Final Project Submission¶ Please fill out: Student name: GROUP 8 Christabel Atolwa - Chair Sydney Mumbo Chepkemoi Mercy James Ndiritu Nicholas Njubi Zacheaus Nyaga Student pace: part time Scheduled project review date/time: Instructor name: Samwel Jane/ Samwel G. Mwangi/ Everline Asiko/ Veronica Isiaho/ Mildred Jepko

1. Project Overview

For this project, we used multiple linear regression modeling to analyze house sales in a northwestern county.

Problem Statement Homeowners in Northwestern County are faced with the complex task of understanding the various elements that impact the pricing of their homes. There is a need for a user-friendly tool that simplifies this complexity, offering homeowners clear insights into the factors influencing house prices and how they can strategically make changes in their properties in order sell them at higher prices or rather reasonable prices in the market.

Data Understanding This project uses the King County House Sales dataset, which can be found in kc_house_data.csv in the data folder in the GitHub repository. The description of the column names can be found in column_names.md in the same folder.

2. Reading and Understanding the Data

In [2]:
```
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import  pandas as pd

from sklearn import linear_model


from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import warnings
warnings.filterwarnings('ignore')
```

3. Data Loading and Exploration

In [4]:
```
df=pd.read_csv(r'kc_house_data.csv')
df.head()
```

Out[4]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_reno
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	0.0	1955	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	400.0	1951	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	0.0	1933	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	910.0	1965	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	0.0	1987	

5 rows × 21 columns

In [5]:
```
# Number of rows and columns
df.shape
```

Out[5]: (21597, 21)

In [6]:
```
df.describe()
```

Out[6]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	yr_built	yr_renovated	zipcode	2
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	21597.000000	17755.000000	21597.000000	
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	1788.596842	1970.999676	83.636778	98077.951845	
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	827.759761	29.375234	399.946414	53.513072	
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	370.000000	1900.000000	0.000000	98001.000000	
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	1190.000000	1951.000000	0.000000	98033.000000	
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	1560.000000	1975.000000	0.000000	98065.000000	
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	2210.000000	1997.000000	0.000000	98118.000000	
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9410.000000	2015.000000	2015.000000	98199.000000	

In [7]:
```
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
```

In [8]:
```
df.dtypes
```

Out[8]:
```
id                int64
date             object
price           float64
bedrooms          int64
bathrooms       float64
sqft_living       int64
sqft_lot          int64
floors          float64
waterfront       object
view             object
condition        object
grade            object
sqft_above        int64
sqft_basement    object
yr_built          int64
yr_renovated    float64
zipcode           int64
lat             float64
long            float64
sqft_living15     int64
sqft_lot15        int64
dtype: object
```

