Phase Two Project

Student Name: Paul Mbuitu Muriithi

Course: DSF-FT05

King County House Sales With Multiple Linear Regression

Overview

The real estate market is a complex ecosystem influenced by numerous factors, making it crucial to understand the dynamics that drive house prices. In this project, the aim is to delve into the realm of house sales analysis in King County using multiple linear regression modeling. By leveraging the power of data analysis and machine learning techniques, the relationships between various attributes and the sale prices of houses in the region will be explored so that they can be used to make profitable decisions by a housing development company.

Business Problem

The stakeholders are searching for the qualities that lead to higher home sale prices. The aim is to develop an accurate and reliable multiple linear regression model by leveraging the King County House Sales dataset, a model that can predict house prices based on various independent variables.

Main Objective

To develop an accurate and reliable multiple linear regression model that can predict house prices based on various independent variables.

Specific Objectives

- To find out which attributes have a significant impact on house prices in ing County.
- To find out the relationship between the independent variables and the sales prices of houses.
- To find out how accurately house prices can be predicted using the available attributes.

Hypotheses

- **Null hypothesis(Ho):** There is no relationship between our features and our target variable, price.
- **Alternative hypothesis(Ha):** There is a relationship between our features and our target variable, price.

A significance level (alpha) of 0.05 will be used to decide if to reject or fail to reject the null hypothesis.

If the p-value is lower than the significance level, it is considered statistically significant, and we reject the null hypothesis.

Experimental Design

- Data Collection
- Read and check the data
- Cleaning the data
- Exploratory Data Analysis
- Modelling
- Recommendations, Conclusions, and Next Steps

Data Understanding

- King County House Data will be used. The file contains data for 21,597 homes built in King County from 1900 to 2015. Each home in the set contains information regarding features such as the number of bedrooms/bathrooms, number of floors, square footage, zipcode, condition of the house, the year when the house was built, and more.

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
import scipy.stats as stats
import sklearn
import statsmodels.api as sm
from statsmodels.formula.api import ols
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error

%matplotlib inline
```

In [2]:
```
# reading the King County House Data
df = pd.read_csv("kc_house_data.csv")

# previewing the DataFrame
df.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqf
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	

5 rows × 21 columns

In [3]:
```
# getting info for the 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
```

- The data types in the dataset are integers, objects and floats.
- There are missing values in waterfont, view and yr_renovated.

In [4]:
```
# checking for duplicates
df.id.duplicated().sum()
```

Out[4]: 177

In [5]:
```
# showing duplicates
df.loc[df["id"].duplicated()==True]
```

Out[5]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_abo
94	6021501535	12/23/2014	700000.0	3	1.50	1580	5000	1.0	NO	NONE	...	8 Good	12
314	4139480200	12/9/2014	1400000.0	4	3.25	4290	12103	1.0	NO	GOOD	...	11 Excellent	26
325	7520000520	3/11/2015	240500.0	2	1.00	1240	12092	1.0	NO	NONE	...	6 Low Average	9
346	3969300030	12/29/2014	239900.0	4	1.00	1000	7134	1.0	NO	NONE	...	6 Low Average	10
372	2231500030	3/24/2015	530000.0	4	2.25	2180	10754	1.0	NO	NONE	...	7 Average	11
...	...	...	...	...	...	...	...	...	...	...	...	...	
20165	7853400250	2/19/2015	645000.0	4	3.50	2910	5260	2.0	NO	NONE	...	9 Better	29
20597	2724049222	12/1/2014	220000.0	2	2.50	1000	1092	2.0	NO	NONE	...	7 Average	9
20654	8564860270	3/30/2015	502000.0	4	2.50	2680	5539	2.0	NaN	NONE	...	8 Good	26
20764	6300000226	5/4/2015	380000.0	4	1.00	1200	2171	1.5	NO	NONE	...	7 Average	12
21565	7853420110	5/4/2015	625000.0	3	3.00	2780	6000	2.0	NO	NONE	...	9 Better	27

177 rows × 21 columns

In [6]:
```
# reviewing duplicates
df.loc[df["id"]== 8820903380]
```

Out[6]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sc
717	8820903380	7/28/2014	452000.0	6	2.25	2660	13579	2.0	NO	NONE	...	7 Average	2660	
718	8820903380	1/2/2015	730000.0	6	2.25	2660	13579	2.0	NO	NONE	...	7 Average	2660	

2 rows × 21 columns

In [7]:
```
# reviewing duplicates
df.loc[df["id"]== 6021501535]
```

Out[7]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft
93	6021501535	7/25/2014	430000.0	3	1.5	1580	5000	1.0	NO	NONE	...	8 Good	1290	
94	6021501535	12/23/2014	700000.0	3	1.5	1580	5000	1.0	NO	NONE	...	8 Good	1290	

2 rows × 21 columns

In [8]:
```
# reviewing duplicates
df.loc[df["id"]== 7853400250]
```

Out[8]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sc
20164	7853400250	6/4/2014	610000.0	4	3.5	2910	5260	2.0	NO	NONE	...	9 Better	2910	
20165	7853400250	2/19/2015	645000.0	4	3.5	2910	5260	2.0	NO	NONE	...	9 Better	2910	

2 rows × 21 columns

In [9]:
```python
# reviewing duplicates
df.loc[df["id"]== 2724049222]
```

Out[9]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above
20596	2724049222	8/2/2014	163800.0	2	2.5	1000	1092	2.0	NaN	NONE	...	7 Average	990
20597	2724049222	12/1/2014	220000.0	2	2.5	1000	1092	2.0	NO	NONE	...	7 Average	990

2 rows × 21 columns

The duplicates shows that the same house has been sold multiple times over a period. To approach this, rows with duplicates will be dropped and keep the latest the house was sold.

In [10]:
```python
# dropping duplicates
df.drop_duplicates(subset="id", keep="last", inplace=True)
```

Handling Missing values

In [11]:
```
# calculating the number of missing values in each column
df.isna().sum()
```

Out[11]:
```
id                 0
date               0
price              0
bedrooms           0
bathrooms          0
sqft_living        0
sqft_lot           0
floors             0
waterfront      2353
view              63
condition          0
grade              0
sqft_above         0
sqft_basement      0
yr_built           0
yr_renovated    3813
zipcode            0
lat                0
long               0
sqft_living15      0
sqft_lot15         0
dtype: int64
```

Rows with missing values will be dropped as they are categorical and it would be good not to fill them with biased information.

