Final Project Submission

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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.

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.

Table of content

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.

In [1]:

```
# Importing standard packages and libraries
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.datasets import make_regression
from sklearn.linear_model import LinearRegression
import sklearn.metrics as metrics
from random import gauss
from mpl_toolkits.mplot3d import Axes3D
from scipy import stats as stats
%matplotlib inline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

LOADING DATA

In [2]:
```python
# Loading the csv file

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

DATA INSPECTION AND UNDERSTANDING

In [3]:
```python
# Previewing a sample
df.head()
```

Out[3]:

ving	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_renov
1180	5650	1.0	NaN	NONE	...	7 Average	1180	0.0	1955	
2570	7242	2.0	NO	NONE	...	7 Average	2170	400.0	1951	19
770	10000	1.0	NO	NONE	...	6 Low Average	770	0.0	1933	
1960	5000	1.0	NO	NONE	...	7 Average	1050	910.0	1965	
1680	8080	1.0	NO	NONE	...	8 Good	1680	0.0	1987	

In [4]:
```python
# Checking the shape of our dataframe
df.shape
```

Out[4]: (21597, 21)

In [5]:
```
# 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.

In [6]:
```
# Checking data numerical summaries
df.describe()
```

Out[6]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	215
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	

DATA CLEANING

In [7]:

```
# 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 missing values in our data

In [8]:

```
# Checking the proportion of our missing data
df_clean.isnull().mean()
```

Out[8]:

```
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.

In [9]:
```python
# 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:
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: yr_renovated, Length: 70, dtype: int64

Value counts for view:
NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64

Value counts for waterfront:
NO     19075
YES      146
Name: waterfront, 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

In [10]:
```python
# dropping irrelevant columns

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

Handling missing values

In [11]:
```python
# Filling missing values in waterfront column with 'NO'

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

In [12]:
```python
# Filling missing valuees in view column with 'NONE'

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

In [13]:
```python
# Check if missing values have been handled

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

Out[13]:
```
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.

In [14]:

```python
#  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.

In [15]:

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

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

Out[15]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
94	6021501535	12/23/2014	700000.0	3	1.50	1580	5000	1.0	
314	4139480200	12/9/2014	1400000.0	4	3.25	4290	12103	1.0	
325	7520000520	3/11/2015	240500.0	2	1.00	1240	12092	1.0	
346	3969300030	12/29/2014	239900.0	4	1.00	1000	7134	1.0	
372	2231500030	3/24/2015	530000.0	4	2.25	2180	10754	1.0	
...	...	...	...	...	...	...	...	...	
20165	7853400250	2/19/2015	645000.0	4	3.50	2910	5260	2.0	
20597	2724049222	12/1/2014	220000.0	2	2.50	1000	1092	2.0	
20654	8564860270	3/30/2015	502000.0	4	2.50	2680	5539	2.0	
20764	6300000226	5/4/2015	380000.0	4	1.00	1200	2171	1.5	
21565	7853420110	5/4/2015	625000.0	3	3.00	2780	6000	2.0	

177 rows × 17 columns

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

In [16]:
```python
df_clean.drop_duplicates(subset=["id"], inplace=True)
```

In [17]:
```python
# confirm duplicates have been dropped.

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

Out[17]:

id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition

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"

In [18]:
```python
potential_placeholders = [" " , "-", "--", "?", "??" , "#","#####" , "-1" , "9

# 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()
            count = (df_clean[column] == value).sum()
            print(f"Column '{column}': Found {count} occurrences of potential 
            found_placeholder = True

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

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

In [19]:
```python
# 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
```

In [20]:

```
# Confirm removal of placeholders

potential_placeholders = [" " , "-", "--", "?", "??" , "#","#####" , "-1" , "9

# 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()
            count = (df_clean[column] == value).sum()
            print(f"Column '{column}': Found {count} occurrences of potential 
            found_placeholder = True

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

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

In [21]:

```
df_clean.info()
```

```
 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 are categorical.

Handling non-numerical data

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

In [22]:

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

Value counts for 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: grade, dtype: int64
```

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

In [23]:

```
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['conditio

# 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.

In [24]:

```python
# 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-Time series feature

- 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.

In [25]:

```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.

In [26]:

```python
##one hot encoding for season

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

In [27]:

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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  int32  
 17  grade_encoded      21420 non-null  int32  
 18  view_encoded       21420 non-null  int32  
 19  season_Fall        21420 non-null  int32  
 20  season_Summer      21420 non-null  int32  
 21  season_Winter      21420 non-null  int32  
dtypes: float64(4), int32(6), int64(9), object(3)
memory usage: 3.3+ MB
```

In [28]:
```
# 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
```

Out[28]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	sqft_above	sqft_base
0	221900.0	3	1.00	1180	5650	1.0	0	1180	
1	538000.0	3	2.25	2570	7242	2.0	0	2170	
2	180000.0	2	1.00	770	10000	1.0	0	770	
3	604000.0	4	3.00	1960	5000	1.0	0	1050	
4	510000.0	3	2.00	1680	8080	1.0	0	1680	

EXPLORATORY DATA ANALYSIS

Handling outliers

In [29]:
```python
numeric_columns1 = df3[[ 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', '
       '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))

    # 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
```

