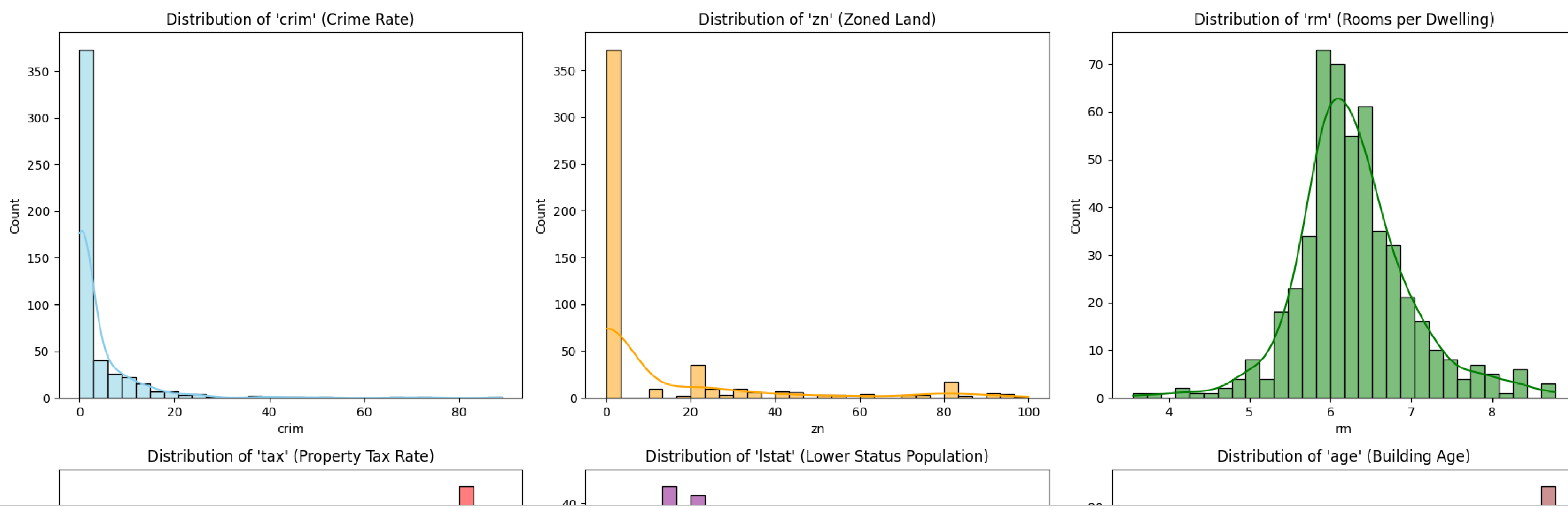
```
import pandas as pd
import numpy as np
```

```
df=pd.read_csv('Boston.csv')
print(df)
```

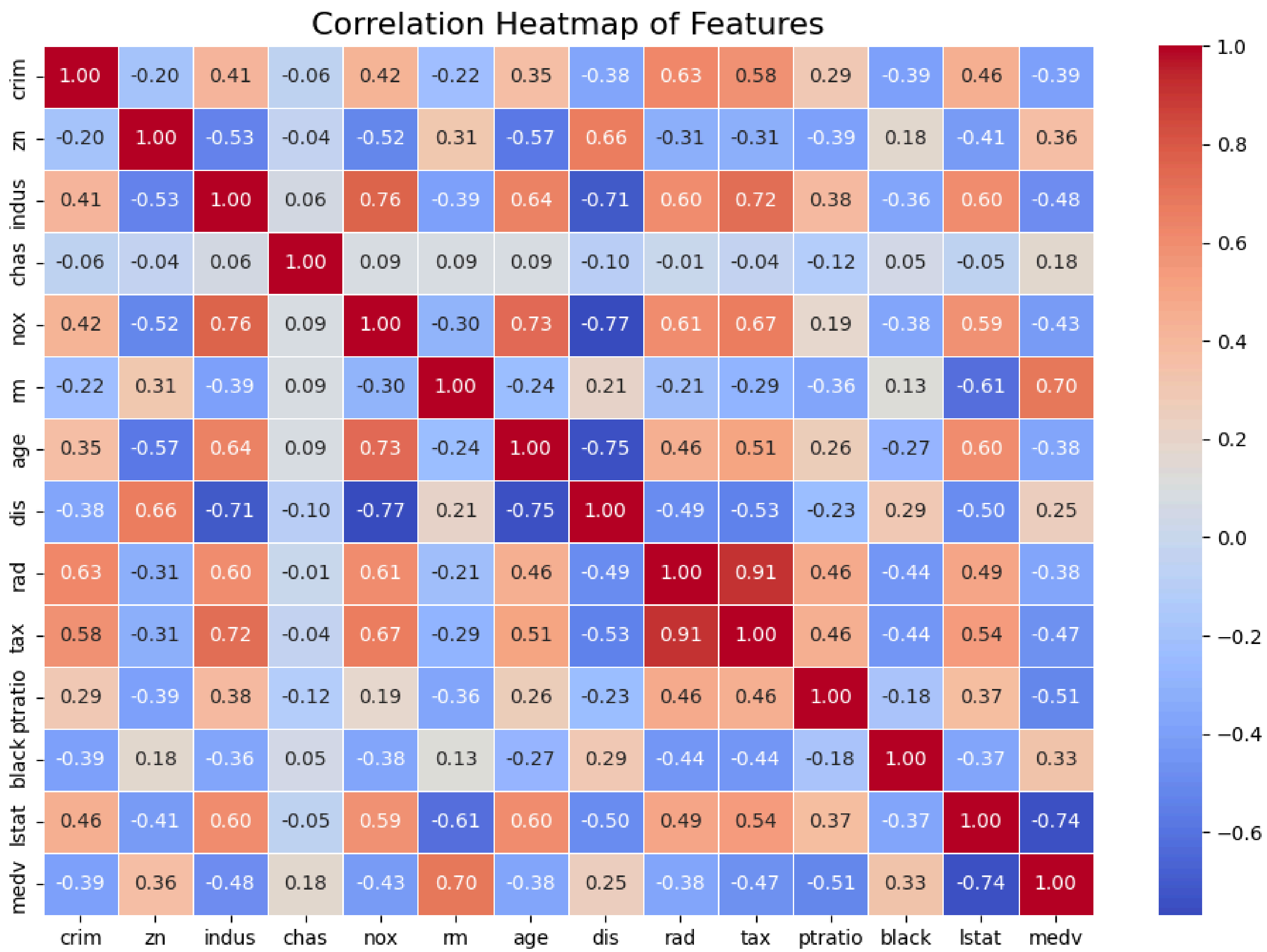
```
     Unnamed: 0     crim    zn  indus  chas    nox     rm   age     dis  rad  \
0             1  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1
1             2  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2
2             3  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2
3             4  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3
4             5  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3
..          ...      ...   ...    ...   ...    ...    ...   ...     ...  ...
501         502  0.06263   0.0  11.93     0  0.573  6.593  69.1  2.4786    1
502         503  0.04527   0.0  11.93     0  0.573  6.120  76.7  2.2875    1
503         504  0.06076   0.0  11.93     0  0.573  6.976  91.0  2.1675    1
504         505  0.10959   0.0  11.93     0  0.573  6.794  89.3  2.3889    1
505         506  0.04741   0.0  11.93     0  0.573  6.030  80.8  2.5050    1

     tax  ptratio   black  lstat  medv
0    296     15.3  396.90   4.98  24.0
1    242     17.8  396.90   9.14  21.6
2    242     17.8  392.83   4.03  34.7
3    222     18.7  394.63   2.94  33.4
4    222     18.7  396.90   5.33  36.2
..   ...      ...     ...    ...   ...
501  273     21.0  391.99   9.67  22.4
502  273     21.0  396.90   9.08  20.6
503  273     21.0  396.90   5.64  23.9
504  273     21.0  393.45   6.48  22.0
505  273     21.0  396.90   7.88  11.9

[506 rows x 15 columns]
```

```
# Plotting the distribution of important features in the dataset
fig, axs = plt.subplots(2, 3, figsize=(18, 10))
# Feature: 'crim'
sns.histplot(df['crim'], bins=30, kde=True, color='skyblue', ax=axs[0, 0])
axs[0, 0].set_title("Distribution of 'crim' (Crime Rate)")
# Feature: 'zn'
sns.histplot(df['zn'], bins=30, kde=True, color='orange', ax=axs[0, 1])
axs[0, 1].set_title("Distribution of 'zn' (Zoned Land)")
# Feature: 'rm'
sns.histplot(df['rm'], bins=30, kde=True, color='green', ax=axs[0, 2])
axs[0, 2].set_title("Distribution of 'rm' (Rooms per Dwelling)")
# Feature: 'tax'
sns.histplot(df['tax'], bins=30, kde=True, color='red', ax=axs[1, 0])
axs[1, 0].set_title("Distribution of 'tax' (Property Tax Rate)")
# Feature: 'lstat'
sns.histplot(df['lstat'], bins=30, kde=True, color='purple', ax=axs[1, 1])
axs[1, 1].set_title("Distribution of 'lstat' (Lower Status Population)")
# Feature: 'age'
sns.histplot(df['age'], bins=30, kde=True, color='brown', ax=axs[1, 2])
axs[1, 2].set_title("Distribution of 'age' (Building Age)")
plt.tight_layout()
plt.show()
```




```
# Computing the correlation matrix
correlation_matrix = df[numerical_columns].corr()

plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
plt.title("Correlation Heatmap of Features", fontsize=16)
```

```
plt.show()
```




```
missing_values = df.isnull().sum()
missing_values
```

