Final Project Submission

Please fill out:

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- Student pace: full time
- Scheduled project review date/time:
- Instructor name: Joseph Mata
- Blog post URL:

In [157…

```
# Your code here - remember to use markdown cells for comments as well!
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.preprocessing import StandardScaler, OrdinalEncoder, OneHotEncc
from scipy.stats import norm

#map
import plotly.express as px
import plotly.offline as pyo
import plotly.graph_objs as go
pyo.init_notebook_mode()
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplc
init_notebook_mode(connected=True)

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
#loading the data set
df = pd.read_csv('data/kc_house_data.csv')
```

In [3]:

```
# checking the content of the dataframe
df
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floor
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.
...	...	...	...	...	...	...	...	.
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.

21597 rows × 21 columns

Basic information about the dataset

In [4]:

```
# checking basic information about the data
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
```

The data file has 21597 rows, and 21 columns. Some of the rows has missing information: waterfront, view, yr_renovated. Most of the data types are int and float type, there are 6 of them with categorical values. The date column should be in datatype, I will change this in the followings. Similarly yr_built represent the year when the house was built, this should be a datetype as well.

In [5]:
```
numeric = ['price', 'bedrooms','bathrooms','sqft_living','sqft_lot', 'floors
ordinal = ['grade', 'condition']
categorical = ['waterfront', 'view', 'zipcode','yr_built']
```

In [6]:
```
# distribution of numeric features
#fig, ax = plt.subplots(figsize = (12,12))
#sns.histplot(data=df[numeric], x= 'price')
```

In [7]:
```
# checking the number of missing information
df.isna().sum()
```

Out[7]:
```
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
```

There are 3 columns that has missing information, namely: waterfront, view and yr_renovated.

In [8]:
```python
# checking the summary statistic
df.describe()
```

sqft_living	sqft_lot	floors	sqft_above	yr_built	yr_renovated	zipcode	
597.000000	2.159700e+04	21597.000000	21597.000000	21597.000000	17755.000000	21597.000000	215
080.321850	1.509941e+04	1.494096	1788.596842	1970.999676	83.636778	98077.951845	
918.106125	4.141264e+04	0.539683	827.759761	29.375234	399.946414	53.513072	
370.000000	5.200000e+02	1.000000	370.000000	1900.000000	0.000000	98001.000000	
430.000000	5.040000e+03	1.000000	1190.000000	1951.000000	0.000000	98033.000000	
910.000000	7.618000e+03	1.500000	1560.000000	1975.000000	0.000000	98065.000000	
550.000000	1.068500e+04	2.000000	2210.000000	1997.000000	0.000000	98118.000000	
540.000000	1.651359e+06	3.500000	9410.000000	2015.000000	2015.000000	98199.000000	

Based on the above summary statistics, the following infromations stands out:

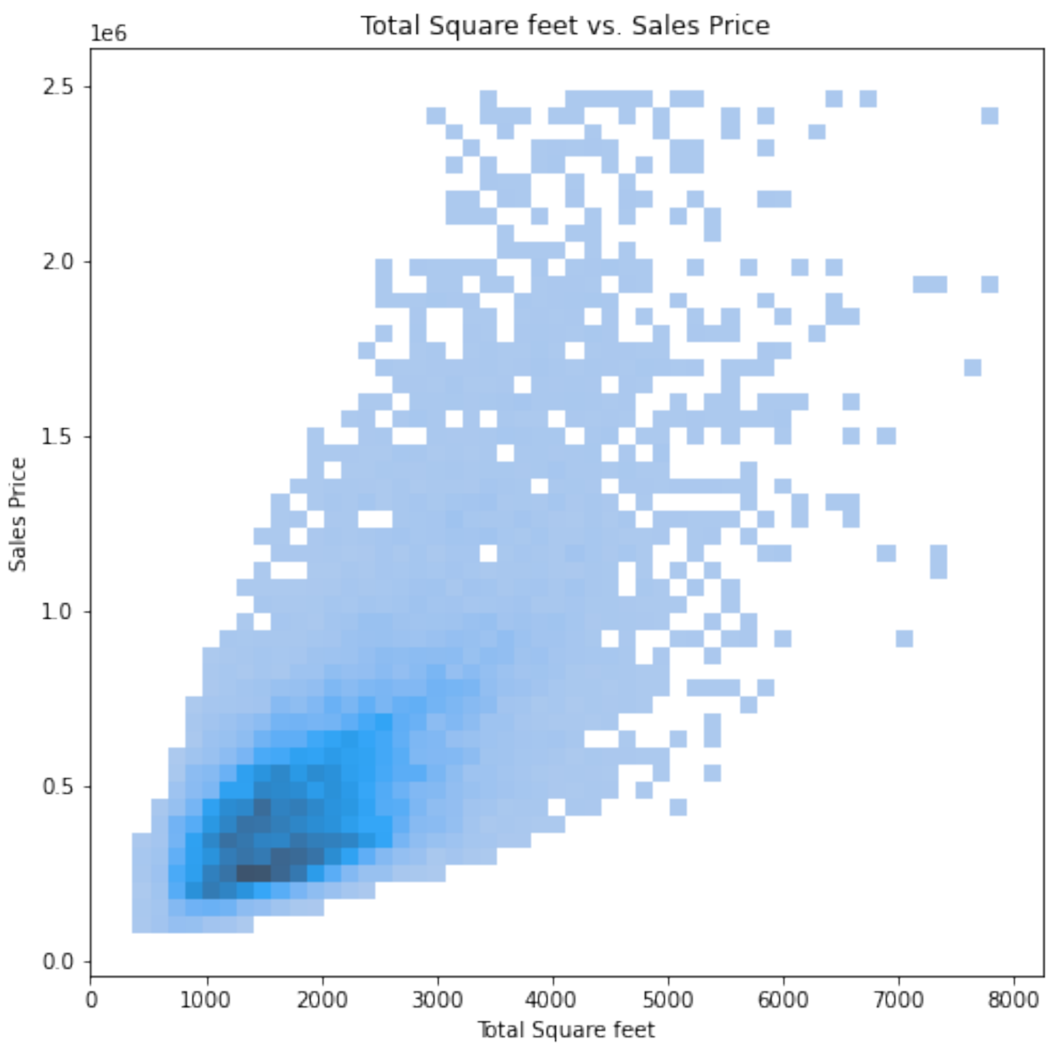
- There are outliers in the number of bedrooms, the max value is 33. This need to be further investigated and later on it might be remove.
- Bathrooms seemingly has outlier too with 8 bathrooms, when the iqr 75% is only 2.5.
- srft_living, sqft_above and sqft_lot15 also seems to have outliers based on it's max value (13540, 9410 and 871200). These also need to be investigated.
- There are lot of missing values in yr_renovated.

In [182…

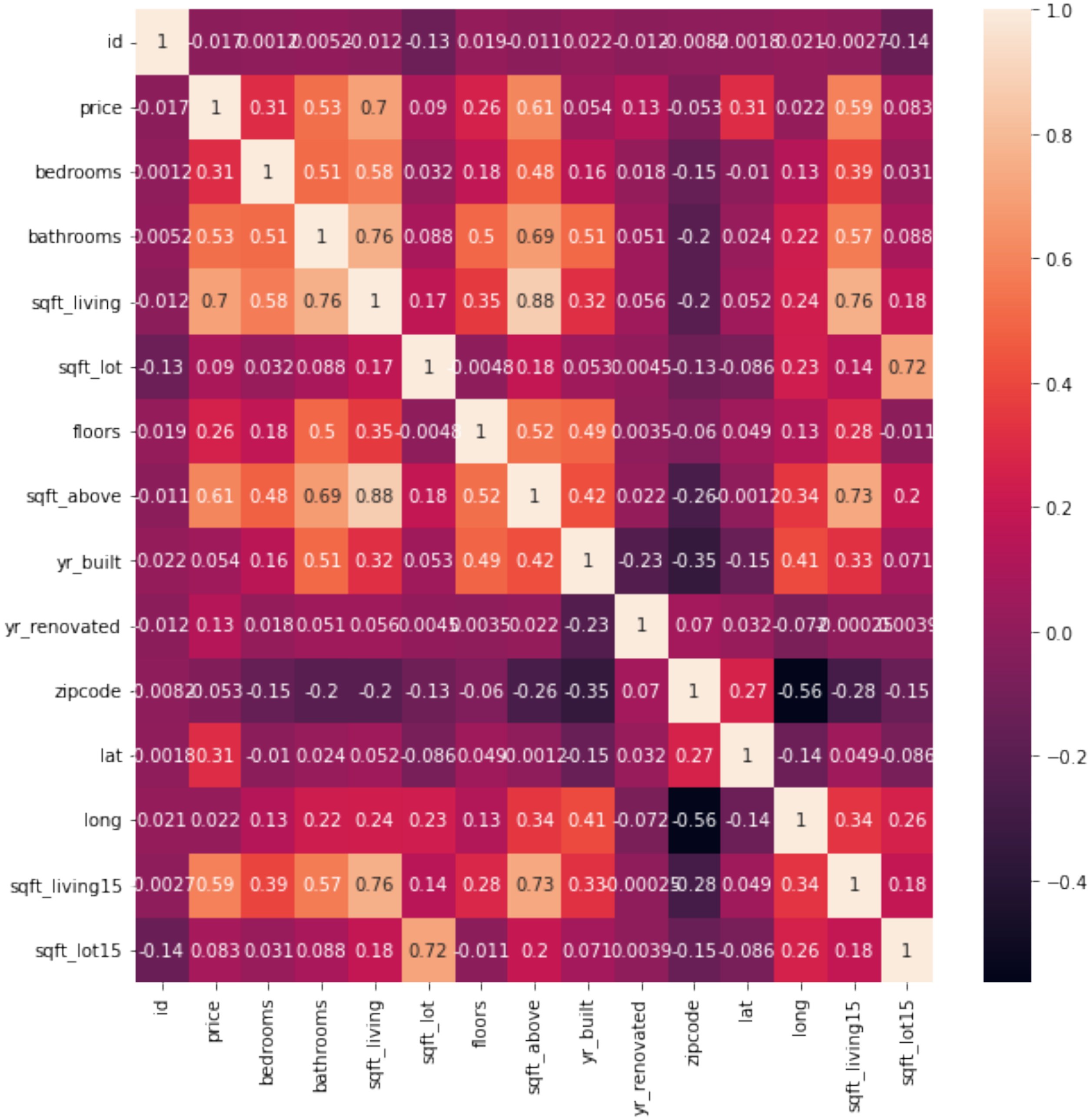
```
# sqft_living vs price
fig, ax = plt.subplots(figsize = (8,8))
sns.histplot(data =df, x ='sqft_living', y='price', bins = 50)
ax.set_title('Total Square feet vs. Sales Price')
ax.set_xlabel('Total Square feet')
ax.set_ylabel('Sales Price')
```

Out[182]:

