house-price-prediction

August 27, 2023

[9]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit
from pandas.plotting import scatter_matrix
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from joblib import dump, load
```

[15]:
```
from google.colab import files
uploaded=files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving data.csv to data.csv
```

[17]:
```
housing = pd.read_csv("data.csv")
housing.head()
```

[17]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7			

```
 4  396.90   5.33  36.2
```

[18]:
```
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    int64  
 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(11), int64(3)
memory usage: 55.5 KB
```

[19]:
```
housing.describe()
```

[19]:

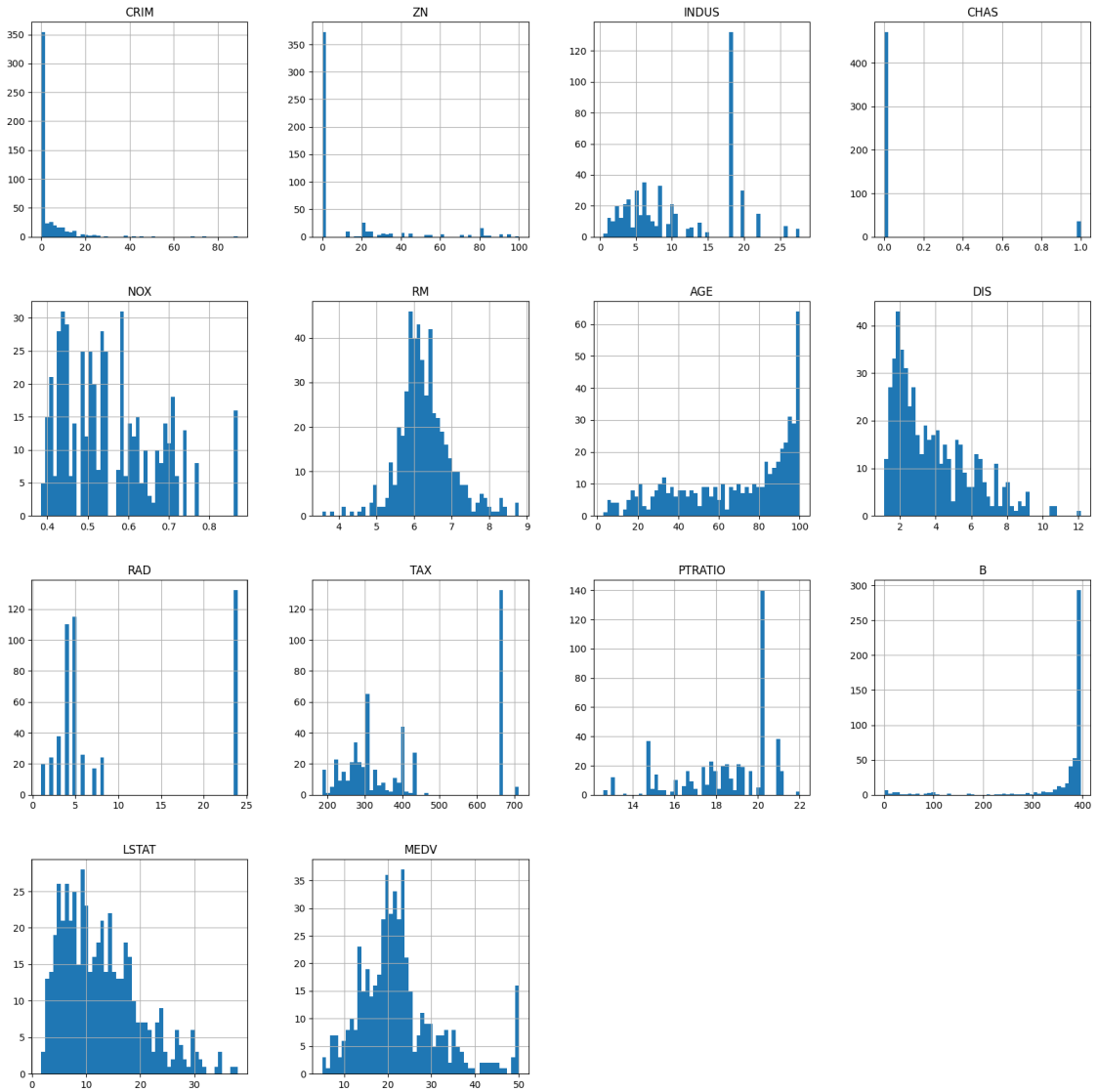
	CRIM	ZN	INDUS	CHAS	NOX	RM	\
count	506.000000	506.000000	506.000000	506.000000	506.000000	501.000000	
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284341	
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.705587	
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.884000	
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208000	
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.625000	
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	

	AGE	DIS	RAD	TAX	PTRATIO	B	\
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	
mean	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	
std	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	
min	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	
25%	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	
50%	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	
75%	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	
max	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	

	LSTAT	MEDV
count	506.000000	506.000000
mean	12.653063	22.532806
std	7.141062	9.197104
min	1.730000	5.000000
25%	6.950000	17.025000
50%	11.360000	21.200000
75%	16.955000	25.000000
max	37.970000	50.000000

[20]:
```
# Plotting the data

housing.hist(bins=50, figsize=(20,20))
plt.show()
```



[21]:
```
# Doing the train test split

train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
```

[22]:
```
train_set.head()
```

[22]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	\
477	15.02340	0.0	18.10	0	0.6140	5.304	97.3	2.1007	24	666	
15	0.62739	0.0	8.14	0	0.5380	5.834	56.5	4.4986	4	307	
332	0.03466	35.0	6.06	0	0.4379	6.031	23.3	6.6407	1	304	
423	7.05042	0.0	18.10	0	0.6140	6.103	85.1	2.0218	24	666	
19	0.72580	0.0	8.14	0	0.5380	5.727	69.5	3.7965	4	307	

	PTRATIO	B	LSTAT	MEDV
477	20.2	349.48	24.91	12.0
15	21.0	395.62	8.47	19.9
332	16.9	362.25	7.83	19.4
423	20.2	2.52	23.29	13.4
19	21.0	390.95	11.28	18.2

[23]:
```
test_set.head()
```

[23]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	\
173	0.09178	0.0	4.05	0	0.510	6.416	84.1	2.6463	5	296	
274	0.05644	40.0	6.41	1	0.447	6.758	32.9	4.0776	4	254	
491	0.10574	0.0	27.74	0	0.609	5.983	98.8	1.8681	4	711	
72	0.09164	0.0	10.81	0	0.413	6.065	7.8	5.2873	4	305	
452	5.09017	0.0	18.10	0	0.713	6.297	91.8	2.3682	24	666	

	PTRATIO	B	LSTAT	MEDV
173	16.6	395.50	9.04	23.6
274	17.6	396.90	3.53	32.4
491	20.1	390.11	18.07	13.6
72	19.2	390.91	5.52	22.8
452	20.2	385.09	17.27	16.1

[24]:
```
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing, housing["CHAS"]):
    strat_train_set = housing.loc[train_index]
    strat_test_set = housing.loc[test_index]
```

[25]:
```
strat_train_set["CHAS"].value_counts()
```

[25]:
```
0    376
1     28
Name: CHAS, dtype: int64
```

[26]:
```
strat_test_set["CHAS"].value_counts()
```

[26]:
```
0    95
1     7
Name: CHAS, dtype: int64
```

[27]:
```
housing = strat_train_set.copy()
```

[28]:
```
# Correlations

corr_matrix = housing.corr()
```

[29]:
```
corr_matrix["MEDV"].sort_values(ascending=False)
```

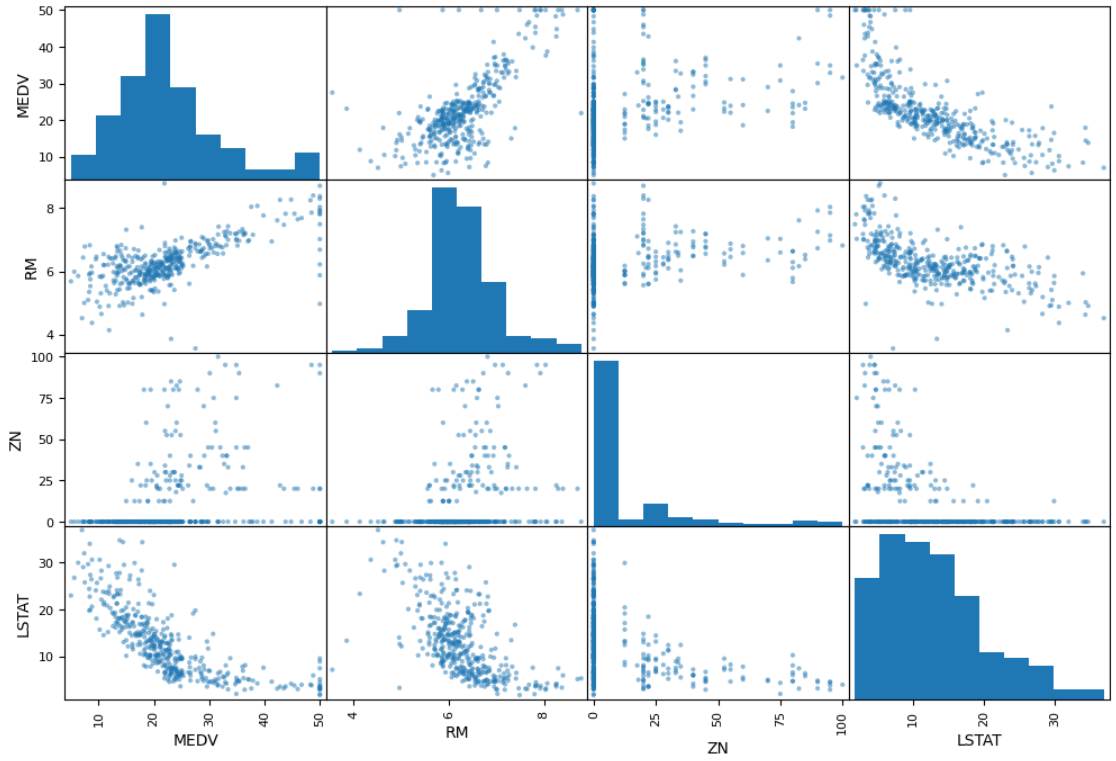
[29]:
```
MEDV       1.000000
RM         0.680857
B          0.361761
ZN         0.339741
DIS        0.240451
CHAS       0.205066
AGE       -0.364596
RAD       -0.374693
CRIM      -0.393715
NOX       -0.422873
TAX       -0.456657
INDUS     -0.473516
PTRATIO   -0.493534
LSTAT     -0.740494
Name: MEDV, dtype: float64
```

[30]:
```
# Plotting the columns to understand Correlations

attributes = ["MEDV" , "RM" , "ZN" , "LSTAT"]
scatter_matrix(housing[attributes] , figsize=(12,8))
```

[30]:
```
array([[<Axes: xlabel='MEDV', ylabel='MEDV'>,
        <Axes: xlabel='RM', ylabel='MEDV'>,
        <Axes: xlabel='ZN', ylabel='MEDV'>,
        <Axes: xlabel='LSTAT', ylabel='MEDV'>],
       [<Axes: xlabel='MEDV', ylabel='RM'>,
        <Axes: xlabel='RM', ylabel='RM'>,
        <Axes: xlabel='ZN', ylabel='RM'>,
        <Axes: xlabel='LSTAT', ylabel='RM'>],
```

```
[<Axes: xlabel='MEDV', ylabel='ZN'>,
 <Axes: xlabel='RM', ylabel='ZN'>,
 <Axes: xlabel='ZN', ylabel='ZN'>,
 <Axes: xlabel='LSTAT', ylabel='ZN'>],
[<Axes: xlabel='MEDV', ylabel='LSTAT'>,
 <Axes: xlabel='RM', ylabel='LSTAT'>,
 <Axes: xlabel='ZN', ylabel='LSTAT'>,
 <Axes: xlabel='LSTAT', ylabel='LSTAT'>]], dtype=object)
```



[31]:
```
# Trying out attribute combinations

housing["TAXRM"] = housing["TAX"] / housing["RM"]
housing.head()
```

[31]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	\
254	0.04819	80.0	3.64	0	0.392	6.108	32.0	9.2203	1	315	
348	0.01501	80.0	2.01	0	0.435	6.635	29.7	8.3440	4	280	
476	4.87141	0.0	18.10	0	0.614	6.484	93.6	2.3053	24	666	
321	0.18159	0.0	7.38	0	0.493	6.376	54.3	4.5404	5	287	
326	0.30347	0.0	7.38	0	0.493	6.312	28.9	5.4159	5	287	

	PTRATIO	B	LSTAT	MEDV	TAXRM
254	16.4	392.89	6.57	21.9	51.571709

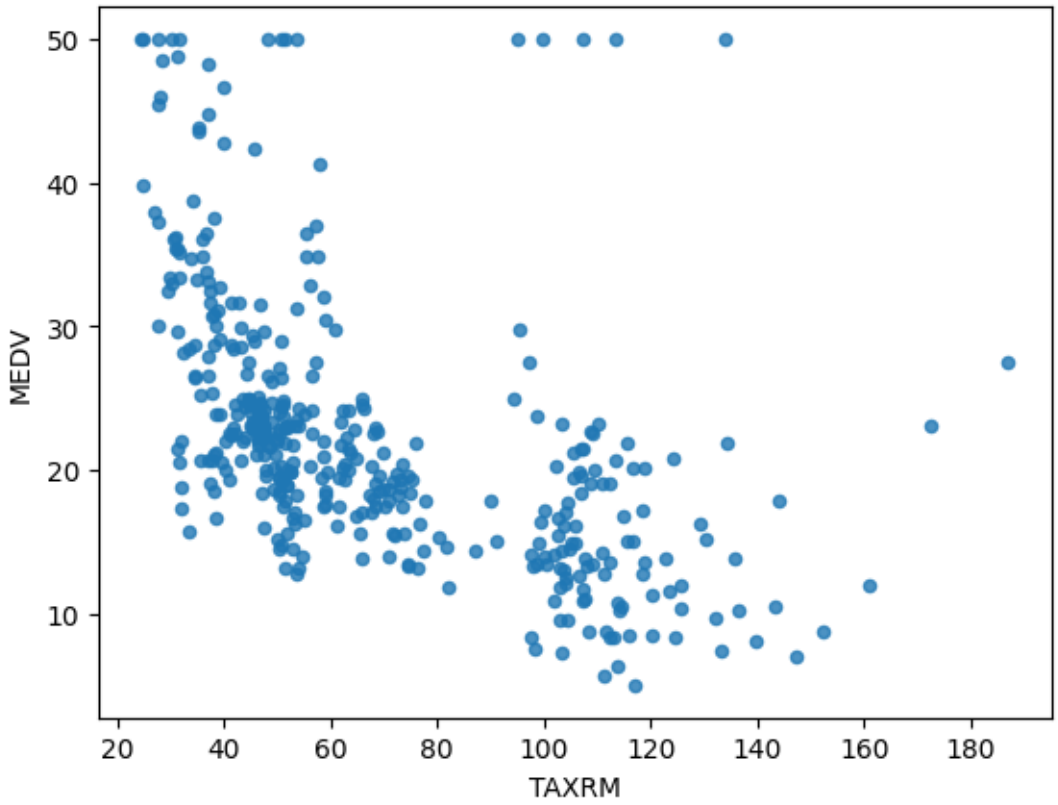
```
348     17.0  390.94   5.99  24.5   42.200452
476     20.2  396.21  18.68  16.7  102.714374
321     19.6  396.90   6.87  23.1   45.012547
326     19.6  396.90   6.15  23.0   45.468948
```

[32]:
```
corr_matrix = housing.corr()
corr_matrix["MEDV"].sort_values(ascending=False)
```

[32]:
```
MEDV       1.000000
RM         0.680857
B          0.361761
ZN         0.339741
DIS        0.240451
CHAS       0.205066
AGE       -0.364596
RAD       -0.374693
CRIM      -0.393715
NOX       -0.422873
TAX       -0.456657
INDUS     -0.473516
PTRATIO   -0.493534
TAXRM     -0.528626
LSTAT     -0.740494
Name: MEDV, dtype: float64
```

[33]:
```
housing.plot(kind="scatter" , x="TAXRM" , y="MEDV" , alpha=0.8)
```

[33]:
```
<Axes: xlabel='TAXRM', ylabel='MEDV'>
```



[34]:
```
housing.shape
```

[34]: (404, 15)

[35]:
```
housing.describe() # Before we started filling the missing values
```

[35]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	\
count	404.000000	404.000000	404.000000	404.000000	404.000000	399.000000	
mean	3.602814	10.836634	11.344950	0.069307	0.558064	6.279481	
std	8.099383	22.150636	6.877817	0.254290	0.116875	0.716784	
min	0.006320	0.000000	0.740000	0.000000	0.389000	3.561000	
25%	0.086962	0.000000	5.190000	0.000000	0.453000	5.876500	
50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.209000	
75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.630500	
max	73.534100	100.000000	27.740000	1.000000	0.871000	8.780000	

	AGE	DIS	RAD	TAX	PTRATIO	B	\
count	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	
mean	69.039851	3.746210	9.735149	412.341584	18.473267	353.392822	
std	28.258248	2.099057	8.731259	168.672623	2.129243	96.069235	
min	2.900000	1.129600	1.000000	187.000000	13.000000	0.320000	

```
25%     44.850000    2.035975    4.000000  284.000000   17.400000  374.617500
50%     78.200000    3.122200    5.000000  337.000000   19.000000  390.955000
75%     94.100000    5.100400   24.000000  666.000000   20.200000  395.630000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            LSTAT        MEDV       TAXRM
count  404.000000  404.000000  399.000000
mean    12.791609   22.509406   67.696004
std      7.235740    9.385531   31.577122
min      1.730000    5.000000   24.645639
25%      6.847500   16.600000   44.910026
50%     11.570000   21.150000   54.831220
75%     17.102500   25.000000   98.673976
max     36.980000   50.000000  187.026116
```

[36]:
```
# Splitting into features and labels

housing = strat_train_set.drop("MEDV" , axis=1)
housing_labels = strat_train_set["MEDV"].copy()
```

[37]:
```
# Filling missing values attributes

imputer = SimpleImputer(strategy="median") # To fill the missing cells of␣
 ↪columns with median values
imputer.fit(housing)
```

[37]:
```
SimpleImputer(strategy='median')
```

[38]:
```
imputer.statistics_
```

[38]:
```
array([2.86735e-01, 0.00000e+00, 9.90000e+00, 0.00000e+00, 5.38000e-01,
       6.20900e+00, 7.82000e+01, 3.12220e+00, 5.00000e+00, 3.37000e+02,
       1.90000e+01, 3.90955e+02, 1.15700e+01])
```

[39]:
```
X = imputer.transform(housing)
housing_tr = pd.DataFrame(X, columns=housing.columns)
```

[40]:
```
housing_tr.describe() # After we fill the missing data
```

[40]:
```
             CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  404.000000  404.000000  404.000000  404.000000  404.000000  404.000000
mean     3.602814   10.836634   11.344950    0.069307    0.558064    6.278609
std      8.099383   22.150636    6.877817    0.254290    0.116875    0.712366
min      0.006320    0.000000    0.740000    0.000000    0.389000    3.561000
25%      0.086962    0.000000    5.190000    0.000000    0.453000    5.878750
50%      0.286735    0.000000    9.900000    0.000000    0.538000    6.209000
75%      3.731923   12.500000   18.100000    0.000000    0.631000    6.630000
```

```
max     73.534100  100.000000   27.740000    1.000000    0.871000    8.780000

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  404.000000  404.000000  404.000000  404.000000  404.000000  404.000000
mean    69.039851    3.746210    9.735149  412.341584   18.473267  353.392822
std     28.258248    2.099057    8.731259  168.672623    2.129243   96.069235
min      2.900000    1.129600    1.000000  187.000000   13.000000    0.320000
25%     44.850000    2.035975    4.000000  284.000000   17.400000  374.617500
50%     78.200000    3.122200    5.000000  337.000000   19.000000  390.955000
75%     94.100000    5.100400   24.000000  666.000000   20.200000  395.630000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            LSTAT
count  404.000000
mean    12.791609
std      7.235740
min      1.730000
25%      6.847500
50%     11.570000
75%     17.102500
max     36.980000
```

[41]:
```
my_pipeline = Pipeline([
    ("imputer" , SimpleImputer(strategy="median")),
    ("std_scaler" , StandardScaler())
])
```

[42]:
```
housing_num_tr = my_pipeline.fit_transform(housing) # Before Imputing of Data
housing_num_tr
```

[42]:
```
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]])
```

[43]:
```
housing_num_tr.shape
```

[43]:
```
(404, 13)
```

[44]:
```
# 1) Use Linear Regression Model

model = LinearRegression()
model.fit(housing_num_tr , housing_labels)
```

[44]:
```
LinearRegression()
```

[45]:
```
# Evaluating the model

housing_predictions = model.predict(housing_num_tr)
lin_mse = mean_squared_error(housing_labels, housing_predictions)
lin_rmse = np.sqrt(lin_mse)
print("RMSE value is:", lin_rmse) # RSME value is too large
```

```
RMSE value is: 4.835301058716238
```

[46]:
```
# Using better evaluation technique - Cross Validation

scores = cross_val_score(model , housing_num_tr , housing_labels ,␣
 ↪scoring="neg_mean_squared_error" , cv=10) # 10 is for 10 folds
rmse_scores = np.sqrt(-scores)
rmse_scores
```

[46]:
```
array([4.22235612, 4.26438649, 5.09424333, 3.83081183, 5.37600331,
       4.41092152, 7.47272243, 5.48554135, 4.14606627, 6.0717752 ])
```

[48]:
```
# Printing the Score, Mean Score, Standard Deviation of RMSE

def print_scores(scores):
    print("Scores:",scores)
    print("Mean:",scores.mean())
    print("Standard Deviation:",scores.std())

print_scores(rmse_scores)
```

```
Scores: [4.22235612 4.26438649 5.09424333 3.83081183 5.37600331 4.41092152
 7.47272243 5.48554135 4.14606627 6.0717752 ]
Mean: 5.037482786117752
Standard Deviation: 1.059438240560695
```

[49]:
```
# 2) Use Decision Tree Regression Model

model = DecisionTreeRegressor()
model.fit(housing_num_tr , housing_labels)
```

[49]:
```
DecisionTreeRegressor()
```

[50]:
```
# Again evaluating the model

housing_predictions = model.predict(housing_num_tr)
mse = mean_squared_error(housing_labels, housing_predictions)
rmse = np.sqrt(mse)
print("RMSE value is:", rmse) # RSME value is zero means model is overfit
```

```
RMSE value is: 0.0
```

[51]:
```
# Using better evaluation technique - Cross Validation

scores = cross_val_score(model , housing_num_tr , housing_labels ,␣
 ↪scoring="neg_mean_squared_error" , cv=10) # 10 is for 10 folds
rmse_scores = np.sqrt(-scores)
rmse_scores
```

[51]:
```
array([4.31325241, 5.65100898, 5.2638667 , 3.64989141, 4.00203073,
       2.95330324, 4.61101941, 3.74309364, 3.42417873, 4.11229863])
```

[52]:
```
# Printing the Score, Mean Score, Standard Deviation of RMSE

def print_scores(scores):
    print("Scores:",scores)
    print("Mean:",scores.mean())
    print("Standard Deviation:",scores.std())

print_scores(rmse_scores)
```

```
Scores: [4.31325241 5.65100898 5.2638667  3.64989141 4.00203073 2.95330324
 4.61101941 3.74309364 3.42417873 4.11229863]
Mean: 4.172394388142086
Standard Deviation: 0.7826748672655879
```

[53]:
```
# 3) Use Random Forest Regression Model

model = RandomForestRegressor()
model.fit(housing_num_tr , housing_labels)
```

[53]:
```
RandomForestRegressor()
```

[54]:
```
# Again evaluating the model

housing_predictions = model.predict(housing_num_tr)
mse = mean_squared_error(housing_labels, housing_predictions)
rmse = np.sqrt(mse)
print("RMSE value is:", rmse)
```

```
RMSE value is: 1.1745828256689408
```

[55]:
```
# Using better evaluation technique - Cross Validation

scores = cross_val_score(model , housing_num_tr , housing_labels ,␣
 ↪scoring="neg_mean_squared_error" , cv=10) # 10 is for 10 folds
rmse_scores = np.sqrt(-scores)
rmse_scores
```

[55]:
```
array([2.84839164, 2.89694495, 4.48248591, 2.51489994, 3.45281138,
       2.77378514, 4.78396701, 3.39867732, 3.16069948, 3.18225874])
```

[56]:
```
# Printing the Score, Mean Score, Standard Deviation of RMSE

def print_scores(scores):
    print("Scores:",scores)
    print("Mean:",scores.mean())
    print("Standard Deviation:",scores.std())

print_scores(rmse_scores)
```

```
Scores: [2.84839164 2.89694495 4.48248591 2.51489994 3.45281138 2.77378514
 4.78396701 3.39867732 3.16069948 3.18225874]
Mean: 3.3494921528188946
Standard Deviation: 0.700141424283212
```

[60]:
```
# importing the joblib libraray
import joblib
```

[61]:
```
dump(model, "HousePricePrediction.joblib")
```

[61]:
```
['HousePricePrediction.joblib']
```

[62]:
```
X_test = strat_test_set.drop("MEDV" , axis=1)
y_test = strat_test_set["MEDV"].copy()

X_test_prepared = my_pipeline.transform(X_test)

final_predictions = model.predict(X_test_prepared)

final_mse = mean_squared_error(y_test , final_predictions)
final_rmse = np.sqrt(final_mse)

print("RSME value is:" , final_rmse)
```

```
RSME value is: 2.9240217821269616
```

[63]:
```
model = load("HousePricePrediction.joblib")
```

```
features = np.array([[-5.43942006, 4.12628155, -1.6165014, -0.67288841, -1.
↪42262747,
      -11.44443979304, -49.31238772,  7.61111401, -26.0016879 , -0.5778192 ,
      -0.97491834,  0.41164221, -66.86091034]])
model.predict(features)
```

[63]: array([24.007])