In [30]:
```python
# 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_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.

In [31]:

```
numeric_columns1 = df3[[ 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', '
       '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))

    # 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
```

Correlation

In [32]:

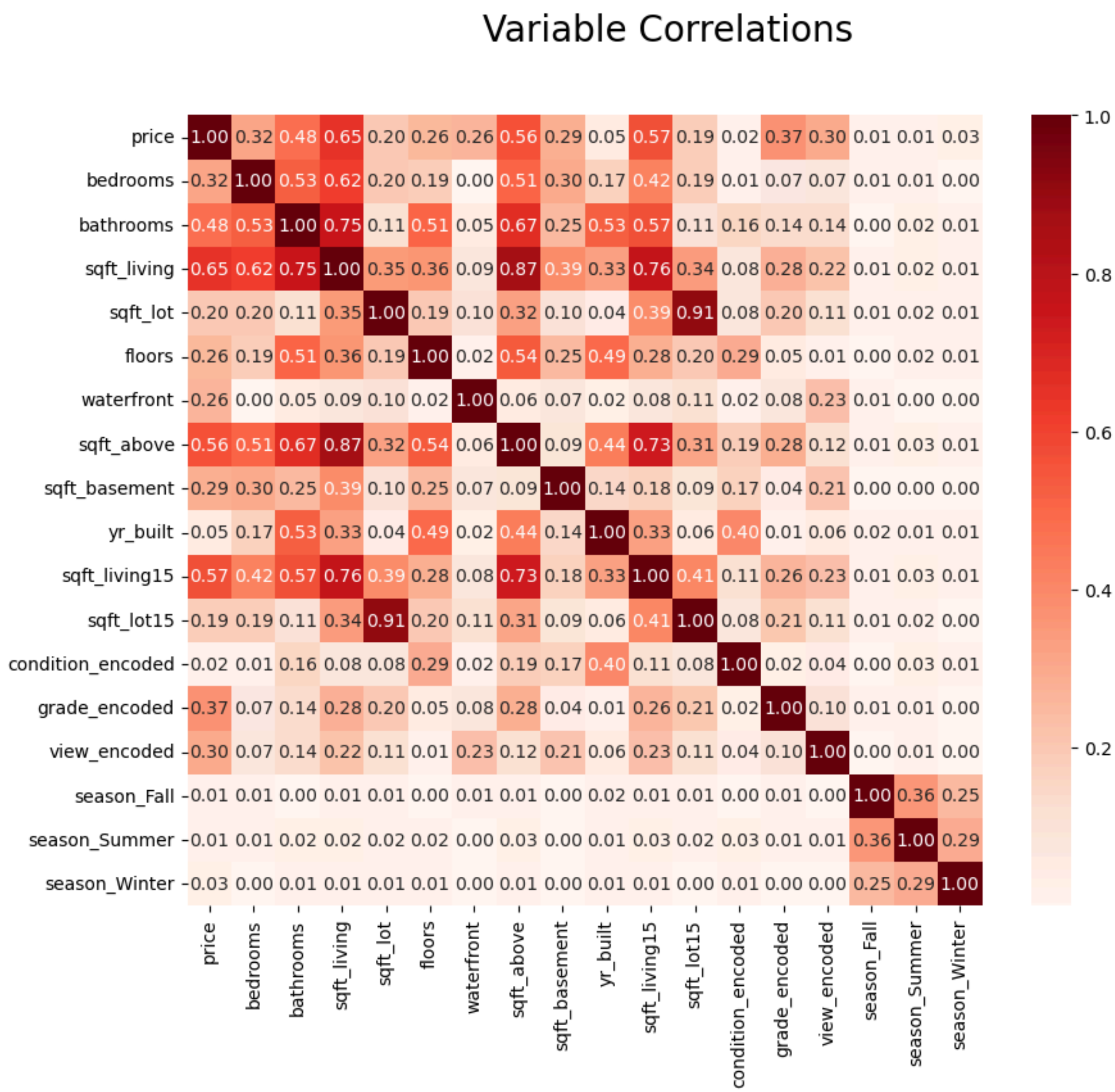
```python
# Calculate correlation matrix
correlation_matrix = df3.corr()

# 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.

In [33]:

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



MODELING

Baseline model

Simple Linear Regression

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

In [35]:

```
from statsmodels.formula.api import ols


# 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()
```

Out[35]:

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:	03:18:46	**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:

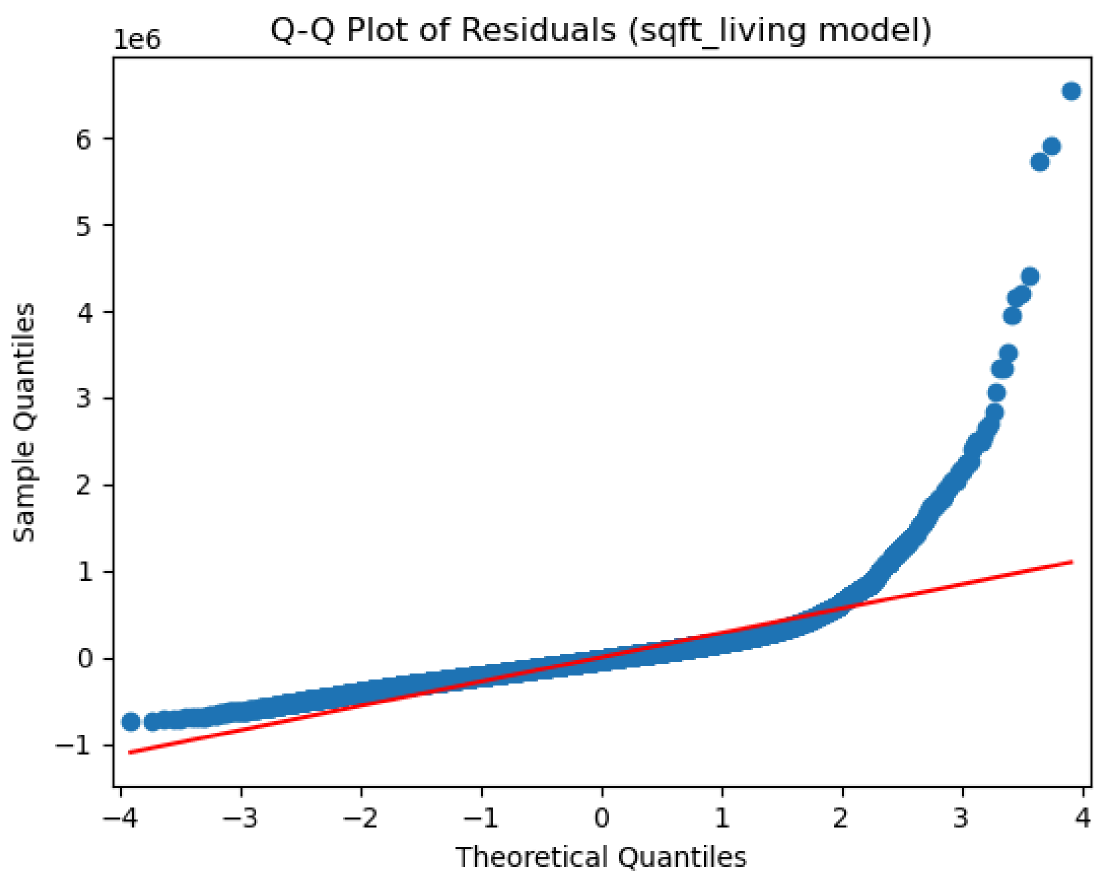
```
* Intercept: The intercept term represents the value of the dependent
variable when all independent variables are set to zero. In this case,
the intercept is -4.349e+04.
* sqft_living: The coefficient for 'sqft_living' is 283.4564, indicati
ng that for each unit increase in square footage of living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

In [36]:

```python
# Assuming 'sqft_living_model' is the fitted regression model
# This code computes and stores the residuals of the 'sqft_living_model', which
# assessing the model's goodness of fit, checking for heteroscedasticity or au

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.

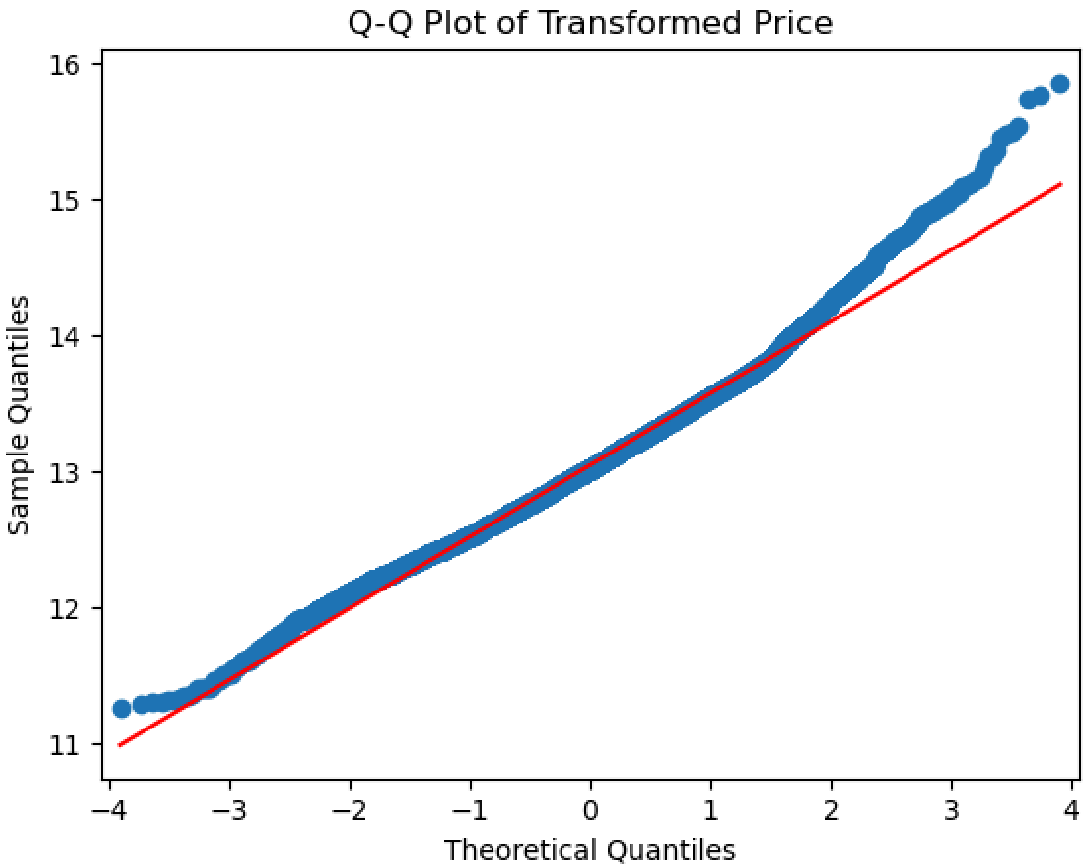
In [37]:

```
# Log-transformation can often help when these assumptions are not met. Let's u
# and re-check the assumptions.

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.

In [38]:

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

# 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()
```



- The points on the plot closely follow the diagonal line (line='s' indicates a standardized line), it suggests that the 'price' variable is approximately normally distributed.
- 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.

In [39]:

```python
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()
```

Out[39]:

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:	03:18:47	**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.

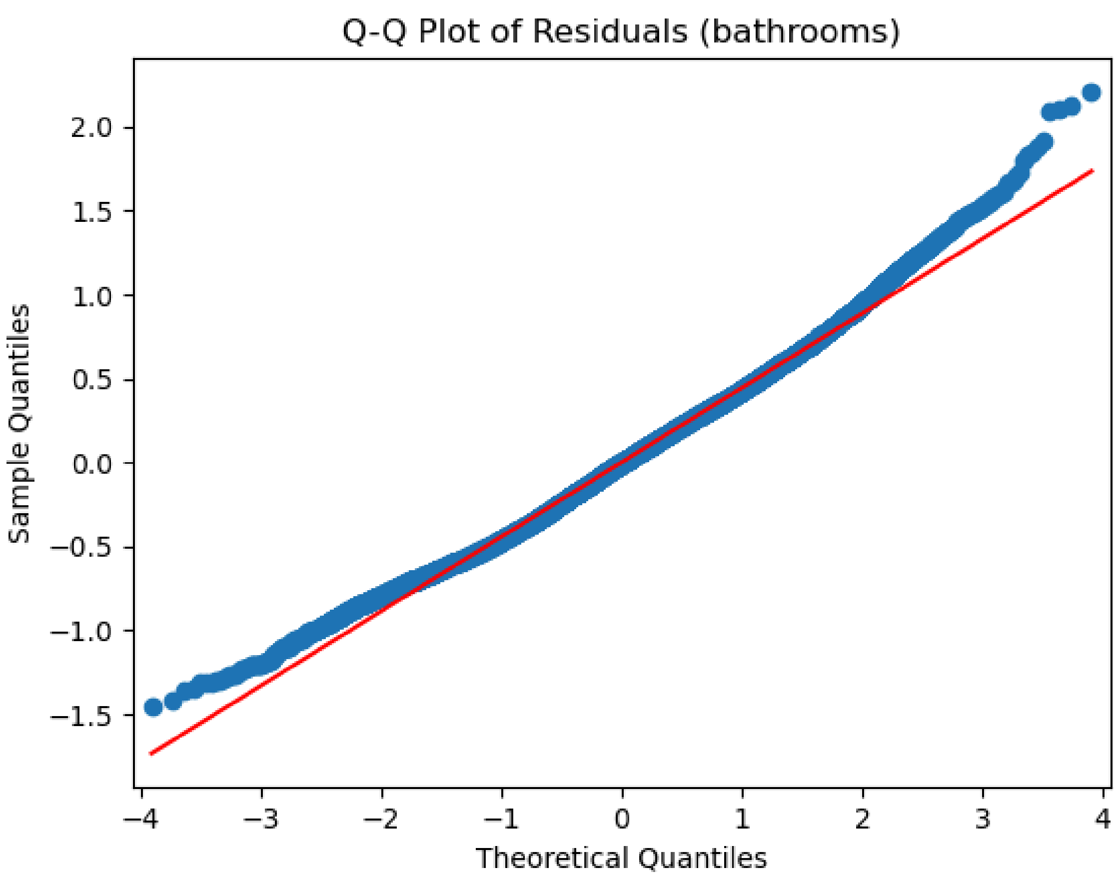
- R-squared is 0.290, indicating that approximately 29.0% of the variance in 'price' is explained by 'bathrooms'.
- The associated probability (Prob (F-statistic)) is close to 0, suggesting that the regression model is statistically significant.
- Coefficients:

* 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

In [40]:
```python
# 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

In [41]:

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


# Dependent variable
y = df3["price"]
```

In [42]:

```
#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()

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

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  price   R-squared:                       0.59
4
Model:                            OLS   Adj. R-squared:                  0.59
3
Method:                 Least Squares   F-statistic:                     183
8.
Date:                Wed, 10 Apr 2024   Prob (F-statistic):               0.0
0
Time:                        03:18:48   Log-Likelihood:                -7020.
1
No. Observations:               21420   AIC:                         1.408e+0
4
Df Residuals:                   21402   BIC:                         1.422e+0
4
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:                   1.98
3
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               31.06
6
Skew:                          -0.051   Prob(JB):                     1.79e-0
7
Kurtosis:                       3.157   Cond. No.                     1.50e+0
6
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 1.5e+06. This might indicate that there ar
e
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)

Violation of assumptions

- Linearity

In [43]:

```
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 varial
# 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: 0.9888132810806641
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.

