HOUSE PRICE PREDICTION

The competition goal is to predict sale prices for homes. You're given a training and testing data set in csv format as well as a data dictionary.

Project Prerequisites

- Jupyter Notebook
- Housing dataset

Code:

Dragon Real Estate - Price Predictor

In [1]:

```
import pandas as pd
```

In [2]:

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

In [3]:

```
housing.head()
```

Out[3]:

	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 [4]:

```
housing.info()
```

```
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
```

In [5]:

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

Out[5]:

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

In [6]:

```
housing.describe()
```

Out[6]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
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	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284341	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	12.653063	22.532806
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.705587	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	7.141062	9.197104
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	1.730000	5.000000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.884000	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	6.950000	17.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208000	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	11.360000	21.200000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.625000	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	16.955000	25.000000
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	37.970000	50.000000

In [7]:

```
%matplotlib inline
```

In [8]:

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

Train-Test Splitting

In [9]:

```
#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]
```

In [10]:

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

In [11]:

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

In [12]:

```
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
```

In [13]:

```
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]
```

In [14]:

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

Out[14]:

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

In [15]:

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

Out[15]:

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

In [16]:

```
#95/7
```

In [17]:

```
#376/28
```

In [18]:

```
housing = strat_train_set.copy()
```

Looking for Correlation

In [19]:

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

Out[19]:

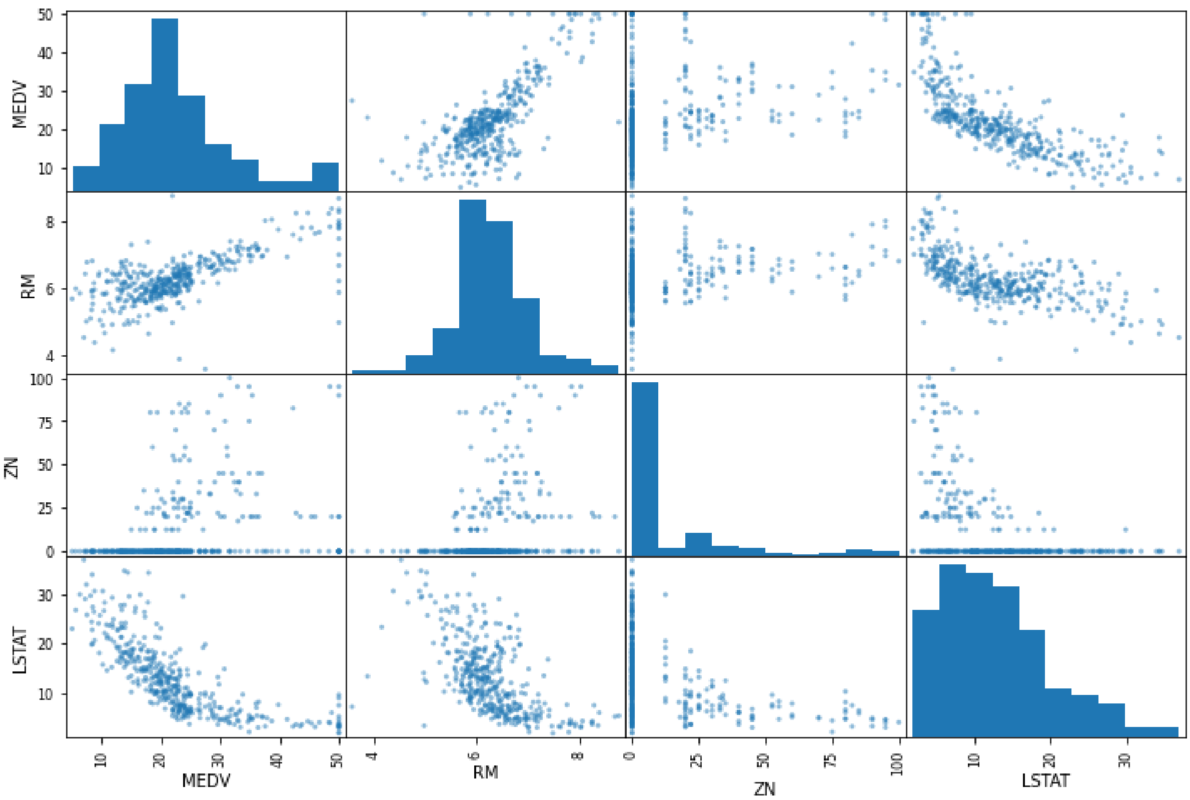
```
MEDV       1.000000
RM         0.680857
B          0.361761
ZN         0.339741
DIS        0.240451
CHAS       0.205066
AGE       -0.364596
RAD       -0.374693
CRIM      -0.393715
NOX       -0.422873
TAX       -0.456657
INDUS     -0.473516
PTRATIO   -0.493534
LSTAT     -0.740494
Name: MEDV, dtype: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

In [20]:

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

Out[20]:

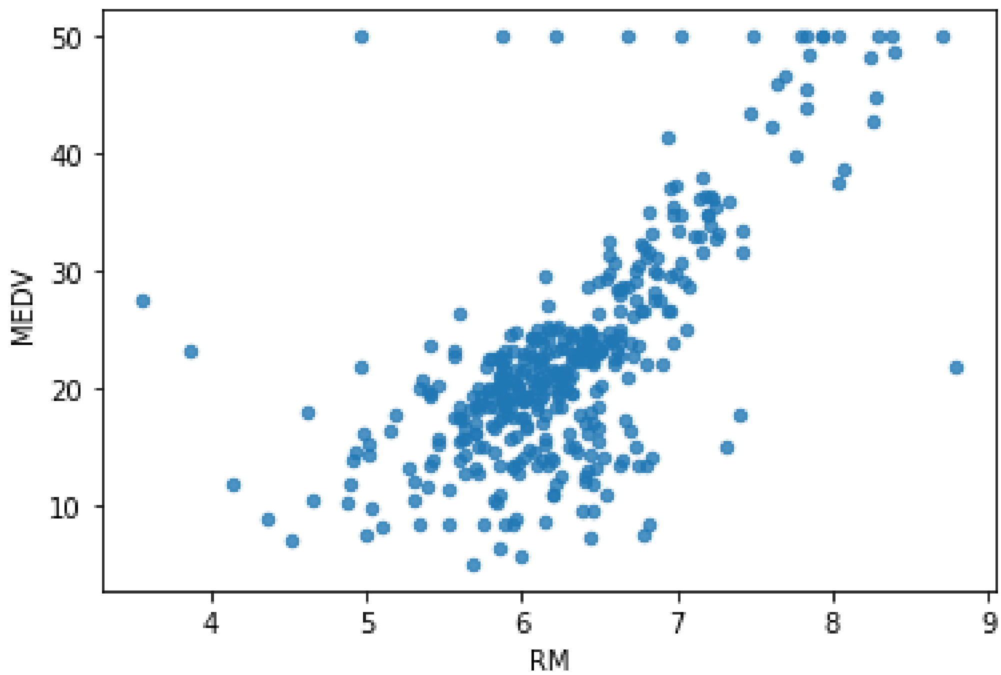
```
array([[,
        ,
        ,
        ],
       [,
        ,
        ,
        ],
       [,
        ,
        ,
        ],
       [,
        ,
        ,
        ]], dtype=object)
```



In [21]:

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

Out[21]:



Trying out Attribute combinations

In [22]:

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

In [23]:

```
housing.head()
```

Out[23]:

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

In [24]:

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

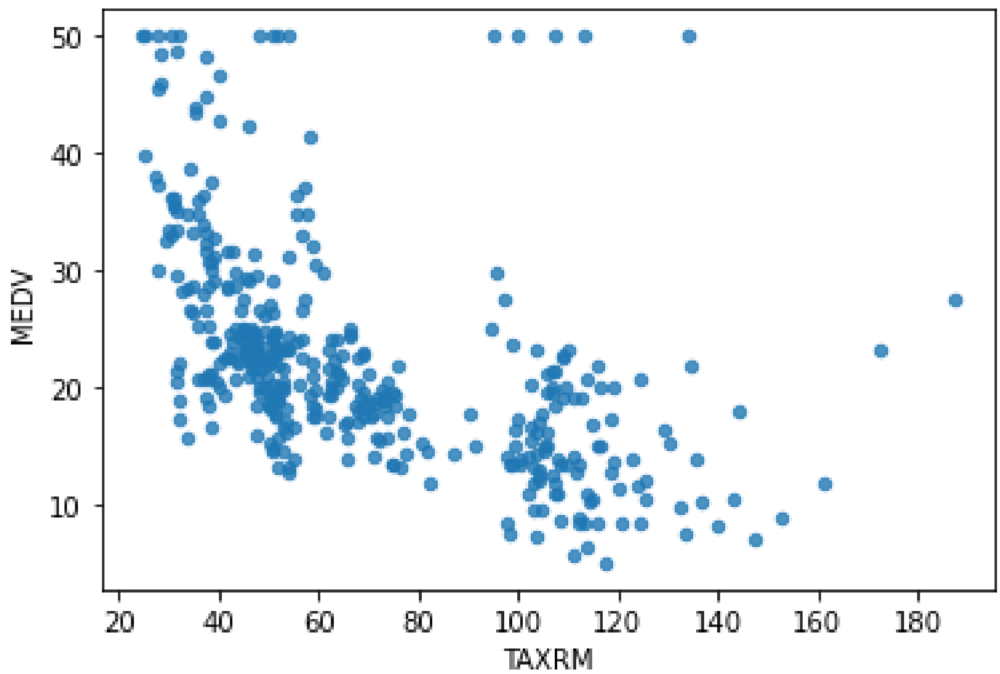
Out[24]:

