Lab Assignment 9: Linear Regression for Price Prediction

Aim: To implement Linear Regression for predicting housing prices using the Boston Housing dataset, focusing on cost function analysis, gradient descent, and model evaluation.

Task 1: Load and Explore the Dataset

1. Load the Boston Housing dataset using pandas or sklearn.datasets.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv('HousingData.csv')
df.head()
```

```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD  TAX
PTRATIO  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900    1  296
15.3
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671    2  242
17.8
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671    2  242
17.8
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622    3  222
18.7
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622    3  222
18.7

        B  LSTAT  MEDV
0  396.90   4.98  24.0
1  396.90   9.14  21.6
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90    NaN  36.2
```

2. Display dataset characteristics:

– Number of records and features

```
df.shape
```

```
(506, 14)
```

```
num_records, num_features = df.shape
print(f"Number of records: {num_records}")
print(f"Number of features: {num_features}")
```

```
Number of records: 506
Number of features: 14
```

– Description of each feature

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     486 non-null    float64
 1   ZN       486 non-null    float64
 2   INDUS    486 non-null    float64
 3   CHAS     486 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      486 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64  
 9   TAX      506 non-null    int64  
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    486 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

```python
df.rename(columns={'MEDV': 'PRICE'}, inplace=True)

boston_description = """
The Boston Housing dataset contains information collected by the U.S
Census Service concerning housing in the Boston, Massachusetts area.

Features:
1. CRIM - per capita crime rate by town
2. ZN - proportion of residential land zoned for large lots
3. INDUS - proportion of non-retail business acres per town
4. CHAS - Charles River dummy variable (1 if tract bounds river; 0
otherwise)
5. NOX - nitrogen oxides concentration (parts per 10 million)
6. RM - average number of rooms per dwelling
7. AGE - proportion of owner-occupied units built before 1940
8. DIS - weighted distance to five employment centers
9. RAD - index of accessibility to radial highways
10. TAX - property tax rate per $10,000
11. PTRATIO - pupil-teacher ratio by town
12. B - proportion of Black residents in town
13. LSTAT - percentage of lower status population
```

```
14. PRICE - median value of owner-occupied homes in $1000s (Target)
"""

print(boston_description)
```

```
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Census Service concerning housing in the Boston, Massachusetts area.

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13. LSTAT - percentage of lower status population
14. PRICE - median value of owner-occupied homes in $1000s (Target)
```
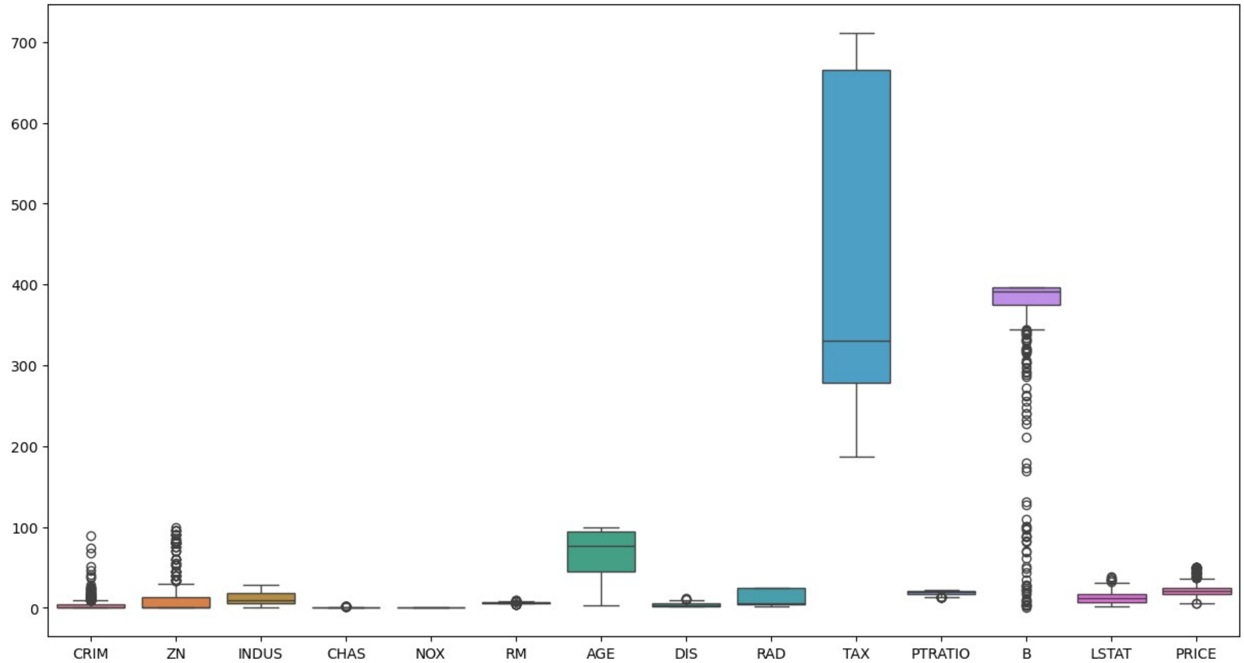

– Summary statistics (mean, median, standard deviation, etc.).

```
df.describe()
```

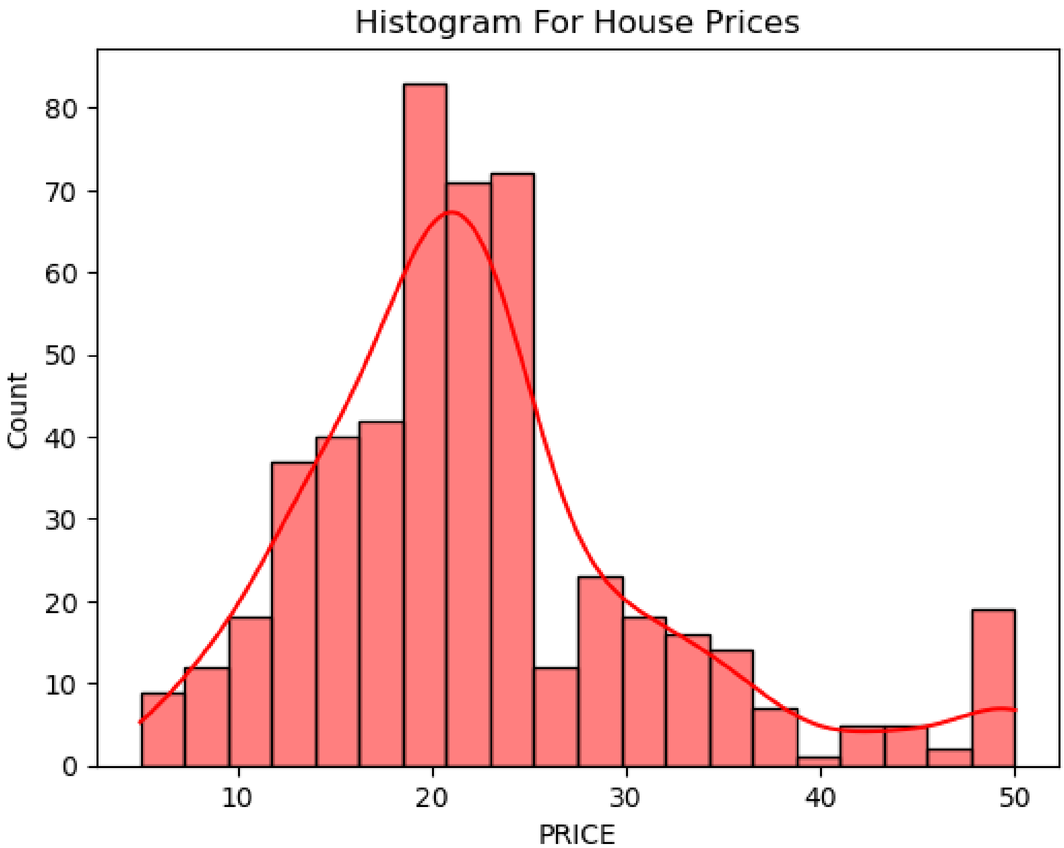
```
             CRIM          ZN       INDUS        CHAS         NOX
RM  \
count  486.000000  486.000000  486.000000  486.000000  506.000000
506.000000
mean     3.611874   11.211934   11.083992    0.069959    0.554695
6.284634
std      8.720192   23.388876    6.835896    0.255340    0.115878
0.702617
min      0.006320    0.000000    0.460000    0.000000    0.385000
3.561000
25%      0.081900    0.000000    5.190000    0.000000    0.449000
5.885500
50%      0.253715    0.000000    9.690000    0.000000    0.538000
6.208500
75%      3.560263   12.500000   18.100000    0.000000    0.624000
6.623500
max     88.976200  100.000000   27.740000    1.000000    0.871000
8.780000

              AGE         DIS         RAD         TAX     PTRATIO
```

```
B  \
count  486.000000  506.000000  506.000000  506.000000  506.000000
506.000000
mean    68.518519    3.795043    9.549407  408.237154   18.455534
356.674032
std     27.999513    2.105710    8.707259  168.537116    2.164946
91.294864
min      2.900000    1.129600    1.000000  187.000000   12.600000
0.320000
25%     45.175000    2.100175    4.000000  279.000000   17.400000
375.377500
50%     76.800000    3.207450    5.000000  330.000000   19.050000
391.440000
75%     93.975000    5.188425   24.000000  666.000000   20.200000
396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000
396.900000

            LSTAT       PRICE
count  486.000000  506.000000
mean    12.715432   22.532806
std      7.155871    9.197104
min      1.730000    5.000000
25%      7.125000   17.025000
50%     11.430000   21.200000
75%     16.955000   25.000000
max     37.970000   50.000000

plt.figure(figsize=(15,8))
sns.boxplot(df)
plt.show()
```

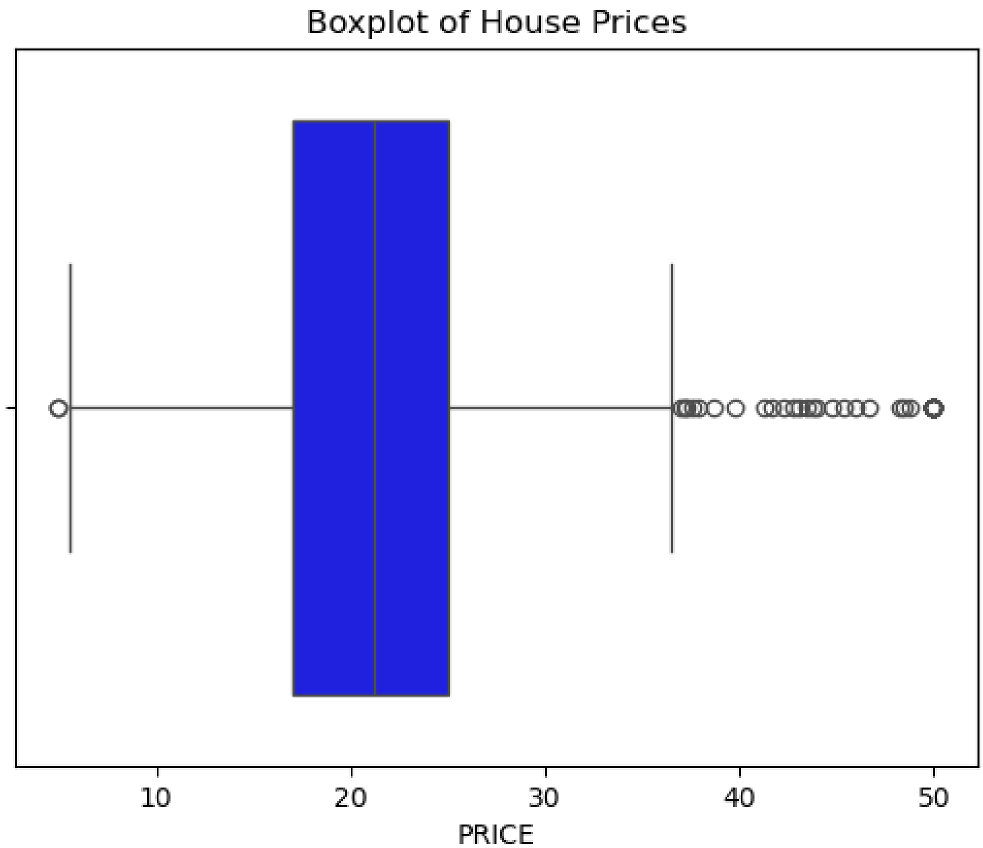


3. Visualize the distribution of target variable (housing prices).

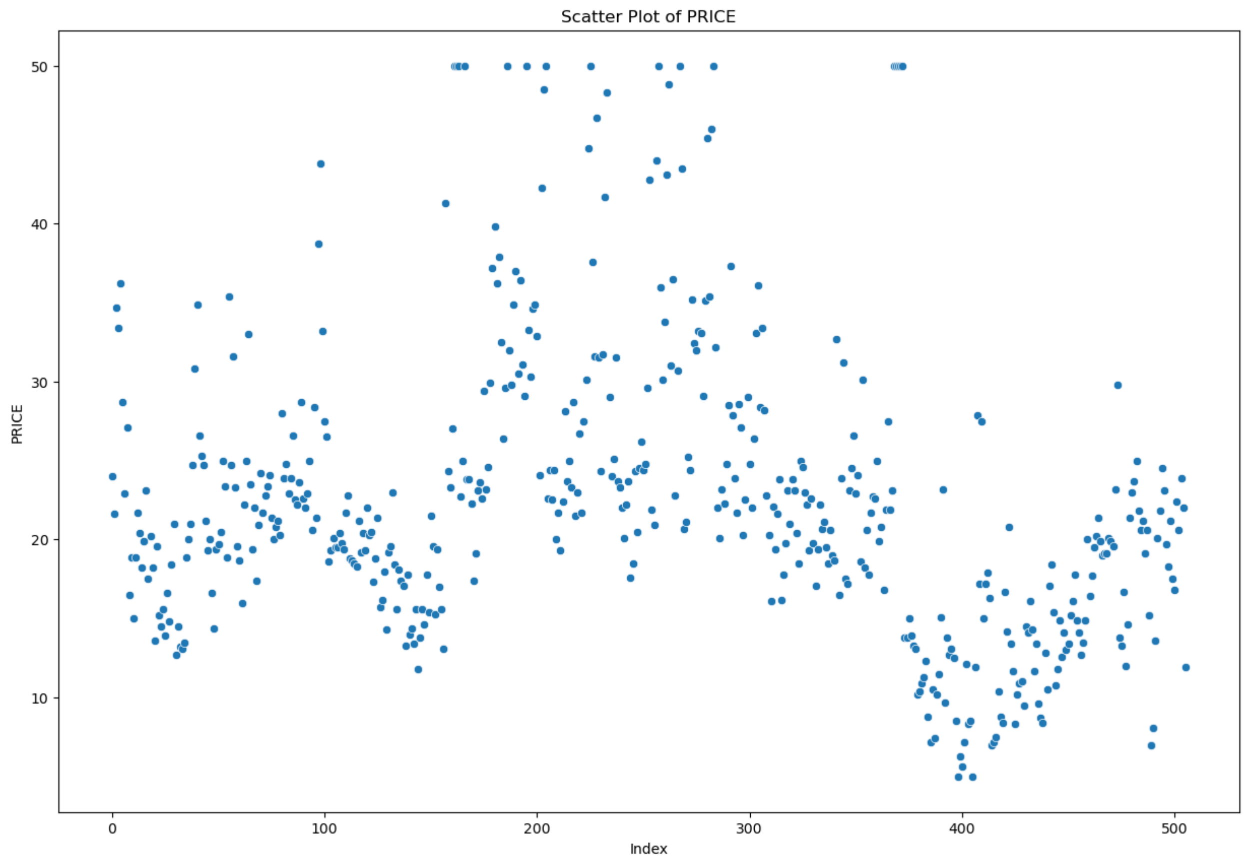
```
sns.histplot(data = df['PRICE'],kde = True,bins = 20,color = 'red')
plt.title('Histogram For House Prices')
plt.show()
```



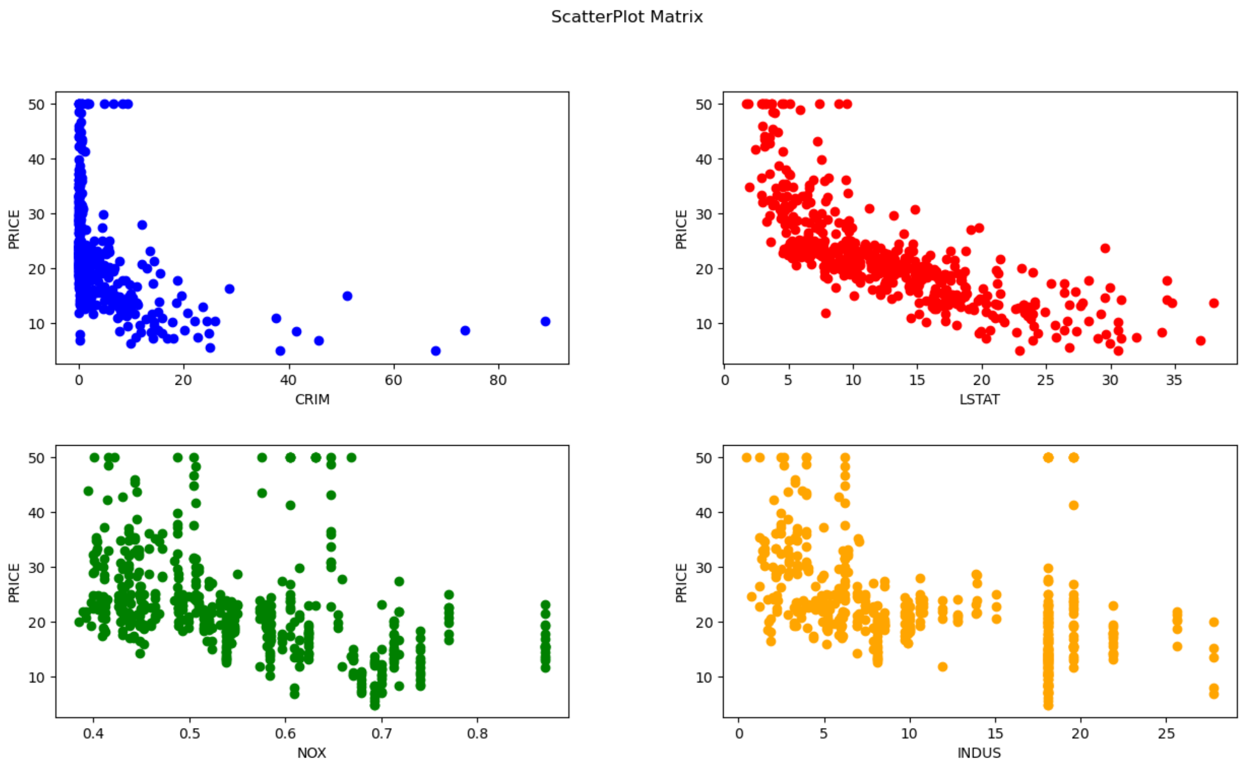

```
sns.boxplot(x=df['PRICE'], color='blue')
plt.title('Boxplot of House Prices')
plt.show()
```



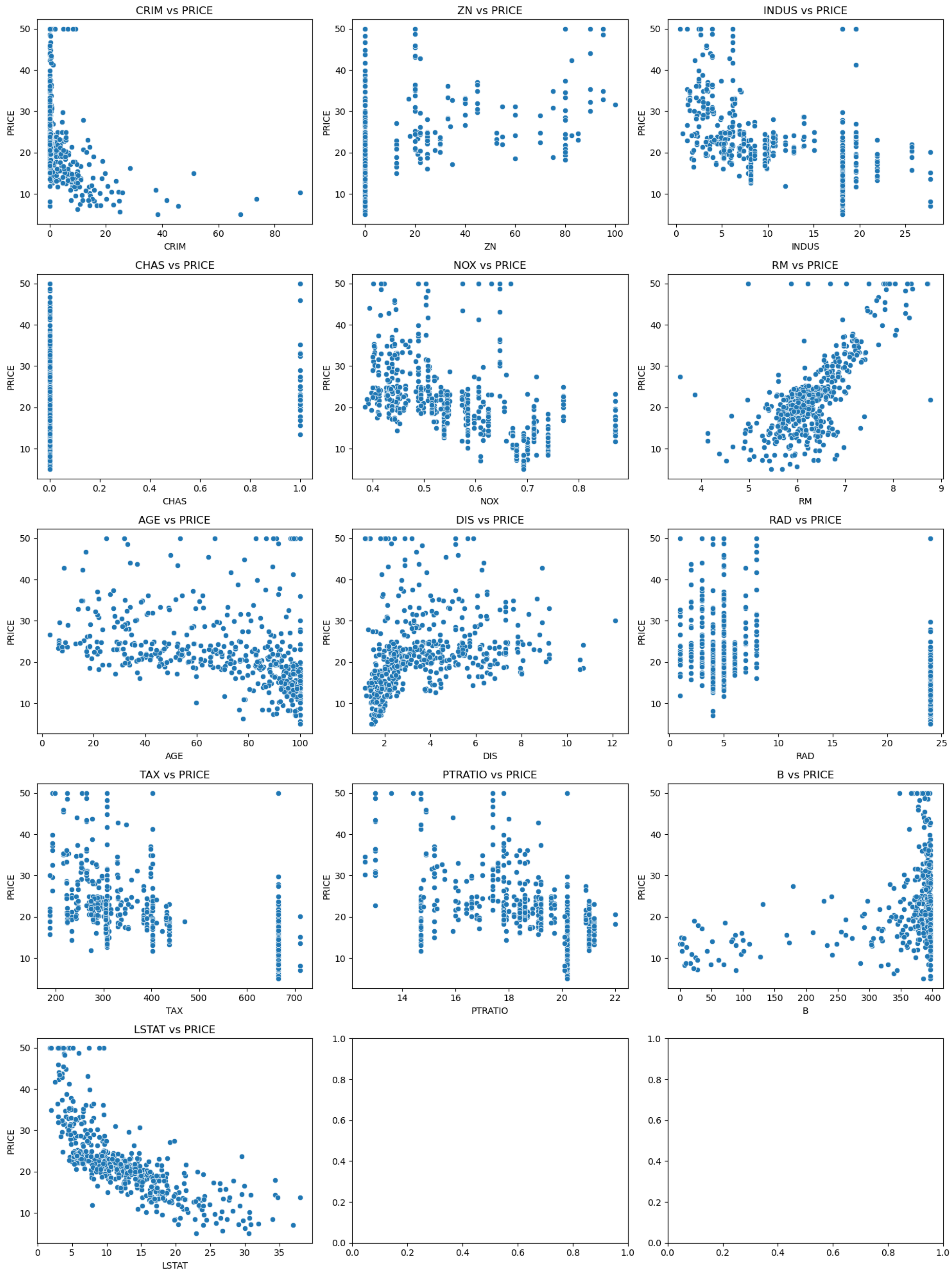

```
plt.figure(figsize=(15, 10))
sns.scatterplot(x=df.index, y=df["PRICE"])
plt.xlabel("Index")
plt.ylabel("PRICE")
plt.title("Scatter Plot of PRICE")
plt.show()
```




```
fig = plt.figure(figsize=(15, 8))
gs = fig.add_gridspec(2, 2, hspace=.3, wspace=.3)
(ax1, ax2), (ax3, ax4) = gs.subplots(sharex='none', sharey='none')
fig.suptitle('ScatterPlot Matrix')
ax1.scatter(df["CRIM"], df["PRICE"], c ="blue")
ax1.set(xlabel='CRIM', ylabel='PRICE')
ax2.scatter(df["LSTAT"], df["PRICE"], c ="red")
ax2.set(xlabel='LSTAT', ylabel='PRICE')
ax3.scatter(df["NOX"], df["PRICE"], c ="green")
ax3.set(xlabel='NOX', ylabel='PRICE')
ax4.scatter(df["INDUS"], df["PRICE"], c ="orange")
ax4.set(xlabel='INDUS', ylabel='PRICE')
plt.show()
```



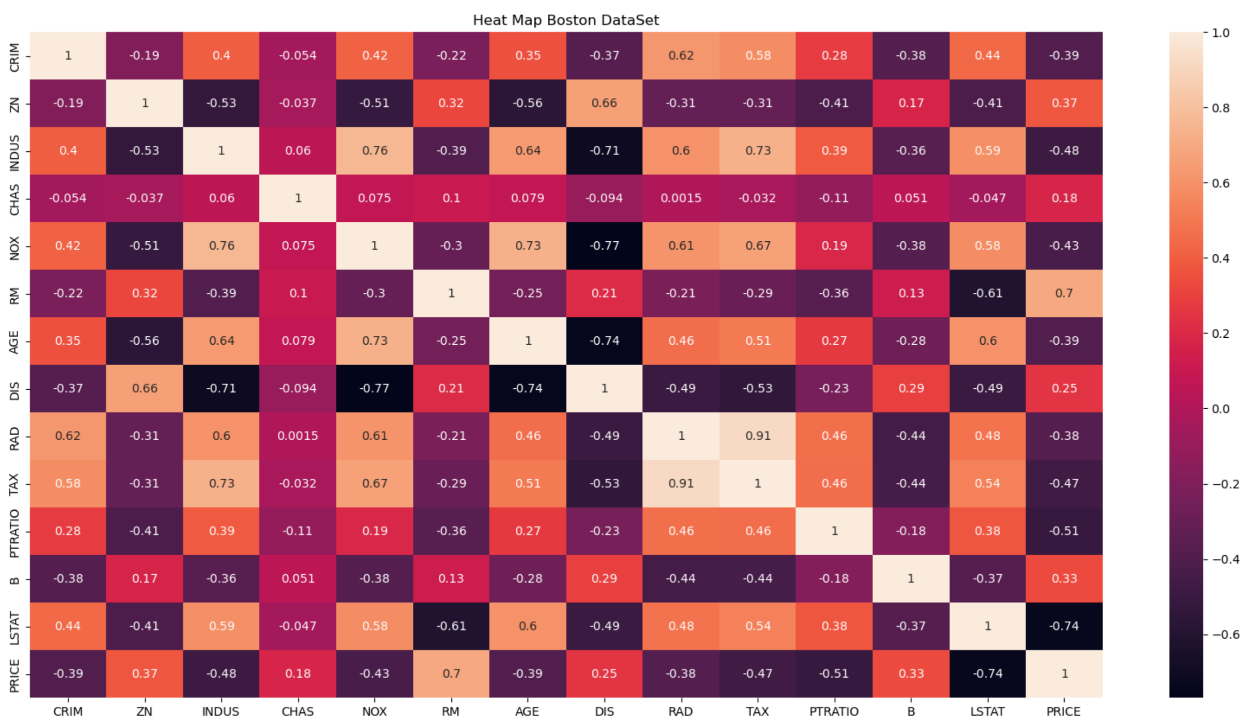

```
features = ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS',
'RAD', 'TAX',
            'PTRATIO', 'B', 'LSTAT']

fig, axes = plt.subplots(nrows=5, ncols=3, figsize=(15, 20))
axes = axes.flatten()
for idx, feature in enumerate(features):
    sns.scatterplot(data=df, x=feature, y='PRICE', ax=axes[idx])
    axes[idx].set_title(f'{feature} vs PRICE')

plt.tight_layout()
plt.show()
```


CRIM vs PRICE
PRICE
CRIM
ZN vs PRICE
PRICE
ZN
INDUS vs PRICE
PRICE
INDUS
CHAS vs PRICE
PRICE
CHAS
NOX vs PRICE
PRICE
NOX
RM vs PRICE
PRICE
RM
AGE vs PRICE
PRICE
AGE
DIS vs PRICE
PRICE
DIS
RAD vs PRICE
PRICE
RAD
TAX vs PRICE
PRICE
TAX
PTRATIO vs PRICE
PRICE
PTRATIO
B vs PRICE
PRICE
B
LSTAT vs PRICE
PRICE
LSTAT

```
corr = df.corr()
corr
```

```
              CRIM        ZN     INDUS      CHAS       NOX        RM
AGE  \
CRIM      1.000000 -0.191178  0.401863 -0.054355  0.417130 -0.219150
0.354342
ZN       -0.191178  1.000000 -0.531871 -0.037229 -0.513704  0.320800 -
0.563801
INDUS     0.401863 -0.531871  1.000000  0.059859  0.764866 -0.390234
0.638431
CHAS     -0.054355 -0.037229  0.059859  1.000000  0.075097  0.104885
0.078831
NOX       0.417130 -0.513704  0.764866  0.075097  1.000000 -0.302188
0.731548
RM       -0.219150  0.320800 -0.390234  0.104885 -0.302188  1.000000 -
0.247337
AGE       0.354342 -0.563801  0.638431  0.078831  0.731548 -0.247337
1.000000
DIS      -0.374166  0.656739 -0.711709 -0.093971 -0.769230  0.205246 -
0.744844
RAD       0.624765 -0.310919  0.604533  0.001468  0.611441 -0.209847
0.458349
TAX       0.580595 -0.312371  0.731055 -0.032304  0.668023 -0.292048
0.509114
PTRATIO   0.281110 -0.414046  0.390954 -0.111304  0.188933 -0.355501
0.269226
B        -0.381411  0.171303 -0.360532  0.051264 -0.380051  0.128069 -
0.275303
LSTAT     0.444943 -0.414193  0.590690 -0.047424  0.582641 -0.614339
0.602891
PRICE    -0.391363  0.373136 -0.481772  0.181391 -0.427321  0.695360 -
0.394656

               DIS       RAD       TAX   PTRATIO         B     LSTAT
PRICE
CRIM     -0.374166  0.624765  0.580595  0.281110 -0.381411  0.444943 -
0.391363
ZN        0.656739 -0.310919 -0.312371 -0.414046  0.171303 -0.414193
0.373136
INDUS    -0.711709  0.604533  0.731055  0.390954 -0.360532  0.590690 -
0.481772
CHAS     -0.093971  0.001468 -0.032304 -0.111304  0.051264 -0.047424
0.181391
NOX      -0.769230  0.611441  0.668023  0.188933 -0.380051  0.582641 -
0.427321
RM        0.205246 -0.209847 -0.292048 -0.355501  0.128069 -0.614339
0.695360
AGE      -0.744844  0.458349  0.509114  0.269226 -0.275303  0.602891 -
0.394656
```

```
DIS       1.000000 -0.494588 -0.534432 -0.232471  0.291512 -0.493328
0.249929
RAD      -0.494588  1.000000  0.910228  0.464741 -0.444413  0.479541 -
0.381626
TAX      -0.534432  0.910228  1.000000  0.460853 -0.441808  0.536110 -
0.468536
PTRATIO -0.232471  0.464741  0.460853  1.000000 -0.177383  0.375966 -
0.507787
B         0.291512 -0.444413 -0.441808 -0.177383  1.000000 -0.369889
0.333461
LSTAT    -0.493328  0.479541  0.536110  0.375966 -0.369889  1.000000 -
0.735822
PRICE     0.249929 -0.381626 -0.468536 -0.507787  0.333461 -0.735822
1.000000

plt.figure(figsize = (20,10))
plt.title('Heat Map Boston DataSet')
sns.heatmap(corr,annot = True)
plt.show()
```

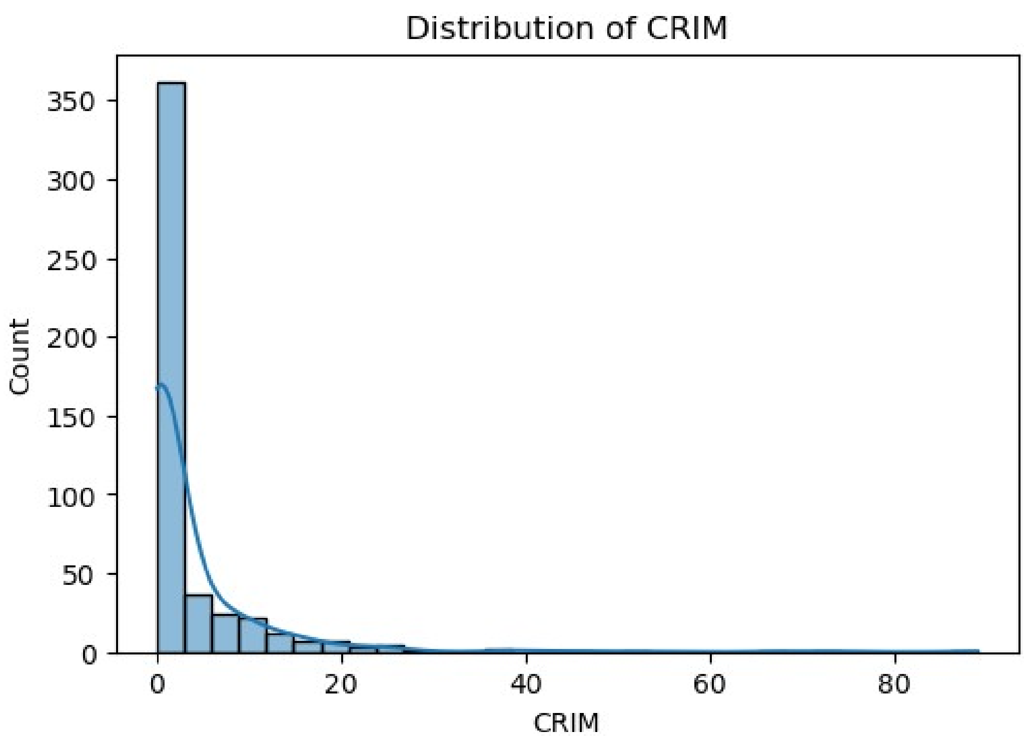


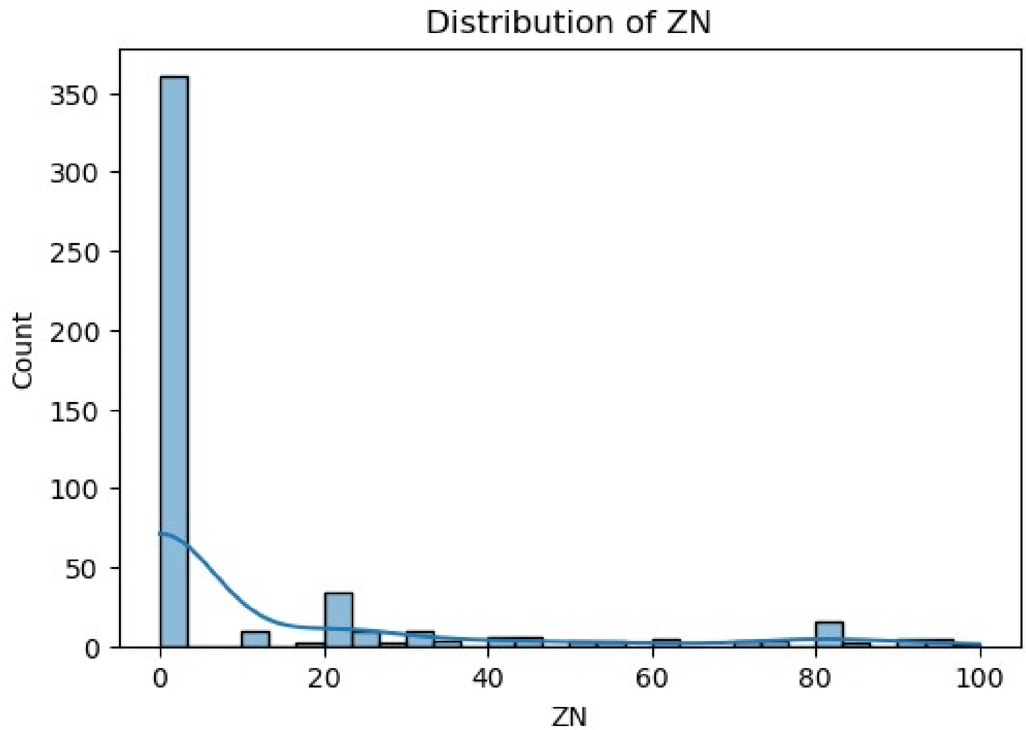
Task 2: Data Preprocessing

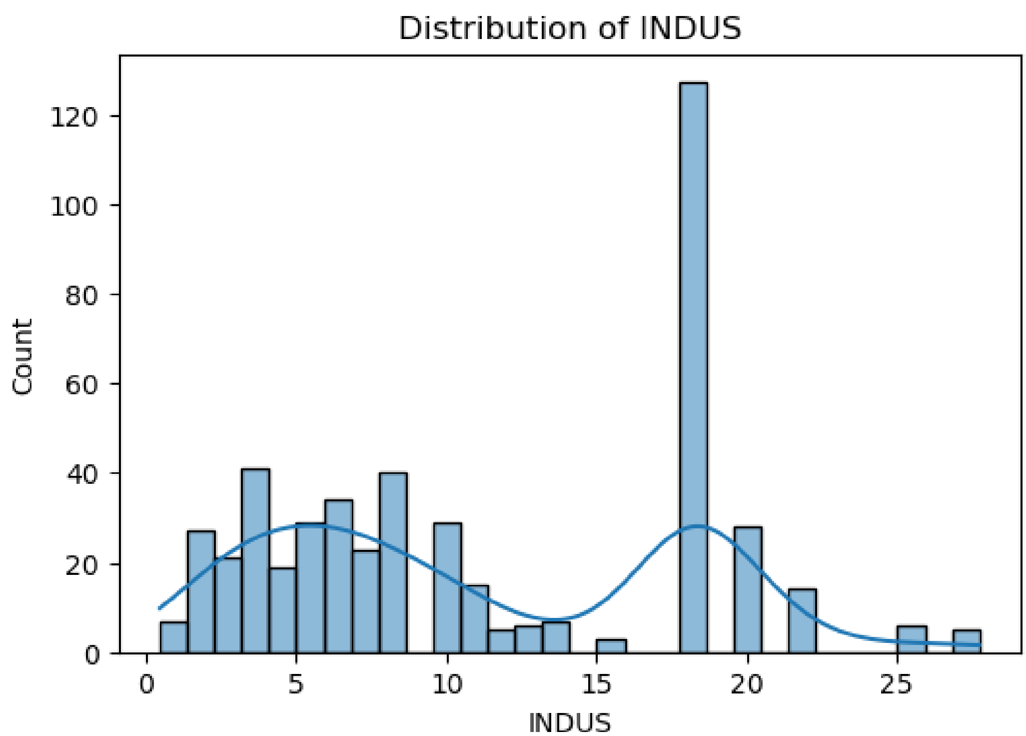
1. Check for missing values and handle them if necessary.

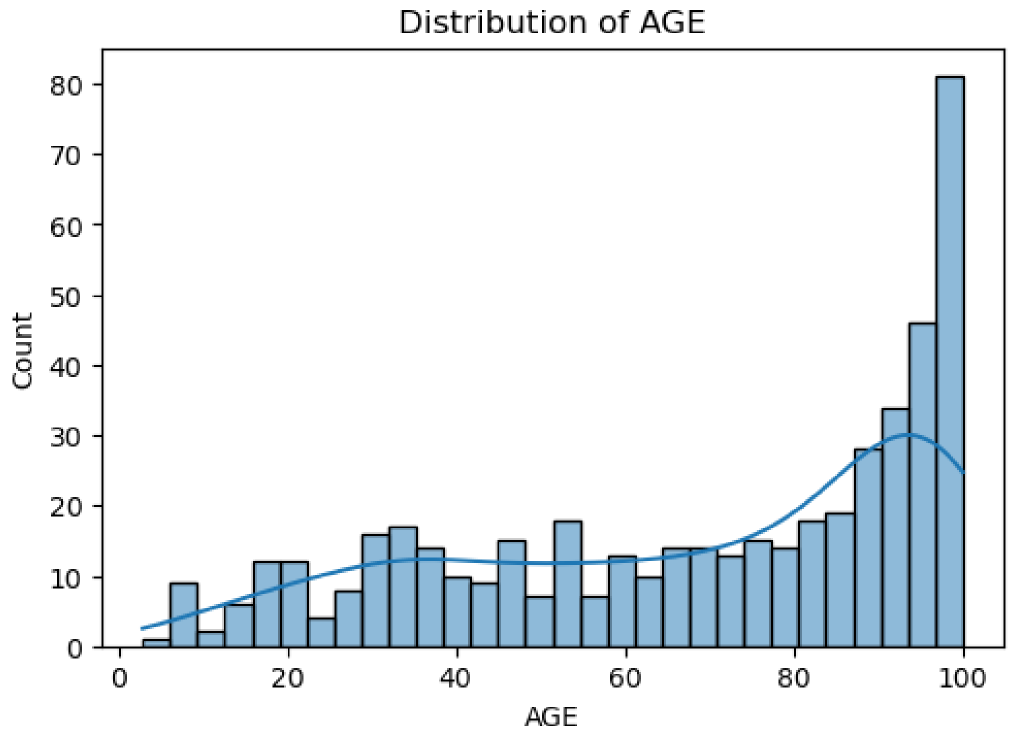
```
df.isnull().sum()

CRIM        20
ZN          20
```

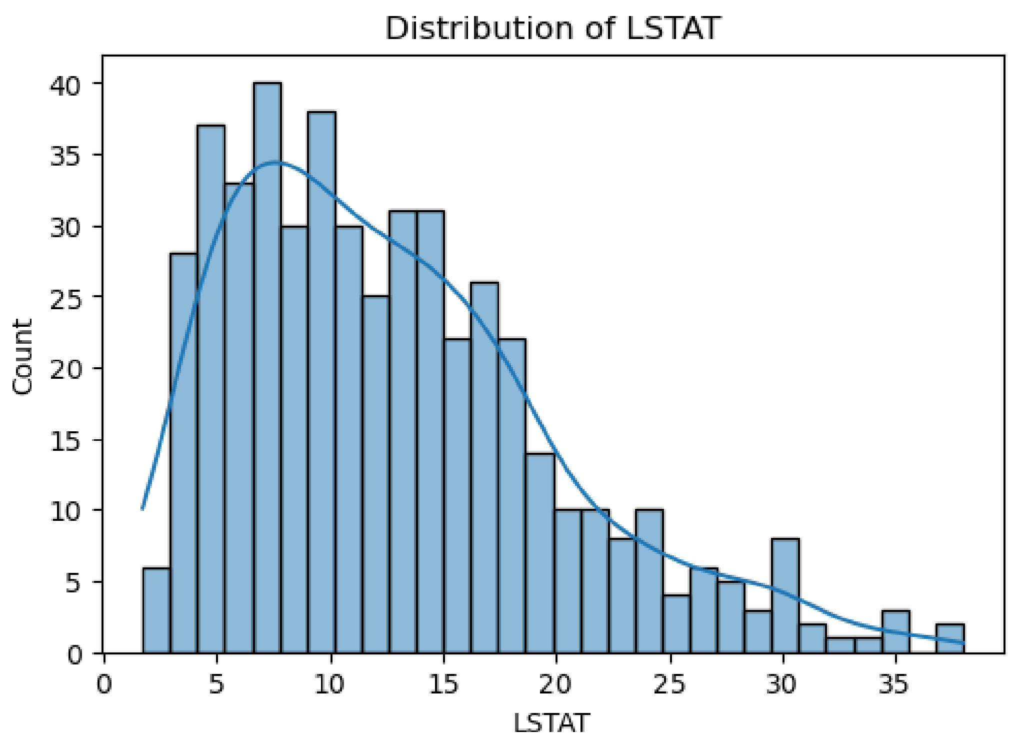
```
INDUS      20
CHAS       20
NOX         0
RM          0
AGE        20
DIS         0
RAD         0
TAX         0
PTRATIO     0
B           0
LSTAT      20
PRICE       0
dtype: int64

features = ["CRIM", "ZN", "INDUS", "AGE", "LSTAT"]
for feature in features:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[feature], bins=30, kde=True)
    plt.title(f"Distribution of {feature}")
    plt.show()
```




Distribution of ZN
Count
ZN
0
50
100
150
200
250
300
350
0
20
40
60
80
100


Distribution of INDUS
Count
INDUS
0
20
40
60
80
100
120
0
5
10
15
20
25






```python
df["CRIM"].fillna(df["CRIM"].median(), inplace=True)
df["ZN"].fillna(df["ZN"].median(), inplace=True)
df["INDUS"].fillna(df["INDUS"].median(), inplace=True)
```

```
df["AGE"].fillna(df["AGE"].median(), inplace=True)
df["LSTAT"].fillna(df["LSTAT"].median(), inplace=True)
df["CHAS"].fillna(df["CHAS"].mode()[0], inplace=True)

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

```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
PRICE      0
dtype: int64
```

2. Standardize or normalize numerical features for better performance.

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df[['CRIM', 'ZN', 'INDUS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
'PTRATIO', 'B', 'LSTAT','PRICE']] = scaler.fit_transform(
    df[['CRIM', 'ZN', 'INDUS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
'TAX', 'PTRATIO', 'B', 'LSTAT','PRICE']])

df.head()
```

```
       CRIM        ZN     INDUS  CHAS       NOX        RM       AGE
DIS  \
0 -0.405592  0.314369 -1.301706   0.0 -0.144217  0.413672 -0.132771
0.140214
1 -0.403140 -0.468160 -0.591052   0.0 -0.740262  0.194274  0.366141
0.557160
2 -0.403142 -0.468160 -0.591052   0.0 -0.740262  1.282714 -0.282080
0.557160
3 -0.402549 -0.468160 -1.321115   0.0 -0.835284  1.016303 -0.839258
1.077737
4 -0.398265 -0.468160 -1.321115   0.0 -0.835284  1.228577 -0.533356
1.077737

        RAD       TAX   PTRATIO         B     LSTAT     PRICE
0 -0.982843 -0.666608 -1.459000  0.441052 -1.096193  0.159686
1 -0.867883 -0.987329 -0.303094  0.441052 -0.502779 -0.101524
2 -0.867883 -0.987329 -0.303094  0.396427 -1.231709  1.324247
```

```
3 -0.752922 -1.106115  0.113032  0.416163 -1.387195  1.182758
4 -0.752922 -1.106115  0.113032  0.441052 -0.176116  1.487503
```

3. Split the dataset into training (80%) and testing (20%) sets.

```
from sklearn.model_selection import train_test_split
X = df.drop(columns=["PRICE"])
y = df["PRICE"]
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=
0.2,random_state= 42)
```

Task 3: Implement Linear Regression

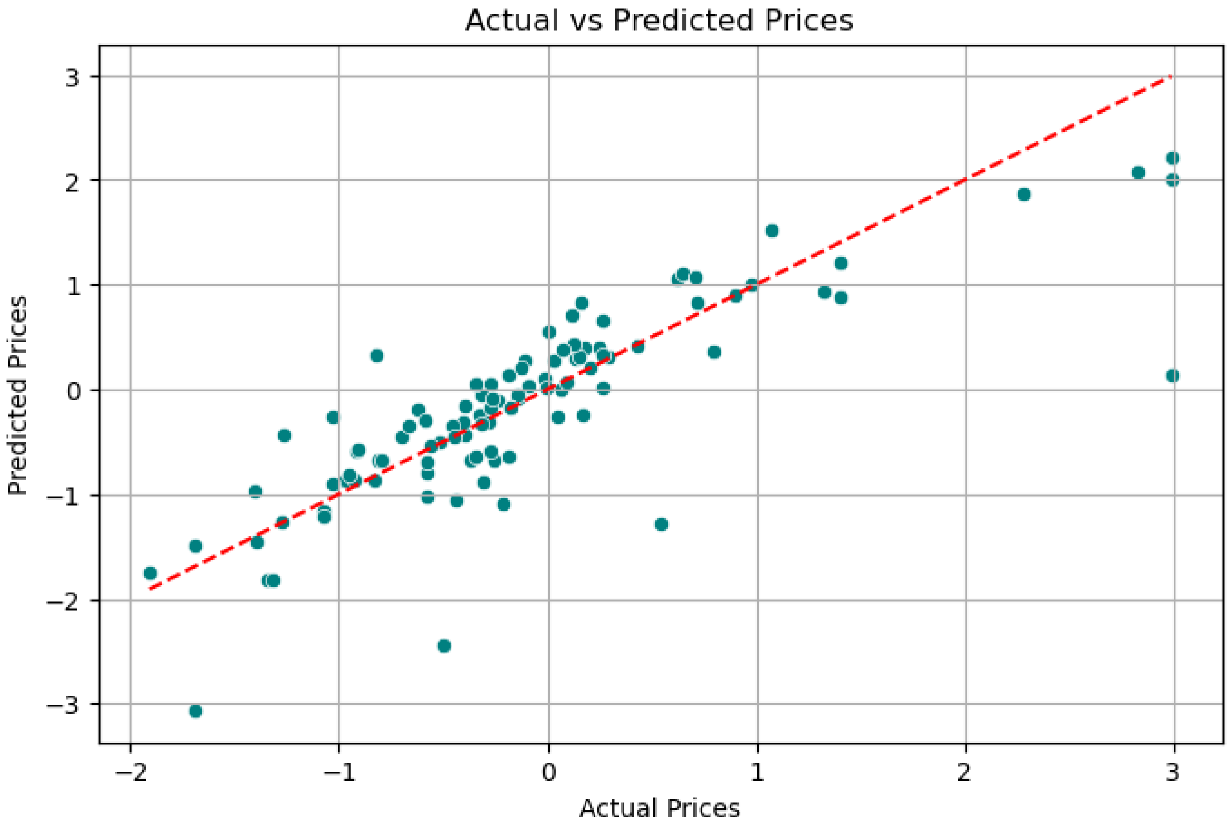
1. Implement Linear Regression using Scikit-learn.

```
from sklearn.linear_model import LinearRegression
lr_model = LinearRegression()
lr_model.fit(X_train,y_train)
y_pred = lr_model.predict(X_test)

coefficients = lr_model.coef_
intercept = lr_model.intercept_

print(coefficients)

[-0.10490832  0.07054757 -0.01870313  0.35693057 -0.20131692
0.36036817
 -0.05436351 -0.34485431  0.20659449 -0.16592289 -0.20950314
0.11944471
 -0.33889095]

print(intercept)

-0.031951925948351986
```

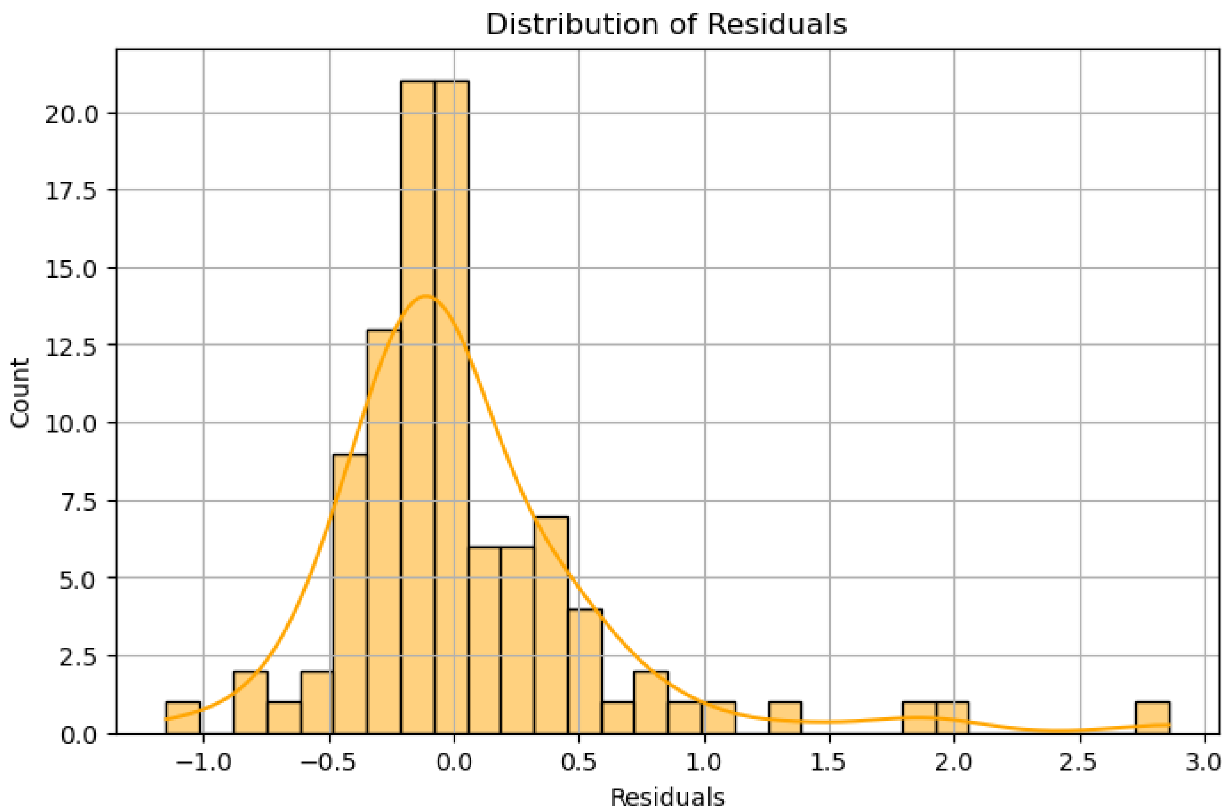
2. Analyze the cost function (Mean Squared Error) and its behavior.

```
from sklearn.metrics import mean_absolute_error
mae = mean_absolute_error(y_test,y_pred)
print("Mean Absolute Error:\n",mae)

Mean Absolute Error:
 0.3427006269536008

plt.figure(figsize=(8,5))
sns.scatterplot(x=y_test, y=y_pred, color='teal')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()],
'r--')
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual vs Predicted Prices")
```

```
plt.grid(True)
plt.show()
```




```
residuals = y_test - y_pred
plt.figure(figsize=(8,5))
sns.histplot(residuals, kde=True, color='orange', bins=30)
plt.title("Distribution of Residuals")
plt.xlabel("Residuals")
plt.grid(True)
plt.show()
```



Task 4: Model Evaluation and Interpretation

1. Evaluate model performance using:

```
from sklearn.metrics import mean_squared_error

mse = mean_squared_error(y_test,y_pred)
rmse = mse ** 0.5

print("Mean Squared Error:\n",mse)
print("Root Mean Squared Error:\n",rmse)

Mean Squared Error:
 0.2961326252871748
Root Mean Squared Error:
 0.5441806917625568
```

3. Plot residuals to check for patterns or anomalies.

```
plt.figure(figsize=(8, 5))
sns.residplot(x=y_pred, y=y_test - y_pred, lowess=True, color="blue",
line_kws={"color": "red"})
plt.axhline(y=0, color="black", linestyle="--", linewidth=1)
plt.xlabel("Predicted Values")
plt.ylabel("Residuals (Actual - Predicted)")
```

```
plt.title("Residual Plot")
plt.show()
```