

```
In [1]: 1 import numpy as np
        2 import pandas as pd
        3
```

```
In [2]: 1 data = pd.read_csv("boston.csv")
```

```
In [3]: 1 data.head()
        2
```

```
Out[3]:
```

	Unnamed: 0	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO
0	0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3
1	1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8
2	2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8
3	3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7
4	4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7

```
In [4]: 1 data.columns
```

```
Out[4]: Index(['Unnamed: 0', 'CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS',
              'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT', 'Price'],
              dtype='object')
```

```
In [5]: 1 data.head(n=10)
```

```
Out[5]:
```

	Unnamed: 0	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO
0	0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3
1	1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8
2	2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8
3	3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7
4	4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7
5	5	0.02985	0.0	2.18	0.0	0.458	6.430	58.7	6.0622	3.0	222.0	18.7
6	6	0.08829	12.5	7.87	0.0	0.524	6.012	66.6	5.5605	5.0	311.0	15.3
7	7	0.14455	12.5	7.87	0.0	0.524	6.172	96.1	5.9505	5.0	311.0	15.3
8	8	0.21124	12.5	7.87	0.0	0.524	5.631	100.0	6.0821	5.0	311.0	15.3
9	9	0.17004	12.5	7.87	0.0	0.524	6.004	85.9	6.5921	5.0	311.0	15.3

```
In [6]: 1 data.shape
```

```
Out[6]: (506, 15)
```

```
In [7]: 1 data.isnull().sum()
```

```
Out[7]: 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
        B             0
        LSTAT         0
        Price         0
        dtype: int64
```

```
In [8]: 1 data.describe()
```

```
Out[8]:
```

	Unnamed: 0	CRIM	ZN	INDUS	CHAS	NOX	RM
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	252.500000	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634
std	146.213884	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617
min	0.000000	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000
25%	126.250000	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500
50%	252.500000	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500
75%	378.750000	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500
max	505.000000	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000

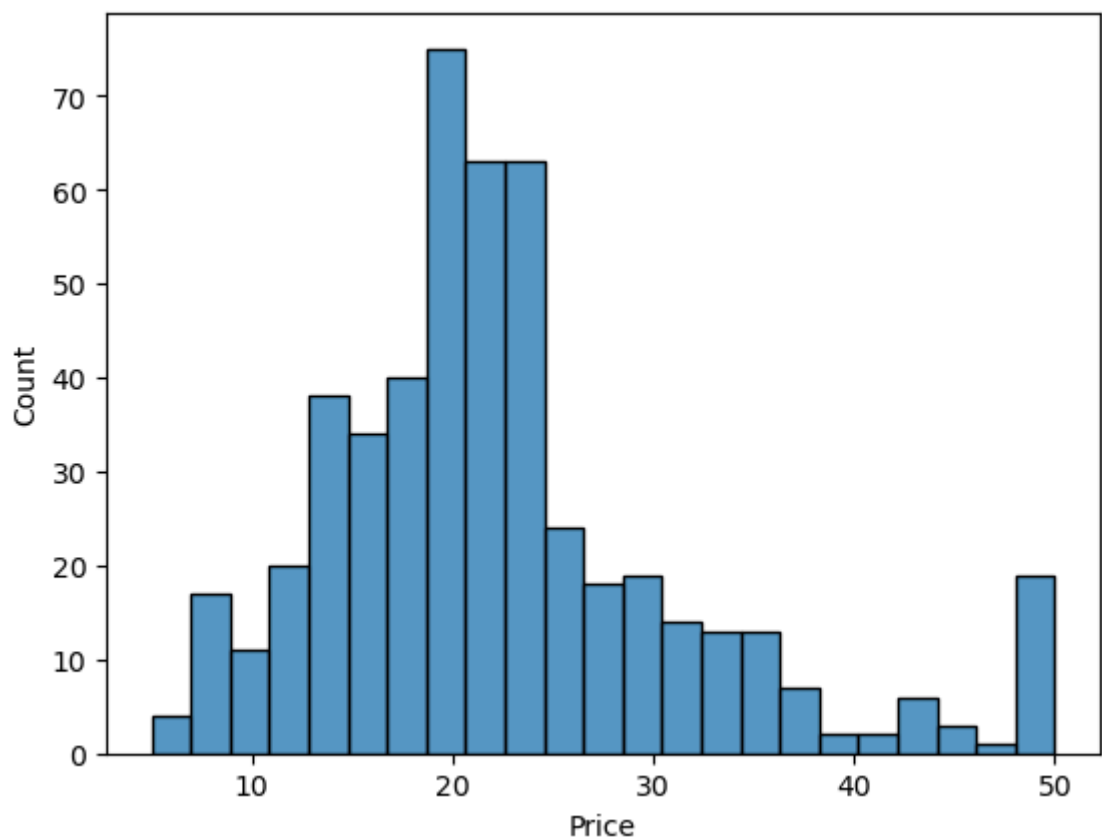
```
In [9]: 1 data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 15 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Unnamed: 0    506 non-null    int64
1   CRIM          506 non-null    float64
2   ZN            506 non-null    float64
3   INDUS         506 non-null    float64
4   CHAS          506 non-null    float64
5   NOX           506 non-null    float64
6   RM            506 non-null    float64
7   AGE           506 non-null    float64
8   DIS           506 non-null    float64
9   RAD           506 non-null    float64
10  TAX           506 non-null    float64
11  PTRATIO       506 non-null    float64
12  B             506 non-null    float64
13  LSTAT         506 non-null    float64
14  Price         506 non-null    float64
dtypes: float64(14), int64(1)
memory usage: 59.4 KB
```

```
In [10]: 1 import seaborn as sns
```

