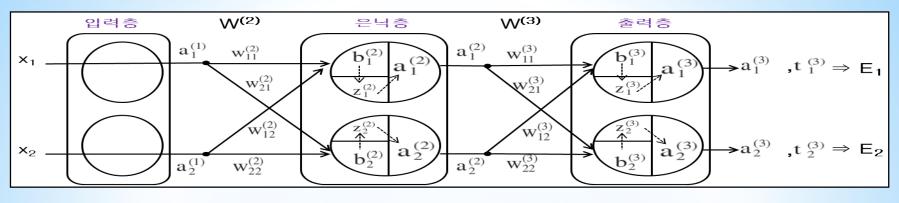
파이썬(Python)으로 구현하는

## 오차역전파 (Back Propagation)

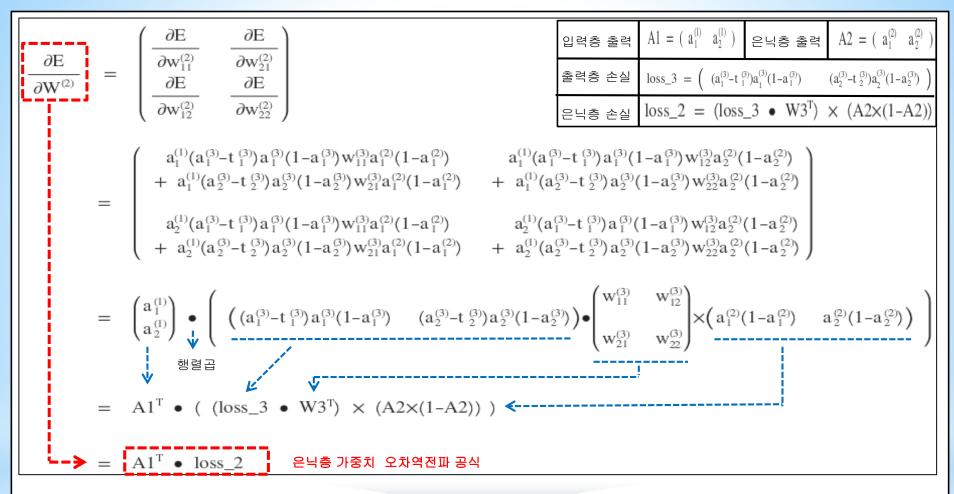
- 은닉층에서의 오차역전파 공식-

## Review - 선형회귀 값 (Z) • 출력 값 (A), 손실 값 (E), 가중치 (W), 바이어스 (b)



입력층 선형회귀 값 (Z1)	입력 층에는 가중치가 없기 때문에 선형회귀 값은 적용하지 않음	입력층 출력 값 (A1)	$a_2^{(1)} = x_2$ $a_1^{(1)} = x_1$
은닉층 선형회귀 값 (Z2)	$z_1^{(2)} = a_1^{(1)} w_{11}^{(2)} + a_2^{(1)} w_{12}^{(2)} + b_1^{(2)}$	은닉층 출력 값 (A2)	$a_1^{(2)} = sigmoid(z_1^{(2)})$
	$z_2^{(2)} = a_1^{(1)} w_{21}^{(2)} + a_2^{(1)} w_{22}^{(2)} + b_2^{(2)}$		$a_2^{(2)} = sigmoid(z_2^{(2)})$
출력층 선형회귀 값 (Z3)	$z_1^{(3)} = a_1^{(2)} w_{11}^{(3)} + a_2^{(2)} w_{12}^{(3)} + b_1^{(3)}$	출력층 출력 값 (A3)	$a_1^{(3)} = sigmoid(z_1^{(3)})$
	$z_2^{(3)} = a_1^{(2)} w_{21}^{(3)} + a_2^{(2)} w_{22}^{(3)} + b_2^{(3)}$		$a_2^{(3)} = sigmoid(z_2^{(3)})$
W <sup>(2)</sup> , W <sup>(3)</sup>	$W^{(2)} = \begin{pmatrix} w_{11}^{(2)} & w_{21}^{(2)} \\ w_{12}^{(2)} & w_{22}^{(2)} \end{pmatrix} \qquad W^{(3)} = \begin{pmatrix} w_{11}^{(3)} & w_{21}^{(3)} \\ w_{12}^{(3)} & w_{22}^{(3)} \end{pmatrix}$	b <sup>(2)</sup> , b <sup>(3)</sup>	$b^{(2)} = \begin{pmatrix} b_1^{(2)} & b_2^{(2)} \end{pmatrix} b^{(3)} = \begin{pmatrix} b_1^{(3)} & b_2^{(3)} \end{pmatrix}$
최종 손실 값 (E)	$E = \frac{1}{n} \sum_{i=1}^{n} (t_i^{(3)} - a_i^{(3)})^2 = \frac{1}{2} \{ (t_1^{(3)} - a_1^{(3)})^2 + (t_2^{(3)} - a_2^{(3)})^2 \}$	$= E_1 + E_2$	$E_{1} = \frac{1}{2} (t_{1}^{(3)} - a_{1}^{(3)})^{2} \left[ E_{2} = \frac{1}{2} (t_{2}^{(3)} - a_{2}^{(3)})^{2} \right]$

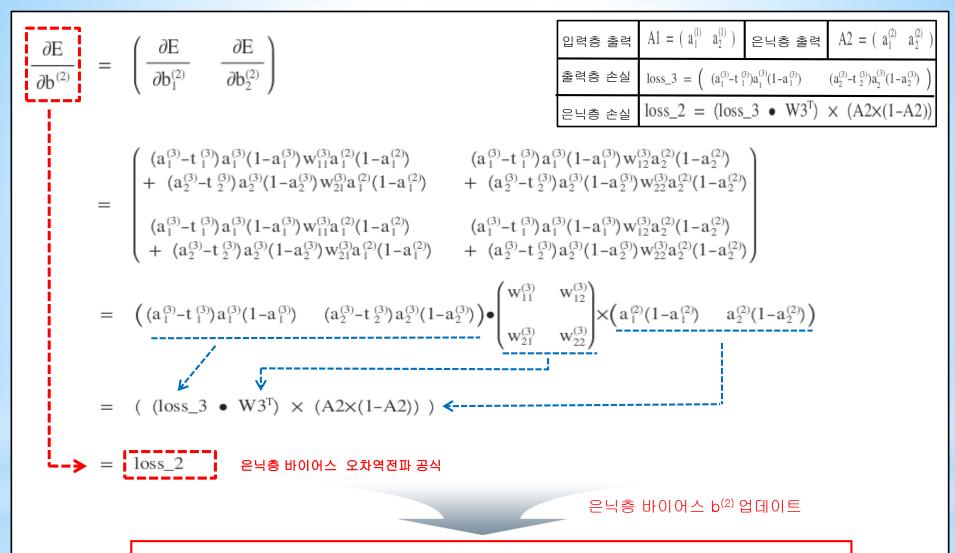
## 은닉층 가중치 오차역전파 (Back Propagation) 공식



은닉층 가중치 W<sup>(2)</sup> 업데이트

$$\mathbf{W}^{(2)} = \mathbf{W}^{(2)} - \alpha \frac{\partial \mathbf{E}}{\partial \mathbf{W}^{(2)}} = \mathbf{W}^{(2)} - \alpha \times (\mathbf{A}\mathbf{1}^{\mathsf{T}} \bullet \mathbf{loss}\mathbf{\underline{2}})$$

## 은닉층 바이어스 오차역전파 (Back Propagation) 공식



$$b^{(2)} = b^{(2)} - \alpha \frac{\partial E}{\partial b^{(2)}} = b^{(2)} - \alpha \times loss_2$$