Serd Arkhipenka, drkhipor  $\sqrt{1}$   $A/f(x|\theta) = \frac{2L}{\theta^{2}} \cdot e^{\frac{-x^{2}}{2\theta^{2}}}$   $L(\theta|x) = \log \prod_{t=1}^{\infty} \frac{x_{t}}{\theta^{1}} \cdot e^{\frac{-x_{t}^{2}}{2\theta^{2}}}$   $= \sum_{t} \log x_{t} - \sum_{t} \log \theta^{2} + \sum_{t} \log e^{\frac{-x_{t}^{2}}{2\theta^{2}}}$   $= \sum_{t} \log x_{t} - 2n \log \theta - \sum_{t} \frac{x_{t}^{2}}{2\theta^{2}}$   $\frac{d}{d\theta} L(\theta|x) = \frac{2n}{\theta} + \frac{1}{\theta^{3}} \sum_{t} x_{t}^{2} = 0$ 

 $\hat{Q} = \sqrt{\frac{\sum_{k} \chi_{k}^{2}}{2h}}$ 

b) 
$$f(x|\alpha, \theta) = \alpha \theta^{-\alpha} \cdot x^{\alpha-\gamma} \cdot \exp \{-\left(\frac{x}{\Theta}\right)^{\alpha}\}$$
 $L(\alpha, \theta) x i = \log \prod_{t=1}^{n} \alpha \theta^{-\alpha} \cdot x_{t}^{\alpha-\gamma} \cdot \exp \{-\left(\frac{x_{t}}{\Theta}\right)^{\alpha}\}$ :

 $= \sum_{t} \log \alpha + \sum_{t} \log \theta^{-\alpha} + \sum_{t} \log x_{t}^{(\alpha-\gamma)} - \sum_{t} \left(\frac{x_{t}}{\Theta}\right)^{\alpha} = \sum_{t} (\log \alpha - \alpha \cdot n) \cdot \log \alpha + (\alpha - 1) \sum_{t} \log x_{t}^{\alpha-\gamma} - \sum_{t} \left(\frac{x_{t}}{\Theta}\right)^{\alpha}$ 
 $\frac{d}{dx} = \sum_{t} (\log \alpha + \sum_{t} x_{t}^{\alpha})^{\frac{1}{\alpha}}$ 
 $\frac{d}{dx} = \frac{\alpha}{\theta} = \sum_{t} x_{t}^{\alpha}$ 
 $\frac{d}{dx} = \left(\frac{\sum_{t} x_{t}^{\alpha}}{n}\right)^{\frac{1}{\alpha}}$ 

C)  $\frac{1}{\theta}$  is a decreasing function. To maximize this function oshould be the smallest value that  $= \chi_t$ . Hence,  $\hat{\theta} = \max\{\chi_1, \dots, \chi_n\}$ 

a)  $p(l|x) = \frac{p(x(l), P(l))}{p(x)}$ P(4) = P(62) = 0.5 p((1)c=4161)p(x=u) = P(1) 8. p(1=4) P120=41627. P(62) p(62176=4)= p12=41 = 14-2/Pel2) = 2 Pel2) - 9 pen=4) = pex=4) 4>4, pl/212=4)>pl/212=4) Class=2 6/P1(1)=0.4 P1(2)=0.3 p((11x=6)=P(x=6141.p((1)) = 4 p(x=6) pll212=6/= Pln=6/(2) pl/2) = 1 15 p(x=6) P12261 # > 75, pll 12=6) > pll 21x=6/ Class=1

C)  $P(x \in C_5 - \alpha, 5 + \alpha) = \int_{5-4}^{5+\alpha} p(x) dx =$   $= \int_{5-\alpha}^{5+\alpha} 0.5 dx = z d$ Hence, the optimal value of  $\alpha = 0.5$ 

## Q3:

1) As the covariance is class-independent, the discriminant:

$$g_i(x) = -\frac{1}{2}\log|S_i| - \frac{1}{2}(x - m_i)^T S_i^{-1}(x - m_i) + \log \hat{P}(C_i)$$

## Confusion matrix:

23	7
7	63

Preision = 23/(23+7) = 0.767

Recall = 23/(23+7) = 0.767

F-score = 2\*0.767\*0.767/(0.767+0.767) = 0.767

2) As the covariance is class-dependent, the discriminant:

$$g_i(x) = -\frac{1}{2}(x - m_i)^T S^{-1}(x - m_i) + \log \hat{P}(C_i)$$

## Confusion matrix:

28	10
2	60

Preision = 28/(28+10) = 0.737

Recall = 28/(28+2) = 0.933

F-score = 2\*0. 737\*0. 933/(0.737+0. 933) = 0.823

3) As the covariance is a diagonal matrix, the discriminant:

$$g_i(x) = -\frac{1}{2} \sum_{j=1}^{d} \left(\frac{x_j^t - m_{ij}}{s_j}\right)^2 + \log \hat{P}(C_i)$$

## Confusion matrix:

28	13
2	57

Preision = 28/(28+13) = 0.683

Recall = 28/(28+2) = 0.933

F-score = 2\*0. 683\*0. 933/(0.683+0. 933) = 0.789