Final Project Submission

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INTRODUCTION

In the fast-paced world of real estate, providing clients with accurate insights is key. Real estate agencies guide homeowners through crucial decisions like pricing, market analysis, and property inspections. This project aims to equip agencies with a powerful regression-based tool. This tool predicts potential property value increases based on factors like bedrooms, year built, floors, living space, condition, and location. With this model, agencies can offer tailored advice, ensuring clients make informed decisions for maximizing returns in the competitive market

BUSINESS UNDERSTANDING

The dataset provided contains information about various houses sold, including their features and sale prices. This data can be valuable for real estate agencies in several ways:

Market Analysis: The agency can use the data to analyze market trends, such as which types of houses are in high demand, which neighborhoods have seen increasing property values, and how various features (like waterfront views or renovated properties) affect selling prices.

Property Valuation: Understanding the relationship between house features and sale prices can help the agency accurately value properties for sellers and buyers, ensuring fair and competitive pricing.

Targeted Marketing: By identifying patterns in buyer preferences, the agency can tailor marketing efforts to attract potential buyers interested in specific types of properties or neighborhoods.

DATA UNDERSTANDING

King County, Washington, located in the northwestern United States, boasts a vibrant housing market anchored by the bustling city of Seattle. Over the years, the county has seen remarkable growth, driven by its thriving economy and cultural significance. This has attracted a surge of residents, spurring high demand for housing across urban and suburban landscapes. Seattle, renowned for its striking skyline, has become particularly desirable for tech professionals and city enthusiasts alike. Known for its competitiveness, King County's real estate market offers diverse neighborhoods catering to various preferences, from historic districts to contemporary suburban developments.

Target Variable

price: Sale price of the house .

Unique identifier

id - Unique identifier for a house

Property Characteristics:

bedrooms: Number of bedrooms.

bathrooms: Number of bathrooms.

sqft_living: Square footage of living space in the home.

sqft_lot: Square footage of the lot.

floors: Number of floors (levels) in the house.

waterfront: Indicates whether the house is on a waterfront (categorical: YES/NO).

view: Quality of view from the house, categorized into various types.

condition: Overall condition of the house, categorized based on maintenance.

grade: Overall grade of the house, reflecting construction and design quality.

Additional Features:

sqft_above: Square footage of house apart from the basement.

sqft_basement: Square footage of the basement.

yr_built: Year when the house was built.

yr_renovated: Year when the house was renovated.

zipcode: ZIP Code of the property.

lat: Latitude coordinate of the property.

long: Longitude coordinate of the property.

sqft_living15: Square footage of interior housing living space for the nearest 15 neighbors.

sqft_lot15: Square footage of the land lots of the nearest 15 neighbors.

PROBLEM STATEMENT

In King County,stakeholders in the real estate industry face challenges in understanding the factors influencing property valuation and market trends. This study seeks to address these challenges by analyzing the complexies between property features, location-related factors, market preferences, and temporal dynamics. By gaining insights into these factors, stakeholders can make more informed decisions regarding property investments, pricing strategies, and market positioning. Ultimately, the goal is to provide actionable insights that empower stakeholders to navigate and succeed in the dynamic King County real estate market.

OBJECTIVES

Main Objective:

The primary objective of this project is to construct a predictive regression model to aid real estate agencies in advising clients on house prices. The model is designed to forecast potential fluctuations in property value based on property characteristics, providing valuable insights to empower clients in making well-informed investment decisions.

Specific Objectives:

i). Identify Key Factors Influencing House Prices:

Examine various features, such as bedrooms, bathrooms, and square footage, to determine their impact on sale price. Investigate location-related attributes like zip code and geographic coordinates to further understand their influence on property prices.

ii). Evaluate Model Performance:

Utilize metrics such as mean squared error, R-squared values, and residual analysis to assess the model's effectiveness in accurately predicting house prices.

iii). Offer Actionable Recommendations:

Provide practical suggestions to real estate agencies for enhancing profitability and market presence. Utilize insights derived from the model to optimize marketing strategies and improve overall decision-making processes.

TABLE OF CONTENT

1. DATA PREPARATION

```
# 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
%matplotlib inline
import seaborn as sns  # for enhanced data visualization.

from statsmodels.stats.outliers_influence import variance_inflation_factor  # For
from statsmodels.graphics.regressionplots import plot_partregress_grid  # For par
from sklearn.model_selection import train_test_split  # Used to split data into t
from sklearn.feature_selection import RFE  # Recursive Feature Elimination for fe
from sklearn.preprocessing import StandardScaler  # Standardizing/Scaling feature
from sklearn.preprocessing import PolynomialFeatures  # Generate polynomial featu
from sklearn.linear_model import LinearRegression  # Linear Regression model.
from sklearn.metrics import mean_squared_error, r2_score  # Evaluation metrics fo
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 mean
import warnings  # handle warnings during code execution.
warnings.filterwarnings("ignore")  # Ignore warnings to improve code readability.
```

```
# Loading and preview of the dataset
df = pd.read_csv("kc_house_data.csv")
df
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080
...	...	...	...	...	...	...	..
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076

21597 rows × 21 columns

```
# Checking the dataset
df.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
```

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.

The data contains 21597 rows and 21 columns

2. DATA CLEANING

Data cleaning involves the process of identifying and resolving issues related to the quality of the dataset. Its primary objective is to ensure that the data is accurate, consistent, and devoid of errors. Below are some of the data cleaning and preparation methods that were employed:

1. Handling Missing Values
2. Handling Duplicates
3. Dealing with placeholders:
4. Transforming data
5. Handling outliers

```
# Create a new dataframe of the raw data to clean
df1 = pd.read_csv("kc_house_data.csv")
```

```
# Dropping columns
df1 = df1.drop(['date','long','lat','zipcode'], axis=1)
df1
```

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7129300520	221900.0	3	1.00	1180	5650	1.0
1	6414100192	538000.0	3	2.25	2570	7242	2.0
2	5631500400	180000.0	2	1.00	770	10000	1.0
3	2487200875	604000.0	4	3.00	1960	5000	1.0
4	1954400510	510000.0	3	2.00	1680	8080	1.0
...	...	...	...	...	...	...	...
21592	263000018	360000.0	3	2.50	1530	1131	3.0
21593	6600060120	400000.0	4	2.50	2310	5813	2.0
21594	1523300141	402101.0	2	0.75	1020	1350	2.0
21595	291310100	400000.0	3	2.50	1600	2388	2.0
21596	1523300157	325000.0	2	0.75	1020	1076	2.0

21597 rows × 17 columns

Next steps: View recommended plots

Reasons

They do not have an impact in our final objectives and to decompress the data we can remove them

```
# calculate the percentage of missing columns
df1.isnull().sum()
```

```
id                  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
```

```
sqft_living15      0
sqft_lot15         0
dtype: int64
```

Handling missing values in categorical columns

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

```
# Change waterfront missing value to NO, then to binary values.
df1.loc[df1.waterfront.isnull(), 'waterfront'] = 'NO'
df1['waterfront'] = df['waterfront'].apply(lambda x: 0 if x == 'NO' else 1)


# Change view missing value to NONE, then to numerical ordered values.
df1.loc[df.view.isnull(), 'view'] = "NONE"
view_dict = {'NONE': 0, 'FAIR': 1, 'AVERAGE': 2, 'GOOD': 3, 'EXCELLENT': 4}
df1['view'].replace(view_dict, inplace=True)
```

REASONS

waterfront Missing Values:

- Missing values in the 'waterfront' column were replaced with 'NO' since absence of information suggests the property lacks a waterfront feature and the majority data was 'NO' thats not far from the truth

View Missing Values:

- Missing values in the view column were replaced with 'NONE', indicating that the property doesn't have a specified view also the majority was NONE so we are not far from the truth.

Handling missing values in numerical columns

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

```
# Replace missing values in 'yr_renovated' with 0
df1.loc[df.yr_renovated.isnull(), 'yr_renovated'] = 0

# Create a new column 'renovated' based on the 'yr_renovated' values
df1['renovated'] = df['yr_renovated'].apply(lambda x: 0 if x == 0 else 1)
```

REASON

yr_renovated missing Values:

Replace missing values in 'yr_renovated' with 0 since the missing value indicates that the property has not been renovated.

Adding column renovated accounts for the difference in price for a renovated house over one that is not

```
# Confirm missing values are fixed
df1.isnull().sum()
```

```
id               0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
sqft_living15    0
sqft_lot15       0
renovated        0
dtype: int64
```

CHECKING FOR DUPLICATES

Based of the data the id column is the column we are worried about it having duplicates since it is a unique identifier for each property

```
# Checking for duplicates using the 'id' column
df1[df1.duplicated(subset=["id"])]
```

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
94	6021501535	700000.0	3	1.50	1580	5000	1.0
314	4139480200	1400000.0	4	3.25	4290	12103	1.0
325	7520000520	240500.0	2	1.00	1240	12092	1.0
346	3969300030	239900.0	4	1.00	1000	7134	1.0
372	2231500030	530000.0	4	2.25	2180	10754	1.0
...	...	...	...	...	...	...	...
20165	7853400250	645000.0	4	3.50	2910	5260	2.0
20597	2724049222	220000.0	2	2.50	1000	1092	2.0
20654	8564860270	502000.0	4	2.50	2680	5539	2.0
20764	6300000226	380000.0	4	1.00	1200	2171	1.5
21565	7853420110	625000.0	3	3.00	2780	6000	2.0

177 rows × 18 columns

```
# Dropping the duplicated data based on the 'id' column
df1.drop_duplicates(subset=["id"], inplace=True)
```

REASON

Removing duplicates leads to a more accurate representation of the dataset since duplicate entries in the id column can introduce inconsistencies during the analysis and modeling.

```
# confirm duplicates were handled
df1[df1.duplicated(subset=["id"])]
```

id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	vie

CHECKING FOR PLACEHOLDERS

Placeholders are values used to denote missing, unknown, or invalid data within a dataset. Common examples include "N/A", "-", "UNKNOWN", "NULL", and specific numeric values like 9999 or -9999. It's important to identify and handle placeholders properly during data preprocessing to ensure accurate analysis and modeling.

```
# Define a comprehensive list of potential placeholder values
common_placeholders = ["", "na", "n/a", "nan", "none", "null", "-", "--", "?", "?

# Loop through each column and check for potential placeholders
found_placeholder = False
for column in df1.columns:
    unique_values = df1[column].unique()
    for value in unique_values:
        if pd.isna(value) or (isinstance(value, str) and value.strip().lower() in
            count = (df1[column] == value).sum()
            print(f"Column '{column}': Found {count} occurrences of potential pla
            found_placeholder = True

if not found_placeholder:
    print("No potential placeholders found in the DataFrame.")
```

```
Column 'sqft_basement': Found 452 occurrences of potential placeholder '?'
```

```
# Replace '?' values in the sqft_basement column with '0' and convert to float
df1['sqft_basement'] = df1['sqft_basement'].replace('?', '0').astype(float)

# Create basement column as binary value (0 for no basement, 1 for basement prese
df1['basement'] = df1['sqft_basement'].apply(lambda x: 0 if x == 0 else 1)
```

```
# confirm no more placeholders
# Define a comprehensive list of potential placeholder values
common_placeholders = ["", "na", "n/a", "nan", "none", "null", "-", "--", "?", "?

