

# Pattern Recognition Homework 2

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## 1 Cost of substitution

Risk of choosing class  $\omega_i$  is cost of choosing the wrong class (Substitution Error).

$$R(\omega_i|\mathbf{x}) = \lambda_s(1 - P(\omega_i|\mathbf{x}))$$

Risk of associating  $\mathbf{x}$  with the class  $\omega_i$  should be less than cost of rejection

$$\lambda_s(1 - P(\omega_i|\mathbf{x})) \leq \lambda_r \implies P(\omega_i|\mathbf{x}) \geq 1 - \frac{\lambda_r}{\lambda_s}$$

## 2 Gaussian assumption

### 2.1 A

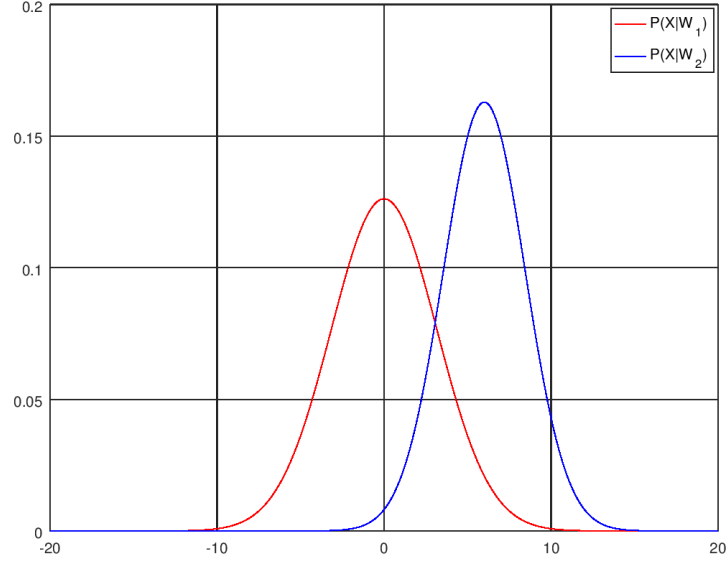
I assume both  $P(\mathbf{x}|\omega_1)$  and  $P(\mathbf{x}|\omega_2)$  are in the form of a Gaussian distribution.

$$P(x|\omega_1) = k_1 e^{-\frac{x^2}{20}} = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \implies \mu = 0, \sigma^2 = 10, k_1 = \frac{1}{\sqrt{20\pi}}$$

$$P(x|\omega_2) = k_2 e^{-\frac{(x-6)^2}{12}} = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \implies \mu = 6, \sigma^2 = 6, k_2 = \frac{1}{\sqrt{12\pi}}$$

The following octave code will provide a graph of these two densities.

```
X = [-20:0.1:20];  
plot (X, normpdf(X,0,sqrt(10)), "r;P(X|W_{1})");  
hold on;  
plot (X, normpdf(X,6,sqrt(6)), "b;P(X|W_{2})");  
grid on;
```



## 2.2 B

I assume that cost of choosing the right class is zero therefore  $\lambda_{11}=\lambda_{22}=0$ .

$$R(\omega_1|\mathbf{x}) = \lambda_{11}P(\omega_1|\mathbf{x}) + \lambda_{12}P(\omega_2|\mathbf{x}) = 0 \times P(\omega_1|\mathbf{x}) + \sqrt{3}P(\omega_2|\mathbf{x}) = \sqrt{3}P(\omega_2|\mathbf{x})$$

$$R(\omega_2|\mathbf{x}) = \lambda_{22}P(\omega_2|\mathbf{x}) + \lambda_{21}P(\omega_1|\mathbf{x}) = 0 \times P(\omega_2|\mathbf{x}) + \sqrt{5}P(\omega_1|\mathbf{x}) = \sqrt{5}P(\omega_1|\mathbf{x})$$

