In [556…

```
# importing dependencies
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import make_regression
from sklearn import tree
from sklearn.metrics import mean_squared_error
```

In [557…

```
houseData5 = pd.read_csv(r'C:\Users\VAIO\Documents\houseData5.csv')
pd.set_option('max_columns', None)
pd.set_option("max_rows", None)
```

In [563…

```
#prepare the data
X = houseData5.loc[:, ~houseData5.columns.isin(['sale_price_$',
                                                 'listing_price_to_nearest_1000'
                                                ]
                                               )
                  ]
y = houseData5['sale_price_$']
```

In [579…

```
# train test split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)

# reset the indices
X_train,y_train,X_test,y_test = X_train.reset_index(drop=True),y_train.reset_index(drop=Tr
```

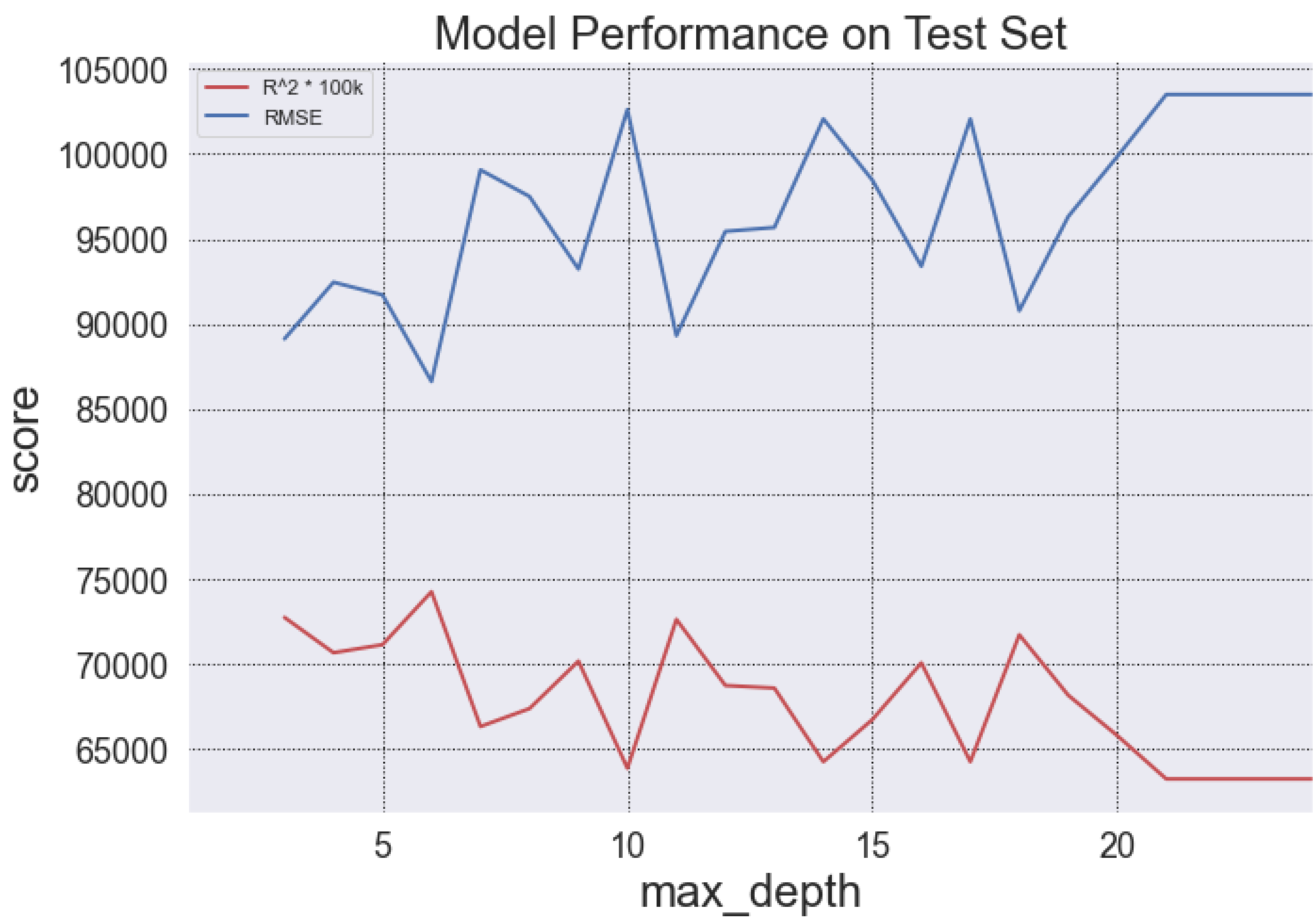
In [ ]:

```
#https://towardsdatascience.com/understanding-train-test-split-scikit-learn-python-ea676d5
from sklearn.tree import DecisionTreeRegressor

# Lets use a regression tree because our sale_price us continuous.
#We want to find the ideal depth of our tree so let's graph depth vs oos score

max_depth_range = list(range(3, 25))
# List to store the average R^2 and RMSE for each value of max_depth:
r2_list = []
RMSE_list = []
for depth in max_depth_range:
    reg = DecisionTreeRegressor(criterion = ('squared_error'),
                                max_depth = depth,
                                random_state = 0
                               )
    reg.fit(X_train, y_train)

    R2k = (reg.score(X_test, y_test))*100000
    RMSE = round(mean_squared_error(y_true=y_test, y_pred = reg.predict(X_test), squared=F
    r2_list.append(R2k)
    RMSE_list.append(RMSE)
```

In [296…

```
fig, ax = plt.subplots(nrows = 1, ncols = 1,
                       figsize = (10,7),
                       facecolor = 'white');
ax.plot(max_depth_range,
       r2_list,
```

```
        lw=2,
        color='r',
        label = "R^2 * 100k")
ax.plot(max_depth_range,
        RMSE_list,
        lw=2,
        color='b',
        label = "RMSE")
ax.legend()
ax.set_xlim([1, max(max_depth_range)])
ax.grid(True,
        axis = 'both',
        zorder = 0,
        linestyle = ':',
        color = 'k')
ax.tick_params(labelsize = 18)
ax.set_xlabel('max_depth', fontsize = 24)
ax.set_ylabel('score', fontsize = 24)
ax.set_title('Model Performance on Test Set', fontsize = 24)
fig.tight_layout()
```



In [297…

```
#It looks like maybe 6 deep is ideal
reg = DecisionTreeRegressor(criterion = ('squared_error'), max_depth = 6, random_state = (
reg.fit(X_train, y_train)
# Let's get those scores

# In sample predictions
yhat_in_sample = reg.predict(X_train)

# oos predictions
yhat_oos = reg.predict(X_test)

# IN SAMPLE
```

```python
print(f"In sample R^2: {round(reg.score(X_train, y_train), 6)}")
print(f"In sample RMSE {round(mean_squared_error(y_true=y_train, y_pred=yhat_in_sample, sc

# OOS
print(f"OOS R^2: {round(reg.score(X_test, y_test), 6)}")
print(f"OOS RMSE {round(mean_squared_error(y_true=y_test, y_pred=yhat_oos, squared=False),
```

```
In sample R^2: 0.929561
In sample RMSE 48295.713543
OOS R^2: 0.742588
OOS RMSE 86622.109789
```

In [485…

```python
text_representation = tree.export_text(reg, feature_names= ['num_half_bathrooms',
                                                             'walk_score',
                                                             'sq_footage',
                                                             'pct_tax_deductibl',
                                                             'num_total_rooms',
                                                             'num_full_bathrooms',
                                                             'num_floors_in_building',
                                                             'num_bedrooms',
                                                             'kitchen_type',
                                                             'garage_exists',
                                                             'full_address_or_zip_code',
                                                             'fuel_type','dogs_allowed',
                                                             'dining_room_type',
                                                             'date_of_sale',
                                                             'coop_condo',
                                                             'community_district_num',
                                                             'cats_allowed',
                                                             'approx_year_built',
                                                             'Missing_taxes',
                                                             'Missing_maintenance_cost',
                                                             'Missing_common_charges',
                                                             'Missing_parking_charges',
                                                             'additional_costs_$',
                                                             'zip_code'
                                                            ]
                                       )
print(text_representation)
```

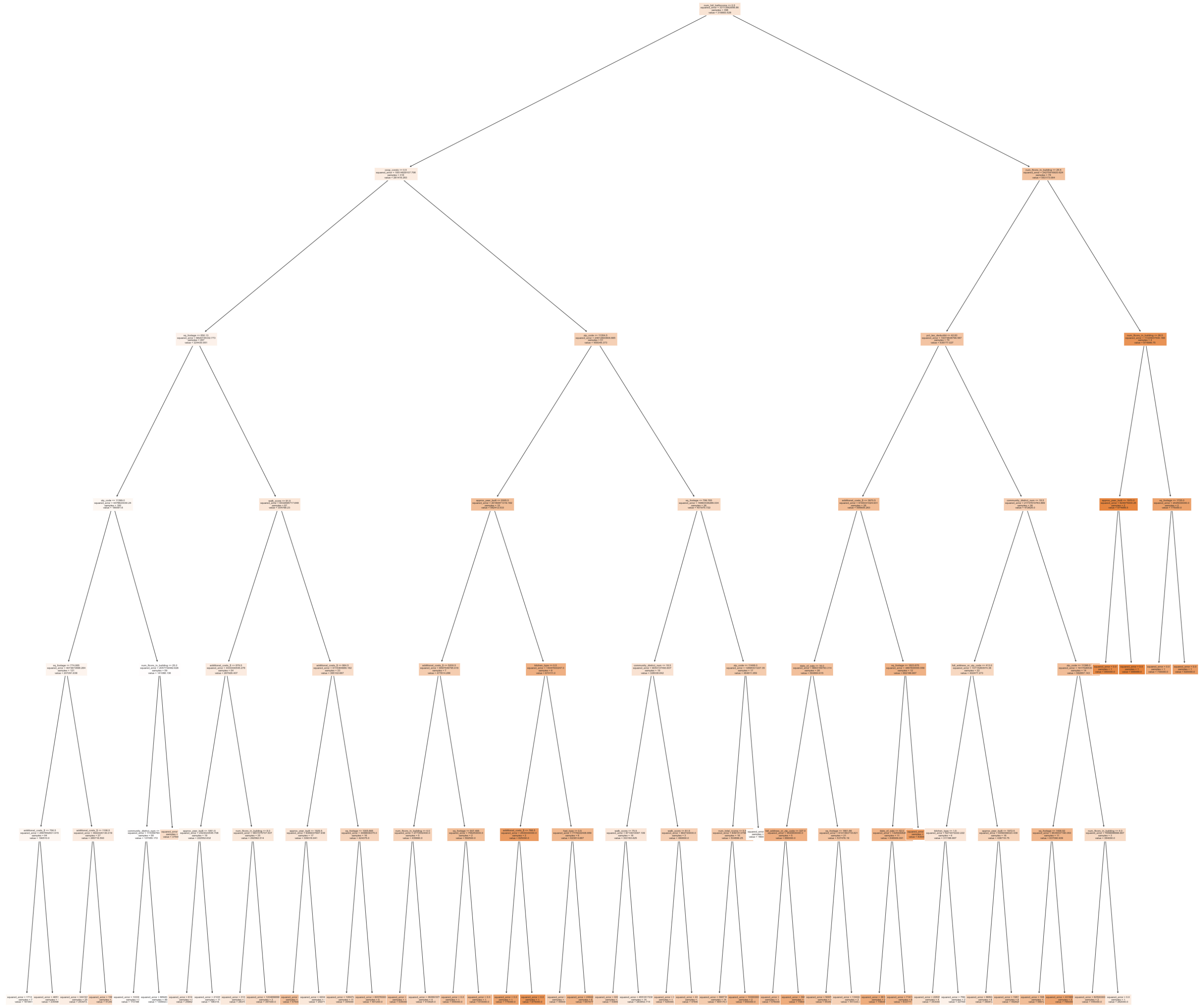
```
|--- num_full_bathrooms <= 0.50
|   |--- coop_condo <= 0.50
|   |   |--- sq_footage <= 850.13
|   |   |   |--- zip_code <= 11399.00
|   |   |   |   |--- sq_footage <= 774.07
|   |   |   |   |   |--- additional_costs_$ <= 756.50
|   |   |   |   |   |   |--- value: [181951.14]
|   |   |   |   |   |--- additional_costs_$ >  756.50
|   |   |   |   |   |   |--- value: [235586.67]
|   |   |   |   |--- sq_footage >  774.07
|   |   |   |   |   |--- additional_costs_$ <= 1106.50
|   |   |   |   |   |   |--- value: [253973.92]
|   |   |   |   |   |--- additional_costs_$ >  1106.50
|   |   |   |   |   |   |--- value: [412500.00]
|   |   |   |--- zip_code >  11399.00
|   |   |   |   |--- num_floors_in_building <= 25.00
|   |   |   |   |   |--- community_district_num <= 17.50
|   |   |   |   |   |   |--- value: [172188.89]
|   |   |   |   |   |--- community_district_num >  17.50
|   |   |   |   |   |   |--- value: [130602.04]
|   |   |   |   |--- num_floors_in_building >  25.00
|   |   |   |   |   |--- value: [375000.00]
|   |   |--- sq_footage >  850.13
|   |   |   |--- walk_score <= 91.50
|   |   |   |   |--- additional_costs_$ <= 879.50
```

```
|   |   |   |   |   |--- approx_year_built <= 1951.50
|   |   |   |   |   |   |--- value: [258625.00]
|   |   |   |   |   |--- approx_year_built >  1951.50
|   |   |   |   |   |   |--- value: [196318.18]
|   |   |   |   |--- additional_costs_$ >  879.50
|   |   |   |   |   |--- num_floors_in_building <= 8.00
|   |   |   |   |   |   |--- value: [283709.00]
|   |   |   |   |   |--- num_floors_in_building >  8.00
|   |   |   |   |   |   |--- value: [387000.00]
|   |   |   |--- walk_score >  91.50
|   |   |   |   |--- additional_costs_$ <= 864.50
|   |   |   |   |   |--- approx_year_built <= 1929.50
|   |   |   |   |   |   |--- value: [575000.00]
|   |   |   |   |   |--- approx_year_built >  1929.50
|   |   |   |   |   |   |--- value: [292711.75]
|   |   |   |   |--- additional_costs_$ >  864.50
|   |   |   |   |   |--- sq_footage <= 1005.67
|   |   |   |   |   |   |--- value: [394000.00]
|   |   |   |   |   |--- sq_footage >  1005.67
|   |   |   |   |   |   |--- value: [491200.00]
|   |--- coop_condo >  0.50
|   |   |--- zip_code <= 11354.50
|   |   |   |--- approx_year_built <= 2005.50
|   |   |   |   |--- additional_costs_$ <= 5200.50
|   |   |   |   |   |--- num_floors_in_building <= 4.00
|   |   |   |   |   |   |--- value: [535000.00]
|   |   |   |   |   |--- num_floors_in_building >  4.00
|   |   |   |   |   |   |--- value: [410825.00]
|   |   |   |   |--- additional_costs_$ >  5200.50
|   |   |   |   |   |--- sq_footage <= 907.49
|   |   |   |   |   |   |--- value: [555000.00]
|   |   |   |   |   |--- sq_footage >  907.49
|   |   |   |   |   |   |--- value: [610000.00]
|   |   |   |--- approx_year_built >  2005.50
|   |   |   |   |--- kitchen_type <= 0.50
|   |   |   |   |   |--- additional_costs_$ <= 766.50
|   |   |   |   |   |   |--- value: [775000.00]
|   |   |   |   |   |--- additional_costs_$ >  766.50
|   |   |   |   |   |   |--- value: [875000.00]
|   |   |   |   |--- kitchen_type >  0.50
|   |   |   |   |   |--- fuel_type <= 0.50
|   |   |   |   |   |   |--- value: [455000.00]
|   |   |   |   |   |--- fuel_type >  0.50
|   |   |   |   |   |   |--- value: [657577.60]
|   |   |--- zip_code >  11354.50
|   |   |   |--- sq_footage <= 799.77
|   |   |   |   |--- community_district_num <= 18.50
|   |   |   |   |   |--- walk_score <= 75.50
|   |   |   |   |   |   |--- value: [438500.00]
|   |   |   |   |   |--- walk_score >  75.50
|   |   |   |   |   |   |--- value: [283852.71]
|   |   |   |   |--- community_district_num >  18.50
|   |   |   |   |   |--- walk_score <= 81.50
|   |   |   |   |   |   |--- value: [425000.00]
|   |   |   |   |   |--- walk_score >  81.50
|   |   |   |   |   |   |--- value: [478400.00]
|   |   |   |--- sq_footage >  799.77
|   |   |   |   |--- zip_code <= 11406.00
|   |   |   |   |   |--- num_total_rooms <= 5.50
|   |   |   |   |   |   |--- value: [484170.57]
|   |   |   |   |   |--- num_total_rooms >  5.50
|   |   |   |   |   |   |--- value: [650000.00]
|   |   |   |   |--- zip_code >  11406.00
|   |   |   |   |   |--- value: [160000.00]
|--- num_full_bathrooms >  0.50
|   |--- num_floors_in_building <= 25.50
```

```
|   |   |--- pct_tax_deductibl <= 42.83
|   |   |   |--- additional_costs_$ <= 3970.50
|   |   |   |   |--- date_of_sale <= 16.00
|   |   |   |   |   |--- full_address_or_zip_code <= 327.00
|   |   |   |   |   |   |--- value: [576000.00]
|   |   |   |   |   |--- full_address_or_zip_code >  327.00
|   |   |   |   |   |   |--- value: [706000.00]
|   |   |   |   |--- date_of_sale >  16.00
|   |   |   |   |   |--- sq_footage <= 1661.86
|   |   |   |   |   |   |--- value: [553500.00]
|   |   |   |   |   |--- sq_footage >  1661.86
|   |   |   |   |   |   |--- value: [441333.33]
|   |   |   |--- additional_costs_$ >  3970.50
|   |   |   |   |--- sq_footage <= 1823.67
|   |   |   |   |   |--- date_of_sale <= 42.00
|   |   |   |   |   |   |--- value: [706000.00]
|   |   |   |   |   |--- date_of_sale >  42.00
|   |   |   |   |   |   |--- value: [633777.78]
|   |   |   |   |--- sq_footage >  1823.67
|   |   |   |   |   |--- value: [830000.00]
|   |   |--- pct_tax_deductibl >  42.83
|   |   |   |--- community_district_num <= 18.50
|   |   |   |   |--- full_address_or_zip_code <= 413.00
|   |   |   |   |   |--- kitchen_type <= 1.50
|   |   |   |   |   |   |--- value: [353000.00]
|   |   |   |   |   |--- kitchen_type >  1.50
|   |   |   |   |   |   |--- value: [227500.00]
|   |   |   |   |--- full_address_or_zip_code >  413.00
|   |   |   |   |   |--- approx_year_built <= 1972.50
|   |   |   |   |   |   |--- value: [380812.50]
|   |   |   |   |   |--- approx_year_built >  1972.50
|   |   |   |   |   |   |--- value: [492625.00]
|   |   |   |--- community_district_num >  18.50
|   |   |   |   |--- zip_code <= 11396.00
|   |   |   |   |   |--- sq_footage <= 1406.92
|   |   |   |   |   |   |--- value: [589125.00]
|   |   |   |   |   |--- sq_footage >  1406.92
|   |   |   |   |   |   |--- value: [765000.00]
|   |   |   |   |--- zip_code >  11396.00
|   |   |   |   |   |--- num_floors_in_building <= 4.00
|   |   |   |   |   |   |--- value: [445000.00]
|   |   |   |   |   |--- num_floors_in_building >  4.00
|   |   |   |   |   |   |--- value: [262000.00]
|   |--- num_floors_in_building >  25.50
|   |   |--- num_floors_in_building <= 26.50
|   |   |   |--- approx_year_built <= 1970.00
|   |   |   |   |--- value: [950000.00]
|   |   |   |--- approx_year_built >  1970.00
|   |   |   |   |--- value: [999999.00]
|   |   |--- num_floors_in_building >  26.50
|   |   |   |--- sq_footage <= 1725.00
|   |   |   |   |--- value: [730000.00]
|   |   |   |--- sq_footage >  1725.00
|   |   |   |   |--- value: [820000.00]
```

In [489…

```
fig = plt.figure(figsize=(50,50))
tree.plot_tree(reg, feature_names = X_train.columns, class_names=y, filled=True, fontsize=
plt.show()
fig.savefig(fname = 'decision_tree.png', dpi= 200)
```



In [ ]:

```
# from sklearn.tree import DecisionTreeClassifier
# classifier= DecisionTreeClassifier(criterion='entropy', random_state=0)
# classifier.fit(X_train, y_train)
# #Predicting the test set result
# y_pred= classifier.predict(X_test)
# classifier.score()
```

In [353…

```
#lets try some different OLS regression methods
import statsmodels.api as sm

OLSmodel1 = sm.OLS(y_train, X_train).fit()
OLSmodel1.summary()
```

Out[353…

OLS Regression Results

Dep. Variable:	sale_price_$	**R-squared (uncentered):**	0.937
Model:	OLS	**Adj. R-squared (uncentered):**	0.933
Method:	Least Squares	**F-statistic:**	222.2

Date:	Tue, 24 May 2022	**Prob (F-statistic):**	3.71e-206
Time:	14:01:54	**Log-Likelihood:**	-5087.4
No. Observations:	396	**AIC:**	1.022e+04
Df Residuals:	371	**BIC:**	1.032e+04
Df Model:	25		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
num_half_bathrooms	5.002e+04	1.96e+04	2.553	0.011	1.15e+04	8.85e+04
walk_score	981.4685	405.594	2.420	0.016	183.917	1779.020
sq_footage	26.8503	16.698	1.608	0.109	-5.984	59.684
pct_tax_deductibl	-3791.0074	1008.688	-3.758	0.000	-5774.469	-1807.545
num_total_rooms	-2161.5332	7778.794	-0.278	0.781	-1.75e+04	1.31e+04
num_full_bathrooms	1.133e+05	1.67e+04	6.791	0.000	8.05e+04	1.46e+05
num_floors_in_building	5993.2612	1040.144	5.762	0.000	3947.944	8038.578
num_bedrooms	6.583e+04	1.15e+04	5.722	0.000	4.32e+04	8.85e+04
kitchen_type	-1.921e+04	7005.627	-2.742	0.006	-3.3e+04	-5434.655
garage_exists	1.488e+04	1.4e+04	1.064	0.288	-1.26e+04	4.24e+04
full_address_or_zip_code	-25.3290	14.708	-1.722	0.086	-54.251	3.593
fuel_type	2780.5788	5285.483	0.526	0.599	-7612.683	1.32e+04
dogs_allowed	1.367e+04	1.5e+04	0.909	0.364	-1.59e+04	4.33e+04
dining_room_type	1.49e+04	3758.294	3.965	0.000	7511.226	2.23e+04
date_of_sale	-97.8663	76.771	-1.275	0.203	-248.827	53.094
coop_condo	2.256e+05	4.75e+04	4.747	0.000	1.32e+05	3.19e+05
community_district_num	5726.5213	1987.571	2.881	0.004	1818.203	9634.840
cats_allowed	8186.4007	1.39e+04	0.588	0.557	-1.92e+04	3.55e+04
approx_year_built	-33.4209	51.143	-0.653	0.514	-133.988	67.146
Missing_taxes	4.178e+04	4.21e+04	0.992	0.322	-4.11e+04	1.25e+05
Missing_maintenance_cost	8497.6366	2.84e+04	0.299	0.765	-4.74e+04	6.44e+04
Missing_common_charges	3.758e+04	2.88e+04	1.304	0.193	-1.91e+04	9.42e+04
Missing_parking_charges	6778.0234	1.24e+04	0.546	0.585	-1.76e+04	3.12e+04
additional_costs_$	10.6314	5.335	1.993	0.047	0.140	21.123
zip_code	6.6169	3.435	1.926	0.055	-0.138	13.372

Omnibus:	52.812	**Durbin-Watson:**	2.112
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	166.790
Skew:	0.582	**Prob(JB):**	6.05e-37
Kurtosis:	5.959	**Cond. No.**	1.50e+05

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 1.5e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [492…

```
from sklearn.metrics import mean_squared_error, r2_score

# Let's get those scores

# In sample predictions
yhat_in_sampleOLS1 = OLSmodel1.predict(X_train)

# oos predictions
yhat_oosOLS1 = OLSmodel1.predict(X_test)

# IN SAMPLE
print(f"In sample OLS R^2: {round(r2_score(y_true = y_train, y_pred= yhat_in_sampleOLS1),
print(f"In sample OLS RMSE: ${round(mean_squared_error(y_true=y_train, y_pred=yhat_in_samp

# OOS
print(f"OOS R^2: {round(r2_score(y_true = y_test, y_pred= yhat_oosOLS1), 6)}")
print(f"OOS RMSE: ${round(mean_squared_error(y_true=y_test, y_pred=yhat_oosOLS1, squared=F


print((OLSmodel1.params).sort_values(ascending=False))
#print((OLSmodel1.params).idxmax)
```

```
In sample OLS R^2: 0.745128
In sample OLS RMSE: $91867.96
OOS R^2: 0.782819
OOS RMSE: $79565.6
coop_condo                   225599.210952
num_full_bathrooms           113313.881925
num_bedrooms                  65833.595700
num_half_bathrooms            50018.385203
Missing_taxes                 41784.095494
Missing_common_charges        37575.668254
dining_room_type              14901.456664
garage_exists                 14877.300830
dogs_allowed                  13674.503448
Missing_maintenance_cost       8497.636642
cats_allowed                   8186.400710
Missing_parking_charges        6778.023408
num_floors_in_building         5993.261242
community_district_num         5726.521305
fuel_type                      2780.578849
walk_score                      981.468516
sq_footage                       26.850339
additional_costs_$               10.631353
zip_code                          6.616863
full_address_or_zip_code        -25.329048
approx_year_built               -33.420926
date_of_sale                    -97.866288
num_total_rooms               -2161.533248
pct_tax_deductibl             -3791.007389
kitchen_type                 -19210.370598
dtype: float64
```

In [348…

```
# lets try another OLS method
```

```python
from sklearn import linear_model

lm = linear_model.LinearRegression()
OLSmodel2 = lm.fit(X_train,y_train)
```

In [349…

```python
from sklearn.metrics import mean_squared_error, r2_score

# Let's get those scores

# In sample predictions
yhat_in_sampleOLS2 = OLSmodel2.predict(X_train)

# oos predictions
yhat_oosOLS2 = OLSmodel2.predict(X_test)

# IN SAMPLE
print(f"In sample OLS R^2: {round(r2_score(y_true = y_train, y_pred= yhat_in_sampleOLS2),
print(f"In sample OLS RMSE: ${round(mean_squared_error(y_true=y_train, y_pred=yhat_in_samp

# OOS
print(f"OOS R^2: {round(r2_score(y_true = y_test, y_pred= yhat_oosOLS2), 6)}")
print(f"OOS RMSE: ${round(mean_squared_error(y_true=y_test, y_pred=yhat_oosOLS2, squared=F
```

```
In sample OLS R^2: 0.745389
In sample OLS RMSE: $91820.87
OOS R^2: 0.7827
OOS RMSE: $79587.27
```

In [350…

```python
lm.coef_
```

Out[350…

```
array([ 4.86051122e+04,  1.00726564e+03,  2.75787158e+01, -3.78572947e+03,
       -1.70758341e+03,  1.11485130e+05,  5.80580645e+03,  6.52273220e+04,
       -1.94234885e+04,  1.48594628e+04, -2.51976823e+01,  3.02019476e+03,
        1.43245381e+04,  1.50175636e+04, -9.54119867e+01,  2.16749192e+05,
        5.96381868e+03,  8.07901925e+03,  2.25824485e+02,  4.52901474e+04,
        1.01793020e+04,  3.81465194e+04,  7.88065883e+03,  1.21330914e+01,
        6.78311305e+00])
```

In [351…

```python
lm.intercept_
```

Out[351…

```
-522063.31937626924
```

In [581…

```python
# All good but we definitely saw some variance. Lets try random forest
#https://towardsdatascience.com/random-forest-in-python-24d0893d51c0

r2_listRF = []
RMSE_listRF = []
position_list = []
max_depth_range = list(range(3, 20))
max_features_range = list(range(5,23))
for depth in max_depth_range:
    for features in max_features_range:
        rf = RandomForestRegressor(criterion='squared_error',
                                   oob_score= True,
                                   n_estimators = 50,
                                   max_features= features,
                                   max_depth= depth,
                                   random_state = 0
                                  )
        rf.fit(X_train, y_train)
```

```
            r2RF= (rf.score(X_test, y_test))
            RMSERF= round(mean_squared_error(y_true=y_test, y_pred = rf.predict(X_test), squar
            position = str(depth) + ' x ' + str(features)
            r2_listRF.append(r2RF)
            RMSE_listRF.append(RMSERF)
            position_list.append(position)
# print('indices             ',list(range(1,len(max_depth_range))))
# print('max_depth_range:    ', max_depth_range, '\n', 'max_features_range:', max_features
# print('r2: ', max(r2_listRF), r2_listRF.index(max(r2_listRF) ) )
print('max_depth_range x max_features_range')
print('r2: ',
      round(max(r2_listRF),4),
      position_list[ int(r2_listRF.index(max(r2_listRF)))]

     )
print('RMSE:',
      min(RMSE_listRF),
      position_list[ int(RMSE_listRF.index(min(RMSE_listRF)))]

     )
```

```
max_depth_range x max_features_range
r2:  0.8843 7 x 11
RMSE: 57524.32 7 x 11
```

In [ ]:

```
# 500trees
# max_depth_range x max_features_range
# r2:  0.8603 17d x 10f
# RMSE: 63811.64 17d x 10f

# 100t
# max_depth_range x max_features_range
# r2:  0.8613 17d x 14f
# RMSE: 63574.74 17d x 14f

# 50t
# max_depth_range x max_features_range
# r2:  0.8669 17d x 14f
# RMSE: 62296.22 17d x 14f
```

In [580…

```
# so we know that depth of 17 and 14 feature try are ideal.


rf = RandomForestRegressor(criterion='squared_error',
                           n_estimators = 50,
                           oob_score=True,
                           max_features= 14,
                           max_depth= 17,
                           random_state = 0
                          )
rf.fit(X_train, y_train)

# In sample predictions
yhat_in_sample = rf.predict(X_train)

# oos predictions
yhat_oos = rf.predict(X_test)

# IN SAMPLE
print(f"In sample R^2: {round(rf.score(X_train, y_train), 6)}")
print(f"In sample RMSE {round(mean_squared_error(y_true=y_train, y_pred=yhat_in_sample, sq

# OOS
```

```
print(f"OOS R^2: {round(rf.score(X_test, y_test), 6)}")
print(f"OOS RMSE {round(mean_squared_error(y_true=y_test, y_pred=yhat_oos, squared=False),
```

```
In sample R^2: 0.974242
In sample RMSE 29272.587125
OOS R^2: 0.871798
OOS RMSE 60542.335003
```