Final Project Submission

Please fill out:

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- Student pace: self paced
- Scheduled project review date/time: 01 December 2023
- Instructor name: Hardik Idnani
- Blog post URL:

Overview

The undertaking serves as a valuable showcase for applying the knowledge acquired during Phase 2 to real-world data. By employing data analysis and linear regression, our objective is to derive a minimum of three key insights that can inform decision-making regarding the profitability of renovating older homes. A crucial aspect involves comprehending the factors influencing house prices.

Business Problem

The real estate agency seeks to offer strategic advice to potential homebuyers planning to acquire and renovate properties. This advice aims to pinpoint essential renovation priorities that can maximize the property's market value growth, along with providing estimates of value increments to optimize their resale potential.

Data

The dataset utilized for this model comprises information from houses in King County, which were sold between 2014 and 2015. It encompasses 21,597 entries, incorporating details about the house such as the number of bedrooms, bathrooms, and its rating (grade).

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

In [2]:
```
data = pd.read_csv("data/kc_house_data.csv")
```

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21597 non-null  int64  
 1   date           21597 non-null  object 
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64  
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64  
 6   sqft_lot       21597 non-null  int64  
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64  
 11  grade          21597 non-null  int64  
 12  sqft_above     21597 non-null  int64  
 13  sqft_basement  21597 non-null  object 
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64  
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64  
 20  sqft_lot15     21597 non-null  int64  
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

In [4]:
```
data.describe()
```

Out[4]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lo
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+0
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+0
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+0
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+0
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+0
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+0
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+0
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+0

In [5]:
```
data.head()
```

Out[5]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
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

In [6]:
```
# I want to check the duplicates
data[data.duplicated(keep=False, subset=['id'])]
```

Out[6]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floor
93	6021501535	7/25/2014	430000.0	3	1.50	1580	5000	1.
94	6021501535	12/23/2014	700000.0	3	1.50	1580	5000	1.
313	4139480200	6/18/2014	1380000.0	4	3.25	4290	12103	1.
314	4139480200	12/9/2014	1400000.0	4	3.25	4290	12103	1.
324	7520000520	9/5/2014	232000.0	2	1.00	1240	12092	1.
...	...	...	...	...	...	...	...	.
20654	8564860270	3/30/2015	502000.0	4	2.50	2680	5539	2.
20763	6300000226	6/26/2014	240000.0	4	1.00	1200	2171	1.
20764	6300000226	5/4/2015	380000.0	4	1.00	1200	2171	1.
21564	7853420110	10/3/2014	594866.0	3	3.00	2780	6000	2.
21565	7853420110	5/4/2015	625000.0	3	3.00	2780	6000	2.

353 rows × 21 columns

In [7]:
```
# Now, I am eliminating duplicates while preserving the initial row
data = data.drop_duplicates(keep= 'first', subset= ['id'])
```

To enhance data readability, we can omit the following variables, as they are not directly linked to the target variable "price":

- view: Indicates whether the house has been viewed.
- lat and long: Represent the coordinates of the house.
- zipcode: Unlikely to influence the outcome, as house prices post-renovation are not correlated with their zip codes.
- date: Indicates the sale date of the house.
- sqft_lot15 and sqft_living15: Reflect the size of other houses in the vicinity.
- id: Serves as the unique identification number for the listed house.
- yr_built: indicates which year the house was built

In [8]:
```
to_drop = ['view', 'lat', 'long', 'zipcode', 'date', 'sqft_lot15',
data = data.drop(to_drop, axis= 1)
```

In [9]:
```
# Let's examine whether there are any null values present in our da
data.isna().sum()
```

Out[9]:
```
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2353
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_renovated     3804
dtype: int64
```

In [10]:
```
# We discovered that the variable "sqft_basement" contains some uns
data['sqft_basement'].value_counts()
```

Out[10]:
```
0.0       12717
?           452
600.0       216
500.0       206
700.0       205
          ...
1920.0        1
3480.0        1
2730.0        1
2720.0        1
248.0         1
Name: sqft_basement, Length: 304, dtype: int64
```

In [11]:
```
# We identified 454 instances of missing values in the "sqft_baseme
# To address this, we will replace the "?" entries with 0 to render
data['sqft_basement'] = data['sqft_basement'].replace('?',0)
```

In [12]:
```
# Observing that the "waterfront" variable contains some missing da
data['waterfront'].unique()
```

Out[12]:
```
array([nan,  0.,  1.])
```

In [13]:
```
# Upon examination, we have identified missing data that can be fil
data['waterfront'].fillna(value = 0, inplace = True)
```

In [14]:
```
# We've also identified missing data in the "yr_renovated" variable
data['yr_renovated'].unique()
```

Out[14]:
```
array([   0., 1991.,   nan, 2002., 2010., 1992., 2013., 1994., 197
8.,
       2005., 2003., 1984., 1954., 2014., 2011., 1983., 1945., 199
0.,
       1988., 1977., 1981., 1995., 2000., 1999., 1998., 1970., 198
9.,
       2004., 1986., 2007., 1987., 2006., 1985., 2001., 1980., 197
1.,
       1979., 1997., 1950., 1969., 1948., 2009., 2015., 1974., 200
8.,
       1968., 2012., 1963., 1951., 1962., 1953., 1993., 1996., 195
5.,
       1982., 1956., 1940., 1976., 1946., 1975., 1964., 1973., 195
7.,
       1959., 1960., 1967., 1965., 1934., 1972., 1944., 1958.])
```

In [15]:
```
# Upon examination, we have detected missing data that can be fille
data['yr_renovated'].fillna(value = 0, inplace = True)
```

In [16]:
```
# Upon closer examination, using float in models is not optimal.
# As a solution, we will multiply the bathroom values by 100, allow
data['bathrooms'] = data['bathrooms'] * 100
```

In [17]:
```
# We must convert the data into either integers or floats to facili
data['waterfront'] = data['waterfront'].astype(int)
data['bathrooms'] = data['bathrooms'].astype(int)
data['yr_renovated'] = data['yr_renovated'].astype(float).astype(in
data['floors'] = data['floors'].astype(float).astype(int)
data['sqft_basement'] = data['sqft_basement'].astype(float).astype(
```

In [18]:
```
data.describe()
```

Out[18]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floor
count	2.142000e+04	21420.000000	21420.000000	21420.000000	2.142000e+04	21420.00000
mean	5.407393e+05	3.373950	211.842904	2083.132633	1.512804e+04	1.44799
std	3.679311e+05	0.925405	76.871996	918.808412	4.153080e+04	0.55211
min	7.800000e+04	1.000000	50.000000	370.000000	5.200000e+02	1.00000
25%	3.225000e+05	3.000000	175.000000	1430.000000	5.040000e+03	1.00000
50%	4.500000e+05	3.000000	225.000000	1920.000000	7.614000e+03	1.00000
75%	6.450000e+05	4.000000	250.000000	2550.000000	1.069050e+04	2.00000
max	7.700000e+06	33.000000	800.000000	13540.000000	1.651359e+06	3.00000

In [19]:
```
# We aim to streamline the data by transforming the information abo
# Instead of specifying the year, we will simplify it to a straight
check = lambda x : x != 0
data['reno_bool'] = check(data['yr_renovated'])
```

In [20]:
```
# Since many houses lack a basement, we can modify the variable to '
data['base_flag'] = check (data['sqft_basement'])
```

In [21]:
```
data['reno_bool'] = data['reno_bool'].astype(int)
data['base_flag'] = data['base_flag'].astype(int)
```

In [22]:
```
# Now, we can eliminate the columns used in creating our new variab
data = data.drop(['sqft_basement', 'yr_renovated'], axis=1)
```

In [23]:
```
data.head()
```

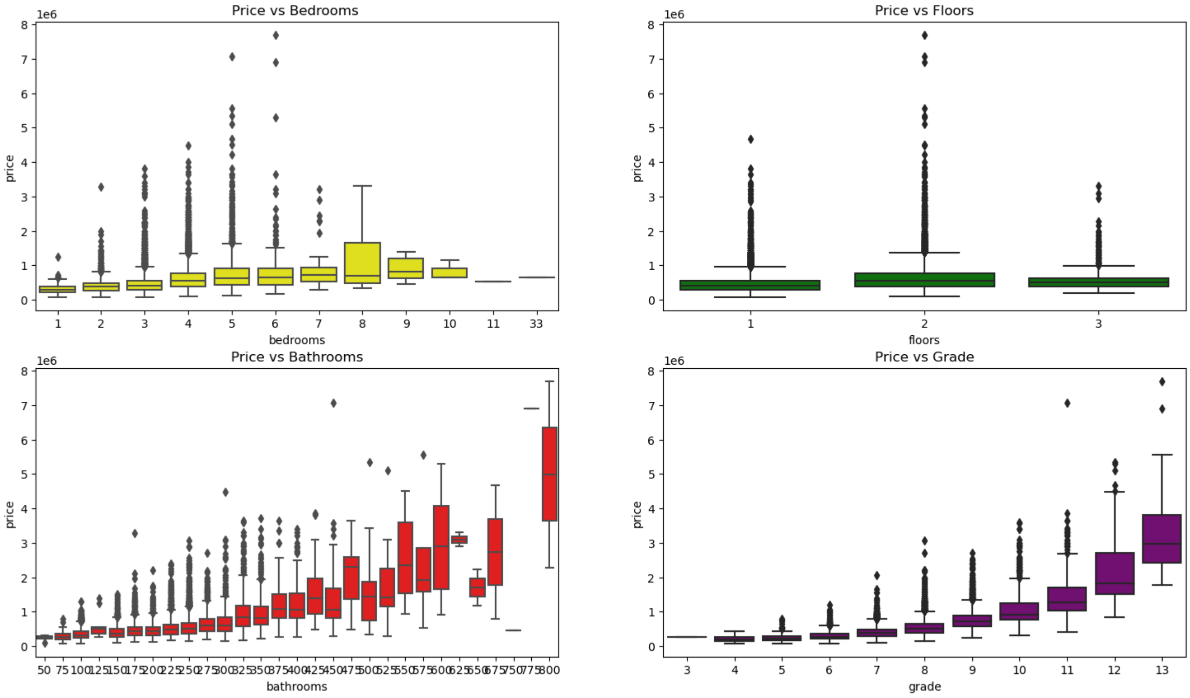
Out[23]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade
0	221900.0	3	100	1180	5650	1	0	3	7
1	538000.0	3	225	2570	7242	2	0	3	7
2	180000.0	2	100	770	10000	1	0	3	6
3	604000.0	4	300	1960	5000	1	0	5	7
4	510000.0	3	200	1680	8080	1	0	3	8

Examine the outliers

We must identify and exclude any outliers in our dataset to enhance its applicability.

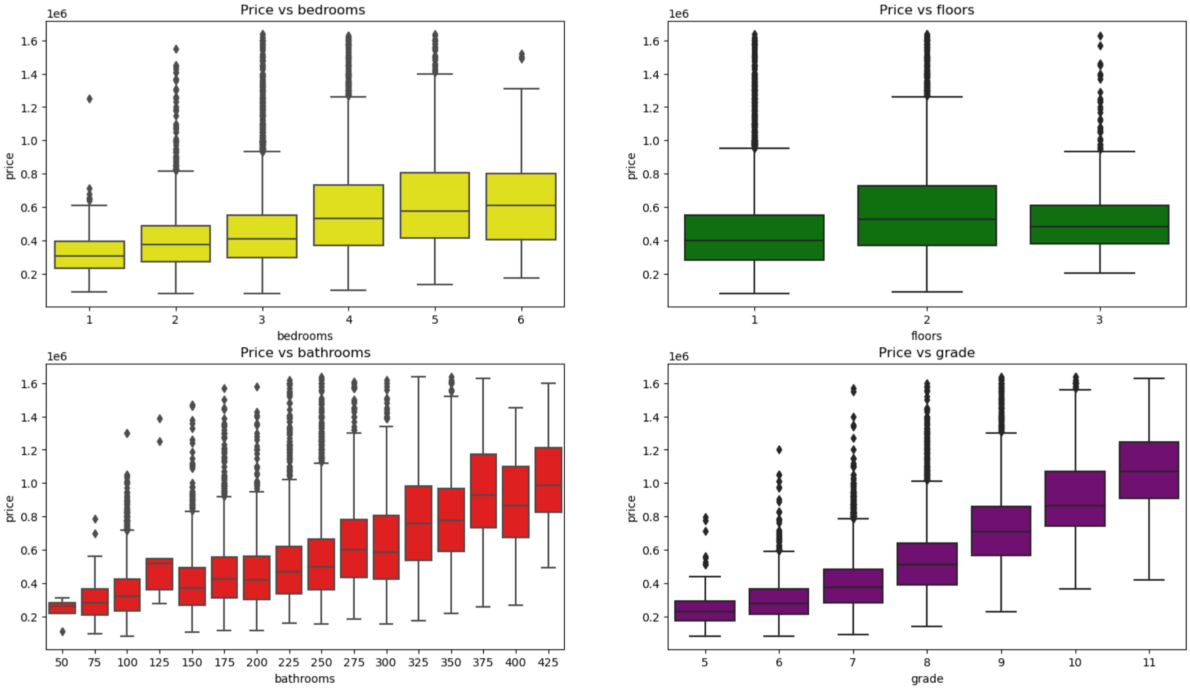
In [24]:
```
# Examine the distribution of the base through percentiles and medi

fig= plt.figure(figsize=(18,10))

ax=fig.add_subplot(2,2,1)
sns.boxplot(data=data, x=data["bedrooms"], y=data["price"], hue=None
ax.set_title("Price vs Bedrooms ")

ax=fig.add_subplot(2,2,2)
sns.boxplot(data=data, x=data["floors"], y=data["price"], hue=None,
ax.set_title("Price vs Floors")

ax=fig.add_subplot(2,2,3)
sns.boxplot(data=data, x=data["bathrooms"], y=data["price"], hue=No
ax.set_title("Price vs Bathrooms")


ax=fig.add_subplot(2,2,4)
sns.boxplot(data=data, x=data["grade"], y=data["price"], hue=None,
ax.set_title("Price vs Grade")

plt.savefig(".\images\outliers.png", dpi = 150, bbox_inches = 'tigh

plt.show()
```



In [25]:
```
# We will include all variables except for "reno_bool" and "waterfr
# This is essential to assess whether renovations can influence pri

columns= ['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lo
outliers=[]

for col in columns:
    mean=np.mean(data[col])
    std=np.std(data[col])
    for i in range(len(data)):
        item = data[col].iloc[i]
        z_score=(item-mean)/std
        if np.abs(z_score)>3:
            outliers.append(i)

outliers = set(outliers)
outliers = list(outliers)

# print (col)
```

In [26]:
```
# We can now eliminate the outliers to create a cleaner dataset.
data.drop(data.index[outliers], inplace= True)
```

In [27]:
```
# I want to check the boxplot once more for the outliers.

# Examine the distribution of the base through percentiles and medi


fig= plt.figure(figsize=(18,10))

ax=fig.add_subplot(2,2,1)
sns.boxplot(data=data, x=data["bedrooms"], y=data["price"], hue=None
ax.set_title("Price vs bedrooms ")

ax=fig.add_subplot(2,2,2)
sns.boxplot(data=data, x=data["floors"], y=data["price"], hue=None,
ax.set_title("Price vs floors")

ax=fig.add_subplot(2,2,3)
sns.boxplot(data=data, x=data["bathrooms"], y=data["price"], hue=No
ax.set_title("Price vs bathrooms")


ax=fig.add_subplot(2,2,4)
sns.boxplot(data=data, x=data["grade"], y=data["price"], hue=None,
ax.set_title("Price vs grade")

plt.savefig(".\images\outliers.png", dpi = 150, bbox_inches = 'tigh

plt.show()
```



Model 1

In [28]:
```
outcome = 'price'
predictors = data.drop(['price'], axis= 1)
pred_sum = "+".join(predictors.columns)
formula = outcome + "~" + pred_sum
```

