

PRML-HW25 FO5 神经网络

一、

1. 反向传播算法：

- ① 将输入向量 x_n 应用到网络，并使用加权和激活函数计算前向传播普通
过网络，以找到所有隐藏单元和输出单元的激活值。
- ② 使用误差方程评估所有输出单元的误差。
- ③ 使用反向传播算法反向传播，获得网络中每个隐藏单元的 δ_j 。
- ④ 使用链式法则计算所需参数。

2. 反向传播算法的作用：利用链式法则，把输出误差从后往前传播，
计算每个参数的梯度，从而知道应该如何调整它。

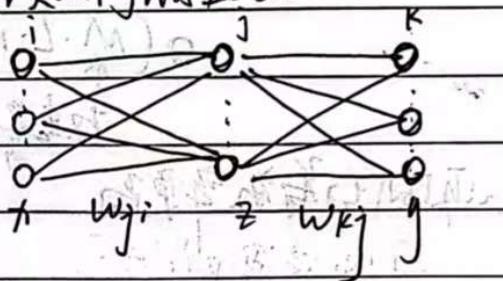
① 前向传播：

$$a_j = \sum_i w_{ji} z_i$$

$$z_j = h(a_j)$$

$$a_k = \sum_j w_{kj} z_j$$

$$y_k = g(a_k) \quad \text{损失函数 } L = \frac{1}{2} \|y_k - t_k\|^2$$



② 反向传播：

$$\delta_k = y_k - t_k \quad \text{或 } \sum_j h'(a_j) \cdot w_{kj}$$

$$\delta_j = \frac{\partial L}{\partial a_j} = \sum_k \frac{\partial L}{\partial a_k} \frac{\partial a_k}{\partial a_j} = \sum_k \delta_k \cdot w_{kj} \cdot h'(a_j) = h'(a_j) \cdot \sum_k w_{kj} \delta_k$$

③ 参数更新：

$$\frac{\partial L}{\partial w_{ji}} = \delta_j x_i \quad \frac{\partial L}{\partial w_{kj}} = \delta_k z_j$$

3. 链式法则: $\frac{d}{dx} [f(g(x))] = f'(g(x)) \cdot g'(x)$

反向传播算法易于链式法则计算神经网络中每个权重的梯度。

4. 前向传播计算复杂度: $O\left(\sum_{l=1}^{L-1} n_l \cdot n_{l+1}\right) \approx O(L \cdot n^2)$

反向传播: $= O\left(\sum_{l=1}^{L-1} n_l \cdot n_{l+1}\right) \approx O(L \cdot n^2)$

数值梯度: $\frac{\partial L}{\partial w_{ij}} \approx \frac{L(w_{ij} + \epsilon) - L(w_{ij} - \epsilon)}{\epsilon}$

$O(M \cdot L \cdot n^2)$

权重参数个数

反向传播效率更高。

5. 不能，线性激活函数只能对输入进行线性变换，神经网络会退化为一个浅层的线性模型，无法捕获多层中的非线性关系。

6. 互补: ① 线性模型存在精度受限

② 随着人工智能的发展，非线性模型以提高功能。

③ 神经网络通过组合简单的神经元，可以表示更复杂的特征。

1. 异或 \oplus XOR

同或 \odot 或 \equiv XNOR

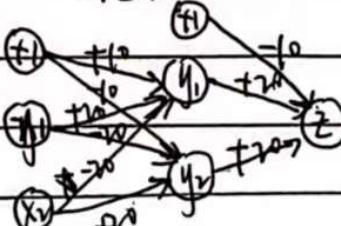
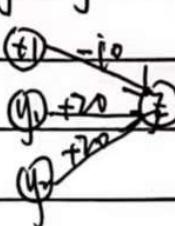
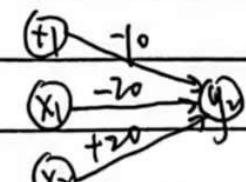
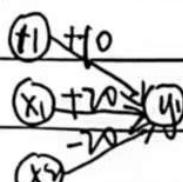
$$x_1 \oplus x_2 = (\overline{x_1} \wedge x_2) \vee (\overline{x_2} \wedge x_1)$$

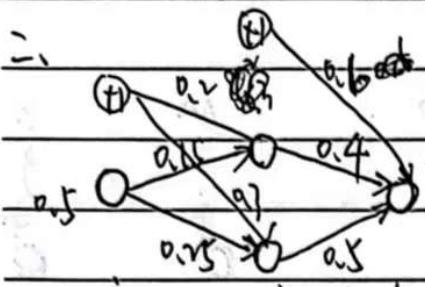
$$x_1 \wedge \overline{x_2}$$

$$\overline{x_1} \wedge x_2$$

$$y_1 \vee y_2$$

$$x_1 \oplus x_2$$





$$h(x) = \frac{1}{1+e^{-x}}$$

$$1. a_{11}^{(1)} = 0.15 \times 0.5 + 0.2 = 0.275$$

$$a_{12}^{(1)} = 0.25 \times 0.5 + 0.3 = 0.425$$

$$z_{11} = h(a_{11}) = \frac{1}{1+e^{-0.275}} = 0.568$$

$$z_{12} = h(a_{12}) = \frac{1}{1+e^{-0.425}} = 0.606$$

$$a_{11}^{(2)} = 0.568 \times 0.4 + 0.606 \times 0.5 + 0.6 = 1.13$$

$$y_1 = h(a_{11}^{(2)}) = \frac{1}{1+e^{-1.13}} = 0.75$$

$$2. \delta_k = t_k - y_1 = 1 - 0.75 = -0.25$$

$$\delta_k = (y_1 - t_k) \cdot g'(z)$$

$$3. \frac{\partial E}{\partial w_{jk}}$$

$$= (0.75 - 1) \cdot g'(z) \cdot (1 - g(z))$$

$$\frac{\partial E}{\partial w_{jk}} = \delta_k z_j = -0.25 \times 0.6 = -0.15$$

$$\delta_k = (1 - 0.75) \times 0.15 = 0.045$$

$$\frac{\partial E}{\partial w_{21}} = \delta_2 z_1 = 0.045 \times 0.568 = 0.025$$

$$\frac{\partial E}{\partial w_{22}} = \delta_2 z_2 = 0.045 \times 0.606 = 0.028$$

$$4. w_{21} = 0.4 - 0.1 \times 0.025 = 0.397$$

$$w_{22} = 0.5 - 0.1 \times 0.028 = 0.497$$

$$\exists 1. \quad w^{(1)}: (D+1) \times M$$

$$w^{(n)}: (M+1) \times K$$

$$z_1 \quad \begin{matrix} (1,2)^T \\ (2,1)^T \\ (3,1)^T \end{matrix}$$

$$a^{(1)} = w^{(1)}x$$

$$z = g(a^{(1)})$$

$$a^{(n)} = \begin{bmatrix} 1 \\ g(a^{(1)}) \end{bmatrix}$$

$$y = \sigma \left(w \left[\begin{bmatrix} 1 \\ g(a^{(1)}) \end{bmatrix} \right] \right) = \sigma \left(w^{(n)} \left[\begin{bmatrix} 1 \\ g(a^{(1)}) \end{bmatrix} \right] \right)$$

$$3. \quad \frac{\partial y_K}{\partial w_{md}} = \frac{\partial y_K}{\partial w_{km}} \cdot \frac{\partial w_{km}}{\partial w_{md}} = z_m \quad \text{N}$$

$$y_K = z_m w_{km}, \quad \cancel{w_{km}}$$

$$(S1) \quad = \sigma(x_0 \cdot w_{md}) \cdot w_{km} \quad \sigma'(a) = \sigma(a)(1-\sigma(a))$$

$$\frac{\partial y_K}{\partial w_{md}} = \frac{\partial y_K}{\partial a_K^{(n)}} \cdot \frac{\partial a_K^{(n)}}{\partial z_m} \cdot \frac{\partial z_m}{\partial a_m^{(1)}} \cdot \frac{\partial a_m^{(1)}}{\partial w_{md}}$$

$$P_{1,0} = 1250 \downarrow \quad \downarrow \quad \downarrow \quad \frac{36}{100} = \frac{36}{100} \quad \text{Xd}$$

$$= y_K(1-y_K) \quad \cancel{w_{km}} \quad z_m(1-z_m) \quad \text{Xd}$$

$$\therefore \frac{\partial y_K}{\partial w_{md}} = y_K(1-y_K) \cdot w_{km} \cdot z_m(1-z_m) \cdot \text{Xd}$$

四、1. $W_{out} = \frac{32-1}{1} = 31 \Rightarrow 31 \times 31$

2. $K_{eff} = 5 + (5-1) \times (2-1) = 9 \Rightarrow 64 \times 64$

3. 参数共享、局部感知、平行不适用

五 1. 神经网络: neural networks 2. 过拟合 overfitting

3. 正则化 regularization

4. 随机梯度下降: stochastic gradient descent

5. 逻辑回归: logistic regression.

6. 线性回归: linear regression

7. 广义线性模型: generalized linear regression

8. 均方误差: mean squared error

9. 平均绝对误差: mean absolute error