



DeepLearning.AI

# Optimization in Neural Networks and Newton's Method

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## Regression with a perceptron

# Regression Problem Motivation

# Regression Problem Motivation

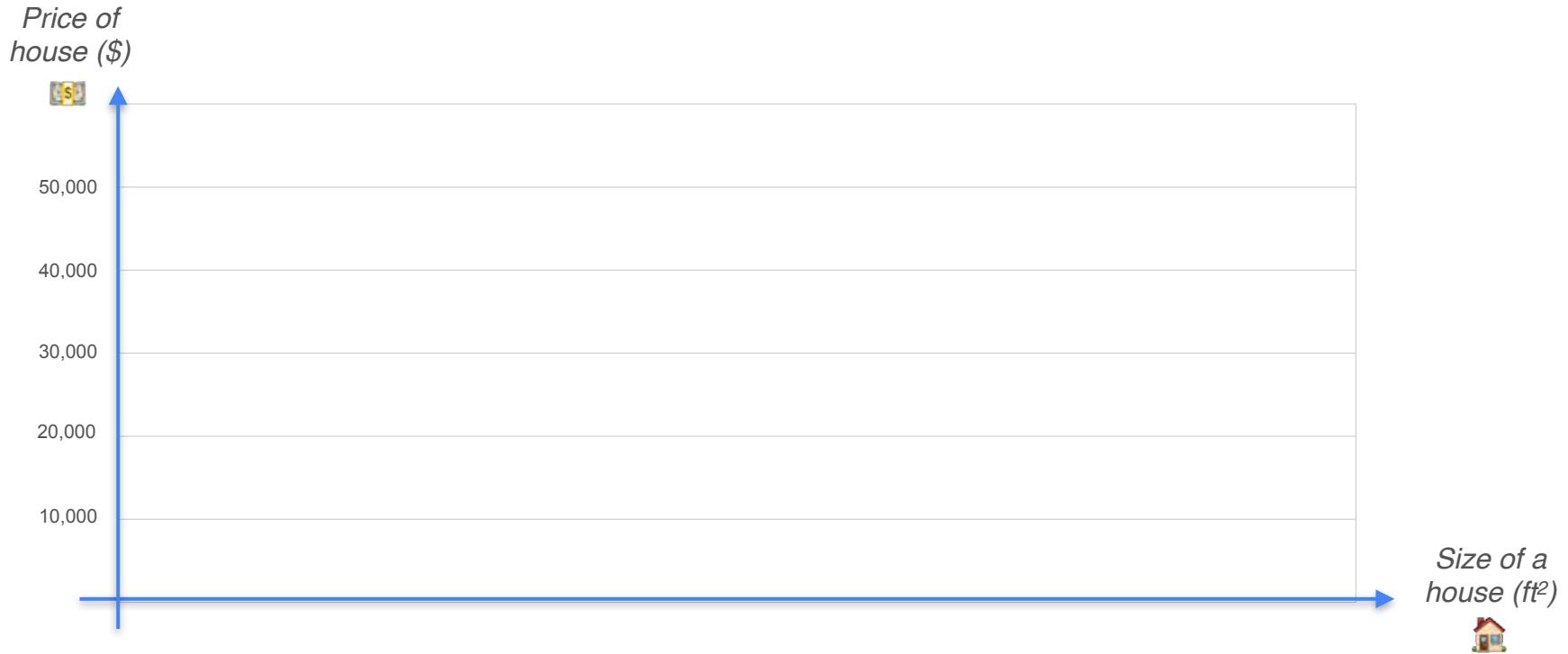
*Predicting*

***the price of a house***

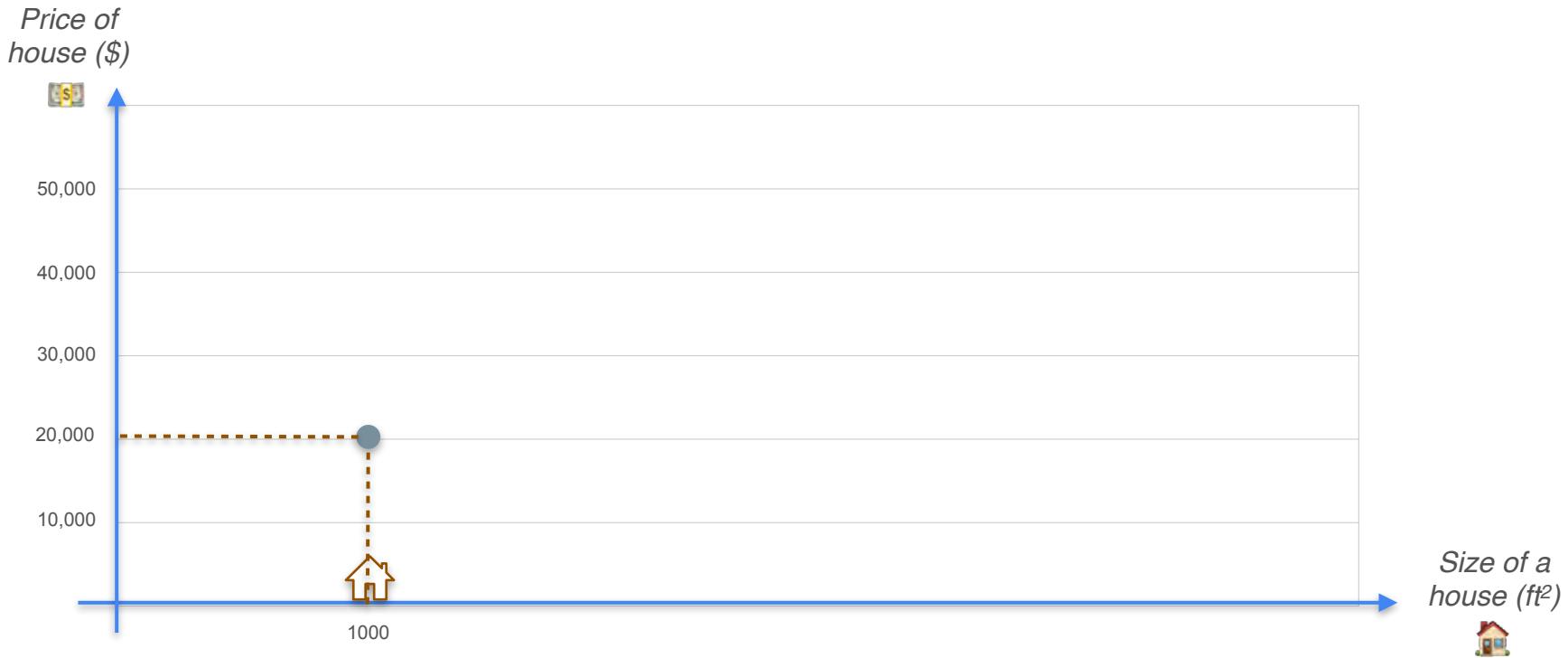
*from*

***the size of the house***

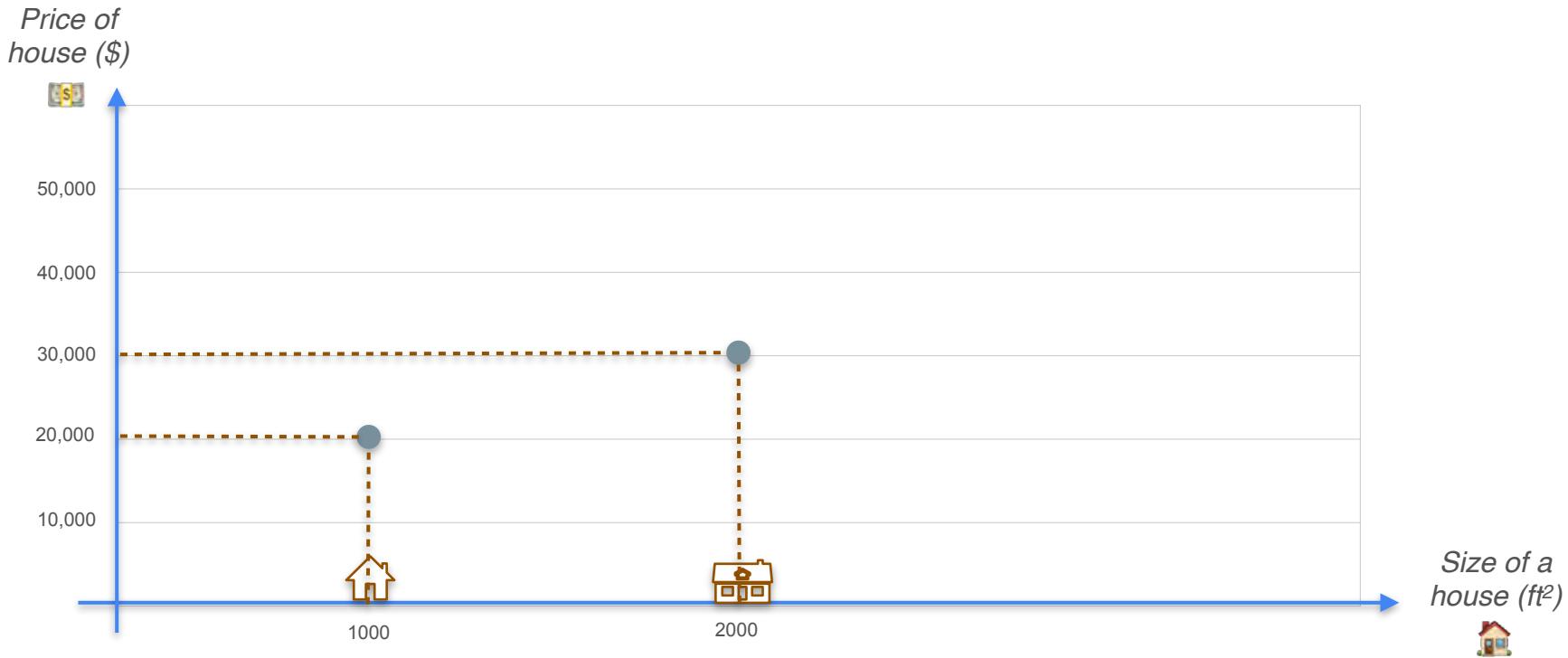
# Regression Problem Motivation



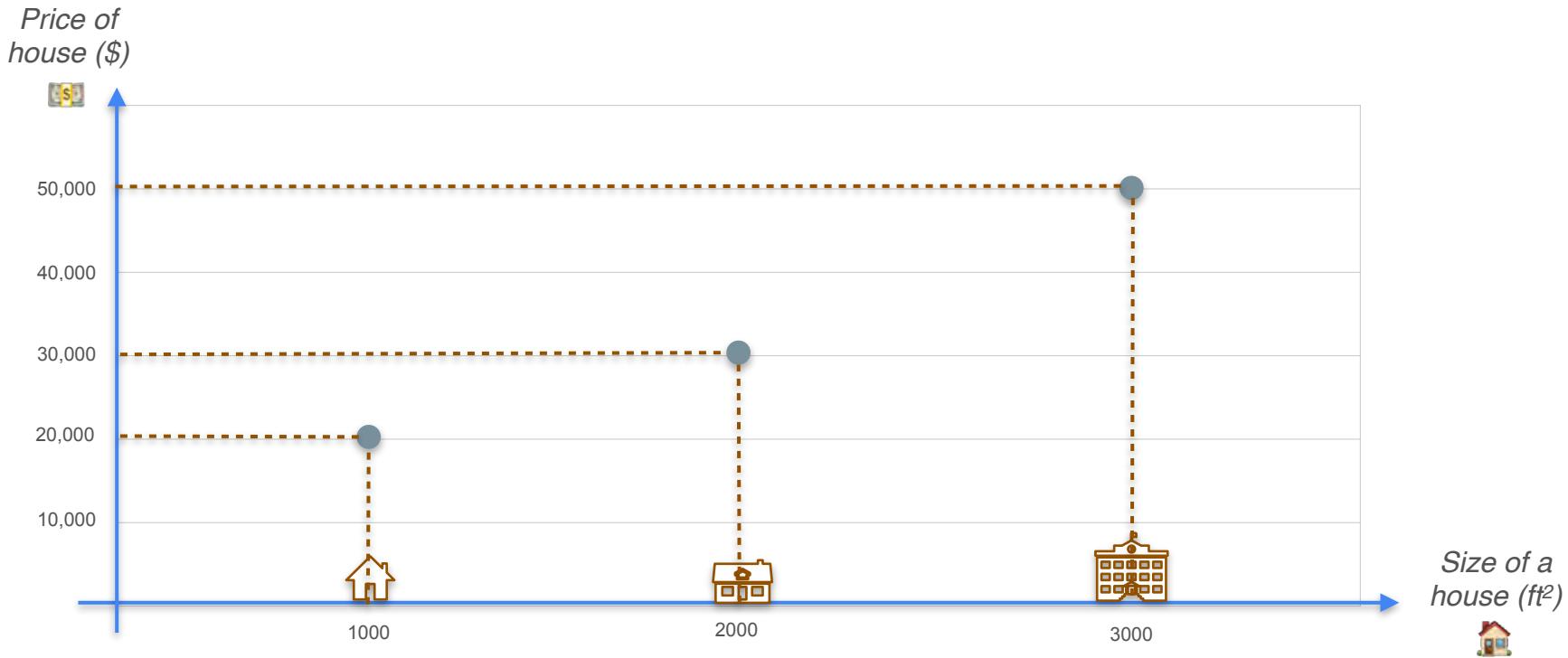
# Regression Problem Motivation



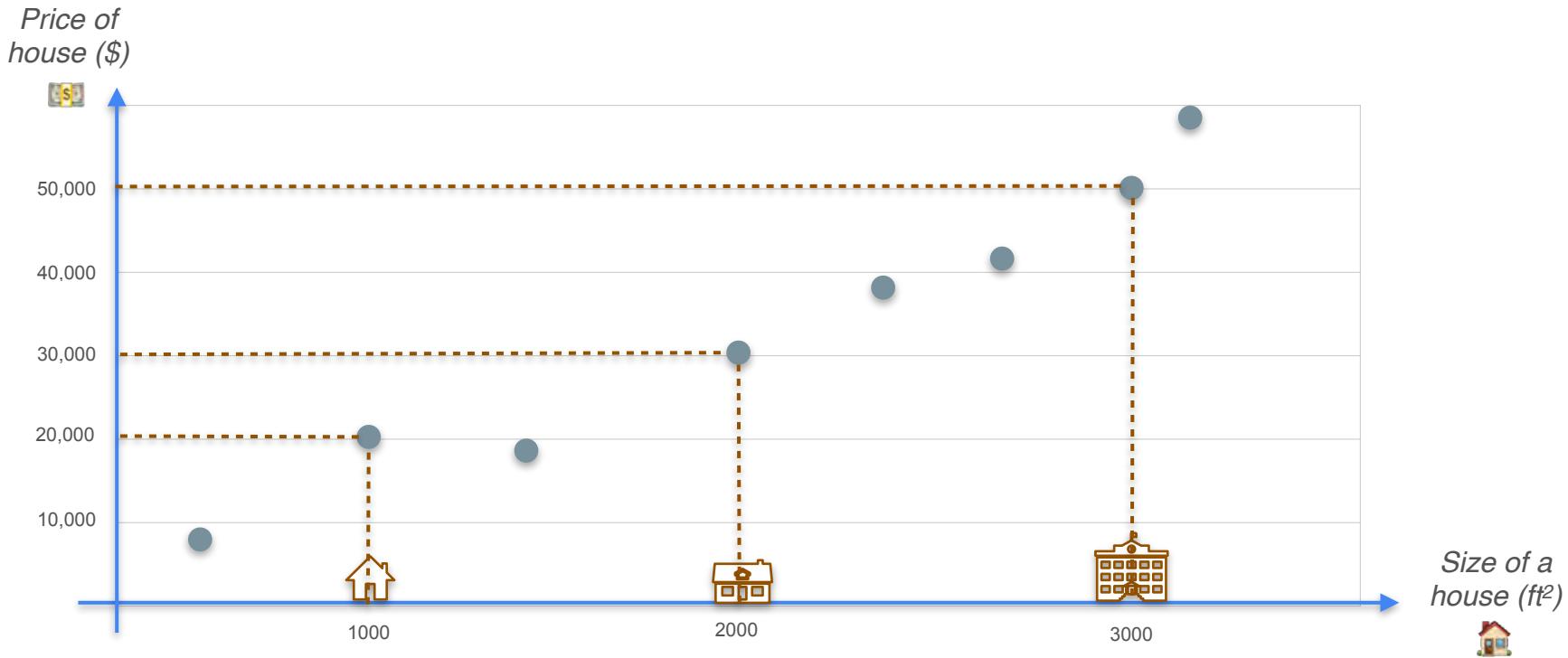
# Regression Problem Motivation



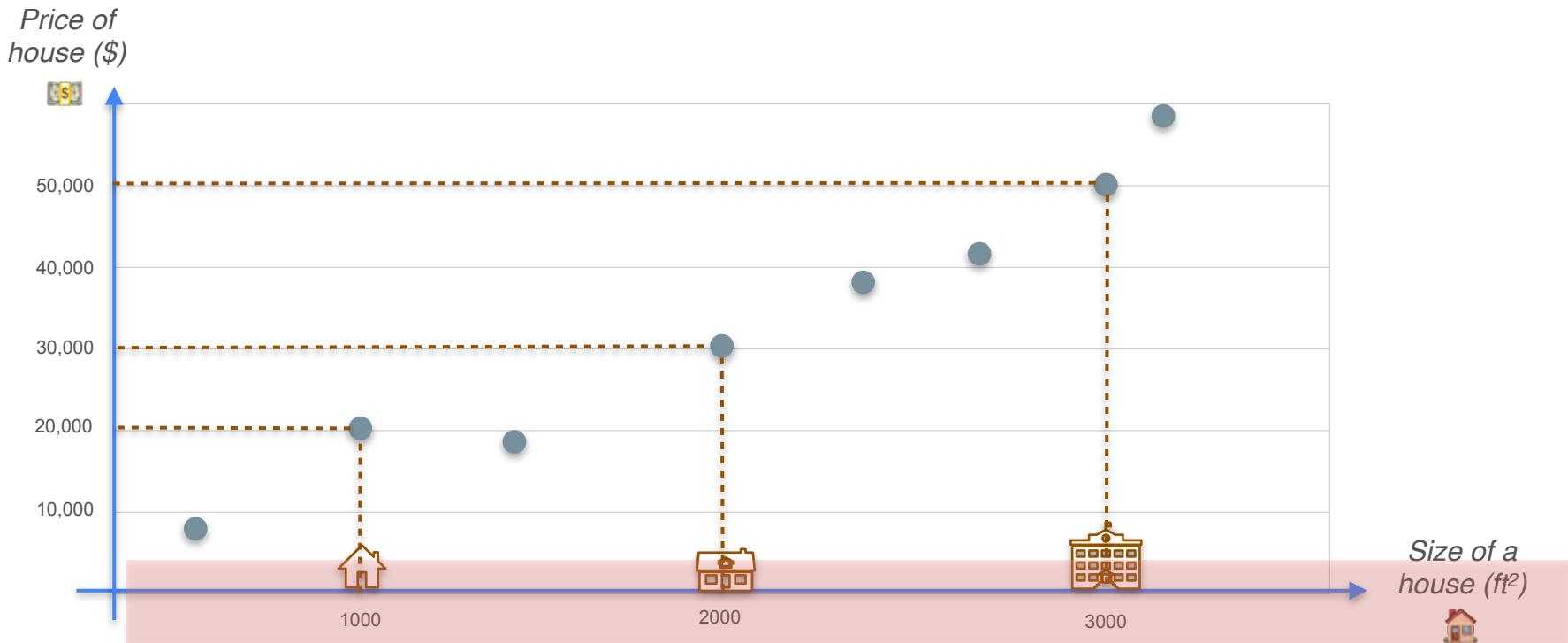
# Regression Problem Motivation



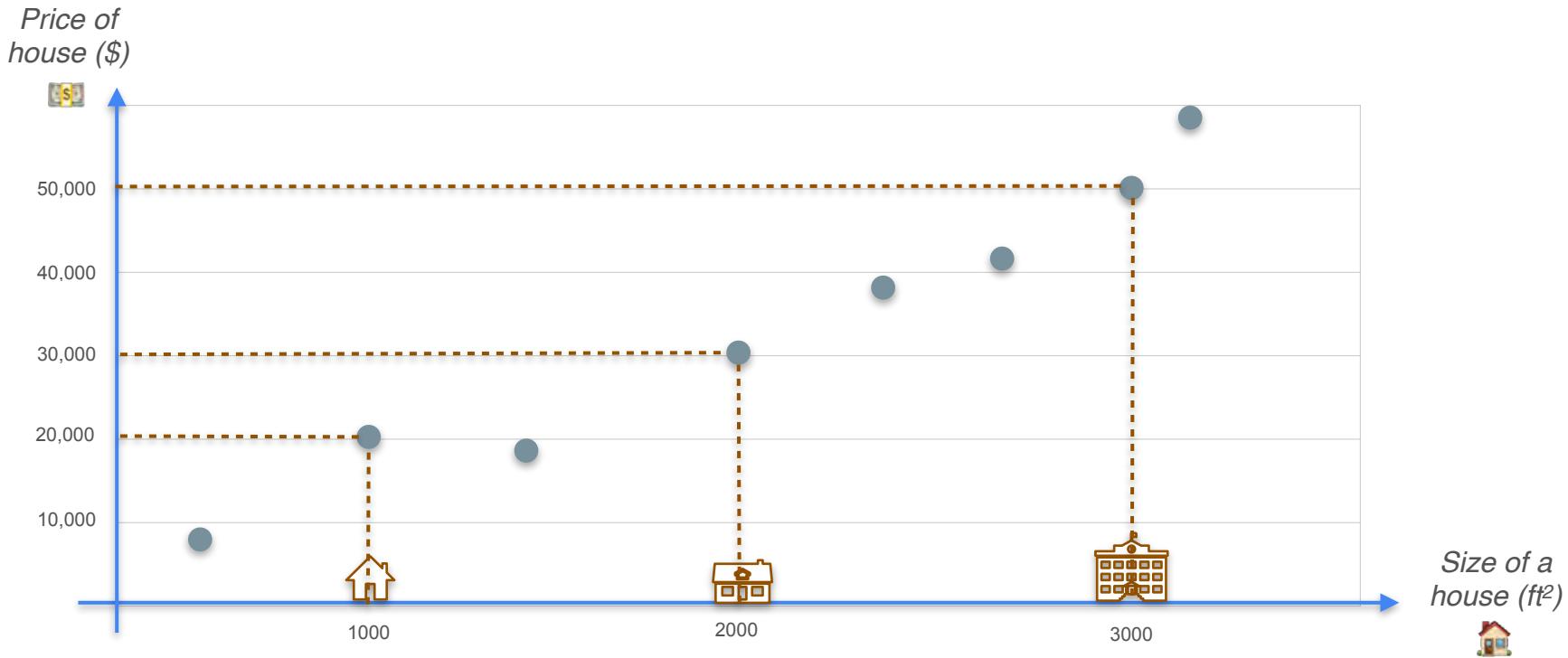
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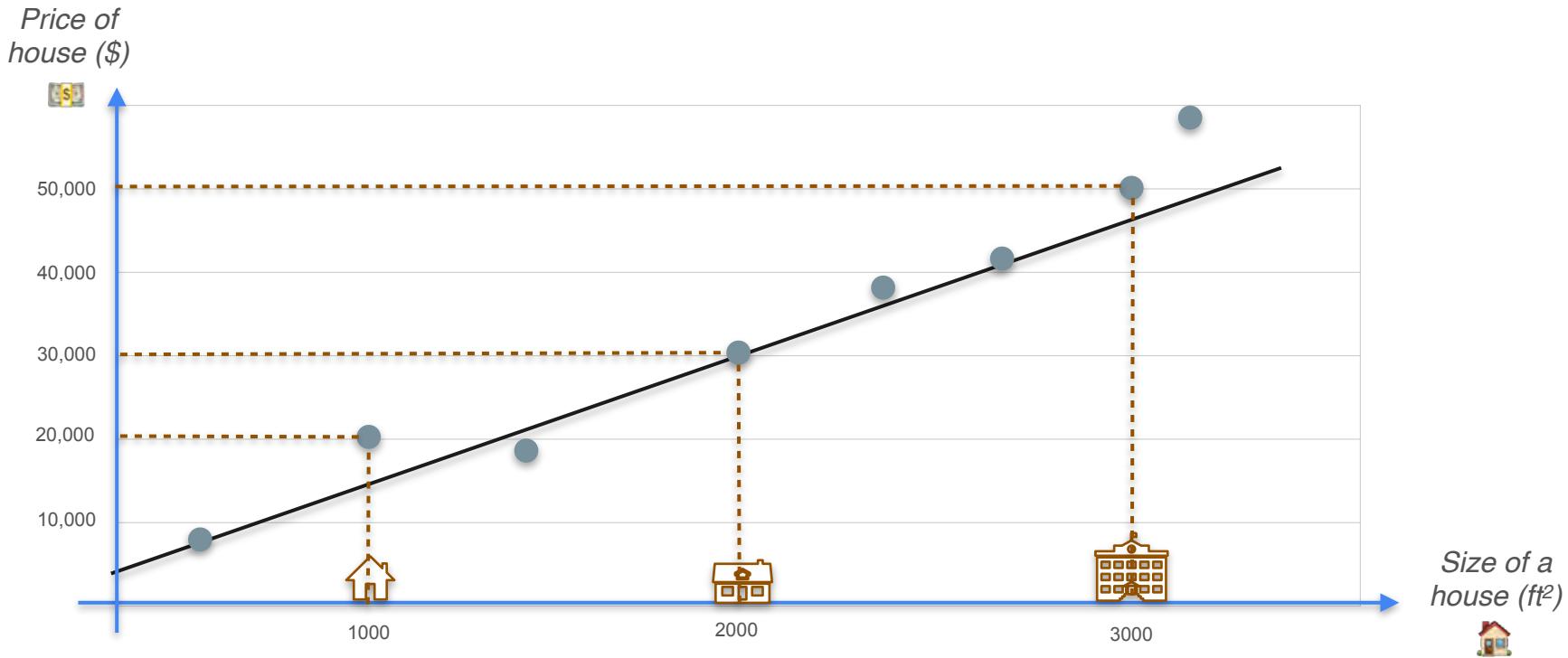
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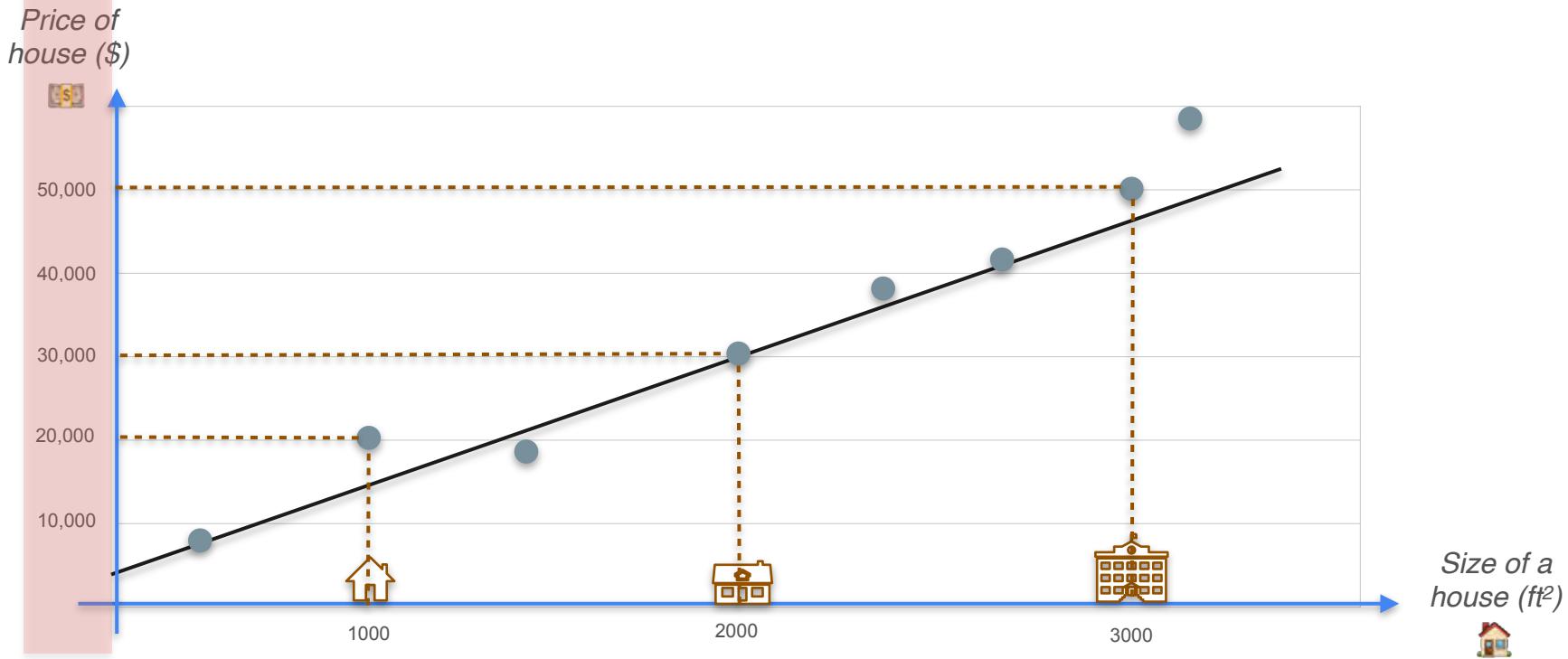
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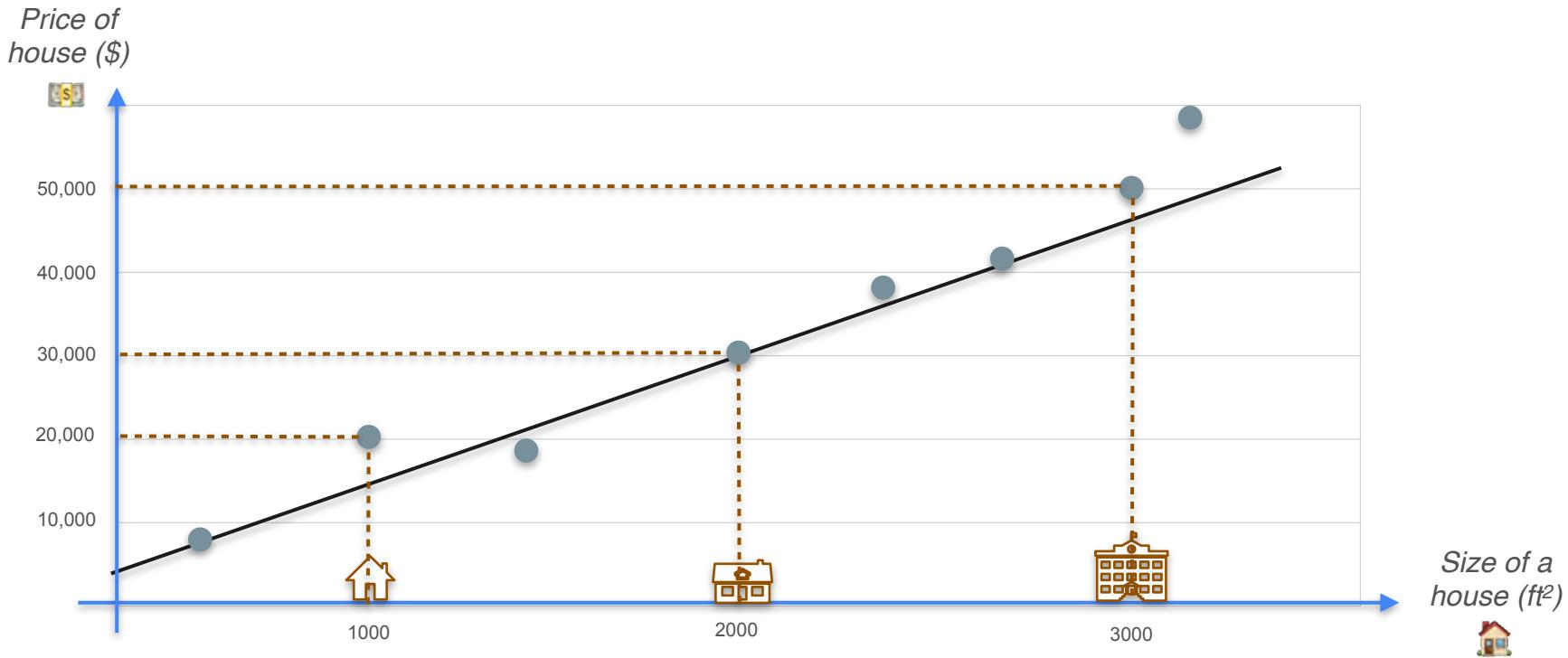
# Regression Problem Motivation



# Regression Problem Motivation



# Regression Problem Motivation



# Regression With a Perceptron

	<i>Size of a house (ft<sup>2</sup>)</i> 		<i>Price of house (\$)</i> 
			
			
			

# Regression With a Perceptron

	<i>Size of a house (ft<sup>2</sup>)</i> 		<i>Price of house (\$)</i> 
	$1000\text{ft}^2$		\$20,000
	$2000\text{ft}^2$		\$30,000
	$3000\text{ft}^2$		\$50,000

# Regression With a Perceptron

	<i>Size of a house (ft<sup>2</sup>)</i> 	<i>Number of rooms</i> 	<i>Price of house (\$)</i> 
	1000ft <sup>2</sup>	2	\$20,000
	2000ft <sup>2</sup>	4	\$30,000
	3000ft <sup>2</sup>	7	\$50,000

# Regression With a Perceptron

*Inputs*

*Size of a  
house (ft<sup>2</sup>)*



*Number of  
rooms*

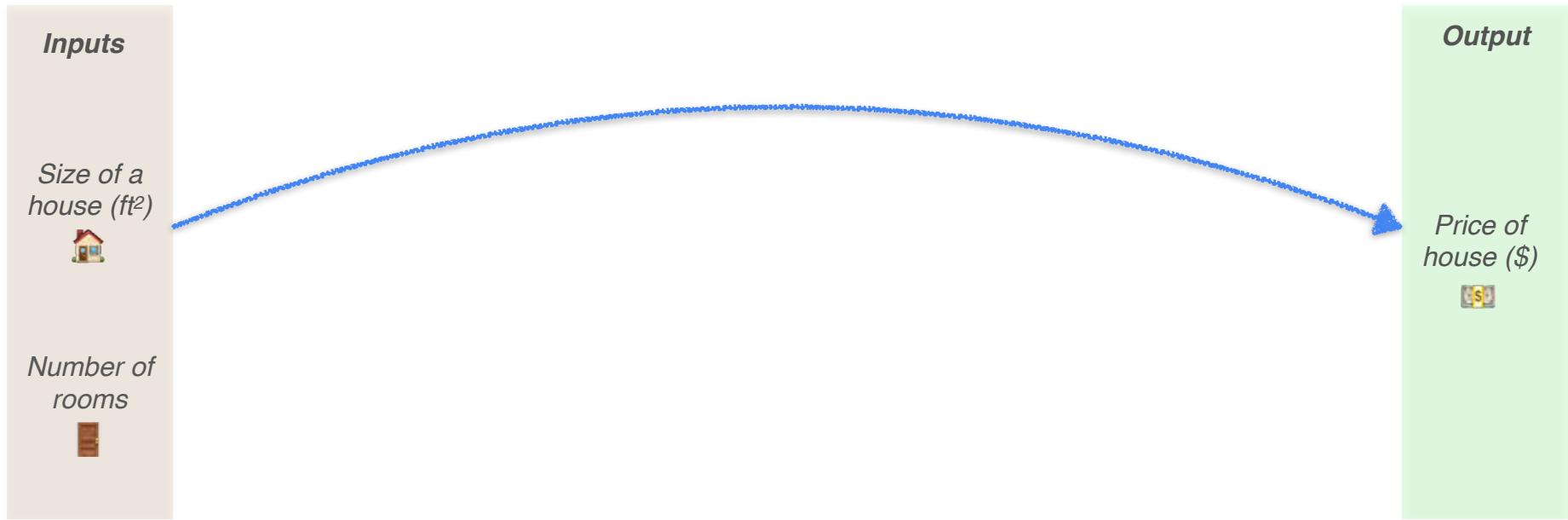


*Output*

*Price of  
house (\$)*



# Regression With a Perceptron



# Regression With a Perceptron

Single Layer Neural Network Perceptron

*Inputs*

*Size of a  
house (ft<sup>2</sup>)*



*Number of  
rooms*



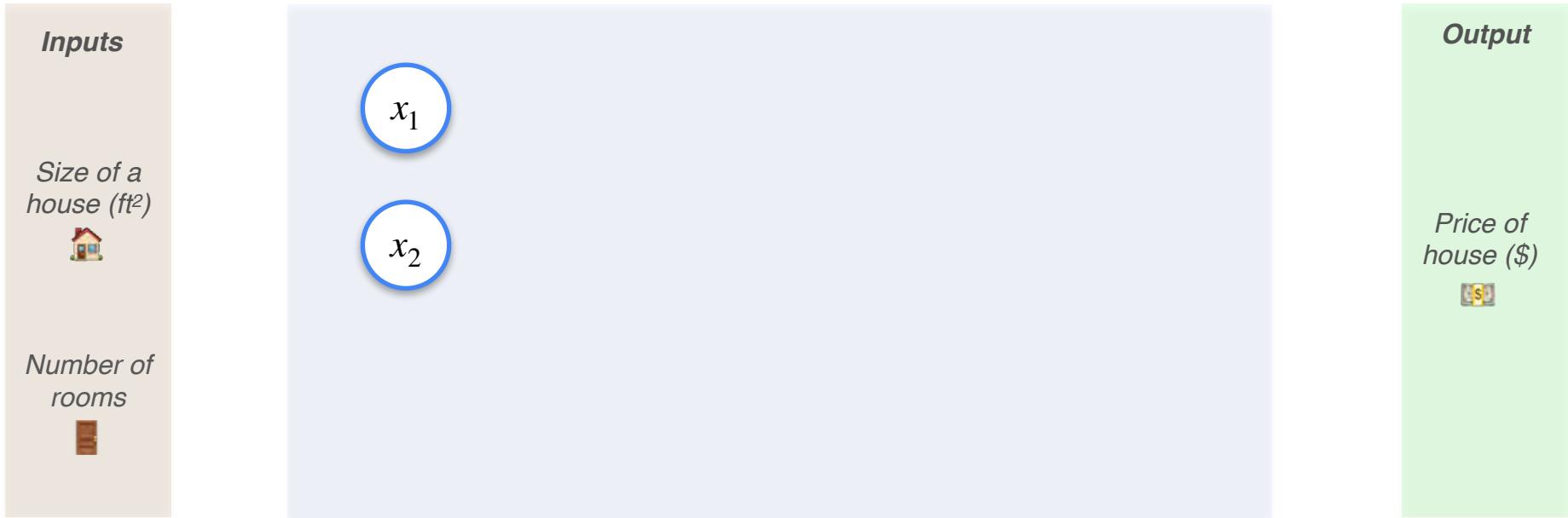
*Output*

*Price of  
house (\$)*



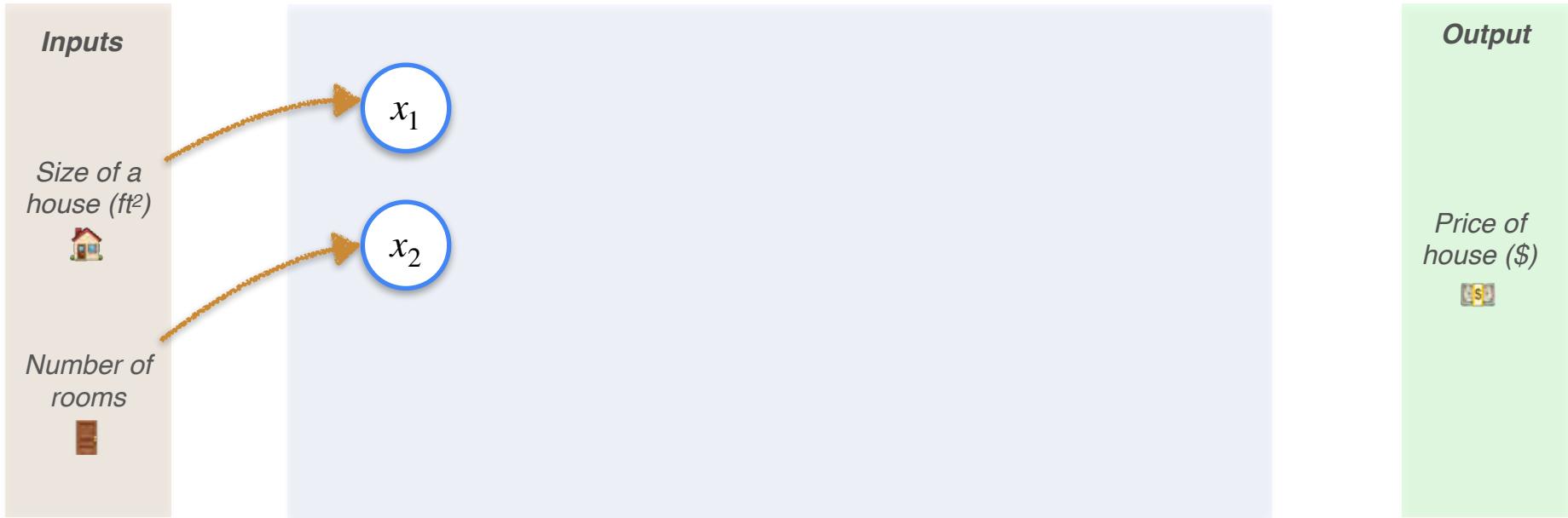
# Regression With a Perceptron

Single Layer Neural Network Perceptron



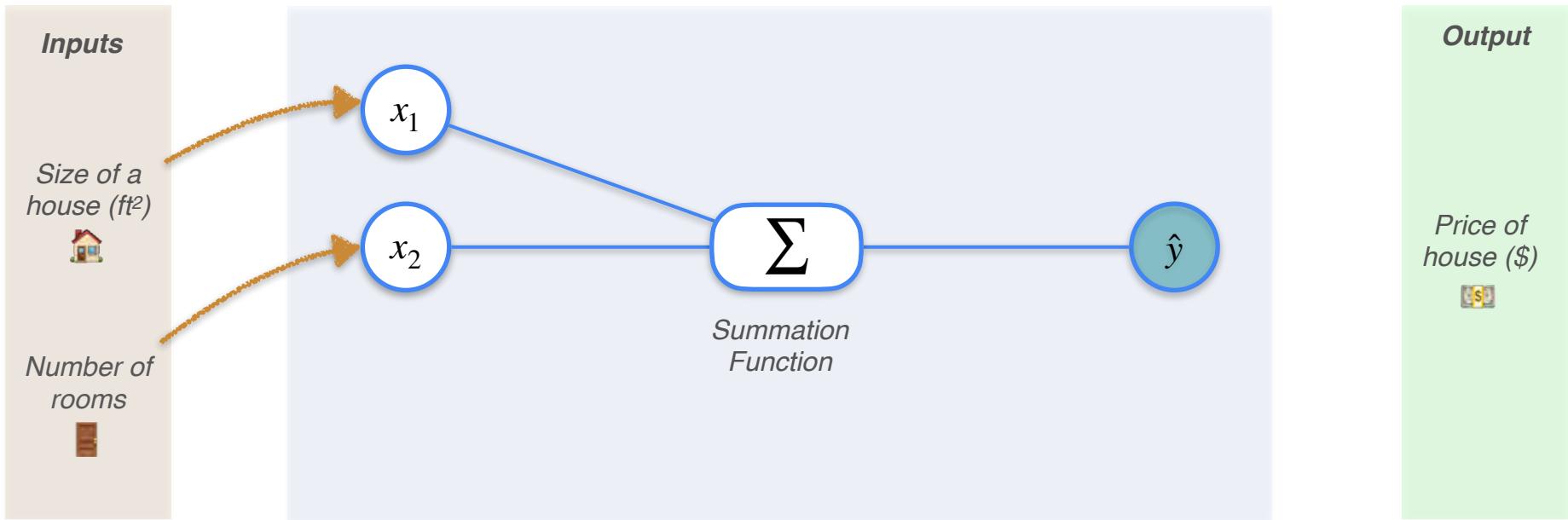
# Regression With a Perceptron

Single Layer Neural Network Perceptron



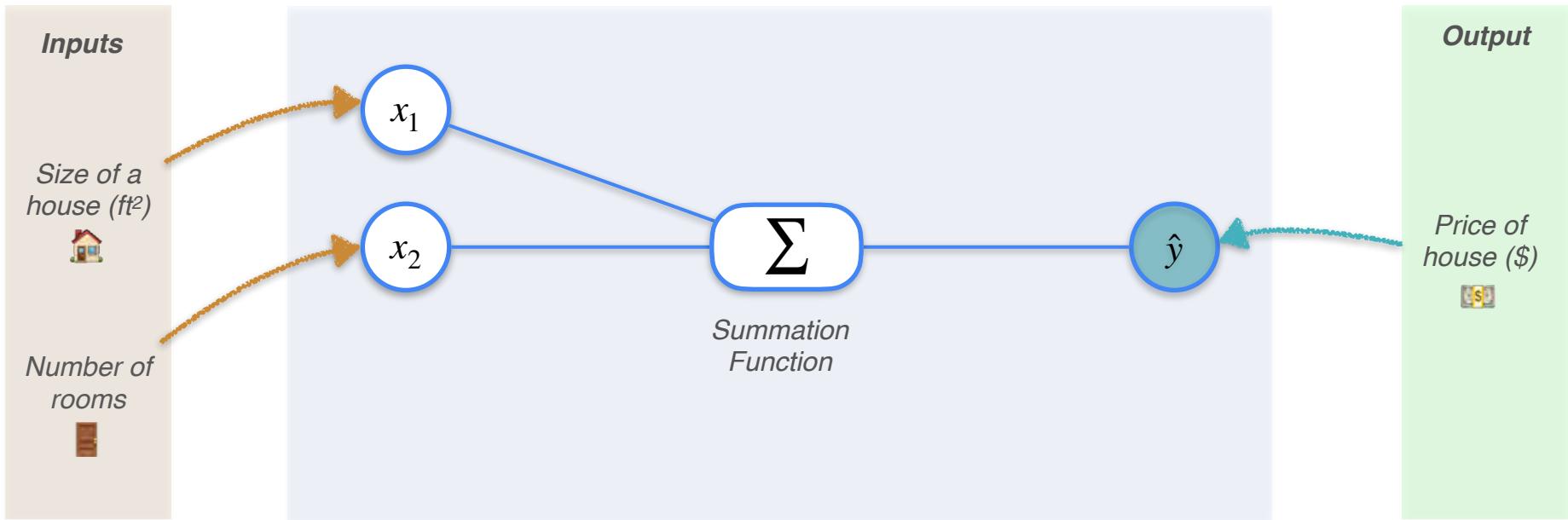
# Regression With a Perceptron

Single Layer Neural Network Perceptron



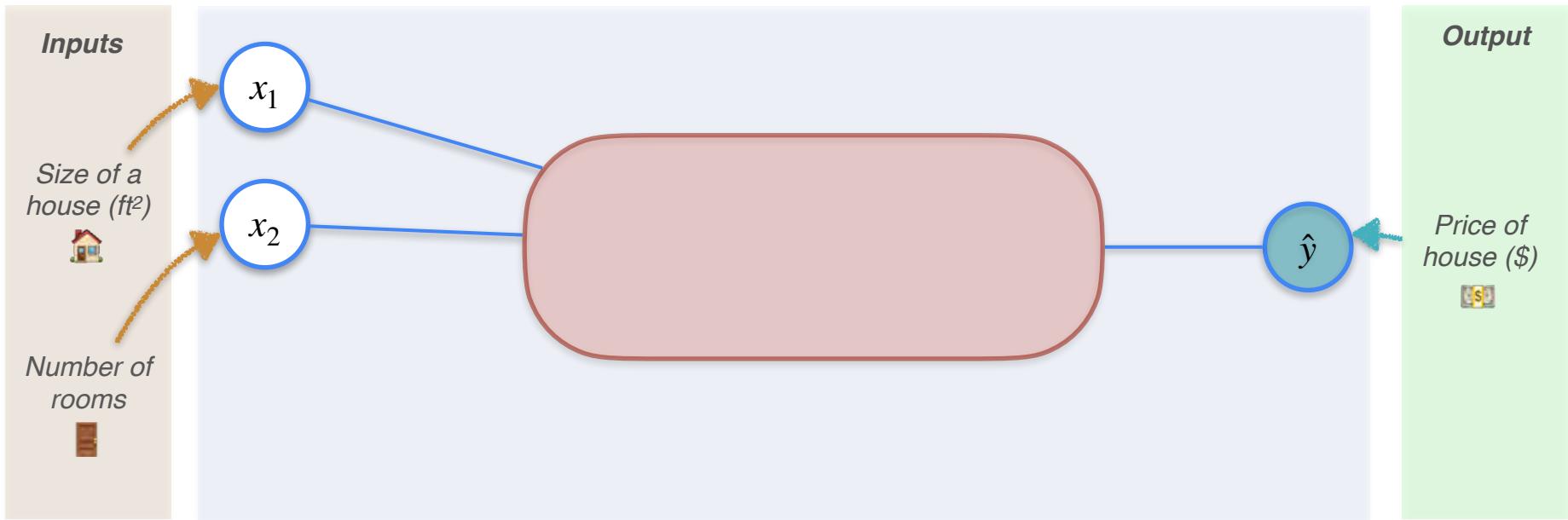
# Regression With a Perceptron

Single Layer Neural Network Perceptron



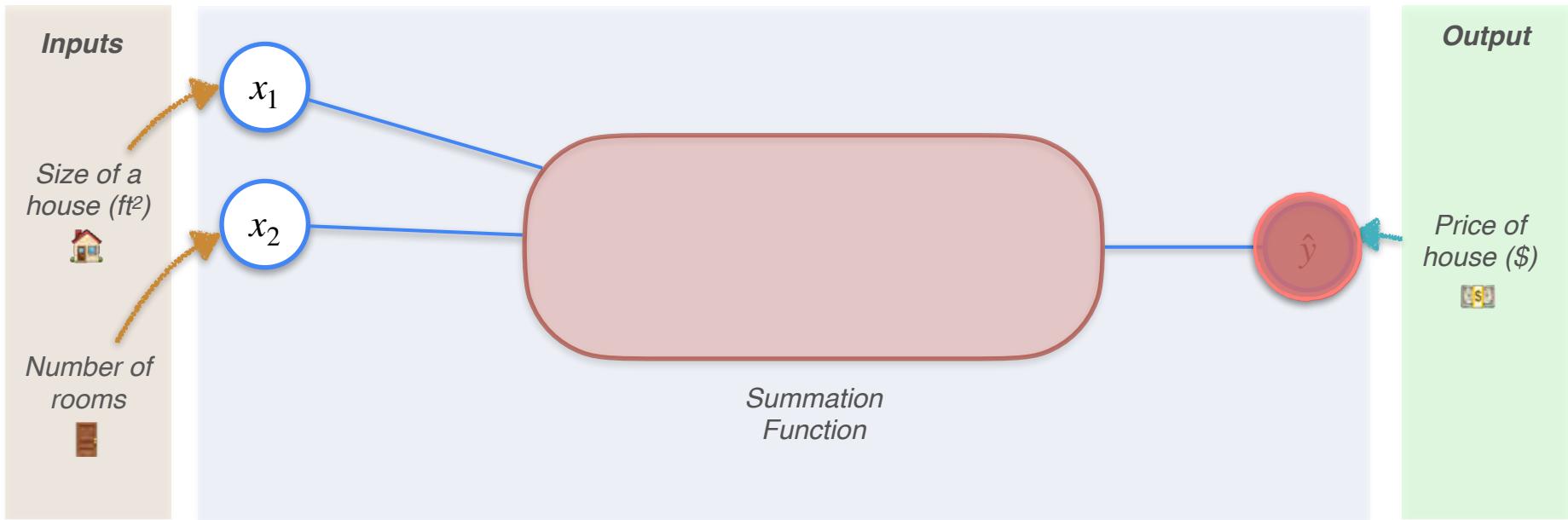
# Regression With a Perceptron

Single Layer Neural Network Perceptron



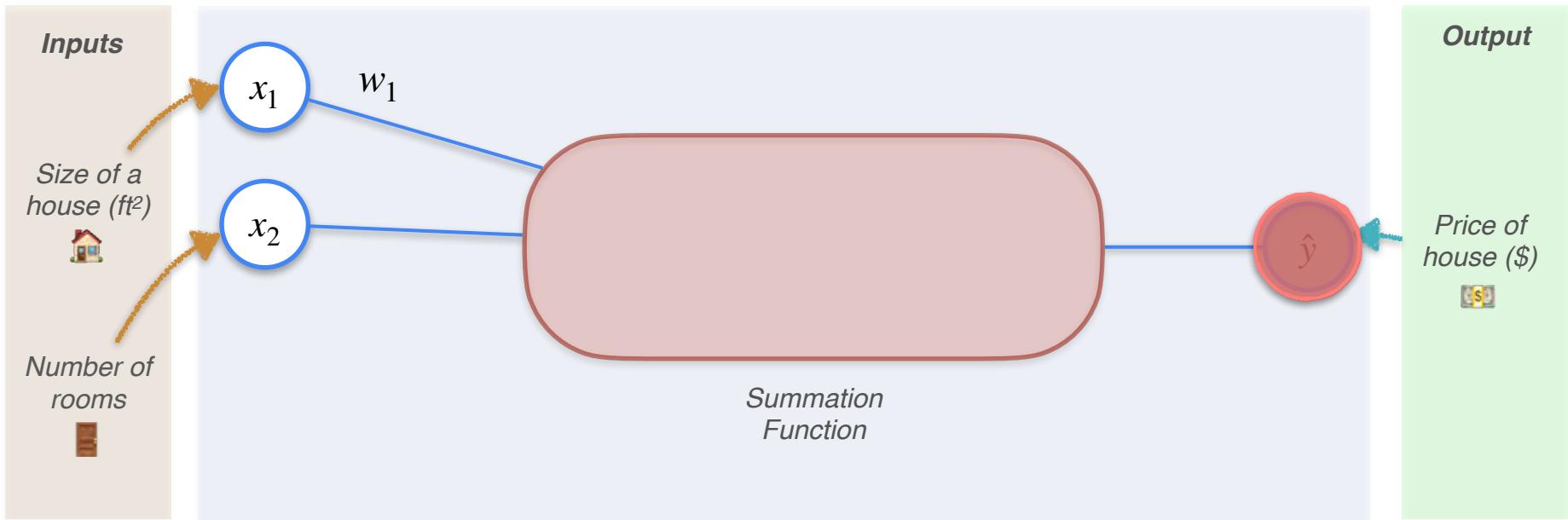
# Regression With a Perceptron

Single Layer Neural Network Perceptron



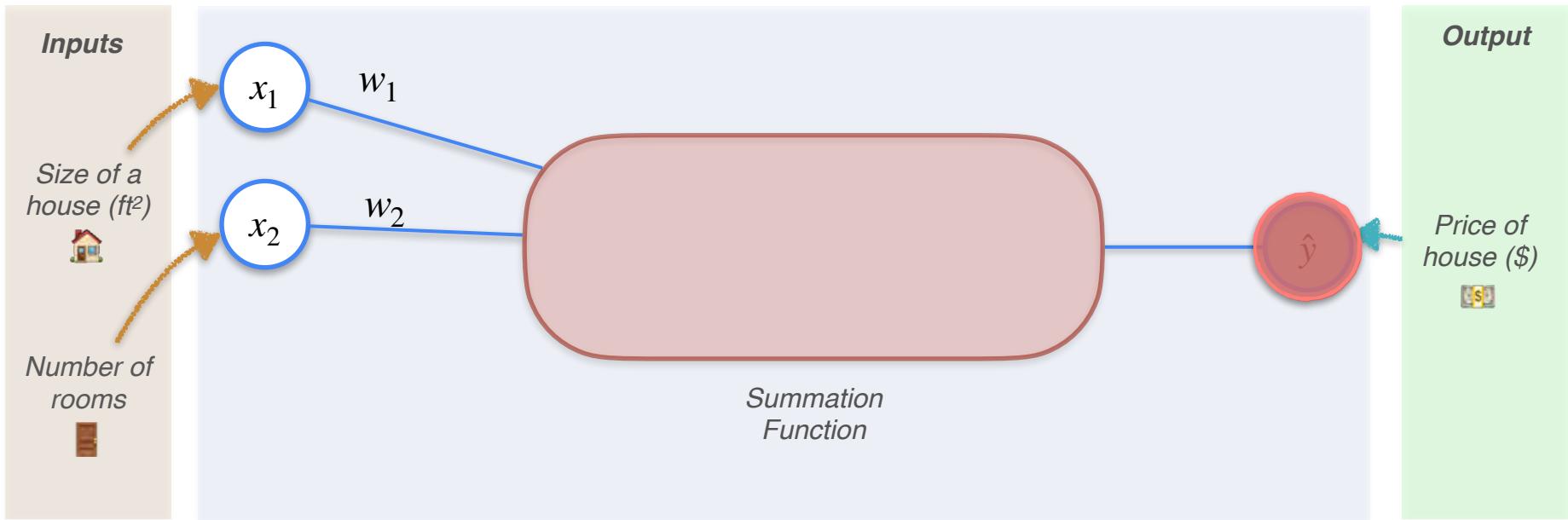
# Regression With a Perceptron

Single Layer Neural Network Perceptron



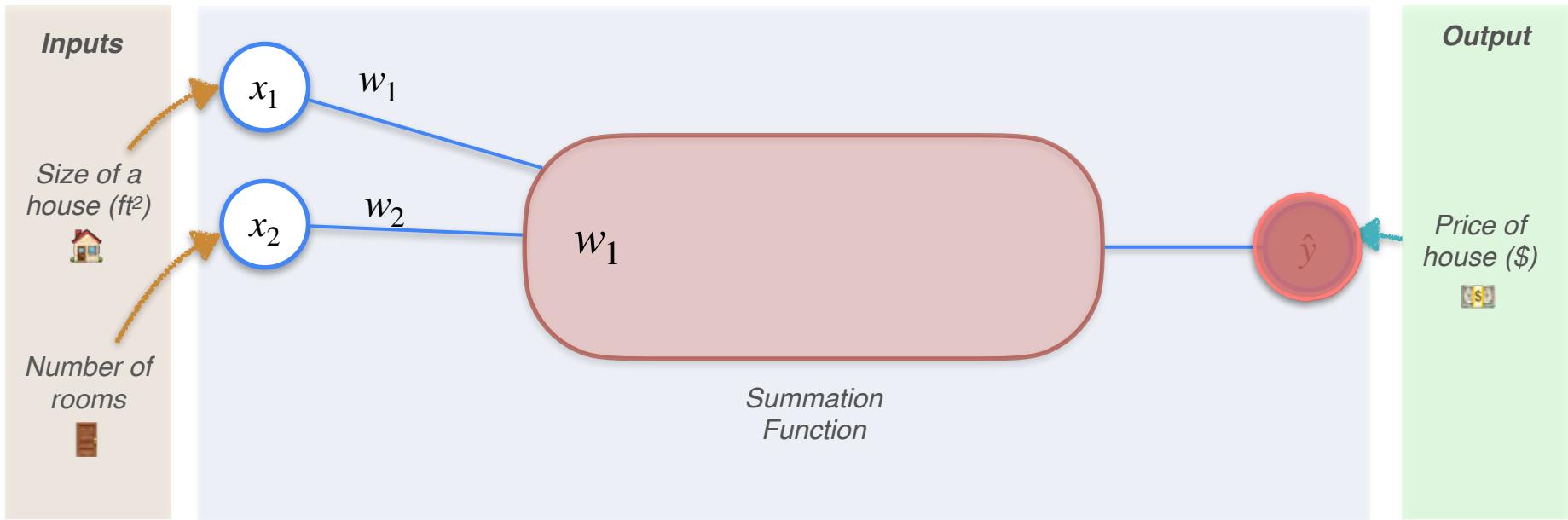
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Single Layer Neural Network Perceptron



