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
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	6.421	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	7.147	54.2	6.0622	3	222	18.7	396.90	5.33

In [4]:
```
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
```

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	
count	506.000000	506.000000	506.000000	506.000000	506.000000	501.000000	506.000000	506.(
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284341	68.574901	3.7
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.705587	28.148861	2.1
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.1
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.884000	45.025000	2.1
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208000	77.500000	3.2
75%	3.677082	12.500000	18.100000	0.000000	0.624000	6.625000	94.075000	5.1
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.1

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(t
est_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(tes
t_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 Correlations

In [19]:
```
corr_matrix = housing.corr()
corr_matrix['MEDV'].sort_values(ascending=False)
```

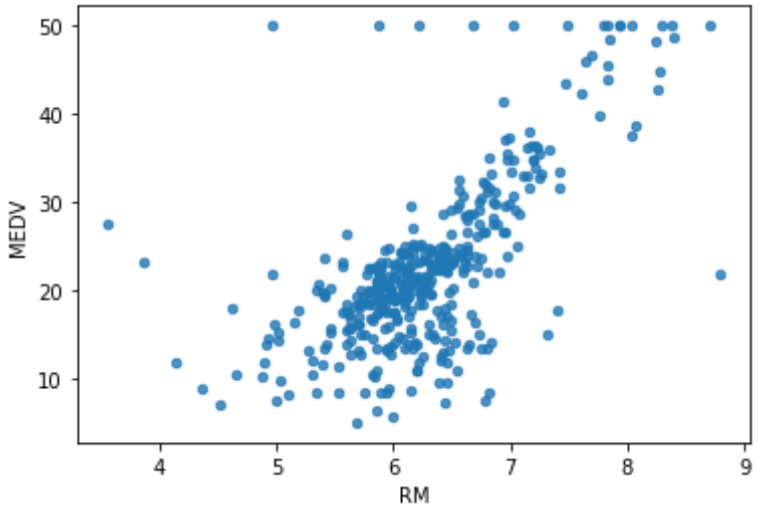
Out[19]:
```
MEDV       1.000000
RM         0.680857
B          0.361761
ZN         0.339741
DIS        0.240451
CHAS       0.205066
AGE       -0.364596
RAD       -0.374693
CRIM      -0.393715
NOX       -0.422873
TAX       -0.456657
INDUS     -0.473516
```

```
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))
```

In [21]:
```
housing.plot(kind="scatter", x="RM", y="MEDV", alpha=0.8)
```

Out[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2117a623748>
```



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	LST

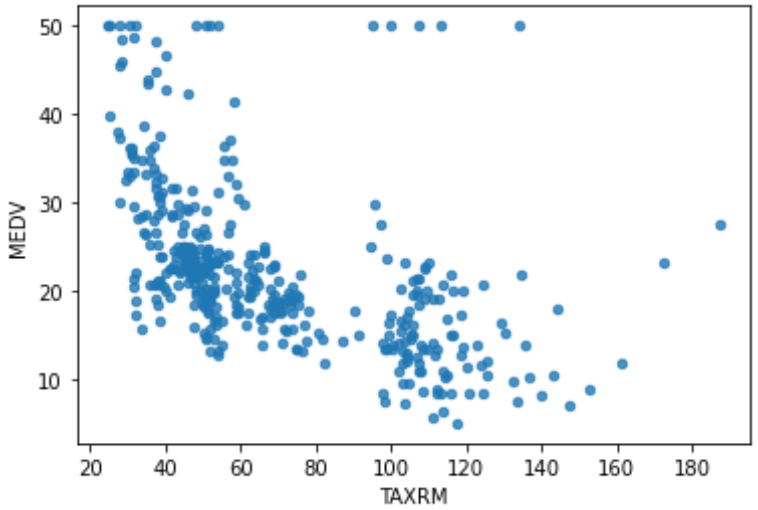
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST
254	0.04819	80.0	3.64	0	0.392	6.108	32.0	9.2203	1	315	16.4	392.89	6
348	0.01501	80.0	2.01	0	0.435	6.635	29.7	8.3440	4	280	17.0	390.94	5
476	4.87141	0.0	18.10	0	0.614	6.484	93.6	2.3053	24	666	20.2	396.21	18
321	0.18159	0.0	7.38	0	0.493	6.376	54.3	4.5404	5	287	19.6	396.90	6
326	0.30347	0.0	7.38	0	0.493	6.312	28.9	5.4159	5	287	19.6	396.90	6

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]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2117c739d48>
```



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]:
```
a = housing.dropna(subset=["RM"]) #Option 1
a.shape
# Note that the original housing dataframe will remain unchanged
```

Out[28]: (399, 13)

In [29]:
```
housing.drop("RM", axis=1).shape # Option 2
# Note that there is no RM column and also note that the original housi
ng dataframe will remain unchanged
```

Out[29]: (404, 12)

In [30]:
```
median = housing["RM"].median() # Compute median for Option 3
```

In [31]:
```
housing["RM"].fillna(median) # Option 3
# Note that the original housing dataframe will remain unchanged
```

Out[31]:
```
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 [32]:
```
housing.shape
```

Out[32]: (404, 13)

In [33]:
```
housing.describe() # before we started filling missing attributes
```

Out[33]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
count	404.000000	404.000000	404.000000	404.000000	404.000000	399.000000	404.000000	404.(
mean	3.602814	10.836634	11.344950	0.069307	0.558064	6.279481	69.039851	3.7
std	8.099383	22.150636	6.877817	0.254290	0.116875	0.716784	28.258248	2.(
min	0.006320	0.000000	0.740000	0.000000	0.389000	3.561000	2.900000	1.1
25%	0.086963	0.000000	5.190000	0.000000	0.453000	5.876500	44.850000	2.(
50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.209000	78.200000	3.1

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.630500	94.100000	5.1
max	73.534100	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.1

In [34]:
```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")
imputer.fit(housing)
```

Out[34]:
```
SimpleImputer(add_indicator=False, copy=True, fill_value=None,
              missing_values=nan, strategy='median', verbose=0)
```

In [35]:
```
imputer.statistics_
```

Out[35]:
```
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 [36]:
```
X = imputer.transform(housing)
```

In [37]:
```
housing_tr = pd.DataFrame(X, columns=housing.columns)
```

In [38]:
```
housing_tr.describe()
```

Out[38]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
count	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	6.278609	69.039851	3.7
std	8.099383	22.150636	6.877817	0.254290	0.116875	0.712366	28.258248	2.0
min	0.006320	0.000000	0.740000	0.000000	0.389000	3.561000	2.900000	1.1
25%	0.086963	0.000000	5.190000	0.000000	0.453000	5.878750	44.850000	2.0
50%	0.286735	0.000000	9.900000	0.000000	0.538000	6.209000	78.200000	3.1

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
75%	3.731923	12.500000	18.100000	0.000000	0.631000	6.630000	94.100000	5.1
max	73.534100	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.1

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
2. Standardization (value - mean)/std Sklearn provides a class called StandardScaler for this

Creating a Pipeline

In [39]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

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

In [40]:
```
housing_num_tr = my_pipeline.fit_transform(housing)
```

In [41]:
```
housing_num_tr.shape
```

Out[41]:
```
(404, 13)
```

Selecting a desired model for Dragon Real Estates

In [42]:
```
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[42]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nod
es=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.
0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

In [43]:
```
some_data = housing.iloc[:5]
```

In [44]:
```
some_labels = housing_labels.iloc[:5]
```

In [45]:
```
prepared_data = my_pipeline.transform(some_data)
```

In [46]:
```
model.predict(prepared_data)
```

Out[46]:
```
array([22.441, 25.214, 16.392, 23.315, 23.641])
```

In [47]:
```
list(some_labels)
```

Out[47]:
```
[21.9, 24.5, 16.7, 23.1, 23.0]
```

Evaluating the model

In [48]:
```
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 [49]:
```
rmse
```

Out[49]:
```
1.2067041562835843
```

Using better evaluation technique - Cross Validation

In [50]:
```
# 1 2 3 4 5 6 7 8 9 10
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 [51]:
```
rmse_scores
```

Out[51]:
```
array([2.75393875, 2.80828274, 4.46224067, 2.42998307, 3.53736642,
       2.75735195, 5.00212728, 3.36020413, 3.08359348, 3.33504582])
```

In [52]:
```
def print_scores(scores):
    print("Scores:", scores)
    print("Mean: ", scores.mean())
    print("Standard deviation: ", scores.std())
```

In [53]:
```
print_scores(rmse_scores)
```

```
Scores: [2.75393875 2.80828274 4.46224067 2.42998307 3.53736642 2.75735
195
 5.00212728 3.36020413 3.08359348 3.33504582]
Mean:  3.3530134327017933
Standard deviation:  0.7693717484522391
```

Quiz: Convert this notebook into a python file and run the pipeline using Visual Studio Code

Saving the model

In [54]:
```
from joblib import dump, load
dump(model, 'Dragon.joblib')
```

Out[54]:
```
['Dragon.joblib']
```

Testing the model on test data

In [55]:
```
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 [56]:
```
final_rmse
```

Out[56]:
```
2.927325768831125
```

In [57]:
```
prepared_data[0]
```

Out[57]:
```
array([-0.43942006,  3.12628155, -1.12165014, -0.27288841, -1.42262747,
       -0.23979304, -1.31238772,  2.61111401, -1.0016859 , -0.5778192 ,
       -0.97491834,  0.41164221, -0.86091034])
```

Using the model

In [58]:
```
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 , -0.577
8192 ,
       -0.97491834,  0.41164221, -66.86091034]])
model.predict(features)
```

Out[58]:
```
array([24.398])
```

In [ ]:
```

```