Muawa Real Estate - Price Predictor

```
import pandas as pd
```

Load and Prepare Data

```
housing=pd.read_csv("data.csv")
housing.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98
1	0.02731	0.0	7.07	0	0.469	NaN	78.9	4.9671	2	242	17.8	396.90	9.14
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94
4	0.06905	0.0	2.18	0	0.458	NaN	54.2	6.0622	3	222	18.7	396.90	5.33

Housing Data Summary

```
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       495 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
```

```
housing["CHAS"].value_counts()
```

```
0    471
1     35
Name: CHAS, dtype: int64
```

```
housing.describe()
```

	CRIM	ZN	INDUS	CHAS	NOX
count	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695

Strategies for Handling Missing Data

There have three Options to handle missing values

1: Get rid of the missing data points.

2: Get rid of the whole attribute.

3: Set the value to some value(0,mean or median)

```
# Option 1
a=housing.dropna(subset=["RM"])
a.shape
```

```
(495, 14)
```

```
# Option 2
housing.drop("RM",axis=1)
```

	CRIM	ZN	INDUS	CHAS	NOX	AGE	DIS	RAD	TAX	PTRA
0	0.00632	18.0	2.31	0	0.538	65.2	4.0900	1	296	1
1	0.02731	0.0	7.07	0	0.469	78.9	4.9671	2	242	1
2	0.02729	0.0	7.07	0	0.469	61.1	4.9671	2	242	1
3	0.03237	0.0	2.18	0	0.458	45.8	6.0622	3	222	1
4	0.06905	0.0	2.18	0	0.458	54.2	6.0622	3	222	1
...	...	...	...	...	...	...	...	...	...	
501	0.06263	0.0	11.93	0	0.573	69.1	2.4786	1	273	2
502	0.04527	0.0	11.93	0	0.573	76.7	2.2875	1	273	2
503	0.06076	0.0	11.93	0	0.573	91.0	2.1675	1	273	2

```
# Option 3
#Changes will not be made to the original housing data until we use inplace=True.
median=housing["RM"].median()
housing["RM"].fillna(median)
```

```
0      6.575
1      6.202
2      7.185
3      6.998
4      6.202
       ...
501    6.593
502    6.120
503    6.976
504    6.794
505    6.030
Name: RM, Length: 506, dtype: float64
```

Fit Imputer to Housing Data

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

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

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

```
imputer.statistics_
```

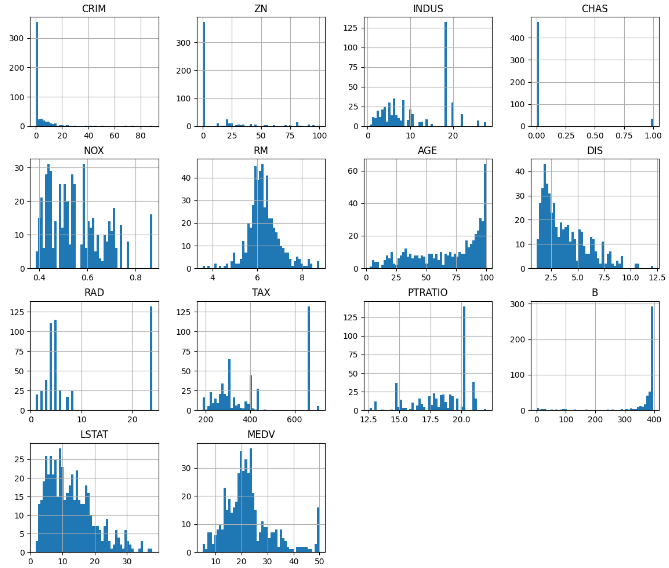
```
array([2.56510e-01, 0.00000e+00, 9.69000e+00, 0.00000e+00, 5.38000e-01,
       6.20200e+00, 7.75000e+01, 3.20745e+00, 5.00000e+00, 3.30000e+02,
       1.90500e+01, 3.91440e+02, 1.13600e+01, 2.12000e+01])
```