```
Text(0, 0.5, 'Sales Price')
```



In [9]:
```
# Checking the preliminary correlation
fig, ax = plt.subplots(figsize = (10,10))
corr = df.corr()
sns.heatmap(corr, cmap = 'rocket', annot = True)
plt.show()
```



sqft_living has the highest correlation with price 0.7, following sqft_bove with 0.61. The sqft_living seems to be the sum of sqft_above and sqft_basement, this might be droped later on to avoide multicollinearity.

In [10]:
```
#outliers = df['bedrooms','bathrooms', 'sqft_living','sqft_lot', 'price']
fig, ax = plt.subplots(figsize = (9,7))
sns.scatterplot(data = df, x='sqft_living', y ='price')
ax.set_title('House size vs Sales Price')
ax.set_xlabel('House size (sqft)')
ax.set_ylabel('House Sales Price')
```

Out[10]:
```
Text(0, 0.5, 'House Sales Price')
```

Checking the values of the object datatypes

In [11]:
```
# checking how many values under waterfront
df['waterfront'].value_counts()
```

Out[11]:
```
NO     19075
YES      146
Name: waterfront, dtype: int64
```

In [12]:
```
# checking how many values under view
df['view'].value_counts()
# this should be ordinal variable, I will replace the text with numerice val
```

Out[12]:
```
NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64
```

In [13]:
```
# checking how many values under condition
df['condition'].value_counts()
```

Out[13]:
```
Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: condition, dtype: int64
```

In [14]:
```
# checking how many values under grade
df['grade'].value_counts()
```

Out[14]:
```
7 Average        8974
8 Good           6065
9 Better         2615
6 Low Average    2038
10 Very Good     1134
11 Excellent      399
5 Fair            242
12 Luxury          89
4 Low              27
13 Mansion         13
3 Poor              1
Name: grade, dtype: int64
```

In [15]:
```
df['sqft_basement'].value_counts()
```

Out[15]:
```
0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
1920.0        1
3480.0        1
2730.0        1
2720.0        1
248.0         1
Name: sqft_basement, Length: 304, dtype: int64
```

In [16]:
```
df['bedrooms'].value_counts()
```

Out[16]:
```
3      9824
4      6882
2      2760
5      1601
6       272
1       196
7        38
8        13
9         6
10        3
11        1
33        1
Name: bedrooms, dtype: int64
```

In [17]:
```
# removing the string value after the number in grade
df['grade'] = df['grade'].str.split().str[0]
df.head()
```

Out[17]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	w
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 [18]:
```
# changing the datatype of date to date
df['date'] = pd.to_datetime(df['date'])
```

In [19]:
```
# changing the the floors cols to integer
df['floors'] = df['floors'].astype(int)
```

In [20]:
```
# replacing missing values in the waterfront column to 'NO'
df['waterfront'].fillna('NO', inplace = True)
```

In [21]:
```
# replacing missing values in the view column to 'NONE'
df['view'].fillna('NONE', inplace = True)
```

In [22]:
```
# replacing missing data with 0 in yr-renovated, assuming they have not been
# later I will make a new boolean column if it has or not has renovation, an
df['yr_renovated'].fillna(0, inplace = True)
```

In [23]:
```
# changing the view categories into numeric values to represent ordinality
df['view'] = df['view'].replace(['NONE','AVERAGE','GOOD', 'FAIR', 'EXCELLENT
```

In [24]:
```
df['view'].value_counts()
```

Out[24]:
```
1    19485
2      957
3      508
4      330
5      317
Name: view, dtype: int64
```

In [25]:
```
# changing the condition to numeric values
df['condition'] = df['condition'].replace(['Poor','Fair', 'Average', 'Good',
```

In [26]:
```
# replacing the no and yes values in waterfront with 0 and 1
# changing the condition to numeric values
df['waterfront'] = df['waterfront'].replace(['NO','YES'],[0,1])
```

In [27]:
```
# changing the data type to category for condition
df['condition'] = df['condition'].astype("category")
df['view'] = df['view'].astype("category")
df['grade'] = df['grade'].astype("category")
df['waterfront'] = df['waterfront'].astype('category')
```

In [28]:
```
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  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  int64
 8   waterfront     21597 non-null  category
 9   view           21597 non-null  category
 10  condition      21597 non-null  category
 11  grade          21597 non-null  category
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
 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
dtypes: category(4), datetime64[ns](1), float64(5), int64(10), object(1)
memory usage: 2.9+ MB
```

In [29]:
```
# replacing missing data with 0 in yr-renovated, assuming they have not been
df['yr_renovated'].fillna(0, inplace = True)
```

In [30]:
```
df['yr_renovated'].value_counts()
```

Out[30]:
```
0.0       20853
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
```

In [31]:
```
# due to the lot of missing values, I will convert this to boolean, whether
#df['yr_renovated'] = df['yr_renovated'].astype(int)
df['renovated'] = None
for i in range(len(df)):
    if df['yr_renovated'][i] == 0:
        df['renovated'][i] = 0
    else:
        df['renovated'][i] = 1
```

In [ ]:
```
#changing the datatype
df['renovated'] = df['renovated'].astype(int)
```

In [32]:
```
# drop yr_renovated column
df.drop('yr_renovated', axis = 1, inplace = True)
```

In [33]:
```
#droping the id col
df.drop('id', axis = 1, inplace=True)
```

In [34]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           21597 non-null  datetime64[ns]
 1   price          21597 non-null  float64
 2   bedrooms       21597 non-null  int64
 3   bathrooms      21597 non-null  float64
 4   sqft_living    21597 non-null  int64
 5   sqft_lot       21597 non-null  int64
 6   floors         21597 non-null  int64
 7   waterfront     21597 non-null  category
 8   view           21597 non-null  category
 9   condition      21597 non-null  category
 10  grade          21597 non-null  category
 11  sqft_above     21597 non-null  int64
 12  sqft_basement  21597 non-null  object
 13  yr_built       21597 non-null  int64
 14  zipcode        21597 non-null  int64
 15  lat            21597 non-null  float64
 16  long           21597 non-null  float64
 17  sqft_living15  21597 non-null  int64
 18  sqft_lot15     21597 non-null  int64
 19  renovated      21597 non-null  object
dtypes: category(4), datetime64[ns](1), float64(4), int64(9), object(2)
memory usage: 2.7+ MB
```

In [35]:

```
# replace '?' in sqft_basement
df['sqft_basement'] = df['sqft_basement'].apply(lambda x: x.replace('?', '0'
df['sqft_basement'] = df['sqft_basement'].apply(lambda x: x.replace('0.0', '
```

In [36]:

```
# changing the datatype to int
df['sqft_basement'] = df['sqft_basement'].astype(float)
df['sqft_basement'] = df['sqft_basement'].astype(int)
```

In [37]:

```
# checking the datatype change
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           21597 non-null  datetime64[ns]
 1   price          21597 non-null  float64
 2   bedrooms       21597 non-null  int64
 3   bathrooms      21597 non-null  float64
 4   sqft_living    21597 non-null  int64
 5   sqft_lot       21597 non-null  int64
 6   floors         21597 non-null  int64
 7   waterfront     21597 non-null  category
 8   view           21597 non-null  category
 9   condition      21597 non-null  category
 10  grade          21597 non-null  category
 11  sqft_above     21597 non-null  int64
 12  sqft_basement  21597 non-null  int64
 13  yr_built       21597 non-null  int64
 14  zipcode        21597 non-null  int64
 15  lat            21597 non-null  float64
 16  long           21597 non-null  float64
 17  sqft_living15  21597 non-null  int64
 18  sqft_lot15     21597 non-null  int64
 19  renovated      21597 non-null  object
dtypes: category(4), datetime64[ns](1), float64(4), int64(10), object(1)
memory usage: 2.7+ MB
```

In [38]:
```
# checking if there any missining values left
df.isna().sum()
```

Out[38]:
```
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
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
renovated        0
dtype: int64
```

In [39]:
```
# separating the date column to year and month
df['year'] = pd.to_datetime(df['date']).dt.year
df['month'] = pd.to_datetime(df['date']).dt.month
#droping the date column
df.drop('date', axis = 1, inplace = True)
df.head()
```

Out[39]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	conditior
0	221900.0	3	1.00	1180	5650	1	0	1	3
1	538000.0	3	2.25	2570	7242	2	0	1	3
2	180000.0	2	1.00	770	10000	1	0	1	3
3	604000.0	4	3.00	1960	5000	1	0	1	5
4	510000.0	3	2.00	1680	8080	1	0	1	3

5 rows × 21 columns

In [40]:
```
# changing the data type of the month
df['month'] = df['month'].astype('category')
df['year'] = df['year'].astype('category')
df['zipcode'] = df['zipcode'].astype('category')
```

In [41]:
```
df.info()
```

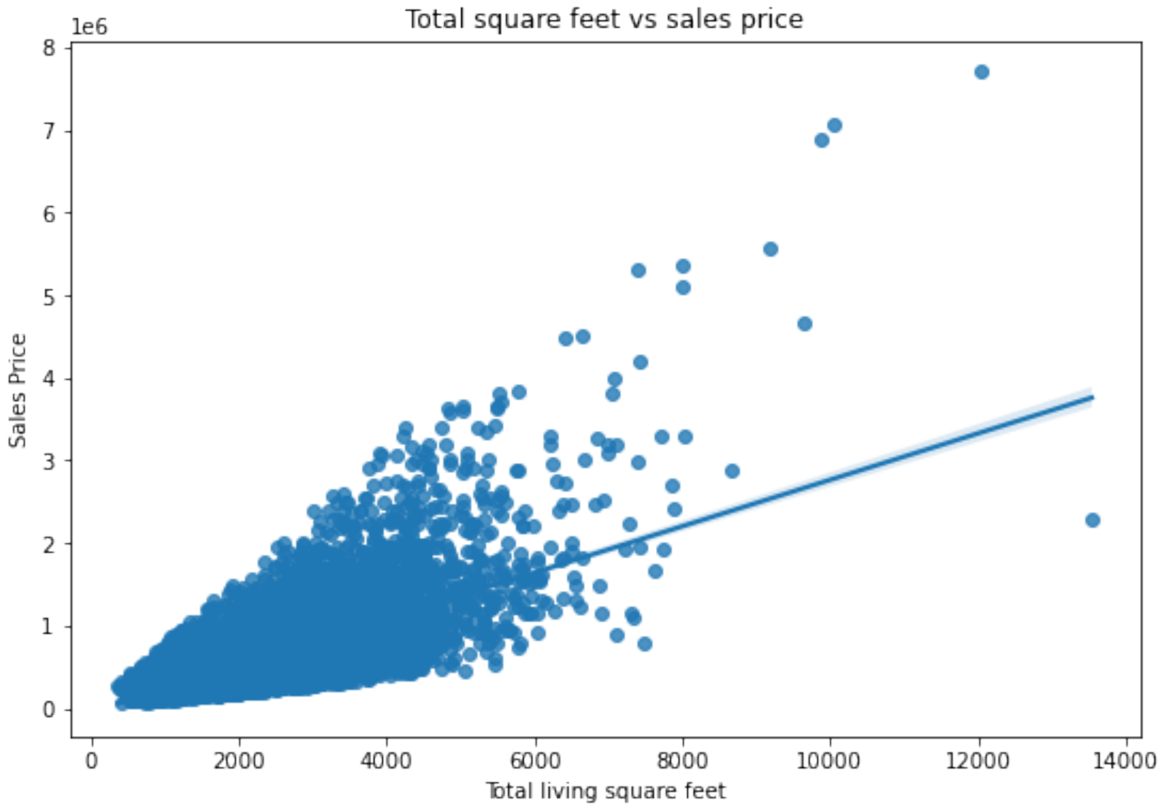
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          21597 non-null  float64
 1   bedrooms       21597 non-null  int64
 2   bathrooms      21597 non-null  float64
 3   sqft_living    21597 non-null  int64
 4   sqft_lot       21597 non-null  int64
 5   floors         21597 non-null  int64
 6   waterfront     21597 non-null  category
 7   view           21597 non-null  category
 8   condition      21597 non-null  category
 9   grade          21597 non-null  category
 10  sqft_above     21597 non-null  int64
 11  sqft_basement  21597 non-null  int64
 12  yr_built       21597 non-null  int64
 13  zipcode        21597 non-null  category
 14  lat            21597 non-null  float64
 15  long           21597 non-null  float64
 16  sqft_living15  21597 non-null  int64
 17  sqft_lot15     21597 non-null  int64
 18  renovated      21597 non-null  object
 19  year           21597 non-null  category
 20  month          21597 non-null  category
dtypes: category(7), float64(4), int64(9), object(1)
memory usage: 2.5+ MB
```

In [45]:

```
# square feet living vs. sales price graph
fig, ax = plt.subplots(figsize =(9,6))
sns.regplot(data = df, x = 'sqft_living', y='price')
ax.set_title('Total square feet vs sales price')
ax.set_xlabel('Total living square feet')
ax.set_ylabel('Sales Price')
```

Out[45]:

```
Text(0, 0.5, 'Sales Price')
```

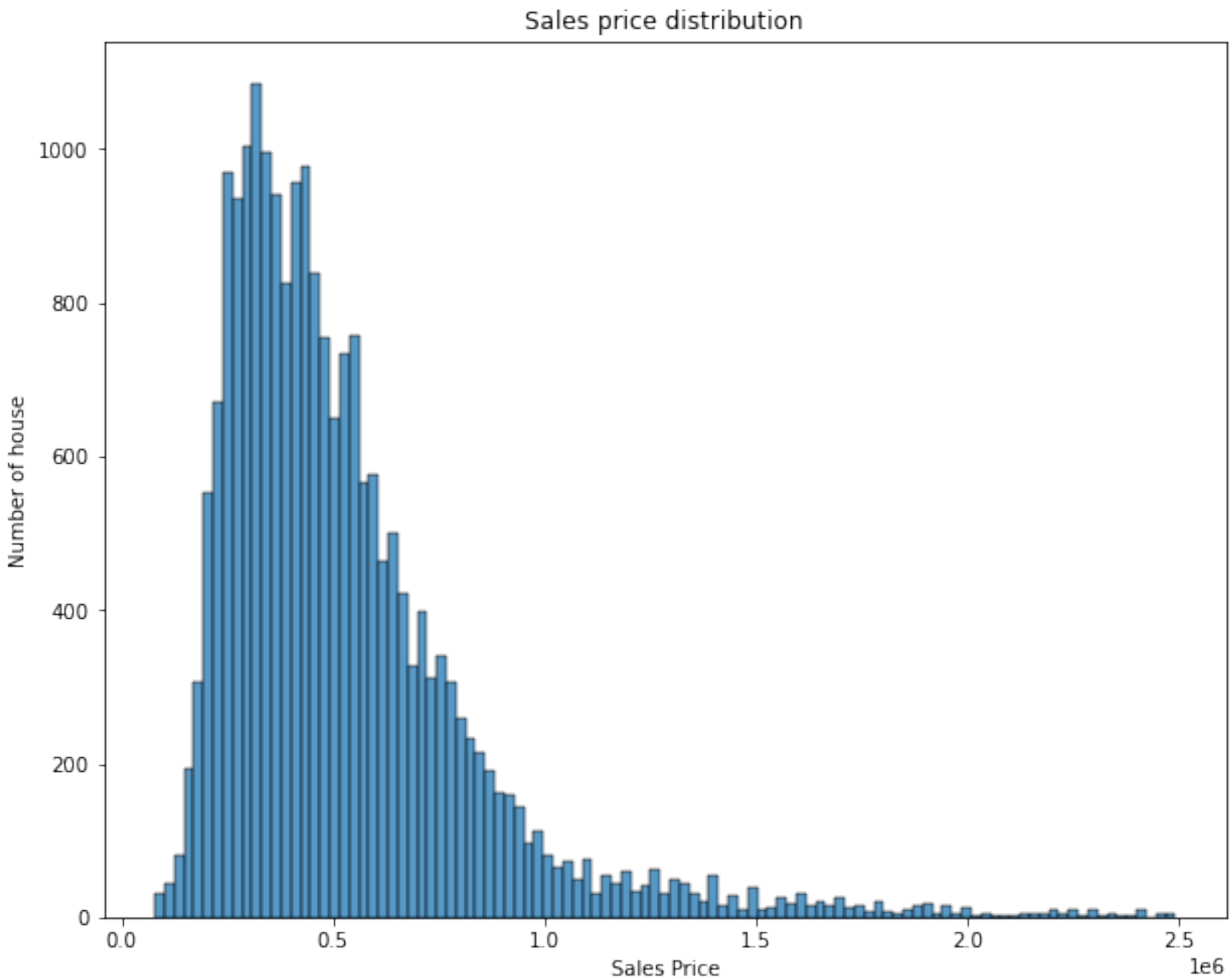


In [173…

```
# sales price distribution

fig, ax = plt.subplots(figsize = (10,8))
sns.histplot(data = df, x= 'price')
ax.set_title('Sales price distribution')
ax.set_ylabel('Number of house')
ax.set_xlabel('Sales Price')
```

Out[173]:

```
Text(0.5, 0, 'Sales Price')
```



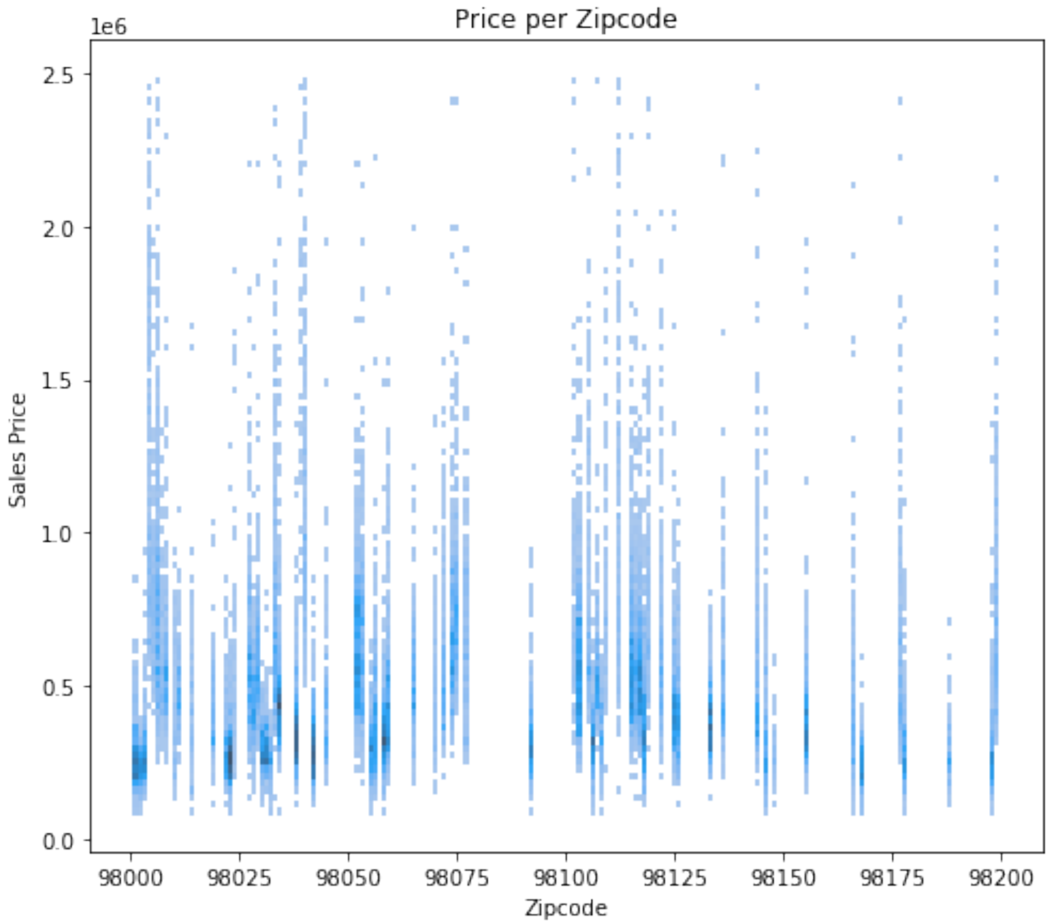
The sales price distribution is highly positively skewed with a long right tail due to outliers.

In [172…

```
# checking how the location (zipcode) influences the price of a house
fig, ax = plt.subplots(figsize=(8,7))
sns.histplot(data = df, x= 'zipcode', y='price')
ax.set_title('Price per Zipcode')
ax.set_xlabel('Zipcode')
ax.set_ylabel('Sales Price')
```

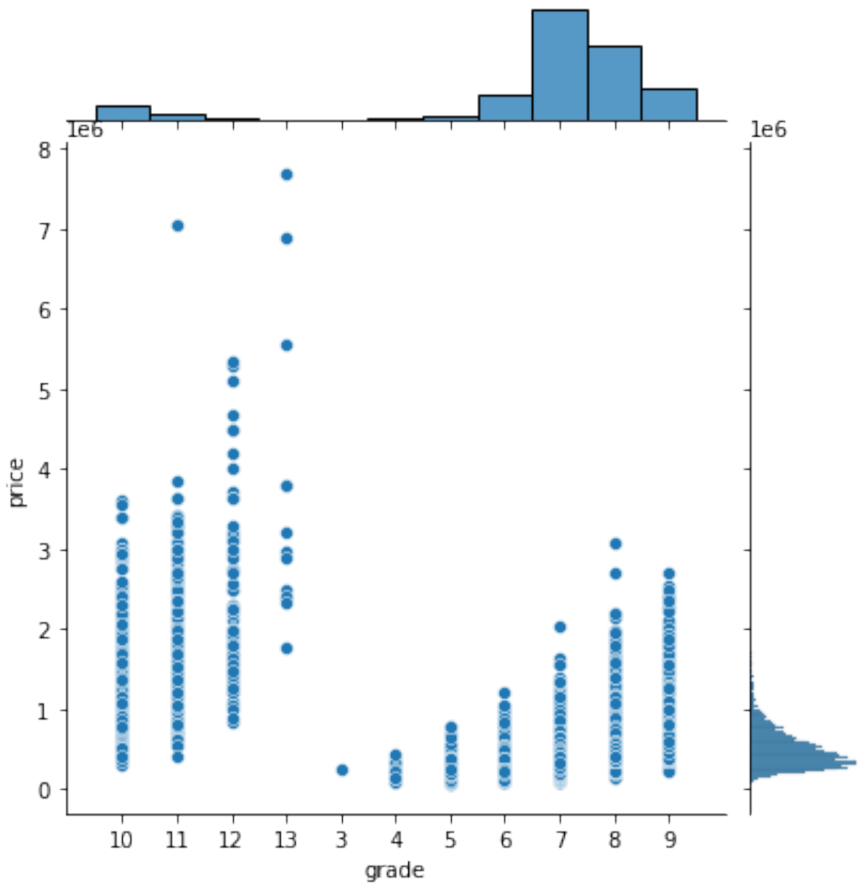
Out[172]:

```
Text(0, 0.5, 'Sales Price')
```



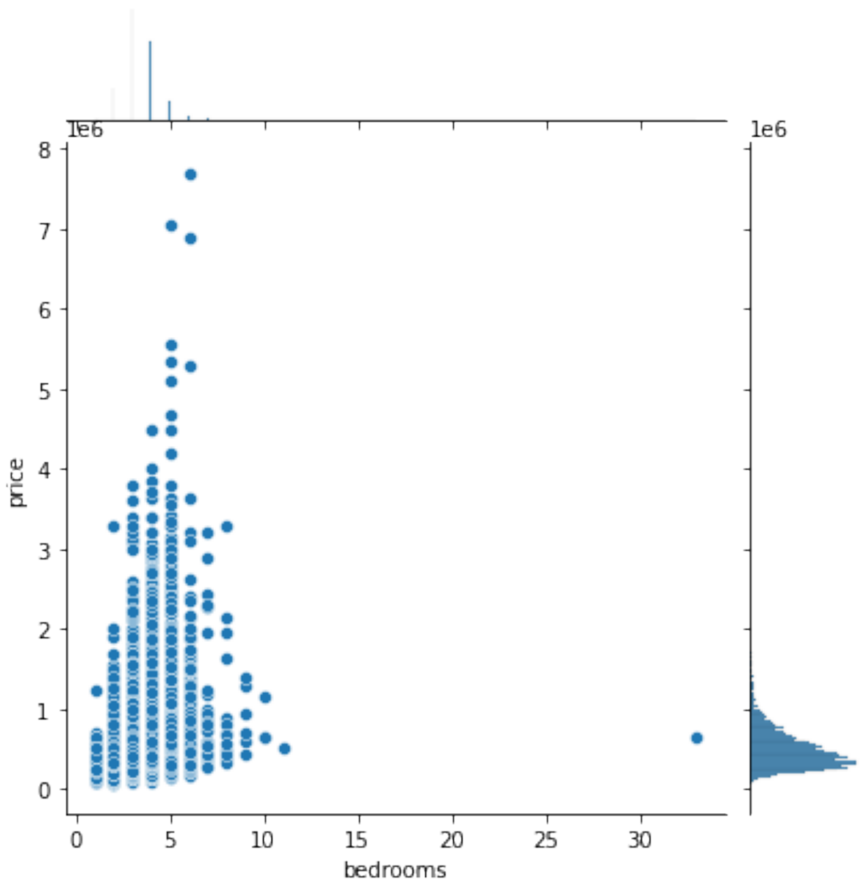
In [48]:

