HousePricing

February 8, 2021

1 Housing Prices: Can you predict the home sales prices in Melbourne?

1.0.1 Initialize

[1]:
```
import math
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

1.0.2 Load Data

[2]:
```
dfMlb = pd.read_csv('house_prices.csv')
dfMlb.head()
```

[2]:
```
       Suburb           Address  Rooms Type    Price Method SellerG      Date  \
0  Abbotsford      85 Turner St      2    h  1480000      S  Biggin  03/12/16
1  Abbotsford   25 Bloomburg St      2    h  1035000      S  Biggin  04/02/16
2  Abbotsford      5 Charles St      3    h  1465000     SP  Biggin  04/03/17
3  Abbotsford  40 Federation La      3    h   850000     PI  Biggin  04/03/17
4  Abbotsford       55a Park St      4    h  1600000     VB  Nelson  04/06/16

   Distance  Postcode  …  Bathroom  Car  Landsize  BuildingArea  YearBuilt  \
0       2.5      3067  …         1  1.0       202           NaN        NaN
1       2.5      3067  …         1  0.0       156          79.0     1900.0
2       2.5      3067  …         2  0.0       134         150.0     1900.0
3       2.5      3067  …         2  1.0        94           NaN        NaN
4       2.5      3067  …         1  2.0       120         142.0     2014.0

   CouncilArea Lattitude  Longtitude             Regionname Propertycount
0        Yarra  -37.7996    144.9984  Northern Metropolitan          4019
1        Yarra  -37.8079    144.9934  Northern Metropolitan          4019
2        Yarra  -37.8093    144.9944  Northern Metropolitan          4019
3        Yarra  -37.7969    144.9969  Northern Metropolitan          4019
4        Yarra  -37.8072    144.9941  Northern Metropolitan          4019
```

[5 rows x 21 columns]

[3]:
```
dfMlb.columns # Display all columns
```

[3]:
```
Index(['Suburb', 'Address', 'Rooms', 'Type', 'Price', 'Method', 'SellerG',
       'Date', 'Distance', 'Postcode', 'Bedroom2', 'Bathroom', 'Car',
       'Landsize', 'BuildingArea', 'YearBuilt', 'CouncilArea', 'Lattitude',
       'Longtitude', 'Regionname', 'Propertycount'],
      dtype='object')
```

1.0.3 Clean Data

[4]:
```
# Fill empty cells with the median from that column
median_year_built = math.floor(dfMlb.YearBuilt.median())
dfMlb.YearBuilt = dfMlb.YearBuilt.fillna(median_year_built)
```

[5]:
```
median_car = math.floor(dfMlb.Car.median())
dfMlb.Car = dfMlb.Car.fillna(median_car)
```

[6]:
```
median_building_area = math.floor(dfMlb.BuildingArea.median())
dfMlb.BuildingArea = dfMlb.BuildingArea.fillna(median_building_area)
```

[7]:
```
# Drop remaining rows with empty cells
for column in dfMlb.columns:
    dfMlb = dfMlb[dfMlb[str(column)].notna()]
# Remove data where values are 0
dfMlb = dfMlb[dfMlb.Landsize != 0]
dfMlb = dfMlb[dfMlb.Price != 0]
# Get average price to calculate MAE in a future
avg_price = math.floor(dfMlb.Price.mean())
```

[8]:
```
# Drop unique, redudant and useless columns
dfMlb = dfMlb.drop(columns=['Address', 'Date', 'Lattitude', 'Longtitude'])
# Rename misspelled columns inplace
dfMlb.rename(columns={'SellerG': 'Seller', 'Bedroom2': 'Bedroom', 'Regionname':␣
↪'RegionName', 'Propertycount': 'PropertyCount'}, inplace=True)
```

[9]:
```
dfMlb.describe(include='all')
```

[9]:
```
           Suburb         Rooms   Type         Price Method  Seller  \
count       10272  10272.000000  10272  1.027200e+04  10272   10272
unique        305           NaN      3           NaN      5     237
top     Reservoir           NaN      h           NaN      S  Nelson
freq          301           NaN   8033           NaN   7017    1239
mean          NaN      3.068536    NaN  1.142861e+06    NaN     NaN
std           NaN      0.899147    NaN  6.493972e+05    NaN     NaN
min           NaN      1.000000    NaN  1.310000e+05    NaN     NaN
```

```
25%          NaN      3.000000    NaN  7.100000e+05    NaN      NaN
50%          NaN      3.000000    NaN  9.675000e+05    NaN      NaN
75%          NaN      4.000000    NaN  1.400000e+06    NaN      NaN
max          NaN     10.000000    NaN  9.000000e+06    NaN      NaN

            Distance      Postcode       Bedroom      Bathroom           Car  \
count   10272.000000  10272.000000  10272.000000  10272.000000  10272.000000
unique           NaN           NaN           NaN           NaN           NaN
top              NaN           NaN           NaN           NaN           NaN
freq             NaN           NaN           NaN           NaN           NaN
mean       10.402434   3102.092971      3.038162      1.570678      1.659073
std         5.578720     91.127321      0.916483      0.707189      0.985341
min         0.000000   3000.000000      0.000000      0.000000      0.000000
25%         6.700000   3044.000000      2.000000      1.000000      1.000000
50%         9.850000   3081.000000      3.000000      1.000000      2.000000
75%        13.000000   3146.000000      4.000000      2.000000      2.000000
max        47.400000   3977.000000     20.000000      8.000000     10.000000

             Landsize  BuildingArea     YearBuilt CouncilArea  \
count    10272.000000  10272.000000  10272.000000       10272
unique            NaN           NaN           NaN          33
top               NaN           NaN           NaN    Moreland
freq              NaN           NaN           NaN        1030
mean       647.930199    141.715375   1965.026967         NaN
std       4548.807775    101.695480     30.162665         NaN
min          1.000000      0.000000   1196.000000         NaN
25%        258.000000    126.000000   1960.000000         NaN
50%        516.000000    126.000000   1970.000000         NaN
75%        670.000000    137.000000   1970.000000         NaN
max     433014.000000   6791.000000   2018.000000         NaN

                    RegionName  PropertyCount
count                    10272   10272.000000
unique                       8            NaN
top      Southern Metropolitan            NaN
freq                      3303            NaN
mean                       NaN    7304.301889
std                        NaN    4392.989470
min                        NaN     249.000000
25%                        NaN    4019.000000
50%                        NaN    6482.000000
75%                        NaN    9704.000000
max                        NaN   21650.000000
```

[10]:
```
# Check if we have succesfully removed all null vars
dfMlb.isnull().sum()
```

[10]:
```
Suburb           0
Rooms            0
Type             0
Price            0
Method           0
Seller           0
Distance         0
Postcode         0
Bedroom          0
Bathroom         0
Car              0
Landsize         0
BuildingArea     0
YearBuilt        0
CouncilArea      0
RegionName       0
PropertyCount    0
dtype: int64
```

[11]:
```
# Transform numerical values that are categorical to object type
dfMlb['YearBuilt'] = dfMlb['YearBuilt'].astype('object',copy=False)
dfMlb['Postcode'] = dfMlb['Postcode'].astype('object',copy=False)
# Encode categorical variables (to numerical)
from sklearn import model_selection, preprocessing
for col in dfMlb.columns:
    if dfMlb[col].dtype == 'object':
        lbl = preprocessing.LabelEncoder()
        lbl.fit(list(dfMlb[col].values))
        dfMlb[col] = lbl.transform(list(dfMlb[col].values))
```

[12]:
```
dfMlb.dtypes
```

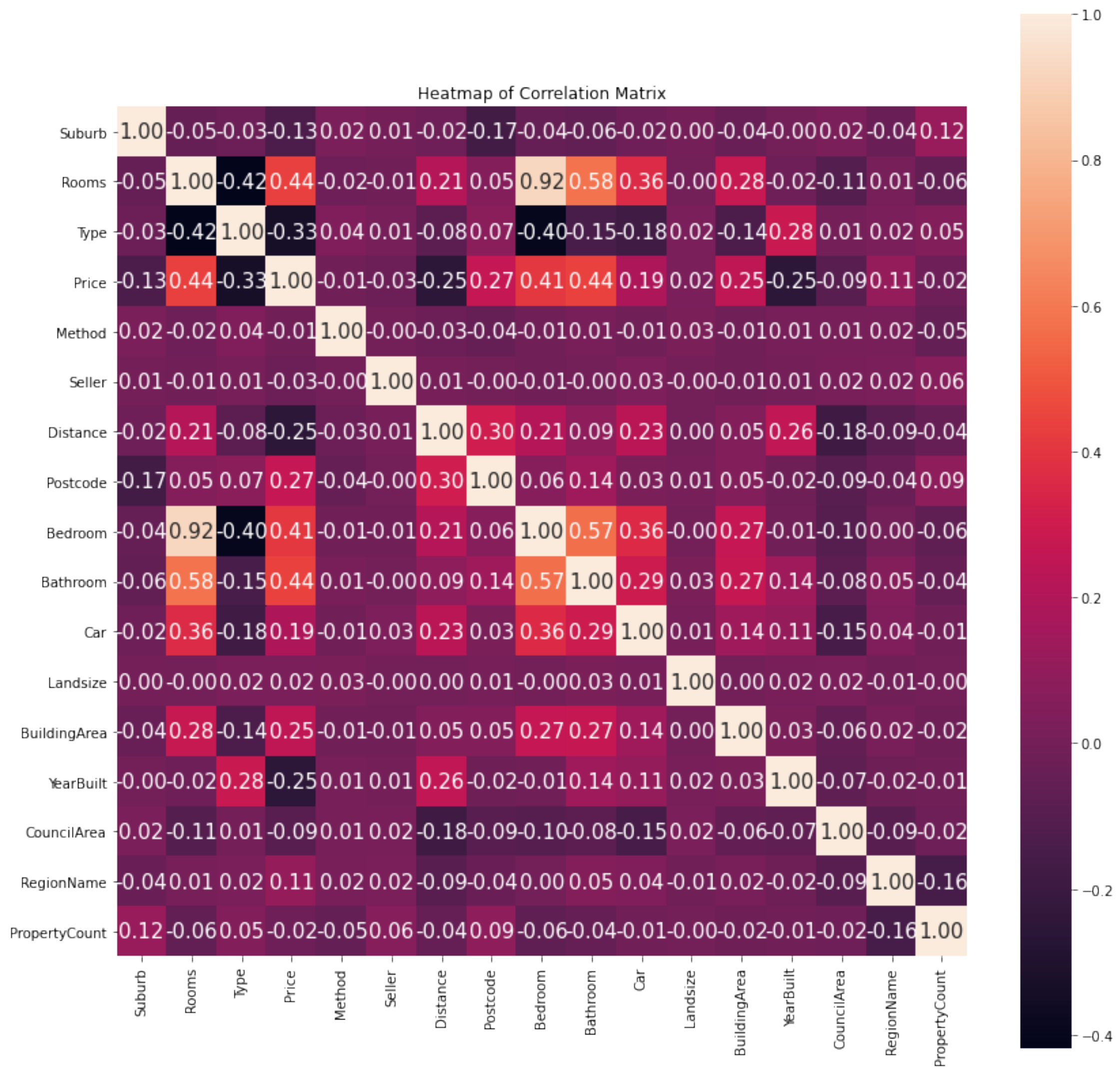
[12]:
```
Suburb             int64
Rooms              int64
Type               int64
Price              int64
Method             int64
Seller             int64
Distance         float64
Postcode           int64
Bedroom            int64
Bathroom           int64
Car              float64
Landsize           int64
BuildingArea     float64
YearBuilt          int64
CouncilArea        int64
```

```
RegionName          int64
PropertyCount       int64
dtype: object
```

1.0.4 Feature Engineering

[13]:
```
import matplotlib as mpl
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

corr = dfMlb.corr()
corr = (corr)
plt.figure(figsize=(14,14))
sns.heatmap(corr, cbar = True,  square = True, annot=True, fmt= '.
 ↪2f',annot_kws= {'size': 15}, xticklabels=corr.columns.values,␣
 ↪yticklabels=corr.columns.values)
plt.title('Heatmap of Correlation Matrix')
```

[13]:
```
Text(0.5, 1.0, 'Heatmap of Correlation Matrix')
```



1.0.5 Select Data

[14]:
```python
# Select a Prediction Target
y = dfMlb.loc[:,['Price']]
```

[15]:
```python
y.head()
```

[15]:

	Price
0	1480000
1	1035000
2	1465000
3	850000
4	1600000

[16]:
```python
# Selected Set of Features
x = dfMlb.loc[:, ['Suburb', 'Rooms', 'Type', 'Method', 'Seller', 'Distance',␣
 ↪'Postcode', 'Bathroom', 'Car', 'Landsize', 'BuildingArea', 'YearBuilt',␣
 ↪'CouncilArea', 'RegionName', 'PropertyCount']]
```

[17]:
```python
x.describe()
```

[17]:
```
             Suburb         Rooms          Type        Method        Seller  \
count  10272.000000  10272.000000  10272.000000  10272.000000  10272.000000
mean     149.215343      3.068536      0.347741      1.362344    115.884930
std       88.614796      0.899147      0.697428      1.077439     69.122205
min        0.000000      1.000000      0.000000      0.000000      0.000000
25%       61.000000      3.000000      0.000000      1.000000     63.000000
50%      150.000000      3.000000      0.000000      1.000000    121.000000
75%      227.000000      4.000000      0.000000      1.000000    173.000000
max      304.000000     10.000000      2.000000      4.000000    236.000000

           Distance      Postcode      Bathroom           Car       Landsize  \
count  10272.000000  10272.000000  10272.000000  10272.000000   10272.000000
mean      10.402434     72.466803      1.570678      1.659073     647.930199
std        5.578720     47.399684      0.707189      0.985341    4548.807775
min        0.000000      0.000000      0.000000      0.000000       1.000000
25%        6.700000     33.000000      1.000000      1.000000     258.000000
50%        9.850000     63.000000      1.000000      2.000000     516.000000
75%       13.000000    109.000000      2.000000      2.000000     670.000000
max       47.400000    192.000000      8.000000     10.000000  433014.000000

       BuildingArea     YearBuilt   CouncilArea    RegionName  PropertyCount
count  10272.000000  10272.000000  10272.000000  10272.000000   10272.000000
mean     141.715375     89.670463     14.209502      3.743477    7304.301889
std      101.695480     27.966337      9.796792      2.062906    4392.989470
min        0.000000      0.000000      0.000000      0.000000     249.000000
25%      126.000000     84.000000      6.000000      2.000000    4019.000000
50%      126.000000     94.000000     15.000000      5.000000    6482.000000
75%      137.000000     94.000000     23.000000      5.000000    9704.000000
max     6791.000000    142.000000     32.000000      7.000000   21650.000000
```

1.0.6 Build Model

1. Define
2. Fit
3. Predict
4. Evaluate

[18]:
```python
# Define

from sklearn.tree import DecisionTreeRegressor
```

```
modelDtrMlb = DecisionTreeRegressor()
```

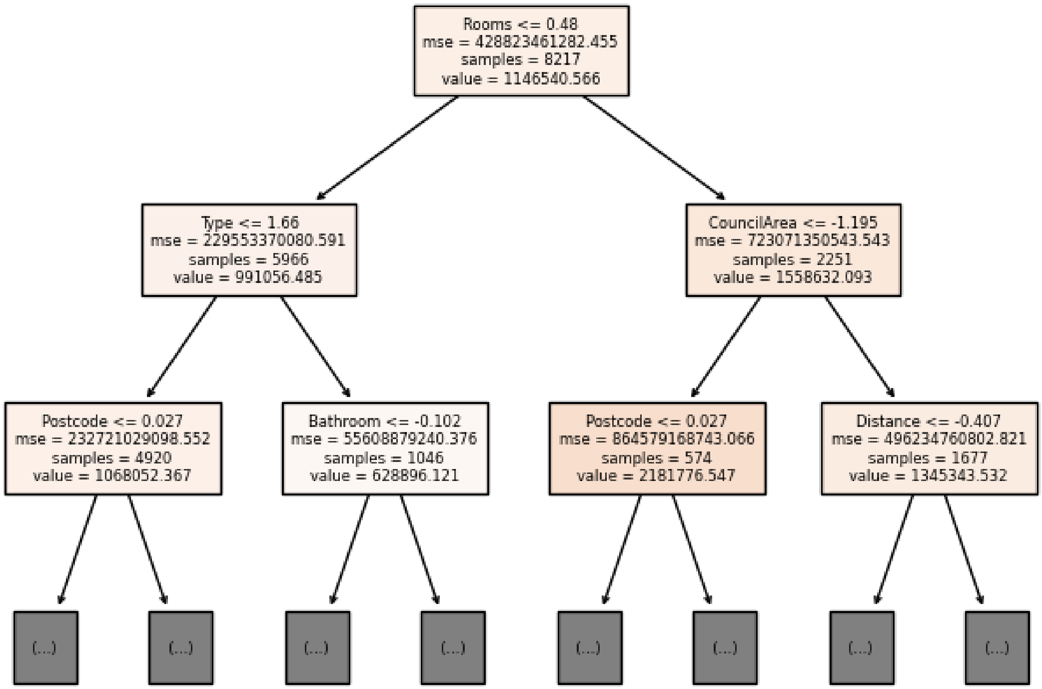
[19]:
```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
↪random_state=1)
```

[20]:
```
# Feature Scaling (Normalize IV)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

[21]:
```
# Build decision tree model
from sklearn.metrics import mean_absolute_error

# define
mdlDtrMlbSpl = DecisionTreeRegressor(random_state=1)

# fit
mdlDtrMlbSpl.fit(x_train, y_train)

# predict
y_test_pred = mdlDtrMlbSpl.predict(x_test)

# evaluate
mae = mean_absolute_error(y_test, y_test_pred)
print('MAE (after train-test-split): ', round(mae,2))
print("Current mae is ", round(mae/avg_price*100,2), "%")
```

```
MAE (after train-test-split):  251205.52
Current mae is  21.98 %
```

[22]:
```
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6), dpi=100)
plot_tree(mdlDtrMlbSpl, max_depth=2, feature_names=x.columns, fontsize=6,␣
↪filled=True)
plt.show()
```



1.0.7 Improve Decision Tree model

[23]:
```
# We will try to get our MAE down to 15%
# Function to tweak max_leaf_nodes parameter
def get_mae_lfndsDTR(X_trn, X_tst, y_trn, y_tst, mx_lf_nds):
    mdlDtrMlbDpt = DecisionTreeRegressor(random_state=1,␣
 ↪max_leaf_nodes=mx_lf_nds)
    mdlDtrMlbDpt.fit(X_trn, y_trn)
    y_tst_prd = mdlDtrMlbDpt.predict(X_tst)
    mae = mean_absolute_error(y_test, y_tst_prd)
    return mae

# Funtion to tweak min_samples_leaf parameter
def get_mae_smplfsDTR(X_trn, X_tst, y_trn, y_tst, mn_spls_lf):
    mdlDtrMlbDpt = DecisionTreeRegressor(random_state=1,␣
 ↪min_samples_leaf=mn_spls_lf)
    mdlDtrMlbDpt.fit(X_trn, y_trn)
    y_tst_prd = mdlDtrMlbDpt.predict(X_tst)
    mae = mean_absolute_error(y_test, y_tst_prd)
    return mae
```

```
# Funtion to tweak max_depth parameter
def get_mae_mxdpthDTR(X_trn, X_tst, y_trn, y_tst, mx_dpth):
    mdlDtrMlbDpt = DecisionTreeRegressor(random_state=1, max_depth=mx_dpth)
    mdlDtrMlbDpt.fit(X_trn, y_trn)
    y_tst_prd = mdlDtrMlbDpt.predict(X_tst)
    mae = mean_absolute_error(y_test, y_tst_prd)
    return mae
```

[24]:
```
# For loops to get the ranges for the hyper parameter tunning
for i in [5, 50, 500, 5000, 50000]:
    mae = get_mae_lfndsDTR(x_train, x_test, y_train, y_test, i)
    print('Max leaf nodes: ', i, '\t MAE', round(mae, 2), '\t % MAE ',␣
 ↪round(mae/avg_price*100,2))

for i in [5, 10]:
    mae = get_mae_smplfsDTR(x_train, x_test, y_train, y_test, i)
    print('Min samples per leaf: ', i, '\t MAE', round(mae, 2), '\t % MAE ',␣
 ↪round(mae/avg_price*100,2))

for i in [5, 10, 15, 20]:
    mae = get_mae_mxdpthDTR(x_train, x_test, y_train, y_test, i)
    print('Max depth: ', i, '\t MAE', round(mae, 2), '\t % MAE ', round(mae/
 ↪avg_price*100,2))
```

```
Max leaf nodes:  5       MAE 338975.62   % MAE   29.66
Max leaf nodes:  50      MAE 247512.97   % MAE   21.66
Max leaf nodes:  500     MAE 226680.59   % MAE   19.83
Max leaf nodes:  5000    MAE 249952.48   % MAE   21.87
Max leaf nodes:  50000   MAE 250348.93   % MAE   21.91
Min samples per leaf:  5         MAE 217297.08   % MAE   19.01
Min samples per leaf:  10        MAE 214211.42   % MAE   18.74
Max depth:  5    MAE 254204.12   % MAE   22.24
Max depth:  10   MAE 219378.22   % MAE   19.2
Max depth:  15   MAE 243619.52   % MAE   21.32
Max depth:  20   MAE 248162.38   % MAE   21.71
```

