DATA CLEANING

In [1]:
```
#import all libraries
import itertools
import numpy as np
import pandas as pd
from numbers import Number
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
import pickle
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
```

In [2]:
```
#import dataset
housedata = pd.read_csv("/Users/Shen/Documents/Flatiron/Final_Project_Phase_2/da
```

In [3]:
```
#take a look at the data features
housedata.columns
```

Out[3]:
```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'greenbelt', 'nuisance', 'view',
       'condition', 'grade', 'heat_source', 'sewer_system', 'sqft_above',
       'sqft_basement', 'sqft_garage', 'sqft_patio', 'yr_built',
       'yr_renovated', 'address', 'lat', 'long'],
      dtype='object')
```

In [4]:
```
housedata.shape
```

Out[4]:
```
(30155, 25)
```

In [5]:
```
#review data type for later cleaning
housedata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30155 entries, 0 to 30154
Data columns (total 25 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             30155 non-null  int64
 1   date           30155 non-null  object
 2   price          30155 non-null  float64
 3   bedrooms       30155 non-null  int64
 4   bathrooms      30155 non-null  float64
 5   sqft_living    30155 non-null  int64
 6   sqft_lot       30155 non-null  int64
 7   floors         30155 non-null  float64
 8   waterfront     30155 non-null  object
 9   greenbelt      30155 non-null  object
 10  nuisance       30155 non-null  object
 11  view           30155 non-null  object
 12  condition      30155 non-null  object
 13  grade          30155 non-null  object
```

```
 14   heat_source    30123 non-null  object
 15   sewer_system   30141 non-null  object
 16   sqft_above     30155 non-null  int64
 17   sqft_basement  30155 non-null  int64
 18   sqft_garage    30155 non-null  int64
 19   sqft_patio     30155 non-null  int64
 20   yr_built       30155 non-null  int64
 21   yr_renovated   30155 non-null  int64
 22   address        30155 non-null  object
 23   lat            30155 non-null  float64
 24   long           30155 non-null  float64
dtypes: float64(5), int64(10), object(10)
memory usage: 5.8+ MB
```

In [6]:

```
#drop nans
housedata.isna().sum().sort_values(ascending=False)
```

Out[6]:

```
heat_source      32
sewer_system     14
long              0
nuisance          0
date              0
price             0
bedrooms          0
bathrooms         0
sqft_living       0
sqft_lot          0
floors            0
waterfront        0
greenbelt         0
condition         0
view              0
lat               0
grade             0
sqft_above        0
sqft_basement     0
sqft_garage       0
sqft_patio        0
yr_built          0
yr_renovated      0
address           0
id                0
dtype: int64
```

In [7]:

```
#drop nans
housedata=housedata.dropna()
```

In [8]:

```
#convert date dtype to datetime
housedata['date']=pd.to_datetime(housedata['date'])
housedata['date'].dtype
```

Out[8]:

```
dtype('<M8[ns]')
```

In [9]:

```
housedata['price'].describe().round(2)
```

Out[9]:

```
count      30111.00
mean     1108970.65
std       896515.83
min        27360.00
25%       649236.00
50%       860000.00
75%      1300000.00
```

```
max      30750000.00
Name: price, dtype: float64
```

In [10]:
```
#identify price outliers
price=housedata.loc[housedata['price']>5000000.00]
```

In [11]:
```
#drop price outliers above 5m
housedata = housedata[housedata['price'] < 5000000.00]
```

In [12]:
```
#clean up datatype - 'bedrooms' to float
housedata['bedrooms'] = housedata['bedrooms'].astype(float)
```

In [13]:
```
housedata['bedrooms'].value_counts()
```

Out[13]:
```
3.0     12705
4.0      9526
2.0      3913
5.0      2730
6.0       477
1.0       376
7.0        75
0.0        38
8.0        37
9.0        14
10.0        3
11.0        1
13.0        1
Name: bedrooms, dtype: int64
```

In [14]:
```
#drop bedrooms outliers - above 8 and 0.0
housedata = housedata[housedata['bedrooms'] < 8.0]
```

In [15]:
```
#identify sqftliving outliers
housedata['sqft_living'].describe()
```

Out[15]:
```
count    29840.000000
mean      2090.666287
std        925.766474
min          3.000000
25%       1410.000000
50%       1910.000000
75%       2600.000000
max      13540.000000
Name: sqft_living, dtype: float64
```

In [16]:
```
#identify sqftliving outliers > 5000  - 251 houses
sqft_living=housedata.loc[housedata['sqft_living']>5000.00]
sqft_living['sqft_living'].count()
```

Out[16]:
```
251
```

In [17]:
```
#drop sqftliving outliers > 5000  - 251 houses
housedata = housedata[housedata['sqft_living'] < 5000.00]
```

In [18]:
```
#find unique values for each column
housedata_uniques = housedata.apply(lambda x: x.unique())
```

In [19]:
```
#Datacleaning - separate zip out of address by splitting address by ","
housedata[['address','city','state and zip','country','addresother','addressothe
```

In [20]:
```
#Datacleaning - separate zip out of "state and zip" by extracting zip code
import re
```

In [21]:
```
housedata['zip']=housedata['state and zip'].apply(lambda x: re.sub("[^0-9]", "",
```

In [22]:
```
#zip column created and remove all records outside of king county - the zipcodes
housedata['zip']=housedata['zip'].astype(str)
housedata['zip']=housedata['zip'].str.strip()
housedata['kingscounty']=housedata['zip'].map(lambda x:x.startswith('98'))
```

In [23]:
```
housedata['kingscounty'].value_counts()
```

Out[23]:
```
True     28685
False      900
Name: kingscounty, dtype: int64
```

In [24]:
```
housedata = housedata[housedata['kingscounty'] != False]
```

In [25]:
```
#end of cleaning addresses + leave all king county recors
housedata.kingscounty.value_counts()
```

Out[25]:
```
True    28685
Name: kingscounty, dtype: int64
```

In [26]:
```
#88 zipcodes remained
len(housedata.zip.unique())
```

Out[26]:
```
88
```

In [27]:
```
#examine the corr between features
housedata.corr()
```

Out[27]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sc
id	1.000000	-0.024539	-0.000095	-0.000766	-0.014516	-0.117270	0.037784	
price	-0.024539	1.000000	0.325609	0.482332	0.618722	0.074800	0.232343	
bedrooms	-0.000095	0.325609	1.000000	0.579859	0.646703	-0.011917	0.183124	
bathrooms	-0.000766	0.482332	0.579859	1.000000	0.753833	0.013700	0.430677	
sqft_living	-0.014516	0.618722	0.646703	0.753833	1.000000	0.091172	0.361616	
sqft_lot	-0.117270	0.074800	-0.011917	0.013700	0.091172	1.000000	-0.028351	
floors	0.037784	0.232343	0.183124	0.430677	0.361616	-0.028351	1.000000	
sqft_above	-0.009018	0.540825	0.533688	0.640634	0.864461	0.102921	0.518839	
sqft_basement	-0.012116	0.200994	0.214607	0.211350	0.272582	-0.010055	-0.270515	
sqft_garage	0.000979	0.259770	0.305181	0.440821	0.485297	0.066604	0.170694	
sqft_patio	-0.038132	0.278057	0.168688	0.291951	0.361587	0.147707	0.113785	
yr_built	0.025867	0.109599	0.183282	0.468965	0.343879	0.004584	0.525767	

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sc
yr_renovated	-0.027873	0.086264	0.004463	0.037110	0.031246	0.009094	-0.017488	
lat	0.001296	0.379134	-0.027830	0.031785	0.029581	-0.078929	0.042347	-
long	0.012002	0.109082	0.142617	0.185946	0.256106	0.178973	0.087432	
kingscounty	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

In [28]:
```
#remove columns will not be used in the analysis later on
housedatanew=housedata.drop(['yr_renovated','kingscounty','addresother','address
```

In [29]:
```
#change waterfront column values to numerical values
housedatanew['waterfront']=housedatanew['waterfront'].apply(lambda x: 1 if x== "
```

In [30]:
```
#change waterfront column values to numerical values
housedatanew['waterfront']=housedatanew['waterfront'].astype(int)
```

In [31]:
```
#change waterfront column values to numerical values
housedatanew['waterfront'].value_counts()
```

Out[31]:
```
0    28270
1      415
Name: waterfront, dtype: int64
```

In [32]:
```
#change greenbelt and nuisance column values to numerical values
housedatanew['greenbelt']=housedatanew['greenbelt'].apply(lambda x: 1 if x=="YES
housedatanew['nuisance']=housedatanew['nuisance'].apply(lambda x: 1 if x=="YES"
```

In [33]:
```
#change greenbelt and nuisance column values to numerical values

housedatanew['greenbelt']=housedatanew['greenbelt'].astype(int)
housedatanew['nuisance']=housedatanew['nuisance'].astype(int)
```

In [34]:
```
from sklearn.preprocessing import OrdinalEncoder
```

In [35]:
```
#change view column values (none average fair good excellent) to numerical value

housedatanew['view']=housedatanew['view'].astype('category')
```

In [36]:
```
#change view column values to numerical values using cat recorder categories fun

housedatanew['view'].dtype
```

Out[36]:
```
CategoricalDtype(categories=['AVERAGE', 'EXCELLENT', 'FAIR', 'GOOD', 'NONE'], or
dered=False)
```

In [37]:
```
#change view column values to numerical values using cat recorder categories fun

housedatanew['view']=housedatanew['view'].cat.reorder_categories(['NONE', 'AVERA
```

In [38]:
```
#change view column values to numerical values using cat recorder categories fun

housedatanew['view']=housedatanew['view'].cat.codes
```

In [39]:
```
#change 'condition' column values  (poor, fair, good, average, verygood) to nume

housedatanew['view']=housedatanew['view'].astype(int)
```

In [40]:
```
#change 'condition' column values  (poor, fair, good, average, verygood) to nume

housedatanew['condition']=housedatanew['condition'].astype('category')
```

In [41]:
```
#change 'condition' column values  (poor, fair, good, average, verygood) to nume

housedatanew['condition']=housedatanew['condition'].cat.reorder_categories(['Poo
```

In [42]:
```
#change 'condition' column values  (poor, fair, good, average, verygood) to nume

housedatanew['condition']=housedatanew['condition'].cat.codes
```

In [43]:
```
#change 'condition' column values  (poor, fair, good, average, verygood) to nume

housedatanew['condition']=housedatanew['condition'].astype(int)
```

In [44]:
```
#change 'grade' column values  (substandard poor low pair low average...luxury)

housedatanew['grade'].value_counts()
```

Out[44]:
```
7 Average        11527
8 Good            8818
9 Better          3536
6 Low Average     2840
10 Very Good      1230
5 Fair             384
11 Excellent       261
4 Low               46
12 Luxury           33
3 Poor               9
2 Substandard        1
Name: grade, dtype: int64
```

In [45]:
```
#change 'grade' column values  (substandard poor low pair low average...luxury)

housedatanew['grade']=housedatanew['grade'].astype('category')
```

In [46]:
```
#change 'grade' column values  (substandard poor low pair low average...luxury)

housedatanew['grade']=housedatanew['grade'].cat.reorder_categories(['2 Substanda
```

In [47]:
```
#change 'grade' column values  (substandard poor low pair low average...luxury)

housedatanew['grade']=housedatanew['grade'].cat.codes
```

In [48]:
```
#change 'grade' column values  (substandard poor low pair low average...luxury)

housedatanew['grade']=housedatanew['grade'].astype(int)
```

In [49]:
```
#align catcodes to the actual grading
housedatanew['grade']=np.array(housedatanew['grade'])+2
```

In [50]:
```
housedatanew['heat_source']=housedatanew['heat_source'].astype(str)
```

In [51]:
```
housedatanew['persqft']=housedatanew['price']/housedatanew['sqft_living']
```

---------------------END OF DATA CLEANING

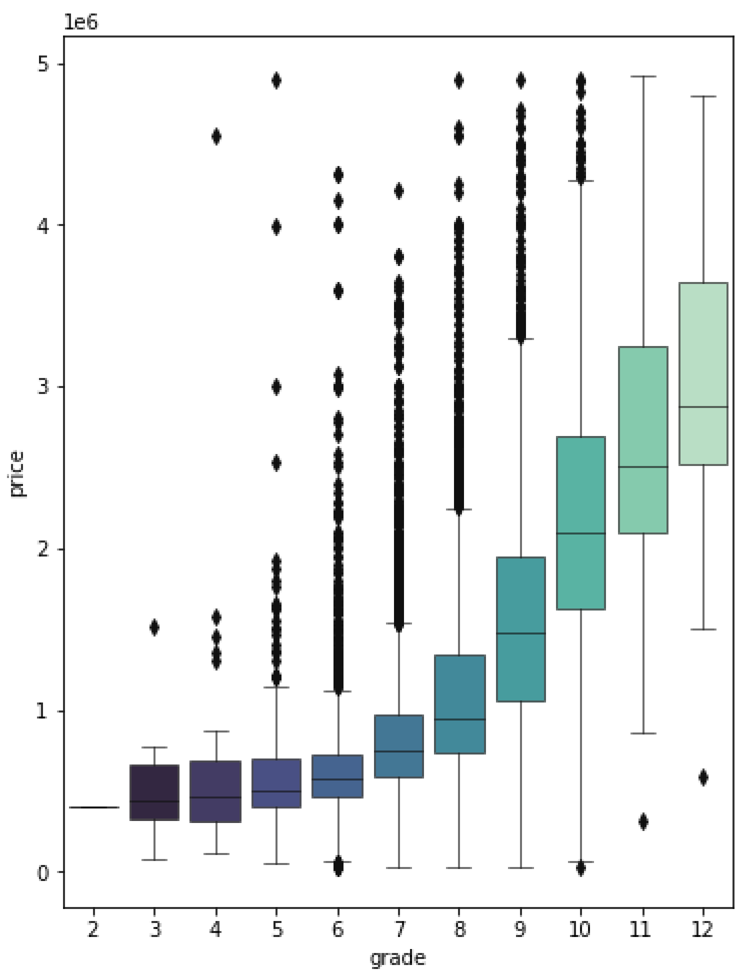
In [52]:
```
housedatanew.columns
```

Out[52]:
```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'greenbelt', 'nuisance', 'view',
       'condition', 'grade', 'heat_source', 'sewer_system', 'sqft_above',
       'sqft_basement', 'sqft_garage', 'sqft_patio', 'yr_built', 'address',
       'lat', 'long', 'city', 'country', 'zip', 'persqft'],
      dtype='object')
```

Initial Data Insights

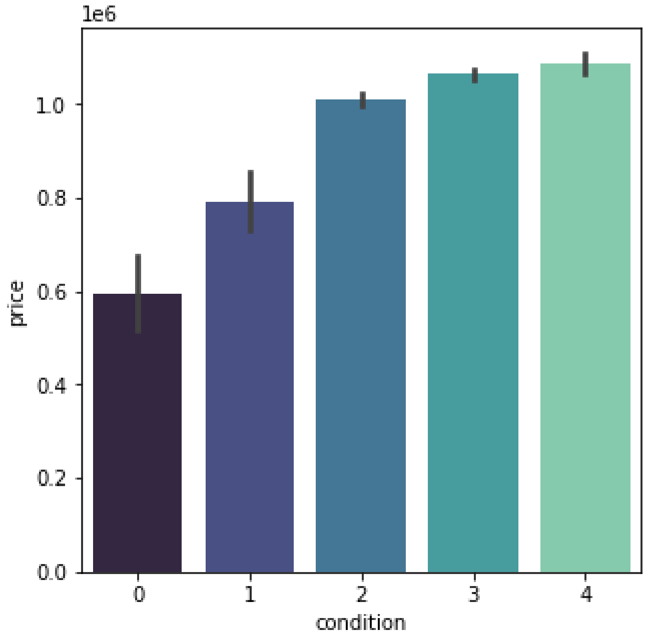
In [53]:
```
#boxplot grade vs price
fig, ax = plt.subplots(figsize = (6, 8))
sns.boxplot(data=housedatanew,x='grade',y='price',palette="mako",linewidth = 0.6
```

Out[53]: <AxesSubplot:xlabel='grade', ylabel='price'>



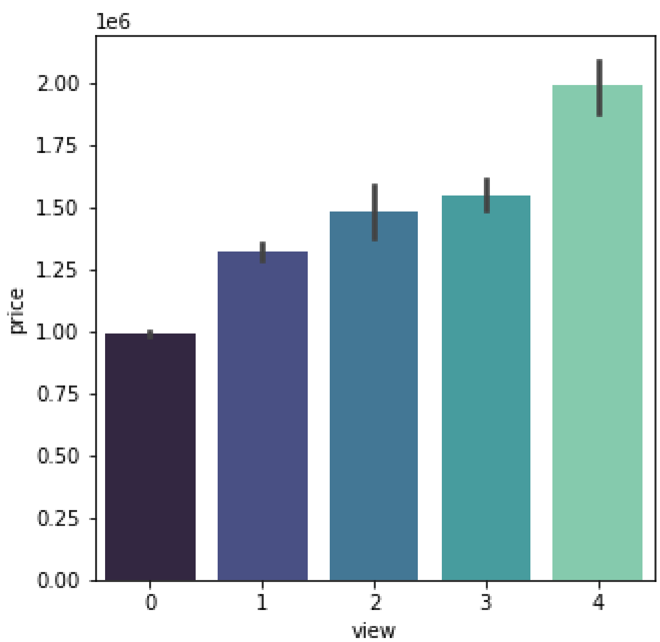
In [54]:
```
#bar plot condition vs price
fig, ax = plt.subplots(figsize = (5, 5))
```

Out[54]: <AxesSubplot:xlabel='condition', ylabel='price'>



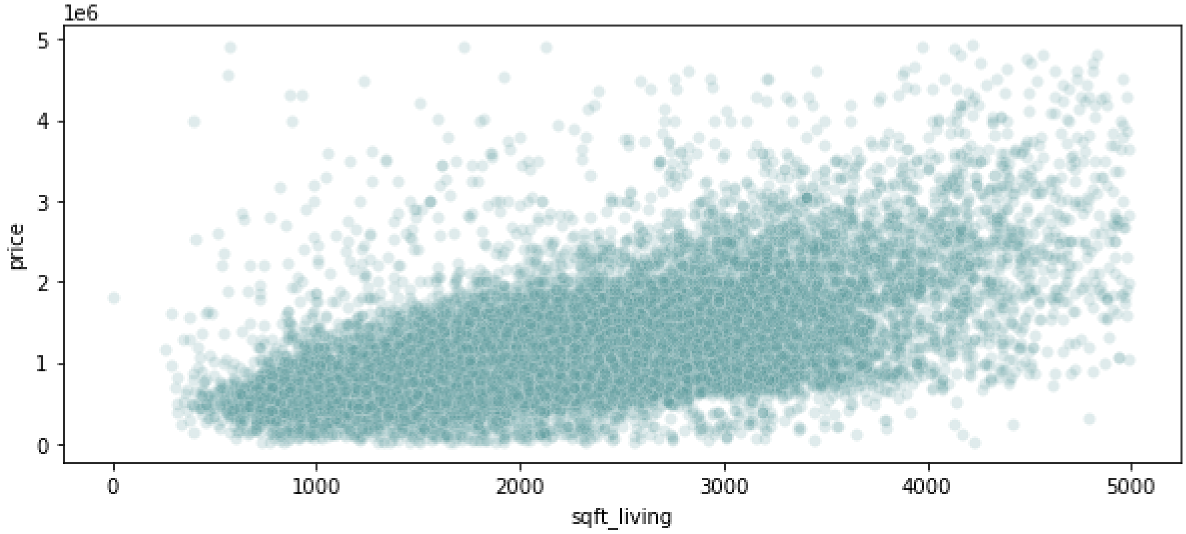
In [55]:
```
#bar plot view vs price
fig, ax = plt.subplots(figsize = (5, 5))
sns.barplot(data=housedatanew,x='view',y='price',palette="mako")
plt.show
```

Out[55]: <function matplotlib.pyplot.show(close=None, block=None)>



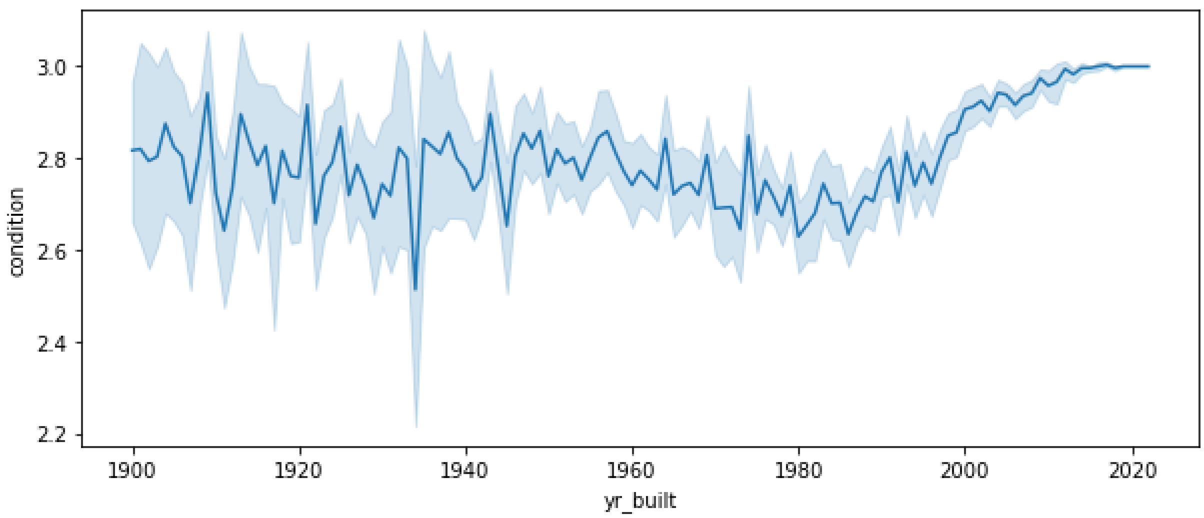
In [56]:
```
#scatter plot sqftliving vs price
fig, ax = plt.subplots(figsize = (10,4))
sns.scatterplot(data=housedatanew,x='sqft_living',y='price',color='cadetblue',al
```

Out[56]: <AxesSubplot:xlabel='sqft_living', ylabel='price'>



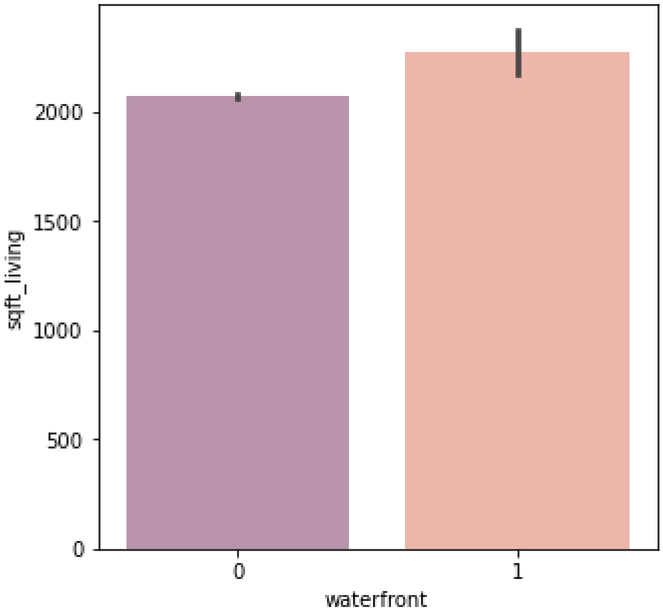
In [57]:
```
#lineplot yr built vs condition
fig, ax = plt.subplots(figsize = (10, 4))
sns.lineplot(data=housedatanew,x='yr_built',y='condition',palette='rocket')
```

Out[57]: <AxesSubplot:xlabel='yr_built', ylabel='condition'>



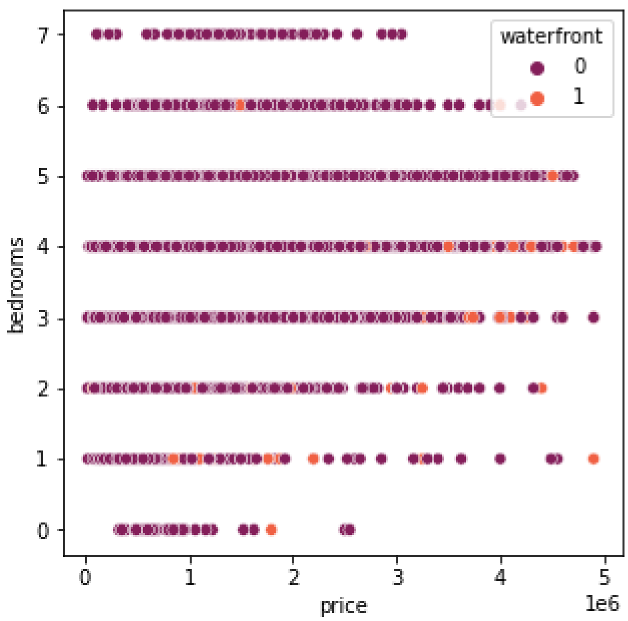
In [58]:
```
#barplot waterfront vs sqft_living
fig, ax = plt.subplots(figsize = (5, 5))
sns.barplot(data=housedatanew,x='waterfront',y='sqft_living',palette='rocket',al
```

Out[58]: <AxesSubplot:xlabel='waterfront', ylabel='sqft_living'>

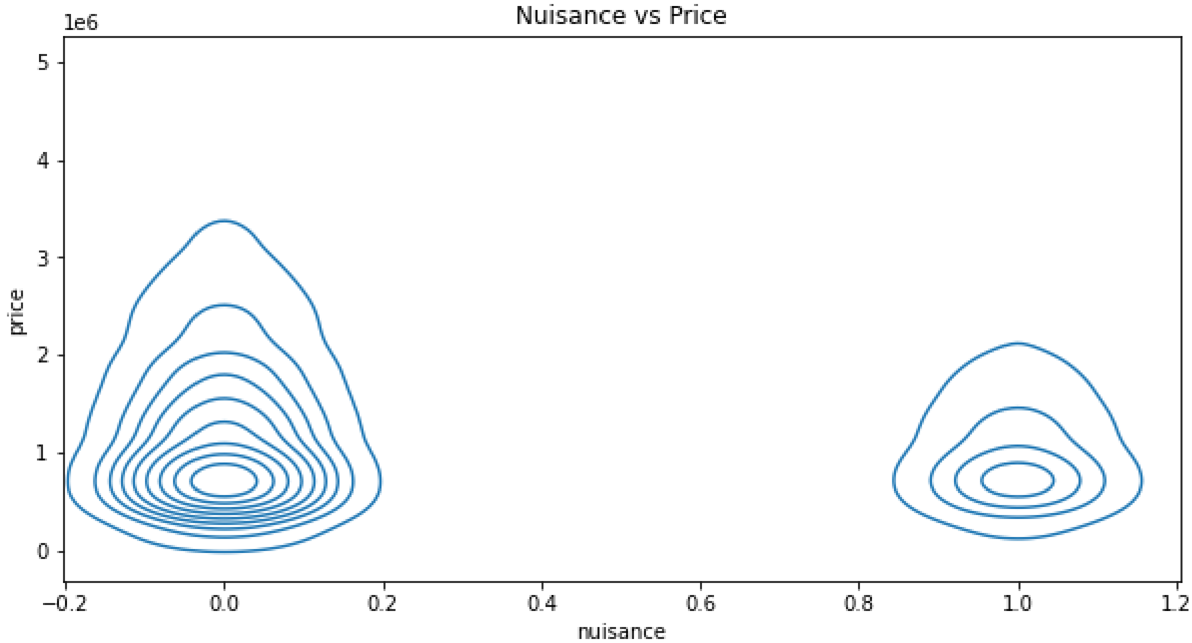


In [59]:
```
#scatter plot price bedrooms and waterfront
fig, ax = plt.subplots(figsize = (5, 5))
sns.scatterplot(data=housedatanew,x='price',y='bedrooms',hue='waterfront',palett
```

Out[59]: <AxesSubplot:xlabel='price', ylabel='bedrooms'>

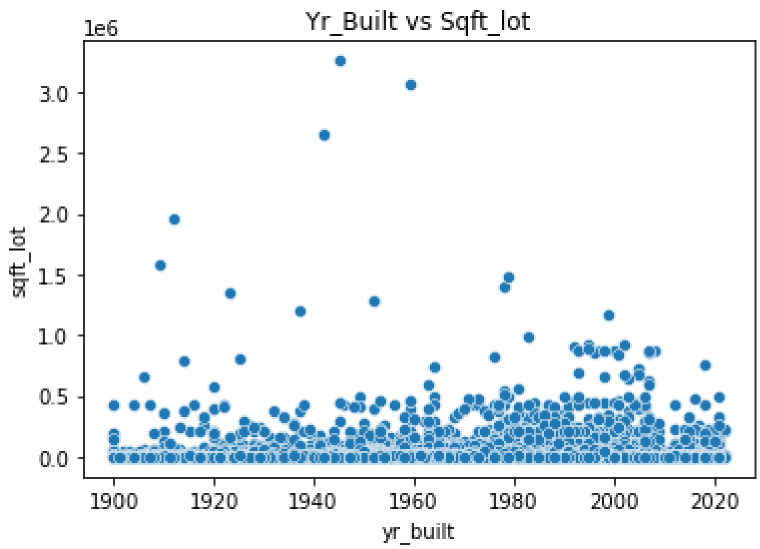


In [60]:
```
#kdeplot nuisance vs price
fig, ax = plt.subplots(figsize = (10, 5))
gf=sns.kdeplot(data=housedatanew,x='nuisance',y='price',palette='rocket')
plt.title("Nuisance vs Price")
plt.show()
```

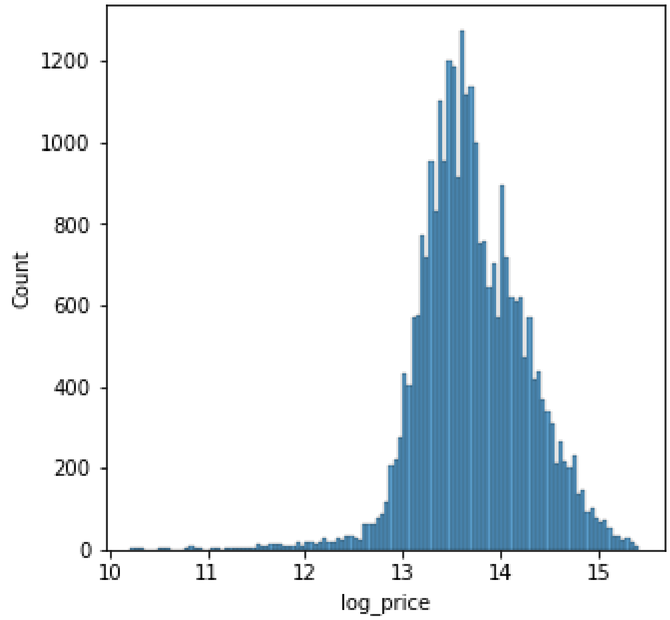


In [61]:
```
#scatter plot yr built and sqft lot
sns.scatterplot(x='yr_built',y='sqft_lot',data=housedatanew, palette ='rocket')
plt.title("Yr_Built vs Sqft_lot")
```

Out[61]:
```
Text(0.5, 1.0, 'Yr_Built vs Sqft_lot')
```



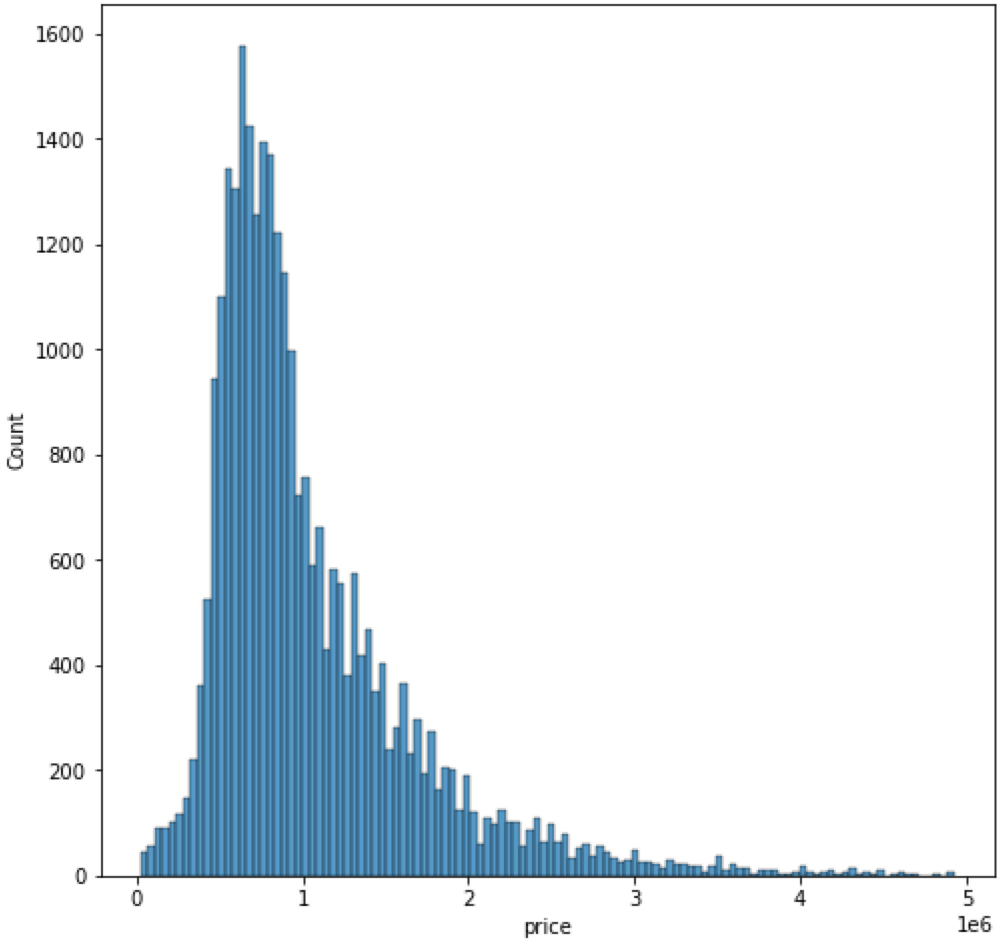
In [62]:
```
# log price to standardize
housedatanew['log_price']=np.log(housedatanew['price'])

fig, ax = plt.subplots(figsize = (5, 5))

ax = sns.histplot(data = housedatanew, x= housedatanew['log_price'])
plt.show();
```



In [63]:
```
np.exp(13.5)
```

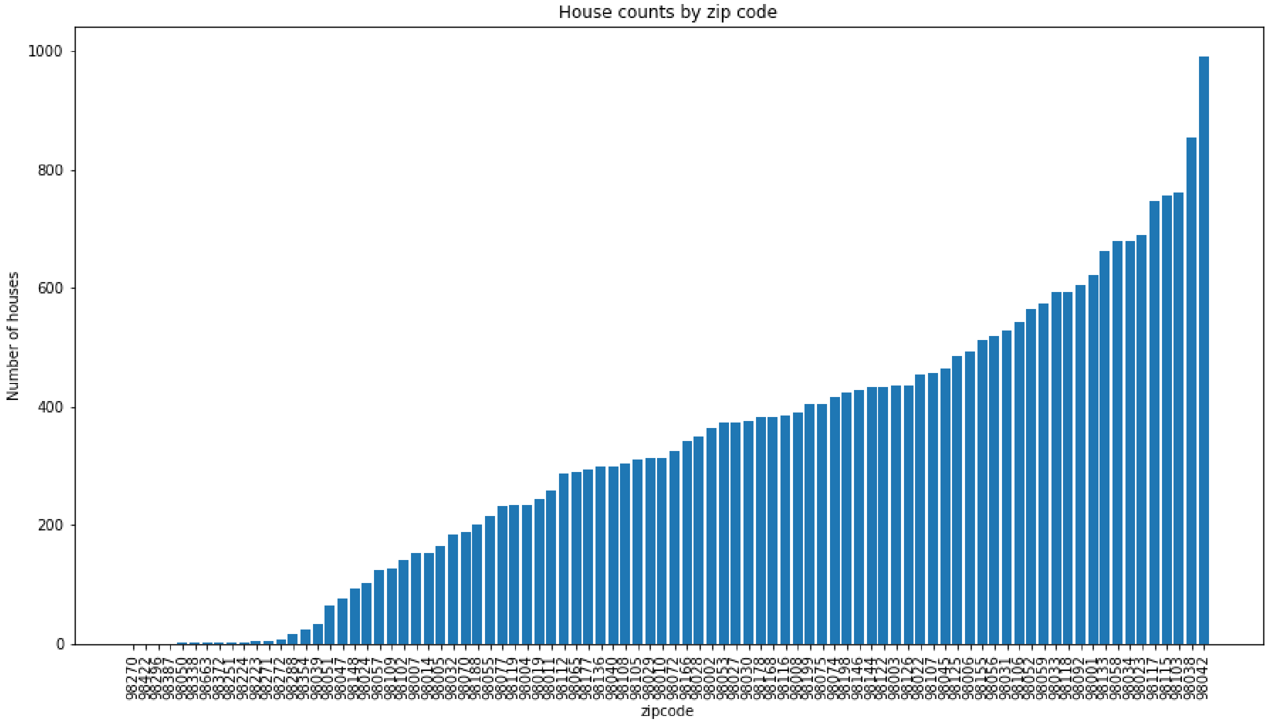
Out[63]:
```
729416.3698477013
```

In [64]:
```
#visualize price distribution
fig, ax = plt.subplots(figsize = (8, 8))

ax = sns.histplot(data = housedatanew, x= housedatanew['price'])
plt.show();
```



In [65]:
```
#house counts for each zip
x=housedatanew['zip'].value_counts().sort_values().index
y=housedatanew['zip'].value_counts().sort_values().values
fig, ax = plt.subplots(figsize=(15,8))
ax.bar(x,y)
ax.set_title('House counts by zip code')
ax.set_xlabel('zipcode')
ax.set_ylabel('Number of houses')

plt.xticks(rotation=90)


plt.show
```

Out[65]: <function matplotlib.pyplot.show(close=None, block=None)>



In [66]:
```
#average price by zip
persqft_housetype=housedatanew.groupby('zip').agg({'price':'mean','sqft_living':
pricetable=persqft_housetype.sort_values(by = ('waterfront'),ascending = False)
pricetable=pricetable.reset_index()
pricetable['mostexpensivezip']=range(1,len(pricetable)+1)
pricetable
```

Out[66]:

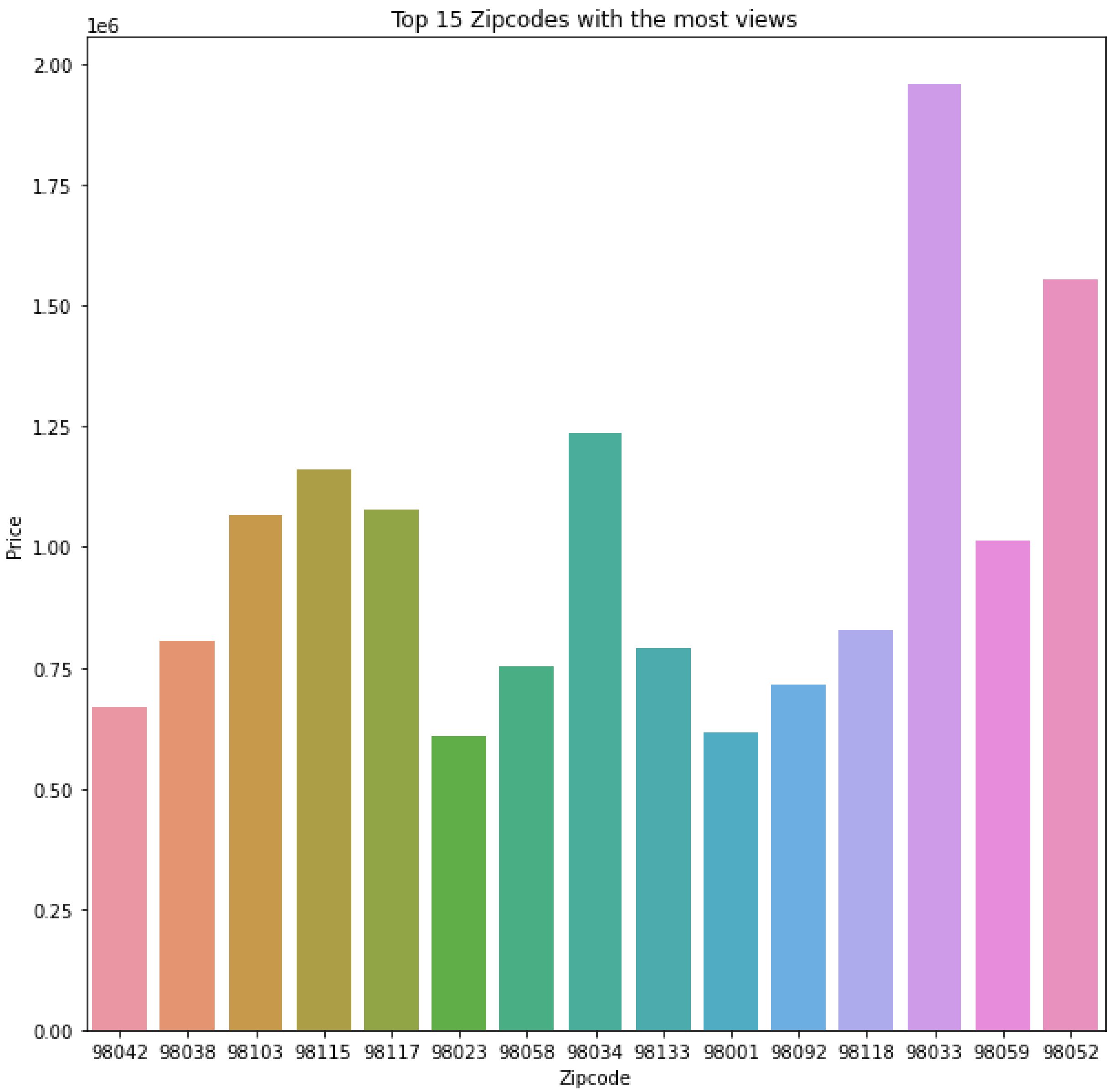
	zip	price	sqft_living	bedrooms	bathrooms	waterfront	view	yr_built	grade	mos
0	98042	668456.62	2129.77	3.54	2.33	991	991	1990.97	7.51	
1	98038	804131.26	2218.01	3.48	2.46	855	855	1996.63	7.58	
2	98103	1067443.52	1650.68	3.07	2.09	760	760	1956.75	7.42	
3	98115	1161628.76	1862.63	3.19	2.04	755	755	1952.26	7.40	
4	98117	1078119.51	1748.63	3.07	2.08	747	747	1955.39	7.37	
...	...	...	...	...	...	...	...	...	...	
83	98663	597450.00	960.00	2.00	2.50	2	2	2020.00	8.00	
84	98270	2375000.00	3590.00	4.00	3.50	1	1	2006.00	9.00	
85	98296	700000.00	2152.00	4.00	2.50	1	1	2009.00	8.00	
86	98387	679950.00	1190.00	2.00	2.00	1	1	2022.00	7.00	
87	98422	312750.00	2480.00	3.00	2.00	1	1	1988.00	8.00	

88 rows × 10 columns

In [67]:
```
#top 15 zipcodes with the highest view scores
view15= pricetable.nlargest(15, "view")
```

In [68]:
```
#top 15 zipcodes with the highest view scores - visualization
```

```
fig, ax = plt.subplots(figsize = (10, 10))
sns.barplot(data = view15,
            x = view15['zip'],
             y=view15['price'],
            ax = ax)
plt.xlabel("Zipcode")
plt.ylabel("Price")
plt.title("Top 15 Zipcodes with the most views")
plt.show();
```



Base Line Modeling for All Houses

In [69]:
```
#creating coef sunmmary to examine the coef between the features below with pric
heatmap_vac=housedatanew[['price','sqft_living','view','grade','waterfront','con
```

In [70]:
```
#creating heatmap to examin the coef between the features below with price

feature_cols= ['view','waterfront','greenbelt','nuisance','grade','sqft_living']
X = housedatanew[feature_cols]
X_standard = X.apply(lambda x: (x - x.mean())/x.std())
```

```
y = housedatanew['price']
```

In [71]:
```
import statsmodels.api as sm
X_aug = sm.add_constant(X_standard)
res = sm.OLS(y_standard, X_aug).fit()
```

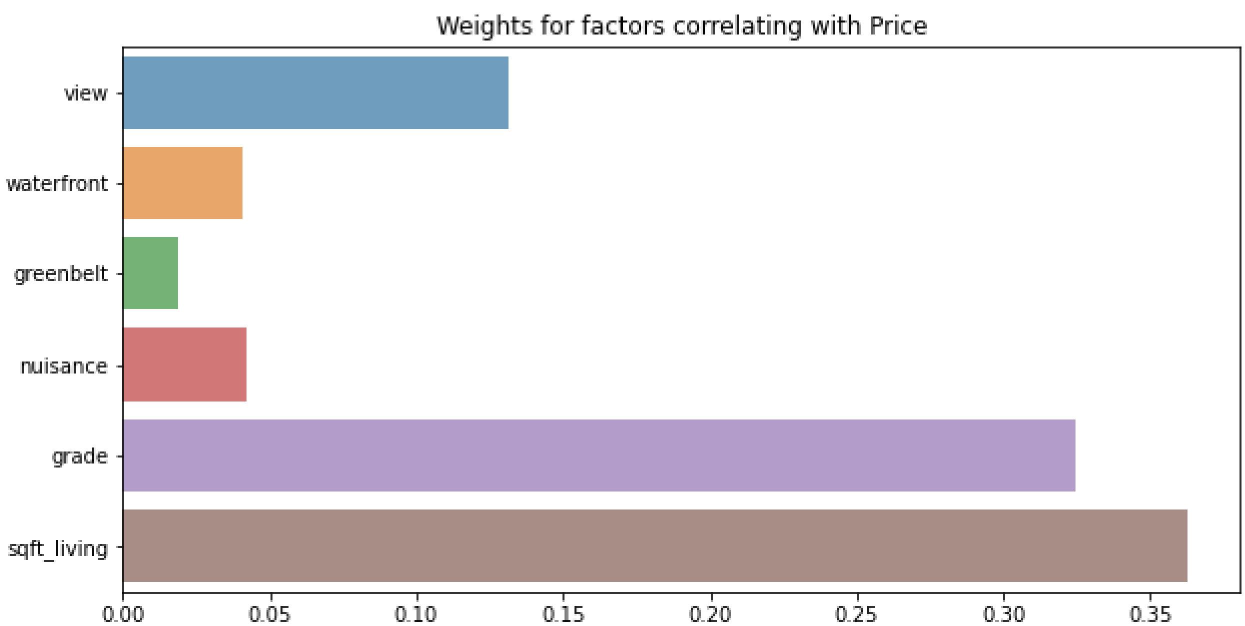
In [72]:
```
res
```

Out[72]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x7fbbec32c070>
```

In [73]:
```
#review weights for each feature
weights=res.params
weights
```

Out[73]:
```
const          -8.673617e-19
view            1.311544e-01
waterfront      4.096339e-02
greenbelt       1.885904e-02
nuisance        4.202821e-02
grade           3.244387e-01
sqft_living     3.624522e-01
dtype: float64
```

In [74]:
```
plt.figure(figsize=(10,5))
sns.barplot(y=weights[1::].index,x=weights[1::].values,alpha=0.7)
plt.title("Weights for factors correlating with Price")
plt.show()
```



In [75]:
```
res.summary()
```

Out[75]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.461
Model:	OLS	**Adj. R-squared:**	0.461
Method:	Least Squares	**F-statistic:**	4093.
Date:	Fri, 09 Dec 2022	**Prob (F-statistic):**	0.00
Time:	17:53:21	**Log-Likelihood:**	-31829.

No. Observations:	28685	**AIC:**	6.367e+04
Df Residuals:	28678	**BIC:**	6.373e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-8.674e-19	0.004	-2e-16	1.000	-0.008	0.008
view	0.1312	0.005	27.011	0.000	0.122	0.141
waterfront	0.0410	0.005	8.602	0.000	0.032	0.050
greenbelt	0.0189	0.004	4.305	0.000	0.010	0.027
nuisance	0.0420	0.004	9.652	0.000	0.033	0.051
grade	0.3244	0.006	52.383	0.000	0.312	0.337
sqft_living	0.3625	0.006	58.312	0.000	0.350	0.375

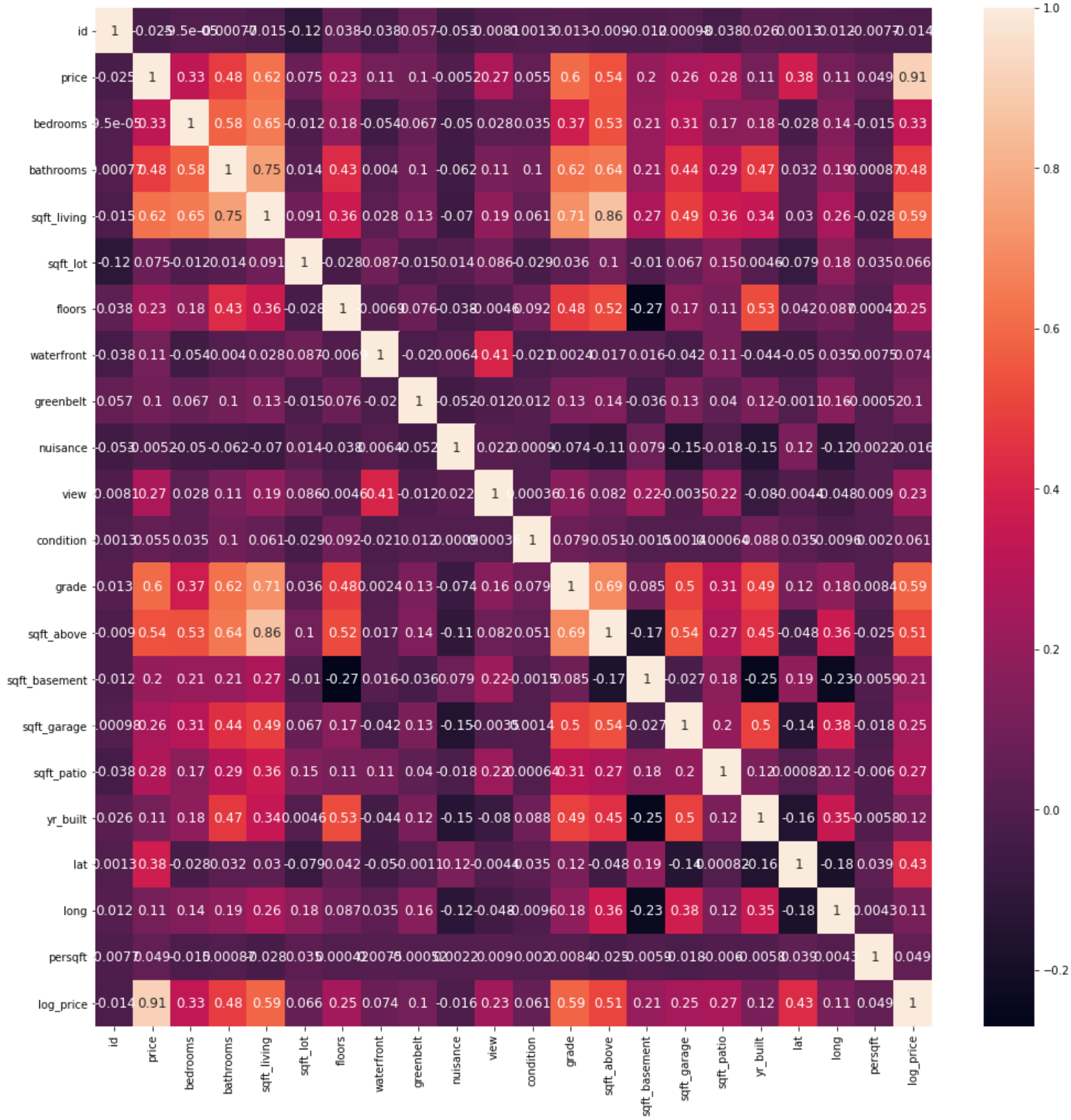
Omnibus:	9206.091	**Durbin-Watson:**	1.975
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	54087.553
Skew:	1.420	**Prob(JB):**	0.00
Kurtosis:	9.098	**Cond. No.**	2.54

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

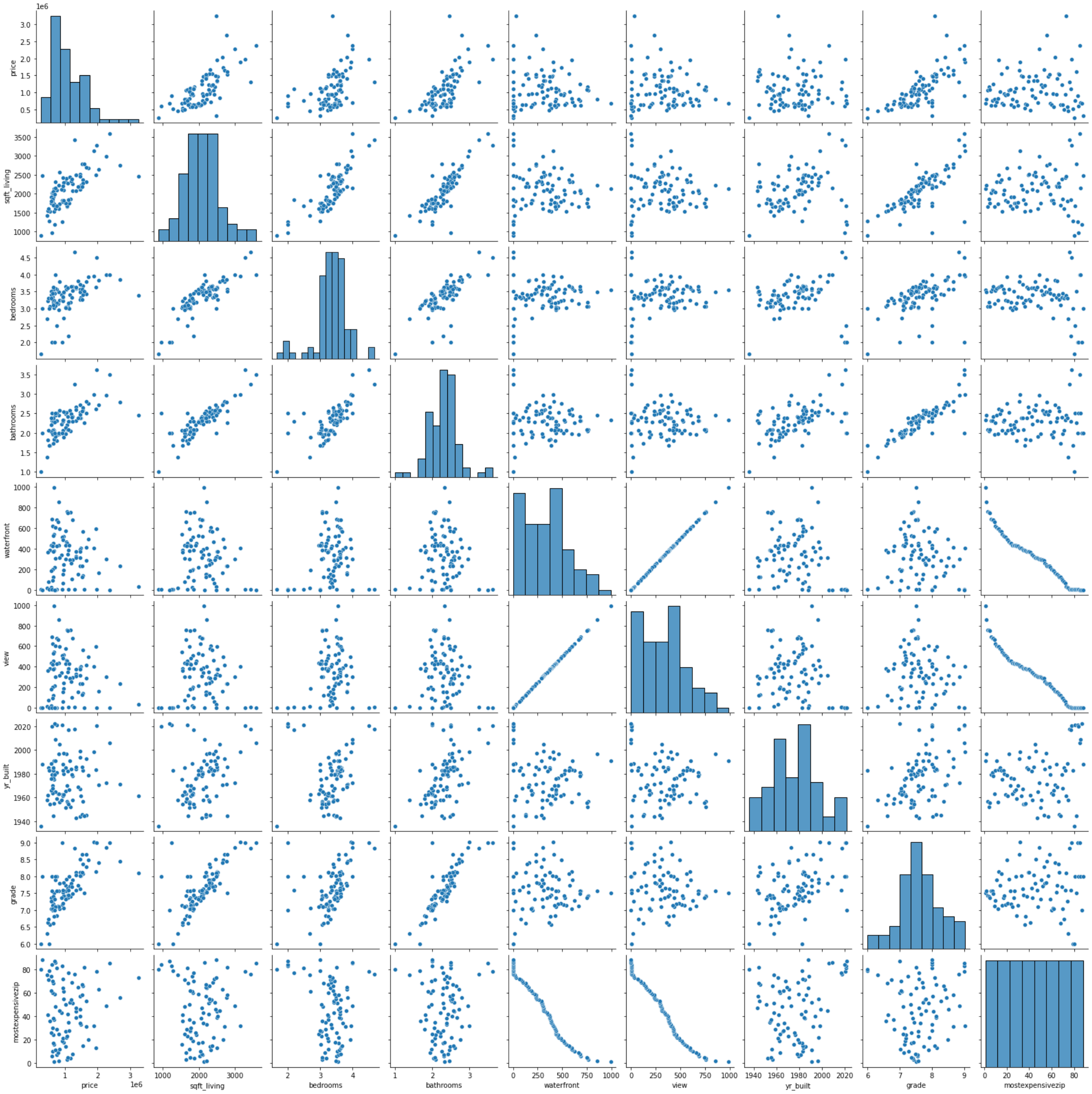
In [76]:

```
#using heatmap to validate the coef number
fig, ax = plt.subplots(figsize=(17,17))
sns.heatmap(housedatanew.corr(),annot=True,annot_kws={'size':12})
```

Out[76]: <AxesSubplot:>



In [77]:
```
#plotting out the weights
sns.pairplot(pricetable)
plt.show()
```

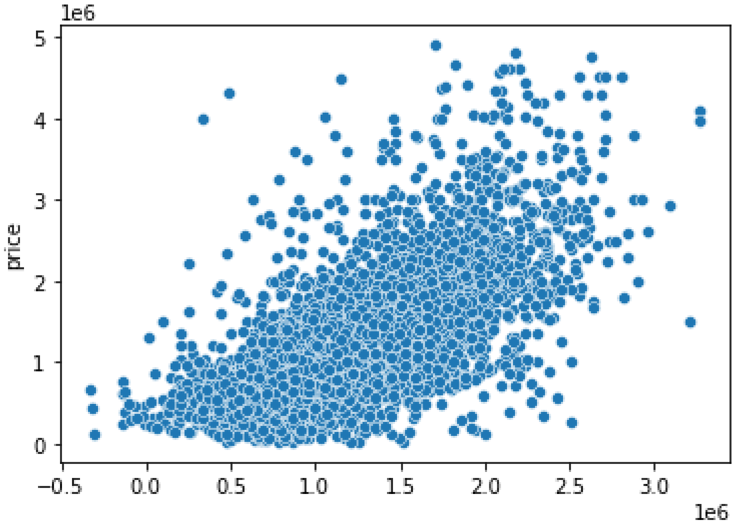


In [78]:
```
#test modeling - first try - all columns without heatsource and sewer system
col_selector = ['zip','bedrooms','sqft_living','sqft_lot','floors','waterfront',
X = housedatanew[col_selector]
y = housedatanew['price']

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

In [79]:
```
lr = LinearRegression()
lr.fit(X_train,y_train)
print(lr.score(X_train,y_train))
print(lr.score(X_test,y_test))
preds = lr.predict(X_test)
sns.scatterplot(preds,y_test)
```

```
0.5064633014896209
0.49628485257520594
```

Out[79]: <AxesSubplot:ylabel='price'>



In [80]:
```
list(zip(lr.coef_,X_train.columns))
```

Out[80]:
```
[(-521.7297900077295, 'zip'),
 (-55483.291633337794, 'bedrooms'),
 (258.90124458598643, 'sqft_living'),
 (0.0074061627383343875, 'sqft_lot'),
 (20595.00582012207, 'floors'),
 (254140.92628818963, 'waterfront'),
 (89986.96670386188, 'greenbelt'),
 (76894.02914653401, 'view'),
 (18421.64603875926, 'condition'),
 (237839.57092609318, 'grade'),
 (41.696813638686706, 'sqft_patio'),
 (-5388.914213925569, 'yr_built'),
 (76143.28416863576, 'bathrooms')]
```

Beginning of model testing for "Vacation Home"

Creating engineering feature of view/waterfront + no nuisance

In [81]:
```
#Import original dataframe, rename to vacation_housedata
vacation_housedata=housedatanew
```

In [82]:
```
vacation_housedata['Vacationgrade']=vacation_housedata['view']+vacation_housedat
```

In [83]:
```
vacation_housedata['EnvironmentRank']= vacation_housedata['Vacationgrade'].apply
```

In [84]:
```
vacation_housedata['EnvironmentRank'].value_counts()
```

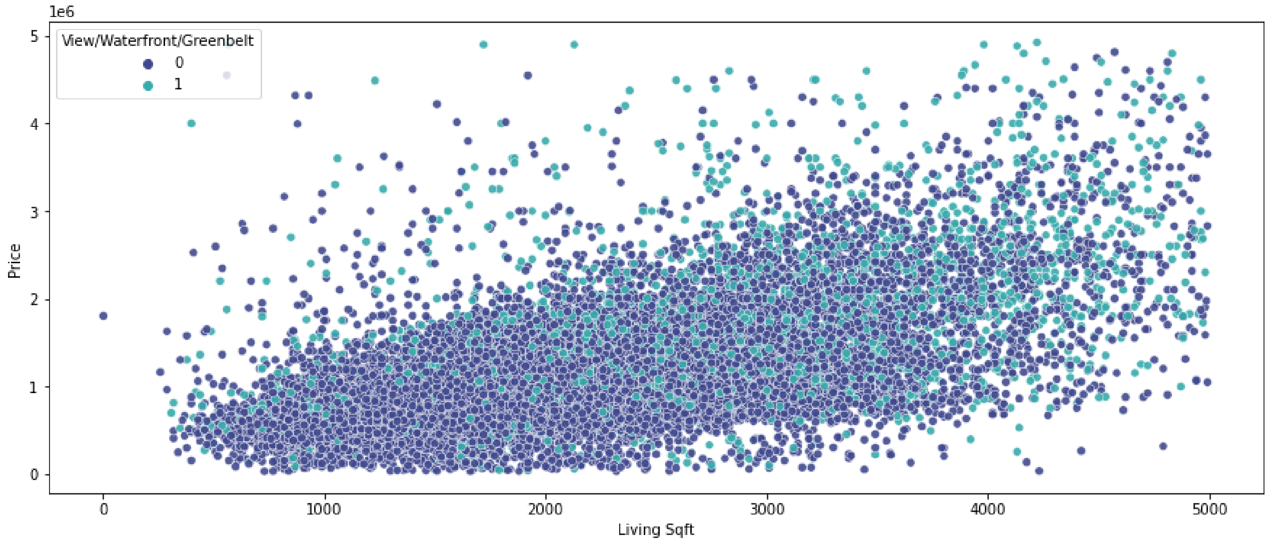
Out[84]:
```
0    24680
1     4005
Name: EnvironmentRank, dtype: int64
```

In [85]:
```
vacation_housedata=vacation_housedata[vacation_housedata['EnvironmentRank']!=0]
```

In [86]:
```
viewzip=vacation_housedata.groupby('zip')['Vacationgrade','price'].mean().round(
top15viewzip=viewzip.sort_values(by='Vacationgrade', ascending=False).head(15)
top15viewzip=top15viewzip.reset_index()
```

In [87]:
```
fig, ax = plt.subplots(figsize = (15, 6))
sns.scatterplot(data=housedatanew,x='sqft_living',y='price',hue='EnvironmentRank
ax.set(xlabel='Living Sqft', ylabel='Price')
plt.legend(title='View/Waterfront/Greenbelt', loc='upper left')
plt.show
```

Out[87]: <function matplotlib.pyplot.show(close=None, block=None)>



In [88]:
```
top15viewzip['zip']=top15viewzip['zip'].astype(str)
```

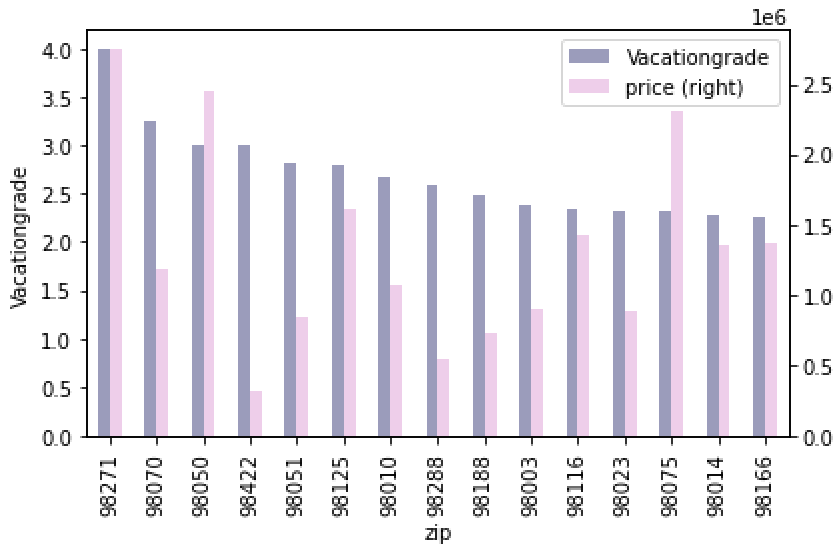
In [89]:
```
top15view_housedata=vacation_housedata[vacation_housedata['zip'].isin(top15viewz
```

In [90]:
```
top15view_housedata=top15view_housedata[top15view_housedata['zip']!=False]
```

In [91]:
```
counts=pd.DataFrame(top15view_housedata['zip'].value_counts(),columns=['zip',"co
```

In [92]:
```
plt.figure(figsize=(20,6))

#populate bar graph to show the trend
top15viewzip.plot(secondary_y='price', x='zip', colormap = 'tab20b',kind='bar',
plt.tight_layout()
```

<Figure size 1440x432 with 0 Axes>



In [93]:
```
vacation_housedata.loc[vacation_housedata['zip']=='98271']
```

Out[93]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterf
13294	1454600255	2022-05-23	2750000.0	3.0	3.5	3510	18543	1.0	

1 rows × 31 columns

Vacation-Modeling First Run -

including
'zip','bedrooms','sqft_living','sqft_lot','floors','waterfront','greenbelt','view','condition','grade','sqft_patio','yr_built',

'bathrooms','sewer_system','heat_source','view','waterfront','greenbelt'

In [94]:
```
cols =['bedrooms', 'bathrooms', 'sqft_living',
        'sqft_lot', 'floors', 'waterfront', 'greenbelt', 'nuisance', 'view',
        'condition', 'grade', 'heat_source', 'sewer_system','sqft_above',
        'sqft_basement', 'sqft_garage', 'sqft_patio', 'yr_built',
        'lat', 'long', 'city', 'zip', 'persqft',
        'Vacationgrade', 'EnvironmentRank']
```

In [95]:
```
col_selector = ['zip','bedrooms','sqft_living','sqft_lot','floors','waterfront',
vacX = vacation_housedata[col_selector]
vacy = np.log(vacation_housedata['price'])

vacX_train, vacX_test, vacy_train, vacy_test = train_test_split(vacX, vacy, test
```

In [96]:
```
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(handle_unknown = 'ignore')

ohe_train = ohe.fit_transform(vacX_train[['zip', 'heat_source', 'sewer_system']]
ohe_test = ohe.transform(vacX_test[['zip', 'heat_source', 'sewer_system']]).toar

ohe_train = pd.DataFrame(ohe_train, columns = ohe.get_feature_names())
ohe_test = pd.DataFrame(ohe_test, columns = ohe.get_feature_names())
```

```
ohe_train.index = vacX_train.index
ohe_test.index = vacX_test.index

vacX_train = pd.concat([vacX_train, ohe_train],1)
vacX_test = pd.concat([vacX_test, ohe_test],1)
vacX_train

vacX_train.drop(columns =['zip', 'heat_source', 'sewer_system'], inplace = True)
vacX_test.drop(columns =['zip', 'heat_source', 'sewer_system'], inplace = True)
```

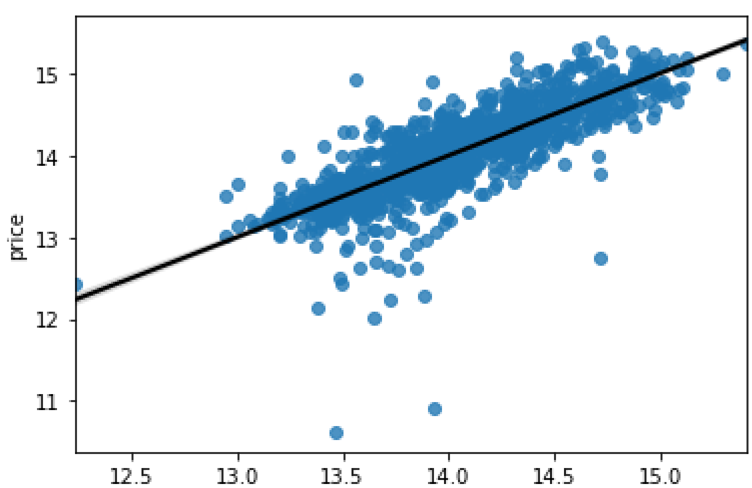
In [97]:
```
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
ss.fit(vacX_train)
vacX_standardized_train = ss.transform(vacX_train)
vacX_standardized_test = ss.transform(vacX_test)

vacX_standardized_train.mean(axis = 0)
vacX_standardized_train.std(axis = 0)

vacX_standardized_test.mean(axis = 0)
vacX_standardized_test.std(axis = 0)

lr.fit(vacX_train, vacy_train)

print(lr.score(vacX_test,vacy_test))
```

```
0.6587192772716308
```

In [98]:
```
lr = LinearRegression()
lr.fit(vacX_train,vacy_train)
print(lr.score(vacX_train,vacy_train))
print(lr.score(vacX_test,vacy_test))
preds = lr.predict(vacX_test)
sns.regplot(preds,vacy_test,line_kws={'color':'black'})
```

```
0.646528529628593
0.6587192772716308
```

Out[98]: <AxesSubplot:ylabel='price'>



Vaction-Modeling Run 2 - change sqft_living to sqft_above

In [99]:
```
col_selector = ['bedrooms', 'bathrooms',
        'sqft_lot', 'floors', 'waterfront', 'greenbelt', 'nuisance', 'view',
        'condition', 'grade', 'heat_source', 'sewer_system','sqft_above',
        'sqft_basement', 'sqft_garage', 'sqft_patio', 'yr_built',
```

```
        'lat', 'long', 'city', 'zip', 'persqft']
vacX2 = vacation_housedata[col_selector]
vacy2 = vacation_housedata['price']

vacX2_train, vacX2_test, vacy2_train, vacy2_test = train_test_split(vacX2, vacy2
```

In [100…

```
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(handle_unknown = 'ignore')

ohe_train = ohe.fit_transform(vacX2_train[['zip', 'heat_source', 'sewer_system',
ohe_test = ohe.transform(vacX2_test[['zip', 'heat_source', 'sewer_system','city'

ohe_train = pd.DataFrame(ohe_train, columns = ohe.get_feature_names())
ohe_test = pd.DataFrame(ohe_test, columns = ohe.get_feature_names())

ohe_train.index = vacX2_train.index
ohe_test.index = vacX2_test.index

vacX2_train = pd.concat([vacX2_train, ohe_train],1)
vacX2_test = pd.concat([vacX2_test, ohe_test],1)
vacX2_train

vacX2_train.drop(columns =['zip', 'heat_source', 'sewer_system','city'], inplace
vacX2_test.drop(columns =['zip', 'heat_source', 'sewer_system','city'], inplace
```

In [101…

```
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
ss.fit(vacX2_train)
vacX2_standardized_train = ss.transform(vacX2_train)
vacX2_standardized_test = ss.transform(vacX2_test)

vacX2_standardized_train.mean(axis = 0)
vacX2_standardized_train.std(axis = 0)

vacX2_standardized_test.mean(axis = 0)
vacX2_standardized_test.std(axis = 0)

lr.fit(vacX2_train, vacy2_train)
lr.score(vacX2_test,vacy2_test)
```

Out[101…

```
0.8252022542153867
```

In [102…

```
lr = LinearRegression()
lr.fit(vacX2_train, vacy2_train)
lr.score(vacX2_train,vacy2_train)
lr.score(vacX2_test,vacy2_test)
```

Out[102…

```
0.8252022542153867
```

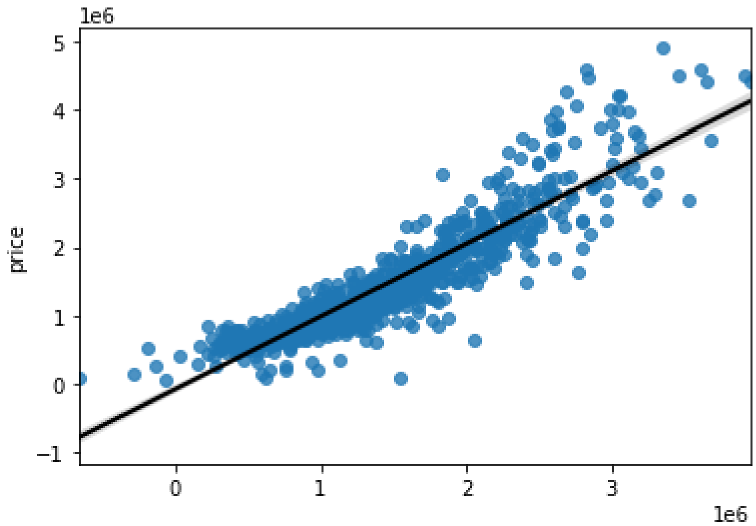
In [103…

```
lr = LinearRegression()
lr.fit(vacX2_train,vacy2_train)
print(lr.score(vacX2_train,vacy2_train))
print(lr.score(vacX2_test,vacy2_test))
preds = lr.predict(vacX2_test)
sns.regplot(preds,vacy2_test,line_kws={'color':'black'})
```

```
0.8340184201782266
0.8252022542153867
```

Out[103…

```
<AxesSubplot:ylabel='price'>
```



Vaction-Modeling Run 3 - remove yr_built and condition

In [104…
```
col_selector = ['zip','bedrooms','sqft_above','sqft_lot','floors','waterfront','
vacX3 = vacation_housedata[col_selector]
vacy = vacation_housedata['price']

vacX3_train, vacX3_test, vacy_train, vacy_test = train_test_split(vacX3, vacy, t
```

In [105…
```
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(handle_unknown = 'ignore')

ohe_train = ohe.fit_transform(vacX3_train[['zip', 'heat_source', 'sewer_system']
ohe_test = ohe.transform(vacX3_test[['zip', 'heat_source', 'sewer_system']]).toa

ohe_train = pd.DataFrame(ohe_train, columns = ohe.get_feature_names())
ohe_test = pd.DataFrame(ohe_test, columns = ohe.get_feature_names())

ohe_train.index = vacX3_train.index
ohe_test.index = vacX3_test.index

vacX3_train = pd.concat([vacX3_train, ohe_train],1)
vacX3_test = pd.concat([vacX3_test, ohe_test],1)
vacX3_train

vacX3_train.drop(columns =['zip', 'heat_source', 'sewer_system'], inplace = True
vacX3_test.drop(columns =['zip', 'heat_source', 'sewer_system'], inplace = True)
```

In [106…
```
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
ss.fit(vacX3_train)
vacX3_standardized_train = ss.transform(vacX3_train)
vacX3_standardized_test = ss.transform(vacX3_test)

vacX3_standardized_train.mean(axis = 0)
vacX3_standardized_train.std(axis = 0)

vacX3_standardized_test.mean(axis = 0)
vacX3_standardized_test.std(axis = 0)

lr.fit(vacX3_train, vacy_train)
print(lr.score(vacX3_test,vacy_test))
```

```
0.6714110356426067
```

