In [1]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:

```python
housing = pd.read_csv('housing.data.csv')
```

EDA

In [3]:

```python
housing.head()
```

Out[3]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90

In [4]:

```python
housing.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       501 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  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

In [5]:

```python
housing.describe()
```

Out[5]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE
count	506.000000	506.000000	506.000000	506.000000	506.000000	501.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.280130	68.574901
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.701888	28.148861
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885000	45.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208000	77.500000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.618000	94.075000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000

In [6]:

```
# housing['CHAS'].value_counts()

# housing['CHAS']

# housing['CHAS'][501]

# housing['CHAS'][[501,502]]

# housing[['CHAS', 'CRIM']]

# housing[['CHAS', 'CRIM']].loc[[501,502]]

# housing.hist(bins=50, figsize=(15, 10));
```

Train-test Splitting

In [7]:

```
# def train_test_split(data, test_ratio):
#     np.random.seed(42)
#     shuffled = np.random.permutation(len(data))

#     print(f'shuffled[0]: {shuffled[0]}')

#     test_set_size = int(len(data) * test_ratio)
#     test_indices = shuffled[:test_set_size]
#     train_indices = shuffled[test_set_size:]
#     return data.iloc[train_indices], data.iloc[test_indices]
```

In [8]:

```
# train_set, test_set = train_test_split(housing, 0.2)

# print(f'train_set: {len(train_set)}\ntest_set: {len(test_set)}')
```

In [9]:

```
# from sklearn.model_selection import train_test_split
# train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
# print(f'train_set: {len(train_set)}\ntest_set: {len(test_set)}')
```

StratifiedShuffleSplit

The StratifiedShuffleSplit class performs stratified random sampling, which means that it ensures that the proportion of different categories in the target variable is preserved in the training and test sets. In this case, the target variable is CHAS, which is a binary variable indicating whether the property is located on the Charles River (1) or not (0).

In [10]:
```
def tt_split():
    from sklearn.model_selection import StratifiedShuffleSplit
    split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
    for train_indices, test_indices in split.split(housing, housing['CHAS']):
        strat_train_set = housing.loc[train_indices]
        strat_test_set = housing.loc[test_indices]

    print(f'strat_train_set: {len(strat_train_set)}\nstrat_test_set: {len(strat_tes

    return strat_train_set, strat_test_set
```

In [11]:
```
# strat_train_set, strat_test_set = tt_split()
```

In [12]:
```
# strat_train_set.info()