```
# See imputer is work or not
x=imputer.transform(housing)
housing=pd.DataFrame(x,columns=housing.columns)
housing.describe()
```

	CRIM	ZN	INDUS	CHAS	NOX
count	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695
std	8.601545	23.322453	6.860353	0.253994	0.115878
min	0.006320	0.000000	0.460000	0.000000	0.385000
25%	0.082045	0.000000	5.190000	0.000000	0.449000
50%	0.256510	0.000000	9.690000	0.000000	0.538000
75%	3.677083	12.500000	18.100000	0.000000	0.624000

Housing Data Visualization

```
%matplotlib inline
import matplotlib.pyplot as plt
housing.hist(bins=50,figsize=(14,12))
plt.show()
```

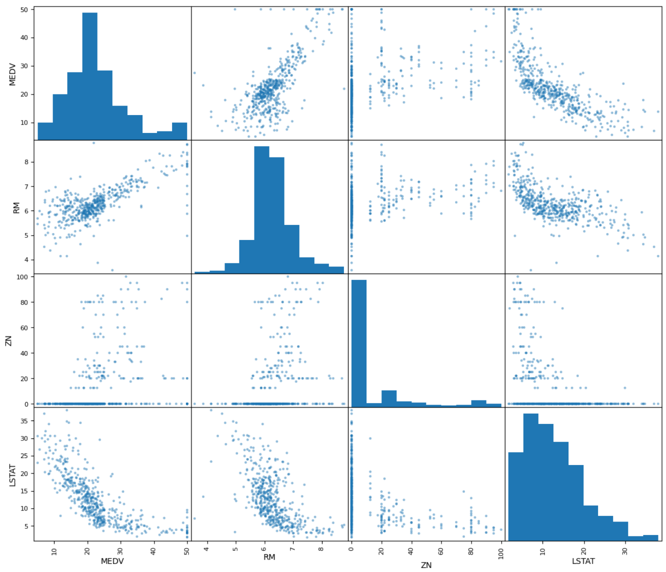


Looking for Correlation

```
#MEDV stands for Median Value of Owner-Occupied Homes ....Target Attribute
corr_matrix=housing.corr()
corr_matrix['MEDV'].sort_values(ascending=False)
```

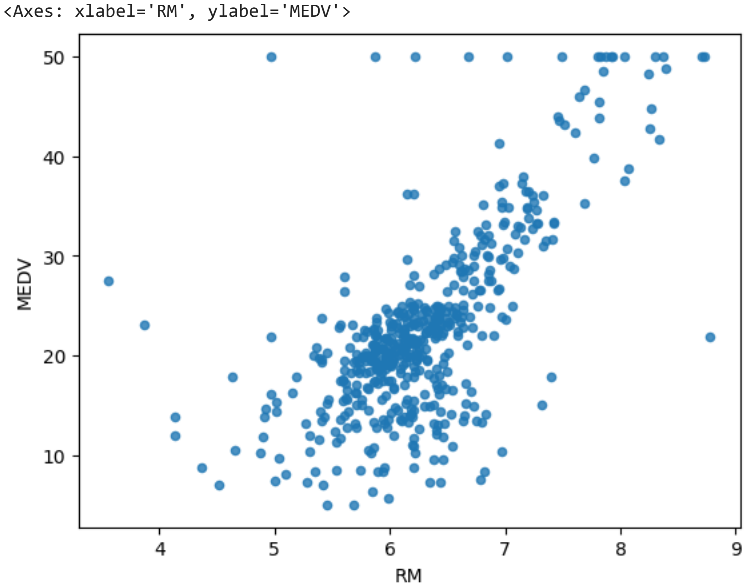
```
MEDV       1.000000
RM         0.693280
ZN         0.360445
B          0.333461
DIS        0.249929
CHAS       0.175260
AGE       -0.376955
RAD       -0.381626
CRIM      -0.388305
NOX       -0.427321
TAX       -0.468536
INDUS     -0.483725
PTRATIO   -0.507787
LSTAT     -0.737663
Name: MEDV, dtype: float64
```

```
from pandas.plotting import scatter_matrix
attributes=["MEDV","RM","ZN","LSTAT"]
scatter_matrix(housing[attributes],figsize=(14,12))
plt.show()
```




```
# Let's examine the correlation between the variable RM and the target variable MEDV.#
housing.plot(kind="scatter",x="RM",y="MEDV",alpha=0.8)
```

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



Trying out Attribute Combinations

Attribute combinations involve creating new features by combining existing ones, enhancing the model's ability to capture complex relationships in the data.

```
housing["TAXRM"]=housing['TAX']/housing['RM']
housing["TAXRM"]
```

```
0      45.019011
1      39.019671
```

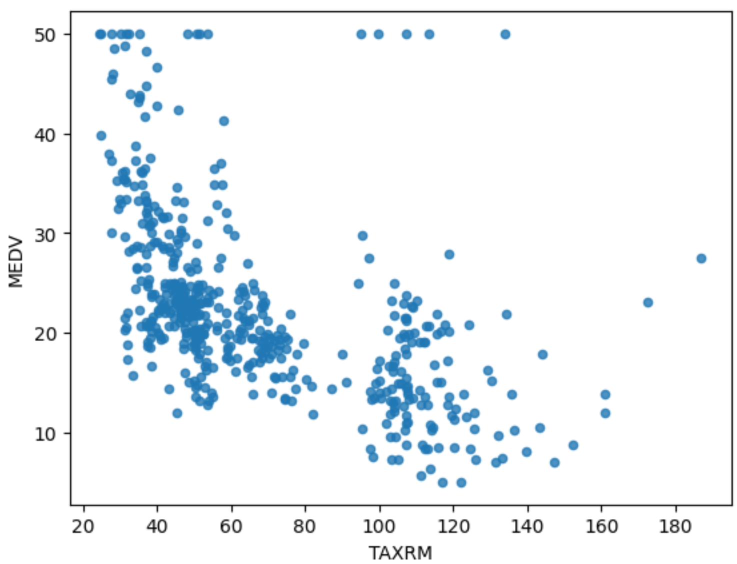
```
2      33.681280
3      31.723350
4      35.794905
         ...
501    41.407553
502    44.607843
503    39.134174
504    40.182514
505    45.273632
Name: TAXRM, Length: 506, dtype: float64
```

```
housing.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTA
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.9
1	0.02731	0.0	7.07	0.0	0.469	6.202	78.9	4.9671	2.0	242.0	17.8	396.90	9.1
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.0
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.9
4	0.06905	0.0	2.18	0.0	0.458	6.202	54.2	6.0622	3.0	222.0	18.7	396.90	5.3

```
#"Examine the correlation between the variable TAXRM and the target variable MEDV."
housing.plot(kind="scatter",x="TAXRM",y="MEDV",alpha=0.8)
```

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



Train-Test Splitting (User-defined function)

```
# User defined function
import numpy as np
def split_train_test(data,test_ratio):
  np.random.seed(42)
  shuffled=np.random.permutation(len(data))
  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]
```

```
train_set,test_set=split_train_test(housing,0.2)
print(f"Rows in Train Set: {len(train_set)}\nRows in Test Set: {len(test_set)}\n")
```

```
Rows in Train Set: 405
Rows in Test Set: 101
```

Train-Test Splitting(2nd Method)

```
from pandas.core.common import random_state
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"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
```

StratifiedShuffleSplit

StratifiedShuffleSplit maintains class distribution in train-test splits, crucial for balanced and representative evaluations, especially in imbalanced datasets.

```

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(housing,housing['CHAS']):
  strat_train_set=housing.loc[train_index]
  strat_test_set=housing.loc[test_index]

  #Train Data
  housing_tr=strat_train_set.copy()
   #Test Data
  housing_test=strat_test_set.copy()
```

Data Segmentation: Housing Features and Labels

```
Housing_Features=housing_tr.drop("MEDV",axis=1)
Housing_Label=housing_tr["MEDV"].copy()
```

Scikit-Learn Design

Primally, Three types of objects

1: Estimators- It estimates some parameters based on dataset e.g imputer and it has a fit method - Fit the datasets and calculates parameters.

2: Transformers - Transform method takes input and return output based on learning from fit().It also has a convenience function called fit_transform() which fits and then transforms.

3: Predictores - LinearRegression model is an example of predictor. fit() and predict() are two common functions.It also gives 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 providees a class called MinMaxScaler for this

2: Standardization

(value-mean)/std

sklearn provides a class called Standard Scaler for this

Creating a Pipeline

We use a pipeline in machine learning to streamline and automate the process of data preprocessing and model training. A pipeline allows you to sequence multiple data processing steps and model training into a single entity, which offers several benefits.

When we want to automate this process, we use a pipeline.

```
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler

# add as many as you want in your pipeline
my_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    ('std_scaler', StandardScaler()),
])
```

```
housing_features=my_pipeline.fit_transform(Housing_Features)
housing_features
```

```
array([[-0.43942006,  3.12628155, -1.12165014, ...,  0.41164221,
        -0.86091034, -0.50684753],
       [-0.44352175,  3.12628155, -1.35893781, ...,  0.39131918,
        -0.94116739, -0.80471992],
       [ 0.15682292, -0.4898311 ,  0.98336806, ...,  0.44624347,
         0.81480158,  1.11876022],
       ...,
       [-0.43525657, -0.4898311 , -1.23083158, ...,  0.41831233,
        -1.27603303, -1.02424292],
       [ 0.14210728, -0.4898311 ,  0.98336806, ..., -3.15239177,
         0.73869575,  1.09824544],
       [-0.43974024, -0.4898311 ,  0.37049623, ...,  0.41070422,
         0.09940681, -0.65613593]])
```

Selecting a desired model for Muawa Real Estate

Linear Regression Model

```
from sklearn.linear_model import LinearRegression
model=LinearRegression()
model.fit(housing_features,Housing_Label)
```

```
▾ LinearRegression
LinearRegression()
```

```
some_data=Housing_Features.iloc[:5]
some_labels=Housing_Label.iloc[:5]
```

```
prepared_data=my_pipeline.transform(some_data)
model.predict(prepared_data)
```

```
array([22.63627048, 26.916074  , 18.87924022, 25.0429817 , 24.1781656 ])
```

```
# Results that are most similar indicate good predictions.
some_labels
```

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

Evaluating the Model

```
from sklearn.metrics import mean_squared_error
housing_predictions=model.predict(housing_features)
lin_mse=mean_squared_error(Housing_Label,housing_predictions)
lin_rmse=np.sqrt(lin_mse)
```

```
print("Root mean Square Error:",lin_rmse)
```

```
Root mean Square Error: 4.246884319353141
```

Decision Tree Regressor Model

```
from sklearn.tree import DecisionTreeRegressor
model1=DecisionTreeRegressor()
model1.fit(housing_features,Housing_Label)
```

```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

A root mean square error of 0.0 may indicate overfitting of the data.

```
housing_prediction=model1.predict(housing_features)
mse=mean_squared_error(Housing_Label,housing_prediction)
rmse=np.sqrt(mse)
print("Root mean Square Error:",rmse)
```

```
Root mean Square Error: 0.0
```

If overfitting occurs, we can use cross-validation

Using Better Evaluation Technique - Cross Validation

```
from sklearn.model_selection import cross_val_score
scores=cross_val_score(model1,housing_features,Housing_Label,scoring="neg_mean_squared_error",cv=10)
rmse_score=np.sqrt(-scores)
```

```
rmse_score
```

```
array([4.16483537, 5.52219469, 4.87534864, 4.55944477, 3.27913861,
       4.40624557, 6.42288876, 3.72578851, 3.86710486, 3.82482026])
```

Create a function to observe the scores of each model.

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

Linear Regression

```
print("Linear Regression")
print_scores(lin_rmse)
```

```
Linear Regression
Scores:  4.246884319353141
Mean:  4.246884319353141
Standard Deviation:  0.0
```

Decision Tree

```
print("Decision Tree ")
print_scores(rmse_score)
```

```
Decision Tree
Scores:  [4.16483537 5.52219469 4.87534864 4.55944477 3.27913861 4.40624557
 6.42288876 3.72578851 3.86710486 3.82482026]
Mean:  4.464781002229873
Standard Deviation:  0.8911708479163778
```

```
from joblib import dump,load
dump(model1,'RealEstate.joblib')
```

```
['RealEstate.joblib']
```

Model Testing

```
Housing_F = housing_test.drop("MEDV", axis=1)
Housing_L = housing_test["MEDV"].copy()

housing_fe = my_pipeline.fit_transform(Housing_F)
# Make predictions using the model
final_predictions = model1.predict(housing_fe)
# Calculate the final mean squared error and root mean squared error
final_mse = mean_squared_error(Housing_L, final_predictions)
final_rmse = np.sqrt(final_mse)

print(f"Final RMSE: {final_rmse:.2f}")
```

```
Final RMSE: 4.49
```

Application Phase

```
3#Take input from Users and predict Price



CRIM = input("\nPlease enter CRIM: ").strip()
ZN = input("\nPlease enter ZN: ").strip()
INDUS = input("\nPlease enter INDUS: ").strip()
CHAS = input("\nPlease enter CHAS: ").strip()
NOX = input("\nPlease enter NOX: ").strip()
RM = input("\nPlease enter RM : ").strip()
AGE = input("\nPlease enter AGE: ").strip()
DIS = input("\nPlease enter DIS: ").strip()
RAD = input("\nPlease enter RAD: ").strip()
TAX = input("\nPlease enter TAX: ").strip()
PTRATID = input("\nPlease enter PTRATID: ").strip()
B = input("\nPlease enter B: ").strip()
LSTAT = input("\nPlease enter LSTAT: ").strip()
TAXRM = input("\nPlease enter TAXRM: ").strip()
```

```
Please enter CRIM: 0.06905

Please enter ZN: 0.0

Please enter INDUS: 2.18

Please enter CHAS: 0

Please enter NOX: 0.458

Please enter RM : 6.998

Please enter AGE: 54.2

Please enter DIS: 6.0622

Please enter RAD: 3

Please enter TAX: 222

Please enter PTRATID: 18.7

Please enter B: 96.90

Please enter LSTAT: 5.33

Please enter TAXRM: 35.79
```

```
# Create a DataFrame from user input
user_input = pd.DataFrame({
    'CRIM': [CRIM],
    'ZN': [ZN],
    'INDUS': [INDUS],
    'CHAS': [CHAS],
    'NOX': [NOX],
    'RM': [RM],
    'AGE': [AGE],
    'DIS': [DIS],
    'RAD': [RAD],
    'TAX': [TAX],
    'PTRATID': [PTRATID],
    'B': [RAD],
    'LSTAT': [LSTAT],
    'TAXRM': [TAXRM]
})

print("\n\nUser Input Feature Vector:")
print("==========================\n")
print(user_input)
```

```
User Input Feature Vector:
==========================

      CRIM   ZN INDUS CHAS    NOX     RM   AGE     DIS RAD  TAX PTRATID  B  \
0  0.06905  0.0  2.18    0  0.458  6.998  54.2  6.0622   3  222    18.7  3

  LSTAT  TAXRM
0  5.33  35.79
```

```
user = my_pipeline.transform(user_input)

# Make predictions using the model
value = model1.predict(user)
```

```
from prettytable import PrettyTable
```

```
pretty_table = PrettyTable()
pretty_table.add_column("       ** Median Value(MEDV) **       ",[value])
print(pretty_table)
```

```
+----------------------------------------+
|        ** Median Value(MEDV) **        |
+----------------------------------------+
|                 [21.2]                 |
+----------------------------------------+
```

Thank you for reviewing this document.

0s completed at 12:04 AM