## 2.3 C

$$\sqrt{3}P(\omega_2|\mathbf{x}) = \sqrt{5}P(\omega_1|\mathbf{x}) \implies \frac{\sqrt{3}P(\mathbf{x}|\omega_2)P(\omega_2)}{P(\mathbf{x})} = \frac{\sqrt{5}P(\mathbf{x}|\omega_1)P(\omega_1)}{P(\mathbf{x})}$$

note:  $P(\omega_1) = P(\omega_2)$

$$\sqrt{3}P(\mathbf{x}|\omega_2) = \sqrt{5}P(\mathbf{x}|\omega_1)$$

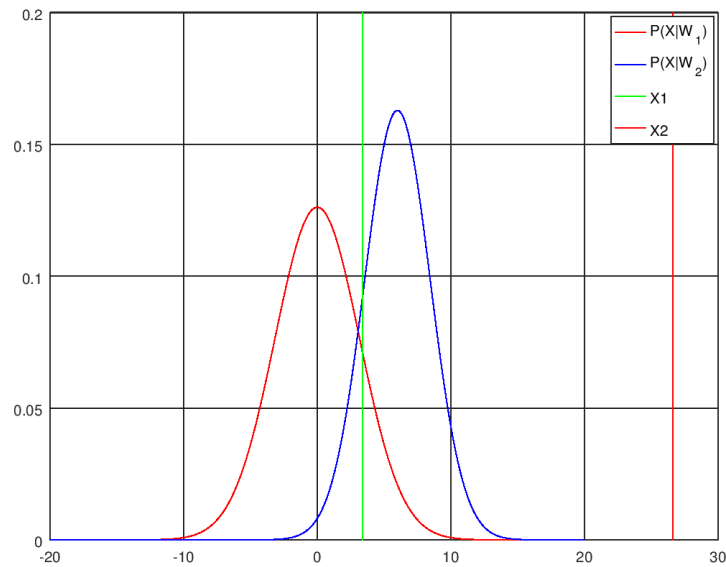
now lets replace likelihoods with their expressions :

$$\sqrt{3} \frac{1}{\sqrt{12\pi}} e^{-\frac{(x-6)^2}{12}} = \sqrt{5} \frac{1}{\sqrt{20\pi}} e^{-\frac{x^2}{20}} \implies e^{-\frac{(x-6)^2}{12}} = e^{-\frac{x^2}{20}} \implies$$

$$8x^2 - 240x + 720 = 0 \implies x = [3.38104, 26.61895]$$

The following octave code will add these two decision boundaries to the previous graph.

```
X = [-20:0.1:20];
plot (X, normpdf(X,0,sqrt(10)), "r;P(X|W_{1})");
hold on;
plot (X, normpdf(X,6,sqrt(6)), "b;P(X|W_{2})");
x=3.38104
plot([x,x],[0,0.2], "g;X1;")
x=26.61895
plot([x,x],[0,0.2], "r;X2;")
grid on;
```



## 2.4 D

Let  $\text{aria}_1$  be the aria before first decision boundary  $x_1=3.38104$ ,  $\text{aria}_2$  aria in between of two decision boundaries, and  $\text{aria}_3$  aria after the second decision boundary  $x_2=26.61895$ .

in  $\text{aria}_1$  decision rule will choose  $\omega_1 \implies R_1$ .

in  $\text{aria}_2$  decision rule will choose  $\omega_2 \implies R_2$ .

in  $\text{aria}_3$  decision rule will choose  $\omega_1 \implies R_1$ .

$$\begin{aligned} & \int_{-\infty}^{x_1} 0P(\omega_1|x) + \lambda_{12}P(\omega_2|x) + \int_{x_1}^{x_2} \lambda_{21}P(\omega_1|x) + 0P(\omega_2|x) + \int_{x_2}^{\infty} 0P(\omega_1|x) + \lambda_{12}P(\omega_2|x) = \\ & \int_{-\infty}^{x_1} \lambda_{12}P(x|\omega_2)P(\omega_2) + \int_{x_1}^{x_2} \lambda_{21}P(x|\omega_1)P(\omega_1) + \int_{x_2}^{\infty} \lambda_{12}P(x|\omega_2)P(\omega_2) = \\ & \int_{-\infty}^{x_1} \sqrt{3}N(6, 6)\frac{1}{2} + \int_{x_1}^{x_2} \sqrt{5}N(0, 10)\frac{1}{2} + \int_{x_2}^{\infty} \sqrt{3}N(6, 6)\frac{1}{2} \approx 0.28 \end{aligned}$$

