Skills Network

Final Project: House Sales in King County, USA

Table of Contents

Estimated Time Needed: **75 min**

Instructions

In this assignment, you are a Data Analyst working at a Real Estate Investment Trust. The Trust would like to start investing in Residential real estate. You are tasked with determining the market price of a house given a set of features. You will analyze and predict housing prices using attributes or features such as square footage, number of bedrooms, number of floors, and so on. This is a template notebook; your job is to complete the ten questions. Some hints to the questions are given.

As you are completing this notebook, take and save the **screenshots** of the final outputs of your solutions (e.g., final charts, tables, calculation results etc.). They will need to be shared in the following Peer Review section of the Final Project module.

About the Dataset

This dataset contains house sale prices for King County, which includes Seattle. It includes homes sold between May 2014 and May 2015. It was taken from here. It was also slightly modified for the purposes of this course.

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)

Import the required libraries

In [ ]:
```
# All Libraries required for this lab are listed below. The libraries pre-installed on Skills Network Labs are commented.
# !mamba install -qy pandas==1.3.4 numpy==1.21.4 seaborn==0.9.0 matplotlib==3.5.0 scikit-learn==0.20.1
# Note: If your environment doesn't support "!mamba install", use "!pip install"
```

In [1]:
```
# Surpress warnings:
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn
```

In [5]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler,PolynomialFeatures
from sklearn.linear_model import LinearRegression
%matplotlib inline
```

Module 1: Importing Data Sets

Download the dataset by running the cell below.

In [ ]:
```
import piplite
await piplite.install('seaborn')
```

In [16]:
```
from pyodide.http import request

async def download(url, filename):
    response = await pyfetch(url)
    if response.status == 200:
        with open(filename, "wb") as f:
            f.write(await response.bytes())
```

In [17]:
```
filepath='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/FinalModule_Coursera
```

In [ ]:
```
await download(filepath, "housing.csv")
file_name="housing.csv"
```

Load the csv:

In [ ]:
```
df = pd.read_csv(file_name)
```

> Note: This version of the lab is working on JupyterLite, which requires the dataset to be downloaded to the interface.While working on the downloaded version of this notebook on their local machines(Jupyter Anaconda), the learners can simply **skip the steps above,** and simply use the URL directly in the `pandas.read_csv()` function. You can uncomment and run the statements in the cell below.

In [29]:
```
filepath='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/FinalModule_Coursera
df = pd.read_csv(filepath)
```

We use the method `head` to display the first 5 columns of the dataframe.

In [30]:
```
df.head()
```

Out[30]:

	Unnamed: 0	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	...	grade	sqft_above	sqft_basement	yr_buil
0	0	7129300520	20141013T000000	221900.0	3.0	1.00	1180	5650	1.0	0	...	7	1180	0	195
1	1	6414100192	20141209T000000	538000.0	3.0	2.25	2570	7242	2.0	0	...	7	2170	400	195
2	2	5631500400	20150225T000000	180000.0	2.0	1.00	770	10000	1.0	0	...	6	770	0	193
3	3	2487200875	20141209T000000	604000.0	4.0	3.00	1960	5000	1.0	0	...	7	1050	910	196
4	4	1954400510	20150218T000000	510000.0	3.0	2.00	1680	8080	1.0	0	...	8	1680	0	198

5 rows × 22 columns

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.

In [49]:
```
#Enter Your Code, Execute and take the Screenshot
df.dtypes
```

```
Out[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
```

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

```
In [32]: df.describe()
```

Out[32]:

	Unnamed: 0	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grad
count	21613.00000	2.161300e+04	2.161300e+04	21600.000000	21603.000000	21613.000000	2.161300e+04	21613.000000	21613.000000	21613.000000	...	21613.00000
mean	10806.00000	4.580302e+09	5.400881e+05	3.372870	2.115736	2079.899736	1.510697e+04	1.494309	0.007542	0.234303	...	7.65687
std	6239.28002	2.876566e+09	3.671272e+05	0.926657	0.768996	918.440897	4.142051e+04	0.539989	0.086517	0.766318	...	1.17545
min	0.00000	1.000102e+06	7.500000e+04	1.000000	0.500000	290.000000	5.200000e+02	1.000000	0.000000	0.000000	...	1.00000
25%	5403.00000	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0.000000	0.000000	...	7.00000
50%	10806.00000	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.000000	...	7.00000
75%	16209.00000	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0.000000	0.000000	...	8.00000
max	21612.00000	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.000000	...	13.00000

8 rows × 21 columns

Module 2: Data Wrangling

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.

```
In [33]: #Enter Your Code, Execute and take the Screenshot
         df.drop(columns=df.columns[0], axis=1, inplace=True)
         df.drop(columns=df.columns[0], axis=1, inplace=True)
         df.describe()
```

Out[33]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above
count	2.161300e+04	21600.000000	21603.000000	21613.000000	2.161300e+04	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000	21613.000000
mean	5.400881e+05	3.372870	2.115736	2079.899736	1.510697e+04	1.494309	0.007542	0.234303	3.409430	7.656873	1788.390691
std	3.671272e+05	0.926657	0.768996	918.440897	4.142051e+04	0.539989	0.086517	0.766318	0.650743	1.175459	828.090978
min	7.500000e+04	1.000000	0.500000	290.000000	5.200000e+02	1.000000	0.000000	0.000000	1.000000	1.000000	290.000000
25%	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0.000000	0.000000	3.000000	7.000000	1190.000000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.000000	3.000000	7.000000	1560.000000
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0.000000	0.000000	4.000000	8.000000	2210.000000
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.000000	5.000000	13.000000	9410.000000

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

```
In [34]: 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
```

We can replace the missing values of the column `'bedrooms'` with the mean of the column `'bedrooms'` using the method `replace()`. Don't forget to set the `inplace` parameter to `True`

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

We also replace the missing values of the column `'bathrooms'` with the mean of the column `'bathrooms'` using the method `replace()` . Don't forget to set the `inplace` parameter top `True`

In [36]:
```
mean=df['bathrooms'].mean()
df['bathrooms'].replace(np.nan,mean, inplace=True)
```

In [37]:
```
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
```

Module 3: Exploratory Data Analysis

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.

In [40]:
```
#Enter Your Code, Execute and take the Screenshot
df['floors'].value_counts().to_frame()
```

Out[40]:

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

Question 4

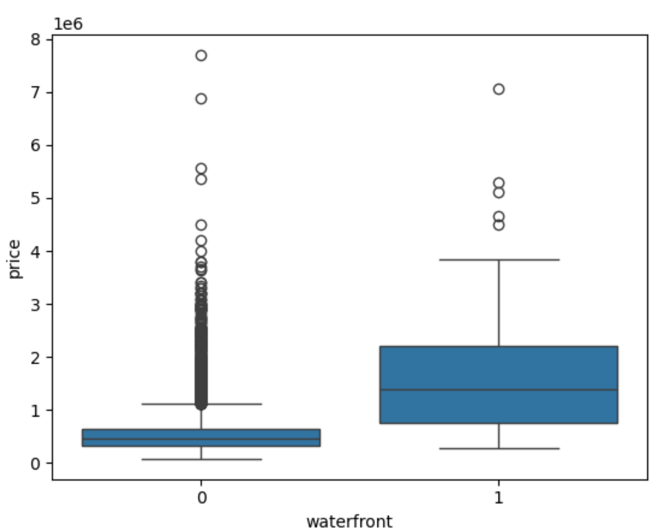
Use the function `boxplot` in the seaborn library to determine whether houses with a waterfront view or without a waterfront view have more price outliers. Take a screenshot of your code and boxplot. You will need to submit the screenshot for the final project.

In [43]:
```
df['waterfront'].unique()
```

Out[43]: `array([0, 1])`

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

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

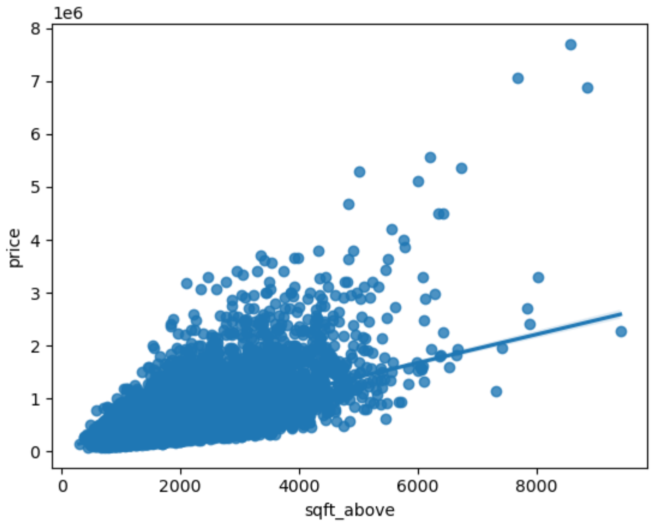


Question 5

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.

In [45]:
```python
#Enter Your Code, Execute and take the Screenshot
sns.regplot(x='sqft_above',y='price',data=df)
```

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



We can use the Pandas method `corr()` to find the feature other than price that is most correlated with price.

In [50]:
```python
df.select_dtypes(exclude=['object']).corr()['price'].sort_values()
```

Out[50]:
```
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        0.525738
sqft_living15    0.585379
sqft_above       0.605567
grade            0.667434
sqft_living      0.702035
price            1.000000
Name: price, dtype: float64
```

Module 4: Model Development

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

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

Out[51]: 0.00046769430149007363

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.

In [52]:
```python
#Enter Your Code, Execute and take the Screenshot
lr = LinearRegression()
lr.fit(df[['sqft_living']],df[['price']])
print(lr.score(df[['sqft_living']],df[['price']]))
```

0.4928532179037931

Question 7

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

In [53]:
```python
features =["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.

In [55]:
```
#Enter Your Code, Execute and take the Screenshot
lm = LinearRegression()
lm.fit(df[features],df[['price']])
lm.score(df[features],df[['price']])
```

Out[55]: 0.6576933722289244

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()`

In [56]:
```
Input=[('scale',StandardScaler()),('polynomial', PolynomialFeatures(include_bias=False)),('model',LinearRegression())]
```

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.

In [59]:
```
#Enter Your Code, Execute and take the Screenshot
pipe = Pipeline(Input)
pipe.fit(df[features],df[['price']])
yhat = pipe.predict(df[features])
print(pipe.score(df[features],df[['price']]))
```

```
0.7513406322380792
```

Module 5: Model Evaluation and Refinement

Import the necessary modules:

In [60]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
print("done")
```

```
done
```

We will split the data into training and testing sets:

In [61]:
```
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
```

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.

In [62]:
```
from sklearn.linear_model import Ridge
```

In [63]:
```
#Enter Your Code, Execute and take the Screenshot
rm = Ridge(alpha=0.1)
rm.fit(x_train,y_train)
print(rm.score(x_test,y_test))
```

```
0.6478759163939114
```

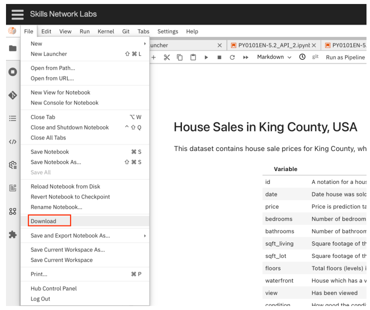
Question 10

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.

In [64]:
```python
#Enter Your Code, Execute and take the Screenshot
pf = PolynomialFeatures(degree=2)
x_train_pr = pf.fit_transform(x_train)
x_test_pr = pf.fit_transform(x_test)
rim = Ridge(alpha=0.1)
rim.fit(x_train_pr,y_train)
print(rim.score(x_test_pr,y_test))
```

```
0.7002744271710593
```

Once you complete your notebook you will have to share it. You can download the notebook by navigating to "File" and clicking on "Download" button.



This will save the (.ipynb) file on your computer. Once saved, you can upload this file in the "My Submission" tab, of the "Peer-graded Assignment" section.

About the Authors:

Joseph Santarcangelo has a PhD in Electrical Engineering, his research focused on using machine learning, signal processing, and computer vision to determine how videos impact human cognition. Joseph has been working for IBM since he completed his PhD.

Other contributors: Michelle Carey, Mavis Zhou

<!--## Change Log | Date (YYYY-MM-DD) | Version | Changed By | Change Description | | ----------------- | ------- | --------------- | --- | | 2020-12-01 | 2.2 | Aije Egwaikhide | Coverted Data describtion from text to table | | 2020-10-06 | 2.1 | Lakshmi Holla | Changed markdown instruction of Question1 | | 2020-08-27 | 2.0 | Malika Singla | Added lab to GitLab | | 2022-06-13 | 2.3 | Svitlana Kramar | Updated Notebook sharing instructions | | <hr> | | | | --!>