IBM Developer

SKILLS NETWORK

Data Analysis with Python

House Sales in King County, USA

This dataset contains house sale prices for King County, which includes Seattle. It includes homes sold between May 2014 and May 2015.

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)

You will require the following libraries:

In [4]:
```
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

Load the csv:

In [5]:
```
file_name='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(file_name)
```

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

In [6]:
```
df.head()
```

Out[6]:

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

5 rows × 22 columns

Question 1

Display the data types of each column using the function dtypes, then take a screenshot and submit it, include your code in the image.

In [7]:
```
df.dtypes
```

Out[7]:
```
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.

In [8]:

```
df.describe()
```

Out[8]:

	Unnamed: 0	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	vie
count	21613.00000	2.161300e+04	2.161300e+04	21600.000000	21603.000000	21613.000000	2.161300e+04	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	0.23430
std	6239.28002	2.876566e+09	3.671272e+05	0.926657	0.768996	918.440897	4.142051e+04	0.539989	0.086517	0.76631
min	0.00000	1.000102e+06	7.500000e+04	1.000000	0.500000	290.000000	5.200000e+02	1.000000	0.000000	0.00000
25%	5403.00000	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0.000000	0.00000
50%	10806.00000	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.00000
75%	16209.00000	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0.000000	0.00000
max	21612.00000	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.00000

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. Take a screenshot and submit it, make sure the `inplace` parameter is set to `True`

In [9]:
```
df.drop(["id", "Unnamed: 0"], axis=1, inplace = True)

df.describe()
```

Out[9]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grac
count	2.161300e+04	21600.000000	21603.000000	21613.000000	2.161300e+04	21613.000000	21613.000000	21613.000000	21613.000000	21613.0000(
mean	5.400881e+05	3.372870	2.115736	2079.899736	1.510697e+04	1.494309	0.007542	0.234303	3.409430	7.6568
std	3.671272e+05	0.926657	0.768996	918.440897	4.142051e+04	0.539989	0.086517	0.766318	0.650743	1.1754
min	7.500000e+04	1.000000	0.500000	290.000000	5.200000e+02	1.000000	0.000000	0.000000	1.000000	1.0000(
25%	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0.000000	0.000000	3.000000	7.0000(
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.000000	3.000000	7.0000(
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0.000000	0.000000	4.000000	8.0000(
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.000000	5.000000	13.0000(

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

In [10]:
```
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 [11]:
```
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 [12]:
```
mean=df['bathrooms'].mean()
df['bathrooms'].replace(np.nan,mean, inplace=True)
```

In [13]:
```
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 dataframe.

In [16]:
```
df['floors'].value_counts().to_frame()
```

Out[16]:

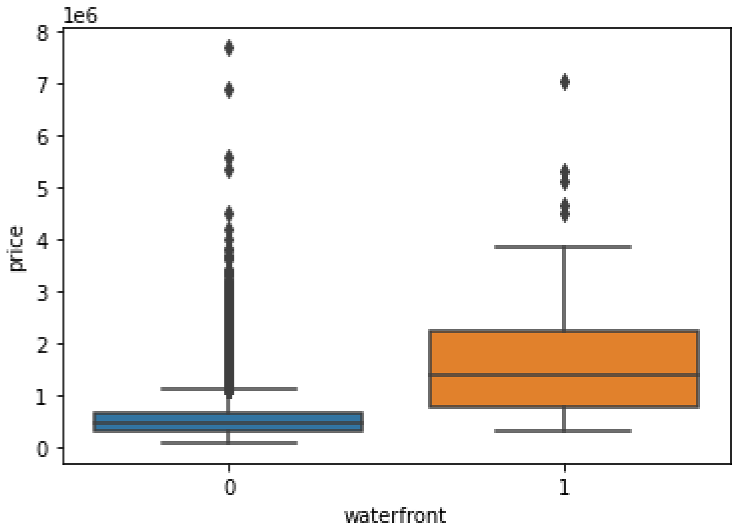
	floors
1.0	10680
2.0	8241
1.5	1910
3.0	613
2.5	161
3.5	8

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.

In [17]:
```
sns.boxplot(x="waterfront", y="price", data=df)
```

Out[17]: <AxesSubplot:xlabel='waterfront', ylabel='price'>

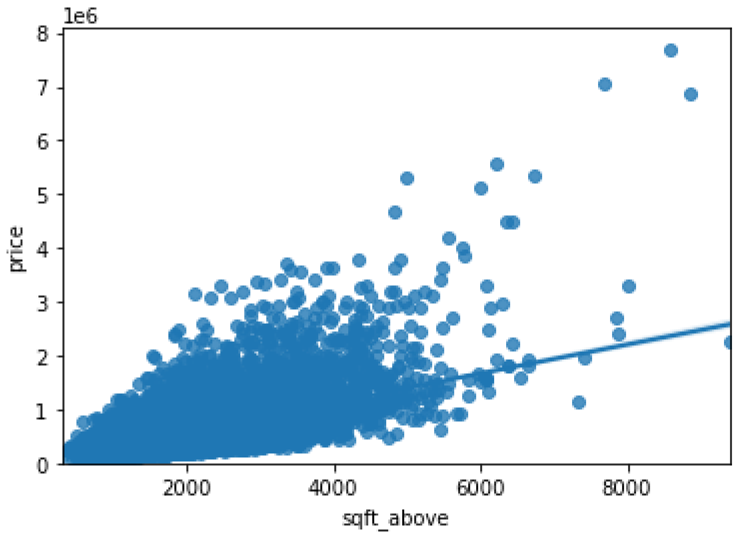


Question 5

Use the function `regplot` in the seaborn library to determine if the feature `sqft_above` is negatively or positively correlated with price.

In [18]:
```
sns.regplot(x="sqft_above", y="price", data=df)
plt.ylim(0,)
```

Out[18]: (0.0, 8081250.0)



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

In [19]:
```
df.corr()['price'].sort_values()
```

Out[19]:
```
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 [20]:
```
X = df[['long']]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)
lm.score(X, Y)
```

Out[20]:
```
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.

In [21]:
```
lm = LinearRegression()
X = df[['sqft_living']]
Y = df['price']
lm.fit(X,Y)
lm.score(X,Y)
```

Out[21]: 0.4928532179037931

Question 7

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

In [ ]:
```
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.

In [22]:
```
lm = LinearRegression()
lm

X = df[['floors']]
Y = df['price']

lm.fit(X,Y)
lm.score(X,Y)
```

Out[22]: 0.06594310068341092

In [23]:
```
lm = LinearRegression()
lm

X = df[['waterfront']]
Y = df['price']

lm.fit(X,Y)
lm.score(X,Y)
```

Out[23]: 0.07095267538578309

In [24]:
```
lm = LinearRegression()
lm

X = df[['lat']]
Y = df['price']

lm.fit(X,Y)
lm.score(X,Y)
```

Out[24]: 0.09425113672917462

In [25]:
```
lm = LinearRegression()
lm

X = df[['bedrooms']]
Y = df['price']

lm.fit(X,Y)
lm.score(X,Y)
```

Out[25]: 0.09535546506131365

In [26]:
```
lm = LinearRegression()
lm

X = df[['sqft_basement']]
Y = df['price']

lm.fit(X,Y)
lm.score(X,Y)
```

Out[26]: 0.104856815269744

In [27]:
```
lm = LinearRegression()
lm

X = df[['view']]
Y = df['price']

lm.fit(X,Y)

lm.score(X,Y)
```

Out[27]: 0.15784211584121532

In [28]:
```python
lm = LinearRegression()
lm

X = df[['bathrooms']]
Y = df['price']

lm.fit(X,Y)

lm.score(X,Y)
```

Out[28]: 0.27639993060314383

In [29]:
```python
lm = LinearRegression()
lm

X = df[['sqft_living15']]
Y = df['price']

lm.fit(X,Y)

lm.score(X,Y)
```

Out[29]: 0.3426684607560172

In [30]:
```python
lm = LinearRegression()
lm

X = df[['sqft_above']]
Y = df['price']

lm.fit(X,Y)

lm.score(X,Y)
```

Out[30]: 0.36671175283827917

In [31]:
```
lm = LinearRegression()
lm

X = df[['grade']]
Y = df['price']

lm.fit(X,Y)

lm.score(X,Y)
```

Out[31]: 0.44546848610928724

In [32]:
```
lm = LinearRegression()
lm

X = df[['sqft_living']]
Y = df['price']

lm.fit(X,Y)
lm.score(X,Y)
```

Out[32]: 0.4928532179037931

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 [35]:
```
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.

In [41]:
```
pipe=Pipeline(Input)
pipe
pipe.fit(X,Y)
```

Out[41]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('polynomial', PolynomialFeatures(include_bias=False)),
                ('model', LinearRegression())])
```

In [42]:
```
pipe.score(X,Y)
```

Out[42]:
```
0.7513417707683823
```

Module 5: Model Evaluation and Refinement

Import the necessary modules:

In [36]:
```
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 [37]:
```
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.

In [58]:
```
from sklearn.linear_model import Ridge
```

In [59]:
```
pr=PolynomialFeatures(degree=2)
x_train_pr=pr.fit_transform(x_train[['floors', 'waterfront','lat' ,'bedrooms' ,'sqft_basement' ,'view' ,'bathrooms','sq
ft_living15','sqft_above','grade','sqft_living']])
x_test_pr=pr.fit_transform(x_test[['floors', 'waterfront','lat' ,'bedrooms' ,'sqft_basement' ,'view' ,'bathrooms','sqft
_living15','sqft_above','grade','sqft_living']])
```

In [60]:
```
RigeModel=Ridge(alpha=0.1)
RigeModel.fit(x_train, y_train)
RigeModel.score(x_test, y_test)
```

Out[60]:
```
0.6478759163939113
```

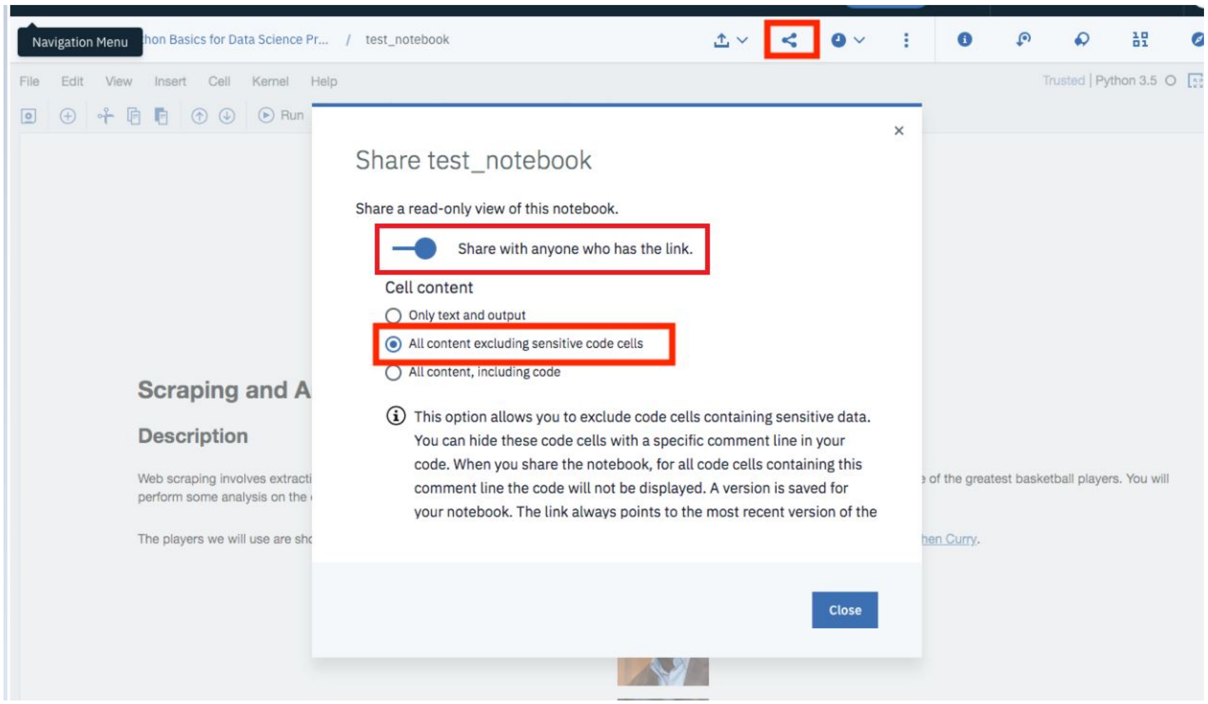
Question 10

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.

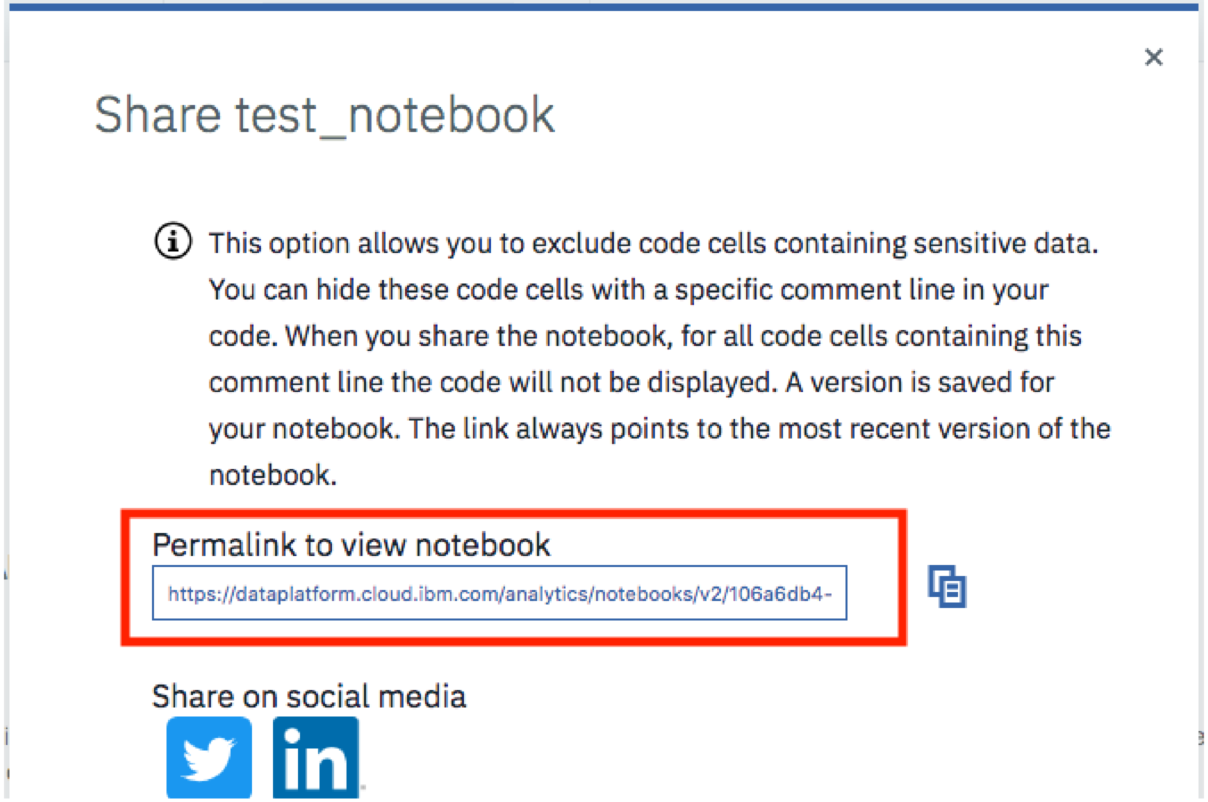
In [66]:
```
pr=PolynomialFeatures(degree=2)
x_train_pr=pr.fit_transform(x_train[features])
x_test_pr=pr.fit_transform(x_test[features])

RigeModel = Ridge(alpha=0.1)
RigeModel.fit(x_train_pr, y_train)
RigeModel.score(x_test_pr, y_test)
```

Out[66]:
```
0.7002744273468813
```

Once you complete your notebook you will have to share it. Select the icon on the top right a marked in red in the image below, a dialogue box should open, and select the option all content excluding sensitive code cells.



You can then share the notebook via a URL by scrolling down as shown in the following image:



About the Authors:

Joseph Santarcangelo (https://www.linkedin.com/in/joseph-s-50398b136/?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDA0101ENSkillsNetwork20235326-2021-01-01) 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 (https://www.linkedin.com/in/michelleccarey/?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDA0101ENSkillsNetwork20235326-2021-01-01), Mavis Zhou (https://www.linkedin.com/in/jiahui-mavis-zhou-a4537814a?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDA0101ENSkillsNetwork20235326-2021-01-01)

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

```
In [ ]:
```