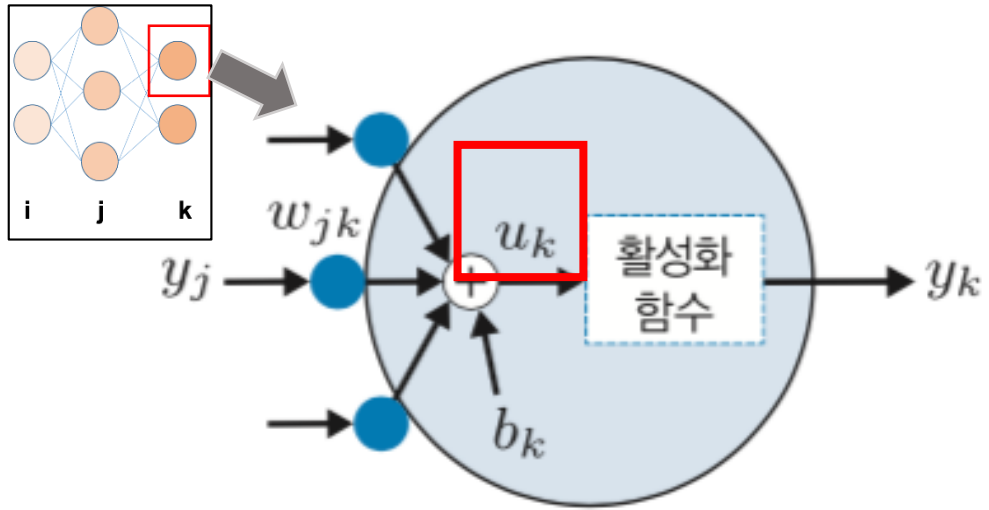


Machine Learning

오류역전파

출력층 기울기

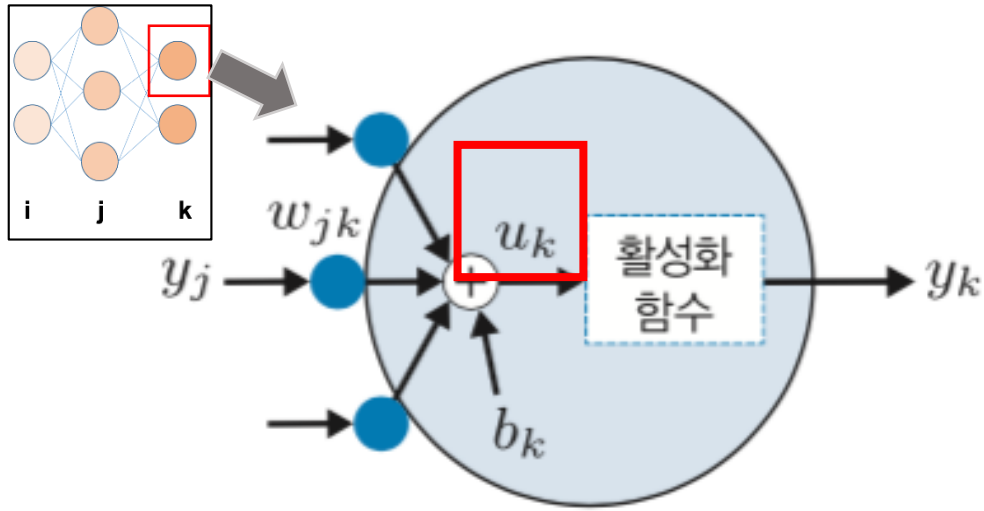
layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



$$\begin{aligned}
 u_k &= y_1 w_{1k} + y_2 w_{2k} + \dots + y_m w_{mk} \\
 &= \sum_{q=1}^m y_q w_{qk} + b_k
 \end{aligned}$$

출력층 기울기

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



$$u_k = y_1 w_{1k} + y_2 w_{2k} + \dots + y_m w_{mk}$$

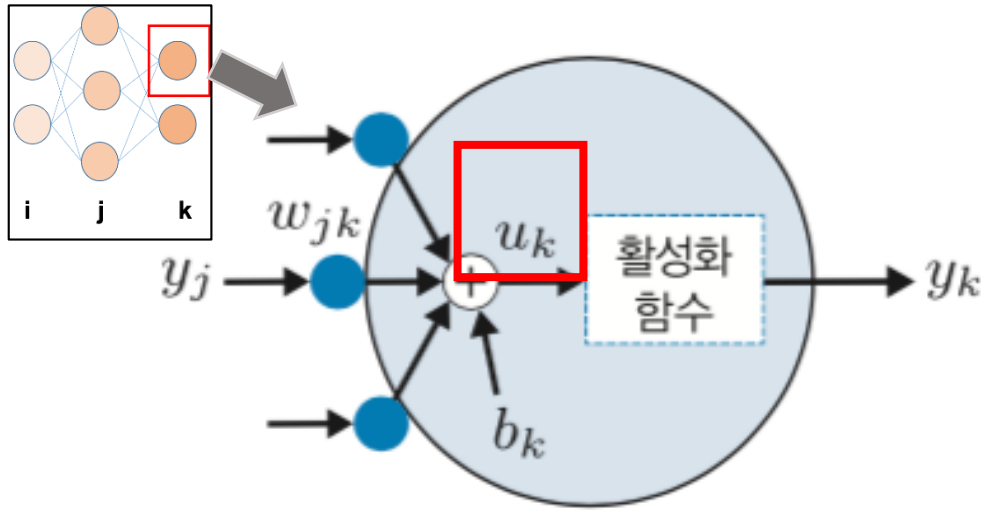
$$= \sum_{q=1}^m y_q w_{qk} + b_k$$

$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial w_{jk}}$$

$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial u_k} \frac{\partial u_k}{\partial w_{jk}}$$