```
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
```

In [25]:

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

Out[25]:



In [26]:

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

Missing Attributes

In [27]:

```
#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)
```

In [28]:

```
median = housing["RM"].median() # Compute median for option 3
```

In [29]:

```
housing["RM"].fillna(median) #option 3
# Note that the original housing dataframe will remain unchanged
```

Out[29]:

```
254    6.108
348    6.635
476    6.484
321    6.376
326    6.312
       ...
155    6.152
423    6.103
98     7.820
455    6.525
216    5.888
Name: RM, Length: 404, dtype: float64
```

In [30]:

```
housing.shape
```

Out[30]:

```
(404, 13)
```

In [31]:

```
housing.describe() # before we started filling missing attributes
```

Out[31]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
count	404.000000	404.000000	404.000000	404.000000	404.000000	399.000000	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	6.279481	69.039851	3.746210	9.735149	412.341584	18.473267	353.392822	12.791609
std	8.099383	22.150636	6.877817	0.254290	0.116875	0.716784	28.258248	2.099057	8.731259	168.672623	2.129243	96.069235	7.235740
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	1.730000
25%	0.086962	0.000000	5.190000	0.000000	0.453000	5.876500	44.850000	2.035975	4.000000	284.000000	17.400000	374.617500	6.847500
50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.209000	78.200000	3.122200	5.000000	337.000000	19.000000	390.955000	11.570000
75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.630500	94.100000	5.100400	24.000000	666.000000	20.200000	395.630000	17.102500
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	36.980000

In [32]:

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

Out[32]:

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

In [33]:

```
imputer.statistics_
```

Out[33]:

```
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])
```

In [34]:

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

In [35]:

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

In [36]:

```
housing_tr.describe()
```

Out[36]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
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	404.000000
mean	3.602814	10.836634	11.344950	0.069307	0.558064	6.278609	69.039851	3.746210	9.735149	412.341584	18.473267	353.392822	12.791609
std	8.099383	22.150636	6.877817	0.254290	0.116875	0.712366	28.258248	2.099057	8.731259	168.672623	2.129243	96.069235	7.235740
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	1.730000
25%	0.086962	0.000000	5.190000	0.000000	0.453000	5.878750	44.850000	2.035975	4.000000	284.000000	17.400000	374.617500	6.847500
50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.209000	78.200000	3.122200	5.000000	337.000000	19.000000	390.955000	11.570000
75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.630000	94.100000	5.100400	24.000000	666.000000	20.200000	395.630000	17.102500
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	36.980000

Scikit-learn Design

Creating a Pipeline

In [37]:

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
my_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    ('std_scaler', StandardScaler()),
])
```

In [38]:

```
housing_num_tr = my_pipeline.fit_transform(housing)
```

In [39]:

```
housing_num_tr.shape
```

Out[39]:

```
(404, 13)
```

Selecting a desired model for Dragon Real Estates

In [40]:

```
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[40]:

```
RandomForestRegressor()
```

In [41]:

```
some_data = housing.iloc[:5]
```

In [42]:

```
some_labels = housing_labels.iloc[:5]
```

In [43]:

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

In [44]:

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

Out[44]:

```
array([22.386, 25.445, 16.711, 23.359, 23.516])
```

In [45]:

```
list(some_labels)
```

Out[45]:

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

Evaluating the model

In [46]:

```
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)
```

In [47]:

```
rmse
```

Out[47]:

```
1.2590074414489214
```

Using better evaluation technique - Cross Validation

In [48]:

```
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)
```

In [49]:

```
rmse_scores
```

Out[49]:

```
array([2.92328324, 2.87129474, 4.53911313, 2.46011985, 3.51632274,
       2.64641187, 4.90507004, 3.35355316, 3.01721253, 3.31064709])
```

In [50]:

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

In [51]:

```
print_scores(rmse_scores)
```

```
Scores: [2.92328324 2.87129474 4.53911313 2.46011985 3.51632274 2.64641187
 4.90507004 3.35355316 3.01721253 3.31064709]
Mean:  3.3543028399576533
Standard deviation:  0.75300654884809
```

Saving the model

In [52]:

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

Out[52]:

```
['Dragon.joblib']
```

Testing the model on test data

In [58]:

```
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))
```

In [59]:

```
final_rmse
```

Out[59]:

```
3.022342997754958
```

In [ ]: