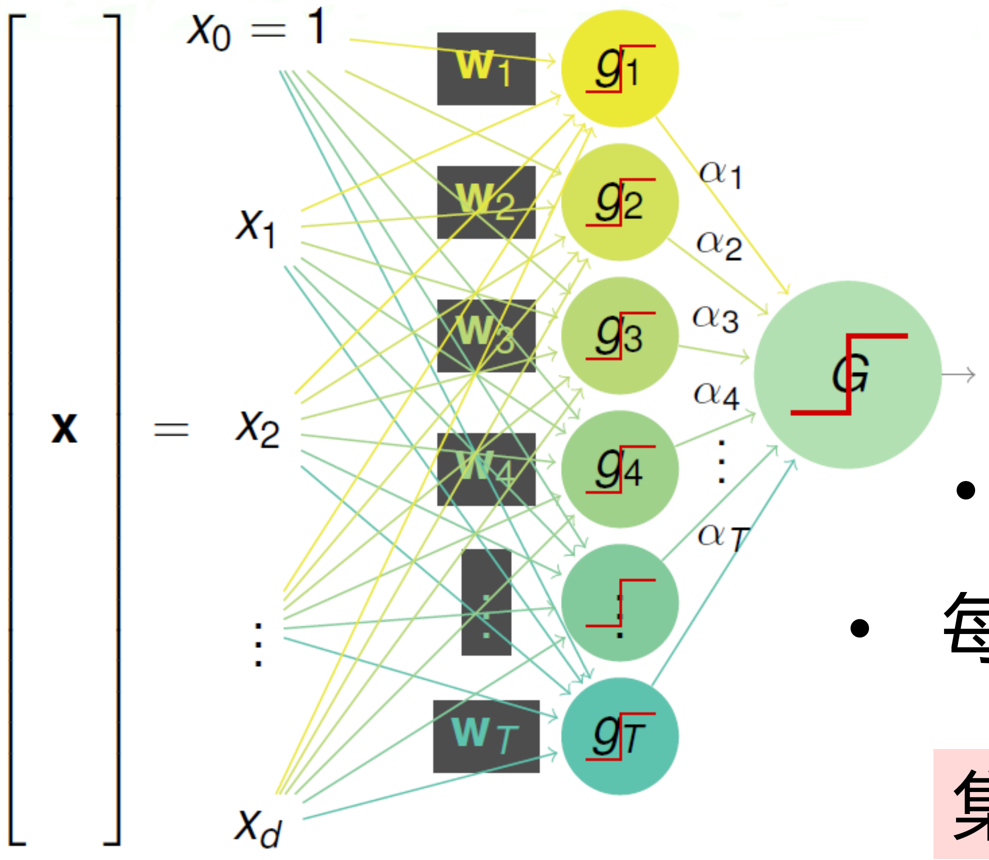
第十讲 神经网络到深度学习(*From Neural Networks to Deep Learning*)

多个感知器的线性集成(*Linear Aggregation of Perceptrons*)



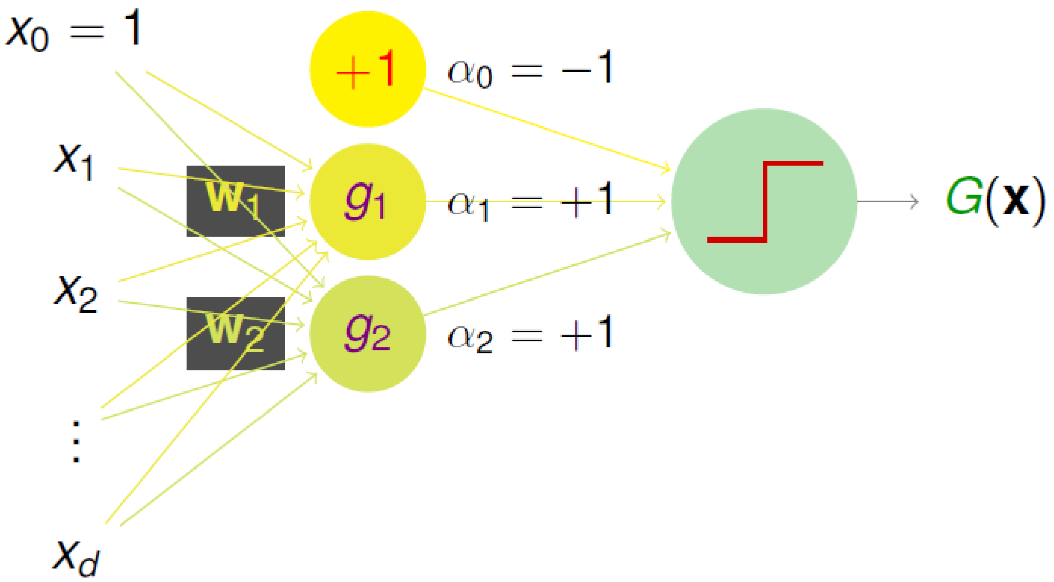
$$G(\mathbf{x}) = sign\left(\sum_{t=1}^{T} \alpha_t \underbrace{sign(\mathbf{w}_t^T \mathbf{x})}_{g_t(\mathbf{x})}\right)$$

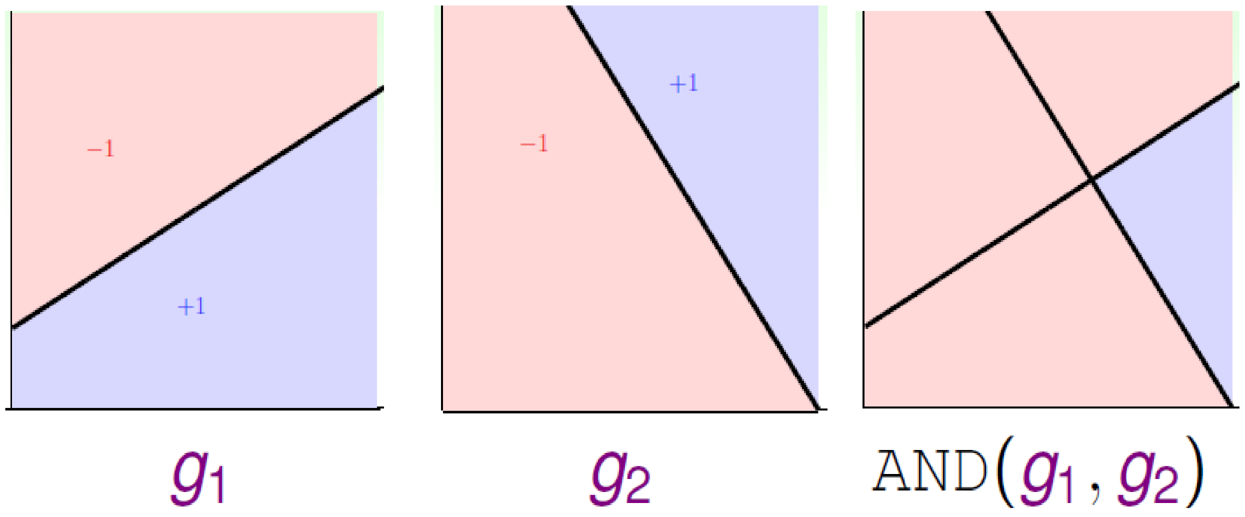
- 一共两层，每层都有权向量： $\mathbf{w}_t$和$\boldsymbol{\alpha}$
- 每层用符号函数*sign*()分别得到： g_t和G

集成后得到分类面G的边界是怎样的?

Source: NTU-LIN

用集成方式实现逻辑运算





$$G(\mathbf{x}) = sign(-1 + g_1(\mathbf{x}) + g_2(\mathbf{x}))$$

$if\ \ g_1(\mathbf{x}) = g_2(\mathbf{x}) = +1$: $\quad G(\mathbf{x}) = +1$

$otherwise$: $\quad G(\mathbf{x}) = -1$

$$G(\mathbf{x}) \equiv AND(g_1(\mathbf{x}), g_2(\mathbf{x}))$$

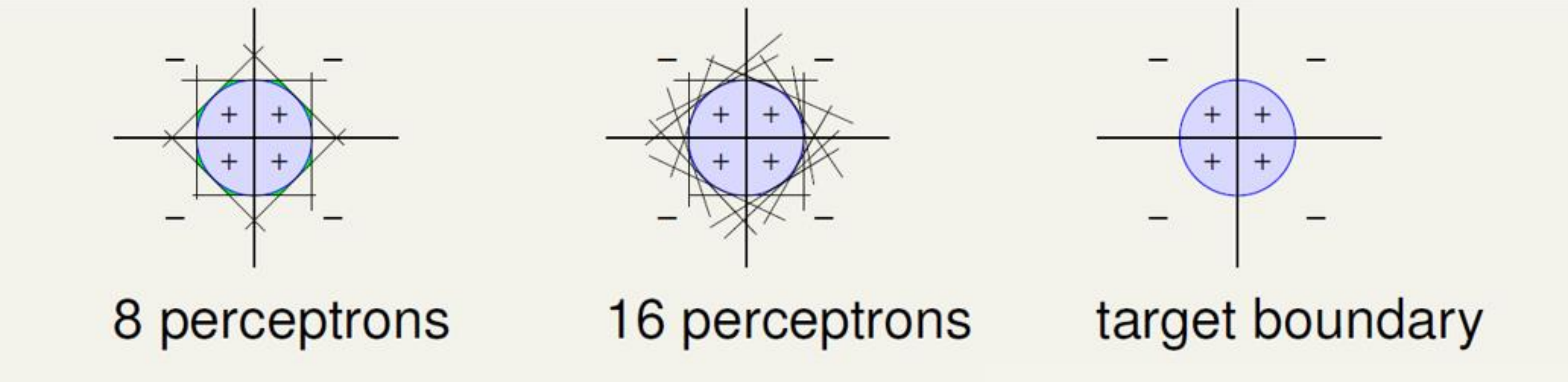
集成也能实现逻辑运算OR、NOT

Source: NTU-LIN

10.1 神经网络动机

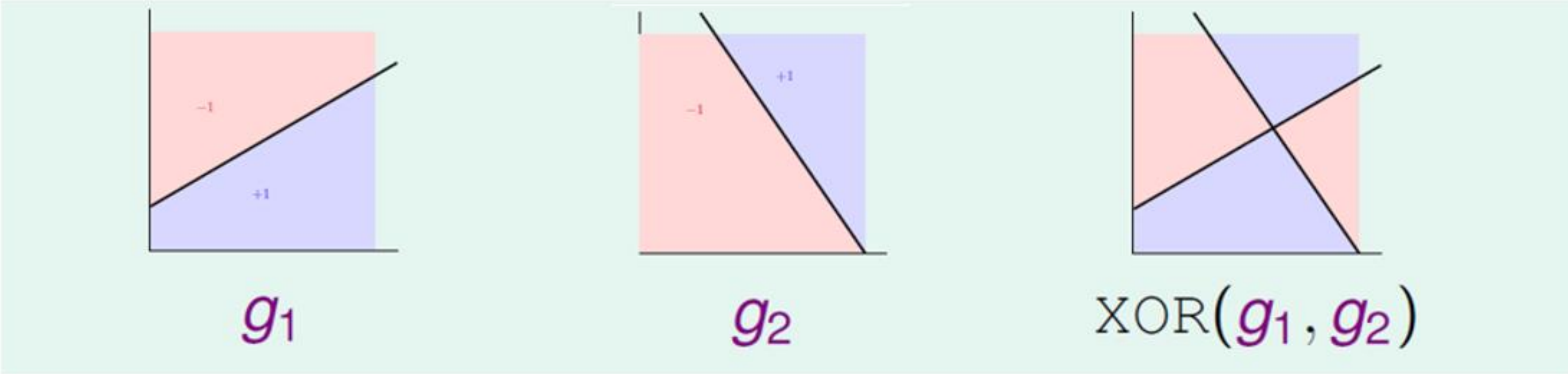
两层集成的强大能力：

足够多的感知器可得到光滑的非线性分类面



两层集成的不足：

在两层结构下，做不到“线性可分”，无法实现“异或(*XOR*)”逻辑



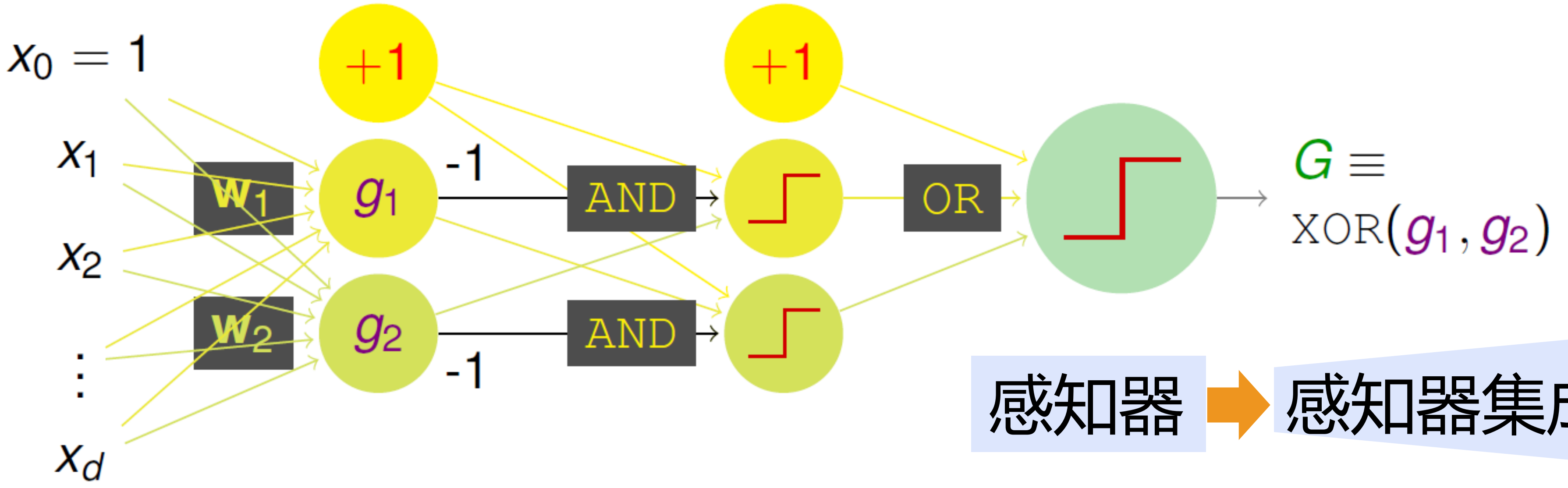
Source: NTU-LIN

如何实现“异或”逻辑?

- 途径1：非线性变换
- 途径2：在两层实现简单逻辑基础上，再增加层数

$$XOR(g_1, g_2) = OR(AND(-g_1, g_2) + AND(g_1, -g_2))$$

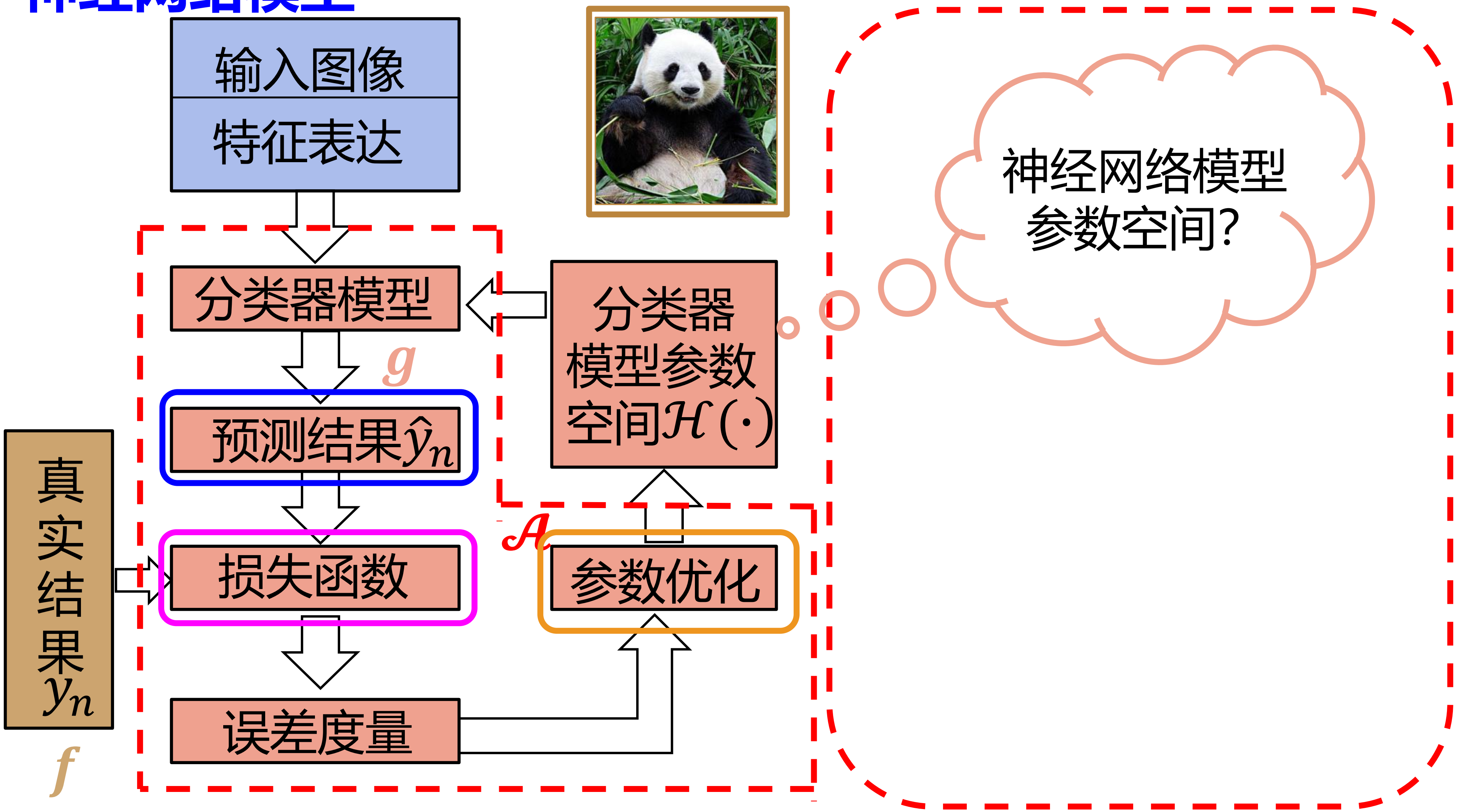
多层感知机—基本的神经网络



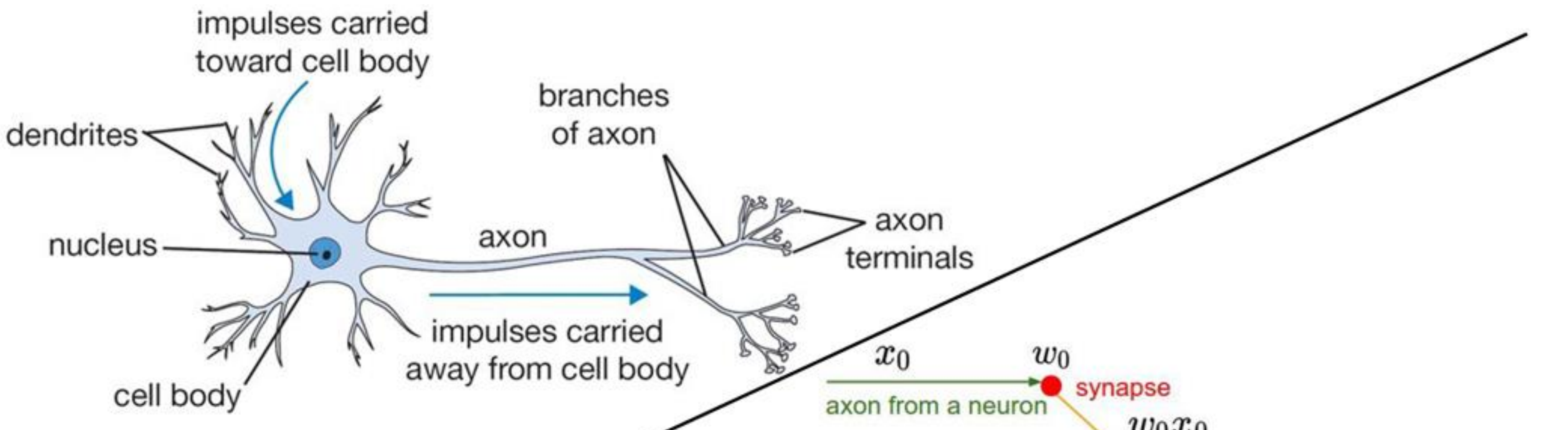
Source: NTU-LIN

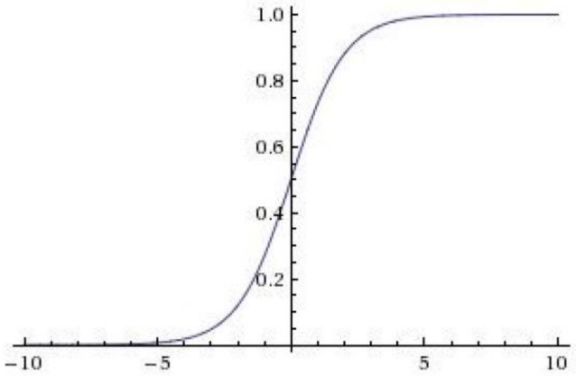
10.2 神经网络模型参数空间

神经网络模型



神经网络(*Neural Networks*)：





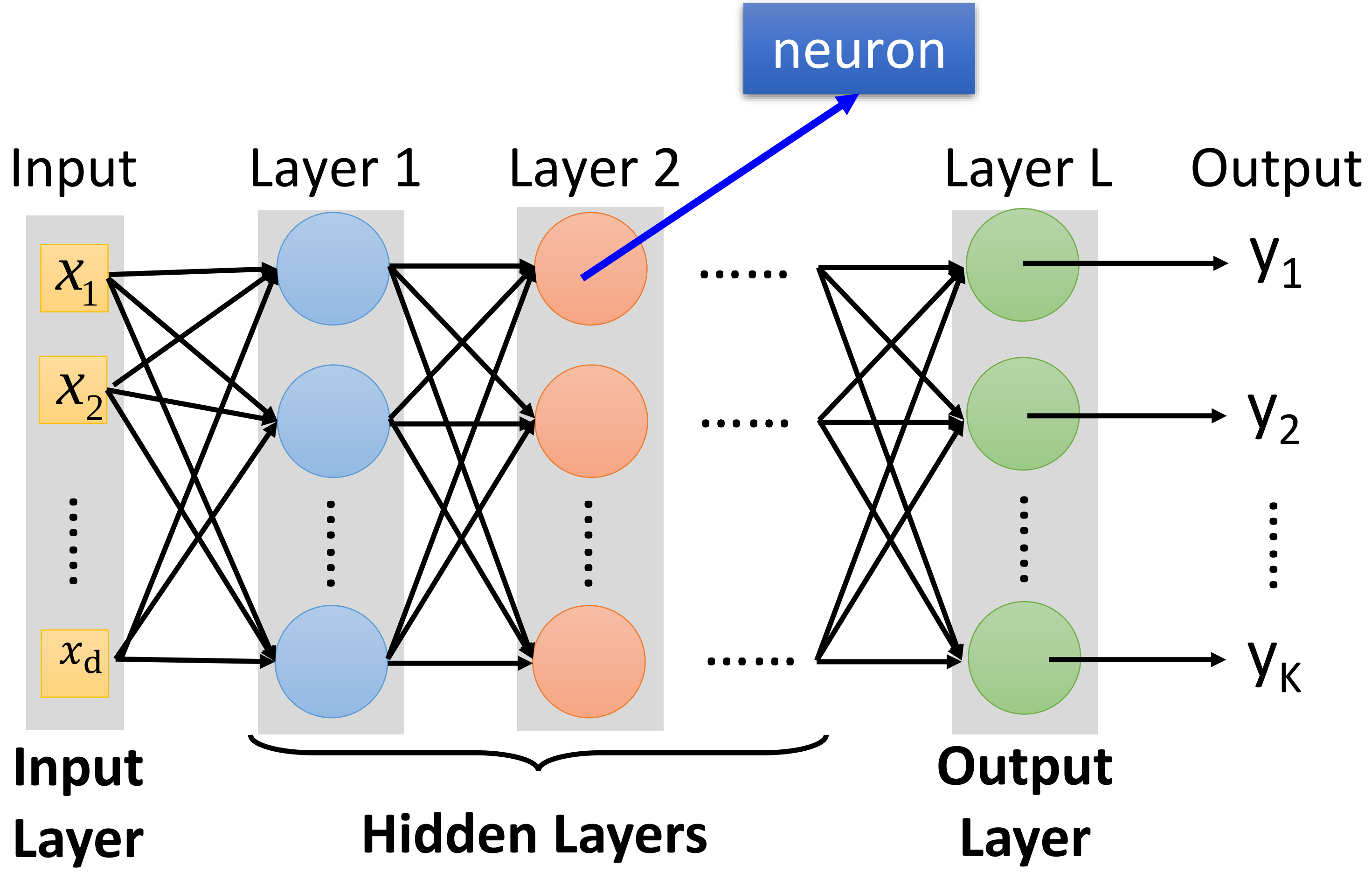
Sigmoid 激活函数

(*Sigmoid activation function*)

$$\frac{1}{1+e^{-x}}$$

Source: CS2331n-Standford

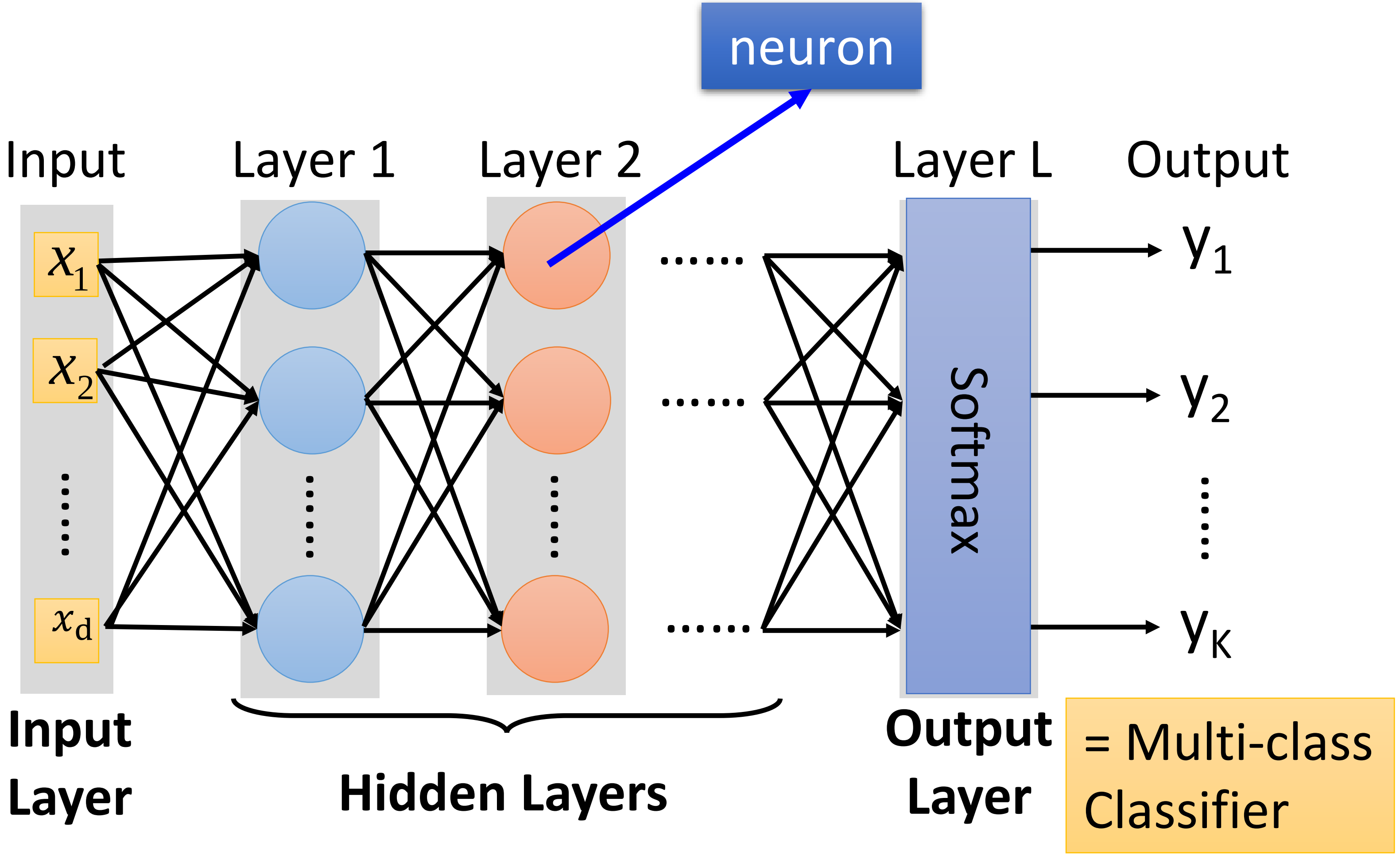
全链接前馈神经网络(*Fully Connect Feedforward Network*):



Source: NTU-LEE

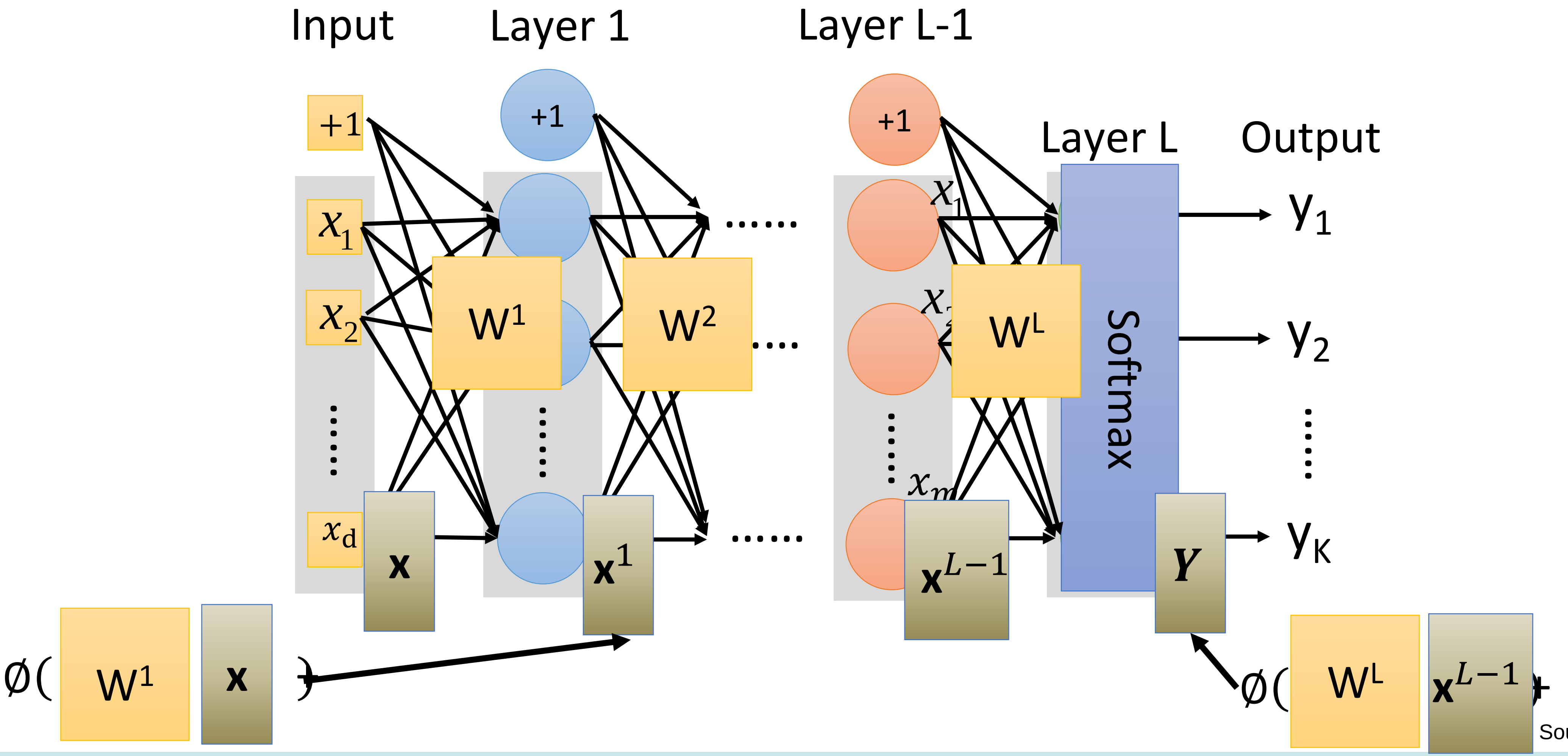
10.2 神经网络模型参数空间

全链接前馈神经网络(*Fully Connect Feedforward Network*):



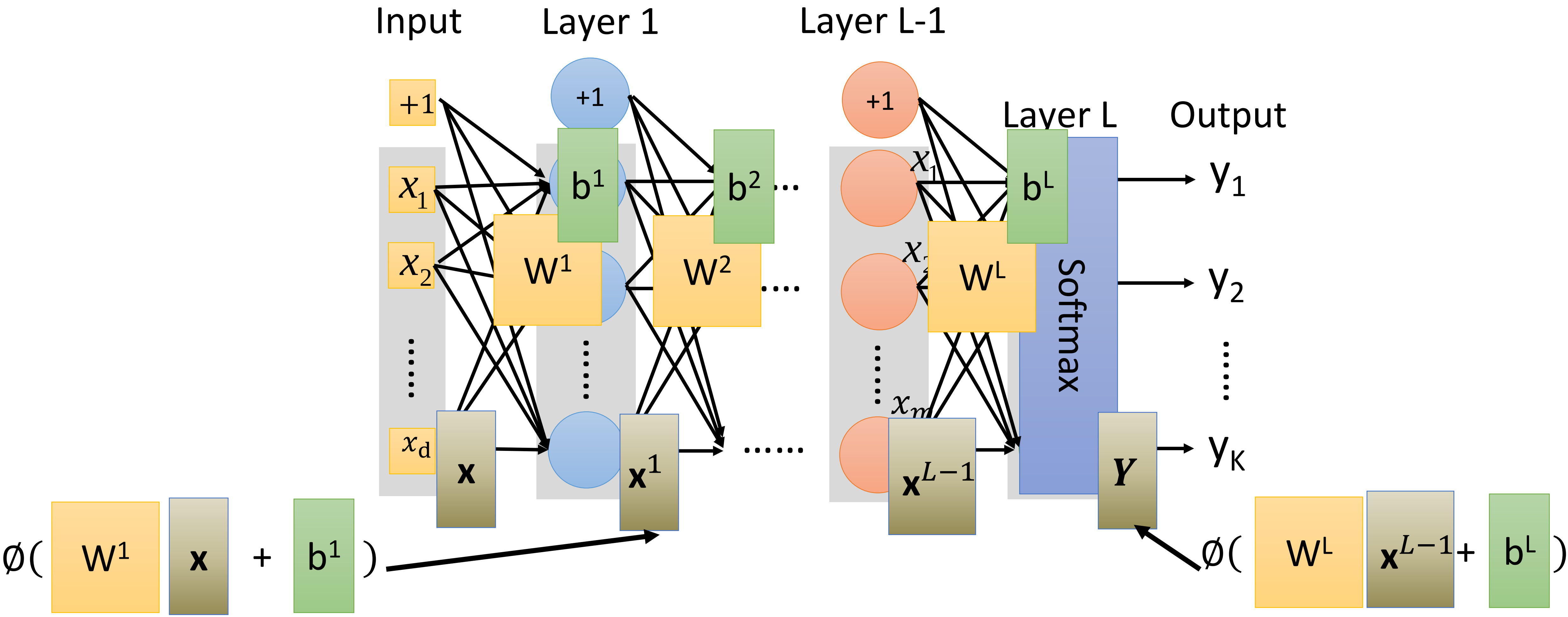
Source: NTU-LEE

全链接前馈神经网络(*Fully Connect Feedforward Network*):



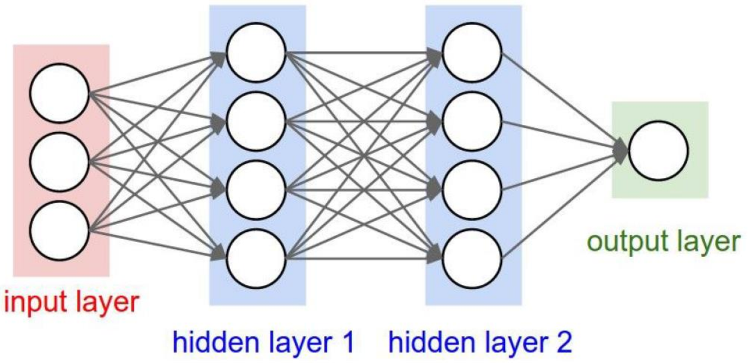
Source: NTU-LEE

全链接前馈神经网络(*Fully Connect Feedforward Network*)：



Source: NTU-LEE

神经网络模型：



为简单起见，输出端考虑二分类问题

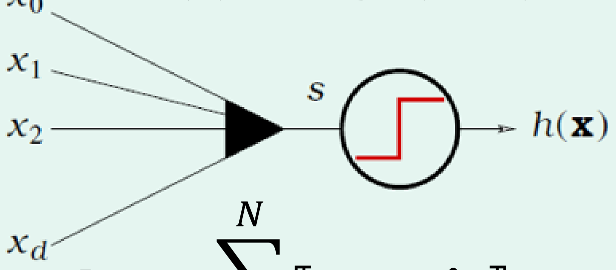
为简单起见，输出层选择线性回归模型

$$\text{Output: } S=\mathbf{w}^T\phi^{(2)}(\phi^{(1)}(\mathbf{x}))$$

$$L_{in}=\frac{1}{N}\sum_{n=1}^{N}(S-y_n)^2$$

线性分类(感知器)：

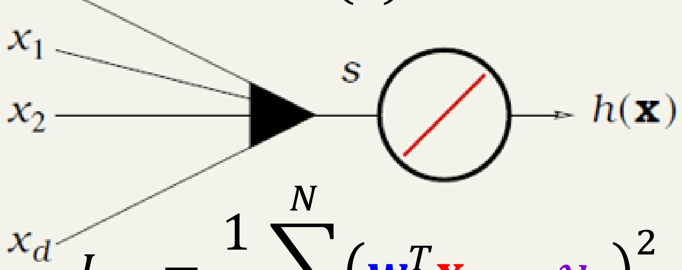
$$h(\mathbf{x})=\text{sign}(\mathbf{w}^T\mathbf{x})$$



$$L_{in}=\sum_{n=1}^{N}[\![y_n\neq\hat{y}_n]\!]$$

线性回归：

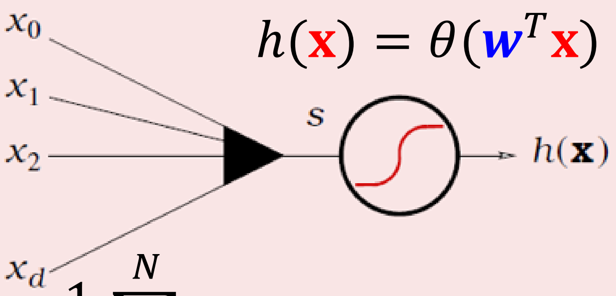
$$h(\mathbf{x})=\mathbf{w}^T\mathbf{x}$$



$$L_{in}=\frac{1}{N}\sum_{n=1}^{N}\left(\mathbf{w}^T\mathbf{x}_n-y_n\right)^2$$

逻辑斯蒂回归：

$$h(\mathbf{x})=\theta(\mathbf{w}^T\mathbf{x})$$



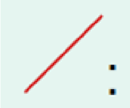
$$L_{in}=\frac{1}{N}\sum_{n=1}^{N}\ln(1+exp(-y_n\mathbf{w}^T\mathbf{x}_n))$$

Source: NTU-LIN

10.2 神经网络模型参数空间

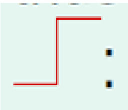
激活(activation)/变换(transformation)函数：

激活函数可以是任意形式吗?

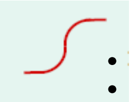


线性网络，作用不大

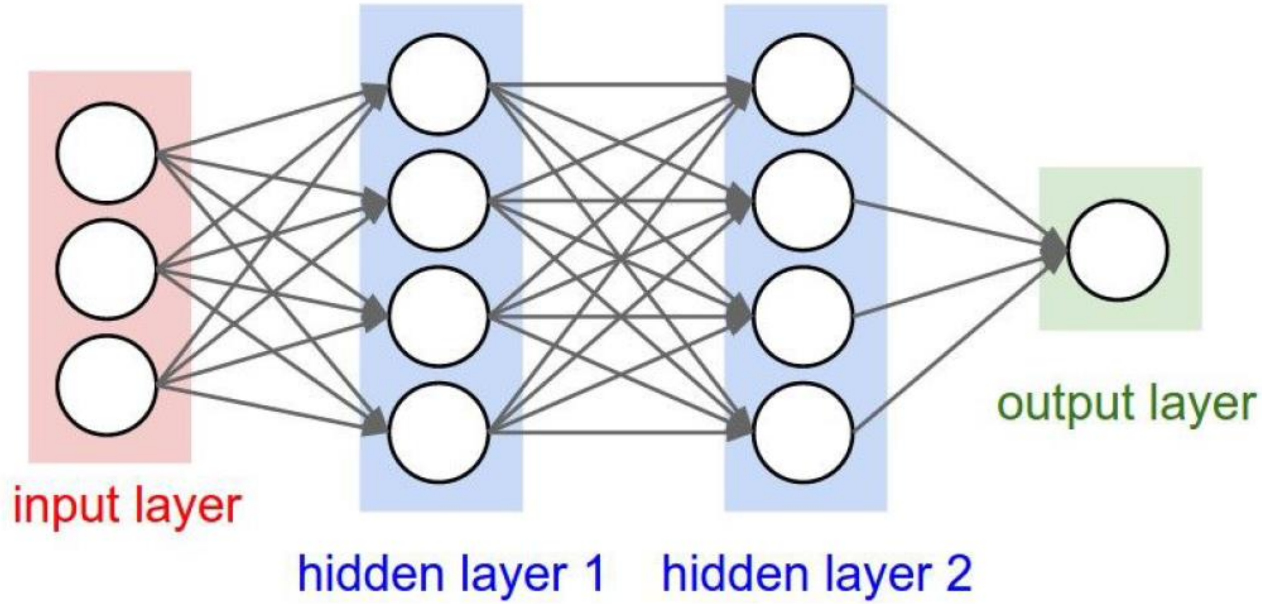
$$s = \mathbf{w}^{(3)}\left(\mathbf{w}^{(2)}\left(\mathbf{w}^{(1)}\mathbf{x} + b^{(1)}\right) + b^{(2)}\right) + b^{(3)}$$
$$= \mathbf{W}\mathbf{x} + b$$



NP难问题，难以获得最佳的$\mathbf{w}$



非线性变换，增强网络的性能



$$s = \mathbf{w}^{(3)}\phi\left(\mathbf{w}^{(2)}\phi\left(\mathbf{w}^{(1)}\mathbf{x} + b^{(1)}\right) + b^{(2)}\right) + b^{(3)}$$

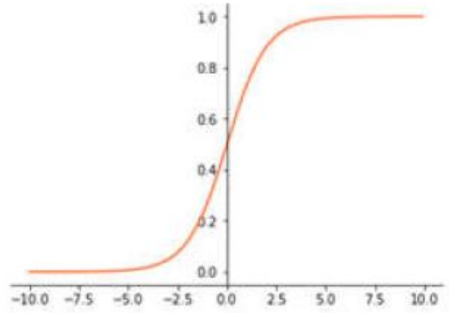
Source: NTU-LIN

10.2 神经网络模型参数空间

激活(activation)/变换(transformation)函数：

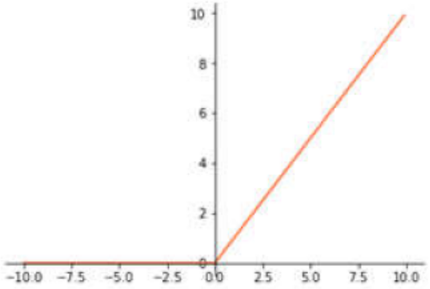
Sigmoid

$$1/(1+e^{-x})$$



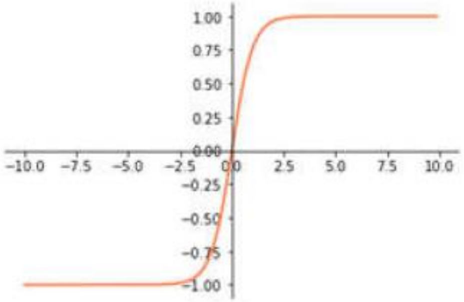
ReLU

$$\max(0, x)$$



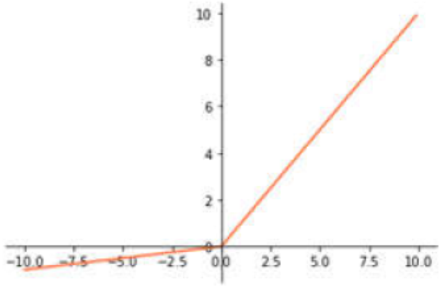
tanh

$$\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$$



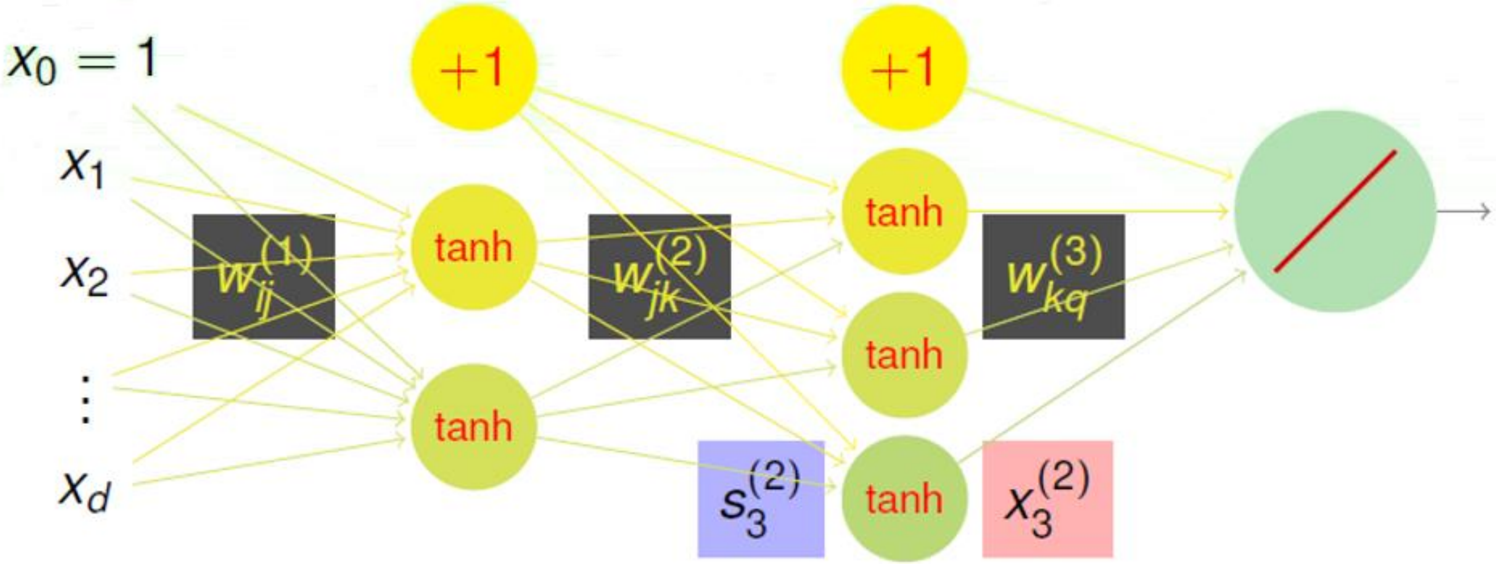
Leaky ReLU

$$\max(0.1x, x)$$



- 每一个感知器单元都应具有非线性特性
- 非线性函数应该具有可导性质便于训练

10. 2 神经网络模型参数空间



符号含义:

$d^{(l)}$: 网络第l层的神经元个数

$w_{ij}^{(l)}$: 网络的第$l-1$层到第l层的权系数矩阵元素

$S_j^{(l)}$: 网络第l层第j个神经元的输入

$x_j^{(l)}$: 网络第l层第j个神经元的输出

$$\boldsymbol{w}_{ij}^{(l)}: \begin{cases} 1 \le l \le L & \text{layers} \\ 0 \le i \le d^{(l-1)} & \text{inputs} \\ 1 \le j \le d^{(l)} & \text{outputs} \end{cases}$$

$$S_j^{(l)} = \sum_{i=0}^{d^{(l-1)}} w_{ij}^{(l)} x_i^{(l-1)}$$

$$x_j^{(l)} = \begin{cases} \tanh(S_j^{(l)}) & if\ l < L \\ S_j^{(l)} & if\ l = L \end{cases}$$

将输入样本$\mathbf{x}$作为input layer，经过hidden layers得到$\mathbf{x}^{(l)}$，在output layer去预测$x_1^{(L)}$

Source: NTU-LIN

10.1 神经网络动机（*Motivation of Neural Networks*）

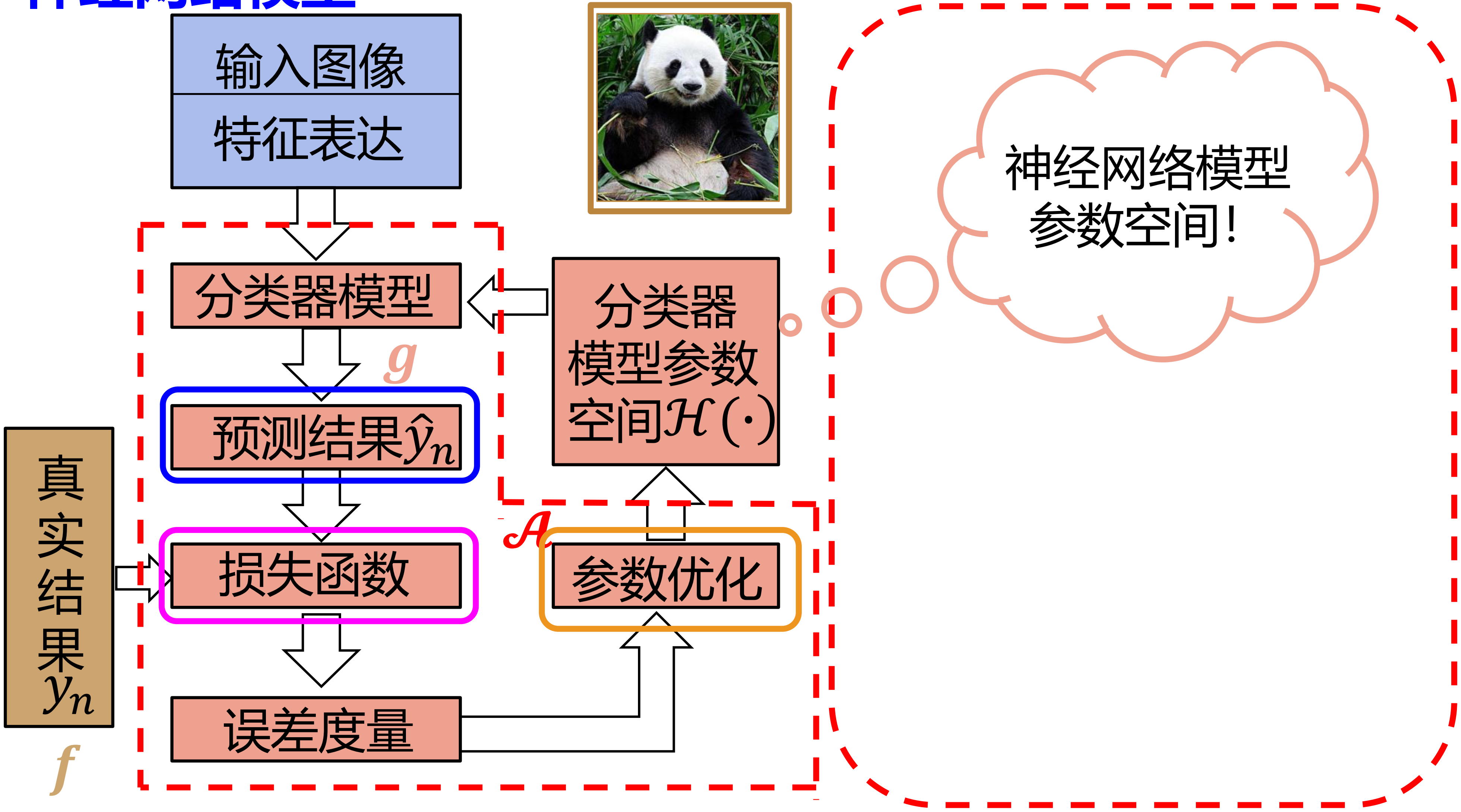
10.2 神经网络模型(*Neural Network Hypothesis*)

10.3 神经网络学习（*Neural Network Learning*）

10.4 深度神经网络（*Deep Neural Networks*）

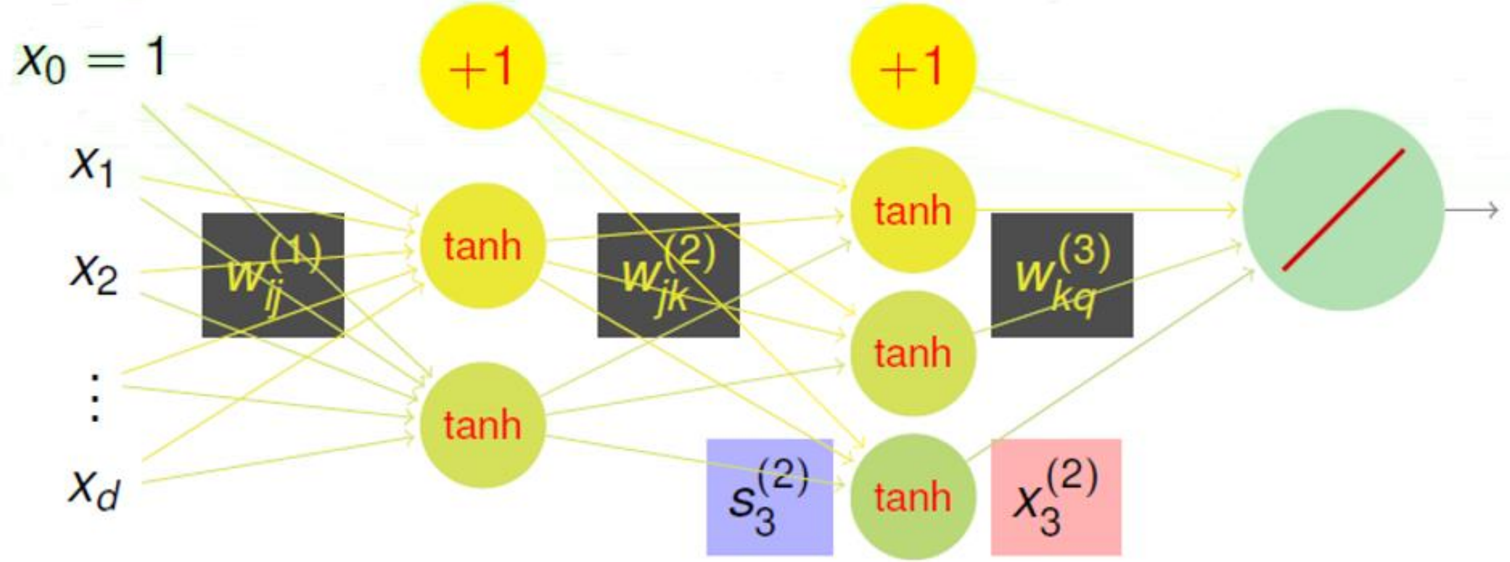
10.3 神经网络学习

神经网络模型



10.3 神经网络学习

如何学习网络权重 $w_{ij}^{(l)}$ ？



$d^{(l)}$：网络第l层的神经元个数

$w_{ij}^{(l)}$：网络的第$l-1$层到第l层的权系数矩阵元素

$s_j^{(l)}$：网络第l层第j个神经元的输入

$x_j^{(l)}$：网络第l层第j个神经元的输出

$$\mathbf{w}_{ij}^{(l)}:\begin{cases}1\le l\le L & \text{layers}\\ 0\le i\le d^{(l-1)} & \text{inputs}\\ 1\le j\le d^{(l)} & \text{outputs}\end{cases}$$

$$s_j^{(l)}=\sum_{i=0}^{d^{(l-1)}} w_{ij}^{(l)}x_i^{(l-1)}$$

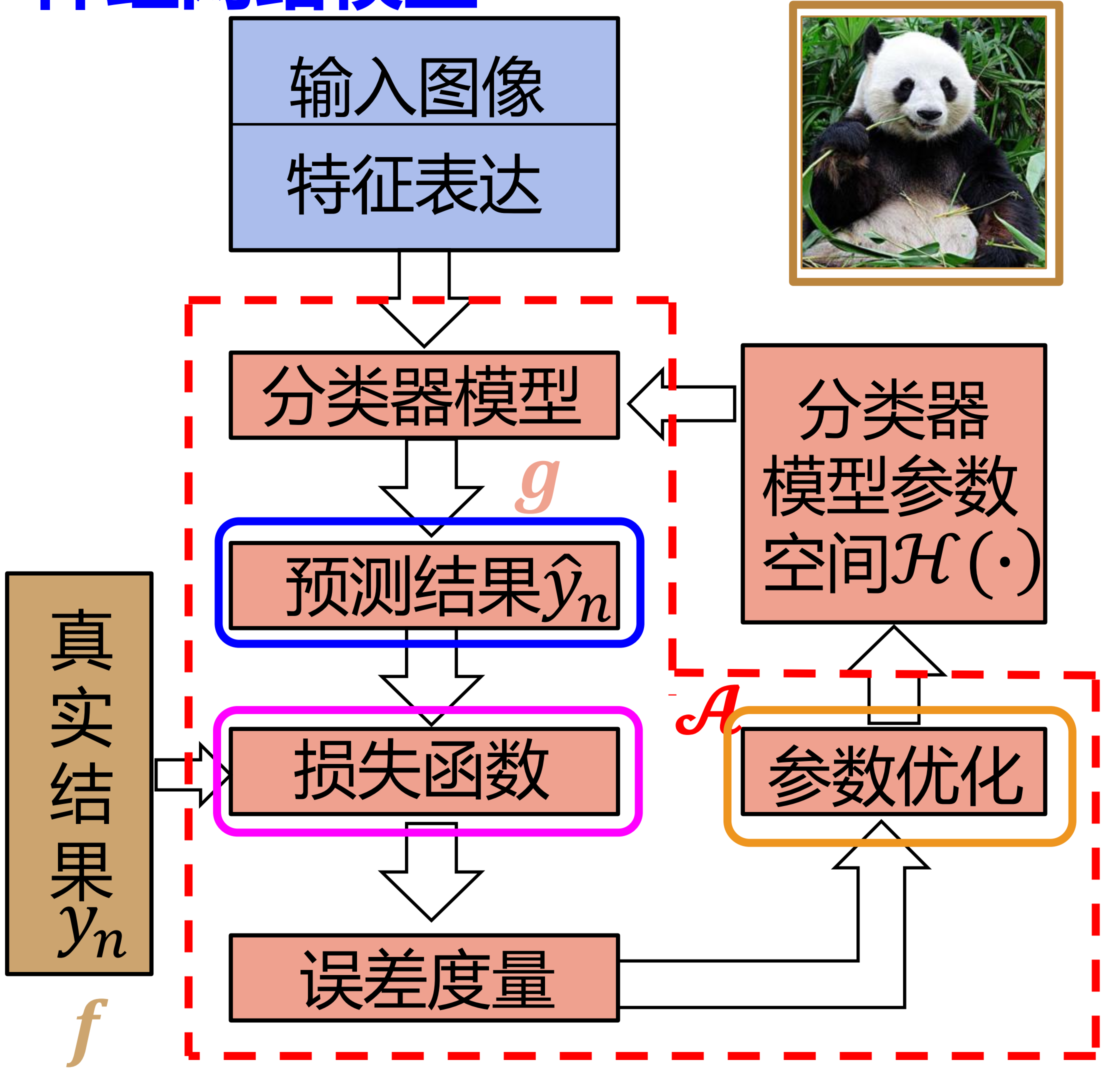
$$x_j^{(l)}=\begin{cases}\tanh(s_j^{(l)}) & if\ l<L\\ s_j^{(l)} & if\ l=L\end{cases}$$

将输入样本$\mathbf{x}$作为input layer，经过hidden layers得到$\mathbf{x}^{(l)}$，在output layer去预测$x_1^{(L)}$

Source: NTU-LIN

10.3 神经网络学习

神经网络模型



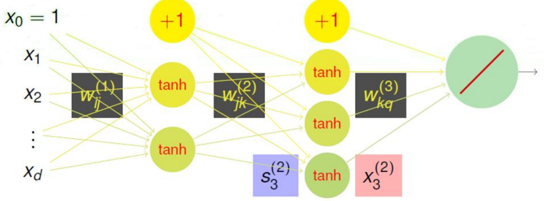
$$\hat{y}_n = NNet(\mathbf{x}_n)$$

$$L_n = (y_n - NNet(\mathbf{x}_n))^2$$

参数优化? 随机梯度下降法

求解网络中所有的$\boldsymbol{w}_{ij}^{(l)}$，

使L_n最小化，即为最佳解



$$\boldsymbol{w}_{ij}^{(l)} : \begin{cases} 1 \le l \le L \\ 0 \le i \le d^{(l-1)} \\ 1 \le j \le d^{(l)} \end{cases}$$

$$s_j^{(l)} = \sum_{i=0}^{d^{(l-1)}} w_{ij}^{(l)} x_i^{(l-1)}$$

$$x_j^{(l)} = \begin{cases} \tanh(s_j^{(l)}) & if\ l < L \\ s_j^{(l)} & if\ l = L \end{cases}$$

神经网络中如何求解梯度：$\frac{\partial L_n}{\partial \mathbf{w}_{ij}^{(l)}}$

$$L_n = (y_n - NNet(\mathbf{x}_n))^2 = (y_n - S_1^{(L)})^2 = (y_n - \sum_{i=0}^{d^{(L-1)}} w_{i1}^{(L)} x_i^{(L-1)})^2$$

网络输出层：第L层

$(0 \le i \le d^{(L-1)}, j = 1, l = L)$

$$\frac{\partial L_n}{\partial w_{i1}^{(L)}} = \frac{\partial L_n}{\partial S_1^{(L)}} \cdot \frac{\partial S_1^{(L)}}{\partial w_{i1}^{(L)}}$$

$$= -2(y_n - S_1^{(L)}) \cdot (x_i^{(L-1)})$$

$$\delta_j^{(L)} = -2(y_n - S_1^{(L)})$$

网络其他层：第l层

$(0 \le i \le d^{(l-1)}, 1 \le j \le d^{(l)})$

$$\frac{\partial L_n}{\partial w_{ij}^{(l)}} = \frac{\partial L_n}{\partial S_j^{(l)}} \cdot \frac{\partial S_j^{(l)}}{\partial w_{ij}^{(l)}}$$

$$= \delta_j^{(l)} \cdot (x_i^{(l-1)})$$

$$\delta_j^{(l)} = ?$$

$$\mathbf{w}_{ij}^{(l)}: \begin{cases} 1 \le l \le L \\ 0 \le i \le d^{(l-1)} \\ 1 \le j \le d^{(l)} \end{cases}$$

$$S_j^{(l)} = \sum_{i=0}^{d^{(l-1)}} w_{ij}^{(l)} x_i^{(l-1)}$$

$$x_j^{(l)} = \begin{cases} \tanh(S_j^{(l)}) & if\ l < L \\ S_j^{(l)} & if\ l = L \end{cases}$$

Source: NTU-LIN

神经网络中如何求解梯度： $\delta_j^{(l)} = \frac{\partial L_n}{\partial S_j^{(l)}}$

$$S_j^{(l)} \xrightarrow{\tanh} x_j^{(l)} \xrightarrow{w_{jk}^{(l+1)}} \begin{pmatrix} S_1^{(l+1)} \\ \vdots \\ S_k^{(l+1)} \\ \vdots \end{pmatrix} \longrightarrow \cdots \longrightarrow L_n$$

$$\delta_j^{(l)} = \frac{\partial L_n}{\partial S_j^{(l)}} = \sum_{k=1}^{d^{(l+1)}} \frac{\partial L_n}{\partial S_k^{(l+1)}} \cdot \frac{\partial S_k^{(l+1)}}{\partial x_j^{(l)}} \cdot \frac{\partial x_j^{(l)}}{\partial S_j^{(l)}}$$

$$= \sum_{k=1}^{d^{(l+1)}} (\delta_k^{(l+1)}) \cdot (w_{jk}^{(l+1)}) \cdot (\tanh'(S_j^{(l)}))$$

$\delta_j^{(l)}$能够通过反传$\delta_k^{(l+1)}$求得

$$w_{ij}^{(l)} : \begin{cases} 1 \le l \le L \\ 0 \le i \le d^{(l-1)} \\ 1 \le j \le d^{(l)} \end{cases}$$

$$S_j^{(l)} = \sum_{i=0}^{d^{(l-1)}} w_{ij}^{(l)} x_i^{(l-1)}$$

$$x_j^{(l)} = \begin{cases} \tanh(S_j^{(l)}) if\ l < L \\ S_j^{(l)} \quad if\ l = L \end{cases}$$

Source: NTU-LIN

利用反向传播算法实现神经网络学习(*Back propagation (Backprop) Algorithm*)

初始化所有的权系数$\mathbf{w}_{ij}^{(l)}$

$for\ t = 0,1,\ldots T$

① 随机性(*stochastic*)：从训练样本集中任选一个$\mathbf{x}_n$，$n \in \{1,2,\ldots N\}$

② 前向传播(*forward*)：利用$\mathbf{x}^{(0)} = \mathbf{x}_n$计算所有的$x_i^{(l)}$

③ 后向传播(*backward*)：在$\mathbf{x}^{(0)} = \mathbf{x}_n$基础上，计算所有的$\delta_j^{(l)}$

④ 梯度下降(*gradient descent*)：$\mathbf{w}_{ij}^{(l)} \leftarrow \mathbf{w}_{ij}^{(l)} - \eta x_i^{(l-1)} \delta_j^{(l)}$

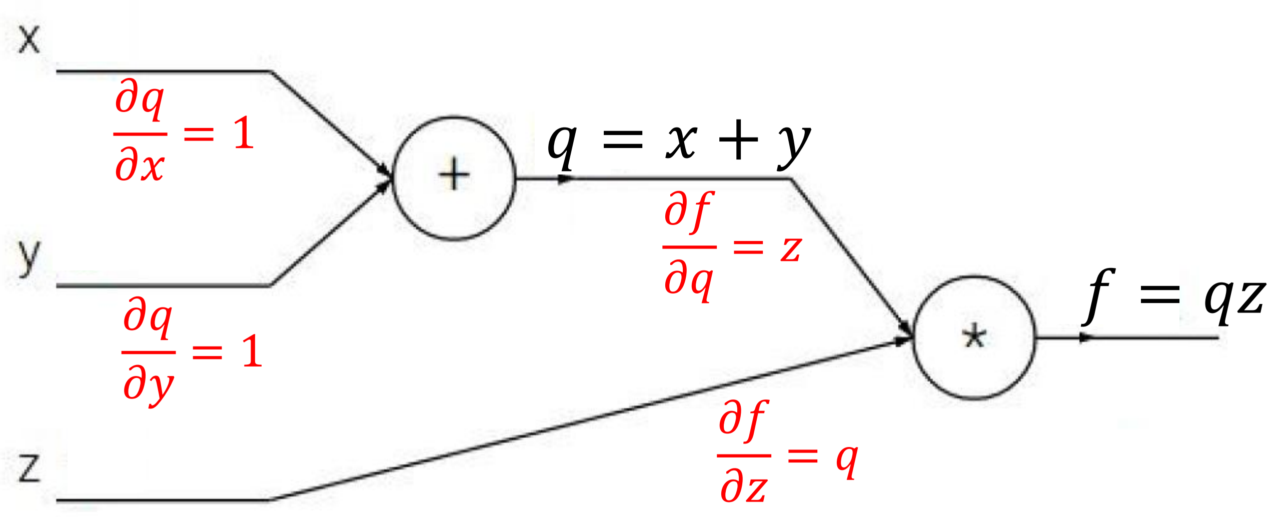
返回结果：$g_{NNET}(\mathbf{x}) = \left(\cdots \tanh\left(\sum_j \mathbf{w}_{jk}^{(2)} \cdot \tanh\left(\sum_i \mathbf{w}_{ij}^{(1)} x_i\right)\right)\right)$

- 所有梯度下降法的技巧都可使用
- 步骤①②③可并行处理，提高效率

反向传播算法是当前神经网络学习的有效技术

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：

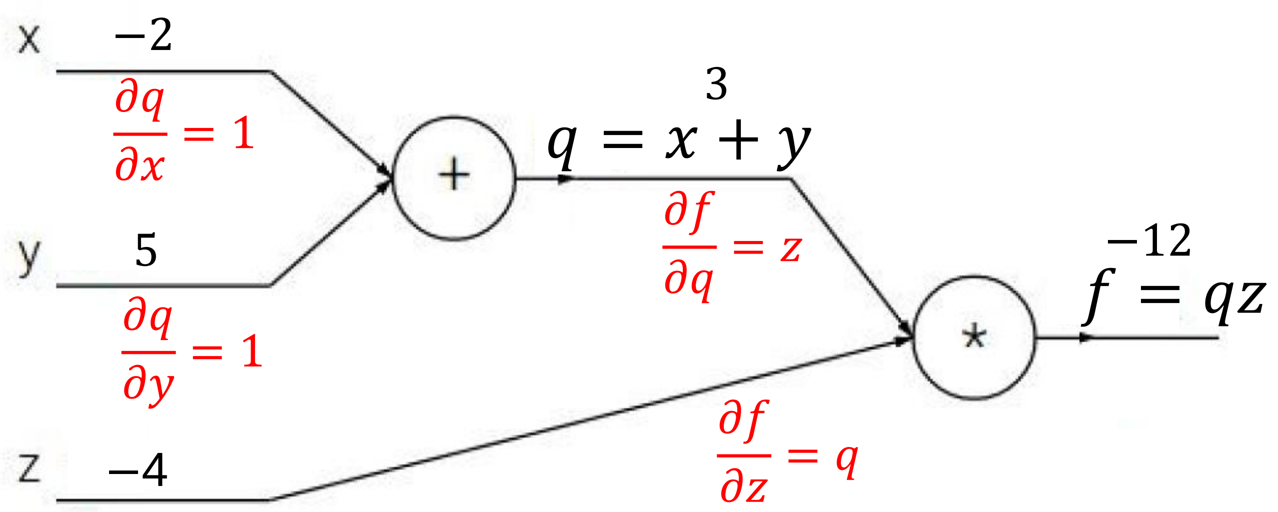
$$f = (x + y)z$$



Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：

$$f = (x + y)z$$



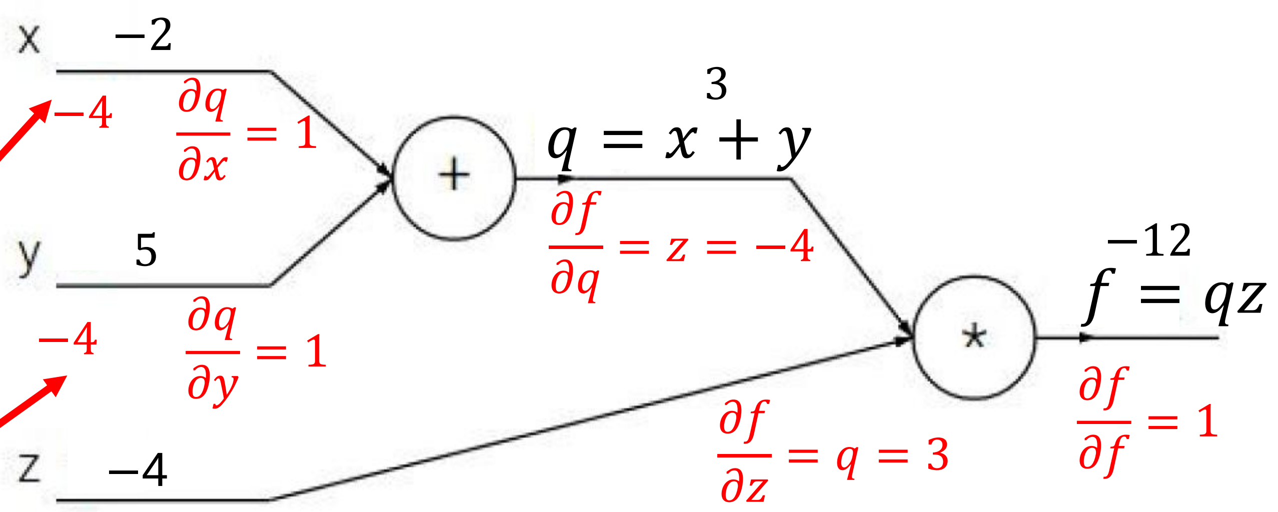
if: $x = -2, y = 5, z = -4$

$want$: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：

$$f = (x+y)z$$



$if: \quad x = -2, y = 5, z = -4$

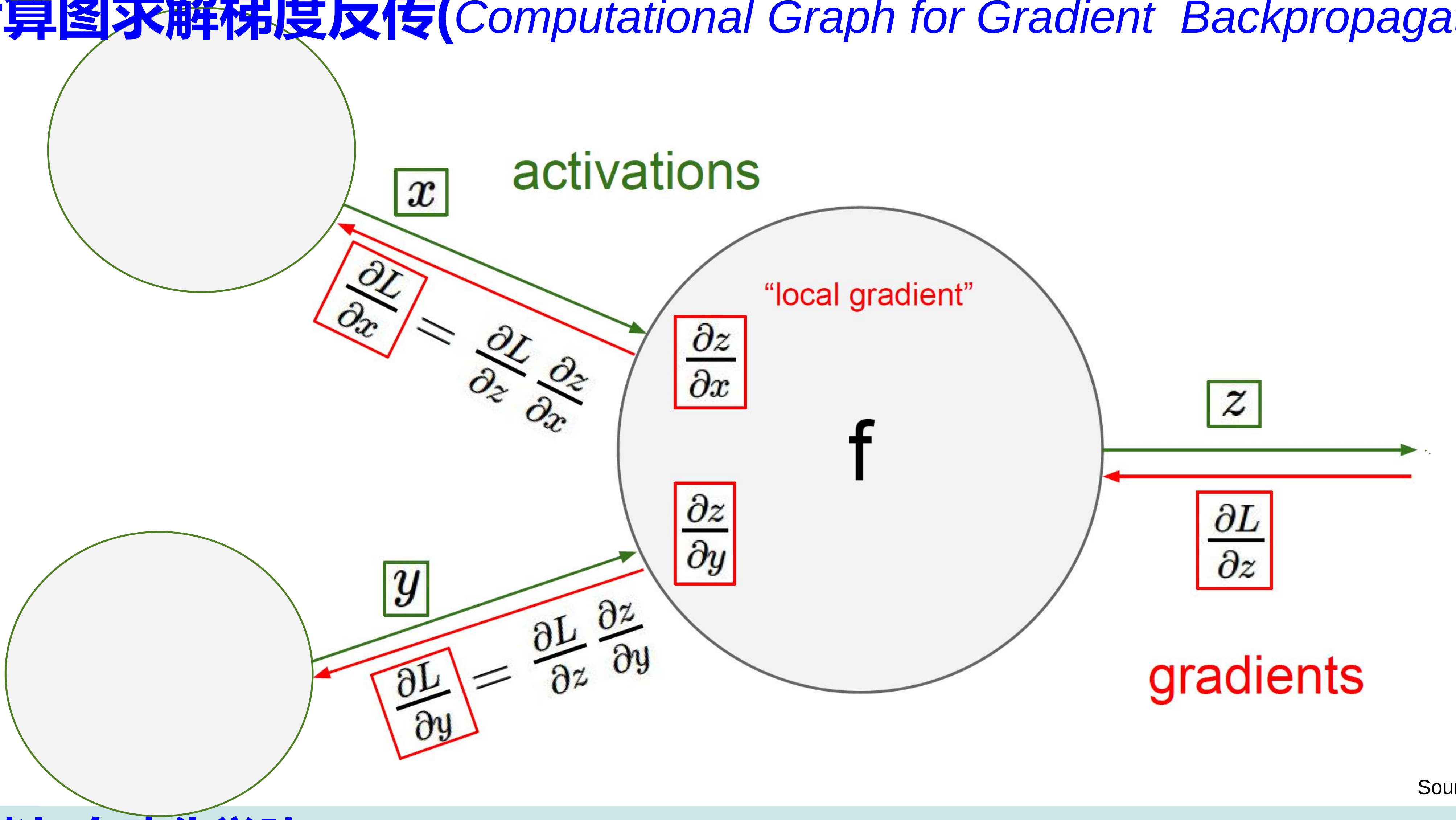
$want: \quad \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

Chain Rule: $\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x}$

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial y}$$

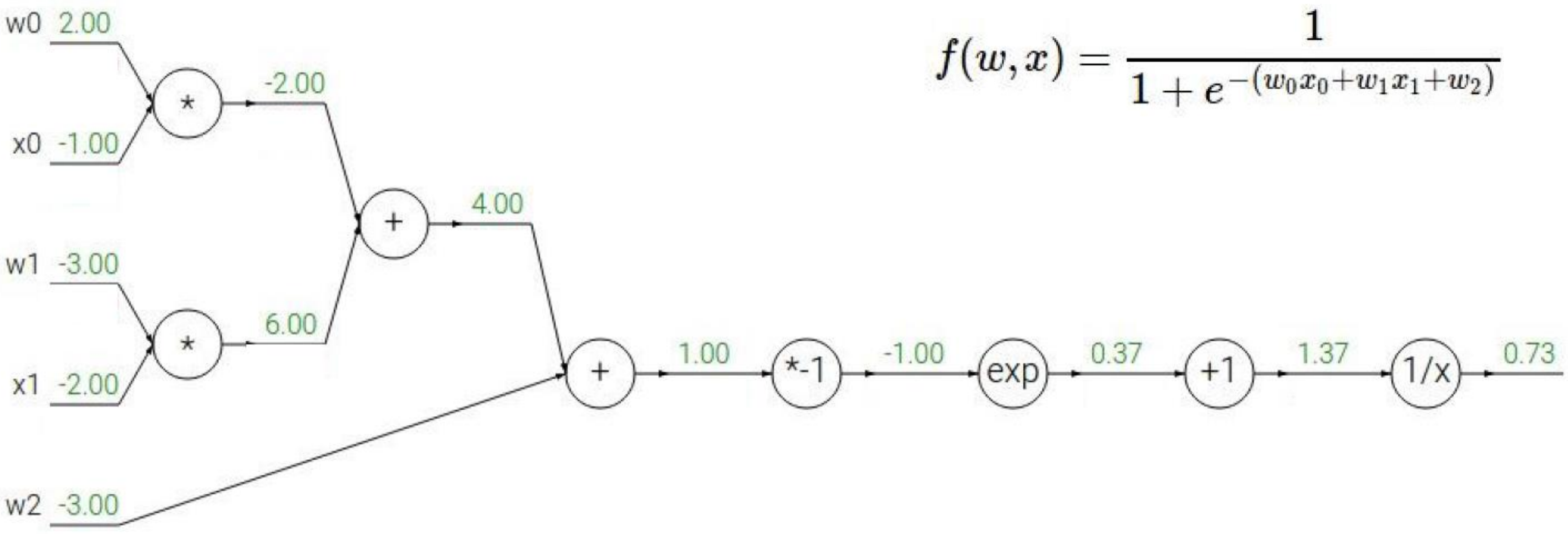
Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：



Source: CS231n-Standford

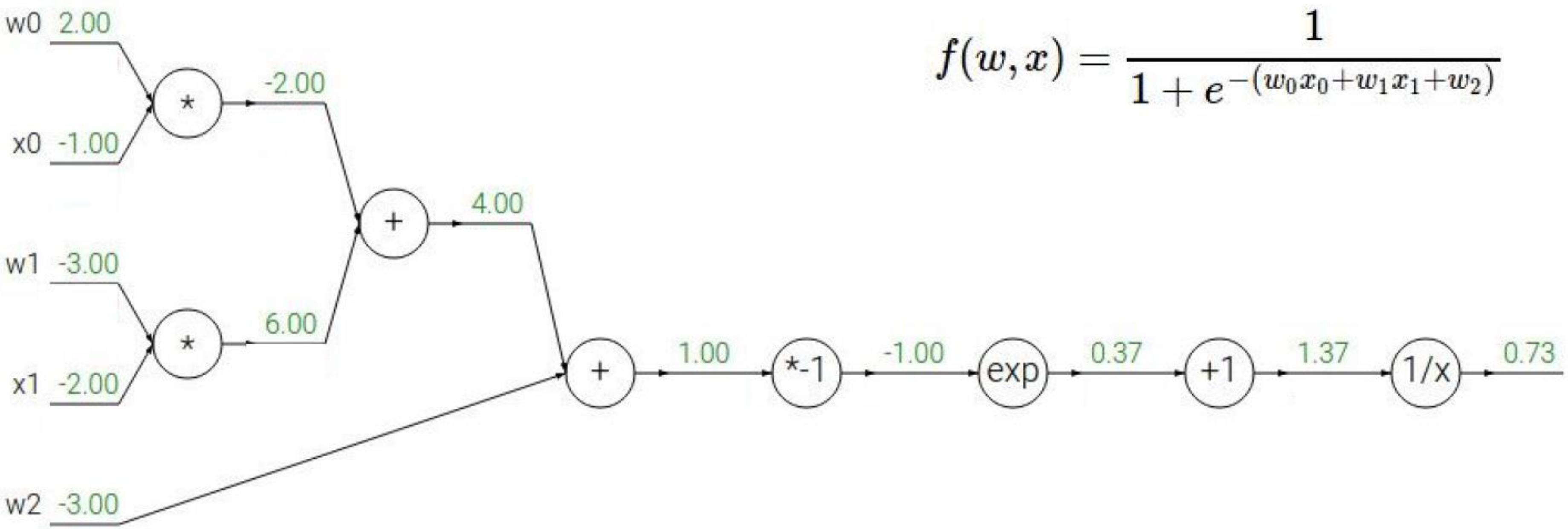
用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：



$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：



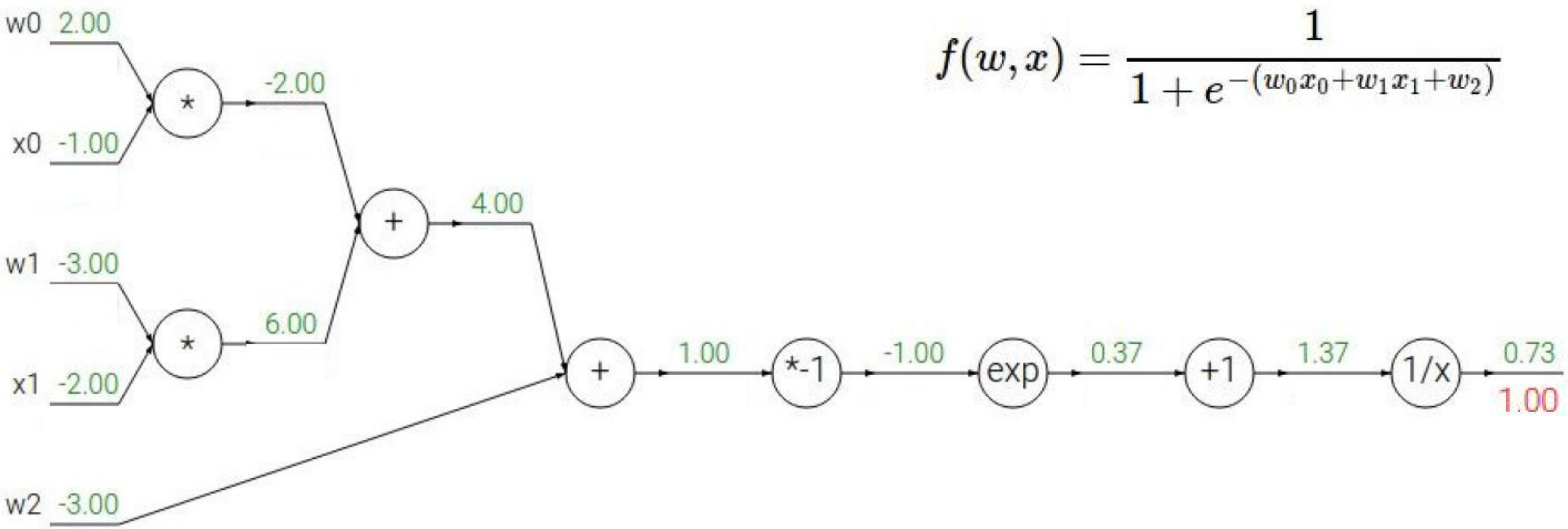
$$f(w,x)=\frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

$$f(x)=e^x \quad \rightarrow \quad \frac{df}{dx}=e^x \qquad\Bigg|\qquad f(x)=\frac{1}{x} \quad \rightarrow \quad \frac{df}{dx}=-1/x^2$$

$$f_a(x)=ax \quad \rightarrow \quad \frac{df}{dx}=a \qquad\Bigg|\qquad f_c(x)=c+x \quad \rightarrow \quad \frac{df}{dx}=1$$

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：



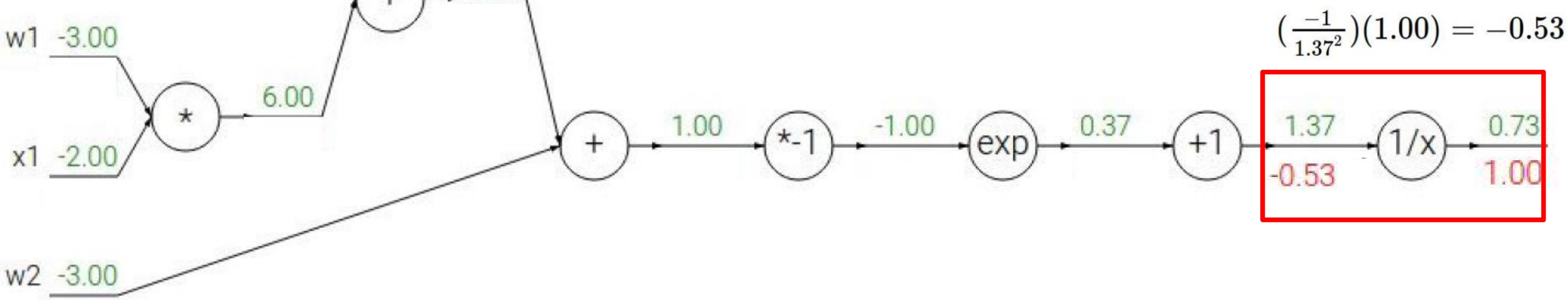
$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x$		$f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$	
$f_a(x) = ax \quad \rightarrow \quad \frac{df}{dx} = a$		$f_c(x) = c + x \quad \rightarrow \quad \frac{df}{dx} = 1$	

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：

$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$



$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x$

$f_a(x) = ax \quad \rightarrow \quad \frac{df}{dx} = a$

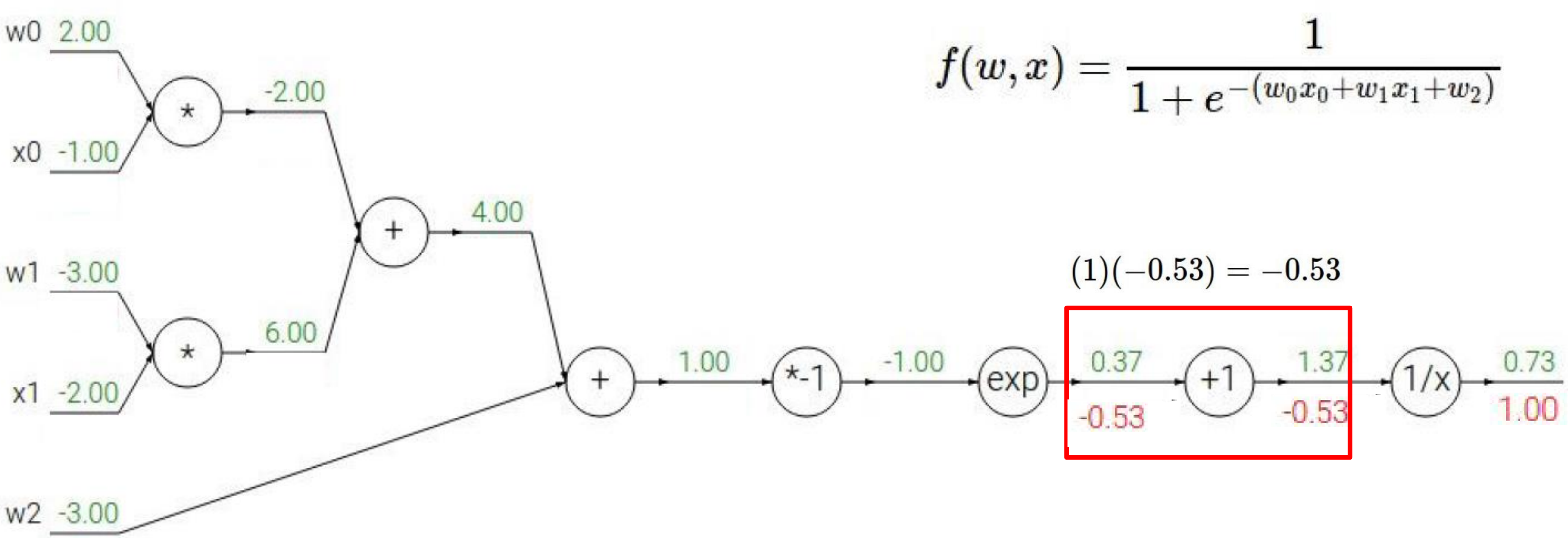
$\boxed{f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2}$

$f_c(x) = c + x \quad \rightarrow \quad \frac{df}{dx} = 1$

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：

$$f(w,x)=\frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$



$$f(x)=e^x \quad \rightarrow \quad \frac{df}{dx}=e^x$$

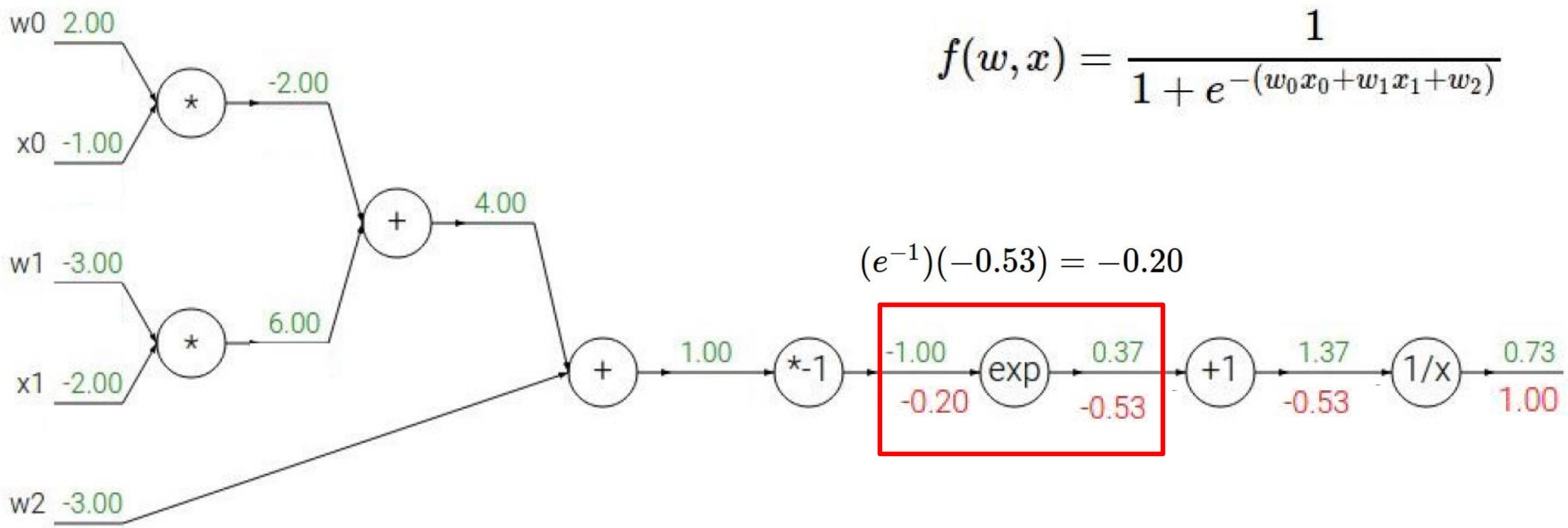
$$f_a(x)=ax \quad \rightarrow \quad \frac{df}{dx}=a$$

$$f(x)=\frac{1}{x} \quad \rightarrow \quad \frac{df}{dx}=-1/x^2$$

$$\boxed{f_c(x)=c+x \quad \rightarrow \quad \frac{df}{dx}=1}$$

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：



$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

$$(e^{-1})(-0.53) = -0.20$$

$$\boxed{f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x}$$

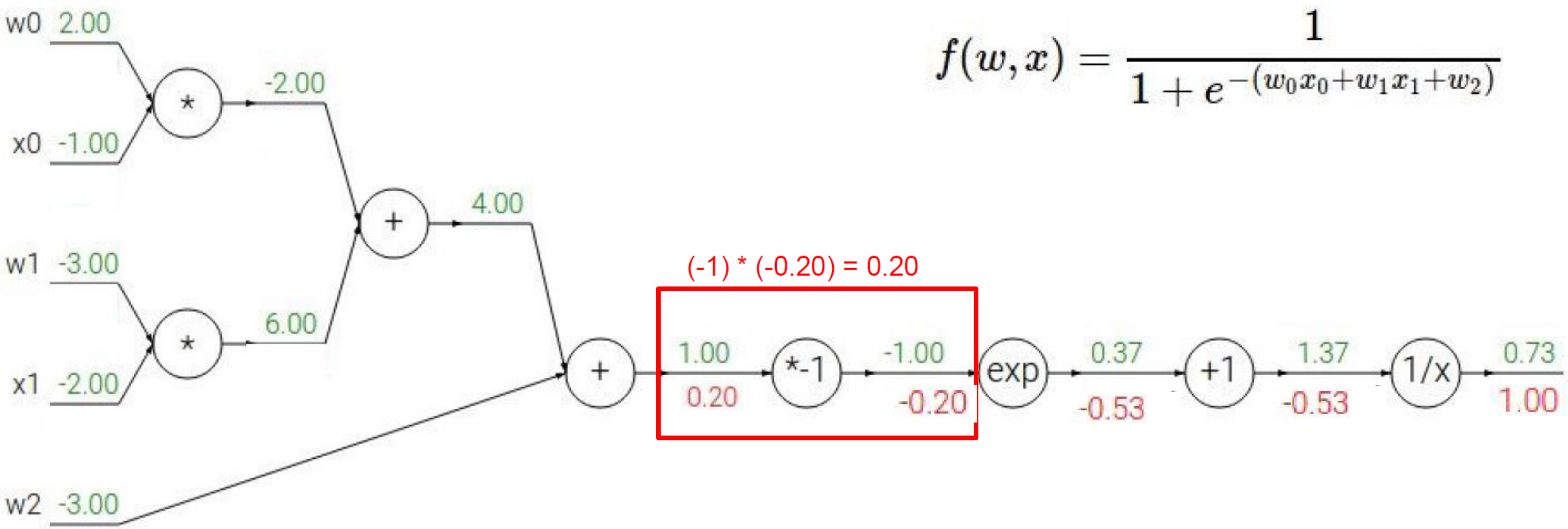
$$f_a(x) = ax \quad \rightarrow \quad \frac{df}{dx} = a$$

$$f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$$

$$f_c(x) = c + x \quad \rightarrow \quad \frac{df}{dx} = 1$$

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：



$$f(w,x)=\frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

$$f(x)=e^x \quad\rightarrow\quad \frac{df}{dx}=e^x$$

$$\boxed{f_a(x)=ax \quad\rightarrow\quad \frac{df}{dx}=a}$$

$$f(x)=\frac{1}{x} \quad\rightarrow\quad \frac{df}{dx}=-1/x^2$$

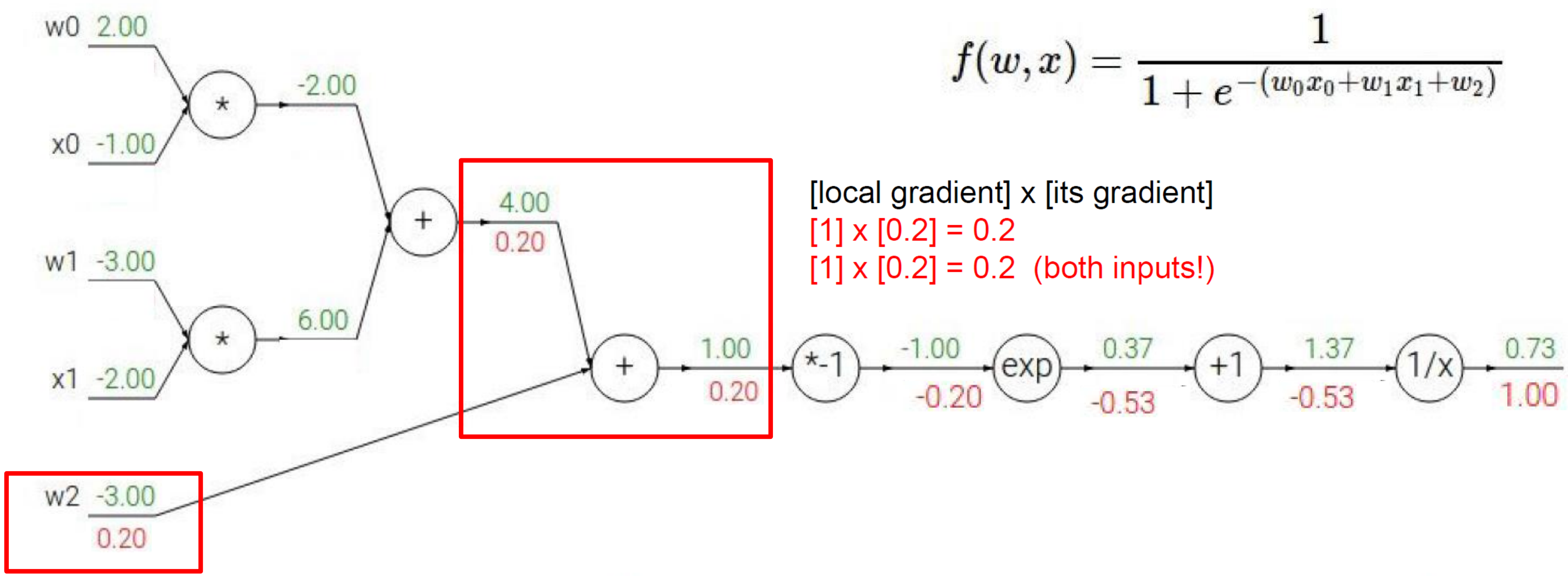
$$f_c(x)=c+x \quad\rightarrow\quad \frac{df}{dx}=1$$

Source: CS231n-Standford

10.3 神经网络学习

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：

$$f(w,x)=\frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

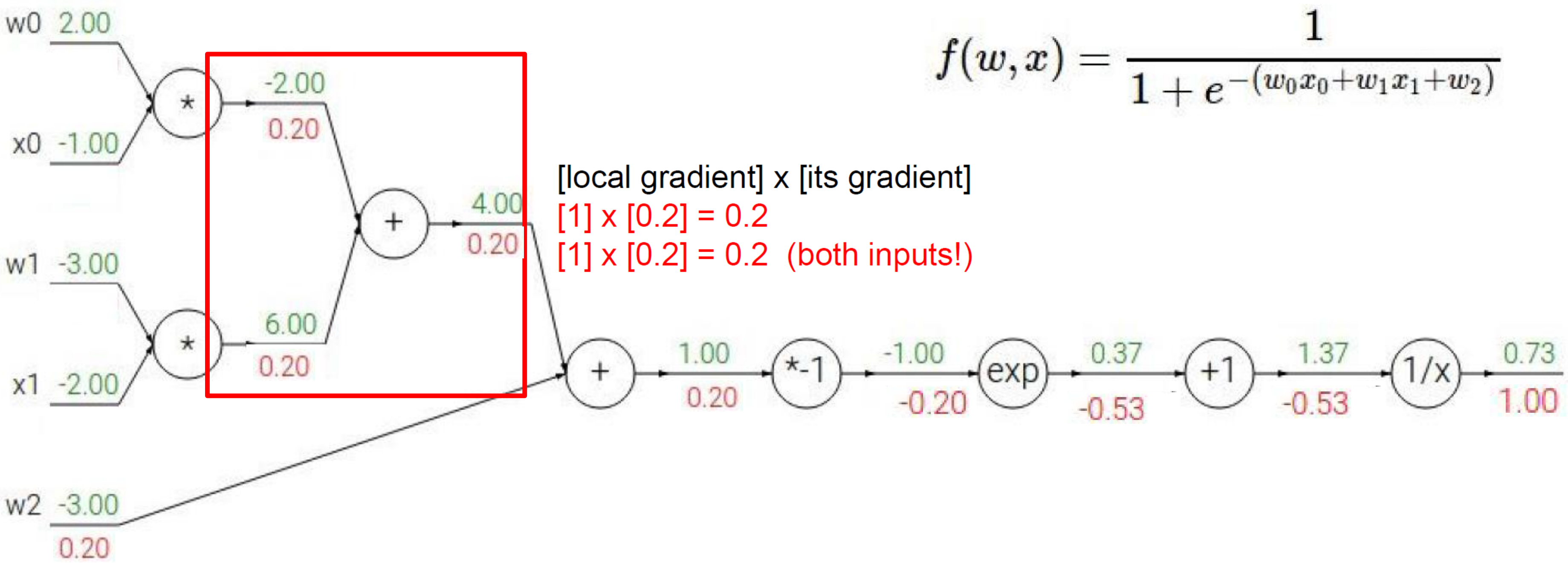


$$f(x)=e^x \quad\rightarrow\quad \frac{df}{dx}=e^x \qquad\qquad f(x)=\frac{1}{x} \quad\rightarrow\quad \frac{df}{dx}=-1/x^2$$

$$f_a(x)=ax \quad\rightarrow\quad \frac{df}{dx}=a \qquad\qquad f_c(x)=c+x \quad\rightarrow\quad \frac{df}{dx}=1$$

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：



$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

[local gradient] x [its gradient]

[1] x [0.2] = 0.2

[1] x [0.2] = 0.2 (both inputs!)

$$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x$$

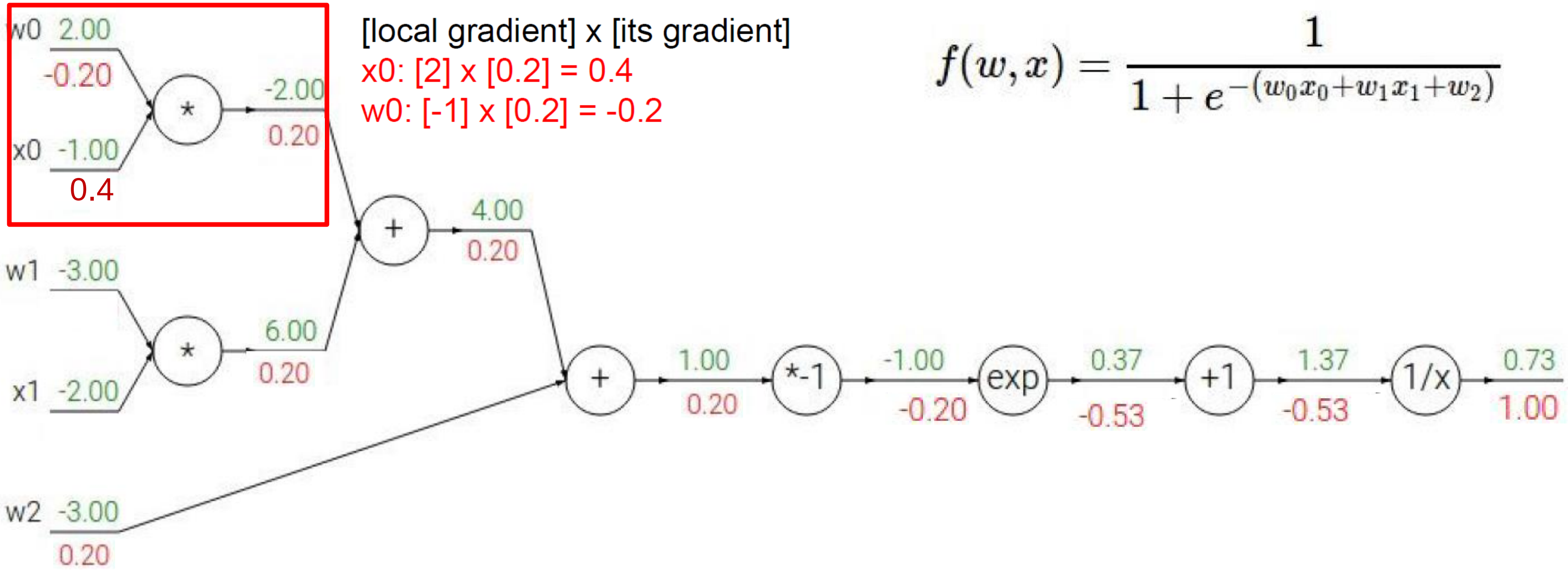
$$f_a(x) = ax \quad \rightarrow \quad \frac{df}{dx} = a$$

$$f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$$

$$f_c(x) = c + x \quad \rightarrow \quad \frac{df}{dx} = 1$$

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：



$$f(w,x)=\frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

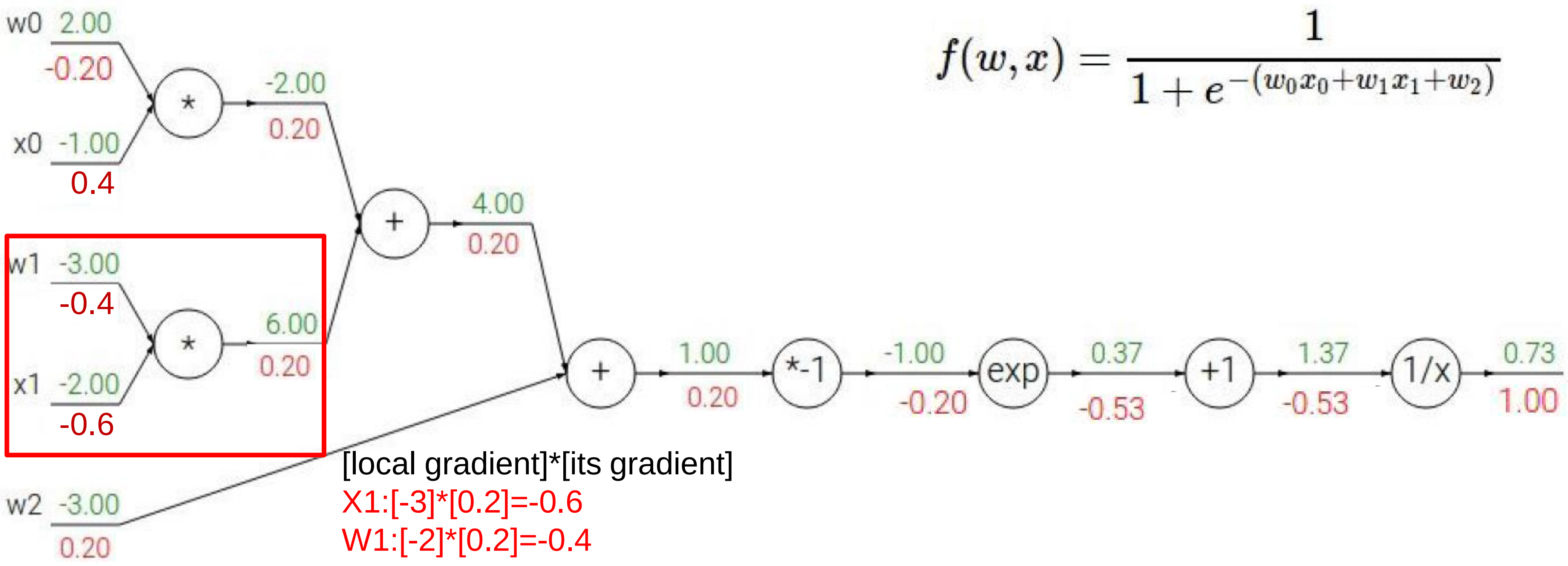
$$f(x)=e^x \quad\rightarrow\quad \frac{df}{dx}=e^x \qquad\qquad f(x)=\frac{1}{x} \quad\rightarrow\quad \frac{df}{dx}=-1/x^2$$

$$f_a(x)=ax \quad\rightarrow\quad \frac{df}{dx}=a \qquad\qquad f_c(x)=c+x \quad\rightarrow\quad \frac{df}{dx}=1$$

Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：

$$f(w,x)=\frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$



$$f(x)=e^x \quad\rightarrow\quad \frac{df}{dx}=e^x \qquad\qquad f(x)=\frac{1}{x} \quad\rightarrow\quad \frac{df}{dx}=-1/x^2$$

$$f_a(x)=ax \quad\rightarrow\quad \frac{df}{dx}=a \qquad\qquad f_c(x)=c+x \quad\rightarrow\quad \frac{df}{dx}=1$$

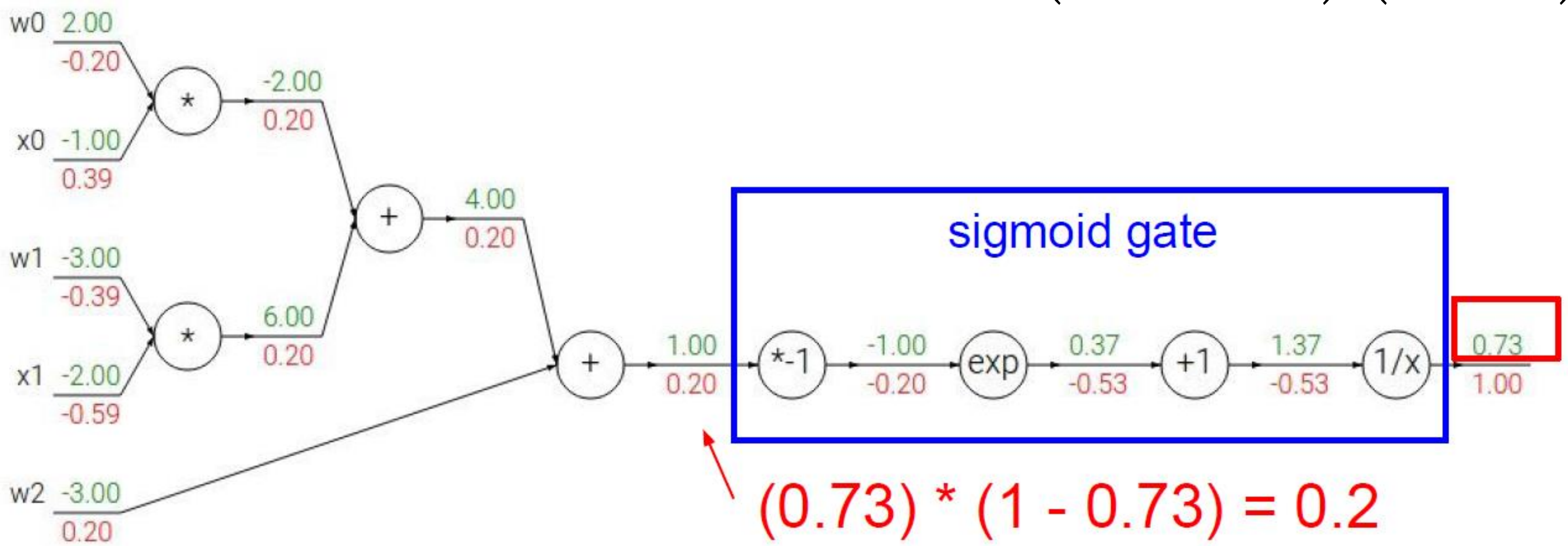
Source: CS231n-Standford

用计算图求解梯度反传(*Computational Graph for Gradient Backpropagation*)：

$$f(w,x)=\frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

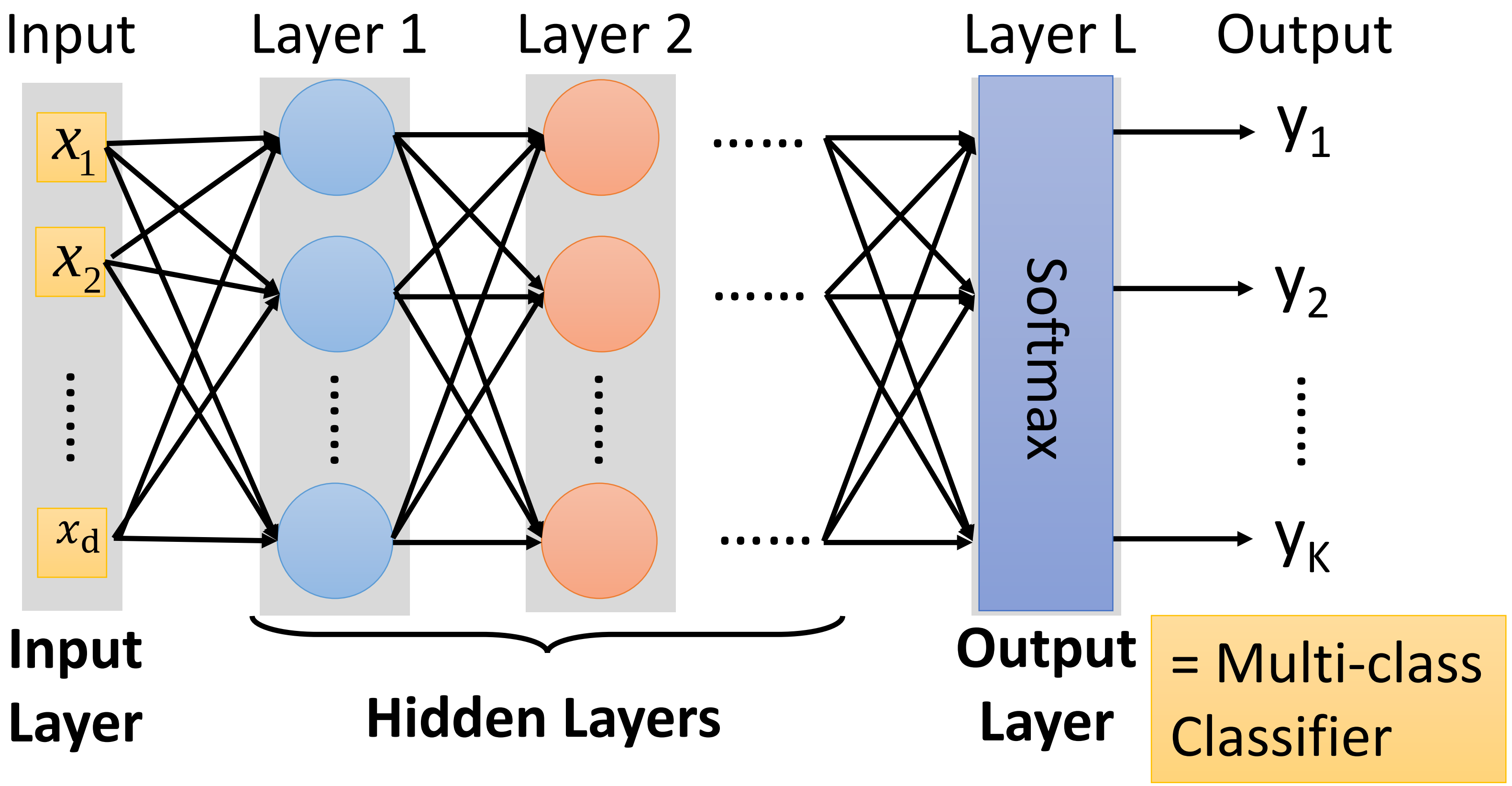
$$\theta(x)=\frac{1}{1+e^{-x}}$$ sigmoid function

$$\frac{d\theta(x)}{dx}=\frac{e^{-x}}{(1+e^{-x})^2}=\left(\frac{1+e^{-x}-1}{1+e^{-x}}\right)\left(\frac{1}{1+e^{-x}}\right)=(1-\theta(x))\theta(x)$$



Source: CS231n-Standford

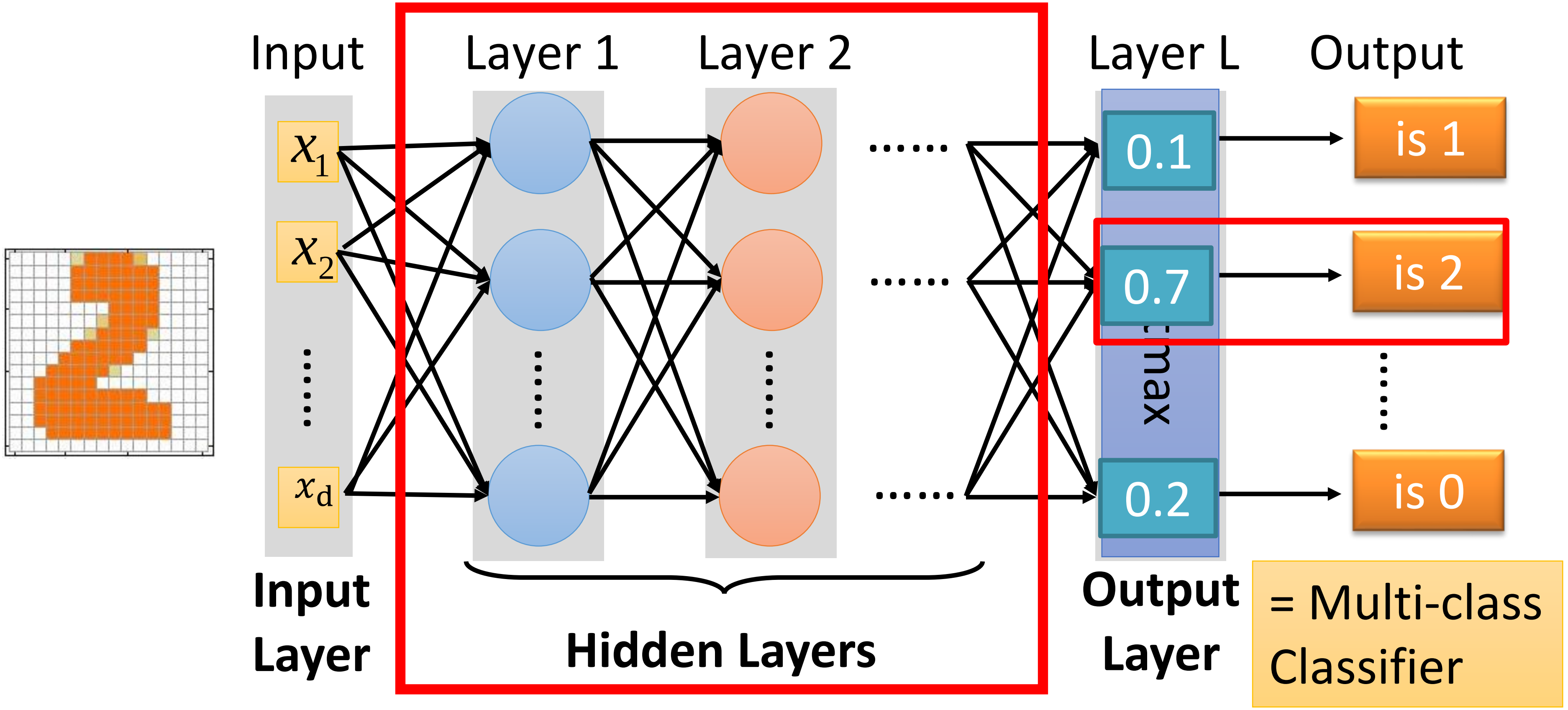
神经网络(*Neural Networks*):



Source: NTU-LEE

10.4 深度神经网络

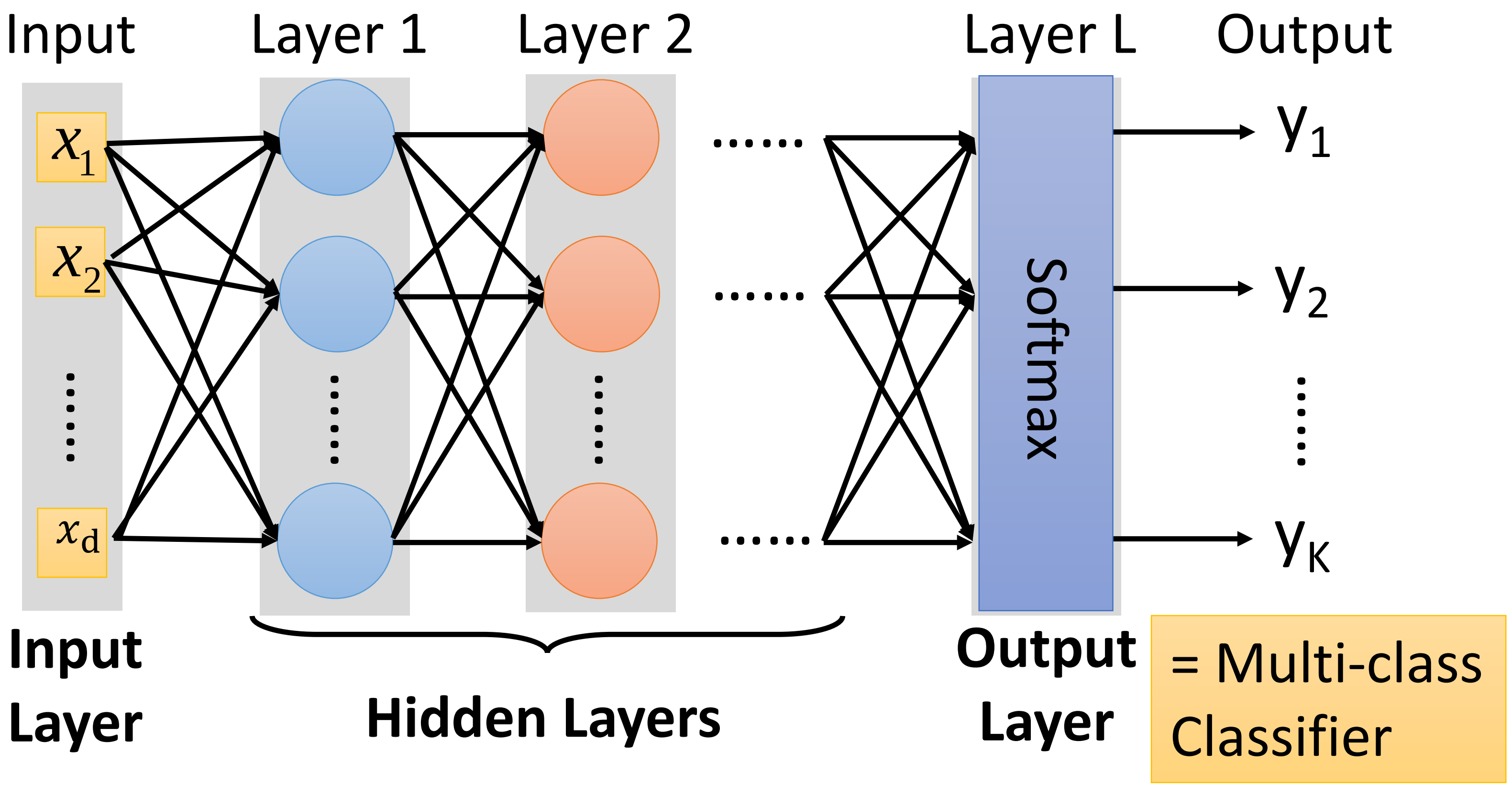
神经网络(*Neural Networks*)：



Source: NTU-LEE

神经网络(*Neural Networks*):

Deep = Many hidden layers

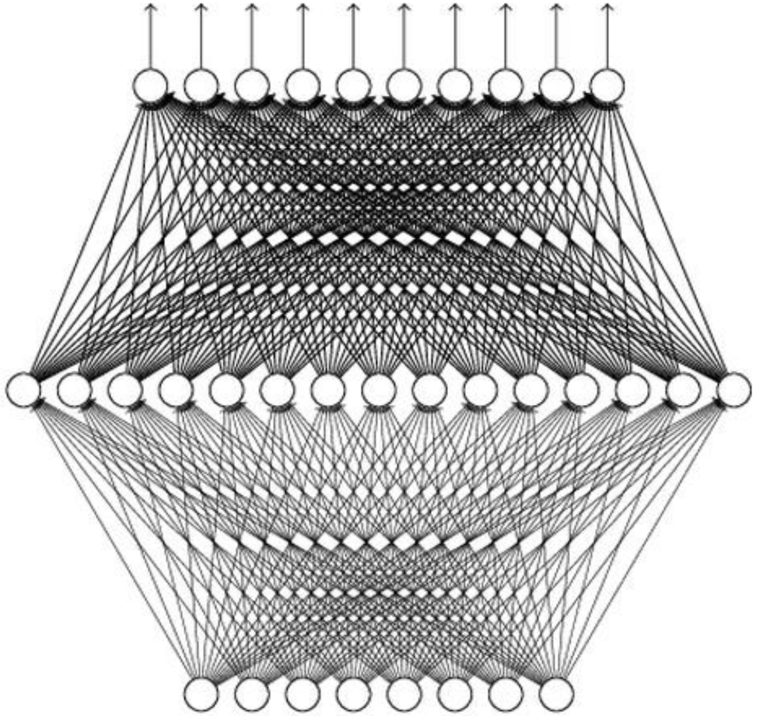


Source: NTU-LEE

为什么要用深度网络?

Layer X Size	Word Error Rate (%)
1 X 2k	24.2
2 X 2k	20.4
3 X 2k	18.4
4 X 2k	17.8
5 X 2k	17.2
7 X 2k	17.1

?



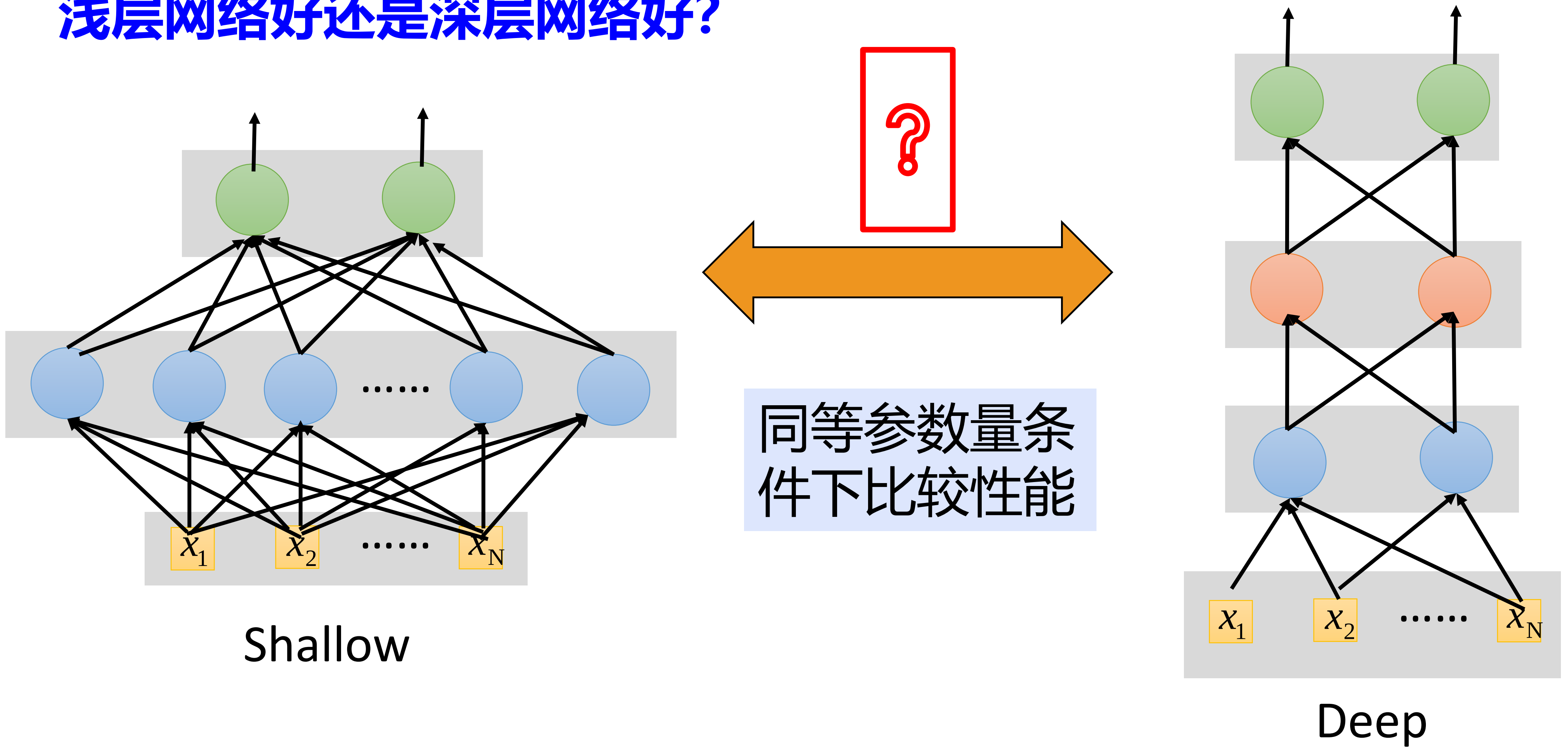
$$f : R^N \rightarrow R^M$$

只要有足够多神经元，一个隐含层的网络结构也能拟合出任意复杂的连续曲面

按照学习理论，参数多、性能好

Source: NTU-LEE

浅层网络好还是深层网络好?



Source: NTU-LEE

为什么要用深度网络?

Layer X Size	Word Error Rate (%)	Layer X Size	Word Error Rate (%)
1 X 2k	24.2		
2 X 2k	20.4		
3 X 2k	18.4		
4 X 2k	17.8		
5 X 2k	17.2	1 X 3772	22.5
7 X 2k	17.1	1 X 4634	22.6
		1 X 16k	22.1

Source: NTU-LEE

深度学习存在的挑战和关键技术

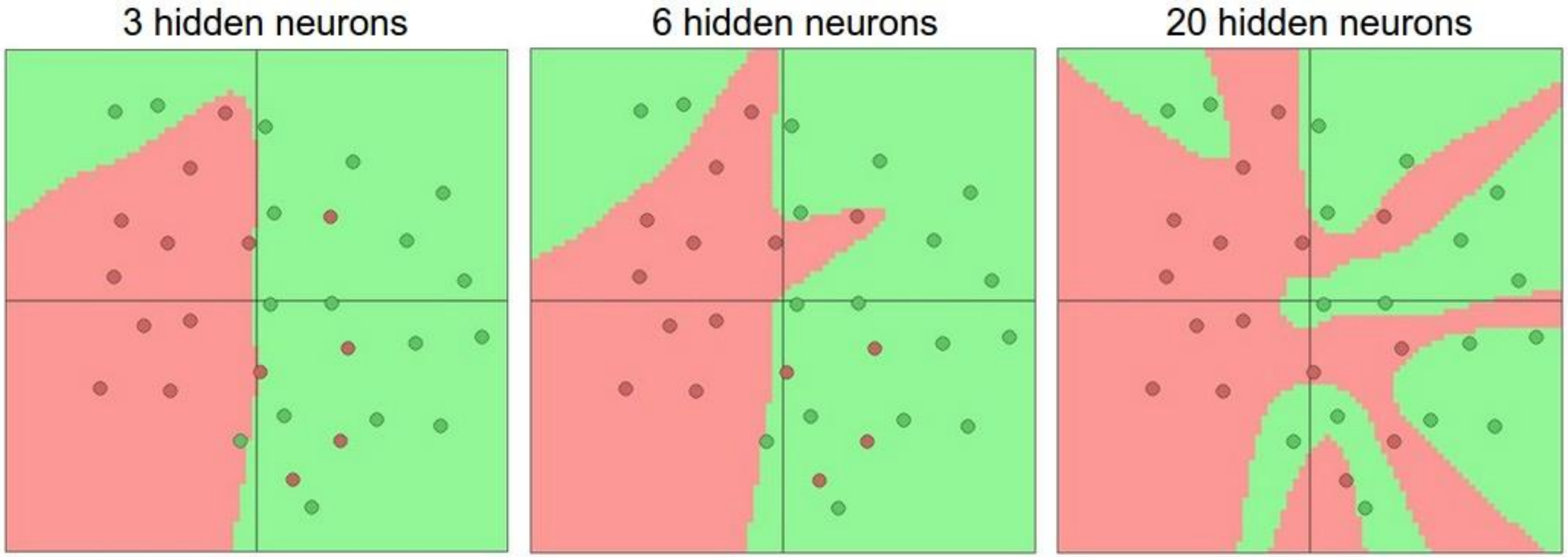
- 如何设计或确定网络结构
  - “领域知识”有助于选择网络结构，如计算机视觉中常常用卷积神经网络

下次课详细讲解

Source: NTU-LIN

深度学习存在的挑战和关键技术

- 如何设计或确定网络结构
  - “领域知识”有助于选择网络结构，如计算机视觉中常常用卷积神经网络
- 模型复杂度高影响泛化能力



Source:CS231n-Standford

深度学习存在的挑战和关键技术

- 如何设计或确定网络结构
  - “领域知识”有助于选择网络结构，如计算机视觉中常常用卷积神经网络
- 模型复杂度高导致过拟合
  - “大数据”有助于增加训练集，提升泛化能力
  - “正则化”—如Dropout等手段，增强对噪声的容忍度
- 模型复杂难以找到最优解
  - 仔细选择初始值，避免落入局部极值，包括预训练等
  - 防止梯度消失，采用合适的激活函数、设计更好的网络结构
- 计算复杂度高
  - 平行化、批量化、GPU等

Source: NTU-LIN

10.1 神经网络动机 (Motivation of Neural Networks)

多层网络结构具有更强的分类能力

10.2 神经网络模型参数空间(Neural Network Hypothesis)

基于线性模型构建多层结构

10.3 神经网络学习 (Neural Network Learning)

通过反向传播法有效实现梯度计算

10.4 深度神经网络 (Deep Neural Networks)

介绍了其优越性和面临的挑战