DS2_Assignment1_NF

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1 DS2 Assignment 1 - Nicolas Fernandez

1.1 Predicting Property Prices from the Xindian District of New Taipei City, Taiwan

The task is to predict property prices using data taken from UC Irvine in order to build a web app where buyers/sellers could rate their homes.

The precise dataset being used is a cleaned version uploaded within Janos Divenyi's github repository.

The task asks to create a 20% subsample from the data and then create a 70/30% split from that subsample for a training and test sets.

1.2 Reading Data and Creating Training and Test Splits

[1]:
```
# Importing required libraries
import pandas as pd
import numpy as np

# Reading the data
#real_estate_data = pd.read_csv("https://raw.githubusercontent.com/divenyijanos/
↪ceu-ml/2023/data/real_estate/real_estate.csv")
real_estate_data = pd.read_csv('real_estate.csv')
display(real_estate_data.head())
print(real_estate_data.info())
```

```
   id  transaction_date  house_age  distance_to_the_nearest_MRT_station  \
0   1          2012.917       32.0                             84.87882
1   2          2012.917       19.5                            306.59470
2   3          2013.583       13.3                            561.98450
3   4          2013.500       13.3                            561.98450
4   5          2012.833        5.0                            390.56840

   number_of_convenience_stores  latitude  longitude  house_price_of_unit_area
0                            10  24.98298  121.54024                      37.9
1                             9  24.98034  121.53951                      42.2
2                             5  24.98746  121.54391                      47.3
3                             5  24.98746  121.54391                      54.8
4                             5  24.97937  121.54245                      43.1
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 414 entries, 0 to 413
Data columns (total 8 columns):
 #   Column                               Non-Null Count  Dtype  
---  ------                               --------------  -----  
 0   id                                   414 non-null    int64  
 1   transaction_date                     414 non-null    float64
 2   house_age                            414 non-null    float64
 3   distance_to_the_nearest_MRT_station  414 non-null    float64
 4   number_of_convenience_stores         414 non-null    int64  
 5   latitude                             414 non-null    float64
 6   longitude                            414 non-null    float64
 7   house_price_of_unit_area             414 non-null    float64
dtypes: float64(6), int64(2)
memory usage: 26.0 KB
None
```

1.2.1 Feature Engineering

From the data there's a superfluous `id` column that will be dropped. The `transaction_date` column contains information about the year and month of the observation however it is in a non-standard format (`pd.to_datetime()` cannot be used) and will not be included for base feature models. The `latitude` and `longitude` columns contains geographical data for each column but that cannot be made sense of without feature engineering.

Feature Engineering will be done prior to sampling and splitting the data to ensure that the splits for testing will always remain the same.

From research, New Taipei City is actually within Taipei City and used to be known as Taipei County but was renamed because it exceeded a population of 2 million which meant that it had to be redifined as it's own city by law. Xindian is a county within the redefined Taipei County. For the purposes of this analysis the city center for Taipei City (not New Taipei) will be considered the city center for which all observations will be compared to. The geographical data will then be converted to km distance from the city center based on the provided coordinates and added to the dataframe as a new column. The latitude for the city center that will be used is 25.03583333 and the longitude is 121.5683333. The information was pulled from here and verified with Google Maps.

The transaction dates within the data follow the format 2013.500, for example, with the number to the left of the decimal being the year and the number to the right of the decimal being the decimal representation of the month (.500 = June = 6/12). The only quirk to this is that .000 = December. This data will be converted and split into two columns, one for the year and another for the month.

These features are likely to be important because from general domain knowledge property prices tend to increase the closer they are to the geographical city center of the respective major city and also property prices from year to year tend to increase as well, sometimes due more to general trends in the market and also sometimes due to general inflation. Enabling this data to be used will likely prove beneficial for model building.

[2]:
```
# Importing required library
from sklearn.model_selection import train_test_split

# Dropping the id column because it's unecessary
real_estate_data.drop(columns=['id'], inplace=True)

# Defining function for creating year and month columns from transaction_date␣
↪as categorical columns
def date_fix(df):
    df['year'] = df['transaction_date'].astype(int)
    df['year'] = df['year'].astype('category')

    df['month'] = np.where(df['transaction_date'] % 1 == 0, 12,
                           round((df['transaction_date'] % 1) * 12).astype(int))
    df['month'] = df['month'].astype('category')

# Defining function for calculating distance from city center in km
def cc_distance(lat, lon):
    # City center coordinates (Taipei)
    cc_lat = 25.03583333
    cc_lon = 121.5683333

    # Convert latitude and longitude from degrees to radians
    lat, lon, cc_lat, cc_lon = np.radians([lat, lon, cc_lat, cc_lon])

    # Calculating difference from city center
    diff_lon = lon - cc_lon
    diff_lat = lat - cc_lat

    # Using the Haversine Formula to calculate distance from radians
    a = np.sin(diff_lat / 2) ** 2 + np.cos(lat) * np.cos(cc_lat) * np.
↪sin(diff_lon / 2) ** 2
    c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1 - a))
    km_distance = 6371 * c  # 6371 = Radius of Earth in km

    return km_distance

# Running above functions on data for feature engineering
date_fix(real_estate_data)
real_estate_data['km_distance_from_cc'] = real_estate_data.apply(lambda row:␣
↪cc_distance(row['latitude'], row['longitude']), axis=1)

# Dropping `transaction_date`, `latitude`, and `longitude` columns from data as␣
↪they are no longer necessary
real_estate_data.drop(columns=['transaction_date', 'latitude', 'longitude'],␣
↪inplace=True)
```

```
# Setting the pseudo random seed for the due date of the assignment
prng = np.random.RandomState(20240322)

# Creating a randomly selected 20% sample of the data, creating target variable␣
↪'outcome'
real_estate_sample = real_estate_data.sample(frac=0.2, random_state=prng)
outcome = real_estate_sample["house_price_of_unit_area"]
all_features_sample = real_estate_sample.
↪drop(columns=['house_price_of_unit_area'])

# Selecting the numeric, non-feature engineered columns as base features for␣
↪model evaluation as a list
base_features = ['house_age', 'distance_to_the_nearest_MRT_station',␣
↪'number_of_convenience_stores']

# Creating training and testing splits from the sample, using a 30% split per␣
↪specifications
X_train, X_test, y_train, y_test = train_test_split(all_features_sample,␣
↪outcome, test_size=0.3, random_state=prng)

print(f"Size of the training set: {X_train.shape}, size of the test set:␣
↪{X_test.shape}")
X_train.head()
```

```
Size of the training set: (58, 6), size of the test set: (25, 6)
```

[2]:

```
     house_age  distance_to_the_nearest_MRT_station  \
331       25.6                           4519.69000
386        0.0                            185.42960
267       34.7                            482.75810
252        5.9                             90.45606
197       34.4                            126.72860

     number_of_convenience_stores  year  month  km_distance_from_cc
331                             0  2013      4            12.172024
386                             0  2012     10             8.089499
267                             5  2012     10             7.465233
252                             9  2012     10             7.296297
197                             8  2013      3             7.949250
```

1.3 Evalaution Function

[3]:

```
# Defining the loss function, using Root Mean Squared Log Error
def calculateRMSLE(prediction, y_obs):
    return round(np.sqrt(np.mean((np.log(np.where(prediction < 0, 0,␣
↪prediction) + 1) - np.log(y_obs + 1))**2)), 4)
```

RMSLE is an appropriate loss function since its a calculation that is less sensitive to outliers by design, appropriate for property price prediction. The risk (from a business perspective) from making a wrong prediction could be either under or over pricing homes in certain areas because RMSLE may treat values as outliers that may have be more important than they seem. Overall, however, property prices are susceptible to large increases based on several factors and can increase in price in orders of magnitude rather than a more gradual scale and for this reason using a loss function on a logarithmic scale is preferred.

1.4 Rigid Models

Initially OLS models without any non-linearity will be created

1.4.1 Benchmark Model

[4]:
```
# Creating a simple benchmark model for comparison, mean value of target␣
↪variable for training set
benchmark = np.mean(y_train)

# Calculating performance of benchmark on test set using loss function
benchmark_pred = ['Benchmark', calculateRMSLE(benchmark, y_train),␣
↪calculateRMSLE(benchmark, y_test)]

# Storing and displaying results in a dataframe
results = pd.DataFrame([benchmark_pred], columns=['Model', 'Train', 'Test'])
results
```

[4]:
```
       Model   Train    Test
0  Benchmark  0.3434  0.3221
```

1.4.2 OLS Single Feature - `distance_to_the_nearest_MRT_station`

[5]:
```
# Importing required library
from sklearn.linear_model import LinearRegression

# Creating OLS model trained on only `distance_to_the_nearest_MRT_station`
ols_single = LinearRegression().
↪fit(X_train[['distance_to_the_nearest_MRT_station']], y_train)

# Creating predictions for model and calculating RMSLE
train_error = calculateRMSLE(ols_single.
↪predict(X_train[['distance_to_the_nearest_MRT_station']]), y_train)
test_error = calculateRMSLE(ols_single.
↪predict(X_test[['distance_to_the_nearest_MRT_station']]), y_test)
ols_single_pred = ['Single Feature OLS', train_error, test_error]

# Adding to results
results.loc[len(results)] = ols_single_pred
results
```

[5]:
```
                 Model   Train    Test
0            Benchmark  0.3434  0.3221
1   Single Feature OLS  0.2250  0.2305
```

This model improves upon using the average of the target variable as a predictive model for our target as the RMSLE's improves using a single feature from the dataset. The model can be significantly improved as it likely does not catch much of the complexity of the data but using `distance_to_the_nearest_MRT_station`, determined to be the most signficant variable to predicting property prices, as an explanatory variable has improved our predictions.

1.4.3 Multivariate OLS

Building an OLS model that uses all the available meaningful base features instead of a single variable.

[6]:
```python
# Creating multivariate OLS model and fitting to training data
ols_multi = LinearRegression().fit(X_train[base_features], y_train)

# Creating predictions
train_error = calculateRMSLE(ols_multi.predict(X_train[base_features]), y_train)
test_error = calculateRMSLE(ols_multi.predict(X_test[base_features]), y_test)
ols_multi_pred = ['Base Multi OLS', train_error, test_error]

# Adding to results
results.loc[len(results)] = ols_multi_pred
results
```

[6]:
```
                 Model   Train    Test
0            Benchmark  0.3434  0.3221
1   Single Feature OLS  0.2250  0.2305
2       Base Multi OLS  0.1993  0.2317
```

The multivariate model using all the available base features improved the predictive power on the training set but performed slightly worse on the test set. Using all the available features does not increase the predictive power over using only a single feature. This implies that the other features in the data (`house_age` and `number_of_convenience_stores`) causes a slight overfit compared to only using `distance_to_the_nearest_MRT_station` and that we may have introduced more noise, bias, and/or variance into our model.

1.5 Flexible Models

Below more flexible models will be created

1.5.1 Polynomial OLS with Interactions

[7]:
```python
# Importing required library
from sklearn.preprocessing import PolynomialFeatures
```

```
# Creating Polynomial object to create polynomial terms and interactions in␣
↪training data
poly_interactions = PolynomialFeatures(degree=2, include_bias=False,␣
↪interaction_only=True)
X_poly = poly_interactions.fit_transform(X_train[base_features])

# Creating polynomial OLS model
ols_poly = LinearRegression().fit(X_poly, y_train)

# Creating predictions
train_error = calculateRMSLE(ols_poly.predict(X_poly), y_train)
test_error = calculateRMSLE(ols_poly.predict(poly_interactions.
↪transform(X_test[base_features])), y_test)
ols_poly_pred = ['Base Poly OLS', train_error, test_error]

# Adding to results
results.loc[len(results)] = ols_poly_pred
results
```

[7]:
```
                Model   Train    Test
0           Benchmark  0.3434  0.3221
1  Single Feature OLS  0.2250  0.2305
2      Base Multi OLS  0.1993  0.2317
3       Base Poly OLS  0.1742  0.1611
```

Adding polynomial and interaction terms using base features only to the model has improved the RMSLE on the test set somewhat significantly. It appears that adding these terms to the OLS model and making it more flexible has captured non-linearity in the data. Also the interaction terms may be reducing bias in the model which would also increase the performance on the test set.

1.5.2 OLS Model with Feature Engineered Data

[8]:
```
# Importing required libraries
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

# Setting up OneHotEncoder for handling categorical variables 'year' and 'month'
one_hot_encoder = OneHotEncoder(sparse_output=False, drop="first")
categorical_vars = ['year', 'month']

# Using ColumnTransformer to create the dummies based on defined OneHotEncoder
column_transformer = ColumnTransformer([("create_dummies", one_hot_encoder,␣
↪categorical_vars)],
                                       remainder="passthrough")
```

```
# Creating OLS model for FE data with Pipeline
pipe_ols_fe = Pipeline([("preprocess", column_transformer),
                       ("ols", LinearRegression())])

# Fitting the data
pipe_ols_fe.fit(X_train, y_train)

# Creating predictions
train_error = calculateRMSLE(pipe_ols_fe.predict(X_train), y_train)
test_error = calculateRMSLE(pipe_ols_fe.predict(X_test), y_test)
ols_fe_pred = ['FE OLS', train_error, test_error]

# Adding to results
results.loc[len(results)] = ols_fe_pred
results
```

[8]:
```
                Model   Train    Test
0           Benchmark  0.3434  0.3221
1  Single Feature OLS  0.2250  0.2305
2      Base Multi OLS  0.1993  0.2317
3       Base Poly OLS  0.1742  0.1611
4              FE OLS  0.1625  0.2512
```

The OLS model with feature engineering performed worse on the test set than the non-feature engieered models. This model is not accounting for any non-linearity in the data and also not adding interaction terms, but in general it appears that the feature engineered variables are causing an overfit on the test set given the higher RMSLE scores.

1.5.3 Polynomial OLS with Feature Engineered Data

[9]:
```
# Importing required library
from sklearn.feature_selection import VarianceThreshold # To account for␣
 ↪categorical values with zero variance

# Initiating VarianceThreshold to drop categorial variables with no variance
drop_no_variance = VarianceThreshold()

# Creating model with Pipeline
pipe_ols_poly_fe = Pipeline([
    ('preprocess', column_transformer),
    ('interactions', poly_interactions),
    ('drop_zero_variance', drop_no_variance),
    ('ols', LinearRegression())
])

# Fitting the data
pipe_ols_poly_fe.fit(X_train, y_train)
```

```
# Creating predictions
train_error = calculateRMSLE(pipe_ols_poly_fe.predict(X_train), y_train)
test_error = calculateRMSLE(pipe_ols_poly_fe.predict(X_test), y_test)
ols_poly_fe_pred = ['FE Poly OLS', train_error, test_error]

# Adding to results
results.loc[len(results)] = ols_poly_fe_pred
results
```

[9]:

```
                Model   Train    Test
0           Benchmark  0.3434  0.3221
1  Single Feature OLS  0.2250  0.2305
2      Base Multi OLS  0.1993  0.2317
3       Base Poly OLS  0.1742  0.1611
4              FE OLS  0.1625  0.2512
5         FE Poly OLS  0.0363  1.1234
```

The polynomial and interaction terms included in the OLS model using the feature engineered data performed better on the training set but performed terribly on the test set. There is a clear overfit when adding interactions and polynomial terms on the feature engineered data to account for non-linearity, much moreso than without with additional terms. This implies that while there is some non-linearity in the data, it clearly relates to the features from the base features rather than the feature engineered data.

1.5.4 LASSO

[10]:

```
# Importing required library
from sklearn.linear_model import LassoCV

# Setting LASSO to a pipeline
pipe_lasso = Pipeline([
    ('preprocess', column_transformer),
    ('interactions', poly_interactions),
    ('drop_zero_variance', drop_no_variance),
    ('lasso', LassoCV())
])

# Fitting the model to the data
pipe_lasso.fit(X_train, y_train)

# Creating predictions
train_error = calculateRMSLE(pipe_lasso.predict(X_train), y_train)
test_error = calculateRMSLE(pipe_lasso.predict(X_test), y_test)
lasso_pred = ['FE LASSO', train_error, test_error]

# Adding to results
results.loc[len(results)] = lasso_pred
```

```
results
```

[10]:

```
                 Model   Train    Test
0            Benchmark  0.3434  0.3221
1  Single Feature OLS  0.2250  0.2305
2       Base Multi OLS  0.1993  0.2317
3        Base Poly OLS  0.1742  0.1611
4               FE OLS  0.1625  0.2512
5          FE Poly OLS  0.0363  1.1234
6             FE LASSO  0.1718  0.1873
```

The LASSO model using the feature engineered data and the polynomial and interaction terms from the FE Poly OLS model significantly improved the results from the FE Poly OLS' performance. The lambda tuning parameter sorted through the coefficients and effectively removed the predictors that it deemed to be unnecessary by reducing their coefficients to (effectively) 0. As a result, as already mentioned, the RMSLE value on the test set is improved comparatively. It's worth noting however that it still does not outperform the Base Poly OLS model and it's still likely that the feature engineered data is causing an overfit in some capacity when not handled correctly.

1.5.5 Random Forest

[11]:

```python
# Importing required library
from sklearn.ensemble import RandomForestRegressor

# Creating a Random Forest model with Pipeline
pipe_rf = Pipeline([('preprocess', column_transformer),
    ("rf", RandomForestRegressor(random_state=prng))])

# Fitting the model to the feature engineered data
pipe_rf.fit(X_train, y_train)

# Creating predictions
train_error = calculateRMSLE(pipe_rf.predict(X_train), y_train)
test_error = calculateRMSLE(pipe_rf.predict(X_test), y_test)
rf_pred = ['RF', train_error, test_error]

# Adding to results
results.loc[len(results)] = rf_pred
results
```

[11]:

```
                 Model   Train    Test
0            Benchmark  0.3434  0.3221
1  Single Feature OLS  0.2250  0.2305
2       Base Multi OLS  0.1993  0.2317
3        Base Poly OLS  0.1742  0.1611
4               FE OLS  0.1625  0.2512
5          FE Poly OLS  0.0363  1.1234
6             FE LASSO  0.1718  0.1873
```

```
7                   RF  0.0760  0.1882
```

The Random Forest model does a better job of creating a predictive model on the feature engineered data than the other models trained on it. This can be attributed to the nature of a Random Forest model using bagging and regularization to become more robust to noise within the data since it averages predictions among many trees, in this case 100 (the default value). The feature importance decided by the algorithm is also doing a better job of capturing the relationships in the data to the target variable compared to other FE models. The RF however is not predicting as well as the Base Poly OLS or FE LASSO models which implies that the RF is not capturing some of the non-linearity that the the other two seem to be capturing and also some of the feature engineered variables add additional complexity.

Below a table is shown with the feature importance of the Random Forest model created from the feature engineered data.

```
[12]: # Creating dataframe for readability for displaying variable importance
rf_var_imp = pd.DataFrame(
    pipe_rf['rf'].feature_importances_,
    pipe_rf[:-1].get_feature_names_out())\
    .reset_index()\
    .rename({"index": "variable", 0: "imp"}, axis=1)\
    .sort_values(by=["imp"], ascending=False)\
    .reset_index(drop = True)

# Creating cumulative sum column
rf_var_imp['cumulative_imp'] = rf_var_imp['imp'].cumsum()

# Displaying dataframe with formatting
rf_var_imp.style.format({'imp': lambda x: f'{x:,.1%}', 'cumulative_imp': lambda␣
 ↪x: f'{x:,.1%}'})
```

```
[12]: <pandas.io.formats.style.Styler at 0x1d591da3bd0>
```

From these results we can see that `distance_to_the_nearest_MRT_station` is in fact the most important feature in the data, as theorized earlier. The next three significant features (although significantly less so than MRT station distance) are `km_distance_from_cc`, `house_age`, and `number_of_convenience_stores`. This makes sense as people in general value properties more that are closer to the city center and the older the house usually the less expensive it tends to be. It also appears that a house being closer to more convenience stores also influences the price of properties in Taipei which implies that people in that cit value having better access to convenience stores.

Conversely, the date of the purchase appears to have little to do with making a good prediction. This could be that since there isn't much variance in the amount of time within the data that the transaction date has little variance.

Below we take a look at a single tree to illustrate:

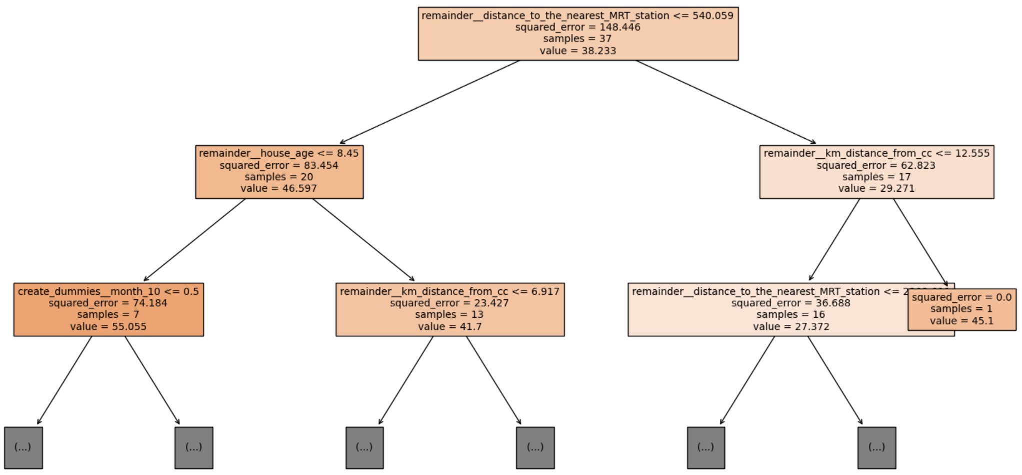
[13]:
```python
# Importing required libraries
from sklearn import tree
import matplotlib.pyplot as plt

# Look at single trees
chosen_tree = pipe_rf["rf"].estimators_[0]

plt.figure(figsize=(20,10))

# Plot tree with adjusted settings
tree.plot_tree(chosen_tree,
               feature_names=pipe_rf[:-1].get_feature_names_out(),
               max_depth=2, # Plotting only a depth of 2 splits
               fontsize=10,  # Adjust font size of text in nodes
               filled=True)  # Fill nodes with colors

plt.show()
```



1.5.6 XGBoost Model

[14]:
```python
# Importing required library
import xgboost as xgb

# Creating XGB model, fitting to feature engineered training data
xgb_fe = xgb.XGBRegressor(enable_categorical=True).fit(X_train, y_train)

# Creating predictions
train_error = calculateRMSLE(xgb_fe.predict(X_train), y_train)
```

```
test_error = calculateRMSLE(xgb_fe.predict(X_test), y_test)
xgb_pred = ['XGB', train_error, test_error]

# Adding to results
results.loc[len(results)] = xgb_pred
results
```

[14]:
```
                Model   Train    Test
0           Benchmark  0.3434  0.3221
1  Single Feature OLS  0.2250  0.2305
2      Base Multi OLS  0.1993  0.2317
3       Base Poly OLS  0.1742  0.1611
4              FE OLS  0.1625  0.2512
5         FE Poly OLS  0.0363  1.1234
6            FE LASSO  0.1718  0.1873
7                  RF  0.0760  0.1882
8                 XGB  0.0000  0.2012
```

[15]:
```
# Viewing features from XGBoost model to see how it split the data, which␣
 ↪categories it used, etc.
xgb_fe.get_booster().trees_to_dataframe().head()
```

[15]:
```
   Tree  Node   ID                             Feature       Split  Yes  \
0     0     0  0-0  distance_to_the_nearest_MRT_station  665.063599  0-1
1     0     1  0-1                            house_age    7.100000  0-3
2     0     2  0-2                      km_distance_from_cc   12.772239  0-5
3     0     3  0-3                                month         NaN  0-8
4     0     4  0-4  distance_to_the_nearest_MRT_station  329.974701  0-9

    No Missing         Gain  Cover                Category
0  0-2     0-2  4822.441410   58.0                    None
1  0-4     0-4   838.944946   37.0                    None
2  0-6     0-6   303.041748   21.0                    None
3  0-7     0-7   180.757812   12.0  [0, 1, 2, 3, 5, 8, 11]
4  0-10   0-10   366.385590   25.0                    None
```

From the results of the XGB we can see that the model performs perfectly on the training set but performs worse on the test set than the RF model. The XGBoost model is still doing a better job of predicting on the test set than most models but is also worse than the Base Poly OLS model. The interpretation of this is that the XGBoost model is capturing some but not all of the non-linearity in the data and is therefore performing worse than the two models mentioned on the test set. It could also be that some of the features used may be adding more noise/bias/variance to the data rather than helping and XGBoost may not be doing as good of a job of accounting for this as the Random Forest model.

1.6 Initial Analysis

From the models constructed so far, it would appear that the Base Poly OLS model is our best choice for going forward and creating a web app designed to aid buyers/sellers to rate their homes. As it stands, however, I would like to test adding more data to the training set to see how the models fare and if they improve or worsen. Along with this, a potential more careful, theoretical approach of choosing polynomial and interaction terms could yield a better OLS model than the Base Poly OLS that is currently constructed. Some more options for potential improvement are cross-validation, hyperparameter tuning (e.g. adding a grid search to the RF), or using another model type altogether.

1.7 Rerunning Models on Full Dataset, Excluding Test Sets

Below several of the models created (both rigid and flexible) will be tested on the overall dataset. We will be careful to give the models trained on the full dataset the same comparison base and not include that test data in the training set.

[16]:
```
# Creating the training set for the full data excluding the test set
real_estate_full = real_estate_data.loc[~real_estate_data.index.isin(X_test.
  ↪index)]
y_train_full = real_estate_full['house_price_of_unit_area']
X_train_full = real_estate_full.drop(columns=["house_price_of_unit_area"])

# Checking sample size results
print(f'Size of original dataset: {real_estate_data.shape[0]}')
print(f'Shape of full training set: {X_train_full.shape}, shape of test set:␣
  ↪{X_test.shape}')
```

```
Size of original dataset: 414
Shape of full training set: (389, 6), shape of test set: (25, 6)
```

[17]:
```
# Running the single OLS on the full training set
ols_single_full = LinearRegression().
  ↪fit(X_train_full[['distance_to_the_nearest_MRT_station']], y_train_full)

# Creating predictions for model and calculating RMSLE
train_error = calculateRMSLE(ols_single_full.
  ↪predict(X_train_full[['distance_to_the_nearest_MRT_station']]), y_train_full)
test_error = calculateRMSLE(ols_single_full.
  ↪predict(X_test[['distance_to_the_nearest_MRT_station']]), y_test)
ols_single_pred_full = ['Single Feature OLS Full', train_error, test_error]

# Adding to results
results.loc[len(results)] = ols_single_pred_full

# Running the base features Polynomial OLS on the full training set
X_poly_full = poly_interactions.fit_transform(X_train_full[base_features])
```

```
# Creating polynomial OLS model
ols_poly_full = LinearRegression().fit(X_poly_full, y_train_full)

# Creating predictions
train_error = calculateRMSLE(ols_poly_full.predict(X_poly_full), y_train_full)
test_error = calculateRMSLE(ols_poly_full.predict(poly_interactions.
 ↪transform(X_test[base_features])), y_test)
ols_poly_pred_full = ['Base Poly OLS Full', train_error, test_error]

# Adding to results
results.loc[len(results)] = ols_poly_pred_full

# Running the Random Forest model on the full training set
pipe_rf_full = Pipeline([('preprocess', column_transformer),
    ("rf", RandomForestRegressor(random_state=prng))])

# Fitting the model to the feature engineered data
pipe_rf_full.fit(X_train_full, y_train_full)

# Creating predictions
train_error = calculateRMSLE(pipe_rf_full.predict(X_train_full), y_train_full)
test_error = calculateRMSLE(pipe_rf_full.predict(X_test), y_test)
rf_pred_full = ['RF Full', train_error, test_error]

# Adding to results
results.loc[len(results)] = rf_pred_full
results
```

[17]:

```
                      Model   Train    Test
0                 Benchmark  0.3434  0.3221
1        Single Feature OLS  0.2250  0.2305
2            Base Multi OLS  0.1993  0.2317
3             Base Poly OLS  0.1742  0.1611
4                    FE OLS  0.1625  0.2512
5               FE Poly OLS  0.0363  1.1234
6                  FE LASSO  0.1718  0.1873
7                        RF  0.0760  0.1882
8                       XGB  0.0000  0.2012
9   Single Feature OLS Full  0.3477  0.2211
10       Base Poly OLS Full  0.2531  0.1677
11                  RF Full  0.0770  0.1265
```

The models chosen to be trained on the full set were the least flexible single feature OLS, the flexible polynomial OLS using base features, and the Random Forest. From the results we can see that the single feature OLS and RF models improved on the test set but the Base Poly OLS model performed worse when trained on the full training set, though only slightly. Both of these models still perform better than the single feature OLS and between them the RF model improved significantly. This can be attributed to adding more data that allowed the RF model to better generalize the trends in the data through regularization and bagging to produce a better prediction on the test set.

1.8 Final Analysis

More data tends to improve and regularize any potentially extraneous data points in smaller sample sizes it would appear that this held true in this case as well. Having seen how the RF model performed significantly better it gives me more confidence that I should launch the web app using the RF model as theoretically with even more data to train the model on the predictive power should further increase (though the gains of said increase may reduce). Additionally, further tweaking of RF model could yield even better results.