King County Housing Prices Prediction

DSF-PT7, Group 17:

1. Agatha Nyambati
2. Mary Musyoka
3. Phoebe Wawire
4. Shamla Araya
5. Zenah Biwott

Introduction:

King County, located in the state of Washington, encompasses a diverse range of urban, suburban, and rural communities, including the city of Seattle. The housing market in King County has been characterized by rapid growth, high demand, and escalating prices over the past decade, influenced by factors such as population growth, economic prosperity, and limited housing supply.

The King County Housing Price Prediction Project is an initiative aimed at accurately forecasting housing prices in King County, Washington. This project leverages advanced data analytics and machine learning techniques to provide precise and actionable insights into the factors influencing housing prices in the region. By analyzing historical data and current market trends, we aim to develop a robust predictive model that can assist homebuyers, sellers, real estate agents, and policymakers in making informed decisions.

Objectives:

1. Determine the key influencing factors for the housing prices in the region.
2. Provide a valuable EDA (Exploratory Data Analysis) for stakeholders such as homebuyers, sellers, real estate professionals, and policymakers to make data-driven decisions regarding property transactions and urban planning.
3. Develop a machine learning model capable of predicting housing prices with high accuracy based on a variety of factors including property features, location, and market conditions.

Data Understanding

The data set we are using for this project is from Kaggel website. This dataset contains more than 21,000 rows and 21 columns which describe or quantify the different aspects of the housing situation in the region. These features are crucial for achieving the objectives stated above. We will load the data and check if there are any missing or null values that could impair our analysis. To do this properly we will follow the following steps:

1. Load the dataset.
2. Data cleaning where we will check for missing values and any limitations within the dataset and prepare the dataset.
3. Data exploration where we will clearly identify all the features and select the ones we are willing to work with.
4. Analysis of the data to come up with insights that we can learn about the housing situation in the region
5. Preparing the data for machine learning models to predict the housing prices given different variables.

---

1. Loading the Data

In [1]:
```
# Start by importing all the necessary libraries fot our project

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score,mean_absolute
from statsmodels.formula.api import ols
import statsmodels.api as sm
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# Load the actual data

df = pd.read_csv('/Users/madservices/Documents/FlatIron/dsc-data-scier

# Check the firs 5 rows of the dataset
df.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	water
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	

5 rows × 21 columns

Column Names and descriptions for Kings County Data Set

- **id** - unique identified for a house
- **dateDate** - house was sold
- **pricePrice** - is prediction target

- **bedroomsNumber** - of Bedrooms/House
- **bathroomsNumber** - of bathrooms/bedrooms
- **sqft_livingsquare** - footage of the home
- **sqft_lotsquare** - footage of the lot
- **floorsTotal** - floors (levels) in house
- **waterfront** - House which has a view to a waterfront
- **view** - Has been viewed
- **condition** - How good the condition is (Overall)
- **grade** - overall grade given to the housing unit, based on King County grading system
- **sqft_above** - square footage of house apart from basement
- **sqft_basement** - square footage of the basement
- **yr_built** - Built Year
- **yr_renovated** - Year when house was renovated
- **zipcode** - zip
- **lat** - Latitude coordinate
- **long** - Longitude coordinate
- **sqft_living15** - The square footage of interior housing living space for the nearest 15 neighbors
- **sqft_lot15** - The square footage of the land lots of the nearest 15 neighbors

In [3]:
```
# Statistical summary of the dataset
df.describe()
```

Out[3]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04
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

Here we see that housing price ranges from $78,000.00to7$,700000.00 with an average being around $540,000.00

In [4]:
```
# General information about the columns in the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21597 non-null  int64  
 1   date           21597 non-null  object 
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64  
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64  
 6   sqft_lot       21597 non-null  int64  
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64  
 11  grade          21597 non-null  int64  
 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(8), int64(11), object(2)
memory usage: 3.5+ MB
```

From the above codes we learn that the dataset contains 21597 rows (entries) and 21 columns. The data type of the columns include integers, strings, and float numbers.

2. Data Cleaning

In [5]:
```
# Check for missing values in the dataset
df.isnull().sum()
```

Out[5]:
```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

As can be seen we have missing values from the "waterfront", "view" and "yr_renovated" columns. We need to check and handle them before we can proceed to EDA.

In [6]:
```
# Let us start with the waterfront column and see what the unique valu
df['waterfront'].unique()
```

Out[6]:
```
array([nan,  0.,  1.])
```

The above code shows that the values for the waterfront column are 0 and 1 which means if a house has a waterfront its value is 1 otherwise it is 0. With this understanding we will fill the nan values with 0s.

In [7]:
```
# Filling the nan values with 0
df['waterfront'].fillna(0, inplace=True)

# Changing the datatype to integer from float
df['waterfront'] = df['waterfront'].astype('int')

# Checking the changes we made
df['waterfront'].unique()

# Now the waterfront column has no missing values and all the values a
```

Out[7]:
```
array([0, 1])
```

In [8]:
```
# Let us do the same chaeck with the view column
df['view'].unique()
```

Out[8]:
```
array([ 0., nan,  3.,  4.,  2.,  1.])
```

According to the column description above the view column shows how many times a house has been viewed before. Based on this the nan values can be anything between 0 and 4 which is the highest value in the column. Therefore it is possible to fill the nan values with with the median value.

In [9]:
```
# Calculating the median value of the view column
median_value_view = df['view'].median()

# Replacing the nan value with the median value
df['view'].fillna(median_value_view, inplace=True)

# Checking the changes we made
df['view'].unique()
```

Out[9]:
```
array([0., 3., 4., 2., 1.])
```

In [10]:
```
# Checking the sqft_basement column
df['sqft_basement'].value_counts()
```

Out[10]:
```
sqft_basement
0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
1920.0        1
3480.0        1
2730.0        1
2720.0        1
248.0         1
Name: count, Length: 304, dtype: int64
```

This column gives the total basement size in sqft. It is a common knowledge that not all the houses have basement. The ones that have no basement are assigned a value 0. The "?" indicates that it is not certain whether the house has basement or not so we will treat it as if it doesn't have. This column contains a non-numeric value and has a string data type. We need to fix this.

In [11]:
```
# Changing the sqft_basement data type to numeric
df['sqft_basement'] = pd.to_numeric(df['sqft_basement'], errors='coer


# Replacing the non_numeric value with the median value
df['sqft_basement'].fillna(0, inplace = True)

# Checking the changes on sqft_basement column
df['sqft_basement'].isnull().sum()
```

Out[11]:
```
0
```

From the data observation above we can see that one house has 33 bedrooms. This eventhough it can be, doesn't seem to be right and needs further investigation.

In [12]:
```
df['bedrooms'].value_counts()
```

Out[12]:
```
bedrooms
3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: count, dtype: int64
```

Let us pull all the data for this house and check

In [13]:
```
# Let's see closely at the 33 bedrooms entry and investigate
df[df["bedrooms"]==33]
```

Out[13]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
15856	2402100895	6/25/2014	640000.0	33	1.75	1620	6000	1.0	

1 rows × 21 columns

In [14]:
```
# Let's see closely at the 10 bedrooms entry and compare
df[df["bedrooms"]==10].describe()
```

Out[14]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floor
count	3.000000e+00	3.000000e+00	3.0	3.000000	3.000000	3.000000	3.00000
mean	5.001934e+09	8.200000e+05	10.0	3.416667	3706.666667	8859.666667	1.66666
std	4.121612e+09	2.858321e+05	0.0	1.664582	839.186114	4457.226754	0.57735
min	6.273001e+08	6.500000e+05	10.0	2.000000	2920.000000	3745.000000	1.00000
25%	3.096700e+09	6.550000e+05	10.0	2.500000	3265.000000	7332.500000	1.50000
50%	5.566100e+09	6.600000e+05	10.0	3.000000	3610.000000	10920.000000	2.00000
75%	7.189251e+09	9.050000e+05	10.0	4.125000	4100.000000	11417.000000	2.00000
max	8.812401e+09	1.150000e+06	10.0	5.250000	4590.000000	11914.000000	2.00000

Now if we check carefully the average price for a 10 bedroom house is $820,000.00 while the price for the 33 bedroom house is$640,000.00. This comparison and even the size of the sqft_living shows that this entry is wrong. So we will drop it off our dataset as it can skew our analysis late on.

In [15]:
```
# Dropping the entry for the house with 33 bedrooms using its id.
df.drop([15856], axis = 0, inplace=True)

# Checking the modification
df["bedrooms"].value_counts()
```

Out[15]:
```
bedrooms
3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
Name: count, dtype: int64
```

In [16]:
```
# check the year renovated column to learn about the values and decide
df['yr_renovated'].unique()
```

Out[16]:
```
array([   0., 1991.,   nan, 2002., 2010., 1992., 2013., 1994., 197
8.,
       2005., 2003., 1984., 1954., 2014., 2011., 1983., 1945., 199
0.,
       1988., 1977., 1981., 1995., 2000., 1999., 1998., 1970., 198
9.,
       2004., 1986., 2007., 1987., 2006., 1985., 2001., 1980., 197
1.,
       1979., 1997., 1950., 1969., 1948., 2009., 2015., 1974., 200
8.,
       1968., 2012., 1963., 1951., 1962., 1953., 1993., 1996., 195
5.,
       1982., 1956., 1940., 1976., 1946., 1975., 1964., 1973., 195
7.,
       1959., 1960., 1967., 1965., 1934., 1972., 1944., 1958.])
```

In [17]:
```
# Since the yr_renovated column describes the year a house was renovat
df['yr_renovated'] = df['yr_renovated'].fillna(0)
```

In [18]:
```
# Let us recheck if our data has any missing or null values
df.isnull().sum()
```

Out[18]:
```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

Good now our dataset has no missing or null values. The id, date and zipcode columns in our dataset are not important for this project so we should drop them.

In [19]:
```
# Dropping the id, date and zipcode columns from our dataset
df.drop(['id', 'date', 'zipcode'], axis = 1, inplace=True)
```

Let us Remove the outliers from our dataset

In [20]:
```
# Calculate IQR for selected columns
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1

# Define outlier boundaries
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Find outliers
outliers = ((df < lower_bound) | (df > upper_bound)).any(axis=1)

# Print indices of outliers
outlier_indices = df.index[outliers]
```

In [21]:
```
# droping all columns with outliers
clean_df = df.drop(outlier_indices)
```

Let us check for duplicates as well

In [22]:
```
# Check for duplicated houses

#Function to get the number of duplictes
def get_duplicates(df):
    df=df[df.duplicated(keep=False)]
    return df

# Get duplicates
duplicates = get_duplicates(df)
duplicates.value_counts().sum()
```

Out[22]: 10

In [23]:
```
# Check for duplicates
clean_df = clean_df.drop_duplicates(keep=False)

duplicates = get_duplicates(clean_df)
duplicates.value_counts().sum()
```

Out[23]: 0

3: Data Exploration

Let us check the columns of our dataset and see which ones we can use for our objectives.

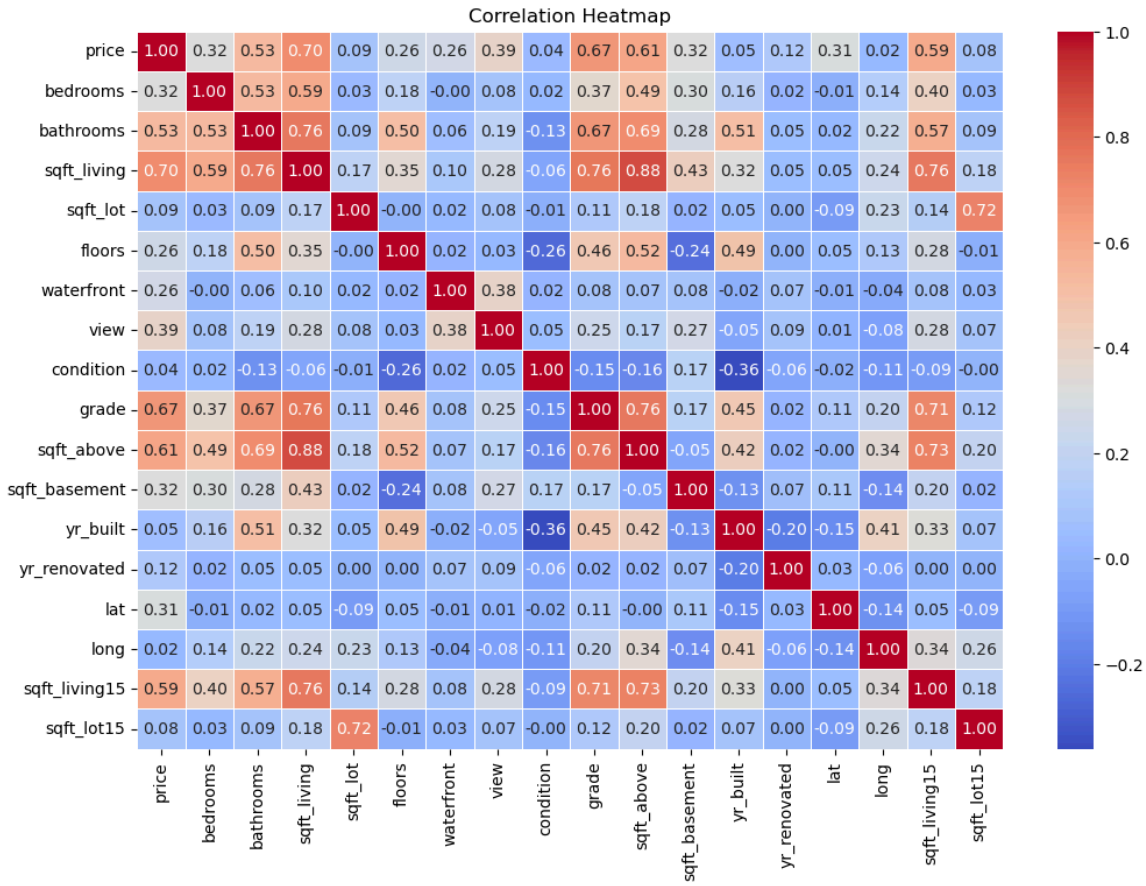
Objective 1. Determine the key influencing factors for the housing prices in the region.

To do this let us examine how all the features in our dataset are related to the Price column

In [24]:
```
# Checking the correlation between all the features in our dataset anc
correlation_matrix = df.corr()
correlation_matrix['price'].sort_values(ascending=False)
```

Out[24]:
```
price            1.000000
sqft_living      0.701929
grade            0.667964
sqft_above       0.605392
sqft_living15    0.585267
bathrooms        0.525915
view             0.393502
sqft_basement    0.321103
bedrooms         0.315961
lat              0.306687
waterfront       0.264308
floors           0.256820
yr_renovated     0.117858
sqft_lot         0.089879
sqft_lot15       0.082849
yr_built         0.053965
condition        0.036031
long             0.022047
Name: price, dtype: float64
```

In [25]:
```
# Compute the correlation matrix
correlation_matrix = df.corr()

# Plot the correlation heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f
plt.title('Correlation Heatmap')
plt.show()
```

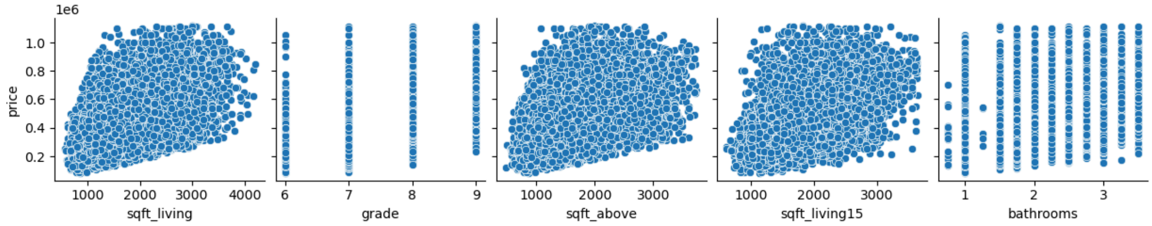


	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	lat	long	sqft_living15	sqft_lot15
price	1.00	0.32	0.53	0.70	0.09	0.26	0.26	0.39	0.04	0.67	0.61	0.32	0.05	0.12	0.31	0.02	0.59	0.08
bedrooms	0.32	1.00	0.53	0.59	0.03	0.18	-0.00	0.08	0.02	0.37	0.49	0.30	0.16	0.02	-0.01	0.14	0.40	0.03
bathrooms	0.53	0.53	1.00	0.76	0.09	0.50	0.06	0.19	-0.13	0.67	0.69	0.28	0.51	0.05	0.02	0.22	0.57	0.09
sqft_living	0.70	0.59	0.76	1.00	0.17	0.35	0.10	0.28	-0.06	0.76	0.88	0.43	0.32	0.05	0.05	0.24	0.76	0.18
sqft_lot	0.09	0.03	0.09	0.17	1.00	-0.00	0.02	0.08	-0.01	0.11	0.18	0.02	0.05	0.00	-0.09	0.23	0.14	0.72
floors	0.26	0.18	0.50	0.35	-0.00	1.00	0.02	0.03	-0.26	0.46	0.52	-0.24	0.49	0.00	0.05	0.13	0.28	-0.01
waterfront	0.26	-0.00	0.06	0.10	0.02	0.02	1.00	0.38	0.02	0.08	0.07	0.08	-0.02	0.07	-0.01	-0.04	0.08	0.03
view	0.39	0.08	0.19	0.28	0.08	0.03	0.38	1.00	0.05	0.25	0.17	0.27	-0.05	0.09	0.01	-0.08	0.28	0.07
condition	0.04	0.02	-0.13	-0.06	-0.01	-0.26	0.02	0.05	1.00	-0.15	-0.16	0.17	-0.36	-0.06	-0.02	-0.11	-0.09	-0.00
grade	0.67	0.37	0.67	0.76	0.11	0.46	0.08	0.25	-0.15	1.00	0.76	0.17	0.45	0.02	0.11	0.20	0.71	0.12
sqft_above	0.61	0.49	0.69	0.88	0.18	0.52	0.07	0.17	-0.16	0.76	1.00	-0.05	0.42	0.02	-0.00	0.34	0.73	0.20
sqft_basement	0.32	0.30	0.28	0.43	0.02	-0.24	0.08	0.27	0.17	0.17	-0.05	1.00	-0.13	0.07	0.11	-0.14	0.20	0.02
yr_built	0.05	0.16	0.51	0.32	0.05	0.49	-0.02	-0.05	-0.36	0.45	0.42	-0.13	1.00	-0.20	-0.15	0.41	0.33	0.07
yr_renovated	0.12	0.02	0.05	0.05	0.00	0.00	0.07	0.09	-0.06	0.02	0.02	0.07	-0.20	1.00	0.03	-0.06	0.00	0.00
lat	0.31	-0.01	0.02	0.05	-0.09	0.05	-0.01	0.01	-0.02	0.11	-0.00	0.11	-0.15	0.03	1.00	-0.14	0.05	-0.09
long	0.02	0.14	0.22	0.24	0.23	0.13	-0.04	-0.08	-0.11	0.20	0.34	-0.14	0.41	-0.06	-0.14	1.00	0.34	0.26
sqft_living15	0.59	0.40	0.57	0.76	0.14	0.28	0.08	0.28	-0.09	0.71	0.73	0.20	0.33	0.00	0.05	0.34	1.00	0.18
sqft_lot15	0.08	0.03	0.09	0.18	0.72	-0.01	0.03	0.07	-0.00	0.12	0.20	0.02	0.07	0.00	-0.09	0.26	0.18	1.00

As can be seen above, sqft_living, grade, sqft_above, sqft_living15, bathrooms are the top 5 columns highly correlated with the house price. This strong positive correlation indicate that these features have great impact on the house price in King County. While view, sqft_basement, bedrooms, lat, waterfront, floors have moderate positive correlation. The rest of the features have low correlation which means their impact in determining the house price is low. Let us demonstrate this further using plots.

In [26]:
```
# let us create data frames with these category of features
highly_influencers = df[['sqft_living', 'grade', 'sqft_above', 'sqft_
moderate_influencers = df[['view','sqft_basement', 'bedrooms', 'lat',
no_influencers = df[['yr_renovated', 'sqft_lot', 'sqft_lot15', 'yr_bu
```

In [27]:
```
# Pair Plotting features with the house price
sns.pairplot(clean_df, y_vars=['price'], x_vars=highly_influencers.co
plt.show()
```



Based on the correlation analysis and considering the goal of predicting house prices (price) in King County, here are the most important features we should consider:

Primary Features:

sqft_living: Square footage of the living area (Correlation: 0.70).

grade: Overall grade given to the housing unit (Correlation: 0.67).

sqft_above: Square footage of the house above ground level (Correlation: 0.61).

bathrooms: Number of bathrooms in the house (Correlation: 0.53).

Additional Features:

bedrooms: Number of bedrooms in the house (Correlation: 0.31).

Why These Features?

Strong Correlation: These features exhibit the highest correlations with price based on our analysis, indicating a strong linear relationship with house prices in King County.

Market Relevance: Features like sqft_living, grade, and bathrooms are fundamental factors influencing property values, reflecting buyer preferences and market dynamics in the region.

Predictive Power: Models incorporating these features are likely to yield more accurate predictions of house prices due to their significant impact on property valuations.

4: Data Analysis

Since price is our target variable, let us first investigate it.

In [28]:
```
clean_df.sort_values(['price'], ascending=False)
```

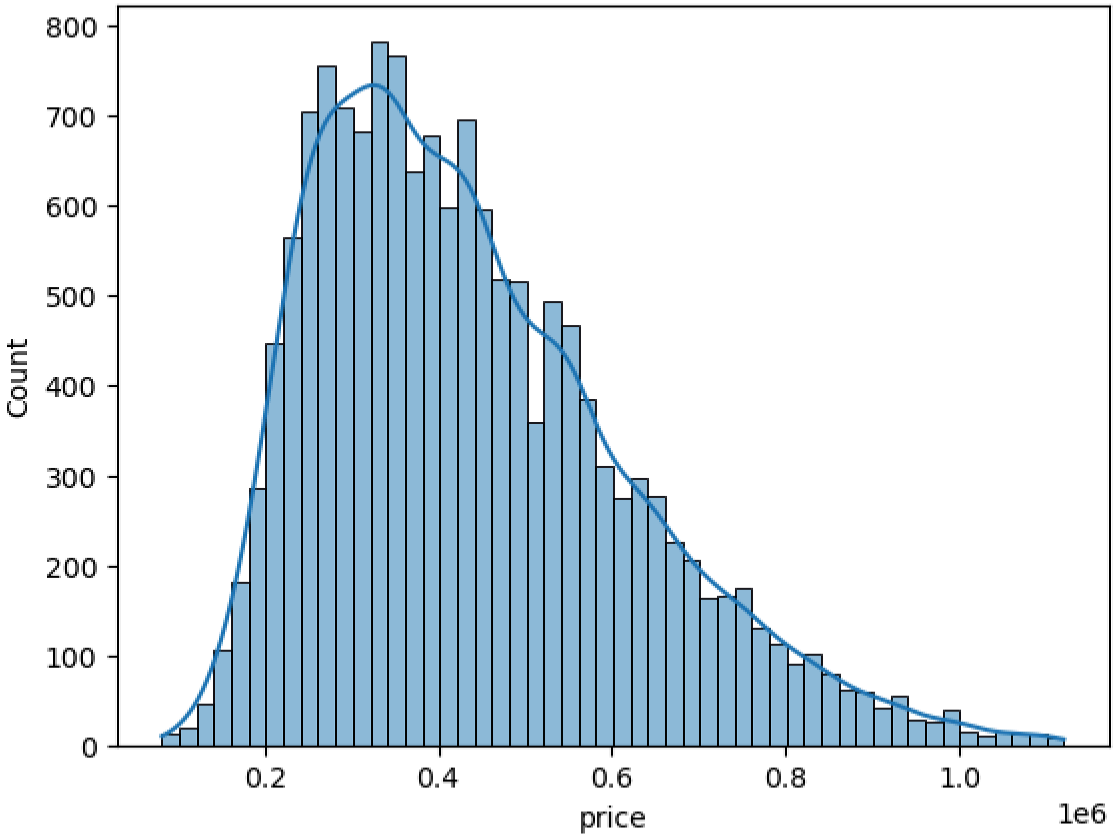
Out[28]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	conditi
639	1120000.0	3	1.50	3000	5750	2.0	0	0.0	
11096	1110000.0	5	3.25	3070	5000	2.0	0	0.0	
7662	1110000.0	5	3.50	3090	3600	2.0	0	0.0	
20753	1110000.0	4	3.00	2770	2650	2.0	0	0.0	
14995	1110000.0	4	1.50	2740	4000	2.0	0	0.0	
...	...	...	...	...	...	...	...	...	
18924	90000.0	3	1.00	980	2490	2.0	0	0.0	
5860	89000.0	3	1.00	900	4750	1.0	0	0.0	
13743	86500.0	3	1.00	840	9480	1.0	0	0.0	
10242	85000.0	2	1.00	830	9000	1.0	0	0.0	
8267	82000.0	3	1.00	860	10426	1.0	0	0.0	

14988 rows × 18 columns

What we see from here is that the price ranges from $78kfor2bedroomhousewith780sqftlivingspace, 1floor, 1bathroomto$7.7mil for a 6 bedroom, with 8 bathrooms, 2.5 floors and 12050sqft living space. This is a huge gap and maybe the high price could blow our distribution. Let us investigate it.

In [29]:
```
# Plotting the price distribution
sns.histplot(clean_df['price'], kde=True)
plt.show()
```



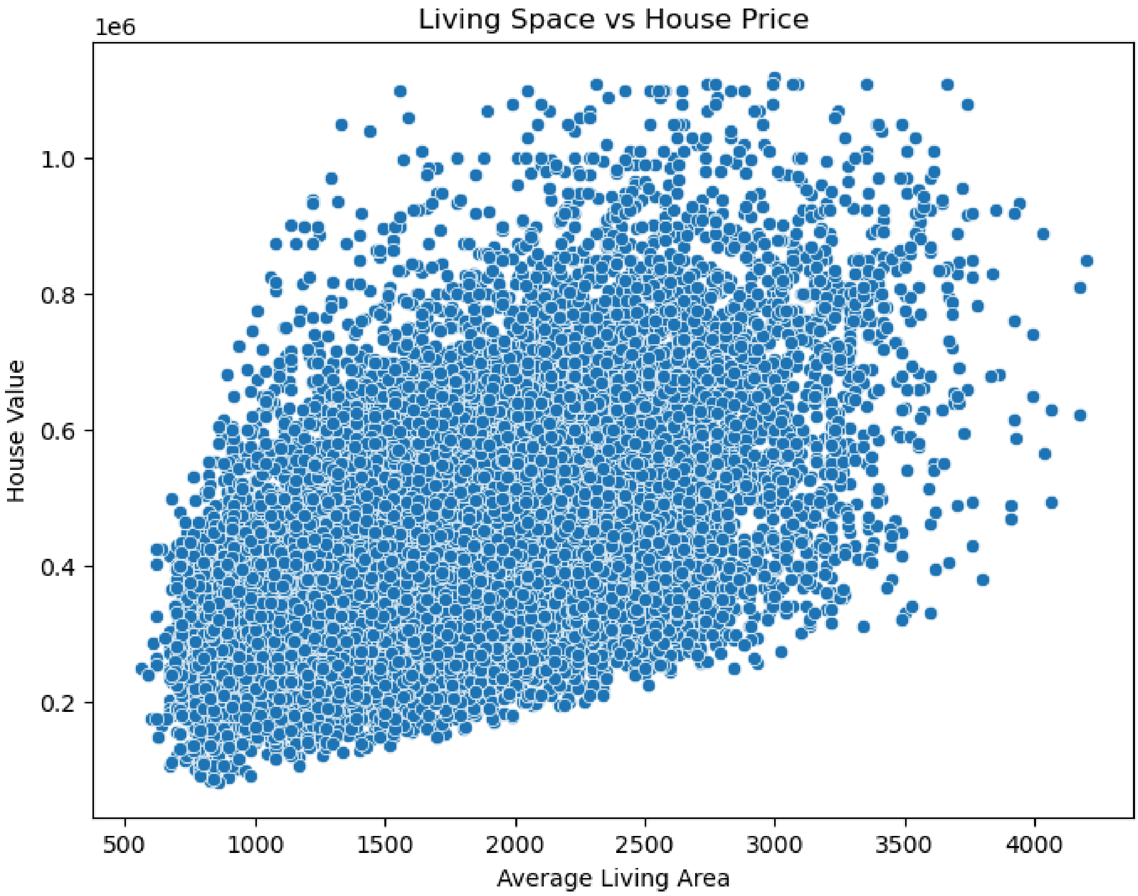
Now that we have the outliers removed from the dataset let's see how the living space relates to the house price.

Analysis 1

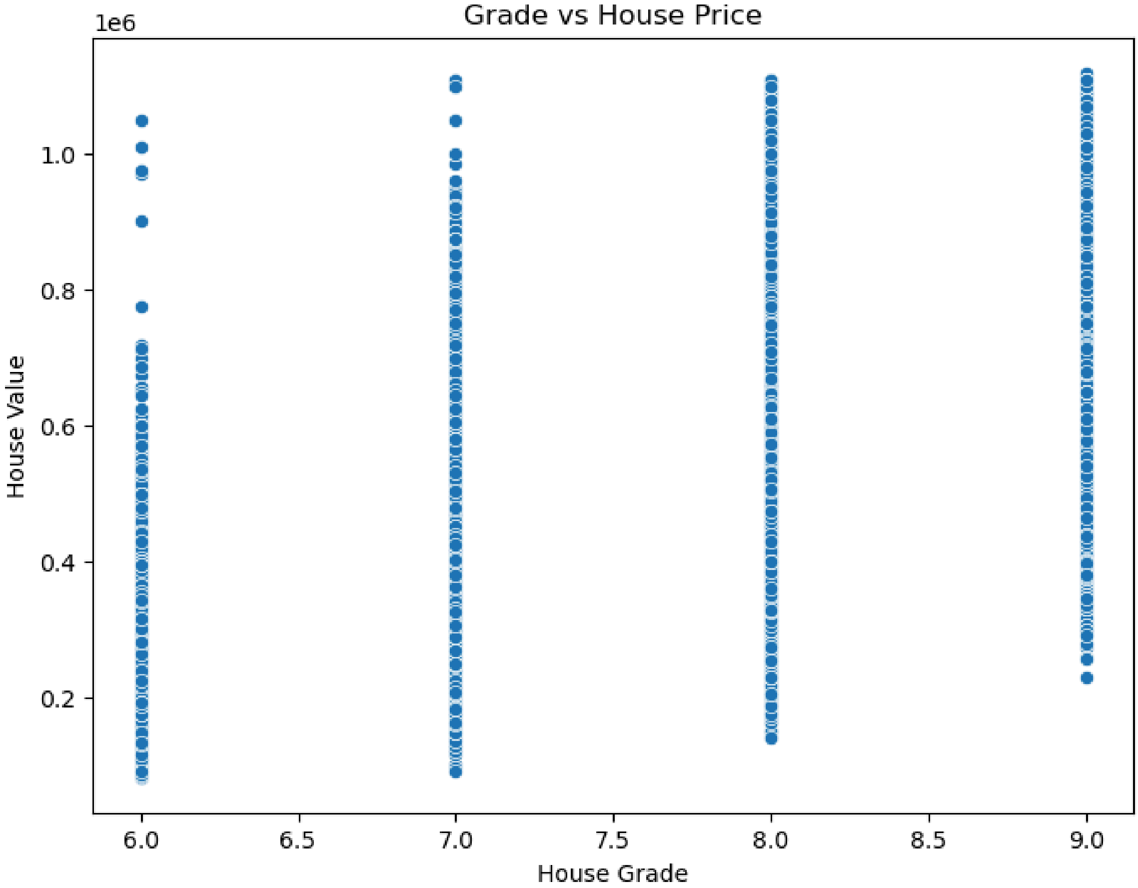
Analyse how does the square footage of the living area relate to price

To understand the relationship between the square footage of the living area and the price, we can create a scatter plot. This will give us a visual representation of the data.

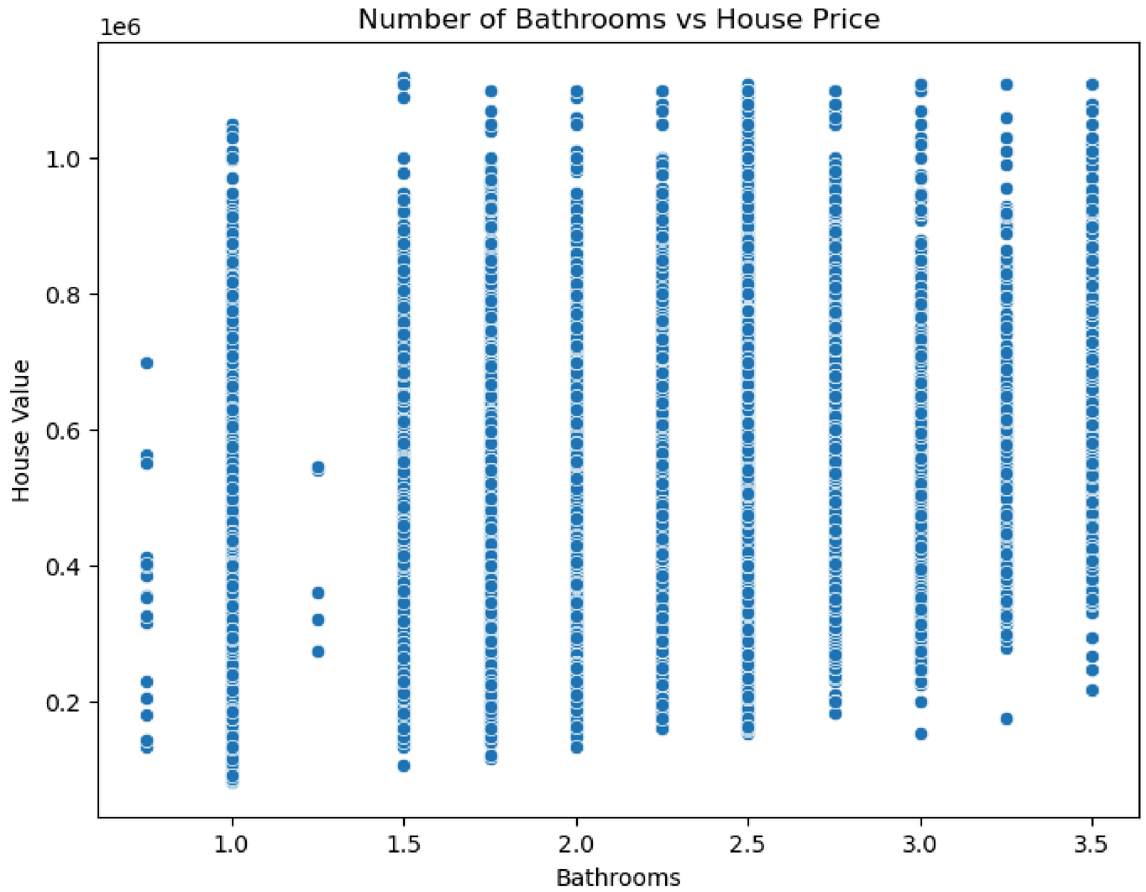
In [30]:
```
# Plotting living space against house price
plt.figure(figsize=(8, 6))
sns.scatterplot(x='sqft_living', y='price', data=clean_df)
plt.title('Living Space vs House Price')
plt.xlabel('Average Living Area')
plt.ylabel('House Value')
plt.show()
```



In [31]:
```
# Plotting influential features with the house price
plt.figure(figsize=(8, 6))
sns.scatterplot(x='grade', y='price', data=clean_df)
plt.title('Grade vs House Price')
plt.xlabel('House Grade')
plt.ylabel('House Value')
plt.show()
```



In [32]:
```
# Plotting influential features with the house price
plt.figure(figsize=(8, 6))
sns.scatterplot(x='bathrooms', y='price', data=clean_df)
plt.title('Number of Bathrooms vs House Price')
plt.xlabel('Bathrooms')
plt.ylabel('House Value')
plt.show()
```



Observation:

The scatter plot shows that sqft_living, grade and bathrooms features are strongly positively correlated with the house price, indicating that houses with larger living areas, above average grade and with multiple bathrooms generally command higher prices.

Implication:

This insight suggests that square footage followed by grade and bathrooms are significant factors in determining property prices in King County, which aligns with common expectations in real estate markets.

Recommendation 1:

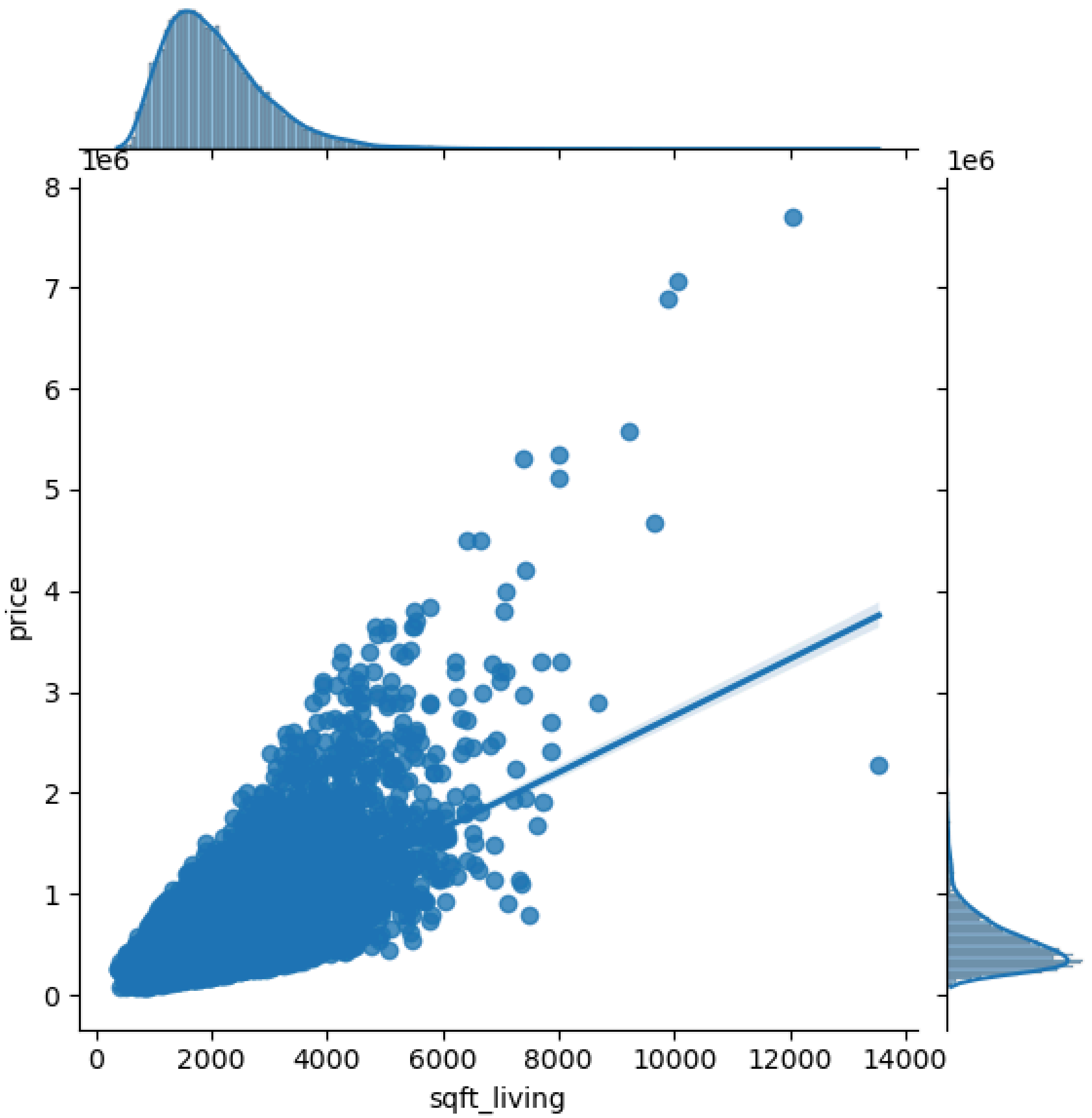
Based on the analysis and demonstrations houses with large living spaces, higher grading, and numerous bathrooms cost more than others. Therefore it is advisable to look for houses with such features to invest in and make profit on resale or to consider the features in order to find more affordable houses to buy.

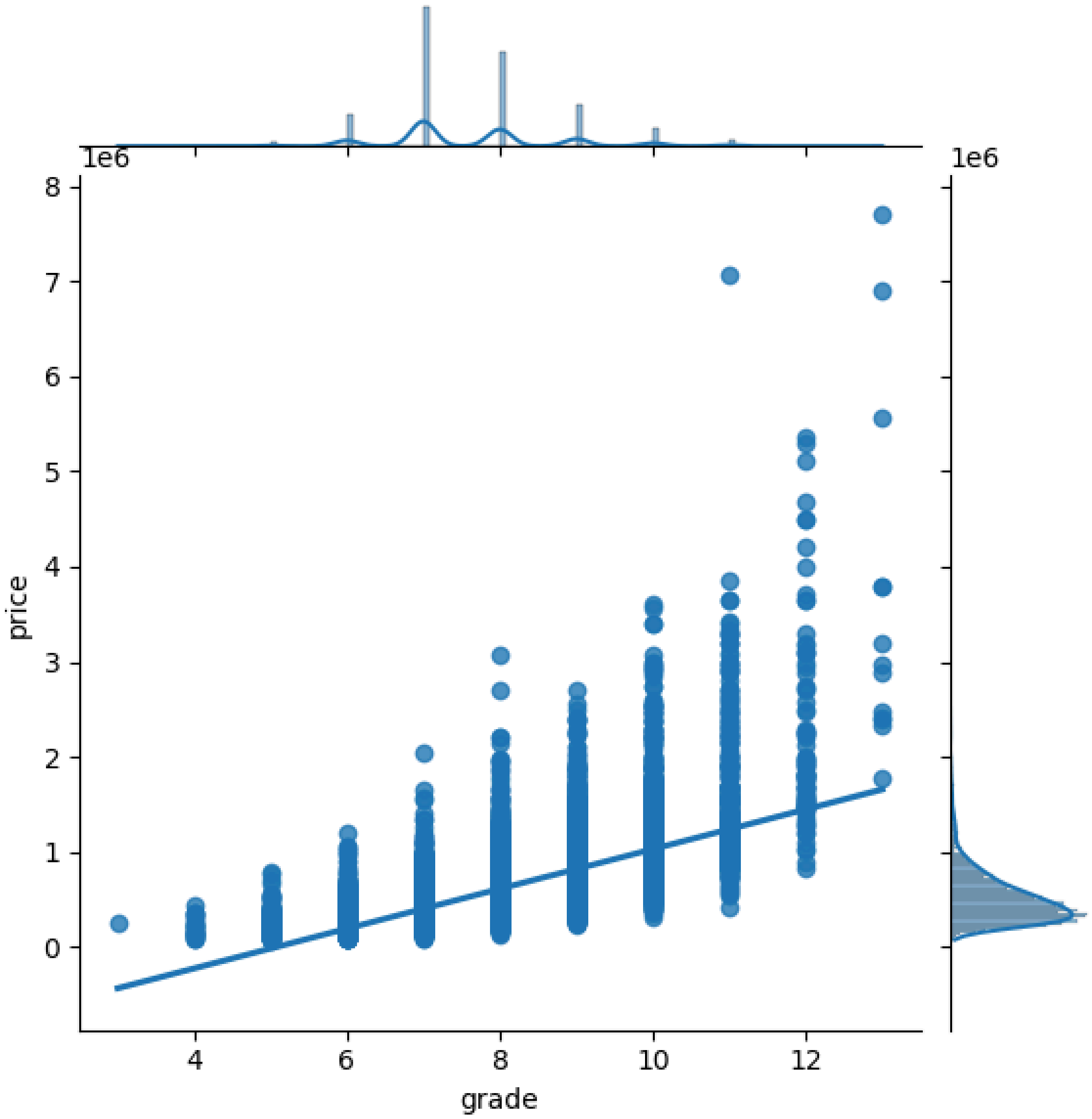
Objective 2: Provide a valuable EDA (Exploratory Data Analysis) for stakeholders such as homebuyers, sellers, real estate professionals, and policymakers to make data-driven decisions regarding property transactions and urban planning.

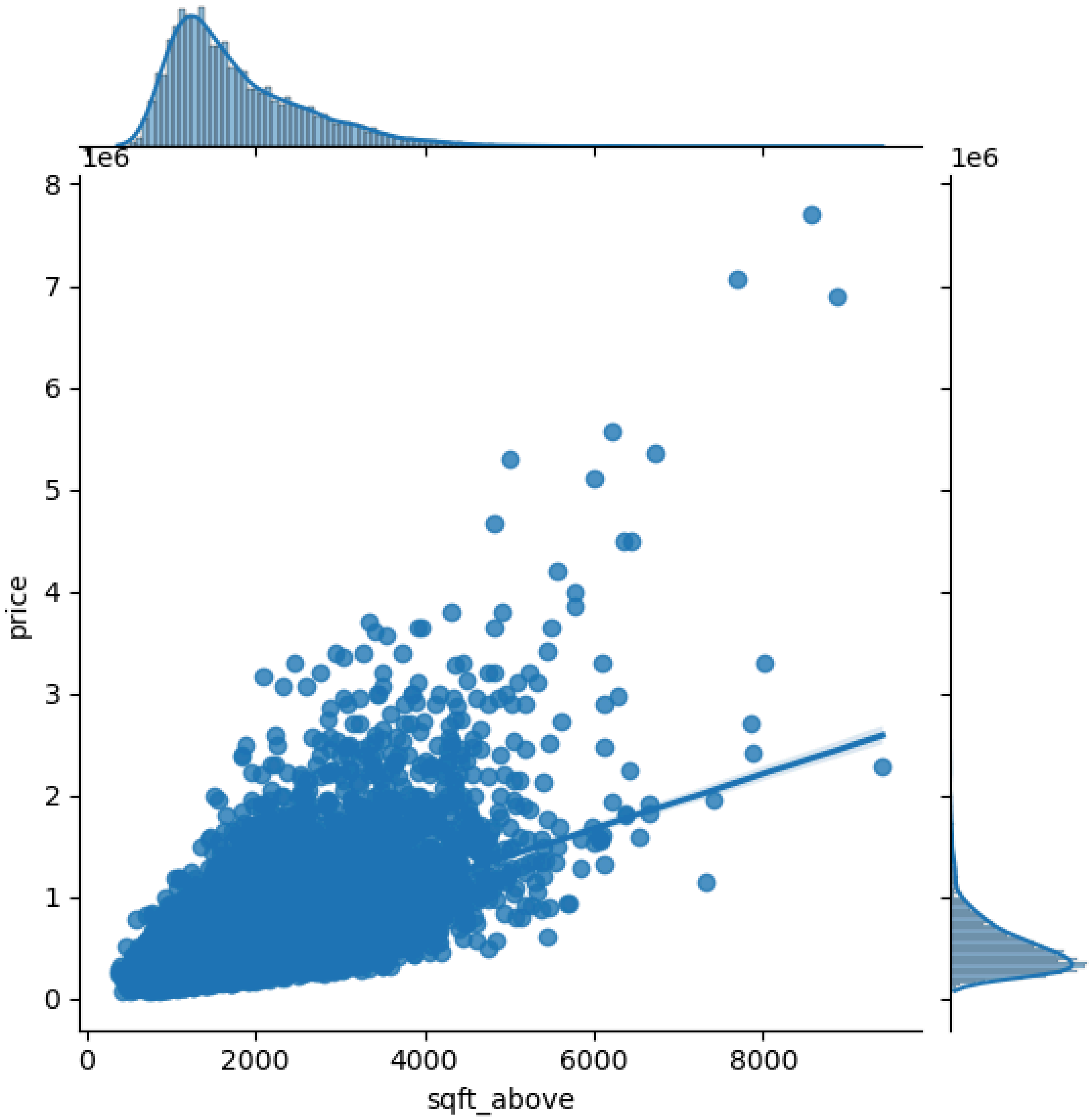
Analysis 2

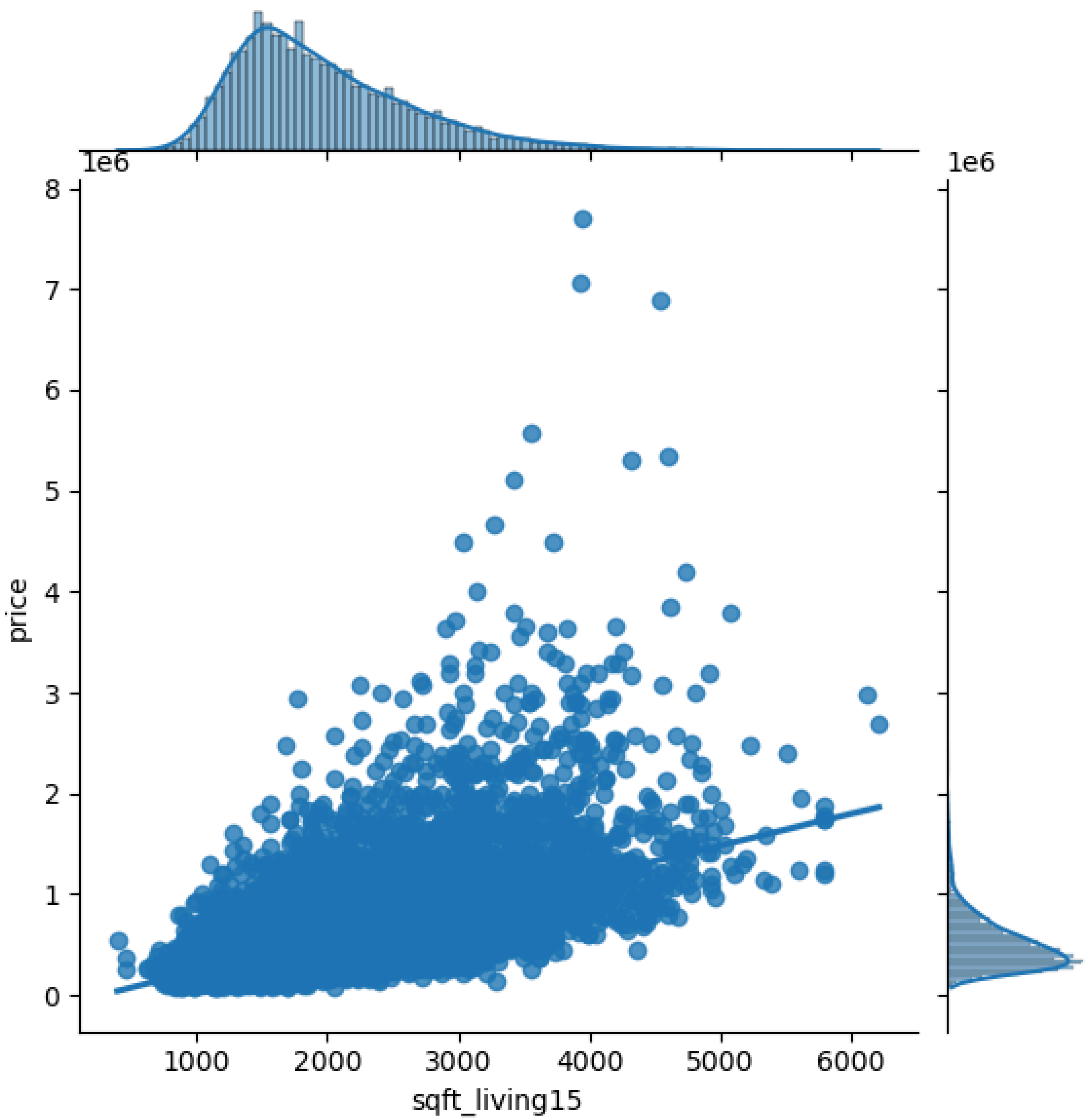
Analyse The Impact of the highly_influencers to price

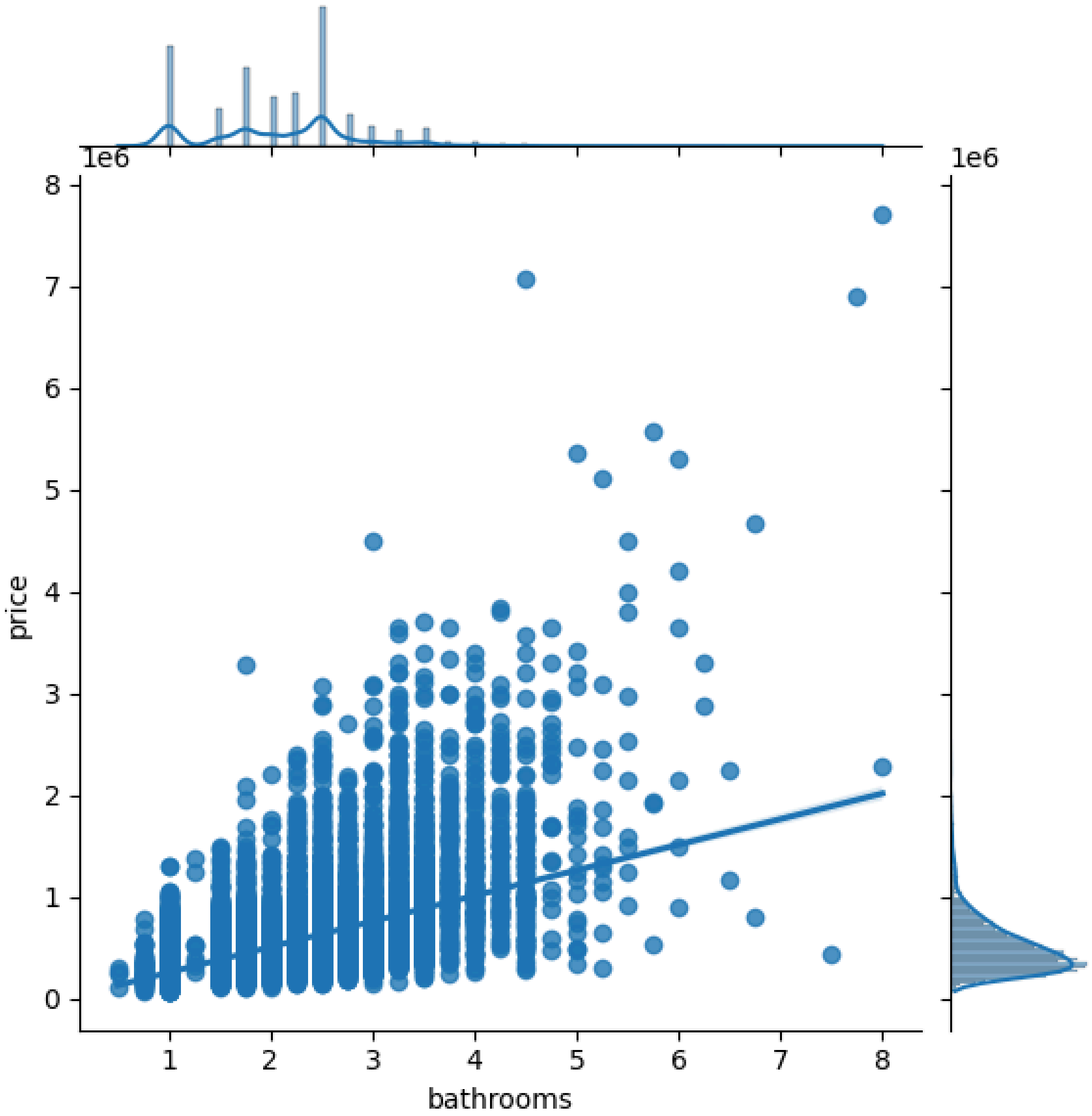
In [33]:
```
# Exploratory Data Analysis
for feature in highly_influencers:
    sns.jointplot(x = df[feature], y = df['price'], kind = 'reg')
```




1e6
1e6
8
7
6
5
4
3
2
1
0
price
4
6
8
10
12
grade


1e6
8
7
6
5
4
3
2
1
0
price
0
2000
4000
6000
8000
sqft_above
1e6


1e6
8
7
6
5
4
3
2
1
0
price
1000
2000
3000
4000
5000
6000
sqft_living15
1e6



Recommendation 2:

This EDA shows that the housing market in King County is highly influenced by the total footage of living space. Even though the grade a house receives and the number of bathrooms of a house as well influence the price, the power of the total footage of living space is vividly clear. Stakeholders such as homebuyers, sellers, real estate professionals, and policymakers need to pay attention of the total footage of living space to get insights and make data-driven decisions regarding property transactions and urban planning based on this EDA.

Objective 3 Develop a Multiple Regression Model for Predicting House Prices:

a. Objective: Build a predictive model that accurately estimates housing prices based on various features

b. Feature Selection: Use techniques such as Recursive Feature Elimination (RFE), to select relevant features.

c. Model Selection: Test various models and select the one that performs with above average accuracy.

d. Linear Models: Linear Regression

e. Finally we will do Model Evaluation: Use metrics like R-squared, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) to evaluate model performance. Perform cross-validation to ensure robustness.

Model 1

In [34]:
```
# Creating a dataframe with selected features

df1 = df[['bedrooms','bathrooms','price','waterfront','condition']]
df1.head()
```

Out[34]:

	bedrooms	bathrooms	price	waterfront	condition
0	3	1.00	221900.0	0	3
1	3	2.25	538000.0	0	3
2	2	1.00	180000.0	0	3
3	4	3.00	604000.0	0	5
4	3	2.00	510000.0	0	3

In [35]:
```
# Transform the dataframe
df_transformed_1 = df1.copy()
df_transformed_1['price_log'] = np.log(df_transformed_1['price'])
print(df_transformed_1.head())
```

```
   bedrooms  bathrooms     price  waterfront  condition  price_log
0         3       1.00  221900.0           0          3  12.309982
1         3       2.25  538000.0           0          3  13.195614
2         2       1.00  180000.0           0          3  12.100712
3         4       3.00  604000.0           0          5  13.311329
4         3       2.00  510000.0           0          3  13.142166
```

In [36]:
```
# Separate features and target variable
X = df_transformed_1[['bedrooms','bathrooms','waterfront','condition']
y = df_transformed_1['price_log']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.

# Create and train the model
model = LinearRegression()
model.fit(X_train, y_train)

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

# Evaluate the model
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)


print(f'R-squared: {r2}')
print(f'Mean Absolute Error: {mae}')
print('Coefficients:', model.coef_)
print('Intercept:', model.intercept_)
```

```
R-squared: 0.32444782772387404
Mean Absolute Error: 0.3463239556238238
Coefficients: [0.04354581 0.3559081  0.87554247 0.08357308]
Intercept: 11.858860373149204
```

Interpretation of Results

R-squared

R-squared: 0.3244: This indicates that approximately 32.44% of the variance in the logarithmically transformed house prices (price_log) can be explained by the model. This is a moderate level of explanatory power and suggests that while the selected features ('bedrooms', 'bathrooms', 'waterfront', 'condition') are relevant, there are other important factors influencing house prices not captured by this model.

Mean Absolute Error (MAE)

MAE: 0.3452: This represents the average magnitude of errors in predicting the logarithmically transformed prices. In this case, the MAE is 0.3452 units on the log scale, which is a typical prediction error magnitude for this transformed variable.

Model 2

In [37]:
```
# Select relevant features
df2 = df[['price','sqft_living', 'grade', 'bathrooms']]

# Transform variables
df_transformed_2 = df2.copy()
df_transformed_2['price_log'] = np.log(df_transformed_2['price'])
df_transformed_2.head()
```

Out[37]:

	price	sqft_living	grade	bathrooms	price_log
0	221900.0	1180	7	1.00	12.309982
1	538000.0	2570	7	2.25	13.195614
2	180000.0	770	6	1.00	12.100712
3	604000.0	1960	7	3.00	13.311329
4	510000.0	1680	8	2.00	13.142166

In [38]:
```
# Separate features and target variable
X = df_transformed_2[['sqft_living', 'grade','bathrooms']]
y = df_transformed_2['price_log']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.

# Create and train the model
model = LinearRegression()
model.fit(X_train, y_train)

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

# Evaluate the model
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)


print(f'R-squared: {r2}')
print(f'Mean Absolute Error: {mae}')
print('Coefficients:', model.coef_)
print('Intercept:', model.intercept_)
```

```
R-squared: 0.551175224211654
Mean Absolute Error: 0.2832943470967524
Coefficients: [ 0.00022653  0.18971437 -0.01728759]
Intercept: 11.161694871756431
```

Interpretation of Results

R-squared

R-squared: 0.5511: This indicates that approximately 55.11% of the variance in the logarithmically transformed house prices (price_log) can be explained by the model. This is a moderate level of explanatory power and suggests that while the selected features (sqft_living, grade, bathrooms) are relevant, there could be other important factors influencing house prices not captured by this model.

Mean Absolute Error (MAE)

MAE: 0.2832: This represents the average magnitude of errors in predicting the logarithmically transformed prices. In this case, the MAE is 0.2832 units on the log scale, which is a typical prediction error magnitude for this transformed variable.

Model 3

In [39]:
```
# Selecting different features from the data set
df3 = df[['price','sqft_living', 'grade', 'sqft_above', 'bathrooms',

# Transforming the variables
df_transformed_3 = df3.copy()
df_transformed_3['sqft_living_log'] = np.log1p(df_transformed_3['sqft_
df_transformed_3['sqft_above'] = np.log1p(df_transformed_3['sqft_above
df_transformed_3['price_log'] = np.log(df_transformed_3['price'])
df_transformed_3.head()
```

Out[39]:

	price	sqft_living	grade	sqft_above	bathrooms	bedrooms	sqft_living_log	price_log
0	221900.0	1180	7	7.074117	1.00	3	7.074117	12.309982
1	538000.0	2570	7	7.682943	2.25	3	7.852050	13.195614
2	180000.0	770	6	6.647688	1.00	2	6.647688	12.100712
3	604000.0	1960	7	6.957497	3.00	4	7.581210	13.311329
4	510000.0	1680	8	7.427144	2.00	3	7.427144	13.142166

In [40]:
```
# # Separate features and target variable
X = df_transformed_3[['sqft_living', 'grade', 'sqft_above', 'bathrooms
y = df_transformed_3['price_log']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.

# Create and train the model
model = LinearRegression()
model.fit(X_train, y_train)

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

# Evaluate the model
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)


print(f'R-squared: {r2}')
print(f'Mean Absolute Error: {mae}')
print('Coefficients:', model.coef_)
print('Intercept:', model.intercept_)
```

```
R-squared: 0.5573214108677681
Mean Absolute Error: 0.28003622865725314
Coefficients: [ 0.00028895  0.20126344 -0.18594717 -0.00326576 -0.01
669707]
Intercept: 12.34536944779032
```

Interpretation of Results

R-squared

R-squared: 0.5573: This indicates that approximately 55.73% of the variance in the logarithmically transformed house prices (price_log) can be explained by the model. This is a moderate level of explanatory power, suggesting that the selected features explain a significant portion of the variation in house prices.

Mean Absolute Error (MAE)

MAE: 0.2802: This represents the average magnitude of the errors in predicting the logarithmically transformed prices. An MAE of 0.2800 units on the log scale indicates a reasonably good prediction accuracy, better than the previous model with fewer features.

Coefficients

sqft_living (0.6514): For each additional unit increase in square footage of living space, the logarithm of the price is expected to increase by approximately 0.6514 units, holding other factors constant. This shows a substantial positive impact of living space on house prices.

Model 4

In [41]:
```
# Selecting features for model 5
df4 = df[['sqft_living', 'grade', 'price', 'bathrooms', 'lat', 'long']
df_transformed_4 = df4.copy()

#Transform features
df_transformed_4['price_log'] = np.log(df_transformed_4['price'])
df_transformed_4.head()
```

Out[41]:

	sqft_living	grade	price	bathrooms	lat	long	price_log
0	1180	7	221900.0	1.00	47.5112	-122.257	12.309982
1	2570	7	538000.0	2.25	47.7210	-122.319	13.195614
2	770	6	180000.0	1.00	47.7379	-122.233	12.100712
3	1960	7	604000.0	3.00	47.5208	-122.393	13.311329
4	1680	8	510000.0	2.00	47.6168	-122.045	13.142166

In [42]:
```
# Separate features and target variable
X = df_transformed_4[['sqft_living', 'grade', 'lat', 'long']]
y = df_transformed_4['price_log']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.

# Create and train the model
model = LinearRegression()
model.fit(X_train, y_train)

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

# Evaluate the model
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f'R-squared: {r2}')
print(f'Mean Absolute Error: {mae}')
print('Coefficients:', model.coef_)
print('Intercept:', model.intercept_)
```

```
R-squared: 0.7063608450810133
Mean Absolute Error: 0.21953428946767334
Coefficients: [ 2.43805906e-04  1.59188965e-01  1.43172655e+00 -2.70
519235e-01]
Intercept: -89.83181608893119
```

Interpretation of Results

R-squared

R-squared: 0.7063: This indicates that approximately 70.63% of the variance in the logarithmically transformed house prices (price_log) can be explained by the model.

Mean Absolute Error (MAE)

MAE: 0.2195: This represents the average magnitude of the errors in predicting the logarithmically transformed prices. In this case, the MAE is 0.2195 units on the log scale. A lower MAE indicates better prediction accuracy. This idicaates that our model which have an MAE of 0.2195 is more accurate in predicting the log-transformed house prices than our Previous model with an MAE of 0.2789.

Coefficients

sqft_living (0.0002439): For each additional unit increase in square footage of living space, the logarithm of the price is expected to increase by approximately 0.0002439 units, holding other factors constant.

grade (0.1591): Each one-unit increase in the grade of the house is associated with an increase in the logarithm of the price by about 0.1591 units, holding other factors constant.

lat (1.4346): Each one-degree increase in latitude is associated with an increase in the logarithm of the price by approximately 1.4346 units, holding other factors constant. This indicates that latitude has a significant impact on house prices in the logarithmic scale.

long (-0.2694): Each one-degree increase in longitude is associated with a decrease in the logarithm of the price by approximately 0.2694 units, holding other factors constant.

Intercept

Intercept (-89.8274): The intercept represents the expected value of the logarithm of the house price when all predictors are zero. Since we're dealing with logarithmic transformation, this **interpretation is in terms of logarithmic units.

Summary of Overall Models Performance:

Model 1: shows a relatively low R-squared value (0.3244), indicating that it explains only 32.44% of the variance in the data. Its MAE is 0.3452, suggesting a moderate level of prediction error.

Model 2: shows an improved R-squared value 0f 0.5511 explaining 55.11% of the variance and a 0.28 MAE value. However this is not satisfactory level of prediction given the significance of the model.

Model 3: has a lower R-squared value (0.5485), explaining 54.85% of the variance. Its MAE is 0.278, indicating a weaker predictive performance than Model 2.

Model 4: has the highest R-squared value (0.7063), explaining 70.63% of the variance. It also has the lowest MAE (0.21), suggesting it provides the most accurate predictions.

Recommendation 3:

The best model for predicting housing prices in King County, based on the provided dataset and transformation techniques, is Model 4. This model has a high R-squared value of 0.7063, indicating it explains 70.63% of the variance in the logarithmically transformed house prices. It also has a low MAE of 0.2194, indicating it has the lowest prediction error. This model effectively captures the mean and standard deviation of the logarithmically transformed house prices.

With the highest R-squared value of 0.7063, and lowest MAE of 0.2194, this Model is the most accurate and reliable model for predicting housing prices.

Moderate Fit:

An R-squared value of 0.7 indicates a moderate level of explanatory power. This suggests that our model is capturing some, but not all, of the important factors influencing house prices. In real estate data, it is common for multiple factors to influence the house prices.

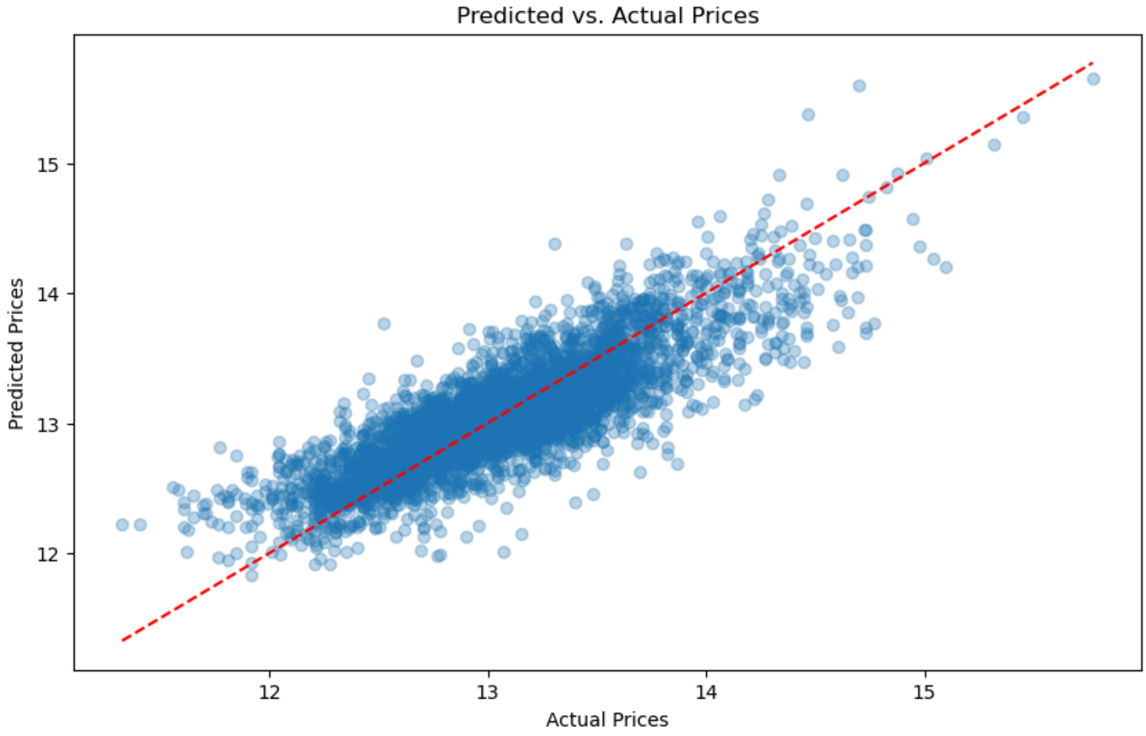
Error Magnitude: The MAE of 0.2 provides a clear understanding of the average prediction error. Given that MAE is in the same units as our target variable (log-transformed house prices), we can interpret this as the average deviation of our predictions from the actual values.

In [43]:
```
# Define the predictors and target variable
X = df_transformed_4[['sqft_living','grade' ,'lat','long']]
y = df_transformed_4['price_log']

# Add a constant to the model (intercept)
X = sm.add_constant(X)

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

# Print the summary
print(model.summary())
```

```
                          OLS Regression Results
======================================================================
==========
Dep. Variable:              price_log   R-squared:
0.708
Model:                            OLS   Adj. R-squared:
0.708
Method:                 Least Squares   F-statistic:
1.309e+04
Date:                Sun, 21 Jul 2024   Prob (F-statistic):
0.00
Time:                        20:44:33   Log-Likelihood:
-3496.0
No. Observations:               21596   AIC:
7002.
Df Residuals:                   21591   BIC:
7042.
Df Model:                           4
Covariance Type:            nonrobust
======================================================================
===========
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
const         -89.2467      1.781    -50.123      0.000     -92.737
-85.757
sqft_living     0.0002   3.29e-06     73.955      0.000       0.000
0.000
grade           0.1575      0.003     61.265      0.000       0.152
0.163
lat             1.4335      0.014    100.513      0.000       1.406
1.461
long           -0.2651      0.014    -18.465      0.000      -0.293
-0.237
======================================================================
==========
Omnibus:                      565.312   Durbin-Watson:
1.993
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
918.964
Skew:                           0.249   Prob(JB):
2.81e-200
Kurtosis:                       3.880   Cond. No.
2.09e+06
======================================================================
==========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors
is correctly specified.
[2] The condition number is large, 2.09e+06. This might indicate tha
t there are
strong multicollinearity or other numerical problems.
```

Visualize Predicted vs. Actual Prices

In [44]:
```
# Assuming y_test and y_pred are your actual and predicted prices
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.3)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], colo
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Predicted vs. Actual Prices")
plt.show()
```



Perform Residual Analysis

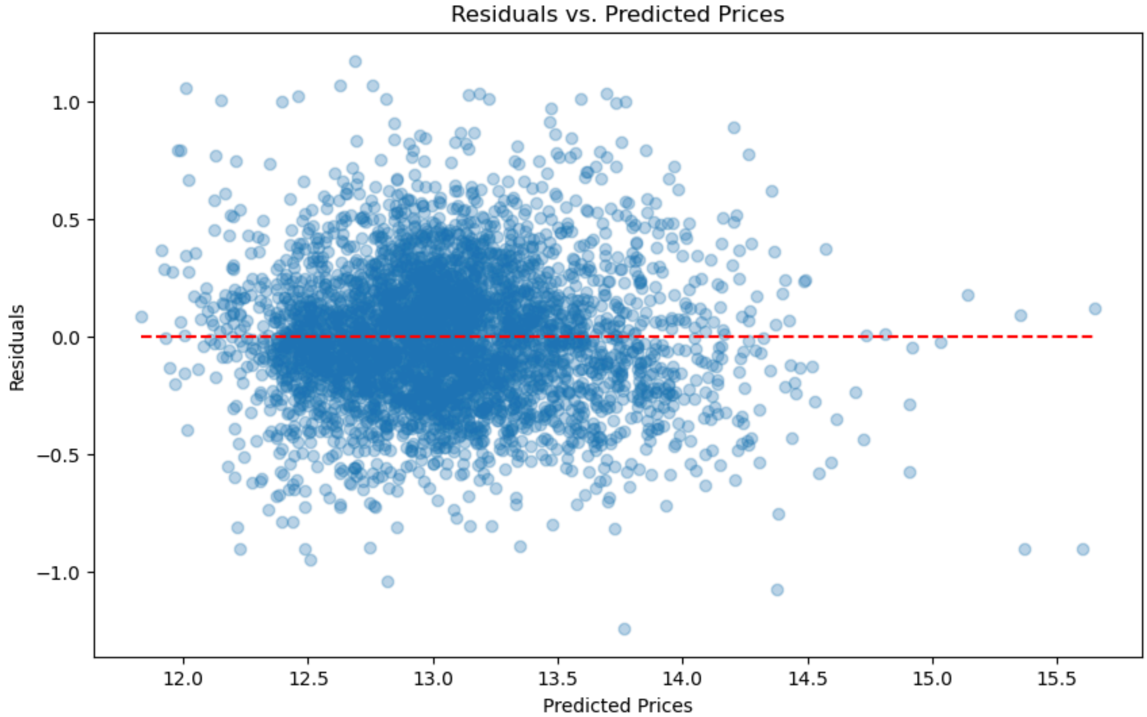
Residual analysis involves examining the residuals (differences between actual and predicted values). Residual plots and histograms can help identify systematic errors or biases.

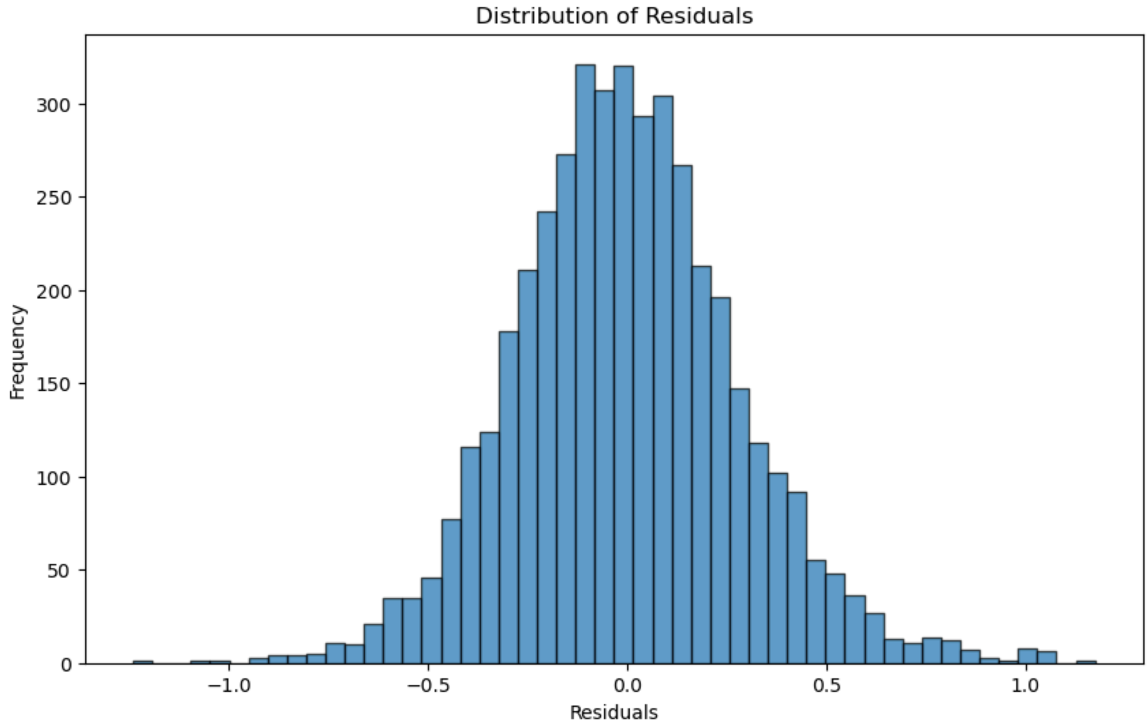
Residuals vs. Predicted Prices A residuals vs. predicted prices plot helps check for patterns. Ideally, residuals should be randomly distributed around zero.

Histogram of Residuals

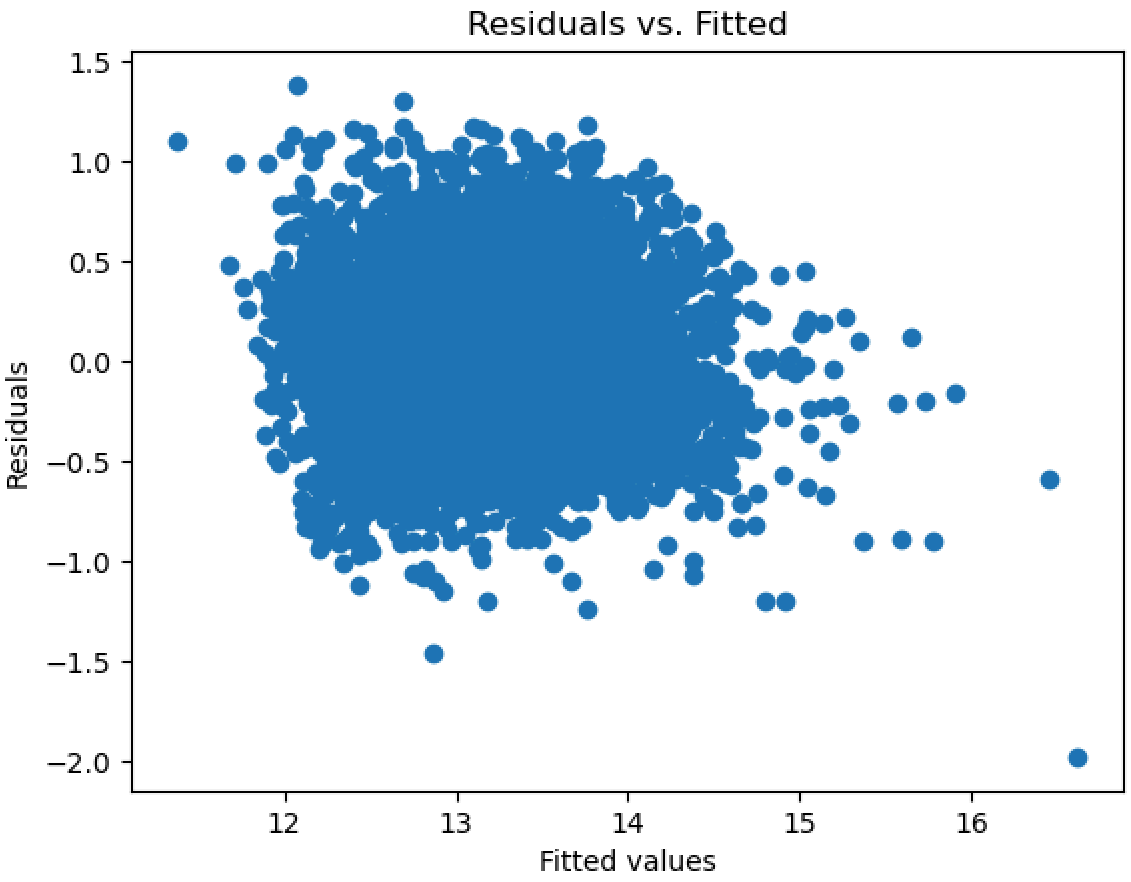
A histogram of residuals will help us check if they are normally distributed around zero.

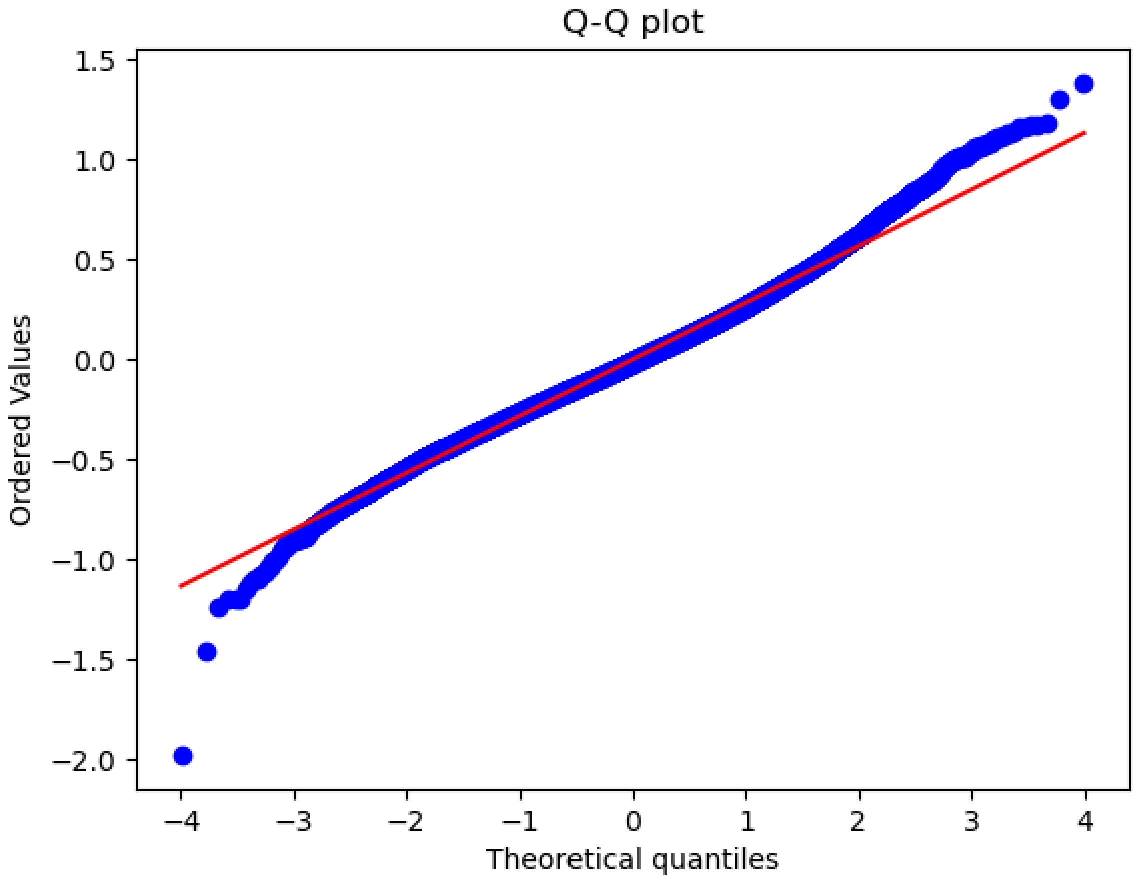
In [45]:
```
#Calculate residuals
residuals = y_test - y_pred

# Plot Residuals vs. Predicted Prices
plt.figure(figsize=(10, 6))
plt.scatter(y_pred, residuals, alpha=0.3)
plt.hlines(0, min(y_pred), max(y_pred), colors='red', linestyles='dasl
plt.xlabel("Predicted Prices")
plt.ylabel("Residuals")
plt.title("Residuals vs. Predicted Prices")
plt.show()

# Plot Histogram of Residuals
plt.figure(figsize=(10, 6))
plt.hist(residuals, bins=50, edgecolor='k', alpha=0.7)
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.title("Distribution of Residuals")
plt.show()
```




Distribution of Residuals
Frequency
Residuals
300
250
200
150
100
50
0
−1.0
−0.5
0.0
0.5
1.0

In [46]:
```
# Investigate if the residuals are normally distributed
import scipy.stats as stats
# Residuals vs. Fitted
plt.scatter(model.fittedvalues, model.resid)
plt.xlabel('Fitted values')
plt.ylabel('Residuals')
plt.title('Residuals vs. Fitted')
plt.show()

# Q-Q plot
stats.probplot(model.resid, dist="norm", plot=plt)
plt.title('Q-Q plot')
plt.show()
```





Conclusion:

The project aimed to:

1: Identify key features influencing housing prices in the region.

2: Provide a valuable Exploratory Data Analysis (EDA) for stakeholders such as homebuyers, sellers, real estate professionals, and policymakers to make informed decisions regarding property transactions and urban planning.

3: Develop a machine learning model to accurately predict housing prices based on property features, location, and market conditions.

Using the King County housing dataset, we examined the data, cleaned it of missing and NaN values, performed an analysis, and developed a model that predicts housing prices with 70% accuracy based on various factors.

Recommendations

Investment Strategy: Houses with larger living spaces, higher grades, and more bathrooms tend to be more expensive. Investors should focus on these features to maximize resale profits or find affordable options by considering these factors.

Market Insights: The EDA reveals that the King County housing market is significantly influenced by the total footage of living space. Stakeholders can use these insights for data-driven decisions in property transactions and urban planning.

Model Selection: The best model for predicting housing prices in King County is Model 4, which has an R-squared value of 0.7063 and a low Mean Absolute Error (MAE) of 0.2194. This model explains 70.63% of the variance in logarithmically transformed house prices and has the lowest prediction error, effectively capturing the mean and standard deviation of the transformed prices