Data Analytics for house pricing dataset

October 1, 2024

0.1 The Dataset

Variable	Description
id	A notation for a house
date	Date house was sold
price	Price is prediction target
bedrooms	Number of bedrooms
bathrooms	Number of bathrooms
sqft_living	Square footage of the home
sqft_lot	Square footage of the lot
floors	Total floors (levels) in house
waterfront	House which has a view to a waterfront
view	Has been viewed
condition	How good the condition is overall
grade	overall grade given to the housing unit, based on King County grading system
sqft_above	Square footage of house apart from basement
sqft_basement	Square footage of the basement
yr_built	Built Year
yr_renovated	Year when house was renovated
zipcode	Zip code
lat	Latitude coordinate
long	Longitude coordinate
sqft_living15	Living room area in 2015(implies– some renovations) This might or might not have affected the lotsize area
sqft_lot15	LotSize area in 2015(implies– some renovations)

0.2 Import the required libraries

[69]:
```
# Surpress warnings:
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

```python
import seaborn as sns
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler,PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
%matplotlib inline
```

1 Module 1: Importing Data Sets

[25]:
```python
filepath='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/FinalModule_Coursera/
↪data/kc_house_data_NaN.csv'
df = pd.read_csv(filepath)
```

[26]:
```python
df.head()
```

[26]:
```
   Unnamed: 0          id             date     price  bedrooms  bathrooms  \
0           0  7129300520  20141013T000000  221900.0       3.0       1.00
1           1  6414100192  20141209T000000  538000.0       3.0       2.25
2           2  5631500400  20150225T000000  180000.0       2.0       1.00
3           3  2487200875  20141209T000000  604000.0       4.0       3.00
4           4  1954400510  20150218T000000  510000.0       3.0       2.00

   sqft_living  sqft_lot  floors  waterfront  …  grade  sqft_above  \
0         1180      5650     1.0           0  …      7        1180
1         2570      7242     2.0           0  …      7        2170
2          770     10000     1.0           0  …      6         770
3         1960      5000     1.0           0  …      7        1050
4         1680      8080     1.0           0  …      8        1680

   sqft_basement  yr_built  yr_renovated  zipcode      lat     long  \
0              0      1955             0    98178  47.5112 -122.257
1            400      1951          1991    98125  47.7210 -122.319
2              0      1933             0    98028  47.7379 -122.233
3            910      1965             0    98136  47.5208 -122.393
4              0      1987             0    98074  47.6168 -122.045

   sqft_living15  sqft_lot15
0           1340        5650
1           1690        7639
2           2720        8062
3           1360        5000
4           1800        7503

[5 rows x 22 columns]
```

1.0.1 Question 1

Display the data types of each column using the function dtypes. Take a screenshot of your code and output. You will need to submit the screenshot for the final project.

[27]:
```
df.dtypes
```

[27]:
```
Unnamed: 0         int64
id                 int64
date              object
price            float64
bedrooms         float64
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
```

We use the method describe to obtain a statistical summary of the dataframe.

[28]:
```
df.describe()
```

[28]:
```
        Unnamed: 0            id         price      bedrooms     bathrooms  \
count  21613.00000  2.161300e+04  2.161300e+04  21600.000000  21603.000000
mean   10806.00000  4.580302e+09  5.400881e+05      3.372870      2.115736
std     6239.28002  2.876566e+09  3.671272e+05      0.926657      0.768996
min        0.00000  1.000102e+06  7.500000e+04      1.000000      0.500000
25%     5403.00000  2.123049e+09  3.219500e+05      3.000000      1.750000
50%    10806.00000  3.904930e+09  4.500000e+05      3.000000      2.250000
75%    16209.00000  7.308900e+09  6.450000e+05      4.000000      2.500000
max    21612.00000  9.900000e+09  7.700000e+06     33.000000      8.000000

        sqft_living      sqft_lot        floors    waterfront          view  \
count  21613.000000  2.161300e+04  21613.000000  21613.000000  21613.000000
mean    2079.899736  1.510697e+04      1.494309      0.007542      0.234303
std      918.440897  4.142051e+04      0.539989      0.086517      0.766318
```

```
min      290.000000  5.200000e+02     1.000000     0.000000     0.000000
25%     1427.000000  5.040000e+03     1.000000     0.000000     0.000000
50%     1910.000000  7.618000e+03     1.500000     0.000000     0.000000
75%     2550.000000  1.068800e+04     2.000000     0.000000     0.000000
max    13540.000000  1.651359e+06     3.500000     1.000000     4.000000

       …         grade    sqft_above  sqft_basement      yr_built  \
count  …  21613.000000  21613.000000   21613.000000  21613.000000
mean   …      7.656873   1788.390691     291.509045   1971.005136
std    …      1.175459    828.090978     442.575043     29.373411
min    …      1.000000    290.000000       0.000000   1900.000000
25%    …      7.000000   1190.000000       0.000000   1951.000000
50%    …      7.000000   1560.000000       0.000000   1975.000000
75%    …      8.000000   2210.000000     560.000000   1997.000000
max    …     13.000000   9410.000000    4820.000000   2015.000000

       yr_renovated       zipcode           lat          long  sqft_living15  \
count  21613.000000  21613.000000  21613.000000  21613.000000   21613.000000
mean      84.402258  98077.939805     47.560053   -122.213896    1986.552492
std      401.679240     53.505026      0.138564      0.140828     685.391304
min        0.000000  98001.000000     47.155900   -122.519000     399.000000
25%        0.000000  98033.000000     47.471000   -122.328000    1490.000000
50%        0.000000  98065.000000     47.571800   -122.230000    1840.000000
75%        0.000000  98118.000000     47.678000   -122.125000    2360.000000
max     2015.000000  98199.000000     47.777600   -121.315000    6210.000000

          sqft_lot15
count   21613.000000
mean    12768.455652
std     27304.179631
min       651.000000
25%      5100.000000
50%      7620.000000
75%     10083.000000
max    871200.000000

[8 rows x 21 columns]
```

2 Module 2: Data Wrangling

2.0.1 Question 2

Drop the columns "id" and "Unnamed: 0" from axis 1 using the method drop(), then use the method describe() to obtain a statistical summary of the data. Make sure the inplace parameter is set to True. Take a screenshot of your code and output. You will need to submit the screenshot for the final project.

[29]:
```
df.drop(["id", "Unnamed: 0"], axis=1, inplace=True)
```

[30]:
```
df.describe()
```

[30]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	2.161300e+04	21600.000000	21603.000000	21613.000000	2.161300e+04
mean	5.400881e+05	3.372870	2.115736	2079.899736	1.510697e+04
std	3.671272e+05	0.926657	0.768996	918.440897	4.142051e+04
min	7.500000e+04	1.000000	0.500000	290.000000	5.200000e+02
25%	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06

	floors	waterfront	view	condition	grade
count	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000
mean	1.494309	0.007542	0.234303	3.409430	7.656873
std	0.539989	0.086517	0.766318	0.650743	1.175459
min	1.000000	0.000000	0.000000	1.000000	1.000000
25%	1.000000	0.000000	0.000000	3.000000	7.000000
50%	1.500000	0.000000	0.000000	3.000000	7.000000
75%	2.000000	0.000000	0.000000	4.000000	8.000000
max	3.500000	1.000000	4.000000	5.000000	13.000000

	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode
count	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000
mean	1788.390691	291.509045	1971.005136	84.402258	98077.939805
std	828.090978	442.575043	29.373411	401.679240	53.505026
min	290.000000	0.000000	1900.000000	0.000000	98001.000000
25%	1190.000000	0.000000	1951.000000	0.000000	98033.000000
50%	1560.000000	0.000000	1975.000000	0.000000	98065.000000
75%	2210.000000	560.000000	1997.000000	0.000000	98118.000000
max	9410.000000	4820.000000	2015.000000	2015.000000	98199.000000

	lat	long	sqft_living15	sqft_lot15
count	21613.000000	21613.000000	21613.000000	21613.000000
mean	47.560053	-122.213896	1986.552492	12768.455652
std	0.138564	0.140828	685.391304	27304.179631
min	47.155900	-122.519000	399.000000	651.000000
25%	47.471000	-122.328000	1490.000000	5100.000000
50%	47.571800	-122.230000	1840.000000	7620.000000
75%	47.678000	-122.125000	2360.000000	10083.000000
max	47.777600	-121.315000	6210.000000	871200.000000

[31]:
```
df.isna().sum()
```

[31]:
```
date              0
price             0
bedrooms         13
bathrooms        10
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
dtype: int64
```

We can see we have missing values for the columns bedrooms and bathrooms

[32]:
```
print("number of NaN values for the column bedrooms :", df['bedrooms'].isnull().
 ↪sum())
print("number of NaN values for the column bathrooms :", df['bathrooms'].
 ↪isnull().sum())
```

```
number of NaN values for the column bedrooms : 13
number of NaN values for the column bathrooms : 10
```

[33]:
```
mean = df['bedrooms'].mean()
df.replace(np.nan, mean, inplace=True)
```

[35]:
```
mean2 = df['bathrooms'].mean()
df.replace(np.nan, mean, inplace=True)
```

[36]:
```
print("number of NaN values for the column bedrooms :", df['bedrooms'].isnull().
 ↪sum())
print("number of NaN values for the column bathrooms :", df['bathrooms'].
 ↪isnull().sum())
```

```
number of NaN values for the column bedrooms : 0
number of NaN values for the column bathrooms : 0
```

3 Module 3: Exploratory Data Analysis

3.0.1 Question 3

Use the method value_counts to count the number of houses with unique floor values, use the method .to_frame() to convert it to a data frame. Take a screenshot of your code and output. You will need to submit the screenshot for the final project.

[43]:
```
df['floors'].value_counts().to_frame()
```

[43]:

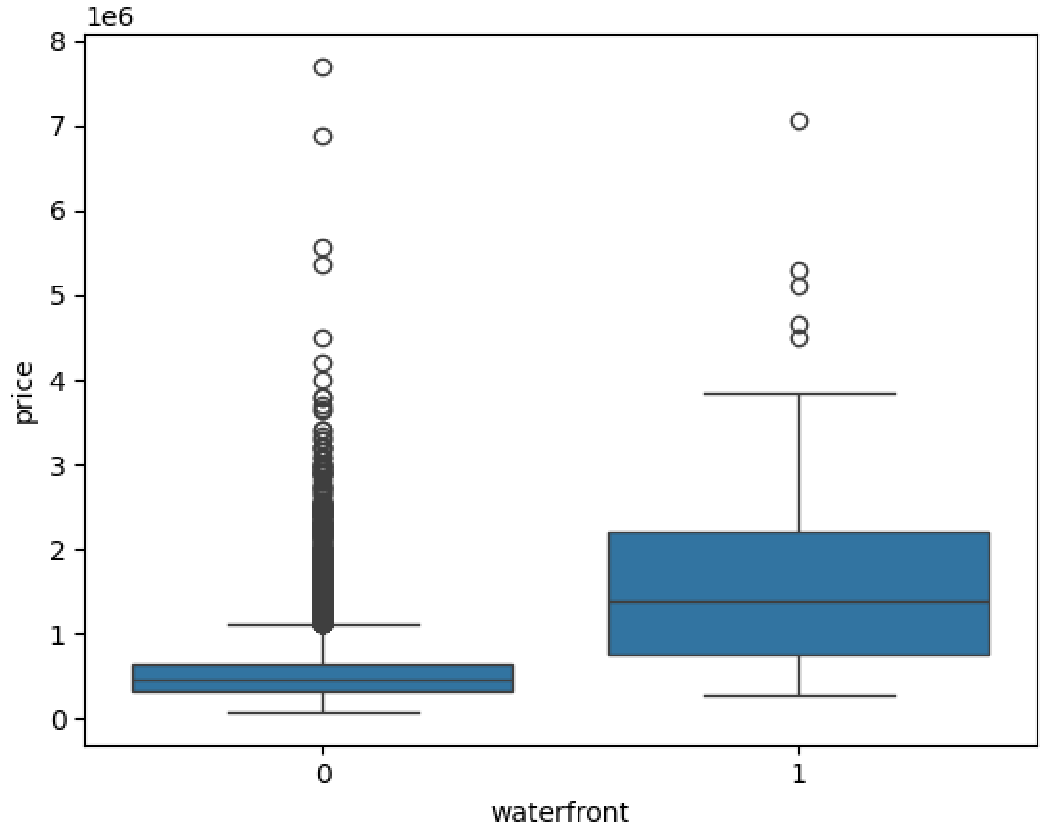
	count
floors	
1.0	10680
2.0	8241
1.5	1910
3.0	613
2.5	161
3.5	8

3.0.2 Question 4

Use the function boxplot in the seaborn library to determine whether houses with a waterfront view or without a waterfront view have more price outliers. Take a screenshot of your code and boxplot. You will need to submit the screenshot for the final project.

[44]:
```
sns.boxplot ( x= 'waterfront', y= 'price', data=df)
```

[44]:
```
<Axes: xlabel='waterfront', ylabel='price'>
```

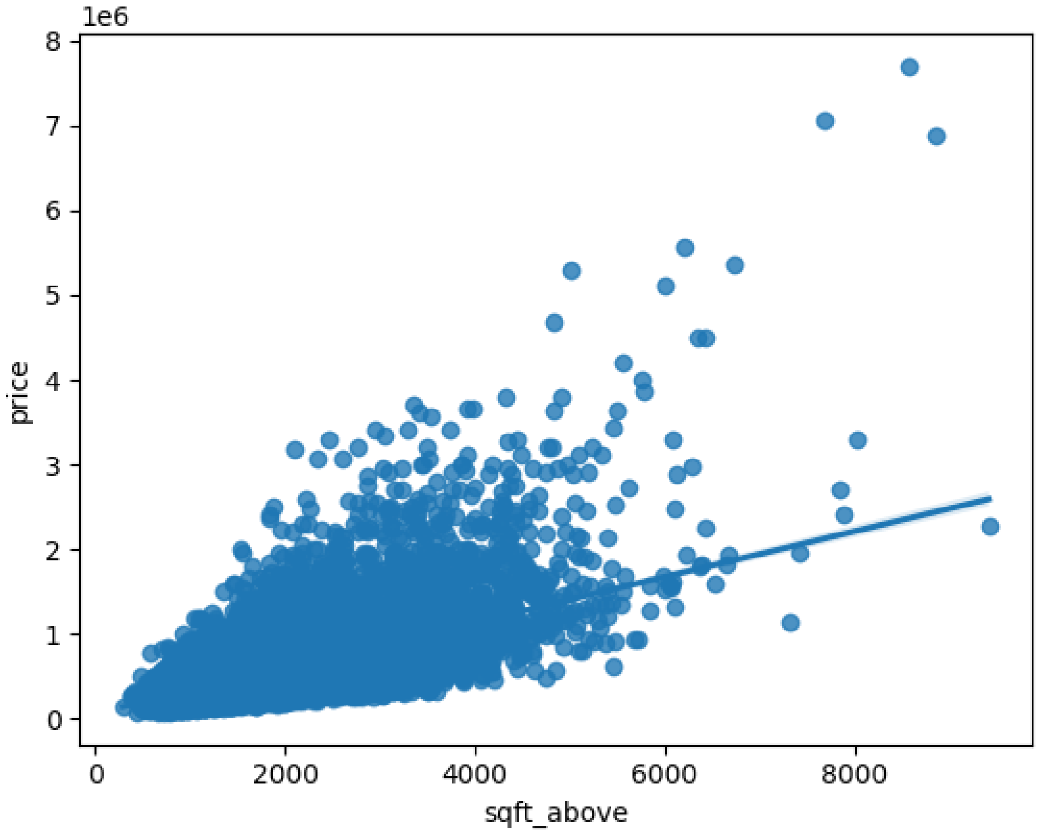


3.0.3 Question 5

Use the function regplot in the seaborn library to determine if the feature sqft_above is negatively or positively correlated with price. Take a screenshot of your code and scatterplot. You will need to submit the screenshot for the final project.

[45]:
```
sns.regplot( x='sqft_above', y='price', data=df)
```

[45]:
```
<Axes: xlabel='sqft_above', ylabel='price'>
```



[49]:
```
df.dtypes
```

[49]:
```
date              object
price            float64
bedrooms         float64
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
```

[50]:
```
# Drop the 'date' column
df_numeric = df.drop(columns=['date'])

# Calculate the correlation matrix for numeric columns only
correlation_matrix = df_numeric.corr()

# Get the correlation values with respect to 'price' and sort them
price_correlation = correlation_matrix['price'].sort_values()
print(price_correlation)
```

```
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         0.308797
sqft_basement    0.323816
view             0.397293
bathrooms        0.525223
sqft_living15    0.585379
sqft_above       0.605567
grade            0.667434
sqft_living      0.702035
price            1.000000
Name: price, dtype: float64
```

4 Module 4: Model Development

We can Fit a linear regression model using the longitude feature 'long' and caculate the R^2.

[51]:
```
X = df[['long']]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)
lm.score(X, Y)
```

[51]: 0.00046769430149007363

4.0.1 Question 6

Fit a linear regression model to predict the 'price' using the feature 'sqft_living' then calculate the R^2. Take a screenshot of your code and the value of the R^2. You will need to submit it for the final project.

[52]:
```
X= df[['sqft_living']]
Y= df['price']
lm= LinearRegression()
lm.fit(X,Y)
lm.score(X,Y)
```

[52]:
```
0.4928532179037931
```

4.0.2 Question 7

Fit a linear regression model to predict the 'price' using the list of features:

[64]:
```
features = df[["floors", "waterfront","lat" ,"bedrooms" ,"sqft_basement",␣
↪,"view" ,"bathrooms","sqft_living15","sqft_above","grade","sqft_living"]]
```

Then calculate the R^2. Take a screenshot of your code and the value of the R^2. You will need to submit it for the final project.

[65]:
```
lm.fit(features,Y)
lm.score(features,Y)
```

[65]:
```
0.6576153966053727
```

4.0.3 This will help with Question 8

Create a list of tuples, the first element in the tuple contains the name of the estimator:

'scale'

'polynomial'

'model'

The second element in the tuple contains the model constructor

StandardScaler()

PolynomialFeatures(include_bias=False)

LinearRegression()

[67]:
```
Input = [('scale', StandardScaler()), ('polynomial',␣
↪PolynomialFeatures(include_bias = False)), ('model', LinearRegression())]
```

4.0.4 Question 8

Use the list to create a pipeline object to predict the 'price', fit the object using the features in the list features, and calculate the R^2. Take a screenshot of your code and the value of the R^2. You will need to submit it for the final project.

[70]:
```
pipe = Pipeline(Input)
features = features.astype(float)
pipe.fit (features, Y)
ypipe = pipe.predict(features)
r2_score(Y, ypipe)
```

[70]:
```
0.7499839618515916
```

5 Module 5: Model Evaluation and Refinement

[71]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
```

We will split the data into training and testing sets:

[72]:
```
features =["floors", "waterfront","lat" ,"bedrooms" ,"sqft_basement" ,"view"␣
 ↪,"bathrooms","sqft_living15","sqft_above","grade","sqft_living"]
X = df[features]
Y = df['price']

x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.15,␣
 ↪random_state=1)


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
```

5.0.1 Question 9

Create and fit a Ridge regression object using the training data, set the regularization parameter to 0.1, and calculate the R^2 using the test data. Take a screenshot of your code and the value of the R^2. You will need to submit it for the final project.

[73]:
```
from sklearn.linear_model import Ridge

ridge_model = Ridge(alpha=0.1)
ridge_model.fit(x_train, y_train)
yridge = ridge_model.predict(x_test)
r2_score( y_test, yridge)
```

[73]: 0.6478659006870546

5.0.2 Question 10

Perform a second order polynomial transform on both the training data and testing data. Create and fit a Ridge regression object using the training data, set the regularisation parameter to 0.1, and calculate the R^2 utilising the test data provided. Take a screenshot of your code and the R^2. You will need to submit it for the final project.

[76]:
```
poly = PolynomialFeatures(degree = 2)
x_train_poly = poly.fit_transform(x_train)
x_test_poly = poly.fit_transform(x_test)
ridge_model.fit(x_train_poly, y_train)
yhat = ridge_model.predict(x_test_poly)
r2_score(y_test, yhat)
```

[76]: 0.7001498445907909

[ ]:
```
```