Step 1 - Importing Required Libraries

Objective-

To analyze and derive meaningful insights from the TMDB dataset to understand movie trends, factors influencing movie success, and build predictive or recommendation models to enhance user engagement.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')     # warnings module is used to
display warning messages that alert the programmer
```

Step 2 - Exploring and Loading Data

```
df= pd.read_csv('tmdb_5000_movies.csv') # we are storing data into df

 df.head() #  head gives 5 rows and column information

      budget                                             genres  \
0  237000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
1  300000000  [{"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": 12, "nam...

                                       homepage      id  \
0                   http://www.avatarmovie.com/   19995
1  http://disney.go.com/disneypictures/pirates/     285
2   http://www.sonypictures.com/movies/spectre/  206647
3            http://www.thedarkknightrises.com/   49026
4          http://movies.disney.com/john-carter   49529

                                            keywords original_language
\
0  [{"id": 1463, "name": "culture clash"}, {"id":...                en

1  [{"id": 270, "name": "ocean"}, {"id": 726, "na...                en

2  [{"id": 470, "name": "spy"}, {"id": 818, "name...                en
```

```
3  [{"id": 849, "name": "dc comics"}, {"id": 853,...                en

4  [{"id": 818, "name": "based on novel"}, {"id":...                en


                             original_title  \
0                                    Avatar
1  Pirates of the Caribbean: At World's End
2                                   Spectre
3                     The Dark Knight Rises
4                               John Carter

                                            overview  popularity  \
0  In the 22nd century, a paraplegic Marine is di...  150.437577
1  Captain Barbossa, long believed to be dead, ha...  139.082615
2  A cryptic message from Bond’s past sends him o...  107.376788
3  Following the death of District Attorney Harve...  112.312950
4  John Carter is a war-weary, former military ca...   43.926995

                                production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289...
1  [{"name": "Walt Disney Pictures", "id": 2}, {"...
2  [{"name": "Columbia Pictures", "id": 5}, {"nam...
3  [{"name": "Legendary Pictures", "id": 923}, {"...
4        [{"name": "Walt Disney Pictures", "id": 2}]

                                production_countries release_date
revenue  \
0  [{"iso_3166_1": "US", "name": "United States o...   2009-12-10
2787965087
1  [{"iso_3166_1": "US", "name": "United States o...   2007-05-19
961000000
2  [{"iso_3166_1": "GB", "name": "United Kingdom"...   2015-10-26
880674609
3  [{"iso_3166_1": "US", "name": "United States o...   2012-07-16
1084939099
4  [{"iso_3166_1": "US", "name": "United States o...   2012-03-07
284139100

   runtime                                   spoken_languages
status  \
0    162.0  [{"iso_639_1": "en", "name": "English"}, {"iso...
Released
1    169.0           [{"iso_639_1": "en", "name": "English"}]
Released
2    148.0  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"},...
Released
3    165.0           [{"iso_639_1": "en", "name": "English"}]
Released
4    132.0           [{"iso_639_1": "en", "name": "English"}]
```

```
Released

                                               tagline  \
0                    Enter the World of Pandora.
1  At the end of the world, the adventure begins.
2                           A Plan No One Escapes
3                                 The Legend Ends
4             Lost in our world, found in another.

                                       title  vote_average  vote_count

0                                     Avatar           7.2       11800

1  Pirates of the Caribbean: At World's End           6.9        4500

2                                    Spectre           6.3        4466

3                      The Dark Knight Rises           7.6        9106

4                                John Carter           6.1        2124
```

```
df.tail()
```

```
      budget                                             genres  \
4798  220000  [{"id": 28, "name": "Action"}, {"id": 80, "nam...
4799    9000  [{"id": 35, "name": "Comedy"}, {"id": 10749, "...
4800       0  [{"id": 35, "name": "Comedy"}, {"id": 18, "nam...
4801       0                                                 []
4802       0                [{"id": 99, "name": "Documentary"}]

                                               homepage      id  \
4798                                                NaN    9367
4799                                                NaN   72766
4800  http://www.hallmarkchannel.com/signedsealeddel...  231617
4801                        http://shanghaicalling.com/  126186
4802                                                NaN   25975

                                               keywords
original_language  \
4798  [{"id": 5616, "name": "united states\u2013mexi...
es
4799                                                 []
en
4800  [{"id": 248, "name": "date"}, {"id": 699, "nam...
en
4801                                                 []
en
4802  [{"id": 1523, "name": "obsession"}, {"id": 224...
en
```

```
                 original_title  \
4798                El Mariachi
4799                  Newlyweds
4800  Signed, Sealed, Delivered
4801           Shanghai Calling
4802          My Date with Drew

                                               overview  popularity  \
4798  El Mariachi just wants to play his guitar and ...   14.269792
4799  A newlywed couple's honeymoon is upended by th...    0.642552
4800  "Signed, Sealed, Delivered" introduces a dedic...    1.444476
4801  When ambitious New York attorney Sam is sent t...    0.857008
4802  Ever since the second grade when he first saw ...    1.929883

                                   production_companies  \
4798           [{"name": "Columbia Pictures", "id": 5}]
4799                                                 []
4800  [{"name": "Front Street Pictures", "id": 3958}...
4801                                                 []
4802  [{"name": "rusty bear entertainment", "id": 87...

                                   production_countries release_date
revenue  \
4798  [{"iso_3166_1": "MX", "name": "Mexico"}, {"iso...   1992-09-04
2040920
4799                                                 []   2011-12-26
0
4800  [{"iso_3166_1": "US", "name": "United States o...   2013-10-13
0
4801  [{"iso_3166_1": "US", "name": "United States o...   2012-05-03
0
4802  [{"iso_3166_1": "US", "name": "United States o...   2005-08-05
0

      runtime                              spoken_languages    status
\
4798     81.0  [{"iso_639_1": "es", "name": "Espa\u00f1ol"}]  Released

4799     85.0                                            []  Released

4800    120.0       [{"iso_639_1": "en", "name": "English"}]  Released

4801     98.0       [{"iso_639_1": "en", "name": "English"}]  Released

4802     90.0       [{"iso_639_1": "en", "name": "English"}]  Released


                                                tagline  \
4798  He didn't come looking for trouble, but troubl...
4799  A newlywed couple's honeymoon is upended by th...
```

```
4800                                               NaN
4801                           A New Yorker in Shanghai
4802                                               NaN

                          title  vote_average  vote_count
4798                El Mariachi           6.6         238
4799                  Newlyweds           5.9           5
4800  Signed, Sealed, Delivered           7.0           6
4801           Shanghai Calling           5.7           7
4802          My Date with Drew           6.3          16
```

```
df.shape
```

```
(4803, 20)
```

This dataset contain 4803 rows and 20 column

```
df.dtypes
```

```
budget                    int64
genres                   object
homepage                 object
id                        int64
keywords                 object
original_language        object
original_title           object
overview                 object
popularity              float64
production_companies     object
production_countries     object
release_date             object
revenue                   int64
runtime                 float64
spoken_languages         object
status                   object
tagline                  object
title                    object
vote_average            float64
vote_count                int64
dtype: object
```

```
df.info()  # df.info() provides a summary of the DataFrame, showing the number of non-null entries, column names, data types, and memory usage.
```

```
<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 
 3   id                    4803 non-null   int64  
 4   keywords              4803 non-null   object 
 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 
 11  release_date          4802 non-null   object 
 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 
 16  tagline               3959 non-null   object 
 17  title                 4803 non-null   object 
 18  vote_average          4803 non-null   float64
 19  vote_count            4803 non-null   int64  
dtypes: float64(3), int64(4), object(13)
memory usage: 750.6+ KB
```

```
df.isnull().sum()
```

```
budget                     0
genres                     0
homepage                3091
id                         0
keywords                   0
original_language          0
original_title             0
overview                   3
popularity                 0
production_companies       0
production_countries       0
release_date               1
revenue                    0
runtime                    2
spoken_languages           0
status                     0
tagline                  844
title                      0
vote_average               0
vote_count                 0
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

Step 3: Data Cleaning Or Data Preprossing

In above cell we observe their are missing values are presents

We Observe these columns having missing values homepage = 3091 , overview = 3, release_date = 1, runtime = 2 , tagline = 844

Treating the missing values

```
df['homepage'].fillna('No homepage', inplace=True)
df['overview'].fillna('No overview available', inplace=True)
df['release_date'].fillna('2000-01-01', inplace=True)   # or:
df.dropna(subset=['release_date'], inplace=True)

df['runtime'].fillna(df['runtime'].median(), inplace=True)
df['tagline'].fillna('No tagline', inplace=True)

 df.isnull().sum()
```

```
budget                  0
genres                  0
homepage                0
id                      0
keywords                0
original_language       0
original_title          0
overview                0
popularity              0
production_companies    0
production_countries    0
release_date            0
revenue                 0
runtime                 0
spoken_languages        0
status                  0
tagline                 0
title                   0
vote_average            0
vote_count              0
dtype: int64
```

Remove inimportant columns

```
drop_cols = ['homepage','id','original_title',]

df.drop(columns=drop_cols, inplace=True)
```

create a new column like release_year

```
df['release_date'] = pd.to_datetime(df['release_date'],
errors='coerce')
df['release_year'] = df['release_date'].dt.year
```

List of variable

```
Continuous = ['budget', 'popularity', 'revenue', 'runtime',
'vote_average']
Discrete_Count = [ 'vote_count']
Categorical = ['genres', 'keywords', 'original_language',
               'overview', 'production_companies',
'production_countries',
               'spoken_languages', 'status', 'tagline', 'title']
Time_Series = ['release_date','release_year']
```

Apply the descriptive statistics

```
df[Continuous].describe()
```

	budget	popularity	revenue	runtime	vote_average
count	4.803000e+03	4803.000000	4.803000e+03	4803.000000	4803.000000
mean	2.904504e+07	21.492301	8.226064e+07	106.874245	6.092172
std	4.072239e+07	31.816650	1.628571e+08	22.607364	1.194612
min	0.000000e+00	0.000000	0.000000e+00	0.000000	0.000000
25%	7.900000e+05	4.668070	0.000000e+00	94.000000	5.600000
50%	1.500000e+07	12.921594	1.917000e+07	103.000000	6.200000
75%	4.000000e+07	28.313505	9.291719e+07	117.500000	6.800000
max	3.800000e+08	875.581305	2.787965e+09	338.000000	10.000000

```
df[Discrete_Count].describe()
```

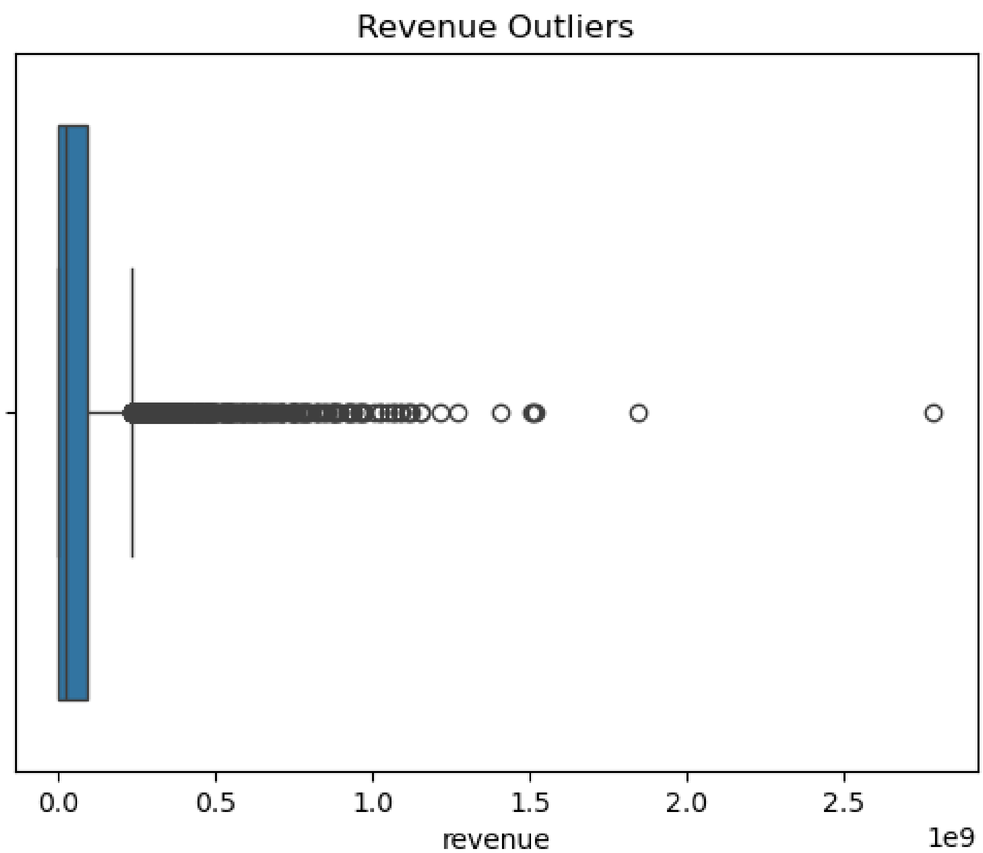
	vote_count
count	4803.000000
mean	690.217989
std	1234.585891
min	0.000000
25%	54.000000
50%	235.000000
75%	737.000000
max	13752.000000

```
df[Categorical].describe()

                                  genres keywords original_language  \
count                               4803     4803              4803
unique                              1175     4222                37
top     [{"id": 18, "name": "Drama"}]       []                en
freq                                 370      412              4505

                     overview production_companies  \
count                    4803                 4803
unique                   4801                 3697
top     No overview available                   []
freq                        3                  351

                                      production_countries  \
count                                                 4803
unique                                                 469
top     [{"iso_3166_1": "US", "name": "United States o...
freq                                                  2977

                                spoken_languages    status     tagline
\
count                                       4803      4803        4803

unique                                       544         3        3945

top     [{"iso_639_1": "en", "name": "English"}]  Released  No tagline

freq                                        3171      4795         844


            title
count        4803
unique       4800
top     The Host
freq            2

df[Time_Series].describe()

                          release_date  release_year
count                             4803   4803.000000
mean    2002-12-27 18:18:30.805746688   2002.468249
min               1916-09-04 00:00:00   1916.000000
25%               1999-07-14 00:00:00   1999.000000
50%               2005-10-01 00:00:00   2005.000000
75%               2011-02-16 00:00:00   2011.000000
max               2017-02-03 00:00:00   2017.000000
std                                NaN     12.413112

Q1 = df['revenue'].quantile(0.25)
Q3 = df['revenue'].quantile(0.75)
```

```
IQR = Q3 - Q1

# Define bounds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Find outliers
outliers = df[(df['revenue'] < lower_bound) | (df['revenue'] >
upper_bound)]

# Print number of outliers and sample
print("Number of revenue outliers:", outliers.shape[0])
print(outliers[['title', 'revenue']].head())
```

```
Number of revenue outliers: 472
                                      title     revenue
0                                    Avatar  2787965087
1  Pirates of the Caribbean: At World's End   961000000
2                                   Spectre   880674609
3                     The Dark Knight Rises  1084939099
4                               John Carter   284139100
```

```
sns.boxplot(x=df['revenue'])
plt.title("Revenue Outliers")
plt.show()
```



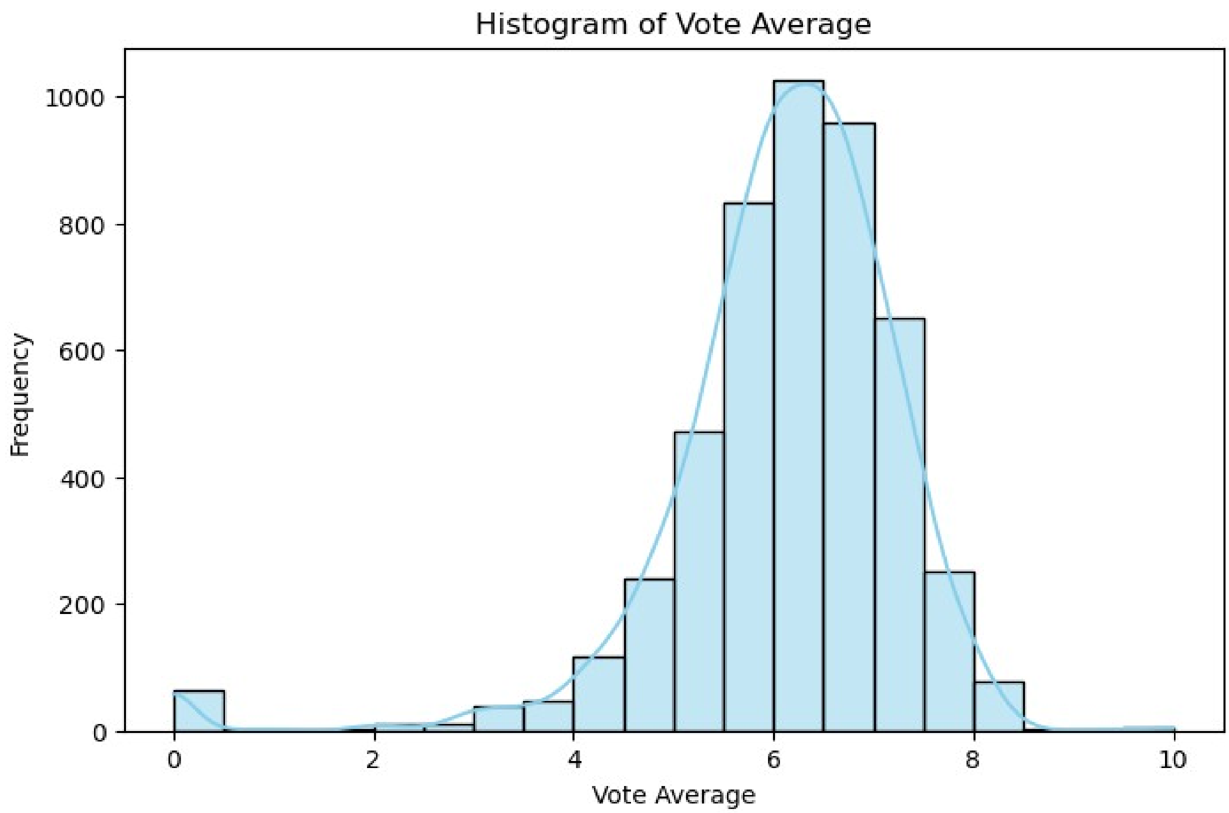
Stpe - 4 Exploratory Data Analysis

1.Univariate Analysis (Single Variable)

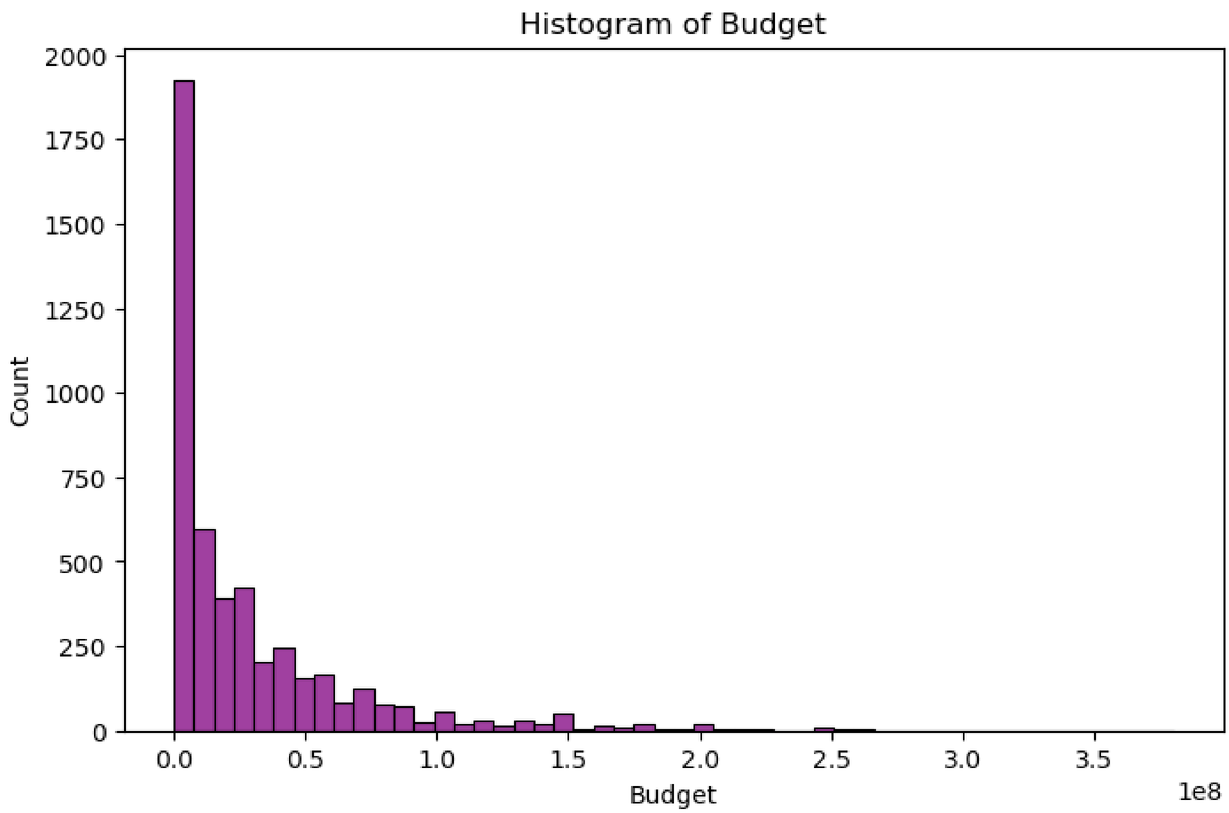
observations:-

- Vote average centers around 6 to 7.
- Distribution is slightly left-skewed, with more moderately rated movies.
- Few very low or very high ratings, indicating consistent public opinion

```
plt.figure(figsize=(8, 5))
sns.histplot(df['vote_average'], kde=True, bins=20, color='skyblue')
plt.title('Histogram of Vote Average')
plt.xlabel('Vote Average')
plt.ylabel('Frequency')
plt.show()
```



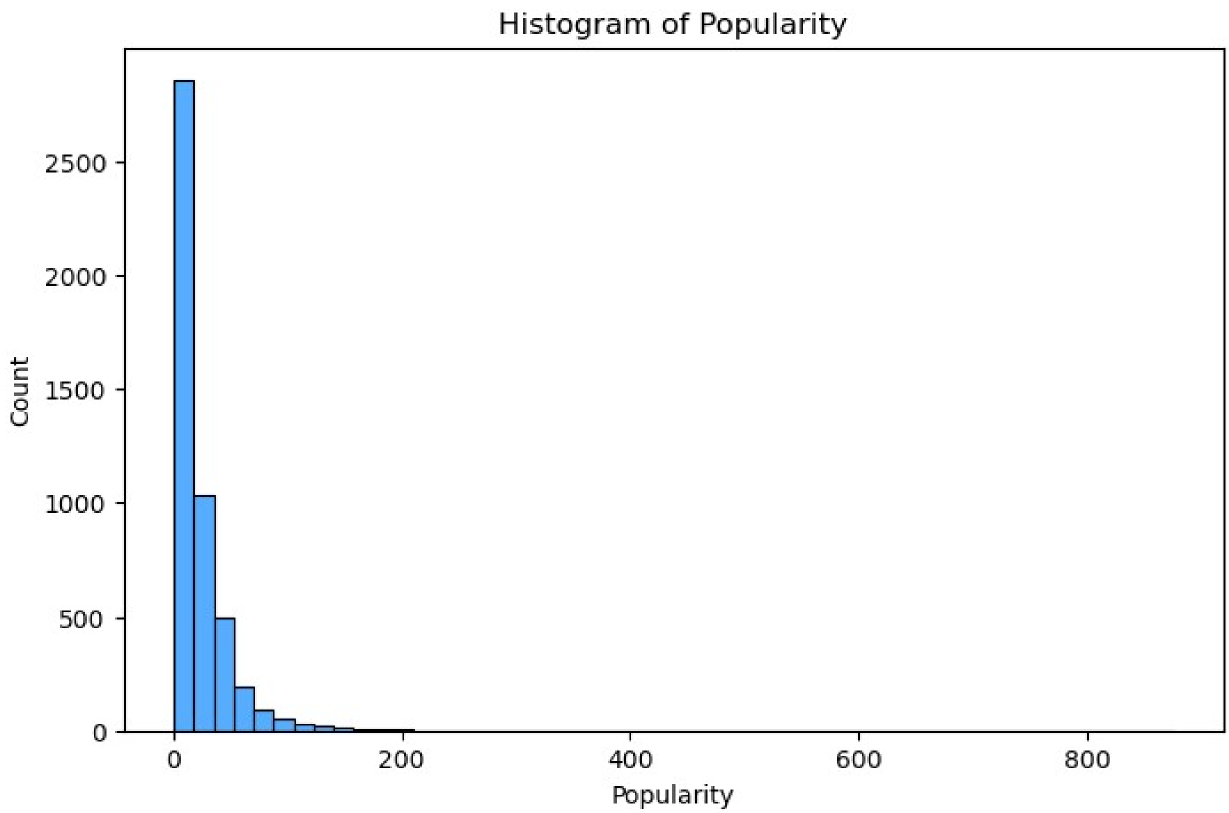

```
plt.figure(figsize=(8, 5))
sns.histplot(df['budget'], bins=50, color='purple')
plt.title('Histogram of Budget')
plt.xlabel('Budget')
plt.ylabel('Count')
plt.show()
```



observations:-

- Budget is heavily right-skewed.
- Most movies have low to moderate budgets.
- A few outliers with very high budgets dominate the scale

```
plt.figure(figsize=(8, 5))
sns.histplot(df['popularity'], bins=50, color='dodgerblue')
plt.title('Histogram of Popularity')
plt.xlabel('Popularity')
plt.ylabel('Count')
plt.show()
```

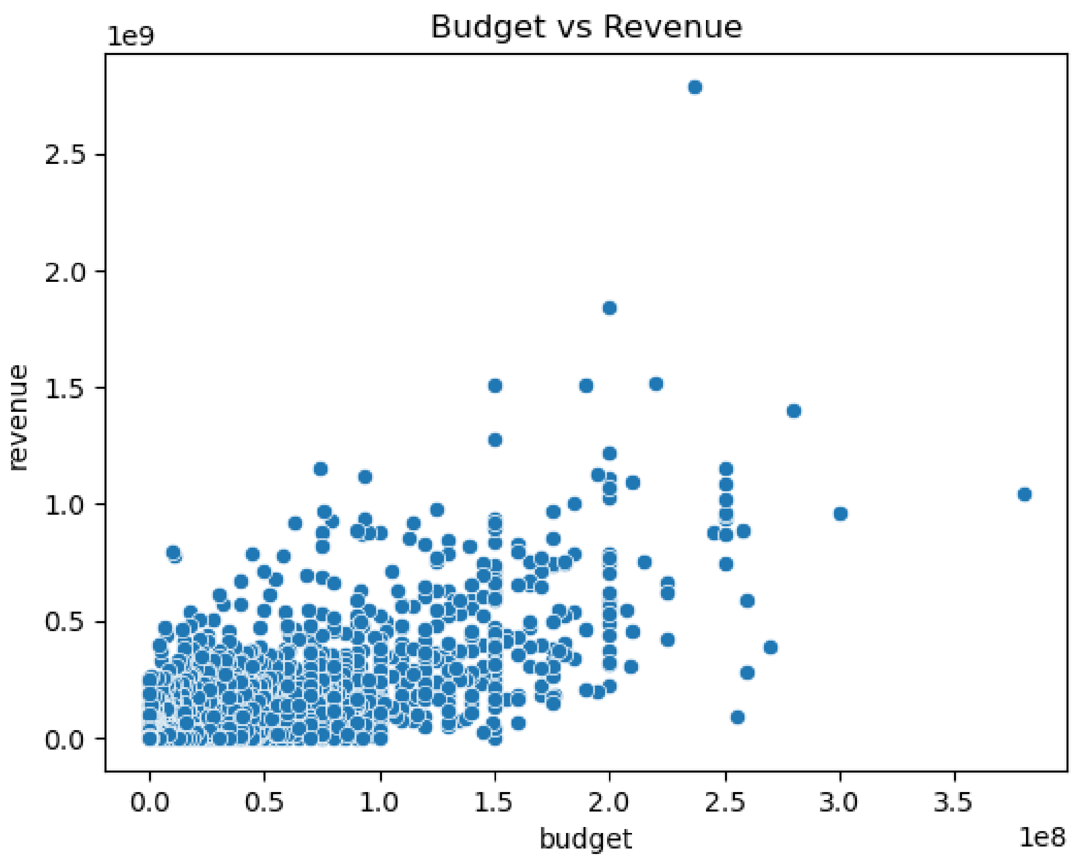


Observations:

- Popularity is right-skewed.
- Most movies have low popularity scores.
- A few movies are extremely popular, creating a long tail.

2. Bivariate Analysis (Two Variables)

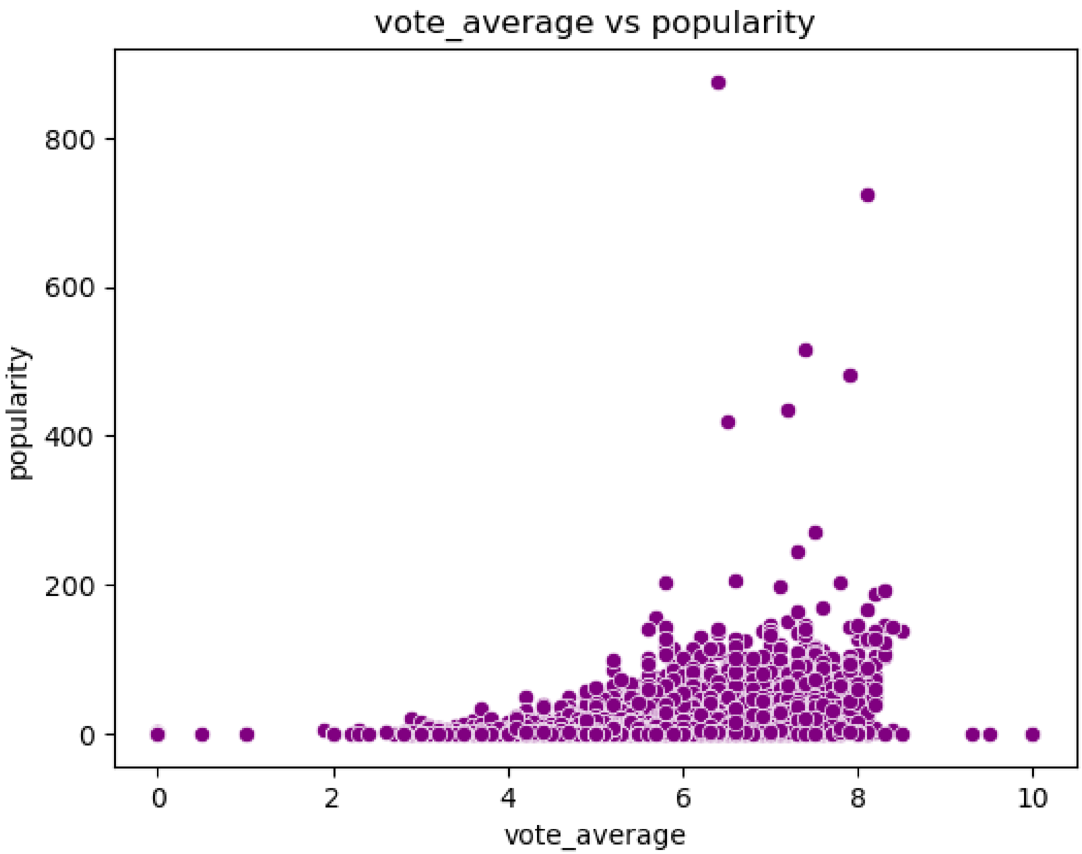
```
# Budget vs Revenue
sns.scatterplot(x='budget', y='revenue', data=df)
plt.title("Budget vs Revenue")
plt.show()
```



Observation:

- Generally, higher budgets lead to higher revenues, but there are many low-budget outliers.

```
sns.scatterplot(x='vote_average', y='popularity',data=df,color=
'purple')
plt.title("vote_average vs popularity")
plt.show()
```

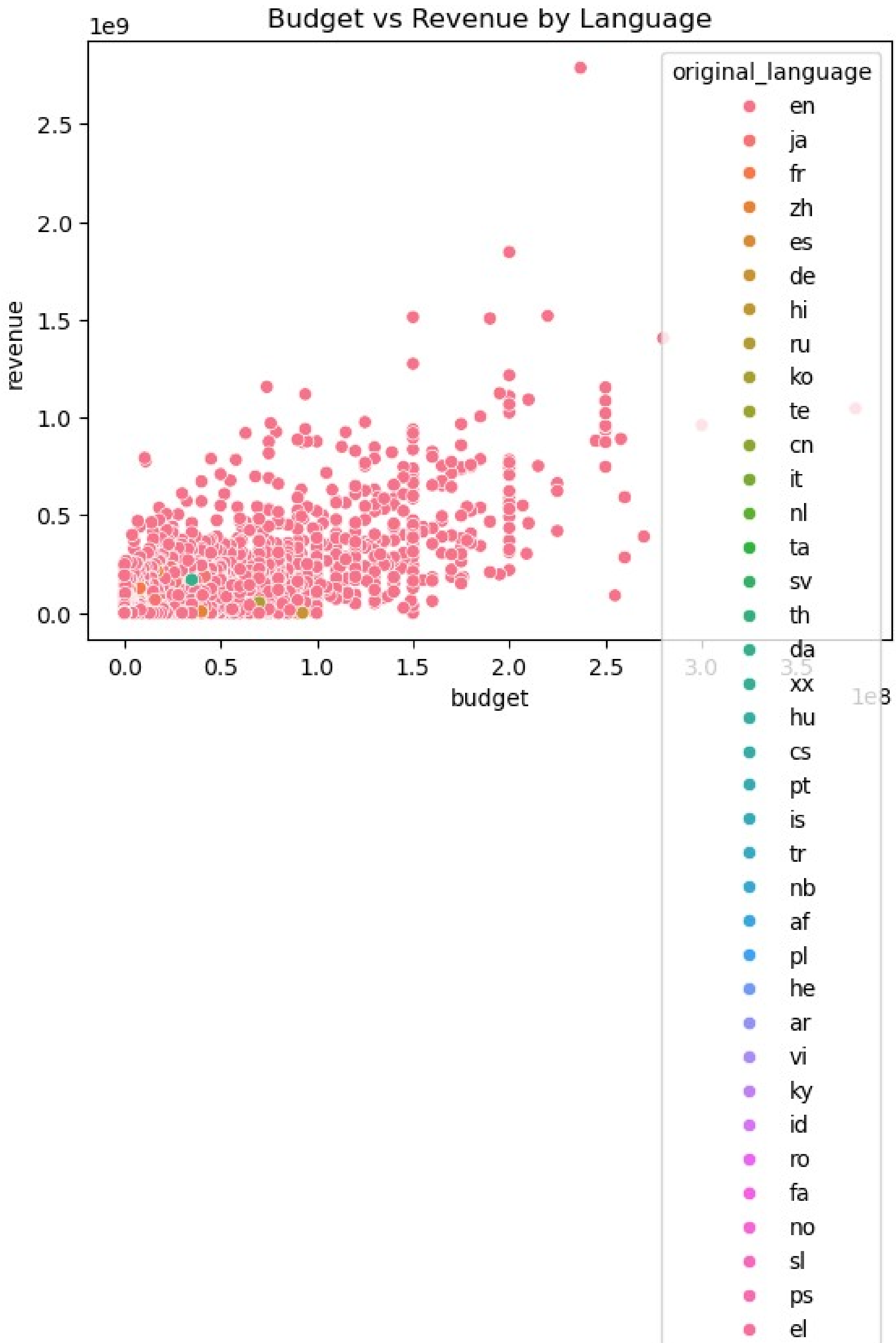


Observation :

- There's no strong correlation — movies with average ratings (5–7) vary widely in popularity. Some low-rated movies are still very popular

3. Multivariate Analysis:- Explore the interaction among three or more variables.

```
sns.scatterplot(x='budget', y='revenue', hue='original_language',
data=df)
plt.title("Budget vs Revenue by Language")
plt.show()
```

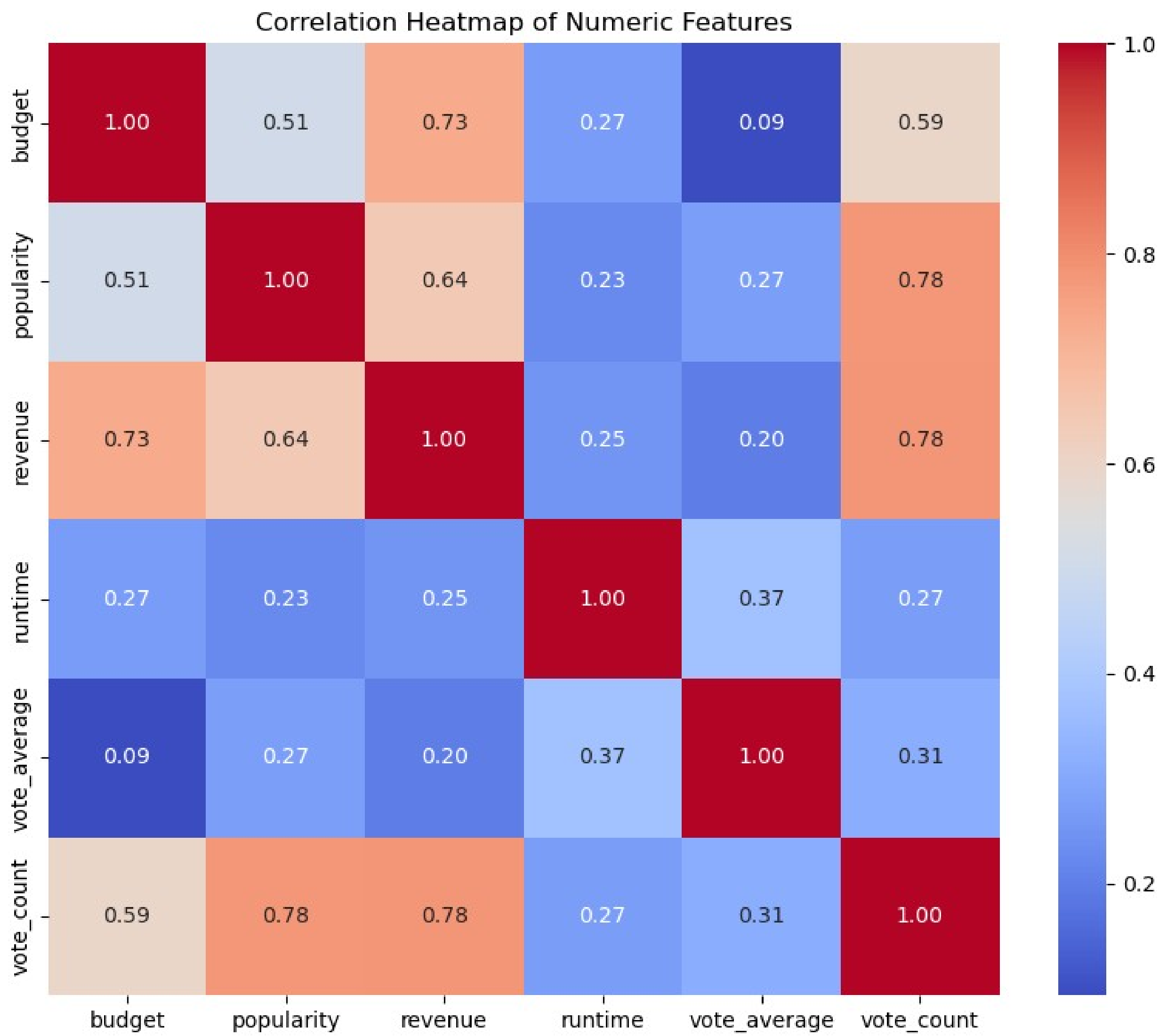


Observation:

- English-language movies dominate the high-budget/high-revenue space.

Correlation Heatmap

```
# Selecting numeric columns for correlation
numeric_df = df.select_dtypes(include=['float64', 'int64'])

# Compute the correlation matrix
corr_matrix = numeric_df.corr()

# Plotting the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",
square=True)
plt.title("Correlation Heatmap of Numeric Features")
plt.show()
```



Strong correlation:

- budget and revenue are positively correlated — higher budgets often bring higher revenues.
- vote_count and popularity also show a strong positive relationship.

Weak or no correlation:

- vote_average has weak correlation with most variables.
- runtime shows a slight positive correlation with revenue and budget.

GroupBy Analysis

- Summarize data based on a categorical column

```
df.groupby('original_language')
['vote_average'].mean().sort_values(ascending=False).head()

original_language
te    7.500
id    7.400
he    7.400
fa    7.375
ar    7.300
Name: vote_average, dtype: float64
```

Observation:

- Some non-English films receive higher average ratings.

Crosstab Analysis

- Explore frequency relationships between two categorical variables.

```
pd.crosstab(df['status'], df['original_language'])

original_language  af  ar  cn  cs  da  de  el    en  es  fa  ...  ru
sl  sv  \
status                                                       ...

Post Production     0   0   0   1   0   0   0     2   0   0  ...   0
0   0
Released            1   2  12   1   7  27   1  4498  32   4  ...  11
1   5
Rumored             0   0   0   0   0   0   0     5   0   0  ...   0
0   0

original_language  ta  te  th  tr  vi  xx  zh
status
Post Production     0   0   0   0   0   0   0
Released            2   1   3   1   1   1  27
```

```
Rumored             0    0    0    0    0    0    0

[3 rows x 37 columns]
```

Filtering

- Extract specific subsets of data.

```
df[(df['vote_average'] > 8) & (df['revenue'] > 1e8)][['title',
'vote_average', 'revenue']]

                                             title  vote_average
revenue
65                                 The Dark Knight           8.2
1004558444
95                                    Interstellar           8.1
675120017
96                                       Inception           8.1
825532764
329   The Lord of the Rings: The Return of the King           8.1
1118888979
662                                     Fight Club           8.3
100853753
690                                 The Green Mile           8.2
284600000
809                                   Forrest Gump           8.2
677945399
1553                                        Se7en           8.1
327311859
1818                             Schindler's List           8.3
321365567
1987                          Howl's Moving Castle           8.2
234710455
1990                       The Empire Strikes Back           8.2
538400000
2091                      The Silence of the Lambs           8.1
272742922
2247                             Princess Mononoke           8.2
159375308
2294                                 Spirited Away           8.3
274925095
2453                            Dead Poets Society           8.1
235860116
2912                                     Star Wars           8.1
775398007
3232                                  Pulp Fiction           8.3
213928762
3337                                 The Godfather           8.4
245066411
```

```
3719                    One Flew Over the Cuckoo's Nest             8.2
108981275
```

Observations

1. High Ratings (8.1 – 8.4)

- All movies have vote_average ≥ 8.1, indicating critical acclaim and strong audience approval.
- Examples: The Godfather (8.4), Pulp Fiction (8.3), Fight Club (8.3).

2. Strong Revenue:

- of these films also have high revenue, showing both commercial and critical success.
- The Dark Knight – $1.004B
- The Return of the King – $1.118B
- Inception – $825M