

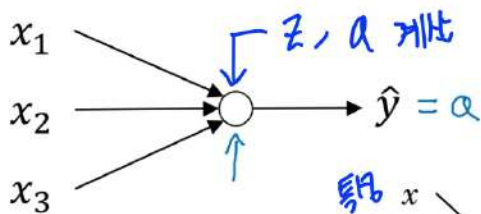


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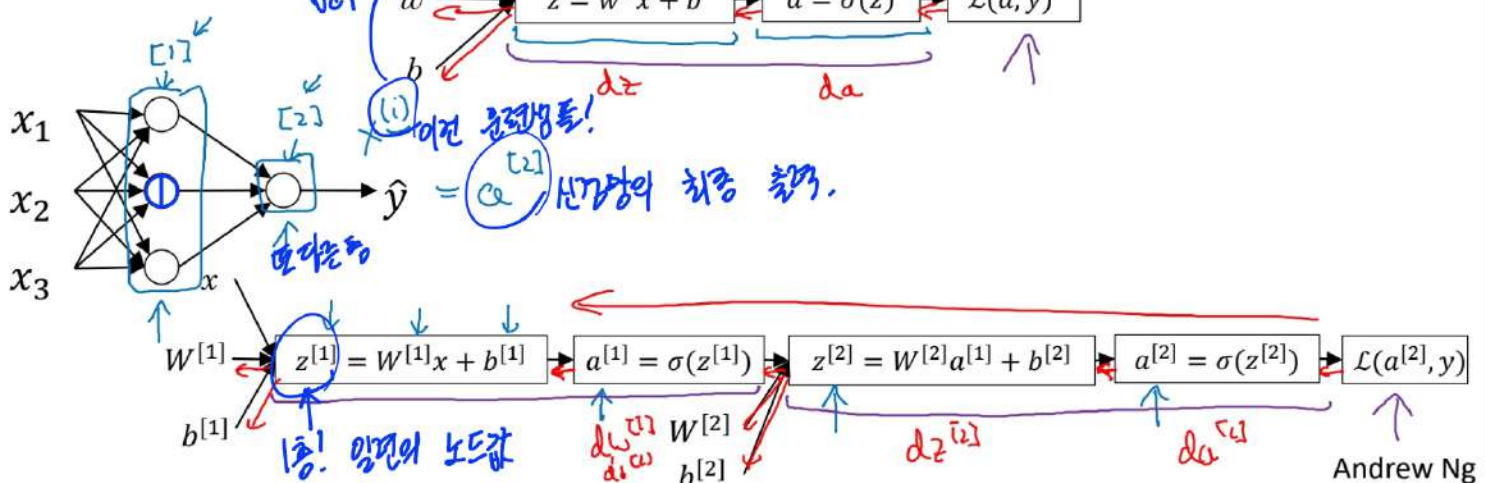
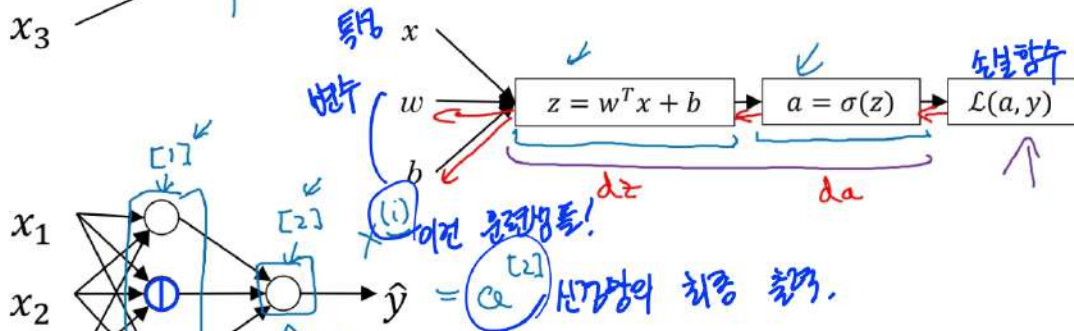
# One hidden layer Neural Network

## Neural Networks Overview

What is a Neural Network?



로지스틱 레이어는 도함수 계산을 위해  
역방향 계산을 했었다.  
마찬가지!



Andrew Ng



# Neural Network Representation

: 관련 계수가 입력값  $X$ 와 출력값  $Y$ .  
(온도의 상승에 따른 관련계수  $X$ )

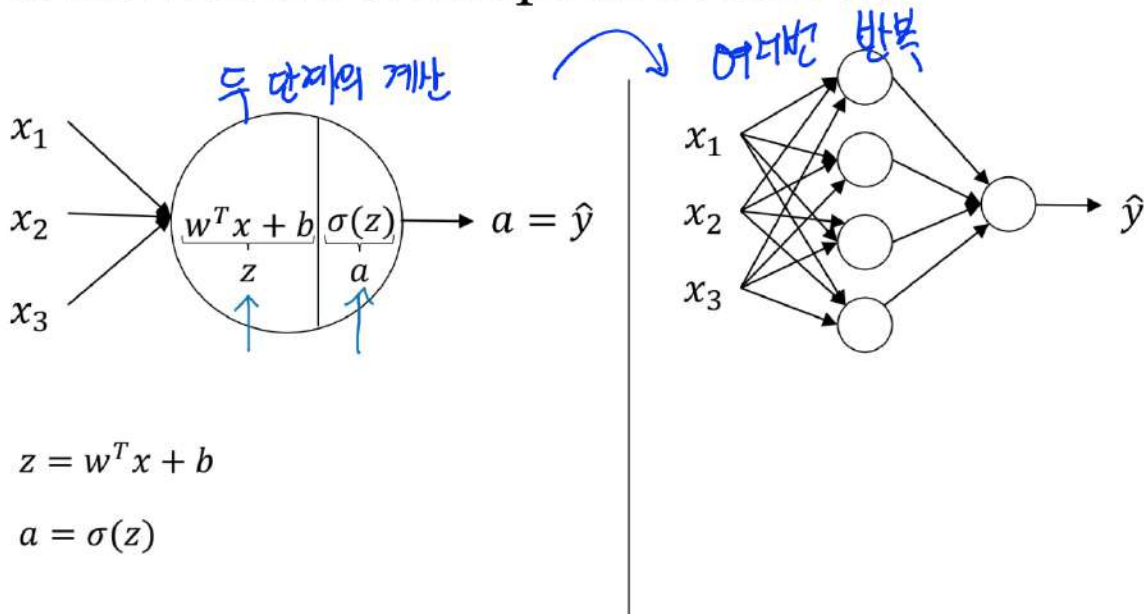


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## One hidden layer Neural Network

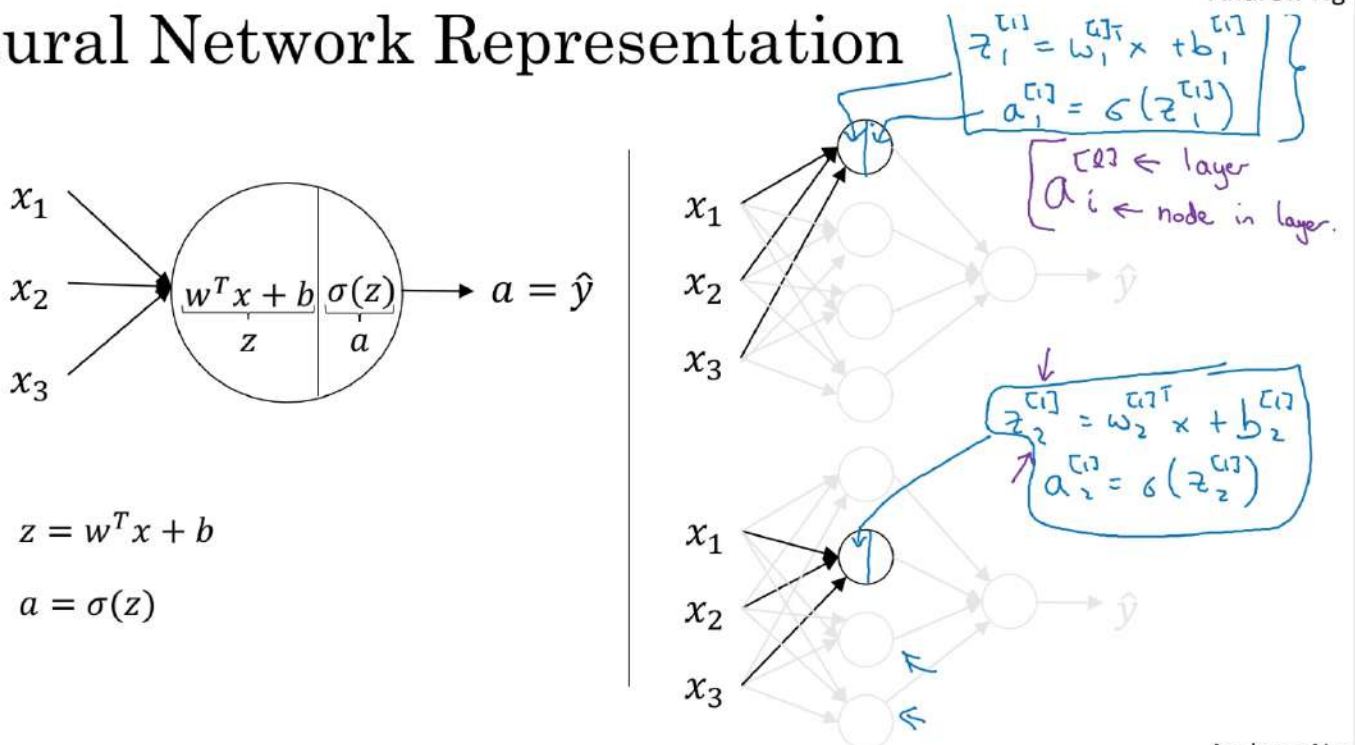
### Computing a Neural Network's Output

## Neural Network Representation



## Neural Network Representation

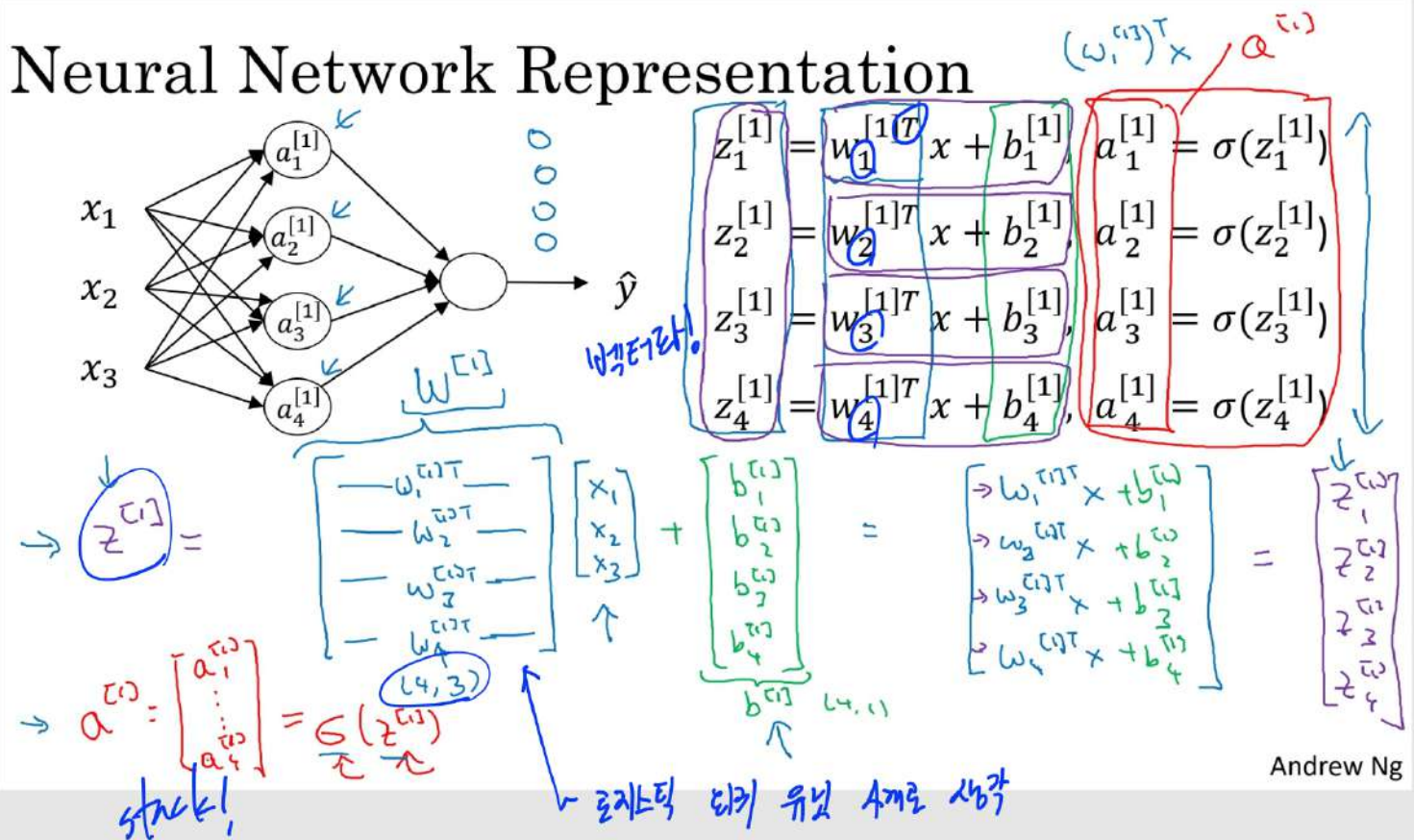
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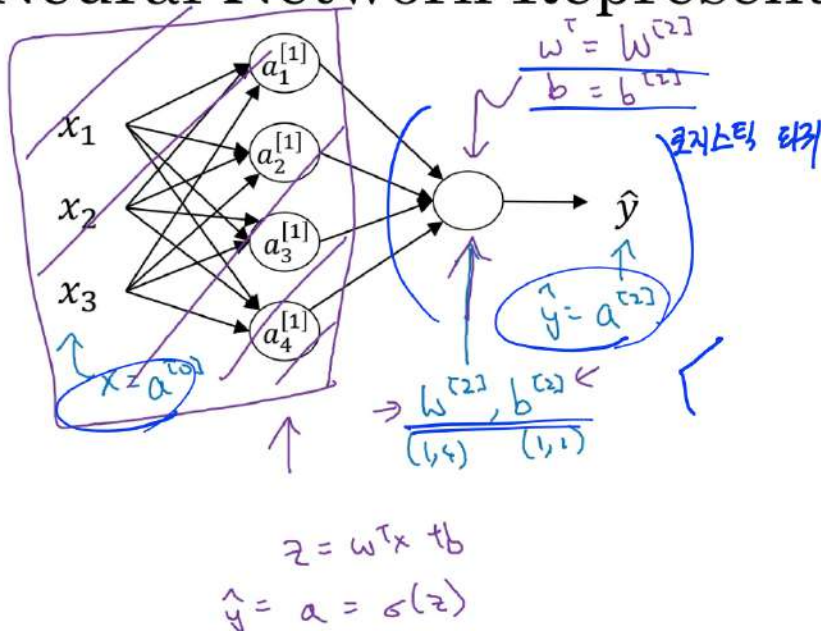
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# Neural Network Representation



# Neural Network Representation learning



Given input  $x$ :

$$\begin{aligned} \rightarrow z^{[1]} &= W^{[1]} a^{[0]} + b^{[1]} \\ &\quad (4,1) \quad (4,3) \quad (3,1) \quad (4,1) \\ \rightarrow a^{[1]} &= \sigma(z^{[1]}) \\ &\quad (4,1) \quad (4,1) \\ \rightarrow z^{[2]} &= W^{[2]} a^{[1]} + b^{[2]} \\ &\quad (1,1) \quad (1,4) \quad (4,1) \quad (1,1) \\ \rightarrow a^{[2]} &= \sigma(z^{[2]}) \\ &\quad (1,1) \quad (1,1) \end{aligned}$$