	0
Unnamed: 0	0
crim	0
zn	0
indus	0
chas	0
nox	0
rm	0
age	0
dis	0
rad	0
tax	0
ptratio	0
black	0
lstat	0
medv	0

dtype: int64

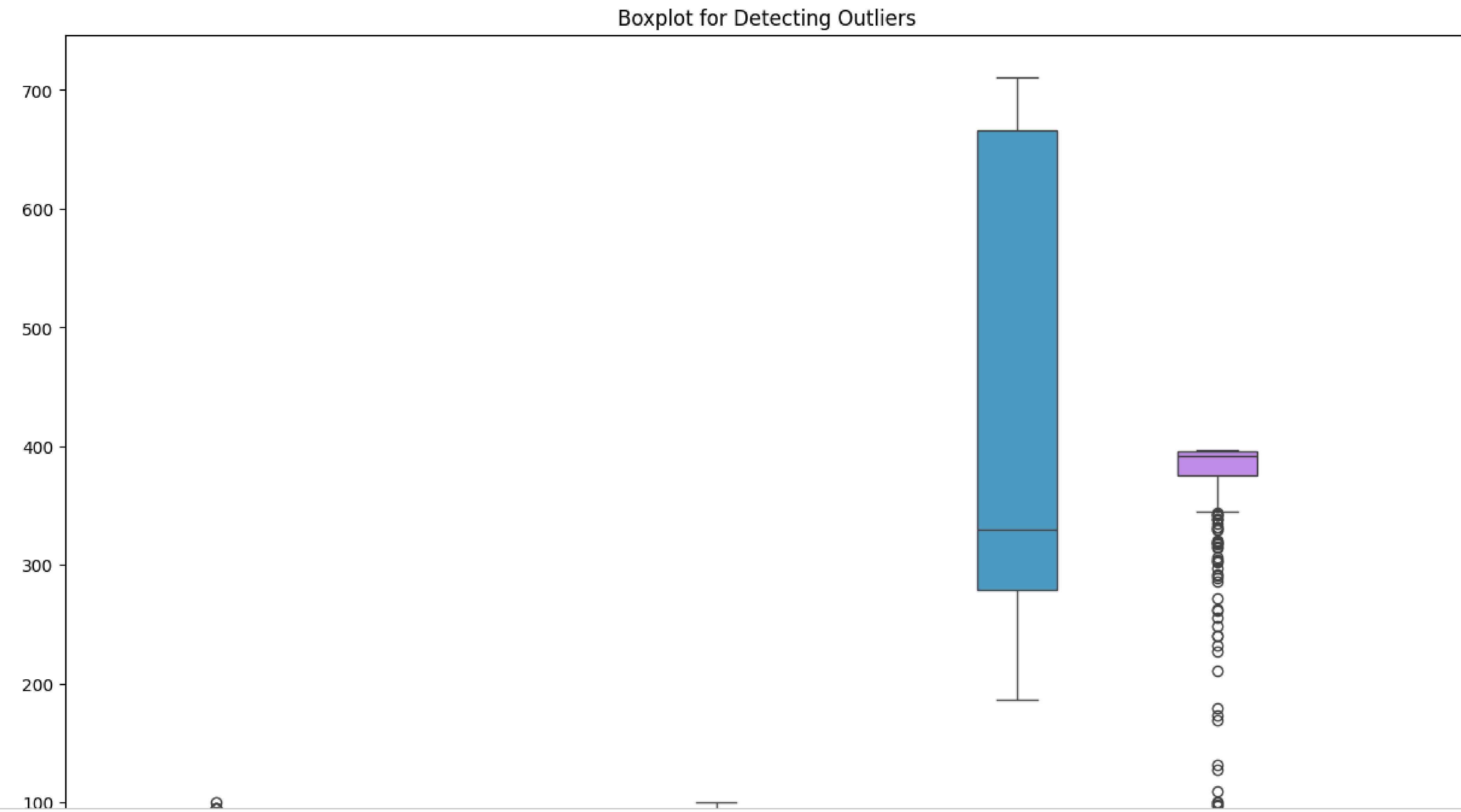
```
# Drop the 'Unnamed: 0' column
df = df.drop(columns=['Unnamed: 0'])
df.head()
```

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.2

```
df.describe()
```

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	12.653063	22.532806
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	7.141062	9.197104
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	1.730000	5.000000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	6.950000	17.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	11.360000	21.200000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	16.955000	25.000000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	37.970000	50.000000

```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(15, 10))
sns.boxplot(data=df)
plt.xticks(rotation=90)
plt.title("Boxplot for Detecting Outliers")
plt.show()
```

