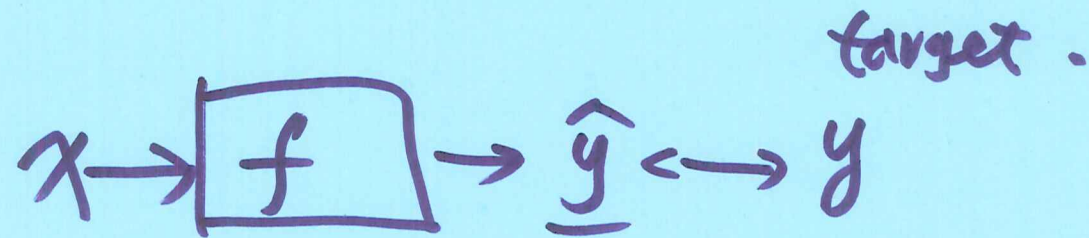


Lecture 10. Feedforward Neural Networks

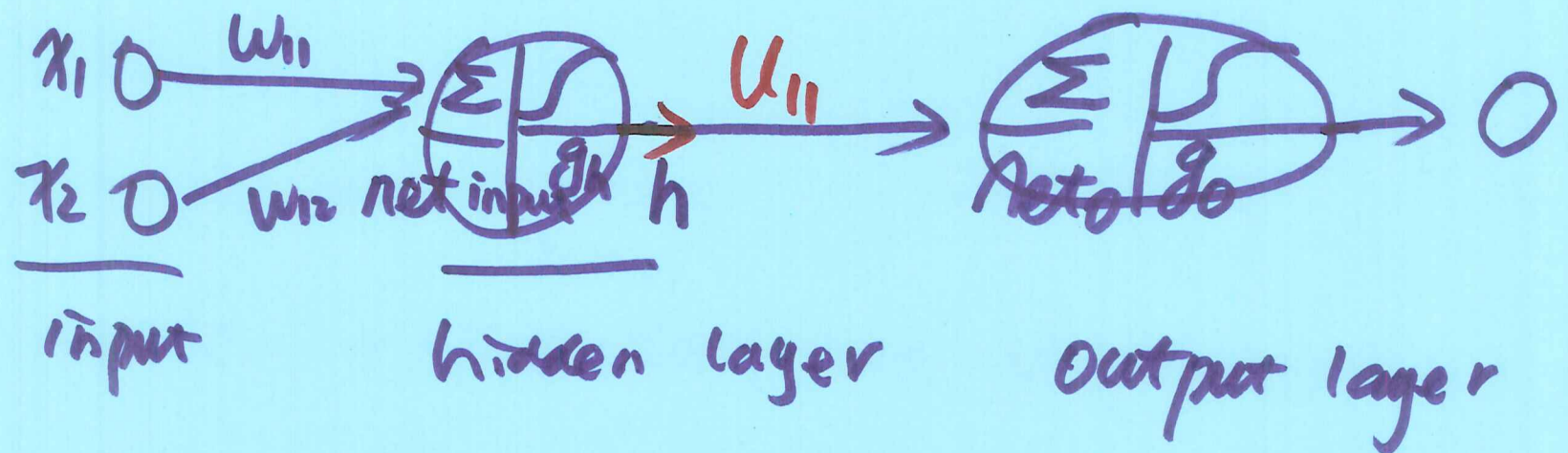


① Linear model: $f = w^T x$

② Loss function: $L(w) = \sum_{i=1}^n (\hat{y}_i - y_i)^2$

③ Optimization: ~~find~~ find out / learn w that can minimize $L(w)$

1. Model of Neural Network.



g_h : g_o : activation function

1.1. Hidden layer / Units / Nodes.

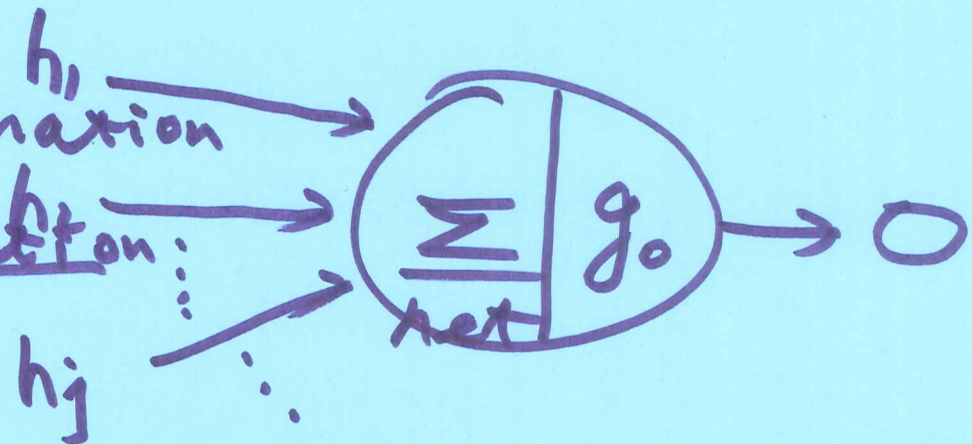
1) provides / extracts a set of features from data

Output of ^a ~~the~~ hidden node:

$$h = \underline{g_h(\text{Net})} \quad \underline{\text{net} = x_1 w_{11} + x_2 w_{12}}$$

1.2 Output Nodes.

1) provide transformation to the approximation:



$$O = g_o(\text{net}), \quad \text{net} = u_{11}h_1 + \dots + u_{j1}h_j \dots$$
$$= \sum_{j=1}^{n_h} u_{ij} \cdot h_j$$

2) . Activation function.

① $g_o(x) = \text{sigm}(x)$

② linear units.

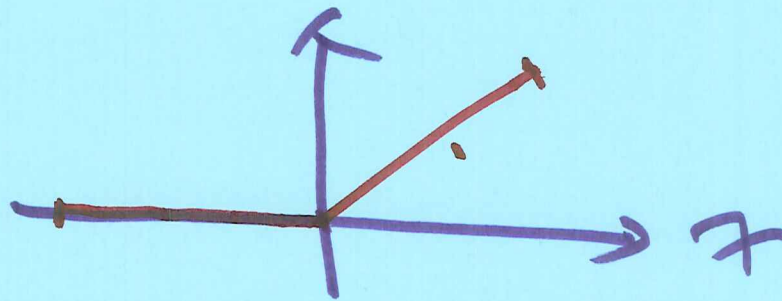
③ $\text{softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$

n_h is the # of hidden nodes.

2) Activation function.

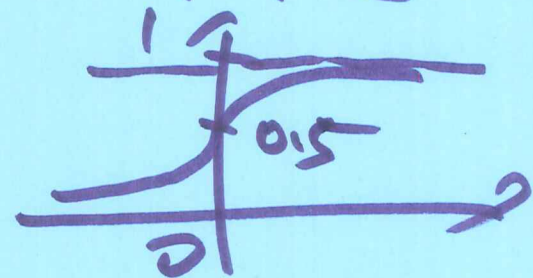
(1) Rectified linear units. (Relu)

$$g(\underline{x}) = \max \{0, x\} \quad x \in \mathbb{R}.$$

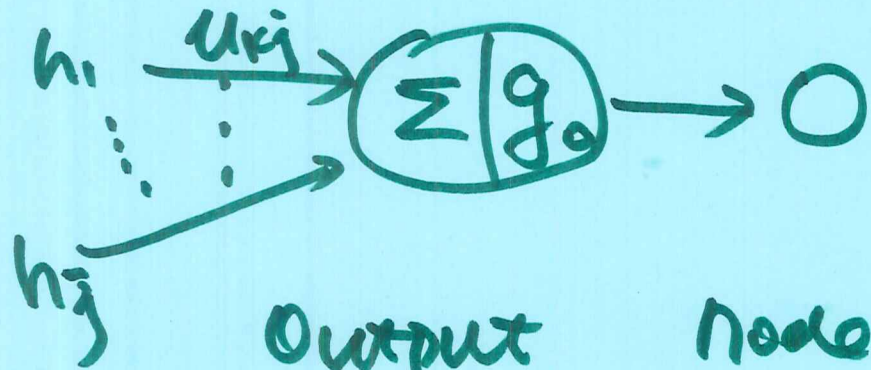


(2) Sigmoid.

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



(3) Hidden-to-output function z



Output node 1:

$$O_1 = g_0(\text{Net})$$

$$\text{Net} = \sum_j u_{1j} \cdot h_j$$

Output node k :

$$O_k = g_0(\text{Net})$$

$$\text{Net} = \sum_j (u_{kj} \cdot h_j)$$

Model for the NN (1st page)

$$O = g_o(\text{Net}_o)$$

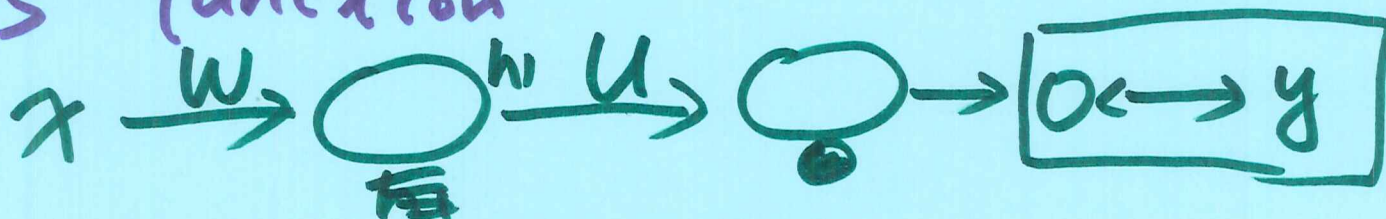
$$= g_o(U_{o1} \cdot \underline{h})$$

$$= g_o(U_{o1} \cdot g_h(\text{Net}_h))$$

$$= g_o(U_{o1} \cdot g_h(x_1 \cdot W_{11} + x_2 \cdot W_{12}))$$

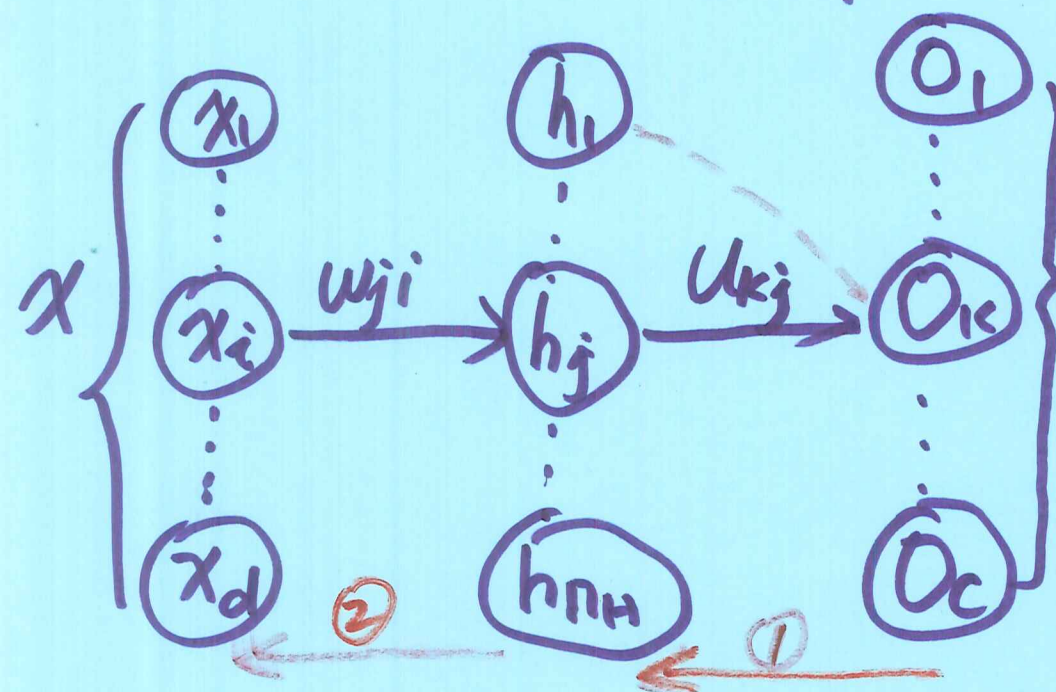
Model 1.

2. Loss function



$$\text{Loss}(w, u) = \frac{1}{2} \sum_{i=1}^m (\underline{o_i} - y_i)^2$$

Lecture 11. Neural Network Optimization



$$h_j = g_H(\text{net}_j); \text{net}_j = \sum_{i=1}^d w_{ji} x_i$$

$$o_k = g_o(\text{net}_k); \text{net}_k = \sum_{j=1}^{n_H} u_{kj} \cdot h_j$$

$\underline{o} \leftrightarrow y$ model;

target

Loss on a single sample:

$$\underline{L(w, u)} = \frac{1}{2} \sum_{k=1}^c (y_k - o_k)^2$$

1. SGD to learn w and u .

for ep in range(max_epoch):

for a single sample $(x, y) \in (X, Y)$:

$\forall i \in [1, d], j \in [1, n_H], k \in [1, c]$

$$w_{ji} = w_{ji} - \epsilon \cdot \frac{\partial L(w, u)}{\partial w_{ji}}$$

$$u_{kj} = u_{kj} - \epsilon \cdot \frac{\partial L(w, u)}{\partial u_{kj}}$$

1.1 Backpropagation Algorithm

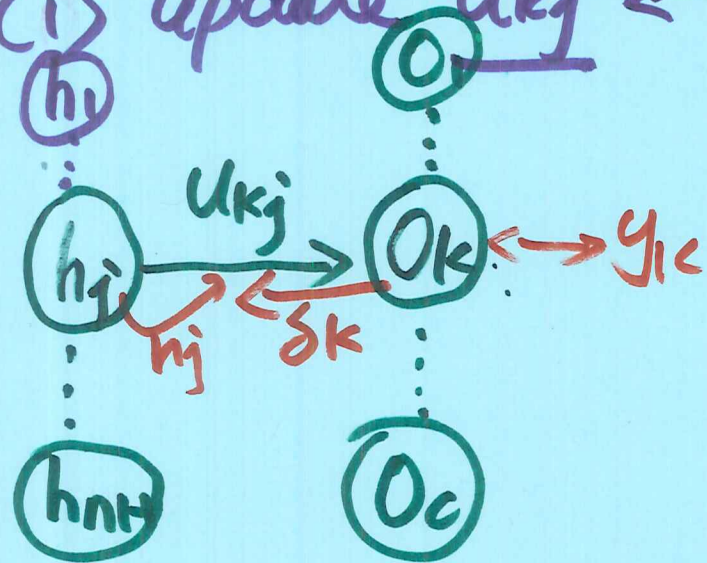
(BP)

: compute the two gradients.

→ update Hidden-to-output weights } ①
 $K=1, \dots, C, U_{K1}, \dots, U_{Kj}, \dots, U_{KnH}$

→ update input-to-Hidden weights } ②
 $J=1, \dots, PH: \underline{u_{j1}}, \dots, \underline{u_{ji}}, \dots, \underline{u_{jd}}$

(1) update $U_{Kj} \leftarrow \nabla_{U_{Kj}} L(w, u)$



$$L(w, u) = \frac{1}{2} \sum_{k=1}^C (y_k - \underline{O_k})^2$$

$$\underline{O_k} = g_o(\underline{net_k}), \underline{net_k} = \sum_{j=1}^{nH} \underline{U_{kj}} \cdot h_j$$

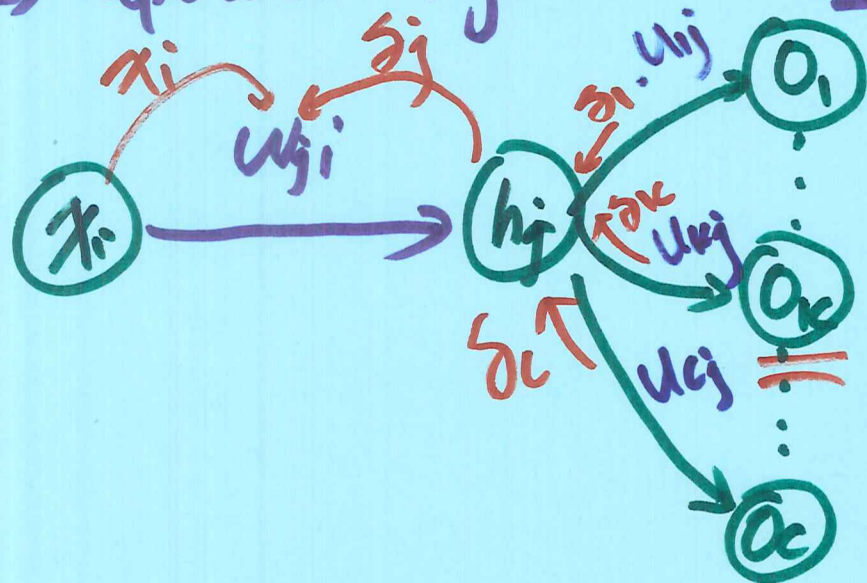
$$\nabla_{U_{Kj}} L(w, u) = \frac{\partial L}{\partial O_k} \cdot \frac{\partial O_k}{\partial net_k} \cdot \frac{\partial net_k}{\partial U_{Kj}}$$

$$= -(y_k - O_k) \cdot g'_o \cdot h_j$$

$$= \delta_k \cdot h_j$$

δ_k : feed back from k th output

(2) update $w_{ji} \leftarrow \frac{\partial L}{\partial w_{ji}}$



$$\frac{\partial L}{\partial w_{ji}} \cdot L(w, u)$$

$$L(w, u) = \frac{1}{2} \sum_{k=1}^n (y_k - o_k)^2$$

$$o_k = g_o(\text{net}_k); \text{net}_k = \sum_{j=1}^n u_{kj} \cdot h_j$$

$$h_j = g_h(\text{net}_j); \text{net}_j = \sum_{i=1}^n w_{ji} \cdot x_i$$

$$\frac{\partial L}{\partial w_{ji}} \cdot L(w, u)$$

$$\sum_k \left[\frac{\partial L}{\partial o_k} \cdot \frac{\partial o_k}{\partial \text{net}_k} \cdot \frac{\partial \text{net}_k}{\partial h_j} \right] \cdot \frac{\partial h_j}{\partial \text{net}_j} \cdot \frac{\partial \text{net}_j}{\partial w_{ji}}$$

$$= \left(\frac{\partial L}{\partial h_j} \right) \cdot \frac{\partial h_j}{\partial \text{net}_j} \cdot \frac{\partial \text{net}_j}{\partial w_{ji}}$$

$$= \left[\sum_k - (y_k - o_k) \cdot g_o' \cdot u_{kj} \right] \cdot g_h' \cdot x_i$$

$$= \delta_j \cdot x_i$$

$$\nabla_{u_{kj}} L(w, u) = \delta_k \cdot h_j : \delta_k = -(y_k - o_k) \cdot g'_o$$

$$\nabla_{w_j} L(w, u) = \delta_j \cdot x_i : \delta_j = \left[\sum_{k=1}^c -(y_k - o_k) \cdot g'_o \cdot u_{kj} \right] \cdot g'_i$$

$\hookrightarrow g'_i$