In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler,PolynomialFeatures
from sklearn.linear_model import LinearRegression
%matplotlib inline
```

In [2]:
```
# Load the dataset
filepath = "kc_house_data.csv"
df = pd.read_csv(filepath)
```

In [3]:
```
# first 5 rows
df.head()
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	w
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	

5 rows × 21 columns

In [4]:
```
# datatypes for all columns
df.dtypes
```

Out[4]:
```
id                 int64
date              object
price            float64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
grade              int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

In [5]:
```
# drop the id column
df.drop("id",axis=1,inplace=True)
df.describe()
```

Out[5]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	
count	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04	21613.000000	216
mean	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+04	1.494309	
std	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+04	0.539989	
min	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02	1.000000	
25%	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	

In [6]:
```
# look for missing values
print("Missing Values")
for column in df.columns:
    print(f"{column} = {df[column].isnull().sum()}")
```

```
Missing Values
date = 0
price = 0
bedrooms = 0
bathrooms = 0
sqft_living = 0
sqft_lot = 0
floors = 0
waterfront = 0
view = 0
condition = 0
grade = 0
sqft_above = 0
sqft_basement = 0
yr_built = 0
yr_renovated = 0
zipcode = 0
lat = 0
long = 0
sqft_living15 = 0
sqft_lot15 = 0
```

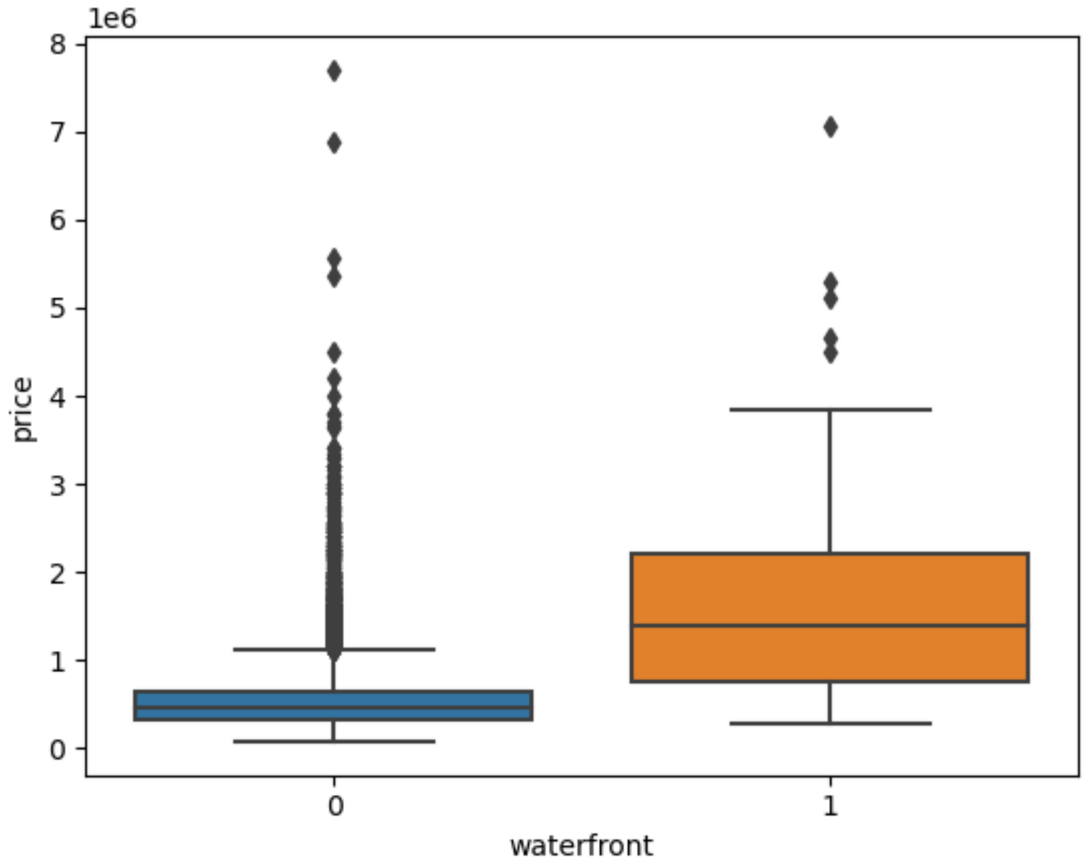
In [7]:
```
# count the number of houses with unique floor values
df["floors"].value_counts().to_frame()
```

Out[7]:

	floors
1.0	10680
2.0	8241
1.5	1910
3.0	613
2.5	161
3.5	8

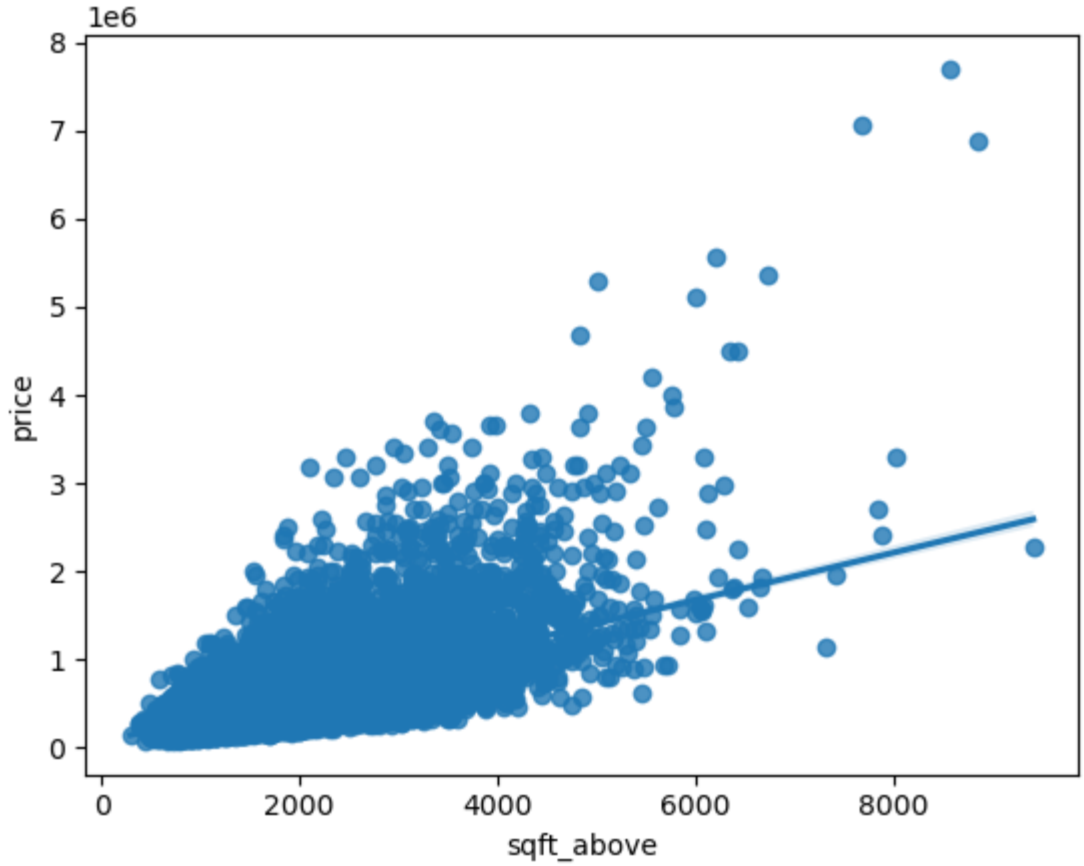
In [8]:
```
# Correlation between houses with a waterfront view and price
# no waterfront = 0
# waterfront =  1

sns.boxplot(data=df,x="waterfront",y="price")
```

Out[8]:
```
<AxesSubplot:xlabel='waterfront', ylabel='price'>
```



In [9]:
```
# sqft_above: Square footage of house apart from basement
# correlation between square footage and price
sns.regplot(data=df,x="sqft_above",y="price")
```

Out[9]: <AxesSubplot:xlabel='sqft_above', ylabel='price'>



In [10]:
```
print("It shows a positive relation")
```

It shows a positive relation

In [11]:
```
# correlation with other features
df.corr()['price'].sort_values()
```

Out[11]:
```
zipcode         -0.053203
long             0.021626
condition        0.036362
yr_built         0.054012
sqft_lot15       0.082447
sqft_lot         0.089661
yr_renovated     0.126434
floors           0.256794
waterfront       0.266369
lat              0.307003
bedrooms         0.308350
sqft_basement    0.323816
view             0.397293
bathrooms        0.525138
sqft_living15    0.585379
sqft_above       0.605567
grade            0.667434
sqft_living      0.702035
price            1.000000
Name: price, dtype: float64
```

In [12]:
```
print("sqft_living shows a pearson coefficent of 0.702035 which indicates mode
```

```
sqft_living shows a pearson coefficent of 0.702035 which indicates moderate p
ositive relation with price
```

In [13]:
```
# linear regression model to predict the 'price' using the feature 'sqft_livin

# get the features
X = df[["sqft_living"]]
Y =  df['price']

# fit the model
linear_reg = LinearRegression().fit(X,Y)
```

In [14]:
```
# get the R^2 score
print(f"The R^2 score is {linear_reg.score(X,Y)}")
```

```
The R^2 score is 0.4928532179037931
```

In [15]:
```
# create a multiple linear regression to predict price

# each feature has a pearson coefficent > 0.25
features =["floors", "waterfront","lat" ,"bedrooms" ,"sqft_basement" ,"view" ,
X = df[features]

# fit the model
linear_reg = LinearRegression().fit(X,Y)
```

In [16]:
```
# get the R^2 score
print(f"The R^2 score is {linear_reg.score(X,Y)}")
```

```
The R^2 score is 0.6577151058279331
```

In [17]:
```
# create a polynomial regression model using pipelining

Input=[
    ('scale',StandardScaler()),
    ('polynomial', PolynomialFeatures(include_bias=False)),
    ('model',LinearRegression())
]

# create pipeline
pipeline = Pipeline(Input)

# fit pipeline
pipeline.fit(X,Y)
```

Out[17]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('polynomial', PolynomialFeatures(include_bias=False)),
                ('model', LinearRegression())])
```

In [18]:
```
# get the R^2 score
print(f"The R^2 score is {pipeline.score(X,Y)}")
```

```
The R^2 score is 0.7513468418265049
```

In [19]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
```

In [20]:
```
features =["floors", "waterfront","lat" ,"bedrooms" ,"sqft_basement" ,"view" ,
X = df[features]
Y = df['price']

x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.15, rand


print("number of test samples:", x_test.shape[0])
print("number of training samples:",x_train.shape[0])
```

```
number of test samples: 3242
number of training samples: 18371
```

In [21]:
```
# create a ridge regression
from sklearn.linear_model import Ridge

ridge_regression = Ridge(alpha=0.1)
ridge_regression.fit(x_train,y_train)
```

Out[21]:
```
Ridge(alpha=0.1)
```

In [22]:
```
# get the R^2 score
print(f"The R^2 score is {ridge_regression.score(x_test,y_test)}")
```

```
The R^2 score is 0.6480374087702243
```

In [23]:
```
# create a ridge regression with feature transformation
# feature transform for second degree polynomial
pf = PolynomialFeatures(degree=2)
x_train_transform = pf.fit_transform(x_train)
x_test_transform = pf.fit_transform(x_test)
```

In [24]:
```
# create a ridge regression
ridge_regression2 = Ridge(alpha=0.1)
ridge_regression2.fit(x_train_transform,y_train)
```

Out[24]:
```
Ridge(alpha=0.1)
```

In [25]:
```
# get the R^2 score
print(f"The R^2 score is {ridge_regression2.score(x_test_transform,y_test)}")
```

```
The R^2 score is 0.7004432066573696
```

In [ ]:
```
```