Final Project Submission

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Students pace: Part time

Scheduled project review date/time:

Instructor name: Samuel Jane

Blog post URL:

Optimizing Real Estate Pricing Strategy for Maximized Profits

```
from IPython.display import Image, display
image_path = '/content/Real estate.jpg'
display(Image(filename=image_path))
```

Overview:

Premiere Property Group, a prominent real estate agency in King County, has experienced a decline in profits over the past three years. To address this challenge, the agency has sought analytical expertise to devise a strategic pricing approach aimed at optimizing profits.

This initiative involves a deep dive into the vast array of housing data from King County, focusing on pivotal factors that influence house prices. Central to this analysis are variables such as the age of properties, their condition and ratings within different locations, the presence of views and waterfronts, and the impact of seasonal trends on sales.

The ultimate goal is to establish a comprehensive pricing strategy that not only maximizes profits for Premiere Property Group but also adapts to the fluctuating dynamics of the King County real estate market.

General Objective

To develop a comprehensive and data-driven pricing strategy that maximizes profitability for Premiere Property Group by thoroughly analyzing various factors influencing house prices in King County.

This general objective encompasses the overarching aim of the project, focusing on leveraging data analysis to enhance the agency's pricing approach in response to the recent decline in profits.

Specific Objectives

Age and Price Analysis: Determine the impact of a house's age (year built) on its selling price and identify any significant patterns or trends that can be utilized in pricing strategies.

Condition/Grade and Location Impact: Assess the correlation between the condition or rating of a house and its sales price, especially considering the property's location, to understand how these factors influence valuation.

Seasonal Pricing Trends: Investigate if there are seasonal variations in house prices, particularly examining if houses sold in winter have different pricing dynamics compared to other seasons, and how this knowledge can be applied strategically.

Effect of Views and Waterfront Accessibility: Quantify the extent to which views and waterfront accessibility influence property pricing, and determine the value addition of these features to the overall property valuation.

These specific objectives are designed to address each of the research questions in detail, providing a structured approach to understanding the key drivers of house prices in King County. This approach will enable Premiere Property Group to make informed, data-backed decisions in their pricing strategies.

Data

Utilizing the King County Housing Data Set, which encompasses details such as house size, location, condition, and various features, this project endeavors to construct an advanced multiple regression model. The primary objective is to develop a predictive model that can accurately estimate a house's price by incorporating the key factors. The emphasis is on optimizing the model's precision to enable effective predictions in the dynamic real estate landscape of King County.

Column Names and descriptions for King County Data Set

- **id** - unique identified for a house
- **date** - Date house was sold
- **price** - Price is prediction target
- **bedrooms** - Number of Bedrooms/House
- **bathrooms** - Number of bathrooms/bedrooms
- **sqft_living** - square footage of the home
- **sqft_lot** - square footage of the lot
- **floors** - Total 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

Previewing the Data

```
#load necessary libraries
import numpy as np
import pandas as pd
import seaborn as sns
import markdown
import matplotlib.pyplot as plt
%matplotlib inline
import geopandas as gpd
import scipy.stats as stats
import statsmodels.formula.api as smf
import statsmodels.stats.api as sms
import statsmodels.api as sm
from statsmodels.formula.api import ols
from sklearn import datasets, linear_model
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn import metrics
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error, make_scorer
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
```

```
#Load and preview the data
df = pd.read_csv('/content/kc_house_data.csv')
df.head()
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfr
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	N
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

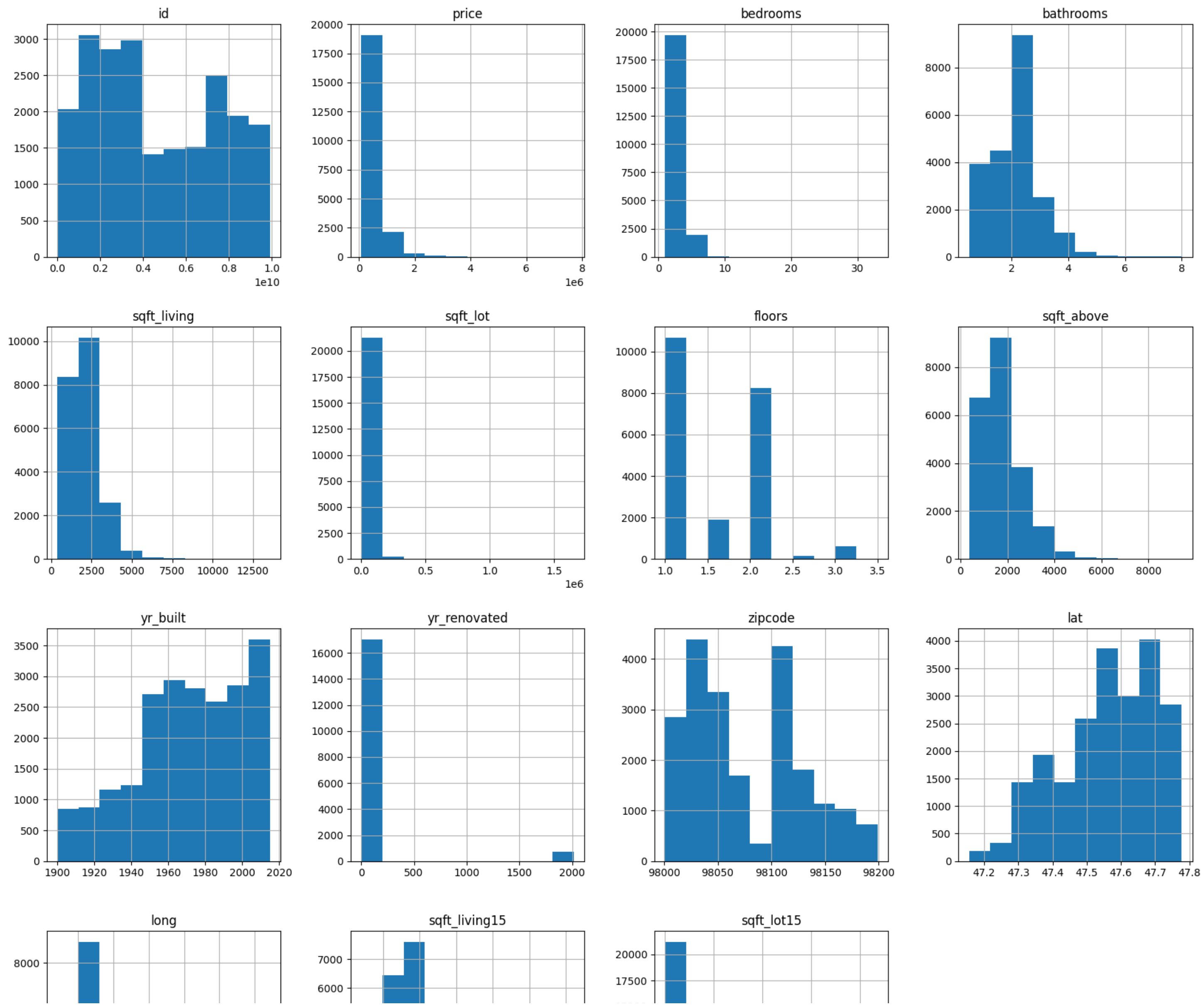
```
df.info()
```

```
<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
```

Data Cleanup and Feature Engineering

```
#Summary of features before clean up

df.hist(figsize=(20,20));
```



```
#Finding the number of null values in the data frame
df.isna().sum()

    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


#1. Check for counts of unique values in waterfront
df['waterfront'].value_counts()

    NO     19075
    YES      146
    Name: waterfront, dtype: int64


#2. Fill in the missing values with No and convert to binary

df['waterfront'] = df['waterfront'].fillna('NO')
df['waterfront'] = df['waterfront'].map({'YES': 1, 'NO': 0})

#3. Check if code was responsive

df['waterfront'].value_counts()

    0    21451
    1      146
    Name: waterfront, dtype: int64


#4. Check for counts of unique values in view
df['view'].value_counts()

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

```
#5. Fill the missing values with None and check if code was responsive

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

df['view'].value_counts()

     NONE         19485
     AVERAGE        957
     GOOD           508
     FAIR           330
     EXCELLENT      317
     Name: view, dtype: int64


#6. Check for counts of unique values in year renovated
df['yr_renovated'].value_counts()

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


#7. Fill 0 in missing values of the year renovated
df['yr_renovated'].fillna(0, inplace=True)


#8. To check the number of houses sold multiple times in the period under review
df['id'].value_counts()

     795000620     3
     8910500150    2
     7409700215    2
     1995200200    2
     9211500620    2
                  ..
     3649100387    1
     2767603649    1
     1446403617    1
     5602000275    1
     1523300157    1
     Name: id, Length: 21420, dtype: int64


#9. Convert View, condition and grade into representative numbers and replace question mark in sq f
df['view'] = df['view'].map({'NONE': 1,'FAIR': 2,'AVERAGE': 3,'GOOD': 4,'EXCELLENT': 5}).astype(flo
df['condition'] = df['condition'].map({'Poor': 1,'Fair': 2,'Average': 3,'Good': 4,'Very Good': 5}).
df['grade'] = df['grade'].map({'3 Poor': 1,'4 Low': 2,'5 Fair': 3,'6 Low Average': 4,'7 Average': 5
df['sqft_basement'] = df['sqft_basement'].replace('?', 0).astype(float)


df.head()
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfr
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

```
df.shape
```

```
(21597, 21)
```

```
df.isna().sum()
```

```
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
```

```
df.head()
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfr
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

```
df.duplicated().value_counts()
```

```
False    21597
dtype: int64
```

Feature Engineering

```
# create a new column 'Sale_Number' based on the count of values in 'id' column
Sales_in_df = df['id'].value_counts()
df['Sale_Number'] = df['id'].map(Sales_in_df)

# Converting 'date' column to datetime
df['date'] = pd.to_datetime(df['date'])

# Calculating age of the house
df['age_of_house'] = df['date'].dt.year - df['yr_built']

# Calculating years since renovation (handling houses that were never renovated)
df['years_since_renovation'] = df.apply(
    lambda row: row['date'].year - row['yr_renovated'] if row['yr_renovated'] != 0 else 0,
    axis=1)

# Calculating price per square foot
df['price_per_sqft'] = (df['price'] / df['sqft_living']).round(2)

# Calculating lot utilization ratio
df['lot_utilization'] = (df['sqft_living'] / df['sqft_lot']).round(2)

# Calculating neighborhood average price
neighborhood_avg_price = df.groupby('zipcode')['price'].mean().round(2).rename('neighborhood_avg_pr
df = df.join(neighborhood_avg_price, on='zipcode')

# Combining condition and grade scores
df['grade_score'] = df['condition'] + df['grade']

#Create a Season column and populate it as Spring, Summer, Fall, Winter
def get_season(month):
    if 3 <= month <= 5:
        return 'Spring'
    elif 6 <= month <= 8:
        return 'Summer'
    elif 9 <= month <= 11:
        return 'Fall'
    else:
        return 'Winter'
df['season'] = df['date'].dt.month.apply(get_season)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 29 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   id                      21597 non-null  int64
```

```
 1   date                    21597 non-null  datetime64[ns]
 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              21597 non-null  int64
 9   view                    21597 non-null  float64
 10  condition               21597 non-null  float64
 11  grade                   21597 non-null  float64
 12  sqft_above              21597 non-null  int64
 13  sqft_basement           21597 non-null  float64
 14  yr_built                21597 non-null  int64
 15  yr_renovated            21597 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
 21  Sale_Number             21597 non-null  int64
 22  age_of_house            21597 non-null  int64
 23  years_since_renovation  21597 non-null  float64
 24  price_per_sqft          21597 non-null  float64
 25  lot_utilization         21597 non-null  float64
 26  neighborhood_avg_price  21597 non-null  float64
 27  grade_score             21597 non-null  float64
 28  season                  21597 non-null  object
dtypes: datetime64[ns](1), float64(15), int64(12), object(1)
memory usage: 4.8+ MB
```