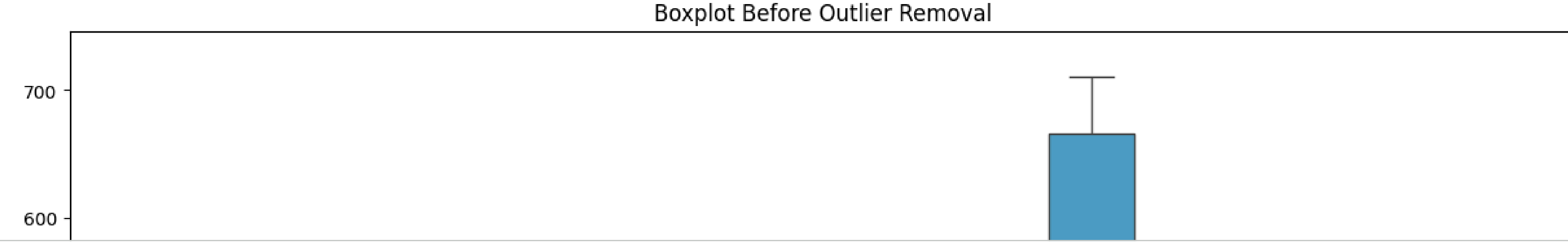



```
# Calculate Q1 (25th percentile) and Q3 (75th percentile)
Q1 = df.select_dtypes(include=['float64', 'int64']).quantile(0.25)
Q3 = df.select_dtypes(include=['float64', 'int64']).quantile(0.75)

IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
outliers_iqr = ((df.select_dtypes(include=['float64', 'int64']) < lower_bound) | (df.select_dtypes(include=['float64', 'int64']) > upper_bound))
df_no_outliers_iqr = df[~outliers_iqr.any(axis=1)]s
df.shape, df_no_outliers_iqr.shape
```

```
((506, 14), (268, 14))
```

```
# Plot boxplot before removing outliers
plt.figure(figsize=(15, 10))
sns.boxplot(data=df)
plt.xticks(rotation=90)
plt.title("Boxplot Before Outlier Removal")
plt.show()
```

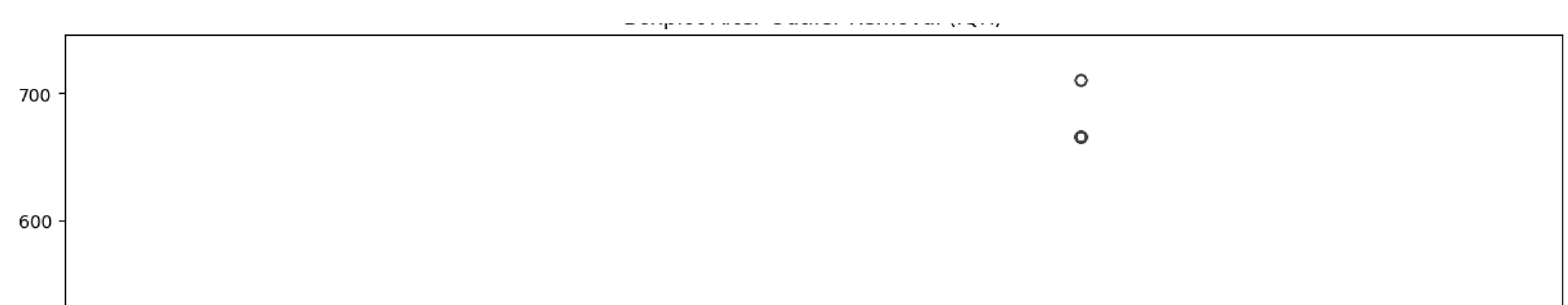
```
# Plot boxplot after removing outliers using IQR method
plt.figure(figsize=(15, 10))
sns.boxplot(data=df_no_outliers_iqr)
plt.xticks(rotation=90)
plt.title("Boxplot After Outlier Removal (IQR)")
plt.show()
```

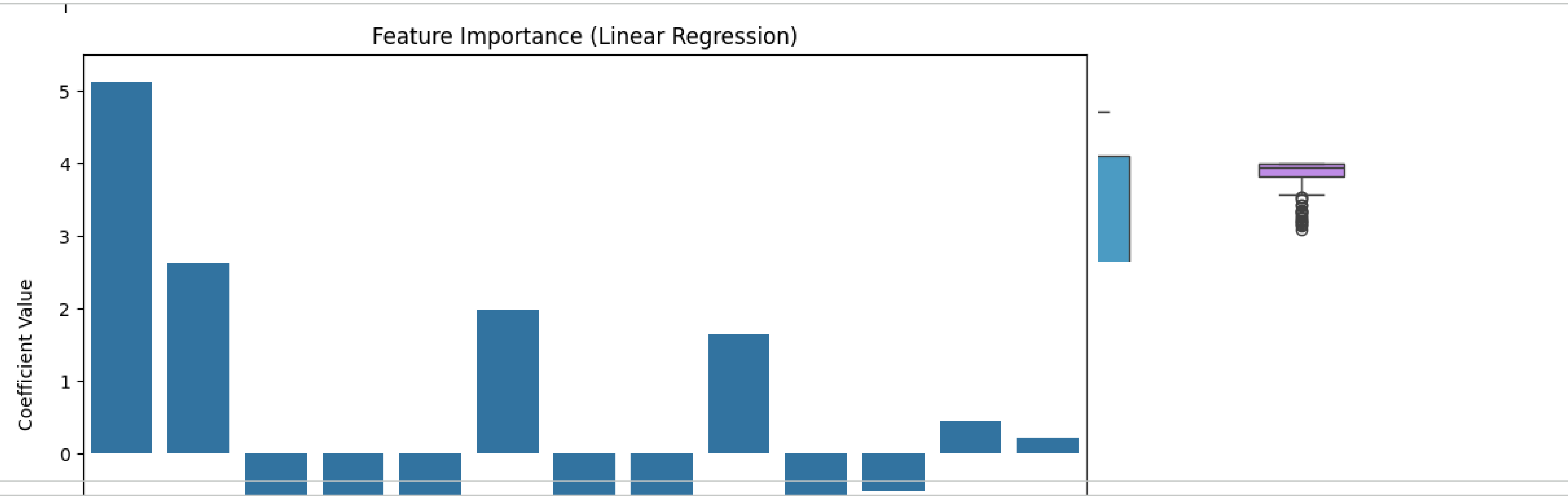



```
from sklearn.preprocessing import StandardScaler
features_to_scale = df.drop(columns=['chas', 'medv'])

scaler = StandardScaler()
scaled_features = scaler.fit_transform(features_to_scale)
df_scaled = pd.DataFrame(scaled_features, columns=features_to_scale.columns)
df_scaled['chas'] = df['chas']
df_scaled['medv'] = df['medv']
df_scaled.head()
```

	crim	zn	indus	nox	rm	age	dis	rad	tax	ptratio	black	lstat	chas	medv
0	-0.419782	0.284830	-1.287909	-0.144217	0.413672	-0.120013	0.140214	-0.982843	-0.666608	-1.459000	0.441052	-1.075562	0	24.0
1	-0.417339	-0.487722	-0.593381	-0.740262	0.194274	0.367166	0.557160	-0.867883	-0.987329	-0.303094	0.441052	-0.492439	0	21.6
2	-0.417342	-0.487722	-0.593381	-0.740262	1.282714	-0.265812	0.557160	-0.867883	-0.987329	-0.303094	0.396427	-1.208727	0	34.7
3	-0.416750	-0.487722	-1.306878	-0.835284	1.016303	-0.809889	1.077737	-0.752922	-1.106115	0.113032	0.416163	-1.361517	0	33.4
4	-0.412482	-0.487722	-1.306878	-0.835284	1.228577	-0.511180	1.077737	-0.752922	-1.106115	0.113032	0.441052	-1.026501	0	36.2

```
# Extract the coefficients (feature importance)
coefficients = pd.DataFrame(model.coef_, X.columns, columns=["Coefficient"])
coefficients["abs_coefficient"] = coefficients["Coefficient"].abs()
coefficients = coefficients.sort_values("abs_coefficient", ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(x=coefficients.index, y=coefficients['Coefficient'])
plt.title("Feature Importance (Linear Regression)")
plt.xlabel("Feature")
plt.ylabel("Coefficient Value")
plt.xticks(rotation=90)
plt.show()
```





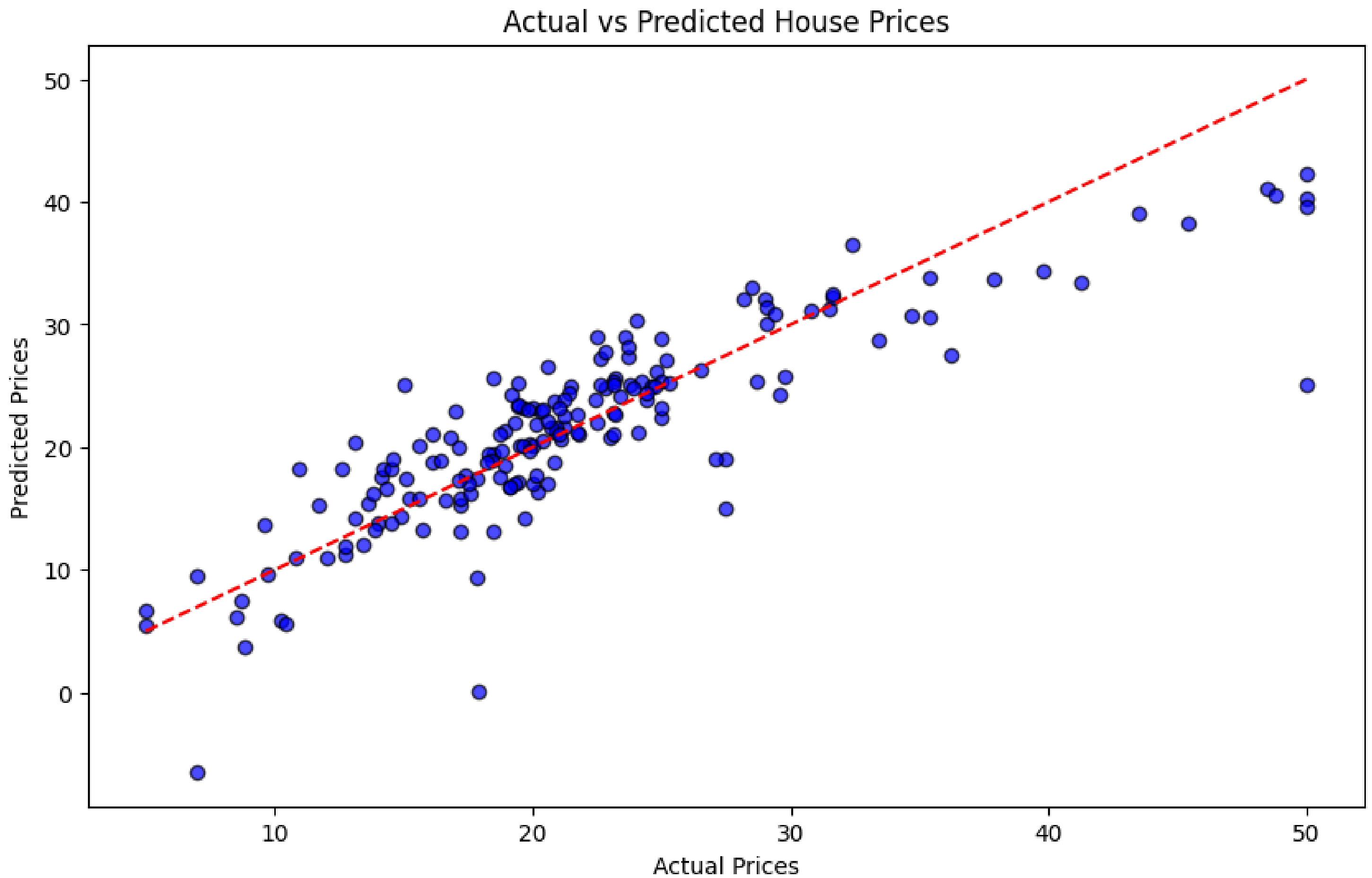

```
from sklearn.model_selection import train_test_split

X = df_scaled.drop(columns=['medv', 'indus', 'age'])  # Remove features with low coefficient values
y = df_scaled['medv']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.35, random_state=42)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((328, 11), (178, 11), (328,), (178,))
```

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"R² Score: {r2:.2f}")
```

```
Mean Squared Error (MSE): 20.31
R² Score: 0.73
```

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, color='blue', edgecolor='k', alpha=0.7)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='red', linestyle='--')
plt.title("Actual vs Predicted House Prices")
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.show()
```




```
independent_vars = ["crim","zn","indus","nox","rm","age","dis","rad","tax","ptratio","black","lstat","chas"]
```

```
results = {}

for col in independent_vars:
    X = df[[col]]
    y = df["medv"]

    model = LinearRegression()
    model.fit(X, y)

    y_pred = model.predict(X)

    # Store actual vs predicted for each feature
    results[col] = pd.DataFrame({
        "Actual_MEDV": y,
        "Predicted_MEDV": y_pred
    })

# Display result keys
list(results.keys())
```

```
['crim',
 'zn',
 'indus',
 'nox',
 'rm',
```

```
 'age',
 'dis',
 'rad',
 'tax',
 'ptratio',
 'black',
 'lstat',
 'chas']
```

```
results["rm"]   # Example: show for RM
```

	Actual_MEDV	Predicted_MEDV
0	24.0	25.175746
1	21.6	23.774021
2	34.7	30.728032
3	33.4	29.025938
4	36.2	30.382152
...	...	...
501	22.4	25.339584
502	20.6	21.034286
503	23.9	28.825691
504	22.0	27.169108
505	11.9	20.215096

