Data Analytics Track - Stage 1 Task: Feature Engineering & Exploration.

In [1]:
```
# Step 1: Data Preparation
```

In [2]:
```
import pandas as pd
```

In [5]:
```
# Load each dataset (since they are in the same folder, no path needed)
movies = pd.read_csv('movies.csv')
ratings = pd.read_csv('ratings.csv')
tags = pd.read_csv('tags.csv')
links = pd.read_csv('links.csv')
```

In [6]:
```
# View first few rows of each
print("Movies:")
display(movies.head())
```

```
Movies:
```

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

In [7]:
```
print("\nRatings:")
display(ratings.head())
```

```
Ratings:
```

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931

In [8]:
```
print("\nTags:")
display(tags.head())
```

```
Tags:
```

	userId	movieId	tag	timestamp
0	2	60756	funny	1445714994
1	2	60756	Highly quotable	1445714996
2	2	60756	will ferrell	1445714992
3	2	89774	Boxing story	1445715207
4	2	89774	MMA	1445715200

In [9]:
```
print("\nLinks:")
display(links.head())
```

```
Links:
```

	movieId	imdbId	tmdbId
0	1	114709	862.0
1	2	113497	8844.0
2	3	113228	15602.0
3	4	114885	31357.0
4	5	113041	11862.0

In [10]:
```
# Step 2: Feature Engineering
# Merge ratings with movies
merged_df = pd.merge(ratings, movies, on='movieId', how='left')
# Merge with tags
```

In [11]:
```
merged_df = pd.merge(merged_df, tags, on=['movieId', 'userId'], how='left')
```

```python
# Merge with links (optional)
merged_df = pd.merge(merged_df, links, on='movieId', how='left')
# Display a few rows of the final dataset
merged_df.head()
```

Out[11]:

	userId	movieId	rating	timestamp_x	title	genres	tag	timestamp_y	imdbId	tmdbId
0	1	1	4.0	964982703	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	NaN	NaN	114709	862.0
1	1	3	4.0	964981247	Grumpier Old Men (1995)	Comedy|Romance	NaN	NaN	113228	15602.0
2	1	6	4.0	964982224	Heat (1995)	Action|Crime|Thriller	NaN	NaN	113277	949.0
3	1	47	5.0	964983815	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller	NaN	NaN	114369	807.0
4	1	50	5.0	964982931	Usual Suspects, The (1995)	Crime|Mystery|Thriller	NaN	NaN	114814	629.0

In [12]:

```python
# STEP 5: DATA CLEANING
# Check for missing values
print("Missing values per column:\n", merged_df.isnull().sum())
# Drop duplicates if any
merged_df.drop_duplicates(inplace=True)
# Convert timestamp columns to datetime format
merged_df['timestamp_x'] = pd.to_datetime(merged_df['timestamp_x'], unit='s', errors='coerce')
merged_df['timestamp_y'] = pd.to_datetime(merged_df['timestamp_y'], unit='s', errors='coerce')
# Rename for clarity
merged_df.rename(columns={'timestamp_x': 'rating_timestamp', 'timestamp_y': 'tag_timestamp'}, inplace=True)
print("\n✅ Data cleaned and timestamps converted successfully.")
merged_df.head()
```

```
Missing values per column:
 userId             0
movieId            0
rating             0
timestamp_x        0
title              0
genres             0
tag            99201
timestamp_y    99201
imdbId             0
tmdbId            13
dtype: int64

✅ Data cleaned and timestamps converted successfully.
```

Out[12]:

	userId	movieId	rating	rating_timestamp	title	genres	tag	tag_timestamp	imdbId	t
0	1	1	4.0	2000-07-30 18:45:03	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	NaN	NaT	114709	
1	1	3	4.0	2000-07-30 18:20:47	Grumpier Old Men (1995)	Comedy|Romance	NaN	NaT	113228	1
2	1	6	4.0	2000-07-30 18:37:04	Heat (1995)	Action|Crime|Thriller	NaN	NaT	113277	
3	1	47	5.0	2000-07-30 19:03:35	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller	NaN	NaT	114369	
4	1	50	5.0	2000-07-30 18:48:51	Usual Suspects, The (1995)	Crime|Mystery|Thriller	NaN	NaT	114814	

