Optional_Peer_Graded_Assignment.jupyterlite

October 8, 2024

Import the required libraries we need for the lab.

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

```
[2]: 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
```

<ipython-input-2-b3fdaf15785b>:1: DeprecationWarning:

Pyarrow will become a required dependency of pandas in the next major release of pandas (pandas 3.0),

(to allow more performant data types, such as the Arrow string type, and better interoperability with other libraries)

but was not found to be installed on your system.

If this would cause problems for you,

please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

import pandas as pd

Read the dataset in the csv file from the URL

```
[3]: from js import fetch import io

URL = 'https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/

GIBMDeveloperSkillsNetwork-ST0151EN-SkillsNetwork/labs/boston_housing.csv'

resp = await fetch(URL)

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

```
[4]: boston_df=pd.read_csv(boston_url)
```

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

```
[5]: boston_df
```

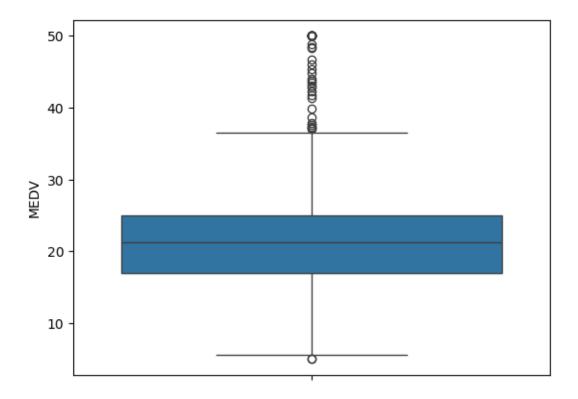
```
[5]:
           Unnamed: 0
                            CRIM
                                     ZN
                                          INDUS
                                                  CHAS
                                                           NOX
                                                                    RM
                                                                          AGE
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                                                                                         RAD
                        0.00632
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             TAX
                   PTRATIO
                             LSTAT
                                     MEDV
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           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
           222.0
                      18.7
                              2.94
                                     33.4
     4
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                                     36.2
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                                     22.4
     501
           273.0
                      21.0
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     503
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                      21.0
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     504
           273.0
                              6.48
                                     22.0
                      21.0
     505
           273.0
                      21.0
                              7.88
                                     11.9
```

[506 rows x 14 columns]

Median value of owner-occupied homes

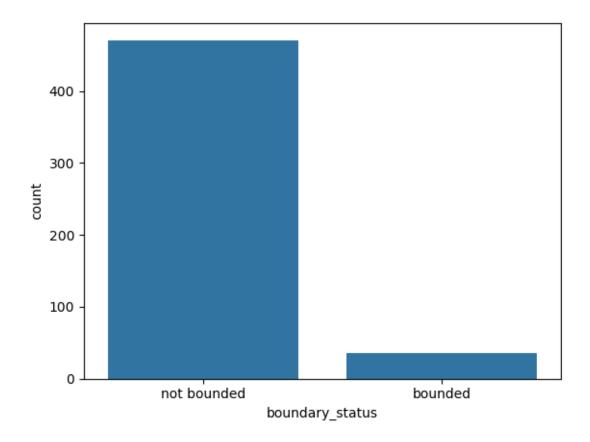
```
[6]: sns.boxplot(y=boston_df["MEDV"])
```

[6]: <AxesSubplot:ylabel='MEDV'>



Charles river variable

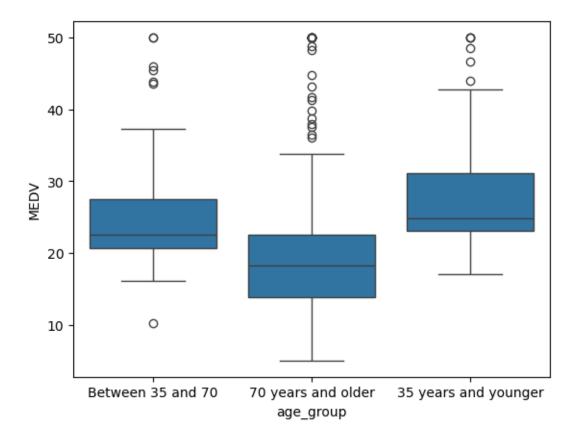
[7]: <AxesSubplot:xlabel='boundary_status', ylabel='count'>



MEDV variable vs the AGE variable

```
[8]: boston_df.loc[boston_df['AGE'] <= 35, 'age_group'] = '35 years 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 years and older' sns.boxplot(x='age_group', y='MEDV', data=boston_df)
```

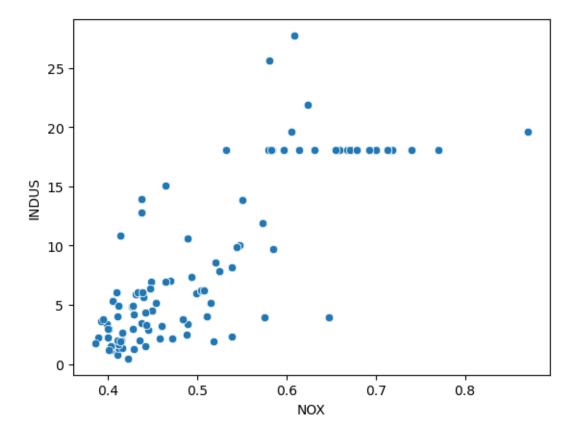
[8]: <AxesSubplot:xlabel='age_group', ylabel='MEDV'>



Scatter plot between Nitric oxide concentrations and the proportion of non-retail business acres per town

```
[9]: sns.scatterplot(x=boston_df["NOX"], y=boston_df["INDUS"], data=boston_df)
```

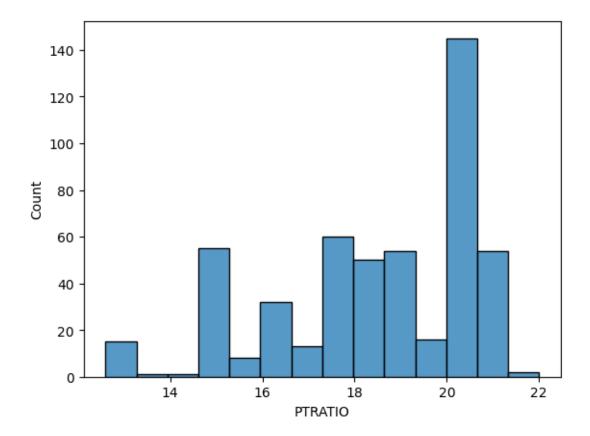
[9]: <AxesSubplot:xlabel='NOX', ylabel='INDUS'>



histogram for the pupil to teacher ratio variable

```
[10]: sns.histplot(boston_df['PTRATIO'])
```

[10]: <AxesSubplot:xlabel='PTRATIO', ylabel='Count'>



Is there a significant difference in median value of houses bounded by the Charles river or not?

Null Hypothesis (H0): There is no significant difference in MEDV across houses bounded by the river. Alternative Hypothesis (H1): There is diff in MEDV across houses bounded by the river.

```
[13]: group_0 = boston_df[boston_df['CHAS'] == 0]['MEDV']
group_1 = boston_df[boston_df['CHAS'] == 1]['MEDV']
scipy.stats.ttest_ind(group_0, group_1, equal_var=True)
```

p value is larger than alpha, we fail to reject the NULL hypothesis, There is not significant diff. Is there a difference in Median values of houses (MEDV) for each proportion of owner occupied units built prior to 1940 (AGE)? (ANOVA)

Null Hypothesis (H0): There is no significant difference in MEDV between houses built prior and after 1940. Alternative Hypothesis (H1): there is a significantly different MEDV between houses built proir and after 1940.

make the two different categories

```
[21]: boston_df.loc[(boston_df['AGE'] > 84), 'age_group'] = 'prior to 1940' boston_df.loc[(boston_df['AGE'] <= 84), 'age_group'] = 'after 1940'
```

test for equality of variances using levene test

[22]: LeveneResult(statistic=1.4055510245413045, pvalue=0.2363550102480432)

since we checked variance equality, we can make one way ANOVA

F Statistic: 70.89786758512082, P-Value: 3.9330184294042697e-16

p value is larger than alpha, we fail to reject the NULL hypothesis, There is not significant diff

Can we conclude that there is no relationship between Nitric oxide concentrations and proportion of non-retail business acres per town? (Pearson Correlation)

null hypothesis: the is no correlation alternative hypothesis: there is correlation

```
[30]: scipy.stats.pearsonr(boston_df["NOX"], boston_df["INDUS"])
```

[30]: PearsonRResult(statistic=0.7636514469209192, pvalue=7.913361061210442e-98)

p value is larger than alpha, we fail to reject the NULL hypothesis, There is no relationship between the two continious variables

What is the impact of an additional weighted distance to the five Boston employment centres on the median value of owner occupied homes? (Regression analysis)

H0: additional weighted distance have no effect on median value of owner occupied homes. H1: additional weighted distance have effect on median value of owner occupied homes.

```
[36]: X = boston_df["DIS"]
y = boston_df["MEDV"]
## add an intercept (beta_0) to our model
X = sm.add_constant(X)

model = sm.OLS(y, X).fit()
predictions = model.predict(X)

# Print out the statistics
model.summary()
```

[36]:

Dep. Variable:	MEDV	R-squared:	0.062
Model:	OLS	Adj. R-squared:	0.061
Method:	Least Squares	F-statistic:	33.58
Date:	Tue, 08 Oct 2024	Prob (F-statistic):	1.21e-08
Time:	10:15:49	Log-Likelihood:	-1823.9
No. Observations:	506	AIC:	3652.
Df Residuals:	504	BIC:	3660.
Df Model:	1		
Covariance Type:	nonrobust		
acof	atd onn t	D> + [0.025 0.0	751

	coef	std err	t	$P> \mathbf{t} $	[0.025]	0.975]
\mathbf{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
Omnib	us:	139.779	Durl	oin-Wats	son:	0.570
Prob(O	mnibus):	0.000	Jarq	ue-Bera	(JB):	305.104
Skew:		1.466	Prob	o(JB):		5.59 e-67
Kurtos	is:	5.424	Cone	d. No.		9.32

Notes:

p value is less than alpha, we reject the null hypthesis There is evidence that the ditatnces have effect on median price

[]:

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