## 3 Communication noise

### 3.1 A

We decide  $m$  is one when

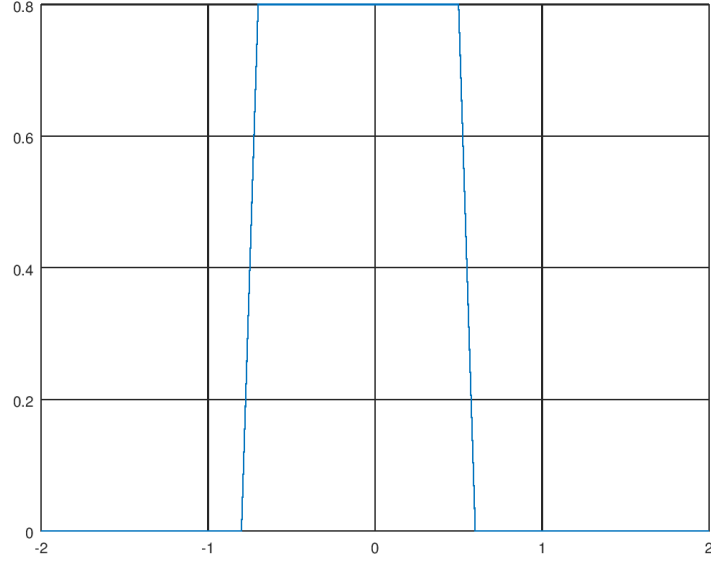
$$\begin{aligned} P(r|m=1)P(m=1) &> P(r|m=0)P(m=0) \implies P(r|m=1)\frac{1}{4} > P(r|m=0)\frac{3}{4} \\ &\implies P(r|m=1) > 3P(r|m=0) \end{aligned}$$

otherwise  $m$  is zero.

### 3.2 B

The uniform distribution can be produce by the following octave code:

```
X = [-2:0.1:2];
plot (X, unifpdf(X, (-3/4), (2/4)));
grid on;
```



Our decision rule in last part still stands.

We will define the new likelihoods for the uniform pdf.

$$P(r|m=1) \begin{cases} \frac{4}{5}, & \text{if } \frac{1}{4} < r < \frac{6}{4} \\ 0, & \text{otherwise} \end{cases}$$

$$P(r|m=0) \begin{cases} \frac{4}{5}, & \text{if } \frac{-3}{4} < r < \frac{2}{4} \\ 0, & \text{otherwise} \end{cases}$$

from our rule:

$$m = \begin{cases} 0, & \frac{-3}{4} < r < \frac{2}{4} \\ 1, & \frac{2}{4} < r < \frac{6}{4} \end{cases}$$

And for the Probability of the error:

$$P(Error) = P(m=1|m=0).P(m=0) + P(m=0|m=1)P(m=1) =$$

$$p(\frac{1}{4} < r < \frac{2}{4}|m=1).P(m=1) = (\frac{2}{4} - \frac{1}{4}) \times \frac{4}{5} \times \frac{1}{4} = \frac{1}{20}$$

## 4 Linear Transformation and Mahalanobis distance

```
S = [1,0,0;0,5,4;0,4,5];
[Phi, Lambda] = eig(S);
```

$$\Phi = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -0.77011 & 0.77011 \\ 0 & 0.77011 & 0.77011 \end{bmatrix}$$

$$\Lambda = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 9 \end{bmatrix}$$

### 4.1 A

```
S = [1,0,0;0,5,4;0,4,5];
mu = [3;1;2];
X0 = [5;6;3];
```

```
(1/( (2*pi)^(3/2) * det(S)^0.5 )) * exp( ( -(X0-mu)' * inv(S) * (X0-mu) )/2 )

ans = 1.9300e-05
```

### 4.2 B

I Wasn't sure if I should suggest an orthonormal transformation or use the  $\Phi$  calculated in the first part.

$$\Phi = \begin{bmatrix} \frac{2}{7} & \frac{6}{7} & \frac{3}{7} \\ \frac{3}{7} & \frac{2}{7} & \frac{-6}{7} \\ \frac{6}{7} & \frac{-3}{7} & \frac{2}{7} \end{bmatrix}$$

anyhow I suggest the previous matrix and continue with the  $\Phi$  in the first part:

$$y = \Phi^T x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -0.77011 & 0.77011 \\ 0 & 0.77011 & 0.77011 \end{bmatrix}^T x$$

$$||y||^2 = y^T y = (\Phi^T x)^T \Phi^T x = x^T \Phi \Phi^T x = x^T x = ||x||^2$$