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
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
```

3. Data Cleaning

In [9]:
```
#Check for and drop any duplicates
df = df.drop_duplicates()
df
```

Out[9]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	0.0	1955	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	400.0	1951	

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	0.0	1933	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	910.0	1965	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	0.0	1987	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	NO	NONE	...	8 Good	1530	0.0	2009	
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	NO	NONE	...	8 Good	2310	0.0	2014	
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	NO	NONE	...	7 Average	1020	0.0	2009	
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	NaN	NONE	...	8 Good	1600	0.0	2004	
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	NO	NONE	...	7 Average	1020	0.0	2008	

21597 rows × 21 columns

In [10]:
```
# Split the grade column
# Create two columns, one for the numerical value(grade_num)
# The second column for for the string value (grade_exp)
df[["grade_num", "grade_exp"]] = df["grade"].str.split(" ",1, expand=True)
df
```

Out[10]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	sqft_basement	yr_built	yr_renovated	zipcode	
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	0.0	1955	0.0	98178	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	400.0	1951	1991.0	98125	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	0.0	1933	NaN	98028	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	910.0	1965	0.0	98136	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	0.0	1987	0.0	98074	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	NO	NONE	...	0.0	2009	0.0	98103	
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	NO	NONE	...	0.0	2014	0.0	98146	
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	NO	NONE	...	0.0	2009	0.0	98144	
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	NaN	NONE	...	0.0	2004	0.0	98027	
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	NO	NONE	...	0.0	2008	0.0	98144	

21597 rows × 23 columns

In [11]:
```
# Change grade_num data type to int
df['grade_num'] = df['grade_num'].astype(int)
#Create new column for numeric values of condition
df["condition_num"] = df["condition"].replace({'Poor': 0, 'Fair': 1, 'Average': 2, 'Good': 3,'Very Good':4})
df
```

Out[11]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	yr_built	yr_renovated	zipcode	lat	long
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	1955	0.0	98178	47.5112	-122.25
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	1951	1991.0	98125	47.7210	-122.31
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	1933	NaN	98028	47.7379	-122.23
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	1965	0.0	98136	47.5208	-122.39
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	1987	0.0	98074	47.6168	-122.04
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	NO	NONE	...	2009	0.0	98103	47.6993	-122.34
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	NO	NONE	...	2014	0.0	98146	47.5107	-122.36
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	NO	NONE	...	2009	0.0	98144	47.5944	-122.29
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	NaN	NONE	...	2004	0.0	98027	47.5345	-122.06
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	NO	NONE	...	2008	0.0	98144	47.5941	-122.29

21597 rows × 24 columns

In [12]:
```
selected_cols = ['bedrooms', 'bathrooms', 'sqft_living','condition_num','price']
selected_data = df[selected_cols]
selected_data.isnull().sum()
```

Out[12]:
```
bedrooms        0
bathrooms       0
sqft_living     0
condition_num   0
price           0
dtype: int64
```

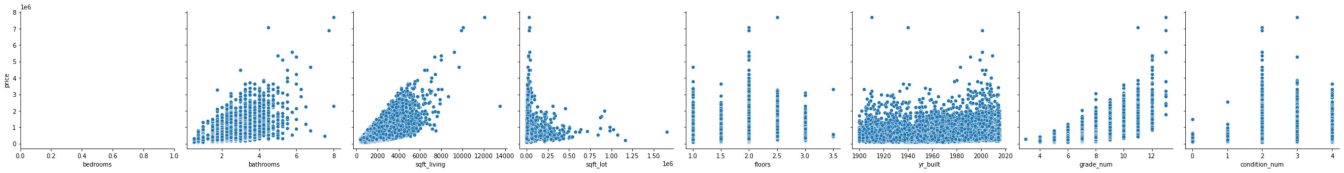
4. Distribution of Data

Steps

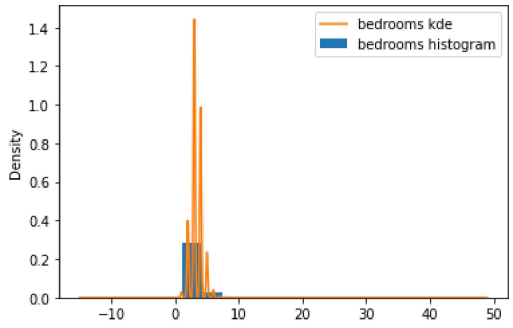
Create scatter plots for all variables where X axis is the price variables.

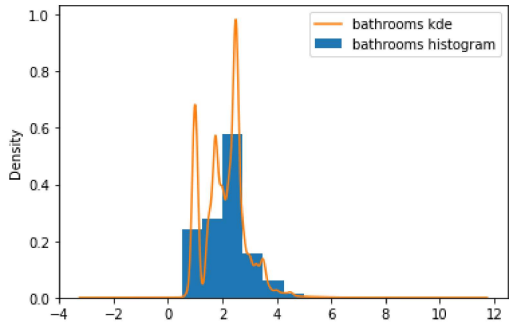
Create a heatmap to check correlation between the variable

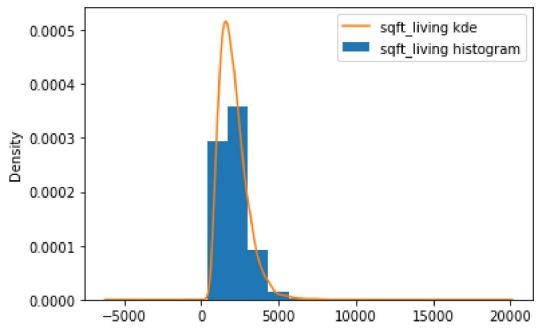
In [13]:
```
# Let's see how price is related with other variables using scatter plot.
sns.pairplot(df, x_vars=['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'yr_built', 'grade_num', 'condition_num'], y_vars='p
plt.show()
```

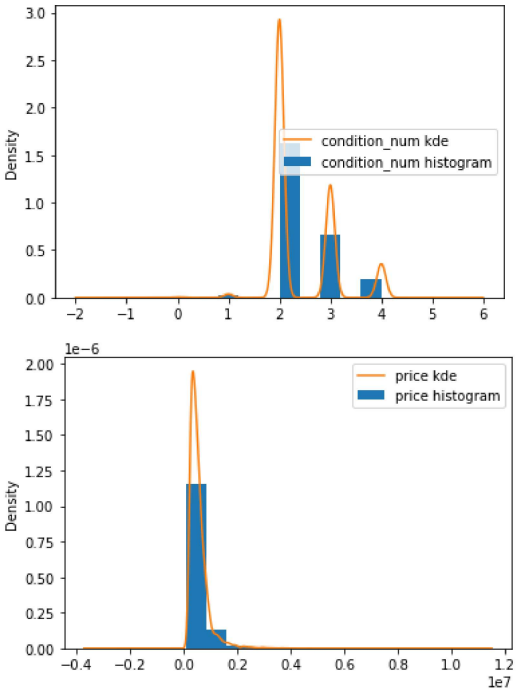


In [14]:
```
for column in selected_data:
    selected_data[column].plot.hist(density=True, label = column+' histogram')
    selected_data[column].plot.kde(label =column+' kde')
    plt.legend()
    plt.show()
```





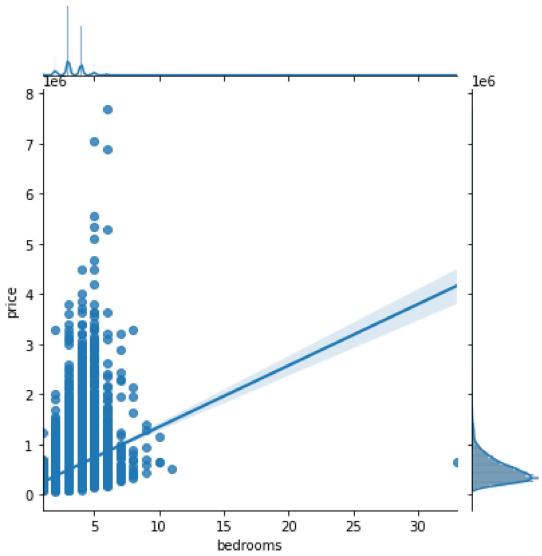


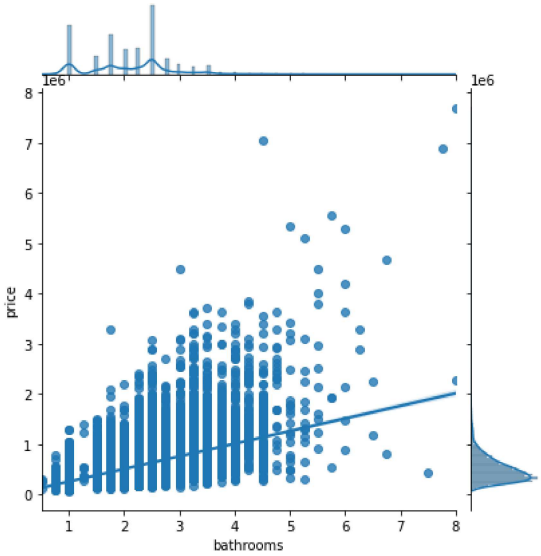


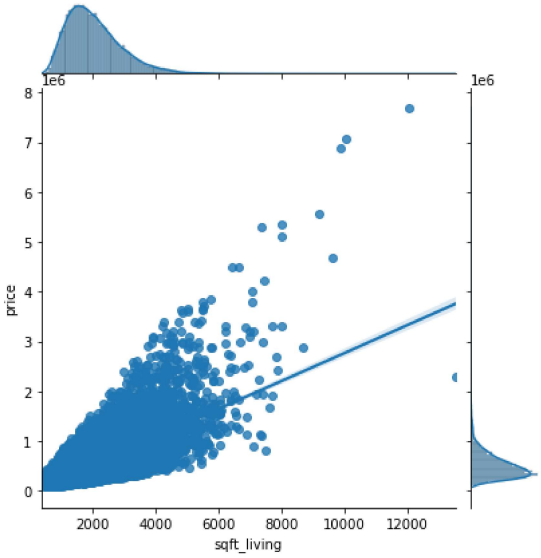
From the diagrams,the variables selected do not have a perfect normal distribution.

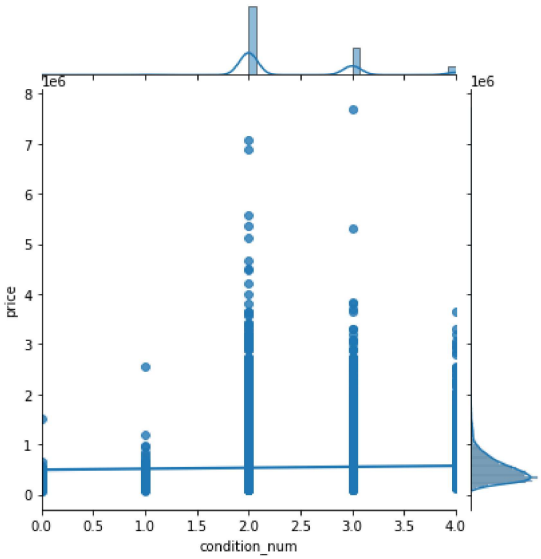
Checking Linearity

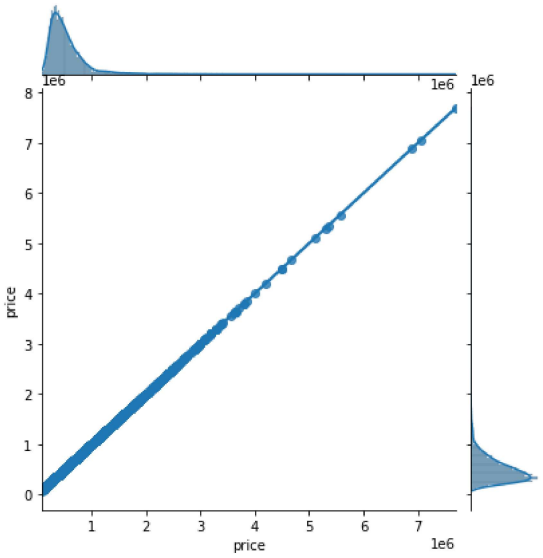
In [15]:
```
for column in selected_data.columns:
    # Create a jointplot for each column against 'price'
    sns.jointplot(x=column, y='price', data=selected_data, kind='reg')
    plt.show()
```




1e6
1e6
price
bathrooms

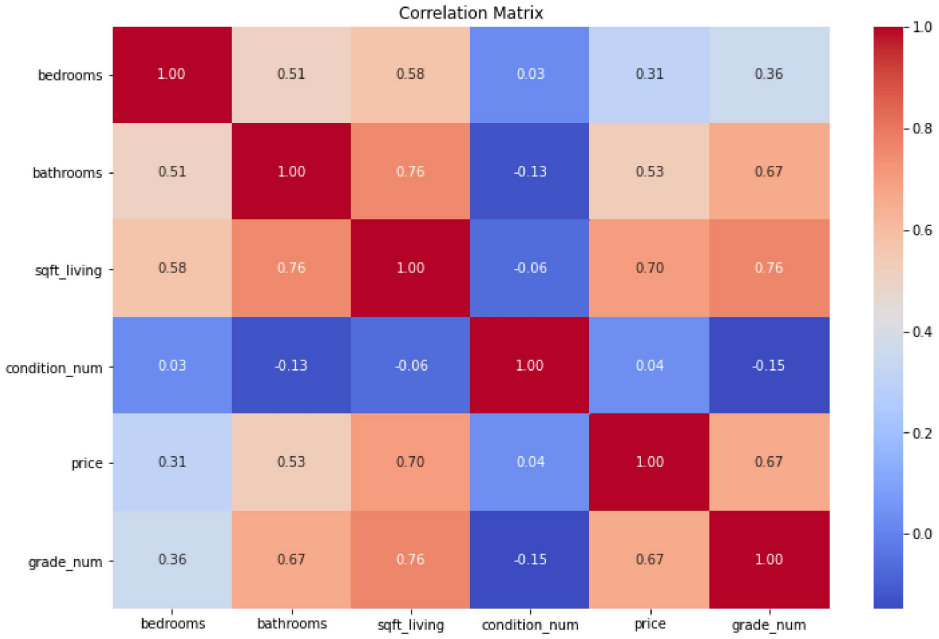

1e6
1e6
price
sqft_living


1e6
1e6
price
condition_num



There is an observation of linearity however,alot is concentrated at one point. Sqft_living ,bedroom and bathrooms have a good linear relationship with price.

In [18]:
```
# Explore relationships between features using a correlation matrix
selected_cols = ['bedrooms', 'bathrooms', 'sqft_living','condition_num','price','grade_num']
selected_data = df[selected_cols]
correlation_matrix = selected_data.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



From the plots above we can see that price variable has a strong correlation with sqft_living followed by grade,bathroom,bedroom and condition.

5.Data Modelling

a) Simple Linear Regression

In [19]:
```
#assigning X and Y variables
X= df['sqft_living']
y= df['price']

# TRAIN TEST SPLIT

X_train, X_test, y_train, y_test= train_test_split( X, y, train_size=0.7, test_size=0.3, random_state=100)

#Displaying part of the X_train and y_train values
X_train.head()
```

Out[19]:
```
8816     2030
15679    2050
3091     2060
```

```
4410     2150
14938     820
Name: sqft_living, dtype: int64
```

In [20]:
```
y_train.head()
```

Out[20]:
```
8816     588000.0
15679    645000.0
3091     348000.0
4410     335000.0
14938    295000.0
Name: price, dtype: float64
```

In [21]:
```
import statsmodels.api as sm
#add a constant to your X_train model manually in order to get your intercept

X_train_sm = sm.add_constant(X_train)

#fit the regression line using Ordinary Least Squares (OLS)

lr = sm.OLS(y_train, X_train_sm).fit()


lr.params #to print the intercept, and the slope of the regression line fitted
```

Out[21]:
```
const         -33413.976324
sqft_living      276.032468
dtype: float64
```

In [22]:
```
lr.summary()
```

Out[22]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.494
Model:	OLS	**Adj. R-squared:**	0.494
Method:	Least Squares	**F-statistic:**	1.475e+04
Date:	Thu, 04 Jan 2024	**Prob (F-statistic):**	0.00
Time:	09:13:24	**Log-Likelihood:**	-2.0973e+05
No. Observations:	15117	**AIC:**	4.195e+05
Df Residuals:	15115	**BIC:**	4.195e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.341e+04	5182.680	-6.447	0.000	-4.36e+04	-2.33e+04
sqft_living	276.0325	2.273	121.436	0.000	271.577	280.488

Omnibus:	9057.805	**Durbin-Watson:**	2.018
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	192163.580
Skew:	2.483	**Prob(JB):**	0.00
Kurtosis:	19.746	**Cond. No.**	5.66e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.66e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

b) Multiple linear Regression Model

In [23]:
```
# Selecting features and target variable
X = df[['sqft_living', 'sqft_above', 'sqft_living15', 'bathrooms', 'bedrooms', 'lat', 'condition_num']]
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)
```

In [24]:
```
X_train_sm = sm.add_constant(X_train)

# Fitting the model
model = sm.OLS(y_train, X_train_sm).fit()

# Print out the statistics
model.summary()
```

Out[24]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.593

Model:	OLS	**Adj. R-squared:**	0.593
Method:	Least Squares	**F-statistic:**	3590.
Date:	Thu, 04 Jan 2024	**Prob (F-statistic):**	0.00
Time:	09:14:48	**Log-Likelihood:**	-2.3822e+05
No. Observations:	17277	**AIC:**	4.765e+05
Df Residuals:	17269	**BIC:**	4.765e+05
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.35e+07	6.22e+05	-53.847	0.000	-3.47e+07	-3.23e+07
sqft_living	261.4690	5.126	51.009	0.000	251.422	271.516
sqft_above	-0.9036	4.759	-0.190	0.849	-10.232	8.425
sqft_living15	66.4584	4.148	16.021	0.000	58.328	74.589
bathrooms	2.238e+04	3663.675	6.110	0.000	1.52e+04	2.96e+04
bedrooms	-5.756e+04	2511.700	-22.918	0.000	-6.25e+04	-5.26e+04
lat	7.017e+05	1.31e+04	53.678	0.000	6.76e+05	7.27e+05
condition_num	5.884e+04	2856.295	20.601	0.000	5.32e+04	6.44e+04

Omnibus:	13762.696	**Durbin-Watson:**	1.992
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	765544.149
Skew:	3.402	**Prob(JB):**	0.00
Kurtosis:	34.893	**Cond. No.**	1.26e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.26e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

Key Findings Model Fit: The R-squared value is 0.593, indicating that about 59.3% of the variability in house prices is explained by the model. This suggests a moderate fit - the model captures a significant portion of the factors affecting house prices but not all. Feature Impact: Living Area (sqft_living): The coefficient is approximately 261.47, indicating that for each additional square foot in living area, the house price increases by about
$261, assuming other factors are constant. Above Ground Living Area (sqft_above) : Surprisingly,$
$this feature has a very small and statistically insignificant effect (-0.90) on house price. This suggests that additional above$
$-$ $ground living space may not significantly impact the price, when living space in general is already accounted for. Neighborhood Living Area (sqft_living15)$
$:$ $Each additional square foot in the average living area of the 15 nearest neighbors adds around$
66 to the house price. Bathrooms: Each additional bathroom is associated with an increase of approximately
$22,380 in house price. Bedrooms : Conversely, each additional bedroom is associated with a decrease of about 57,560$ in house price. This could be due to larger houses being more expensive, but smaller rooms (more bedrooms) reducing individual room value. Latitude (lat): Latitude has a significant positive impact, with an increase of around
$701,700 per unit increase in latitude, indicating location - specific price differences. Condition (condition_encoded) : Better condition ratings increase the house pric$
58,840 for each step up in condition. Focus on Key Features: For stakeholders like sellers or real estate developers, focusing on increasing living area and improving the condition of the property could yield higher returns. Consider Location: The significant impact of latitude suggests that location is a key factor in pricing strategies. Room Utilization: The negative impact of more bedrooms on price suggests a careful consideration of room utilization and layout in house design or renovation. In essence, our model helps understand what influences house prices. Larger living spaces and better conditions significantly boost prices. Location also plays a crucial role, with certain latitudes being more desirable. Surprisingly, more bedrooms might decrease a house's value, possibly due to space distribution considerations. While this model offers valuable insights, it doesn't capture every aspect of the housing market

In [25]:
```
# Predicting on the test set
X_test_sm = sm.add_constant(X_test)
y_pred = model.predict(X_test_sm)

# Calculate R-squared and RMSE
r_squared = r2_score(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred, squared=False)

print(f'R-squared: {r_squared}')
print(f'RMSE: {rmse}')
```

```
R-squared: 0.5867375861685376
RMSE: 231977.35717052015
```

R-squared (0.587): This value indicates that approximately 58.7% of the variation in house prices is explained by the model. In practical terms, this suggests a moderate level of accuracy - the model is capturing a significant portion of the factors that affect house prices, but there's still a notable amount of variation that it doesn't account for. For a non-technical audience, this means the model is reasonably good at predicting house prices based on the features included (like square footage, number of bathrooms/bedrooms, condition, etc.), but it's not capturing everything.

In [26]:
```
# Example: Creating an interaction term
df['living_condition_interaction'] = df['sqft_living'] * df['condition_num']

# Adding this new feature to the model
```

```
X_interact = df[['sqft_living', 'sqft_above', 'sqft_living15', 'bathrooms', 'bedrooms', 'lat', 'condition_num', 'living_condition_interacti
X_train, X_test, y_train, y_test = train_test_split(X_interact, y, test_size=0.2, random_state=42)

X_train_sm = sm.add_constant(X_train)
model_interact = sm.OLS(y_train, X_train_sm).fit()
print(model_interact.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.597
Model:                            OLS   Adj. R-squared:                  0.597
Method:                 Least Squares   F-statistic:                     3203.
Date:                Thu, 04 Jan 2024   Prob (F-statistic):               0.00
Time:                        09:15:01   Log-Likelihood:            -2.3812e+05
No. Observations:               17277   AIC:                         4.763e+05
Df Residuals:                   17268   BIC:                         4.763e+05
Df Model:                           8
Covariance Type:            nonrobust
================================================================================================
                                   coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------
const                       -3.297e+07    6.2e+05    -53.196      0.000   -3.42e+07   -3.18e+07
sqft_living                   147.3043      9.516     15.479      0.000     128.651     165.957
sqft_above                     11.1008      4.807      2.309      0.021       1.679      20.522
sqft_living15                  66.5184      4.124     16.129      0.000      58.434      74.602
bathrooms                   2.209e+04   3642.617      6.065      0.000     1.5e+04    2.92e+04
bedrooms                   -5.812e+04   2497.533    -23.272      0.000    -6.3e+04   -5.32e+04
lat                         6.948e+05    1.3e+04     53.425      0.000    6.69e+05     7.2e+05
condition_num              -2.983e+04   6857.424     -4.349      0.000   -4.33e+04   -1.64e+04
living_condition_interaction    44.8227      3.155     14.206      0.000      38.638      51.007
==============================================================================
Omnibus:                    13704.731   Durbin-Watson:                   1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           754614.523
Skew:                           3.383   Prob(JB):                         0.00
Kurtosis:                      34.662   Cond. No.                     2.30e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.3e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The coefficient for the interaction term ('living_condition_interaction') is approximately 44.82. This suggests that the combined effect of living area and house condition has a significant positive impact on house prices. In other words, the benefit of having a larger living area in terms of price is enhanced when the house is in better condition.

In [27]:
```
# Creating interaction terms
df['living_bathrooms_interaction'] = df['sqft_living'] * df['bathrooms']
df['bedrooms_above_interaction'] = df['bedrooms'] * df['sqft_above']

# Adding these new features to the model
X_interact2 = df[['sqft_living', 'sqft_above', 'sqft_living15', 'bathrooms',
                  'bedrooms', 'lat', 'condition_num',
                  'living_condition_interaction', 'living_bathrooms_interaction',
                  'bedrooms_above_interaction']]

X_train, X_test, y_train, y_test = train_test_split(X_interact2, y, test_size=0.2, random_state=42)

X_train_sm = sm.add_constant(X_train)
model_interact2 = sm.OLS(y_train, X_train_sm).fit()
print(model_interact2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.639
Model:                            OLS   Adj. R-squared:                  0.639
Method:                 Least Squares   F-statistic:                     3053.
Date:                Thu, 04 Jan 2024   Prob (F-statistic):               0.00
Time:                        09:15:07   Log-Likelihood:            -2.3718e+05
No. Observations:               17277   AIC:                         4.744e+05
Df Residuals:                   17266   BIC:                         4.745e+05
Df Model:                          10
Covariance Type:            nonrobust
================================================================================================
                                   coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------
const                       -3.229e+07   5.88e+05    -54.876      0.000   -3.34e+07   -3.11e+07
sqft_living                  -106.6744     11.140     -9.576      0.000    -128.510     -84.839
sqft_above                     45.7384     10.980      4.166      0.000      24.217      67.260
sqft_living15                  95.0598      3.962     23.995      0.000      87.294     102.825
bathrooms                   -1.074e+05   5031.423    -21.342      0.000   -1.17e+05   -9.75e+04
bedrooms                    -2.189e+04   5260.031     -4.161      0.000   -3.22e+04   -1.16e+04
lat                          6.868e+05   1.23e+04     55.675      0.000    6.63e+05    7.11e+05
condition_num               -5.891e+04   6540.784     -9.006      0.000   -7.17e+04   -4.61e+04
living_condition_interaction    59.9218      3.014     19.881      0.000      54.014      65.830
living_bathrooms_interaction    66.3255      1.786     37.132      0.000      62.824      69.827
bedrooms_above_interaction      -9.5294      2.601     -3.663      0.000     -14.628      -4.430
==============================================================================
Omnibus:                     9322.854   Durbin-Watson:                   2.001
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           579672.314
Skew:                           1.807   Prob(JB):                         0.00
Kurtosis:                      31.146   Cond. No.                     4.08e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.08e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The R-squared value has increased to 0.639, meaning the model now explains approximately 63.9% of the variability in house prices, indicating a better fit compared to previous models. Living Area and Bathrooms Interaction: The 'living_bathrooms_interaction' term has a positive coefficient of approximately 66.33. This indicates that the combined effect of living area and the number of bathrooms significantly increases house prices. The larger the house and the more bathrooms it has, the greater the increase in price. Bedrooms and Above Ground Living Area Interaction: The 'bedrooms_above_interaction' term has a negative coefficient of approximately -9.53, suggesting that the number of bedrooms, when considered in conjunction with above-ground living area, slightly reduces house prices. In simpler terms, our model now shows that not just the size and features of a house matter, but how they combine also makes a big difference. For example, big houses with many bathrooms tend to be worth a lot more. However, having too many bedrooms in relation to the living space might not be as beneficial as one might think. These insights are especially useful for those looking to sell, buy, or renovate properties, highlighting which combinations of features can add the most value.

In [28]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Function to calculate VIF
def calculate_vif(df):
    vif_data = pd.DataFrame()
    vif_data["feature"] = df.columns
    vif_data["VIF"] = [variance_inflation_factor(df.values, i) for i in range(df.shape[1])]
    return vif_data

# Calculate VIF for the features
vif = calculate_vif(X_train)
print(vif)
```

```
                        feature         VIF
0                   sqft_living  225.787727
1                    sqft_above  162.871591
2                 sqft_living15   24.312257
3                     bathrooms   44.976344
4                      bedrooms  117.761746
5                           lat  154.337388
6                condition_num   93.158538
7  living_condition_interaction   99.362559
8  living_bathrooms_interaction   46.177216
9    bedrooms_above_interaction  139.128956
```

The high VIF values indicate that the model may suffer from multicollinearity, which can distort the regression coefficients, making them unreliable and unstable. This can affect the interpretability of the model and the conclusions drawn from it. We decided to remove 'sqft_above' due to its high multicollinearity, and we keep the interaction terms that provided significant insights.

In [29]:
```
# Removing 'sqft_above' and using interaction terms
X_refined = df[['sqft_living', 'sqft_living15', 'bathrooms', 'bedrooms',
                'lat', 'condition_num', 'living_condition_interaction',
                'living_bathrooms_interaction', 'bedrooms_above_interaction']]

# Splitting the data again
X_train_refined, X_test_refined, y_train, y_test = train_test_split(X_refined, y, test_size=0.2, random_state=42)
```

In [32]:
```
X_train_final = sm.add_constant(X_train_refined)
model_final = sm.OLS(y_train, X_train_final).fit()
model_final.summary()
```

Out[32]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.638
Model:	OLS	**Adj. R-squared:**	0.638
Method:	Least Squares	**F-statistic:**	3387.
Date:	Thu, 04 Jan 2024	**Prob (F-statistic):**	0.00
Time:	09:15:41	**Log-Likelihood:**	-2.3719e+05
No. Observations:	17277	**AIC:**	4.744e+05
Df Residuals:	17267	**BIC:**	4.745e+05
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.205e+07	5.86e+05	-54.709	0.000	-3.32e+07	-3.09e+07
sqft_living	-85.5062	9.918	-8.621	0.000	-104.947	-66.065
sqft_living15	96.7773	3.942	24.550	0.000	89.051	104.504
bathrooms	-9.778e+04	4474.641	-21.852	0.000	-1.07e+05	-8.9e+04
bedrooms	-3.982e+04	3023.245	-13.172	0.000	-4.57e+04	-3.39e+04
lat	6.823e+05	1.23e+04	55.497	0.000	6.58e+05	7.06e+05
condition_num	-5.637e+04	6515.358	-8.651	0.000	-6.91e+04	-4.36e+04
living_condition_interaction	58.2109	2.987	19.486	0.000	52.355	64.066
living_bathrooms_interaction	62.1736	1.483	41.924	0.000	59.267	65.081
bedrooms_above_interaction	0.3315	1.079	0.307	0.759	-1.784	2.447

Omnibus:	9311.884	**Durbin-Watson:**	2.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	583489.837

Skew:	1.801	**Prob(JB):**	0.00
Kurtosis:	31.241	**Cond. No.**	4.01e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.01e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [33]:
```
# Making predictions on the test set
X_test_final = sm.add_constant(X_test_refined)
y_pred_final = model_final.predict(X_test_final)

# Calculate R-squared and RMSE for the final model
r_squared_final = r2_score(y_test, y_pred_final)
rmse_final = mean_squared_error(y_test, y_pred_final, squared=False)

print(f'Final Model R-squared: {r_squared_final}')
print(f'Final Model RMSE: {rmse_final}')
```

```
Final Model R-squared: 0.6213409130750152
Final Model RMSE: 222053.09664697203
```

Discussion of the Final Regression Model After several iterations and refinements, our final regression model has been optimized to provide a more accurate and insightful understanding of the factors influencing house prices. In this final iteration, we addressed the issue of multicollinearity, which was evident in our initial models. Specifically, we removed the 'sqft_above' feature due to its high correlation with other variables, particularly 'sqft_living'. This step was crucial to enhance the stability and reliability of our model.

The final model includes key features such as 'sqft_living', 'sqft_living15', 'bathrooms', 'bedrooms', and 'lat', along with the 'condition_encoded' variable. Notably, we incorporated interaction terms like 'living_condition_interaction', 'living_bathrooms_interaction', and 'bedrooms_above_interaction'. These terms allowed us to capture the combined effects of certain features on house prices, providing a significant view of how different aspects of a property interact to influence its value. For instance, the interaction between living area and house condition revealed that larger homes in better condition command significantly higher prices.

Our final model demonstrated an improved fit, as indicated by a higher R-squared value compared to the initial model. This improvement suggests that our model is now better equipped to explain the variability in house prices. However, it's essential to acknowledge that no model can capture the full complexity of real estate pricing, and certain factors outside the scope of our dataset may also play a significant role.

In conclusion, the final regression model offers valuable insights for stakeholders in the real estate market. While it should be used as a guide rather than a definitive predictor, it serves as a robust tool for understanding key trends and relationships in the housing market. The model's findings can assist realtors in making informed decisions by highlighting the property features that are most impactful on prices.