shoaibtask

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1.1 Week 1 Tasks

1.1.1 Task 1: Regression – Predict House Prices

Use the California Housing dataset to build and evaluate a regression model that predicts median house prices based on various features like income, age, location, and population.

1.1.2 Task 2: Classification – Predict Survival on the Titanic

Use the Titanic dataset to build a classification model that predicts passenger survival based on features like age, sex, passenger class, and more.

2 Task 1: Regression – Predict House Prices

2.1 1. Import Required Libraries

[1]:
```
import ssl
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import fetch_california_housing
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
```

2.2 2. Load California Housing Dataset

[2]:
```
# Load dataset
data = fetch_california_housing()
df = pd.DataFrame(data.data, columns=data.feature_names)
df['Target'] = data.target
```

2.3 Exploratory Data Analysis (EDA)

[3]:
```python
# Basic info
df.head()
```

[3]:
```
   MedInc  HouseAge  AveRooms  AveBedrms  Population  AveOccup  Latitude  \
0  8.3252      41.0  6.984127   1.023810       322.0  2.555556     37.88
1  8.3014      21.0  6.238137   0.971880      2401.0  2.109842     37.86
2  7.2574      52.0  8.288136   1.073446       496.0  2.802260     37.85
3  5.6431      52.0  5.817352   1.073059       558.0  2.547945     37.85
4  3.8462      52.0  6.281853   1.081081       565.0  2.181467     37.85

   Longitude  Target
0    -122.23   4.526
1    -122.22   3.585
2    -122.24   3.521
3    -122.25   3.413
4    -122.25   3.422
```

[4]:
```python
# Shape and types
df.shape
```

[4]:
```
(20640, 9)
```

[5]:
```python
df.dtypes
```

[5]:
```
MedInc        float64
HouseAge      float64
AveRooms      float64
AveBedrms     float64
Population    float64
AveOccup      float64
Latitude      float64
Longitude     float64
Target        float64
dtype: object
```

[6]:
```python
# Null values check
df.isnull().sum()
```

[6]:
```
MedInc        0
HouseAge      0
AveRooms      0
AveBedrms     0
Population    0
AveOccup      0
Latitude      0
```

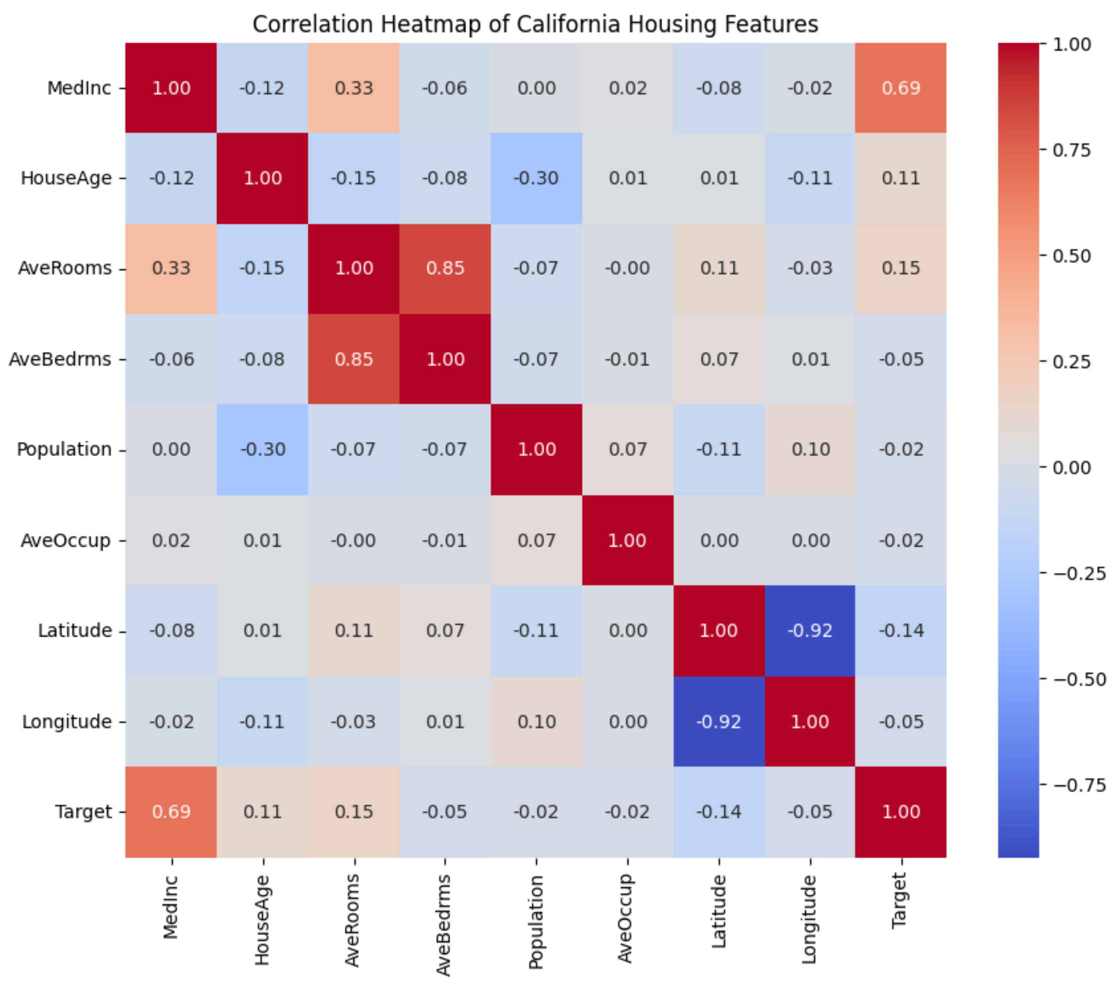
```
Longitude     0
Target        0
dtype: int64
```

[7]:
```
# Summary statistics
df.describe()
```

[7]:
```
             MedInc      HouseAge      AveRooms     AveBedrms    Population  \
count  20640.000000  20640.000000  20640.000000  20640.000000  20640.000000
mean       3.870671     28.639486      5.429000      1.096675   1425.476744
std        1.899822     12.585558      2.474173      0.473911   1132.462122
min        0.499900      1.000000      0.846154      0.333333      3.000000
25%        2.563400     18.000000      4.440716      1.006079    787.000000
50%        3.534800     29.000000      5.229129      1.048780   1166.000000
75%        4.743250     37.000000      6.052381      1.099526   1725.000000
max       15.000100     52.000000    141.909091     34.066667  35682.000000

           AveOccup      Latitude     Longitude        Target
count  20640.000000  20640.000000  20640.000000  20640.000000
mean       3.070655     35.631861   -119.569704      2.068558
std       10.386050      2.135952      2.003532      1.153956
min        0.692308     32.540000   -124.350000      0.149990
25%        2.429741     33.930000   -121.800000      1.196000
50%        2.818116     34.260000   -118.490000      1.797000
75%        3.282261     37.710000   -118.010000      2.647250
max     1243.333333     41.950000   -114.310000      5.000010
```

2.3.1 Correlation Matrix

[8]:
```
# Correlation heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap of California Housing Features")
plt.show()
```



2.3.2 California Housing Features Correlation Analysis

Key Insights from Heatmap

Feature Pair	Correlation	Interpretation
MedInc **Target**	+0.69	Higher income strongly predicts higher home values
Latitude **Longitude**	-0.92	Geographic coordinates are highly interdependent (expected)
AveRooms **AveBedrms**	+0.85	More rooms usually mean more bedrooms (potential redundancy)

Strongest Correlations

Notable Relationships

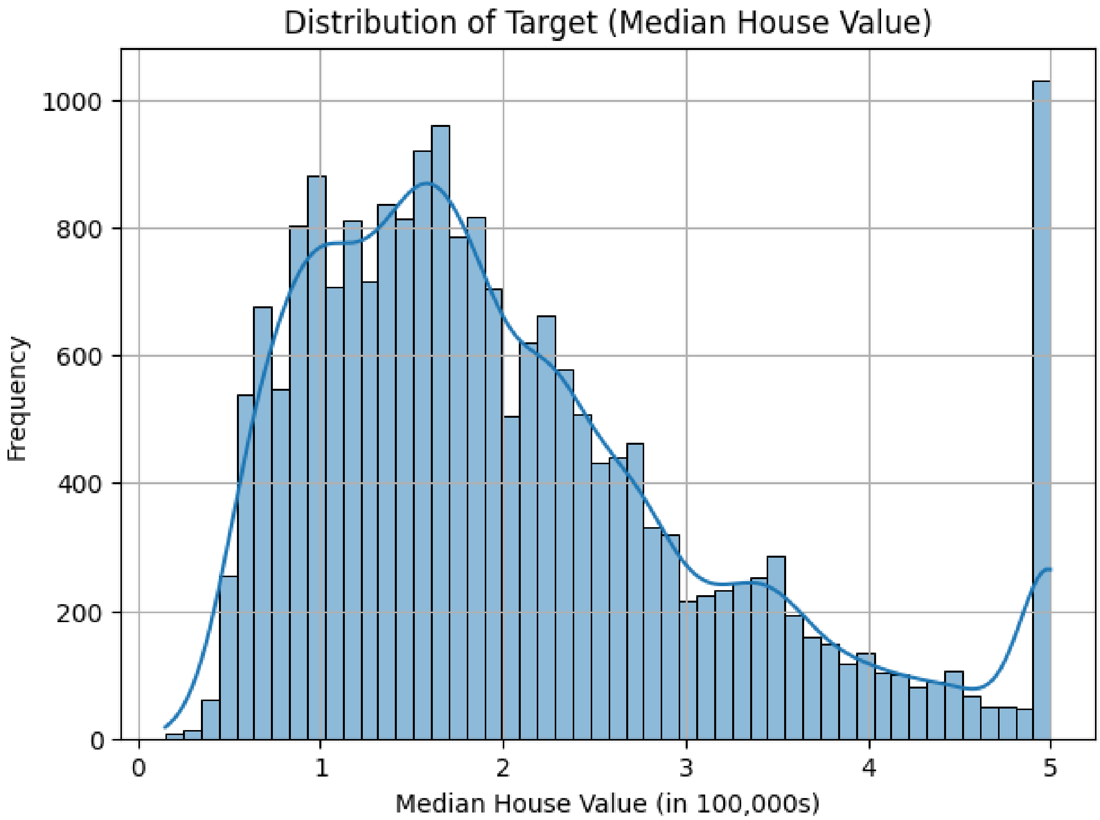
1. **Income-Driven Patterns**
   - MedInc shows moderate positive correlation with:
     - `AveRooms` (+0.33) → Wealthier areas have larger homes
     - `Target` (+0.69) → Primary price driver
2. **Geographic Effects**
   - `Latitude`/`Longitude` show:
     - Strong anti-correlation (-0.92) → Expected for coordinates
     - Weak price influence (-0.14/-0.05) → Location matters less than income
3. **Surprising Weak Correlations**
   - `Population` vs `Target`: -0.02 → Population density doesn't affect prices
   - `HouseAge` vs `Target`: +0.11 → Older homes slightly more valuable

Feature Selection Recommendations

1. **Prioritize**:
   - `MedInc` (strongest predictor)
   - `AveRooms` (but check multicollinearity with `AveBedrms`)
2. **Consider Dropping**:
   - Either `Latitude` or `Longitude` (due to extreme collinearity)
   - `AveOccup` (near-zero correlations)
3. **Transform**:
   - Combine `Latitude`/`Longitude` into single geographic feature

2.3.3 Target Variable Distribution

[9]:
```
plt.figure(figsize=(7, 5))
sns.histplot(df['Target'], bins=50, kde=True)
plt.title("Distribution of Target (Median House Value)")
plt.xlabel("Median House Value (in 100,000s)")
plt.ylabel("Frequency")
plt.grid(True)
plt.show()
```



