

~~Question 1~~

Question 1

$$1a) \mathcal{L}(\lambda) = \prod_{n=1}^N p(x_n | \lambda) = \prod_{n=1}^N \lambda e^{-\lambda x_n}$$

$$\ell(\lambda) = \log \mathcal{L}(\lambda) = \sum_{n=1}^N [\log \lambda + \log e^{-\lambda x_n}] = N \log \lambda - \lambda \sum_{n=1}^N x_n$$

$$\frac{\partial \ell(\lambda)}{\partial \lambda} = 0 \Rightarrow \frac{N}{\lambda} - \sum_{n=1}^N x_n = 0 \Rightarrow \lambda = \frac{N}{\sum_{n=1}^N x_n} = \frac{1}{\bar{x}}$$

$$1b) p(\lambda | \mathbf{x}) \propto p(\mathbf{x} | \lambda) p(\lambda)$$

$$\propto \left(\prod_{n=1}^N \lambda e^{-\lambda x_n} \right) \frac{b^a}{\Gamma(a)} \lambda^{a-1} e^{-b\lambda}$$

$$\propto \lambda^N e^{-\lambda \sum x_n} \lambda^{a-1} e^{-b\lambda}$$

$$\propto e^{-\lambda (b + \sum_{n=1}^N x_n)} \lambda^{N+a-1} \sim \text{Gamma} \left(N+a-1, b + \sum_{n=1}^N x_n \right)$$

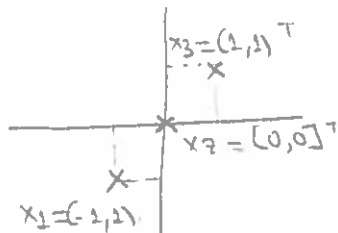
$$1c) \log p(\lambda | \mathbf{x}) = -\lambda (b + \sum x_n) + (N+a-1) \log \lambda$$

$$\frac{\partial \log p(\lambda | \mathbf{x})}{\partial \lambda} = -(b + \sum x_n) + \frac{N+a-1}{\lambda} = 0 \Rightarrow \lambda = \frac{N+a-1}{b + \sum x_n}$$

$$\Rightarrow \overset{\text{MAP}}{\lambda} = \frac{1 + \frac{a-1}{N}}{\frac{b}{N} + \frac{1}{N} \sum x_n} = \frac{1 + \frac{a-1}{N}}{\frac{b}{N} + \bar{x}} \xrightarrow{N \rightarrow \infty} \frac{1}{\bar{x}} \quad (\text{MAP} \rightarrow \text{MLE})$$

Question 2

2 a)



$$\vec{v} = \begin{pmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{pmatrix}^T$$

$\downarrow \qquad \downarrow$
 $\cos 45^\circ \quad \sin 45^\circ$

$$\vec{x}_1 = [-1, 1]^T$$

$$\vec{x}_2 = [0, 0]^T$$

$$\vec{x}_3 = [1, 1]^T$$

2 b). $z_1 = \vec{x}_1^T \vec{v} = -\sqrt{2}$

$$z_2 = \vec{x}_2^T \vec{v} = 0$$

$$z_3 = \vec{x}_3^T \vec{v} = \sqrt{2}$$

$$\mathbb{E}\{z_1, z_2, z_3\} = 0$$

$$\text{Var}\{z_1, \dots, z_3\} = \frac{1}{3} \sum_{n=1}^3 (z_n - \bar{z})^2 = \frac{1}{3} [(-\sqrt{2})^2 + 0^2 + (\sqrt{2})^2] = \frac{4}{3}$$



2 c) All points perfectly located on the direction of the first principal component

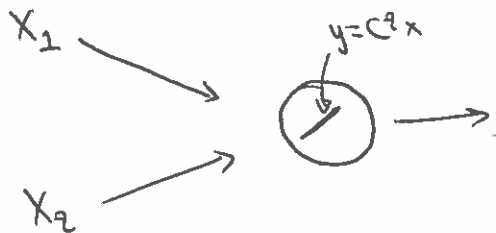
$$\hat{\vec{x}}_1 = z_1 \vec{v} = -\sqrt{2} \begin{pmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{pmatrix}^T = [-1, 1]^T$$

$$\hat{\vec{x}}_2 = z_2 \vec{v} = [0, 0]^T$$

$$\hat{\vec{x}}_3 = z_3 \vec{v} = \sqrt{2} \begin{pmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{pmatrix}^T = [1, 1]^T$$