# strat_train_set['CHAS'].value_counts()

# strat_test_set['CHAS'].value_counts()

# housing['CHAS'].value_counts()

# print(376/471, 28/35)
# print(95/471, 7/35)
```

Looking for Correlations

In [13]:
```
corr_mat = housing.corr()
corr_mat
```

Out[13]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.216740	0.352734	-0.37
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.304066	-0.569537	0.66
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.386184	0.644779	-0.70
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.093596	0.086518	-0.09
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.295820	0.731470	-0.76
RM	-0.216740	0.304066	-0.386184	0.093596	-0.295820	1.000000	-0.235180	0.19
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.235180	1.000000	-0.74
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.198815	-0.747881	1.00
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.203795	0.456022	-0.49
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.286652	0.506456	-0.53
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.349952	0.261515	-0.23
B	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.125702	-0.273534	0.29
LSTAT	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.611215	0.602339	-0.49
MEDV	-0.388305	0.360445	-0.483725	0.175260	-0.427321	0.692684	-0.376955	0.24

In [14]:
```
corr_mat['MEDV'].sort_values(ascending=False)
```

Out[14]:
```
MEDV       1.000000
RM         0.692684
ZN         0.360445
B          0.333461
DIS        0.249929
CHAS       0.175260
AGE       -0.376955
RAD       -0.381626
CRIM      -0.388305
NOX       -0.427321
TAX       -0.468536
INDUS     -0.483725
PTRATIO   -0.507787
LSTAT     -0.737663
Name: MEDV, dtype: float64
```

In [15]:
```
def strong_corr():
    corr_mat = housing.corr()
    strong_corr = corr_mat['MEDV'].abs().sort_values(ascending=False)
    strong_corr = strong_corr[strong_corr >= .5]
    return corr_mat['MEDV'][strong_corr.index]
```

In [16]:
```
strong_corr()
```

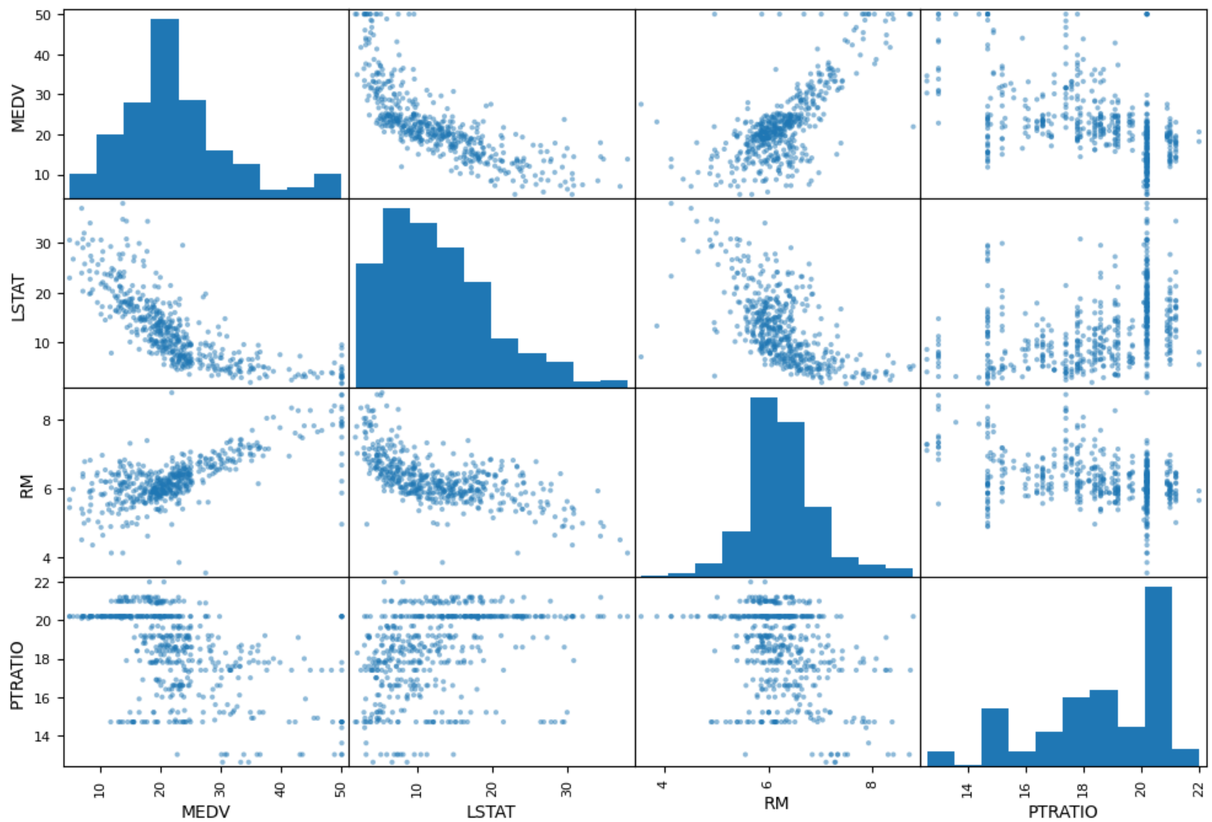
```
Out[16]: MEDV       1.000000
         LSTAT     -0.737663
         RM         0.692684
         PTRATIO   -0.507787
         Name: MEDV, dtype: float64
```

```
In [17]: from pandas.plotting import scatter_matrix
```

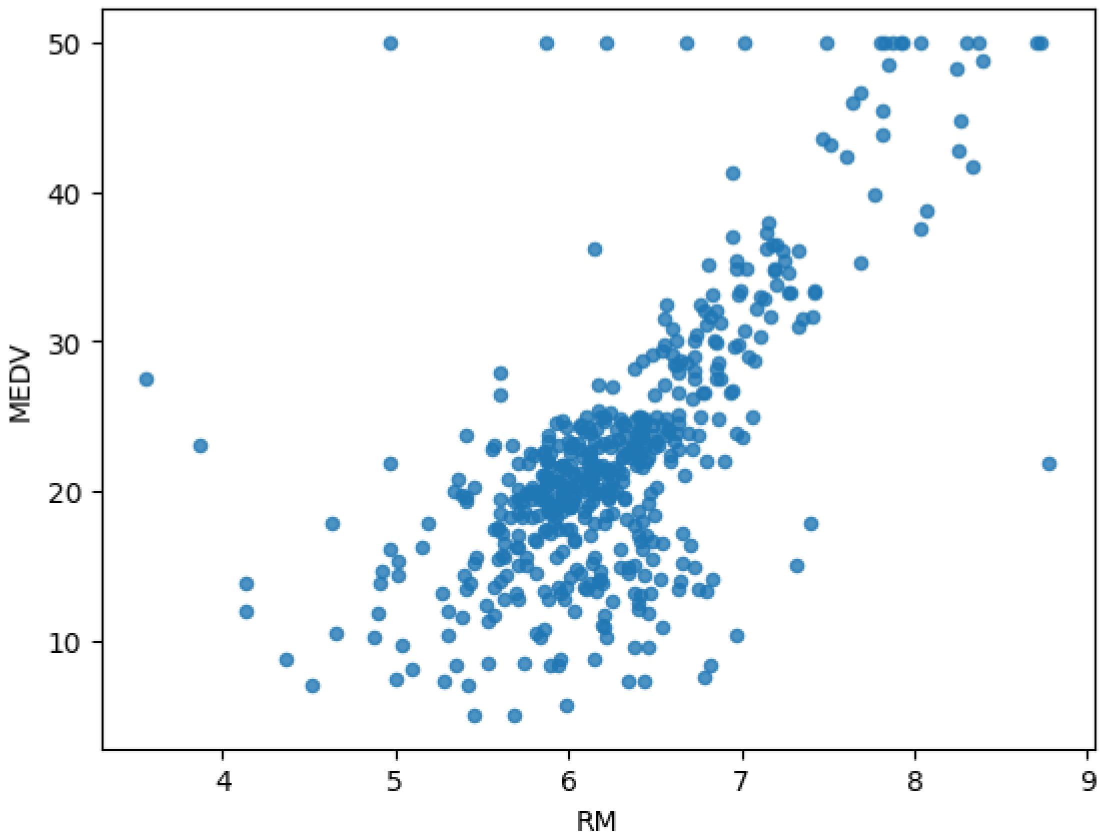
```
In [18]: def strong_corr_scatter():
             scatter_matrix(housing[strong_corr().index], figsize=(12,8));

         def corr_scatter(col):
             housing.plot(kind='scatter', x=col, y='MEDV', alpha=.8)
```

```
In [19]: strong_corr_scatter()
```




```
In [20]: corr_scatter('RM')
```



Trying out Attribute combinations

In [21]:
```
housing['TAXRM'] = housing['TAX']/housing['RM']
```

In [22]:
```
housing.head()
```

Out[22]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90

In [23]:
```
strong_corr()
```

Out[23]:
```
MEDV       1.000000
LSTAT     -0.737663
RM         0.692684
TAXRM     -0.530276
PTRATIO   -0.507787
Name: MEDV, dtype: float64
```

In [24]:
```
# strong_corr_scatter()
```

In [25]:
```
# corr_scatter('TAXRM')
```

In [26]:
```
# Handling missing attributes:
#     1. get rid of missing pts.
#     2. get rid of whole attr.
#     3. set val to 0, mean or med
```

In [27]:
```
#     1. get rid of missing pts.
a = housing.dropna(subset=['RM'])
a.shape
```

Out[27]:
```
(501, 15)
```

In [28]:
```
#     2. get rid of whole attr.
a = housing.drop('RM', axis=1)
a.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   AGE      506 non-null    float64
 6   DIS      506 non-null    float64
 7   RAD      506 non-null    int64  
 8   TAX      506 non-null    float64
 9   PTRATIO  506 non-null    float64
 10  B        506 non-null    float64
 11  LSTAT    506 non-null    float64
 12  MEDV     506 non-null    float64
 13  TAXRM    501 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

In [29]:
```
#     3. set val to 0, mean or med
med = housing['RM'].median() # Store it for later use (to fill missing val(s) in te
housing['RM'].fillna(med) # Won't affect orig housing df (use inplace=True for hard
```

Out[29]:
```
0      6.575
1      6.421
2      7.185
3      6.998
4      7.147
       ...  
501    6.593
502    6.120
503    6.976
504    6.794
505    6.030
Name: RM, Length: 506, dtype: float64
```

Impute missing values

In [30]:
```
housing_orig = housing
strat_train_set, strat_test_set = tt_split()
housing = strat_train_set
```

```
strat_train_set: 404
strat_test_set: 102
```

In [31]:
```
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 404 entries, 254 to 216
Data columns (total 15 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     404 non-null    float64
 1   ZN       404 non-null    float64
 2   INDUS    404 non-null    float64
 3   CHAS     404 non-null    int64  
 4   NOX      404 non-null    float64
 5   RM       400 non-null    float64
 6   AGE      404 non-null    float64
 7   DIS      404 non-null    float64
 8   RAD      404 non-null    int64  
 9   TAX      404 non-null    float64
 10  PTRATIO  404 non-null    float64
 11  B        404 non-null    float64
 12  LSTAT    404 non-null    float64
 13  MEDV     404 non-null    float64
 14  TAXRM    400 non-null    float64
dtypes: float64(13), int64(2)
memory usage: 50.5 KB
```

In [32]:
```
housing.describe()
```

Out[32]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE
count	404.000000	404.000000	404.000000	404.000000	404.000000	400.000000	404.000000
mean	3.602814	10.836634	11.344950	0.069307	0.558064	6.277143	69.039851
std	8.099383	22.150636	6.877817	0.254290	0.116875	0.713716	28.258248
min	0.006320	0.000000	0.740000	0.000000	0.389000	3.561000	2.900000
25%	0.086962	0.000000	5.190000	0.000000	0.453000	5.878750	44.850000
50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.210000	78.200000
75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.630000	94.100000
max	73.534100	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000

In [33]:
```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='median')
```

```
imputer.fit(housing)
```

Out[33]:

```
SimpleImputer
SimpleImputer(strategy='median')
```

In [34]:

```
imputer.statistics_
```

Out[34]:

```
array([2.86735000e-01, 0.00000000e+00, 9.90000000e+00, 0.00000000e+00,
       5.38000000e-01, 6.21000000e+00, 7.82000000e+01, 3.12220000e+00,
       5.00000000e+00, 3.37000000e+02, 1.90000000e+01, 3.90955000e+02,
       1.15700000e+01, 2.11500000e+01, 5.44293624e+01])
```

In [35]:

```
X = imputer.transform(housing)
print(X)
```

```
[[4.81900000e-02 8.00000000e+01 3.64000000e+00 ... 6.57000000e+00
  2.19000000e+01 5.15717092e+01]
 [1.50100000e-02 8.00000000e+01 2.01000000e+00 ... 5.99000000e+00
  2.45000000e+01 4.22004521e+01]
 [4.87141000e+00 0.00000000e+00 1.81000000e+01 ... 1.86800000e+01
  1.67000000e+01 1.02714374e+02]
 ...
 [8.18700000e-02 0.00000000e+00 2.89000000e+00 ... 3.57000000e+00
  4.38000000e+01 3.52941176e+01]
 [4.75237000e+00 0.00000000e+00 1.81000000e+01 ... 1.81300000e+01
  1.41000000e+01 1.02068966e+02]
 [4.56000000e-02 0.00000000e+00 1.38900000e+01 ... 1.35100000e+01
  2.33000000e+01 4.68750000e+01]]
```

