House Price Prediction 🏠 💰

- **Dataset**: The Boston Housing Dataset
- **Source**: https://www.kaggle.com/datasets/vikrishnan/boston-house-prices/data (https://www.kaggle.com/datasets/vikrishnan/boston-house-prices/data)

The Boston Housing Dataset:-

The Boston Housing Dataset is a derived from information collected by the U.S. Census Service concerning housing in the area of Boston MA.

In [2380]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics
import seaborn as sns
%matplotlib inline
import sklearn.linear_model
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import r2_score
from sklearn.decomposition import PCA
from sklearn.model_selection import cross_val_score
```

In [2263]:
```
dataset=pd.read_csv('Random-Boston-house-price-data.csv')
dataset.head(5)
```

Out[2263]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
0	2.81838	0.0	18.10	0	0.532	5.762	40.3	4.0983	24	666.0	20.2	392.92	10.42	21.8
1	0.25915	0.0	21.89	0	0.624	5.693	96.0	1.7883	4	437.0	21.2	392.11	17.19	16.2
2	0.08826	0.0	10.81	0	0.413	6.417	6.6	5.2873	4	305.0	19.2	383.73	6.72	24.2
3	0.04684	0.0	3.41	0	0.489	6.417	66.1	3.0923	2	270.0	17.8	392.18	8.81	22.6
4	0.03551	25.0	4.86	0	0.426	6.167	46.7	5.4007	4	281.0	19.0	390.64	7.51	22.9

In [2266]:
```
# Display the shape of dataset
dataset.shape
```

Out[2266]: (506, 14)

The following describes the dataset columns:

1. **CRIM (Per Capita Crime Rate by Town)**
   This column shows how much crime occurs in a town, adjusted for the number of people living there.
   Example:
   - A lower value like `0.00632` means the crime rate is very low.
   - A higher value like `10.5` would indicate a higher crime rate.

---

2. **ZN (Proportion of Residential Land Zoned for Large Lots)**
   This measures how much of the town's land is used for big houses (over 25,000 square feet).
   Example:
   - A value of `18.0` means 18% of the town is reserved for large residential lots.
   - A value of `0.0` means no land is zoned for such houses.

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3. **INDUS (Proportion of Non-Retail Business Acres)**
   This indicates how much of the town's land is used for industries and non-shopping businesses.
   Example:
   - A value of `7.07` means 7.07% of the town is industrial.
   - Lower values suggest the town is more residential.

---

4. **CHAS (Charles River Dummy Variable)**
   A binary indicator of whether a town is near the Charles River.
   - `1` = The town touches the river.
   - `0` = The town doesn't touch the river.
   - *Example:**
   - If CHAS = `0`, the town is far from the river.
   - If CHAS = `1`, it may have riverside views or activities.

---

5. **NOX (Nitric Oxides Concentration)**
   This measures air pollution in the town (in parts per 10 million).
   Example:
   - A value of `0.538` means moderate pollution levels.
   - Lower values are healthier, while higher values indicate poor air quality.

---

6. **RM (Average Number of Rooms per Dwelling)**
   The average number of rooms in houses in the town.
   Example:
   - A value of `6.575` means most houses have about 6–7 rooms.
   - Larger values suggest bigger houses.

---

7. **AGE (Proportion of Owner-Occupied Units Built Before 1940)**
   Shows how old the houses are in the town.
   Example:
   - A value of `65.2` means 65.2% of the houses are older than 1940.
   - Higher values suggest the town has many historic or older houses.

---

8. **DIS (Weighted Distance to Boston Employment Centers)**
   Indicates how far a town is from major employment hubs in Boston.
   Example:
   - A value of `4.0900` means the town is moderately far from Boston jobs.
   - Higher values mean the town is further away, while lower values mean it's closer.

---

9. **RAD (Index of Accessibility to Radial Highways)**
   A number showing how easy it is to reach major highways from the town.
   Example:
   - A value of `1` means the town has limited highway access.
   - A higher value like `10` means excellent access to highways.

---

10. **TAX (Property Tax Rate per $10,000)**
    Indicates the tax rate on properties in the town.
    Example:
    - A value of `296.0` means $296 tax for every $10,000 property value.
    - Higher values indicate more expensive areas for property tax.

---

11. **PTRATIO (Pupil-Teacher Ratio by Town)**
    Represents how many students there are per teacher in schools in the town.
    Example:
    - A value of `15.3` means there are about 15 students for every teacher.
    - Lower values suggest smaller class sizes.

---

12. **B (Proportion of Blacks by Town)**
    `Bk` is the proportion of Black residents.
    Example:
    - A value of `396.90` suggests a high proportion of Black residents.
    - Lower values mean fewer Black residents.

---

13. **LSTAT (Percentage of Lower-Status Population)**
    This measures the proportion of the population with a lower socioeconomic status.
    Example:
    - A value of `4.98` means only 4.98% of the population is considered lower-status.
    - Higher values mean a larger lower-status population.

---

14. **PRICE (Median Value of Owner-Occupied Homes)**
    The median home price in the town (in thousands of dollars).
    Example:
    - A value of `24.0` means the median home value is $24,000.
    - Higher values indicate wealthier areas.

In [2267]:
```
# Display the columns name
dataset.columns
```

Out[2267]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'PRICE'],
      dtype='object')
```

In [2268]:
```
# Display the datatype of each column
dataset.dtypes
```

Out[2268]:
```
CRIM       float64
ZN         float64
INDUS      float64
CHAS         int64
NOX        float64
RM         float64
AGE        float64
DIS        float64
RAD          int64
TAX        float64
PTRATIO    float64
B          float64
LSTAT      float64
PRICE      float64
dtype: object
```

In [2269]:
```
# Display the information of dataset
dataset.info()
```

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

In [2270]:
```
# Extract statistical information from dataset
dataset.describe()
```

Out[2270]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO
count	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
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000

In [2271]:
```
# Checking for missing values
dataset.isnull().sum()
```

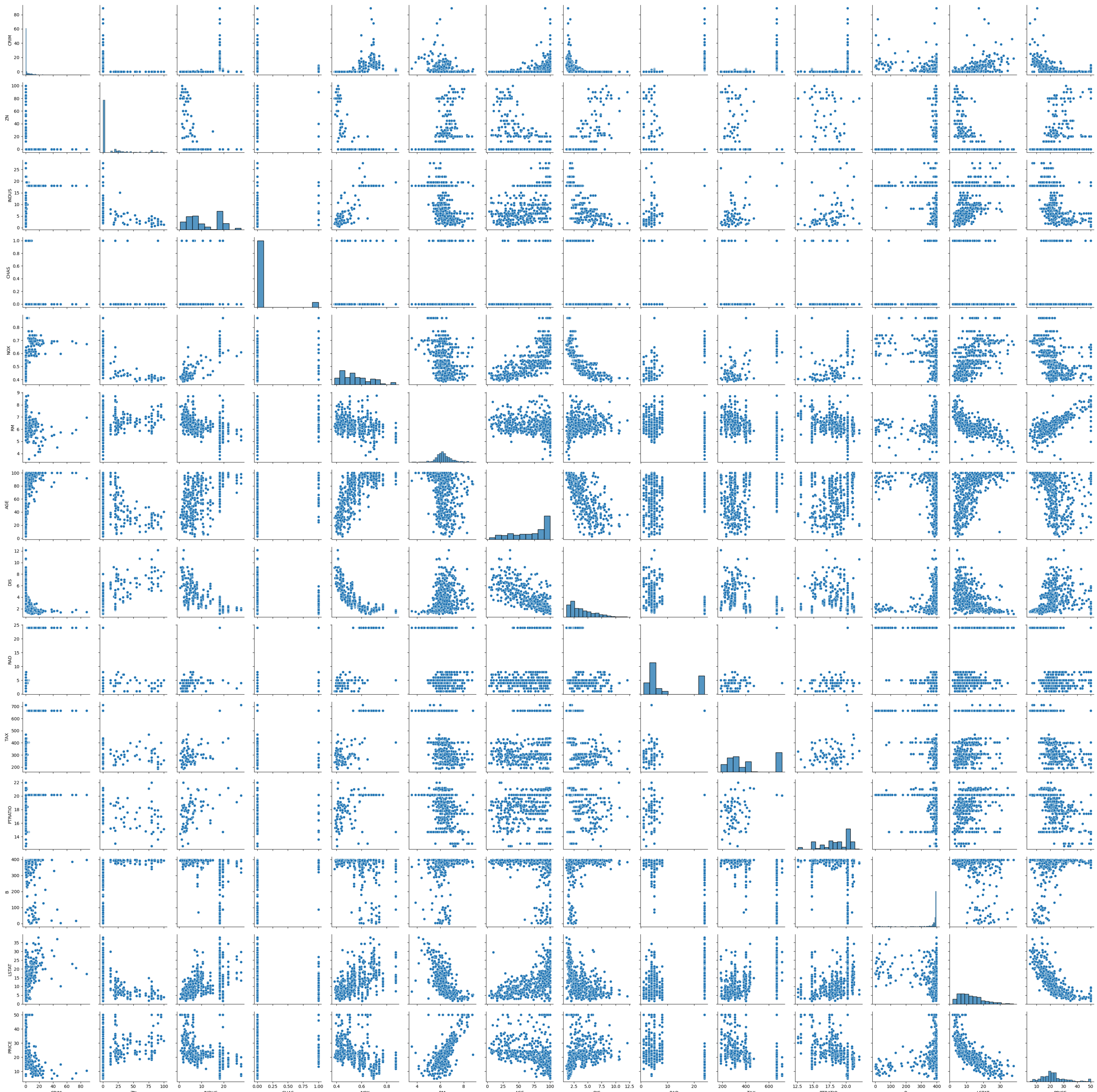
Out[2271]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
PRICE      0
dtype: int64
```

Visual representations (e.g., histogram, scatter plot, etc.) of the dataset.

Pair Plot: The below code output will be a grid of plots where:

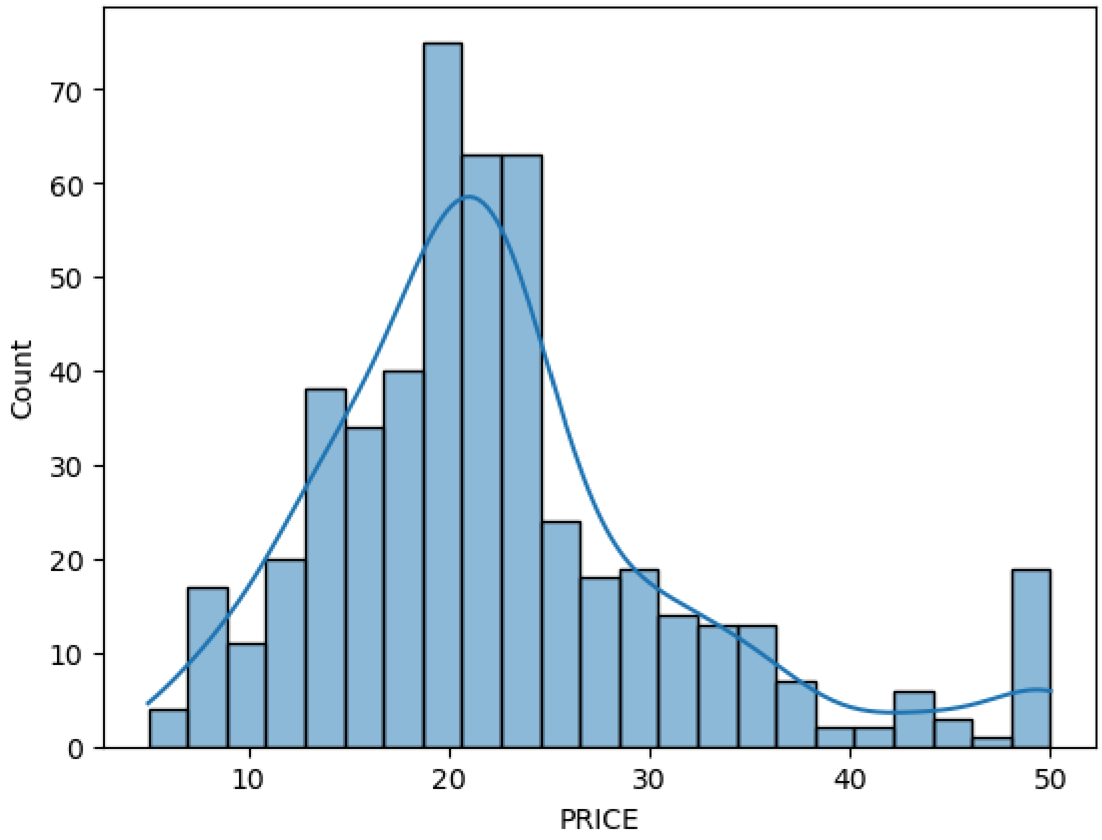
- Each **scatter plot** shows the **relationship between two variables**.
- **Diagonal plots** often display **histograms** or kernel density estimates (KDEs) for individual variables.

In [2406]:
```
sns.pairplot(dataset, height=2.5)
plt.tight_layout()
```



The below lines of code provide insights into the **shape of the distribution of** `PRICE` .

In [2273]:
```
sns.histplot(dataset['PRICE'], kde=True) # KDE=Kernel Density Estimate curve
plt.show()
```



In [2274]:
```
print("Skewness: %f" % dataset['PRICE'].skew())
print("Kurtosis: %f" % dataset['PRICE'].kurt())
```

```
Skewness: 1.108098
Kurtosis: 1.495197
```

What is skewness?: It's measure of the asymmetry of a distribution.

- If the skewness is close to 0, it indicates that the distribution is approximately symmetric.
- A positive skewness (greater than 0) suggests that the distribution has a longer right tail, meaning it is skewed to the right.
- A negative skewness (less than 0) suggests that the distribution has a longer left tail, meaning it is skewed to the left.

Wht is kurtosis?: It's measure the tails and the peakedness of a distribution.

- A kurtosis value of 3 is often considered normal (mesokurtic) and is the kurtosis of a normal distribution.
- Positive kurtosis (greater than 3) indicates heavier tails and a more peaked distribution (leptokurtic).
- Negative kurtosis (less than 3) indicates lighter tails and a flatter distribution (platykurtic).

Data Correlation

Correlation measures the relationship between two variables and is expressed as a value between -1 and 1:

- 1: Perfect positive correlation (as one variable increases, the other increases proportionally).
- 0: No correlation (no linear relationship between the variables).
- -1: Perfect negative correlation (as one variable increases, the other decreases proportionally).

In [2275]:
```
# Finding correlation between the features
corr=dataset.corr()
corr.shape
```

Out[2275]: (14, 14)

In [2276]:
```
print(corr)
```

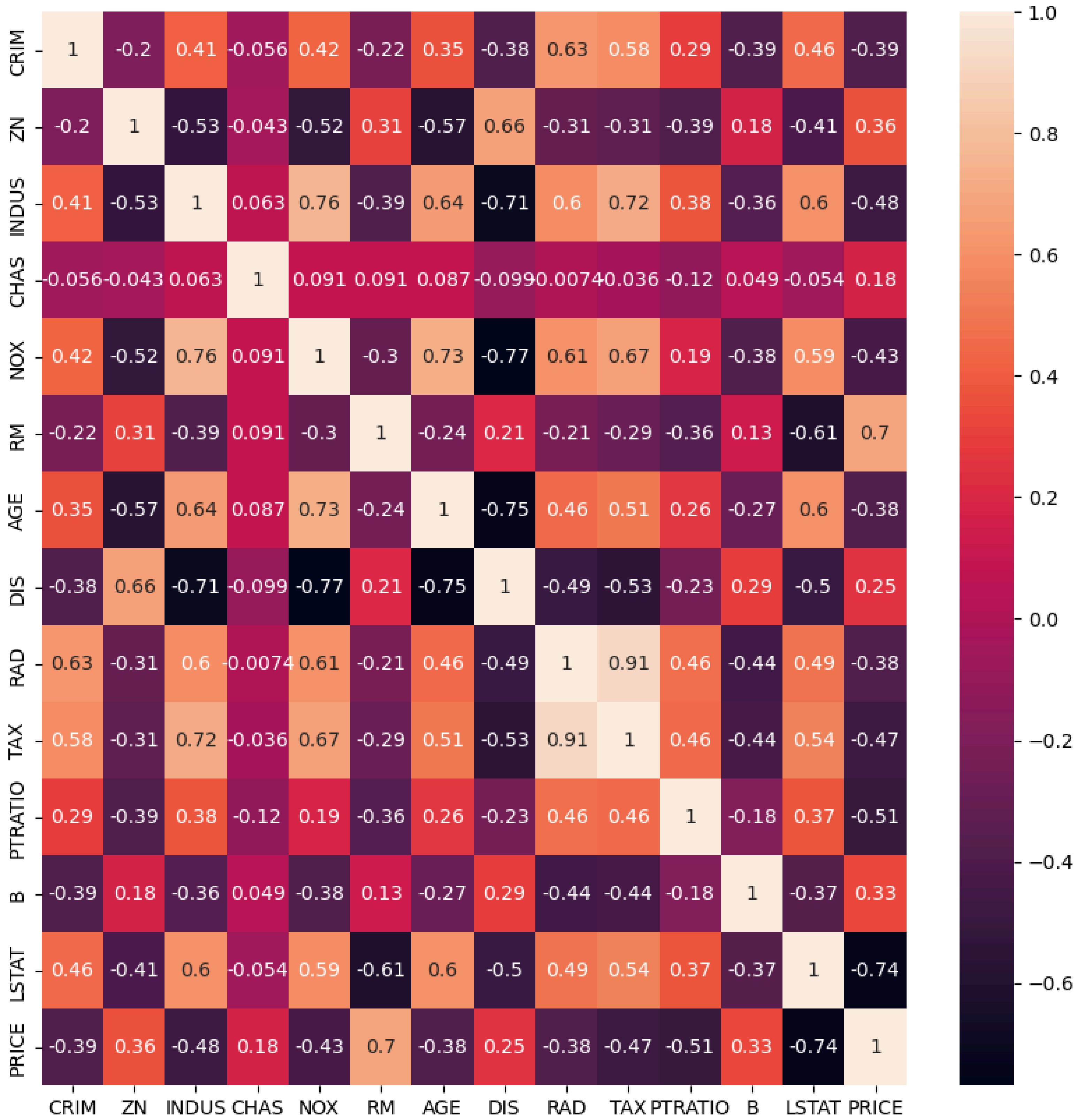
```
             CRIM        ZN     INDUS      CHAS       NOX        RM       AGE  \
CRIM     1.000000 -0.200469  0.406583 -0.055892  0.420972 -0.219247  0.352734
ZN      -0.200469  1.000000 -0.533828 -0.042697 -0.516604  0.311991 -0.569537
INDUS    0.406583 -0.533828  1.000000  0.062938  0.763651 -0.391676  0.644779
CHAS    -0.055892 -0.042697  0.062938  1.000000  0.091203  0.091251  0.086518
NOX      0.420972 -0.516604  0.763651  0.091203  1.000000 -0.302188  0.731470
RM      -0.219247  0.311991 -0.391676  0.091251 -0.302188  1.000000 -0.240265
AGE      0.352734 -0.569537  0.644779  0.086518  0.731470 -0.240265  1.000000
DIS     -0.379670  0.664408 -0.708027 -0.099176 -0.769230  0.205246 -0.747881
RAD      0.625505 -0.311948  0.595129 -0.007368  0.611441 -0.209847  0.456022
TAX      0.582764 -0.314563  0.720760 -0.035587  0.668023 -0.292048  0.506456
PTRATIO  0.289946 -0.391679  0.383248 -0.121515  0.188933 -0.355501  0.261515
B       -0.385064  0.175520 -0.356977  0.048788 -0.380051  0.128069 -0.273534
LSTAT    0.455621 -0.412995  0.603800 -0.053929  0.590879 -0.613808  0.602339
PRICE   -0.388305  0.360445 -0.483725  0.175260 -0.427321  0.695360 -0.376955

              DIS       RAD       TAX   PTRATIO         B     LSTAT     PRICE
CRIM    -0.379670  0.625505  0.582764  0.289946 -0.385064  0.455621 -0.388305
ZN       0.664408 -0.311948 -0.314563 -0.391679  0.175520 -0.412995  0.360445
INDUS   -0.708027  0.595129  0.720760  0.383248 -0.356977  0.603800 -0.483725
CHAS    -0.099176 -0.007368 -0.035587 -0.121515  0.048788 -0.053929  0.175260
NOX     -0.769230  0.611441  0.668023  0.188933 -0.380051  0.590879 -0.427321
RM       0.205246 -0.209847 -0.292048 -0.355501  0.128069 -0.613808  0.695360
AGE     -0.747881  0.456022  0.506456  0.261515 -0.273534  0.602339 -0.376955
DIS      1.000000 -0.494588 -0.534432 -0.232471  0.291512 -0.496996  0.249929
RAD     -0.494588  1.000000  0.910228  0.464741 -0.444413  0.488676 -0.381626
TAX     -0.534432  0.910228  1.000000  0.460853 -0.441808  0.543993 -0.468536
PTRATIO -0.232471  0.464741  0.460853  1.000000 -0.177383  0.374044 -0.507787
B        0.291512 -0.444413 -0.441808 -0.177383  1.000000 -0.366087  0.333461
LSTAT   -0.496996  0.488676  0.543993  0.374044 -0.366087  1.000000 -0.737663
PRICE    0.249929 -0.381626 -0.468536 -0.507787  0.333461 -0.737663  1.000000
```

Correlation Matrix

In [2277]:

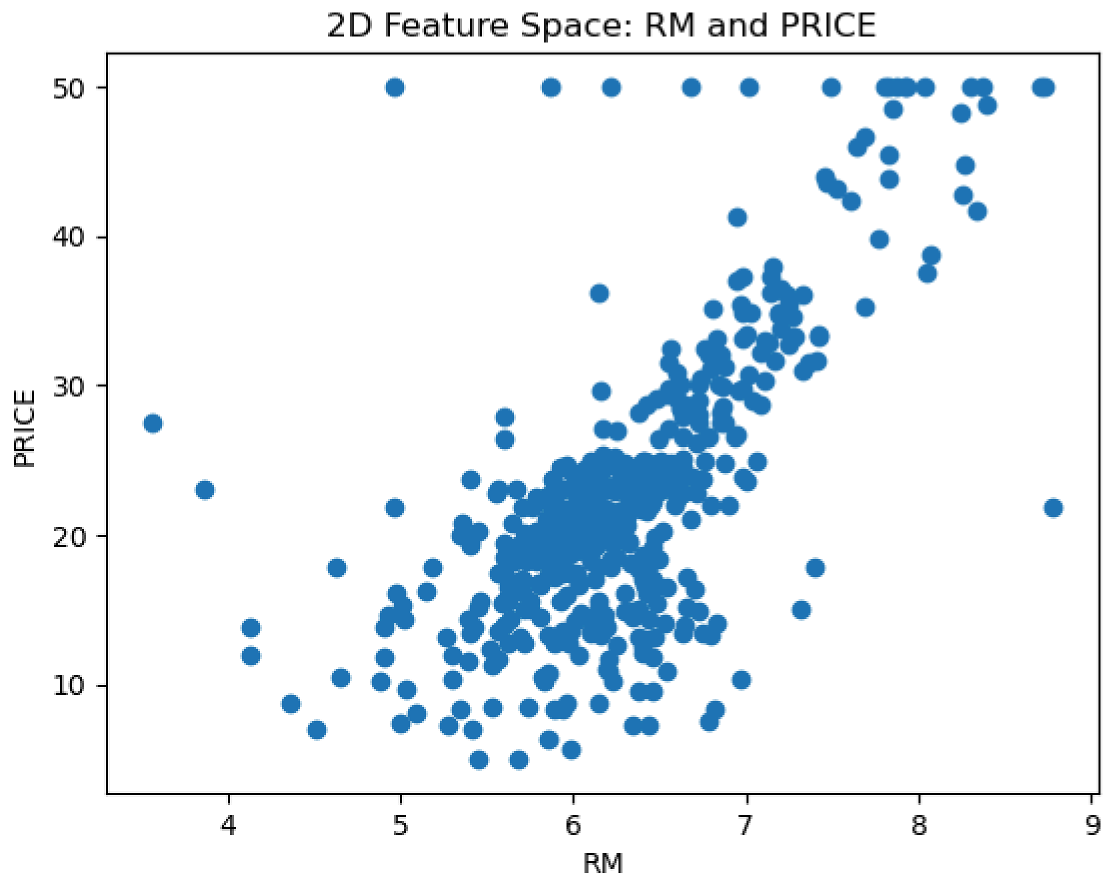
```
# Show the heatmap
plt.figure(figsize=(10,10))
sns.heatmap(corr, annot=True)
plt.show()
```



2D Feature Space

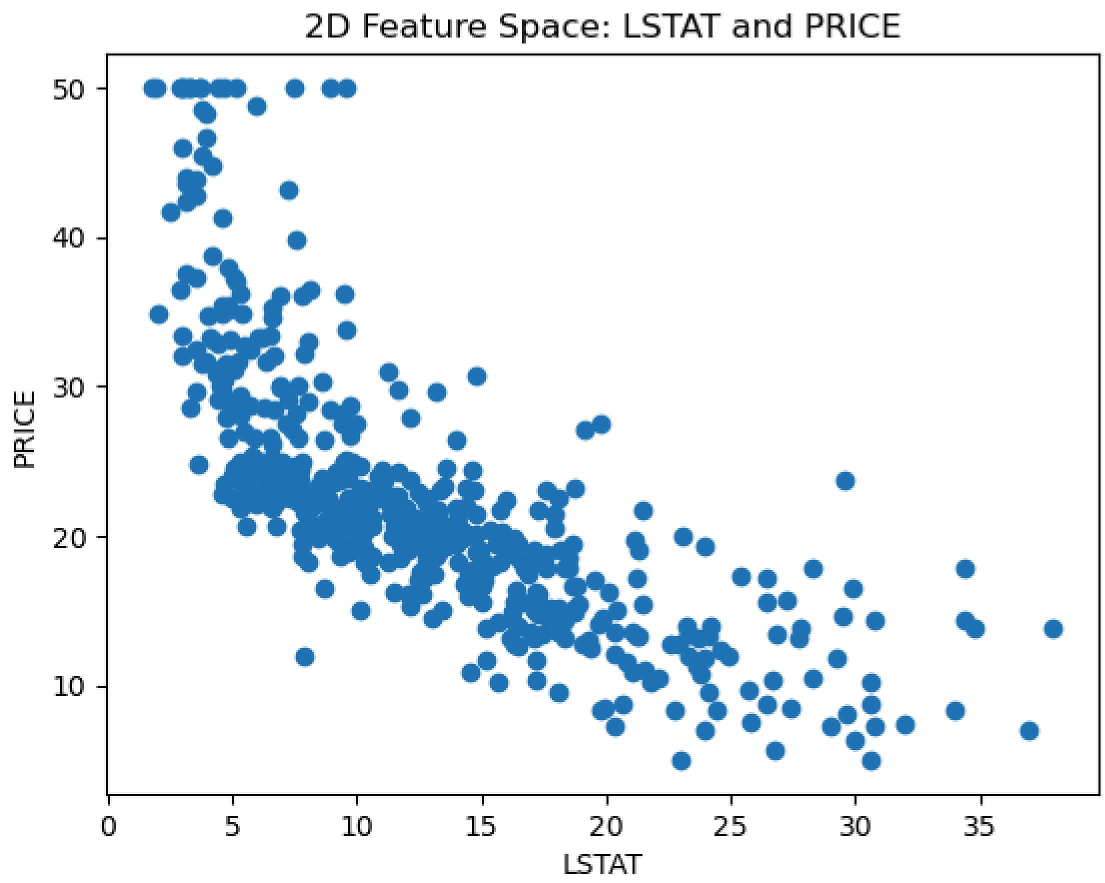
- Explained any 3 features using scatter plot

In [2378]:
```
fig, ax = plt.subplots()
ax.scatter(x = dataset['RM'], y = dataset['PRICE'])
plt.ylabel('PRICE')
plt.xlabel('RM')
plt.title('2D Feature Space: RM and PRICE')
plt.show()
```



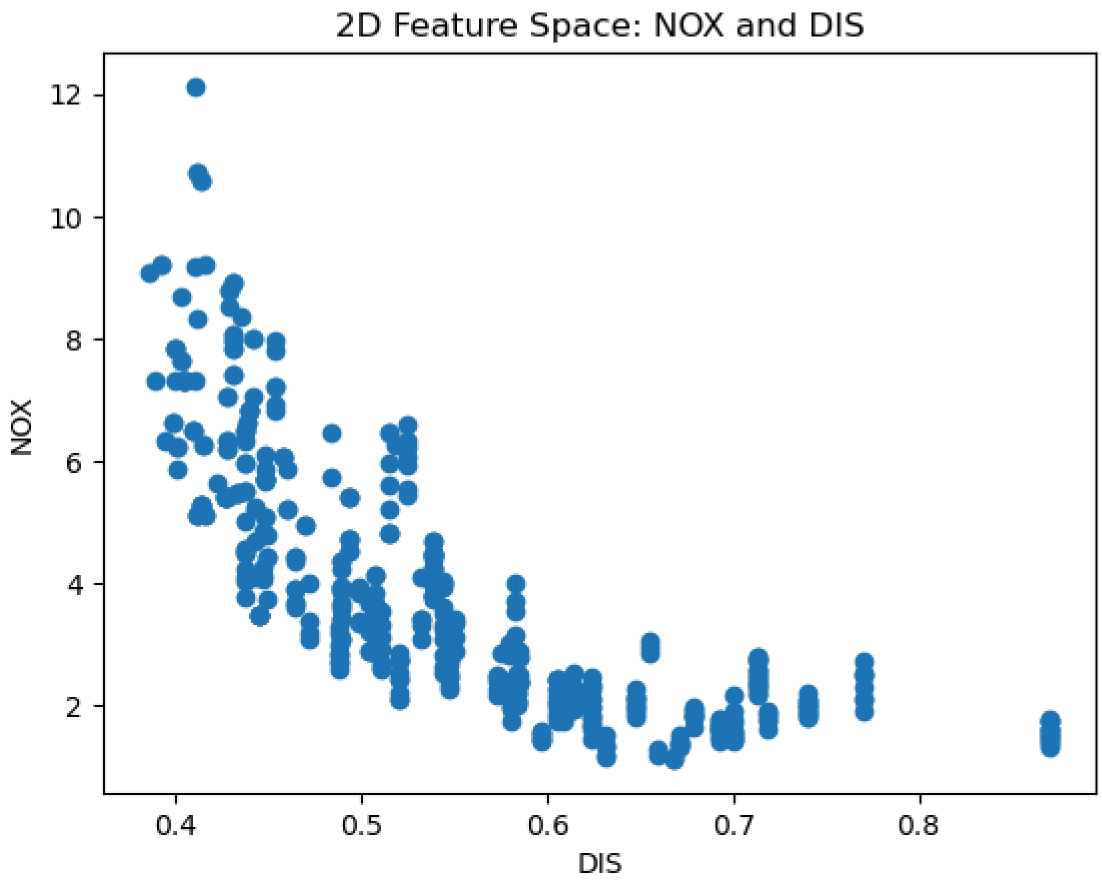
- Prices of houses increase with the increase in value of average number of rooms in houses in the town.
- Hence it is positively correlated.

In [2279]:
```
fig, ax = plt.subplots()
ax.scatter(x = dataset['LSTAT'], y = dataset['PRICE'])
plt.ylabel('PRICE')
plt.xlabel('LSTAT')
plt.title('2D Feature Space: LSTAT and PRICE')
plt.show()
```



- Areas with low lower socioeconomic status tend to have higher housing prices.
- As lower socioeconomic status increase, housing prices generally decrease.
- Hence it is negatively correlated.

In [2280]:
```
fig, ax = plt.subplots()
ax.scatter(x = dataset['NOX'], y = dataset['DIS'])
plt.ylabel('NOX')
plt.xlabel('DIS')
plt.title('2D Feature Space: NOX and DIS')
plt.show()
```



- Areas with low value of air pollution in the town(NOX) tend to have a far distance of town from major employment hubs in Boston.
- As lower air pollution increase, distance of town from employment hubs is also increase.

3D Feature Space

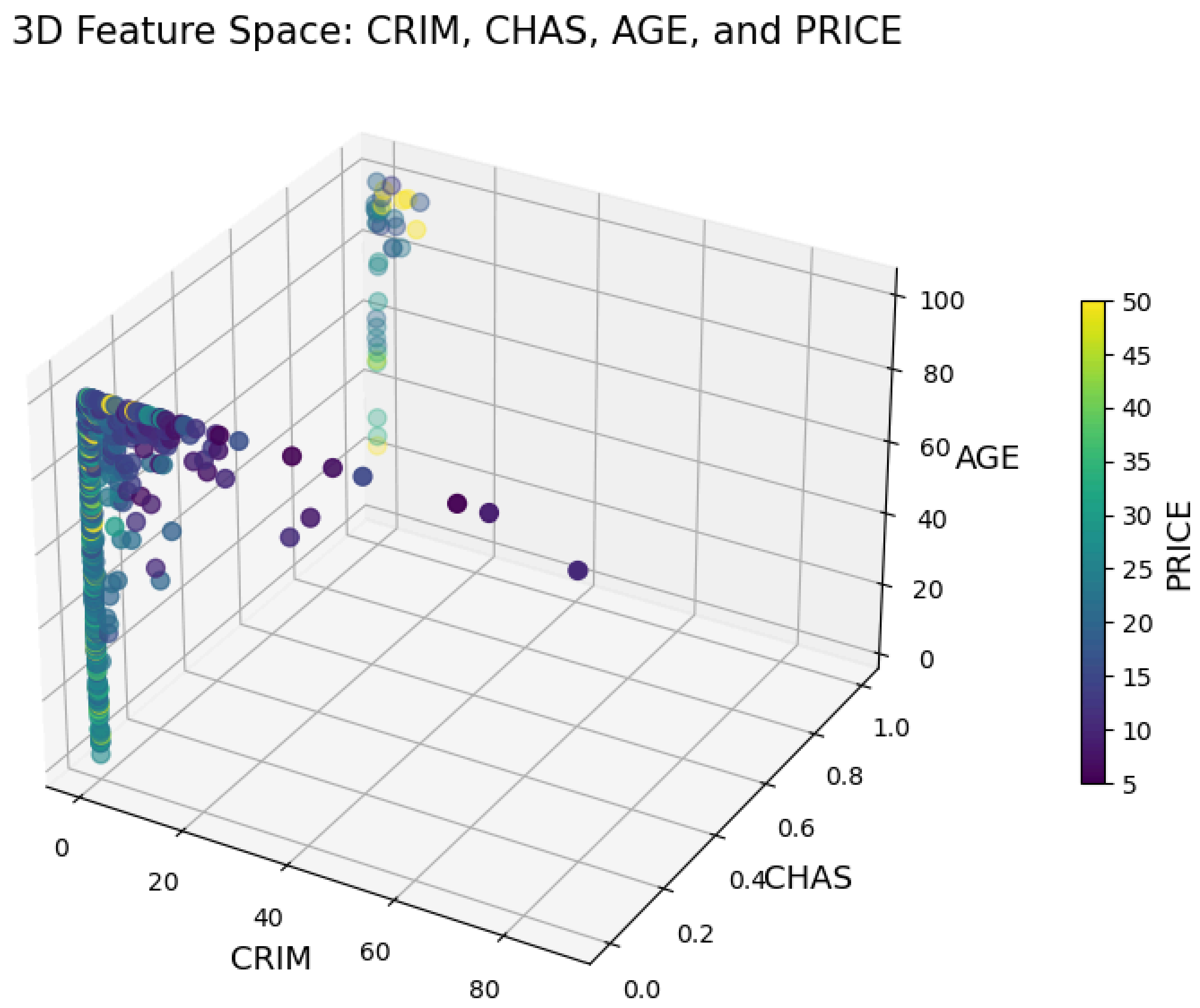
In [2281]:
```
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')

# Scatter plot
scatter = ax.scatter(
    xs=dataset['CRIM'],  # X-axis (CRIM)
    ys=dataset['CHAS'],   # Y-axis (NOX)
    zs=dataset['AGE'],   # Z-axis (AGE)
    c=dataset['PRICE'],  # Color indicates PRICE
    cmap='viridis',      # Colormap for PRICE
    s=50                 # Marker size
)

# Adding colorbar
cbar = plt.colorbar(scatter, ax=ax, pad=0.1, shrink=0.5)
cbar.set_label('PRICE', fontsize=13)

# Adding labels
ax.set_xlabel('CRIM', fontsize=13)
ax.set_ylabel('CHAS', fontsize=13)
ax.set_zlabel('AGE', fontsize=13)
plt.title('3D Feature Space: CRIM, CHAS, AGE, and PRICE', fontsize=15)

# Show the plot
plt.show()
```



- Areas with low crime rates and moderate to newer homes tend to have higher housing prices.
- Areas with higher crime rates are generally associated with lower housing prices, regardless of home age or proximity to the Charles River.

Divide the data domain of the datasets into 80:20

- Where 80% is assigned to training datasets and 20% is assigned to test datasets.

In [2282]:
```
row,col=dataset.shape
TR=round(row*0.8)
print(TR)
TT=row-TR
print(TT)

dataset_train=dataset.iloc[0:TR,:]
print('dataset_train:',dataset_train.shape)
dataset_train.to_csv('housing_train.csv', index=False)

dataset_test=dataset.iloc[TR:row,:]
print('dataset_test:',dataset_test.shape)
dataset_test.to_csv('housing_test.csv', index=False)
```

```
405
101
dataset_train: (405, 14)
dataset_test: (101, 14)
```

In [2283]:
```
x_dataset_train=dataset_train.iloc[:,0:13] # Independent variables
print('x_dataset_train:',x_dataset_train.shape)

y_dataset_train=dataset_train['PRICE'] # Target variables
print('y_dataset_train:',y_dataset_train.shape)

x_dataset_test=dataset_test.iloc[:,0:13] # Independent variables
print('x_dataset_test:',x_dataset_test.shape)

y_dataset_test=dataset_test['PRICE'] # Target variables
print('y_dataset_test:',y_dataset_test.shape)
```

```
x_dataset_train: (405, 13)
y_dataset_train: (405,)
x_dataset_test: (101, 13)
y_dataset_test: (101,)
```

→ Before we begin training and testing datasets using different models, it's crucial to understand how we evaluate the model's predictions.

→ Below are some key terms that we need to familiarize with first(Regression Evaluation Metrics):

1. **Mean Absolute Error (MAE)**
   MAE is the average of the absolute differences between the actual values and the predicted values. It tells you, on average, how much your predictions are "off" from the actual values.

---

2. **Mean Squared Error (MSE)** MSE is the average of the squared differences between actual and predicted values. By squaring the differences, it penalizes larger errors more heavily than smaller ones.

---

3. **Root Mean Squared Error (RMSE)** RMSE is the square root of MSE. It brings the units back to the same scale as the original target variable, making it easier to interpret than MSE.

---

4. **R^2 (R-squared)** R^2 measures how well the independent variables explain the variance in the target variable.

   - Range: 0 to 1
   - $R^2 = 1$: Perfect fit (all data points are explained by the model).
   - $R^2 = 0$: The model does no better than predicting the mean of the target variable.
   - $R^2 < 0$: The model performs worse than predicting the mean.

Linear Regression

Train model

In [2284]:
```
# Train model
linear_model = LinearRegression() # Create a Linear regressor
linear_model.fit(x_dataset_train, y_dataset_train) # Train the model using the training sets
```

Out[2284]:
```
LinearRegression()
```

Test model

In [2285]:
```
# Model prediction on train data
yhat_pred_linear = linear_model.predict(x_dataset_test)
```

Save it in csv file

In [2286]:
```
# Save it csv file
yhat_pred_linear=pd.DataFrame(yhat_pred_linear)

dataset_test = dataset_test.reset_index(drop=True)
yhat_pred_linear = yhat_pred_linear.reset_index(drop=True)

dataset_linear_predict=pd.concat([dataset_test,yhat_pred_linear], axis=1)
dataset_linear_predict.columns.values[-1] = 'predict'
dataset_linear_predict.to_csv('dataset_linear_predict.csv', index=False)
```

In [2287]:
```
dataset_linear_predict.head(5)
```

Out[2287]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE	predict
0	5.87205	0.0	18.10	0	0.693	6.405	96.0	1.6768	24	666.0	20.2	396.90	19.37	12.5	19.510717
1	9.33889	0.0	18.10	0	0.679	6.380	95.6	1.9682	24	666.0	20.2	60.72	24.08	9.5	12.645642
2	0.65665	20.0	3.97	0	0.647	6.842	100.0	2.0107	5	264.0	13.0	391.93	6.90	30.1	35.599789
3	0.79041	0.0	9.90	0	0.544	6.122	52.8	2.6403	4	304.0	18.4	396.90	5.98	22.1	27.438011
4	0.03738	0.0	5.19	0	0.515	6.310	38.5	6.4584	5	224.0	20.2	389.40	6.75	20.7	21.564429

Model Evaluation

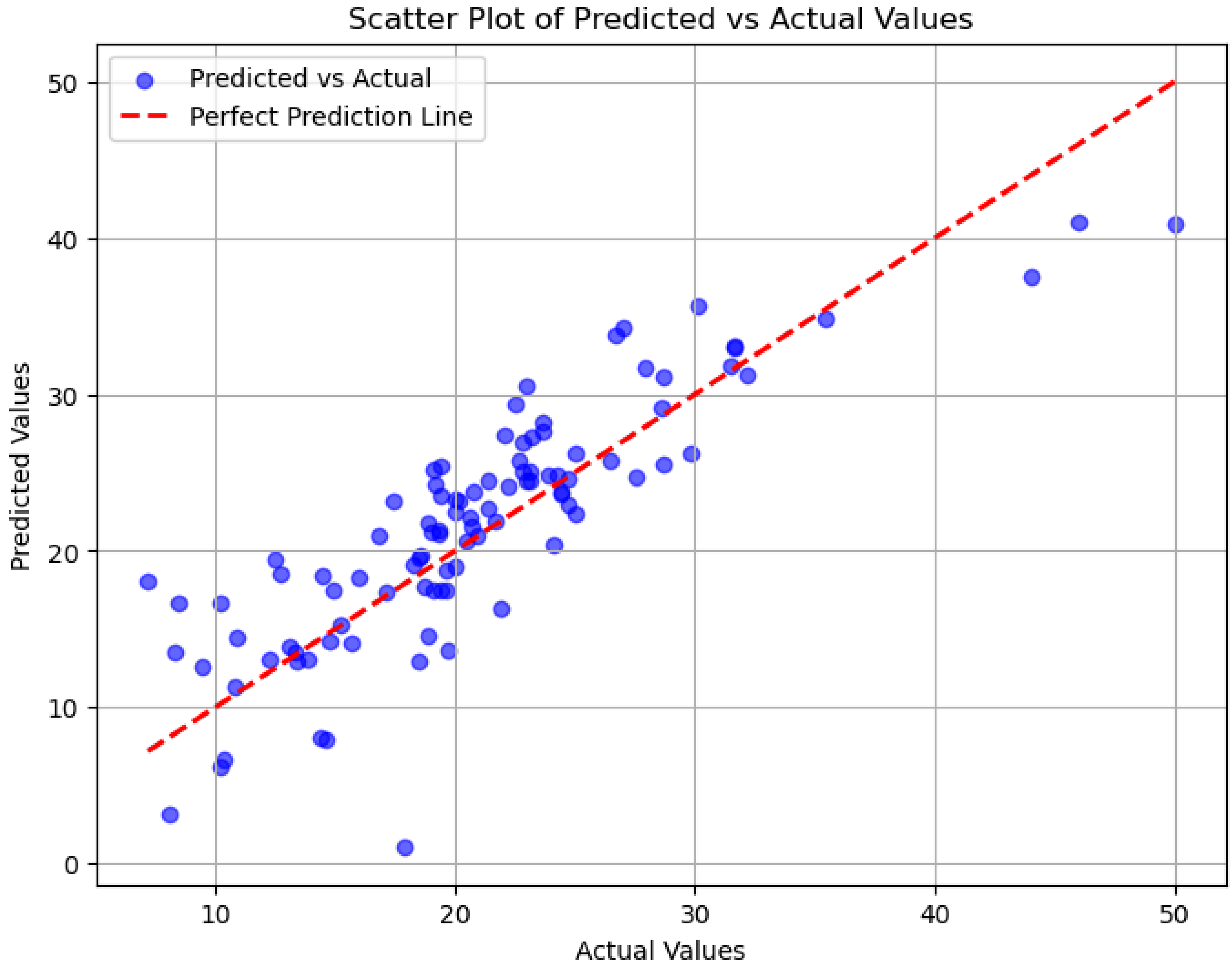
In [2288]:
```
print('MAE:',metrics.mean_absolute_error(y_dataset_test, yhat_pred_linear))
print('MSE:',metrics.mean_squared_error(y_dataset_test, yhat_pred_linear))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_dataset_test, yhat_pred_linear)))
print("R² (R-squared):", r2_score(y_dataset_test, yhat_pred_linear))
```

```
MAE: 3.1935974916809586
MSE: 17.5923029362562
RMSE: 4.194317934570077
R² (R-squared): 0.6814101607337995
```

In [2346]:
```
plt.figure(figsize=(8, 6))
plt.scatter(y_dataset_test, yhat_pred_linear, color='blue', alpha=0.6, label='Predicted vs Actual')

# Add a line of perfect predictions
plt.plot([y_dataset_test.min(), y_dataset_test.max()],
         [y_dataset_test.min(), y_dataset_test.max()],
         color='red', linestyle='--', linewidth=2, label='Perfect Prediction Line')

# Add labels, title, and legend
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title(f"Scatter Plot of Predicted vs Actual Values")
plt.legend()
plt.grid(True)
plt.show()
```



Ridge Regression

Train model

In [2289]:
```
# Train model
ridge_model = Ridge(alpha=1.0)  # Regularization strength alpha
ridge_model.fit(x_dataset_train, y_dataset_train)
```

Out[2289]: `Ridge()`

Test Model

In [2290]:
```
yhat_pred_ridge = ridge_model.predict(x_dataset_test)
```

Save it in csv file

In [2291]:
```
# Save it csv file
yhat_pred_ridge=pd.DataFrame(yhat_pred_ridge)

dataset_test = dataset_test.reset_index(drop=True)
yhat_pred_ridge = yhat_pred_ridge.reset_index(drop=True)

dataset_ridge_predict=pd.concat([dataset_test,yhat_pred_ridge], axis=1)
dataset_ridge_predict.columns.values[-1] = 'predict'
dataset_ridge_predict.to_csv('dataset_ridge_predict.csv', index=False)
```

In [2292]:
```
dataset_ridge_predict.head(5)
```

Out[2292]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE	predict
0	5.87205	0.0	18.10	0	0.693	6.405	96.0	1.6768	24	666.0	20.2	396.90	19.37	12.5	19.657303
1	9.33889	0.0	18.10	0	0.679	6.380	95.6	1.9682	24	666.0	20.2	60.72	24.08	9.5	12.447759
2	0.65665	20.0	3.97	0	0.647	6.842	100.0	2.0107	5	264.0	13.0	391.93	6.90	30.1	36.035712
3	0.79041	0.0	9.90	0	0.544	6.122	52.8	2.6403	4	304.0	18.4	396.90	5.98	22.1	27.593450
4	0.03738	0.0	5.19	0	0.515	6.310	38.5	6.4584	5	224.0	20.2	389.40	6.75	20.7	22.427219

Model Evaluation

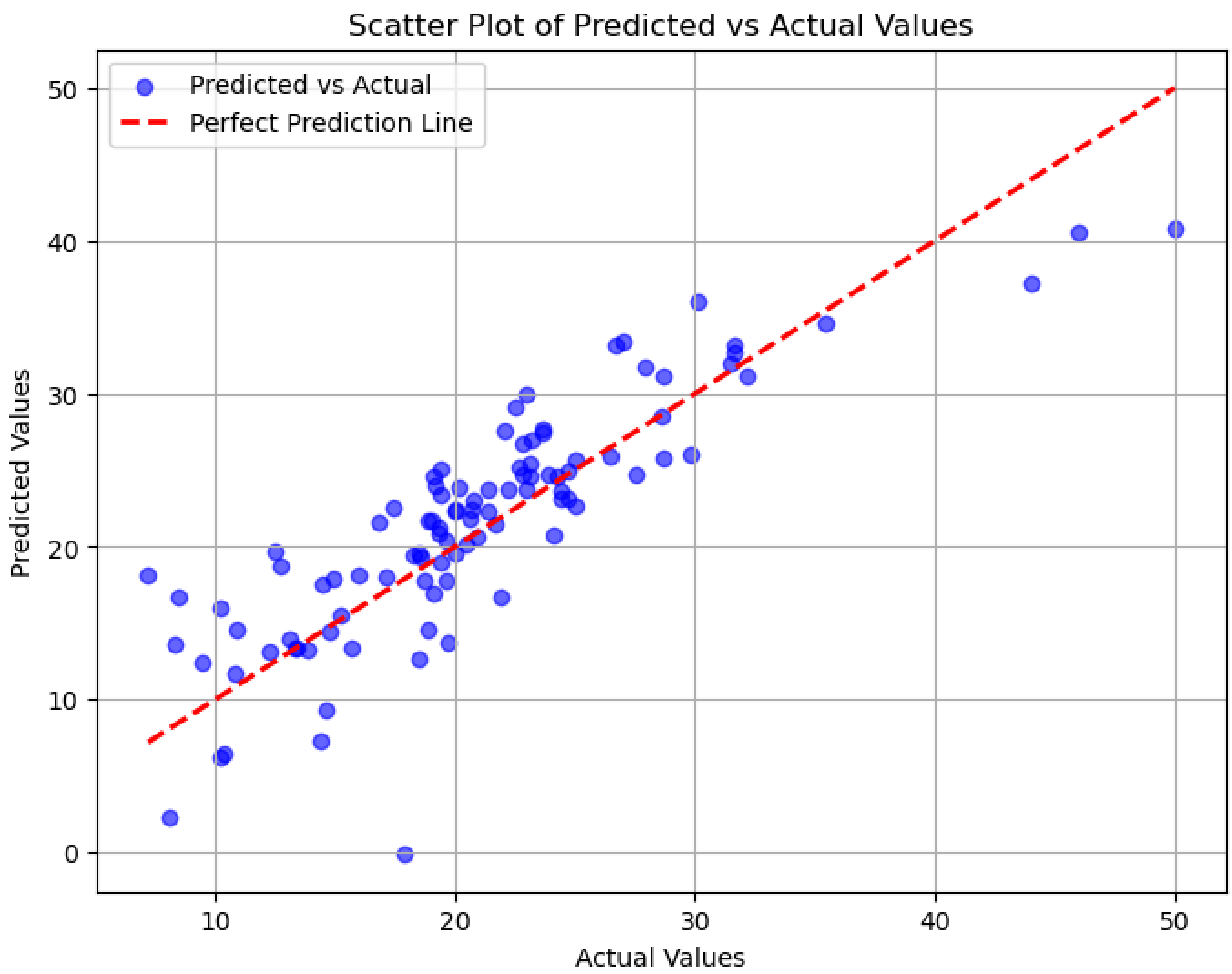
In [2293]:
```
print('MAE:',metrics.mean_absolute_error(y_dataset_test, yhat_pred_ridge))
print('MSE:',metrics.mean_squared_error(y_dataset_test, yhat_pred_ridge))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_dataset_test, yhat_pred_ridge)))
print("R² (R-squared):", r2_score(y_dataset_test, yhat_pred_ridge))
```

```
MAE: 3.1159208775427256
MSE: 17.3963985680925
RMSE: 4.170899011974816
R² (R-squared): 0.6849579134862938
```

In [2345]:
```
plt.figure(figsize=(8, 6))
plt.scatter(y_dataset_test, yhat_pred_ridge, color='blue', alpha=0.6, label='Predicted vs Actual')

# Add a line of perfect predictions
plt.plot([y_dataset_test.min(), y_dataset_test.max()],
         [y_dataset_test.min(), y_dataset_test.max()],
         color='red', linestyle='--', linewidth=2, label='Perfect Prediction Line')

# Add labels, title, and legend
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title(f"Scatter Plot of Predicted vs Actual Values")
plt.legend()
plt.grid(True)
plt.show()
```



Lasso Regression

Train model

In [2294]:
```
# Train model
lasso_model = Lasso(alpha=0.1)  # Regularization strength alpha
lasso_model.fit(x_dataset_train, y_dataset_train)
```

Out[2294]:
```
Lasso(alpha=0.1)
```

Test Model

In [2295]:
```
yhat_pred_lasso = lasso_model.predict(x_dataset_test)
```

Save it in csv file

In [2296]:
```
# Save it csv file
yhat_pred_lasso=pd.DataFrame(yhat_pred_lasso)

dataset_test = dataset_test.reset_index(drop=True)
yhat_pred_lasso = yhat_pred_lasso.reset_index(drop=True)

dataset_lasso_predict=pd.concat([dataset_test,yhat_pred_lasso], axis=1)
dataset_lasso_predict.columns.values[-1] = 'predict'
dataset_lasso_predict.to_csv('dataset_lasso_predict.csv', index=False)
```

In [2297]:
```
dataset_lasso_predict.head(5)
```

Out[2297]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE	predict
0	5.87205	0.0	18.10	0	0.693	6.405	96.0	1.6768	24	666.0	20.2	396.90	19.37	12.5	19.830082
1	9.33889	0.0	18.10	0	0.679	6.380	95.6	1.9682	24	666.0	20.2	60.72	24.08	9.5	12.116328
2	0.65665	20.0	3.97	0	0.647	6.842	100.0	2.0107	5	264.0	13.0	391.93	6.90	30.1	36.738694
3	0.79041	0.0	9.90	0	0.544	6.122	52.8	2.6403	4	304.0	18.4	396.90	5.98	22.1	27.915111
4	0.03738	0.0	5.19	0	0.515	6.310	38.5	6.4584	5	224.0	20.2	389.40	6.75	20.7	23.650481

Model Evaluation

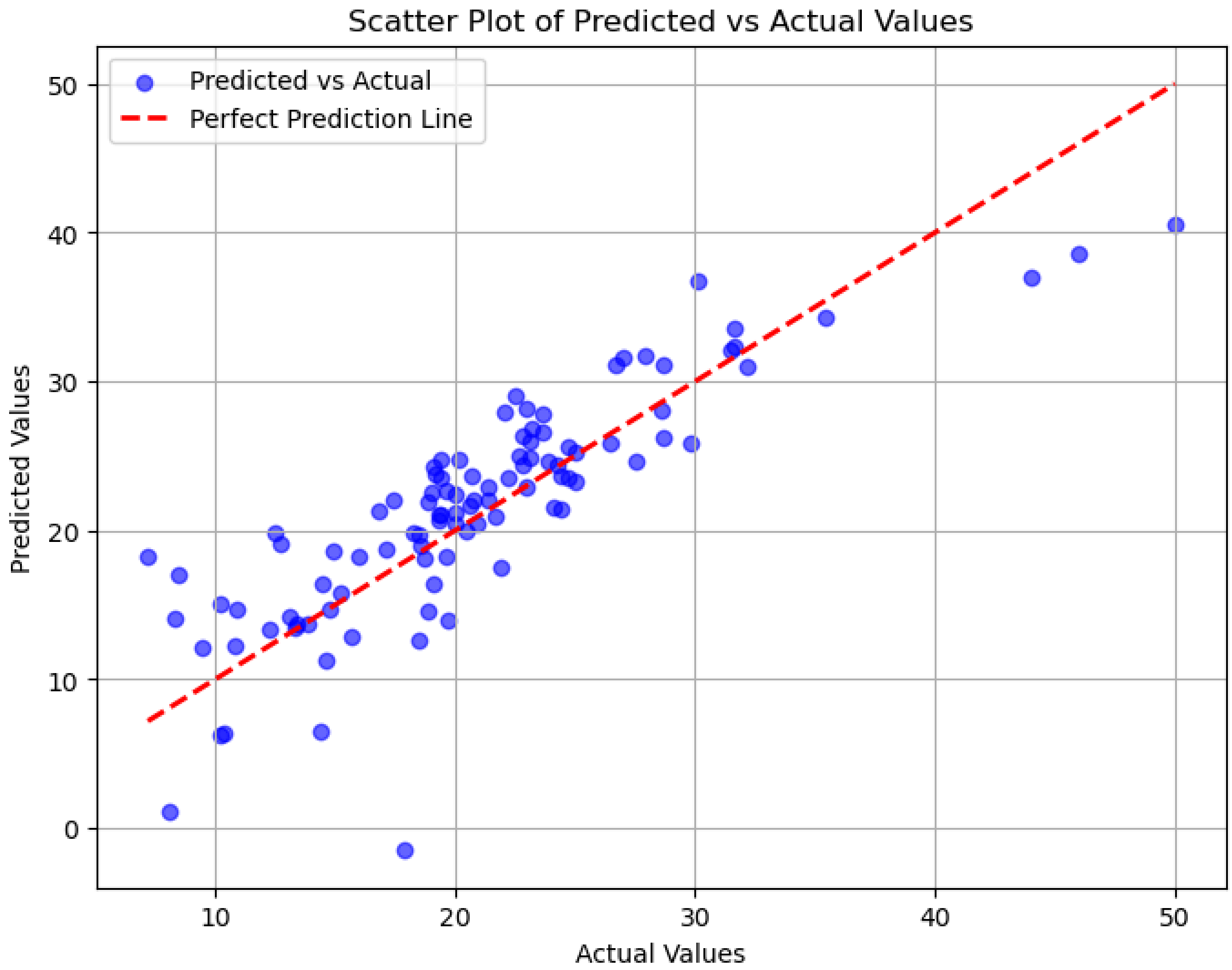
In [2407]:
```
print('MAE:',metrics.mean_absolute_error(y_dataset_test, yhat_pred_lasso))
print('MSE:',metrics.mean_squared_error(y_dataset_test, yhat_pred_lasso))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_dataset_test, yhat_pred_lasso)))
print("R² (R-squared):", r2_score(y_dataset_test, yhat_pred_lasso))
```

```
MAE: 3.1372266607758537
MSE: 17.885065420000693
RMSE: 4.229073825319285
R² (R-squared): 0.6761083447647764
```

In [2344]:
```
plt.figure(figsize=(8, 6))
plt.scatter(y_dataset_test, yhat_pred_lasso, color='blue', alpha=0.6, label='Predicted vs Actual')

# Add a line of perfect predictions
plt.plot([y_dataset_test.min(), y_dataset_test.max()],
         [y_dataset_test.min(), y_dataset_test.max()],
         color='red', linestyle='--', linewidth=2, label='Perfect Prediction Line')

# Add labels, title, and legend
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title(f"Scatter Plot of Predicted vs Actual Values")
plt.legend()
plt.grid(True)
plt.show()
```



Elastic-Net Regression

Train model

In [2299]:
```
# Elastic-Net Regression
elastic_model = ElasticNet(alpha=0.1, l1_ratio=0.5)  # Combination of Lasso (L1) and Ridge (L2)
elastic_model.fit(x_dataset_train, y_dataset_train)
```

Out[2299]:
```
ElasticNet(alpha=0.1)
```

Test Model

In [2300]:
```
yhat_pred_elastic = elastic_model.predict(x_dataset_test)
```

Save it in csv file

In [2301]:
```
# Save it csv file
yhat_pred_elastic=pd.DataFrame(yhat_pred_elastic)

dataset_test = dataset_test.reset_index(drop=True)
yhat_pred_elastic = yhat_pred_elastic.reset_index(drop=True)

dataset_elastic_predict=pd.concat([dataset_test,yhat_pred_elastic], axis=1)
dataset_elastic_predict.columns.values[-1] = 'predict'
dataset_elastic_predict.to_csv('dataset_elastic_predict.csv', index=False)
```

In [2302]:
```
dataset_elastic_predict.head(5)
```

Out[2302]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE	predict
0	5.87205	0.0	18.10	0	0.693	6.405	96.0	1.6768	24	666.0	20.2	396.90	19.37	12.5	19.687830
1	9.33889	0.0	18.10	0	0.679	6.380	95.6	1.9682	24	666.0	20.2	60.72	24.08	9.5	11.937087
2	0.65665	20.0	3.97	0	0.647	6.842	100.0	2.0107	5	264.0	13.0	391.93	6.90	30.1	36.979141
3	0.79041	0.0	9.90	0	0.544	6.122	52.8	2.6403	4	304.0	18.4	396.90	5.98	22.1	28.085939
4	0.03738	0.0	5.19	0	0.515	6.310	38.5	6.4584	5	224.0	20.2	389.40	6.75	20.7	23.661524

Model Evaluation

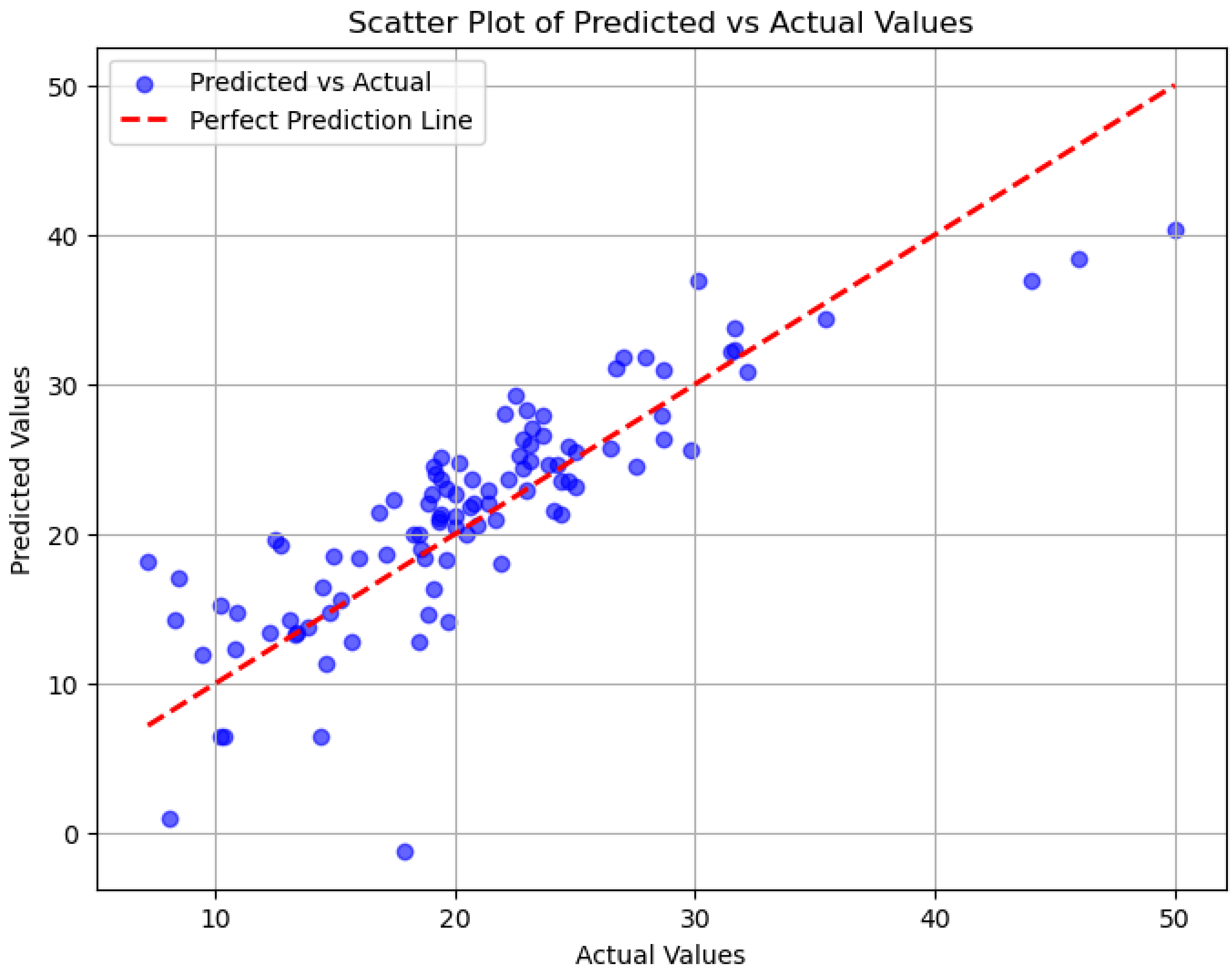
In [2303]:
```
print('MAE:',metrics.mean_absolute_error(y_dataset_test, yhat_pred_elastic))
print('MSE:',metrics.mean_squared_error(y_dataset_test, yhat_pred_elastic))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_dataset_test, yhat_pred_elastic)))
print("R² (R-squared):", r2_score(y_dataset_test, yhat_pred_elastic))
```

```
MAE: 3.184957752521577
MSE: 18.210715813735945
RMSE: 4.267401529471529
R² (R-squared): 0.6702109413962117
```

In [2343]:
```
plt.figure(figsize=(8, 6))
plt.scatter(y_dataset_test, yhat_pred_elastic, color='blue', alpha=0.6, label='Predicted vs Actual')

# Add a line of perfect predictions
plt.plot([y_dataset_test.min(), y_dataset_test.max()],
         [y_dataset_test.min(), y_dataset_test.max()],
         color='red', linestyle='--', linewidth=2, label='Perfect Prediction Line')

# Add labels, title, and legend
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title(f"Scatter Plot of Predicted vs Actual Values")
plt.legend()
plt.grid(True)
plt.show()
```



Support Vector Machine (SVM)

Train model

In [2328]:
```
# Elastic-Net Regression
svm_model = SVR(kernel='rbf')  # Radial Basis Function kernel for non-linear relationships
svm_model.fit(x_dataset_train, y_dataset_train)
```
Out[2328]:
```
SVR()
```

Test Model

In [2329]:
```
yhat_pred_svm = svm_model.predict(x_dataset_test)
```

Save it in csv file

In [2330]:
```
# Save it csv file
yhat_pred_svm=pd.DataFrame(yhat_pred_svm)

dataset_test = dataset_test.reset_index(drop=True)
yhat_pred_svm = yhat_pred_svm.reset_index(drop=True)

dataset_svm_predict=pd.concat([dataset_test,yhat_pred_svm], axis=1)
dataset_svm_predict.columns.values[-1] = 'predict'
dataset_svm_predict.to_csv('dataset_svm_predict.csv', index=False)
```

In [2307]:
```
dataset_svm_predict.head(5)
```
Out[2307]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE	predict
0	5.87205	0.0	18.10	0	0.693	6.405	96.0	1.6768	24	666.0	20.2	396.90	19.37	12.5	15.693739
1	9.33889	0.0	18.10	0	0.679	6.380	95.6	1.9682	24	666.0	20.2	60.72	24.08	9.5	13.299049
2	0.65665	20.0	3.97	0	0.647	6.842	100.0	2.0107	5	264.0	13.0	391.93	6.90	30.1	22.998533
3	0.79041	0.0	9.90	0	0.544	6.122	52.8	2.6403	4	304.0	18.4	396.90	5.98	22.1	22.899503
4	0.03738	0.0	5.19	0	0.515	6.310	38.5	6.4584	5	224.0	20.2	389.40	6.75	20.7	24.386636

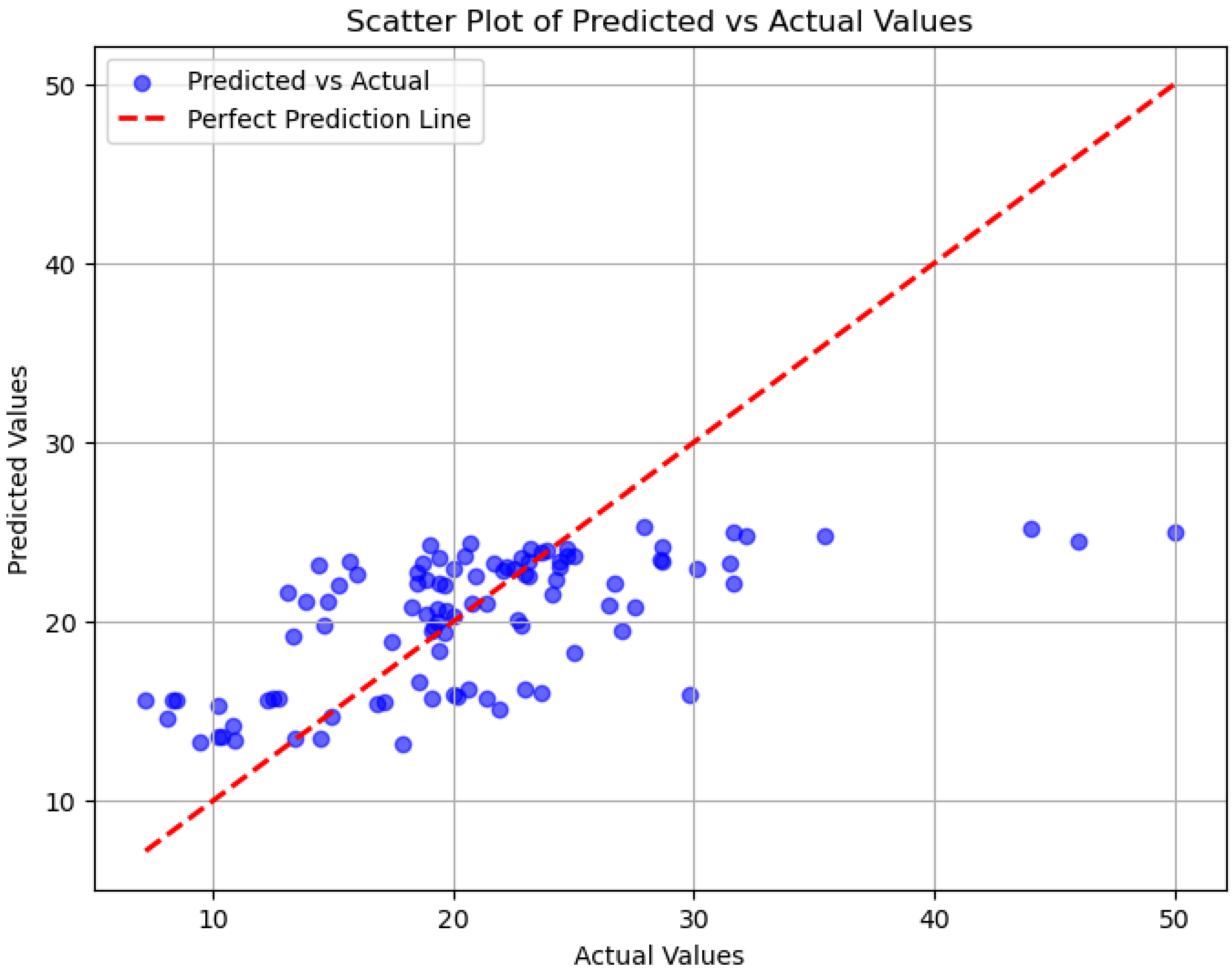
Model Evaluation

In [2341]:
```
print('MAE:',metrics.mean_absolute_error(y_dataset_test, yhat_pred_svm))
print('MSE:',metrics.mean_squared_error(y_dataset_test, yhat_pred_svm))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_dataset_test, yhat_pred_svm)))
print("R² (R-squared):", r2_score(y_dataset_test, yhat_pred_svm))
```
```
MAE: 4.263769039790573
MSE: 35.68774818956788
RMSE: 5.973922345458457
R² (R-squared): 0.35370860764027645
```

In [2342]:
```
plt.figure(figsize=(8, 6))
plt.scatter(y_dataset_test, yhat_pred_svm, color='blue', alpha=0.6, label='Predicted vs Actual')

# Add a line of perfect predictions
plt.plot([y_dataset_test.min(), y_dataset_test.max()],
         [y_dataset_test.min(), y_dataset_test.max()],
         color='red', linestyle='--', linewidth=2, label='Perfect Prediction Line')

# Add labels, title, and legend
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title(f"Scatter Plot of Predicted vs Actual Values")
plt.legend()
plt.grid(True)
plt.show()
```



Decision Tree

Train model

In [2309]:
```
# Decision Tree Regression
tree_model = DecisionTreeRegressor(max_depth=5)  # Limit depth to prevent overfitting
tree_model.fit(x_dataset_train, y_dataset_train)
```

Out[2309]: DecisionTreeRegressor(max_depth=5)

Test Model

In [2310]:
```
yhat_pred_tree = tree_model.predict(x_dataset_test)
```

Save it in csv file

In [2326]:
```
# Save it csv file
yhat_pred_tree=pd.DataFrame(yhat_pred_tree)

dataset_test = dataset_test.reset_index(drop=True)
yhat_pred_tree = yhat_pred_tree.reset_index(drop=True)

dataset_tree_predict=pd.concat([dataset_test,yhat_pred_tree], axis=1)
dataset_tree_predict.columns.values[-1] = 'predict'
dataset_tree_predict.to_csv('dataset_tree_predict.csv', index=False)
```

In [2312]:
```
dataset_tree_predict.head(5)
```

Out[2312]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE	predict
0	5.87205	0.0	18.10	0	0.693	6.405	96.0	1.6768	24	666.0	20.2	396.90	19.37	12.5	14.105882
1	9.33889	0.0	18.10	0	0.679	6.380	95.6	1.9682	24	666.0	20.2	60.72	24.08	9.5	8.772000
2	0.65665	20.0	3.97	0	0.647	6.842	100.0	2.0107	5	264.0	13.0	391.93	6.90	30.1	25.853846
3	0.79041	0.0	9.90	0	0.544	6.122	52.8	2.6403	4	304.0	18.4	396.90	5.98	22.1	24.006061
4	0.03738	0.0	5.19	0	0.515	6.310	38.5	6.4584	5	224.0	20.2	389.40	6.75	20.7	24.006061

Model Evaluation

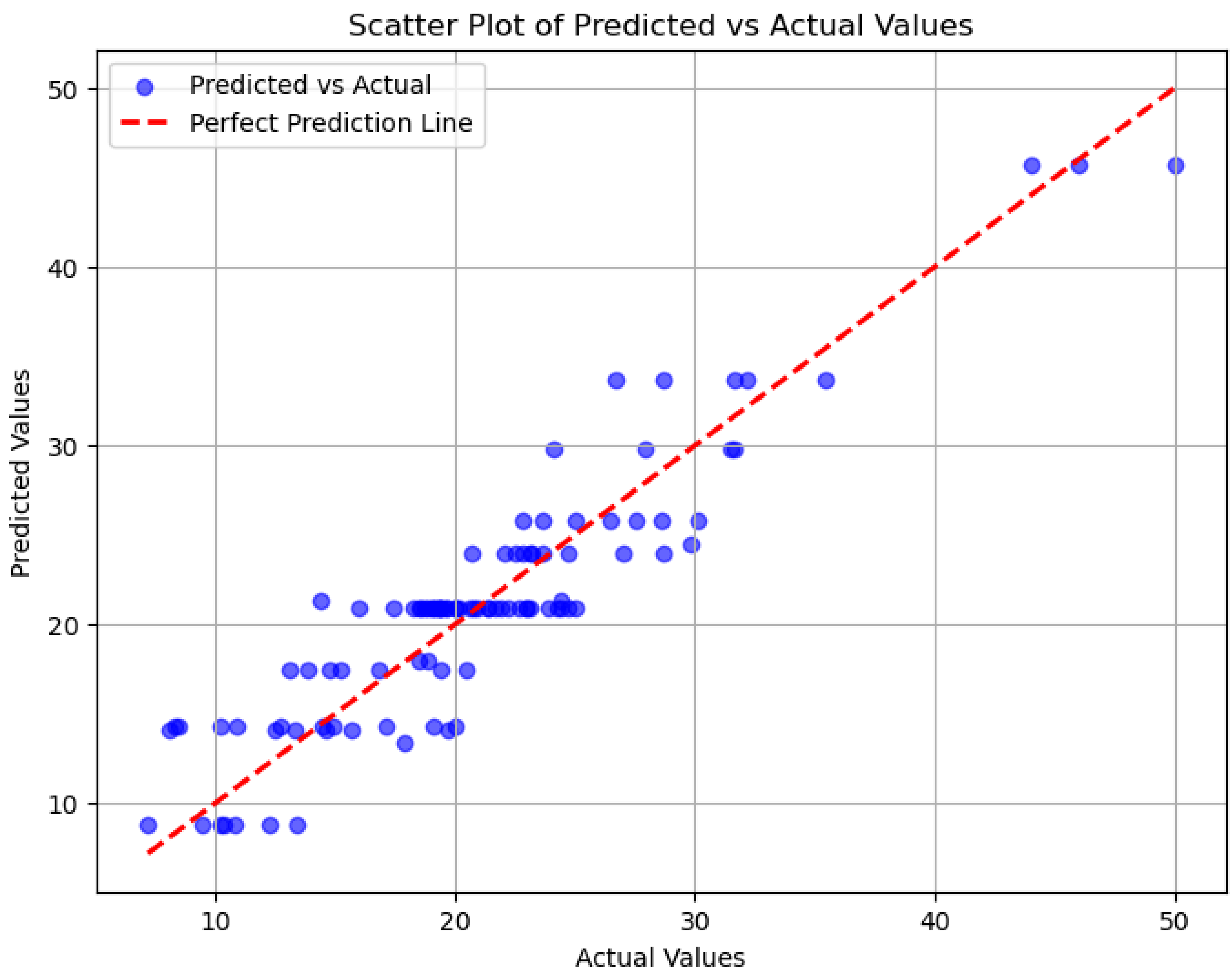
In [2337]:
```
print('MAE:',metrics.mean_absolute_error(y_dataset_test, yhat_pred_tree))
print('MSE:',metrics.mean_squared_error(y_dataset_test, yhat_pred_tree))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_dataset_test, yhat_pred_tree)))
print("R² (R-squared):", r2_score(y_dataset_test, yhat_pred_tree))
```

```
MAE: 2.3984650715257785
MSE: 8.532367550904276
RMSE: 2.9210216621764853
R² (R-squared): 0.8454821056428884
```

In [2340]:
```
plt.figure(figsize=(8, 6))
plt.scatter(y_dataset_test, yhat_pred_tree, color='blue', alpha=0.6, label='Predicted vs Actual')

# Add a line of perfect predictions
plt.plot([y_dataset_test.min(), y_dataset_test.max()],
         [y_dataset_test.min(), y_dataset_test.max()],
         color='red', linestyle='--', linewidth=2, label='Perfect Prediction Line')

# Add labels, title, and legend
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title(f"Scatter Plot of Predicted vs Actual Values")
plt.legend()
plt.grid(True)
plt.show()
```



Random Forest

Train model

In [2314]:
```
rf = RandomForestRegressor(n_estimators=100, max_depth=5, random_state=42)
rf.fit(x_dataset_train, y_dataset_train)
```

Out[2314]:
```
RandomForestRegressor(max_depth=5, random_state=42)
```

Test Model

In [2315]:
```
yhat_pred_rf = rf.predict(x_dataset_test)
```

Save it in csv file

In [2316]:
```
# Save it csv file
yhat_pred_rf=pd.DataFrame(yhat_pred_rf)

dataset_test = dataset_test.reset_index(drop=True)
yhat_pred_rf = yhat_pred_rf.reset_index(drop=True)

dataset_rf_predict=pd.concat([dataset_test,yhat_pred_rf], axis=1)
dataset_rf_predict.columns.values[-1] = 'predict'
dataset_rf_predict.to_csv('dataset_rf_predict.csv', index=False)
```

In [2317]:
```
dataset_rf_predict.head(5)
```

Out[2317]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE	predict
0	5.87205	0.0	18.10	0	0.693	6.405	96.0	1.6768	24	666.0	20.2	396.90	19.37	12.5	14.896960
1	9.33889	0.0	18.10	0	0.679	6.380	95.6	1.9682	24	666.0	20.2	60.72	24.08	9.5	12.089834
2	0.65665	20.0	3.97	0	0.647	6.842	100.0	2.0107	5	264.0	13.0	391.93	6.90	30.1	29.660039
3	0.79041	0.0	9.90	0	0.544	6.122	52.8	2.6403	4	304.0	18.4	396.90	5.98	22.1	23.534172
4	0.03738	0.0	5.19	0	0.515	6.310	38.5	6.4584	5	224.0	20.2	389.40	6.75	20.7	23.546594

Model Evaluation

In [2335]:
```
print('MAE:',metrics.mean_absolute_error(y_dataset_test, yhat_pred_rf))
print('MSE:',metrics.mean_squared_error(y_dataset_test, yhat_pred_rf))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_dataset_test, yhat_pred_rf)))
print("R² (R-squared):", r2_score(y_dataset_test, yhat_pred_rf))
```

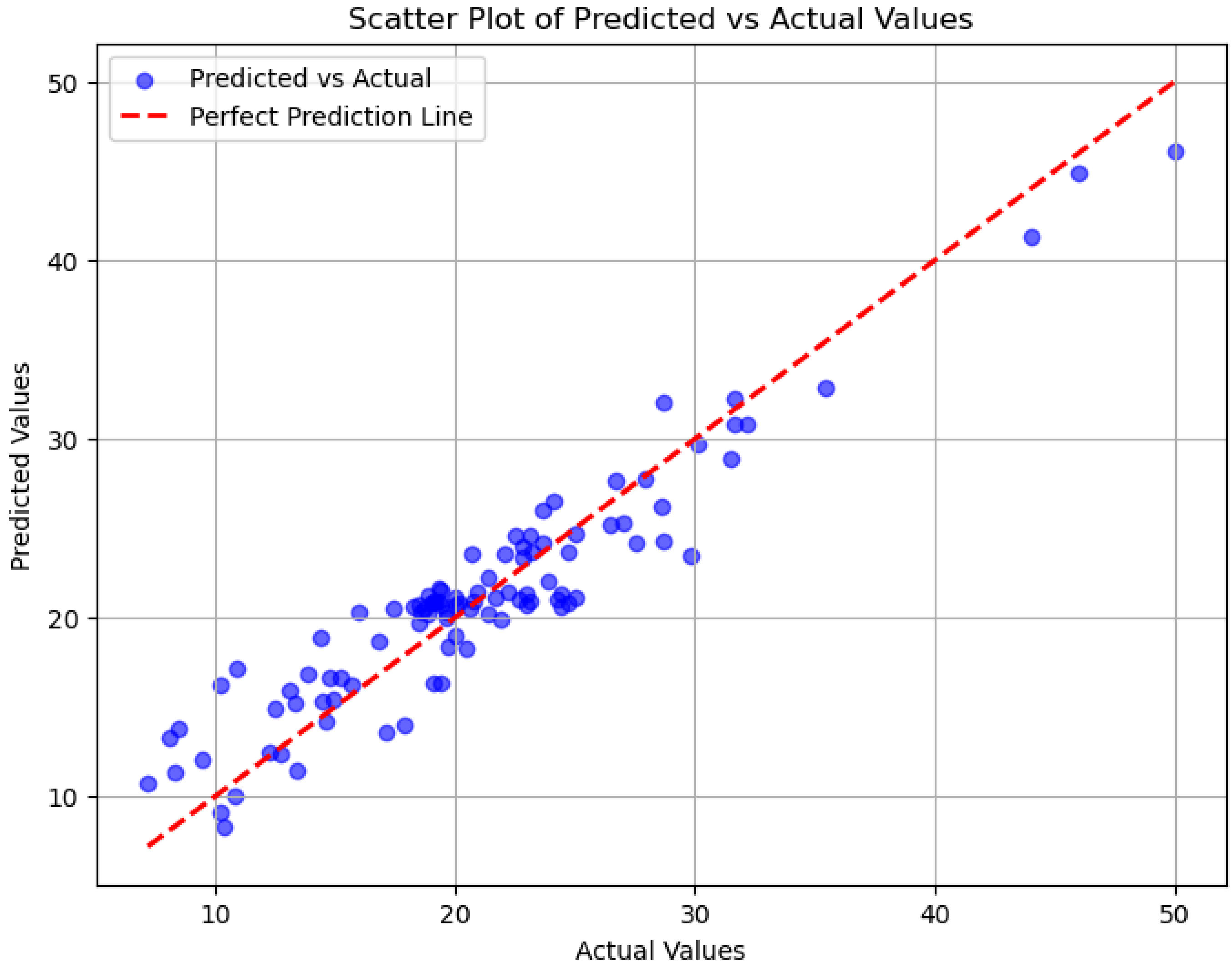
```
MAE: 2.029679117921366
MSE: 6.068409704663133
RMSE: 2.463414237326547
R² (R-squared): 0.8901034344727178
```

In [2336]:

```
plt.figure(figsize=(8, 6))
plt.scatter(y_dataset_test, yhat_pred_rf, color='blue', alpha=0.6, label='Predicted vs Actual')

# Add a line of perfect predictions
plt.plot([y_dataset_test.min(), y_dataset_test.max()],
         [y_dataset_test.min(), y_dataset_test.max()],
         color='red', linestyle='--', linewidth=2, label='Perfect Prediction Line')

# Add labels, title, and legend
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title(f"Scatter Plot of Predicted vs Actual Values")
plt.legend()
plt.grid(True)
plt.show()
```



Comparison of all Regression Model

Model Name	MAE	MSE	RMSE	R²
Linear Regression	3.193	17.592	4.194	0.6814
Ridge Regression	3.115	17.396	4.170	0.684
Lasso Regression	3.137	17.885	4.229	0.676
Elastic-Net Regression	3.184	18.210	4.267	0.670
Support Vector Machine (SVM)	4.263	35.687	5.973	0.353
Decision Tree	2.398	8.532	2.921	0.845
Random Forest	2.029	6.068	2.463	0.890

- Random Forest demonstrates the best performance among all models, with the lowest errors (MAE, MSE, and RMSE) and the highest R^2, indicating that it explains 89% of the variance in the dataset effectively.
- `Random Forest` is the most suitable model for this dataset

Cross Validation:-

Cross-validation is used to evaluate the performance of a machine learning model by dividing the dataset into multiple subsets (or folds) and training and testing the model on different portions of the data. It ensures that the model's performance is evaluated on unseen data and reduces the risk of overfitting.

- I am using **5-fold cross validation** (cv=5) for all above regression model.

In [2398]:

```
x_dataset=dataset.iloc[:,0:13] # Independent variables
print('x_dataset_train:',x_dataset.shape)

y_dataset=dataset['PRICE'] # Target variables
print('y_dataset_train:',y_dataset.shape)
```

```
x_dataset_train: (506, 13)
y_dataset_train: (506,)
```

Linear Regression

In [2399]:

```
linear_model = LinearRegression()
cv_scores = cross_val_score(linear_model, x_dataset, y_dataset, cv=5, scoring='r2')
# r² will be used as the evaluation metric.

print("R² Scores for each fold:", cv_scores)

mean_r2 = np.mean(cv_scores) # Average R² across all folds
print("Mean R² (Cross-Validation):", mean_r2)
```

```
R² Scores for each fold: [0.73833971 0.74587414 0.6953567  0.6637133  0.68141016]
Mean R² (Cross-Validation): 0.7049388036578506
```

Ridge Regression

In [2400]:

```
ridge_model=Ridge(alpha=1.0)
cv_scores = cross_val_score(ridge_model, x_dataset, y_dataset, cv=5, scoring='r2')
# r² will be used as the evaluation metric.

print("R² Scores for each fold:", cv_scores)

mean_r2 = np.mean(cv_scores) # Average R² across all folds
print("Mean R² (Cross-Validation):", mean_r2)
```

```
R² Scores for each fold: [0.73883986 0.73761911 0.6942155  0.65750362 0.68495791]
Mean R² (Cross-Validation): 0.7026272008497456
```

Lasso Regression

In [2401]:

```
lasso_model=Lasso(alpha=0.1)
cv_scores = cross_val_score(lasso_model, x_dataset, y_dataset, cv=5, scoring='r2')
# r² will be used as the evaluation metric.

print("R² Scores for each fold:", cv_scores)

mean_r2 = np.mean(cv_scores) # Average R² across all folds
print("Mean R² (Cross-Validation):", mean_r2)
```

```
R² Scores for each fold: [0.73196842 0.7288265  0.67984875 0.64844195 0.67610834]
Mean R² (Cross-Validation): 0.6930387933125047
```

Elastic-Net Regression

In [2402]:

```
elastic_model=ElasticNet(alpha=0.1,l1_ratio=0.5)
cv_scores = cross_val_score(elastic_model, x_dataset, y_dataset, cv=5, scoring='r2')
# r² will be used as the evaluation metric.

print("R² Scores for each fold:", cv_scores)

mean_r2 = np.mean(cv_scores) # Average R² across all folds
print("Mean R² (Cross-Validation):", mean_r2)
```

```
R² Scores for each fold: [0.72847258 0.72804756 0.68140213 0.64941963 0.67021094]
Mean R² (Cross-Validation): 0.6915105699336159
```

Support Vector Machine (SVM)

In [2403]:

```
svm_model=SVR(kernel='rbf')
cv_scores = cross_val_score(svm_model, x_dataset, y_dataset, cv=5, scoring='r2')
# r² will be used as the evaluation metric.

print("R² Scores for each fold:", cv_scores)

mean_r2 = np.mean(cv_scores) # Average R² across all folds
print("Mean R² (Cross-Validation):", mean_r2)
```

```
R² Scores for each fold: [ 0.2935867   0.28912171 -0.01642956  0.12497988  0.35370861]
Mean R² (Cross-Validation): 0.20899346837721683
```

Decision Tree

In [2404]:

```
tree_model=DecisionTreeRegressor(max_depth=5)
cv_scores = cross_val_score(tree_model, x_dataset, y_dataset, cv=5, scoring='r2')
# r² will be used as the evaluation metric.

print("R² Scores for each fold:", cv_scores)

mean_r2 = np.mean(cv_scores) # Average R² across all folds
print("Mean R² (Cross-Validation):", mean_r2)
```

```
R² Scores for each fold: [0.7458558  0.68400883 0.87739796 0.7366682  0.84548211]
Mean R² (Cross-Validation): 0.777882579336309
```

Random Forest

In [2405]:

```
rf = RandomForestRegressor(n_estimators=100, max_depth=5, random_state=42)
cv_scores = cross_val_score(rf, x_dataset, y_dataset, cv=5, scoring='r2')
# r² will be used as the evaluation metric.

print("R² Scores for each fold:", cv_scores)

mean_r2 = np.mean(cv_scores) # Average R² across all folds
print("Mean R² (Cross-Validation):", mean_r2)
```

```
R² Scores for each fold: [0.88396245 0.7557336  0.88369658 0.86978387 0.89010343]
Mean R² (Cross-Validation): 0.8566559890821239
```

Comparison of Cross Validation Result:

Model Name	Mean R^2
Linear Regression	0.704
Ridge Regression	0.702
Lasso Regression	0.693
Elastic-Net Regression	0.691
Support Vector Machine (SVM)	0.208
Decision Tree	0.777
Random Forest	0.856

Final Thought 📌 📍

Most effective model: `Random Forest`

- **Random Forest** works best for this project.