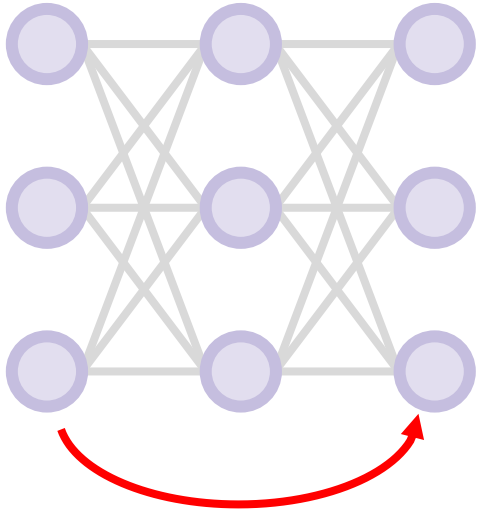
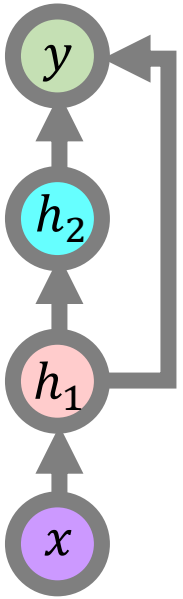
Deep Learning101

ResNet이란?

(feat. 기울기 소실문제)





신박AI

안녕하세요 여러분! 신박Ai입니다

신박AI

오늘 우리는 딥러닝에서 매우 중요한
주제인 Skip Connection과
Vanishing Gradient 문제,

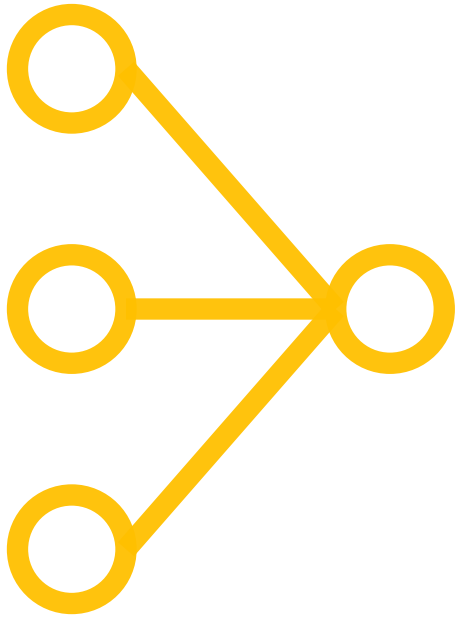
신박AI

그리고 이를 해결하는 ResNet에
대해 알아보도록 하겠습니다.

신박AI

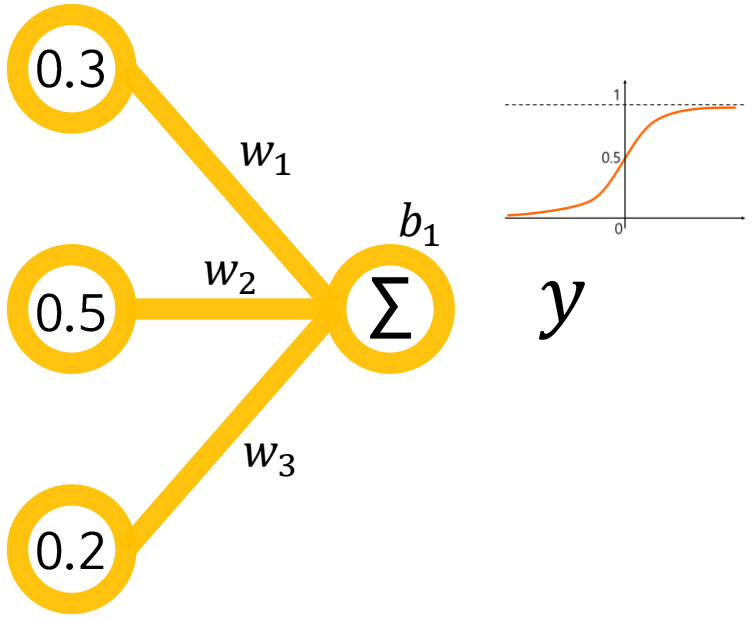
그럼 바로 시작하도록 하겠습니다!

딥러닝 모델의 기초는 신경망(Neural Network)입니다.



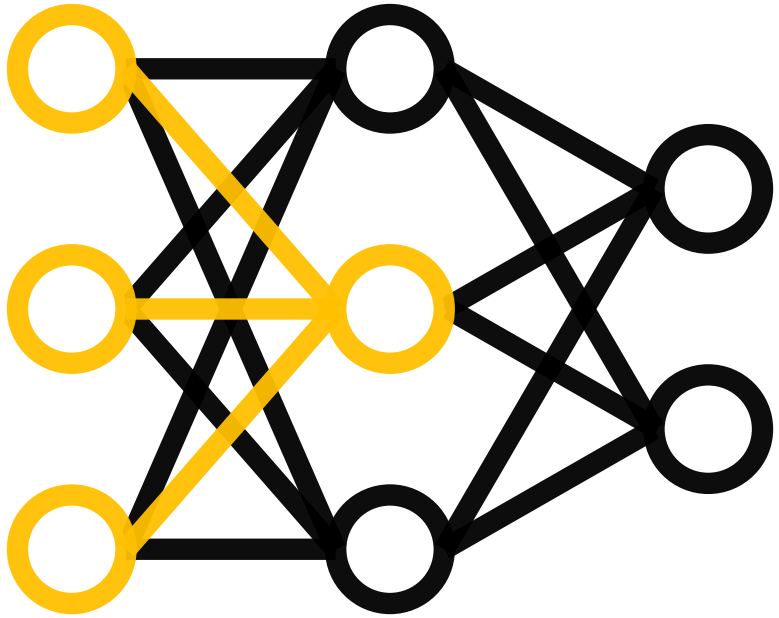
신박AI

신경망은 뉴런으로 구성되어 있으며, 각 뉴런은 입력값을 받아 가중치와 편향을 적용한 후, 활성화 함수를 통해 출력을 계산합니다.



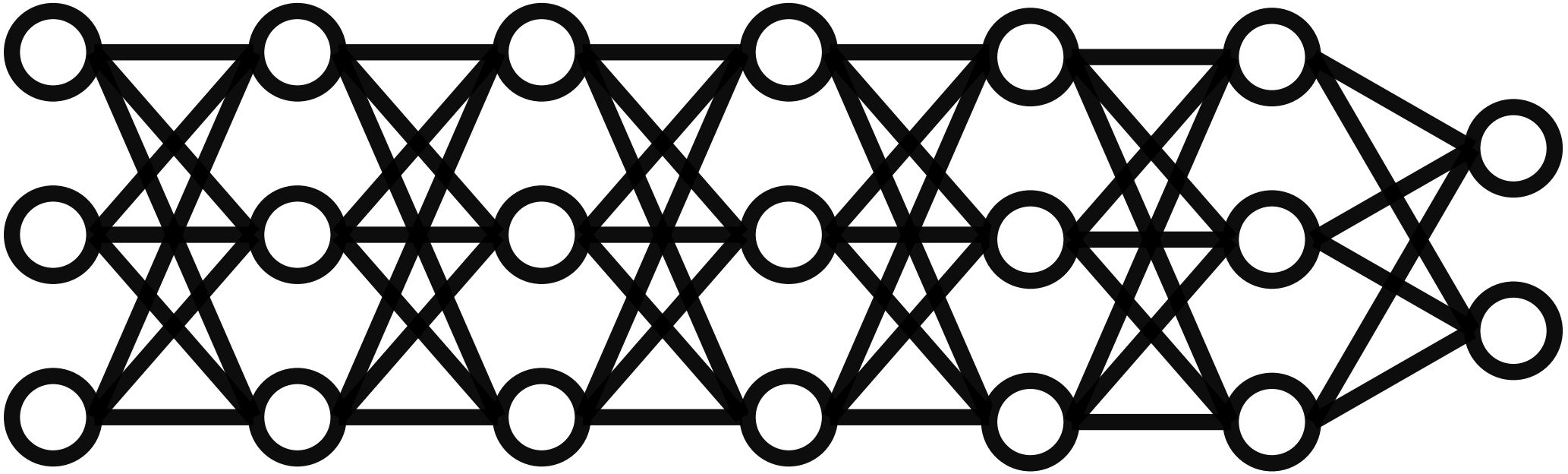
신박AI

이러한 뉴런들이 여러 층으로 구성되면 다층 퍼셉트론(Multi-Layer Perceptron, MLP)이라고 부릅니다.



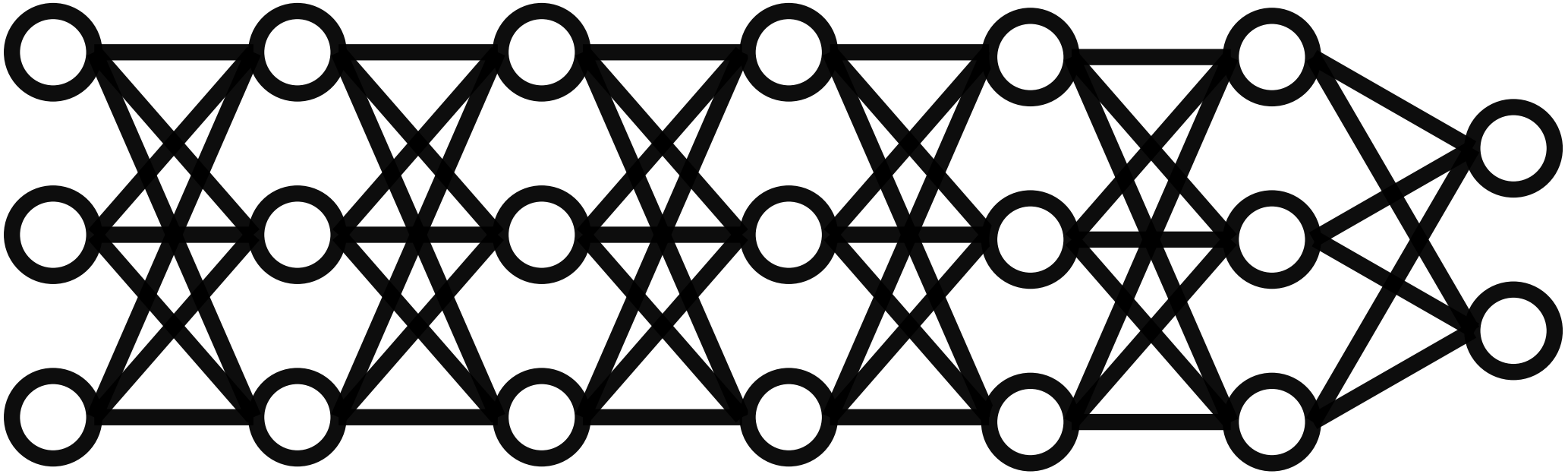
신박AI

다층 퍼셉트론이 발전하여 다층 신경망이 되고..



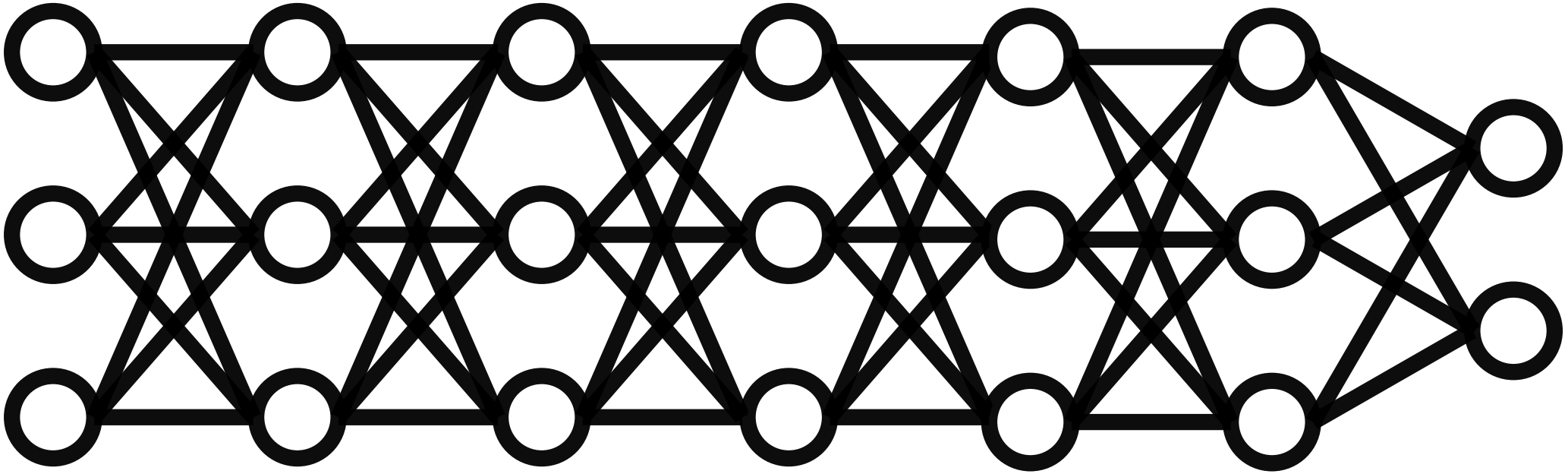
신박AI

일반적인 관점에서 더 깊은 (층이 더 많은) 다층 신경망이 될수록, 더 복잡한 과제를 수행할 수 있어서,



신박AI

오늘날 컴퓨팅 파워의 발전과 더불어 딥러닝 혁명이 일어나게 된 것은 사실입니다.



신박AI

그런데 딥러닝에 관한 연구가 지속되면서 뭔가 이상한 현상을 하나 발견하게 되었습니다.

Deep Residual Learning for Image Recognition

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun
Microsoft Research
{kahe, v-xiangz, v-shren, jiansun}@microsoft.com

Abstract

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers—8× deeper than VGG nets [41] but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test *set. This result won the 1st place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers.*

The depth of representations is of central importance

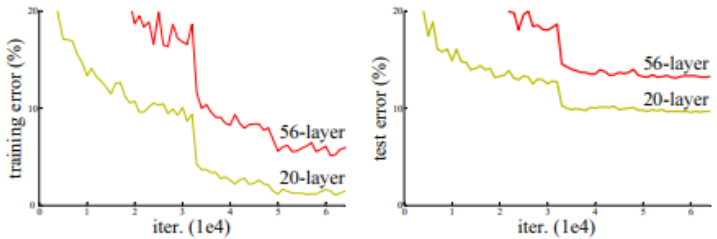


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

greatly benefited from very deep models.

Driven by the significance of depth, a question arises: *Is learning better networks as easy as stacking more layers?* An obstacle to answering this question was the notorious problem of vanishing/exploding gradients [1, 9], which hamper convergence from the beginning. This problem,

신박AI

그런데 딥러닝에 관한 연구가 지속되면서 뭔가 이상한 현상을 하나 발견하게 되었습니다.

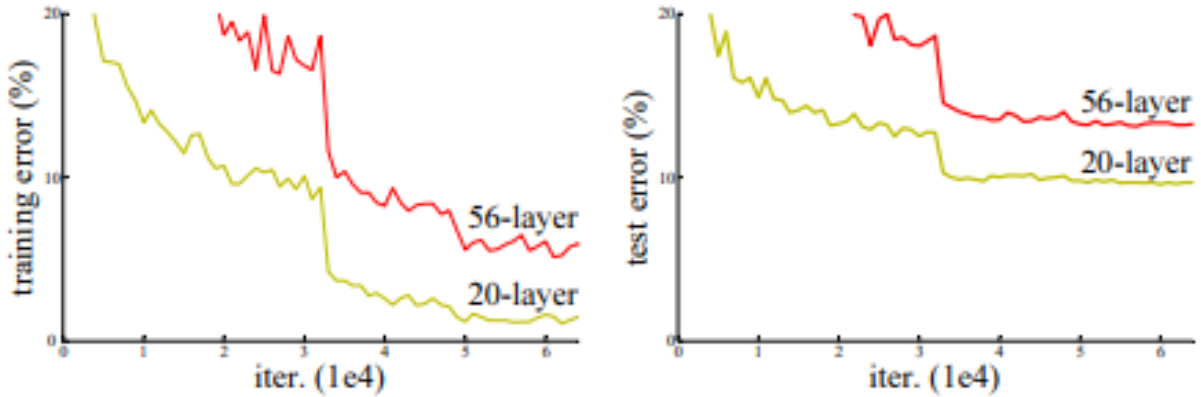


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

더 깊은 네트워크가 오히려 성능이 떨어지는 현상을 발견하게 됩니다.

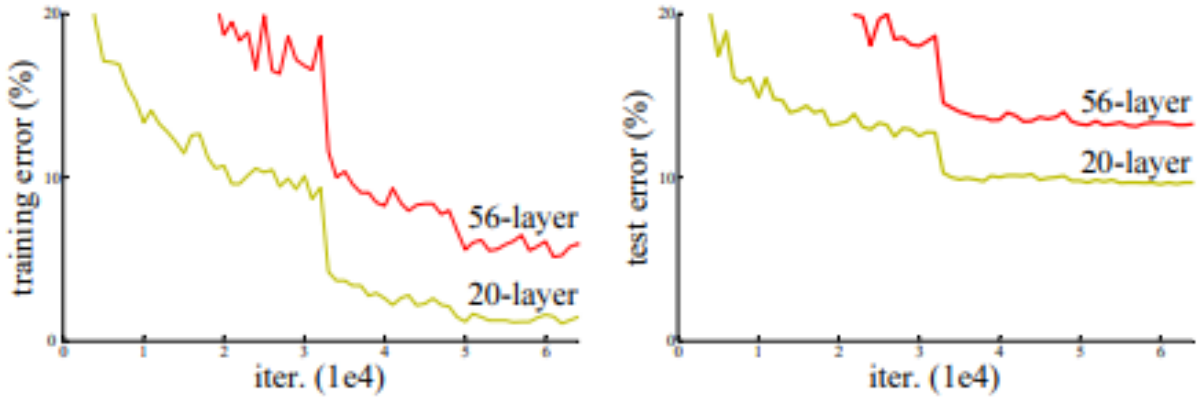


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

신박AI

더 깊은 네트워크가 오히려 성능이 떨어지는 현상을 발견하게 됩니다.

56개의 층으로 이루어진 네트워크가..

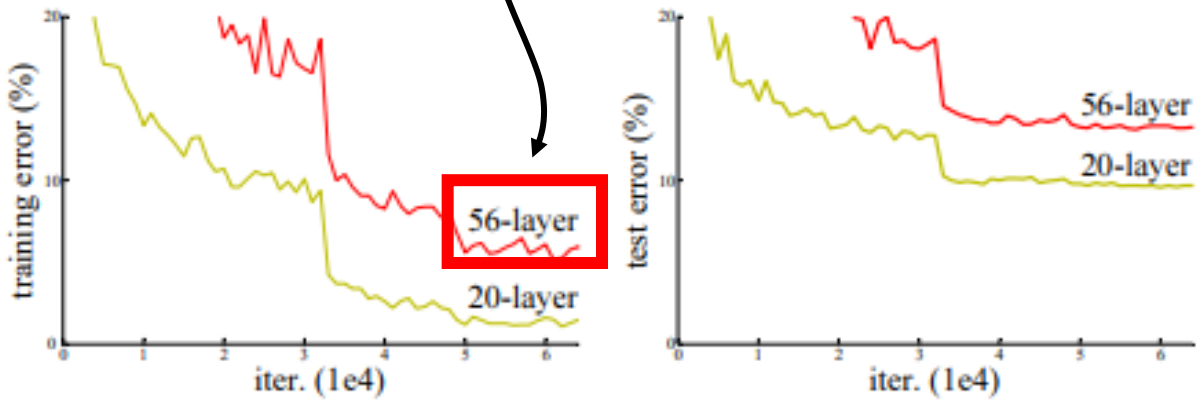


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

더 깊은 네트워크가 오히려 성능이 떨어지는 현상을 발견하게 됩니다.

20개의 층으로 이루어진 네트워크보다..

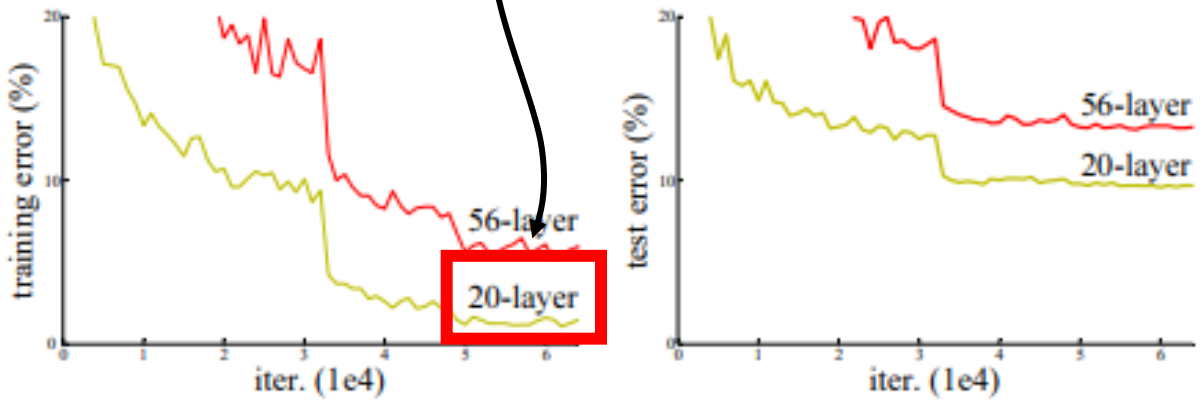


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

신박AI

더 깊은 네트워크가 오히려 성능이 떨어지는 현상을 발견하게 됩니다.

에러율이 높은 것이었습니다!

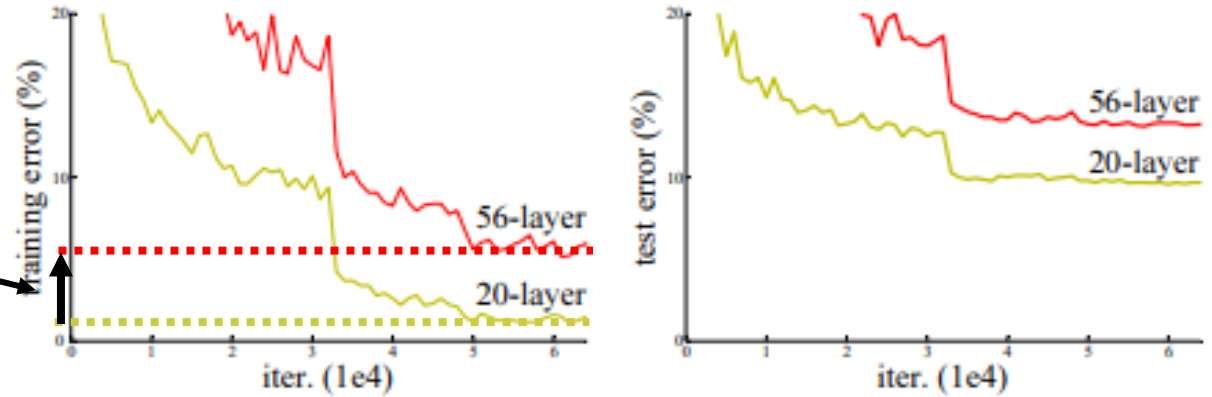


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

신박AI

이러한 깊은 모델의 성능저하 degradation 문제는 여러 복합적인 요소들의 상호작용으로 발생하는 것으로 생각되는데요,

에러율이 높은 것이었습니다!

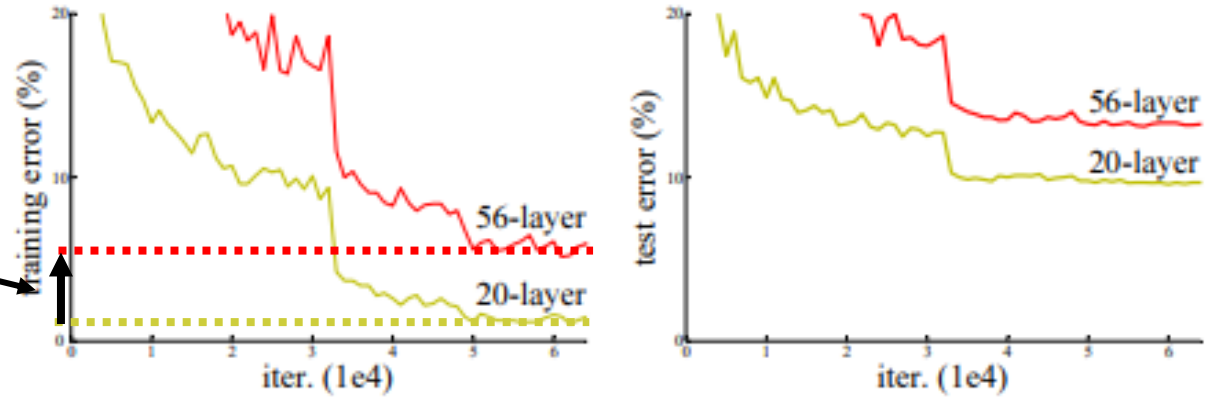
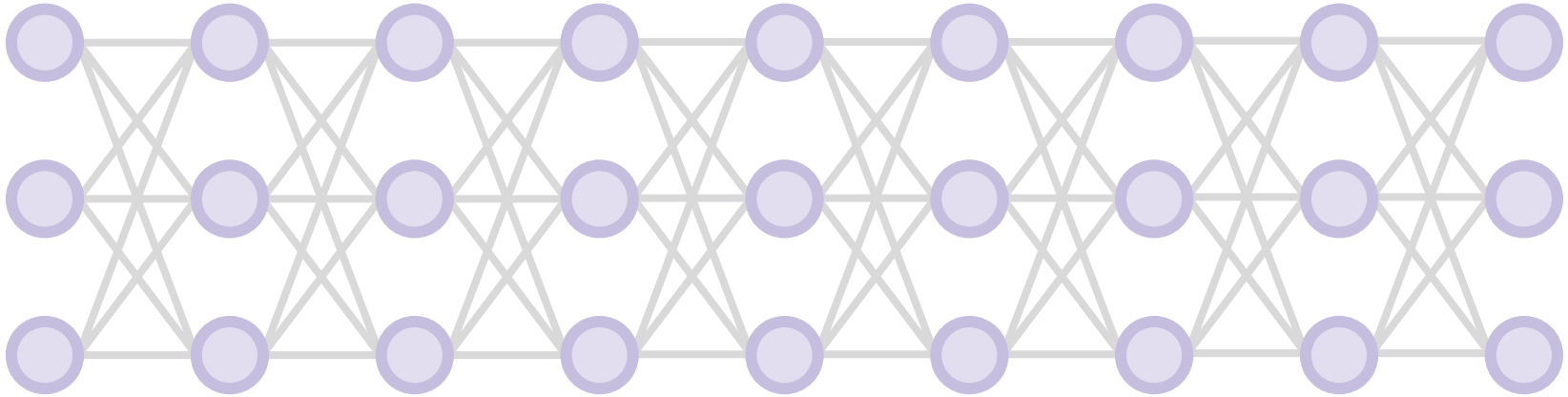


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

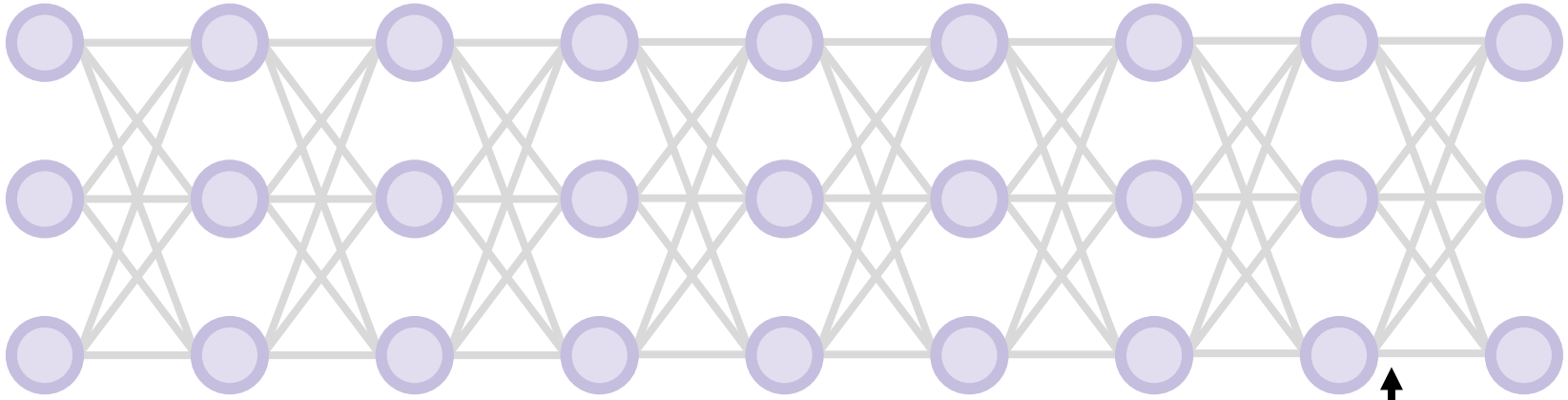
오늘 영상에서는 다루고자 하는, 모델의 성능저하의 중요한 요인 중 하나는

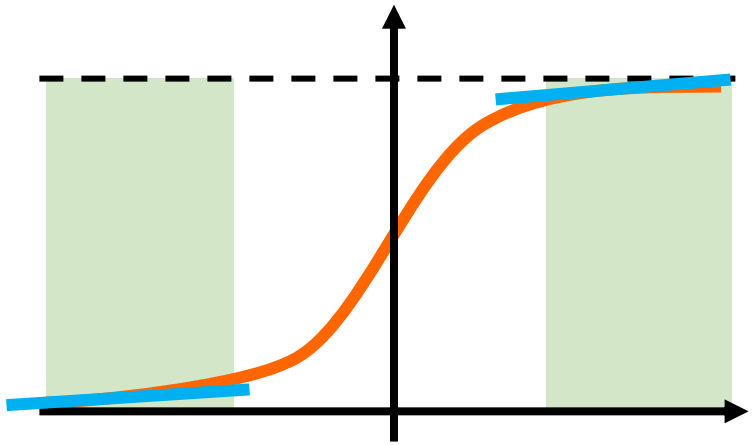
바로 기울기 소실 현상 vanishing/explosion gradient problem 입니다.

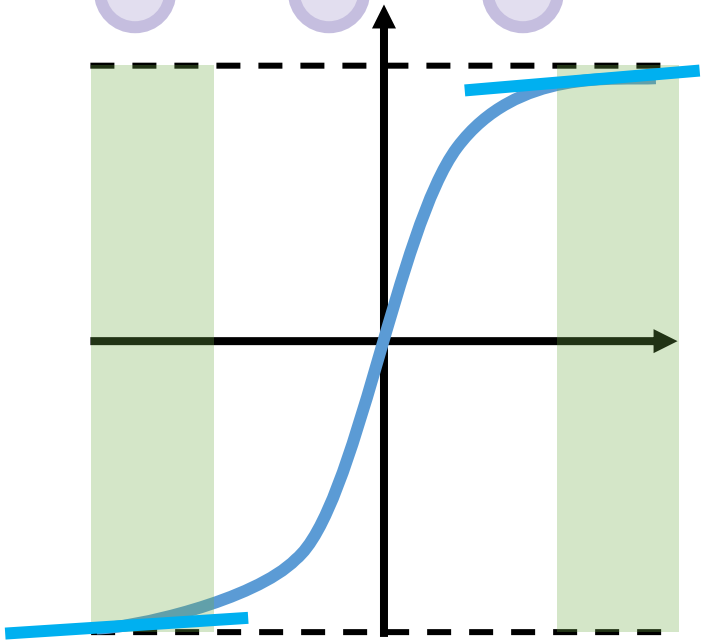


신박AI

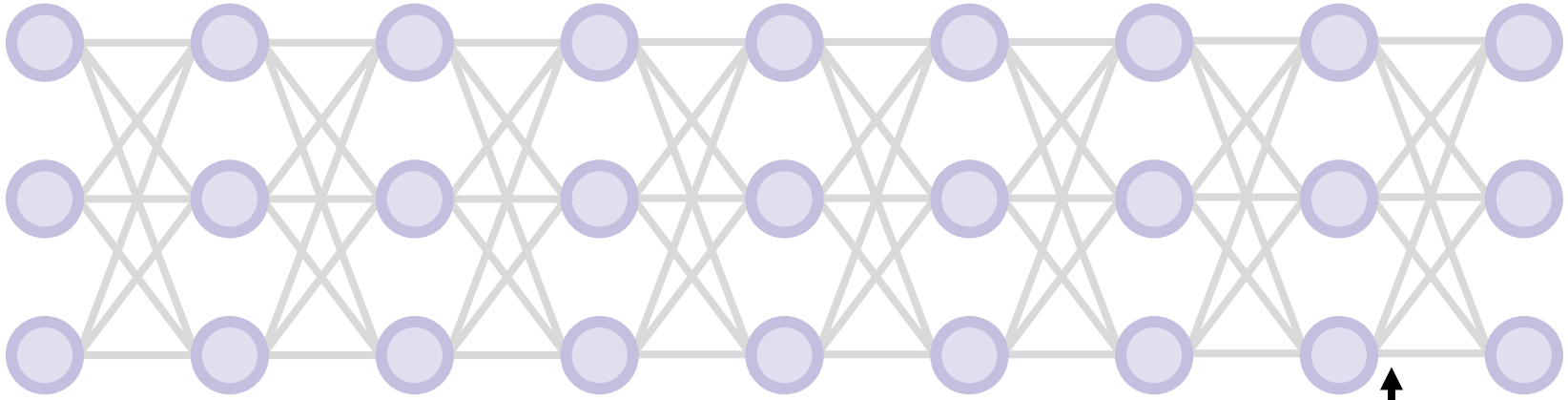
기울기 소실 현상은 주로 시그모이드나 tanh 계열의 활성화 함수를 쓸 때 나타나는 현상입니다.

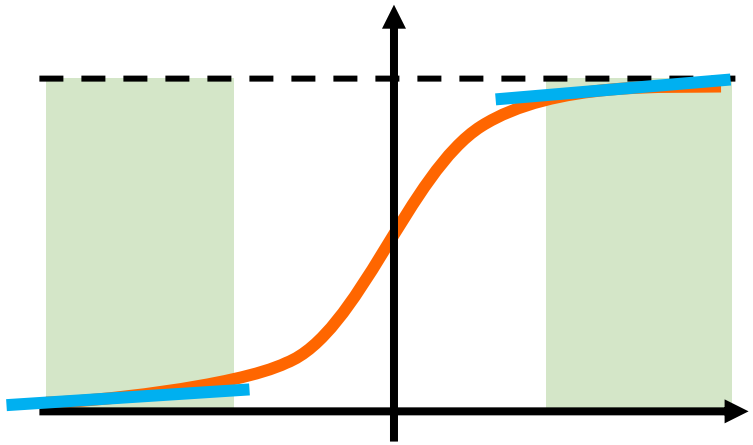


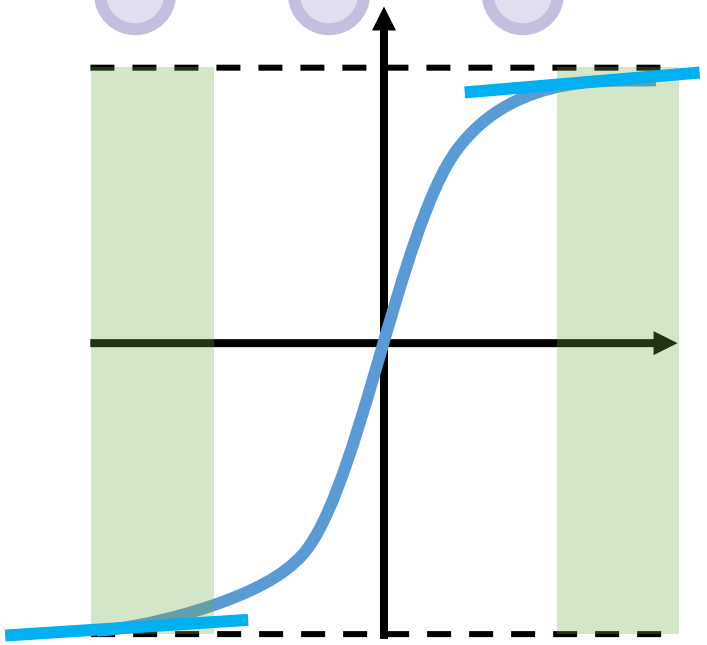




시그모이드 계열의 활성화 함수는 그 특성상 네트워크의 층이 깊을 수록

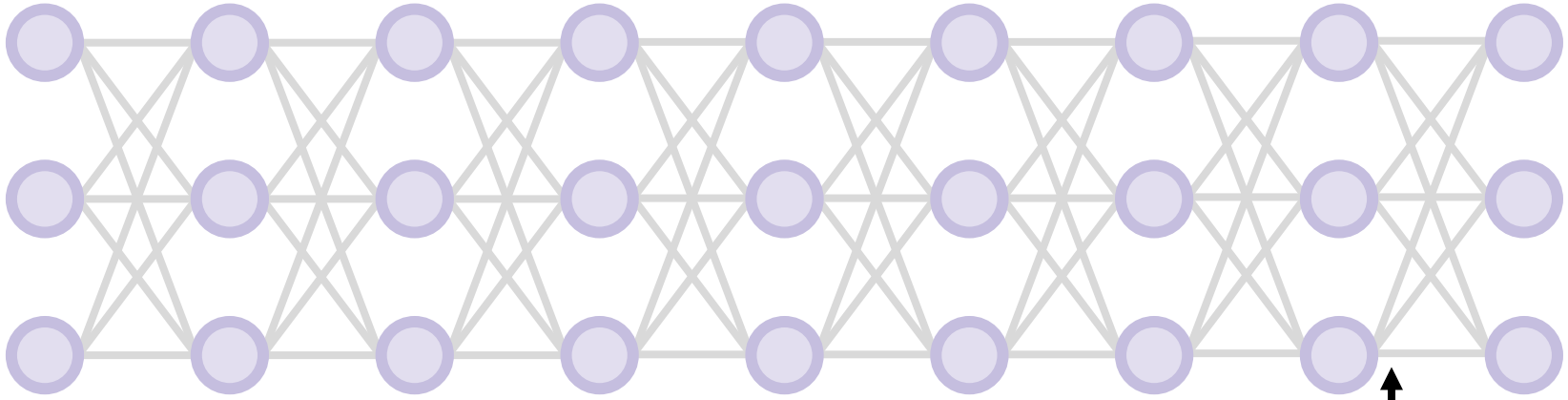


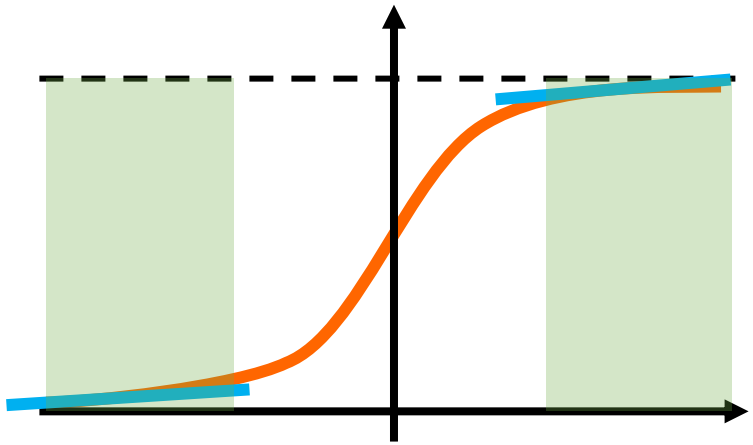


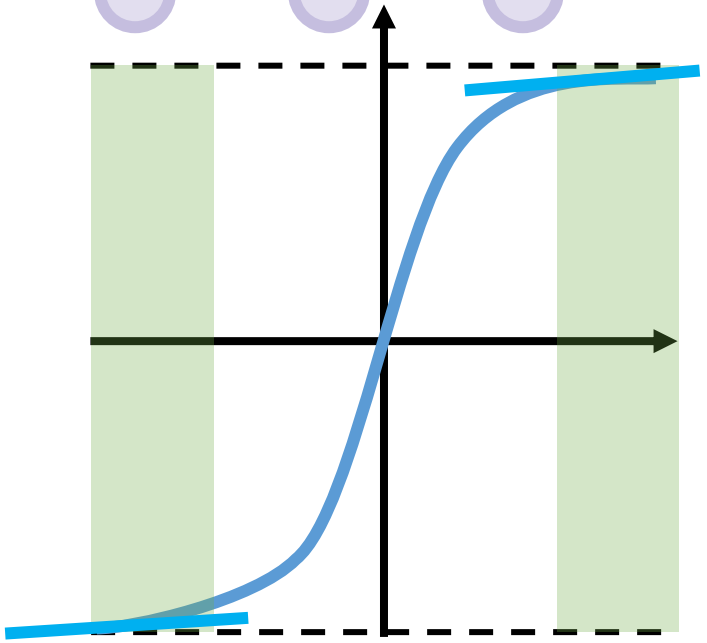


신박AI

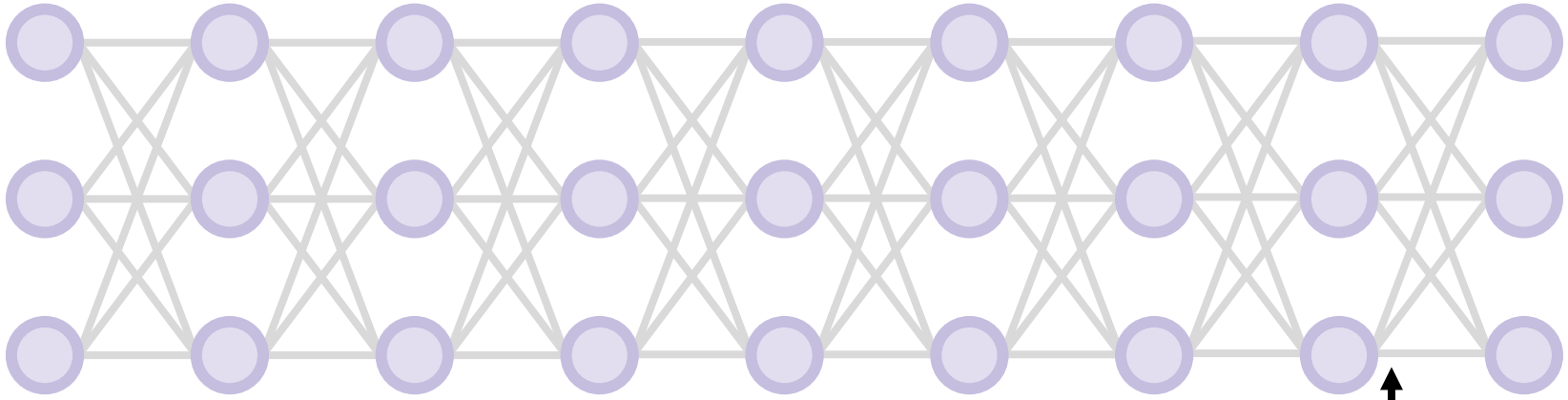
출력값이 양극단 (0 또는 1로)으로 가게 되는 성향이 있고,

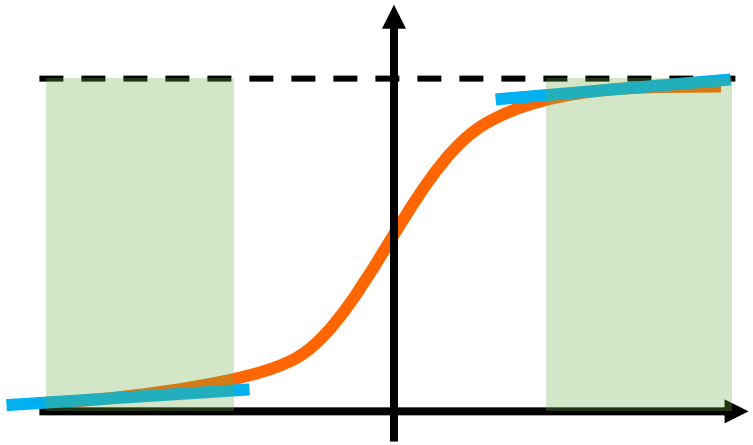


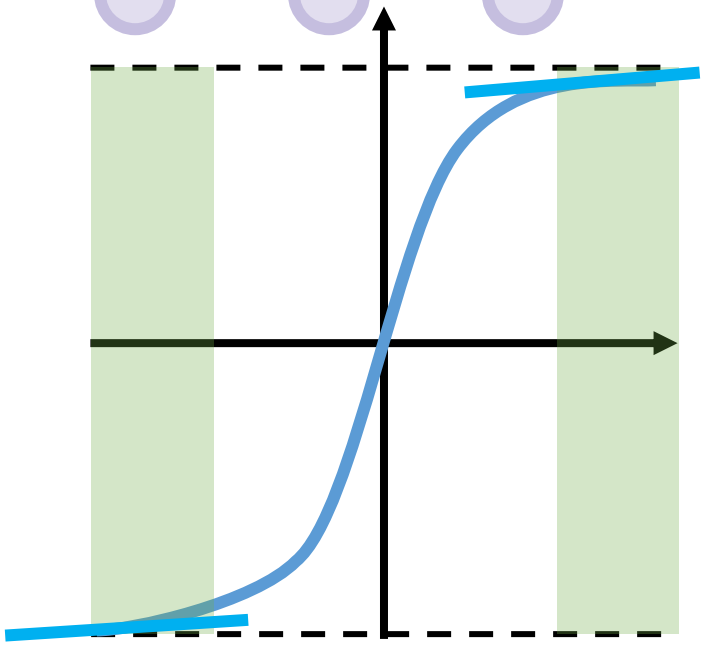




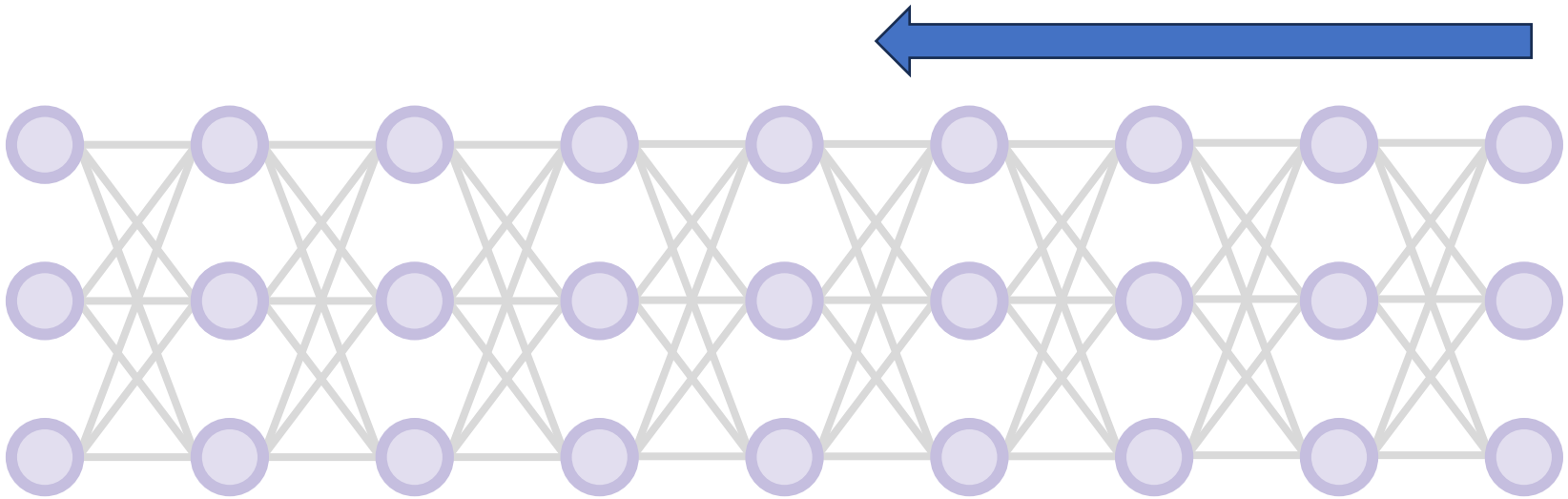
출력값이 양극단으로 갈 수록 입력값의 차이가 미미해지는 경향이 생기게 됩니다.



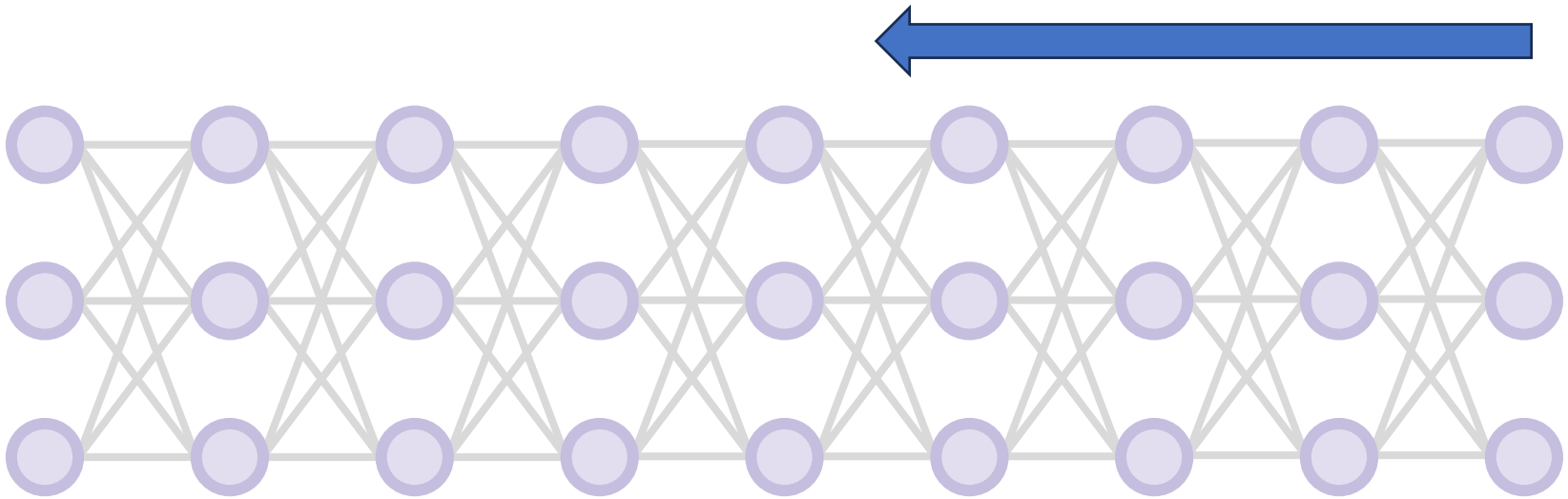




뿐만 아니라, 오차로부터 시작된 역전파의 그래디언트가 초기층으로 내려갈 수록,



체인룰에 의해서 곱해져야할 항들이 점점 많아지게 되고,



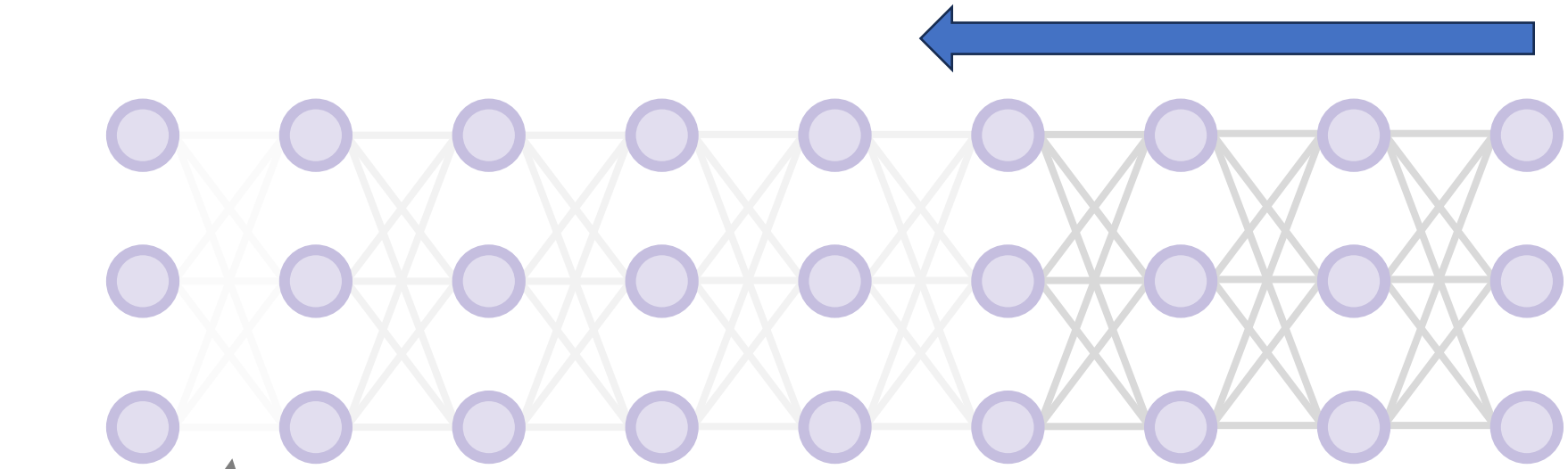
$$\frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial b}\cdot\frac{\partial b}{\partial c} \leftarrow \frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial b} \leftarrow \frac{\partial L}{\partial a}$$

$$\frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial b}\cdot\frac{\partial b}{\partial c}\cdot\frac{\partial c}{\partial d}$$

$$\frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial b}\cdot\frac{\partial b}{\partial c}\cdot\frac{\partial c}{\partial d}\cdot\frac{\partial d}{\partial e}\cdot\frac{\partial e}{\partial f}\cdot\frac{\partial f}{\partial g}\cdot\frac{\partial g}{\partial h}$$

신박AI

그래서 층이 깊어질 수록 초기층에 가까운 가중치들의 기울기가 거의 0에 가까워지는 현상이 발생하게 됩니다.



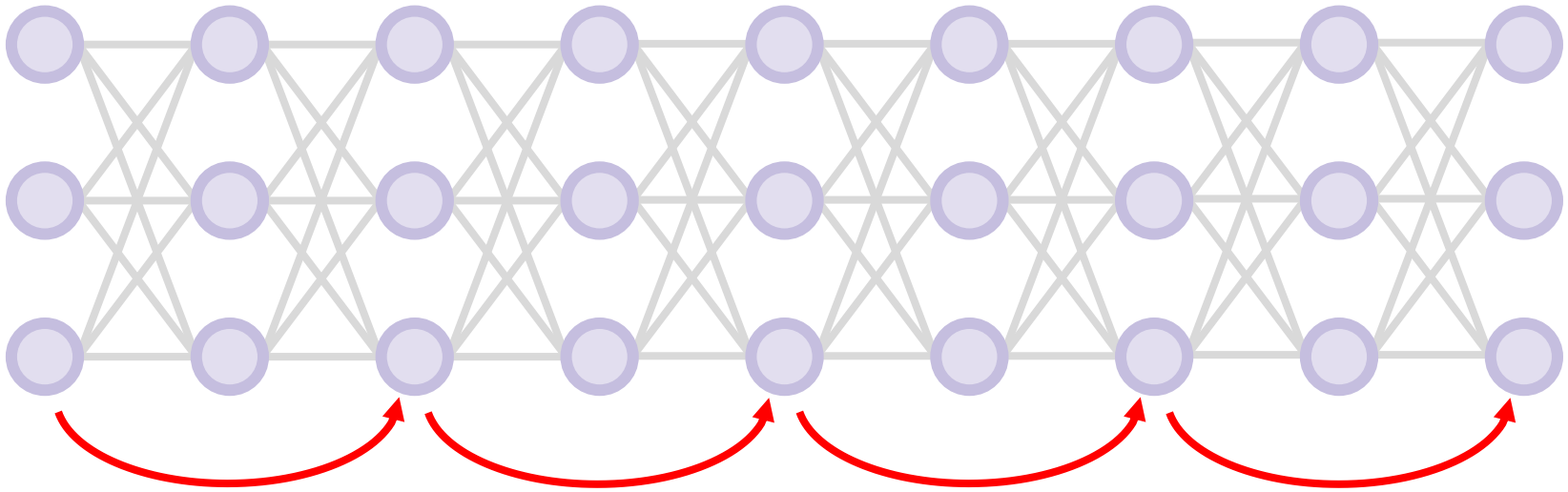
$$\frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial b}\cdot\frac{\partial b}{\partial c}\leftarrow\frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial b}\leftarrow\frac{\partial L}{\partial a}$$

$$\frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial b}\cdot\frac{\partial b}{\partial c}\cdot\frac{\partial c}{\partial d}$$

$$\frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial b}\cdot\frac{\partial b}{\partial c}\cdot\frac{\partial c}{\partial d}\cdot\frac{\partial d}{\partial e}\cdot\frac{\partial e}{\partial f}\cdot\frac{\partial f}{\partial g}\cdot\frac{\partial g}{\partial h}$$

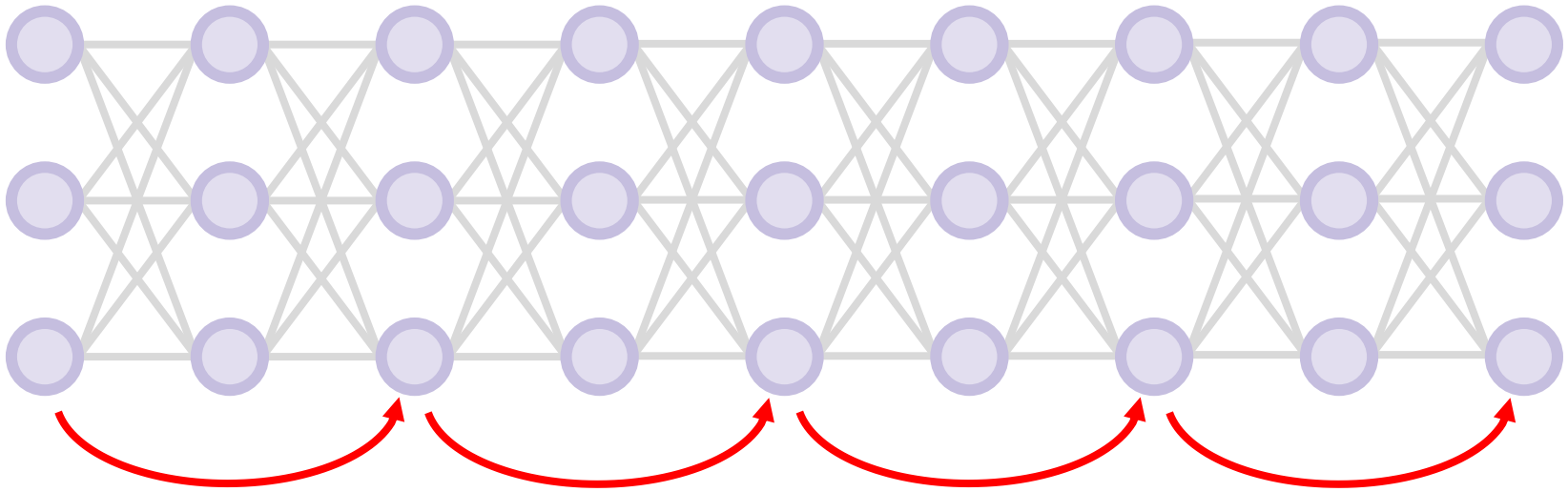
신박AI

이런 현상을 극복하기 위해 개발된 방법이 바로 skip-connection 건너뛰기 혹은 Residual connection 잔차 연결 방법입니다.



신박AI

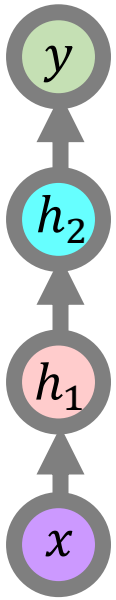
ResNet이라는 이름도 Residual connection을 사용한다하여,
Residual Neural Network, 줄여서 ResNet이라 쓰는 것입니다.



자 그러면 우선 이 skip-connection 건너뛰기 연결이 어떻게 기울기 소실 문제를 줄여나가는지, 간단한 손계산을 통해 알아보도록 하겠습니다.

간단한 계산을 위해, 간단한 모델을 가정하도록 하겠습니다.

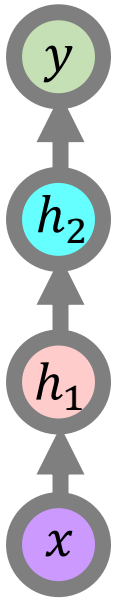
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



신박AI

다음처럼, 입력층, 은닉층1, 은닉층2, 출력층 각 하나의 노드만을 갖는 간단한 신경망을 가정해봅시다

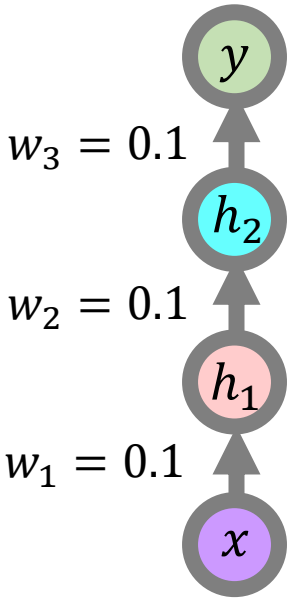
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



신박AI

편의상 각 가중치들 값은 다 0.1로 가정하도록 하겠습니다.

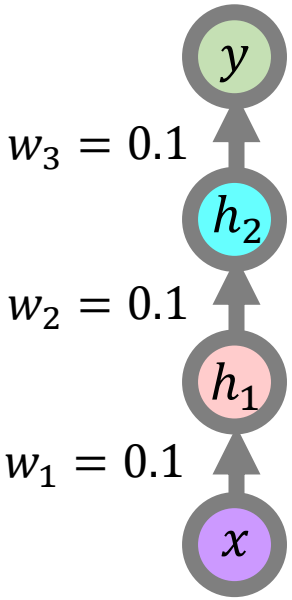
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



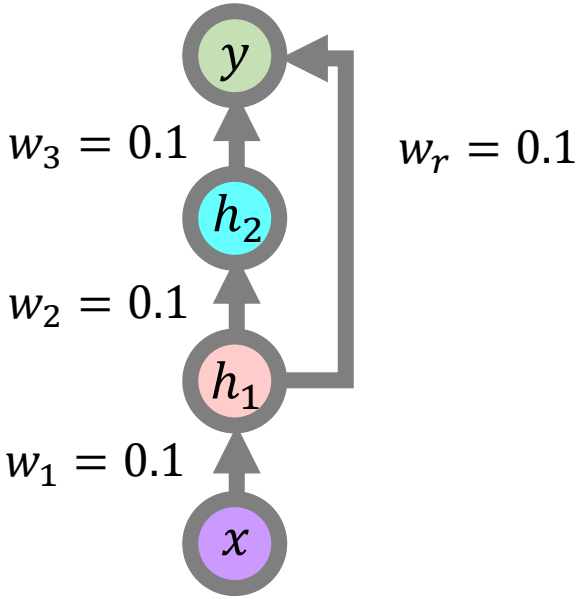
신박AI

그리고 시나리오2는 skip connection이 있는 잔차 신경망입니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



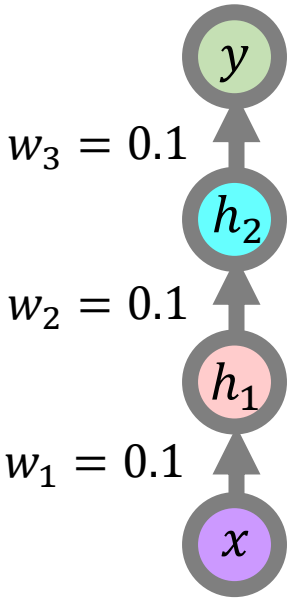
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



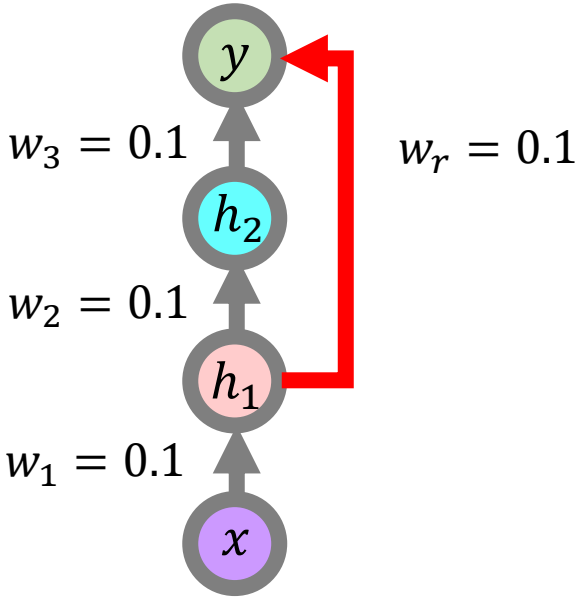
신박AI

시나리오1과 모든 조건이 동일하고, 잔차연결만 추가되었습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



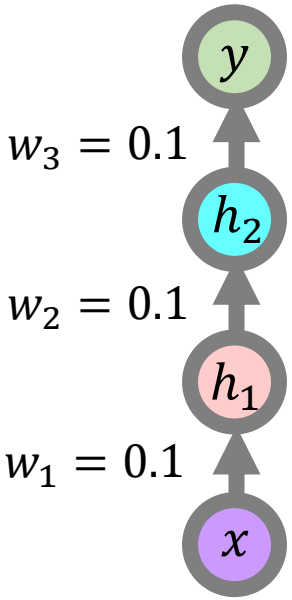
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



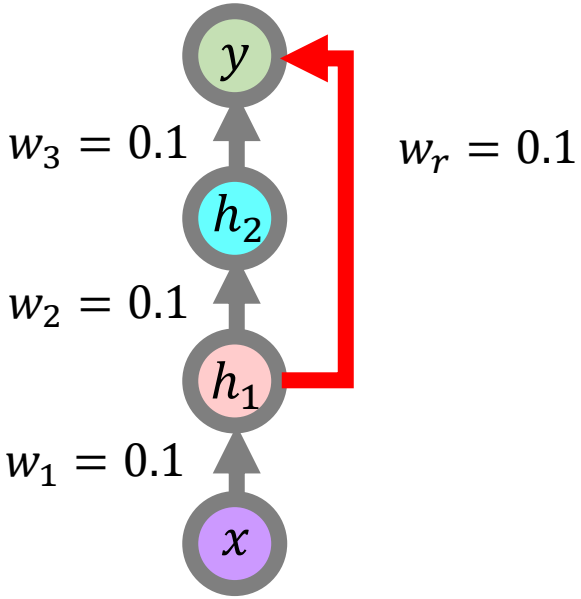
신박AI

즉 이 두 시나리오에서 비교하고자 하는 것은,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



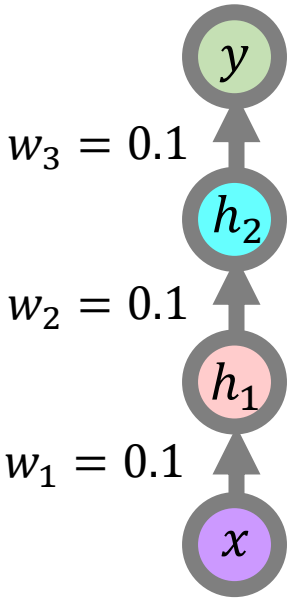
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



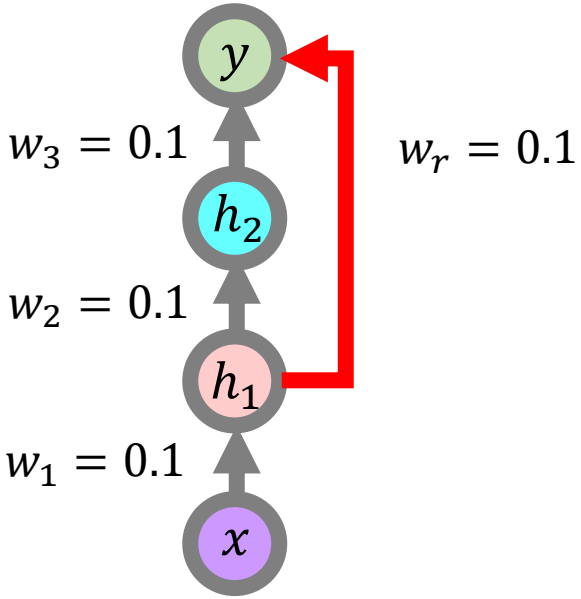
신박AI

모든 조건이 동일한데, 잔차연결만 했을 경우 그래디언트가 어떻게 달라지는지를 살펴보고자 하는 것입니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



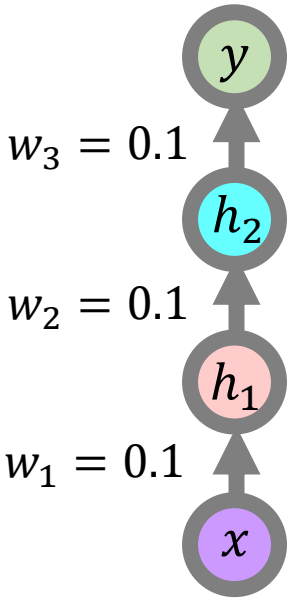
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



신박AI

그러면 시나리오1부터 시작해보도록 하겠습니다.

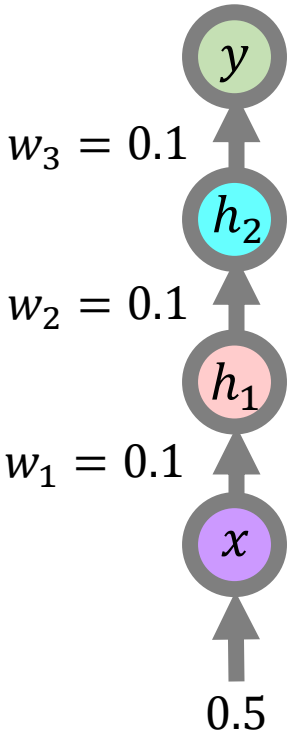
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



신박AI

입력값이 0.5라고 했을 때,

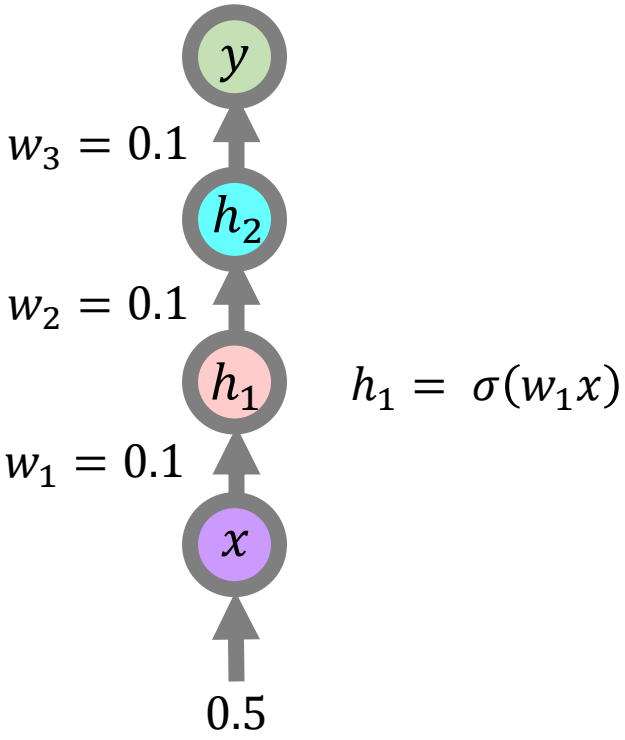
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



신박AI

은닉층1의 계산 공식은 다음과 같습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

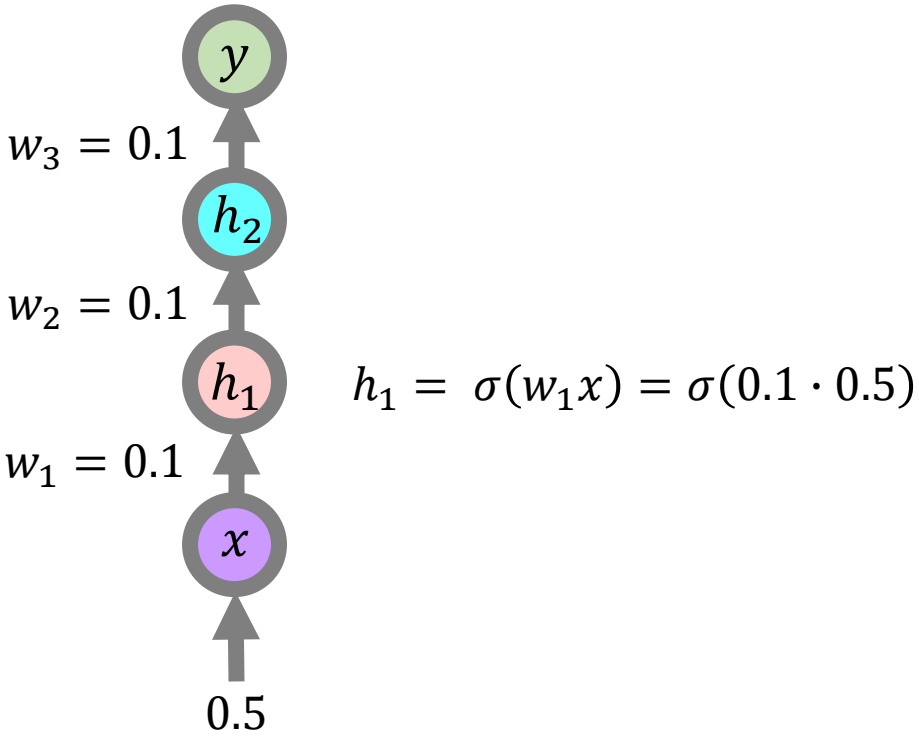


$h_1 = \sigma(w_1 x)$

신박AI

입력값과 w_1 값을 대입하고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

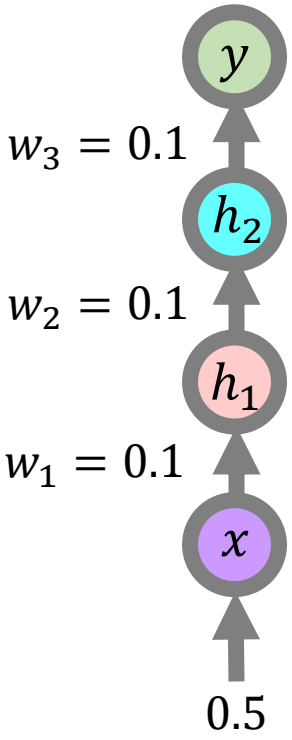


$$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5)$$

신박AI

시그모이드 활성화 함수까지 계산하면 h_1은 0.5125가 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

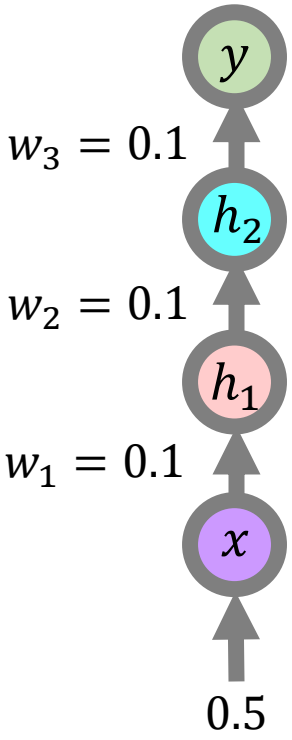


$$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$$

신박AI

그리고 은닉층2의 계산 공식은 다음과 같습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



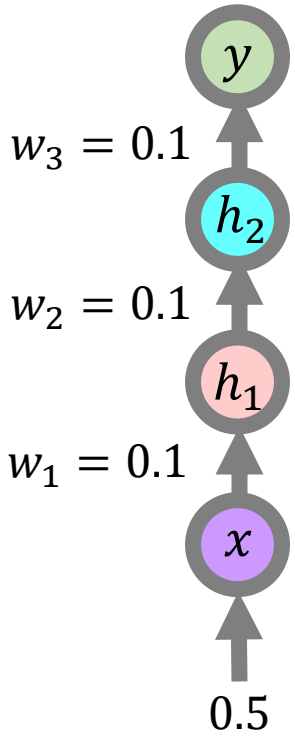
$h_2 = \sigma(w_2 h_1)$

$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$

신박AI

마찬가지로 h_1과 w_2의 값을 대입하고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



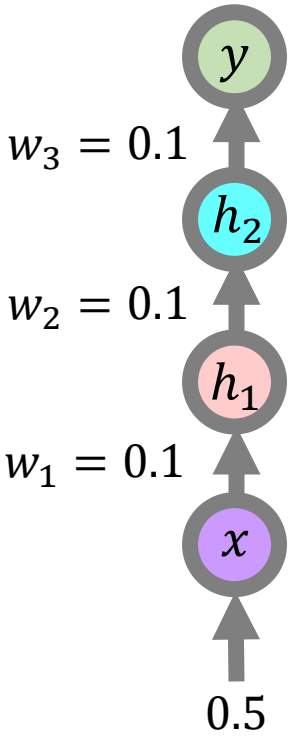
$$h_2 = \sigma(w_2 h_1) = \sigma(0.1 \cdot 0.5125)$$

$$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$$

신박AI

시그모이드 활성화 함수까지 계산하면 h_2의 값은 0.5128이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



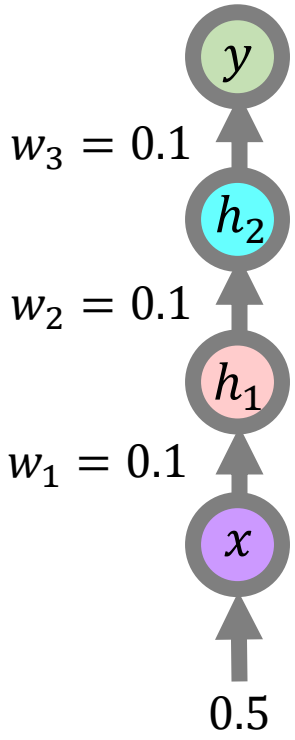
$$h_2 = \sigma(w_2 h_1) = \sigma(0.1 \cdot 0.5125) = \sigma(0.05125) \approx 0.5128$$

$$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$$

신박AI

그리고 출력층의 계산공식은 다음과 같습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



$$y = \sigma(w_3 h_2)$$

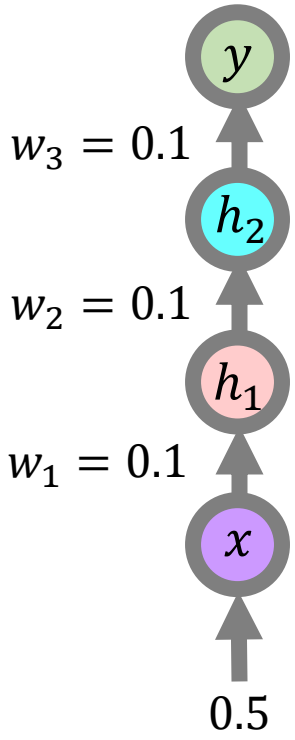
$$h_2 = \sigma(w_2 h_1) = \sigma(0.1 \cdot 0.5125) = \sigma(0.05125) \approx 0.5128$$

$$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$$

신박AI

마찬가지로 h_2과 w_3의 값을 대입하고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



$$y = \sigma(w_3 h_2) = \sigma(0.1 \cdot 0.5128)$$

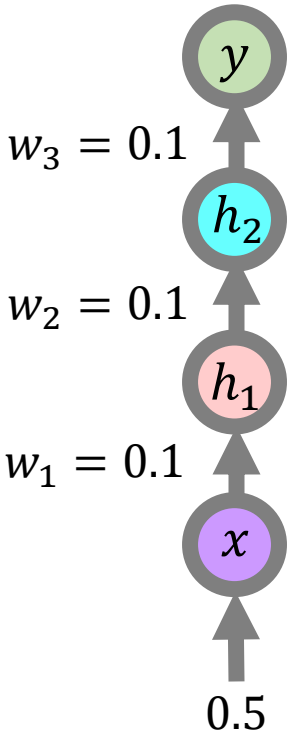
$$h_2 = \sigma(w_2 h_1) = \sigma(0.1 \cdot 0.5125) = \sigma(0.05125) \approx 0.5128$$

$$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$$

신박AI

시그모이드 활성화 함수를 계산하면, 최종 출력값 y는 0.5128이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



$$y = \sigma(w_3 h_2) = \sigma(0.1 \cdot 0.5128) = \sigma(0.05128) \approx 0.5128$$

$$h_2 = \sigma(w_2 h_1) = \sigma(0.1 \cdot 0.5125) = \sigma(0.05125) \approx 0.5128$$

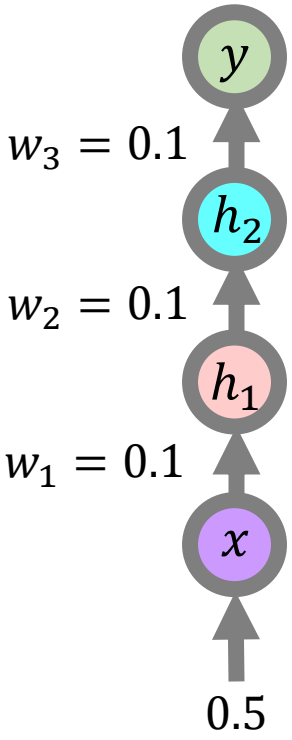
$$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$$

신박AI

그에 따른 오차는 MSE오차 공식을 사용하여,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss = (y_{true} - y)^2$$



$$y = \sigma(w_3 h_2) = \sigma(0.1 \cdot 0.5128) = \sigma(0.05128) \approx 0.5128$$

$$h_2 = \sigma(w_2 h_1) = \sigma(0.1 \cdot 0.5125) = \sigma(0.05125) \approx 0.5128$$

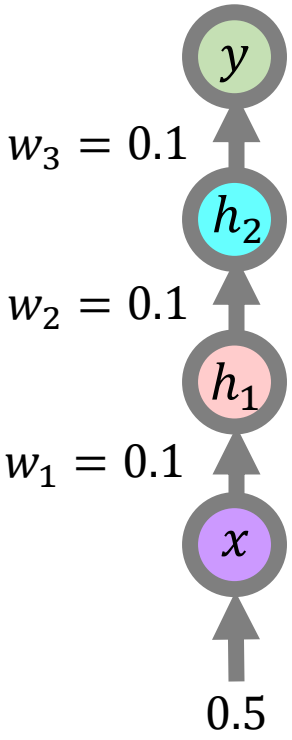
$$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$$

신박AI

오차는 다음과 같이 0.2372가 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss = (y_{true} - y)^2 = (1 - 0.5128)^2 \approx 0.2372$$



$$y = \sigma(w_3 h_2) = \sigma(0.1 \cdot 0.5128) = \sigma(0.05128) \approx 0.5128$$

$$h_2 = \sigma(w_2 h_1) = \sigma(0.1 \cdot 0.5125) = \sigma(0.05125) \approx 0.5128$$

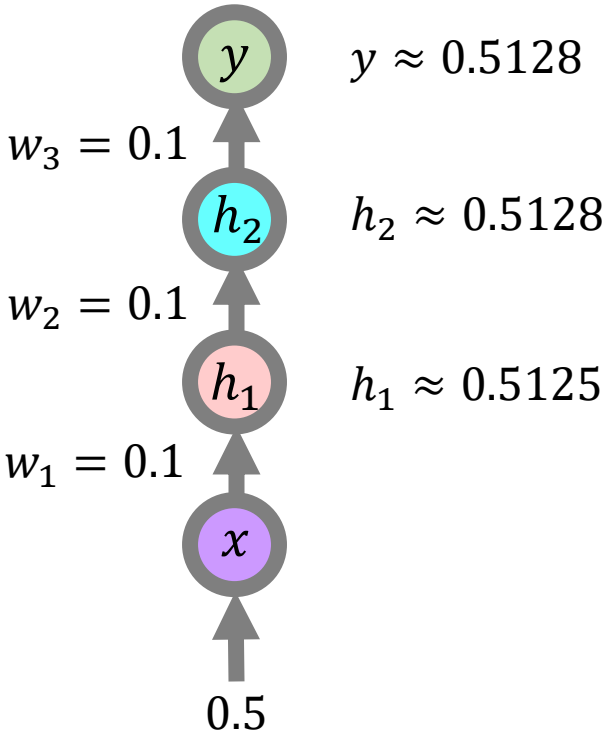
$$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$$

신박AI

자 이제는 역전파로 가중치 변화를 구해보도록 하겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

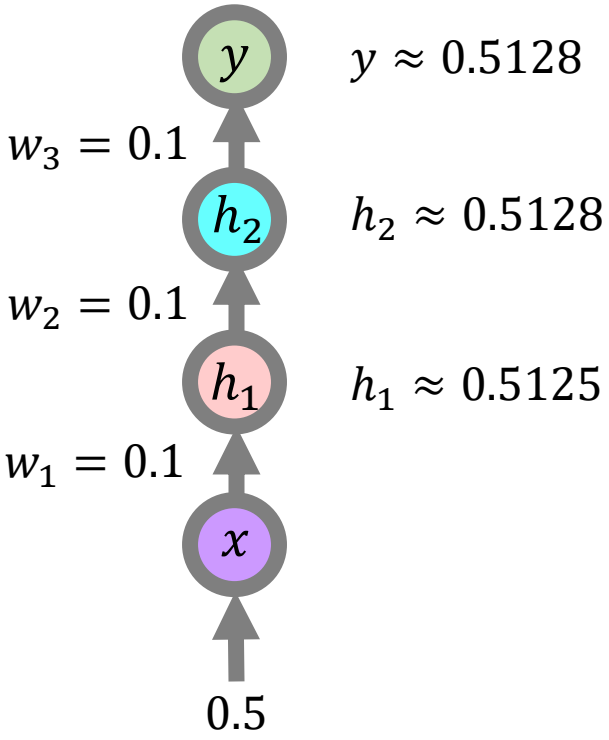
신박AI

역전파 이론 영상에서도 보았듯이, 각 기울기는 체인룰로 구할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial w_3}$$



신박AI

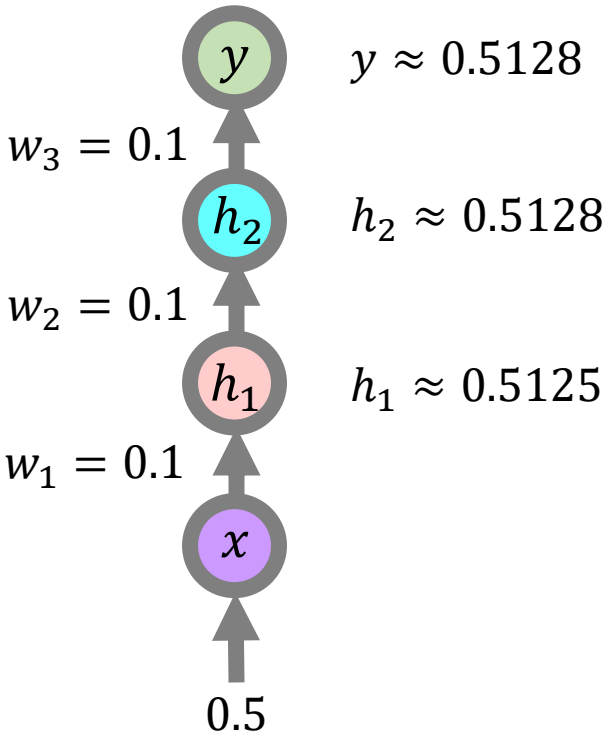
먼저 $\partial L/\partial y$는 다음과 같이 구할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial w_3}$$

$$\frac{\partial L}{\partial y} = 2(y - y_{true}) = 2(0.5128 - 1) = -0.9744$$



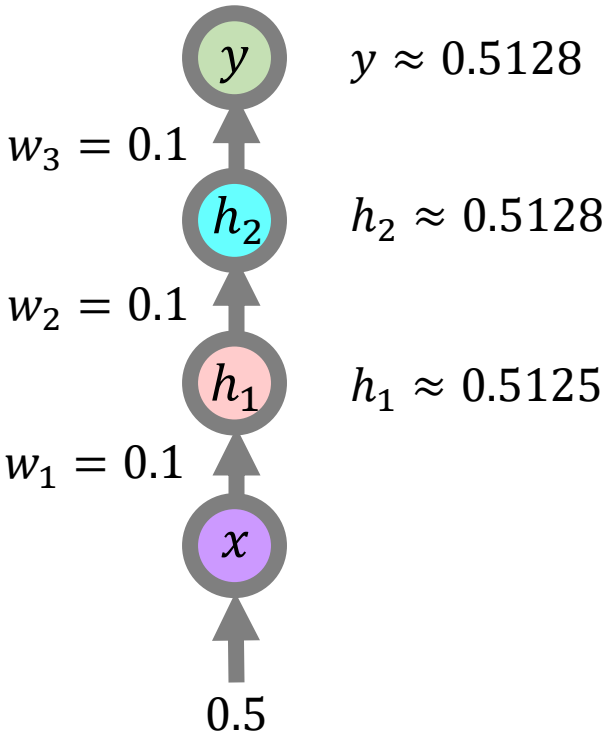
신박AI

$\partial y/\partial(w_3 h_2)$는 다음과 같이 구할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial w_3}$$



$$\frac{\partial L}{\partial y} = 2(y - y_{true}) = 2(0.5128 - 1) = -0.9744$$

$$\frac{\partial y}{\partial (w_3 h_2)} = \sigma'(w_3 h_2) = \mathrm{y}(1 - \mathrm{y}) = 0.5128(1 - 0.5128) \approx 0.2498$$

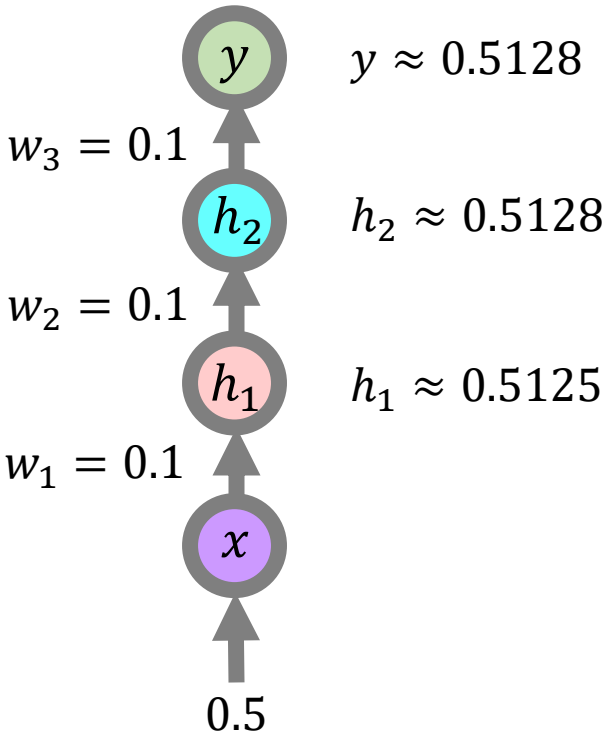
신박AI

여기에서 y는 $\sigma(w_3 h_2)$ 이기 때문에 시그모이드 미분 공식에 의하여, $y(1-y)$ 로 바뀌는 것입니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial w_3}$$



$$\frac{\partial L}{\partial y} = 2(y - y_{true}) = 2(0.5128 - 1) = -0.9744$$

$$\frac{\partial \sigma(w_3 h_2)}{\partial (w_3 h_2)} = \sigma'(w_3 h_2) = y(1-y) = 0.5128(1 - 0.5128) \approx 0.2498$$

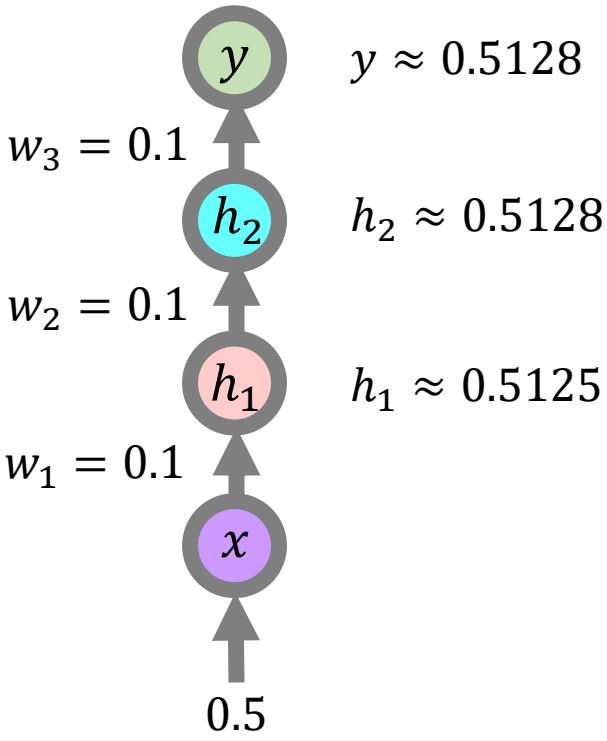
$$\because \sigma'(T) = \sigma(T)\big(1 - \sigma(T)\big)$$

신박AI

또 $\partial(w_3 h_2)/\partial w_3$는 미분에 의해 w_3가 없어져서 다음과 같이 계산됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial w_3}$$

$$\frac{\partial L}{\partial y} = 2(y - y_{true}) = 2(0.5128 - 1) = -0.9744$$

$$\frac{\partial y}{\partial (w_3 h_2)} = \sigma'(w_3 h_2) = \mathrm{y}(1 - \mathrm{y}) = 0.5128(1 - 0.5128) \approx 0.2498$$

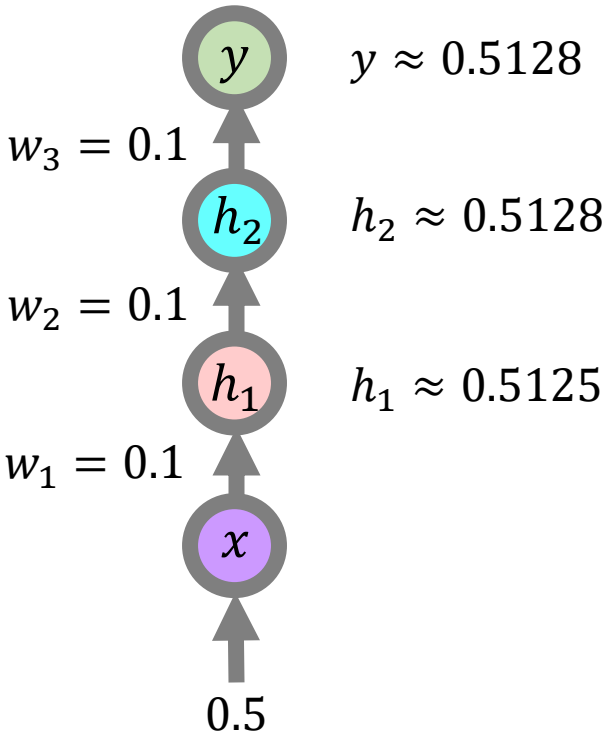
$$\frac{\partial (w_3 h_2)}{\partial w_3} = h_2 \approx 0.5128$$

신박AI

이제 각각의 값들을 넣으면, $\partial L/\partial w_3$은 -0.1248이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial w_3} = -0.9744 \cdot 0.2498 \cdot 0.5128 = -0.1248$$

$$\frac{\partial L}{\partial y} = 2(y - y_{true}) = 2(0.5128 - 1) = -0.9744$$

$$\frac{\partial y}{\partial (w_3 h_2)} = \sigma'(w_3 h_2) = \mathrm{y}(1 - \mathrm{y}) = 0.5128(1 - 0.5128) \approx 0.2498$$

$$\frac{\partial (w_3 h_2)}{\partial w_3} = h_2 \approx 0.5128$$

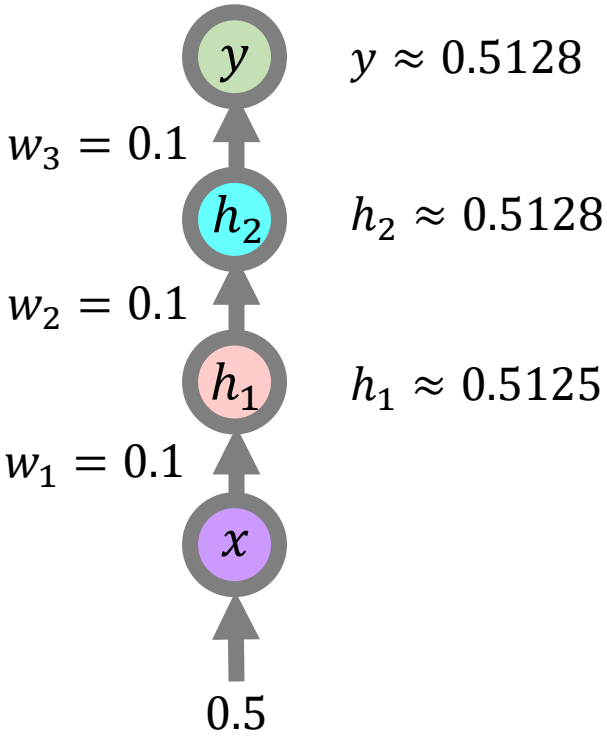
신박AI

이제 각각의 값들을 넣으면, $\partial L/\partial w_3$은 -0.1248이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

$$\frac{\partial L}{\partial w_3} = -0.1248$$

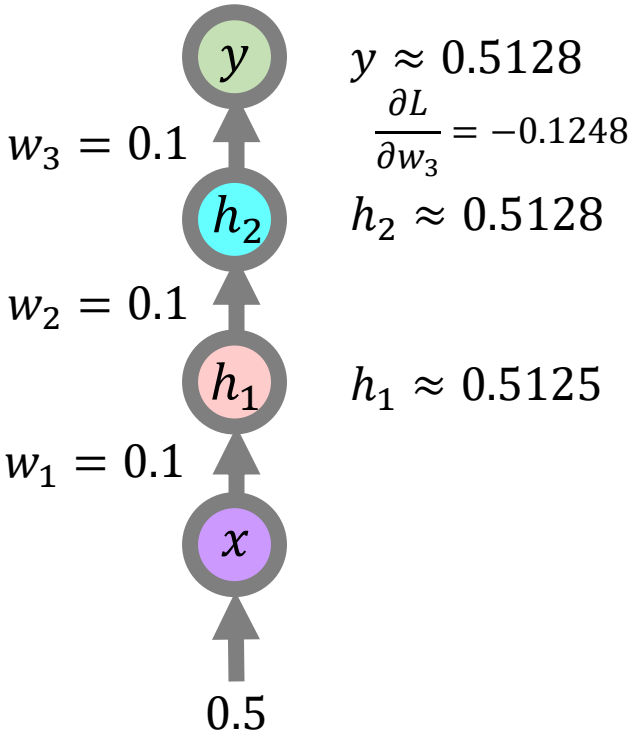


신박AI

이제 각각의 값들을 넣으면, $\partial L/\partial w_3$은 -0.1248이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

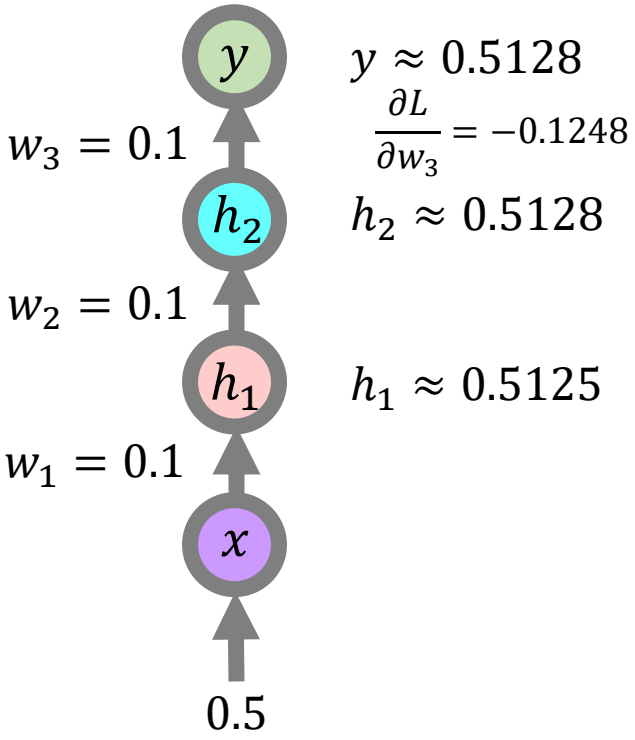
신박AI

이제 $\partial L/\partial w_2$를 계산할 차례입니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

$$\frac{\partial L}{\partial w_2} =$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

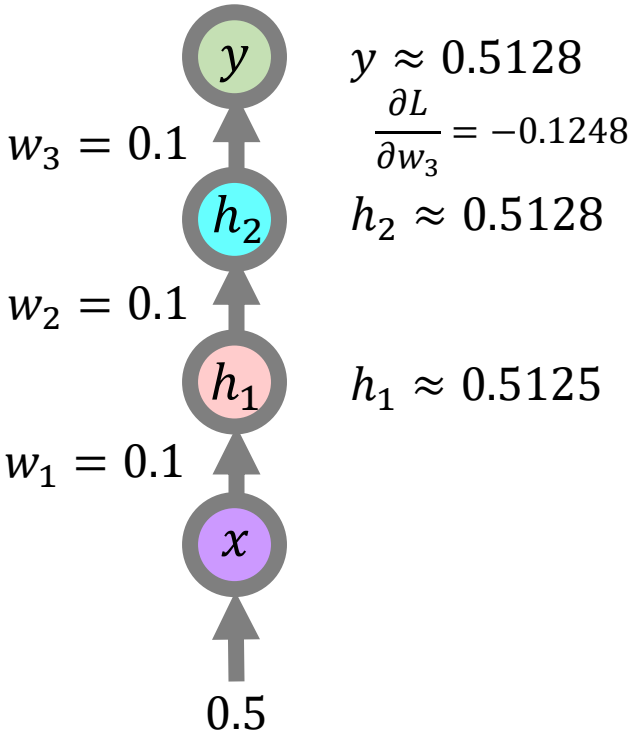
신박AI

$\partial L/\partial w_2$는 체인룰에 의하여 다음과 같이 전개할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

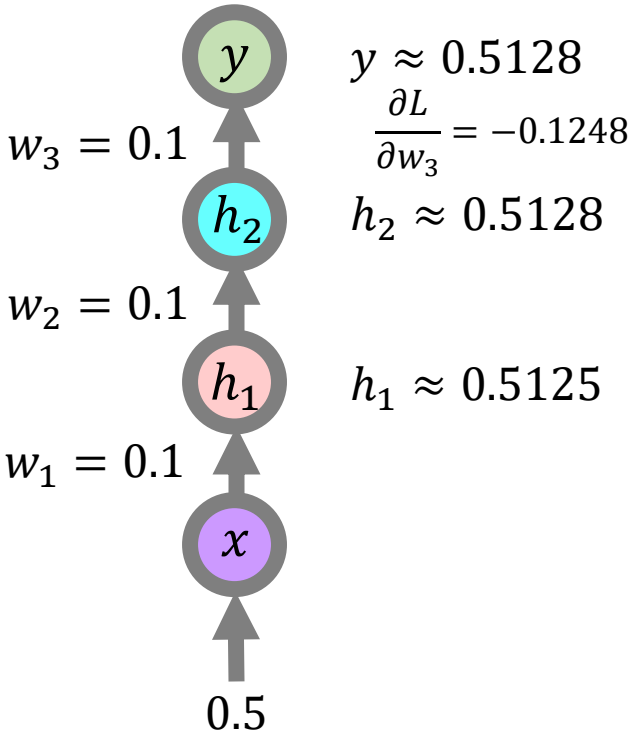
$h_1 \approx 0.5125$

신박AI

그리고 이 부분은 앞에서 이미 계산된 부분이므로 재사용 할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

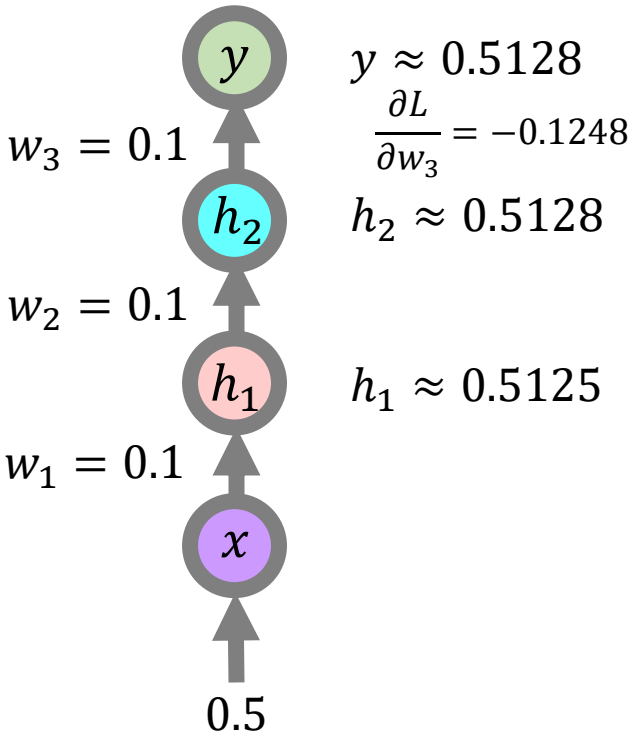
$$= -0.9744 \cdot 0.2498 \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

신박AI

그리고 이 부분은 미분으로 h_2가 사라지고 w_3 만 남게 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

$$= -0.9744 \cdot 0.2498 \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

신박AI

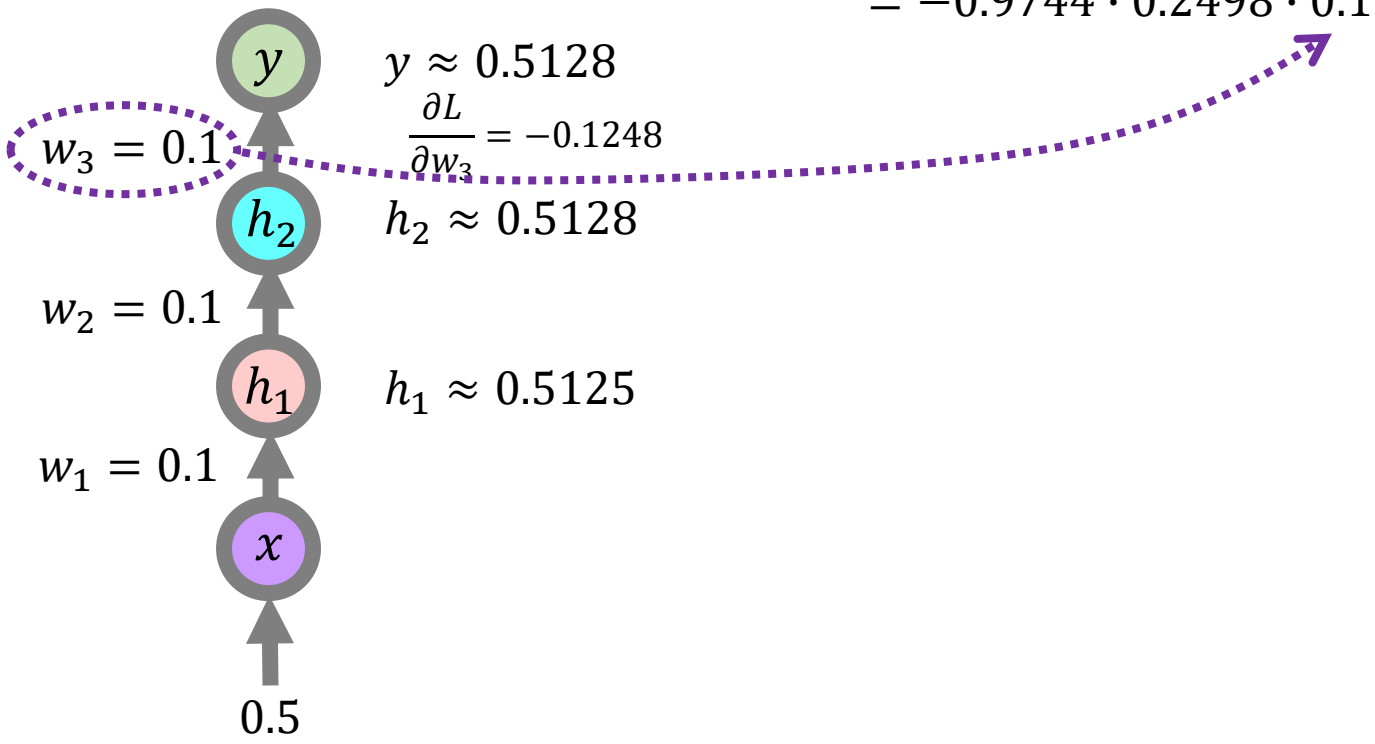
그러면 이렇게 바꾸어 쓸 수가 있고..

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

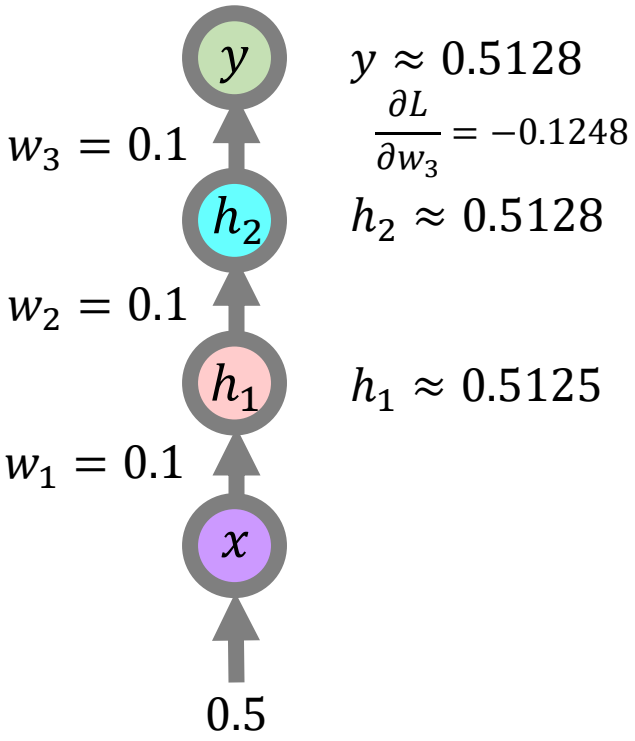


신박AI

그리고 네번째 항은, h_2가 $w_2 h_1$의 시그모이드 값이기 때문에,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

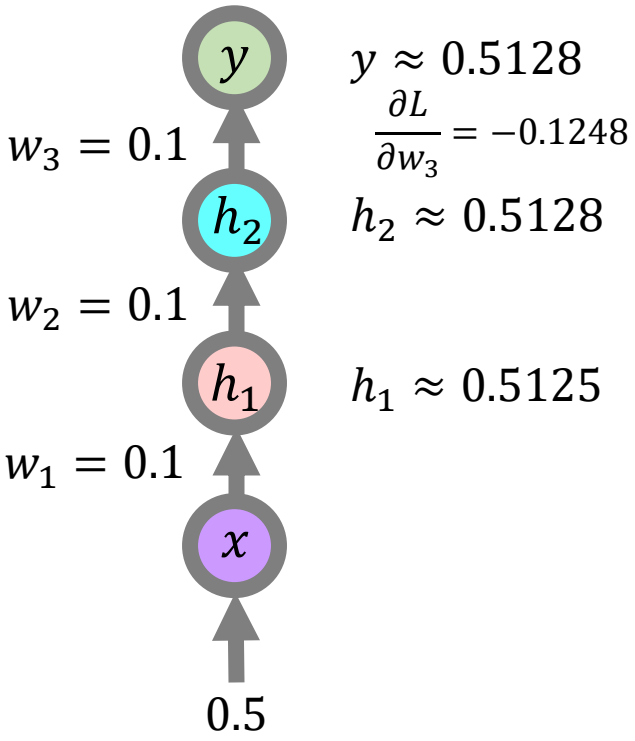
$$\because \sigma'(w_2 h_1) = \sigma(w_2 h_1)\big(1 - \sigma(w_2 h_1)\big)$$

신박AI

다음과 같이 바꿀 수 있고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot h_2(1 - h_2) \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

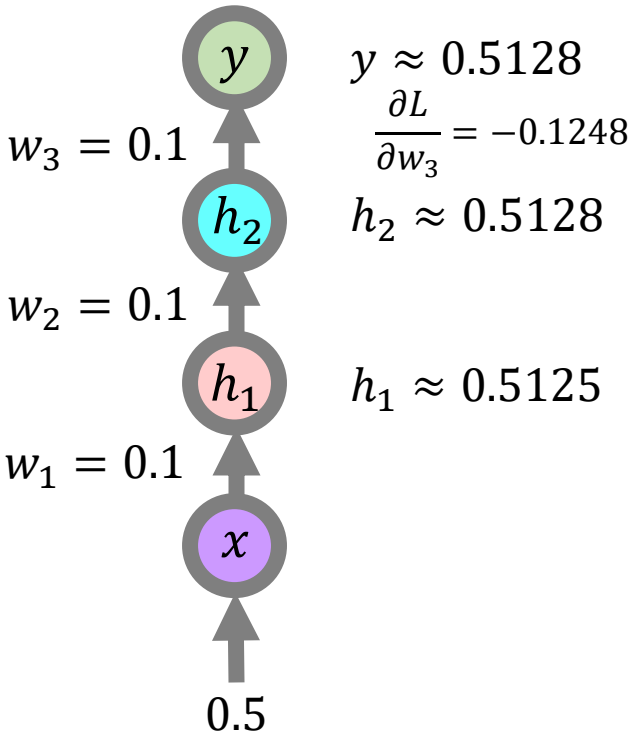
$$\because \sigma'(w_2 h_1) = \sigma(w_2 h_1)\big(1 - \sigma(w_2 h_1)\big)$$

신박AI

h_2 값을 대입하여 계산하면 0.2498이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

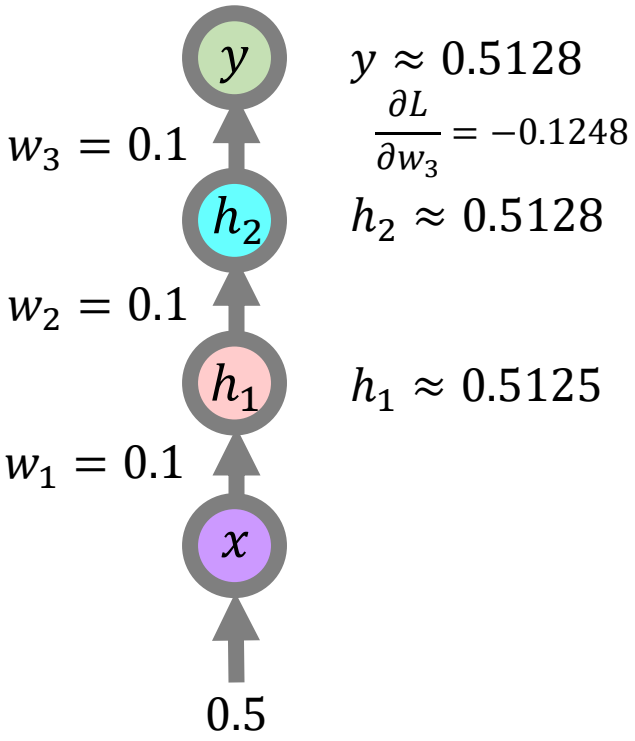
$$\because \sigma'(w_2 h_1) = \sigma(w_2 h_1)\big(1 - \sigma(w_2 h_1)\big)$$

신박AI

그리고 마지막 항은 미분에 의해서 w_2 가 사라지고 h_1만 남게 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

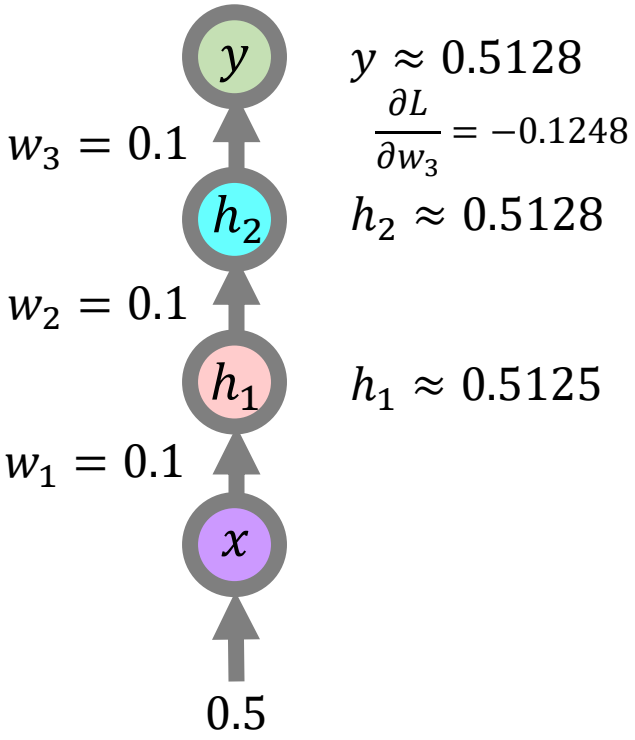
$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

신박AI

그러면 마지막 항까지 숫자를 넣어서 계산하면..

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

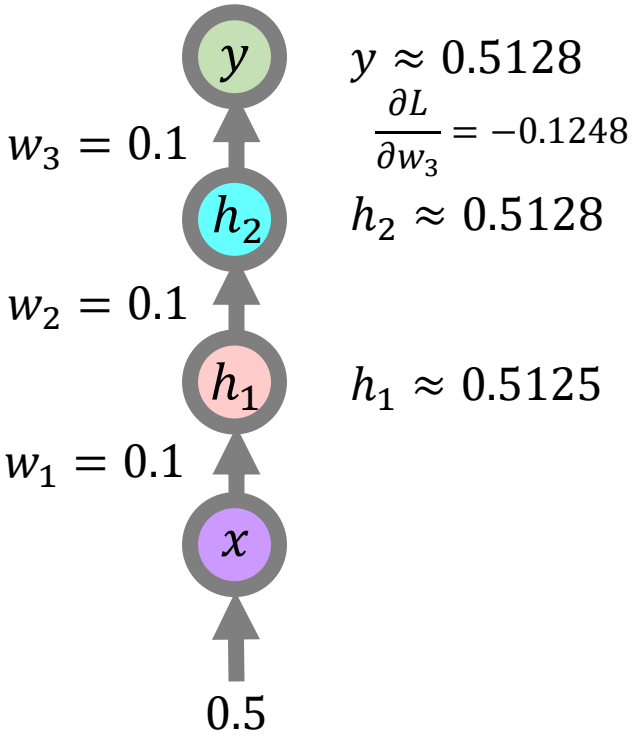
$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot 0.5125$$

신박AI

$\partial L/\partial w_2$ 의 값은 대략 -0.00311 이 나옵니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot 0.5125$$

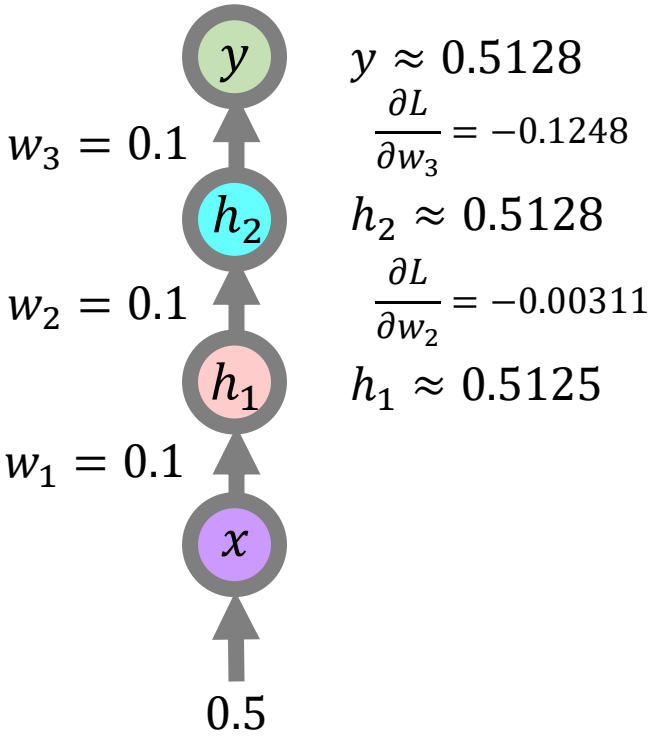
$$= -0.00311$$

신박AI

이렇게 귀퉁이에 다시 기록을 해두고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

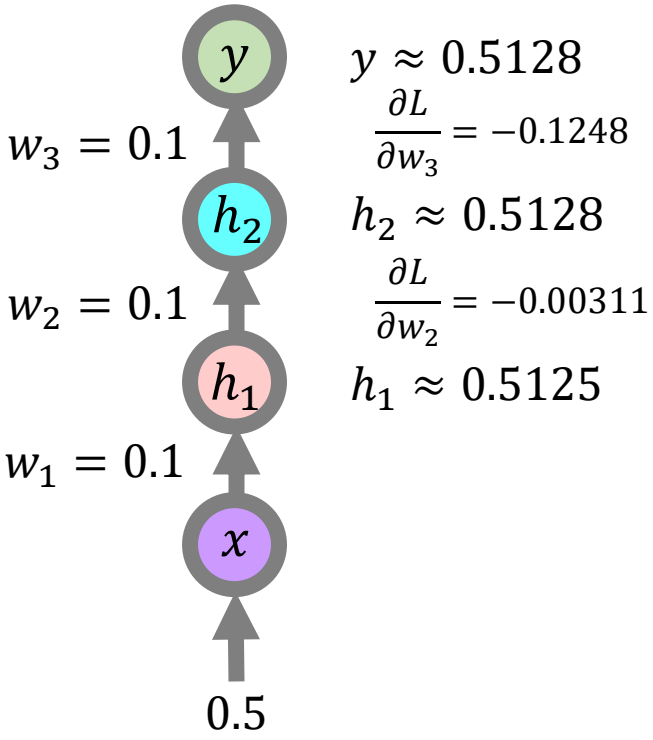
신박AI

$\partial L/\partial w_1$을 계산해보도록 하겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

$\frac{\partial L}{\partial w_1}$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

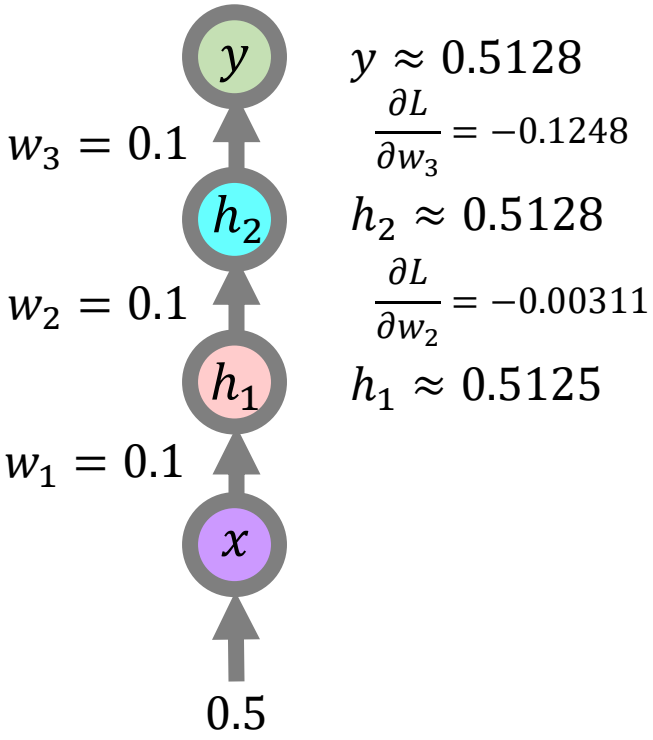
신박AI

$\partial L/\partial w_1$ 은 체인룰에 의해서 다음과 같이 전개됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

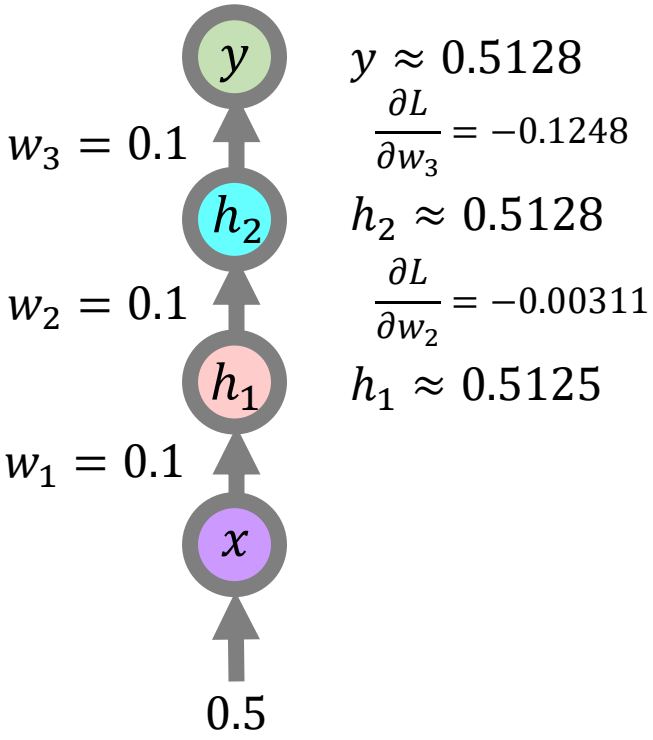
$h_1 \approx 0.5125$

신박AI

그런데 사실 우리가 좀 전에 $\partial L/\partial w_2$계산할 때, 이미 여기까지 다 계산을 했었기 때문에,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

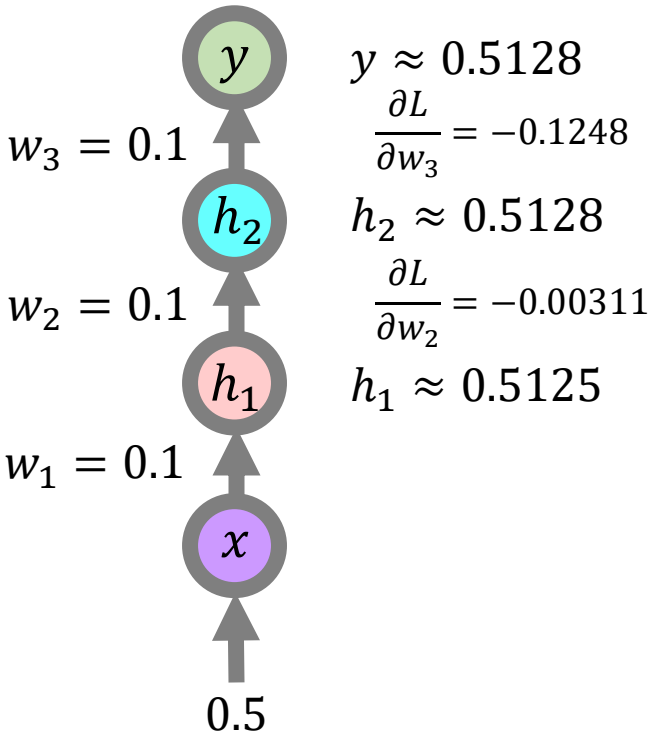
$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial w_2}$$

신박AI

그 값을 그대로 재활용하면 수월합니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

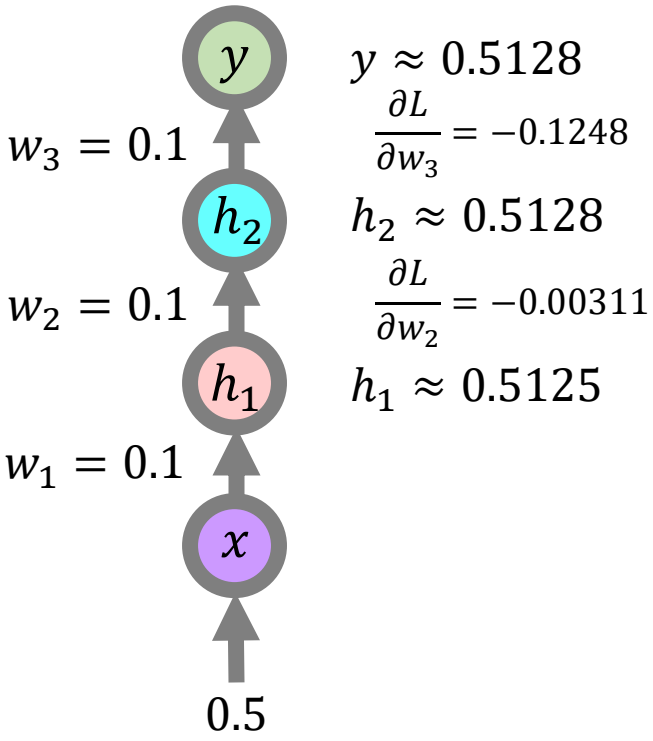
$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

신박AI

그러면 이렇게 간단히 줄일 수 있고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

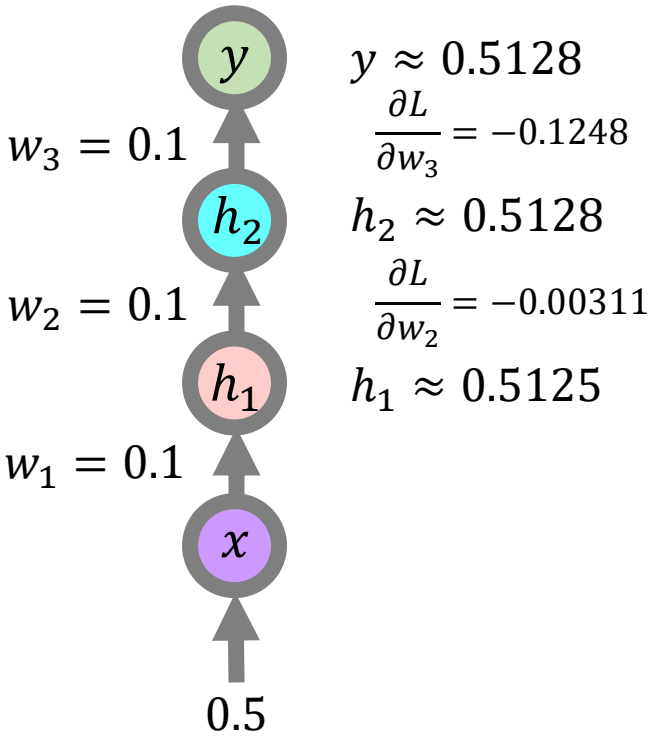
$$= -0.00608 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

신박AI

그리고 h_1은 미분에 의해서 w_2로 간단히 바꿀수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

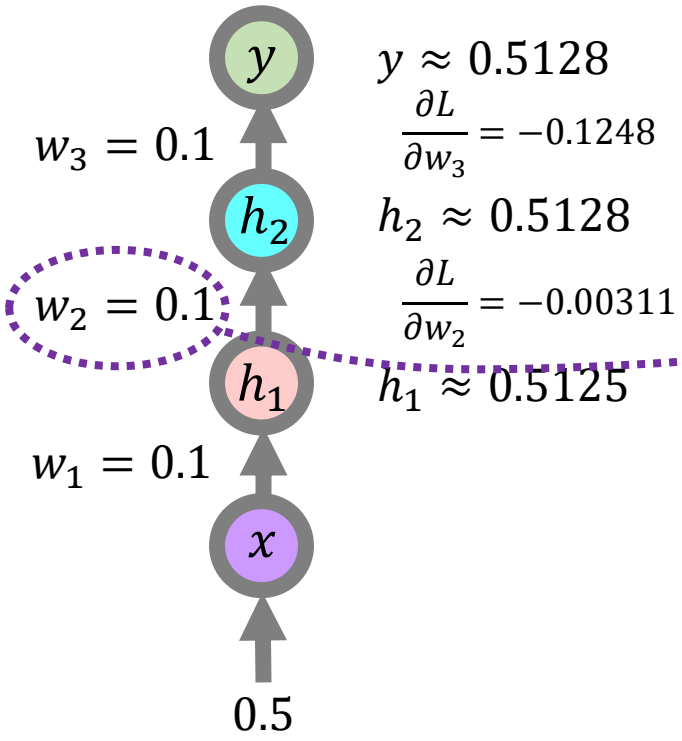
$$= -0.00608 \cdot \cancel{\frac{\partial (w_2 h_1)}{\partial h_1}} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

신박AI

그리고 값을 대입하면, 다음과 같습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

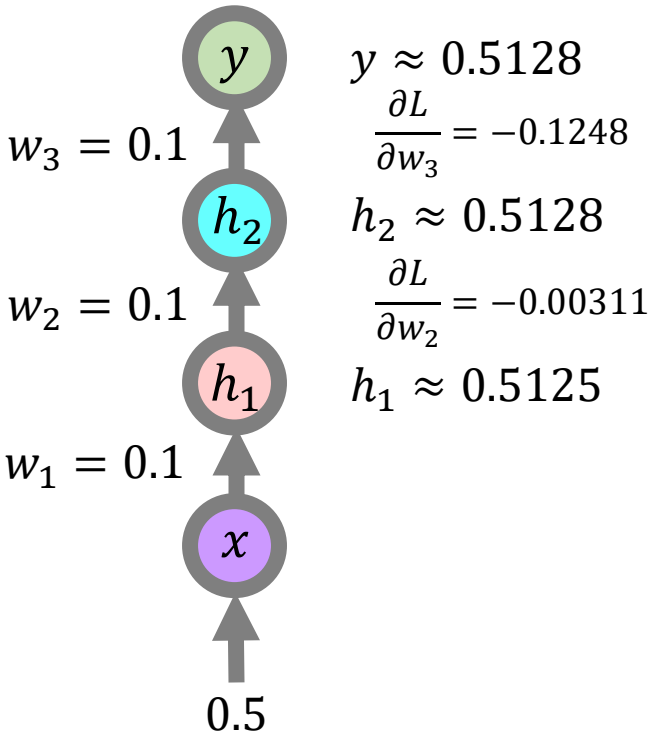
$$= -0.00608 \cdot 0.1 \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

신박AI

그리고 네번째 항은, h_1이 $w_1 x$의 시그모이드 값이기 때문에,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

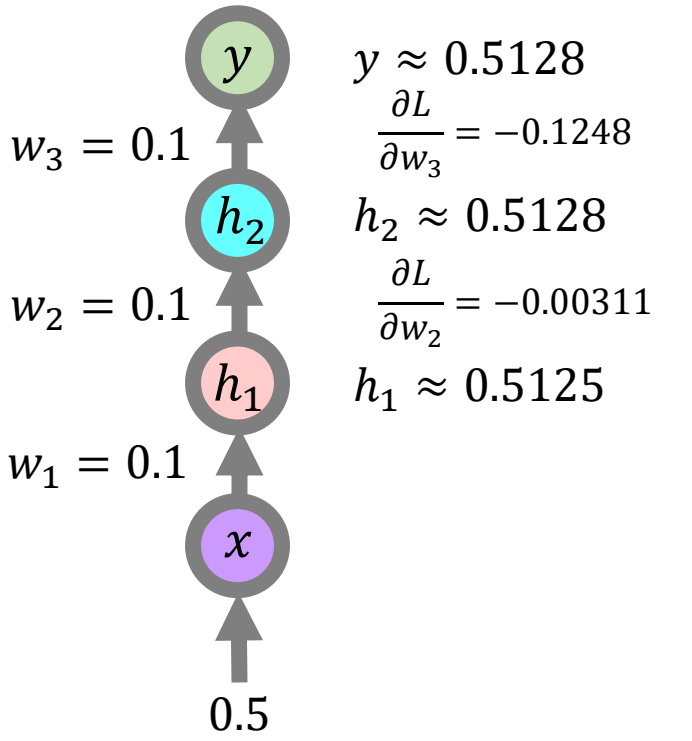
$$= -0.00608 \cdot 0.1 \frac{\partial h_1}{\partial (w_1 x)} \frac{\partial (w_1 x)}{\partial w_1}$$

신박AI

다음과 같이 바꿀 수 있고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.00608 \cdot 0.1 \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

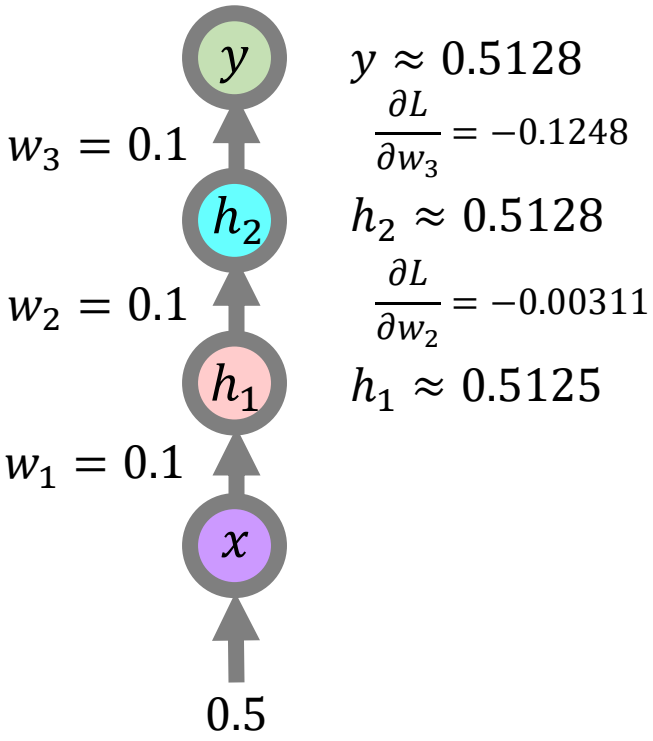
$$= -0.00608 \cdot 0.1 \cdot h_1 (1 - h_1) \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

신박AI

h_1 에 0.5125를 대입하여 계산하면 다음 값이 나옵니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.00608 \cdot 0.1 \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

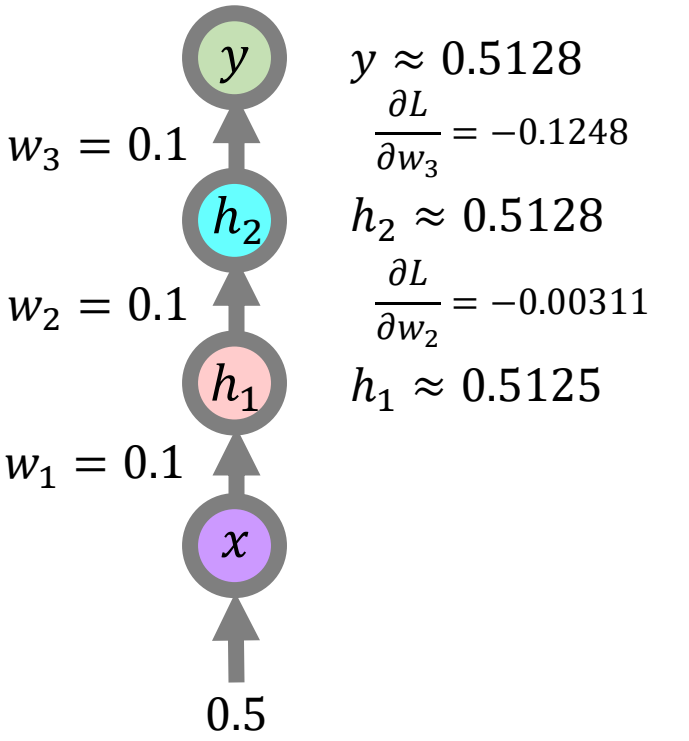
$$= -0.00608 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

신박AI

마지막 항은 w_1의 미분에 의해서, 간단히 x가 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.00608 \cdot 0.1 \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

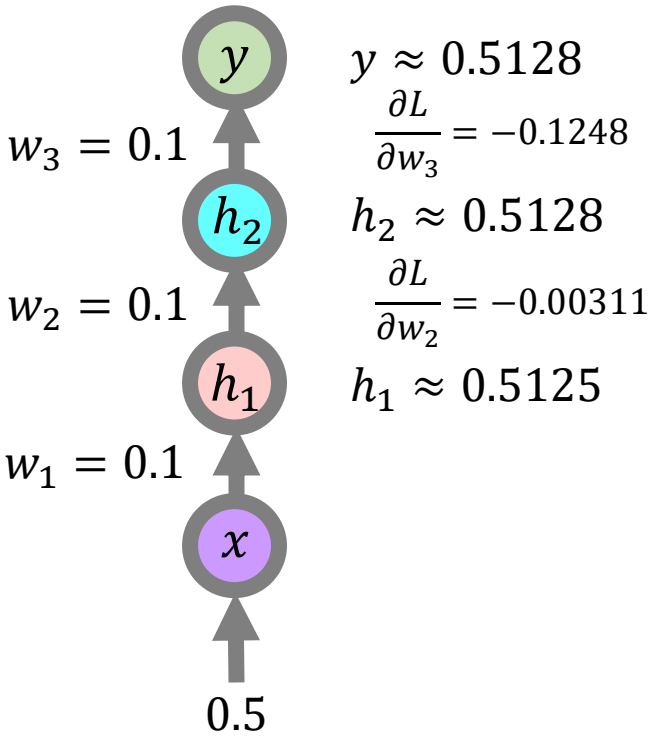
$$= -0.00608 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

신박AI

값으로 바꾸려면 다음과 같이 0.5를 넣으면 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.00608 \cdot 0.1 \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

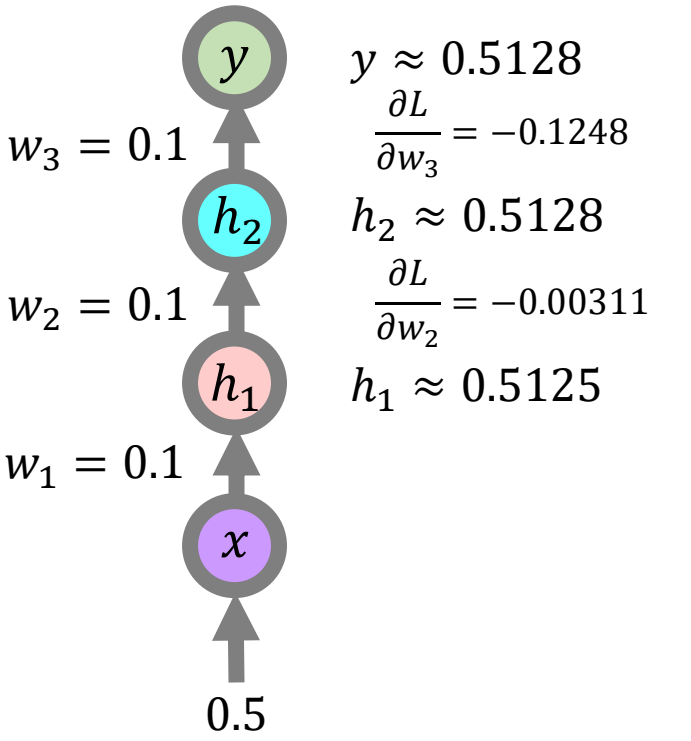
$$= -0.00608 \cdot 0.1 \cdot 0.2498 \cdot 0.5$$

신박AI

그러면 최종 $\partial L/\partial w_1$ 값은 -0.000076이 나옵니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2)} \cdot \frac{\partial (w_3 h_2)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.9744 \cdot 0.2498 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

$$= -0.00608 \cdot 0.1 \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$

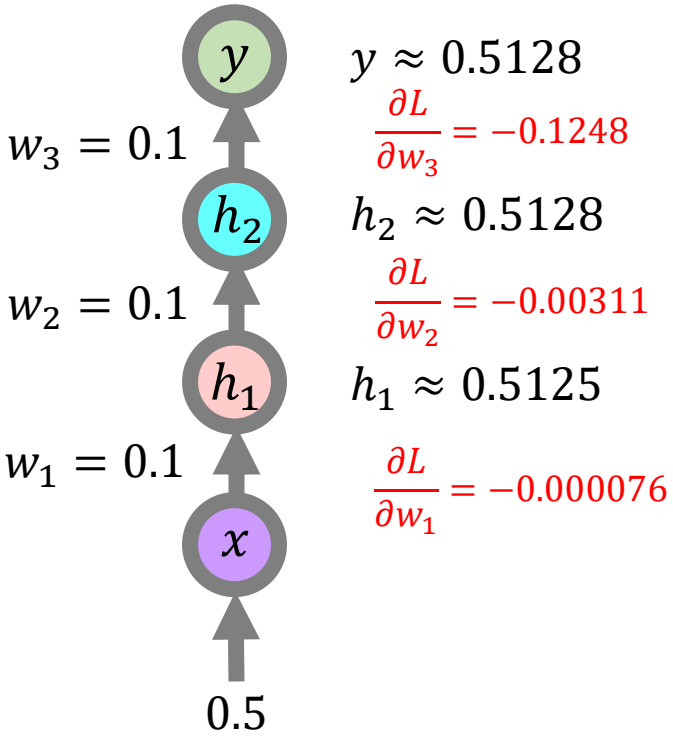
$$= -0.00608 \cdot 0.1 \cdot 0.2498 \cdot 0.5$$

$$= -0.000076$$

신박AI

그러면 시나리오 1의 각각의 기울기 값들을 다음과 같이 정리할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

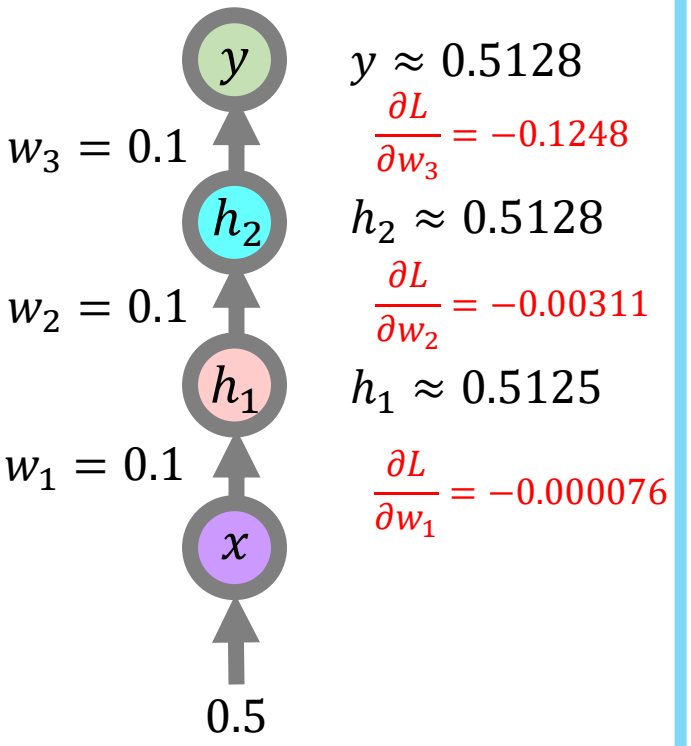
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

신박AI

이젠 시나리오2를 살펴보도록 하겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

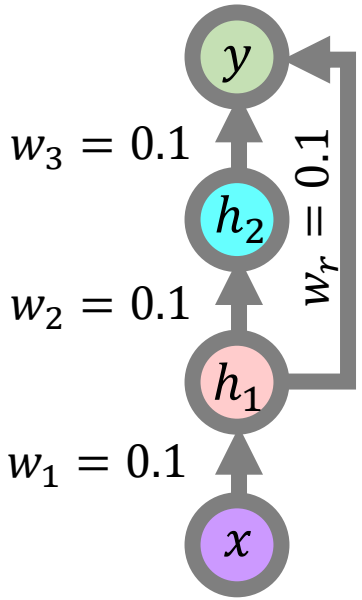
$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

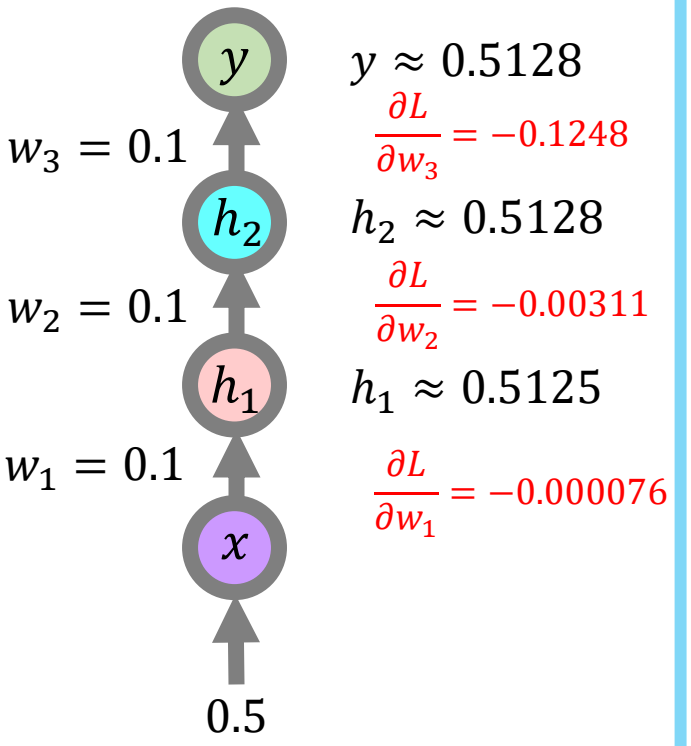


신박AI

잔차신경망도 입력이 0.5로 같을 경우, h_1과 h_2 까지는 과정이 동일합니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

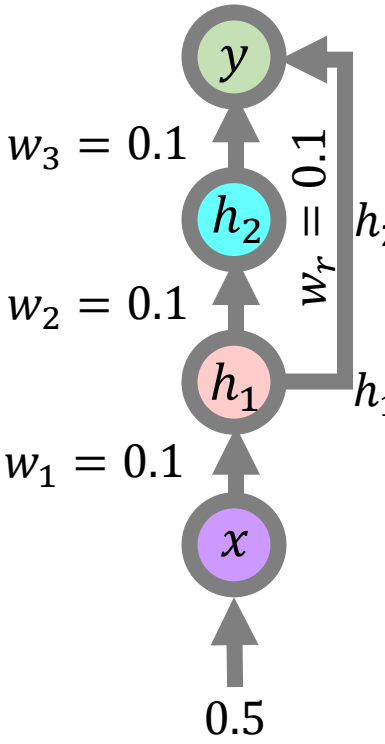
$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



$h_2 = \sigma(w_2 h_1) = \sigma(0.1 \cdot 0.5125) = \sigma(0.05125) \approx 0.5128$

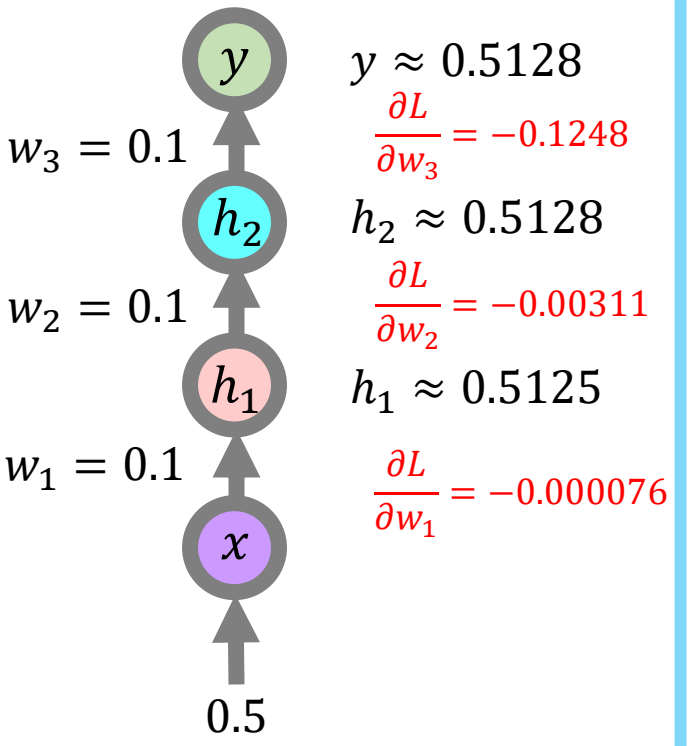
$h_1 = \sigma(w_1 x) = \sigma(0.1 \cdot 0.5) = \sigma(0.05) \approx 0.5125$

신박AI

그리고 출력 y의 경우 다음 공식으로 계산할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

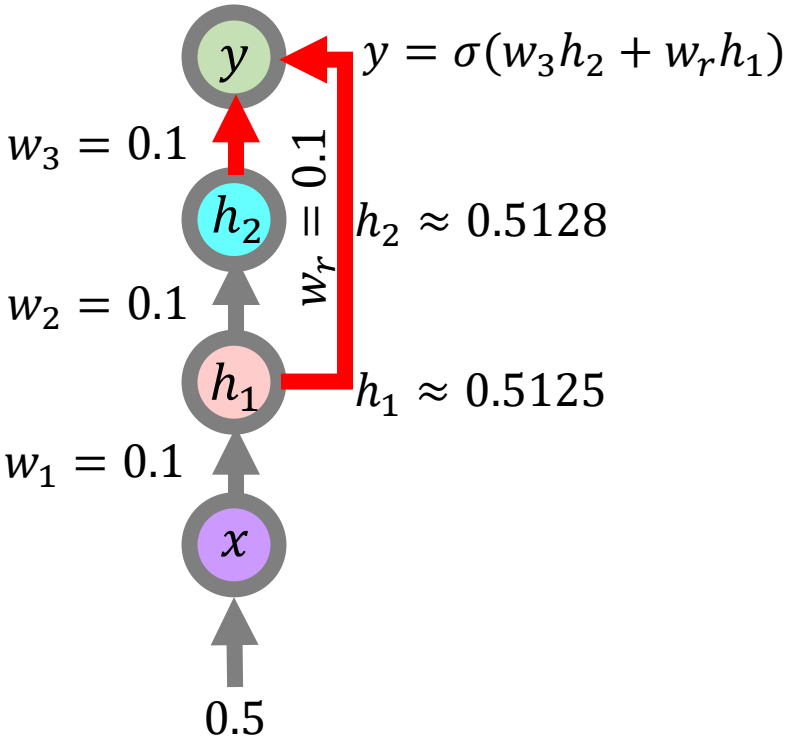
$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



$y = \sigma(w_3 h_2 + w_r h_1)$

$h_2 \approx 0.5128$

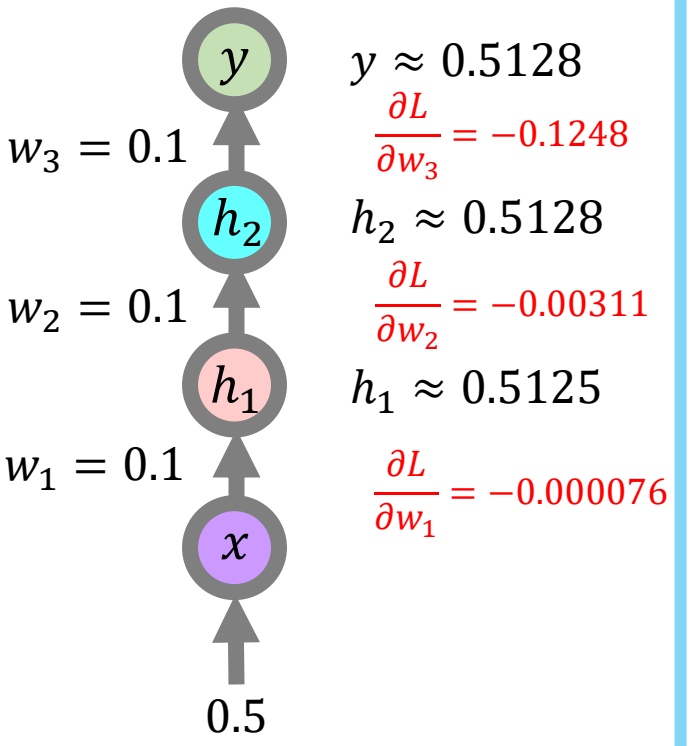
$h_1 \approx 0.5125$

신박AI

그리고 출력 y의 경우 다음 공식으로 계산할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

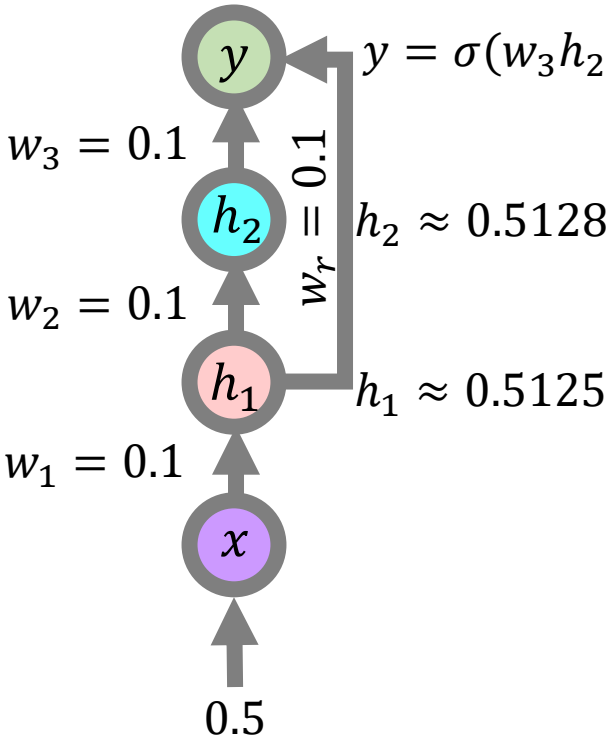
$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



$y = \sigma(w_3 h_2 + w_r h_1) = \sigma(0.1 \cdot 0.5128 + 0.1 \cdot 0.5125) = 0.5256$

$h_2 \approx 0.5128$

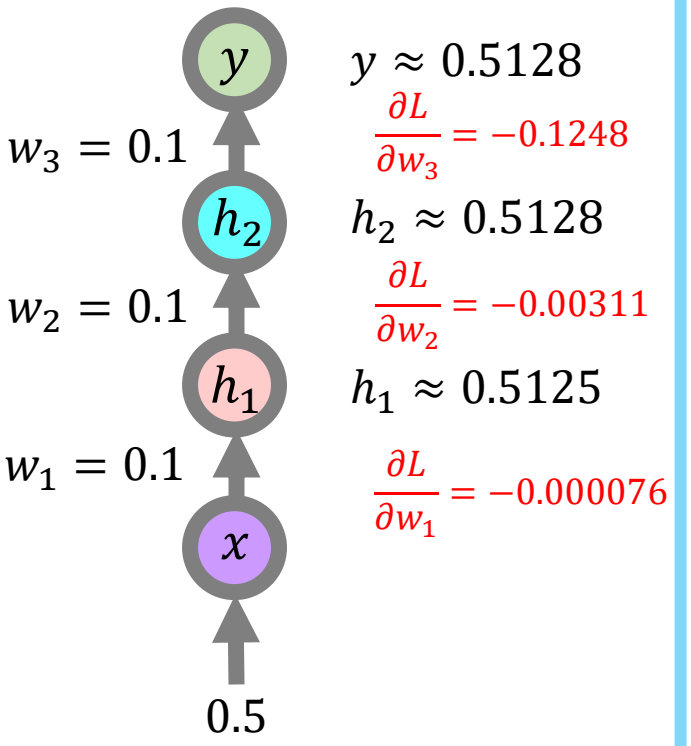
$h_1 \approx 0.5125$

신박AI

동일하게 MSE 손실함수를 사용하여 손실을 계산하면,

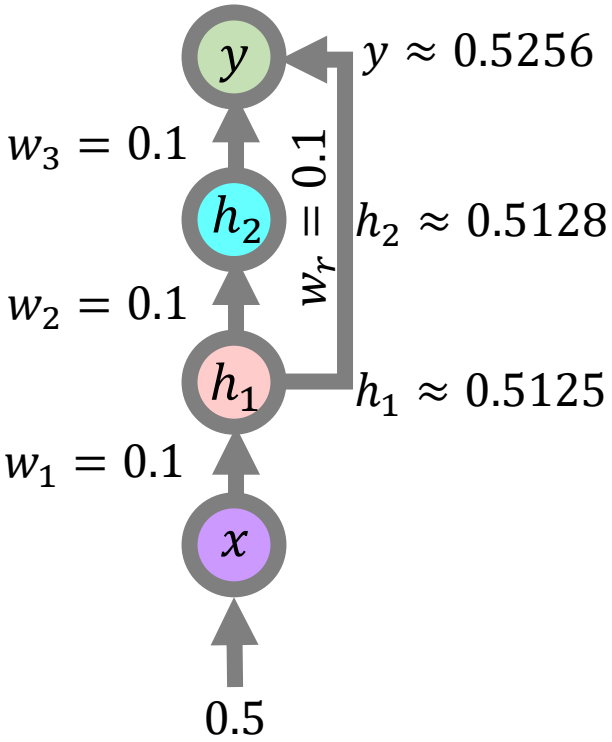
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss = (y_{true} - y)^2$$

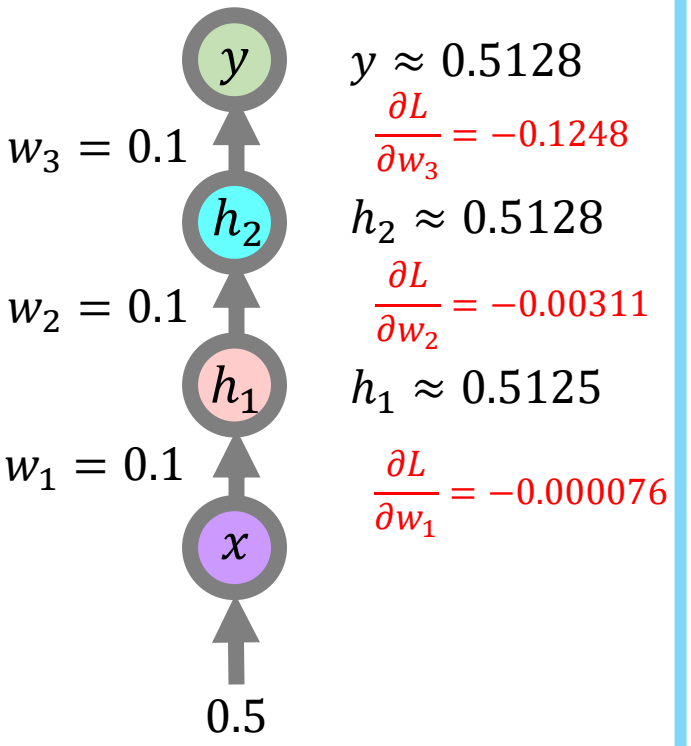


신박AI

손실값은 0.2247이 나옵니다.

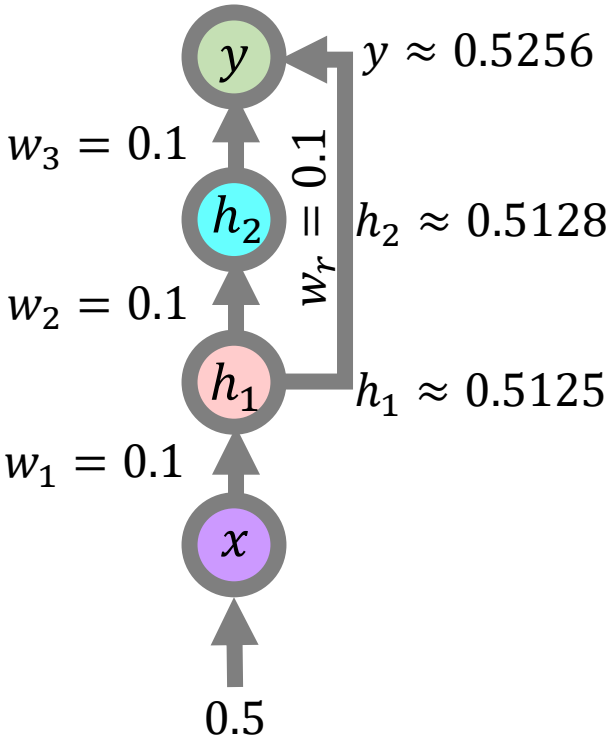
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss = (y_{true} - y)^2 = (1 - 0.5256)^2 \approx 0.2247$$

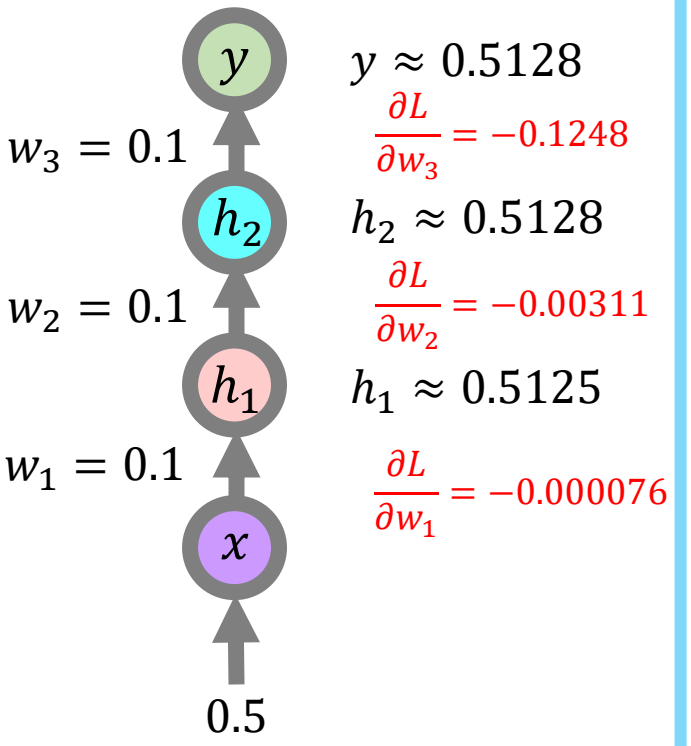


신박AI

이제는 이 손실을 사용하여 역전파를 통해 기울기를 구할 차례입니다.

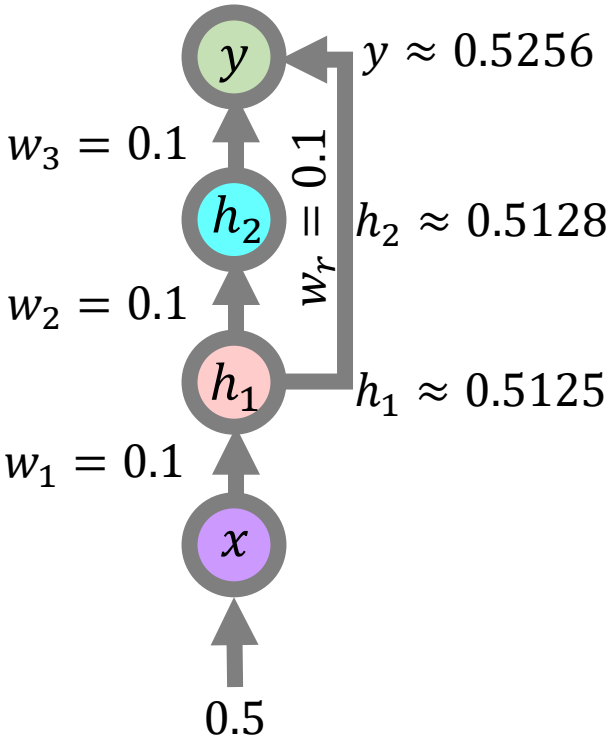
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

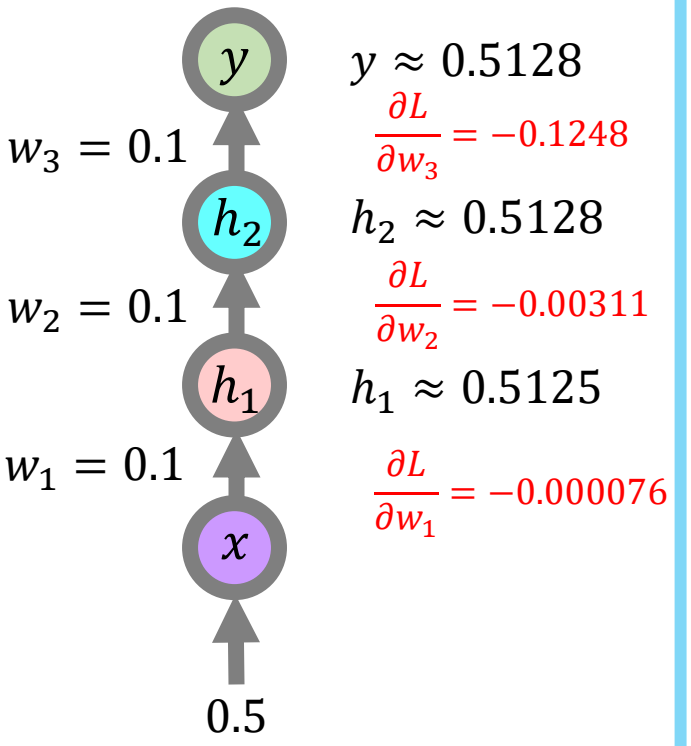


신박AI

먼저 $\partial L/\partial w_3$를 구해보도록 하겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

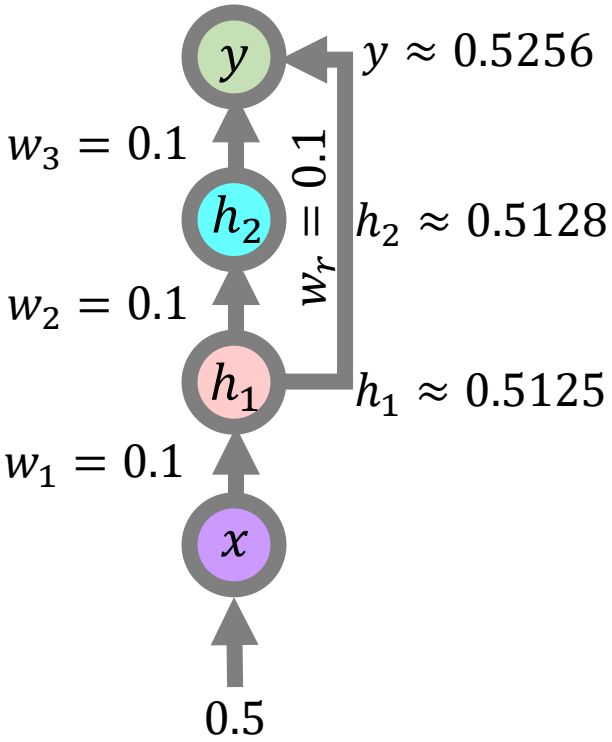
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$\frac{\partial L}{\partial w_3}$



$y \approx 0.5256$

$h_2 \approx 0.5128$

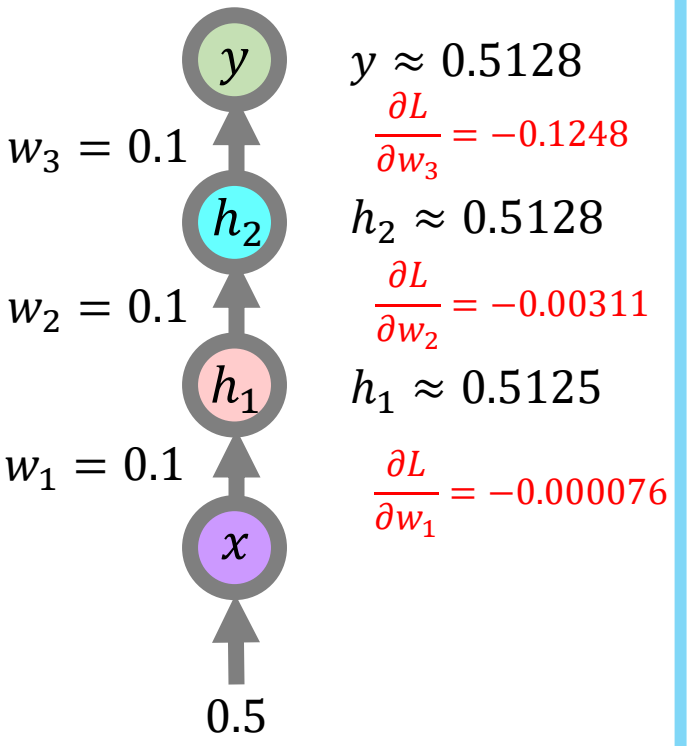
$h_1 \approx 0.5125$

신박AI

$\partial L/\partial w_3$는 체인룰에 의해서 다음과 같이 전개할 수 있습니다.

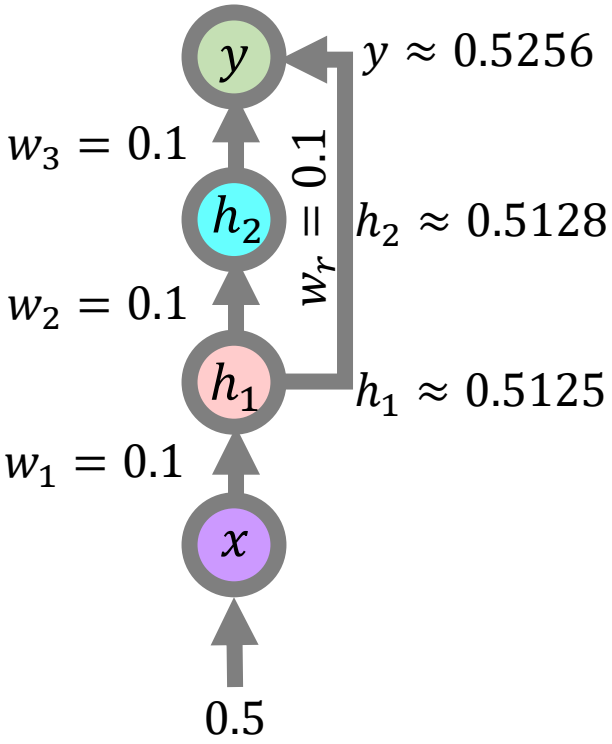
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$



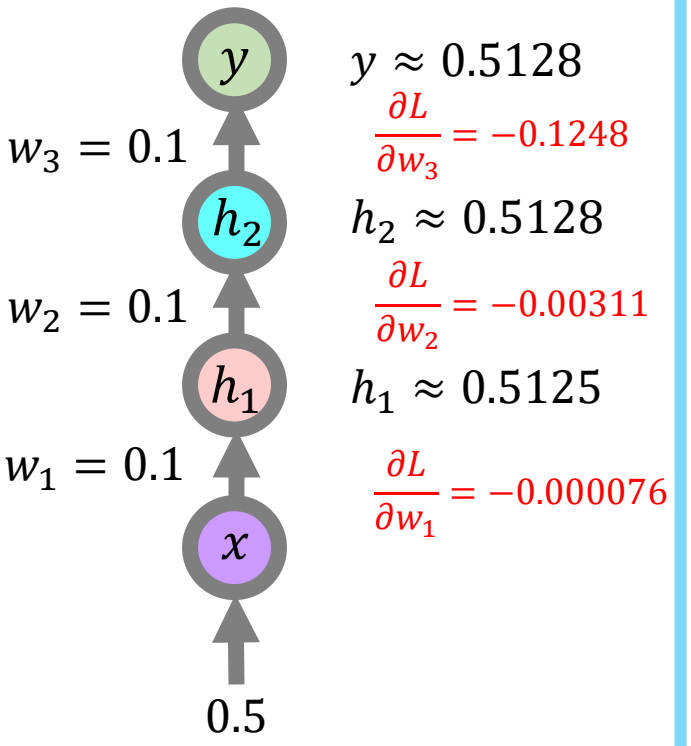
$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial w_3}$$

신박AI

$\partial L/\partial y$는 다음 공식으로 구할 수 있습니다.

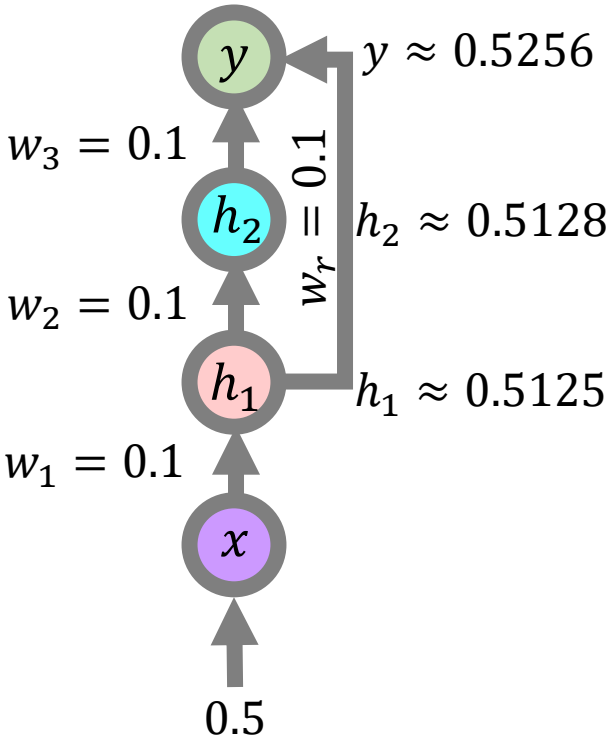
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$



$$\frac{\partial L}{\partial w_3} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial w_3}$$

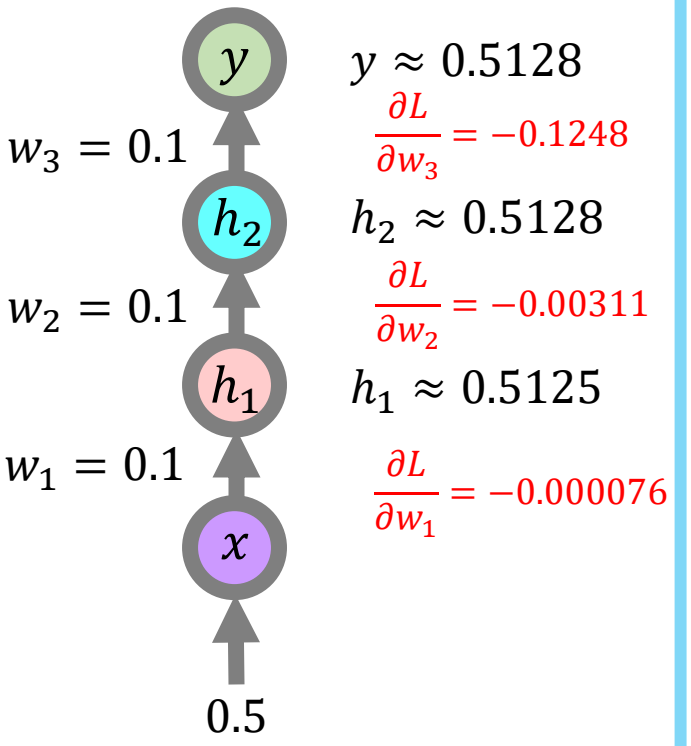
$$\frac{\partial L}{\partial y} = 2(y - y_{true}) = 2(0.5256 - 1) = -0.9488$$

신박AI

그리고 두번째 항은 y값의 정의에 따라 다음과 같이 치환하면,

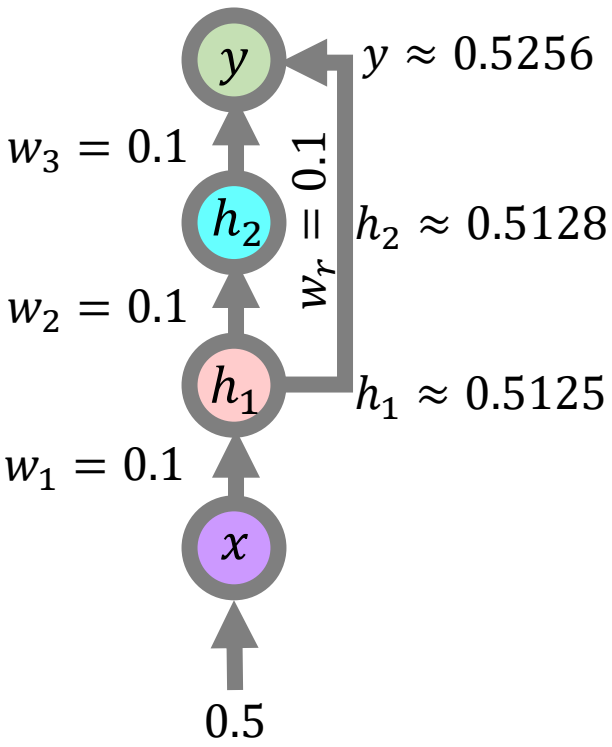
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$



$$\frac{\partial L}{\partial w_3} = -0.9488 \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial w_3}$$

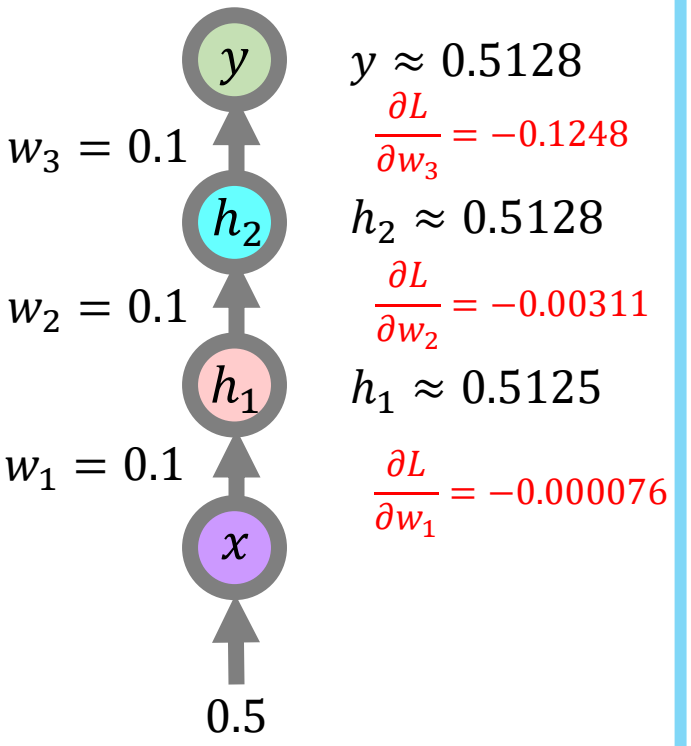
$$\frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} = \frac{\partial (\sigma(w_3 h_2 + w_r h_1))}{\partial (w_3 h_2 + w_r h_1)}$$

신박AI

시그모이드 미분 공식에 의하여 다음과 같이 간단하게 바꿀 수 있고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

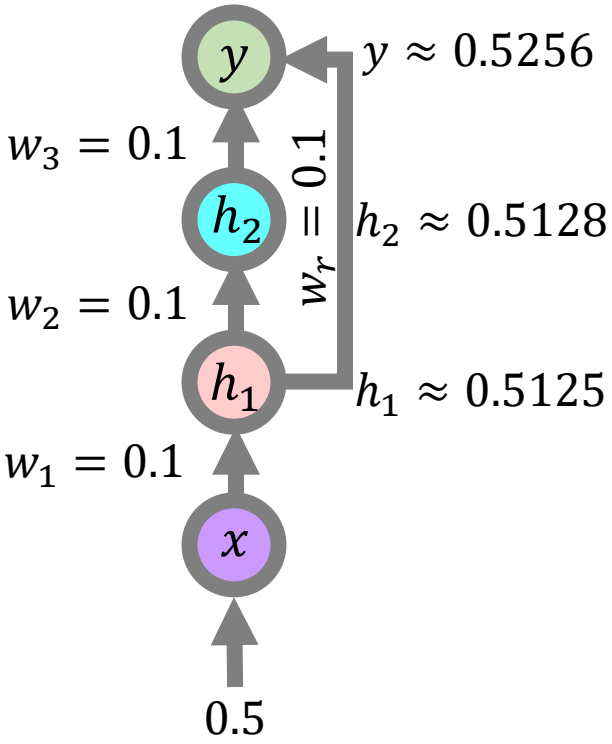
$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$



$y \approx 0.5256$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_3} = -0.9488 \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial w_3}$$

$$\frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} = \frac{\partial (\sigma(w_3 h_2 + w_r h_1))}{\partial (w_3 h_2 + w_r h_1)}$$

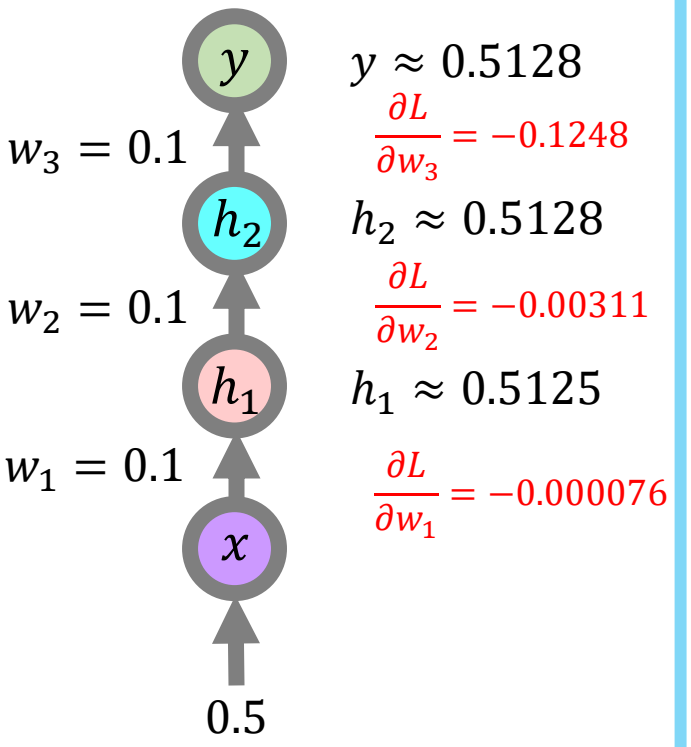
$$= y(1-y)$$

신박AI

값을 넣어 계산하면 대략 0.24930이 나옵니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

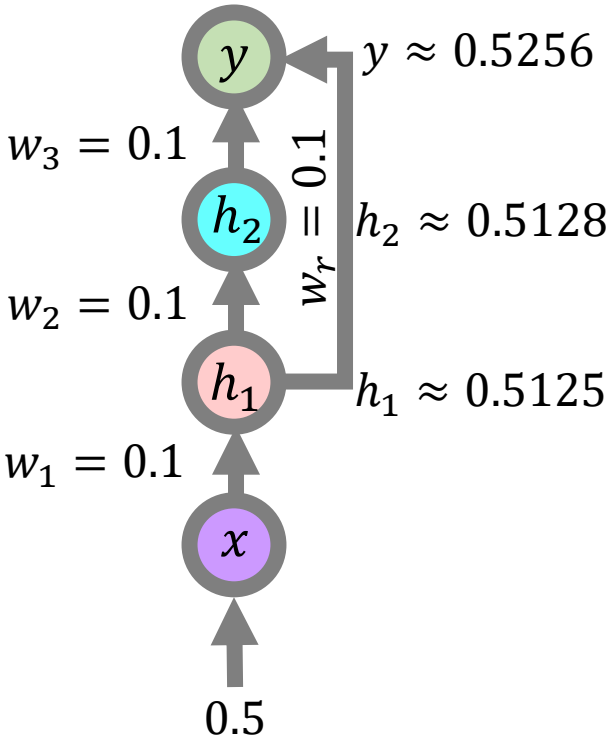
$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$



$y \approx 0.5256$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_3} = -0.9488 \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial w_3}$$

$$\frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} = \frac{\partial (\sigma(w_3 h_2 + w_r h_1))}{\partial (w_3 h_2 + w_r h_1)}$$

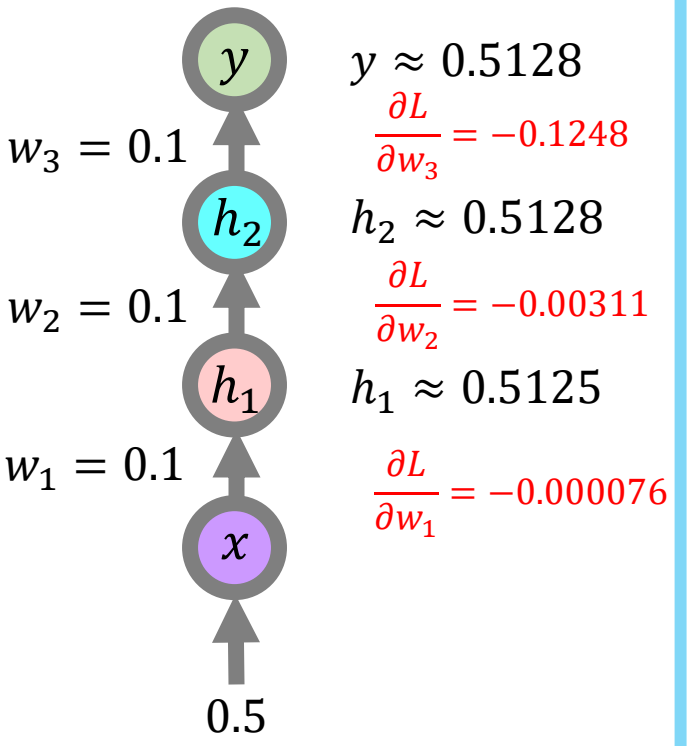
$$= y(1-y) = 0.5256(1-0.5256)$$
$$\approx 0.2493$$

신박AI

그리고 마지막 항은,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

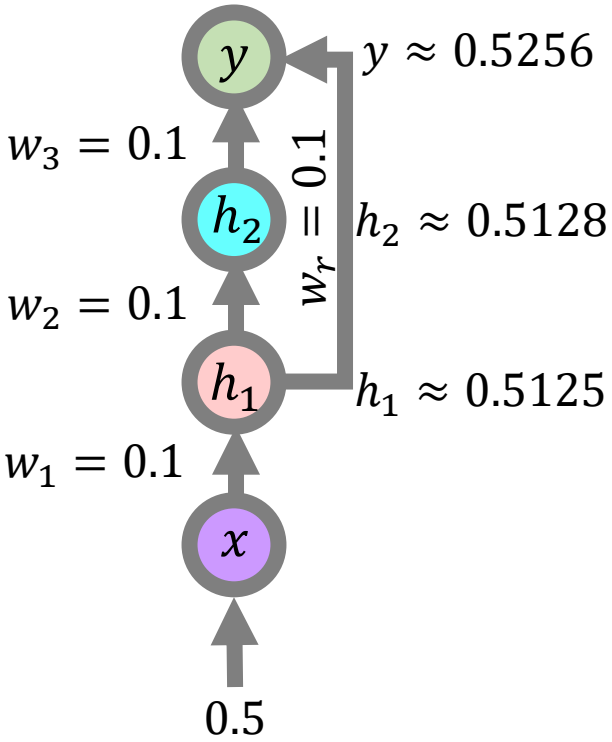
$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$



$y \approx 0.5256$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_3} = -0.9488 \cdot 0.2493 \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial w_3}$$

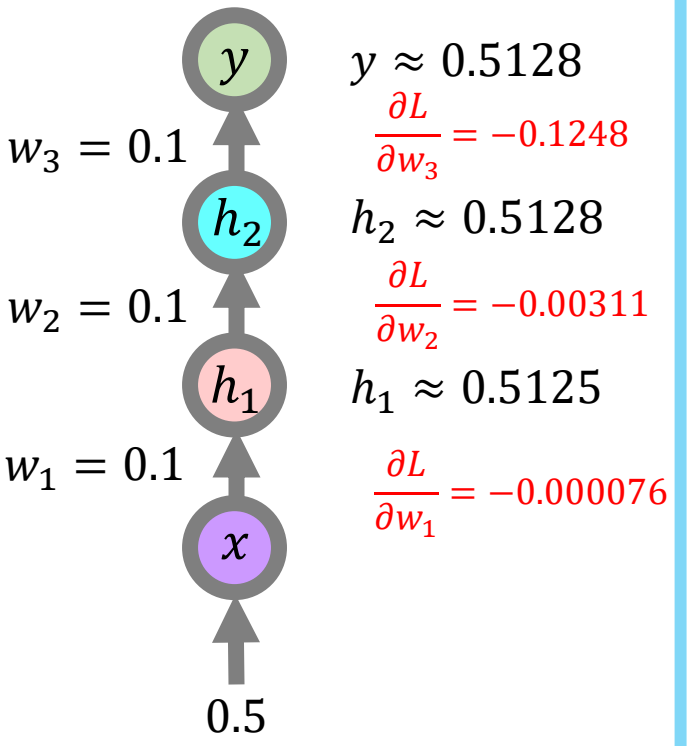
$$\frac{\partial (w_3 h_2 + w_r h_1)}{\partial w_3}$$

신박AI

미분에 의해서 h_2만 남게 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

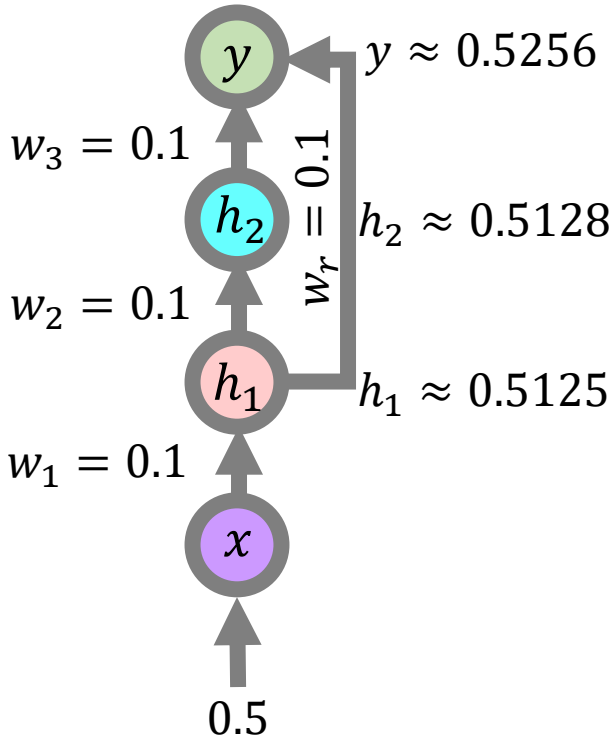
$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$



$y \approx 0.5256$

$h_2 \approx 0.5128$

$h_1 \approx 0.5125$

$$\frac{\partial L}{\partial w_3} = -0.9488 \cdot 0.2493 \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial w_3}$$

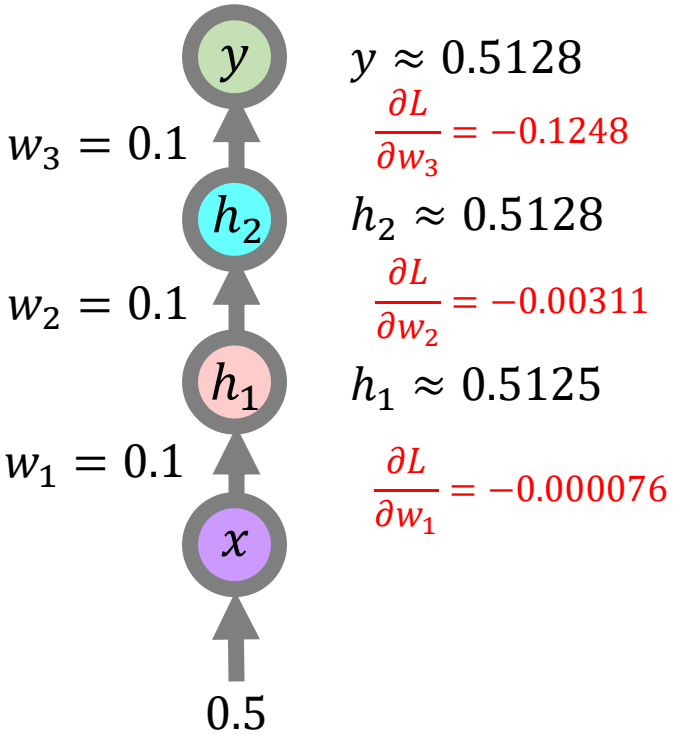
$$\frac{\partial (w_3 h_2 + w_r h_1)}{\partial w_3}$$

신박AI

그러면 h_2의 값인 0.5128을 대입하면

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

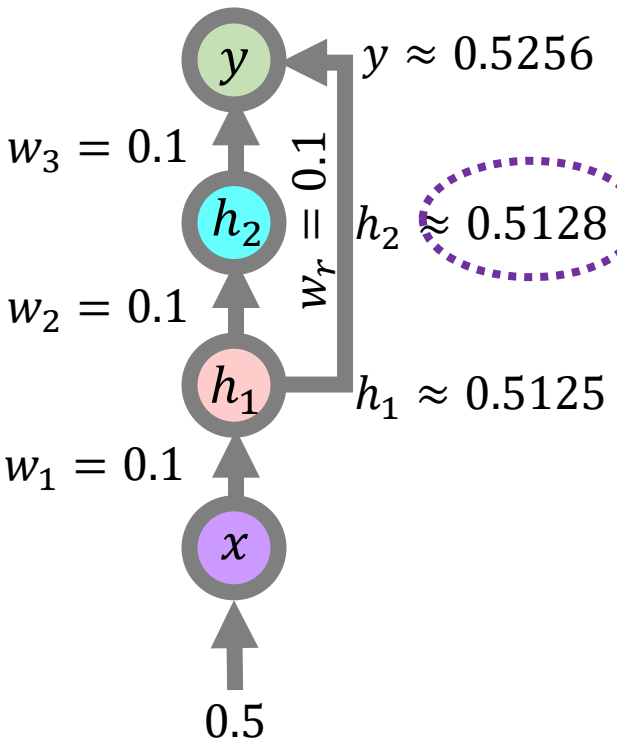
$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_3} = -0.9488 \cdot 0.2493 \cdot 0.5128$$

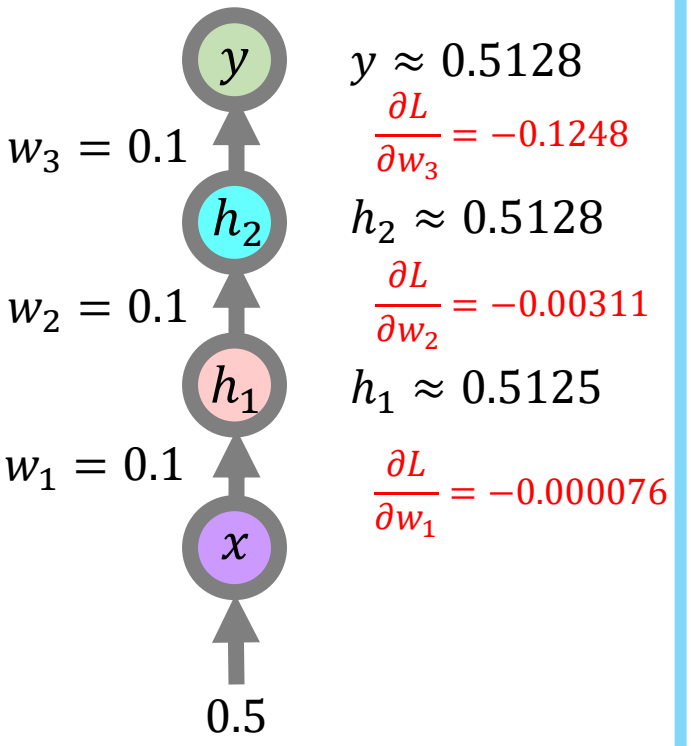


신박AI

$\partial L/\partial w_3$은 대략 -0.12130이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

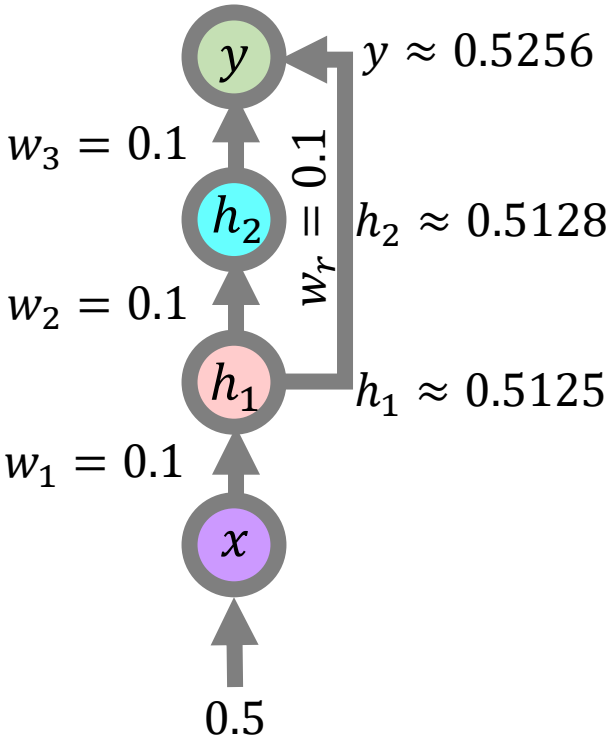
$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

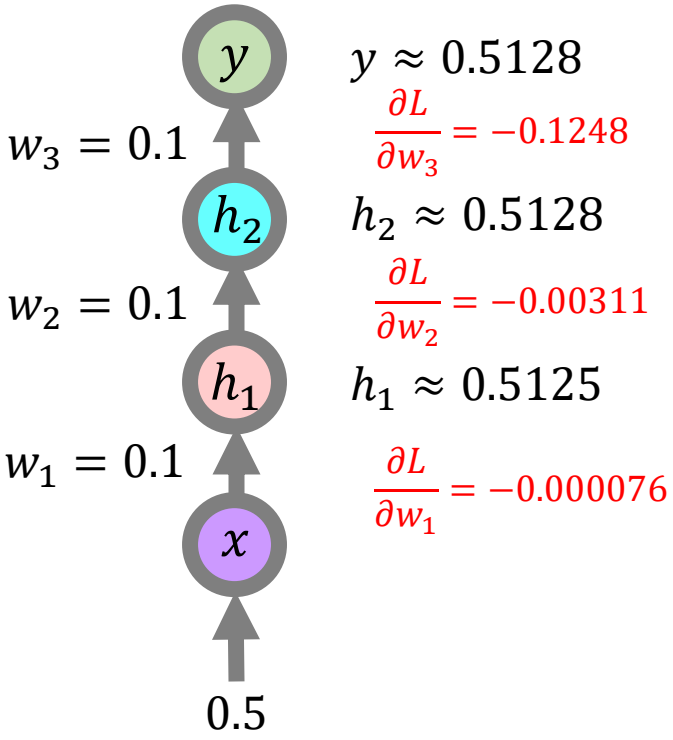


신박AI

$\partial L/\partial w_3$은 대략 -0.12130이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

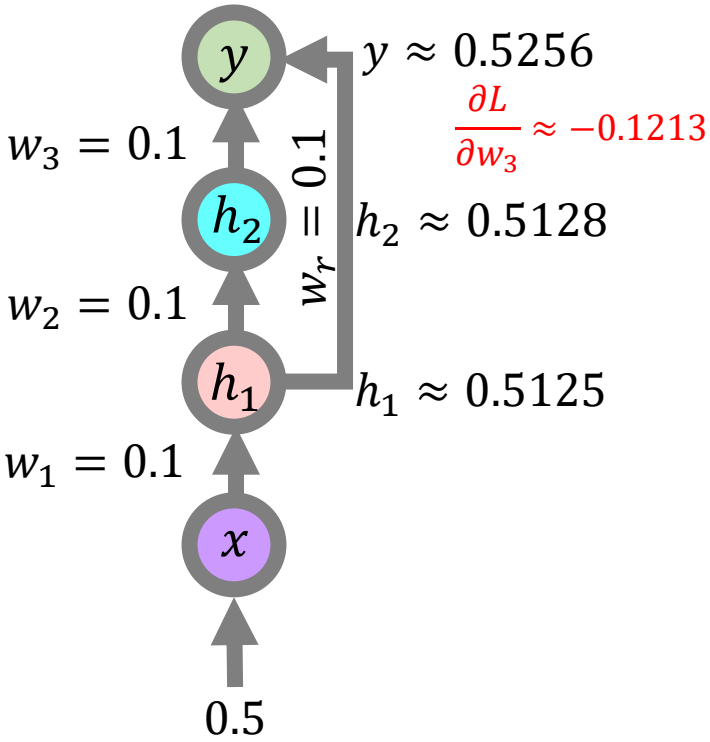
$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

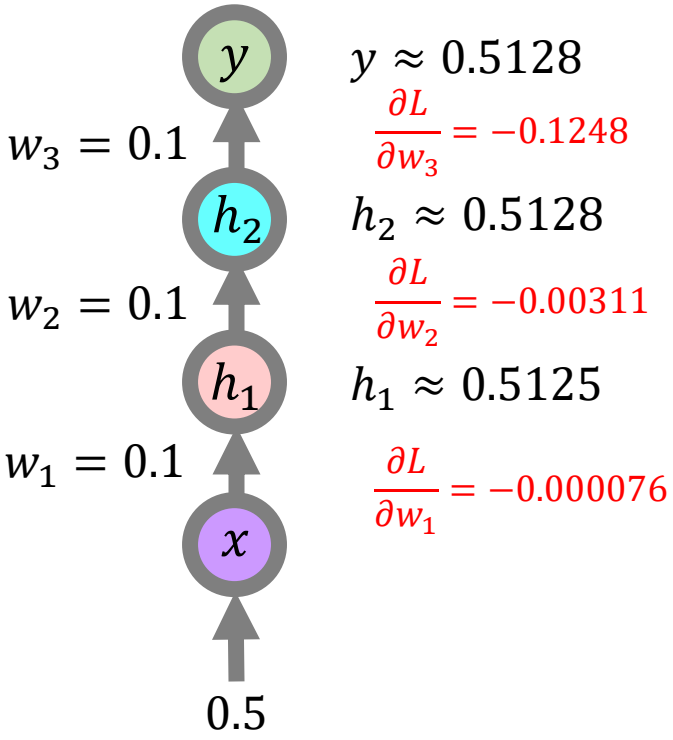
$h_1 \approx 0.5125$

신박AI

이제 $\partial L/\partial w_2$를 구해보도록 하겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

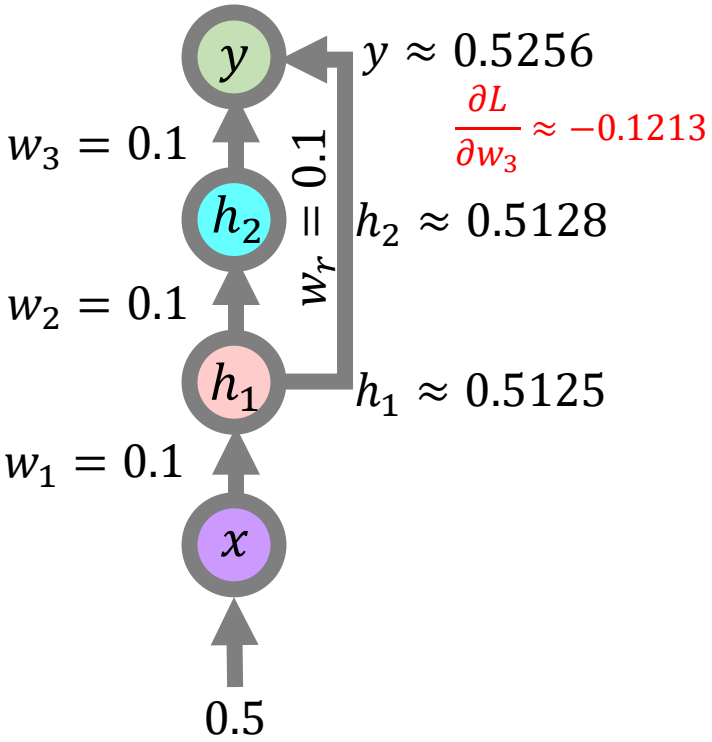
$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$ $\frac{\partial L}{\partial w_2}$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

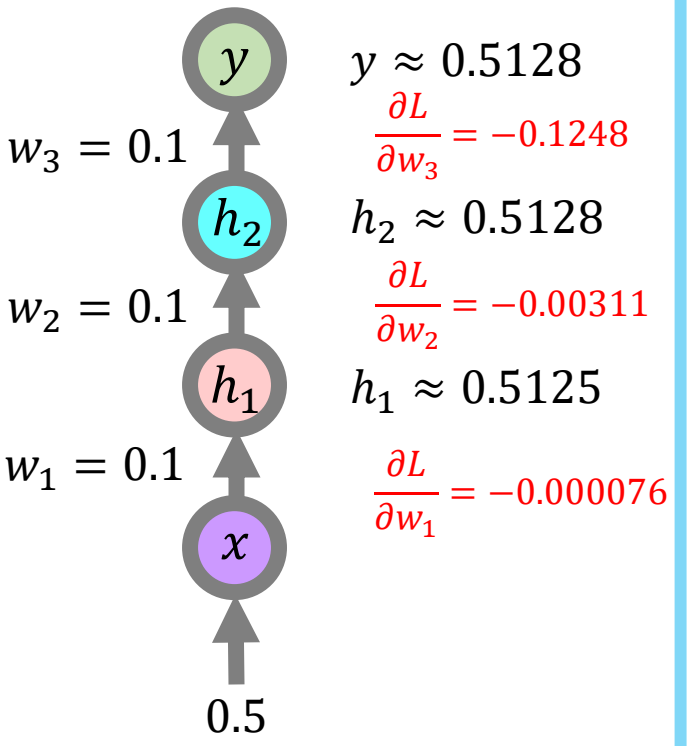
$h_1 \approx 0.5125$

신박AI

$\partial L/\partial w_2$는 체인룰에 의해서 다음과 같이 전개할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

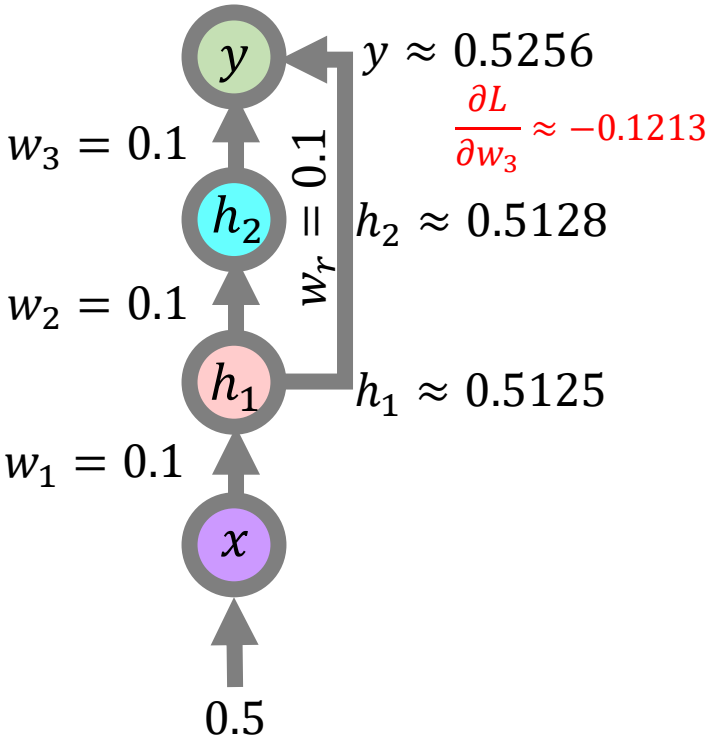
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial h_2} \cdot \frac{\partial h_2}{\partial w_2 h_1} \cdot \frac{\partial w_2 h_1}{\partial w_2}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

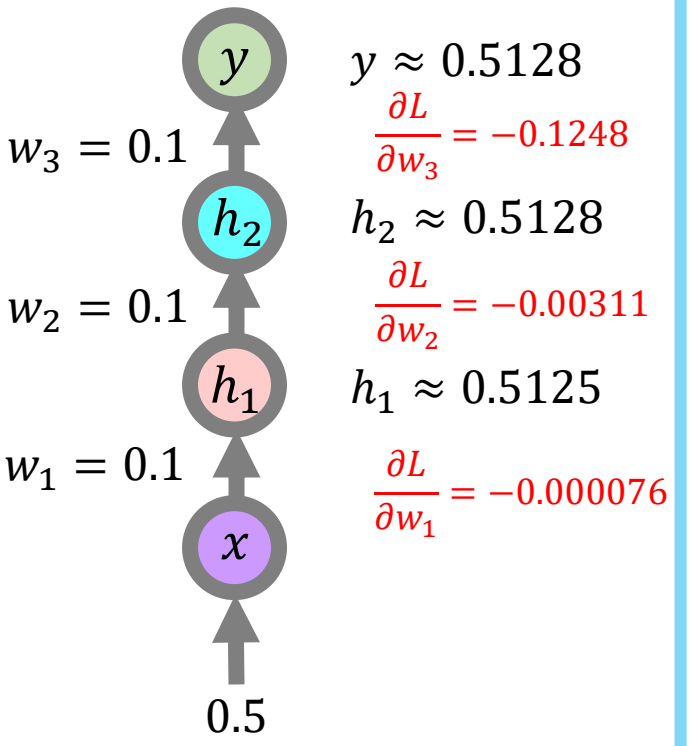
$h_1 \approx 0.5125$

신박AI

그런데 이 부분은 앞서 구한 부분이니 재사용하도록 하겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

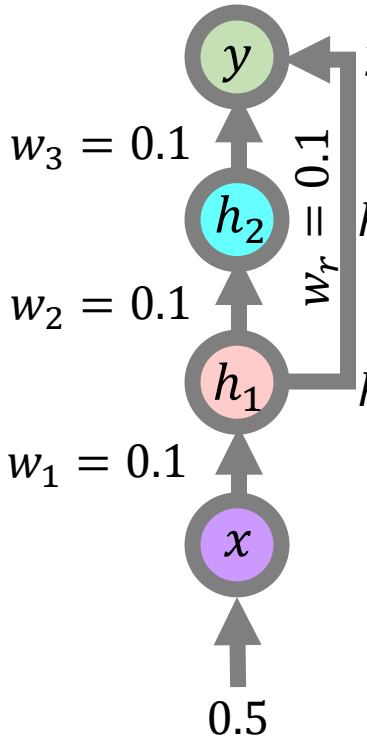
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial h_2} \cdot \frac{\partial h_2}{\partial w_2 h_1} \cdot \frac{\partial w_2 h_1}{\partial w_2}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

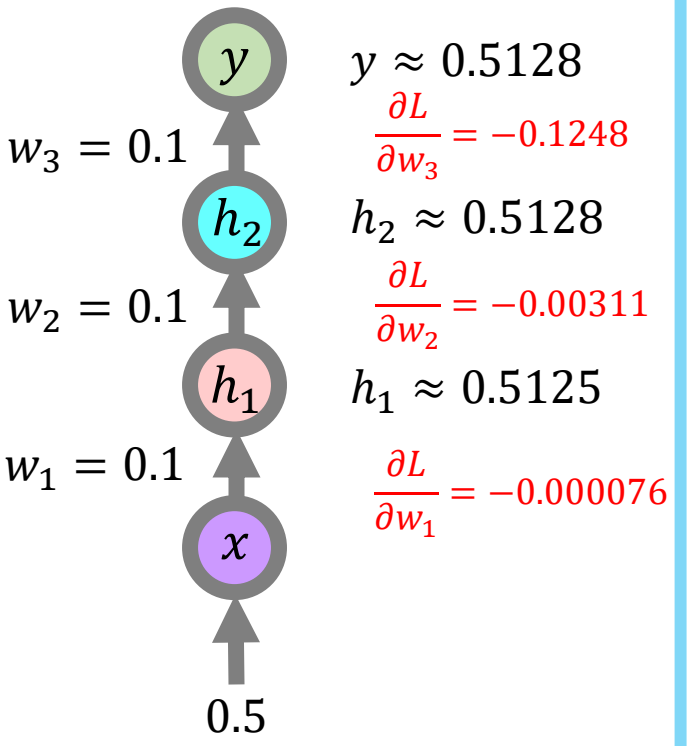
$h_1 \approx 0.5125$

신박AI

그런데 이 부분은 앞서 구한 부분이니 재사용하도록 하겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

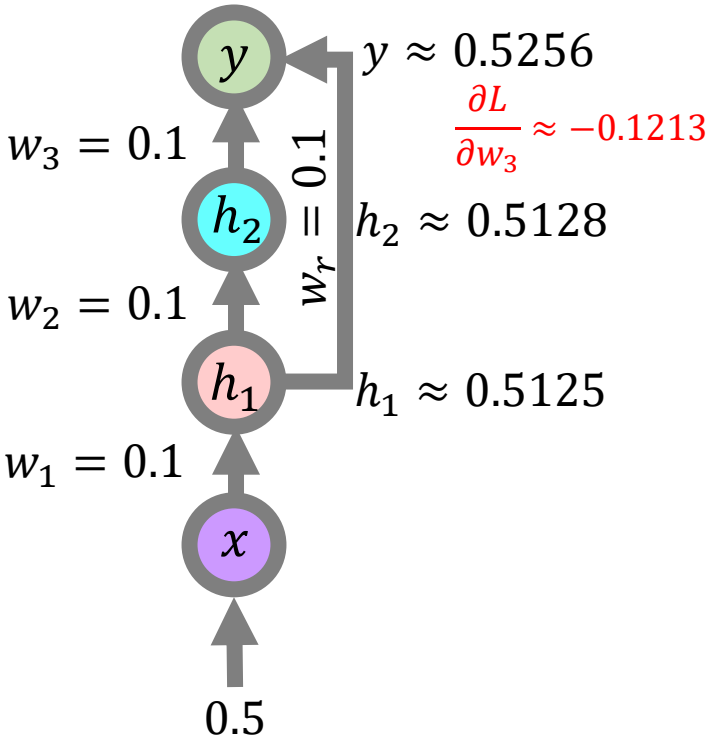
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial h_2} \cdot \frac{\partial h_2}{\partial w_2 h_1} \cdot \frac{\partial w_2 h_1}{\partial w_2}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

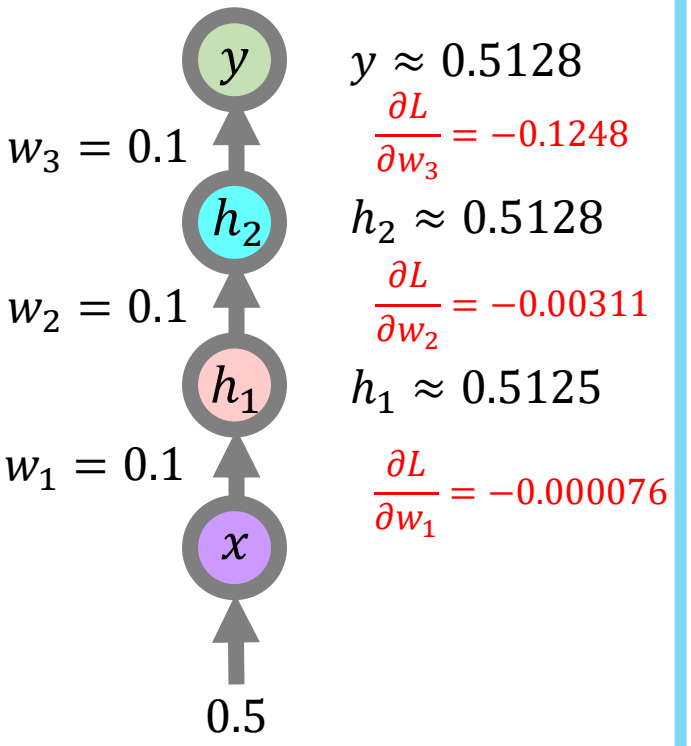
$h_1 \approx 0.5125$

신박AI

그리고 세번째 항은 h_2 편미분에 의해서,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

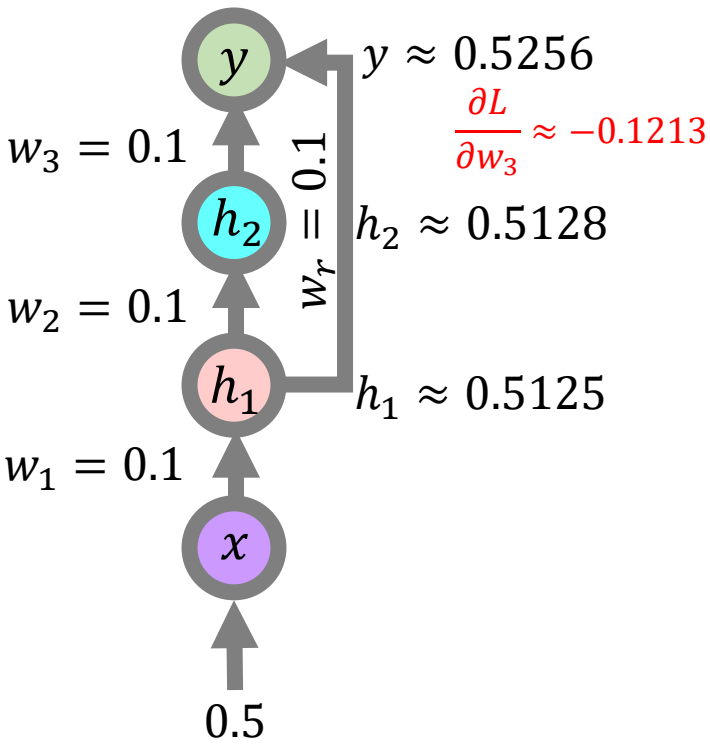
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot \frac{\partial(w_3 h_2 + w_r h_1)}{\partial h_2} \cdot \frac{\partial h_2}{\partial w_2 h_1} \cdot \frac{\partial w_2 h_1}{\partial w_2}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

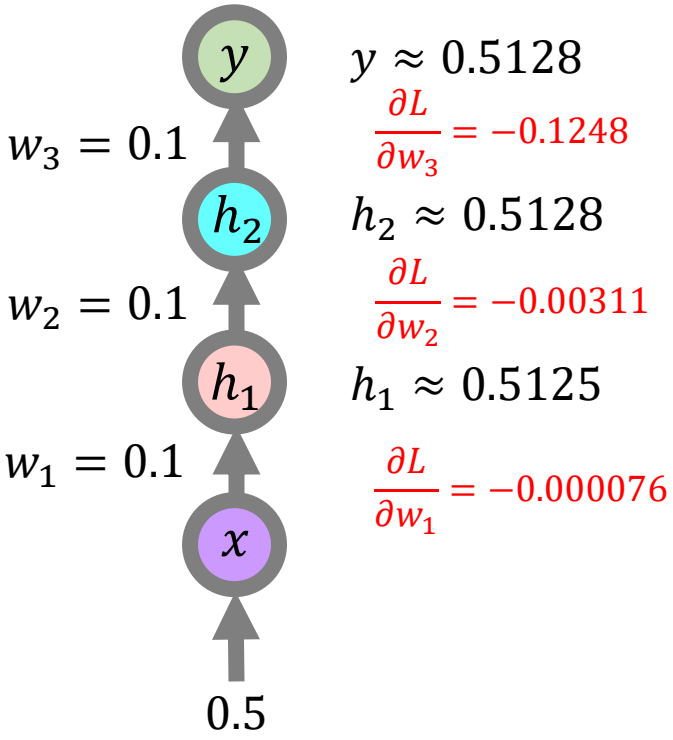
$h_1 \approx 0.5125$

신박AI

w_3가 됩니다.

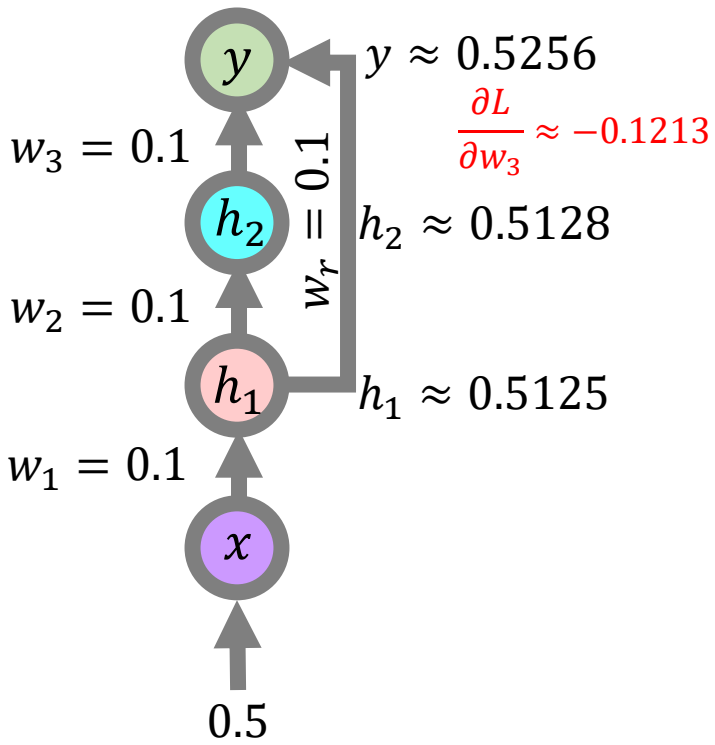
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2247 \quad \frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot w_3 \cdot \frac{\partial h_2}{\partial w_2 h_1} \cdot \frac{\partial w_2 h_1}{\partial w_2}$$

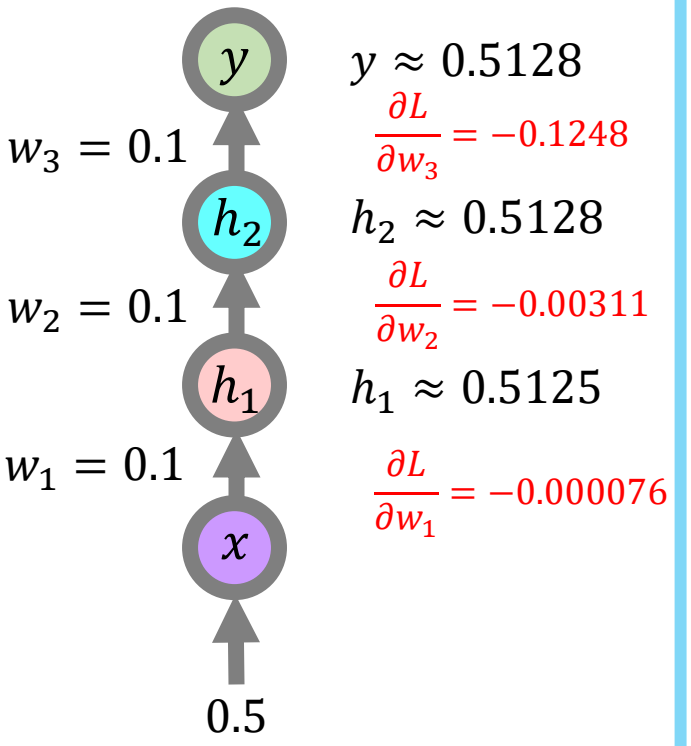


신박AI

그러면 w_3의 값은 0.1이기 때문에 그 값을 대입하면 다음과 같이 되고,

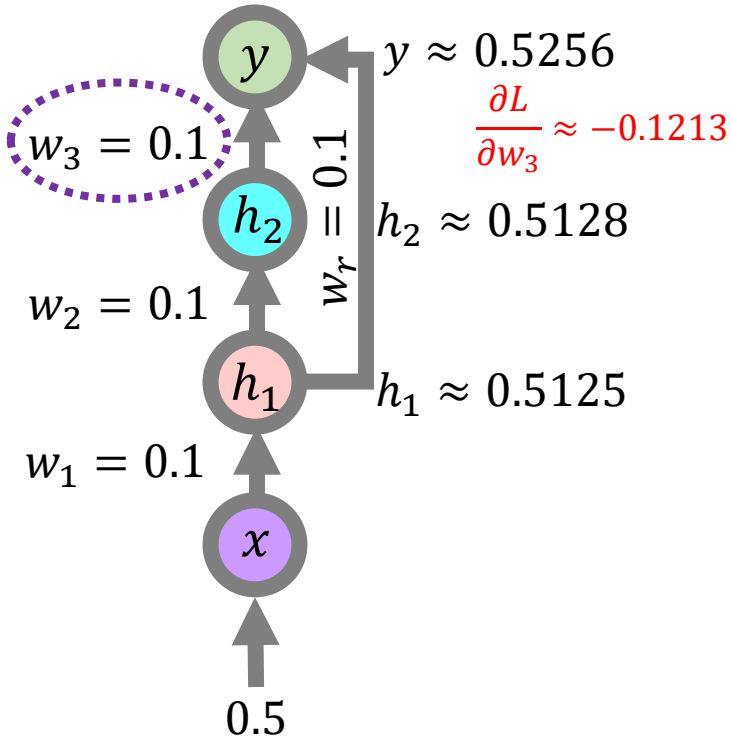
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2247 \quad \frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot \frac{\partial h_2}{\partial w_2 h_1} \cdot \frac{\partial w_2 h_1}{\partial w_2}$$

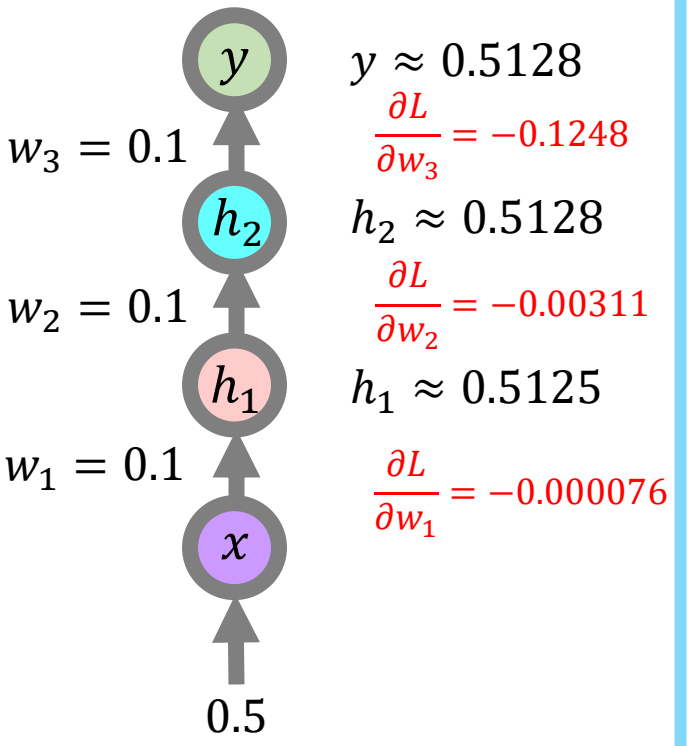


신박AI

그리고 네번째항은 시그모이드 미분 공식에 의하여,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

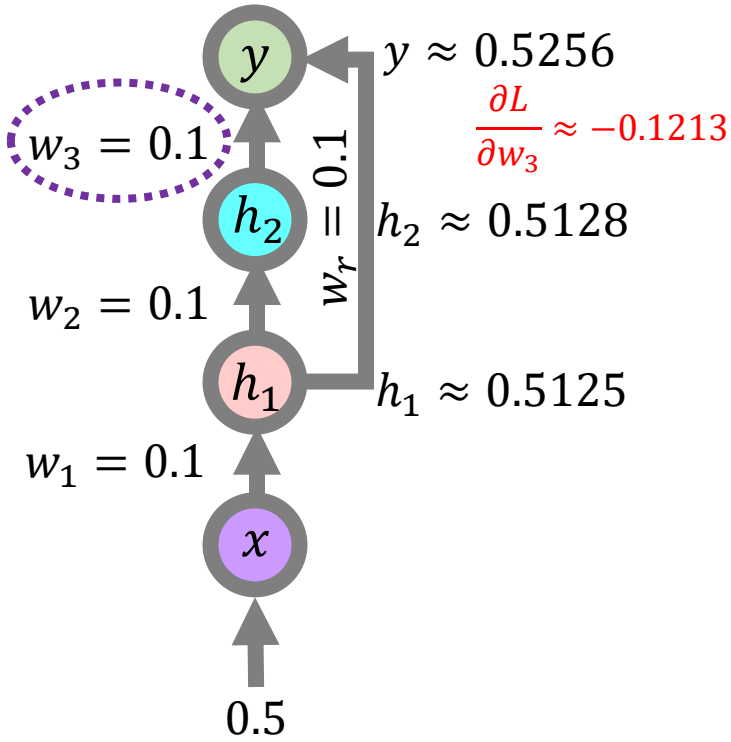
$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot \frac{\partial h_2}{\partial w_2 h_1} \cdot \frac{\partial w_2 h_1}{\partial w_2}$$

$\because h_2 = \sigma(w_2 h_1)$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

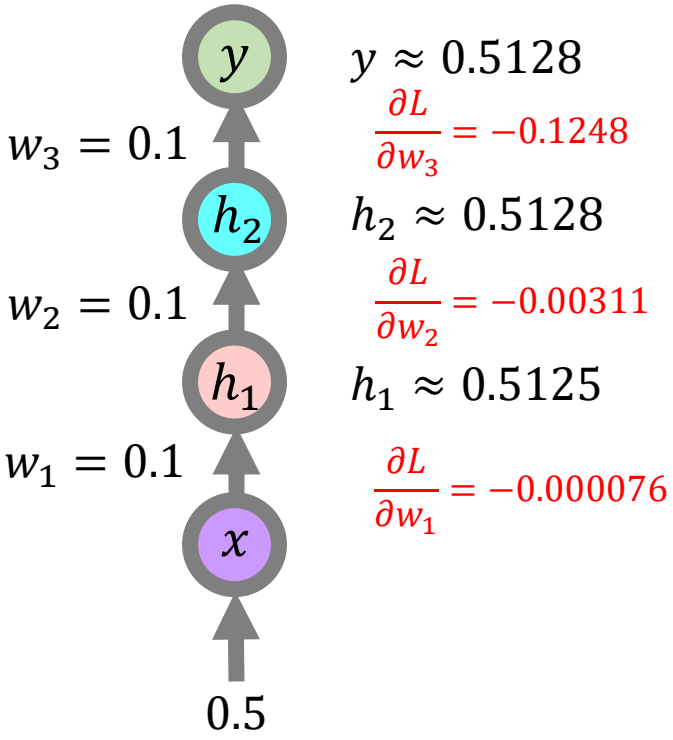
$h_1 \approx 0.5125$

신박AI

다음처럼 바뀌고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

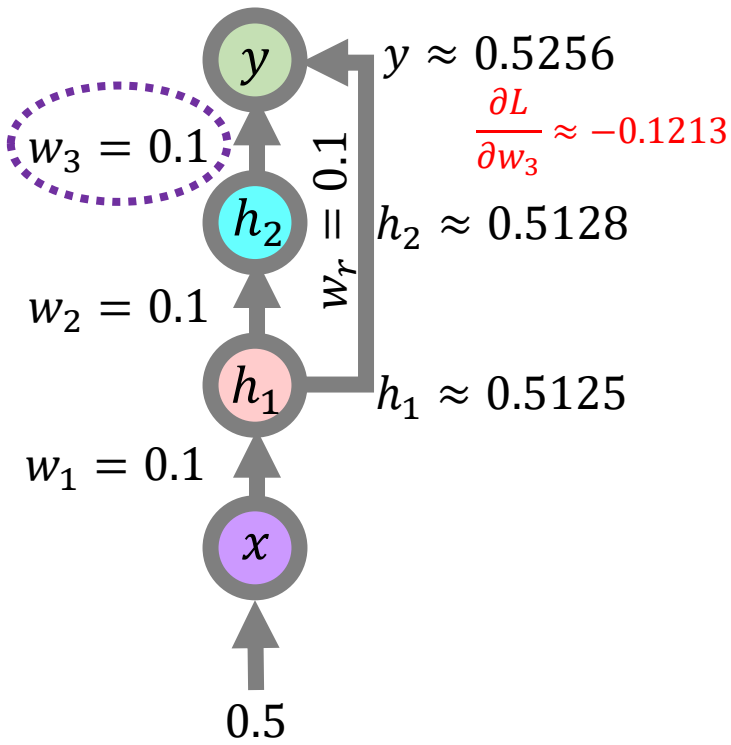
$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot h_2(1-h_2) \cdot \frac{\partial w_2 h_1}{\partial w_2}$$

$\because h_2 = \sigma(w_2 h_1)$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

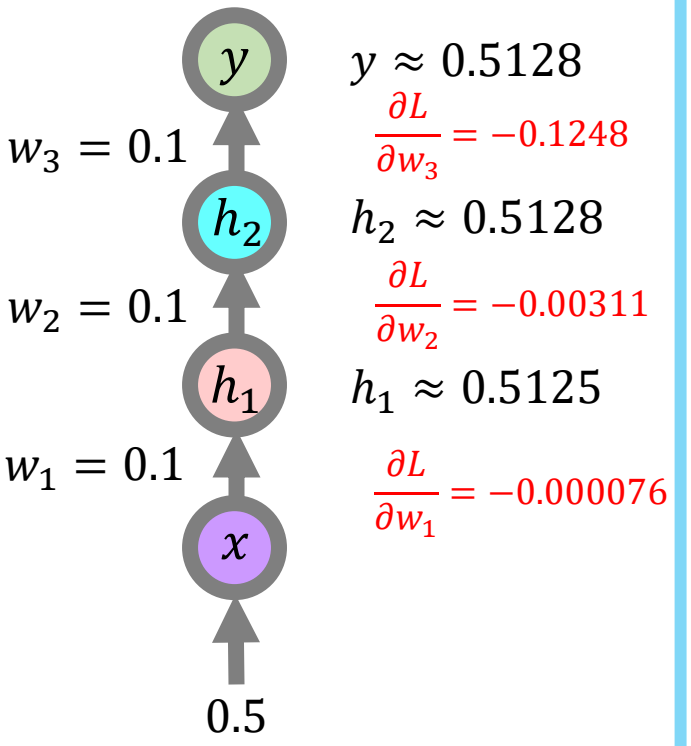
$h_1 \approx 0.5125$

신박AI

h_2 에 0.5128을 대입하여 계산하면, 0.2498이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$

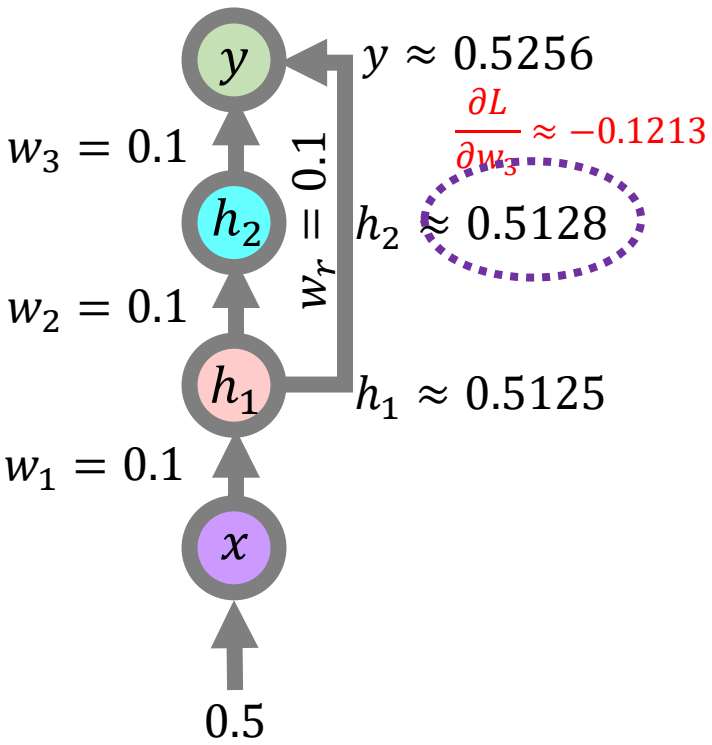


시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial w_2 h_1}{\partial w_2}$$

$\because h_2 = \sigma(w_2 h_1)$

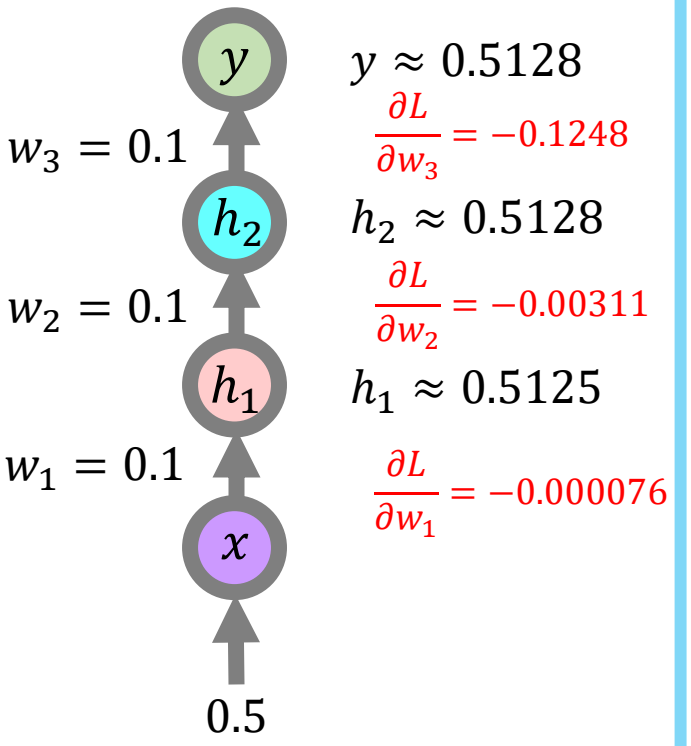


신박AI

마지막항은 w_2의 편미분공식에 의하여, h_1이 되고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

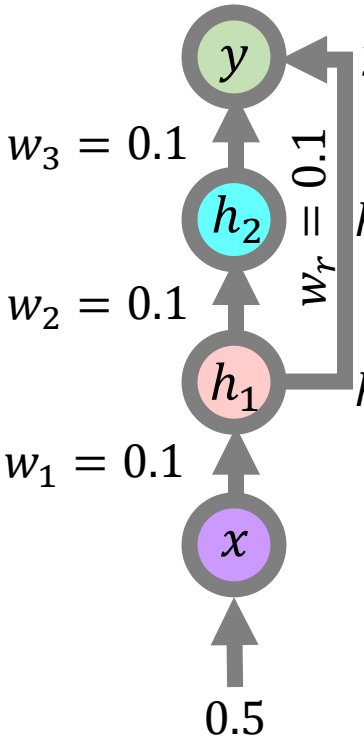
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial \cancel{w_2} h_1}{\partial \cancel{w_2}}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

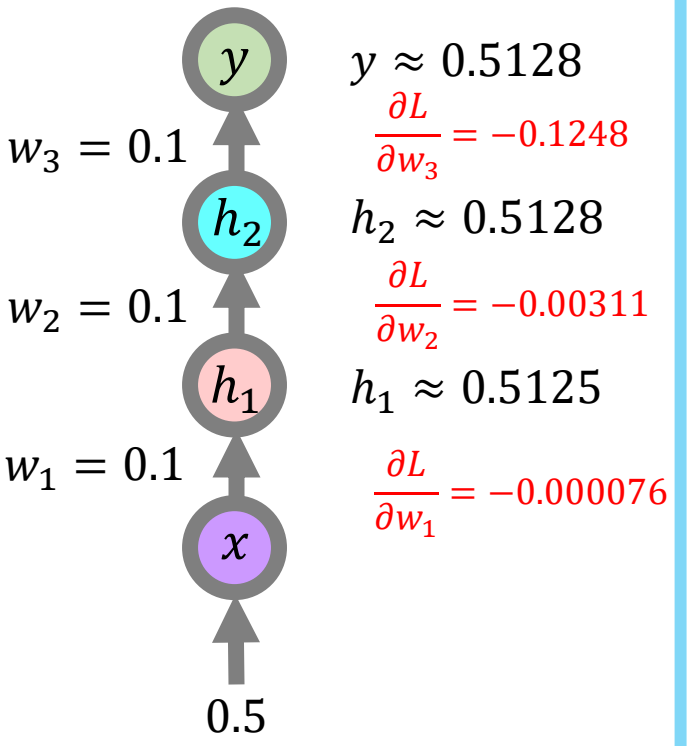
$h_1 \approx 0.5125$

신박AI

h_1 값인 0.5125를 대입하면 다음처럼 정리가 가능합니다.

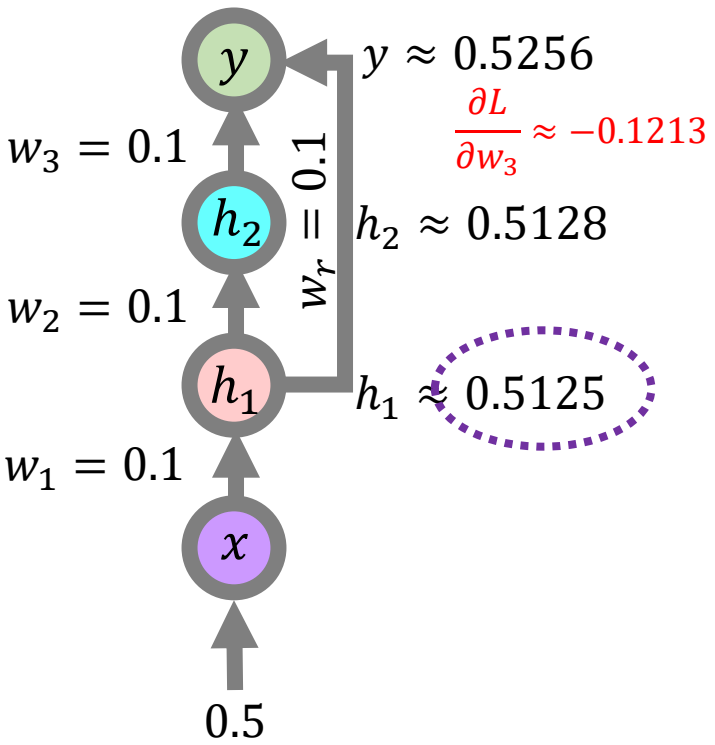
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2247 \quad \frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot 0.5125$$

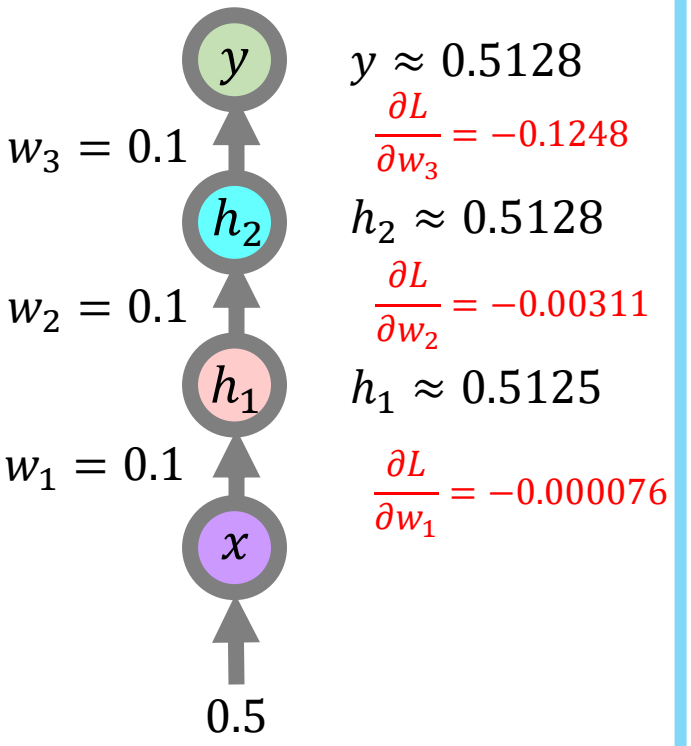


신박AI

그러면 $\partial L/\partial w_2$ 은 -0.00300이 됨을 확인할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

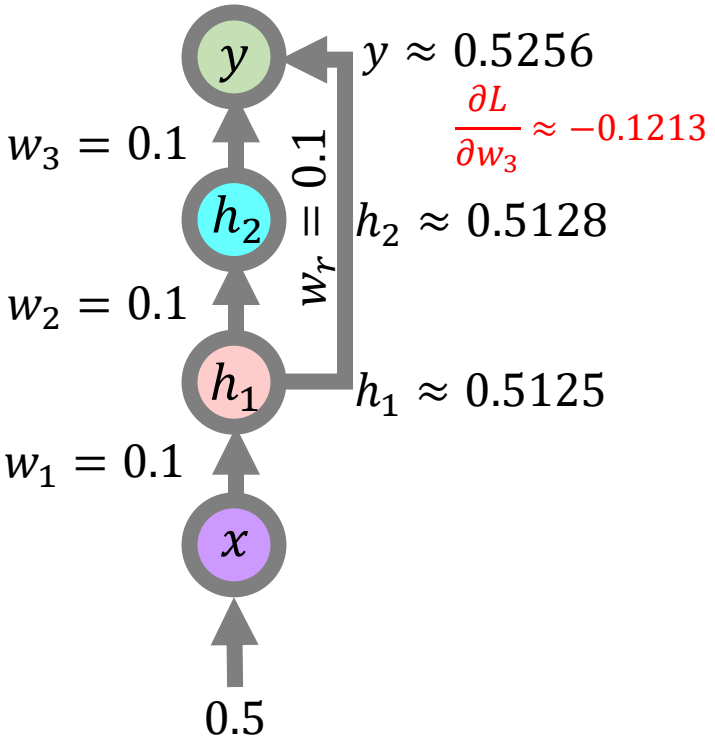
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_2} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot 0.5125 = -0.0030$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

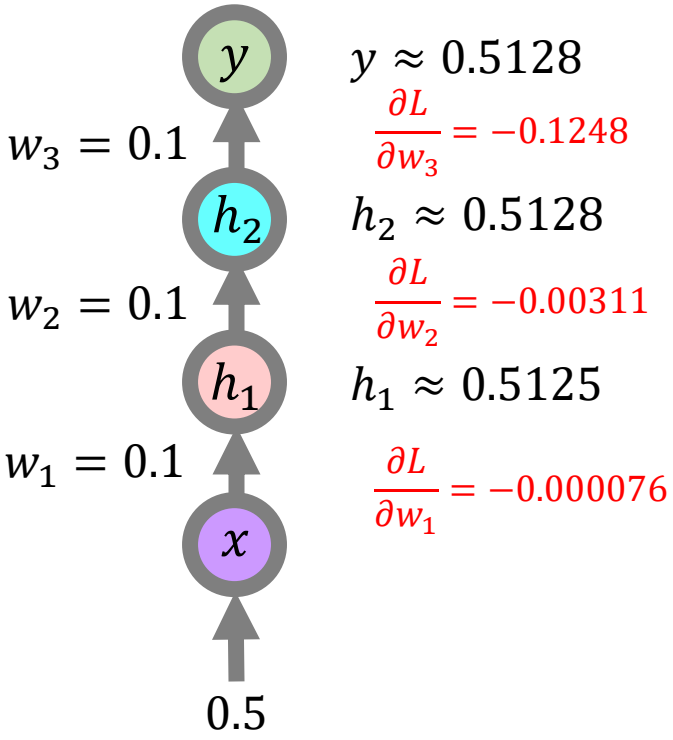
$h_1 \approx 0.5125$

신박AI

이제는 $\partial L/\partial w_1$을 구할 차례입니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

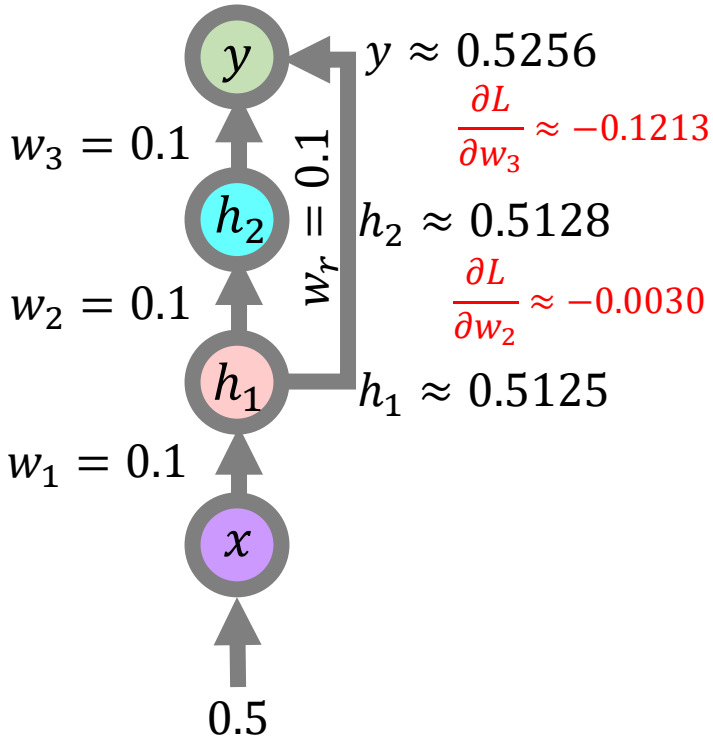
$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$ $\frac{\partial L}{\partial w_1}$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

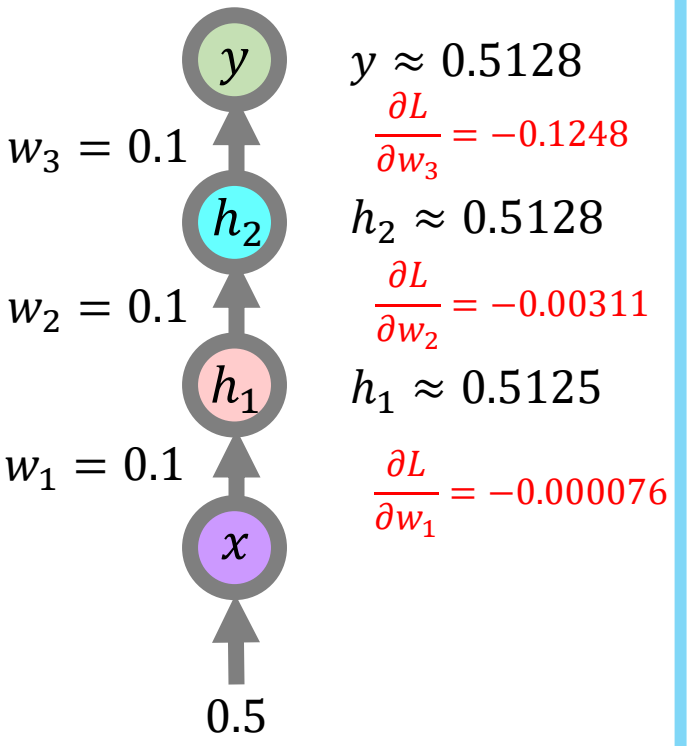
$h_1 \approx 0.5125$

신박AI

마찬가지로 $\partial L/\partial w_1$도 체인룰에 의해 다음과 같이 전개할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

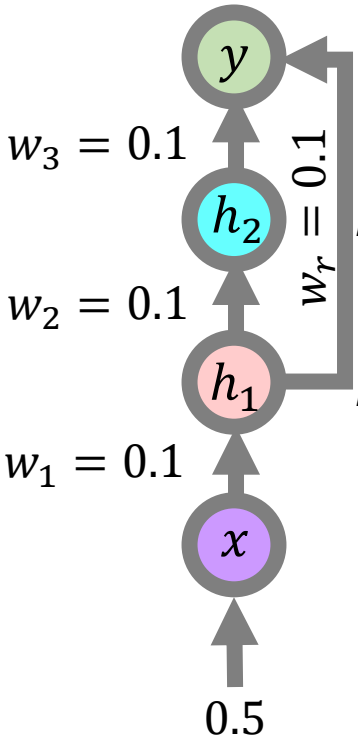
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial w_1 x} \cdot \frac{\partial w_1 x}{\partial w_1}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

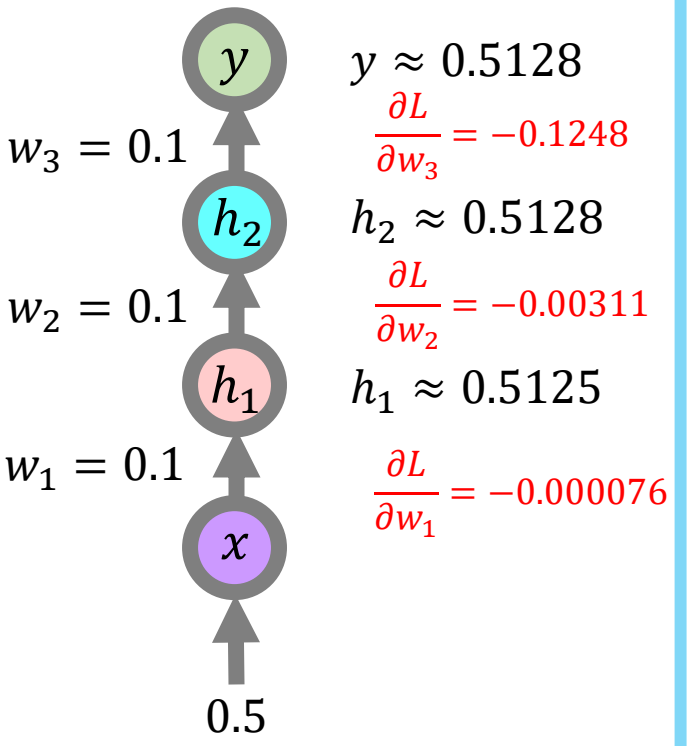
$h_1 \approx 0.5125$

신박AI

그런데 이 부분은 앞서 구한 부분이니 재사용하도록 하겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

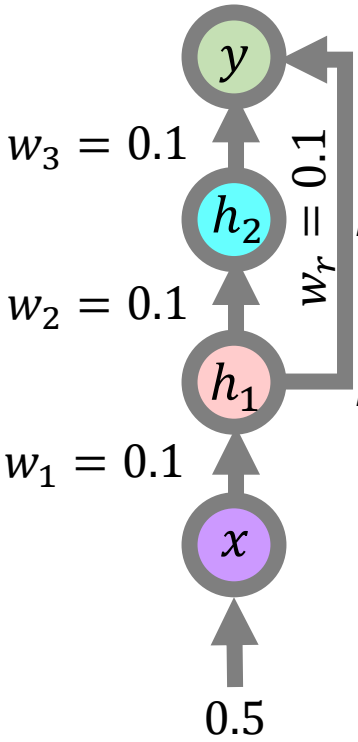
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \frac{\partial (w_3 h_2 + w_r h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial w_1 x} \cdot \frac{\partial w_1 x}{\partial w_1}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

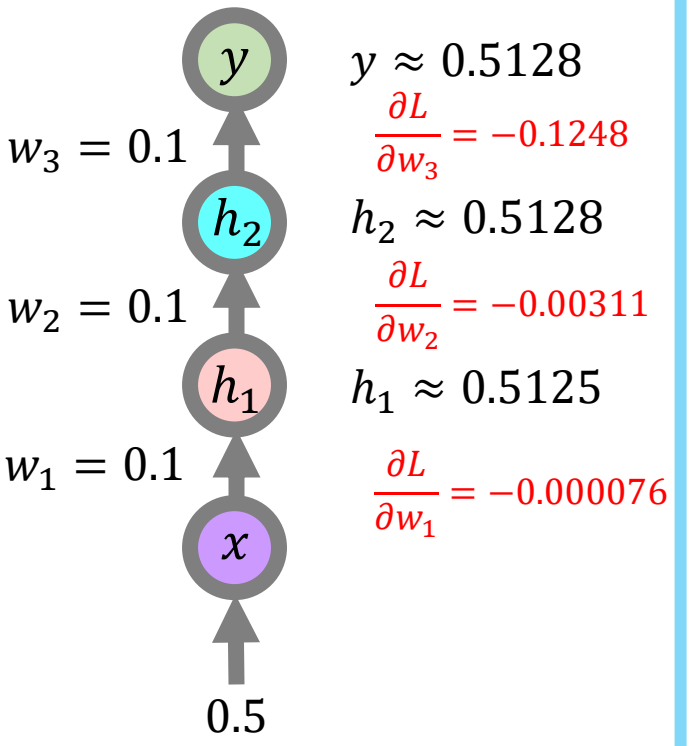
$h_1 \approx 0.5125$

신박AI

그런데 이 부분은 앞서 구한 부분이니 재사용하도록 하겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

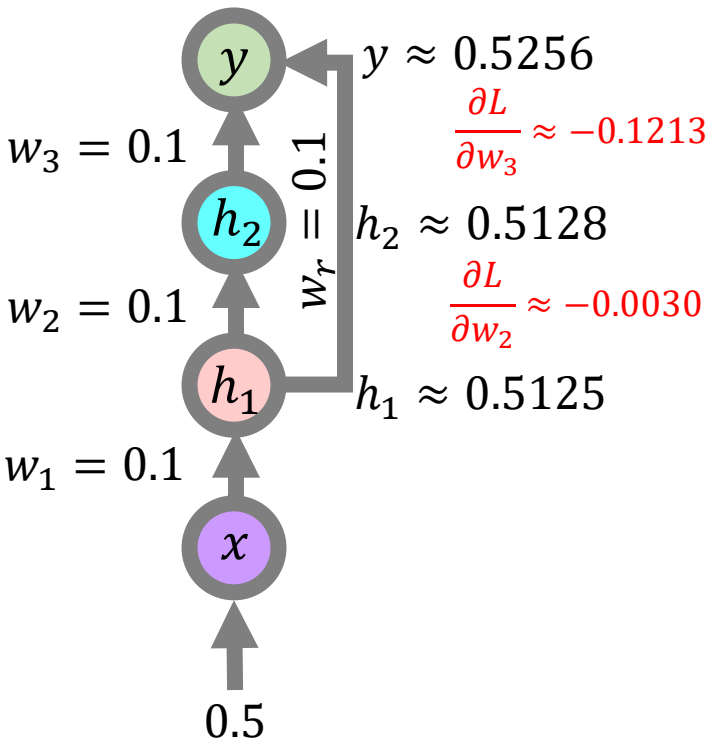
$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2247$$

$$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial w_1 x} \cdot \frac{\partial w_1 x}{\partial w_1}$$

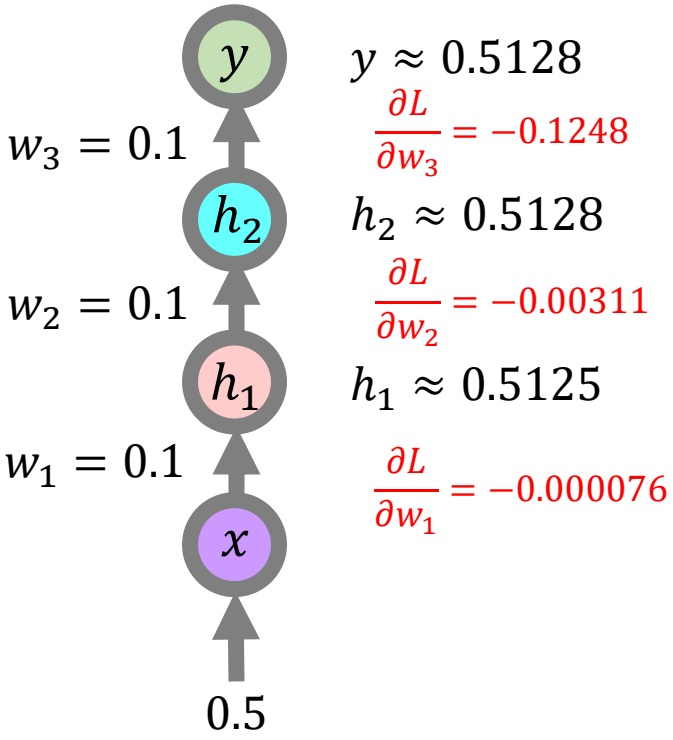


신박AI

그리고 세번째 항은 h_1 편미분에 의해서,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

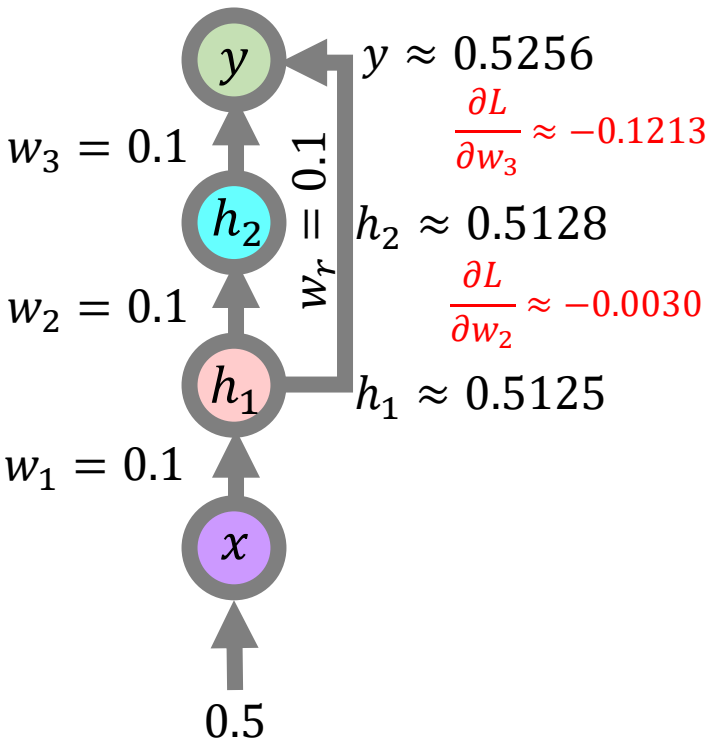
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot \frac{\partial(w_3 h_2 + w_r h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial w_1 x} \cdot \frac{\partial w_1 x}{\partial w_1}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

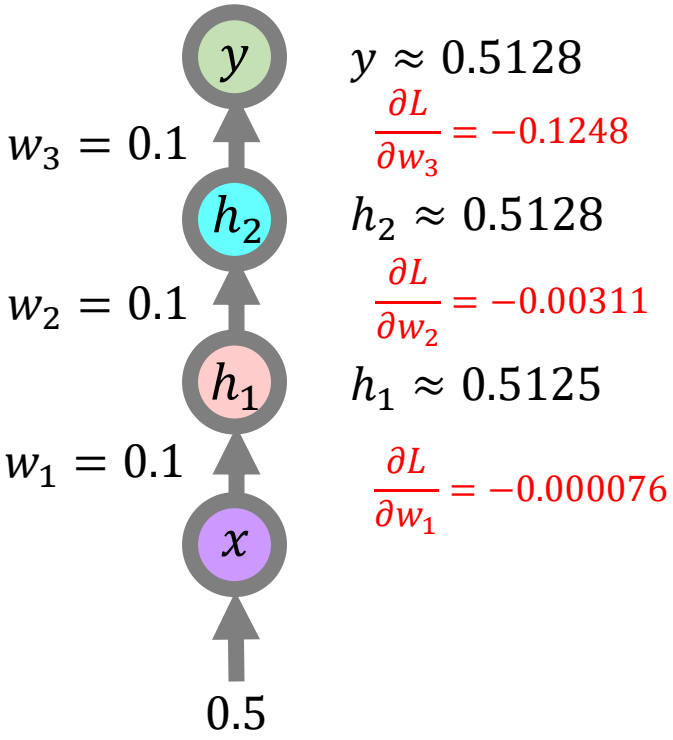
$h_1 \approx 0.5125$

신박AI

w_r이 됩니다.

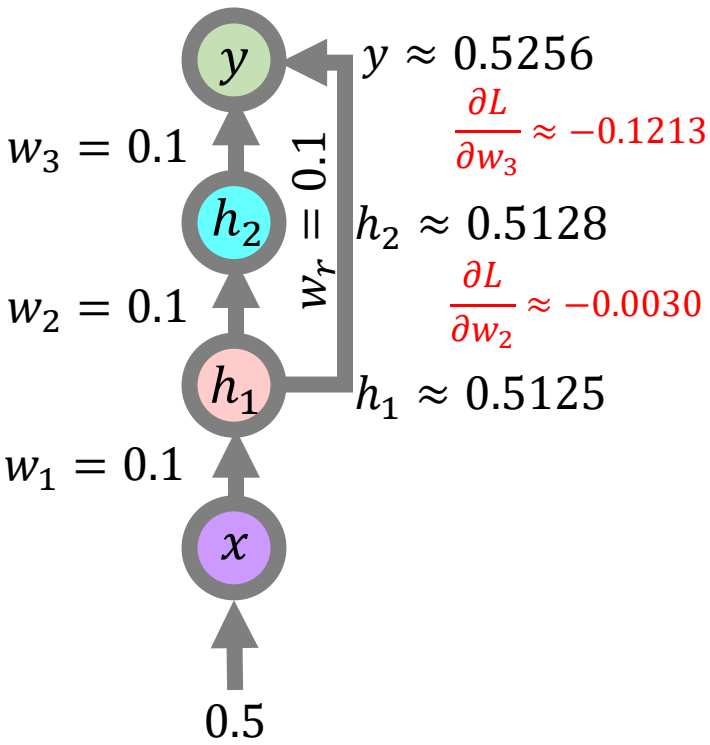
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2247 \quad \frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot w_r \cdot \frac{\partial h_1}{\partial w_1 x} \cdot \frac{\partial w_1 x}{\partial w_1}$$

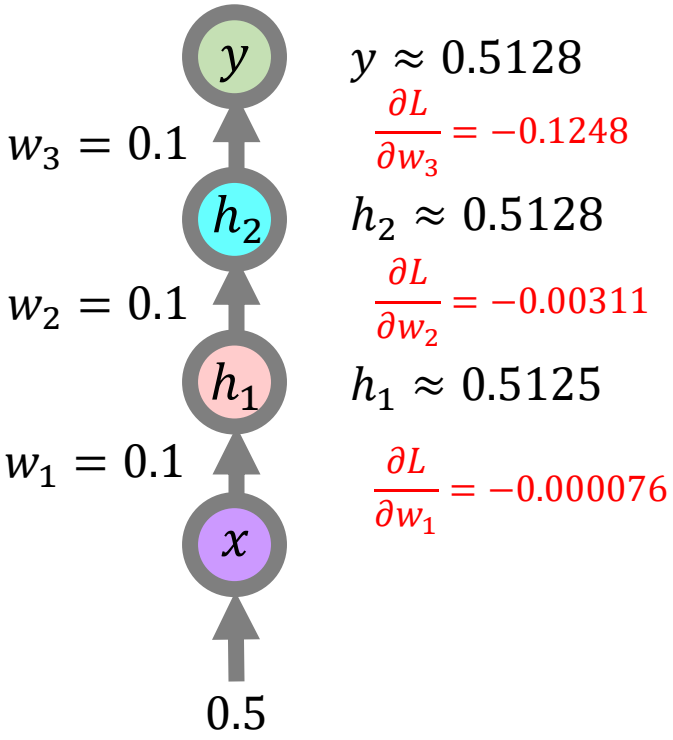


신박AI

w_r이 됩니다.

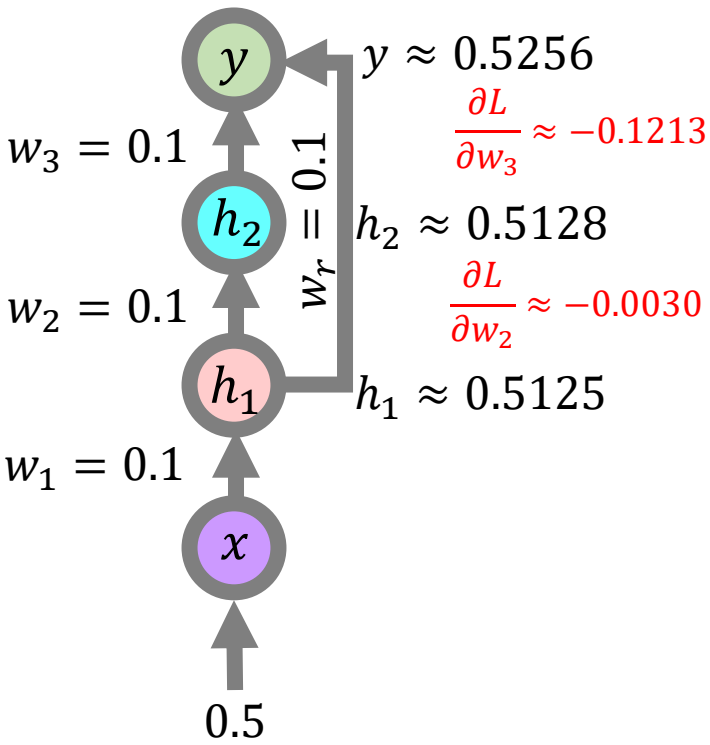
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2247 \quad \frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot w_r \cdot \frac{\partial h_1}{\partial w_1 x} \cdot \frac{\partial w_1 x}{\partial w_1}$$

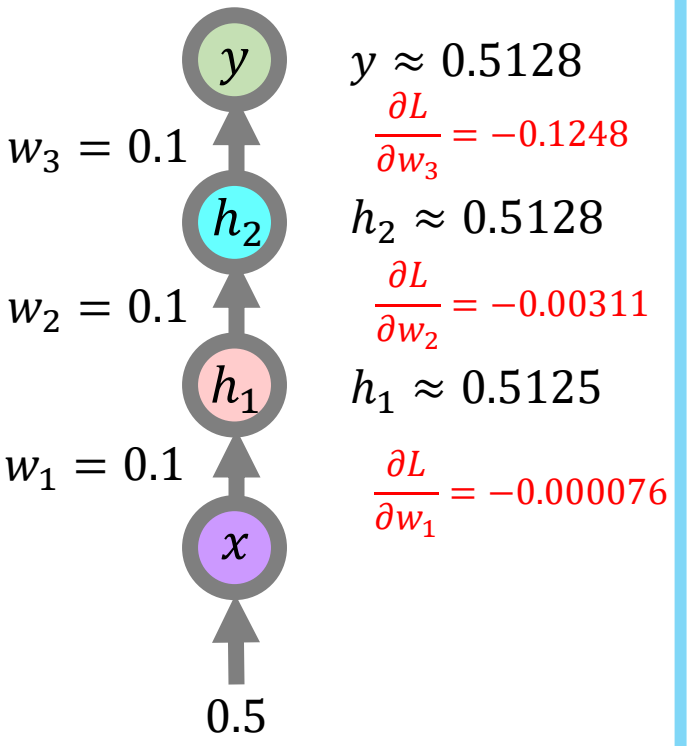


신박AI

그러면 w_r의 값은 0.1이기 때문에 그 값을 대입하면 다음과 같이 되고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

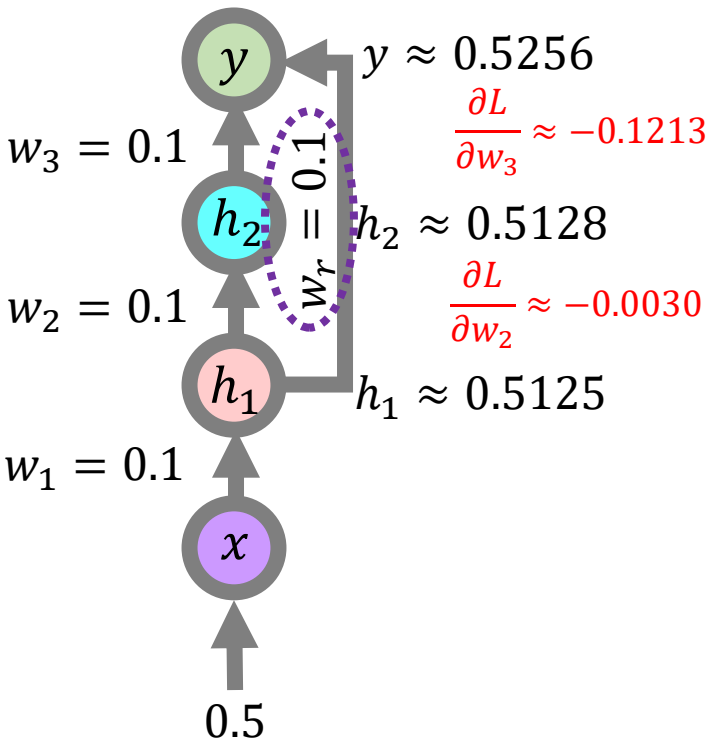
$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2247$$

$$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot \frac{\partial h_1}{\partial w_1 x} \cdot \frac{\partial w_1 x}{\partial w_1}$$

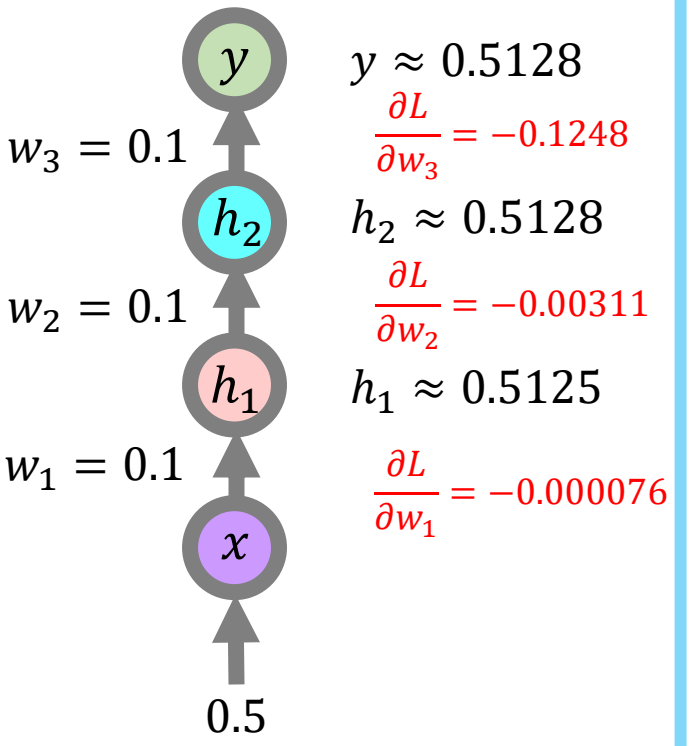


신박AI

그리고 네번째 항은 시그모이드 미분 공식에 의하여,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2372$$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

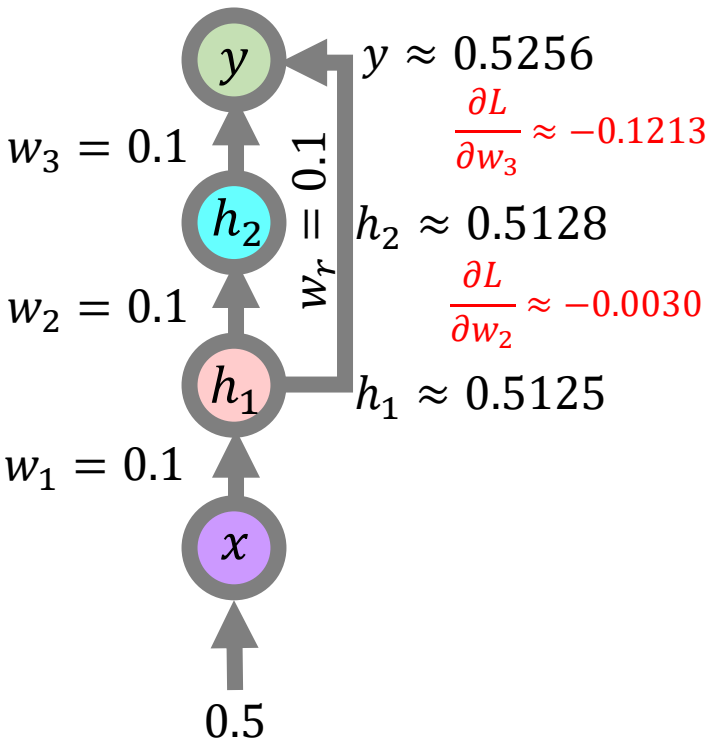
$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2247$$

$$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot \frac{\partial h_1}{\partial w_1 x} \cdot \frac{\partial w_1 x}{\partial w_1}$$

$\because h_1 = \sigma(w_1 x)$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

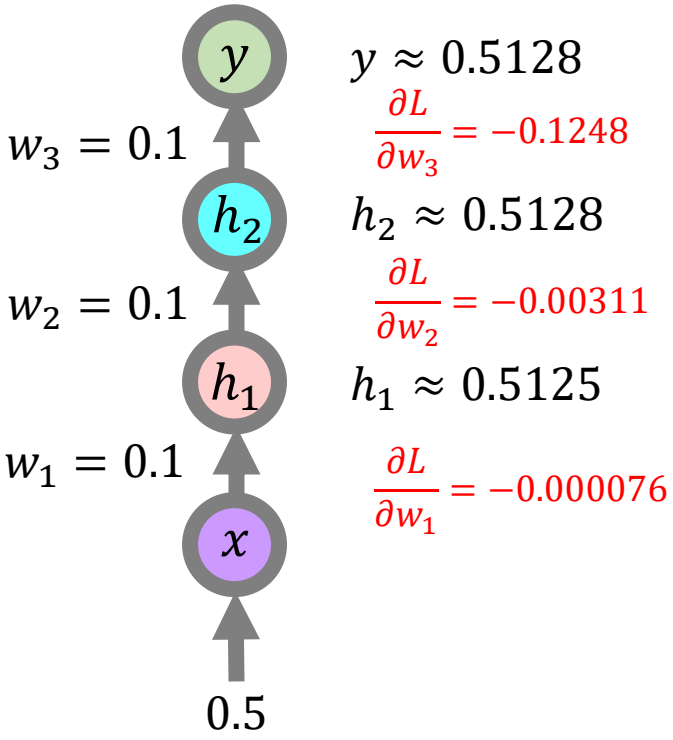
$h_1 \approx 0.5125$

신박AI

다음처럼 바뀌고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

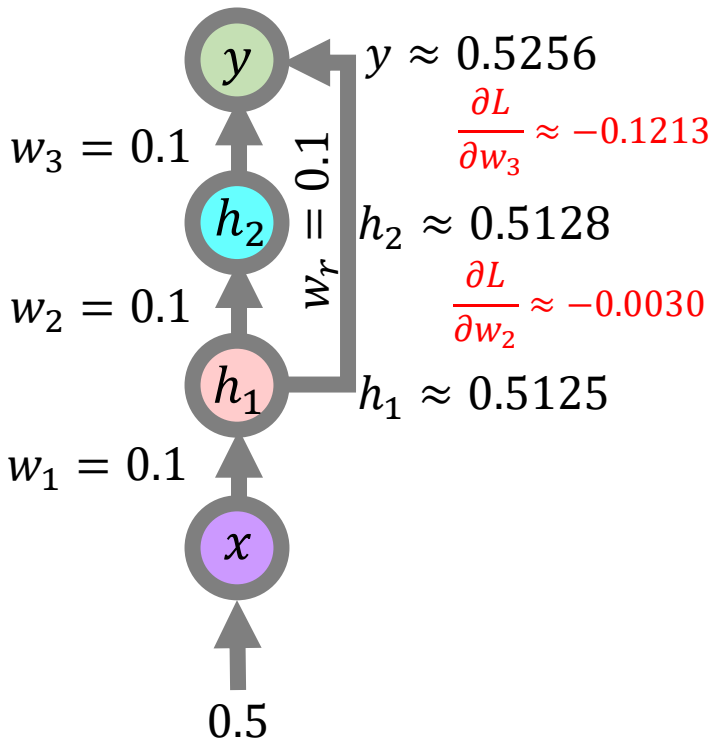
$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot h_1(1 - h_1) \cdot \frac{\partial w_1 x}{\partial w_1}$$

$\because h_1 = \sigma(w_1 x)$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

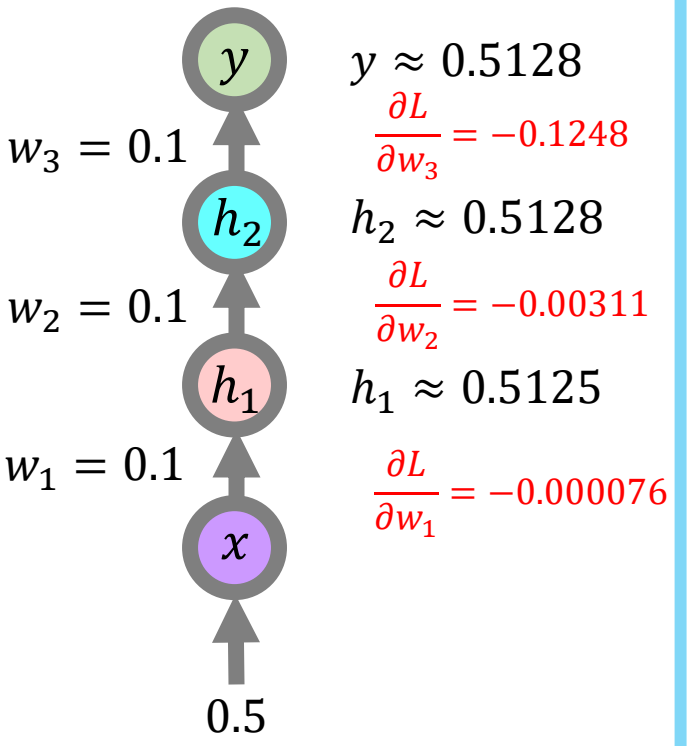
$h_1 \approx 0.5125$

신박AI

h_1 에 0.5125을 대입하여 계산하면, 대략 0.2498이 됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

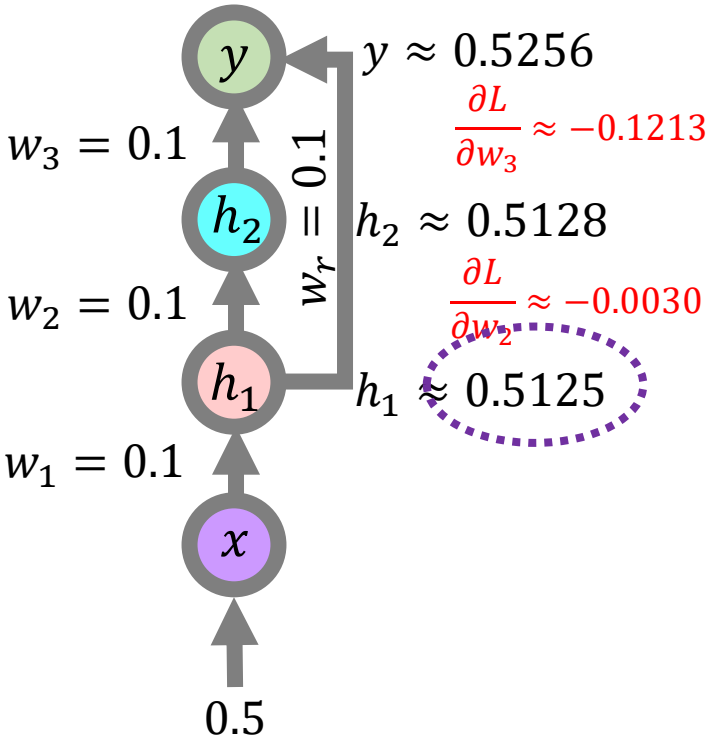
$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$ $\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial w_1 x}{\partial w_1}$

$\because h_1 = \sigma(w_1 x)$

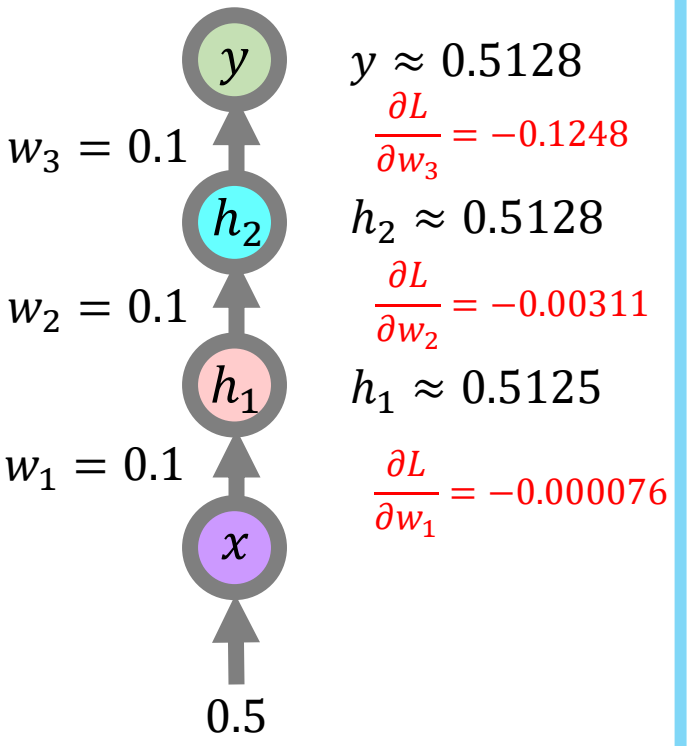


신박AI

마지막항은 w_1의 편미분공식에 의하여, x가 되고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

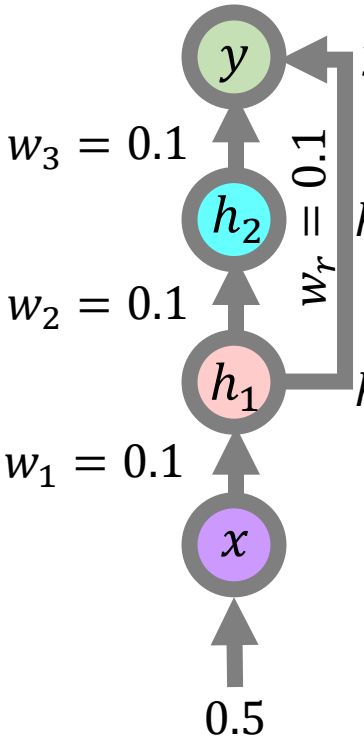
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot \frac{\partial w_1 x}{\partial w_1}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

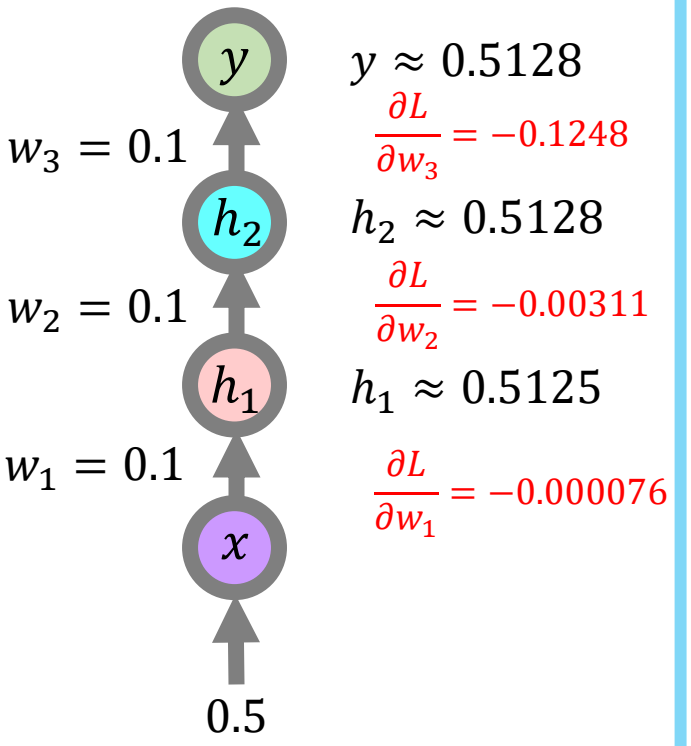
$h_1 \approx 0.5125$

신박AI

입력값인 0.5를 대입하면 다음처럼 정리가 가능합니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

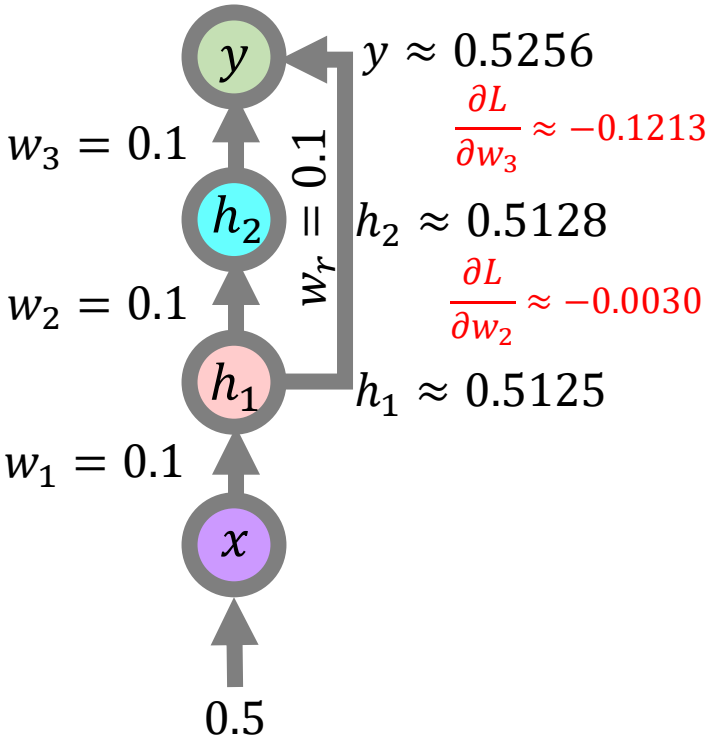
$$loss \approx 0.2372$$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$$loss \approx 0.2247$$

$$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot 0.5$$

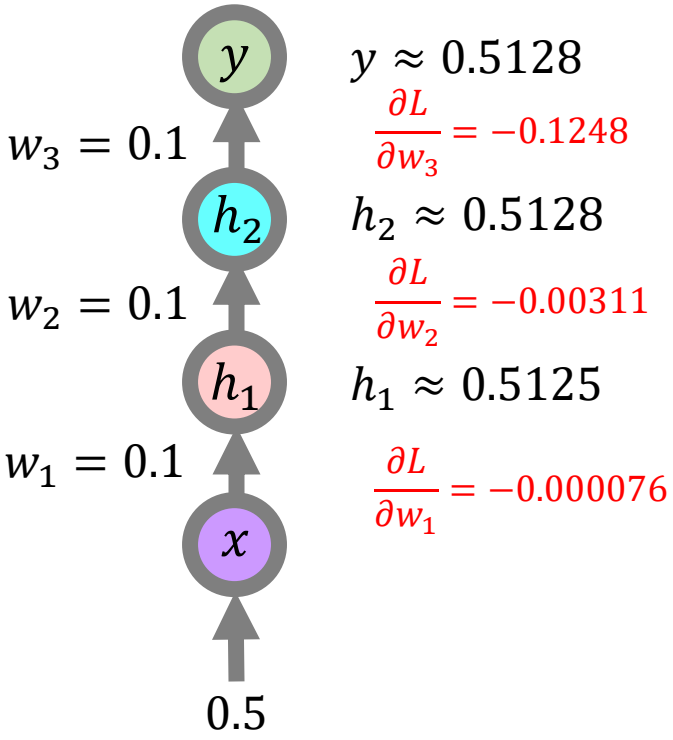


신박AI

그러면 $\partial L/\partial w_1$ 은 -0.00295이 됨을 확인할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

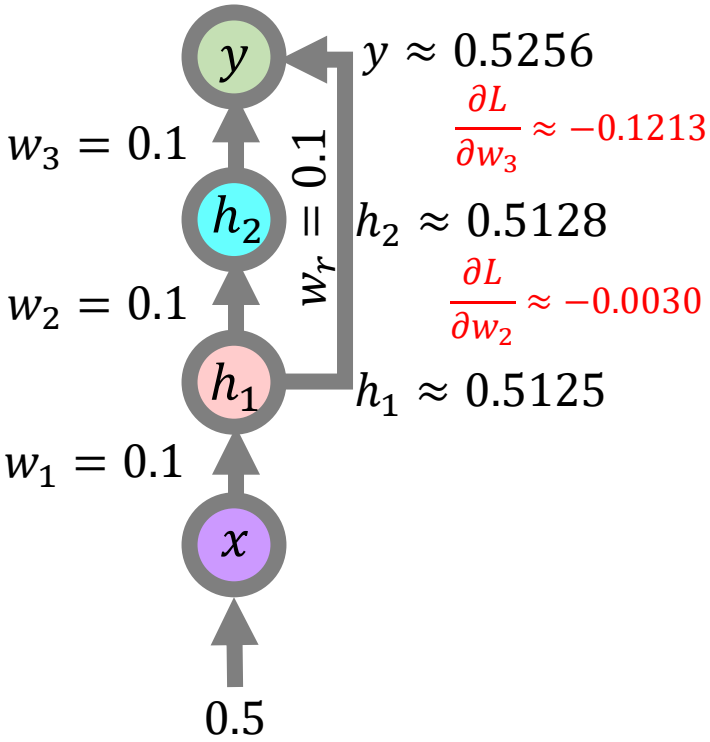
$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot 0.5 = -0.00295$$

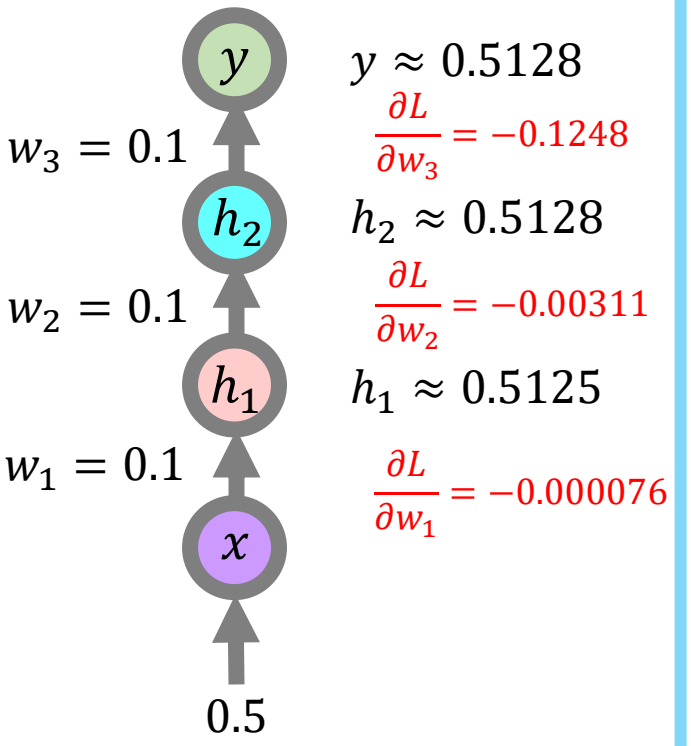


신박AI

하지만 $\partial L/\partial w_1$ 은 이것이 전부가 아닙니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

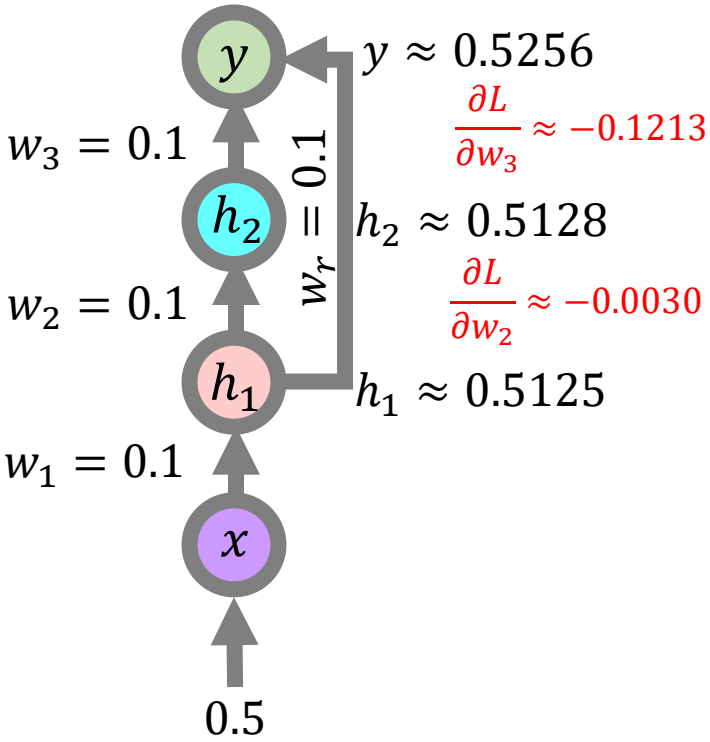
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot 0.5 = -0.00295$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

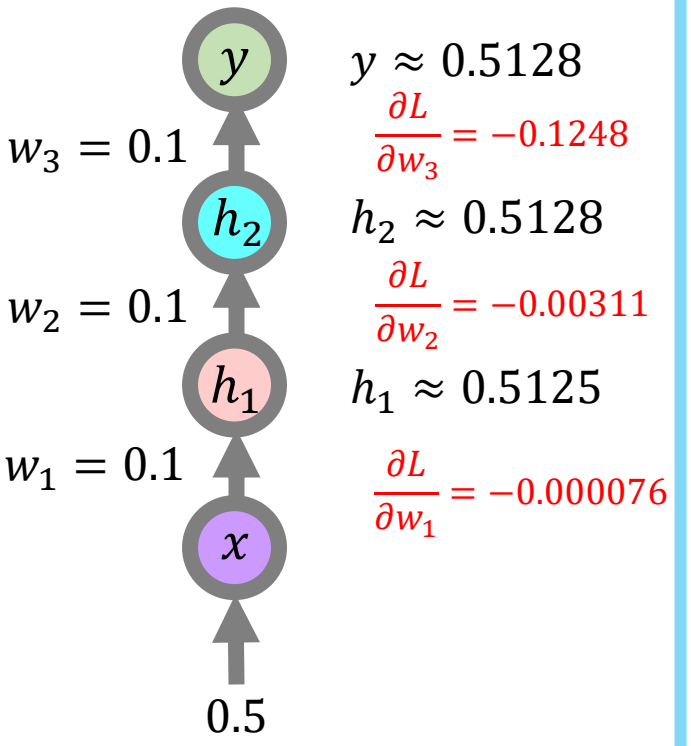
$h_1 \approx 0.5125$

신박AI

왜냐하면 이 계산은 다음 빨간 경로의 역전파이기 때문입니다.

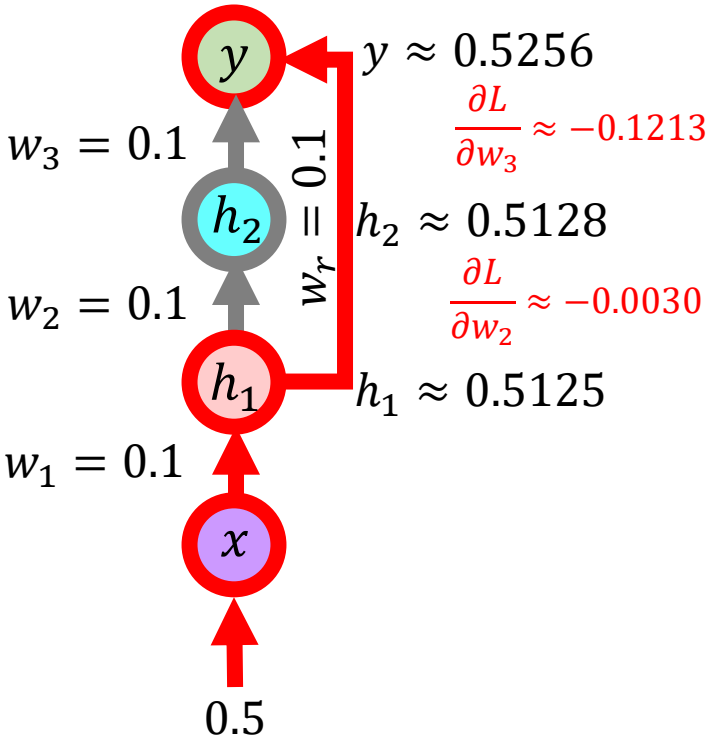
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$ $\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.2498 \cdot 0.5 = -0.00295$

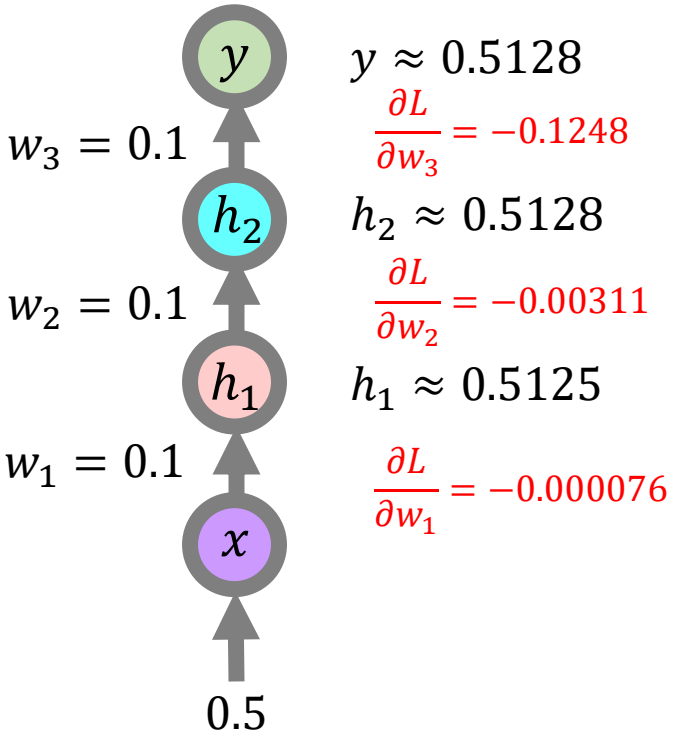


신박AI

우리는 $\partial L/\partial w_1$에 영향을 주는 파란 경로 또한 역전파를 구해주어야 합니다.

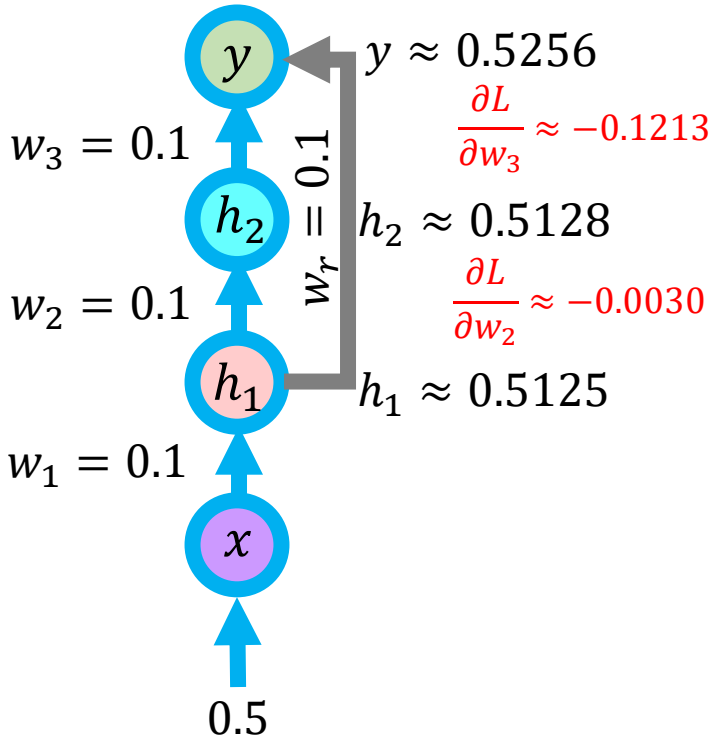
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$ $\dfrac{\partial L}{\partial w_1} = -0.00295$

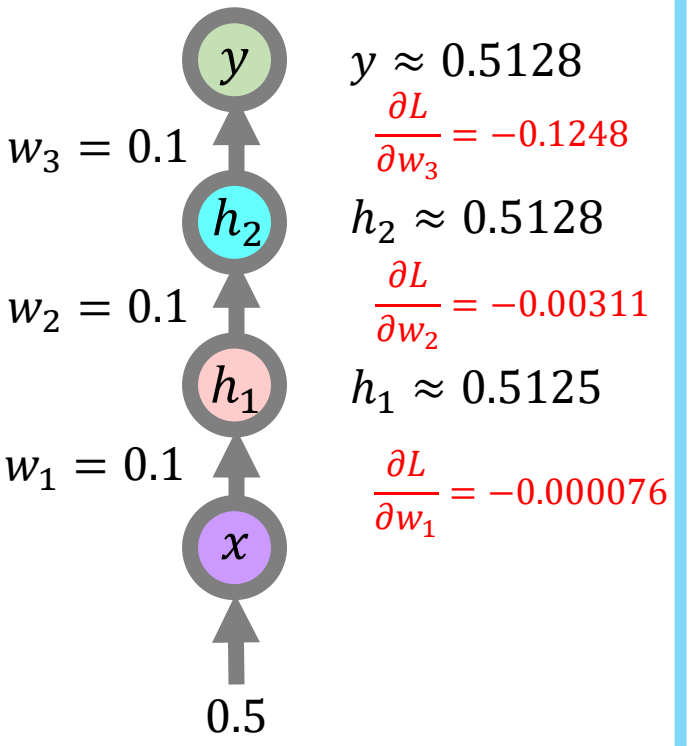


신박AI

그에 대한 공식은 체인룰에 의해 다음과 같습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

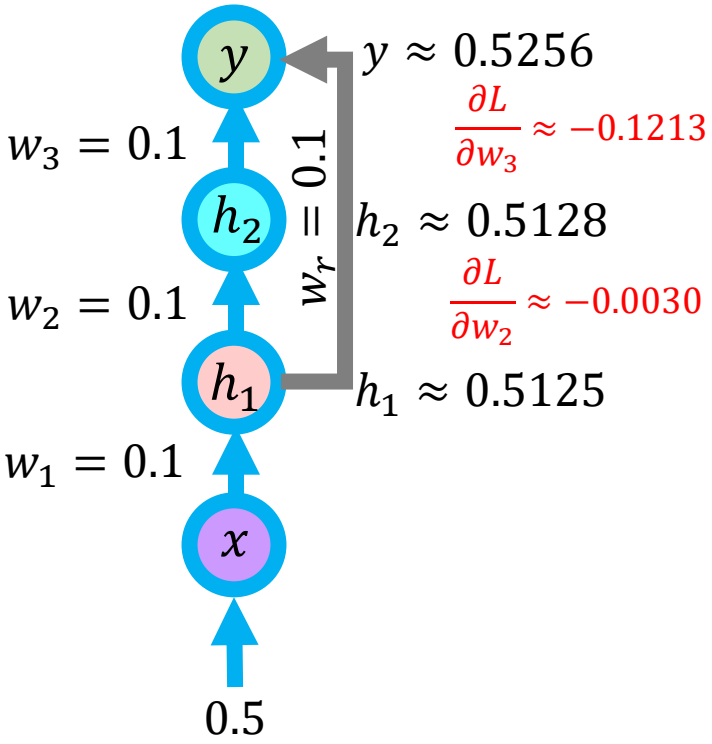
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$ $\frac{\partial L}{\partial w_1} = -0.00295$

$\frac{\partial L}{\partial w_1}$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

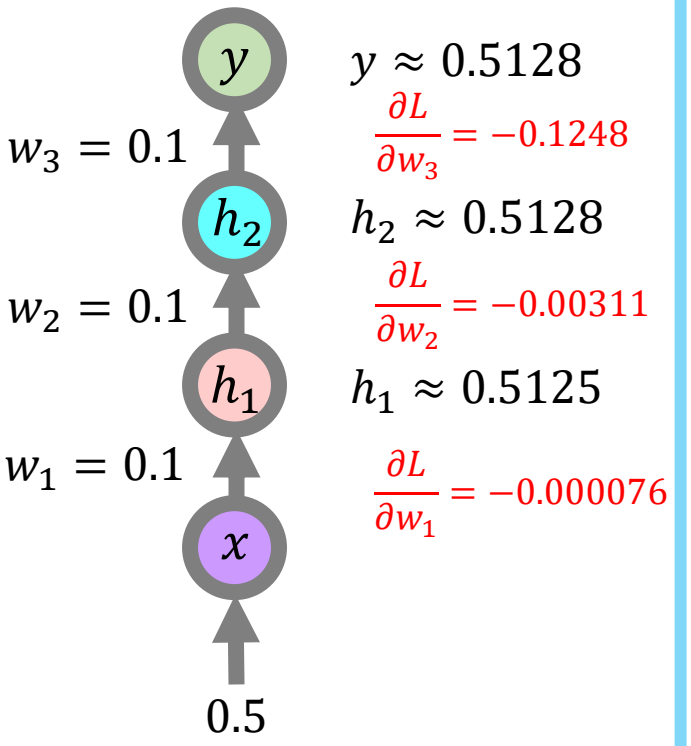
$h_1 \approx 0.5125$

신박AI

그에 대한 공식은 체인룰에 의해 다음과 같습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

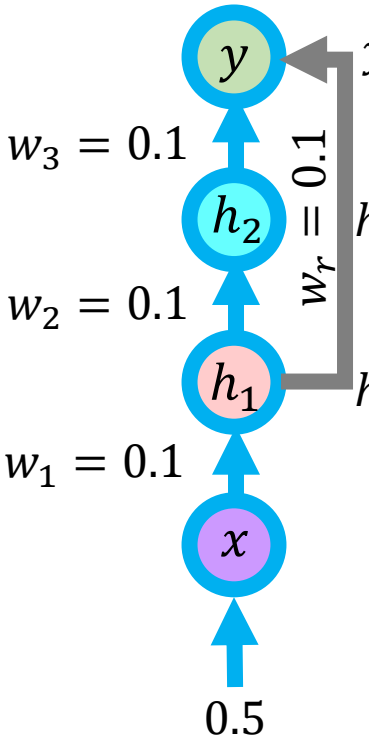
$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$\frac{\partial L}{\partial w_1} = -0.00295$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial (w_3 h_2 + w_r h_1)} \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

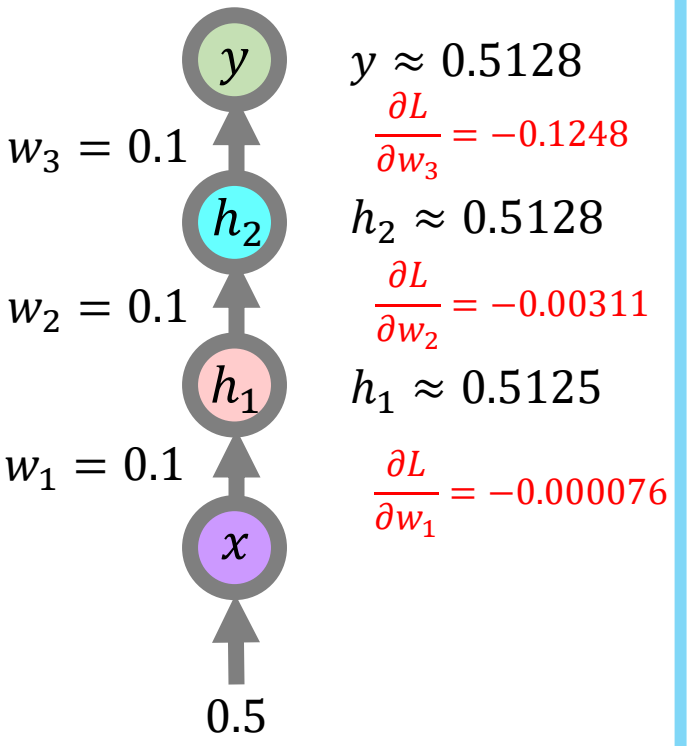
$h_1 \approx 0.5125$

신박AI

앞의 두 항은 앞에서 계산한 값으로 바로 바꿀 수 있고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

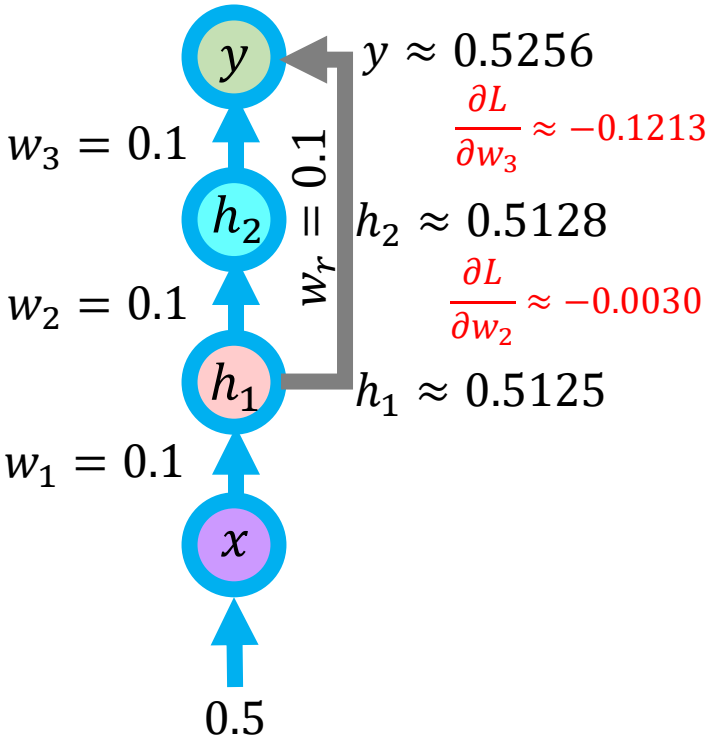
$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$\frac{\partial L}{\partial w_1} = -0.00295$

$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot \frac{\partial (w_3 h_2 + w_r h_1)}{\partial h_2} \cdot \frac{\partial h_2}{\partial (w_2 h_1)} \cdot \frac{\partial (w_2 h_1)}{\partial h_1} \cdot \frac{\partial h_1}{\partial (w_1 x)} \cdot \frac{\partial (w_1 x)}{\partial w_1}$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

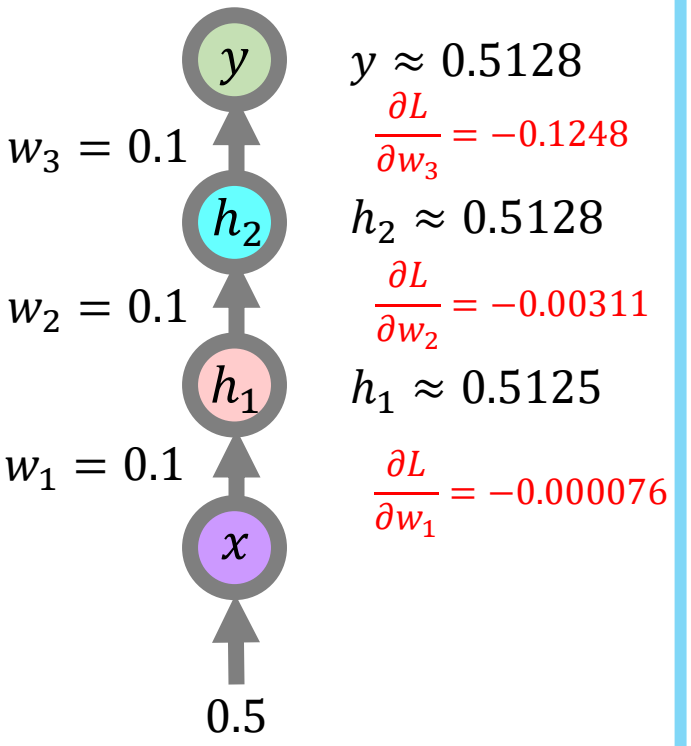
$h_1 \approx 0.5125$

신박AI

뒤의 항들도 간단하게 다음과 같이 바꾸어 쓸수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

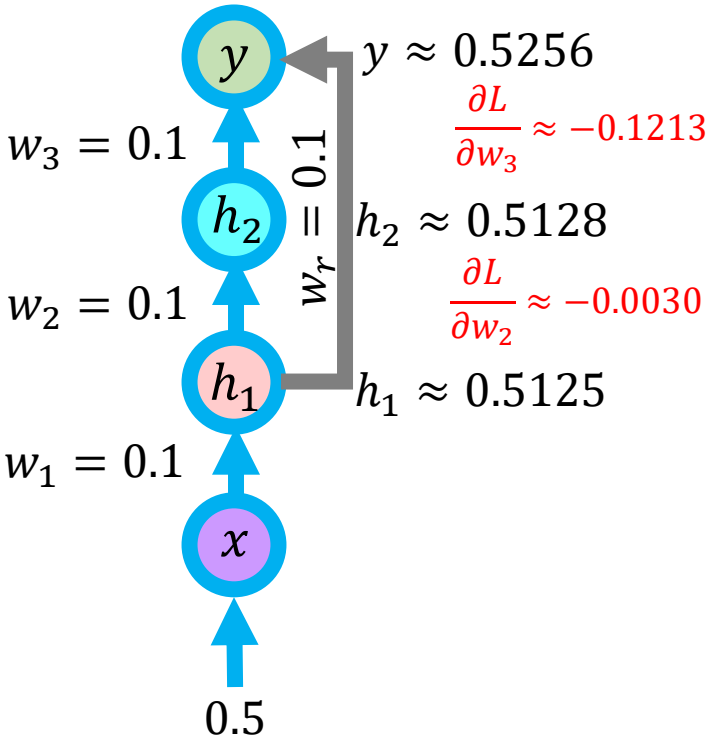
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$ $\frac{\partial L}{\partial w_1} = -0.00295$

$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot w_3 \cdot h_2(1-h_2) \cdot w_2 \cdot h_1(1-h_1) \cdot x$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

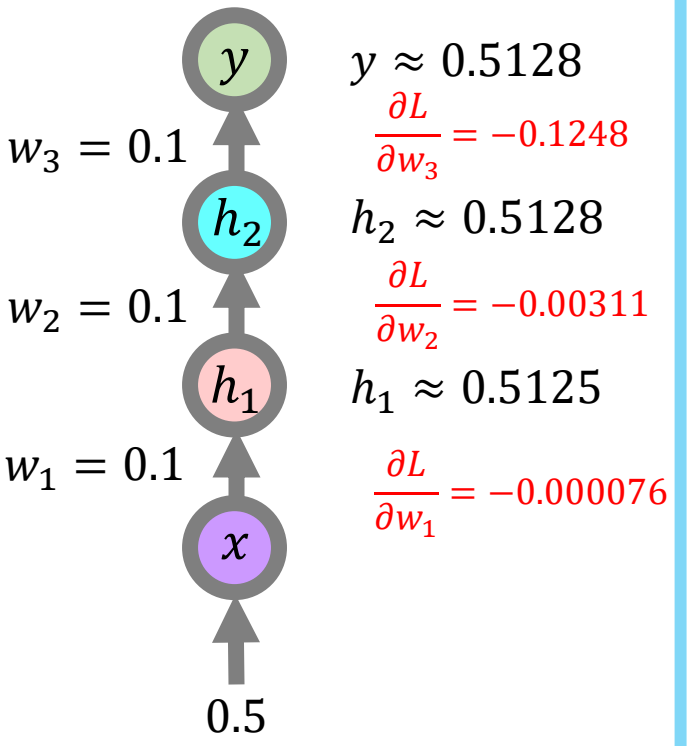
$h_1 \approx 0.5125$

신박AI

알려진 값들을 대입하면 다음과 같이 정리할 수 있고,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

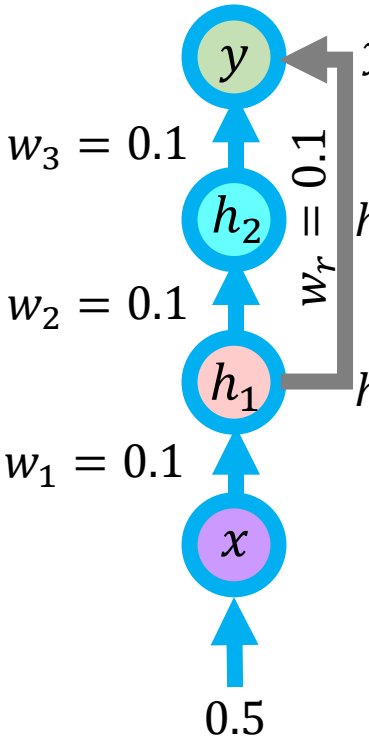
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2247$

$\frac{\partial L}{\partial w_1} = -0.00295$

$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot w_3 \cdot h_2(1-h_2) \cdot w_2 \cdot h_1(1-h_1) \cdot x$

$= -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.5128(1-0.5128) \cdot 0.1 \cdot 0.5125(1-0.5125) \cdot 0.5$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

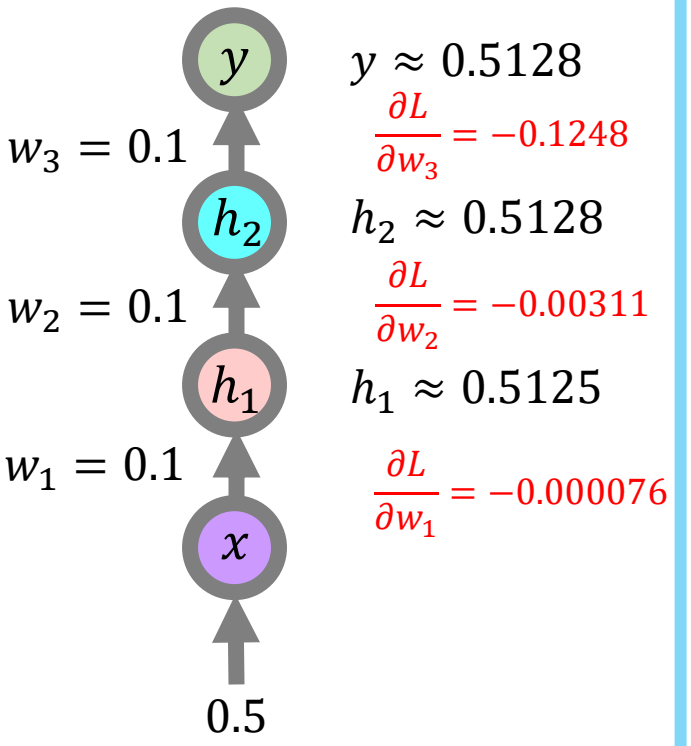
$h_1 \approx 0.5125$

신박AI

그러면 또 다른 $\partial L/\partial w_1$ 값은 -0.000074가 되고..

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

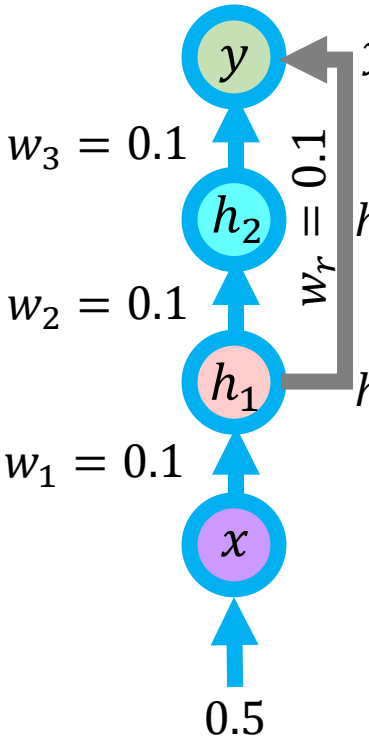
$loss \approx 0.2247$

$\frac{\partial L}{\partial w_1} = -0.00295$

$\frac{\partial L}{\partial w_1} = -0.9488 \cdot 0.2493 \cdot w_3 \cdot h_2(1-h_2) \cdot w_2 \cdot h_1(1-h_1) \cdot x$

$= -0.9488 \cdot 0.2493 \cdot 0.1 \cdot 0.5128(1-0.5128) \cdot 0.1 \cdot 0.5125(1-0.5125) \cdot 0.5$

$= -0.000074$



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

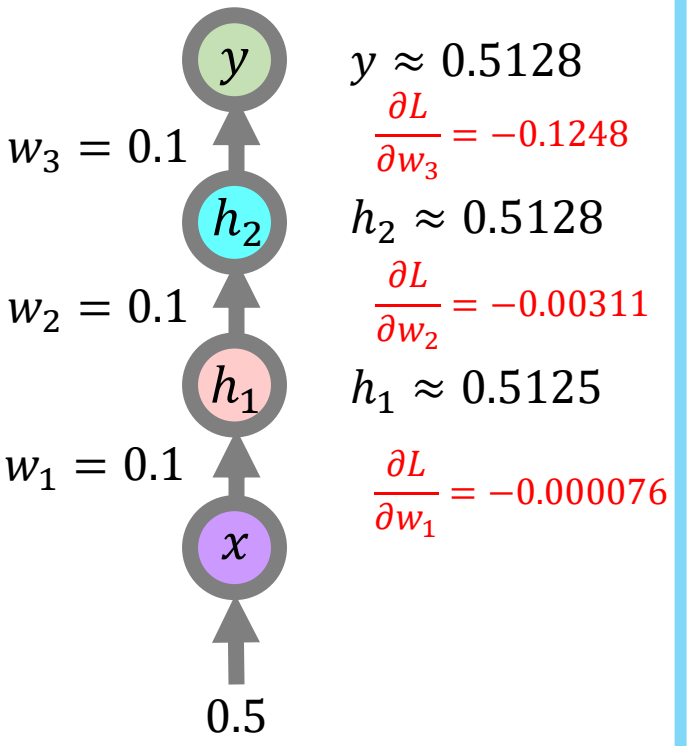
$h_1 \approx 0.5125$

신박AI

이 둘을 더한 값인 -0.003024가 최종 $\partial L/\partial w_1$ 값이 되겠습니다.

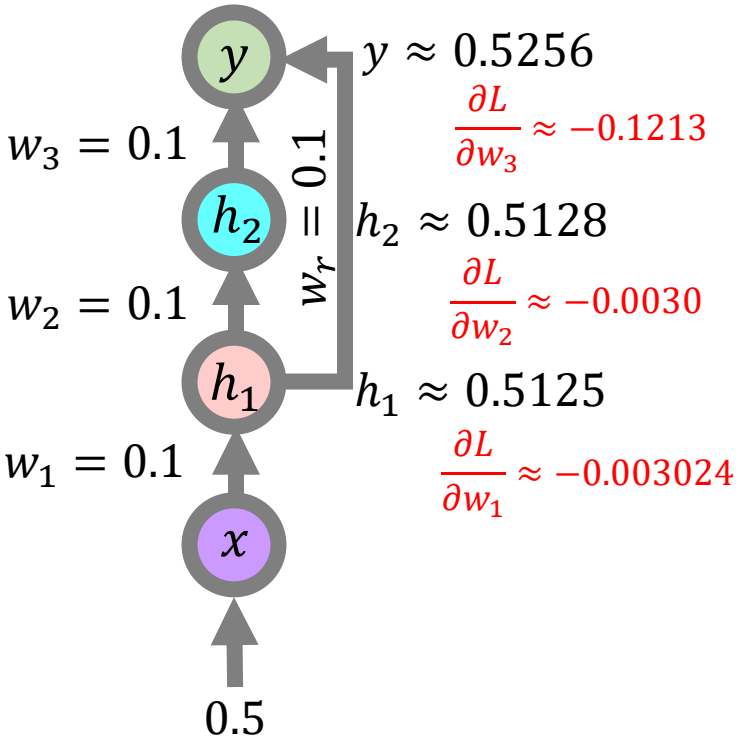
시나리오1: 그냥 신경망
(활성화함수는 시그모이드)

$loss \approx 0.2372$



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)

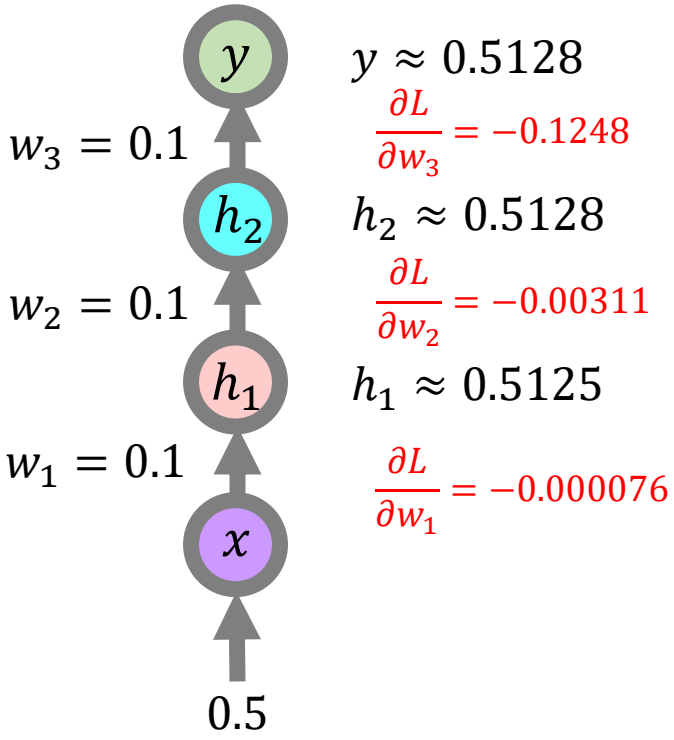
$loss \approx 0.2247$ $\frac{\partial L}{\partial w_1} = -0.00295 - 0.000074 = 0.003024$



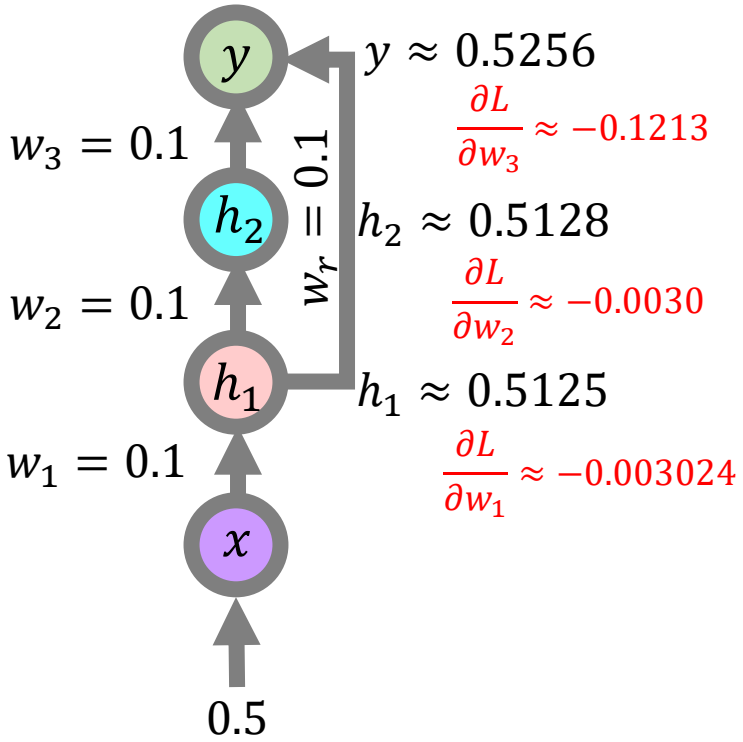
신박AI

이 둘을 더한 값인 −0.003024가 최종 $\partial L/\partial w_1$ 값이 되겠습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



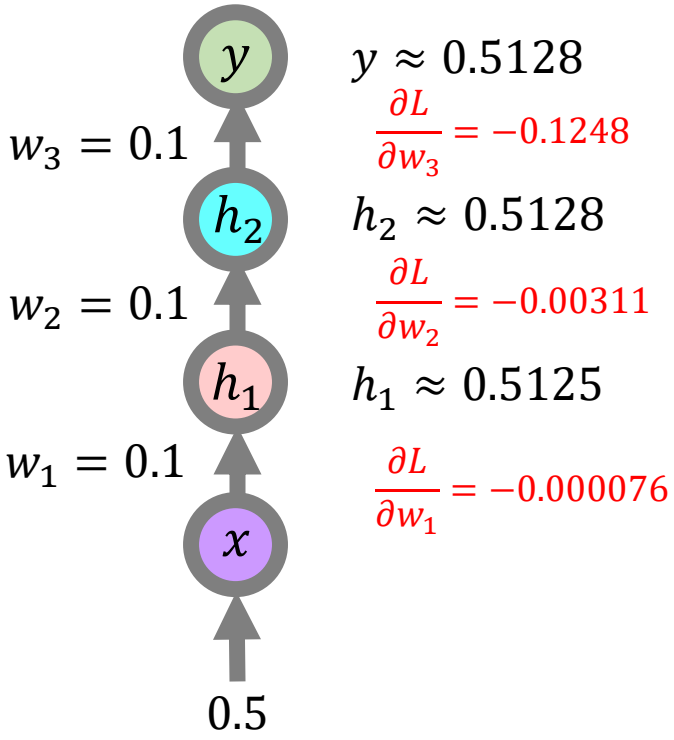
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



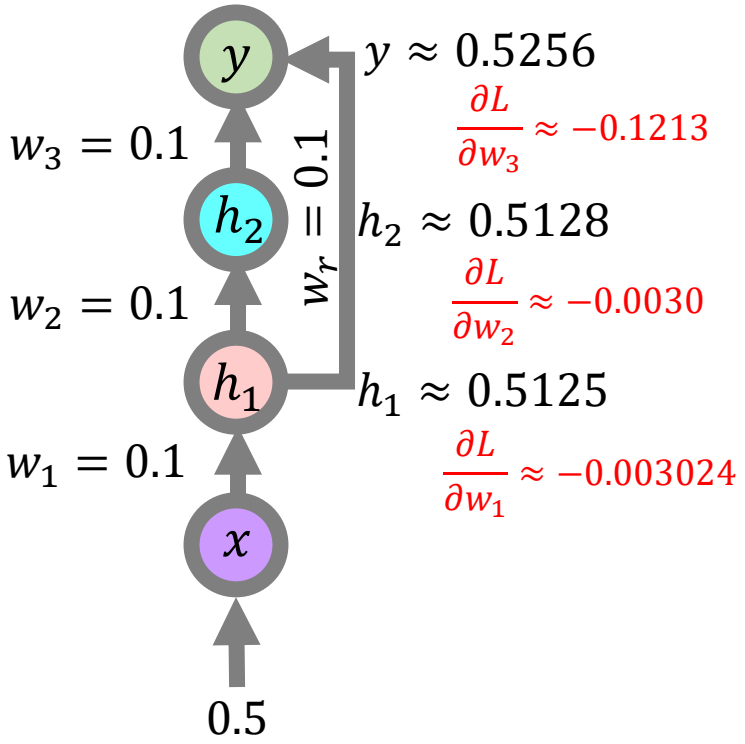
신박AI

자 드디어 첫번째 결론에 도달할 시점에 이르렀습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



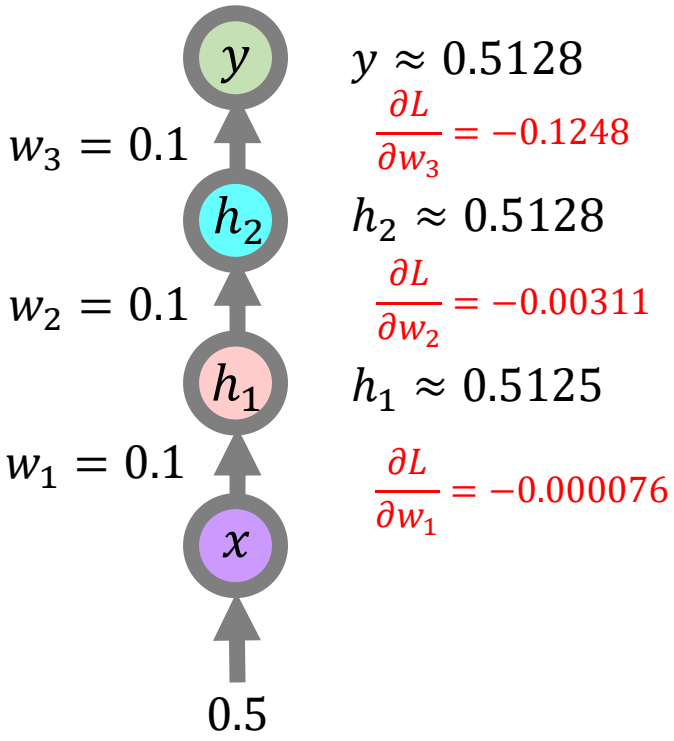
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



신박AI

잔차가 없는 그냥 신경망의 경우,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

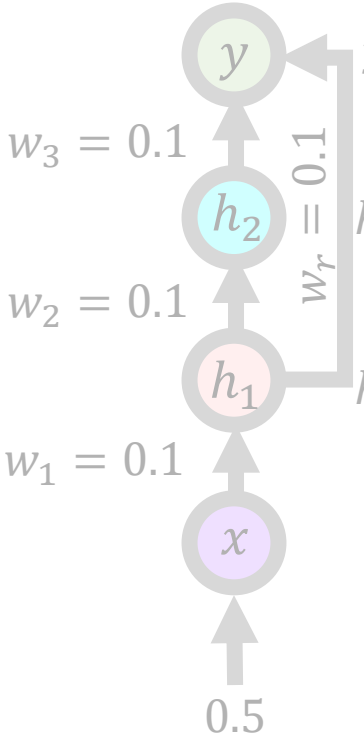
$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

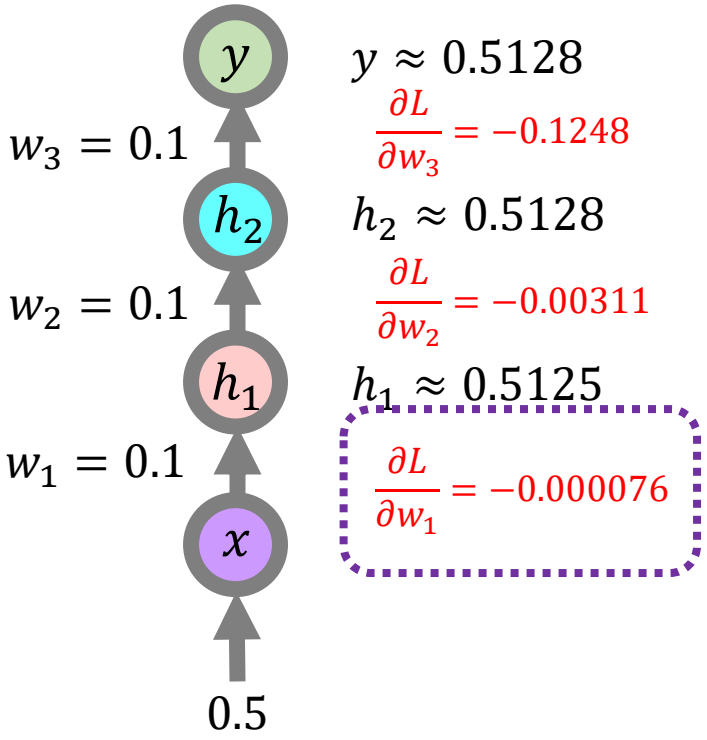
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} \approx -0.003024$

신박AI

역전파가 초기층으로 갈 수록 그 기울기값이 급속히 작아지는 것을 확인할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



$y \approx 0.5128$

$\frac{\partial L}{\partial w_3} = -0.1248$

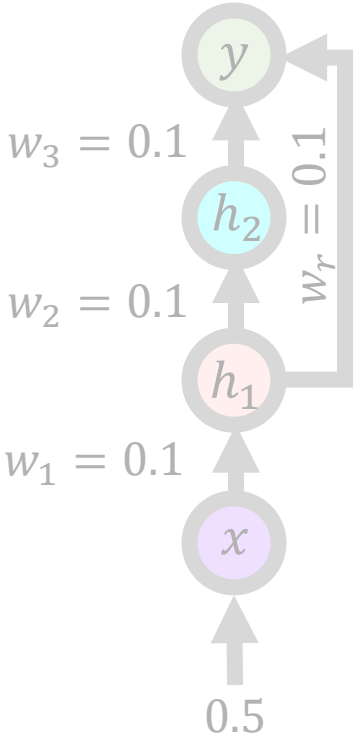
$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} = -0.00311$

$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} = -0.000076$

시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



$y \approx 0.5256$

$\frac{\partial L}{\partial w_3} \approx -0.1213$

$h_2 \approx 0.5128$

$\frac{\partial L}{\partial w_2} \approx -0.0030$

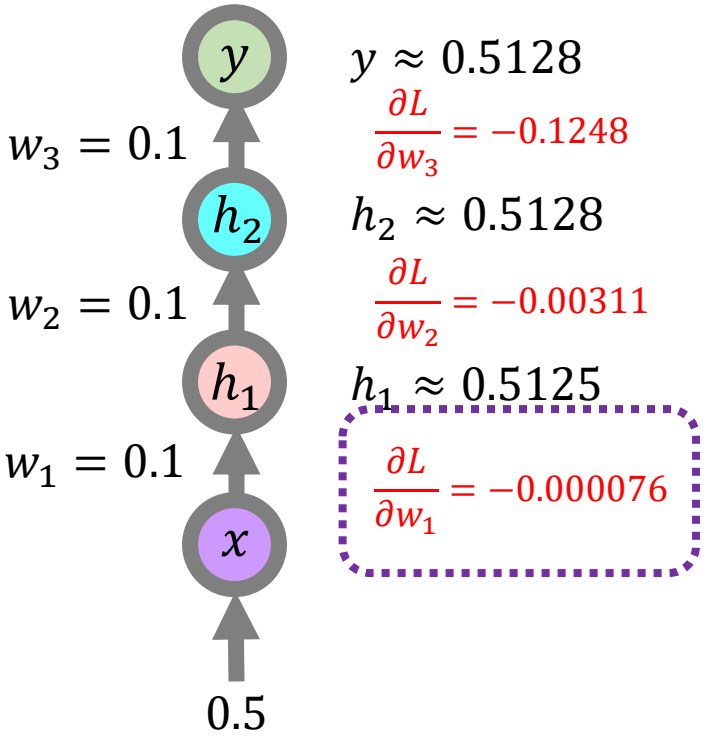
$h_1 \approx 0.5125$

$\frac{\partial L}{\partial w_1} \approx -0.003024$

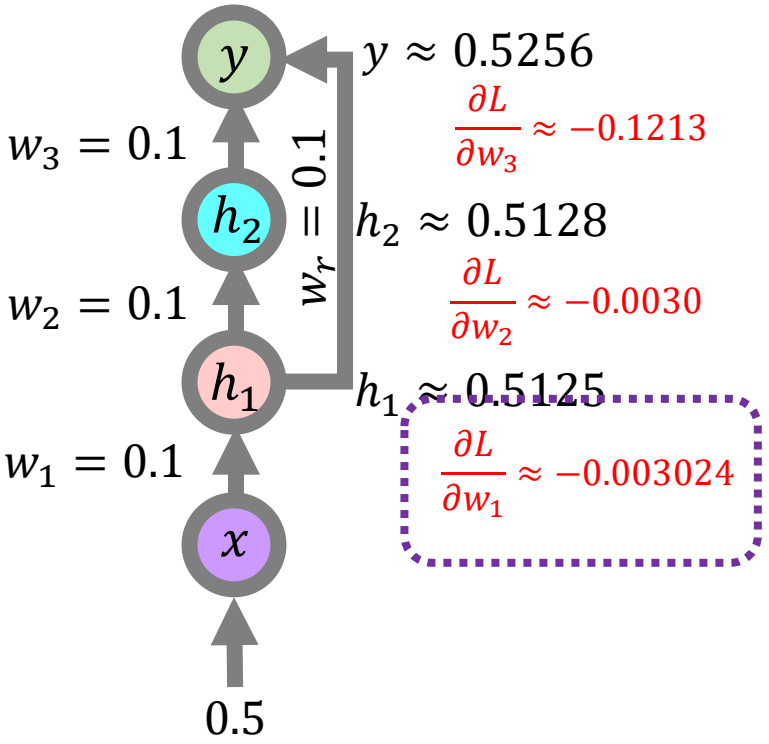
신박AI

그러나 잔차 신경망의 경우는, 초기층으로 간다 할지라도, 그냥 신경망에 비해 기울기가 급속히 변하지 않는 것을 볼 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



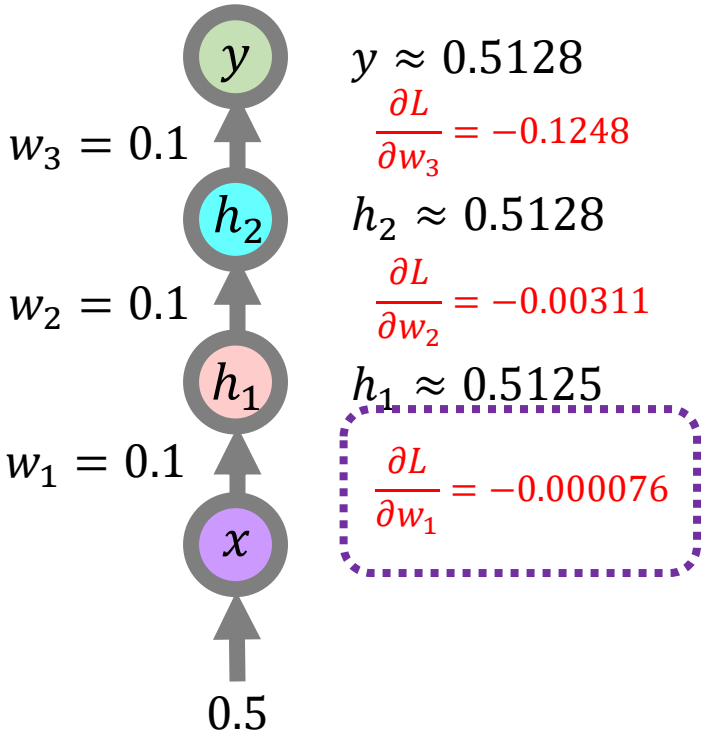
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



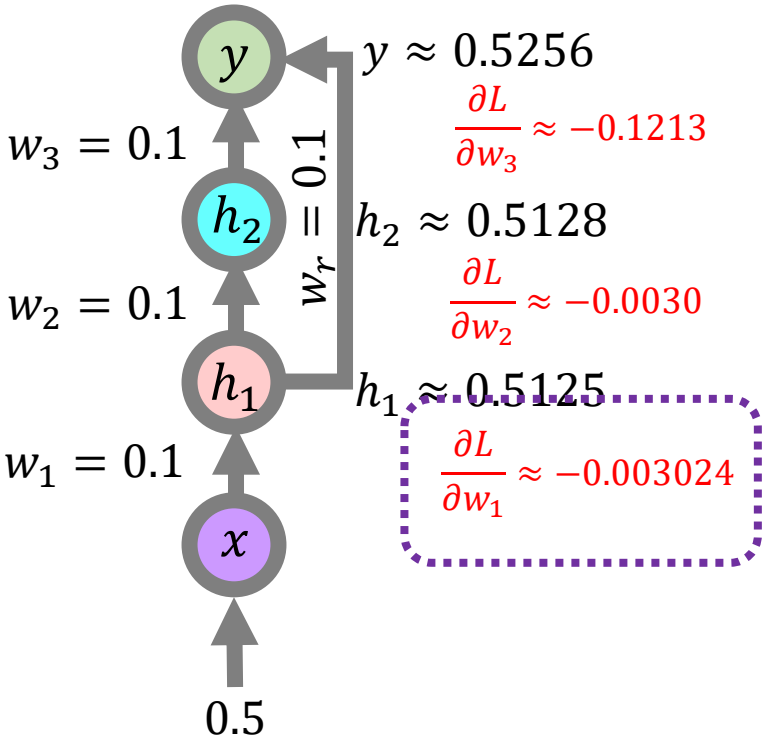
신박AI

이것이 바로 잔차 신경망, skip-connection이 어떻게 깊은 신경망의 학습을 용이하게 하는지를 보여주는 좋은 예라고 할 수 있습니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



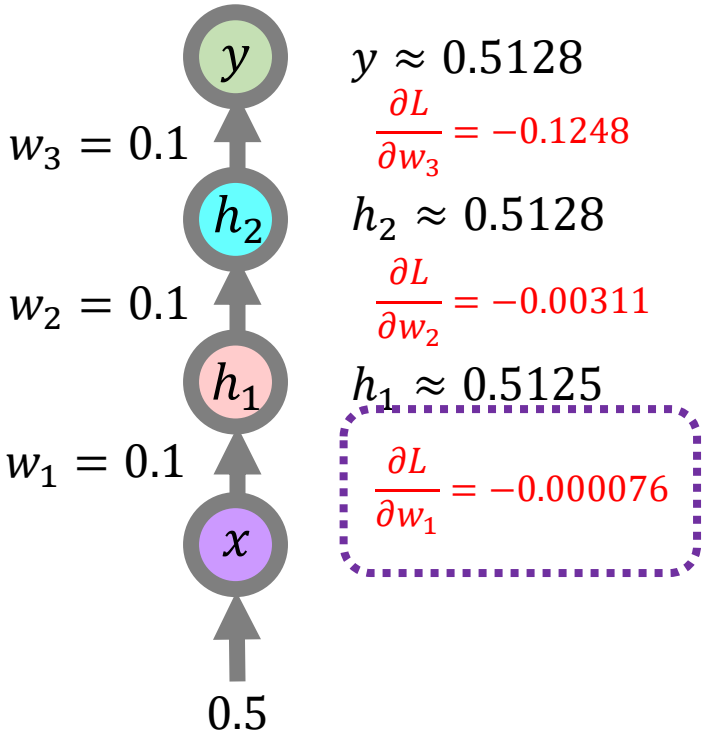
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



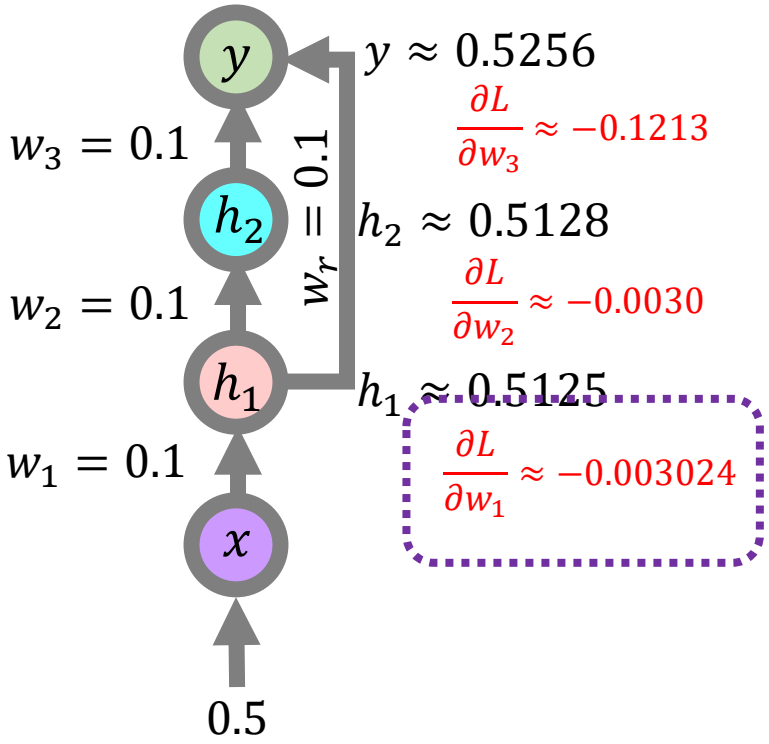
신박AI

지금은 계산 편의상 고작 3개의 층으로만 이루어진 모델이기에, 큰 차이점을 못느끼실 수도 있지만,

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



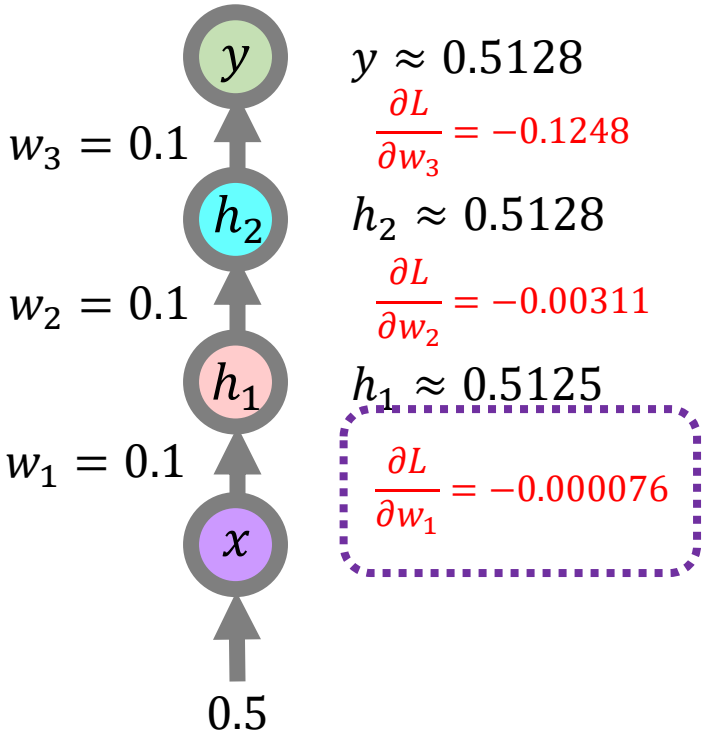
시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



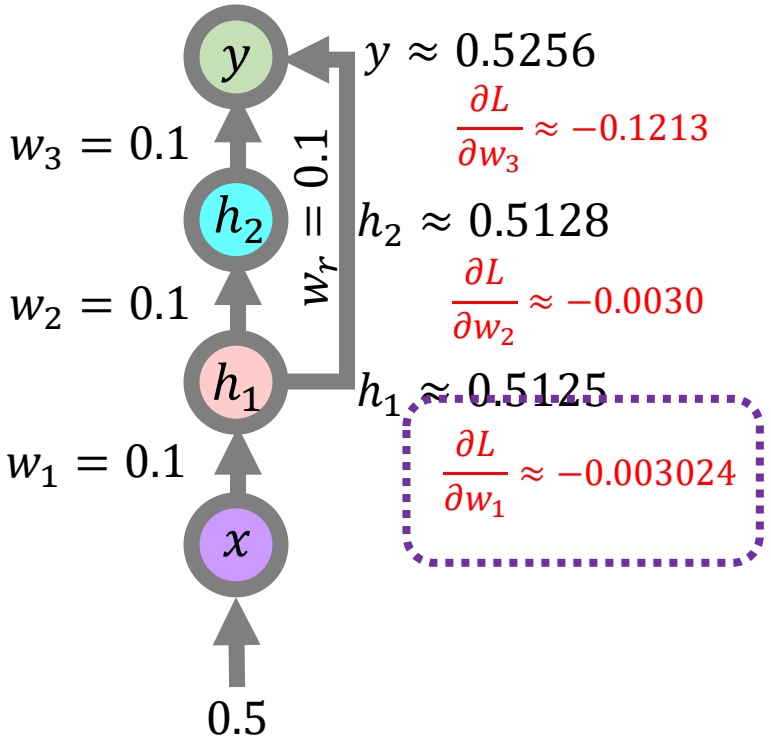
신박AI

실제 40층, 50층 같은 깊은 신경망에서는 그 차이가 훨씬 중요하게 작용할 것으로 생각됩니다.

시나리오1: 그냥 신경망
(활성화함수는 시그모이드)



시나리오2: 잔차 신경망
(활성화함수는 시그모이드)



신박AI

제가 준비한 ResNet영상은
여기까지 입니다.

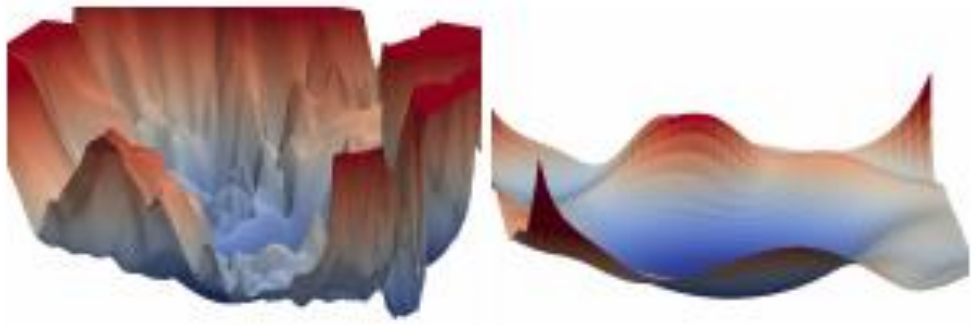
신박AI

다들 ResNet이 여러 점에서좋다는 것은
알지만, 실제로 어떻게 기울기 소실 문제를
해결하는지를 눈으로 확인해드리고자

다소 긴 손계산 풀이과정을 통해 설명드리게
된 점을 널리 양해 부탁드립니다.

신박AI

이 외에도 ResNet은 손실평면을 매끄럽게 해서 모델의 최적화를 돕는 장점도 있는등



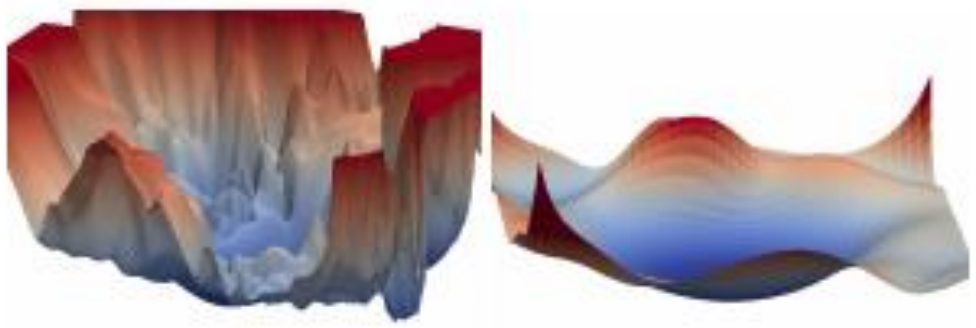
(a) Without skip connections (b) Skip connections network

Is the Skip Connection Provable to Reform the Neural Network Loss Landscape?

Lifu Wang[1], **Bo Shen**[1*], **Ning Zhao**[2] and **Zhiyuan Zhang**[1]
[1]Department of Electronic and Information Engineering, Beijing Jiaotong University, Beijing, China
Key Laboratory of Communication and Information Systems, Beijing Municipal Commission of Education Beijing Jiaotong University, Beijing, China
[2]Department of Electronic and Information Engineering, Beijing Jiaotong University, Beijing, China
State Key Lab of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, China
{Lifu_Wang, bshen, n_zhao, zhangzhiyuan}@bjtu.edu.cn

신박AI

다소 간단한 skip-connection 방식으로
딥러닝의 여러 한계를 극복한,



(a) Without skip connections (b) Skip connections network

Is the Skip Connection Provable to Reform the Neural Network Loss Landscape?

Lifu Wang[1], **Bo Shen**[1*], **Ning Zhao**[2] and **Zhiyuan Zhang**[1]
[1]Department of Electronic and Information Engineering, Beijing Jiaotong University, Beijing, China
Key Laboratory of Communication and Information Systems, Beijing Municipal Commission of Education Beijing Jiaotong University, Beijing, China
[2]Department of Electronic and Information Engineering, Beijing Jiaotong University, Beijing, China
State Key Lab of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, China
{Lifu_Wang, bshen, n_zhao, zhangzhiyuan}@bjtu.edu.cn

신박AI

딥러닝 역사에 중요한 이정표로 남을
ResNet모델이 되겠습니다.

신박AI

영상 끝까지 시청해 주셔서 감사합니다.
그럼 다음 시간에 또 만나요!

신박AI

감사합니다!

좋은 하루 되세요!!

이 채널은 여러분의 관심과 사랑이 필요합니다

신박AI

‘좋아요’와 ‘구독’버튼은 강의 준비에 큰 힘이 됩니다!

신박AI

그리고 영상 자료를 사용하실때는
출처 '신박AI'를 밝혀주세요

신박AI

신박AI