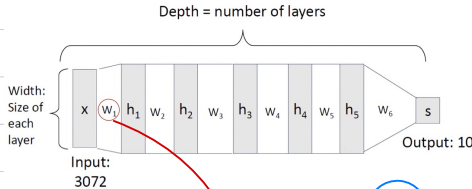


Back propagation

함수 합성의 미분 ex) $f \circ g(x) \Rightarrow g'(x) \cdot f'(g(x))$

$$= \frac{df}{dg} \cdot \frac{dg}{dx} = \frac{df}{dx}$$



Q. 이러한 DNN에서

$$w_i = w_i - \eta \cdot \nabla L$$

↳ 바지 구하기 어렵음
∴ Chain rule 이용

Gradient Descent

Method: at each step, move in direction of negative gradient

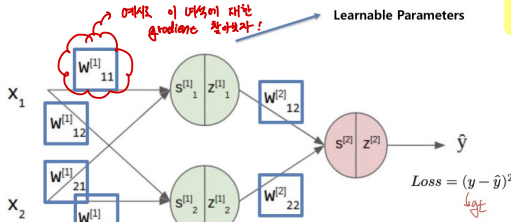
```
w0 = initialize()
for iter in range(numIters):
    g = ∇wL(w)
    w = w + -stepsize*g
return w
```

Learning rate

#initialize

eval gradient

update w



Then, How to calculate gradient on each layer ?

$$\frac{\partial Loss}{\partial w_{11}^{(1)}}, \frac{\partial Loss}{\partial w_{12}^{(1)}}, \dots, \frac{\partial Loss}{\partial w_{22}^{(2)}}$$

$$\frac{\partial L}{\partial w_{11}^{(1)}} = \frac{\partial L}{\partial z_1^{(1)}} \times \frac{\partial z_1^{(1)}}{\partial s_1^{(1)}} \times \frac{\partial s_1^{(1)}}{\partial w_{11}^{(1)}}$$

$$s_1^{(1)} = w_{11}^{(1)}x_1 + w_{21}^{(1)}x_2$$

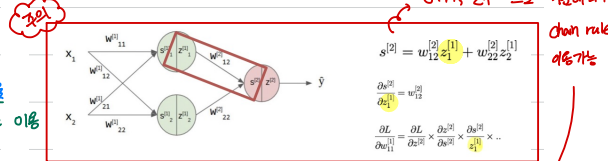
$$z_1^{(1)} = \tanh(s_1^{(1)})$$

$$s^{(2)} = w_{12}^{(2)}z_1^{(1)} + w_{22}^{(2)}z_2^{(1)}$$

$$z^{(2)} = \tanh(s^{(2)})$$

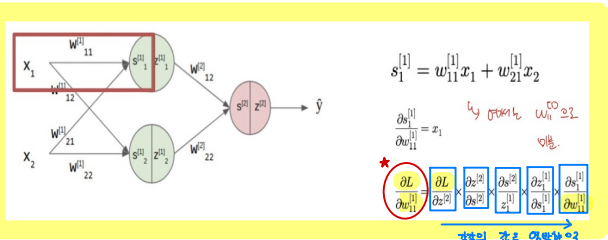
$$L = (y - z^{(2)})^2$$

이걸 계산해 줘야 함



$$z_1^{(1)} = \tanh(s_1^{(1)})$$

$w_{11}^{(1)}$ 이 도달할 때까지
이어서 전개 가능



$$s_1^{(1)} = w_{11}^{(1)}x_1 + w_{21}^{(1)}x_2$$

↳ 여기서 $w_{11}^{(1)}$ 으로
미분

$$\frac{\partial L}{\partial w_{11}^{(1)}} = \frac{\partial L}{\partial s_1^{(1)}} \times \frac{\partial s_1^{(1)}}{\partial z_1^{(1)}} \times \frac{\partial z_1^{(1)}}{\partial w_{11}^{(1)}}$$

각각의 값을 역방향으로
정제하면서 구할 수 있음