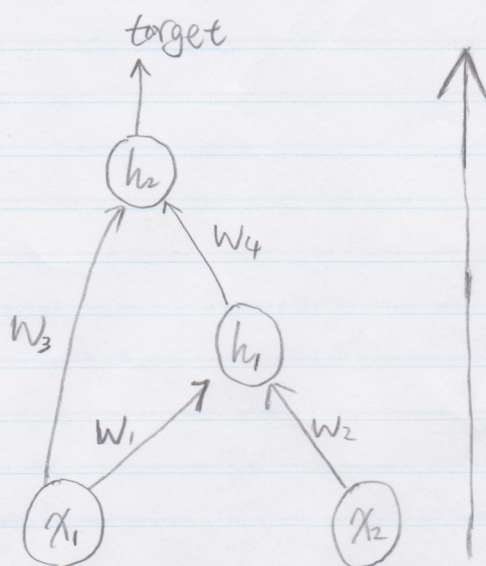


A2 Part 3:



$$h_2 = \frac{1}{1 + \exp(-z_2)} = \text{target} \equiv \hat{t}$$

$$z_2 = w_3 x_1 + w_4 h_1$$

$$h_1 = \frac{1}{1 + \exp(-z_1)}$$

$$z_1 = w_1 x_1 + w_2 x_2$$

$$W = [w_1 \ w_2 \ w_3 \ w_4] , \quad w_k \in [-1 : 0.25 : 1] , \quad 9 \text{ values}$$

$$D = \begin{bmatrix} x_{1,1} & x_{1,2} \\ x_{2,1} & x_{2,2} \\ \vdots & \vdots \\ x_{N,1} & x_{N,2} \end{bmatrix}$$

$$\text{Search space : } 9^4 = 6561 \text{ of } W$$

$$\text{cost} = - \sum_{i=1}^N [t_i \log \hat{t}_i + (1 - t_i) \log (1 - \hat{t}_i)]$$

$$\text{likelihood: } P(D|W) = \exp(-\text{cost})$$

Bayes rule:

$$P(W|D) = \frac{P(W) P(D|W)}{P(D)}$$

$$\text{where } P(D) = \sum_W P(W) P(D|W)$$

Prediction on test data X_j :

Bayesian estimate:

$$\hat{t}_j^{(\text{Bayes})} \equiv \underset{\text{Bayes}}{P}(t_j | X_j) = \sum_W P(W | D) \overbrace{P(t_j | X_j, W)}^{\hat{t}_j}$$

Maximum a-posteriori (MAP):

$$\begin{aligned} W_{\text{MAP}} &= \underset{W}{\text{arg max}} P(W | D) \\ &= \underset{W}{\text{arg max}} \frac{P(W) P(D | W)}{P(D)} \\ &= \underset{W}{\text{arg max}} P(W) P(D | W) \end{aligned}$$

$$\hat{t}_j^{(\text{MAP})} \equiv \underset{\text{MAP}}{P}(t_j | X_j) = P(t_j | X_j, W_{\text{MAP}})$$

Maximum likelihood (ML):

$$\begin{aligned} W_{\text{ML}} &= \underset{W}{\text{arg max}} P(D | W) \\ \hat{t}_j^{(\text{ML})} &\equiv \underset{\text{ML}}{P}(t_j | X_j) = P(t_j | X_j, W_{\text{ML}}) \end{aligned}$$

If $P(W) \sim \text{uniform}(W)$, then:

$$W_{\text{MAP}} = W_{\text{ML}} = \underset{W}{\text{arg max}} P(W) P(D | W)$$

So

$$\hat{t}^{(\text{MAP})} = \hat{t}^{(\text{ML})}$$

Evaluation function (Contrastive divergence):

$$\text{ErrorSum} = -\sum_{i=1}^N [t_i \log(\hat{t}_i) + (1-t_i) \log(\hat{1}-\hat{t}_i)] \\ + \sum_{i=1}^N [t_i \log(t_i) + (1-t_i) \log(1-t_i)]$$

$$\text{ErrorPerBit} = \frac{\text{ErrorSum}}{N \log(2)}$$