출력층 기울기

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n

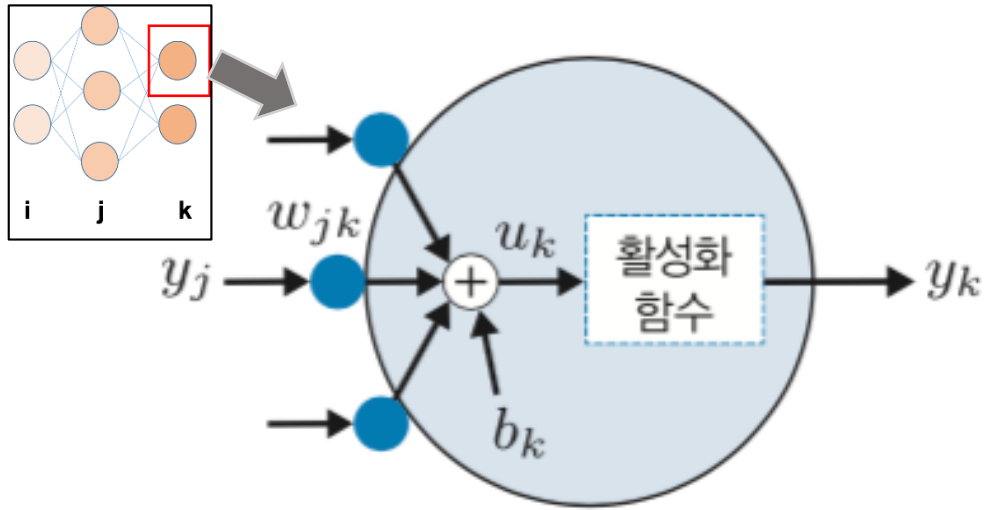


$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial u_k} \frac{\partial u_k}{\partial w_{jk}}$$

$$\begin{aligned} \frac{\partial u_k}{\partial w_{jk}} &= \frac{\partial (\sum_{q=1}^m y_q w_{qk} + b_k)}{\partial w_{jk}} \\ &= \frac{\partial}{\partial w_{jk}} (y_1 w_{1k} + \dots + y_j w_{jk} + \dots + y_m w_{mk}) \\ &= y_j \end{aligned}$$

출력층 기울기

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial u_k} \frac{\partial u_k}{\partial w_{jk}}$$

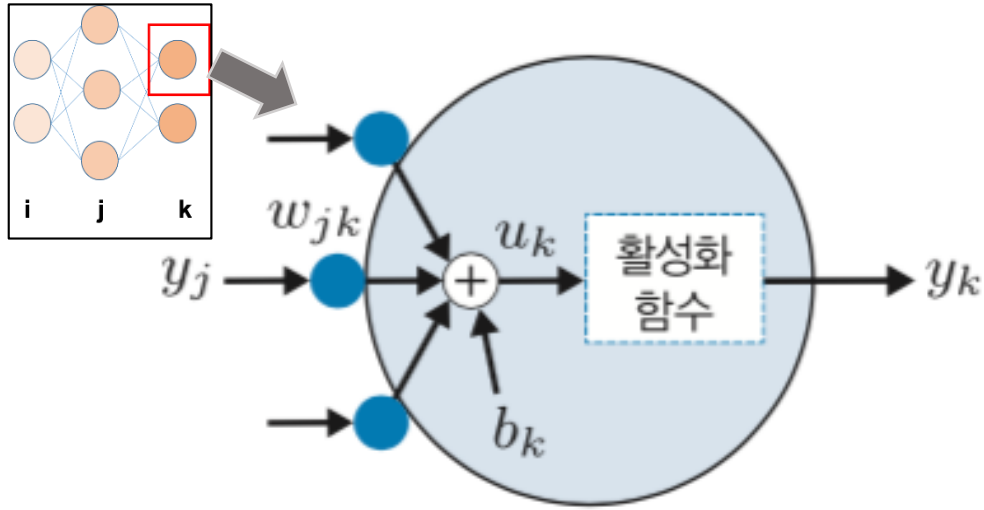
$$\frac{\partial u_k}{\partial w_{jk}} = y_j$$

$$\delta_k = \frac{\partial E}{\partial u_k} = \frac{\partial E}{\partial y_k} \frac{\partial y_k}{\partial u_k}$$

$$\frac{\partial E}{\partial w_{jk}} = y_j \delta_k$$

출력층 기울기: bias

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial u_k} \frac{\partial u_k}{\partial w_{jk}}$$

$$\frac{\partial u_k}{\partial w_{jk}} = y_j \quad \frac{\partial E}{\partial w_{jk}} = y_j \delta_k$$

$$\frac{\partial E}{\partial b_k} = \frac{\partial E}{\partial u_k} \frac{\partial u_k}{\partial b_k}$$

$$\frac{\partial u_k}{\partial b_k} = \frac{\partial (\sum_{q=1}^m y_q w_{qk} + b_k)}{\partial b_k}$$

