# Step 1: Import necessary libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear\_model import LinearRegression, Ridge
from sklearn.model\_selection import train\_test\_split
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.pipeline import Pipeline

df = pd.read\_csv("kc\_house\_data.csv")
df.head()

| ₹ |   | id         | date            | price    | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view | • • • | grade | sqft_abov |
|---|---|------------|-----------------|----------|----------|-----------|-------------|----------|--------|------------|------|-------|-------|-----------|
|   | 0 | 7129300520 | 20141013T000000 | 221900.0 | 3        | 1.00      | 1180        | 5650     | 1.0    | 0          | 0    |       | 7     | 1180.     |
|   | 1 | 6414100192 | 20141209T000000 | 538000.0 | 3        | 2.25      | 2570        | 7242     | 2.0    | 0          | 0    |       | 7     | 2170.     |
|   | 2 | 5631500400 | 20150225T000000 | 180000.0 | 2        | 1.00      | 770         | 10000    | 1.0    | 0          | 0    |       | 6     | 770.      |
|   | 3 | 2487200875 | 20141209T000000 | 604000.0 | 4        | 3.00      | 1960        | 5000     | 1.0    | 0          | 0    |       | 7     | 1050.     |
|   | 4 | 1954400510 | 20150218T000000 | 510000.0 | 3        | 2.00      | 1680        | 8080     | 1.0    | 0          | 0    |       | 8     | 1680.     |

5 rows × 21 columns

# Step 3: Display data types of each column
df.describe()

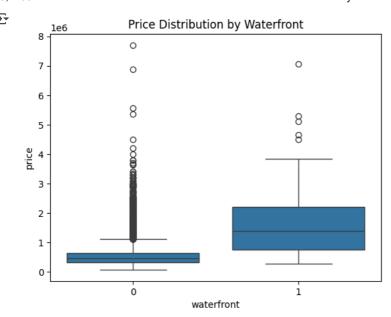
| ₹ | id    |              | price        | bedrooms     | bathrooms sqft_living |              | sqft_lot floors |              | waterfront   | view         |     |
|---|-------|--------------|--------------|--------------|-----------------------|--------------|-----------------|--------------|--------------|--------------|-----|
|   | count | 2.161300e+04 | 2.161300e+04 | 21613.000000 | 21613.000000          | 21613.000000 | 2.161300e+04    | 21613.000000 | 21613.000000 | 21613.000000 | 216 |
|   | mean  | 4.580302e+09 | 5.400881e+05 | 3.370842     | 2.114757              | 2079.899736  | 1.510697e+04    | 1.494309     | 0.007542     | 0.234303     |     |
|   | std   | 2.876566e+09 | 3.671272e+05 | 0.930062     | 0.770163              | 918.440897   | 4.142051e+04    | 0.539989     | 0.086517     | 0.766318     |     |
|   | min   | 1.000102e+06 | 7.500000e+04 | 0.000000     | 0.000000              | 290.000000   | 5.200000e+02    | 1.000000     | 0.000000     | 0.000000     |     |
|   | 25%   | 2.123049e+09 | 3.219500e+05 | 3.000000     | 1.750000              | 1427.000000  | 5.040000e+03    | 1.000000     | 0.000000     | 0.000000     |     |
|   | 50%   | 3.904930e+09 | 4.500000e+05 | 3.000000     | 2.250000              | 1910.000000  | 7.618000e+03    | 1.500000     | 0.000000     | 0.000000     |     |
|   | 75%   | 7.308900e+09 | 6.450000e+05 | 4.000000     | 2.500000              | 2550.000000  | 1.068800e+04    | 2.000000     | 0.000000     | 0.000000     |     |
|   | max   | 9.900000e+09 | 7.700000e+06 | 33.000000    | 8.000000              | 13540.000000 | 1.651359e+06    | 3.500000     | 1.000000     | 4.000000     |     |

floor\_counts = df["floors"].value\_counts().to\_frame()
floor\_counts.columns = ['count']
print(floor\_counts)

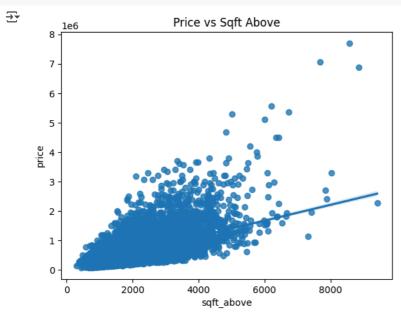
```
count floors

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

# Step 6: Boxplot to check price outliers by waterfront view
sns.boxplot(x="waterfront", y="price", data=df)
plt.title("Price Distribution by Waterfront")
plt.show()



```
# Step 7: regplot to check correlation between 'sqft_above' and 'price'
sns.regplot(x="sqft_above", y="price", data=df)
plt.title("Price vs Sqft Above")
plt.show()
```



```
# Step 8: Linear Regression with single feature 'sqft_living'
lr = LinearRegression()
lr.fit(df[['sqft_living']], df['price'])
print("R^2 (sqft_living):", lr.score(df[['sqft_living']], df['price']))
```

R^2 (sqft\_living): 0.4928532179037931

R^2 (multiple features): 0.6577312410909923

```
# Step 10: Train/Test split for model validation
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
# Step 11: Pipeline - Scale, Polynomial Transform, Linear Regression
pipe = Pipeline([
    ('scale', StandardScaler()),
    ('poly', PolynomialFeatures(degree=2)),
    ('model', LinearRegression())
])
pipe.fit(X_train, y_train)
print("R^2 (Pipeline Polynomial Regression):", pipe.score(X_test, y_test))
R^2 (Pipeline Polynomial Regression): 0.7530582530920498
# Step 12: Ridge Regression (Linear)
ridge = Ridge(alpha=0.1)
ridge.fit(X_train, y_train)
print("R^2 (Ridge Regression):", ridge.score(X_test, y_test))
→ R^2 (Ridge Regression): 0.673131854065206
# Step 13: Ridge Regression (Polynomial Features)
poly = PolynomialFeatures(degree=2)
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)
ridge_poly = Ridge(alpha=0.1)
ridge_poly.fit(X_train_poly, y_train)
\label{lem:print("R^2 (Polynomial Ridge):", ridge_poly.score(X_test_poly, y_test))} \\
```

R^2 (Polynomial Ridge): 0.7442033165284614