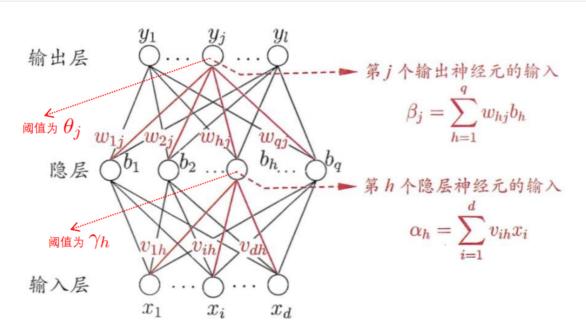
# 单层前馈神经网络

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#### 1. 单层前馈神经网络

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## 1. 单层前馈神经网络



### 1.1. 符号解释

1.  $X^k = \{x_1^k, x_2^k, \cdots, x_d^k\}$ : 输入的第k个数据,共d维

2.  $V_{d imes q}$ : 輸入层到隐藏层的权重, q为隐藏层结点的个数

 $3.\gamma_h, (1 \leq h \leq q)$ : 輸入层到隐藏层的阈值 (偏置)

 $4. \, \alpha_h, (1 \leq h \leq q)$ : 隐藏层的输入

 $5.b_h, (1 \leq h \leq q)$ : 隐藏层的输出

6.  $W_{q imes l}$ : 隐藏层到输出层的权重,l为输出层结点的个数

7.  $\theta_j$ ,  $(1 \leq j \leq l)$ : 隐藏层到输出层的阈值 (偏置)

8.  $\beta_j$ ,  $(1 \leq j \leq l)$ ,输出层的输入

9.  $\hat{y}_{i}^{k}$ ,  $(1 \leq j \leq l)$ : 输出层的输出

10.  $y_i^k$ ,  $(1 \leq j \leq l)$ : 输出层的label

11. f: sigmoid函数,其导数特点为f'(x)=f(x)(1-f(x))

12.  $E_K$ : 损失函数

#### 1.2. 前馈计算

1. 输入层到隐藏层

$$egin{aligned} lpha_h &= \sum_{i=1}^d v_{ih} x_i^k \ &\downarrow i &\downarrow i &\downarrow i &\downarrow i \ b_h &= f(lpha_h - \gamma_h) \end{aligned}$$
  $h \leq q$ 

2. 隐藏层到输出层

$$eta_j = \sum_{h=1}^q w_{hj} b_h \hat{y}_j^k = f(eta_j - heta_j)$$
其中, $1 \le j \le l$  (17)

3. 损失函数

$$E_k = \frac{1}{2} \sum_{j=1}^{l} \left( \hat{y}_j^k - y_j^k \right)^2 \tag{18}$$

#### 1.3. 反向传播

 $1. w_{hj}$ 

$$E_k = rac{1}{2}\sum_{j=1}^l ig(\hat{y}_j^k - y_j^kig)^2$$
  $\hat{y}_j^k = f(eta_j - heta_j)$   $f$  为Sigmoid函数  $\beta_j = \sum_{h=1}^q w_{hj}b_h$ 

因此,

$$\frac{\partial E_k}{\partial w_{hj}} = \frac{\partial E_k}{\partial \hat{y}_j^k} \cdot \frac{\partial \hat{y}_j^k}{\partial \beta_j} \cdot \frac{\partial \beta_j}{\partial w_{hj}} \tag{19}$$

分开计算:

$$\frac{\partial E_k}{\partial \hat{y}_j^k} = \frac{\partial \left[\frac{1}{2} \sum_{j=1}^l \left(\hat{y}_j^k - y_j^k\right)^2\right]}{\partial \hat{y}_j^k} \\
= \frac{1}{2} \times 2 \times \left(\hat{y}_j^k - y_j^k\right) \times 1 \\
= \hat{y}_j^k - y_j^k \\
\frac{\partial \hat{y}_j^k}{\partial \beta_j} = \frac{\partial \left[f(\beta_j - \theta_j)\right]}{\partial \beta_j} \\
= f'(\beta_j - \theta_j) \times 1 \\
= f(\beta_j - \theta_j) \times \left[1 - f(\beta_j - \theta_j)\right] \\
= \hat{y}_j^k \left(1 - \hat{y}_j^k\right) \\
\frac{\partial \beta_j}{\partial w_{hj}} = \frac{\partial \left(\sum_{h=1}^q w_{hj}b_h\right)}{\partial w_{hj}} \\
= b_h$$
(20)

