Group 8 DSF PT6-Phase 2 Project

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1. Business Understanding

Overview : Housing sales in a northwestern county between the year `2014` and `2015`

Problem Statement : Finsco Limited, a real estate group investing in USA real estate has opened a consultancy arm. for their first project, they would like to understand how home renovations might increase the estimated value of homes, and by what amount.

The goal is to get insights to provide advice to homeowners, real estate investors and clients who do house-flipping

They have tasked the Hepta Group to conduct multiple linear regression modelling to analyze house sales in a Northwestern County they have been provided with.

Stakeholders : -Homeowners : *These are the people who want to increase the value of their homes and want to know the kind of renovations to do*. -Real estate agency : *The company that is conducting this model to help homeowners know what renovations to do to increase the value of their homes.*

Understanding : We have several parameters/variables in our data that when adjusted/improved, may positively affect the value of homes in this county. `We need to find and observe which parameter greatly influences the value of the homes and perhaps, what parameters might give the best value of the homes.` *Our dependent variable is the value of homes; what we are trying to predict. Our independent variables are the home renovations, and there are several, we will use this to help us find the best possible values of the homes.*

The above two concepts (`dependent` and `independent`) lead us to the concept we are going to use which is the multiple linear regression. `Multiple linear regression` is used when we want to predict a dependent variable (value of homes) using two or more independent variables (the several parameters present in our data).

Key items to check before we build the model;

- Have a basic understanding of the data
- Which parameters greatly/least influence the value of homes for the homeowners?

- Which parameters are irrelevant to our model (*through observation after understanding our problem*)

Implications

- With the insights provided, Finsco Limited and its clients can strategically invest in real estate by choosing renovations that significantly increase home values.
- Homeowners working with Finsco's consultancy learn which renovations offer the best returns, helping them wisely enhance their properties.
- House flippers working with FINSCO consultancy can tailor their strategies to target high-ROI renovations.
- The consultancy's success not only benefits Finsco and its clients but also stimulates economic growth through increased renovation and property transaction activities.

2. Data understanding

Data Source & Size The data we are going to use is called `kc_house_data.csv` from the `King County House Sales` and `it has 21597 records`.

Variables description Below is the description of our variables;

- `id` - Unique identifier for a house
- `date` - Date house was sold
- `price` - Sale price (prediction target)
- `bedrooms` - Number of bedrooms
- `bathrooms` - Number of bathrooms
- `sqft_living` - Square footage of living space in the home
- `sqft_lot` - Square footage of the lot
- `floors` - Number of floors (levels) in house
- `waterfront` - Whether the house is on a waterfront
  - Includes Duwamish, Elliott Bay, Puget Sound, Lake Union, Ship Canal, Lake Washington, Lake Sammamish, other lake, and river/slough waterfronts
- `view` - Quality of view from house
  - Includes views of Mt. Rainier, Olympics, Cascades, Territorial, Seattle Skyline, Puget Sound, Lake Washington, Lake Sammamish, small lake / river / creek, and other
- `condition` - How good the overall condition of the house is. Related to maintenance of house.
  - See the King County Assessor Website for further explanation of each condition code
- `grade` - Overall grade of the house. Related to the construction and design of the house.
  - See the King County Assessor Website for further explanation of each building grade code
- `sqft_above` - Square footage of house apart from basement
- `sqft_basement` - Square footage of the basement

- `yr_built` - Year when house was built
- `yr_renovated` - Year when house was renovated
- `zipcode` - ZIP Code used by the United States Postal Service
- `lat` - Latitude coordinate
- `long` - Longitude coordinate
- `sqft_living15` - The square footage of interior housing living space for the nearest 15 neighbors
- `sqft_lot15` - The square footage of the land lots of .the nearest 15 neighbors

The `target variable from the above dataset is the price`, where as the `others form the predictor/independent variables`. From these datasets we can already start seeing some predictor variables that may have an impact on the target variable (*ofcourse this is by observation*), for example how will changing the number of bedrooms affect the house prices for the home owners.

Limitations : From a quick observation of the data, we have noticed the `presence of missing values` in some of the predictor variables like waterfront and view. We will first have to check if the variables having missing values significantly affect the value of homes or not. Also we have noticed that `there are non-numerical variables`. Linear regression only uses numerical columns. We will have to adjust this columns to numbers if at all we are going to use them in building our model (NB: it is a requirement that we use atleast one non-numeric column)

```
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Load the dataset
data = pd.read_csv('kc_house_data.csv')

# Displaying the first few rows of the data frame
data.head()
```

```
           id        date     price  bedrooms  bathrooms  sqft_living
\
0  7129300520  10/13/2014  221900.0         3       1.00         1180

1  6414100192   12/9/2014  538000.0         3       2.25         2570

2  5631500400   2/25/2015  180000.0         2       1.00          770

3  2487200875   12/9/2014  604000.0         4       3.00         1960

4  1954400510   2/18/2015  510000.0         3       2.00         1680


   sqft_lot  floors waterfront  view  ...          grade sqft_above  \
0      5650     1.0        NaN  NONE  ...      7 Average       1180
```

```
1      7242     2.0         NO  NONE  ...      7 Average       2170
2     10000     1.0         NO  NONE  ...  6 Low Average        770
3      5000     1.0         NO  NONE  ...      7 Average       1050
4      8080     1.0         NO  NONE  ...         8 Good       1680

   sqft_basement yr_built  yr_renovated  zipcode      lat     long  \
0            0.0     1955           0.0    98178  47.5112 -122.257
1          400.0     1951        1991.0    98125  47.7210 -122.319
2            0.0     1933           NaN    98028  47.7379 -122.233
3          910.0     1965           0.0    98136  47.5208 -122.393
4            0.0     1987           0.0    98074  47.6168 -122.045

   sqft_living15  sqft_lot15
0           1340        5650
1           1690        7639
2           2720        8062
3           1360        5000
4           1800        7503

[5 rows x 21 columns]
```

```
# Getting basic information about the datatype
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  object
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object
 9   view           21534 non-null  object
 10  condition      21597 non-null  object
 11  grade          21597 non-null  object
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
 14  yr_built       21597 non-null  int64
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
```

```
dtypes: float64(6), int64(9), object(6)
memory usage: 3.5+ MB
None

# Descriptive statistics of our dataset
data.describe()

                 id         price      bedrooms     bathrooms
sqft_living  \
count  2.159700e+04  2.159700e+04  21597.000000  21597.000000
21597.000000
mean   4.580474e+09  5.402966e+05      3.373200      2.115826
2080.321850
std    2.876736e+09  3.673681e+05      0.926299      0.768984
918.106125
min    1.000102e+06  7.800000e+04      1.000000      0.500000
370.000000
25%    2.123049e+09  3.220000e+05      3.000000      1.750000
1430.000000
50%    3.904930e+09  4.500000e+05      3.000000      2.250000
1910.000000
75%    7.308900e+09  6.450000e+05      4.000000      2.500000
2550.000000
max    9.900000e+09  7.700000e+06     33.000000      8.000000
13540.000000

           sqft_lot        floors    sqft_above      yr_built
yr_renovated  \
count  2.159700e+04  21597.000000  21597.000000  21597.000000
17755.000000
mean   1.509941e+04      1.494096   1788.596842   1970.999676
83.636778
std    4.141264e+04      0.539683    827.759761     29.375234
399.946414
min    5.200000e+02      1.000000    370.000000   1900.000000
0.000000
25%    5.040000e+03      1.000000   1190.000000   1951.000000
0.000000
50%    7.618000e+03      1.500000   1560.000000   1975.000000
0.000000
75%    1.068500e+04      2.000000   2210.000000   1997.000000
0.000000
max    1.651359e+06      3.500000   9410.000000   2015.000000
2015.000000

            zipcode           lat          long  sqft_living15
sqft_lot15
count  21597.000000  21597.000000  21597.000000   21597.000000
21597.000000
mean   98077.951845     47.560093   -122.213982    1986.620318
```

```
12758.283512
std       53.513072      0.138552      0.140724     685.230472
27274.441950
min    98001.000000     47.155900   -122.519000     399.000000
651.000000
25%    98033.000000     47.471100   -122.328000    1490.000000
5100.000000
50%    98065.000000     47.571800   -122.231000    1840.000000
7620.000000
75%    98118.000000     47.678000   -122.125000    2360.000000
10083.000000
max    98199.000000     47.777600   -121.315000    6210.000000
871200.000000

# Check for missing values
print(data.isnull().sum())

id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64

# Sampling 5 random rows of our dataset
data.sample(5)

               id       date     price  bedrooms  bathrooms
sqft_living  \
21437  2254502071  5/23/2014  375000.0         2       2.50
750
8905    822059038  7/31/2014  290000.0         6       4.50
2810
10235  3876200060   5/2/2014  382500.0         4       1.75
```

```
1560
13619  8078390150  6/26/2014  675750.0         4       2.50
2770
955     510002065  3/23/2015  700000.0         4       1.00
1980

       sqft_lot  floors waterfront  view  ...      grade sqft_above  \
21437      1430     2.0         NO  NONE  ...     8 Good        750
8905      11214     1.0        NaN  NONE  ...     8 Good       2010
10235      8700     1.0         NO  NONE  ...  7 Average       1560
13619     10274     2.0         NO  NONE  ...   9 Better       2770
955        4560     1.5         NO  NONE  ...  7 Average       1980

       sqft_basement yr_built  yr_renovated  zipcode      lat     long
\
21437            0.0     2006           0.0    98122  47.6093 -122.310

8905               ?     1958           NaN    98031  47.4045 -122.197

10235            0.0     1967           NaN    98034  47.7274 -122.181

13619            0.0     1989           0.0    98029  47.5748 -122.018

955              0.0     1920           0.0    98103  47.6606 -122.331


       sqft_living15  sqft_lot15
21437           1320        2790
8905            1940        8349
10235           2080        8000
13619           2270        7210
955             1810        3245

[5 rows x 21 columns]
```

```
# Getting data types of our dataset
data.dtypes
```

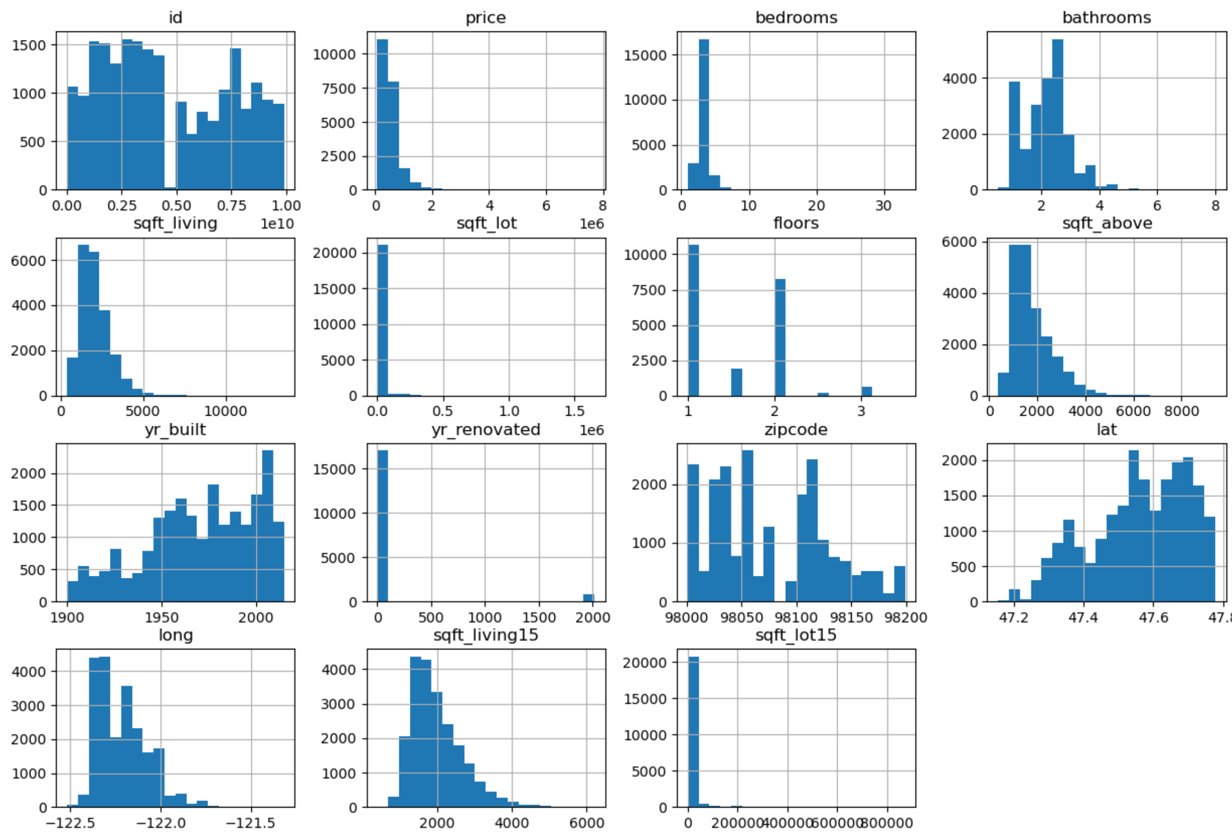
```
id                  int64
date               object
price             float64
bedrooms            int64
bathrooms         float64
sqft_living         int64
sqft_lot            int64
floors            float64
waterfront         object
view               object
condition          object
grade              object
sqft_above          int64
```

```
sqft_basement     object
yr_built           int64
yr_renovated     float64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

```
# Explore unique values and frequency counts for categorical variables
categorical_cols = ['waterfront', 'view', 'condition', 'grade',
'zipcode']
for col in categorical_cols:
    print(data[col].value_counts())
```

```
waterfront
NO     19075
YES      146
Name: count, dtype: int64
view
NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: count, dtype: int64
condition
Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: count, dtype: int64
grade
7 Average        8974
8 Good           6065
9 Better         2615
6 Low Average    2038
10 Very Good     1134
11 Excellent      399
5 Fair            242
12 Luxury          89
4 Low              27
13 Mansion         13
3 Poor              1
Name: count, dtype: int64
zipcode
98103    602
98038    589
```

```
98115    583
98052    574
98117    553
        ...
98102    104
98010    100
98024     80
98148     57
98039     50
Name: count, Length: 70, dtype: int64

# Visualising how data using histogram
# Histograms for only numerical variables

data.hist(bins=20, figsize=(15,10))
plt.show()
```



A. Data Cleaning

```
data['sqft_basement'].value_counts()
## 1st we can see there are a lot of zeros
## the missing values are 454(indicated as ?)
```

```
sqft_basement
0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
1920.0        1
3480.0        1
2730.0        1
2720.0        1
248.0         1
Name: count, Length: 304, dtype: int64
```

```
## lets strip the ? to be an empty space then we impute the blanks
data['sqft_basement'] =
data['sqft_basement'].replace('?',None).astype("float")
data['sqft_basement'].isna().sum()
```

```
454
```

```
print("Mean:",data['sqft_basement'].mean())
print("Median:",data['sqft_basement'].median())

## let's check the skewness of this variable so that we know how we
will impute
print("Skewness:",data['sqft_basement'].skew())
## this data is positively skewed/highly skewed/right skewed, the tail
is on the right side of the distribution
```

```
Mean: 291.851723974838
Median: 0.0
Skewness: 1.574329769495408
```

```
## imputing the missing value using the median
data['sqft_basement'].fillna(data['sqft_basement'].median(),
inplace=True)
data['sqft_basement'].isna().sum() #now there are no missing values
```

```
0
```

Dropping Columns

```
## We have decided to drop these columns

dropped_columns = ['date', 'view', 'sqft_above', 'sqft_basement',
'yr_renovated', 'sqft_living15', 'sqft_lot15', 'long', 'lat', 'id',
'zipcode']
data1 = data.drop(columns = dropped_columns)
data1.head(2)
```

```
       price  bedrooms  bathrooms  sqft_living  sqft_lot  floors
waterfront  \
0  221900.0         3       1.00         1180      5650     1.0
NaN
1  538000.0         3       2.25         2570      7242     2.0
NO

  condition      grade  yr_built
0   Average  7 Average      1955
1   Average  7 Average      1951
```

Missing Data

Column `waterfront` has missing values, we will fill the missing values with `NA` as they are empty spaces. We don't want to manipulate the analysis by increasing the number of `YES's/NO's`

```
print("Missing values:", data1['waterfront'].isna().sum())
print("Table BEFORE dealing with missing values")
data1['waterfront'].value_counts()

Missing values: 2376
Table BEFORE dealing with missing values

waterfront
NO     19075
YES      146
Name: count, dtype: int64

data1['waterfront'].fillna("NA",inplace=True)
print("Missing values:", data1['waterfront'].isna().sum())
print("Table AFTER dealing with missing values")
data1['waterfront'].value_counts()

Missing values: 0
Table AFTER dealing with missing values

waterfront
NO     19075
NA      2376
YES      146
Name: count, dtype: int64
```

Encoding Data

```
# Checking the data types of our columns
data1.dtypes

price          float64
bedrooms         int64
bathrooms      float64
```

```
sqft_living      int64
sqft_lot         int64
floors         float64
waterfront      object
condition       object
grade           object
yr_built         int64
dtype: object
```

They are 3 i.e., `waterfront`, `condition` and `grade` Based on our business problem which is ***Advice to homeowners by a real estate agency on how*** **`home renovations`** ***might increase the estimated*** **`values of their homes`** ***and by what amount using multiple linear regression***, we are going to choose `condition` variable, encode it and use it in our model. The reason is because if we improve the condition of the house e.g from average to good, then the value of the home might increase. Following the above decision, we will drop the other two categorical variables i.e., waterfront and grade

We are going to use ordinal encoding to transform our selected categorical variable to numeric variable. Why we have selected ordinal encoding is because the choices observe some sequence/hierachy

```
# Summary and count of the condition column values
data1['condition'].value_counts()

condition
Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: count, dtype: int64

## Create the codes
condition_codes = {'Poor':1, 'Fair':2, 'Average':3, 'Good':4, 'Very 
Good':5}

## Inputting our codes back into our data frame
data1['condition_coded'] = data1['condition'].replace(condition_codes)
data1.head(2)

      price  bedrooms  bathrooms  sqft_living  sqft_lot  floors 
waterfront  \
0  221900.0         3       1.00         1180      5650     1.0 
NA
1  538000.0         3       2.25         2570      7242     2.0 
NO

  condition      grade  yr_built  condition_coded
0   Average  7 Average      1955                3
1   Average  7 Average      1951                3
```

```
# Dropping more columns that contain objects

drop_columns = ['waterfront', 'condition', 'grade']
data2 = data1.drop(columns = drop_columns)
data2.head(2)
```

```
      price  bedrooms  bathrooms  sqft_living  sqft_lot  floors
yr_built  \
0  221900.0         3       1.00         1180      5650     1.0
1955
1  538000.0         3       2.25         2570      7242     2.0
1951

   condition_coded
0                3
1                3
```

Correlation

```
## Correlation of our selected variables to the price
data2.corr()['price'].sort_values(ascending = False)
```

```
price              1.000000
sqft_living        0.701917
bathrooms          0.525906
bedrooms           0.308787
floors             0.256804
sqft_lot           0.089876
yr_built           0.053953
condition_coded    0.036056
Name: price, dtype: float64
```

From the correlation results above we can already start to see that variables like sqft_living, bathrooms, bedrooms and floors will produce a better model as compared to their other counterparts. Our newly coded condition variable is the least on the correlation table, implying it will not be very significant to our model when compared to the rest.

```
data2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   price            21597 non-null  float64
 1   bedrooms         21597 non-null  int64
 2   bathrooms        21597 non-null  float64
 3   sqft_living      21597 non-null  int64
 4   sqft_lot         21597 non-null  int64
 5   floors           21597 non-null  float64
```

```
 6   yr_built         21597 non-null  int64
 7   condition_coded  21597 non-null  int64
dtypes: float64(3), int64(5)
memory usage: 1.3 MB

data2.isna().sum()
##by now we dont have any missing value

price              0
bedrooms           0
bathrooms          0
sqft_living        0
sqft_lot           0
floors             0
yr_built           0
condition_coded    0
dtype: int64

## The final data to proceed to the modelling step
df = data2.copy(deep=True)
df.head()

      price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  
yr_built  \
0  221900.0         3       1.00         1180      5650     1.0  
1955
1  538000.0         3       2.25         2570      7242     2.0  
1951
2  180000.0         2       1.00          770     10000     1.0  
1933
3  604000.0         4       3.00         1960      5000     1.0  
1965
4  510000.0         3       2.00         1680      8080     1.0  
1987

   condition_coded
0                3
1                3
2                3
3                5
4                3
```

3. Modelling

A. Data Splitting

- Variable X contains all the independent features except the 'price' column.
- y contains the 'price' column, the target variable.
- We will use 20% of the data for testing and 80% for training.

```python
from sklearn.model_selection import train_test_split

# Getting out independent features. We will exclude the price
X = df.drop('price', axis=1)

# Dependent variable price which is our target
y = df['price']

# Split the data into training and testing sets
# We will use 20% of the data for testing and 80% for training.

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=40)
```

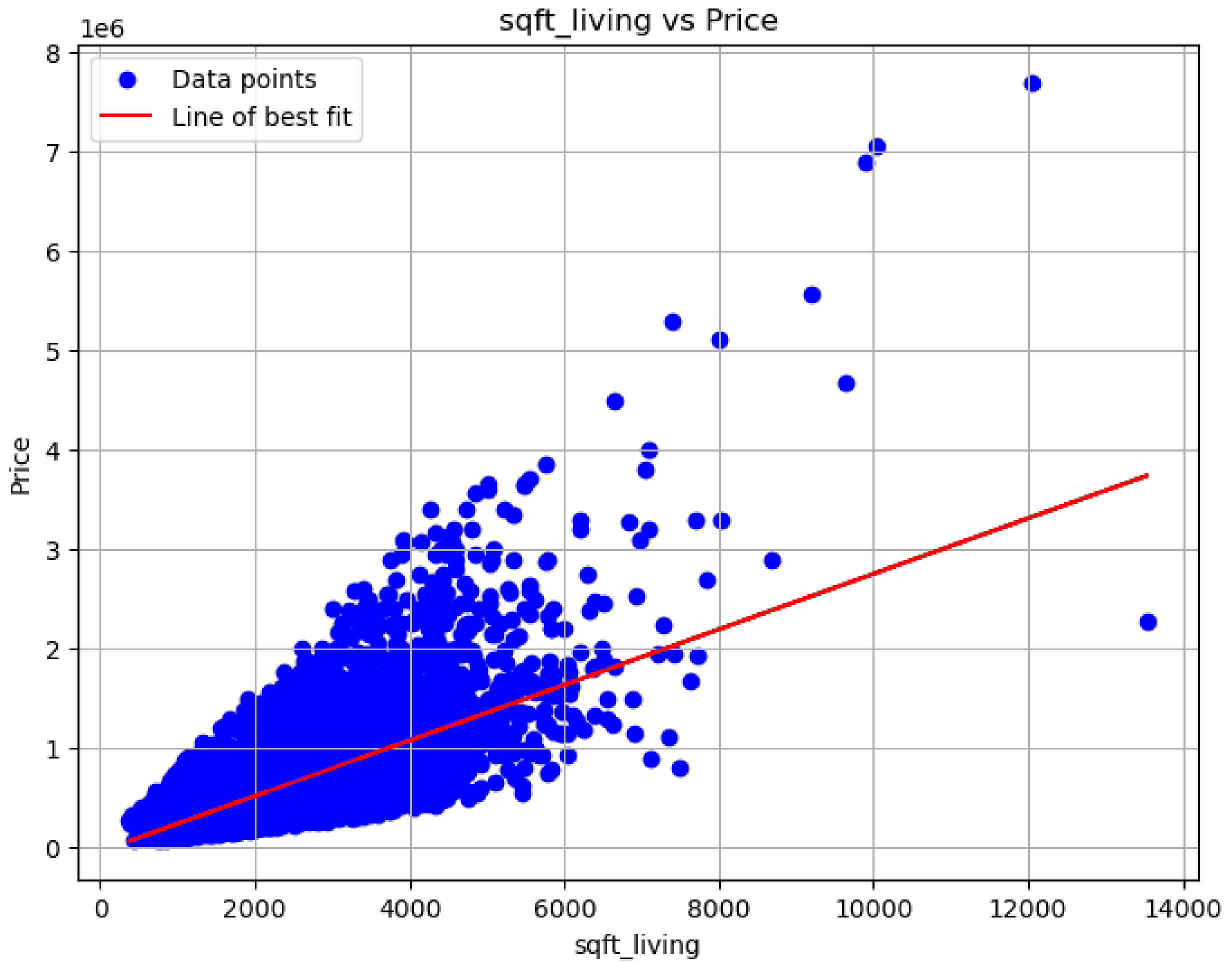
B. Simple Linear Regression for each Independent Variable

```python
# We are going to create a function for plotting a simple linear
regression model
# This will make the plotting of linear regression models for all our
features efficient

# Importing necessary libraries
import statsmodels.api as sm
import seaborn as sns

# Creating a function for simple linear regression
def simple_linear_regression(X, y):
    # Add constant to X
    X = sm.add_constant(X)

    # Fit OLS regression model
    model = sm.OLS(y, X).fit()

    # Get the coefficients
    intercept = model.params.iloc[0]
    slope = model.params.iloc[1]

    # Predictions
    y_pred = model.predict(X)

    # Plotting
    # plt.figure(figsize=(6, 4))
    # sns.scatterplot(x=X.iloc[:, 1], y=y, alpha=0.5)
    # sns.lineplot(x=X.iloc[:, 1], y=y_pred, color='red')

    # plt.title(f'{X.columns[1]} vs Price')
    # plt.xlabel(X.columns[1])
    # plt.ylabel('Price')
    # plt.show()
```

```
    plt.figure(figsize=(8, 6))  #Set figure size
    plt.scatter(X.iloc[:, 1], y ,color="blue", label="Data points")
#original data points
    plt.plot(X.iloc[:, 1], y_pred, color="red", label="Line of best
fit") ## notice we've fixed the regression equation here
    plt.title(f'{X.columns[1]} vs Price')
    plt.xlabel(X.columns[1])
    plt.ylabel('Price')
    plt.legend()
    plt.grid(True)
    plt.show()

    # Print the summary of the regression results
    print(model.summary())
    print('')
    print(f"price = {slope}*({X.columns[1]}) + {intercept}, This is in
the form y = mx+c") # Creatiing and printing our function
    print("f_value:", model.fvalue)
    print("p_value:", model.f_pvalue)
    print('')
```

i. sqft_living

```
X_sqft_living = X_train[['sqft_living']]
y = y_train
simple_linear_regression(X_sqft_living, y)
```



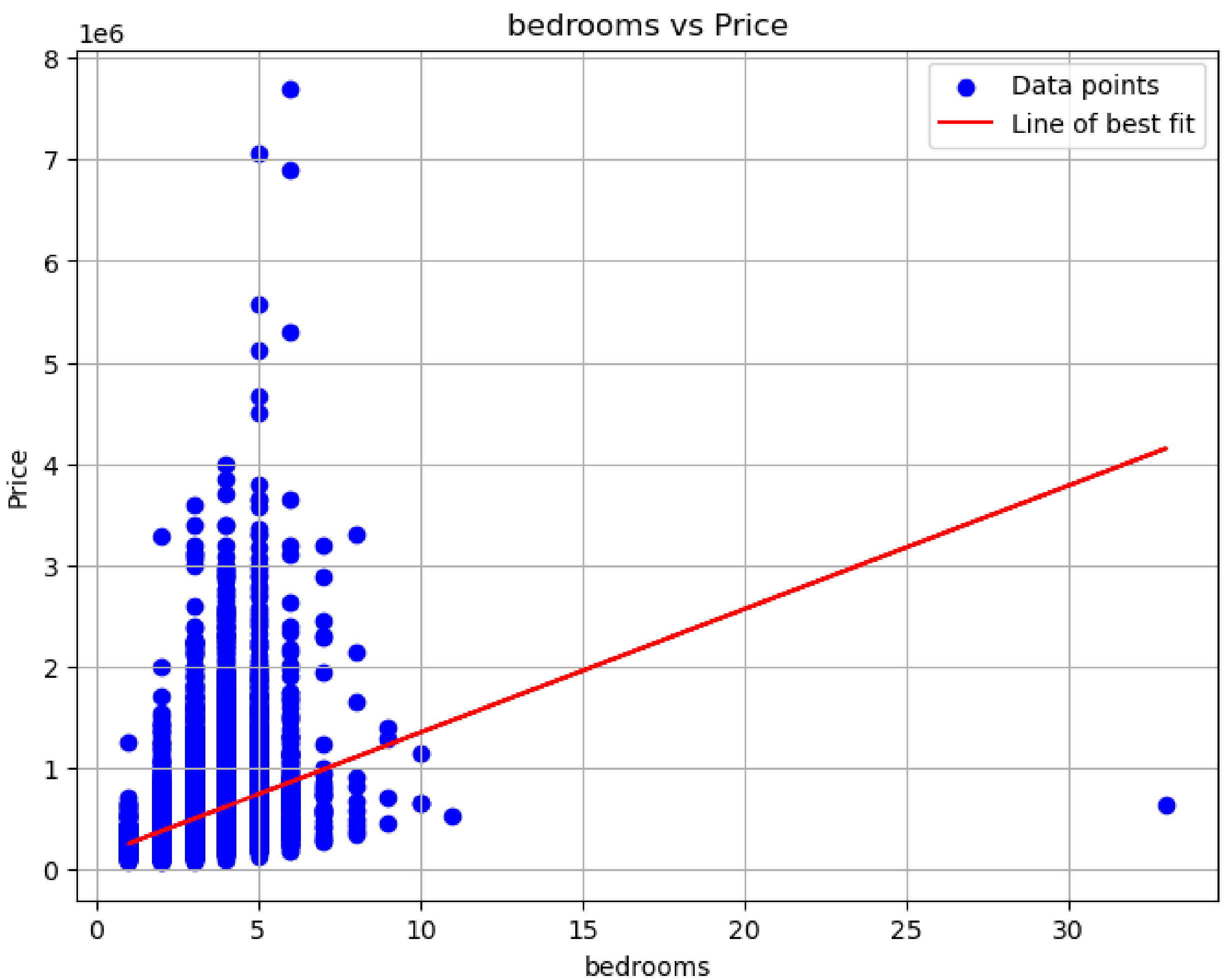

```
                            OLS Regression Results

==============================================================================
Dep. Variable:                  price   R-squared:
0.489
Model:                            OLS   Adj. R-squared:
0.489
Method:                 Least Squares   F-statistic:
1.656e+04
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
0.00
Time:                        18:37:11   Log-Likelihood:                 -
2.4012e+05
No. Observations:               17277   AIC:
4.802e+05
Df Residuals:                   17275   BIC:
4.803e+05
Df Model:                           1
```

```
Covariance Type:            nonrobust

==============================================================================
=========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
---------
const       -4.074e+04   4945.683     -8.238      0.000   -5.04e+04
-3.11e+04
sqft_living   279.2624      2.170    128.675      0.000     275.008
283.516
==============================================================================
========
Omnibus:                    12143.926   Durbin-Watson:
2.010
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
489855.060
Skew:                           2.894   Prob(JB):
0.00
Kurtosis:                      28.435   Cond. No.
5.64e+03
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.64e+03. This might indicate that
there are
strong multicollinearity or other numerical problems.

price = 279.262427562963*(sqft_living) + -40744.59249028359, This is
in the form y = mx+c
f_value: 16557.204671729098
p_value: 0.0
```

- The coefficient for sqft_living is approximately 279. For every 1 unit increase in square footage of living space (sqft_living), the house price is estimated to increase by $279, whereas, while other sqft_living is constant the house price is expected to decrease by 40744.
- Given a p-value of 0.000, the coefficient for sqft_living is statistically significant. This means that the sqft_living space has a significant impact on the house price.
- The R-squared value is 0.489, indicating that ~ 49.2% of the variance in house prices is explained by the sqft_living space. This suggests that the model provides a moderate fit to the data.
- The F-statistic is 1.656e+04, with a p-value of 0.000, which means that our regression model is statistically significant.

ii. Bedrooms

```
# Call the function for bedrooms
X_bedrooms = X_train[['bedrooms']]
print("Regression results for bedrooms:")
simple_linear_regression(X_bedrooms, y)

Regression results for bedrooms:
```




```
                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.095
Model:                            OLS   Adj. R-squared:
0.095
Method:                 Least Squares   F-statistic:
1820.
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
```

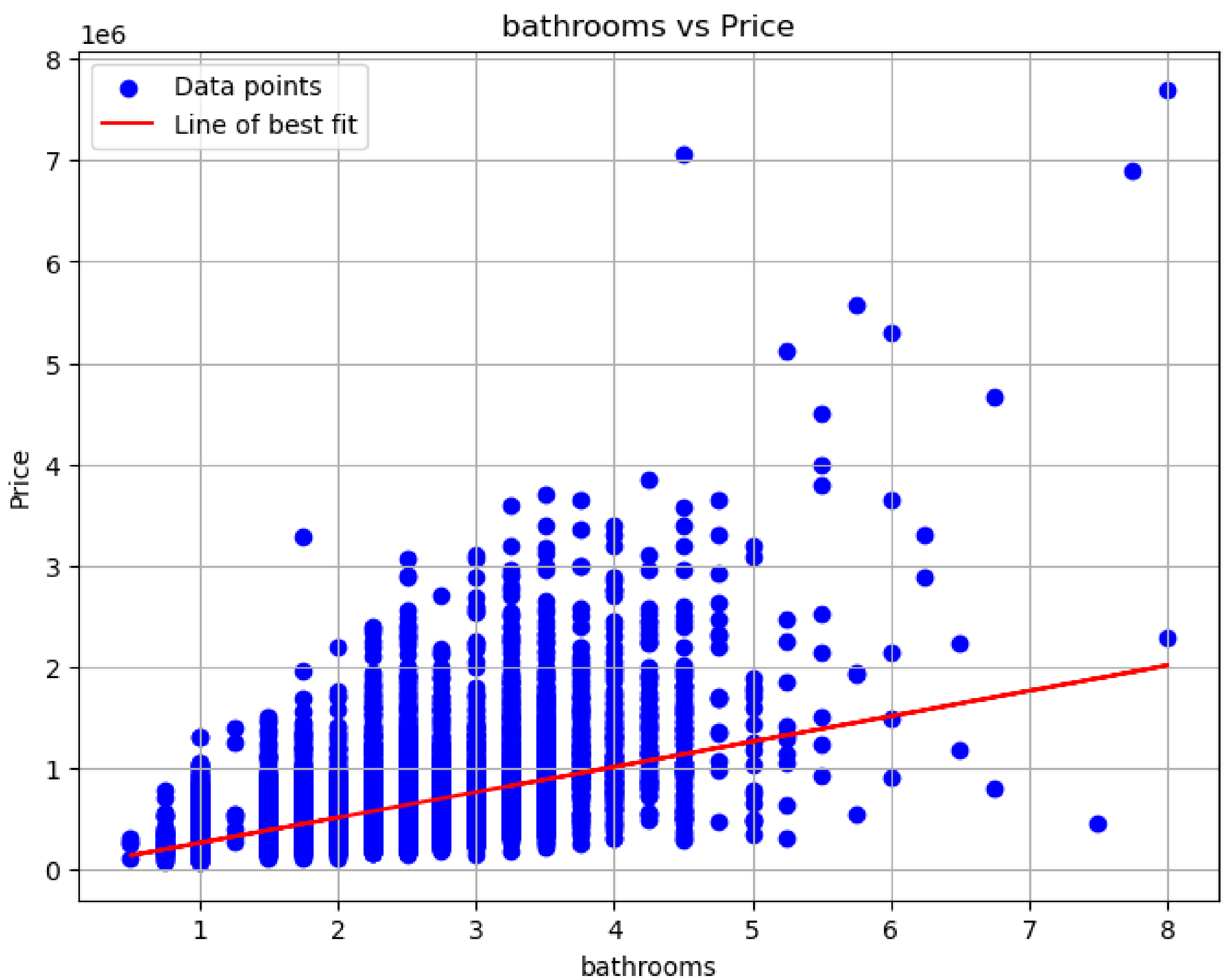
```
0.00
Time:                        18:37:12   Log-Likelihood:            -
2.4506e+05
No. Observations:               17277   AIC:
4.901e+05
Df Residuals:                   17275   BIC:
4.901e+05
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
const       1.301e+05      1e+04     13.006      0.000     1.1e+05
1.5e+05
bedrooms    1.218e+05   2855.071     42.659      0.000    1.16e+05
1.27e+05
======================================================================
========
Omnibus:                    15325.768   Durbin-Watson:
2.012
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1091222.015
Skew:                           3.965   Prob(JB):
0.00
Kurtosis:                      41.118   Cond. No.
14.2
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

price = 121794.12831776463*(bedrooms) + 130065.79490555076, This is in
the form y = mx+c
f_value: 1819.779672482757
p_value: 0.0
```

- The coefficient for bedrooms is around 121,794. Meaning additional bedroom in a house, the price of the house might increase by USD 121,794, whereas if there are no other changes in bedrooms, the the value of the house will be 130065.
- The p-value of 0.000 means the coefficient for bedrooms is statistically significant
- The R-squared value is 0.095, meaning ~ 9.5% of the variance in house prices is explained by the number of bedrooms.

- The F-statistic is 1820.0, with a p-value of 0.000, meaning the regression model is statistically significant.

iii. Bathrooms

```
# Call the function for bathrooms
X_bathrooms = X_train[['bathrooms']]
print("Regression results for bathrooms:")
simple_linear_regression(X_bathrooms, y)

Regression results for bathrooms:
```




```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                  price   R-squared:
0.276
Model:                            OLS   Adj. R-squared:
0.275
```

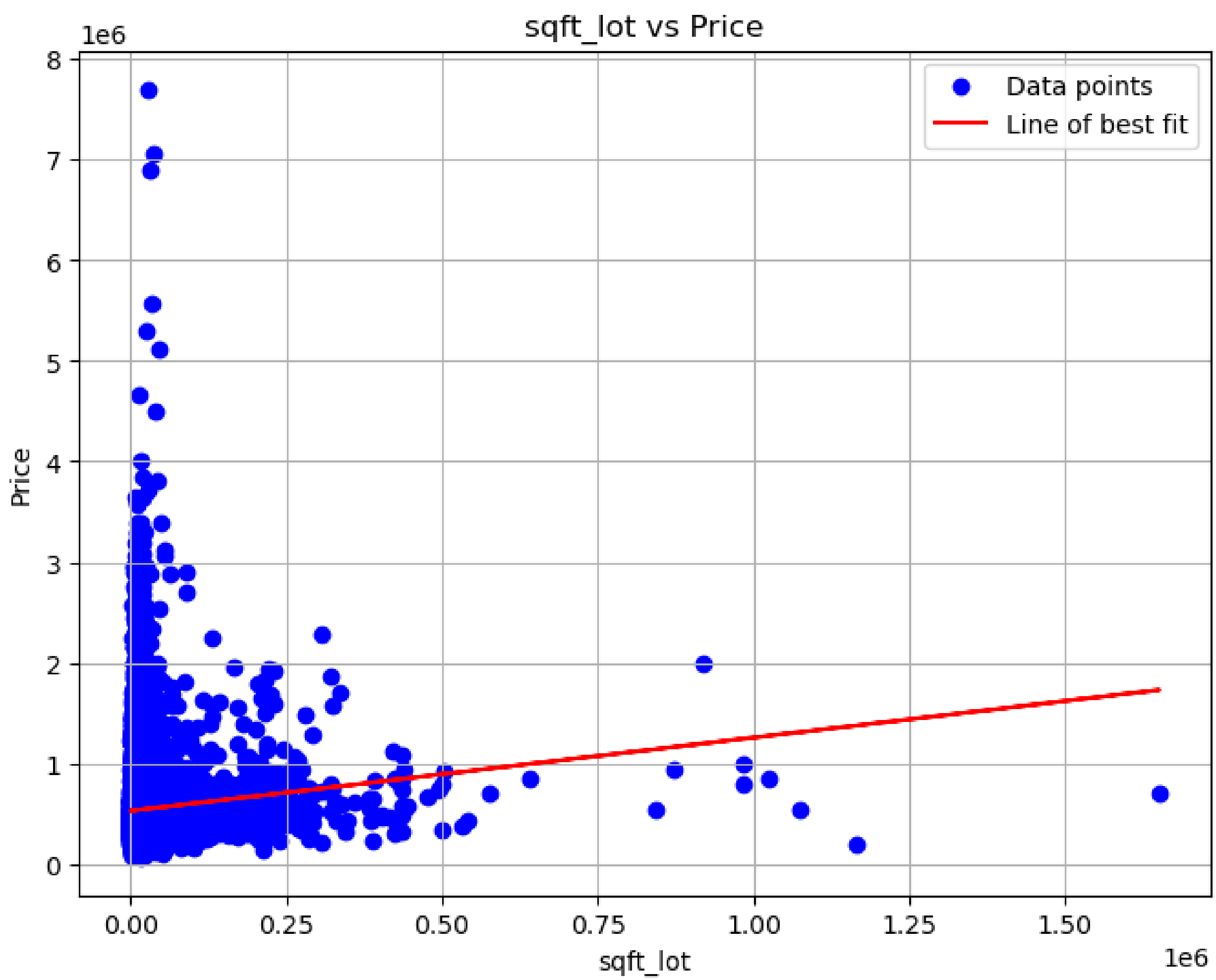
```
Method:                 Least Squares   F-statistic:
6569.
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
0.00
Time:                        18:37:12   Log-Likelihood:            -
2.4314e+05
No. Observations:               17277   AIC:
4.863e+05
Df Residuals:                   17275   BIC:
4.863e+05
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
const       1.141e+04   6958.084      1.640      0.101   -2228.620
2.5e+04
bathrooms     2.5e+05   3084.344     81.052      0.000    2.44e+05
2.56e+05
======================================================================
========
Omnibus:                    14070.987   Durbin-Watson:
2.027
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
794843.170
Skew:                           3.522   Prob(JB):
0.00
Kurtosis:                      35.473   Cond. No.
7.76
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

price = 249991.5449970878*(bathrooms) + 11409.928954557778, This is in
the form y = mx+c
f_value: 6569.388742409433
p_value: 0.0
```

- The coefficient for bathrooms is approximately 250,000. This means that for an additional bathroom in a house, the price of the house will increase by USD 250,000 whereas if no renovation is done in bathrooms, then the value of the house is expected to be 11409.

- The coefficient for bathrooms is statistically significant, as indicated by the p-value of 0.000.
- This suggests that the number of bathrooms has a significant impact on the house price.

iv. Sqft Lot

```
# Call the function for sqft_lot
X_sqft_lot = X_train[['sqft_lot']]
print("Regression results for sqft_lot:")
simple_linear_regression(X_sqft_lot, y)

Regression results for sqft_lot:
```




```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                      price   R-squared:
```

```
0.007
Model:                            OLS   Adj. R-squared:
0.007
Method:                 Least Squares   F-statistic:
119.0
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
1.26e-27
Time:                        18:37:12   Log-Likelihood:            -
2.4587e+05
No. Observations:               17277   AIC:
4.917e+05
Df Residuals:                   17275   BIC:
4.918e+05
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
const       5.303e+05   2966.401    178.759      0.000    5.24e+05
5.36e+05
sqft_lot       0.7275      0.067     10.911      0.000       0.597
0.858
==============================================================================
========
Omnibus:                    15595.690   Durbin-Watson:
2.006
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1044159.618
Skew:                           4.109   Prob(JB):
0.00
Kurtosis:                      40.188   Cond. No.
4.73e+04
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 4.73e+04. This might indicate that
there are
strong multicollinearity or other numerical problems.

price = 0.7274845493935727*(sqft_lot) + 530271.7004753138, This is in
the form y = mx+c
f_value: 119.0405586196337
```

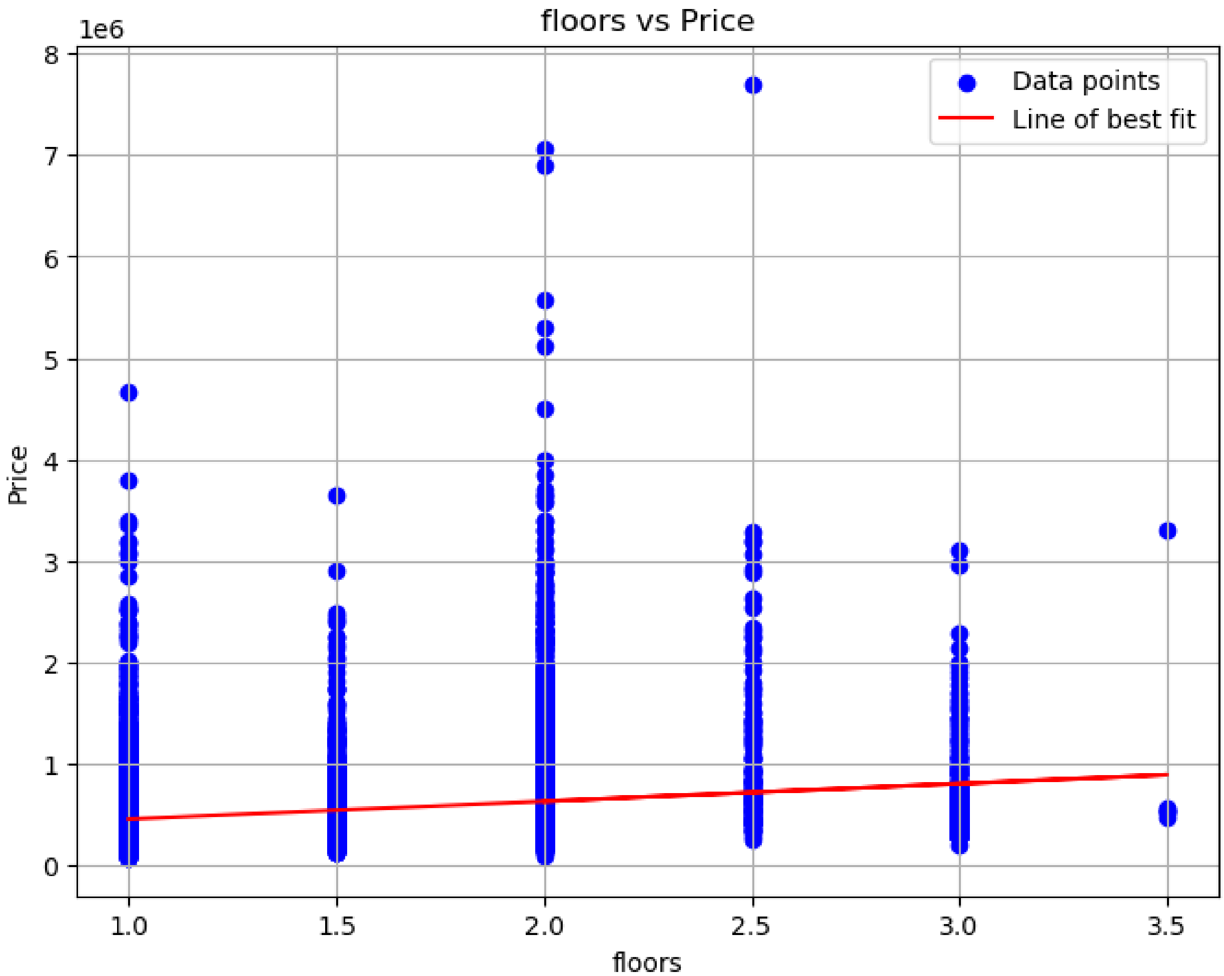
```
p_value: 1.2627869637889872e-27
```

- The coefficient for sqft_lot is approximately 0.727, meaning a one-unit increase in the square footage of the lot, the price of the house will increase by USD 0.727, if no other change is sqft_lot is done in the house, then the value of the home is expected to be 530271.
- Given the p-value of 0.000, This suggests that the square footage of the lot has a significant impact on the house price.
- Approximately 0.8% of the variance in house prices is explained by the square footage of the lot (sqft_lot).
- The overall regression model is statistically significant.

v. Floors

```
# Call the function for floors
X_floors = X_train[['floors']]
print("Regression results for floors:")
simple_linear_regression(X_floors, y)
```

```
Regression results for floors:
```




```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                  price   R-squared:
0.066
Model:                            OLS   Adj. R-squared:
0.066
Method:                 Least Squares   F-statistic:
1213.
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
5.31e-257
Time:                        18:37:13   Log-Likelihood:                 -
2.4534e+05
No. Observations:               17277   AIC:
4.907e+05
Df Residuals:                   17275   BIC:
4.907e+05
Df Model:                           1
```

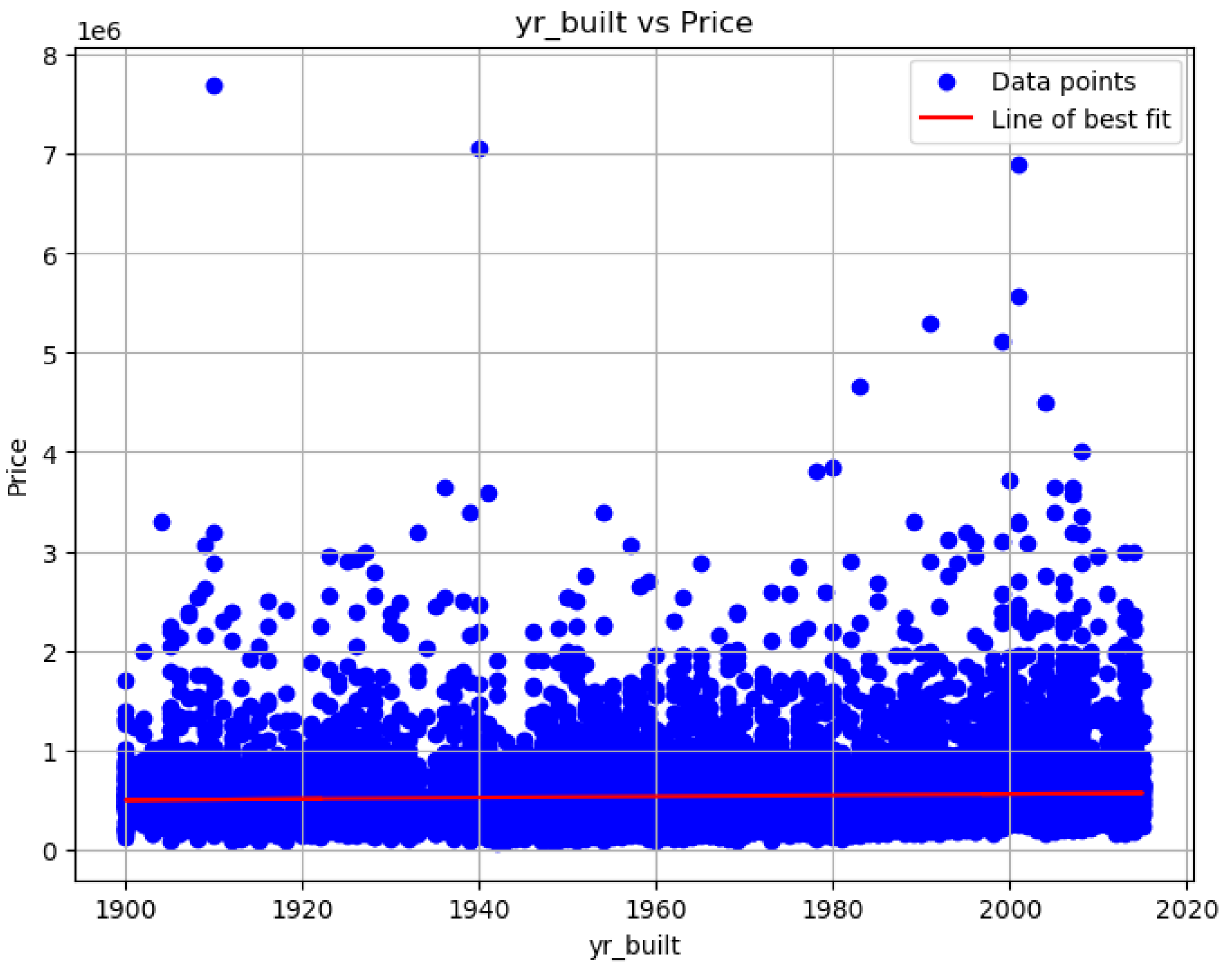
```
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
const       2.801e+05   7971.267     35.139      0.000    2.64e+05
2.96e+05
floors      1.745e+05   5008.961     34.834      0.000    1.65e+05
1.84e+05
==============================================================================
Omnibus:                    15790.117   Durbin-Watson:
2.008
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1148912.256
Skew:                           4.163   Prob(JB):
0.00
Kurtosis:                      42.073   Cond. No.
6.38
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

price = 174483.3344052792*(floors) + 280103.3012835714, This is in the
form y = mx+c
f_value: 1213.423949281076
p_value: 5.308358683083986e-257
```

- The coefficient for floors is approximately 174,483. This means that for every additional floor in a house, the price of the house will increase by USD 174,483, if floor(floor modification) is not changed, then the value of the house is expected to be 280103.
- As indicated by the p-value of 0.000, the number of floors has a significant impact on the house price.
- Around 6.7% of the variance in house prices is explained by the number of floors (floors)
- The overall regression model is statistically significant given the F-statistic

vi. Year Built

```python
# Call the function for yr_built
X_yr_built = X_train[['yr_built']]
print("Regression results for yr_built:")
simple_linear_regression(X_yr_built, y)
```

```
Regression results for yr_built:
```



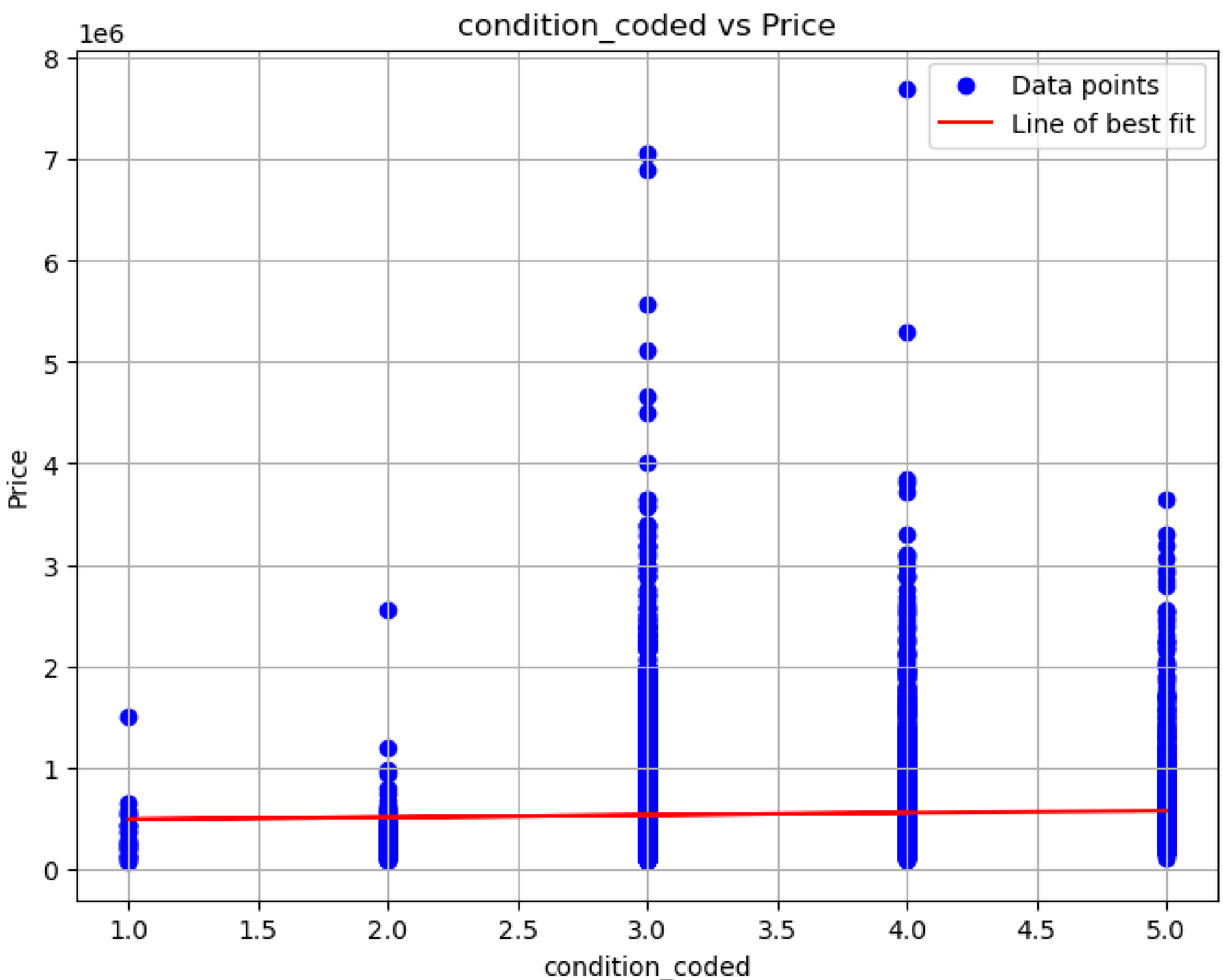

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                  price   R-squared:
0.002
Model:                            OLS   Adj. R-squared:
0.002
Method:                 Least Squares   F-statistic:
40.19
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
2.36e-10
Time:                        18:37:13   Log-Likelihood:                 -
2.4591e+05
No. Observations:               17277   AIC:
4.918e+05
Df Residuals:                   17275   BIC:
```

```
4.918e+05
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
const      -6.465e+05   1.87e+05     -3.450      0.001   -1.01e+06   -
2.79e+05
yr_built     602.6068     95.054      6.340      0.000     416.292
788.922
==============================================================================
========
Omnibus:                    15607.659   Durbin-Watson:
2.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1044645.468
Skew:                           4.115   Prob(JB):
0.00
Kurtosis:                      40.194   Cond. No.
1.32e+05
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.32e+05. This might indicate that
there are
strong multicollinearity or other numerical problems.

price = 602.6068272638458*(yr_built) + -646471.1768189413, This is in
the form y = mx+c
f_value: 40.19104577848836
p_value: 2.3601119184005135e-10
```

- The coefficient for yr_built is approximately 602.61. For every additional year since the year built, the price of the house is estimated to increase by USD 602.61, if year is not considered, then still the value of the house is expected to decrease by 646471.
- The year the house was built has a significant influence on the house price.
- 0.2% of the variance in house prices is explained by the year the house was built
- The regression model is statistically significant given the F-statistic

vii. Condition Coded

```
# Call the function for condition_coded
X_condition_coded = X_train[['condition_coded']]
print("Regression results for condition_coded:")
simple_linear_regression(X_condition_coded, y)

Regression results for condition_coded:
```




```
                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.001
Model:                            OLS   Adj. R-squared:
0.001
Method:                 Least Squares   F-statistic:
24.91
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
```

```
6.08e-07
Time:                        18:37:13   Log-Likelihood:          -
2.4591e+05
No. Observations:               17277   AIC:
4.918e+05
Df Residuals:                   17275   BIC:
4.918e+05
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
=============
                      coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
-------------
const            4.681e+05   1.49e+04     31.367      0.000
4.39e+05    4.97e+05
condition_coded  2.146e+04   4300.180      4.991      0.000
1.3e+04    2.99e+04
======================================================================
========
Omnibus:                    15577.833   Durbin-Watson:
2.003
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1036374.512
Skew:                           4.104   Prob(JB):
0.00
Kurtosis:                      40.045   Cond. No.
20.0
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

price = 21460.518165208247*(condition_coded) + 468134.58549233497,
This is in the form y = mx+c
f_value: 24.906181000021636
p_value: 6.077447064239542e-07
```

- The coefficient for condition_coded is approximately USD 21,460. If the condition improves for example from good to very good, the price of the house might increase by USD 21,460, if no change in the condition of the house, then the value of the house will be 468134
- This suggests that the condition code of the house has an impact on the house price.
- ~ 0.2% of the variance in house prices is explained by the condition code of the house

- The regression model is statistically significant.

C. Multiple Linear Regression

We use training data to model our multiple linear regression

```
import statsmodels.api as sm

# Add a constant term to the independent variables (required for OLS
regression)
X_train_ols = sm.add_constant(X_train)

# Create and fit the OLS model
ols_model = sm.OLS(y_train, X_train_ols)
ols_results = ols_model.fit()

# Print the summary of the OLS regression results
print(ols_results.summary())
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.556
Model:                            OLS   Adj. R-squared:
0.555
Method:                 Least Squares   F-statistic:
3084.
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
0.00
Time:                        18:37:13   Log-Likelihood:             -
2.3892e+05
No. Observations:               17277   AIC:
4.779e+05
Df Residuals:                   17269   BIC:
4.779e+05
Df Model:                           7

Covariance Type:            nonrobust

======================================================================
=============
                      coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
-------------
const            6.342e+06   1.62e+05     39.263      0.000
6.03e+06    6.66e+06
bedrooms        -6.779e+04   2503.940    -27.072      0.000    -
7.27e+04   -6.29e+04
```

```
bathrooms         6.513e+04   4315.497     15.093      0.000
5.67e+04    7.36e+04
sqft_living       302.1749      3.368     89.723      0.000
295.574     308.776
sqft_lot           -0.3332      0.046     -7.310      0.000      -
0.423      -0.244
floors            5.817e+04   4264.216     13.642      0.000
4.98e+04    6.65e+04
yr_built        -3290.3978     81.902    -40.175      0.000   -
3450.934   -3129.862
condition_coded  1.869e+04   3122.388      5.987      0.000
1.26e+04    2.48e+04
======================================================================
========
Omnibus:                    11729.996   Durbin-Watson:
2.002
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
466829.361
Skew:                           2.748   Prob(JB):
0.00
Kurtosis:                      27.865   Cond. No.
3.85e+06
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 3.85e+06. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

Summary of the Multiple Regression Model

Model Performance

- The R-squared value of 0.556 indicates that ~ 55.6% of the variance in the price is explained by the independent variables included in the model.
- A high F-statistic of 3084 and a low Prob(F-statistic)) means that our model is statistically significant.
- Intercept (const): The intercept is the estimated value of the dependent variable when all independent variables are set to zero. In this case, it's approximately USD 6.35 million.

  Coefficients for independent variables:
- bedrooms: For each additional bedroom, there is an estimated decrease of approximately USD 67,790 in the price.
- bathrooms: For each additional bathroom, there is an estimated increase of approximately USD 65,1300 in the price.

- sqft_living: For each additional square foot of living space, there is an estimated increase of approximately USD 302.17 in the price.
- sqft_lot: For each additional square foot of lot size, there is an estimated decrease of approximately USD 0.333 in the price.
- floors: For each additional floor, there is an estimated increase of approximately USD 58,170 in the price.
- yr_built: For each additional year of the house's age, there is an estimated decrease of approximately USD 3,290 in the price.
- condition_coded: Improvement of the overall condition of the house from 1 rating to another (e.g. good to very good) will increase the price of the house by approximately USD 19,610

Summary

- The high condition number suggests potential multicollinearity or numerical problems in the model.

D. Multicollinearity

i. Exploring Data for Multicollinearity

```
# Previwing our data - independent variables
X_train.head(2)
```

```
      bedrooms  bathrooms  sqft_living  sqft_lot  floors  yr_built  \
2093         4        2.0         2130      2800     1.0      1922
9738         3        1.0         1160      3700     1.5      1909

      condition_coded
2093                5
9738                3
```

```
# Training data preview - target variable
y_train.head(2)
```

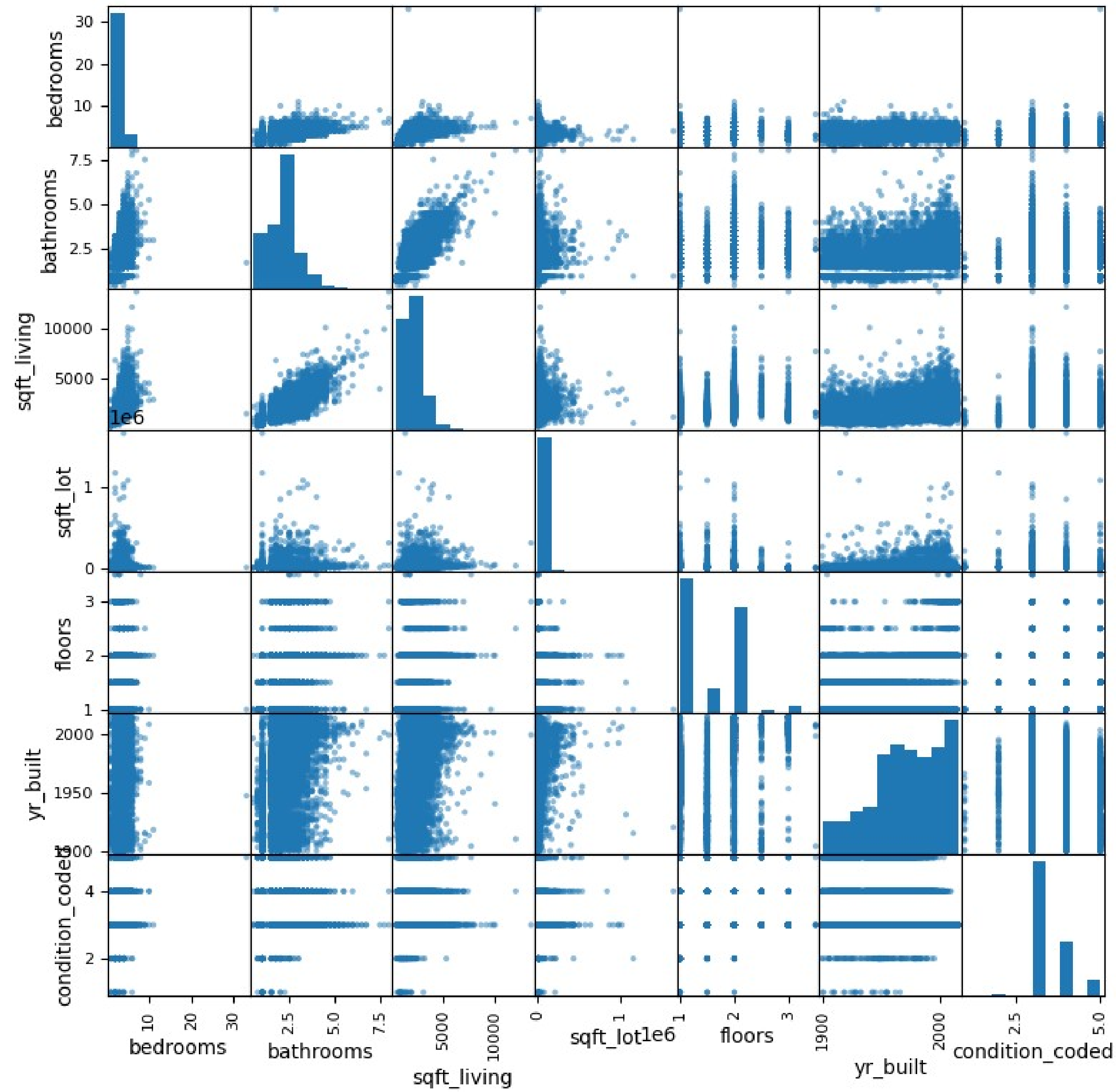
```
2093    800000.0
9738    315000.0
Name: price, dtype: float64
```

```
X = X_train
X.corr()
```

```
                 bedrooms  bathrooms  sqft_living  sqft_lot    floors
\
bedrooms         1.000000   0.511014     0.577830  0.034186  0.180796

bathrooms        0.511014   1.000000     0.758566  0.085941  0.503578
```

```
sqft_living       0.577830   0.758566     1.000000  0.169754  0.356850

sqft_lot          0.034186   0.085941     0.169754  1.000000 -0.002811

floors            0.180796   0.503578     0.356850 -0.002811  1.000000

yr_built          0.158268   0.507776     0.318708  0.050062  0.488767

condition_coded   0.022288  -0.134546    -0.062333 -0.010503 -0.262695


                  yr_built  condition_coded
bedrooms          0.158268         0.022288
bathrooms         0.507776        -0.134546
sqft_living       0.318708        -0.062333
sqft_lot          0.050062        -0.010503
floors            0.488767        -0.262695
yr_built          1.000000        -0.366237
condition_coded -0.366237         1.000000
```

```
# Scatterplot for our independent variables
pd.plotting.scatter_matrix(X,figsize  = [9, 9]);
plt.show()
```




```
## Getting the correlation of the independent variables
X.corr()
```

```
                bedrooms  bathrooms  sqft_living  sqft_lot    floors  \
bedrooms        1.000000   0.511014     0.577830  0.034186  0.180796
bathrooms       0.511014   1.000000     0.758566  0.085941  0.503578
sqft_living     0.577830   0.758566     1.000000  0.169754  0.356850
sqft_lot        0.034186   0.085941     0.169754  1.000000 -0.002811
```

```
floors            0.180796   0.503578     0.356850 -0.002811  1.000000

yr_built          0.158268   0.507776     0.318708  0.050062  0.488767

condition_coded   0.022288  -0.134546    -0.062333 -0.010503 -0.262695


                  yr_built  condition_coded
bedrooms          0.158268         0.022288
bathrooms         0.507776        -0.134546
sqft_living       0.318708        -0.062333
sqft_lot          0.050062        -0.010503
floors            0.488767        -0.262695
yr_built          1.000000        -0.366237
condition_coded  -0.366237         1.000000
```

Generally, a correlation with an absolute value around 0.7-0.8 or higher is considered a high correlation. We will use 0.75 as our cut-off

```
# Checking how many correlations have is more than 0.75
abs(X.corr()) > 0.75
```

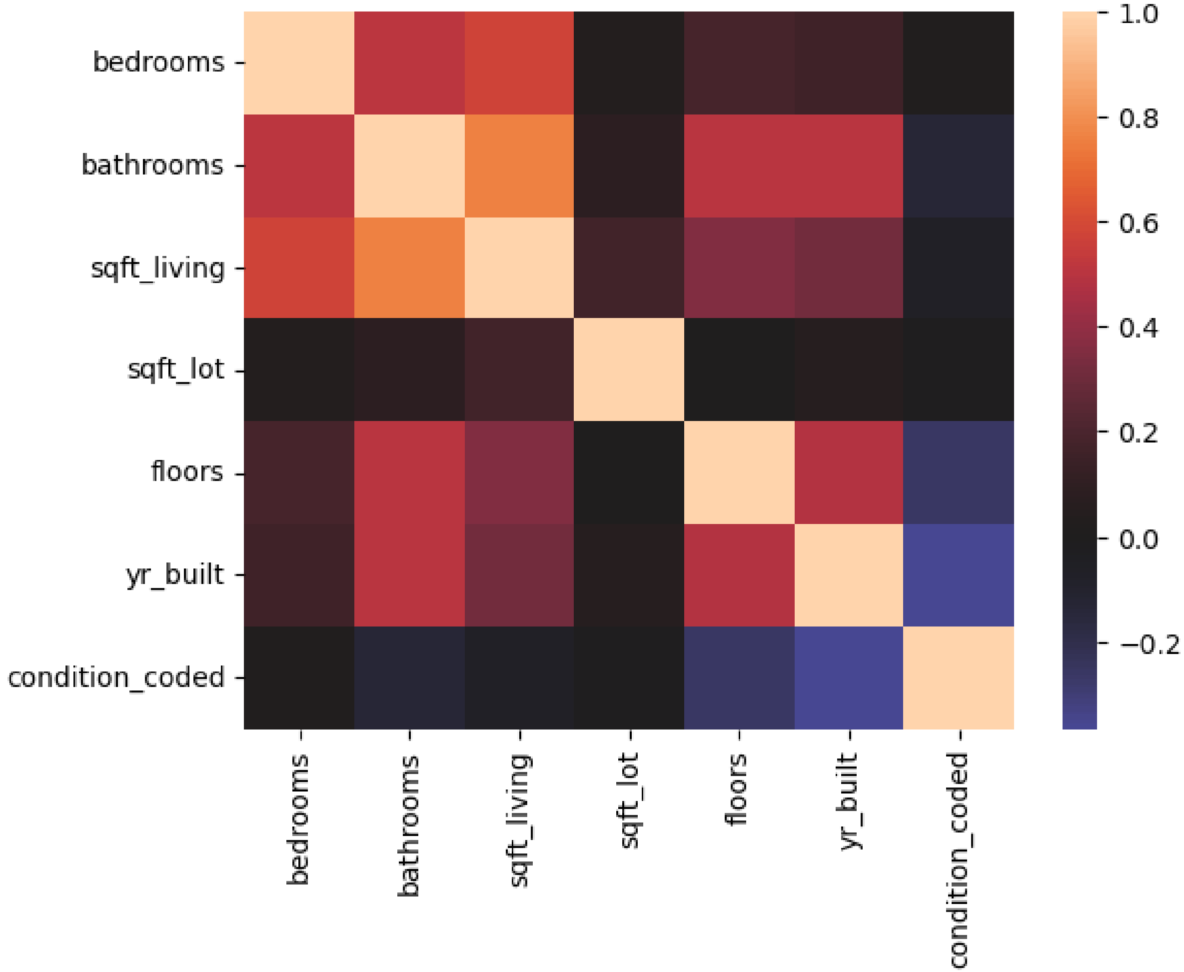
```
                  bedrooms  bathrooms  sqft_living  sqft_lot  floors
yr_built  \
bedrooms              True      False        False     False   False
False
bathrooms            False       True         True     False   False
False
sqft_living          False       True         True     False   False
False
sqft_lot             False      False        False      True   False
False
floors               False      False        False     False    True
False
yr_built             False      False        False     False   False
True
condition_coded      False      False        False     False   False
False

                  condition_coded
bedrooms                    False
bathrooms                   False
sqft_living                 False
sqft_lot                    False
floors                      False
yr_built                    False
condition_coded              True
```

"bathrooms" and "sqft_living" are highly correlated. Also, This relationship may influence regression model stability and interpretation.

```python
df2=X.corr().abs().stack().reset_index().sort_values(0,
ascending=False)

# zip the variable name columns (Which were only named level_0 and
level_1 by default) in a new column named "pairs"
df2['pairs'] = list(zip(df2.level_0, df2.level_1))

# set index to pairs
df2.set_index(['pairs'], inplace = True)

#d rop level columns
df2.drop(columns=['level_1', 'level_0'], inplace = True)

# rename correlation column as cc rather than 0
df2.columns = ['cc']

df2.drop_duplicates(inplace=True)

# Returning pairs that are highly correlated

df2[(df2.cc>.75) & (df2.cc <1)]
```

	cc
pairs	
(bathrooms, sqft_living)	0.758566

```python
## Lets use heatmap to check the correlation

import seaborn as sns
sns.heatmap(X.corr(), center=0);
```




```
# Preview the new df
X.head()

       bedrooms  bathrooms  sqft_living  sqft_lot  floors  yr_built  \
2093          4       2.00         2130      2800     1.0      1922
9738          3       1.00         1160      3700     1.5      1909
4382          3       1.75         1820     15570     1.0      1948
11641         3       1.75         1660      8301     1.0      1955
13114         2       2.25         1390      1222     3.0      2009

       condition_coded
2093                 5
9738                 3
4382                 3
11641                5
13114                3

# Create new df
data = X.copy()
data.head()
```

```
       bedrooms  bathrooms  sqft_living  sqft_lot  floors  yr_built  \
2093          4       2.00         2130      2800     1.0      1922
9738          3       1.00         1160      3700     1.5      1909
4382          3       1.75         1820     15570     1.0      1948
11641         3       1.75         1660      8301     1.0      1955
13114         2       2.25         1390      1222     3.0      2009

       condition_coded
2093                 5
9738                 3
4382                 3
11641                5
13114                3
```

We will create a new column called bathroom_density to hold the ratio of bathrooms to the number of bedrooms

```
# We will only address the 2 highly correlated columns bathrooms and
sqft_living
# The ratio of bathrooms to the number of bedrooms

data['bathroom_density'] = data['bathrooms'] / data['bedrooms']

# Preview our new data frame
data.head()

       bedrooms  bathrooms  sqft_living  sqft_lot  floors  yr_built  \
2093          4       2.00         2130      2800     1.0      1922
9738          3       1.00         1160      3700     1.5      1909
4382          3       1.75         1820     15570     1.0      1948
11641         3       1.75         1660      8301     1.0      1955
13114         2       2.25         1390      1222     3.0      2009

       condition_coded  bathroom_density
2093                 5          0.500000
9738                 3          0.333333
4382                 3          0.583333
11641                5          0.583333
13114                3          1.125000
```

ii. Dropping column bathrooms

"Bathrooms" has a correlation coefficient of 0.76 with "sqft_living", indicating a high positive correlation. "Bathrooms" has a correlation coefficient of 0.51 with "bedrooms", indicating a moderate positive correlation

Also

"Bathrooms" has a correlation coefficient of 0.525906 with "price", indicating a moderate positive correlation. "Sqft_living" has a higher correlation coefficient of 0.701917 with "price", indicating a stronger positive correlation.

So we will drop the bathrooms column

```
# Drop the 'bathrooms' column from the DataFrame
data.drop('bathrooms', axis=1, inplace=True)
data.head()
```

```
       bedrooms  sqft_living  sqft_lot  floors  yr_built  
condition_coded  \
2093          4         2130      2800     1.0      1922  
5
9738          3         1160      3700     1.5      1909  
3
4382          3         1820     15570     1.0      1948  
3
11641         3         1660      8301     1.0      1955  
5
13114         2         1390      1222     3.0      2009  
3

       bathroom_density
2093           0.500000
9738           0.333333
4382           0.583333
11641          0.583333
13114          1.125000
```

```
data.corr()
```

```
                  bedrooms  sqft_living  sqft_lot    floors  yr_built  
\
bedrooms          1.000000     0.577830  0.034186  0.180796  0.158268  

sqft_living       0.577830     1.000000  0.169754  0.356850  0.318708  

sqft_lot          0.034186     0.169754  1.000000 -0.002811  0.050062  

floors            0.180796     0.356850 -0.002811  1.000000  0.488767  

yr_built          0.158268     0.318708  0.050062  0.488767  1.000000  

condition_coded   0.022288    -0.062333 -0.010503 -0.262695 -0.366237  

bathroom_density -0.234908     0.311833  0.062219  0.418674  0.425651  


                  condition_coded  bathroom_density
bedrooms                 0.022288         -0.234908
```

```
sqft_living                -0.062333          0.311833
sqft_lot                   -0.010503          0.062219
floors                     -0.262695          0.418674
yr_built                   -0.366237          0.425651
condition_coded             1.000000         -0.162988
bathroom_density           -0.162988          1.000000
```

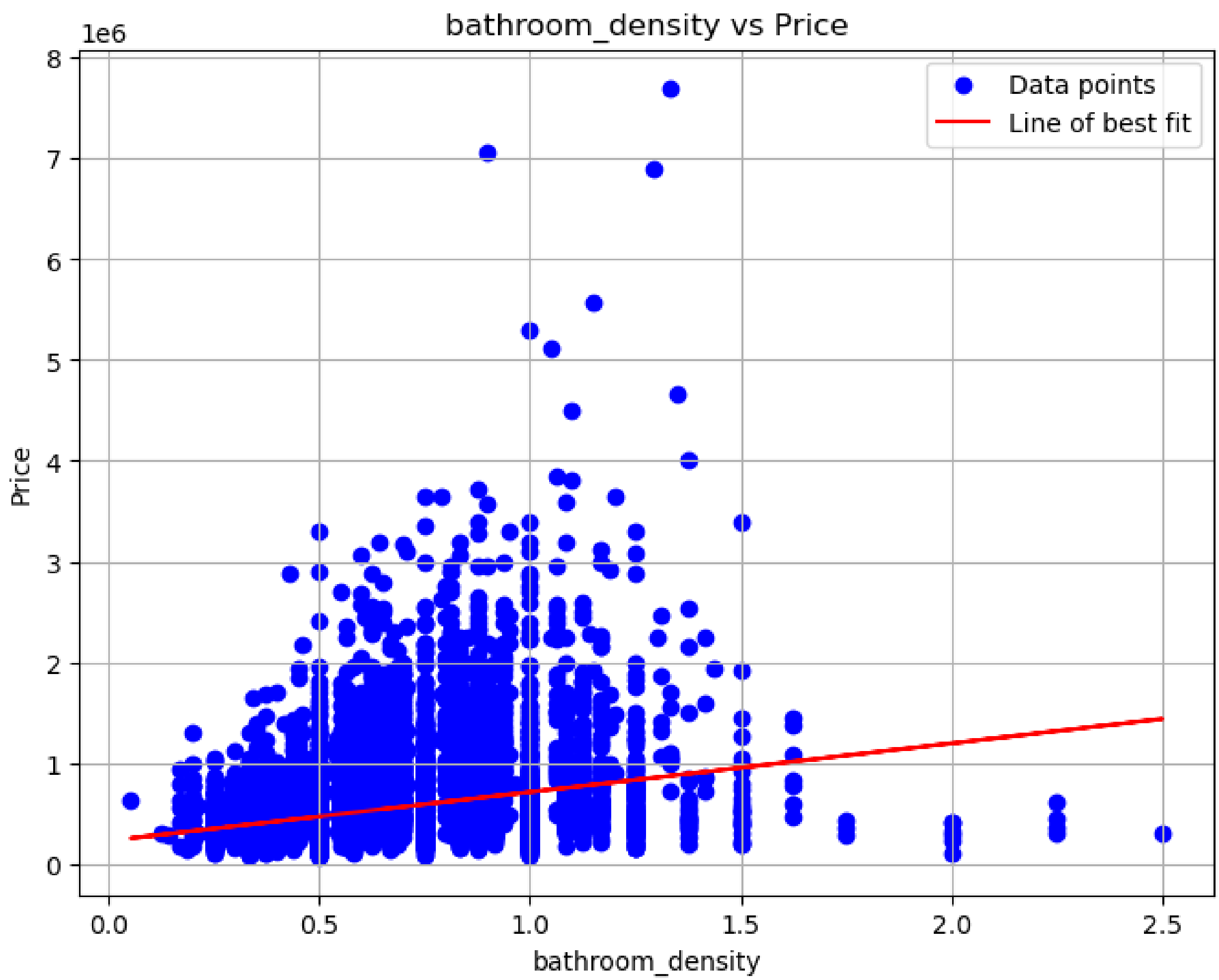
```
## Rechecking the correlation between the features
abs(data.corr()) > 0.75
```

```
                  bedrooms  sqft_living  sqft_lot  floors  yr_built  \
bedrooms              True        False     False   False     False
sqft_living          False         True     False   False     False
sqft_lot             False        False      True   False     False
floors               False        False     False    True     False
yr_built             False        False     False   False      True
condition_coded      False        False     False   False     False
bathroom_density     False        False     False   False     False

                  condition_coded  bathroom_density
bedrooms                    False             False
sqft_living                 False             False
sqft_lot                    False             False
floors                      False             False
yr_built                    False             False
condition_coded              True             False
bathroom_density            False              True
```

```
# creating another copy of the data as X-Train
X_train = data.copy()
```

```
#### Exploring the newly created column
X_bathdensity = X_train[['bathroom_density']]
print("Regression results for yr_built:")
simple_linear_regression(X_bathdensity, y)
```

```
Regression results for yr_built:
```



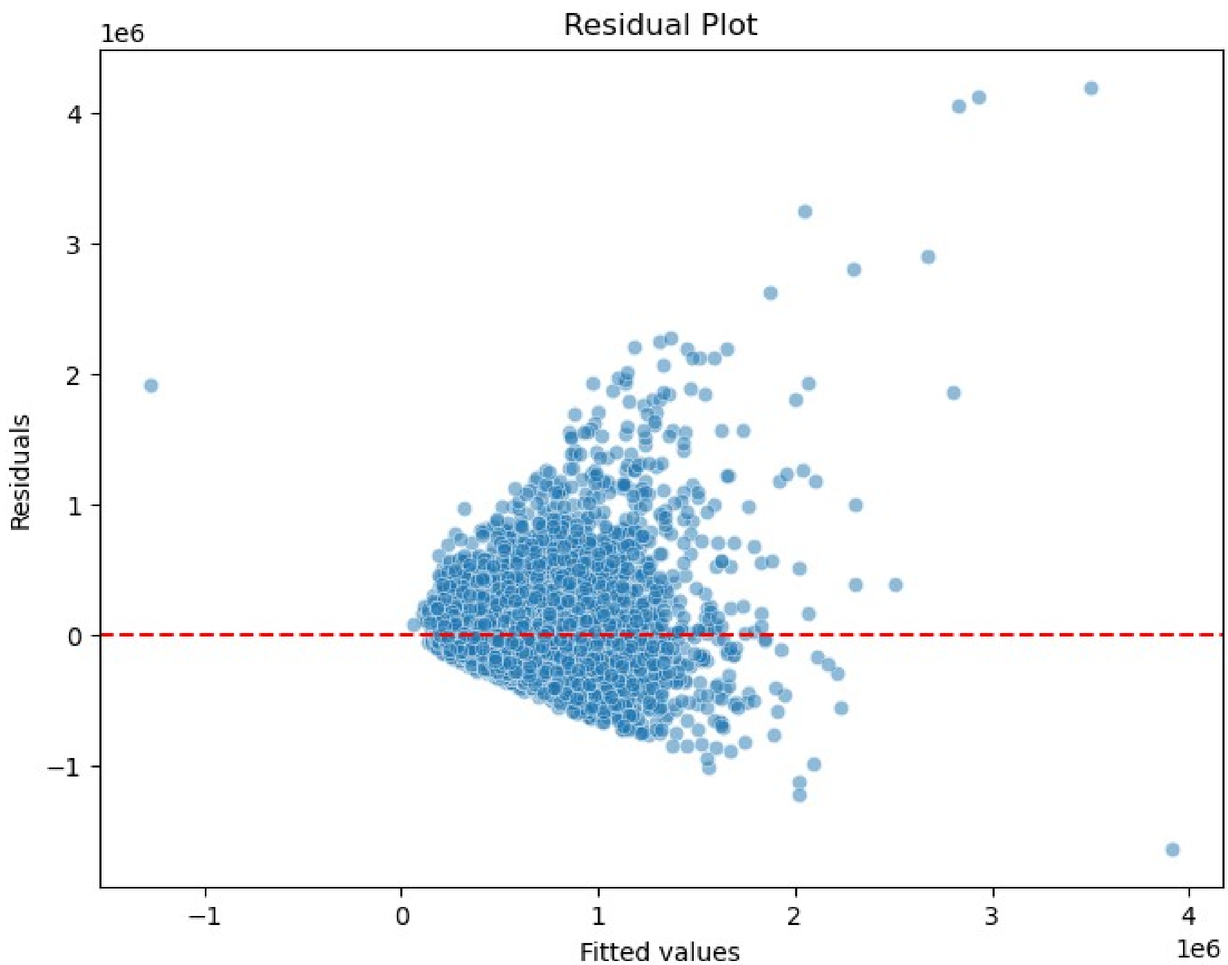

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                  price   R-squared:
0.078
Model:                            OLS   Adj. R-squared:
0.078
Method:                 Least Squares   F-statistic:
1460.
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
1.18e-306
Time:                        18:37:17   Log-Likelihood:                 -
2.4523e+05
No. Observations:               17277   AIC:
4.905e+05
Df Residuals:                   17275   BIC:
4.905e+05
Df Model:                           1
```

```
Covariance Type:            nonrobust

======================================================================
==============
                       coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
--------------
const              2.311e+05   8551.700     27.028      0.000
2.14e+05    2.48e+05
bathroom_density  4.835e+05   1.27e+04     38.204      0.000
4.59e+05    5.08e+05
======================================================================
========
Omnibus:                    15134.349   Durbin-Watson:
2.007
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
982780.240
Skew:                           3.918   Prob(JB):
0.00
Kurtosis:                      39.108   Cond. No.
6.71
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

price = 483465.1676656219*(bathroom_density) + 231135.55331064545,
This is in the form y = mx+c
f_value: 1459.5795917258044
p_value: 1.1842970305104985e-306
```

iii. Feature Selections and modelling

```
# Concatenate X_train and y_train into a single data frame (We need
both price and independent variables for correlations)

train_data = pd.concat([X_train, y_train], axis=1)

# Calculate the p correlation coefficient
correlation_matrix = train_data.corr()

# Extract the correlations
correlation_with_y = correlation_matrix['price'].drop('price')
correlation = correlation_with_y.sort_values(ascending=False)
```

```
correlation

sqft_living         0.699565
bedrooms            0.308711
bathroom_density    0.279121
floors              0.256187
sqft_lot            0.082727
yr_built            0.048178
condition_coded     0.037943
Name: price, dtype: float64

# Multiple Regression (top 4 most corr)
# Extract the feature variables and target variable

X = X_train[['sqft_living', 'bedrooms', 'bathroom_density','floors']]
y = y_train

X = sm.add_constant(X)

# Fit OLS regression model
select_model = sm.OLS(y, X).fit()

# Scatter plot
plt.figure(figsize=(8, 6))
sns.scatterplot(x=select_model.fittedvalues, y=select_model.resid,
alpha=0.5)
plt.axhline(y=0, color='red', linestyle='--')
plt.title('Residual Plot')
plt.xlabel('Fitted values')
plt.ylabel('Residuals')
plt.show()

# Print the summary of the regression results
print(select_model.summary())
```



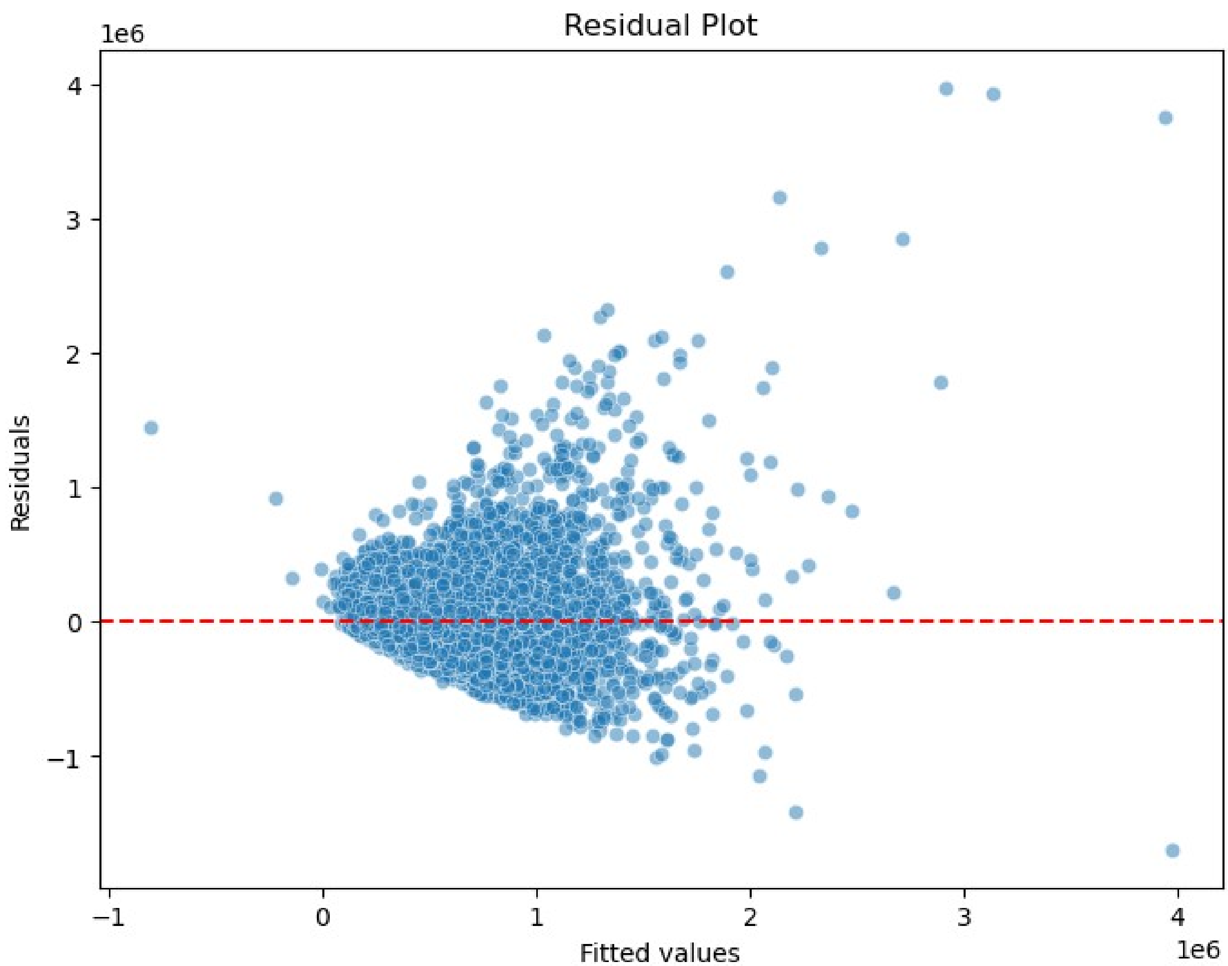

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                  price   R-squared:
0.503
Model:                            OLS   Adj. R-squared:
0.503
Method:                 Least Squares   F-statistic:
4372.
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
0.00
Time:                        18:37:17   Log-Likelihood:            -
2.3988e+05
No. Observations:               17277   AIC:
4.798e+05
Df Residuals:                   17272   BIC:
4.798e+05
Df Model:                           4
```

```
Covariance Type:            nonrobust

==============================================================================
==============
                        coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
--------------
const              7.783e+04   1.19e+04      6.552      0.000
5.45e+04    1.01e+05
sqft_living         311.6452      3.183     97.914      0.000
305.407     317.884
bedrooms          -5.631e+04   3127.702    -18.005      0.000   -
6.24e+04   -5.02e+04
bathroom_density   1515.7304   1.26e+04      0.121      0.904   -
2.31e+04    2.61e+04
floors             2069.2793   4247.491      0.487      0.626   -
6256.234    1.04e+04
==============================================================================
========
Omnibus:                    11850.922   Durbin-Watson:
2.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
444443.297
Skew:                           2.813   Prob(JB):
0.00
Kurtosis:                      27.202   Cond. No.
1.86e+04
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.86e+04. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

iv. All Features Modelling

```
# Building a model with all the features

X_train_c = sm.add_constant(X_train)
final_multiple_model = sm.OLS(y_train, X_train_c)
final_multiple_model = final_multiple_model.fit()

# Print a summary of the regression results


# Scatter plot
```

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x=final_multiple_model.fittedvalues,
y=final_multiple_model.resid, alpha=0.5)
plt.axhline(y=0, color='red', linestyle='--')
plt.title('Residual Plot')
plt.xlabel('Fitted values')
plt.ylabel('Residuals')
plt.show()

# Print the summary of the regression results
print(final_multiple_model.summary())
```




```
                                OLS Regression Results

======================================================================
========
Dep. Variable:                           price   R-squared:
0.554
Model:                                     OLS   Adj. R-squared:
```

```
0.553
Method:                 Least Squares   F-statistic:
3059.
Date:                Tue, 09 Apr 2024   Prob (F-statistic):
0.00
Time:                        18:37:17   Log-Likelihood:            -
2.3896e+05
No. Observations:               17277   AIC:
4.779e+05
Df Residuals:                   17269   BIC:
4.780e+05
Df Model:                           7

Covariance Type:            nonrobust

======================================================================
==============
                       coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
--------------
const             6.027e+06   1.58e+05     38.135      0.000
5.72e+06    6.34e+06
bedrooms         -4.021e+04   3017.400    -13.325      0.000   -
4.61e+04   -3.43e+04
sqft_living        314.9737      3.066    102.731      0.000
308.964     320.983
sqft_lot            -0.3508      0.046     -7.683      0.000      -
0.440      -0.261
floors            6.064e+04   4287.097     14.144      0.000
5.22e+04     6.9e+04
yr_built         -3173.2507     81.072    -39.141      0.000   -
3332.159   -3014.342
condition_coded     1.91e+04   3129.629      6.103      0.000
1.3e+04    2.52e+04
bathroom_density  1.521e+05   1.25e+04     12.199      0.000
1.28e+05    1.77e+05
======================================================================
========
Omnibus:                    11767.200   Durbin-Watson:
2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
478168.608
Skew:                           2.754   Prob(JB):
0.00
Kurtosis:                      28.177   Cond. No.
3.76e+06
======================================================================
========
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 3.76e+06. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

The Final equation for our model

price=(-40,210×bedrooms)+(314.97×sqft_living)−(0.35×sqft_lot)+(60,640×floors)−(-3173.25×yr_built)+(19,100×condition_coded)+(152,100×bathroom_density)+ 6,027,000

Model Performance

- R-squared: 55.8% of the variance in the price is explained by the independent variables included in the model.
- F-statistic: We have a high F-statistic of 3059 and a low F-statistic probability which suggests that the overall model is statistically significant.

v. Further Adressing the multicollineary using VIFs

```
from statsmodels.stats.outliers_influence import
variance_inflation_factor
from statsmodels.tools.tools import add_constant

# Add constant term to the independent variables
X_train_with_const = add_constant(X_train[['bedrooms', 'sqft_living',
'sqft_lot', 'floors', 'yr_built', 'condition_coded',
'bathroom_density']])

# Calculate VIFs for each independent variable
vif_data = pd.DataFrame()
vif_data["feature"] = X_train_with_const.columns
vif_data["VIF"] =
[variance_inflation_factor(X_train_with_const.values, i) for i in
range(X_train_with_const.shape[1])]

# Print VIFs
print(vif_data)
```

```
            feature          VIF
0             const  7142.086783
1          bedrooms     2.262858
2       sqft_living     2.281996
3          sqft_lot     1.042720
4            floors     1.532751
5          yr_built     1.625214
6   condition_coded     1.184428
7  bathroom_density     2.005565
```

Conclusion on multicollinearity

The VIF values for all independent features are below the commonly used threshold of 5. This means that there is low multicollinearity among the features. We will conclude based on this that our model is stable and reliable for house price prediction given our features.

E. Model Evaluation

```
# Previewing the first 5 rows
X_test.head()

       bedrooms  bathrooms  sqft_living  sqft_lot  floors  yr_built  \
2398          3       1.00          950      4500     1.0      1943
14724         2       1.00         1190      6200     1.0      1948
20980         4       3.00         5520      8313     2.0      2008
12156         3       2.00         1980     12150     1.0      1994
19485         2       1.75         1870      6625     1.0      1948

       condition_coded
2398                 4
14724                3
20980                3
12156                3
19485                3

## Aligning test data with training data
## Deleting the bathrooms column
# Adding the bathroom_density
X_test["bathroom_density"] = X_test["bathrooms"] / X_test["bedrooms"]
X_test.drop('bathrooms', axis=1, inplace=True)
X_test.head()

       bedrooms  sqft_living  sqft_lot  floors  yr_built
condition_coded  \
2398          3          950      4500     1.0      1943
4
14724         2         1190      6200     1.0      1948
3
20980         4         5520      8313     2.0      2008
3
12156         3         1980     12150     1.0      1994
3
19485         2         1870      6625     1.0      1948
3

       bathroom_density
2398           0.333333
14724          0.500000
20980          0.750000
12156          0.666667
19485          0.875000
```

```python
# Additional imports
from sklearn.metrics import mean_squared_error, r2_score

# Make predictions using the model with selected features as used above on our select features regression model
X_test_select = sm.add_constant(X_test[['sqft_living', 'bedrooms', 'bathroom_density', 'floors']])
y_pred_select = select_model.predict(X_test_select)

# Calculate the evaluation metrics for the model with selected features
# We will use MSE, RSME and R-squared to evaluate our model
mse_select_model = mean_squared_error(y_test, y_pred_select)
rmse_select_model = np.sqrt(mse_select_model)
r_squared_select_model = r2_score(y_test, y_pred_select)

# Print evaluation metrics for the model with selected features
print("Evaluation metrics for model with selected features:")
print("Mean Squared Error (MSE):", mse_select_model)
print("Root Mean Squared Error (RMSE):", rmse_select_model)
print("R-squared:", r_squared_select_model)
print()
```

```
Evaluation metrics for model with selected features:
Mean Squared Error (MSE): 63854708809.887505
Root Mean Squared Error (RMSE): 252694.89272616393
R-squared: 0.5219348196988434
```

Conclusion of the select features model

- The Mean Squared Error (MSE) indicates that, on average, the model's predictions are off by approximately USD 63,854,708,809.
- The Root Mean Squared Error (RMSE) suggests that, on average, the model's predictions are off by approximately USD 252,694.89.
- The R-squared value of ~0.5004 suggests that around 52.19% of the variance in the price is explained by the selected features.

```python
# Make predictions using the model with all features
X_test_c = sm.add_constant(X_test)  # Add constant term for intercept
y_pred_all = final_multiple_model.predict(X_test_c)

# Calculate evaluation metrics for the model with all features
mse_final_model = mean_squared_error(y_test, y_pred_all)
rmse_final_model = np.sqrt(mse_final_model)
r_squared_final_model = r2_score(y_test, y_pred_all)

# Print evaluation metrics for the model with all features
print("Evaluation metrics for model with all features:")
print("Mean Squared Error (MSE):", mse_final_model)
```

```
print("Root Mean Squared Error (RMSE):", rmse_final_model)
print("R-squared:", r_squared_final_model)
```

```
Evaluation metrics for model with all features:
Mean Squared Error (MSE): 58831328055.65425
Root Mean Squared Error (RMSE): 242551.7018197445
R-squared: 0.5595436894400523
```

Conclusion of all features model

Evaluation

- Mean Squared Error (MSE): Approximately USD 58,831,328,055
- Root Mean Squared Error (RMSE): Approximately USD 242,551.70
- R-squared: Approximately 0.60

Comparison of the select feature model

- The R-squared value is higher, meaning 55.6% of the variance in the price is explained by all the features.

Conclusion

- The model using all features provides better predictive performance compared to the model with selected features.

4. Results

- The size of the living area has a significant positive effect on the home price. For every additional square foot of living space, the price tends to increase by approximately $282.20 on average.

- The number of bedrooms in a property also positively impacts its price. Each additional bedroom contributes to an average increase of about $121,700 in the property price.

- The number of bathrooms in a property is positively correlated with its price. On average, each additional bathroom adds approximately $254,400 to the property price.

- The size of the lot (in square feet) has a relatively minor impact on the property price. For every unit increase in the square footage of the lot, the price tends to increase by about $0.82 on average.

- The number of floors in a property is also a significant factor in determining its price. On average, each additional floor contributes to an increase of around $176,400 in the property price.

- The age of the property (year built) has a relatively minor impact on its price. For every additional year since the property was built, the price tends to increase by approximately $600.43 on average.

- The coded condition of the property has a moderate effect on its price with the value of the house increasing by $24,330 on average if the condition of the house improves from one rating to another (e.g 1 to 2)
- We proceeded and found out that the bathroom was highly correlated to other independent variables ie: bedrooms,sqft_living, floors, and yr_built where the correlation was above 0.75 which is a high positive correlation.
- We created a new column representing the ratio of bathrooms to the number of bedrooms
- Because of this high multicollinearity effect of the bathroom we dropped it
- The multiple regression model with select features shows an MSE of approximately 63 billion, an RMSE of around 25k, and an R-squared value of approximately 0.52.
- The model with all features yields an MSE of roughly 58.8 billion, an RMSE of about 242,551, and a higher R-squared value of around 0.6.
- This suggests that the model with all features performs slightly better, meaning that including additional features improves the model's predictive accuracy.

5. Recommendations to Finsco Limited

1. Finsco Limited can advise its client to focus on increasing the size of the living room: Renovations that increase the square footage of living space have a significant impact on home value. For every additional square foot of living space added, the estimated home value can increase by approximately USD 320 to USD 322.
2. Upgrading bedrooms can also increase clients' home value. Investing in bedroom renovations, such as improving the layout, fixtures, colours and furnishing, could increase the value of the property by around USD 48,290 to USD 65,110 per bedroom, based on our regression results.
3. Improve Overall Condition will increase the value of the property. Renovations focused on improving the condition of the home, such as repairing structural issues, outside colouring, updating fixtures, and mowing may result in an estimated value increase of approximately USD 20,530, according to our analysis.
4. Bathroom is a minimum requirement for a house, from our model and correlation test, we found out that it is highly correlated to most of the other independent variables, implying it impacts the value of homes a lot. Assumption, improving the quality of the bathroom will increase the value of the home.
5. Overall, making renovations in the entire house to improve the house's overall condition will be better than doing partial renovations in the bathrooms, and bedrooms or increasing the living room space. Overall house improvements will have a better impact on the value of the property than just renovating part of the house

6. Next Steps

1. The Hepta team will gather feedback from the Finsco team after this first iteration and gather any additional requirements and feedback.
2. Market Research: Hepta group will conduct market research to identify trends and patterns in the real estate market such as renovations and, property features demands. This will help us make informed conclusions while we continue to improve on the model.
3. Data Enrichment: The Hepta group will also work with the Finsco team to ensure we have enough additional data on other features that might help us improve our model. This may include users' preferences, renovations past data and other features that might have property prices.
4. Model improvement: Our Data scientists will try other regression algorithms to compare and see if we can use a better model for this project.