### 4.3 C

$$\begin{aligned} \Lambda^{-1/2} \Phi^T x &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 9 \end{bmatrix}^{-1/2} \begin{bmatrix} 1 & 0 & 0 \\ 0 & -0.77011 & 0.77011 \\ 0 & 0.77011 & 0.77011 \end{bmatrix}^T x \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0.33333 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & -0.77011 & 0.77011 \\ 0 & 0.77011 & 0.77011 \end{bmatrix}^T x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -0.77011 & 0.77011 \\ 0 & 0.23570 & 0.23570 \end{bmatrix} x \end{aligned}$$

Because  $(\Lambda^{-1/2} \Phi^T x)$  is a linear transformation of  $x$  and  $p(x|\omega) \sim N(\mu, \Sigma)$  we can conclude

$$P((\Lambda^{-1/2} \Phi^T x)|\omega) \sim N((\Lambda^{-1/2} \Phi^T \mu), (\Lambda^{-1/2} \Phi^T x) \Sigma (\Lambda^{-1/2} \Phi^T x)^T)$$

This transformation will cause  $\Sigma$  to become  $I$  and to move the distribution to the center we need to move the points according to  $(\Lambda^{-1/2} \Phi^T)(x - \mu)$ .

### 4.4 D

```
S = [1,0,0;0,5,4;0,4,5];
mu = [3;1;2];
X0 = [5;6;3];
[Phi, Lambda] = eig(S);
```

```
A = Phi*(Lambda^(-0.5));
```

```
X_w = A*(X0-mu)
```

$$X(w) = (\Lambda^{-1/2} \Phi^T)(x - \mu) = \begin{bmatrix} 2 \\ -2.8284 \\ 1.4142 \end{bmatrix} \quad (19)$$



## 4.5 E

```
S = [1,0,0;0,5,4;0,4,5];  
mu = [3;1;2];  
X0 = [5;6;3];  
[Phi, Lambda] = eig(S);
```

```
A = Phi*(Lambda^(-0.5));
```

```
X_w = A'*(X0-mu);
```

```
function m = mahalanobis_dist(X, Sigma, Mu)  
m = (X-Mu)' * inv(Sigma) * (X-Mu);  
endfunction
```

```
mahalanobis_dist(X0, S, mu)  
mahalanobis_dist(X_w, eye(3), 0)
```

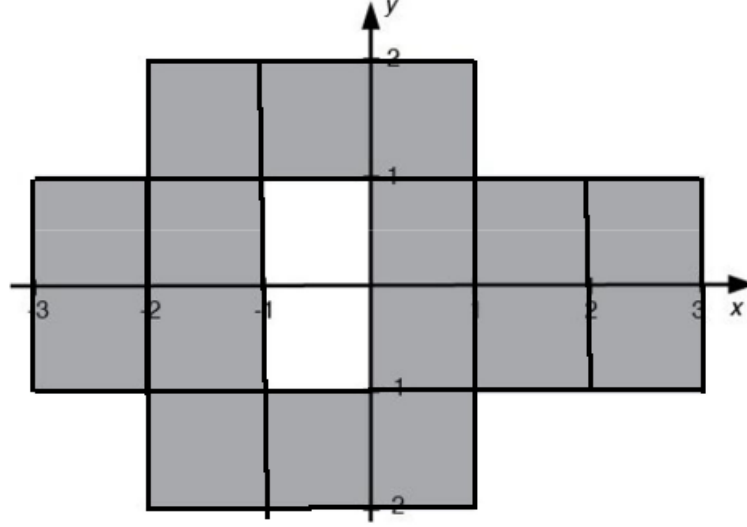
```
Ans = 14
```

```
Ans = 14
```

Yes, Linear Transformation doesn't change Mahalanobis distance.

## 5 Gray Squares

### 5.1 A



they are equal gray area on both side of x axis so  $P(\omega_1) = P(\omega_2) = 0.5$ .

$$P(1 < Y < 2|\omega_1) = \frac{P(Y|\omega_1)}{P(\omega_1)} = \frac{\frac{2}{16}}{\frac{1}{2}} = \frac{1}{4}$$

$$P(0 < Y < 1|\omega_1) = \frac{P(Y|\omega_1)}{P(\omega_1)} = \frac{\frac{2}{16}}{\frac{1}{2}} = \frac{1}{4}$$

$$P(-1 < Y < 0|\omega_1) = \frac{P(Y|\omega_1)}{P(\omega_1)} = \frac{\frac{2}{16}}{\frac{1}{2}} = \frac{1}{4}$$

$$P(-2 < Y < 1|\omega_1) = \frac{P(Y|\omega_1)}{P(\omega_1)} = \frac{\frac{2}{16}}{\frac{1}{2}} = \frac{1}{4}$$

$$P(1 < Y < 2|\omega_2) = \frac{P(Y|\omega_2)}{P(\omega_2)} = \frac{\frac{1}{16}}{\frac{1}{2}} = \frac{1}{8}$$

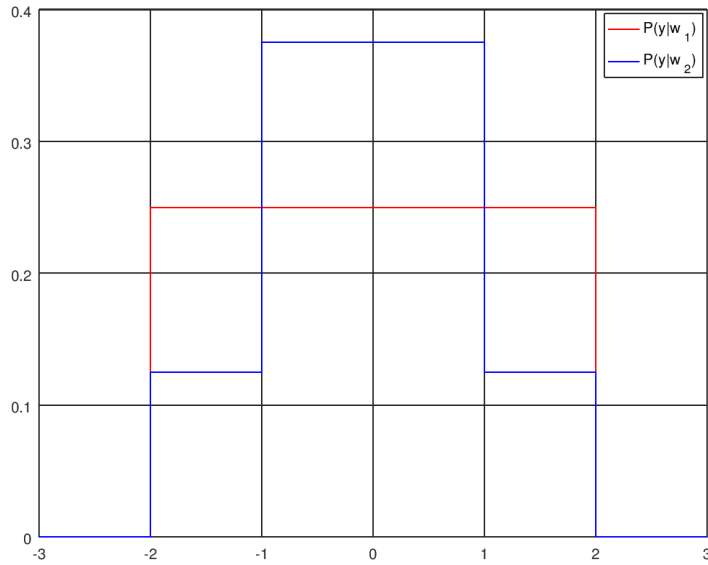
$$P(0 < Y < 1|\omega_2) = \frac{P(Y|\omega_2)}{P(\omega_2)} = \frac{\frac{3}{16}}{\frac{1}{2}} = \frac{3}{8}$$

$$P(-1 < Y < 0|\omega_2) = \frac{P(Y|\omega_2)}{P(\omega_2)} = \frac{\frac{3}{16}}{\frac{1}{2}} = \frac{3}{8}$$

$$P(-2 < Y < 1|\omega_2) = \frac{P(Y|\omega_2)}{P(\omega_2)} = \frac{\frac{1}{16}}{\frac{1}{2}} = \frac{1}{8}$$

## 5.2 B

```
Y = [-3, -2, -2+0.00001, -1, 0, 1, 2-0.00001, 2, 3];
P_Y_W1 = [0, 0, 1/4, 1/4, 1/4, 1/4, 1/4, 0, 0];
plot(Y, P_Y_W1, "r;P(y|w_1);")
hold on
Y = [-3, -2, -2+0.00001, -1, -1+0.00001, 1, 1+0.00001, 2, 2+0.00001, 3]
P_Y_W2 = [0, 0, 1/8, 1/8, 3/8, 3/8, 1/8, 1/8, 0, 0]
plot(Y, P_Y_W2, "b;P(y|w_2);")
```



## 5.3 C

We classify a point as  $\omega_1$  when

$$P(y|\omega_1)P(\omega_1) > P(y|\omega_2)P(\omega_2)$$

$$\text{note : } P(\omega_1) = P(\omega_2)$$

$$P(y|\omega_1) > P(y|\omega_2)$$

and We classify a point as  $\omega_2$  when

$$P(y|\omega_2) > P(y|\omega_1)$$

therefore

$$c = \begin{cases} \omega_1, & -2 < y < 1 \text{ or } 1 < y < 2 \\ \omega_2, & -1 < y < 1 \end{cases} \quad (24)$$

and for the probability of error:

$$\begin{aligned} P(error) &= P(c = \omega_1|\omega_2)P(\omega_1) + P(c = \omega_2|\omega_1)P(\omega_2) = \\ &P(\omega_1)P(-1 < y < 1|\omega_2) + P(\omega_2)P(-2 < y < 1 \text{ or } 1 < y < 2|\omega_1) = \\ &\frac{1}{2} \times \frac{4}{8} + \frac{1}{2} \times \frac{2}{8} = \frac{3}{8} \end{aligned}$$