


```

9     if data[i][-1]=='Iris-virginica':
10         data[i][-1]=3 # relabeling Iris virginica class as "0"
11         data[i][0]=1 # initializing first column as 1 for bias

```

In [440]:

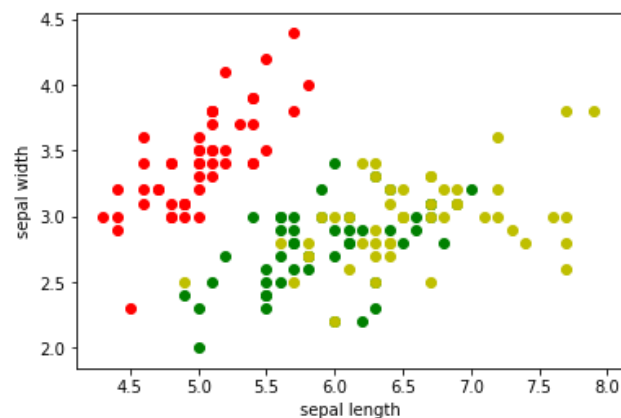
```
1 #data
```

In [441]:

```

1 for i in range(len(data)):
2     if data[i][-1]==1:
3         plt.scatter(data[i,1],data[i,2],c='r')
4     if data[i][-1]==2:
5         plt.scatter(data[i,1],data[i,2],c='g')
6     if data[i][-1]==3:
7         plt.scatter(data[i,1],data[i,2],c='y')
8     plt.xlabel('sepal length')
9     plt.ylabel('sepal width')
10
11 plt.show() # a plot between sepal length and sepal width

```

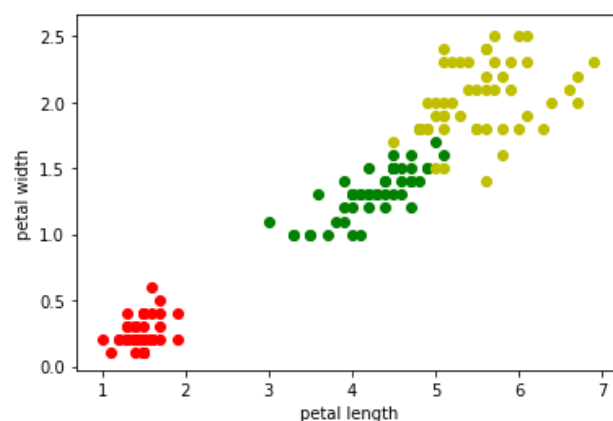


In [442]:

```

1 for i in range(len(data)):
2     if data[i][-1]==1:
3         plt.scatter(data[i,3],data[i,4],c='r')
4     if data[i][-1]==2:
5         plt.scatter(data[i,3],data[i,4],c='g')
6     if data[i][-1]==3:
7         plt.scatter(data[i,3],data[i,4],c='y')
8     plt.xlabel('petal length')
9     plt.ylabel('petal width')
10
11 plt.show() # a plot between petal length and petal width

```



Implementing Forward Propagation MLP for Iris dataset

In [443]:

```

1 input_no_of_nodes = 4 # as features are 4-dimensional i.e. sepal length,pet
2 # and petal width
3 no_of_hidden_layers = 1 # just for simplicity , I am taking one hidden laye

```

```

4 no_of_classes = 3 # setosa, virginica and versicolor
5
6 # initializing input weights for output layer
7
8 weight1 = [] # initializing weights
9
10
11 for k in range(3):
12     w=[]
13     for j in range(5):
14         w.append(np.random.randn())
15     weight1.append(w)
16
17 print("input weight vector for output layer:\n ",weight1)
18
19 # initializing input weights for hidden layer
20
21 weight2 = [] # initializing weights
22
23 bias= 1
24
25
26
27 for k in range(4):
28     w=[]
29     for j in range(5):
30         w.append(np.random.randn())
31     weight2.append(w)
32
33 print("\ninput weight vector for hidden layer:\n " weight2)

```

input weight vector for output layer:

```

[[0.18204651248854653, -0.3195494800785854, 0.8506967596147637, -1.527883060
1839293, 0.8468775949912822], [-0.7105553426733896, 1.5427545553212112, -0.521
2290329153958, 1.3199837146608846, 1.3027364165285165], [-1.2581738482758533,
0.1954909533767402, -0.5293114051138316, 0.8982568826527799, -1.26789205684944
4]]

```

input weight vector for hidden layer:

```

[[0.012079880287338243, -1.0994786150270182, 0.6706515214739192, 0.696574387
9098967, 0.874415795996476], [1.0953417415957751, 2.2584676519018334, 0.326125
3541951244, 0.32904108755751343, 0.5200729353112302], [1.1755338637157928, 0.1
0241462477627439, 0.9286554122455126, 0.6679682394666533, -0.223888796096033
7], [0.309703588072365, -1.740283841682843, -0.2776661070260824, 1.73557043354
72464, -0.9442540729403734]]

```

In [444]:

```

1 #for dk(p), if class label belongs to class 1, we make 1st value as 1 and 0
2 #others
3
4 labels=[]
5 for i in range(150):
6     if data[i][-1]==1:
7         labels.append([1,0,0])
8     if data[i][-1]==2:
9         labels.append([0,1,0])
10    if data[i][-1]==3:
11        labels.append([0,0,1])

```

In [445]:

```

1 forward_prop_output=[]
2
3 # Input on input layer -1 (hidden layer ) by using McCullouch Pit mode
4
5 u1=[]
6 for j in range(4):
7     sum=0
8     for i in range(5):
9         sum += weight2[j][i]*data[j][i]
10    u1.append(sum)
11    #print("Input on layer 1 (hidden layer) : ",u)

```

```

12
13     # For output on layer 1, by using sigmoid function,
14
15     v1=[]
16     v1.append(1) # appending bias=1
17
18     for i in range(4):
19         sig=1/(1+ np.exp(-u1[i]))
20         v1.append(sig)
21     #print("output on layer 1 : ",v)
22
23
24     # For input on layer 2 by using McCullouch Pit model,
25
26     u2=[]
27     for j in range(3):
28         sum=0
29         for i in range(5):
30             sum += weight1[j][i]*v1[i]
31         u2.append(sum)
32     #print("input of layer 2",u)
33
34
35     # For output on layer 2(output layer), by using sigmoid function,
36
37     v2=[]
38
39     for i in range(3):
40         sig=1/(1+ np.exp(-u2[i]))
41         v2.append(sig)
42     #print("output on layer 2 (output layer) : ",v)
43     forward_prop_output.append(v2)
44     yk=forward_prop_output
45

```

```

In [446]: 1     def forward_prop(p):
2           forward_prop_output=[]
3
4           # Input on input layer -1 (hidden layer ) by using McCullouch Pit model
5
6           u1=[]
7           for j in range(4):
8               sum=0
9               for i in range(5):
10                  sum += weight2[j][i]*data[p][i]
11              u1.append(sum)
12          #print("Input on layer 1 (hidden layer) : ",u)
13
14          # For output on layer 1, by using sigmoid function,
15
16          v1=[]
17          v1.append(1) # appending bias=1
18
19          for i in range(4):
20              sig=1/(1+ np.exp(-u1[i]))
21              v1.append(sig)
22          #print("output on layer 1 : ",v)
23
24
25          # For input on layer 2 by using McCullouch Pit model,
26
27          u2=[]
28          for j in range(3):
29              sum=0
30              for i in range(5):
31                  sum += weight1[j][i]*v1[i]
32              u2.append(sum)
33          #print("input of layer 2",u)

```

[illegible]

Implementing Backpropagation MLP for iris dataset

```
In [449]: 1 def back_prop(p):
2           # computing delta w_ji(θ) (learning rule) #weight2
3
4           learning_rate = 0.5 #assuming
5
6           forward_prop_output=[]
7
8           # Input on input layer -1 (hidden layer ) by using McCullouch Pit mode
9
10          u1=[]
11          for j in range(4):
12              sum=0
13              for i in range(5):
14                  sum += weight2[j][i]*data[p][i]
15              u1.append(sum)
```

```

17         #print("Input on layer 1 (hidden layer) : ",u)
18
19         # For output on layer 1, by using sigmoid function,
20
21         v1=[]
22         v1.append(1) # appending bias=1
23
24         for i in range(4):
25             sig=1/(1+ np.exp(-u1[i]))
26             v1.append(sig)
27         #print("output on layer 1 : ",v)
28
29
30         # For input on layer 2 by using McCullouch Pit model,
31
32         u2=[]
33         for j in range(3):
34             sum=0
35             for i in range(5):
36                 sum += weight1[j][i]*v1[i]
37             u2.append(sum)
38             #print("input of layer 2",u)
39
40
41         # For output on layer 2(output layer), by using sigmoid function,
42
43         v2=[]
44
45         for i in range(3):
46             sig=1/(1+ np.exp(-u2[i]))
47             v2.append(sig)
48             #print("output on layer 2 (output layer) : ",v)
49         forward_prop_output.append(v2)
50         yk=forward_prop_output
51
52
53
54
55         for k in range(3):
56             for j in range(5):
57                 delta_w_kj_1 = (labels[p][k] - yk[0][k])*(yk[0][k])*(1-yk[0][k])
58
59         delta_w_kj_1=learning_rate*delta_w_kj_1
60         #print(delta_w_kj_1)
61
62
63         # computing delta w_ji(0) (learning rule) #weight2
64
65         learning_rate = 0.5 #assuming
66
67
68         for k in range(3):
69             for j in range(5):
70                 for l in range(5):
71                     delta_w_ji_0 = (labels[p][k] - yk[0][k])*yk[0][k]*(1-yk[0][k])
72
73         delta_w_ji_0=learning_rate*delta_w_ji_0
74         #print(delta_w_ji_0)
75
76         # modifying weight1 and weight2 according to delta_w
77         #print("previous weight1 matrix : ", weight1)
78         temp1=0
79         for k in range(3):
80             for j in range(5):
81                 temp1 =weight1[k][j]
82                 weight1[k][j] =temp1+delta_w_kj_1
83
84

```

```

85     #print("modified input weight vector for output layer:\n ",weight1)
86
87     #print("Previous weight2 matrix : ", weight2)
88
89     temp2=0
90     for k in range(4):
91         for j in range(5):
92             temp2=weight2[k][j]
93             weight2[k][j] = temp2+ delta_w_ji_0
94
95
96     #print("modified input weight vector for hidden layer:\n ",weight2)
97
98     return
99

```

```

In [450]: 1 error1=0
          2 for p in range(150):
          3     output1=forward_prop(p)
          4     #print(output)
          5     for j in range(3):
          6         error1 += pow((labels[p][j] - output1[0][j]),2)
          7     E1 = error1/2
          8     print(E1)      #error after forward propagation initially
56.751504851834625

```

```

In [451]: 1 for n in range(50):# number of iterations
          2     error=0
          3     for i in range(150):
          4         output=forward_prop(i)
          5         #print(output)
          6         #error = 0
          7         for j in range(3):
          8             error += pow((labels[i][j] - output[0][j]),2)
          9         E = error/2
          10        #print(E)
          11        #if E<0.1:
          12            # break
          13        back_prop(i)
          14    print("Minimized error after 100 iteration: ", E) # Our objective was to Minimize the error
          15
          16    # if error difference is not much then incearease the number of iteration to 100

```

Minimized error after 100 iteration: 54.775238213652585

```

In [452]: 1 print("Final input weight matrix for hidden layer: \n",weight2)
          2 print("\nFinal input weight matrix for output layer: \n" weight1)

```

Final input weight matrix for hidden layer:
[[[-0.2431105734390827, -1.3546690687534335, 0.4154610677474975, 0.44138393418347427, 0.6192253422700504], [0.8401512878693501, 2.003277198175414, 0.07093490046870354, 0.07385063383109278, 0.26488248158481115], [0.9203434099893685, -0.15277582895014669, 0.673464958519087, 0.4127778574023155, -0.4790792498224527], [0.05451313434594388, -1.9954742954092584, -0.5328565607525014, 1.480379979820831, -1.1994445266667888]]]

Final input weight matrix for output layer:
[[[0.2529551252114036, -0.24864086735572838, 0.9216053723376181, -1.4569744474610702, 0.9177862077141367], [-0.6396467299505352, 1.6136631680440703, -0.4503204201925382, 1.3908923273837437, 1.3736450292513755], [-1.1872652355529942, 0.2663995660995988, -0.45840279239097464, 0.9691654953756343, -1.196983444126585]]]

Incorporating momentum factor

```

In [423]: 1 gamma=0.9

```

```

2 mom1=0
3 mom2=0
In [424]: 1 #Modifying little bit the definition of backpropagation for error learning
2
3 def back_prop(p,mom1,mom2):
4     # computing delta w_ji(0) (learning rule) #weight2
5
6     learning_rate = 0.5 #assuming
7
8     forward_prop_output=[]
9
10    # Input on input layer -1 (hidden layer ) by using McCullouch Pit mod
11
12    u1=[]
13    for j in range(4):
14        sum=0
15        for i in range(5):
16            sum += weight2[j][i]*data[p][i]
17        u1.append(sum)
18        #print("Input on layer 1 (hidden layer) : ",u)
19
20    # For output on layer 1, by using sigmoid function,
21
22    v1=[]
23    v1.append(1) # appending bias=1
24
25    for i in range(4):
26        sig=1/(1+ np.exp(-u1[i]))
27        v1.append(sig)
28    #print("output on layer 1 : ",v)
29
30
31    # For input on layer 2 by using McCullouch Pit model,
32
33    u2=[]
34    for j in range(3):
35        sum=0
36        for i in range(5):
37            sum += weight1[j][i]*v1[i]
38        u2.append(sum)
39        #print("input of layer 2",u)
40
41
42    # For output on layer 2(output layer), by using sigmoid function,
43
44    v2=[]
45
46    for i in range(3):
47        sig=1/(1+ np.exp(-u2[i]))
48        v2.append(sig)
49        #print("output on layer 2 (output layer) : ",v)
50    forward_prop_output.append(v2)
51    yk=forward_prop_output
52
53
54    for k in range(3):
55        for j in range(5):
56            delta_w_kj_1 = (labels[p][k] - yk[0][k])*(yk[0][k])*(1-yk[0][k]
57
58    delta_w_kj_1=learning_rate*delta_w_kj_1
59    #print(delta_w_kj_1)
60
61
62    # computing delta w_ji(0) (learning rule) #weight2
63
64    learning_rate = 0.5 #assuming
65
66

```



```

67     for k in range(3):
68         for j in range(5):
69             for l in range(5):
70                 delta_w_ji_0 = (labels[p][k] - yk[0][k])*yk[0][k]*(1-yk[0]
71
72     delta_w_ji_0=learning_rate*delta_w_ji_0
73     #print(delta_w_ji_0)
74
75     # modifying weight1 and weight2 according to delta_w
76     #print("previous weight1 matrix : ", weight1)
77
78     # Here, I am using the concept of momentum factor
79     mom1 += pow(gamma,i)*(delta_w_kj_1)
80     mom2 += pow(gamma,i)*(delta_w_ji_0)
81
82     temp1=0
83     for k in range(3):
84         for j in range(5):
85             temp1 =weight1[k][j]
86             weight1[k][j] =temp1+(mom1 + delta_w_kj_1)
87
88
89     #print("modified input weight vector for output layer:\n ",weight1)
90
91     #print("Previous weight2 matrix : ", weight2)
92
93     temp2=0
94     for k in range(4):
95         for j in range(5):
96             temp2=weight2[k][j]
97             weight2[k][j] = temp2+ (mom2 + delta_w_ji_0)
98
99
100    #print("modified input weight vector for hidden layer:\n ",weight2)
101
102    return mom1,mom2
103

```

```

In [425]: 1 for n in range(100):# number of iterations
2         error=0
3         for i in range(150):
4             output=forward_prop(i)
5             #print(output)
6             #error = 0
7             for j in range(3):
8                 error += pow((labels[i][j] - output[0][j]),2)
9             E = error/2
10            #print(E)
11            #if E<0.1:
12                # break
13
14            back_prop(i,mom1,mom2)
15
16    print("Minimized error after 100 iteration: ", E) # Our objective was to Minimize the error
17
18    # if error difference is not much then incearease the number of iteration k

```

Minimized error after 100 iteration: 43.510786166850934

In []: 1