In [13]:

```python
# STEP 6: FEATURE ENGINEERING
```

In [14]:

```python
import numpy as np
```

In [15]:

```python
# 1️⃣ Extract release year from the movie title
merged_df['release_year'] = merged_df['title'].str.extract(r'\((\d{4})\)').astype(float)
```

In [18]:

```python
# 2️⃣ Count number of genres per movie
merged_df['genre_count'] = merged_df['genres'].apply(lambda x: len(x.split('|')) if isinstance(x, str) else 0)
```

In [19]:
```python
# 3️⃣Calculate how old the movie is (as of 2025)
merged_df['movie_age'] = 2025 - merged_df['release_year']
```

In [20]:
```python
# 4️⃣Average rating per movie
movie_avg_rating = merged_df.groupby('movieId')['rating'].mean().reset_index(name='avg_rating')
merged_df = merged_df.merge(movie_avg_rating, on='movieId', how='left')
```

In [21]:
```python
# 5️⃣Number of ratings per movie
movie_rating_count = merged_df.groupby('movieId')['rating'].count().reset_index(name='rating_count')
merged_df = merged_df.merge(movie_rating_count, on='movieId', how='left')
```

In [22]:
```python
# 6️⃣Rating hour (to see what time of day people tend to rate)
merged_df['rating_hour'] = merged_df['rating_timestamp'].dt.hour
```

In [24]:
```python
# 7️⃣Weekday rating (0 = Monday)
merged_df['rating_weekday'] = merged_df['rating_timestamp'].dt.day_name()
```

In [28]:
```python
print("✅ Feature engineering complete! Here are the new columns:\n")
print(merged_df[['title', 'release_year', 'genre_count', 'movie_age', 'avg_rating', 'rating_count', 'rating_hou
```