Question 3

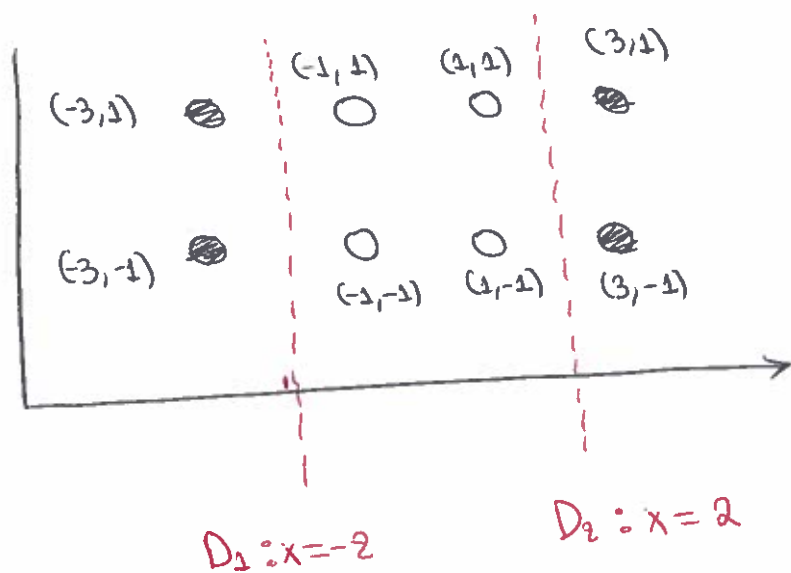
a) $Y = C^2 (w_5 w_1 + w_6 w_2) x_1 + C^2 (w_5 w_3 + w_6 w_4) x_2$



b) Yes, each layer can be thought as a linear transformation of the previous one, implemented by matrix multiplication. Therefore we can simply multiply matrices to find a representation with single layer

c) Hidden layer will contain linear activation functions. Output layer will contain sigmoid activation.

Question 4a



$$\phi_1(x) = \begin{cases} 1, & x > -2 \\ -1, & \text{otherwise} \end{cases}$$

$$\phi_2(x) = \begin{cases} 1, & x < 2 \\ -1, & \text{otherwise} \end{cases}$$

We have built a classifier $f_{t-1}(\vec{x})$ and want to improve it by adding a new classifier $f(\vec{x}) = f_{t-1}(\vec{x}) + \beta_t h_t(\vec{x})$

Can we choose optimally $h_t(\vec{x})$ and β_t ?

Question 4b.i

▷ Minimize exponential loss function:

$$(h_t^*(\vec{x}), \beta_t^*) = \operatorname{argmin} \sum e^{-y_n f(\vec{x}_n)}$$

$$= \operatorname{argmin} \sum e^{-y_n [f_{t-1}(\vec{x}_n) + \beta_t h_t(\vec{x}_n)]}$$

$$= \operatorname{argmin} \sum \underbrace{e^{-y_n f_{t-1}(\vec{x}_n)}}_{w_t(n)} \cdot e^{-y_n \beta_t h_t(\vec{x}_n)}$$

$$= \operatorname{argmin} \sum w_t(n) e^{-y_n \beta_t h_t(\vec{x}_n)}$$

$$y_n h_t(\vec{x}_n) = \begin{cases} 1, & \text{correctly classified} \\ & h_t(\vec{x}_n) = y_n \\ -1, & \text{otherwise} \end{cases}$$

$$= \operatorname{argmin} \left[\sum_n w_t(n) e^{\beta_t} \mathbb{I}[y_n \neq h_t(\vec{x}_n)] + \sum_n w_t(n) e^{-\beta_t} \underbrace{\mathbb{I}[y_n = h_t(\vec{x}_n)]}_{\mathbb{I} - \mathbb{I}[y_n \neq h_t(\vec{x}_n)]} \right]$$

$$= \operatorname{argmin} (e^{\beta_t} - e^{-\beta_t}) \sum_n w_t(n) \mathbb{I}[y_n \neq h_t(\vec{x}_n)] + e^{-\beta_t} \sum w_t(n)$$

$$E = (e^{b_t} - e^{-b_t}) \sum w_t(n) \mathbb{I}(y_n \neq h_t(\vec{x}_n)) + e^{-b_t} \sum w_t(n)$$

$$\frac{\partial E}{\partial b_t} = (e^{b_t} + e^{-b_t}) \sum w_t(n) \mathbb{I}(y_n \neq h_t(\vec{x}_n)) - e^{-b_t} \sum w_t(n) = 0$$

$$(e^{2b_t} + 1) \epsilon_t - 1 = 0$$

Question 4b.ii

$$\epsilon_t e^{2b_t} + \epsilon_t - 1 = 0$$

$$\epsilon_t e^{2b_t} = 1 - \epsilon_t$$

$$e^{2b_t} = \frac{1 - \epsilon_t}{\epsilon_t}$$

$$b_t = \frac{1}{2} \log \frac{1 - \epsilon_t}{\epsilon_t}$$