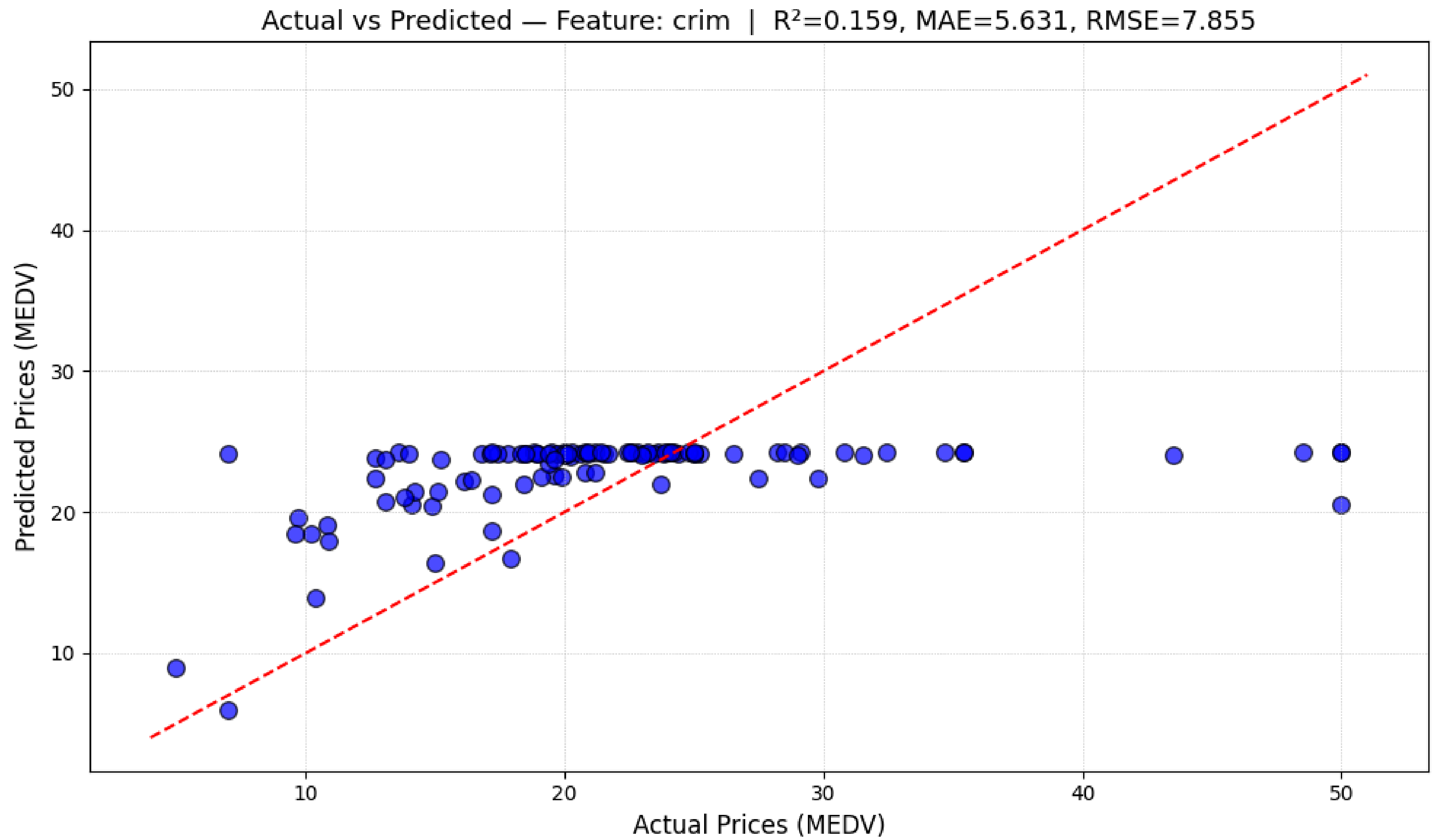
506 rows × 2 columns

```
for col in independent_vars:
    print("\n==============================")
    print(f"Feature: {col}")
    print(results[col])
```

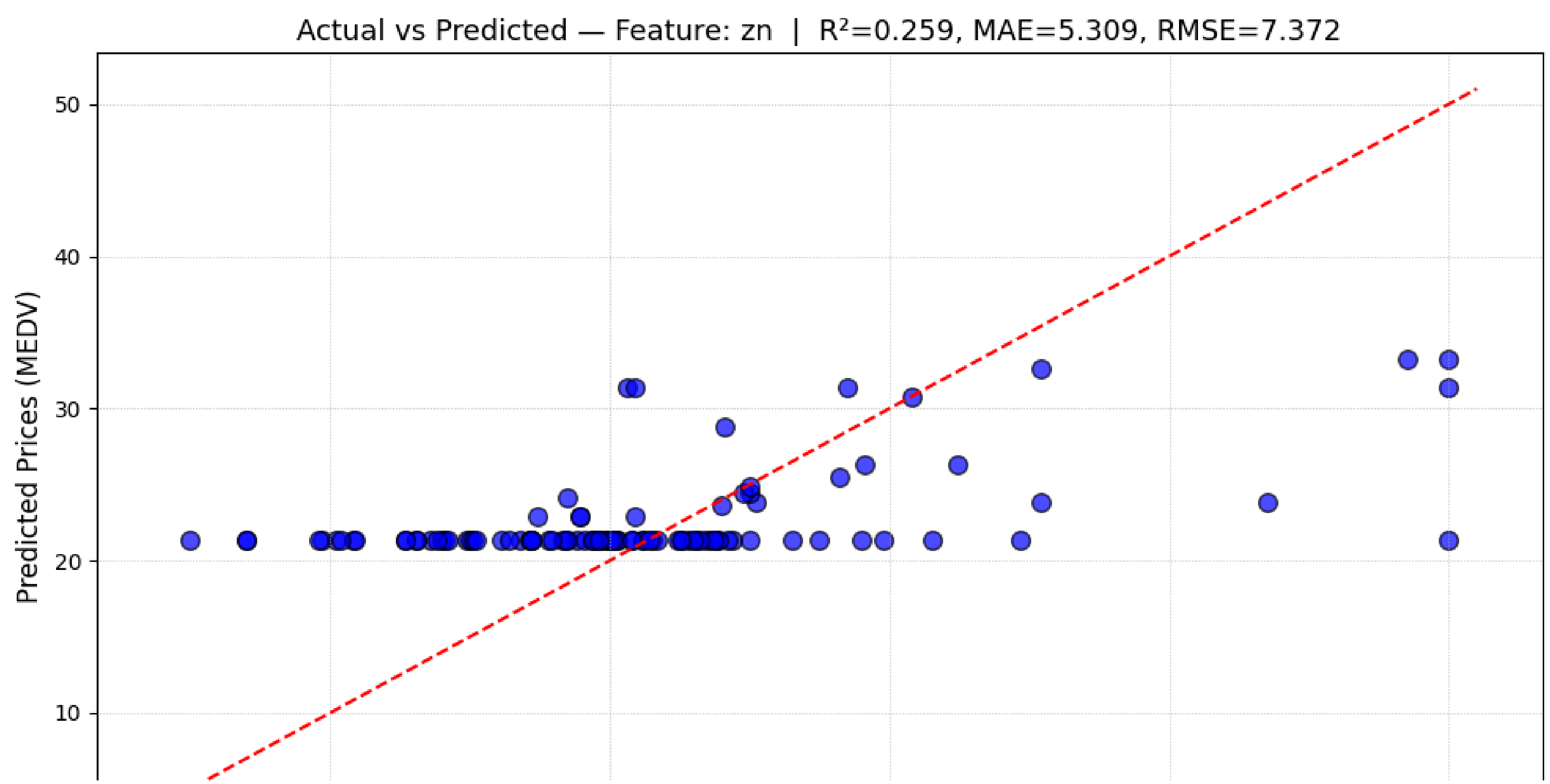
```
     Actual_MEDV  Predicted_MEDV
0           24.0       29.339845
1           21.6       23.946907
2           34.7       23.946907
3           33.4       22.005449
4           36.2       22.005449
..           ...             ...
501         22.4       17.043946
502         20.6       17.043946
503         23.9       17.043946
504         22.0       17.043946
505         11.9       17.043946

[506 rows x 2 columns]

==============================
Feature: black
     Actual_MEDV  Predicted_MEDV
0           24.0       23.884120
1           21.6       23.884120
2           34.7       23.747396
3           33.4       23.807863
4           36.2       23.884120
..           ...             ...
501         22.4       23.719178
502         20.6       23.884120
503         23.9       23.884120
504         22.0       23.768224
505         11.9       23.884120

[506 rows x 2 columns]

==============================
Feature: lstat
     Actual_MEDV  Predicted_MEDV
0           24.0       29.822595
1           21.6       25.870390
2           34.7       30.725142
```

```
# Cell 2: train/test per feature, metrics, plot & save

summary = []

# Settings
test_size = 0.2
random_state = 42

for col in independent_vars:
    X = df[[col]].values.reshape(-1, 1)   # feature as 2D array
    y = df["medv"].values                 # target

    # train/test split
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=test_size, random_state=random_state
    )

    # fit model
    model = LinearRegression()
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # metrics
```

```
    r2 = r2_score(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))   # FIXED RMSE

    # Plot Actual vs Predicted (test set)
    plt.figure(figsize=(10, 6))
    plt.scatter(y_test, y_pred, color='blue', edgecolor='k', alpha=0.7, s=70, marker='o')

    # y = x reference line
    mins = min(y_test.min(), y_pred.min()) - 1
    maxs = max(y_test.max(), y_pred.max()) + 1
    plt.plot([mins, maxs], [mins, maxs], color='red', linestyle='--', linewidth=1.5)

    # labels and title
    plt.xlabel("Actual Prices (MEDV)", fontsize=12)
    plt.ylabel("Predicted Prices (MEDV)", fontsize=12)
    plt.title(f"Actual vs Predicted — Feature: {col}  |  R²={r2:.3f}, MAE={mae:.3f}, RMSE={rmse:.3f}", fontsize=13)
    plt.grid(True, linestyle=':', linewidth=0.5)
    plt.tight_layout()

    # save
    filename = f"plots/{col}_actual_vs_pred_test.png"
    plt.savefig(filename, dpi=150)
    plt.show()

    # store summary info
    summary.append({
        "feature": col,
        "r2": r2,
        "mae": mae,
        "rmse": rmse,
        "coef": float(model.coef_[0]),
        "intercept": float(model.intercept_),
        "plot_file": filename
    })

    print(f"Saved plot: {filename}  |  feature={col}  R2={r2:.4f}  MAE={mae:.4f}  RMSE={rmse:.4f}\n")
```

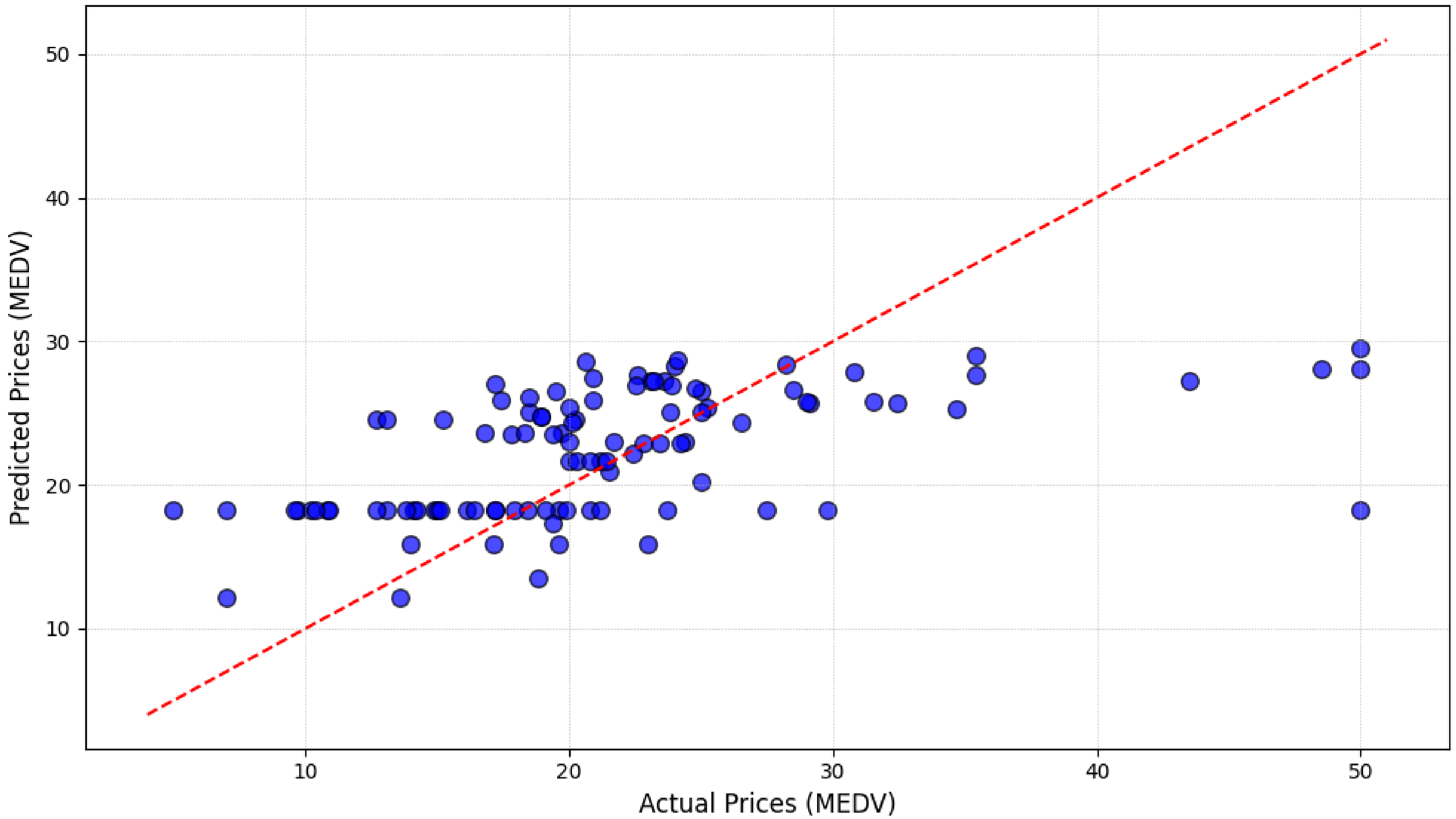



```
Saved plot: plots/crim_actual_vs_pred_test.png  |  feature=crim  R2=0.1587  MAE=5.6311  RMSE=7.8546
```



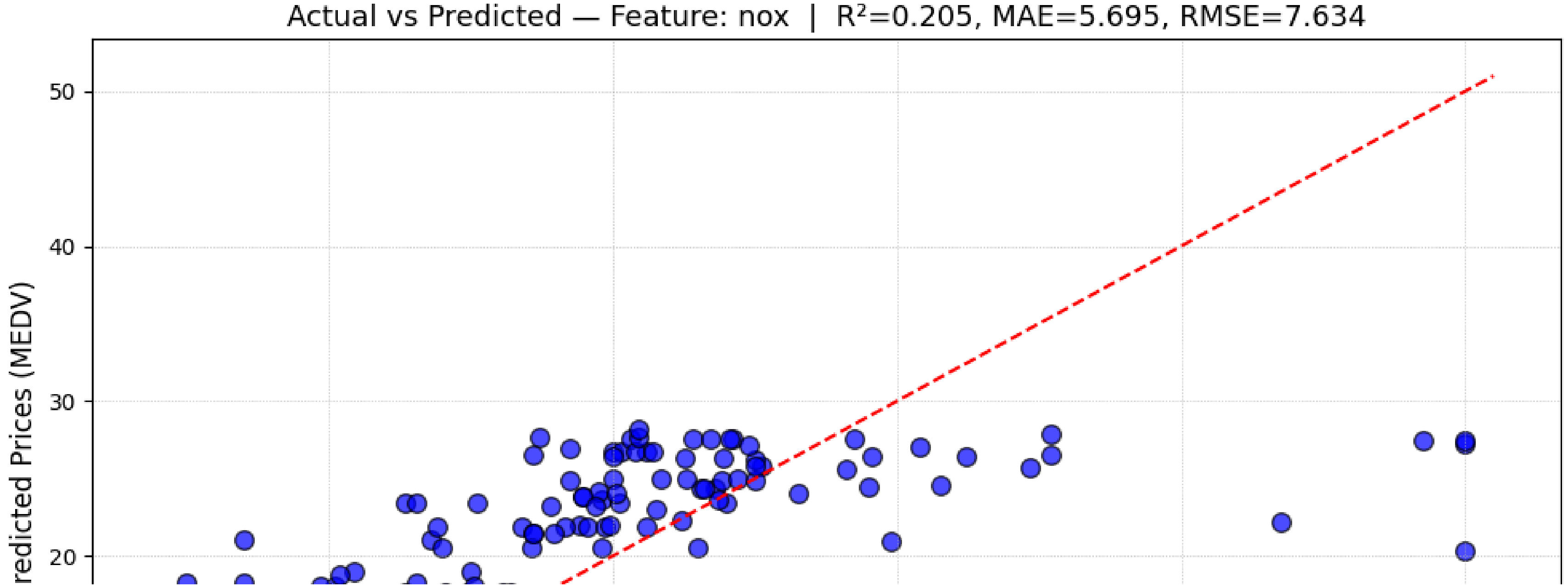

```
Saved plot: plots/zn_actual_vs_pred_test.png  |  feature=zn  R2=0.2589  MAE=5.3093  RMSE=7.3721
```

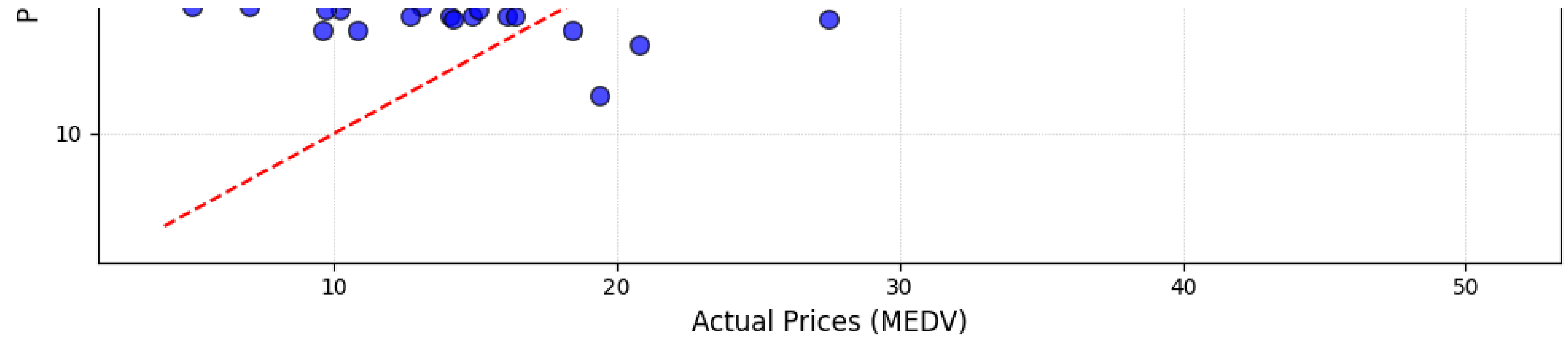
Actual vs Predicted — Feature: indus | R^2=0.276, MAE=5.250, RMSE=7.284



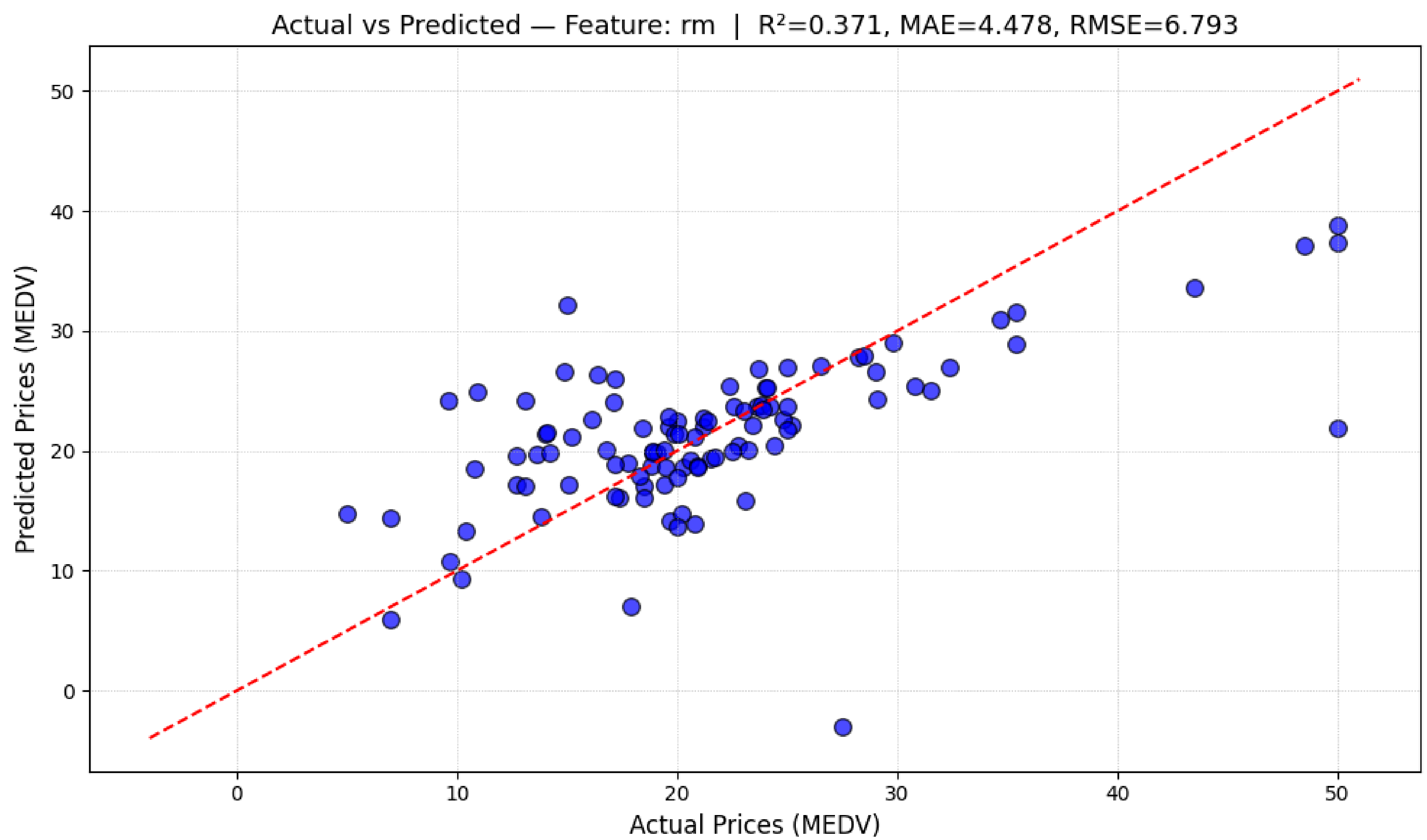

```
Saved plot: plots/indus_actual_vs_pred_test.png  |  feature=indus  R2=0.2764  MAE=5.2496  RMSE=7.2845
```

Actual vs Predicted — Feature: nox | R^2=0.205, MAE=5.695, RMSE=7.634

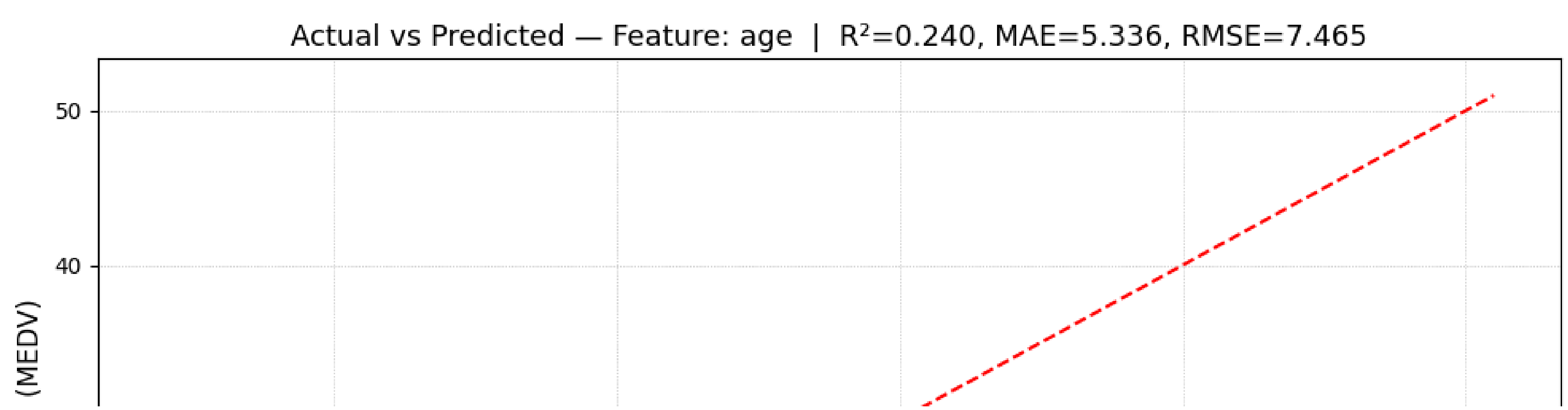


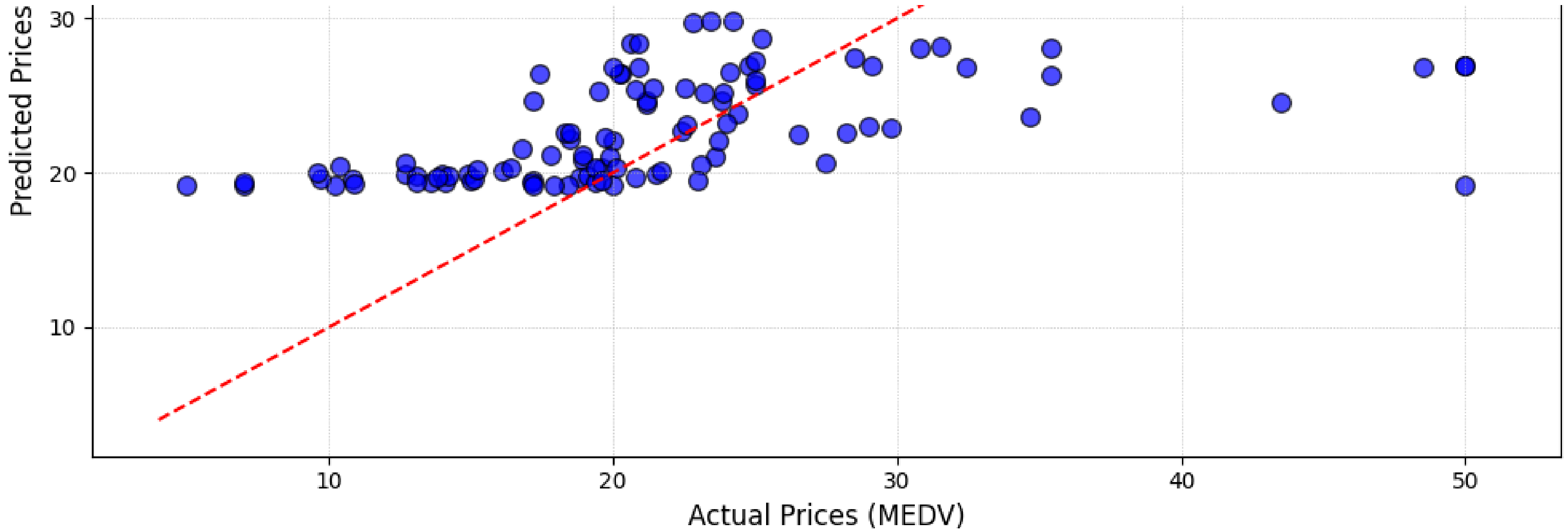



```
Saved plot: plots/nox_actual_vs_pred_test.png  |  feature=nox  R2=0.2052  MAE=5.6954  RMSE=7.6345
```




```
Saved plot: plots/rm_actual_vs_pred_test.png  |  feature=rm  R2=0.3708  MAE=4.4783  RMSE=6.7930
```






```
Saved plot: plots/age_actual_vs_pred_test.png  |  feature=age  R2=0.2400  MAE=5.3357  RMSE=7.4654
```

Actual vs Predicted — Feature: dis | R^2=0.073, MAE=5.968, RMSE=8.244