# Loop through each column and check for potential placeholders
found_placeholder = False
for column in df1.columns:
    unique_values = df1[column].unique()
    for value in unique_values:
        if pd.isna(value) or (isinstance(value, str) and value.strip().lower() in
            count = (df1[column] == value).sum()
            print(f"Column '{column}': Found {count} occurrences of potential pla
            found_placeholder = True

if not found_placeholder:
    print("No placeholders found in the DataFrame.")
```

```
No placeholders found in the DataFrame.
```

EXPLANATION

The use of '?' as a placeholder in the 'sqft_basement' column indicates missing or unknown values that need to be handled

Adding a new column basement also improves on the model we will create to affect prices

TRANSFORMING THE DATA

```
df1.dtypes
```

```
id                 int64
price            float64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition         object
grade             object
sqft_above         int64
sqft_basement    float64
yr_built           int64
yr_renovated     float64
sqft_living15      int64
sqft_lot15         int64
renovated          int64
basement           int64
dtype: object
```

```
# Define the mapping for condition
cond_dict = {'Poor': 0, 'Fair': 1, 'Average': 2, 'Good': 3, 'Very Good': 4}

# Replace condition values with numerical ordered values
df1['condition'].replace(cond_dict, inplace=True)

# Extract the numerical part of grade and convert to integer
df1['grade'] = df1['grade'].map(lambda x: int(x.split(' ')[0]))
```

```
# Confirm all data has been transformed
df1.dtypes
```

```
id                 int64
price            float64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
```

```
grade              int64
sqft_above         int64
sqft_basement    float64
yr_built           int64
yr_renovated     float64
sqft_living15      int64
sqft_lot15         int64
renovated          int64
basement           int64
dtype: object
```

EXPLANATIONS

1.Condition column

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

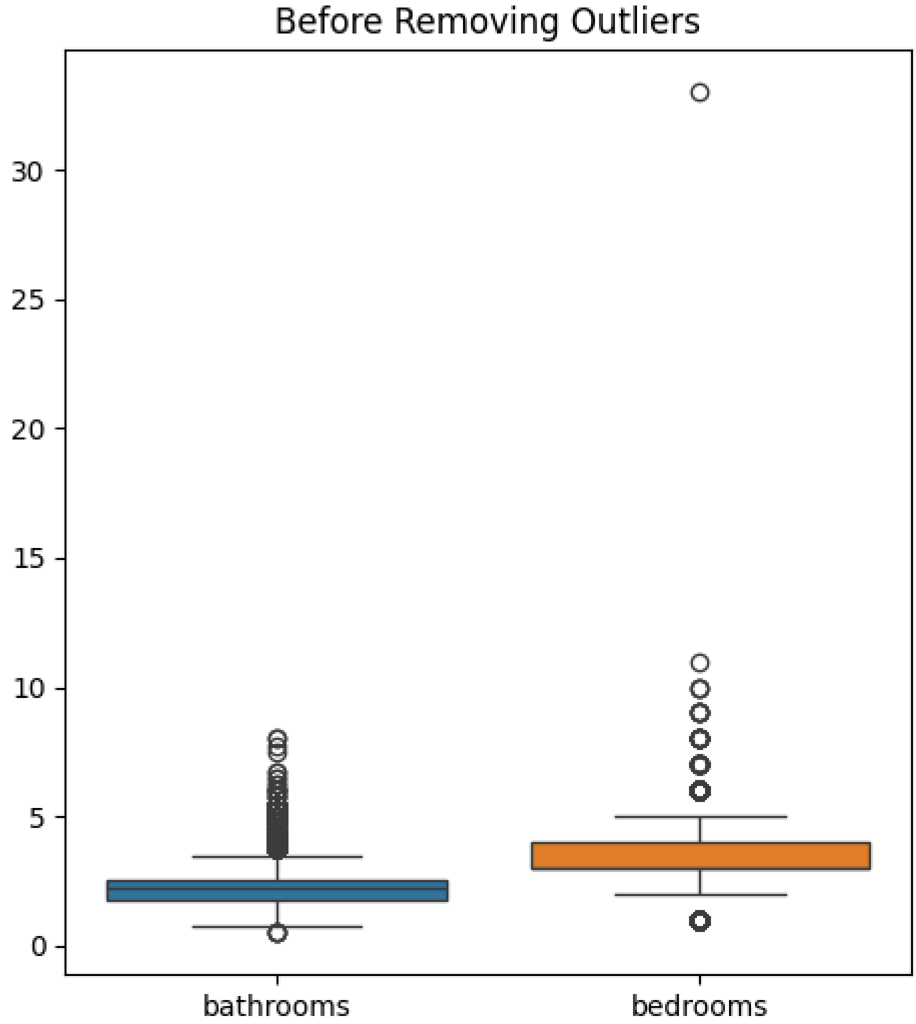
2.Grade Column:

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

Handling outliers

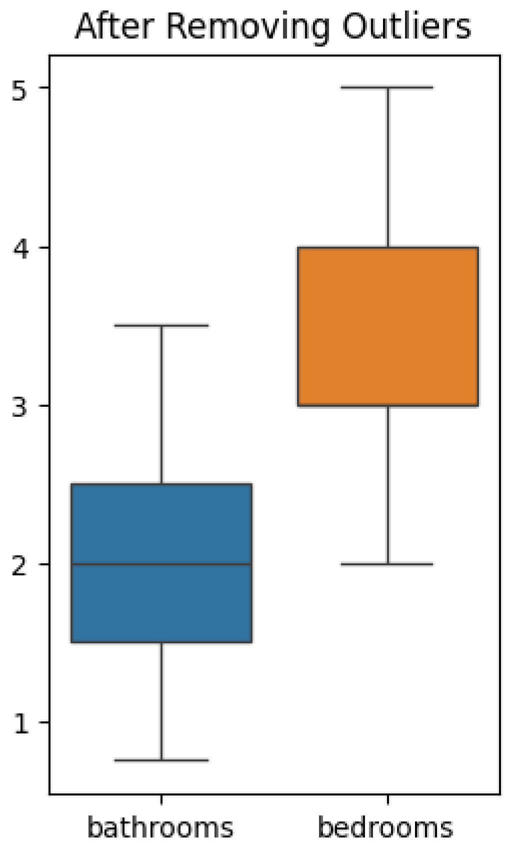
```
# Before removing outliers
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.boxplot(data=df1[['bathrooms', 'bedrooms']])
plt.title('Before Removing Outliers')
```

```
Text(0.5, 1.0, 'Before Removing Outliers')
```




```
# Remove outliers
Q1 = df1.quantile(0.25)
Q3 = df1.quantile(0.75)
IQR = Q3 - Q1

df_filtered = df1[~((df1 < (Q1 - 1.5 * IQR)) | (df1 > (Q3 + 1.5 * IQR))).any(axis
```

```
# Remove outliers
Q1 = df1.quantile(0.25)
Q3 = df1.quantile(0.75)
IQR = Q3 - Q1

df_filtered = df1[~((df1 < (Q1 - 1.5 * IQR)) | (df1 > (Q3 + 1.5 * IQR))).any(axis

# After removing outliers
plt.subplot(1, 2, 2)
sns.boxplot(data=df_filtered[['bathrooms', 'bedrooms']])
plt.title('After Removing Outliers')

plt.show()
```



Reason

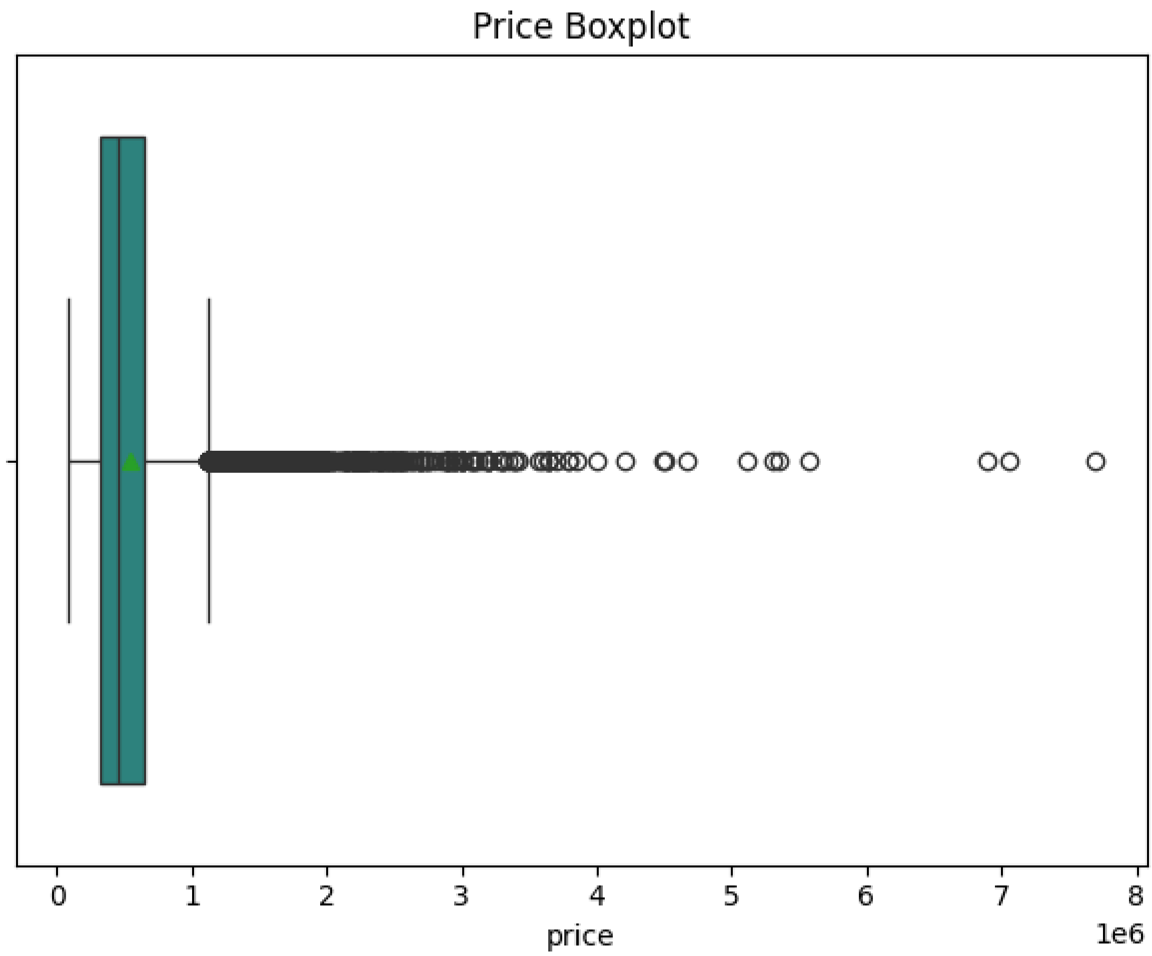
To remove values that were out of bound

3.EXPLORATORY DATA ANALYSIS

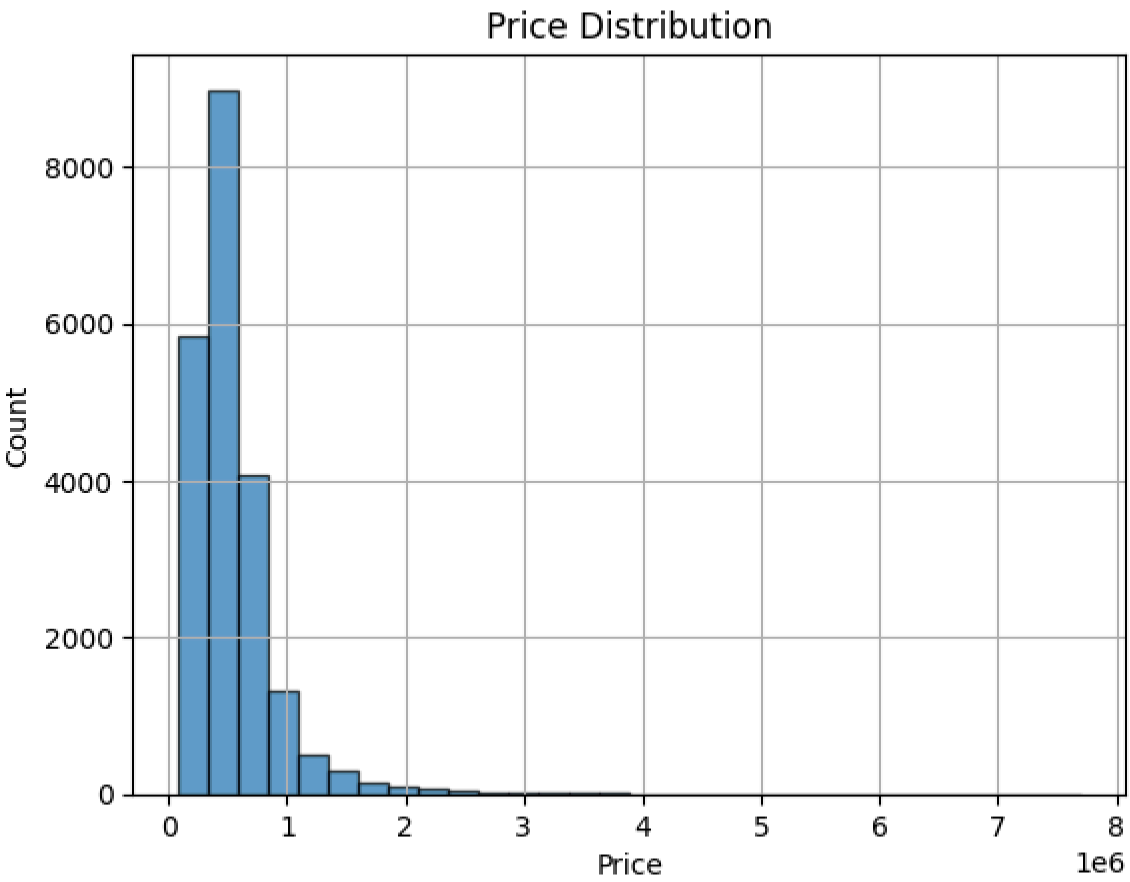
1. Univariate Analysis
2. Bivariate Analysis
3. MultiVariate Analysis

Univariate Analysis

