Final Project Submission

Please fill out:

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- Scheduled project review date/time:
- Instructor name:
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```
# Your code here - remember to use markdown cells for comments as well!
# Importing standard packages
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns





import statsmodels.api as sm
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.datasets import make_regression
from sklearn.linear_model import LinearRegression
from sklearn import metrics
import sklearn.metrics as metrics
from random import gauss
from mpl_toolkits.mplot3d import Axes3D
from scipy import stats as stats
from math import sqrt
%matplotlib inline
```

INTRODUCTION

In this project, we explore the King County House Sales dataset, which contains information on houses sold in King County, USA. Our objective is to provide accurate insights to assist homeowners and real estate agencies in crucial decisions regarding property valuation and market trends. By leveraging linear regression modeling, we aim to develop a powerful tool that predicts potential property value increases based on key factors such as bedrooms, floors, living space, condition, and location. This tool will offer valuable guidance for pricing strategies, understanding market dynamics, and making well-informed property-related decisions.

BUSINESS UNDERSTANDING

The real estate market in King County, USA, is dynamic and competitive, making it essential for homeowners and real estate agencies to stay informed about property values and market trends. By analyzing the King County House Sales dataset, we aim to provide valuable insights that empower homeowners and agencies to make informed decisions.

For real estate agencies, having access to a predictive model that factors in key features such as bedrooms, year built, living space, and location can significantly enhance their market analysis capabilities. This tool can assist agencies in accurately valuing properties, identifying market trends, and developing effective pricing strategies to attract buyers or renters.

Overall, our project aims to bridge the gap between data analysis and real-world decision-making in the real estate industry, providing actionable insights that drive success for homeowners and agencies alike.

DATA UNDERSTANDING

In the data understanding phase, we will explore and analyze the dataset to gain a better understanding of its structure, contents, and potential insights it can offer.

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 (levels) in house
- `waterfront` - Whether the house is on a waterfront
  - Includes Duwamish, Elliott Bay, Puget Sound, Lake Union, Ship Canal, Lake Washington, Lake Sammamish, other lake, and river/slough waterfronts
- `view` - Quality of view from house

- Includes views of Mt. Rainier, Olympics, Cascades, Territorial, Seattle Skyline, Puget Sound, Lake Washington, Lake Sammamish, small lake / river / creek, and other
- `condition` - How good the overall condition of the house is. Related to maintenance of house.
    - See the [King County Assessor Website] for further explanation of each condition code
- `grade` - Overall grade of the house. Related to the construction and design of the house.
    - See the [King County Assessor Website] for further explanation of each building grade code
- `sqft_above` - Square footage of house apart from basement
- `sqft_basement` - Square footage of the basement
- `yr_built` - Year when house was built
- `yr_renovated` - Year when house was renovated
- `zipcode` - ZIP Code used by the United States Postal Service
- `lat` - Latitude coordinate
- `long` - Longitude coordinate
- `sqft_living15` - The square footage of interior housing living space for the nearest 15 neighbors
- `sqft_lot15` - The square footage of the land lots of the nearest 15 neighbors

PROBLEM STATEMENT

There is a critical need to provide accurate insights into the factors influencing housing prices. Our objective is to analyze a comprehensive dataset containing various attributes of properties and their corresponding prices to identify the primary drivers impacting housing prices. By understanding these factors, we aim to equip homeowners with valuable information to make informed decisions regarding pricing, investment, and negotiation strategies. The ultimate goal is to optimize the process of buying and selling properties, ensuring maximum value for homeowners and facilitating successful transactions in the real estate market.

OBJECTIVES

Primary objective

The primary objective of this project is to develop a predictive regression model that forecasts house prices based on property characteristics, enabling real estate agencies to offer informed advice to clients regarding potential fluctuations in property value.

Specific objectives

1. Identify the key factors influencing housing prices based on historical data.
2. Quantify the impact of these factors on the buying and selling prices of houses.

3. Develop predictive models to forecast housing prices accurately.
4. Provide actionable recommendations to stakeholders based on the analysis to enhance their decision-making processes in the real estate market.

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DATA LOADING

```
# Loading the csv file

f1 = r"/content/kc_house_data.csv"
df = pd.read_csv(f1)
```

DATA INSPECTION AND UNDERSTANDING

```
# Previewing a sample

df.head()

{"type":"dataframe","variable_name":"df"}

# Checking the shape of our dataframe

df.shape

(21597, 21)

# Checking the info and uniformity of our dataframe

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
```

- We have three different data types in our dataset - float64, int64, object.

```
# Checking data numerical summaries

df.describe()
```


```
{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 8,\n  \"fields\": [\n
{\n      \"column\": \"id\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 3436536175.18902,\n
\"min\": 21597.0,\n        \"max\": 9900000190.0,\n
\"num_unique_values\": 8,\n        \"samples\": [\n
4580474287.770987,\n          3904930410.0,\n          21597.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"price\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\":
2608586.228000891,\n        \"min\": 21597.0,\n        \"max\":
7700000.0,\n        \"num_unique_values\": 8,\n        \"samples\": [\
n          540296.5735055795,\n          450000.0,\n          21597.0\
n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"bedrooms\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 7633.260597421209,\n        \"min\":
0.9262988945421479,\n        \"max\": 21597.0,\n
\"num_unique_values\": 7,\n        \"samples\": [\n          21597.0,\
n          3.3731999814789093,\n          4.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"bathrooms\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
7634.7896127930435,\n        \"min\": 0.5,\n        \"max\": 21597.0,\
```

```
n        \"num_unique_values\": 8,\n        \"samples\": [\n
2.1158262721674306,\n          2.25,\n          21597.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"sqft_living\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
7754.222939040549,\n        \"min\": 370.0,\n        \"max\":
21597.0,\n        \"num_unique_values\": 8,\n        \"samples\": [\n
2080.3218502569803,\n          1910.0,\n          21597.0\n        ],\
n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"sqft_lot\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
578831.6596667598,\n        \"min\": 520.0,\n        \"max\":
1651359.0,\n        \"num_unique_values\": 8,\n        \"samples\": [\
n          15099.408760475992,\n          7618.0,\n          21597.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"floors\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\":
7635.135339320982,\n        \"min\": 0.5396827909775457,\n
\"max\": 21597.0,\n        \"num_unique_values\": 7,\n
\"samples\": [\n          21597.0,\n          1.4940964022780943,\n
2.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"sqft_above\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 7349.081332800358,\n        \"min\":
370.0,\n        \"max\": 21597.0,\n        \"num_unique_values\": 8,\n
\"samples\": [\n          1788.5968421540028,\n          1560.0,\n
21597.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"yr_built\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 7070.470126873352,\n        \"min\":
29.375234132441644,\n        \"max\": 21597.0,\n
\"num_unique_values\": 8,\n        \"samples\": [\n
1970.9996758809093,\n          1975.0,\n          21597.0\n        ],\
n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"yr_renovated\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
6189.752455574011,\n        \"min\": 0.0,\n        \"max\": 17755.0,\n
\"num_unique_values\": 5,\n        \"samples\": [\n
83.6367783722895,\n          2015.0,\n          399.9464138788162\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"zipcode\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
40800.52387987497,\n        \"min\": 53.51307235352816,\n
\"max\": 98199.0,\n        \"num_unique_values\": 8,\n
\"samples\": [\n          98077.95184516368,\n          98065.0,\n
21597.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"lat\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 7621.298120453811,\n        \"min\": 0.1385517681730718,\n
```

```
\"max\": 21597.0,\n        \"num_unique_values\": 8,\n
\"samples\": [\n          47.56009299439737,\n          47.5718,\n
21597.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"long\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 7672.813309437553,\n        \"min\": -122.519,\n
\"max\": 21597.0,\n        \"num_unique_values\": 8,\n
\"samples\": [\n          -122.2139824975691,\n          -122.231,\n
21597.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"sqft_living15\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 7107.282453987786,\n        \"min\":
399.0,\n        \"max\": 21597.0,\n        \"num_unique_values\": 8,\n
\"samples\": [\n          1986.6203176367087,\n          1840.0,\n
21597.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"sqft_lot15\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 303841.8018906116,\n        \"min\":
651.0,\n        \"max\": 871200.0,\n        \"num_unique_values\": 8,\
n        \"samples\": [\n          12758.283511598833,\n
7620.0,\n          21597.0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe"}
```


DATA CLEANING

```
# Making a copy of the merged data set to retain an original copy.
# df_clean is our clean dataset

df_clean = df.copy()
```

Checking for completeness of our data

```
# Checking the proportion of our missing data

df_clean.isnull().mean()
```

```
id                 0.000000
date               0.000000
price              0.000000
bedrooms           0.000000
bathrooms          0.000000
sqft_living        0.000000
sqft_lot           0.000000
floors             0.000000
waterfront         0.110015
view               0.002917
condition          0.000000
grade              0.000000
sqft_above         0.000000
```

```
sqft_basement    0.000000
yr_built         0.000000
yr_renovated     0.177895
zipcode          0.000000
lat              0.000000
long             0.000000
sqft_living15    0.000000
sqft_lot15       0.000000
dtype: float64
```

- Let's check the value counts of the columns with missing values.

```
# Calculate value counts for each column
value_counts_col1 = df['yr_renovated'].value_counts()
value_counts_col2 = df['view'].value_counts()
value_counts_col3 = df['waterfront'].value_counts()

print("Value counts for yr_renovated:")
print(value_counts_col1)

print("\nValue counts for view:")
print(value_counts_col2)

print("\nValue counts for waterfront:")
print(value_counts_col3)

Value counts for yr_renovated:
yr_renovated
0.0       17011
2014.0       73
2013.0       31
2003.0       31
2007.0       30
          ...
1951.0        1
1953.0        1
1946.0        1
1976.0        1
1948.0        1
Name: count, Length: 70, dtype: int64

Value counts for view:
view
NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
```

```
Name: count, dtype: int64

Value counts for waterfront:
waterfront
NO     19075
YES      146
Name: count, dtype: int64
```

- A larger percentage of the data has the values 0.0. We can drop this column as replacing missing values with the mean or the most frequent value will lead to inaccuracy of our data.
- Most of the houses do not have a view. The proportion of missing data is very small and hence we can replace the missing values with NONE.
- Majority of the houses do not have a waterfront. We can replace the missing values here with NO as it is the most frequent.

Dropping irrelevant columns

```
# dropping irrelevant columns

df_clean = df_clean.drop(columns=["lat", "long", "zipcode",
"yr_renovated"])
```

Handling missing values

```
# Filling missing values in waterfront column with 'NO'

df_clean['waterfront'].fillna('NO', inplace=True)

# Filling missing valuees in view column with 'NONE'

df_clean['view'].fillna('NONE', inplace=True)

# Check if missing values have been handled

df_clean.isnull().mean()

id               0.0
date             0.0
price            0.0
bedrooms         0.0
bathrooms        0.0
sqft_living      0.0
sqft_lot         0.0
floors           0.0
waterfront       0.0
view             0.0
condition        0.0
grade            0.0
sqft_above       0.0
sqft_basement    0.0
```

```
yr_built         0.0
sqft_living15    0.0
sqft_lot15       0.0
dtype: float64
```

- We now have no missing values.

```
#  Checking for duplicates

duplicates = df_clean[df_clean.duplicated()]

if duplicates.empty:
    print("No duplicates found.")
else:
    print("Duplicates found.")
    print(duplicates)

No duplicates found.
```

- Let us check for duplicates in th ID column as it is our unique identifier.

