

CARNEGIE MELLON UNIVERSITY
APPLIED STOCHASTIC PROCESSES
(COURSE 18-751)
HOMEWORK 8

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Q.1

(a)

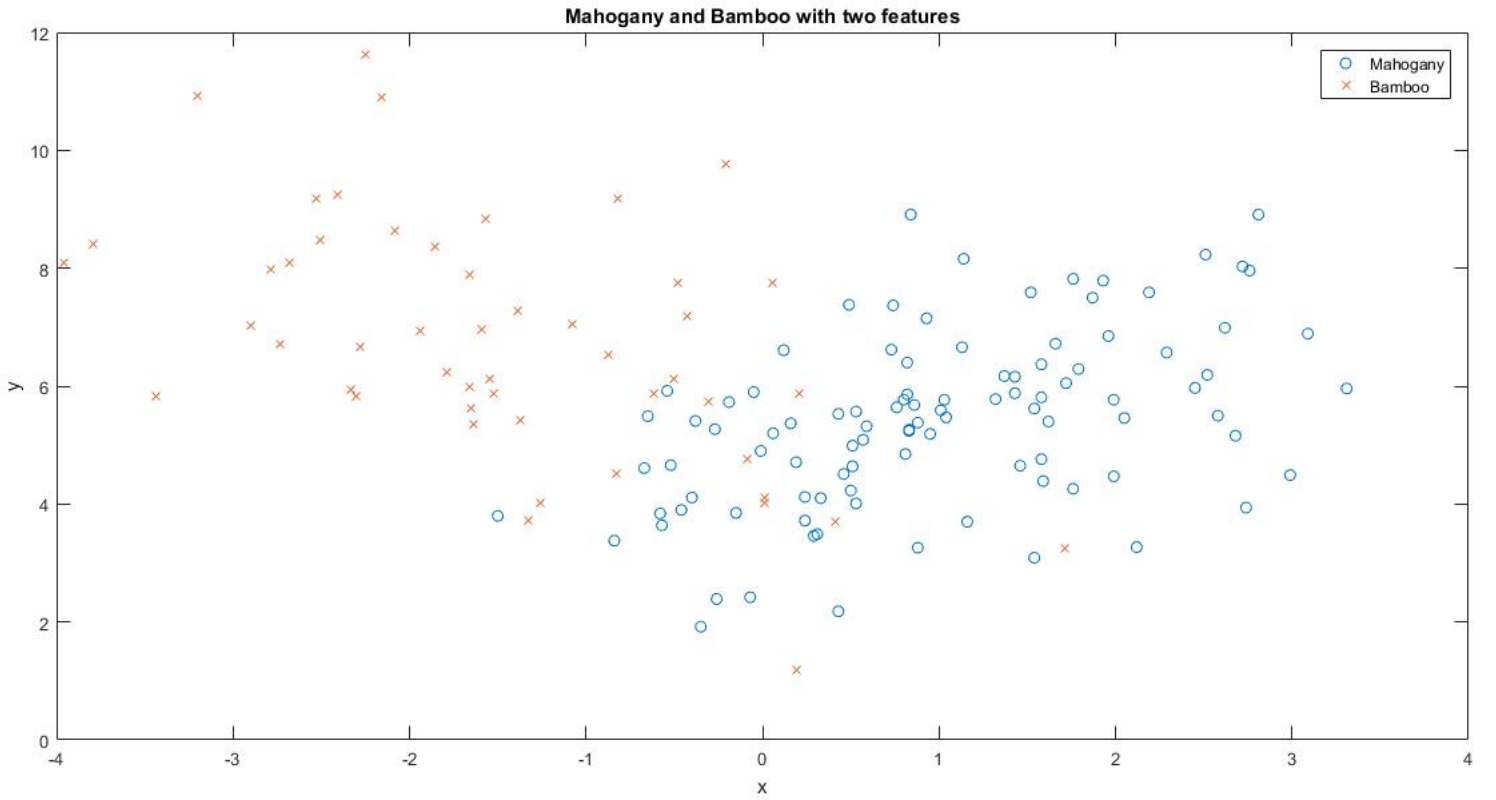


Figure 1: Mahogany and Bamboo with two features

(b)

$$P[M] = \frac{\#NumberofMahoganyInSample}{\#TotalSampleSize} = \frac{100}{150} = \frac{2}{3}$$

$$P[B] = \frac{\#NumberofBambooInSample}{\#TotalSampleSize} = \frac{50}{150} = \frac{1}{3}$$

$$\mu_{M_x} = \frac{1}{M} \sum_x M_x = 1.0044$$

$$\mu_{M_y} = \frac{1}{M} \sum_y M_y = 5.4160$$

$$\mu_M = [1.0044, 5.4160]^T$$

$$\mu_{B_x} = \frac{1}{B} \sum_x B_x = -1.4752$$

$$\mu_{B_y} = \frac{1}{B} \sum_y B_y = 6.7724$$

$$\mu_B = [-1.4752, 6.7724]^T$$

$$\text{cov}[X, Y]_M = K_M = \begin{bmatrix} 1.0852 & 0.7399 \\ 0.7399 & 2.1879 \end{bmatrix}$$

$$\text{cov}[X, Y]_B = K_B = \begin{bmatrix} 1.3980 & -1.3145 \\ -1.3145 & 4.4088 \end{bmatrix}$$