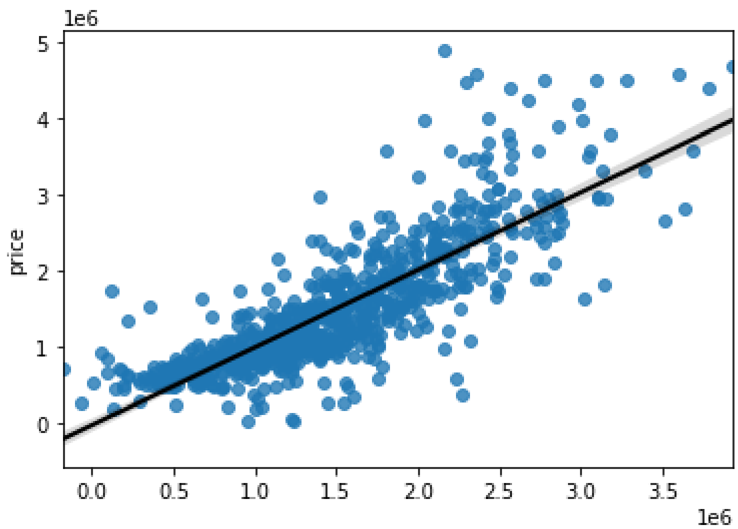
In [107…
```
lr = LinearRegression()
lr.fit(vacX3_train, vacy_train)
lr.score(vacX3_train,vacy_train)
lr.score(vacX3_test,vacy_test)
```

Out[107…
```
0.6714110356426067
```

In [108…
```
lr = LinearRegression()
lr.fit(vacX3_train,vacy_train)
print(lr.score(vacX3_train,vacy_train))
print(lr.score(vacX3_test,vacy_test))
preds = lr.predict(vacX3_test)
sns.regplot(preds,vacy_test,line_kws={'color':'black'})
```

```
0.6805225675655048
0.6714110356426067
```

Out[108…
```
<AxesSubplot:ylabel='price'>
```



Vaction-Modeling Test 4 - remove floors, bedrooms + 'EnvironmentRank'

In [109…
```
col_selector = ['zip','sqft_above','sqft_lot','bathrooms','sqft_living','waterfr
vacX4 = vacation_housedata[col_selector]
vacy = vacation_housedata['price']

vacX4_train, vacX4_test, vacy_train, vacy_test = train_test_split(vacX4, vacy, t
```

In [110…
```
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(handle_unknown = 'ignore')

ohe_train = ohe.fit_transform(vacX4_train[['zip', 'heat_source', 'sewer_system']
ohe_test = ohe.transform(vacX4_test[['zip', 'heat_source', 'sewer_system']]).toa

ohe_train = pd.DataFrame(ohe_train, columns = ohe.get_feature_names())
ohe_test = pd.DataFrame(ohe_test, columns = ohe.get_feature_names())

ohe_train.index = vacX4_train.index
ohe_test.index = vacX4_test.index

vacX4_train = pd.concat([vacX4_train, ohe_train],1)
vacX4_test = pd.concat([vacX4_test, ohe_test],1)
```

```
vacX4_train.drop(columns =['zip', 'heat_source', 'sewer_system'], inplace = True
vacX4_test.drop(columns =['zip', 'heat_source', 'sewer_system'], inplace = True)
```

In [111…

```
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
ss.fit(vacX4_train)
vacX4_standardized_train = ss.transform(vacX4_train)
vacX4_standardized_test = ss.transform(vacX4_test)

vacX4_standardized_train.mean(axis = 0)
vacX4_standardized_train.std(axis = 0)

vacX4_standardized_test.mean(axis = 0)
vacX4_standardized_test.std(axis = 0)

lr.fit(vacX4_train, vacy_train)
lr.score(vacX4_test,vacy_test)
```

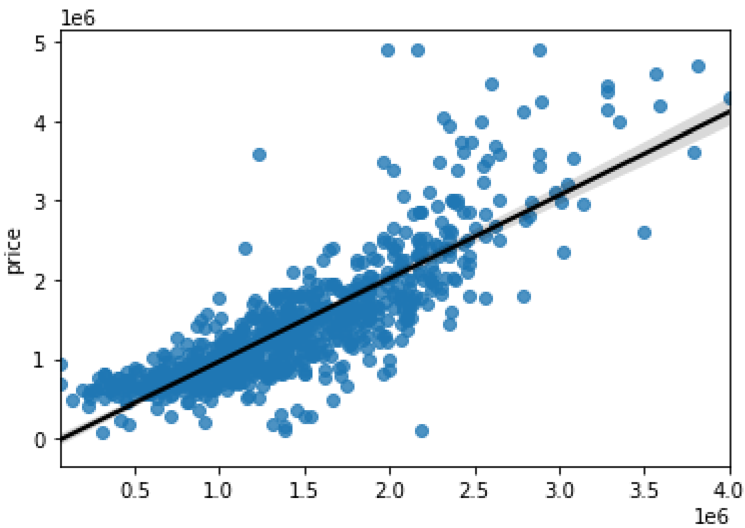
Out[111… 0.6863677705187722

In [112…

```
lr = LinearRegression()
lr.fit(vacX4_train,vacy_train)
print(lr.score(vacX4_train,vacy_train))
print(lr.score(vacX4_test,vacy_test))
preds = lr.predict(vacX4_test)
sns.regplot(preds,vacy_test,line_kws={'color':'black'})
```

```
0.6838871612839512
0.6863677705187722
```

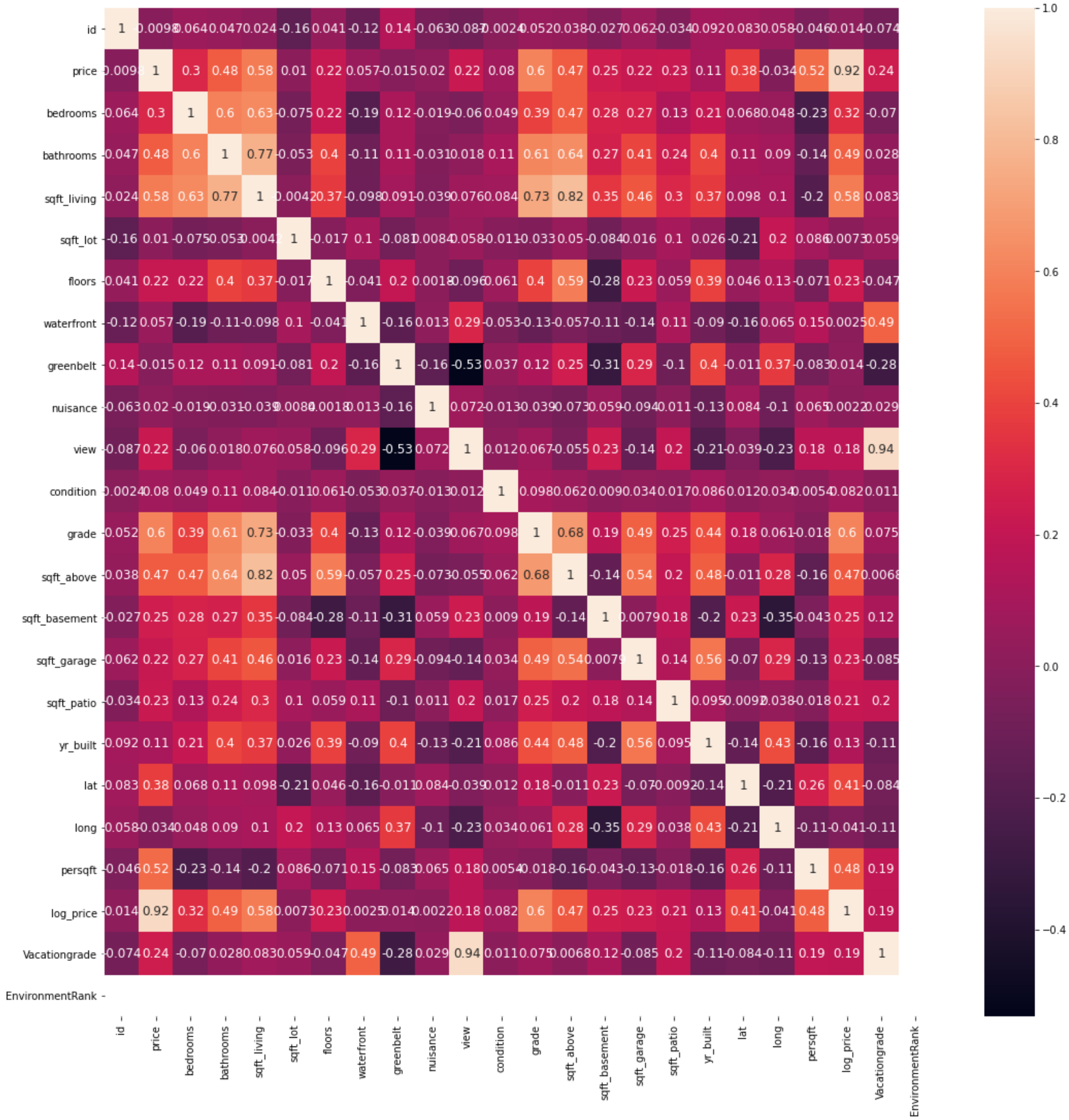
Out[112… <AxesSubplot:ylabel='price'>



In [113…

```
fig, ax = plt.subplots(figsize=(18,18))
sns.heatmap(vacation_housedata.corr(),annot=True,annot_kws={'size':12})
```

Out[113… <AxesSubplot:>



Vaction-Modeling Test 5 - excluding environment rank

In [114…
```
col_selector = ['zip','sqft_above','bathrooms','sqft_garage','condition','sqft_l
vacX5 = vacation_housedata[col_selector]
vacy = vacation_housedata['price']

vacX5_train, vacX5_test, vacy_train, vacy_test = train_test_split(vacX5, vacy, t
```

In [115…
```
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(handle_unknown = 'ignore')

ohe_train = ohe.fit_transform(vacX5_train[['zip', 'heat_source', 'sewer_system']
ohe_test = ohe.transform(vacX5_test[['zip', 'heat_source', 'sewer_system']]).toa

ohe_train = pd.DataFrame(ohe_train, columns = ohe.get_feature_names())
ohe_test = pd.DataFrame(ohe_test, columns = ohe.get_feature_names())
```

```
ohe_train.index = vacX5_train.index
ohe_test.index = vacX5_test.index

vacX5_train = pd.concat([vacX5_train, ohe_train],1)
vacX5_test = pd.concat([vacX5_test, ohe_test],1)


vacX5_train.drop(columns =['zip', 'heat_source', 'sewer_system'], inplace = True
vacX5_test.drop(columns =['zip', 'heat_source', 'sewer_system'], inplace = True)
```

In [116…

```
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
ss.fit(vacX5_train)
vacX5_standardized_train = ss.transform(vacX5_train)
vacX5_standardized_test = ss.transform(vacX5_test)

vacX5_standardized_train.mean(axis = 0)
vacX5_standardized_train.std(axis = 0)

vacX5_standardized_test.mean(axis = 0)
vacX5_standardized_test.std(axis = 0)

lr.fit(vacX5_train, vacy_train)
lr.score(vacX5_test,vacy_test)
```

Out[116…

```
0.6568744161214908
```

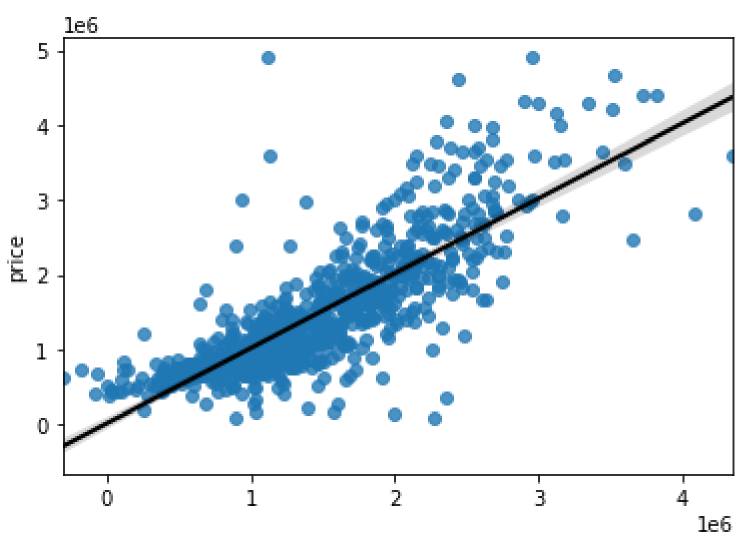
In [117…

```
lr = LinearRegression()
lr.fit(vacX5_train,vacy_train)
print(lr.score(vacX5_train,vacy_train))
print(lr.score(vacX5_test,vacy_test))
preds = lr.predict(vacX5_test)
sns.color_palette("rocket", as_cmap=True)
sns.regplot(preds,vacy_test,line_kws={'color':'black'})
```

```
0.6796983287165705
0.6568744161214908
```

Out[117…

```
<AxesSubplot:ylabel='price'>
```



Vacation-Modeling Run 6 - all columns except id and date

In [180…

```
vacation_housedata.columns
```

Out[180…
```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'greenbelt', 'nuisance', 'view',
       'condition', 'grade', 'heat_source', 'sewer_system', 'sqft_above',
       'sqft_basement', 'sqft_garage', 'sqft_patio', 'yr_built', 'address',
       'lat', 'long', 'city', 'country', 'zip', 'persqft', 'log_price',
       'Vacationgrade', 'EnvironmentRank', 'year', 'month', 'month_year'],
      dtype='object')
```

In [181…
```
vacation_housedata['price'].median()
```

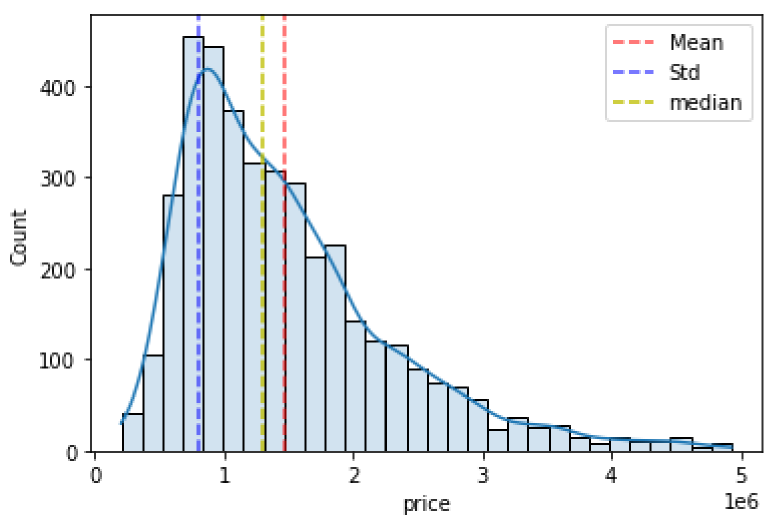
Out[181…
```
1295000.0
```

In [182…
```
vacation_housedata['price'].describe().round(2)
```

Out[182…
```
count       3925.00
mean     1472698.02
std       809291.95
min       207333.00
25%       870000.00
50%      1295000.00
75%      1840000.00
max      4925000.00
Name: price, dtype: float64
```

In [183…
```
sequential_colors = sns.color_palette("RdPu", 10)

sns.histplot(data=vacation_housedata,x=vacation_housedata['price'],alpha=0.2,kde

plt.axvline(vacation_housedata['price'].mean(), color='r', linestyle='--', label
plt.axvline(vacation_housedata['price'].std(), color='blue', linestyle='--', lab
plt.axvline(vacation_housedata['price'].median(), color='y', linestyle='--', lab

plt.legend()
```

Out[183…
```
<matplotlib.legend.Legend at 0x7fbbed309820>
```



In [184…
```
#reduce subset to 3992
vacation_housedata=vacation_housedata[vacation_housedata['grade']> 4]
```

In [185…
```
#3969
vacation_housedata=vacation_housedata[vacation_housedata['price']>200000.00]
len(vacation_housedata)
```

Out[185… 3925

In [186…
```
#remove condition below 2

vacation_housedata=vacation_housedata[vacation_housedata['condition']>1]
```

In [187…
```
#combine heat_source
vacation_housedata.heat_source=vacation_housedata.heat_source.replace('Oil','Oil
vacation_housedata.heat_source=vacation_housedata.heat_source.replace('Gas','Gas
vacation_housedata.heat_source=vacation_housedata.heat_source.replace('Electrici
vacation_housedata.heat_source=vacation_housedata.heat_source.replace('Other','E
```

In [188…
```
#combine sewer_system
vacation_housedata.sewer_system=vacation_housedata.sewer_system.replace('PRIVATE
vacation_housedata.sewer_system=vacation_housedata.sewer_system.replace('PUBLIC
```

In [189…
```
col_selector = ['bedrooms', 'bathrooms',
       'sqft_lot', 'floors', 'waterfront', 'greenbelt', 'nuisance', 'view',
       'condition', 'grade', 'heat_source', 'sewer_system','sqft_above',
       'sqft_basement', 'sqft_garage', 'sqft_patio', 'yr_built',
       'lat', 'long', 'city', 'zip', 'persqft',
       'Vacationgrade', 'EnvironmentRank']
vacX6 = vacation_housedata[col_selector]
vacy = vacation_housedata['price']

vacX6_train, vacX6_test, vacy_train, vacy_test = train_test_split(vacX6, vacy, t
```

In [190…
```
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(handle_unknown = 'ignore')

ohe_train = ohe.fit_transform(vacX6_train[['city','zip', 'heat_source', 'sewer_s
ohe_test = ohe.transform(vacX6_test[['city','zip', 'heat_source', 'sewer_system'

ohe_train = pd.DataFrame(ohe_train, columns = ohe.get_feature_names())
ohe_test = pd.DataFrame(ohe_test, columns = ohe.get_feature_names())

ohe_train.index = vacX6_train.index
ohe_test.index = vacX6_test.index

vacX6_train = pd.concat([vacX6_train, ohe_train],1)
vacX6_test = pd.concat([vacX6_test, ohe_test],1)


vacX6_train.drop(columns =['city','zip', 'heat_source', 'sewer_system'], inplace
vacX6_test.drop(columns =['city','zip', 'heat_source', 'sewer_system'], inplace
```

In [191…
```
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
ss.fit(vacX6_train)
vacX6_standardized_train = ss.transform(vacX6_train)
vacX6_standardized_test = ss.transform(vacX6_test)

vacX6_standardized_train.mean(axis = 0)
vacX6_standardized_train.std(axis = 0)

vacX6_standardized_test.mean(axis = 0)
vacX6_standardized_test.std(axis = 0)
```

```
lr.fit(vacX6_train, vacy_train)
lr.score(vacX6_test,vacy_test)
```

Out[191… 0.8318479602164723

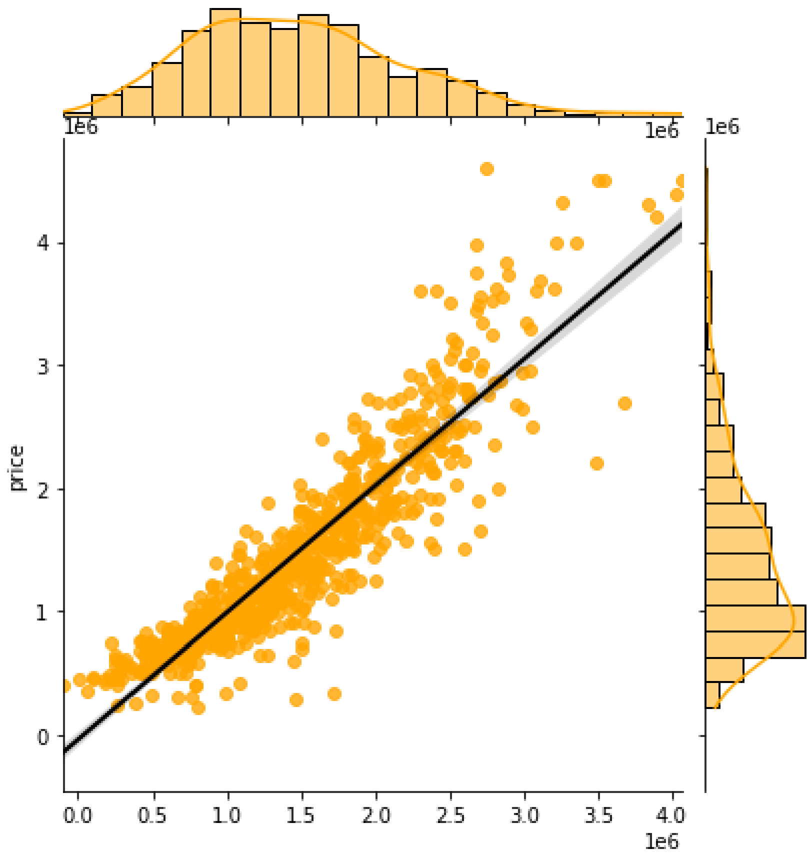
In [192…

```
lr = LinearRegression()
lr.fit(vacX6_train,vacy_train)
print(lr.score(vacX6_train,vacy_train))
print(lr.score(vacX6_test,vacy_test))
preds = lr.predict(vacX6_test)
plt.figure(figsize=(25,5))
sns.jointplot(preds,vacy_test, kind='reg', color='Orange',line_kws={'color':'bla
```

```
0.8330073212947154
0.8318479602164723
```

Out[192… <seaborn.axisgrid.JointGrid at 0x7fbc098363a0>

<Figure size 1800x360 with 0 Axes>



Model Testing 6 Achieved best score - visualization

In [131…

```
modellist=list(zip(lr.coef_,vacX2_train.columns))
#lr.fit(vacX2_train, vacy2_train)
#lr.score(vacX2_train,vacy2_train)
#lr.score(vacX2_test,vacy2_test)
modellist
```

Out[131…

```
[(52916.760262331794, 'bedrooms'),
 (86801.69340594616, 'bathrooms'),
 (0.0700135637670769, 'sqft_lot'),
 (-80265.08094925089, 'floors'),
 (118572.8738786928, 'waterfront'),
```

```
(-13302.098714899757, 'greenbelt'),
(-24759.166365907276, 'nuisance'),
(-27906.283468189962, 'view'),
(13022.83721379617, 'condition'),
(124429.0608942358, 'grade'),
(371.57467980524143, 'sqft_above'),
(219.0900064820762, 'sqft_basement'),
(-114.81030628504232, 'sqft_garage'),
(67.22693765604345, 'sqft_patio'),
(-883.6548278832943, 'yr_built'),
(-74574.37760108912, 'lat'),
(-295826.6958734514, 'long'),
(1169.979215307696, 'persqft'),
(77364.49155036881, 'x0_98001'),
(5.209585651755333e-09, 'x0_98002'),
(-281710.38206275227, 'x0_98003'),
(143149.950866528, 'x0_98004'),
(1731.6791892934089, 'x0_98005'),
(53900.669082951106, 'x0_98006'),
(-120583.24041614066, 'x0_98007'),
(215052.0831083275, 'x0_98008'),
(522472.05800976563, 'x0_98010'),
(-121852.51421577125, 'x0_98011'),
(-272461.73077469296, 'x0_98014'),
(-48186.14371712766, 'x0_98019'),
(-88779.69096958636, 'x0_98022'),
(-912.0279528694518, 'x0_98023'),
(-303546.2826752406, 'x0_98024'),
(-86669.4505901804, 'x0_98027'),
(132361.02075481246, 'x0_98028'),
(-130457.76787927744, 'x0_98029'),
(-236746.40595585306, 'x0_98030'),
(199311.07197219733, 'x0_98031'),
(-61835.678056024655, 'x0_98032'),
(-127634.30947010207, 'x0_98033'),
(157280.33981603387, 'x0_98034'),
(521371.64074446354, 'x0_98038'),
(171919.90695795242, 'x0_98039'),
(-25212.0009703229, 'x0_98040'),
(-50940.80229293739, 'x0_98042'),
(3556.8404747326676, 'x0_98045'),
(240147.94180885892, 'x0_98050'),
(-101975.05288322034, 'x0_98051'),
(-53700.07575923971, 'x0_98052'),
(-178919.5709807905, 'x0_98053'),
(56946.77163040073, 'x0_98055'),
(-54728.49508943068, 'x0_98056'),
(-10685.158020681905, 'x0_98057'),
(-11272.96264225134, 'x0_98058'),
(-4493.645341783464, 'x0_98059'),
(-5058.656677436971, 'x0_98065'),
(-5741.474194240785, 'x0_98070'),
(-110810.23114707628, 'x0_98072'),
(75711.77631963084, 'x0_98074'),
(-75575.08912473521, 'x0_98075'),
(-81560.29145286219, 'x0_98077'),
(-132190.36743934854, 'x0_98092'),
(576670.065180779, 'x0_98102'),
(20558.863148816985, 'x0_98103'),
(49442.06762300822, 'x0_98105'),
(-74558.05263241929, 'x0_98106'),
(93509.06555606687, 'x0_98107'),
(-194054.81844443877, 'x0_98108'),
(-92750.9244471936, 'x0_98109'),
(-294084.7486206509, 'x0_98112'),
```

```
(-48186.143717128114, 'x0_98115'),
(-88779.69096960982, 'x0_98116'),
(-171355.91523587442, 'x0_98117'),
(-912.0279528704123, 'x0_98118'),
(-163254.75200761156, 'x0_98119'),
(16193.82565085555, 'x0_98122'),
(23204.835860988827, 'x0_98125'),
(-43008.635464629115, 'x0_98126'),
(-24474.008482690573, 'x0_98133'),
(-216635.36977720642, 'x0_98136'),
(307794.6585450871, 'x0_98144'),
(-108483.58657286363, 'x0_98146'),
(-18517.262426813162, 'x0_98155'),
(521371.64074446453, 'x0_98166'),
(171919.9069579533, 'x0_98168'),
(-74480.90644711288, 'x0_98177'),
(3556.8404747336463, 'x0_98178'),
(240147.94180886052, 'x0_98188'),
(-101975.05288321612, 'x0_98198'),
(213365.84367238526, 'x0_98199'),
(242070.91229744357, 'x0_98224'),
(-56946.115881533784, 'x0_98270'),
(52871.39330930327, 'x0_98271'),
(-77288.59443016295, 'x0_98288'),
(-117702.16905701644, 'x0_98422'),
(-5066.085891761148, 'x1_Electricity'),
(-5058.656677436818, 'x1_Electricity/Solar'),
(-110810.23114707597, 'x1_Gas'),
(-187444.9621833179, 'x1_Gas/Solar'),
(178485.3487965113, 'x1_Oil'),
(150872.3597356022, 'x1_Oil/Solar'),
(263156.73850290285, 'x1_Other'),
(-124575.00148511802, 'x2_PRIVATE'),
(37378.658315391236, 'x2_PRIVATE RESTRICTED'),
(-31808.5932021088, 'x2_PUBLIC'),
(214224.89467782236, 'x2_PUBLIC RESTRICTED'),
(-127369.64270393329, 'x3_ Auburn'),
(-89537.03824816545, 'x3_ Baring'),
(-126351.61454088354, 'x3_ Bellevue'),
(99552.31852819744, 'x3_ Black Diamond'),
(291051.3911868898, 'x3_ Bothell'),
(88988.43175957378, 'x3_ Burien'),
(-71351.02686214761, 'x3_ Carnation'),
(-6706.30835801224, 'x3_ Clyde Hill'),
(-52607.759254297576, 'x3_ Covington'),
(118602.50833232756, 'x3_ Dash Point'),
(40687.61953694625, 'x3_ Des Moines'),
(-37044.920528342365, 'x3_ Dilworth'),
(-82197.46657615309, 'x3_ Duvall'),
(-60998.79430071217, 'x3_ Enumclaw'),
(-111158.95779957248, 'x3_ Fall City'),
(59900.78439000496, 'x3_ Federal Way'),
(-65528.2785224437, 'x3_ Hobart'),
(-61835.678056022996, 'x3_ Issaquah'),
(-133581.78296361753, 'x3_ Kenmore'),
(-141952.6042042793, 'x3_ Kent'),
(-21286.3610401061, 'x3_ Kirkland'),
(-159228.49298698767, 'x3_ Lake Forest Park'),
(-197751.37747163372, 'x3_ Maple Valley'),
(-46786.81690835094, 'x3_ Marysville'),
(86447.36631366904, 'x3_ Medina'),
(157280.33981603314, 'x3_ Mercer Island'),
(-4493.645341787618, 'x3_ Newcastle'),
(9053.327480168846, 'x3_ Normandy Park'),
(23497.645689979858, 'x3_ North Bend'),
```

```
(-32550.973169733166, 'x3_ Preston'),
(-4251.335851749609, 'x3_ Ravensdale'),
(4251.335852340111, 'x3_ Redmond')]
```

In [132…
```
coeflist=pd.DataFrame(modellist,columns=['Coef',"Feature"])
```

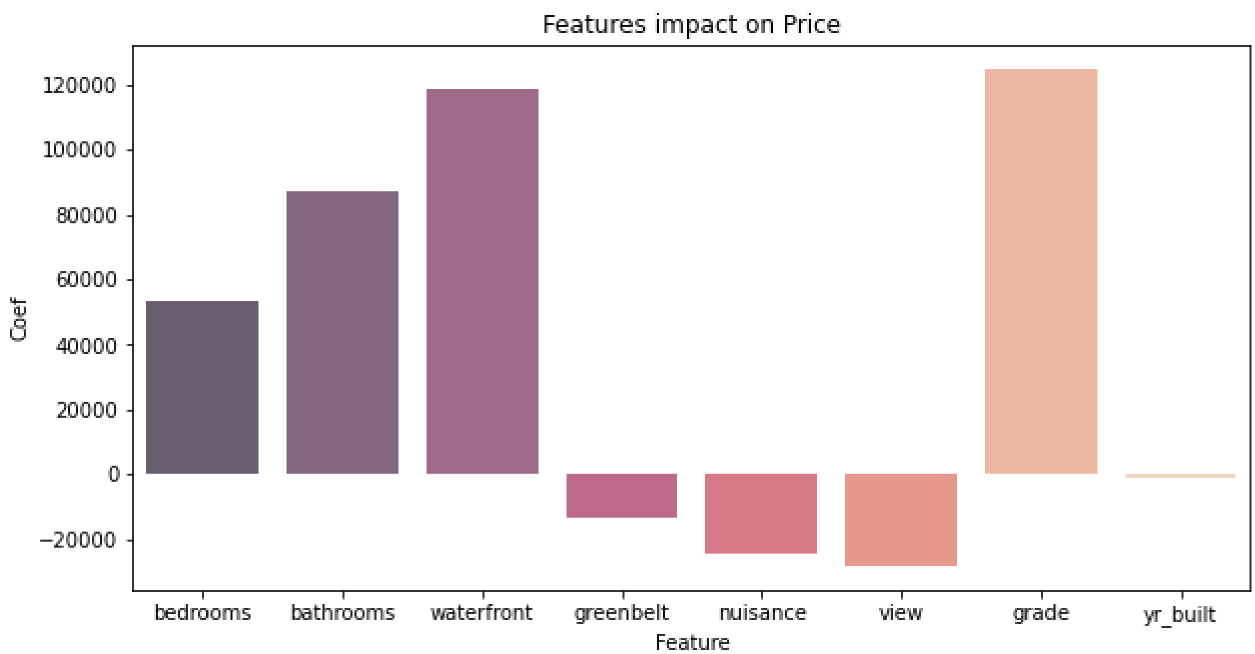
In [133…
```
#analysis of results for general features
ptfeature_general=coeflist.iloc[0:19]
```

In [134…
```
#analysis of results for general features
selected=['bedrooms','bathrooms','grade','waterfront','view','greenbelt','nuisan
```

In [135…
```
#analysis of results for general features
ppt=ptfeature_general['Feature'].isin(selected)
```

In [136…
```
#analysis of results for general features
download=ptfeature_general[ppt]
download.to_csv(f'feature1.csv')
```

In [139…
```
#analysis of results for general features - visualization

plt.figure(figsize=(10,5))
sns.barplot(data=ptfeature_general[ppt],y='Coef',x='Feature',alpha=0.7,palette='
plt.title("Features impact on Price")
plt.show()
```



In [140…
```
selected=['bedrooms','bathrooms','grade','waterfront','view','greenbelt','nuisan
```

In [141…
```
coeflist.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 138 entries, 0 to 137
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   Coef     138 non-null    float64
 1   Feature  138 non-null    object 
```

```
dtypes: float64(1), object(1)
memory usage: 2.3+ KB
```

In [142…

```
coeflist=pd.DataFrame(modellist,columns=['Coef',"Feature"])
```

In [143…

```
#analysis of price results for city - visualization

coecity=coeflist.iloc[106:140]
```

In [153…

```
coecity.Feature=coeflist.Feature.apply(lambda x: x.replace("x3_",""))
```

In [154…

```
coecity
```

Out[154…

	Coef	Feature
106	-127369.642704	Auburn
107	-89537.038248	Baring
108	-126351.614541	Bellevue
109	99552.318528	Black Diamond
110	291051.391187	Bothell
111	88988.431760	Burien
112	-71351.026862	Carnation
113	-6706.308358	Clyde Hill
114	-52607.759254	Covington
115	118602.508332	Dash Point
116	40687.619537	Des Moines
117	-37044.920528	Dilworth
118	-82197.466576	Duvall
119	-60998.794301	Enumclaw
120	-111158.957800	Fall City
121	59900.784390	Federal Way
122	-65528.278522	Hobart
123	-61835.678056	Issaquah
124	-133581.782964	Kenmore
125	-141952.604204	Kent
126	-21286.361040	Kirkland
127	-159228.492987	Lake Forest Park
128	-197751.377472	Maple Valley
129	-46786.816908	Marysville
130	86447.366314	Medina
131	157280.339816	Mercer Island
132	-4493.645342	Newcastle

	Coef	Feature
133	9053.327480	Normandy Park
134	23497.645690	North Bend
135	-32550.973170	Preston
136	-4251.335852	Ravensdale
137	4251.335852	Redmond

In [156…
```
coecity=coecity.rename(columns = {'Feature':'City'})
```

In [157…
```
worstcity=coecity.sort_values('Coef', ascending=False).tail(5)
```

In [158…
```
bestcity=coecity.sort_values('Coef', ascending=False).head(5)
```

In [ ]:
```
bestcity=bestcity.append(worstcity,ignore_index=True)
```

In [159…
```
#analysis of results for general features - visualization

plt.figure(figsize=(10,5))
sns.barplot(data=bestcity,y='Coef',x='City',palette='rocket',alpha=.6)
plt.title("City vs Price")

plt.xticks(rotation=30)
plt.show()
```

In [160…
```
#heat_source and sewer system
coeflist
```

Out[160…

	Coef	Feature
0	52916.760262	bedrooms

	Coef	Feature
1	86801.693406	bathrooms
2	0.070014	sqft_lot
3	-80265.080949	floors
4	118572.873879	waterfront
...	...	...
133	9053.327480	Normandy Park
134	23497.645690	North Bend
135	-32550.973170	Preston
136	-4251.335852	Ravensdale
137	4251.335852	Redmond

138 rows × 2 columns

In [161…

```
#heat_source and sewer system analysis
ptfeature_heat_sewer=coeflist.iloc[95:106]
ptfeature_heat_sewer
```

Out[161…

	Coef	Feature
95	-5066.085892	Electricity
96	-5058.656677	Electricity/Solar
97	-110810.231147	Gas
98	-187444.962183	Gas/Solar
99	178485.348797	Oil
100	150872.359736	Oil/Solar
101	263156.738503	Other
102	-124575.001485	PRIVATE
103	37378.658315	PRIVATE RESTRICTED
104	-31808.593202	PUBLIC
105	214224.894678	PUBLIC RESTRICTED

In [163…

```
ptfeature_heat_sewer.Feature=ptfeature_heat_sewer.Feature.apply(lambda x: x.repl
```

In [164…

```
addlist=['heat','heat','heat','heat','heat','heat','heat','sewer','sewer','sewer
```

In [165…

```
ptfeature_heat_sewer['type']=np.array(addlist)
```

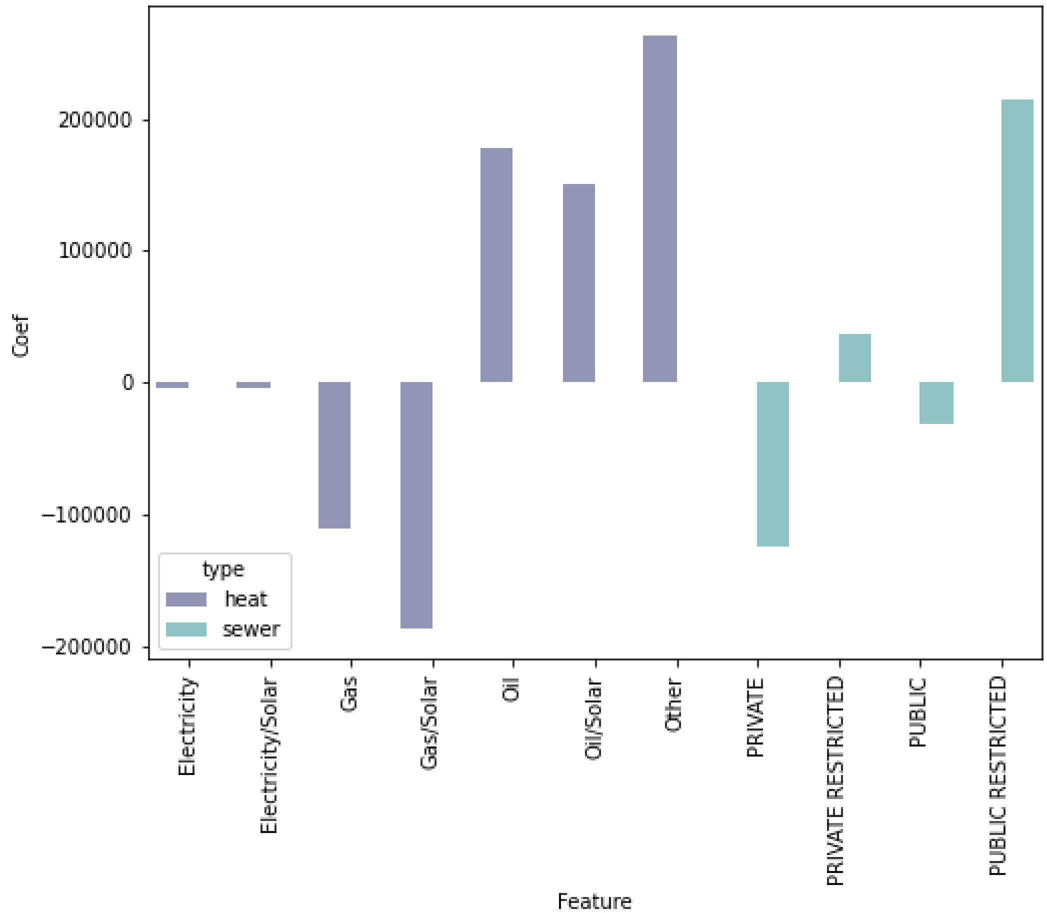
In [166…

```
plt.figure(figsize=(8,6))
sns.barplot(x=ptfeature_heat_sewer['Feature'],y=ptfeature_heat_sewer['Coef'],hue
plt.xticks(rotation=90)
```

Out[166…

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10]),
 [Text(0, 0, 'Electricity'),
```

```
 Text(1, 0, 'Electricity/Solar'),
 Text(2, 0, 'Gas'),
 Text(3, 0, 'Gas/Solar'),
 Text(4, 0, 'Oil'),
 Text(5, 0, 'Oil/Solar'),
 Text(6, 0, 'Other'),
 Text(7, 0, 'PRIVATE'),
 Text(8, 0, 'PRIVATE RESTRICTED'),
 Text(9, 0, 'PUBLIC'),
 Text(10, 0, 'PUBLIC RESTRICTED')])
```



In [167…

```
zipinfo=vacation_housedata.groupby('zip')['price','bedrooms'].mean().round(2)
```

In [168…

```
zipinfo
```

Out[168…

zip	price	bedrooms
98001	772100.41	3.51
98002	731390.00	3.20
98003	899564.10	3.51
98004	3366861.78	4.02
98005	2054548.73	3.92
...	...	...
98199	1854607.97	3.43
98270	2375000.00	4.00

	price	bedrooms
zip		
98271	2750000.00	3.00
98288	654750.00	2.75
98422	312750.00	3.00

76 rows × 2 columns

In [170…

```
zipinfo
```

Out[170…

	price	bedrooms
zip		
98001	772100.41	3.51
98002	731390.00	3.20
98003	899564.10	3.51
98004	3366861.78	4.02
98005	2054548.73	3.92
...	...	...
98199	1854607.97	3.43
98270	2375000.00	4.00
98271	2750000.00	3.00
98288	654750.00	2.75
98422	312750.00	3.00

76 rows × 2 columns

In [174…

```
vacation_housedata['year']=pd.DatetimeIndex(vacation_housedata['date']).year
vacation_housedata['year']
```

Out[174…

```
1        2021
2        2021
3        2021
6        2021
9        2021
         ...
30098    2021
30114    2022
30120    2021
30145    2021
30151    2021
Name: year, Length: 3925, dtype: int64
```

In [175…

```
vacation_housedata['month']=pd.DatetimeIndex(vacation_housedata['date']).month
vacation_housedata['month']
```

Out[175…

```
1        12
2         9
3        12
```

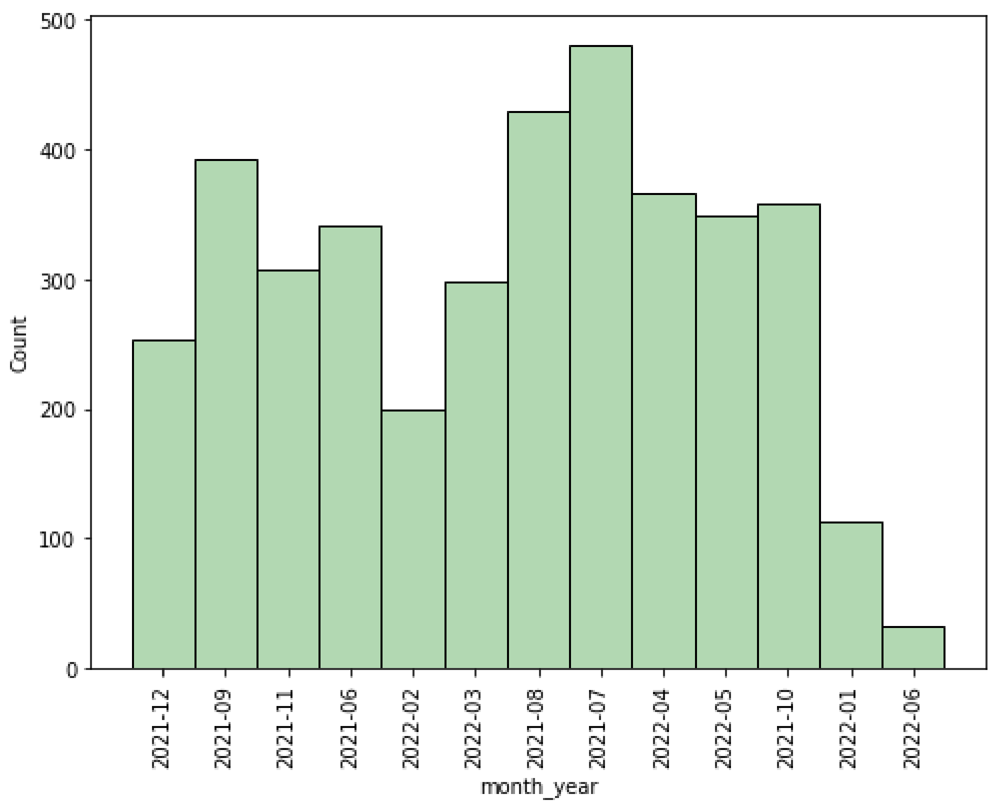
```
6         11
9          6
          ..
30098      8
30114      2
30120      8
30145     12
30151      6
Name: month, Length: 3925, dtype: int64
```

In [176…
```
vacation_housedata['month_year'] = pd.to_datetime(vacation_housedata['date']).dt
vacation_housedata['date']=vacation_housedata['date'].sort_values(ascending=True
```

In [177…
```
vacation_housedata['month_year']=vacation_housedata['month_year'].astype(str)
```

In [178…
```
plt.figure(figsize=(8,6))
sns.histplot(data=vacation_housedata,x=vacation_housedata['month_year'],color='g
plt.xticks(rotation=90)
```

Out[178…
```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12],
 [Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, '')])
```



In [ ]:
```
#failed to create a map..
import folium
```

```
home_locations = finalmapdata[['long','lat','price']]
map = folium.Map(location =[finalmapdata.lat.mean(),finalmapdata.long.mean()],zo
for x, location_info in finalmapdata.iterrows():
folium.Marker([location_info["lat"], location_info["long"]], popup=location_info
display(map)
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: