Jain Real Estate - House Price Prediction

In [1]:

```
#importing libraries

import pandas as pd
import numpy as np
```

In [2]:

```
house=pd.read_csv('data.csv')
```

In [3]:

```
#     1. CRIM      per capita crime rate by town
#     2. ZN        proportion of residential land zoned for lots over
#                  25,000 sq.ft.
#     3. INDUS     proportion of non-retail business acres per town
#     4. CHAS      Charles River dummy variable (= 1 if tract bounds
#                  river; 0 otherwise)
#     5. NOX       nitric oxides concentration (parts per 10 million)
#     6. RM        average number of rooms per dwelling
#     7. AGE       proportion of owner-occupied units built prior to 1940
#     8. DIS       weighted distances to five Boston employment centres
#     9. RAD       index of accessibility to radial highways
#     10. TAX      full-value property-tax rate per $10,000
#     11. PTRATIO  pupil-teacher ratio by town
#     12. B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks
#                  by town
#     13. LSTAT    % lower status of the population
#     14. MEDV     Median value of owner-occupied homes in $1000's
```

In [4]:

```
house.head()
```

Out[4]:

	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	396.90	5.33	36.2

In [5]:

```
house.shape
```

Out[5]:

(506, 14)

In [6]:

```
house.describe()
```

Out[6]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTR

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTR
count	506.000000	506.000000	506.000000	506.000000	506.000000	498.000000	506.000000	506.000000	506.000000	506.000000	506.0
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.295556	68.574901	3.795043	9.549407	408.237154	18.4
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.697106	28.148861	2.105710	8.707259	168.537116	2.1
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.6
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.888250	45.025000	2.100175	4.000000	279.000000	17.4
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.211000	77.500000	3.207450	5.000000	330.000000	19.0
75%	3.677082	12.500000	18.100000	0.000000	0.624000	6.629750	94.075000	5.188425	24.000000	666.000000	20.2
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.0

In [7]:

```
house.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       498 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
```

Exploring the columns

In [8]:

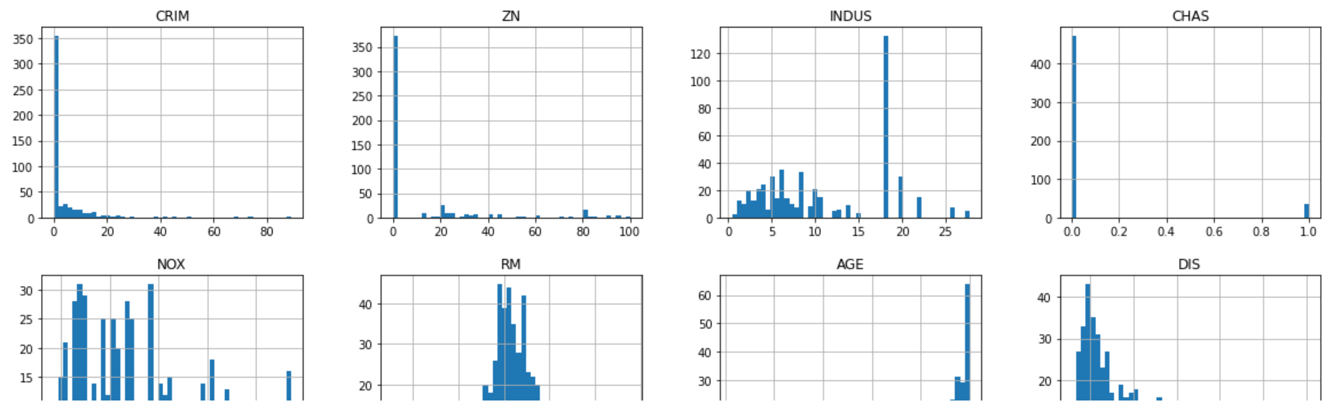
```
%matplotlib inline
```

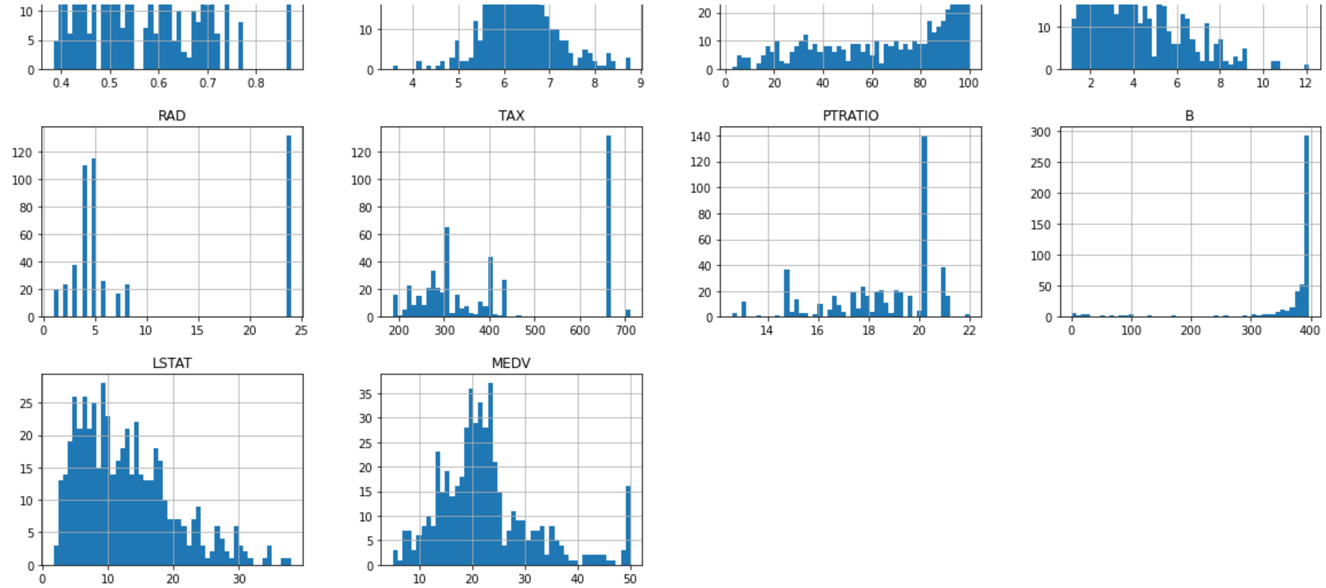
In [9]:

```
import matplotlib.pyplot as plt
```

In [10]:

```
house.hist(bins=50, figsize=(20,15))
plt.show()
```





spliting data: Train-Test

In [11]:

```
def train_test(data, test_ratio):
    np.random.seed(42)
    shuffled_data=np.random.permutation(len(data))
#     print(shuffled_data)
    test_size=int(len(data)*test_ratio)
    test_indices = shuffled_data[:test_size]
    train_indices = shuffled_data[test_size:]
    return data.iloc[train_indices], data.iloc[test_indices]
```

In [12]:

```
# train_set, test_set= train_test(house, 0.2)
```

In [13]:

```
# print(f"Rows in train set: {len(train_set)}\nRows in test set: {len(test_set)}\n")
```

In [14]:

```
from sklearn.model_selection import train_test_split
```

In [15]:

```
train_set, test_set=train_test_split(house, test_size=0.2, random_state=42)
print(f"Rows in train set: {len(train_set)}\nRows in test set: {len(test_set)}\n")
```

```
Rows in train set: 404
Rows in test set: 102
```

In [16]:

```
# stratified shuffled sampling
from sklearn.model_selection import StratifiedShuffleSplit
split = StratifiedShuffleSplit(n_splits=1,test_size=0.2,random_state=42)
for train_index, test_index in split.split(house, house['CHAS']):
    strs_train_set=house.loc[train_index]
    strs_test_set=house.loc[test_index]
```

In [17]:

```
strs_train_set['CHAS'].value_counts()
```

Out[17]:

```
0    376
1     28
Name: CHAS, dtype: int64
```

In [18]:

```
strs_test_set['CHAS'].value_counts()
```

Out[18]:

```
0    95
1     7
Name: CHAS, dtype: int64
```

In [19]:

```
#ratio of 0&1 in strs_train_set and strs_test_set
a=376/28
b=95/7
print(a)
print(b)
```

```
13.428571428571429
13.571428571428571
```

In [20]:

```
house=strs_train_set.copy()
```

Looking for Correlations

In [21]:

```
corr_matrix=house.corr()
#pearson correlations
corr_matrix['MEDV'].sort_values(ascending=False)
```

Out[21]:

```
MEDV       1.000000
RM         0.690027
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
```

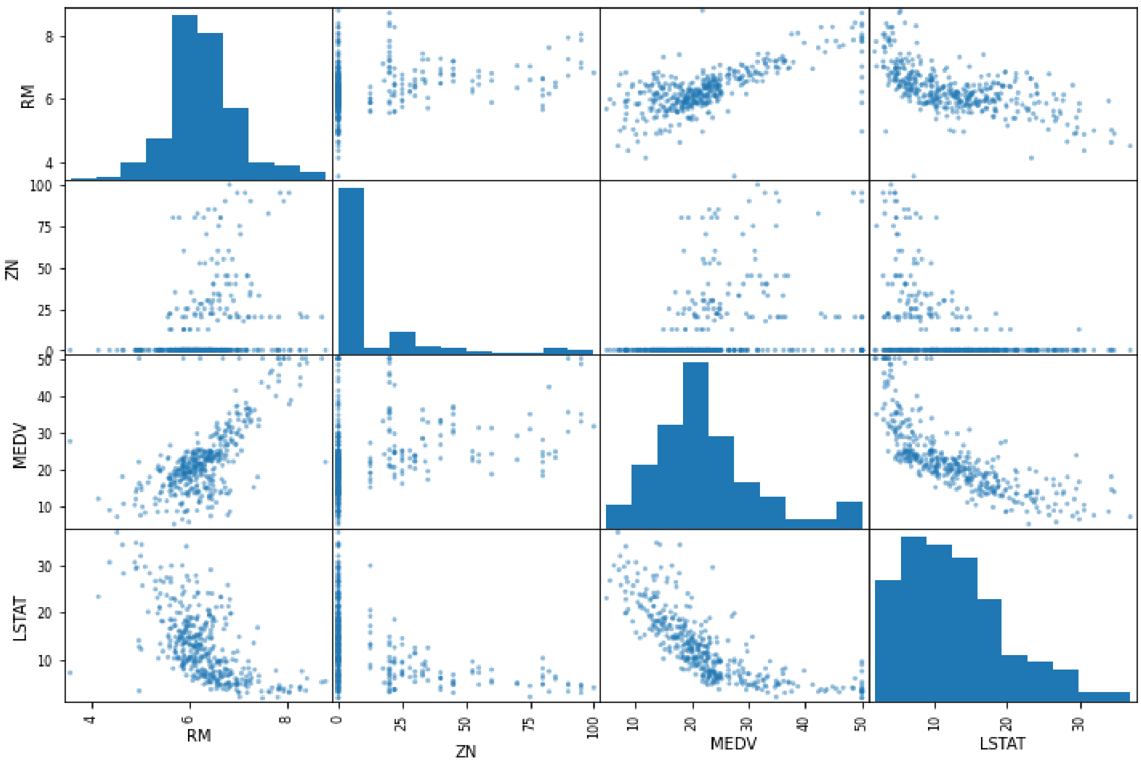
In [22]:

```
from pandas.plotting import scatter_matrix
attr=["RM","ZN","MEDV","LSTAT"]
scatter_matrix(house[attr],figsize=(12,8))
```

Out[22]:

```
array([[<AxesSubplot:xlabel='RM', ylabel='RM'>,
```

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

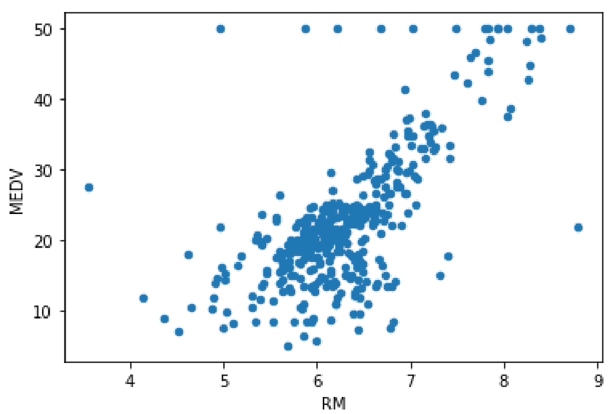


In [23]:

```
house.plot(kind="scatter",x='RM',y="MEDV", alpha=1)
```

Out[23]:

```
<AxesSubplot:xlabel='RM', ylabel='MEDV'>
```



Attribute combinations

In [24]:

```
house["Tax_per_RM"]=house['TAX']/house['RM']
house["Tax_per_RM"].head()
```

