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PRO REALTY REAL ESTATE INVESTOR

PROJECT OVERVIEW.

King County is located in the U.S. state of Washington. According to the 2020 census, it was the most populous county in Washington and the 13th-most populous in the United States. Given the King county's House Sales dataset, we undertook a research on behalf Pro Realty Real Estate Investors to find out the best performing metrics affecting house sale prices. With the use of Multiple linear regression analysis we are able to gain insights into the home sales market to help improve the home owners'/ investors' decision making when it comes to buying or investing in homes.

BUSINESS PROBLEM.

Pro Realty, a leading real estate firm, is poised for expansion and aspires to solidify its position as the premier real estate investor. To achieve this goal, Pro Realty recognizes the critical need to optimize its Return on Investment (ROI). The company aims to leverage the vast potential within the King County dataset to seeks strategic insights and data-driven solutions to enhance decision-making, identify lucrative investment opportunities, and ultimately maximize ROI. How can Pro Realty harness the power of the King County dataset to inform its expansion strategy, mitigate risks, and position itself as a dominant force in the real estate market.

STAKE HOLDER(PRO REALTY) OBJECTIVES.

1.Identify factors influencing house prices in King County.

2.Predict housing prices with high accuracy.

3.Make informed investment decisions by targetting properties with high potential returns.

4.Minimise risk by avoiding overpaying for properties.

5.Optimize portfolio diversification by investing in different neighbourhoods and property types.

1. Prepare kc_house_data.csv for analysis

include the relevant imports and load the data into a dataframe called df:

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline
import seaborn as sns
import mpl_toolkits
import statsmodels.api as sm
import calendar
import warnings
warnings.filterwarnings('ignore')
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score,mean_absolute_error
```

```
from sklearn.metrics import mean_squared_error, r2_score,mean_absolute_error
from sklearn import ensemble
from sklearn.preprocessing import scale
from sklearn.decomposition import PCA
```

In [2]:

```
df = pd.read_csv('kc_house_data.csv')
df.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	s
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	0	0	...	7	
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	0	0	...	7	
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	0	0	...	6	
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	0	0	...	7	
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	0	0	...	8	

5 rows × 21 columns

use df.describe to get a concise overview about data distribution within each column in our data.

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21613 non-null  int64
 1   date           21613 non-null  object
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64
 6   sqft_lot       21613 non-null  int64
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64
 9   view           21613 non-null  int64
 10  condition      21613 non-null  int64
```

```
 10  condition      21613 non-null  int64
 11  grade          21613 non-null  int64
 12  sqft_above     21613 non-null  int64
 13  sqft_basement  21613 non-null  int64
 14  yr_built       21613 non-null  int64
 15  yr_renovated   21613 non-null  int64
 16  zipcode        21613 non-null  int64
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64
 20  sqft_lot15     21613 non-null  int64
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

In [4]:

```
df['bathrooms'] = df['bathrooms'].astype(np.int64)
df['floors'] = df['floors'].astype(np.int64)
print(df.dtypes)
```

```
id                 int64
date              object
price            float64
bedrooms           int64
bathrooms          int64
sqft_living        int64
sqft_lot           int64
floors             int64
waterfront         int64
view               int64
condition          int64
grade              int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

In [5]:

```
df.head()
```

Out[5]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	s
0	7129300520	20141013T000000	221900.0	3	1	1180	5650	1	0	0	...	7	
1	6414100192	20141209T000000	538000.0	3	2	2570	7242	2	0	0	...	7	
2	5631500400	20150225T000000	180000.0	2	1	770	10000	1	0	0	...	6	
3	2487200875	20141209T000000	604000.0	4	3	1960	5000	1	0	0	...	7	
4	1954400510	20150218T000000	510000.0	3	2	1680	8080	1	0	0	...	8	

5 rows × 21 columns

In [6]:

```
df['date'] = pd.to_datetime(df['date'])
df['month'] = df['date'].apply(lambda r:r.month)
df['month'] = df['month'].apply(lambda x: calendar.month_abbr[x])
df.head()
```

Out[6]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	sqft_above	sqft_bas
0	7129300520	2014-10-13	221900.0	3	1	1180	5650	1	0	0	...	1180	
1	6414100192	2014-12-09	538000.0	3	2	2570	7242	2	0	0	...	2170	
2	5631500400	2015-02-25	180000.0	2	1	770	10000	1	0	0	...	770	
3	2487200875	2014-12-09	604000.0	4	3	1960	5000	1	0	0	...	1050	
4	1954400510	2015-02-18	510000.0	3	2	1680	8080	1	0	0	...	1680	

5 rows × 22 columns

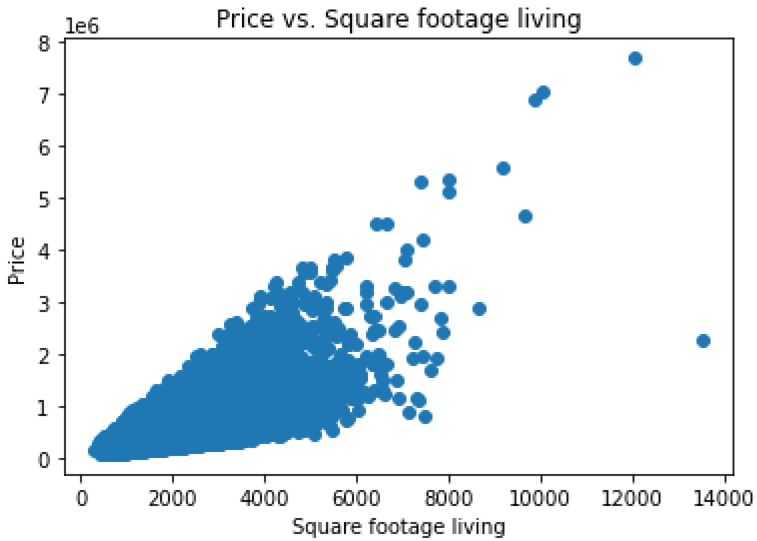
DATA ANALYSIS AND PREPARATION

1 How are the various variables presented in our dataset are affecting housing prices

i.How are the various variables presented in our dataset are affecting housing prices.

In [7]:

```
# Analyze relationships between features (e.g., price vs. sqft_living)
plt.scatter(df['sqft_living'], df['price'])
plt.xlabel('Square footage living')
plt.ylabel('Price')
plt.title('Price vs. Square footage living')
plt.savefig('price_vs_Square_footage_living')
plt.show()
```

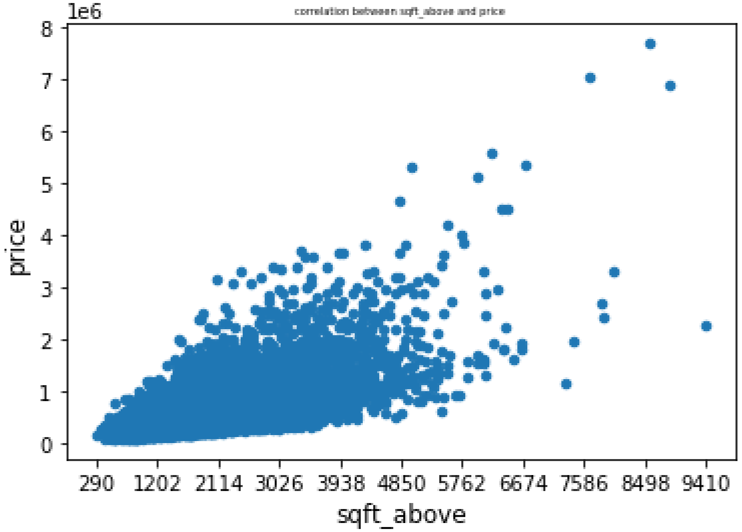


this graph shows there is a positive linear correlation between squarefoot living and price which in turn makes it a very good property for predicing house sale prices.

In [8]:

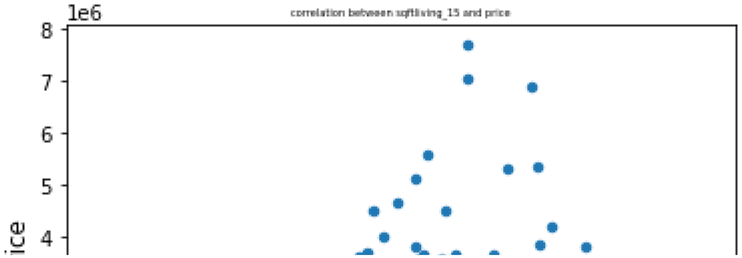
```
count, bin_edges = np.histogram(df['sqft_above'], bins=10)
df.plot(
    kind='scatter',
    x='sqft_above',
    y='price',
        xticks=bin_edges
        )
plt.title('correlation between sqft_above and price ', fontsize=5)
plt.xlabel('sqft_above', fontsize=12)
plt.ylabel('price', fontsize=12)
```

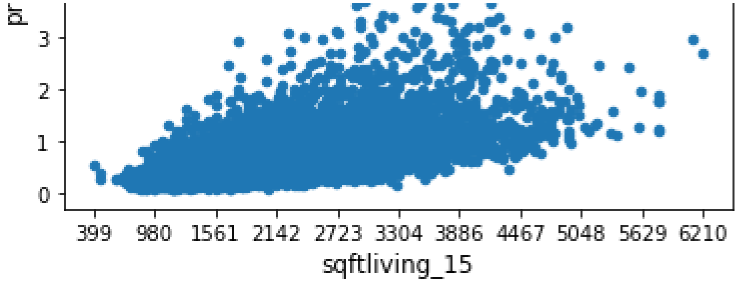
```
plt.savefig('correlation_between_sqft_above_and_price')
plt.show()
```



In [9]:

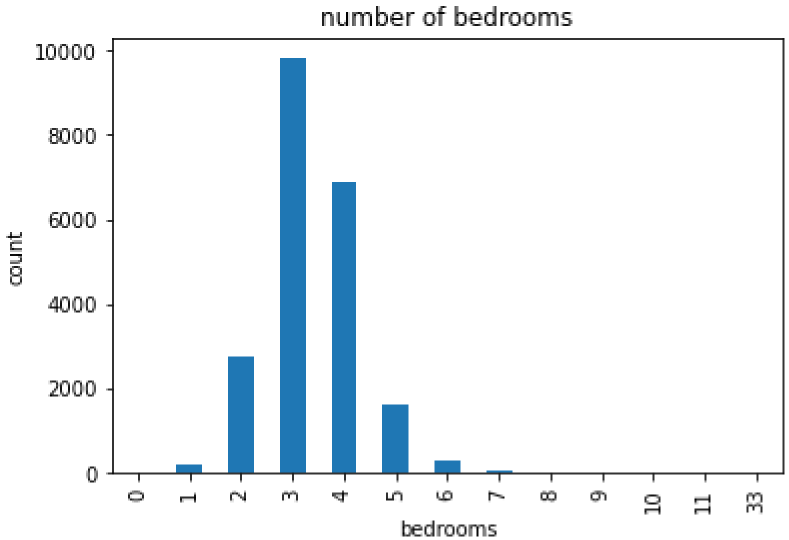
```
count, bin_edges = np.histogram(df['sqft_living15'], bins=10)
df.plot(
    kind='scatter',
    x='sqft_living15',
    y='price',
        xticks=bin_edges
        )
plt.title('correlation between sqftliving_15 and price', fontsize=5)
plt.xlabel('sqftliving_15', fontsize=12)
plt.ylabel('price', fontsize=12)

plt.savefig('correlation_between_sqftliving_15_and_price')
plt.show()
```





In [10]:

```
df['bedrooms'].value_counts().sort_values(ascending=True).reindex([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 33]).p

plt.title('number of bedrooms')
plt.xlabel('bedrooms')
plt.ylabel('count')
sns.despine
plt.savefig('number_of_bedrooms')
```

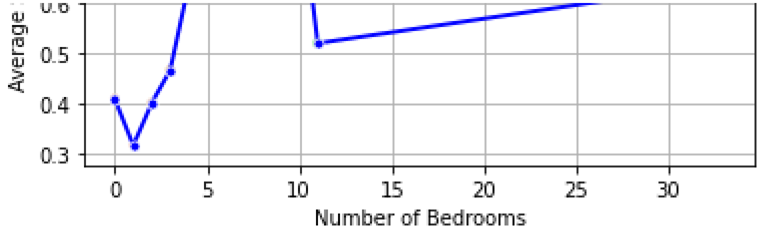


As one can observe from the above visualization 3 bedroom houses are the most popular among home buyers when looking for homes to buy followed by 4 bedroom houses.

In [11]:

```
# Group data by bedrooms and calculate average price
avg_price_by_bedrooms = df.groupby("bedrooms")["price"].mean().reset_index()
```

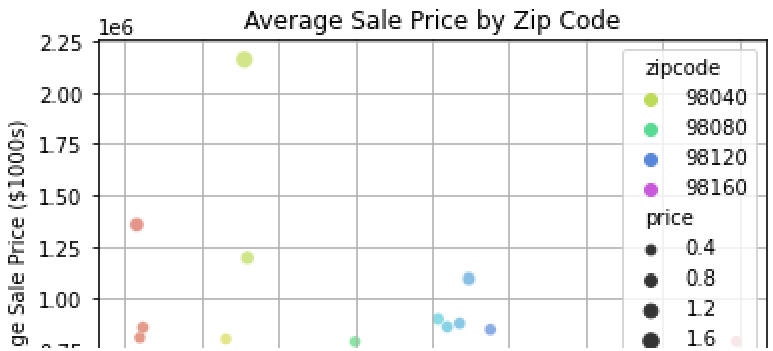
```
# Create scatter plot
sns.scatterplot(
    x="bedrooms",
    y="price",
    data=avg_price_by_bedrooms,
    hue="bedrooms",
    palette="hls",
    size="price",
    alpha=0.7,
    legend=False,
)

# Add smoother line
sns.lineplot(
    x="bedrooms",
    y="price",
    data=avg_price_by_bedrooms,
    color="blue",
    linewidth=2,
    marker="o",
    markersize=5,
)

# Customize plot
plt.title("Average Sale Price by Number of Bedrooms")
plt.xlabel("Number of Bedrooms")
plt.ylabel("Average Sale Price ($1000s)")
plt.grid(True)

# Show plot

plt.savefig('Average_Sale_Price_by_Number_of_Bedrooms')
plt.show()
```

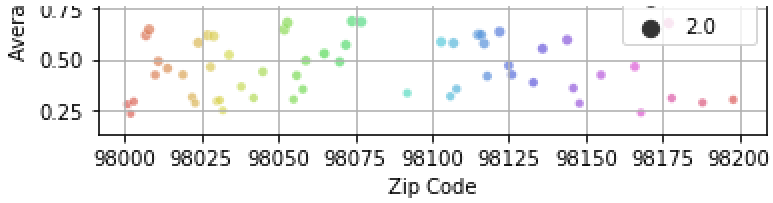


The visualization above shows the number of bedrooms can be a significant factor influencing housing prices, but it's important to consider the context and other factors at play. We shall proceed to Analyze additional variables like location,year built,square footage etc. these can provide a much better understanding of the relationship between bedrooms and price in a specific mark.

In [12]:

```
avg_price_by_zip = df.groupby("zipcode")["price"].mean().reset_index()

sns.scatterplot(
    x="zipcode",
    y="price",
    data=avg_price_by_zip,
    size="price",
    alpha=0.7,
    hue="zipcode",
    palette="hls",
)
plt.title("Average Sale Price by Zip Code")
plt.xlabel("Zip Code")
plt.ylabel("Average Sale Price ($1000s)")
plt.grid(True)

plt.savefig('Average_Sale_Price_by_Zip_Code')
plt.show()
```

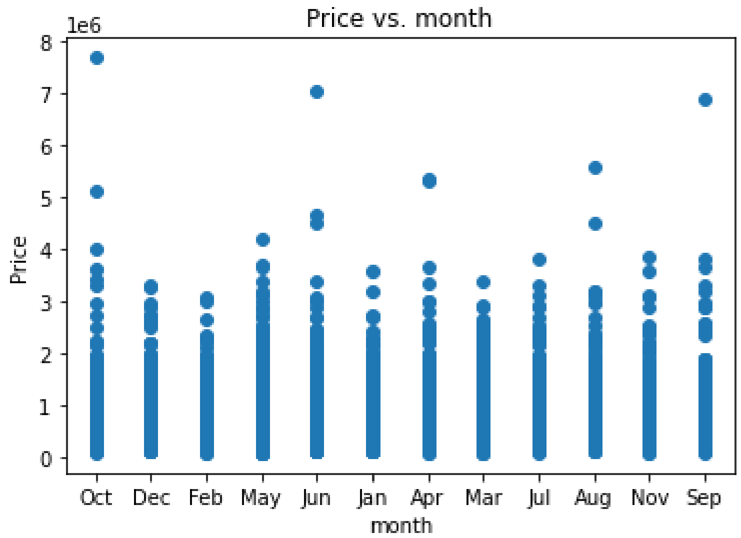




Different areas have varying factors like desirability, proximity to amenities, and school quality affecting house prices.The scatter plot doesn't show a rich correlation between price and zipcode so will drop this column.

In [13]:

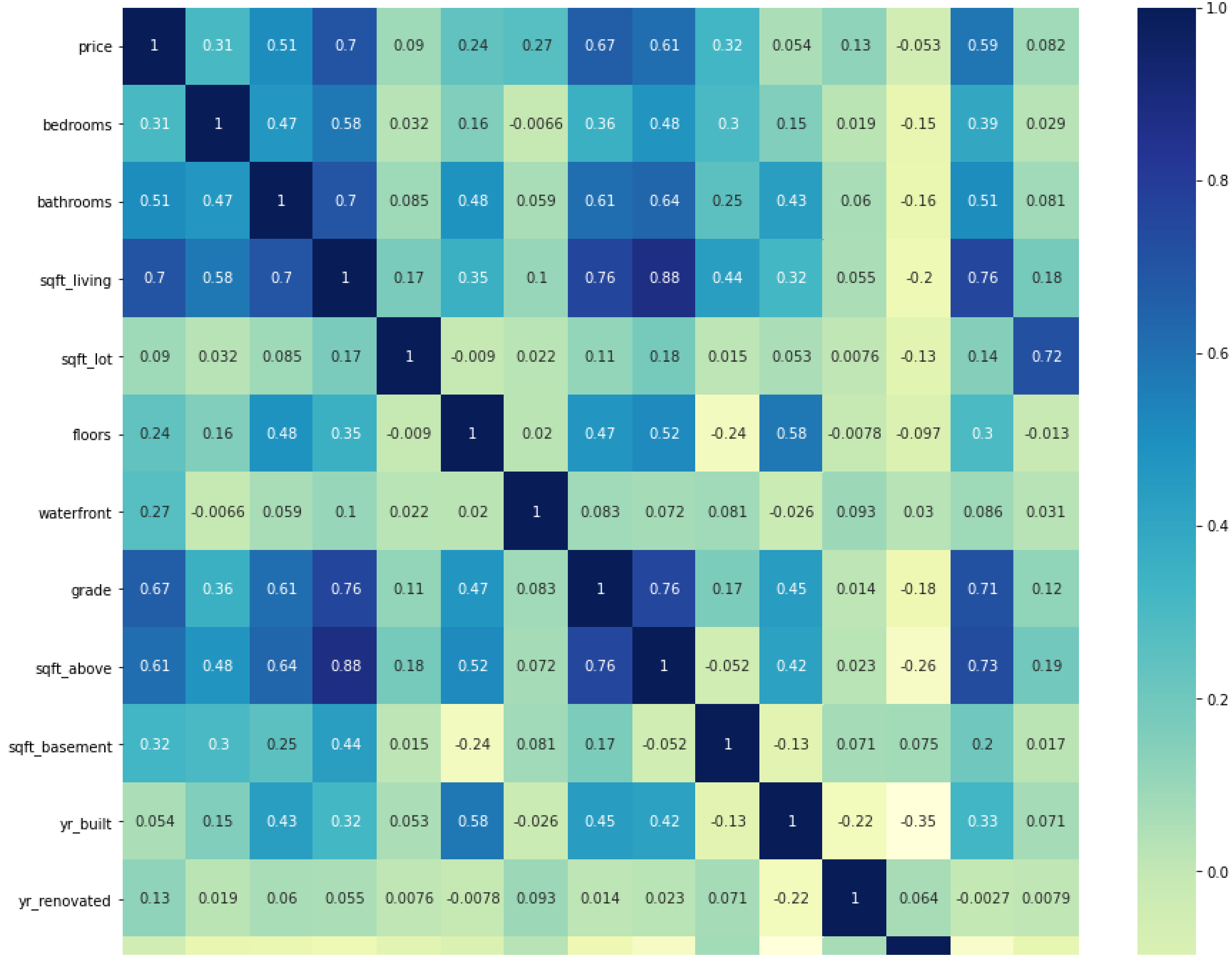
```
plt.scatter(df['month'], df['price'])
plt.xlabel('month')
plt.ylabel('Price')
plt.title('Price vs. month')

plt.savefig('Price_vs_month')
plt.show()
```

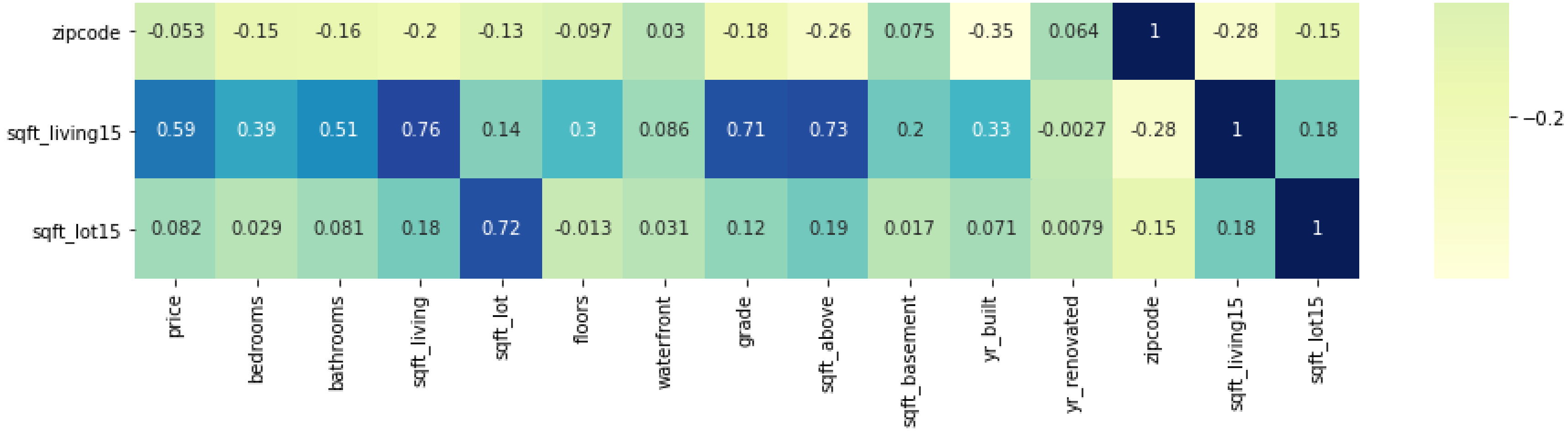


In [14]:

```
df=df[['price', 'bedrooms', 'bathrooms', 'sqft_living',
    'sqft_lot', 'floors', 'waterfront', 'grade',
    'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
     'sqft_living15', 'sqft_lot15']]
fig, ax = plt.subplots(figsize=(15,15))
sns.heatmap(df.corr(), cmap = 'YlGnBu', annot=True, ax=ax)
```

```
sns.heatmap(df.corr(),cmap = 'YlGnBu',annot=True,ax=ax)
plt.savefig('correlation_heatmap')
```





Key Points:

The numbers represent correlation coefficients, indicating the strength and relationships between variables. These range from -1 (strong negative correlation) to 1 (strong positive correlation), with 0 indicating no correlation. Positive coefficients suggest variables tend to increase or decrease together, while negative coefficients suggest opposite trends.

Strongest Positive Correlations with Price:

.sqft_living (0.702): Suggests a strong positive relationship between house price and living space, indicating larger homes tend to have higher prices.

.grade (0.667): Higher-grade homes (likely reflecting better quality and features) generally have higher prices. .bathrooms (0.525): Suggests homes with more bathrooms tend to have higher prices.

.sqft_above (0.606): This reflects that above-ground living area is a significant factor influencing price.

Moderate Positive Correlations with Price:

.sqft_living15 (0.585): This suggests living space in the surrounding area is also somewhat correlated with price.

.view (0.397): Homes with better views tend to have higher prices.

.bedrooms (0.308): More bedrooms are associated with higher prices, but the correlation is less strong than other factors.

Weak or No Correlation with Price:

Weak or No Correlation with Price:

.id: the house ID is not informative for price prediction.

.sqft_lot (0.089): Lot size has a very weak correlation with price.

.yr_built (0.054): Year built has minimal correlation with price.

In [15]:

```
df.columns
```

Out[15]:

```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'grade', 'sqft_above', 'sqft_basement', 'yr_built',
       'yr_renovated', 'zipcode', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [16]:

```
df = pd.read_csv('kc_house_data.csv')
# Explore categorical features
print(df['waterfront'].value_counts())
print(df['condition'].value_counts())
print(df['grade'].value_counts())
```

```
0    21450
1      163
Name: waterfront, dtype: int64
3    14031
4     5679
5     1701
2      172
1       30
Name: condition, dtype: int64
7     8981
8     6068
9     2615
6     2038
10    1134
11     399
5      242
12      90
4       29
13      13
3        3
1        1
```

```
Name: grade, dtype: int64
```

Waterfront Access: Waterfront access is relatively rare, suggesting it might be a significant factor influencing house prices.

Condition Distribution: Houses are mostly in average or good condition, with fewer in very good or poor condition.

Grade Distribution: Grades are more evenly distributed, suggesting a wider range of quality levels in the housing market.

In [17]:

```
df = pd.read_csv('kc_house_data.csv')
# Select the categorical features to encode
categorical_features = ['waterfront']

# One-hot encode the features
df = pd.get_dummies(df, columns=categorical_features, drop_first=True)

# Print the encoded DataFrame to see the new columns
df.head()
```

Out[17]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	view	condition	...	sqft_abov
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	0	3	...	118
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	0	3	...	217
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	0	3	...	77
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	0	5	...	105
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	0	3	...	168

5 rows × 21 columns

In [18]:

```
# Specify columns to drop as a list
columns_to_drop = ['date', 'view', 'sqft_basement', 'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_living15',

# Drop the columns
df = df.drop(columns_to_drop, axis=1)

# Verify the updated DataFrame
print(df.head())
print(df.columns)
```

```
           id     price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  \
0  7129300520  221900.0         3       1.00         1180      5650     1.0
1  6414100192  538000.0         3       2.25         2570      7242     2.0
2  5631500400  180000.0         2       1.00          770     10000     1.0
3  2487200875  604000.0         4       3.00         1960      5000     1.0
4  1954400510  510000.0         3       2.00         1680      8080     1.0

   condition  grade  sqft_above  yr_built  waterfront_1
0          3      7        1180      1955             0
1          3      7        2170      1951             0
2          3      6         770      1933             0
3          5      7        1050      1965             0
4          3      8        1680      1987             0
Index(['id', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
       'floors', 'condition', 'grade', 'sqft_above', 'yr_built',
       'waterfront_1'],
      dtype='object')
```

MODEL BUILDING AND PREDICTION

SIMPLE LINEAR REGRESSION

In [19]:

```
y = df['price']
features = ['sqft_living']
# Define features
X = df[features]  # Extract feature matrix

X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2, random_state=0)  # Split data

model = LinearRegression(fit_intercept=True)  # Create model instance
model.fit(X_train, y_train)  # Train the model

preds = model.predict(X_valid)  # Make predictions on validation set
```

In [20]:

```
mse = mean_squared_error(y_valid, preds)
r2 = r2_score(y_valid, preds)
# Number of observations
n = len(y_valid)

# Number of features (assuming X_valid has features)
```

```
p = X_valid.shape[1]

# Calculate Adjusted R-squared
adjusted_r2 = 1 - (1 - r2) * (n - 1) / (n - p - 1)

# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(y_valid, preds)

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)
print("Mean squared error:", mse)
print("R-squared:", r2)
print("Adjusted R-squared:", adjusted_r2)
print("Mean Absolute Error:", mae)
print("Root Mean Squared Error:", rmse)
```

```
Mean squared error: 61940787124.624756
R-squared: 0.4791577237265374
Adjusted R-squared: 0.47903718628699254
Mean Absolute Error: 170780.9262814558
Root Mean Squared Error: 248879.06124185046
```

MULTIPLE LINEAR REGRESSION

Correlation Analysis: referring to the correlation heatmap done earlier.Check the correlation between each feature and the target variable. Features with higher absolute correlation values are generally more influential for a regression model.

In [21]:

```
correlation_matrix = df.corr()
correlation_with_price = correlation_matrix['price'].abs().sort_values(ascending=False)
print(correlation_with_price)
```

```
price           1.000000
sqft_living     0.702035
grade           0.667434
sqft_above      0.605567
bathrooms       0.525138
bedrooms        0.308350
waterfront_1    0.266369
floors          0.256794
sqft_lot        0.089661
yr_built        0.054012
condition       0.036362
```

```
condition        0.036361
id               0.016762
Name: price, dtype: float64
```

In [22]:

```
y = df['price']
features = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
       'floors', 'condition', 'grade', 'sqft_above', 'yr_built', 'waterfront_1']
# Define features
X = df[features]  # Extract feature matrix

X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2, random_state=0)  # Split data

model = LinearRegression(fit_intercept=True)  # Create model instance
model.fit(X_train, y_train) # Train the model

preds = model.predict(X_valid)
```

In [23]:

```
mse = mean_squared_error(y_valid, preds)
r2 = r2_score(y_valid, preds)
# Number of observations
n = len(y_valid)

# Number of features (assuming X_valid has features)
p = X_valid.shape[1]

# Calculate Adjusted R-squared
adjusted_r2 = 1 - (1 - r2) * (n - 1) / (n - p - 1)

# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(y_valid, preds)

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)
print("Mean squared error:", mse)
print("R-squared:", r2)
print("Adjusted R-squared:", adjusted_r2)
print("Mean Absolute Error:", mae)
print("Root Mean Squared Error:", rmse)
```

```
Mean squared error: 43056428188.69171
R-squared: 0.6379508703871847
Adjusted R-squared: 0.6371112388250029
Mean Absolute Error: 137762.189130765
```

```
Root Mean Squared Error: 207500.42936989723
```

Improved Performance: The multiple linear regression model outperforms the simple model in terms of both MSE and R-squared. The model now explains about 63.8% of the variance in house prices, indicating a stronger prediction model compared to the previous version. The lower MSE and RMSE values suggest improved accuracy in predicting house prices. The adjusted R-squared indicates that the model's performance remains robust even after considering the number of features.

Compare the actual values to predicted values

In [29]:

```
y_train.head()
```

Out[29]:

```
5268     495000.0
16909    635000.0
16123    382500.0
12181    382500.0
12617    670000.0
Name: price, dtype: float64
```

In [25]:

```
preds
```

Out[25]:

```
array([ 291161.35310854, 1525444.05841141,  527889.65227109, ...,
        300614.02570025,  236702.30472415,  392030.34268276])
```

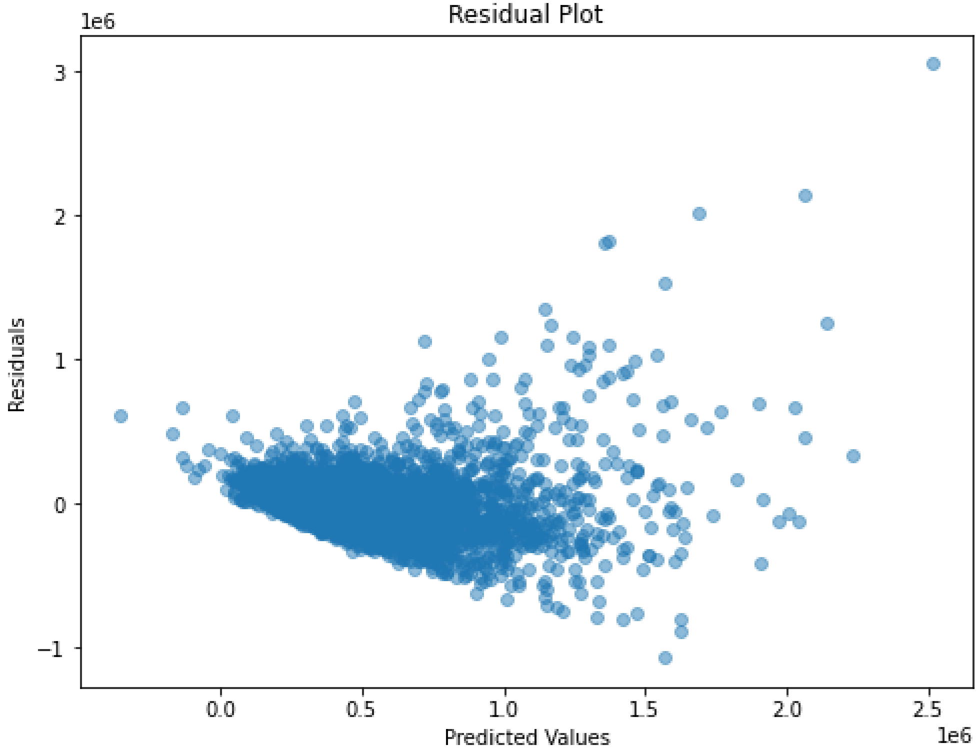
RESIDUAL CALCULATIONS.

we now need to measure how much the model's predictions vary from the true values.Doing this offers valuable insights into model performance and potential areas for improvement. It can also help identify patterns in errors, suggesting model refinements.

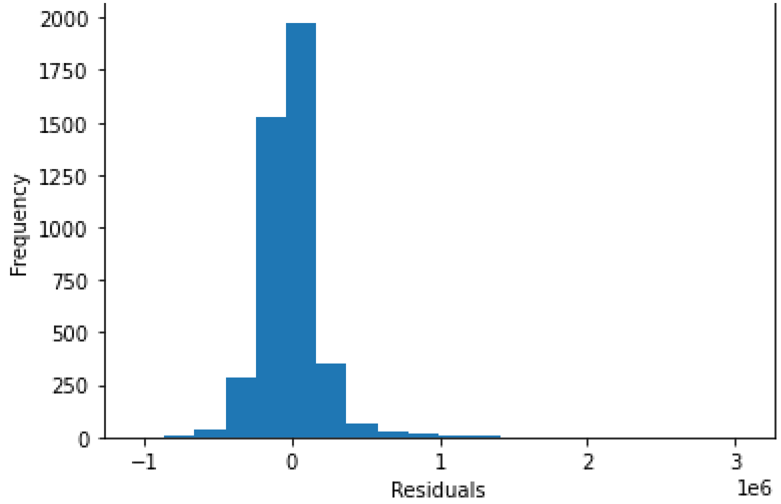
In [26]:

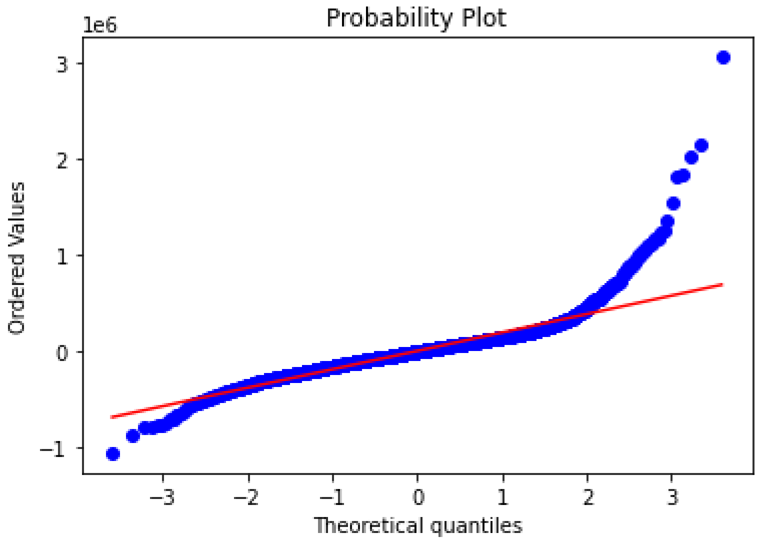
```
import matplotlib.pyplot as plt
from scipy.stats import probplot

# Calculate residuals
residuals = y_valid - preds

# Residual plot
plt.figure(figsize=(8, 6))
plt.scatter(preds, residuals, alpha=0.5)
plt.xlabel("Predicted Values")
plt.ylabel("Residuals")
```

```
plt.ylabel("Residuals")
plt.title("Residual Plot")

plt.savefig('Residual_Plot')
plt.show()
# Histogram of residuals
plt.hist(residuals, bins=20)
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.title("Histogram of Residuals")

plt.savefig('Histogram_of_Residuals')
plt.show()
# Normal QQ plot
probplot(residuals, plot=plt)

plt.savefig('qq_plot')
plt.show()
```



Histogram of Residuals





In [27]:
```
#linear regression model
coefficients = model.coef_
intercept = model.intercept_

# Print coefficients and intercept
print("Intercept:", intercept)
print("Coefficients:", dict(zip(features, coefficients)))
```

```
Intercept: 6594806.173468306
```

```
Coefficients: {'bedrooms': -40534.7460891066, 'bathrooms': 45644.2546254829, 'sqft_living': 193.6144819536221, 's
qft_lot': -0.22665732852328802, 'floors': 28276.95990945274, 'condition': 17487.65839016383, 'grade': 128293.3691
5138796, 'sqft_above': -16.310839493711683, 'yr_built': -3791.67552436416, 'waterfront_1': 740707.4898833618}
```

Bedrooms: For each additional bedroom, the predicted price decreases by approximately 40,534.

Bathrooms:For each additional bathroom, the predicted price increases by approximately 45,644.

Sqft_living: For each additional square foot of living space, the predicted price increases by approximately 193.61.

Sqft_lot: For each additional square foot of the lot, the predicted price decreases by approximately 0.23 (note: the coefficient is small, suggesting this feature may not have a strong impact).

Floors: For each additional floor, the predicted price increases by approximately 28,277.

Condition: For each unit increase in condition, the predicted price increases by approximately 17,488.

Grade: For each increase in the grade, the predicted price increases by approximately 128,293.

Sqft_above: For each additional square foot above ground, the predicted price decreases by approximately 16.31.

Yr_built: For each additional year of the building's age, the predicted price decreases by approximately 3,791.68.

Waterfront_1: If the property has waterfront (coded as 1), the predicted price increases by approximately 740,707.

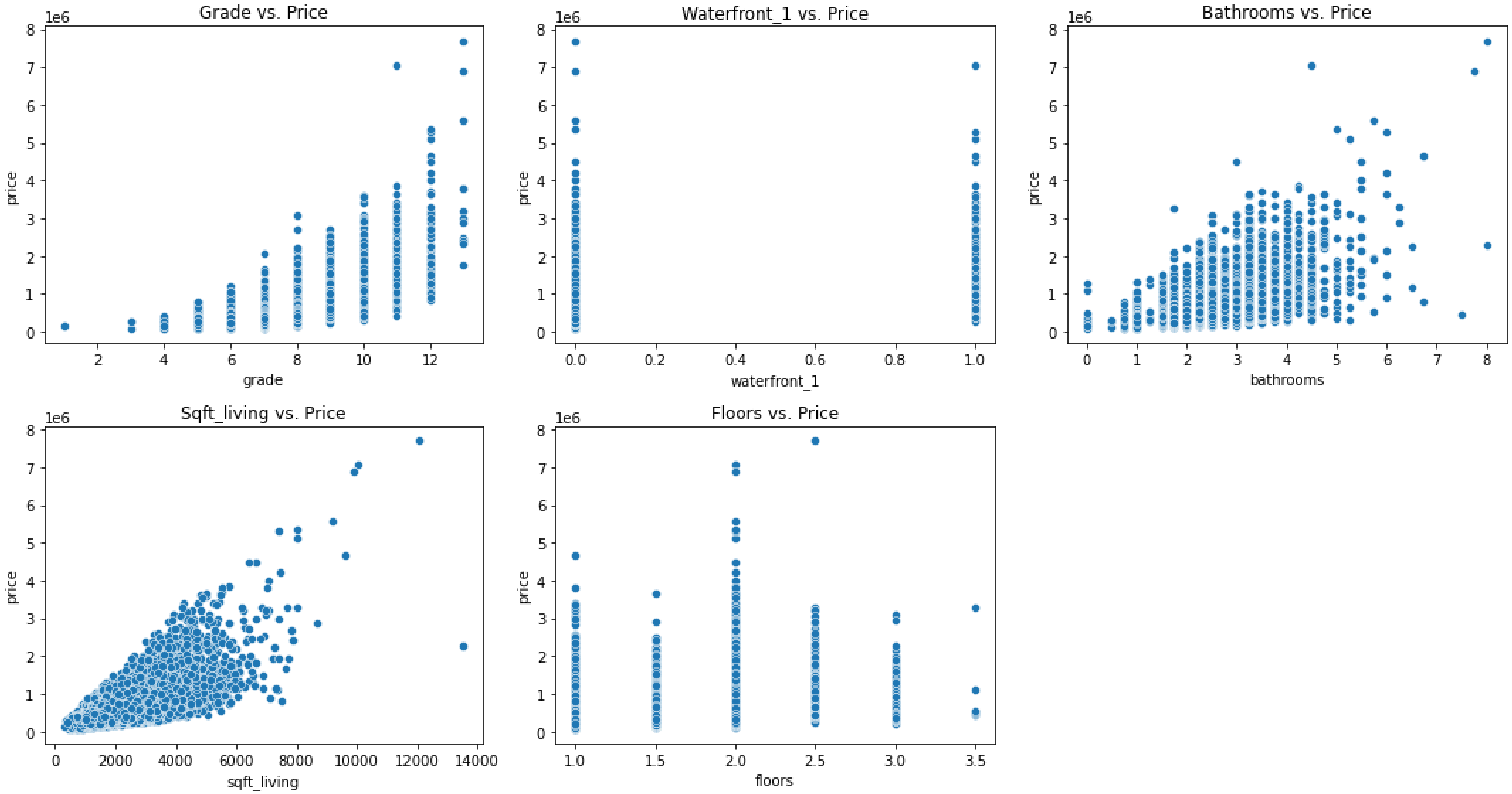
From the above analysis the following are our key features;

```
Grade
Waterfront
Bathrooms
sqft_living
floors
```

In [28]:

```python
# Key features
key_features = ['grade', 'waterfront_1', 'bathrooms', 'sqft_living', 'floors']

# Plotting relationships with the target variable
plt.figure(figsize=(15, 8))
for i, feature in enumerate(key_features, 1):
    plt.subplot(2, 3, i)
```

```
    sns.scatterplot(x=df[feature], y=df['price'])
    plt.title(f'{feature.capitalize()} vs. Price')

plt.tight_layout()

plt.savefig('realtionship_variable_graph')
plt.show()
```



Interpretation: Grade: As the grade increases, the price tends to increase, indicating a positive relationship.

Waterfront: Properties with waterfront (coded as 1) tend to have significantly higher prices.

Bathrooms: The price tends to increase with the number of bathrooms.

Sqft_living: A positive relationship between square footage of living space and price.

Floors: Properties with more floors tend to have higher prices.

RECOMMENDATIONS

Based on the above performed analysis Pro Realty should consider the following key features as having a positive impact on predicted prices therefore potentially increasing the companys' ROI(return on investment)

Waterfront Properties: As observed the properties with waterfront according to our model are seen to have significantly higher prices. Pro Realty should consider marketing strategies that highlight and capitalize on this desirable feature.

Grade: is defined as the assesment of the overall quality of construction build.A higher grade value indicates good quality finishes and construction.Pro Realty should focus on promoting and showcasing properties with higher grades to attract buyers looking for well-constructed and aesthetically appealing homes. This could involve detailed property descriptions, professional photography, and virtual tours to highlight the quality of construction.

Bathrooms: Recognizing the importance of functionality and convenience, Pro Realty should emphasize properties with multiple bathrooms. This feature caters to the needs of larger families and appeals to a broader range of potential buyers. Marketing materials should highlight the convenience and versatility offered by properties with multiple bathrooms.

sqft_living: This is the total square footage of the living space.The positive relationship aligns with the common expectation that larger homes provide more space and amenities catering to various preferences of potential buyers.

Floors: The positve relationship between floors and price suggests that properties with more floors generate higher sale prices.Pro Realty should consider highlighting and promoting multi-floor properties, emphasizing the potential for additional living space and architectural appeal. This feature may attract buyers seeking a unique and multi-level living experience.

by Incorporating these recommendations into Pro Realty's marketing and sales strategies can enhance the appeal of properties, attract a broader range of potential buyers, and potentially lead to higher returns on investment.

CONCLUSION

The multiple linear regression model between the various features and price provides an insight into how changes in feature in turn affects changes in predicted prices,However we should acknowledge the limitations of the model.While it captures linear relationships , it may not capture complex interactions between features.So Pro Realty should continue the refinement of the model by exploring additional features in the subsequent years as well as adopting Advanced techniques to enhance their ability to aaccurately predict house prices.