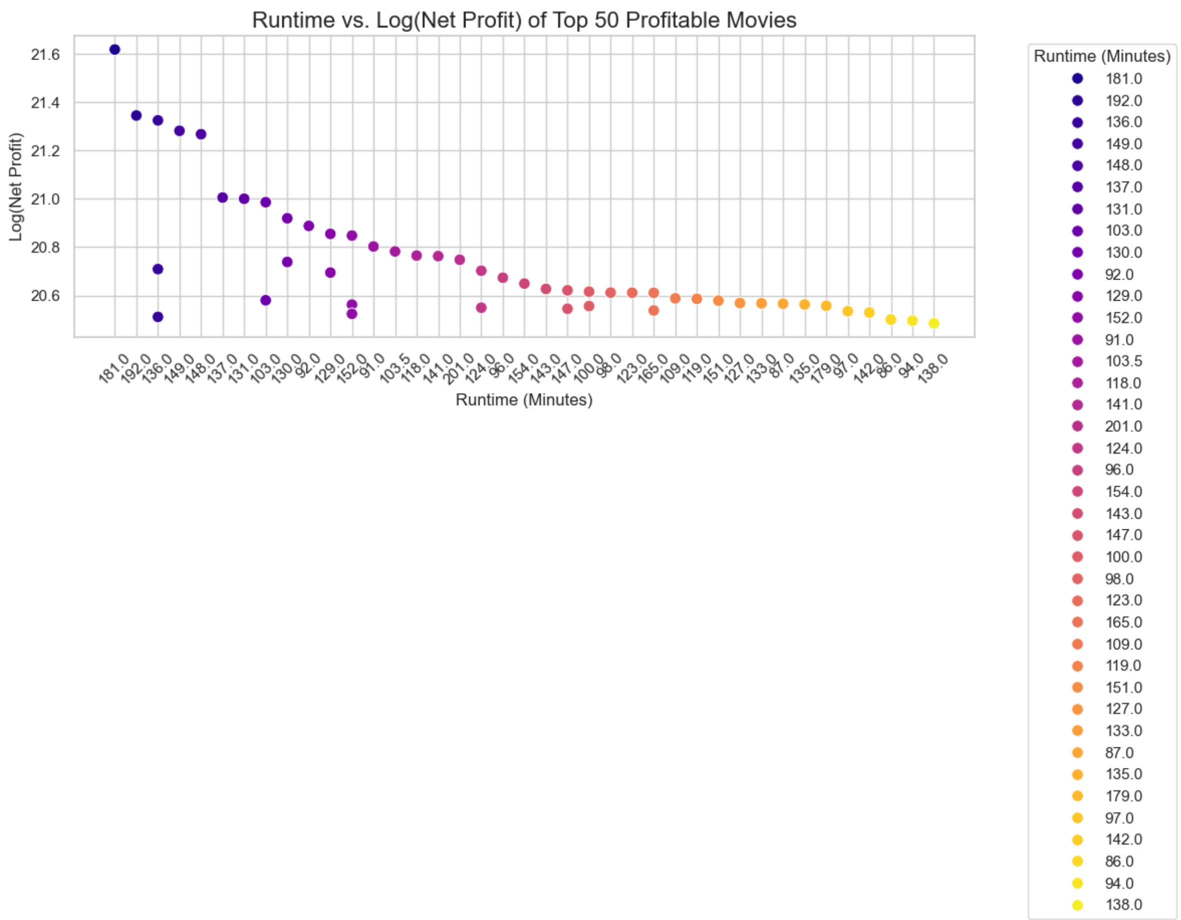
5.3. Do longer movies tend to have higher net profits?

Runtime of Top Profitable Movies

we want to compare the **runtime** of the top profitable movies to see if **longer movies** tend to be more profitable.