여기까지 훈련 샘플!  
행렬의 연산 살펴!

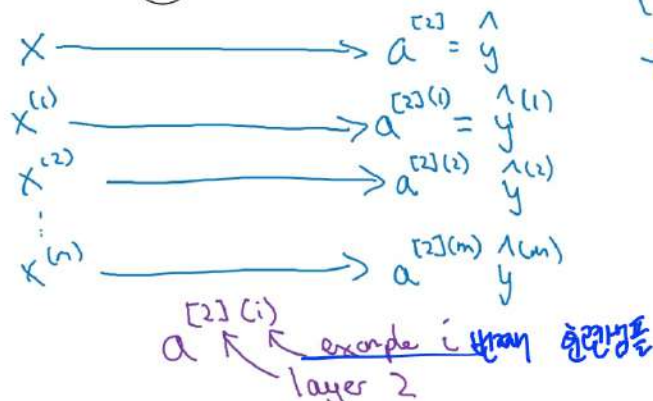
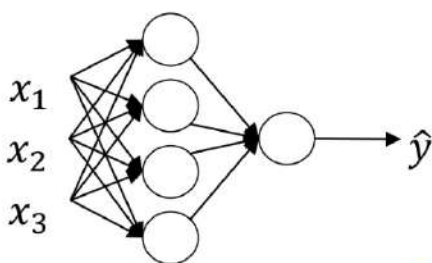


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## One hidden layer Neural Network

### Vectorizing across multiple examples

## Vectorizing across multiple examples



$$\begin{cases} z^{[1]} = W^{[1]}x + b^{[1]} \\ a^{[1]} = \sigma(z^{[1]}) \\ z^{[2]} = W^{[2]}a^{[1]} + b^{[2]} \\ a^{[2]} = \sigma(z^{[2]}) \end{cases}$$

for  $i = 1$  to  $m$ ,

$$\begin{aligned} z^{[1]}(i) &= W^{[1]}x^{(i)} + b^{[1]} \\ a^{[1]}(i) &= \sigma(z^{[1]}(i)) \\ z^{[2]}(i) &= W^{[2]}a^{[1]}(i) + b^{[2]} \\ a^{[2]}(i) &= \sigma(z^{[2]}(i)) \end{aligned}$$

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## Vectorizing across multiple examples

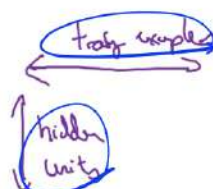
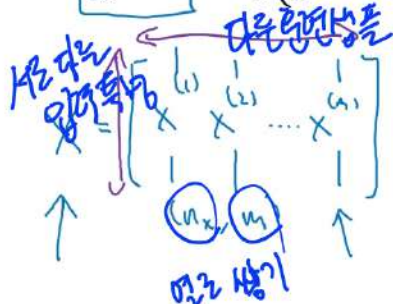
for  $i = 1$  to  $m$ :

$$z^{[1]}(i) = W^{[1]}x^{(i)} + b^{[1]}$$

$$a^{[1]}(i) = \sigma(z^{[1]}(i))$$

$$z^{[2]}(i) = W^{[2]}a^{[1]}(i) + b^{[2]}$$

$$a^{[2]}(i) = \sigma(z^{[2]}(i))$$



$$\begin{aligned} z^{[1]} &= W^{[1]}X + b^{[1]} \\ A^{[1]} &= \sigma(z^{[1]}) \\ z^{[2]} &= W^{[2]}A^{[1]} + b^{[2]} \\ A^{[2]} &= \sigma(z^{[2]}) \end{aligned}$$

$$z^{[1]} = \begin{bmatrix} z^{[1]}(1) & z^{[1]}(2) & \dots & z^{[1]}(m) \\ 1 & 1 & \dots & 1 \end{bmatrix}$$

$$A^{[1]} = \begin{bmatrix} a^{[1]}(1) & a^{[1]}(2) & \dots & a^{[1]}(m) \\ 1 & 1 & \dots & 1 \end{bmatrix}$$

filler units

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# One hidden layer Neural Network

## Explanation for vectorized implementation

### Justification for vectorized implementation

Handwritten notes showing the simplification of the vectorized implementation:

$$z^{[1](1)} = W^{[1]} x^{(1)} + b^{[1]}, \quad z^{[1](2)} = W^{[1]} x^{(2)} + b^{[1]}, \quad z^{[1](3)} = W^{[1]} x^{(3)} + b^{[1]}$$

Arrows point to the  $b^{[1]}$  terms, indicating they are simplified by adding them to each column of the matrix product.

$$W^{[1]} = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix}, \quad W^{[1]} x^{(1)} = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix}, \quad W^{[1]} x^{(2)} = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix}, \quad W^{[1]} x^{(3)} = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

Dimensions:  $(3, 3) \times (3, m)$

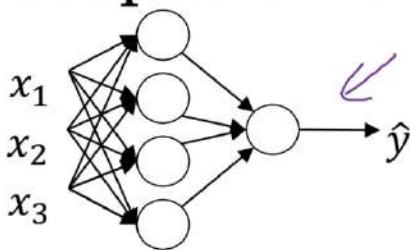
$$z^{[1]} = W^{[1]} X + b^{[1]} = \begin{bmatrix} z^{[1](1)} & z^{[1](2)} & z^{[1](3)} & \dots \end{bmatrix} = z^{[1]}$$

Arrows indicate that the bias vector  $b^{[1]}$  is added to each column of the matrix product  $W^{[1]} X$ .

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!실용적으로도 편하게 쓰일 수 있음

### Recap of vectorizing across multiple examples



$$X = \begin{bmatrix} | & | & \dots & | \\ x^{(1)} & x^{(2)} & \dots & x^{(m)} \\ | & | & \dots & | \end{bmatrix}$$

$$A^{[1]} = \begin{bmatrix} | & | & \dots & | \\ a^{[1](1)} & a^{[1](2)} & \dots & a^{[1](m)} \\ | & | & \dots & | \end{bmatrix}$$

for  $i = 1$  to  $m$

- $z^{[1](i)} = W^{[1]} x^{(i)} + b^{[1]}$
- $a^{[1](i)} = \sigma(z^{[1](i)})$
- $z^{[2](i)} = W^{[2]} a^{[1](i)} + b^{[2]}$
- $a^{[2](i)} = \sigma(z^{[2](i)})$

Handwritten notes showing the vectorized implementation:

$$Z^{[1]} = W^{[1]} X + b^{[1]}, \quad A^{[1]} = \sigma(Z^{[1]}), \quad Z^{[2]} = W^{[2]} A^{[1]} + b^{[2]}, \quad A^{[2]} = \sigma(Z^{[2]})$$

Arrows indicate the flow of data from  $X$  to  $Z^{[1]}$ , then to  $A^{[1]}$ , then to  $Z^{[2]}$ , and finally to  $A^{[2]}$ .

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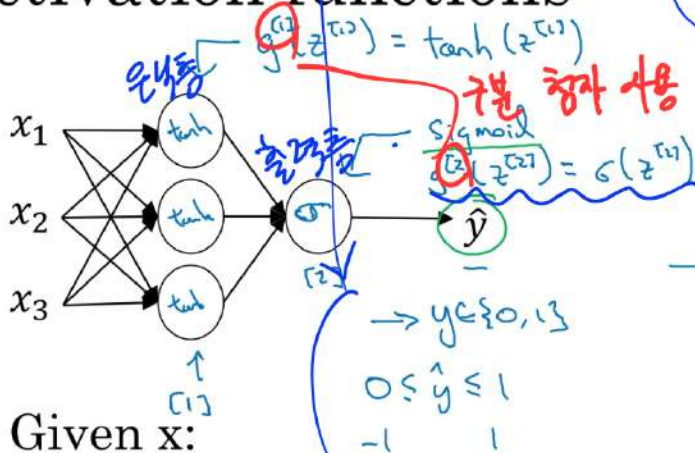
## One hidden layer Neural Network

시그모이드 & tanh  
 $\rightarrow z \begin{matrix} \uparrow \\ \downarrow \end{matrix}$  미지 도함수 광범위 작어짐  $\rightarrow 0$

## Activation functions

시그릿이 드 란이라 한수 쓴  
한 가지 예! 아연 분규할 때  
출력 증대 6

## Activation functions



Given  $x$ :

$$z^{[1]} = W^{[1]}x + b^{[1]}$$

$$\rightarrow a^{[1]} = \sigma(z^{[1]})$$

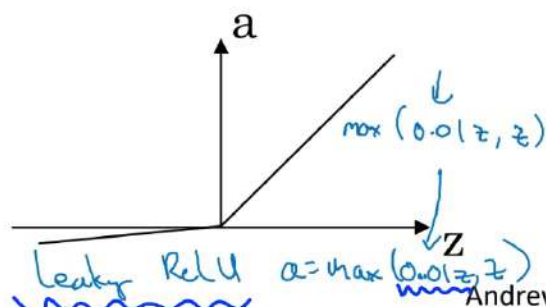
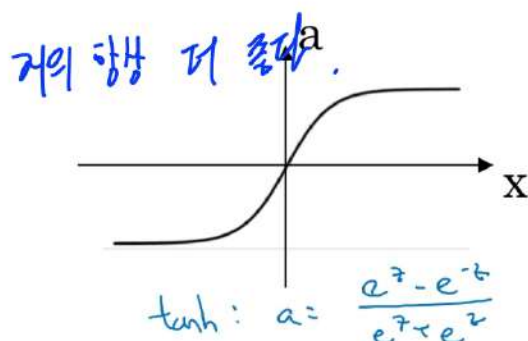
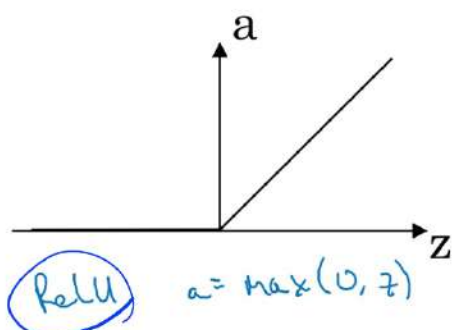
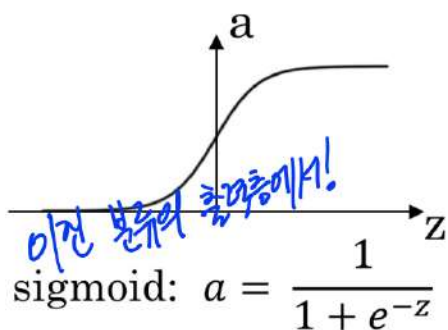
$$z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$$

$$\rightarrow a^{[2]} = \sigma(z^{[2]}) \quad g(z^{[2]})$$

17Eh...

(무늬종류, 단색과 양색의 종류, 가품의 리라)

## Pros and cons of activation functions

[illegible]

Andrew Ng 자 아끼미

- 2인 박출 원인

가 026 매역  
다<sup>2</sup>/<sub>A</sub>

하수배출  
(tanh, 84cm)

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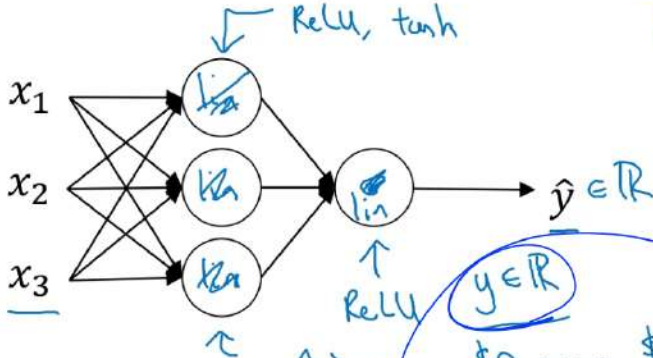


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# One hidden layer Neural Network

Why do you  
need non-linear  
activation functions?

## Activation function



Given  $x$ :

- $z^{[1]} = W^{[1]}x + b^{[1]}$
- $a^{[1]} = g^{[1]}(z^{[1]}) \quad z^{[1]}$
- $z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$
- $a^{[2]} = g^{[2]}(z^{[2]}) \quad z^{[2]}$

$\uparrow$ :  $x$ 에 대한 선형 함수

$g(z) = z$   
"linear activation  
function"  
항등 함수.

$lin \rightarrow 0$  경우 편향 리지스틱 리케보다 나이지 않는다!

(선형 모델은 쓸모가 없다)  
선형 함수들의 조합은 또 다른 선형 함수

$$a^{[1]} = z^{[1]} = W^{[1]}x + b^{[1]}$$

$$a^{[2]} = z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$$

$$a^{[2]} = W^{[2]}(W^{[1]}x + b^{[1]}) + b^{[2]}$$

$$= (W^{[2]}W^{[1]})x + (W^{[2]}b^{[1]} + b^{[2]})$$

$$= W'x + b'$$

$g(z) = z$  선형 함수 입력의  
선형 함수만을 출력!

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리케 문제에 대한 미신리닝을 할 때  
영가 실수값이라면 출력층에서 (않...?)  
선형 타당화 함수를 써도 괜찮다!







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# One hidden layer Neural Network

## Gradient descent for neural networks

### Gradient descent for neural networks

Parameters:  $W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}$   
 $(n^{[1]}, n^{[2]})$   $(n^{[2]}, n^{[3]})$   $(n^{[3]}, 1)$

input feature  $n_x = n^{[0]}$ , hidden unit  $n^{[1]}$ , output  $n^{[2]} = 1$   
 선행항수의 개수

Cost function:  $J(W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}) = \frac{1}{m} \sum_{i=1}^m L(\hat{y}^{(i)}, y^{(i)})$   
 $\alpha^{[2]}$

Gradient descent: 0이 아닌 값으로 변수 초기화!

→ Repeat {  
 Compute predictions  $(\hat{y}^{(i)}, i=1, \dots, m)$   $n$ 에 대한 비용함수의 도함수  
 $\frac{\partial J}{\partial W^{[1]}} = \frac{\partial J}{\partial W^{[1]}}$ ,  $\frac{\partial J}{\partial b^{[1]}} = \frac{\partial J}{\partial b^{[1]}}$ , ...  
 $W^{[1]} := W^{[1]} - \alpha \frac{\partial J}{\partial W^{[1]}}$   
 $b^{[1]} := b^{[1]} - \alpha \frac{\partial J}{\partial b^{[1]}}$   
 $W^{[2]} := \dots$ ,  $b^{[2]} := \dots$   
 어떻게 편미분 계산하냐!  
 변수들이 수렴하게 될 때까지 반복!

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### Formulas for computing derivatives

Forward propagation: 정방향 전파

$z^{[1]} = W^{[1]}x + b^{[1]}$   
 $A^{[1]} = g^{[1]}(z^{[1]}) \leftarrow$   
 $z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$   
 $A^{[2]} = g^{[2]}(z^{[2]}) = \sigma(z^{[2]})$   
 모든 벡터라 상태!

Back propagation: 역전파

$\delta z^{[2]} = A^{[2]} - Y$  ground truth  $Y = [y^{(1)}, y^{(2)}, \dots, y^{(m)}]$   
 $\delta W^{[2]} = \frac{1}{m} \delta z^{[2]} A^{[1]T}$   
 $\delta b^{[2]} = \frac{1}{m} \text{np.sum}(\delta z^{[2]}, \text{axis}=1, \text{keepdims}=\text{True})$   
 $\delta z^{[1]} = W^{[2]T} \delta z^{[2]} \otimes g^{[1]'}(z^{[1]})$   
 $\delta W^{[1]} = \frac{1}{m} \delta z^{[1]} x^T$   
 $\delta b^{[1]} = \frac{1}{m} \text{np.sum}(\delta z^{[1]}, \text{axis}=1, \text{keepdims}=\text{True})$   
 rank  $(n^{[1]}) \leftarrow$   
 rank  $(n^{[2]}, 1) \leftarrow$   
 element-wise product  
 문맥에서 사용했던 활성화함수의 도함수  
 reshape  
 혹은 사용

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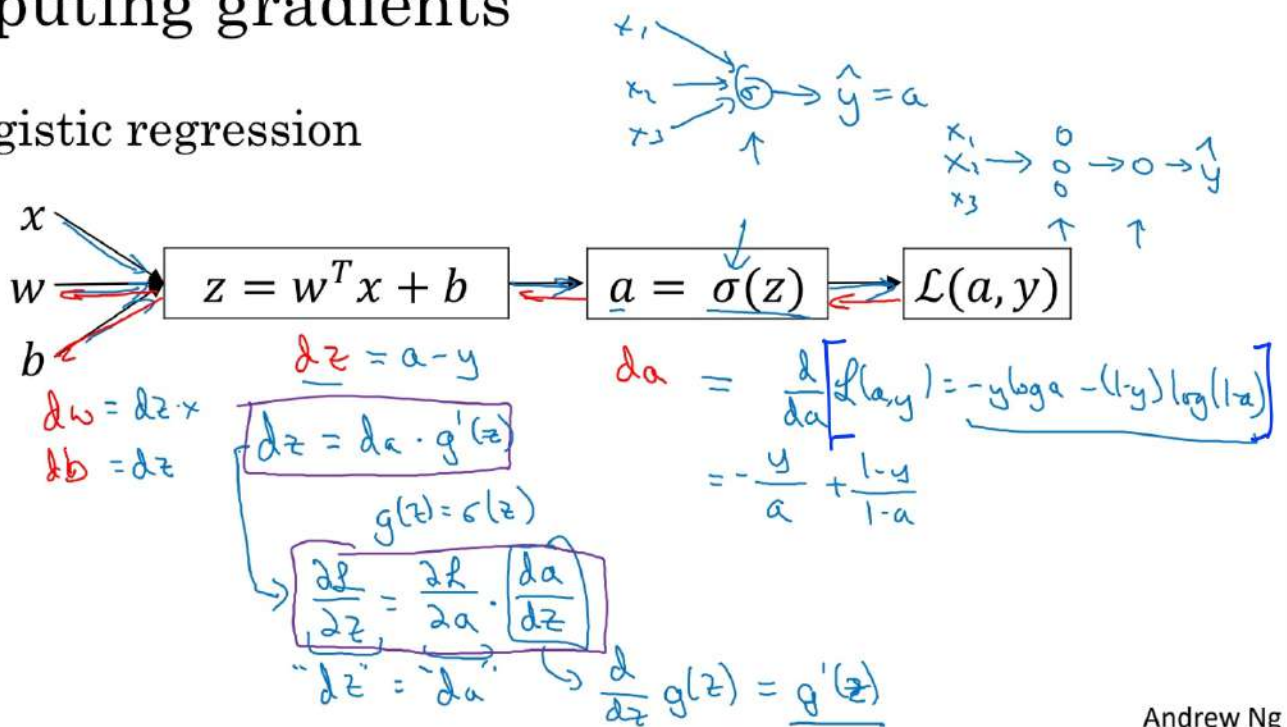
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# One hidden layer Neural Network

## Backpropagation intuition (Optional)

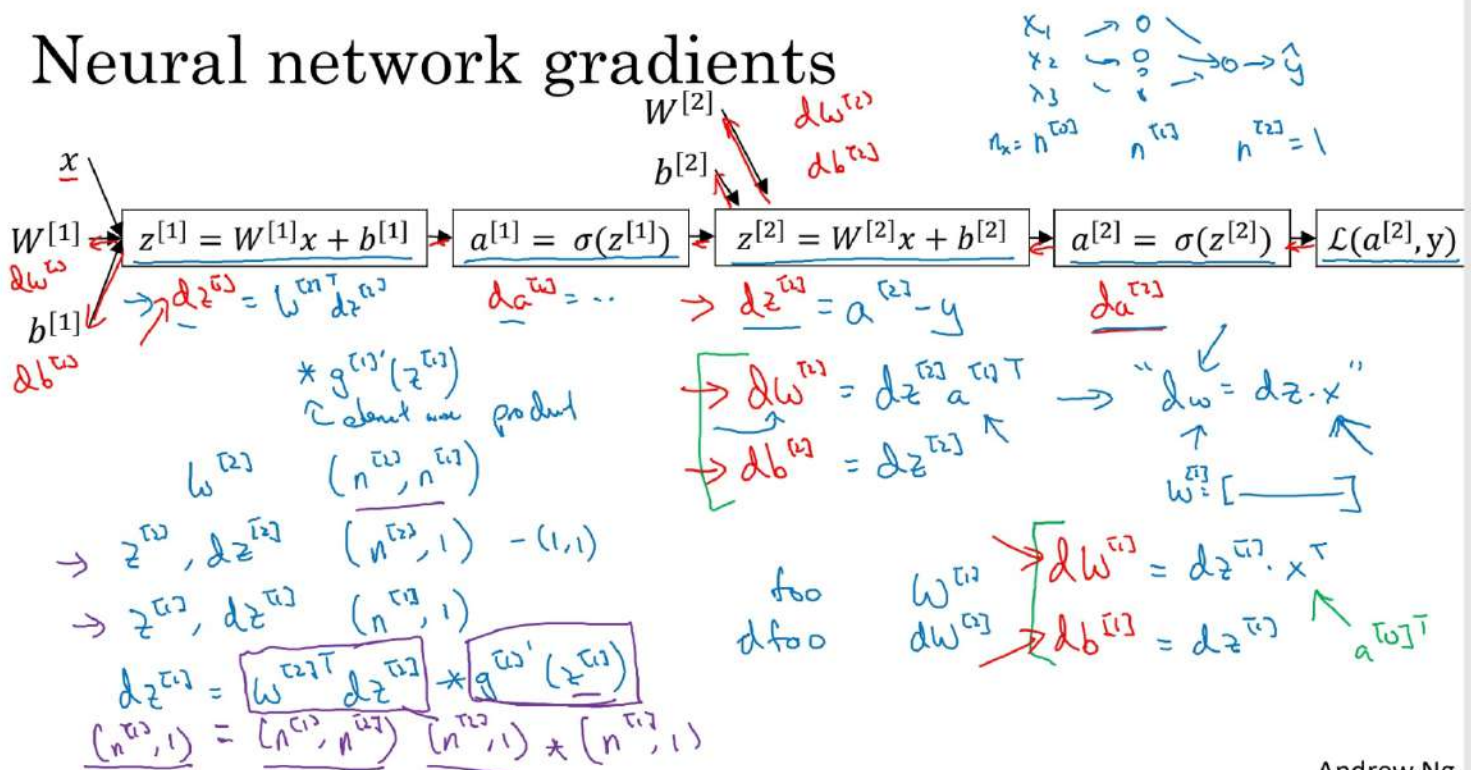
### Computing gradients

#### Logistic regression



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### Neural network gradients



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# Summary of gradient descent

$$dz^{[2]} = a^{[2]} - y$$

$$dW^{[2]} = dz^{[2]} a^{[1]T}$$

$$db^{[2]} = dz^{[2]}$$

$$dz^{[1]} = W^{[2]T} dz^{[2]} * g^{[1]'}(z^{[1]})$$

$$dW^{[1]} = dz^{[1]} x^T$$

$$db^{[1]} = dz^{[1]}$$

$$da = -\frac{y}{a} + \frac{1-y}{1-a}$$

$$dz = a - y$$

$$dw = dz x$$

$$db = dz$$

$x \rightarrow x_0 \rightarrow dz$  계산 안 함

Vectorized Implementation:

$$z^{[1]} = W^{[0]} x + b^{[0]}$$

$$a^{[1]} = g^{[0]}(z^{[1]})$$

$$z^{[1]} = \begin{bmatrix} z^{[1](1)} \\ z^{[1](2)} \\ \dots \\ z^{[1](n)} \end{bmatrix}$$

$$z^{[1]} = W^{[0]} X + b^{[0]}$$

$$A^{[1]} = g^{[0]}(z^{[1]})$$

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# Summary of gradient descent

$$\underline{dz}^{[2]} = \underline{a}^{[2]} - \underline{y}$$

$$dW^{[2]} = dz^{[2]} a^{[1]T}$$

$$db^{[2]} = dz^{[2]}$$

$$dz^{[1]} = W^{[2]T} dz^{[2]} * g^{[1]'}(z^{[1]})$$

$(n^{[1]}, 1)$

$$dW^{[1]} = dz^{[1]} x^T$$

$$db^{[1]} = dz^{[1]}$$

$$\underline{dZ}^{[2]} = \underline{A}^{[2]} - \underline{Y}$$

$$dW^{[2]} = \frac{1}{m} dZ^{[2]} A^{[1]T}$$

$$db^{[2]} = \frac{1}{m} \text{np.sum}(dZ^{[2]}, \text{axis} = 1, \text{keepdims} = \text{True})$$

$$dZ^{[1]} = \underbrace{W^{[2]T}}_{(n^{[2]}, m)} dZ^{[2]} * \underbrace{g^{[1]'}(Z^{[1]})}_{(n^{[1]}, m)}$$

$$dW^{[1]} = \frac{1}{m} dZ^{[1]} X^T$$

$$db^{[1]} = \frac{1}{m} \text{np.sum}(dZ^{[1]}, \text{axis} = 1, \text{keepdims} = \text{True})$$

$$J(\cdot) = \frac{1}{m} \sum_{i=1}^n \mathcal{L}(\hat{y}_i, y_i)$$

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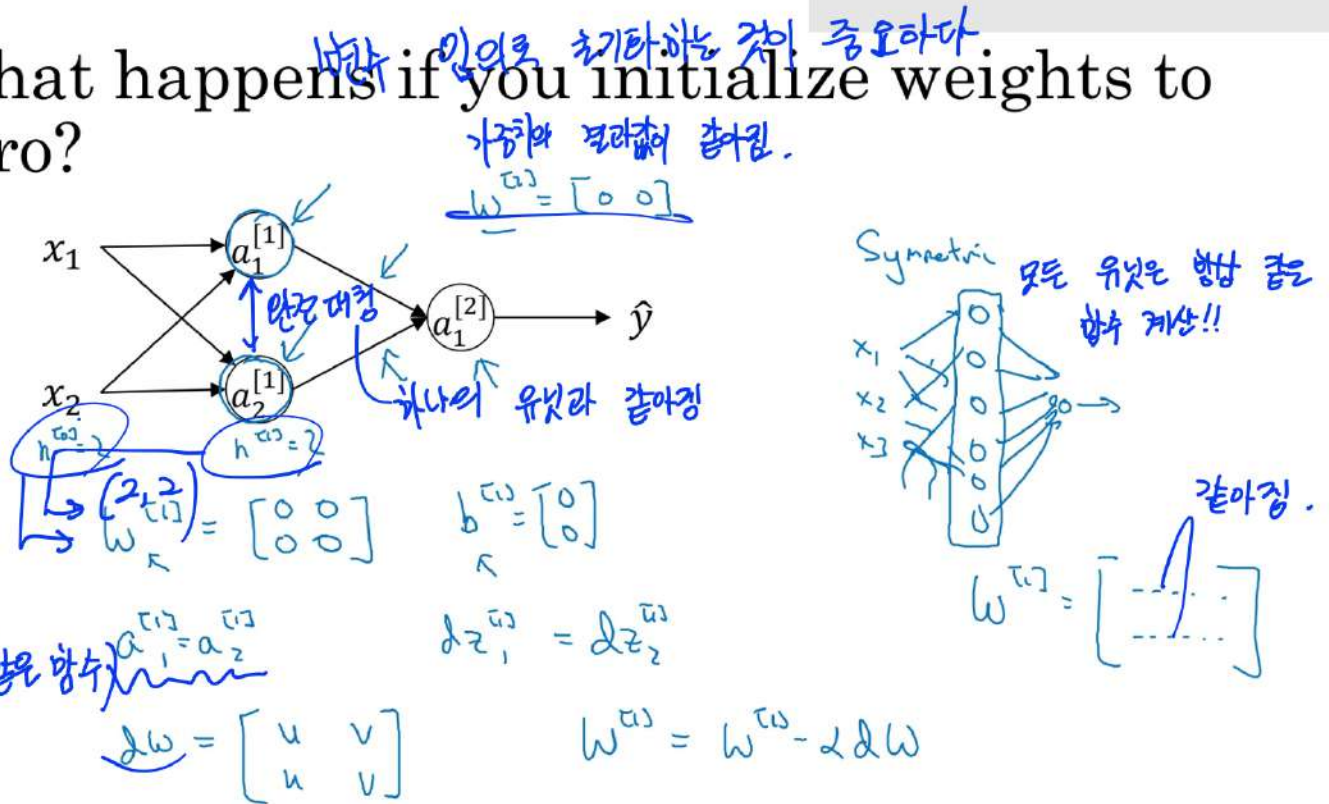


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# One hidden layer Neural Network

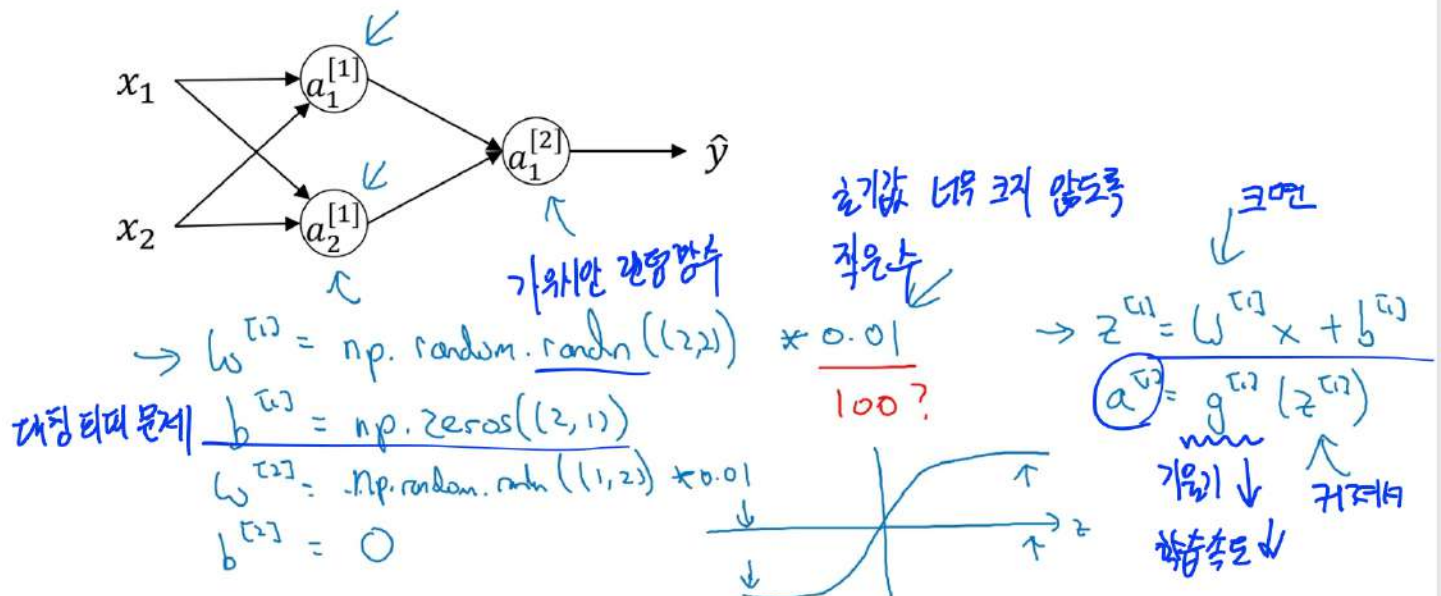
## Random Initialization

What happens if you initialize weights to zero?



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## Random initialization



Andrew Ng





