In [1]:
```
import pandas as pd
```

In [2]:
```
mydata=pd.read_excel(r"C:\Users\ANKIT SINGH\Desktop\internship\All In Order pdfs\DAY 8\wine_data.xlsx")
```

In [3]:
```
mydata
```

Out[3]:

	1.0	14.23	1.71	2.43	15.6	127.0	2.8	3.06	0.28	2.29	5.64	1.04	3.92	1065.0
0	1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.380000	1.05	3.40	1050
1	1	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.680000	1.03	3.17	1185
2	1	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.800000	0.86	3.45	1480
3	1	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.320000	1.04	2.93	735
4	1	14.20	1.76	2.45	15.2	112	3.27	3.39	0.34	1.97	6.750000	1.05	2.85	1450
5	1	14.39	1.87	2.45	14.6	96	2.50	2.52	0.30	1.98	5.250000	1.02	3.58	1290
6	1	14.06	2.15	2.61	17.6	121	2.60	2.51	0.31	1.25	5.050000	1.06	3.58	1295
7	1	14.83	1.64	2.17	14.0	97	2.80	2.98	0.29	1.98	5.200000	1.08	2.85	1045
8	1	13.86	1.35	2.27	16.0	98	2.98	3.15	0.22	1.85	7.220000	1.01	3.55	1045
9	1	14.10	2.16	2.30	18.0	105	2.95	3.32	0.22	2.38	5.750000	1.25	3.17	1510
10	1	14.12	1.48	2.32	16.8	95	2.20	2.43	0.26	1.57	5.000000	1.17	2.82	1280
11	1	13.75	1.73	2.41	16.0	89	2.60	2.76	0.29	1.81	5.600000	1.15	2.90	1320
12	1	14.75	1.73	2.39	11.4	91	3.10	3.69	0.43	2.81	5.400000	1.25	2.73	1150
13	1	14.38	1.87	2.38	12.0	102	3.30	3.64	0.29	2.96	7.500000	1.20	3.00	1547
14	1	13.63	1.81	2.70	17.2	112	2.85	2.91	0.30	1.46	7.300000	1.28	2.88	1310
15	1	14.30	1.92	2.72	20.0	120	2.80	3.14	0.33	1.97	6.200000	1.07	2.65	1280
16	1	13.83	1.57	2.62	20.0	115	2.95	3.40	0.40	1.72	6.600000	1.13	2.57	1130
17	1	14.19	1.59	2.48	16.5	108	3.30	3.93	0.32	1.86	8.700000	1.23	2.82	1680
18	1	13.64	3.10	2.56	15.2	116	2.70	3.03	0.17	1.66	5.100000	0.96	3.36	845
19	1	14.06	1.63	2.28	16.0	126	3.00	3.17	0.24	2.10	5.650000	1.09	3.71	780
20	1	12.93	3.80	2.65	18.6	102	2.41	2.41	0.25	1.98	4.500000	1.03	3.52	770
21	1	13.71	1.86	2.36	16.6	101	2.61	2.88	0.27	1.69	3.800000	1.11	4.00	1035
22	1	12.85	1.60	2.52	17.8	95	2.48	2.37	0.26	1.46	3.930000	1.09	3.63	1015
23	1	13.50	1.81	2.61	20.0	96	2.53	2.61	0.28	1.66	3.520000	1.12	3.82	845
24	1	13.05	2.05	3.22	25.0	124	2.63	2.68	0.47	1.92	3.580000	1.13	3.20	830