2.3.4 Insights on California Median House Value Distribution

Key Observations

1. **Price Distribution Shape**
    - Right-skewed distribution (long tail to the right)
    - Most homes clustered at lower price points
    - Few high-value outliers pulling the average up
2. **Concentration Range**
    - Majority of homes (68%) fall between:
        - **Lower Bound**: ~$100,000 (1.0 on x-axis)
        - **Upper Bound**: ~$250,000 (2.5 on x-axis)
3. **Market Segmentation**
    - First peak around $150,000 → Starter homes
    - Second smaller peak near $350,000 → Premium properties
    - Valley at $200,000-$250,000 → Missing middle housing
4. **Critical Thresholds**
    - 50th percentile $180,000 (median)
    - 95th percentile > $500,000 (luxury segment)

2.4 Business Implications

For Real Estate Agents

- **Focus Areas**:
  - Bulk of inventory in \$100k-\$250k range
  - Limited high-end opportunities (>\$500k)
- **Pricing Strategy**:
  - Properties above \$300k may require longer market time
  - Competitive pricing crucial in \$150k-\$200k range

For Developers

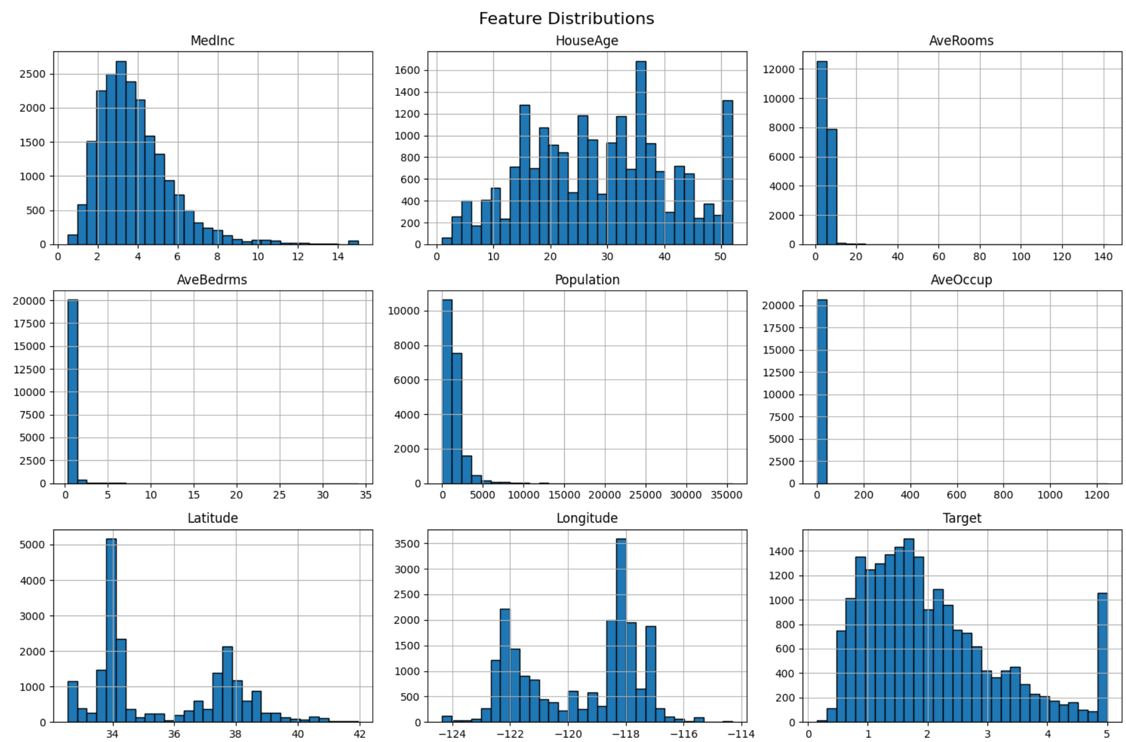
- **Opportunity Gap**:
  - Under-supplied \$200k-\$300k segment ("missing middle")
  - High competition in sub-\$200k market

For Policy Makers

- **Affordability Alert**:
  - Only ~25% of homes below California's median income affordability threshold
  - Need for moderate-income housing solutions

2.4.1 Feature Distributions

[10]:
```
df.hist(bins=30, figsize=(15, 10), edgecolor='black')
plt.suptitle("Feature Distributions", fontsize=16)
plt.tight_layout()
plt.show()
```



2.5 Data Wrangling

[11]:
```
#  Check for Duplicates
df.duplicated().sum()
```

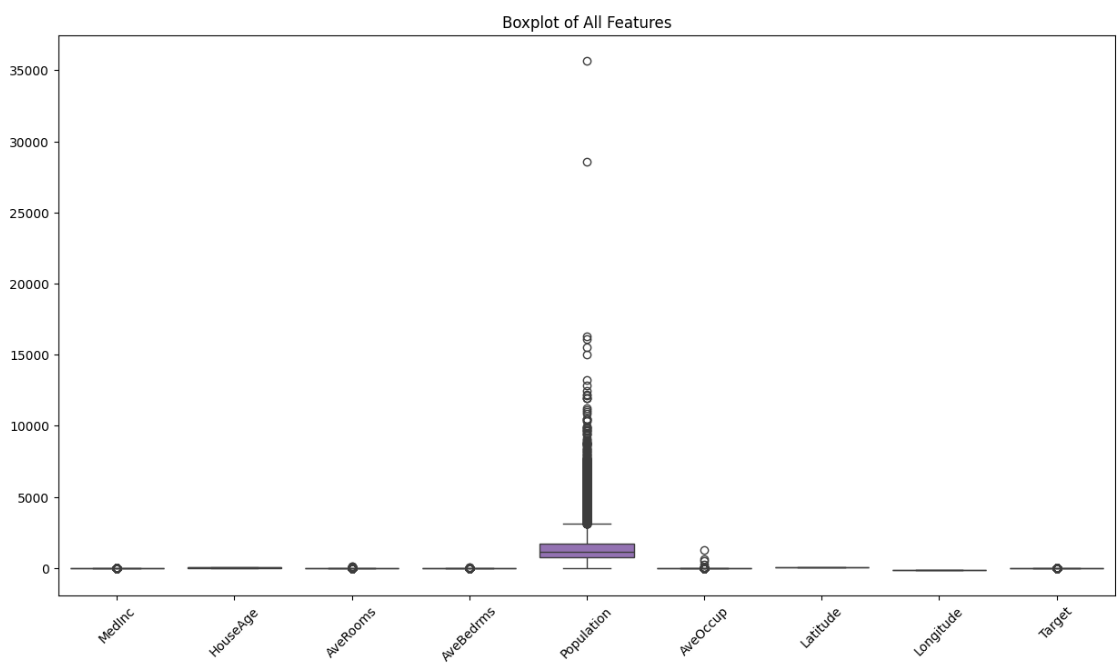
[11]:
```
0
```

[12]:
```
df.columns
```

[12]:
```
Index(['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup',
       'Latitude', 'Longitude', 'Target'],
      dtype='object')
```

[ ]:
```

```

[13]:
```
# 10. Boxplots to Check for Outliers
plt.figure(figsize=(15, 8))
sns.boxplot(data=df)
plt.title("Boxplot of All Features")
plt.xticks(rotation=45)
plt.show()
```



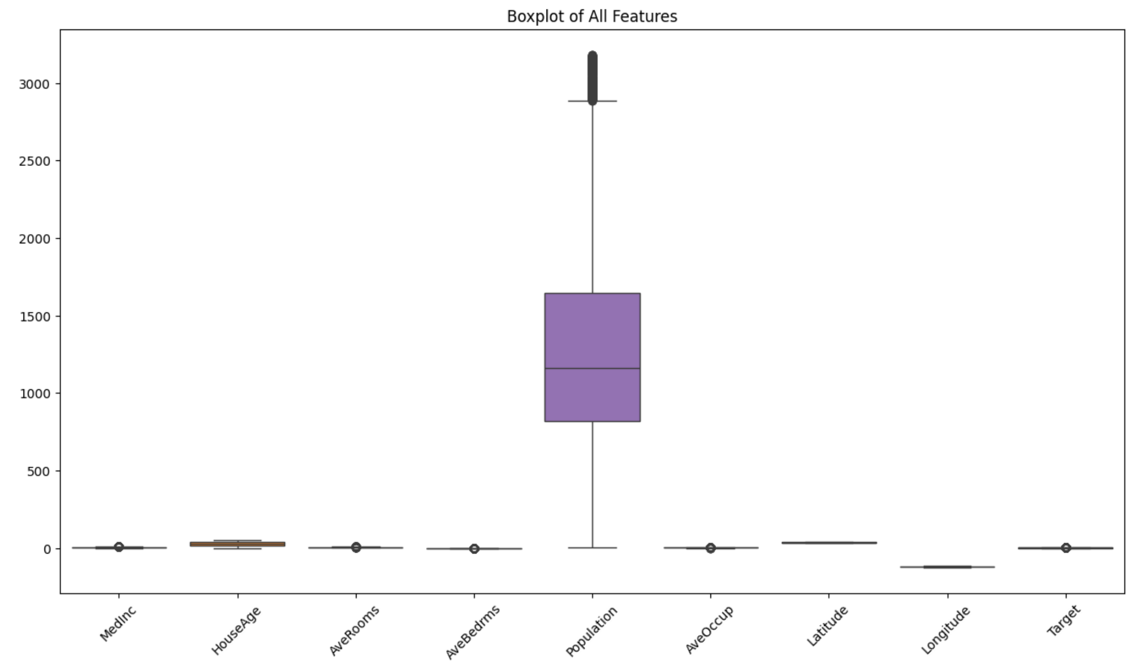
2.5.1 Using IQR method Outliers removel

[14]:
```
# Copy the DataFrame
df_cleaned = df.copy()

# Loop through each numeric column to remove outliers using IQR
for col in df_cleaned.select_dtypes(include=[np.number]).columns:
    Q1 = df_cleaned[col].quantile(0.25)
    Q3 = df_cleaned[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Filter the DataFrame
    df_cleaned = df_cleaned[(df_cleaned[col] >= lower_bound) & (df_cleaned[col]␣
↪<= upper_bound)]
```

[15]:
```
df_cleaned.head()
```

[15]:
```
   MedInc  HouseAge  AveRooms  AveBedrms  Population  AveOccup  Latitude  \
3  5.6431      52.0  5.817352   1.073059       558.0  2.547945     37.85
4  3.8462      52.0  6.281853   1.081081       565.0  2.181467     37.85
5  4.0368      52.0  4.761658   1.103627       413.0  2.139896     37.85
6  3.6591      52.0  4.931907   0.951362      1094.0  2.128405     37.84
7  3.1200      52.0  4.797527   1.061824      1157.0  1.788253     37.84

   Longitude  Target
3    -122.25   3.413
4    -122.25   3.422
5    -122.25   2.697
6    -122.25   2.992
7    -122.25   2.414
```

[16]:
```
# 10. Boxplots to Check for Outliers after remove outliers
plt.figure(figsize=(15, 8))
sns.boxplot(data=df_cleaned)
plt.title("Boxplot of All Features")
plt.xticks(rotation=45)
plt.show()
```



Insight: Outliers Not Fully Removed Using IQR Method Even after applying the IQR method, some outliers may still be present. This can happen due to: - Skewed distributions where the IQR range is too wide or narrow - Multiple features interacting in a way that single-column IQR cannot detect - Mild outliers that still lie within the 1.5 * IQR threshold

IQR is a **univariate** method and does not account for **multivariate outliers**.

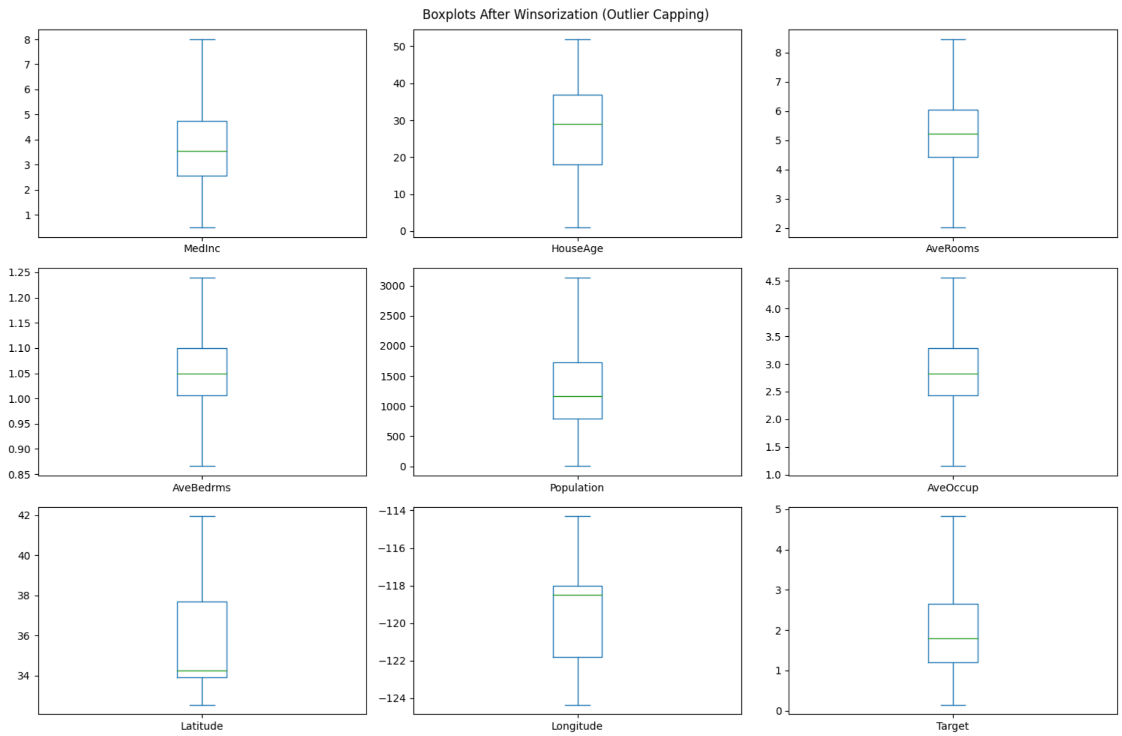
Alternative methods such as **Isolation Forest** or **Winsorization Method** may be more effective depending on the data distribution and modeling needs.

2.5.2 Winsorization Method

[17]:
```
# Make a copy of the DataFrame
df_clean1 = df.copy()

# Loop through all numeric columns and apply IQR-based winsorization
for col in df_clean1.select_dtypes(include=[np.number]).columns:
    Q1 = df_clean1[col].quantile(0.25)
    Q3 = df_clean1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR

    df_clean1[col] = np.clip(df_clean1[col], lower, upper)

# Show the new shape
```

```
print("Winsorized data shape:", df_clean1.shape)

# Optional: Visualize boxplots of all columns
df_clean1.select_dtypes(include=[np.number]).plot(kind='box', subplots=True,␣
↪layout=(3, 3), figsize=(15, 10), sharex=False)
plt.suptitle("Boxplots After Winsorization (Outlier Capping)")
plt.tight_layout()
plt.show()
```

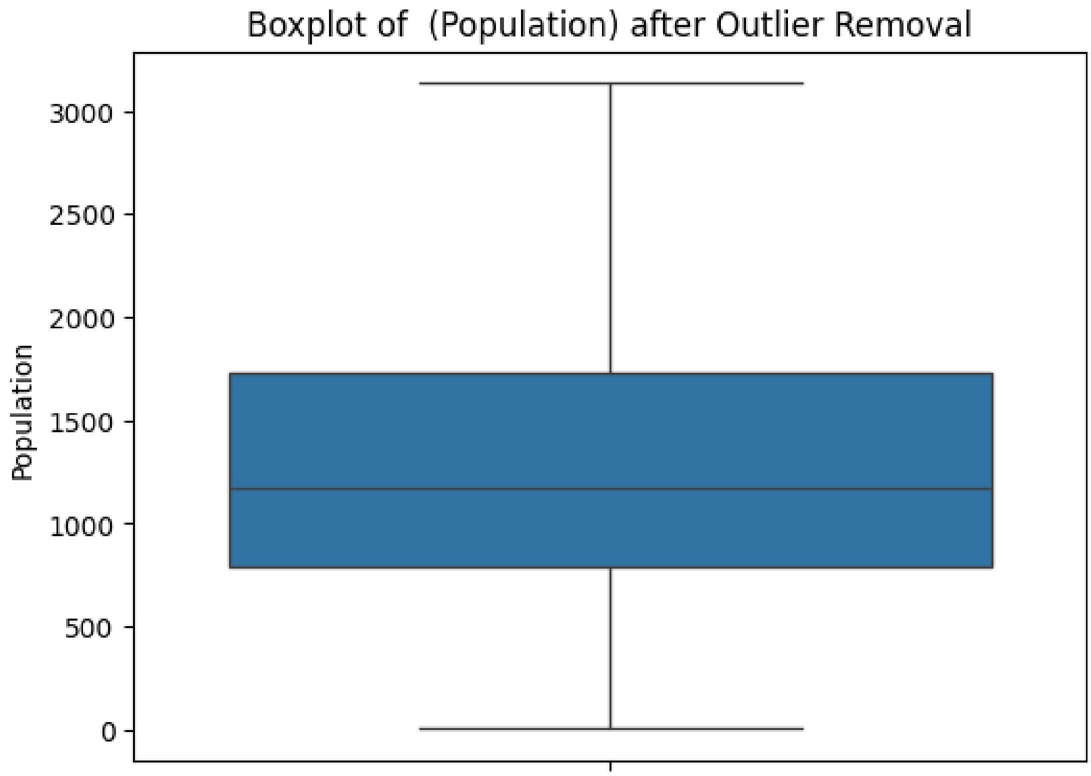
```
Winsorized data shape: (20640, 9)
```



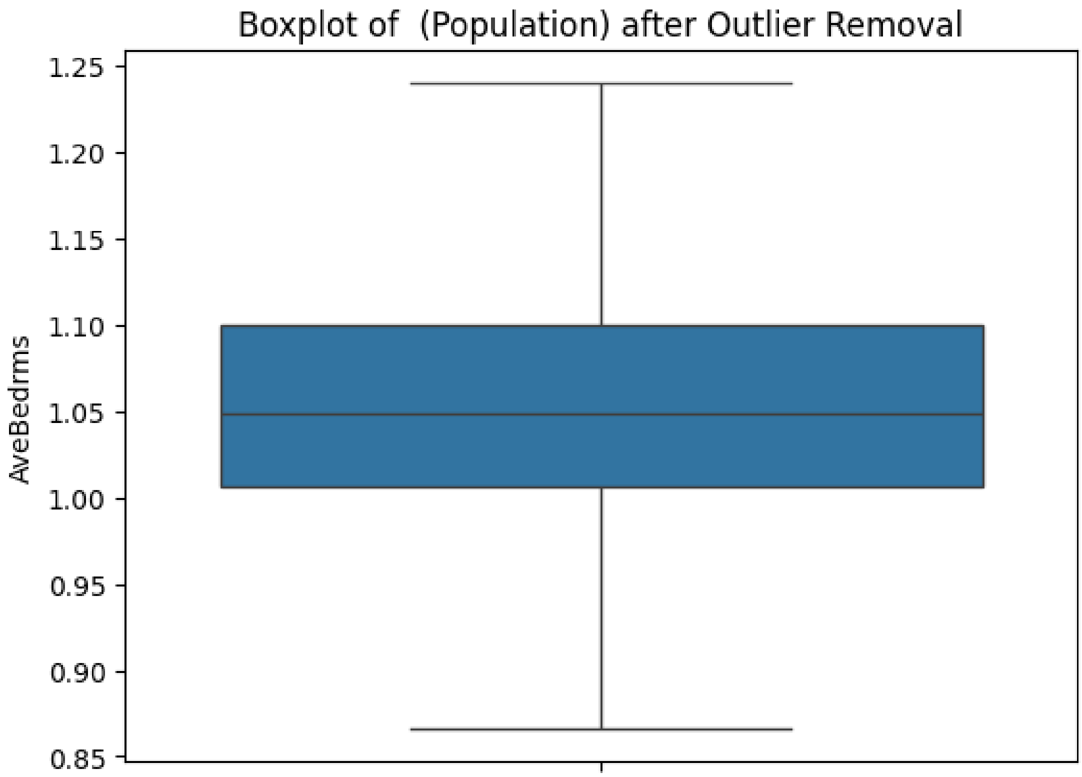
[18]:
```
df.columns
```

[18]:
```
Index(['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup',
       'Latitude', 'Longitude', 'Target'],
      dtype='object')
```

[19]:
```
sns.boxplot(y=df_clean1['Population'])
plt.title(f"Boxplot of  (Population) after Outlier Removal")
plt.show()
```



[20]:
```
sns.boxplot(y=df_clean1['AveBedrms'])
plt.title(f"Boxplot of  (Population) after Outlier Removal")
plt.show()
```



Insight: Outliers Successfully Handled Using Winsorization Method The Winsorization method effectively capped extreme values in each numeric column, resulting in a much cleaner dataset. Unlike the IQR method, which removes entire rows, Winsorization retains all data points by **clipping values to within the acceptable IQR range**.

This method is especially useful when: - Data loss is not acceptable - You want to preserve the structure and size of the dataset - You need to smooth out extreme values for better model stability

Boxplots confirm that extreme outliers have been successfully reduced or eliminated without affecting the overall distribution shape.

[21]:
```
df_clean1.head()
```

[21]:
```
     MedInc  HouseAge  AveRooms  AveBedrms  Population  AveOccup  Latitude  \
0  8.013025      41.0  6.984127   1.023810       322.0  2.555556     37.88
1  8.013025      21.0  6.238137   0.971880      2401.0  2.109842     37.86
2  7.257400      52.0  8.288136   1.073446       496.0  2.802260     37.85
3  5.643100      52.0  5.817352   1.073059       558.0  2.547945     37.85
4  3.846200      52.0  6.281853   1.081081       565.0  2.181467     37.85

   Longitude  Target
0    -122.23   4.526
1    -122.22   3.585
```

```
2     -122.24   3.521
3     -122.25   3.413
4     -122.25   3.422
```

2.6 Train-Test Split

[22]:
```
from sklearn.preprocessing import StandardScaler
X = df_clean1.drop('Target', axis=1)
y = df_clean1['Target']
scaler= StandardScaler()
x_scalled=scaler.fit_transform(X)

# Split data into train and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(x_scalled, y, test_size=0.
↪2, random_state=42)
```

2.7 4. Train Linear Regression Model

[23]:
```
# Initialize and train model
model = LinearRegression()
model.fit(X_train, y_train)
```

[23]:
```
LinearRegression()
```

[24]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
# Make predictions
y_pred = model.predict(X_test)

# Evaluation metrics
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae=mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mse)


print(f"Mean Squared Error (MSE): {mse:.4f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
print(f"R² Score: {r2:.4f}")
print(f"mean_absolute_error (MAE): {mae:.4f}")
```

