##Project Report

Data set Description

Dataset is of multiple movies and related columns to that movies
It is divided into two sections :
smaller dataset (10k rows)
id,original_language,original_title,release_date,vote_average,vote_count,genre,overview,revenue,runtime
and
larger dataset (1Million rows)
Id, title, genre, userId, rating, gender, age

Columns are self-explanatory and others are :
Avg_voting is out of 10.
Revenue is a movie’s collection.
Rating is out of 5*
Users and movies have different IDs.

data quality/integrity/ethics issues

- The larger dataset has one to many relationship between the columns like :
  single movie with its genre and id (1->many) rating, age, gender i.e.one movie was rated by multiple users of any gender and different ratings
- Incomplete Genre Data: The 'genres' column has only 6020 non-null values out of a total of 1000209 rows. This means that genre information is missing for a large portion of the movies in the dataset. This could limit the usefulness of the dataset for certain types of analysis or recommendations.
- Biased User Demographics: The dataset only includes information on gender and age of the users, and it is not clear how representative the sample is of the general population. The dataset is not be inclusive of all types of users, which could lead to biased recommendations or conclusions based on the data.
- Limited Rating Scale: The rating column only ranges from 1 to 5, which could limit the granularity of the analysis and recommendations that can be made from the data.
- Potential for Fraudulent Ratings: There is no information on how the ratings were obtained from the users, which could leave the dataset open to potential fraudulent ratings or other data quality issues.
- Privacy Concerns: The dataset contains personal information such as gender and age, which could raise privacy concerns if the data is not handled appropriately.
- Lack of Contextual Information: The dataset does not provide any contextual information about the movies, such as release date or production budget, which could limit the analysis and insights that can be drawn from the data.
- While in the smaller data there are missing values: There are missing values in almost all columns, with the number of non-null values ranging from 5336 to 10014. This can be problematic for data analysis since missing data can bias results and decrease the representativeness of the dataset.
- Inconsistent data types: Some columns contain data of inconsistent data types. For example, The "release_date" column is also of type "object" while it will be more appropriate to represent it as a datetime object.

- Data integrity issues: There is a data integrity issues in the dataset, such inconsistencies. For example, Unicode formatting utf-8 is not suitable for many different languages hence data is likely to have movie title as garbage column
- Bias: The dataset may be biased towards certain genres or languages, which can impact the representativeness of the dataset and bias any analysis or modeling based on it.
- Privacy and ethics: The dataset may contain personal information about individuals involved in the movies, such as the actors or crew, that may need to be protected or anonymized to maintain privacy and ethical considerations.
- In summary, the dataset has missing values, inconsistent data, data integrity issues, and potential biases and privacy/ethical considerations. These issues need to be addressed and carefully considered in any data analysis or modeling based on this dataset.

Data preparation/wrangling

#Data-wrangling and Data preparation operations :

- ✓ Merging the datasets
- ✓ Groupby() & Merge
- ✓ Simple reading csv files and identifying the types of data
- ✓ Using median and mode in the data columns to fill the null values
- ✓ Categorizing using data slice and dice
- ✓ Dealing with outliers

All outcomes at the end of the report

Data mining fundamentals **(25 points)**

#Data Mining technique used:

- ✓ Linear Regression
- ✓ Logistic Regression
- ✓ Support Vector Machine to find SVM score.
- ✓ Correlation and Heatmap to relate different parameters of data.
- ✓ KNN for clustering analysis and Silhouette's coefficient

**All outcomes at the end of the report*

Data Visualization:

Please find all the data visualization techniques performed as per the relevance of the data:

(Loading csv)

In [122]:

```
import pandas as pd
import numpy as np
import seaborn as sn
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.model_selection import train_test_split

desired_width = 40
pd.set_option('display.width', desired_width)
pd.set_option('display.max_columns', 20)
df = pd.read_csv(r'combinedData.csv', low_memory=False)

df.info()
```

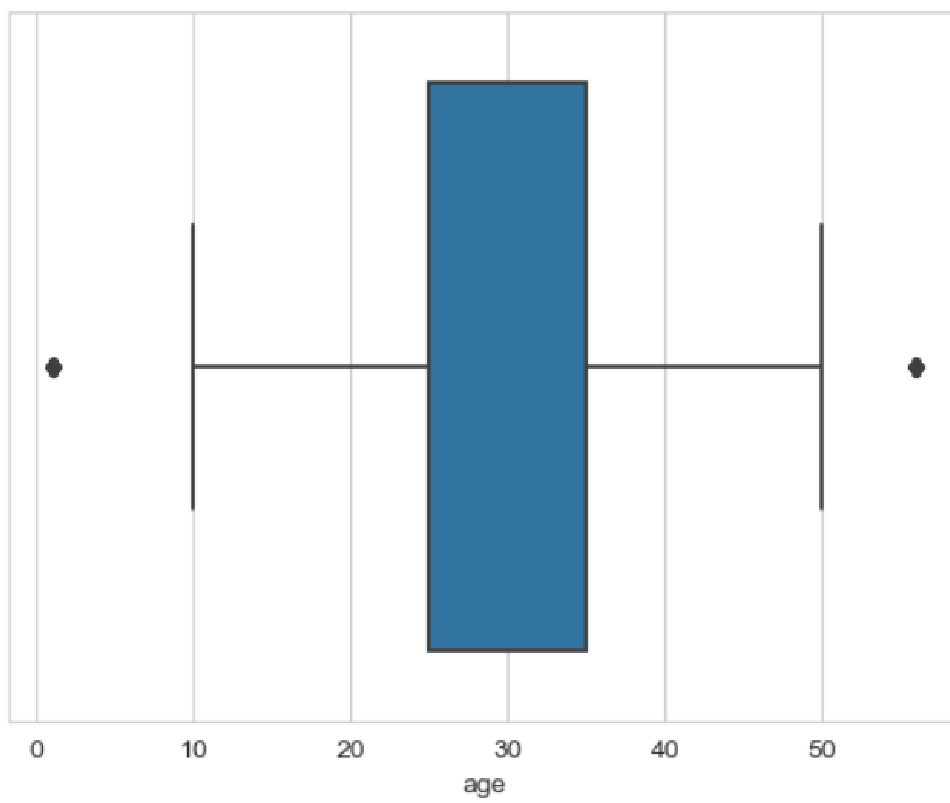
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 7 columns):
 #   Column   Non-Null Count    Dtype
---  ------   --------------    -----
 0   movieId  1000209 non-null  int64
 1   title    1000209 non-null  object
 2   genres   6020 non-null     object
 3   userId   1000209 non-null  int64
 4   rating   1000209 non-null  int64
 5   gender   1000209 non-null  object
 6   age      1000209 non-null  int64
dtypes: int64(4), object(3)
memory usage: 53.4+ MB
```

1. Boxplot

In [120]:

```
sn.boxplot(dataframe.age)
plt.show()
```

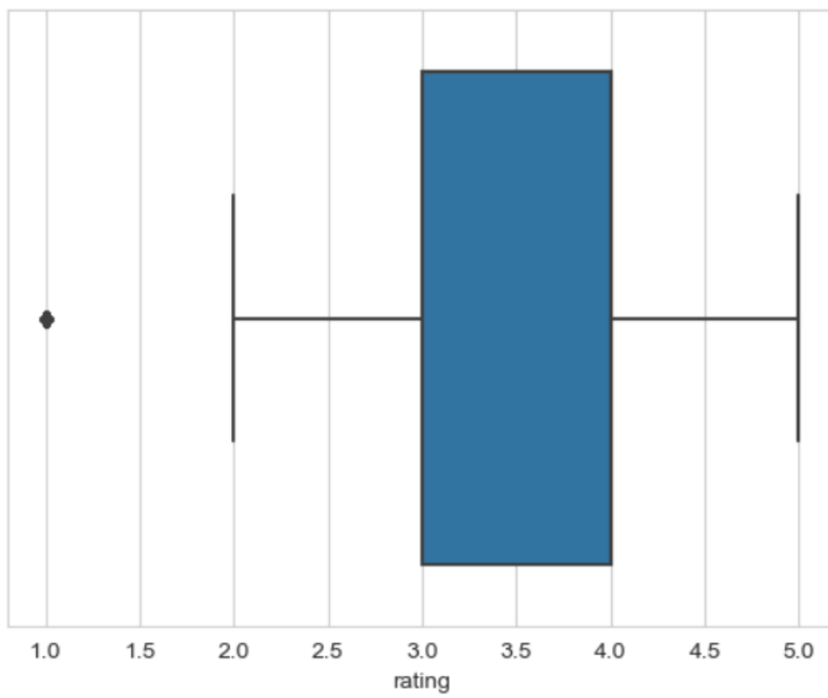
```
C:\Users\adhir\anaconda\lib\site-packages\seaborn\_decorators.py:36: Futu
arg: x. From version 0.12, the only valid positional argument will be `da
t keyword will result in an error or misinterpretation.
  warnings.warn(
```



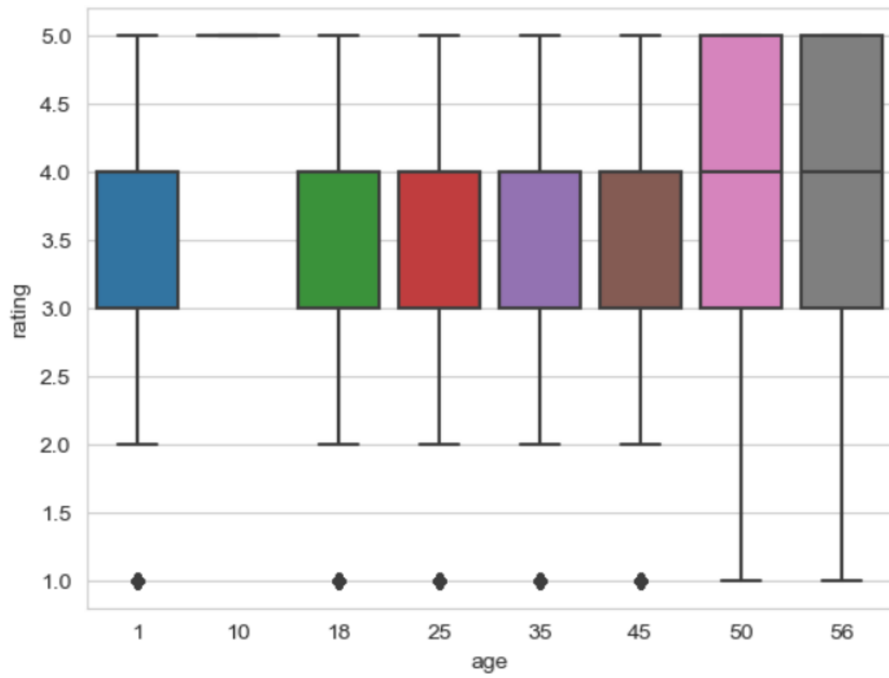
In [121]:

```
sn.boxplot(dataframe.rating)
plt.show()
```

```
C:\Users\adhir\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
arg: x. From version 0.12, the only valid positional argument will be `data`, and passin
t keyword will result in an error or misinterpretation.
  warnings.warn(
```

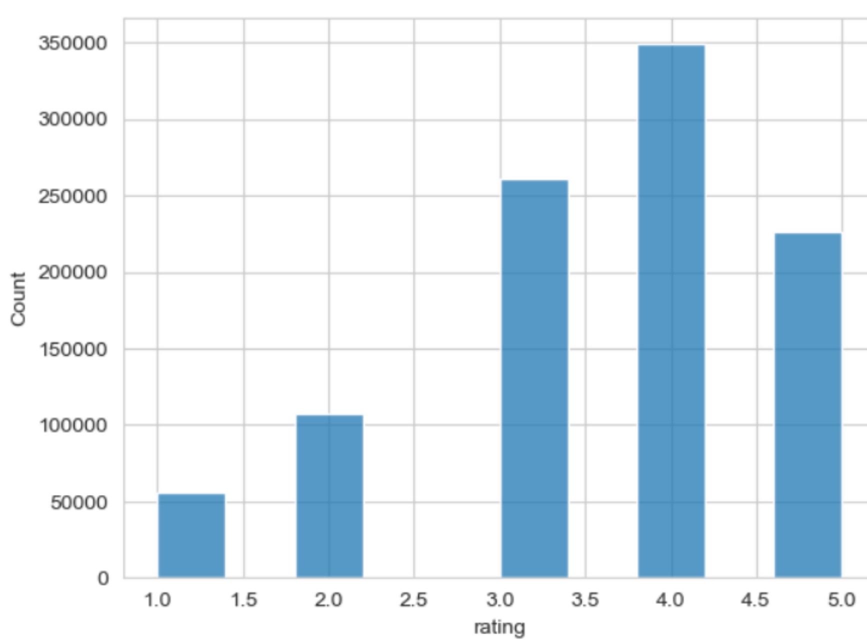


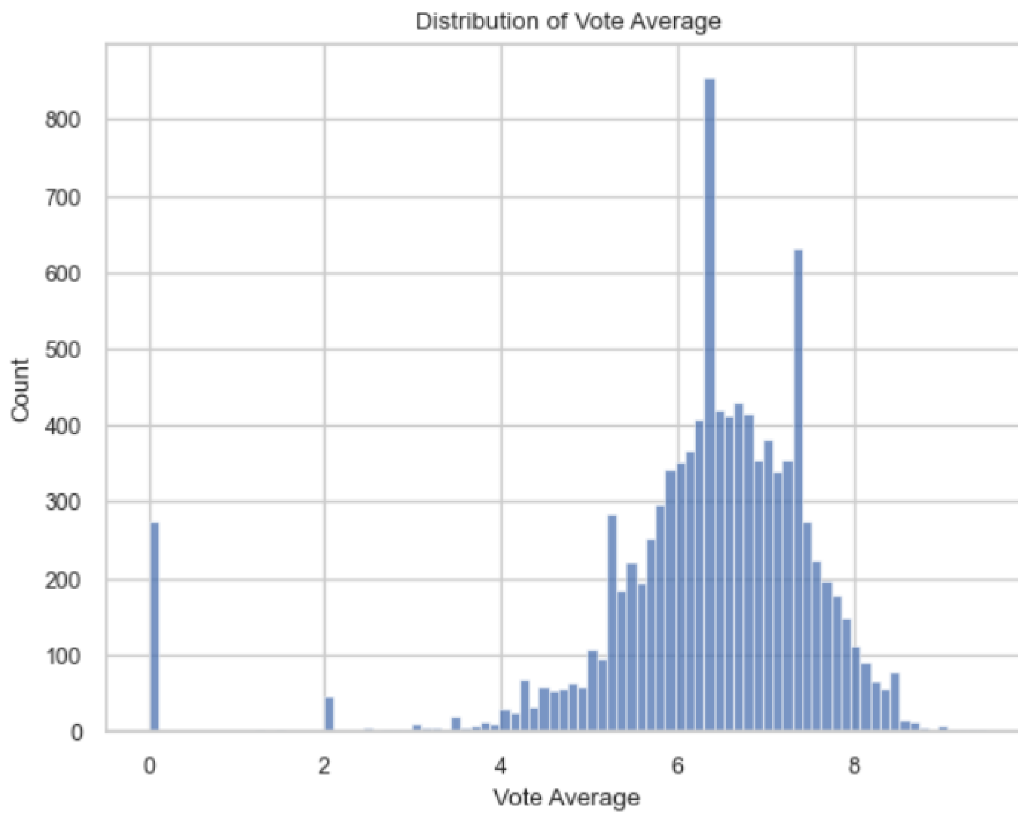
In [125]:
```python
sn.boxplot(data=df, x='age', y='rating')
plt.show()
```



2. Histplot

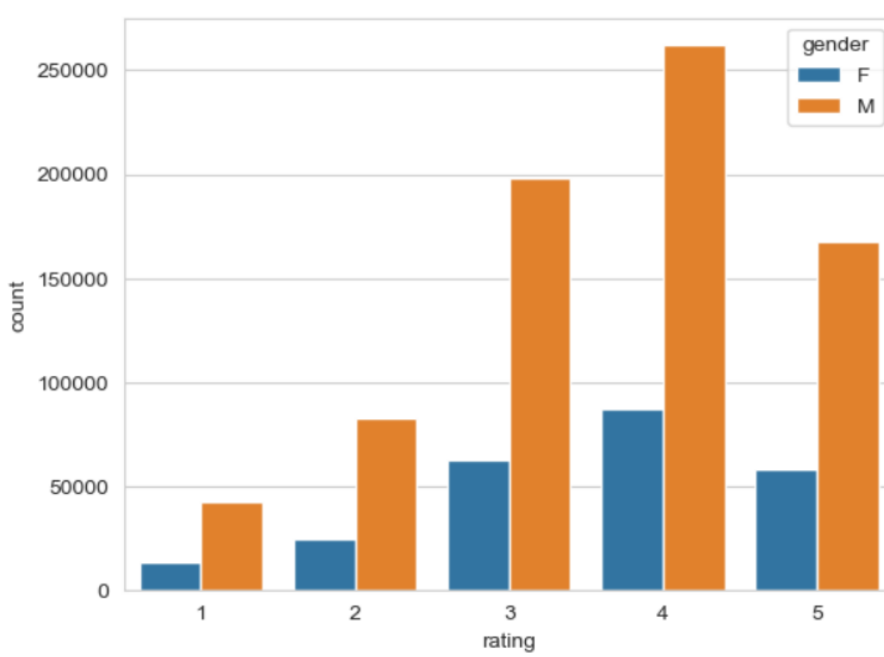
In [123]:
```python
sn.histplot(data=df, x='rating', bins=10)
plt.show()
```





3. Countplot

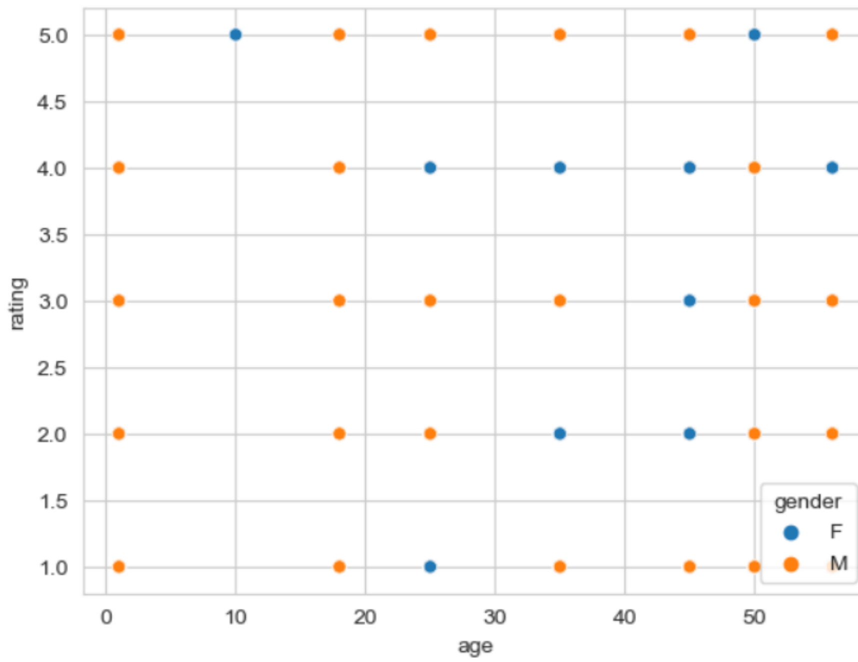
In [124]:
```
sn.countplot(data=df, x='rating', hue='gender')
plt.show()
```



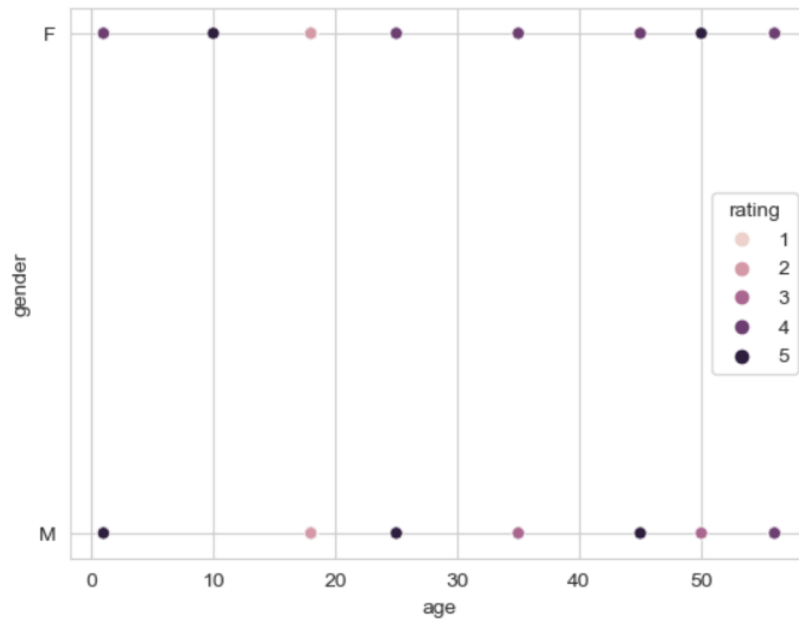
4. Scatterplot

In [126]:
```
sn.scatterplot(data=df, x='age', y='rating', hue='gender')
plt.show()
```

```
C:\Users\adhir\anaconda\lib\site-packages\IPython\core\pylabtools.py:151: UserWarning: Creatin
e slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```

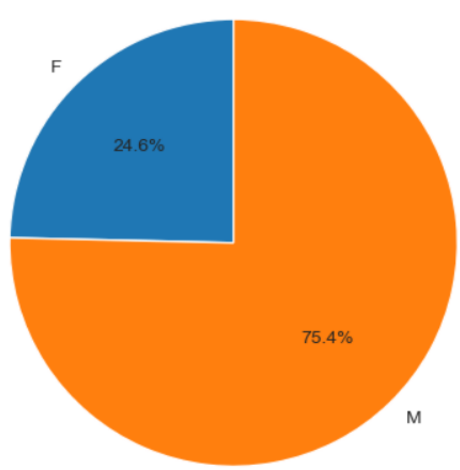


In [128]:
```
sn.scatterplot(data=df, x='age', y='gender', hue='rating')
plt.show()
```



5. Piechart

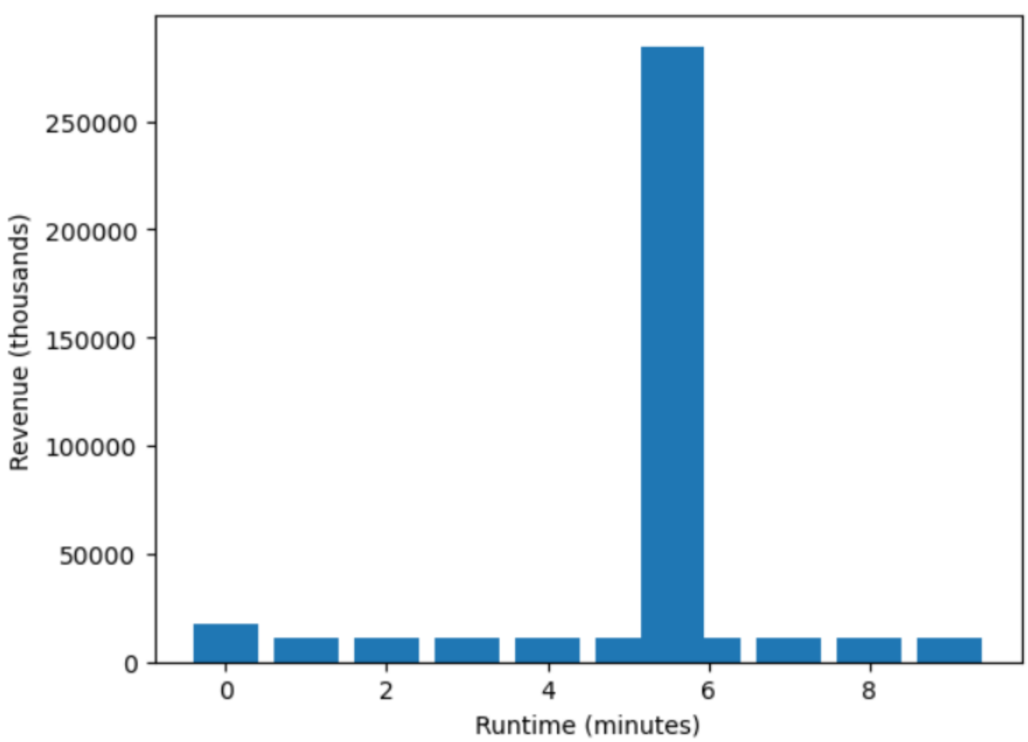
In [127]:
```
rating_counts = df.groupby('gender')['rating'].count()

sn.set_style("whitegrid")
plt.pie(rating_counts, labels=rating_counts.index, autopct='%1.1f%%', startangle=90)
plt.axis('equal')
plt.show()
```



6. Barchart

In [118]:

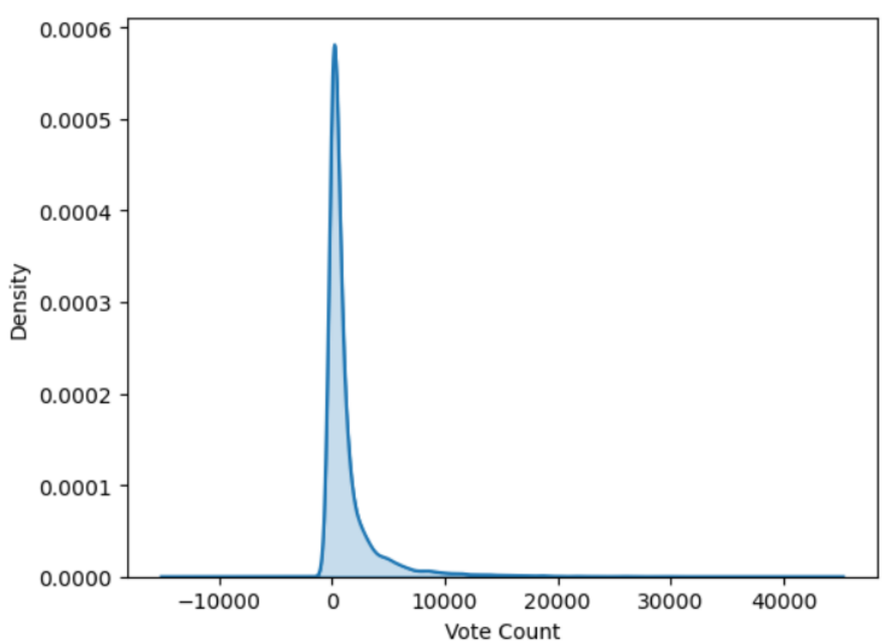
```
# Filter out rows where runtime is less than 10
df.loc[df['runtime'] >= 10 , 'runtime'] = None
df.loc[df['revenue'] < 10000, 'revenue'] = None

# Calculate the mean of the runtime column
mean_runtime = df['runtime'].mean()
mean_rev = df['revenue'].mean()

# Fill any missing values in the runtime column with the mean
df['runtime'] = df['runtime'].fillna(mean_runtime)
df['revenue'] = df['revenue'].fillna(mean_rev)

# Convert revenue to thousands
df['revenue'] = df['revenue'] /10000

# Reset the index of the DataFrame for safer side
# df = df.reset_index(drop=True)

# Create a horizontal bar chart with revenue on the x-axis and runtime on the y-axis
plt.bar(df['runtime'], df['revenue'])

# Set the x-label and y-label of the plot
plt.xlabel('Runtime (minutes)')
plt.ylabel('Revenue (thousands)')

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



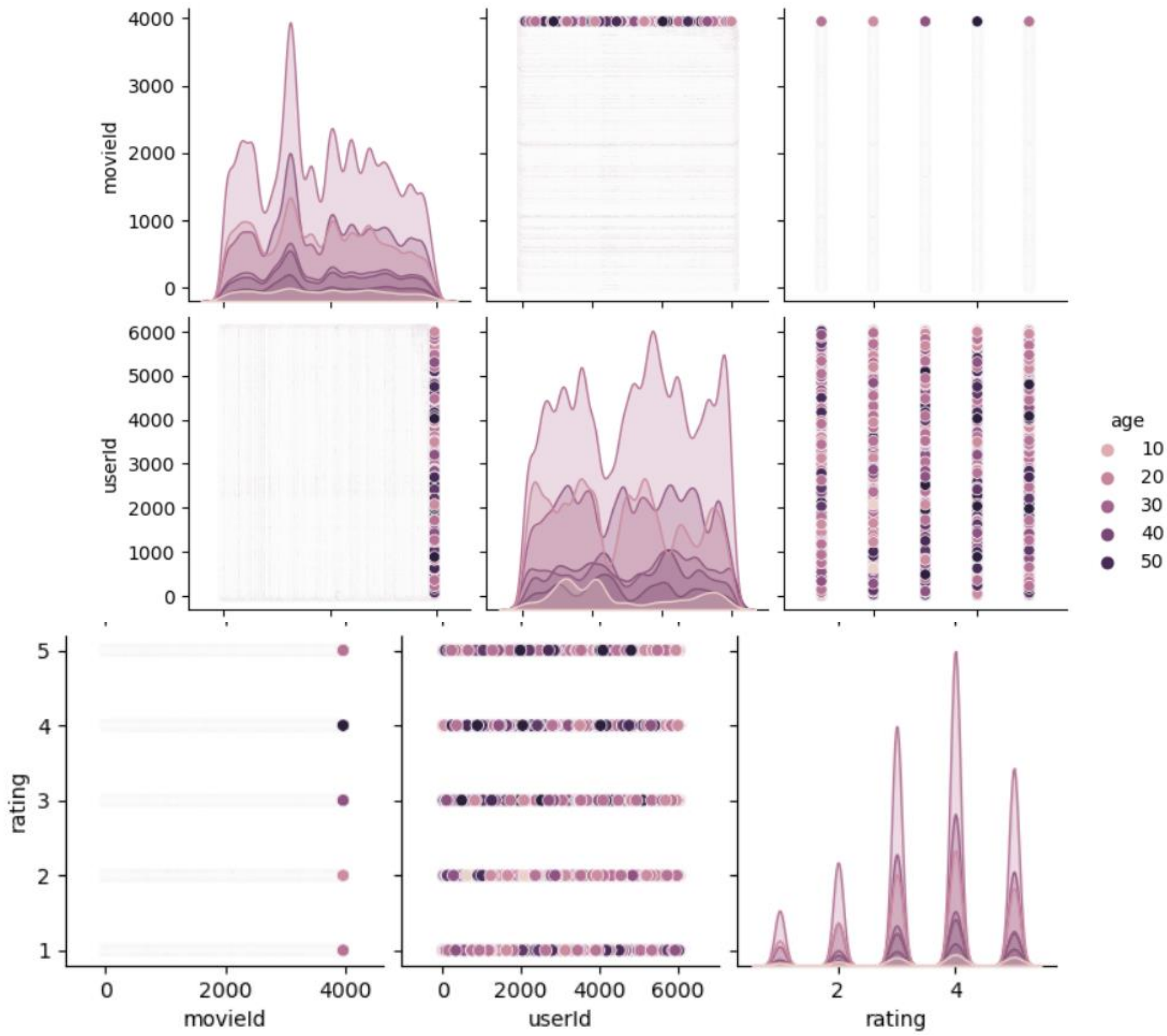
7. Density distribution

In [117]:

```
#density distribution chart of different columns

# Filter out null values from the "vote_count" column
df_filtered = df.dropna(subset=['vote_count'])

# Create a density distribution chart using Seaborn
sn.kdeplot(df_filtered['vote_count'], shade=True)

# Set the x-label and y-label of the plot
plt.xlabel('Vote Count')
plt.ylabel('Density')

# Show the plot
df.vote_count.plot(kind='kde')
plt.show()
```



8. Pairplots


movieId
userId
rating
age
10
20
30
40
50
0
2000
4000
6000
1000
3000
5000
1
2
3
4
5

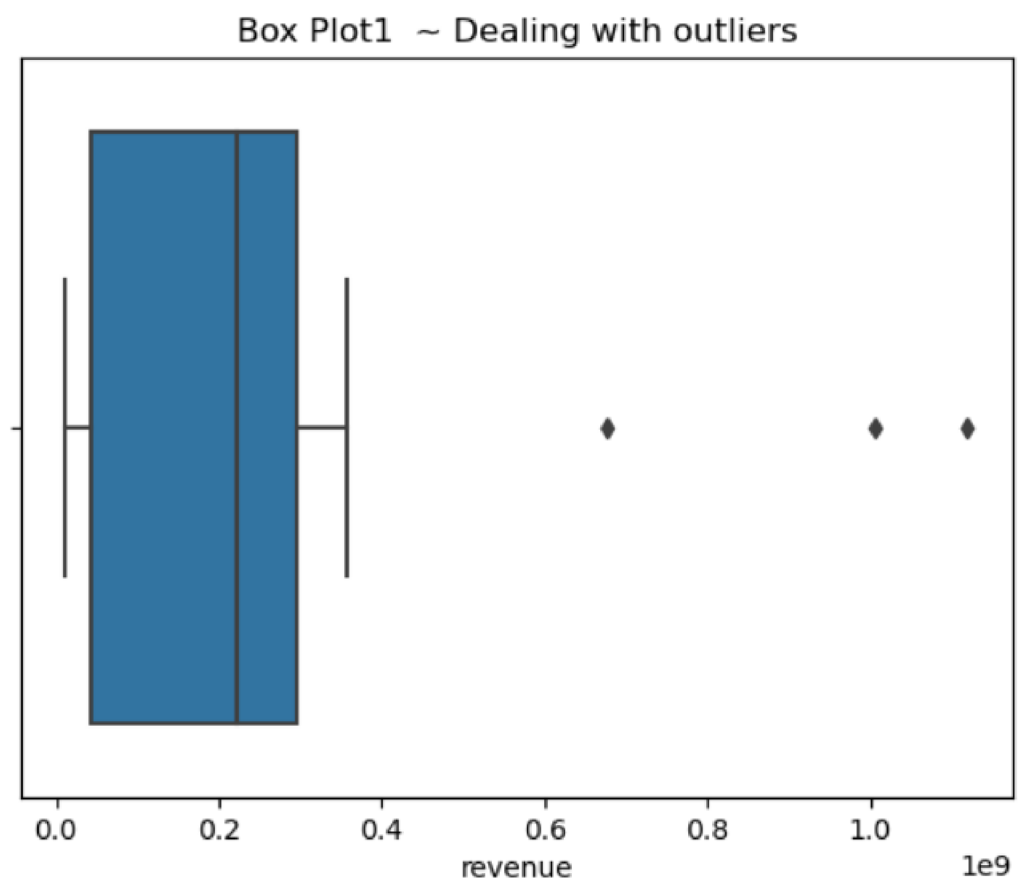
Outcomes

Dealing with outlier :

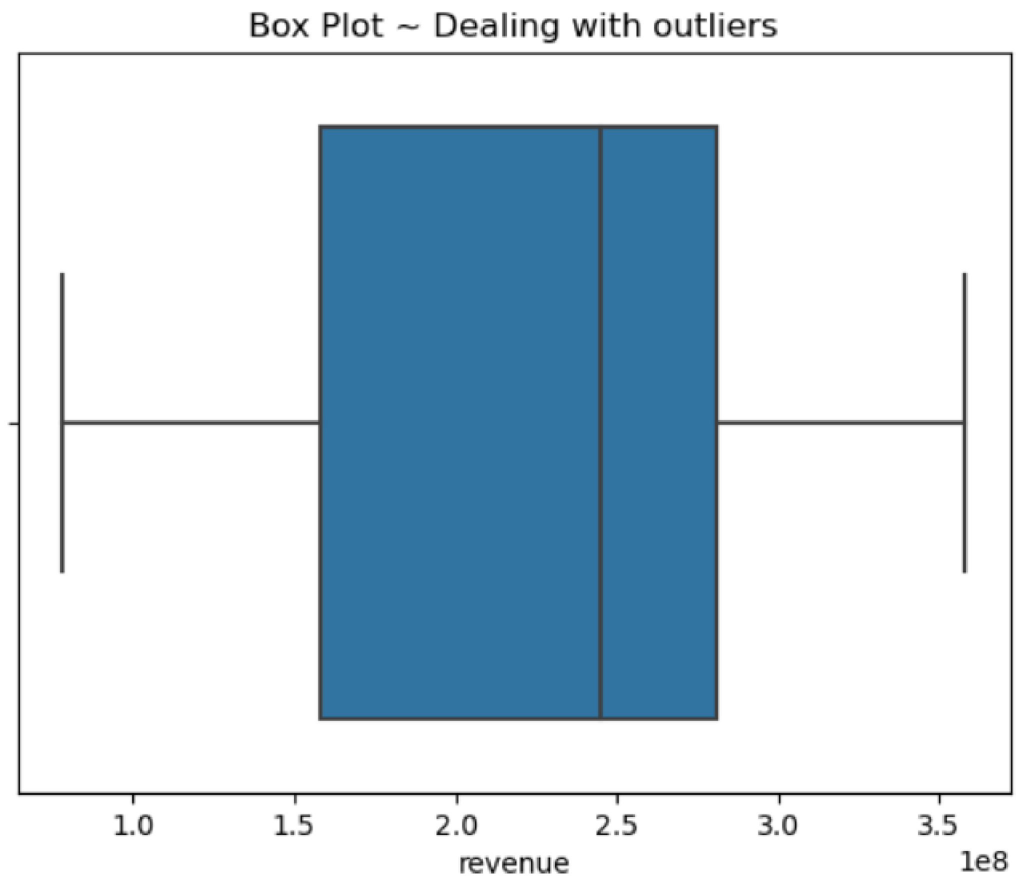
In [126]:

```
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import OneHotEncoder, StandardScaler

df = pd.read_csv('movies.csv', low_memory=False)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10014 entries, 0 to 10013
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   sr_no              10014 non-null  object 
 1   id                 10002 non-null  float64
 2   original_language  10002 non-null  object 
 3   original_title     10001 non-null  object 
 4   release_date       9962 non-null   object 
 5   vote_average       10000 non-null  float64
 6   vote_count         10000 non-null  float64
 7   genre              10000 non-null  object 
 8   overview           9900 non-null   object 
 9   revenue            5336 non-null   float64
 10  runtime            9762 non-null   float64
dtypes: float64(5), object(6)
memory usage: 860.7+ KB
```



Box Plot1 ~ Dealing with outliers
0.0
0.2
0.4
0.6
0.8
1.0
revenue
1e9


Box Plot ~ Dealing with outliers
1.0
1.5
2.0
2.5
3.0
3.5
1e8
revenue

Basic data wrangling operations and their outcomes

```
df['release_date'] = pd.to_datetime(df.release_date) # adds to df as datetime type
print(df.release_date.head(2))
print(df.release_date.dt.year.head(2)) # returns lastSaleDate2 as year format
print(df.release_date.dt.month.head(2)) # returns lastSaleDate2 as month format
print(df.release_date.dt.week.head(2)) # returns lastSaleDate2 as week format
print(df.release_date.dt.day.head(2)) # returns lastSaleDate2 as day format
print(df.release_date.dt.dayofweek.head(2)) # returns as dayofweek format
```

```
0   2021-09-30
1   2021-11-03
Name: release_date, dtype: datetime64[ns]
0    2021.0
1    2021.0
Name: release_date, dtype: float64
0     9.0
1    11.0
Name: release_date, dtype: float64
0    39.0
1    44.0
Name: release_date, dtype: float64
0    30.0
1     3.0
Name: release_date, dtype: float64
0    3.0
1    2.0
Name: release_date, dtype: float64
```

In [9]:

```python
#-----------------group by--------------------
df3 = df.groupby('movieId').age.median().reset_index()
df3.columns = ('movieId', 'movieId_median_value')
df4 = pd.merge(df, df3, on = 'movieId', how = 'left')
print(df4.info())
print(df4.head(2))
```

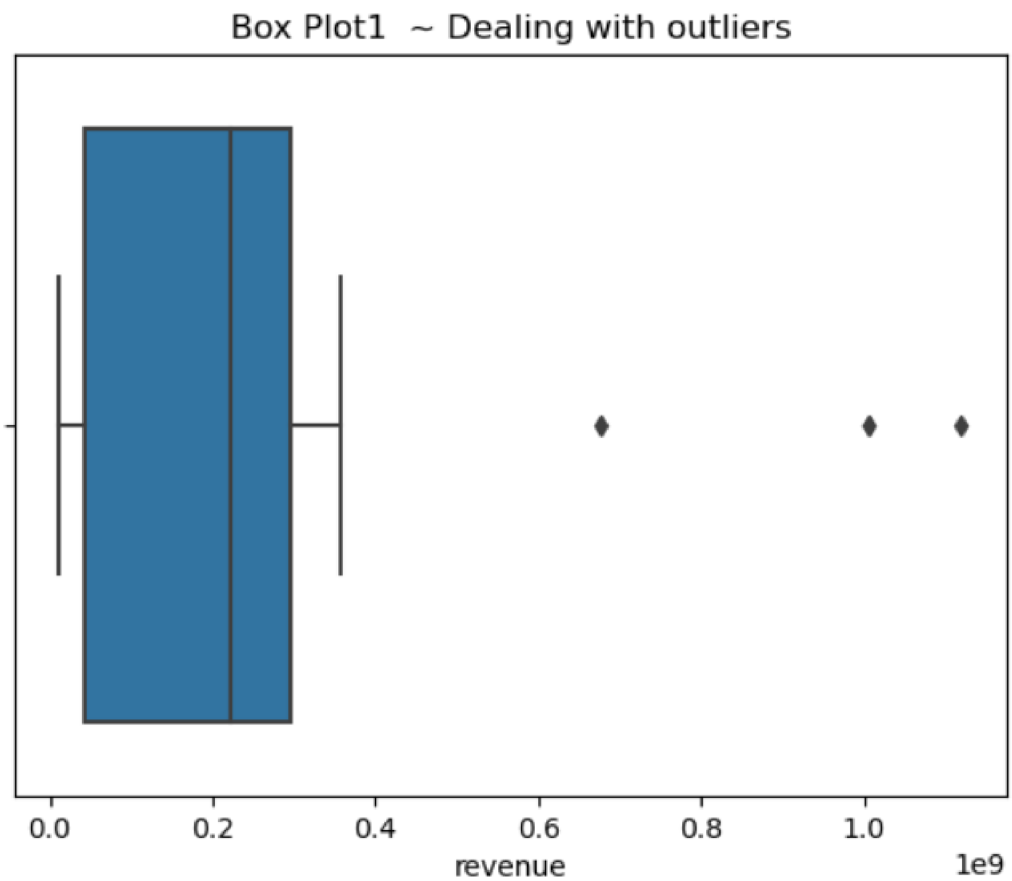
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns (total 8 columns):
 #   Column                Non-Null Count    Dtype  
---  ------                --------------    -----  
 0   movieId               1000209 non-null  int64  
 1   title                 1000209 non-null  object 
 2   genres                6020 non-null     object 
 3   userId                1000209 non-null  int64  
 4   rating                1000209 non-null  int64  
 5   gender                1000209 non-null  object 
 6   age                   1000209 non-null  int64  
 7   movieId_median_value  1000209 non-null  float64
dtypes: float64(1), int64(4), object(3)
memory usage: 68.7+ MB
None
   movieId             title  \
0        1  Toy Story (1995)   
1        1  Toy Story (1995)   

                        genres  \
0  Animation|Children's|Comedy   
1  Animation|Children's|Comedy   

   userId  rating gender  age  \
```

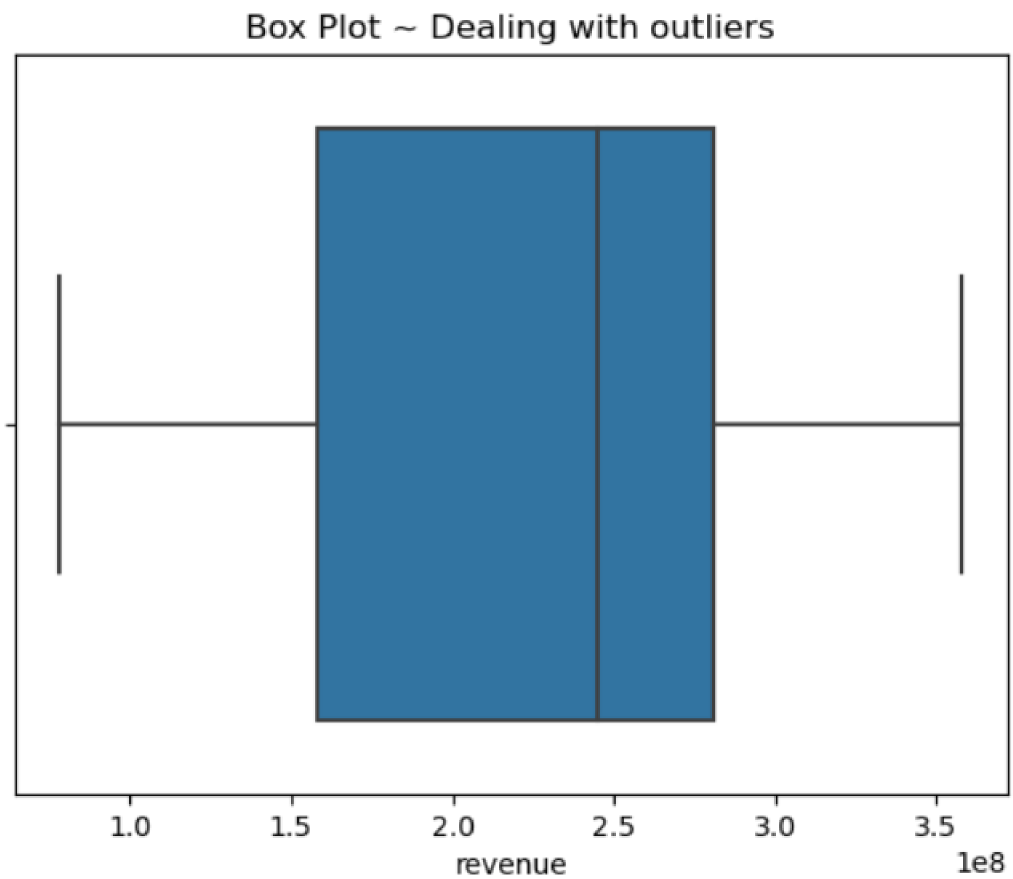
In [14]:

```python
#------------Slicing and Dicing of Data-----------------------
moderateMoviesDF = df[(df.rating>1) & (df.rating<5)]
print('moderateMoviesDF',moderateMoviesDF['movieId'].nunique())

flopMoviesDF = df[(df.rating==1)]
print('flopMoviesDF',flopMoviesDF['movieId'].nunique())

twoStarMoviesDF = df[(df.rating==2)]
print('twoStareMoviesDF',twoStarMoviesDF['movieId'].nunique())

threeStarMoviesDF = df[(df.rating==3)]
print('threeStarMoviesDF',threeStarMoviesDF['movieId'].nunique())

fourStarMoviesDF = df[(df.rating==4)]
print('fourStarMoviesDF',fourStarMoviesDF['movieId'].nunique())

superhitMoviesDF = df[(df.rating==5)]
print('superhitMoviesDF',superhitMoviesDF['movieId'].nunique())
```

```
moderateMoviesDF 3663
flopMoviesDF 3274
twoStareMoviesDF 3405
threeStarMoviesDF 3512
fourStarMoviesDF 3489
superhitMoviesDF 3232
```

```python
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import OneHotEncoder, StandardScaler

df = pd.read_csv('movies.csv', low_memory=False)
df.info()

#before outliers

df3 = df[(df.vote_average >= 8.5) & (df.revenue >= 10000000)]
sn.boxplot(df3.revenue).set_title('Box Plot1  ~ Dealing with outliers')
plt.show()

# Calculate the IQR for the revenue column
q1 = df['revenue'].quantile(0.25)
q3 = df['revenue'].quantile(0.75)
iqr = q3 - q1

# Filter the data to only include rows with revenue within 1.5 times the IQR of the median
median = df3['revenue'].median()
df4 = df3[(df3['revenue'] >= median - 1.5 * iqr) & (df3['revenue'] <= median + 1.5 * iqr)]

# Check the new shape of the DataFrame to see how many rows were removed
sn.boxplot(df4.revenue).set_title('Box Plot ~ Dealing with outliers')
plt.show()
```


Box Plot1 ~ Dealing with outliers
0.0
0.2
0.4
0.6
0.8
1.0
revenue
1e9



Categorizing using slicing

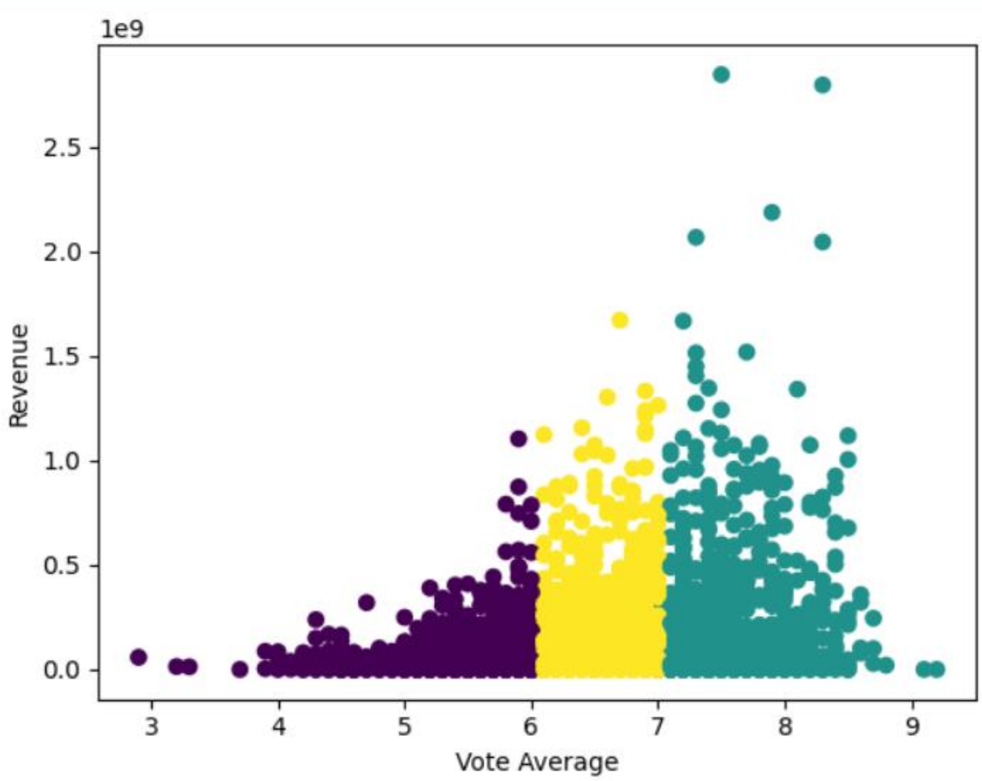
In [128]:
```
df['release_date'] = pd.to_datetime(df.release_date) # adds to df as datetime type
print(df.release_date.head(2))
print(df.release_date.dt.year.head(2)) # returns lastSaleDate2 as year format
print(df.release_date.dt.month.head(2)) # returns lastSaleDate2 as month format
print(df.release_date.dt.week.head(2)) # returns lastSaleDate2 as week format
print(df.release_date.dt.day.head(2)) # returns lastSaleDate2 as day format
print(df.release_date.dt.dayofweek.head(2)) # returns as dayofweek format
```

```
0   2021-09-30
1   2021-11-03
Name: release_date, dtype: datetime64[ns]
0    2021.0
1    2021.0
Name: release_date, dtype: float64
0     9.0
1    11.0
Name: release_date, dtype: float64
0    39.0
1    44.0
Name: release_date, dtype: float64
0    30.0
1     3.0
Name: release_date, dtype: float64
0    3.0
1    2.0
Name: release_date, dtype: float64
```

Visulization using K-means clustering

In [125]:

```
# Drop rows with missing values
data = df.dropna()

# Select the columns to cluster on
X = data[['genre', 'vote_average']]

# Convert genre column to numerical using one-hot encoding
X = pd.get_dummies(X, columns=['genre'])

# Apply K-Means algorithm with 3 clusters
kmeans = KMeans(n_clusters=3, random_state=42).fit(X)

# Add cluster labels to the data
data['cluster'] = kmeans.labels_

# Visualize the clusters using a scatter plot
plt.scatter(data['vote_average'], data['revenue'], c=data['cluster'])
plt.xlabel('Vote Average')
plt.ylabel('Revenue')
plt.show()
```



Logistic Regression

```python
# Data Mining - classification & regression - Logistic Regression
import pandas as pd
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.model_selection import train_test_split

desired_width = 400
pd.set_option('display.width', desired_width)        # sets run screen width to 400
pd.set_option('display.max_columns', 20)             # sets run screen column display to 20
df = pd.read_csv(r'movies.csv')   # reads Zillow file
df.info()

# Drop duplicates
df.drop_duplicates(inplace=True)

# Fill numerical columns with mean
df.fillna(df.mean(), inplace=True)

# Create new column 'gender' with random values 0 or 1
df['gender'] = np.random.randint(0, 2, size=len(df))

# Save the processed data to a new CSV file
df.to_csv('df2.csv', index=False)

df = pd.read_csv('df2.csv', low_memory=False)

# replaces the NaN with 0 to have even 15,000 in all 7 variables
X = df[['vote_average', 'vote_count', 'revenue', 'runtime']] # reduced df as upper case X matrix
y = df.gender
# predictor variable lower case y as array

df['gender'] = df.gender.apply(lambda x: 'male' if x < 1 else 'female')
y2 = df.gender
```

```python
log = LogisticRegression()
print(log.fit(X,y2))
print(log.score(X,y2))

X_train, X_test, y2_train, y2_test = train_test_split(X,y2)
print(X_train.shape, y2_train.shape, X_test.shape, y2_test.shape)
print(log.fit(X_train, y2_train))
print(log.score(X_test, y2_test))
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10014 entries, 0 to 10013
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   sr_no              10014 non-null  object
 1   id                 10002 non-null  float64
 2   original_language  10002 non-null  object
 3   original_title     10001 non-null  object
 4   release_date       9962 non-null   object
 5   vote_average       10000 non-null  float64
 6   vote_count         10000 non-null  float64
 7   genre              10000 non-null  object
 8   overview           9900 non-null   object
 9   revenue            5336 non-null   float64
 10  runtime            9762 non-null   float64
dtypes: float64(5), object(6)
memory usage: 860.7+ KB
```


```
 9   revenue            5336 non-null   float64
 10  runtime            9762 non-null   float64
dtypes: float64(5), object(6)
memory usage: 860.7+ KB
```


```
C:\Users\adhir\AppData\Local\Temp\ipykernel_19708\100805663.py:16:
reductions (with 'numeric_only=None') is deprecated; in a future v
ns before calling the reduction.
  df.fillna(df.mean(), inplace=True)
```

```
LogisticRegression()
0.49910125823846613
(7510, 4) (7510,) (2504, 4) (2504,)
LogisticRegression()
0.4976038338658147
```

As we can see it has only 49% score so Logistic regression model has an accuracy score of around 50%, which means it is not a good model for predicting gender based on movie ratings, vote counts, revenue, and runtime. It also shows that splitting the dataset into training and testing sets did not improve the accuracy of the model.

Linear Regression

```
import pandas as pd
import numpy as np
import seaborn as sn
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import OneHotEncoder, StandardScaler

df = pd.read_csv('movies.csv', low_memory=False)

# Drop duplicates
df.drop_duplicates(inplace=True)

# Fill numerical columns with mean
df.fillna(df.mean(), inplace=True)

# Create new column 'gender' with random values 0 or 1
df['gender'] = np.random.randint(0, 2, size=len(df))

# Save the processed data to a new CSV file
df.to_csv('df2.csv', index=False)

df = pd.read_csv('df2.csv', low_memory=False)

# Drop duplicates
df.drop_duplicates(inplace=True)

# Fill numerical columns with mean
df.fillna(df.mean(), inplace=True)
```

```python
# Create new column 'gender' with random values 0 or 1
df['gender'] = np.random.randint(0, 2, size=len(df))

# Save the processed data to a new CSV file
df.to_csv('df2.csv', index=False)

df = pd.read_csv('df2.csv', low_memory=False)

X = df[['revenue', 'vote_count', 'runtime','gender']] # reduced
y = df.vote_average                                          #
lg = LinearRegression()
print(lg.fit(X,y))
print(lg.score(X,y))
X_train, X_test, y_train, y_test = train_test_split(X,y)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
print(lg.fit(X_train, y_train))
print(lg.score(X_test, y_test))
```

```
LinearRegression()
0.10039770471091614
(7510, 4) (7510,) (2504, 4) (2504,)
LinearRegression()
0.0901431961105279
```

As we can see Linear regression has 9% score only and the model may not capture the relationship between the features and the target variable accurately hence its not good method to use for our dataset

Support Vector Machine

```
df = pd.read_csv('df2.csv', low_memory=False)
df2 = df[['vote_average', 'vote_count', 'revenue', 'runtime','gender']]   # reduced df
df2.fillna(0, inplace=True)
X = df[['vote_average', 'vote_count', 'gender', 'runtime']] # reduced df as upper case X matrix
X1 = X                                                  # duplicate of X
y = df.revenue
df['revenue'] = df.revenue.apply(lambda x: 'low' if x < 500000 else 'high')
y2 = df.revenue
X_train, X_test, y_train, y_test = train_test_split(X,y)
X1_train, X1_test, y2_train, y2_test = train_test_split(X1,y2)
svr_reg = SVR()                                         # assign svr_reg to the SVR function
svc_class = SVC()                                       # assign svc_class to the SVC function
svr_reg.fit(X_train, y_train)                           # fit a SVR() model using 11,250 data points
print('svr_score = ', svr_reg.score(X_test, y_test))
svc_class.fit(X1_train, y2_train)                       # fit a SVC() model using 11,250 data points
print('svc_score = ', svc_class.score(X1_test, y2_test)) #
y2_pred = svc_class.predict(X_test)                     # assigns y2_pred to SVC prediction of X_test data
print(confusion_matrix(y2_test, y2_pred))               #
```

```
C:\Users\adhir\AppData\Local\Temp\ipykernel_19708\4279294242.py:18: FutureWarning: Dropping of nuisance columns in DataFrame
reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid colum
ns before calling the reduction.
  df.fillna(df.mean(), inplace=True)
C:\Users\adhir\AppData\Local\Temp\ipykernel_19708\4279294242.py:29: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view
-versus-a-copy
  df2.fillna(0, inplace=True)
```

```
svr_score =  -0.00015045680899761216
svc_score =  0.9672523961661342
[[2422    0]
 [  82    0]]
```

As we can see the SVR model performs poorly with a negative R-squared score, which indicates that the model does not fit the data well. On the other hand, the SVC model performs well with an accuracy score of approximately 97%. However, when looking at the confusion matrix, we can see that the model is predicting only the low revenue category, with all the high revenue movies being classified as low revenue. Hence not good fit for the dataset

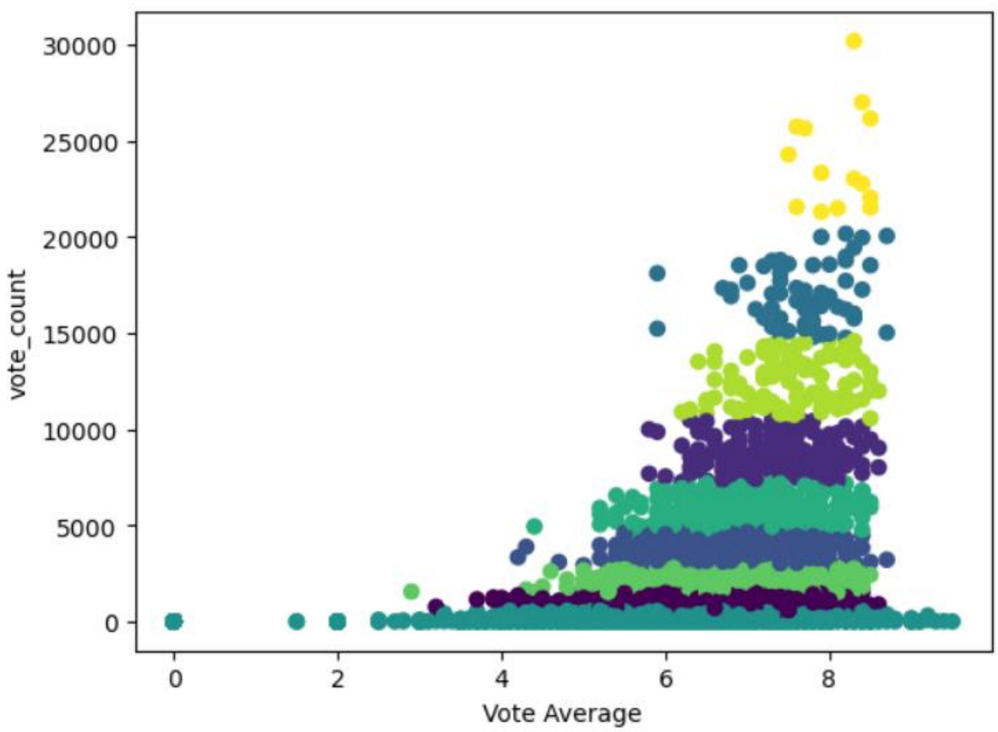
K Means Clustering :

```
df2 = df[['vote_average', 'vote_count', 'revenue', 'runtime','gender']]   # reduced df
df2.fillna(0, inplace=True)
print(df2.head(2))                                   # prints top two rows of df3

k_groups = KMeans(n_clusters=5, random_state=0).fit(df2)  # separates data set into 5 distinguishable groups
print(k_groups.labels_)                              # displays k_groups' label (0 to 4) for each row
print(len(k_groups.labels_),df2.shape)               # displays rows in k_groups as well as rows, columns in df3
print(k_groups.cluster_centers_)         # displays averages of the seven columns for each cluster centroid [0, 1, 2, 3, 4]
print(k_groups.cluster_centers_[0])       # displays averages for each of the seven columns in the cluster centroid [0]

df2['cluster'] = k_groups.labels_                    # add a new column to df3 called 'cluster', the k-group #
print(df2.groupby('cluster').min())                 # display the means of the seven columns of data frame df3

from sklearn.metrics import silhouette_score         # coefficient score where higher is better, 0 = cluster overlap
df3 = df2.drop('cluster', axis = 1)                  # create a new data frame df4 that dropped the cluster column
# for loop to determine optimum K groups
for i in range(3, 10):                               # for loop to determine best number of K clusters between 3 and 10
    k_groups = KMeans(n_clusters = i).fit(df3)       # K clusters must have atleast 2 clusters
    labels = k_groups.labels_
    print('K Groups = ', i, 'Silhouette Coeffient = ', silhouette_score(df3, labels))  # displays i and coefficient
# End of Data Mining - Cluster Analysis
```

```
   vote_average  vote_count      revenue  runtime  gender
0           6.8      1736.0  424000000.0     97.0       1
1           7.1       622.0  165000000.0    157.0       0
[4 2 4 ... 2 0 2]
10014 (10014, 5)
[[6.55161489e+00 1.02770747e+03 2.08579286e+07 1.05501999e+02
  5.14610889e-01]
 [7.17000000e+00 1.17805133e+04 8.47558199e+08 1.28333333e+02
  4.46666667e-01]
 [6.09958804e+00 8.11218653e+02 1.12109670e+08 9.68070186e+01
  5.09572901e-01]
 [7.52727273e+00 1.72090909e+04 1.92505603e+09 1.44363636e+02
  7.27272727e-01]
 [6.80957230e+00 5.93574134e+03 3.57066574e+08 1.15892057e+02
  4.94908350e-01]]
[6.55161489e+00 1.02770747e+03 2.08579286e+07 1.05501999e+02
 5.14610889e-01]
         vote_average  vote_count       revenue  runtime  gender
cluster
0                 2.9         2.0  1.000000e+01      0.0       0
1                 5.8       176.0  6.038731e+08     87.0       0
2                 0.0         0.0  6.667352e+07      0.0       0
3                 6.7      7740.0  1.405404e+09    103.0       0
4                 4.3        50.0  2.348019e+08     70.0       0
K Groups =  3 Silhouette Coeffient =  0.795170622096163 5
K Groups =  4 Silhouette Coeffient =  0.7612152107989971
K Groups =  5 Silhouette Coeffient =  0.7717650818145939
K Groups =  6 Silhouette Coeffient =  0.782072013168272 9
K Groups =  7 Silhouette Coeffient =  0.7897677118640188
K Groups =  8 Silhouette Coeffient =  0.7957006226865337
K Groups =  9 Silhouette Coeffient =  0.7959303423889847
```

Result indicates that the Silhouette Coefficient for 9 clusters is 0.7959, which is quite high and suggests that the clustering can be well-defined and the movies are grouped together in a meaningful way based on their features. This could be useful for further analysis or for making recommendations based on the features of the movies in each cluster.

Here is one example of clustering with k=9



Correlation and Heatmap

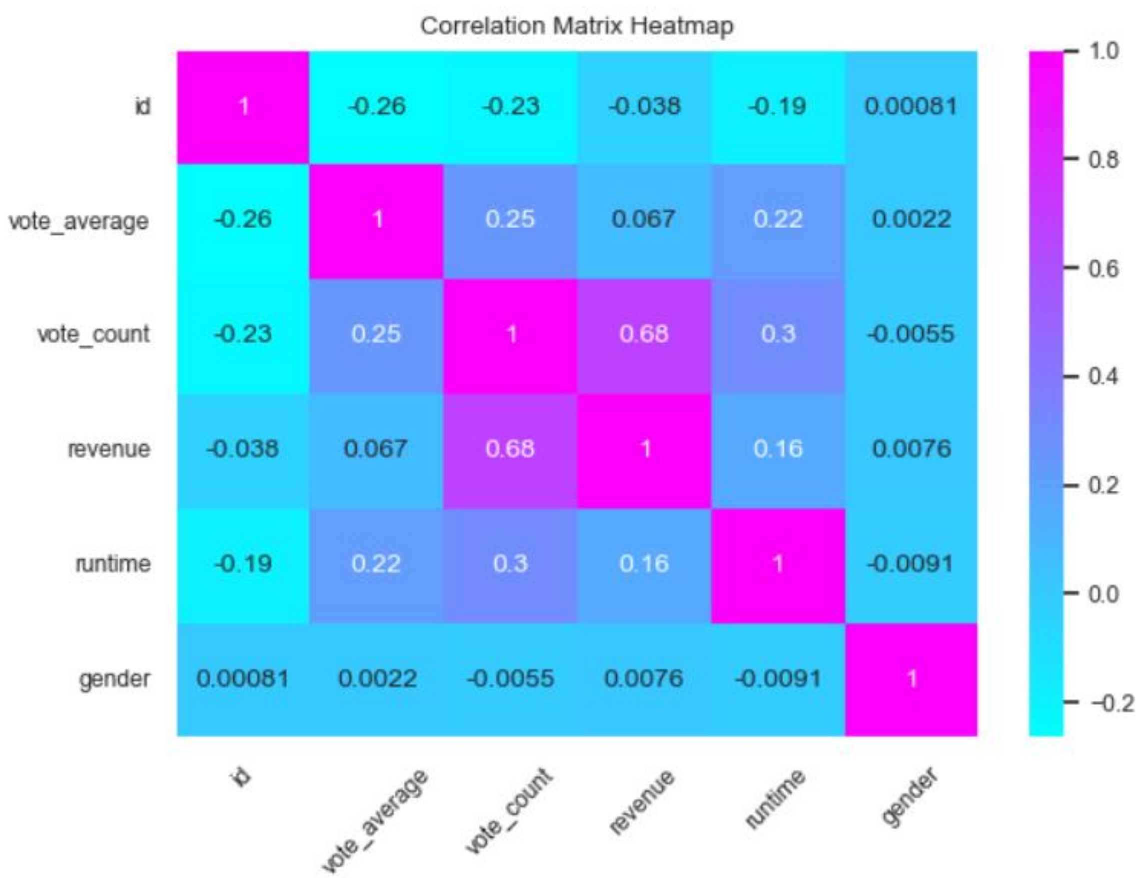
```
In [4]:
import pandas as pd
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.model_selection import train_test_split
import pandas as pd
from sklearn.svm import SVC, SVR
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
import numpy as np
import seaborn as sn
import matplotlib.pyplot as plt

desired_width = 400
pd.set_option('display.width', desired_width)        # sets run screen width to 400
pd.set_option('display.max_columns', 20)             # sets run screen column display to 20
df = pd.read_csv(r'movies.csv')   # reads Zillow file

# Drop duplicates
df.drop_duplicates(inplace=True)

# Fill numerical columns with mean
df.fillna(df.mean(), inplace=True)

# Create new column 'gender' with random values 0 or 1
df['gender'] = np.random.randint(0, 2, size=len(df))

# Save the processed data to a new CSV file
df.to_csv('df2.csv', index=False)

df = pd.read_csv('df2.csv', low_memory=False)
```

```
numeric_cols = df.select_dtypes(include=['int64', 'float64']).columns
#AND
# Replace missing values with column mean
df[numeric_cols] = df[numeric_cols].fillna(df[numeric_cols].mean())
#verifying if there is no null values in any columns
print(df.isnull().sum())


df2 = df[numeric_cols]
print(df2.info())

corr_matrix = df2.corr()
print(corr_matrix)

# Create a heatmap using Seaborn
sn.set(font_scale=0.8)
sn.heatmap(corr_matrix, cmap="cool", annot=True, annot_kws={"size": 10})
plt.title("Correlation Matrix Heatmap")
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()

# Save the plot to disk
plt.savefig("correlation_heatmap.png")
```

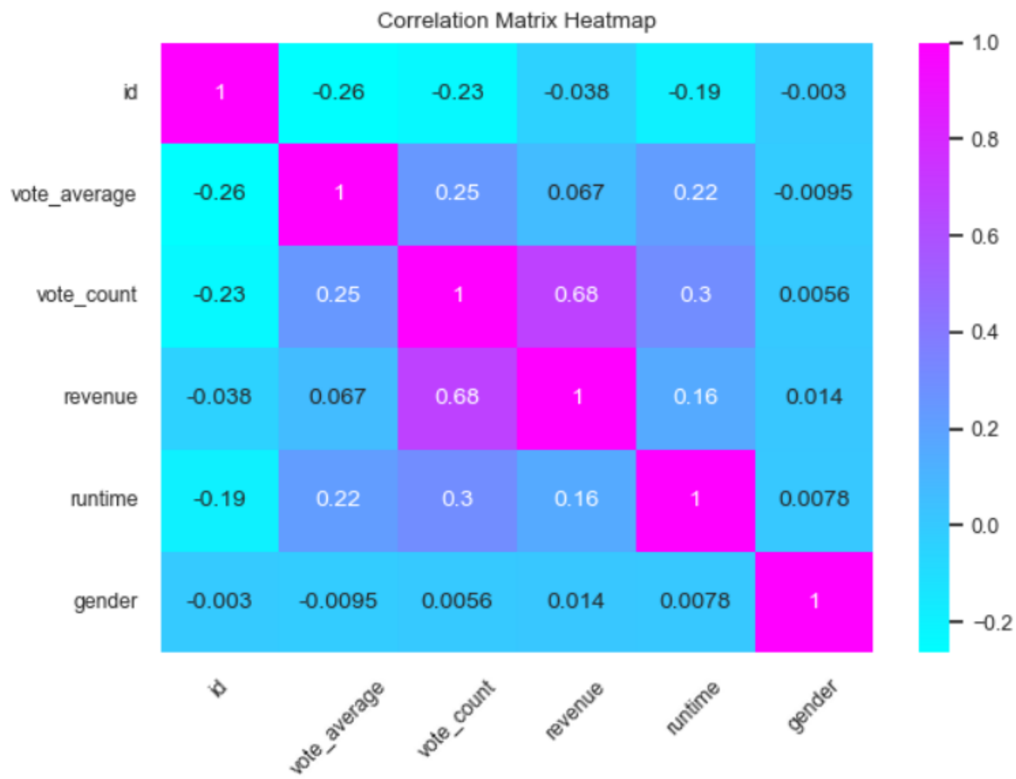
```
sr_no                 0
id                    0
original_language    12
original_title       13
release_date         52
vote_average          0
vote_count            0
genre                14
overview            114
revenue               0
runtime               0
gender                0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10014 entries, 0 to 10013
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            10014 non-null  float64
 1   vote_average  10014 non-null  float64
 2   vote_count    10014 non-null  float64
 3   revenue       10014 non-null  float64
 4   runtime       10014 non-null  float64
 5   gender        10014 non-null  int64
dtypes: float64(5), int64(1)
memory usage: 469.5 KB
```

	id	vote_average	vote_count	revenue	runtime	gender
id	1.000000	-0.264918	-0.231100	-0.037813	-0.192567	0.000811
vote_average	-0.264918	1.000000	0.246775	0.067455	0.222048	0.002187
vote_count	-0.231100	0.246775	1.000000	0.675393	0.301612	-0.005450
revenue	-0.037813	0.067455	0.675393	1.000000	0.155653	0.007555
runtime	-0.192567	0.222048	0.301612	0.155653	1.000000	-0.009063
gender	0.000811	0.002187	-0.005450	0.007555	-0.009063	1.000000

After



Before :


Correlation Matrix Heatmap
id
vote_average
vote_count
revenue
runtime
gender
1
-0.26
-0.23
-0.038
-0.19
-0.003
-0.26
1
0.25
0.067
0.22
-0.0095
-0.23
0.25
1
0.68
0.3
0.0056
-0.038
0.067
0.68
1
0.16
0.014
-0.19
0.22
0.3
0.16
1
0.0078
-0.003
-0.0095
0.0056
0.014
0.0078
1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2