In [28]:
```
# Execute the query and fetch the top 50 profitable movies
query_8 = """
select m.Title, m.runtime, f.netprofit
from Movie m
join Financial f on m.Id = f.Id
order by f.netprofit desc
limit 50;
"""

result_8 = pd.read_sql_query(query_8, conn)
display(result_8.head(10))

result_8['log_netprofit'] = np.log1p(result_8['netprofit'])


plt.figure(figsize=(12, 7))
sns.scatterplot(data=result_8, x='runtime', y='log_netprofit', hue='runtime', palett
plt.title("Runtime vs. Log(Net Profit) of Top 50 Profitable Movies", fontsize=16)
plt.xlabel("Runtime (Minutes)", fontsize=12)
plt.ylabel("Log(Net Profit)", fontsize=12)
plt.legend(title="Runtime (Minutes)", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=45)  # Rotate x-axis labels
plt.tight_layout()
plt.show()
```

	Title	runtime	netprofit
0	Avengers: Endgame	181.0	2.443439e+09
1	Avatar: The Way of Water	192.0	1.860250e+09
2	Star Wars: The Force Awakens	136.0	1.823224e+09
3	Avengers: Infinity War	149.0	1.746240e+09
4	Spider-Man: No Way Home	148.0	1.721847e+09
5	Furious 7	137.0	1.325341e+09
6	Top Gun: Maverick	131.0	1.318733e+09
7	Frozen II	103.0	1.300027e+09
8	Harry Potter and the Deathly Hallows: Part 2	130.0	1.216511e+09
9	The Super Mario Bros. Movie	92.0	1.178767e+09



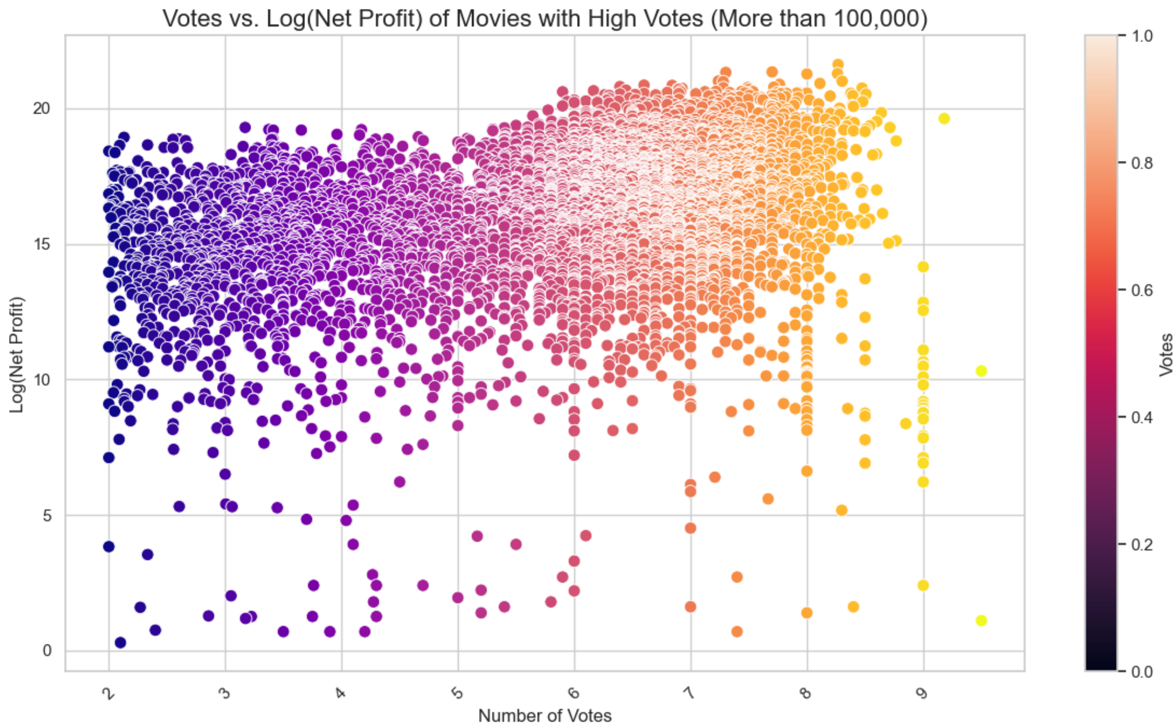
5.4. Do movies with higher vote counts tend to be more profitable?

Analyzing Movies with High Votes and Their Profitability

This analysis will investigate whether **movies with higher votes** tend to be more profitable.

In [105…

```python
# SQL query
query_9 = """
SELECT m.Title, a.votes, f.netprofit
FROM Movie m
JOIN Financial f ON m.Id = f.Id
JOIN Audience a ON m.Id = a.Id
WHERE a.votes > 100000
ORDER BY f.netprofit DESC;
"""

# Execute query
result_9 = pd.read_sql_query(query_9, conn)



# Filter out zero or negative netprofit values and compute log
result_9 = result_9[result_9['netprofit'] > 0]
result_9['log_netprofit'] = np.log1p(result_9['netprofit'])

# Ensure 'votes' column is numeric
result_9['votes'] = pd.to_numeric(result_9['votes'], errors='coerce')

# Set the range for the 'votes' hue
vmin, vmax = result_9['votes'].min(), result_9['votes'].max()

# Create scatter plot
plt.figure(figsize=(12, 7))
scatter = sns.scatterplot(
    data=result_9,
    x='votes',
    y='log_netprofit',
    hue='votes',
    palette='plasma',
    alpha=1,
    s=70,
    legend=False,  # Turn off the legend
    hue_norm=(vmin, vmax)  # Normalize the hue values to the range of votes
)

# Add a colorbar with label
plt.colorbar(scatter.collections[0], label="Votes")

# Title and labels
plt.title("Votes vs. Log(Net Profit) of Movies with High Votes (More than 100,000)",
plt.xlabel("Number of Votes", fontsize=12)
plt.ylabel("Log(Net Profit)", fontsize=12)

# Rotate x-axis labels for better readability
plt.xticks(rotation=45)

# Tight layout to ensure everything fits
plt.tight_layout()

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



5.5. Which actors are most strongly associated with a movie's profitability, and how does their presence in a film impact its net profit?

Analyzing Actor Contribution to Movie Profitability

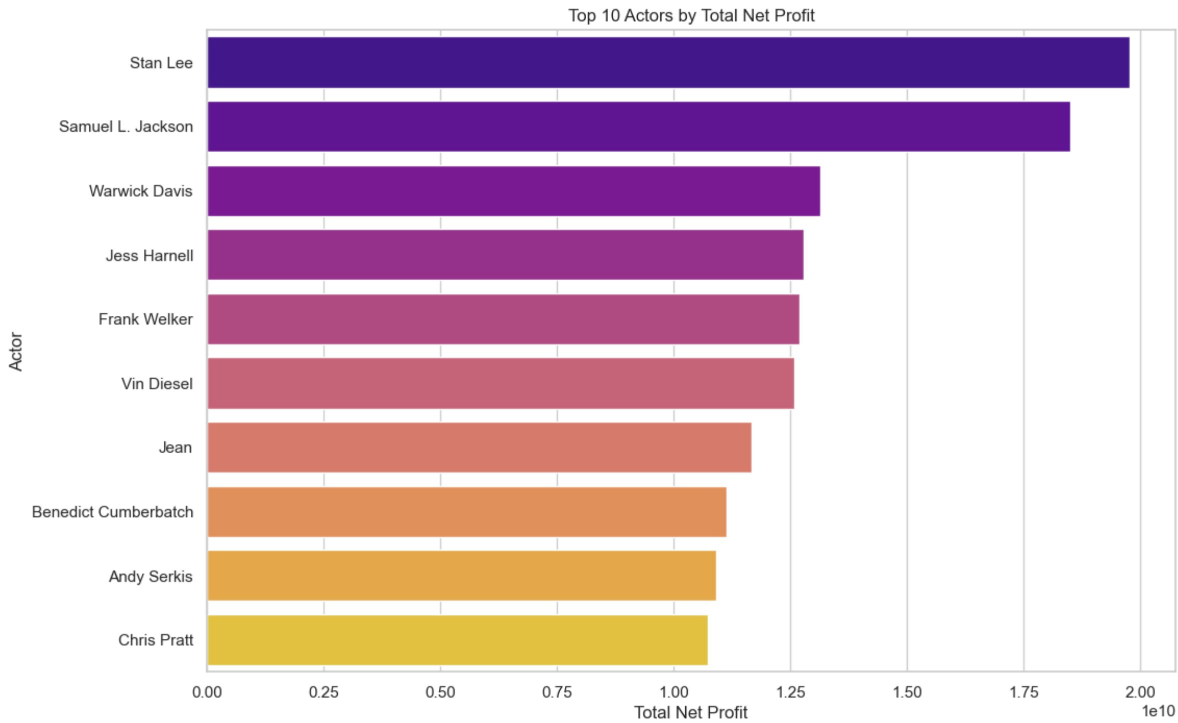
To analyze whether certain actors contribute more to a movie's profitability, we can calculate how much **net profit** is associated with each actor, based on their appearance in the movies.

In [34]:
```
# Execute the SQL query to retrieve necessary data
query_actors = """
select m.Title, f.netprofit, m.Actors
from Movie m
join Financial f on m.Id = f.Id;
"""

