Import the required libraries we need for the lab.

```
import piplite
await piplite.install(['numpy'],['pandas'])
await piplite.install(['seaborn'])

import pandas as pd
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as pyplot
import scipy.stats
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

Read the dataset in the csv file from the URL

```
from js import fetch
import io

URL = 'https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBMDeveloperSkillsNetwork-ST0151EN-
SkillsNetwork/labs/boston_housing.csv'
resp = await fetch(URL)
boston_url = io.BytesIO((await resp.arrayBuffer()).to_py())
boston_df=pd.read_csv(boston_url)
```

Add your code below following the instructions given in the course to complete the peer graded assignment

```
import piplite
await piplite.install(['numpy'],['pandas'])
await piplite.install(['seaborn'])
import pandas as pd
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as pyplot
import scipy.stats
import statsmodels.api as sm
from statsmodels.formula.api import ols
import warnings
warnings.filterwarnings('ignore')
from is import fetch
import io
URL = 'https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBMDeveloperSkillsNetwork-ST0151EN-
SkillsNetwork/labs/boston housing.csv'
```

```
resp = await fetch(URL)
boston_url = io.BytesIO((await resp.arrayBuffer()).to_py())
```

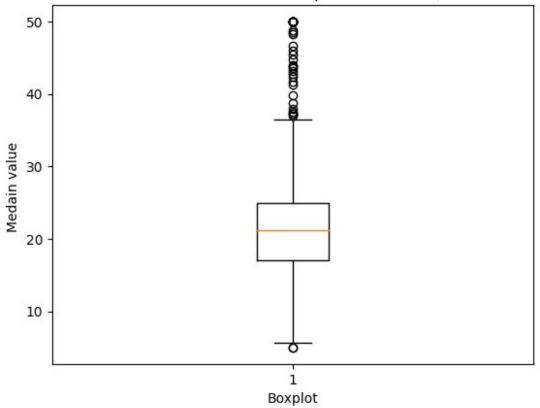
Data

```
import csv
boston df=pd.read csv(boston url)
boston df
                                INDUS
                                                             AGE
     Unnamed: 0
                    CRIM ZN
                                       CHAS
                                                NOX
                                                        RM
DIS
     RAD \
              0
                 0.00632
                          18.0
                                 2.31
                                         0.0
                                              0.538 6.575
                                                           65.2
0
4.0900
        1.0
              1 0.02731
                                 7.07
                                         0.0
                           0.0
                                              0.469 6.421
                                                           78.9
4.9671
        2.0
                 0.02729
                                 7.07
              2
                           0.0
                                         0.0
                                              0.469 7.185
                                                            61.1
4.9671
        2.0
              3
                 0.03237
                           0.0
                                 2.18
                                         0.0
                                              0.458
                                                     6.998
                                                           45.8
6.0622
        3.0
              4
                 0.06905
                           0.0
                                 2.18
                                         0.0
                                              0.458 7.147
                                                            54.2
6.0622
        3.0
501
            501
                 0.06263
                           0.0
                                11.93
                                         0.0
                                              0.573
                                                     6.593
                                                            69.1
2.4786
        1.0
502
            502
                 0.04527
                                11.93
                                              0.573 6.120
                           0.0
                                         0.0
                                                           76.7
2.2875
        1.0
            503
503
                 0.06076
                           0.0
                                11.93
                                         0.0
                                              0.573
                                                     6.976
                                                            91.0
2.1675
        1.0
504
            504
                 0.10959
                           0.0
                                11.93
                                         0.0 0.573 6.794
                                                            89.3
2.3889
        1.0
505
            505
                 0.04741
                           0.0
                               11.93
                                         0.0 0.573 6.030
                                                           80.8
2.5050
       1.0
            PTRATIO
                     LSTAT
       TAX
                            MEDV
0
     296.0
               15.3
                      4.98
                            24.0
1
     242.0
               17.8
                      9.14
                            21.6
2
     242.0
               17.8
                      4.03
                            34.7
3
                      2.94
     222.0
               18.7
                            33.4
4
     222.0
               18.7
                      5.33
                            36.2
                . . .
501
     273.0
               21.0
                      9.67
                            22.4
502
     273.0
               21.0
                      9.08
                            20.6
503
     273.0
               21.0
                      5.64
                            23.9
504
     273.0
               21.0
                            22.0
                      6.48
     273.0
505
               21.0
                      7.88 11.9
[506 rows x 14 columns]
```

Boxplot for Median Value of owner-occupied home :