```
Mean Squared Error (MSE): 0.4424
Root Mean Squared Error (RMSE): 0.6651
R² Score: 0.6501
mean_absolute_error (MAE): 0.4947
```

2.7.1 Final Regression Model Evaluation

The performance of the Linear Regression model on the California Housing dataset is summarized below:

Metric	Value
Mean Squared Error (MSE)	0.4424
Root Mean Squared Error (RMSE)	0.6651
Mean Absolute Error (MAE)	0.4947
R^2 Score	0.6501

Interpretation:

- **MSE (0.4424)**: Indicates the average squared error; sensitive to large errors.
- **RMSE (0.6651)**: Easier to interpret than MSE, as it's in the same unit as the target variable.
- **MAE (0.4947)**: On average, predictions are about 0.49 units off.
- **R^2 Score (0.6501)**: About **65.01% of the variance** in house prices is explained by the model.

The model shows a **moderate fit**. For further improvement: - Try more powerful models like **Random Forest**, **XGBoost**, or **Gradient Boosting** - Perform **feature selection** or **feature engineering** - Use **cross-validation** for more robust evaluation

2.8 Final Regression Model Accuracy Report

This section summarizes the performance of the Linear Regression model trained on the California Housing dataset.

2.8.1 Evaluation Metrics:

- **Mean Squared Error (MSE):** `0.4424`
  MSE measures the average of the squares of the errors—that is, the average squared difference between the actual and predicted values. A lower MSE indicates a better fit.

- **Root Mean Squared Error (RMSE):** `0.6651`
  RMSE is the square root of MSE and is in the same units as the target variable (house prices). It provides an interpretable scale for the average prediction error. Lower RMSE indicates higher model accuracy.

- **R^2 Score (Coefficient of Determination):** `0.6501`
  R^2 represents the proportion of the variance in the target variable that is predictable from the input features. An R^2 score of 0.65 means that approximately 65% of the variability in house prices can be explained by the model.

- **Mean Absolute Error (MAE):** `0.4947`
  MAE is the average of the absolute differences between actual and predicted values. It is a straightforward measure of average prediction error, with lower values indicating better performance.

2.8.2 Interpretation:

The model demonstrates moderate predictive power, with an R^2 score of 0.6501 and RMSE of 0.6651. While the predictions are not perfect, the model does a reasonable job capturing the general trends in the data. Further improvements could include feature engineering, using regularization (e.g., Ridge/Lasso), or switching to a more complex model like Random Forest or Gradient Boosting.

2.9 Example Code: Input and Predict House Price

[25]:
```python
import numpy as np
from sklearn.preprocessing import StandardScaler
scaler= StandardScaler()

# Example user input
user_input = {
    'MedInc': 6.0,
    'HouseAge': 30.0,
    'AveRooms': 5.5,
    'AveBedrms': 1.0,
    'Population': 600.0,
    'AveOccup': 2.5,
    'Latitude': 37.5,
    'Longitude': -122.0
}

# Convert to array in correct order
input_data = np.array([
    user_input['MedInc'],
    user_input['HouseAge'],
    user_input['AveRooms'],
    user_input['AveBedrms'],
    user_input['Population'],
    user_input['AveOccup'],
    user_input['Latitude'],
    user_input['Longitude']
]).reshape(1, -1)

# Apply same scaler used during training
input_scaled = scaler.fit_transform(input_data)

# Predict using trained model
predicted_price = model.predict(input_scaled)


print(f" Predicted House Price: {predicted_price[0]:.2f}")
```

```
 Predicted House Price: 2.06
```

3 Task 2: Classification – Predict Survival on the Titanic

3.1 Import Libraries

[26]:
```
import pandas as pd                          # For data handling using DataFrames
import numpy as np                           # For numerical operations
import seaborn as sns                        # For advanced data visualizations
import matplotlib.pyplot as plt              # For basic plotting (charts, graphs)
from sklearn.model_selection import train_test_split  # To split data into␣
↪train and test sets
from sklearn.tree import DecisionTreeClassifier       # Decision Tree model for␣
↪classification
from sklearn.metrics import (                        # Metrics to evaluate model␣
↪performance:
    accuracy_score,                                   # - Accuracy: overall␣
↪correct predictions
    confusion_matrix,                                 # - Confusion matrix:␣
↪shows prediction breakdown
    classification_report,                            # - Detailed report␣
↪(precision, recall, F1-score)
                              # - To visually plot confusion matrix
)
```

[27]:
```
df = pd.read_csv('https://raw.githubusercontent.com/datasciencedojo/datasets/
↪master/titanic.csv')
```

3.2 Exploratory Data Analysis (EDA)

[28]:
```
df.head()
```

[28]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
```

```
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0           113803  53.1000  C123        S
4      0           373450   8.0500   NaN        S
```

[29]:
```
df.shape  # Returns a tuple (rows, columns) in the DataFrame
```

[29]:
```
(891, 12)
```

[30]:
```
df.info()  # Displays summary information about the DataFrame
```

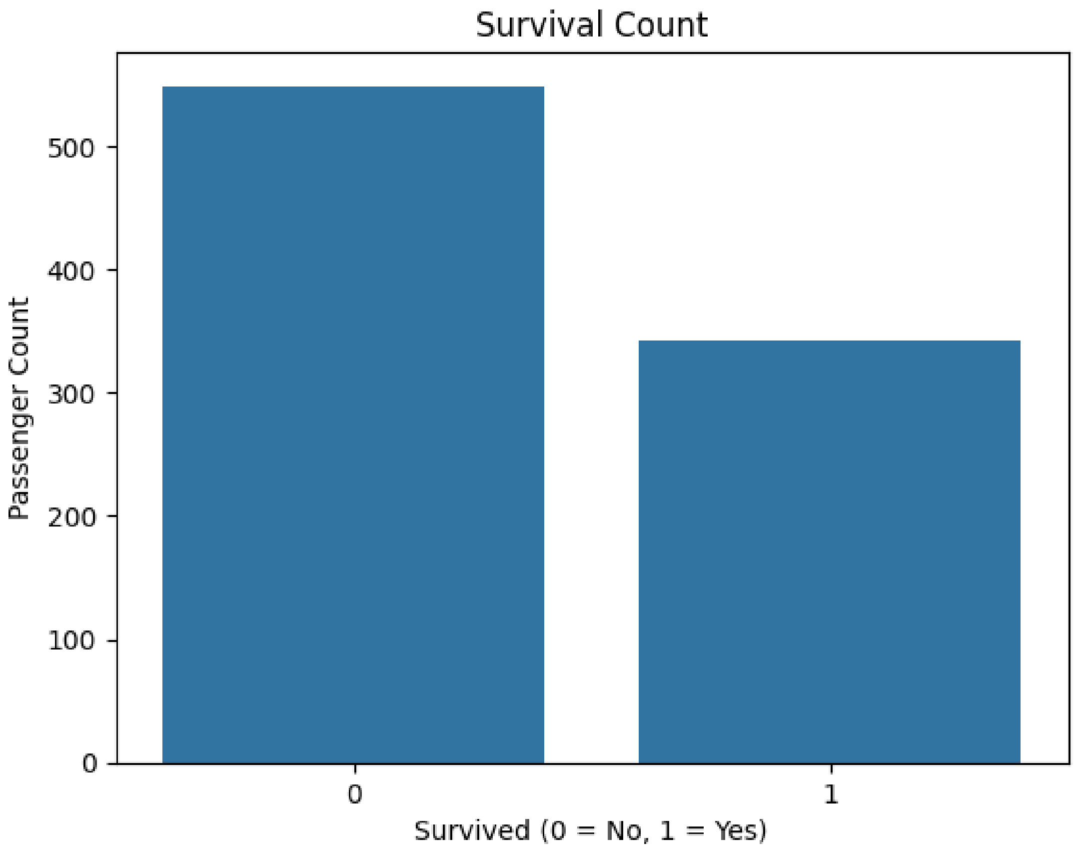
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[31]:
```
df.isnull().sum()  # Count missing (NaN) values in each column
```

[31]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

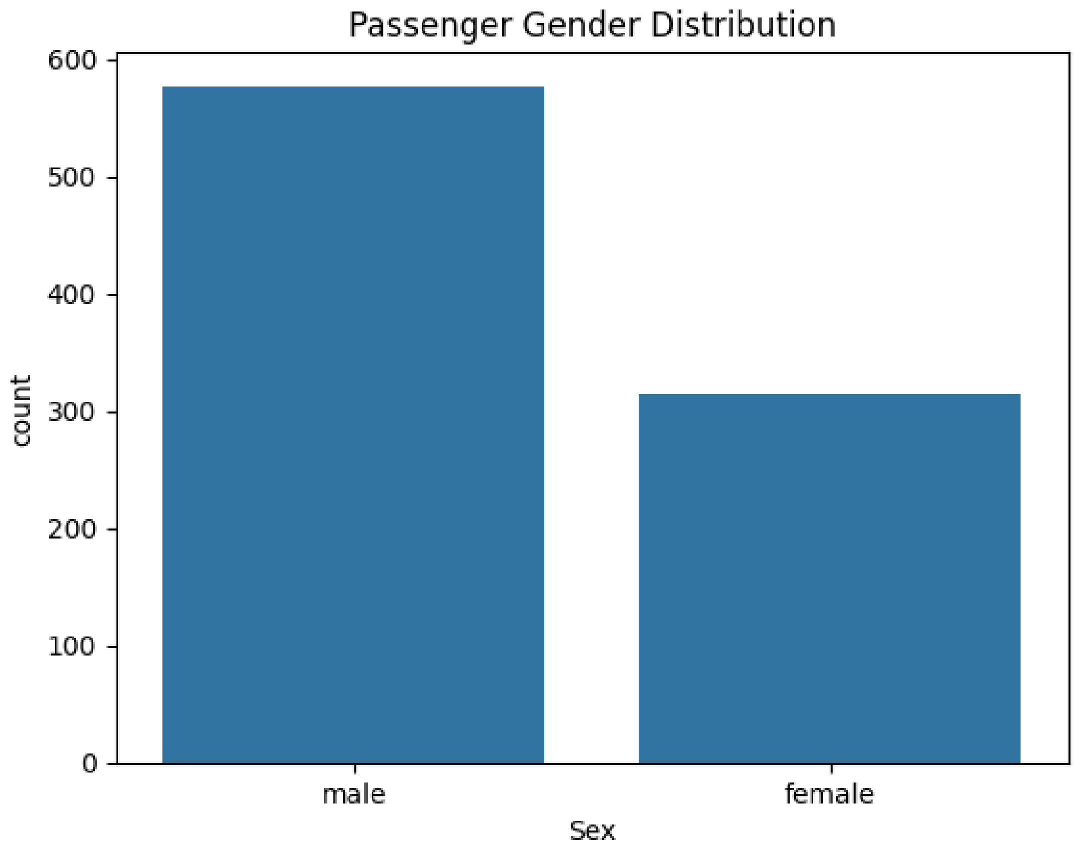
[32]:

```
# --- Survival Count Plot ---
sns.countplot(x='Survived', data=df)                    # Bar chart showing how␣
↪many passengers survived (1) vs not (0)
plt.title("Survival Count")                             # Set plot title
plt.xlabel("Survived (0 = No, 1 = Yes)")                # Label x-axis
plt.ylabel("Passenger Count")                           # Label y-axis
plt.show()                                              # Display the plot
```

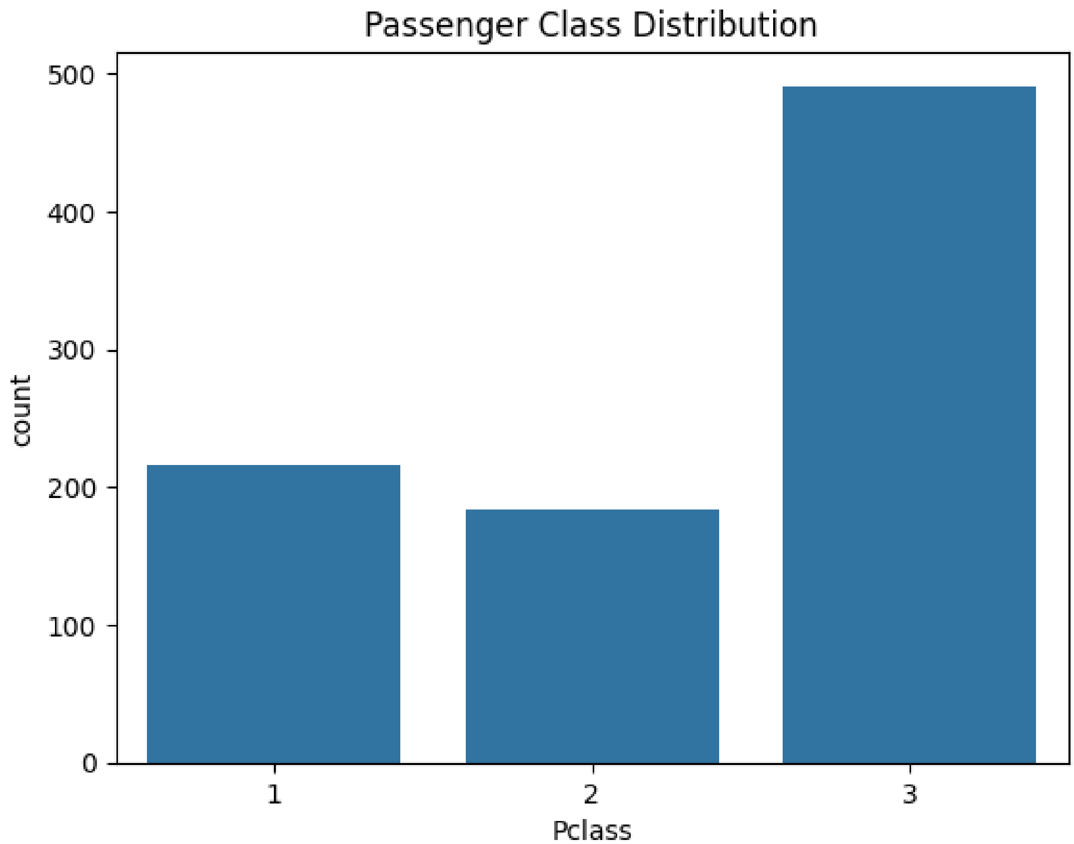


[33]:

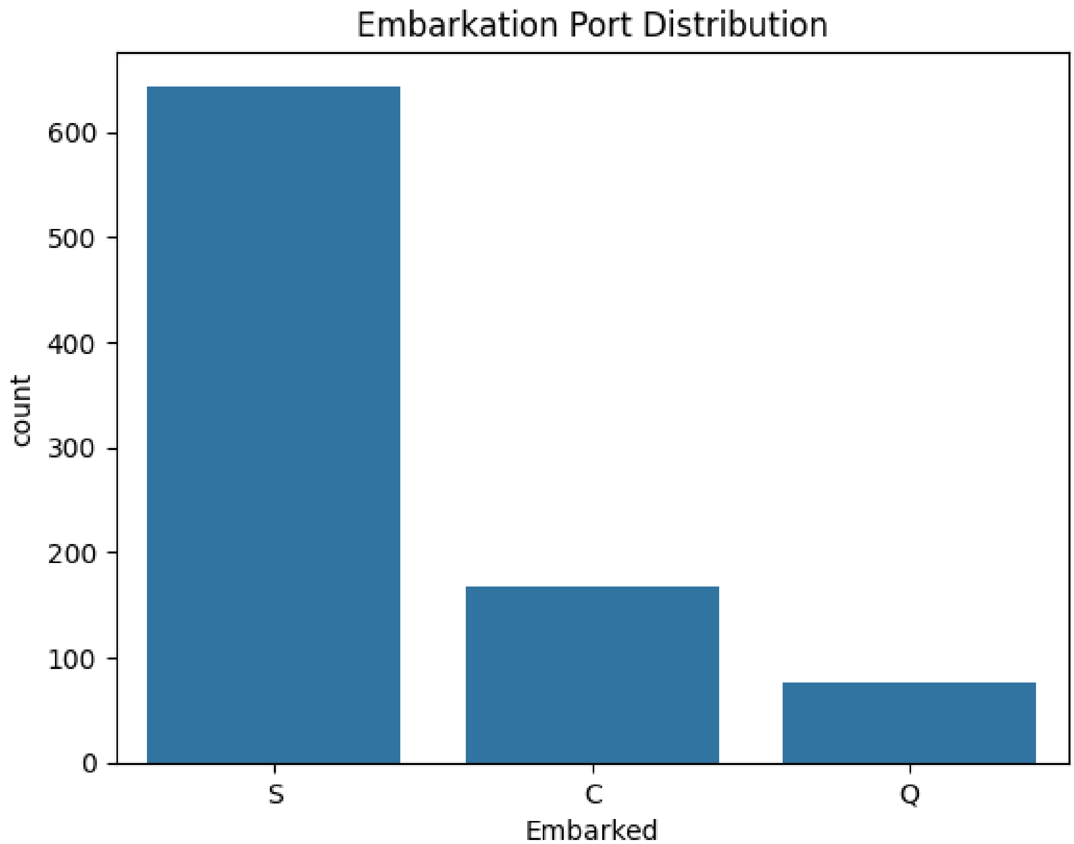
```
# --- Passenger Gender Distribution ---
sns.countplot(x='Sex', data=df)              # Bar chart showing number of male␣
↪and female passengers
plt.title("Passenger Gender Distribution") # Add a descriptive title
plt.show()                                   # Display the plot
```



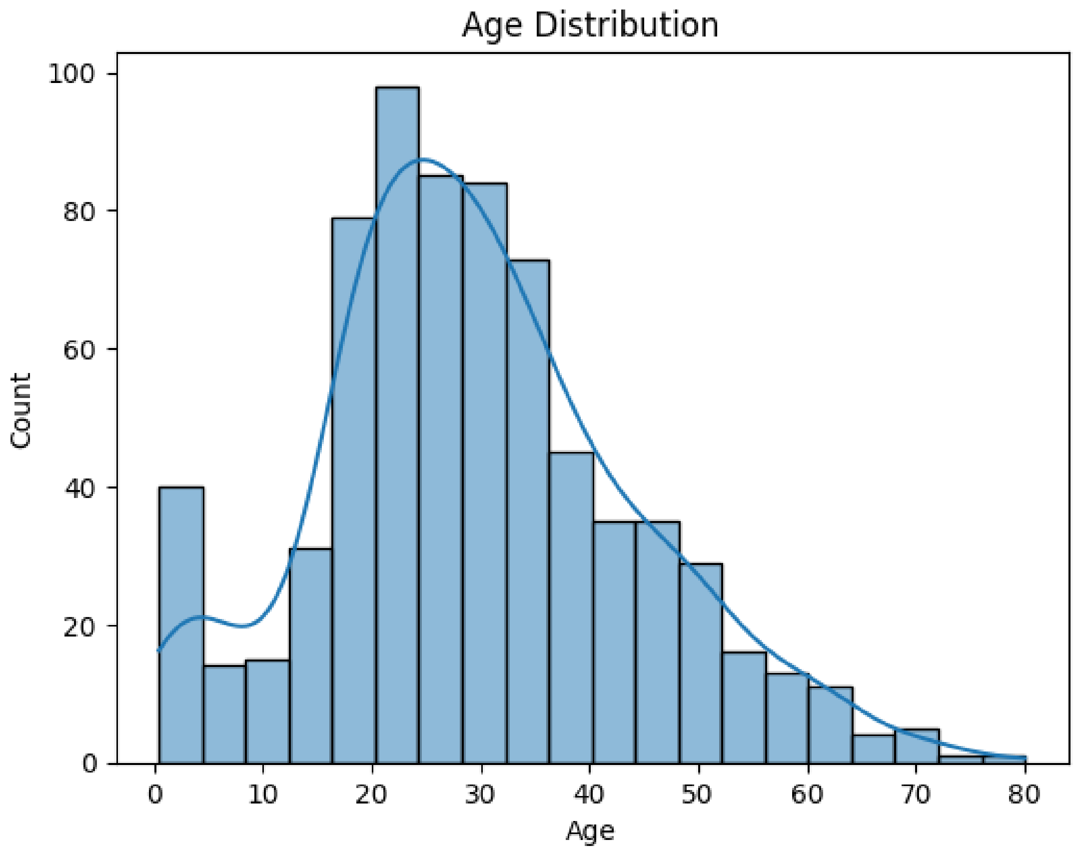
[34]:
```
# --- Passenger Class Distribution ---
sns.countplot(x='Pclass', data=df)          # Bar chart showing count of␣
↪passengers in each class (1st, 2nd, 3rd)
plt.title("Passenger Class Distribution")  # Add a descriptive title to the plot
plt.show()                                  # Display the plot
```



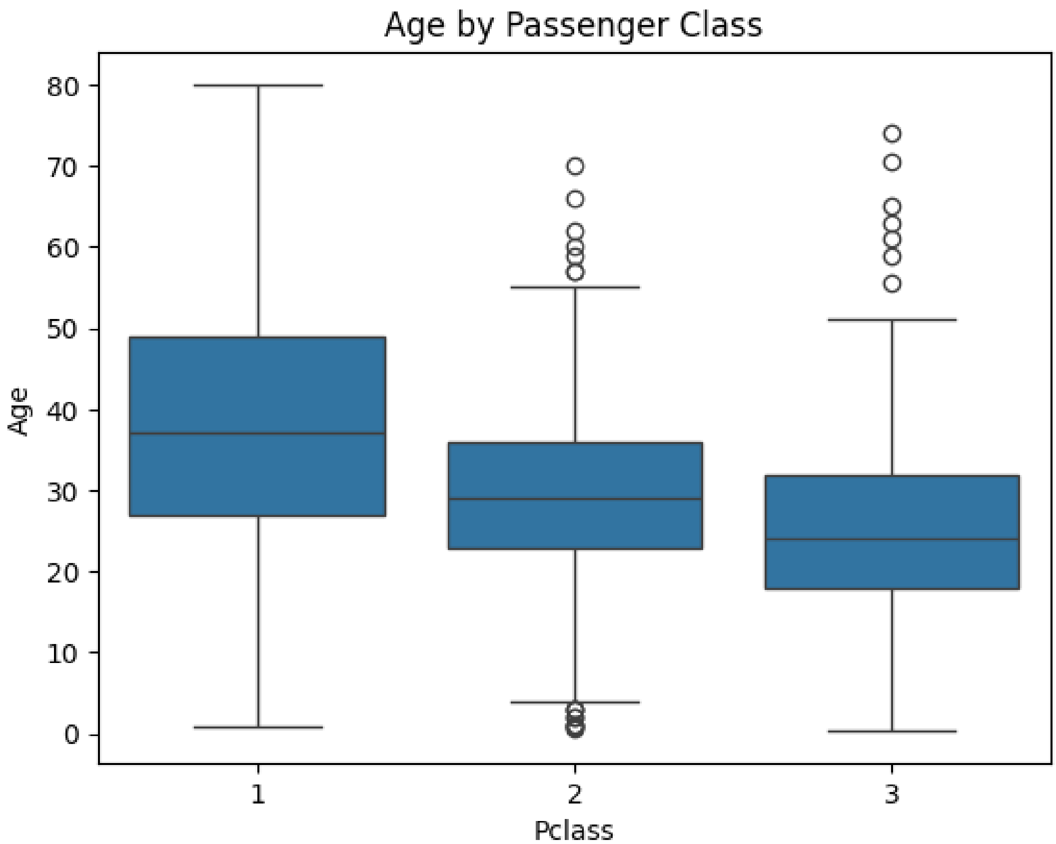
[35]:
```
# --- Embarkation Port Distribution ---
sns.countplot(x='Embarked', data=df)       # Bar chart of count of passengers␣
 ↪from each embarkation port
plt.title("Embarkation Port Distribution") # Add a descriptive title
plt.show()                                 # Display the plot
```