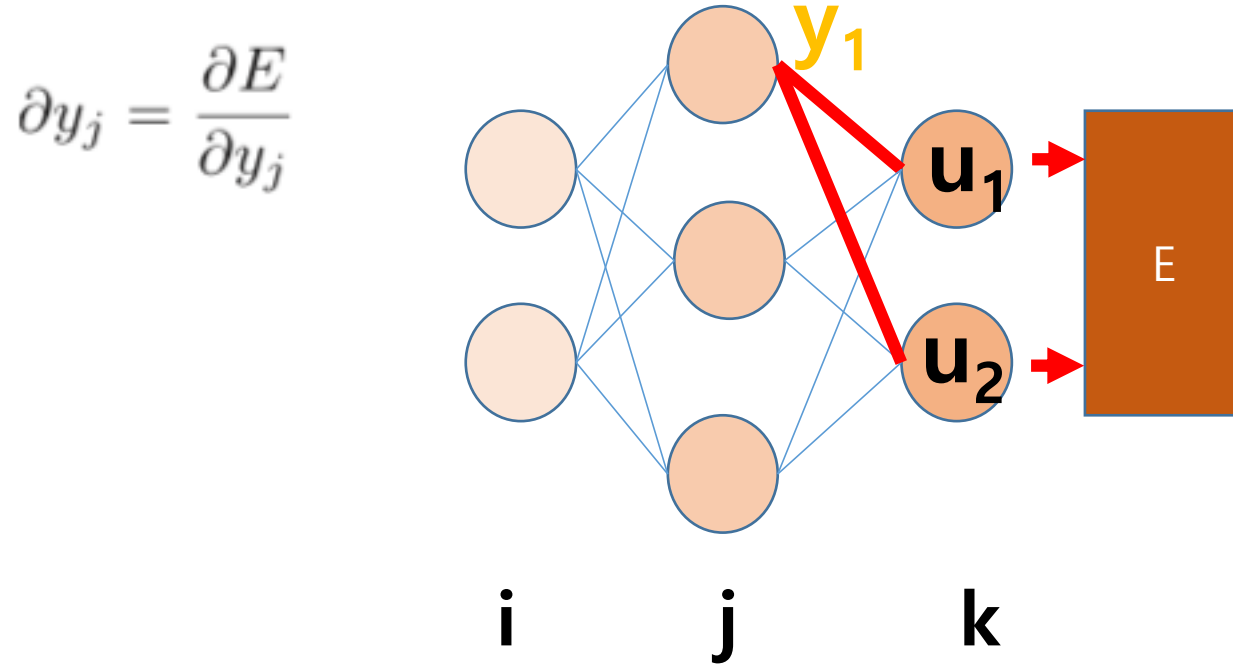
$$= \frac{\partial}{\partial b_k} (y_1 w_{1k} + \dots + y_m w_{mk} + b_k)$$

$$= 1$$

$$\frac{\partial E}{\partial b_k} = \frac{\partial E}{\partial u_k} \frac{\partial u_k}{\partial b_k} = \delta_k * 1 = \delta_k$$

출력층의 입력값 기울기

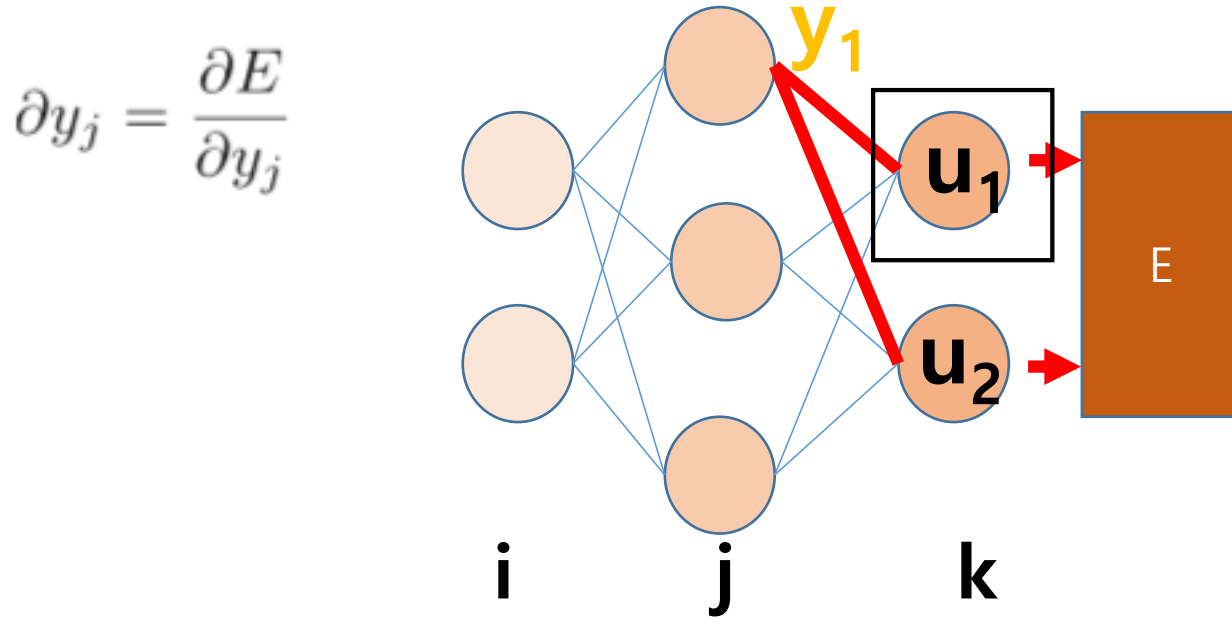
layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



$$\begin{aligned}\frac{\partial E}{\partial y_j} &= \frac{\partial E}{\partial y_j} \\ &= \sum_{r=1}^n \frac{\partial E}{\partial u_r} \frac{\partial u_r}{\partial y_j}\end{aligned}$$