result_actors = pd.read_sql_query(query_actors, conn)

# Display the first few rows of the result
display(result_actors.head(10))

# Step 1: Split the 'actors' column into individual actors
result_actors['actor_list'] = result_actors['Actors'].str.split('-')

# Step 2: Create a new DataFrame to store actor contributions
actor_contributions = []

# Step 3: Distribute the net profit for each movie to the actors in that movie
for _, row in result_actors.iterrows():
    actors = row['actor_list']
    net_profit = row['netprofit']
```

```python
    for actor in actors:
        actor_contributions.append({'Actors': actor, 'netprofit': net_profit})

# Create a DataFrame from the actor contributions list
actor_df = pd.DataFrame(actor_contributions)

# Step 4: Aggregate net profits by actor
actor_profit = actor_df.groupby('Actors')['netprofit'].sum().reset_index()

# Step 5: Sort by net profit to find top actors
actor_profit = actor_profit.sort_values(by='netprofit', ascending=False)

# Step 6: Visualize the top 10 actors by total net profit
plt.figure(figsize=(12, 8))
sns.barplot(data=actor_profit.head(10), x='netprofit', y='Actors', palette='plasma')
plt.title("Top 10 Actors by Total Net Profit")
plt.xlabel("Total Net Profit")
plt.ylabel("Actor")
plt.show()
```

	Title	netprofit	Actors
0	Four Rooms	2.573540e+05	Tim Roth-Jennifer Beals-Antonio Banderas-Valer...
1	Judgment Night	-4.431531e+06	Emilio Estevez-Cuba Gooding Jr.-Denis Leary-St...
2	Star Wars	7.643980e+08	Mark Hamill-Harrison Ford-Carrie Fisher-Peter ...
3	Finding Nemo	8.463355e+08	Albert Brooks-Ellen DeGeneres-Alexander Gould-...
4	Forrest Gump	6.223877e+08	Tom Hanks-Robin Wright-Gary Sinise-Sally Field...
5	American Beauty	1.137655e+08	Kevin Spacey-Annette Bening-Thora Birch-Wes Be...
6	Citizen Kane	2.237827e+07	Orson Welles-Joseph Cotten-Dorothy Comingore-R...
7	Dancer in the Dark	2.723188e+07	Björk-Catherine Deneuve-David Morse-Peter Stor...
8	The Fifth Element	1.739202e+08	Bruce Willis-Milla Jovovich-Gary Oldman-Ian Ho...
9	My Life Without Me	9.800000e+06	Sarah Polley-Amanda Plummer-Scott Speedman-Mar...

```
C:\Users\ehabh\AppData\Local\Temp\ipykernel_8092\3075200833.py:37: 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(data=actor_profit.head(10), x='netprofit', y='Actors', palette='plasm
a')
```



5.6. What is the most produced type of movie in the dataset, and how does its production frequency compare to other types?

Analyzing the Most Produced Genres

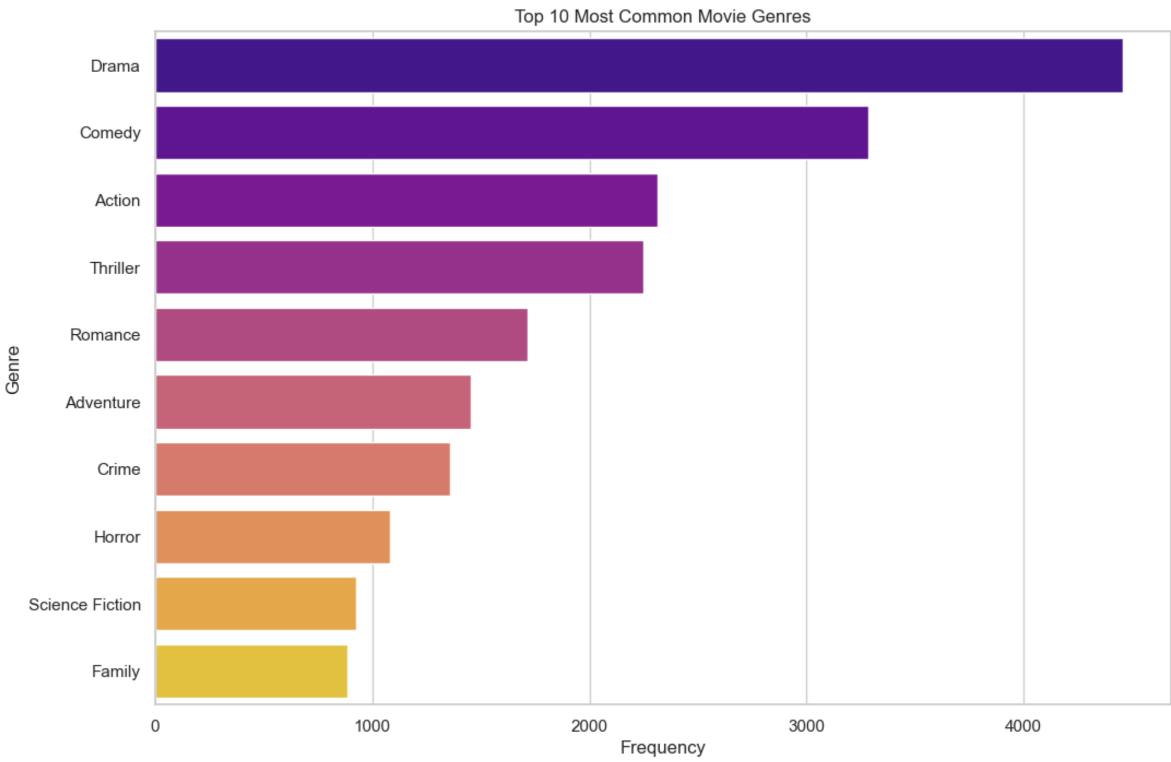
To analyze which **genres** are produced the most (i.e., the most common genres in the dataset), you can follow these steps:

In [37]:
```
# Execute the SQL query to retrieve genres data
query_genres = """
select m.Title, m.genres
from Movie m;
"""

result_genres = pd.read_sql_query(query_genres, conn)

# Display the first few rows of the result
display(result_genres.head(10))

# Step 1: Split the 'genres' column into individual genres
result_genres['genre_list'] = result_genres['genres'].str.split('-')

# Step 2: Create a new list to store individual genres
all_genres = []

# Step 3: Flatten the list of genres across all movies
for _, row in result_genres.iterrows():
    genres = row['genre_list']
    for genre in genres:
        all_genres.append(genre)

# Step 4: Create a DataFrame with genre counts
genre_count = pd.DataFrame(all_genres, columns=['genre'])
```

```python
# Step 5: Count the frequency of each genre
genre_frequency = genre_count['genre'].value_counts().reset_index()

# Step 6: Rename columns for clarity
genre_frequency.columns = ['genre', 'count']

# Step 7: Visualize the top genres
plt.figure(figsize=(12, 8))
sns.barplot(data=genre_frequency.head(10), x='count', y='genre', palette='plasma')
plt.title("Top 10 Most Common Movie Genres")
plt.xlabel("Frequency")
plt.ylabel("Genre")
plt.show()
```

	Title	genres
0	Four Rooms	Crime-Comedy
1	Judgment Night	Action-Crime-Thriller
2	Star Wars	Adventure-Action-Science Fiction
3	Finding Nemo	Animation-Family
4	Forrest Gump	Comedy-Drama-Romance
5	American Beauty	Drama
6	Citizen Kane	Mystery-Drama
7	Dancer in the Dark	Drama-Crime
8	The Fifth Element	Adventure-Fantasy-Action-Thriller-Science Fiction
9	My Life Without Me	Drama-Romance

```
C:\Users\ehabh\AppData\Local\Temp\ipykernel_8092\2823503167.py:35: 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(data=genre_frequency.head(10), x='count', y='genre', palette='plasma')
```



5.7. Which genres generate the most revenue, profit , budget?

Financial Performance of Movies Across Different Genres

This analysis explores the financial performance of movies across different genres by calculating the **net profit** (Revenue - Budget) for each genre.

In [40]:
```
# SQL query to extract necessary data
query = """
    SELECT m.genres, f.budget, f.Revenue, f.Revenue - f.budget AS netprofit
    FROM Movie m
    JOIN Financial f ON m.Id = f.id
    GROUP BY m.genres, f.budget, f.Revenue
"""

# Load data into a DataFrame
data = pd.read_sql_query(query, conn)

# Display the initial data
display(data)

# Split the 'genres' column into individual rows for detailed analysis
data['genres'] = data['genres'].str.split('-')  # Splitting genres by the delimiter
data = data.explode('genres')  # Creating a new row for each genre
display(data)

# Group and sort data by each metric for visualization
sorted_budget = data.groupby('genres', as_index=False)['budget'].sum().sort_values(b
sorted_revenue = data.groupby('genres', as_index=False)['revenue'].sum().sort_values
sorted_netprofit = data.groupby('genres', as_index=False)['netprofit'].sum().sort_va
```

```python
# Combine Budget, Revenue, and Net Profit for a comparative visualization
combined_data = data.melt(id_vars='genres', value_vars=['budget', 'revenue', 'netpro
                          var_name='Metric', value_name='Amount')

# Convert 'Amount' to numeric values, forcing errors to NaN (in case of invalid data
combined_data['Amount'] = pd.to_numeric(combined_data['Amount'], errors='coerce')

# Group by genres and Metric, summing 'Amount'
combined_data = combined_data.groupby(['genres', 'Metric'], as_index=False)['Amount'

# Sort the combined data by 'Amount'
combined_data = combined_data.sort_values(by='Amount', ascending=False)

# Display the sorted data
display(combined_data)
```

	genres	budget	revenue	netprofit
0	Action	0.5	0.5	0.000000e+00
1	Action	100.0	100.0	0.000000e+00
2	Action	1000.0	333333.3333333333	3.323333e+05
3	Action	1000000.0	10499694.0	9.499694e+06
4	Action	1000000.0	4045199.3333333335	3.045199e+06
...	...	...	...	...
9258	Western-Drama-Mystery	5500000.0	15700000.0	1.020000e+07
9259	Western-History	35000000.0	18635620.0	-1.636438e+07
9260	Western-Horror-Thriller	5000000.0	9617000.0	4.617000e+06
9261	Western-Romance	3777.5	25556.0	2.177850e+04
9262	Western-Romance-Drama	3000000.0	10200000.0	7.200000e+06

9263 rows × 4 columns

	genres	budget	revenue	netprofit
0	Action	0.5	0.5	0.000000e+00
1	Action	100.0	100.0	0.000000e+00
2	Action	1000.0	333333.3333333333	3.323333e+05
3	Action	1000000.0	10499694.0	9.499694e+06
4	Action	1000000.0	4045199.3333333335	3.045199e+06
...	...	...	...	...
9261	Western	3777.5	25556.0	2.177850e+04
9261	Romance	3777.5	25556.0	2.177850e+04
9262	Western	3000000.0	10200000.0	7.200000e+06
9262	Romance	3000000.0	10200000.0	7.200000e+06
9262	Drama	3000000.0	10200000.0	7.200000e+06

23309 rows × 4 columns

	genres	Metric	Amount
2	Action	revenue	2.232816e+11
5	Adventure	revenue	2.212506e+11
11	Comedy	revenue	1.743710e+11
4	Adventure	netprofit	1.537230e+11
1	Action	netprofit	1.463984e+11
20	Drama	revenue	1.352783e+11
10	Comedy	netprofit	1.149865e+11
44	Science Fiction	revenue	1.102467e+11
50	Thriller	revenue	1.041858e+11
26	Fantasy	revenue	1.035082e+11
23	Family	revenue	9.620984e+10
19	Drama	netprofit	8.212954e+10
0	Action	budget	7.688320e+10
43	Science Fiction	netprofit	7.355966e+10
8	Animation	revenue	7.099332e+10
25	Fantasy	netprofit	6.973161e+10
3	Adventure	budget	6.752762e+10
22	Family	netprofit	6.496025e+10
49	Thriller	netprofit	6.383465e+10
41	Romance	revenue	5.960157e+10
9	Comedy	budget	5.938444e+10
14	Crime	revenue	5.655169e+10
18	Drama	budget	5.314876e+10
7	Animation	netprofit	5.018458e+10
48	Thriller	budget	4.035114e+10
40	Romance	netprofit	3.891924e+10
42	Science Fiction	budget	3.668702e+10
24	Fantasy	budget	3.377654e+10
13	Crime	netprofit	3.375992e+10
21	Family	budget	3.124958e+10
32	Horror	revenue	2.934802e+10
38	Mystery	revenue	2.925811e+10
12	Crime	budget	2.279177e+10
6	Animation	budget	2.080874e+10

	genres	Metric	Amount
39	Romance	budget	2.068233e+10
31	Horror	netprofit	1.954802e+10
29	History	revenue	1.844035e+10
53	War	revenue	1.745108e+10
37	Mystery	netprofit	1.744169e+10
36	Mystery	budget	1.181642e+10
35	Music	revenue	1.149521e+10
52	War	netprofit	1.034536e+10
30	Horror	budget	9.799995e+09
28	History	netprofit	9.417707e+09
27	History	budget	9.022645e+09
34	Music	netprofit	7.631374e+09
51	War	budget	7.105714e+09
56	Western	revenue	4.468723e+09
33	Music	budget	3.863833e+09
54	Western	budget	2.294586e+09
55	Western	netprofit	2.174137e+09
17	Documentary	revenue	1.559965e+09
16	Documentary	netprofit	1.183602e+09
15	Documentary	budget	3.763636e+08
47	TV Movie	revenue	2.206430e+08
46	TV Movie	netprofit	1.679106e+08
45	TV Movie	budget	5.273244e+07

5.8. How do the number of votes and popularity of movies relate to their net profit for movies with more than 50 votes?

Relationship Between Net Profit, Audience Votes, and Popularity

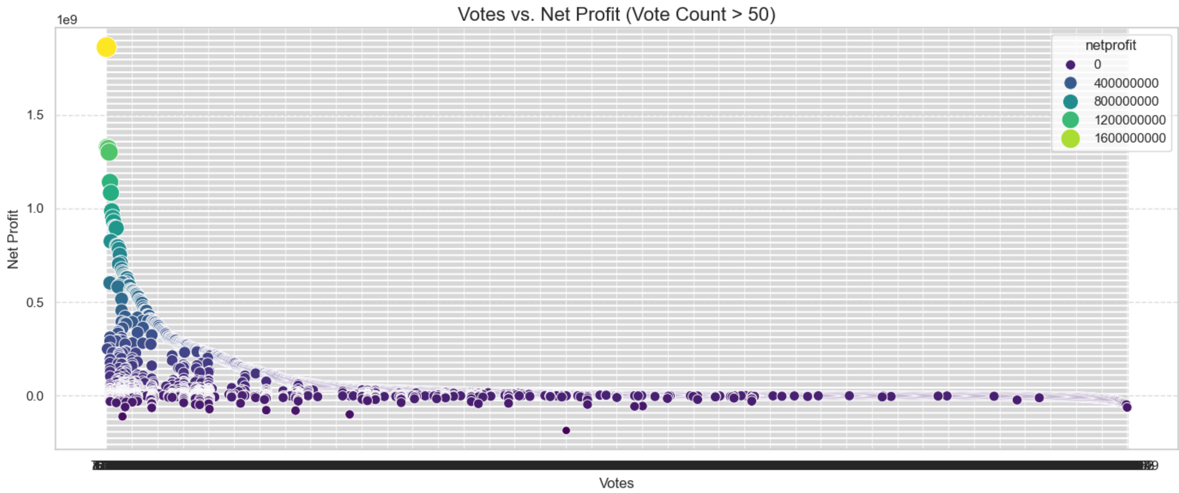
This analysis investigates the relationship between the **net profit** of movies and their **audience votes** and **popularity** for movies that have received more than **50 votes**.

In [43]:
```
query = """
    SELECT f.netprofit, a.votes, a.popularity
```

```
    FROM Financial f
    JOIN Audience a ON f.id = a.id
    WHERE a.vote_count > 50
    ORDER BY f.netprofit DESC;
"""
query_result = pd.read_sql_query(query, conn)

display(query_result)

plt.figure(figsize=(14, 6))
sns.scatterplot(
    data=query_result, x='votes', y='netprofit', hue='netprofit', size='netprofit',
    sizes=(50, 300), palette='viridis'
)

plt.title('Votes vs. Net Profit (Vote Count > 50)', fontsize=16)
plt.xlabel('Votes', fontsize=12)
plt.ylabel('Net Profit', fontsize=12)

plt.grid(True, linestyle='--', alpha=0.7)

plt.tight_layout()
plt.show()
```

	netprofit	votes	popularity
0	1.860250e+09	7.701	1134.931
1	1.325341e+09	7.239	122.389
2	1.318733e+09	8.303	372.213
3	1.300027e+09	7.281	112.847
4	1.140466e+09	6.6	97.921
...	...	...	...
2599	-7.740000e+07	5.4	16.184
2600	-7.962771e+07	4.5	6.254
2601	-9.963233e+07	2.1	2.026666666666667
2602	-1.110072e+08	6.0	21.42
2603	-1.856000e+08	7.9	94.513

2604 rows × 3 columns



6. Creating Views

In [76]:
```
cursor = conn.cursor()

# Create the SalesView
cursor.execute("""
CREATE VIEW IF NOT EXISTS SalesView1 AS
SELECT
    id,
    revenue,
    budget,
    netprofit
FROM
    Financial
""")

# Create the ArtCriticView
cursor.execute("""
CREATE VIEW IF NOT EXISTS ArtCriticView1 AS
SELECT
    md.id,
    md.Title AS Movie_Title,
    md.genres,
    md.actors,
    md.runtime,
    a.popularity,
    a.votes,
    a.vote_count
FROM
    Movie md
INNER JOIN
    Audience a
ON
    md.id = a.id
""")

# Commit changes
conn.commit()

# Print confirmation
print("Views created successfully.")
```

```python
# Test the views (optional: only if you want to see structure/data)
print("\nTesting SalesView structure:")
cursor.execute("PRAGMA table_info(SalesView1)")
print(cursor.fetchall())

print("\nTesting ArtCriticView structure:")
cursor.execute("PRAGMA table_info(ArtCriticView1)")
print(cursor.fetchall())
```

```
Views created successfully.

Testing SalesView structure:
[(0, 'id', 'INTEGER', 0, None, 0), (1, 'revenue', 'VARCHAR(19)', 0, None, 0), (2, 'bu
dget', 'VARCHAR(20)', 0, None, 0), (3, 'netprofit', 'REAL', 0, None, 0)]

Testing ArtCriticView structure:
[(0, 'id', 'INTEGER', 0, None, 0), (1, 'Movie_Title', 'VARCHAR(104)', 0, None, 0),
(2, 'genres', 'VARCHAR(67)', 0, None, 0), (3, 'Actors', 'VARCHAR(5140)', 0, None, 0),
(4, 'runtime', 'VARCHAR(18)', 0, None, 0), (5, 'popularity', 'VARCHAR(18)', 0, None,
0), (6, 'votes', 'VARCHAR(18)', 0, None, 0), (7, 'vote_count', 'VARCHAR(19)', 0, None
, 0)]
```