IMDb Movie Rating Analysis

Author: Meet Vaghamshi

Objective: Explore and analyze movie ratings from IMDb dataset

```
In [5]: import os
    os.listdir()

Out[5]: ['.ipynb_checkpoints', 'tmdb_5000_movies.csv', 'Untitled.ipynb']

In [9]: import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns

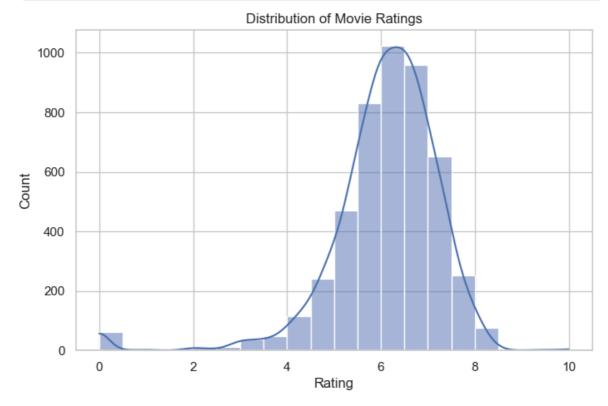
# Optional: To see plots in the notebook
    %matplotlib inline
    sns.set(style="whitegrid")

In [10]: df = pd.read_csv("tmdb_5000_movies.csv") # Replace with your filename
    df.head()
```

	budget	genres	homepage	id	keyword
0	237000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam	http://www.avatarmovie.com/	19995	[{"id 146: "name "cultur clash" {"id":
1	300000000	[{"id": 12, "name": "Adventure"}, {"id": 14, "	http://disney.go.com/disneypictures/pirates/	285	[{"id 27("name "ocean" {"id": 72€ "na
2	245000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam	http://www.sonypictures.com/movies/spectre/	206647	[{"id 47("name "spy" {"id": 81{ "name
3	250000000	[{"id": 28, "name": "Action"}, {"id": 80, "nam	http://www.thedarkknightrises.com/	49026	[{"id 849 "name "d comics" {"id 853,
4	260000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam	http://movies.disney.com/john-carter	49529	[{"id 81{ "name "based o novel" {"id":
df	.describe()				•
	1 2 df df	<pre>0 237000000 1 300000000 2 245000000 4 260000000 df.info()</pre>	[{"id": 28, "name": "Action"}, {"id": 12, "name] 1 30000000 [[("id": 12, "name": "Adventure"], {"id": 14, "] 2 245000000 [[("id": 28, "name": "Action"], {"id": 12, "nam] 3 250000000 [[("id": 28, "name": "Action"], {"id": 80, "nam] 4 260000000 [[("id": 28, "name": "Action"], {"id": 80, "nam] 4 260000000 [[("id": 28, "name": "Action"], {"id": 12, "nam] 4 260000000 [[("id": 28, "name": "Action"], {"id": 12, "nam]	[["id": 28,	("id": 28, "name": "Adventure"), ("id": 14, " http://disney.go.com/disneypictures/pirates/ 285

```
<class 'pandas.core.frame.DataFrame'>
        RangeIndex: 4803 entries, 0 to 4802
        Data columns (total 20 columns):
         # Column
                                 Non-Null Count Dtype
        --- -----
                                  _____
         0 budget
                                 4803 non-null int64
         1 genres
                                 4803 non-null object
         2 homepage
                                 1712 non-null object
                                 4803 non-null int64
            id
                                 4803 non-null object
            keywords
         5 original_language 4803 non-null object
6 original_title 4803 non-null object
         7 overview 4800 non-null object
8 popularity 4803 non-null float64
         9 production_companies 4803 non-null object
         10 production_countries 4803 non-null object
                                 4802 non-null object
         11 release_date
         12 revenue
                                 4803 non-null int64
         13 runtime
                                 4801 non-null float64
         14 spoken_languages 4803 non-null object
15 status 4803 non-null object
                                3959 non-null object
         16 tagline
                                4803 non-null object
4803 non-null float64
         17 title
         1/ LILLE
18 vote_average
         19 vote_count
                                  4803 non-null
                                                  int64
        dtypes: float64(3), int64(4), object(13)
        memory usage: 750.6+ KB
Out[11]: Index(['budget', 'genres', 'homepage', 'id', 'keywords', 'original_language',
                 'original_title', 'overview', 'popularity', 'production_companies',
                 'production_countries', 'release_date', 'revenue', 'runtime',
                 'spoken_languages', 'status', 'tagline', 'title', 'vote_average',
                 'vote_count'],
               dtype='object')
In [13]: # Check for missing values
         df.isnull().sum()
         # Drop rows with missing release_date or vote_average
         df.dropna(subset=['release date', 'vote average'], inplace=True)
         # Convert release date to datetime
         df['release_date'] = pd.to_datetime(df['release_date'], errors='coerce')
         # Create a release year column
         df['release year'] = df['release date'].dt.year
In [14]: # Top 10 movies by rating
         df[['title', 'vote_average']].sort_values(by='vote_average', ascending=False).he
         # Average rating
         df['vote average'].mean()
Out[14]: 6.0934402332361515
In [15]: import seaborn as sns
         import matplotlib.pyplot as plt
         plt.figure(figsize=(8, 5))
         sns.histplot(df['vote average'], bins=20, kde=True)
```

```
plt.title('Distribution of Movie Ratings')
plt.xlabel('Rating')
plt.ylabel('Count')
plt.show()
```



```
In [16]: import ast

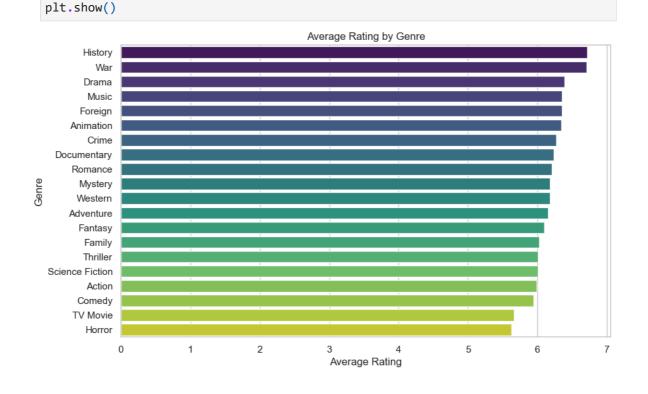
# Convert stringified list to list of dicts

df['genres'] = df['genres'].apply(lambda x: [i['name'] for i in ast.literal_eval

# Create a copy with one genre per row
genre_df = df.explode('genres')

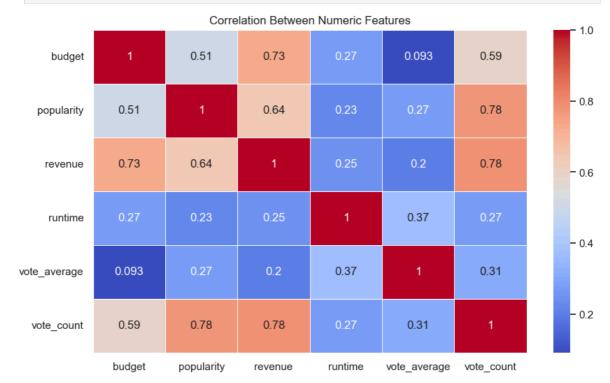
# Average rating per genre
genre_rating = genre_df.groupby('genres')['vote_average'].mean().sort_values(asc genre_rating
```

```
Out[16]:
          genres
          History
                             6.719797
          War
                             6.713889
          Drama
                             6.388594
          Music
                             6.355676
          Foreign
                             6.352941
          Animation
                             6.341453
          Crime
                             6.274138
          Documentary
                             6.238182
                             6.207718
          Romance
          Mystery
                             6.183908
                             6.178049
          Western
          Adventure
                             6.156962
          Fantasy
                             6.096698
          Family
                             6.029630
          Thriller
                             6.010989
          Science Fiction
                             6.005607
          Action
                             5.989515
                             5.945587
          Comedy
          TV Movie
                             5.662500
                             5.626590
          Horror
          Name: vote_average, dtype: float64
In [20]:
         plt.figure(figsize=(10, 6))
         sns.barplot(
              x=genre_rating.values,
              y=genre_rating.index,
              hue=genre_rating.index, # Add hue to apply palette correctly
              palette='viridis',
              dodge=False,
                                       # Ensure bars don't separate
              legend=False
                                       # Hide Legend since hue is just the index
         plt.title('Average Rating by Genre')
         plt.xlabel('Average Rating')
```



plt.ylabel('Genre')

```
In [18]: numeric_cols = ['budget', 'popularity', 'revenue', 'runtime', 'vote_average', 'v
    plt.figure(figsize=(10, 6))
    sns.heatmap(df[numeric_cols].corr(), annot=True, cmap='coolwarm', linewidths=0.5
    plt.title('Correlation Between Numeric Features')
    plt.show()
```



Key Insights:

- Genres like **Documentary** and **History** have higher average ratings.
- Most movies have a rating between 5 and 7.
- Budget and revenue have weak correlation with rating.
- Popularity doesn't directly translate to higher ratings.

In []: