house-price-prediction

June 30, 2024

Boston House Price prediction

Importing Necessary Modelues

[1]:
```
import pandas as pd
import numpy as np
import sklearn
from sklearn.impute import SimpleImputer
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

Importing Dataset for Analysis and Prediction

[2]:
```
data = pd.read_csv('/kaggle/input/boston-house/HousingData.csv')
data.head()
```

[2]:
```
      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
```

Describing Data and his Characterstics

[3]:
```
data.columns
```

[3]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'MEDV'],
```

```
        dtype='object')
```

[4]:
```
data.shape
```

[4]:
```
(506, 14)
```

[5]:
```
data.dtypes
```

[5]:
```
CRIM        float64
ZN          float64
INDUS       float64
CHAS        float64
NOX         float64
RM          float64
AGE         float64
DIS         float64
RAD           int64
TAX           int64
PTRATIO     float64
B           float64
LSTAT       float64
MEDV        float64
dtype: object
```

[6]:
```
# Displaying Data Range

min_values = data.min()
max_values = data.max()
val = pd.DataFrame({'Min':min_values,'Max':max_values})
print(val)
```

```
               Min       Max
CRIM       0.00632   88.9762
ZN         0.00000  100.0000
INDUS      0.46000   27.7400
CHAS       0.00000    1.0000
NOX        0.38500    0.8710
RM         3.56100    8.7800
AGE        2.90000  100.0000
DIS        1.12960   12.1265
RAD        1.00000   24.0000
TAX      187.00000  711.0000
PTRATIO   12.60000   22.0000
B          0.32000  396.9000
LSTAT      1.73000   37.9700
MEDV       5.00000   50.0000
```

Removing Nan Values

[7]:
```
data.isna().sum()
```

[7]:
```
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
MEDV        0
dtype: int64
```

[8]:
```
imp_mean = SimpleImputer(strategy='mean')
imp_median = SimpleImputer(strategy='median')
imp_mode = SimpleImputer(strategy='most_frequent')
```

[9]:
```
data['CRIM'] = imp_median.fit_transform(data[['CRIM']])
```

[10]:
```
data['ZN'] = imp_mode.fit_transform(data[['ZN']])
```

[11]:
```
data['INDUS'] = imp_mean.fit_transform(data[['INDUS']])
```

[12]:
```
data['CHAS'] = imp_mode.fit_transform(data[['CHAS']])
```

[13]:
```
data['AGE'] = imp_median.fit_transform(data[['AGE']])
```

[14]:
```
data['LSTAT'] = imp_mean.fit_transform(data[['LSTAT']])
```

[15]:
```
data.isna().sum()
```

[15]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
```

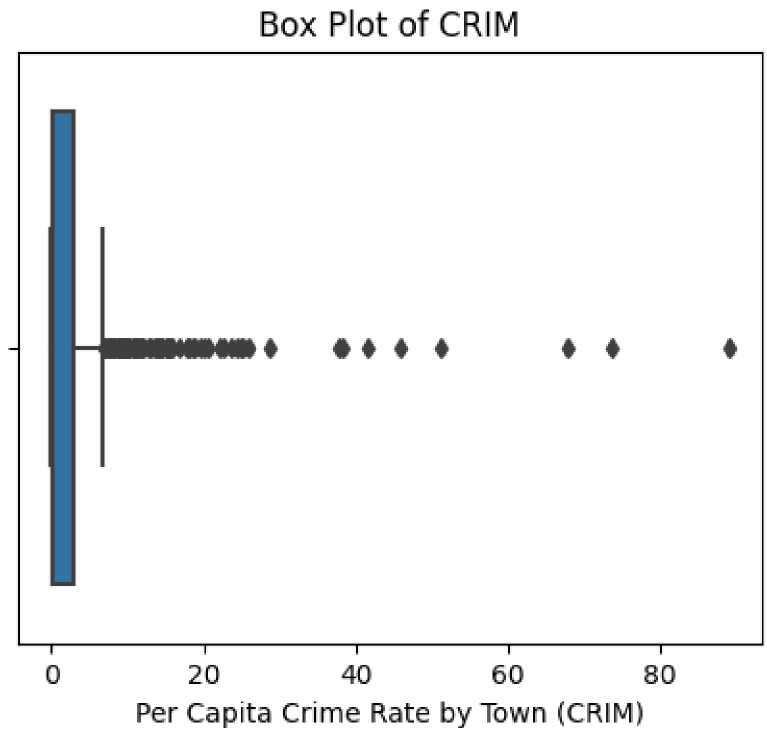
```
B          0
LSTAT      0
MEDV       0
dtype: int64
```

[16]:
```
# Data after Preprocessing
data.head()
```

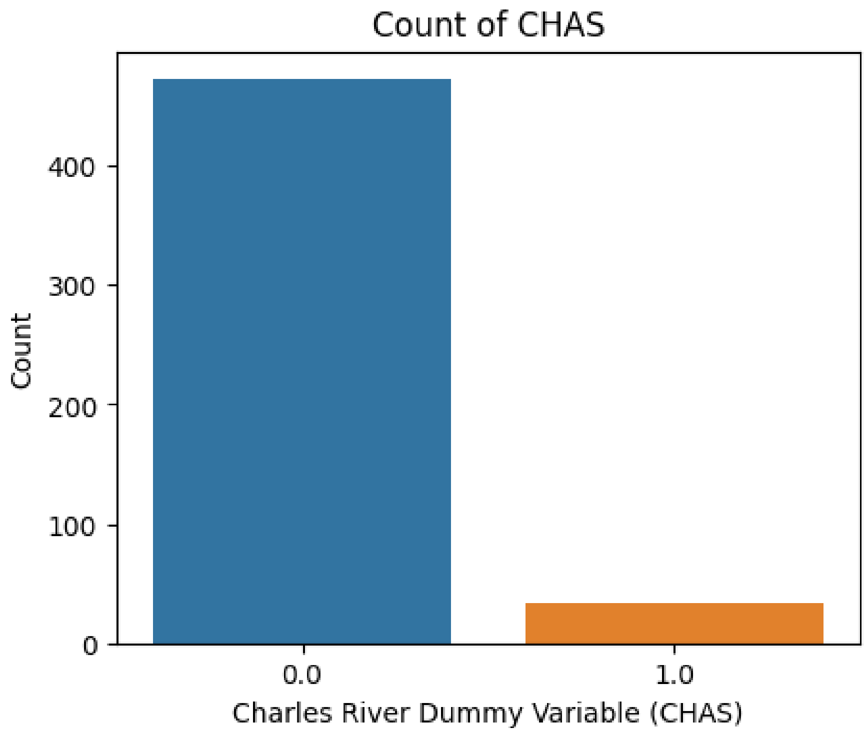
[16]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD  TAX  PTRATIO  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900    1  296     15.3
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671    2  242     17.8
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671    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   4.980000  24.0
1  396.90   9.140000  21.6
2  392.83   4.030000  34.7
3  394.63   2.940000  33.4
4  396.90  12.715432  36.2
```

Visualizing to describe the data

[17]:
```
# Box plot of CRIM

plt.figure(figsize=(5,4))
sns.boxplot(x=data['CRIM'])
plt.title('Box Plot of CRIM')
plt.xlabel('Per Capita Crime Rate by Town (CRIM)')
plt.show()
```

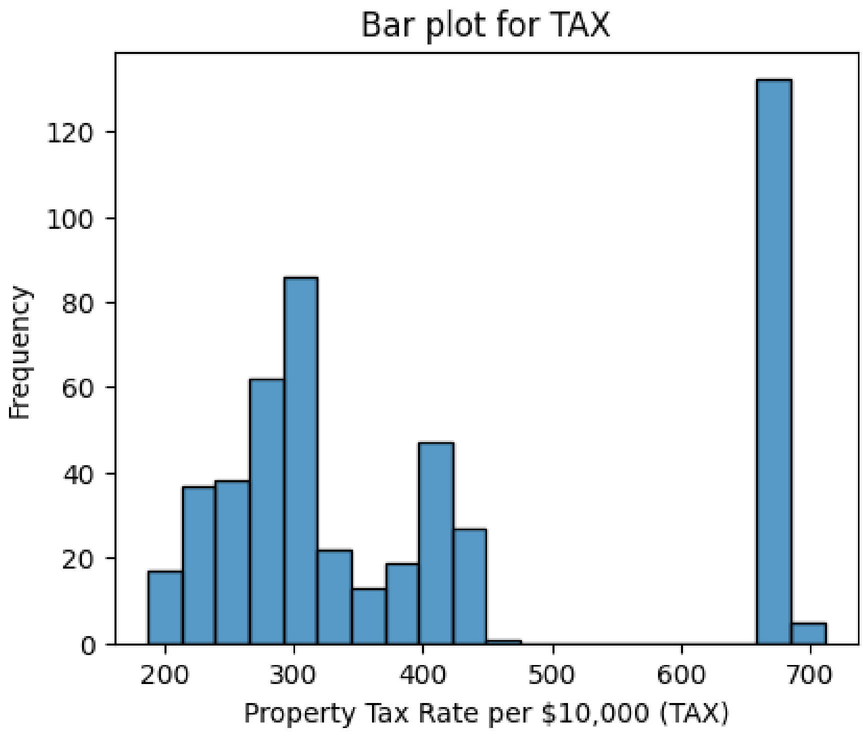


[18]:
```
# Bar plot of CHAS

plt.figure(figsize=(5,4))
sns.countplot(x='CHAS', data=data)
plt.title('Count of CHAS')
plt.xlabel('Charles River Dummy Variable (CHAS)')
plt.ylabel('Count')
plt.show()
```

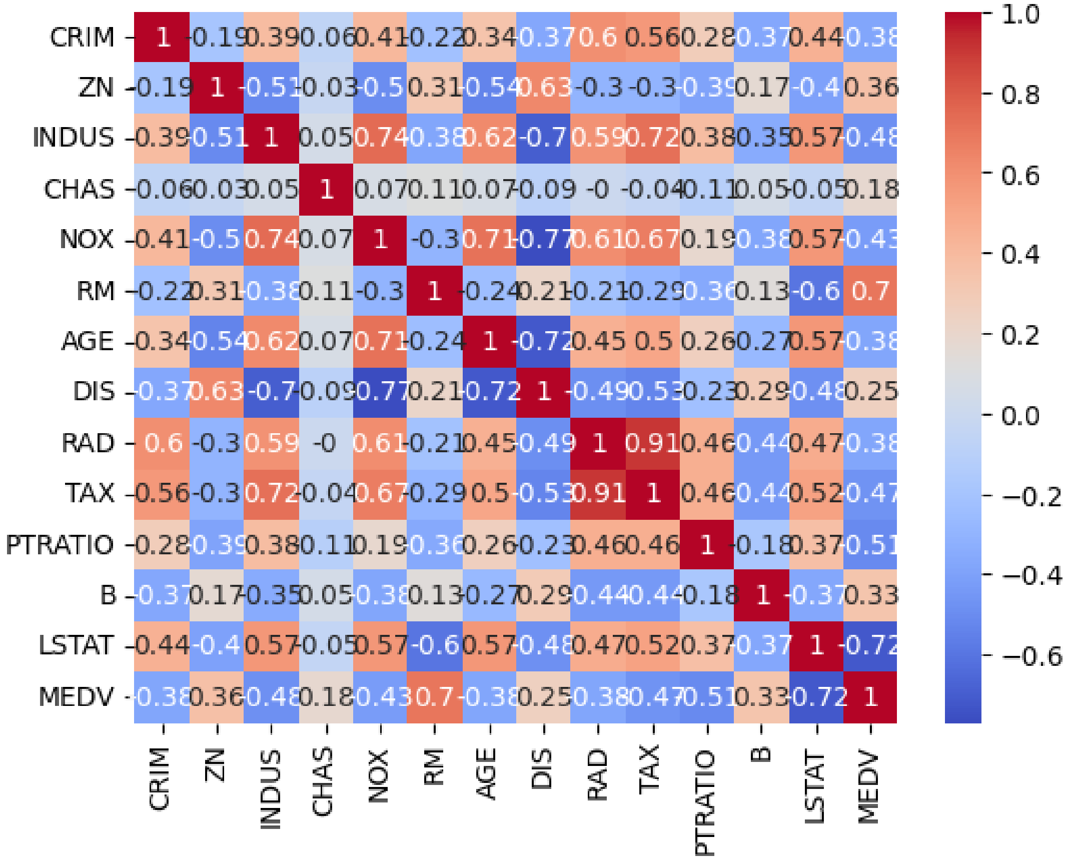


[19]:
```
# Bar Plot for Tax

plt.figure(figsize=(5, 4))
sns.histplot(data['TAX'], bins=20)
plt.title('Bar plot for TAX')
plt.xlabel('Property Tax Rate per $10,000 (TAX)')
plt.ylabel('Frequency')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning:
use_inf_as_na option is deprecated and will be removed in a future version.
Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



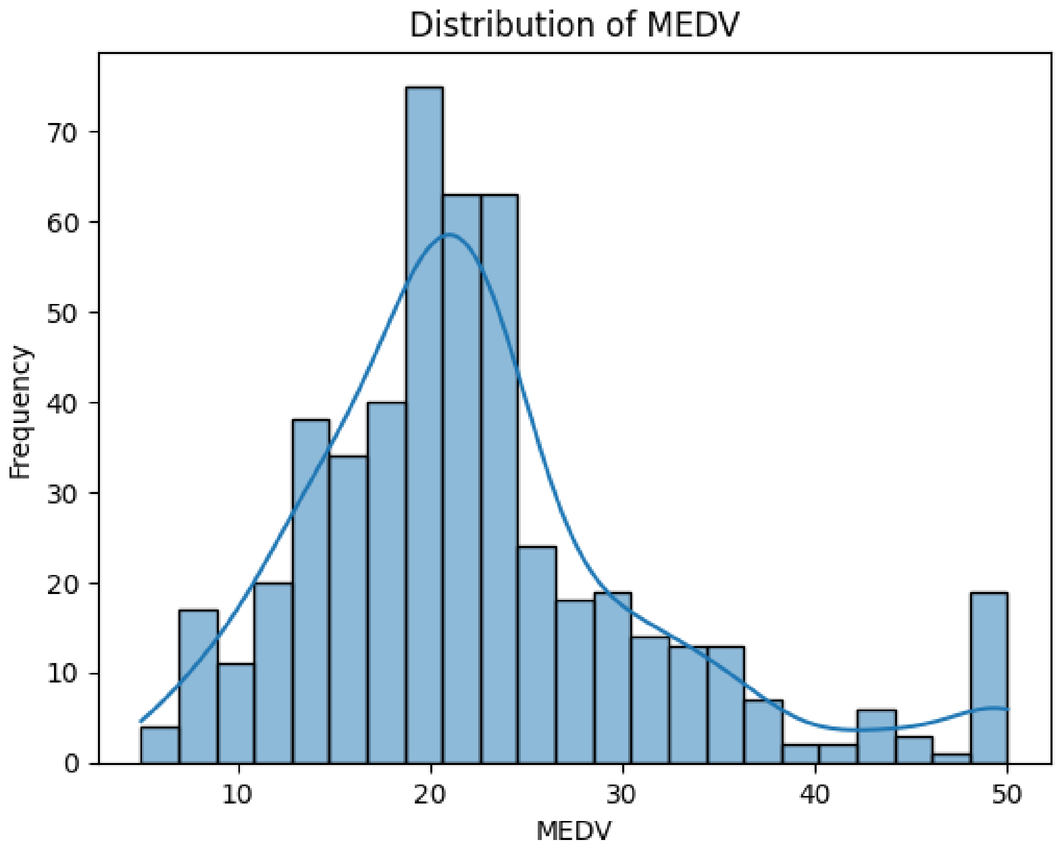
[20]:
```
#Correlation matrix

correlation_matrix = data.corr().round(2)
sns.heatmap(data=correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```



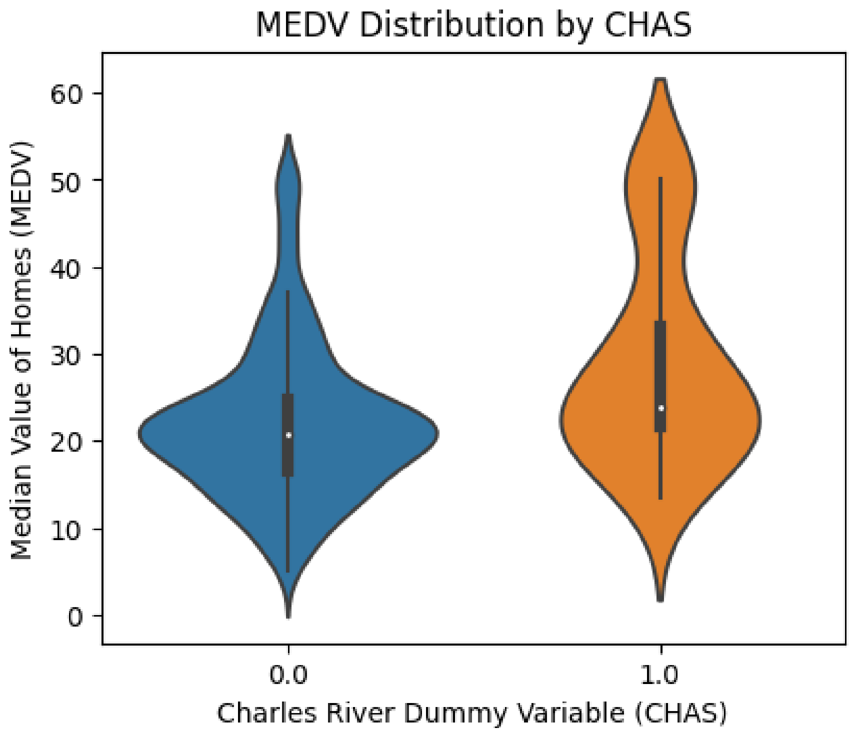
[21]:

```
# Histogram for Medv

sns.histplot(data['MEDV'], kde=True)
plt.xlabel('MEDV')
plt.ylabel('Frequency')
plt.title('Distribution of MEDV')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning:
use_inf_as_na option is deprecated and will be removed in a future version.
Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

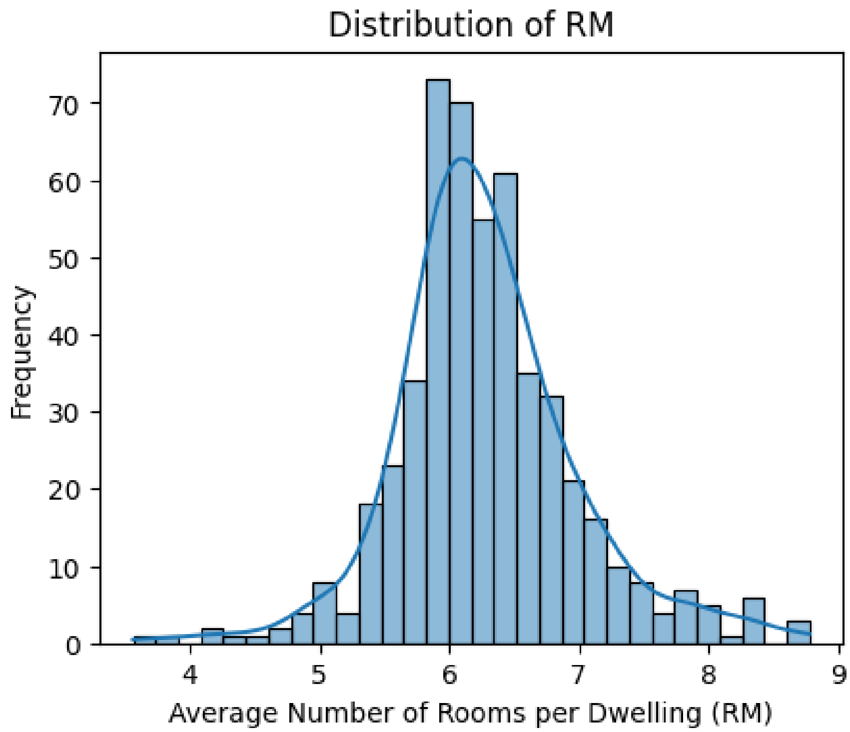


[22]:
```
# Violin plot for Medv and CHAS

plt.figure(figsize=(5,4))
sns.violinplot(x='CHAS', y='MEDV', data=data)
plt.title('MEDV Distribution by CHAS')
plt.xlabel('Charles River Dummy Variable (CHAS)')
plt.ylabel('Median Value of Homes (MEDV)')
plt.show()
```

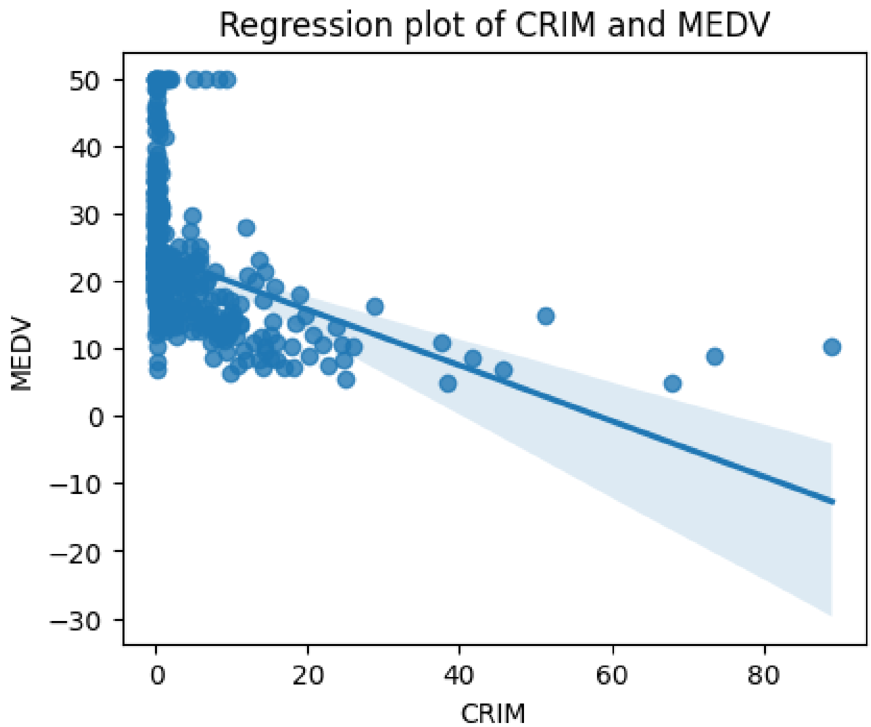


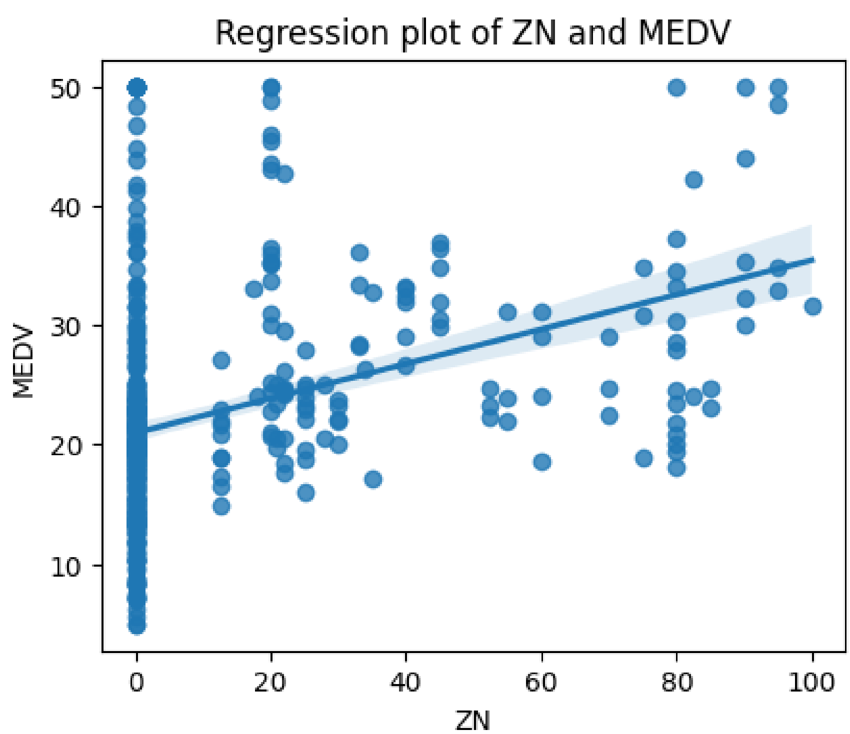
[23]:
```
# Histogram of RM

plt.figure(figsize=(5,4))
sns.histplot(data['RM'], bins=30, kde=True)
plt.title('Distribution of RM')
plt.xlabel('Average Number of Rooms per Dwelling (RM)')
plt.ylabel('Frequency')
plt.show()
```

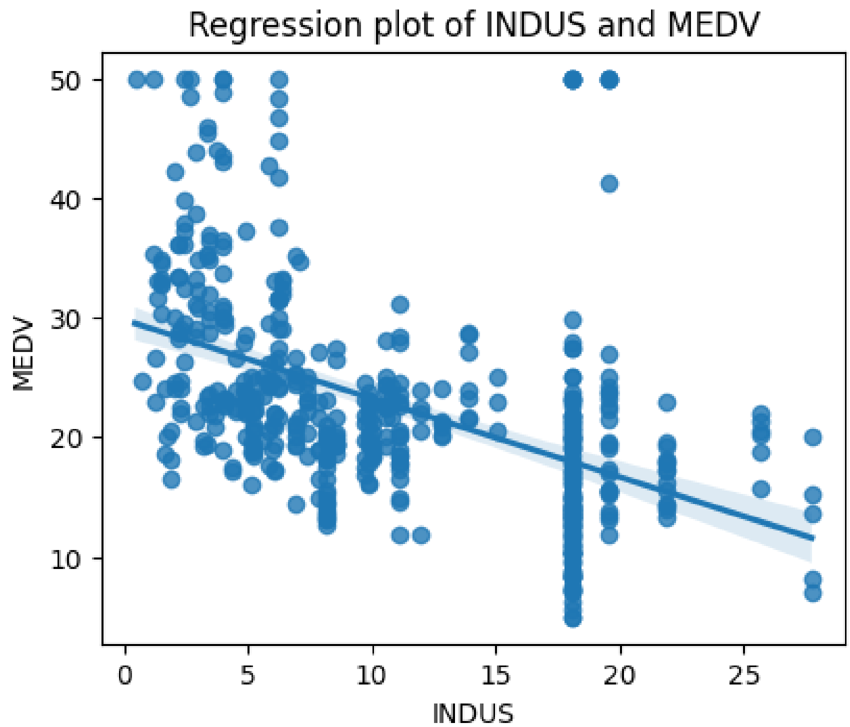
```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning:
use_inf_as_na option is deprecated and will be removed in a future version.
Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

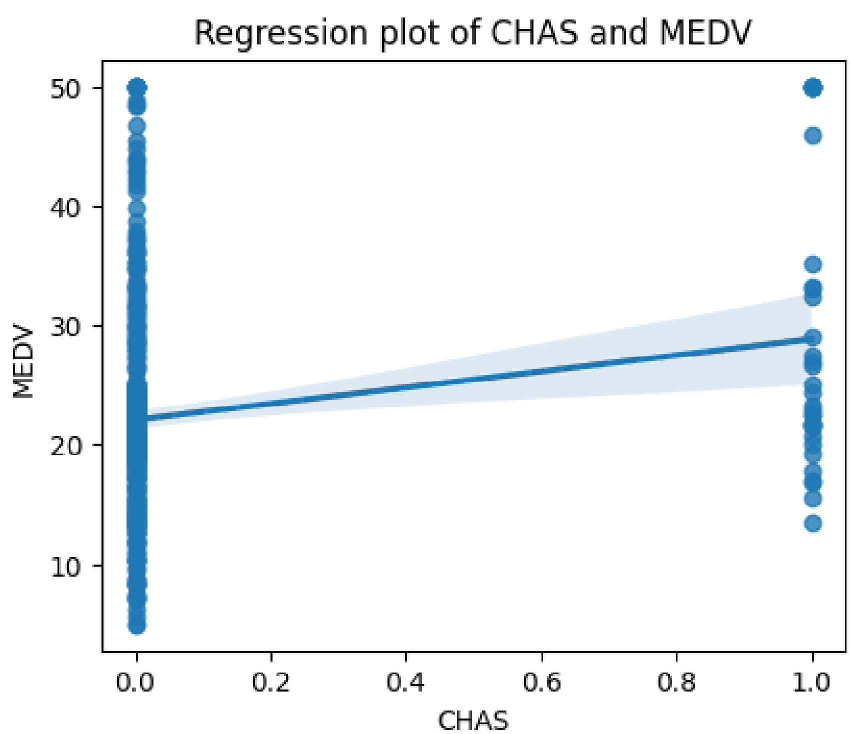


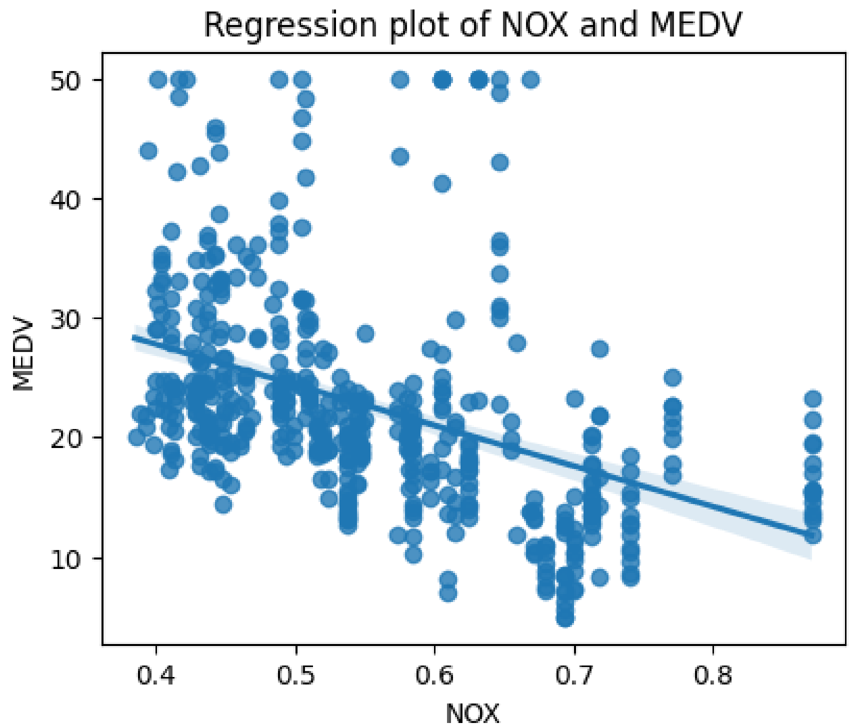
[24]:
```
# Relationship between Average house price and other Features

for column in data.columns[:-1]:
    plt.figure(figsize=(5,4))
    sns.regplot(x=data[column], y=data['MEDV'])
    plt.title(f'Regression plot of {column} and MEDV')
    plt.xlabel(column)
    plt.ylabel('MEDV')
    plt.show()
```


Regression plot of CRIM and MEDV
MEDV
CRIM
50
40
30
20
10
0
−10
−20
−30
0
20
40
60
80

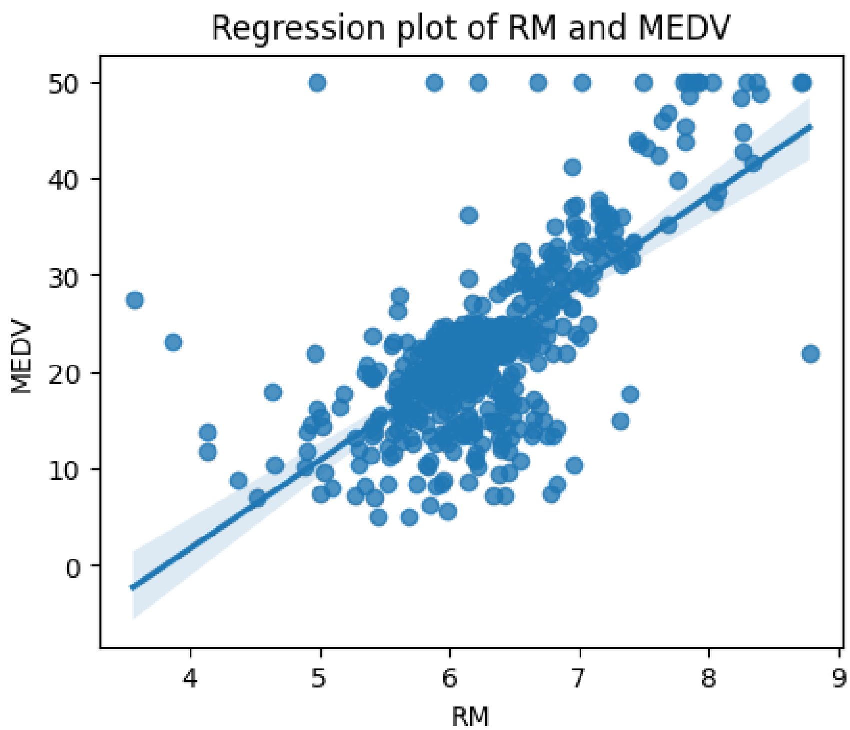

Regression plot of ZN and MEDV
MEDV
ZN
50
40
30
20
10
0
20
40
60
80
100


Regression plot of INDUS and MEDV
MEDV
INDUS
50
40
30
20
10
0
5
10
15
20
25

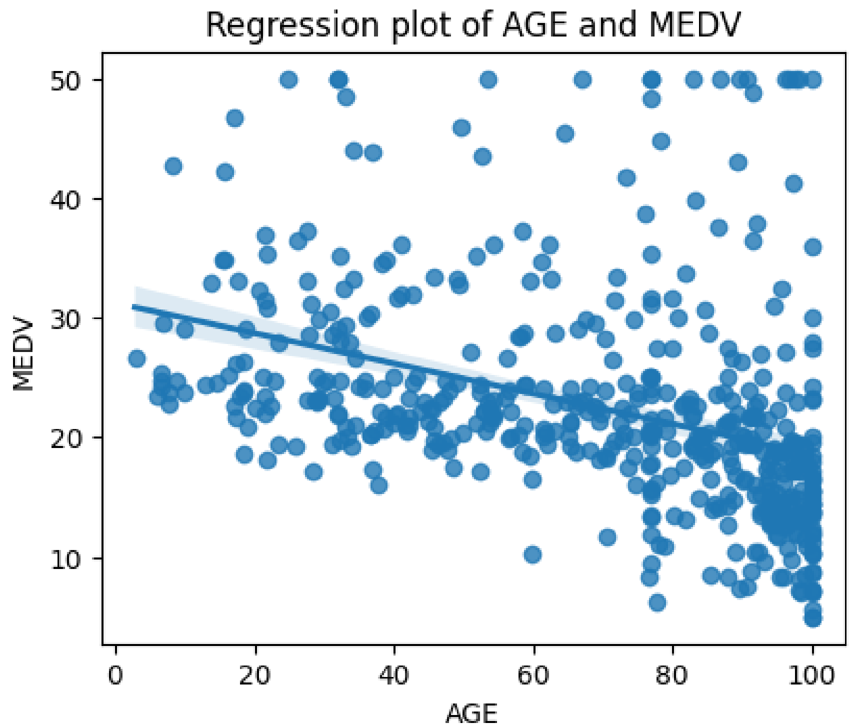

Regression plot of CHAS and MEDV
MEDV
CHAS
50
40
30
20
10
0.0
0.2
0.4
0.6
0.8
1.0

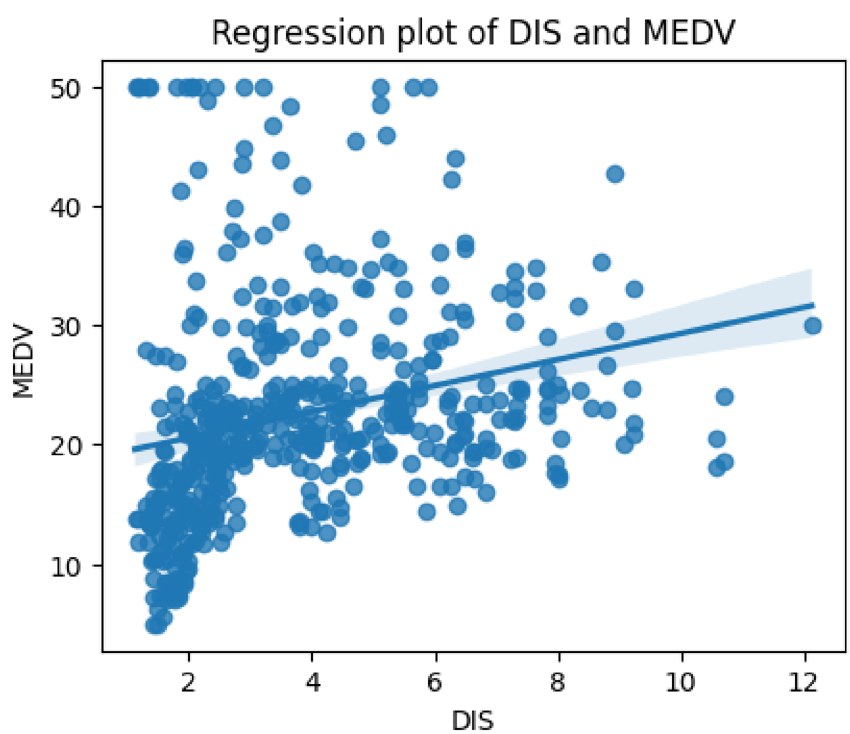


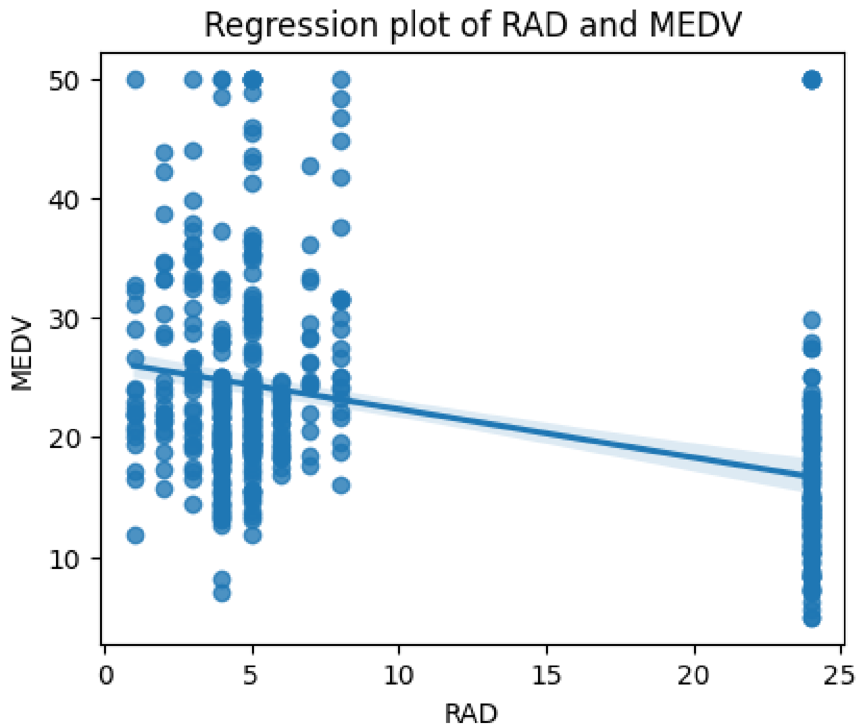
Regression plot of NOX and MEDV
MEDV
NOX
50
40
30
20
10
0.4
0.5
0.6
0.7
0.8

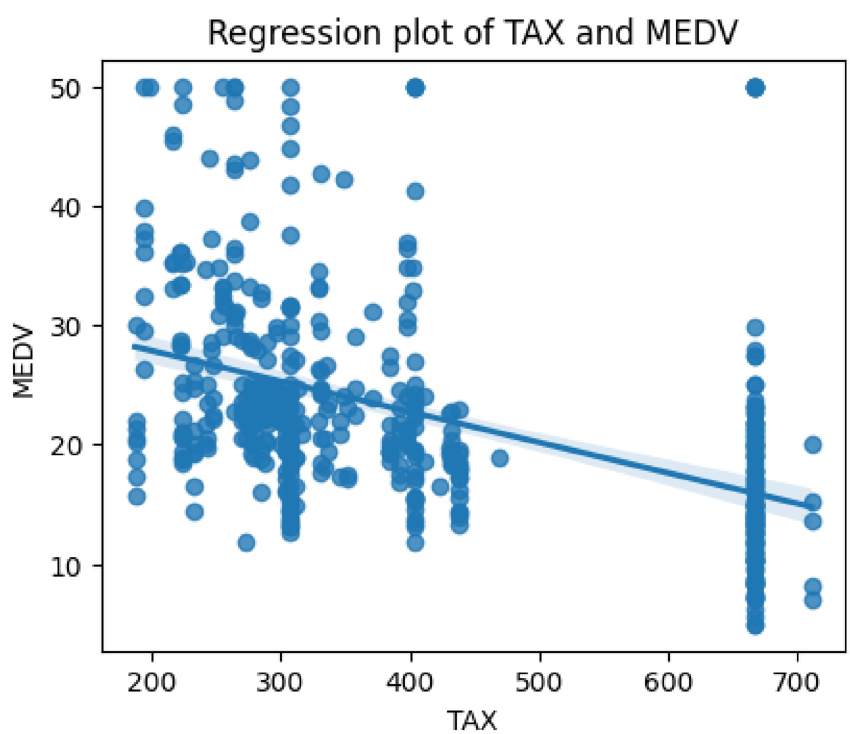


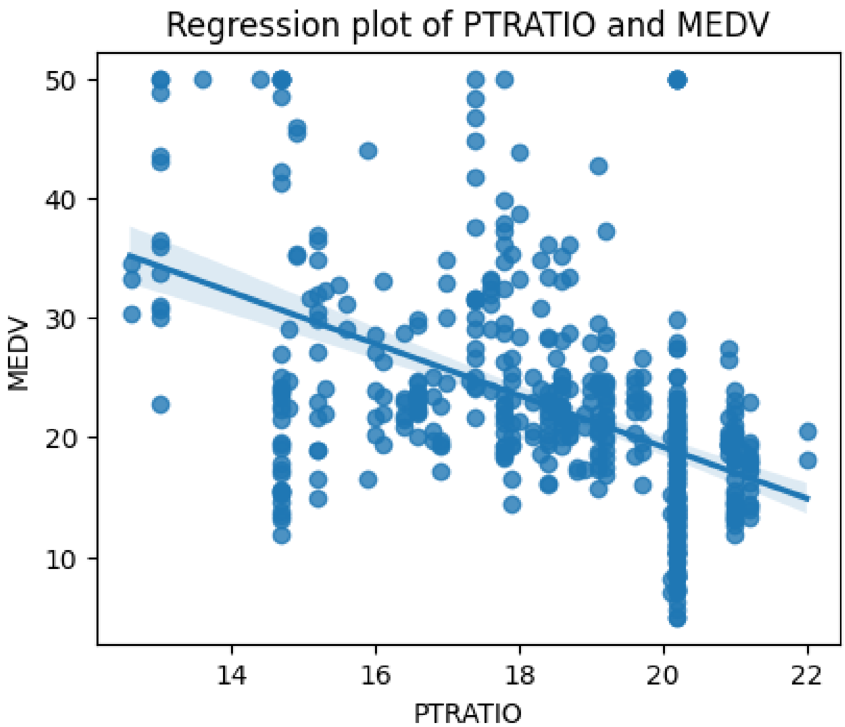
Regression plot of RM and MEDV
MEDV
RM
50
40
30
20
10
0
4
5
6
7
8
9

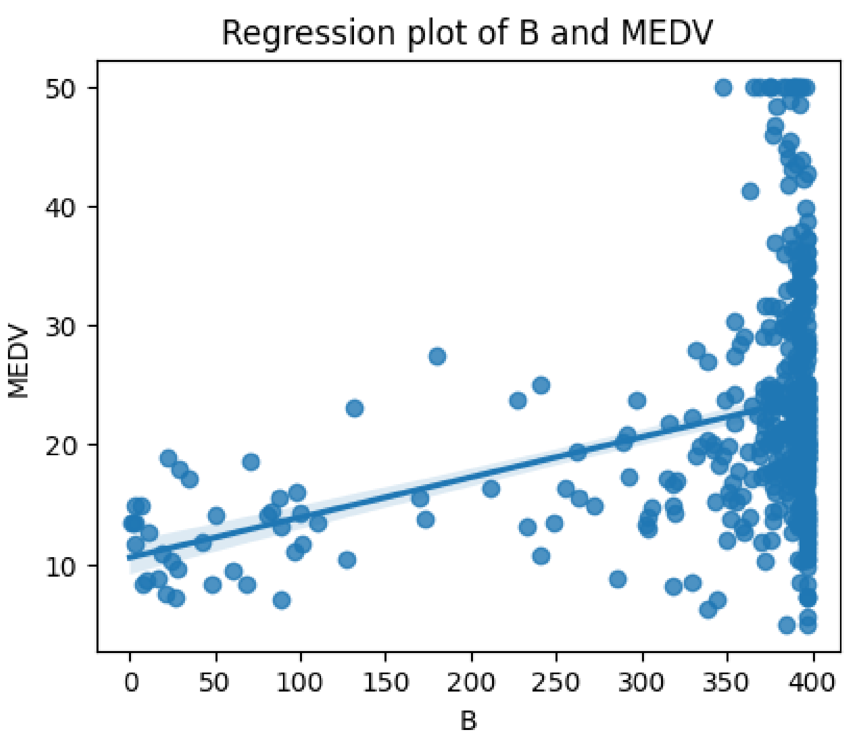

Regression plot of AGE and MEDV
MEDV
AGE
50
40
30
20
10
0
20
40
60
80
100

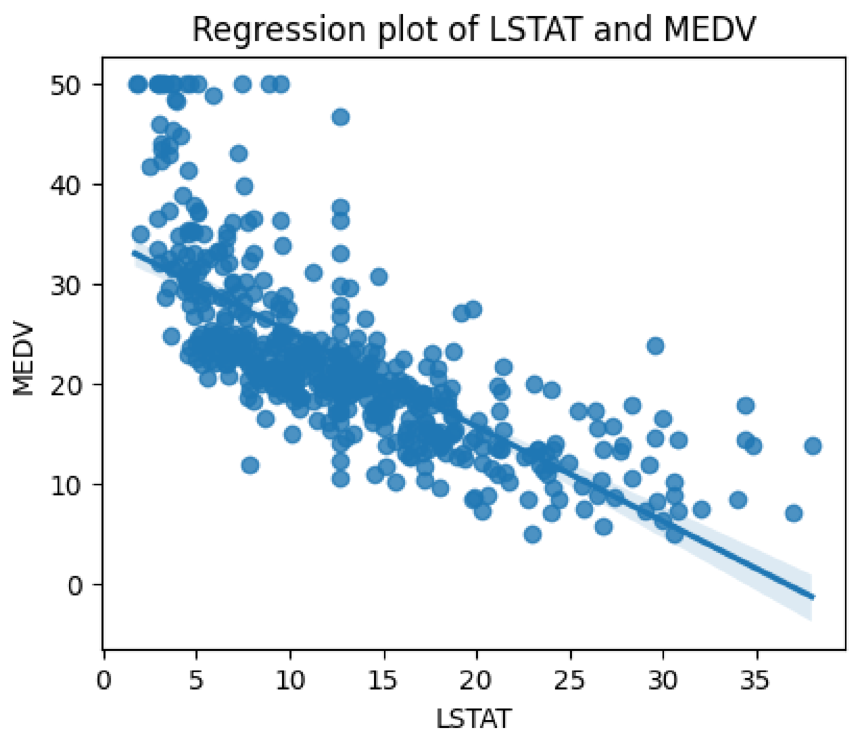

Regression plot of DIS and MEDV
MEDV
DIS
50
40
30
20
10
2
4
6
8
10
12


Regression plot of RAD and MEDV
MEDV
RAD
50
40
30
20
10
0
5
10
15
20
25


Regression plot of TAX and MEDV
MEDV
TAX
50
40
30
20
10
200
300
400
500
600
700

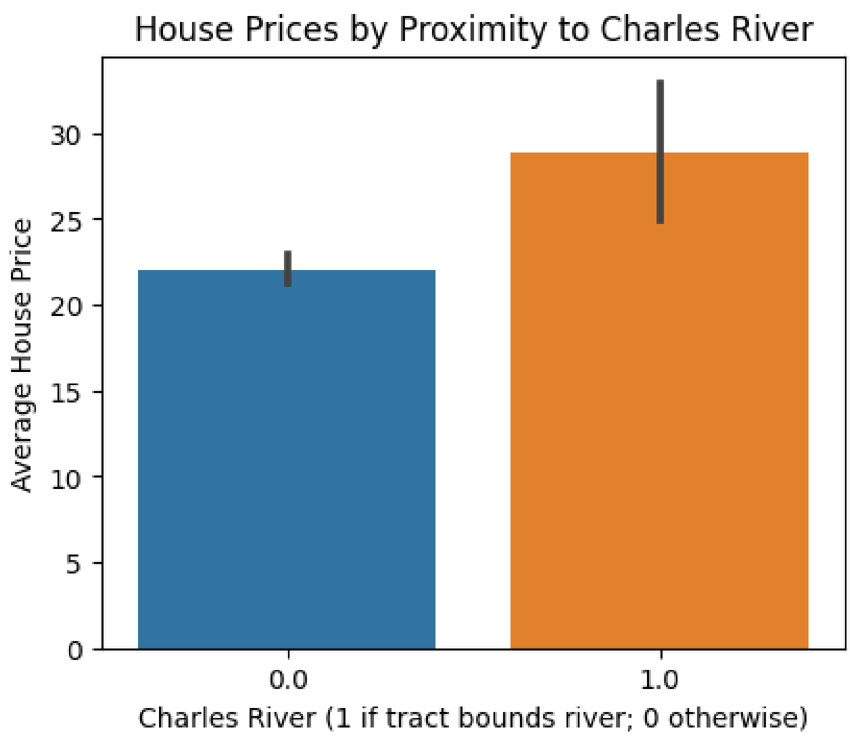

Regression plot of PTRATIO and MEDV
MEDV
PTRATIO
50
40
30
20
10
14
16
18
20
22


Regression plot of B and MEDV
MEDV
B
50
40
30
20
10
0
50
100
150
200
250
300
350
400

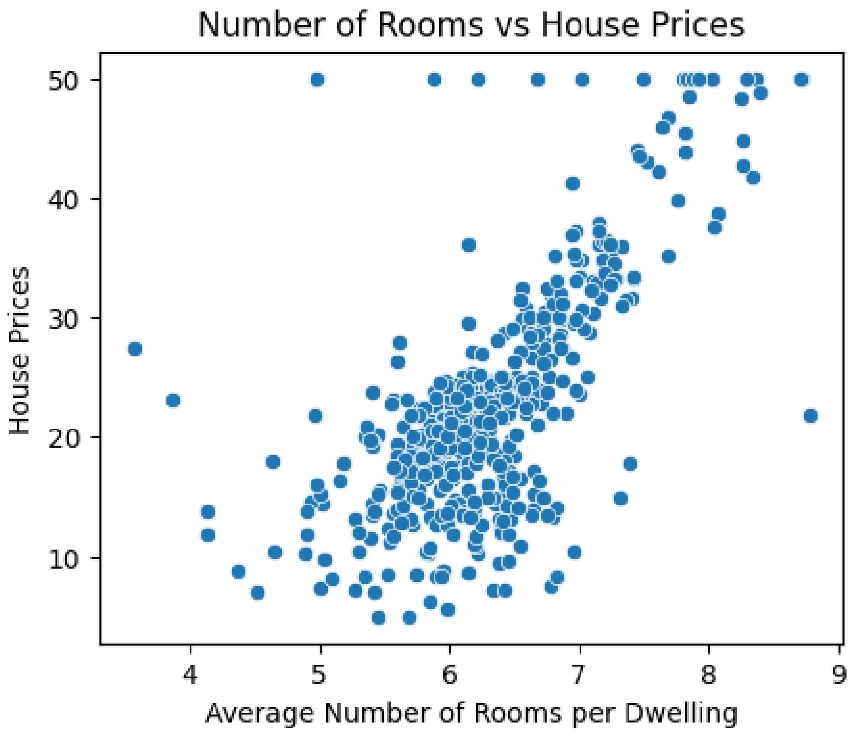


[25]:

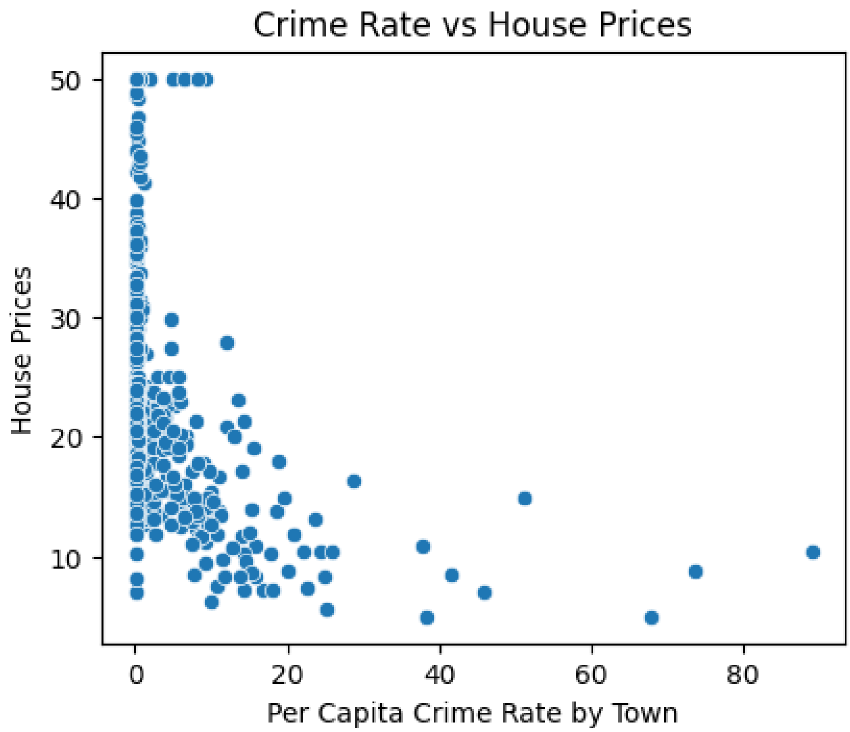
```
# Average house prices by proximity to the Charles River

plt.figure(figsize=(5,4))
sns.barplot(x='CHAS', y='MEDV', data=data)
plt.title('House Prices by Proximity to Charles River')
plt.xlabel('Charles River (1 if tract bounds river; 0 otherwise)')
plt.ylabel('Average House Price')
plt.show()
```



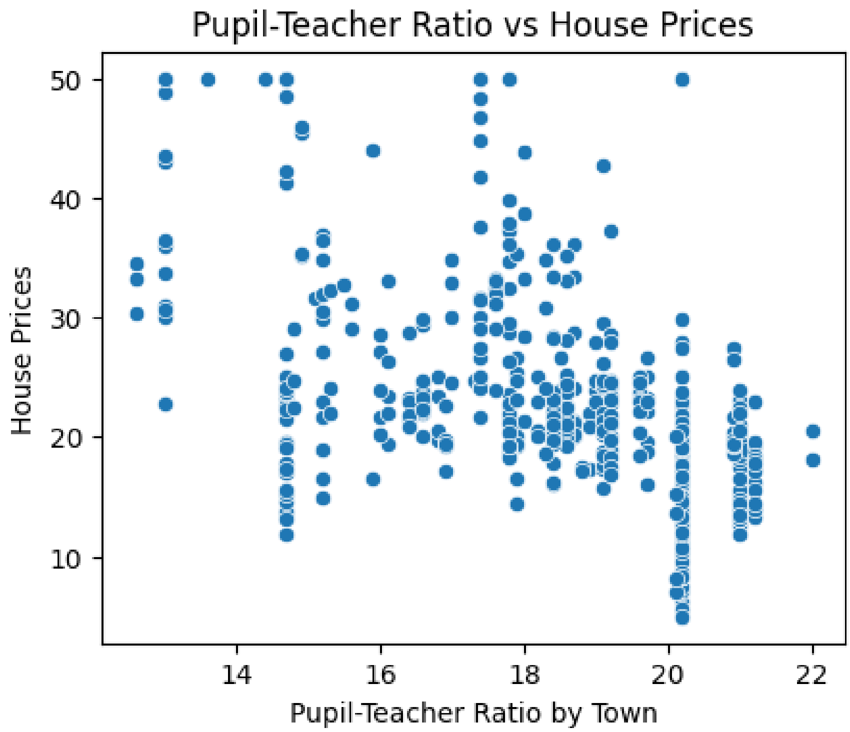
[26]:
```
# Relationship between RM (average number of rooms per dwelling) and MEDV␣
↪(house price)

plt.figure(figsize=(5,4))
sns.scatterplot(x='RM', y='MEDV',data=data)
plt.title('Number of Rooms vs House Prices')
plt.xlabel('Average Number of Rooms per Dwelling')
plt.ylabel('House Prices')
plt.show()
```



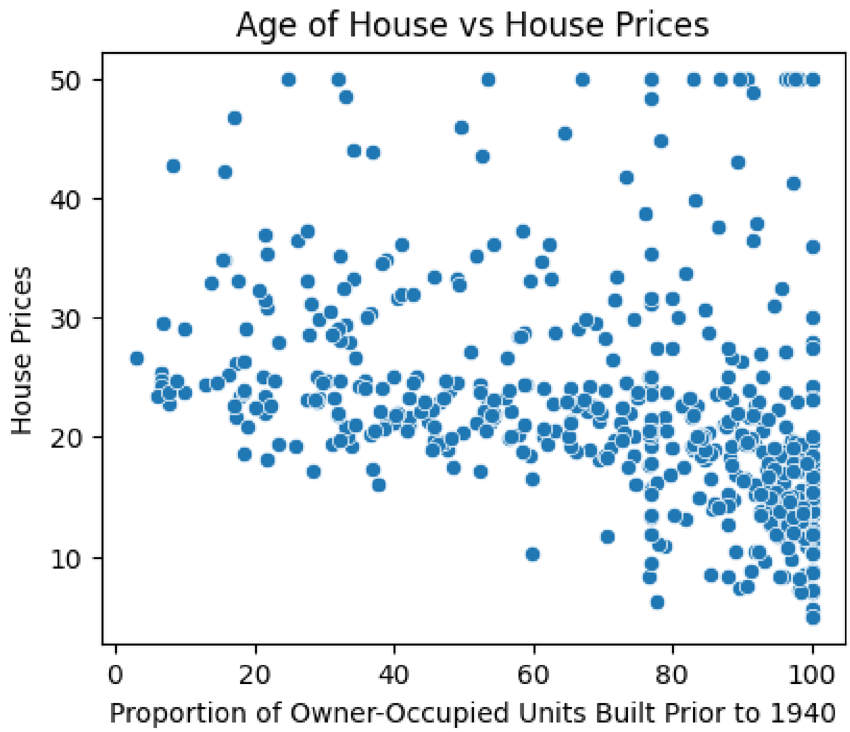
[27]:
```
# Relationship between CRIM (per capita crime rate by town) and MEDV (house␣
↪price)

plt.figure(figsize=(5,4))
sns.scatterplot(x='CRIM', y='MEDV', data=data)
plt.title('Crime Rate vs House Prices')
plt.xlabel('Per Capita Crime Rate by Town')
plt.ylabel('House Prices')
plt.show()
```



[28]:
```
# Relationship between PTRATIO (pupil-teacher ratio by town) and MEDV (house␣
↪price)

plt.figure(figsize=(5,4))
sns.scatterplot(x='PTRATIO', y='MEDV', data=data)
plt.title('Pupil-Teacher Ratio vs House Prices')
plt.xlabel('Pupil-Teacher Ratio by Town')
plt.ylabel('House Prices')
plt.show()
```



[29]:
```
# Relationship between AGE and Aerage house price

plt.figure(figsize=(5,4))
sns.scatterplot(x='AGE', y='MEDV', data=data)
plt.title('Age of House vs House Prices')
plt.xlabel('Proportion of Owner-Occupied Units Built Prior to 1940')
plt.ylabel('House Prices')
plt.show()
```



Building Machine Learning Models

[30]:
```
# Splitting data for Training and Testing

x = data.drop('MEDV', axis=1)
y = data['MEDV']
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪random_state=42)
```

[31]:
```
# Simple Linear Regression Model

model = LinearRegression()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
```

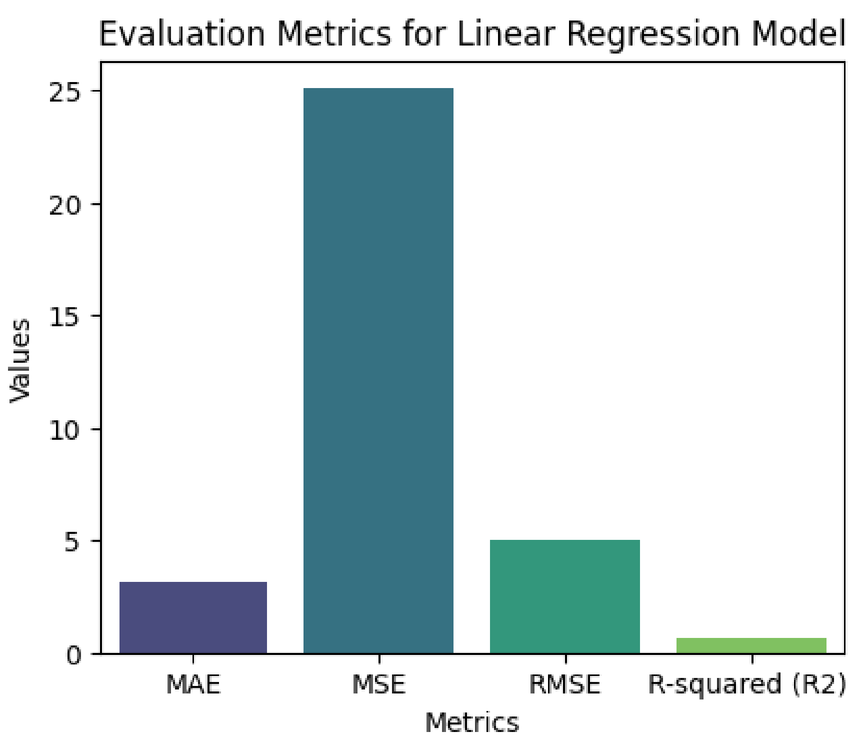
[32]:
```
# Model Evaluationing

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

[33]:
```python
print(f'Mean Absolute Error (MAE): {mae}')
print(f'Mean Squared Error (MSE): {mse}')
print(f'Root Mean Squared Error (RMSE): {rmse}')
print(f'R-squared (R2): {r2}')
```

```
Mean Absolute Error (MAE): 3.1584994146197096
Mean Squared Error (MSE): 25.072290196306753
Root Mean Squared Error (RMSE): 5.007223801300153
R-squared (R2): 0.6581072308584777
```

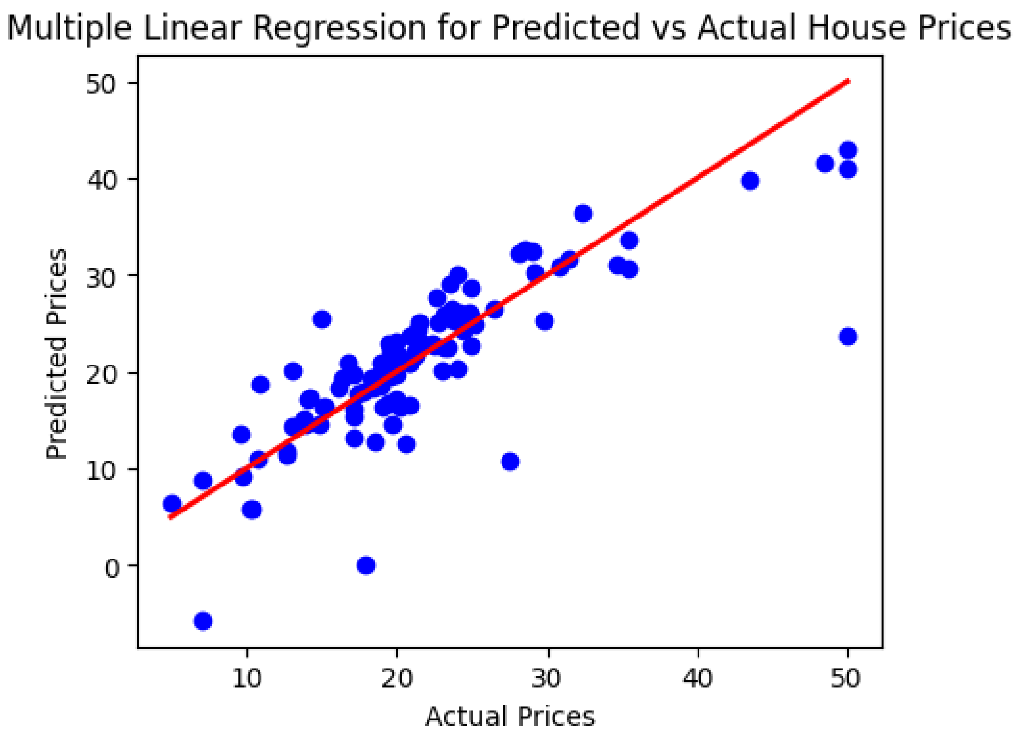
[34]:
```python
#Evaluation metrics for Linear Regression Model

metrics = {'MAE': mae, 'MSE': mse, 'RMSE': rmse, 'R-squared (R2) ': r2}
metric_names = list(metrics.keys())
metric_values = list(metrics.values())
plt.figure(figsize=(5,4))
sns.barplot(x=metric_names, y=metric_values, palette='viridis')
plt.title('Evaluation Metrics for Linear Regression Model')
plt.xlabel('Metrics')
plt.ylabel('Values')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1765: FutureWarning:
unique with argument that is not not a Series, Index, ExtensionArray, or
np.ndarray is deprecated and will raise in a future version.
  order = pd.unique(vector)
```



[35]:

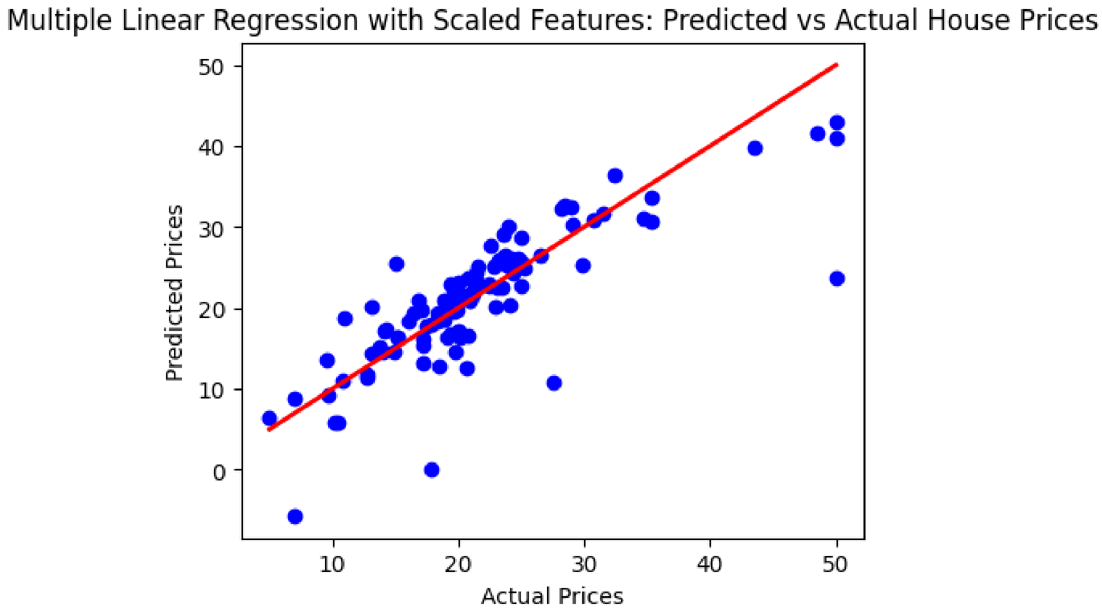
```
# Multiple Linear Regression

plt.figure(figsize=(5,4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
↪linewidth=2)
plt.title('Multiple Linear Regression for Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```



[36]:

```
#Scaling the features

plt.figure(figsize=(5,4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
↪linewidth=2)
plt.title('Multiple Linear Regression with Scaled Features: Predicted vs Actual␣
↪House Prices')
plt.xlabel('Actual Prices')
```

```
plt.ylabel('Predicted Prices')
plt.show()
```

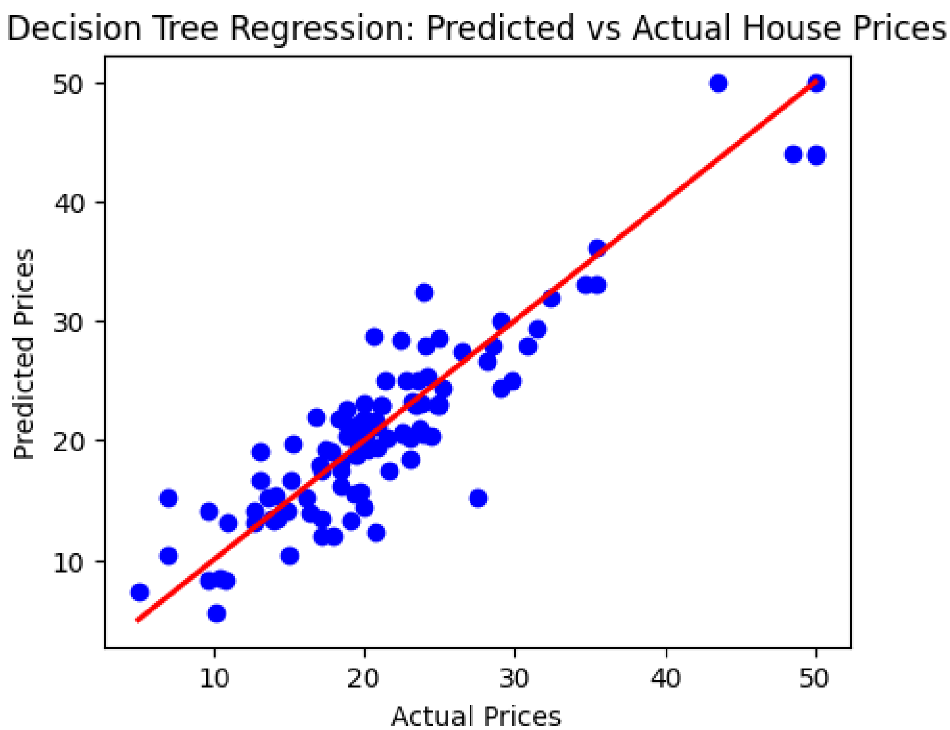


[37]:
```
#predict house prices using a Decision Tree Regressor

from sklearn.tree import DecisionTreeRegressor

tree_model = DecisionTreeRegressor(random_state=42)
tree_model.fit(x_train, y_train)
y_pred = tree_model.predict(x_test)

print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R-squared (R2) Score:", r2_score(y_test, y_pred))
```

```
Mean Squared Error: 12.571274509803924
R-squared (R2) Score: 0.8285745809360402
```

[38]:
```
# Decision Tree Regression for predicted and Actual Prices

plt.figure(figsize=(5,4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
↪linewidth=2)
plt.title('Decision Tree Regression: Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
```

```
plt.show()
```



[39]:

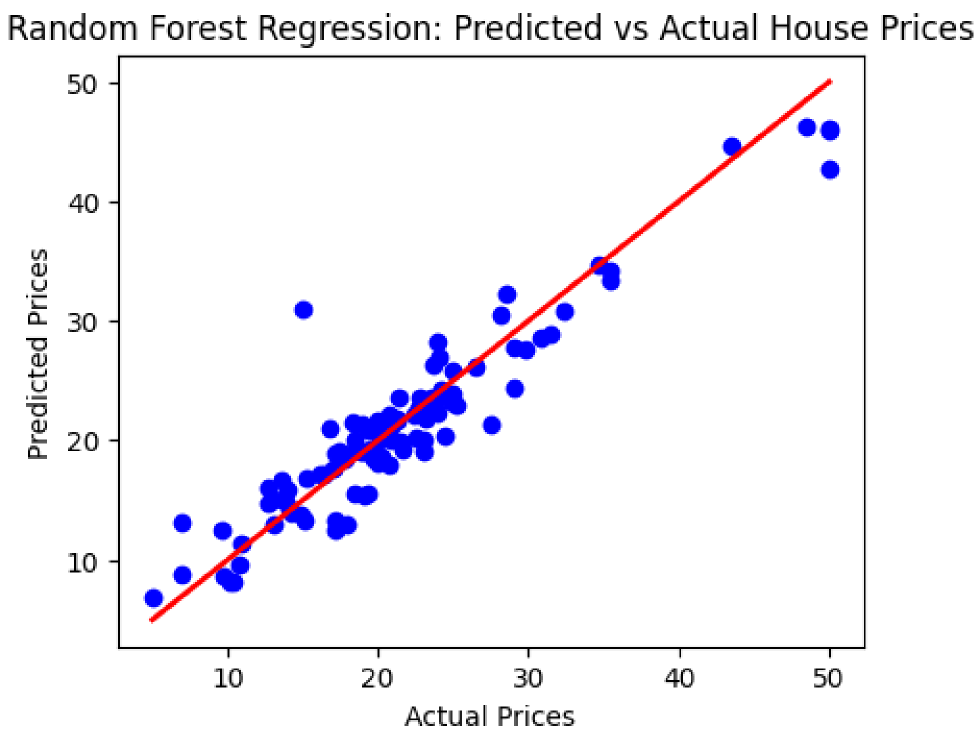
```
#predict house prices using a Random Forest Regressor

from sklearn.ensemble import RandomForestRegressor

forest_model = RandomForestRegressor(random_state=42, n_estimators=100)
forest_model.fit(x_train, y_train)
y_pred = forest_model.predict(x_test)

print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R-squared (R2) Score:", r2_score(y_test, y_pred))
```

```
Mean Squared Error: 8.278940480392155
R-squared (R2) Score: 0.8871060495775506
```

[40]:

```
# Random Forest Regession for Predicted and Actual prices

plt.figure(figsize=(5,4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
↪linewidth=2)
plt.title('Random Forest Regression: Predicted vs Actual House Prices')
```

```
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```

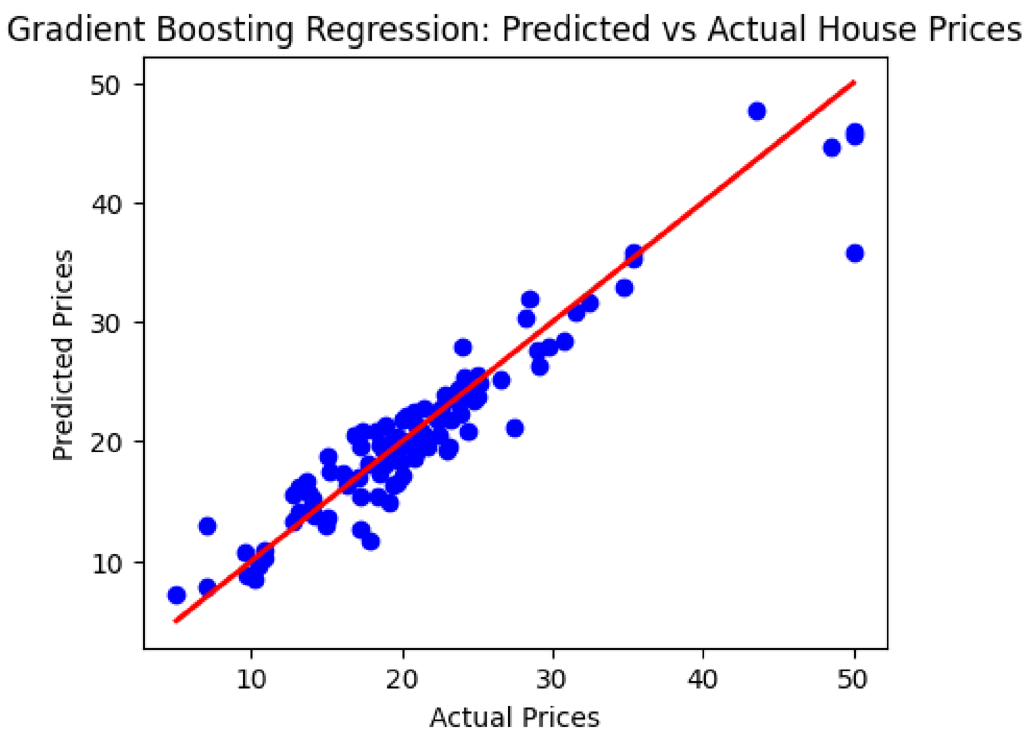


[41]:
```
# predict house prices using a Gradient Boosting Regressor

from sklearn.ensemble import GradientBoostingRegressor

gb_model = GradientBoostingRegressor(random_state=42, n_estimators=100)
gb_model.fit(x_train, y_train)
y_pred = gb_model.predict(x_test)

print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R-squared (R2) Score:", r2_score(y_test, y_pred))
```

```
Mean Squared Error: 7.155319376730123
R-squared (R2) Score: 0.9024280615512894
```

[42]:
```
# Gradient Boosting Regession for Predicted and Actual prices

plt.figure(figsize=(5,4))
plt.scatter(y_test, y_pred, color='blue')
```

```
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
 ↪linewidth=2)
plt.title('Gradient Boosting Regression: Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```



[43]:

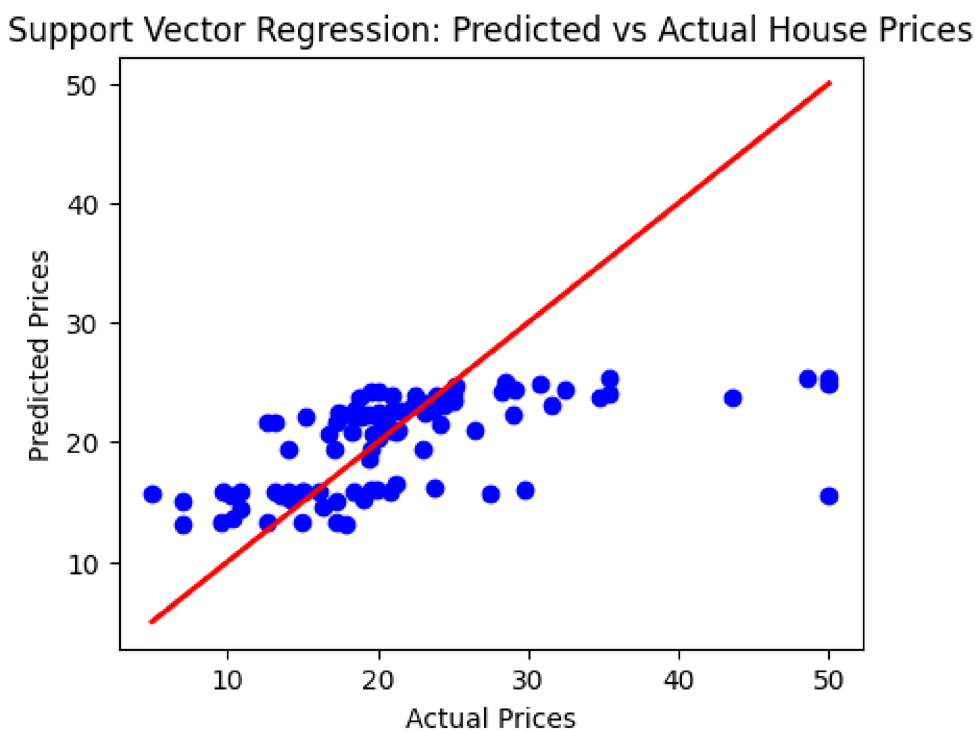
```
#predict house prices using a Support Vector Regressor

from sklearn.svm import SVR

svr_model = SVR(kernel='rbf')
svr_model.fit(x_train, y_train)
y_pred = svr_model.predict(x_test)

print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R-squared (R2) Score:", r2_score(y_test, y_pred))
```

```
Mean Squared Error: 52.931033106567114
R-squared (R2) Score: 0.2782176123267932
```

[44]:

```
# Support Vector Regession for Predicted and Actual prices
```

```
plt.figure(figsize=(5,4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
 ↪linewidth=2)
plt.title('Support Vector Regression: Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```

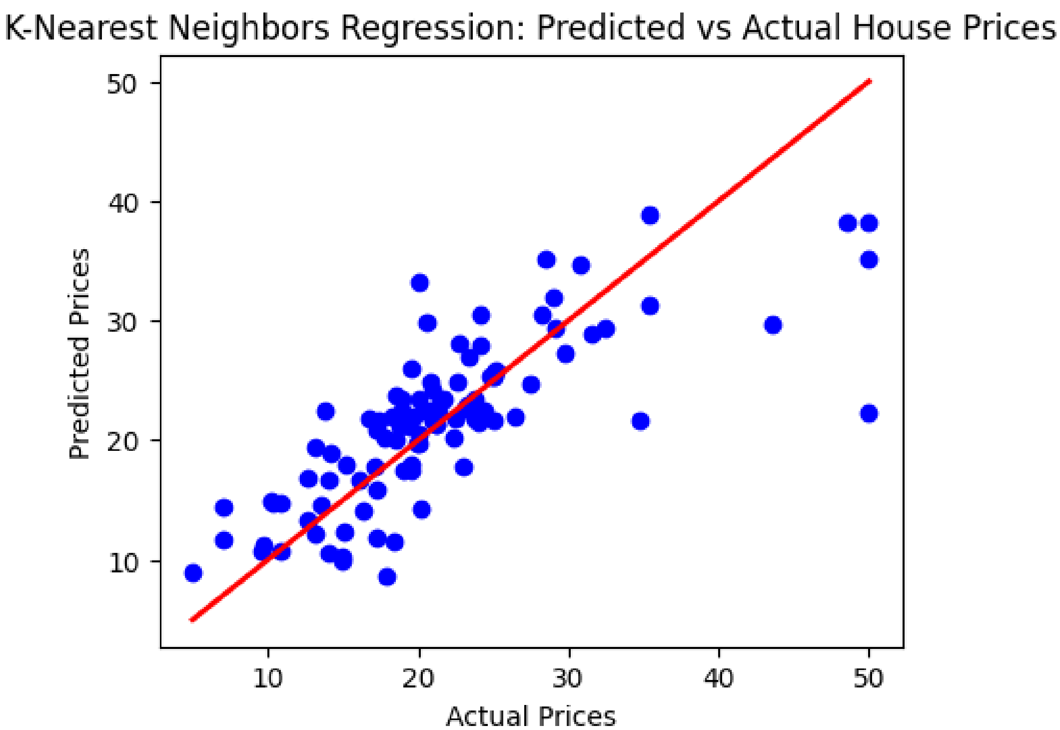


[45]:
```
#predict house prices using a K-Nearest Neighbors Regressor

from sklearn.neighbors import KNeighborsRegressor

knn_model = KNeighborsRegressor(n_neighbors=5)
knn_model.fit(x_train, y_train)
y_pred = knn_model.predict(x_test)

print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R-squared (R2) Score:", r2_score(y_test, y_pred))
```

```
Mean Squared Error: 29.704478431372554
R-squared (R2) Score: 0.5949414151124269
```

[46]:

```
# K-Nearest Neighbors Regession for Predicted and Actual prices

plt.figure(figsize=(5,4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
 ↪linewidth=2)
plt.title('K-Nearest Neighbors Regression: Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```



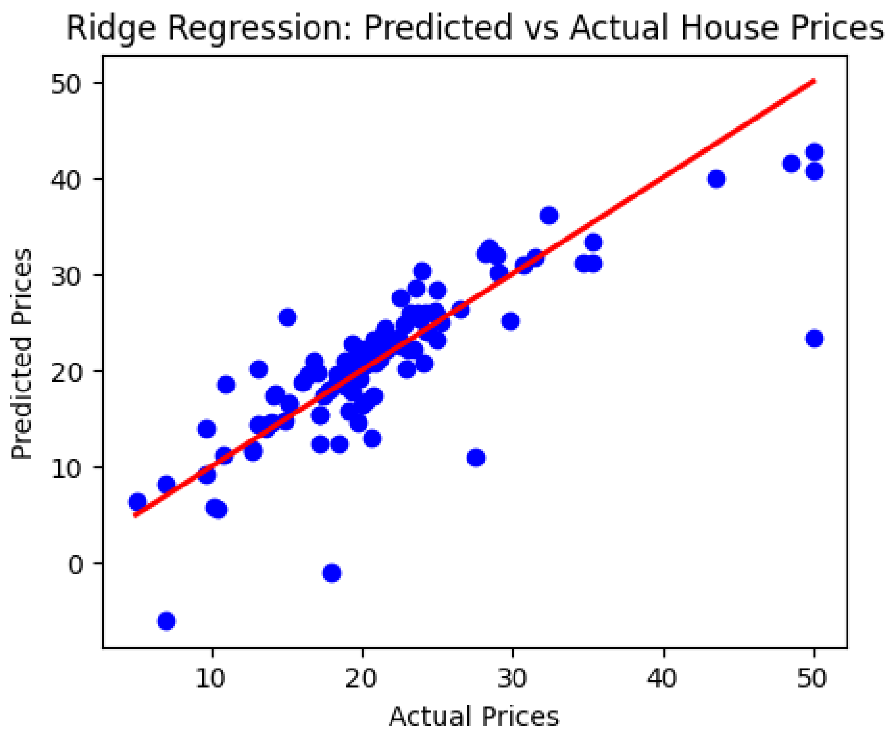
[47]:

```
# predict house prices using Ridge Regression
from sklearn.linear_model import Ridge

ridge_model = Ridge(alpha=1.0)
ridge_model.fit(x_train, y_train)
y_pred = ridge_model.predict(x_test)

print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R^2 Score:", r2_score(y_test, y_pred))
```

```
Mean Squared Error: 25.2687878117523
R^2 Score: 0.6554277343566272
```

[48]:

```
# Ridge Regression for Predicted and Actual prices

plt.figure(figsize=(5, 4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
↪linewidth=2)
plt.title('Ridge Regression: Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```



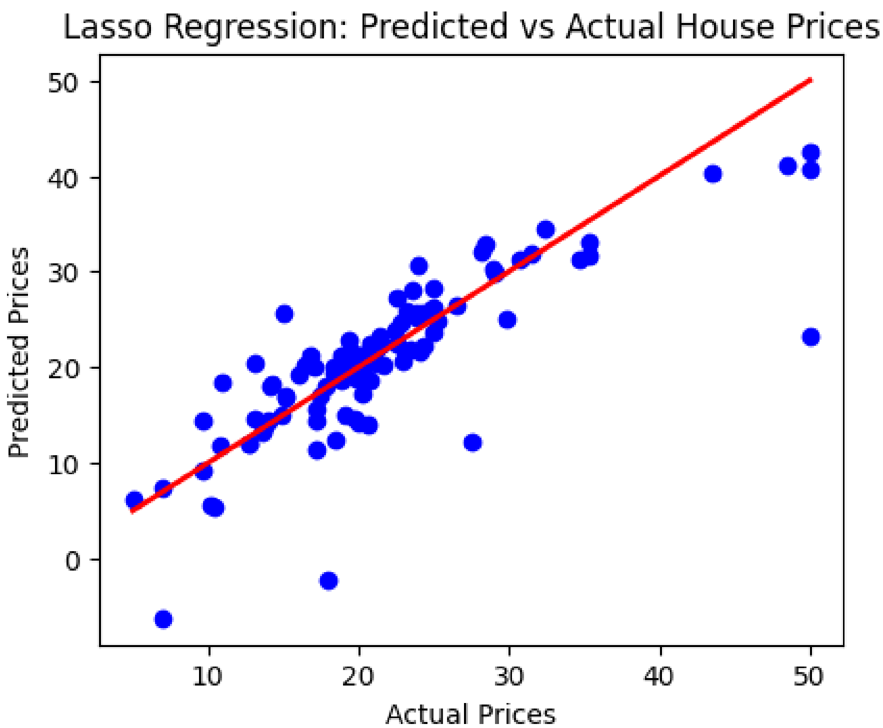
[49]:

```
# predict house prices using Lasso Regression

from sklearn.linear_model import Lasso

lasso_model = Lasso(alpha=0.1)
lasso_model.fit(x_train, y_train)
y_pred = lasso_model.predict(x_test)

print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R^2 Score:", r2_score(y_test, y_pred))
```

```
Mean Squared Error: 25.72864216726899
```

```
R^2 Score: 0.6491570316095543
```

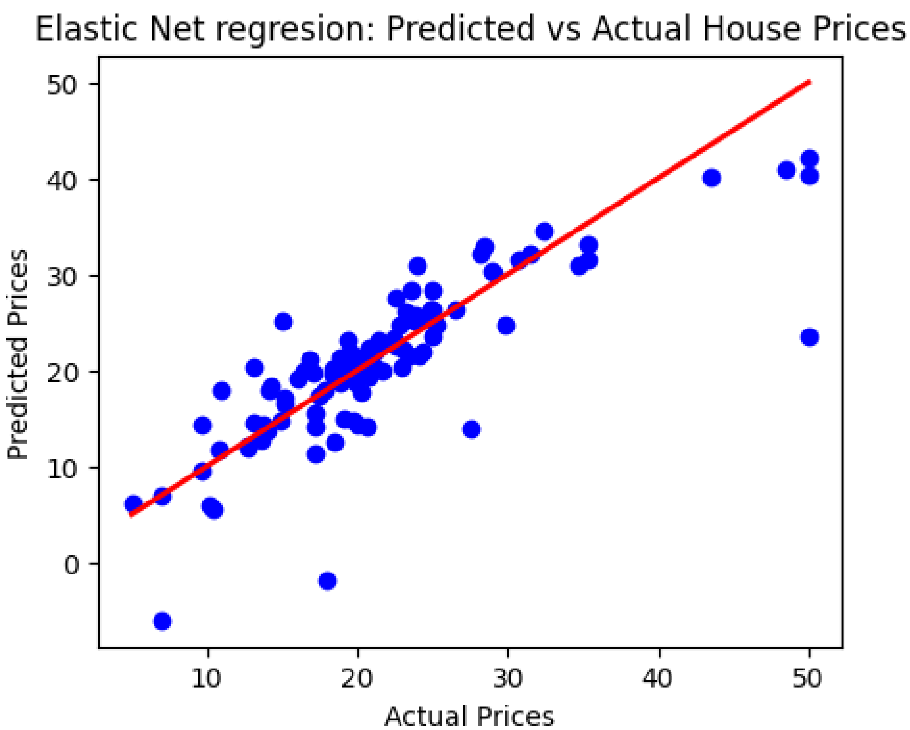
[50]:
```
# Lasso Regession for Predicted and Actual prices

plt.figure(figsize=(5, 4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
 ↪linewidth=2)
plt.title('Lasso Regression: Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```



[51]:
```
# predict house prices using Elastic Net Regression

from sklearn.linear_model import ElasticNet

elastic_model = ElasticNet(alpha=0.1, l1_ratio=0.5)
elastic_model.fit(x_train, y_train)
y_pred = elastic_model.predict(x_test)

print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R^2 Score:", r2_score(y_test, y_pred))
```

```
Mean Squared Error: 24.91093992270312
R^2 Score: 0.6603074483660197
```

[52]:
```
# Elastic Net Regession for Predicted and Actual prices

plt.figure(figsize=(5, 4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',
  linewidth=2)
plt.title('Elastic Net regresion: Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```

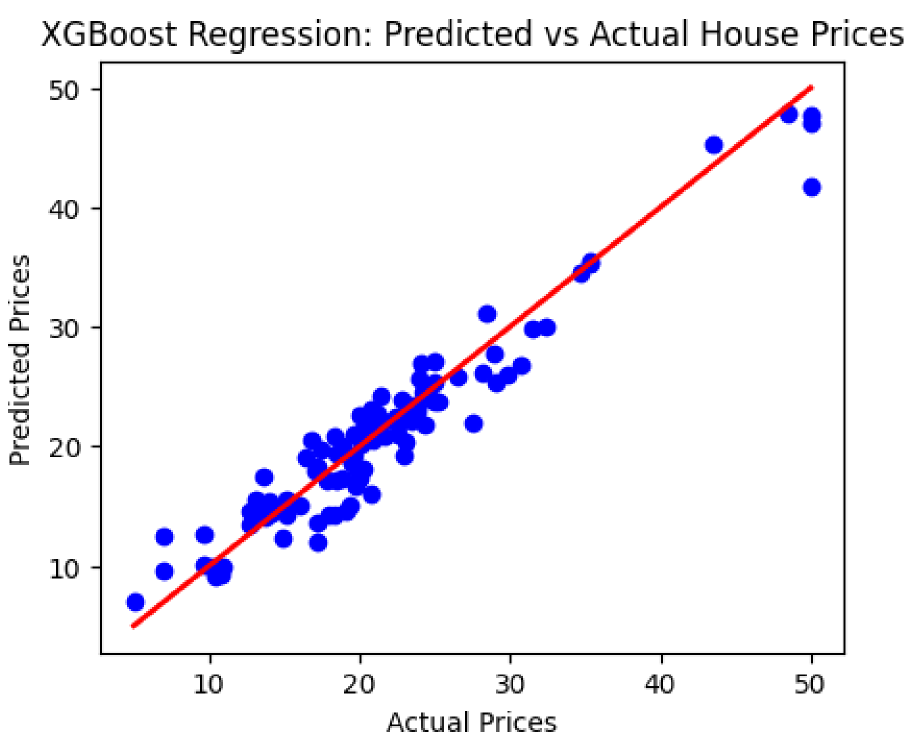


[53]:
```
# predict house prices using XGBoost Regressor

import xgboost as xgb

xgb_model = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=100,
  random_state=42)
xgb_model.fit(x_train, y_train)
y_pred = xgb_model.predict(x_test)
```

```python
print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R^2 Score:", r2_score(y_test, y_pred))
```

```
Mean Squared Error: 5.537024472117028
R^2 Score: 0.9244955839791882
```

[54]:
```python
# XGBoost Regession for Predicted and Actual prices

plt.figure(figsize=(5,4))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',
 ↪linewidth=2)
plt.title('XGBoost Regression: Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```

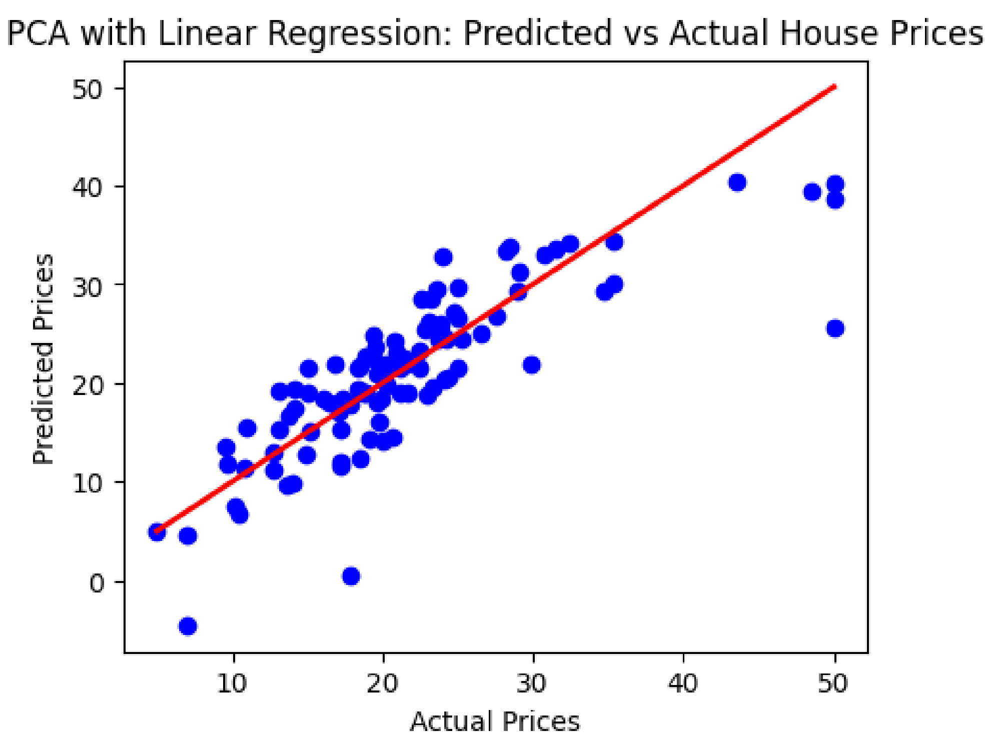


[55]:
```python
# PCA for Dimensionality Reduction

from sklearn.decomposition import PCA

pca = PCA(n_components=10)
x_pca = pca.fit_transform(x)
```

```
xp_train, xp_test, yp_train, yp_test = train_test_split(x_pca, y, test_size=0.
 ↪2, random_state=42)

linear_model = LinearRegression()
linear_model.fit(xp_train, yp_train)
yp_pred = linear_model.predict(xp_test)

print("Mean Squared Error:", mean_squared_error(yp_test, yp_pred))
print("R^2 Score:", r2_score(yp_test, yp_pred))
```

```
Mean Squared Error: 24.264297405017974
R^2 Score: 0.6691252467914937
```

[56]:
```
# PCA for Predicted and Actual prices

plt.figure(figsize=(5,4))
plt.scatter(yp_test, yp_pred, color='blue')
plt.plot([min(yp_test), max(yp_test)], [min(yp_test), max(yp_test)],␣
 ↪color='red', linewidth=2)
plt.title('PCA with Linear Regression: Predicted vs Actual House Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```



[57]:

```
# compare the performance of different models

from sklearn.model_selection import cross_val_score

models = {
    'Linear Regression': LinearRegression(),
    'Decision Tree': DecisionTreeRegressor(random_state=42),
    'Random Forest': RandomForestRegressor(random_state=42, n_estimators=100),
    'Gradient Boosting': GradientBoostingRegressor(random_state=42,␣
 ↪n_estimators=100),
    'Support Vector Regressor': SVR(kernel='rbf')
}

# Compare models using cross-validation
results = {}
for model_name, model in models.items():
    cv_scores = cross_val_score(model, x, y, cv=5, scoring='r2')
    results[model_name] = cv_scores

# Print the results
for model_name, cv_scores in results.items():
    print(f"{model_name}: Mean R-squared (R2) Score = {np.mean(cv_scores):.3f},␣
 ↪Std = {np.std(cv_scores):.3f}")

# Dictionary to store evaluation metrics
evaluation_metrics = {
    'Model': [],
    'MAE': [],
    'MSE': [],
    'RMSE': [],
    'R-Squared': []
}

# Train and evaluate each model
for name, model in models.items():
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)

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

    evaluation_metrics['Model'].append(name)
    evaluation_metrics['MAE'].append(mae)
```

```
    evaluation_metrics['MSE'].append(mse)
    evaluation_metrics['RMSE'].append(rmse)
    evaluation_metrics['R-Squared'].append(r2)
```

```
Linear Regression: Mean R-squared (R2) Score = 0.340, Std = 0.392
Decision Tree: Mean R-squared (R2) Score = 0.221, Std = 0.476
Random Forest: Mean R-squared (R2) Score = 0.633, Std = 0.177
Gradient Boosting: Mean R-squared (R2) Score = 0.675, Std = 0.112
Support Vector Regressor: Mean R-squared (R2) Score = -0.093, Std = 0.283
```

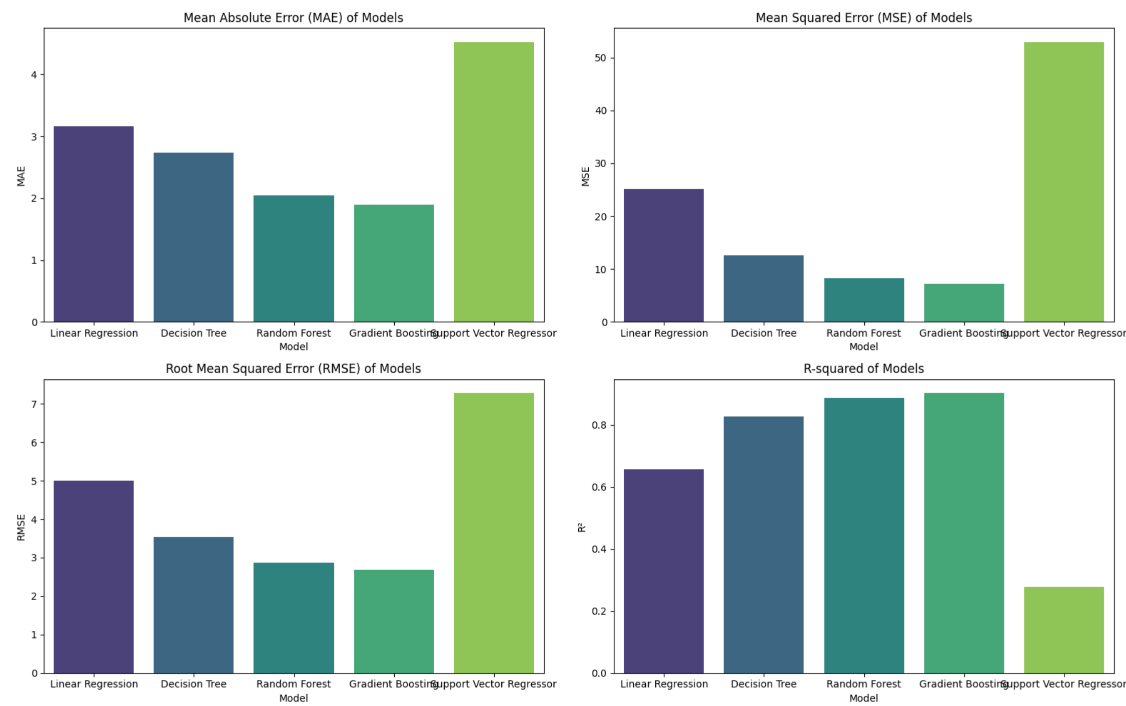
[58]:
```
# Convert the evaluation metrics dictionary to a DataFrame
evaluation_df = pd.DataFrame(evaluation_metrics)
evaluation_df
```

[58]:

	Model	MAE	MSE	RMSE	R-Squared
0	Linear Regression	3.158499	25.072290	5.007224	0.658107
1	Decision Tree	2.732353	12.571275	3.545599	0.828575
2	Random Forest	2.050010	8.278940	2.877315	0.887106
3	Gradient Boosting	1.899569	7.155319	2.674943	0.902428
4	Support Vector Regressor	4.524912	52.931033	7.275372	0.278218

[59]:
```
# Plot all evaluation metrics
fig, axs = plt.subplots(2, 2, figsize=(16,10))

# MAE plot
sns.barplot(x='Model', y='MAE', data=evaluation_df, palette='viridis',␣
 ↪ax=axs[0, 0])
axs[0, 0].set_title('Mean Absolute Error (MAE) of Models')
axs[0, 0].set_xlabel('Model')
axs[0, 0].set_ylabel('MAE')

# MSE plot
sns.barplot(x='Model', y='MSE', data=evaluation_df, palette='viridis',␣
 ↪ax=axs[0, 1])
axs[0, 1].set_title('Mean Squared Error (MSE) of Models')
axs[0, 1].set_xlabel('Model')
axs[0, 1].set_ylabel('MSE')

# RMSE plot
sns.barplot(x='Model', y='RMSE', data=evaluation_df, palette='viridis',␣
 ↪ax=axs[1, 0])
axs[1, 0].set_title('Root Mean Squared Error (RMSE) of Models')
axs[1, 0].set_xlabel('Model')
axs[1, 0].set_ylabel('RMSE')

# R² plot
```

```
sns.barplot(x='Model', y='R-Squared', data=evaluation_df, palette='viridis',␣
↪ax=axs[1, 1])
axs[1, 1].set_title('R-squared of Models')
axs[1, 1].set_xlabel('Model')
axs[1, 1].set_ylabel('R²')

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



[60]:
```
# Clustering the data using KMeans Clustering

from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3, random_state=42)
data['Cluster'] = kmeans.fit_predict(x)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

[61]:
```
# Visualize the Clustered Data using K-Means Clustering
custom_palette = ['#000000', '#00FF00','#0000FF']
plt.figure(figsize=(5,4))
```

```
sns.scatterplot(x='RM', y='MEDV', hue='Cluster', palette=custom_palette,␣
 ↪data=data)
plt.title('KMeans Clustering: Neighborhoods')
plt.xlabel('Average Number of Rooms per Dwelling')
plt.ylabel('House Prices')
plt.show()
```