In [36]:

```
# X.shape

# type(X)
```

In [37]:

```
housing_tr = pd.DataFrame(X, columns=housing.columns)
```

In [38]:

```
housing_tr.describe()
```

Out[38]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE
count	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000
mean	3.602814	10.836634	11.344950	0.069307	0.558064	6.276478	69.039851
std	8.099383	22.150636	6.877817	0.254290	0.116875	0.710197	28.258248
min	0.006320	0.000000	0.740000	0.000000	0.389000	3.561000	2.900000
25%	0.086962	0.000000	5.190000	0.000000	0.453000	5.879750	44.850000
50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.210000	78.200000
75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.629250	94.100000
max	73.534100	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000

Sklearn design

Primarily, three types of objects:

1. Estimators - It estimates some parameter based on a dataset. Eg. Imputer. It has a fit method and transform method. Fit method fits the dataset and calculates internal parameters.

2. Transformaers - Transform method takes input and returns output based on the learnings from fit(). It also has a convenience function called fit_transform() which fits and then transforms.

3. Predictors - LinearRegression model is an example of predictor. fit() and predict() are two common functions. It also has score() function which will evaluate the predictions.

Feature Scaling

Primarily, two types of feature scaling methods:

1. Min-max scaling (Normalization):

(value - min)/(max - min)

Sklearn provides a class called MinMaxScaler for this

2. Standardization

(value - mean)/std

Sklearn provides a class called StandardScaler for this

Creating a pipeline

In [39]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

In [40]:
```
my_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='median')),
    # ...
    ('std_scaler', StandardScaler())
])
```

In [41]:
```
housing_labels = housing['MEDV'].copy()
housing = housing.drop('MEDV', axis=1)
housing = housing.drop('TAXRM', axis=1) # duh! (^///^)
```

In [42]:
```
housing_num_tr = my_pipeline.fit_transform(housing)
```

In [43]:
```
housing_num_tr
```

Out[43]:
```
array([[-0.43942006,  3.12628155, -1.12165014, ..., -0.97491834,
         0.41164221, -0.86091034],
       [-0.44352175,  3.12628155, -1.35893781, ..., -0.69277865,
         0.39131918, -0.94116739],
       [ 0.15682292, -0.4898311 ,  0.98336806, ...,  0.81196637,
         0.44624347,  0.81480158],
       ...,
       [-0.43525657, -0.4898311 , -1.23083158, ..., -0.22254583,
         0.41831233, -1.27603303],
       [ 0.14210728, -0.4898311 ,  0.98336806, ...,  0.81196637,
        -3.15239177,  0.73869575],
       [-0.43974024, -0.4898311 ,  0.37049623, ..., -0.97491834,
         0.41070422,  0.09940681]])
```

In [44]:
```
housing_num_tr.shape
```

Out[44]:
```
(404, 13)
```

In [45]:
```
housing_labels.shape
```

Out[45]:
```
(404,)
```

Selection of desired model

In [46]:
```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor

# model = LinearRegression()
# model = DecisionTreeRegressor()
model = RandomForestRegressor()


model.fit(housing_num_tr, housing_labels)
```

Out[46]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [47]:
```
some_data = housing.iloc[:5]
some_labels = housing_labels.iloc[:5]
prepared_data = my_pipeline.transform(some_data)
```

In [68]:
```
prepared_data[0]
```

Out[68]:
```
array([-0.43942006,  3.12628155, -1.12165014, -0.27288841, -1.42262747,
       -0.23752103, -1.31238772,  2.61111401, -1.0016859 , -0.5778192 ,
       -0.97491834,  0.41164221, -0.86091034])
```

In [48]:
```
model.predict(prepared_data)
```

Out[48]: array([22.199, 25.089, 16.523, 23.55 , 23.52])

In [49]:
```
some_labels
```

Out[49]:
```
254    21.9
348    24.5
476    16.7
321    23.1
326    23.0
Name: MEDV, dtype: float64
```

Evaluating model

In [50]:
```
from sklearn.metrics import mean_squared_error
housing_predictions = model.predict(housing_num_tr)
```

In [51]:
```
mse = mean_squared_error(housing_predictions, housing_labels)
rmse = np.sqrt(mse)
```

In [52]:
```
mse
```

Out[52]: 1.4967560445544552

In [53]:
```
rmse
```

Out[53]: 1.223419815335053

Using better evaluation technique - Cross Validation

In [54]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(model, housing_num_tr, housing_labels, scoring='neg_mean_s
rmse_scores = np.sqrt(-scores)
```

In [55]:
```
rmse_scores
```

Out[55]:
```
array([2.89608734, 2.88467811, 4.70517973, 3.08690116, 3.2042378 ,
       2.49517189, 4.17314398, 3.46038353, 3.08251056, 3.38961143])
```

In [56]:
```
def print_scores(scores):
    print(f'scores: {scores}')
    print(f'mean: {scores.mean()}')
    print(f'std: {scores.std()}')
    print(f'😎: [{scores.mean() - scores.std()}, {scores.mean() + scores.std()}]')
```

In [57]:
```
print_scores(rmse_scores)
```

```
scores: [2.89608734 2.88467811 4.70517973 3.08690116 3.2042378  2.49517189
 4.17314398 3.46038353 3.08251056 3.38961143]
mean: 3.3377905538325927
std: 0.6198105753330576
😎: [2.7179799784995353, 3.95760112916565]
```

LinearRegression

scores: [4.1586198 4.27871326 5.17991609 3.92930031 5.3692877 4.40149594 7.45686894 5.52625729 4.14232706 6.05075518]

mean: 5.049354157234278

std: 1.0502383571588667

😎: [3.9991158000754115, 6.099592514393144]

DecisionTreeRegressor

scores: [4.10567721 5.28119074 5.40857494 4.53993123 4.32790365 3.68947828 7.64642073 5.39237888 3.75093322 3.95205643]

mean: 4.809454531674119

std: 1.1348762306872051

😎: [3.3446293068224495, 5.800670370841967]

RandomForestRegressor

scores: [2.84654616 2.938878 4.64470163 2.92694333 3.21405751 2.57130946 4.65887751 3.38253226 3.04995972 3.37965391]

mean: 3.3613459472235983

std: 0.6860313802362531

😎: [2.6987448932932576, 4.119098411068847]

Saving the model

In [60]:
```
from joblib import dump, load
```

In [61]:
```
# dump(model, 'Boston.joblib')
```

Out[61]:
```
['Boston.joblib']
```

In [62]:
```
strat_test_set_Y = strat_test_set['MEDV'].copy()
strat_test_set_X = strat_test_set.drop('MEDV', axis=1)
strat_test_set_X = strat_test_set_X.drop('TAXRM', axis=1) # duh! (^///^)
```

In [63]:
```
strat_test_set_X_prepared = my_pipeline.transform(strat_test_set_X)
```

In [64]:
```
final_predictions = model.predict(strat_test_set_X_prepared)
```

In [65]:
```
final_mse = mean_squared_error(strat_test_set_Y, final_predictions)
```

In [66]:
```
final_rmse = np.sqrt(final_mse)
```

In [67]:
```
final_rmse
```

Out[67]:
```
3.194701202696397
```

Using the model

In [69]:
```
model = load('Boston.joblib')
```

In [71]:
```
features = np.array([[-0.43942006,  3.12628155, -1.12165014, -0.27288841, -1.422627
       -0.23752103, -1.31238772,  2.61111401, -1.0016859 , -0.5778192 ,
       -0.97491834,  0.41164221, -0.86091034]])
```

In [73]:
```
model.predict(features)
```

Out[73]:
```
array([22.199])
```