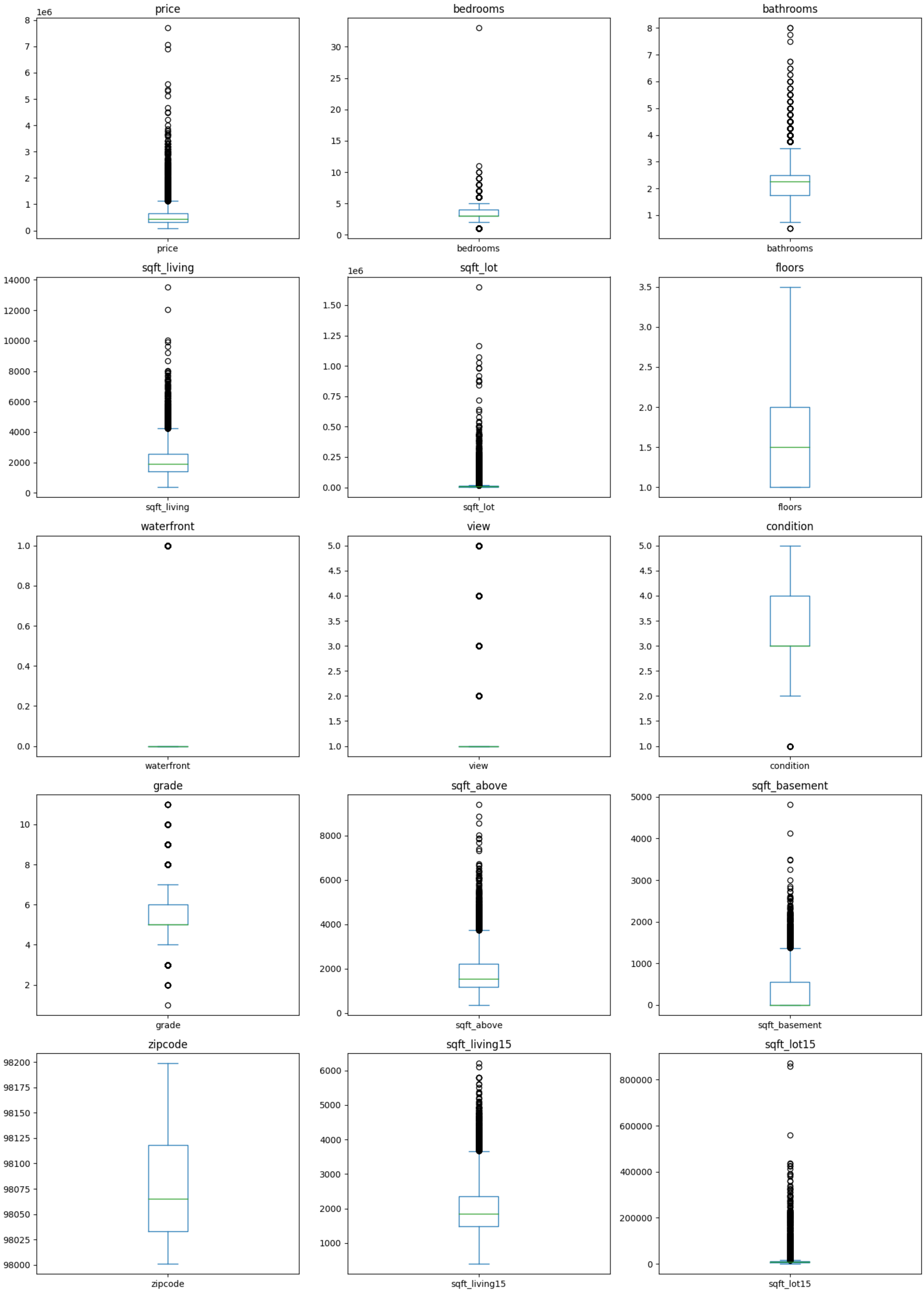
```
df.head()
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	0
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0

5 rows × 29 columns

Outlier Identification

```
# Create individual boxplots for selected columns
columns_to_plot = ['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfro

# Set the number of boxplots per row
boxplots_per_row = 3

# Calculate the number of rows needed
num_rows = -(-len(columns_to_plot) // boxplots_per_row)  # Ceiling division

# Create a subplot grid
fig, axes = plt.subplots(nrows=num_rows, ncols=boxplots_per_row, figsize=(15, 25))

# Flatten the axes array for easier iteration
axes = axes.flatten()

# Plot each boxplot
for i, column in enumerate(columns_to_plot):
    ax = axes[i]
    df[column].plot(kind='box', ax=ax)
    ax.set_title(column)

# Hide any remaining empty subplots
for i in range(len(columns_to_plot), len(axes)):
    fig.delaxes(axes[i])

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




```
# Removing outliers observed in the box plots above
df = df.drop(df[df["bedrooms"] >= 10].index)
df = df.drop(df[df["sqft_living"] > 10000].index)
df = df.drop(df[df["price"] >= 1100000].index)
```

```
# Count the number of sales for each house and merge with the original DataFrame
sale_counts = df.groupby('id').size().reset_index(name='NumSales')
df = pd.merge(df, sale_counts, on='id', how='left')

# Identify houses sold more than once
houses_sold_more_than_once = df[df['NumSales'] > 1].drop_duplicates('id')

# Generate Markdown report
markdown_report = f"# King County House Sales Report\n\n"
markdown_report += "## Houses Sold More Than Once\n\n"

for house_id, num_sales, total_earnings in houses_sold_more_than_once[['id', 'NumSales', 'price']].
    markdown_report += f"House Number {house_id} was sold {num_sales} times in the period under cor

# Export the Markdown report
with open('king_county_house_sales_report.md', 'w') as file:
    file.write(markdown_report)
```

King County House Sales Report

Houses Sold More Than Once

Find the full report under 'king_county_house_sales_report.md'

House Number 6021501535 was sold 2 times in the period under consideration, priced at 430000.0.

House Number 4139480200 was sold 2 times in the period under consideration, priced at 1380000.0.

House Number 7520000520 was sold 2 times in the period under consideration, priced at 232000.0.

House Number 3969300030 was sold 2 times in the period under consideration, priced at 165000.0.

House Number 2231500030 was sold 2 times in the period under consideration, priced at 315000.0.

```
#Rename the 'id' column to 'house_number' and create a new index column named 'id'
df = df.rename(columns={'id': 'house_number'}).reset_index(drop=True)
```

```
#Getting a report of number of renovations per year.


# Group by 'yr_renovated' and count the number of unique houses renovated more than once
renovation_counts = df[df['yr_renovated'] > 0].groupby('yr_renovated')['house_number'].nunique().re

# Sort the renovation report from most renovations to least
renovation_counts = renovation_counts.sort_values(by='NumRenovations', ascending=False)

# Calculate the total number of renovations and the proportion to the number of unique house number
total_renovations = renovation_counts['NumRenovations'].sum()
num_unique_houses = df['house_number'].nunique()
proportion_to_unique_houses = total_renovations / num_unique_houses


# Print the total number of renovations and the proportion to the number of unique house numbers
print(f"\nTotal number of renovations: {total_renovations}")
print(f"Proportion to the number of unique house numbers: {proportion_to_unique_houses:.2%}")

# Print messages for the first 3 and last 3 years of renovations
for index, row in renovation_counts.head(3).iterrows():
    message = f"In {row['yr_renovated']}, there were {row['NumRenovations']} renovations."
    print(message)

# Print messages for the last 3 years of renovations
for index, row in renovation_counts.tail(3).iterrows():
    message = f"In {row['yr_renovated']}, there were {row['NumRenovations']} renovations."
    print(message)

# Generate Markdown report
markdown_report = f"# Renovation Report\n\n"
markdown_report += "## Houses Renovated More Than Once\n\n"
markdown_report += renovation_counts.to_markdown(index=False)

# Save the Markdown report to a file
with open('renovation_report.md', 'w') as file:
    file.write(markdown_report)
```

```
Total number of renovations: 612
Proportion to the number of unique house numbers: 3.03%
In 2014.0, there were 64.0 renovations.
In 2013.0, there were 29.0 renovations.
In 2000.0, there were 26.0 renovations.
In 1971.0, there were 1.0 renovations.
In 1976.0, there were 1.0 renovations.
In 1934.0, there were 1.0 renovations.
```

```
df.describe()
```

	house_number	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	2.036500e+04	2.036500e+04	20365.000000	20365.000000	20365.000000	2.036500e+04	20365.
mean	4.602901e+09	4.745134e+05	3.325804	2.049055	1970.367150	1.458500e+04	1.
std	2.877858e+09	2.048530e+05	0.879369	0.708776	769.183262	4.006855e+04	0.
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.
25%	2.131201e+09	3.150000e+05	3.000000	1.500000	1400.000000	5.000000e+03	1.
50%	3.905081e+09	4.360000e+05	3.000000	2.000000	1850.000000	7.500000e+03	1.
75%	7.338200e+09	6.000000e+05	4.000000	2.500000	2430.000000	1.030000e+04	2.
max	9.900000e+09	1.090000e+06	9.000000	7.500000	7480.000000	1.651359e+06	3.

8 rows × 28 columns

```
#Export the dataframe

# Specify the path where you want to save the CSV file
csv_file_path = 'export.csv'

# Export the entire DataFrame to a CSV file
df.to_csv(csv_file_path, index=False)

print(f'DataFrame exported to {csv_file_path}')
```

```
DataFrame exported to export.csv
```

```
# Rename the original DataFrame to Original_df
Original_df = df.copy()

# Count the number of sales for each house
sale_counts = df.groupby('house_number').size().reset_index(name='NumSales')

# Add a new column indicating the number of sales for each house
df['NumSales'] = df.groupby('house_number')['house_number'].transform('count')

# Identify houses sold more than once
houses_sold_more_than_once = df[df['NumSales'] > 1]

# Keep the most recent sale for houses sold more than once
houses_sold_more_than_once = houses_sold_more_than_once.sort_values(by=['house_number', 'date'], as
houses_sold_more_than_once.drop_duplicates('house_number', keep='first', inplace=True)


# Drop houses sold more than once, keeping the most recent sale
df = pd.concat([df, houses_sold_more_than_once]).drop_duplicates(subset='house_number', keep='last'

# Drop the 'NumSales' column as it is no longer needed
df.drop(columns='NumSales', inplace=True)


df.head()
```

	house_number	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	0
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0

5 rows × 29 columns

```
#Export the dataframe

# Specify the path where you want to save the CSV file
csv_file_path = 'new_export.csv'

# Export the entire DataFrame to a CSV file
df.to_csv(csv_file_path, index=False)

print(f'DataFrame exported to {csv_file_path}')
```

```
DataFrame exported to new_export.csv
```

Objectives

An investigation of the house features to understand how they indivually affect the price.

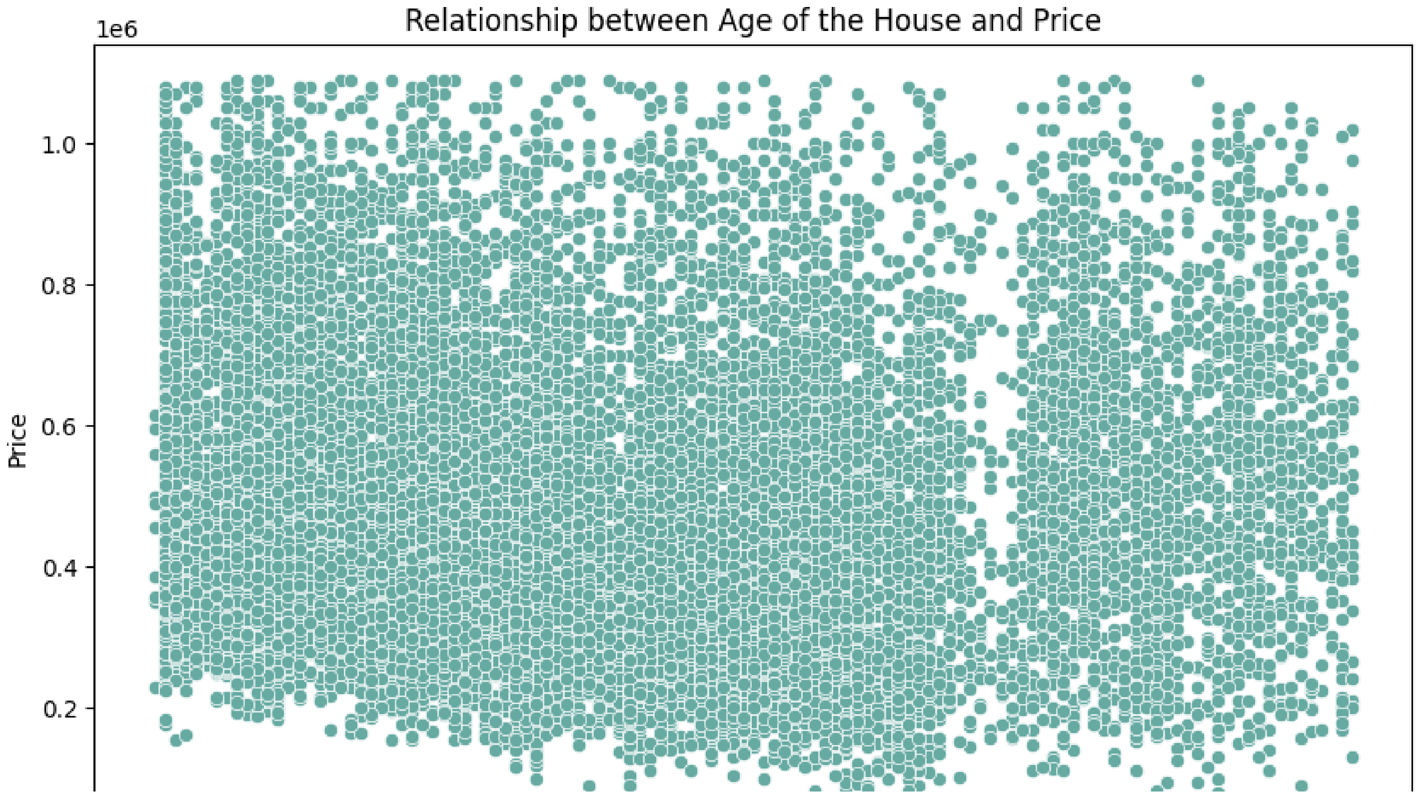
```
#A Summary of the  Features

summary_features = ["price", "yr_built", "bedrooms", "bathrooms", "sqft_living", "sqft_lot",
                    "floors", "condition", "grade", "sqft_living15", "sqft_lot15","waterfront"]
df[summary_features].describe()
```

	price	yr_built	bedrooms	bathrooms	sqft_living	sqft_lot	
count	2.019500e+04	20195.000000	20195.000000	20195.000000	20195.000000	2.019500e+04	20195.(
mean	4.759371e+05	1970.913692	3.326269	2.051498	1973.013964	1.462089e+04	1.4
std	2.045136e+05	29.162762	0.878000	0.708246	769.820134	4.020672e+04	0.5
min	7.800000e+04	1900.000000	1.000000	0.500000	370.000000	5.200000e+02	1.(
25%	3.150005e+05	1952.000000	3.000000	1.500000	1400.000000	5.000000e+03	1.(
50%	4.380000e+05	1975.000000	3.000000	2.000000	1852.000000	7.500000e+03	1.(
75%	6.000000e+05	1996.000000	4.000000	2.500000	2430.000000	1.030500e+04	2.(
max	1.090000e+06	2015.000000	9.000000	7.500000	7480.000000	1.651359e+06	3.5

1. Age and Price Analysis

An analysis of the age of the house and the selling price

```
#A visualisation of the age of the house and price

import matplotlib.pyplot as plt
import seaborn as sns

# Age of the house
df['age_of_house'] = df['date'].dt.year - df['yr_built']

# Selecting the columns of interest
summary_features = ["price", "age_of_house"]

# Creating a scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x=summary_features[1], y=summary_features[0], data=df, color='#66aaa2')
plt.title('Relationship between Age of the House and Price')
plt.xlabel('Age of the House')
plt.ylabel('Price')
plt.show()
```




```
correlation_coefficient = df['age_of_house'].corr(df['price'])
print(f"Correlation Coefficient: {correlation_coefficient}")
```

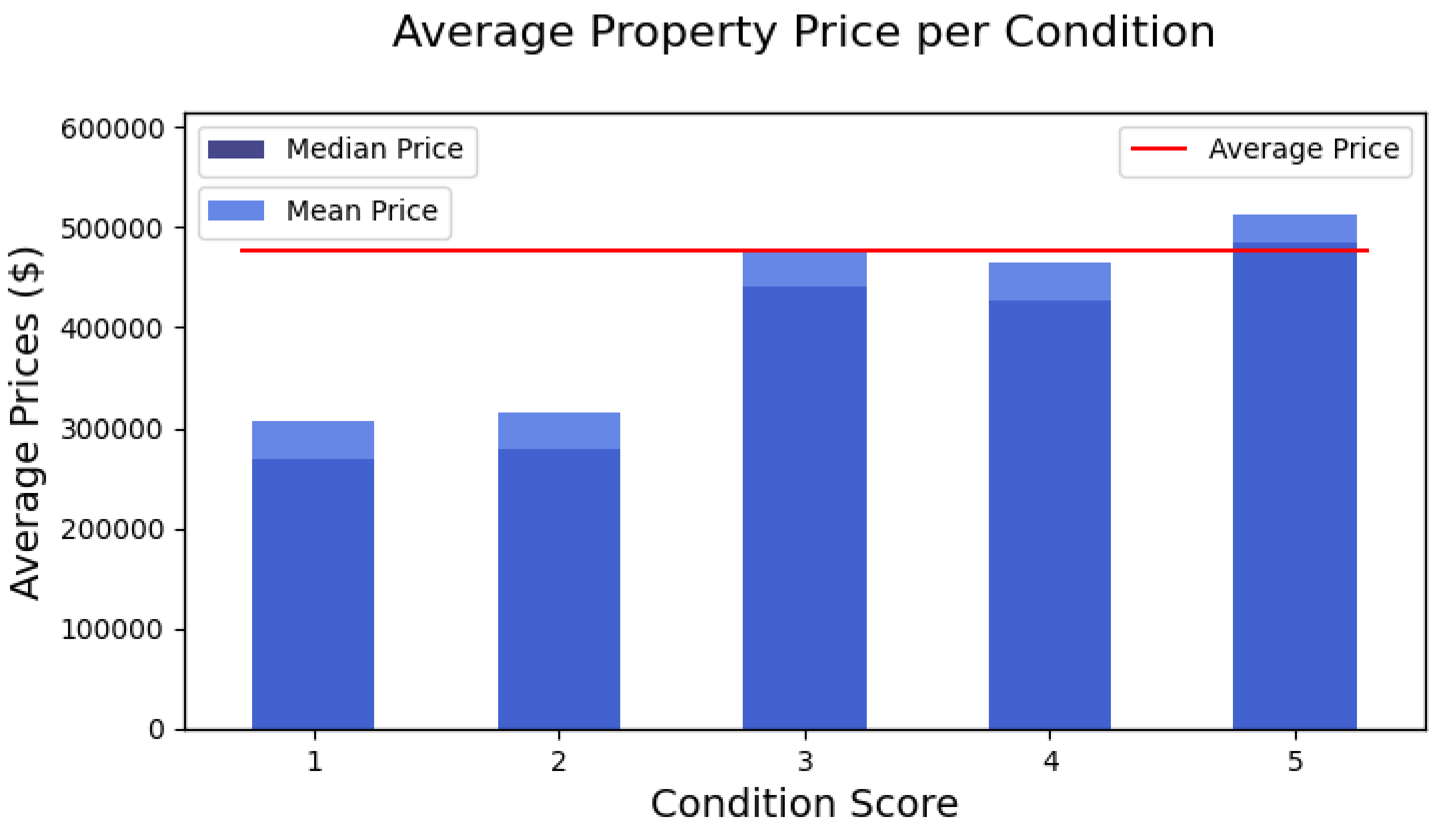
```
Correlation Coefficient: -0.05853062659292519
```

The correlation coefficient is close to 0, it suggests a weak or no linear correlation between the variables. The age at sale and selling price are not strongly related in a linear fashion.

2. Condition/Grade and Location Impact on price

Building grade is a feature from King County government and represents the construction quality of improvements.

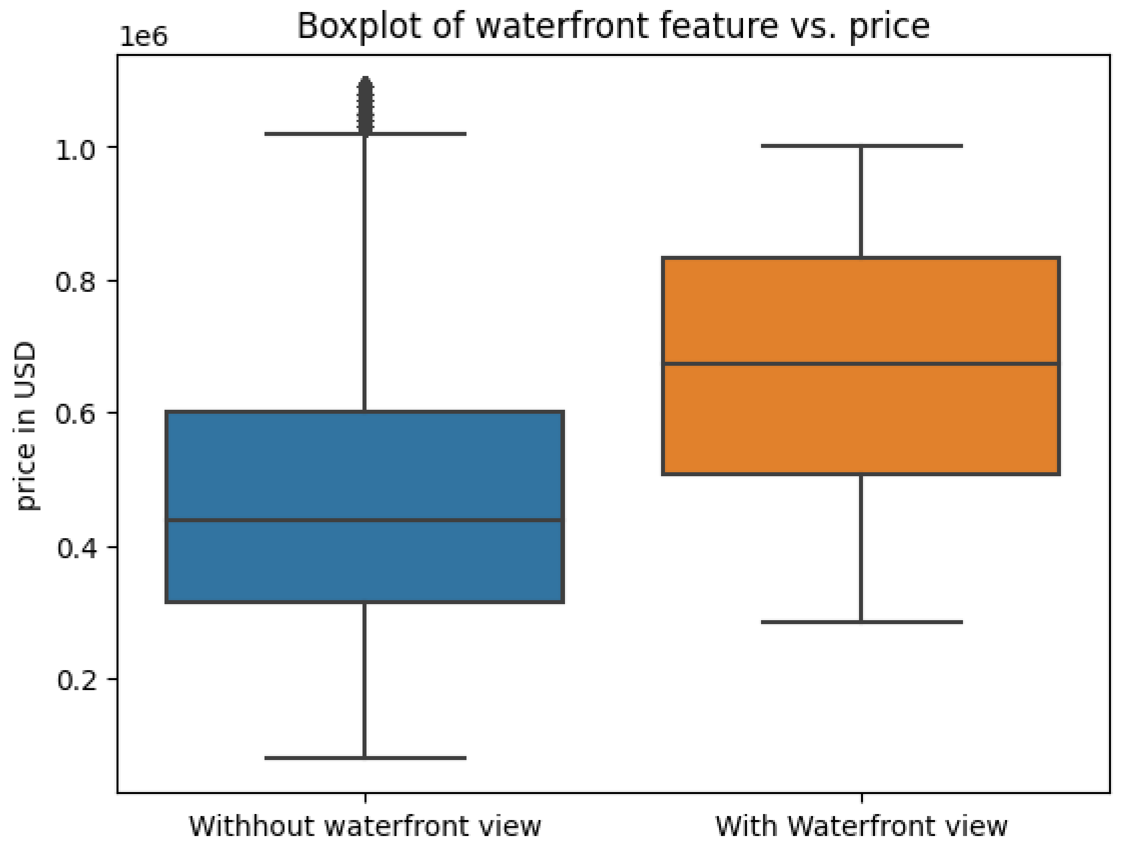
```
#Does the property condition affect the price
condition_mean = df.groupby("condition")["price"].mean()
condition_median = df.groupby("condition")["price"].median()
condition_score = np.arange(1,6)
mean_price = df.price.mean()

#Bar Plot
#set subplot data
fig, ax = plt.subplots(figsize=(8,4))
ax2 = ax.twinx() #set ax2 on same x axis as ax
ax3 = ax.twinx() #same as above, for hline
width = 0.5

#barplots
ax.bar(x=condition_score, height=condition_median, width=width,
       label="Median Price", color="midnightblue", alpha=0.8)
ax2.bar(x=condition_score, height=condition_mean, width=width,
        label="Mean Price", color="royalblue", alpha=0.8)

#horizontal line for mean price
ax3.hlines(mean_price, .7 ,5.3, colors="red", label="Average Price")

#set ylimit to the same scale and display only 1
ax.set_ylim(0,1.2*condition_mean.max())
ax2.set_ylim(0,1.2*condition_mean.max())
ax3.set_ylim(0,1.2*condition_mean.max())
ax2.yaxis.set_visible(False) #hide the 2nd axis
ax3.yaxis.set_visible(False)

#set legend positions
ax.legend(bbox_to_anchor=(0,0,1,1), loc="upper left")
ax2.legend(bbox_to_anchor=(0,-.1,1,1), loc="upper left")
ax3.legend(bbox_to_anchor=(0,0,1,1), loc="upper right")

#adjust graph to be more elaborate
ax.set_ylabel("Average Prices ($)", size=14)
ax.set_xlabel("Condition Score", size=14)
plt.title("Average Property Price per Condition", size=16, y=1.08)

# (How to export image) plt.savefig("images/condition_value.png",bbox_inches = "tight")
plt.legend()
plt.show();

#Assess the statistical significance of the categorical variable 'condition' on the dependent varia
alpha = 0.05
formula = 'price~C(condition)'
lm_condition = smf.ols(formula,df).fit()
anova_condition = sm.stats.anova_lm(lm_condition, typ=2)
if anova_condition["PR(>F)"][0] < alpha:
    print("The property condition has a statistically significant impact on the average property pr
    print("Conditions F-statistic Probability: ", anova_condition["PR(>F)"][0])
```



3. Waterfront Price Correlation Analysis

We have a waterfront feature which characterises houses which have a view of a waterfront. We investigate how this feature relates to price.

```
# Plot boxplot of waterfront feature
sns.boxplot(x = df['waterfront'], y = df['price'])
plt.title("Boxplot of waterfront feature vs. price")
plt.ylabel("price in USD")
plt.xlabel(None)
plt.xticks(np.arange(2), ('Withhout waterfront view', 'With Waterfront view'))
plt.show()
```



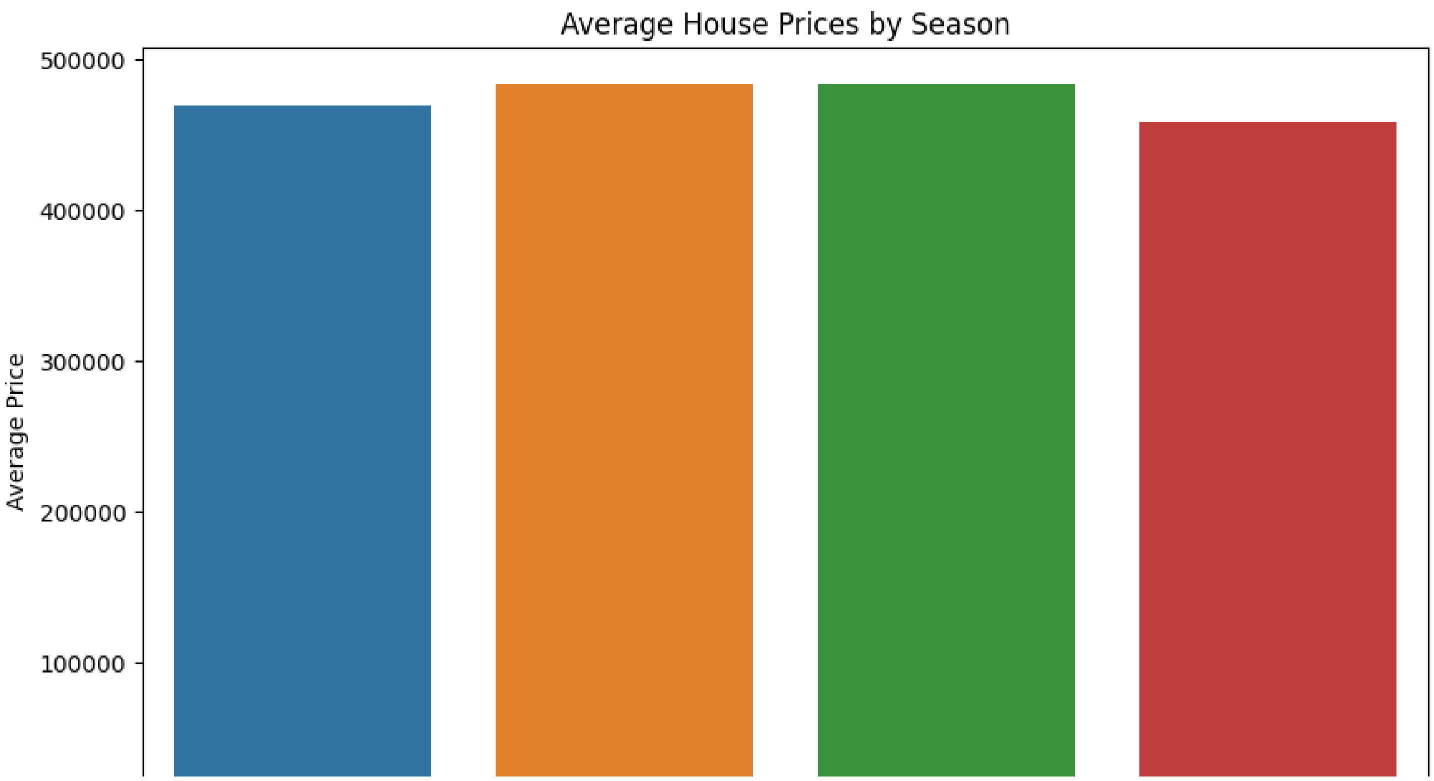

```
#An anlysis of the waterfront feature
waterfrontmean = df[df['waterfront'] == 1]['price'].mean()
nonwaterfrontmean = df[df['waterfront'] == 0]['price'].mean()
print(f"The mean house price for a house with waterfront view is USD {round(waterfrontmean,2)}")
print(f"The mean house price for a house without waterfront view is USD {round(nonwaterfrontmean,2)

#To find out what percentage of houses have the waterfront feature
percentage_waterfront =  len(df[df['waterfront'] == 1])/len(df)*100
print(f"Percentage of Houses with Waterfront Feature: {round(percentage_waterfront, 2)}%")
```

```
The mean house price for a house with waterfront view is USD 671667.0
The mean house price for a house without waterfront view is USD 475451.25
Percentage of Houses with Waterfront Feature: 0.25%
```

Waterfront living is key, with the mean house price for a house with a waterfront view being quite higher than those without the waterfront feature

4. Seasonal Pricing

```
# Visualization 3: Seasonal Price Trends
seasonal_prices = df.groupby('season')['price'].agg(['mean', 'median']).reset_index()
plt.figure(figsize=(10, 6))
sns.barplot(x='season', y='mean', data=seasonal_prices)
plt.title('Average House Prices by Season')
plt.xlabel('Season')
plt.ylabel('Average Price')
seasonal_price_trends_path = 'transformed_seasonal_price_trends.png'
plt.savefig(seasonal_price_trends_path)
```



Data Modeling

Predictive Modeling - Linear Regression

```
#Correlation Heatmap
correlation_matrix = df.select_dtypes(include=[np.number]).corr()
plt.figure(figsize=(25, 18))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',cbar_kws={"shrink":.8},square=True)
plt.title('Correlation Heatmap of Numerical Features')
correlation_heatmap_path = 'transformed_correlation_heatmap.png'
plt.savefig(correlation_heatmap_path)
```


```
correlation_matrix = df.corr(numeric_only=True).abs()
stacked_correlations = correlation_matrix.stack().reset_index().sort_values(0, ascending=False)
stacked_correlations['column_pairs'] = list(zip(stacked_correlations['level_0'], stacked_correlatic
pairs_indexed = stacked_correlations.set_index(['column_pairs'])
pairs_indexed.drop(columns=['level_0', 'level_1'], inplace=True)
pairs_indexed.columns = ['correlation_coefficient']
unique_pairs = pairs_indexed.drop_duplicates()
high_correlation_pairs = unique_pairs[
    (unique_pairs['correlation_coefficient'] > 0.65) & (unique_pairs['correlation_coefficient'] < 1
]

# Display the result
print(high_correlation_pairs)
```

```
                                        correlation_coefficient
column_pairs
(yr_built, age_of_house)                               0.999871
(sqft_above, sqft_living)                              0.853135
(grade_score, grade)                                   0.821837
(yr_renovated, years_since_renovation)                 0.746735
(sqft_living, sqft_living15)                           0.736988
(sqft_above, sqft_living15)                            0.717173
(bathrooms, sqft_living)                               0.715998
(sqft_lot15, sqft_lot)                                 0.708728
(grade, sqft_above)                                    0.708585
(grade, sqft_living)                                   0.703167
(grade, sqft_living15)                                 0.670014
(neighborhood_avg_price, price)                        0.663947
```

In this analysis, we observe significant correlations among various pairs of variables. To address potential multicollinearity issues in our model, we will consider the removal of variables that exhibit high correlation with each other.

Baseline Model

```
# Define independent variables
independent_vars = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront', 'vi

# Add a constant term to the independent variables
X = sm.add_constant(df[independent_vars])

# Define the dependent variable
y = df['price']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Fit the linear regression model using scikit-learn
linear_model = sm.OLS(y_train, X_train).fit()

# Make predictions on the test set
y_pred = linear_model.predict(X_test)

# Calculate metrics
mse_linear = mean_squared_error(y_test, y_pred)
r2_linear = r2_score(y_test, y_pred)

# Print the OLS summary
print(linear_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.565
Model:                            OLS   Adj. R-squared:                  0.565
Method:                 Least Squares   F-statistic:                     1616.
Date:                Thu, 04 Jan 2024   Prob (F-statistic):               0.00
Time:                        11:45:16   Log-Likelihood:            -2.1370e+05
No. Observations:               16156   AIC:                         4.274e+05
Df Residuals:                   16142   BIC:                         4.275e+05
Df Model:                          13
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const         -1.031e+07   2.18e+06     -4.724      0.000   -1.46e+07   -6.03e+06
bedrooms      -1.633e+04   1573.288    -10.380      0.000   -1.94e+04   -1.32e+04
bathrooms      2.765e+04   2587.533     10.685      0.000    2.26e+04    3.27e+04
sqft_living      82.3912      2.740     30.073      0.000      77.021      87.761
sqft_lot          0.0375      0.026      1.448      0.148      -0.013       0.088
floors         4.262e+04   2758.037     15.452      0.000    3.72e+04     4.8e+04
waterfront     9.417e+04   2.25e+04      4.193      0.000    5.01e+04    1.38e+05
view           2.318e+04   1789.811     12.950      0.000    1.97e+04    2.67e+04
condition     -8.404e+04   2415.024    -34.801      0.000   -8.88e+04   -7.93e+04
sqft_basement    13.9114      3.404      4.086      0.000       7.238      20.584
zipcode         100.0133     22.254      4.494      0.000      56.393     143.634
```

```
age_of_house            2563.9068     53.748     47.702      0.000    2458.554    2669.260
years_since_renovation  -832.2492    250.100     -3.328      0.001   -1322.474    -342.025
grade_score             9.986e+04   1626.975     61.376      0.000    9.67e+04    1.03e+05
==============================================================================
Omnibus:                      557.833   Durbin-Watson:                   2.010
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              738.801
Skew:                           0.379   Prob(JB):                    3.73e-161
Kurtosis:                       3.724   Cond. No.                     2.05e+08
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.05e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The model has an Adj. R-squared value of 0.565, indicating that approximately 56.5% of the variability in the dependent variable (price) is explained by the independent variables in the model. However, the p-value for sqft_lot is larger than 0.05 indicating that we do not have strong evidence to reject the null hypothesis. we will therefore drop the sqft_lot in the next iteration.

1st Iteration

```
# Define independent variables
independent_vars = ['bedrooms', 'bathrooms', 'sqft_living', 'floors','zipcode', 'waterfront', 'view

# Add a constant term to the independent variables
X = sm.add_constant(df[independent_vars])

# Define the dependent variable
y = df['price']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Fit the linear regression model using scikit-learn
linear_model = sm.OLS(y_train, X_train).fit()

# Make predictions on the test set
y_pred = linear_model.predict(X_test)

# Calculate metrics
mse_linear = mean_squared_error(y_test, y_pred)
r2_linear = r2_score(y_test, y_pred)

# Print the OLS summary
print(linear_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.565
Model:                            OLS   Adj. R-squared:                  0.565
Method:                 Least Squares   F-statistic:                     1750.
Date:                Thu, 04 Jan 2024   Prob (F-statistic):               0.00
Time:                        11:45:16   Log-Likelihood:            -2.1370e+05
No. Observations:               16156   AIC:                         4.274e+05
Df Residuals:                   16143   BIC:                         4.275e+05
```

```
Df Model:                          12
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                       -1e+07   2.17e+06     -4.604      0.000   -1.43e+07   -5.74e+06
bedrooms                -1.652e+04   1567.794    -10.539      0.000   -1.96e+04   -1.34e+04
bathrooms                2.758e+04   2587.212     10.661      0.000    2.25e+04    3.27e+04
sqft_living                83.0330      2.704     30.711      0.000      77.733      88.332
floors                   4.234e+04   2751.561     15.389      0.000    3.69e+04    4.77e+04
zipcode                    96.8763     22.149      4.374      0.000      53.461     140.291
waterfront               9.436e+04    2.25e+04     4.202      0.000    5.03e+04    1.38e+05
view                     2.334e+04   1786.542     13.063      0.000    1.98e+04    2.68e+04
condition               -8.399e+04   2414.825    -34.782      0.000   -8.87e+04   -7.93e+04
sqft_basement              13.5408      3.395      3.989      0.000       6.886      20.195
age_of_house             2564.5053     53.749     47.713      0.000    2459.152    2669.859
years_since_renovation   -827.9954    250.092     -3.311      0.001   -1318.203    -337.788
grade_score              9.978e+04   1626.069     61.360      0.000    9.66e+04    1.03e+05
==============================================================================
Omnibus:                      556.021   Durbin-Watson:                   2.010
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              736.262
Skew:                           0.378   Prob(JB):                    1.33e-160
Kurtosis:                       3.723   Cond. No.                     2.01e+08
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.01e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The model has an Adj. R-squared value of 0.565, indicating that approximately 56.5% of the variability in the dependent variable (price) is explained by the independent variables in the model. To further improve our model,we will add Seasons to determine whether it affects the house price.

2nd Iteration

```
df=df.join(pd.get_dummies(df.season)).drop(['season'],axis=1)
```

```
# Define independent variables
independent_vars = ['bedrooms', 'bathrooms', 'sqft_living', 'floors','zipcode', 'waterfront', 'view

# Add a constant term to the independent variables
X = sm.add_constant(df[independent_vars])

# Define the dependent variable
y = df['price']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Fit the linear regression model using scikit-learn
linear_model = sm.OLS(y_train, X_train).fit()

# Make predictions on the test set
y_pred = linear_model.predict(X_test)

# Calculate metrics
mse_linear = mean_squared_error(y_test, y_pred)
r2_linear = r2_score(y_test, y_pred)

# Print the OLS summary
print(linear_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.567
Model:                            OLS   Adj. R-squared:                  0.567
Method:                 Least Squares   F-statistic:                     1411.
Date:                Thu, 04 Jan 2024   Prob (F-statistic):               0.00
Time:                        11:45:16   Log-Likelihood:            -2.1366e+05
No. Observations:               16156   AIC:                         4.274e+05
Df Residuals:                   16140   BIC:                         4.275e+05
Df Model:                          15
Covariance Type:            nonrobust
========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
const                  -9.936e+06   2.17e+06     -4.584      0.000   -1.42e+07   -5.69e+06
bedrooms               -1.665e+04   1564.725    -10.638      0.000   -1.97e+04   -1.36e+04
bathrooms               2.756e+04   2581.711     10.677      0.000    2.25e+04    3.26e+04
sqft_living               83.3190      2.698     30.882      0.000      78.031      88.607
floors                  4.229e+04   2745.589     15.402      0.000    3.69e+04    4.77e+04
zipcode                   96.0943     22.101      4.348      0.000      52.773     139.415
waterfront              9.526e+04   2.24e+04      4.251      0.000    5.13e+04    1.39e+05
view                    2.333e+04   1783.018     13.087      0.000    1.98e+04    2.68e+04
condition              -8.363e+04   2410.279    -34.698      0.000   -8.84e+04   -7.89e+04
sqft_basement             13.4984      3.387      3.985      0.000       6.859      20.138
age_of_house            2557.1188     53.638     47.673      0.000    2451.981    2662.256
years_since_renovation  -839.2202    249.577     -3.363      0.001   -1328.419    -350.021
grade_score             9.967e+04   1623.136     61.406      0.000    9.65e+04    1.03e+05
Spring                  2.428e+04   3187.567      7.616      0.000     1.8e+04    3.05e+04
Summer                  1.012e+04   3215.175      3.148      0.002    3820.529    1.64e+04
Fall                    4970.2503   3353.989      1.482      0.138   -1603.940    1.15e+04
==============================================================================
Omnibus:                      546.786   Durbin-Watson:                   2.010
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              728.186
Skew:                           0.372   Prob(JB):                    7.52e-159
Kurtosis:                       3.728   Cond. No.                     2.01e+08
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.01e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
```

1. The model has an Adj. R-squared value of 0.567, indicating that approximately 56.7% of the variability in the dependent variable (price) is explained by the independent variables in the model. This model does not show significant improvement from the previous model without season.
2. For the next Iteration we will add the all the zipcodes to the model to assess its correlation between the sales price.

Final Model

To further improve our model, we will incooporate a new data set with City names to replace the Zipcodes

```
shapefile_path = '/content/Zipcodes_for_King_County_and_Surrounding_Area___zipcode_area.shp'

# Read the shapefile into a GeoDataFrame
gdf = gpd.read_file(shapefile_path)
gdf = gdf.drop_duplicates(subset='ZIPCODE', keep='first')
selected_columns = ['ZIPCODE', 'PREFERRED_']
zipcode_names = gdf[selected_columns]
zipcode_names = zipcode_names.copy()
zipcode_names.rename(columns={'ZIP': 'zipcode', 'PREFERRED_': 'City_Name'}, inplace=True)
```

```
zipcode_names['ZIPCODE'] = zipcode_names['ZIPCODE'].astype('int64')
df = df.merge(zipcode_names, how='left', left_on='zipcode', right_on='ZIPCODE')
```

```
df['City_Name'] = df['City_Name'].map({
    'SAMMAMIISH': 'SAMMAMISH'}).fillna(df['City_Name'])
```

```
df=df.join(pd.get_dummies(df.City_Name)).drop(['City_Name'],axis=1)
# We will drop Bellevue to be the reference column for the cities.
```

```
df.columns
```

```
Index(['house_number', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15', 'Sale_Number',
       'age_of_house', 'years_since_renovation', 'price_per_sqft',
       'lot_utilization', 'neighborhood_avg_price', 'grade_score', 'Fall',
       'Spring', 'Summer', 'Winter', 'ZIPCODE', 'AUBURN', 'BELLEVUE',
       'BLACK DIAMOND', 'BOTHELL', 'CARNATION', 'DUVALL', 'ENUMCLAW',
       'FALL CITY', 'FEDERAL WAY', 'ISSAQUAH', 'KENMORE', 'KENT', 'KIRKLAND',
       'MAPLE VALLEY', 'MEDINA', 'MERCER ISLAND', 'NORTH BEND', 'REDMOND',
       'RENTON', 'SAMMAMISH', 'SEATTLE', 'SNOQUALMIE', 'VASHON',
       'WOODINVILLE'],
      dtype='object')
```

```
df = df.drop(columns=['ZIPCODE','zipcode',])


# Define independent variables
independent_vars = ['bedrooms', 'bathrooms', 'sqft_living',  'floors', 'waterfront', 'view', 'Fall'
       'DUVALL', 'ENUMCLAW', 'FALL CITY','FEDERAL WAY', 'ISSAQUAH', 'KENMORE',
       'KENT', 'KIRKLAND', 'MAPLE VALLEY', 'MEDINA', 'MERCER ISLAND',
       'NORTH BEND', 'REDMOND', 'RENTON', 'SAMMAMISH',  'SNOQUALMIE',
       'VASHON','WOODINVILLE']

# Add a constant term to the independent variables
X = sm.add_constant(df[independent_vars])

# Define the dependent variable
y = df['price']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Fit the linear regression model using scikit-learn
linear_model = sm.OLS(y_train, X_train).fit()

# Make predictions on the test set
y_pred = linear_model.predict(X_test)

# Calculate metrics
mse_linear = mean_squared_error(y_test, y_pred)
r2_linear = r2_score(y_test, y_pred)
rmse = np.sqrt(mse_linear)
# Print the OLS summary
print(linear_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.708
Model:                            OLS   Adj. R-squared:                  0.707
Method:                 Least Squares   F-statistic:                     1115.
Date:                Thu, 04 Jan 2024   Prob (F-statistic):               0.00
Time:                        11:45:17   Log-Likelihood:            -2.1050e+05
No. Observations:               16156   AIC:                         4.211e+05
Df Residuals:                   16120   BIC:                         4.213e+05
Df Model:                          35
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const         -2.042e+05   1.05e+04    -19.450      0.000   -2.25e+05   -1.84e+05
bedrooms      -1.768e+04   1289.244    -13.711      0.000   -2.02e+04   -1.51e+04
bathrooms      2.473e+04   2124.347     11.641      0.000    2.06e+04    2.89e+04
sqft_living     119.4390      2.143     55.742      0.000     115.239     123.639
floors         4.023e+04   2343.988     17.162      0.000    3.56e+04    4.48e+04
waterfront     8.207e+04   1.88e+04      4.358      0.000    4.52e+04    1.19e+05
view           2.913e+04   1477.935     19.709      0.000    2.62e+04     3.2e+04
Fall          -2282.3048   2760.824     -0.827      0.408   -7693.827    3129.217
Spring         2.026e+04   2625.471      7.718      0.000    1.51e+04    2.54e+04
Summer          700.0271   2648.459      0.264      0.792   -4491.246    5891.300
age_of_house   1328.0215     43.368     30.622      0.000    1243.015    1413.028
sqft_basement   -25.4762      2.864     -8.894      0.000     -31.091     -19.862
grade_score    4.914e+04   1023.901     47.991      0.000    4.71e+04    5.11e+04
AUBURN        -2.979e+05   5632.397    -52.890      0.000   -3.09e+05   -2.87e+05
SEATTLE       -1.067e+05   4227.365    -25.243      0.000   -1.15e+05   -9.84e+04
```

```
BLACK DIAMOND -1.958e+05   1.27e+04    -15.370      0.000    -2.21e+05    -1.71e+05
BOTHELL          -1.43e+05   9524.615    -15.010      0.000    -1.62e+05    -1.24e+05
CARNATION      -1.736e+05   1.23e+04    -14.091      0.000    -1.98e+05    -1.49e+05
DUVALL         -1.832e+05   9710.035    -18.871      0.000    -2.02e+05    -1.64e+05
ENUMCLAW       -2.847e+05   8915.118    -31.936      0.000    -3.02e+05    -2.67e+05
FALL CITY      -1.164e+05   1.53e+04     -7.621      0.000    -1.46e+05    -8.65e+04
FEDERAL WAY    -3.051e+05   5879.257    -51.897      0.000    -3.17e+05    -2.94e+05
ISSAQUAH       -9.035e+04   6161.717    -14.662      0.000    -1.02e+05    -7.83e+04
KENMORE        -1.603e+05   8451.605    -18.968      0.000    -1.77e+05    -1.44e+05
KENT           -2.859e+05   5277.575    -54.169      0.000    -2.96e+05    -2.76e+05
KIRKLAND       -5.383e+04   5628.057     -9.564      0.000    -6.49e+04    -4.28e+04
MAPLE VALLEY   -2.436e+05   6561.029    -37.121      0.000    -2.56e+05    -2.31e+05
MEDINA          3.593e+05   6.38e+04      5.630      0.000     2.34e+05     4.84e+05
MERCER ISLAND   1.169e+05   1.07e+04     10.930      0.000     9.59e+04     1.38e+05
NORTH BEND        -1.7e+05   9312.250    -18.255      0.000    -1.88e+05    -1.52e+05
REDMOND        -3.666e+04   5648.385     -6.490      0.000    -4.77e+04    -2.56e+04
RENTON         -2.207e+05   4981.721    -44.303      0.000     -2.3e+05    -2.11e+05
SAMMAMISH      -5.882e+04   6047.988     -9.725      0.000    -7.07e+04     -4.7e+04
SNOQUALMIE     -1.572e+05   8420.458    -18.674      0.000    -1.74e+05    -1.41e+05
VASHON         -1.708e+05   1.34e+04    -12.753      0.000    -1.97e+05    -1.45e+05
WOODINVILLE    -1.041e+05   7078.955    -14.710      0.000    -1.18e+05    -9.03e+04
==============================================================================
Omnibus:                     1166.280   Durbin-Watson:                   2.012
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2348.355
Skew:                           0.497   Prob(JB):                         0.00
Kurtosis:                       4.582   Cond. No.                     1.57e+05
==============================================================================
```

1. The model has an Adj. R-squared value of 0.708, indicating that approximately 70.8% of the variability in the dependent variable (price) is explained by the independent variables in the model.

```
print("Root Mean Squared Error (RMSE) for the model is :", rmse)
```

```
Root Mean Squared Error (RMSE) for the model is : 110526.16077083671
```

Summary of the Final Model

1. R-squared: 0.707

Adjusted R-squared: 0.707 These values indicate the proportion of the variance in the dependent variable ('price') that is explained by the independent variables in the model. An R-squared of 0.708 suggests that approximately 70.8% of the variability in house prices is explained by the model.

2. F-statistic:

1115.0 Prob (F-statistic): 0.00 The F-statistic tests the overall significance of the regression model. A low p-value (0.00) indicates that at least one independent variable is significantly related to the dependent variable eg; waterfront and price.

3. Log-Likelihood:

-2.1050e+05 This is a measure of how well the model explains the observed data. Lower values are better thus our model proves sufficient.

4. AIC and BIC:

AIC: 4.211e+05 BIC: 4.213e+05 These are information criteria that balance the goodness of fit with the complexity of the model. Lower values are generally preferred. Although our values are relatively low, additional data should be added to further refine the model.

5. Number of Observations and Residuals:

No. Observations: 16156 Df Residuals: 16120 These indicate the number of data points used in the analysis and the degrees of freedom for residuals.

6. Number of Independent Variables:

Df Model: 35 It indicates the number of independent variables used in the model.

7. Constant (const):

The intercept. When all independent variables are zero, the estimated mean house price is approximately $ 2,042.

8. Direction of Relationship:

Positive Coefficients: A positive coefficient indicates a positive relationship between the independent variable and the dependent variable. As the value of the independent variable increases, the predicted value of the dependent variable also increases.If the coefficient for 'waterfront' is positive, it suggests that houses with waterfront access are, on average, associated with higher prices compared to houses without waterfront access.

9. Negative Coefficients:

A negative coefficient indicates a negative relationship. As the value of the independent variable increases, the predicted value of the dependent variable decreases.If the coefficient for the variable 'bedrooms' is negative, it suggests that, on average, an increase in the number of bedrooms is associated with a decrease in house price. This might imply that larger houses with more bedrooms are generally less valuable in the given context.

10. Categorical Variables (e.g., Cities):

The coefficients for cities represent the average difference in house prices compared to a reference city.A negative coefficient for a specific city might suggest that, on average, houses in that city have lower prices compared to a reference city (BELLEVUE). Eg, MEDINA area has the highest property value Vs ISSAQUAH which is the lowest.

11. Seasonal Variables (e.g., Fall, Spring, Summer):

Some seasonal variables have coefficients with p-values suggesting insignificance. These variables might not contribute significantly to explaining house prices although we can see that 'spring' (0.000) has the most significant impact on price.

Conclusions

Positive Influencers on Price:

The presence of additional bathrooms, increased square footage, higher floors, waterfront access, captivating views, and elevated grade scores positively impact house prices. Notably, the inclusion of cities like Medina and Mercer Island in the analysis reveals their positive association with higher property values.

Negative Influencers on Price:

The number of bedrooms, certain city affiliations (e.g., Auburn, Federal Way, Kent), in reference to Bellevue, and specific features (e.g., Fall Season, City) exhibit a negative correlation with house prices. Premiere Property Group should be cognizant of these factors when devising pricing strategies.

Seasonal and Unique Factors:

While some seasonal variables do not significantly impact prices, it's crucial to note that the age of the house and the presence of a basement can influence pricing dynamics.

City-Specific Considerations:

Each city has a unique influence on house prices, emphasizing the need for tailored strategies for different locations

Based on the comprehensive analysis of the King County housing data, here are the final recommendations and opportunities for further analysis:

Recommendations:

Dynamic Pricing Strategy:
Implement a pricing strategy that accounts for property size (especially living area square footage), location (specific zipcodes and cities), and property features (like condition and grade). Emphasize premium features like large living spaces, desirable locations, views, and waterfront access in pricing and marketing efforts.

Seasonal Marketing and Sales Tactics:
Capitalize on the higher market activity and prices in Spring and Summer for listing and selling properties. Consider more competitive pricing and marketing strategies in Fall and Winter to attract buyers during slower market periods.

Location-Focused Investment:
Identify and invest in areas with high-demand zipcodes and emerging markets. Leverage insights from location-based analysis to make informed decisions about property acquisitions, developments, or renovations.

Data-Driven Decision Making:
Continue to use data analytics for informed decision-making in all aspects of real estate transactions, from pricing to marketing to investment strategies.

Opportunities for Further Analysis:

Micro-Location Trends:
Conduct a deeper analysis at a neighborhood level within specific zipcodes or cities to uncover more nuanced market trends and investment opportunities.

Long-Term Market Trends:
Analyze historical data over several years to understand long-term trends in the real estate market, including price appreciation rates in different areas.

Economic and Demographic Factors:
Incorporate broader economic indicators and demographic data to understand how macroeconomic conditions and population trends impact the real estate market.

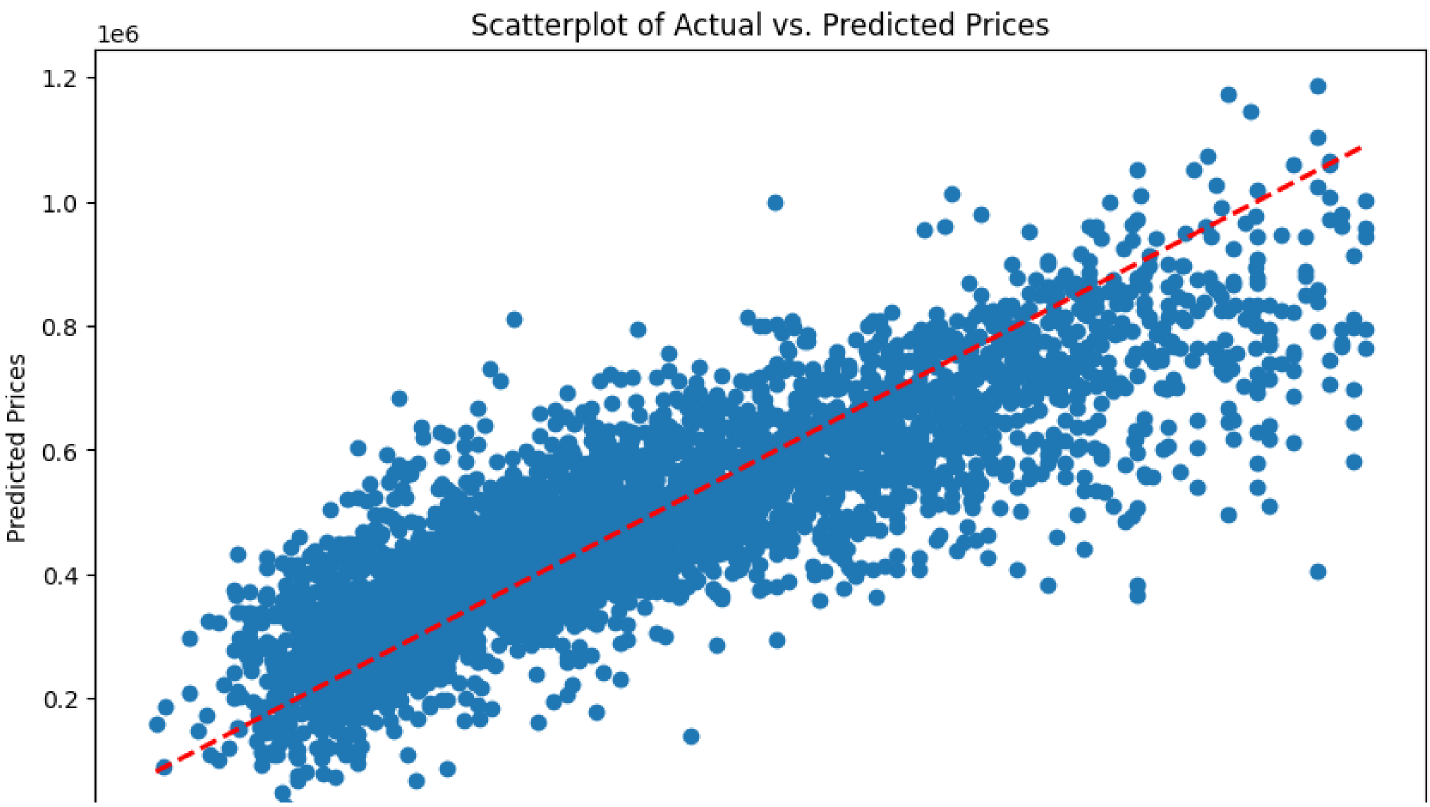
Advanced Predictive Modeling:
Employ more advanced machine learning techniques, such as gradient boosting or neural networks, for more accurate price predictions and market trend analysis.

Impact of Renovations:
Investigate how different types of renovations and improvements impact property values, which could guide investment decisions for property upgrades.

Customer Segmentation and Targeting:
Use data analytics to segment potential buyers or renters and tailor marketing strategies to different target groups.

Impact of External Factors:
Assess the impact of external factors such as new infrastructure developments, zoning changes, or policy shifts on local real estate markets.
By continuously leveraging data analytics and staying attuned to market trends, Premiere Property Group can maintain a competitive edge in the dynamic King County real estate market.

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color='red', linew
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Scatterplot of Actual vs. Predicted Prices')
plt.show()
```

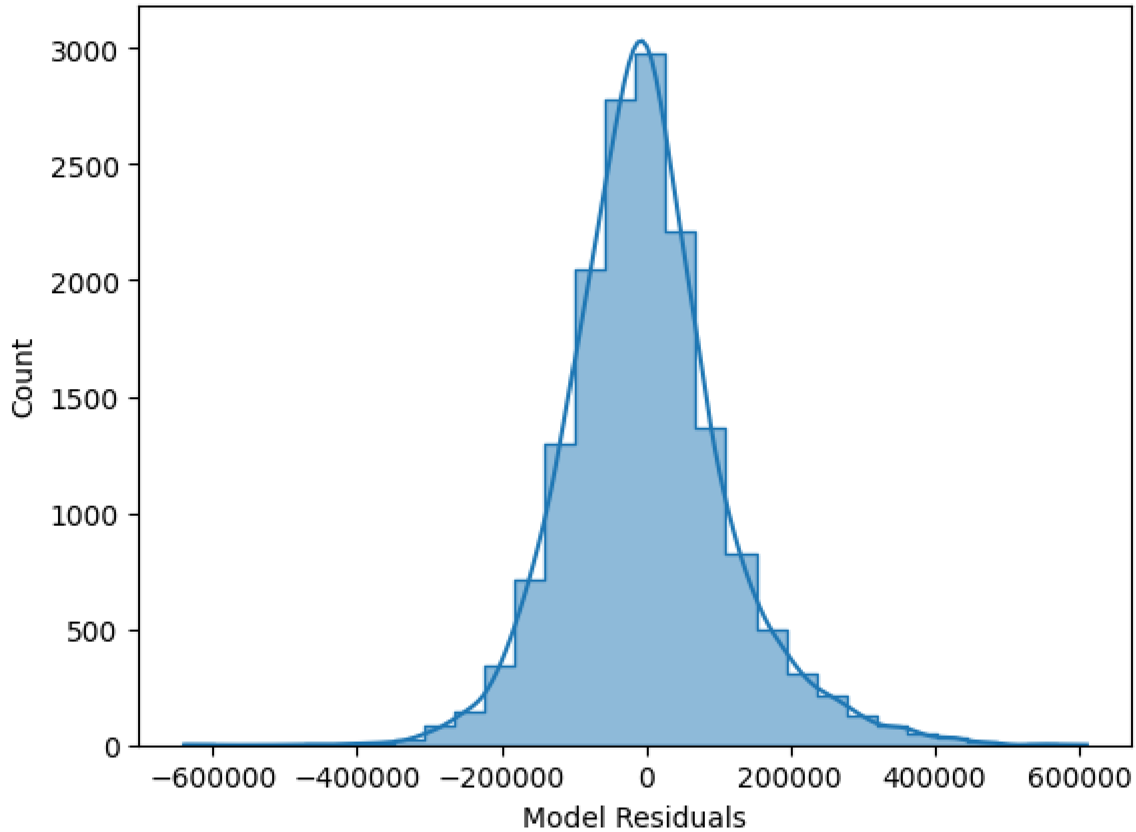


Below is a histogram of the residuals from the above model. It passes the normality test.

Actual Prices
1e6

```
fig, ax = plt.subplots()
sns.histplot(linear_model.resid, bins=30, element="step", kde=True, ax=ax)
ax.set_xlabel("Model Residuals")
```

```
Text(0.5, 0, 'Model Residuals')
```



Random Forest Regressor Iteration

```
from sklearn.ensemble import RandomForestRegressor

# Creating and fitting the Random Forest Regressor
random_forest_model = RandomForestRegressor(n_estimators=100, random_state=42)
random_forest_model.fit(X_train, y_train)

# Predicting on the test set
y_pred_rf = random_forest_model.predict(X_test)

# Evaluating the Random Forest model
rf_mse = mean_squared_error(y_test, y_pred_rf)
rf_rmse = np.sqrt(rf_mse)
rf_r2 = r2_score(y_test, y_pred_rf)

rf_rmse, rf_r2
```

```
(106906.07040961123, 0.7336174090799462)
```

Comparison with Previous Models:

The RMSE has significantly decreased to 102,388.17, indicating a substantial improvement in prediction accuracy.

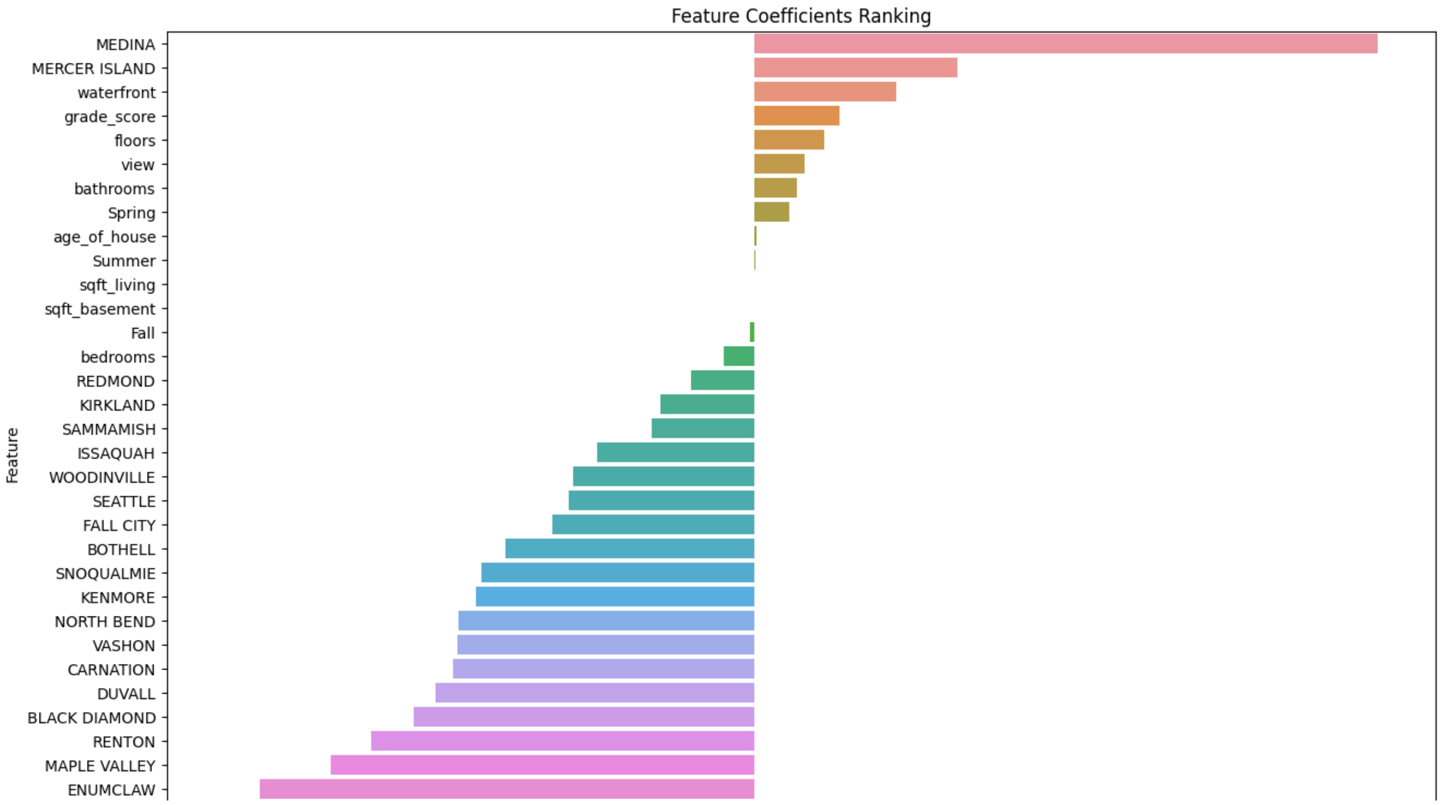
The R^2 score has increased notably from 0.71 to 0.76, showing that the Random Forest model explains a much larger proportion of the variability in house prices.

Interpretation:

The Random Forest Regressor, with its ability to capture complex interactions and non-linear relationships, has provided a significantly better fit to the data than the simpler linear regression models.

This improvement suggests that the factors influencing house prices in King County are multifaceted and non-linear in nature.

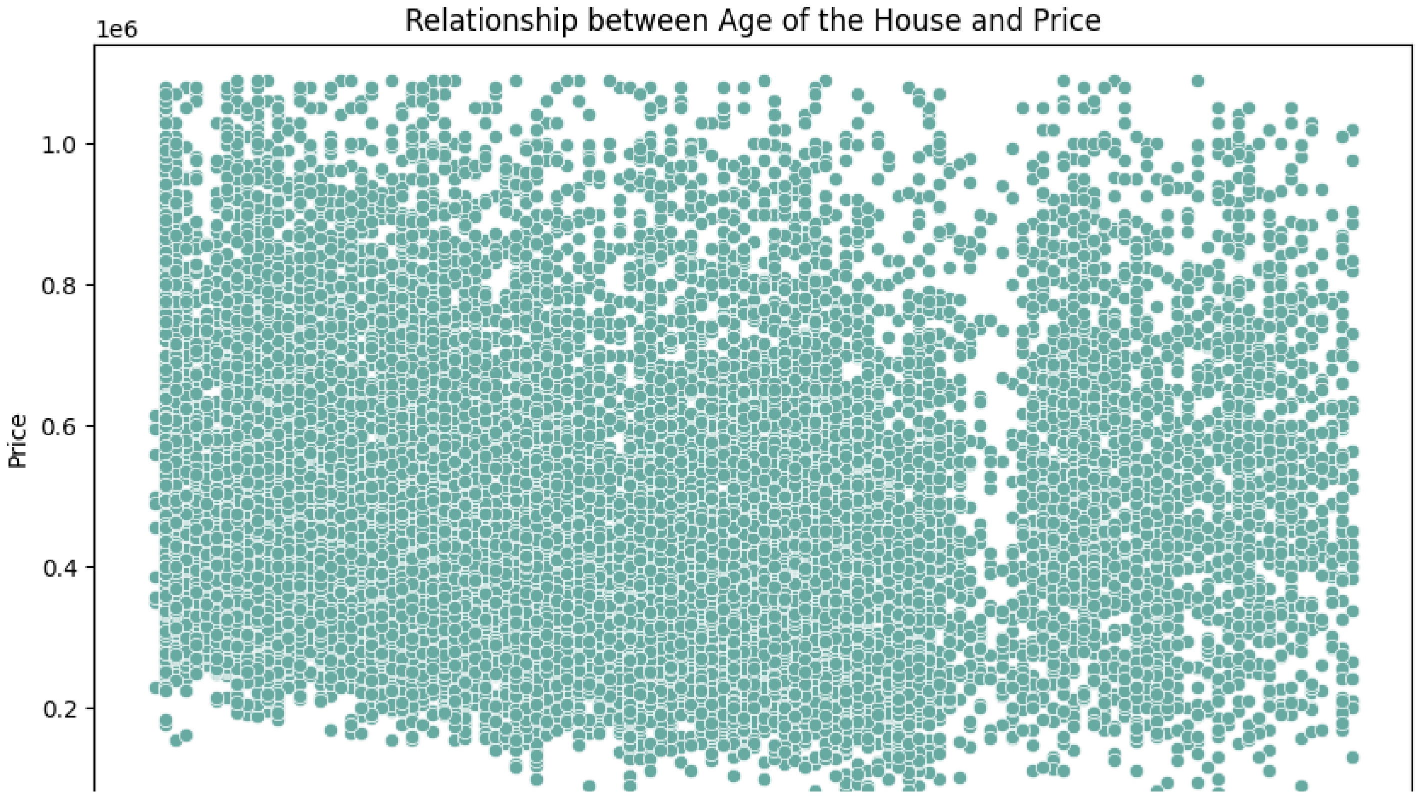
```
# Extracting coefficients and feature names
coefficients = linear_model.params[1:]  # Assuming the first coefficient is the intercept
features = coefficients.index

# Creating a DataFrame
coef_df = pd.DataFrame({'Feature': features, 'Coefficient': coefficients.values})

# Sorting the DataFrame by coefficients in descending order
sorted_coef_df = coef_df.sort_values('Coefficient', ascending=False)

# Optional: Visualizing all features
plt.figure(figsize=(15, 10))
sns.barplot(x='Coefficient', y='Feature', data=sorted_coef_df)
plt.title('Feature Coefficients Ranking')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')

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



Presentation Visualization

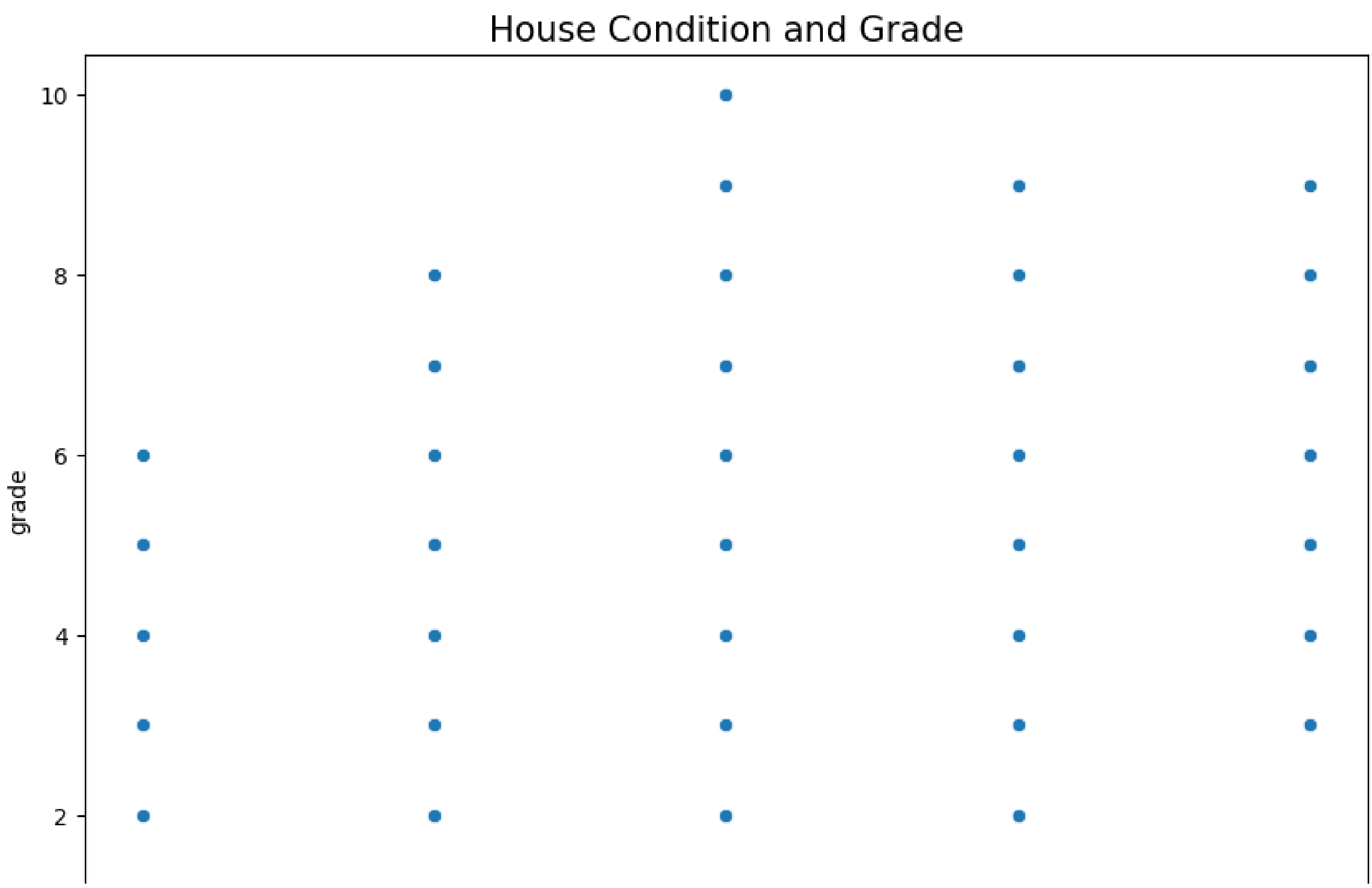
1.Age of the house vs Price

```
import matplotlib.pyplot as plt
import seaborn as sns

# Age of the house
df['age_of_house'] = df['date'].dt.year - df['yr_built']

# Selecting the columns of interest
summary_features = ["price", "age_of_house"]

# Creating a scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x=summary_features[1], y=summary_features[0], data=df, color='#66aaa2')
plt.title('Relationship between Age of the House and Price')
plt.xlabel('Age of the House')
plt.ylabel('Price')
plt.show()
```



2.Grade vs Price


```
#House Condition vs Grade
plt.figure(figsize=(10,7))
sns.scatterplot(x=df['condition'], y=df['grade'])
plt.title('House Condition and Grade', fontsize=15,)
plt.show()
```



```
# Groupby grade_score and take median price
dfgrade_score = df.groupby(df['grade_score'])['price'].median().sort_values(ascending = False)

# Reset index after groupy
dfgrade_score = dfgrade_score.reset_index()

# Check
plt.figure(figsize=(10,7))
dfgrade_score
with sns.axes_style("whitegrid"):
```