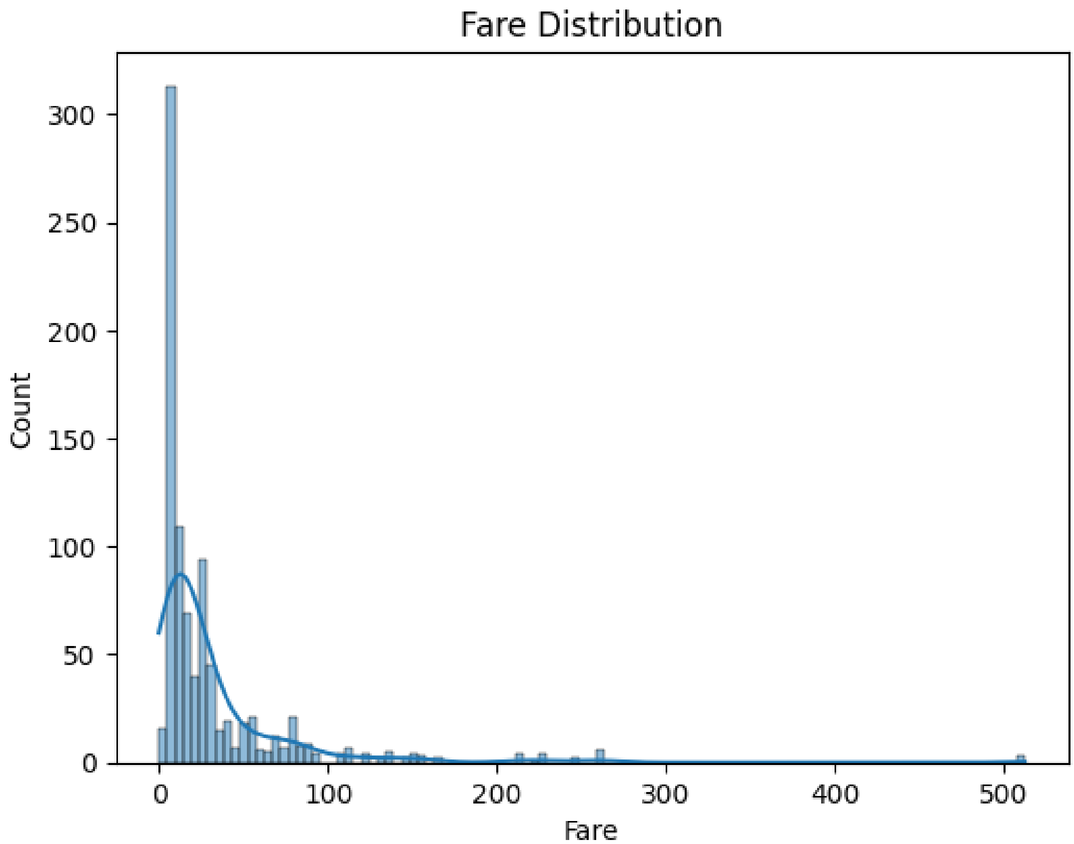
[36]:
```
# --- Age Distribution Plot ---
sns.histplot(df['Age'].dropna(), kde=True)  # Histogram of Age (NaNs removed)␣
 ↪with a KDE curve
plt.title("Age Distribution")               # Add a descriptive title
plt.show()                                  # Render the plot to the screen
```



[37]:
```
# --- Age by Passenger Class ---
sns.boxplot(x='Pclass', y='Age', data=df)  # Box plot showing age distribution␣
 ↪within each passenger class
plt.title("Age by Passenger Class")        # Add a descriptive title
plt.show()                                 # Display the plot
```

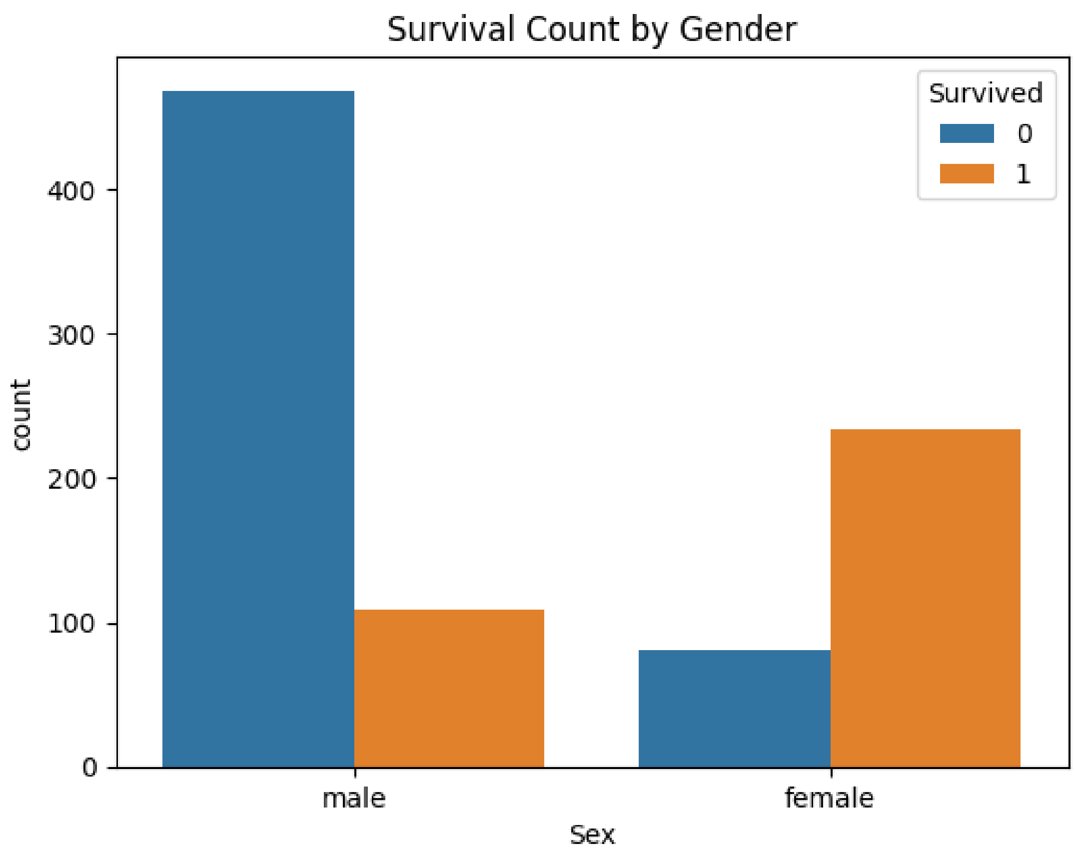


[38]:
```
# --- Fare Distribution ---
sns.histplot(df['Fare'], kde=True)       # Plot histogram of Fare with KDE curve␣
 ↪to show distribution shape
plt.title("Fare Distribution")           # Add a descriptive title to the plot
plt.show()                               # Display the histogram on the screen
```



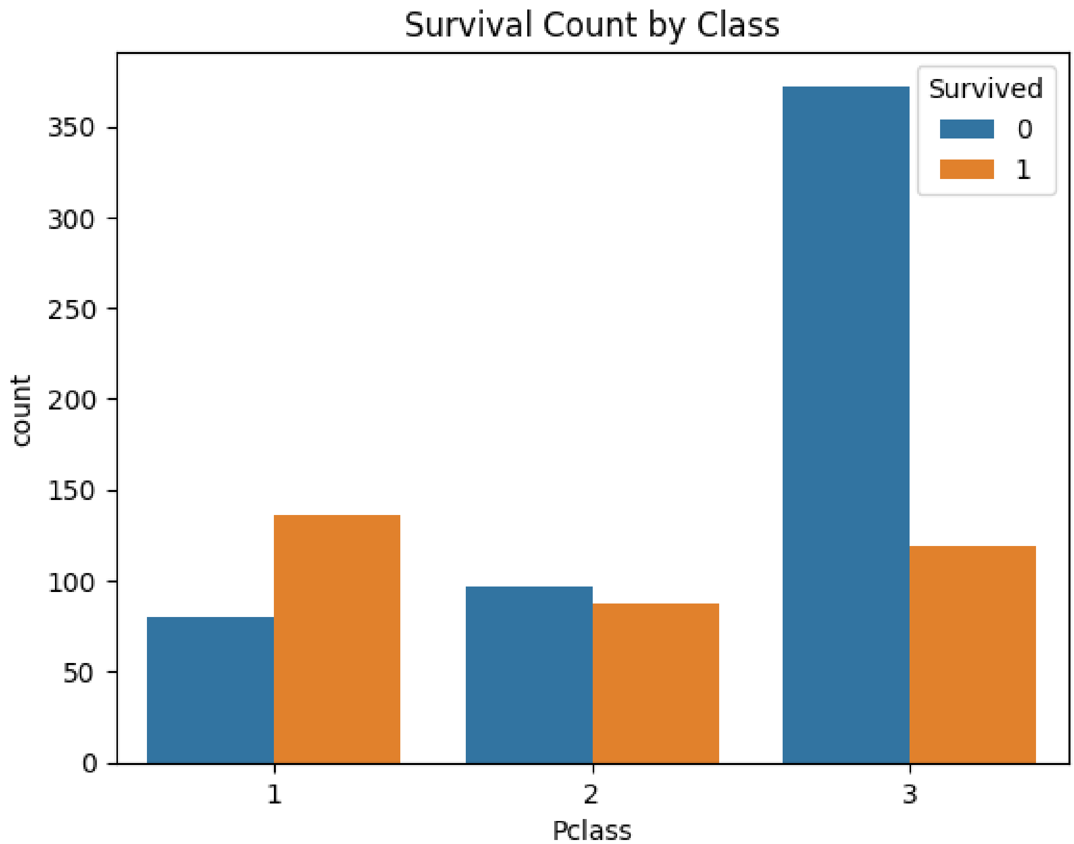
3.2.1 Survival by Sex

[39]:
```
# --- Survival Count by Gender ---
sns.countplot(x='Sex', hue='Survived', data=df)  # Bar chart of male/female␣
 ↪passengers split by survival
plt.title("Survival Count by Gender")            # Add chart title
plt.show()                                       # Display the plot
```



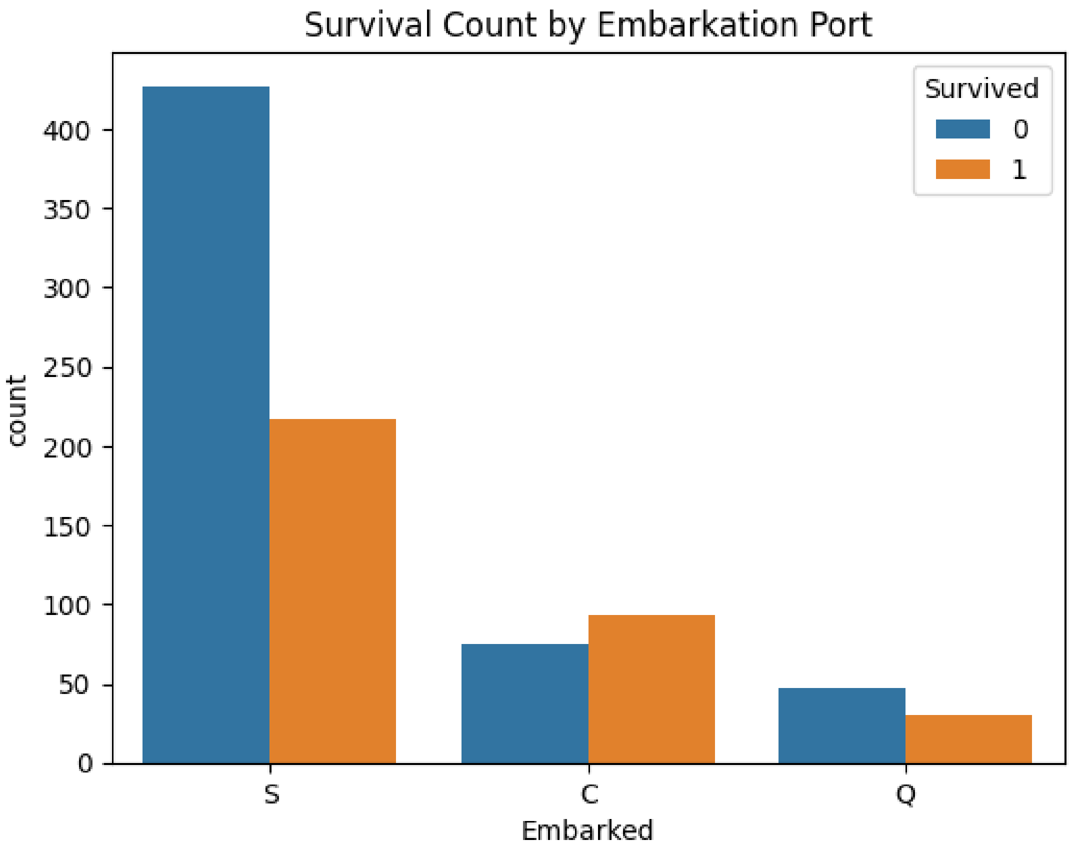
3.2.2 Survival by Pclass

[40]:
```
# --- Survival Count by Passenger Class ---
sns.countplot(x='Pclass', hue='Survived', data=df)  # Bar chart showing␣
↪survival (0 or 1) split within each passenger class
plt.title("Survival Count by Class")                # Add a descriptive title
plt.show()                                          # Display the plot
```



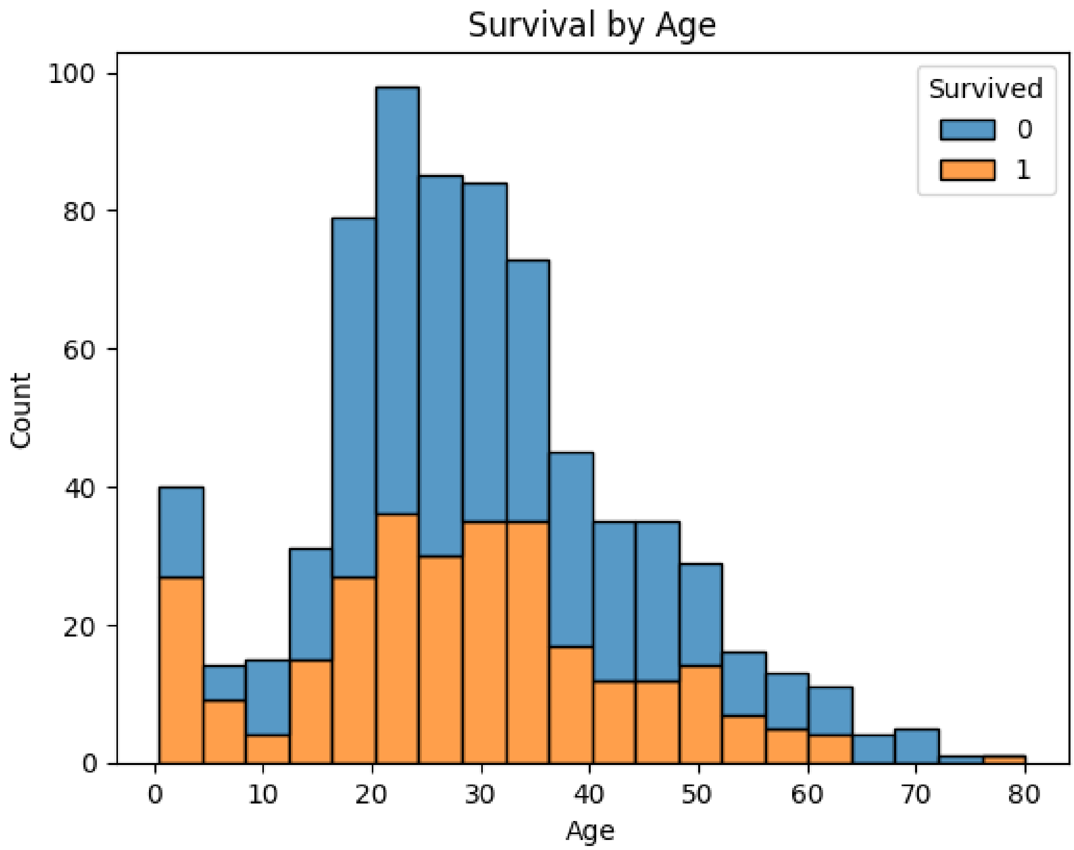
3.2.3 Survival by Embarked

[41]:
```
# --- Survival Count by Embarkation Port ---
sns.countplot(x='Embarked', hue='Survived', data=df)  # Bar chart showing␣
 ↪survival (hue) count for each embarkation port
plt.title("Survival Count by Embarkation Port")       # Add a title to explain␣
 ↪the chart
plt.show()                                            # Display the plot
```



3.2.4 Age vs Survival

[42]:
```
# --- Survival by Age ---
sns.histplot(data=df, x='Age', hue='Survived', multiple='stack')  # Histogram␣
↪of Age stacked by survival (0 = No, 1 = Yes)
plt.title("Survival by Age")                                      # Add a␣
↪descriptive title
plt.show()                                                        # Display the␣
↪plot
```



3.3 Data Wrangling

[43]:
```
df.columns  # List all column names in the DataFrame
```

[43]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

Drop unneeded columns

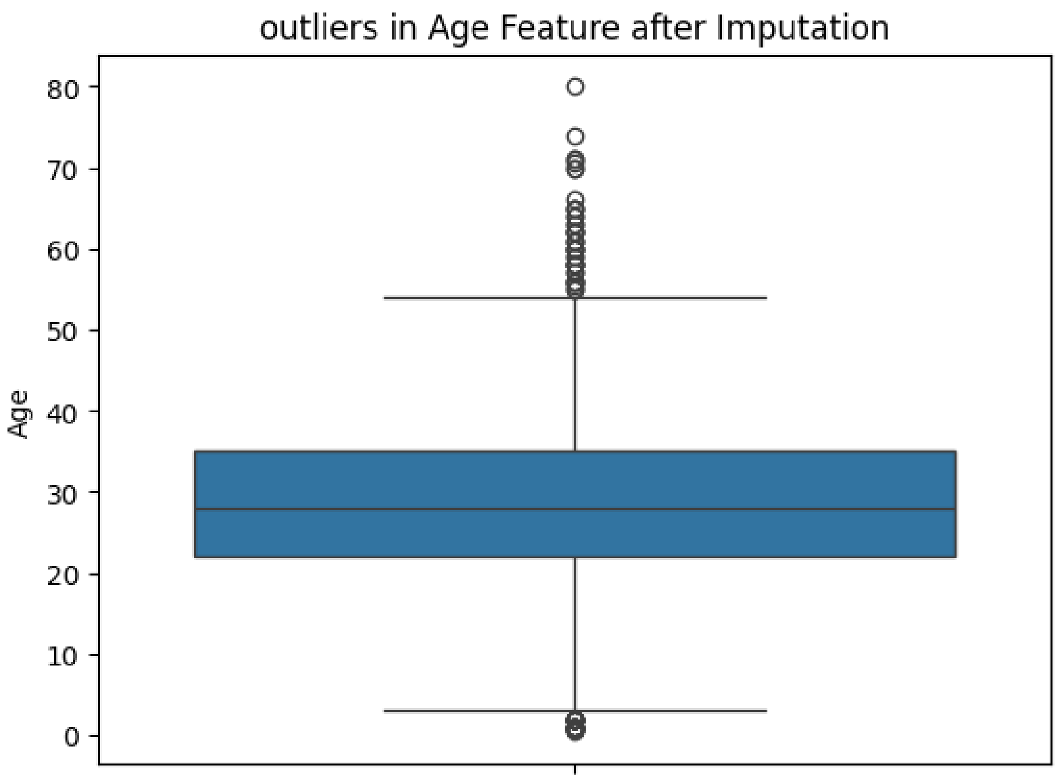
[44]:
```
df.drop(columns=['PassengerId', 'Name', 'Ticket', 'Cabin'], inplace=True)  #␣
↪Drop unnecessary columns
```

Fill missing values

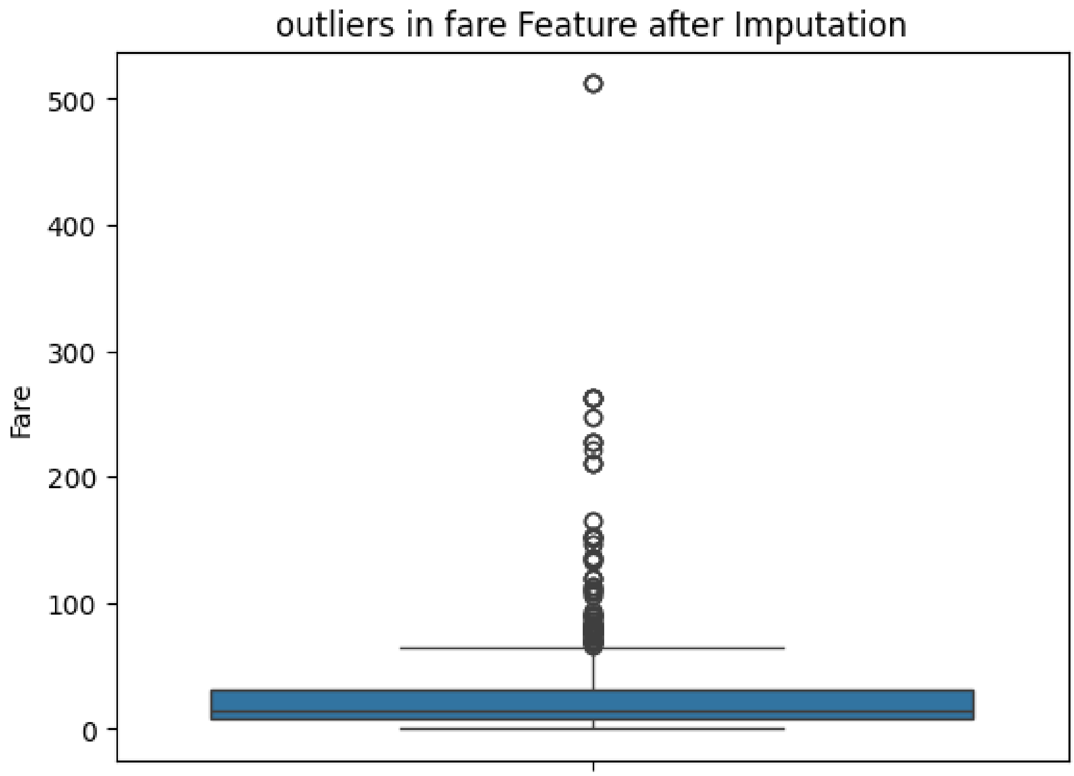
[45]:
```
df['Age'].fillna(df['Age'].median(), inplace=True)  # Fill missing Age values␣
↪with median
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)  # Fill missing␣
↪Embarked with mode
```

Outliers check

[46]:
```
#  Boxplots to Check for Outliers in age column
sns.boxplot(y=df['Age'])
plt.title("outliers in Age Feature after Imputation")
plt.show()
```