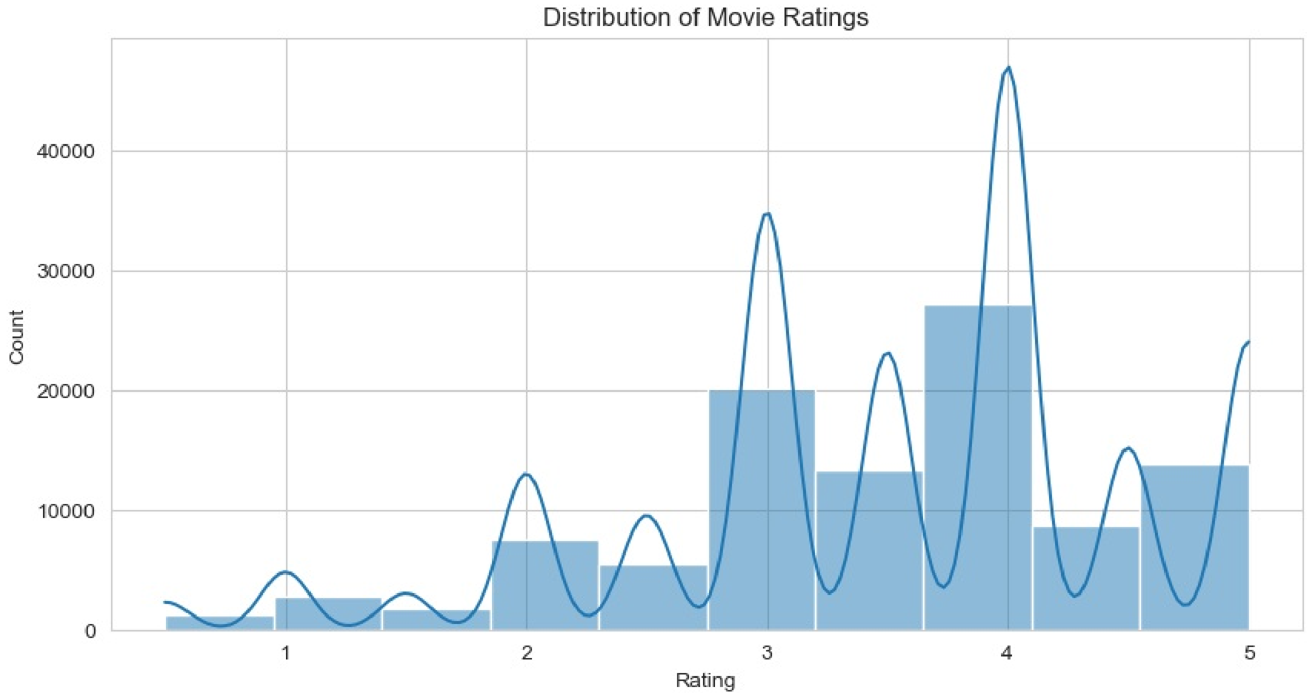
```
✅ Feature engineering complete! Here are the new columns:

                                title  release_year  genre_count  movie_age  \
0                    Toy Story (1995)        1995.0            5       30.0
1             Grumpier Old Men (1995)        1995.0            2       30.0
2                         Heat (1995)        1995.0            3       30.0
3         Seven (a.k.a. Se7en) (1995)        1995.0            2       30.0
4          Usual Suspects, The (1995)        1995.0            3       30.0
...                               ...           ...          ...        ...
102672                   Split (2017)        2017.0            3        8.0
102673   John Wick: Chapter Two (2017)       2017.0            3        8.0
102674                 Get Out (2017)        2017.0            1        8.0
102675                   Logan (2017)        2017.0            2        8.0
102676  The Fate of the Furious (2017)       2017.0            4        8.0

        avg_rating  rating_count  rating_hour
0         3.920930           215           18
1         3.245283            53           18
2         3.946078           102           18
3         3.980392           204           19
4         4.252404           208           18
...            ...           ...          ...
102672    3.333333             6           21
102673    4.307692            13           22
102674    3.633333            15           19
102675    4.241379            29           21
102676    2.333333             3           21

[102677 rows x 7 columns]
```