1.0.8 Hyperparameter tuning for Decision Tree Regressor

[25]:
```
mdlDtrMlbSpl.get_params()
```

[25]:
```
{'ccp_alpha': 0.0,
 'criterion': 'mse',
 'max_depth': None,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
```

```
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'presort': 'deprecated',
 'random_state': 1,
 'splitter': 'best'}
```

[ ]:
```
# Import modules for Hyperparameter Tuning
from scipy.stats import randint
from sklearn.model_selection import RandomizedSearchCV

# The function to measure the quality of a split
criterion = ['mse', 'friedman_mse', 'mae']
# The strategy used to choose the split at each node
splitter = ['best', 'random']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(5, 100, num = 2)] + [None]
# Minimum number of samples required at each leaf node
min_samples_leaf = [int(x) for x in range(1, 10)] + [None]

# Setup the parameters and distribution to sample from: param_dist
param_dist = {
    "criterion": criterion,
    "splitter": splitter,
    "max_depth": max_depth,
    "min_samples_leaf": min_samples_leaf
}

# define
mdlDtrMlbDpt = DecisionTreeRegressor(random_state=1)

# Hyper parameter tune
mdlDtrMlbDptCV = RandomizedSearchCV(estimator = mdlDtrMlbDpt,␣
 ↪param_distributions = param_dist, cv = 5)

# fit
mdlDtrMlbDptCV.fit(x_train, y_train)

# print the tuned parameters and score
print("Tuned Decision Tree Parameters: {}".format(mdlDtrMlbDptCV.best_params_))
print("Best score is {}", format(mdlDtrMlbDptCV.best_score_))
```

[27]:
```
# Predicting the test set results
y_test_pred = mdlDtrMlbDptCV.predict(x_test)

# evaluate
mae = mean_absolute_error(y_test, y_test_pred)
```

```
print('MAE (after train-test-split): ', round(mae,2))
print("Current mae is ", round(mae/avg_price*100,2), "%")
```

```
MAE (after train-test-split):  231069.11
Current mae is  20.22 %
```

1.0.9 Build Random Forest Model

[28]:
```
from sklearn.ensemble import RandomForestRegressor

# define
mdlRfsMlb = RandomForestRegressor(random_state=1)

# fit
mdlRfsMlb.fit(x_train, y_train)

# predict
y_test_pred = mdlRfsMlb.predict(x_test)

# evaluate
mae = mean_absolute_error(y_test, y_test_pred)

print('MAE (Random Forest):', round(mae,2))
print("Current mae is ", round(mae/avg_price*100,2), "%")
```

```
MAE (Random Forest): 179177.72
Current mae is  15.68 %
```

1.0.10 Improve Random Forest model

[29]:
```
# Function to tweak max_leaf_nodes parameter
def get_mae_lfndsRFR(X_trn, X_tst, y_trn, y_tst, mx_lf_nds):
    mdlRfsMlb = RandomForestRegressor(random_state=1, max_leaf_nodes=mx_lf_nds)
    mdlRfsMlb.fit(X_trn, y_trn)
    y_tst_prd = mdlRfsMlb.predict(X_tst)
    mae = mean_absolute_error(y_test, y_tst_prd)
    return mae

# Funtion to tweak min_samples_leaf parameter
def get_mae_smplfsRFR(X_trn, X_tst, y_trn, y_tst, mn_spls_lf):
    mdlRfsMlb = RandomForestRegressor(random_state=1,␣
 ↪min_samples_leaf=mn_spls_lf)
    mdlRfsMlb.fit(X_trn, y_trn)
    y_tst_prd = mdlRfsMlb.predict(X_tst)
    mae = mean_absolute_error(y_test, y_tst_prd)
    return mae
```

```
# Funtion to tweak min_samples_leaf parameter
def get_mae_dpthRFR(X_trn, X_tst, y_trn, y_tst, mx_dpth):
    mdlRfsMlb = RandomForestRegressor(random_state=1, max_depth=mx_dpth)
    mdlRfsMlb.fit(X_trn, y_trn)
    y_tst_prd = mdlRfsMlb.predict(X_tst)
    mae = mean_absolute_error(y_test, y_tst_prd)
    return mae
```

[30]:
```
# Develop similar for loops for the new model
for i in [5, 50, 500, 5000, 50000]:
    mae = get_mae_lfndsRFR(x_train, x_test, y_train, y_test, i)
    print('Max leaf nodes: ', i, '\t MAE', round(mae, 2), '\t % MAE ',␣
 ↪round(mae/avg_price*100,2))

for i in [5, 10, 15, 20, 25, 30]:
    mae = get_mae_smplfsRFR(x_train, x_test, y_train, y_test, i)
    print('Min samples per leaf: ', i, '\t MAE', round(mae, 2), '\t % MAE ',␣
 ↪round(mae/avg_price*100,2))

for i in [5, 10, 15, 20]:
    mae = get_mae_dpthRFR(x_train, x_test, y_train, y_test, i)
    print('Max depth: ', i, '\t MAE', round(mae, 2), '\t % MAE ', round(mae/
 ↪avg_price*100,2))
```

```
Max leaf nodes:  5       MAE 319839.35   % MAE  27.99
Max leaf nodes:  50      MAE 215124.33   % MAE  18.82
Max leaf nodes:  500     MAE 184240.52   % MAE  16.12
Max leaf nodes:  5000    MAE 179938.83   % MAE  15.74
Max leaf nodes:  50000   MAE 179939.17   % MAE  15.74
Min samples per leaf:  5         MAE 176715.67   % MAE  15.46
Min samples per leaf:  10        MAE 180239.45   % MAE  15.77
Min samples per leaf:  15        MAE 183847.22   % MAE  16.09
Min samples per leaf:  20        MAE 188048.31   % MAE  16.45
Min samples per leaf:  25        MAE 192215.27   % MAE  16.82
Min samples per leaf:  30        MAE 194787.86   % MAE  17.04
Max depth:  5    MAE 231046.1    % MAE  20.22
Max depth:  10   MAE 186388.54   % MAE  16.31
Max depth:  15   MAE 178273.73   % MAE  15.6
Max depth:  20   MAE 179051.59   % MAE  15.67
```

1.0.11 Hyperparameter tuning for Random Forest Regressor

[31]:
```
mdlRfsMlb.get_params()
```

[31]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
```

```
'criterion': 'mse',
'max_depth': None,
'max_features': 'auto',
'max_leaf_nodes': 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': 1,
'verbose': 0,
'warm_start': False}
```

[32]:

```
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]
# np.linspace returns evenly spaced numbers over a specified interval.
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(5, 50, num = 5)] + [None]
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]
# Method of selecting samples for training each tree
bootstrap = [True, False]

# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}

mdlRfsMlb = RandomForestRegressor()
# Random search of parameters, across 100 different combinations with all␣
 ↪available logical cores
mdlRfsMlbCV = RandomizedSearchCV(estimator = mdlRfsMlb, param_distributions =␣
 ↪random_grid, n_iter = 100, cv = 3, verbose=2, random_state=42, n_jobs = -1)
# Fit the random search model
mdlRfsMlbCV.fit(x_train, y_train)

print("Tuned Decision Tree Parameters: {}".format(mdlRfsMlbCV.best_params_))
```

```
print("Best score is {}", format(mdlRfsMlbCV.best_score_))
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:  2.6min
[Parallel(n_jobs=-1)]: Done 146 tasks      | elapsed:  9.5min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 19.6min finished

Tuned Decision Tree Parameters: {'n_estimators': 1400, 'min_samples_split': 5,
'min_samples_leaf': 1, 'max_features': 'sqrt', 'max_depth': 38, 'bootstrap':
False}
Best score is {} 0.7907541719586694
```

[33]:

```
# Predicting the test set results
y_test_pred = mdlRfsMlbCV.predict(x_test)

# evaluate
mae = mean_absolute_error(y_test, y_test_pred)
print('MAE (after train-test-split): ', round(mae,2))
print("Current mae is ", round(mae/avg_price*100,2), "%")
```

```
MAE (after train-test-split):  174183.14
Current mae is  15.24 %
```

1.0.12 We did it! We developed a model with a 15.24% MAE

1.0.13 Alejandro Gleason Méndez - ag77698