## Deena 20104016

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

## **Problem Statement**

## **LINEAR REGRESSION**

In [2]: a = pd.read\_csv("13\_placement.csv")

#### Out[2]:

	cgpa	placement_exam_marks	placed
0	7.19	26.0	1
1	7.46	38.0	1
2	7.54	40.0	1
3	6.42	8.0	1
4	7.23	17.0	0
995	8.87	44.0	1
996	9.12	65.0	1
997	4.89	34.0	0
998	8.62	46.0	1
999	4.90	10.0	1

1000 rows × 3 columns

## **HEAD**

In [3]:		1/\		
Out[3]:				
		cgpa	placement_exam_marks	placed
	0	7.19	26.0	1
	1	7.46	38.0	1
	2	7.54	40.0	1
	3	6.42	8.0	1
	4	7.23	17.0	0

# **Data Cleaning and Preprocessing**

#### Out[5]:

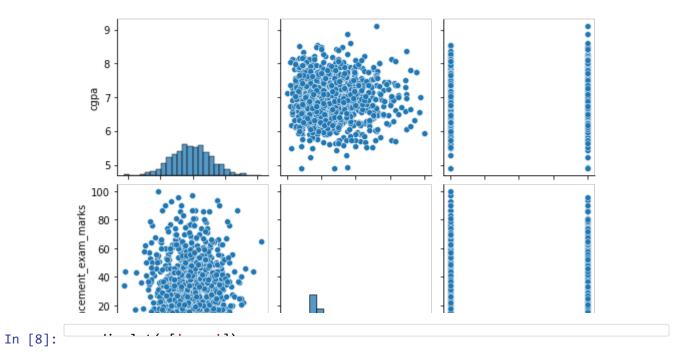
placed	placement_exam_marks	cgpa	
1000.000000	1000.000000	1000.000000	count
0.489000	32.225000	6.961240	mean
0.500129	19.130822	0.615898	std
0.000000	0.000000	4.890000	min
0.000000	17.000000	6.550000	25%
0.000000	28.000000	6.960000	50%
1.000000	44.000000	7.370000	75%
1.000000	100.000000	9.120000	max

## To display heading

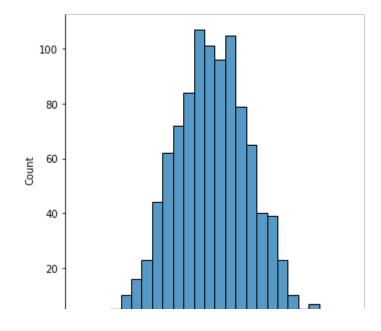
```
In [6]:
Out[6]: Index(['cgpa', 'placement_exam_marks', 'placed'], dtype='object')
```

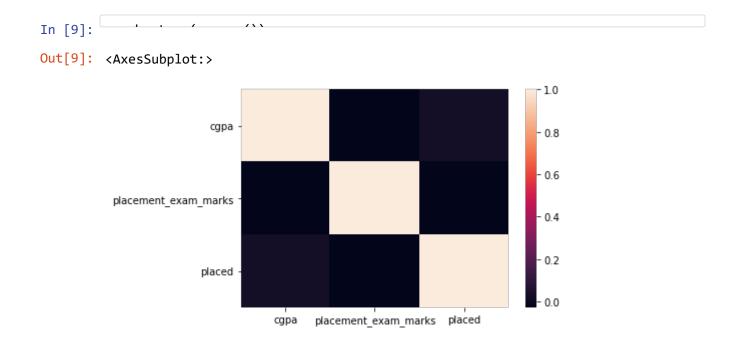
In [7]:

Out[7]: <seaborn.axisgrid.PairGrid at 0x1e11e7a5b80>



Out[8]: <seaborn.axisgrid.FacetGrid at 0x1e120451940>





## TO TRAIN THE MODEL - MODEL BUILDING

### **RIDGE & LASSO**

```
In [21]:
         print(a.coef_)
         print(a.intercept_)
         print(a.score(x_test,y_test))
         [0.]
         0.48428571428571426
         -0.0009877551020409658
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#### 0.48428571 0.48428571 0.48428571 0.48428571 0.48428571

```
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 : 0.499769263706374 Mean Squared Error : 0.2502955064898015

Root Mean Absolute Error : 0.7069436071614015

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