Predictive Housing Price Model for Washington State

Group 3
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1. Data Importing

Dataset description:

- 21 columns
- 21613 rows

Price Details:

```
count      21613.00
mean      540088.14
std       367127.20
min        75000.00
25%       321950.00
50%       450000.00
75%       645000.00
max      7700000.00
Name: price, dtype: object
```

Data Types:

```
id                 int64
date              object
price            float64
bedrooms         float64
bathrooms        float64
sqft_living      float64
sqft_lot         float64
floors           float64
waterfront         int64
view               int64
condition          int64
grade              int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

Null Data Counts:

```
id                  0
date                0
price               0
bedrooms         1134
bathrooms        1068
sqft_living      1110
sqft_lot         1044
floors              0
waterfront          0
view                0
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated        0
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

1. Cleaning and Wrangling
Standardizing the date format

```python
### working copy ###
date_time_cleaned = df_orig.copy()

### Fixing date format###
date_time_cleaned['date'] = pd.to_datetime(df_orig['date'], format='%Y%m%dT%H%M%S', errors='coerce')

### Save the updated DataFrame to a new CSV file ###
date_time_cleaned.to_csv(os.path.join(log_prefix, "house_file_v2.csv"), index=False)

### sample of the cleaned data ###
display(HTML("<u>Sample of Cleaned Data:</u>"))
print(date_time_cleaned.head())
```

```
           id       date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520 2014-10-13 221900.00      3.00       1.00      1180.00
1  6414100192 2014-12-09 538000.00      3.00       2.25      2570.00
2  5631500400 2015-02-25 180000.00      2.00       1.00       770.00
3  2487200875 2014-12-09 604000.00      4.00       3.00      1960.00
4  1954400510 2015-02-18 510000.00      3.00       2.00      1680.00
```

1. Cleaning and Wrangling
Removing Bedrooms and Bathrooms with a value of 0

```
### Filtering and saving the data ###
date_time_cleaned = date_time_cleaned[(date_time_cleaned['bedrooms'] != 0) & (date_time_cleaned['bathrooms'] != 0)]

date_time_cleaned.to_csv(os.path.join(log_prefix, 'filtered_date_time_cleaned.csv'), index=False)
```

```
### Checking progress ###
date_time_cleaned.head()
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built
0	7129300520	2014-10-13	221900.00	3.00	1.00	1180.00	5650.00	1.00	0	0	...	7	1180	0	1955
1	6414100192	2014-12-09	538000.00	3.00	2.25	2570.00	7242.00	2.00	0	0	...	7	2170	400	1951
2	5631500400	2015-02-25	180000.00	2.00	1.00	770.00	10000.00	1.00	0	0	...	6	770	0	1933

1. Cleaning and Wrangling
Removing the bottom and top 1% of data

```
### Removing the top and bottom 1% of data in the price column ###
working_data = pd.read_csv(os.path.join(log_prefix, 'filtered_date_time_cleaned.csv'))

### Establishing lower and upper bound using the bottom and upper 1% ##
upper_bound = working_data['price'].quantile(0.99)
lower_bound = working_data['price'].quantile(0.01)

display(HTML("<u>Defining Bounds to Remove Outliers:</u>"))
print("Upper bound =",round(upper_bound,2))
print("\nLower bound =",round(lower_bound,2))

### Only extracting the data in between the values above the lower bound and values lower than the upper bound ###
working_data2 = working_data[(working_data['price'] >= lower_bound) & (working_data['price'] <= upper_bound)]
```

Defining Bounds to Remove Outliers:

```
Upper bound = 1965006.6

Lower bound = 154000.0
```

1. Cleaning and Wrangling Imputing Part One

```
### Replace NaN values in 'bathrooms' with values from 'avg_bathrooms' ###
df_clean['bathrooms'] = df_clean['bathrooms'].fillna(df_clean['avg_bathrooms'])
```



```
### Replace NaN values in 'bathrooms' with values from 'avg_bathrooms' ###
df_clean['bathrooms'] = df_clean['bathrooms'].fillna(df_clean['avg_bathrooms'])
```



```
### Replace NaN values in 'SQFT' with values from 'avg_sqft_living_bin' ###
df_clean['sqft_living'] = df_clean['sqft_living'].fillna(df_clean['avg_sqft_living'])
```

```
### Replace NaN values in 'sqft_lot' with values from 'avg_sqft_lot' ###
df_clean['sqft_lot'] = df_clean['sqft_lot'].fillna(df_clean['avg_sqft_lot'])
```

1. Cleaning and Wrangling
Imputing Part Two

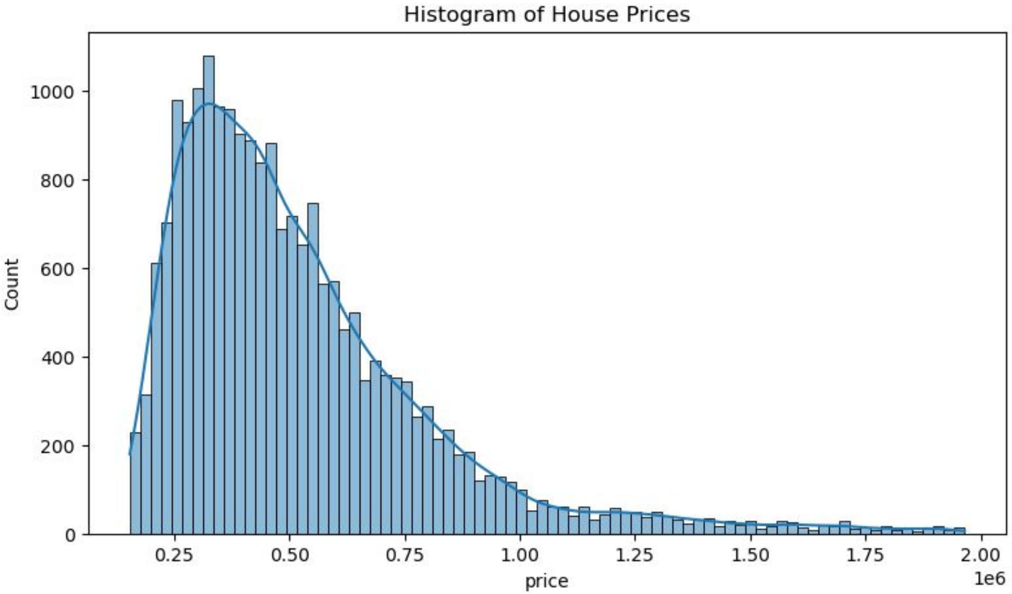
```python
### Check all Null values have been handled ###
null_data = df_clean.isnull().sum()
display(HTML("<u>Null Data Counts:</u>"))
print(null_data)
```

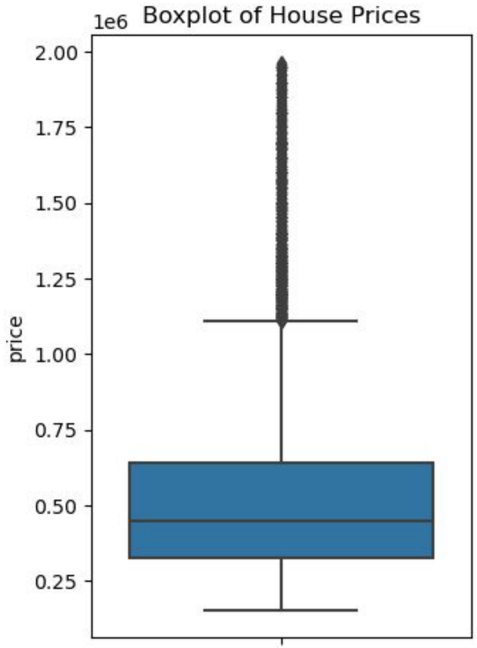
Null Data Counts:

```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront          0
view                0
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated        0
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
price_group         0
avg_bedrooms        0
avg_bathrooms       0
avg_sqft_living     0
avg_sqft_lot        0
dtype: int64
```

2. Data Analysis and Visualization

Our goal is to identify key housing features that significantly impact prices in Washington State.





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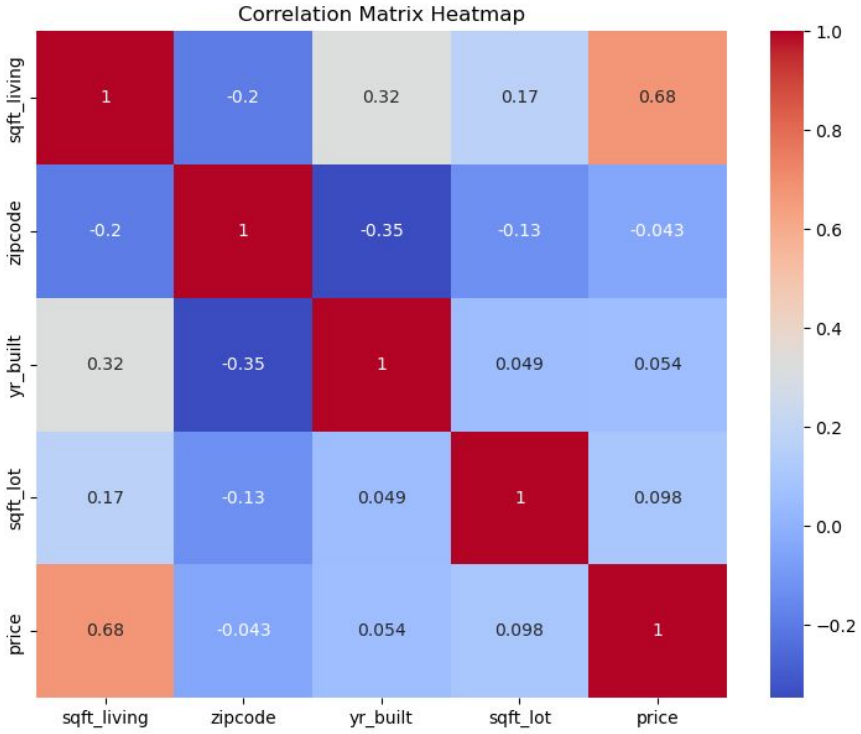

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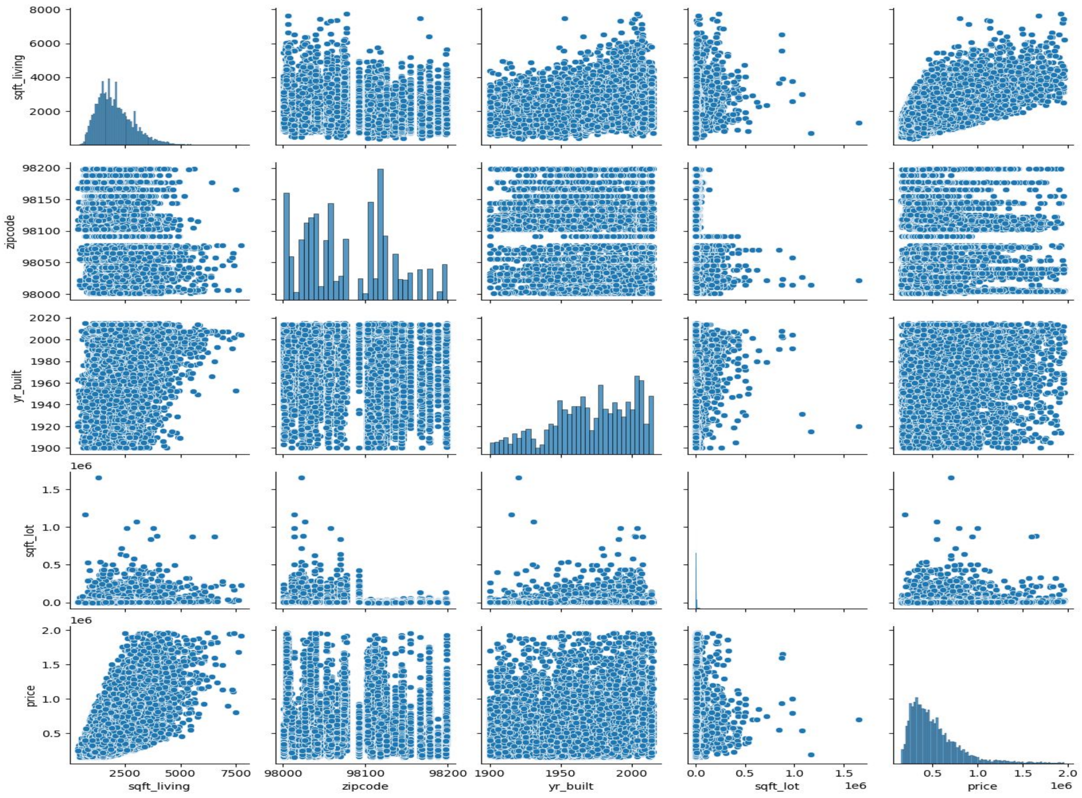


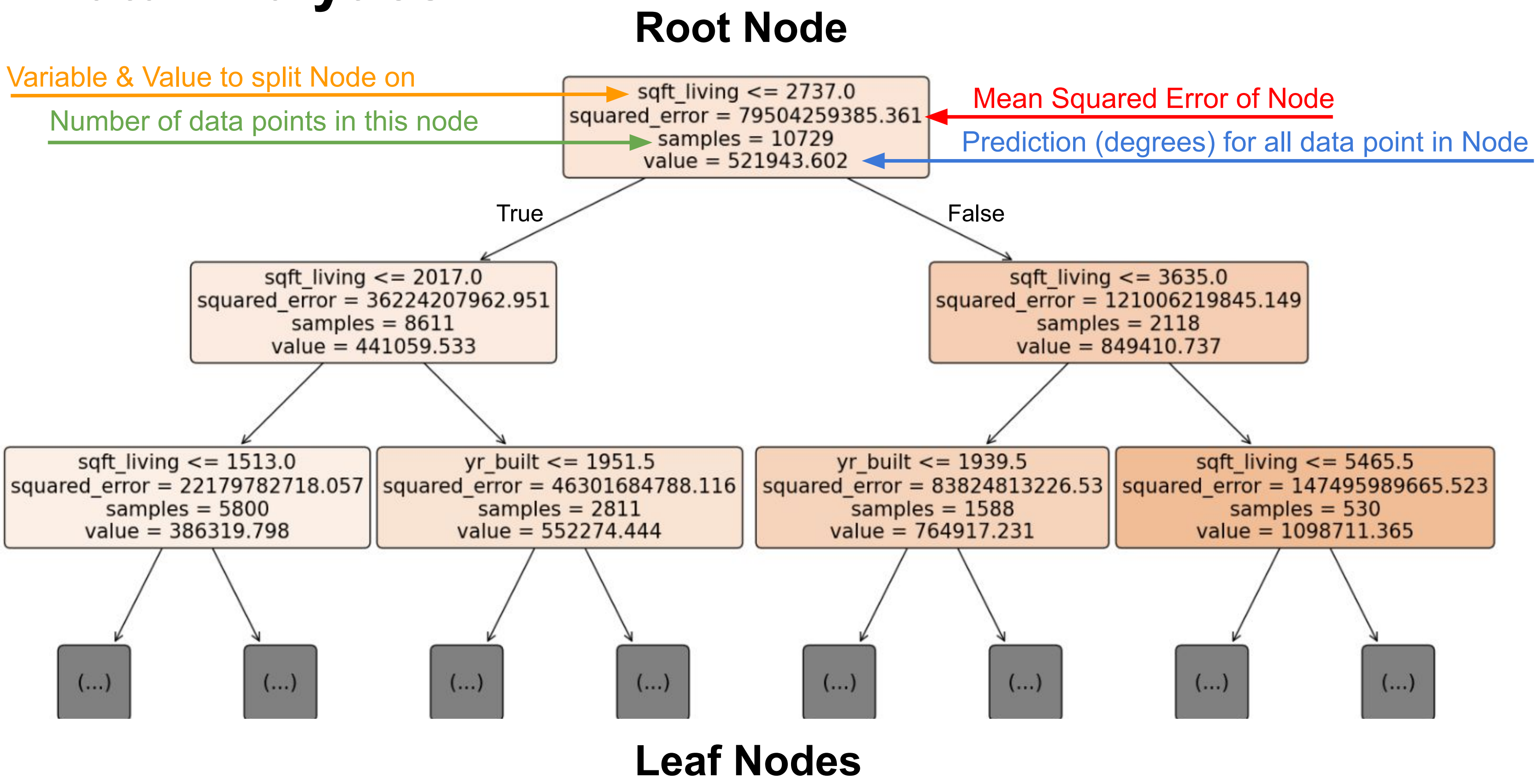
3. Data Analytics

- Final Algorithm Type: RandomForestRegressor from sklearn.ensemble

- Dependent Variable: price

- Independent Variables: sqft_living, zipcode, yr_built, sqft_lot

3. Data Analytics



3. Data Analytics

- Mean Absolute Error: $85,425.55
- Root Mean Squared Error (RMSE): $135,257.50
- Feature Importances:
  - 'sqft_living' 54.71%
  - 'zipcode' 24.54%
  - 'yr_built' 10.64%
  - 'sqft_lot' 10.11%
- R-squared (R2) Value: 0.7797
- Explained Variance Score: 0.7798

References

Bruce, P., Bruce, A., & Gedeck, P. (2020). Practical Statistics for Data Scientists (Second Edition ed.). O'Reilly Media, Inc.

Koehrsen, W. (2017). Random Forest in Python. Retrieved December 6, 2023 from https://towardsdatascience.com/random-forest-in-python-24d0893d51c0