令:

$$g_{j} = -\frac{\partial E_{k}}{\partial \hat{y}_{j}^{k}} \cdot \frac{\partial \hat{y}_{j}^{k}}{\partial \beta_{j}} = -\left(\hat{y}_{j}^{k} - y_{j}^{k}\right) \cdot \hat{y}_{j}^{k} \left(1 - \hat{y}_{j}^{k}\right) = \hat{y}_{j}^{k} \left(1 - \hat{y}_{j}^{k}\right) \left(y_{j}^{k} - \hat{y}_{j}^{k}\right) \quad (21)$$

所以:

$$\Delta w_{hj} = -\eta \frac{\partial E_k}{\partial w_{hj}} 
= -\eta \frac{\partial E_k}{\partial \hat{y}_j^k} \cdot \frac{\partial \hat{y}_j^k}{\partial \beta_j} \cdot \frac{\partial \beta_j}{\partial w_{hj}} 
= \eta g_j b_h$$
(22)

 $2.\theta_i$ 

$$E_k = \frac{1}{2} \sum_{j=1}^{l} (\hat{y}_j^k - y_j^k)^2$$

$$\hat{y}_j^k = f(\beta_j - \theta_j)$$

因此,

$$\frac{\partial E_k}{\partial \theta_j} = \frac{\partial E_k}{\partial \hat{y}_j^k} \cdot \frac{\partial \hat{y}_j^k}{\partial \theta_j} 
= (\hat{y}_j^k - y_j^k) \cdot \frac{\partial \hat{y}_j^k}{\partial \theta_j} 
= (\hat{y}_j^k - y_j^k) \cdot \frac{\partial [f(\beta_j - \theta_j)]}{\partial \theta_j} 
= (\hat{y}_j^k - y_j^k) \cdot f'(\beta_j - \theta_j) \times -1 
= (y_j^k - \hat{y}_j^k) \cdot f'(\beta_j - \theta_j) 
= (y_j^k - \hat{y}_j^k) \hat{y}_j^k (1 - \hat{y}_j^k)$$
(23)

所以:

$$\Delta\theta_{j} = -\eta \frac{\partial E_{k}}{\partial \theta_{j}}$$

$$= -\eta \left( y_{j}^{k} - \hat{y}_{j}^{k} \right) \hat{y}_{j}^{k} \left( 1 - \hat{y}_{j}^{k} \right)$$

$$= -\eta g_{j}$$
(24)

3.  $v_{ih}$ 

$$E_k = \frac{1}{2} \sum_{j=1}^l \left( \hat{y}_j^k - y_j^k \right)^2$$
 
$$\hat{y}_j^k = f(\beta_j - \theta_j) \qquad \qquad f \text{ 为 Sigmoid 函数}$$
 
$$\beta_j = \sum_{h=1}^q w_{hj} b_h$$
 
$$b_h = f(\alpha_h - \gamma_h)$$
 
$$\alpha_h = \sum_{i=1}^d v_{ih} x_i$$

因此,

$$\frac{\partial E_k}{\partial v_{ih}} = \sum_{j=1}^l \frac{\partial E_k}{\partial \hat{y}_j^k} \cdot \frac{\partial \hat{y}_j^k}{\partial \beta_j} \cdot \frac{\partial \beta_j}{\partial b_h} \cdot \frac{\partial b_h}{\partial \alpha_h} \cdot \frac{\partial \alpha_h}{\partial v_{ih}}$$
(25)

分开计算,

$$\frac{\partial \beta_{j}}{\partial b_{h}} = \frac{\partial \left(\sum_{h=1}^{q} w_{hj} b_{h}\right)}{\partial b_{h}}$$

$$= w_{hj}$$

$$\frac{\partial b_{h}}{\partial \alpha_{h}} = \frac{\partial \left[f\left(\alpha_{h} - \gamma_{h}\right)\right]}{\partial \alpha_{h}}$$

$$= f'\left(\alpha_{h} - \gamma_{h}\right) \times 1$$

$$= f\left(\alpha_{h} - \gamma_{h}\right) \times \left[1 - f\left(\alpha_{h} - \gamma_{h}\right)\right]$$

$$= b_{h}\left(1 - b_{h}\right)$$

$$\frac{\partial \alpha_{h}}{\partial v_{ih}} = \frac{\partial \left(\sum_{i=1}^{d} v_{ih} x_{i}\right)}{\partial v_{ih}}$$

$$= r.$$
(26)

令:

$$e_{h} = -\frac{\partial E_{k}}{\partial \alpha_{h}} = -\sum_{i=1}^{l} \frac{\partial E_{k}}{\partial \hat{y}_{i}^{k}} \cdot \frac{\partial \hat{y}_{j}^{k}}{\partial \beta_{j}} \cdot \frac{\partial \beta_{j}}{\partial b_{h}} \cdot \frac{\partial b_{h}}{\partial \alpha_{h}} = b_{h} (1 - b_{h}) \sum_{i=1}^{l} w_{hj} g_{j} \quad (27)$$

所以,

$$\Delta v_{ih} = -\eta \frac{\partial E_k}{\partial v_{ih}} 
= -\eta \sum_{j=1}^l \frac{\partial E_k}{\partial \hat{y}_j^k} \cdot \frac{\partial \hat{y}_j^k}{\partial \beta_j} \cdot \frac{\partial \beta_j}{\partial b_h} \cdot \frac{\partial b_h}{\partial \alpha_h} \cdot \frac{\partial \alpha_h}{\partial v_{ih}} 
= \eta e_h x_i$$
(28)

4.  $\gamma_h$ 

$$E_k = \frac{1}{2} \sum_{j=1}^l \left( \hat{y}_j^k - y_j^k \right)^2$$
 
$$\hat{y}_j^k = f(\beta_j - \theta_j) \qquad \qquad f$$
 为 Sigmoid 函数 
$$\hat{\beta}_j = \sum_{h=1}^q w_{hj} b_h$$
 
$$b_h = f(\alpha_h - \gamma_h)$$

因此,

$$\frac{\partial E_{k}}{\partial \gamma_{h}} = \sum_{j=1}^{l} \frac{\partial E_{k}}{\partial \hat{y}_{j}^{k}} \cdot \frac{\partial \hat{y}_{j}^{k}}{\partial \beta_{j}} \cdot \frac{\partial \beta_{j}}{\partial b_{h}} \cdot \frac{\partial b_{h}}{\partial \gamma_{h}}$$

$$= \sum_{j=1}^{l} \frac{\partial E_{k}}{\partial \hat{y}_{j}^{k}} \cdot \frac{\partial \hat{y}_{j}^{k}}{\partial \beta_{j}} \cdot \frac{\partial \beta_{j}}{\partial b_{h}} \cdot \frac{\partial [f(\alpha_{h} - \gamma_{h})]}{\partial \gamma_{h}}$$

$$= \sum_{j=1}^{l} \frac{\partial E_{k}}{\partial \hat{y}_{j}^{k}} \cdot \frac{\partial \hat{y}_{j}^{k}}{\partial \beta_{j}} \cdot \frac{\partial \beta_{j}}{\partial b_{h}} \cdot f'(\alpha_{h} - \gamma_{h}) \cdot (-1)$$

$$= \sum_{j=1}^{l} \frac{\partial E_{k}}{\partial \hat{y}_{j}^{k}} \cdot \frac{\partial \hat{y}_{j}^{k}}{\partial \beta_{j}} \cdot \frac{\partial \beta_{j}}{\partial b_{h}} \cdot f(\alpha_{h} - \gamma_{h}) \times [1 - f(\alpha_{h} - \gamma_{h})] \cdot (-1)$$

$$= \sum_{j=1}^{l} \frac{\partial E_{k}}{\partial \hat{y}_{j}^{k}} \cdot \frac{\partial \hat{y}_{j}^{k}}{\partial \beta_{j}} \cdot \frac{\partial \beta_{j}}{\partial b_{h}} \cdot b_{h} (1 - b_{h}) \cdot (-1)$$

$$= \sum_{j=1}^{l} \frac{\partial E_{k}}{\partial \hat{y}_{j}^{k}} \cdot \frac{\partial \hat{y}_{j}^{k}}{\partial \beta_{j}} \cdot w_{hj} \cdot b_{h} (1 - b_{h}) \cdot (-1)$$

$$= \sum_{j=1}^{l} \frac{\partial E_{k}}{\partial \hat{y}_{j}^{k}} \cdot \frac{\partial \hat{y}_{j}^{k}}{\partial \beta_{j}} \cdot w_{hj} \cdot b_{h} (1 - b_{h}) \cdot (-1)$$

$$= \sum_{j=1}^{l} g_{j} \cdot w_{hj} \cdot b_{h} (1 - b_{h})$$

$$= e_{h}$$

所以:

$$\Delta \gamma_h = -\eta \frac{\partial E_k}{\partial \gamma_h}$$

$$= -\eta e_h$$
(30)