출력층의 입력값 기울기

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n

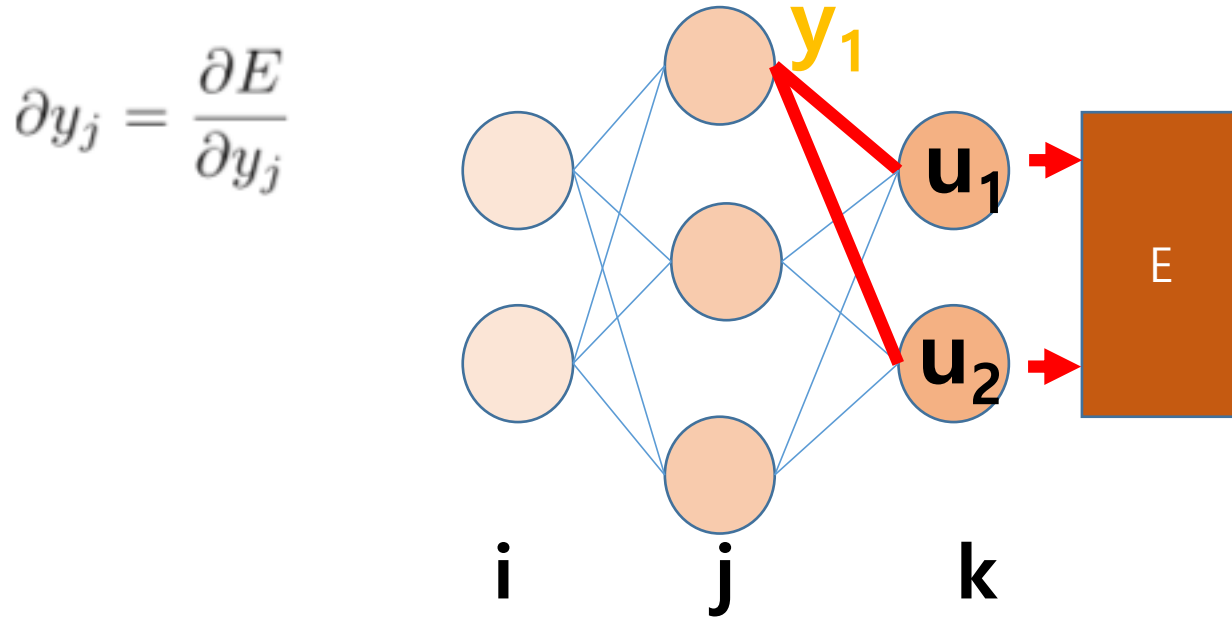


$$\partial y_j = \sum_{r=1}^n \frac{\partial E}{\partial u_r} \frac{\partial u_r}{\partial y_j}$$

$$\begin{aligned} \frac{\partial u_r}{\partial y_j} &= \frac{\partial (\sum_{q=1}^m y_q w_{qr} + b_r)}{\partial y_j} \\ &= \frac{\partial}{\partial y_j} (y_1 w_{1r} + \dots + y_j w_{jr} + \dots + y_m w_{mr} + b_r) \\ &= w_{jr} \end{aligned}$$

출력층의 입력값 기울기

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



$$\frac{\partial y_j}{\partial y_j} = \frac{\partial E}{\partial y_j}$$

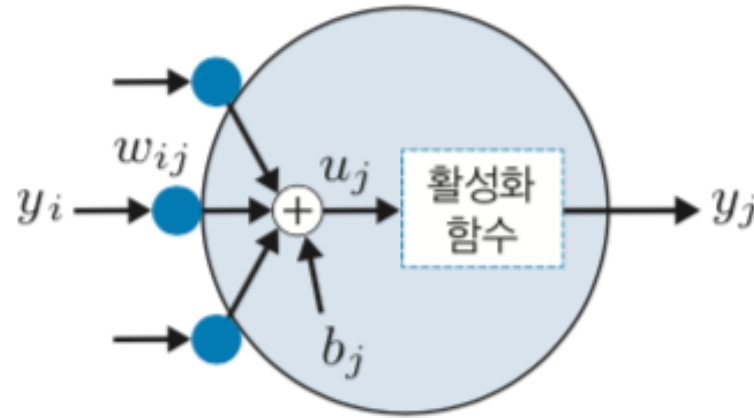
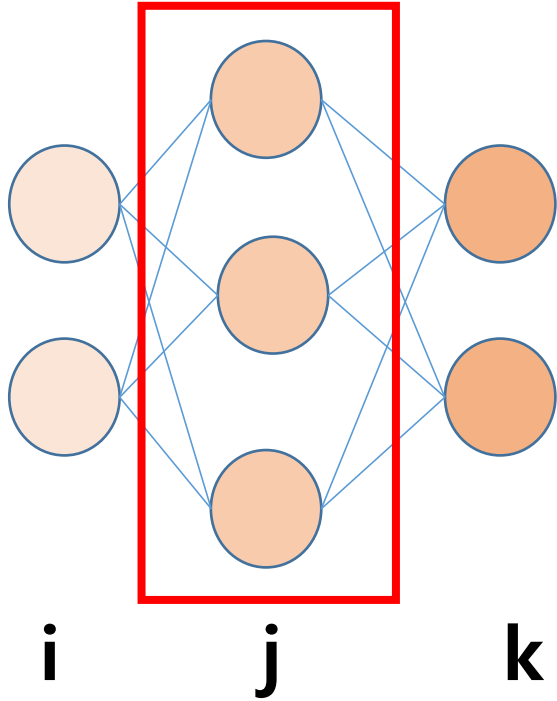
$$\frac{\partial y_j}{\partial y_j} = \sum_{r=1}^n \frac{\partial E}{\partial u_r} \frac{\partial u_r}{\partial y_j}$$