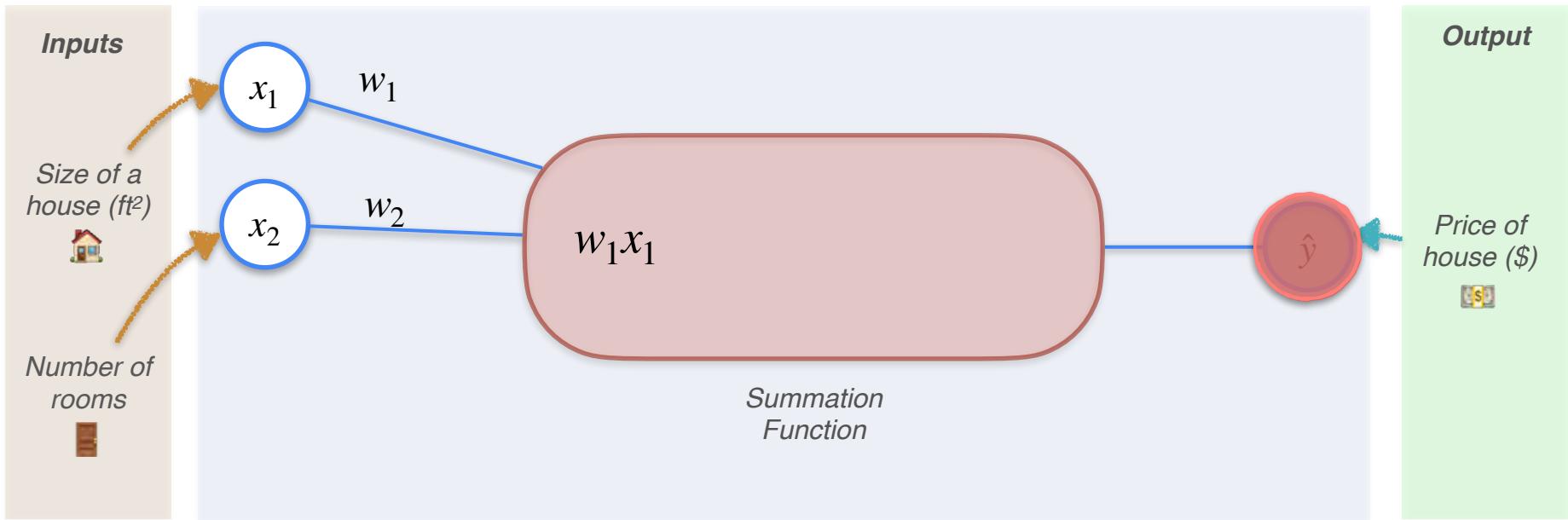
# Regression With a Perceptron

Single Layer Neural Network Perceptron



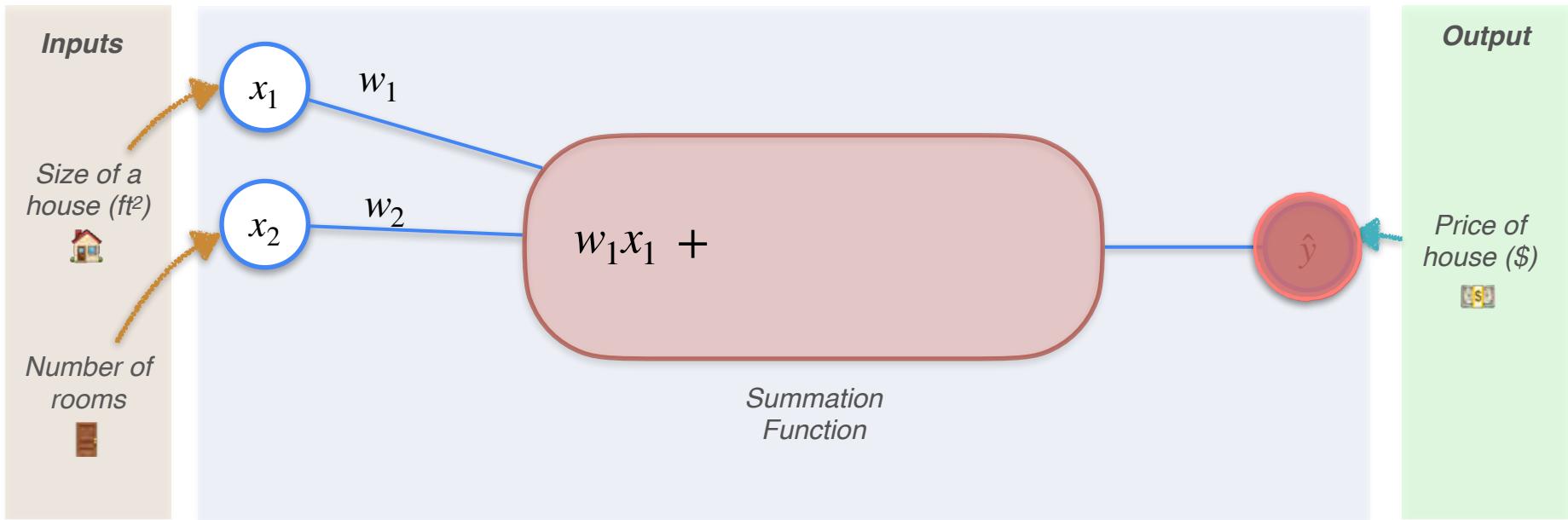
# Regression With a Perceptron

Single Layer Neural Network Perceptron



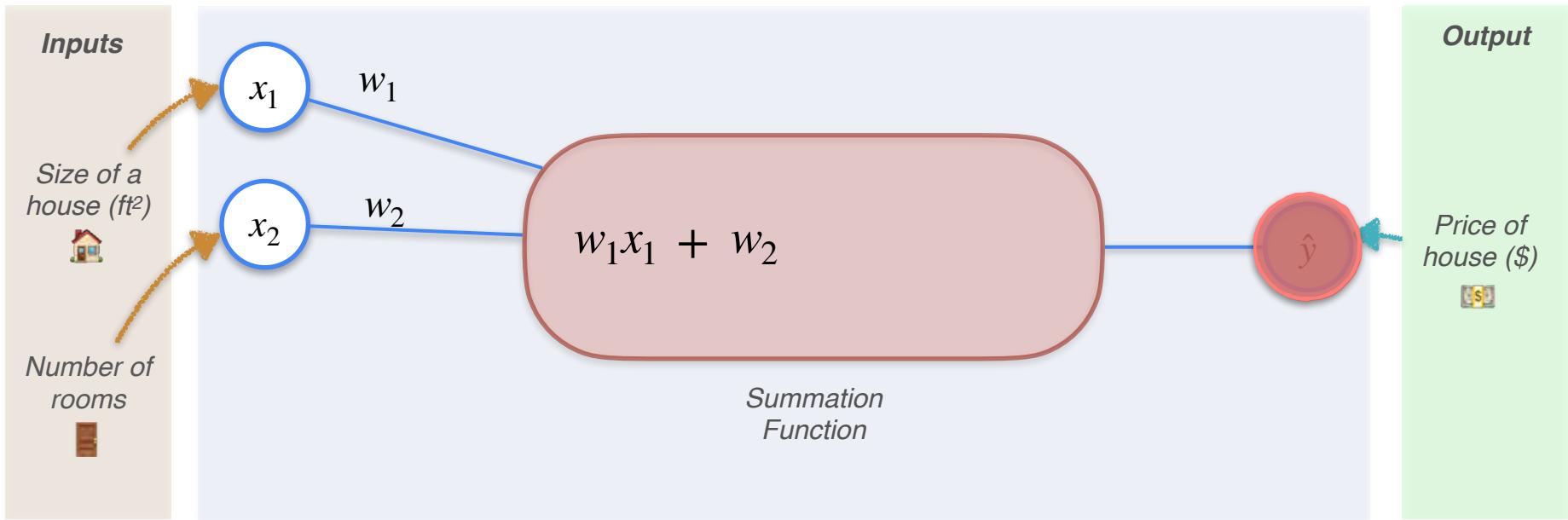
# Regression With a Perceptron

Single Layer Neural Network Perceptron



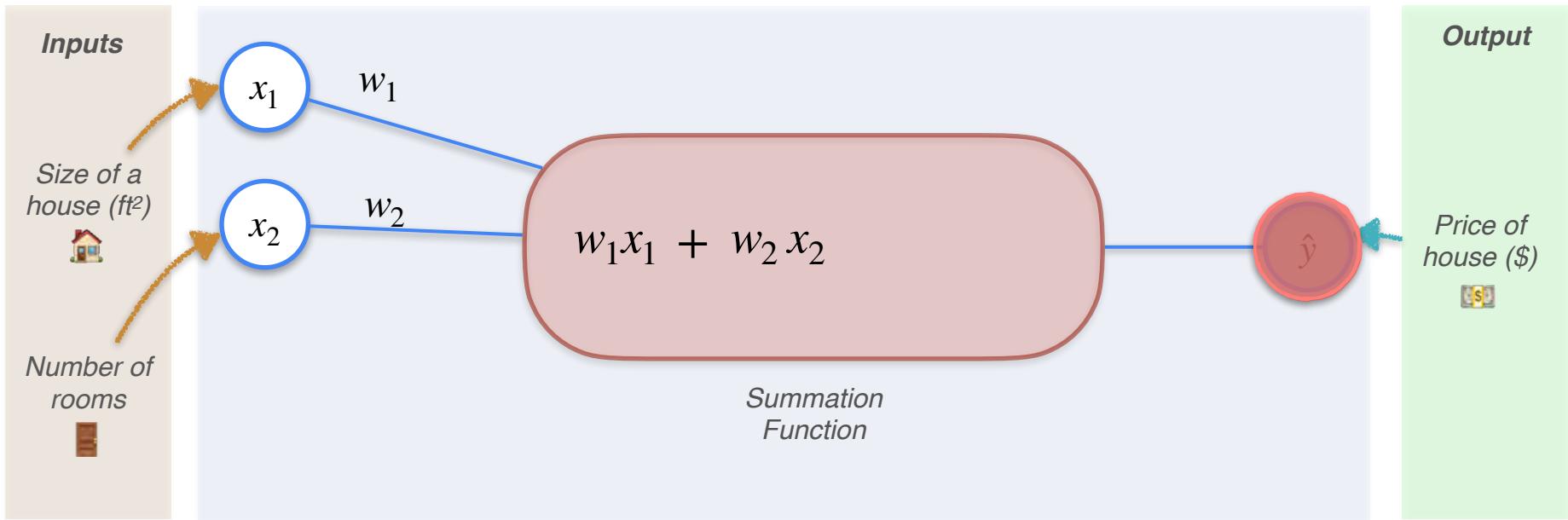
# Regression With a Perceptron

Single Layer Neural Network Perceptron



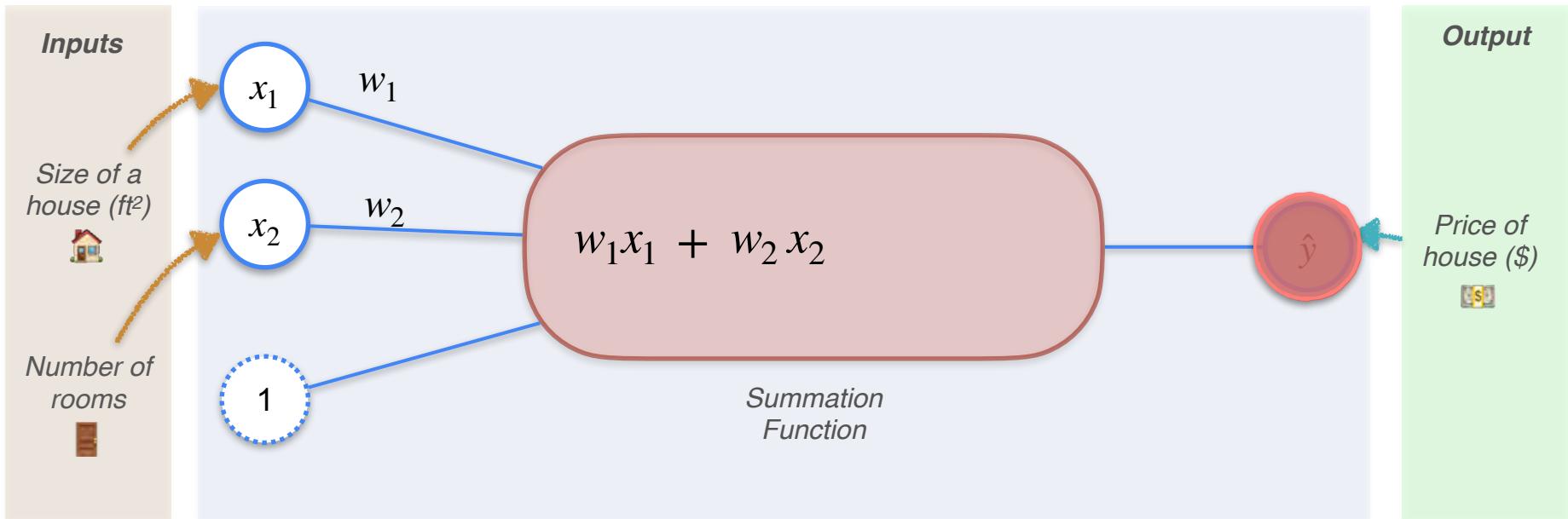
# Regression With a Perceptron

Single Layer Neural Network Perceptron



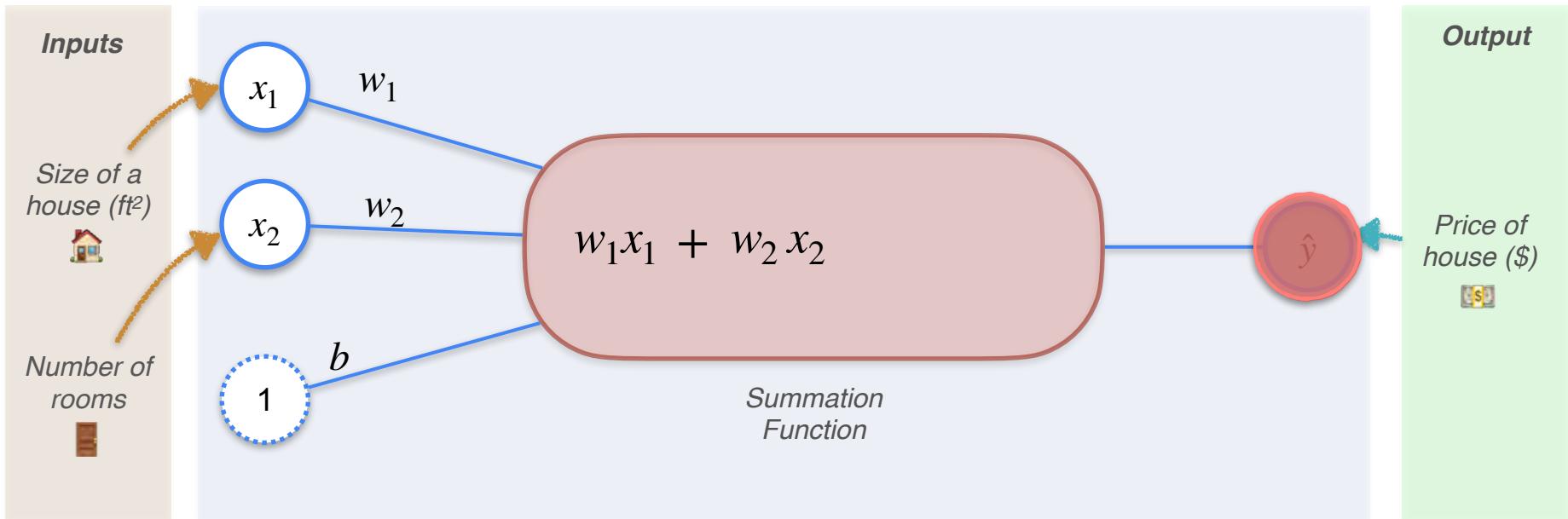
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Single Layer Neural Network Perceptron



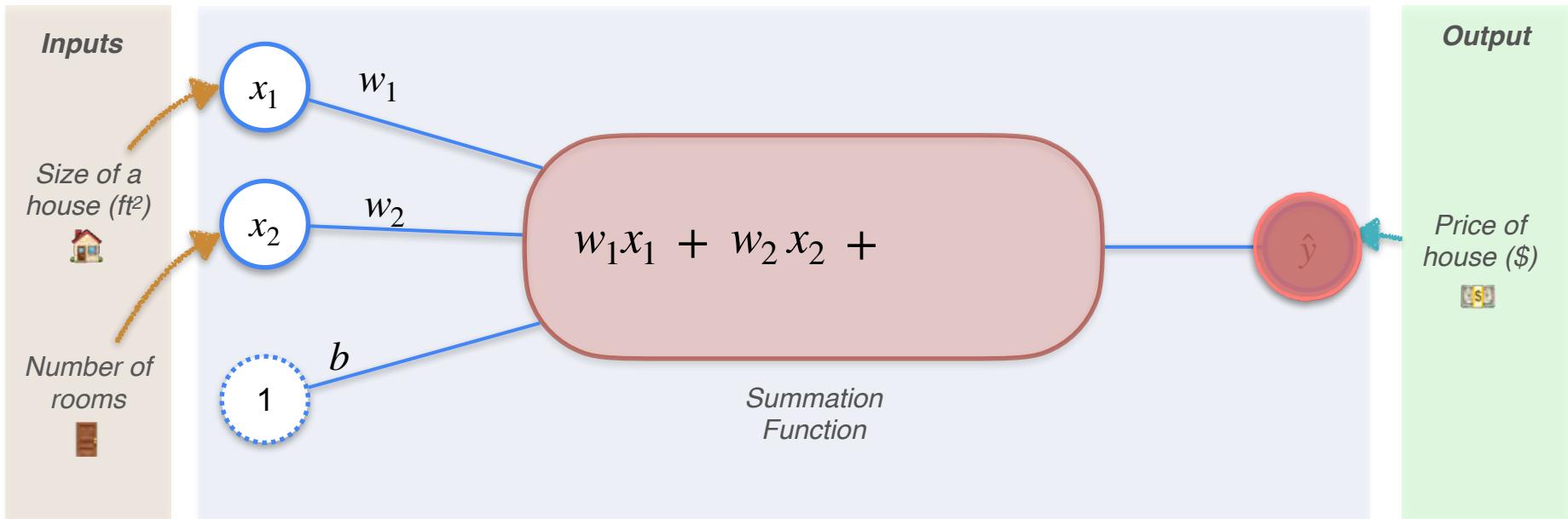
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Single Layer Neural Network Perceptron



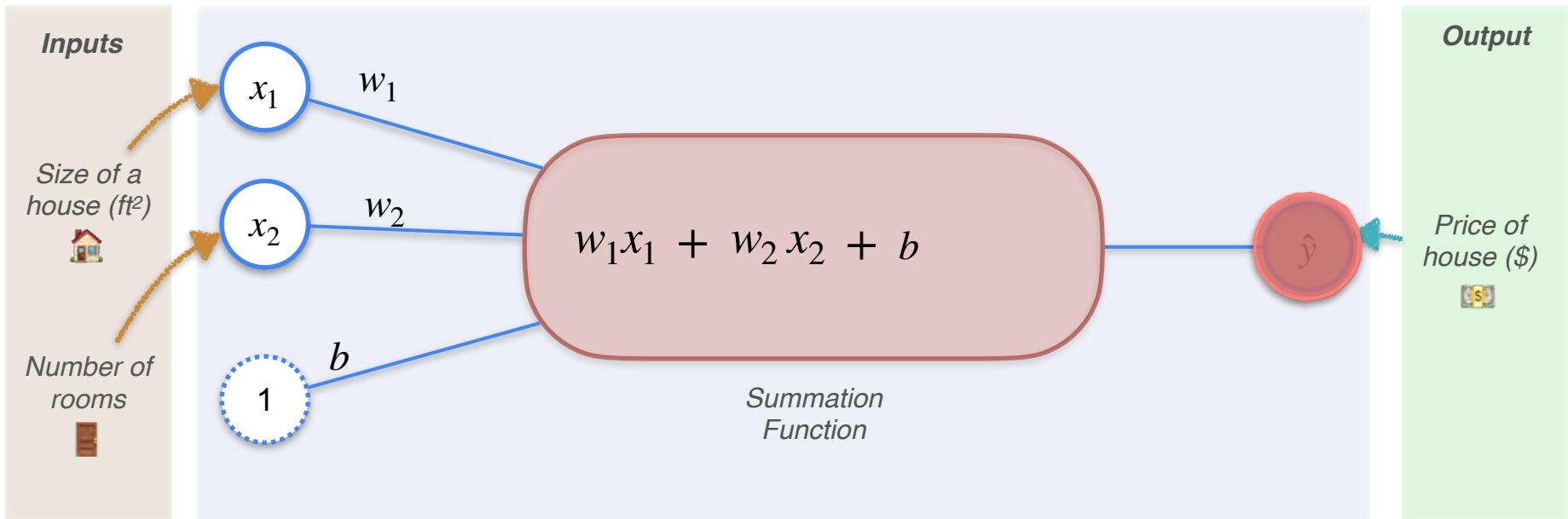
# Regression With a Perceptron

Single Layer Neural Network Perceptron



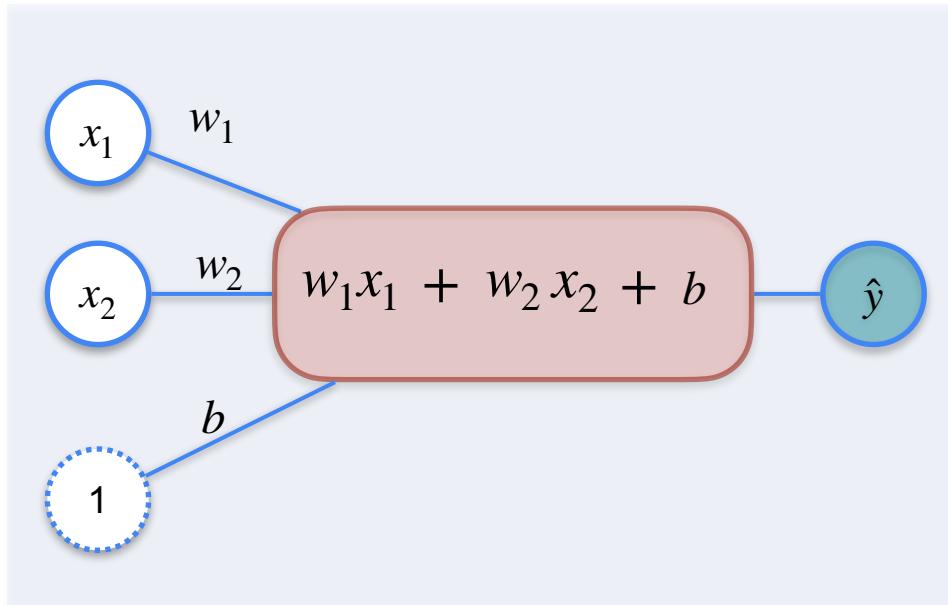
# Regression With a Perceptron

Single Layer Neural Network Perceptron



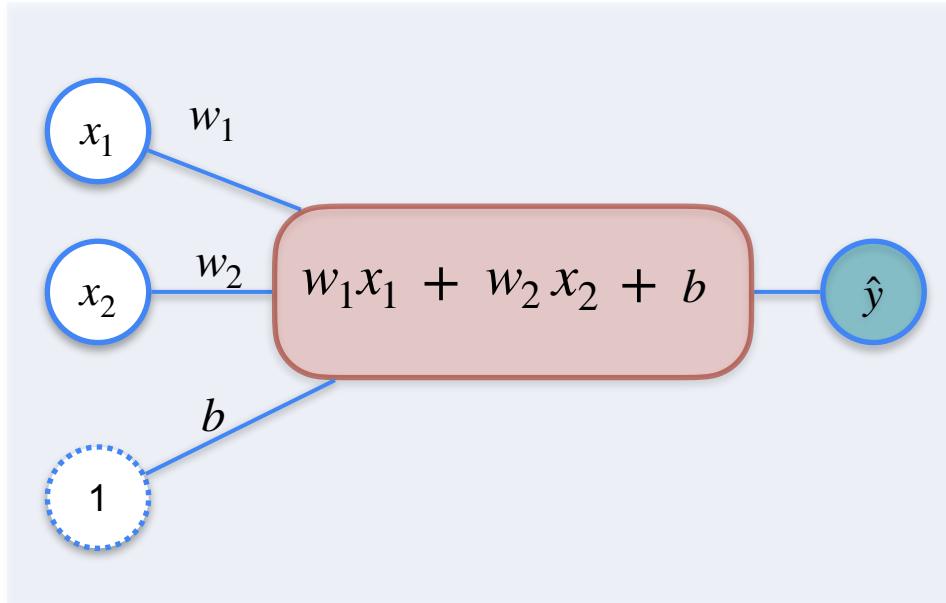
# Regression With a Perceptron

Single Layer Neural Network Perceptron



# Regression With a Perceptron

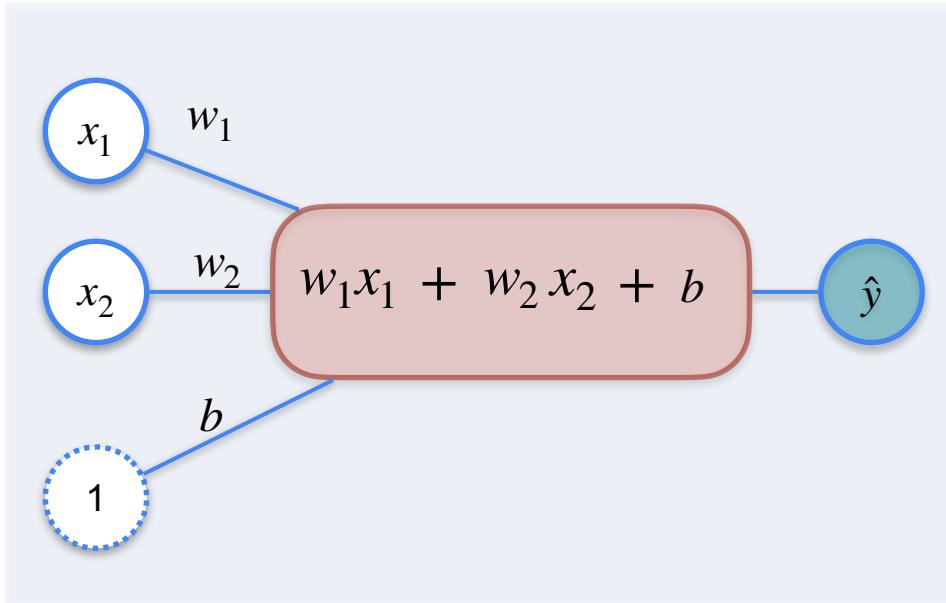
Single Layer Neural Network Perceptron



$\hat{y}$

# Regression With a Perceptron

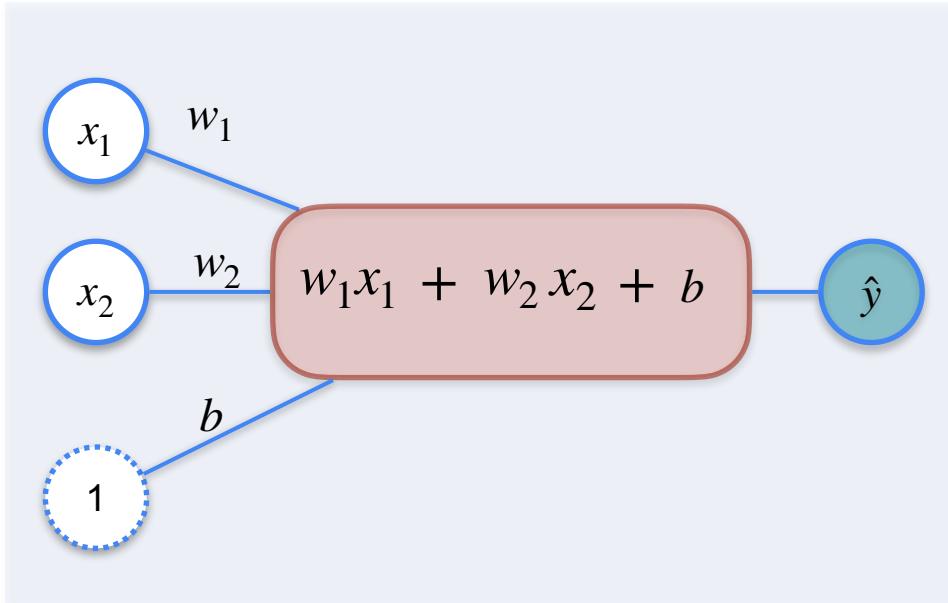
Single Layer Neural Network Perceptron



$$\hat{y} = w_1x_1 + w_2x_2 + b$$

# Regression With a Perceptron

Single Layer Neural Network Perceptron

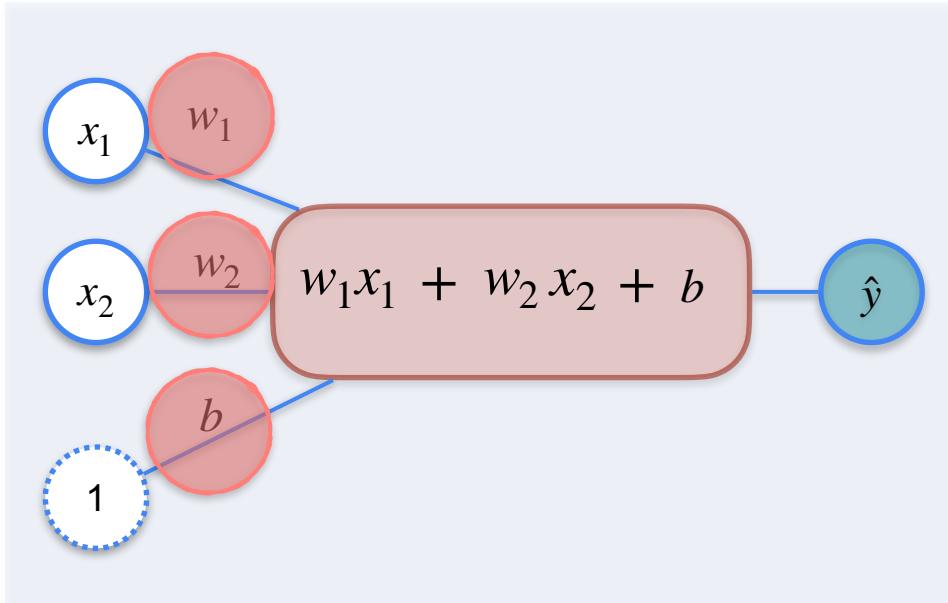


$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Main Goal:**

# Regression With a Perceptron

Single Layer Neural Network Perceptron

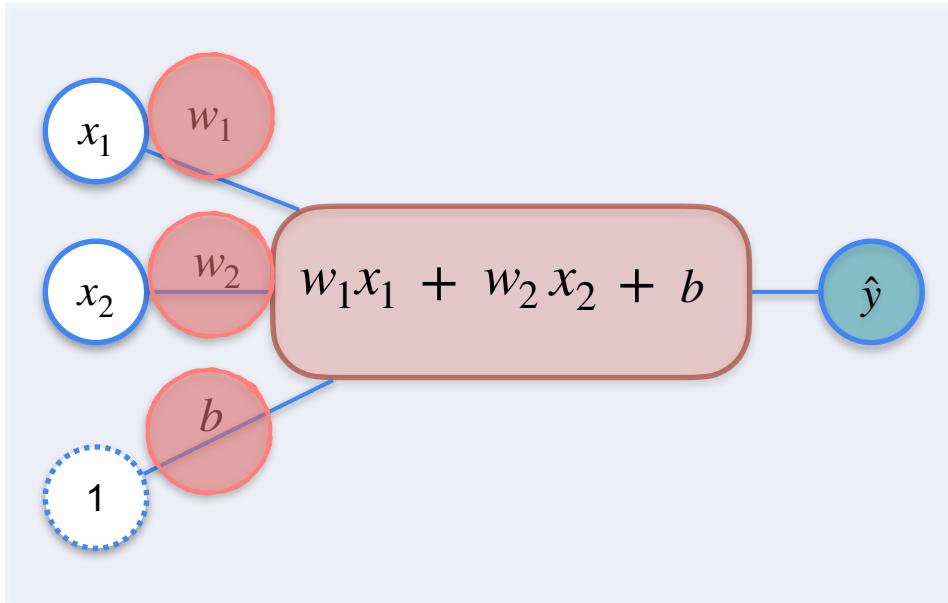


$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Main Goal:

# Regression With a Perceptron

Single Layer Neural Network Perceptron



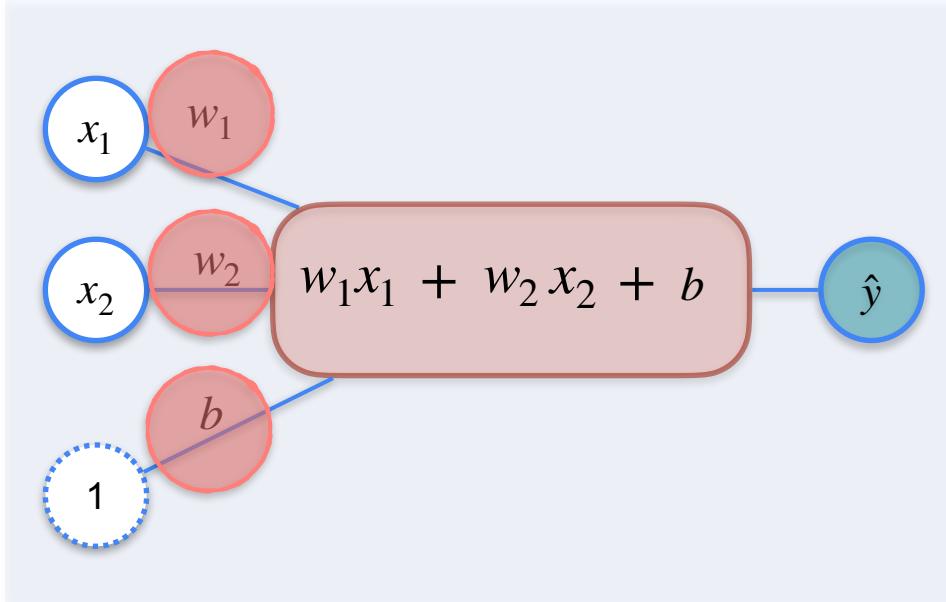
$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Main Goal:**

Find weights and bias that will optimise the predictions.

# Regression With a Perceptron

Single Layer Neural Network Perceptron



$$\hat{y} = w_1x_1 + w_2x_2 + b$$

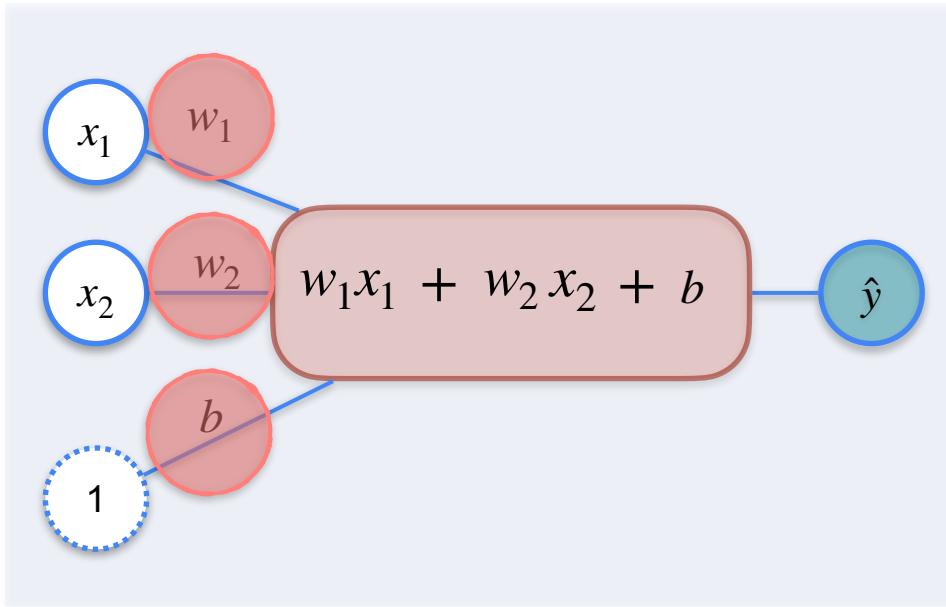
**Main Goal:**

Find weights and bias that will optimise the predictions.

i.e. Reduce the errors in the predictions

# Regression With a Perceptron

Single Layer Neural Network Perceptron



$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Main Goal:**

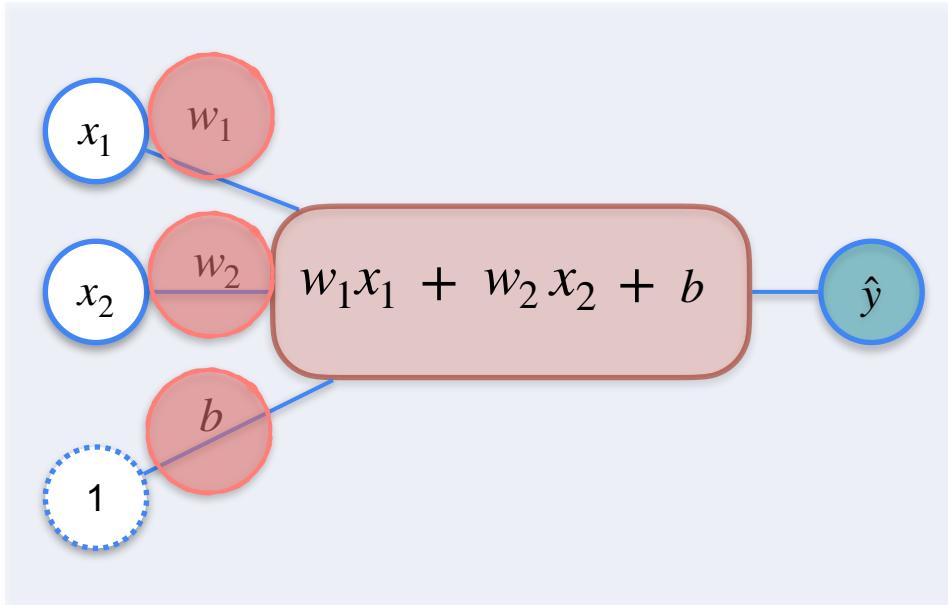
Find weights and bias that will optimise the predictions.

i.e. Reduce the errors in the predictions



# Regression With a Perceptron

Single Layer Neural Network Perceptron



$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Main Goal:**

Find weights and bias that will optimise the predictions.

i.e. Reduce the errors in the predictions



**The  
Loss  
Function**



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# Optimization in Neural Networks and Newton's Method

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## Regression with a perceptron: Loss function

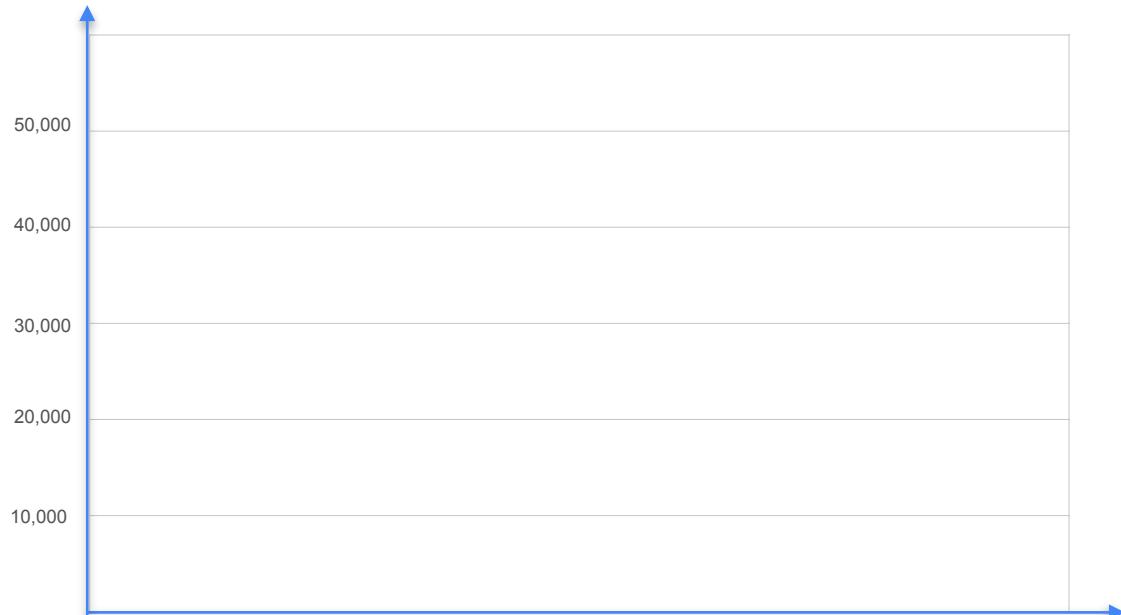
# Mean Squared Error

# Mean Squared Error

	$y$		
	\$20,000		
	\$30,000		
	\$50,000		

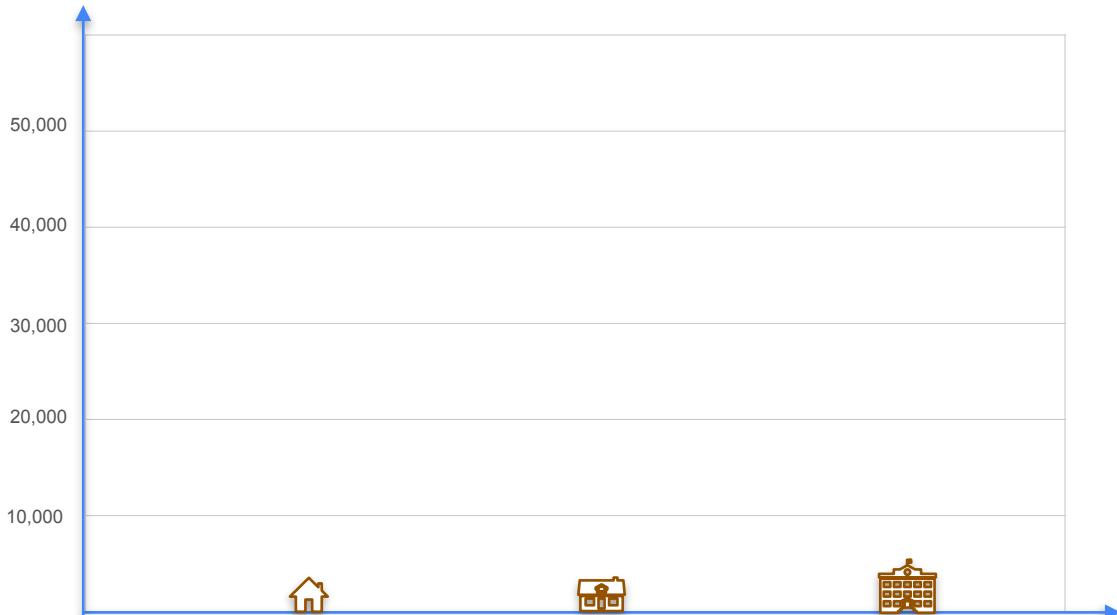
# Mean Squared Error

	$y$		
	\$20,000		
	\$30,000		
	\$50,000		



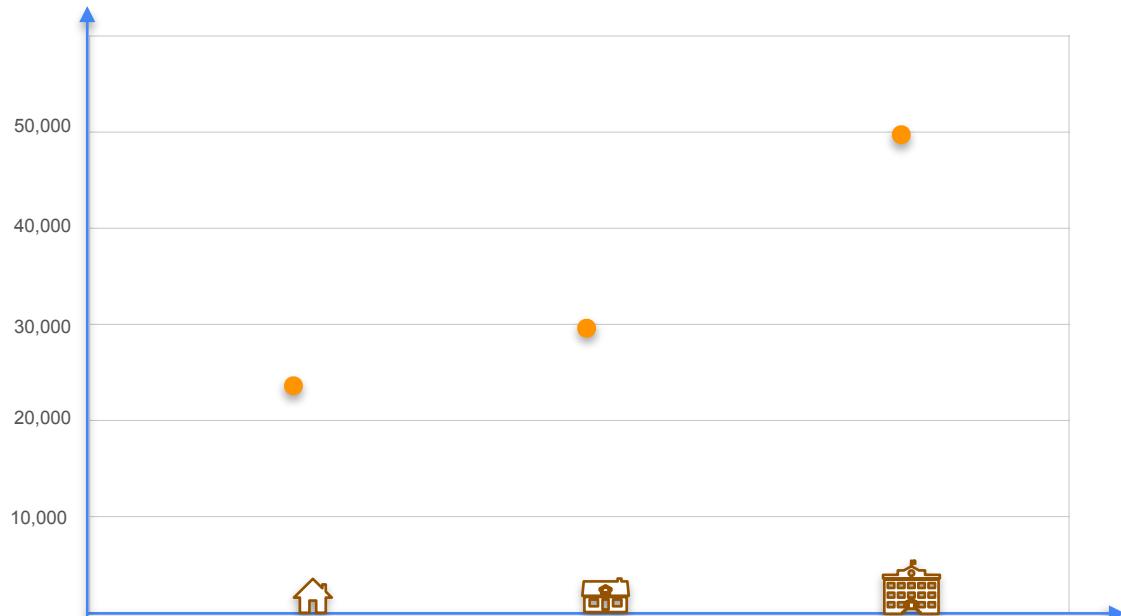
# Mean Squared Error

	$y$		
	\$20,000		
	\$30,000		
	\$50,000		



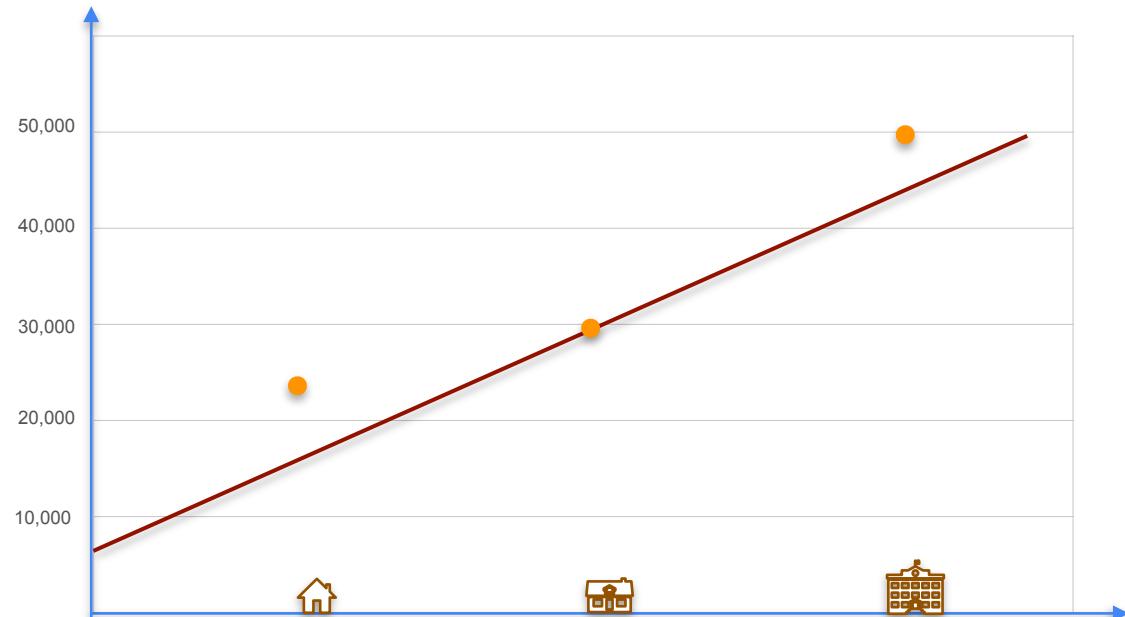
# Mean Squared Error

	$y$		
	\$20,000		
	\$30,000		
	\$50,000		



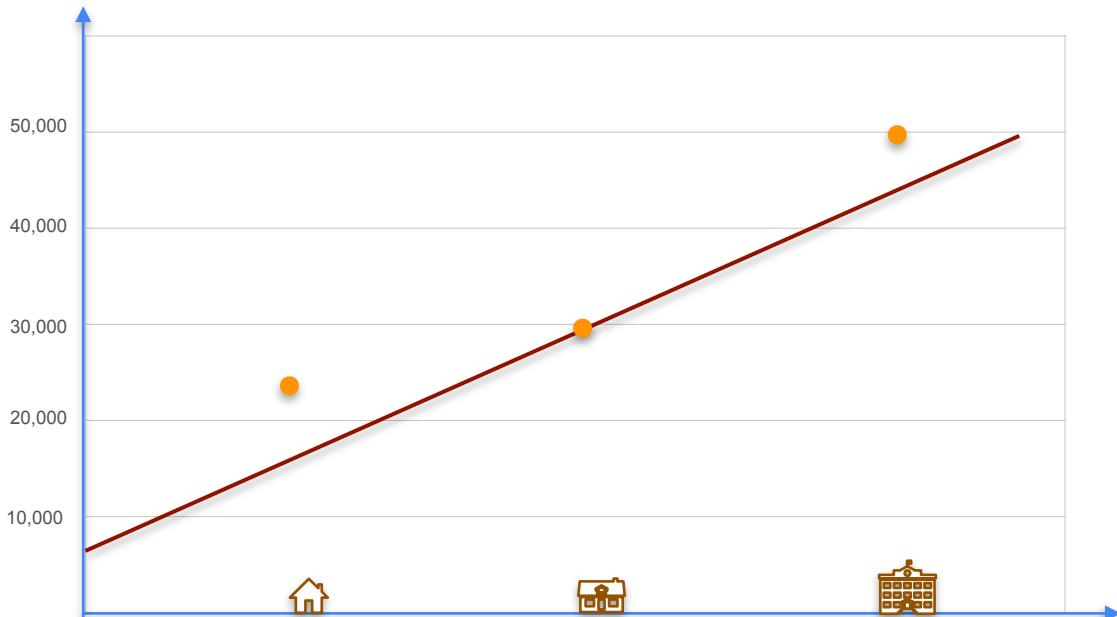
# Mean Squared Error

	$y$		
	\$20,000		
	\$30,000		
	\$50,000		



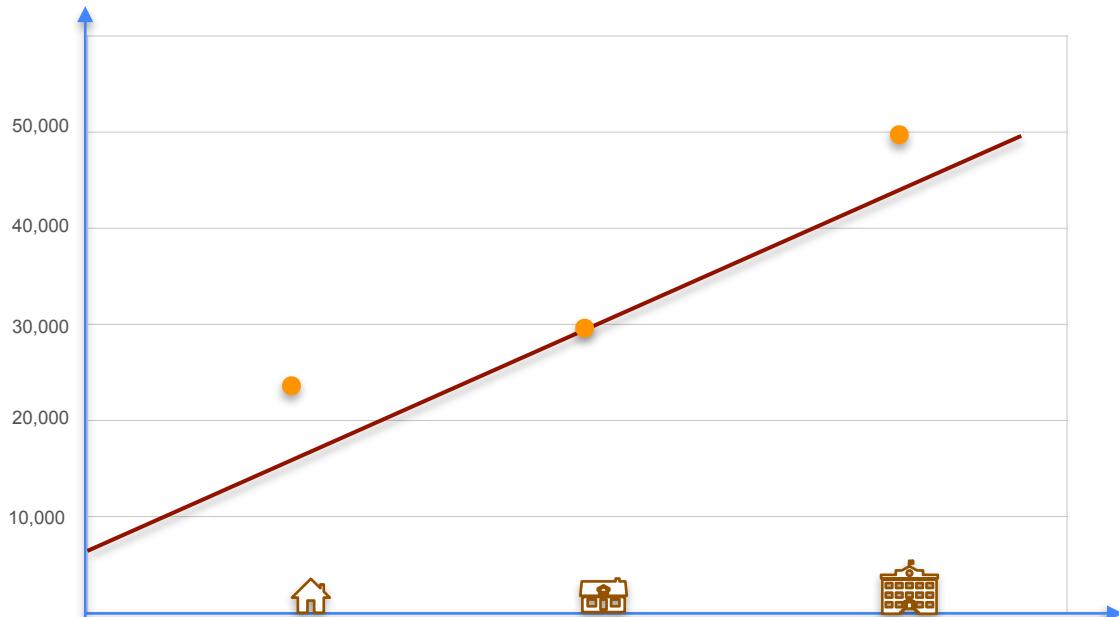
# Mean Squared Error

	$y$	$\hat{y}$	
	\$20,000	\$15,000	
	\$30,000	\$30,000	
	\$50,000	\$45,000	



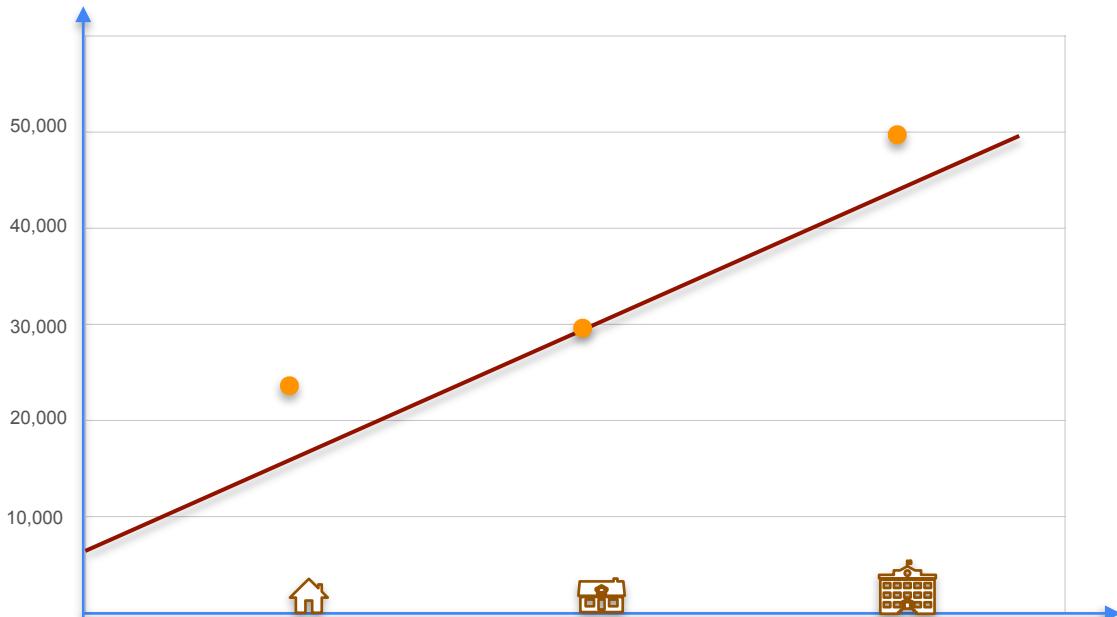
# Mean Squared Error

	$y$	$\hat{y}$	$y - \hat{y}$
	\$20,000	\$15,000	
	\$30,000	\$30,000	
	\$50,000	\$45,000	



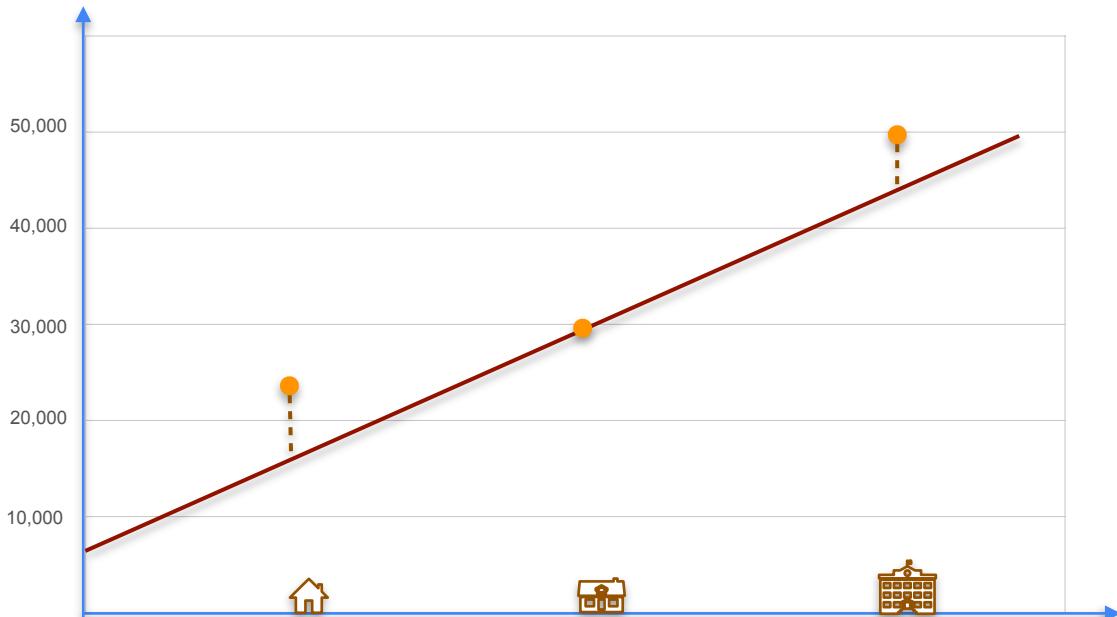
# Mean Squared Error

	$y$	$\hat{y}$	$y - \hat{y}$
<b>Error</b>			
	\$20,000	\$15,000	
<b>Error</b>			
	\$30,000	\$30,000	
	\$50,000	\$45,000	



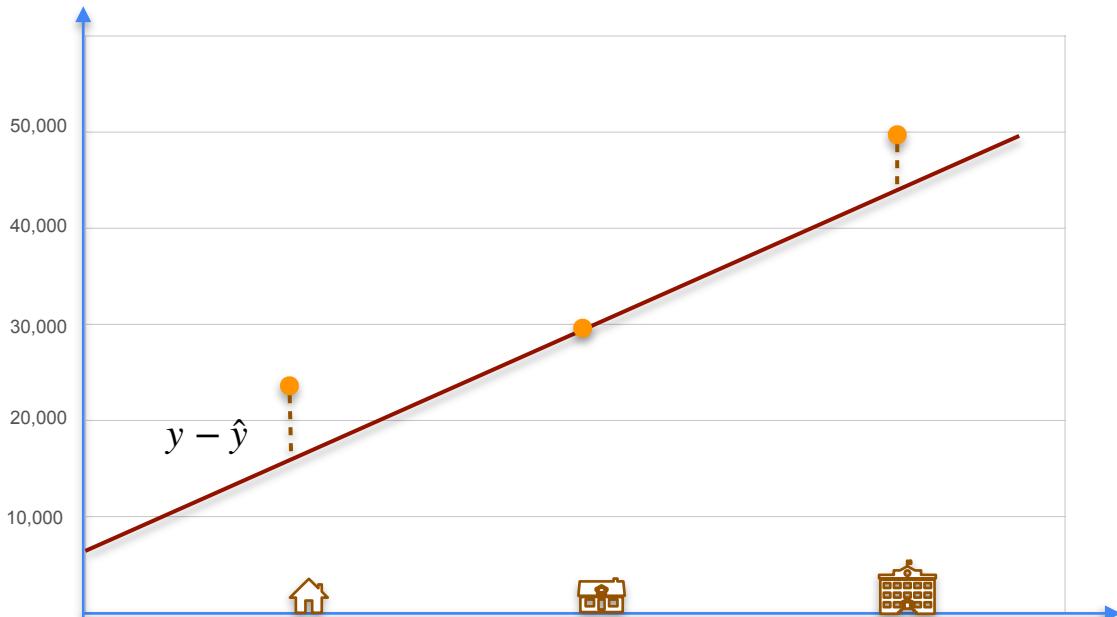
# Mean Squared Error

	$y$	$\hat{y}$	$y - \hat{y}$
	\$20,000	\$15,000	<b>Error</b>
	\$30,000	\$30,000	<b>Error</b>
	\$50,000	\$45,000	<b>Error</b>



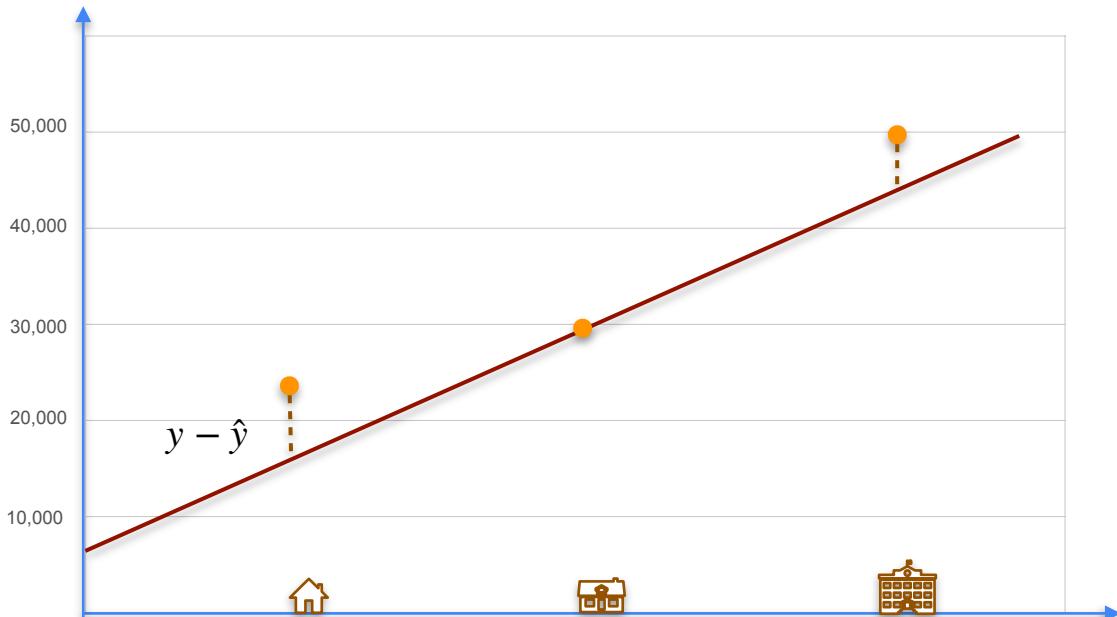
# Mean Squared Error

	$y$	$\hat{y}$	$y - \hat{y}$
	\$20,000	\$15,000	<b>Error</b>
	\$30,000	\$30,000	<b>Error</b>
	\$50,000	\$45,000	<b>Error</b>



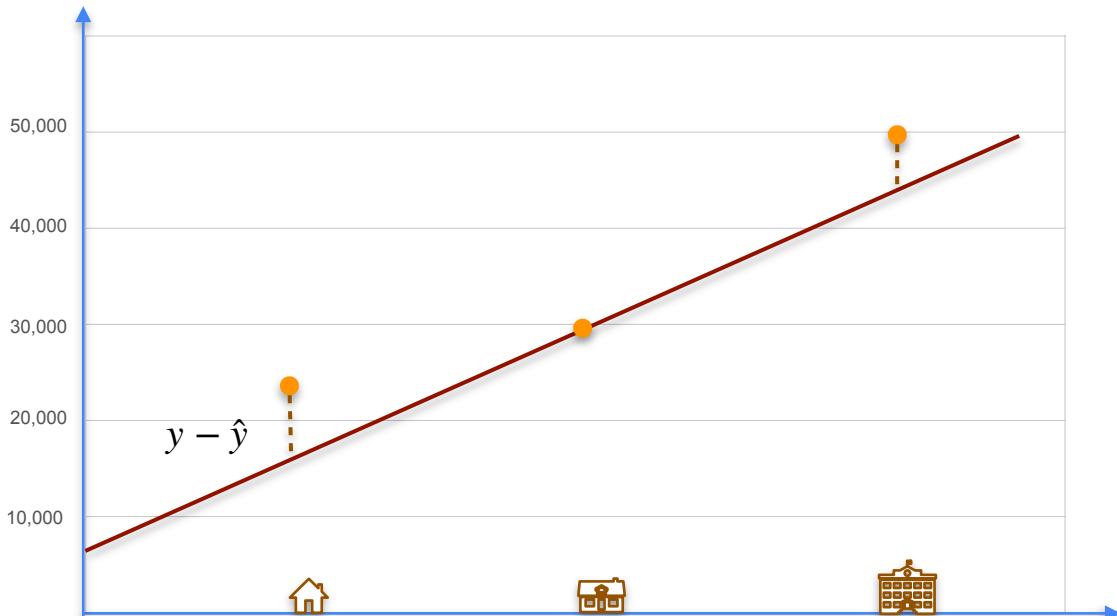
# Mean Squared Error

	$y$	$\hat{y}$	$(y - \hat{y})^2$
	\$20,000	\$15,000	<b>Error</b>
	\$30,000	\$30,000	<b>Error</b>
	\$50,000	\$45,000	<b>Error</b>



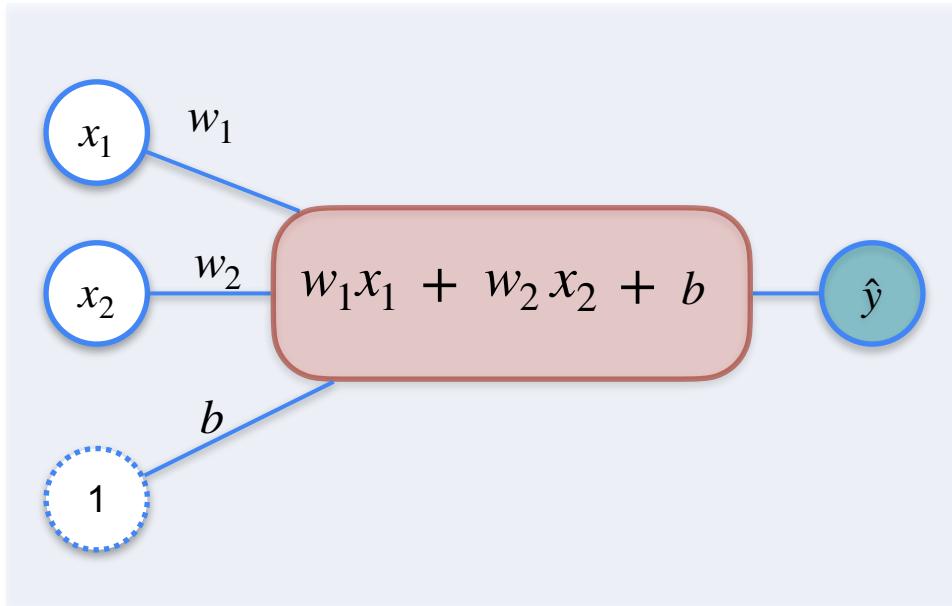
# Mean Squared Error

	$y$	$\hat{y}$	$\frac{1}{2}(y - \hat{y})^2$
	\$20,000	\$15,000	<b>Error</b>
	\$30,000	\$30,000	<b>Error</b>
	\$50,000	\$45,000	<b>Error</b>



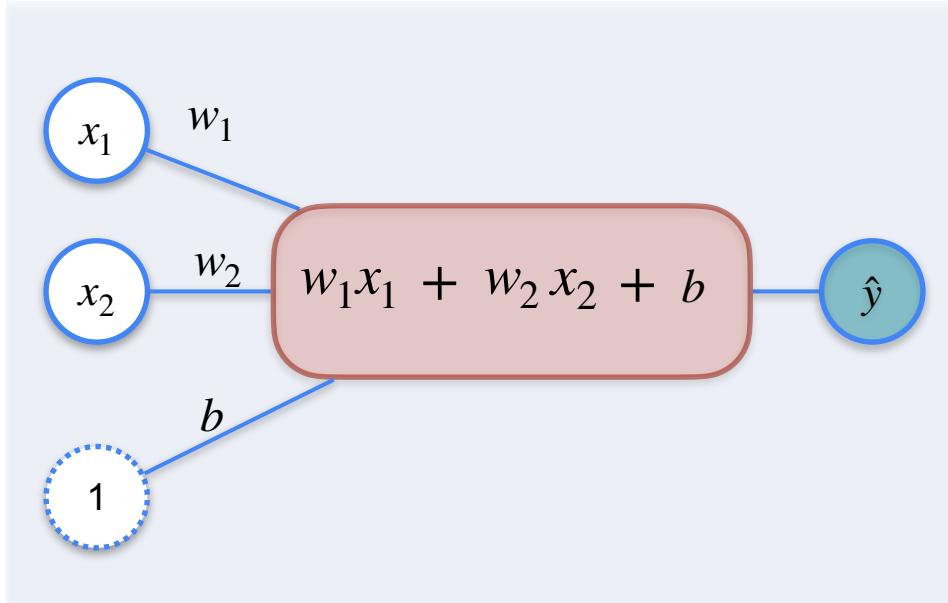
# Regression With a Perceptron

Single Layer Neural Network Perceptron



# Regression With a Perceptron

Single Layer Neural Network Perceptron

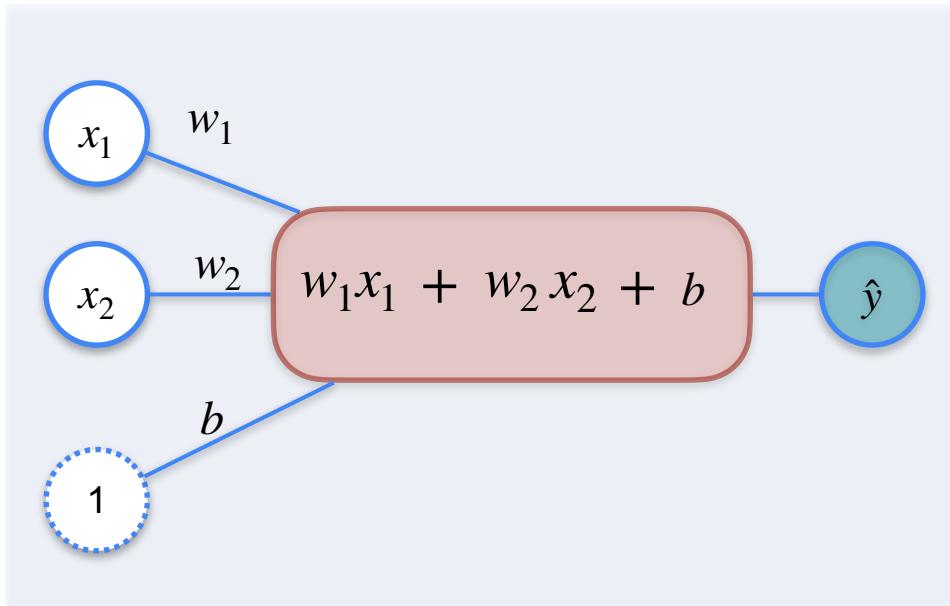


**Prediction Function:**

$$\hat{y}$$

# Regression With a Perceptron

Single Layer Neural Network Perceptron

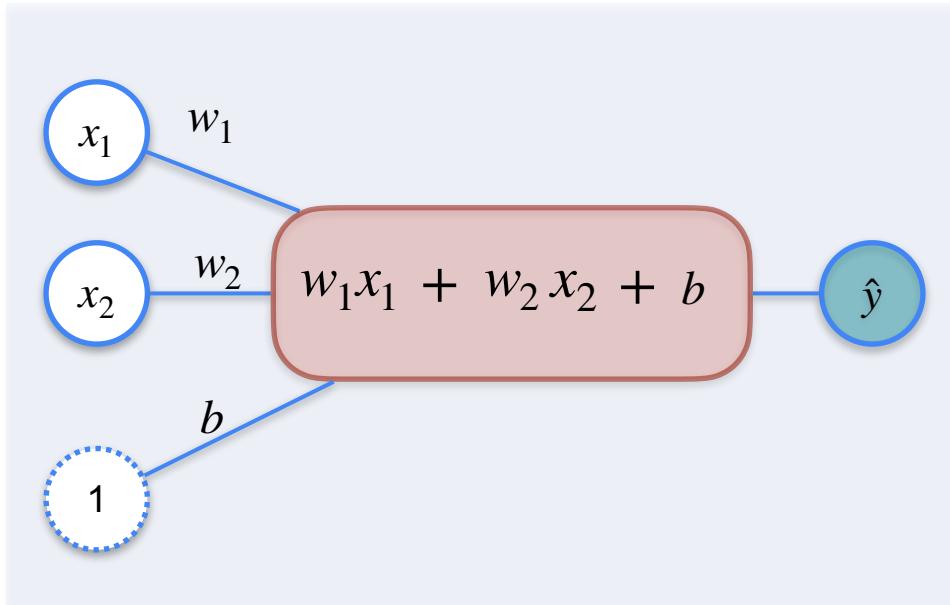


**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

# Regression With a Perceptron

Single Layer Neural Network Perceptron



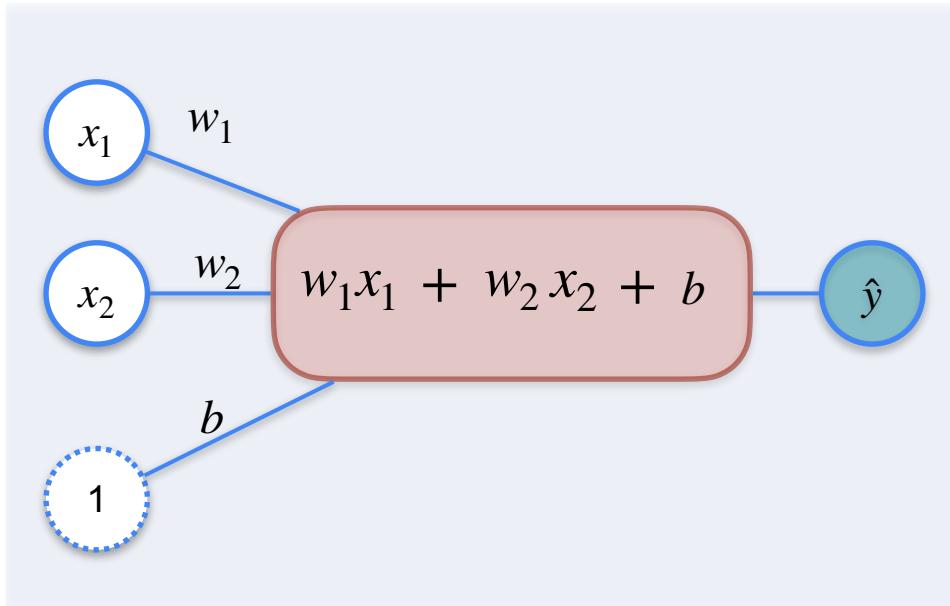
**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

# Regression With a Perceptron

Single Layer Neural Network Perceptron



**Prediction Function:**

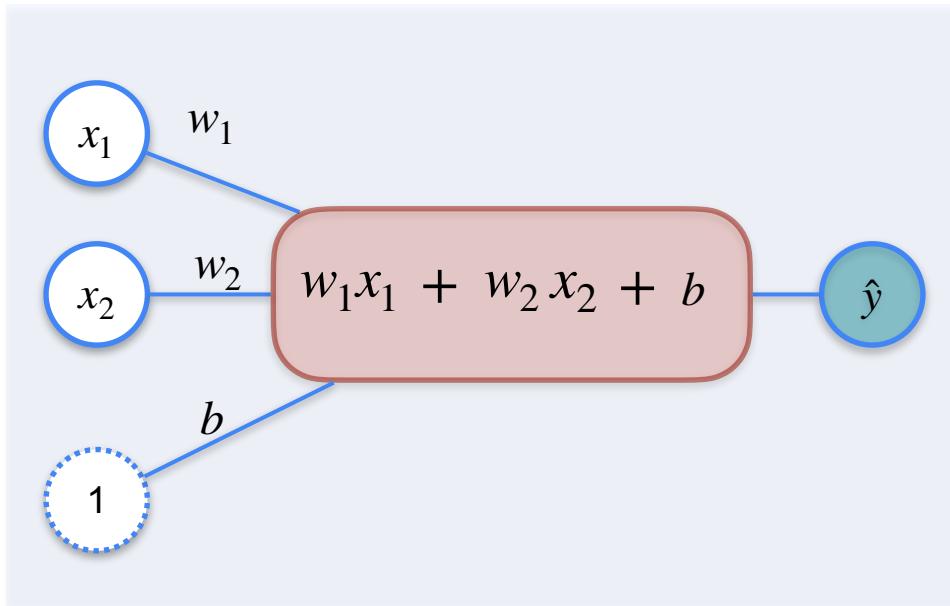
$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$= \frac{1}{2}(y - \hat{y})^2$$

# Regression With a Perceptron

Single Layer Neural Network Perceptron



**Prediction Function:**

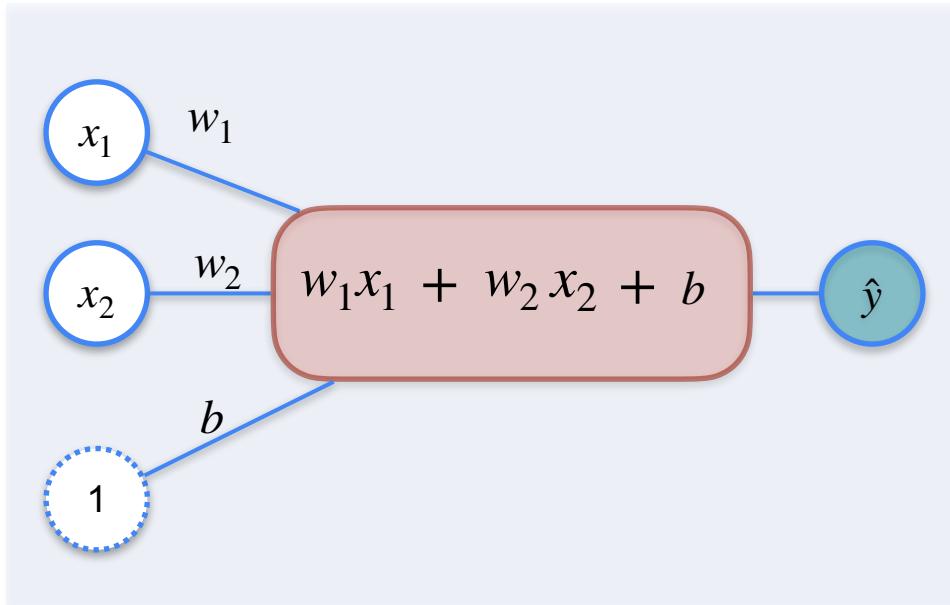
$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

# Regression With a Perceptron

Single Layer Neural Network Perceptron



**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

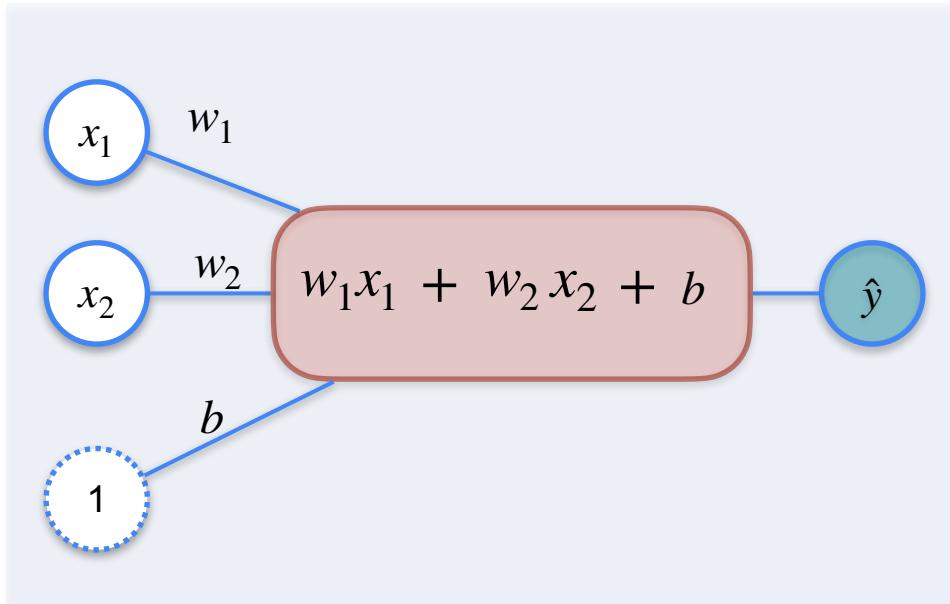
**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

**Main Goal:**

# Regression With a Perceptron

Single Layer Neural Network Perceptron



**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

**Main Goal:**

Find  $w_1$ ,  $w_2$ ,  $b$  that give  $\hat{y}$  with the least error



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# Optimization in Neural Networks and Newton's Method

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## Regression with a perceptron: Gradient Descent

# Regression With a Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

**Main Goal:**

Find  $w_1$ ,  $w_2$ ,  $b$  that give  $\hat{y}$  with the least error

# Regression With a Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

**Main Goal:**

Find  $w_1$ ,  $w_2$ ,  $b$  that give  $\hat{y}$  with the least error

# Regression With a Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

**Main Goal:**

Find  $w_1$ ,  $w_2$ ,  $b$  that give  $\hat{y}$  with the least error

**To find optimal values for:**

# Regression With a Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

**Main Goal:**

Find  $w_1, w_2, b$  that give  $\hat{y}$  with the least error

**To find optimal values for:**

$$w_1, w_2, b$$

# Regression With a Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

**Main Goal:**

Find  $w_1, w_2, b$  that give  $\hat{y}$  with the least error

**To find optimal values for:**

$$w_1, w_2, b$$

*You need gradient descent*

# Regression With a Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

**Main Goal:**

Find  $w_1, w_2, b$  that give  $\hat{y}$  with the least error

**To find optimal values for:**

$$w_1, w_2, b$$

*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha \frac{\partial L}{\partial w_1}$$

# Regression With a Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

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*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha \frac{\partial L}{\partial w_1}$$

$$w_2 \rightarrow w_2 - \alpha \frac{\partial L}{\partial w_2}$$

# Regression With a Perceptron

**Prediction Function:**

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$$w_1 \rightarrow w_1 - \alpha \frac{\partial L}{\partial w_1}$$

$$w_2 \rightarrow w_2 - \alpha \frac{\partial L}{\partial w_2}$$

$$b \rightarrow b - \alpha \frac{\partial L}{\partial b}$$

# Regression With a Perceptron

**Prediction Function:**

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$$w_2 \rightarrow w_2 - \alpha \frac{\partial L}{\partial w_2}$$

$$b \rightarrow b - \alpha \frac{\partial L}{\partial b}$$

# Regression With a Perceptron

Prediction Function:

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

Main Goal:

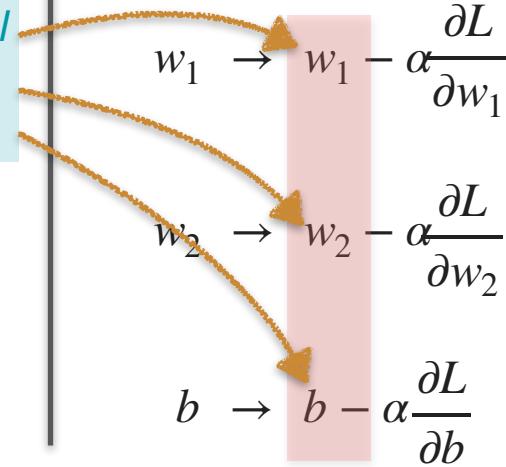
Find  $w_1, w_2, b$  that give  $\hat{y}$  with the least error

To find optimal values for:

$$w_1, w_2, b$$

*You need gradient descent*

*Some initial starting values*



# Regression With a Perceptron

Prediction Function:

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

Main Goal:

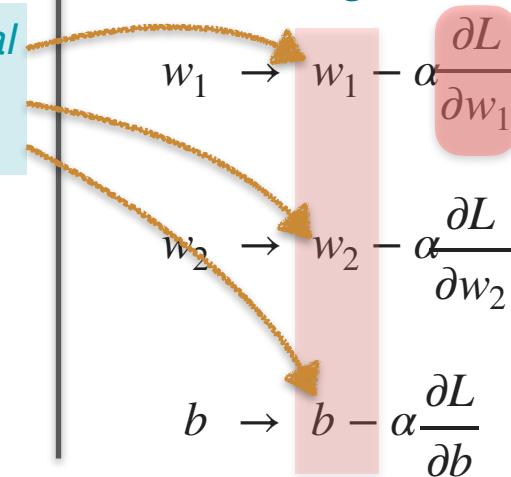
Find  $w_1, w_2, b$  that give  $\hat{y}$  with the least error

To find optimal values for:

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*Some initial starting values*



# Regression With a Perceptron

Prediction Function:

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

Main Goal:

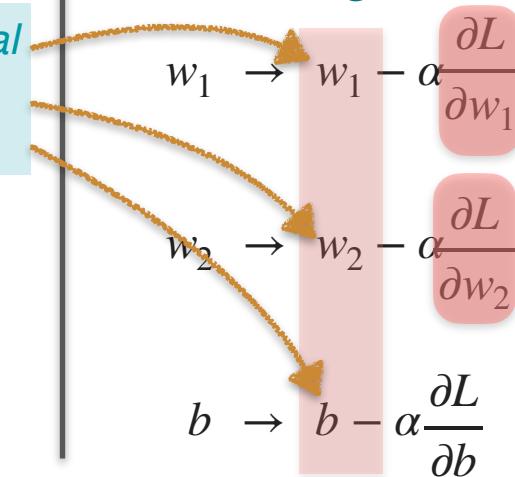
Find  $w_1, w_2, b$  that give  $\hat{y}$  with the least error

To find optimal values for:

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*You need gradient descent*

Some initial starting values



# Regression With a Perceptron

Prediction Function:

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

Main Goal:

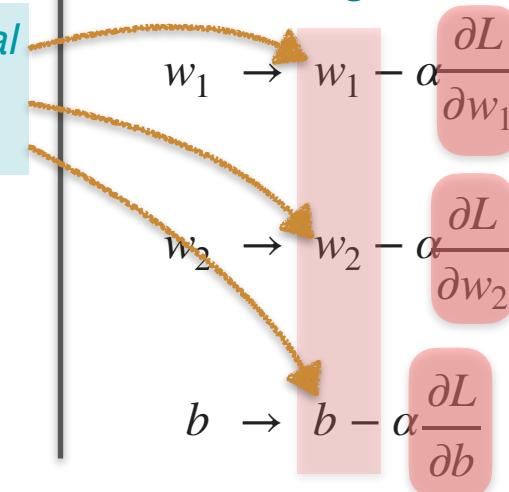
Find  $w_1, w_2, b$  that give  $\hat{y}$  with the least error

To find optimal values for:

$$w_1, w_2, b$$

*You need gradient descent*

Some initial starting values



# Regression With a Perceptron

Prediction Function:

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

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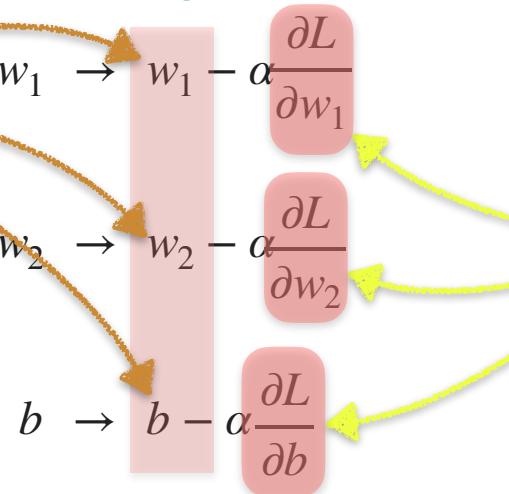
Main Goal:

Find  $w_1, w_2, b$  that give  $\hat{y}$  with the least error

*Some initial starting values*

To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*



**SUB-TASK**  
Find the following partial derivatives

# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

$$\frac{\partial L}{\partial b}$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

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

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

# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

Using chain rule:

$$\frac{\partial L}{\partial b}$$

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

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

# Regression With Perceptron

Prediction Function:

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

Using chain rule:

$$\frac{\partial L}{\partial b}$$

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

# Regression With Perceptron

Prediction Function:

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

Using chain rule:

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

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

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

# Regression With Perceptron

Prediction Function:

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

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

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# Regression With Perceptron

Prediction Function:

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

Using chain rule:

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}}$$

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

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# Regression With Perceptron

Prediction Function:

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$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

Using chain rule:

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot$$

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

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Using chain rule:

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# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

$\frac{\partial L}{\partial \hat{y}}$	
$\frac{\partial \hat{y}}{\partial b}$	
$\frac{\partial \hat{y}}{\partial w_1}$	
$\frac{\partial \hat{y}}{\partial w_2}$	

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**Prediction Function:**

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$\frac{\partial \hat{y}}{\partial w_2}$	

# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

$\frac{\partial L}{\partial \hat{y}}$	$= (y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	
$\frac{\partial \hat{y}}{\partial w_1}$	
$\frac{\partial \hat{y}}{\partial w_2}$	

# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

$\frac{\partial L}{\partial \hat{y}}$	$= (y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	
$\frac{\partial \hat{y}}{\partial w_1}$	
$\frac{\partial \hat{y}}{\partial w_2}$	

# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

$\frac{\partial L}{\partial \hat{y}}$	$= -(y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	
$\frac{\partial \hat{y}}{\partial w_1}$	
$\frac{\partial \hat{y}}{\partial w_2}$	

# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

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$\frac{\partial \hat{y}}{\partial b}$	
$\frac{\partial \hat{y}}{\partial w_1}$	
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$\frac{\partial \hat{y}}{\partial w_1}$	
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$\frac{\partial \hat{y}}{\partial w_1}$	
$\frac{\partial \hat{y}}{\partial w_2}$	

# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

$\frac{\partial L}{\partial \hat{y}}$	$= -(y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	$= 1$
$\frac{\partial \hat{y}}{\partial w_1}$	
$\frac{\partial \hat{y}}{\partial w_2}$	

# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

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$\frac{\partial \hat{y}}{\partial b}$	$= 1$
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# Regression With Perceptron

**Prediction Function:**

$$\hat{y} = w_1x_1 + w_2x_2 + b$$

**Loss Function:**

$$L(y, \hat{y}) = \frac{1}{2}(y - \hat{y})^2$$

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**Main Goal:**

Find  $w_1$  ,  $w_2$  ,  $b$  that give  $\hat{y}$  with the least error

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*Perform Gradient Descent*

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

*Perform Gradient Descent*

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$$w_1 = w_1 - \alpha$$

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# Regression With a Perceptron

**Main Goal:**

Find  $w_1$  ,  $w_2$  ,  $b$  that give  $\hat{y}$  with the least error

$$w_1 = w_1 - \alpha(-x_1(y - \hat{y}))$$

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$$b = b - \alpha \frac{\partial L}{\partial b}$$

# Regression With a Perceptron

**Main Goal:**

Find  $w_1$  ,  $w_2$  ,  $b$  that give  $\hat{y}$  with the least error

**ie. optimal values for:**

$w_1$  ,  $w_2$  ,  $b$

***Perform Gradient Descent***

$$w_1 = w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 = w_2 - \alpha(-x_2(y - \hat{y}))$$

$$b = b - \alpha$$

# Regression With a Perceptron

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$$w_1 = w_1 - \alpha(-x_1(y - \hat{y}))$$

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$$b = b - \alpha(-(y - \hat{y}))$$



DeepLearning.AI

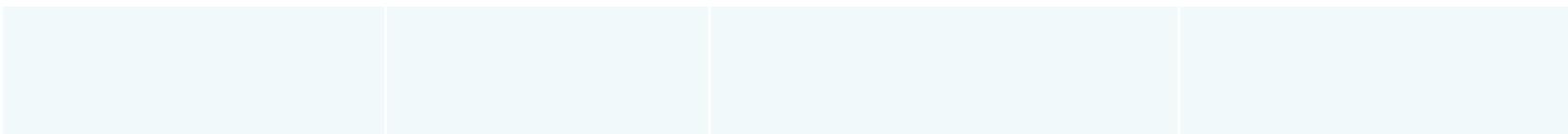
# Optimization in Neural Networks and Newton's Method

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## Classification with a perceptron

# Classification Problem Motivation

# Classification Problem Motivation



# Classification Problem Motivation

<i>Sentence</i>			

# Classification Problem Motivation

<i>Sentence</i>			
<i>Aack aack aack!</i>			

# Classification Problem Motivation

<i>Sentence</i>			
<i>Aack aack aack!</i>			

*Beep beep!*

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# Classification Problem Motivation

<i>Sentence</i>			
<i>Aack aack aack!</i>			
<i>Beep beep!</i>			
<i>Aack beep beep beep!</i>			

# Classification Problem Motivation

<i>Sentence</i>			
<i>Aack aack aack!</i>			
<i>Beep beep!</i>			
<i>Aack beep beep beep!</i>			
<i>Aack beep aack!</i>			

# Classification Problem Motivation

Sentence			Mood
<i>Aack aack aack!</i>			

*Beep beep!*

*Aack beep beep beep!*

*Aack beep aack!*

# Classification Problem Motivation

Sentence			Mood
<i>Aack aack aack!</i>			

*Beep beep!*

*Aack beep beep beep!*

*Aack beep aack!*

# Classification Problem Motivation

Sentence			Mood
<i>Aack aack aack!</i>			<i>Happy</i> 😊

*Beep beep!*

<i>Aack beep beep beep!</i>			
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*Aack beep aack!*

# Classification Problem Motivation

Sentence			Mood
<i>Aack aack aack!</i>			<i>Happy</i> 😊
<i>Beep beep!</i>			😔
<i>Aack beep beep beep!</i>			
<i>Aack beep aack!</i>			

# Classification Problem Motivation

Sentence			Mood
<i>Aack aack aack!</i>			<i>Happy</i> 😊
<i>Beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			
<i>Aack beep aack!</i>			

# Classification Problem Motivation

Sentence			Mood
<i>Aack aack aack!</i>			<i>Happy</i> 😊
<i>Beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			😔
<i>Aack beep aack!</i>			

# Classification Problem Motivation

Sentence			Mood
<i>Aack aack aack!</i>			<i>Happy</i> 😊
<i>Beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep aack!</i>			

# Classification Problem Motivation

Sentence			Mood
<i>Aack aack aack!</i>			<i>Happy</i> 😊
<i>Beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep aack!</i>			😊

# Classification Problem Motivation

Sentence			Mood
<i>Aack aack aack!</i>			<i>Happy</i> 😊
<i>Beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep aack!</i>			<i>Happy</i> 😊

# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>			<i>Happy</i> 😊
<i>Beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep aack!</i>			<i>Happy</i> 😊

# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3		<i>Happy</i> 😊
<i>Beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep aack!</i>			<i>Happy</i> 😊

# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊
<i>Beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep aack!</i>			<i>Happy</i> 😊

# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊
<i>Beep beep!</i>	0		<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep aack!</i>			<i>Happy</i> 😊

# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊
<i>Beep beep!</i>	0	2	<i>Sad</i> 😞
<i>Aack beep beep beep!</i>			<i>Sad</i> 😞
<i>Aack beep aack!</i>			<i>Happy</i> 😊

# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊
<i>Beep beep!</i>	0	2	<i>Sad</i> 😞
<i>Aack beep beep beep!</i>	1		<i>Sad</i> 😞
<i>Aack beep aack!</i>			<i>Happy</i> 😊

# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊
<i>Beep beep!</i>	0	2	<i>Sad</i> 😞
<i>Aack beep beep beep!</i>	1	3	<i>Sad</i> 😞
<i>Aack beep aack!</i>			<i>Happy</i> 😊

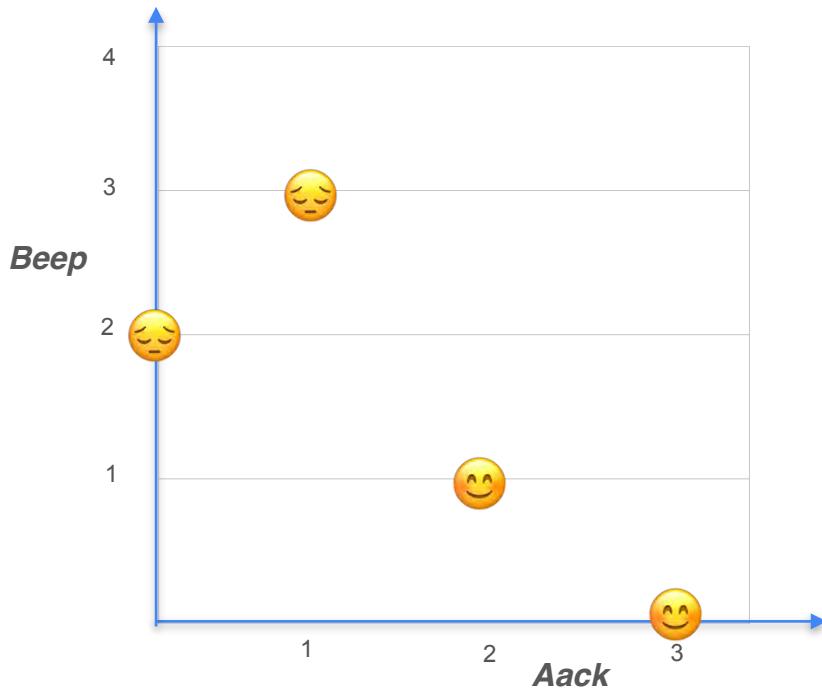
# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊
<i>Beep beep!</i>	0	2	<i>Sad</i> 😞
<i>Aack beep beep beep!</i>	1	3	<i>Sad</i> 😞
<i>Aack beep aack!</i>	2		<i>Happy</i> 😊

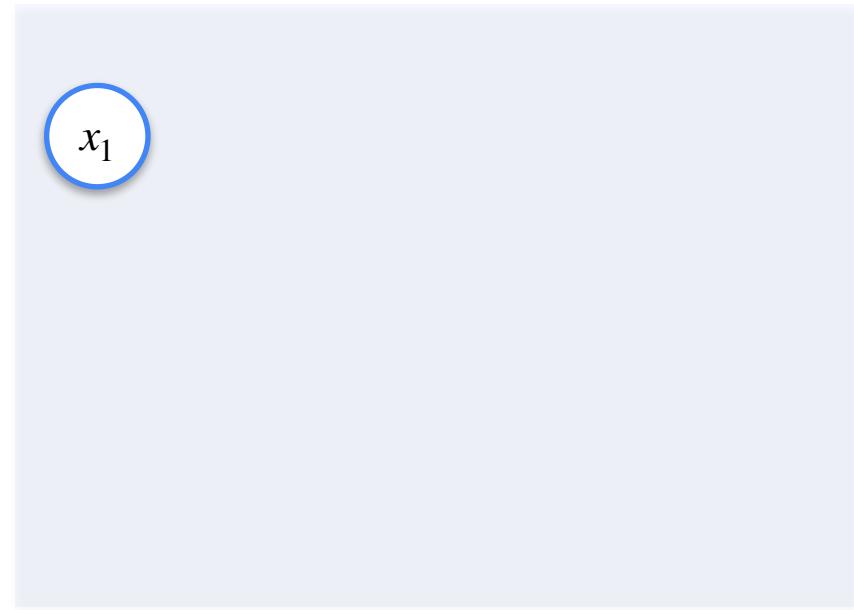
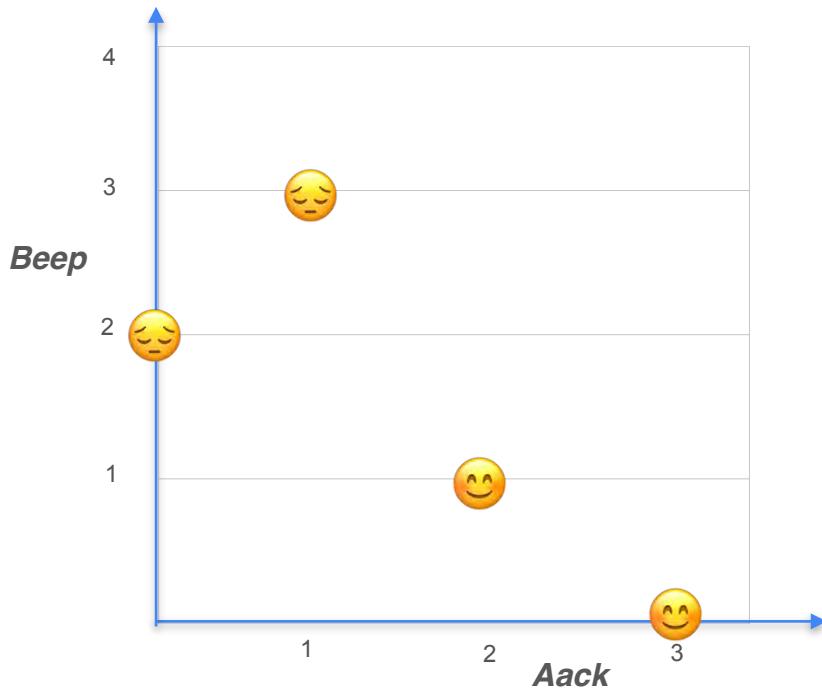
# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊
<i>Beep beep!</i>	0	2	<i>Sad</i> 😞
<i>Aack beep beep beep!</i>	1	3	<i>Sad</i> 😞
<i>Aack beep aack!</i>	2	1	<i>Happy</i> 😊

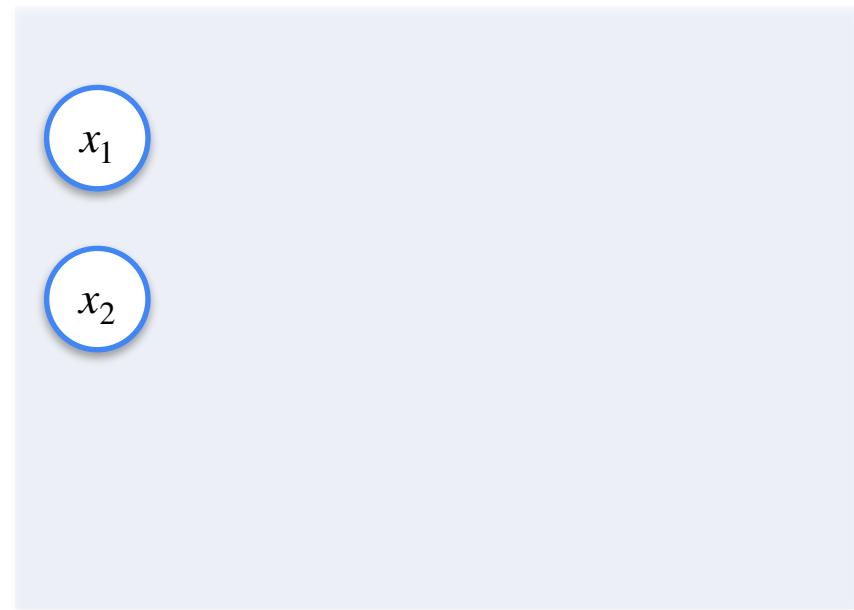
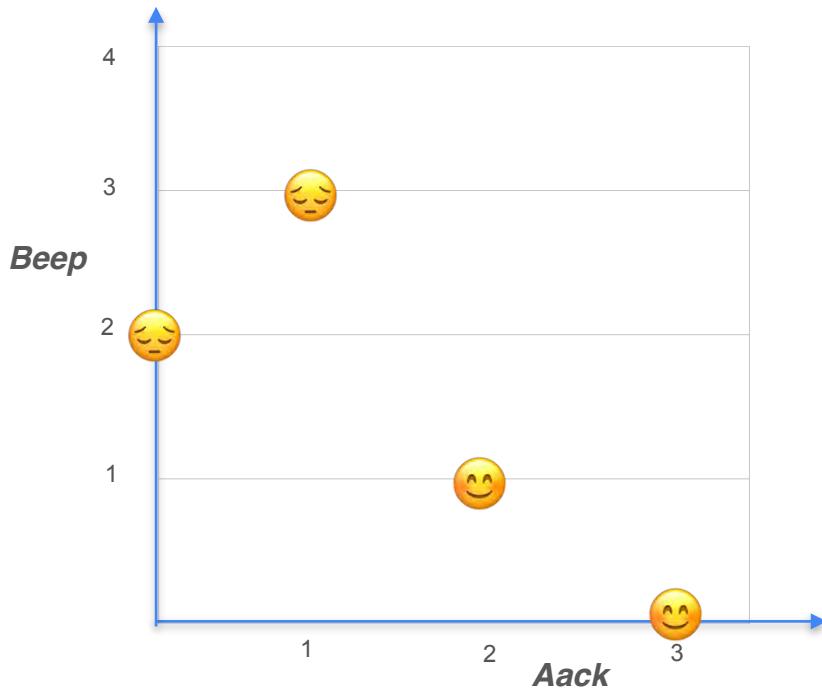
# Classification Problem Motivation



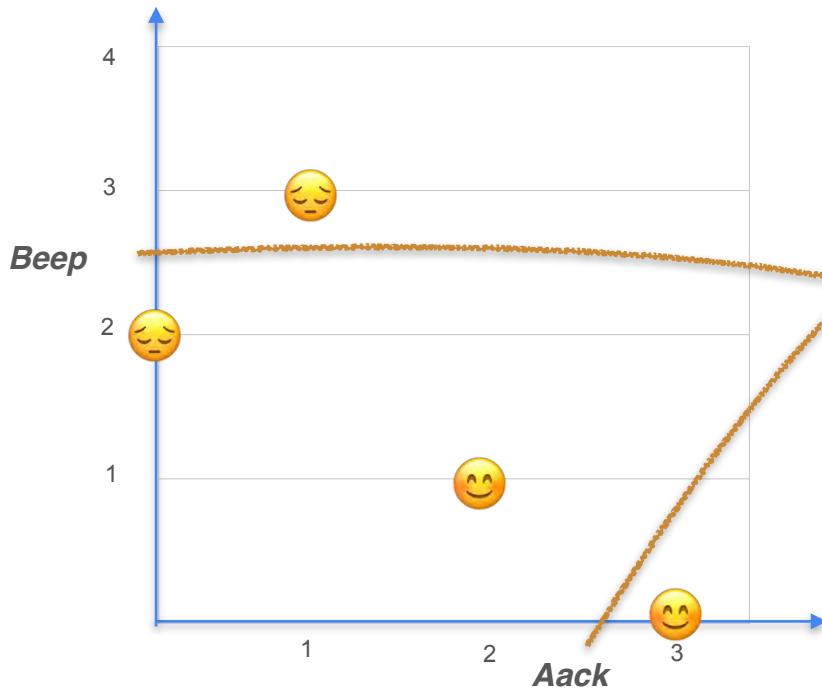
# Classification Problem Motivation



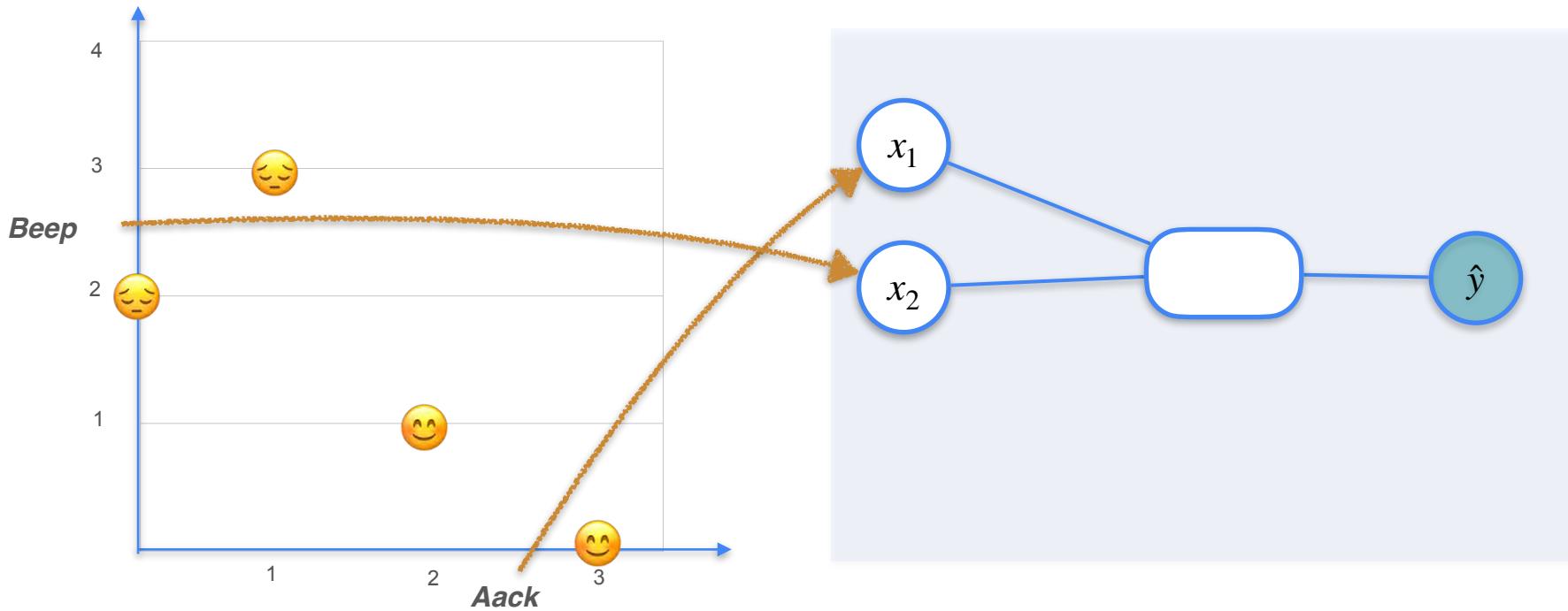
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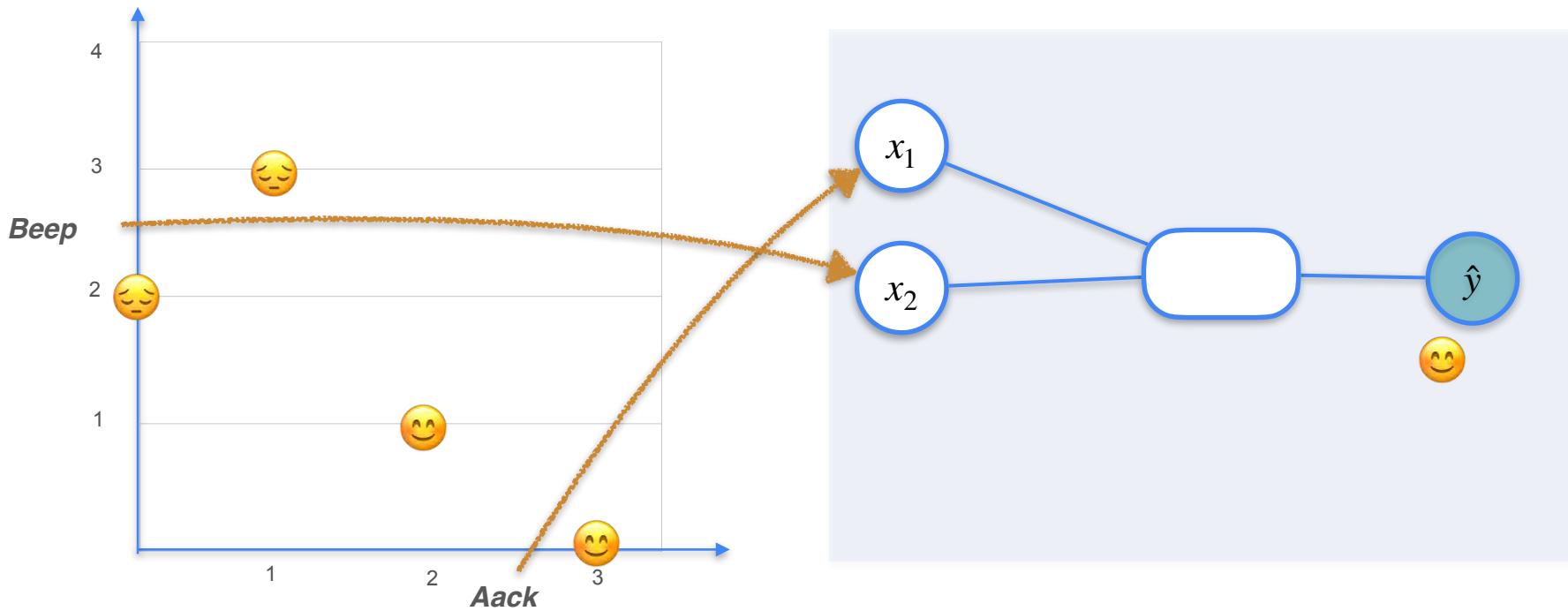
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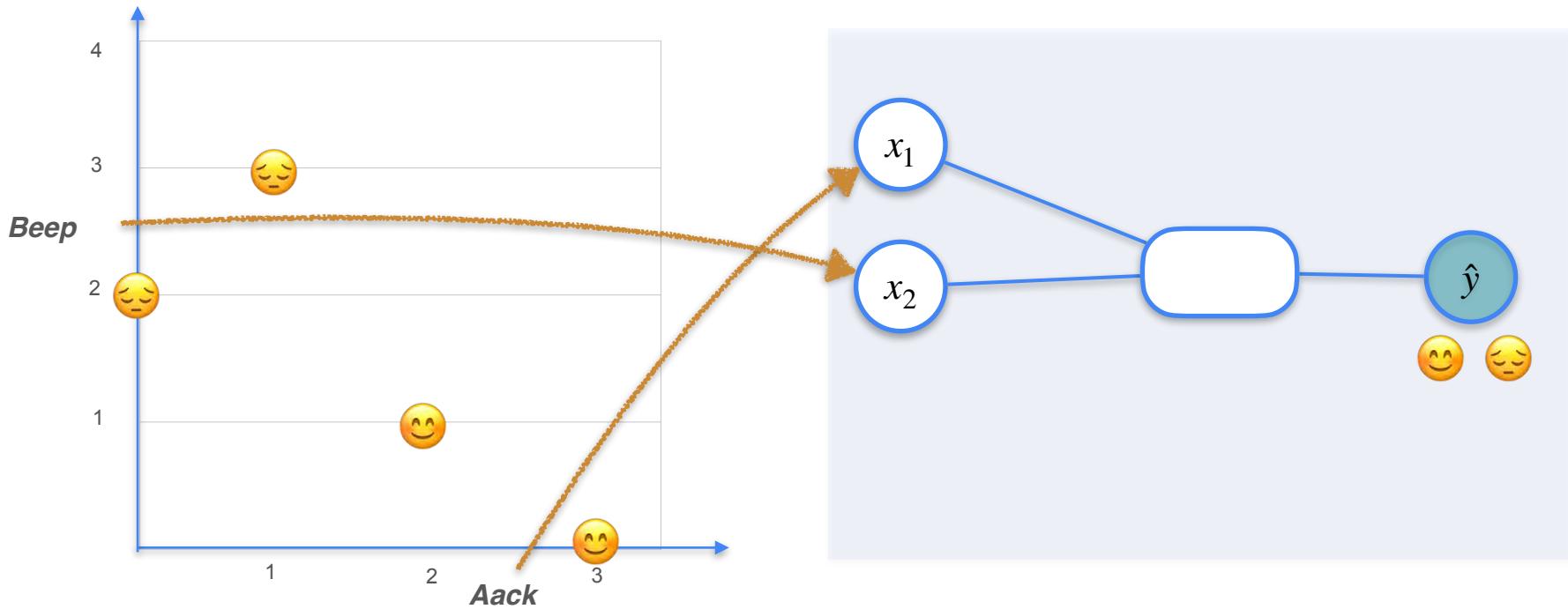
# Classification Problem Motivation