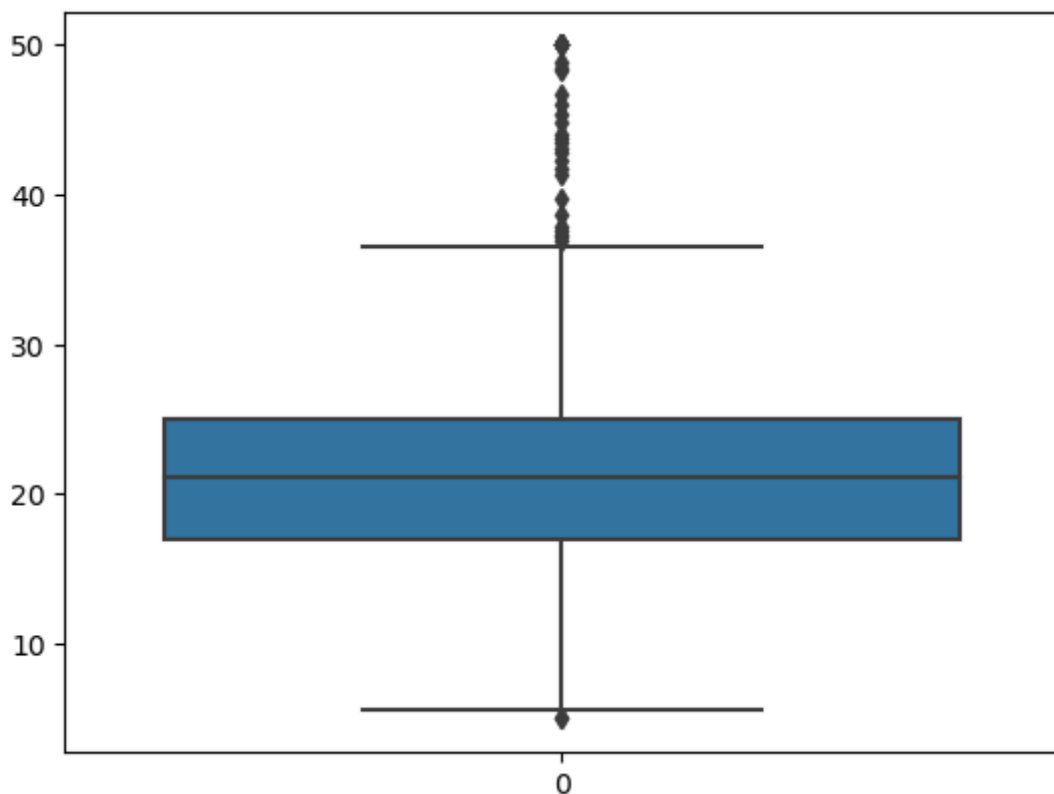
```
In [11]: 1 sns.histplot(data["Price"])
2
```

```
Out[11]: <Axes: xlabel='Price', ylabel='Count'>
```



```
In [12]: 1 sns.boxplot(data["Price"])
```

```
Out[12]: <Axes: >
```



```
In [13]: 1 from sklearn.preprocessing import StandardScaler
2 # Split the data into input and output variables
3 X = data.drop('Price', axis=1)
4 y = data['Price']
5 # Scale the input features
6 scaler = StandardScaler()
7 X = scaler.fit_transform(X)
```

```
In [14]: 1 from sklearn.model_selection import train_test_split
2 # Split the data into training and testing sets
3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

```
In [15]: 1 print('Training set shape:', X_train.shape, y_train.shape)
2 print('Testing set shape:', X_test.shape, y_test.shape)
```

Training set shape: (354, 14) (354,)
Testing set shape: (152, 14) (152,)

```
In [16]: 1 from keras.models import Sequential
2 from keras.layers import Dense, Dropout
3
```

In [17]:

```
1 # Define the model architecture
2 model = Sequential()
3 model.add(Dense(128,activation = 'relu',input_dim =14))
4 model.add(Dense(64,activation = 'relu'))
5 model.add(Dense(32,activation = 'relu'))
6 model.add(Dense(16,activation = 'relu'))
7 model.add(Dense(1))
```

C:\Users\STES\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:8
8: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

In [18]:

```
1 # Display the model summary
2 print(model.summary())
```

Model: "sequential"

Layer (type)	Output Shape	
dense (Dense)	(None, 128)	
dense_1 (Dense)	(None, 64)	
dense_2 (Dense)	(None, 32)	
dense_3 (Dense)	(None, 16)	
dense_4 (Dense)	(None, 1)	



Total params: 12,801 (50.00 KB)

Trainable params: 12,801 (50.00 KB)

Non-trainable params: 0 (0.00 B)

None


In [19]:

```
1
2 # Compile the model
3 model.compile(optimizer = 'adam',loss = 'mean_squared_error',metrics=['m
4
5 x_val=X_train
6 y_val=y_train
7
```


In [20]:

```
1 history = model.fit(X_train,
2                     y_train,
3                     epochs=20,
4                     batch_size=512,
5                     validation_data=(x_val, y_val))
```


Epoch 1/20

1/1  1s 1s/step - loss: 624.6559 - mae: 23.1586 - val_loss: 622.1426 - val_mae: 23.1068


Epoch 2/20

1/1  0s 48ms/step - loss: 622.1426 - mae: 23.1068 - val_loss: 620.0562 - val_mae: 23.0625


Epoch 3/20

1/1  0s 49ms/step - loss: 620.0562 - mae: 23.0625 - val_loss: 618.4172 - val_mae: 23.0253


Epoch 4/20

1/1  0s 47ms/step - loss: 618.4172 - mae: 23.0253 - val_loss: 617.0788 - val_mae: 22.9923


Epoch 5/20

1/1  0s 46ms/step - loss: 617.0788 - mae: 22.9923 - val_loss: 615.6612 - val_mae: 22.9577


Epoch 6/20

1/1  0s 46ms/step - loss: 615.6611 - mae: 22.9577 - val_loss: 614.0786 - val_mae: 22.9198


Epoch 7/20

1/1  0s 47ms/step - loss: 614.0786 - mae: 22.9198 - val_loss: 612.3089 - val_mae: 22.8784


Epoch 8/20

1/1  0s 47ms/step - loss: 612.3089 - mae: 22.8784 - val_loss: 610.3096 - val_mae: 22.8320


Epoch 9/20

1/1  0s 47ms/step - loss: 610.3096 - mae: 22.8320 - val_loss: 608.0159 - val_mae: 22.7791


Epoch 10/20

1/1  0s 49ms/step - loss: 608.0159 - mae: 22.7791 - val_loss: 605.3791 - val_mae: 22.7185


Epoch 11/20

1/1  0s 49ms/step - loss: 605.3790 - mae: 22.7185 - val_loss: 602.3395 - val_mae: 22.6489


Epoch 12/20

1/1  0s 47ms/step - loss: 602.3395 - mae: 22.6489 - val_loss: 598.8791 - val_mae: 22.5700


Epoch 13/20

1/1  0s 47ms/step - loss: 598.8791 - mae: 22.5700 - val_loss: 595.0938 - val_mae: 22.4838


Epoch 14/20

1/1  0s 48ms/step - loss: 595.0938 - mae: 22.4838 - val_loss: 591.0748 - val_mae: 22.3923


Epoch 15/20

1/1  0s 47ms/step - loss: 591.0748 - mae: 22.3923 - val_loss: 586.8221 - val_mae: 22.2952


Epoch 16/20

1/1  0s 48ms/step - loss: 586.8221 - mae: 22.2952 - val_loss: 582.3458 - val_mae: 22.1927


Epoch 17/20

1/1  0s 48ms/step - loss: 582.3458 - mae: 22.1927 - val_loss: 577.6431 - val_mae: 22.0842


Epoch 18/20

1/1  0s 47ms/step - loss: 577.6431 - mae: 22.0842 - val_loss: 572.6659 - val_mae: 21.9685

Epoch 19/20

1/1  0s 47ms/step - loss: 572.6659 - mae: 21.9685 - val_loss: 567.3625 - val_mae: 21.8447

Epoch 20/20

1/1  0s 48ms/step - loss: 567.3625 - mae: 21.8447 - val_loss: 561.7023 - val_mae: 21.7116

In [22]: 1 results = model.evaluate(X_test, y_test)

5/5 ————— 0s 2ms/step - loss: 471.2321 - mae: 20.0160

In []: 1