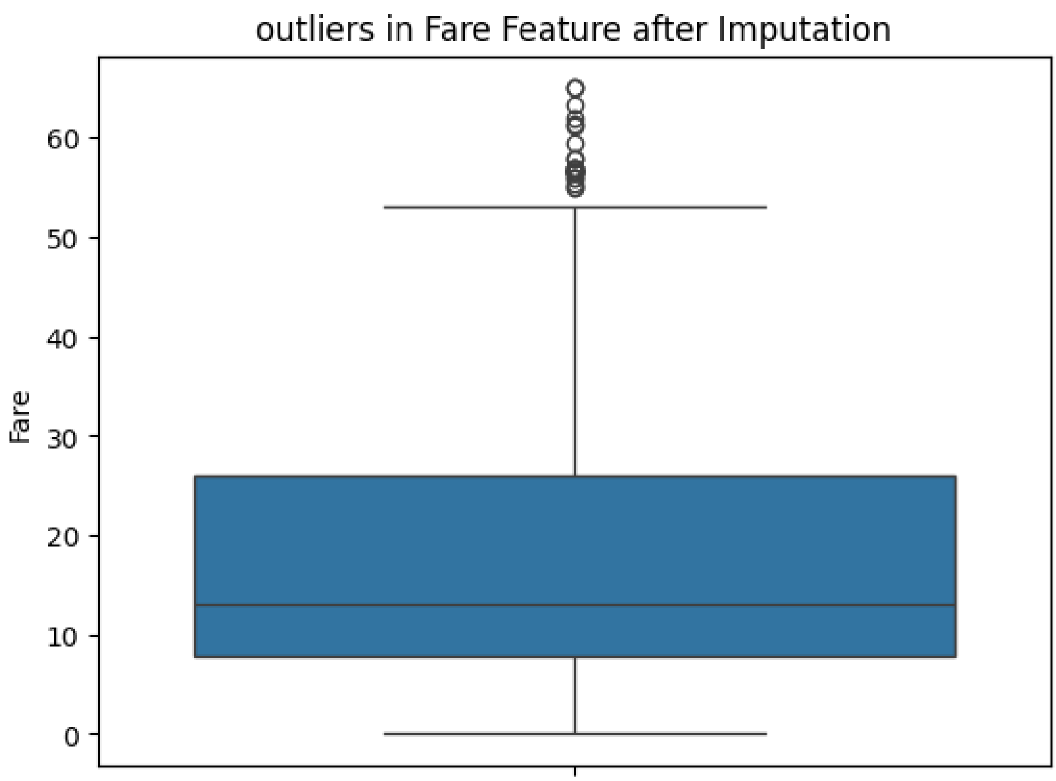


[47]:
```
#  Boxplots to Check for Outliers in fare column
sns.boxplot(y=df['Fare'])
plt.title("outliers in fare Feature after Imputation")
plt.show()
```

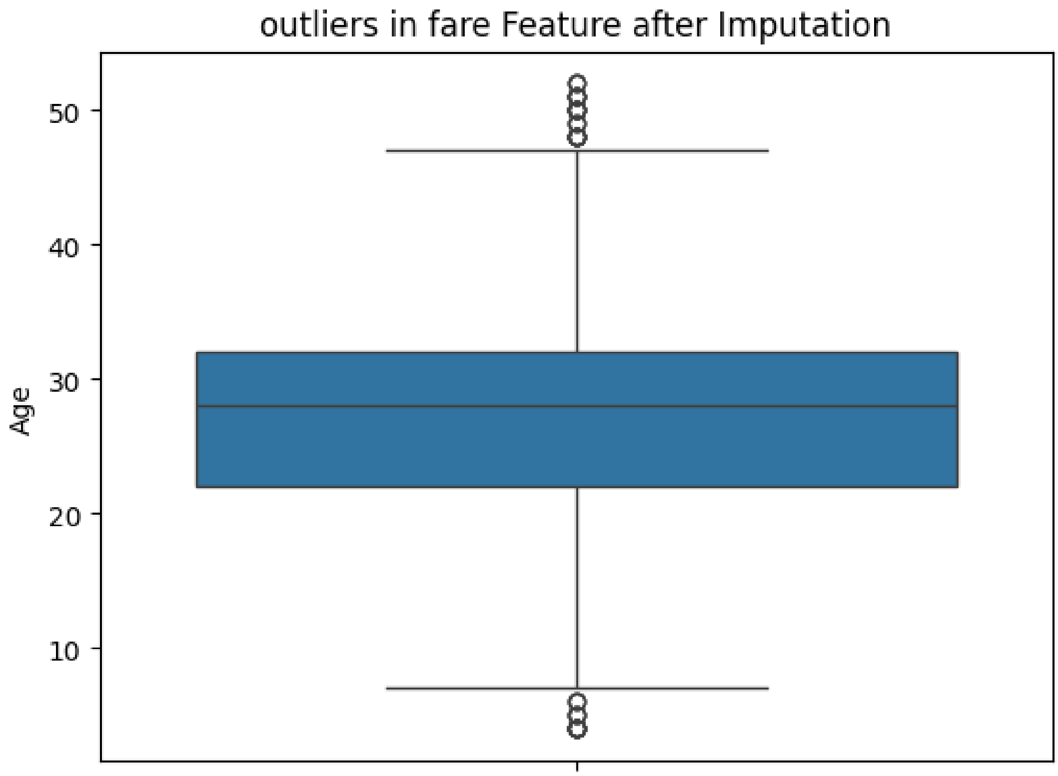


Using IQR method Outliers removel

[48]:
```
Q1 = df['Fare'].quantile(0.25)
Q3 = df['Fare'].quantile(0.75)
IQR = Q3 - Q1

# Step 2: Define lower and upper bounds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Step 3: Filter the DataFrame to remove outliers in 'Fare'
df= df[(df['Fare'] >= lower_bound) & (df['Fare'] <= upper_bound)]

#  Boxplots to Check for Outliers in age column
sns.boxplot(y=df['Fare'])
plt.title("outliers in Fare Feature after Imputation")
plt.show()
```



[49]:
```
#  Calculate Q1, Q3, and IQR for the 'Age' column
Q1 = df['Age'].quantile(0.25)
Q3 = df['Age'].quantile(0.75)
IQR = Q3 - Q1

# Step 2: Define lower and upper bounds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
df= df[(df['Age'] >= lower_bound) & (df['Age'] <= upper_bound)]
#  Calculate Q1, Q3, and IQR for the 'Fare' column
sns.boxplot(y=df['Age'])
plt.title("outliers in fare Feature after Imputation")
plt.show()
```



[50]:
```
df.head()
```

[50]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S
5	0	3	male	28.0	0	0	8.4583	Q

Encode categorical features

[51]:
```
df['Sex'] = df['Sex'].map({'male': 0, 'female': 1})
df['Embarked'] = df['Embarked'].map({'S': 0, 'C': 1, 'Q': 2})
```

[52]:
```
df.head()
```

[52]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	0	22.0	1	0	7.2500	0
2	1	3	1	26.0	0	0	7.9250	0
3	1	1	1	35.0	1	0	53.1000	0
4	0	3	0	35.0	0	0	8.0500	0
5	0	3	0	28.0	0	0	8.4583	2

3.3.1 Scaler Usage by Model Type

Scenarios	Scaler Needed?	Why
Decision Trees	No	Scale doesn't affect splits

3.3.2 Define Features and Target

[53]:
```
X = df.drop('Survived', axis=1)
y = df['Survived']
```

3.3.3 Train/Test Split

[54]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

3.3.4 Train Decision Tree Classifier

[64]:
```
model = DecisionTreeClassifier(class_weight='balanced')
model.fit(X_train, y_train)
```

[64]:
```
DecisionTreeClassifier(class_weight='balanced')
```

3.3.5 Evaluate the Model

[66]:
```
y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
# Generate confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Optional: Print it
print("Confusion Matrix:\n", cm)

print(f"Accuracy: {accuracy:.4f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[82 12]
 [15 33]]
Accuracy: 0.8099

Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.87      0.86        94
```

```
           1       0.73      0.69      0.71        48

    accuracy                           0.81       142
   macro avg       0.79      0.78      0.78       142
weighted avg       0.81      0.81      0.81       142
```

3.4 Model Evaluation Summary (Decision Tree Classifier)

3.4.1 Accuracy:

- **Overall Accuracy:** `0.8099` (81%)

3.4.2 Confusion Matrix:

```
       Predicted
         | 0  |  1
------+-----+-----
Actual 0 | 82 | 12
Actual 1 | 15 | 33
```

- **True Negatives (TN)**: 82 → Correctly predicted non-survivors
- **False Positives (FP)**: 12 → Predicted survivor, but was not
- **False Negatives (FN)**: 15 → Predicted non-survivor, but was a survivor
- **True Positives (TP)**: 33 → Correctly predicted survivors

---

3.4.3 Classification Report

Class	Precision	Recall	F1-Score	Support
0 (Not Survived)	0.85	0.87	0.86	94
1 (Survived)	0.73	0.69	0.71	48

3.4.4 Average Metrics

Metric	Macro Avg	Weighted Avg
Precision	0.79	0.81
Recall	0.78	0.81
F1-Score	0.78	0.81

3.4.5 Interpretation

- The model performs **very well for Class 0** (non-survivors), with strong precision and recall.
- For **Class 1 (survivors)**, precision and recall are slightly lower, but still acceptable.
- Overall, the model generalizes well and maintains balanced performance across classes.

3.4.6 Hyperparameter Tuning for Decision Tree using GridSearchCV

[67]:
```
from sklearn.model_selection import GridSearchCV
param_grid = {
    'max_depth': [3, 5, 7, 10, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'criterion': ['gini', 'entropy']
}

# Initialize Decision Tree model
model = DecisionTreeClassifier(random_state=42)

# Grid Search with 5-fold cross-validation
grid_search = GridSearchCV(model, param_grid, cv=5, n_jobs=-1,␣
↪scoring='accuracy')
grid_search.fit(X_train, y_train)

# Best parameters and model
print("Best Parameters:", grid_search.best_params_)
print("Best Cross-Validation Accuracy:", grid_search.best_score_)

# Predict with best model
best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test)
# Generate confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Optional: Print it
print("Confusion Matrix:\n", cm)

# Evaluation
print("\nTest Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Best Parameters: {'criterion': 'entropy', 'max_depth': 5, 'min_samples_leaf': 4,
'min_samples_split': 10}
Best Cross-Validation Accuracy: 0.803927961496662
Confusion Matrix:
 [[89  5]
```

```
 [19 29]]

Test Accuracy: 0.8309859154929577

Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.95      0.88        94
           1       0.85      0.60      0.71        48

    accuracy                           0.83       142
   macro avg       0.84      0.78      0.79       142
weighted avg       0.83      0.83      0.82       142
```

3.5 Best Parameters

```json
{
  "criterion": "entropy",
  "max_depth": 5,
  "min_samples_leaf": 4,
  "min_samples_split": 10
}
```

3.6 Best Cross-Validation Accuracy

0.8039

3.7 Confusion Matrix

[[89 5] [19 29]]

3.8 Test Accuracy

0.8309

3.9 Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.82	0.95	0.88	94
1	0.85	0.60	0.71	48

Accuracy: 0.83
Macro Avg – Precision: 0.84, Recall: 0.78, F1-Score: 0.79
Weighted Avg – Precision: 0.83, Recall: 0.83, F1-Score: 0.82

3.10 Final Model Evaluation Report

3.10.1 Best Cross-Validation Accuracy

0.8039

3.10.2 Confusion Matrix

[[89 5] [19 29]]

3.10.3 Test Accuracy

0.8310

3.10.4 Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.82	0.95	0.88	94
1	0.85	0.60	0.71	48

Overall Accuracy: 0.83
Macro Average – Precision: 0.84 | Recall: 0.78 | F1-Score: 0.79
Weighted Average – Precision: 0.83 | Recall: 0.83 | F1-Score: 0.82

3.10.5 Final Accuracy of the Model: `83.10%`

3.10.6 Weekly Learning Summary

This week, I explored the core concepts of supervised learning, tackling both regression and classification problems. For regression, I used the California Housing dataset to build a Linear Regression model, predicting median house prices and evaluating its performance using Mean Squared Error (MSE) and R^2 Score. In the classification task, I preprocessed the Titanic dataset by handling missing values and encoding categorical features, then trained a Decision Tree Classifier to predict passenger survival. I evaluated the model's accuracy and interpreted the confusion matrix to analyze its predictions. Through these exercises, I gained practical skills in exploratory data analysis (EDA), data wrangling, and model evaluation, while reinforcing the importance of train-test splits and avoiding overfitting.