$$\frac{\partial u_r}{\partial y_j} = w_{jr}$$

$$\frac{\partial y_j}{\partial y_j} = \sum_{r=1}^n \delta_r w_{jr}$$

은닉층의 가중치 기울기

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n

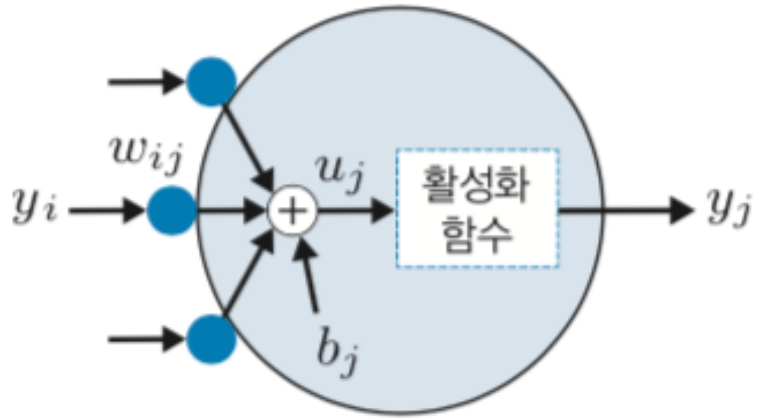
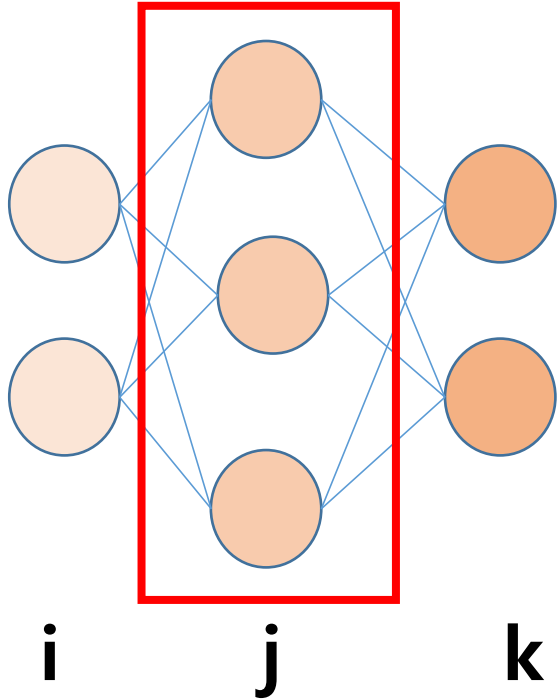


$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial u_j} \frac{\partial u_j}{\partial w_{ij}}$$

$$\begin{aligned} \frac{\partial u_j}{\partial w_{ij}} &= \frac{\partial (\sum_{p=1}^l y_p w_{pj} + b_j)}{\partial w_{ij}} \\ &= \frac{\partial}{\partial w_{ij}} (y_1 w_{1j} + \dots + y_i w_{ij} + \dots + y_l w_{lj} + b_j) \\ &= y_i \end{aligned}$$

은닉층의 가중치 기울기

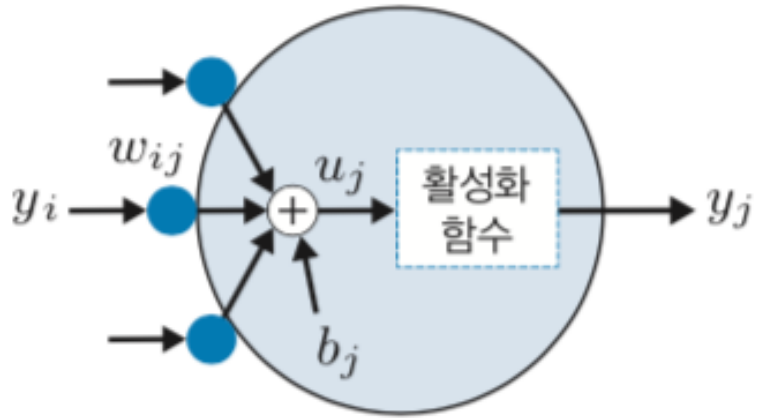
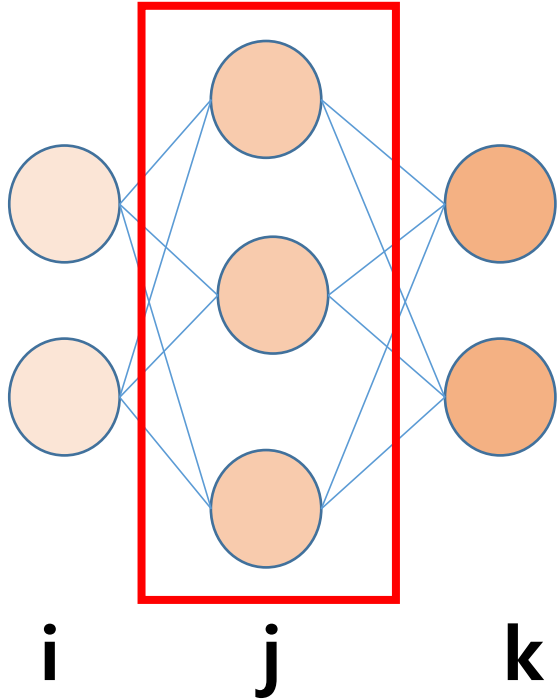
layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial u_j} \frac{\partial u_j}{\partial w_{ij}}$$
$$\frac{\partial u_j}{\partial w_{ij}} = y_i$$

은닉층의 가중치 기울기

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial u_j} \frac{\partial u_j}{\partial w_{ij}}$$

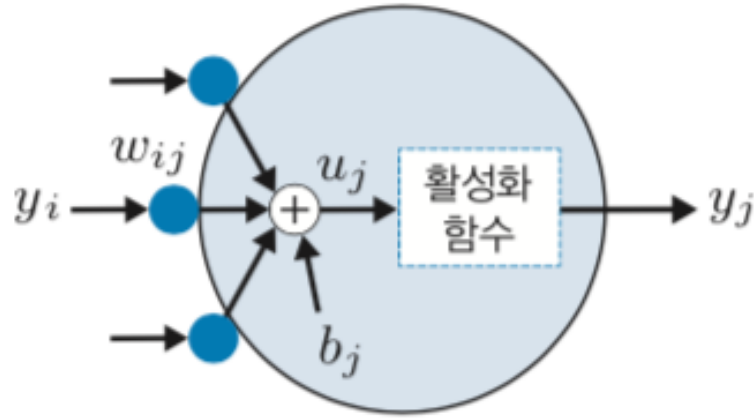
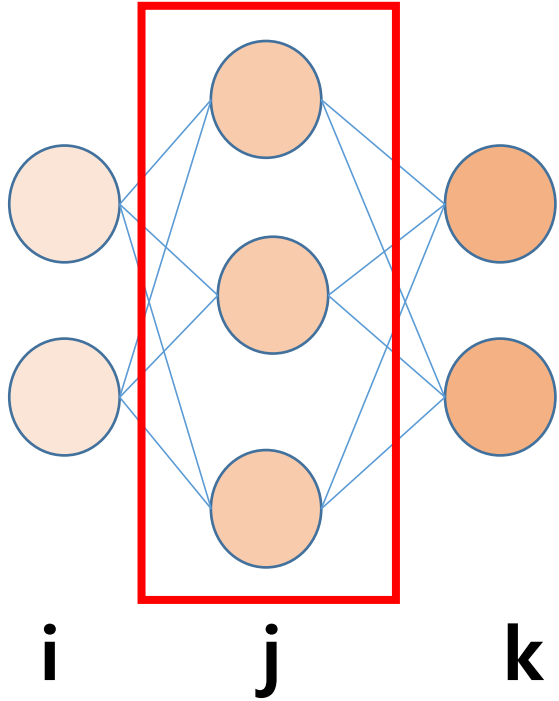
$$\frac{\partial u_j}{\partial w_{ij}} = y_i$$

$$\frac{\partial E}{\partial u_j} = \frac{\partial E}{\partial y_j} \frac{\partial y_j}{\partial u_j}$$

$$\delta_j = \frac{\partial E}{\partial u_j} = \frac{\partial E}{\partial y_j} \frac{\partial y_j}{\partial u_j} = \delta y_j \frac{\partial y_j}{\partial u_j}$$

은닉층의 가중치 기울기

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial u_j} \frac{\partial u_j}{\partial w_{ij}}$$

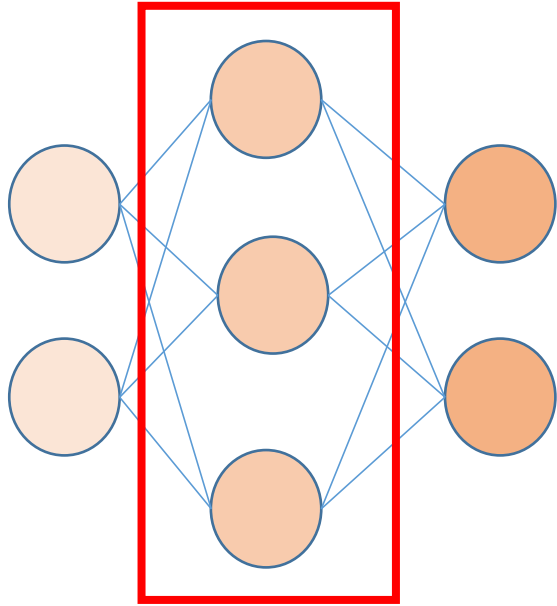
$$\frac{\partial E}{\partial u_j} = \frac{\partial E}{\partial y_j} \frac{\partial y_j}{\partial u_j} = \delta_j$$

$$\frac{\partial u_j}{\partial w_{ij}} = y_i$$

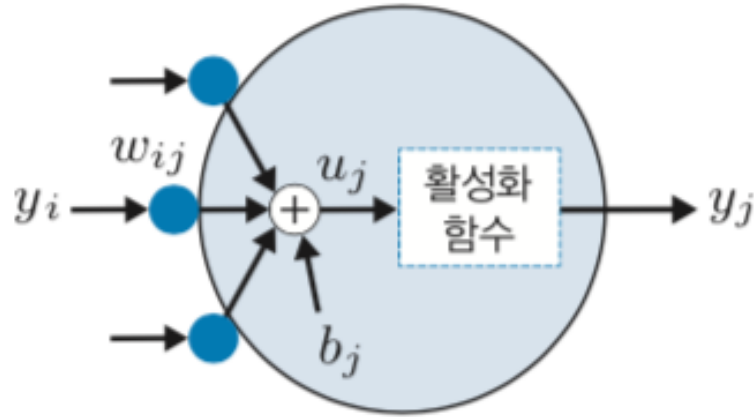
$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial u_j} \frac{\partial u_j}{\partial w_{ij}} = y_i \delta_j$$

