# Dragon Real Estate - Price Predictor

import pandas as pd

housing = pd.read\_csv("data.csv")

housing.head()



	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	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

#### housing.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):

Data	columns	(total 14 columns	5):
#	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	В	506 non-null	float64
12	LSTAT	506 non-null	float64
13	MEDV	506 non-null	float64
dtype	es: float	:64(11), int64(3)	
memor	y usage:	55.5 KB	

housing['CHAS'].value\_counts()

<del>→</del> CHAS

0 471 1 35

Name: count, dtype: int64

# housing.describe()

₹		CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	L
	count	506.000000	506.000000	506.000000	506.000000	506.000000	501.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.00
	mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.289537	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	12.65
	std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702907	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	7.14
	min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	1.73
	25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.888000	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	6.95
	50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.209000	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	11.36
	75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.629000	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	16.95
	max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	37.97

%matplotlib inline

- # # For plotting histogram
- # import matplotlib.pyplot as plt
- # housing.hist(bins=50, figsize=(20, 15))

### Train-Test Splitting

```
# For learning purpose
import numpy as np
def split_train_test(data, test_ratio):
    np.random.seed(42)
    shuffled = np.random.permutation(len(data))
    print(shuffled)
    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")
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
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]
strat_test_set['CHAS'].value_counts()
→ CHAS
    0 95
    1
    Name: count, dtype: int64
strat_train_set['CHAS'].value_counts()
→ CHAS
    0 376
    Name: count, dtype: int64
# 95/7
# 376/28
housing = strat_train_set.copy()
```

# Looking for Correlations

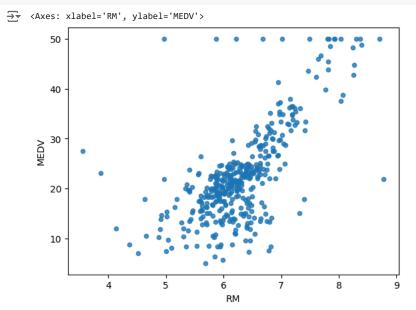
```
corr_matrix = housing.corr()
corr_matrix['MEDV'].sort_values(ascending=False)
```

```
<del>→</del> MEDV
                1.000000
    RM
                0.680118
                0.361761
    ΖN
                0.339741
    DIS
                0.240451
               0.205066
    CHAS
    AGE
               -0.364596
               -0.374693
    RAD
    CRIM
               -0.393715
    NOX
               -0.422873
               -0.456657
    INDUS
               -0.473516
    PTRATIO
              -0.493534
```

LSTAT -0.740494 Name: MEDV, dtype: float64

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

housing.plot(kind="scatter", x="RM", y="MEDV", alpha=0.8)



## Trying out Attribute combinations

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

housing.head()

₹		CRIM	711	TNDUC	CHAC	NOV	ВМ	AGE	DTC	DAD	TAV	DTDATTO		LCTAT	MEDV	TAVDM
_		CKIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	IAX	PTRATIO	В	LSTAT	MEDV	TAXRM
	254	0.04819	80.0	3.64	0	0.392	6.108	32.0	9.2203	1	315	16.4	392.89	6.57	21.9	51.571709
	348	0.01501	80.0	2.01	0	0.435	6.635	29.7	8.3440	4	280	17.0	390.94	5.99	24.5	42.200452
	476	4.87141	0.0	18.10	0	0.614	6.484	93.6	2.3053	24	666	20.2	396.21	18.68	16.7	102.714374
	321	0.18159	0.0	7.38	0	0.493	6.376	54.3	4.5404	5	287	19.6	396.90	6.87	23.1	45.012547
	326	0.30347	0.0	7.38	0	0.493	6.312	28.9	5.4159	5	287	19.6	396.90	6.15	23.0	45.468948

corr\_matrix = housing.corr()
corr\_matrix['MEDV'].sort\_values(ascending=False)

```
→ MEDV

               1.000000
               0.680118
    В
               0.361761
               0.339741
    ΖN
    DIS
               0.240451
    CHAS
               0.205066
              -0.364596
    AGE
              -0.374693
    RAD
    CRIM
              -0.393715
    NOX
              -0.422873
    TAX
              -0.456657
    INDUS
              -0.473516
    PTRATIO
              -0.493534
    TAXRM
              -0.527283
    LSTAT
              -0.740494
    Name: MEDV, dtype: float64
```

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

50

40

20

20

40

60

80

100

120

140

160

180
```

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

### Missing Attributes

```
# To take care of missing attributes, you have three options:
     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)
a = housing.dropna(subset=["RM"]) #Option 1
# Note that the original housing dataframe will remain unchanged
→ (399, 13)
housing.drop("RM", axis=1).shape # Option 2
# Note that there is no RM column and also note that the original housing dataframe will remain unchanged
→ (404, 12)
median = housing["RM"].median() # Compute median for Option 3
housing["RM"].fillna(median) # Option 3
# Note that the original housing dataframe will remain unchanged
    254
           6.108
    348
           6.635
    476
           6.484
    321
           6.376
    326
           6.312
    155
           6.152
    423
    98
           7.820
```

housing.shape

455

216

6.525

5.888

Name: RM, Length: 404, dtype: float64

**→** (404, 13)

 $housing.describe() \ \ \text{\# before we started filling missing attributes}$ 



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



simpleImputer
SimpleImputer(strategy='median')

imputer.statistics\_

X = imputer.transform(housing)

housing\_tr = pd.DataFrame(X, columns=housing.columns)

housing\_tr.describe()

<b>→</b>		CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	L
	count	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.000000	404.00
	mean	3.602814	10.836634	11.344950	0.069307	0.558064	6.285139	69.039851	3.746210	9.735149	412.341584	18.473267	353.392822	12.79
	std	8.099383	22.150636	6.877817	0.254290	0.116875	0.709110	28.258248	2.099057	8.731259	168.672623	2.129243	96.069235	7.23
	min	0.006320	0.000000	0.740000	0.000000	0.389000	3.561000	2.900000	1.129600	1.000000	187.000000	13.000000	0.320000	1.73
	25%	0.086962	0.000000	5.190000	0.000000	0.453000	5.884750	44.850000	2.035975	4.000000	284.000000	17.400000	374.617500	6.84
	50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.216000	78.200000	3.122200	5.000000	337.000000	19.000000	390.955000	11.57
	75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.630250	94.100000	5.100400	24.000000	666.000000	20.200000	395.630000	17.10
	max	73.534100	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	36.98

#### Scikit-learn 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. Transformers 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 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 provides a class called MinMaxScaler for this

# Creating a Pipeline

```
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)

Tree RandomForestRegressor()

some_data = housing.iloc[:5]

some_labels = housing_labels.iloc[:5]

prepared_data = my_pipeline.transform(some_data)

model.predict(prepared_data)

Tree array([22.28 , 25.636, 16.6 , 23.39 , 23.427])

list(some_labels)

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

### Evaluating the model

```
from sklearn.metrics import mean_squared_error
housing_predictions = model.predict(housing_num_tr)
mse = mean_squared_error(housing_labels, housing_predictions)
rmse = np.sqrt(mse)
```

**→** 1.248558644244959

# Using better evaluation technique - Cross Validation

```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(model, housing_num_tr, housing_labels, scoring="neg_mean_squared_error", cv=10)
rmse_scores = np.sqrt(-scores)
rmse_scores
⇒ array([2.86723166, 2.81231295, 4.3748573 , 2.74891253, 3.32402344,
           2.64400338, 4.89236806, 3.3339339 , 3.45804938, 3.19782011])
def print_scores(scores):
    print("Scores:", scores)
    print("Mean: ", scores.mean())
    print("Standard deviation: ", scores.std())
print_scores(rmse_scores)
Scores: [2.86723166 2.81231295 4.3748573 2.74891253 3.32402344 2.64400338
     4.89236806 3.3339339 3.45804938 3.19782011]
     Mean: 3.365351272268311
     Standard deviation: 0.6960281165722647
Quiz: Convert this notebook into a python file and run the pipeline using Visual Studio Code
Saving the model
from joblib import dump, load
dump(model, 'Dragon.joblib')
→ ['Dragon.joblib']

    Testing the model on test data

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(final_predictions, list(Y_test))
final_rmse
→ 2.9379472659077632
prepared_data[0]
→ array([-0.43942006, 3.12628155, -1.12165014, -0.27288841, -1.42262747,
            -0.25011401, -1.31238772, 2.61111401, -1.0016859, -0.5778192,
           -0.97491834, 0.41164221, -0.86091034])
Using the model
from joblib import dump, load
import numpy as np
model = load('Dragon.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)
→ array([24.783])
```

# 1 2 3 4 5 6 7 8 9 10

Start coding or generate with AI.