In [29]:
```
model= ols(formula=formula, data=data).fit()
model.summary()
```

Out[29]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.533
Model:	OLS	**Adj. R-squared:**	0.532
Method:	Least Squares	**F-statistic:**	2105.
Date:	Fri, 01 Dec 2023	**Prob (F-statistic):**	0.00
Time:	16:25:58	**Log-Likelihood:**	-2.7391e+05
No. Observations:	20341	**AIC:**	5.478e+05
Df Residuals:	20329	**BIC:**	5.479e+05
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-6.495e+05	1.39e+04	-46.671	0.000	-6.77e+05	-6.22e+05
bedrooms	-2.046e+04	1825.138	-11.211	0.000	-2.4e+04	-1.69e+04
bathrooms	-211.2116	28.452	-7.423	0.000	-266.980	-155.444
sqft_living	127.1091	5.613	22.646	0.000	116.107	138.111
sqft_lot	-1.0910	0.094	-11.574	0.000	-1.276	-0.906
floors	-5711.7855	3113.702	-1.834	0.067	-1.18e+04	391.321
waterfront	3.376e+05	2.01e+04	16.784	0.000	2.98e+05	3.77e+05
condition	5.304e+04	1979.682	26.792	0.000	4.92e+04	5.69e+04
grade	1.077e+05	1808.823	59.537	0.000	1.04e+05	1.11e+05
sqft_above	3.4359	6.058	0.567	0.571	-8.439	15.310
reno_bool	1.315e+05	6807.655	19.315	0.000	1.18e+05	1.45e+05
base_flag	4.685e+04	4520.509	10.364	0.000	3.8e+04	5.57e+04

Omnibus:	2318.397	**Durbin-Watson:**	1.960

Omnibus:	3318.397	**Durbin-Watson:**	1.960
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7929.343
Skew:	0.930	**Prob(JB):**	0.00
Kurtosis:	5.429	**Cond. No.**	2.90e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.9e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

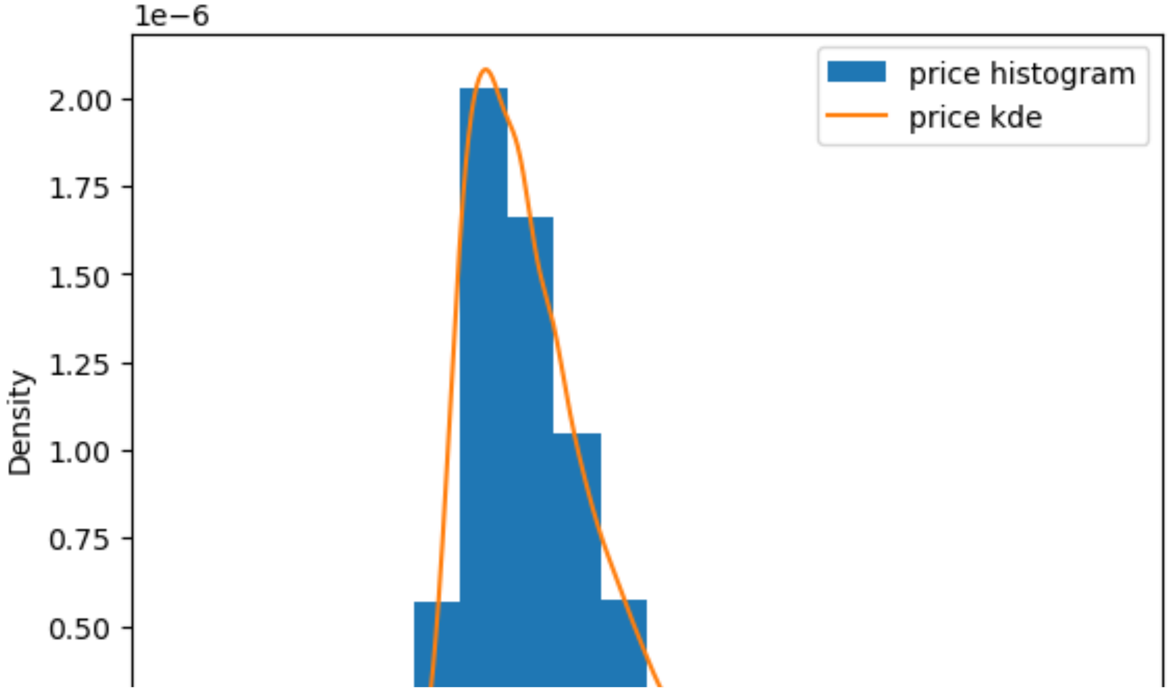
Summary on Model 1

Currently, the P-values suggest that all independent variables, except for sqft_above, are statistically significant. Although the adjusted R-squared is satisfactory, there is room for improvement through the handling of categorical data, log transformation, and normalization.

The skewness at 0.930 indicates a positive skew, while the kurtosis at 5.429 signifies a leptokurtic curve. It suggests the presence of outliers, but these may be necessary for extracting valuable information from certain columns and rendering them usable.

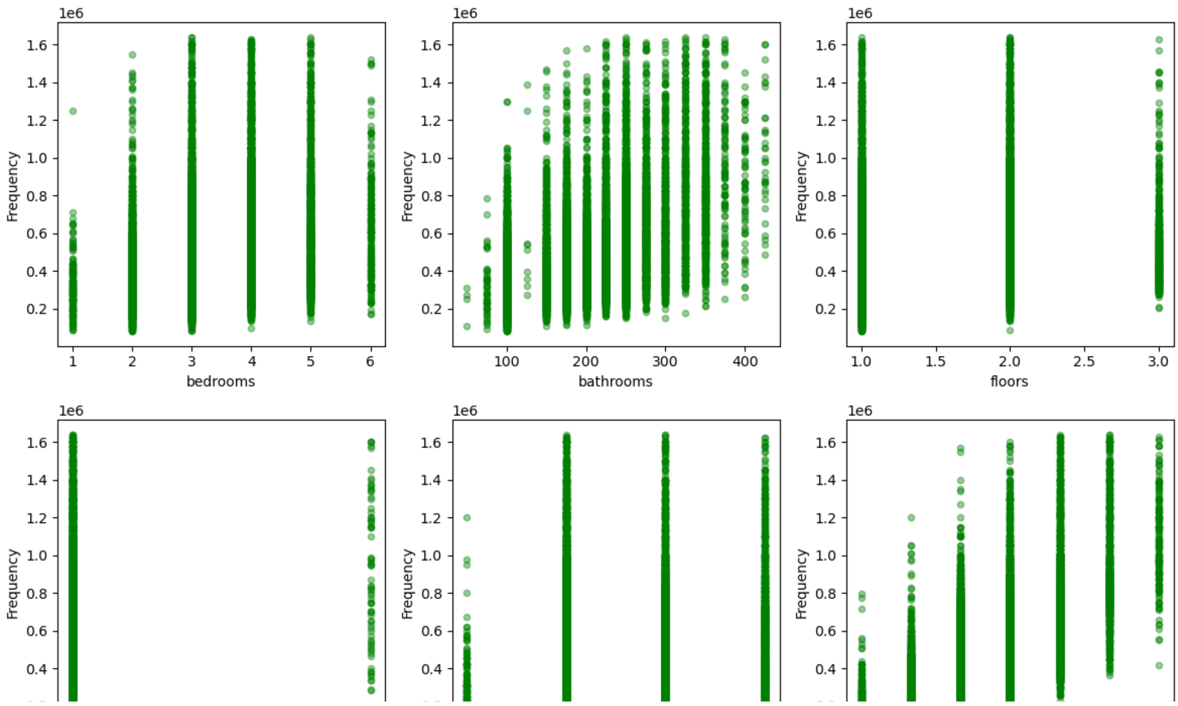
Checking assumptions

In [30]:
```
# KDE
for column in data:
    data[column].plot.hist(density=True, label = column +' histogra
    data[column].plot.kde(label = column + ' kde')
    plt.legend()
    plt.show()
```



Dealing with Categorical Data

In [31]:
```
# We should create a histogram to confirm whether the data at hand

fig, axs = plt.subplots(3, 3, figsize=(12, 12))

columns = ['bedrooms', 'bathrooms', 'floors', 'waterfront', 'condit

for i, column in enumerate(columns):
    row = i // 3
    col = i % 3
    data.plot(kind='scatter', x=column, y='price', ax=axs[row, col]
    axs[row, col].set_xlabel(column)
    axs[row, col].set_ylabel('Frequency')

plt.tight_layout()

plt.savefig(".\images\categorical.png", dpi = 150, bbox_inches = 't

plt.show()
```



Observing the clustered distribution in the scatter plot for the columns:

- bedrooms
- bathrooms
- floors
- waterfront
- condition
- grade
- reno_bool
- base_flag

It becomes evident that these are categorical data. To utilize them effectively, we should create dummy variables.

