King County Housing with Multiple Linear Regression

Author: Pengju Sun

Date: 03/22/2021

Business Problem

The stakholders in a housing development company are searching for qualities that lead to higher home sale prices. The data was used for ananlysing is from the data of houses in King County. My goal is to develop models to make predictions about sale price of houses based on certain variables or features, so that they can be used to make profitable decisions by a housing development company.

Hypothesis

Null Hypothesis: There is no relationship between features and sale price of houses.

Alternative Hypothesis: There is a relationship between features and sale price of houses.

A significance level (alpha) of 0.05 will being used to make the determination, and will make the final recommendations accordingly.

Data Description

King County House Data: a dataset that we were provided at the onset of the project. This file contains data for 21,597 homes built in King County from 1900 to 2015. Each home in the set contains information regarding features such as number of bedrooms/bathrooms, number of floors, square footage, zip code, condition, and more.

In [1]:
```
# import the packeages that I will be using for this project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, make_scorer,mean_absolute_er
from sklearn.metrics import r2_score
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import PolynomialFeatures
from math import sqrt
```

Kings Country House Data

In [2]:
```
# reading the csv file
data = pd.read_csv('data/kc_house_data.csv')
# previewing the DataFrame
data.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0

5 rows × 21 columns

In [3]:
```
# getting info
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.shape
```

Out[4]:
```
(21597, 21)
```

In [5]:
```
# Chaning the date data type from object to datetime
data.date = pd.to_datetime(data['date'])
# Creating a new column 'sold_year'
data['sold_year'] = data['date'].dt.year
# Calculating the age of the each house when they were sold
data['house_age'] = data['sold_year'] - data['yr_built']
```

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

Out[6]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3

8 rows × 21 columns

- The dataset contains a wide range of houses price from 7,8000 dollars all the way up to 7.7 million dollars. The mean house price is 540,297 dollars, while the median house price is 450,000 dollars
- Therer were 21579 houses sold in King County from 2014 to 2015
- The oldest solded house is 115 years while the youngest solded house is 18 years. The age of the house is 43 years.
- The mean square-feet of living space is 2,080 square feet, but there are houses as small as 370 sqft and as large as 13,540 sqft in this dataset.

Data Cleaning

1. Looking at objects(strings), confirm that this data is supposed to be encoded as strings

In [7]:
```
# The data type of sqft_basement is object. Apparently sqft_basement is nume
# so we can conclude that numeric data sqft_basement was wrongly encoded as
```

In [8]:
```
data.sqft_basement.value_counts()
# 454 notknown data encoded as string "?"
```

Out[8]:
```
0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
652.0         1
1990.0        1
283.0         1
1525.0        1
2810.0        1
Name: sqft_basement, Length: 304, dtype: int64
```

In [9]:
```
#replacing "?" by "0" and changing datatype to numeric data
data.sqft_basement = data.sqft_basement.str.replace('?','0').astype('float')
```

In [10]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 23 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  datetime64[ns]
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     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  float64
 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
 21  sold_year      21597 non-null  int64
 22  house_age      21597 non-null  int64
dtypes: datetime64[ns](1), float64(9), int64(13)
memory usage: 3.8 MB
```

2. Detecting and Dealing with NULL Values

In [11]:
```
total = data.isnull().sum().sort_values(ascending=False)
percent = (data.isnull().sum()/len(data)*100).sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent']
missing_data.head(20)
```

Out[11]:

	Total	Percent
yr_renovated	3842	17.789508
waterfront	2376	11.001528
view	63	0.291707
id	0	0.000000
sqft_basement	0	0.000000
sold_year	0	0.000000
sqft_lot15	0	0.000000
sqft_living15	0	0.000000
long	0	0.000000
lat	0	0.000000
zipcode	0	0.000000
yr_built	0	0.000000
grade	0	0.000000
sqft_above	0	0.000000
date	0	0.000000
condition	0	0.000000
floors	0	0.000000
sqft_lot	0	0.000000
sqft_living	0	0.000000
bathrooms	0	0.000000

In [12]:
```
Null_val_col = ['waterfront', 'view', 'yr_renovated']
```

In [13]:
```
for col in Null_val_col:
    print(data[col].unique())
    print(data[col].nunique())
```

```
[nan  0.  1.]
2
[ 0. nan  3.  4.  2.  1.]
5
[   0. 1991.   nan 2002. 2010. 1992. 2013. 1994. 1978. 2005. 2003. 1984.
 1954. 2014. 2011. 1983. 1945. 1990. 1988. 1977. 1981. 1995. 2000. 1999.
 1998. 1970. 1989. 2004. 1986. 2007. 1987. 2006. 1985. 2001. 1980. 1971.
 1979. 1997. 1950. 1969. 1948. 2009. 2015. 1974. 2008. 1968. 2012. 1963.
 1951. 1962. 1953. 1993. 1996. 1955. 1982. 1956. 1940. 1976. 1946. 1975.
 1964. 1973. 1957. 1959. 1960. 1967. 1965. 1934. 1972. 1944. 1958.]
70
```

In [14]:
```
for col in Null_val_col:
    print(data[col].value_counts())
```

```
0.0    19075
1.0      146
Name: waterfront, dtype: int64
0.0    19422
2.0      957
3.0      508
1.0      330
4.0      317
Name: view, dtype: int64
0.0       17011
2014.0       73
2003.0       31
2013.0       31
2007.0       30
          ...
1948.0        1
1951.0        1
1971.0        1
1934.0        1
1944.0        1
Name: yr_renovated, Length: 70, dtype: int64
```

In [15]:
```
#For categorical data, I choose to fill the most frequent data
def fillna(col):
    col.fillna(col.value_counts().index[0],inplace = True)
    return col
data[Null_val_col] = data[Null_val_col].apply(lambda col:fillna(col))
```

In [16]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 23 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  datetime64[ns]
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     21597 non-null  float64
 9   view           21597 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  float64
 14  yr_built       21597 non-null  int64
 15  yr_renovated   21597 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
 21  sold_year      21597 non-null  int64
 22  house_age      21597 non-null  int64
dtypes: datetime64[ns](1), float64(9), int64(13)
memory usage: 3.8 MB
```

Data Feature Exploration (Exploratory Data Analysis)

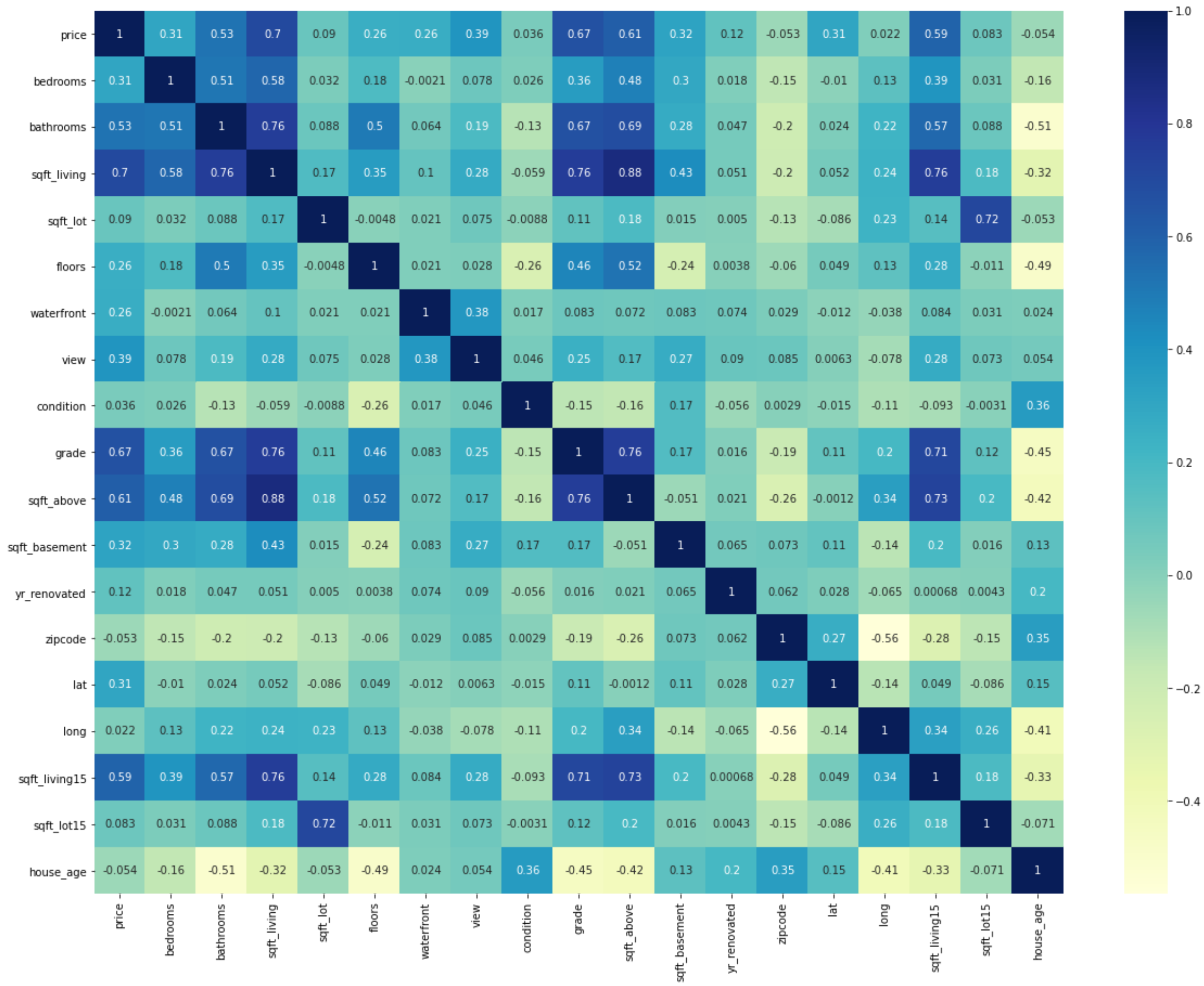
In [17]:
```
# Drop columns that I dont need
data.drop(columns = ['id','date','sold_year','yr_built'],inplace = True)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 19 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  float64
 6   waterfront     21597 non-null  float64
 7   view           21597 non-null  float64
 8   condition      21597 non-null  int64  
 9   grade          21597 non-null  int64  
 10  sqft_above     21597 non-null  int64  
 11  sqft_basement  21597 non-null  float64
 12  yr_renovated   21597 non-null  float64
 13  zipcode        21597 non-null  int64  
 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  house_age      21597 non-null  int64  
dtypes: float64(9), int64(10)
memory usage: 3.1 MB
```

1. Finding Correlation between various features and the target variable

In [19]:
```
corr = data.corr()
plt.subplots(figsize=(20,15))
sns.heatmap(corr,annot=True,cmap="YlGnBu")
plt.savefig('Heatmap')
```



In [20]:
```
corr['price'].sort_values(ascending = False)
```

Out[20]:
```
price            1.000000
sqft_living      0.701917
grade            0.667951
sqft_above       0.605368
sqft_living15    0.585241
bathrooms        0.525906
view             0.393497
sqft_basement    0.321108
bedrooms         0.308787
lat              0.306692
waterfront       0.264306
floors           0.256804
yr_renovated     0.117855
sqft_lot         0.089876
sqft_lot15       0.082845
condition        0.036056
long             0.022036
zipcode         -0.053402
house_age       -0.053890
Name: price, dtype: float64
```

2. Use 'stack' and a subset to return only the hightly correlated pairs for features.

In [21]:
```
data_features = data.drop('price', axis = 1)
corr_features = data_features.corr()
a = corr_features.abs().stack().reset_index().sort_values(0,ascending = Fals
a['pairs'] = list(zip(a.level_0, a.level_1))
a.drop(columns=['level_1', 'level_0'], inplace = True)
a.set_index(['pairs'],inplace = True)
a.columns = ['cc']
a.drop_duplicates(inplace = True)
a[(a.cc>0.75) & (a.cc<1)]
```

Out[21]:

	cc
pairs	
(sqft_living, sqft_above)	0.876448
(grade, sqft_living)	0.762779
(sqft_living15, sqft_living)	0.756402
(sqft_above, grade)	0.756073
(sqft_living, bathrooms)	0.755758

1. square foot living area, grade(amount of floors), square feet above the ground level and sqft_15 features displayed the highest correlation wih the price of the house.

2. Moreover, there is a high correlation of sqft_living with e.g. number of bathrooms and grade. This is common sense, as the square feet increase, so does the number of floors and bathrooms.
3. sqft_living,sqft_above and sqft_basement are moderately to strongly corrleated with price. The three variables were also strongly realted to each other. Especially for sqft_living and sqft_above, the corrleation cofficient is over 8.5, so I will be removing sqft_above from the analysis to reduce multicollinearity.

In [22]:
```
data.drop(columns = ['sqft_above'],inplace = True)
```

3. Explore Categorical Data

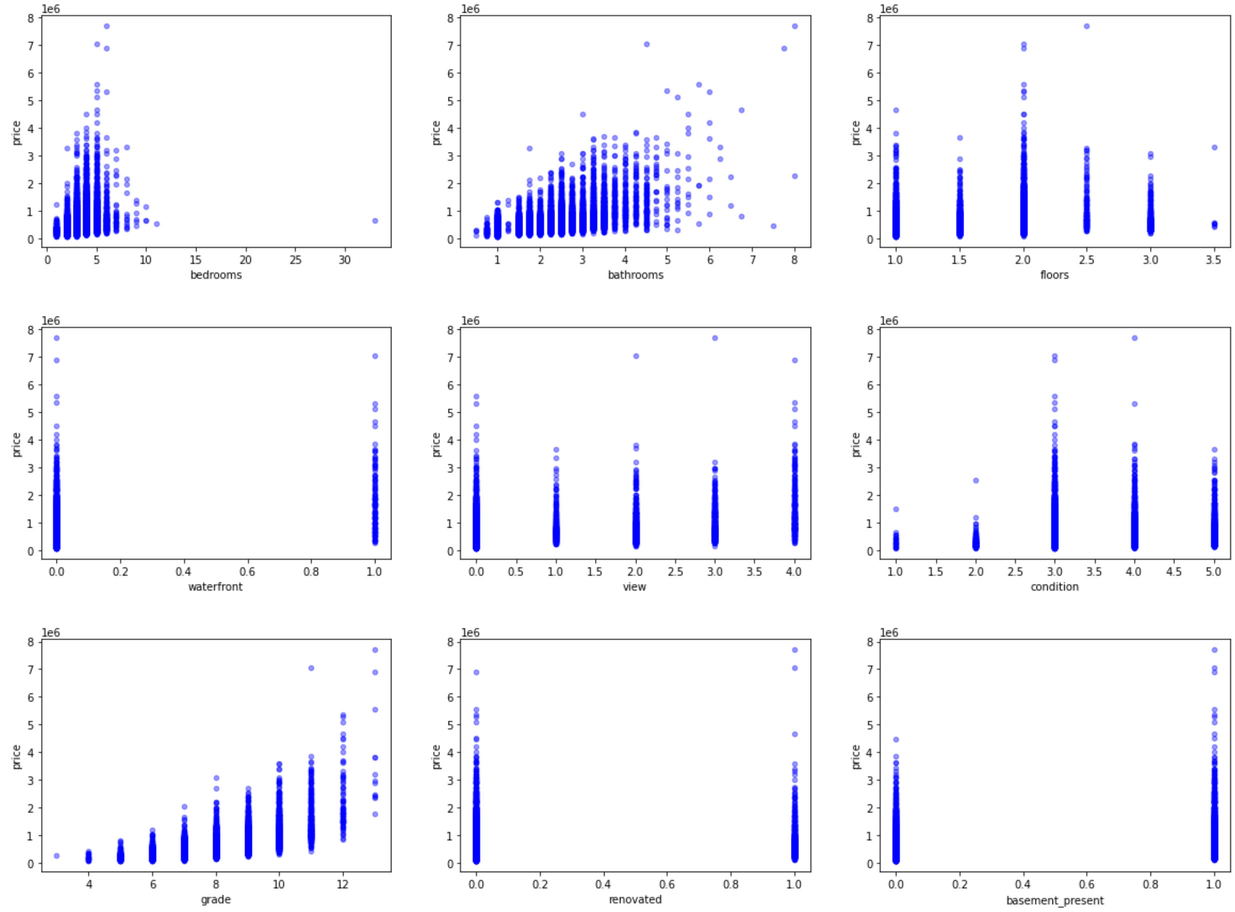
In [23]:
```
#Convert "yr_renovated" to dichotomous variables
data['renovated'] = data['yr_renovated'].apply(lambda x: 1 if x > 0 else 0)
```

In [24]:
```
data.drop('yr_renovated', axis = 1, inplace = True)
```

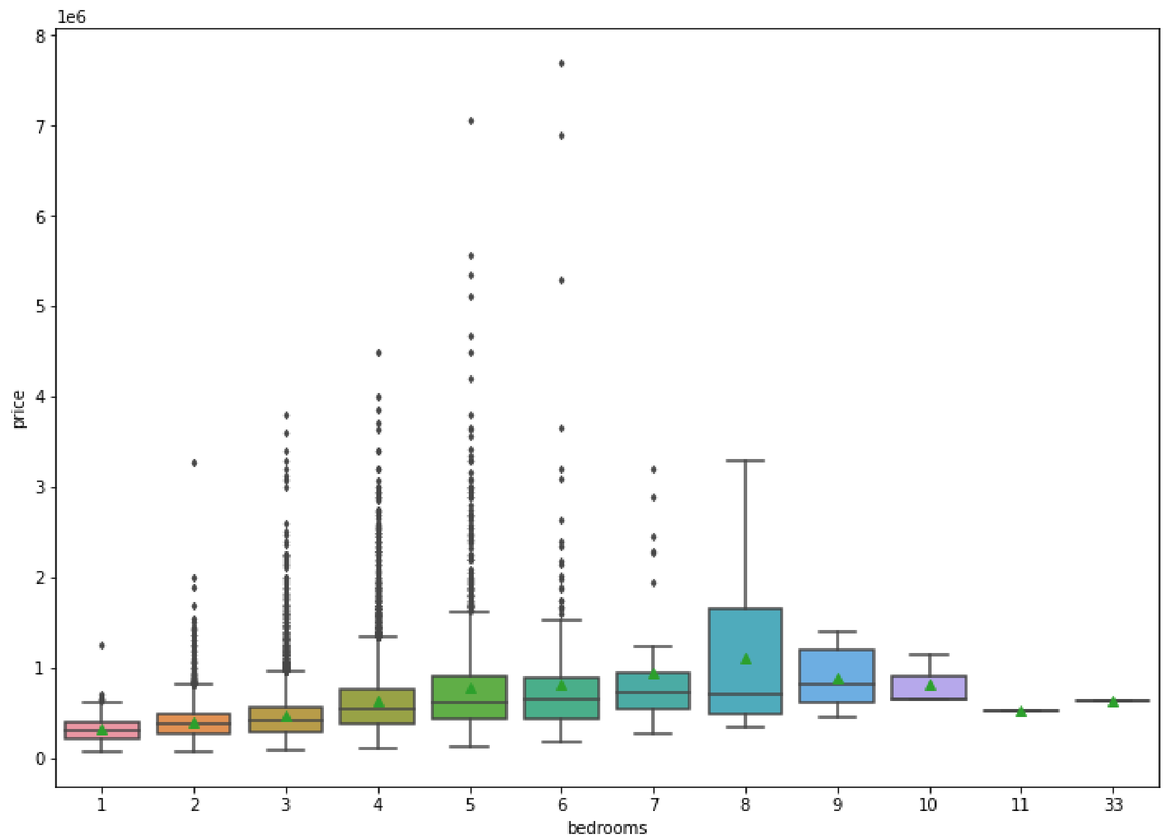
In [25]:
```
#Convert "sqft_basement" to dichotomous variables
data['basement_present'] = data['sqft_basement'].apply(lambda x: 1 if x > 0
```

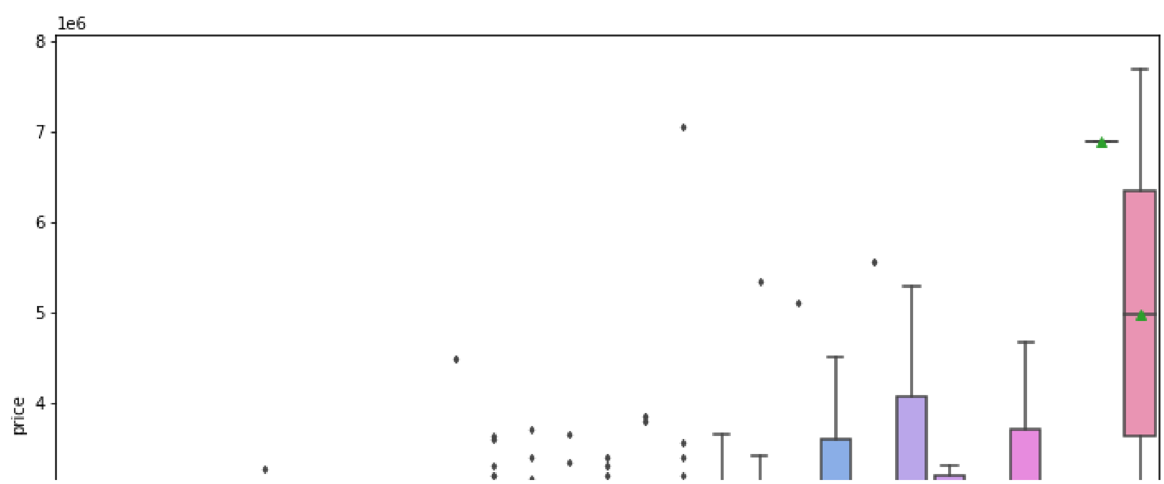
In [26]:
```
data.drop('sqft_basement', axis = 1, inplace = True)
```

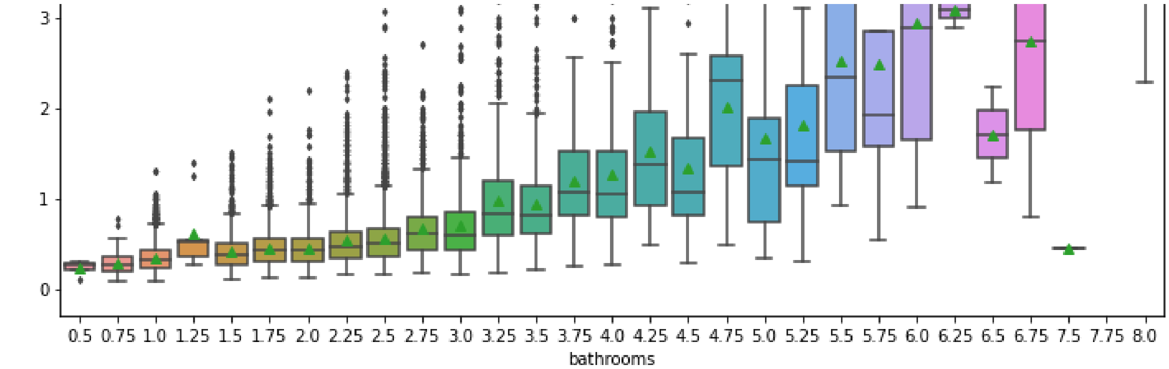
In [27]:
```
#Identify categorical variables
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(20,4))
for xcol, ax in zip(['bedrooms','bathrooms','floors'], axes):
    data.plot(kind='scatter', x=xcol, y='price', ax=ax, alpha=0.4, color='b
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(20,4))
for xcol, ax in zip(['waterfront','view','condition'], axes):
    data.plot(kind='scatter', x=xcol, y='price', ax=ax, alpha=0.4, color='b
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(20,4))
for xcol, ax in zip(['grade','renovated','basement_present'], axes):
    data.plot(kind='scatter', x=xcol, y='price', ax=ax, alpha=0.4, color='b
```

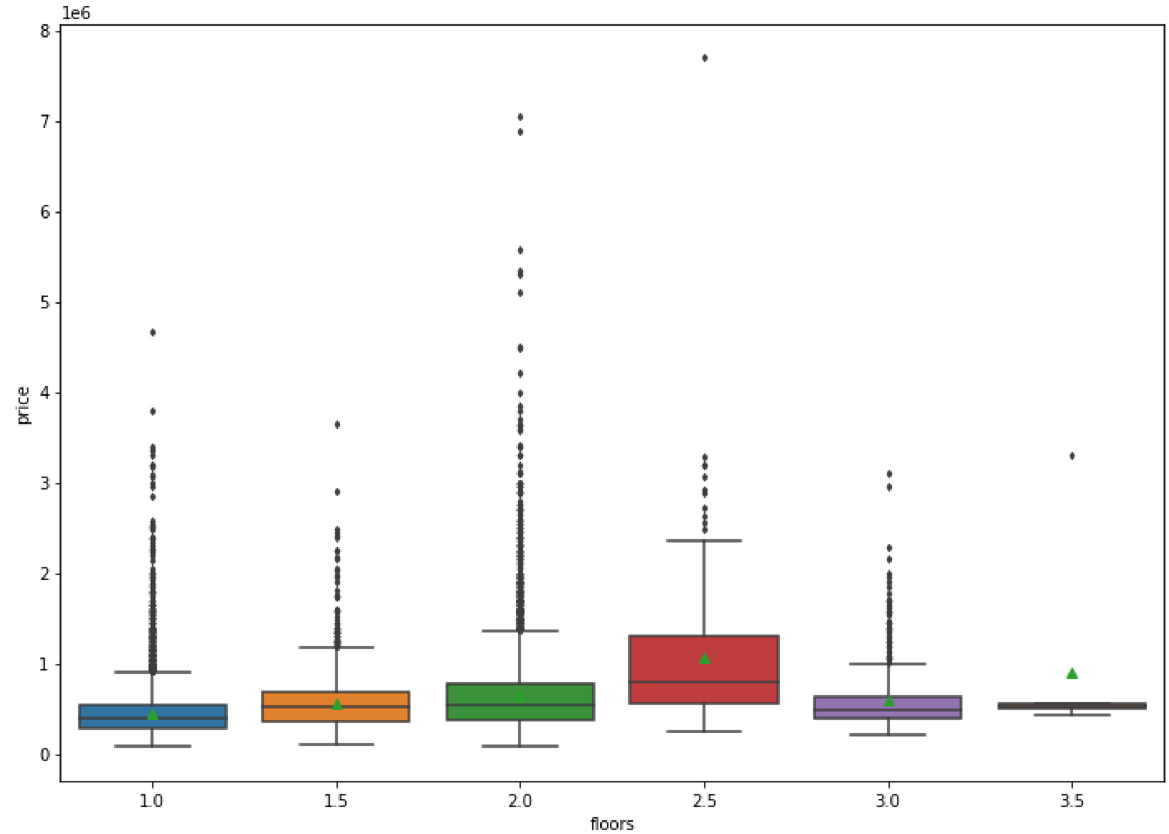


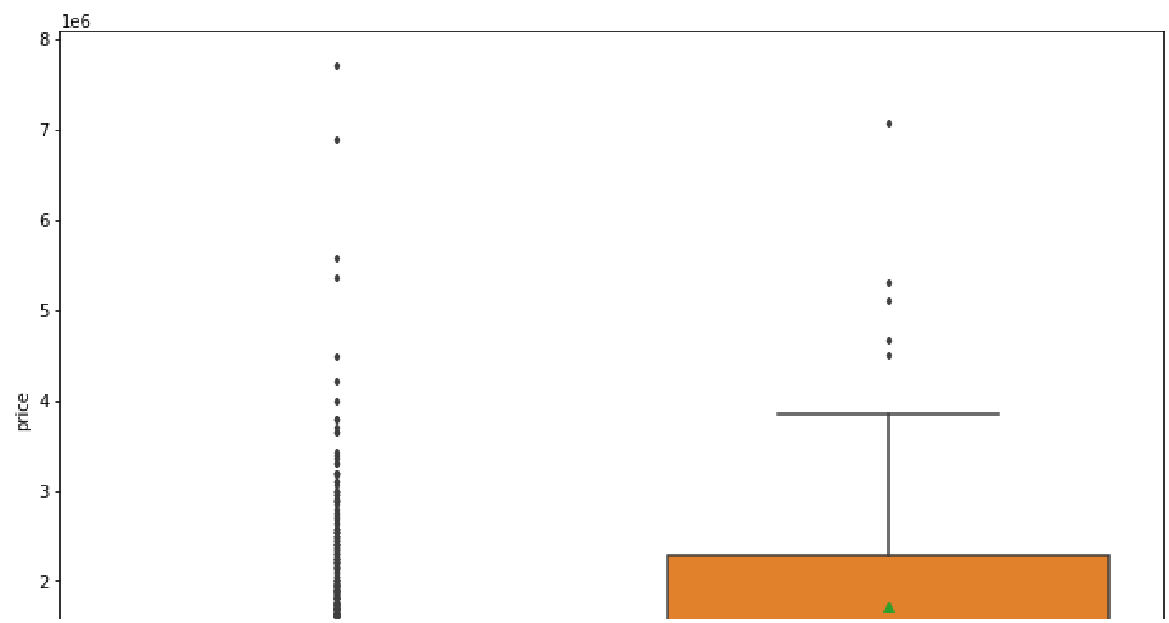
In [28]:
```
cat_feat = ['bedrooms','bathrooms','floors','waterfront','view','condition',
fig,ax = plt.subplots(10, figsize=(12,100))
sns.boxplot(x = 'bedrooms', y = 'price', data = data,width = 0.8, showmeans
sns.boxplot(x = 'bathrooms', y = 'price', data = data,width = 0.8, showmeans
sns.boxplot(x = 'floors', y = 'price', data = data,width = 0.8, showmeans =
sns.boxplot(x = 'waterfront', y = 'price', data = data,width = 0.8, showmean
sns.boxplot(x = 'view', y = 'price', data = data,width = 0.8, showmeans = Tr
sns.boxplot(x = 'condition', y = 'price', data = data,width = 0.8, showmeans
sns.boxplot(x = 'grade', y = 'price', data = data,width = 0.8, showmeans = T
sns.boxplot(x = 'renovated', y = 'price', data = data,width = 0.8, showmeans
sns.boxplot(x = 'basement_present', y = 'price', data = data,width = 0.8, sh
#Passing the entire dataset in long-form mode will aggregate over repeated v
sns.lineplot(x = 'house_age', y = 'price', data = data, ax = ax[9])
plt.show()
```

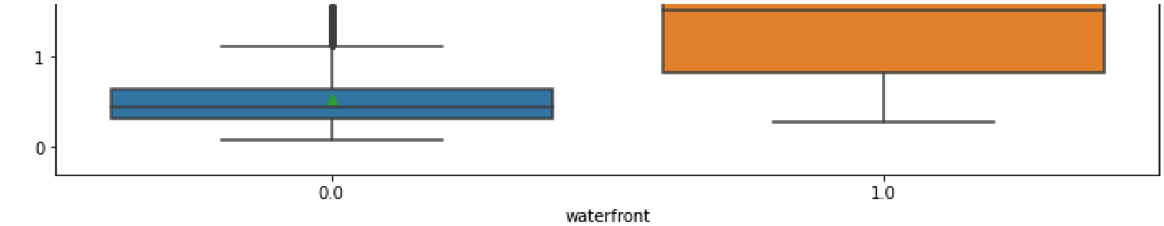


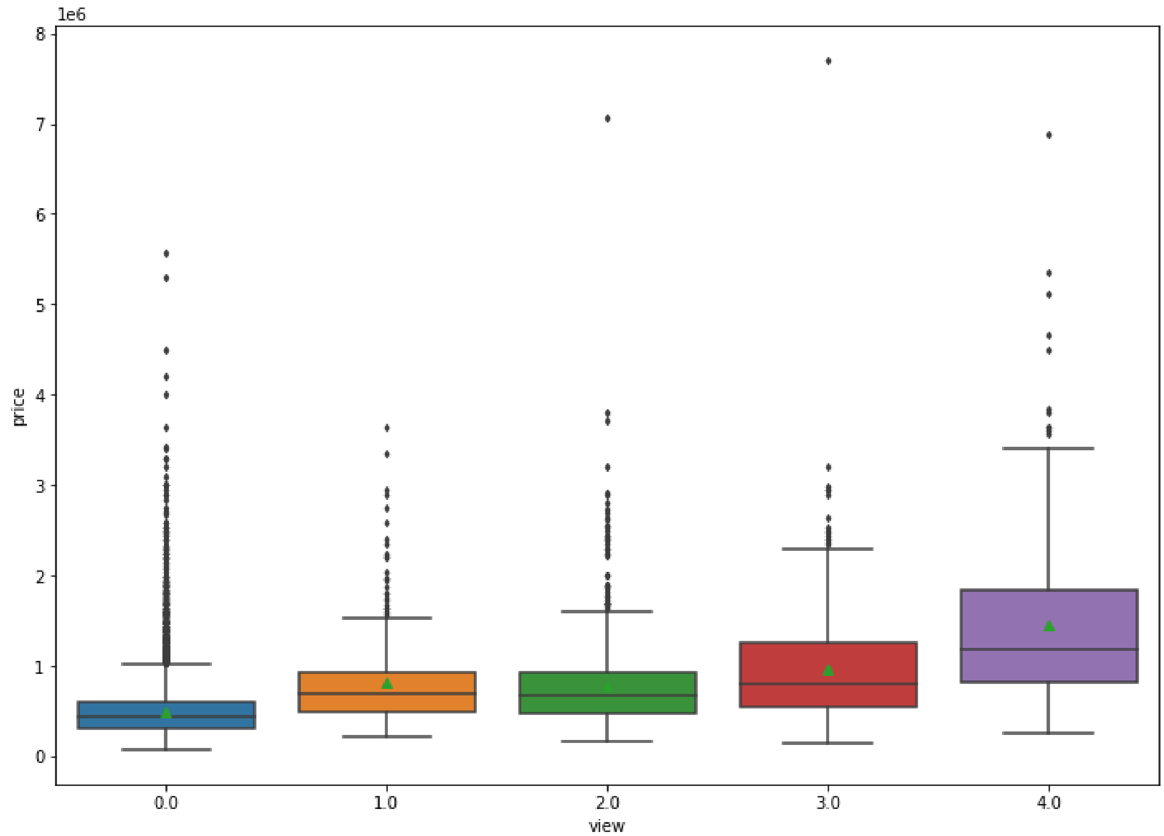


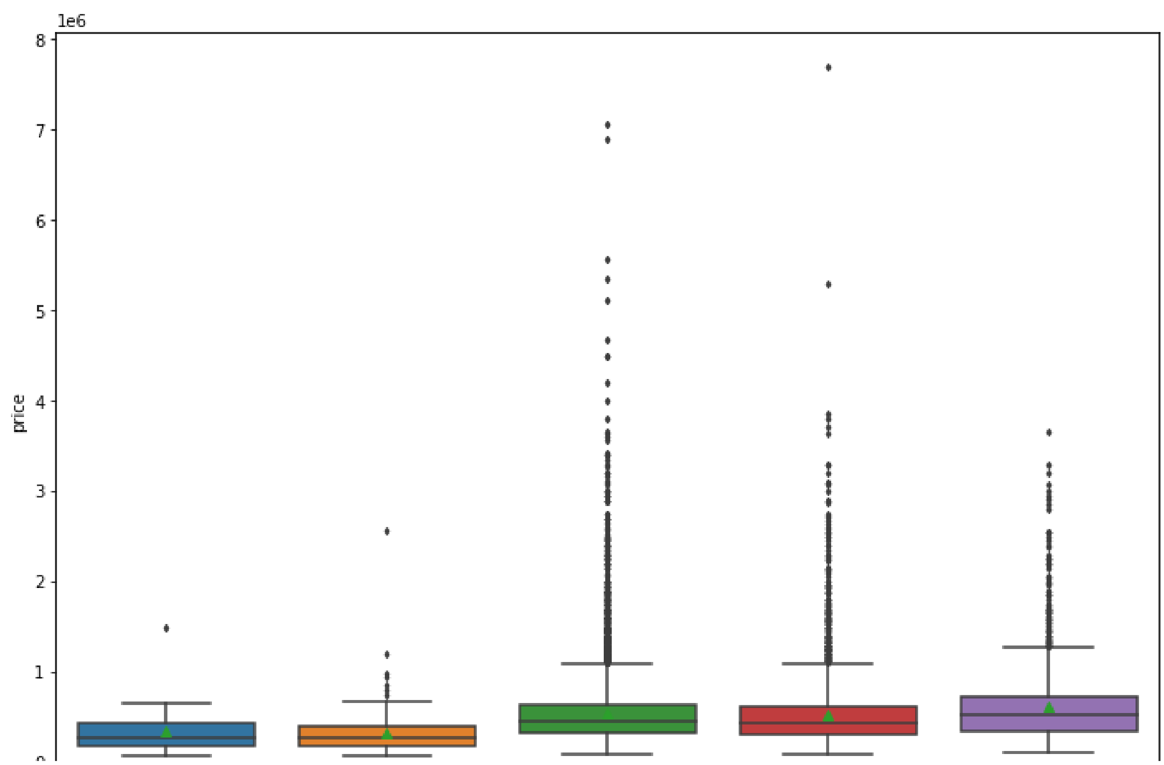

0.5 0.75 1.0 1.25 1.5 1.75 2.0 2.25 2.5 2.75 3.0 3.25 3.5 3.75 4.0 4.25 4.5 4.75 5.0 5.25 5.5 5.75 6.0 6.25 6.5 6.75 7.5 7.75 8.0
bathrooms

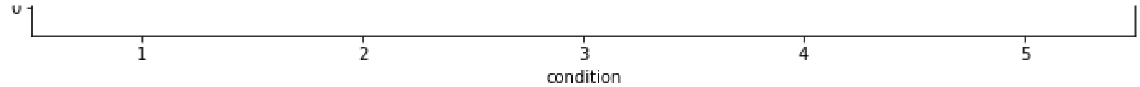

1e6
price
floors
1.0 1.5 2.0 2.5 3.0 3.5

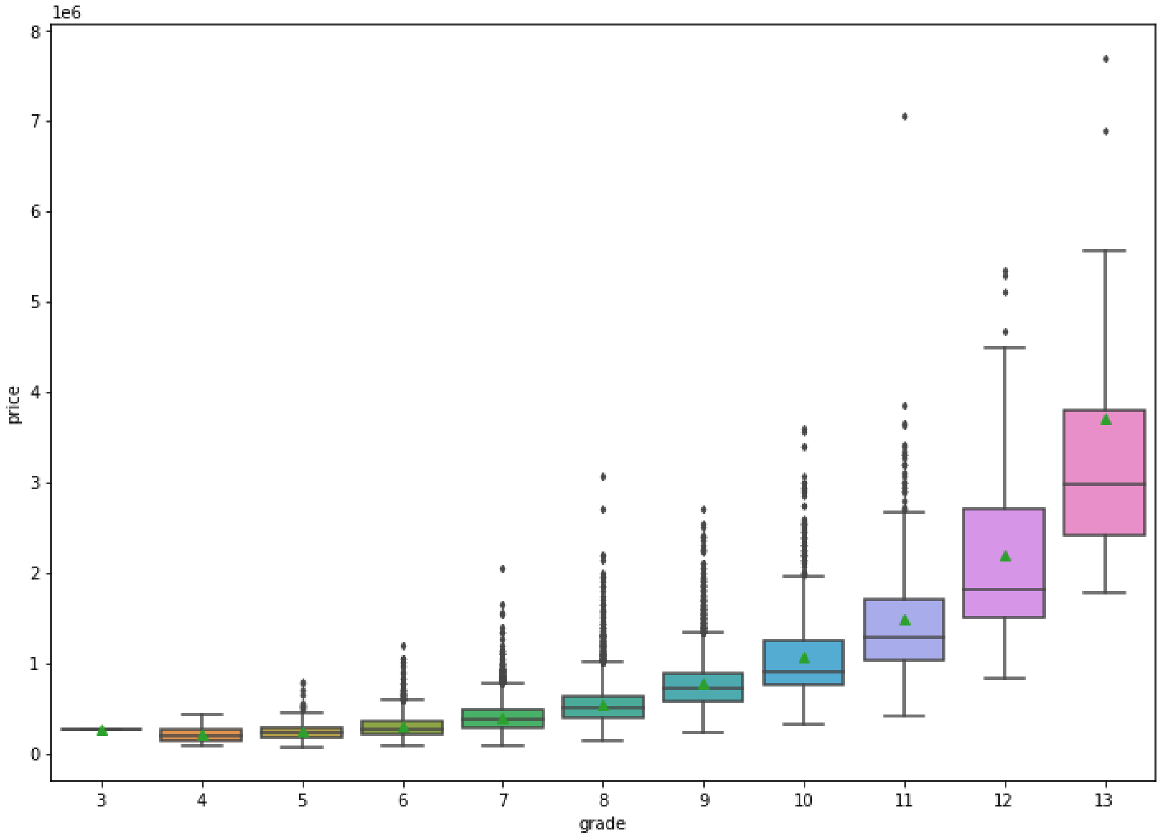

1e6
price

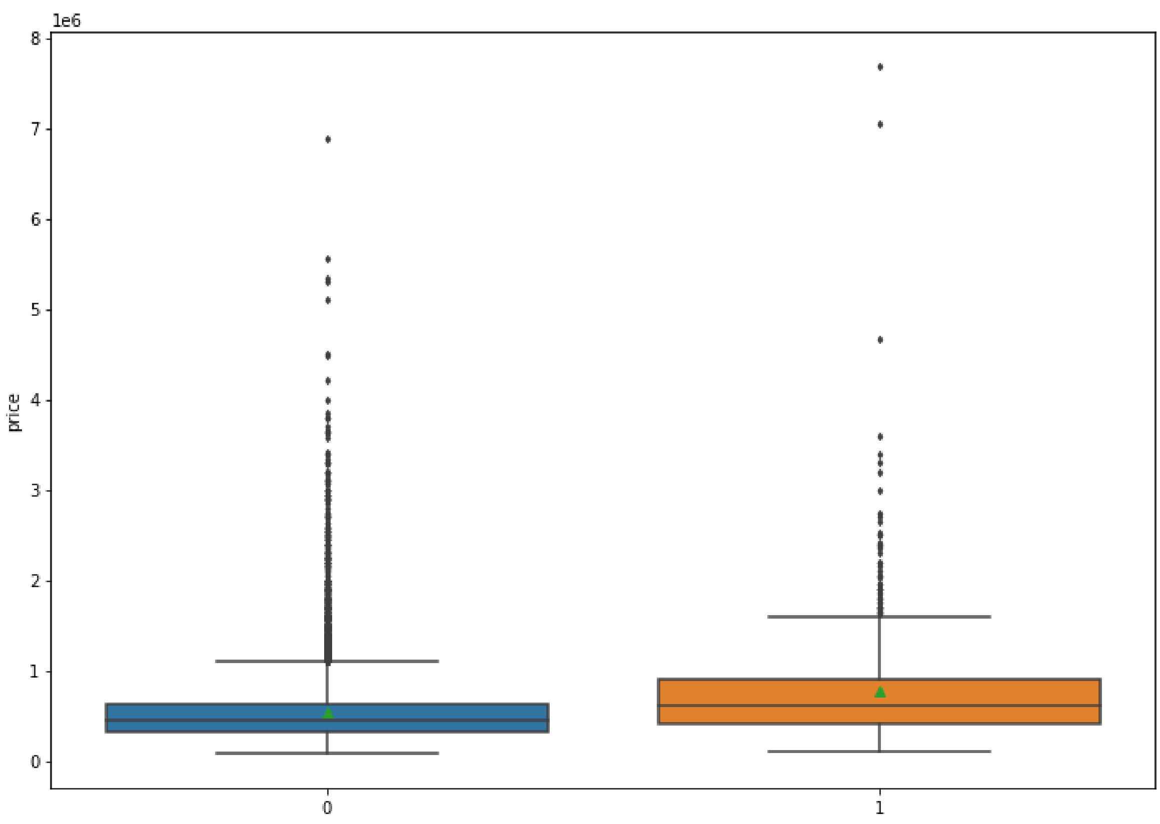

1
0
0.0
1.0
waterfront

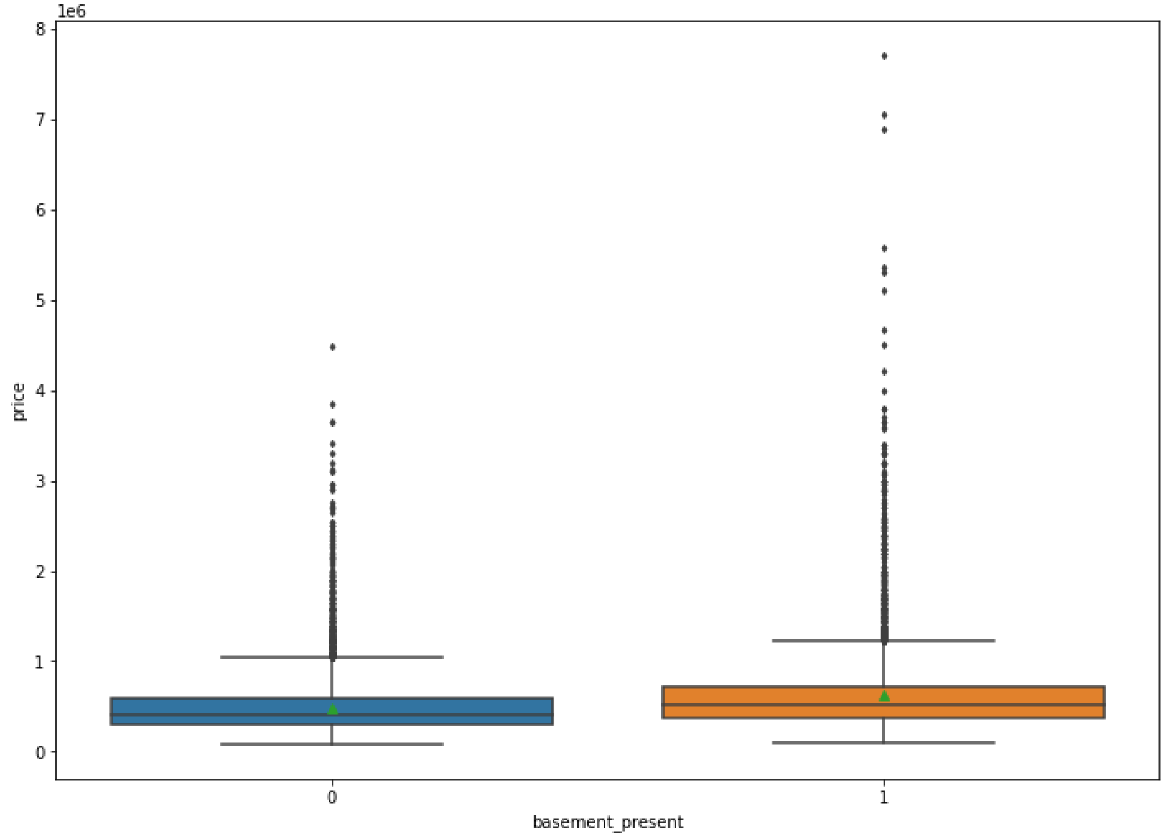

1e6
8
7
6
5
4
3
2
1
0
price
0.0
1.0
2.0
3.0
4.0
view

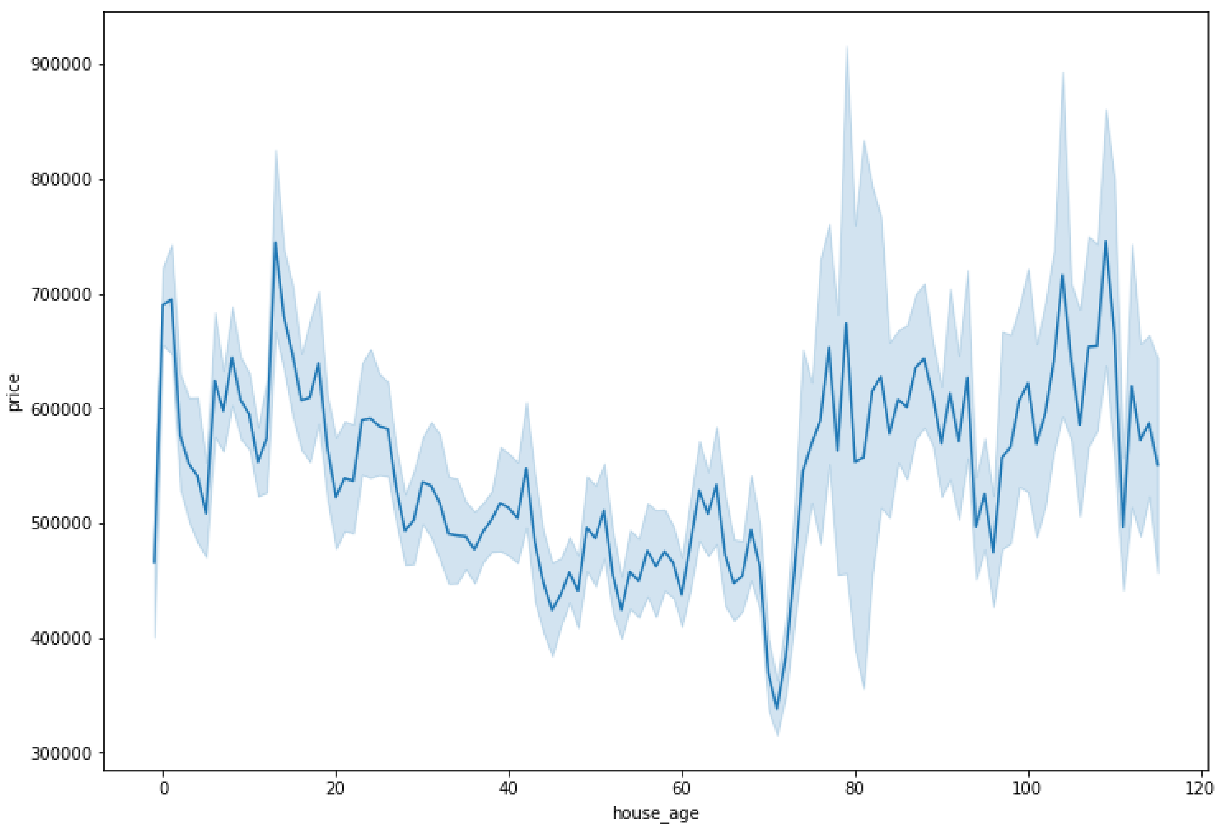

1e6
8
7
6
5
4
3
2
1
price


1
2
3
4
5
condition


1e6
price
0
1
2
3
4
5
6
7
8
3
4
5
6
7
8
9
10
11
12
13
grade


1e6
price
0
1
2
3
4
5
6
7
8
0
1
renovated





There seems to be an anomaly in the bedrooms.One house has 33 bedrooms. Although such houses do exist, the price of this house is less than a million,and it has 1.75 bathrooms and is on 1 floor.This suggests that the house has 3 bedrooms and the 33 is a data entry error.So it is safer to change 33 to 3.

In [29]:
```
data[data.bedrooms== 33]
```

Out[29]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	gı
15856	640000.0	33	1.75	1620	6000	1.0	0.0	0.0	5	

In [30]:
```
data['bedrooms'].iloc[15856] = 3
```

1. The house of houses with more number of bathrooms are higher but it kind of plateaus near 7-8 bathrooms
2. The price of houses increases for houses with 0-2.5 (around 3) floors and then subsequently decreases
3. Houses with more number of floors have higher price.
4. Houses having a waterfront are valued higher.
5. In case of view and grade, prices increase as their number increase.
6. Condition does not convey much information.
7. Bedsrooms, bathrooms, floors, views, and grade were moderately to strongly associated with price.
8. I would expect a linear relationship with newer houses being significantly more expensive. However, this is not the case as seen by the graph. The corrlelation coefficent is -0.05389, which shows a very insignificantly negative relationship between house age and price. So I will be removing house_age from the analysis.

In [31]:
```
data.head()
```

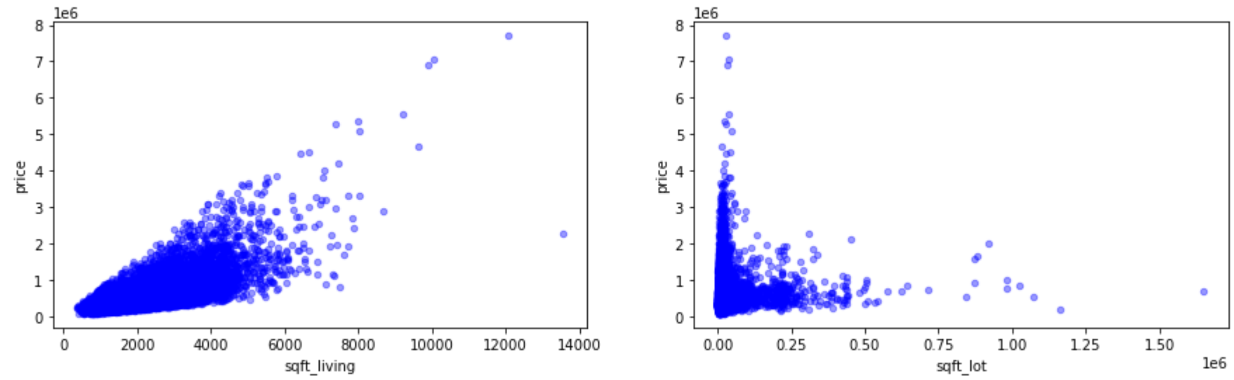
Out[31]:

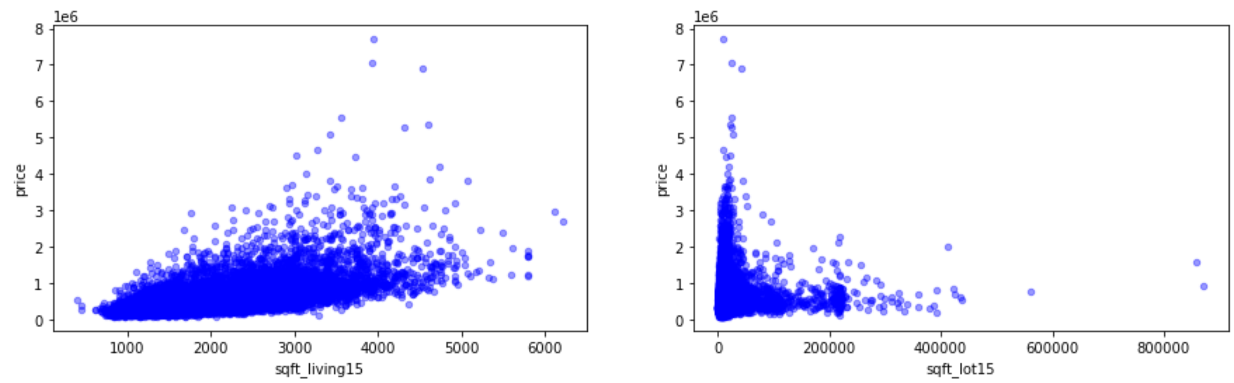
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade
0	221900.0	3	1.00	1180	5650	1.0	0.0	0.0	3	7
1	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	3	7
2	180000.0	2	1.00	770	10000	1.0	0.0	0.0	3	6
3	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	5	7
4	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	3	8

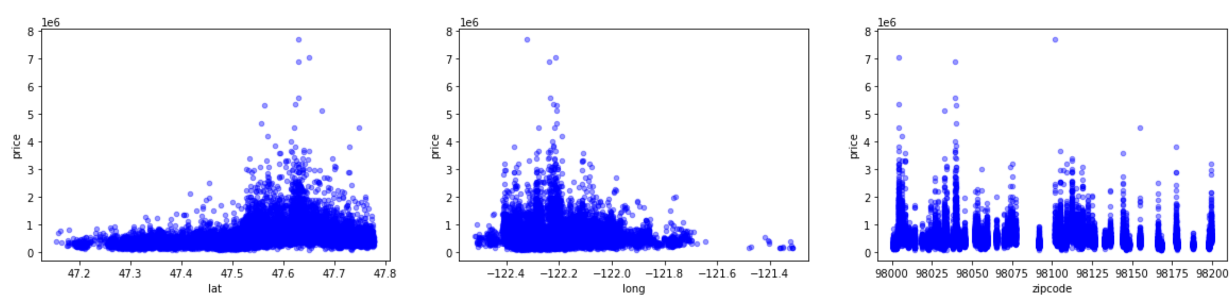
4. Explore Continous Data

In [32]:
```
data_1 = data
```

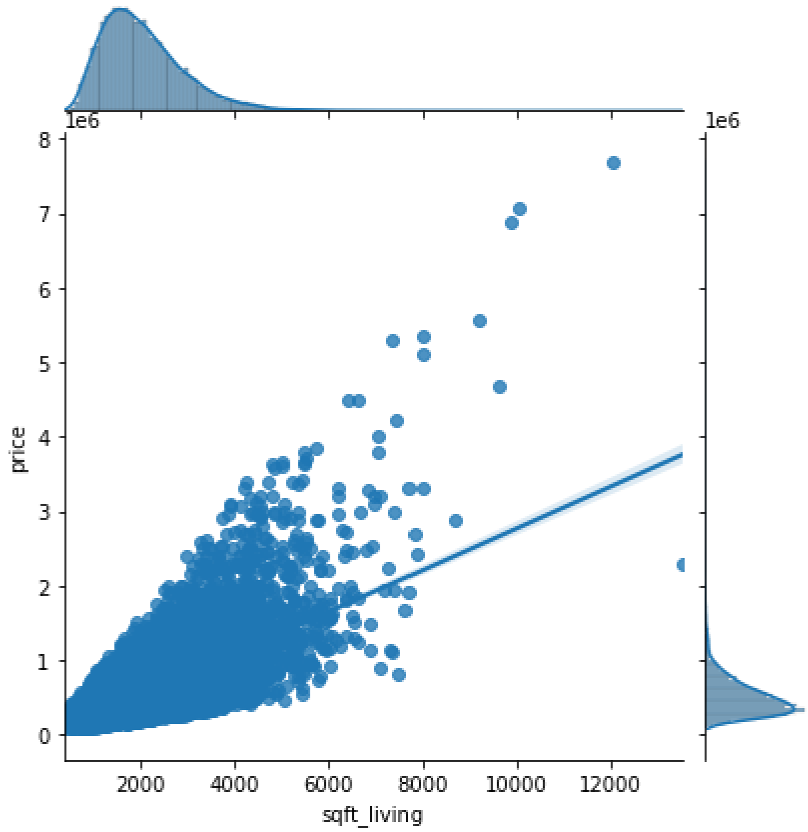
In [33]:
```
#Identify continous data
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,4))
for xcol, ax in zip(['sqft_living','sqft_lot'], axes):
    data.plot(kind='scatter', x=xcol, y='price', ax=ax, alpha=0.4, color='b

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,4))
for xcol, ax in zip(['sqft_living15','sqft_lot15'], axes):
    data.plot(kind='scatter', x=xcol, y='price', ax=ax, alpha=0.4, color='b

fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(20,4))
for xcol, ax in zip(['lat','long','zipcode'], axes):
    data.plot(kind='scatter', x=xcol, y='price', ax=ax, alpha=0.4, color='b
```





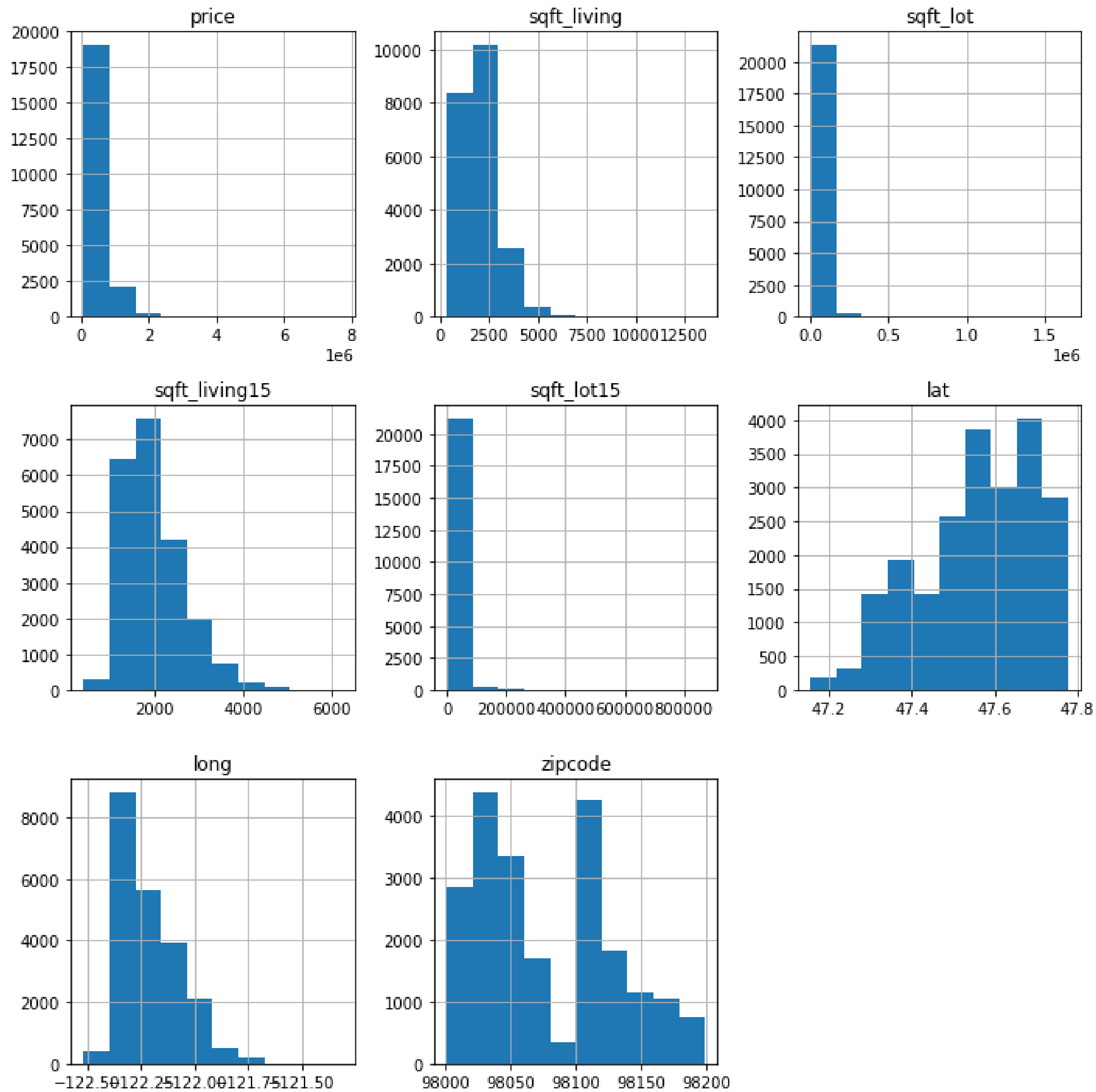


In [34]:
```
sns.jointplot(x = data['sqft_living'],y= data['price'], data = data, kind =
plt.savefig('Joinplot_sqft_living_vs_Price')
```



In [35]:
```
cont_target_feature = ['price','sqft_living','sqft_lot','sqft_living15','sq
cont_feature = ['sqft_living','sqft_lot','sqft_living15','sqft_lot15','lat',
```

In [36]:
```
data_1[cont_target_feature].hist(figsize = (10,10))
plt.tight_layout();
```



In [37]:
```
data_1.head()
```

Out[37]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade
0	221900.0	3	1.00	1180	5650	1.0	0.0	0.0	3	7
1	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	3	7
2	180000.0	2	1.00	770	10000	1.0	0.0	0.0	3	6
3	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	5	7
4	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	3	8

In [38]:
```
data_1.describe()
```

Out[38]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597
mean	5.402966e+05	3.371811	2.115826	2080.321850	1.509941e+04	1.494096	0
std	3.673681e+05	0.904096	0.768984	918.106125	4.141264e+04	0.539683	0
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	0
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	0
max	7.700000e+06	11.000000	8.000000	13540.000000	1.651359e+06	3.500000	1

Data Feature Engineering

1. Dealing with Caegorical Variables - Creating Dummy Variables

In [39]:
```
categorical_cols = ['bedrooms','bathrooms','floors','waterfront','view','coı
```

In [40]:
```
bd_dummies = pd.get_dummies(data_1['bedrooms'], prefix='bd', drop_first=True
bth_dummies = pd.get_dummies(data_1['bathrooms'], prefix='bth', drop_first=
fl_dummies = pd.get_dummies(data_1['floors'], prefix='fl', drop_first=True)
wf_dummies = pd.get_dummies(data_1['waterfront'], prefix='wf', drop_first=Tr
vw_dummies = pd.get_dummies(data_1['view'], prefix='vw', drop_first=True)
con_dummies = pd.get_dummies(data_1['condition'], prefix='con', drop_first=
gd_dummies = pd.get_dummies(data_1['grade'], prefix='gd', drop_first=True)
rn_dummies = pd.get_dummies(data_1['renovated'], prefix='rn', drop_first=Tru
bs_dummies = pd.get_dummies(data_1['basement_present'], prefix='bs', drop_fi
data_2 = data_1.drop(['bedrooms','bathrooms','floors','waterfront','view','c
data_3 = data_2.join([bd_dummies,bth_dummies,fl_dummies,wf_dummies,vw_dummie
data_3.head()
```

Out[40]:

	price	sqft_living	sqft_lot	zipcode	lat	long	sqft_living15	sqft_lot15	house_age
0	221900.0	1180	5650	98178	47.5112	-122.257	1340	5650	59
1	538000.0	2570	7242	98125	47.7210	-122.319	1690	7639	63
2	180000.0	770	10000	98028	47.7379	-122.233	2720	8062	82
3	604000.0	1960	5000	98136	47.5208	-122.393	1360	5000	49
4	510000.0	1680	8080	98074	47.6168	-122.045	1800	7503	28

5 rows × 73 columns

Model Testing

Model 1

In [41]:
```
feature_cols = data_3.columns[1:]
```

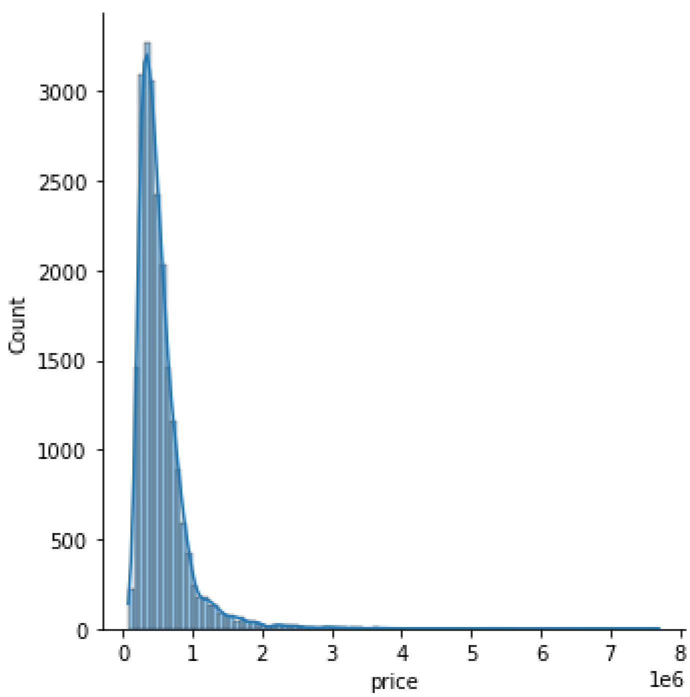
In [42]:
```
feature_cols
```

Out[42]:
```
Index(['sqft_living', 'sqft_lot', 'zipcode', 'lat', 'long', 'sqft_living1
5',
       'sqft_lot15', 'house_age', 'bd_2', 'bd_3', 'bd_4', 'bd_5', 'bd_6',
       'bd_7', 'bd_8', 'bd_9', 'bd_10', 'bd_11', 'bth_0.75', 'bth_1.0',
       'bth_1.25', 'bth_1.5', 'bth_1.75', 'bth_2.0', 'bth_2.25', 'bth_2.
5',
       'bth_2.75', 'bth_3.0', 'bth_3.25', 'bth_3.5', 'bth_3.75', 'bth_4.
0',
       'bth_4.25', 'bth_4.5', 'bth_4.75', 'bth_5.0', 'bth_5.25', 'bth_5.
5',
       'bth_5.75', 'bth_6.0', 'bth_6.25', 'bth_6.5', 'bth_6.75', 'bth_7.
5',
       'bth_7.75', 'bth_8.0', 'fl_1.5', 'fl_2.0', 'fl_2.5', 'fl_3.0', 'fl
_3.5',
       'wf_1.0', 'vw_1.0', 'vw_2.0', 'vw_3.0', 'vw_4.0', 'con_2', 'con_
3',
       'con_4', 'con_5', 'gd_4', 'gd_5', 'gd_6', 'gd_7', 'gd_8', 'gd_9',
       'gd_10', 'gd_11', 'gd_12', 'gd_13', 'rn_1', 'bs_1'],
      dtype='object')
```

In [43]:
```
X = data_3[feature_cols]
```

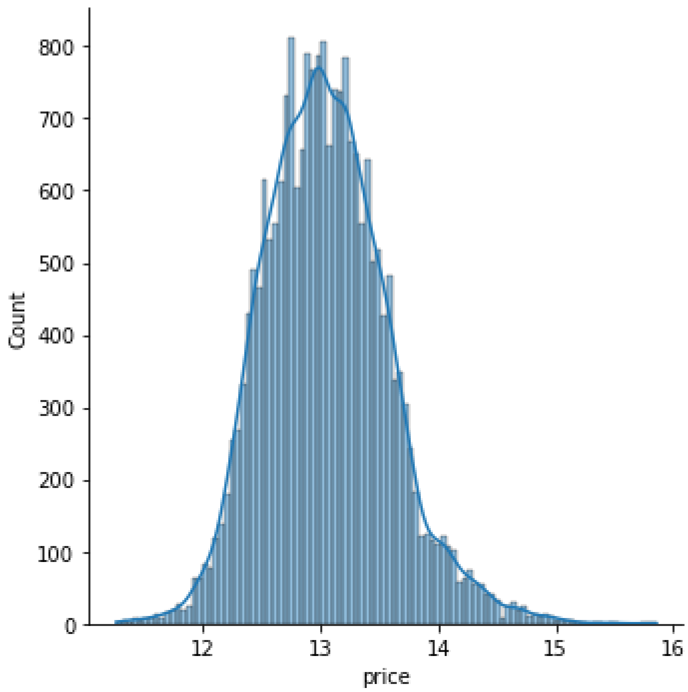
In [44]:
```
print("Skewness: %f" % data_3['price'].skew())
print("Kurtosis: %f" % data_3['price'].kurt())
sns.displot(data_3['price'], bins=100,kde = True);
```

```
Skewness: 4.023365
Kurtosis: 34.541359
```



In [45]:
```
#Comments
y = np.log(data_3['price'])
```

In [46]:
```
sns.displot(y, bins=100,kde = True);
```



In [47]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, r
```

In [48]:
```
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

Out[48]:
```
((17277, 72), (17277,), (4320, 72), (4320,))
```

In [49]:
```
linreg = LinearRegression()
model_1 = linreg.fit(X_train, y_train)
y_hat_train = model_1.predict(X_train)
y_hat_test = model_1.predict(X_test)
```

In [50]:
```
print(linreg.intercept_)
print(linreg.coef_)
print(zip(feature_cols, linreg.coef_))
```

```
-1.6189702605297054
[ 1.49986121e-04  4.79892139e-07 -7.15548286e-04  1.37201255e+00
 -1.52711797e-01  9.49268426e-05 -2.47507737e-07  3.53010295e-03
  5.20402575e-02  7.87283922e-03 -4.15719535e-03 -2.25939413e-02
 -7.64928442e-02 -1.04695136e-01 -8.84587559e-02 -8.58011782e-02
 -4.17260011e-02 -2.45169163e-12  4.30566893e-02  4.06675754e-02
  1.96161984e-01  6.74723763e-02  1.11769778e-01  1.32591915e-01
  1.22986631e-01  1.43161785e-01  1.57643679e-01  1.76898346e-01
  2.14144703e-01  2.20679981e-01  2.89610671e-01  2.40692877e-01
  2.77077901e-01  2.19855283e-01  3.32612243e-01  3.28382727e-01
  3.26023814e-01  3.03513570e-01  1.16634725e-01  9.83751585e-01
  1.13454134e-01  3.44396168e-01 -5.71093150e-01  1.43791710e-01
  4.67595493e-01 -5.98274001e-01  7.09764619e-02  7.37755101e-02
  1.40576619e-01  1.48267326e-01  1.74440993e-01  3.74446013e-01
  1.62929530e-01  1.15771056e-01  1.68017171e-01  2.76492846e-01
  6.45982273e-03  1.37694945e-01  1.89353300e-01  2.47412866e-01
 -6.44725197e-01 -5.28060366e-01 -3.78592066e-01 -1.91359105e-01
 -2.38457211e-02  1.55189517e-01  2.67896053e-01  3.43637774e-01
  3.96279701e-01  6.20937944e-01  6.87069694e-02  3.43507324e-02]
<zip object at 0x0000024C9E156780>
```

In [51]:
```
r2_score_train = r2_score(y_train, y_hat_train)
r2_score_train
```

Out[51]: `0.7779753432067725`

In [52]:
```
r2_score_test = r2_score(y_test, y_hat_test)
r2_score_train
```

Out[52]: `0.7779753432067725`

In [53]:
```
# K-fold cross evaluation
mse = make_scorer(mean_squared_error)
cv_5_results  = np.mean(np.sqrt(cross_val_score(linreg, X_train, y_train, cv
cv_10_results = np.mean(np.sqrt(cross_val_score(linreg, X_train, y_train, cv
cv_20_results = np.mean(np.sqrt(cross_val_score(linreg, X_train, y_train, cv
cv_5_results,cv_10_results,cv_20_results
```

Out[53]: `(0.25009205571861737, 0.2501366251592576, 0.2500550366858205)`

In [54]:
```
#Calcualte RMSE for train dataset and test dataset
train_mse = np.sqrt(mean_squared_error(y_train, y_hat_train))
test_mse = np.sqrt(mean_squared_error(y_test, y_hat_test))
print('Train Root of Mean Squared Error:', train_mse)
print('Test Root of Mean Squared Error:', test_mse)
```

```
Train Root of Mean Squared Error: 0.2482680942462596
Test Root of Mean Squared Error: 0.2538084454658139
```

In [55]:
```
import statsmodels.api as sm
predictors = X_train
predictors_int = sm.add_constant(predictors)
model = sm.OLS(y_train,predictors_int).fit()
model.summary()
```

Out[55]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.778
Model:	OLS	**Adj. R-squared:**	0.777
Method:	Least Squares	**F-statistic:**	849.1
Date:	Sun, 21 Mar 2021	**Prob (F-statistic):**	0.00
Time:	20:08:27	**Log-Likelihood:**	-443.89
No. Observations:	17277	**AIC:**	1032.
Df Residuals:	17205	**BIC:**	1590.
Df Model:	71		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-1.6190	4.076	-0.397	0.691	-9.609	6.371
sqft_living	0.0001	5.04e-06	29.777	0.000	0.000	0.000
sqft_lot	4.799e-07	6.84e-08	7.017	0.000	3.46e-07	6.14e-07
zipcode	-0.0007	4.61e-05	-15.515	0.000	-0.001	-0.001
lat	1.3720	0.015	91.034	0.000	1.342	1.402
long	-0.1527	0.018	-8.274	0.000	-0.189	-0.117
sqft_living15	9.493e-05	4.87e-06	19.476	0.000	8.54e-05	0.000
sqft_lot15	-2.475e-07	1e-07	-2.474	0.013	-4.44e-07	-5.14e-08
house_age	0.0035	0.000	31.378	0.000	0.003	0.004
bd_2	0.0520	0.022	2.381	0.017	0.009	0.095
bd_3	0.0079	0.022	0.360	0.719	-0.035	0.051
bd_4	-0.0042	0.022	-0.186	0.852	-0.048	0.040
bd_5	-0.0226	0.023	-0.963	0.336	-0.069	0.023
bd_6	-0.0765	0.029	-2.678	0.007	-0.132	-0.021
bd_7	-0.1047	0.050	-2.104	0.035	-0.202	-0.007
bd_8	-0.0885	0.080	-1.102	0.270	-0.246	0.069
bd_9	-0.0858	0.146	-0.586	0.558	-0.373	0.201
bd_10	-0.0417	0.182	-0.229	0.819	-0.399	0.315
bd_11	-4.488e-11	9.59e-12	-4.678	0.000	-6.37e-11	-2.61e-11
bth_0.75	0.0431	0.180	0.239	0.811	-0.309	0.395
bth_1.0	0.0407	0.176	0.231	0.818	-0.305	0.386

bth_1.25	0.1962	0.197	0.996	0.319	-0.190	0.582
bth_1.5	0.0675	0.176	0.382	0.702	-0.278	0.413
bth_1.75	0.1118	0.176	0.634	0.526	-0.234	0.458
bth_2.0	0.1326	0.176	0.752	0.452	-0.213	0.478
bth_2.25	0.1230	0.176	0.697	0.486	-0.223	0.469
bth_2.5	0.1432	0.176	0.812	0.417	-0.203	0.489
bth_2.75	0.1576	0.177	0.893	0.372	-0.188	0.504
bth_3.0	0.1769	0.177	1.001	0.317	-0.169	0.523
bth_3.25	0.2141	0.177	1.211	0.226	-0.132	0.561
bth_3.5	0.2207	0.177	1.249	0.212	-0.126	0.567
bth_3.75	0.2896	0.178	1.628	0.104	-0.059	0.638
bth_4.0	0.2407	0.178	1.351	0.177	-0.108	0.590
bth_4.25	0.2771	0.180	1.542	0.123	-0.075	0.629
bth_4.5	0.2199	0.179	1.230	0.219	-0.130	0.570
bth_4.75	0.3326	0.186	1.793	0.073	-0.031	0.696
bth_5.0	0.3284	0.186	1.762	0.078	-0.037	0.694
bth_5.25	0.3260	0.194	1.676	0.094	-0.055	0.707
bth_5.5	0.3035	0.197	1.543	0.123	-0.082	0.689
bth_5.75	0.1166	0.231	0.504	0.614	-0.337	0.570
bth_6.0	0.9838	0.219	4.501	0.000	0.555	1.412
bth_6.25	0.1135	0.253	0.448	0.654	-0.383	0.610
bth_6.5	0.3444	0.251	1.374	0.169	-0.147	0.836
bth_6.75	-0.5711	0.309	-1.847	0.065	-1.177	0.035
bth_7.5	0.1438	0.338	0.426	0.670	-0.518	0.806
bth_7.75	0.4676	0.317	1.476	0.140	-0.153	1.089
bth_8.0	-0.5983	0.257	-2.324	0.020	-1.103	-0.094
fl_1.5	0.0710	0.008	9.437	0.000	0.056	0.086
fl_2.0	0.0738	0.006	12.133	0.000	0.062	0.086
fl_2.5	0.1406	0.023	6.083	0.000	0.095	0.186
fl_3.0	0.1483	0.014	10.967	0.000	0.122	0.175
fl_3.5	0.1744	0.095	1.833	0.067	-0.012	0.361
wf_1.0	0.3744	0.028	13.144	0.000	0.319	0.430
vw_1.0	0.1629	0.016	10.367	0.000	0.132	0.194
vw_2.0	0.1158	0.010	12.099	0.000	0.097	0.135
vw_3.0	0.1680	0.013	12.545	0.000	0.142	0.194
vw_4.0	0.2765	0.020	13.736	0.000	0.237	0.316
con_2	0.0065	0.057	0.113	0.910	-0.106	0.119

con_3	0.1377	0.054	2.571	0.010	0.033	0.243
con_4	0.1894	0.054	3.535	0.000	0.084	0.294
con_5	0.2474	0.054	4.593	0.000	0.142	0.353
gd_4	-0.6447	0.255	-2.525	0.012	-1.145	-0.144
gd_5	-0.5281	0.252	-2.092	0.036	-1.023	-0.033
gd_6	-0.3786	0.252	-1.501	0.133	-0.873	0.116
gd_7	-0.1914	0.252	-0.759	0.448	-0.686	0.303
gd_8	-0.0238	0.252	-0.095	0.925	-0.518	0.471
gd_9	0.1552	0.252	0.615	0.539	-0.340	0.650
gd_10	0.2679	0.253	1.061	0.289	-0.227	0.763
gd_11	0.3436	0.253	1.358	0.174	-0.152	0.840
gd_12	0.3963	0.255	1.555	0.120	-0.103	0.896
gd_13	0.6209	0.265	2.343	0.019	0.101	1.140
rn_1	0.0687	0.011	6.169	0.000	0.047	0.091
bs_1	0.0344	0.005	7.079	0.000	0.025	0.044

Omnibus:	274.979	**Durbin-Watson:**	1.981
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	538.356
Skew:	0.034	**Prob(JB):**	1.25e-117
Kurtosis:	3.862	**Cond. No.**	1.01e+16

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.73e-18. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Model 2

In [56]:
```
wf_dummies = pd.get_dummies(data_1['waterfront'], prefix='wf', drop_first=Tr
vw_dummies = pd.get_dummies(data_1['view'], prefix='vw', drop_first=True)
gd_dummies = pd.get_dummies(data_1['grade'], prefix='gd', drop_first=True)
rn_dummies = pd.get_dummies(data_1['renovated'], prefix='rn', drop_first=Tru
bs_dummies = pd.get_dummies(data_1['basement_present'], prefix='bs', drop_fi
data_4 = data_1.drop(['waterfront','view','grade','renovated','basement_pres
data_5 = data_4.join([wf_dummies,vw_dummies,gd_dummies,rn_dummies,bs_dummies
data_5.drop(['gd_4','gd_5','gd_6','gd_7'],axis = 1, inplace = True)
data_5.head()
```

Out[56]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	zipcode	lat	lo
0	221900.0	3	1.00	1180	5650	1.0	3	98178	47.5112	-122.2
1	538000.0	3	2.25	2570	7242	2.0	3	98125	47.7210	-122.3
2	180000.0	2	1.00	770	10000	1.0	3	98028	47.7379	-122.2
3	604000.0	4	3.00	1960	5000	1.0	5	98136	47.5208	-122.3
4	510000.0	3	2.00	1680	8080	1.0	3	98074	47.6168	-122.0

5 rows × 26 columns

In [57]:
```
feature_cols = data_5.columns[1:]
```

In [58]:
```
feature_cols
```

Out[58]:
```
Index(['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'condition', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot1
5',
       'house_age', 'wf_1.0', 'vw_1.0', 'vw_2.0', 'vw_3.0', 'vw_4.0', 'gd
_8',
       'gd_9', 'gd_10', 'gd_11', 'gd_12', 'gd_13', 'rn_1', 'bs_1'],
      dtype='object')
```

In [59]:
```
from sklearn.preprocessing import StandardScaler
```

In [60]:
```
X = data_5[feature_cols]
y = np.log(data_5['price'])
```

In [61]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, r
```

In [62]:
```
# define the sclaer
scaler = StandardScaler()
# fit on the trainning dataset
scaler.fit(X_train)
# scale the training dataset
X_train = scaler.transform(X_train)
# scale the test dataset
X_test =  scaler.transform(X_test)
```

In [63]:
```
linreg = LinearRegression()
model_2 = linreg.fit(X_train, y_train)
y_hat_train = model_2.predict(X_train)
y_hat_test = model_2.predict(X_test)
```

In [64]:
```
print(linreg.intercept_)
print(linreg.coef_)
print(zip(feature_cols, linreg.coef_))
r2_score_train = r2_score(y_train, y_hat_train)
r2_score_train
```

```
13.046761309802708
[-0.01211117  0.0570678   0.14287489  0.0199333   0.04432916  0.0413747
 -0.04173621  0.19830344 -0.02847509  0.07477055 -0.00825652  0.08735292
  0.03115715  0.02003099  0.02411319  0.02449371  0.03076061  0.07924905
  0.11051951  0.0982681   0.06648474  0.03390728  0.01664079  0.01563701
  0.02349202]
<zip object at 0x0000024C9E5E8E40>
```

Out[64]:
```
0.7633151562304519
```

In [65]:
```
X_train_scaled = pd.DataFrame(X_train,columns = feature_cols)
X_train_scaled.reset_index(drop = True)
y_train.reset_index(drop = True)
```

Out[65]:
```
0        12.936034
1        13.017003
2        12.971540
3        14.038654
4        14.594835
           ...
17272    12.205823
17273    12.901717
17274    13.475520
17275    14.375126
17276    13.384728
Name: price, Length: 17277, dtype: float64
```

In [66]:
```
import statsmodels.api as sm
predictors = X_train_scaled
predictors_int = sm.add_constant(predictors)
```

In [67]:
```
model = sm.OLS(y_train.values,predictors_int).fit()
model.summary()
```

Out[67]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.763
Model:	OLS	**Adj. R-squared:**	0.763
Method:	Least Squares	**F-statistic:**	2225.
Date:	Sun, 21 Mar 2021	**Prob (F-statistic):**	0.00
Time:	20:08:27	**Log-Likelihood:**	-996.24
No. Observations:	17277	**AIC:**	2044.
Df Residuals:	17251	**BIC:**	2246.
Df Model:	25		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	13.0468	0.002	6685.045	0.000	13.043	13.051
bedrooms	-0.0121	0.003	-4.637	0.000	-0.017	-0.007
bathrooms	0.0571	0.004	15.713	0.000	0.050	0.064
sqft_living	0.1429	0.005	30.710	0.000	0.134	0.152
sqft_lot	0.0199	0.003	6.947	0.000	0.014	0.026
floors	0.0443	0.003	16.397	0.000	0.039	0.050
condition	0.0414	0.002	19.076	0.000	0.037	0.046
zipcode	-0.0417	0.003	-16.559	0.000	-0.047	-0.037
lat	0.1983	0.002	93.970	0.000	0.194	0.202
long	-0.0285	0.003	-10.841	0.000	-0.034	-0.023
sqft_living15	0.0748	0.003	22.177	0.000	0.068	0.081
sqft_lot15	-0.0083	0.003	-2.858	0.004	-0.014	-0.003
house_age	0.0874	0.003	29.273	0.000	0.082	0.093
wf_1.0	0.0312	0.002	13.141	0.000	0.027	0.036
vw_1.0	0.0200	0.002	10.113	0.000	0.016	0.024
vw_2.0	0.0241	0.002	11.945	0.000	0.020	0.028
vw_3.0	0.0245	0.002	12.094	0.000	0.021	0.028
vw_4.0	0.0308	0.002	12.712	0.000	0.026	0.036
gd_8	0.0792	0.002	32.002	0.000	0.074	0.084
gd_9	0.1105	0.003	40.030	0.000	0.105	0.116
gd_10	0.0983	0.003	36.368	0.000	0.093	0.104
gd_11	0.0665	0.002	26.720	0.000	0.062	0.071
gd_12	0.0339	0.002	15.486	0.000	0.030	0.038

gd_13	0.0166	0.002	8.120	0.000	0.013	0.021
rn_1	0.0156	0.002	7.567	0.000	0.012	0.020
bs_1	0.0235	0.002	9.936	0.000	0.019	0.028

Omnibus:	357.067	**Durbin-Watson:**	1.990
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	725.406
Skew:	-0.102	**Prob(JB):**	3.02e-158
Kurtosis:	3.983	**Cond. No.**	5.83

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

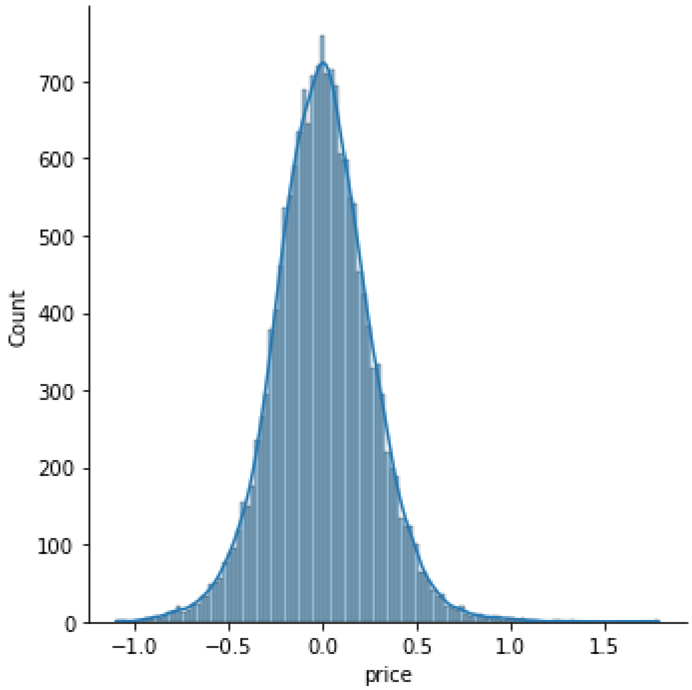
In [68]:
```
# K-fold cross evaluation
mse = make_scorer(mean_squared_error)
cv_5_results  = np.mean(np.sqrt(cross_val_score(linreg, X_train, y_train, cv
cv_10_results_results = np.mean(np.sqrt(cross_val_score(linreg, X_train, y_t
cv_20_results_results = np.mean(np.sqrt(cross_val_score(linreg, X_train, y_t
cv_5_results,cv_10_results,cv_20_results_results
```

Out[68]:
```
(0.25680591175743106, 0.2501366251592576, 0.2567711087172351)
```

In [69]:
```
#Calculate residuals for train dataset and test dataset
train_residuals = y_hat_train - y_train
test_residuals = y_hat_test - y_test
```

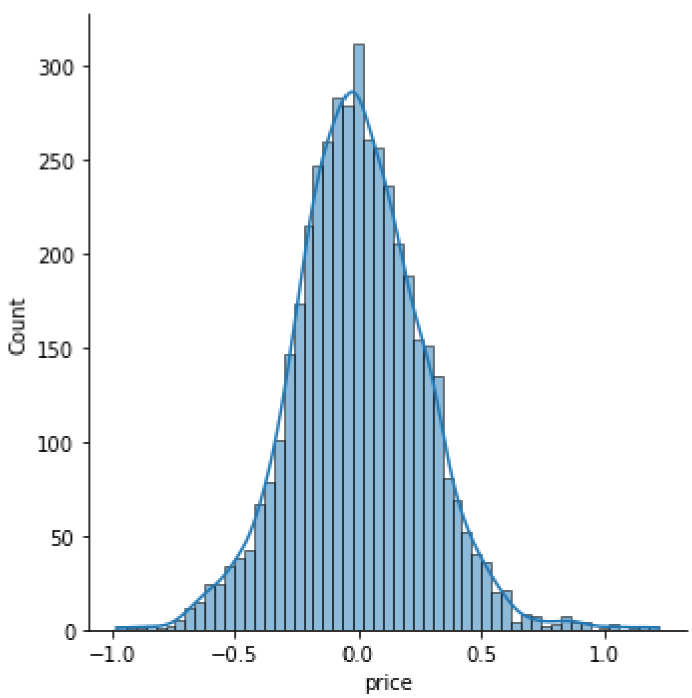
In [70]:
```
sns.displot(x= train_residuals, kind = 'hist', kde = True)
```

Out[70]: <seaborn.axisgrid.FacetGrid at 0x24c9ebdfaf0>



In [71]:
```
sns.displot(x= test_residuals, kind = 'hist', kde = True)
```

Out[71]: <seaborn.axisgrid.FacetGrid at 0x24c9f9bec40>



In [72]:
```
#Calcualte RMSE for train dataset and test dataset
train_mse = np.sqrt(mean_squared_error(y_train, y_hat_train))
test_mse = np.sqrt(mean_squared_error(y_test, y_hat_test))
print('Train Root of Mean Squared Error:', train_mse)
print('Test Root of Mean Squared Error:', test_mse)
```

```
Train Root of Mean Squared Error: 0.25633359658665
Test Root of Mean Squared Error: 0.2588939486589958
```

Model 3

In [73]:
```
X = data_5[feature_cols]
y = np.log(data_5['price'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, r
```

In [74]:
```
#Fitting a polynomial on the training set
degree=[1,2,3]
r2_score_polydegrees=[]
rmse_polyfeatures=[]
test_root_mean_sqaure_error = []
mean_absolute_sqare_error = []
for degrees in degree:
    Poly = make_pipeline(PolynomialFeatures(degree=degrees,interaction_only=
    Poly.fit(X_train, y_train)
    ####################################
    mse = mean_squared_error(y_train, Poly.predict(X_train))
    r2_score_polydegrees.append(Poly.score(X_train,y_train))
    rmse_polyfeatures.append(np.sqrt(mean_squared_error(y_train, Poly.predic
    test_root_mean_sqaure_error.append(np.sqrt(mean_squared_error(y_test, Po
print(r2_score_polydegrees)
print(rmse_polyfeatures)
print(test_root_mean_sqaure_error)
```

```
[0.7633151562304517, 0.8086854547520677, 0.8465161327031625]
[0.25633359658665, 0.23045933358877124, 0.20641995239677463]
[0.25889394865899573, 0.24014936707147885, 1135060186.963989]
```

In [75]:
```
#Polynomialregression degree 2 gives me the best model. Fiting best model on
model_final = make_pipeline(PolynomialFeatures(degree = 2,interaction_only=T
model_final.fit(X_train, y_train)
```

Out[75]:
```
Pipeline(steps=[('polynomialfeatures',
                 PolynomialFeatures(include_bias=False, interaction_only=
True)),
                ('standardscaler', StandardScaler()),
                ('linearregression', LinearRegression())])
```

In [76]:
```
rmse_train = np.sqrt(mean_squared_error(y_train, model_final.predict(X_trair
r2_score_train = model_final.score(X_train, y_train)
print(r2_score_train,rmse_train)
```

```
0.8086854547520677 0.23045933358877124
```

In [77]:
```
feature_names = model_final['polynomialfeatures'].get_feature_names()
```

In [78]:
```
coef = model_final['linearregression'].coef_
incept = model_final['linearregression'].intercept_
```

In [79]:
```
incept,len(coef)
```

Out[79]:
```
(13.046784688362743, 325)
```

In [80]:
```
df = pd.DataFrame(data = coef, index = feature_names)
```

In [81]:
```
df.head(5)
```

Out[81]:

	0
x0	30.459130
x1	-13.132641
x2	-14.698641
x3	-12.061531
x4	-45.075236

In [82]:
```
rmse_test=np.sqrt(mean_squared_error(y_test, model_final.predict(X_test)))
r2_score_test=(model_final.score(X_test,y_test))
print(r2_score_test,rmse_test)
```

```
0.7908473967883167 0.24014936707147885
```

In [83]:
```
y_test_pred = model_final.predict(X_test)
```

In [84]:
```
# Transfer log price to actual price
y_test_pred_real = np.exp(y_test_pred)
y_test_real = np.exp(y_test)
mean_absolute_error(y_test_real, y_test_pred_real)
```

Out[84]:
```
101427.2482687995
```

In [85]:
```
np.mean(y_test_real)
```

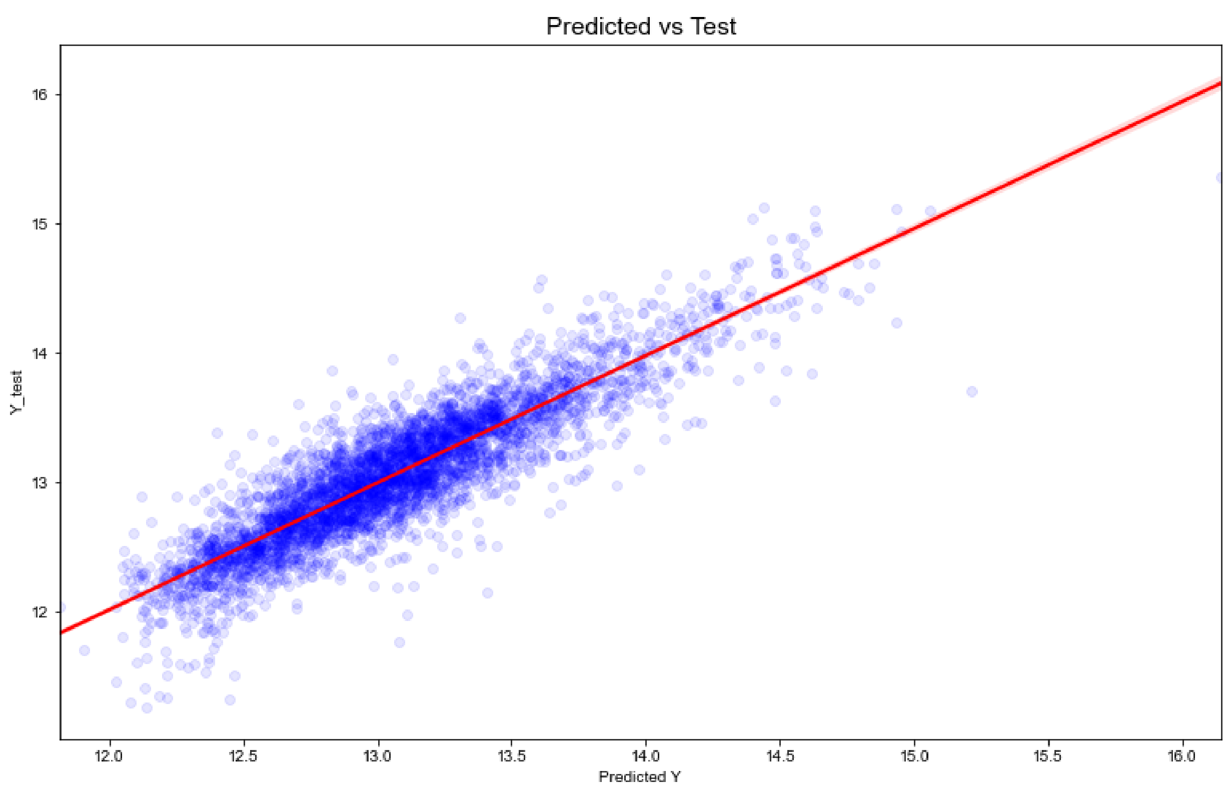
Out[85]:
```
541825.3400462962
```

Model Diagnostics

In [86]:
```
y_hat_train = model_final.predict(X_train)
y_hat_test = model_final.predict(X_test)
#Calculate residuals for train dataset and test dataset
train_residuals = y_hat_train - y_train
test_residuals = y_hat_test - y_test
```

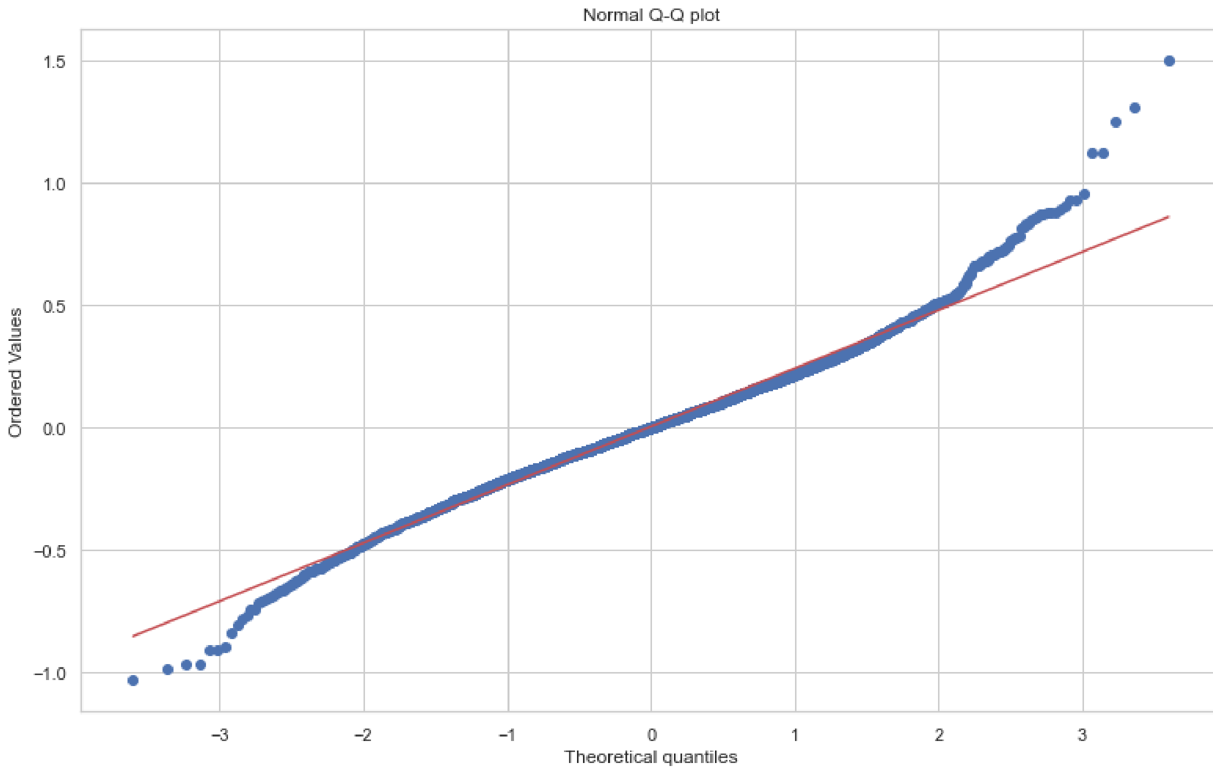
In [87]:
```
#Regression plot for residuals
plt.figure(figsize=(13,8))
#sns.set(style="whitegrid")
sns.regplot(y_hat_test,y_test,scatter_kws={'color':'b','alpha':0.1},color='r
sns.set(font_scale=1.3)
plt.title('Predicted vs Test')
plt.ylabel('Y_test')
plt.xlabel('Predicted Y')
```

Out[87]:
```
Text(0.5, 0, 'Predicted Y')
```



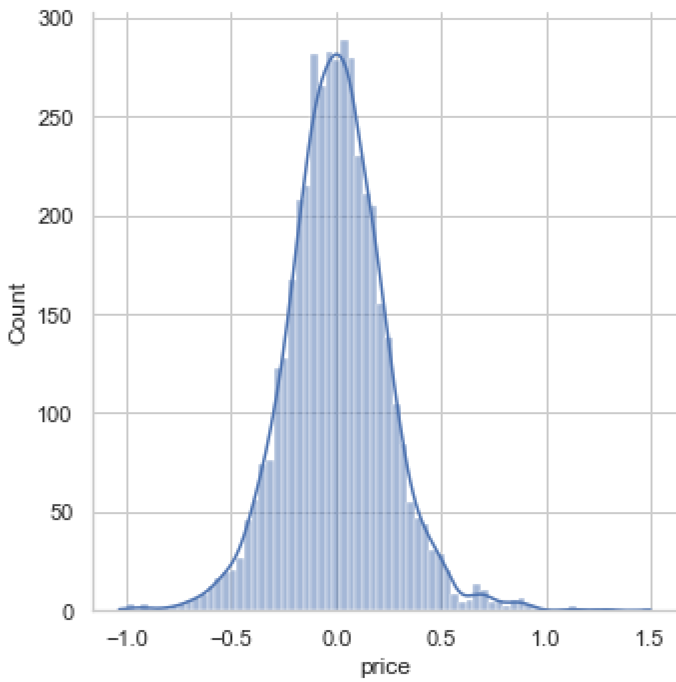
In [89]:
```
#Normal Q-Q plot
sns.set(style="whitegrid")
plt.figure(figsize=(13,8))
stats.probplot(test_residuals, dist="norm", plot=plt)
plt.title("Normal Q-Q plot")
```

Out[89]: Text(0.5, 1.0, 'Normal Q-Q plot')



In [90]:
```
# Normal Distribution Assumption
sns.displot(x= test_residuals, kind = 'hist', kde = True)
```

Out[90]: <seaborn.axisgrid.FacetGrid at 0x24c9e179dc0>



In [91]:
```
#Residual Plot
plt.figure(figsize=(13,8))
plt.scatter(y_hat_test ,test_residuals,alpha=0.2)
plt.xlabel('Predicted Y (Home prices)')
plt.ylabel('Residuals')
plt.title("Residual Plot")
```

Out[91]:
```
Text(0.5, 1.0, 'Residual Plot')
```