In [29]:
```python
# STEP 7: EXPLORATORY DATA ANALYSIS (EDA)
```

In [30]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
```

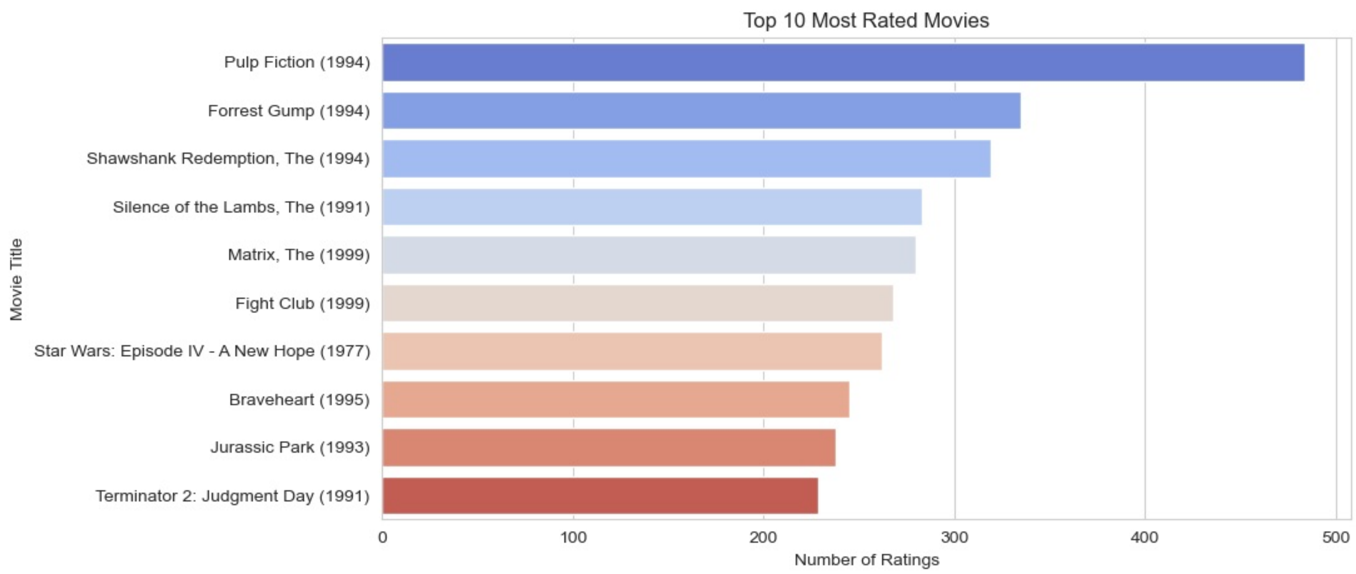
In [31]:
```python
sns.set_style('whitegrid')
plt.rcParams['figure.figsize'] = (10,5)
```

In [32]:
```python
# 1️⃣ Distribution of Ratings
sns.histplot(merged_df['rating'], bins=10, kde=True)
plt.title("Distribution of Movie Ratings")
plt.xlabel("Rating")
plt.ylabel("Count")
plt.show()
```



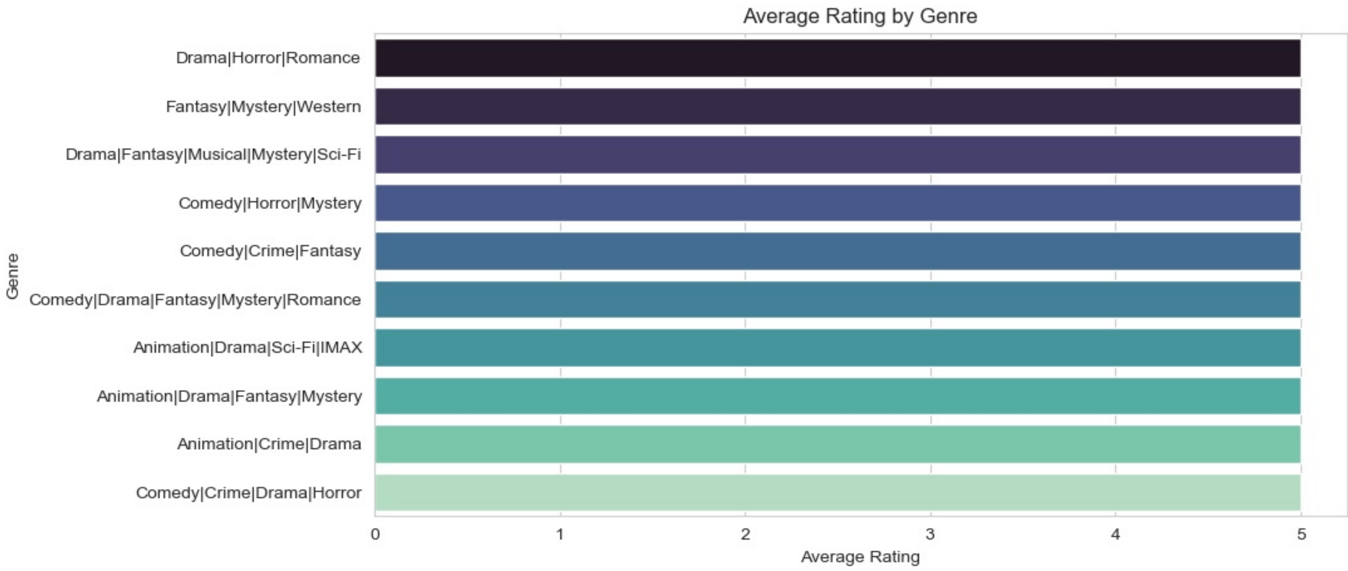
In [33]:
```python
#2️⃣ Top 10 Movies by Number of Ratings
top_movies = merged_df.groupby('title')['rating'].count().sort_values(ascending=False).head(10)
sns.barplot(x=top_movies.values, y=top_movies.index, palette='coolwarm')
plt.title("Top 10 Most Rated Movies")
plt.xlabel("Number of Ratings")
plt.ylabel("Movie Title")
plt.show()
```