```
plt.figure(figsize=(6, 5))

# Price boxplot

sns.boxplot(x=df1['price'], palette='viridis', showmeans=True)
plt.title('Price Boxplot')

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




```
# Price distribution plot
prices = df1['price']
plt.hist(prices, bins=30, edgecolor='black', alpha=0.7)
plt.xlabel('Price')
plt.ylabel('Count')
plt.title('Price Distribution')
plt.grid(True)
plt.show()
```



Conclusion

This graph shows the distribition of house prices in the data. According to this graph, most houses cost less than 1,000,000.

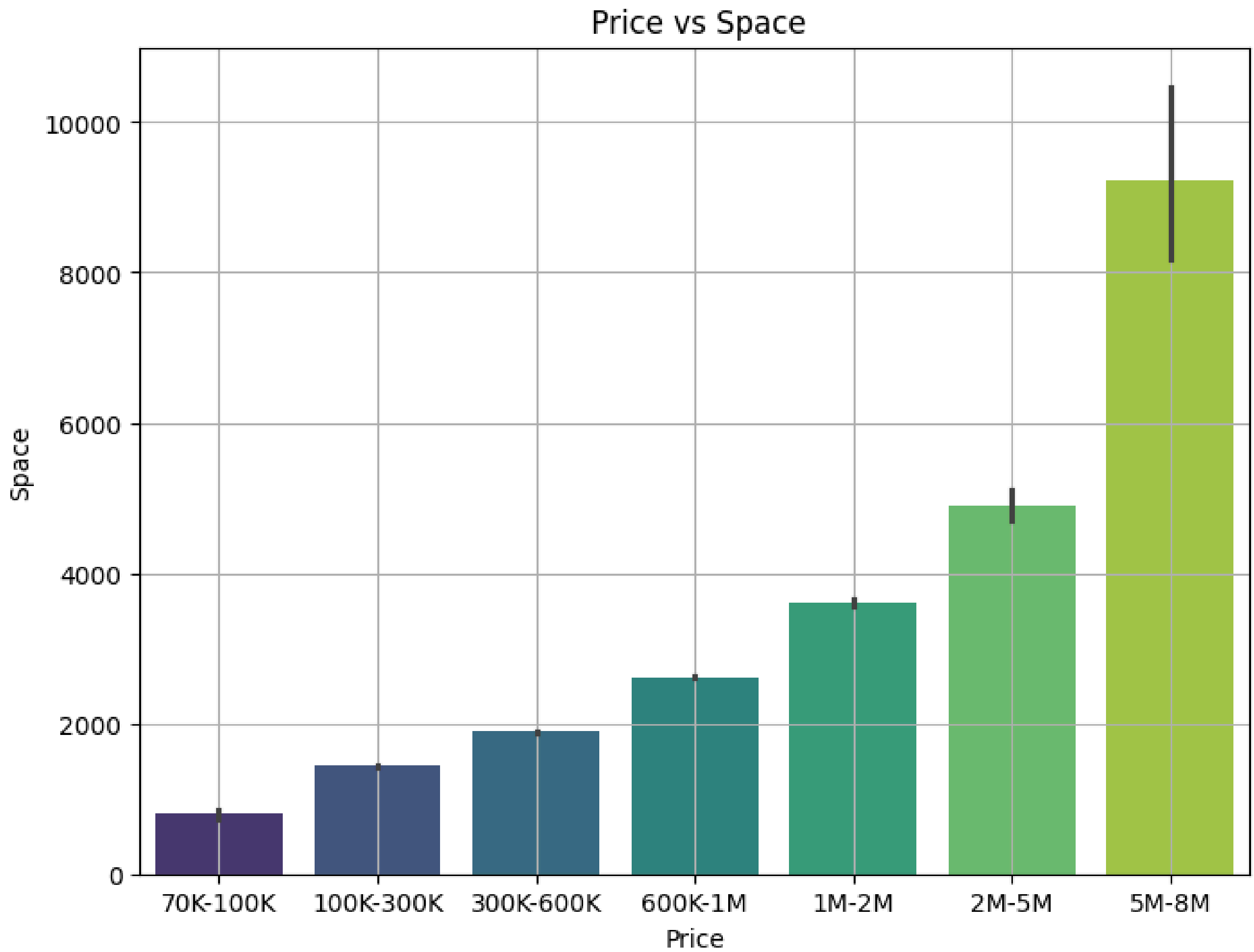
Bivariate Analysis

```
# Define the labels with ranges
labels = ["70K-100K", "100K-300K", "300K-600K", "600K-1M", "1M-2M", "2M-5M", "5M-


# Cut the data into the specified ranges and assign labels
dfpr = pd.DataFrame(df1)
dfpr["pricerange"] = pd.cut(dfpr.price,
                                  bins=[70000, 100000, 300000, 600000, 1000000, 2
                                  labels=labels)

# Count the occurrences of each category
counts = dfpr['pricerange'].value_counts()
print(counts)
```

```
pricerange
300K-600K    10692
600K-1M       4763
100K-300K     4485
1M-2M         1252
2M-5M          191
```

```
70K-100K        30
5M-8M            7
Name: count, dtype: int64
```

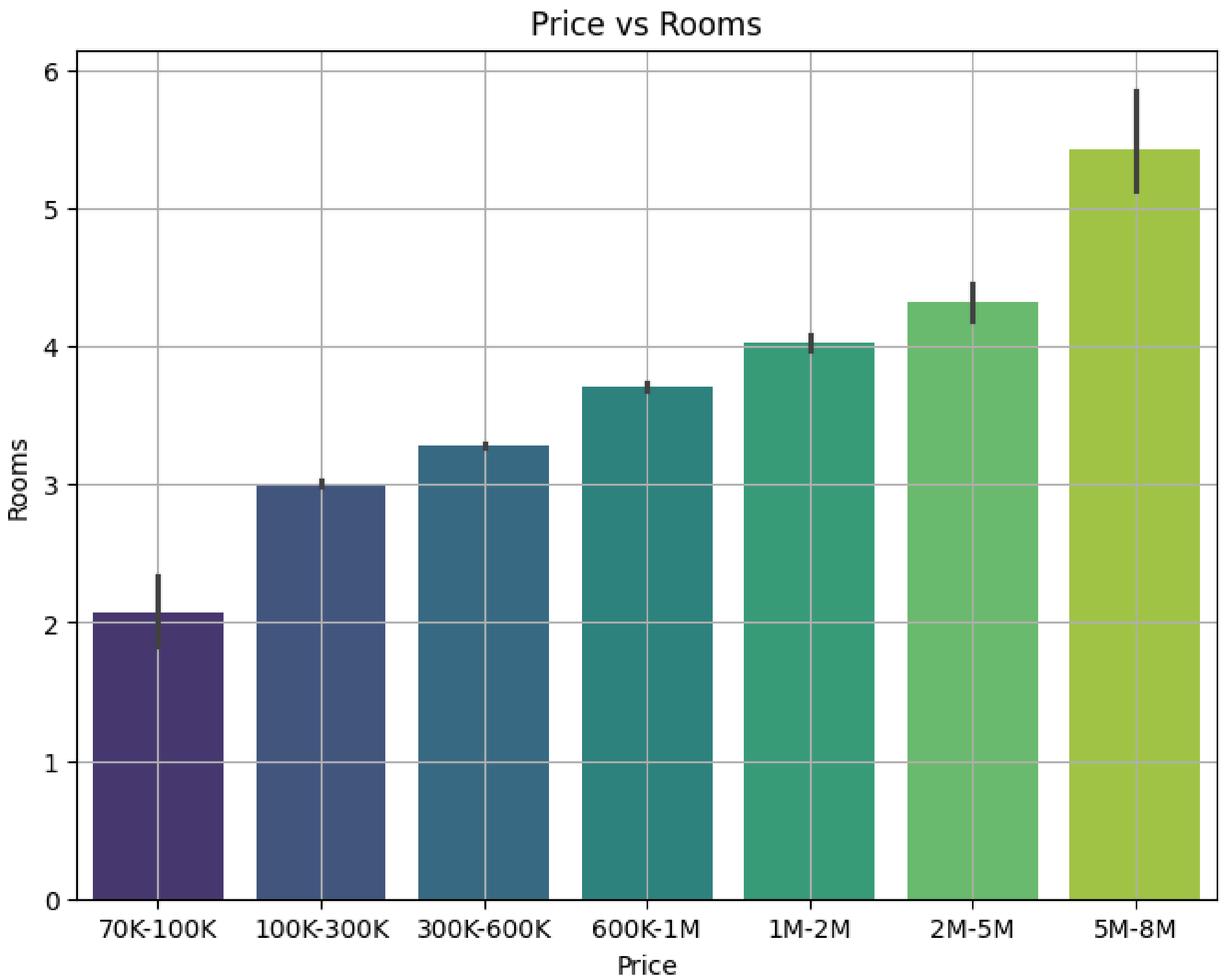
```
price_sf = pd.DataFrame(dfpr)

# Bar graph of Price against Living Space
plt.figure(figsize=(8, 6))
sns.barplot(data=price_sf, x='pricerange', y='sqft_living', palette='viridis')
plt.xlabel('Price')
plt.ylabel('Space')
plt.title(' Price vs Space')
plt.grid(True)
plt.show()
```