```
# checking how the overall condition of the house influences the price

p = sns.jointplot(data = df, x = 'grade', y='price')
```



As the graph shows as the overal grade of the house increases so as the sales price. Not surprising that in grade 12 - Luxury and 13 -Mansion are selling for the highest amounts.

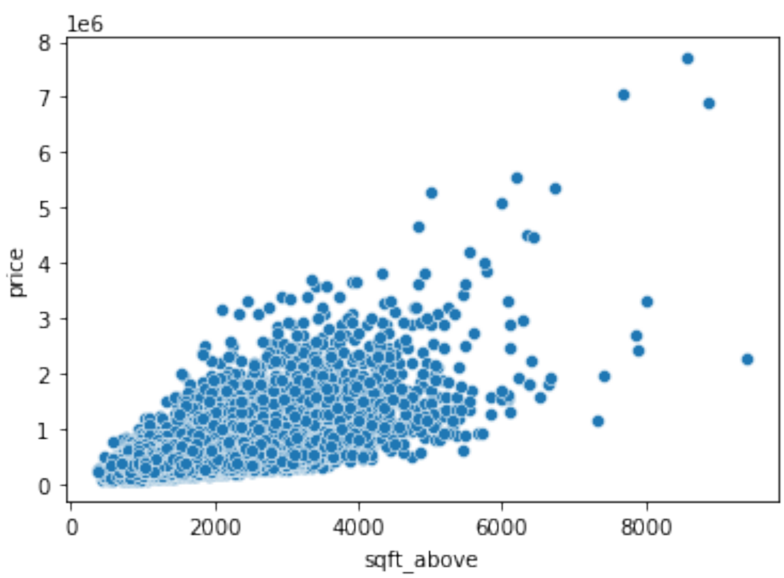
In [49]:
```
# checking bedrooms vs sales price
p = sns.jointplot(data = df, x = 'bedrooms', y='price')
```



Lot of houses with 5-6 bedrooms are on the higher end on sales price, they might be the ones with categories as luxury or mansion.

In [50]:
```
#checking sqft_above vs price
sns.scatterplot(data = df, x='sqft_above', y='price')
```

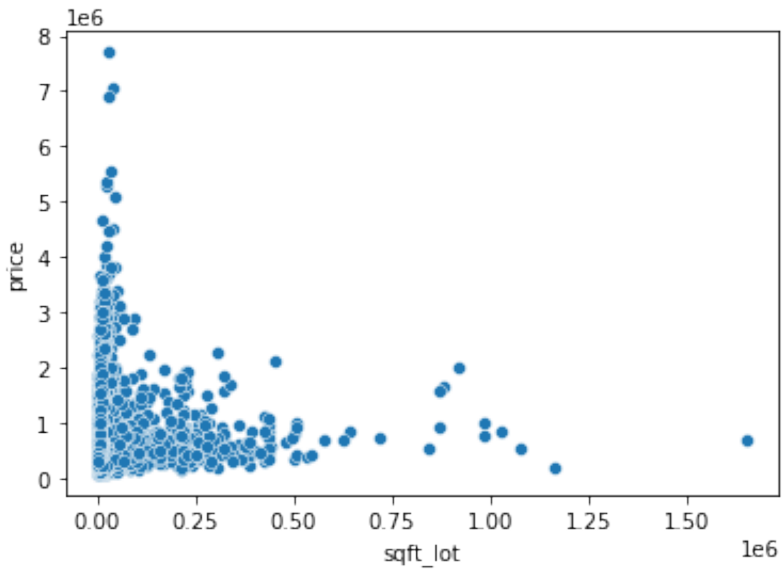
Out[50]: <AxesSubplot:xlabel='sqft_above', ylabel='price'>



sqft_above and price seemingly has a linear relationship. There are some outliers above 6-7000 square feet.

In [51]:
```
# sqft_lot
sns.scatterplot(data = df, x='sqft_lot', y='price')
```

Out[51]:
```
<AxesSubplot:xlabel='sqft_lot', ylabel='price'>
```



sqft_lot doesn't have a linear realtionship with price. This might be feature to drop later on in the model.

In [52]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          21597 non-null  float64
 1   bedrooms       21597 non-null  int64
 2   bathrooms      21597 non-null  float64
 3   sqft_living    21597 non-null  int64
 4   sqft_lot       21597 non-null  int64
 5   floors         21597 non-null  int64
 6   waterfront     21597 non-null  category
 7   view           21597 non-null  category
 8   condition      21597 non-null  category
 9   grade          21597 non-null  category
 10  sqft_above     21597 non-null  int64
 11  sqft_basement  21597 non-null  int64
 12  yr_built       21597 non-null  int64
 13  zipcode        21597 non-null  category
 14  lat            21597 non-null  float64
 15  long           21597 non-null  float64
 16  sqft_living15  21597 non-null  int64
 17  sqft_lot15     21597 non-null  int64
 18  renovated      21597 non-null  object
 19  year           21597 non-null  category
 20  month          21597 non-null  category
dtypes: category(7), float64(4), int64(9), object(1)
memory usage: 2.5+ MB
```

Base Model

For the base model I will select the numeric columns from my dataset.

In [53]:
```
# select numeric columns for base model
num_cols = df.select_dtypes(include='number')
num_cols.head()
```

Out[53]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_basement
0	221900.0	3	1.00	1180	5650	1	1180	0
1	538000.0	3	2.25	2570	7242	2	2170	400
2	180000.0	2	1.00	770	10000	1	770	0
3	604000.0	4	3.00	1960	5000	1	1050	910
4	510000.0	3	2.00	1680	8080	1	1680	0

In [54]:
```
# standardize, fit, transform the numeric columns
ss = StandardScaler()
ss.fit(num_cols)
num_cols_scaled = ss.transform(num_cols)

# create the new dataframe
scaled_new_num = pd.DataFrame(num_cols_scaled, columns = num_cols.columns, i
```

In [55]:
```
# coefficient interpretation before the scaling
lr = LinearRegression()
model = lr.fit(num_cols.drop(['price', 'long' ,'lat'], axis = 1), num_cols['

list(zip(model.coef_, num_cols.drop(['price', 'long' ,'lat'], axis = 1)))
```

Out[55]:
```
[(-65165.75692037638, 'bedrooms'),
 (70373.39716513667, 'bathrooms'),
 (204.43363034021604, 'sqft_living'),
 (0.018651902777749207, 'sqft_lot'),
 (57895.306020175565, 'floors'),
 (45.839711185697524, 'sqft_above'),
 (53.0752025717984, 'sqft_basement'),
 (-3700.3246922448966, 'yr_built'),
 (91.73984158761596, 'sqft_living15'),
 (-0.691266208756133, 'sqft_lot15')]
```

Coefficient interpretation before the scaling:

- with the one unti increase of bedrooms, the price decreases by 65165 USD, this can't be right
- with the one unit increase in bathrooms the price increases by 70373 USD
- with one sqft increase the price increases by 204 USD
- with one unit increase it the year built, or the older the house gets the price decreaes by 3700 USD

In [57]:
```
# create the baseline model
X_stand = scaled_new_num.drop(['price', 'long' ,'lat'], axis = 1)
y = num_cols['price']

baseline_model = sm.OLS(y, sm.add_constant(X_stand))
baseline_results = baseline_model.fit()
```

In [58]:
```
# print out the baseline summary report
print(baseline_results.summary())
```

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:                  price   R-squared:                       0.5
69
Model:                            OLS   Adj. R-squared:                  0.5
```

```
69
Method:                 Least Squares   F-statistic:                     285
0.
Date:                Fri, 28 Oct 2022   Prob (F-statistic):               0.
00
Time:                        11:03:02   Log-Likelihood:          -2.9830e+
05
No. Observations:               21597   AIC:                      5.966e+
05
Df Residuals:                   21586   BIC:                      5.967e+
05
Df Model:                          10
Covariance Type:            nonrobust
==============================================================================
=====
                    coef    std err          t      P>|t|      [0.025      0
.975]
------------------------------------------------------------------------------
-----
const          5.403e+05   1641.465    329.155      0.000    5.37e+05    5.4
4e+05
bedrooms      -6.036e+04   2068.840    -29.177      0.000   -6.44e+04   -5.6
3e+04
bathrooms      5.411e+04   2966.254     18.243      0.000    4.83e+04    5.9
9e+04
sqft_living    1.877e+05    1.98e+04     9.471      0.000    1.49e+05    2.2
7e+05
sqft_lot        772.4066   2369.563      0.326      0.744   -3872.112    541
6.925
floors         3.194e+04   2357.642     13.546      0.000    2.73e+04    3.6
6e+04
sqft_above     3.794e+04    1.79e+04     2.124      0.034    2933.925     7.
3e+04
sqft_basement  2.334e+04   9437.191      2.474      0.013    4845.395    4.1
8e+04
yr_built      -1.087e+05   2160.157    -50.318      0.000   -1.13e+05   -1.0
4e+05
sqft_living15  6.286e+04   2605.299     24.128      0.000    5.78e+04     6.
8e+04
sqft_lot15    -1.885e+04   2385.466     -7.903      0.000   -2.35e+04   -1.4
2e+04
==============================================================================
==
Omnibus:                    15473.122   Durbin-Watson:                   1.9
84
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           712324.6
21
Skew:                           2.937   Prob(JB):                         0.
00
Kurtosis:                      30.515   Cond. No.                         35
.2
==============================================================================
==
```

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

In [180…

```
base_r2 = 0.569
```

r2: The model is explaining about 57 % of the variance in price (y). one unit increase in standard deviation of sqft_living is increasing the sales price by 187700 USD

At a significance level of 0.05 sqft_lot (0.744) is not statisically significant

now lets increase predictions by removing the sqft_lot lets increase the prediction by adding the zipcode into the model

Skew: the data are positively , highly skewed. Kurtosis: 30.5 , shows that the data have heavy tails and that there are more outliers.

In [174…

```
# coeff after scaling
model1 = lr.fit(scaled_new_num.drop(['price', 'long' ,'lat'], axis = 1), num

list(zip(model1.coef_, scaled_new_num.drop(['price', 'long' ,'lat'], axis =
```

Out[174]:

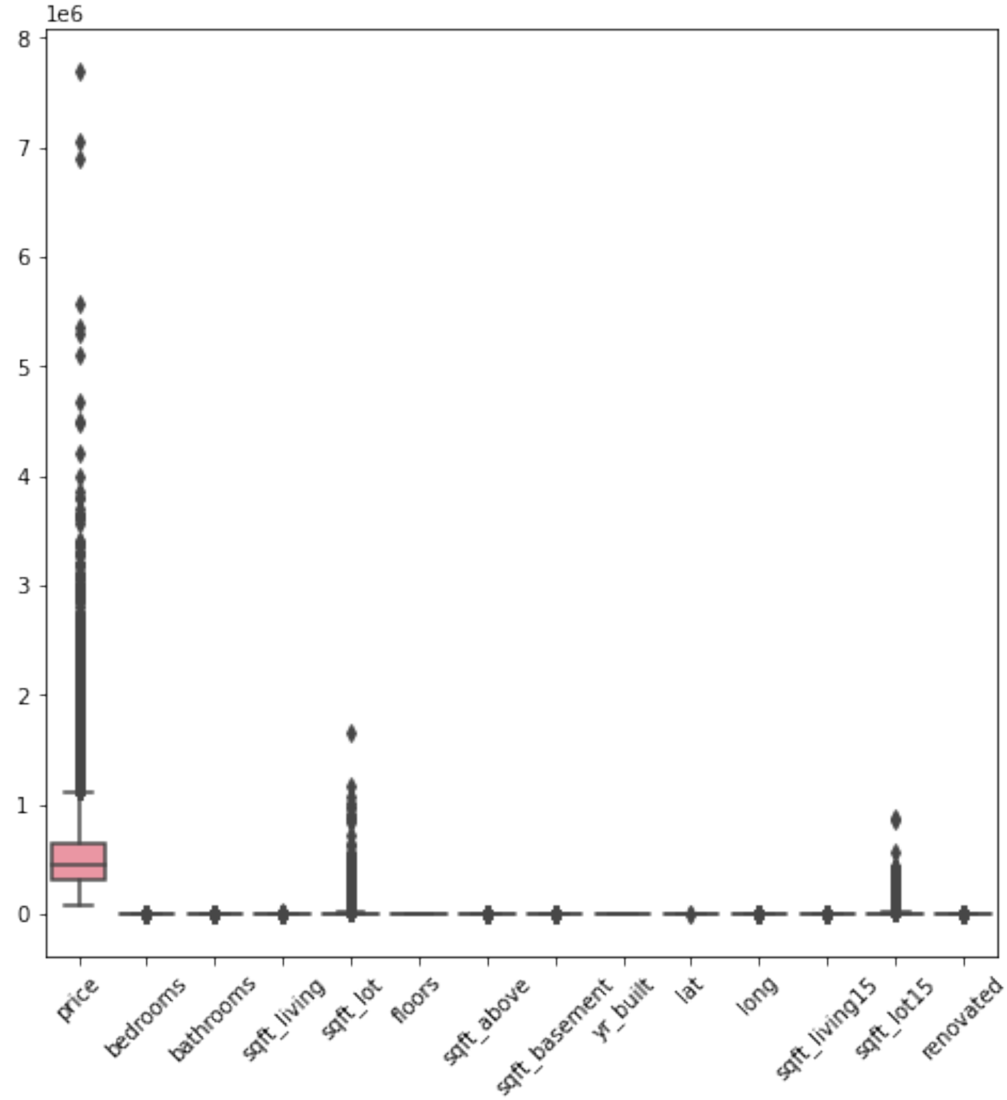
```
[(-60361.571096101594, 'bedrooms'),
 (54114.7844476965, 'bathrooms'),
 (187687.42281692784, 'sqft_living'),
 (772.4065943899386, 'sqft_lot'),
 (31937.690434629778, 'floors'),
 (37943.38991118728, 'sqft_above'),
 (23342.986110163787, 'sqft_basement'),
 (-108695.38766692171, 'yr_built'),
 (62861.47956360654, 'sqft_living15'),
 (-18853.46358469615, 'sqft_lot15')]
```

with every unit of increase in standard diviation in bathrooms, there is 54114 standard diviation increase in price. I am not sure if this data makes sense

Removing outliers

In [60]:

```
fig, ax = plt.subplots(figsize= (8,8))
sns.boxplot(data = df)
ax.tick_params(axis ='x', rotation = 45)
```



As we can see in the above boxplot, price has the most outliers. I will start checking the outliers and clean them, to make sure they don't skew our data.

In [61]:
```
price = df.sort_values(by='price', ascending = False)
price.head(100)
```

Out[61]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	co
7245	7700000.0	6	8.00	12050	27600	2	0	3	
3910	7060000.0	5	4.50	10040	37325	2	1	2	
9245	6890000.0	6	7.75	9890	31374	2	0	5	
4407	5570000.0	5	5.75	9200	35069	2	0	1	
1446	5350000.0	5	5.00	8000	23985	2	0	5	
...	...	...	...	...	...	...	...	...	
3018	2530000.0	4	5.50	6930	45100	1	0	1	
17544	2510000.0	3	3.25	5480	57990	2	1	5	
7304	2500000.0	4	4.00	3330	24354	1	0	1	
17137	2500000.0	4	3.75	3480	14850	1	0	5	
7499	2500000.0	4	3.25	3960	16224	2	0	2	

100 rows × 21 columns

In [62]:
```
df = df[df['price'] < 2500000]
```

In [63]:
```
df['price'].max()
```

Out[63]:
```
2490000.0
```

In [64]:
```
df
```

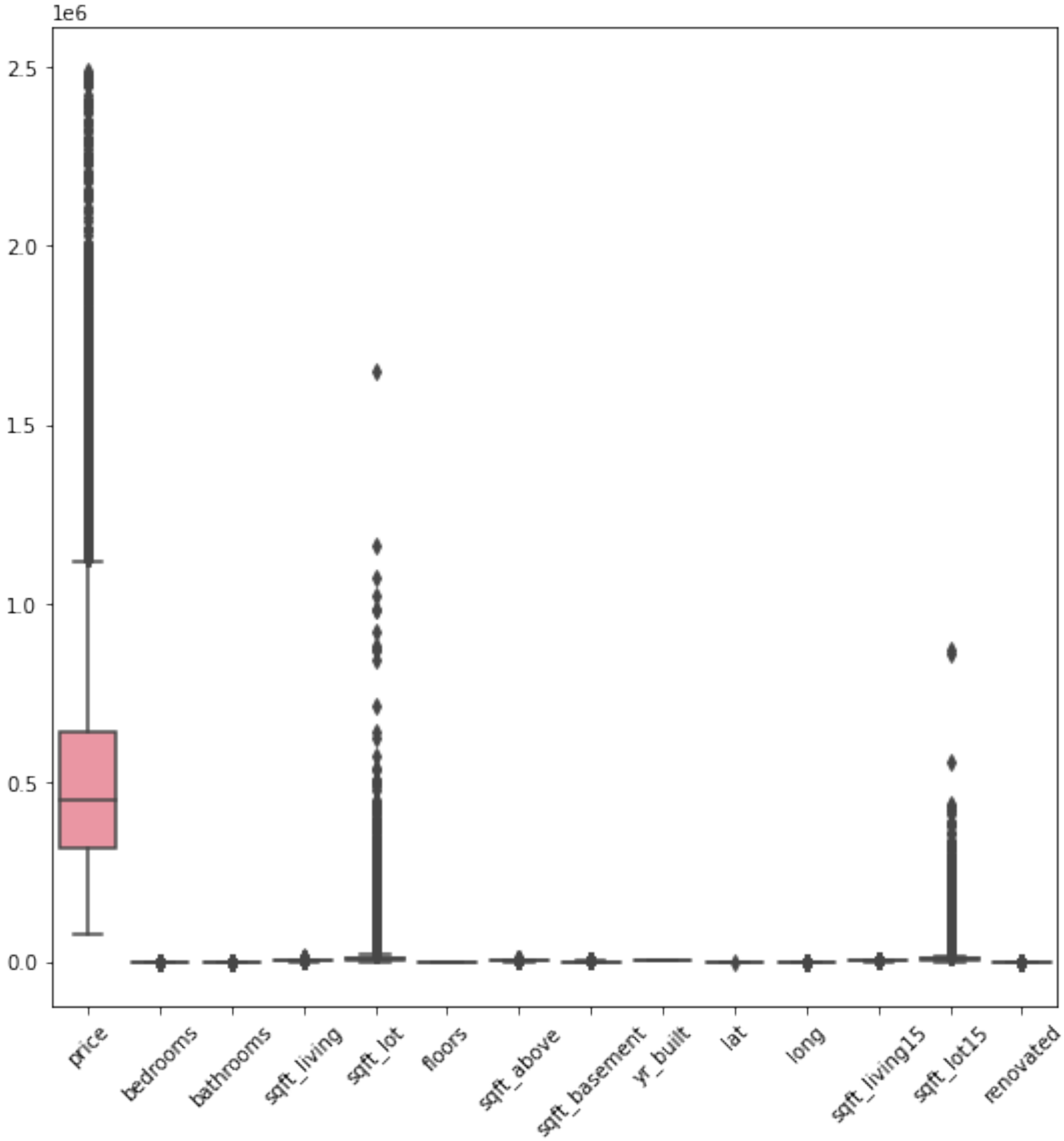
Out[64]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	con
0	221900.0	3	1.00	1180	5650	1	0	1	
1	538000.0	3	2.25	2570	7242	2	0	1	
2	180000.0	2	1.00	770	10000	1	0	1	
3	604000.0	4	3.00	1960	5000	1	0	1	
4	510000.0	3	2.00	1680	8080	1	0	1	
...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	1131	3	0	1	
21593	400000.0	4	2.50	2310	5813	2	0	1	
21594	402101.0	2	0.75	1020	1350	2	0	1	
21595	400000.0	3	2.50	1600	2388	2	0	1	
21596	325000.0	2	0.75	1020	1076	2	0	1	

21495 rows × 21 columns

In [65]:

```
fig, ax = plt.subplots(figsize= (9,9))
sns.boxplot(data = df)
ax.tick_params(axis ='x', rotation = 45)
```



In [66]:
```
df.describe()
```

Out[66]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	flo
count	2.149500e+04	21495.000000	21495.000000	21495.000000	2.149500e+04	21495.000
mean	5.274094e+05	3.367946	2.106397	2063.969063	1.506559e+04	1.444
std	3.101881e+05	0.923039	0.754709	882.045179	4.149343e+04	0.551
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000
25%	3.200000e+05	3.000000	1.500000	1420.000000	5.040000e+03	1.000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.600000e+03	1.000
75%	6.400000e+05	4.000000	2.500000	2540.000000	1.059100e+04	2.000
max	2.490000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.000

In [67]:

```
# removing outliers in the bedrooms
above = df.sort_values(by='sqft_living', ascending = False)
above.head(40)
```

Out[67]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	co
12764	2280000.0	7	8.00	13540	307752	3	0	5	
13398	2420000.0	5	4.75	7880	24250	2	0	2	
16759	1920000.0	5	5.75	7730	230868	2	0	1	
14019	1680000.0	4	3.75	7620	29536	2	0	3	
4020	800000.0	7	6.75	7480	41664	2	0	2	
11859	1950000.0	4	3.25	7420	167869	2	0	3	
2711	1110000.0	5	3.50	7350	12231	2	0	5	
18579	1140000.0	5	4.00	7320	217800	2	0	1	
21490	2240000.0	5	6.50	7270	130017	2	0	1	
6495	1940000.0	4	5.75	7220	223462	2	0	5	
21034	900000.0	5	6.00	7120	40806	2	0	5	
11673	1140000.0	6	4.25	6900	244716	2	0	1	
21328	1490000.0	5	6.00	6880	279968	2	0	3	
4807	2480000.0	5	3.75	6810	7500	2	0	1	
11093	1820000.0	4	4.50	6640	53330	2	0	1	
18960	1240000.0	7	5.50	6630	13782	2	0	1	
1537	1300000.0	6	3.50	6563	32670	2	0	1	
3098	1500000.0	4	5.50	6550	217374	1	0	1	

20436	1600000.0	4	5.50	6530	871200	2	0	2
10074	1900000.0	5	4.25	6510	16471	2	0	3
17885	2460000.0	4	5.25	6500	14986	2	0	1
19200	2000000.0	5	4.25	6490	10862	2	0	3
2123	1330000.0	3	3.75	6400	76665	1	0	2
5697	2470000.0	5	4.75	6390	13180	2	0	1
13387	1820000.0	4	4.50	6380	88714	2	0	1
20455	1800000.0	4	3.50	6370	205603	2	0	1
6035	2390000.0	4	4.00	6330	13296	2	0	2
20562	1180000.0	6	6.50	6260	10955	2	0	1
12271	1960000.0	5	4.50	6200	23373	3	0	4
20822	1280000.0	6	5.25	6160	27490	2	0	1
3118	1320000.0	4	5.25	6110	10369	2	0	1
10939	1610000.0	5	4.50	6085	142725	3	0	1
419	1550000.0	5	4.25	6070	171626	2	0	1
1099	1570000.0	5	4.50	6070	14731	2	0	1
2234	1760000.0	4	5.00	6055	21630	1	0	3
577	930000.0	4	4.00	6050	84942	2	0	2
527	1600000.0	6	5.00	6050	230652	2	0	3
15208	1150000.0	6	4.50	6040	219542	2	0	1
15553	1830000.0	3	3.75	6030	39317	2	0	1
5054	1530000.0	4	3.50	5990	111078	2	0	1

40 rows × 21 columns

In [68]:
```
# removing any sqft_living which is greater then 9000 sqft
df= df[df['sqft_living'] < 9000]
# checking the new max value of the column
df['sqft_living'].max()
```
Out[68]: 7880

In [69]:
```
#checking how many outliers we have for more than 6 bathrooms
len(df[df['bathrooms'] >= 6])
```
Out[69]: 7

In [70]:
```
#removing the outliers in the bathrooms column
df=df[df['bathrooms'] <= 6]
# checking if the outlier have been removed
df['bathrooms'].max()
```

Out[70]:
```
6.0
```

In [71]:
```
# saving the zipcode column for later use
zipcode = df['zipcode']
zipcode
```

Out[71]:
```
0        98178
1        98125
2        98028
3        98136
4        98074
         ...
21592    98103
21593    98146
21594    98144
21595    98027
21596    98144
Name: zipcode, Length: 21490, dtype: category
Categories (70, int64): [98001, 98002, 98003, 98004, ..., 98178, 98188, 9819
8, 98199]
```

Train - Test Split

Splitting up the dataframe to the train and test. I will use the price as the targe variable.

In [72]:
```
# Splitting up the datafram into train - test
y = df['price']
X = df.drop(['price'], axis = 1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, r
```

In [73]:
```
# check the size of train for X and y.
print(f'There are {X_train.shape[0]} rows, and {X_train.shape[1]} columns in
print(f'There are {y_train.shape[0]} rows in y train data.')
```

```
There are 15043 rows, and 20 columns in the X train data.
There are 15043 rows in y train data.
```

In [74]:
```
# check the size of test for X and y.
print(f'There are {X_test.shape[0]} rows, and {X_test.shape[1]} columns in t
print(f'There are {y_test.shape[0]} rows in y test data.')
```

```
There are 6447 rows, and 20 columns in the X test data.
There are 6447 rows in y test data.
```

In [75]:
```
# check if the X and y has the same size
X_train.shape[0] == y_train.shape[0]
```

Out[75]:
```
True
```

In [104…
```
X_train
```

Out[104]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	gra
3806	3	1.50	2210	6300	1	0	1	5	
11484	3	1.00	1660	7500	1	0	1	4	
11959	4	3.00	2500	6278	2	0	1	3	
16201	3	2.75	2160	4086	1	0	1	3	
11257	3	2.00	1990	3000	1	0	2	5	
...	...	...	...	...	...	...	...	...	
11338	4	1.50	1500	3075	2	0	1	5	
12023	2	1.75	1550	4257	1	0	3	3	
5415	3	1.50	1280	5065	2	0	1	4	
863	3	3.50	2480	3200	2	0	1	3	
15870	4	2.50	2150	7944	2	0	1	3	

15043 rows × 20 columns

In [105…
```
# standardize the train
ss = StandardScaler()
ss.fit(X_train)
cols_scaled = ss.transform(X_train)

# create new dataframe
scaled = pd.DataFrame(cols_scaled, columns = X_train.columns, index = X_trai
```

One-Hot Encoder for zipcode

In [106…
```
# instantiate hotencoder , only do it once for train and test here
ohe = OneHotEncoder(drop = 'first', sparse = False)
```

In [107…
```
cat_cols = ['zipcode']
ohe_cat = ohe.fit_transform(X_train[cat_cols])
ohe.get_feature_names_out()
```

Out[107]:
```
array(['zipcode_98002', 'zipcode_98003', 'zipcode_98004', 'zipcode_98005',
       'zipcode_98006', 'zipcode_98007', 'zipcode_98008', 'zipcode_98010',
       'zipcode_98011', 'zipcode_98014', 'zipcode_98019', 'zipcode_98022',
       'zipcode_98023', 'zipcode_98024', 'zipcode_98027', 'zipcode_98028',
       'zipcode_98029', 'zipcode_98030', 'zipcode_98031', 'zipcode_98032',
       'zipcode_98033', 'zipcode_98034', 'zipcode_98038', 'zipcode_98039',
       'zipcode_98040', 'zipcode_98042', 'zipcode_98045', 'zipcode_98052',
       'zipcode_98053', 'zipcode_98055', 'zipcode_98056', 'zipcode_98058',
       'zipcode_98059', 'zipcode_98065', 'zipcode_98070', 'zipcode_98072',
       'zipcode_98074', 'zipcode_98075', 'zipcode_98077', 'zipcode_98092',
       'zipcode_98102', 'zipcode_98103', 'zipcode_98105', 'zipcode_98106',
       'zipcode_98107', 'zipcode_98108', 'zipcode_98109', 'zipcode_98112',
       'zipcode_98115', 'zipcode_98116', 'zipcode_98117', 'zipcode_98118',
       'zipcode_98119', 'zipcode_98122', 'zipcode_98125', 'zipcode_98126',
       'zipcode_98133', 'zipcode_98136', 'zipcode_98144', 'zipcode_98146',
       'zipcode_98148', 'zipcode_98155', 'zipcode_98166', 'zipcode_98168',
       'zipcode_98177', 'zipcode_98178', 'zipcode_98188', 'zipcode_98198',
       'zipcode_98199'], dtype=object)
```

In [108…
```
new_train_df = pd.DataFrame(ohe_cat, columns = ohe.get_feature_names(),index
new_train_df.head()
```

Out[108]:

	x0_98002	x0_98003	x0_98004	x0_98005	x0_98006	x0_98007	x0_98008	x0_
3806	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
11484	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
11959	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16201	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
11257	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 69 columns

In [109…
```
X_train_concat = pd.concat([scaled, new_train_df], axis = 1).drop(['zipcode'
```

In [110…
```
X_train_concat
```

Out[110]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	co
3806	-0.397872	-0.806378	0.165538	-0.211872	-0.805067	-0.068375	-0.282225	2
11484	-0.397872	-1.473193	-0.462412	-0.182662	-0.805067	-0.068375	-0.282225	0.
11959	0.676090	1.194064	0.496639	-0.212408	1.019922	-0.068375	-0.282225	-0.
16201	-0.397872	0.860657	0.108452	-0.265767	-0.805067	-0.068375	-0.282225	-0.
11257	-0.397872	-0.139564	-0.085642	-0.292203	-0.805067	-0.068375	1.211098	2
...	...	...	...	...	...	...	...	
11338	0.676090	-0.806378	-0.645088	-0.290377	1.019922	-0.068375	-0.282225	2
12023	-1.471835	-0.472971	-0.588002	-0.261604	-0.805067	-0.068375	2.704421	-0.
5415	-0.397872	-0.806378	-0.896268	-0.241935	1.019922	-0.068375	-0.282225	0.
863	-0.397872	1.860879	0.473804	-0.287334	1.019922	-0.068375	-0.282225	-0.
15870	0.676090	0.527250	0.097035	-0.171853	1.019922	-0.068375	-0.282225	-0.

15043 rows × 88 columns

In [111…

```
# standardize the test
ss = StandardScaler()
ss.fit(X_test)
cols_scaled = ss.transform(X_test)

# create new dataframe
scaled = pd.DataFrame(cols_scaled, columns = X_test.columns, index = X_test.
```

In [112…

```
# X_test hot encoder
cat_cols = ['zipcode']
ohe_cat = ohe.transform(X_test[cat_cols])
ohe.get_feature_names_out()
```

Out[112]:
```
array(['zipcode_98002', 'zipcode_98003', 'zipcode_98004', 'zipcode_98005',
       'zipcode_98006', 'zipcode_98007', 'zipcode_98008', 'zipcode_98010',
       'zipcode_98011', 'zipcode_98014', 'zipcode_98019', 'zipcode_98022',
       'zipcode_98023', 'zipcode_98024', 'zipcode_98027', 'zipcode_98028',
       'zipcode_98029', 'zipcode_98030', 'zipcode_98031', 'zipcode_98032',
       'zipcode_98033', 'zipcode_98034', 'zipcode_98038', 'zipcode_98039',
       'zipcode_98040', 'zipcode_98042', 'zipcode_98045', 'zipcode_98052',
       'zipcode_98053', 'zipcode_98055', 'zipcode_98056', 'zipcode_98058',
       'zipcode_98059', 'zipcode_98065', 'zipcode_98070', 'zipcode_98072',
       'zipcode_98074', 'zipcode_98075', 'zipcode_98077', 'zipcode_98092',
       'zipcode_98102', 'zipcode_98103', 'zipcode_98105', 'zipcode_98106',
       'zipcode_98107', 'zipcode_98108', 'zipcode_98109', 'zipcode_98112',
       'zipcode_98115', 'zipcode_98116', 'zipcode_98117', 'zipcode_98118',
       'zipcode_98119', 'zipcode_98122', 'zipcode_98125', 'zipcode_98126',
       'zipcode_98133', 'zipcode_98136', 'zipcode_98144', 'zipcode_98146',
       'zipcode_98148', 'zipcode_98155', 'zipcode_98166', 'zipcode_98168',
       'zipcode_98177', 'zipcode_98178', 'zipcode_98188', 'zipcode_98198',
       'zipcode_98199'], dtype=object)
```

In [113…
```python
new_test_df = pd.DataFrame(ohe_cat, columns = ohe.get_feature_names(),index
new_test_df.head()
```

Out[113]:

	x0_98002	x0_98003	x0_98004	x0_98005	x0_98006	x0_98007	x0_98008	x0
3550	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3633	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
14408	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
18301	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
8875	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 69 columns

In [114…
```python
X_test_concat = pd.concat([scaled, new_test_df], axis = 1).drop(['zipcode'],
```

In [115…
```python
X_test_concat
```

Out[115]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	c
3550	0.713139	0.190252	-0.452228	-0.188315	-0.806045	-0.082896	-0.277282	-0
3633	0.713139	0.522022	0.834477	-0.176747	0.982177	-0.082896	-0.277282	-0
14408	-0.400083	-0.473289	-1.112660	-0.170384	-0.806045	-0.082896	-0.277282	-0
18301	0.713139	0.522022	-0.520548	-0.198228	-0.806045	-0.082896	-0.277282	-0
8875	-1.513304	-1.468600	-1.579517	-0.236670	-0.806045	-0.082896	-0.277282	-0
...	...	...	...	...	...	...	...	
3118	0.713139	4.171497	4.614883	-0.112969	0.982177	-0.082896	-0.277282	-0
13020	-1.513304	-1.468600	-1.249301	-0.199765	-0.806045	-0.082896	-0.277282	-0
519	0.713139	1.517334	1.278561	4.237722	0.982177	-0.082896	-0.277282	-0
4073	-0.400083	-1.468600	-0.953245	-0.166196	-0.806045	-0.082896	-0.277282	0
5032	-0.400083	-0.473289	-0.372520	-0.173577	-0.806045	-0.082896	-0.277282	-0

6447 rows × 88 columns

2nd Model

In [117…

```
# loging y np.log(y) with hot-encoded zipcode
y_train_log = np.log(y_train)
y_test_log = np.log(y_test)
m2_X_train = X_train_concat
m2_X_test = X_test_concat
model2 = LinearRegression()
model2.fit(m2_X_train, y_train_log)
m2_r2_train = model2.score(m2_X_train,y_train_log)
m2_r2_test = model2.score(m2_X_test,y_test_log)
print(model2.score(m2_X_train,y_train_log))
print(model2.score(m2_X_test,y_test_log))

# need to log all the y
```

```
0.8734360707928088
0.8709309058147522
```

In [118…

```
# y hat
y_pred = model2.predict(m2_X_test)
y_pred = np.exp(y_pred) # np.exp removes the normalization from the y hat
```

In [121…

```
#MAE
m2_mae = mean_absolute_error(y_pred, y_test)
m2_mae
# how much the measuring is off
# the measuring in houseprice is off by 72422 USD (mean avg error)
```

Out[121]:

```
72422.69501229191
```

In [122…

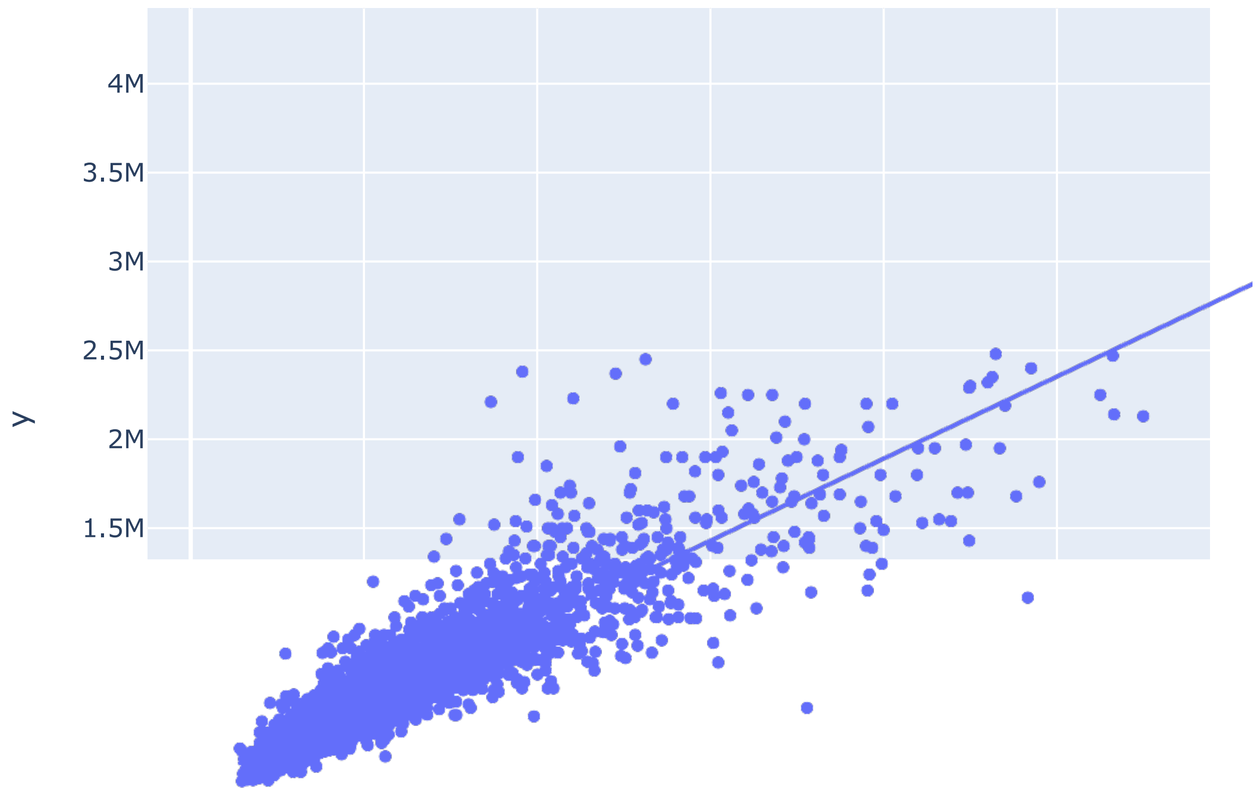
```
#RMSE
m2_rmse = np.sqrt(mean_squared_error(y_pred, y_test))
m2_rmse
# how much the measuring is off, outliers
# the price of a house is off by 122071 USD, sensitive for outliers
```

Out[122]:

```
122071.47637004108
```

In [183…

```
# prediction graph
fig = px.scatter(x=y_pred, y =y_test, trendline = 'ols')
fig.show('notebook')
```



The 2nd model explains around 87.6% of the variance in price for the train and 86.2% variance for the test data. That is not bad, however both the MAE and RMSE has a high error. MEA is off by 74766 USD, while RMSE is off by 126441 USD. In the next model I will drop some colliner features to see how this will change the prediction.

In the following model I will check for collinearity and if there any features that are highly correlated with each other I will remove some of them and see how it effect my model.

In [124…

```
# check for multicollinearity
data_pred = X_train_concat.iloc[:, 0:20]

# get the correlation
data_pred.corr()
# save absolute value of correlation matrix as a data frame
# converts all values to absolute value
# stacks the row:column pairs into a multindex
# reset the index to set the multindex to seperate columns
# sort values. 0 is the column automatically generated by the stacking
d = data_pred.corr().abs().stack().reset_index().sort_values(0, ascending =
#zip variable name columns in a new column named 'pairs'
d['pairs'] = list(zip(d.level_0, d.level_1))
#set index to pairs
d.set_index(['pairs'], inplace = True)
# drop level col
d.drop(columns=['level_1', 'level_0'], inplace = True)
# rename the correlation column as cc
d.columns = ['cc']
#drop duplicates
d.drop_duplicates(inplace = True)

d[(d.cc > 0.75) & (d.cc <1)]
```

Out[124]:

	cc
pairs	
(sqft_above, sqft_living)	0.868732
(month, year)	0.782748
(sqft_living, sqft_living15)	0.754418
(sqft_living, grade)	0.754151

sqtf_above highly correlated to sqft_living, also sqft_basement moderatly correlate. Not surprising as the sqft_living is the total of sqft_above and sqft_basement. I will remove these from my next model to see what is the effect on the r2 and residuals.

3rd Model

In [125...
```
# droping some of the highly correlated features
y_train_log = np.log(y_train)
y_test_log = np.log(y_test)
m3_X_train = X_train_concat.drop(['sqft_above', 'sqft_living15'], axis= 1)
m3_X_test = m2_X_test.drop(['sqft_above', 'sqft_living15'], axis= 1)
model3 = LinearRegression()
model3.fit(m3_X_train, y_train_log)
m3_r2_train = model3.score(m3_X_train,y_train_log)
m3_r2_test = model3.score(m3_X_test,y_test_log)
print(model3.score(m3_X_train,y_train_log))
print(model3.score(m3_X_test,y_test_log))
```

```
0.8695326533837777
0.8668419797993704
```

By removing the sqft_above, sqft_living15 and year, the R2 decreased slightly to 86,9%. The model still explains 86.6% of the variance in sales price.

In [126...
```
# scatterplot the two R2 values
train_score = model2.score(m2_X_train,y_train)
test_score = model2.score(m2_X_test,y_test)

#sns.scatterplot()
```

In [127...
```
# y predictor
m3_y_pred = model3.predict(m3_X_test)
m3_y_pred = np.exp(m3_y_pred)
```

In [128...
```
#MAE
m3_mae = mean_absolute_error(y_test, m3_y_pred)
m3_mae
# how much the measuring is off
# the measuring in houseprice is off by 73588 USD (mean avg error)
```

Out[128]:
```
73588.99742511535
```

In [129...
```
# sensitive for outliers
#RMSE
m3_rmse = np.sqrt(mean_squared_error(m3_y_pred, y_test, squared = False))
m3_rmse
# how much the measuring is off, outliers
# the price of a house is off by 358 USD
```

Out[129]:
```
358.53376532749905
```

In [167...
```
# coefficient interpretation
list(zip(((np.exp(model3.coef_)-1)*100), m3_X_test.iloc[:,0:13].drop(['long'
```

Out[167]:
```
[(-0.008892171950236616, 'bedrooms'),
 (3.0126308921728517, 'bathrooms'),
 (23.4799276287335, 'sqft_living'),
 (2.5036736892261935, 'sqft_lot'),
 (-2.0777264818453545, 'floors'),
 (2.9475327201313295, 'waterfront'),
 (4.812598863199757, 'view'),
 (3.678182171325295, 'condition'),
 (12.684385158241263, 'grade'),
 (-3.4440882907219805, 'sqft_basement'),
 (-1.265128894380696, 'yr_built')]
```

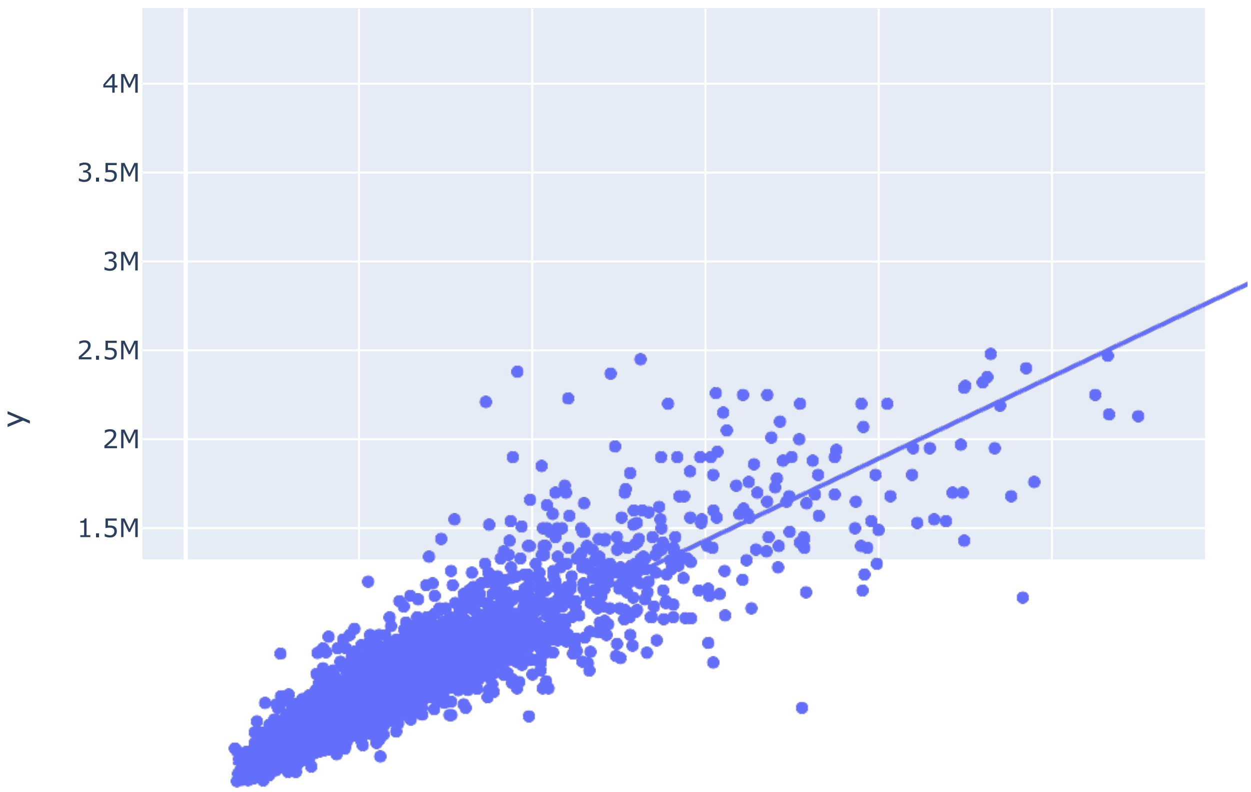
In [ ]:
```
#plt.qqplot(y_train_log,line='r')
```

In [ ]:
```
#m3_X_test.shape
```

In [ ]:
```
#m3_X_train.shape
```

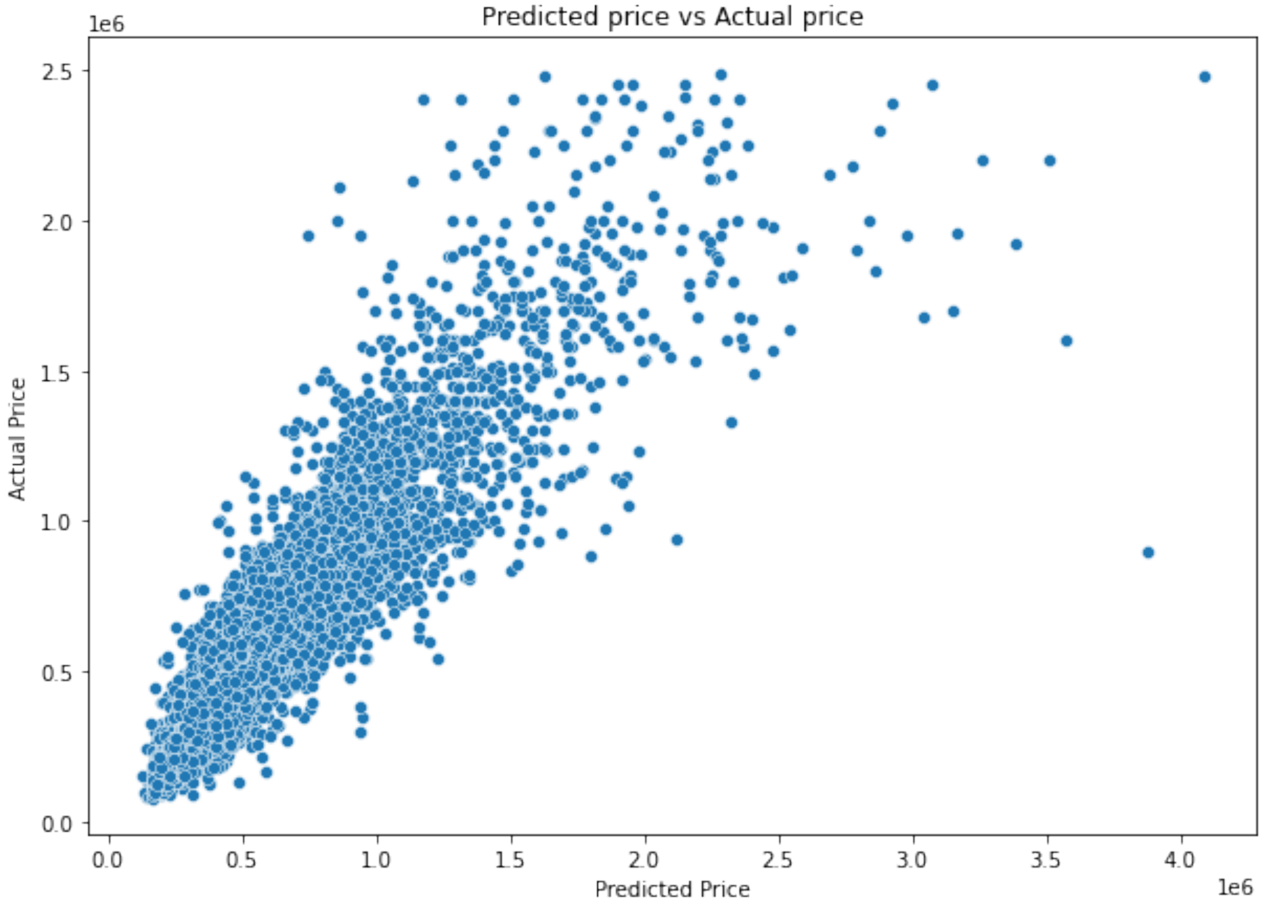
In [ ]:
```
# residual plots
#fig, ax = plt.subplots(figsize =(8,7))
#train_preds = model3.predict(m3_X_train)
#rest_residuals = model3.predict(m3_X_test)

#train_residuals = m3_X_train - train_preds
#test_residuals = y_test - test_preds

#sns.scatter(train_preds, train_residuals, label ='Train')
#sns.scatter(test_preds, test_residuals, label='Test')
```

In [177…
```
# prediction graph
fig = px.scatter(x=y_pred, y =y_test, trendline = 'ols')
fig.show('notebook')
```



In [184…

```
# Predicted price versus the actual price
train_preds = model3.predict(m3_X_train)
fig, ax = plt.subplots(figsize = (10,7))
sns.scatterplot(x=np.exp(train_preds),y= y_train) # reverse the log
ax.set_title('Predicted price vs Actual price')
ax.set_xlabel('Predicted Price')
ax.set_ylabel('Actual Price')
plt.show()
```



The above graph shows that my 3rd model had a 85% , Up until 1.5 million USD the model predict accurately, after the model is not that accuratly predicting the sales price.

4th Model

In [131…

```
# remove collinear variable grade
y_train_log = np.log(y_train)
y_test_log = np.log(y_test)

m4_X_test = m3_X_test.drop(['grade'], axis= 1)
m4_X_train = m3_X_train.drop(['grade'], axis= 1)
model4 = LinearRegression()
model4.fit(m4_X_train, y_train_log)

m4_r2_train = model4.score(m4_X_train,y_train_log)
m4_r2_test = model4.score(m4_X_test,y_test_log)
print(model4.score(m4_X_train,y_train_log))
print(model4.score(m4_X_test,y_test_log))
```

```
0.8538036224204687
0.8487933495108261
```

The 4th model captures 84.87% of the variance in price.

In [133...
```
m4_X_train
```

Out[133]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	co
3806	-0.397872	-0.806378	0.165538	-0.211872	-0.805067	-0.068375	-0.282225	2
11484	-0.397872	-1.473193	-0.462412	-0.182662	-0.805067	-0.068375	-0.282225	0.
11959	0.676090	1.194064	0.496639	-0.212408	1.019922	-0.068375	-0.282225	-0.
16201	-0.397872	0.860657	0.108452	-0.265767	-0.805067	-0.068375	-0.282225	-0.
11257	-0.397872	-0.139564	-0.085642	-0.292203	-0.805067	-0.068375	1.211098	2
...	...	...	...	...	...	...	...	
11338	0.676090	-0.806378	-0.645088	-0.290377	1.019922	-0.068375	-0.282225	2
12023	-1.471835	-0.472971	-0.588002	-0.261604	-0.805067	-0.068375	2.704421	-0.
5415	-0.397872	-0.806378	-0.896268	-0.241935	1.019922	-0.068375	-0.282225	0.
863	-0.397872	1.860879	0.473804	-0.287334	1.019922	-0.068375	-0.282225	-0.
15870	0.676090	0.527250	0.097035	-0.171853	1.019922	-0.068375	-0.282225	-0.

15043 rows × 85 columns

In [134...
```
# y hat
y_pred = model4.predict(m4_X_test)
y_pred = np.exp(y_pred)
```

In [135...
```
#MAE
m4_mae = mean_absolute_error(y_pred, y_test)
m4_mae
```

Out[135]: 79489.47761953853

In [136...
```
#RMSE
m4_rmse = np.sqrt(mean_squared_error(y_pred, y_test))
m4_rmse
```

Out[136]: 141973.41530054298

mae, the measuring in houseprice is off by 79489 USD (mean avg error), this is a slight increase from the previous model. rmse, the price of a house is off by 141973 USD, sensitive for outliers

In [137...
```
m3_X_train.head()
```

Out[137]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	cc
3806	-0.397872	-0.806378	0.165538	-0.211872	-0.805067	-0.068375	-0.282225	2
11484	-0.397872	-1.473193	-0.462412	-0.182662	-0.805067	-0.068375	-0.282225	0.
11959	0.676090	1.194064	0.496639	-0.212408	1.019922	-0.068375	-0.282225	-0.
16201	-0.397872	0.860657	0.108452	-0.265767	-0.805067	-0.068375	-0.282225	-0.
11257	-0.397872	-0.139564	-0.085642	-0.292203	-0.805067	-0.068375	1.211098	2

5 rows × 86 columns

In [169…

```
# coefficient interpretation
list(zip(((np.exp(model4.coef_)-1)*100), np.exp(m4_X_test).iloc[:,0:13].drop
#list(zip((((model3.coef_)-1)* 100), m3_X_test.iloc[:,0:13].drop(['long' ,'l
#model.coef_, num_cols.drop(['price', 'long' ,'lat'], axis = 1)))
```

Out[169]:

```
[(-1.087662298444081, 'bedrooms'),
 (3.508222001071548, 'bathrooms'),
 (34.40081406591737, 'sqft_living'),
 (2.7473417400535105, 'sqft_lot'),
 (-1.9874618535397848, 'floors'),
 (3.065598092304467, 'waterfront'),
 (5.671998435739867, 'view'),
 (3.7907619817989957, 'condition'),
 (-5.407909203194572, 'sqft_basement'),
 (1.8428972878659078, 'yr_built'),
 (7.846426900843517, 'sqft_lot15')]
```

By removing grade did dicrease the R2 around 2%, which proves that grade is indeed important and it adds to the model because the grade of the house influence how much the house will sell for. MAE and RMSE also increased. MAE increased to 79489 USD, the RSME drasticly increased to 141973 USD. I will keep the grade in the next model and remove the year feature.

5th Model

In [143…

```
# remove year but keep grade
y_train_log = np.log(y_train)
y_test_log = np.log(y_test)

m5_X_test = m3_X_test.drop(['year'], axis= 1)
m5_X_train = m3_X_train.drop(['year'], axis= 1)
model5 = LinearRegression()
model5.fit(m5_X_train, y_train_log)
m5_r2_train = model5.score(m5_X_train,y_train_log)
m5_r2_test = model5.score(m5_X_test,y_test_log)
print(model5.score(m5_X_train,y_train_log))
print(model5.score(m5_X_test,y_test_log))
```

```
0.8681058346031685
0.8654663163144184
```

By droping the year feature the R2 score improved. This 5th model capture 86.8% of the the variance in sales price for the train data and 86.5% of the test data.

In [144…

```
# y hat
y_pred = model5.predict(m5_X_test)
y_pred = np.exp(y_pred)
```

In [145…

```
#MAE
m5_mae = mean_absolute_error(y_pred, y_test)
m5_mae
# how much the measuring is off
# the measuring in houseprice is off by 76005 USD
```

Out[145]:

```
73998.09500253294
```

In [146…

```
#RMSE
m5_rmse = np.sqrt(mean_squared_error(y_pred, y_test))
m5_rmse
# how much the measuring is off, outliers
# the price of a house is off by 131456 USD
```

Out[146]:

```
129220.31086467957
```

fig = px.scatter(x=y_pred, y =y_test, trendline = 'ols') fig.show('notebook')

While the R2 impoved, 86,5 % of the variation captured in this model, compared to model 4. The error also decreased from the previous model for both the MAE and RMSE. MAE - price is off by 73998 USD. Based on the RMSE the price is off by 129220 USD.

Model Summary

In [188…

```
# summary of score from each model
#baseline model with numerical features
print('Baseline Model: ')
print(f'Baseline R2: {base_r2}\n')

# one-hot endcoded zipcode
print('Model2: ')
print(f'Model2 Train R2: {m2_r2_train}')
print(f'Model2 Test R2: {m2_r2_test}')
print(f'Model2 MAE: {m2_mae}')
print(f'Model2 RMSE: {m2_rmse}\n')

#model 3
print('Model3: ')
print(f'Model3 Train R2: {m3_r2_train}')
print(f'Model3 Test R2: {m3_r2_test}')
print(f'Model3 MAE: {m3_mae}')
print(f'Model3 RMSE: {m3_rmse}\n')

# model 4, removed sqft_above, sft_living15
print('Model4: ')
print(f'Model4 Train R2: {m4_r2_train}')
print(f'Model4 Test R2: {m4_r2_test}')
print(f'Model4 MAE: {m4_mae}')
print(f'Model4 RMSE: {m4_rmse}\n')

# model 5 , removed year feature
print('Model5: ')
print(f'Model5 Test R2: {m5_r2_test}')
print(f'Model5 Test R2: {m5_r2_test}')
print(f'Model5 MAE: {m5_mae}')
print(f'Model5 RMSE: {m5_rmse}')
```

```
Baseline Model:
Baseline R2: 0.569

Model2:
Model2 Train R2: 0.8734360707928088
Model2 Test R2: 0.8709309058147522
Model2 MAE: 72422.69501229191
Model2 RMSE: 122071.47637004108

Model3:
Model3 Train R2: 0.8695326533837777
Model3 Test R2: 0.8668419797993704
Model3 MAE: 73588.99742511535
Model3 RMSE: 358.53376532749905

Model4:
Model4 Train R2: 0.8538036224204687
Model4 Test R2: 0.8487933495108261
Model4 MAE: 79489.47761953853
Model4 RMSE: 141973.41530054298

Model5:
Model5 Test R2: 0.8654663163144184
Model5 Test R2: 0.8654663163144184
Model5 MAE: 73998.09500253294
Model5 RMSE: 129220.31086467957
```

EDA for Recommendation

In [ ]:

```
# yound couple with a child below 1 year old
# they are looking for a house / apartman in Seatle specific neighborhoods
# they have a budget of 600000 USD
# wouldn't mind if the house is a fixer-upper
```

In [147…

```
# prefered neighborhood
zips = [98117, 98102, 98103, 98115, 98105, 98125, 98133, 98177, 98112, 98119

fixer_upper = pd.DataFrame()
fixer_upper['diff'] = m3_y_pred - y_test.values
fixer_upper['zipcode'] = zipcode
z = fixer_upper.groupby('zipcode').sum()['diff'].sort_values().head(10)
fixer_upper_loc = z.index
common_loc = set(zips).intersection(fixer_upper_loc)
common_loc
```

Out[147]:

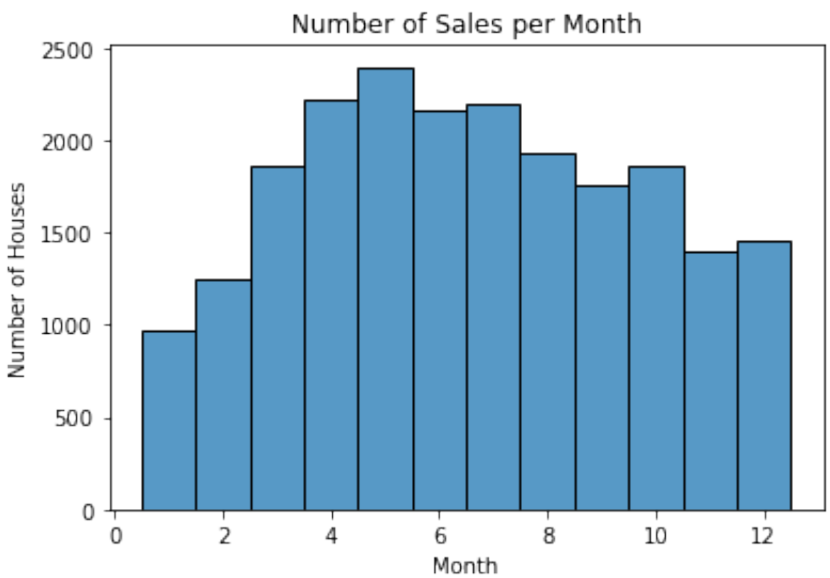
```
{98102, 98103, 98115}
```

In [148…

```
#best time of the year for buying a house
month = df['month'].value_counts()
month = month.sort_index
month
fig, ax = plt.subplots(figsize=(6,4))
sns.histplot(data = df, x= 'month')
ax.set_title('Number of Sales per Month')
ax.set_xlabel('Month')
ax.set_ylabel('Number of Houses')
```

Out[148]:

```
Text(0, 0.5, 'Number of Houses')
```



There is a seasonality in the number of houses available on the market. Based on the graph, the best time of the year to buy is from March to October.

In [189…

```
# checking the average price for the selected zipcodes
two_beds = df[df['bedrooms'] == 2]
two_beds = df[(df['zipcode']== 98103)| (df['zipcode'] == 98103) | (df['zipcc
#t = two_beds.groupby('zipcode')#['price'].mean()
#t
two_beds.pivot_table(columns = 'zipcode',values='price', aggfunc = 'mean').m
```

Out[189]:

```
zipcode
98103    585048.779070
98115    619944.149228
dtype: float64
```

In [150…

```
# checking the number of two bedroom houses
two_beds['grade'].value_counts()
```

Out[150]:
```
7      699
8      478
6      124
9      101
10      25
5       14
11       4
12       0
13       0
3        0
4        0
Name: grade, dtype: int64
```

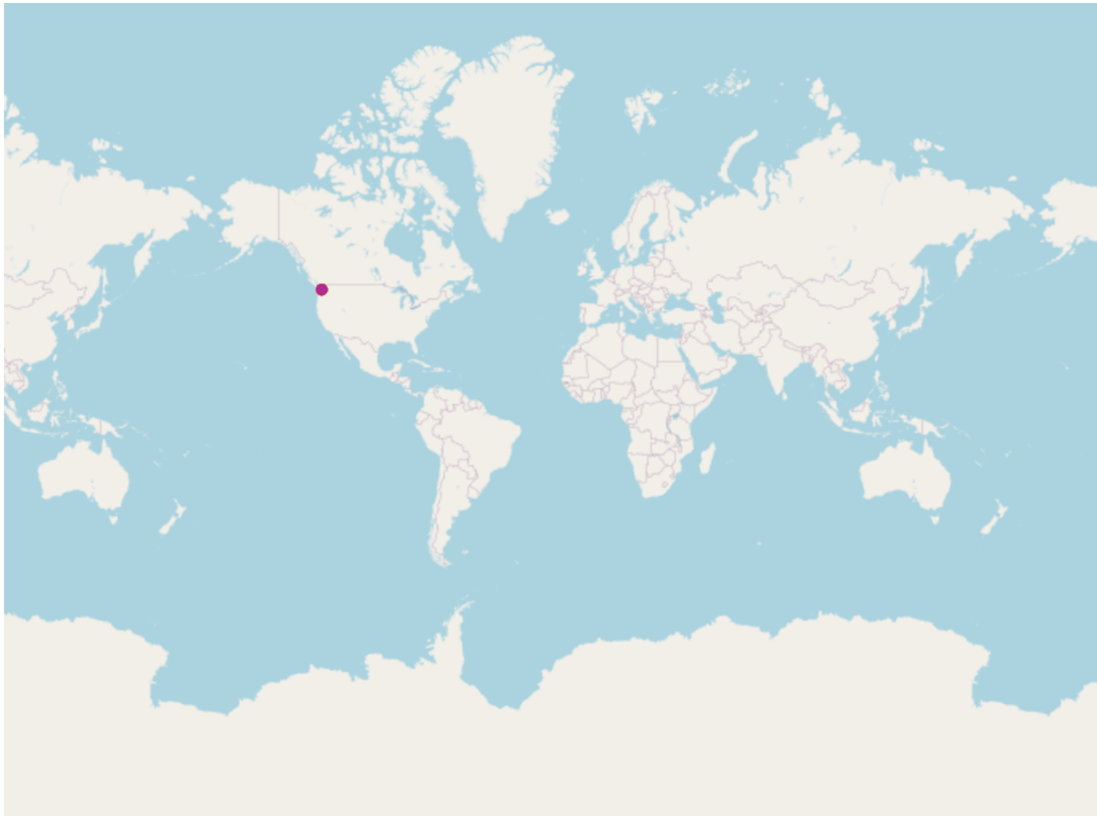
In [151…
```
# checking the number of houses in the selected grades
two_beds['grade'] = two_beds['grade'].astype(int)
two_beds['grade'].value_counts()
```

Out[151]:
```
7      699
8      478
6      124
9      101
10      25
5       14
11       4
Name: grade, dtype: int64
```

In [190…
```
# minimum price for each zipcode
good_grade = two_beds[(two_beds['grade'] != 5) & (two_beds['grade'] !=6) & (
good_grade['grade'].value_counts()
good_grade.pivot_table(columns = 'zipcode',values='price',aggfunc = 'min').m
```

Out[190]:
```
zipcode
98103    238000.0
98115    200000.0
dtype: float64
```

In [191…
```
#map for target
fig = px.scatter_mapbox(good_grade.loc[good_grade['price'] <= 600000], lat='
fig.update_layout(mapbox_style='open-street-map')
fig.show()
```



```
In [ ]:
```