```
C:\Users\MR. ROWLINGS\AppData\Local\Temp\ipykernel_7996\3726818738.py:3: 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=top_movies.values, y=top_movies.index, palette='coolwarm')
```

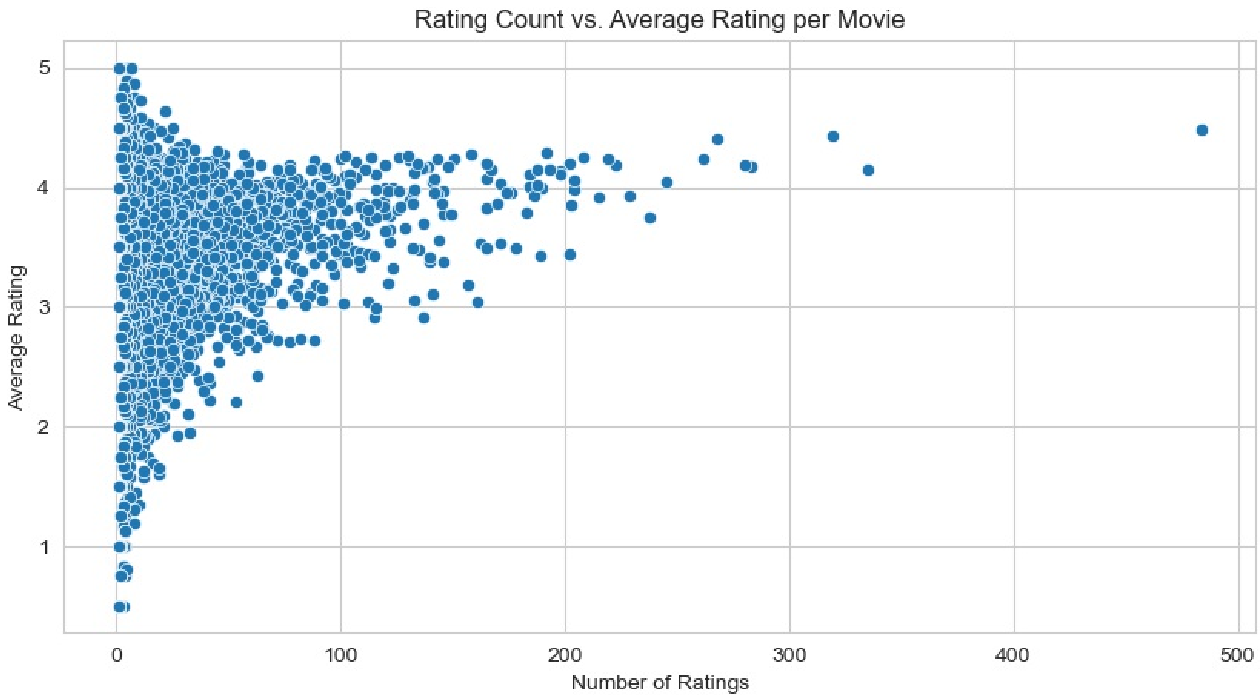


In [34]:
```python
#3️⃣Average Rating per Genre
genre_avg = merged_df.groupby('genres')['rating'].mean().sort_values(ascending=False).head(10)
sns.barplot(x=genre_avg.values, y=genre_avg.index, palette='mako')
plt.title("Average Rating by Genre")
plt.xlabel("Average Rating")
plt.ylabel("Genre")
plt.show()
```

```
C:\Users\MR. ROWLINGS\AppData\Local\Temp\ipykernel_7996\3992641893.py:3: 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_avg.values, y=genre_avg.index, palette='mako')
```

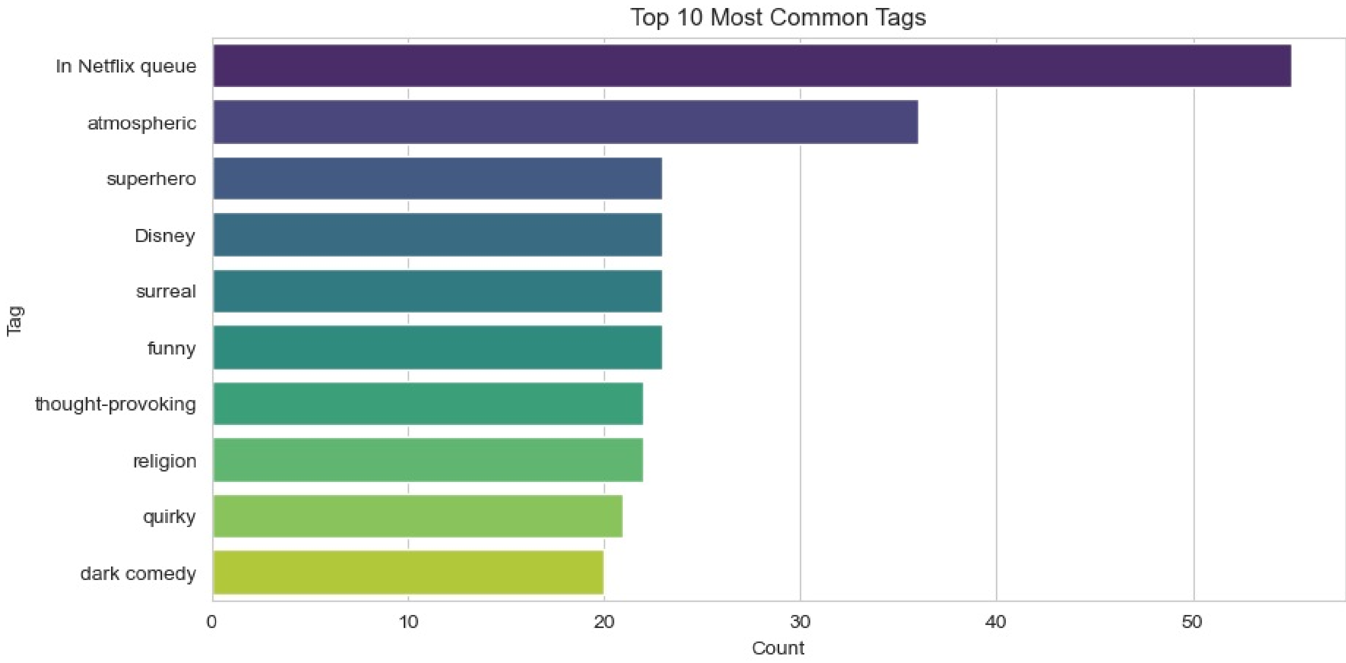


In [36]:
```
# 4  Relationship between Number of Ratings and Average Rating
sns.scatterplot(data=merged_df.drop_duplicates('movieId'),
x='rating_count', y='avg_rating')
plt.title("Rating Count vs. Average Rating per Movie")
plt.xlabel("Number of Ratings")
plt.ylabel("Average Rating")
plt.show()
```

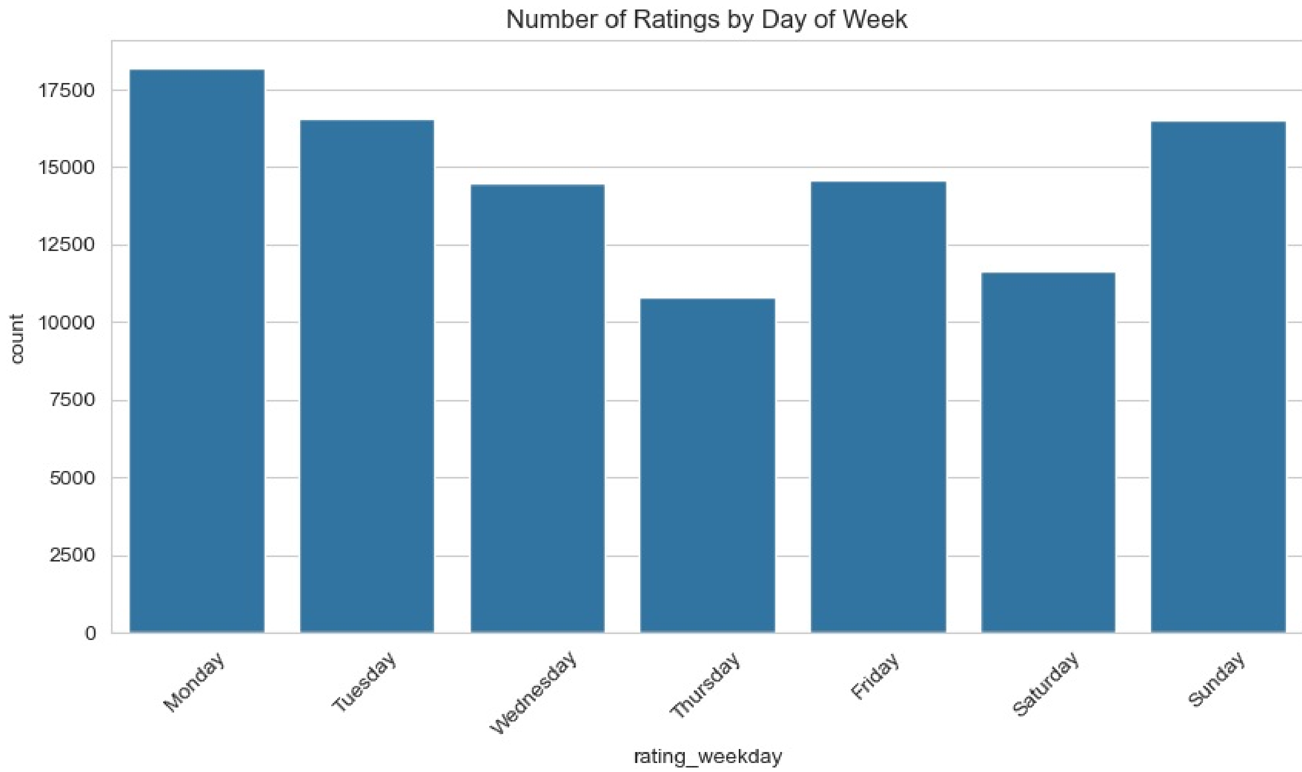


In [38]:
```
# 5  Most Common Tags
top_tags = merged_df['tag'].value_counts().head(10)
sns.barplot(x=top_tags.values, y=top_tags.index, palette='viridis')
plt.title("Top 10 Most Common Tags")
plt.xlabel("Count")
plt.ylabel("Tag")
plt.show()
```

```
C:\Users\MR. ROWLINGS\AppData\Local\Temp\ipykernel_7996\447396862.py:3: 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=top_tags.values, y=top_tags.index, palette='viridis')
```



In [39]:
```
# 6  Ratings by Day of the Week
sns.countplot(x='rating_weekday', data=merged_df,
order=['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday'])
plt.title("Number of Ratings by Day of Week")
plt.xticks(rotation=45)
plt.show()
```



Key Insights

1. Ratings Distribution: Most users give ratings between 3.0 and 4.5, showing a positive bias.
2. Most Rated Movies: A few popular titles dominate the ratings count.
3. Genres: Certain genres like Drama and Action tend to have higher average ratings.
4. Tags: User tags show engagement trends (e.g., “classic”, “funny”, “sci-fi” appear often).
5. Activity Pattern: Ratings peak around weekends.
6. Correlation: Movies with more ratings often have slightly lower average ratings — a popularity trade-off. These insights help in designing a recommendation system by identifying popular genres, user preferences, and engagement patterns.

In [40]:
```
merged_df.to_csv("cleaned_movielens.csv", index=False)
print("✅ Cleaned dataset saved as 'cleaned_movielens.csv'")
```

```
✅ Cleaned dataset saved as 'cleaned_movielens.csv'
```

In [ ]: