

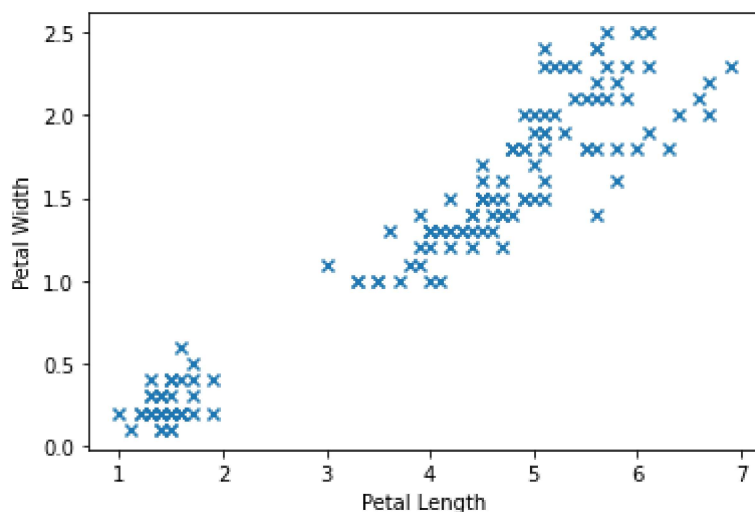
```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from scipy import stats
import seaborn as sns
import statsmodels.api as sm
from sklearn import linear_model
```

```
In [2]: #read in the data for iris
iris = sns.load_dataset('iris')
iris.head()
```

```
Out[2]:
```

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

```
In [5]: x = iris['petal_length']
y = iris['petal_width']
plt.scatter(x,y,marker = 'x')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
plt.show()
```



```
In [6]: #Linear Regression
model = sm.OLS(y,x)
result = model.fit()
print(result.summary())
```

OLS Regression Results

=====						
==						
Dep. Variable:	petal_width	R-squared (uncentered):	0.9			
67						
Model:	OLS	Adj. R-squared (uncentered):	0.9			
67						
Method:	Least Squares	F-statistic:	441			
7.						
Date:	Wed, 03 Aug 2022	Prob (F-statistic):	1.22e-1			
12						
Time:	20:54:28	Log-Likelihood:	-8.71			
79						
No. Observations:	150	AIC:	19.			
44						
Df Residuals:	149	BIC:	22.			
45						
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

petal_length	0.3365	0.005	66.463	0.000	0.327	0.347
=====						
Omnibus:	19.720	Durbin-Watson:	0.857			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	23.498			
Skew:	0.957	Prob(JB):	7.90e-06			
Kurtosis:	3.311	Cond. No.	1.00			
=====						

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
In [9]: # Linear Regression with intercept i.e with constant term
# we -need to add a conatant column
x1 = iris['petal_length']
y1 = iris['petal_width']
x1 = sm.add_constant(x1)#added a constant column
x1.head()
```

```
Out[9]:
```

	const	petal_length
0	1.0	1.4
1	1.0	1.4
2	1.0	1.3
3	1.0	1.5
4	1.0	1.4

```
In [11]: #fittinf regression model
model1 = sm.OLS(y1,x1)
result1 = model1.fit()
print(result1.summary())
```

OLS Regression Results

```

=====
Dep. Variable:          petal_width    R-squared:                0.927
Model:                  OLS            Adj. R-squared:          0.927
Method:                 Least Squares   F-statistic:              1882.
Date:                   Wed, 03 Aug 2022 Prob (F-statistic):       4.68e-86
Time:                   22:16:59        Log-Likelihood:           24.796
No. Observations:       150            AIC:                     -45.59
Df Residuals:           148            BIC:                     -39.57
Df Model:                1
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.3631	0.040	-9.131	0.000	-0.442	-0.285
petal_length	0.4158	0.010	43.387	0.000	0.397	0.435

```

=====
Omnibus:                 5.765    Durbin-Watson:           1.455
Prob(Omnibus):           0.056    Jarque-Bera (JB):        5.555
Skew:                    0.359    Prob(JB):                0.0622
Kurtosis:                3.611    Cond. No.                10.3
=====

```

Notes:

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

```

In [12]: #conditions for linear regression
#loading iris data set
iris = sns.load_dataset('iris')
iris.head()

```

```

Out[12]:
   sepal_length  sepal_width  petal_length  petal_width  species
0             5.1           3.5           1.4           0.2    setosa
1             4.9           3.0           1.4           0.2    setosa
2             4.7           3.2           1.3           0.2    setosa
3             4.6           3.1           1.5           0.2    setosa
4             5.0           3.6           1.4           0.2    setosa

```

```

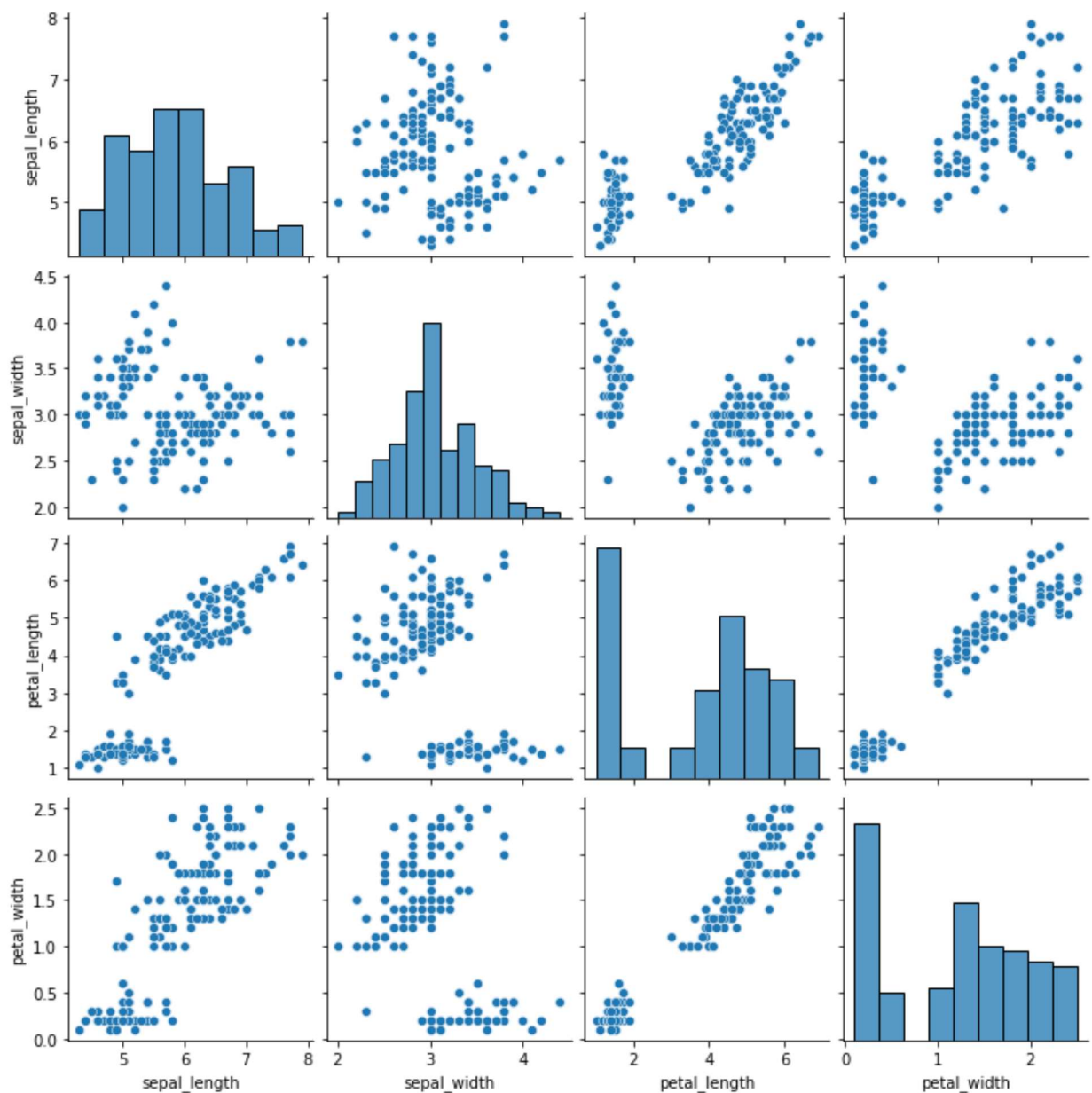
In [13]: sns.pairplot(iris[['sepal_length', 'sepal_width', 'petal_length', 'petal_width']].dropna())

