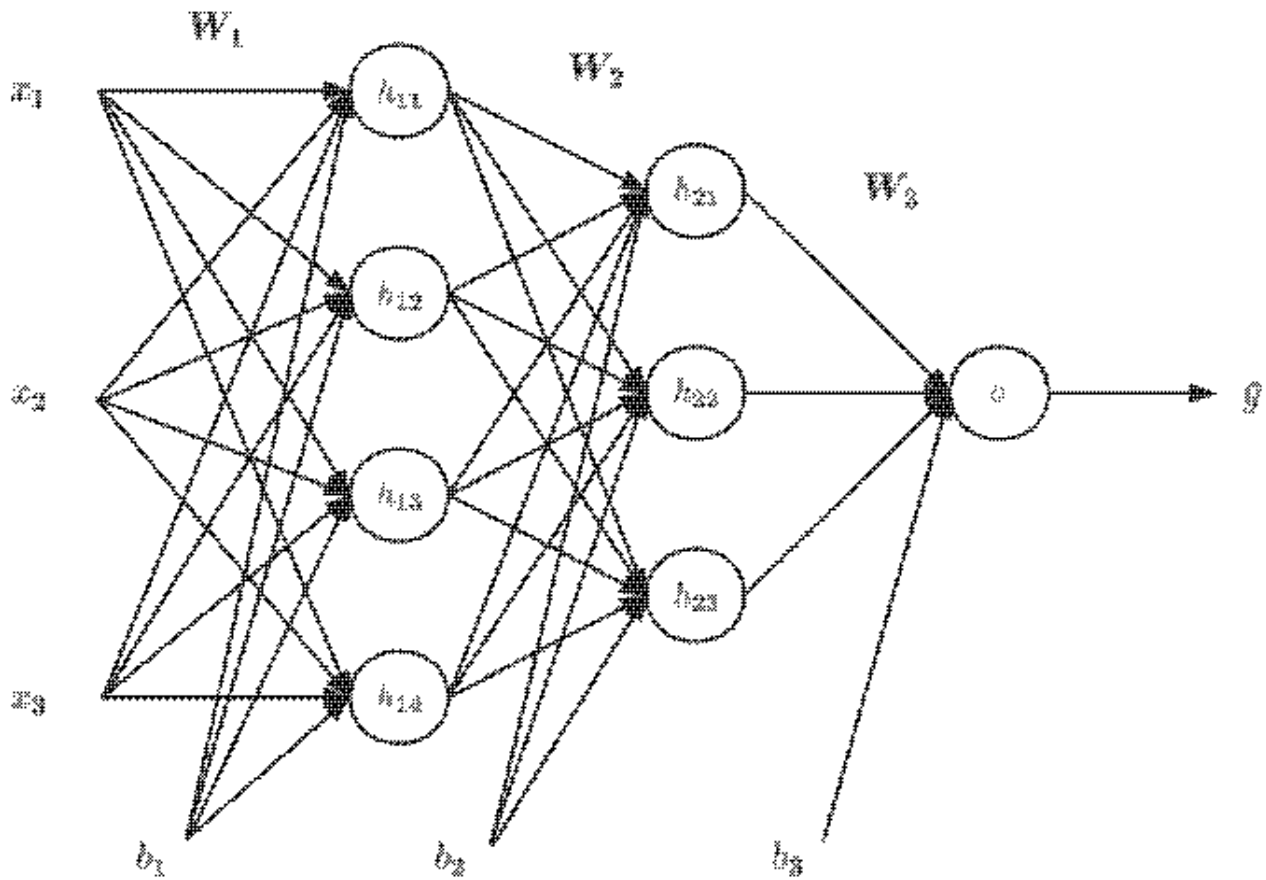


题目 1

考虑含两组隐层单元的三层前馈神经网络，如图所示。



$$W_1 = \begin{bmatrix} 0.1 & 0.1 & 0.3 \\ 0.2 & 0.3 & 0.2 \\ 0.1 & 0.2 & 0.1 \\ 0.3 & 0.1 & 0.1 \end{bmatrix}$$

$$W_2 = W_2^T$$

$$W_3 = [0.2 \quad 0.2 \quad 0.4]$$

$$[b_1 \quad b_2 \quad b_3] = [0.5 \quad 0.5 \quad 0.2]$$

各参数的初始值如上所示。定义该网络的隐藏层单元的激活函数为 $h = \cos(z)$ ，输出单元为 Logistic 函数。

- 当输入为 $(x_1, x_2, x_3) = (0.05, 0.10, 0.05)$ 时，计算该神经网络输出 y 的值。请写明必要的计算过程。
- 在 a) 的基础上，若 $y = 0.95$ ，采用最小化均方误差作为优化准则，请根据 BP 算法计算参数 W_3 的梯度。
- 在 b) 的基础上，若采用梯度下降更新参数，且学习率设置为 0.1，写出更新后的参数 W_3 。

。

解：

a)

隐藏层 Layer 1:

$$a^{[0]} = x$$
$$z^{[1]} = \mathbf{W}_1 a^{[0]} + b_1 = \begin{bmatrix} 0.1 & 0.1 & 0.3 \\ 0.2 & 0.3 & 0.2 \\ 0.1 & 0.2 & 0.1 \\ 0.3 & 0.1 & 0.1 \end{bmatrix} \begin{bmatrix} 0.05 \\ 0.10 \\ 0.05 \end{bmatrix} + \begin{bmatrix} 0.5 \\ 0.5 \\ 0.5 \\ 0.5 \end{bmatrix} = \begin{bmatrix} 0.53 \\ 0.55 \\ 0.53 \\ 0.53 \end{bmatrix}$$

隐藏层 Layer 2:

$$a^{[1]} = h(z^{[1]}) = \begin{bmatrix} 0.8628 \\ 0.8525 \\ 0.8628 \\ 0.8628 \end{bmatrix}$$
$$z^{[2]} = \mathbf{W}_2 a^{[1]} + b_2 = \begin{bmatrix} 0.1 & 0.2 & 0.1 & 0.3 \\ 0.1 & 0.3 & 0.2 & 0.1 \\ 0.3 & 0.2 & 0.1 & 0.1 \end{bmatrix} \begin{bmatrix} 0.8628 \\ 0.8525 \\ 0.8628 \\ 0.8628 \end{bmatrix} + \begin{bmatrix} 0.5 \\ 0.5 \\ 0.5 \end{bmatrix} = \begin{bmatrix} 1.1019 \\ 1.1009 \\ 1.1019 \end{bmatrix}$$

隐藏层 Layer 3:

$$a^{[2]} = h(z^{[2]}) = \begin{bmatrix} 0.4519 \\ 0.4528 \\ 0.4519 \end{bmatrix}$$
$$z^{[3]} = \mathbf{W}_3 a^{[2]} + b_3 = \begin{bmatrix} 0.2 & 0.2 & 0.4 \end{bmatrix} \begin{bmatrix} 0.4519 \\ 0.4528 \\ 0.4519 \end{bmatrix} + 0.2 = 0.5617$$

输出单元为 Logistic 函数:

$$\hat{y} = \sigma(z^{[3]}) = \frac{1}{1 + e^{-z^{[3]}}} = 0.6368$$

b) 已知 $y = 0.95$, $\hat{y} = 0.6368$,

损失函数

$$e = (y - \hat{y})^2$$

模型输出

$$\hat{y} = a^{[3]} = \sigma(z^{[3]}) = \frac{1}{1 + e^{-z^{[3]}}}$$

而

$$z^{[3]} = \mathbf{W}_3 a^{[2]} + b_3$$

$$\frac{\partial e}{\partial \mathbf{W}_3} = \frac{\partial e}{\partial y} \frac{\partial y}{\partial z^{[3]}} \frac{\partial z^{[3]}}{\partial \mathbf{W}_3} = 2(y - \hat{y})$$

因此，链式法则分别求导：

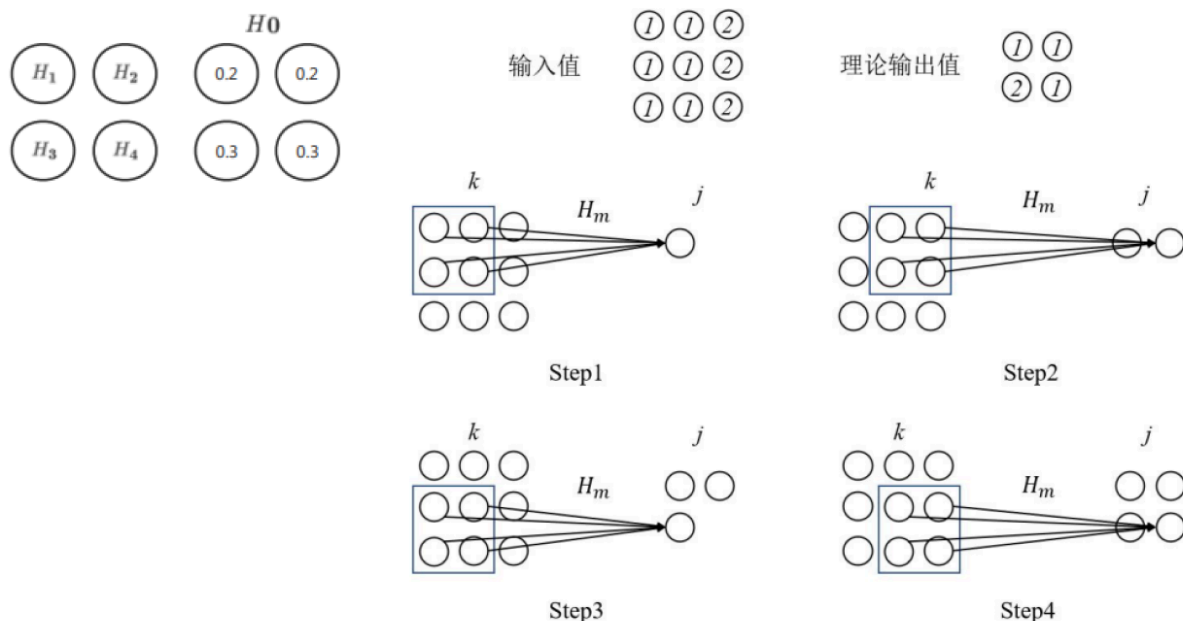
$$\begin{aligned} \frac{\partial e}{\partial \hat{y}} &= 2(\hat{y} - y) \\ \frac{\partial \hat{y}}{\partial z^{[3]}} &= \frac{e^{-z^{[3]}}}{(1 + e^{-z^{[3]}})^2} = \hat{y}(1 - \hat{y}) \\ \frac{\partial z^{[3]}}{\partial \mathbf{W}_3} &= a^{[2]T} \\ \Rightarrow \frac{\partial e}{\partial \mathbf{W}_3} &= \frac{\partial e}{\partial y} \cdot \frac{\partial y}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial \mathbf{W}_3} = 2(\hat{y} - y)\hat{y}(1 - \hat{y})a^{[2]T} \\ &= [-0.0655 \quad -0.0656 \quad -0.0655] \end{aligned}$$

c)

$$\begin{aligned} \mathbf{W}_3 &:= \mathbf{W}_3 - \eta \frac{\partial e}{\partial \mathbf{W}_3} \\ \mathbf{W}_3 &= [0.2065 \quad 0.2066 \quad 0.4065] \end{aligned}$$

题目 3

尝试对单卷积层的神经网络权值 \mathbf{H}_m 进行更新。初始权向量 \mathbf{H}_0 ，输入值与理论输出值如下图所示。



神经网络损失函数为 $L = \frac{1}{2}(y - d)^2$ ，学习率 $\alpha = 0.5$ 。其中 y 为网络输出， d 为理论输出。如图，卷积层将分四步扫描输入值，并返回四个输出。请根据输入值与初始权值，计算该网络输出值，并根据理论输出值更新权值参数。

解：

$$X = \begin{bmatrix} 1 & 1 & 2 \\ 1 & 1 & 2 \\ 1 & 1 & 2 \end{bmatrix} \quad H_0 = \begin{bmatrix} 0.2 & 0.2 \\ 0.3 & 0.3 \end{bmatrix} \quad d = \begin{bmatrix} 1 & 1 \\ 2 & 1 \end{bmatrix}$$

$$\hat{y}_{11} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} * \begin{bmatrix} 0.2 & 0.2 \\ 0.3 & 0.3 \end{bmatrix} = 1 \quad \hat{y}_{12} = \begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix} * \begin{bmatrix} 0.2 & 0.2 \\ 0.3 & 0.3 \end{bmatrix} = 1.5$$

$$\hat{y}_{21} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} * \begin{bmatrix} 0.2 & 0.2 \\ 0.3 & 0.3 \end{bmatrix} = 1 \quad \hat{y}_{22} = \begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix} * \begin{bmatrix} 0.2 & 0.2 \\ 0.3 & 0.3 \end{bmatrix} = 1.5$$

$$\therefore \hat{y} = \begin{bmatrix} 1 & 1.5 \\ 1 & 1.5 \end{bmatrix}$$

$$L = \frac{1}{2}(\hat{y} - d)^2 \Rightarrow \frac{\partial L}{\partial \hat{y}} = \hat{y} - d = \begin{bmatrix} 0 & 0.5 \\ -1 & 0.5 \end{bmatrix}$$

$$\frac{\partial L}{\partial h_{ij}} = \sum_{m,n} \frac{\partial L}{\partial \hat{y}_{m,n}} \cdot \frac{\partial \hat{y}_{m,n}}{\partial h_{ij}}$$

$$\frac{\partial \hat{y}}{\partial h_{11}} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \quad \frac{\partial \hat{y}}{\partial h_{12}} = \begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix}$$

$$\frac{\partial \hat{y}}{\partial h_{21}} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \quad \frac{\partial \hat{y}}{\partial h_{22}} = \begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix}$$

$$\begin{aligned}\frac{\partial L}{\partial h_{11}} &= \frac{\partial L}{\partial \hat{y}_{11}} \cdot \frac{\partial \hat{y}_{11}}{\partial h_{11}} + \frac{\partial L}{\partial \hat{y}_{12}} \cdot \frac{\partial \hat{y}_{12}}{\partial h_{11}} + \frac{\partial L}{\partial \hat{y}_{21}} \cdot \frac{\partial \hat{y}_{21}}{\partial h_{11}} + \frac{\partial L}{\partial \hat{y}_{22}} \cdot \frac{\partial \hat{y}_{22}}{\partial h_{11}} \\ &= 0 \cdot 1 + 0.5 \cdot 1 - 1 \cdot 1 + 0.5 \cdot 1 = 0\end{aligned}$$

$$\begin{aligned}\frac{\partial L}{\partial h_{12}} &= \frac{\partial L}{\partial \hat{y}_{11}} \cdot \frac{\partial \hat{y}_{11}}{\partial h_{12}} + \frac{\partial L}{\partial \hat{y}_{12}} \cdot \frac{\partial \hat{y}_{12}}{\partial h_{12}} + \frac{\partial L}{\partial \hat{y}_{21}} \cdot \frac{\partial \hat{y}_{21}}{\partial h_{12}} + \frac{\partial L}{\partial \hat{y}_{22}} \cdot \frac{\partial \hat{y}_{22}}{\partial h_{12}} \\ &= 0 \cdot 1 + 0.5 \cdot 2 - 1 \cdot 1 + 0.5 \cdot 2 = 1\end{aligned}$$

$$\begin{aligned}\frac{\partial L}{\partial h_{21}} &= \frac{\partial L}{\partial \hat{y}_{11}} \cdot \frac{\partial \hat{y}_{11}}{\partial h_{21}} + \frac{\partial L}{\partial \hat{y}_{12}} \cdot \frac{\partial \hat{y}_{12}}{\partial h_{21}} + \frac{\partial L}{\partial \hat{y}_{21}} \cdot \frac{\partial \hat{y}_{21}}{\partial h_{21}} + \frac{\partial L}{\partial \hat{y}_{22}} \cdot \frac{\partial \hat{y}_{22}}{\partial h_{21}} \\ &= 0 \cdot 1 + 0.5 \cdot 1 - 1 \cdot 1 + 0.5 \cdot 1 = 0\end{aligned}$$

$$\begin{aligned}\frac{\partial L}{\partial h_{22}} &= \frac{\partial L}{\partial \hat{y}_{11}} \cdot \frac{\partial \hat{y}_{11}}{\partial h_{22}} + \frac{\partial L}{\partial \hat{y}_{12}} \cdot \frac{\partial \hat{y}_{12}}{\partial h_{22}} + \frac{\partial L}{\partial \hat{y}_{21}} \cdot \frac{\partial \hat{y}_{21}}{\partial h_{22}} + \frac{\partial L}{\partial \hat{y}_{22}} \cdot \frac{\partial \hat{y}_{22}}{\partial h_{22}} \\ &= 0 \cdot 1 + 0.5 \cdot 2 - 1 \cdot 1 + 0.5 \cdot 2 = 1\end{aligned}$$

$$\text{then } \frac{\partial L}{\partial H_0} = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}$$

$$\text{we have } H_1 \leftarrow H_0 - \alpha \frac{\partial L}{\partial H_0} = \begin{bmatrix} 0.2 & 0.2 \\ 0.3 & 0.3 \end{bmatrix} - 0.5 \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0.2 & -0.3 \\ 0.3 & -0.2 \end{bmatrix}$$