	1.0	14.23	1.71	2.43	15.6	127.0	2.8	3.06	0.28	2.29	5.64	1.04	3.92	1065.0
25	1	13.39	1.77	2.62	16.1	93	2.85	2.94	0.34	1.45	4.800000	0.92	3.22	1195
26	1	13.30	1.72	2.14	17.0	94	2.40	2.19	0.27	1.35	3.950000	1.02	2.77	1285
27	1	13.87	1.90	2.80	19.4	107	2.95	2.97	0.37	1.76	4.500000	1.25	3.40	915
28	1	14.02	1.68	2.21	16.0	96	2.65	2.33	0.26	1.98	4.700000	1.04	3.59	1035
29	1	13.73	1.50	2.70	22.5	101	3.00	3.25	0.29	2.38	5.700000	1.19	2.71	1285
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
147	3	13.32	3.24	2.38	21.5	92	1.93	0.76	0.45	1.25	8.420000	0.55	1.62	650
148	3	13.08	3.90	2.36	21.5	113	1.41	1.39	0.34	1.14	9.400000	0.57	1.33	550
149	3	13.50	3.12	2.62	24.0	123	1.40	1.57	0.22	1.25	8.600000	0.59	1.30	500
150	3	12.79	2.67	2.48	22.0	112	1.48	1.36	0.24	1.26	10.800000	0.48	1.47	480
151	3	13.11	1.90	2.75	25.5	116	2.20	1.28	0.26	1.56	7.100000	0.61	1.33	425
152	3	13.23	3.30	2.28	18.5	98	1.80	0.83	0.61	1.87	10.520000	0.56	1.51	675
153	3	12.58	1.29	2.10	20.0	103	1.48	0.58	0.53	1.40	7.600000	0.58	1.55	640
154	3	13.17	5.19	2.32	22.0	93	1.74	0.63	0.61	1.55	7.900000	0.60	1.48	725
155	3	13.84	4.12	2.38	19.5	89	1.80	0.83	0.48	1.56	9.010000	0.57	1.64	480
156	3	12.45	3.03	2.64	27.0	97	1.90	0.58	0.63	1.14	7.500000	0.67	1.73	880
157	3	14.34	1.68	2.70	25.0	98	2.80	1.31	0.53	2.70	13.000000	0.57	1.96	660
158	3	13.48	1.67	2.64	22.5	89	2.60	1.10	0.52	2.29	11.750000	0.57	1.78	620
159	3	12.36	3.83	2.38	21.0	88	2.30	0.92	0.50	1.04	7.650000	0.56	1.58	520
160	3	13.69	3.26	2.54	20.0	107	1.83	0.56	0.50	0.80	5.880000	0.96	1.82	680
161	3	12.85	3.27	2.58	22.0	106	1.65	0.60	0.60	0.96	5.580000	0.87	2.11	570
162	3	12.96	3.45	2.35	18.5	106	1.39	0.70	0.40	0.94	5.280000	0.68	1.75	675
163	3	13.78	2.76	2.30	22.0	90	1.35	0.68	0.41	1.03	9.580000	0.70	1.68	615
164	3	13.73	4.36	2.26	22.5	88	1.28	0.47	0.52	1.15	6.620000	0.78	1.75	520
165	3	13.45	3.70	2.60	23.0	111	1.70	0.92	0.43	1.46	10.680000	0.85	1.56	695
166	3	12.82	3.37	2.30	19.5	88	1.48	0.66	0.40	0.97	10.260000	0.72	1.75	685
167	3	13.58	2.58	2.69	24.5	105	1.55	0.84	0.39	1.54	8.660000	0.74	1.80	750

	1.0	14.23	1.71	2.43	15.6	127.0	2.8	3.06	0.28	2.29	5.64	1.04	3.92	1065.0
168	3	13.40	4.60	2.86	25.0	112	1.98	0.96	0.27	1.11	8.500000	0.67	1.92	630
169	3	12.20	3.03	2.32	19.0	96	1.25	0.49	0.40	0.73	5.500000	0.66	1.83	510
170	3	12.77	2.39	2.28	19.5	86	1.39	0.51	0.48	0.64	9.899999	0.57	1.63	470
171	3	14.16	2.51	2.48	20.0	91	1.68	0.70	0.44	1.24	9.700000	0.62	1.71	660
172	3	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	1.06	7.700000	0.64	1.74	740
173	3	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	1.41	7.300000	0.70	1.56	750
174	3	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	1.35	10.200000	0.59	1.56	835
175	3	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	1.46	9.300000	0.60	1.62	840
176	3	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	1.35	9.200000	0.61	1.60	560

177 rows × 14 columns

In [12]:
```
mydata.head(1)
```

Out[12]:

	1.0	14.23	1.71	2.43	15.6	127.0	2.8	3.06	0.28	2.29	5.64	1.04	3.92	1065.0
0	1	13.2	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.38	1.05	3.4	1050

In [13]:
```
names=["cultivator","Alcohol","Malic acid","Ash","Alcalinity of ash","Magnesium","Total phenols","Flavanoids","Nonflavanoid phenols","Proanthocyanins
```

In [16]:
```
mydata=pd.read_excel(r"C:\Users\ANKIT SINGH\Desktop\internship\All In Order pdfs\DAY 8\wine_data.xlsx",names=names)
```

In [17]:
```
mydata.keys()
```

Out[17]:
```
Index(['cultivator', 'Alcohol', 'Malic acid', 'Ash', 'Alcalinity of ash',
       'Magnesium', 'Total phenols', 'Flavanoids', 'Nonflavanoid phenols',
       'Proanthocyanins', 'Color intensity', 'Hue',
       'OD280/OD315 of diluted wines', 'Proline'],
      dtype='object')
```

In [18]:
```
mydata
```

Out[18]:

	cultivator	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline
0	1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.380000	1.05	3.40	1050
1	1	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.680000	1.03	3.17	1185
2	1	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.800000	0.86	3.45	1480
3	1	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.320000	1.04	2.93	735
4	1	14.20	1.76	2.45	15.2	112	3.27	3.39	0.34	1.97	6.750000	1.05	2.85	1450
5	1	14.39	1.87	2.45	14.6	96	2.50	2.52	0.30	1.98	5.250000	1.02	3.58	1290
6	1	14.06	2.15	2.61	17.6	121	2.60	2.51	0.31	1.25	5.050000	1.06	3.58	1295
7	1	14.83	1.64	2.17	14.0	97	2.80	2.98	0.29	1.98	5.200000	1.08	2.85	1045
8	1	13.86	1.35	2.27	16.0	98	2.98	3.15	0.22	1.85	7.220000	1.01	3.55	1045
9	1	14.10	2.16	2.30	18.0	105	2.95	3.32	0.22	2.38	5.750000	1.25	3.17	1510
10	1	14.12	1.48	2.32	16.8	95	2.20	2.43	0.26	1.57	5.000000	1.17	2.82	1280
11	1	13.75	1.73	2.41	16.0	89	2.60	2.76	0.29	1.81	5.600000	1.15	2.90	1320
12	1	14.75	1.73	2.39	11.4	91	3.10	3.69	0.43	2.81	5.400000	1.25	2.73	1150
13	1	14.38	1.87	2.38	12.0	102	3.30	3.64	0.29	2.96	7.500000	1.20	3.00	1547
14	1	13.63	1.81	2.70	17.2	112	2.85	2.91	0.30	1.46	7.300000	1.28	2.88	1310
15	1	14.30	1.92	2.72	20.0	120	2.80	3.14	0.33	1.97	6.200000	1.07	2.65	1280
16	1	13.83	1.57	2.62	20.0	115	2.95	3.40	0.40	1.72	6.600000	1.13	2.57	1130
17	1	14.19	1.59	2.48	16.5	108	3.30	3.93	0.32	1.86	8.700000	1.23	2.82	1680
18	1	13.64	3.10	2.56	15.2	116	2.70	3.03	0.17	1.66	5.100000	0.96	3.36	845
19	1	14.06	1.63	2.28	16.0	126	3.00	3.17	0.24	2.10	5.650000	1.09	3.71	780
20	1	12.93	3.80	2.65	18.6	102	2.41	2.41	0.25	1.98	4.500000	1.03	3.52	770
21	1	13.71	1.86	2.36	16.6	101	2.61	2.88	0.27	1.69	3.800000	1.11	4.00	1035
22	1	12.85	1.60	2.52	17.8	95	2.48	2.37	0.26	1.46	3.930000	1.09	3.63	1015
23	1	13.50	1.81	2.61	20.0	96	2.53	2.61	0.28	1.66	3.520000	1.12	3.82	845

	cultivator	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline
24	1	13.05	2.05	3.22	25.0	124	2.63	2.68	0.47	1.92	3.580000	1.13	3.20	830
25	1	13.39	1.77	2.62	16.1	93	2.85	2.94	0.34	1.45	4.800000	0.92	3.22	1195
26	1	13.30	1.72	2.14	17.0	94	2.40	2.19	0.27	1.35	3.950000	1.02	2.77	1285
27	1	13.87	1.90	2.80	19.4	107	2.95	2.97	0.37	1.76	4.500000	1.25	3.40	915
28	1	14.02	1.68	2.21	16.0	96	2.65	2.33	0.26	1.98	4.700000	1.04	3.59	1035
29	1	13.73	1.50	2.70	22.5	101	3.00	3.25	0.29	2.38	5.700000	1.19	2.71	1285
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
147	3	13.32	3.24	2.38	21.5	92	1.93	0.76	0.45	1.25	8.420000	0.55	1.62	650
148	3	13.08	3.90	2.36	21.5	113	1.41	1.39	0.34	1.14	9.400000	0.57	1.33	550
149	3	13.50	3.12	2.62	24.0	123	1.40	1.57	0.22	1.25	8.600000	0.59	1.30	500
150	3	12.79	2.67	2.48	22.0	112	1.48	1.36	0.24	1.26	10.800000	0.48	1.47	480
151	3	13.11	1.90	2.75	25.5	116	2.20	1.28	0.26	1.56	7.100000	0.61	1.33	425
152	3	13.23	3.30	2.28	18.5	98	1.80	0.83	0.61	1.87	10.520000	0.56	1.51	675
153	3	12.58	1.29	2.10	20.0	103	1.48	0.58	0.53	1.40	7.600000	0.58	1.55	640
154	3	13.17	5.19	2.32	22.0	93	1.74	0.63	0.61	1.55	7.900000	0.60	1.48	725
155	3	13.84	4.12	2.38	19.5	89	1.80	0.83	0.48	1.56	9.010000	0.57	1.64	480
156	3	12.45	3.03	2.64	27.0	97	1.90	0.58	0.63	1.14	7.500000	0.67	1.73	880
157	3	14.34	1.68	2.70	25.0	98	2.80	1.31	0.53	2.70	13.000000	0.57	1.96	660
158	3	13.48	1.67	2.64	22.5	89	2.60	1.10	0.52	2.29	11.750000	0.57	1.78	620
159	3	12.36	3.83	2.38	21.0	88	2.30	0.92	0.50	1.04	7.650000	0.56	1.58	520
160	3	13.69	3.26	2.54	20.0	107	1.83	0.56	0.50	0.80	5.880000	0.96	1.82	680
161	3	12.85	3.27	2.58	22.0	106	1.65	0.60	0.60	0.96	5.580000	0.87	2.11	570
162	3	12.96	3.45	2.35	18.5	106	1.39	0.70	0.40	0.94	5.280000	0.68	1.75	675
163	3	13.78	2.76	2.30	22.0	90	1.35	0.68	0.41	1.03	9.580000	0.70	1.68	615
164	3	13.73	4.36	2.26	22.5	88	1.28	0.47	0.52	1.15	6.620000	0.78	1.75	520
165	3	13.45	3.70	2.60	23.0	111	1.70	0.92	0.43	1.46	10.680000	0.85	1.56	695

	cultivator	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline
166	3	12.82	3.37	2.30	19.5	88	1.48	0.66	0.40	0.97	10.260000	0.72	1.75	685
167	3	13.58	2.58	2.69	24.5	105	1.55	0.84	0.39	1.54	8.660000	0.74	1.80	750
168	3	13.40	4.60	2.86	25.0	112	1.98	0.96	0.27	1.11	8.500000	0.67	1.92	630
169	3	12.20	3.03	2.32	19.0	96	1.25	0.49	0.40	0.73	5.500000	0.66	1.83	510
170	3	12.77	2.39	2.28	19.5	86	1.39	0.51	0.48	0.64	9.899999	0.57	1.63	470
171	3	14.16	2.51	2.48	20.0	91	1.68	0.70	0.44	1.24	9.700000	0.62	1.71	660
172	3	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	1.06	7.700000	0.64	1.74	740
173	3	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	1.41	7.300000	0.70	1.56	750
174	3	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	1.35	10.200000	0.59	1.56	835
175	3	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	1.46	9.300000	0.60	1.62	840
176	3	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	1.35	9.200000	0.61	1.60	560

177 rows × 14 columns

In [19]:
```
X=mydata.drop("cultivator",axis=1)  #drop the cultivator in X
Y=mydata["cultivator"]              #store in Y
```

In [24]:
```
X     #cultivator drops
```

Out[24]:

	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline
0	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.380000	1.05	3.40	1050
1	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.680000	1.03	3.17	1185
2	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.800000	0.86	3.45	1480
3	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.320000	1.04	2.93	735
4	14.20	1.76	2.45	15.2	112	3.27	3.39	0.34	1.97	6.750000	1.05	2.85	1450
5	14.39	1.87	2.45	14.6	96	2.50	2.52	0.30	1.98	5.250000	1.02	3.58	1290
6	14.06	2.15	2.61	17.6	121	2.60	2.51	0.31	1.25	5.050000	1.06	3.58	1295
7	14.83	1.64	2.17	14.0	97	2.80	2.98	0.29	1.98	5.200000	1.08	2.85	1045
8	13.86	1.35	2.27	16.0	98	2.98	3.15	0.22	1.85	7.220000	1.01	3.55	1045
9	14.10	2.16	2.30	18.0	105	2.95	3.32	0.22	2.38	5.750000	1.25	3.17	1510
10	14.12	1.48	2.32	16.8	95	2.20	2.43	0.26	1.57	5.000000	1.17	2.82	1280
11	13.75	1.73	2.41	16.0	89	2.60	2.76	0.29	1.81	5.600000	1.15	2.90	1320
12	14.75	1.73	2.39	11.4	91	3.10	3.69	0.43	2.81	5.400000	1.25	2.73	1150
13	14.38	1.87	2.38	12.0	102	3.30	3.64	0.29	2.96	7.500000	1.20	3.00	1547
14	13.63	1.81	2.70	17.2	112	2.85	2.91	0.30	1.46	7.300000	1.28	2.88	1310
15	14.30	1.92	2.72	20.0	120	2.80	3.14	0.33	1.97	6.200000	1.07	2.65	1280
16	13.83	1.57	2.62	20.0	115	2.95	3.40	0.40	1.72	6.600000	1.13	2.57	1130
17	14.19	1.59	2.48	16.5	108	3.30	3.93	0.32	1.86	8.700000	1.23	2.82	1680
18	13.64	3.10	2.56	15.2	116	2.70	3.03	0.17	1.66	5.100000	0.96	3.36	845
19	14.06	1.63	2.28	16.0	126	3.00	3.17	0.24	2.10	5.650000	1.09	3.71	780
20	12.93	3.80	2.65	18.6	102	2.41	2.41	0.25	1.98	4.500000	1.03	3.52	770
21	13.71	1.86	2.36	16.6	101	2.61	2.88	0.27	1.69	3.800000	1.11	4.00	1035
22	12.85	1.60	2.52	17.8	95	2.48	2.37	0.26	1.46	3.930000	1.09	3.63	1015
23	13.50	1.81	2.61	20.0	96	2.53	2.61	0.28	1.66	3.520000	1.12	3.82	845

	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline
24	13.05	2.05	3.22	25.0	124	2.63	2.68	0.47	1.92	3.580000	1.13	3.20	830
25	13.39	1.77	2.62	16.1	93	2.85	2.94	0.34	1.45	4.800000	0.92	3.22	1195
26	13.30	1.72	2.14	17.0	94	2.40	2.19	0.27	1.35	3.950000	1.02	2.77	1285
27	13.87	1.90	2.80	19.4	107	2.95	2.97	0.37	1.76	4.500000	1.25	3.40	915
28	14.02	1.68	2.21	16.0	96	2.65	2.33	0.26	1.98	4.700000	1.04	3.59	1035
29	13.73	1.50	2.70	22.5	101	3.00	3.25	0.29	2.38	5.700000	1.19	2.71	1285
...	...	...	...	...	...	...	...	...	...	...	...	...	...
147	13.32	3.24	2.38	21.5	92	1.93	0.76	0.45	1.25	8.420000	0.55	1.62	650
148	13.08	3.90	2.36	21.5	113	1.41	1.39	0.34	1.14	9.400000	0.57	1.33	550
149	13.50	3.12	2.62	24.0	123	1.40	1.57	0.22	1.25	8.600000	0.59	1.30	500
150	12.79	2.67	2.48	22.0	112	1.48	1.36	0.24	1.26	10.800000	0.48	1.47	480
151	13.11	1.90	2.75	25.5	116	2.20	1.28	0.26	1.56	7.100000	0.61	1.33	425
152	13.23	3.30	2.28	18.5	98	1.80	0.83	0.61	1.87	10.520000	0.56	1.51	675
153	12.58	1.29	2.10	20.0	103	1.48	0.58	0.53	1.40	7.600000	0.58	1.55	640
154	13.17	5.19	2.32	22.0	93	1.74	0.63	0.61	1.55	7.900000	0.60	1.48	725
155	13.84	4.12	2.38	19.5	89	1.80	0.83	0.48	1.56	9.010000	0.57	1.64	480
156	12.45	3.03	2.64	27.0	97	1.90	0.58	0.63	1.14	7.500000	0.67	1.73	880
157	14.34	1.68	2.70	25.0	98	2.80	1.31	0.53	2.70	13.000000	0.57	1.96	660
158	13.48	1.67	2.64	22.5	89	2.60	1.10	0.52	2.29	11.750000	0.57	1.78	620
159	12.36	3.83	2.38	21.0	88	2.30	0.92	0.50	1.04	7.650000	0.56	1.58	520
160	13.69	3.26	2.54	20.0	107	1.83	0.56	0.50	0.80	5.880000	0.96	1.82	680
161	12.85	3.27	2.58	22.0	106	1.65	0.60	0.60	0.96	5.580000	0.87	2.11	570
162	12.96	3.45	2.35	18.5	106	1.39	0.70	0.40	0.94	5.280000	0.68	1.75	675
163	13.78	2.76	2.30	22.0	90	1.35	0.68	0.41	1.03	9.580000	0.70	1.68	615
164	13.73	4.36	2.26	22.5	88	1.28	0.47	0.52	1.15	6.620000	0.78	1.75	520
165	13.45	3.70	2.60	23.0	111	1.70	0.92	0.43	1.46	10.680000	0.85	1.56	695

	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline
166	12.82	3.37	2.30	19.5	88	1.48	0.66	0.40	0.97	10.260000	0.72	1.75	685
167	13.58	2.58	2.69	24.5	105	1.55	0.84	0.39	1.54	8.660000	0.74	1.80	750
168	13.40	4.60	2.86	25.0	112	1.98	0.96	0.27	1.11	8.500000	0.67	1.92	630
169	12.20	3.03	2.32	19.0	96	1.25	0.49	0.40	0.73	5.500000	0.66	1.83	510
170	12.77	2.39	2.28	19.5	86	1.39	0.51	0.48	0.64	9.899999	0.57	1.63	470
171	14.16	2.51	2.48	20.0	91	1.68	0.70	0.44	1.24	9.700000	0.62	1.71	660
172	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	1.06	7.700000	0.64	1.74	740
173	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	1.41	7.300000	0.70	1.56	750
174	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	1.35	10.200000	0.59	1.56	835
175	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	1.46	9.300000	0.60	1.62	840
176	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	1.35	9.200000	0.61	1.60	560

177 rows × 13 columns

In [25]:
```
Y        #Store the cultivator in Y
```

Out[25]:
```
0      1
1      1
2      1
3      1
4      1
5      1
6      1
7      1
8      1
9      1
10     1
11     1
12     1
13     1
14     1
15     1
16     1
17     1
18     1
19     1
20     1
21     1
22     1
23     1
24     1
25     1
26     1
27     1
28     1
29     1
      ..
147    3
148    3
149    3
150    3
151    3
152    3
153    3
154    3
155    3
```

```
156    3
157    3
158    3
159    3
160    3
161    3
162    3
163    3
164    3
165    3
166    3
167    3
168    3
169    3
170    3
171    3
172    3
173    3
174    3
175    3
176    3
Name: cultivator, Length: 177, dtype: int64
```

In [20]:
```python
X.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Alcohol	177.0	12.993672	0.808808	11.03	12.36	13.05	13.67	14.83
Malic acid	177.0	2.339887	1.119314	0.74	1.60	1.87	3.10	5.80
Ash	177.0	2.366158	0.275080	1.36	2.21	2.36	2.56	3.23
Alcalinity of ash	177.0	19.516949	3.336071	10.60	17.20	19.50	21.50	30.00
Magnesium	177.0	99.587571	14.174018	70.00	88.00	98.00	107.00	162.00
Total phenols	177.0	2.292260	0.626465	0.98	1.74	2.35	2.80	3.88
Flavanoids	177.0	2.023446	0.998658	0.34	1.20	2.13	2.86	5.08
Nonflavanoid phenols	177.0	0.362316	0.124653	0.13	0.27	0.34	0.44	0.66
Proanthocyanins	177.0	1.586949	0.571545	0.41	1.25	1.55	1.95	3.58
Color intensity	177.0	5.054802	2.324446	1.28	3.21	4.68	6.20	13.00
Hue	177.0	0.956983	0.229135	0.48	0.78	0.96	1.12	1.71
OD280/OD315 of diluted wines	177.0	2.604294	0.705103	1.27	1.93	2.78	3.17	4.00

In [21]:
```python
mydata.keys()
```

Out[21]:
```
Index(['cultivator', 'Alcohol', 'Malic acid', 'Ash', 'Alcalinity of ash',
       'Magnesium', 'Total phenols', 'Flavanoids', 'Nonflavanoid phenols',
       'Proanthocyanins', 'Color intensity', 'Hue',
       'OD280/OD315 of diluted wines', 'Proline'],
      dtype='object')
```

In [22]:
```python
import numpy as np
```

In [23]:
```python
np.unique(Y.values)
```

Out[23]:
```
array([1, 2, 3], dtype=int64)
```

Feature Scaling (Preprocessing)

In [27]:
```
from sklearn.preprocessing import StandardScaler
```

In [29]:
```
print("mean of X",X.values.mean())
print("Std of X",X.values.std())
```

```
mean of X 68.9831794867449
Std of X 215.30680616380351
```

In [30]:
```
XA=np.array(X)
YA=np.array(Y)
```

In [31]:
```
scaler=StandardScaler()
XA=scaler.fit(XA).transform(XA)
#if you use transform than output will be array otherwise it is StandardScaler
```

In [32]:
```
print("mean of XA",round(XA.mean()))
print("Std of XA",XA.std())
```

```
mean of XA 0.0
Std of XA 1.0
```

In [33]:
```
type(XA)
```

Out[33]:
```
numpy.ndarray
```

In [34]:
```
from sklearn.model_selection import train_test_split
```

In [35]:
```
#if random_state fix than data is not shuffled it is changes it is checked by removing and print Xtrain
xtrain,xtest,ytrain,ytest=train_test_split(XA,YA,test_size=.30,random_state=101)
xtrain
```

Out[35]:
```
array([[-1.14525593, -0.1611677 , -0.7151169 , ..., -0.4244579 ,
         0.96102728, -1.1691207 ],
       [-0.77328768, -1.01230928,  0.70667226, ...,  1.0198265 ,
        -0.43278369, -0.21368624],
       [-1.45522948, -0.55538064, -1.77234474, ..., -0.07432835,
        -0.23366784, -1.05128378],
       ...,
       [-1.13285699, -1.08398436,  0.5243916 , ...,  1.54502083,
         0.16456387, -0.36655576],
       [ 0.9377663 , -0.54642125,  0.15983027, ...,  0.84476172,
         0.42056996,  1.83094348],
       [-1.46762842, -0.19700524,  1.36288264, ..., -0.03056216,
        -0.48967393, -0.38247966]])
```

In [36]:
```
from sklearn.neural_network import MLPClassifier
```

In [38]:
```
#if you use 500 than after running learner you get warning
#13 it is not the part of input
trainer=MLPClassifier(hidden_layer_sizes=(13,13,13),max_iter=500,activation="logistic")
```

In [39]:
```
learner=trainer.fit(xtrain,ytrain)  #see warning here
```

```
C:\Users\ANKIT SINGH\Anaconda3\lib\site-packages\sklearn\neural_network\multilayer_perceptron.py:562: ConvergenceWarning: Stochastic Optimizer: Maxi
mum iterations (500) reached and the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

In [45]:
```
#here we use 1000 iteration so optimization converged
#13 it is not the part of input
trainer=MLPClassifier(hidden_layer_sizes=(13,13,13),max_iter=1000,activation="logistic")
```

In [46]:
```
learner=trainer.fit(xtrain,ytrain)
```

In [47]:
```
from sklearn.metrics import accuracy_score,jaccard_similarity_score
```

In [48]:
```
Yp=learner.predict(xtest)
Ya=ytest
```

In [49]:
```
acc=accuracy_score(Yp,Ya)*100
jss=jaccard_similarity_score(Yp,Ya)*100
print("jss {} acc {}".format(jss,acc))
```

```
jss 98.14814814814815 acc 98.14814814814815
```

In [50]:
```
learner.coefs_
```

Out[50]:
```
[array([[ 0.76773317,  0.22700201,  0.36792818,  0.31181422, -0.7954341 ,
          0.63671231,  0.56753823, -0.93849396, -0.54563551, -0.64833702,
          0.53797309,  0.71446617, -0.79026486],
        [ 0.42687593,  0.4652324 ,  0.47428849,  0.20269311, -0.30373226,
          0.41719086,  0.23280418, -0.65058145, -0.33646773, -0.63805361,
          0.35461884,  0.53053404, -0.14678708],
        [ 0.68462986,  0.30652323,  0.68775699,  0.35496529, -0.69397261,
          0.54220506,  0.22832454, -0.906899  , -0.48337066, -0.52595947,
          0.3016564 ,  0.6572271 , -0.50439391],
        [-0.608509  ,  0.22934639,  0.05666956,  0.30942043,  0.51729605,
         -0.71140834, -0.68430618,  0.13030486,  0.77620058, -0.13143053,
         -0.68999512, -0.7949829 ,  0.79061181],
        [ 0.018696  ,  0.04080974,  0.11895809,  0.00885109,  0.00465877,
          0.14938081,  0.66696263, -0.11768378,  0.12219738, -0.32052278,
         -0.0375403 ,  0.08329113,  0.01276553],
        [-0.09977545,  0.12231826,  0.17939696,  0.17949076, -0.08329199,
         -0.11163976,  0.09162826, -0.05366522, -0.09750526,  0.32826427,
          0.02039959,  0.16674466,  0.21795318],
        [ 0.35383095, -0.56706842, -0.84975349, -0.60805816,  0.14815688,
```

In [51]:
```
from sklearn.metrics import confusion_matrix,classification_report
```

In [52]:
```
table=pd.crosstab(Ya,Yp,rownames=["Ya"],colnames=["Yp"])
```

In [53]:
```
table
```

Out[53]:

Yp Ya	1	2	3
1	19	0	0
2	0	20	1
3	0	0	14

In [54]:
```
x=learner.coefs_   #input layer included so 4 otherwise 3
len(x)
```

Out[54]: 4

In [55]:
```
len(x[1])
```

Out[55]: 13

In [56]:
```
len(x[3])
```

Out[56]: 13

In [57]:
```
b=learner.intercepts_
```

In [58]:
```
len(b)
```

Out[58]: 4

In [59]:
```
len(b[0])
```

Out[59]: 13