In [32]:
```
categorical = ['bedrooms', 'bathrooms', 'floors', 'waterfront', 'co
```

In [33]:
```
bed_dummies = pd.get_dummies(data['bedrooms'], prefix='bed', drop_f
bath_dummies = pd.get_dummies(data['bathrooms'], prefix='bath', dro
flr_dummies = pd.get_dummies(data['floors'], prefix='flr', drop_fir
wtr_dummies = pd.get_dummies(data['waterfront'], prefix='wtr', drop_
cond_dummies = pd.get_dummies(data['condition'], prefix='cond', dro
grade_dummies = pd.get_dummies(data['grade'], prefix='grade', drop_
reno_dummies = pd.get_dummies(data['reno_bool'], prefix='reno', dro
base_dummies = pd.get_dummies(data['base_flag'], prefix='base', dro
```

In [34]:
```
dummies = pd.concat([bed_dummies, bath_dummies, flr_dummies, wtr_du
```

In [35]:
```
bed_dummies = pd.get_dummies(data['bedrooms'], prefix='bed')
bath_dummies = pd.get_dummies(data['bathrooms'], prefix='bath')
flr_dummies = pd.get_dummies(data['floors'], prefix='flr')
wtr_dummies = pd.get_dummies(data['waterfront'], prefix='wtr')
cond_dummies = pd.get_dummies(data['condition'], prefix='cond')
grade_dummies = pd.get_dummies(data['grade'], prefix='grade')
reno_dummies = pd.get_dummies(data['reno_bool'], prefix='reno')

base_dummies = pd.get_dummies(data['base_flag'], prefix='base')
```

In [36]:
```
dummies_full = pd.concat([bed_dummies, bath_dummies, flr_dummies, w
```

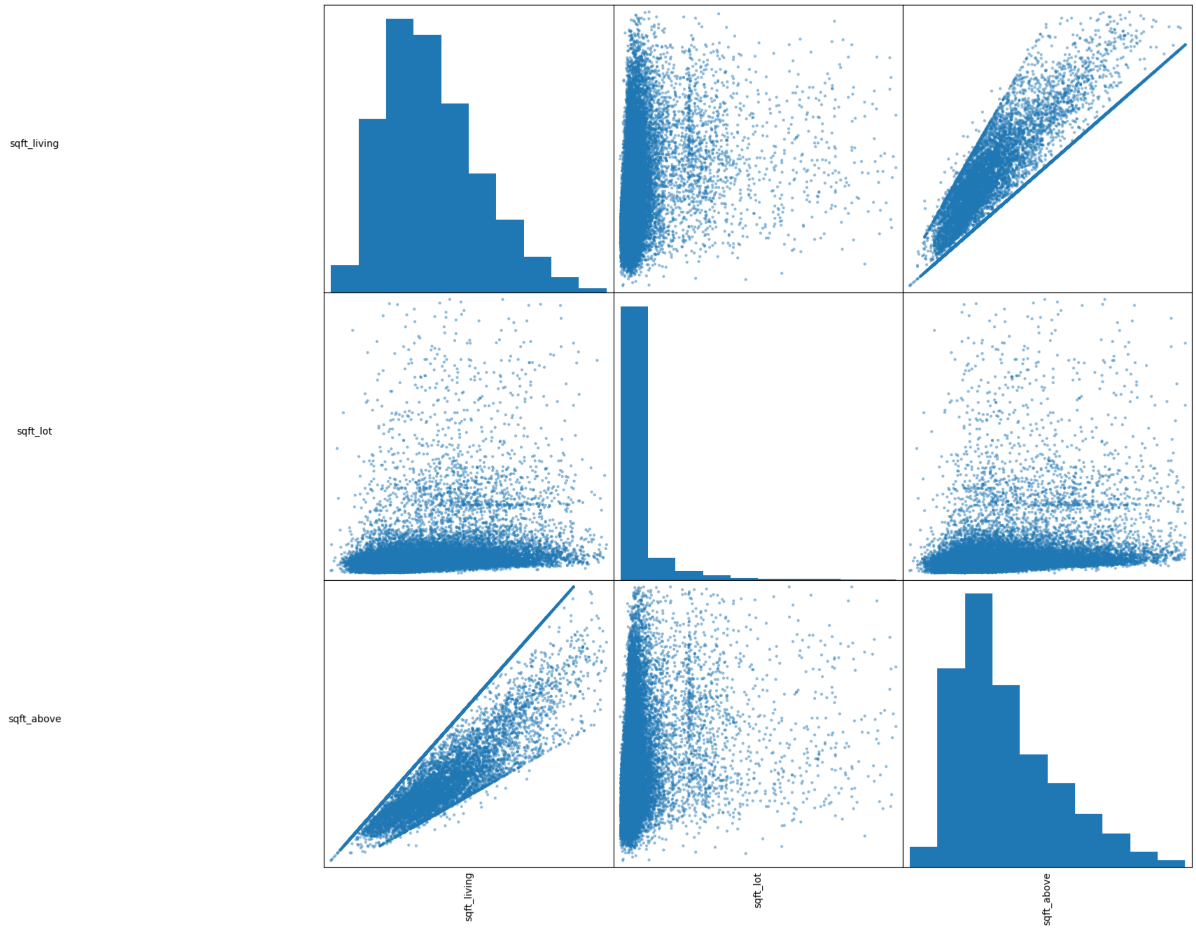
In [37]:
```
data_1 = data.drop(categorical, axis=1)
```

Multicollinearity

To enhance model performance and ensure accurate coefficients, it is essential to eliminate highly correlated variables.

In [38]:
```
data_pred = data_1.iloc[:, 1:]
```

In [39]:
```
sm = pd.plotting.scatter_matrix(data_pred,figsize  = [16, 16]);

# Rotate the text
[s.xaxis.label.set_rotation(90) for s in sm.reshape(-1)]
[s.yaxis.label.set_rotation(0) for s in sm.reshape(-1)]

#Consider adjusting the label offset when rotating to avoid overlap
[s.get_yaxis().set_label_coords(-1,0.5) for s in sm.reshape(-1)]

# Conceal the ticks
[s.set_xticks(()) for s in sm.reshape(-1)]
[s.set_yticks(()) for s in sm.reshape(-1)]

plt.show()
```



In [40]:
```
# Present the correlation in numerical format.
data_pred.corr()
```

Out[40]:

	sqft_living	sqft_lot	sqft_above
sqft_living	1.000000	0.219082	0.84521
sqft_lot	0.219082	1.000000	0.20770
sqft_above	0.845210	0.207700	1.00000

In [41]:
```
abs(data_pred.corr()) > 0.75
```

Out[41]:

	sqft_living	sqft_lot	sqft_above
sqft_living	True	False	True
sqft_lot	False	True	False
sqft_above	True	False	True

In [42]:
```
# This will display pairs with identical correlation values, preven
df=data_pred.corr().abs().stack().reset_index().sort_values(0, asce

# Create a new column named "pairs" by zipping the variable name co
# which were initially named "level_0" and "level_1" by default.
df['pairs'] = list(zip(df.level_0, df.level_1))

# Set the index to pairs
df.set_index(['pairs'], inplace = True)

# Drop ther columns in "levels"
df.drop(columns=['level_1', 'level_0'], inplace = True)

# Rename the correlation column to "cc" instead of "0".
df.columns = ['cc']

# Remove duplicates.
# Exercise caution, especially if you have variables that are perfe
# as this action could be risky.
df.drop_duplicates(inplace=True)
```

In [43]:
```
df[(df.cc>0.75) & (df.cc < 1.0)]
```

Out[43]:

	cc
pairs	
(sqft_living, sqft_above)	0.84521

Dealing with Multicollinearity

We identified a high correlation between the variables "sqft_above" and "sqft_living." It is appropriate to address this by dropping one variable from the pair. In this case, we will eliminate "sqft_above," given that its description corresponds to the square footage of the house.

In [44]:
```
dt = data_1.drop(['sqft_above'], axis= 1)
```

In [45]:
```
dt.head()
```

Out[45]:

	price	sqft_living	sqft_lot
0	221900.0	1180	5650
1	538000.0	2570	7242
2	180000.0	770	10000
3	604000.0	1960	5000
4	510000.0	1680	8080

Model 2

In [46]:
```
dt_1_dummies = pd.concat([dt, dummies], axis= 1)
```

In [47]:
```
dt_1_dummies.head()
```

Out[47]:

	price	sqft_living	sqft_lot	bed_2	bed_3	bed_4	bed_5	bed_6	bath_75	bath_100	.
0	221900.0	1180	5650	0	1	0	0	0	0	1	.
1	538000.0	2570	7242	0	1	0	0	0	0	0	.
2	180000.0	770	10000	1	0	0	0	0	0	1	.
3	604000.0	1960	5000	0	0	1	0	0	0	0	.
4	510000.0	1680	8080	0	1	0	0	0	0	0	.

5 rows × 37 columns

In [48]:
```
predictors = dt_1_dummies.drop(['price'], axis = 1)
pred_sum = "+".join(predictors.columns)
formula = outcome + "~" + pred_sum
```

In [49]:
```
model = ols(formula = formula, data = dt_1_dummies).fit()
model.summary()
```

Out[49]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.557
Model:	OLS	**Adj. R-squared:**	0.556
Method:	Least Squares	**F-statistic:**	707.7
Date:	Fri, 01 Dec 2023	**Prob (F-statistic):**	0.00
Time:	16:26:03	**Log-Likelihood:**	-2.7337e+05
No. Observations:	20341	**AIC:**	5.468e+05
Df Residuals:	20304	**BIC:**	5.471e+05
Df Model:	36		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-8880.3248	8.52e+04	-0.104	0.917	-1.76e+05	1.58e+05
sqft_living	120.6559	3.071	39.284	0.000	114.636	126.676
sqft_lot	-1.0623	0.092	-11.488	0.000	-1.244	-0.881
bed_2	-6399.8661	1.35e+04	-0.474	0.635	-3.29e+04	2.01e+04
bed_3	-5.026e+04	1.35e+04	-3.729	0.000	-7.67e+04	-2.38e+04
bed_4	-5.679e+04	1.38e+04	-4.127	0.000	-8.38e+04	-2.98e+04
bed_5	-5.805e+04	1.45e+04	-3.999	0.000	-8.65e+04	-2.96e+04
bed_6	-6.037e+04	1.82e+04	-3.313	0.001	-9.61e+04	-2.47e+04
bath_75	9.278e+04	8.61e+04	1.077	0.281	-7.61e+04	2.62e+05
bath_100	1.168e+05	8.33e+04	1.403	0.161	-4.64e+04	2.8e+05
bath_125	1.383e+05	1e+05	1.382	0.167	-5.78e+04	3.34e+05
bath_150	9.195e+04	8.34e+04	1.103	0.270	-7.15e+04	2.55e+05
bath_175	8.647e+04	8.33e+04	1.038	0.299	-7.69e+04	2.5e+05
bath_200	9.046e+04	8.34e+04	1.085	0.278	-7.3e+04	2.54e+05
bath_225	7.772e+04	8.34e+04	0.932	0.351	-8.57e+04	2.41e+05
bath_250	4.87e+04	8.34e+04	0.584	0.559	-1.15e+05	2.12e+05
bath_275	7.819e+04	8.35e+04	0.937	0.349	-8.54e+04	2.42e+05

bath_300	8.902e+04	8.36e+04	1.065	0.287	-7.48e+04	2.53e+05
bath_325	1.167e+05	8.37e+04	1.393	0.164	-4.74e+04	2.81e+05
bath_350	1.043e+05	8.37e+04	1.247	0.212	-5.97e+04	2.68e+05
bath_375	1.943e+05	8.5e+04	2.286	0.022	2.77e+04	3.61e+05
bath_400	1.016e+05	8.58e+04	1.184	0.236	-6.66e+04	2.7e+05
bath_425	1.778e+05	8.84e+04	2.012	0.044	4601.006	3.51e+05
flr_2	-1.191e+04	3633.602	-3.277	0.001	-1.9e+04	-4785.042
flr_3	5.127e+04	7793.927	6.578	0.000	3.6e+04	6.65e+04
wtr_1	3.257e+05	1.97e+04	16.547	0.000	2.87e+05	3.64e+05
cond_3	1.631e+04	1.39e+04	1.176	0.240	-1.09e+04	4.35e+04
cond_4	6.337e+04	1.39e+04	4.548	0.000	3.61e+04	9.07e+04
cond_5	1.302e+05	1.44e+04	9.061	0.000	1.02e+05	1.58e+05
grade_6	3.825e+04	1.2e+04	3.187	0.001	1.47e+04	6.18e+04
grade_7	1.118e+05	1.18e+04	9.433	0.000	8.85e+04	1.35e+05
grade_8	2.153e+05	1.22e+04	17.612	0.000	1.91e+05	2.39e+05
grade_9	3.648e+05	1.29e+04	28.366	0.000	3.4e+05	3.9e+05
grade_10	4.841e+05	1.4e+04	34.517	0.000	4.57e+05	5.12e+05
grade_11	5.988e+05	1.84e+04	32.607	0.000	5.63e+05	6.35e+05
reno_1	1.251e+05	6666.666	18.761	0.000	1.12e+05	1.38e+05
base_1	4.481e+04	2834.264	15.810	0.000	3.93e+04	5.04e+04

Omnibus:	3249.639	**Durbin-Watson:**	1.964
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	8265.134
Skew:	0.892	**Prob(JB):**	0.00
Kurtosis:	5.564	**Cond. No.**	4.91e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.91e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

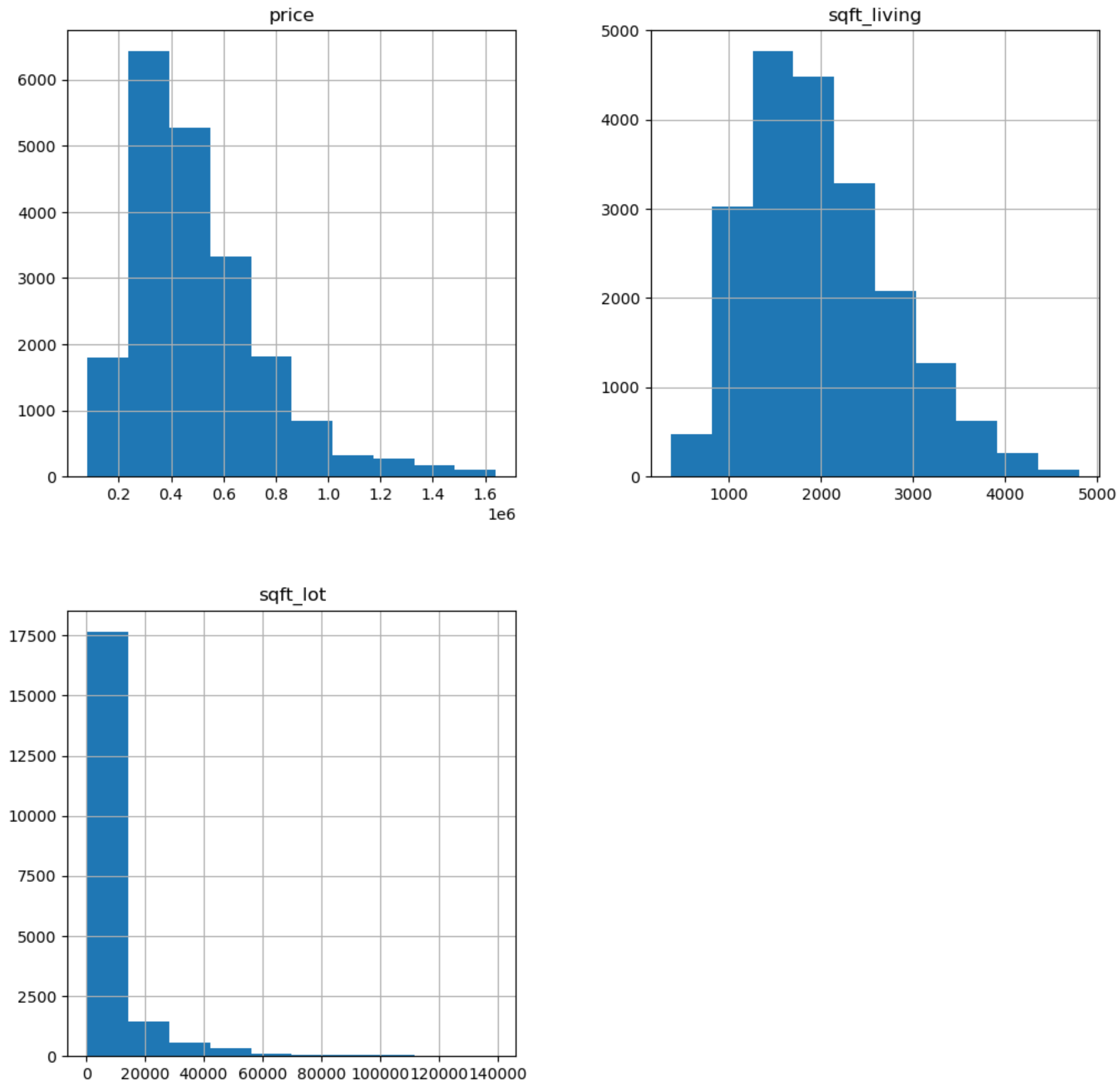
Summary on Model 2

Addressing multicollinearity resulted in an increase in the R-squared value, indicating that we are moving in the right direction.

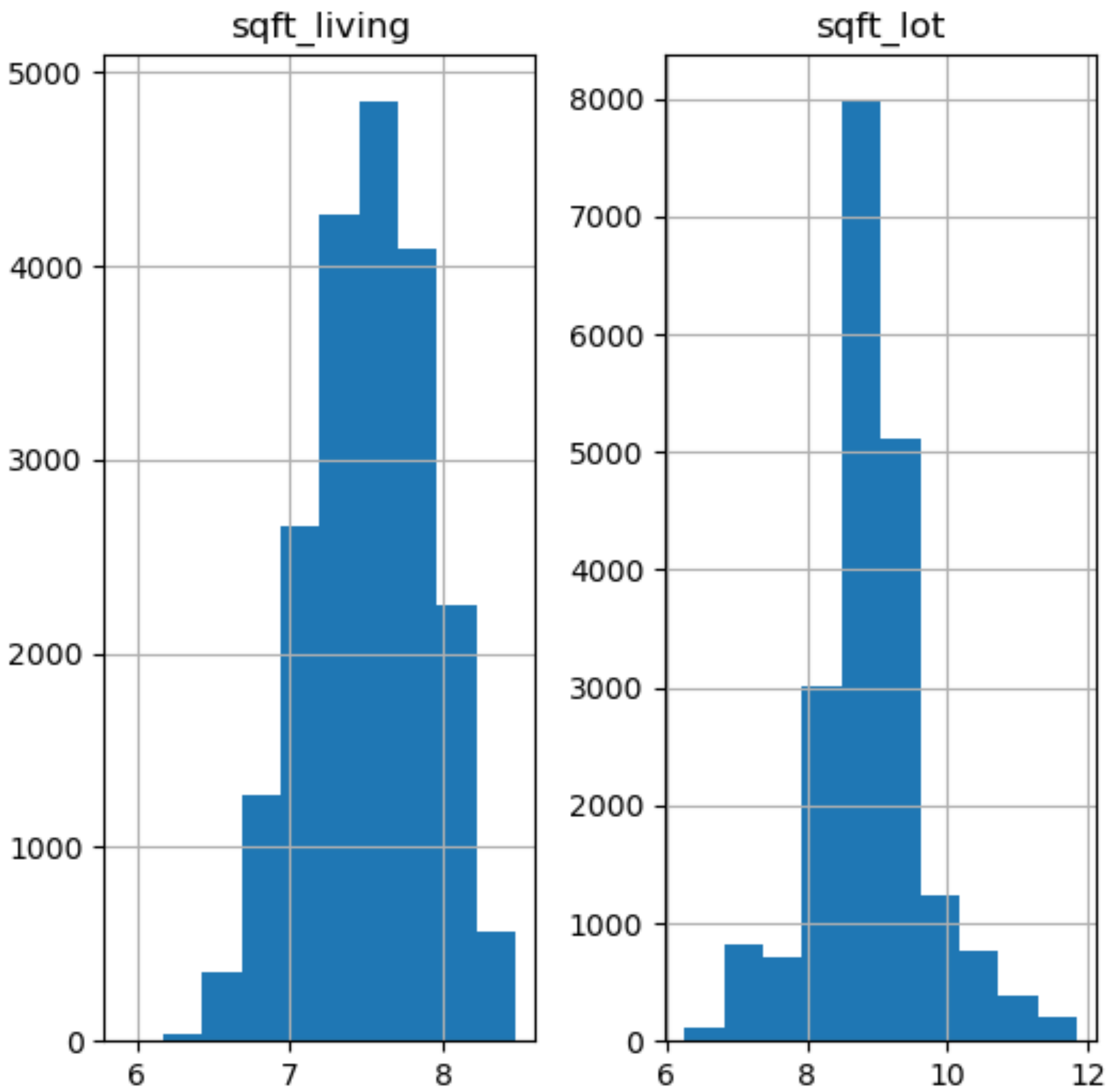
Applying log transformation and normalization

In [50]:
```
# We aim to visualize our data through a histogram.
# Upon examination, I propose performing a log transformation and n
# to bring the mean, median, and mode closer to zero.

fig = plt.figure(figsize = (12,12))
ax = fig.gca()
dt.hist(ax = ax);
```

```
/var/folders/zr/m5b0ldvs7695p_h8w70ndwc40000gn/T/ipykernel_57858/3
211950891.py:7: UserWarning: To output multiple subplots, the figu
re containing the passed axes is being cleared.
  dt.hist(ax = ax);
```

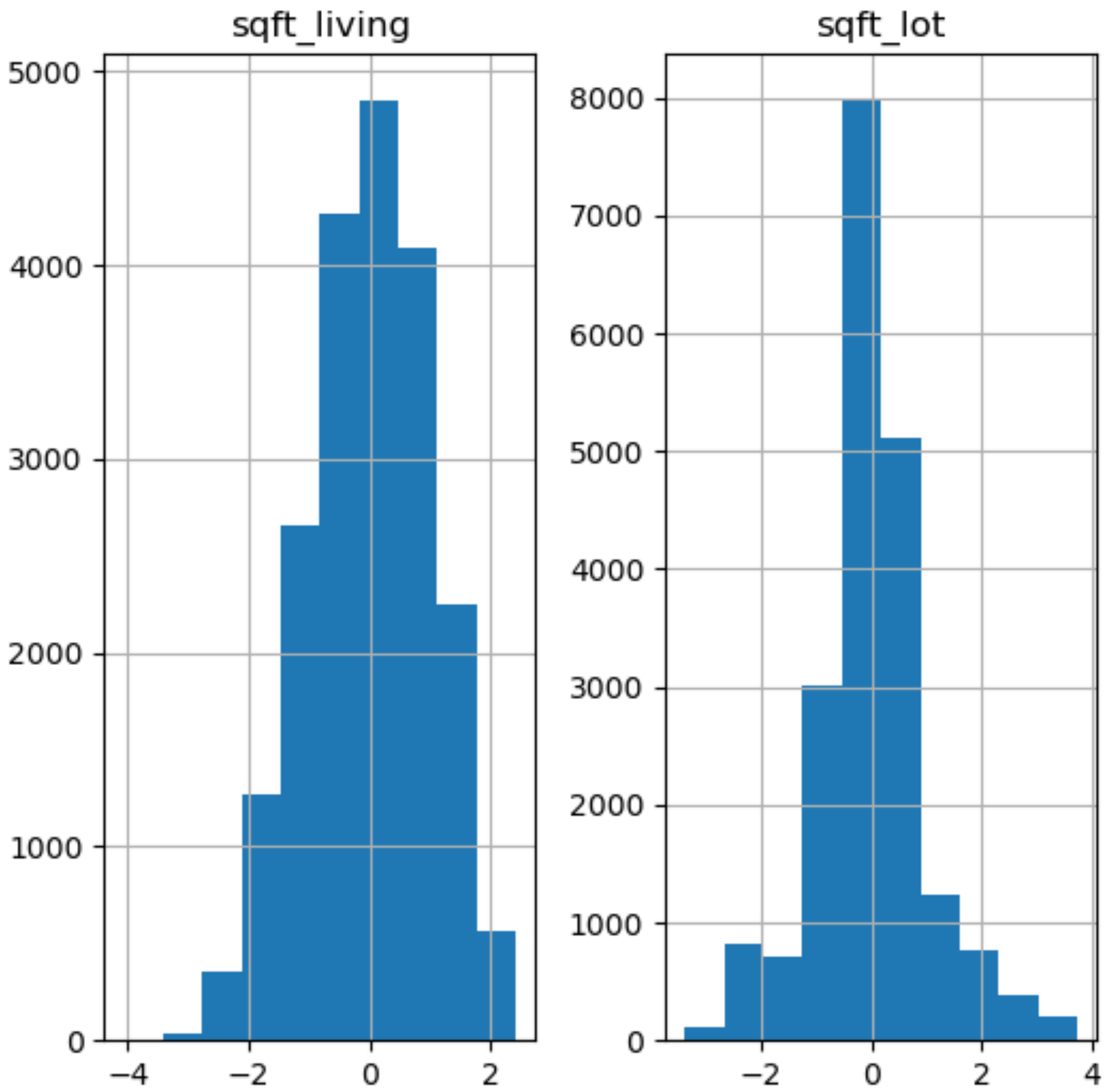


In [51]:
```
# Let's examine the data after the transformation.

data_log = pd.DataFrame([])
data_log['sqft_living'] = np.log(dt['sqft_living'])
data_log['sqft_lot'] = np.log(dt['sqft_lot'])
data_log.hist(figsize = [6, 6]);
```



In [52]:
```
log_living = data_log['sqft_living']
log_lot = data_log['sqft_lot']

# We can normalize our data

scaled_living = (log_living - np.mean(log_living)) / np.sqrt(np.var
scaled_lot = (log_lot - np.mean(log_lot)) / np.sqrt(np.var(log_lot)
```

In [53]:
```
# Now, let's assess the current state of our data.

data_cont_scaled = pd.DataFrame([])

data_cont_scaled['sqft_living'] = scaled_living
data_cont_scaled['sqft_lot'] = scaled_lot

data_cont_scaled.hist(figsize = [6, 6]);
```



Model 3

In [54]:
```
# Let's evaluate our model

dt_1 = pd.concat([dt['price'] ,data_cont_scaled, dummies], axis = 1
```

In [55]:
```
predictors = dt_1.drop(['price'], axis = 1)
pred_sum = "+".join(predictors.columns)
formula = outcome + "~" + pred_sum
```

In [56]:
```
model = ols(formula = formula, data = dt_1).fit()
model.summary()
```

Out[56]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.558
Model:	OLS	**Adj. R-squared:**	0.557
Method:	Least Squares	**F-statistic:**	712.6
Date:	Fri, 01 Dec 2023	**Prob (F-statistic):**	0.00
Time:	16:26:04	**Log-Likelihood:**	-2.7333e+05
No. Observations:	20341	**AIC:**	5.467e+05
Df Residuals:	20304	**BIC:**	5.470e+05
Df Model:	36		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3.123e+05	8.52e+04	3.665	0.000	1.45e+05	4.79e+05
sqft_living	1.014e+05	2529.251	40.075	0.000	9.64e+04	1.06e+05
sqft_lot	-2.901e+04	1497.178	-19.374	0.000	-3.19e+04	-2.61e+04
bed_2	-3.283e+04	1.35e+04	-2.431	0.015	-5.93e+04	-6355.299
bed_3	-8.306e+04	1.36e+04	-6.121	0.000	-1.1e+05	-5.65e+04
bed_4	-8.775e+04	1.39e+04	-6.304	0.000	-1.15e+05	-6.05e+04
bed_5	-8.22e+04	1.47e+04	-5.603	0.000	-1.11e+05	-5.34e+04
bed_6	-8.219e+04	1.83e+04	-4.482	0.000	-1.18e+05	-4.62e+04
bath_75	1.098e+05	8.6e+04	1.276	0.202	-5.88e+04	2.78e+05
bath_100	1.174e+05	8.31e+04	1.412	0.158	-4.55e+04	2.8e+05
bath_125	1.049e+05	9.98e+04	1.051	0.293	-9.08e+04	3.01e+05
bath_150	7.751e+04	8.32e+04	0.931	0.352	-8.56e+04	2.41e+05
bath_175	6.968e+04	8.32e+04	0.838	0.402	-9.34e+04	2.33e+05
bath_200	6.938e+04	8.32e+04	0.834	0.404	-9.37e+04	2.32e+05
bath_225	6.295e+04	8.32e+04	0.756	0.449	-1e+05	2.26e+05
bath_250	3.177e+04	8.32e+04	0.382	0.703	-1.31e+05	1.95e+05
bath_275	6.539e+04	8.33e+04	0.785	0.433	-9.79e+04	2.29e+05

bath_300	7.558e+04	8.34e+04	0.906	0.365	-8.79e+04	2.39e+05
bath_325	1.125e+05	8.36e+04	1.346	0.178	-5.13e+04	2.76e+05
bath_350	1.054e+05	8.35e+04	1.262	0.207	-5.83e+04	2.69e+05
bath_375	1.987e+05	8.48e+04	2.343	0.019	3.24e+04	3.65e+05
bath_400	1.124e+05	8.56e+04	1.313	0.189	-5.54e+04	2.8e+05
bath_425	2.025e+05	8.82e+04	2.297	0.022	2.97e+04	3.75e+05
flr_2	-3.129e+04	3815.818	-8.201	0.000	-3.88e+04	-2.38e+04
flr_3	-4473.8620	8380.682	-0.534	0.593	-2.09e+04	1.2e+04
wtr_1	3.378e+05	1.97e+04	17.159	0.000	2.99e+05	3.76e+05
cond_3	8779.6520	1.38e+04	0.634	0.526	-1.84e+04	3.59e+04
cond_4	5.88e+04	1.39e+04	4.228	0.000	3.15e+04	8.61e+04
cond_5	1.225e+05	1.44e+04	8.539	0.000	9.44e+04	1.51e+05
grade_6	1.943e+04	1.2e+04	1.620	0.105	-4081.559	4.29e+04
grade_7	7.796e+04	1.19e+04	6.548	0.000	5.46e+04	1.01e+05
grade_8	1.813e+05	1.23e+04	14.702	0.000	1.57e+05	2.05e+05
grade_9	3.457e+05	1.29e+04	26.700	0.000	3.2e+05	3.71e+05
grade_10	4.871e+05	1.4e+04	34.769	0.000	4.6e+05	5.15e+05
grade_11	6.22e+05	1.82e+04	34.110	0.000	5.86e+05	6.58e+05
reno_1	1.254e+05	6654.320	18.842	0.000	1.12e+05	1.38e+05
base_1	2.955e+04	2960.604	9.980	0.000	2.37e+04	3.54e+04

Omnibus:	3280.745	**Durbin-Watson:**	1.963
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	8404.741
Skew:	0.897	**Prob(JB):**	0.00
Kurtosis:	5.588	**Cond. No.**	465.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Summary of Model 3 and Comparison

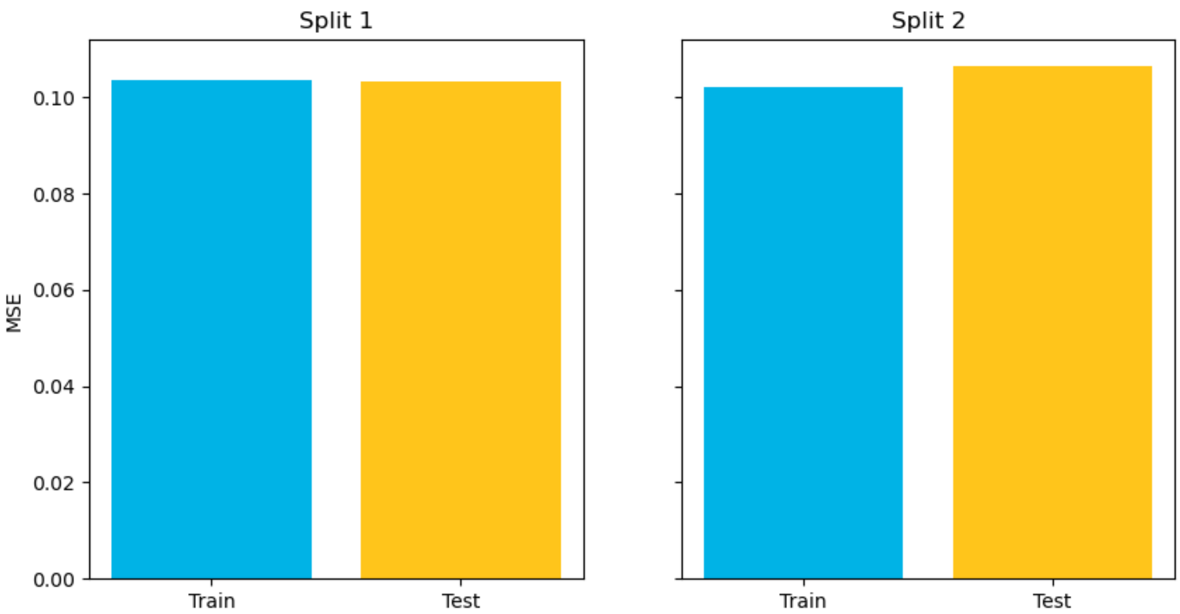
Following the transformation of our data and reintroduction of categorical variables, the model appears robust. The R-squared value of 0.558 is considered good, suggesting that the model is likely at its optimal fit. We can now proceed with model validation.

Validation

In [57]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
```

In [58]:
```
y = np.log(dt_1['price'])
x = dt_1.drop('price', axis = 1)
```

In [59]:
```
# Configure data and model set up

linreg = LinearRegression()

# Split with random_state 87
x_train_1, x_test_1, y_train_1, y_test_1 = train_test_split(x, y, r
linreg.fit(x_train_1, y_train_1)
train_mse_1 = mean_squared_error(y_train_1, linreg.predict(x_train_
test_mse_1 = mean_squared_error(y_test_1, linreg.predict(x_test_1))

# Split with random_state 41
x_train_2, x_test_2, y_train_2, y_test_2 = train_test_split(x, y, r
linreg.fit(x_train_2, y_train_2)
train_mse_2 = mean_squared_error(y_train_2, linreg.predict(x_train_
test_mse_2 = mean_squared_error(y_test_2, linreg.predict(x_test_2))

# Plot metrics
fig, (left, right) = plt.subplots(ncols=2, figsize=(10,5), sharey=T
labels = ["Train", "Test"]
colors = ["#00B3E6", "#FFC51B"]
left.bar(labels, [train_mse_1, test_mse_1], color=colors)
left.set_title("Split 1")
left.set_ylabel("MSE")
right.bar(labels, [train_mse_2, test_mse_2], color=colors)
right.set_title("Split 2");
```



Train-Test Split Analysis

It is evident that the train and test splits for both random_state 87 and random_state 41 exhibit only minimal differences.

In [60]:
```
# Now, let's evaluate it with random_state 4
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size
```

In [61]:
```
linreg = LinearRegression()
linreg.fit(x_train, y_train)
LinearRegression()
```

Out[61]:
```
▾ LinearRegression
LinearRegression()
```

Calculate the Mean Squared Error

In [62]:
```
linreg = LinearRegression()
linreg.fit(x_train, y_train)

y_hat_train = linreg.predict(x_train)
y_hat_test = linreg.predict(x_test)
```

In [63]:
```
train_residuals = y_hat_train - y_train
test_residuals = y_hat_test - y_test
```

In [64]:
```
train_mse = mean_squared_error(y_train, y_hat_train)
test_mse = mean_squared_error(y_test, y_hat_test)
print('Train Mean Squared Error:', train_mse)
print('Test Mean Squared Error:', test_mse)
```

```
Train Mean Squared Error: 0.10386598952456463
Test Mean Squared Error: 0.10185845860770103
```

In [65]:
```
train_mse - test_mse
```

Out[65]:
```
0.0020075309168636063
```

R-squared value of the model

In [66]:
```
print('R2 score: {:.2%}'.format(r2_score(y_test, y_hat_test)))
```

```
R2 score: 55.14%
```

Comments and Model Validation

The discrepancy is so minimal that rounding it to two decimal places results in 0.00. This suggests that the model is likely at its optimal fit.

In [67]:
```
# Obtain the top 5 variables

from sklearn.feature_selection import RFE

selector = RFE(linreg, n_features_to_select=3)
selector = selector.fit(x_train, y_train.values)

selector.support_
```

Out[67]:
```
array([False, False, False, False, False, False, False, False, Fal
se,
       False, False, False, False, False, False, False, False, Fal
se,
       False, False, False, False, False, False, False, False, Fal
se,
       False, False, False, False,  True,  True,  True, False, Fal
se])
```

In [68]:
```
# Obtain top 3 variables
selected_columns = x_train.columns[selector.support_]
linreg.fit(x_train[selected_columns], y_train)
print(selected_columns)
```

```
Index(['grade_9', 'grade_10', 'grade_11'], dtype='object')
```

Evaluation

After three iterations, we discovered that the final model utilized the top independent variables. Using sklearn's feature selector, we identified variables with a strong relationship with the dependent variable, price. The top variables influencing the price were:

- grade_11
- grade_10
- grade_9

Addressing the key renovation properties to maximize the property's market value, we identified the top five contributors:

1. sqft_living: Increasing the square footage of the home can raise the price by 83,010.
2. flr_3: Having a three-story house would increase the property's worth by 66,690.
3. bath_425: Adding 4.25 bathrooms can increase the property's worth by 304,400.
4. wtr_1: Having a waterfront view will increase the property's worth by 305,700.
5. grade_11: Achieving a building grade of 11 in King County can increase the property's worth by 714,500.

This linear regression model effectively addresses the business problem of identifying key renovation properties to maximize the property's market value.

While the model provides meaningful insights, validating the outliers with more data could enhance its accuracy. It is noteworthy that the results align with real-world expectations, providing a sensible justification for the price increases associated with the identified factors.

Conclusion

The King County grading system used in this dataset reflects the quality of the houses, ranging from grade 1 to 13. The model results indicate that Grades 11, 10, and 9 are the top three in the ranking system, aligning with the realistic expectations of higher-quality renovations. Renovating a house to attain Grade 11, 10, or 9 not only increases its value but also suggests that additional improvements can further enhance the property's worth.

(source: https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r))

In summary, the primary drivers for maximizing a house's market value include:

1. Investing in high-quality materials and luxury options during renovation.
2. Securing a house with a waterfront view, if feasible.
3. Adding more bathrooms.