Conclusion

This graph shows that bigger houses tend to have a higher price, so a house worth about 90,000 is expected to be smaller than a house worth about 6,000,000. We know that most houses cost less than 1,000,000 therefore, this indicates that most houses have less than 3000 square feet of living space and Houses with more than 4000 square feet of living space cost from 2,000,000

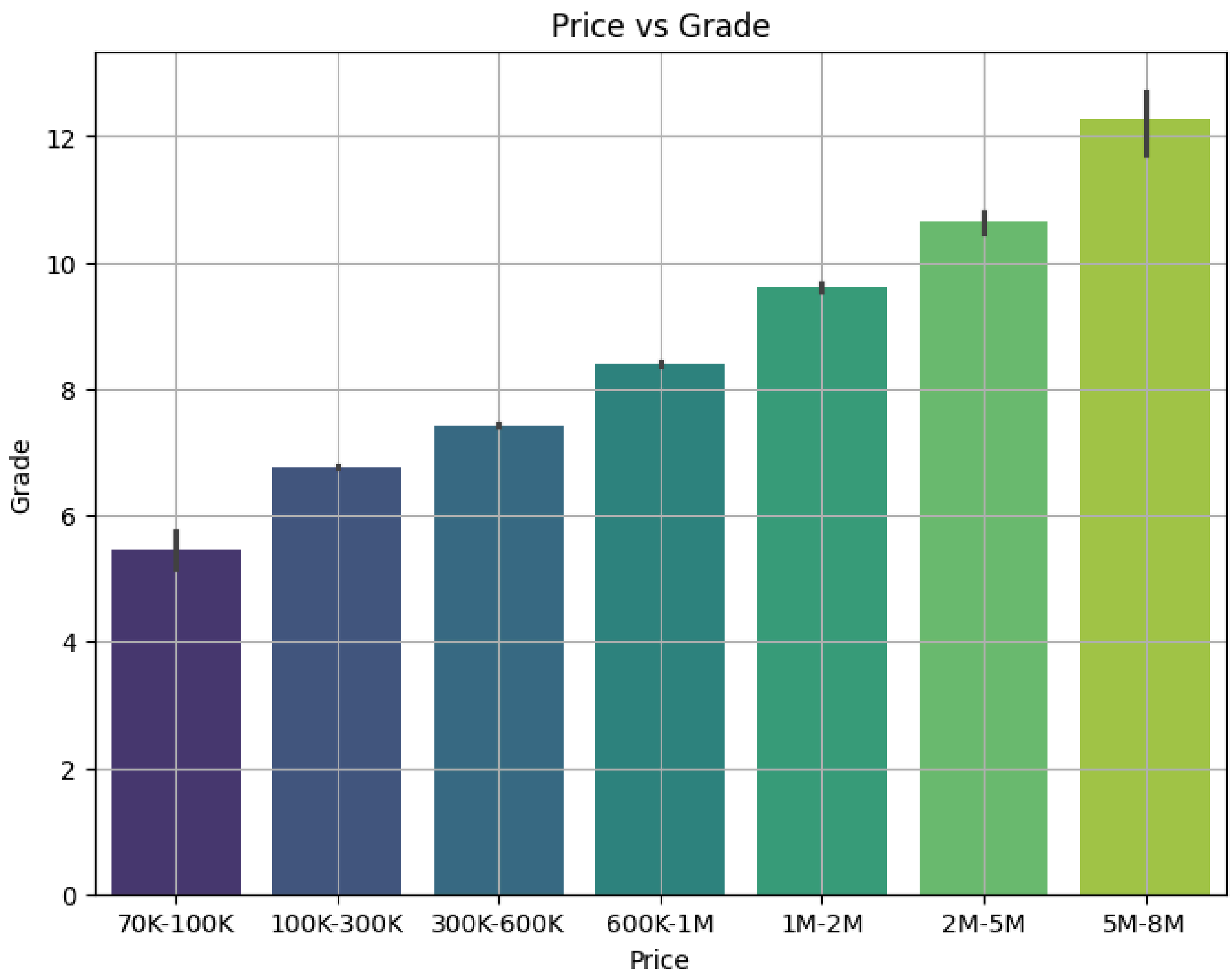
```
price_rm = pd.DataFrame(dfpr)

# Bar graph of Price against Rooms
plt.figure(figsize=(8, 6))
sns.barplot(data=price_rm, x='pricerange', y='bedrooms', palette='viridis')
plt.xlabel('Price')
plt.ylabel('Rooms')
plt.title('Price vs Rooms')
plt.grid(True)
plt.show()
```



Conclusion

According to this graph, house prices increases with number of rooms, therefore houses with 5 or more rooms sell at around 5,000,000 while those with 2 or less rooms sell at around 70,000. We can also conclude that most houses have less than 4 bedrooms and the ones that have 4 or more bedrooms cost more than 1,000,000

```
price_gr = pd.DataFrame(dfpr)

# Bar graph of Price against Grade
plt.figure(figsize=(8, 6))
sns.barplot(data=price_gr, x='pricerange', y='grade', palette='viridis')
plt.xlabel('Price')
plt.ylabel('Grade')
plt.title('Price vs Grade')
plt.grid(True)
plt.show()
```



Conclusion

Houses with higher grades tend to be of higher quality therefore they also have a higher price, for instance houses worth about 80,000 tend to have a lower grade (5 - 7) while houses worth about 6,000,000 tend to have a higher grade (12 - 13). Since most houses cost less than 1,000,000, from this graph we can conclude that most houses have a grade of 7(average) and 8 (good)

MultiVariate Analysis

```
df2 = pd.DataFrame(df1)
```

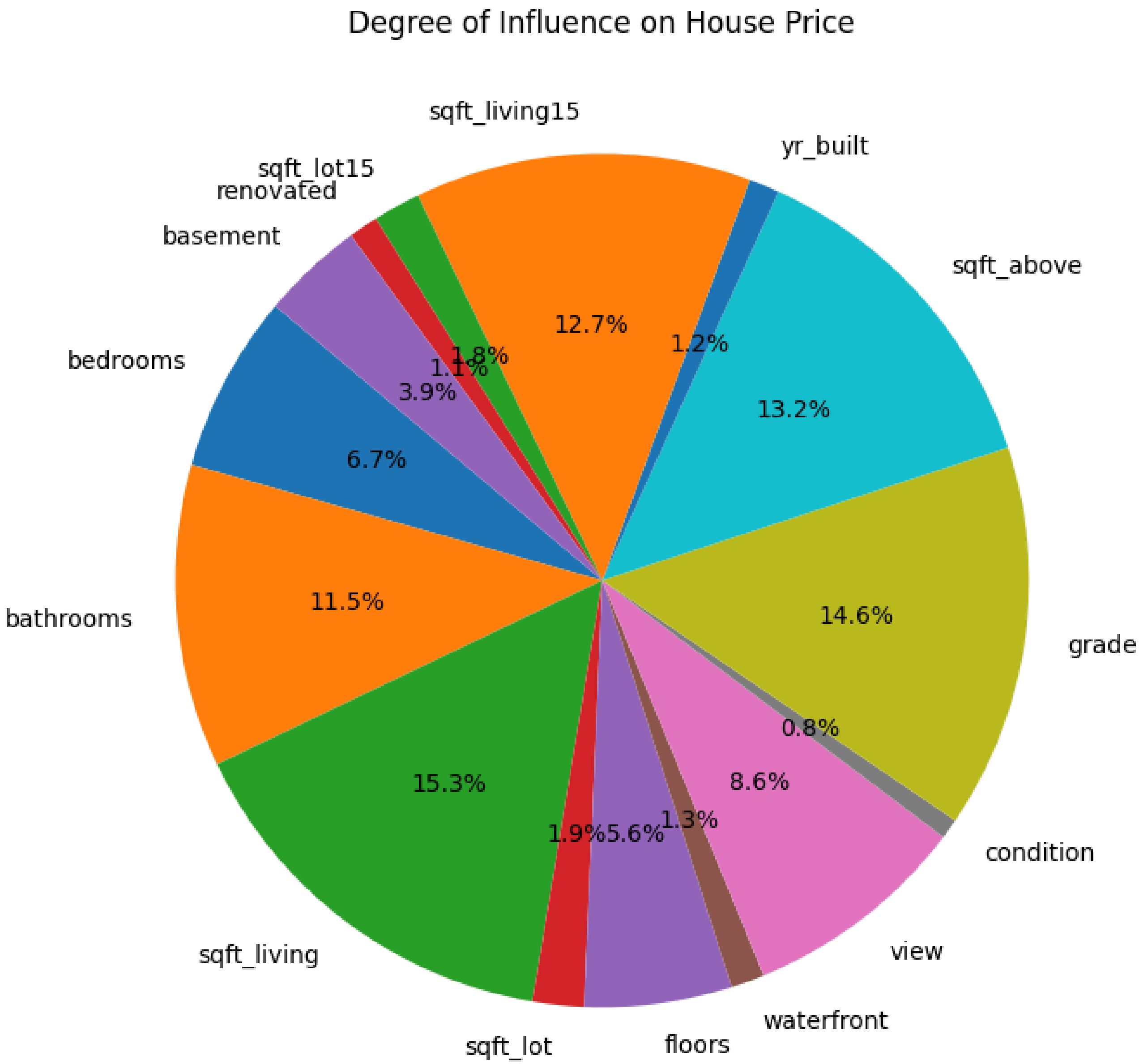
```
drop_var = ['id', 'yr_renovated','sqft_basement']
dfcor = df2.drop(drop_var, axis=1)
```

```
correlation = dfcor.corr()['price'].drop('price')  # Drop 'price' column from cor
```

```
correlation
```

```
bedrooms         0.309453
bathrooms        0.526229
sqft_living      0.701875
sqft_lot         0.089111
floors           0.256286
waterfront       0.058080
view             0.393113
condition        0.034779
grade            0.668020
sqft_above       0.605294
yr_built         0.052906
sqft_living15    0.584549
sqft_lot15       0.082438
renovated        0.051166
basement         0.177593
Name: price, dtype: float64
```

```
plt.figure(figsize=(8, 8))
plt.pie(correlation.abs(), labels=correlation.index, autopct='%1.1f%%', startangl
plt.title('Degree of Influence on House Price')
plt.show()
```



Conclusion

The piechart above shows how much of an infuence each variable has on the price of a house. Variables such as Living space have a significant influence on price (15.3%) while variables such as Waterfront have less significant influence on price(1.3%) This shows what buyers in this area prioritize when looking for a house.

4.STATISTICAL ANALYSIS

Statistical analysis is used to understand relationships within the dataset, identifying patterns, and gaining insights. In regression modeling project for predicting property value based on home renovations, here are the key steps in statistical analysis:

1. Descriptive Statistics

2. Correlation matrix
3. Distribution Analysis
4. Inferential Statistics using Hypothesis Testing and Analysis of Variance
5. MultiColinierity

Descriptive Statistics

- Understanding the characteristics of the data.

```
df1.describe()
```

	id	price	bedrooms	bathrooms	sqft_living	sqft_l
count	2.142000e+04	2.142000e+04	21420.000000	21420.000000	21420.000000	2.142000e+
mean	4.580940e+09	5.407393e+05	3.373950	2.118429	2083.132633	1.512804e+
std	2.876761e+09	3.679311e+05	0.925405	0.768720	918.808412	4.153080e+
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+
25%	2.123537e+09	3.225000e+05	3.000000	1.750000	1430.000000	5.040000e+
50%	3.904921e+09	4.500000e+05	3.000000	2.250000	1920.000000	7.614000e+
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.069050e+
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+

The rows provide descriptive statistics including count, mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum values for each column in the dataset.

```
# Generate some sample data
data = np.random.normal(loc=50, scale=10, size=100)

# Calculate descriptive statistics
mean = np.mean(data)
median = np.median(data)
mode = pd.Series(data).mode()[0]
std_dev = np.std(data)
variance = np.var(data)

print("Mean:", mean)
print("Median:", median)
print("Mode:", mode)
print("Standard Deviation:", std_dev)
print("Variance:", variance)
```

```
Mean: 50.20062317984853
Median: 50.518467150848046
Mode: 21.807369904138948
```

```
Standard Deviation: 9.813865630575917
Variance: 96.31195861499923
```

Conclusions

For Dataset:

Price Distribution:

The prices of houses in the dataset vary widely, with a mean price of approximately $540, 296.6 and a standard deviation of around$367,368.1. The prices range from $78, 000 to$ 7,700,000.

Property Characteristics:

The dataset contains information on various property characteristics such as the number of bedrooms, bathrooms, square footage of living space, and lot size. For example, the average number of bedrooms is approximately 3.37, with a standard deviation of about 0.93.

Year Built:

The houses in the dataset were built between 1900 and 2015, with an average year of construction around 1971. The standard deviation indicates that there is some variability in the construction years.

Renovation:

The dataset also includes information on renovations. However, the majority of houses have not been renovated, as indicated by the median value of 0 and the 75th percentile value of 0. The maximum renovation year is 2015.

Geographical Information:

The dataset covers houses located in various zip codes within a certain geographical area, with latitude ranging from approximately 47.16 to 47.78 and longitude ranging from approximately -122.52 to -121.32.

For Sample Data:

Normal Distribution:

The sample data follows approximately a normal distribution, as indicated by the mean, median, and mode being close in value.

Central Tendency:

The mean, median, and mode are all around 50, indicating that the data is centered around this value.

Dispersion:

The standard deviation is approximately 9.94, suggesting that the data points are spread out around the mean by this amount on average.

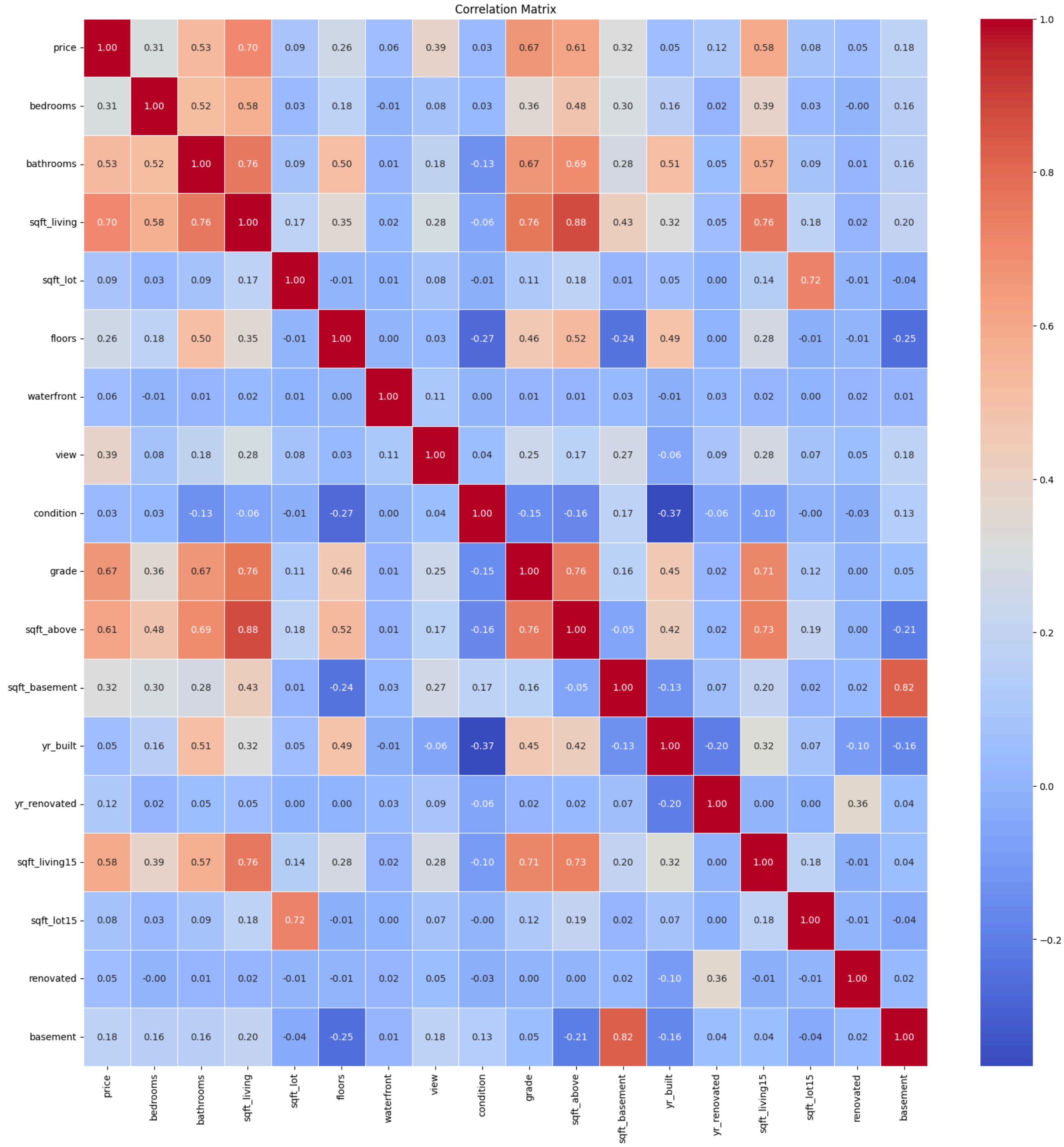
Variance:

The variance is approximately 98.75, which is the square of the standard deviation. It quantifies the amount of dispersion in the data.

Overall, descriptive statistics provide valuable insights into the characteristics and distribution of the data, allowing for a better understanding of the dataset's properties and trend

Correlation Matrix

```
# Exclude the 'id' column from the correlation matrix
correlation_matrix = df1.drop(columns=['id']).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', linewidth

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

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


Correlation Matrix

CONCLUSION

Price has a moderate positive correlation with sqft living (0.76), sqft above (0.61), sqft basement (0.32), yr_built (0.45) and sqft living15 (0.71). This means that as the values of these features increase, the price of the house also tends to increase. There is a weak positive correlation between price and bedrooms (0.31) and bathrooms (0.53). Price has a weak negative correlation with yr_renovated (-0.05). It is important to note that correlation does not imply causation. Just because two features are correlated does not mean that one causes the other. There could be a third underlying factor that causes both features to change.

Distribution Analysis:

Distribution analysis involves understanding the distribution of data, such as whether it follows a normal distribution and skewed distribution

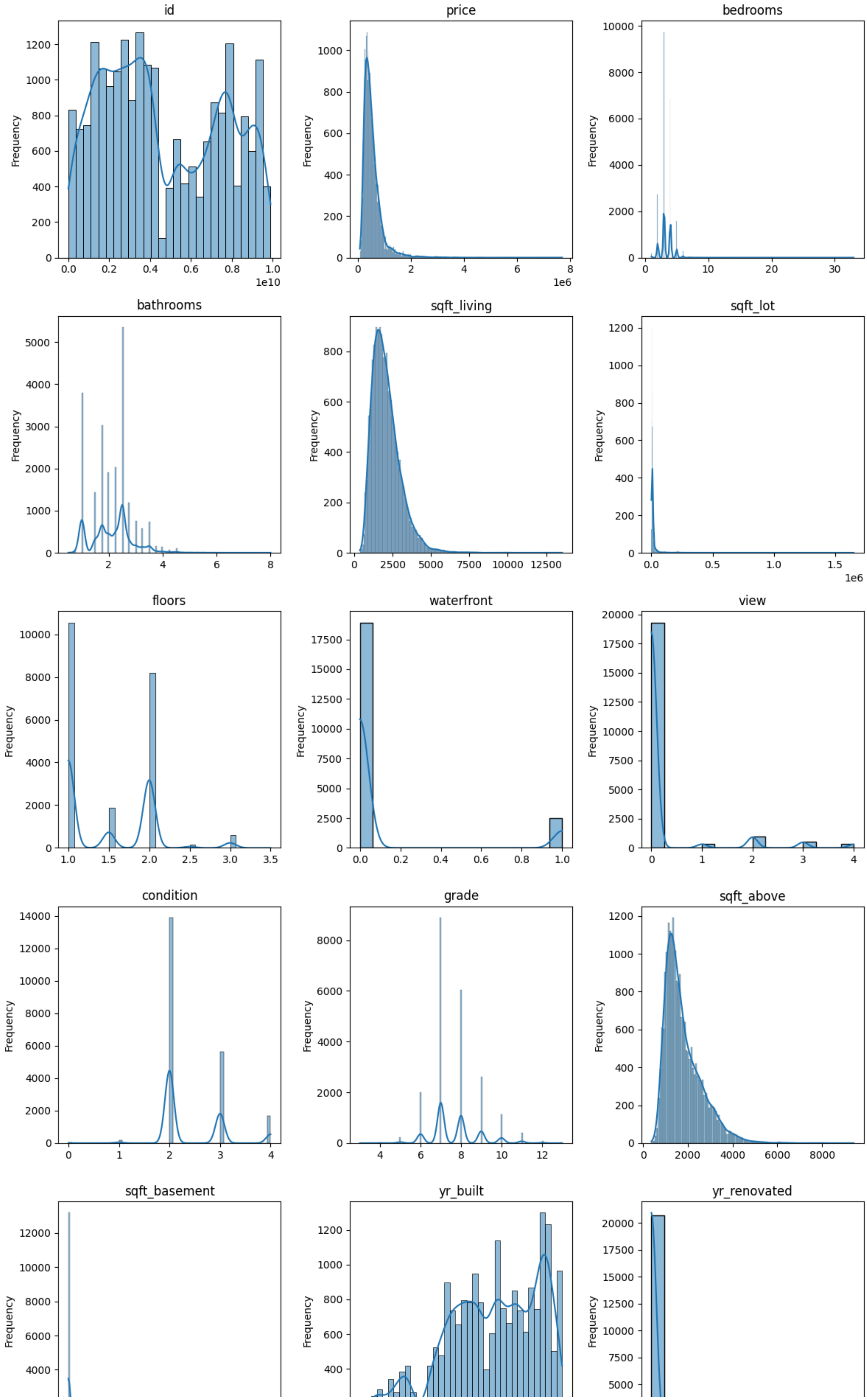
```
from scipy.stats import skew

# Compute skewness for each numerical variable
skewness = df1.apply(lambda x: skew(x.dropna()))

# Select variables with skewness above a certain threshold (e.g., 0.5)
skewed_variables = skewness[abs(skewness) > 0.5].index

# Log transformation for skewed variables
df1_log = df1.copy()  # Create a copy of the original DataFrame to preserve the o
df1_log[skewed_variables] = df1_log[skewed_variables].apply(lambda x: np.log1p(x)

# Check the distributions before and after transformation if needed
# For example, you can use histograms or density plots to visualize the distribut

# Print the first few rows of the transformed data to verify
print(df1_log.head())
```

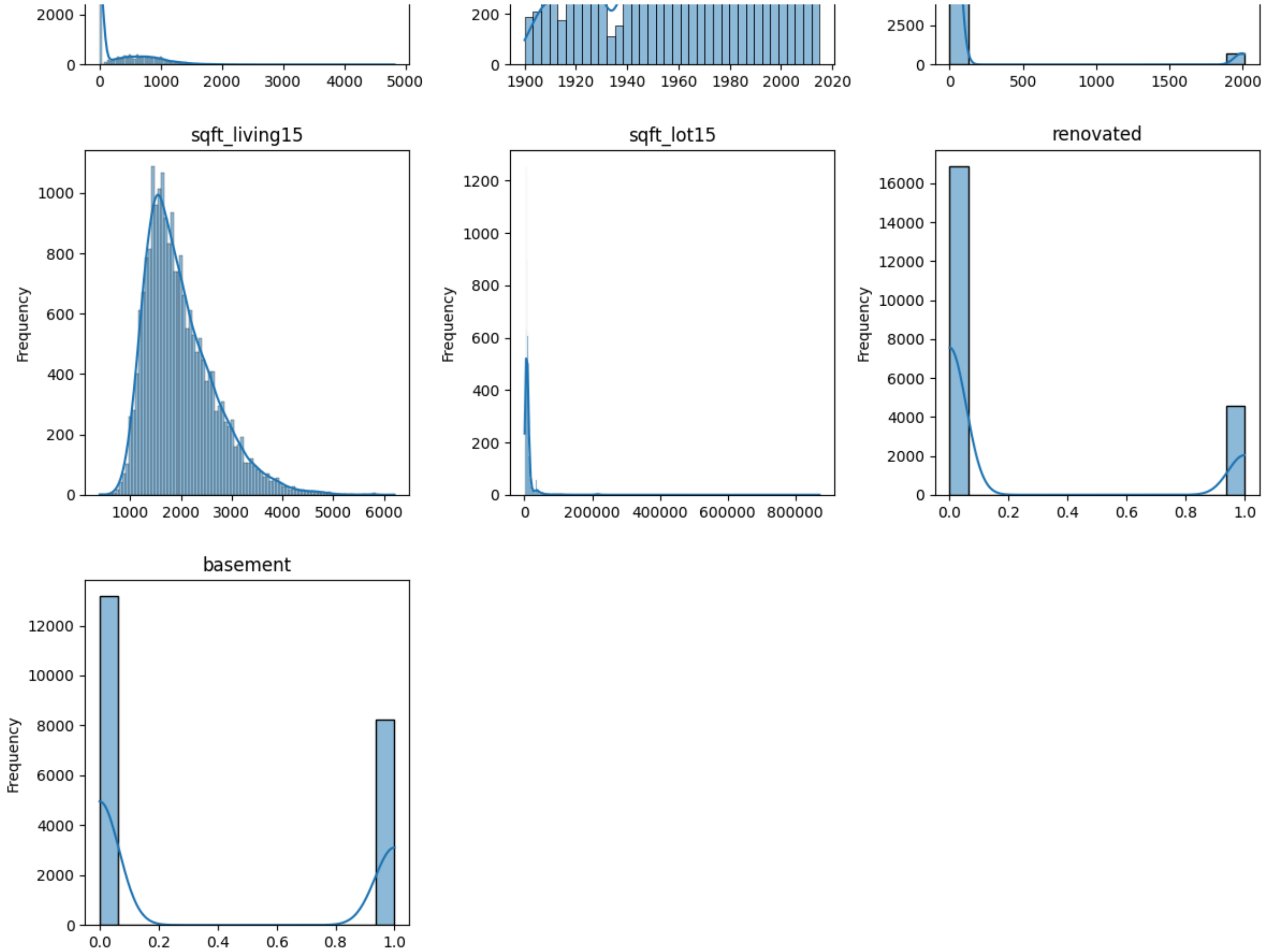
```
           id      price  bedrooms  bathrooms  sqft_living  sqft_lot  \
0  7129300520  12.309987  1.386294   0.693147     7.074117  8.639588
1  6414100192  13.195616  1.386294   1.178655     7.852050  8.887791
2  5631500400  12.100718  1.098612   0.693147     6.647688  9.210440
3  2487200875  13.311331  1.609438   1.386294     7.581210  8.517393
4  1954400510  13.142168  1.386294   1.098612     7.427144  8.997271
```

	floors	waterfront	view	condition	grade	sqft_above	sqft_basement
0	0.693147	0.693147	0.0	1.098612	2.079442	7.074117	0.000000
1	1.098612	0.000000	0.0	1.098612	2.079442	7.682943	5.993961
2	0.693147	0.000000	0.0	1.098612	1.945910	6.647688	0.000000
3	0.693147	0.000000	0.0	1.609438	2.079442	6.957497	6.814543
4	0.693147	0.000000	0.0	1.098612	2.197225	7.427144	0.000000

	yr_built	yr_renovated	sqft_living15	sqft_lot15	renovated	basement
0	1955	0.000000	7.201171	8.639588	0.000000	0
1	1951	7.596894	7.433075	8.941153	0.693147	1
2	1933	0.000000	7.908755	8.995041	0.693147	0
3	1965	0.000000	7.215975	8.517393	0.000000	1
4	1987	0.000000	7.496097	8.923191	0.000000	0

```
# Selecting numerical columns
numerical_columns = df1.select_dtypes(include=[np.number]).columns

# Calculate the number of rows and columns for subplots
num_cols = len(numerical_columns)
num_rows = (num_cols + 2) // 3  # Calculate the number of rows needed, rounding u

# Plot histograms for numerical variables
plt.figure(figsize=(12, num_rows * 4))  # Adjust the height based on the number o
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(num_rows, 3, i)
    sns.histplot(df1[col], kde=True)
    plt.title(col)
    plt.xlabel('')
    plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```


id
price
bedrooms
bathrooms
sqft_living
sqft_lot
floors
waterfront
view
condition
grade
sqft_above
sqft_basement
yr_built
yr_renovated
Frequency
1e10
1e6


sqft_living15
sqft_lot15
renovated
basement
Frequency

Conclusion

Here are the transformed variables:

price: The distribution of house prices seems to have been skewed before the transformation, with a long tail to the right. After the log transformation, the distribution appears to be more symmetric. bedrooms, bathrooms, sqft_living, sqft_lot, floors, waterfront, view, condition, grade, sqft_above, sqft_basement, yr_built, yr_renovated, sqft_living15, sqft_lot15: These variables also showed skewness in their original distributions. After the log transformation, the skewness seems to have been reduced, resulting in more symmetric distributions. renovated, basement: These are binary variables (0 or 1) indicating whether a house has been renovated or has a basement. Since they are binary, they don't exhibit skewness, and the log transformation doesn't apply to them. Overall, the log transformation appears to have effectively reduced the skewness in the numerical variables, making their distributions more symmetric and suitable for statistical analysis. However, it's important to note that the transformation alters the scale and interpretation of the variables, so further analysis should be conducted accordingly.

Inferential Statistics

```
from scipy.stats import f_oneway

# List of features of interest
features_of_interest = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floo
                        'sqft_living15', 'sqft_lot15', 'basement','grade', 'view

# 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 = [df1[column][df1['price'] == category]
              for category in df1['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 si
    else:
        print(f"{column}: Fail to reject the null hypothesis. There is no statist

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

```
bedrooms: Reject the null hypothesis. There is a statistically significant re
bathrooms: Reject the null hypothesis. There is a statistically significant r
sqft_living: Reject the null hypothesis. There is a statistically significant
sqft_lot: Fail to reject the null hypothesis. There is no statistically signi
floors: Reject the null hypothesis. There is a statistically significant rela
sqft_above: Reject the null hypothesis. There is a statistically significant
yr_built: Reject the null hypothesis. There is a statistically significant re
renovated: Fail to reject the null hypothesis. There is no statistically sign
sqft_living15: Reject the null hypothesis. There is a statistically significa
sqft_lot15: Fail to reject the null hypothesis. There is no statistically sig
basement: Reject the null hypothesis. There is a statistically significant re
grade: Reject the null hypothesis. There is a statistically significant relat
view: Reject the null hypothesis. There is a statistically significant relati
waterfront: Fail to reject the null hypothesis. There is no statistically sig
condition: Reject the null hypothesis. There is a statistically significant r

ANOVA Results:
                  bedrooms  bathrooms  sqft_living  sqft_lot        floors  \
F-statistic   1.744564e+00   3.742263      7.72898  0.731092  1.657081e+00
```

```
P-value      4.820263e-116   0.000000      0.00000  1.000000  5.251187e-95

              sqft_above      yr_built  renovated  sqft_living15  sqft_lot15  \
F-statistic    5.128945  1.236232e+00   1.034321       5.219333    0.713326
P-value        0.000000  2.054786e-17   0.093877       0.000000    1.000000

                 basement     grade            view  waterfront  condition
F-statistic  1.291038e+00  7.355157   1.993969e+00    1.017819   1.046436
P-value      1.268430e-24  0.000000  6.682406e-182    0.244793   0.038190
```

Conclusion

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.

Multicollinearity

This will compute the Variance Inflation Factor (VIF) for each predictor variable in your regression model. High VIF values indicate multicollinearity, suggesting that certain variables are highly correlated with each other. Check for multicollinearity among property characteristics.

```
import pandas as pd
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Compute Variance Inflation Factor (VIF) to detect multicollinearity
X = df1[['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot','floors', 'waterfront
vif_df = pd.DataFrame()
vif_df["feature"] = X.columns
vif_df["VIF"] = [variance_inflation_factor(X.values, i) for i in range(len(X.colu
print("\nMultiCollinearity Analysis (VIF):")
print(vif_df)
```

```
MultiCollinearity Analysis (VIF):
          feature         VIF
0        bedrooms   23.314138
1       bathrooms   25.442845
2     sqft_living  896.284080
3        sqft_lot    2.358225
4          floors   16.457636
5      waterfront    1.146344
6            view    1.305167
7       condition   15.873836
8           grade  142.311179
9      sqft_above  670.021880
10  sqft_basement   51.019410
11       yr_built  111.779180
12   yr_renovated    1.211552
13  sqft_living15   26.392559
```

```
     14     sqft_lot15    2.570197
     15      renovated    1.464321
     16       basement    5.634670
```

```
# creating a function that takes in a dataframe and threshold and returns top cor
def corr_check(df1, threshold):
    '''
    Enter dataframe and threshold for correlation
    Returns table of the highly correlated pairs
    '''
    corr_df = df1.corr().abs().stack().reset_index().sort_values(0, ascending=Fal
    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(df1, 0.7)
print(result)
```

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

```
df3 = df2.drop(columns=[])
df3
```

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7129300520	221900.0	3	1.00	1180	5650	1.0
1	6414100192	538000.0	3	2.25	2570	7242	2.0
2	5631500400	180000.0	2	1.00	770	10000	1.0
3	2487200875	604000.0	4	3.00	1960	5000	1.0
4	1954400510	510000.0	3	2.00	1680	8080	1.0
...	...	...	...	...	...	...	...
21592	263000018	360000.0	3	2.50	1530	1131	3.0
21593	6600060120	400000.0	4	2.50	2310	5813	2.0
21594	1523300141	402101.0	2	0.75	1020	1350	2.0
21595	291310100	400000.0	3	2.50	1600	2388	2.0
21596	1523300157	325000.0	2	0.75	1020	1076	2.0

21420 rows × 19 columns

Next steps: View recommended plots

Conclusion

The analysis reveals significant multicollinearity among several features, notably 'sqft_living', 'sqft_above', 'grade', 'yr_built', and 'sqft_basement', with VIF values exceeding commonly accepted thresholds. This indicates strong correlations among these variables, potentially leading to unstable coefficient estimates and reduced interpretability in regression models. Consideration should be given to dropping or combining these features, implementing dimensionality reduction techniques, or applying regularization methods to mitigate multicollinearity effects and improve model performance.

5.DATA MODELLING

1. Baseline Model
2. Polynomial Regression
3. Log Transformation

Baseline Model

A baseline model is a simple model used as a reference point for comparing the performance of more sophisticated models.

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


# model need to have only numeric variables.
def only_numeric(data):
    '''returns a dataframe with only numeric values'''
    for column in df3.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]  # target varriable
    X = data.drop(target, axis=1)  #Property features
    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 s
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: {tes

    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
```

Train test split

Train Test Split The raw data was split to a train and test set for a baseline model. The df2(data after dropping strong multicolinierity) 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(df)
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
train_set, test_set = train_test(df3, 0.25)
```

Linear Regression Model

```
selected_features = ['price','bathrooms', 'sqft_living',
       'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_basement', 'yr_built', 'yr_renovated', 'sqft_living15','renovated',

# Filter the dataset
filtered_data = df1[selected_features]

# Define X and y based on filtered_data
X = filtered_data.drop('price', axis=1)
y = filtered_data['price']

# 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_s

# 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)

# 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: 44675162792.18972
R-squared: 0.6310776936345524
          Feature    Coefficient
0       bathrooms   24486.020198
1     sqft_living  124438.685165
2          floors   15754.675856
3      waterfront    8869.730499
4            view   54456.352105
5       condition   12345.267908
6           grade  153828.575901
7   sqft_basement    2801.921923
8        yr_built -102220.578567
9    yr_renovated    9582.208981
10  sqft_living15   14357.192815
11      renovated    1737.045374
12       basement    1959.510757
```

```
# Select relevant features
features =['bathrooms', 'sqft_living',
       'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_basement', 'yr_built', 'yr_renovated', 'sqft_living15','renovated',
# Create a design matrix X and target variable y
X = sm.add_constant(df1[features])
y = df3['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:                       0.63
Model:                            OLS   Adj. R-squared:                  0.63
Method:                 Least Squares   F-statistic:                     2817
Date:                Mon, 08 Apr 2024   Prob (F-statistic):              0.0
Time:                        19:10:39   Log-Likelihood:           -2.9422e+0
No. Observations:               21420   AIC:                       5.885e+0
Df Residuals:                   21406   BIC:                       5.886e+0
Df Model:                          13
Covariance Type:            nonrobust
==============================================================================
                    coef    std err          t      P>|t|      [0.025      0.
------------------------------------------------------------------------------
const          5.949e+06   1.41e+05     42.111      0.000    5.67e+06    6.23
bathrooms      3.247e+04   3593.022      9.037      0.000    2.54e+04    3.95
sqft_living     136.3686      3.921     34.778      0.000     128.683     144
floors         3.446e+04   3884.554      8.872      0.000    2.68e+04    4.21
waterfront     2.803e+04   4786.857      5.855      0.000    1.86e+04    3.74
view           7.162e+04   2180.794     32.843      0.000    6.73e+04    7.59
condition      1.895e+04   2595.995      7.298      0.000    1.39e+04     2.4
grade          1.273e+05   2331.439     54.587      0.000    1.23e+05    1.32
sqft_basement     0.3769      7.572      0.050      0.960     -14.465      15
yr_built      -3500.0466     73.083    -47.891      0.000   -3643.296   -3356
yr_renovated     20.5780      4.698      4.380      0.000      11.370      29
sqft_living15    19.7436      3.720      5.307      0.000      12.451      27
renovated      3622.2238   4014.680      0.902      0.367   -4246.849    1.15
basement       8548.4830   5862.990      1.458      0.145   -2943.416      2
==============================================================================
Omnibus:                    17777.241   Durbin-Watson:                   1.98
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1560100.71
Skew:                           3.472   Prob(JB):                        0.0
Kurtosis:                      44.229   Cond. No.                   3.35e+0
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
[2] The condition number is large, 3.35e+05. This might indicate that there a
strong multicollinearity or other numerical problems.
```

Conclusion

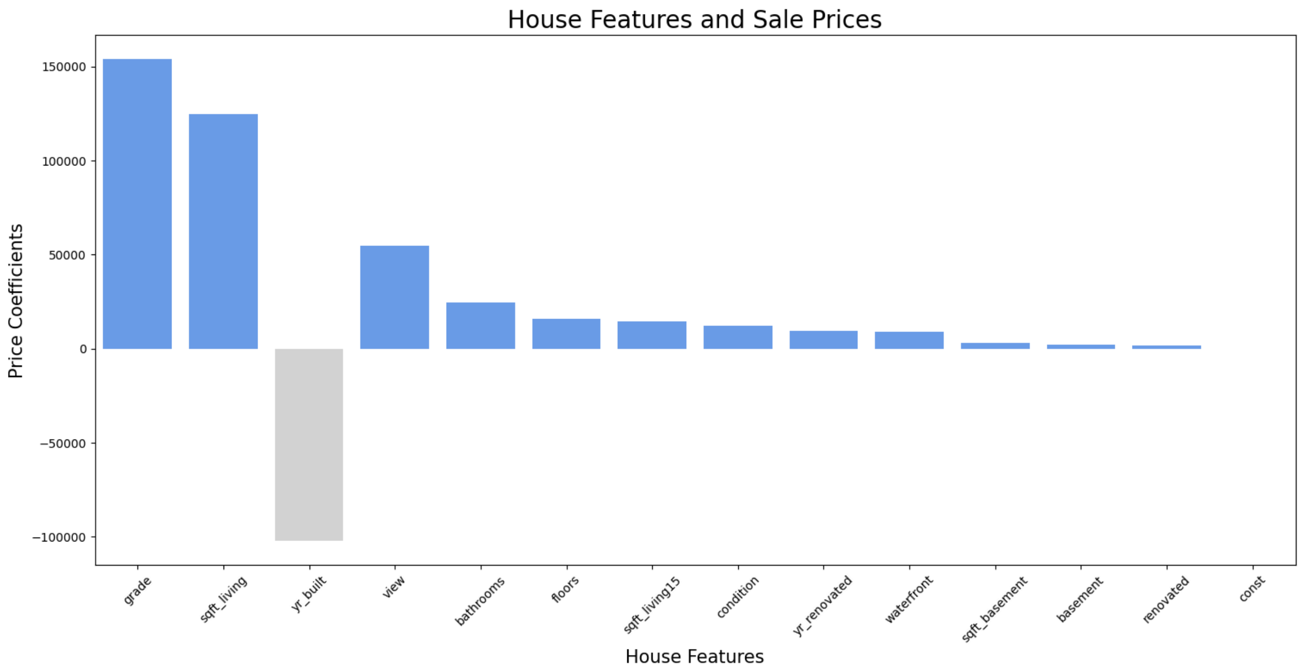
The model effectively identifies significant factors influencing house prices and offers valuable insights for real estate agencies to advise clients. While it demonstrates moderate performance with a 63.1% R-squared value, further evaluation is needed for predictive accuracy. Nonetheless, the model fulfills the project's objectives by influencing decision-making processes and optimizing marketing strategies based on property characteristics and market trends.

Multiple Regression

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

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

```
Metrics:
Mean Squared Error (MSE): 44675162792.18969
R-squared (R2) Score: 0.6310776936345526
```

```
# Select relevant features
selected_features =['bedrooms','bathrooms', 'sqft_living',
       'floors', 'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'sqft_living15','renovated',
# Filter the dataset
filtered_data = df1[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_s

# 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 abs

# 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], palett
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()
```



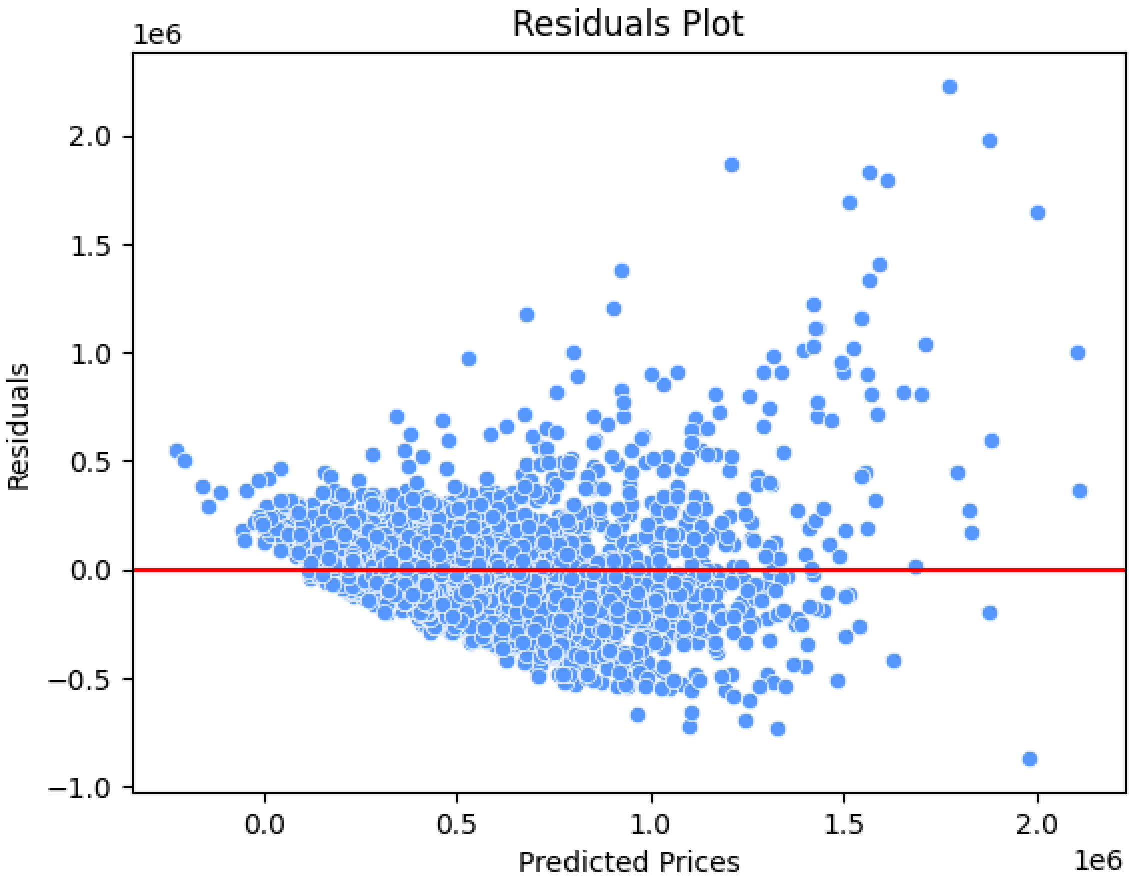
Conclusion

The negative coefficient in yr_built goes to explain that it will cause a decrease in price

Residual Analysis

```
# Select relevant features
selected_features =  ['bedrooms','bathrooms', 'sqft_living',
       'floors', 'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'sqft_living15','renovated',
# Filter the dataset
filtered_data = df1[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)]

# 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_s

# 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_r
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: 44675162792.18972
Refined Model - R-squared: 0.6310776936345524
          Feature    Coefficient
0           const       0.000000
1       bathrooms   24486.020198
2     sqft_living  124438.685165
3          floors   15754.675856
4      waterfront    8869.730499
5            view   54456.352105
6       condition   12345.267908
7           grade  153828.575901
8    sqft_basement    2801.921923
9        yr_built -102220.578567
10    yr_renovated    9582.208981
11   sqft_living15   14357.192815
12       renovated    1737.045374
13        basement    1959.510757
```



Conclusion

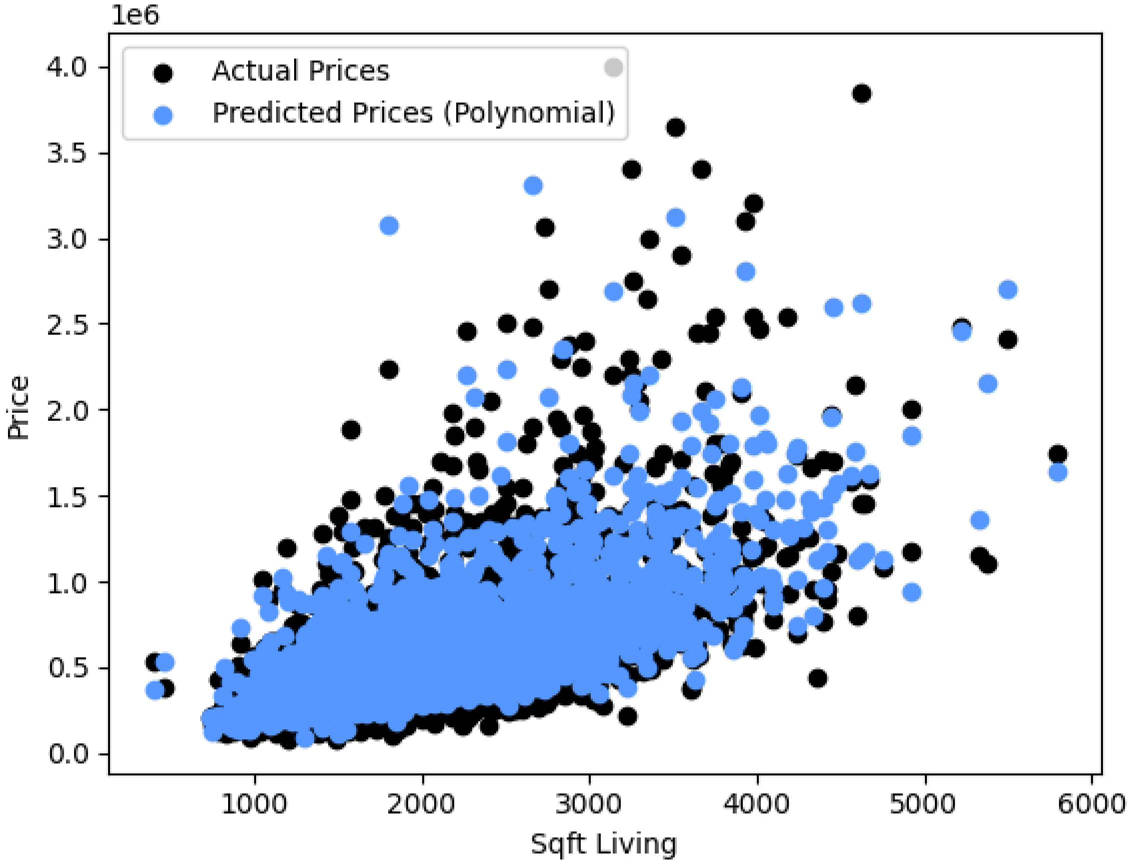
Key features such as bathrooms, square footage, waterfront views, property condition, grade, and year built demonstrate significant impacts on prices. Although the model achieves a respectable R-squared value of approximately 0.631, indicating a good fit, the mean squared error suggests room for improvement in prediction accuracy.

Polynomial Regression

- Polynomial regression involves converting features into higher-order polynomial terms. This method allows us to capture non-linear relationships by utilizing multiple linear regression techniques.

```
# Select relevant features
selected_features = ['bedrooms', 'bathrooms', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'yr_renovated', 'sqft_living15',
       'sqft_lot15', 'renovated', 'basement']

# Filter the dataset
filtered_data = df1[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_s

# 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_living15"], y_test, color='black', label='Actual Prices'
plt.scatter(X_test["sqft_living15"], y_pred_poly,color='#589aff', label='Predicte
plt.xlabel('Sqft Living')
plt.ylabel('Price')
plt.legend()
plt.show()
```

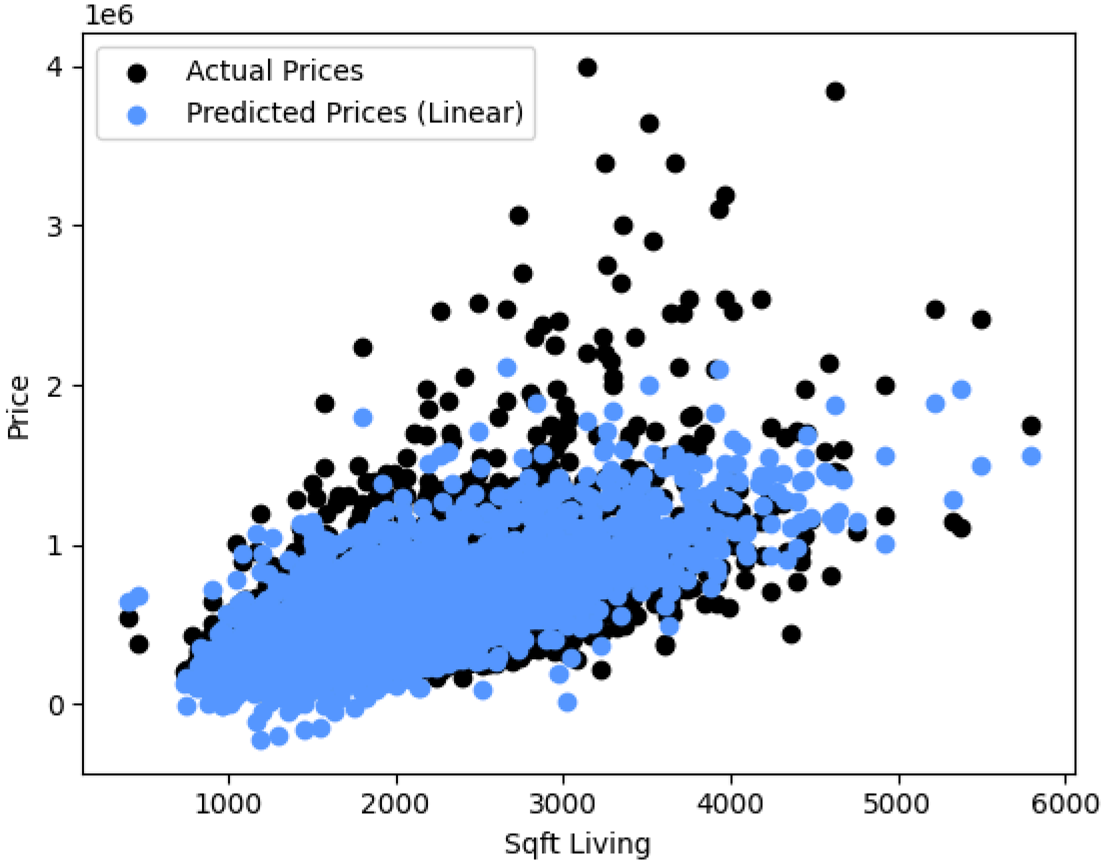
```
Polynomial Model (Degree 2)- MSE: 35248607685.76943
Polynomial Model (Degree 2)- R-squared: 0.708921091030063
```



Multiple Linear regression model using polynomial regression features

```
# Select relevant features
selected_features = ['bathrooms', 'sqft_living',
       'floors', 'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'sqft_living15','renovated',

# Filter the dataset
filtered_data = df1[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

# 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_living15"], y_test, color='black', label='Actual Prices'
plt.scatter(X_test["sqft_living15"], y_pred_linear, color='#589aff', label='Predi
plt.xlabel('Sqft Living')
plt.ylabel('Price')
plt.legend()
plt.show()
```

```
Multiple Linear Regression - MSE: 44636451231.249535
Multiple Linear Regression - R-squared: 0.6313973692093564
```




```
# 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()
```