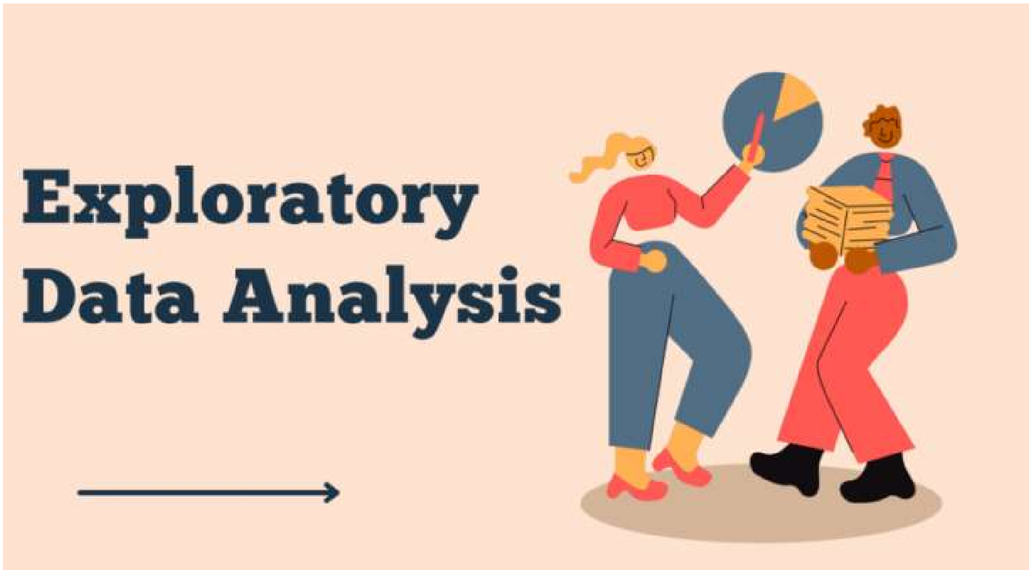
MOVIE RATING PREDICTION WITH PYTHON

Problem Statement :-

- "Develop a Python-based model to predict movie ratings based on various features . Utilize machine learning algorithms to analyze historical movie data, extracting patterns and relationships to make accurate predictions. The model aims to assist movie producers and distributors in forecasting audience reception, optimizing marketing strategies, and maximizing box office success."

!



In [1]:
```
# import libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

In [2]:
```
import warnings

# Set the warning filter to 'ignore'
warnings.filterwarnings('ignore')
```

In [3]:
```
# read data set

movies = pd.read_csv(r"E:\Projects\Codsoft_Projects\MOVIE RATING PREDICTION WITH PYTHON\Dataset\movies.dat", sep='::
movies.head()
```

Out[3]:

	1	Toy Story (1995)	Animation|Children's|Comedy
0	2	Jumanji (1995)	Adventure|Children's|Fantasy
1	3	Grumpier Old Men (1995)	Comedy|Romance
2	4	Waiting to Exhale (1995)	Comedy|Drama
3	5	Father of the Bride Part II (1995)	Comedy
4	6	Heat (1995)	Action|Crime|Thriller

In [4]:
```
movies.columns =['MovieID', 'Title', 'Genres']
movies.dropna(inplace=True)
movies.head()
```

Out[4]:

	MovieID	Title	Genres
0	2	Jumanji (1995)	Adventure|Children's|Fantasy
1	3	Grumpier Old Men (1995)	Comedy|Romance
2	4	Waiting to Exhale (1995)	Comedy|Drama
3	5	Father of the Bride Part II (1995)	Comedy
4	6	Heat (1995)	Action|Crime|Thriller

In [5]:
```
movies.shape
```

Out[5]:
```
(3882, 3)
```

In [6]:
```
movies.describe()
```

Out[6]:

	MovieID
count	3882.000000
mean	1986.560793
std	1146.483260
min	2.000000
25%	983.250000
50%	2010.500000
75%	2980.750000
max	3952.000000

In [7]:
```
movies.isnull().sum()
```

Out[7]:
```
MovieID    0
Title      0
Genres     0
dtype: int64
```

In [8]:
```
#Input ratings dataset
ratings = pd.read_csv(r"E:\Projects\Codsoft_Projects\MOVIE RATING PREDICTION WITH PYTHON\Dataset\ratings.dat\ratings
ratings.columns =['UserID', 'MovieID', 'Rating', 'Timestamp']
ratings.dropna(inplace=True)

#Read the sample ratings dataset
ratings.head()
```

Out[8]:

	UserID	MovieID	Rating	Timestamp
0	1	661	3	978302109
1	1	914	3	978301968
2	1	3408	4	978300275
3	1	2355	5	978824291
4	1	1197	3	978302268

In [9]:
```
ratings.shape
```

Out[9]:
```
(1000208, 4)
```

In [10]:
```
ratings.describe()
```

Out[10]:

	UserID	MovieID	Rating	Timestamp
count	1.000208e+06	1.000208e+06	1.000208e+06	1.000208e+06
mean	3.024515e+03	1.865541e+03	3.581563e+00	9.722437e+08
std	1.728411e+03	1.096041e+03	1.117102e+00	1.215256e+07
min	1.000000e+00	1.000000e+00	1.000000e+00	9.567039e+08
25%	1.506000e+03	1.030000e+03	3.000000e+00	9.653026e+08
50%	3.070000e+03	1.835000e+03	4.000000e+00	9.730180e+08
75%	4.476000e+03	2.770000e+03	4.000000e+00	9.752209e+08
max	6.040000e+03	3.952000e+03	5.000000e+00	1.046455e+09

In [11]:
```
ratings.isnull().sum()
```

Out[11]:
```
UserID       0
MovieID      0
Rating       0
Timestamp    0
dtype: int64
```

In [12]:
```
#Input users dataset
users = pd.read_csv(r"E:\Projects\Codsoft_Projects\MOVIE RATING PREDICTION WITH PYTHON\Dataset\users.dat",sep='::',e
users.columns =['UserID', 'Gender', 'Age', 'Occupation', 'Zip-code']
users.dropna(inplace=True)

#Read the sample users dataset
users.head()
```

Out[12]:

	UserID	Gender	Age	Occupation	Zip-code
0	2	M	56	16	70072
1	3	M	25	15	55117
2	4	M	45	7	02460
3	5	M	25	20	55455
4	6	F	50	9	55117

In [13]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()

# Fit and transform the data
users['Gender'] = label_encoder.fit_transform(users['Gender'])
users.head()
```

Out[13]:

	UserID	Gender	Age	Occupation	Zip-code
0	2	1	56	16	70072
1	3	1	25	15	55117
2	4	1	45	7	02460
3	5	1	25	20	55455
4	6	0	50	9	55117

In [14]:
```
users.shape
```

Out[14]: (6039, 5)

In [15]:
```
users.describe()
```

Out[15]:

	UserID	Gender	Age	Occupation
count	6039.000000	6039.000000	6039.000000	6039.000000
mean	3021.000000	0.717172	30.644146	8.146547
std	1743.453469	0.450411	12.891387	6.329991
min	2.000000	0.000000	1.000000	0.000000
25%	1511.500000	0.000000	25.000000	3.000000
50%	3021.000000	1.000000	25.000000	7.000000
75%	4530.500000	1.000000	35.000000	14.000000
max	6040.000000	1.000000	56.000000	20.000000

In [16]:
```
users.isnull().sum()
```

Out[16]:
```
UserID        0
Gender        0
Age           0
Occupation    0
Zip-code      0
dtype: int64
```

Data Cleaning :-

Concatenating the Datasets

In [17]:
```
df=pd.concat([movies,ratings,users],axis=1)
df.dropna()
df.head(5)
```

Out[17]:

	MovieID	Title	Genres	UserID	MovieID	Rating	Timestamp	UserID	Gender	Age	Occupation	Zip-code
0	2.0	Jumanji (1995)	Adventure|Children's|Fantasy	1	661	3	978302109	2.0	1.0	56.0	16.0	70072
1	3.0	Grumpier Old Men (1995)	Comedy|Romance	1	914	3	978301968	3.0	1.0	25.0	15.0	55117
2	4.0	Waiting to Exhale (1995)	Comedy|Drama	1	3408	4	978300275	4.0	1.0	45.0	7.0	02460
3	5.0	Father of the Bride Part II (1995)	Comedy	1	2355	5	978824291	5.0	1.0	25.0	20.0	55455
4	6.0	Heat (1995)	Action|Crime|Thriller	1	1197	3	978302268	6.0	0.0	50.0	9.0	55117

In [18]:
```
df.shape
```

Out[18]:
```
(1000208, 12)
```

Removing unnecessary columns

In [19]:
```
df=df.drop(["Timestamp","Occupation","Zip-code","MovieID","UserID"],axis=1)
df.head()
```

Out[19]:

	Title	Genres	Rating	Gender	Age
0	Jumanji (1995)	Adventure|Children's|Fantasy	3	1.0	56.0
1	Grumpier Old Men (1995)	Comedy|Romance	3	1.0	25.0
2	Waiting to Exhale (1995)	Comedy|Drama	4	1.0	45.0
3	Father of the Bride Part II (1995)	Comedy	5	1.0	25.0
4	Heat (1995)	Action|Crime|Thriller	3	0.0	50.0

In [20]:
```
df.describe()
```

Out[20]:

	Rating	Gender	Age
count	1.000208e+06	6039.000000	6039.000000
mean	3.581563e+00	0.717172	30.644146
std	1.117102e+00	0.450411	12.891387
min	1.000000e+00	0.000000	1.000000
25%	3.000000e+00	0.000000	25.000000
50%	4.000000e+00	1.000000	25.000000
75%	4.000000e+00	1.000000	35.000000
max	5.000000e+00	1.000000	56.000000

In [21]:
```
df.isnull().sum()
```

Out[21]:
```
Title      996326
Genres     996326
Rating          0
Gender     994169
Age        994169
dtype: int64
```

Handling Missing values

In [22]:
```
df=df.dropna()
df.shape
```

Out[22]:
```
(3882, 5)
```

In [23]:
```
# all 5 rating movies list count = 840
df[df['Rating'] == 5]
```

Out[23]:

	Title	Genres	Rating	Gender	Age
3	Father of the Bride Part II (1995)	Comedy	5	1.0	25.0
5	Sabrina (1995)	Comedy|Romance	5	1.0	35.0
6	Tom and Huck (1995)	Adventure|Children's	5	1.0	25.0
9	American President, The (1995)	Comedy|Drama|Romance	5	0.0	25.0
13	Cutthroat Island (1995)	Action|Adventure|Romance	5	1.0	25.0
...	...	...	...	...	...
3860	Giant Gila Monster, The (1959)	Horror|Sci-Fi	5	1.0	25.0
3865	Phantom of the Opera, The (1943)	Drama|Thriller	5	1.0	35.0
3866	Runaway (1984)	Sci-Fi|Thriller	5	1.0	18.0
3870	Sorority House Massacre (1986)	Horror	5	1.0	25.0
3880	Two Family House (2000)	Drama	5	1.0	56.0

840 rows × 5 columns

In [24]:

```
# all 5 rating movies list and Age Less Then 25 count = 208

df[(df['Rating'] == 5) & (df['Age'] < 25 ) ]
```

Out[24]:

	Title	Genres	Rating	Gender	Age
17	Ace Ventura: When Nature Calls (1995)	Comedy	5	1.0	1.0
36	It Takes Two (1995)	Comedy	5	0.0	18.0
39	Richard III (1995)	Drama|War	5	0.0	18.0
44	How to Make an American Quilt (1995)	Drama|Romance	5	1.0	18.0
45	Seven (Se7en) (1995)	Crime|Thriller	5	1.0	18.0
...	...	...	...	...	...
3797	Naked Gun: From the Files of Police Squad!, Th...	Comedy	5	1.0	18.0
3798	Naked Gun 2 1/2: The Smell of Fear, The (1991)	Comedy	5	1.0	18.0
3804	Devil Rides Out, The (1968)	Horror	5	1.0	18.0
3823	Solas (1999)	Drama	5	1.0	18.0
3866	Runaway (1984)	Sci-Fi|Thriller	5	1.0	18.0

208 rows × 5 columns

In [25]:

```
# all  movies rating less than 3 list and Age Lass Then 25 count = 47163

df[(df['Rating'] < 3) & (df['Age'] < 25 )]
```

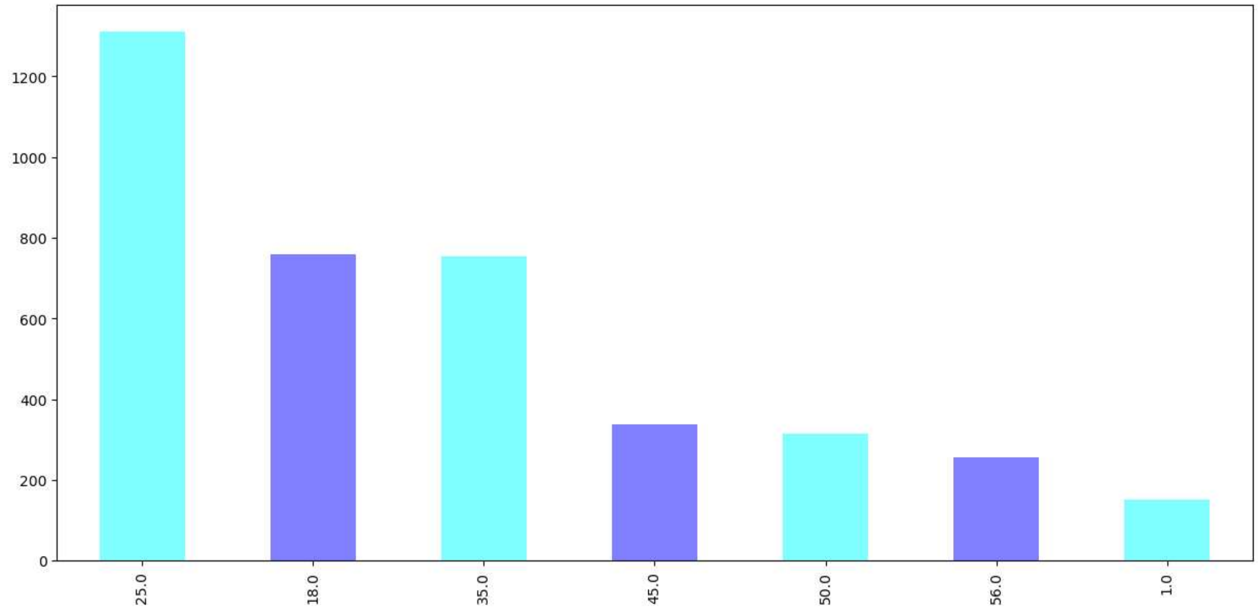
Out[25]:

	Title	Genres	Rating	Gender	Age
66	French Twist (Gazon maudit) (1995)	Comedy|Romance	2	1.0	18.0
82	Last Summer in the Hamptons (1995)	Comedy|Drama	2	1.0	18.0
90	Vampire in Brooklyn (1995)	Comedy|Romance	2	0.0	18.0
124	Silence of the Palace, The (Saimt el Qusur) (1...	Drama	2	1.0	18.0
150	Batman Forever (1995)	Action|Adventure|Comedy|Crime	2	1.0	18.0
...	...	...	...	...	...
3651	Trixie (1999)	Comedy	2	1.0	18.0
3731	Anatomy of a Murder (1959)	Drama|Mystery	1	1.0	18.0
3732	Freejack (1992)	Action|Sci-Fi	2	1.0	18.0
3841	Beautiful (2000)	Comedy|Drama	2	0.0	1.0
3867	Slumber Party Massacre, The (1982)	Horror	2	1.0	18.0

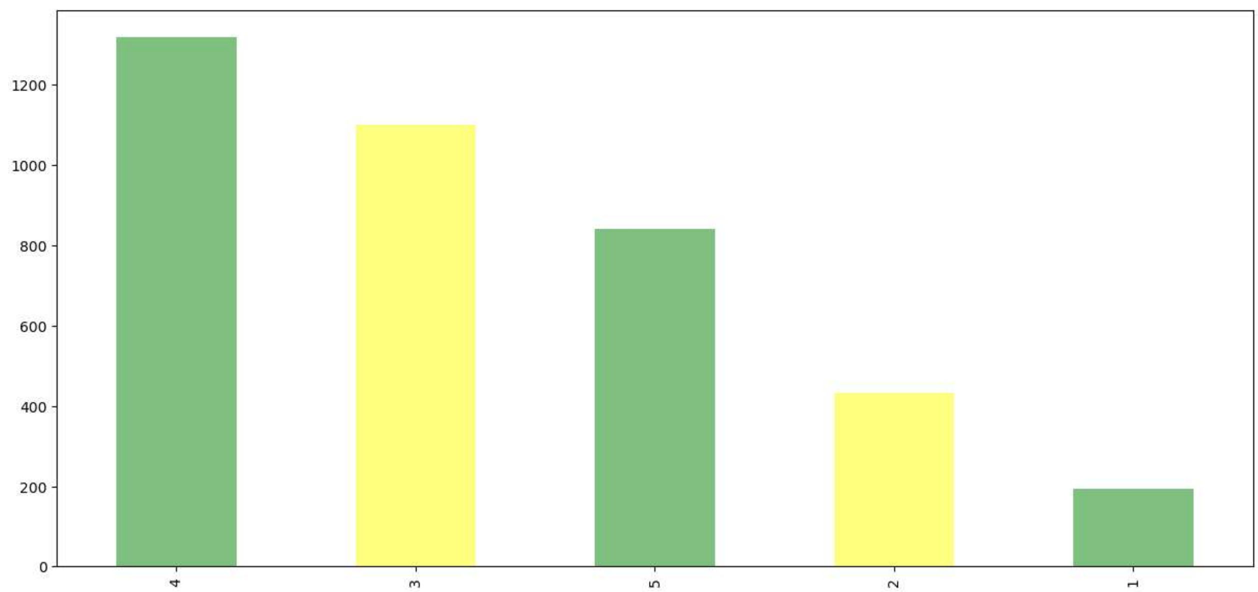
132 rows × 5 columns

Data Visualization

In [26]:
```
df['Age'].value_counts().plot(kind='bar', color= ['cyan', 'blue'],alpha=0.5,figsize=(15,7))
plt.show()
```

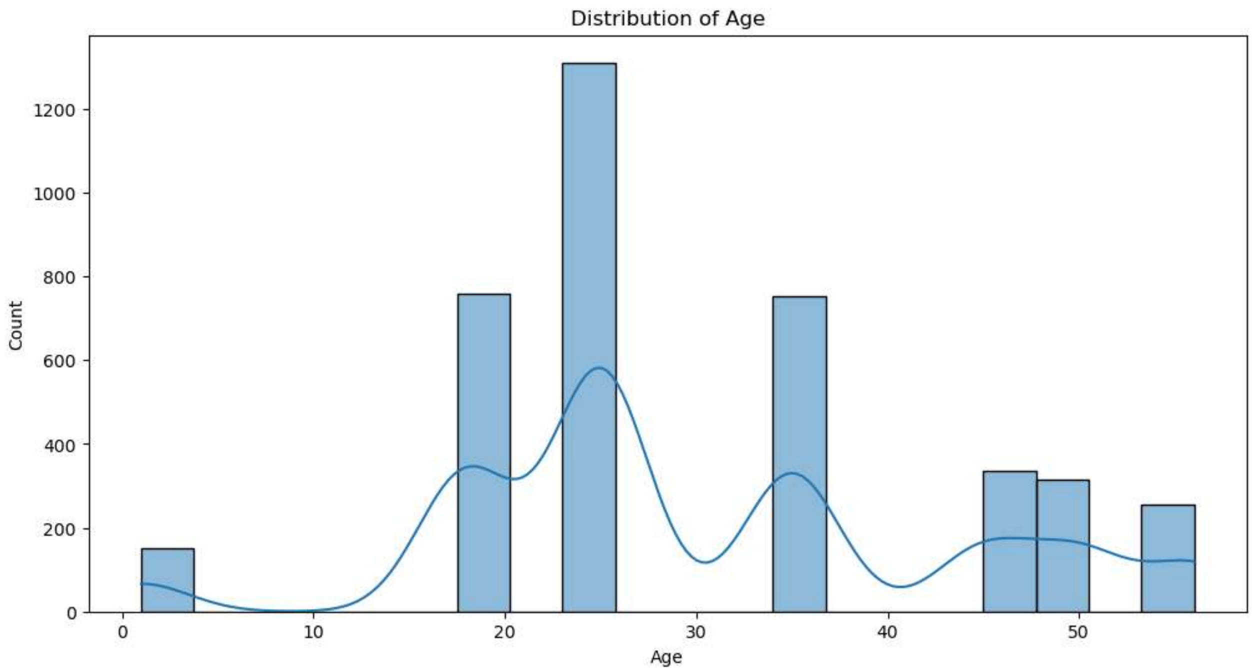


In [27]:
```
df['Rating'].value_counts().plot(kind='bar', color=['green', 'yellow'],alpha=0.5,figsize=(15,7))
plt.show()
```



In [28]:

```
# 2. Histogram for 'Age'
plt.figure(figsize=(12, 6))
sns.histplot(data=df, x='Age', bins=20, kde=True)
plt.title('Distribution of Age')
plt.show()
```

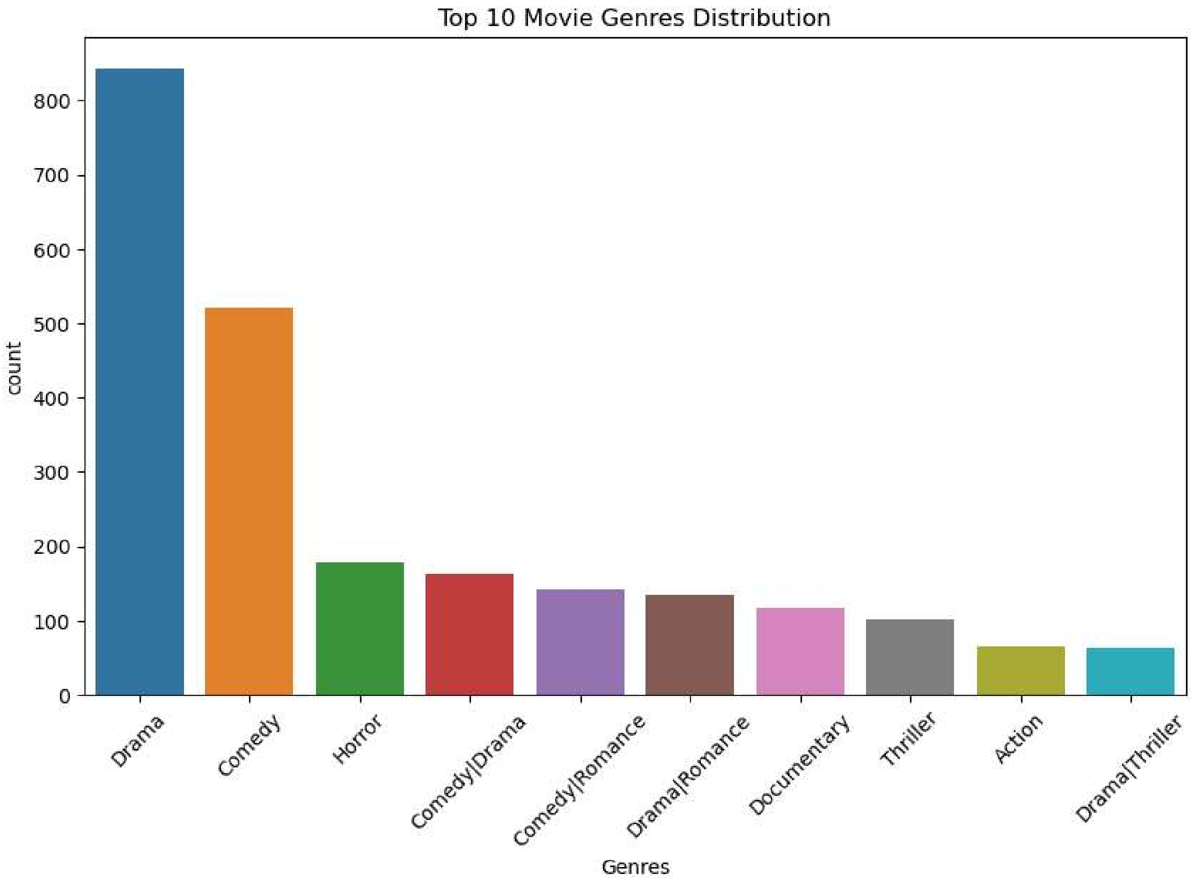


In [29]:

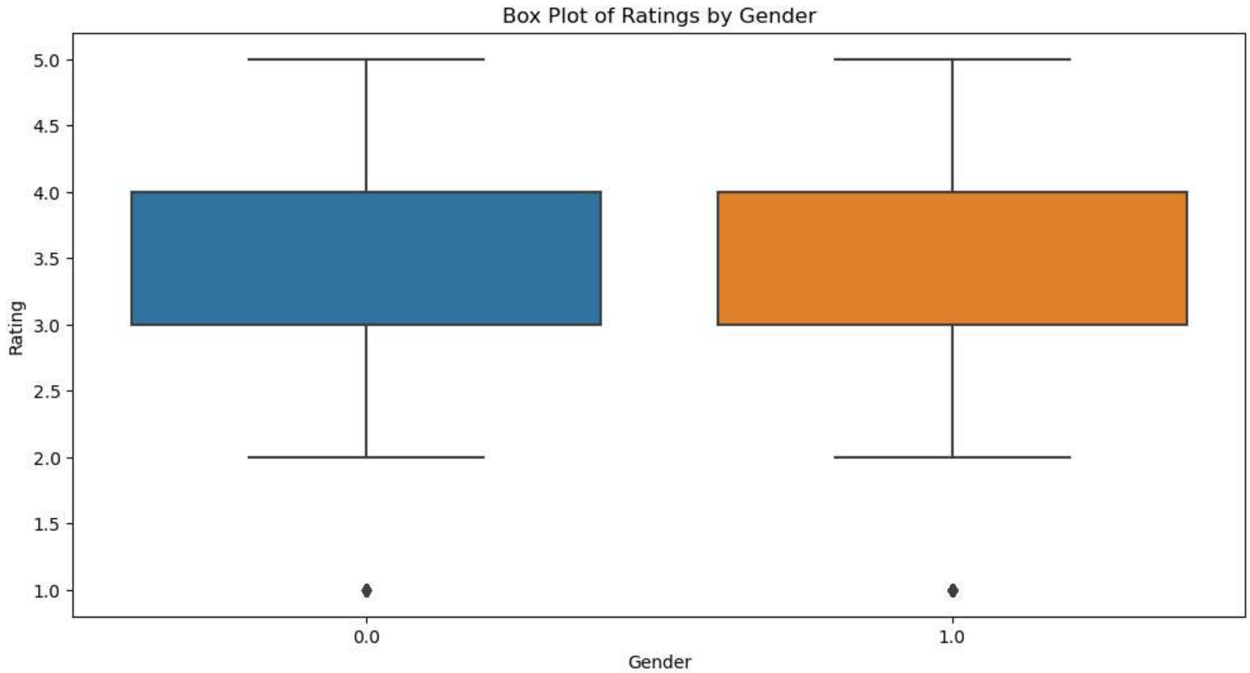
```
# Get the top 10 genres by count
top_genres = df['Genres'].value_counts().nlargest(10).index

# Filter the DataFrame to include only the top 10 genres
df_top_genres = df[df['Genres'].isin(top_genres)]


# Plot the count plot for the top 10 genres
plt.figure(figsize=(10, 6))
sns.countplot(x='Genres', data=df_top_genres, order=top_genres)
plt.title('Top 10 Movie Genres Distribution')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.show()
```

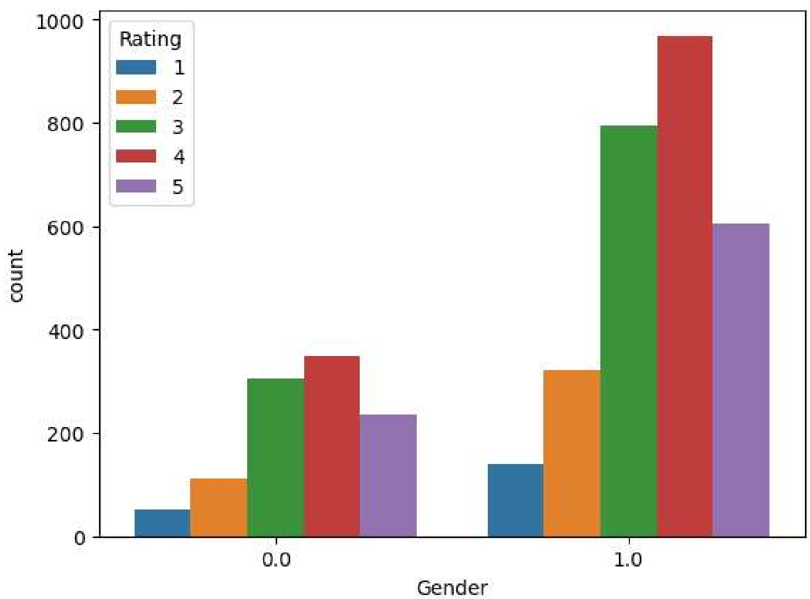


In [30]:
```
# 3. Box plot for 'Rating' by 'Gender'
plt.figure(figsize=(12, 6))
sns.boxplot(data=df, x='Gender', y='Rating')
plt.title('Box Plot of Ratings by Gender')
plt.show()
```



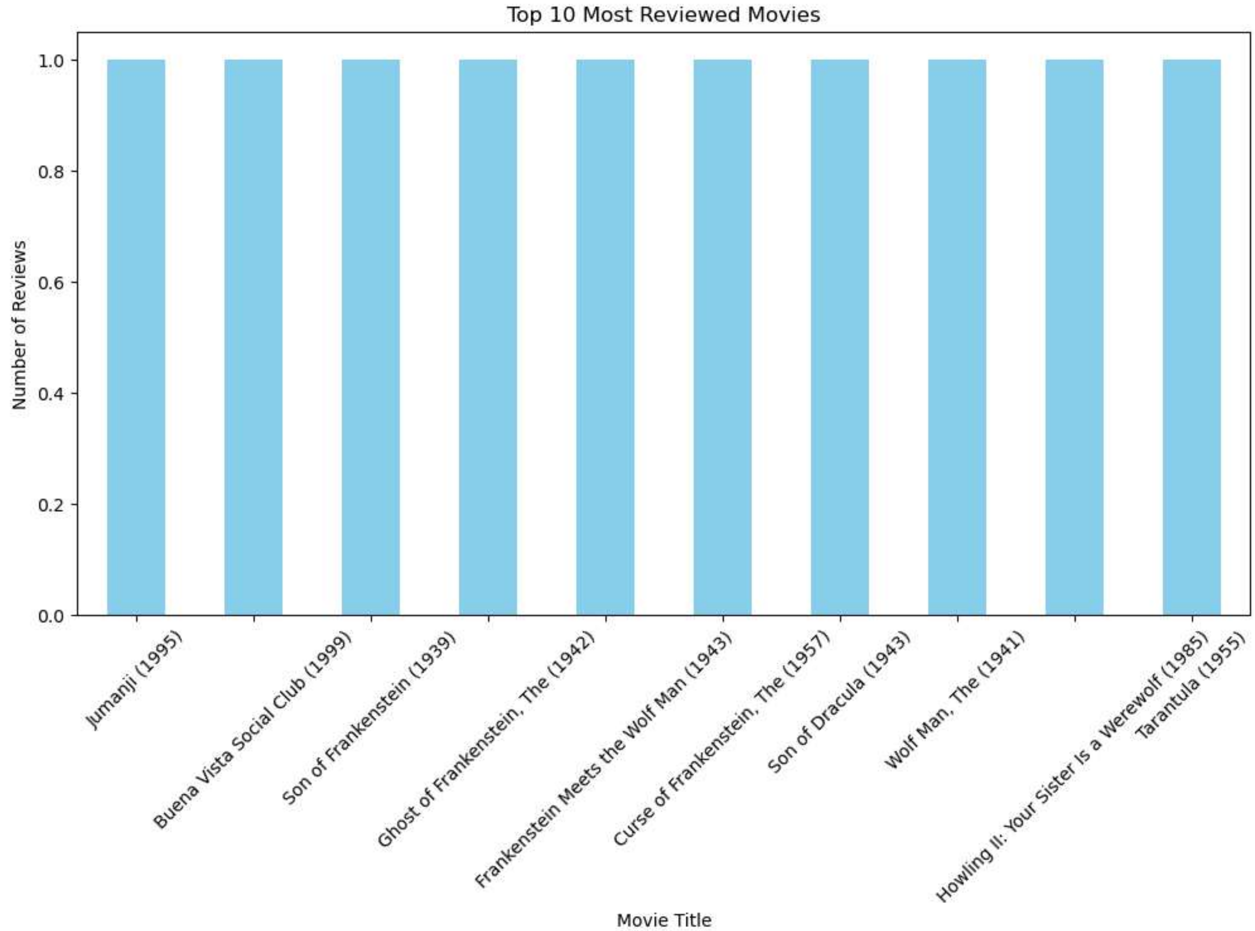
In [31]:
```
sns.countplot(x=df['Gender'],hue=df['Rating'])
```

Out[31]: <Axes: xlabel='Gender', ylabel='count'>



In [32]:

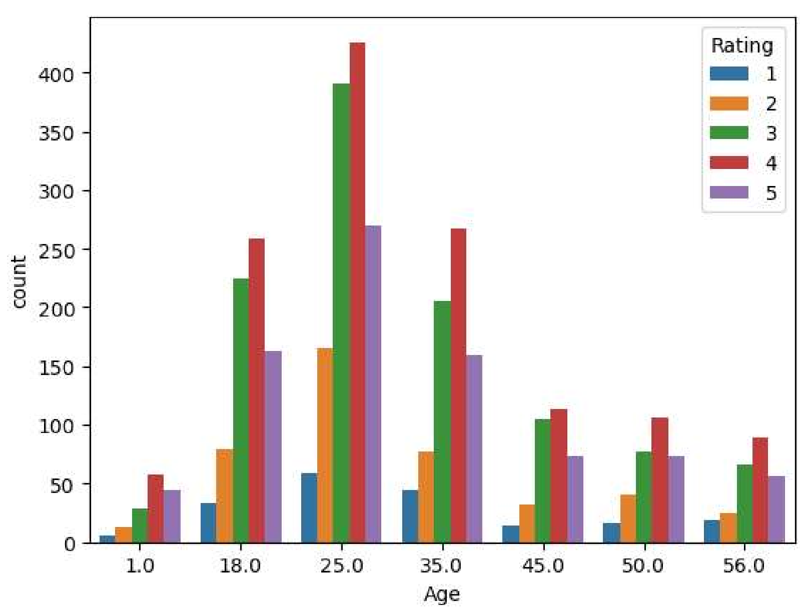
```
# 4. Bar chart for 'Title'
top_titles = df['Title'].value_counts().nlargest(10)
plt.figure(figsize=(12, 6))
top_titles.plot(kind='bar', color='skyblue')
plt.title('Top 10 Most Reviewed Movies')
plt.xlabel('Movie Title')
plt.ylabel('Number of Reviews')
plt.xticks(rotation=45)
plt.show()
```



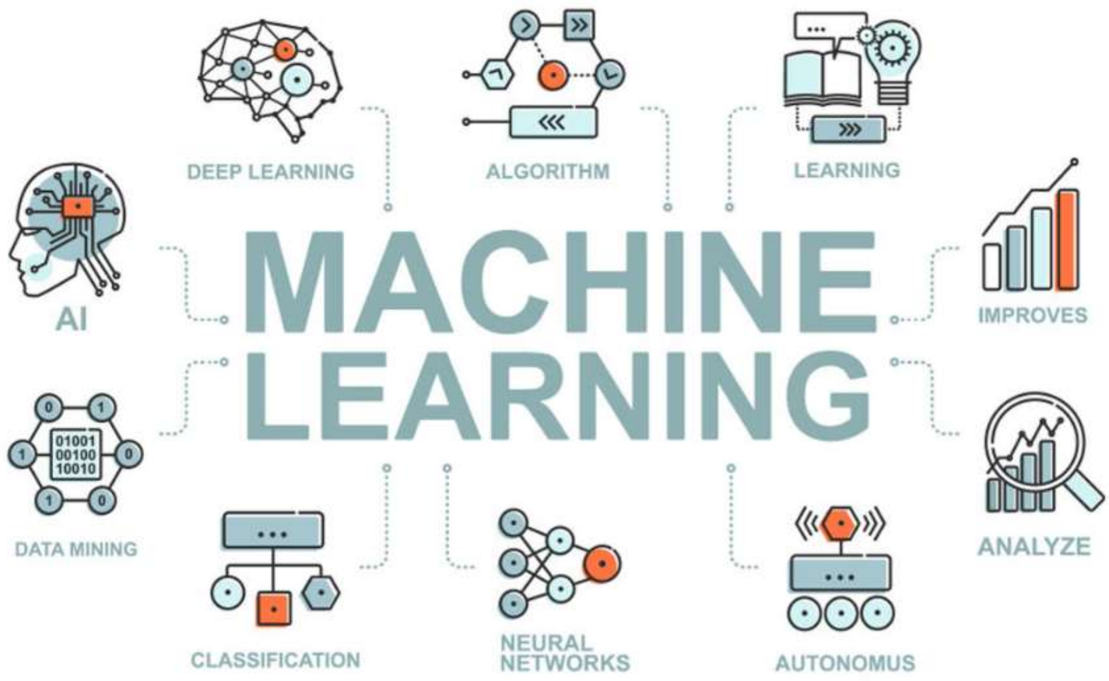
In [33]:

```
sns.countplot(x=df['Age'],hue=df['Rating'])
```

Out[33]: `<Axes: xlabel='Age', ylabel='count'>`



!



In [34]:
```
# Splitting the features and targets

x=df.drop(['Rating','Genres','Title'],axis=1)
y=df['Rating']
```

In [35]:
```
x.head()
```

Out[35]:

	Gender	Age
0	1.0	56.0
1	1.0	25.0
2	1.0	45.0
3	1.0	25.0
4	0.0	50.0

In [36]:
```
### Importing the dependencies

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
```

In [37]:
```
### Machine Learning models Libraries:
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import KFold,cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
```

In [38]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=3)
```

In [39]:
```
print(x.shape,x_train.shape,x_test.shape)
```

```
(3882, 2) (3105, 2) (777, 2)
```

Accuracy Score

In [40]:
```
models = [LogisticRegression(max_iter=1000),DecisionTreeClassifier(),RandomForestClassifier(),KNeighborsClassifier()
```

In [41]:
```
def compare_models_train_test():
    for model in models:
        model.fit(x_train,y_train)
        y_predicted = model.predict(x_test)
        accuracy = accuracy_score(y_test,y_predicted)
        print("Accuracy of the ",model,"=",accuracy)
        print("="*100)
```

In [42]:
```
compare_models_train_test()
```

```
Accuracy of the  LogisticRegression(max_iter=1000) = 0.3552123552123552
====================================================================================================
Accuracy of the  DecisionTreeClassifier() = 0.33462033462033464
====================================================================================================
Accuracy of the  RandomForestClassifier() = 0.32947232947232946
====================================================================================================
Accuracy of the  KNeighborsClassifier() = 0.2908622908622909
====================================================================================================
```

Cross Validation

In [43]:
```
models = [LogisticRegression(max_iter=1000),DecisionTreeClassifier(),RandomForestClassifier(),KNeighborsClassifier()
```

In [44]:
```
def compare_models_cv():
    for model in models:
        cv_score =cross_val_score(model,x,y,cv=5)
        mean_accuracy = sum(cv_score)/len(cv_score)
        mean_accuracy= mean_accuracy*100
        mean_accuracy = round(mean_accuracy,2)
        print("cv_score of the",model,"=",cv_score)
        print("mean_accuracy % of the",model,"=",mean_accuracy,"%")
        print("="*100)
```

In [45]:
```
compare_models_cv()
```

```
cv_score of the LogisticRegression(max_iter=1000) = [0.33976834 0.33976834 0.33247423 0.32731959 0.34020619]
mean_accuracy % of the LogisticRegression(max_iter=1000) = 33.59 %
====================================================================================================
cv_score of the DecisionTreeClassifier() = [0.32046332 0.31917632 0.30541237 0.31958763 0.32603093]
mean_accuracy % of the DecisionTreeClassifier() = 31.81 %
====================================================================================================
cv_score of the RandomForestClassifier() = [0.32046332 0.31917632 0.30541237 0.31958763 0.32603093]
mean_accuracy % of the RandomForestClassifier() = 31.81 %
====================================================================================================
cv_score of the KNeighborsClassifier() = [0.25096525 0.28571429 0.25515464 0.33891753 0.31701031]
mean_accuracy % of the KNeighborsClassifier() = 28.96 %
====================================================================================================
```

In [46]:

```
# Sample data (replace with your actual data)
# X = your feature matrix, y = your target variable
# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

models = [
    LogisticRegression(max_iter=1000),
    DecisionTreeClassifier(),
    RandomForestClassifier(),
    KNeighborsClassifier()
]

# Hyperparameter grids for each model
param_grids = [
    {'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000]},
    {'max_depth': [None, 10, 20, 30, 40, 50],
     'min_samples_split': [2, 5, 10],
     'min_samples_leaf': [1, 2, 4]},
    {'n_estimators': [50, 100, 200],
     'max_depth': [None, 10, 20, 30, 40, 50],
     'min_samples_split': [2, 5, 10],
     'min_samples_leaf': [1, 2, 4]},
    {'n_neighbors': [3, 5, 7, 9],
     'weights': ['uniform', 'distance'],
     'metric': ['euclidean', 'manhattan']}
]

best_models = []

for i, model in enumerate(models):
    grid_search = GridSearchCV(model, param_grids[i], cv=5, scoring='accuracy')
    grid_search.fit(x_train, y_train)

    best_model = grid_search.best_estimator_
    best_models.append(best_model)

    print(f"Best hyperparameters for {type(model).__name__}: {grid_search.best_params_}")
    print(f"Best cross-validated accuracy: {grid_search.best_score_:.4f}")

    y_pred = best_model.predict(x_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Test accuracy for {type(model).__name__}: {accuracy:.4f}\n")

# You can now use best_models for further analysis or predictions.
```

```
Best hyperparameters for LogisticRegression: {'C': 0.001}
Best cross-validated accuracy: 0.3356
Test accuracy for LogisticRegression: 0.3552

Best hyperparameters for DecisionTreeClassifier: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2}
Best cross-validated accuracy: 0.3272
Test accuracy for DecisionTreeClassifier: 0.3346

Best hyperparameters for RandomForestClassifier: {'max_depth': 40, 'min_samples_leaf': 2, 'min_samples_split': 10,
'n_estimators': 100}
Best cross-validated accuracy: 0.3353
Test accuracy for RandomForestClassifier: 0.3346

Best hyperparameters for KNeighborsClassifier: {'metric': 'euclidean', 'n_neighbors': 5, 'weights': 'uniform'}
Best cross-validated accuracy: 0.2680
Test accuracy for KNeighborsClassifier: 0.2909
```

In [47]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
```

In [48]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score

tuned_results = []

for idx, model in enumerate(best_models):
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    accuracy = accuracy_score(y_test, y_pred)

    # Specify average='micro' for multiclass classification
    precision = precision_score(y_test, y_pred, average='micro')
    recall = recall_score(y_test, y_pred, average='micro')
    f1 = f1_score(y_test, y_pred, average='micro')

    # Specify either 'ovo' (one-vs-one) or 'ovr' (one-vs-rest) for multi_class
    roc_auc = roc_auc_score(y_test, model.predict_proba(x_test), multi_class='ovr')

    tuned_results.append([f'Model_{idx}', accuracy, precision, recall, f1, roc_auc])
```

In [49]:

```
columns = ['Models', 'Accuracy', 'Precision', 'Recall', 'F1 Score', 'ROC AUC']
```

In [50]:

```
# Step 8: Compare Tuned Models
tuned_results_df = pd.DataFrame(tuned_results, columns=columns)

print(tuned_results_df)
```

```
    Models  Accuracy  Precision    Recall  F1 Score   ROC AUC
0  Model_0  0.355212   0.355212  0.355212  0.355212  0.499970
1  Model_1  0.334620   0.334620  0.334620  0.334620  0.512917
2  Model_2  0.334620   0.334620  0.334620  0.334620  0.515403
3  Model_3  0.290862   0.290862  0.290862  0.290862  0.496500
```

In [51]:

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           1       0.00      0.00      0.00        26
           2       0.12      0.04      0.06       101
           3       0.30      0.29      0.29       222
           4       0.33      0.52      0.40       276
           5       0.16      0.09      0.12       152

    accuracy                           0.29       777
   macro avg       0.18      0.19      0.17       777
weighted avg       0.25      0.29      0.26       777
```

!

Insights :-

- all 5 rating movies list = 480
- all 5 rating movies list and Age Less Then 25 count = 208
- all movies rating less than 3 list and Age Lass Then 25 count = 47163
- Top Movie Genres is Drama
- Top Rated movies is jumanji
- Average age distribution for movie rating is 25 years
- Most of the ratings are done by Mens

Conclusion :-

Upon evaluating various performance metrics for movie rating prediction models, Logistic Regression emerges as the top-performing model. It exhibits the highest cross-validated score, accuracy, precision, recall, F1 score, and ROC AUC among the considered models. Thus, Logistic Regression stands out as the most suitable choice for predicting movie ratings, offering robust performance across multiple evaluation criteria.

In [ ]: