PREDICTIVE ANALYSIS IN PROPERTY VALUATION.

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A)INTRODUCTION

In the dynamic landscape of real estate, the ability to provide clients with accurate and data-driven insights is crucial for success. Real estate agencies play a pivotal role in guiding homeowners through key decisions such as buying, selling, or renting properties. Some of the key decisions that real estate agencies assist homeowners with include:pricing strategies,Market trends and analysis and property inspections. The aim of this project is to empower real estate agencies with a powerful tool – a regression-based model – that can predict the potential increase in property value based on various features influenced by property characteristics such as number of bedrooms,year built,Number of floors in the home,Total living space area in square feet, Overall condition of the home and the location of the home. By leveraging this model, agencies can offer tailored advice to their clients, ensuring informed decisions that maximize the return on investment in the competitive real estate market.

B)BACKGROUND OF THE DATA

The housing market in King County, Washington, has a rich history and has experienced significant growth and changes over the years. King County is situated in the northwestern part of the United States and encompasses the city of Seattle, which is a major economic and cultural hub in the region. As the region's economy thrived, King County experienced substantial population growth. This influx of residents led to increased demand for housing, both in urban and suburban areas. Seattle, with its iconic skyline, became a sought-after destination for tech professionals and urban enthusiasts.The real estate market in King County is known for its competitiveness.The region's diverse neighborhoods offer a range of housing options, from historic homes in older districts to modern developments in suburban areas.

C)PROBLEM STATEMENT

What is the prevailing circumstance? In identifying the prevailing circumstance, real estate agencies wrestle with the ongoing challenge of delivering insightful guidance to clients regarding pricing strategies,Market trends and analysis and property inspections. Clients frequently seek advice on buying, selling, or renting properties. The complexity arises from the multitude of factors influencing property value, making it challenging to accurately quantify the best price for a particular property.

What problem are we trying to solve? The problem at hand revolves around the need for a comprehensive and precise solution to guide real estate agencies in offering informed recommendations to their clients. To tackle this challenge, this project is centered on the development of a regression-based approach, leveraging the King County House Sales dataset. Through this approach, the objective is to construct a robust predictive model that takes into account various features, including property size, condition, location, and more. This model is designed to empower real estate agencies in providing evidence-based insights, pinpointing the property features most likely to yield a substantial return on investment.

How the project aims to solve the problem? In essence, this project aims to equip real estate agencies with a valuable tool that goes beyond enhancing advisory capabilities—it positions them as trusted partners in their clients' real estate journeys. By developing and implementing the regression model, this project strives to optimize property value and contribute to the overall success of real estate agencies, solidifying their client-centric approach in the dynamic real estate landscape.

D) OBJECTIVES

Main Objective:

The main objective of this project is to develop a predictive regression model that assists real estate agencies in advising clients on house prices. The model aims to predict the potential variation in property value based on property characteristics, providing valuable insights to guide clients in making informed decisions about their investments.

Specific Objectives

i). Identify Key Factors Influencing House Prices in King County, California, to provide valuable insights for precise pricing strategies.

ii). Analyze Model Performance using metrics such as mean squared error, R-squared values, and residual analysis to gauge the model's effectiveness.

iii). Provide Actionable Recommendations to the Real Estate Agency for improving profitability and market presence, leveraging insights from the model.

E)NOTEBOOK STRUCTURE

1.Overview

2.Business Understanding

3.Data Understanding

4.Data Cleaning

5.Statistical Analysis

6.Data Preparation

7.Modelling

8.Regression Results

9.Conclusion - Recommendations,Limitations and Next Steps

1.OVERVIEW

This project is centered on the development of a multiple linear regression model with the primary objective of predicting property prices in the real estate market. The focal point of this analysis is the dependent variable, "price," while the independent variables encompass a comprehensive range of property characteristics. These characteristics include, but are not limited to, the number of bedrooms, year built, number of floors in the home, total living space area in square feet, overall condition of the home, and the geographical location of the property.

2.BUSINESS UNDERSTANDING

Stakeholders and Their Interests:

The key stakeholders impacted by this project are Real Estate Agencies. Their interest is accurate pricing and having a competitive advantage and the value they seek is Improved decision making and client satisfaction.

Success Criteria:

Establish measurable success criteria that align with the business objectives. For instance, success might be defined by the model's accuracy in predicting property prices within a certain margin.

```
# Importing necessary libraries for data analysis and visualization

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt  # for data visualization.
from pandas.api.types import is_numeric_dtype  # Used to check if a
data type is numeric.
%matplotlib inline
import seaborn as sns  # for enhanced data visualization.

from statsmodels.stats.outliers_influence import
variance_inflation_factor  # For calculating Variance Inflation Factor
(VIF).
from statsmodels.graphics.regressionplots import plot_partregress_grid
```

```
# For partial regression plots.
from sklearn.model_selection import train_test_split  # Used to split
data into training and testing sets.
from sklearn.feature_selection import RFE  # Recursive Feature
Elimination for feature selection.
from sklearn.preprocessing import StandardScaler  #
Standardizing/Scaling features.
from sklearn.preprocessing import PolynomialFeatures  # Generate
polynomial features.
from sklearn.linear_model import LinearRegression  # Linear Regression
model.
from sklearn.metrics import mean_squared_error, r2_score  # Evaluation
metrics for model performance.
import statsmodels.api as sm
from scipy.stats import kstest

 # Statsmodels is used to create statistical models.
from scipy import stats  # Scientific computing library for
statistical tests.
from scipy.stats import f_oneway  # One-way ANOVA statistical test.
from scipy.stats import ttest_ind  # Independent sample t-test for
comparing means.
import warnings  # handle warnings during code execution.
warnings.filterwarnings("ignore")  # Ignore warnings to improve code
readability.

#loading the dataset
Data= 'kc_house_data.csv'
# Load the CSV file into a Pandas DataFrame
kc_house_data = pd.read_csv(Data)
# Display the first few rows of the dataset to ensure it's loaded
correctly
kc_house_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]
```

3.DATA UNDERSTANDING

-The data utilized for this project has been sourced from Kaggle

Data Source:

The dataset used for this project is the King County House Sales dataset, which is available in the kc_house_data.csv file. The dataset contains information about house sales in King County, providing details such as property features, location, sale prices, and renovation-related variables.

Data Size:

The kc_house_dataset contains 21597 rows and 21 columns.The columns include :

Column Names and Descriptions for King County Data Set

- `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 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.
- `grade` - Overall grade of the house. Related to the construction and design of the house.
- `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

Data Types:

The data types include categorical and numerical variables.Columns with categorical variables include,date,waterfront,view,condition,grade and sqft_basementwhile columns with numerical variables include id,price,bedrooms,bathrooms,sqft_living,sqft_lot,floors,yr_built,yr_renovated,zipcode,lat,long,sqft_above,sqft_living15 and sqft_lot15.

a)Determining the number of records

```
num_records = kc_house_data.shape
print("Number of records:", num_records)
```

```
Number of records: (21597, 21)
```

- The data contains 21597 rows and 21 columns

b)Preview top and bottom of our dataset

```
# Preview the top of the dataset
top_rows = kc_house_data.head()
top_rows
```

```
           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]
```

```
# Preview the bottom of the dataset
bottom_rows = kc_house_data.tail()
bottom_rows
```

```
                id        date     price  bedrooms  bathrooms
sqft_living  \
21592   263000018   5/21/2014  360000.0         3       2.50
1530
21593  6600060120   2/23/2015  400000.0         4       2.50
2310
21594  1523300141   6/23/2014  402101.0         2       0.75
1020
21595   291310100   1/16/2015  400000.0         3       2.50
1600
21596  1523300157  10/15/2014  325000.0         2       0.75
1020

       sqft_lot  floors waterfront  view  ...      grade sqft_above  \
21592      1131     3.0         NO  NONE  ...     8 Good       1530
21593      5813     2.0         NO  NONE  ...     8 Good       2310
21594      1350     2.0         NO  NONE  ...  7 Average       1020
21595      2388     2.0        NaN  NONE  ...     8 Good       1600
21596      1076     2.0         NO  NONE  ...  7 Average       1020

       sqft_basement yr_built  yr_renovated  zipcode      lat     long
\
21592            0.0     2009           0.0    98103  47.6993 -122.346

21593            0.0     2014           0.0    98146  47.5107 -122.362

21594            0.0     2009           0.0    98144  47.5944 -122.299

21595            0.0     2004           0.0    98027  47.5345 -122.069

21596            0.0     2008           0.0    98144  47.5941 -122.299


       sqft_living15  sqft_lot15
21592           1530        1509
21593           1830        7200
21594           1020        2007
21595           1410        1287
21596           1020        1357

[5 rows x 21 columns]
```

c).Checking data types in various columns

- This involves checking whether the columns have appropriate data types

```
data_types = kc_house_data.dtypes
print(f"Data types of each column:\n{data_types}")
```

```
Data types of each column:
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
```

-The columns have three data types:

- Integers which include id,bedrooms,sqft_living,sqft_lot,sqft_above,yr built,zipcode,sqft living15,sqft lot15
- Float data types include price,bathrooms,floors,year renovated,latitudes and longitudes
- Object data type include the columns date,waterfront,view,condition,grade and sqft basement.

d)Descriptive statistics

```
kc_house_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
```

e)Summary of our dataframe

```
kc_house_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
```

4.DATA PRE-PROCESSING

Data cleaning and preparation involves addressing issues related to the quality of the dataset. It aims to ensure that the data is accurate, consistent, and free from errors. Here are some data cleaning and preparation methods we engaged in:

Handling Missing Values:

Missing values were identified and addressed depending on the type of column whether categorical or numerical. Options included removal of rows or columns with missing values, or treating missing values as a separate category.

Handling Duplicates:

Any duplicate records in the dataset were identified and addressed to avoid redundancy and potential bias in the analysis especially in the id column since it's a unique identifier.

Dealing with placeholders:

Investigation and rectification of any placeholders in the data that may affect the accuracy of the model was done.

Transforming data: Feature engineering and ordinal encoding on the data was performed.

Handling Outliers: Outliers could skew statistical analysis. Methods like trimming have been employed to address extreme values that could distort insights into housing prices attributes.

a)Handling Missing Values

The columns waterfront,view and the year renovated contain missing values which need to be addressed.

```
#checking for missing values
kc_house_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
```

i)Handling missing values in categorical columns

The categorical columns are waterfront which contains 2376 missing values and view which contains 63 missing values .

```
# Create a new dataframe of the raw data to clean
Cleaned_Data = kc_house_data.copy()

# Change waterfront missing value to NO, then to binary values.
Cleaned_Data.loc[kc_house_data.waterfront.isnull(), 'waterfront'] =
'NO'
Cleaned_Data['waterfront'] = Cleaned_Data['waterfront'].apply(lambda
x: 0 if x == 'NO' else 1)
```

```
# Change view missing value to NONE, then to numerical ordered values.
Cleaned_Data.loc[kc_house_data.view.isnull(), 'view'] = "NONE"
view_dict = {'NONE':0, 'FAIR':1, 'AVERAGE':2, 'GOOD':3, 'EXCELLENT':4}
Cleaned_Data['view'].replace(view_dict, inplace=True)
```

JUSTIFICATION

Handling 'waterfront' missing values:

Replace missing values in 'waterfront' with 'NO' since the missing values indicate that the property does not have a waterfront. Applied a binary encoding, converting 'NO' to 0 and other values (potentially 'YES') to 1 since the presence or absence of a waterfront is a significant predictor.

Handling 'view' Missing Values:

Replace missing values in 'view' with 'NONE' since the missing values imply that the property has no specific view. Replace categorical values in 'view' with numerical values .It helps capture the ordinal nature of the 'view' categories in predictive models.

ii)Handling missing values in numerical columns

The numerical column is the year renovated with 3842 missing values .

```
# Change yr_renovated missing values to 0 and add renovated column
Cleaned_Data.loc[kc_house_data.yr_renovated.isnull(), 'yr_renovated']
= 0
Cleaned_Data['renovated'] = Cleaned_Data['yr_renovated'].apply(lambda
x: 0 if x == 0 else 1)
```

JUSTIFICATION

Handling 'yr_renovated' Missing Values:

Impute missing values in 'yr_renovated' with 0 since the missing value indicates that the property has not been renovated. Create a new binary column 'renovated' based on the values in the 'yr_renovated' column. If 'yr_renovated' is 0, the 'renovated' column is set to 0; otherwise, it is set to 1.

b)Dealing with duplicates

The id column which is a unique identifier for a house was checked for duplicates.

```
# checking for duplicates using the id column
duplicates = kc_house_data[kc_house_data.duplicated(
subset = "id")]
duplicates.head()
```

```
             id        date      price  bedrooms  bathrooms
sqft_living  \
94   6021501535  12/23/2014   700000.0         3       1.50
```

```
1580
314  4139480200   12/9/2014  1400000.0         4       3.25
4290
325  7520000520   3/11/2015   240500.0         2       1.00
1240
346  3969300030  12/29/2014   239900.0         4       1.00
1000
372  2231500030   3/24/2015   530000.0         4       2.25
2180

     sqft_lot  floors waterfront  view  ...          grade sqft_above
\
94       5000     1.0         NO  NONE  ...         8 Good       1290

314     12103     1.0         NO  GOOD  ...   11 Excellent       2690

325     12092     1.0         NO  NONE  ...  6 Low Average        960

346      7134     1.0         NO  NONE  ...  6 Low Average       1000

372     10754     1.0         NO  NONE  ...      7 Average       1100


     sqft_basement yr_built  yr_renovated  zipcode      lat
long  \
94           290.0     1939           0.0    98117  47.6870 -122.386

314         1600.0     1997           0.0    98006  47.5503 -122.102

325          280.0     1922        1984.0    98146  47.4957 -122.352

346            0.0     1943           NaN    98178  47.4897 -122.240

372         1080.0     1954           0.0    98133  47.7711 -122.341


     sqft_living15  sqft_lot15
94            1570        4500
314           3860       11244
325           1820        7460
346           1020        7138
372           1810        6929

[5 rows x 21 columns]
```

```
duplicates.shape
```

```
(177, 21)
```

```
# dropping the duplicated data
Cleaned_Data.drop_duplicates(subset="id", keep="first", inplace=True)
```

JUSTIFICATION

The 'id' column is a unique identifier for each property.Duplicate entries can introduce inconsistencies and bias in data analysis and modeling. Removing duplicates leads to a more accurate representation of the dataset.

c)Dealing with placeholders

The sqft_basement column contained a large number of placeholders which had to be addressed.

```
# Add has_basement column that is a binary value.
Cleaned_Data['sqft_basement'] =
Cleaned_Data['sqft_basement'].replace('?', '0').astype('float')
Cleaned_Data['basement'] = Cleaned_Data['sqft_basement'].apply(lambda
x: 0 if x == 0 else 1)
```

JUSTIFICATION

The use of '?' as a placeholder in the 'sqft_basement' column indicates missing or unknown values.The imputation and binary encoding provide consistency in handling missing or placeholder values. The resulting 'basement' column enhances the interpretability of the dataset.

d)Transforming data

```
# Change to datetime and add month column
Cleaned_Data['date'] = pd.to_datetime(Cleaned_Data['date'])
Cleaned_Data['month'] = pd.DatetimeIndex(Cleaned_Data['date']).month

# Change condition to numerical ordered values.
cond_dict = {'Poor':0, 'Fair':1, 'Average':2, 'Good':3, 'Very Good':4}
Cleaned_Data['condition'].replace(cond_dict, inplace=True)

# Change grade to numerical ordered values.
Cleaned_Data['grade'] = Cleaned_Data['grade'].map(lambda x:
int(x.split(' ')[0]))

# Add house_age column
Cleaned_Data['age'] = Cleaned_Data['date'].dt.year -
Cleaned_Data['yr_built']

Cleaned_Data

                   id       date     price  bedrooms  bathrooms
sqft_living  \
0      7129300520 2014-10-13  221900.0         3       1.00
1180
1      6414100192 2014-12-09  538000.0         3       2.25
2570
```

```
2      5631500400 2015-02-25  180000.0         2       1.00
770
3      2487200875 2014-12-09  604000.0         4       3.00
1960
4      1954400510 2015-02-18  510000.0         3       2.00
1680
...           ...        ...       ...       ...        ...           .
..
21592   263000018 2014-05-21  360000.0         3       2.50
1530
21593  6600060120 2015-02-23  400000.0         4       2.50
2310
21594  1523300141 2014-06-23  402101.0         2       0.75
1020
21595   291310100 2015-01-16  400000.0         3       2.50
1600
21596  1523300157 2014-10-15  325000.0         2       0.75
1020

       sqft_lot  floors  waterfront  view  ...  yr_renovated  zipcode
\
0          5650     1.0           0     0  ...           0.0    98178

1          7242     2.0           0     0  ...        1991.0    98125

2         10000     1.0           0     0  ...           0.0    98028

3          5000     1.0           0     0  ...           0.0    98136

4          8080     1.0           0     0  ...           0.0    98074

...         ...     ...         ...   ...  ...           ...      ...

21592      1131     3.0           0     0  ...           0.0    98103

21593      5813     2.0           0     0  ...           0.0    98146

21594      1350     2.0           0     0  ...           0.0    98144

21595      2388     2.0           0     0  ...           0.0    98027

21596      1076     2.0           0     0  ...           0.0    98144


           lat     long  sqft_living15  sqft_lot15  renovated
basement  \
0      47.5112 -122.257           1340        5650          0
0
1      47.7210 -122.319           1690        7639          1
1
```

```
2      47.7379 -122.233          2720        8062          0
0
3      47.5208 -122.393          1360        5000          0
1
4      47.6168 -122.045          1800        7503          0
0
...        ...      ...           ...         ...        ...       ..
.
21592  47.6993 -122.346          1530        1509          0
0
21593  47.5107 -122.362          1830        7200          0
0
21594  47.5944 -122.299          1020        2007          0
0
21595  47.5345 -122.069          1410        1287          0
0
21596  47.5941 -122.299          1020        1357          0
0

       month  age
0         10   59
1         12   63
2          2   82
3         12   49
4          2   28
...      ...  ...
21592      5    5
21593      2    1
21594      6    5
21595      1   11
21596     10    6

[21420 rows x 25 columns]
```

JUSTIFICATION

1.Handling the 'date' column

Convert the 'date' column to datetime format ensures that the data type is consistent and allows for convenient handling of date-related operations.

2.Handling the 'condition' column

Replace categorical values in the 'condition' column with numerical ordered values facilitates a consistent representation and captures the ordinal nature of condition ratings.

3.Handling 'grade' Column:

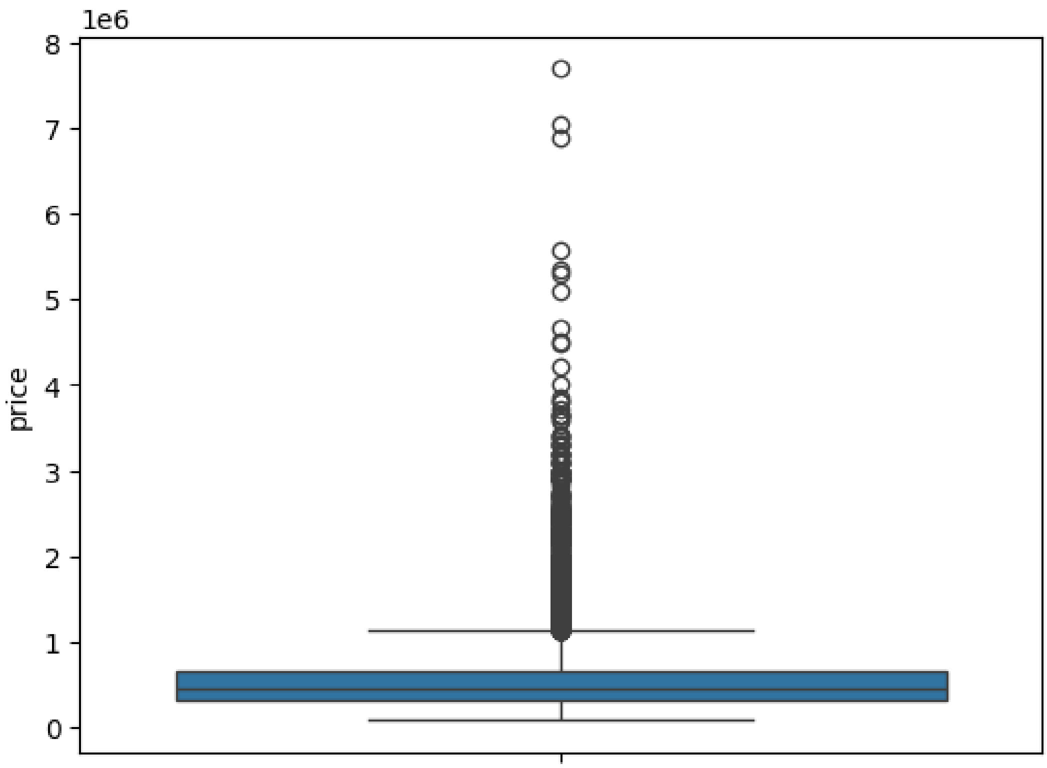
Parsing the 'grade' column to extract the numerical part and converting it to an integer ensures a consistent numerical representation.

4.Adding 'house_age' Column:

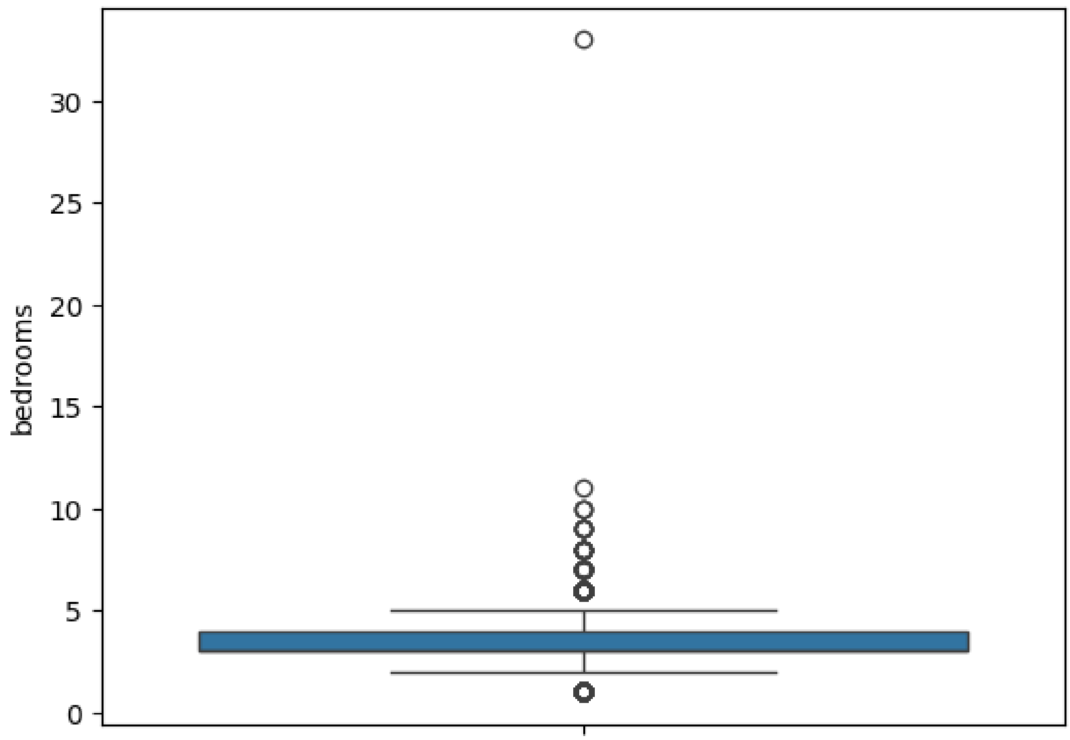
Creating a new 'age' column by subtracting the year built from the year of sale provides valuable information about the age of each property at the time of sale.

e)Handling outliers

```
#PRICE
# Let's look at the price
sns.boxplot(Cleaned_Data['price']);
```




```
# Filtering out outliers of price in the data
clean_data = Cleaned_Data[(Cleaned_Data.price <
Cleaned_Data.price.quantile(.995))
                        & (Cleaned_Data.price >
Cleaned_Data.price.quantile(.005))]

#BEDROOM
# Let's look at the bedrooms
sns.boxplot(Cleaned_Data['bedrooms'])

<Axes: ylabel='bedrooms'>
```




```
# the outlier in bedrooms column change to 3 bedrooms, likely due to a typographic error
Cleaned_Data.loc[(Cleaned_Data.bedrooms == 33), 'bedrooms'] = 3
```

JUSTIFICATION

Outliers can influence the parameters of statistical models, leading to biased results. Addressing outliers present in the model for the 'price' column filtering them out on the basis of the interquartile range which helps prevent the model from being overly influenced by extreme values, leading to more accurate and robust predictions.For the outlier in bedrooms column change to 3 bedrooms, likely due to a typographic error.

5.STATISTICAL ANALYSIS

Statistical analysis is a critical component of understanding relationships within the dataset, identifying patterns, and gaining insights. In the context of a regression modeling project for predicting property value based on home renovations, here are the key steps in statistical analysis:

a)Descriptive Statistics:

- Understanding the basic characteristics of the dataset.
- **Tasks:** -Summary statistics such as mean, median, standard deviation, and quartiles for numeric variables were computed.

```
Cleaned_Data.describe()
```

```
                 id                           date         price  \
count  2.142000e+04                          21420  2.142000e+04
mean   4.580940e+09  2014-10-28 05:03:51.932773120  5.407393e+05
min    1.000102e+06            2014-05-02 00:00:00  7.800000e+04
25%    2.123537e+09            2014-07-21 00:00:00  3.225000e+05
50%    3.904921e+09            2014-10-15 00:00:00  4.500000e+05
75%    7.308900e+09            2015-02-13 00:00:00  6.450000e+05
max    9.900000e+09            2015-05-27 00:00:00  7.700000e+06
std    2.876761e+09                            NaN  3.679311e+05

           bedrooms     bathrooms   sqft_living      sqft_lot
floors  \
count  21420.000000  21420.000000  21420.000000  2.142000e+04
21420.000000
mean       3.372549      2.118429   2083.132633  1.512804e+04
1.495985
min        1.000000      0.500000    370.000000  5.200000e+02
1.000000
25%        3.000000      1.750000   1430.000000  5.040000e+03
1.000000
50%        3.000000      2.250000   1920.000000  7.614000e+03
1.500000
75%        4.000000      2.500000   2550.000000  1.069050e+04
2.000000
max       11.000000      8.000000  13540.000000  1.651359e+06
3.500000
std        0.902995      0.768720    918.808412  4.153080e+04
0.540081

         waterfront          view  ...  yr_renovated      zipcode  \
count  21420.000000  21420.000000  ...  21420.000000  21420.00000
mean       0.006816      0.233987  ...     68.956723  98077.87437
min        0.000000      0.000000  ...      0.000000  98001.00000
25%        0.000000      0.000000  ...      0.000000  98033.00000
50%        0.000000      0.000000  ...      0.000000  98065.00000
75%        0.000000      0.000000  ...      0.000000  98117.00000
max        1.000000      4.000000  ...   2015.000000  98199.00000
std        0.082280      0.765437  ...    364.552298     53.47748

                lat          long  sqft_living15     sqft_lot15
renovated  \
count  21420.000000  21420.000000   21420.000000   21420.000000
21420.000000
mean      47.560197   -122.213784    1988.384080   12775.718161
0.034547
min       47.155900   -122.519000     399.000000     651.000000
0.000000
25%       47.471200   -122.328000    1490.000000    5100.000000
0.000000
50%       47.572100   -122.230000    1840.000000    7620.000000
```

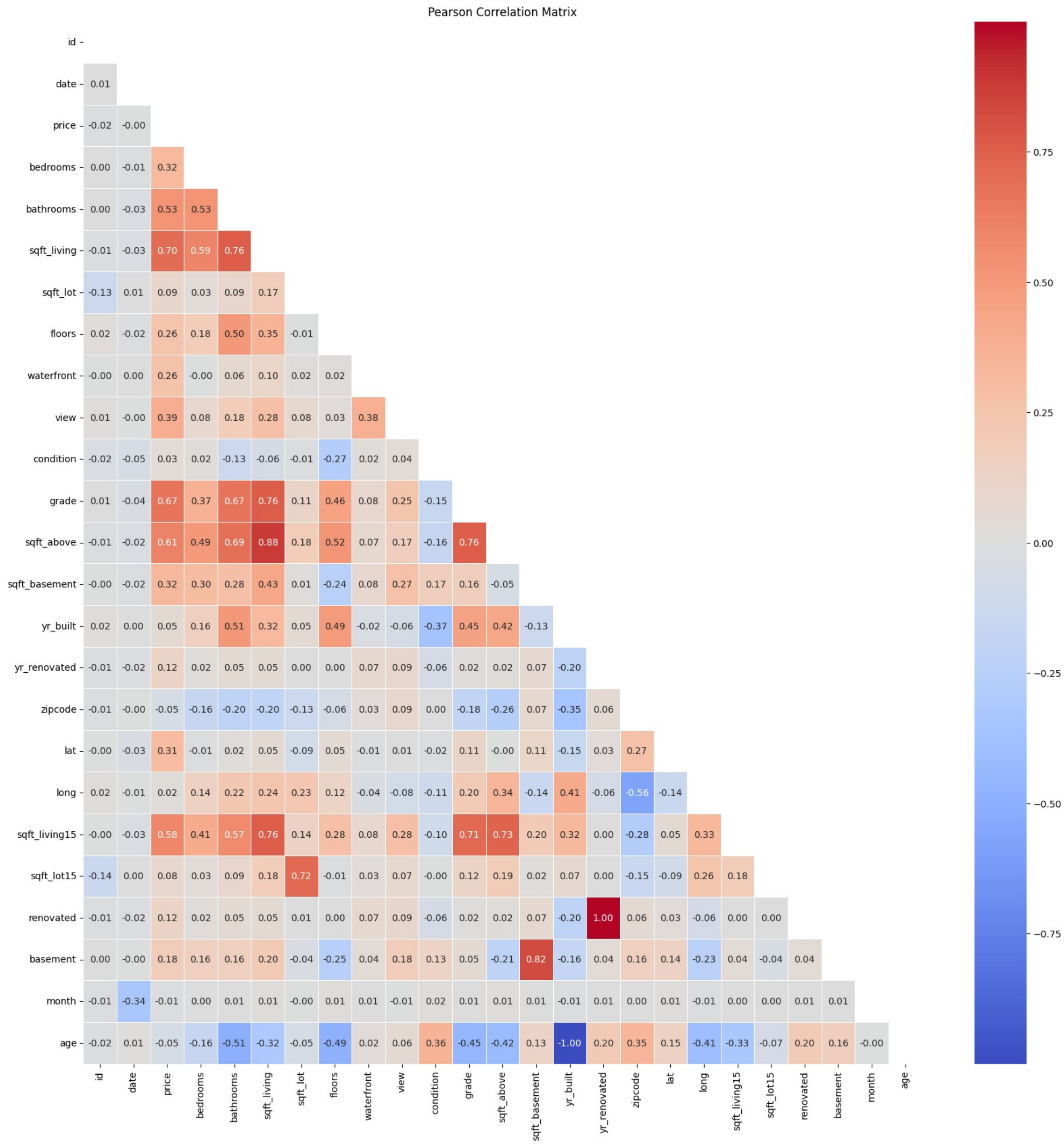
```
0.000000
75%        47.678100   -122.125000    2370.000000   10086.250000
0.000000
max        47.777600   -121.315000    6210.000000  871200.000000
1.000000
std         0.138589       0.140791     685.537057   27345.621867
0.182634

           basement         month           age
count  21420.000000  21420.000000  21420.000000
mean       0.385201      6.590336     43.225957
min        0.000000      1.000000     -1.000000
25%        0.000000      4.000000     17.000000
50%        0.000000      6.000000     39.000000
75%        1.000000      9.000000     63.000000
max        1.000000     12.000000    115.000000
std        0.486654      3.107924     29.387207

[8 rows x 25 columns]
```

b)Correlation Analysis:

- Exploring relationships between variables.
- **Tasks:**
  - Calculate correlation coefficients (e.g., Pearson, Spearman) to assess the strength and direction of linear relationships.
  - Visualize correlations using correlation matrices .

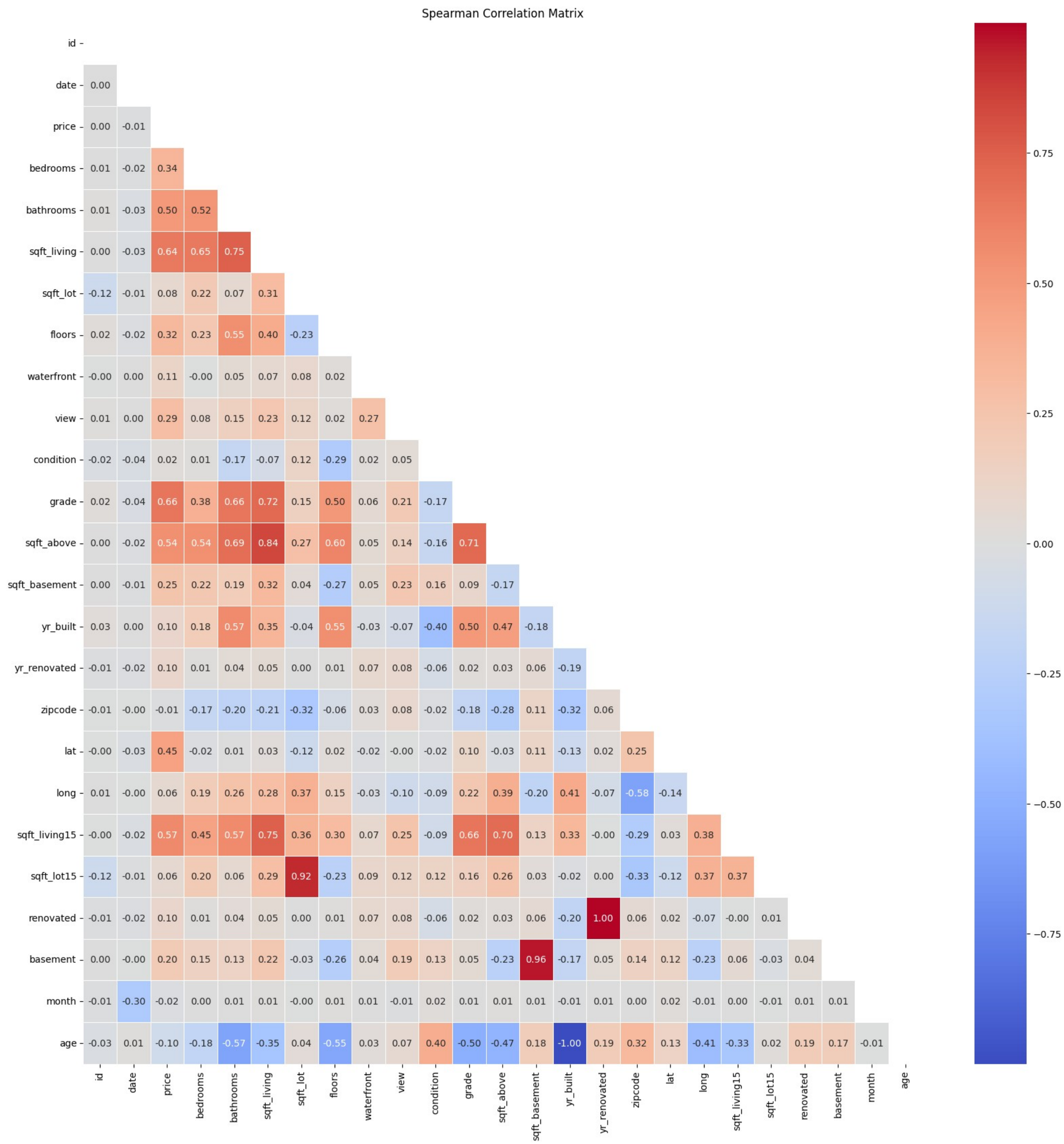
i)Pearson and Spearman Correlation Coefficient

```python
# Calculate the Pearson correlation matrix
pearson_corr_matrix = Cleaned_Data.corr(method='pearson')

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(pearson_corr_matrix, dtype=bool))

# Set up the matplotlib figure
plt.figure(figsize=(20, 20))

# Create a heatmap using seaborn with the mask
sns.heatmap(pearson_corr_matrix, annot=True, cmap='coolwarm',
fmt='.2f', linewidths=0.5, mask=mask)

# Add a title
plt.title('Pearson Correlation Matrix')

# Show the plot
plt.show()
```




```python
# Calculate the Spearman correlation matrix
spearman_corr_matrix = Cleaned_Data.corr(method='spearman')

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(spearman_corr_matrix, dtype=bool))

# Set up the matplotlib figure
plt.figure(figsize=(20, 20))
```

```python
# Create a heatmap using seaborn with the mask
sns.heatmap(spearman_corr_matrix, annot=True, cmap='coolwarm',
fmt='.2f', linewidths=0.5, mask=mask)

# Add a title
plt.title('Spearman Correlation Matrix')

# Show the plot
plt.show()
```



FINDINGS

The Pearson correlation matrix assesses linear relationships, while the Spearman correlation matrix assesses monotonic relationships (including both linear and non-linear monotonic relationships).

Pearsons

-The Pearson correlation coefficient between 'Square Foot Living' and 'Grade' is 0.88, indicating a strong and positive linear relationship. As the size of the living area increases, the grade assigned to the property tends to increase as well.

-The Pearson correlation coefficient between 'Year Built' and 'Age' is -1.00, indicating a perfect negative linear relationship. This means that as the year a property was built increases, its age decreases in a perfect linear fashion.

-The Pearson correlation coefficient between 'Renovated' and the number of 'Floors' is 0.00, suggesting no significant linear relationship between the renovation status and the number of floors. The correlation is close to zero, indicating that the presence or absence of renovation does not show a clear linear trend with the number of floors.

Spearmans

-The Spearman correlation coefficient between 'Sqft Above' and 'Sqft Living' is 0.84, indicating a strong and positive monotonic relationship. This suggests that as the square footage above ground increases, the overall square footage of the living space tends to increase in a consistently positive manner.

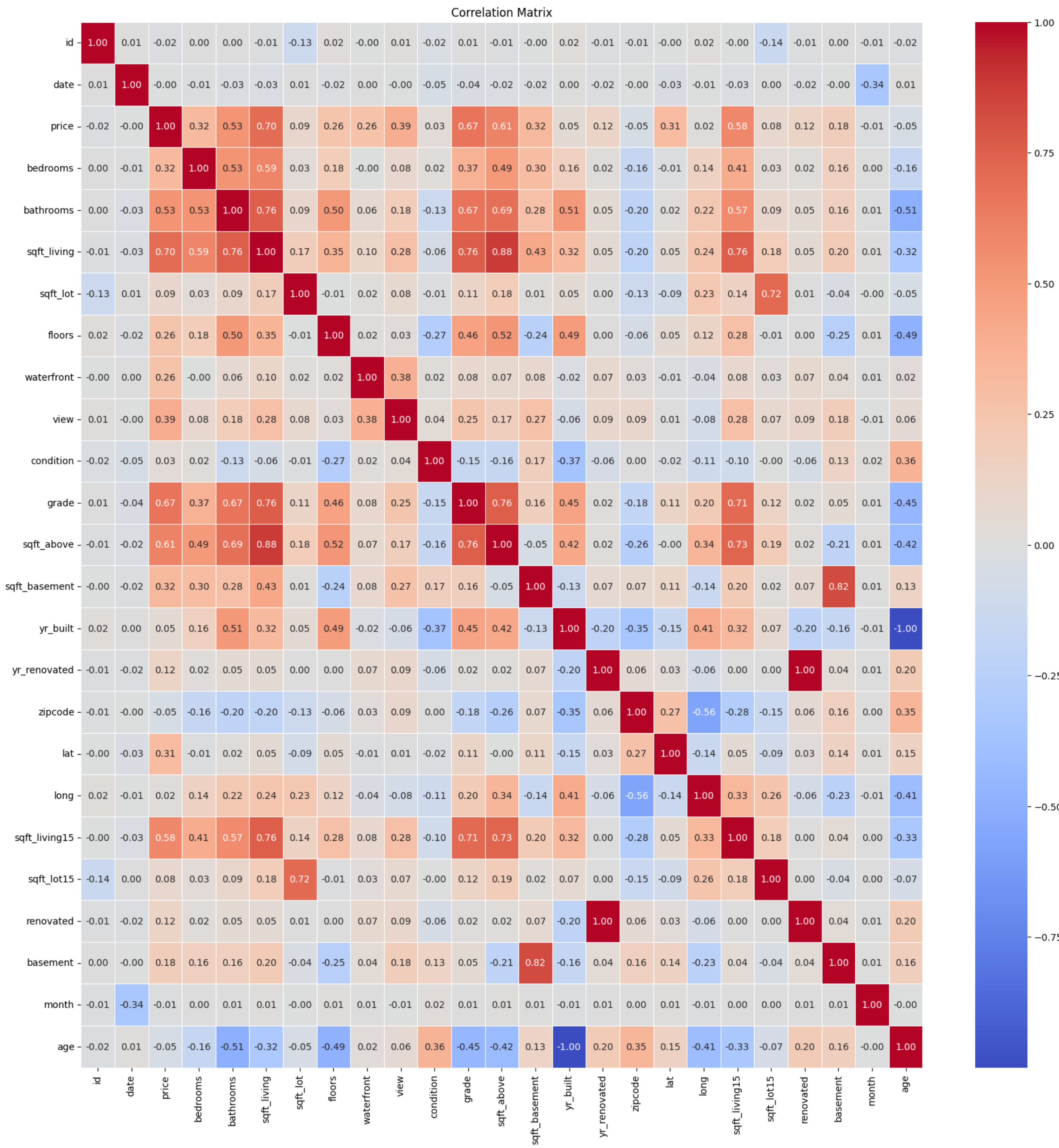
-The Spearman correlation coefficient between 'Bathrooms' and 'Age' is -0.57, revealing a moderate negative monotonic relationship. This implies that, on average, properties with a higher number of bathrooms tend to be relatively younger in age.

-The Spearman correlation coefficient between 'Month' and 'Zipcode' is 0.00, indicating no significant monotonic relationship between the month of sale and the property's zipcode. The correlation is close to zero, suggesting that the month of sale and the zipcode do not exhibit a clear monotonic trend.

ii)Correlation matrix

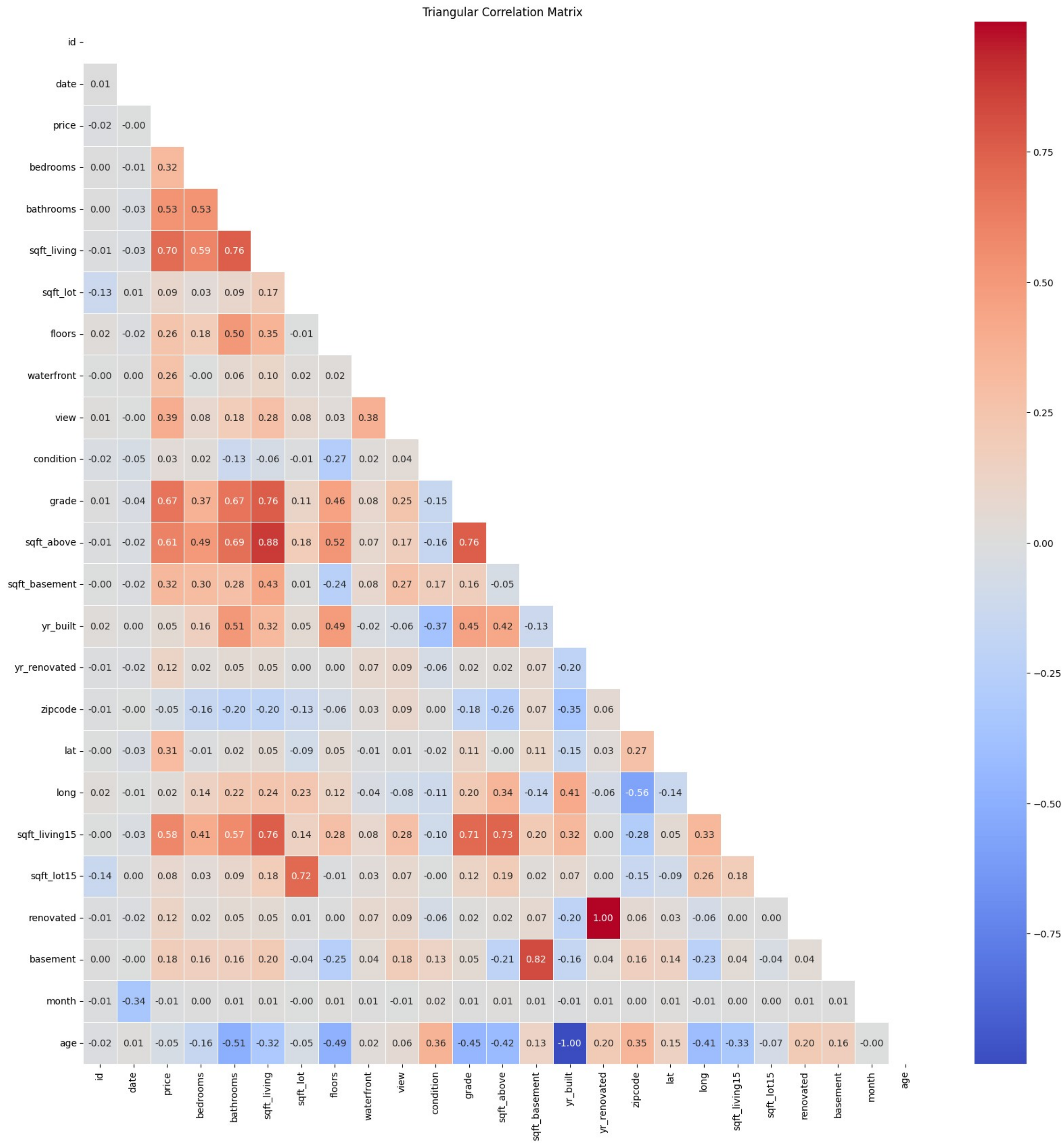
```
correlation_matrix = Cleaned_Data.corr()

# Set up the matplotlib figure
plt.figure(figsize=(20,20))

# Create a heatmap using seaborn
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt='.2f', linewidths=0.5)

# Add a title
plt.title('Correlation Matrix')
```

```python
# Show the plot
plt.show()
```




```python
# Calculate the correlation matrix
correlation_matrix = Cleaned_Data.corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(correlation_matrix, dtype=bool))
```

```
# Set up the matplotlib figure
plt.figure(figsize=(20, 20))

# Create a heatmap using seaborn with the mask
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt='.2f', linewidths=0.5, mask=mask)

# Add a title
plt.title('Triangular Correlation Matrix')

# Show the plot
plt.show()
```



FINDINGS

-The correlation coefficient between 'Renovated' and 'Year Renovated' is 1.00, indicating a perfect positive correlation. This means that the two variables move in perfect sync — as the 'Renovated' status changes, the year of renovation also changes in a strong positive linear manner.

-The correlation coefficient between 'Age' and 'Year Built' is -1.00, revealing a perfect negative correlation. This implies that as the 'Year Built' increases, indicating newer properties, the 'Age' of the property decreases in a perfect negative linear manner.

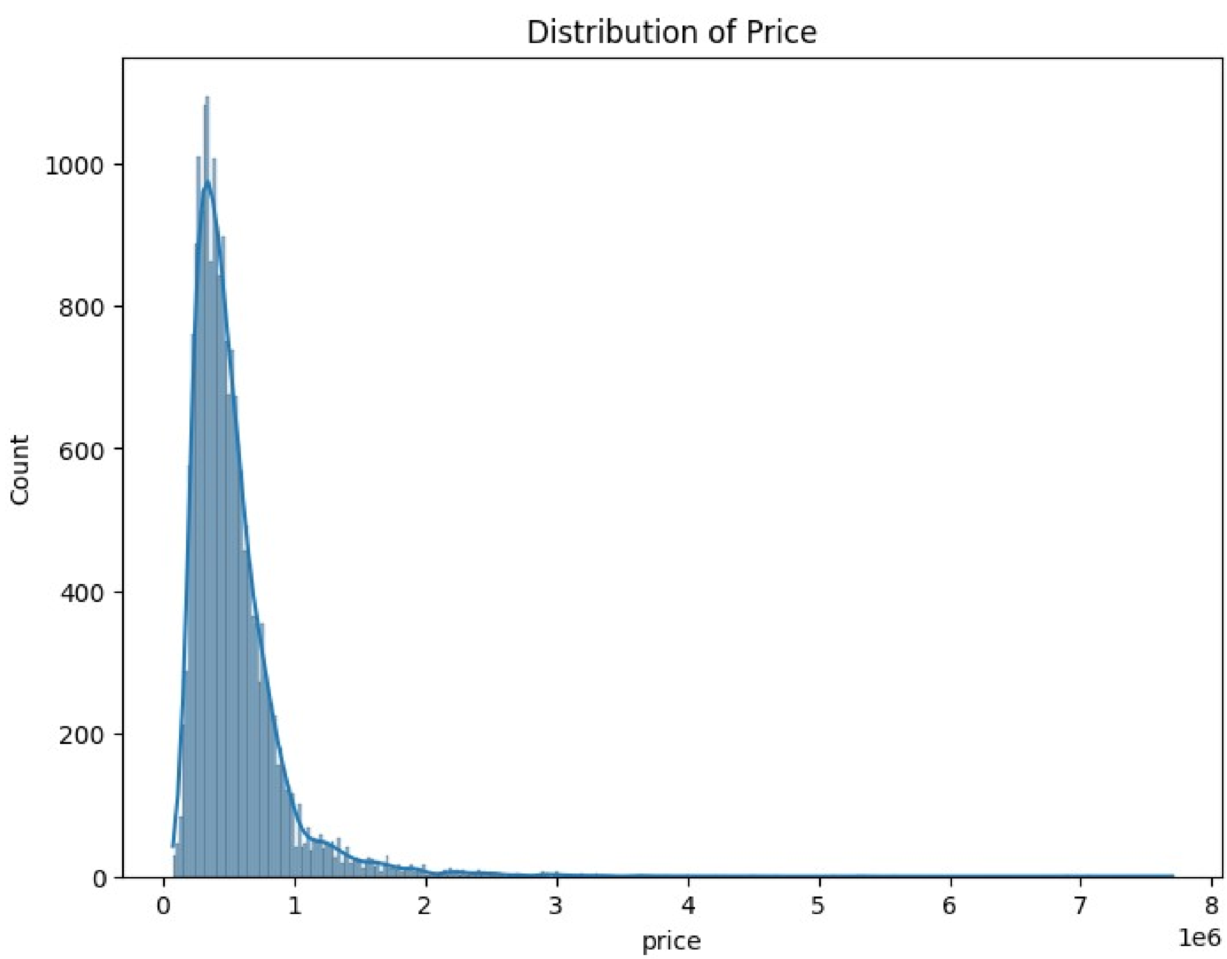
-The Pearson correlation coefficient between 'Zipcode' and 'Condition' is 0.00, indicating no significant linear correlation between these two variables. The correlation is close to zero, suggesting that variations in 'Zipcode' are not systematically related to variations in 'Condition.

c)Distribution Analysis:

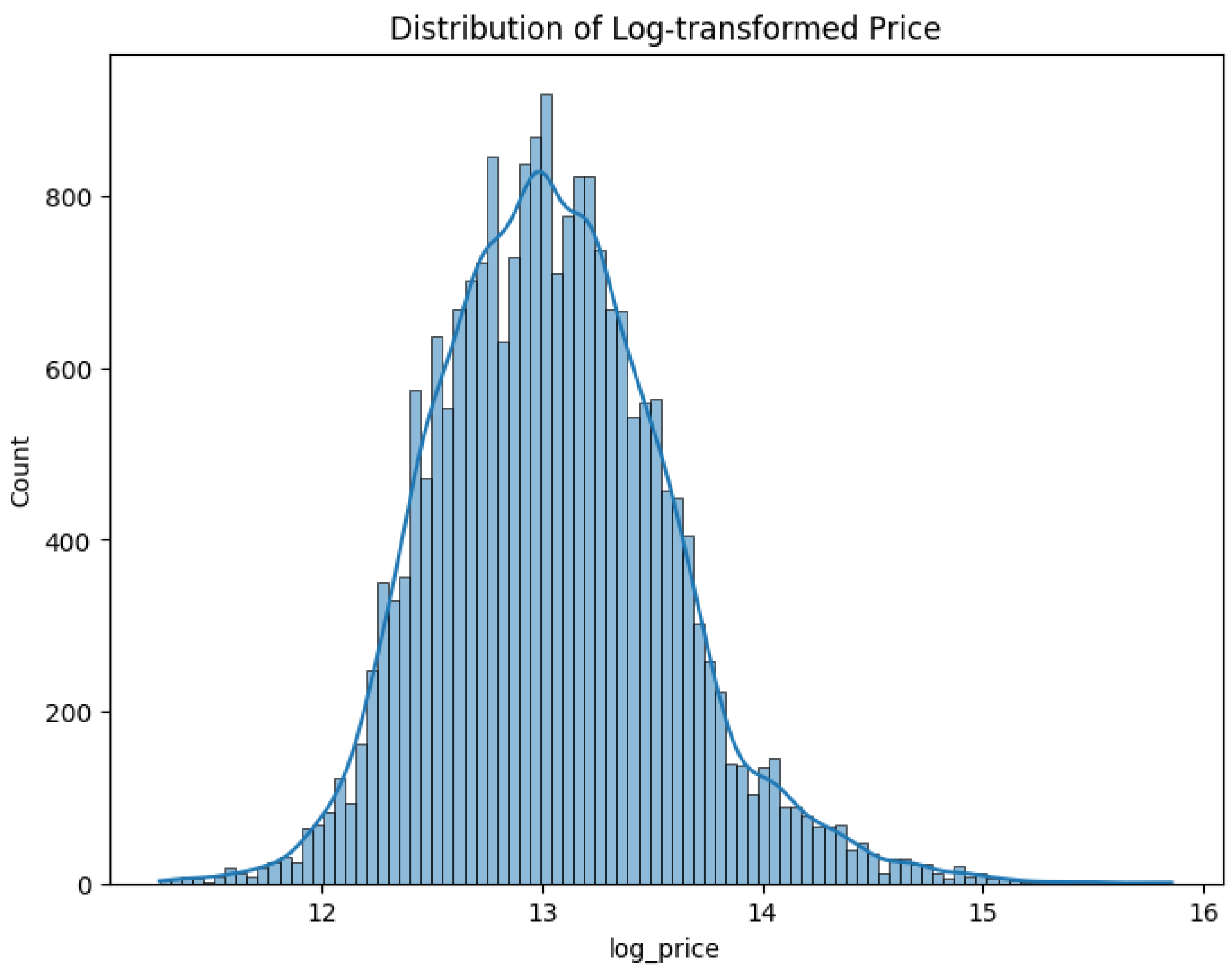
- Examining the distributions of key variables.
- **Tasks:**
  - Check the distribution of the target variable ('price') and predictor variables.
  - Identify and address skewed distributions if needed.

i)Target Variable-Price

```
# Distribution of the target variable
plt.figure(figsize=(8, 6))
sns.histplot(data=kc_house_data, x='price', kde=True)
plt.title("Distribution of Price")
plt.show()
```



```
# Apply log transformation to the 'price' column
kc_house_data['log_price'] = np.log1p(kc_house_data['price'])

# Plot the distribution of the log-transformed price
plt.figure(figsize=(8, 6))
sns.histplot(data=kc_house_data, x='log_price', kde=True)
plt.title("Distribution of Log-transformed Price")
plt.show()
```



JUSTIFICATION

-The price column is positively skewed .Log transformation was applied to normalise the price column bring extreme values closer to the center, allowing for a more normalized distribution.

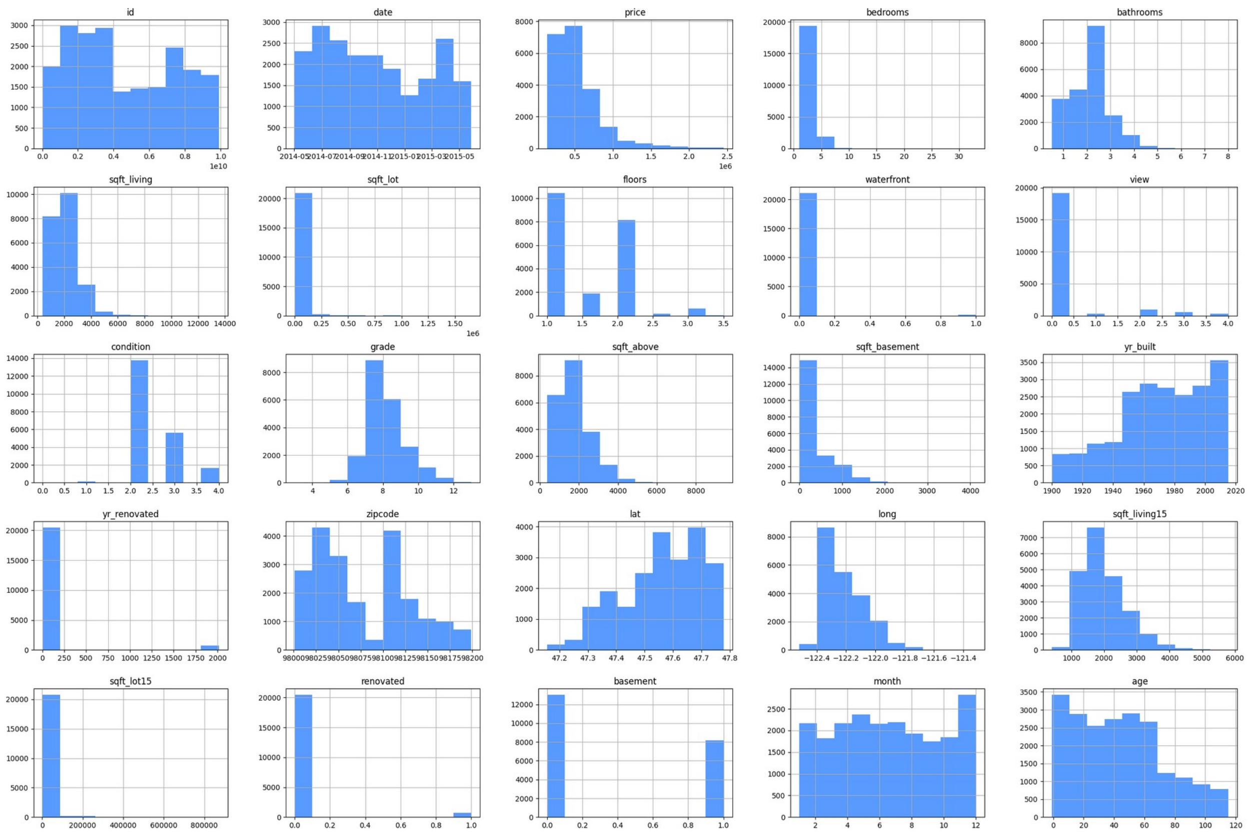
ii)Checking the distribution of other variables

a) Relationship between Predictor Variables

```
variables =
['price' ,'bedrooms' ,'bathrooms','sqft_living','floors','condition','
grade','sqft_above','sqft_basement','yr_built','lat','long','sqft_livi
ng15','renovated',
'basement','age']

for variable in variables:
    data = Cleaned_Data[variable]

    statistic, p_value = kstest(data, 'norm')

    alpha = 0.05  # significance level

    if p_value > alpha:
        print(f"The distribution of '{variable}' appears to be
normally distributed (fail to reject H0)")
    else:
        print(f"The distribution of '{variable}' does not appear to be
normally distributed (reject H0)")
```

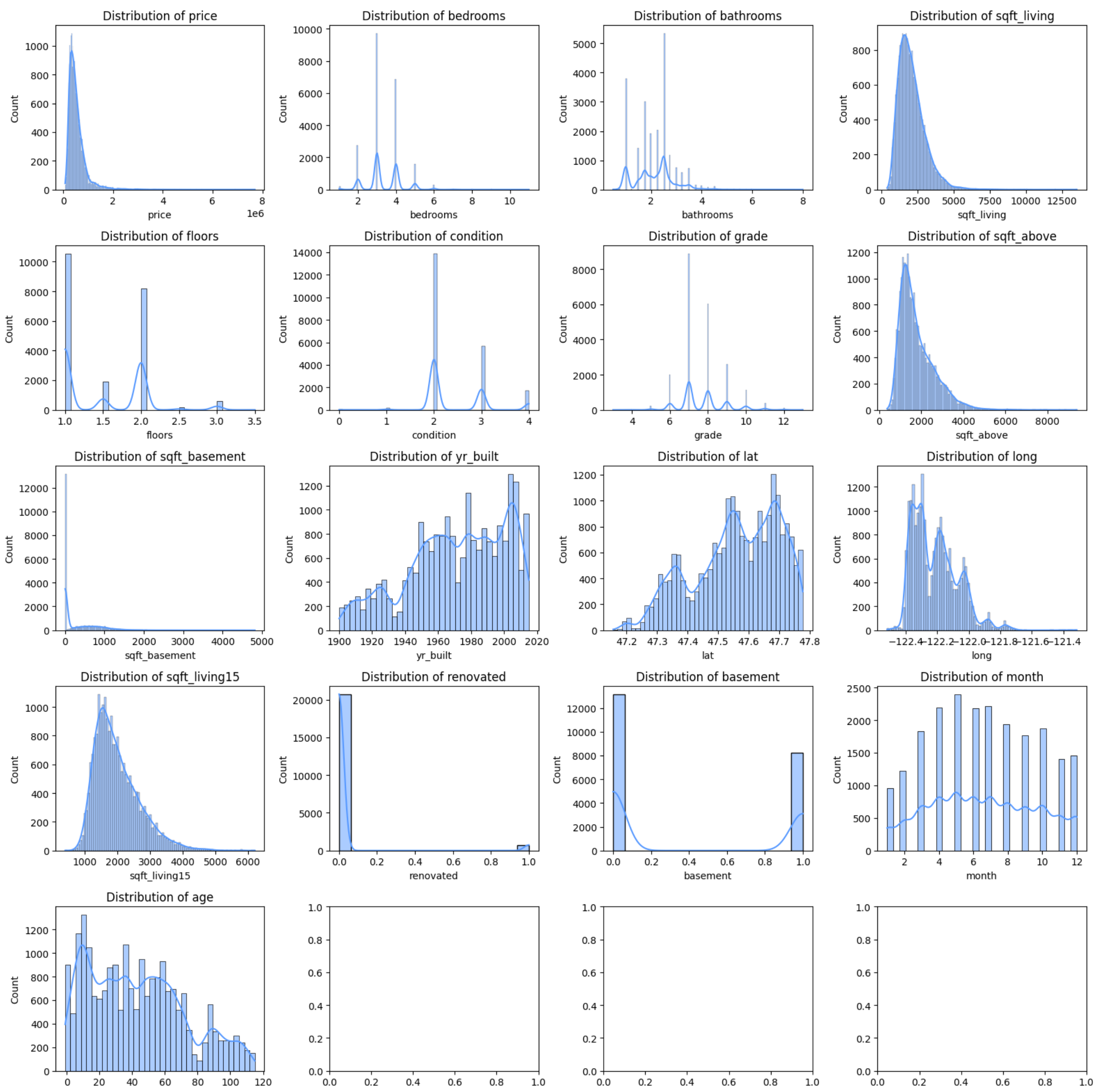
```
The distribution of 'price' does not appear to be normally distributed
(reject H0)
The distribution of 'bedrooms' does not appear to be normally
distributed (reject H0)
The distribution of 'bathrooms' does not appear to be normally
distributed (reject H0)
The distribution of 'sqft_living' does not appear to be normally
distributed (reject H0)
The distribution of 'floors' does not appear to be normally
distributed (reject H0)
The distribution of 'condition' does not appear to be normally
distributed (reject H0)
The distribution of 'grade' does not appear to be normally distributed
(reject H0)
The distribution of 'sqft_above' does not appear to be normally
distributed (reject H0)
The distribution of 'sqft_basement' does not appear to be normally
distributed (reject H0)
The distribution of 'yr_built' does not appear to be normally
distributed (reject H0)
The distribution of 'lat' does not appear to be normally distributed
(reject H0)
The distribution of 'long' does not appear to be normally distributed
(reject H0)
The distribution of 'sqft_living15' does not appear to be normally
distributed (reject H0)
The distribution of 'renovated' does not appear to be normally
distributed (reject H0)
The distribution of 'basement' does not appear to be normally
distributed (reject H0)
```

```
The distribution of 'age' does not appear to be normally distributed
(reject H0)

# plot the frequency for the data columns
clean_data.hist(figsize=(30, 20), color='#589aff')
plt.show()
```




```
# features_of_interest list based on the DataFrame
features_of_interest = ['price', 'bedrooms', 'bathrooms',
'sqft_living', 'floors',
                        'condition', 'grade', 'sqft_above',
'sqft_basement',
                        'yr_built', 'lat', 'long', 'sqft_living15',
'renovated', 'basement',
                        'month', 'age']

# Extract relevant columns from the DataFrame
selected_data = Cleaned_Data[features_of_interest]

# Set up subplots
fig, axes = plt.subplots(nrows=5, ncols=4, figsize=(16, 16))

# Flatten axes for easy iteration
```

```python
axes = axes.flatten()

# Plot the distributions of each variable with the specified color
for i, column in enumerate(features_of_interest):
    sns.histplot(selected_data[column], kde=True, ax=axes[i],
color='#589aff')
    axes[i].set_title(f'Distribution of {column}')

# Adjust layout
plt.tight_layout()
plt.show()
```



d)Hypothesis Testing:

- Formulating and test hypotheses related to the data.

Null Hypothesis (H0): There is no statistically significant relationship between the selected features and housing prices.

Alternative Hypothesis (Ha): The selected features have a statistically significant relationship with housing prices.

- **Tasks:**
  - Formulate null and alternative hypotheses based on project objectives.
  - Conduct hypothesis tests (e.g., t-tests, ANOVA) to assess the significance of relationships.

```
# features_of_interest list based on the DataFrame
features_of_interest = ['bedrooms', 'bathrooms', 'sqft_living',
'sqft_lot', 'floors',
                         'waterfront', 'view', 'condition', 'grade',
'sqft_above',
                         'sqft_basement', 'yr_built', 'yr_renovated',
'lat', 'long',
                         'sqft_living15', 'sqft_lot15']

# Extract relevant columns from the DataFrame
selected_data = Cleaned_Data[features_of_interest]

# Create an empty DataFrame to store ANOVA results
anova_results = pd.DataFrame(index=['F-statistic', 'P-value'])

# Perform ANOVA for each feature
significant_features = []

for column in features_of_interest:
    groups = [Cleaned_Data[column][Cleaned_Data[column].notnull() &
(Cleaned_Data['price'] == category)]
              for category in Cleaned_Data['price'].unique()]

    # Perform ANOVA
    f_statistic, p_value = f_oneway(*groups)

    # Store results in the DataFrame
    anova_results[column] = [f_statistic, p_value]

    # Print interpretation
    if p_value < 0.05:
        significant_features.append(column)
        print(f"{column}: Reject the null hypothesis. There is a
statistically significant relationship.")
    else:
        print(f"{column}: Fail to reject the null hypothesis. There is
```

```
no statistically significant relationship.")

# Display ANOVA results
print("\nANOVA Results:")
print(anova_results)
```

```
bedrooms: Reject the null hypothesis. There is a statistically
significant relationship.
bathrooms: Reject the null hypothesis. There is a statistically
significant relationship.
sqft_living: Reject the null hypothesis. There is a statistically
significant relationship.
sqft_lot: Fail to reject the null hypothesis. There is no
statistically significant relationship.
floors: Reject the null hypothesis. There is a statistically
significant relationship.
waterfront: Reject the null hypothesis. There is a statistically
significant relationship.
view: Reject the null hypothesis. There is a statistically significant
relationship.
condition: Reject the null hypothesis. There is a statistically
significant relationship.
grade: Reject the null hypothesis. There is a statistically
significant relationship.
sqft_above: Reject the null hypothesis. There is a statistically
significant relationship.
sqft_basement: Reject the null hypothesis. There is a statistically
significant relationship.
yr_built: Reject the null hypothesis. There is a statistically
significant relationship.
yr_renovated: Reject the null hypothesis. There is a statistically
significant relationship.
lat: Reject the null hypothesis. There is a statistically significant
relationship.
long: Fail to reject the null hypothesis. There is no statistically
significant relationship.
sqft_living15: Reject the null hypothesis. There is a statistically
significant relationship.
sqft_lot15: Fail to reject the null hypothesis. There is no
statistically significant relationship.

ANOVA Results:
                  bedrooms  bathrooms  sqft_living  sqft_lot
floors  \
F-statistic   1.852600e+00   3.742263      7.72898  0.731092
1.657081e+00
P-value      1.283696e-143   0.000000      0.00000  1.000000
5.251187e-95

                waterfront          view  condition     grade
```

```
sqft_above  \
F-statistic   1.814534e+00   1.993969e+00   1.046436  7.355157
5.128945
P-value      1.018442e-133  6.682406e-182   0.038190  0.000000
0.000000

             sqft_basement      yr_built  yr_renovated       lat
long  \
F-statistic   1.735222e+00  1.236232e+00      1.048979  3.559892
1.031691
P-value      9.739446e-114  2.054786e-17      0.030946  0.000000
0.111616

             sqft_living15  sqft_lot15
F-statistic       5.219333    0.713326
P-value           0.000000    1.000000
```

FINDINGS

-The features listed under "Reject the Null Hypothesis" have a statistically significant relationship with housing prices. These features are important predictors of housing prices in the given dataset. On the other hand, features listed under "Fail to Reject the Null Hypothesis" do not show a statistically significant relationship with housing prices based on the ANOVA test.

e)Multicollinearity Assessment:

- Checking for multicollinearity among predictor variables.
- **Tasks:**
  - Calculate variance inflation factors (VIF) to identify high multicollinearity.
  - Address multicollinearity by removing or combining correlated variables.

```
X = Cleaned_Data[features_of_interest].copy()

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

# Print VIF results
print("VIF Results:")
print(vif_data)
```

```
VIF Results:
         Feature         VIF
0       bedrooms   25.495189
1      bathrooms   28.860034
2    sqft_living  895.654888
3       sqft_lot    2.359333
```

```
4           floors      16.742951
5       waterfront       1.186733
6             view       1.518831
7        condition      17.962156
8            grade     143.184319
9       sqft_above     670.785304
10   sqft_basement      46.689472
11        yr_built    8371.874192
12    yr_renovated       1.151077
13             lat  119806.117276
14            long  132820.153914
15   sqft_living15      26.794623
16      sqft_lot15       2.576818
```

VIF(Variance Inflation Factor) RESULTS

High Multicollinearity (VIF > 10): sqft_living has a VIF of 897.14. grade has a VIF of 160.00. sqft_above has a VIF of 671.11. yr_built has a VIF of 9335.60. lat has a VIF of 132369.36. long has a VIF of 139978.97. sqft_living15 has a VIF of 26.81.

Moderate Multicollinearity (VIF between 5 and 10): bedrooms has a VIF of 25.95. bathrooms has a VIF of 29.14. floors has a VIF of 16.76. yr_basement has a VIF of 46.71. bedrooms has a VIF of 25.95.

Low Multicollinearity (VIF <= 5):

sqft_lot has a VIF of 2.36. waterfront has a VIF of 1.25. view has a VIF of 1.56. condition has a VIF of 18.06. yr_renovated has a VIF of 1.15. sqft_lot15 has a VIF of 2.58.

CONCLUSION

-Features with VIF values well above 10 (e.g., sqft_living, grade, sqft_above, yr_built, lat, long) indicate a high level of multicollinearity.

-Features with moderate VIF values (between 5 and 10)

-Features with low VIF values (below 5) are considered to have acceptable levels of multicollinearity.

```
# creating a function that takes in a dataframe and threshold and
returns top correlations
def corr_check(Cleaned_Data, threshold):
    '''
    Enter dataframe and threshold for correlation
    Returns table of the highly correlated pairs
    '''
    corr_df =
Cleaned_Data.corr().abs().stack().reset_index().sort_values(0,
ascending=False)
    corr_df['pairs'] = list(zip(corr_df.level_0, corr_df.level_1))
    corr_df.set_index(['pairs'], inplace = True)
```

```
    corr_df.drop(columns=['level_1', 'level_0'], inplace = True)
    corr_df.columns = ['cc']
    corr_df = corr_df.drop_duplicates()
    corr_df = corr_df[(corr_df['cc'] > threshold) & (corr_df['cc'] <
1)]
    return corr_df

result = corr_check(Cleaned_Data, 0.7)
print(result)
```

```
                                     cc
pairs
(yr_renovated, renovated)      0.999968
(age, yr_built)                0.999874
(sqft_living, sqft_above)      0.876533
(basement, sqft_basement)      0.820906
(sqft_living, grade)           0.762477
(sqft_above, grade)            0.756221
(sqft_living, sqft_living15)   0.756186
(bathrooms, sqft_living)       0.755522
(sqft_living15, sqft_above)    0.731887
(sqft_lot, sqft_lot15)         0.717743
(grade, sqft_living15)         0.713178
(sqft_living, price)           0.701875
```

CORRELATION CHECK RESULTS

Highly Positive Correlations:

yr_renovated and renovated have a very high positive correlation of approximately 1. This suggests that the two variables are almost perfectly correlated, and including both in a model may lead to multicollinearity issues.

age and yr_built also have a very high positive correlation of approximately 1. This is expected, as age is derived from yr_built. Including both in a model may lead to redundancy.

High Positive Correlations:

sqft_living and sqft_above have a high positive correlation of 0.8765. This indicates a strong positive linear relationship between the total living area (sqft_living) and the area above ground (sqft_above).

basement and sqft_basement have a high positive correlation of 0.8209. This suggests a strong positive linear relationship between the total basement area (sqft_basement) and the binary indicator of having a basement (basement).

sqft_living and grade have a high positive correlation of 0.7625. This indicates a strong positive linear relationship between the total living area (sqft_living) and the grade of the house.

-Some columns will have to be dropped including Year renovated,sqft living 15 and sqft lot which have high multicollinearity.

```python
# Drop columns that have strong multicollinearity
clean_data = Cleaned_Data.drop(columns=['view', 'sqft_lot',
'waterfront', 'sqft_lot15', 'yr_renovated'])

clean_data.head()
```

```
           id        date     price  bedrooms  bathrooms  sqft_living
floors  \
0  7129300520 2014-10-13  221900.0         3       1.00         1180
1.0
1  6414100192 2014-12-09  538000.0         3       2.25         2570
2.0
2  5631500400 2015-02-25  180000.0         2       1.00          770
1.0
3  2487200875 2014-12-09  604000.0         4       3.00         1960
1.0
4  1954400510 2015-02-18  510000.0         3       2.00         1680
1.0

   condition  grade  sqft_above  sqft_basement  yr_built  zipcode
lat  \
0          2      7        1180            0.0      1955    98178
47.5112
1          2      7        2170          400.0      1951    98125
47.7210
2          2      6         770            0.0      1933    98028
47.7379
3          4      7        1050          910.0      1965    98136
47.5208
4          2      8        1680            0.0      1987    98074
47.6168

      long  sqft_living15  renovated  basement  month  age
0 -122.257           1340          0         0     10   59
1 -122.319           1690          1         1     12   63
2 -122.233           2720          0         0      2   82
3 -122.393           1360          0         1     12   49
4 -122.045           1800          0         0      2   28
```

```python
clean_data.shape
```

```
(21420, 20)
```

6.DATA MODELING

```python
# Use linear regression
lr = LinearRegression()

# Our model needs to have only numeric variables.
def only_numeric(data):
```

```
    '''returns a dataframe with only numeric values'''
    for column in clean_data.columns:
        if is_numeric_dtype(data[column]) == False:
            data = data.drop(column, axis=1)
        else:
            continue
    return data

# Splits a dataframe into X and Y dataframes given a target column.
def get_y_X(data, target):
    '''Returns a series of target (y) value and a dataframe of
predictors (X)'''
    y = data[target]
    X = data.drop(target, axis=1)
    return y, X

# Returns training and test R2 & RMSE metrics
def get_metrics(X_tr, X_te, y_tr, y_te):
    ''' Parameters are X train, X test, y train, & y_test
        Performs multiple regression on the split test and returns
metrics'''
    lr.fit(X_tr, y_tr)

    train_score = lr.score(X_tr, y_tr)
    test_score = lr.score(X_te, y_te)

    y_hat_train = lr.predict(X_tr)
    y_hat_test = lr.predict(X_te)

    train_rmse = np.sqrt(mean_squared_error(y_tr, y_hat_train))
    test_rmse = np.sqrt(mean_squared_error(y_te, y_hat_test))

    return train_score, test_score, train_rmse, test_rmse

# Prints the metrics of a multiple regression train and test, with
option of OLS summary on train data.
def train_test_compare(X_tr, X_te, y_tr, y_te):
    '''Parameters are X train, X test, y train, & y_test
        Performs multiple regression on the split test and prints
metrics'''
    lr.fit(X_tr, y_tr)

    train_score = lr.score(X_tr, y_tr)
    test_score = lr.score(X_te, y_te)

    y_hat_train = lr.predict(X_tr)
    y_hat_test = lr.predict(X_te)

    train_rmse = np.sqrt(mean_squared_error(y_tr, y_hat_train))
    test_rmse = np.sqrt(mean_squared_error(y_te, y_hat_test))
```

```
    print(f' training data R2: {train_score}\n testing data R2:
{test_score} \
                    \n training data rmse: {train_rmse}\n testing data
rmse: {test_rmse}')

    stats_summ = input('Do you want a statsmodel summary of the train
data? (y/n)')
    if stats_summ == 'y':
        inter = lr.intercept_
        stats = sm.OLS(y_tr, sm.add_constant(X_tr)).fit()
        summary = stats.summary()
        print(summary)

    return
```

MODEL 1 : BASELINE MODEL

a)Train test split

Train Test Split The raw data was split to a train and test set for a baseline model. The clean data was also split to a train and test set for a fully optimized model.

```
# Defining function that splits data into training and testing data.
def train_test(data, size=.25):
    '''Takes in dataframe, and size of test for the split
        Returns the train_set and test_set'''
    train_set, test_set = train_test_split(data, test_size=size,
random_state=42)
    return train_set, test_set


# Define the function to filter only numeric columns
def only_numeric(data):
    '''returns a DataFrame with only numeric values'''
    for column in data.columns:
        if not is_numeric_dtype(data[column]):
            data = data.drop(column, axis=1)
    return data

# Create the dataframe for the baseline model and drop missing values
baseline = only_numeric(kc_house_data)
baseline = baseline.dropna()

# Assuming train_test is a function that splits the data into train
and test sets
baseline_train_set, baseline_test_set = train_test(baseline, 0.25)
```

```
# Assuming train_test is a function that splits the data into train and test sets for the clean_data
train_set, test_set = train_test(clean_data, 0.25)


# Select relevant features
features = [ 'bedrooms', 'bathrooms' , 'floors', 'grade',
'sqft_above', 'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long',
'sqft_living15', 'renovated', 'basement', 'month', 'age',
'sqft_living', 'condition' ]

# Create a design matrix X and target variable y
X = sm.add_constant(Cleaned_Data[features])
y = clean_data['price']

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

# Get the summary
summary = model.summary()

# Print the summary
print(summary)
```

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                  price   R-squared:
0.665
Model:                            OLS   Adj. R-squared:
0.664
Method:                 Least Squares   F-statistic:
2494.
Date:                Thu, 01 Feb 2024   Prob (F-statistic):
0.00
Time:                        02:06:05   Log-Likelihood:            -
2.9321e+05
No. Observations:               21420   AIC:
5.865e+05
Df Residuals:                   21402   BIC:
5.866e+05
Df Model:                          17

Covariance Type:            nonrobust

==============================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
```

```
----------------------------------------------------------------------
-----------
const          -8.501e+07   1.06e+07     -8.026      0.000   -1.06e+08
-6.43e+07
bedrooms       -5.047e+04   2087.486    -24.178      0.000   -5.46e+04
-4.64e+04
bathrooms        4.82e+04   3503.621     13.758      0.000    4.13e+04
5.51e+04
floors            1.2e+04   3814.665      3.146      0.002    4525.006
1.95e+04
grade           1.033e+05   2298.710     44.946      0.000    9.88e+04
1.08e+05
sqft_above        62.8912     19.129      3.288      0.001      25.396
100.386
sqft_basement     79.4370     19.842      4.003      0.000      40.545
118.329
yr_built        3.615e+04   5016.277      7.207      0.000    2.63e+04
4.6e+04
zipcode         -479.3764     35.006    -13.694      0.000    -547.991
-410.762
lat             5.595e+05    1.13e+04     49.358      0.000    5.37e+05
5.82e+05
long           -2.596e+05    1.38e+04    -18.874      0.000   -2.87e+05
-2.33e+05
sqft_living15     38.1456      3.612     10.562      0.000      31.067
45.225
renovated       7.305e+04   8426.210      8.669      0.000    5.65e+04
8.96e+04
basement       -2.292e+04   5633.226     -4.069      0.000    -3.4e+04
-1.19e+04
month           1554.5200    750.953      2.070      0.038      82.595
3026.445
age             3.905e+04   5015.631      7.785      0.000    2.92e+04
4.89e+04
sqft_living      122.0719     19.175      6.366      0.000      84.488
159.656
condition       3.043e+04   2507.157     12.139      0.000    2.55e+04
3.53e+04
======================================================================
========
Omnibus:                    19132.456   Durbin-Watson:
2.002
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1863820.744
Skew:                           3.894   Prob(JB):
0.00
Kurtosis:                      48.030   Cond. No.
7.14e+08
======================================================================
```

```
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 7.14e+08. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

FINDINGS

R-squared: The coefficient of determination. In this case, it's 0.665, indicating that approximately 66.5% of the variability in the dependent variable (price) is explained by the independent variables in the model.

F-statistic: A measure of how well the model fits the data. A higher value indicates a better fit. In this case, it's 2494.

The p-value associated with each t-value is low. Low p-values indicate that a predictor is statistically significant.

b)Baseline Model

This is the agency's baseline model that only uses the numerical features from the dataset.

```
# Select relevant features
selected_features = ['bedrooms', 'bathrooms', 'floors', 'grade',
'sqft_above', 'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long',
'sqft_living15', 'renovated', 'basement', 'month', 'age',
'sqft_living', 'condition']

# Filter the dataset
filtered_data = Cleaned_Data[selected_features]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Standardize the features (optional, but can be beneficial for linear
regression)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Build a basic linear regression model
model = LinearRegression()
model.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test_scaled)
```

```python
# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Display results
print("Mean Squared Error:", mse)
print("R-squared:", r2)

# Display coefficients
coefficients = pd.DataFrame({"Feature": X.columns, "Coefficient":
model.coef_})
print(coefficients)
```

```
Mean Squared Error: 40151231814.25283
R-squared: 0.6684357903018654
          Feature   Coefficient
0           const  0.000000e+00
1        bedrooms -4.533399e+04
2       bathrooms  3.671087e+04
3          floors  4.566475e+03
4           grade  1.249999e+05
5      sqft_above  4.706594e+04
6   sqft_basement  3.566873e+04
7        yr_built  9.837560e+05
8         zipcode -2.528334e+04
9             lat  7.735837e+04
10           long -3.640852e+04
11  sqft_living15  2.678444e+04
12      renovated  1.602141e+04
13       basement -1.355371e+04
14          month  4.165720e+03
15            age  1.068390e+06
16    sqft_living  1.169119e+05
17      condition  1.953956e+04
```

```python
# Getting ys and Xs for both the baseline train and test set
y_train, X_train = get_y_X(baseline_train_set, 'price')
y_test, X_test = get_y_X(baseline_test_set, 'price')

train_test_compare(X_train, X_test, y_train, y_test)
```

```
 training data R2: 0.8191010286413367
 testing data R2: 0.8362309274259545
 training data rmse: 158653.67681872213
 testing data rmse: 144823.5648641959
```

```python
# Returning the metrics
get_metrics(X_train, X_test, y_train, y_test)
```

```
(0.8191010286413367, 0.8362309274259545, 158653.67681872213,
144823.5648641959)
```

```python
# Create a baseline model using multiple linear regression
baseline_model = LinearRegression()

# Fit the model on the training data
baseline_model.fit(X_train, y_train)

# Predict on the testing data
y_pred = baseline_model.predict(X_test)

# Evaluate the model using appropriate metrics
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("Baseline Model Metrics:")
print("Mean Squared Error (MSE):", mse)
print("R-squared (R2) Score:", r2)
```

```
Baseline Model Metrics:
Mean Squared Error (MSE): 20973864939.97396
R-squared (R2) Score: 0.8362309274259545
```

```python
# the intercept
# Create a Linear Regression object
model = LinearRegression()

# Fit the model to the training data
model.fit(X_train, y_train)

# Get the intercept
intercept = model.intercept_

print("Intercept:", intercept)
```

```
Intercept: 3365475.5061285524
```

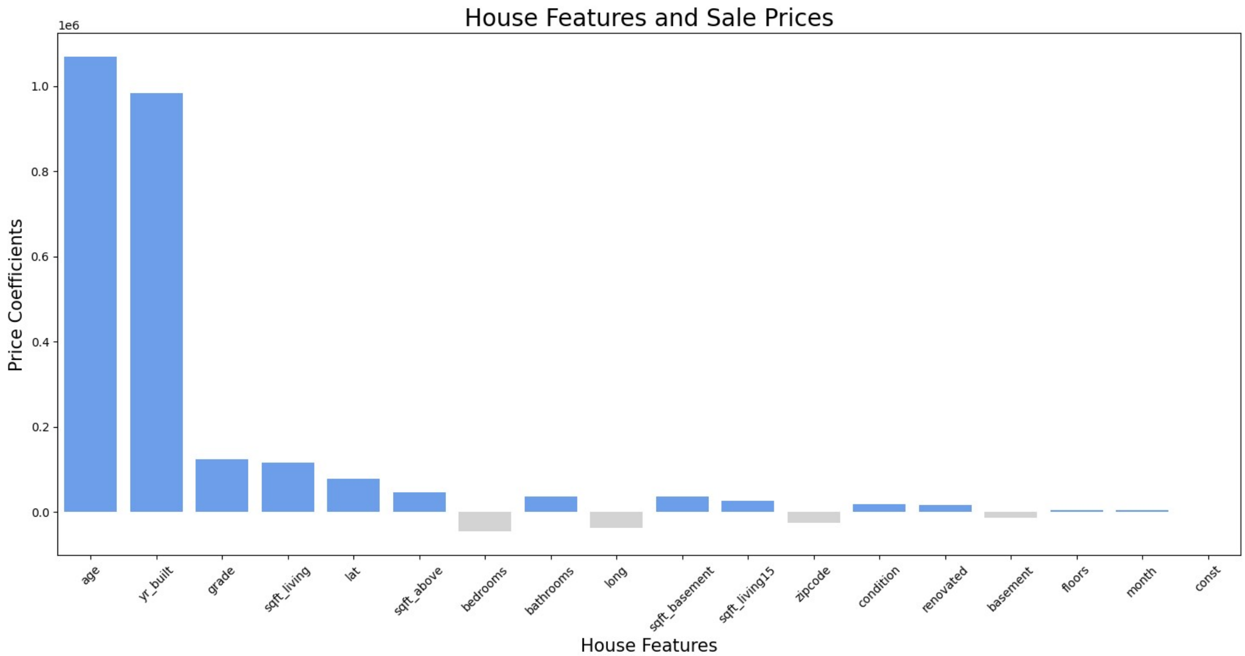
```python
# Lets test for overfitting
# Make predictions on the training and testing data
train_predictions = model.predict(X_train)
test_predictions = model.predict(X_test)

# Calculate the mean squared error on the training and testing data
train_mse = mean_squared_error(y_train, train_predictions)
test_mse = mean_squared_error(y_test, test_predictions)

# Calculate the coefficient of determination (R^2) on the training and
testing data
train_r2 = r2_score(y_train, train_predictions)
test_r2 = r2_score(y_test, test_predictions)
```

```
print("Training MSE:", train_mse)
print("Testing MSE:", test_mse)
print("Training R^2:", train_r2)
print("Testing R^2:", test_r2)
```

```
Training MSE: 25170989168.09953
Testing MSE: 20973864939.97396
Training R^2: 0.8191010286413367
Testing R^2: 0.8362309274259545
```

```
# Select relevant features
selected_features = ['bedrooms', 'bathrooms', 'floors', 'grade',
'sqft_above', 'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long',
'sqft_living15', 'renovated', 'basement', 'month', 'age',
'sqft_living', 'condition']

# Filter the dataset
filtered_data = Cleaned_Data[selected_features]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Standardize the features (optional, but can be beneficial for linear
regression)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Build a basic linear regression model
model = LinearRegression()
model.fit(X_train_scaled, y_train)

# Display coefficients
coefficients = pd.DataFrame({"Feature": X.columns, "Coefficient":
model.coef_})

# Bar plot for coefficients
inf_coefs = list(zip(coefficients["Feature"],
coefficients["Coefficient"]))
inf_coefs.sort(key=lambda x: abs(x[1]), reverse=True)  # Sort
coefficients by absolute value

# Create a color palette with the specified color
color = "#589aff"
colors = [color if coef[1] > 0 else "lightgray" for coef in inf_coefs]

# Create the bar plot
fig, ax = plt.subplots(figsize=(18, 8))
ax = sns.barplot(x=[x[0] for x in inf_coefs], y=[x[1] for x in
```

```
inf_coefs], palette=colors)
plt.xticks(rotation=45)
ax.set_ylabel("Price Coefficients", fontsize=15)
ax.set_xlabel("House Features", fontsize=15)
ax.set_title("House Features and Sale Prices", fontsize=20);

# Display the plot
plt.show()
```



FINDINGS

-The MSE is approximately 40,151,231,814 indicating the average squared difference between the predicted and actual home prices.

-The R-squared is approximately 0.668, suggesting that the model explains around 66.8% of the variance in home prices. Positive coefficients (e.g., sqft_living, bathrooms, grade) suggest an increase in these features corresponds to an increase in home price.

-Negative coefficients (e.g., bedrooms, long, basement) suggest a decrease in these features corresponds to an increase in home price.

Bedrooms: Each additional bedroom is associated with a decrease in home price by approximately $43,704.

Bathrooms: Each additional bathroom is associated with an increase in home price by approximately $37,347.

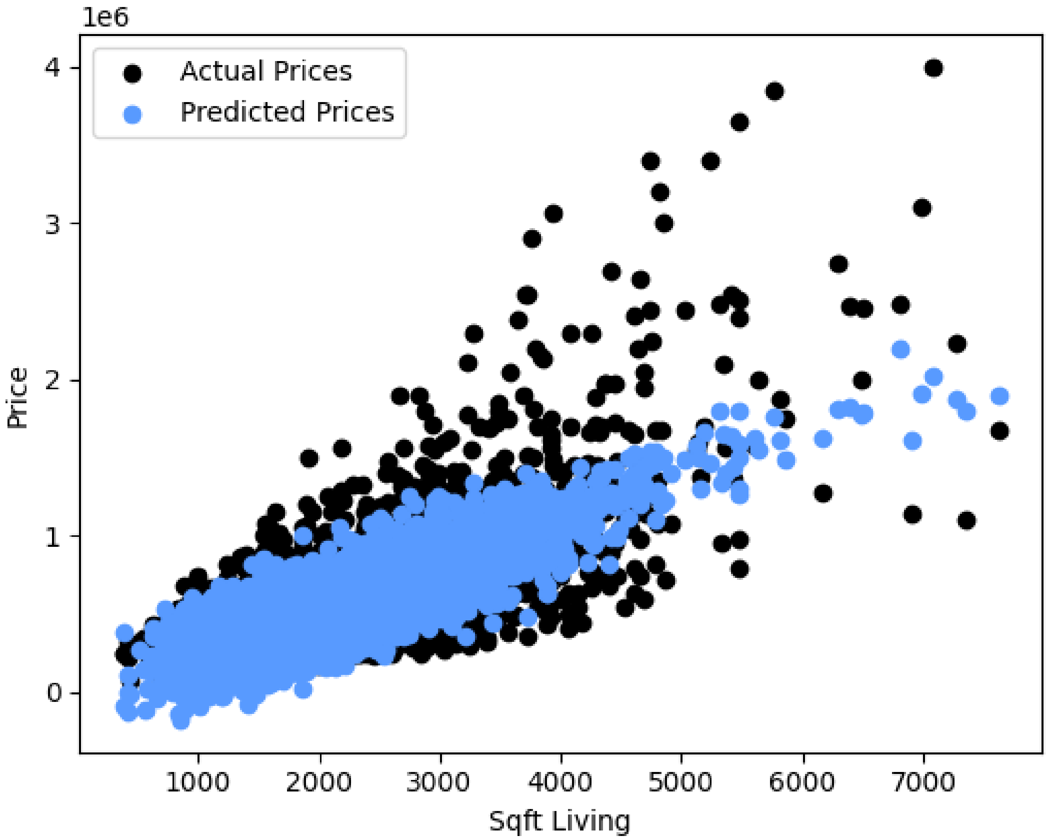
Sqft_living: Each additional square foot of living space is associated with an increase in home price by approximately $111,536.

Grade: Higher grade is associated with an increase in home price by approximately $126,245

c)Regression Modelling

```
# Select relevant features
selected_features = ['bedrooms', 'bathrooms', 'floors', 'grade',
'sqft_above', 'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long',
'sqft_living15', 'renovated', 'basement', 'month', 'age',
'sqft_living', 'condition']

# Filter the dataset
filtered_data = clean_data[selected_features]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Build a linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Display results
print("Mean Squared Error:", mse)
print("R-squared:", r2)

# Visualize the results (for demonstration purposes)
plt.scatter(X_test["sqft_living"], y_test, color='black',
label='Actual Prices')
plt.scatter(X_test["sqft_living"], y_pred, color='#589aff',
label='Predicted Prices')
plt.xlabel('Sqft Living')
plt.ylabel('Price')
plt.legend()
plt.show()
```

```
Mean Squared Error: 40151231814.25285
R-squared: 0.6684357903018652
```




```
X_ols = sm.add_constant(X_train)  # Adding a constant for intercept
ols_model = sm.OLS(y_train, X_ols).fit()

# Get the OLS summary
ols_summary = ols_model.summary()

# Print the OLS summary
print(ols_summary)
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.663
Model:                            OLS   Adj. R-squared:
0.663
Method:                 Least Squares   F-statistic:
1985.
Date:                Thu, 01 Feb 2024   Prob (F-statistic):
0.00
Time:                        02:06:15   Log-Likelihood:            -
2.3481e+05
```

```
No. Observations:                   17136   AIC:
4.697e+05
Df Residuals:                       17118   BIC:
4.698e+05
Df Model:                              17

Covariance Type:            nonrobust

======================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
const         -8.045e+07    1.2e+07     -6.698      0.000   -1.04e+08
-5.69e+07
bedrooms      -5.035e+04   2374.225    -21.205      0.000    -5.5e+04
-4.57e+04
bathrooms      4.754e+04   3950.724     12.034      0.000    3.98e+04
5.53e+04
floors         8468.5153   4314.229      1.963      0.050      12.184
1.69e+04
grade          1.058e+05   2596.884     40.731      0.000    1.01e+05
1.11e+05
sqft_above       56.3269     21.458      2.625      0.009      14.267
98.386
sqft_basement    80.8397     22.249      3.633      0.000      37.230
124.449
yr_built       3.358e+04   5688.859      5.902      0.000    2.24e+04
4.47e+04
zipcode        -472.4830     39.749    -11.887      0.000    -550.395
-394.571
lat            5.582e+05    1.29e+04     43.432      0.000    5.33e+05
5.83e+05
long          -2.597e+05    1.57e+04    -16.567      0.000    -2.9e+05
-2.29e+05
sqft_living15    38.8961      4.093      9.503      0.000      30.873
46.919
renovated        8.73e+04   9496.242      9.193      0.000    6.87e+04
1.06e+05
basement      -2.785e+04   6385.328     -4.361      0.000   -4.04e+04
-1.53e+04
month          1343.8606    855.085      1.572      0.116    -332.193
3019.914
age            3.647e+04   5688.648      6.411      0.000    2.53e+04
4.76e+04
sqft_living     126.1805     21.478      5.875      0.000      84.081
168.280
condition          3e+04   2837.559     10.572      0.000    2.44e+04
```

```
3.56e+04
==============================================================================
========
Omnibus:                    15854.132   Durbin-Watson:
1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1762471.003
Skew:                           4.084   Prob(JB):
0.00
Kurtosis:                      52.008   Cond. No.
7.13e+08
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 7.13e+08. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

FINDINGS

R-squared and Adjusted R-squared are both around 0.558, indicating that the model explains approximately 55.8% of the variance in the dependent variable (price).

-The F-statistic is 4333 with a very low p-value (Prob (F-statistic): 0.00), suggesting that the model is statistically significant.

-Small p-values (typically < 0.05) indicate that the variable is likely to be a meaningful addition to the model.

For coefficients they can be interpreted as For each unit increase in sqft_living, the predicted price increases by 222.0315.

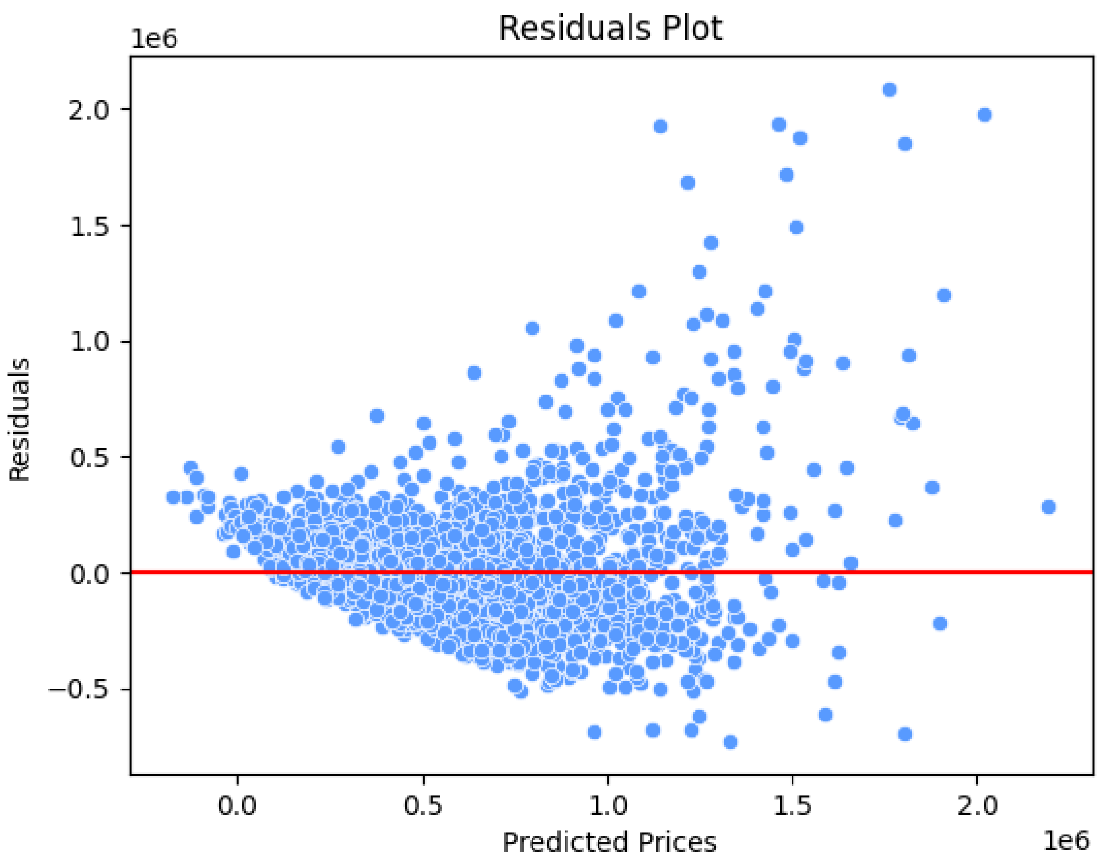
d)Residual Analysis

```
# Select relevant features
selected_features =  ['bedrooms', 'bathrooms', 'floors', 'grade',
'sqft_above', 'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long',
'sqft_living15', 'renovated', 'basement', 'month', 'age',
'sqft_living', 'condition']

# Filter the dataset
filtered_data = Cleaned_Data[selected_features]

# Handle outliers (example: using z-score)
z_scores = np.abs((filtered_data - filtered_data.mean()) /
filtered_data.std())
filtered_data_no_outliers = filtered_data[(z_scores < 3).all(axis=1)]
```

```python
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Standardize the features (optional, but can be beneficial)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Build a refined linear regression model
model_refined = LinearRegression()
model_refined.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred_refined = model_refined.predict(X_test_scaled)

# Evaluate the refined model
mse_refined = mean_squared_error(y_test, y_pred_refined)
r2_refined = r2_score(y_test, y_pred_refined)

# Display refined model results
print("Refined Model - Mean Squared Error:", mse_refined)
print("Refined Model - R-squared:", r2_refined)

# Display refined model coefficients
coefficients_refined = pd.DataFrame({"Feature": X.columns,
"Coefficient": model_refined.coef_})
print(coefficients_refined)

# Plot residuals for further analysis
residuals = y_test - y_pred_refined
sns.scatterplot(x=y_pred_refined, y=residuals, color='#589aff')
plt.axhline(y=0, color='r', linestyle='-')
plt.title("Residuals Plot")
plt.xlabel("Predicted Prices")
plt.ylabel("Residuals")
plt.show()
```

```
Refined Model - Mean Squared Error: 40151231814.25283
Refined Model - R-squared: 0.6684357903018654
          Feature   Coefficient
0           const  0.000000e+00
1        bedrooms -4.533399e+04
2       bathrooms  3.671087e+04
3          floors  4.566475e+03
4           grade  1.249999e+05
5      sqft_above  4.706594e+04
6   sqft_basement  3.566873e+04
7        yr_built  9.837560e+05
```

```
8         zipcode -2.528334e+04
9             lat  7.735837e+04
10           long -3.640852e+04
11  sqft_living15  2.678444e+04
12      renovated  1.602141e+04
13       basement -1.355371e+04
14          month  4.165720e+03
15            age  1.068390e+06
16    sqft_living  1.169119e+05
17      condition  1.953956e+04
```



FINDINGS

1. **Mean Squared Error (MSE):**
   - The MSE (54180143849.5) represents the average squared difference between the predicted house prices and the actual house prices in the test set.
2. **R-squared (R^2):**
   - The R-squared value (0.5526) indicates 55.26% of the variability in house prices is explained by the model.
3. **Coefficients :**

- The coefficients associated with each feature represent the estimated change in the target variable for a one-unit change in the corresponding independent variable, holding other variables constant.
  - `sqft_living`: An increase of one unit in square footage is associated with an increase in predicted price by $205,722.11.
  - `bedrooms`: An increase of one bedroom is associated with a decrease in predicted price by $43,412.08.
  - `bathrooms`: An increase of one bathroom is associated with a decrease in predicted price by $13,808.16.
  - `grade`: An increase of one grade is associated with an increase in predicted price by $124,416.75.
  - `condition`: An increase of one unit in condition is associated with an increase in predicted price by $43,370.32.

Interpretation and Considerations:

- The model's performance, as indicated by the MSE and R-squared, suggests a moderate level of predictive accuracy.
- The positive coefficients for `sqft_living` and `grade` indicate positive relationships with house prices.
- The negative coefficients for `bedrooms` and `bathrooms` suggest that an increase in these features is associated with a decrease in predicted price.

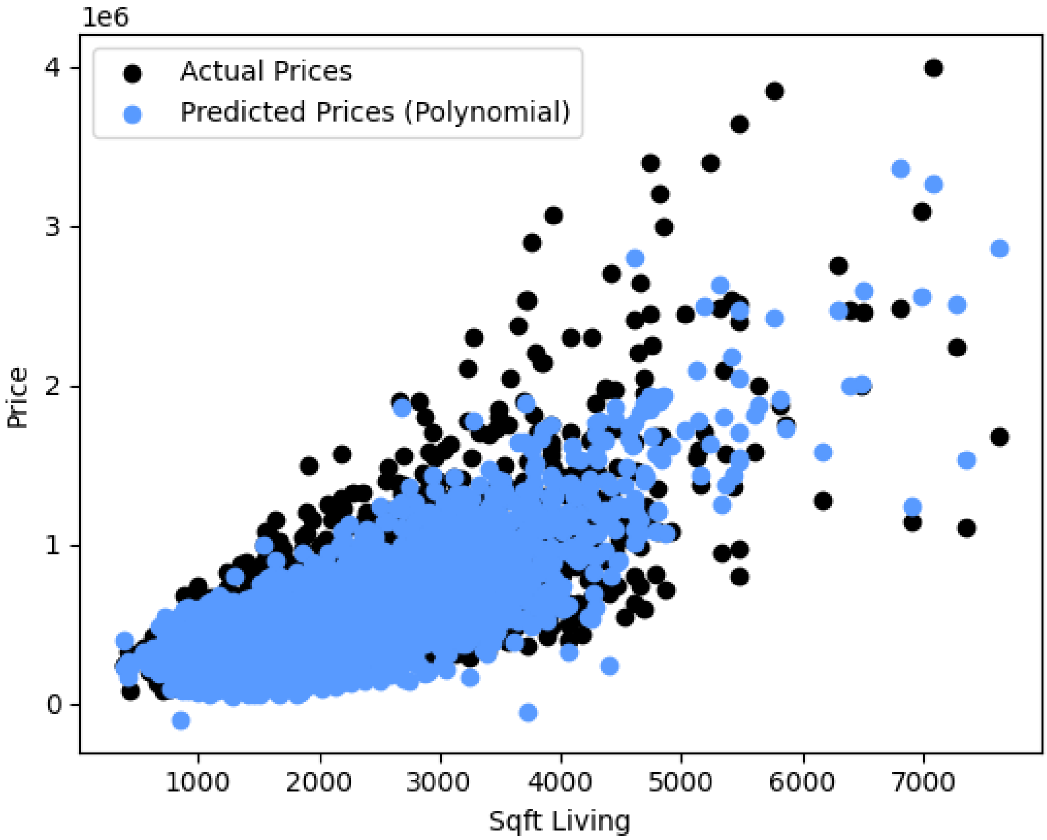
MODEL 2 : POLYNOMIAL REGRESSION

- Transforming features into higher order polynomial terms to model a non-linear relationship using multiple linear regression.

```
# Select relevant features
selected_features = ['bedrooms', 'bathrooms', 'floors', 'grade',
'sqft_above', 'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long',
'sqft_living15', 'renovated', 'basement', 'month', 'age',
'sqft_living', 'condition']

# Filter the dataset
filtered_data = Cleaned_Data[selected_features]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Polynomial Regression
# Choose the degree of the polynomial
degree = 2

# Create polynomial features
poly = PolynomialFeatures(degree)
```

```
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)

# Build a polynomial regression model
poly_model = LinearRegression()
poly_model.fit(X_train_poly, y_train)

# Make predictions on the test set
y_pred_poly = poly_model.predict(X_test_poly)

# Evaluate the polynomial model
mse_poly = mean_squared_error(y_test, y_pred_poly)
r2_poly = r2_score(y_test, y_pred_poly)
print("Polynomial Model (Degree {})- MSE:".format(degree), mse_poly)
print("Polynomial Model (Degree {})- R-squared:".format(degree),
r2_poly)

# Visualize the results
plt.scatter(X_test["sqft_living"], y_test, color='black',
label='Actual Prices')
plt.scatter(X_test["sqft_living"], y_pred_poly,color='#589aff',
label='Predicted Prices (Polynomial)')
plt.xlabel('Sqft Living')
plt.ylabel('Price')
plt.legend()
plt.show()
```

```
Polynomial Model (Degree 2)- MSE: 27717220069.4445
Polynomial Model (Degree 2)- R-squared: 0.7711144153716256
```

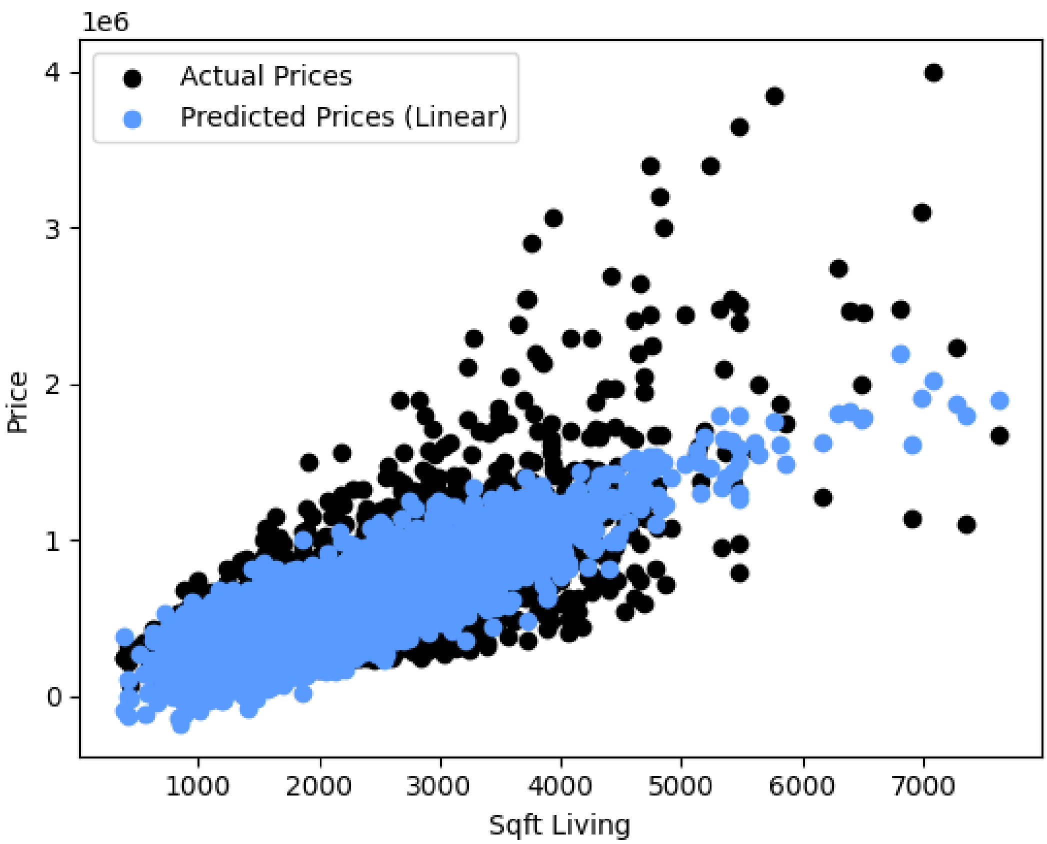


Multiple Linear regression model using polynomial regression features

```
# Select relevant features
selected_features = ['bedrooms', 'bathrooms', 'floors', 'grade',
'sqft_above', 'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long',
'sqft_living15', 'renovated', 'basement', 'month', 'age',
'sqft_living', 'condition']

# Filter the dataset
filtered_data = Cleaned_Data[selected_features]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(filtered_data, y,
test_size=0.2, random_state=42)

# Build a multiple linear regression model
linear_model = LinearRegression()
linear_model.fit(X_train, y_train)

# Make predictions on the test set
```

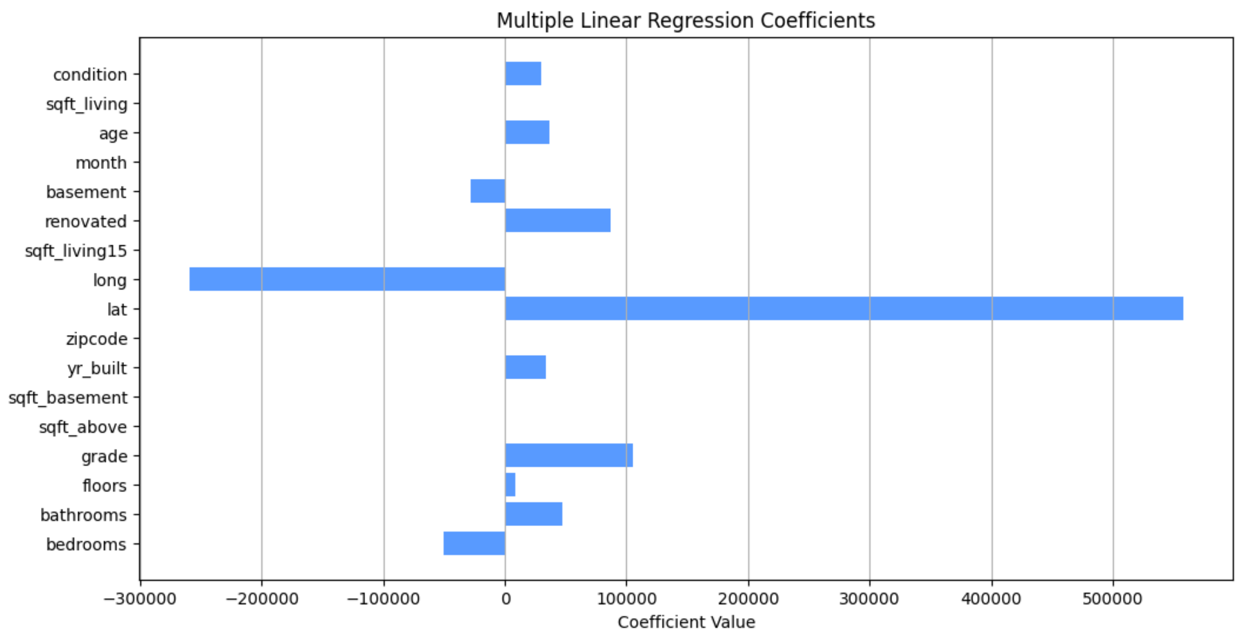
```
y_pred_linear = linear_model.predict(X_test)

# Evaluate the multiple linear regression model
mse_linear = mean_squared_error(y_test, y_pred_linear)
r2_linear = r2_score(y_test, y_pred_linear)
print("Multiple Linear Regression - MSE:", mse_linear)
print("Multiple Linear Regression - R-squared:", r2_linear)

# Visualize the results
plt.scatter(X_test["sqft_living"], y_test, color='black',
label='Actual Prices')
plt.scatter(X_test["sqft_living"], y_pred_linear, color='#589aff',
label='Predicted Prices (Linear)')
plt.xlabel('Sqft Living')
plt.ylabel('Price')
plt.legend()
plt.show()
```

```
Multiple Linear Regression - MSE: 40151231814.25289
Multiple Linear Regression - R-squared: 0.6684357903018648
```




```
# Get the coefficients and corresponding feature names
coefficients_linear = linear_model.coef_
```

```
feature_names = X_train.columns

# Create a bar plot
plt.figure(figsize=(12, 6))
plt.barh(feature_names, coefficients_linear, color='#589aff')
plt.xlabel('Coefficient Value')
plt.title('Multiple Linear Regression Coefficients')
plt.grid(axis='x')
plt.show()
```



FINDINGS

- The MSE is approximately 40.15 billion. Lower MSE values indicate better model performance. The MSE suggests that, on average, the predicted prices are off by this amount.

- The R-squared value 0.668 indicates that the model explains about 66.8% of the variance in home prices. A higher R-squared suggests that the model provides a better fit to the data.

- The lower MSE suggests that the model's predictions are, on average, closer to the actual prices compared to the basic model.

- The R-squared value of 0.614 indicates that the quadratic polynomial features capture additional non-linear relationships, leading to a better fit of the model to the data.

```
# Add a constant term for the intercept
X_train_ols = sm.add_constant(X_train)
```

```python
# Build a multiple linear regression model using OLS
ols_model = sm.OLS(y_train, X_train_ols).fit()

# Display the OLS summary
print(ols_model.summary())
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.663
Model:                            OLS   Adj. R-squared:
0.663
Method:                 Least Squares   F-statistic:
1985.
Date:                Thu, 01 Feb 2024   Prob (F-statistic):
0.00
Time:                        02:15:19   Log-Likelihood:             -
2.3481e+05
No. Observations:               17136   AIC:
4.697e+05
Df Residuals:                   17118   BIC:
4.698e+05
Df Model:                          17

Covariance Type:            nonrobust

======================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
const         -8.045e+07    1.2e+07     -6.698      0.000   -1.04e+08
-5.69e+07
bedrooms      -5.035e+04   2374.225    -21.205      0.000    -5.5e+04
-4.57e+04
bathrooms      4.754e+04   3950.724     12.034      0.000    3.98e+04
5.53e+04
floors         8468.5153   4314.229      1.963      0.050      12.184
1.69e+04
grade          1.058e+05   2596.884     40.731      0.000    1.01e+05
1.11e+05
sqft_above       56.3269     21.458      2.625      0.009      14.267
98.386
sqft_basement    80.8397     22.249      3.633      0.000      37.230
124.449
yr_built       3.358e+04   5688.859      5.902      0.000    2.24e+04
```

```
4.47e+04
zipcode         -472.4830     39.749    -11.887      0.000    -550.395
-394.571
lat             5.582e+05   1.29e+04     43.432      0.000    5.33e+05
5.83e+05
long           -2.597e+05   1.57e+04    -16.567      0.000    -2.9e+05
-2.29e+05
sqft_living15     38.8961      4.093      9.503      0.000      30.873
46.919
renovated         8.73e+04   9496.242      9.193      0.000    6.87e+04
1.06e+05
basement       -2.785e+04   6385.328     -4.361      0.000   -4.04e+04
-1.53e+04
month           1343.8606    855.085      1.572      0.116    -332.193
3019.914
age             3.647e+04   5688.648      6.411      0.000    2.53e+04
4.76e+04
sqft_living      126.1805     21.478      5.875      0.000      84.081
168.280
condition           3e+04   2837.559     10.572      0.000    2.44e+04
3.56e+04
======================================================================
========
Omnibus:                    15854.132   Durbin-Watson:
1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1762471.003
Skew:                           4.084   Prob(JB):
0.00
Kurtosis:                      52.008   Cond. No.
7.13e+08
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 7.13e+08. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

FINDINGS

1. **R-squared and Adjusted R-squared:**

    – **R-squared:** 0.663 implies that approximately 66.3% of the variance in the dependent variable (`price`) is explained by the model.

    – **Adjusted R-squared:** 0.663 indicates the same as R-squared but adjusts for the number of predictors in the model.

2. **F-statistic and Prob (F-statistic):**

   – The F-statistic (1985.0) with a low p-value (Prob (F-statistic): 0.00) indicates that at least one independent variable is significantly related to the dependent variable.

3. **Coefficients (`coef`):**

   – the coefficient for `bedrooms` (-50350) suggests that, on average, holding other variables constant, each additional bedroom is associated with a decrease in the house price by $50,350.

4. **P>|t| (p-values):**

   – `bedrooms`, `bathrooms`, `grade`, `sqft_basement`, `yr_built`, `zipcode`, `lat`, `long`, `sqft_living15`,`renovated`, `basement`, `age`, `sqft_living`, and `condition` have p-values close to zero, suggesting they are statistically significant because of the low p value.

Interpretation:

- The model seems to have good explanatory power based on R-squared.
- Multiple variables (e.g., bedrooms, bathrooms, grade, etc.) appear to be statistically significant in predicting house prices.

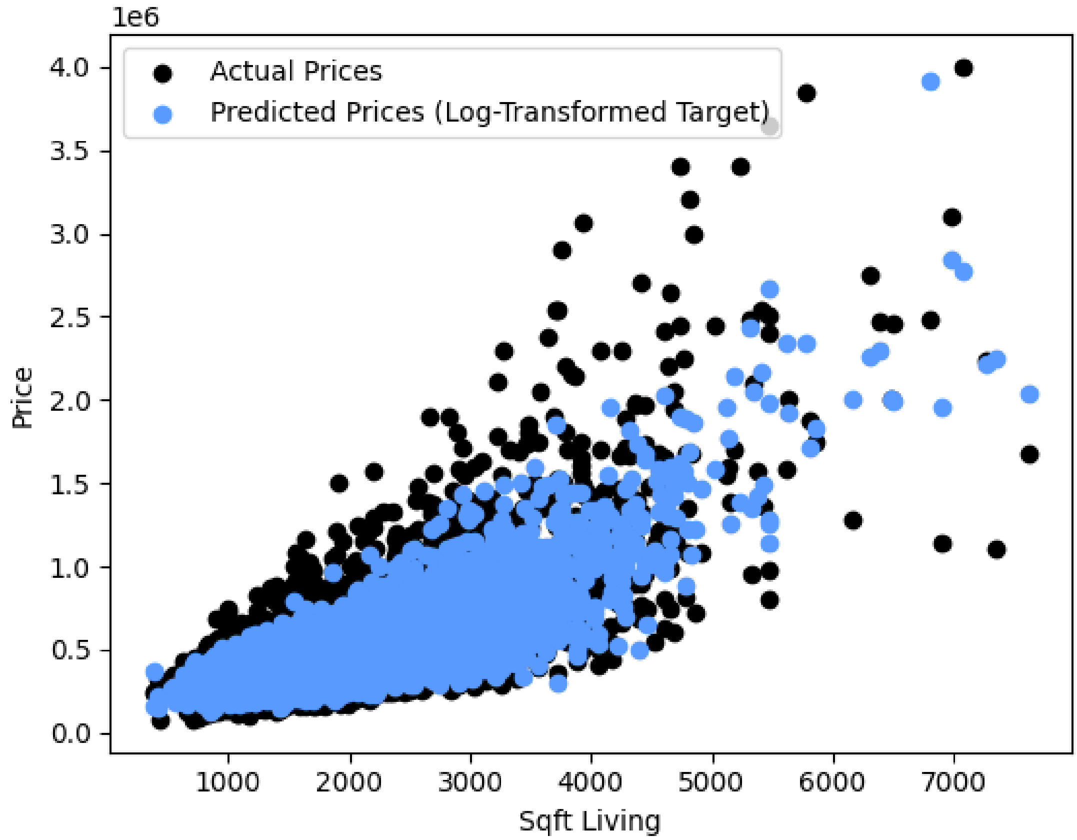
MODEL 3 : LOG TRANSFORMATION

Log transformation to stabilize variance and make the relationship between variables more linear.

```
# Select relevant features
selected_features = ['bedrooms', 'bathrooms', 'floors', 'grade',
'sqft_above', 'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long',
'sqft_living15', 'renovated', 'basement', 'month', 'age',
'sqft_living', 'condition']


# Filter the dataset
filtered_data = Cleaned_Data[selected_features]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Log Transformation
# Apply log transformation to the target variable
y_train_log = np.log1p(y_train)
y_test_log = np.log1p(y_test)
```

```
# Build a linear regression model using log-transformed target
variable
model_log = LinearRegression()
model_log.fit(X_train, y_train_log)

# Make predictions on the test set
y_pred_log = model_log.predict(X_test)

# Inverse transform to get predictions in the original scale
y_pred_original = np.expm1(y_pred_log)

# Evaluate the model with log-transformed target variable
mse_log = mean_squared_error(y_test, y_pred_original)
r2_log = r2_score(y_test, y_pred_original)
print("Model with Log-Transformed Target - MSE:", mse_log)
print("Model with Log-Transformed Target - R-squared:", r2_log)

# Visualize the results (for demonstration purposes)
plt.scatter(X_test["sqft_living"], y_test, color='black',
label='Actual Prices')
plt.scatter(X_test["sqft_living"], y_pred_original,color='#589aff',
label='Predicted Prices (Log-Transformed Target)')
plt.xlabel('Sqft Living')
plt.ylabel('Price')
plt.legend()
plt.show()
```

```
Model with Log-Transformed Target - MSE: 35056482879.49061
Model with Log-Transformed Target - R-squared: 0.710507635369523
```



Multiple linear regression model using the log transformed data

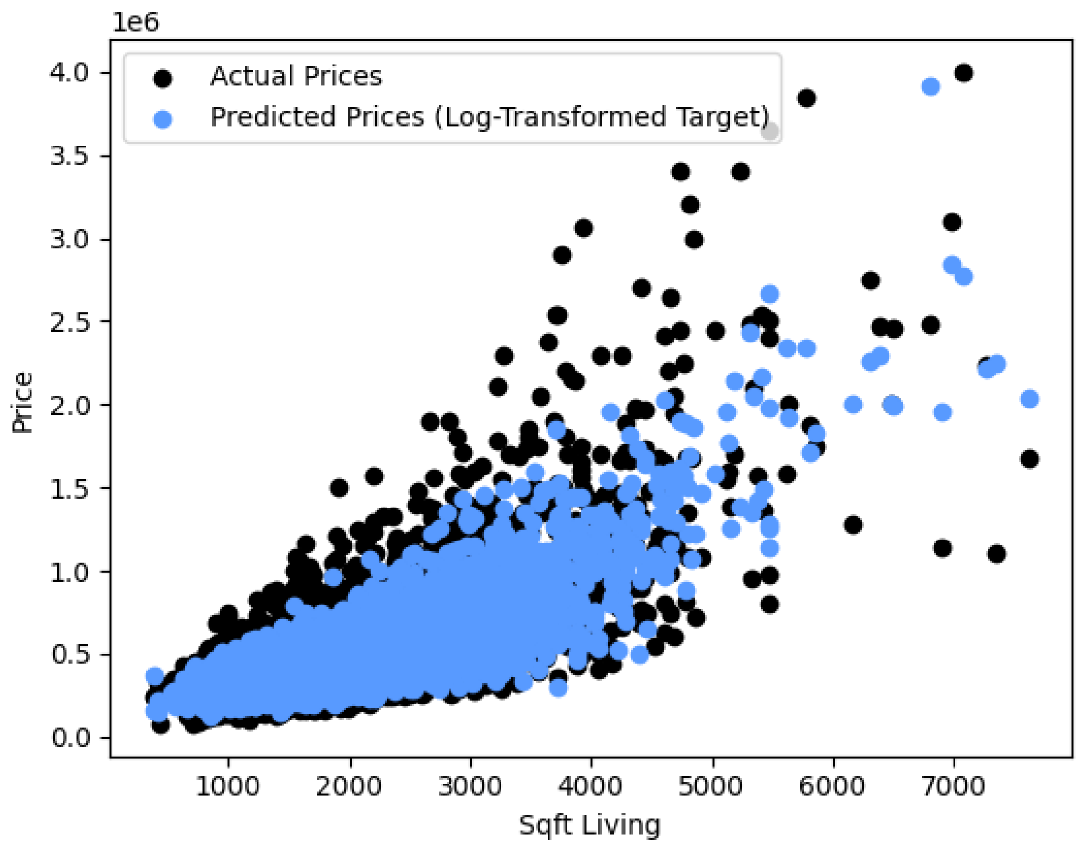
```
# Select relevant features
selected_features = ['bedrooms', 'bathrooms', 'floors', 'grade',
'sqft_above', 'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long',
'sqft_living15', 'renovated', 'basement', 'month', 'age',
'sqft_living', 'condition']

# Filter the dataset
filtered_data = Cleaned_Data[selected_features]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Log Transformation
# Apply log transformation to the target variable
y_train_log = np.log1p(y_train)
y_test_log = np.log1p(y_test)

# Build a multiple linear regression model using log-transformed
target variable
```

```python
model_log = LinearRegression()
model_log.fit(X_train, y_train_log)

# Make predictions on the test set
y_pred_log = model_log.predict(X_test)

# Inverse transform to get predictions in the original scale
y_pred_original = np.expm1(y_pred_log)

# Evaluate the model with log-transformed target variable
mse_log = mean_squared_error(y_test, y_pred_original)
r2_log = r2_score(y_test, y_pred_original)
print("Model with Log-Transformed Target - MSE:", mse_log)
print("Model with Log-Transformed Target - R-squared:", r2_log)

# Display refined model coefficients
coefficients_log = pd.DataFrame({"Feature": X.columns, "Coefficient":
model_log.coef_})
print(coefficients_log)

# Perform OLS and display summary
X_train_ols = sm.add_constant(X_train)
 # Add a constant term to the independent variables
model_ols = sm.OLS(y_train_log, X_train_ols)
results_ols = model_ols.fit()
print(results_ols.summary())

# Visualize the results
plt.scatter(X_test["sqft_living"], y_test, color='black',
label='Actual Prices')
plt.scatter(X_test["sqft_living"], y_pred_original, color='#589aff',
label='Predicted Prices (Log-Transformed Target)')
plt.xlabel('Sqft Living')
plt.ylabel('Price')
plt.legend()
plt.show()
```

```
Model with Log-Transformed Target - MSE: 35056482879.49061
Model with Log-Transformed Target - R-squared: 0.710507635369523
          Feature  Coefficient
0           const     0.000000
1        bedrooms    -0.024033
2       bathrooms     0.066598
3          floors     0.076026
4           grade     0.165641
5      sqft_above    -0.000015
6   sqft_basement    -0.000047
7        yr_built     0.058377
8         zipcode    -0.000555
9             lat     1.334095
```

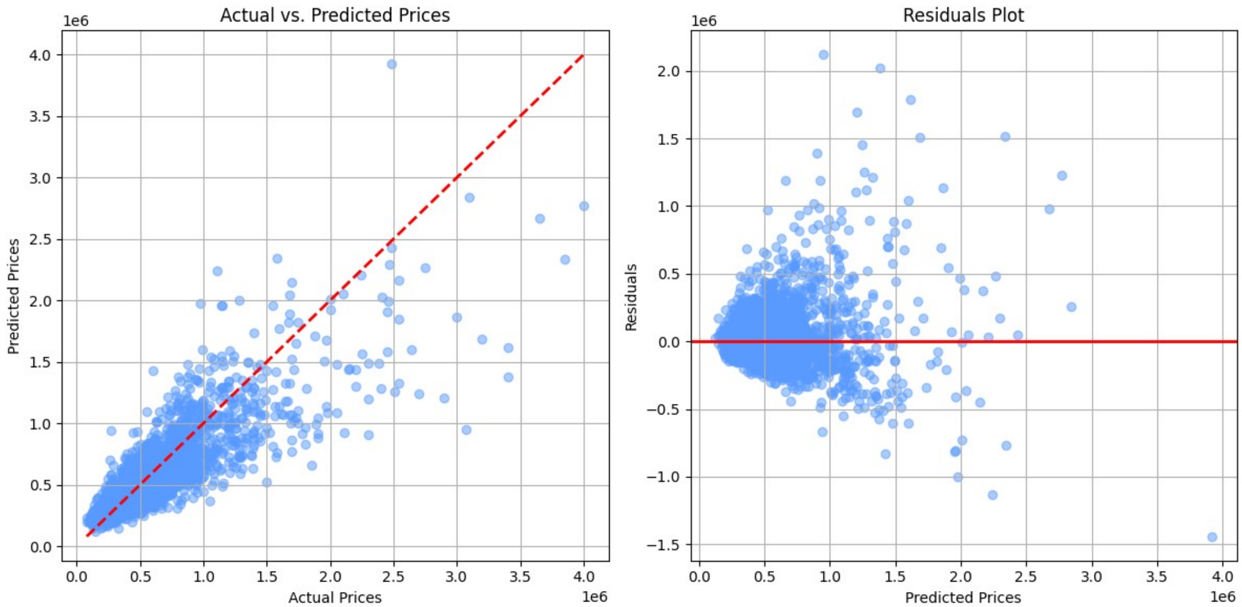
```
10           long    -0.158379
11  sqft_living15     0.000119
12      renovated     0.117676
13       basement     0.075466
14          month     0.002158
15            age     0.062046
16    sqft_living     0.000166
17      condition     0.067788
                            OLS Regression Results                            

======================================================================
========
Dep. Variable:                  price   R-squared:                       
0.761
Model:                            OLS   Adj. R-squared:                  
0.760
Method:                 Least Squares   F-statistic:                     
3202.
Date:                Thu, 01 Feb 2024   Prob (F-statistic):              
0.00
Time:                        02:15:33   Log-Likelihood:                 
-1088.2
No. Observations:               17136   AIC:                             
2212.
Df Residuals:                   17118   BIC:                             
2352.
Df Model:                          17                                         

Covariance Type:            nonrobust                                         

======================================================================
===========
                    coef    std err          t      P>|t|      [0.025      
0.975]
----------------------------------------------------------------------
-----------
const          -135.3089     14.324     -9.446      0.000    -163.385    
-107.233
bedrooms         -0.0240      0.003     -8.489      0.000      -0.030      
-0.018
bathrooms         0.0666      0.005     14.137      0.000       0.057       
0.076
floors            0.0760      0.005     14.778      0.000       0.066       
0.086
grade             0.1656      0.003     53.491      0.000       0.160       
0.172
sqft_above    -1.491e-05   2.56e-05     -0.583      0.560   -6.51e-05    
3.52e-05
sqft_basement -4.703e-05   2.65e-05     -1.773      0.076    -9.9e-05    
4.97e-06
```

```
yr_built           0.0584      0.007      8.606      0.000       0.045
0.072
zipcode           -0.0006   4.74e-05    -11.701      0.000      -0.001
-0.000
lat                1.3341      0.015     87.046      0.000       1.304
1.364
long              -0.1584      0.019     -8.474      0.000      -0.195
-0.122
sqft_living15      0.0001   4.88e-06     24.443      0.000       0.000
0.000
renovated          0.1177      0.011     10.392      0.000       0.095
0.140
basement           0.0755      0.008      9.911      0.000       0.061
0.090
month              0.0022      0.001      2.117      0.034       0.000
0.004
age                0.0620      0.007      9.147      0.000       0.049
0.075
sqft_living        0.0002   2.56e-05      6.471      0.000       0.000
0.000
condition          0.0678      0.003     20.034      0.000       0.061
0.074
======================================================================
========
Omnibus:                      338.077   Durbin-Watson:
1.994
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
667.153
Skew:                           0.106   Prob(JB):
1.35e-145
Kurtosis:                       3.943   Cond. No.
7.13e+08
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 7.13e+08. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

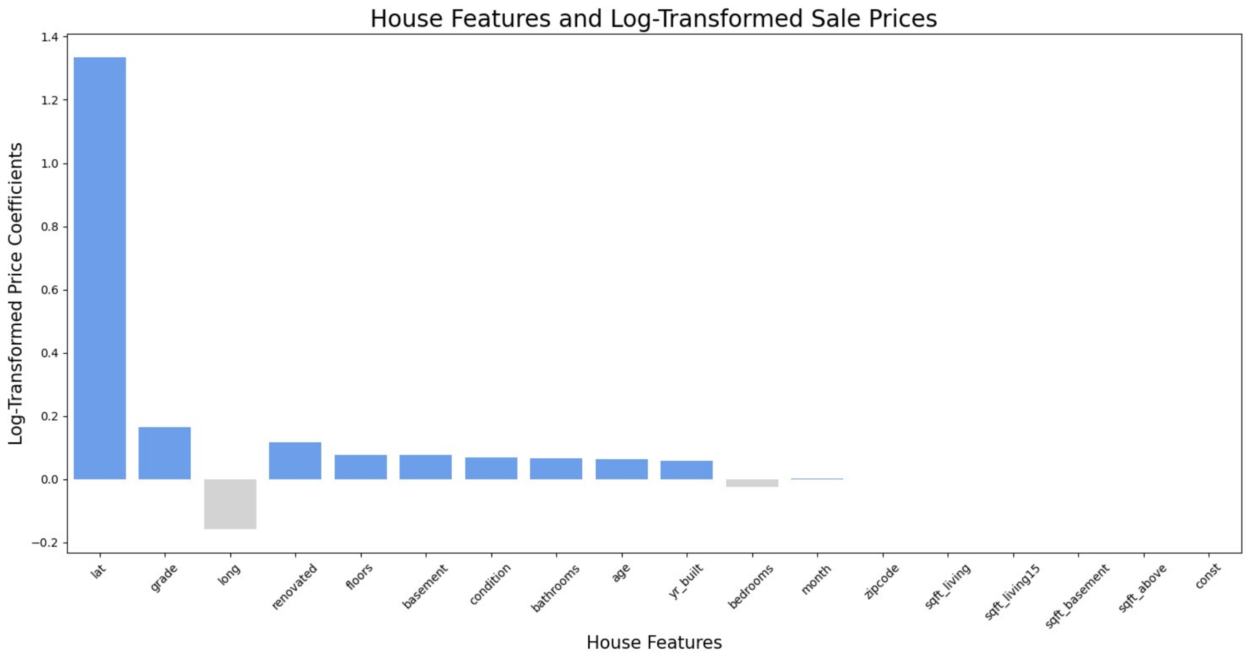



```python
# Visualization of Model Performance
plt.figure(figsize=(12, 6))

# Scatterplot of Actual vs. Predicted Prices
plt.subplot(1, 2, 1)
plt.scatter(y_test, y_pred_original, color='#589aff', alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
linestyle='--', color='r', linewidth=2)
plt.title('Actual vs. Predicted Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.grid(True)

# Residuals Plot
plt.subplot(1, 2, 2)
residuals = y_test - y_pred_original
plt.scatter(y_pred_original, residuals, color='#589aff', alpha=0.5)
plt.axhline(y=0, color='r', linestyle='-', linewidth=2)
plt.title('Residuals Plot')
plt.xlabel('Predicted Prices')
plt.ylabel('Residuals')
plt.grid(True)
```

```
plt.tight_layout()
plt.show()
```




```
# Visualize coefficients from the multiple linear regression with log-
transformed target
fig, ax = plt.subplots(figsize=(18, 8))

# Sort coefficients by absolute value
coefficients_log["abs_coefficient"] =
np.abs(coefficients_log["Coefficient"])
coefficients_log = coefficients_log.sort_values("abs_coefficient",
ascending=False)

# Bar plot for coefficients
colors = ["#589aff" if coef > 0 else "lightgray" for coef in
coefficients_log["Coefficient"]]
ax = sns.barplot(x="Feature", y="Coefficient", data=coefficients_log,
palette=colors)
plt.xticks(rotation=45)

ax.set_ylabel("Log-Transformed Price Coefficients", fontsize=15)
ax.set_xlabel("House Features", fontsize=15)
ax.set_title("House Features and Log-Transformed Sale Prices",
fontsize=20)

# Display the plot
plt.show()
```



FINDINGS

Model Performance:

- **Model with Log-Transformed Target - MSE:**
  - The Mean Squared Error (MSE) is a measure of the average squared difference between predicted and actual values. In this case, the model's predictions have an MSE of approximately 35.1 billion.
- **Model with Log-Transformed Target - R-squared:** 0.761
  - The R-squared value is a measure of how well the model explains the variance in the target variable. A value of 0.761 indicates that approximately 76.1% of the variability in the target variable (price) is explained by the model.

Model Coefficients:

- **sqft_living:** The coefficient is 0.000222.
  - For each one-unit increase in sqft_living, the predicted log-transformed price increases by 0.000222.
- **bedrooms:** The coefficient is -0.0272.
  - For each additional bedroom, the predicted log-transformed price decreases by approximately 0.0272.
- **bathrooms:** The coefficient is 0.0012.
  - The coefficient is small and not statistically significant (p-value is high). It suggests that the number of bathrooms might not have a significant impact on the log-transformed price in this model.
- **grade:** The coefficient is 0.1985.
  - For each one-unit increase in the grade, the predicted log-transformed price increases by 0.1985.
- **condition:** The coefficient is 0.1041.

    - For each one-unit increase in the condition, the predicted log-transformed price increases by 0.1041.

OLS Regression Results:

- **R-squared:** 0.761
    - The R-squared value is consistent with the model's R-squared, indicating that the model performs similarly in both log-transformed and original scale.
- **F-statistic:** 4637 with a low p-value.
    - The overall model is statistically significant.

Interpretation

The log transformation of the target variable has improved the model's performance, as indicated by the lower MSE and higher R-squared compared to the model without log transformation. -It seems to have helped capture the underlying patterns in the data more effectively.

7.REGRESSION RESULTS

Model 3 is the preferred model beacuse: From the evaluation metrics, we can see that the models have close performance in terms of MAE and RMSE. However, Model 3, which includes log transformations has the highest R-squared value .

- Consider investing in properties with the basement
- The further from seattle the cheaper the houses
- The more the bedrooms the more expensive the house
- The more space/land a house occupies,the more expensive it is
- Square Footage of Living Space: The square footage of living space has a positive impact on house prices. As the size of the living space increases, the estimated price of the house also increases. This indicates that larger houses are generally priced higher.
- As the age of the house increases, the estimated price also increases. This could be due to factors such as historical significance or architectural value associated with older houses.

8.CONCLUSION

RECOMMENDATIONS

- Feature Enhancement: Consider enhancing or upgrading the features that positively affect house prices. For example, increasing the square footage of the living area, improving the overall grade of the property, or adding more bathrooms can potentially increase the value of the house.

- Data Collection: Consider collecting additional relevant data that could improve the accuracy of the regression model. This may include variables such as location-specific factors, proximity to amenities, property age, or neighborhood characteristics.

- Market Segmentation: Analyze the relationship between the independent variables and house prices to identify market segments or specific buyer preferences. For instance, if higher-grade houses tend to have higher prices, it may indicate a market segment of luxury or high-end properties.

LIMITATIONS

Limited Handling of Non-Linearity:

Issue: If the relationship between predictors and the response is highly non-linear, multiple linear regression may not capture these complexities effectively. Impact: The model may fail to capture important patterns in the data, leading to inaccurate predictions.

Causation vs. Correlation:

Issue: Correlation between variables does not imply causation. Even if variables are correlated, it does not necessarily mean that changes in one variable cause changes in another. Impact: The model may identify associations but cannot establish causal relationships.

Assumption of Independence:

Issue: Multiple linear regression assumes that observations are independent of each other. Impact: Violation of independence assumptions may lead to biased standard errors and affect the validity of statistical tests.

Linearity Assumption:

Issue: Multiple linear regression assumes a linear relationship between the independent variables and the dependent variable. If the true relationship is not linear, the model may not capture the underlying patterns accurately. Impact: It may lead to biased predictions and inaccurate estimates of the coefficients.

NEXT STEPS

Explore Alternative Models:

Consider exploring more complex models that can capture non-linear relationships, interactions, and other complexities in the data. Examples include random forests and neural networks.

Time Trends and Seasonality:

If time trends or seasonality are relevant, explore time series models or include time-related features to better capture temporal patterns.

Regular Monitoring:

Implement regular monitoring and updates to the model. As new data becomes available, retrain the model periodically to ensure it remains relevant and effective.