(c) Linear Estimators

$$\hat{Y}(x) = \mu_Y + \rho \frac{\sigma_Y}{\sigma_X} (x - \mu_X)$$

the slope is given by

$$slope = \rho \frac{\sigma_Y}{\sigma_X}$$

and the Intercept

$$Intercept = \mu_Y - \rho \frac{\sigma_Y}{\sigma_X} \mu_X$$

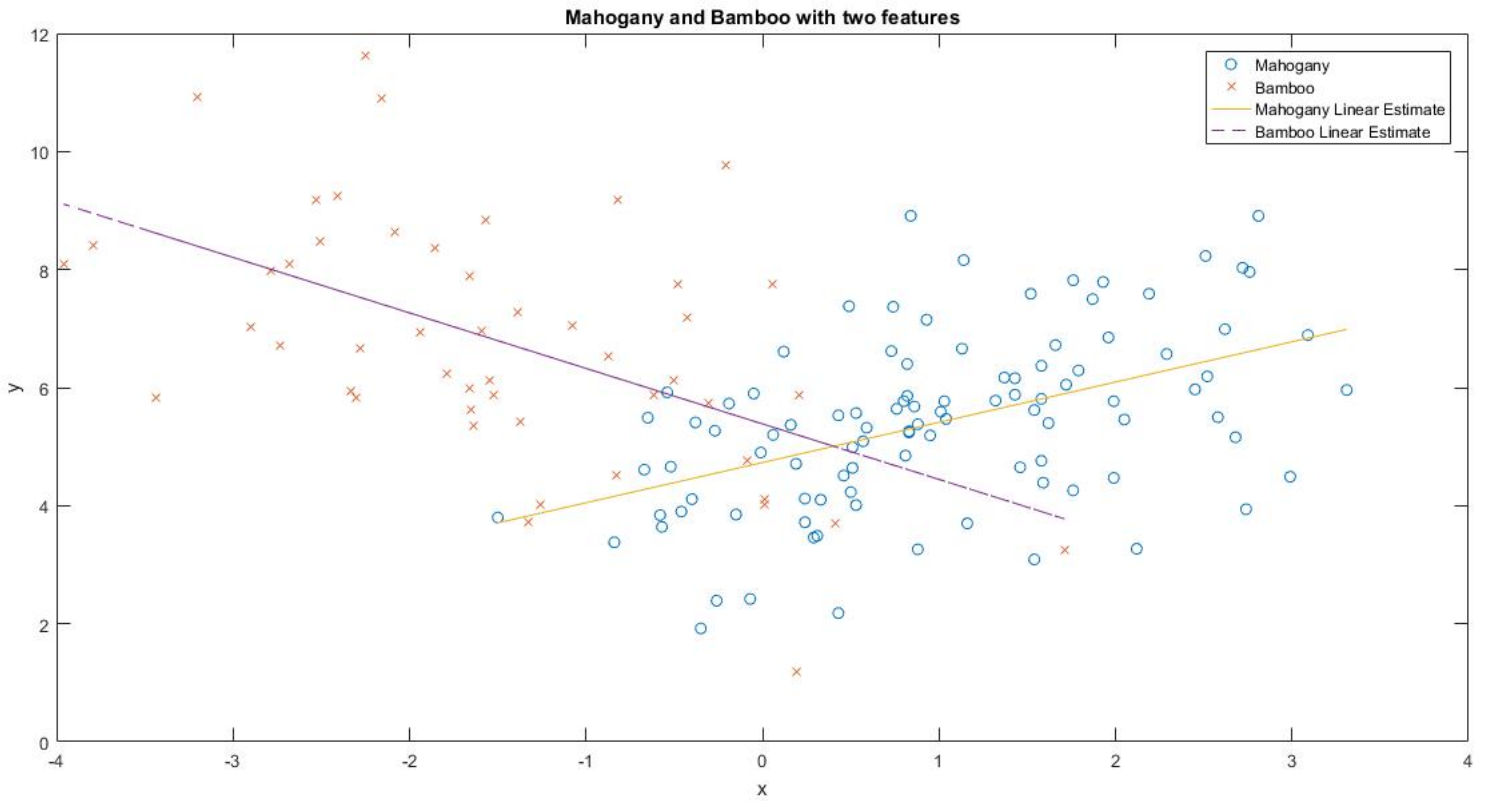


Figure 2: Mahogany and Bamboo with two features

Ans.