```
import matplotlib.pyplot as plt
plt.boxplot('MEDV',data=boston_df)
plt.xlabel("Boxplot")
plt.ylabel("Medain value ")
plt.title("Median value of owner occupied homes in $1000's")
plt.show()
```

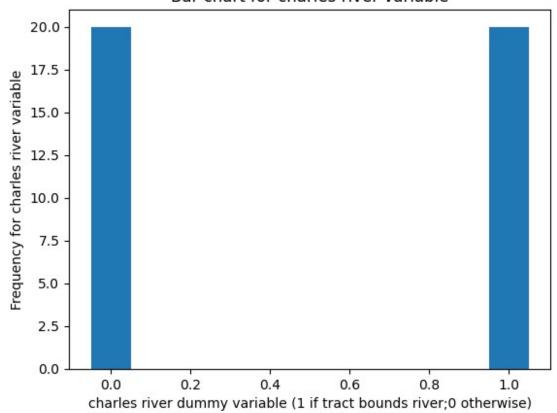
Median value of owner occupied homes in \$1000's



Bar chart for the Charles river variable:

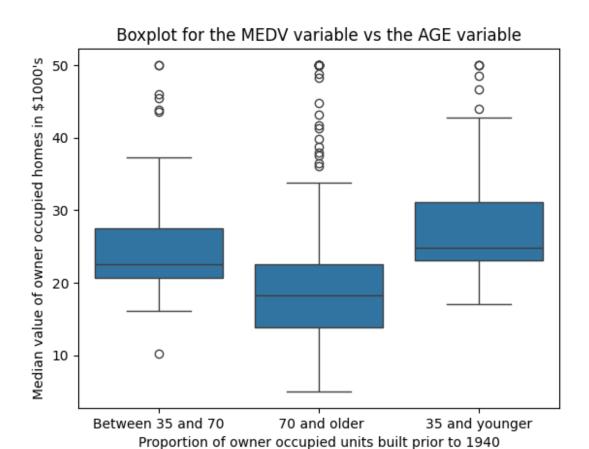
```
import matplotlib.pyplot as plt
plt.bar('CHAS', data=boston_df , height=20.0, width=0.1)
plt.xlabel("charles river dummy variable (1 if tract bounds river;0
otherwise)")
plt.ylabel("Frequency for charles river variable")
plt.title("Bar chart for charles river variable")
plt.show()
```





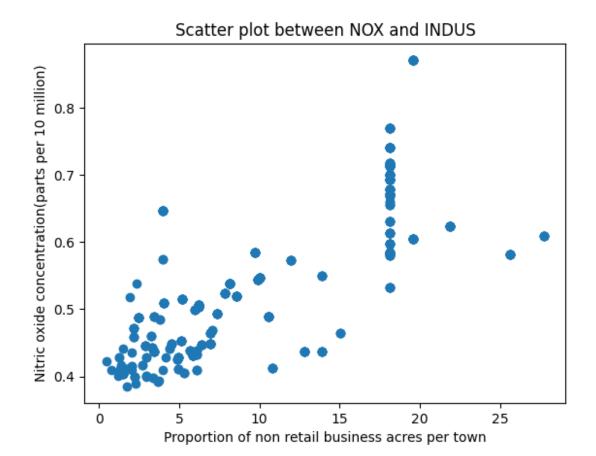
Boxplot for the MEDV variable vs the AGE variable :

```
boston df.loc[boston df['AGE'] \leq 35 , 'Age Group'] = "35 and
younger"
boston df.loc[(boston df['AGE'] > 35) & (boston df['AGE'] < 70) ,
'Age Group' ] = "Between 35 and 70"
boston df.loc[(boston df['AGE'] > 70), 'Age Group'] = " 70 and
older"
boxplot=sns.boxplot(x = 'Age_Group' , y = 'MEDV' , data = boston_df)
boxplot.set(xlabel = "Proportion of owner occupied units built prior
to 1940" , ylabel = "Median value of owner occupied homes in
$1000's" , title = " Boxplot for the MEDV variable vs the AGE variable
" )
[Text(0.5, 0, 'Proportion of owner occupied units built prior to
1940').
Text(0, 0.5, "Median value of owner occupied homes in $1000's"),
Text(0.5, 1.0, 'Boxplot for the MEDV variable vs the AGE variable
')]
```



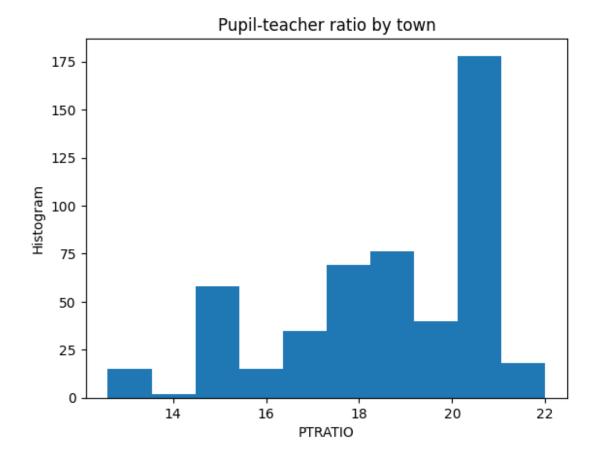
Scatter plot to show the relationship between NOX and INDUS:

```
import numpy as np
import matplotlib.pyplot as plt
plt.scatter(x='INDUS', y='NOX',data=boston_df)
plt.xlabel("Proportion of non retail business acres per town")
plt.ylabel("Nitric oxide concentration(parts per 10 million)")
plt.title("Scatter plot between NOX and INDUS")
plt.show()
```



Histogram for the pupil to teacher ratio variable :

```
import matplotlib.pyplot as plt
plt.hist('PTRATIO', data=boston_df)
plt.xlabel("PTRATIO")
plt.ylabel("Histogram")
plt.title("Pupil-teacher ratio by town")
plt.show()
```



TESTS

T-Test:

using the Boston housing data we need to check is there any significant difference in the median value of houses bounded by charles river or not

Hypothesis

- H0: m1=m2 (there is no difference in the median value of houses bounded by charles river)
- H1: m1!=m2 (there is difference in the median value of houses bounded by charles river)

we can use Levene's test in pyhton to check test significance

scipy.stats.levene(boston_df['MEDV'],boston_df['CHAS'],center='mean')

```
LeveneResult(statistic=532.6811164157666, pvalue=5.402535119732986e-95)
```

use the t test_ind from scipy_stats library

```
scipy.stats .ttest_ind(boston_df['MEDV'],boston_df['CHAS'])
TtestResult(statistic=54.9210289745203, pvalue=1.4651540072350996e-305, df=1010.0)
```

Conclusion: since the p_value is less than alpha value we reject the null hypothesis as there is a statistical difference in the median value of houses bounded by charles river

ANOVA:

Using the boston housing data, is there a difference in the median value of houses for each proportion of owner occupied units built prior to 1940(AGE)

First we group the data into categories as the one way ANOVA cannot work with continuous variable

- 35 years and younger
- Between 35 and 70 years
- 70 years and older

```
boston_df.loc[(boston_df['AGE'] <= 35) , 'Age_Group' ] = "35 and
younger"
boston_df.loc[(boston_df['AGE'] > 35) & (boston_df['AGE'] < 70) ,
'Age_Group' ] = "Between 35 and 70"
boston_df.loc[(boston_df['AGE'] > 70) , 'Age_Group' ] = " 70 and
older"
```

Hypothesis

- H0: m1=m2=m3(" three population means are equal)
- H1: atleast one of the means differ

Test for equality of variance

```
boston_df[boston_df['Age_Group'] == "70 and older"]
['MEDV'], center='mean')

LeveneResult(statistic=nan, pvalue=nan)

thirtyfive_lower = boston_df[boston_df['Age_Group'] == "35 and younger"]['MEDV']
thirtyfive_seventy = boston_df[boston_df['Age_Group'] == "between 35 and 70 years"]['MEDV']
seventy_older = boston_df[boston_df['Age_Group']=="70 and older"]
['MEDV']
```

Now run a one-way ANOVA

```
from scipy.stats import f_oneway
scipy.stats.f_oneway(thirtyfive_lower,thirtyfive_seventy,seventy_older
)
F_onewayResult(statistic=nan, pvalue=nan)
```

correlation:

using the boston housing data set we can conclude that there is no relationship between nitric oxide concentration and proportion of non retail business acres per town

Hypothesis

- H0: There is no relationship between nitric oxide concentration and proportion of non retail business acres per towm
- H1: there is a relationship between nitric oxide concentration and proportion of non retail business acres per town

```
scipy.stats.pearsonr(boston_df['INDUS'],boston_df['NOX'])
PearsonRResult(statistic=0.7636514469209192,
pvalue=7.913361061210442e-98)
```

conclusion:

since the p-value is less than alpha value, we reject hte null hypothesis and conclude that there exists a relationship between nitric oxide concentration and the proportion of non retail business acres per town

Regression with T-test:

Using the boston housing dataset what is the impact of the additional weighted distance to the five Boston employment centres of the median value of owner occupied homes

Hypothesis

- H0: B1 = O(there is no impact of the additional weighed distance to the five boston employment centres of the median value of owner occupied homes)
- H1:B1 is not equal to zero (there is an impact of additional weighed diatance to the five boston employment centres of the median value of owner occupied homes)

```
x=boston df['DIS']
y=boston df['MEDV']
x=sm.add constant(x)
model=sm.OLS(y,x).fit()
predictions = model.predict(x)
model.summary()
<class 'statsmodels.iolib.summary.Summary'>
                             OLS Regression Results
Dep. Variable:
                                  MEDV
                                          R-squared:
0.062
Model:
                                   0LS
                                          Adj. R-squared:
0.061
Method:
                         Least Squares
                                          F-statistic:
33.58
                      Mon, 03 Jun 2024 Prob (F-statistic):
Date:
1.21e-08
                                          Log-Likelihood:
Time:
                              15:54:13
-1823.9
No. Observations:
                                   506
                                          AIC:
3652.
Df Residuals:
                                   504
                                          BIC:
3660.
Df Model:
Covariance Type:
                             nonrobust
                          std err
                                                   P>|t|
                                                               [0.025]
                 coef
```

0.975]					
const	18.3901	0.817	22.499	0.000	16.784
19.996					
DIS	1.0916	0.188	5.795	0.000	0.722
1.462					
=======	=========	=======		========	
======					
Omnibus:		139.	139.779 Durbin-Wa		
0.570					
<pre>Prob(Omnibus):</pre>		0.000 Jarqu		e-Bera (JB):	
305.104					
Skew:		1.4	466 Prob(J	B):	
5.59e-67					
Kurtosis:		5.4	424 Cond.	No.	
9.32					
======					
Notes:					

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.