```

```

Out[13]: <seaborn.axisgrid.PairGrid at 0x1af4e0f4fa0>

```



```
In [14]: #multi linear regression
x2= iris[['sepal_length','sepal_width','petal_length']]
y2= iris[['petal_width']]

#Adding constant column to my predictor variable

x2 = sm.add_constant(x2)
x2.head()
```

```
Out[14]:
```

	const	sepal_length	sepal_width	petal_length
0	1.0	5.1	3.5	1.4
1	1.0	4.9	3.0	1.4
2	1.0	4.7	3.2	1.3
3	1.0	4.6	3.1	1.5
4	1.0	5.0	3.6	1.4

```
In [15]: #regression model fitting
model3 = sm.OLS(y2,x2)
result3 = model3.fit()

print(result3.summary())
```

```

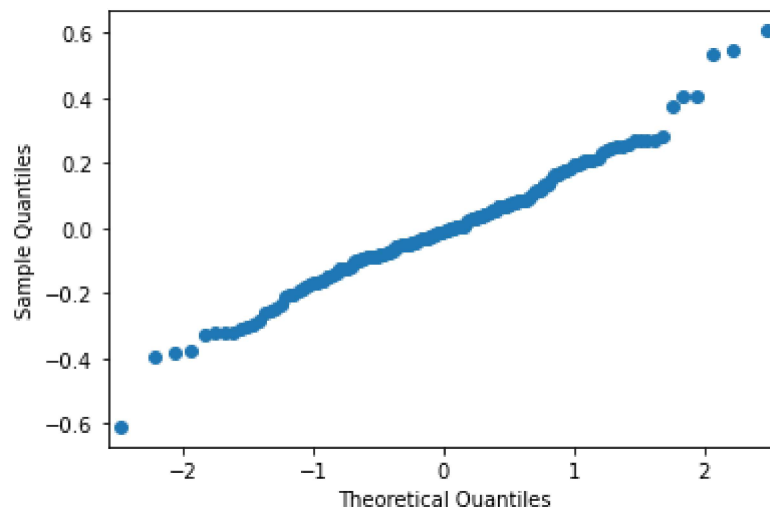
OLS Regression Results
=====
Dep. Variable:          petal_width    R-squared:                0.938
Model:                  OLS           Adj. R-squared:           0.937
Method:                 Least Squares  F-statistic:              734.4
Date:                   Wed, 03 Aug 2022  Prob (F-statistic):      7.83e-88
Time:                   23:09:40       Log-Likelihood:           36.751
No. Observations:       150           AIC:                     -65.50
Df Residuals:           146           BIC:                     -53.46
Df Model:                3
Covariance Type:        nonrobust
=====
                    coef    std err          t      P>|t|      [0.025     0.975]
-----
const             -0.2403      0.178     -1.347     0.180     -0.593      0.112
sepal_length      -0.2073      0.048     -4.363     0.000     -0.301     -0.113
sepal_width        0.2228      0.049      4.553     0.000      0.126      0.320
petal_length       0.5241      0.024     21.399     0.000      0.476      0.572
=====
Omnibus:                5.609    Durbin-Watson:           1.573
Prob(Omnibus):           0.061    Jarque-Bera (JB):         6.811
Skew:                    0.223    Prob(JB):                 0.0332
Kurtosis:                3.944    Cond. No.                  90.1
=====

```

Notes:

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

```
In [16]: #for linear regression to work the residuals are normally distributed to check this we
residuals = result3.resid
sm.qqplot(residuals)
plt.show()#since graph is a straight line so residuals are normally distributed
```



```
In [18]: #evaluation of milti colinearity
correlation = x2.corr()
correlation
```

Out[18]:

	const	sepal_length	sepal_width	petal_length
const	NaN	NaN	NaN	NaN
sepal_length	NaN	1.000000	-0.11757	0.871754
sepal_width	NaN	-0.117570	1.00000	-0.428440
petal_length	NaN	0.871754	-0.42844	1.000000

```
In [ ]:
```