Using the equations above we get

Mahogany Linear Estimator Slope = 0.68

Mahogany Linear Estimator Intercept=4.73

Bamboo Linear Estimator Slope=-0.94

Bamboo Linear Estimator Intercept= 5.39

(d)

$$a = K_W^{-1}(\mu_M - \mu_B)$$

$$K_W^{-1} = \begin{bmatrix} 0.4110 & 0.0358 \\ 0.0358 & 0.1547 \end{bmatrix}$$

$$\mu_M - \mu_B = \begin{bmatrix} 2.4796 \\ -1.3564 \end{bmatrix}$$

$$a = \begin{bmatrix} 0.4110 & 0.0358 \\ 0.0358 & 0.1547 \end{bmatrix} * \begin{bmatrix} 2.4796 \\ -1.3564 \end{bmatrix}$$

$$a = \begin{bmatrix} 0.9705 \\ -0.1211 \end{bmatrix}$$

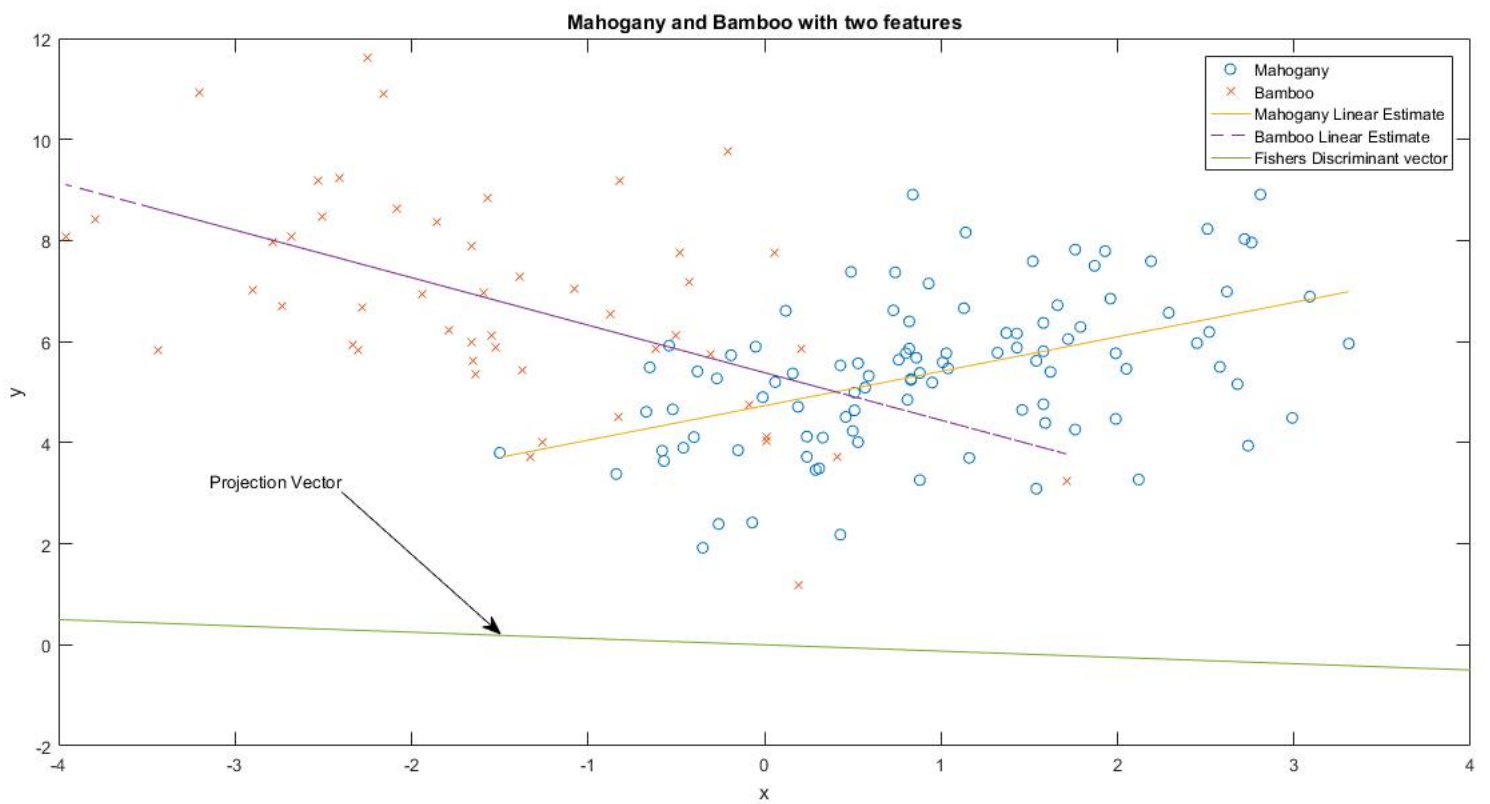


Figure 3: Mahogany and Bamboo with two features including the projection vector

(e)

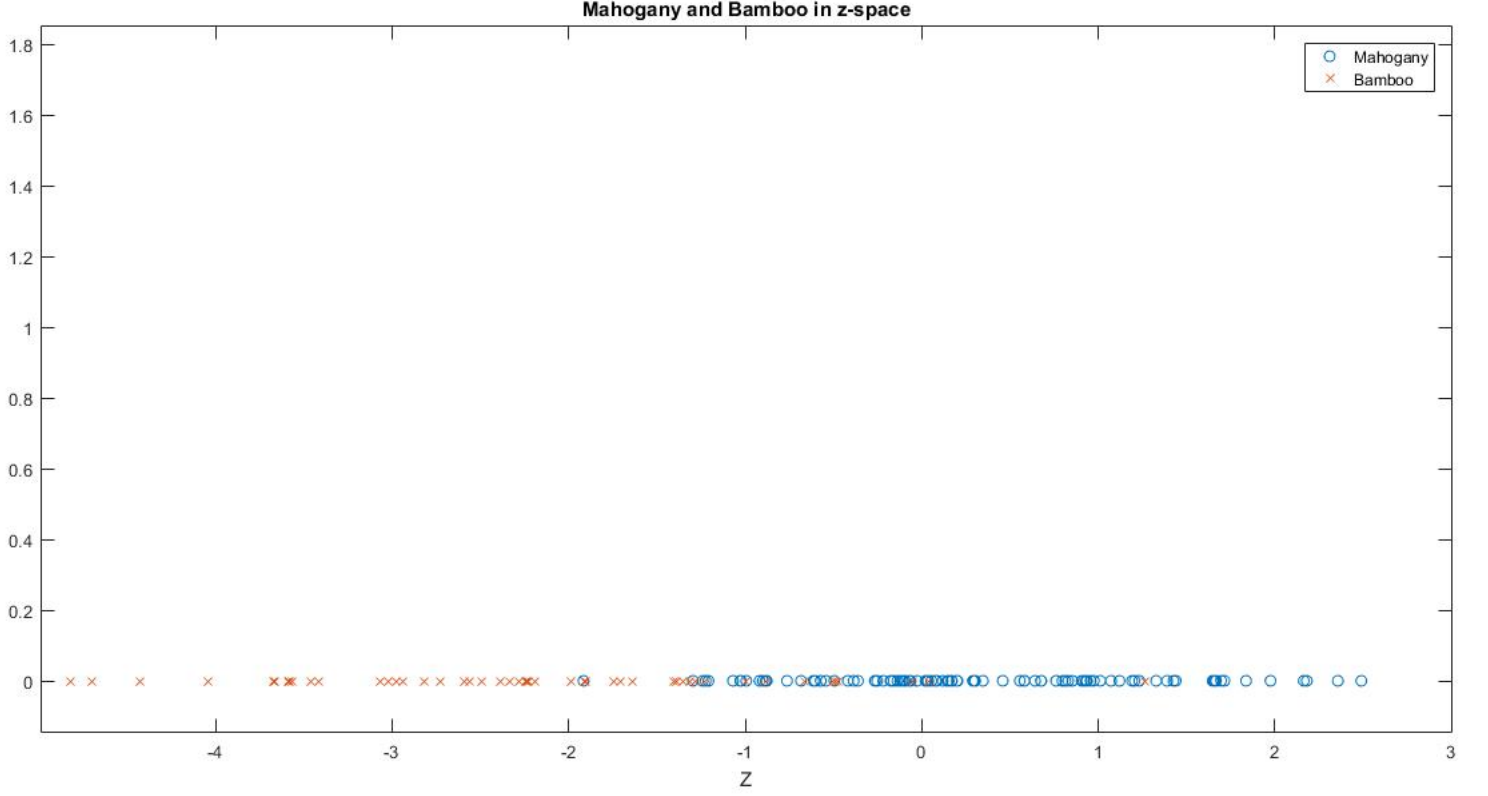


Figure 4: Mahogany and Bamboo projected to z space

$$P[M] = \frac{\#NumberofMahoganyInSampleinz - space}{\#TotalSampleSizeinz - space} = \frac{100}{150} = \frac{2}{3}$$

$$P[B] = \frac{\#NumberofBambooInSampleinz - space}{\#TotalSampleSizeinz - space} = \frac{50}{150} = \frac{1}{3}$$

$$m_M = \frac{1}{M} \sum_z M_z = 0.3191$$

$$m_B = \frac{1}{B} \sum_z B_z = -2.251$$

$$\sigma_M = 0.9383$$

$$\sigma_B = 1.3001$$

Using only the prior prob. we can come up with a simple classifier that will be correct 66% of the time. We say it is a Mahogany every time since prior Prob. of Mahogany 2* prior Prob. of Bamboo .

(g) Verify

$$a^T \mu_M = [0.9705 \quad -0.1211] * \begin{bmatrix} 1.0044 \\ 5.4160 \end{bmatrix} = 0.3191 = \mu_M$$

$$a^T K_M a = [0.9705 \quad -0.1211] * \begin{bmatrix} 1.0852 & 0.7399 \\ 0.7399 & 2.1879 \end{bmatrix} * \begin{bmatrix} 0.9705 \\ -0.1211 \end{bmatrix} = 0.8804 = \sigma_M^2$$

$$a^T \mu_B = [0.9705 \quad -0.1211] * \begin{bmatrix} -1.4752 \\ 6.7724 \end{bmatrix} = -2.2517 = \mu_B$$

$$a^T K_B a = [0.9705 \quad -0.1211] * \begin{bmatrix} 1.3980 & -1.3145 \\ -1.3145 & 4.4088 \end{bmatrix} * \begin{bmatrix} 0.9705 \\ -0.1211 \end{bmatrix} = 1.6904 = \sigma_B^2$$

(h)

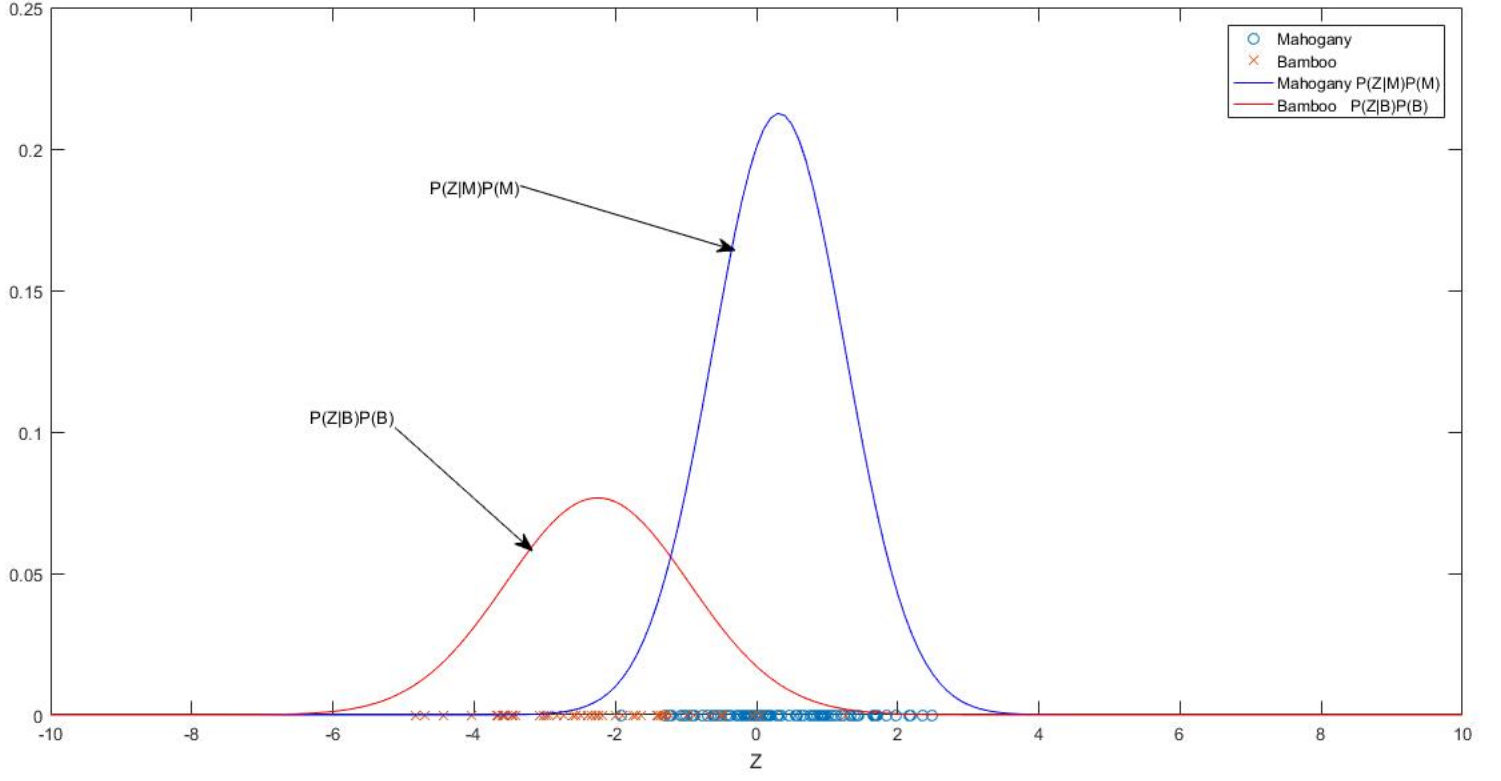


Figure 5: $P[z|M]P[M]$ and $P[z|B]P[B]$

(i)

By solving the quadratic equation we get the following two decision boundary values

$$MAP_1 = -1.0656 \text{ and } MAP_2 = 7.2927$$

So anything between MAP_1 and MAP_2 is going to be labeled as Mahogany and anything out side of this region is going to be labeled as Bamboo

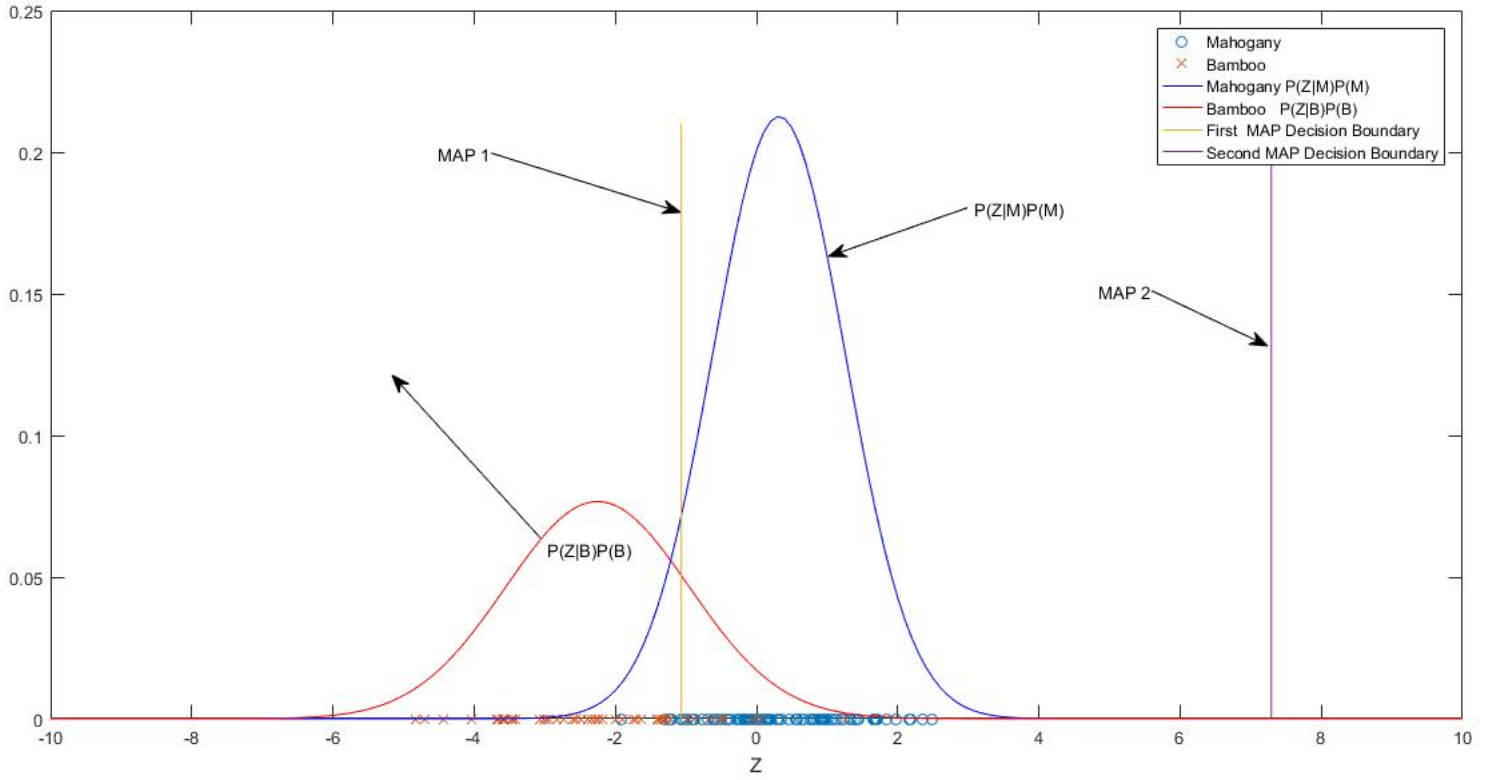


Figure 6: $P[z|M]P[M]$ and $P[z|B]P[B]$ with MAP decision boundaries

	B	M
B	0.2733	0.06
M	0.06	0.6267

Table 1: Confusion Matrix for the data

	B	M
B	0.2731	0.0603
M	0.0603	0.62

Table 2: Confusion Matrix for Normal approximation

(j) Confusion matrix

Using the MAP decision boundaries above we get Table 1

From this we get error rate of

$$errorrate = P[B, M] + P[M, B] = 0.1$$

Using the MAP decision boundaries above we get Table 2(using Q functions refer to code)

From this we get error rate of

$$errorrate = P[B, M] + P[M, B] = 0.1206$$

Code Appendix

```
1 Mahogany = xlsread('Mahogany.csv');
2 Bamboo   = xlsread('Bamboo.csv');
3 %(a)
4 %
5     *****
6 figure;
7 plot(Mahogany(:,1),Mahogany(:,2),'o','DisplayName','Mahogany');
8 hold on;
9 plot(Bamboo(:,1),Bamboo(:,2),'x','DisplayName','Bamboo');
10
11 % legend('show');
12 % title('Mahogany and Bamboo with two features');
13 % xlabel('x');
14 % ylabel('y')
15
16 %figure;
17 %hist(Mahogany(:,2),30);
18 %
19     *****
20
21 %(b)
22 %
23     *****
24
25 %Prior probabilities
26 totalNumberOfDataPoints = length(Mahogany)+length(Bamboo);
27 P_M = length(Mahogany)/totalNumberOfDataPoints;
28 P_B = length(Bamboo)/totalNumberOfDataPoints;
29 %mean values
30
31 Mahoganyx = Mahogany(:,1);
32 Mahoganyy = Mahogany(:,2);
33 Bamboox    = Bamboo(:,1);
34 Bambooy    = Bamboo(:,2);
35
36
37 muMx = mean(Mahoganyx);
38 muMy = mean(Mahoganyy);
39 muBx = mean(Bamboox);
40 muBy = mean(Bambooy);
41
42
43 sigMx = var(Mahoganyx);
44 sigMy = var(Mahoganyy);
45 sigBx = var(Bamboox);
46 sigBy = var(Bambooy);
47
48 muM = [muMx;muMy];
49 muB = [muBx;muBy];
50
51 sigM = [sigMx;sigMy];
```

```

46 sigB = [sigBx;sigBy];
47 %covariance matrix
48 KM = cov(Mahoganyx,Mahoganyy);
49 KB = cov(Bamboox,Bambooy);
50 %
    *****

51 %(c)
52 %
    *****

53 Mahoganyrho = corrcoeff(Mahoganyx,Mahoganyy);
54 Mahoganyrho = Mahoganyrho(1,2);
55
56 Bamboorho = corrcoeff(Bamboox,Bambooy);
57 Bamboorho = Bamboorho(1,2);
58
59 MahoganyLE = muMy + Mahoganyrho*sqrt(sigMy/sigMx)*(Mahoganyx-
    muMx);
60 Bamboole = muBy + Bamboorho*sqrt(sigBy/sigBx)*(Bamboox-muBx);
61
62 MahoganyLESlope = Mahoganyrho*sqrt(sigMy/sigMx);
63 MahoganyLEIntercept = muMy-Mahoganyrho*sqrt(sigMy/sigMx)*muMx;
64 BambooleSlope = Bamboorho*sqrt(sigBy/sigBx);
65 BambooleIntercept = muBy-Bamboorho*sqrt(sigBy/sigBx)*muBx;
66
67 fprintf('Mahogany Linear Estimator Slope: %2.2f y-intercept:
    %2.2f \n'...
68         ,MahoganyLESlope,MahoganyLEIntercept);
69 fprintf('Bamboo Linear Estimator Slope: %2.2f y-intercept: %2.2f
    \n'...
70         ,BambooleSlope,BambooleIntercept);
71
72 hold on;
73 plot(Mahoganyx,MahoganyLE,'DisplayName','Mahogany Linear
    Estimate');
74 hold on;
75 plot(Bamboox,Bamboole,'—','DisplayName','Bamboo Linear Estimate
    ');
76
77 %
    *****

78 %(d)
79 %
    *****

80 %fisher's Linear Discriminate Vector
81 Kw = KM + KB;
82 a = inv(Kw)*(muM-muB);
83 projVectorSlope = a(2)/a(1);
84 projx = -4:0.1:4;
85 projy = projx*projVectorSlope;
86

```

```

87 plot(projx,projy,'DisplayName','Fishers Discriminant vector');
88 legend('show');
89 title('Mahogany and Bamboo with two features');
90 xlabel('x');
91 ylabel('y');
92 hold off;
93 %
94     *****
95 %
96 %
97 %
98 %
99 %
100 figure;
101 plot(Mahoganyz,zeros(length(Mahoganyz),1),'o','DisplayName','
    Mahogany');
102 hold on;
103 plot(Bambooz,zeros(length(Bambooz),1),'x','DisplayName','Bamboo'
    );
104 title('Mahogany and Bamboo in z-space')
105 xlabel('Z');
106 legend('show');
107
108
109 %
110     *****
111 %
112 %
113 %
114 %
115 %
116 %
117 %
118 %
119 %
120 %
121 %
122 %
123 %
124     *****
125 %
126 %
127 %
128 %
129 %
130 %
131 %
132 %
133 %
134 %
135 %
136 mMProj = a'*mM;

```

```

127 sigMProj = a'*KM*a;
128
129 mBProj = a'*muB;
130 sigBProj = a'*KB*a;
131
132 fprintf('mM: %2.2f mMProj: %2.2f \n',mM,mMProj);
133 fprintf('mB: %2.2f mBProj: %2.2f \n',mB,mBProj);
134
135 fprintf('sigM: %2.2f mMProj: %2.2f \n',sdM^2,sigMProj);
136 fprintf('sigB: %2.2f mBProj: %2.2f \n',sdB^2,sigBProj);
137 %
138
139
140
141
142
143
144
145
146
147
148
149
150
151
152
153
154
155
156
157
158
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160
161
162
163
164

```

%(h)

x = -10:0.1:10;

MahoganyApprox = normpdf(x,mM,sdM);

BambooApprox = normpdf(x,mB,sdB);

figure;

plot(Mahoganyz,zeros(length(Mahoganyz),1),'o','DisplayName','Mahogany');

hold on;

plot(Bambooz,zeros(length(Bambooz),1),'x','DisplayName','Bamboo');

plot(x,MahoganyApprox*P_M_z,'b','DisplayName','Mahogany P(Z|M)P(M)');

hold on;

plot(x,BambooApprox*P_B_z,'r','DisplayName','Bamboo P(Z|B)P(B)');

%(i)

%ax^2+bx+c>0 map decision boundary

a = (1/sigBProj-1/sigMProj);

b = -2*(mBProj/sigBProj-mMProj/sigMProj);

c = (mBProj^2/sigBProj-mMProj^2/sigMProj)+log((P_M_z*sigBProj)/(P_B_z*sigMProj));

MapDecsionBoundaryOne = (-b - sqrt(b^2-4*a*c))/(2*a);

MapDecsionBoundaryTwo = (-b + sqrt(b^2-4*a*c))/(2*a);

%plot([MapDecsionBoundaryTwo,MapDecsionBoundaryTwo],[0,0.21],'DisplayName','First MAP Decision Boundary');

%plot([MapDecsionBoundaryOne,MapDecsionBoundaryOne],[0,0.21],'DisplayName','Second MAP Decision Boundary');

xlabel('Z');

legend('show');

PBB = sum(Bambooz<MapDecsionBoundaryTwo)+sum(Bambooz>MapDecsionBoundaryOne);


```

165 PBM = sum(Mahoganyz<MapDecsionBoundaryTwo) + sum(Mahoganyz>
    MapDecsionBoundaryOne);
166 PMB = sum(Bambooz>MapDecsionBoundaryTwo)-sum(Bambooz>
    MapDecsionBoundaryOne);
167 PMM = sum(Mahoganyz>MapDecsionBoundaryTwo)-sum(Mahoganyz>
    MapDecsionBoundaryOne);
168 result = [PBB,PMB;PMB,PMM]./totalNumberOfDataPoints;
169 fprintf('error rate: %2.2f \n',1-sum(diag(result)));
170 %with the gaussian approximation
171 PMMG = (qfunc((MapDecsionBoundaryTwo-mMProj)/sdM)-qfunc((
    MapDecsionBoundaryOne-mMProj)/sdM))*(2/3);
172 PBBG = (1-qfunc((MapDecsionBoundaryTwo-mBProj)/sdB)+qfunc((
    MapDecsionBoundaryOne-mBProj)/sdB))*(1/3);
173 PMBG = ((qfunc((MapDecsionBoundaryTwo-mBProj)/sdB)- qfunc((
    MapDecsionBoundaryOne-mBProj)/sdB)))*(1/3);
174 PBMG = ((1-qfunc((MapDecsionBoundaryTwo-mMProj)/sdM)+ qfunc((
    MapDecsionBoundaryOne-mMProj)/sdM)))*(2/3);
175 resultG = [PBBG,PMBG;PMBG,PMMG];

```