```
# Checking for duplicates using the 'id' column

df_clean[df_clean.duplicated(subset=["id"])]
```

{"repr_error":"0","type":"dataframe"}

- We will drop the duplicates as they can introduce inconsistencies to our data.

```
df_clean.drop_duplicates(subset=["id"], inplace=True)

# confirm duplicates have been dropped.

df_clean[df_clean.duplicated(subset=["id"])]
```

{"repr_error":"Out of range float values are not JSON compliant: nan","type":"dataframe"}

Checking for placeholders

- Placeholders in data cleaning are values used to represent missing or unknown data in a dataset. They stand in for actual data that is unavailable or not recorded.
- Placeholders include - NaN, Nul , Non, " " , s Special co such as;g., -1, 99 ble" "Mi and others.plicable"

```
potential_placeholders = [" " , "-", "--", "?", "??" , "#","#####" ,
"-1" , "9999", "999" , "unknown", "missing", "na" , "n/a"]

# Loop through each column and check for potential placeholders
found_placeholder = False
for column in df_clean.columns:
    unique_values = df_clean[column].unique()
```

```
    for value in unique_values:
        if pd.isna(value) or (isinstance(value, str) and 
value.strip().lower() in potential_placeholders):
            count = (df_clean[column] == value).sum()
            print(f"Column '{column}': Found {count} occurrences of 
potential placeholder '{value}'")
            found_placeholder = True

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

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

```
# Step 1: Identify the placeholder values
placeholder = '?'

# Step 2: Replace the placeholder values with 0
df_clean['sqft_basement'] = 
df_clean['sqft_basement'].replace(placeholder, '0')

# Step 3: Convert the data type of the column to floats
df_clean['sqft_basement'] = df_clean['sqft_basement'].astype(float)

# Check if the conversion was successful
print("Data type after conversion:", df_clean['sqft_basement'].dtype)
```

```
Data type after conversion: float64
```

```
# Confirm removal of placeholders

potential_placeholders = [" " , "-", "--", "?", "??" , "#","#####" , 
"-1" , "9999", "999" , "unknown", "missing", "na" , "n/a"]

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

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

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

```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 21420 entries, 0 to 21596
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21420 non-null  int64
 1   date           21420 non-null  object
 2   price          21420 non-null  float64
 3   bedrooms       21420 non-null  int64
 4   bathrooms      21420 non-null  float64
 5   sqft_living    21420 non-null  int64
 6   sqft_lot       21420 non-null  int64
 7   floors         21420 non-null  float64
 8   waterfront     21420 non-null  object
 9   view           21420 non-null  object
 10  condition      21420 non-null  object
 11  grade          21420 non-null  object
 12  sqft_above     21420 non-null  int64
 13  sqft_basement  21420 non-null  float64
 14  yr_built       21420 non-null  int64
 15  sqft_living15  21420 non-null  int64
 16  sqft_lot15     21420 non-null  int64
dtypes: float64(4), int64(8), object(5)
memory usage: 2.9+ MB
```

- We have inconsistencies with our data types - date, waterfront, view , condition and grade.

Handling non-numerical data

- We are checking for value counts to decide how to best handle our non numerical data.

```
# Calculate value counts for each column
value_counts_col4 = df['condition'].value_counts()
value_counts_col5 = df['grade'].value_counts()


print("Value counts for condition:")
print(value_counts_col4)

print("\nValue counts for grade:")
print(value_counts_col5)
```

```
Value counts for condition:
condition
Average      14020
Good          5677
Very Good     1701
Fair           170
```

```
Poor              29
Name: count, dtype: int64

Value counts for grade:
grade
7 Average        8974
8 Good           6065
9 Better         2615
6 Low Average    2038
10 Very Good     1134
11 Excellent      399
5 Fair            242
12 Luxury          89
4 Low              27
13 Mansion         13
3 Poor              1
Name: count, dtype: int64
```

- We used the LabelEncoding technique as our values ar hierarchical.

```
from sklearn.preprocessing import LabelEncoder

# label encoder object
label_encoder = LabelEncoder()

# Encode the 'condition' column
df_clean['condition_encoded'] =
label_encoder.fit_transform(df_clean['condition'])

# Encode the 'grade' column
df_clean['grade_encoded'] =
label_encoder.fit_transform(df_clean['grade'])

# Encode the 'season' column
df_clean['view_encoded'] =
label_encoder.fit_transform(df_clean['view'])
```

- We handled our waterfront column by changing the categorical values to binary.

```
# Define the mapping from original values to binary values
mapping = {'NO': 0, 'YES': 1}

# Apply the mapping and replace the values in the 'waterfront' column
df_clean['waterfront'] = df_clean['waterfront'].map(mapping)
```

Feature engineering

- We are using the `date` feature to create a new feature called `season`, which represents whether the home was sold in Spring, Summer, Fall, or Winter.
- This will help with understanding seasonal trends in housing sales.

```python
# Converting 'date' to datetime object
df_clean['date'] = pd.to_datetime(df_clean['date'])

# Extract month from 'date'
df_clean['month'] = df_clean['date'].dt.month

# Map month to season
season_mapping = {
    1: 'Winter',
    2: 'Winter',
    3: 'Spring',
    4: 'Spring',
    5: 'Spring',
    6: 'Summer',
    7: 'Summer',
    8: 'Summer',
    9: 'Fall',
    10: 'Fall',
    11: 'Fall',
    12: 'Winter'
}

df_clean['season'] = df_clean['month'].map(season_mapping)

# Dropping 'month' column because we do not need it anymore
df_clean.drop(['month', 'date'], axis=1, inplace=True)
```

- We need to change our season column which is categorical to numerical.

```python
##one hot encoding for season

df2 = pd.get_dummies(df_clean, columns=['season'], dtype=int)
df2 = df2.drop(['season_Spring'], axis=1)

df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 21420 entries, 0 to 21596
Data columns (total 22 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 21420 non-null  int64
 1   price              21420 non-null  float64
 2   bedrooms           21420 non-null  int64
 3   bathrooms          21420 non-null  float64
 4   sqft_living        21420 non-null  int64
 5   sqft_lot           21420 non-null  int64
 6   floors             21420 non-null  float64
 7   waterfront         21420 non-null  int64
 8   view               21420 non-null  object
```

```
 9   condition          21420 non-null  object
 10  grade              21420 non-null  object
 11  sqft_above         21420 non-null  int64
 12  sqft_basement      21420 non-null  float64
 13  yr_built           21420 non-null  int64
 14  sqft_living15      21420 non-null  int64
 15  sqft_lot15         21420 non-null  int64
 16  condition_encoded  21420 non-null  int64
 17  grade_encoded      21420 non-null  int64
 18  view_encoded       21420 non-null  int64
 19  season_Fall        21420 non-null  int64
 20  season_Summer      21420 non-null  int64
 21  season_Winter      21420 non-null  int64
dtypes: float64(4), int64(15), object(3)
memory usage: 3.8+ MB
```

```
# Creating a new dataframe with numerical dtypes only

# columns to exclude
columns_to_exclude = ['view', 'condition', 'grade' , 'id']

# Creating a new dataset df3 excluding the specified columns
df3 = df2.drop(columns=columns_to_exclude)

# Display the first few rows of the new dataset df1
df3.head()

# df3 is our dataframe with numerical dtypes
```

{"summary":"{\n \"name\": \"# df3 is our dataframe with numerical
dtypes\",\n \"rows\": 5,\n \"fields\": [\n   {\n   \"column\":
\"price\",\n   \"properties\": {\n   \"dtype\": \"number\",\n
\"std\": 195127.24566292632,\n   \"min\": 180000.0,\n
\"max\": 604000.0,\n   \"num_unique_values\": 5,\n
\"samples\": [\n   538000.0,\n   510000.0,\n
180000.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"bedrooms\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0,\n   \"min\": 2,\n
\"max\": 4,\n   \"num_unique_values\": 3,\n   \"samples\":
[\n   3,\n   2,\n   4\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"bathrooms\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
0.8587782018658834,\n   \"min\": 1.0,\n   \"max\": 3.0,\n
\"num_unique_values\": 4,\n   \"samples\": [\n   2.25,\n
2.0,\n   1.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"sqft_living\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 695,\n   \"min\": 770,\n

```
\"max\": 2570,\n        \"num_unique_values\": 5,\n
\"samples\": [\n          2570,\n          1680,\n          770\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"sqft_lot\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1991,\n        \"min\": 5000,\n        \"max\": 10000,\n
\"num_unique_values\": 5,\n        \"samples\": [\n          7242,\n
8080,\n          10000\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"floors\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 0.44721359549995804,\n        \"min\": 1.0,\n        \"max\":
2.0,\n        \"num_unique_values\": 2,\n        \"samples\": [\n
2.0,\n          1.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"waterfront\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 0,\n        \"num_unique_values\": 1,\n        \"samples\":
[\n          0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"sqft_above\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 555,\n        \"min\": 770,\n
\"max\": 2170,\n        \"num_unique_values\": 5,\n
\"samples\": [\n          2170\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"sqft_basement\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 401.52210399926923,\n
\"min\": 0.0,\n        \"max\": 910.0,\n        \"num_unique_values\":
3,\n        \"samples\": [\n          0.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"yr_built\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\": 19,\n
\"min\": 1933,\n        \"max\": 1987,\n        \"num_unique_values\":
5,\n        \"samples\": [\n          1951\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"sqft_living15\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
561,\n        \"min\": 1340,\n        \"max\": 2720,\n
\"num_unique_values\": 5,\n        \"samples\": [\n          1690\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"sqft_lot15\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1355,\n        \"min\": 5000,\n        \"max\": 8062,\n
\"num_unique_values\": 5,\n        \"samples\": [\n          7639\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"condition_encoded\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1,\n        \"min\": 0,\n        \"max\": 4,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          4\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
```

```
}\n    },\n    {\n      \"column\": \"grade_encoded\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0,\n        \"min\": 7,\n        \"max\": 9,\n
\"num_unique_values\": 3,\n        \"samples\": [\n          8\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"view_encoded\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0,\n        \"min\": 4,\n        \"max\": 4,\n
\"num_unique_values\": 1,\n        \"samples\": [\n          4\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"season_Fall\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0,\n        \"min\": 0,\n        \"max\": 1,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"season_Summer\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0,\n        \"min\": 0,\n        \"max\": 0,\n
\"num_unique_values\": 1,\n        \"samples\": [\n          0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"season_Winter\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0,\n        \"min\": 0,\n        \"max\": 1,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          1\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\n}","type":"dataframe"}
```


Handling outliers

```
numeric_columns1 = df3[[ 'bedrooms', 'bathrooms', 'sqft_living',
'sqft_lot', 'floors', 'sqft_above', 'sqft_basement', 'yr_built',
       'sqft_living15', 'sqft_lot15']]

# Loop through each numeric column
for column in numeric_columns1:
    # Calculate IQR
    q1 = df3[column].quantile(0.25)
    q3 = df3[column].quantile(0.75)
    iqr = q3 - q1

    # Calculate outlier boundaries
    lower_bound = q1 - 1.5 * iqr
    upper_bound = q3 + 1.5 * iqr

    # Count outliers
    num_outliers = ((df3[column] < lower_bound) | (df3[column] >
upper_bound)).sum()

    # Print the result
    print(f"Column: {column}, Number of outliers: {num_outliers}")
```

```
Column: bedrooms, Number of outliers: 518
Column: bathrooms, Number of outliers: 558
Column: sqft_living, Number of outliers: 568
Column: sqft_lot, Number of outliers: 2406
Column: floors, Number of outliers: 0
Column: sqft_above, Number of outliers: 600
Column: sqft_basement, Number of outliers: 556
Column: yr_built, Number of outliers: 0
Column: sqft_living15, Number of outliers: 503
Column: sqft_lot15, Number of outliers: 2174

# Define a function to handle outliers using IQR method
def handle_outliers_iqr(df3, column):
    q1 = df3[column].quantile(0.25)
    q3 = df3[column].quantile(0.75)
    iqr = q3 - q1
    lower_bound = q1 - 1.5 * iqr
    upper_bound = q3 + 1.5 * iqr
    df3[column] = df3[column].clip(lower=lower_bound,
upper=upper_bound)

# Columns with outliers
outlier_columns = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
'floors', 'sqft_above', 'sqft_basement', 'yr_built',
       'sqft_living15', 'sqft_lot15']

# Apply the handle_outliers_iqr function to each column
for col in outlier_columns:
    handle_outliers_iqr(df3, col)
```

- Checking if our outliers have been handled.

