

## 1. 1 Nonlinear Regression

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed	WindDir9am	WindDir3pm	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm	Cloud9am	Cloud3pm	Temp9am	Temp3pm	RainTomorrow
0	01-12-2008	Albury	13.4	22.9	0.6	NaN	NaN	W	44.0	W	WNW	20.0	24.0	71.0	22.0	1007.7	1007.1	8.0	NaN	16.9	21.8	No
1	02-12-2008	Albury	7.4	25.1	0.0	NaN	NaN	WNW	44.0	NNW	WSW	4.0	22.0	44.0	25.0	1010.6	1007.8	NaN	NaN	17.2	24.3	No
2	03-12-2008	Albury	12.9	25.7	0.0	NaN	NaN	WSW	46.0	W	WSW	19.0	26.0	38.0	30.0	1007.6	1008.7	NaN	NaN	21.0	23.2	No
3	04-12-2008	Albury	9.2	28.0	0.0	NaN	NaN	NE	24.0	SE	E	11.0	9.0	45.0	16.0	1017.6	1012.8	NaN	NaN	18.1	26.5	No
4	05-12-2008	Albury	17.5	32.3	1.0	NaN	NaN	W	41.0	ENE	NW	7.0	20.0	82.0	33.0	1010.8	1006.0	7.0	8.0	17.8	29.7	No
	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed	WindDir9am	WindDir3pm	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm	Cloud9am	Cloud3pm	Temp9am	Temp3pm	RainTomorrow
0	01-12-2008	Albury	13.4	22.9	0.6	NaN	NaN	W	44.0	W	WNW	20.0	24.0	71.0	22.0	1007.7	1007.1	8.0	NaN	16.9	21.8	0
1	02-12-2008	Albury	7.4	25.1	0.0	NaN	NaN	WNW	44.0	NNW	WSW	4.0	22.0	44.0	25.0	1010.6	1007.8	NaN	NaN	17.2	24.3	0
2	03-12-2008	Albury	12.9	25.7	0.0	NaN	NaN	WSW	46.0	W	WSW	19.0	26.0	38.0	30.0	1007.6	1008.7	NaN	NaN	21.0	23.2	0
3	04-12-2008	Albury	9.2	28.0	0.0	NaN	NaN	NE	24.0	SE	E	11.0	9.0	45.0	16.0	1017.6	1012.8	NaN	NaN	18.1	26.5	0
4	05-12-2008	Albury	17.5	32.3	1.0	NaN	NaN	W	41.0	ENE	NW	7.0	20.0	82.0	33.0	1010.8	1006.0	7.0	8.0	17.8	29.7	0
	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm	Cloud9am	Cloud3pm	Temp9am	Temp3pm	RainTomorrow					
0	13.4	22.9	0.6	NaN	NaN	44.0	20.0	24.0	71.0	22.0	1007.7	1007.1	8.0	NaN	16.9	21.8	0					
1	7.4	25.1	0.0	NaN	NaN	44.0	4.0	22.0	44.0	25.0	1010.6	1007.8	NaN	NaN	17.2	24.3	0					
2	12.9	25.7	0.0	NaN	NaN	46.0	19.0	26.0	38.0	30.0	1007.6	1008.7	NaN	NaN	21.0	23.2	0					
3	9.2	28.0	0.0	NaN	NaN	24.0	11.0	9.0	45.0	16.0	1017.6	1012.8	NaN	NaN	18.1	26.5	0					
4	17.5	32.3	1.0	NaN	NaN	41.0	7.0	20.0	82.0	33.0	1010.8	1006.0	7.0	8.0	17.8	29.7	0					
	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm	Cloud9am	Cloud3pm	Temp9am	Temp3pm	RainTomorrow					
0	13.4	22.9	0.6	5.52876	7.568706	44.0	20.0	24.0	71.0	22.0	1007.7	1007.1	8.00000	4.487216	16.9	21.8	0					
1	7.4	25.1	0.0	5.52876	7.568706	44.0	4.0	22.0	44.0	25.0	1010.6	1007.8	4.43216	4.487216	17.2	24.3	0					
2	12.9	25.7	0.0	5.52876	7.568706	46.0	19.0	26.0	38.0	30.0	1007.6	1008.7	4.43216	2.000000	21.0	23.2	0					
3	9.2	28.0	0.0	5.52876	7.568706	24.0	11.0	9.0	45.0	16.0	1017.6	1012.8	4.43216	4.487216	18.1	26.5	0					
4	17.5	32.3	1.0	5.52876	7.568706	41.0	7.0	20.0	82.0	33.0	1010.8	1006.0	7.00000	8.000000	17.8	29.7	0					
	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm	Cloud9am	Cloud3pm	Temp9am	Temp3pm	RainTomorrow					
0	0.569921	0.454139	0.001617	0.038129	0.536788	0.289062	0.153846	0.289157	0.701031	0.212121	0.452579	0.477080	0.888889	0.560902	0.490196							
1	0.411609	0.503356	0.000000	0.038129	0.536788	0.289062	0.030769	0.265060	0.422680	0.242424	0.500832	0.488964	0.492462	0.560902	0.497549							
2	0.556728	0.516779	0.000000	0.038129	0.536788	0.304688	0.146154	0.313253	0.360825	0.292929	0.450915	0.504244	0.492462	0.250000	0.590686							
3	0.459103	0.568233	0.000000	0.038129	0.536788	0.132812	0.084615	0.108434	0.432990	0.151515	0.617304	0.573854	0.492462	0.560902	0.519608							
4	0.678100	0.664430	0.002695	0.038129	0.536788	0.265625	0.053846	0.240964	0.814433	0.323232	0.504160	0.458404	0.777778	1.000000	0.512255							

Figure 1: Pandas head after various modifications

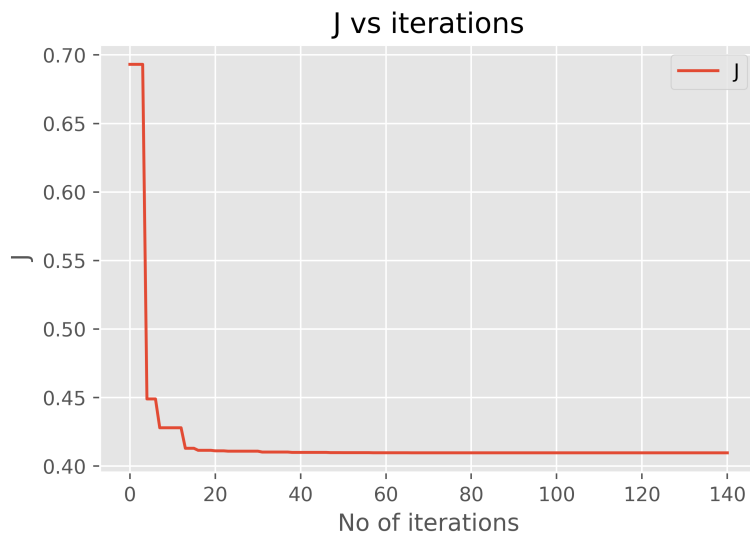


Figure 2: J vs iterations

## 2. Question 2

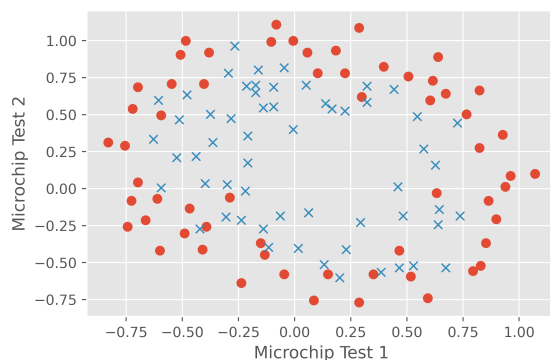


Figure 3: Plotted data

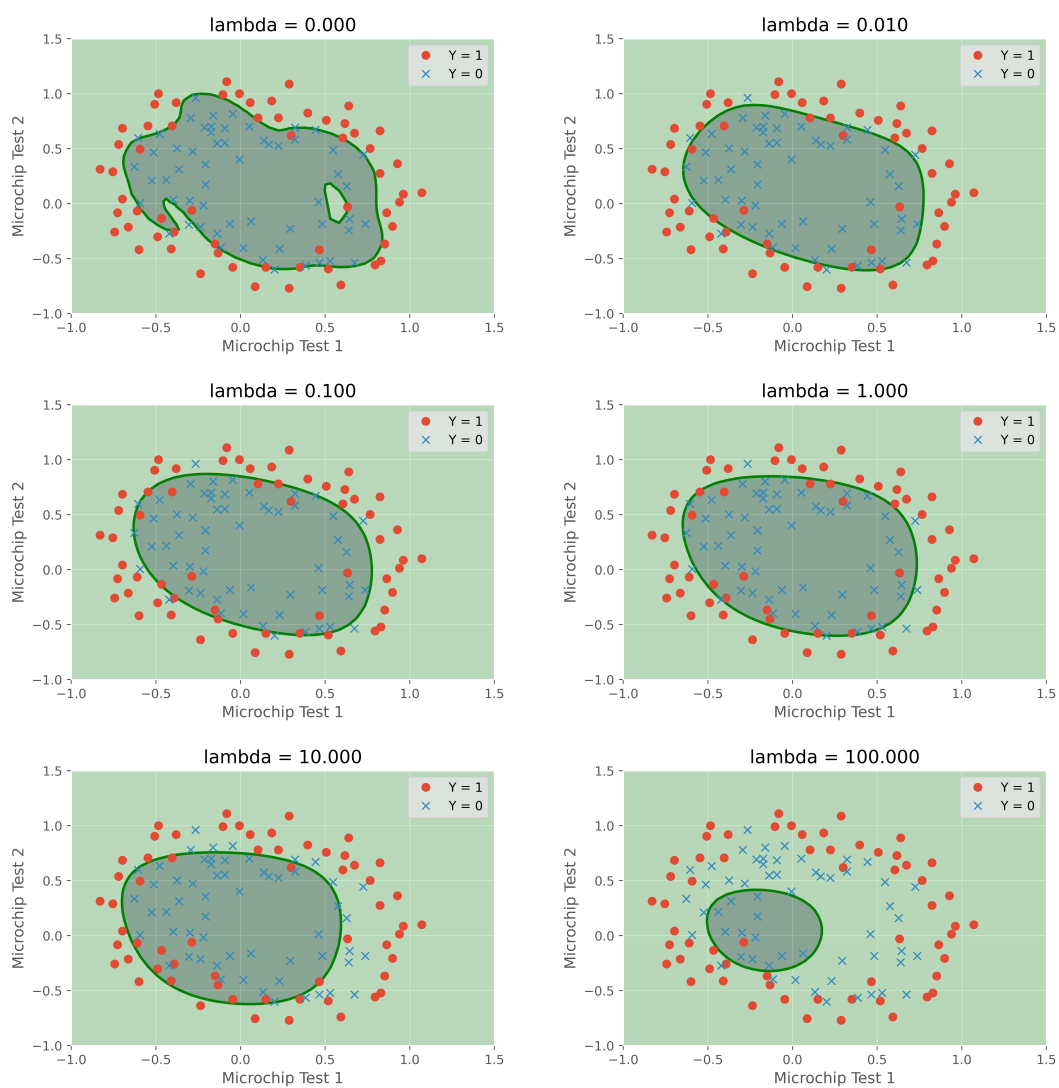


Figure 4: Contour for various values of lambda

With a higher value of  $\lambda$ , we get a stronger regularisation effect. The weight of coefficients tend to get smaller as  $\lambda$  increases. If we take a too small  $\lambda$ , we overfit the data. But if we take a  $\lambda$  that is too large, we might underfit. Thus it becomes important to take a correct  $\lambda$  for regression.

```

1 import numpy as np
2 from matplotlib import pyplot as plt
3 from scipy import optimize
4
5 plt.style.use('ggplot')
6
7 dat = np.loadtxt("nonLinearClass.txt" ,delimiter=',')
8
9 data_zero = dat[dat[:,2] == 0]
10 print(data_zero)
11
12 data_one = dat[dat[:,2] == 1]
13 print(data_one)
14
15 plt.plot(data_zero[:,0],data_zero[:,1], 'o')
16 plt.plot(data_one[:,0],data_one[:,1], 'x')
17
18
19 plt.xlabel('Microchip Test 1')
20 plt.ylabel('Microchip Test 2')
21
22 # Specified in plot order
23 plt.legend(['y = 1', 'y = 0'], loc='upper right')
24
25 def costFunctionReg(w,X,y,lambda_):
26     y = np.round(np.array(y))
27     m,col = X.shape
28     x = X.T
29
30     h = sigmoid(np.dot(w,x))
31
32     J = (-1*np.dot(y,np.log(h)) - np.dot(1-y,np.log(1-h)))/m + lambda_*np.sum(
33         np.square(w))/(2*m) # Cost 'J' should be a scalar
34
35     grad = (h - y)
36     grad_J = np.dot(x,grad.T)
37
38     grad = np.divide(grad_J,m) + lambda_*w/(m) # Gradient 'grad' should
39     be a vector
40     print(J)
41     return J, grad
42
43 def sigmoid(z):
44
45     return 1/(1 + np.exp(-z))
46
47 def mapFeature(x1,x2):
48     a = len(x1)
49     X = np.ones(a)
50     for j in range(1,7):
51         for i in range(j+1):
52             t = (x1**(j-i)) *(x2**i)
53             X= np.concatenate([X,t])
54     return X
55
56 def minCostFun( w_ini, X_train, y_train, iters,lambda_):
57     row,col = X_train.shape
58     m = col
59     options = {'maxiter':iters}

```

```

58
59     res = optimize.minimize(costFunctionReg,w_ini,(X_train,y_train,lambda_),jac
    = True,method='TNC',options = options)
60
61     cost = res.fun
62
63     w_opt = res.x      # Optimized weights rounded off to 3 decimal places
64     return w_opt
65
66 X1 = np.array(dat[:,0])
67 X2 = np.array(dat[:,1])
68
69 Y = dat[:,2]
70 m = X1.size
71
72 lambda_ = 0.001
73
74 X_set = mapFeature(X1,X2,6).T
75 w = minCostFun(np.zeros(28),X_set.T,Y,1000,lambda_)
76
77
78 u = np.linspace(-1, 1.5, 50) # 1D array from -1 to 1.5 based on the limits of data
79 v = np.linspace(-1, 1.5, 50)
80
81 z = np.zeros((u.size, v.size))
82 # Evaluate z = w*x over the grid
83 for i, ui in enumerate(u):
84     for j, vj in enumerate(v):
85         z[i, j] = np.dot(mapFeature(np.array([ui]),np.array([vj])), w)
86
87 z = z.T
88
89 plt.contour(u, v, z, levels=[0], linewidths=2, colors='g') # Plots contour lines
90 plt.contourf(u, v, z, levels=[np.min(z), 0, np.max(z)], cmap='Greens', alpha=0.4) #
    Plots filled contours
91
92 plt.plot(data_zero[:,0],data_zero[:,1],'o', label = 'Y = 1')
93 plt.plot(data_one[:,0],data_one[:,1],'x', label = 'Y = 0')
94
95
96 # Specified in plot order
97
98 plt.xlabel('Microchip Test 1')
99 plt.ylabel('Microchip Test 2')
100 plt.legend()
101 plt.savefig("lambda001",dpi=500)
102 plt.title('lambda = %0.2f' % lambda_)

```

Listing 1: Python code