In [12]:
```
# dropping rows missing values from our dataset
df.dropna(axis='index', inplace=True)
```

In [13]:
```
# confirming the dropped rows
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15636 entries, 1 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             15636 non-null  int64  
 1   date           15636 non-null  object 
 2   price          15636 non-null  float64
 3   bedrooms       15636 non-null  int64  
 4   bathrooms      15636 non-null  float64
 5   sqft_living    15636 non-null  int64  
 6   sqft_lot       15636 non-null  int64  
 7   floors         15636 non-null  float64
 8   waterfront     15636 non-null  object 
 9   view           15636 non-null  object 
 10  condition      15636 non-null  object 
 11  grade          15636 non-null  object 
 12  sqft_above     15636 non-null  int64  
 13  sqft_basement  15636 non-null  object 
 14  yr_built       15636 non-null  int64  
 15  yr_renovated   15636 non-null  float64
 16  zipcode        15636 non-null  int64  
 17  lat            15636 non-null  float64
 18  long           15636 non-null  float64
 19  sqft_living15  15636 non-null  int64  
 20  sqft_lot15     15636 non-null  int64  
dtypes: float64(6), int64(9), object(6)
memory usage: 2.6+ MB
```

Exploratory Data Analysis

- The houses price in the dataset ranges from 82,000 dollars to 7,700,000 dollares.
- The mean house price is 541,642 dollars, while the median house price is 450,000 dollars.

In [14]:
```
# checking the dispersion of years built
df.yr_built.describe()
```

Out[14]:
```
count    15636.000000
mean      1971.195574
std         29.355196
min       1900.000000
25%       1952.000000
50%       1975.000000
75%       1997.000000
max       2015.000000
Name: yr_built, dtype: float64
```

In [15]:
```
# getting counts for each value in condition column
df.condition.value_counts()
```

Out[15]:
```
Average      10138
Good          4112
Very Good     1244
Fair           124
Poor            18
Name: condition, dtype: int64
```

In [16]:
```python
# converting condition rating values into discrete variables
# dictionary to replace the values
to_replace = {
    "Poor": 1,
    "Fair": 2,
    "Average": 3,
    "Good": 4,
    "Very Good": 5
}
# replacing values in the condition colum using the mapping
df["condition"] = df["condition"].map(to_replace)

# obtaining value counts of each category in the condition column
value_counts = df['condition'].value_counts()

print(value_counts)
```

```
3    10138
4     4112
5     1244
2      124
1       18
Name: condition, dtype: int64
```

In [17]:
```python
# getting counts for each value in waterfrontcolumn
df.waterfront.value_counts()
```

Out[17]:
```
NO     15516
YES      120
Name: waterfront, dtype: int64
```

```
In [18]: # getting counts for each value in grade column
         df.grade.value_counts()
```

```
Out[18]: 7 Average        6480
         8 Good           4419
         9 Better         1912
         6 Low Average    1454
         10 Very Good      830
         11 Excellent      287
         5 Fair           161
         12 Luxury         65
         4 Low             16
         13 Mansion        11
         3 Poor             1
         Name: grade, dtype: int64
```

```
In [19]: # removing names and retaining numbers only
         df['grade'] = df['grade'].map(lambda x: x.split(' ')[0]).astype(int)
```

- Grade is a categorical variable related to the construction and design of the house.
- The most common building grade is a 7, which is defined as, "Average grade of construction and design."

```
In [20]: # getting descriptive statistics for square footage of living space in the home
         df.sqft_living.describe()
```

```
Out[20]: count    15636.000000
         mean      2086.886288
         std        919.077862
         min        370.000000
         25%       1430.000000
         50%       1920.000000
         75%       2557.750000
         max      13540.000000
         Name: sqft_living, dtype: float64
```

The mean square-feet of living space is 2,086 square feet, but there are houses as small as 370 sqft and as large as 13,540 sqft in this dataset.

- There are columns in the dataset that may not be useful in the evaluation, hence it's good to drop them.

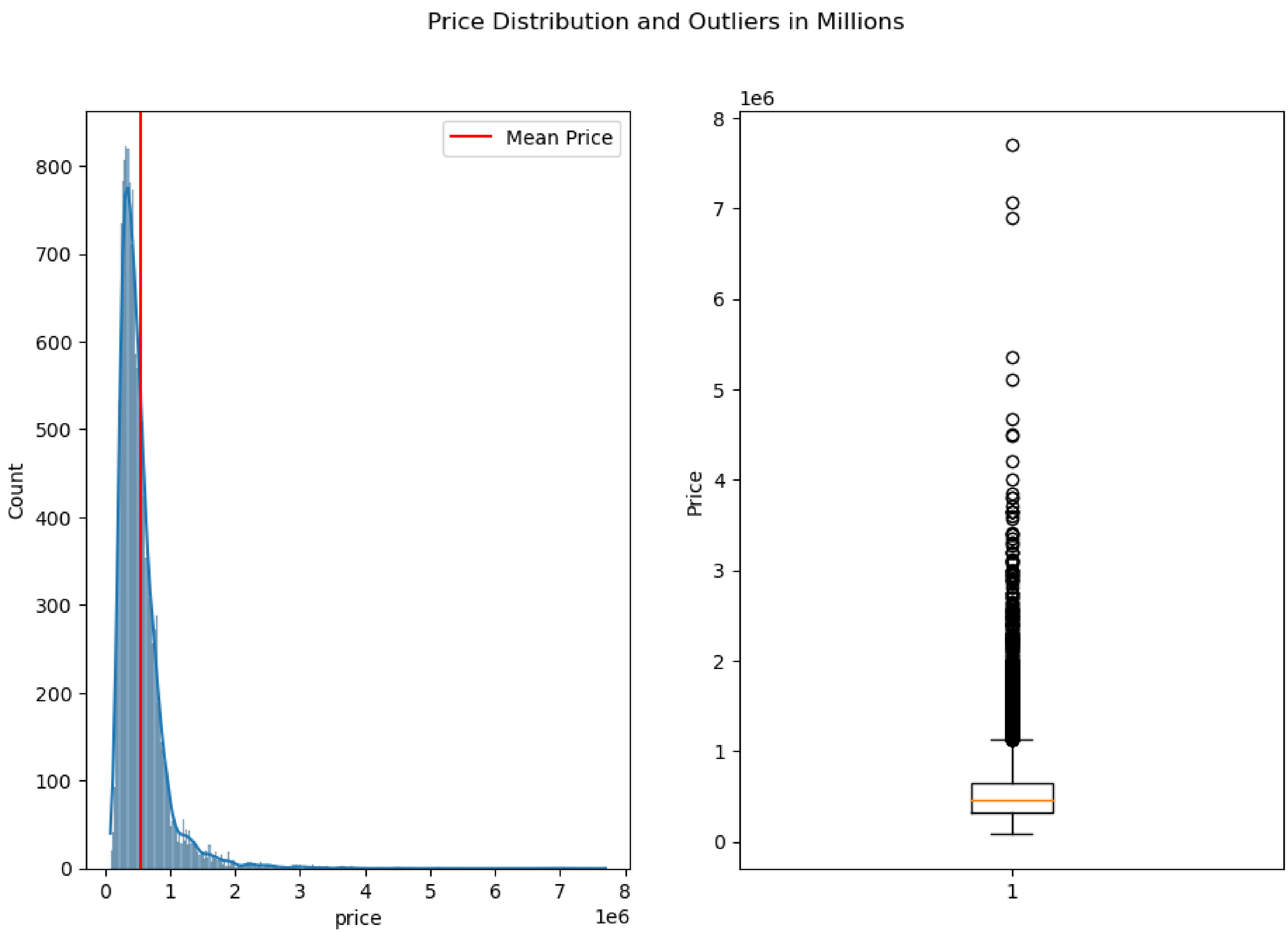
In [21]:
```python
# dropping unwanted columns
drop_columns = ["id", "date", "view", "sqft_above", "sqft_basement",
                "yr_renovated","lat", "long", "sqft_living15", "sqft_lot15"]
df = df.drop(columns=drop_columns).reset_index(drop=True)
df.head()
```

Out[21]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr_built	zipcode
0	538000.0	3	2.25	2570	7242	2.0	NO	3	7	1951	98125
1	604000.0	4	3.00	1960	5000	1.0	NO	5	7	1965	98136
2	510000.0	3	2.00	1680	8080	1.0	NO	3	8	1987	98074
3	1230000.0	4	4.50	5420	101930	1.0	NO	3	11	2001	98053
4	257500.0	3	2.25	1715	6819	2.0	NO	3	7	1995	98003

- Checking for outliers in our price for houses.

In [22]:
```
# creating a figure and axis
fig, ax = plt.subplots(figsize= (11, 7), ncols= 2)
# plotting a histogram with KDE and a vertical line indicating the mean price
sns.histplot(df.price, kde=True, ax=ax[0])
ax[0].axvline(df.price.mean(), color= "red", label="Mean Price")

# plotting a boxplot
ax[1].boxplot(df.price)
ax[1].set_ylabel("Price")

ax[0].legend()
fig.suptitle("Price Distribution and Outliers in Millions")
plt.show()
```



From the above visualizations, it's evident that a majority of price distrubutions ranges to around 1.2 million. Absolute outlires will be considered as any price above 5 million and they will be dropped.

In [23]:
```
# dropping the outliers
# filter dateframe for rows with price less than 5,000,000
df = df.loc[df["price"] < 5_000_000]
df.shape
```

Out[23]:
```
(15631, 11)
```

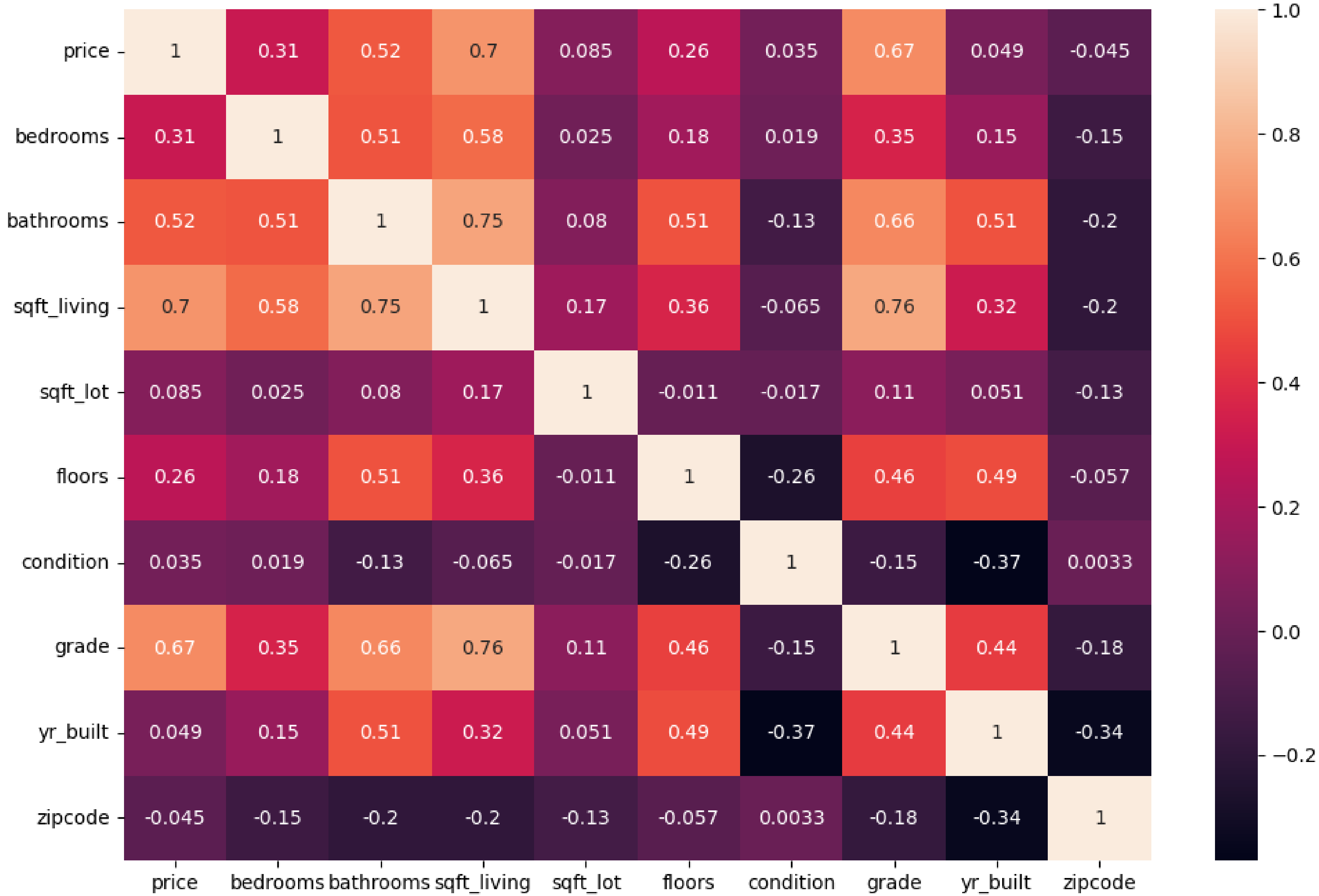
In [24]:
```
df.price.describe()
```

Out[24]:
```
count    1.563100e+04
mean     5.408538e+05
std      3.569532e+05
min      8.250000e+04
25%      3.240000e+05
50%      4.520000e+05
75%      6.450000e+05
max      4.670000e+06
Name: price, dtype: float64
```

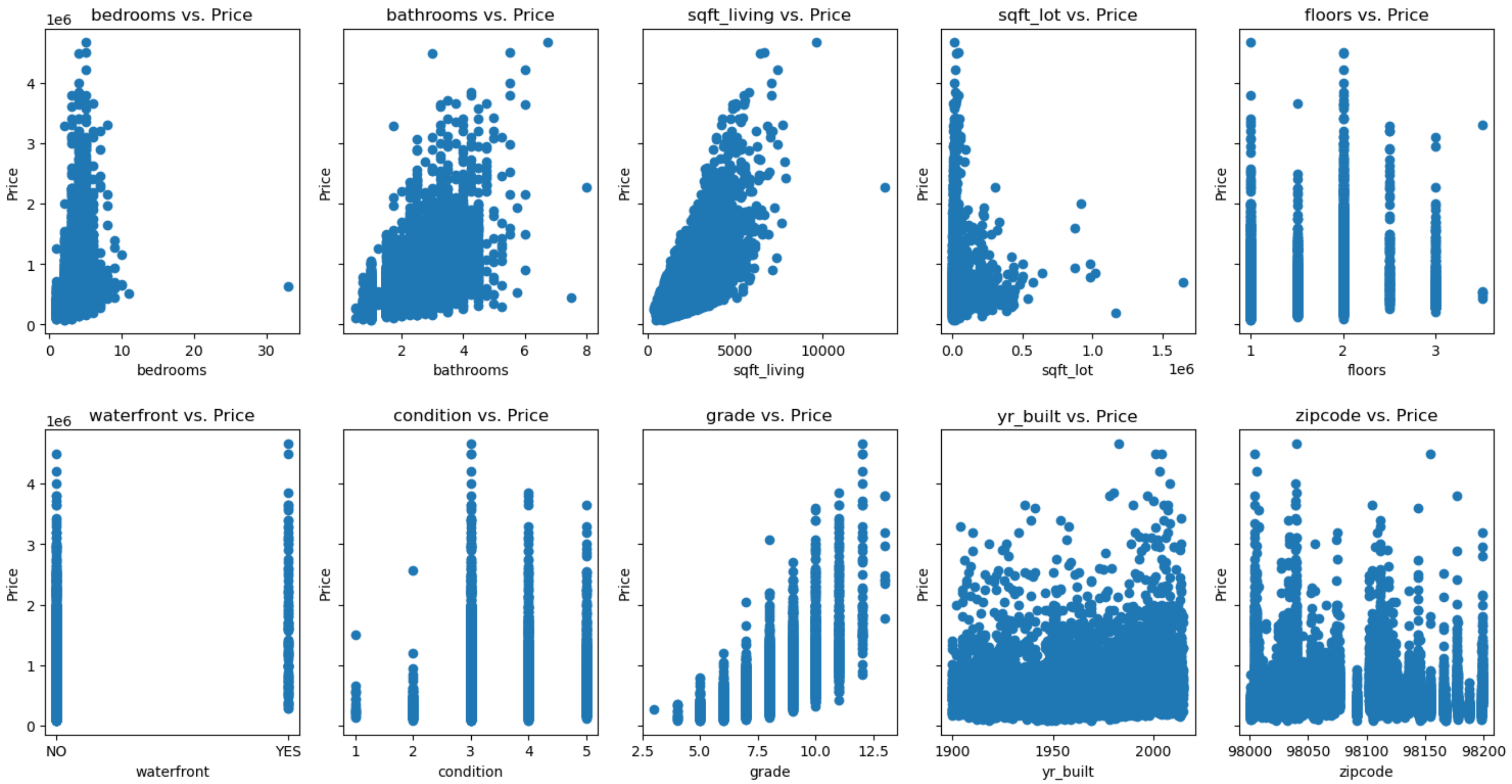
- The houses price in the dataset ranges from 82,500 dollars to 4,670,000 dollares.
- The mean house price is 540,854 dollars, while the median house price is 452,000 dollars.

Modelling

In [25]:
```python
# generate heatmap to display correlations
# creating the `corr` DataFrame, figure and axis objects
corr = df.corr()
fig, ax = plt.subplots(figsize=(12, 8))
sns.heatmap(corr, annot=True);
```



In [26]:
```
# visualizations to see the relationship between
# price(dependentvariable) and predictors(independent variables)

fig = plt.figure(figsize=(15, 8))
axes = fig.subplots(nrows=2, ncols=5, sharey=True)

# Specify the variables for x-axis
x_variables = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
               'floors', 'waterfront', 'condition', 'grade', 'yr_built', 'zipcode'
        ]

# Iterate over the axes and plot the scatter plots
for i, variable in enumerate(x_variables):
    row = i // 5  # Calculate the row index
    col = i % 5   # Calculate the column index

    # Plot scatter plot for each variable
    axes[row, col].scatter(df[variable], df['price'])
    axes[row, col].set_xlabel(variable)
    axes[row, col].set_ylabel('Price')
    axes[row, col].set_title(f'{variable} vs. Price')

# Rotate x-axis labels for 'grade' variable
    #if variable == 'grade':
        #axes[row, col].set_xticklabels(axes[row, col].get_xticks(), rotation=45)

# Adjust the spacing between subplots
plt.tight_layout()

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



Fitting baseline model

- Find which features are most correlated with price excluding the categorical variables.

In [27]:
```
# Exclude 'grade', 'waterfront', 'condition', and 'zipcode'
excluded_features = ['grade', 'waterfront', 'condition', 'zipcode']
correlation_without_excluded = df.drop(columns=excluded_features)

# Calculate correlation with 'price'
correlation_with_price = correlation_without_excluded.corr()['price']

# Sort correlations in descending order
sorted_correlation = correlation_with_price.sort_values(ascending=False)

print(sorted_correlation)
```

```
price          1.000000
sqft_living    0.699621
bathrooms      0.522471
bedrooms       0.308286
floors         0.263004
sqft_lot       0.084767
yr_built       0.049014
Name: price, dtype: float64
```

Since sqft_living is the feature with the strongest correlation, build a simple linear regression with that.

In [28]:
```
Y = df["price"]
X_baseline = df["sqft_living"]
```

In [29]:
```
baseline_model = sm.OLS(Y, sm.add_constant(X_baseline))
baseline_results = baseline_model.fit()
print(baseline_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.489
Model:                            OLS   Adj. R-squared:                  0.489
Method:                 Least Squares   F-statistic:                 1.498e+04
Date:                Fri, 07 Jul 2023   Prob (F-statistic):               0.00
Time:                        17:36:31   Log-Likelihood:            -2.1677e+05
No. Observations:               15631   AIC:                         4.335e+05
Df Residuals:                   15629   BIC:                         4.336e+05
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const       -3.185e+04   5104.013     -6.241      0.000   -4.19e+04   -2.18e+04
sqft_living   274.7472      2.244    122.410      0.000     270.348     279.147
==============================================================================
Omnibus:                     8729.600   Durbin-Watson:                   1.976
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           144443.387
Skew:                           2.333   Prob(JB):                         0.00
Kurtosis:                      17.142   Cond. No.                     5.69e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.69e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

- The model is statistically significant overall, with an F-statistic p-value well below 0.05.
- The model explains about 49% of the variance in price.
- The model coefficients (const and sqft_living) are both statistically significant, with t-statistic p-values well below 0.05.
- If square footage of living space in the home is 0, we would expect price to be about -31,850 dollars.
- For each increase of 1 square footage of living space in the home, we see an associated increase in price of about 275 dollars.

Fitting multiple regression

In [30]:
```
# create a copy of the DataFrame df and drops the column price
X_multiple = df.copy().drop(["price", "zipcode", "grade"], axis=1)

# uses pd.get_dummies() from the pandas library to perform one-hot encoding on categorical variables.
X_multiple = pd.get_dummies(X_multiple, columns=["condition", "waterfront"])
X_multiple = X_multiple.drop(["waterfront_NO", "condition_3"], axis=1)
X_multiple
```

Out[30]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	yr_built	condition_1	condition_2	condition_4	condition_5	waterfront_YES
0	3	2.25	2570	7242	2.0	1951	0	0	0	0	0
1	4	3.00	1960	5000	1.0	1965	0	0	0	1	0
2	3	2.00	1680	8080	1.0	1987	0	0	0	0	0
3	4	4.50	5420	101930	1.0	2001	0	0	0	0	0
4	3	2.25	1715	6819	2.0	1995	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
15631	3	2.50	1310	1294	2.0	2008	0	0	0	0	0
15632	3	2.50	1530	1131	3.0	2009	0	0	0	0	0
15633	4	2.50	2310	5813	2.0	2014	0	0	0	0	0
15634	2	0.75	1020	1350	2.0	2009	0	0	0	0	0
15635	2	0.75	1020	1076	2.0	2008	0	0	0	0	0

15631 rows × 11 columns

Checking for collinearity issues if all of these features are included in one regression model.

In [31]:
```
X_multiple.corr()
```

Out[31]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	yr_built	condition_1	condition_2	condition_4	condition_5
bedrooms	1.000000	0.512366	0.575437	0.025430	0.179738	0.153155	-0.025893	-0.052495	-0.012801	0.021623
bathrooms	0.512366	1.000000	0.751445	0.079630	0.505167	0.506270	-0.038179	-0.076893	-0.170277	-0.040108
sqft_living	0.575437	0.751445	1.000000	0.165271	0.359630	0.316616	-0.027438	-0.061335	-0.084627	-0.022973
sqft_lot	0.025430	0.079630	0.165271	1.000000	-0.010678	0.051168	0.011035	0.051955	0.012254	-0.020046
floors	0.179738	0.505167	0.359630	-0.010678	1.000000	0.486797	-0.020780	-0.052944	-0.259926	-0.117894
yr_built	0.153155	0.506270	0.316616	0.051168	0.486797	1.000000	-0.047400	-0.066272	-0.260380	-0.250596
condition_1	-0.025893	-0.038179	-0.027438	0.011035	-0.020780	-0.047400	1.000000	-0.003036	-0.020283	-0.009984
condition_2	-0.052495	-0.076893	-0.061335	0.051955	-0.052944	-0.066272	-0.003036	1.000000	-0.053419	-0.026295
condition_4	-0.012801	-0.170277	-0.084627	0.012254	-0.259926	-0.260380	-0.020283	-0.053419	1.000000	-0.175660
condition_5	0.021623	-0.040108	-0.022973	-0.020046	-0.117894	-0.250596	-0.009984	-0.026295	-0.175660	1.000000
waterfront_YES	-0.008488	0.061406	0.102814	0.025252	0.016945	-0.024529	0.018832	0.000532	0.013373	0.012586

Based on the correlation matrix above, there are some moderate-to-high correlations between certain predictor variables in the dataset. For example:

- Bedrooms and bathrooms have a correlation coefficient of 0.512, indicating a moderate positive correlation.
- Bathrooms and sqft_living have a correlation coefficient of 0.751, indicating a relatively high positive correlation.

These correlations suggest the presence of collinearity among these variables.

To address collinearity issues, one variable from highly correlated pairs will be removed.

In [32]:

```
# Drop bedrooms, bathrooms and grade from the DataFrame
X_multiple.drop(["bathrooms"], axis=1, inplace=True)

# fittng the model
multiple_model = sm.OLS(Y, sm.add_constant(X_multiple))
multiple_results = multiple_model.fit()
print(multiple_results.summary())
```

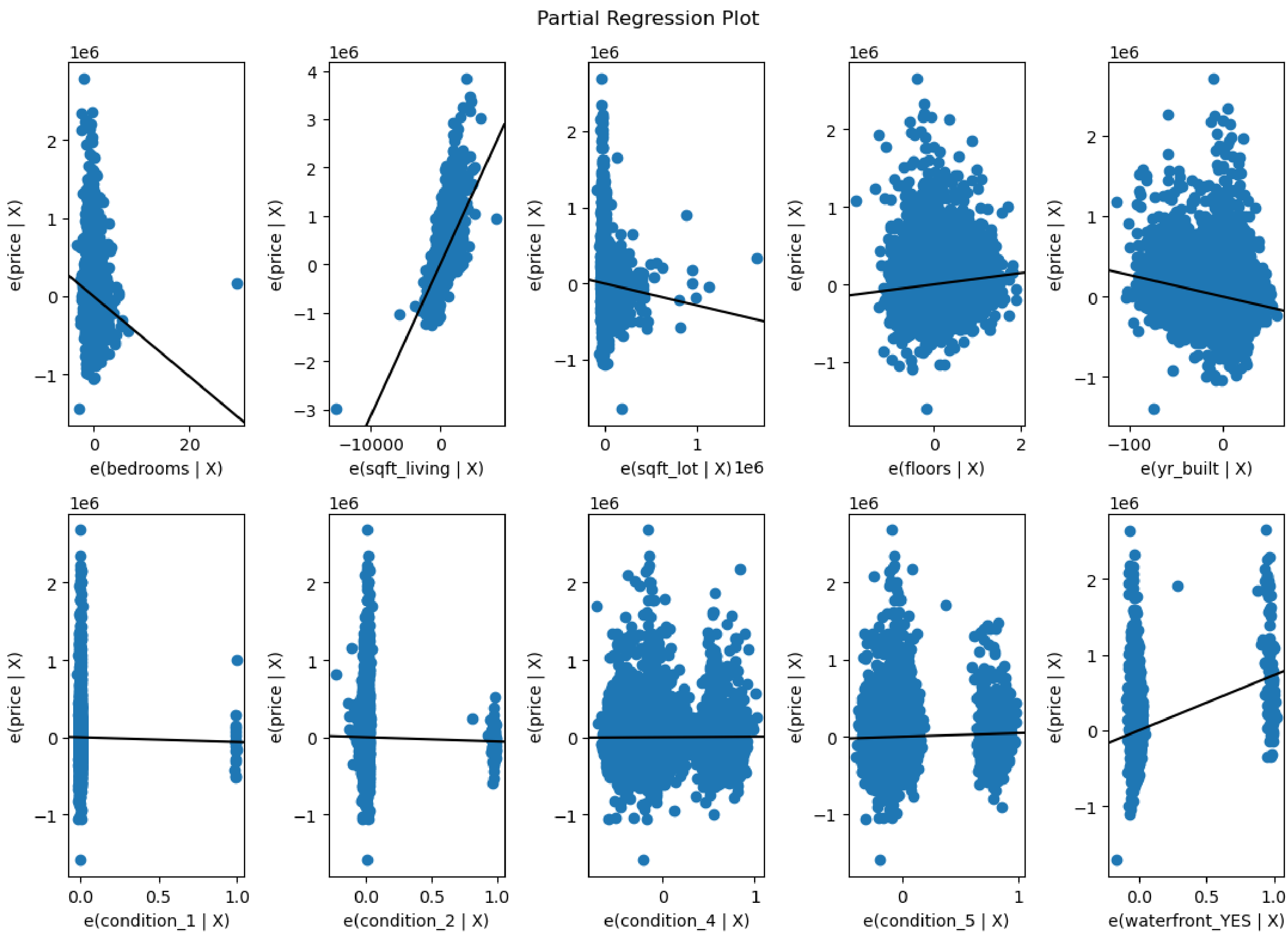
```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  price   R-squared:                       0.580
Model:                            OLS   Adj. R-squared:                  0.580
Method:                 Least Squares   F-statistic:                     2155.
Date:                Fri, 07 Jul 2023   Prob (F-statistic):               0.00
Time:                        17:36:32   Log-Likelihood:            -2.1525e+05
No. Observations:               15631   AIC:                         4.305e+05
Df Residuals:                   15620   BIC:                         4.306e+05
Df Model:                          10                                         
Covariance Type:            nonrobust                                         
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           5.217e+06   1.51e+05     34.567      0.000    4.92e+06    5.51e+06
bedrooms       -5.135e+04   2447.944    -20.976      0.000   -5.61e+04   -4.65e+04
sqft_living      312.0961      2.741    113.873      0.000     306.724     317.468
sqft_lot          -0.2878      0.045     -6.369      0.000      -0.376      -0.199
floors          7.306e+04   4131.331     17.685      0.000     6.5e+04    8.12e+04
yr_built       -2672.7004     77.730    -34.384      0.000   -2825.060   -2520.340
condition_1    -5.988e+04   5.47e+04     -1.094      0.274   -1.67e+05    4.74e+04
condition_2    -5.347e+04   2.11e+04     -2.536      0.011   -9.48e+04   -1.21e+04
condition_4     6298.8930   4603.527      1.368      0.171   -2724.553    1.53e+04
condition_5     4.776e+04   7364.754      6.485      0.000    3.33e+04    6.22e+04
waterfront_YES  7.299e+05   2.16e+04     33.751      0.000    6.88e+05    7.72e+05
==============================================================================
Omnibus:                     7459.678   Durbin-Watson:                   1.977
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           113328.753
Skew:                           1.910   Prob(JB):                         0.00
Kurtosis:                      15.626   Cond. No.                     3.64e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.64e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

- The model overall is statistically significant at standard alpha of 0.05 being 0.0, and it explains 58% percent of the variance in sale price.
- The model coefficients are statistically significant except condition_1, condition_2 and condition_4. What this means is that there's no significant difference between this conditions and condition_3 which is our reference condition.

- In comparison to the baseline model, the multiple model is an improvement with explained variance in price from 49% to 58%
- The constant here explains that all factors held constant, a house with no waterfront and an average condition of the house is related to maintenance of house(condition_3), we would have a sale price of 5,217,000 dollars.

In [33]:
```
fig = plt.figure(figsize=(11, 8))
sm.graphics.plot_partregress_grid(
    multiple_results,
    exog_idx=list(X_multiple.columns.values),
    grid=(2, 5), fig=fig)

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

```
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
```



Transformations

- Considering our predictor scatterplots above, we would need to transform them to follow the assumption of linearity in L.I.N.E

In [34]:
```
# columns to transform
log_cols = ["sqft_living", "sqft_lot"]

# unselected columns
unlog_cols = ["bedrooms", "floors", "yr_built", "waterfront_YES", "condition_1", "condition_2","condition_4",
X_log = X_multiple[log_cols]
for col in X_log.columns:
    X_log[col] = X_log[col] - np.log(X_log[col])

X_log = pd.concat([X_log, X_multiple[unlog_cols]], axis=1)

X_log
```

Out[34]:

	sqft_living	sqft_lot	bedrooms	floors	yr_built	waterfront_YES	condition_1	condition_2	condition_4	condition_5
0	2562.148339	7233.112347	3	2.0	1951	0	0	0	0	0
1	1952.419300	4991.482807	4	1.0	1965	0	0	0	0	1
2	1672.573451	8071.002853	3	1.0	1987	0	0	0	0	0
3	5411.402149	101918.467958	4	1.0	2001	0	0	0	0	0
4	1707.552832	6810.172532	3	2.0	1995	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
15631	1302.822218	1286.834507	3	2.0	2008	0	0	0	0	0
15632	1522.666977	1123.969143	3	3.0	2009	0	0	0	0	0
15633	2302.254997	5804.332148	4	2.0	2014	0	0	0	0	0
15634	1013.072442	1342.792140	2	2.0	2009	0	0	0	0	0
15635	1013.072442	1069.018994	2	2.0	2008	0	0	0	0	0

15631 rows × 10 columns

In [35]:
```python
# fitting log model
log_model = sm.OLS(Y, sm.add_constant(X_log))
log_results = log_model.fit()
print(log_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.580
Model:                            OLS   Adj. R-squared:                  0.580
Method:                 Least Squares   F-statistic:                     2156.
Date:                Fri, 07 Jul 2023   Prob (F-statistic):               0.00
Time:                        17:36:38   Log-Likelihood:            -2.1525e+05
No. Observations:               15631   AIC:                         4.305e+05
Df Residuals:                   15620   BIC:                         4.306e+05
Df Model:                          10
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           5.218e+06   1.51e+05     34.578      0.000    4.92e+06    5.51e+06
sqft_living      312.2346      2.742    113.880      0.000     306.860     317.609
sqft_lot          -0.2878      0.045     -6.371      0.000      -0.376      -0.199
bedrooms       -5.134e+04   2447.805    -20.974      0.000   -5.61e+04   -4.65e+04
floors          7.306e+04   4131.202     17.686      0.000     6.5e+04    8.12e+04
yr_built       -2672.5148     77.727    -34.383      0.000   -2824.870   -2520.160
waterfront_YES  7.299e+05   2.16e+04     33.751      0.000    6.88e+05    7.72e+05
condition_1     -5.99e+04   5.47e+04     -1.094      0.274   -1.67e+05    4.74e+04
condition_2    -5.349e+04   2.11e+04     -2.537      0.011   -9.48e+04   -1.22e+04
condition_4     6303.4025   4603.393      1.369      0.171   -2719.781    1.53e+04
condition_5     4.776e+04   7364.540      6.486      0.000    3.33e+04    6.22e+04
==============================================================================
Omnibus:                     7458.719   Durbin-Watson:                   1.977
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           113302.754
Skew:                           1.909   Prob(JB):                         0.00
Kurtosis:                      15.625   Cond. No.                     3.64e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.64e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

- While this iteration did not increased R2 score still hoped to achieve a higher one.
- To attempt to increase R2 score, 'grade' and 'zipcode' will be included as features. These are categorical variables found in the kc_housing dataset.

In [36]:
```
# adding grade and zipcode columns
# create a copy of the DataFrame df and drops the column price
X_multiple2 = df.copy().drop(["price", "bathrooms"], axis=1)

# uses pd.get_dummies() from the pandas library to perform one-hot encoding on categorical variables.
X_multiple2 = pd.get_dummies(X_multiple2, columns=["condition", "waterfront", "grade", "zipcode"])
X_multiple2 = X_multiple2.drop(["condition_3", "waterfront_NO", "grade_3", "zipcode_98001"], axis=1)
X_multiple2
```

Out[36]:

	bedrooms	sqft_living	sqft_lot	floors	yr_built	condition_1	condition_2	condition_4	condition_5	waterfront_YES	...	zipcode_!
0	3	2570	7242	2.0	1951	0	0	0	0	0	...	
1	4	1960	5000	1.0	1965	0	0	0	1	0	...	
2	3	1680	8080	1.0	1987	0	0	0	0	0	...	
3	4	5420	101930	1.0	2001	0	0	0	0	0	...	
4	3	1715	6819	2.0	1995	0	0	0	0	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
15631	3	1310	1294	2.0	2008	0	0	0	0	0	...	
15632	3	1530	1131	3.0	2009	0	0	0	0	0	...	
15633	4	2310	5813	2.0	2014	0	0	0	0	0	...	
15634	2	1020	1350	2.0	2009	0	0	0	0	0	...	
15635	2	1020	1076	2.0	2008	0	0	0	0	0	...	

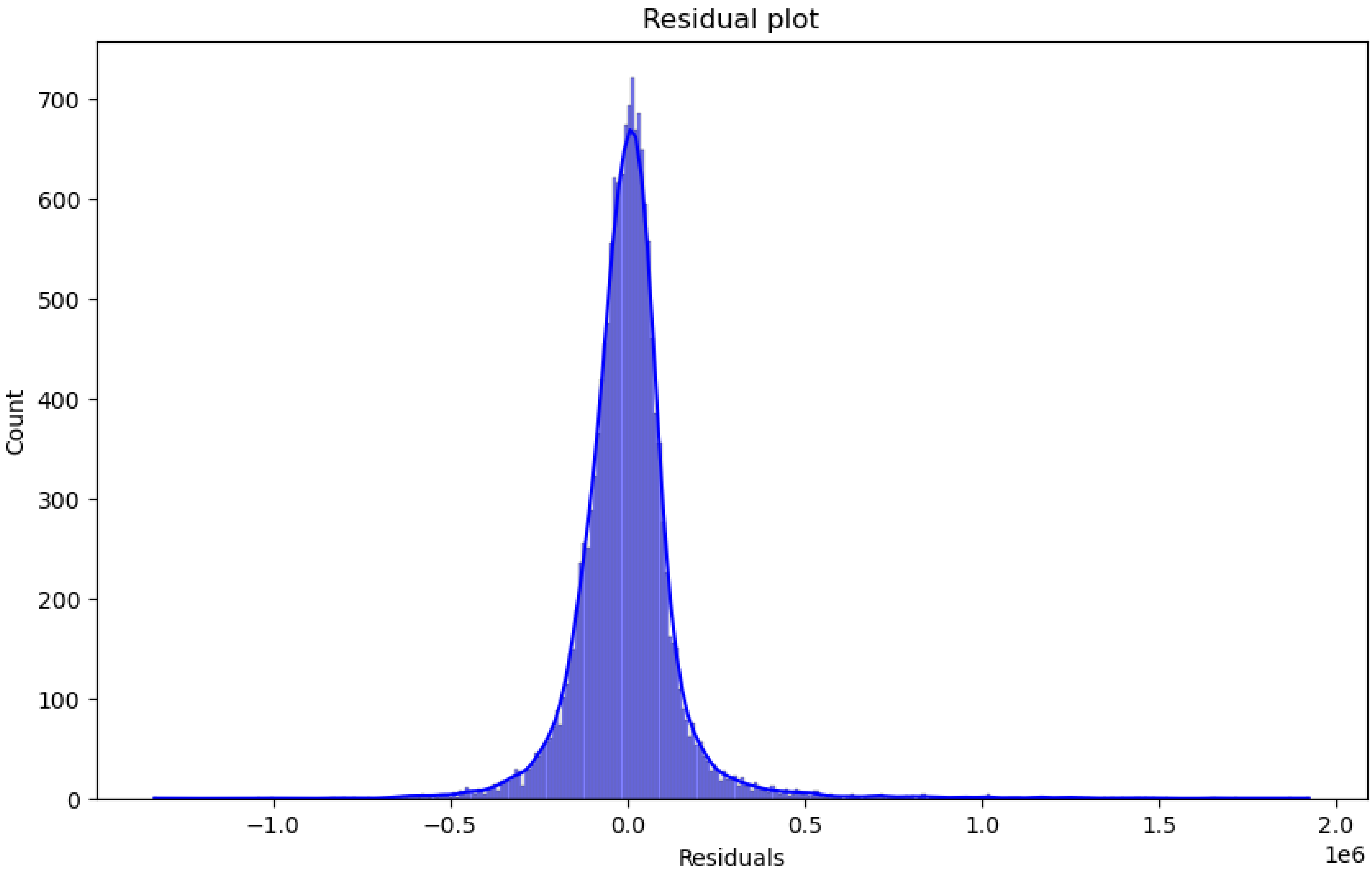
15631 rows × 89 columns

In [37]:
```python
# fitting the model
# fittng the model
multiple_model2 = sm.OLS(Y, sm.add_constant(X_multiple2))
multiple_results2 = multiple_model2.fit()
print(multiple_results2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.825
Model:                            OLS   Adj. R-squared:                  0.824
Method:                 Least Squares   F-statistic:                     825.7
Date:                Fri, 07 Jul 2023   Prob (F-statistic):               0.00
Time:                        17:36:41   Log-Likelihood:            -2.0839e+05
No. Observations:               15631   AIC:                         4.170e+05
Df Residuals:                   15541   BIC:                         4.176e+05
Df Model:                          89
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           1.084e+06   1.95e+05      5.546      0.000    7.01e+05    1.47e+06
bedrooms       -1.042e+04   1665.075     -6.256      0.000   -1.37e+04   -7152.214
sqft_living      163.8884      2.549     64.307      0.000     158.893     168.884
sqft_lot           0.2181      0.032      6.897      0.000       0.156       0.280
floors         -5930.5664   3007.823     -1.972      0.049   -1.18e+04     -34.883
```

- The model overall is statistically significant at standard alpha of 0.05 being 0.0, and it explains about 83% percent of the variance in sale price.
- The constant here explains that all factors held constant, a house with no waterfront, an average condition of the house is related to maintenance of house(condition_3), overall grade of the house related to the construction and design of the house being 3, (poor) and at zipcode_98001, we would have a sale price of 1,084,000 dollars.

In [38]:
```
fig, ax = plt.subplots(figsize=(10,6))
sns.histplot(bins="auto", x=multiple_results2.resid, kde=True, color="blue")
plt.xlabel("Residuals")
plt.title("Residual plot")
plt.show()
```



In [39]:

```python
# MAE
y_pred = multiple_results.predict(sm.add_constant(X_multiple))
print(mean_absolute_error(Y, y_pred))
y_pred2 = multiple_results2.predict(sm.add_constant(X_multiple2))
print(mean_absolute_error(Y, y_pred2))
```

```
155599.72000009075
91226.83575062237
```

- Using mean abosulute error over root mean squared error because of the propensity for RMSE to inflate values due to the square feature.
- The final model has reduced our mean absolute error by about 64,000 dollars

In [40]:

```python
multiple_results2_df = pd.concat([multiple_results2.params, multiple_results2.pvalues], axis=1)
multiple_results2_df.columns = ["coefficient", "pvalue"]
multiple_results2_df
```

Out[40]:

	coefficient	pvalue
const	1.083768e+06	2.968840e-08
bedrooms	-1.041595e+04	4.064906e-10
sqft_living	1.638884e+02	0.000000e+00
sqft_lot	2.180538e-01	5.519377e-12
floors	-5.930566e+03	4.865995e-02
...	...	...
zipcode_98177	2.522487e+05	2.738927e-66
zipcode_98178	3.593425e+04	1.384201e-02
zipcode_98188	2.412819e+04	1.793163e-01
zipcode_98198	1.809617e+04	2.030983e-01
zipcode_98199	3.915411e+05	1.915138e-168

90 rows × 2 columns

In [41]:
```
# Checking those that are not statistically significant
multiple_results2_df[multiple_results2_df["pvalue"] > 0.05]
```

Out[41]:

	coefficient	pvalue
condition_2	-21567.873550	0.116095
grade_4	-71041.225560	0.646147
grade_5	-114899.194485	0.445318
grade_6	-116247.530860	0.438763
grade_7	-103526.325181	0.490486
grade_8	-62391.662785	0.677832
grade_9	34748.944852	0.817120
grade_10	180093.466713	0.231095
zipcode_98002	8070.492917	0.602754
zipcode_98003	-6439.763411	0.643476
zipcode_98022	13450.324852	0.370257
zipcode_98030	1670.069485	0.908223
zipcode_98031	11098.249955	0.432506
zipcode_98032	-8383.989251	0.638428
zipcode_98042	5564.498917	0.642965
zipcode_98058	24488.205307	0.051862
zipcode_98070	213.452070	0.991031
zipcode_98092	-22918.459888	0.084122
zipcode_98188	24128.194193	0.179316
zipcode_98198	18096.173402	0.203098

- Our reference categories are condition_3 for condition, grade_3 for grade, and zipcode_98001 for zipcode, hence the above pvalues means that there is no significant differences when compared to their respective reference category.

Results

- The multiple linear regression model built has an R-squared value of 0.825, which indicates that the model can explain 83% of the variance of the markethouse sale prices which is a good sign that the model is effective in predicting the prices.
- For an average house and its overall grade related to the construction and design of the house being poor, no waterfront and being at zipcode_98001, we would have a sale price of 1,084,000 dollars.
- The model is off by about 91,226 dollars.
- All of available features impactful for inferring and predicting house sale prices and can be considered by home developers in order to increase selling price.

Recommendations

- Increase square-footage of living space.
- Attain the highest possible building condition.
- Attain the highest possible building grade.

By following the above recommendations, a housing development company in King County can increase their chances of selling higher-priced homes.

Conclusion

- The prob(F-statistic) of 0.00 tells us that there is an extremely low probability of achieving these results with the null hypothesis being true, and tells us that our regression is meaningful. Our p-values for our features are well below our alpha or significance level, showing that they are each contributing to the model significantly. With an alpha of 0.05, at a confidence level of 95%, we reject the null hypothesis that there is no relationship between our features and our target variable, price.
- There are some limitations to the model. To meet regression assumptions, we had to try out log-transformation on certain variables. Therefore,any new data used with the model would require similar preprocessing. Additionally, since housing prices vary regionally, the model's usefulness for datafrom other counties may be restricted.

Next Steps

- In the future, reducing noise in the data to improve the accuracy of our model is needed.
- Additionally, it is good to investigate certain features, such as proximity to a top school and coffee shop to see what trends could be discerned from that.