```
numeric_columns1 = df3[[ 'bedrooms', 'bathrooms', 'sqft_living',
'sqft_lot', 'floors', 'sqft_above', 'sqft_basement', 'yr_built',
       'sqft_living15', 'sqft_lot15']]

# Loop through each numeric column
for column in numeric_columns1:
    # Calculate IQR
    q1 = df3[column].quantile(0.25)
    q3 = df3[column].quantile(0.75)
    iqr = q3 - q1

    # Calculate outlier boundaries
    lower_bound = q1 - 1.5 * iqr
    upper_bound = q3 + 1.5 * iqr

    # Count outliers
    num_outliers = ((df3[column] < lower_bound) | (df3[column] >
upper_bound)).sum()
```

```
    # Print the result
    print(f"Column: {column}, Number of outliers: {num_outliers}")
```

```
Column: bedrooms, Number of outliers: 0
Column: bathrooms, Number of outliers: 0
Column: sqft_living, Number of outliers: 0
Column: sqft_lot, Number of outliers: 0
Column: floors, Number of outliers: 0
Column: sqft_above, Number of outliers: 0
Column: sqft_basement, Number of outliers: 0
Column: yr_built, Number of outliers: 0
Column: sqft_living15, Number of outliers: 0
Column: sqft_lot15, Number of outliers: 0
```

EXPLORATORY DATA ANALYSIS

Correlation

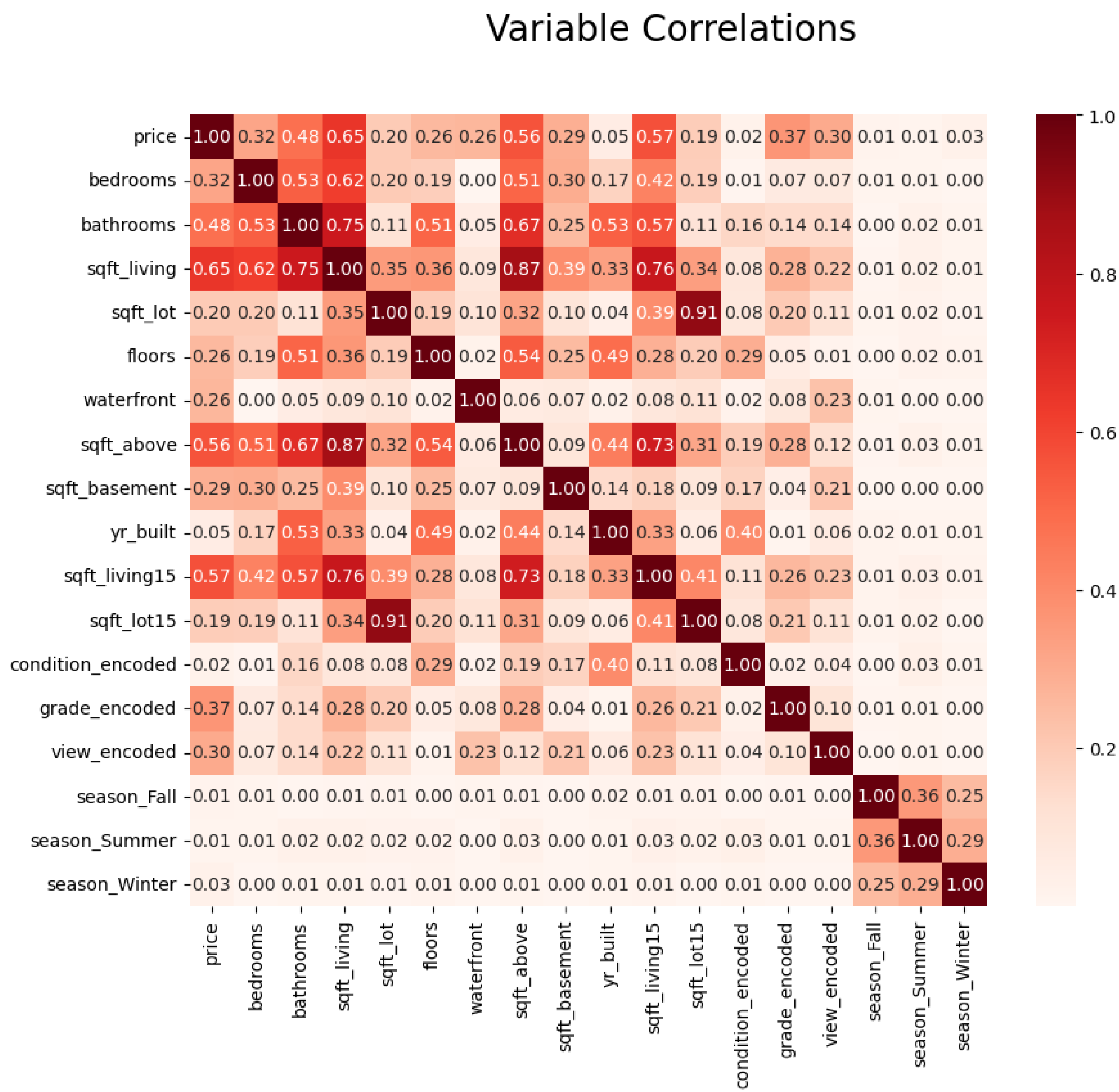
```
# Calculate correlation matrix
correlation_matrix = df3.corr()

# Extract correlation coefficients with 'price'
price_correlations = correlation_matrix['price']

# Sort correlation coefficients in descending order
price_correlations_sorted =
price_correlations.sort_values(ascending=False)

# Print correlation coefficients
print("Correlation Coefficients with Price (Descending Order):")
print(price_correlations_sorted)
```

```
Correlation Coefficients with Price (Descending Order):
price                1.000000
sqft_living          0.646389
sqft_living15        0.568750
sqft_above           0.559166
bathrooms            0.481395
bedrooms             0.318878
sqft_basement        0.285521
waterfront           0.264898
floors               0.256286
sqft_lot             0.196494
sqft_lot15           0.191368
yr_built             0.052906
condition_encoded    0.021223
season_Summer        0.010247
season_Fall         -0.013602
season_Winter       -0.025421
```

```
view_encoded        -0.304492
grade_encoded       -0.367072
Name: price, dtype: float64
```

- These correlation coefficients indicate the strength and direction of the relationship between each feature and the house price:
- Strong Positive Correlation (values close to 1): Features like 'sqft_living', 'sqft_above', 'sqft_living15', and 'bathrooms' have a strong positive correlation with the house price. This suggests that as these feature values increase, the house price tends to increase as well.
- Moderate Positive Correlation (values between 0.3 and 0.7): Features like 'sqft_basement', 'bedrooms', 'waterfront', and 'floors' show a moderate positive correlation with the house price. They influence the price but not as strongly as the features with higher correlation coefficients.
- Weak Positive Correlation (values between 0 and 0.3): Features such as 'sqft_lot', 'sqft_lot15', 'yr_built', and 'condition_encoded' exhibit a weak positive correlation with the house price. Their impact on the price is minimal compared to other features.
- Negative Correlation (values less than 0): Features like 'view_encoded' and 'grade_encoded' have negative correlations with the house price, indicating that as these feature values decrease, the house price tends to increase. However, it's important to note that these correlations are relatively weak compared to the positive correlations.
- Additionally, the 'season' features ('season_Summer', 'season_Fall', 'season_Winter') show very weak correlations with the house price, suggesting they have little influence on pricing.

```
corr = df3.corr().abs()
fig, ax=plt.subplots(figsize=(10,8))
fig.suptitle('Variable Correlations', fontsize=20, y=.98,
fontname='DejaVu Sans')
heatmap = sns.heatmap(corr, cmap='Reds', annot=True , fmt=".2f")
```



MODELING

Baseline modeling

- We are building a simple linear regression model between 'price' and 'sqft_living' to understand the relationship better.

```
from statsmodels.formula.api import ols

# Assuming 'data' is your DataFrame containing the necessary columns
like 'price' and 'sqft_living'

# Simple model for sqft_living
# Formula y ~ x
```

```
sqft_living_formula = 'price ~ sqft_living'
sqft_living_model = ols(sqft_living_formula, df3).fit()

# Finding the predicted values and the residuals for plotting
predicted_values_sqft_living = sqft_living_model.fittedvalues

sqft_living_model.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                  price   R-squared:
0.418
Model:                            OLS   Adj. R-squared:
0.418
Method:                 Least Squares   F-statistic:
1.537e+04
Date:                Wed, 10 Apr 2024   Prob (F-statistic):
0.00
Time:                        10:50:55   Log-Likelihood:             -
2.9911e+05
No. Observations:               21420   AIC:
5.982e+05
Df Residuals:                   21418   BIC:
5.982e+05
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
=========
                  coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
---------
Intercept   -4.349e+04   5087.721     -8.548      0.000   -5.35e+04
-3.35e+04
sqft_living   283.4564      2.286    123.981      0.000     278.975
287.938
==============================================================================
========
Omnibus:                    20682.954   Durbin-Watson:
1.986
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
2707800.341
Skew:                           4.343   Prob(JB):
0.00
```

```
Kurtosis:                      57.392   Cond. No.
5.90e+03
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.9e+03. This might indicate that
there are
strong multicollinearity or other numerical problems.
"""
```

- R-squared measures the proportion of the variance in the dependent variable that is explained by the independent variable(s). In this case, R-squared is 0.418, indicating that approximately 41.8% of the variance in 'price' is explained by 'sqft_living'.
- Our model is statistically significant because our F-statistic p-value is less than 0.05.
- Coefficients:

```
    * Intercept: The intercept term represents the value of the
    dependent variable when all independent variables are set to
    zero. In this case, the intercept is -4.349e+04.
    * sqft_living: The coefficient for 'sqft_living' is 283.4564,
    indicating that for each unit increase in square footage of
    living space, the 'price' is expected to increase by $283.4564,
    holding all other variables constant.
```

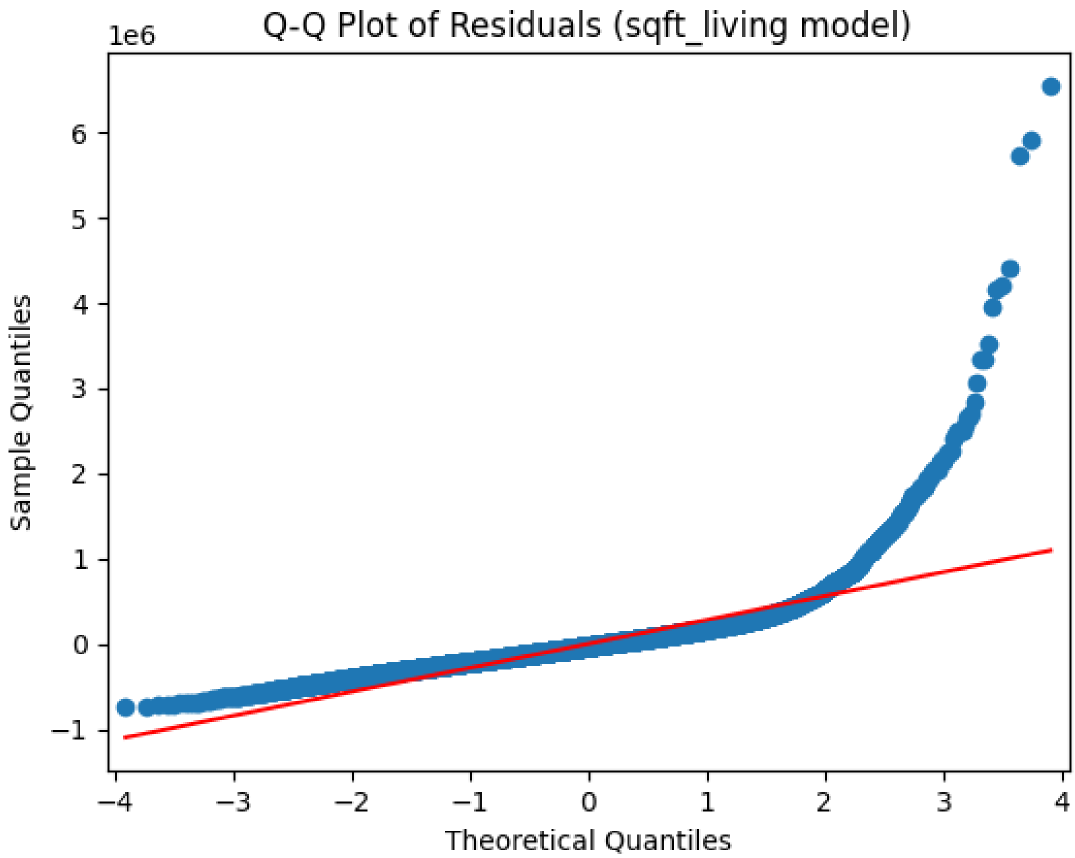
Null Hypothesis:

The null hypothesis for each coefficient is that it is equal to zero.

In this context, for 'sqft_living', the null hypothesis is that the coefficient of 'sqft_living' is equal to zero, implying that there is no linear relationship between square footage of living space and price.

Since the p-value for 'sqft_living' is close to zero, we reject the null hypothesis and conclude that there is a statistically significant linear relationship between 'sqft_living' and 'price'.

```
# Assuming 'sqft_living_model' is the fitted regression model

residuals_sqft_living = sqft_living_model.resid

# Create a Q-Q plot of the residuals
sm.qqplot(residuals_sqft_living, line='s')
plt.title('Q-Q Plot of Residuals (sqft_living model)')
plt.show()
```



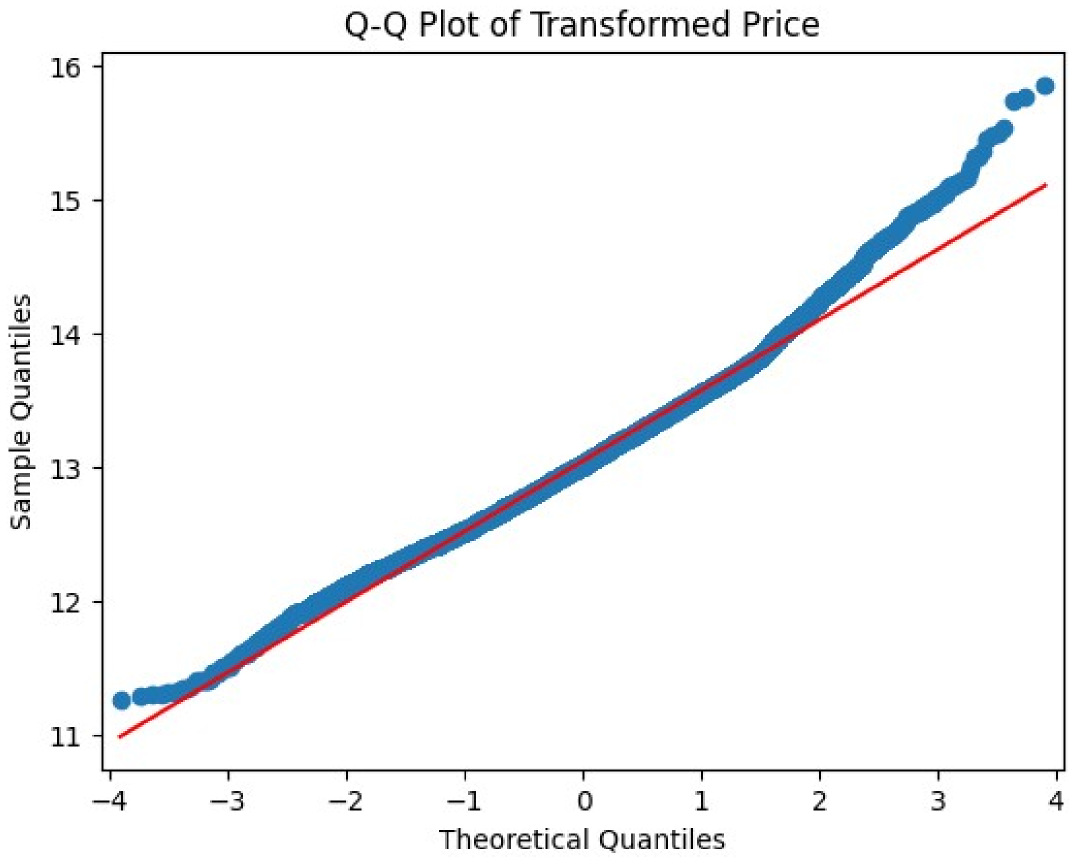
- Homoscedasticity - it means that the spread of the residuals should be uniform across the range of predicted values.
- As we can see, this model violates the homoscedasticity and normality assumptions for linear regression.
- Log-transformation can often help when these assumptions are not met. Let's update the values to their natural logs and re-check the assumptions.

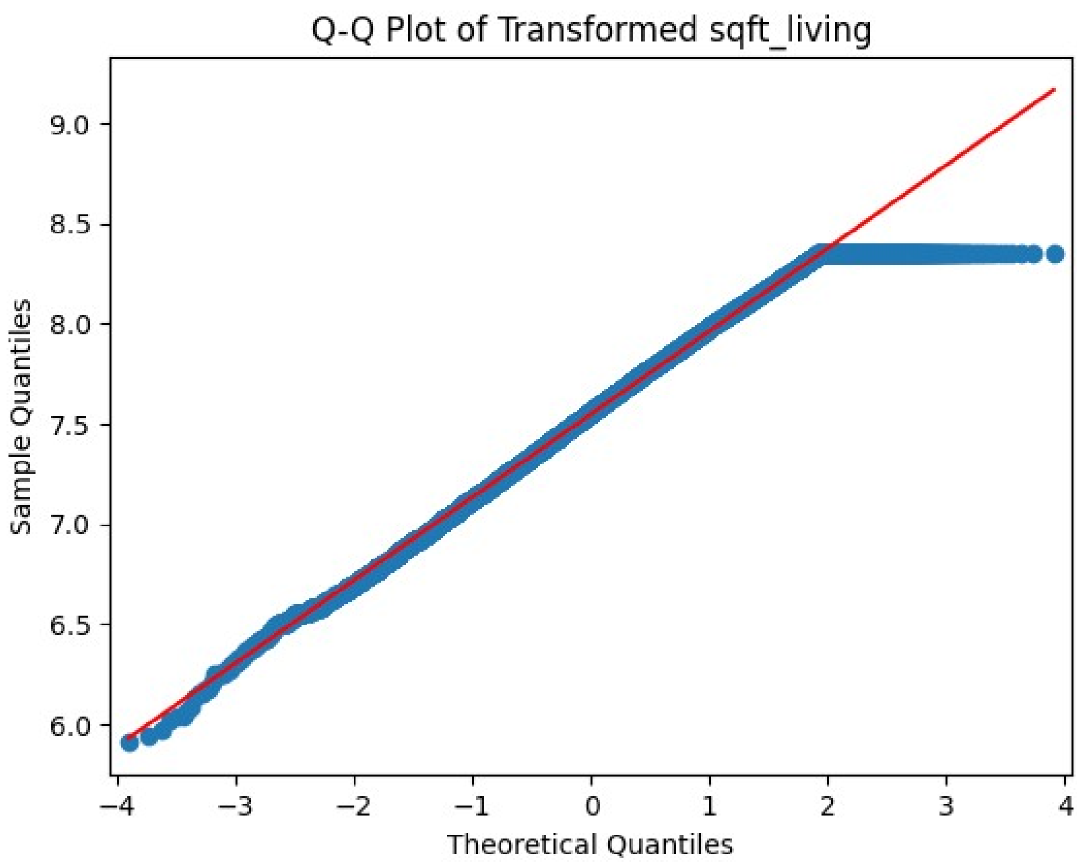
```
# Log transformation

df3['price'] = np.log(df3['price'])
df3['sqft_living'] = np.log(df3['sqft_living'])
```

- Q-Q plots are useful for visually assessing the distributional characteristics of variables and identifying departures from normality.

```
# Create a Q-Q plot for 'price'

sm.qqplot(df3['price'], line='s')
plt.title('Q-Q Plot of Transformed Price')
plt.show()
```

```python
# Create a Q-Q plot for the 'sqft_living' variable
sm.qqplot(df3['sqft_living'], line='s')
plt.title('Q-Q Plot of Transformed sqft_living')
plt.show()
```





- Deviations from the diagonal line suggest departures from normality, such as skewness or heavy tails.
- Now we will create a Simple linear regression for the column price and bathrooms.

```
from statsmodels.formula.api import ols

# Simple model for bathrooms
# Formula y ~ x
bathrooms_formula = 'price ~ bathrooms'
bathrooms_model = ols(bathrooms_formula, df3).fit()

# Finding the predicted values and the residuals for plotting
predicted_values_bathrooms = bathrooms_model.fittedvalues

bathrooms_model.summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                  price   R-squared:
0.290
```

```
Model:                            OLS   Adj. R-squared:
0.290
Method:                 Least Squares   F-statistic:
8756.
Date:                Wed, 10 Apr 2024   Prob (F-statistic):
0.00
Time:                        10:51:17   Log-Likelihood:
-12990.
No. Observations:               21420   AIC:
2.598e+04
Df Residuals:                   21418   BIC:
2.600e+04
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
Intercept     12.2218      0.009   1307.916      0.000      12.204
12.240
bathrooms      0.3935      0.004     93.574      0.000       0.385
0.402
======================================================================
========
Omnibus:                      299.524   Durbin-Watson:
1.968
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
313.033
Skew:                           0.287   Prob(JB):
1.06e-68
Kurtosis:                       3.149   Cond. No.
8.11
======================================================================
========

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

- R-squared is 0.232, indicating that approximately 23.2% of the variance in 'price' is explained by 'bathrooms'.
- The associated probability (Prob (F-statistic)) is close to 0, suggesting that the regression model is statistically significant.

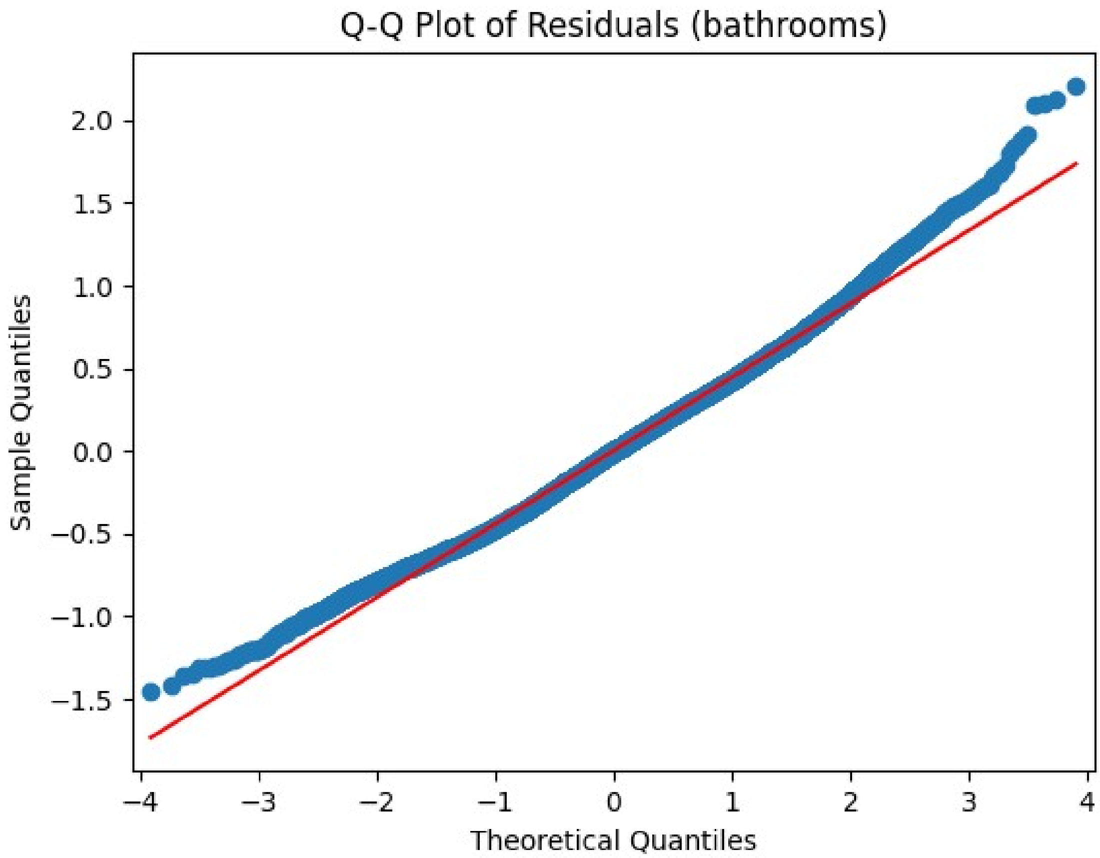
- Coefficients:

```
 * Intercept: The intercept term represents the value of the
dependent variable when all independent variables are set to
zero. In this case, the intercept is 12.2218.
 * Bathrooms: The coefficient for 'bathrooms' is 0.3779,
indicating that for each additional bathroom, the 'price' is
expected to increase by 0.3935 units, holding all other variables
constant.
```

Null Hypothesis:

The null hypothesis for each coefficient is that it is equal to zero. In this context, for 'bathrooms', the null hypothesis is that the coefficient of 'bathrooms' is equal to zero, implying that there is no linear relationship between the number of bathrooms and price. Since the p-value for 'bathrooms' is close to zero, we reject the null hypothesis and conclude that there is a statistically significant linear relationship between the number of bathrooms and price.

```
# Assuming 'sqft_living_model' is the fitted regression model

residuals_bathrooms = bathrooms_model.resid

# Create a Q-Q plot of the residuals
sm.qqplot(residuals_bathrooms, line='s')
plt.title('Q-Q Plot of Residuals (bathrooms)')
plt.show()
```



- This model does not violate the homoscedasticity and normality assumptions for linear regression.

Multiple linear regression model

```
# Independent variables
X = df3.drop("price" ,axis=1)


# Dependent variable
y = df3["price"]

#creating the model/#OrdinaryLeastSquares
import statsmodels.api as sm

# # Add a constant to the independent variables
X_with_const = sm.add_constant(X)


# Fit the OLS model
model = sm.OLS(y, X_with_const)
result = model.fit()
```

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

```
                                 OLS Regression Results

==============================================================================
========
Dep. Variable:                  price   R-squared:
0.594
Model:                            OLS   Adj. R-squared:
0.593
Method:                 Least Squares   F-statistic:
1838.
Date:                Wed, 10 Apr 2024   Prob (F-statistic):
0.00
Time:                        10:51:38   Log-Likelihood:
-7020.1
No. Observations:               21420   AIC:
1.408e+04
Df Residuals:                   21402   BIC:
1.422e+04
Df Model:                          17

Covariance Type:            nonrobust

==============================================================================
===============
                        coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
---------------
const                20.0988      0.246     81.706      0.000
19.617      20.581
bedrooms             -0.0703      0.004    -19.378      0.000      -
0.077      -0.063
bathrooms             0.1100      0.006     18.914      0.000
0.099       0.121
sqft_living           0.1982      0.023      8.693      0.000
0.153       0.243
sqft_lot          -5.567e-06   1.12e-06     -4.977      0.000   -
7.76e-06   -3.37e-06
floors                0.1136      0.006     17.759      0.000
0.101       0.126
waterfront            0.5127      0.029     17.733      0.000
0.456       0.569
sqft_above            0.0002   1.17e-05     17.437      0.000
0.000       0.000
sqft_basement         0.0002   1.23e-05     18.711      0.000
0.000       0.000
yr_built             -0.0047      0.000    -43.846      0.000      -
```

```
0.005      -0.004
sqft_living15          0.0002   5.88e-06     38.685      0.000
0.000       0.000
sqft_lot15         -6.982e-06    1.3e-06     -5.353      0.000   -
9.54e-06   -4.43e-06
condition_encoded      0.0178      0.002      8.809      0.000
0.014       0.022
grade_encoded         -0.0116      0.001    -10.293      0.000      -
0.014      -0.009
view_encoded          -0.0402      0.003    -14.976      0.000      -
0.045      -0.035
season_Fall           -0.0506      0.006     -8.001      0.000      -
0.063      -0.038
season_Summer         -0.0374      0.006     -6.277      0.000      -
0.049      -0.026
season_Winter         -0.0558      0.007     -8.003      0.000      -
0.070      -0.042
======================================================================
========
Omnibus:                       28.276   Durbin-Watson:
1.983
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
31.066
Skew:                          -0.051   Prob(JB):
1.79e-07
Kurtosis:                       3.157   Cond. No.
1.50e+06
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.5e+06. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

- The warning on standard errors suggests that there might be issues with the model's assumptions or with the data itself, which could affect the accuracy of the standard errors and subsequently the validity of the inference drawn from the model.
- We will check for multicollinearity and adress it accordingly
- The R-squared value of 0.594 indicates that approximately 59.4% of the variance in 'price' is explained by the independent variables included in the model.
- Significance of Coefficients: Most of the coefficients have p-values less than 0.05, indicating that they are statistically significant at the 5% significance level).e.

Violation of assumptions

- Linearity

```python
import numpy as np
import statsmodels.api as sm
from statsmodels.stats.diagnostic import linear_rainbow

# Assuming X is your independent variable matrix and y is your
dependent variable vector
# Fit your regression model
model = sm.OLS(y, X).fit()

# Perform the Rainbow test
rainbow_statistic, rainbow_p_value = linear_rainbow(model)
print("Rainbow Test Statistic:", rainbow_statistic)
print("Rainbow Test p-value:", rainbow_p_value)
```

```
Rainbow Test Statistic: 0.9888132810806645
Rainbow Test p-value: 0.7196740919617328
```

- Rainbow Test Statistic: The test statistic measures the deviation from linearity in the regression model. A value close to 1 suggests that the model's fit to the data is linear.
  - Rainbow Test p-value: This p-value assesses the significance of the test statistic. A p-value greater than the significance level (commonly 0.05) indicates that there is no significant departure from linearity in the model. In this case, the p-value being high (71973) suggests that there is no evidence to reject the assumption of linearity in the regression modes.

Independence

- The Durbin-Watson statistic is a measure used to detect the presence of autocorrelation in the residuals of a regression model.
- Autocorrelation occurs when the residuals of the model exhibit correlation with each other, indicating that the assumption of independence of errors is violated.
- Our Durbin-Watson value is 1.983 indicating no autocorrelation meaning that the errors are independent of each other. The assumption of independence of errors is satisfied.

```python
# Define the coefficients and predictions
coefficients = result.params
y_pred = result.predict()

# Calculate R-squared
r_squared = result.rsquared

# Calculate Mean Squared Error (MSE)
mse = result.mse_resid

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)
```

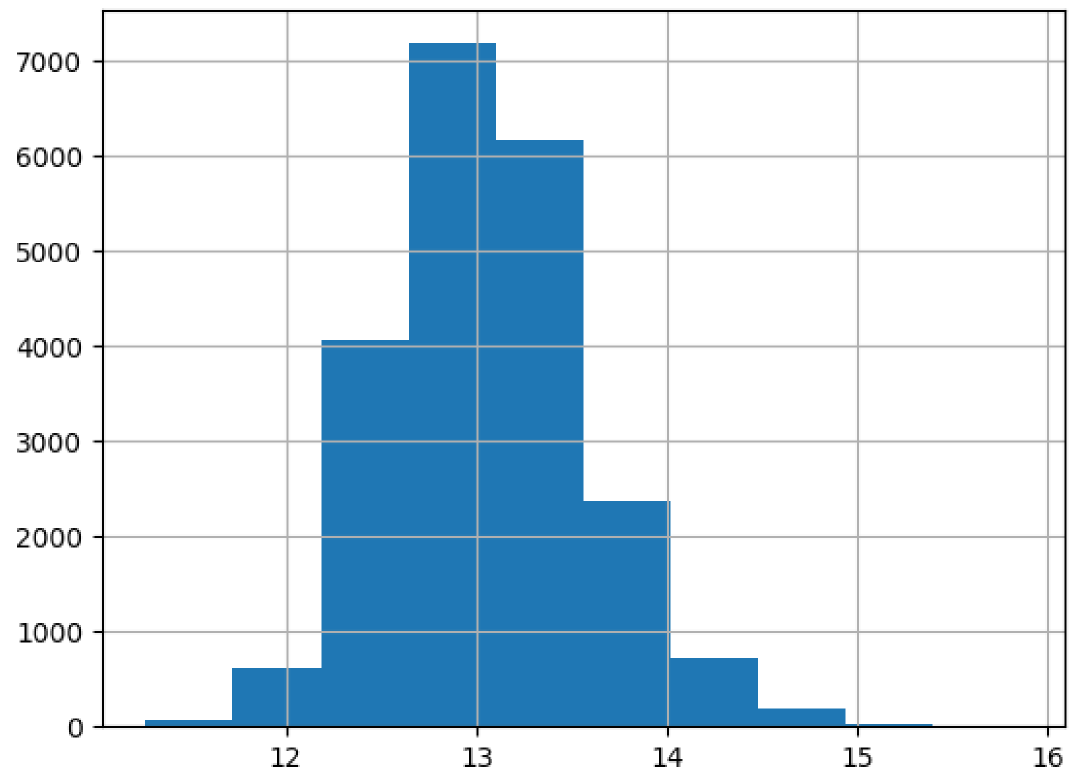
```python
# Print the results
print("R-squared (R2):", r_squared)
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
```

```
R-squared (R2): 0.5935141246373036
Mean Squared Error (MSE): 0.1128650341562048
Root Mean Squared Error (RMSE): 0.3359539167150828
```

- R-squared of 0.593 suggests that approximately 59% of the variance in the dependent variable is explained by the independent variables in the model.
- MSE and RMSE of 0.1128 and 0.336, respectively, indicate the average squared difference and average magnitude of errors between actual and predicted values. Lower values of MSE and RMSE are generally considered better. In this case, RMSE is approximately 0.336, indicating the average error in predicting the dependent variable is around 0.336 units.
- Overall, an R-squared of 0.593 and low values of MSE and RMSE suggest that the model has a decent level of predictive power and performs reasonably well in explaining the variability in the dependent variable.

Checking distribution of our target y

```python
#checking distribution of our target y
y.hist();
```



- Our data is normally distributed.

```
#checking std deviation of the original predictors
np.std(X)

bedrooms                  0.852045
bathrooms                 0.721022
sqft_living               0.414009
sqft_lot               5052.019785
floors                    0.540068
waterfront                0.082278
sqft_above              765.141767
sqft_basement           413.252573
yr_built                 29.386455
sqft_living15           650.717716
sqft_lot15             4368.277039
condition_encoded         1.266860
grade_encoded             2.309329
view_encoded              0.924353
season_Fall               0.424212
season_Summer             0.456171
season_Winter             0.375329
dtype: float64

# standand scaling(subtract the mean of the variable/the std deviation
of the variable)
```

```
#including all the columns
X_scaled = (X-np.mean(X))/np.std(X)

#modeling
X_pred = sm.add_constant(X_scaled)
#building the model
model2 =  sm.OLS(y , X_pred).fit()
model2.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results                            

==============================================================================
========
Dep. Variable:                  price   R-squared:                       
0.594
Model:                            OLS   Adj. R-squared:                  
0.593
Method:                 Least Squares   F-statistic:                     
1838.
Date:                Wed, 10 Apr 2024   Prob (F-statistic):               
0.00
Time:                        10:52:48   Log-Likelihood:                 
-7020.1
No. Observations:               21420   AIC:                         
1.408e+04
Df Residuals:                   21402   BIC:                         
1.422e+04
Df Model:                          17                                         

Covariance Type:            nonrobust                                         

==============================================================================
===============
                        coef    std err          t      P>|t|      
[0.025      0.975]
------------------------------------------------------------------------------
---------------
const               944.3980     54.269     17.402      0.000     
838.026    1050.770
bedrooms             -0.0599      0.003    -19.378      0.000      -
0.066      -0.054
bathrooms             0.0793      0.004     18.914      0.000       
0.071       0.088
sqft_living           0.0820      0.009      8.693      0.000       
0.064       0.101
sqft_lot             -0.0281      0.006     -4.977      0.000      -
0.039      -0.017
```

```
floors                  0.0613      0.003     17.759      0.000
0.055       0.068
waterfront              0.0422      0.002     17.733      0.000
0.038       0.047
sqft_above              0.1566      0.009     17.437      0.000
0.139       0.174
sqft_basement           0.0951      0.005     18.711      0.000
0.085       0.105
yr_built               -0.1375      0.003    -43.846      0.000      -
0.144      -0.131
sqft_living15           0.1479      0.004     38.685      0.000
0.140       0.155
sqft_lot15             -0.0305      0.006     -5.353      0.000      -
0.042      -0.019
condition_encoded       0.0226      0.003      8.809      0.000
0.018       0.028
grade_encoded          -0.0268      0.003    -10.293      0.000      -
0.032      -0.022
view_encoded           -0.0371      0.002    -14.976      0.000      -
0.042      -0.032
season_Fall            -0.0215      0.003     -8.001      0.000      -
0.027      -0.016
season_Summer          -0.0171      0.003     -6.277      0.000      -
0.022      -0.012
season_Winter          -0.0210      0.003     -8.003      0.000      -
0.026      -0.016
======================================================================
========
Omnibus:                       28.276   Durbin-Watson:
1.983
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
31.066
Skew:                          -0.051   Prob(JB):
1.79e-07
Kurtosis:                       3.157   Cond. No.
4.29e+08
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 4.29e+08. This might indicate that
there are
strong multicollinearity or other numerical problems.
"""
```

- We have better and more readable coefficients.
- Let's check for multicollinearity.

Multicollinearity

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


col = df3[['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
'floors',
           'waterfront', 'sqft_above', 'sqft_basement', 'yr_built',
           'sqft_living15', 'sqft_lot15', 'condition_encoded',
'grade_encoded',
           'view_encoded']]

# Convert the DataFrame column values into a NumPy array
X = col.values

# Create a dataframe that will contain the names of all the feature
variables and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = col.columns
vif['VIF'] = [variance_inflation_factor(X, i) for i in
range(X.shape[1])]
vif
```


```
{"summary":"{\n  \"name\": \"vif\",\n  \"rows\": 14,\n  \"fields\": [\
n    {\n      \"column\": \"Features\",\n      \"properties\": {\n
\"dtype\": \"string\",\n        \"num_unique_values\": 14,\n
\"samples\": [\n          \"sqft_living15\",\n
\"condition_encoded\",\n          \"bedrooms\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"VIF\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 1238.410551704582,\n
\"min\": 1.078386679536966,\n        \"max\": 3884.1988552027083,\n
\"num_unique_values\": 14,\n        \"samples\": [\n
28.20950906377554,\n          1.7009581534777636,\n
30.027609002041693\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"vif"}
```


- Variance Inflation Factor measures how much the variance of an estimated regression coefficient is increased due to multicollinearity in the model.
- A VIF of 1 indicates no multicollinearity.
- Typically, a VIF greater than 5 or 10 indicates multicollinearity issues.

- Extremely high VIF values, such as those seen above suggest severe multicollinearity.
- The VIF values for "sqft_living," "sqft_lot," "sqft_above," "yr_built," "sqft_living15," and "sqft_lot15" are high, indicating strong multicollinearity among these variables.
- This suggests that these variables are highly correlated with other predictors in the model, which can lead to unstable coefficient estimates and inflated standard errors.
- We will address the multicollinearity by using the Lasso regularization technique given that our data set is high dimensional.

```
from sklearn.linear_model import Lasso
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error

# Assuming X contains your independent variables and y contains your
target variable

# 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
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Create the Lasso regression model
lasso_model = Lasso(alpha=0.1)

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

# Predict on the testing data
y_pred = lasso_model.predict(X_test_scaled)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)

Mean Squared Error: 0.1581670236737812
```

- The Mean Squared Error (MSE) is a measure of the average squared difference between the actual values (ground truth) and the predicted values generated by a model. In this case, the MSE value of approximately 0.158 indicates that, on average, the squared difference between the actual house prices and the predicted house prices by the Lasso regression model is around 0.158.

- A lower MSE value suggests that the model's predictions are closer to the actual values, indicating better performance.

Feature selection

- We will conduct feature selection on our columns to refine our dataset for building the final multiple linear regression model, thereby laying the groundwork before exploring alternative modeling approaches.

```
from sklearn.feature_selection import RFE

lr_rfe = LinearRegression()
select = RFE(lr_rfe, n_features_to_select=7)

ss = StandardScaler()
ss.fit(df3.drop('price', axis=1))

df3_scaled = ss.transform(df3.drop('price', axis=1))

select.fit(X=df3_scaled, y=df3['price'])

RFE(estimator=LinearRegression(), n_features_to_select=7)

select.support_

array([ True,  True, False, False,  True, False,  True,  True,  True,
        True, False, False, False, False, False, False, False])
```

- We will pick the six (excluding price column) selected columns for our next model.

```
df3.head()
```


```
{"summary":"{\n  \"name\": \"df3\",\n  \"rows\": 21420,\n  \"fields\":
[\n    {\n      \"column\": \"price\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0.5267257661191972,\n
\"min\": 11.26446410567173,\n        \"max\": 15.856730886823913,\n
\"num_unique_values\": 3607,\n        \"samples\": [\n
12.22710001272225,\n          13.015285832940311,\n
12.461896336233012\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"bedrooms\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0.8520646991322228,\n        \"min\":
1.5,\n        \"max\": 5.5,\n        \"num_unique_values\": 6,\n
\"samples\": [\n          3.0,\n          2.0,\n          5.5\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"bathrooms\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0.7210388858169191,\n        \"min\": 0.625,\n        \"max\": 3.625,\
n        \"num_unique_values\": 14,\n        \"samples\": [\n
3.25,\n          0.75,\n          1.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"sqft_living\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
```

0.4140187158220354,\n   \"min\": 5.91350300563827,\n
\"max\": 8.349957272040324,\n   \"num_unique_values\": 808,\n
\"samples\": [\n   7.936660155225426,\n
7.259819610363186,\n   6.063785208687608\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"sqft_lot\",\n   \"properties\":
{\n   \"dtype\": \"number\",\n   \"std\":
5052.137717035551,\n   \"min\": 520.0,\n   \"max\":
19166.25,\n   \"num_unique_values\": 7846,\n   \"samples\":
[\n   6407.0,\n   9145.0,\n   8372.0\n   ],\
n   \"semantic_type\": \"\",\n   \"description\": \"\"\n
}\n   },\n   {\n   \"column\": \"floors\",\n   \"properties\":
{\n   \"dtype\": \"number\",\n   \"std\":
0.540081019042598,\n   \"min\": 1.0,\n   \"max\": 3.5,\n
\"num_unique_values\": 6,\n   \"samples\": [\n   1.0,\n
2.0,\n   3.5\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"waterfront\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0,\n   \"min\": 0,\n
\"max\": 1,\n   \"num_unique_values\": 2,\n   \"samples\":
[\n   1,\n   0\n   ],\n   \"semantic_type\":
\"\",\n   \"description\": \"\"\n   }\n   },\n   {\n
\"column\": \"sqft_above\",\n   \"properties\": {\n
\"dtype\": \"number\",\n   \"std\": 765,\n   \"min\": 370,\n
\"max\": 3750,\n   \"num_unique_values\": 743,\n
\"samples\": [\n   2217,\n   2905\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"sqft_basement\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
413.2622196191133,\n   \"min\": 0.0,\n   \"max\": 1375.0,\n
\"num_unique_values\": 189,\n   \"samples\": [\n   143.0,\
n   1245.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"yr_built\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 29,\n   \"min\": 1900,\n
\"max\": 2015,\n   \"num_unique_values\": 116,\n
\"samples\": [\n   1943,\n   1987\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"sqft_living15\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
650,\n   \"min\": 399,\n   \"max\": 3690,\n
\"num_unique_values\": 639,\n   \"samples\": [\n   2990,\n
1309\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"sqft_lot15\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 4368.379009991409,\n   \"min\":
651.0,\n   \"max\": 17565.625,\n   \"num_unique_values\":
7047,\n   \"samples\": [\n   9598.0,\n   2723.0\n
],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n

```
}\n    },\n    {\n      \"column\": \"condition_encoded\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1,\n        \"min\": 0,\n        \"max\": 4,\n
\"num_unique_values\": 5,\n        \"samples\": [\n          4,\n
1\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"grade_encoded\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 2,\n        \"min\": 0,\n
\"max\": 10,\n        \"num_unique_values\": 11,\n        \"samples\":
[\n          6,\n          8\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"view_encoded\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 4,\n        \"num_unique_values\": 5,\n        \"samples\":
[\n          3,\n          2\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"season_Fall\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          0,\n          1\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"season_Summer\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          1,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"season_Winter\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          1,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"df3"}
```

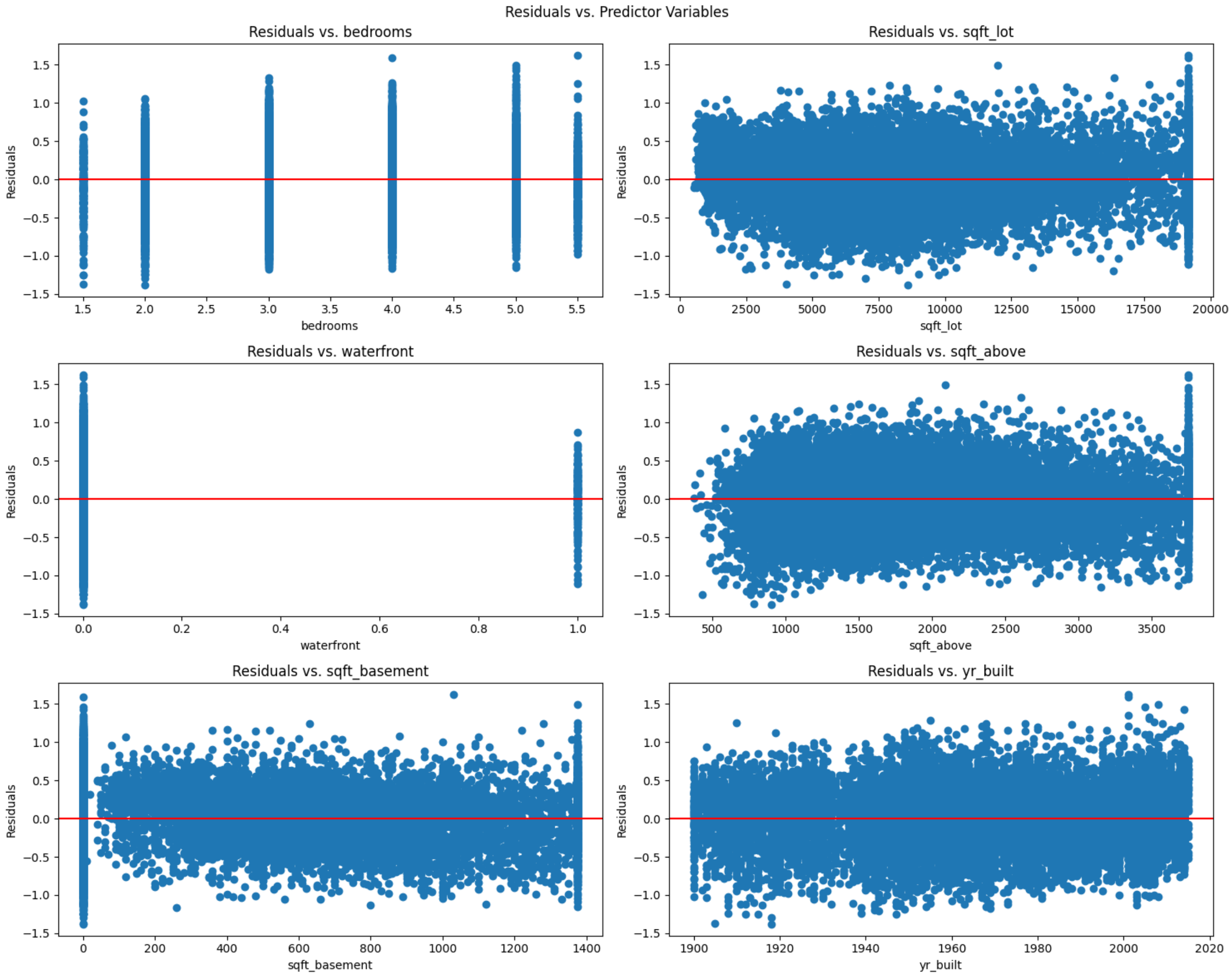

```
# Define your independent variables (features)
X = df3[['bedrooms', 'sqft_lot' , 'waterfront' , 'sqft_above',
'sqft_basement' , 'yr_built' ]]

# Add a constant to the independent variables matrix (required for
OLS)
X = sm.add_constant(X)

# Define your dependent variable (target)
y = df3['price']

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

# Fit the model
results = model.fit()
```

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

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:                  price   R-squared:
0.531
Model:                            OLS   Adj. R-squared:
0.531
Method:                 Least Squares   F-statistic:
4044.
Date:                Wed, 10 Apr 2024   Prob (F-statistic):
0.00
Time:                        10:53:19   Log-Likelihood:
-8547.9
No. Observations:               21420   AIC:
1.711e+04
Df Residuals:                   21413   BIC:
1.717e+04
Df Model:                           6

Covariance Type:            nonrobust

==============================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----------
const            19.0643      0.185    103.093      0.000      18.702
19.427
bedrooms         -0.0683      0.004    -18.503      0.000      -0.075
-0.061
sqft_lot      -1.214e-05   5.25e-07    -23.137      0.000   -1.32e-05
-1.11e-05
waterfront        0.6570      0.030     21.684      0.000       0.598
0.716
sqft_above        0.0006   4.48e-06    122.965      0.000       0.001
0.001
sqft_basement     0.0005   6.64e-06     72.983      0.000       0.000
0.000
yr_built         -0.0034   9.47e-05    -36.393      0.000      -0.004
-0.003
==============================================================================
========
Omnibus:                       17.479   Durbin-Watson:
1.988
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
```

```
17.669
Skew:                          -0.061   Prob(JB):
0.000146
Kurtosis:                       3.069   Cond. No.
7.77e+05
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 7.77e+05. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

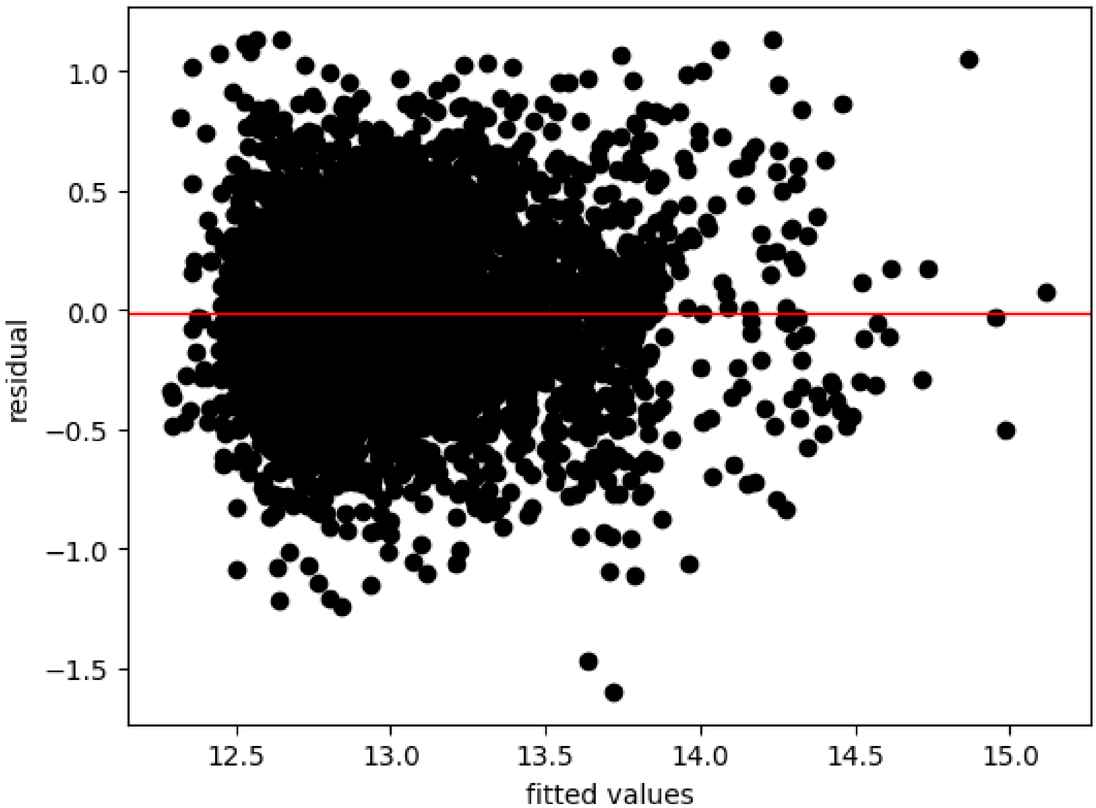
```
# Residuals vs. Predictor Variables (for linearity and independence)
# Assuming 'X' contains predictor variables used in the model

X = df3[['bedrooms', 'sqft_lot' , 'waterfront' , 'sqft_above',
'sqft_basement' , 'yr_built']]

import matplotlib.pyplot as plt
import seaborn as sns


# Get the residuals
residuals = results.resid

# Create a grid of subplots
fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(15, 12))
fig.suptitle("Residuals vs. Predictor Variables")

# Flatten the 2D array of subplots into a 1D array
axes = axes.flatten()

for i, col in enumerate(X.columns):
    ax = axes[i]
    ax.scatter(X[col], residuals)
    ax.axhline(y=0, color='r', linestyle='-')
    ax.set_xlabel(col)
    ax.set_ylabel('Residuals')
    ax.set_title(f'Residuals vs. {col}')

# Adjust spacing and display the plot
plt.tight_layout()
plt.show()
```



- We can observe the violation of assumptions of linearity and homoscedasticity.

```
# Creating a Residual Plot

X= df3[['bedrooms', 'sqft_lot' , 'waterfront' , 'sqft_above',
'sqft_basement' , 'yr_built']]
y= df3['price']

X_train, X_test, admit_train, admit_test = train_test_split(X, y,
test_size=0.2, random_state=0)
regressor = LinearRegression()
regressor.fit(X_train, admit_train)

# This is our prediction our model
y_predict = regressor.predict(X_test)
#
residuals = np.subtract(y_predict, admit_test)

# Plot
plt.scatter(y_predict, residuals, color='black')
plt.ylabel('residual')
```

```
plt.xlabel('fitted values')
plt.axhline(y= residuals.mean(), color='red', linewidth=1)
plt.show()
```



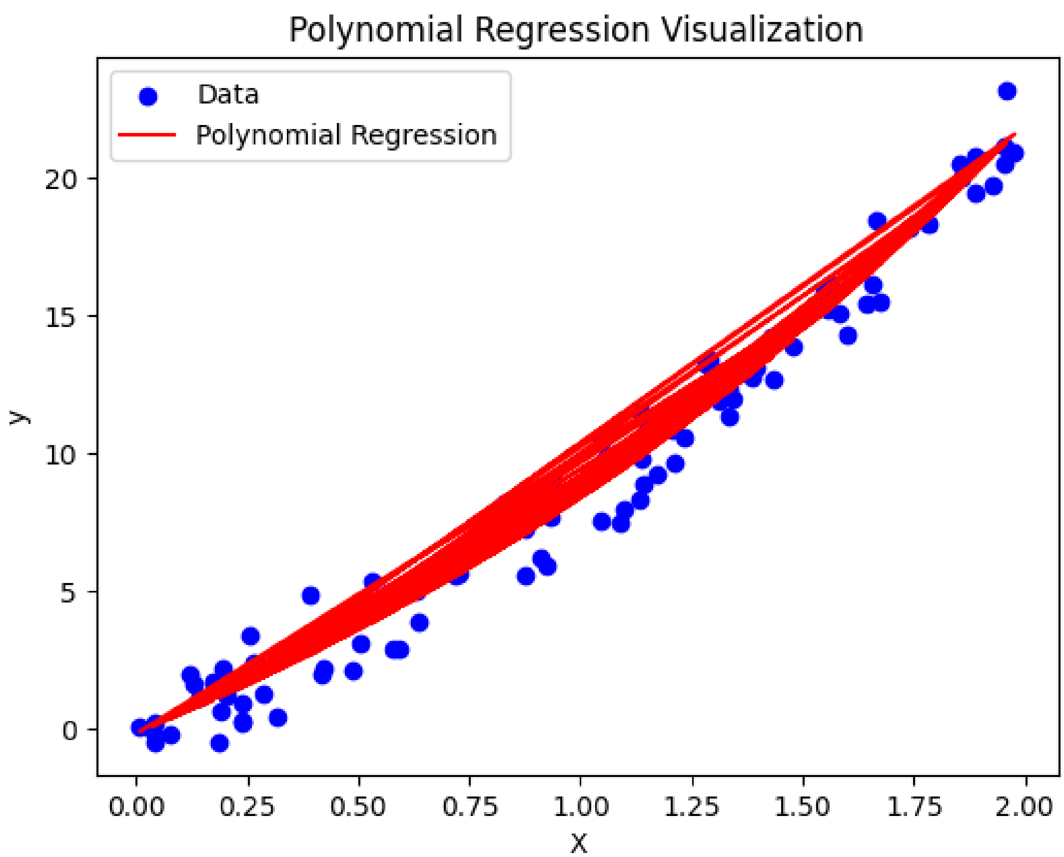

```
# Creating a Polynomial Regression with 3 degrees
poly = PolynomialFeatures(degree=3, include_bias=False)
poly_features = poly.fit_transform(X)

# Split the dataset into train and test sets
X_train, X_test, y_train, y_test = train_test_split(poly_features, y,
test_size=0.3, random_state=10)

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit the scaler to the training data and transform it
X_train_scaled = scaler.fit_transform(X_train)

# Transform the test data using the same scaler
X_test_scaled = scaler.transform(X_test)

# Fit the polynomial regression model
poly_reg_model = LinearRegression()
poly_reg_model.fit(X_train_scaled, y_train)
```

```
# Predict the target variable on the scaled test data
poly_reg_y_predicted = poly_reg_model.predict(X_test_scaled)

# Calculate RMSE
poly_reg_rmse = np.sqrt(mean_squared_error(y_test,
poly_reg_y_predicted))
print("Root Mean Squared Error (RMSE):", poly_reg_rmse)
```

```
Root Mean Squared Error (RMSE): 0.34340991868564386
```

```
# Polynomial Regression with 3 degrees
poly = PolynomialFeatures(degree=3, include_bias=False)
poly_features = poly.fit_transform(X)

# Split the dataset into train and test sets
X_train, X_test, y_train, y_test = train_test_split(poly_features, y,
test_size=0.3, random_state=10)

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit the scaler to the training data and transform it
X_train_scaled = scaler.fit_transform(X_train)

# Transform the test data using the same scaler
X_test_scaled = scaler.transform(X_test)

# Fit the polynomial regression model
poly_reg_model = LinearRegression()
poly_reg_model.fit(X_train_scaled, y_train)

# Predict the target variable on the scaled test data
poly_reg_y_predicted = poly_reg_model.predict(X_test_scaled)

# Calculate RMSE
poly_reg_rmse = np.sqrt(mean_squared_error(y_test,
poly_reg_y_predicted))

# Evaluate the model performance with polynomial features
mse_poly = mean_squared_error(y_test, poly_reg_y_predicted)
rmse_poly = sqrt(mse_poly)
r2_poly = r2_score(y_test, poly_reg_y_predicted)

# Print model performance metrics with polynomial features
print("Model Performance with Polynomial Features:")
print("Mean Squared Error (MSE):", mse_poly)
print("Root Mean Squared Error (RMSE):", rmse_poly)
print("R-squared (R2):", r2_poly)
```

```
Model Performance with Polynomial Features:
Mean Squared Error (MSE): 0.11793037225168054
Root Mean Squared Error (RMSE): 0.34340991868564386
R-squared (R2): 0.5784432831918611

import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression

# Generate some random data
np.random.seed(0)
X = 2 * np.random.rand(100, 1)
y = 3 * X**2 + 5 * X + np.random.randn(100, 1)

# Fit polynomial regression model
poly_features = PolynomialFeatures(degree=3)
X_poly = poly_features.fit_transform(X)
poly_reg = LinearRegression()
poly_reg.fit(X_poly, y)

# Visualize the data and the polynomial regression curve
plt.scatter(X, y, color='blue', label='Data')
plt.plot(X, poly_reg.predict(X_poly), color='red', label='Polynomial
Regression')
plt.xlabel('X')
plt.ylabel('y')
plt.title('Polynomial Regression Visualization')
plt.legend()
plt.show()
```



- An upward-sloping curve suggests a positive correlation, where an increase in the predictor variable(s) is associated with an increase in the target variable.

```
from sklearn.model_selection import cross_val_score

# X' contains the predictors and 'y' contains the target variable from
your dataset
X = df3[['sqft_living', 'sqft_living15' , 'sqft_above', 'bathrooms',
'bedrooms', 'view_encoded' , 'grade_encoded']]
y = df3['price']

# Split the data into training and test sets (75% training, 25% test)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.25, random_state=42)

# Create a linear regression model
multiple_model_3 = LinearRegression()

# Fit the model on the training data
multiple_model_3.fit(X_train, y_train)

# Perform cross-validation and calculate both R^2 and mean squared
error
cv_scores_r2 = cross_val_score(multiple_model_3, X_train, y_train,
```

```
cv=5, scoring='r2')
cv_scores_mse = -cross_val_score(multiple_model_3, X_train, y_train,
cv=5, scoring='neg_mean_squared_error')

# Print the cross-validation scores
print("Cross-validation R^2 scores:", cv_scores_r2)
print("Mean R^2 score:", np.mean(cv_scores_r2))
print("Cross-validation MSE scores:", cv_scores_mse)
print("Mean MSE:", np.mean(cv_scores_mse))

# Evaluate the model on the test set
y_pred_test = multiple_model_3.predict(X_test)
test_r2 = multiple_model_3.score(X_test, y_test)
test_mse = mean_squared_error(y_test, y_pred_test)
print("Test R^2 score:", test_r2)
print("Test MSE:", test_mse)
```

```
Cross-validation R^2 scores: [0.49837495 0.51179891 0.52607659
0.49855351 0.5168576 ]
Mean R^2 score: 0.5103323136219119
Cross-validation MSE scores: [0.14258149 0.13418398 0.12999174
0.13682081 0.13425705]
Mean MSE: 0.13556701332855092
Test R^2 score: 0.5097620447238458
Test MSE: 0.13677834522286209
```

REGRESSION RESULTS

For our baseline model, we conducted simple linear regression analyses to explore the relationships between the housing price and two highly correlated variables: bathrooms and square footage of living space (sqft_living).

First, we tested the hypothesis that the coefficient of 'sqft_living' is zero, suggesting no linear relationship between the size of the living space and the price. However, our analysis revealed a p-value close to zero (less than 0.05) , leading us to reject the null hypothesis. This implies a statistically significant linear relationship between 'sqft_living' and 'price'. The coefficient estimate for 'sqft_living' is 283.4564. It indicates that for each additional unit increase in square footage of living space, we expect the price to increase by $283.4564, assuming all other variables remain constant.

Next, we examined the relationship between the number of bathrooms and the price. Initially, we hypothesized that the coefficient of 'bathrooms' would be zero, indicating no linear relationship. Yet, the analysis yielded a low p-value (close to 0.0), prompting us to reject the null hypothesis. We concluded a statistically significant linear relationship between the number of bathrooms and the price. The coefficient estimate for 'bathrooms' is 0.3779, indicating that for each additional bathroom, the price is expected to increase by 0.3779 units, all else being equal.

From our final multiple linear regression model, the following key findings were observed:

- Bedrooms: Each additional bedroom is associated with a decrease in the estimated price by 0.0683 units, holding all other variables constant. This suggests that, contrary to intuition, an increase in the number of bedrooms is linked with a lower housing price in our model.
- Sqft_lot: The coefficient for square footage of lot area indicates that for each additional square foot of lot area, the estimated price decreases by $1.214e-05, holding all other variables constant. This suggests that larger lot sizes are associated with lower housing prices in our model.
- Waterfront: Properties with a waterfront view are estimated to have a price increase of 0.6570 units compared to those without a waterfront view, holding all other variables constant. This indicates a significant positive impact of waterfront views on housing prices.
- Sqft_above and Sqft_basement: Each additional square foot of living space above ground level (sqft_above) and in the basement (sqft_basement) is associated with an estimated price increase of 0.0006 and 0.0005 units, respectively, holding all other variables constant. This suggests that larger living spaces contribute positively to housing prices.
- Yr_built: With each passing year of construction, the estimated price decreases by 0.0034 units, holding all other variables constant. This implies that newer properties tend to have lower prices compared to older ones.

From this, we can deduce that waterfront view, and living space (both above ground and in the basement) positively influence housing prices. Additionally, newer properties tend to command lower prices compared to older ones. Our analysis also suggests that newer properties generally have lower prices compared to older ones. Additionally, both the number of bedrooms and the size of the lot are associated with lower prices.

Our polynomial regression model is preferred as it achieved the highest R-squared value of 0.58, surpassing both the multiple linear regression model (0.53) and the simple regression analyses (0.41 and 0.29)

The cross-validation results provide valuable insights into the performance of our model. The mean R-squared score of 0.510 and the test R-squared score of 0.510 indicate that our model explains approximately 51% of the variance in the target variable. Additionally, the mean MSE of 0.136 and the test MSE of 0.137 suggest that our model's predictions are, on average, off by approximately 0.137 units. These consistent scores across cross-validation folds and the test set validate the robustness and generalization capability of our model, indicating its reliability in making accurate predictions on unseen data.

CONCLUSION

Based on our analysis, we have uncovered several significant insights into the factors influencing housing prices. Firstly, features such as waterfront views, larger living spaces (both above ground and in the basement), and certain construction attributes positively impact housing prices. Conversely, newer properties tend to command lower prices compared to older ones, and factors like the number of bedrooms and lot size are associated with decreased prices.

Limitations

1. The dataset may lack additional property-specific characteristics that could provide further insights into housing prices.
2. Multicollinearity: The existence of correlated predictors within the dataset can result in multicollinearity problems, complicating the accurate interpretation of the individual impacts of each feature.
3. Overfitting: Polynomial regression models are prone to overfitting. This is where the model tightly conforms to the training data but may struggle to perform well on new, unseen data. Overall the model was the best fit model for this prediction

RECOMMENDATIONS

Further Data Collection: the dataset could be expanded to include additional property-specific characteristics that may influence housing prices, such as proximity to amenities and neighborhood demographics, and property condition. This can provide a more comprehensive understanding of the housing market dynamics.

Guard Against Overfitting: To mitigate the risk of overfitting in polynomial regression models, using techniques such as cross-validation, regularization could be considered, or reducing the complexity of the model by selecting an appropriate degree for the polynomial features.

Continuous Model Monitoring: Continuously monitoring the model's performance and validity over time as new data becomes available or market conditions change. Regular updates and recalibration may be necessary to ensure the model remains relevant and accurate.