은닉층의 bias 기울기

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n



i j k



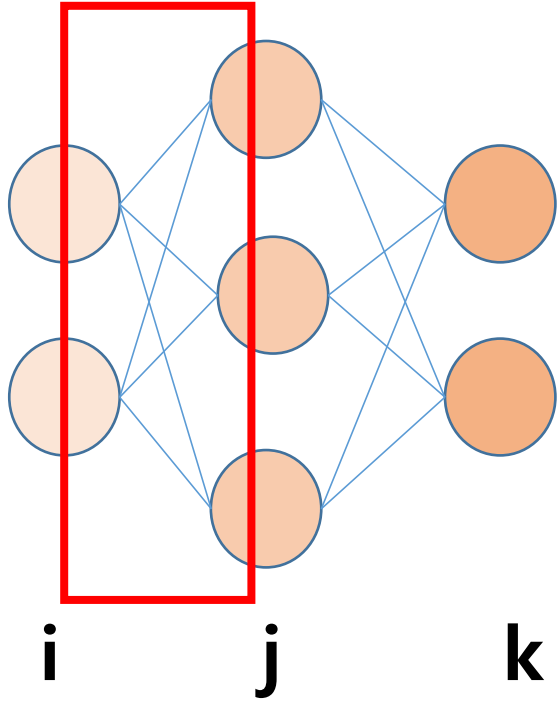
$$\frac{\partial E}{\partial b_j} = \frac{\partial E}{\partial u_j} \frac{\partial u_j}{\partial b_j} \quad \frac{\partial u_j}{\partial b_j} = \frac{\partial (\sum_{p=1}^l y_p w_{pj} + b_j)}{\partial b_j}$$

$$= \frac{\partial}{\partial b_j} (y_1 w_{1j} + \dots + y_i w_{ij} + b_j)$$

$$= 1$$

$$\frac{\partial E}{\partial b_j} = \delta_j$$

은닉층 앞층의 입력 기울기



$$\partial y_i = \sum_{q=1}^m \delta_q w_{iq}$$

layer	첨자	노드 수
Input	i	l
Hidden	j	m
Output	k	n

기울기 요약: 출력층

$$\delta_k = \frac{\partial E}{\partial u_k} = \frac{\partial E}{\partial y_k} \frac{\partial y_k}{\partial u_k}$$

식 5-15

$$\partial w_{jk} = y_j \delta_k$$

식 5-16

$$\partial b_k = \delta_k$$

식 5-17

$$\partial y_j = \sum_{r=1}^n \delta_r w_{jr}$$

식 5-18

$$\partial w_{jk} = \frac{\partial E}{\partial w_{jk}}$$

$$\partial b_k = \frac{\partial E}{\partial b_k}$$

$$\partial y_j = \frac{\partial E}{\partial y_j}$$

기울기 요약: 은닉층

$$\delta_j = \frac{\partial E}{\partial u_j} = \partial y_j \frac{\partial y_j}{\partial u_j}$$

식 5-19

$$\partial w_{ij} = y_i \delta_j$$

식 5-20

$$\partial b_j = \delta_j$$

식 5-21

$$\partial y_i = \sum_{q=1}^m \delta_q w_{iq}$$

식 5-22

$$\partial w_{ij} = \frac{\partial E}{\partial w_{ij}}$$

$$\partial b_j = \frac{\partial E}{\partial b_j}$$

$$\partial y_i = \frac{\partial E}{\partial y_i}$$

회귀 문제 기울기 구하기

- Loss Function: 오차 제곱합
- 은닉층 활성화 함수: Sigmoid Function
- 출력층 활성화 함수: 항등 함수

회귀 문제 기울기 구하기: 오차 제곱합

$$\delta_k = \frac{\partial E}{\partial y_k} \frac{\partial y_k}{\partial u_k}$$

$$\begin{aligned}\frac{\partial E}{\partial y_k} &= \frac{\partial}{\partial y_k} \left(\frac{1}{2} \sum_k (y_k - t_k)^2 \right) \\ &= \frac{\partial}{\partial y_k} \left(\frac{1}{2} (y_0 - t_0)^2 + \frac{1}{2} (y_1 - t_1)^2 + \cdots + \frac{1}{2} (y_k - t_k)^2 + \cdots + \frac{1}{2} (y_n - t_n)^2 \right) \\ &= y_k - t_k\end{aligned}$$

식 5-24

회귀 문제 기울기 구하기: 출력층

(오차제곱합, 항등 함수)

$$\delta_k = \frac{\partial E}{\partial y_k} \frac{\partial y_k}{\partial u_k}$$

$$\frac{\partial E}{\partial y_k} = \frac{\partial}{\partial y_k} \left(\frac{1}{2} \sum_k (y_k - t_k)^2 \right)$$

$$= \frac{\partial}{\partial y_k} \left(\frac{1}{2} (y_0 - t_0)^2 + \frac{1}{2} (y_1 - t_1)^2 + \cdots + \frac{1}{2} (y_k - t_k)^2 + \cdots + \frac{1}{2} (y_n - t_n)^2 \right)$$

$$= y_k - t_k$$

식 5-24

$$\frac{\partial y_k}{\partial u_k} = \frac{\partial u_k}{\partial u_k} = 1$$

$$\delta_k = y_k - t_k$$

회귀 문제 기울기 구하기: 출력층

(오차제곱합, 항등 함수)

$$\delta_k = y_k - t_k$$

$$\partial w_{jk} = y_j \delta_k$$

$$\partial b_k = \delta_k$$

$$\partial y_i = \sum_{r=1}^n \delta_r w_{jr}$$

회귀 문제 기울기 구하기: 은닉층 (sigmoid)

$$\delta_j = \partial y_j \frac{\partial y_j}{\partial u_j}$$
$$\frac{\partial y_j}{\partial u_j} = (1 - y_j)y_j$$

② 항 뜻기

$$\frac{\partial a}{\partial z} = \frac{\partial}{\partial z} \left(\frac{1}{1+e^{-z}} \right) = \frac{\partial}{\partial z} (1+e^{-z})^{-1}$$
$$\therefore e^{-z} \rightarrow -e^{-z}$$
$$\begin{aligned} \frac{\partial a}{\partial z} &= -(1+e^{-z})^{-2} \cdot (1+e^{-z})' \\ &= -(1+e^{-z})^{-2} \cdot (-e^{-z}) \\ &= \frac{e^{-z}}{(1+e^{-z})^2} = \frac{1}{1+e^{-z}} \cdot \frac{e^{-z}}{1+e^{-z}} \\ &= \frac{1}{1+e^{-z}} \cdot \frac{1+e^{-z}-1}{1+e^{-z}} = \frac{1}{1+e^{-z}} \cdot \left(1 - \frac{1}{1+e^{-z}} \right) \\ &= \boxed{a(1-a)} \end{aligned}$$

회귀 문제 기울기 구하기: 은닉층 (sigmoid)

$$\delta_j = \frac{\partial E}{\partial u_j} = \partial y_j \frac{\partial y_j}{\partial u_j}$$

$$\partial w_{ij} = y_i \delta_j$$

$$\partial b_j = \delta_j$$

$$\partial y_i = \sum_{q=1}^m \delta_q w_{iq}$$

$$\delta_j = \partial y_j (1 - y_j) y_j$$

$$\partial w_{ij} = y_i \delta_j$$

$$\partial b_j = \delta_j$$

$$\partial y_i = \sum_{q=1}^m \delta_q w_{iq}$$

분류 문제에서 기울기

$$\delta_k = \frac{\partial E}{\partial u_k}$$

$$E = - \sum_k t_k \log(y_k) \quad \text{식 5-29}$$

$$y_k = \frac{\exp(u_k)}{\sum \exp(u_k)} \quad \text{식 5-30}$$

$$\begin{aligned} E &= - \sum_k \left(t_k \log(\exp(u_k)) - t_k \log \sum_k \exp(u_k) \right) \\ &= - \sum_k \left(t_k \log(\exp(u_k)) \right) + \sum_k \left(t_k \log \sum_k \exp(u_k) \right) \\ &= - \sum_k \left(t_k \log(\exp(u_k)) \right) + \left(\sum_k t_k \right) \left(\log \sum_k \exp(u_k) \right) \end{aligned} \quad \text{식 5-31}$$

$$E = - \sum_k t_k u_k + \log \sum_k \exp(u_k)$$

분류 문제에서 기울기: 출력층

$$\begin{aligned}\delta_k &= \frac{\partial E}{\partial u_k} \\ &= \frac{\partial}{\partial u_k} \left(- \sum_k t_k u_k + \log \sum_k \exp(u_k) \right) \\ &= -t_k + \frac{\exp(u_k)}{\sum_k \exp(u_k)} \\ &= -t_k + y_k \\ &= y_k - t_k\end{aligned}$$

분류 문제에서 기울기: 출력층

$$\delta_k = y_k - t_k$$

$$\partial w_{jk} = y_j \delta_k$$

$$\partial b_k = \delta_k$$

$$\partial y_i = \sum_{r=1}^n \delta_r w_{jr}$$

```
# -- 출력층 --
class OutputLayer(BaseLayer):
    def __init__(self, n_upper, n):
        self.w = np.random.randn(n_upper, n) / np.sqrt(n_upper) # 자비에르 초기화 기반의 초깃값
        self.b = np.zeros(n)

    def forward(self, x):
        self.x = x
        u = np.dot(x, self.w) + self.b
        self.y = np.exp(u) / np.sum(np.exp(u), axis=1, keepdims=True) # 소프트맥스 함수

    def backward(self, t):
        delta = self.y - t

        self.grad_w = np.dot(self.x.T, delta)
        self.grad_b = np.sum(delta, axis=0)
        self.grad_x = np.dot(delta, self.w.T)
```

분류 문제에서 기울기: 은닉층

$$\delta_j = \frac{\partial E}{\partial u_j} = \partial y_j \frac{\partial y_j}{\partial u_j}$$

$$\partial w_{ij} = y_i \delta_j$$

$$\partial b_j = \delta_j$$

$$\partial y_i = \sum_{q=1}^m \delta_q w_{iq}$$

$$\delta_j = \partial y_j (1 - y_j) y_j$$

$$\partial w_{ij} = y_i \delta_j$$

$$\partial b_j = \delta_j$$

$$\partial y_i = \sum_{q=1}^m \delta_q w_{iq}$$

참고문헌

- [도서명] 실체가 손에 잡히는 딥러닝
- [저자] 아즈마 유키나가
- [역자] 최재원
- [출판사] 책만