## Deena 20104016

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as pp
```

## **Problem Statement**

## **LINEAR REGRESSION**

In [2]:	<pre>a = pd.read_csv("world.csv")</pre>

а	=	pa.re	ead_csv("world	.csv )			
		ld	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
	0	1	5.1	3.5	1.4	0.2	Iris-setosa
	1	2	4.9	3.0	1.4	0.2	Iris-setosa
	2	3	4.7	3.2	1.3	0.2	Iris-setosa
	3	4	4.6	3.1	1.5	0.2	Iris-setosa
	4	5	5.0	3.6	1.4	0.2	Iris-setosa
•	145	146	6.7	3.0	5.2	2.3	Iris-virginica
•	146	147	6.3	2.5	5.0	1.9	Iris-virginica
•	147	148	6.5	3.0	5.2	2.0	Iris-virginica
•	148	149	6.2	3.4	5.4	2.3	Iris-virginica
•	149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

#### **HEAD**

In [3]:			1/1				
Out[3]:		ld	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
	0	1	5.1	3.5	1.4	0.2	Iris-setosa
	1	2	4.9	3.0	1.4	0.2	Iris-setosa
	2	3	4.7	3.2	1.3	0.2	Iris-setosa
	3	4	4.6	3.1	1.5	0.2	Iris-setosa
	4	5	5.0	3.6	1.4	0.2	Iris-setosa

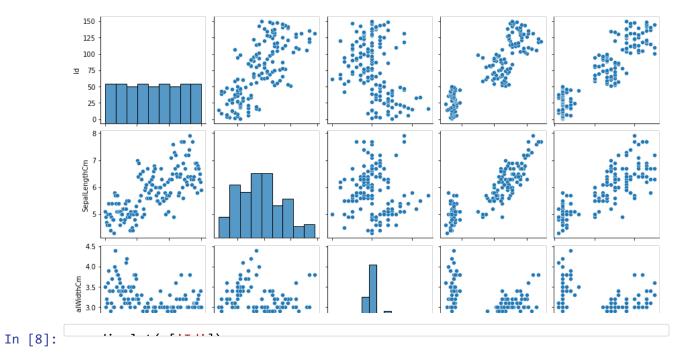
## **Data Cleaning and Preprocessing**

Out[4]:         Id         SepalLengthCm         SepalWidthCm         PetalLengthCm         PetalWidthCm         Species           0 1         5.1         3.5         1.4         0.2         Iris-setosa           1 2         4.9         3.0         1.4         0.2         Iris-setosa           2 3         4.7         3.2         1.3         0.2         Iris-setosa           3 4         4.6         3.1         1.5         0.2         Iris-setosa           In [5]:           Id SepalLengthCm         SepalWidthCm         PetalLengthCm         PetalWidthCm           count 150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         1.14         0.2         Iris-setosa         1.1         1.1         0.2         Iris-setosa         1.2         0.2         1.2         0.2         1.2         0.2         1.2         0.2         1.2         0.2	In [4]:																	
1 2 4.9 3.0 1.4 0.2 Iris-setosa 2 3 4.7 3.2 1.3 0.2 Iris-setosa 3 4 5 5.0 3.6 1.4 0.2 Iris-setosa  In [5]:    Id   SepalLengthCm   SepalWidthCm   PetalLengthCm   PetalWidthCm     count   150.000000   150.000000   150.000000   150.000000     mean   75.500000   5.843333   3.054000   3.758667   1.198667     std   43.445368   0.828066   0.433594   1.764420   0.763161     min   1.00000   4.300000   2.000000   1.000000   0.300000     25%   38.250000   5.100000   2.800000   1.600000   0.300000     50%   75.500000   5.800000   3.000000   4.350000   1.300000     75%   112.750000   6.400000   3.300000   5.100000   1.800000     1.800000   1.800000   1.800000   1.800000     1.800000   1.8000000   1.8000000   1.800000     1.800000   1.8000000   1.8000000   1.8000000     1.8000000   1.8000000   1.8000000   1.8000000     1.8000000   1.8000000   1.8000000   1.8000000     1.8000000   1.8000000   1.8000000   1.8000000     1.8000000   1.8000000   1.8000000   1.8000000     1.8000000   1.8000000   1.8000000   1.8000000     1.8000000   1.8000000   1.8000000     1.8000000   1.8000000   1.8000000     1.8000000   1.8000000   1.8000000     1.8000000   1.8000000   1.8000000     1.8000000000000000000000000000000000000	Out[4]:		ld	SepalLength(	Cm SepalW	idthCm	PetalLength	Cm	PetalWidthCn	n Species								
2 3 4.7 3.2 1.3 0.2 Iris-setosa 3 4 4.6 3.1 1.5 0.2 Iris-setosa 4 5 5.0 3.6 1.4 0.2 Iris-setosa  In [5]:    Id   SepalLengthCm   SepalWidthCm   PetalLengthCm   PetalWidthCm		0	1		5.1	3.5		1.4	0.2	2 Iris-setosa								
3 4   4.6   3.1   1.5   0.2   Iris-setosa		1	2		4.9	3.0		1.4	0.2	2 Iris-setosa								
4 5         5.0         3.6         1.4         0.2         Iris-setosa           In [5]:         Id SepalLengthCm         SepalWidthCm         PetalLengthCm         PetalWidthCm           count 150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.000000         150.00000 <th <="" colspan="8" th=""><th></th><th>2</th><th>3</th><th></th><th>4.7</th><th>3.2</th><th></th><th>1.3</th><th>0.2</th><th>2 Iris-setosa</th></th>	<th></th> <th>2</th> <th>3</th> <th></th> <th>4.7</th> <th>3.2</th> <th></th> <th>1.3</th> <th>0.2</th> <th>2 Iris-setosa</th>									2	3		4.7	3.2		1.3	0.2	2 Iris-setosa
In [5]:    Id   SepalLengthCm   SepalWidthCm   PetalLengthCm   PetalWidthCm		3	4		4.6	3.1		1.5	0.2	2 Iris-setosa								
Out[5]:         Id         SepalLengthCm         SepalWidthCm         PetalLengthCm         PetalWidthCm           count         150.000000         150.000000         150.000000         150.000000         150.000000           mean         75.500000         5.843333         3.054000         3.758667         1.198667           std         43.445368         0.828066         0.433594         1.764420         0.763161           min         1.000000         4.300000         2.000000         1.000000         0.100000           25%         38.250000         5.100000         2.800000         1.600000         0.300000           50%         75.500000         5.800000         3.000000         4.350000         1.800000           75%         112.750000         6.400000         3.300000         5.100000         1.800000		4	5		5.0	3.6		1.4	0.2	2 Iris-setosa								
count         150.000000         150.000000         150.000000         150.000000           mean         75.500000         5.843333         3.054000         3.758667         1.198667           std         43.445368         0.828066         0.433594         1.764420         0.763161           min         1.000000         4.300000         2.000000         1.000000         0.100000           25%         38.250000         5.100000         2.800000         1.600000         0.300000           50%         75.500000         5.800000         3.000000         4.350000         1.800000           75%         112.750000         6.400000         3.300000         5.100000         1.800000	In [5]:			•• /														
mean       75.500000       5.843333       3.054000       3.758667       1.198667         std       43.445368       0.828066       0.433594       1.764420       0.763161         min       1.000000       4.300000       2.000000       1.000000       0.100000         25%       38.250000       5.100000       2.800000       1.600000       0.300000         50%       75.500000       5.800000       3.000000       4.350000       1.300000         75%       112.750000       6.400000       3.300000       5.100000       1.800000																		
std       43.445368       0.828066       0.433594       1.764420       0.763161         min       1.000000       4.300000       2.000000       1.000000       0.100000         25%       38.250000       5.100000       2.800000       1.600000       0.300000         50%       75.500000       5.800000       3.000000       4.350000       1.300000         75%       112.750000       6.400000       3.300000       5.100000       1.800000	Out[5]:			ld	SepalLengt	hCm S	epalWidthCm	Pet	talLengthCm	PetalWidthCm								
min       1.000000       4.300000       2.000000       1.000000       0.100000         25%       38.250000       5.100000       2.800000       1.600000       0.300000         50%       75.500000       5.800000       3.000000       4.350000       1.300000         75%       112.750000       6.400000       3.300000       5.100000       1.800000	Out[5]:	СО	unt				-	Pet										
25%       38.250000       5.100000       2.800000       1.600000       0.300000         50%       75.500000       5.800000       3.000000       4.350000       1.300000         75%       112.750000       6.400000       3.300000       5.100000       1.800000	Out[5]:			150.000000	150.000	0000	150.000000	Pet	150.000000	150.000000								
50%       75.500000       5.800000       3.000000       4.350000       1.300000         75%       112.750000       6.400000       3.300000       5.100000       1.800000	Out[5]:	m	ean	150.000000 75.500000	150.000	3333	150.000000 3.054000	Pet	150.000000 3.758667	150.000000 1.198667								
<b>75%</b> 112.750000 6.400000 3.300000 5.100000 1.800000	Out[5]:	m	ean std	150.000000 75.500000 43.445368	150.000 5.843 0.823	0000 3333 3066	150.000000 3.054000 0.433594	Pet	150.000000 3.758667 1.764420	150.000000 1.198667 0.763161								
	Out[5]:	m <sub>1</sub>	ean std min	150.000000 75.500000 43.445368 1.000000	150.000 5.843 0.824 4.300	0000 3333 8066 0000	150.000000 3.054000 0.433594 2.000000	Pet	150.000000 3.758667 1.764420 1.000000	150.000000 1.198667 0.763161 0.100000								
<b>max</b> 150.000000 7.900000 4.400000 6.900000 2.500000	Out[5]:	m-	ean std min 25%	150.000000 75.500000 43.445368 1.000000 38.250000	150.000 5.843 0.824 4.300 5.100	3333 3066 0000	150.000000 3.054000 0.433594 2.000000 2.800000	Pet	150.000000 3.758667 1.764420 1.000000 1.600000	150.000000 1.198667 0.763161 0.100000 0.300000								
	Out[5]:	m-	ean std min 25%	150.000000 75.500000 43.445368 1.000000 38.250000 75.500000	150.000 5.843 0.824 4.300 5.100 5.800	0000 3333 8066 0000 0000	150.000000 3.054000 0.433594 2.000000 2.800000 3.000000	Pet	150.000000 3.758667 1.764420 1.000000 1.600000 4.350000	150.000000 1.198667 0.763161 0.100000 0.300000 1.300000								

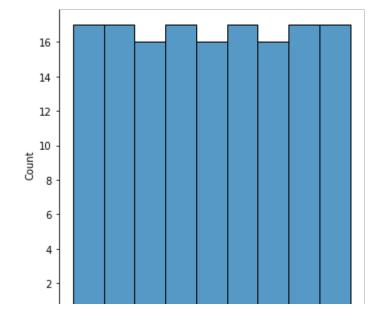
# To display heading

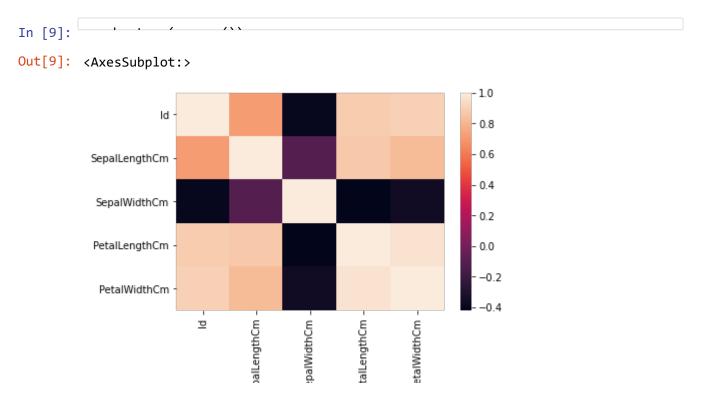
In [7]:

Out[7]: <seaborn.axisgrid.PairGrid at 0x1fe3c6d2dc0>



Out[8]: <seaborn.axisgrid.FacetGrid at 0x1fe3ea92e80>





## TO TRAIN THE MODEL - MODEL BUILDING

```
In [14]: prediction= lr.predict(x_test)
Out[14]: <matplotlib.collections.PathCollection at 0x1fe3f6c8dc0>

3.4
3.3
3.2
3.1
3.0
2.9
2.0
2.5
3.0
3.5
4.0
4.5

Out[15]: -0.11366093168042446
```

#### **RIDGE & LASSO**

```
In [21]: print(a.coef_)
         print(a.intercept_)
         print(a.score(x_test,y_test))
         [-0.00395455]
         3.406400682297664
         -0.11106227161974092
         [3.03467255 3.13353641 2.995127 2.8646267 3.00699067 2.97930879
          2.84880848 3.15330919 3.13749097 3.12562731 3.04258166 3.34312781
          2.92789958 3.10189998 3.1177182 3.15726374 3.24030939 3.0386271
          3.04653621 3.18494562 2.99117245 2.87253581 3.02676344 3.36685514
          3.16517285 2.89230858 3.23240028 3.21262751 2.89626314 2.96744512
          3.05839988 3.39849157 3.16912741 3.25612761 3.06630899 3.1612183
          2.91603591 3.37476425 2.9516269 3.17308196 3.40244613 3.08608176
          3.09003631 3.27985494 2.98721789]
In [22]: from sklearn import metrics
         print(" Mean Absolute Error :",metrics.mean_absolute_error(y_test,prediction))
         print(" Mean Squared Error :",metrics.mean_squared_error(y_test,prediction))
                         . . . . . .
          Mean Absolute Error : 0.36502749673716817
          Mean Squared Error: 0.22302916258453298
          Root Mean Absolute Error: 0.6041750547127613
```

6 of 6