In [44]:

```
# 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)

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

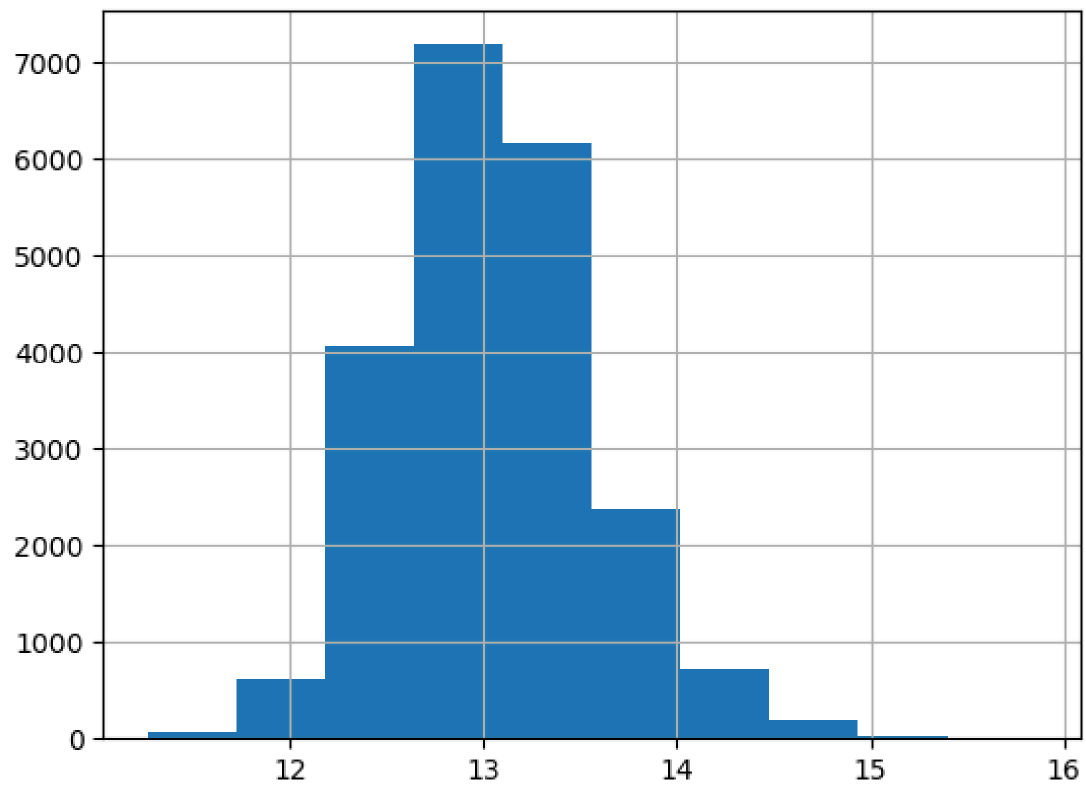
```
R-squared (R2): 0.5935141246373039
Mean Squared Error (MSE): 0.1128650341562047
Root Mean Squared Error (RMSE): 0.3359539167150827
```

- 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

In [45]:

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



- Our data is normally distributed.

In [46]:

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

Out[46]:

```
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
```

In [47]:

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

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

```
C:\Users\USER\anaconda3\lib\site-packages\numpy\core\fromnumeric.py:3438: Fut
ureWarning: In a future version, DataFrame.mean(axis=None) will return a scal
ar mean over the entire DataFrame. To retain the old behavior, use 'frame.mea
n(axis=0)' or just 'frame.mean()'
  return mean(axis=axis, dtype=dtype, out=out, **kwargs)
```

In [48]:

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

Out[48]:

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:	03:18:48	**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	13.0489	0.002	5684.659	0.000	13.044	13.053
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.**	12.3

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

- In this case, R-squared is 0.594, suggesting that approximately 59.4% of the variance in house prices is explained by the independent variables.
- the F-statistic is 1838 with a very low p-value (0.00), indicating that the regression model is statistically significant.
- The coefficients provide insights into the relationship between each predictor variable and the house prices.variables with positive coefficients (e.g., bathrooms, waterfront) are associated with higher house prices, while variables with negative coefficients (e.g., bedrooms, yr_built) are associated with lower house prices.

Multicollinearity

In [49]:

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

# Assuming df3 is your DataFrame containing the data
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 c
vif = pd.DataFrame()
vif['Features'] = col.columns
vif['VIF'] = [variance_inflation_factor(X, i) for i in range(X.shape[1])]
vif
```

Out[49]:

	Features	VIF
0	bedrooms	30.027609
1	bathrooms	26.556517
2	sqft_living	3884.198855
3	sqft_lot	24.035969
4	floors	19.480771
5	waterfront	1.078387
6	sqft_above	77.452221
7	sqft_basement	6.223543
8	yr_built	2898.443416
9	sqft_living15	28.209509
10	sqft_lot15	28.270590
11	condition_encoded	1.700958
12	grade_encoded	15.274797
13	view_encoded	20.001574

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 sabove00), suggest severe multicollinearcase:

The VIF values for "sqft_living," "sqft_lot," "sqft_above," "yr_built," "sqft_living15," and "sqft_lot1onally 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 We will sary to the address multicollineators the Lasso

In [50]:

```
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 var

# 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

# 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

In [51]:
```
from sklearn.feature_selection import RFE

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

In [52]:
```
ss = StandardScaler()
ss.fit(df3.drop('price', axis=1))

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

In [53]:
```
select.fit(X=df3_scaled, y=df3['price'])
```

Out[53]:
```
RFE(estimator=LinearRegression(), n_features_to_select=7)
```

In [54]:
```
select.support_
```

Out[54]:
```
array([ True,  True, False, False,  True, False,  True,  True,  True,
        True, False, False, False, False, False, False, False])
```

In [55]:
```
df3.head()
```

Out[55]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	sqft_above	sqft_bas
0	12.309982	3.0	1.00	7.073270	5650.0	1.0	0	1180.0	
1	13.195614	3.0	2.25	7.851661	7242.0	2.0	0	2170.0	
2	12.100712	2.0	1.00	6.646391	10000.0	1.0	0	770.0	
3	13.311329	4.0	3.00	7.580700	5000.0	1.0	0	1050.0	
4	13.142166	3.0	2.00	7.426549	8080.0	1.0	0	1680.0	

In [56]:
```
select.ranking_
```

Out[56]:
```
array([ 1,  1,  3,  2,  1,  4,  1,  1,  1,  1,  6,  8,  7,  5, 10, 11,  9])
```

In [57]:

```
import statsmodels.api as sm

# Define your independent variables (features)
X = df3[['sqft_living', 'sqft_living15' , 'sqft_above', 'bathrooms', 'bedrooms

# 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()

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

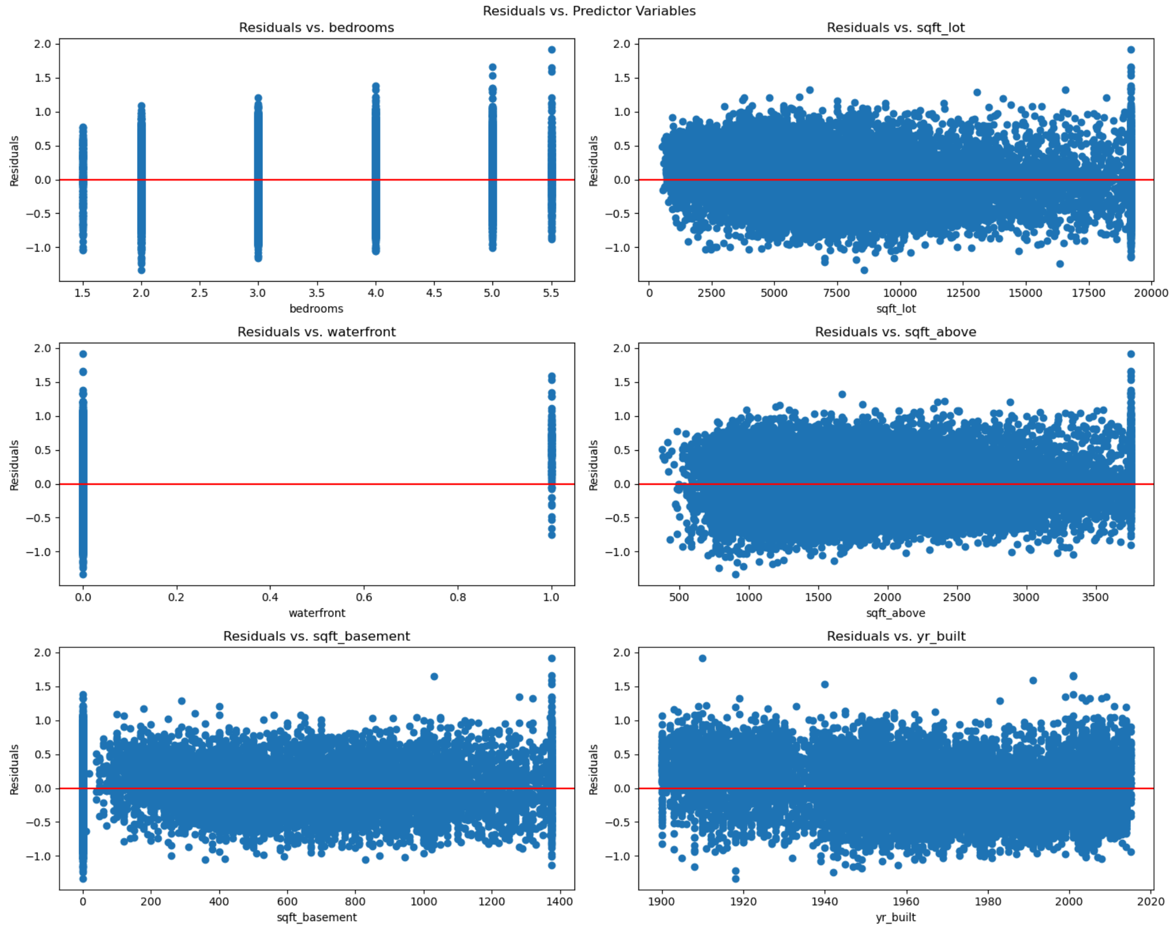
```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  price   R-squared:                       0.51
1
Model:                            OLS   Adj. R-squared:                  0.51
1
Method:                 Least Squares   F-statistic:                     319
2.
Date:                Wed, 10 Apr 2024   Prob (F-statistic):               0.0
0
Time:                        03:18:50   Log-Likelihood:                -9006.
9
No. Observations:               21420   AIC:                         1.803e+0
4
Df Residuals:                   21412   BIC:                         1.809e+0
4
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
====
                    coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
const             8.7930      0.094     93.856      0.000       8.609
8.977
sqft_living       0.5856      0.015     40.018      0.000       0.557
0.614
sqft_living15     0.0002   6.18e-06     28.233      0.000       0.000
0.000
sqft_above    -3.061e-06   6.55e-06     -0.467      0.640   -1.59e-05    9.78
e-06
bathrooms         0.0644      0.005     11.875      0.000       0.054
0.075
bedrooms         -0.0579      0.004    -14.730      0.000      -0.066      -
0.050
view_encoded     -0.0744      0.003    -26.238      0.000      -0.080      -
0.069
grade_encoded    -0.0215      0.001    -18.544      0.000      -0.024      -
0.019
==============================================================================
=
Omnibus:                       91.359   Durbin-Watson:                   1.98
6
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               81.86
6
Skew:                           0.109   Prob(JB):                     1.67e-1
8
Kurtosis:                       2.790   Cond. No.                     1.06e+0
5
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 1.06e+05. This might indicate that there a
```

```
re
strong multicollinearity or other numerical problems.
```

- R-squared is 0.511, indicating that approximately 51.1% of the variance in house prices is explained by the independent variables.
- the F-statistic is 3192 with a p-value of 0.00, indicating that the regression model is statistically significant.
- The condition number is large (1.06e+05), which might indicate strong multicollinearity or other numerical problems. It's essential to further investigate multicollinearity issues if present.
- The regression model appears to be statistically significant, with several predictor variables showing significant effects on house prices

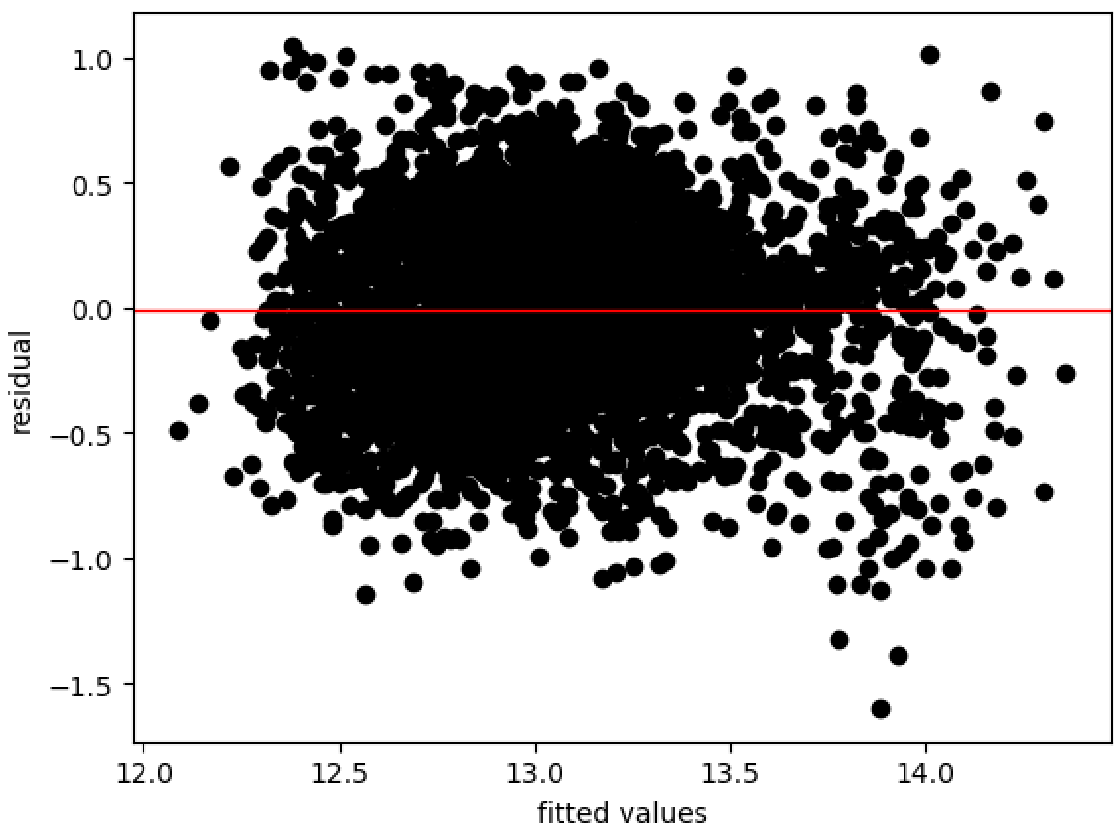
In [58]:

```
# 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'

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()
```


Residuals vs. Predictor Variables
Residuals vs. bedrooms
Residuals vs. sqft_lot
Residuals vs. waterfront
Residuals vs. sqft_above
Residuals vs. sqft_basement
Residuals vs. yr_built
Residuals
bedrooms
sqft_lot
waterfront
sqft_above
sqft_basement
yr_built

In [59]:

```
# Residual Plot
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
#
X= df3[['sqft_living', 'sqft_living15' , 'sqft_above', 'bathrooms', 'bedrooms'
y= df3['price']
#
X_train, X_test, admit_train, admit_test = train_test_split(X, y, test_size=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()
```



In [60]:

```
# Polynomial Regression with 2 degrees
poly = PolynomialFeatures(degree=2, 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_siz

# 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))
poly_reg_rmse
```

Out[60]:

```
0.34173130195385026
```

In [61]:

```python
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from math import sqrt

# 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_siz

# 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): 0.11071476815605068
Root Mean Squared Error (RMSE): 0.3327382877819303
R-squared (R2): 0.604236353410019
```

In [62]:

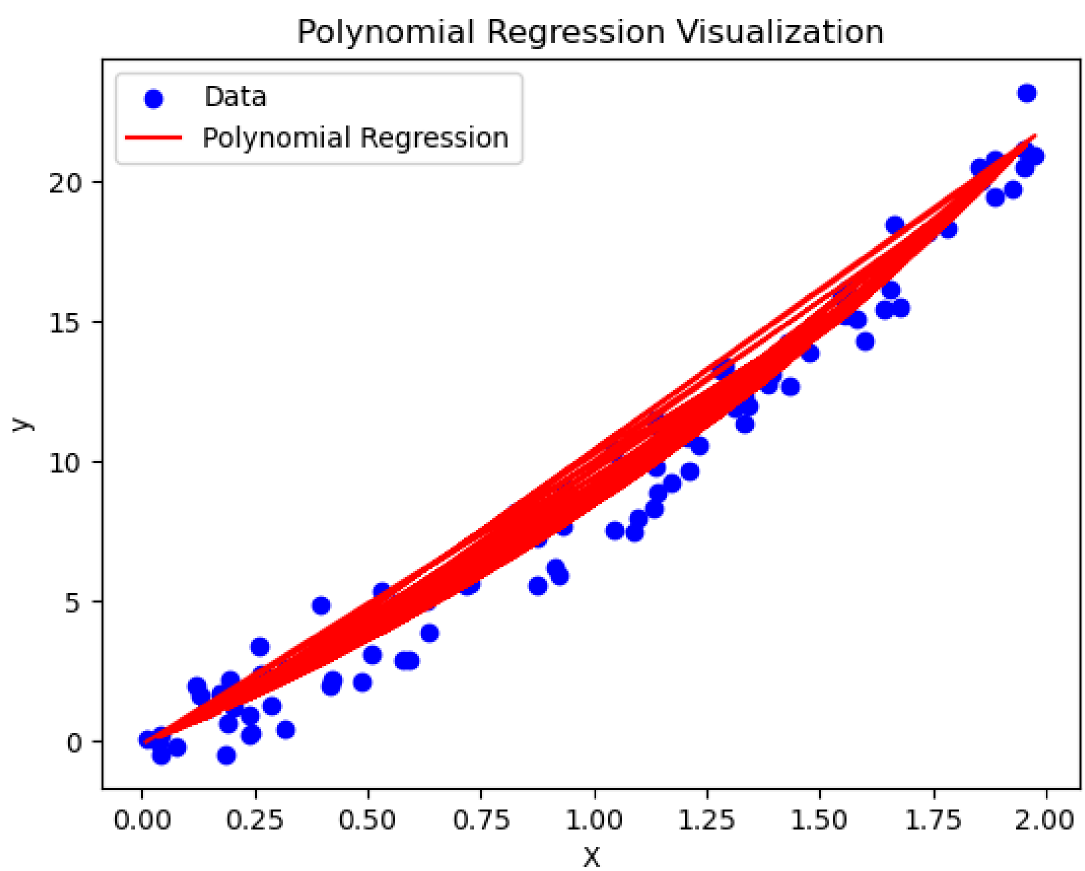
```
# Polynomial Regression with 4 degrees
poly = PolynomialFeatures(degree=4, include_bias=False)
poly_features = poly.fit_transform(X)

# Split the dataset into train and test sets
X_train, X_test, y_train, y_test = train_test_split(poly_features, y, test_siz

# 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))
poly_reg_rmse
```

Out[62]:

```
0.33365265018153306
```

In [63]:

```python
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=4)
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 Regressio
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

In [64]:

```
from sklearn.model_selection import cross_val_score

# X' contains the predictors and 'y' contains the target variable from your dat
X = df3[['sqft_living', 'sqft_living15' , 'sqft_above', 'bathrooms', 'bedrooms
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, rand

# 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, scori
cv_scores_mse = -cross_val_score(multiple_model_3, X_train, y_train, cv=5, sco

# 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 0.5
168576 ]
Mean R^2 score: 0.5103323136219119
Cross-validation MSE scores: [0.14258149 0.13418398 0.12999174 0.13682081 0.1
3425705]
Mean MSE: 0.13556701332855092
Test R^2 score: 0.5097620447238456
Test MSE: 0.13677834522286214
```

FINDINGS AND CONCLUSSIONS

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

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

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.

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