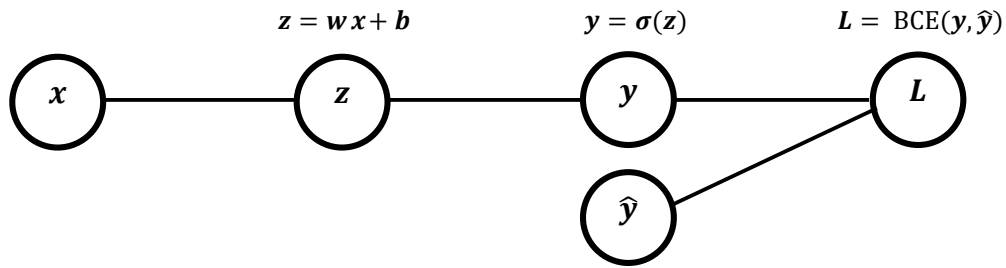


## Backpropagation 실습 - Gradient 계산 과정 보충 설명



Model 구조: 단일 linear layer non-linear activation function으로 sigmoid 함수 채택

$x$ : 모델의 입력 값 ( $x_i$ )

$w, b$ : Linear layer의 weight와 bias (둘 다 scalar)

$\sigma$ : Non-linear activation function인 sigmoid 함수 ( $\sigma(x) = \frac{1}{1+e^{-x}}$ )

$y$ : 모델의 예측 값 ( $y_{\text{pred}}$ ),  $\hat{y}$ : 실제 값 ( $y_i$ )

$L$ : loss function (binary cross entropy (BCE),  $L = \text{BCE}(y, \hat{y}) = -\sum\{\hat{y} \log y + (1 - \hat{y}) \log (1 - y)\}$ )

Chain rule을 활용하여 모델의 optimization (gradient descent)에 필요한 gradient의 값들을 구하자.

$$\begin{aligned} \frac{\partial L}{\partial f_1} &= \frac{\partial L}{\partial y} = \frac{\partial}{\partial y} \left[ -\sum \{ \hat{y} \log y + (1 - \hat{y}) \log (1 - y) \} \right] \quad (\text{단일 } y \text{ 값이므로 } \Sigma \text{ 기호 무시 가능}) \\ &= - \left\{ \frac{\hat{y}}{y} \times \frac{\partial}{\partial y} (y) + \frac{(1 - \hat{y})}{(1 - y)} \times \frac{\partial}{\partial y} (1 - y) \right\} = - \left\{ \frac{\hat{y}}{y} - \frac{(1 - \hat{y})}{(1 - y)} \right\} \\ &= - \left\{ \frac{\hat{y}(1 - y) - (1 - \hat{y})y}{y(1 - y)} \right\} = - \left\{ \frac{\hat{y} - \hat{y}y - y + y\hat{y}}{y(1 - y)} \right\} = - \left\{ \frac{\hat{y} - y}{y(1 - y)} \right\} = \frac{y - \hat{y}}{y(1 - y)} \end{aligned}$$

$$\begin{aligned} \frac{\partial y}{\partial z} &= \frac{\partial}{\partial z} \sigma(z) = \frac{\partial}{\partial z} \left( \frac{1}{1 + e^{-z}} \right) = - \frac{1}{(1 + e^{-z})^2} \times \frac{\partial}{\partial z} (1 + e^{-z}) \\ &= - \frac{1}{(1 + e^{-z})^2} \times (-e^{-z}) = \frac{e^{-z}}{(1 + e^{-z})^2} = \frac{1}{1 + e^{-z}} \times \frac{e^{-z}}{1 + e^{-z}} = \sigma(z) \{1 - \sigma(z)\} \end{aligned}$$

$$\frac{\partial L}{\partial f_2} = \frac{\partial L}{\partial z} = \frac{\partial L}{\partial y} \times \frac{\partial y}{\partial z} = \frac{\partial L}{\partial f_1} \sigma(z) \{1 - \sigma(z)\} = \frac{\partial L}{\partial f_1} \times y(1 - y) \quad \left( = \frac{y - \hat{y}}{y(1 - y)} \times y(1 - y) = y - \hat{y} \right)$$

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial z} \times \frac{\partial z}{\partial w} = \frac{\partial L}{\partial z} \times \frac{\partial}{\partial w} (wx + b) = \frac{\partial L}{\partial f_2} \times x \quad (= (y - \hat{y})x)$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial z} \times \frac{\partial z}{\partial b} = \frac{\partial L}{\partial z} \times \frac{\partial}{\partial b} (wx + b) = \frac{\partial L}{\partial f_2} \times 1 = \frac{\partial L}{\partial f_2} \quad (= y - \hat{y})$$