Out[24]:

```
254     51.571709
348     42.200452
476    102.714374
321     45.012547
326     45.468948
Name: Tax_per_RM, dtype: float64
```

In [25]:

```
corr_matrix=house.corr()
#pearson correlations
corr_matrix['MEDV'].sort_values(ascending=False)
```

Out[25]:

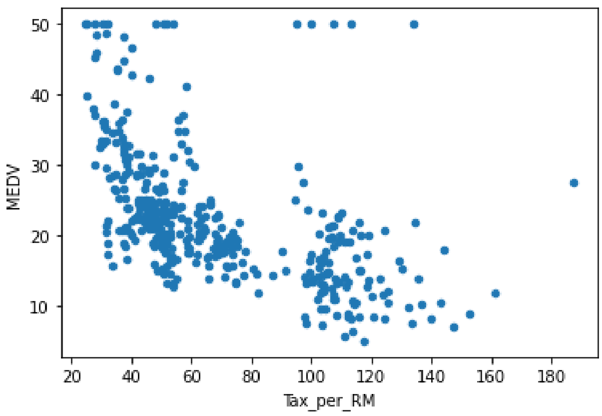
```
MEDV          1.000000
RM            0.690027
B             0.361761
ZN            0.339741
DIS           0.240451
CHAS          0.205066
AGE          -0.364596
RAD          -0.374693
CRIM         -0.393715
NOX          -0.422873
TAX          -0.456657
INDUS        -0.473516
PTRATIO      -0.493534
Tax_per_RM   -0.534273
LSTAT        -0.740494
Name: MEDV, dtype: float64
```

In [26]:

```
house.plot(kind="scatter",x='Tax_per_RM',y="MEDV", alpha=1)
```

Out[26]:

```
<AxesSubplot:xlabel='Tax_per_RM', ylabel='MEDV'>
```



In [27]:

```
#seperate features and attributes
house=strs_train_set.drop("MEDV",axis=1)
house_labels=strs_train_set["MEDV"].copy()
```

Handling Missing values

In [28]:

```
house.describe()
```

Out[28]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTR
count	404.000000	404.000000	404.000000	404.000000	404.000000	398.000000	404.000000	404.000000	404.000000	404.000000	404.0
mean	3.602814	10.836634	11.344950	0.069307	0.558064	6.291523	69.039851	3.746210	9.735149	412.341584	18.4
std	8.099383	22.150636	6.877817	0.254290	0.116875	0.705217	28.258248	2.099057	8.731259	168.672623	2.1
min	0.006320	0.000000	0.740000	0.000000	0.389000	3.561000	2.900000	1.129600	1.000000	187.000000	13.0
25%	0.086963	0.000000	5.190000	0.000000	0.453000	5.884250	44.850000	2.035975	4.000000	284.000000	17.4
50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.217500	78.200000	3.122200	5.000000	337.000000	19.0
75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.634000	94.100000	5.100400	24.000000	666.000000	20.2
max	73.534100	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.0

In [29]:

```
from sklearn.impute import SimpleImputer
imputer=SimpleImputer(strategy="median")
imputer.fit(house)
```

Out[29]:

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

In [30]:

```
imputer.statistics_
```

Out[30]:

```
array([2.86735e-01, 0.00000e+00, 9.90000e+00, 0.00000e+00, 5.38000e-01,
       6.21750e+00, 7.82000e+01, 3.12220e+00, 5.00000e+00, 3.37000e+02,
       1.90000e+01, 3.90955e+02, 1.15700e+01])
```

In [31]:

```
imputer.statistics_.shape
```

Out[31]:

```
(13,)
```

In [32]:

```
x=imputer.transform(house)
house_new=pd.DataFrame(x,columns=house.columns)
```

In [33]:

```
house_new.describe()
```

Out[33]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTR
count	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.0
mean	3.602814	10.836634	11.344950	0.069307	0.558064	6.290423	69.039851	3.746210	9.735149	412.341584	18.4
std	8.099383	22.150636	6.877817	0.254290	0.116875	0.700005	28.258248	2.099057	8.731259	168.672623	2.1
min	0.006320	0.000000	0.740000	0.000000	0.389000	3.561000	2.900000	1.129600	1.000000	187.000000	13.0

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTR
25%	0.086963	0.000000	5.190000	0.000000	0.453000	5.887250	44.850000	2.035975	4.000000	284.000000	17.4
50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.217500	78.200000	3.122200	5.000000	337.000000	19.0
75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.630250	94.100000	5.100400	24.000000	666.000000	20.2
max	73.534100	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.0

Creating Pipeline

Pipeline in ML operates by enabling a sequence of data to be transformed and correlated together in a model that can be tested and evaluated to achieve an outcome, whether positive or negative.It consist of several steps to train a model Pipelines help avoid leaking statistics from your test data into the trained model in cross-validation, by ensuring that the same samples are used to train the transformers and predictors.

In [34]:

```
from sklearn.pipeline import Pipeline
```

In [35]:

```
#feature Scaling
from sklearn.preprocessing import StandardScaler
pipline=Pipeline([
    ('imputer',SimpleImputer(strategy="median")),
    ('std_scaler',StandardScaler()),
])
```

In [36]:

```
house_num=pipline.fit_transform(house)
house_num.shape
```

Out[36]:

```
(404, 13)
```

Desired Model

In [37]:

```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
# model = LinearRegression()
# model = DecisionTreeRegressor()
model = RandomForestRegressor()
model.fit(house_num,house_labels)
```

Out[37]:

```
RandomForestRegressor()
```

In [38]:

```
new_data=house.iloc[:5]
```

In [39]:

```
new_labels=house_labels.iloc[:5]
```

In [40]:

```
prepared_data=pipline.transform(new_data)
```

In [41]:

```
model.predict(prepared_data)
```

Out[41]:

```
array([22.344, 25.412, 16.623, 23.377, 23.544])
```

In [42]:

```
list(new_labels)
```

Out[42]:

```
[21.9, 24.5, 16.7, 23.1, 23.0]
```

Evaluating the model

In [43]:

```
from sklearn.metrics import mean_squared_error

housing_prediction=model.predict(house_num)
mse=mean_squared_error(house_labels,housing_prediction)
rmse= np.sqrt(mse)
rmse
```

Out[43]:

```
1.2457387942760536
```

Cross Validation

In [44]:

```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(model, house_num,house_labels,scoring="neg_mean_squared_error",cv=10)
rmse_scores = np.sqrt(-scores)
```

In [45]:

```
rmse_scores
```

Out[45]:

```
array([2.90674694, 2.84631628, 4.43407189, 2.66555954, 3.33182147,
       2.57257376, 4.9255919 , 3.38643144, 3.09246771, 3.2875258 ])
```

In [46]:

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

In [47]:

```
print_scores(rmse_scores)
```

```
Scores : [2.90674694 2.84631628 4.43407189 2.66555954 3.33182147 2.57257376
 4.9255919  3.38643144 3.09246771 3.2875258 ]
Mean : 3.3449106738361665
Standard deviation : 0.7247307883492123
```

Saving Model

In [48]:

```
from joblib import dump, load
dump(model, 'Estates.joblib')
```

Out[48]:

```
['Estates.joblib']
```

Testing the model on test data

In [49]:

```
X_test = strs_test_set.drop("MEDV", axis=1)
Y_test = strs_test_set["MEDV"].copy()
X_test_prepared = pipline.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)
```

In [50]:

```
final_rmse
```

Out[50]:

```
2.8888616914883656
```

In [51]:

```
prepared_data[0]
```

Out[51]:

```
array([-0.43942006,  3.12628155, -1.12165014, -0.27288841, -1.42262747,
       -0.26092577, -1.31238772,  2.61111401, -1.0016859 , -0.5778192 ,
       -0.97491834,  0.41164221, -0.86091034])
```

In [ ]:

```
```