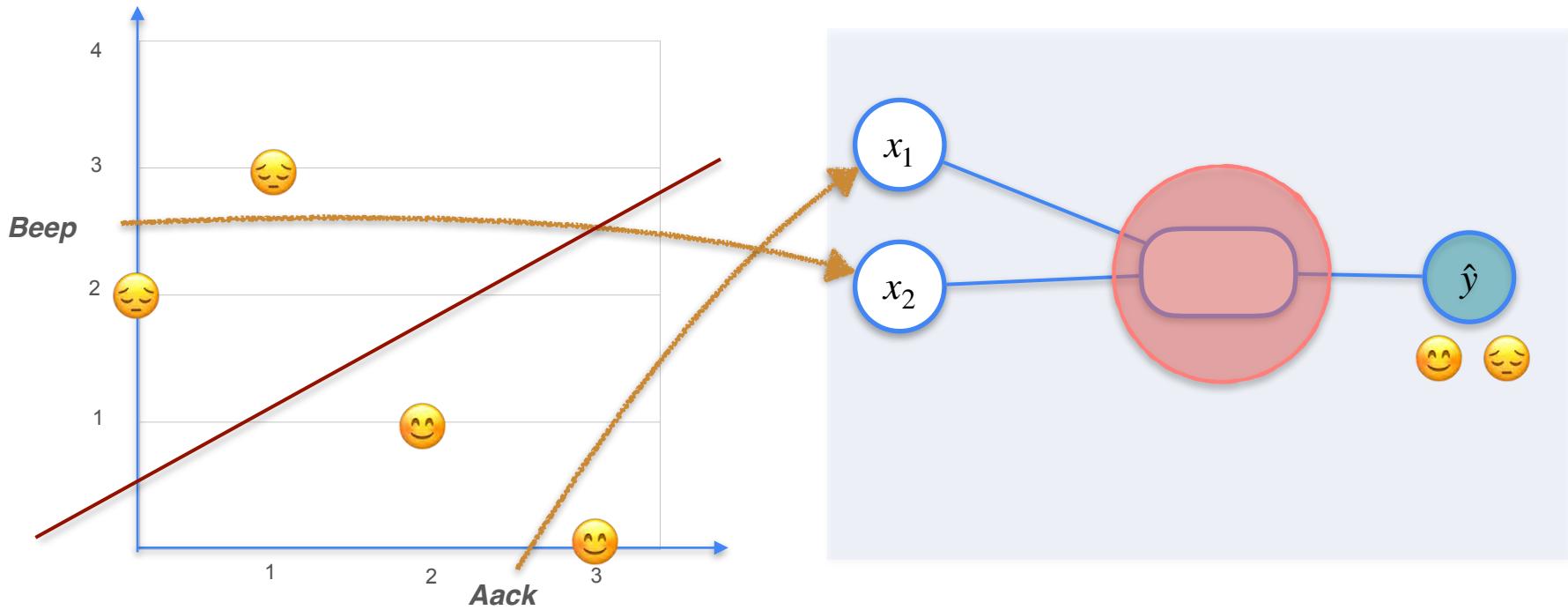
# Classification Problem Motivation



# Classification Problem Motivation

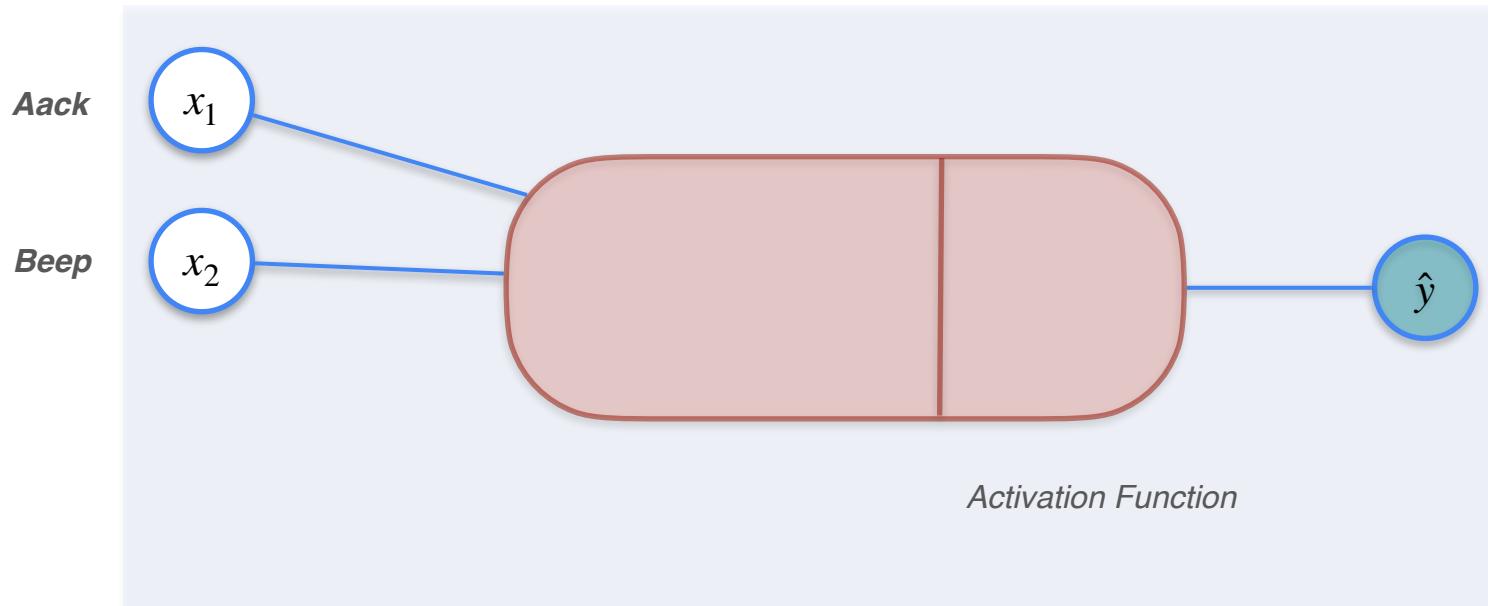


# Classification Problem Motivation



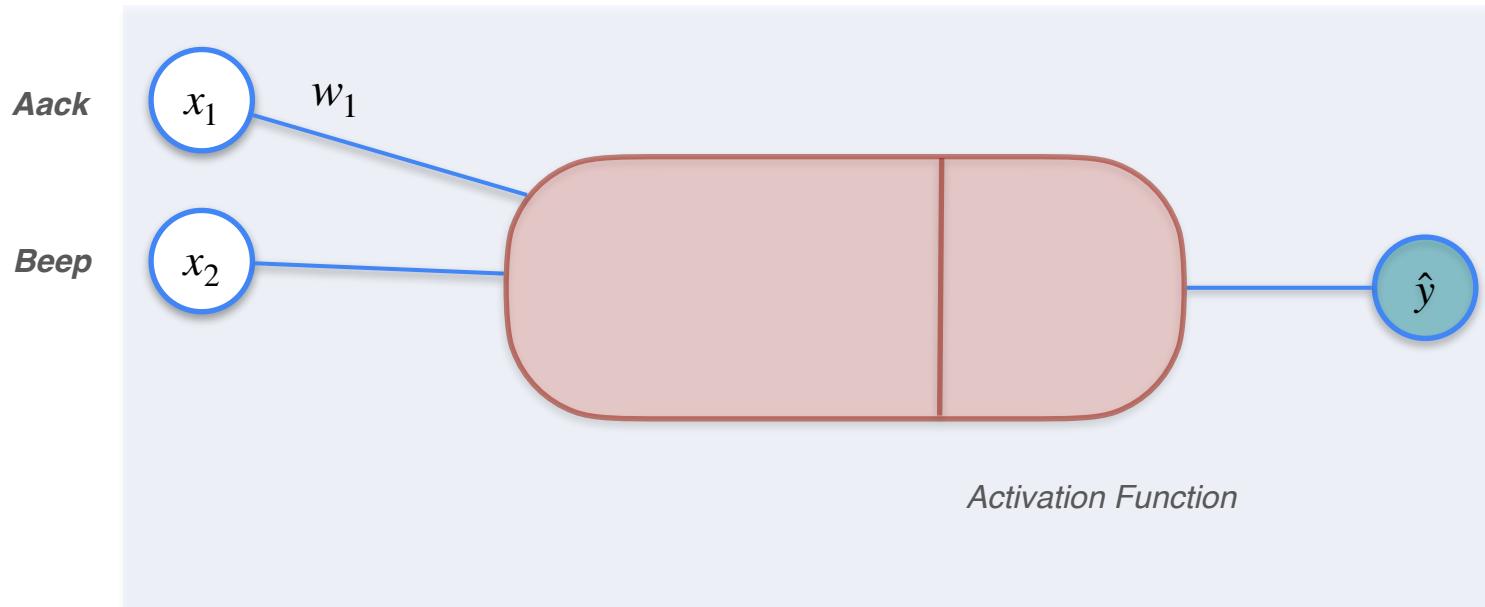
# Classification With a Perceptron

Single Layer Neural Network Perceptron



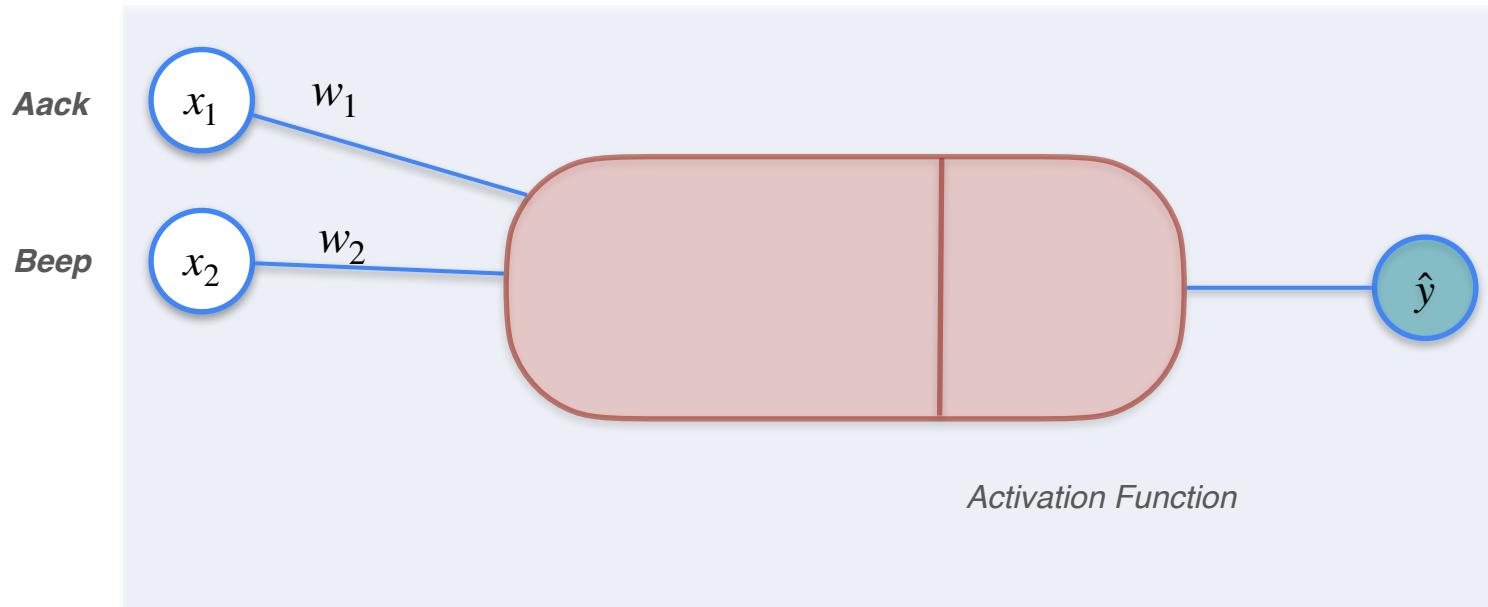
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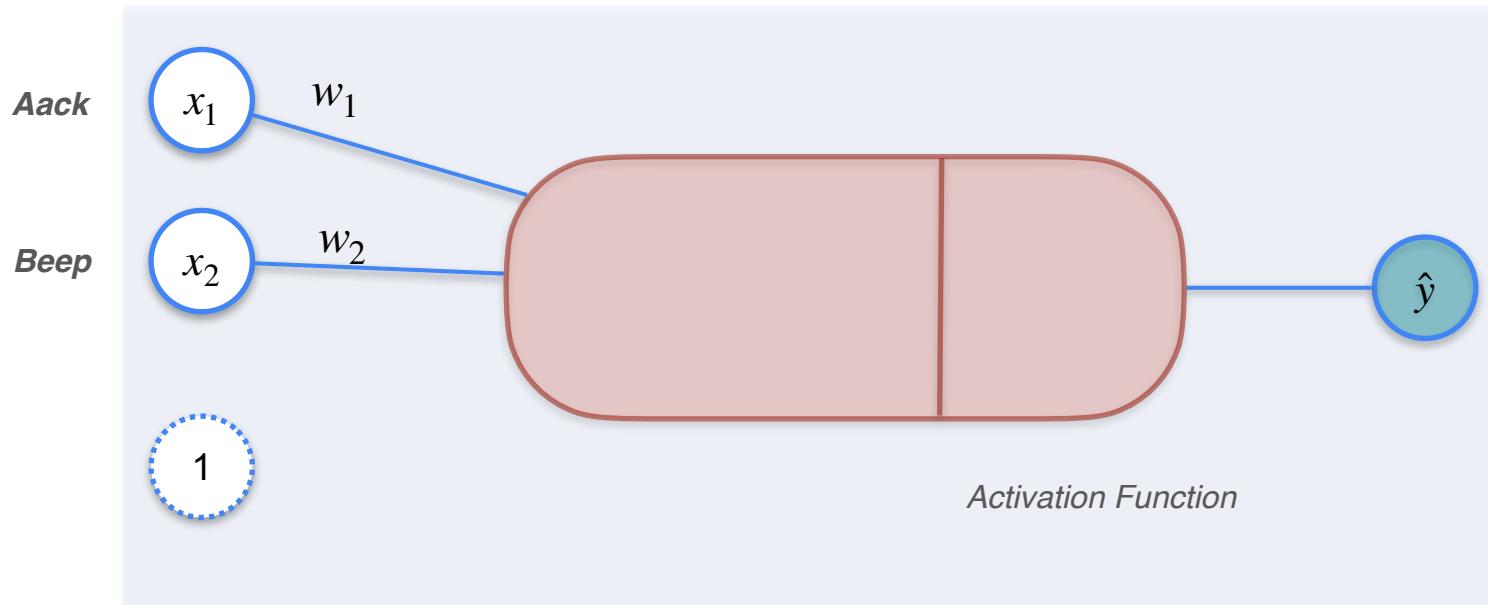
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Single Layer Neural Network Perceptron



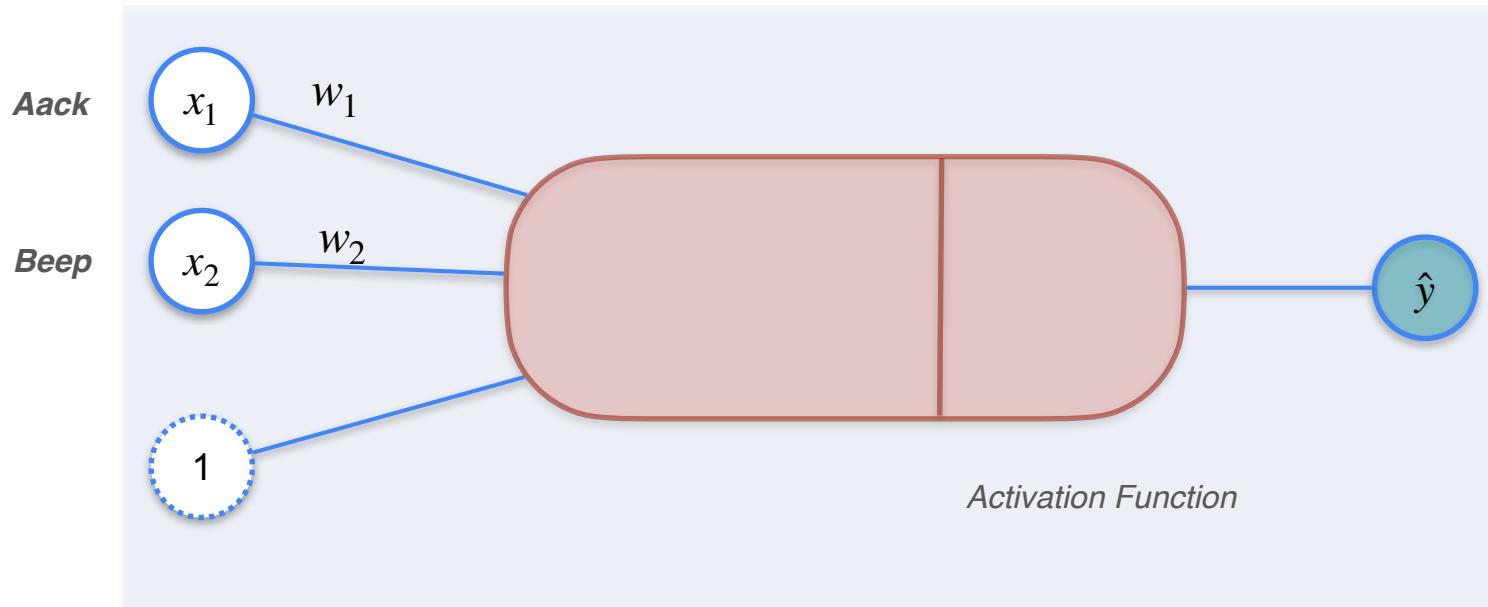
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Single Layer Neural Network Perceptron



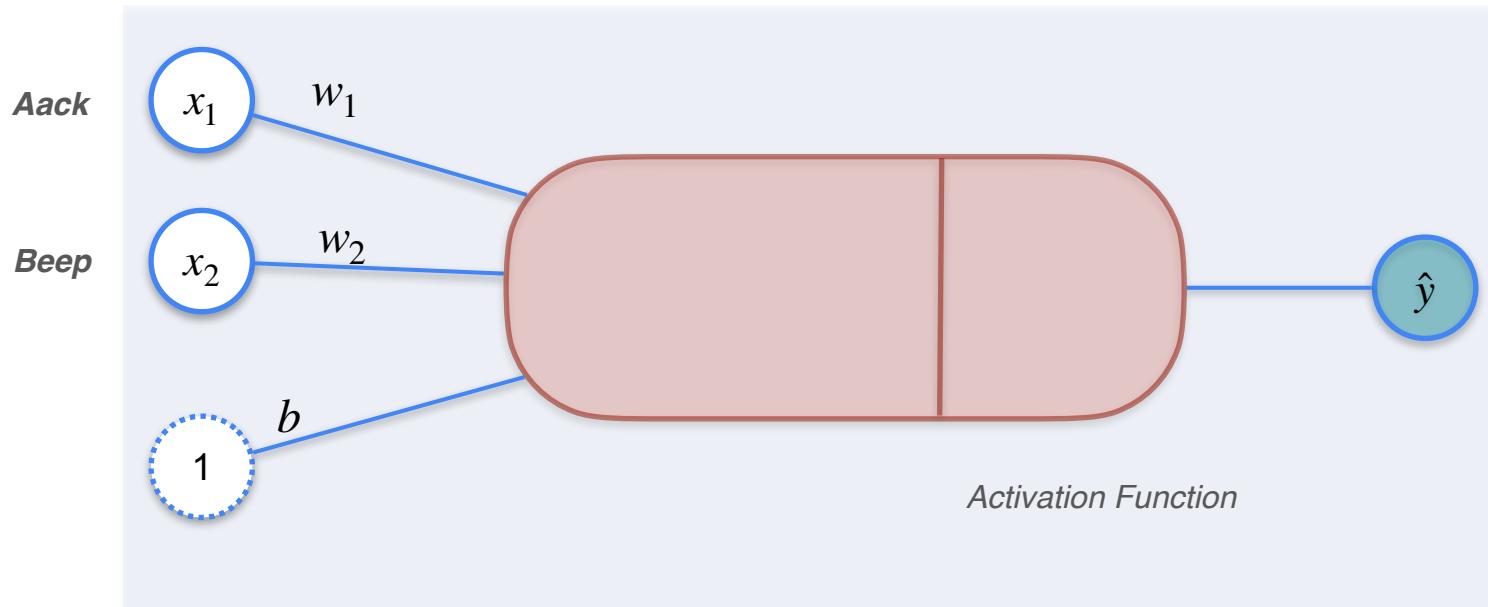
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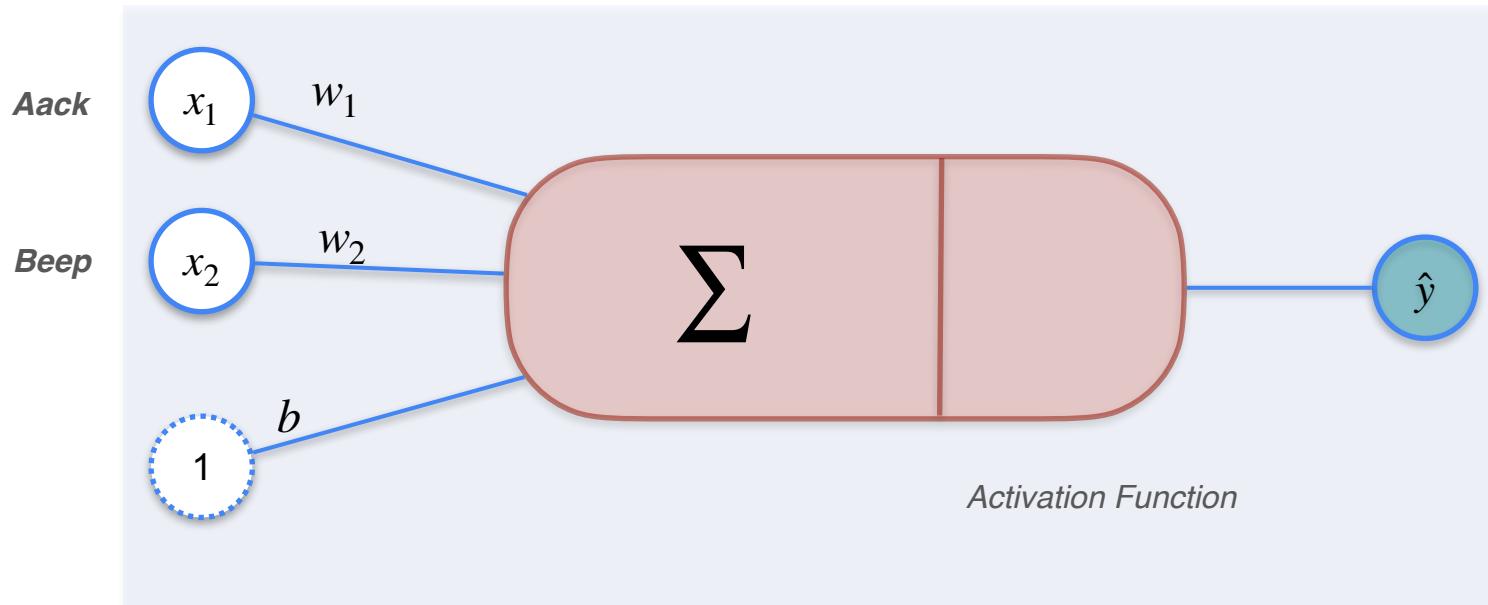
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Single Layer Neural Network Perceptron



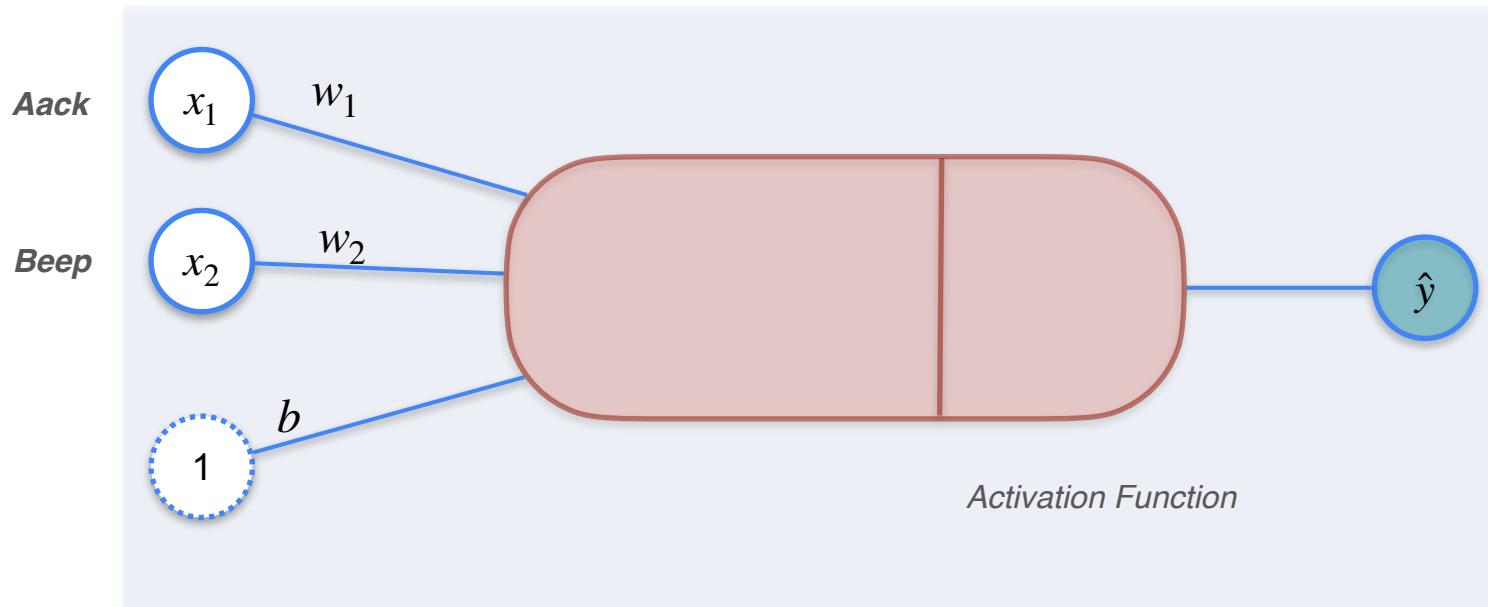
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Single Layer Neural Network Perceptron



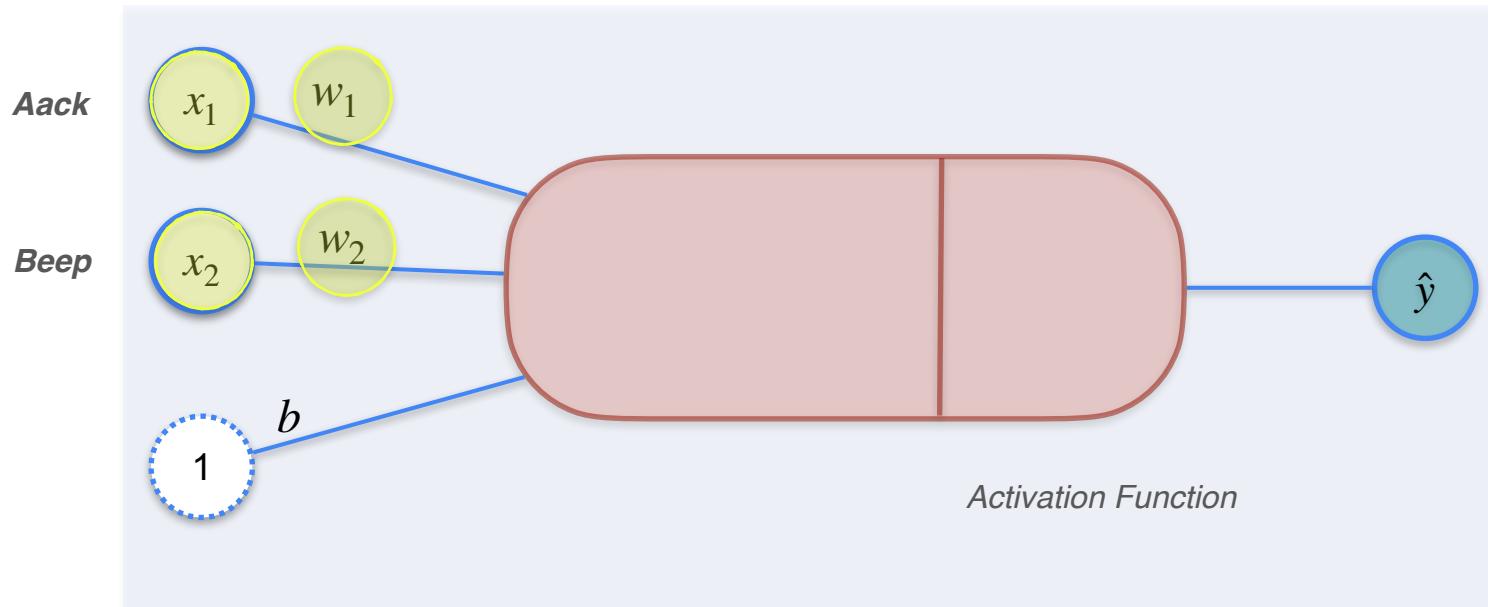
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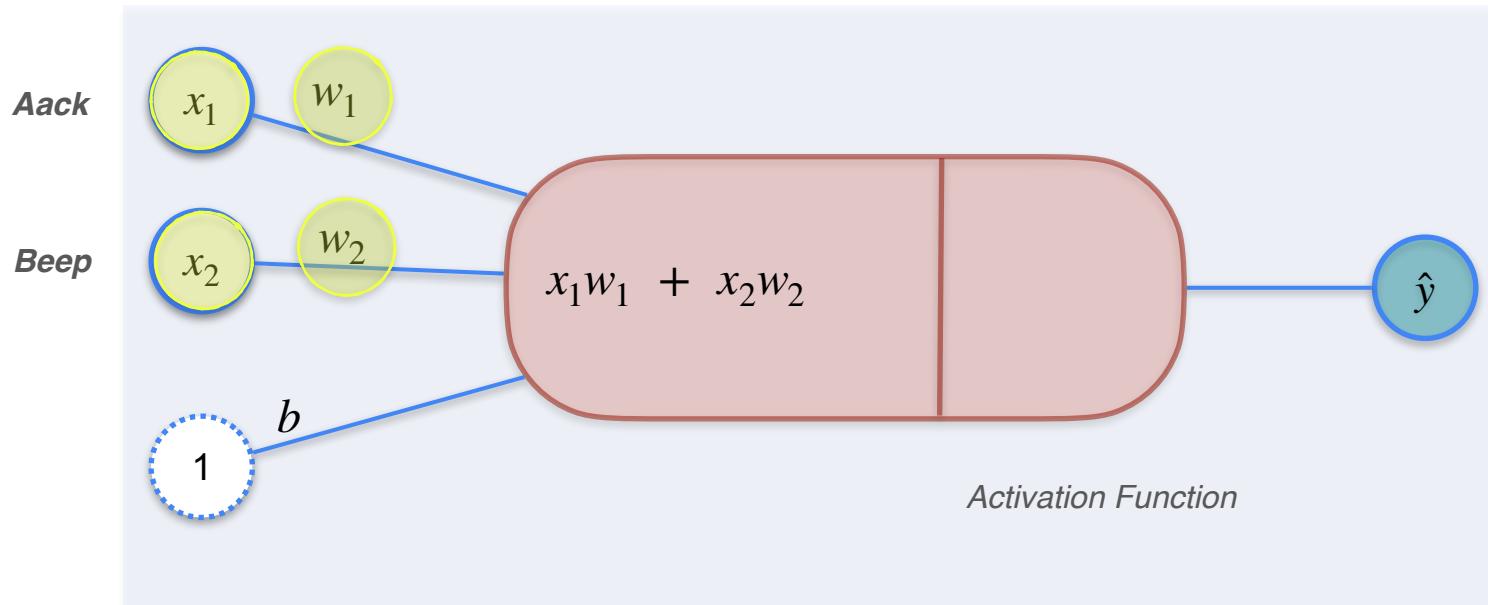
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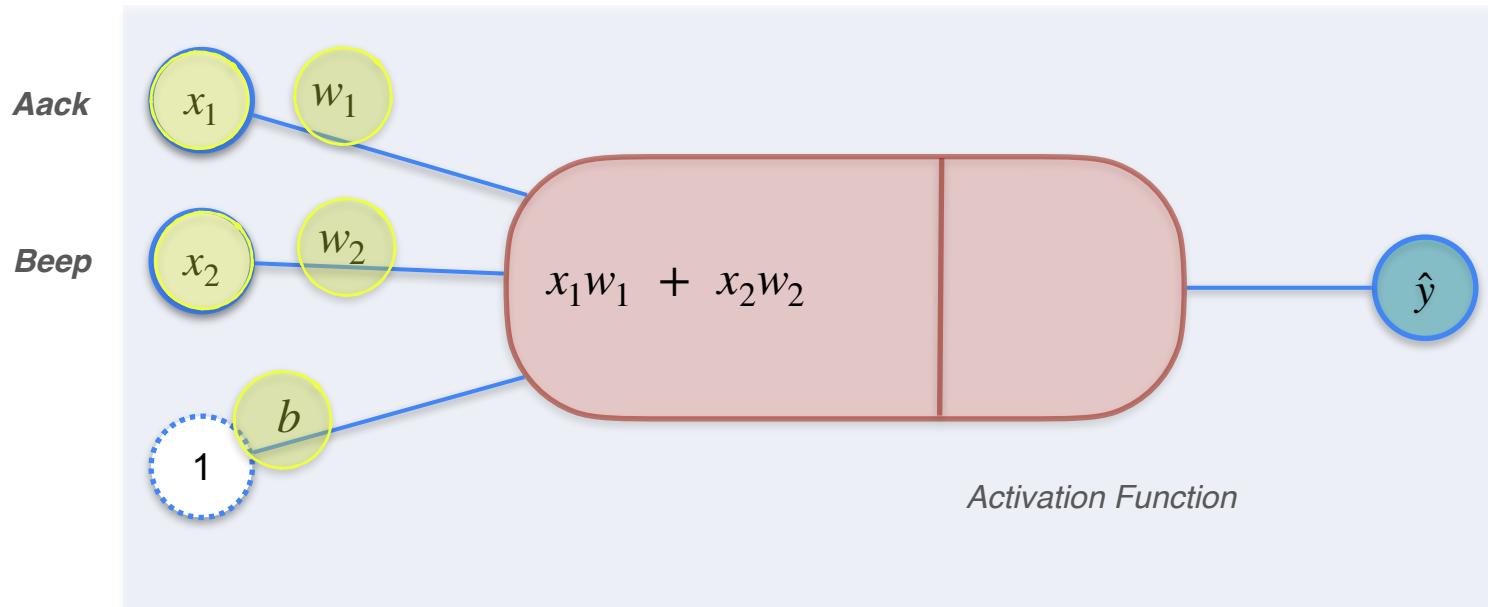
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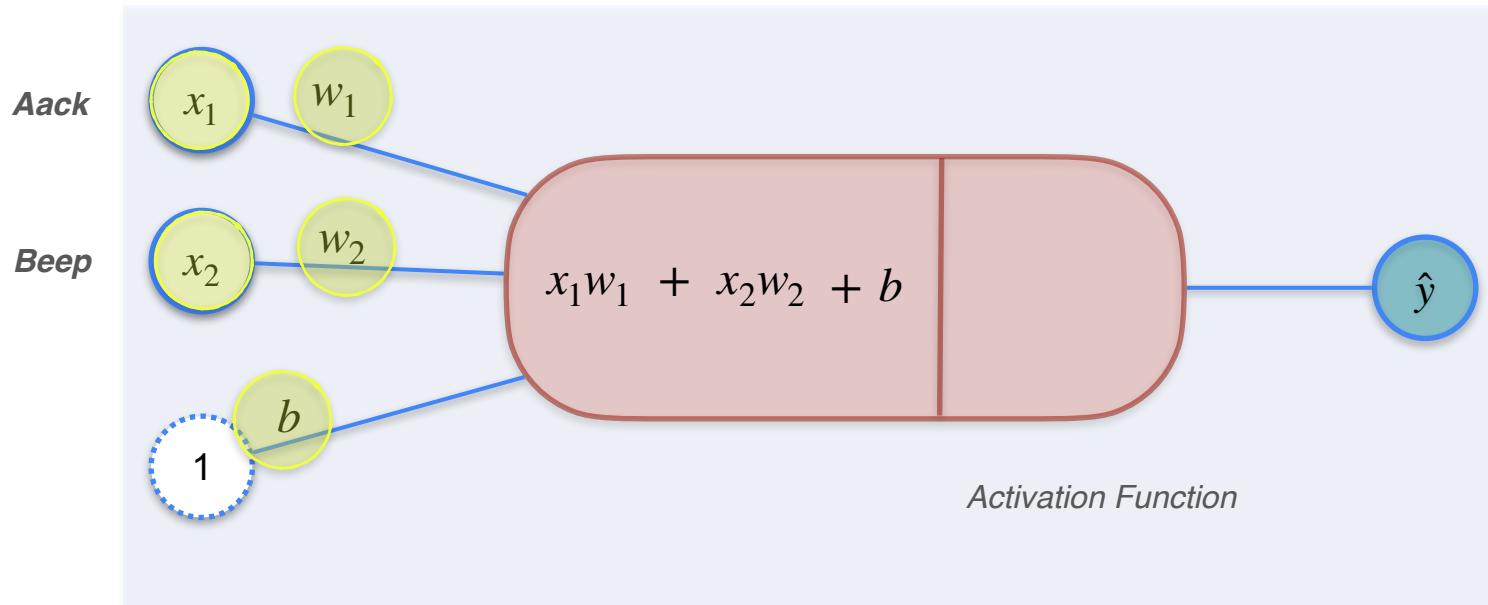
# Classification With a Perceptron

Single Layer Neural Network Perceptron



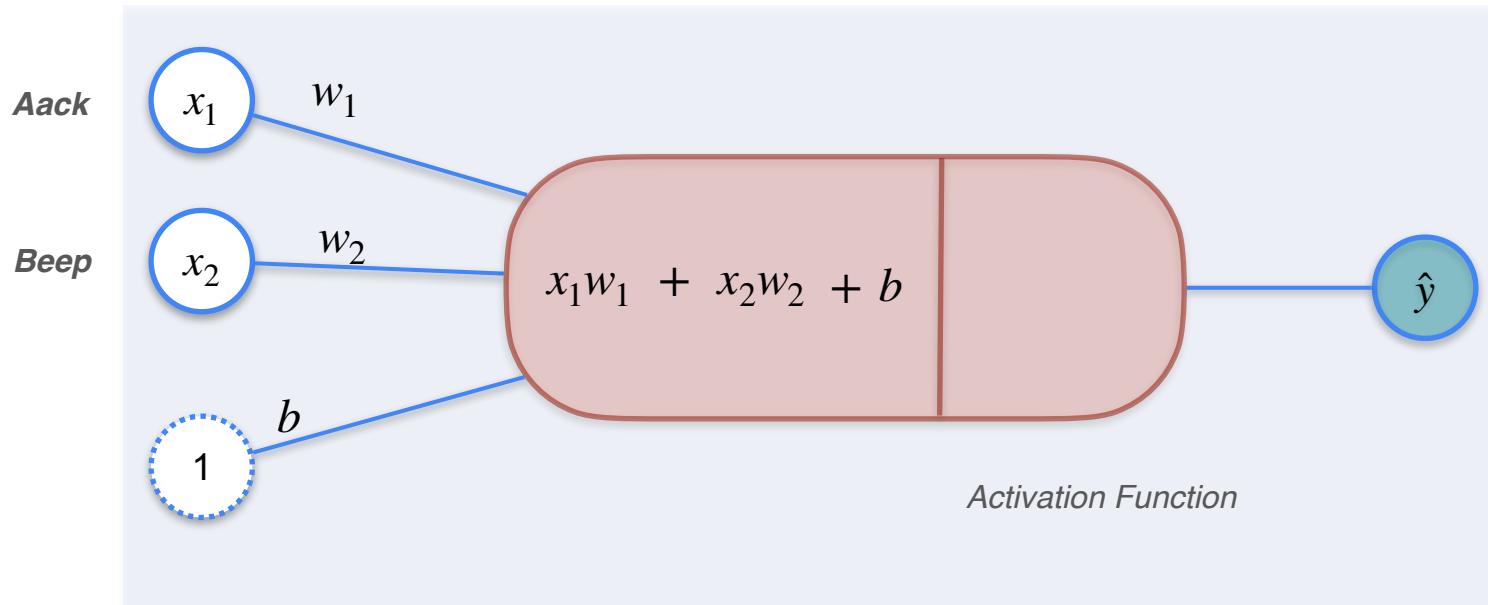
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Single Layer Neural Network Perceptron



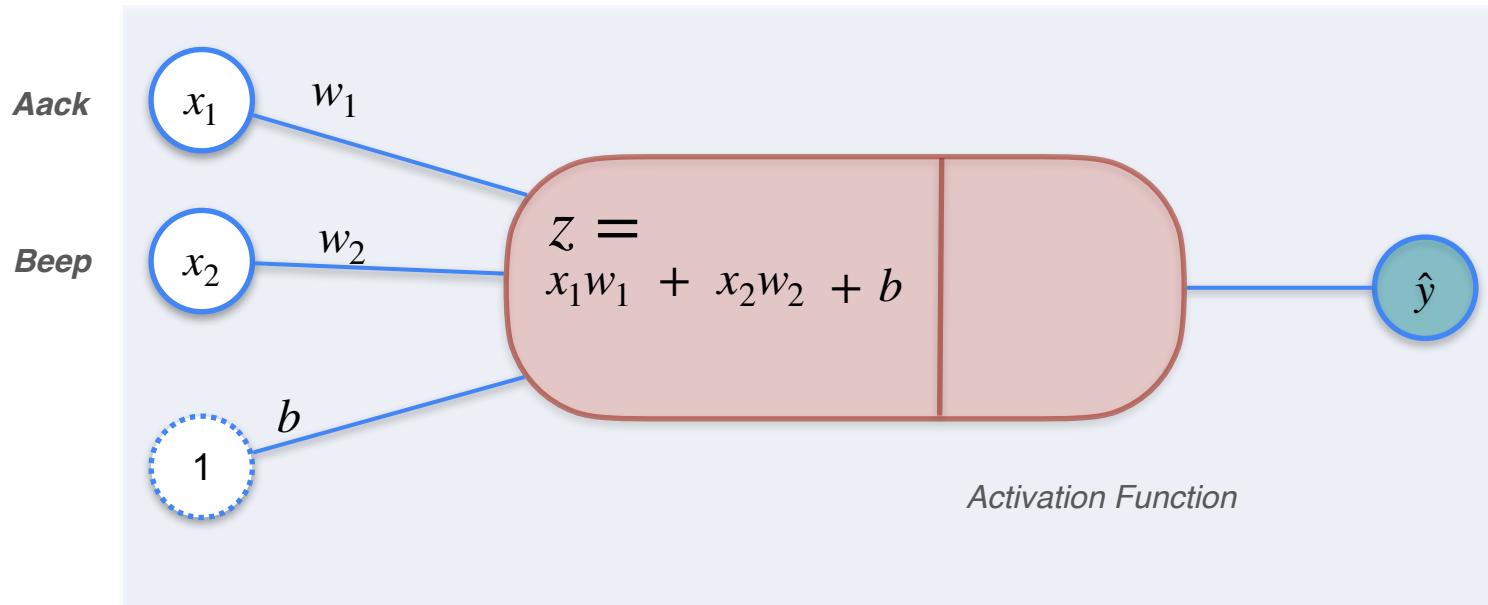
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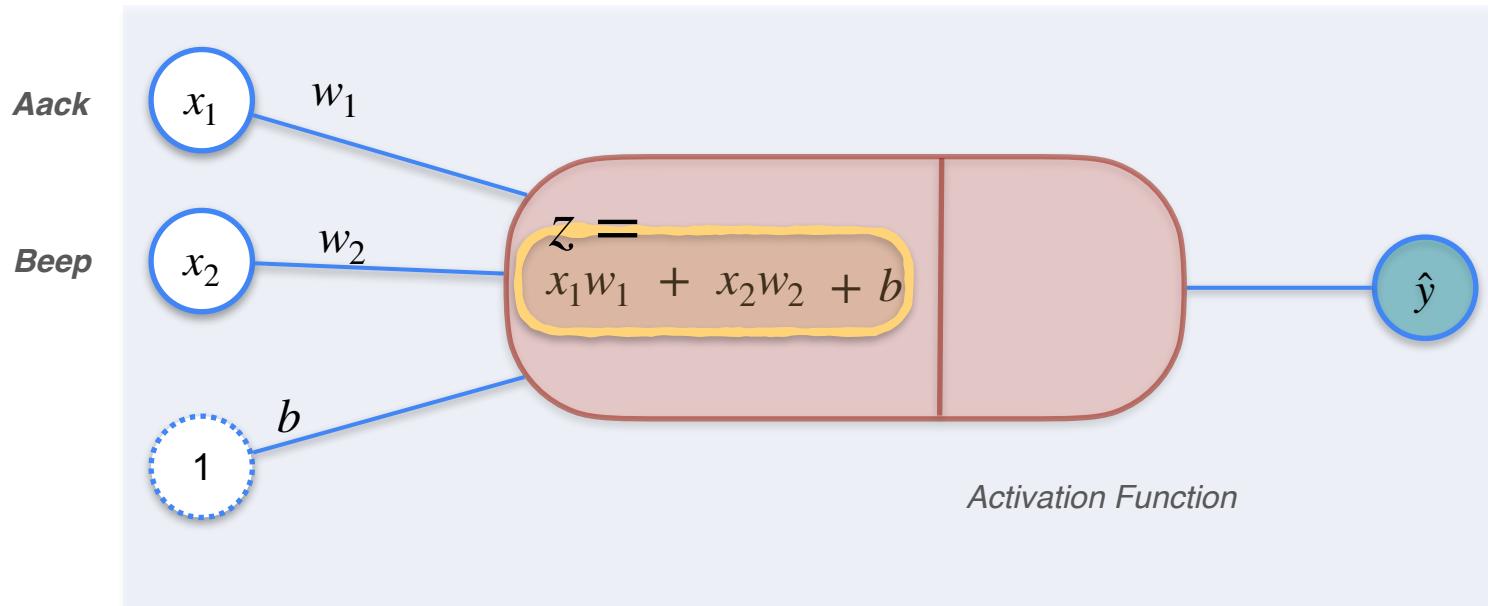
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Single Layer Neural Network Perceptron



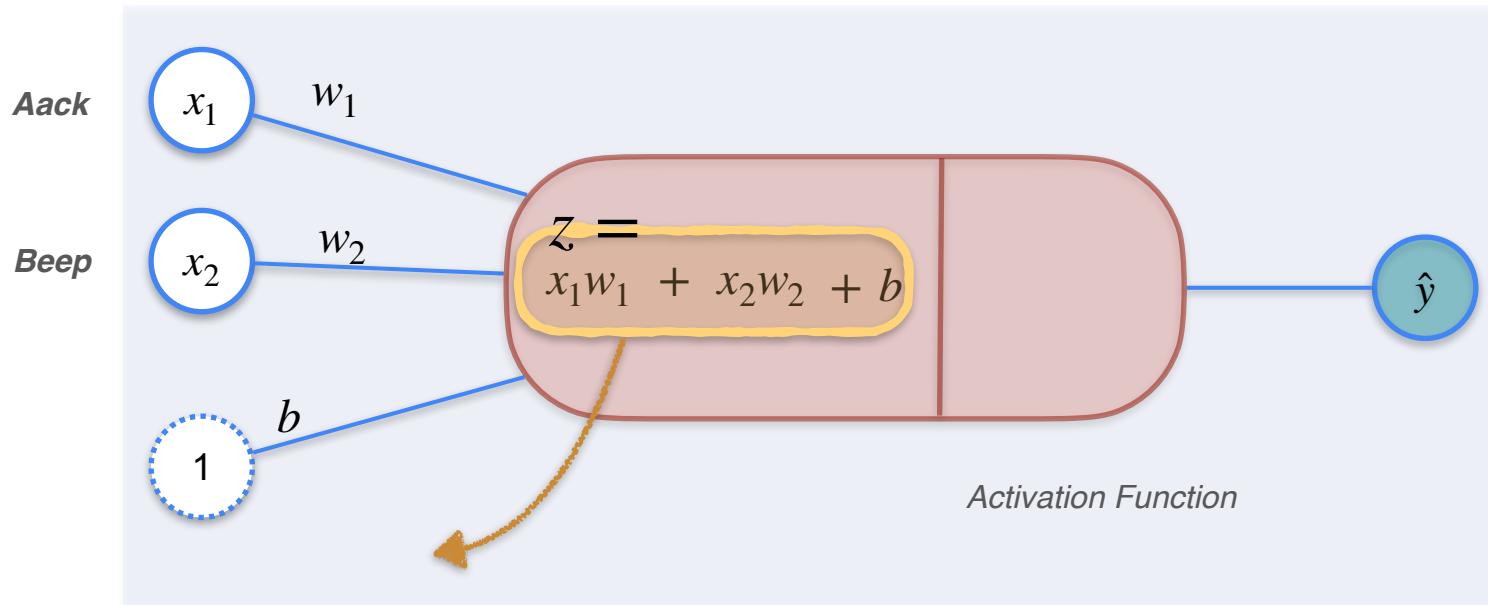
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Single Layer Neural Network Perceptron



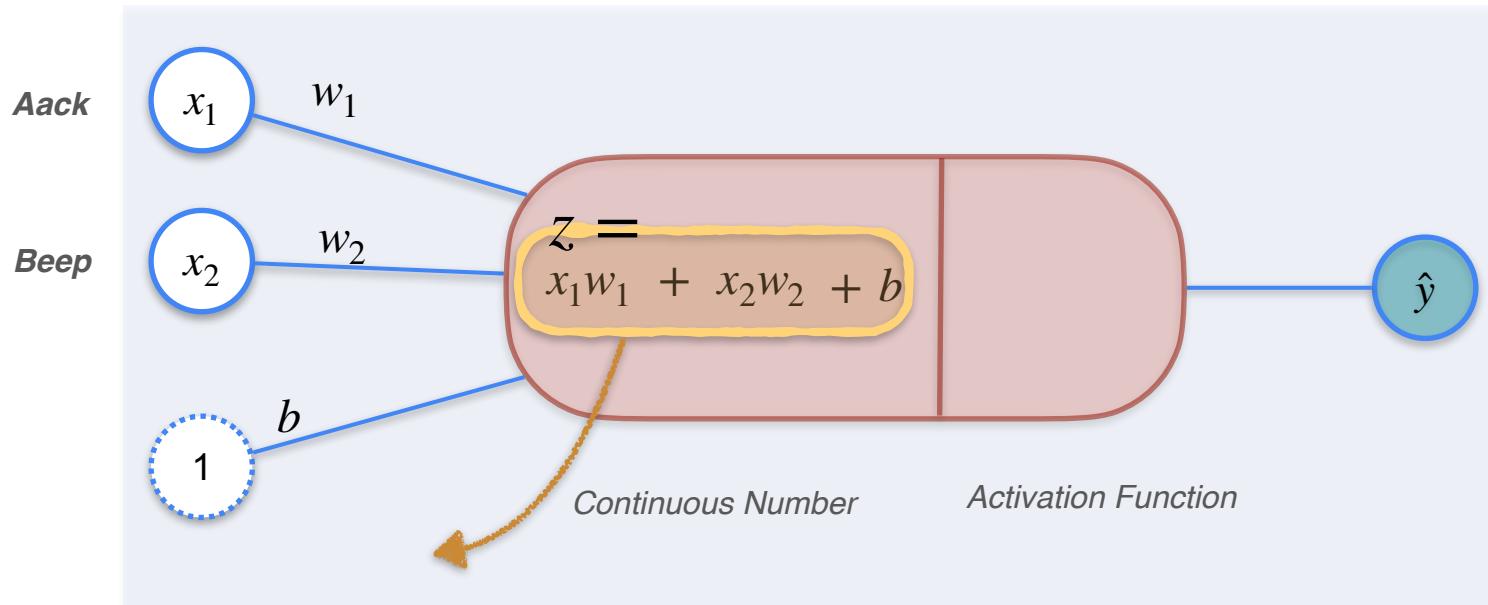
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Single Layer Neural Network Perceptron



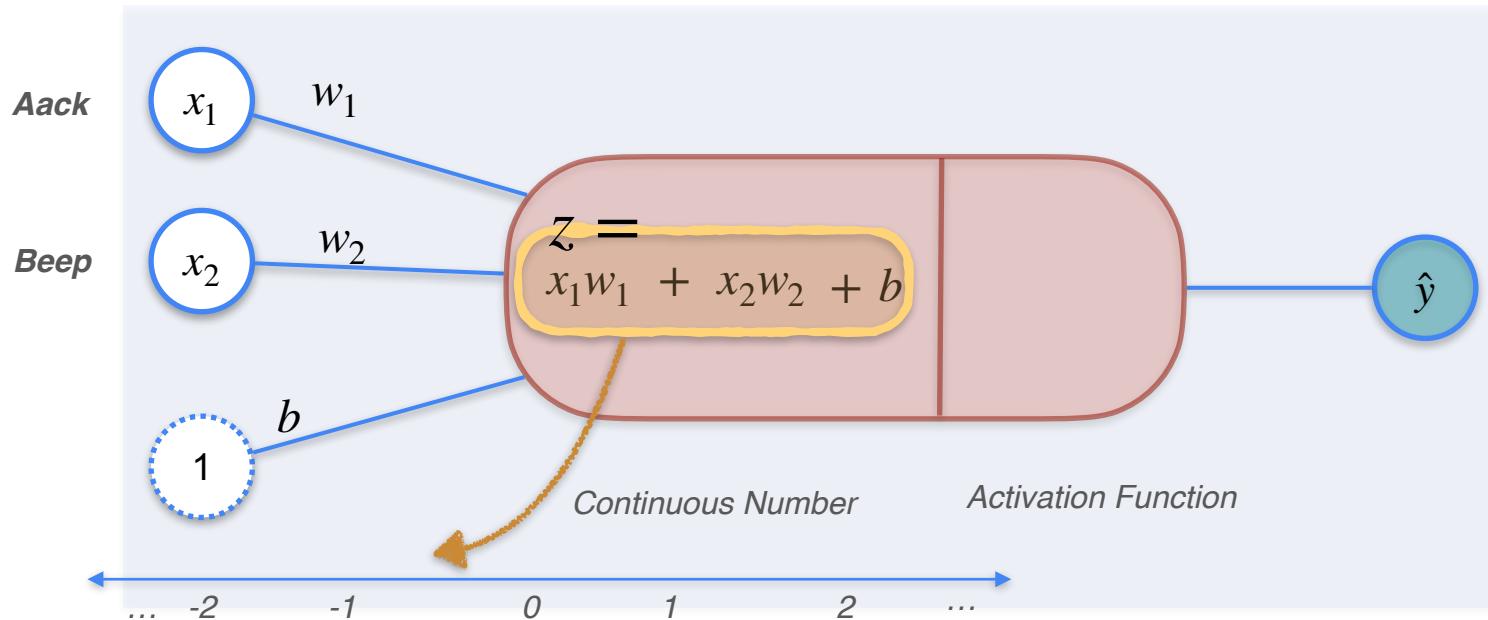
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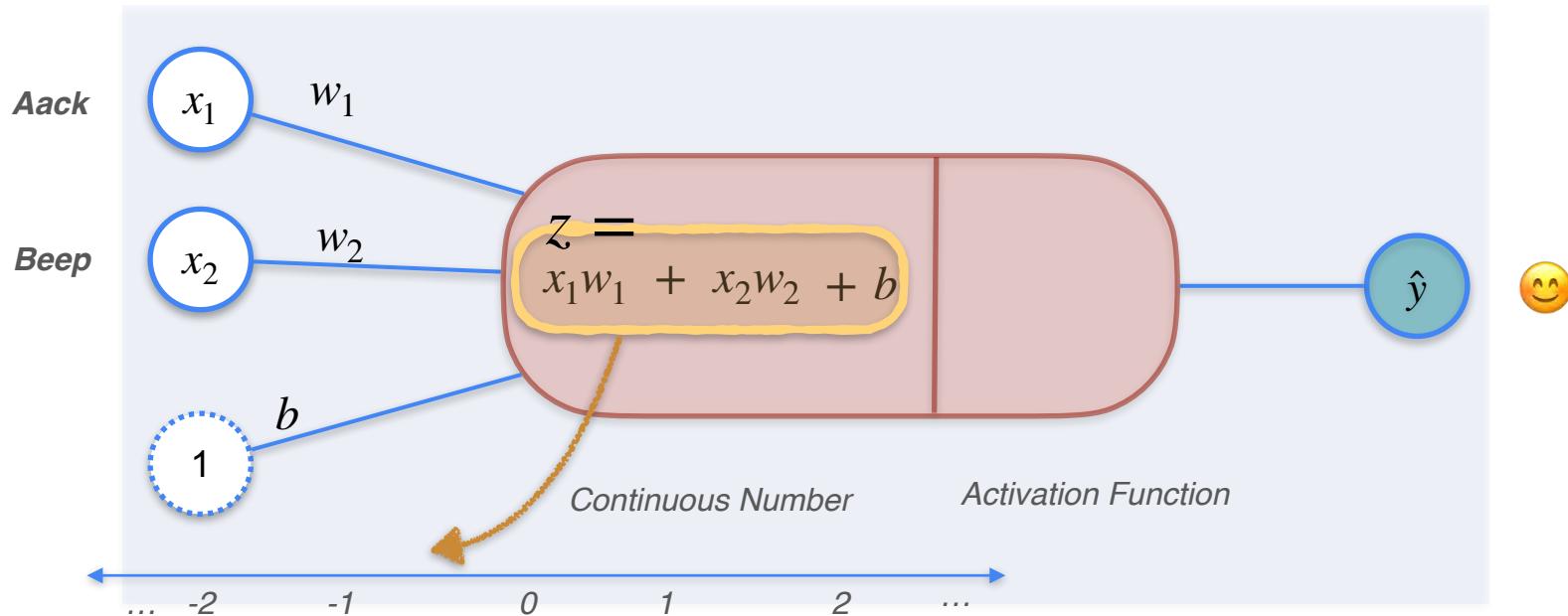
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Single Layer Neural Network Perceptron



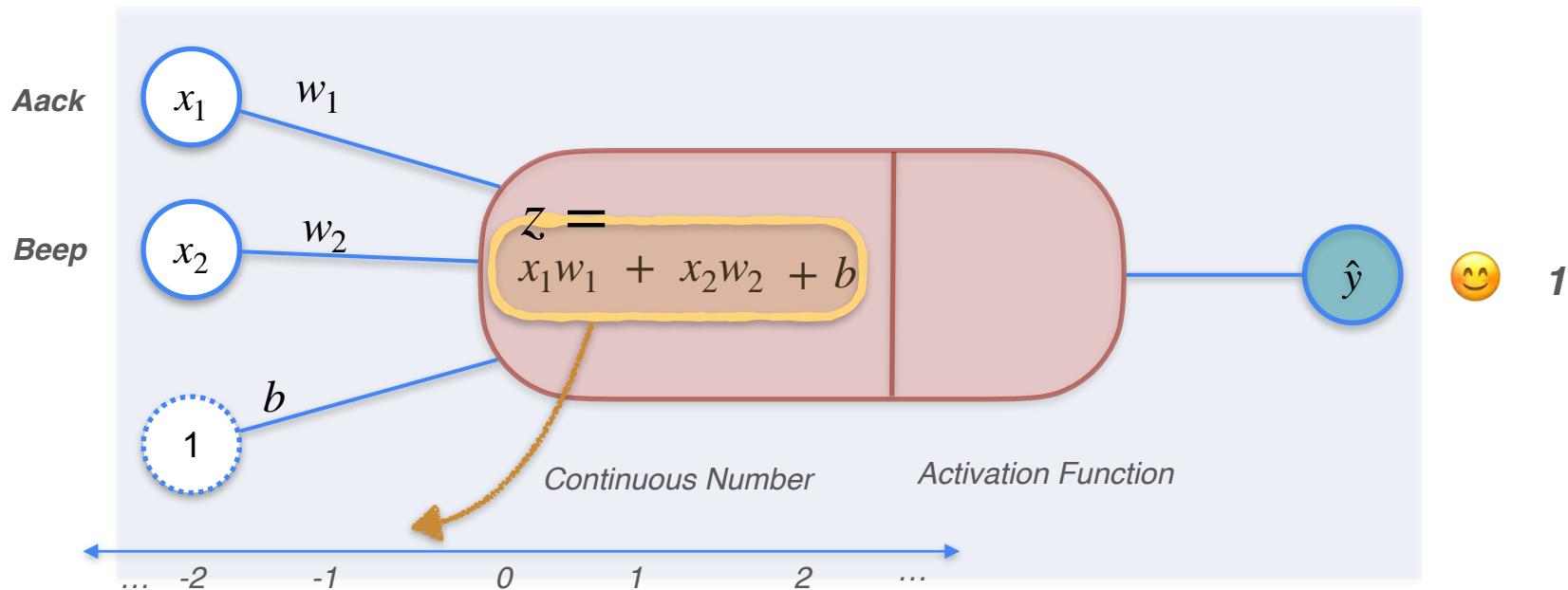
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Single Layer Neural Network Perceptron



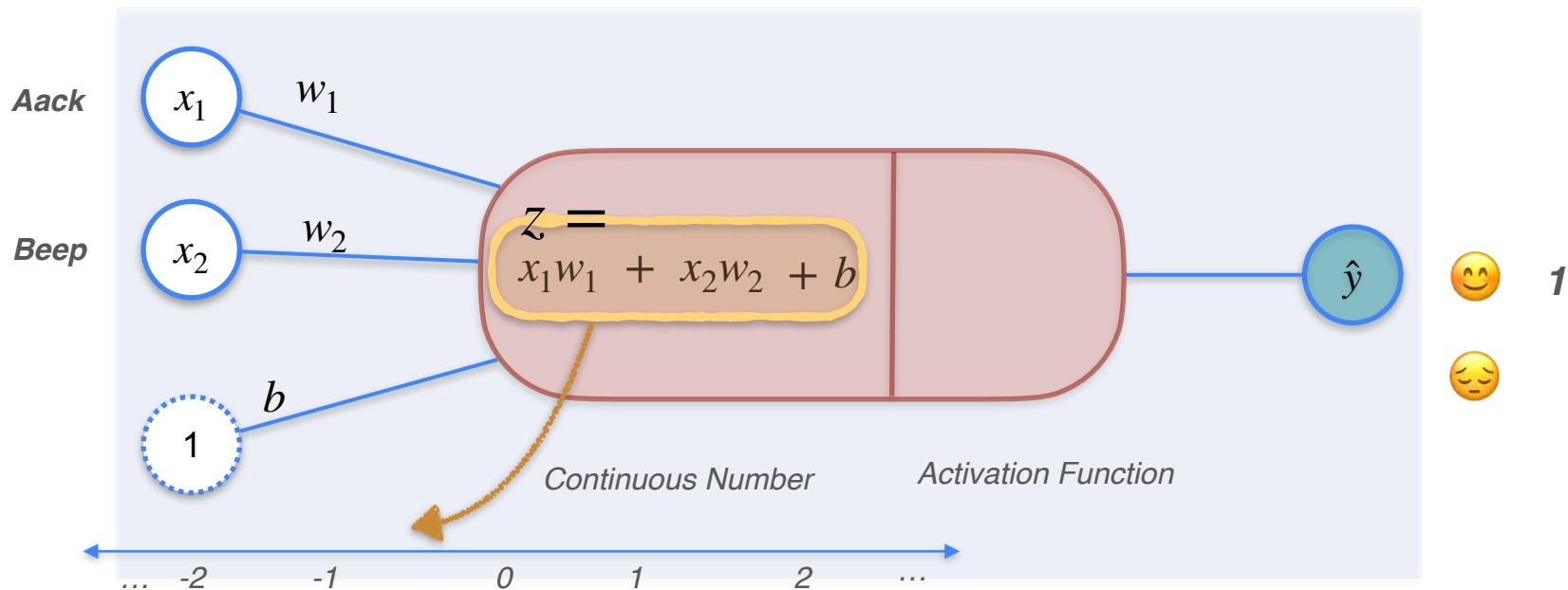
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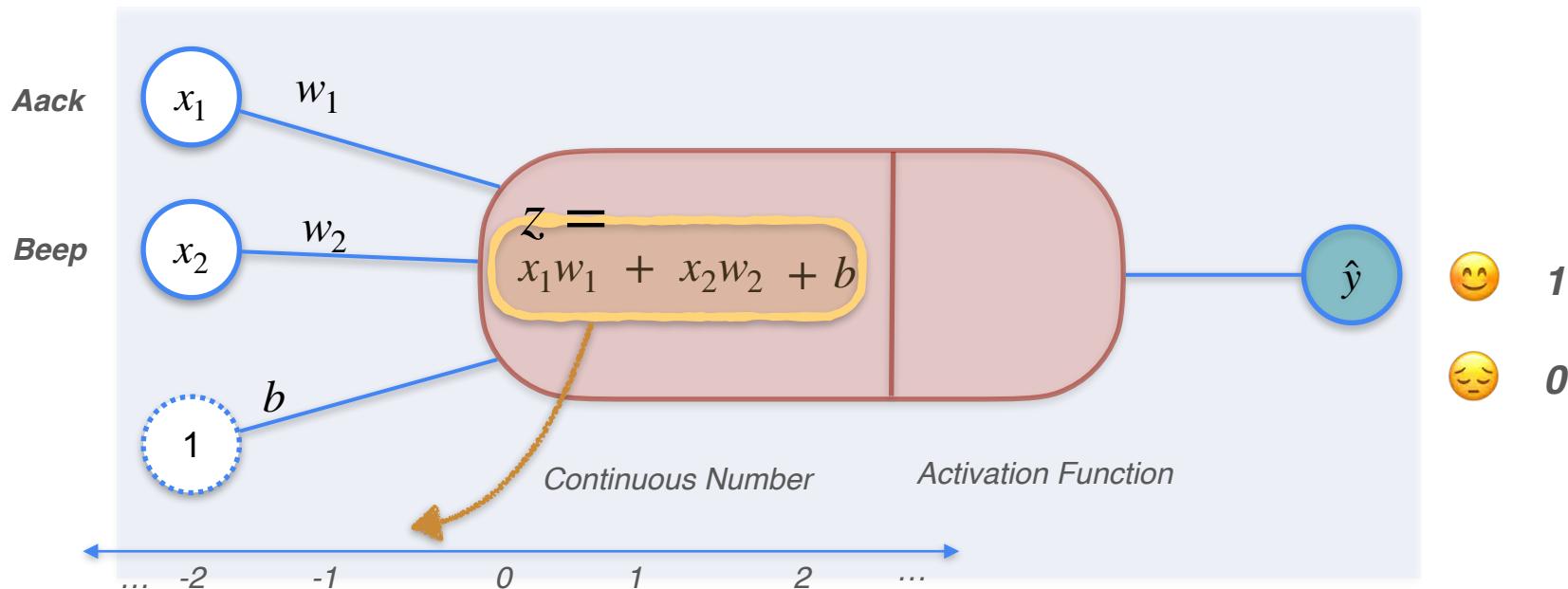
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Single Layer Neural Network Perceptron



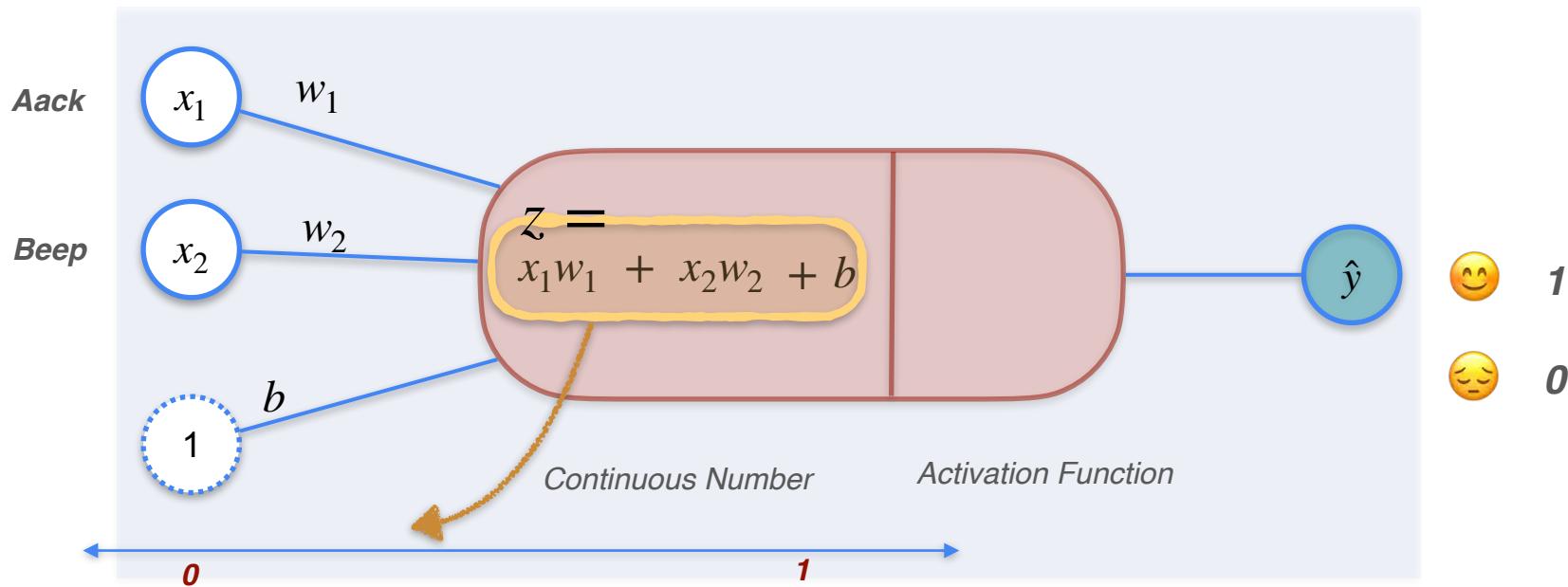
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Single Layer Neural Network Perceptron



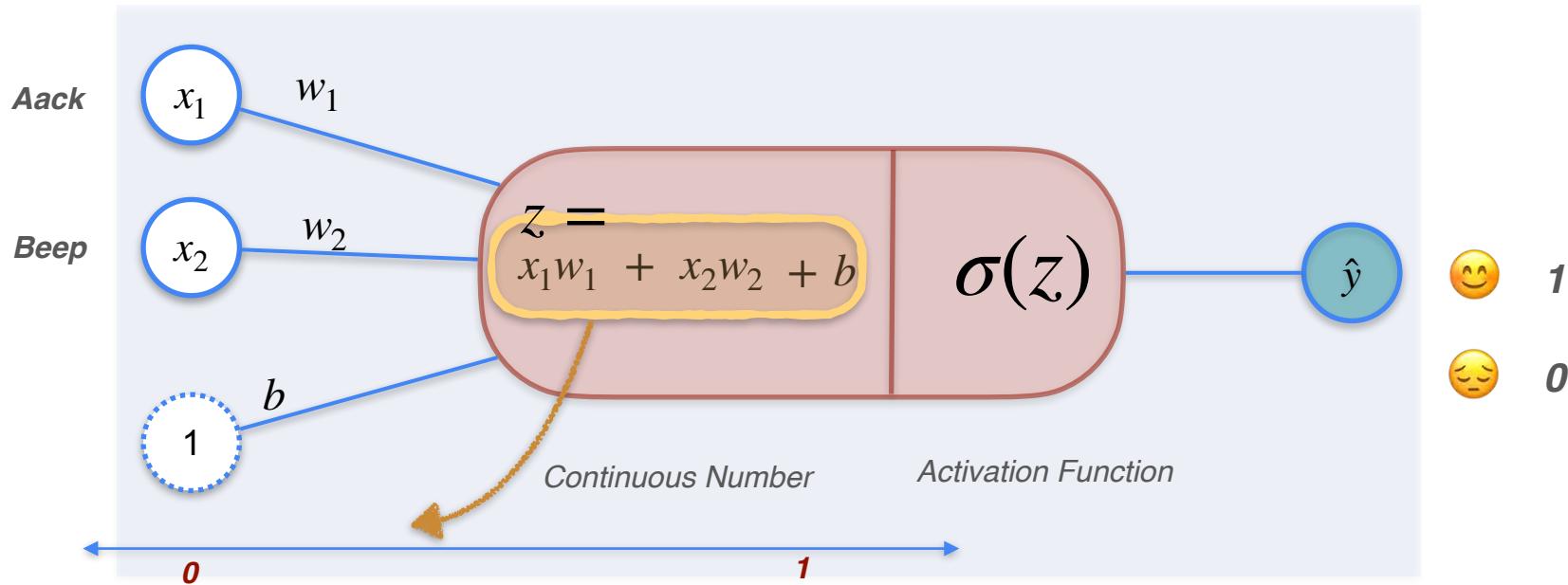
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Single Layer Neural Network Perceptron



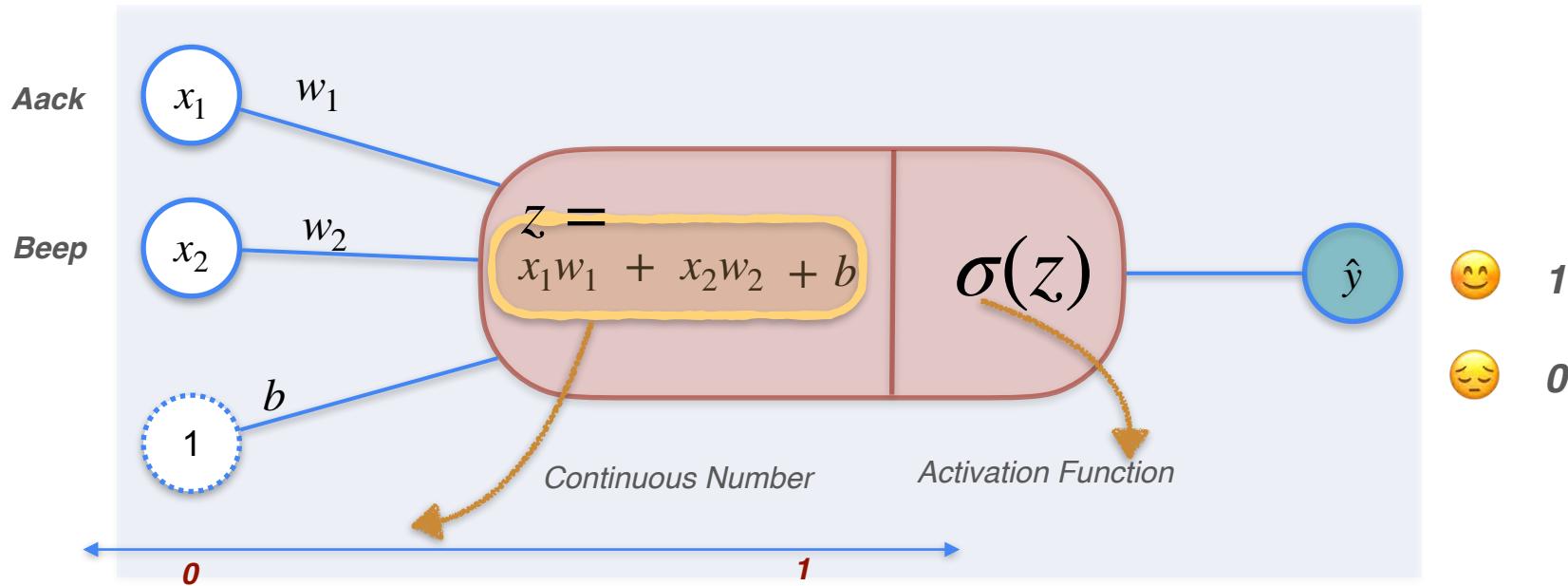
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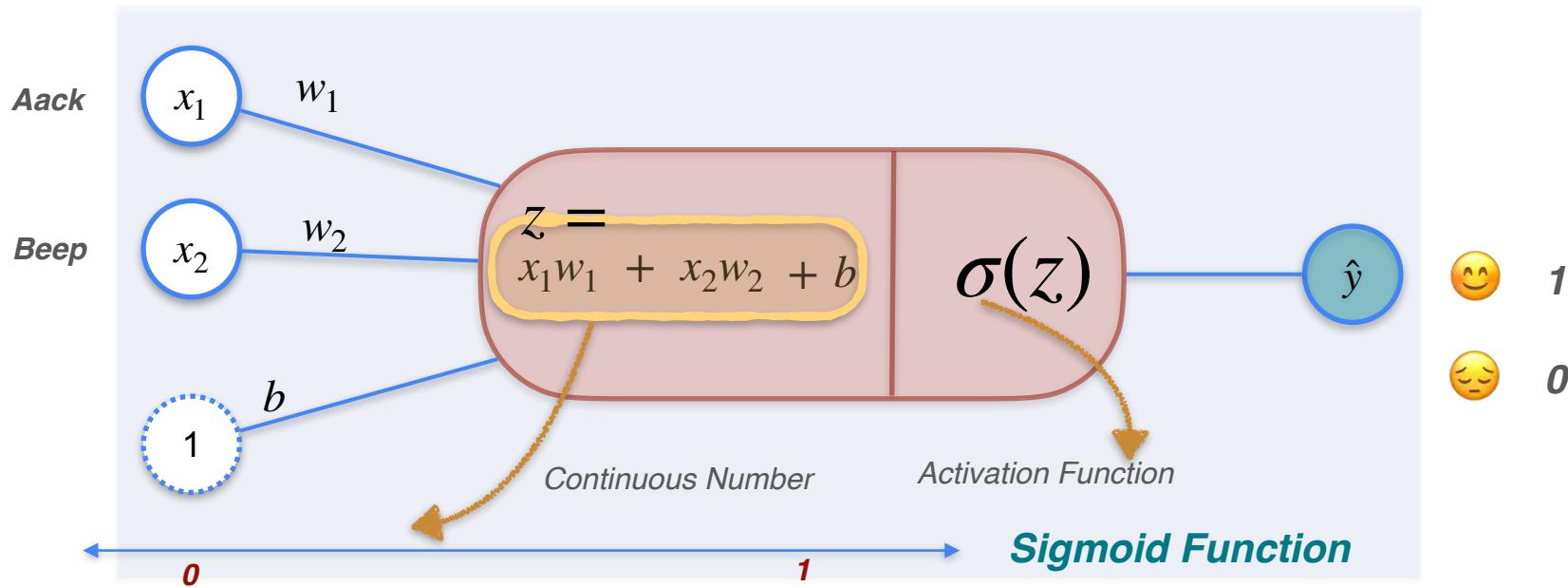
# Classification With a Perceptron

Single Layer Neural Network Perceptron

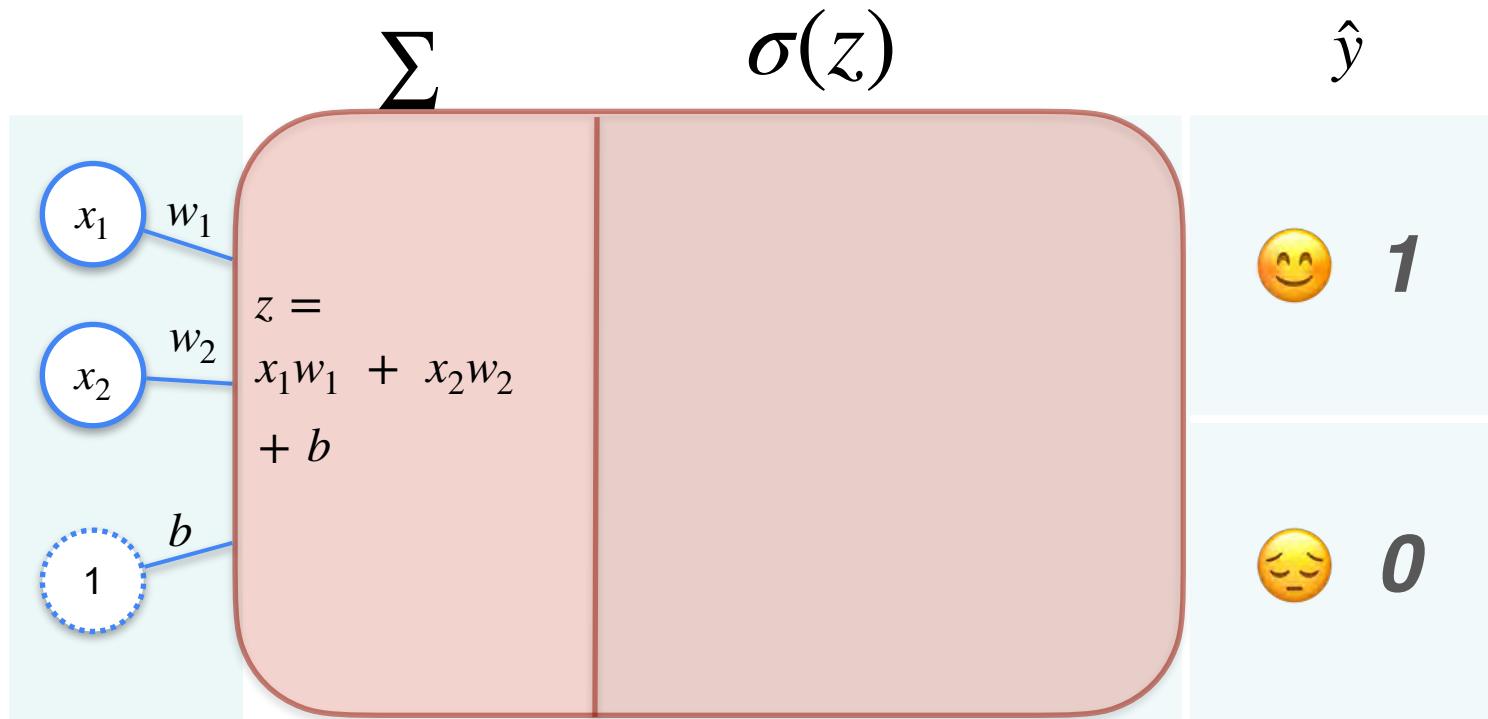


# Classification With a Perceptron

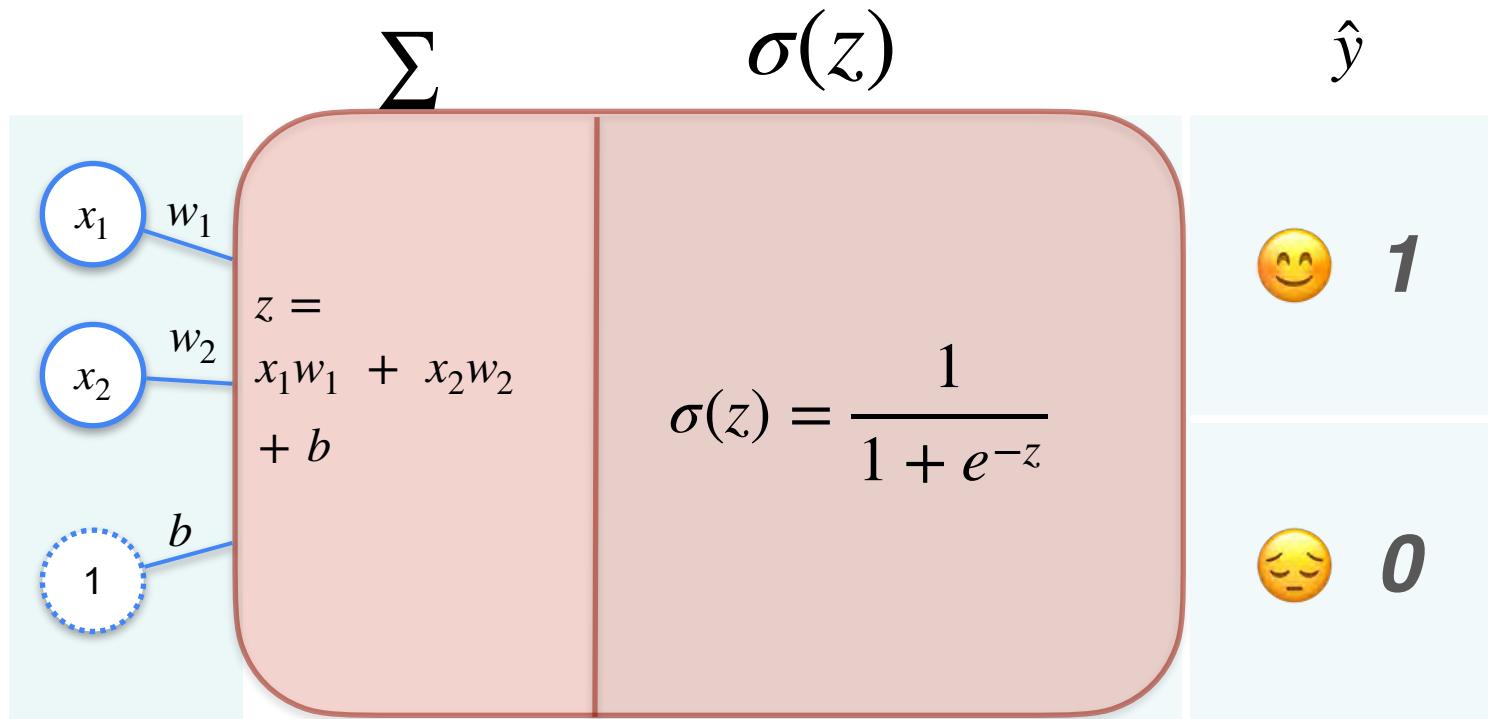
Single Layer Neural Network Perceptron



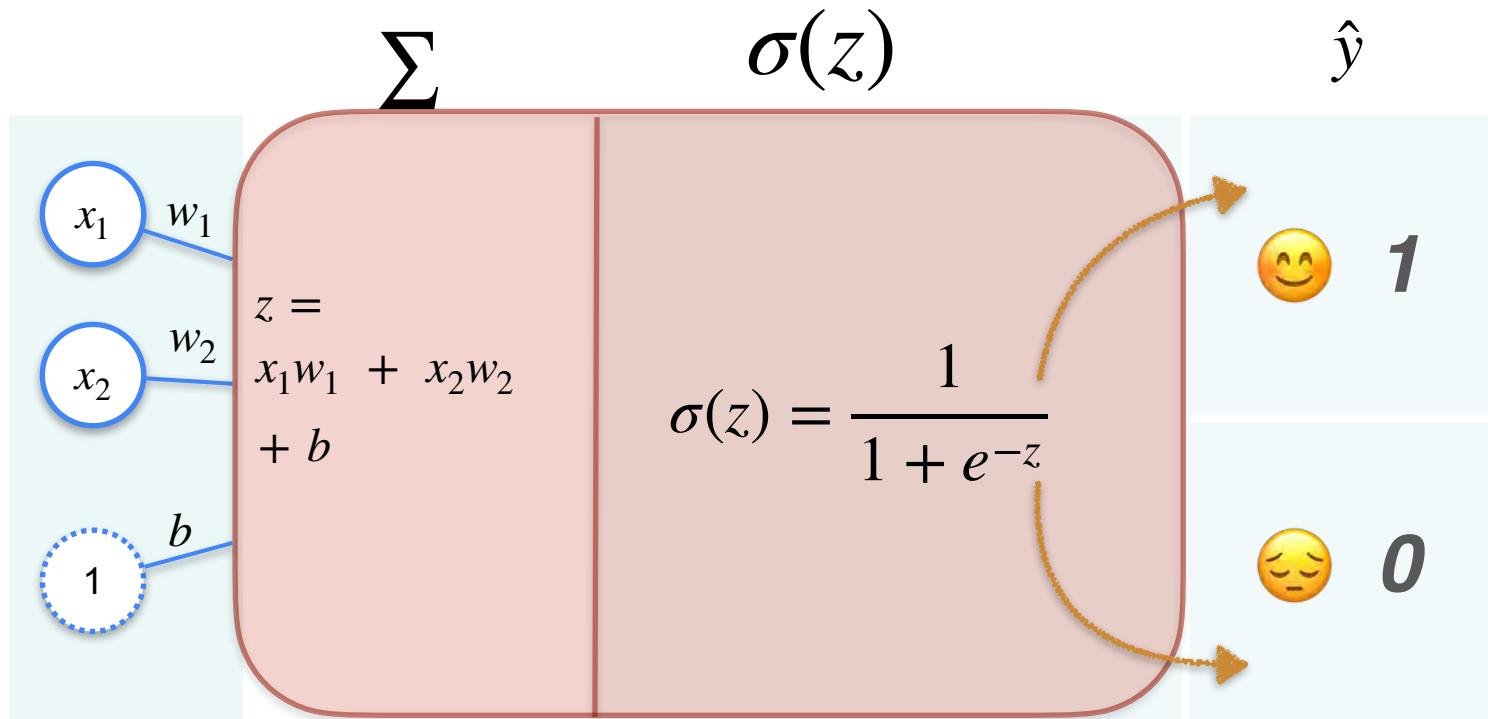
# Sigmoid Function



# Sigmoid Function



# Sigmoid Function





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# Optimization in Neural Networks and Newton's Method

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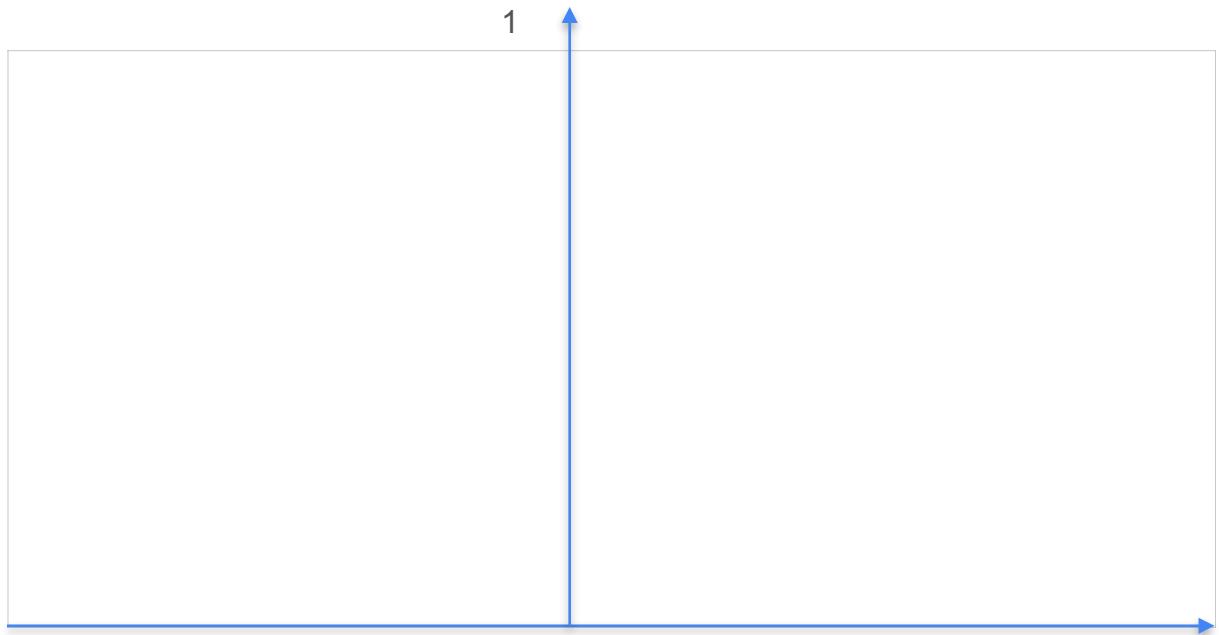
**Classification with a  
perceptron:  
The sigmoid function**

# Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

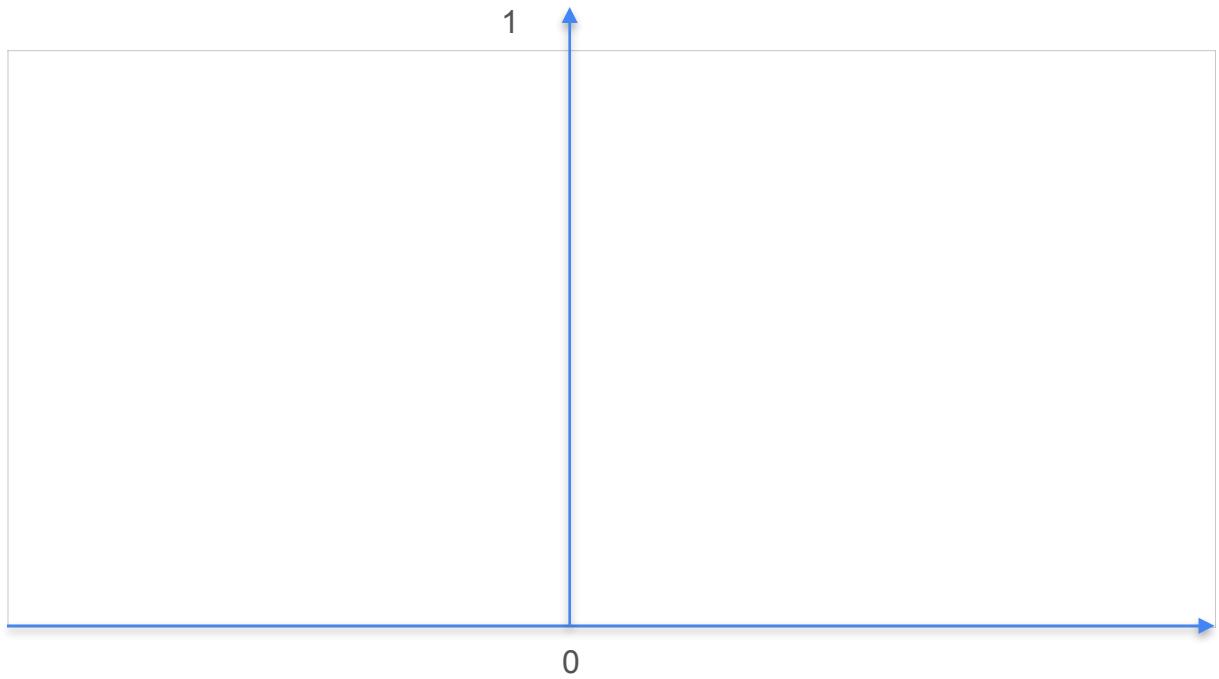
# Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$



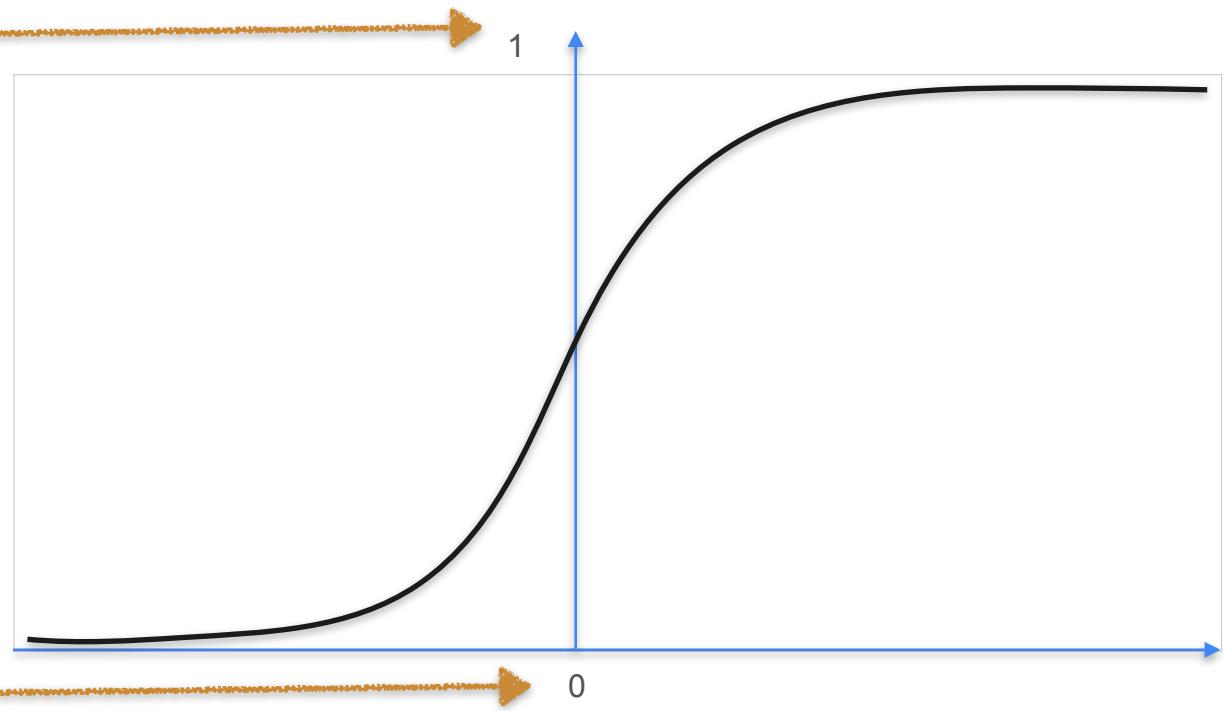
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# Derivative of a Sigmoid Function

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# Derivative of a Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\sigma(z) = (1 + e^{-z})^{-1}$$

# Derivative of a Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\sigma(z) = (1 + e^{-z})^{-1}$$

$$\frac{d}{dz} \sigma(z)$$

# Derivative of a Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\sigma(z) = (1 + e^{-z})^{-1}$$

$$\frac{d}{dz} \sigma(z) = \frac{d}{dz} (1 + e^{-z})^{-1}$$

# Derivative of a Sigmoid Function

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$$\sigma(z) = (1 + e^{-z})^{-1}$$

$$\frac{d}{dz}\sigma(z) = \frac{d}{dz}(1 + e^{-z})^{-1}$$



# Derivative of a Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\frac{d}{dz} \sigma(z)$$

$$\sigma(z) = (1 + e^{-z})^{-1}$$

$$\frac{d}{dz} \sigma(z) = \frac{d}{dz} (1 + e^{-z})^{-1}$$

# Derivative of a Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\frac{d}{dz} \sigma(z) = -1$$

$$\sigma(z) = (1 + e^{-z})^{-1}$$

$$\frac{d}{dz} \sigma(z) = \frac{d}{dz} (1 + e^{-z})^{-1}$$

# Derivative of a Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\frac{d}{dz} \sigma(z) = -1 (1 + e^{-z})^{-1-1}$$

$$\sigma(z) = (1 + e^{-z})^{-1}$$

$$\frac{d}{dz} \sigma(z) = \frac{d}{dz} (1 + e^{-z})^{-1}$$

# Derivative of a Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\frac{d}{dz} \sigma(z) = -1 (1 + e^{-z})^{-1-1} \left( \frac{d}{dz} (1 + e^{-z}) \right)$$

$$\sigma(z) = (1 + e^{-z})^{-1}$$

$$\frac{d}{dz} \sigma(z) = \frac{d}{dz} (1 + e^{-z})^{-1}$$

# Derivative of a Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\frac{d}{dz} \sigma(z) = -1 (1 + e^{-z})^{-1-1} \left( \frac{d}{dz} (1 + e^{-z}) \right)$$

$$\sigma(z) = (1 + e^{-z})^{-1}$$

$$= -1$$

$$\frac{d}{dz} \sigma(z) = \frac{d}{dz} (1 + e^{-z})^{-1}$$

# Derivative of a Sigmoid Function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\sigma(z) = (1 + e^{-z})^{-1}$$

$$\frac{d}{dz}\sigma(z) = \frac{d}{dz}(1 + e^{-z})^{-1}$$

$$\frac{d}{dz}\sigma(z) = -1 (1 + e^{-z})^{-1-1} \left(\frac{d}{dz}(1 + e^{-z})\right)$$

$$= -1 (1 + e^{-z})^{-2}$$

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$$\begin{aligned}\frac{d}{dz}\sigma(z) &= -1 \ (1 + e^{-z})^{-1-1} \ (\frac{d}{dz}(1 + e^{-z})) \\ &= -1 \ (1 + e^{-z})^{-2} \ (\frac{d}{dz}(1) + \frac{d}{dz}(e^{-z}))\end{aligned}$$

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# Derivative of a Sigmoid Function

$$\frac{d}{dz} \sigma(z) = -1 \cdot (1 + e^{-z})^{-2} \cdot (e^{-z}) \cdot (-1)$$

# Derivative of a Sigmoid Function

$$\frac{d}{dz} \sigma(z) = \cancel{1} (1 + e^{-z})^{-2} (e^{-z}) (-1)$$

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# Derivative of a Sigmoid Function

$$\begin{aligned}\frac{d}{dz} \sigma(z) &= \cancel{1} (1 + e^{-z})^{-2} \ (e^{-z}) \cancel{(-1)} \\ &= (1 + e^{-z})^{-2}\end{aligned}$$

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$$= \frac{1}{(1 + e^{-z})^2}$$

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$$= (1 + e^{-z})^{-2} (e^{-z})$$

$$= \frac{1}{(1 + e^{-z})^2} (e^{-z})$$

$$= \frac{e^{-z}}{(1 + e^{-z})^2}$$

# Derivative of a Sigmoid Function

# Derivative of a Sigmoid Function

$$\frac{d}{dz}\sigma(z)$$

# Derivative of a Sigmoid Function

$$\frac{d}{dz}\sigma(z) = \frac{e^{-z}}{(1 + e^{-z})^2}$$

# Derivative of a Sigmoid Function

$$\frac{d}{dz}\sigma(z) = \frac{e^{-z}}{(1 + e^{-z})^2} + 1 - 1$$

# Derivative of a Sigmoid Function

$$\frac{d}{dz}\sigma(z) = \frac{e^{-z} + 1 - 1}{(1 + e^{-z})^2}$$

$$= \frac{1 + e^{-z} - 1}{(1 + e^{-z})^2}$$

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$$\frac{d}{dz}\sigma(z)$$

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$$\frac{d}{dz}\sigma(z) = \frac{1}{(1 + e^{-z})}$$

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$$\frac{d}{dz}\sigma(z) = \frac{1}{(1 + e^{-z})} - \left( \frac{1}{(1 + e^{-z})} \right)$$

# Derivative of a Sigmoid Function

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$$\frac{d}{dz}\sigma(z) = \frac{1}{(1 + e^{-z})} - \left(\frac{1}{(1 + e^{-z})}\right)\left(\frac{1}{(1 + e^{-z})}\right)$$

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Recall that:

# Derivative of a Sigmoid Function

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Recall that:  $\sigma(z) = \frac{1}{1 + e^{-z}}$

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$$\frac{d}{dz}\sigma(z)$$

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Recall that:  $\sigma(z) = \frac{1}{1 + e^{-z}}$

$$\frac{d}{dz}\sigma(z) = \sigma(z)$$

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Recall that:  $\sigma(z) = \frac{1}{1 + e^{-z}}$

$$\frac{d}{dz}\sigma(z) = \sigma(z) (1 - \sigma(z))$$



DeepLearning.AI

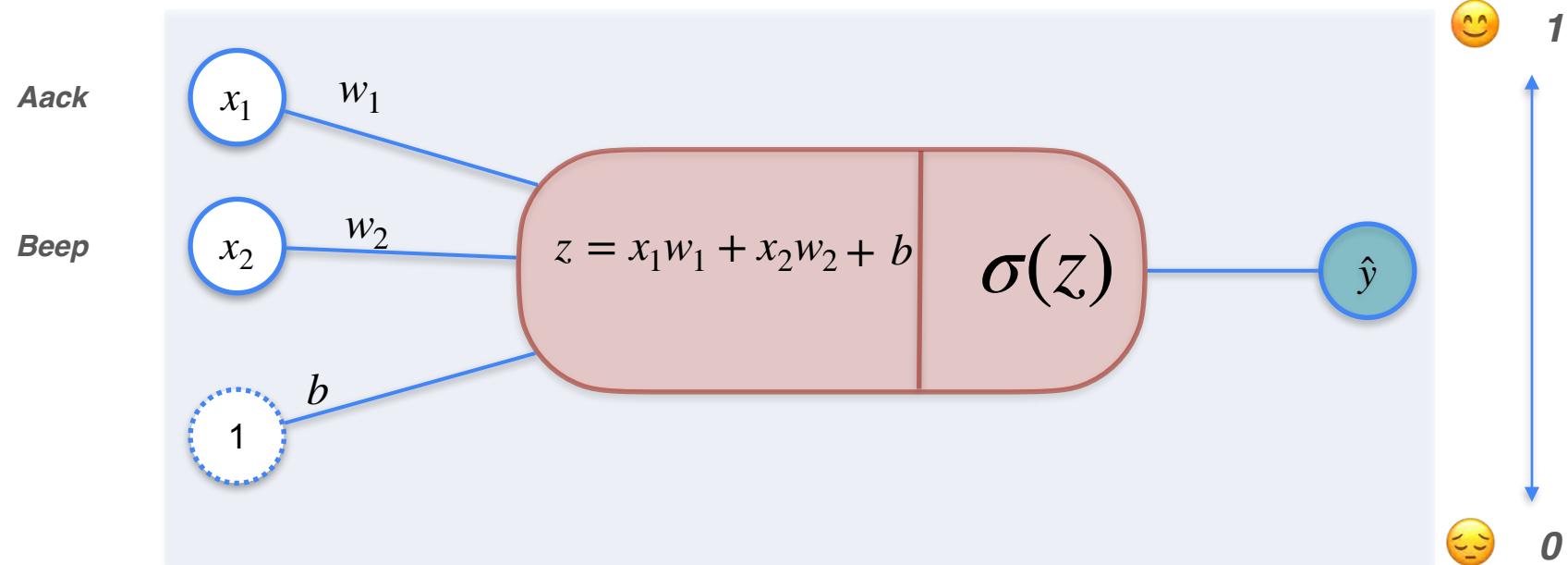
# Optimization in Neural Networks and Newton's Method

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**Classification with a  
perceptron:  
Gradient Descent**

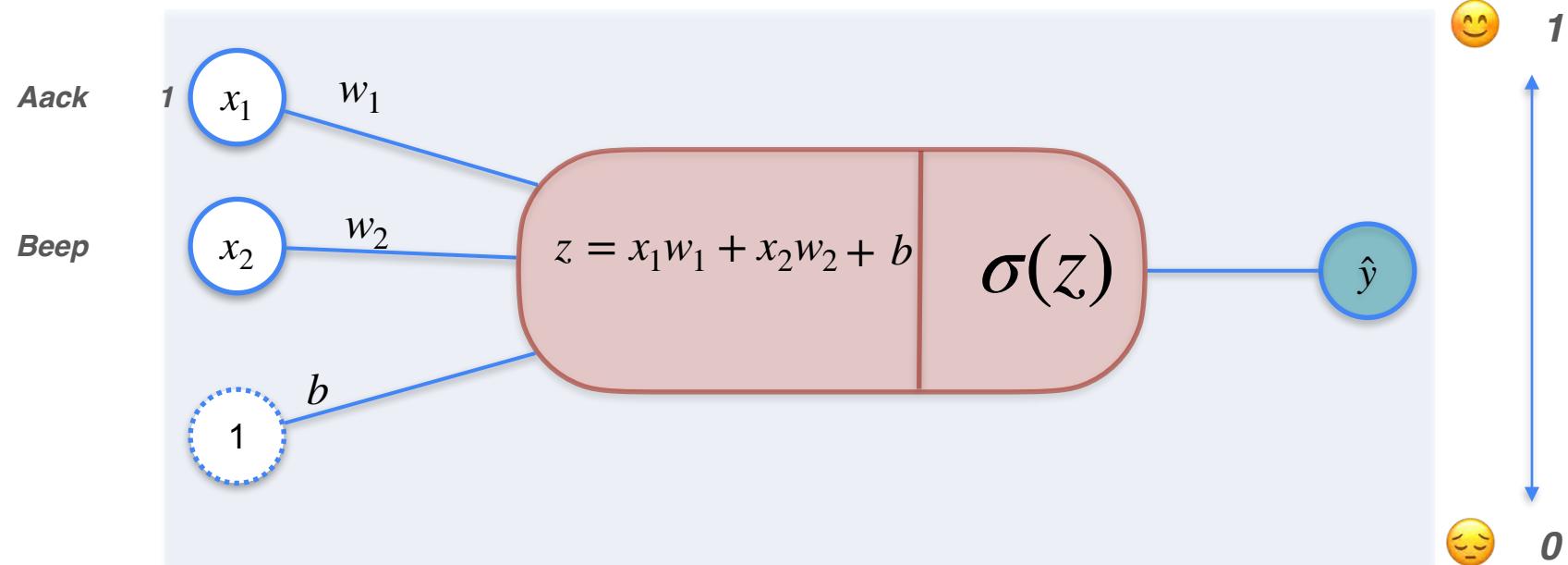
# Classification With a Perceptron

Aack beep beep beep



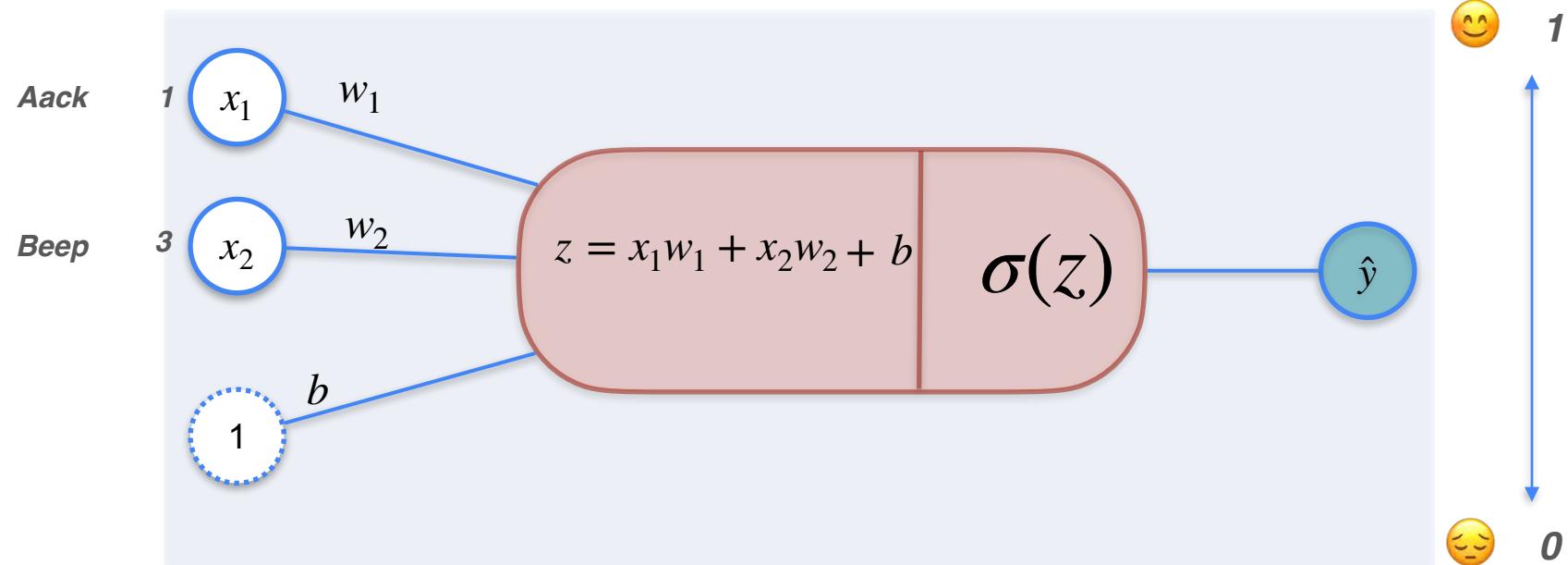
# Classification With a Perceptron

Aack beep beep beep



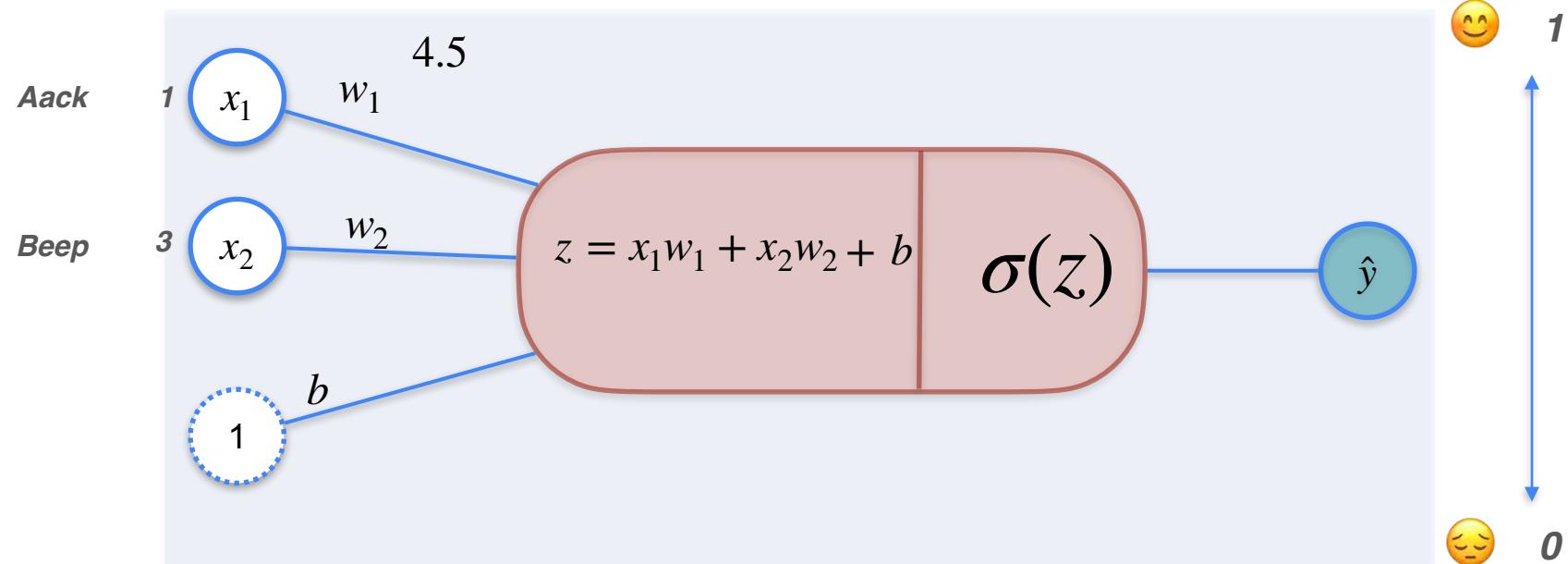
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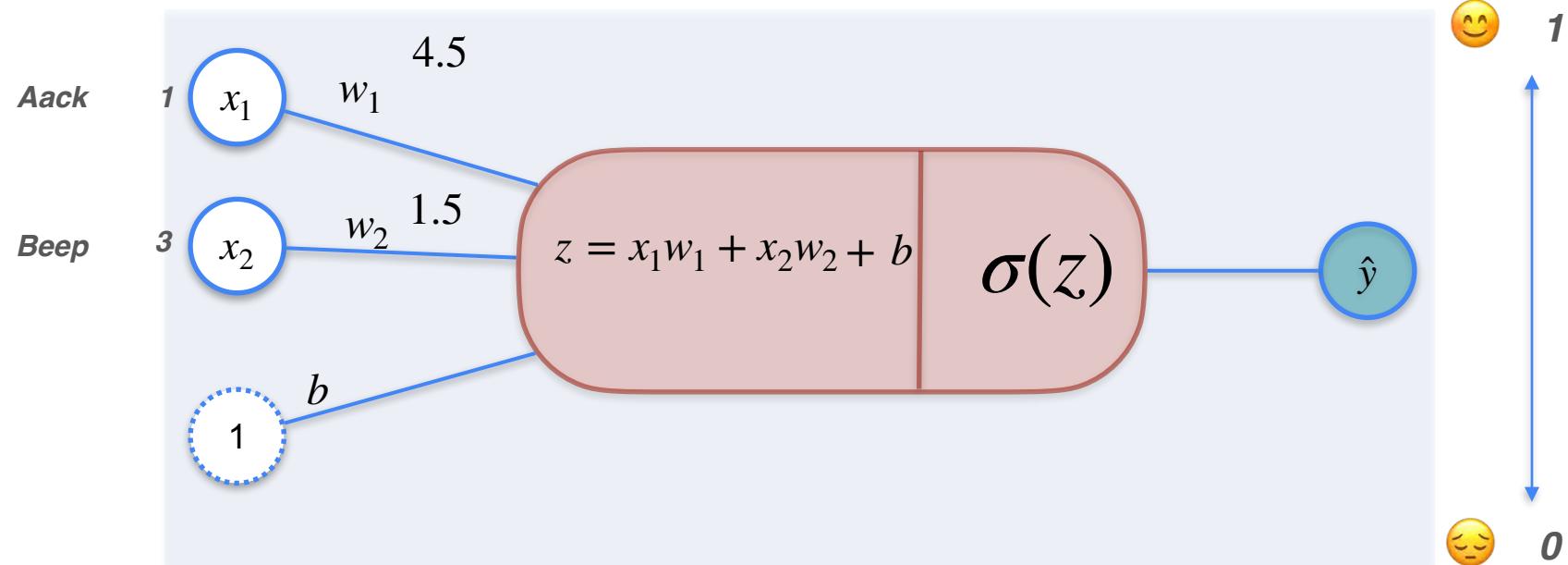
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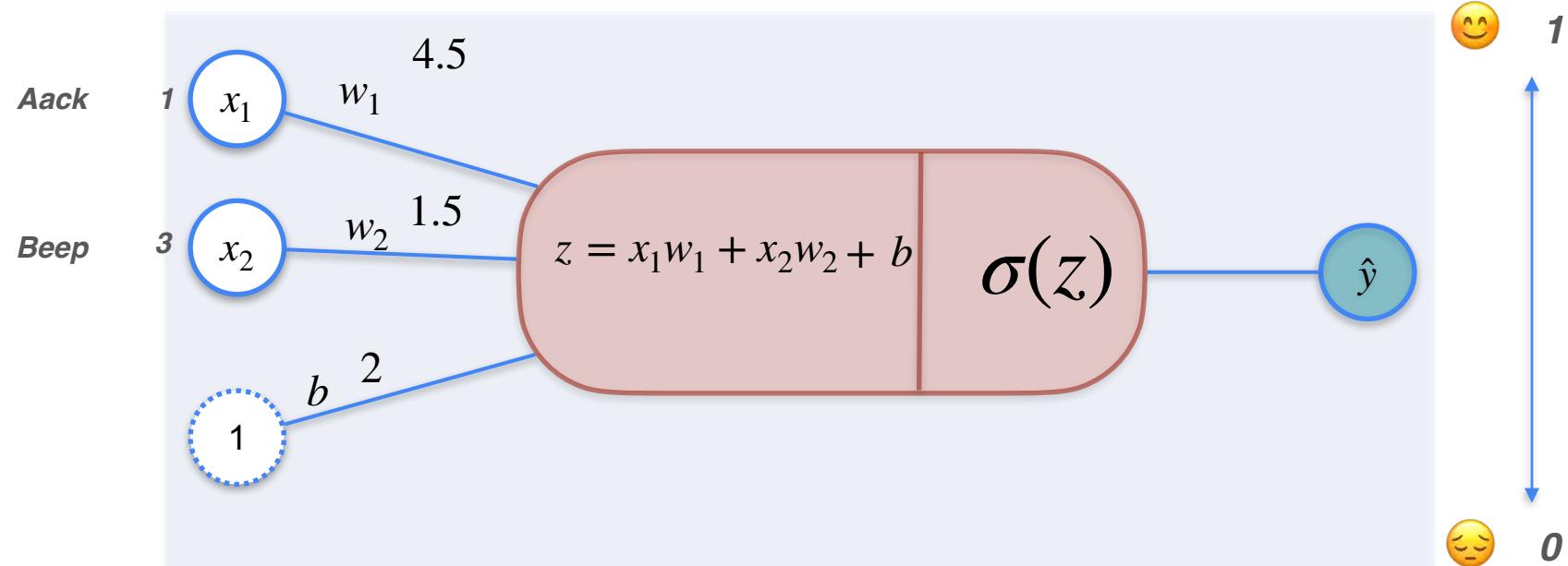
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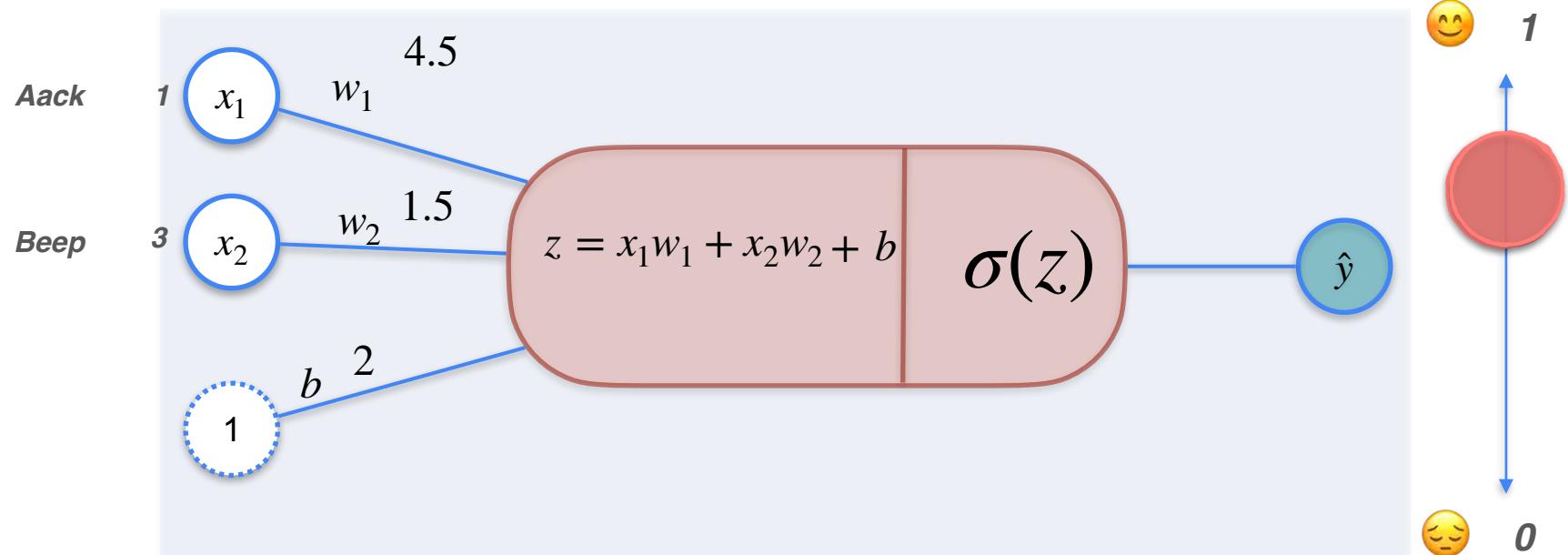
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Aack beep beep beep



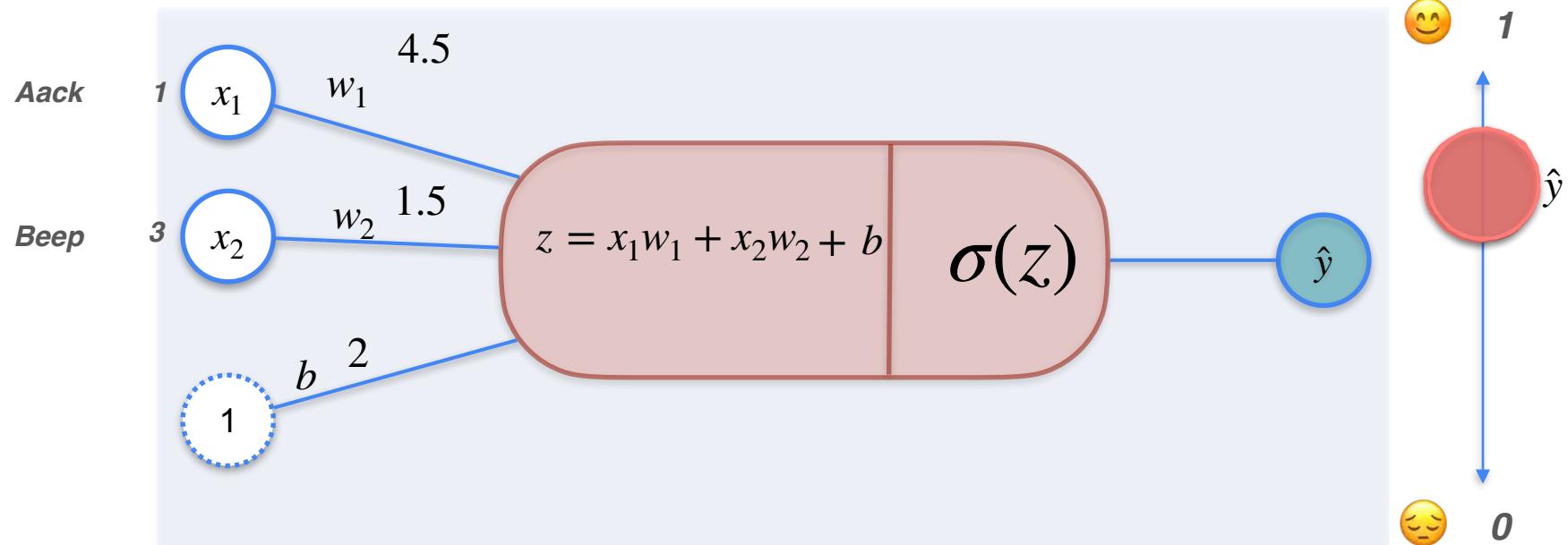
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Aack beep beep beep



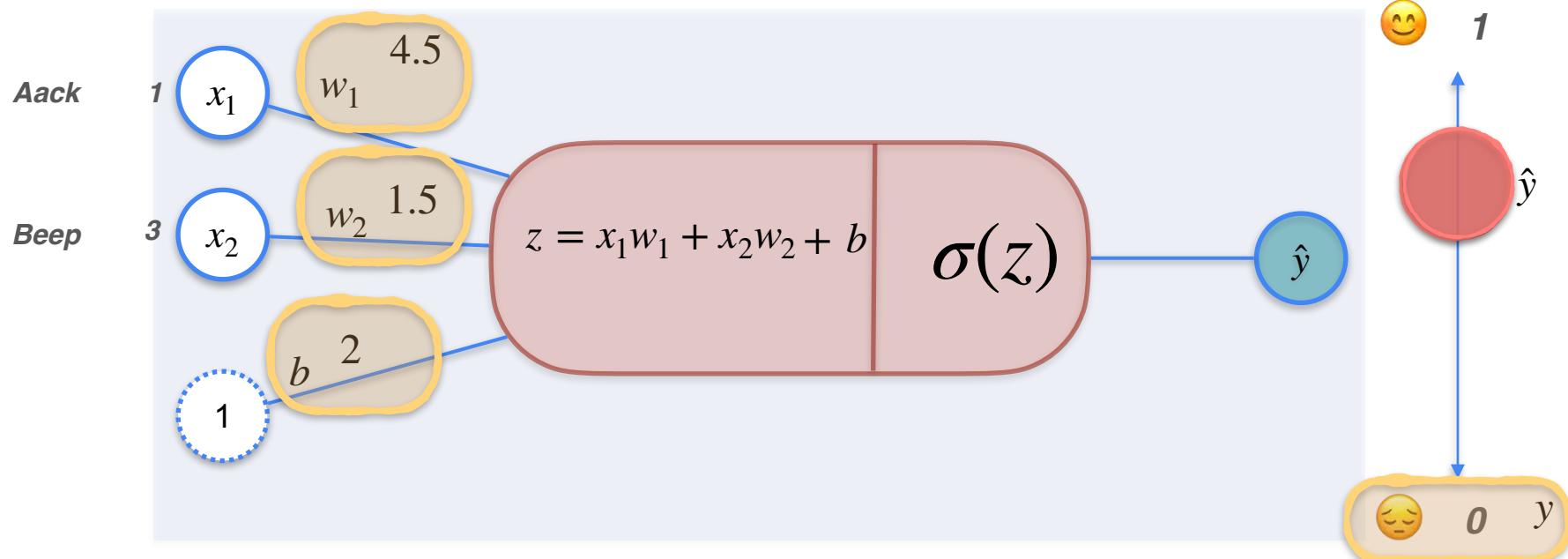
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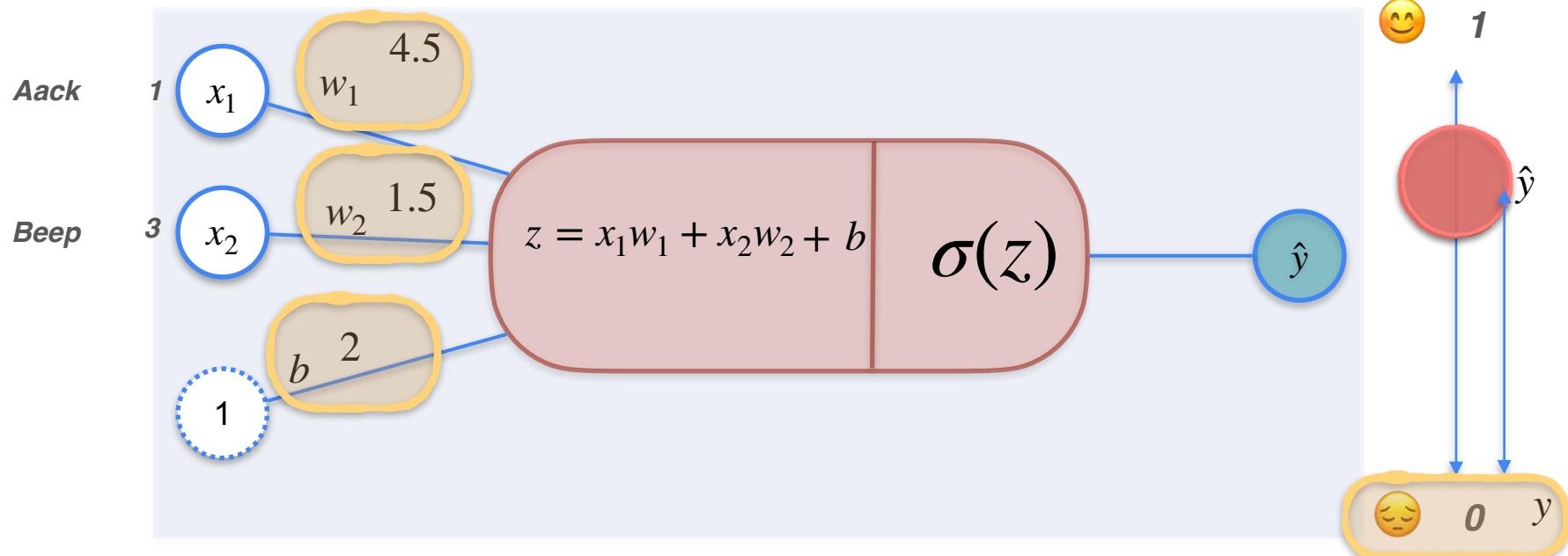
# Classification With a Perceptron

*Aack beep beep beep*



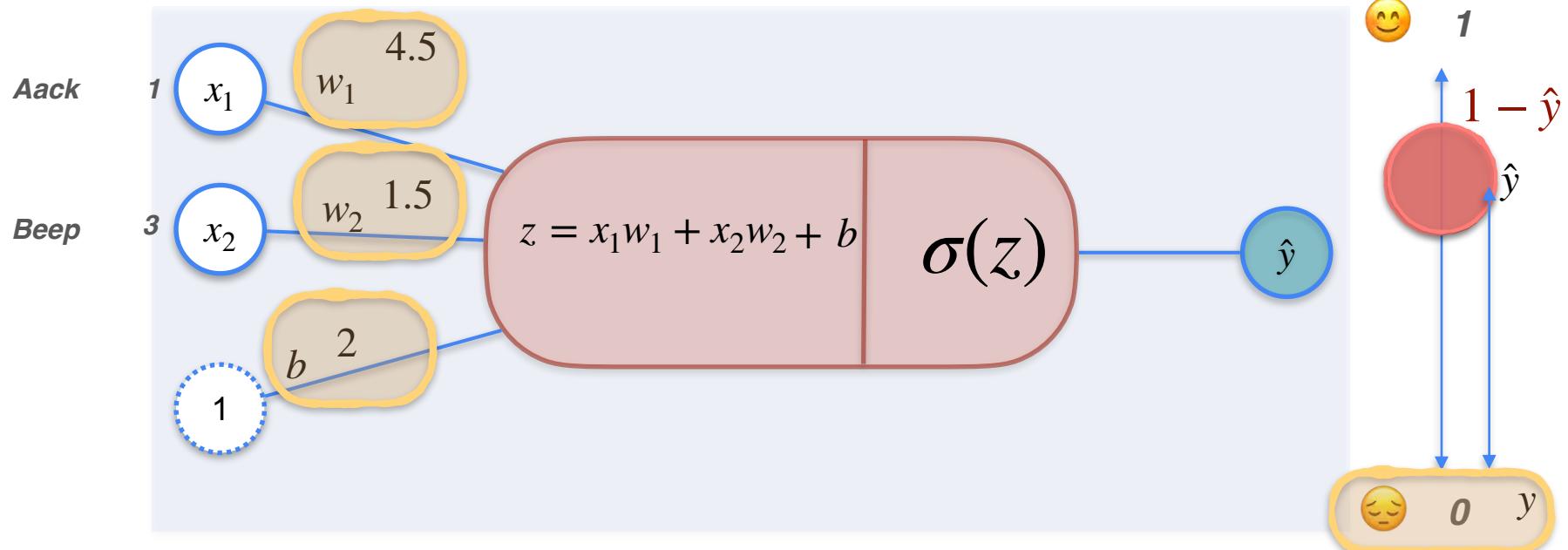
# Classification With a Perceptron

Aack beep beep beep



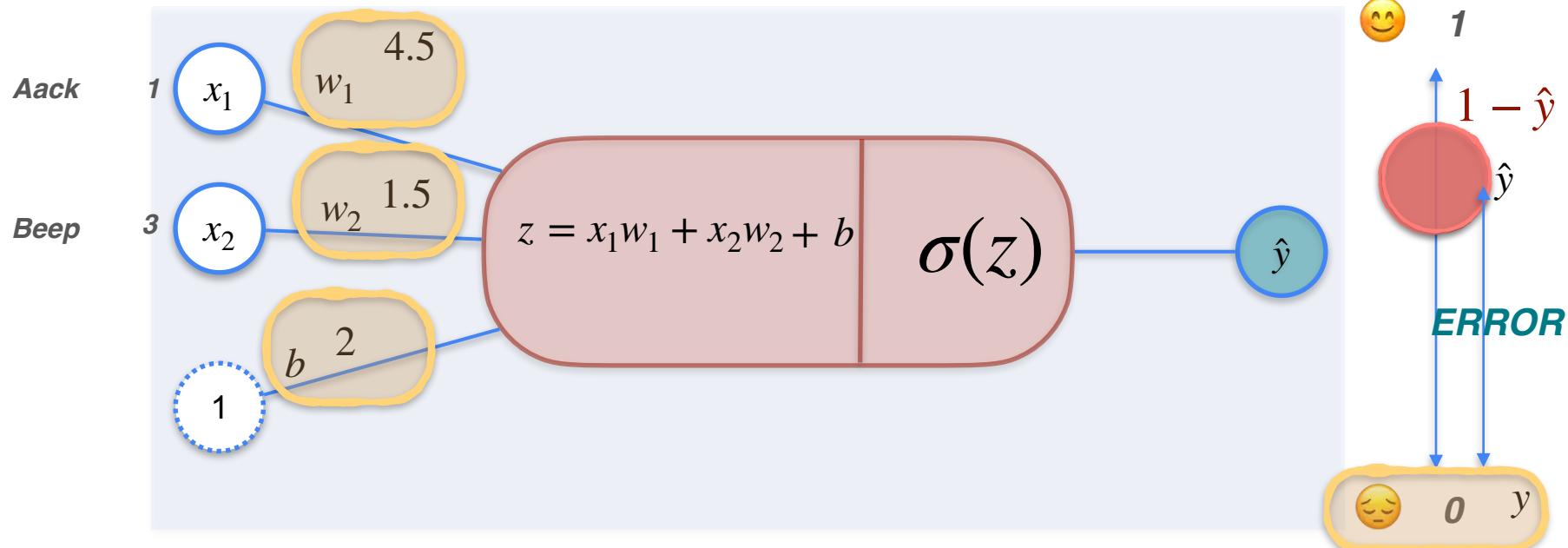
# Classification With a Perceptron

Aack beep beep beep



# Classification With a Perceptron

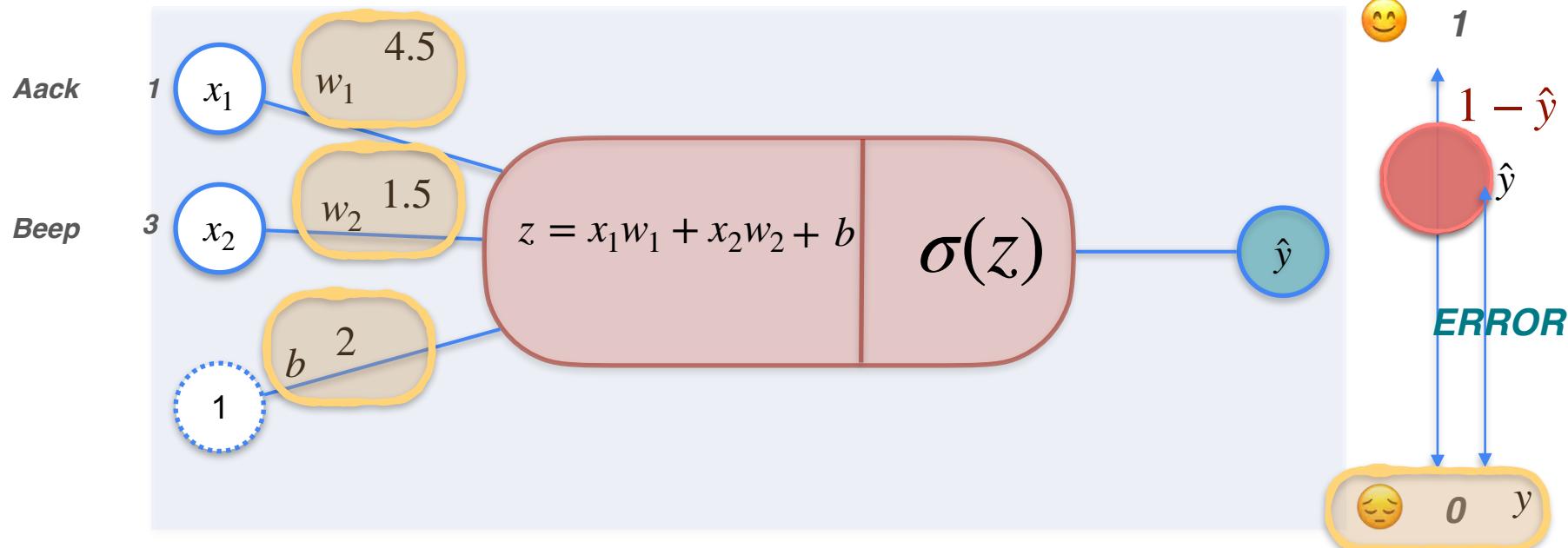
Aack beep beep beep



# Classification With a Perceptron

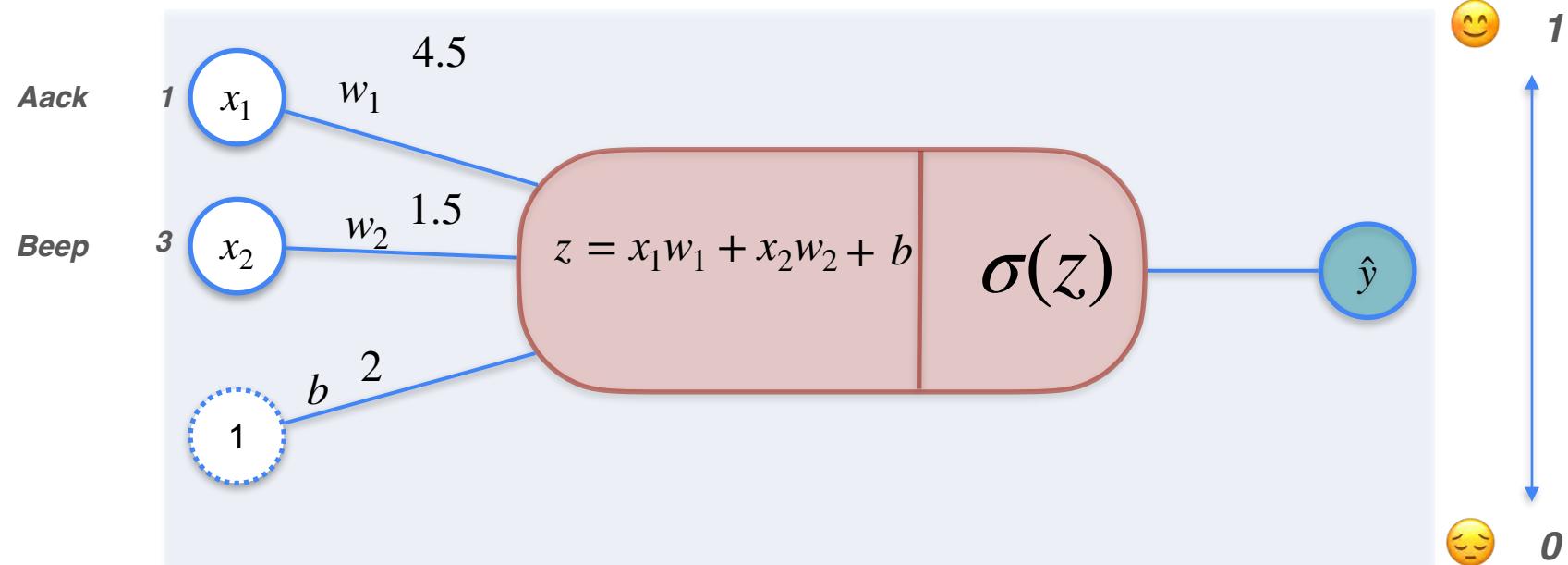
Aack beep beep beep

**LOG LOSS**



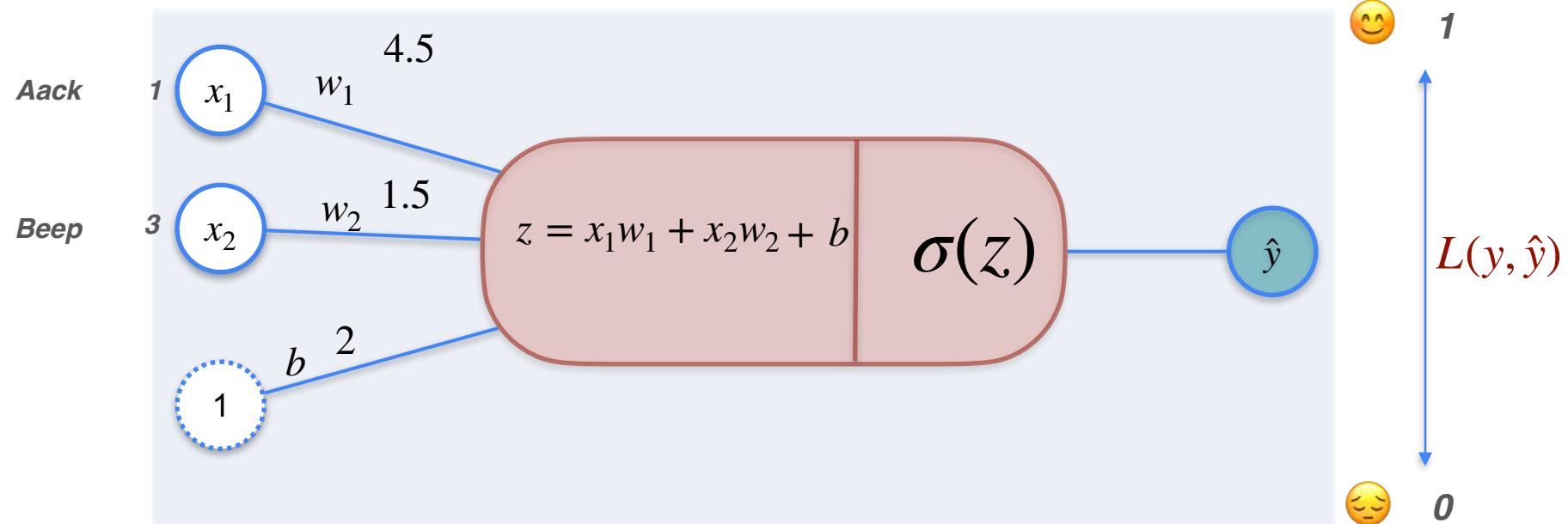
# Classification With a Perceptron

Aack beep beep beep



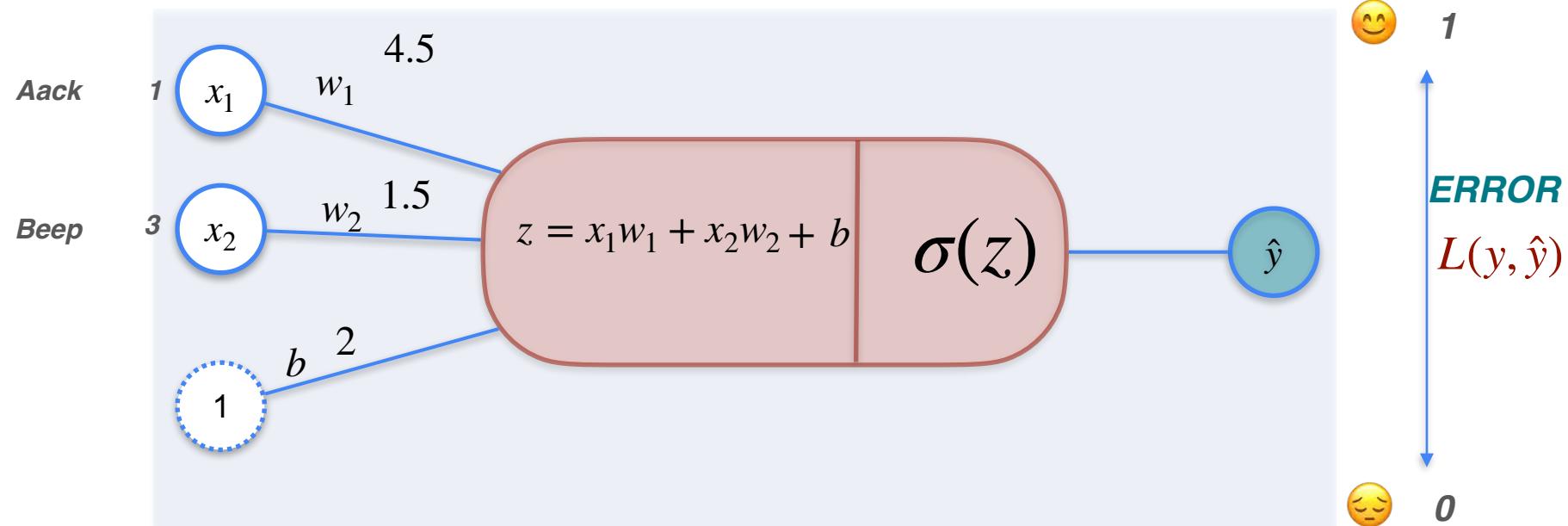
# Classification With a Perceptron

Aack beep beep beep



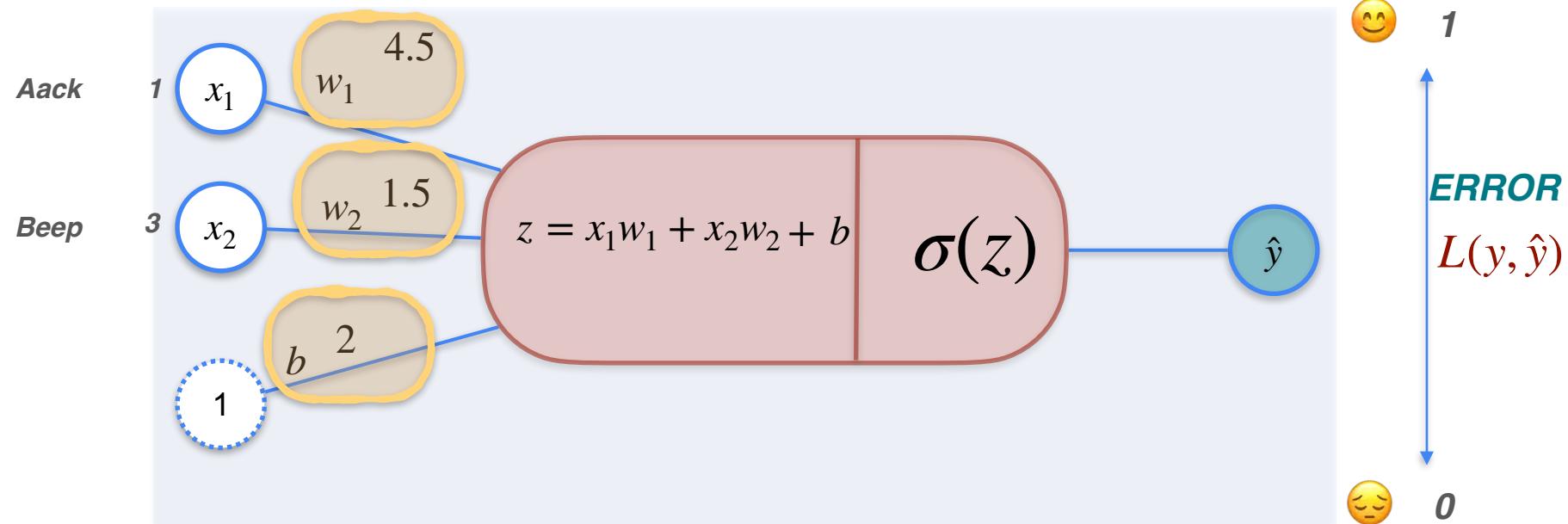
# Classification With a Perceptron

Aack beep beep beep



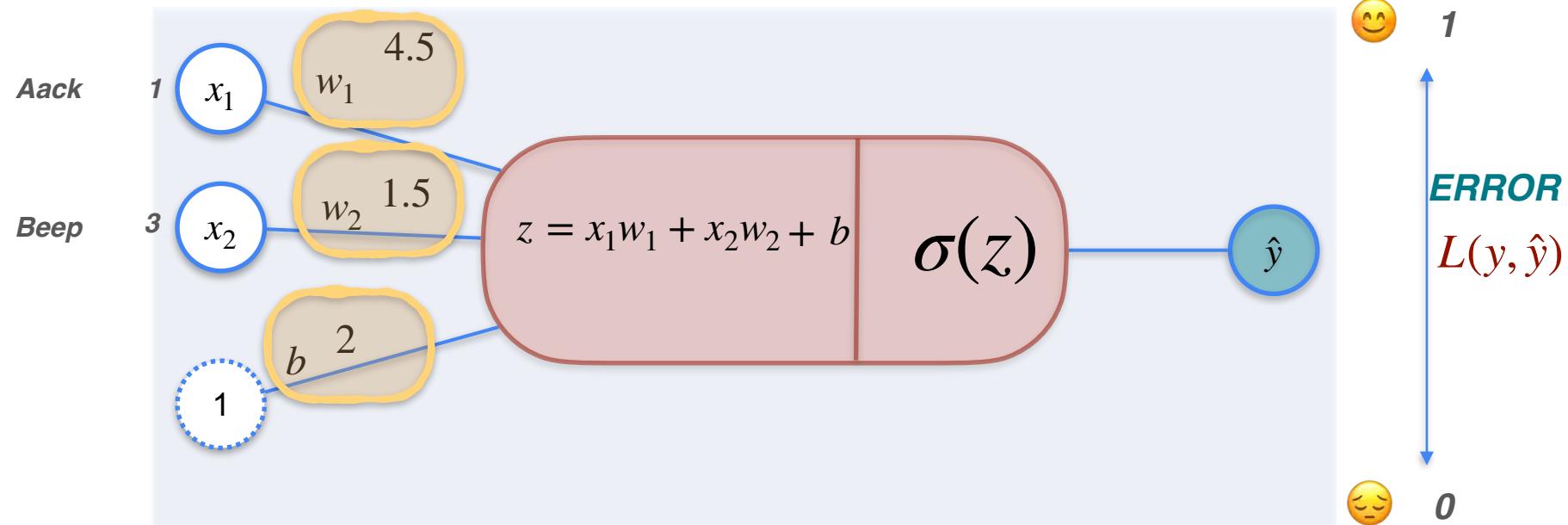
# Classification With a Perceptron

Aack beep beep beep

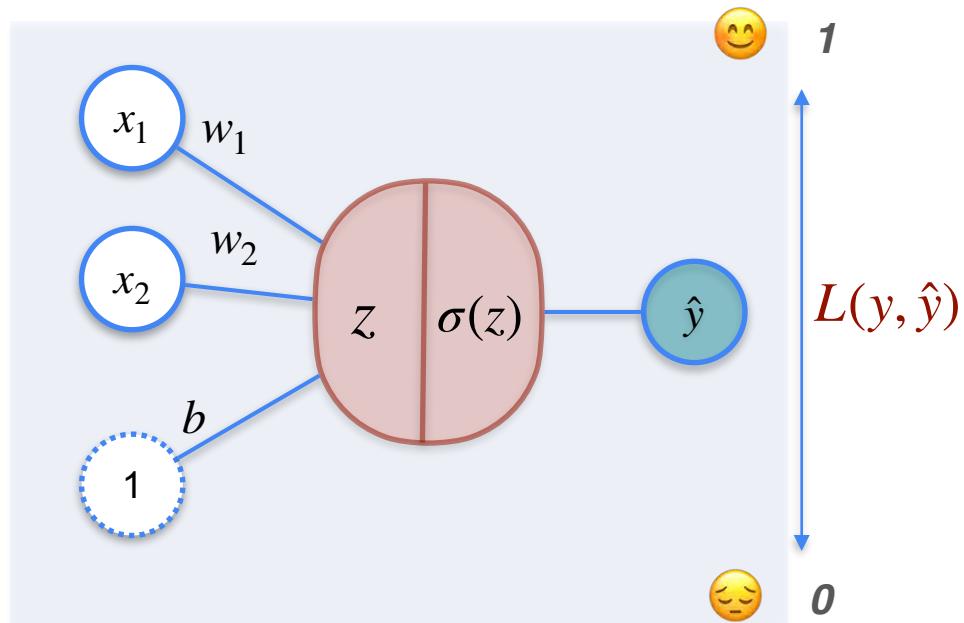


# Classification With a Perceptron

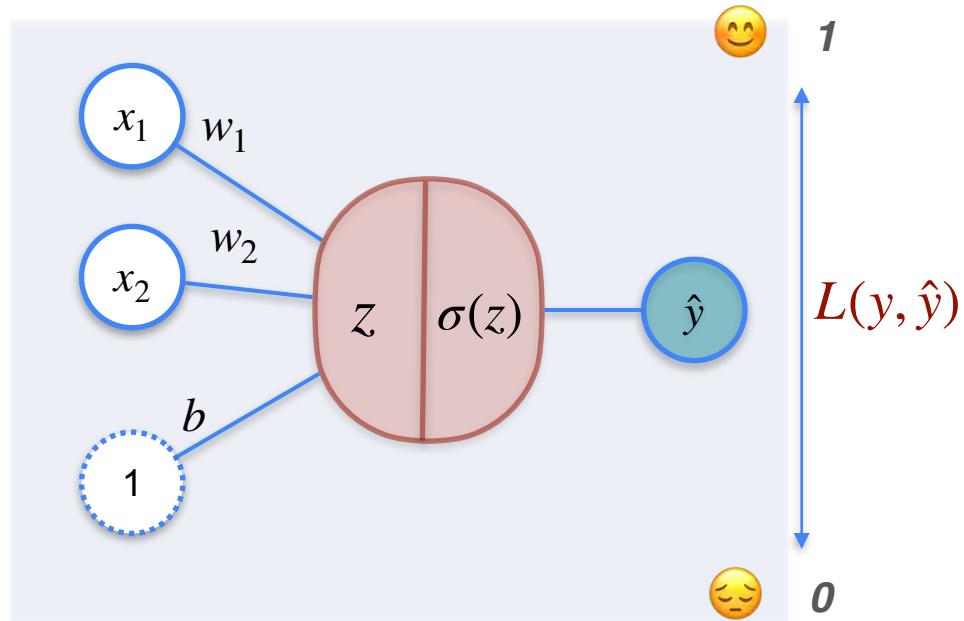
Aack beep beep beep



# Classification With a Perceptron



# Classification With a Perceptron

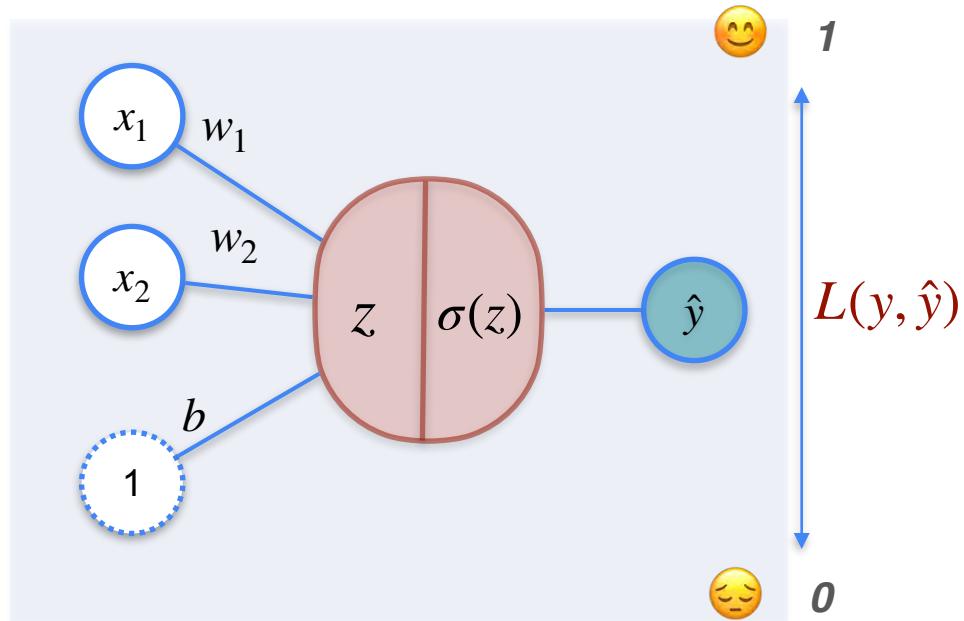


Prediction Function:

$$\hat{y}$$

$$L(y, \hat{y})$$

# Classification With a Perceptron

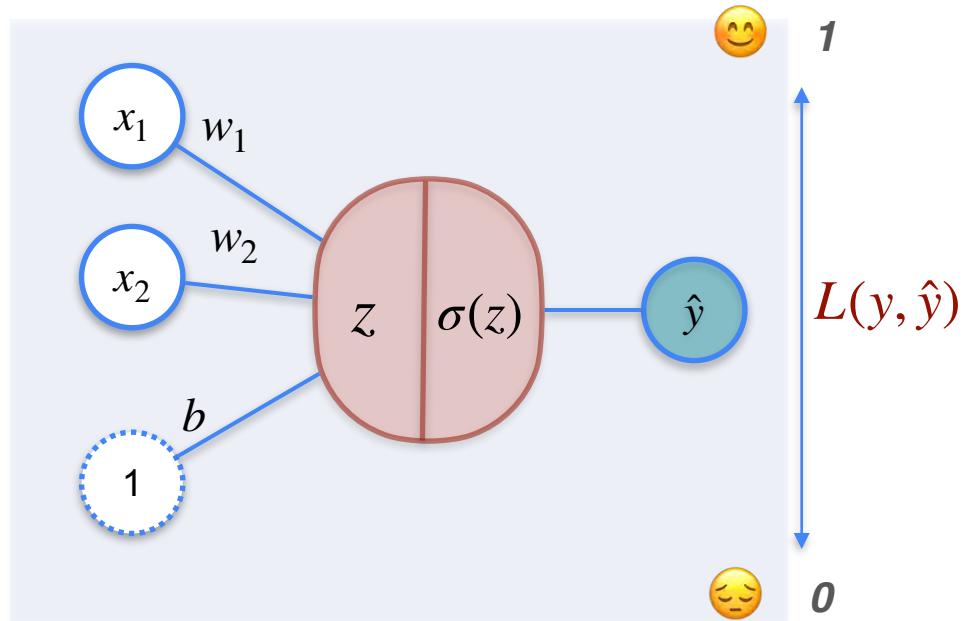


**Prediction Function:**

$$\hat{y} = \sigma(w_1x_1 + w_2x_2 + b)$$

$$L(y, \hat{y})$$

# Classification With a Perceptron



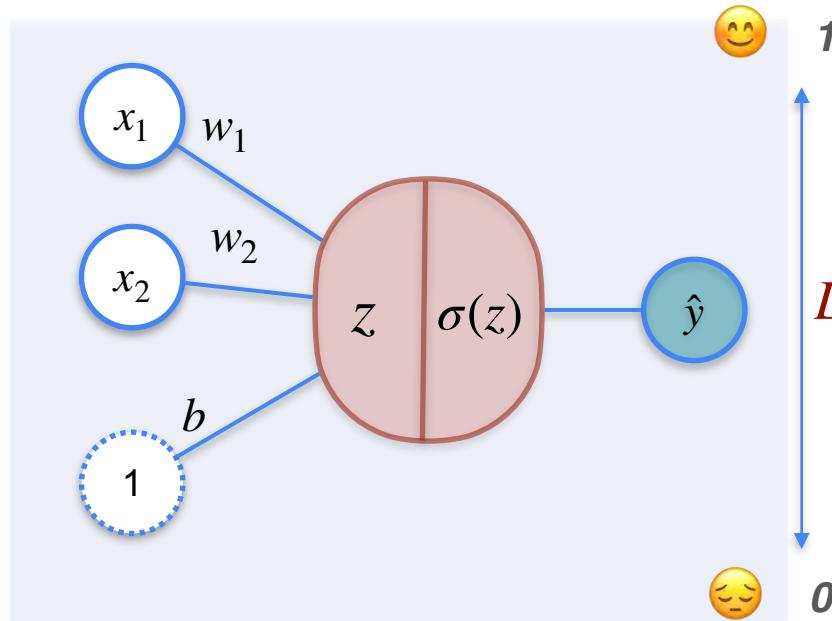
**Prediction Function:**

$$\hat{y} = \sigma(w_1x_1 + w_2x_2 + b)$$

**Loss Function:**

$$L(y, \hat{y})$$

# Classification With a Perceptron



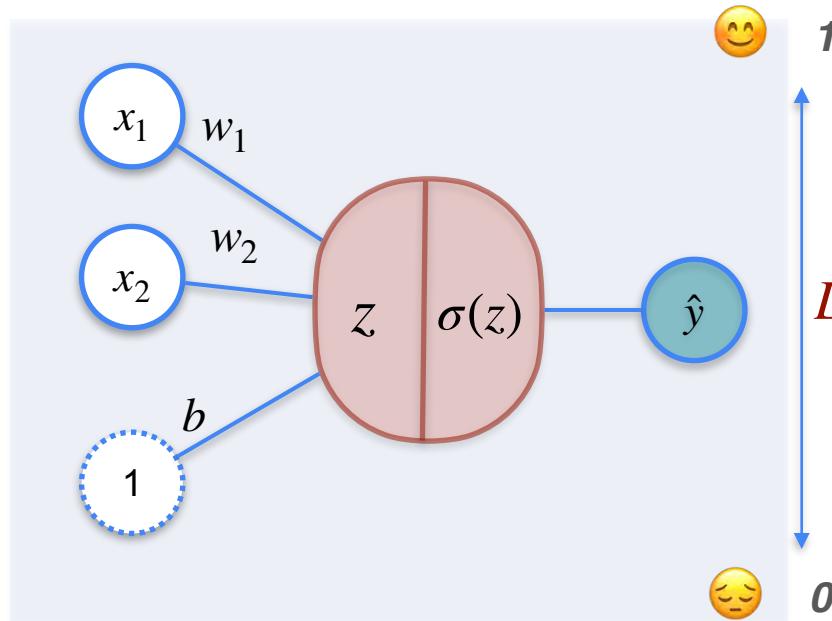
**Prediction Function:**

$$\hat{y} = \sigma(w_1x_1 + w_2x_2 + b)$$

**Loss Function:**

$$L(y, \hat{y}) = -y \ln(\hat{y}) - (1 - y) \ln(1 - \hat{y})$$

# Classification With a Perceptron



**Prediction Function:**

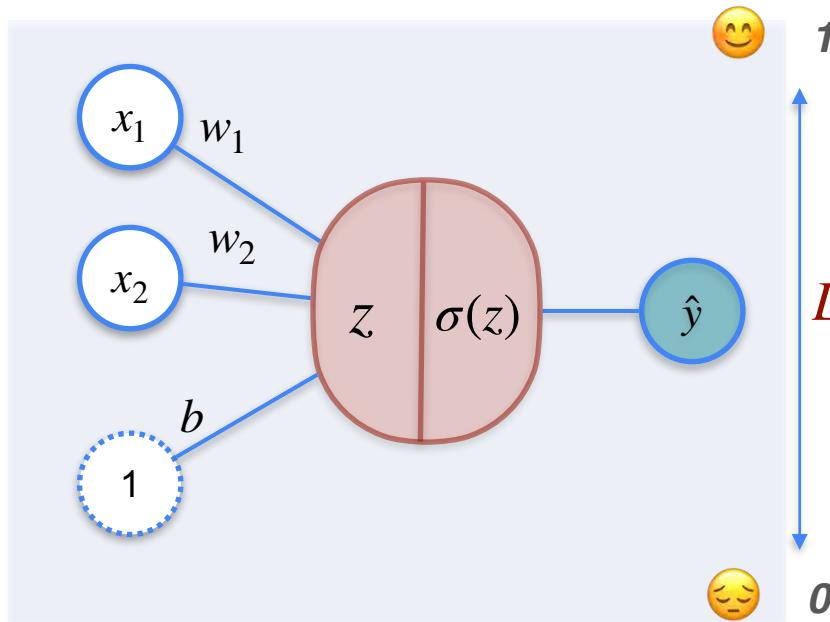
$$\hat{y} = \sigma(w_1x_1 + w_2x_2 + b)$$

**Loss Function:**

$$L(y, \hat{y}) = -y \ln(\hat{y}) - (1 - y) \ln(1 - \hat{y})$$

**Main Goal:**

# Classification With a Perceptron



**Prediction Function:**

$$\hat{y} = \sigma(w_1x_1 + w_2x_2 + b)$$

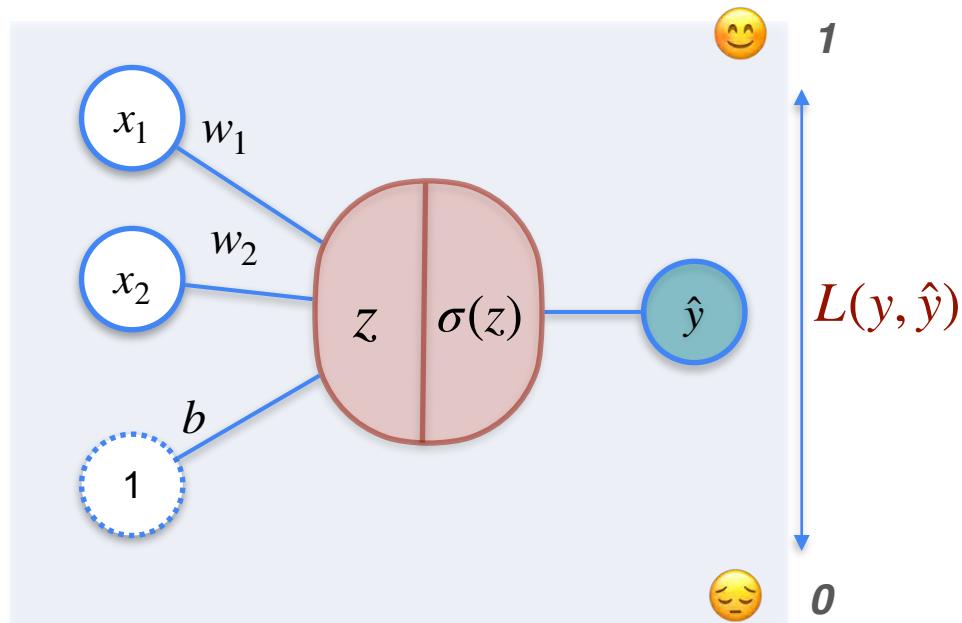
**Loss Function:**

$$L(y, \hat{y}) = -y \ln(\hat{y}) - (1 - y) \ln(1 - \hat{y})$$

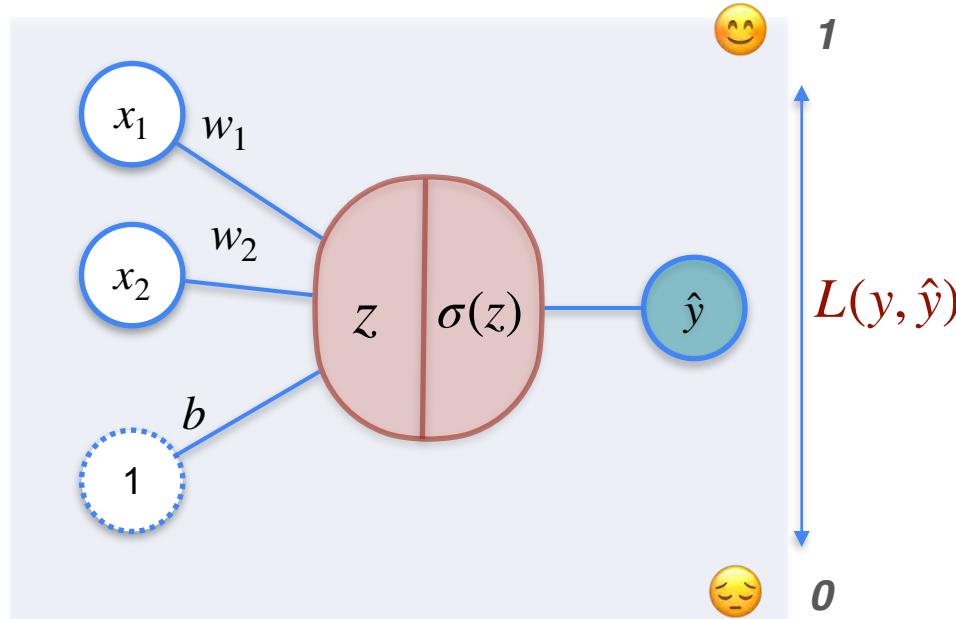
**Main Goal:**

Find  $w_1, w_2, b$  that give  $\hat{y}$  with the least error

# Classification With a Perceptron

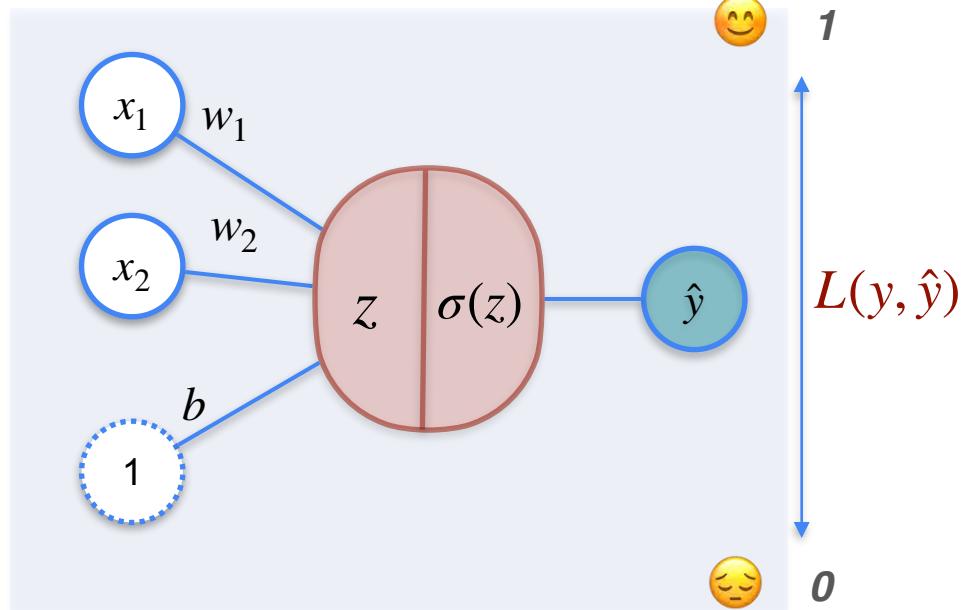


# Classification With a Perceptron



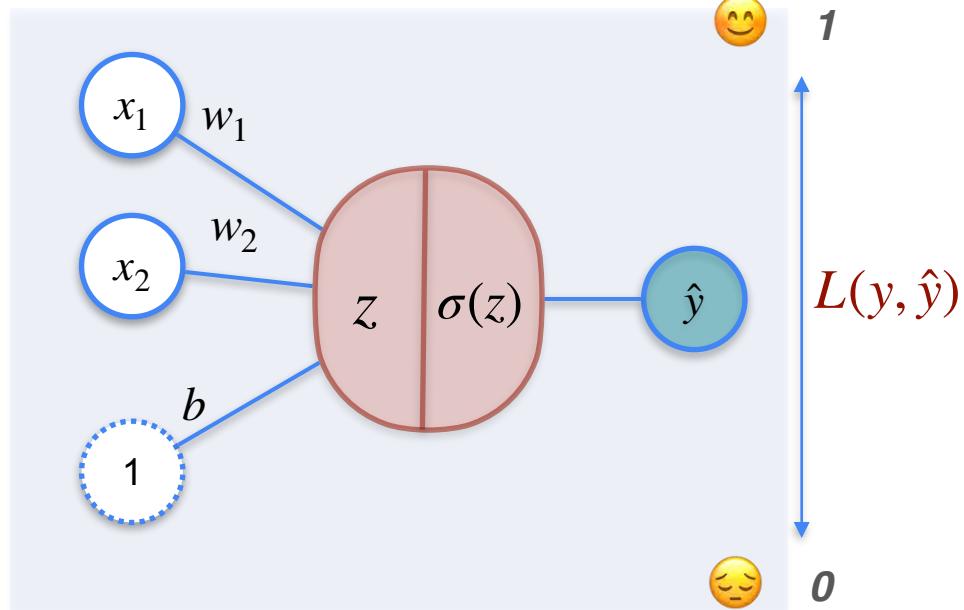
To find optimal values for:

# Classification With a Perceptron



To find optimal values for:  
 $w_1$  ,  $w_2$  ,  $b$

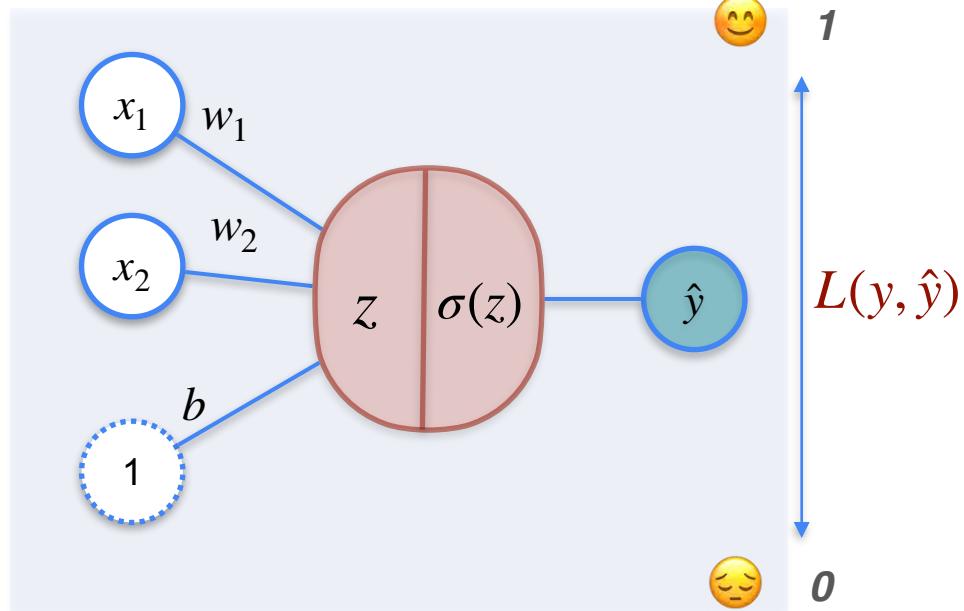
# Classification With a Perceptron



To find optimal values for:  
 $w_1$  ,  $w_2$  ,  $b$

*You need gradient descent*

# Classification With a Perceptron

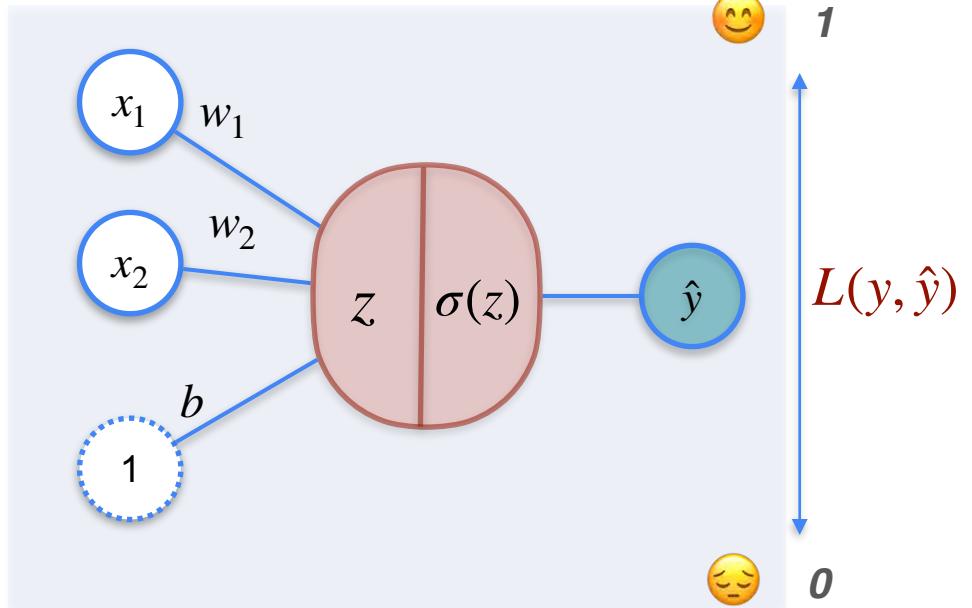


To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha \frac{\partial L}{\partial w_1}$$

# Classification With a Perceptron



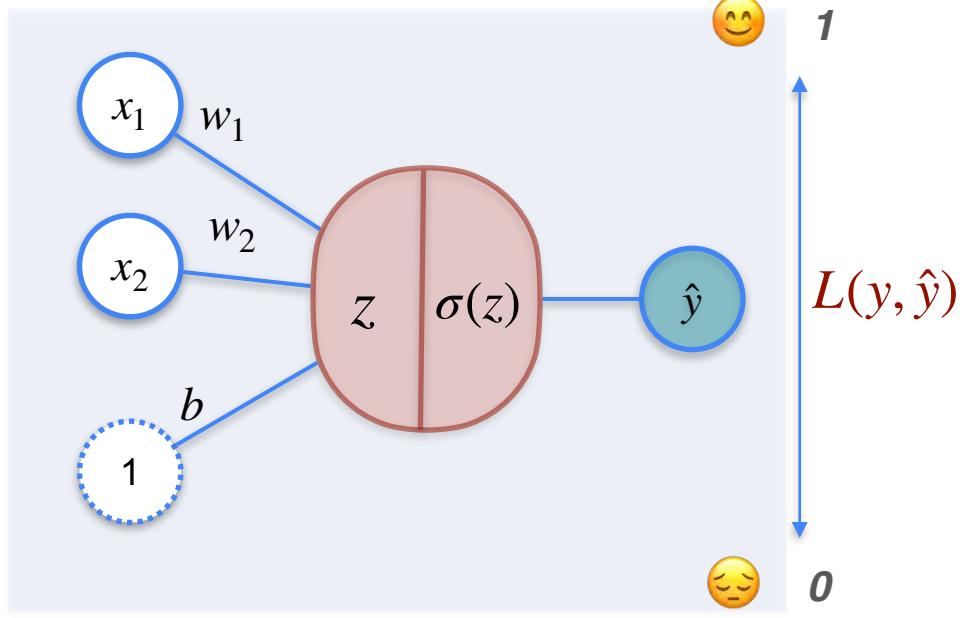
To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha \frac{\partial L}{\partial w_1}$$

$$w_2 \rightarrow w_2 - \alpha \frac{\partial L}{\partial w_2}$$

# Classification With a Perceptron



To find optimal values for:  
 $w_1, w_2, b$

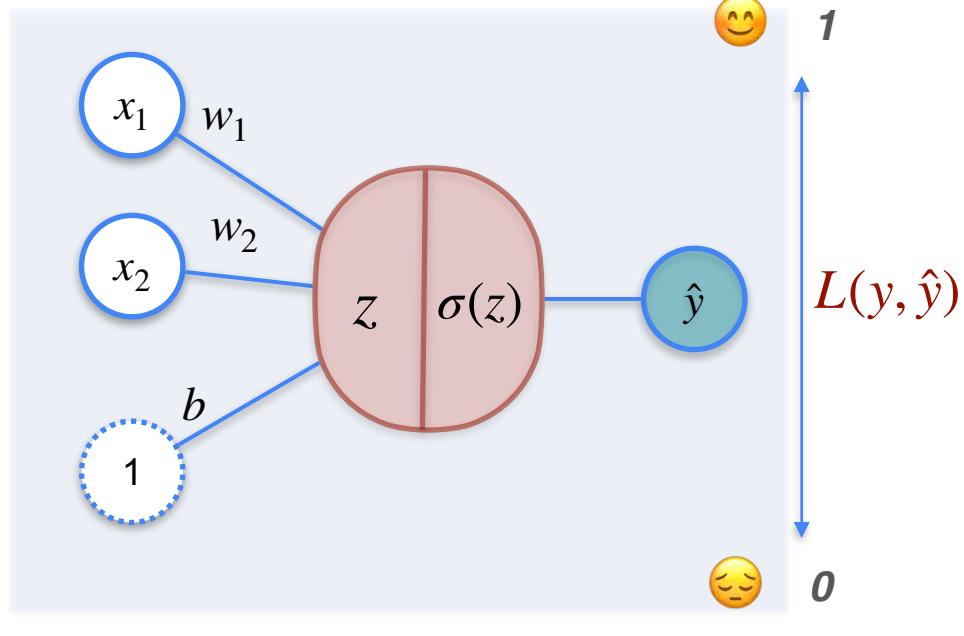
*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha \frac{\partial L}{\partial w_1}$$

$$w_2 \rightarrow w_2 - \alpha \frac{\partial L}{\partial w_2}$$

$$b \rightarrow b - \alpha \frac{\partial L}{\partial b}$$

# Classification With a Perceptron



To find optimal values for:  
 $w_1, w_2, b$

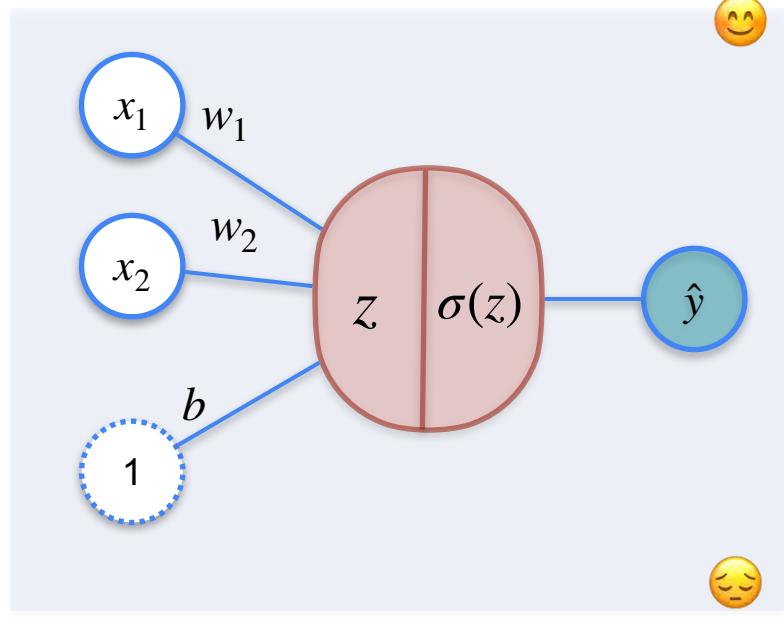
*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha \frac{\partial L}{\partial w_1}$$

$$w_2 \rightarrow w_2 - \alpha \frac{\partial L}{\partial w_2}$$

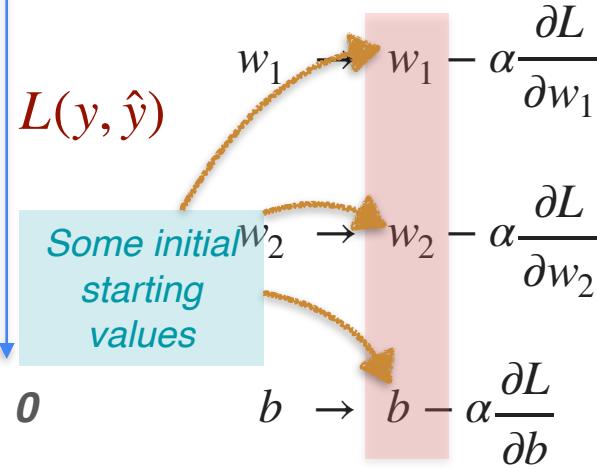
$$b \rightarrow b - \alpha \frac{\partial L}{\partial b}$$

# Classification With a Perceptron

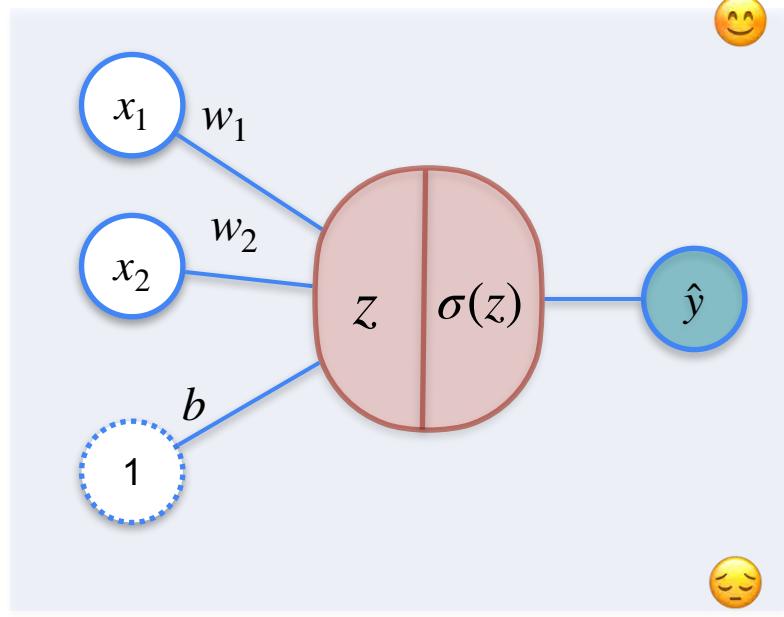


To find optimal values for:  
 $w_1$  ,  $w_2$  ,  $b$

**You need gradient descent**

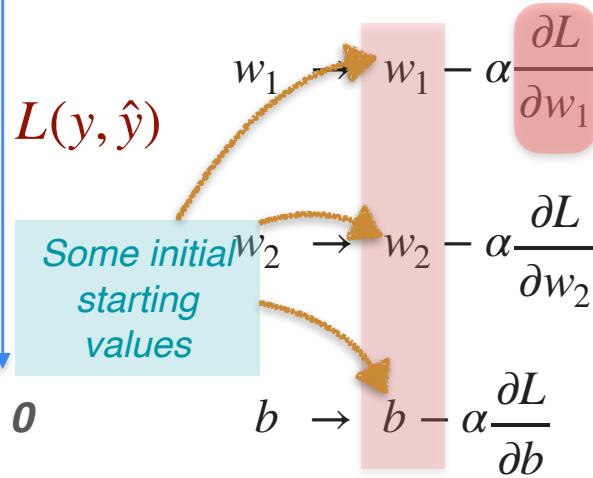


# Classification With a Perceptron

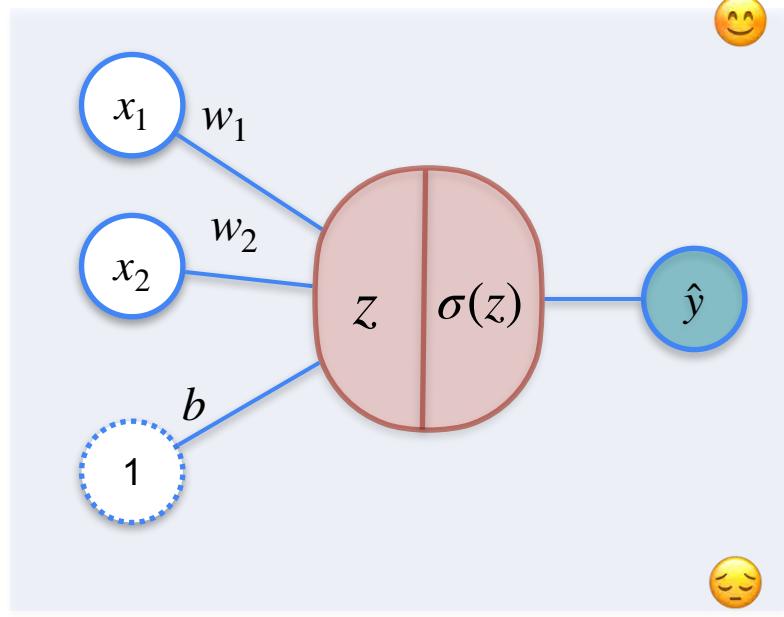


To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

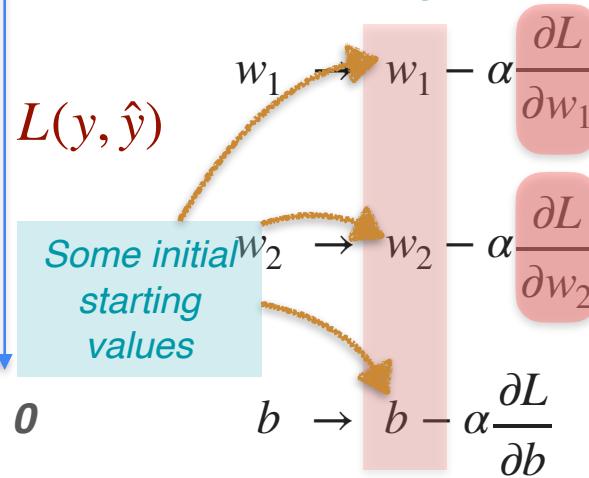


# Classification With a Perceptron

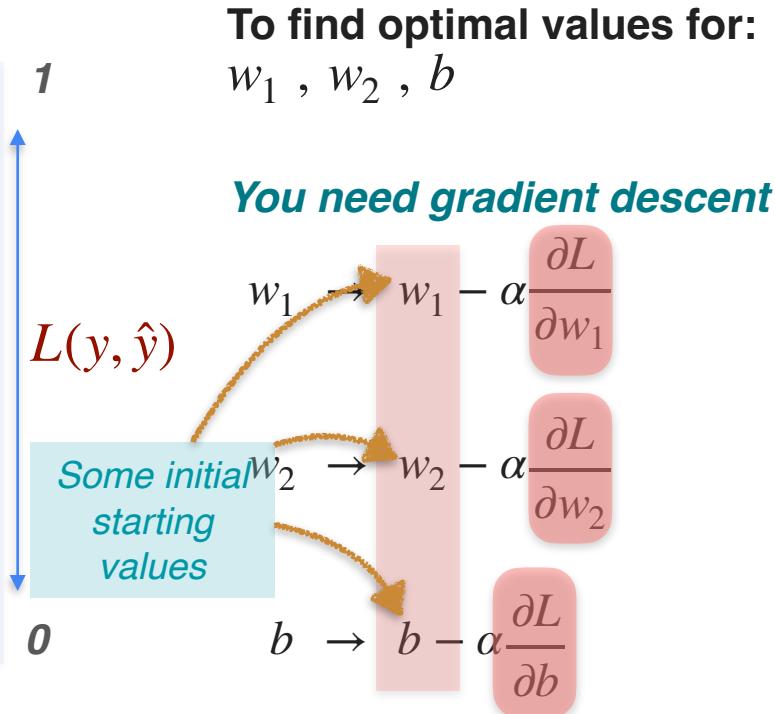
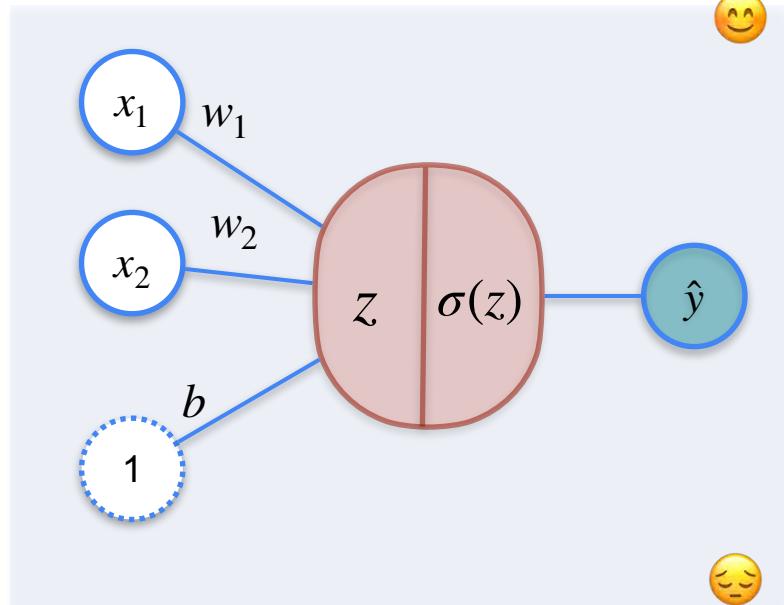


To find optimal values for:  
 $w_1$  ,  $w_2$  ,  $b$

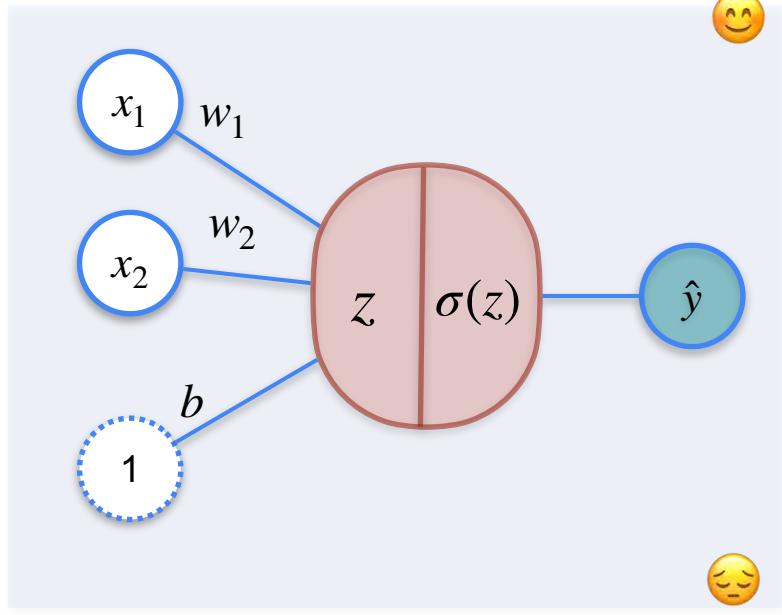
*You need gradient descent*



# Classification With a Perceptron

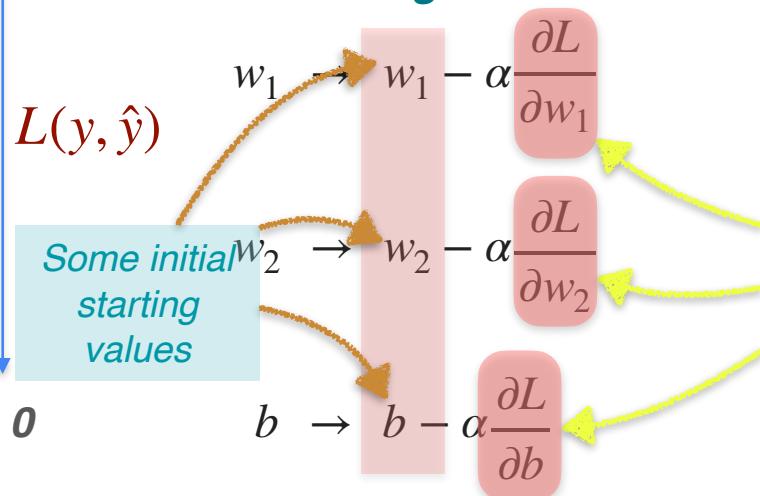


# Classification With a Perceptron



To find optimal values for:  
 $w_1, w_2, b$

**You need gradient descent**



## SUB-TASK

Find the  
following  
partial  
derivatives



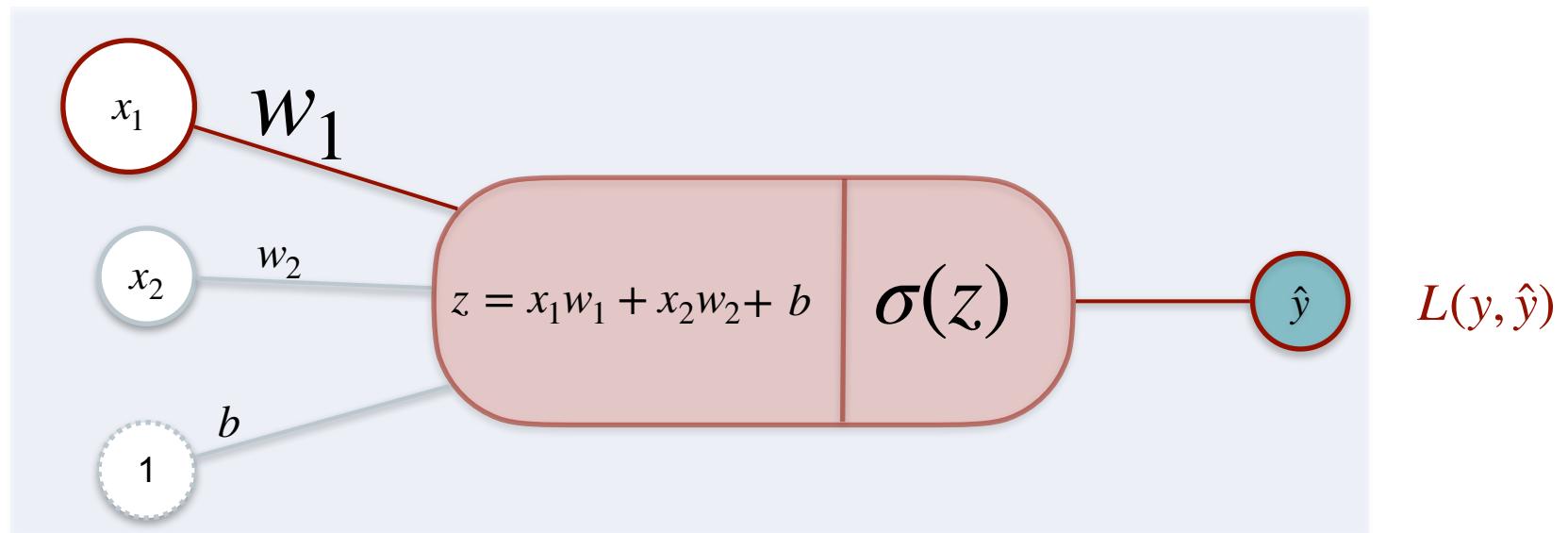
DeepLearning.AI

# Optimization in Neural Networks and Newton's Method

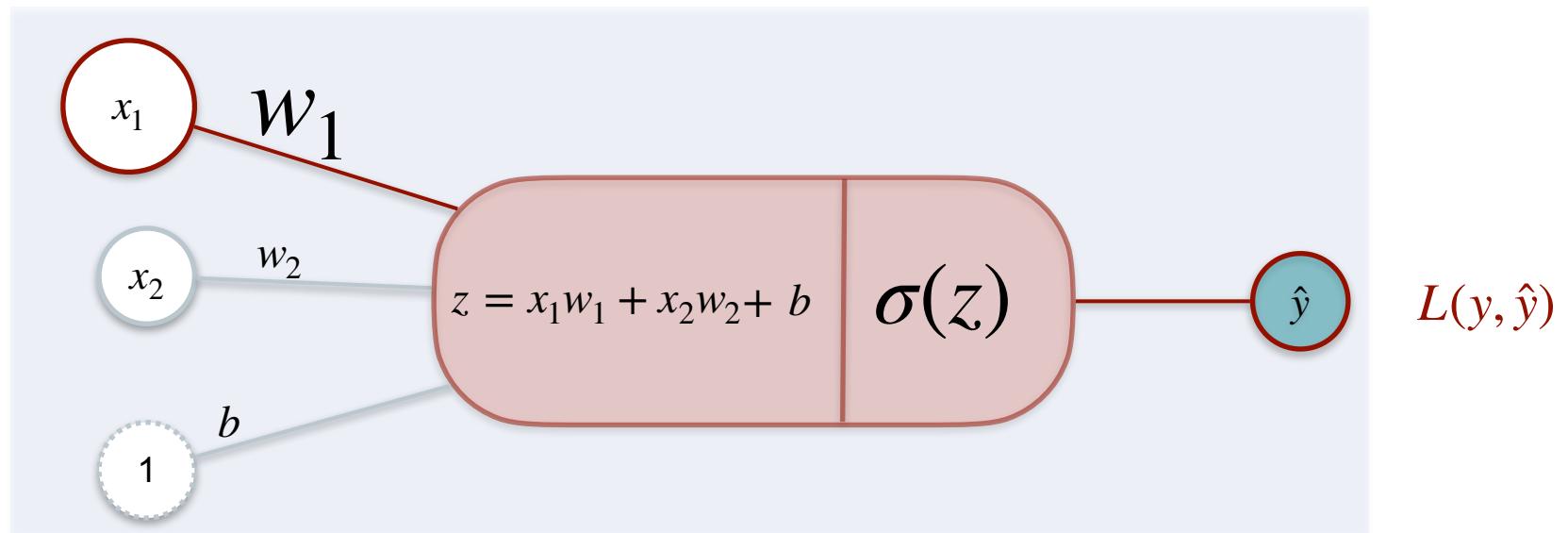
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**Classification with a  
perceptron:  
Calculating the derivatives**

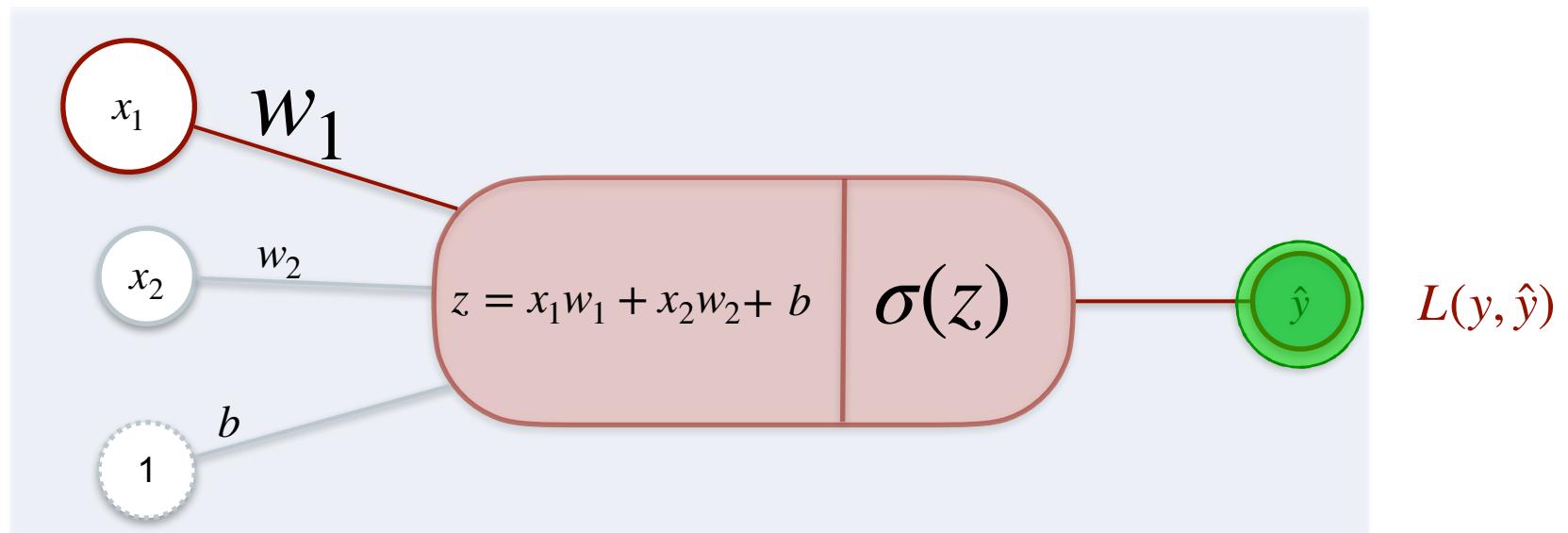
# Classification With a Perceptron



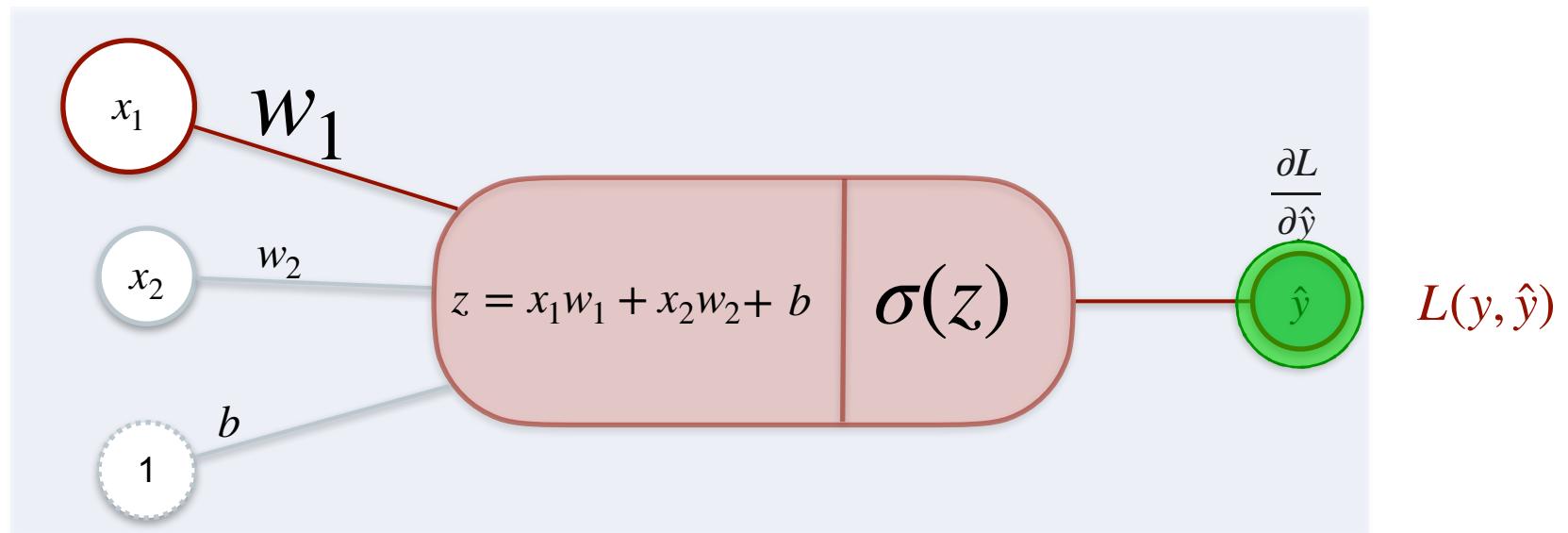
# Classification With a Perceptron



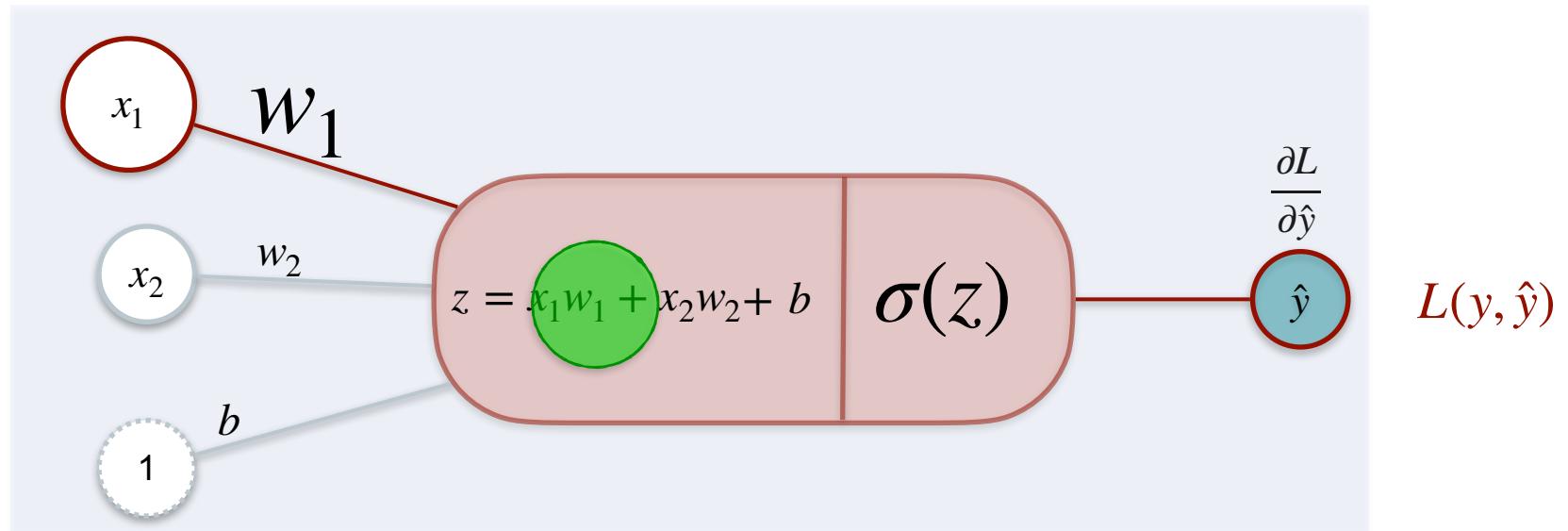
# Classification With a Perceptron



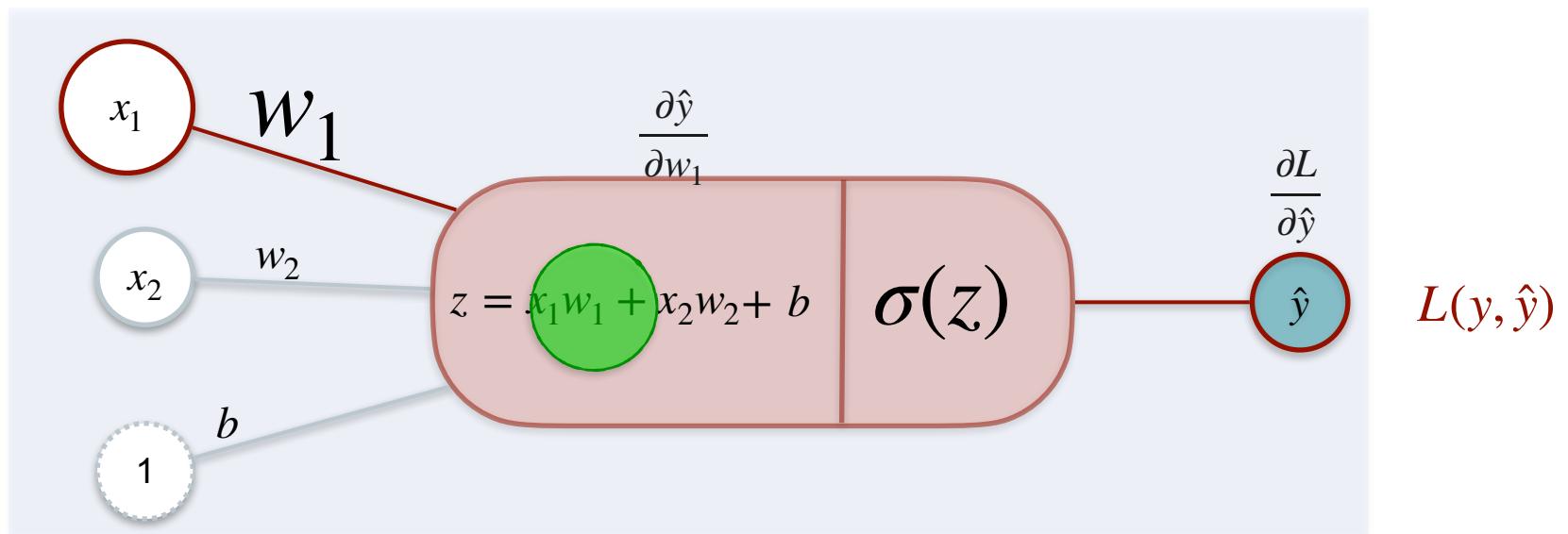
# Classification With a Perceptron



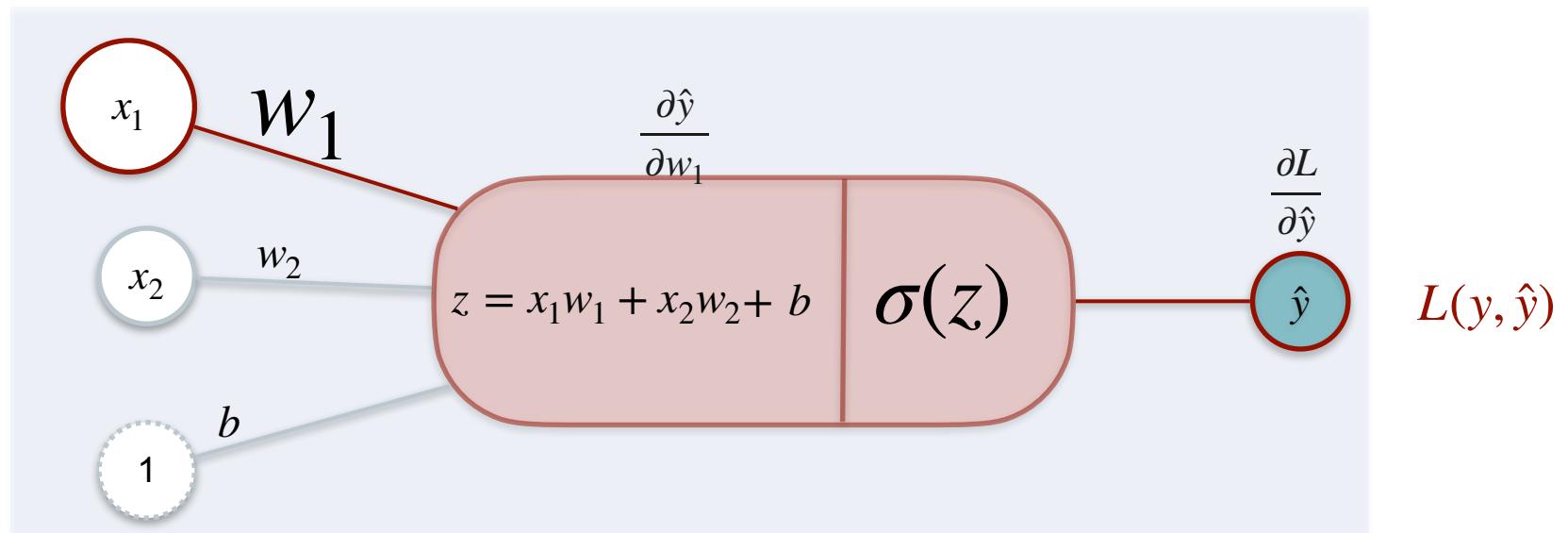
# Classification With a Perceptron



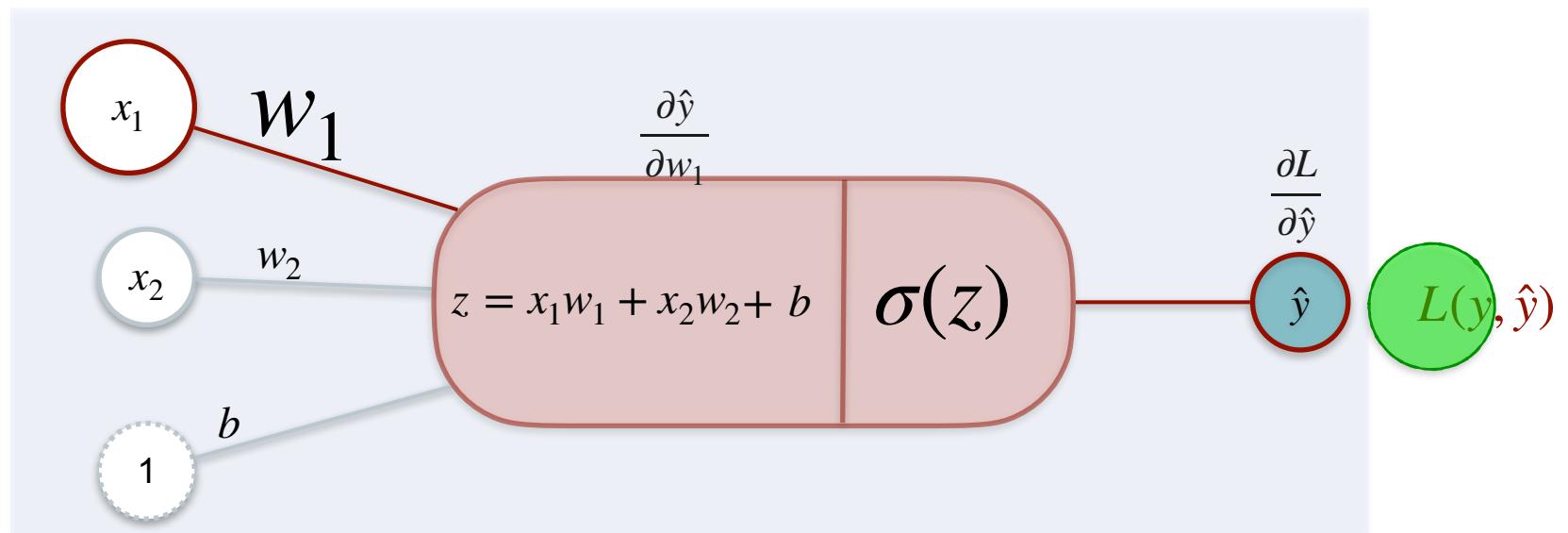
# Classification With a Perceptron



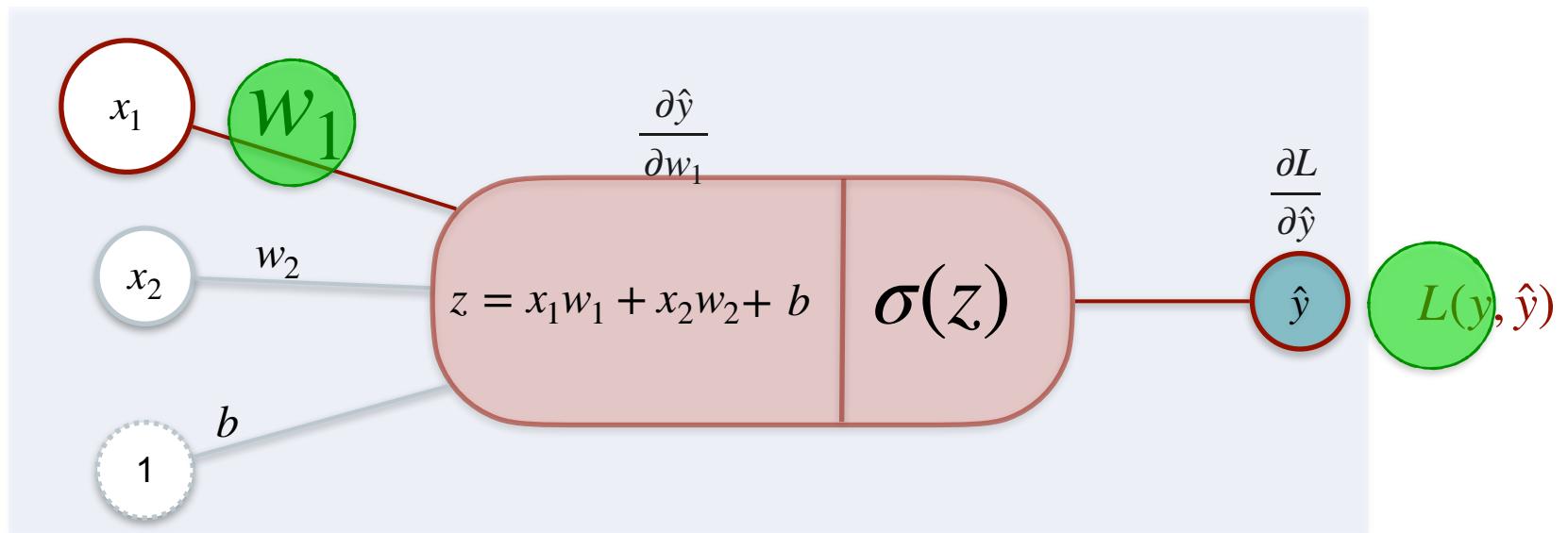
# Classification With a Perceptron



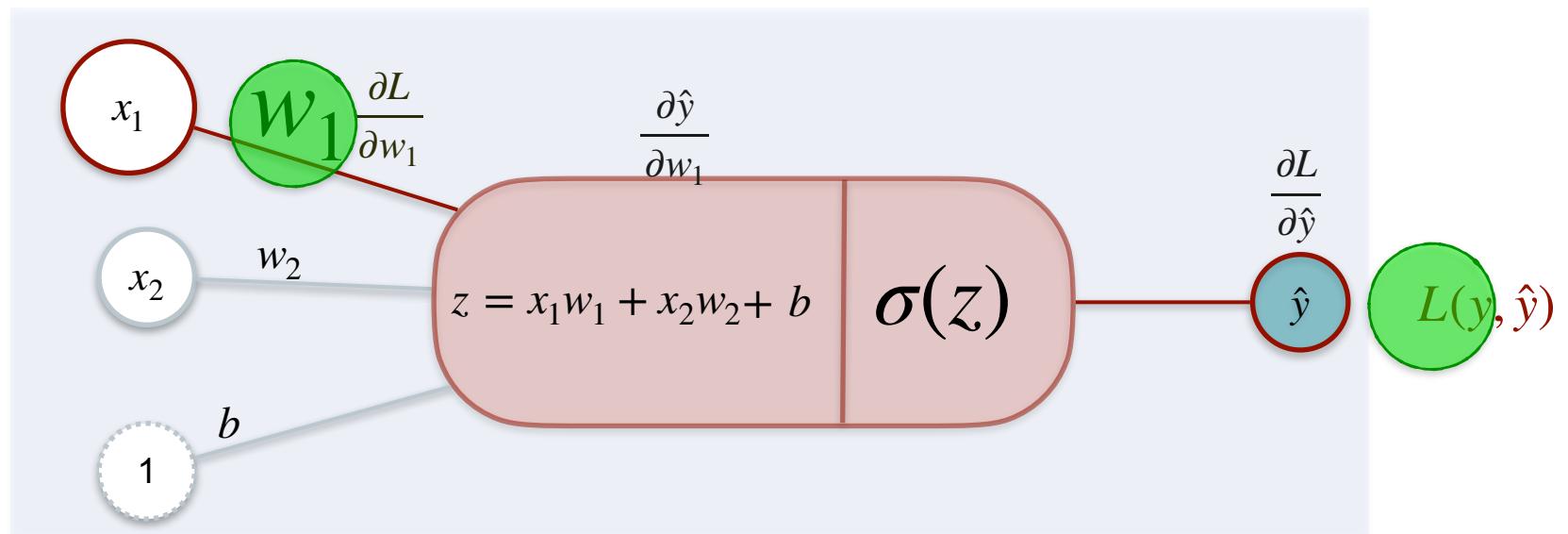
# Classification With a Perceptron



# Classification With a Perceptron

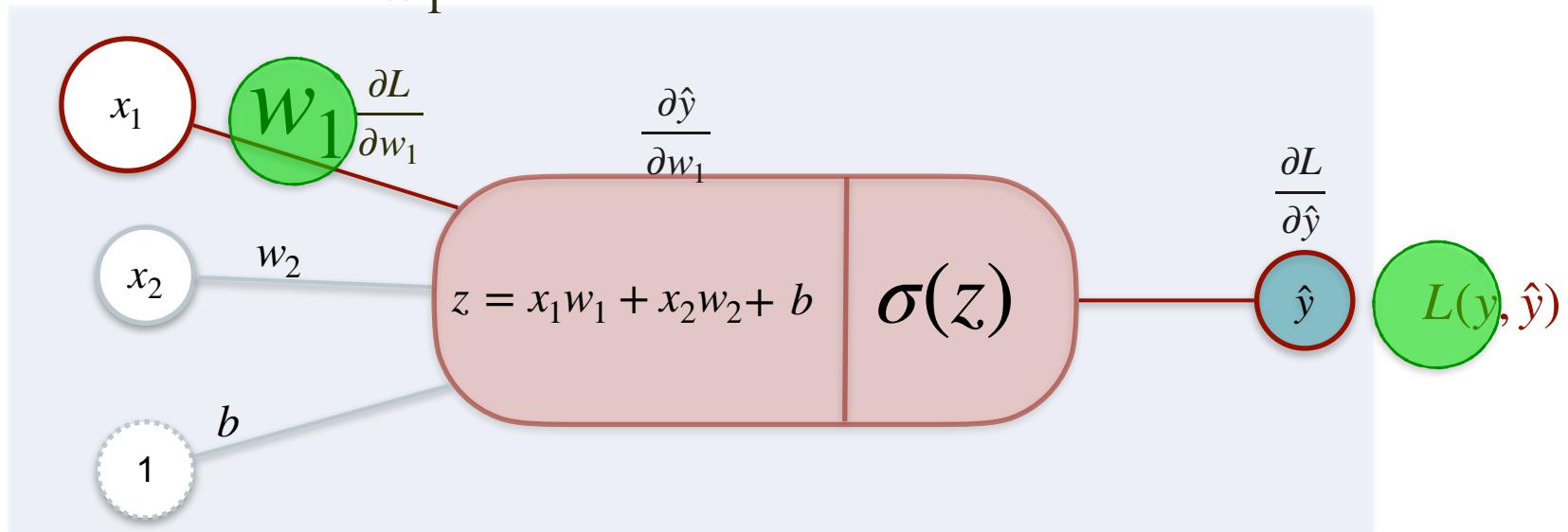


# Classification With a Perceptron



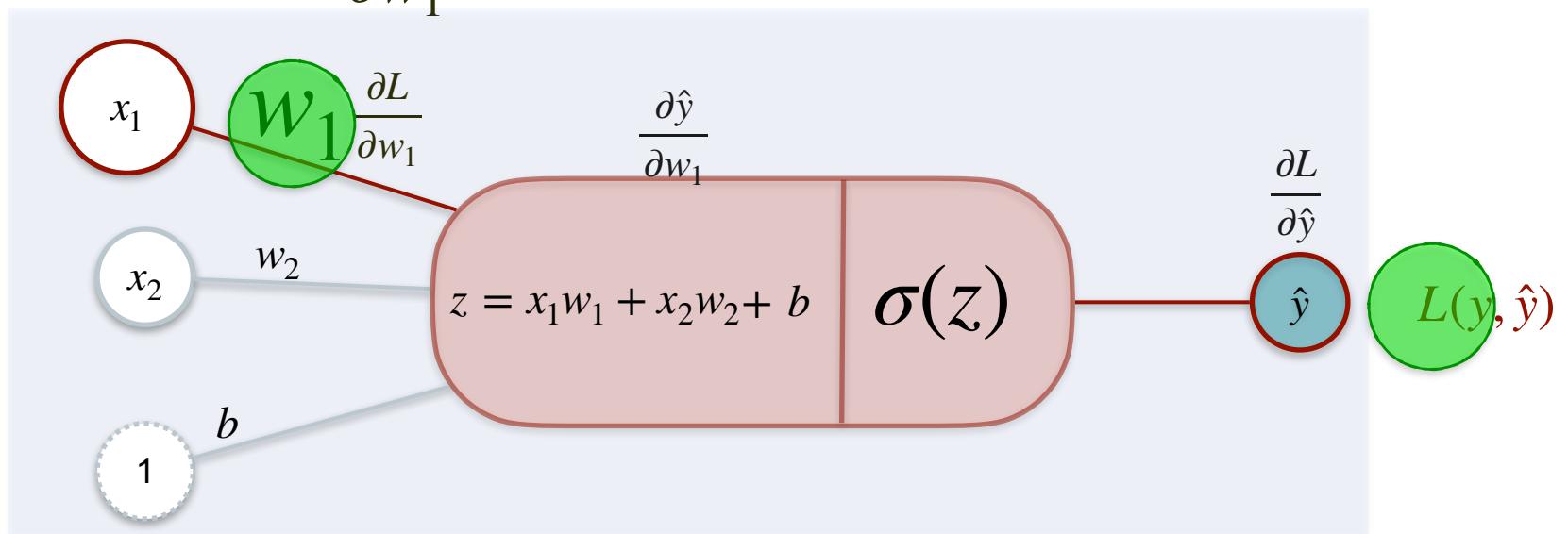
# Classification With a Perceptron

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



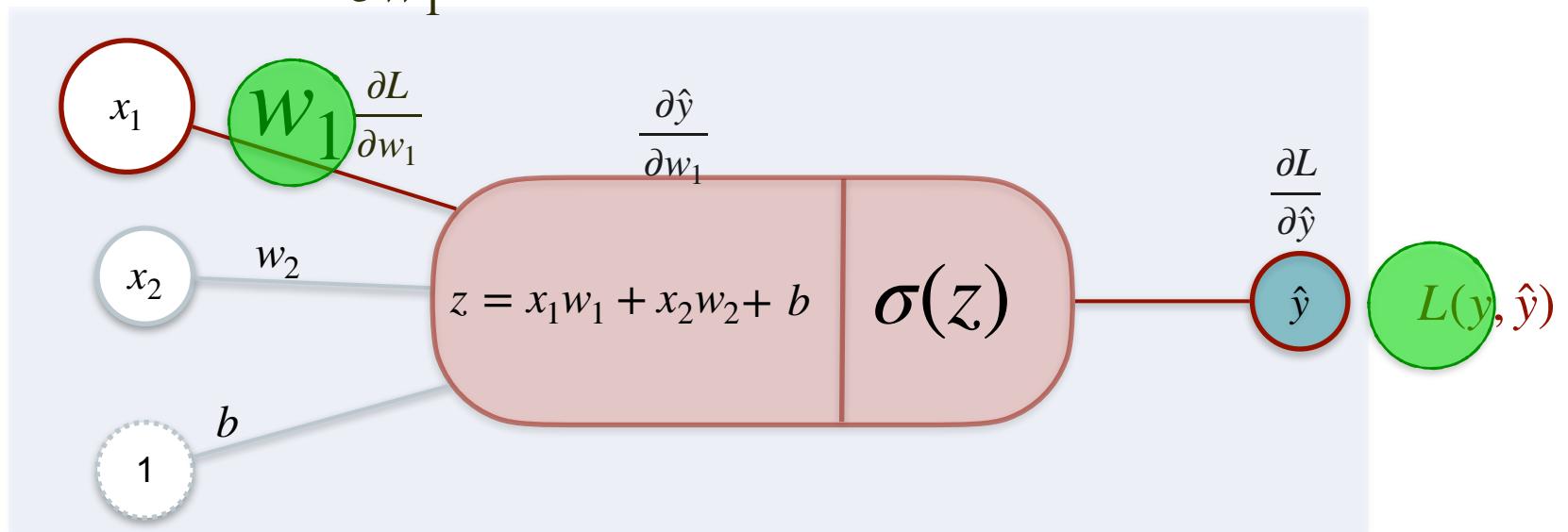
# Classification With a Perceptron

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



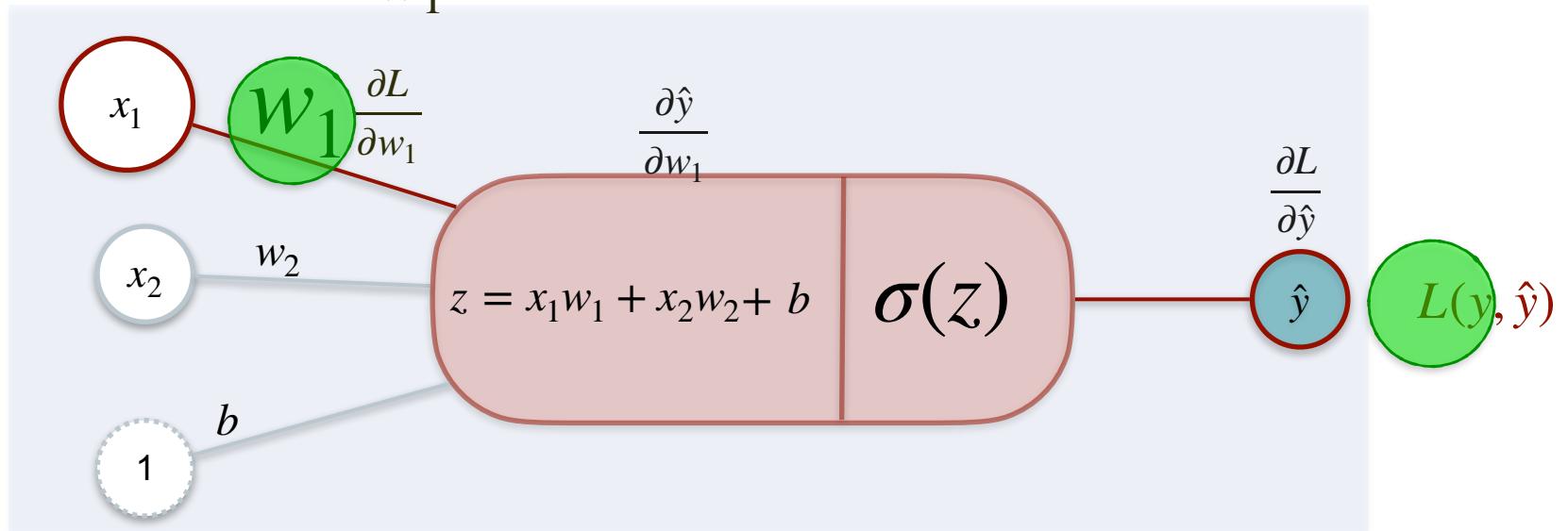
# Classification With a Perceptron

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}}$$



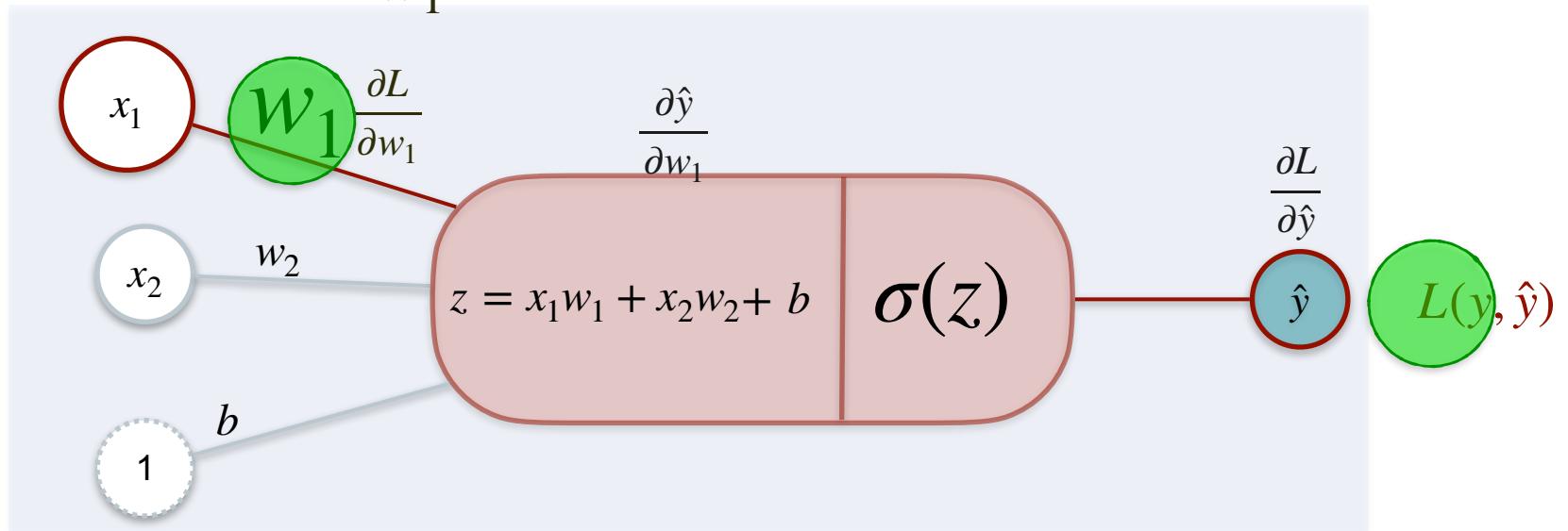
# Classification With a Perceptron

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot$$

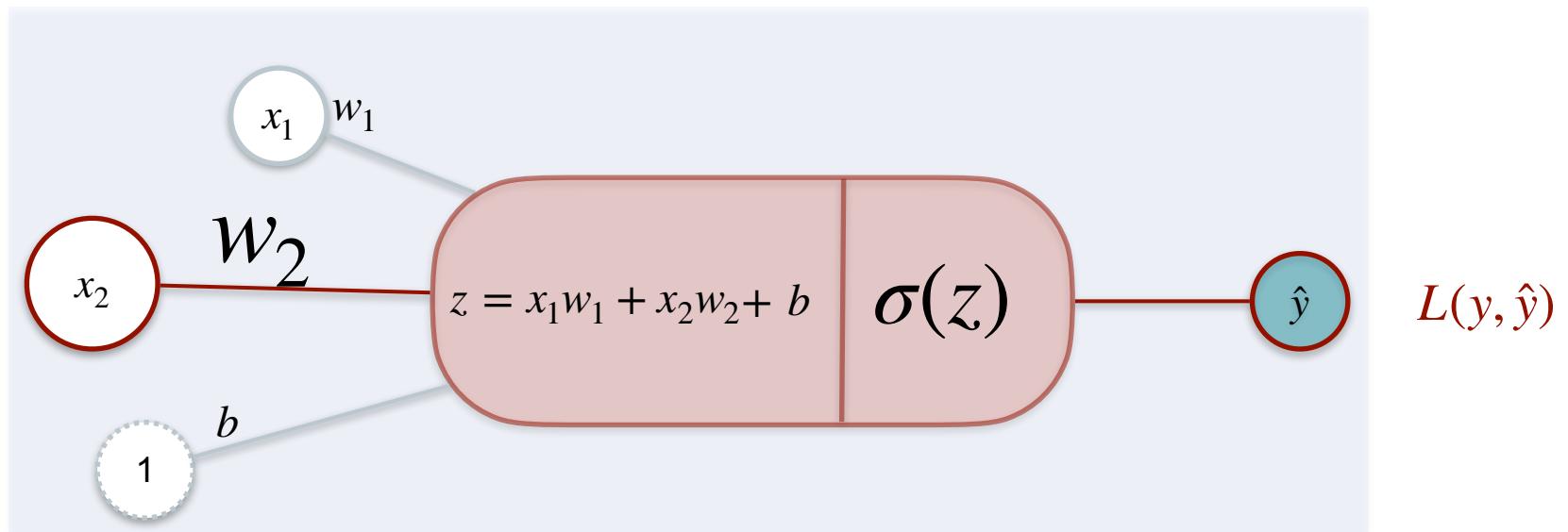


# Classification With a Perceptron

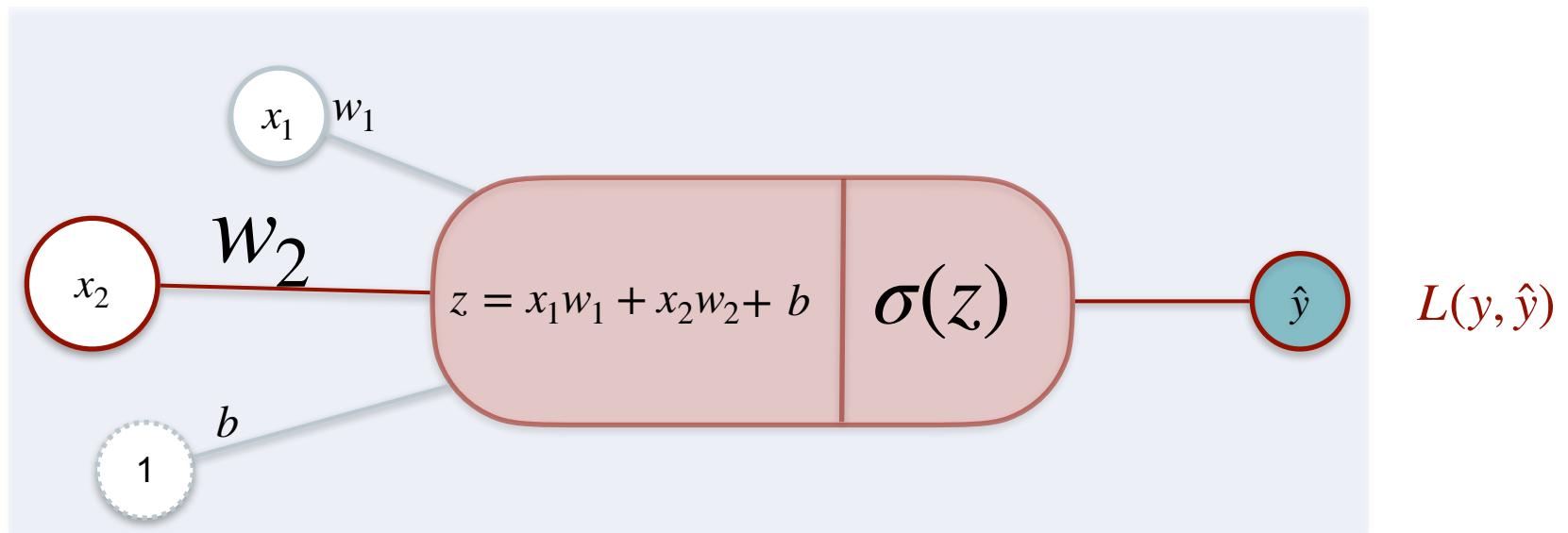
$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1}$$



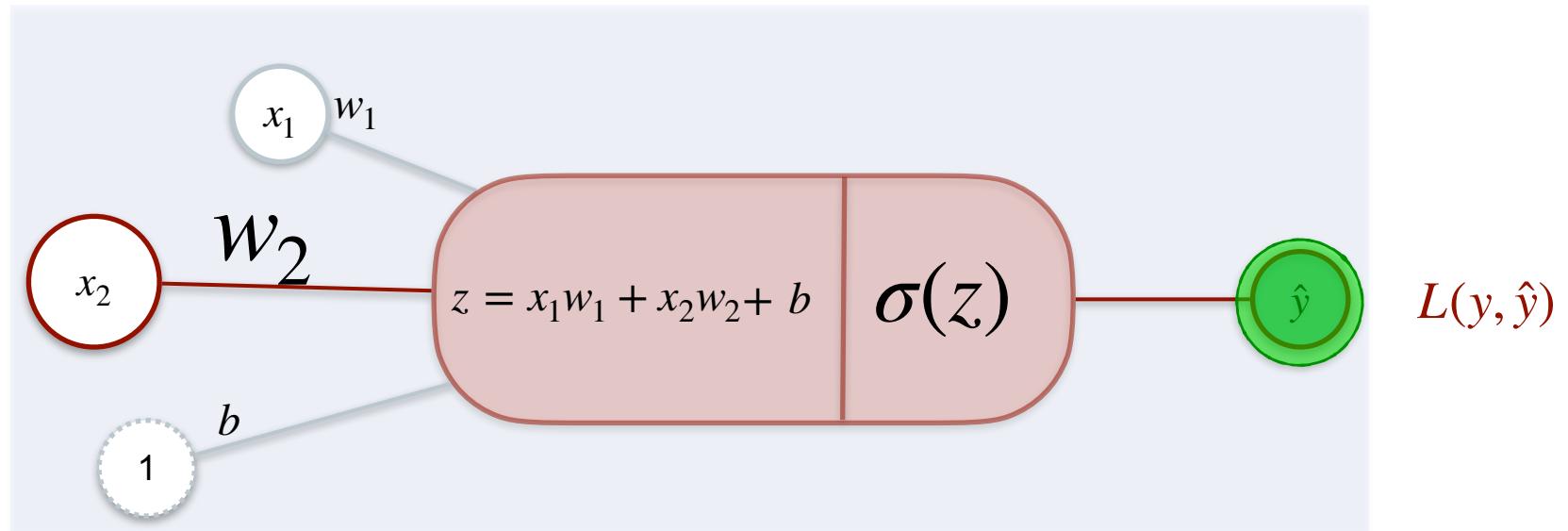
# Classification With a Perceptron



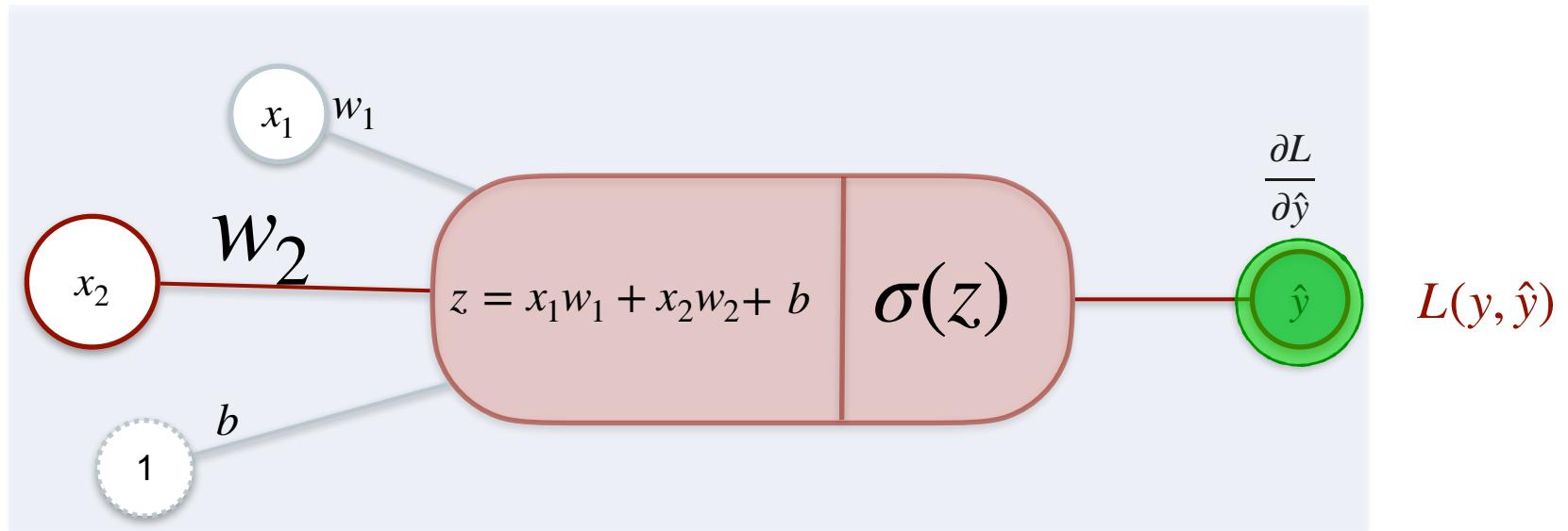
# Classification With a Perceptron



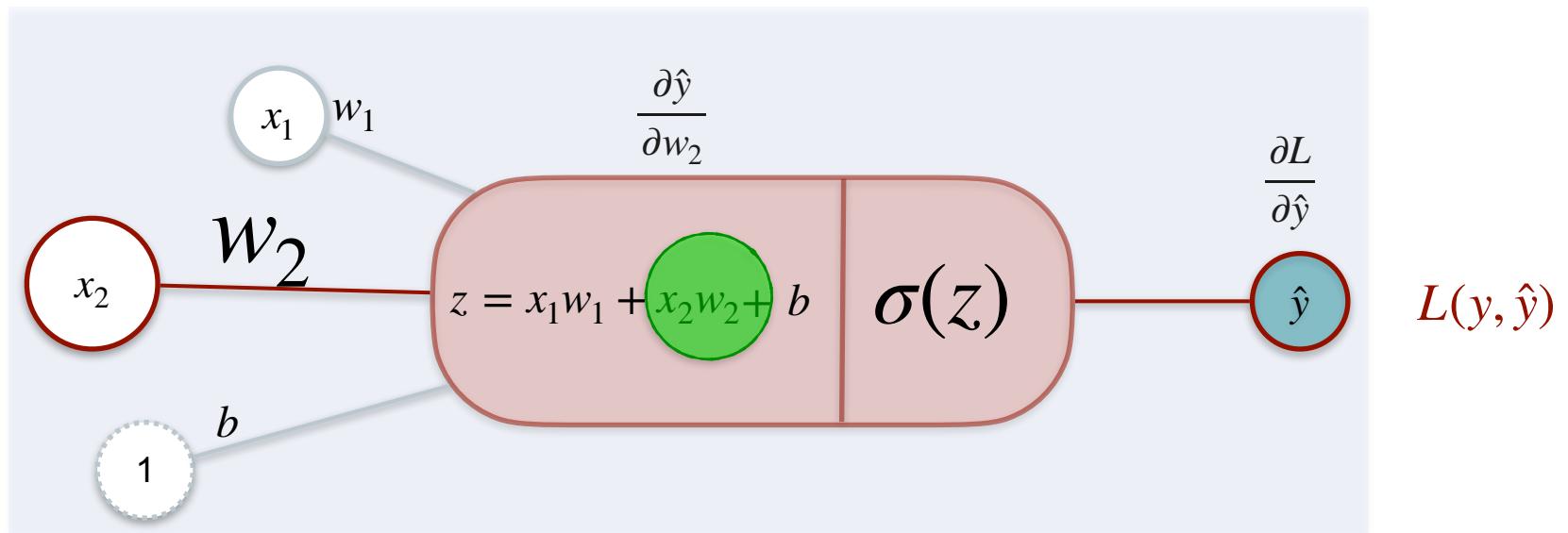
# Classification With a Perceptron



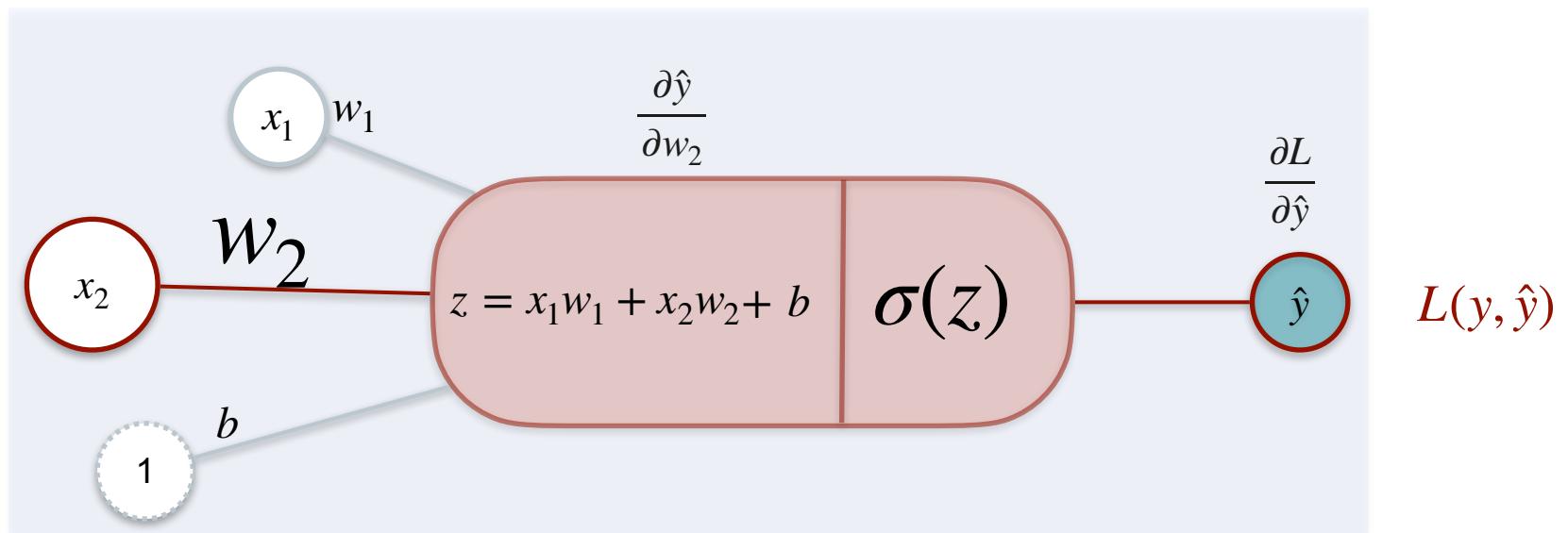
# Classification With a Perceptron



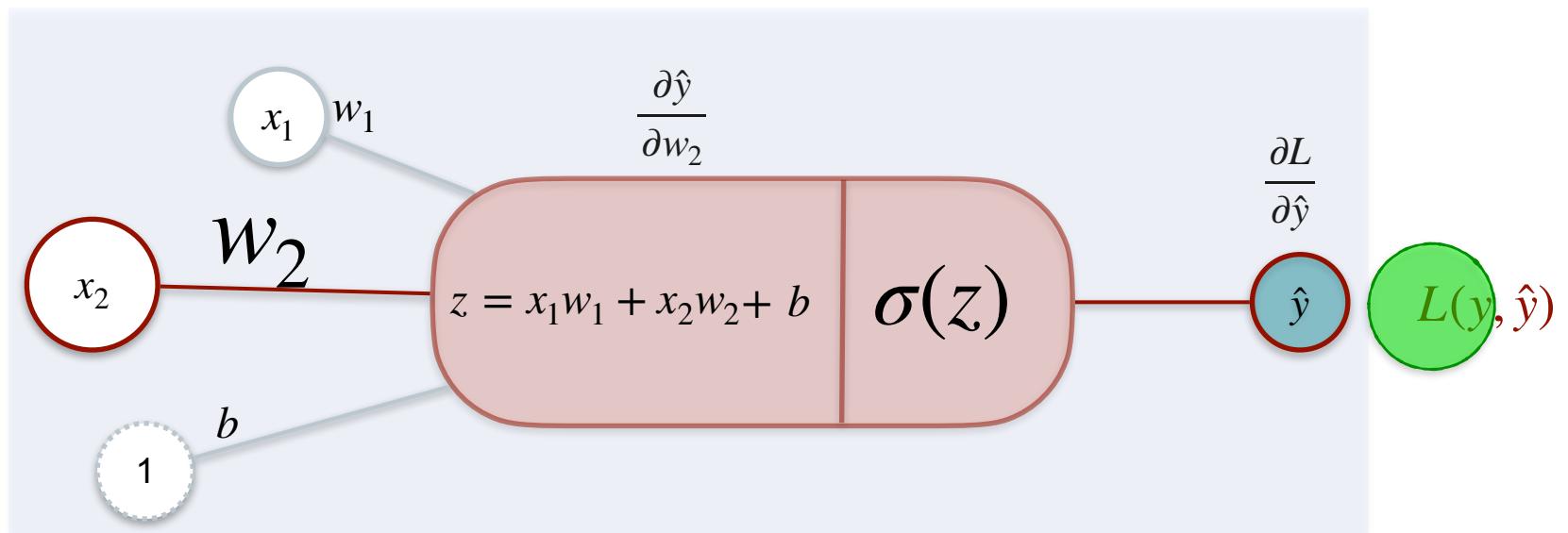
# Classification With a Perceptron



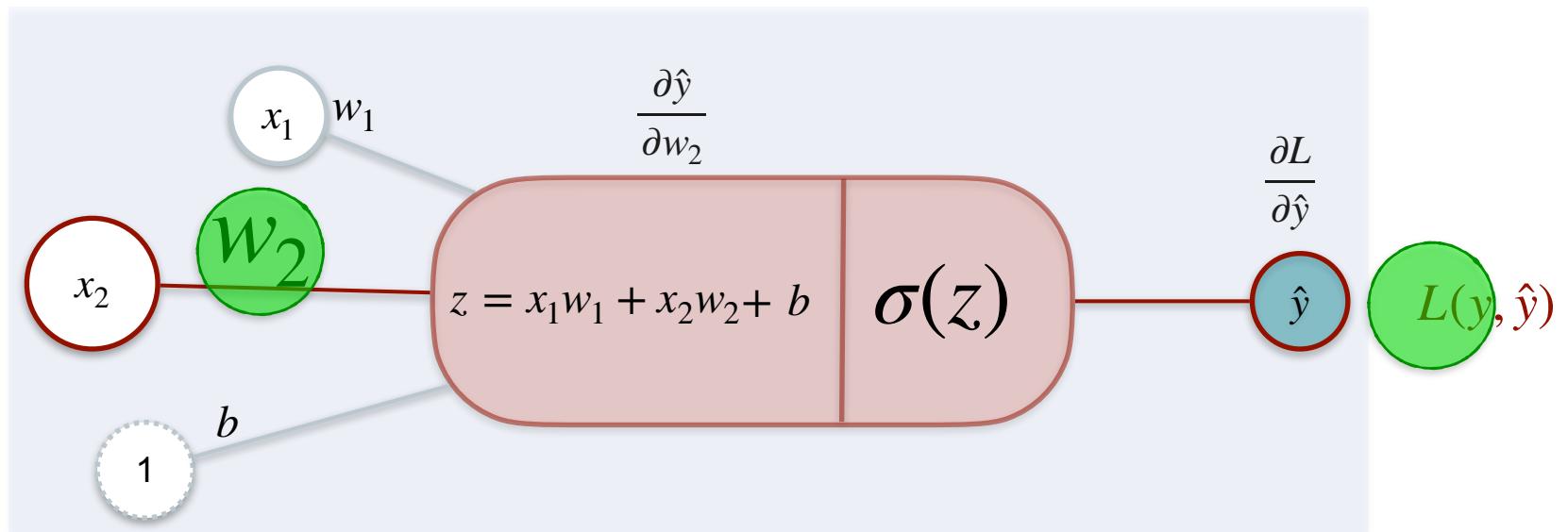
# Classification With a Perceptron



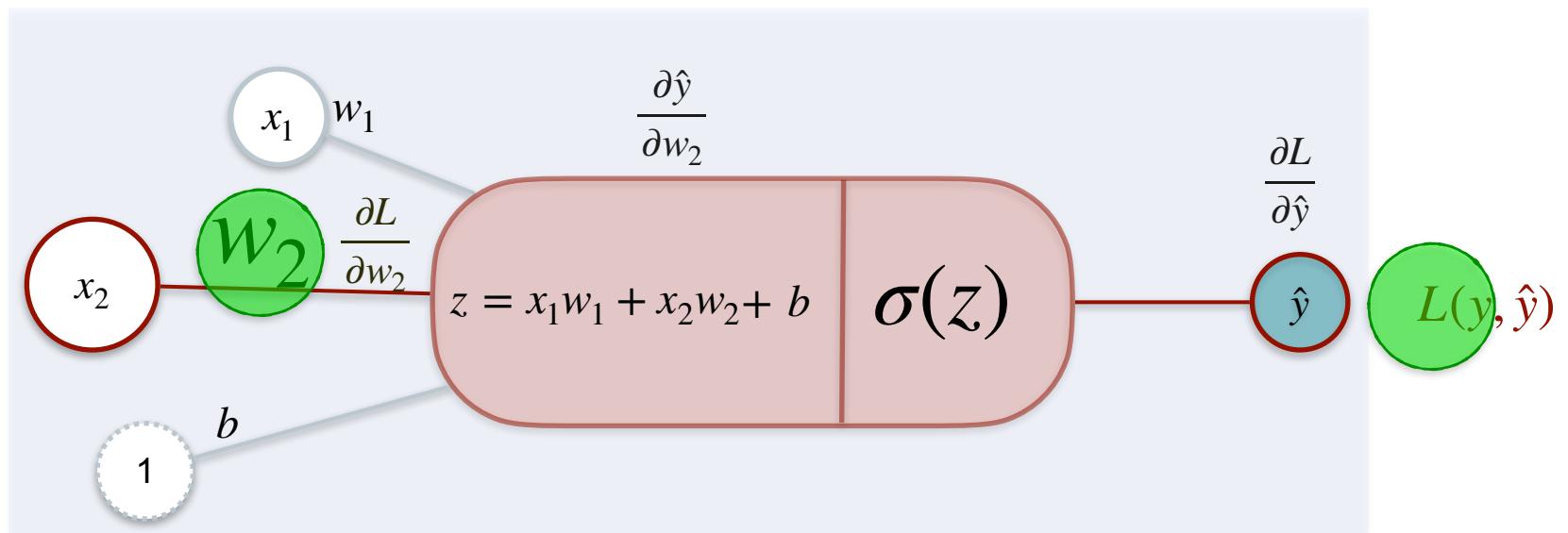
# Classification With a Perceptron



# Classification With a Perceptron

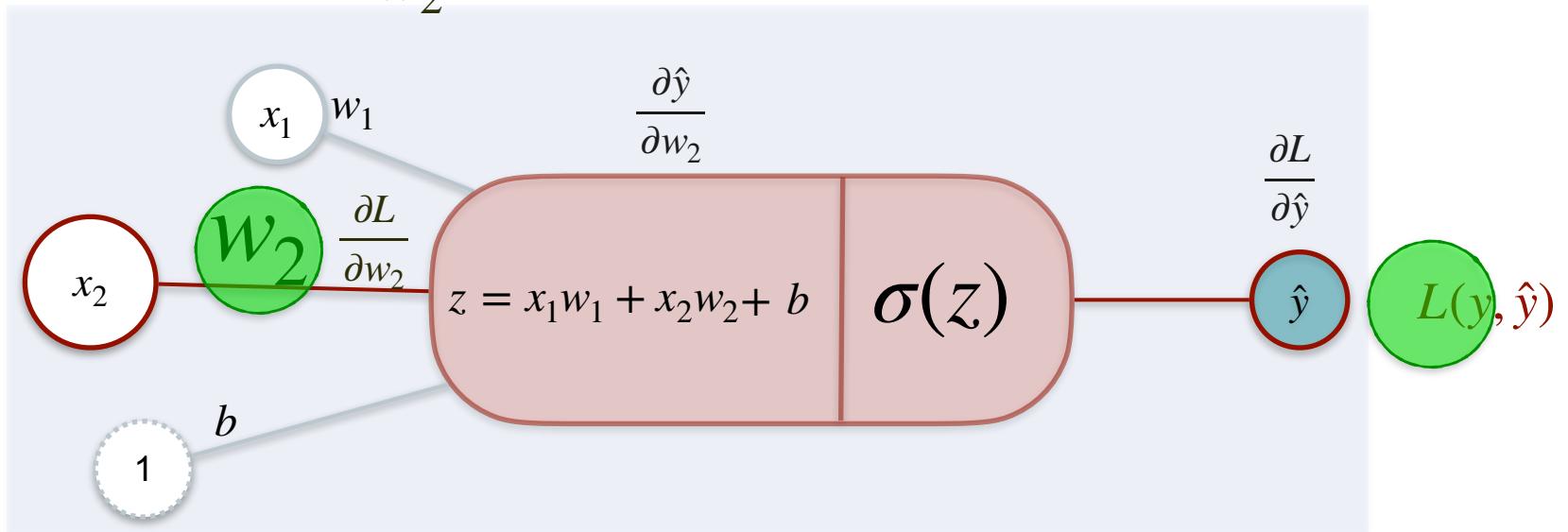


# Classification With a Perceptron

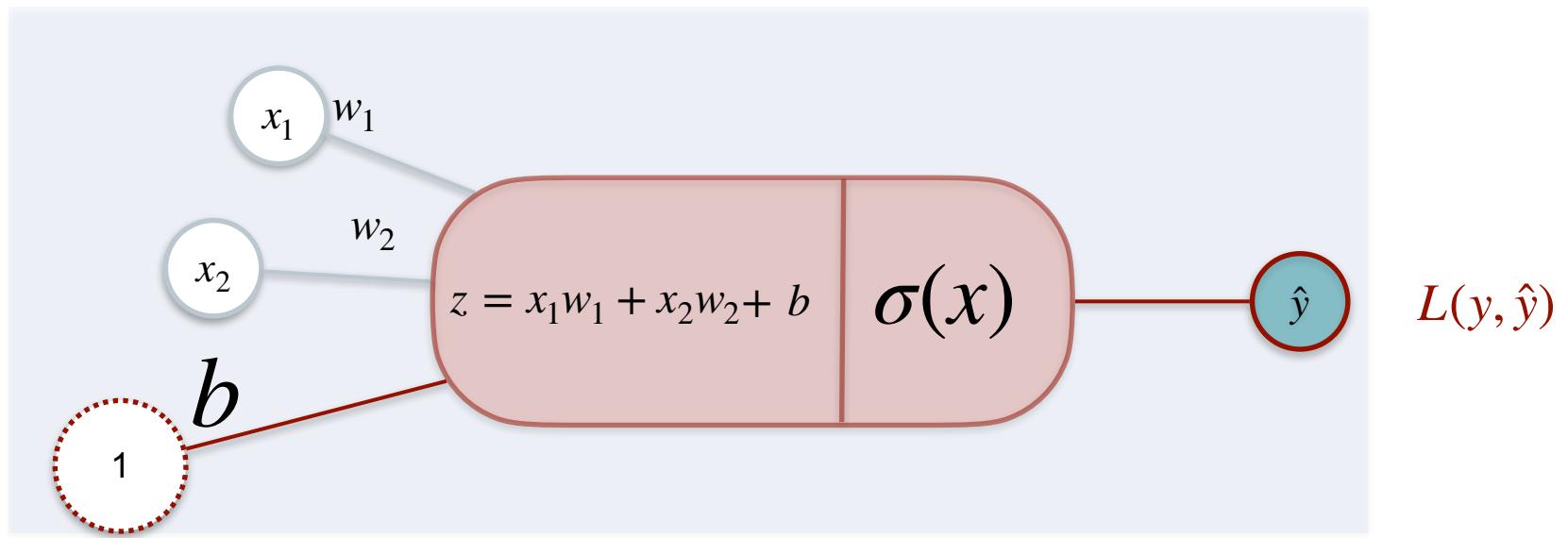


# Classification With a Perceptron

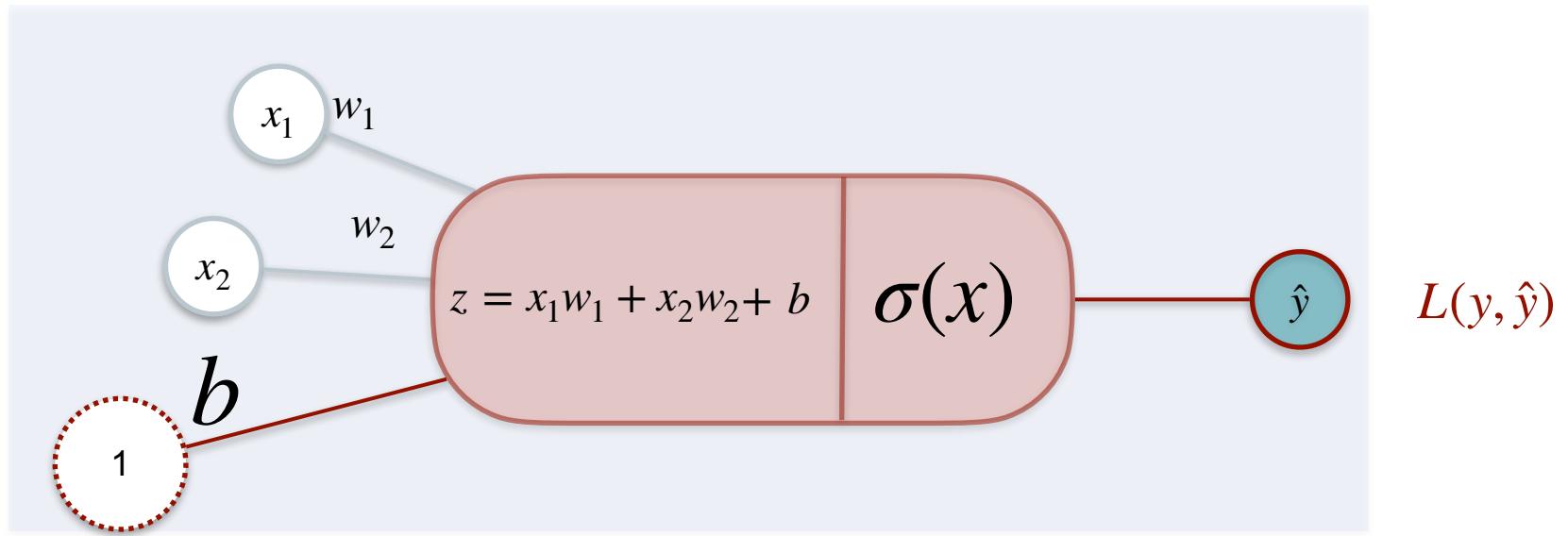
$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$



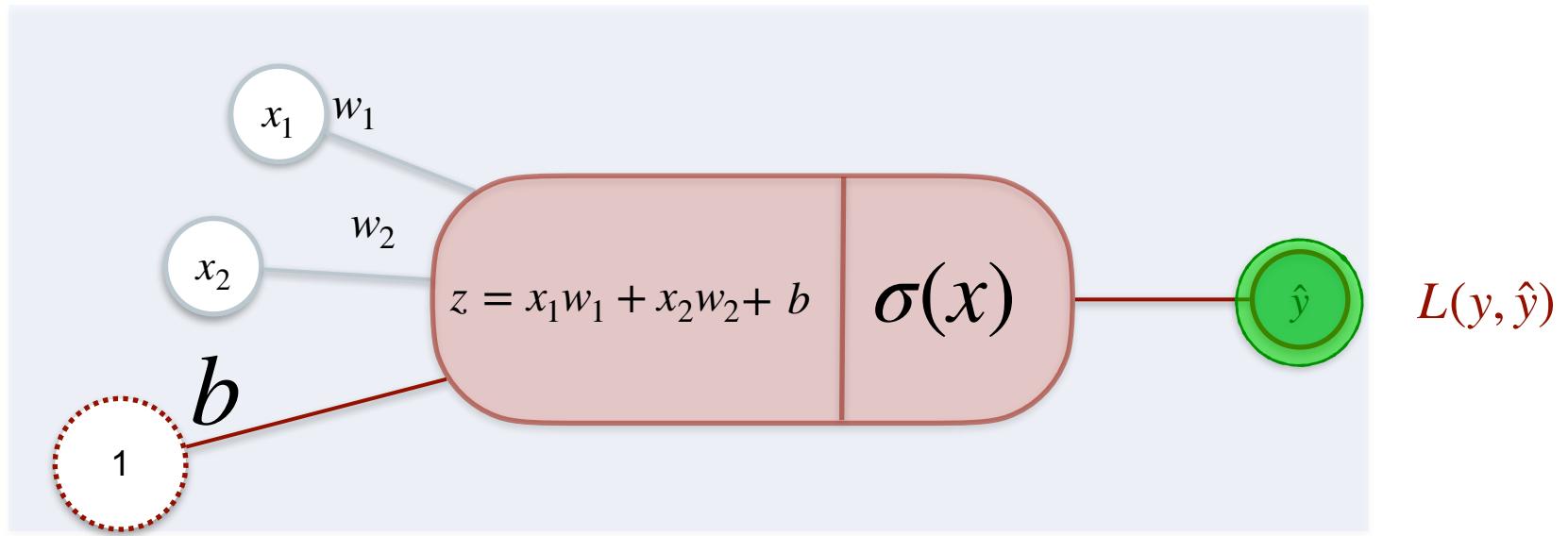
# Classification With a Perceptron



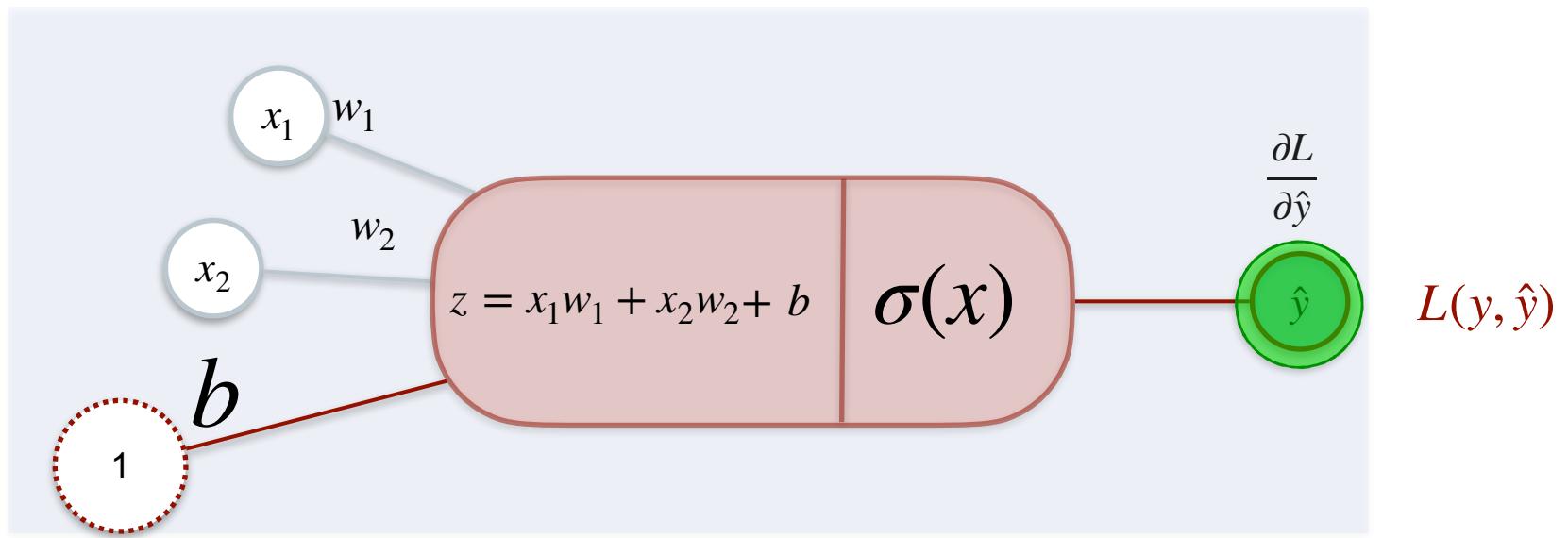
# Classification With a Perceptron



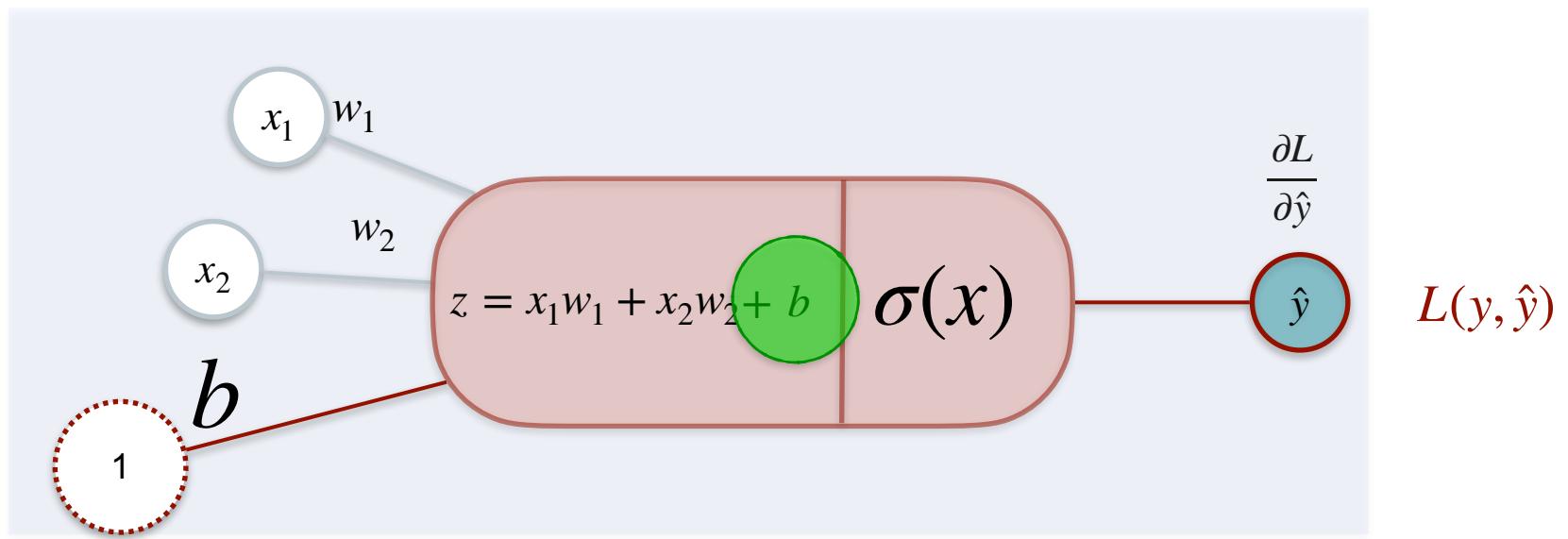
# Classification With a Perceptron



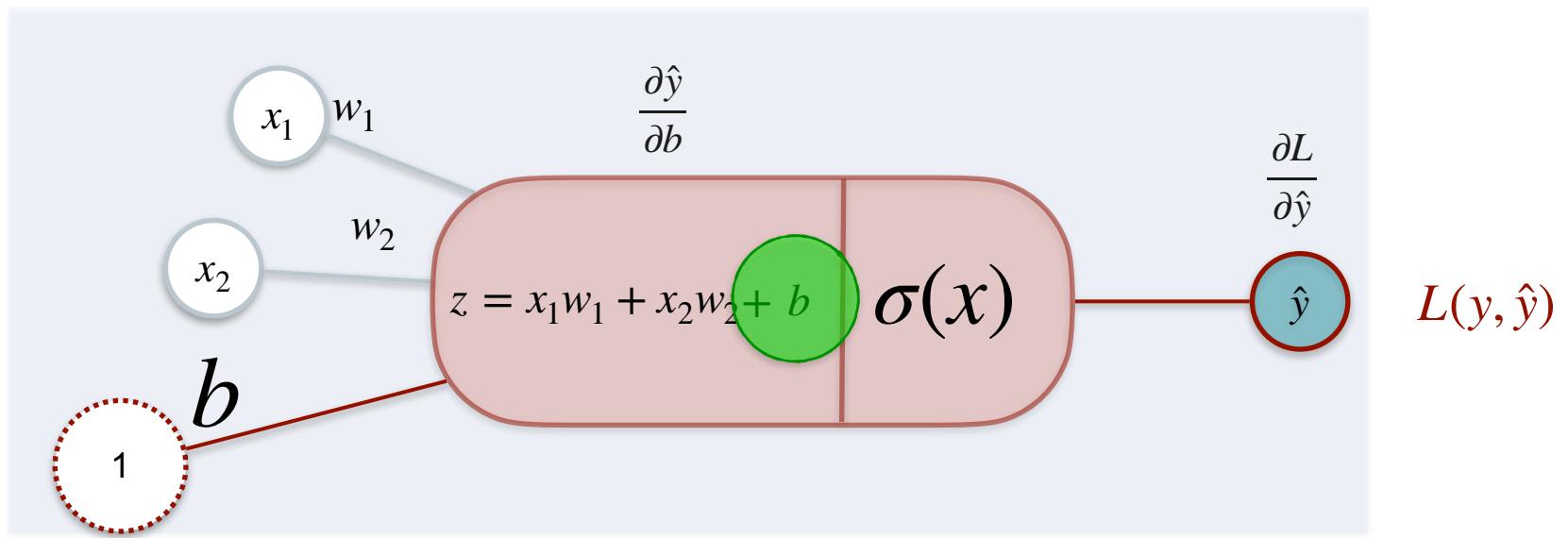
# Classification With a Perceptron



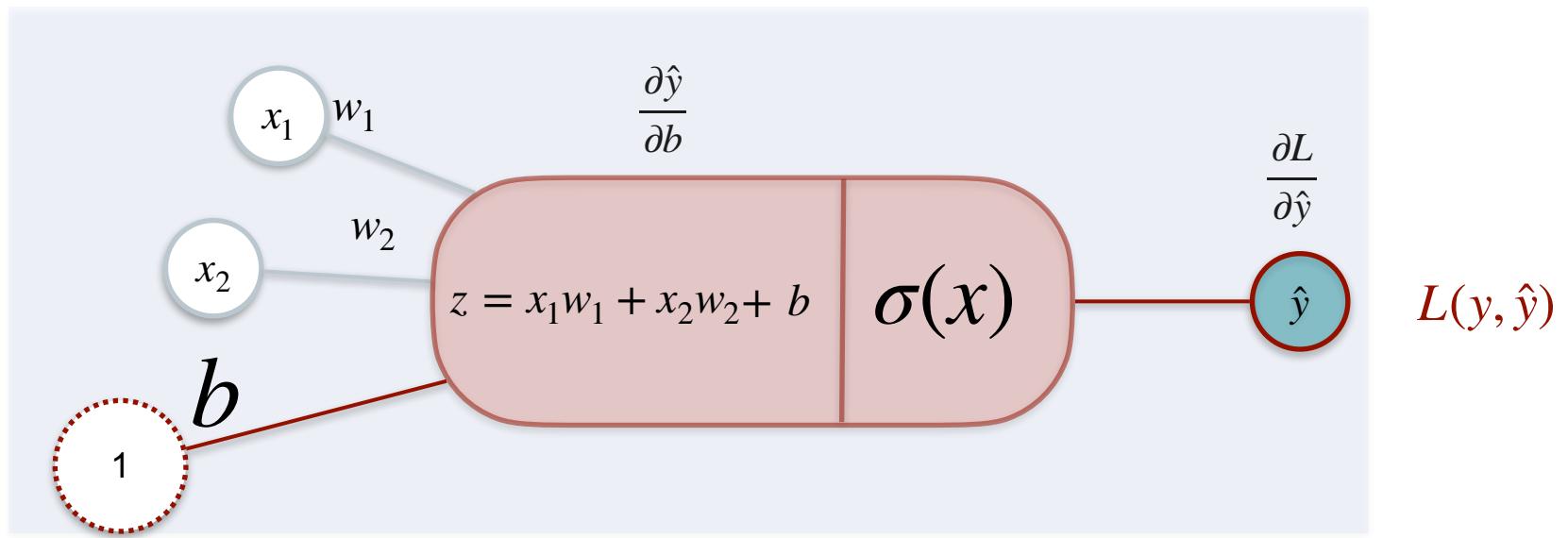
# Classification With a Perceptron



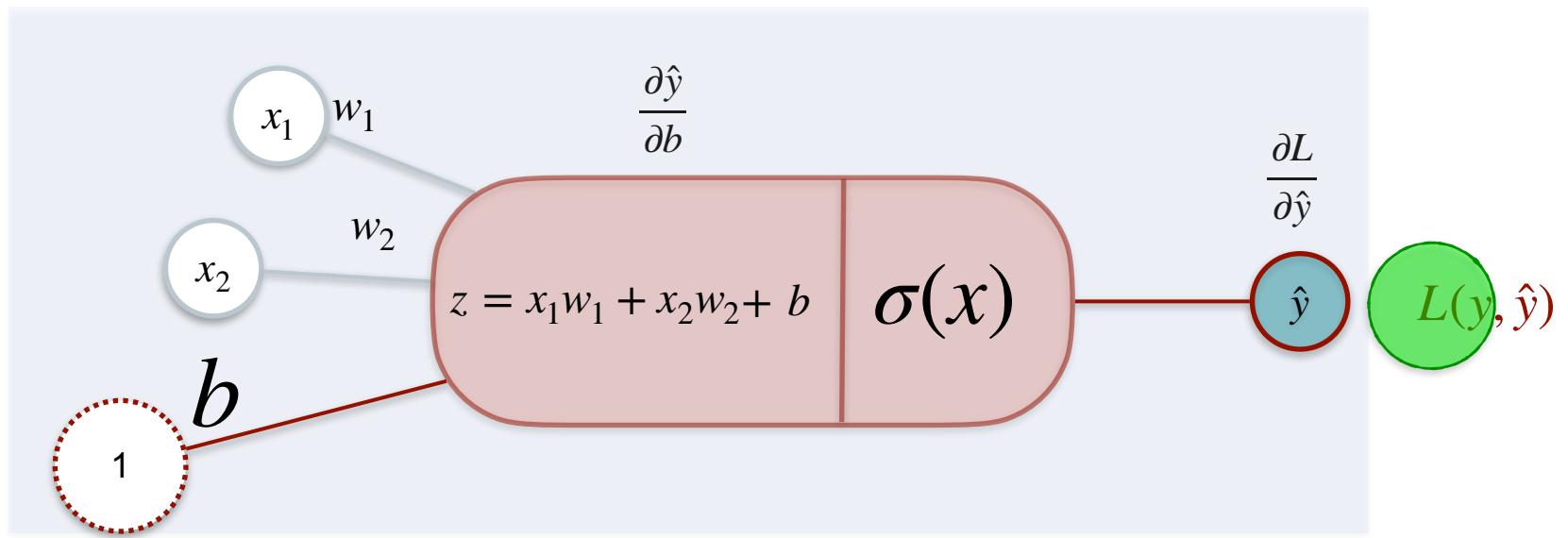
# Classification With a Perceptron



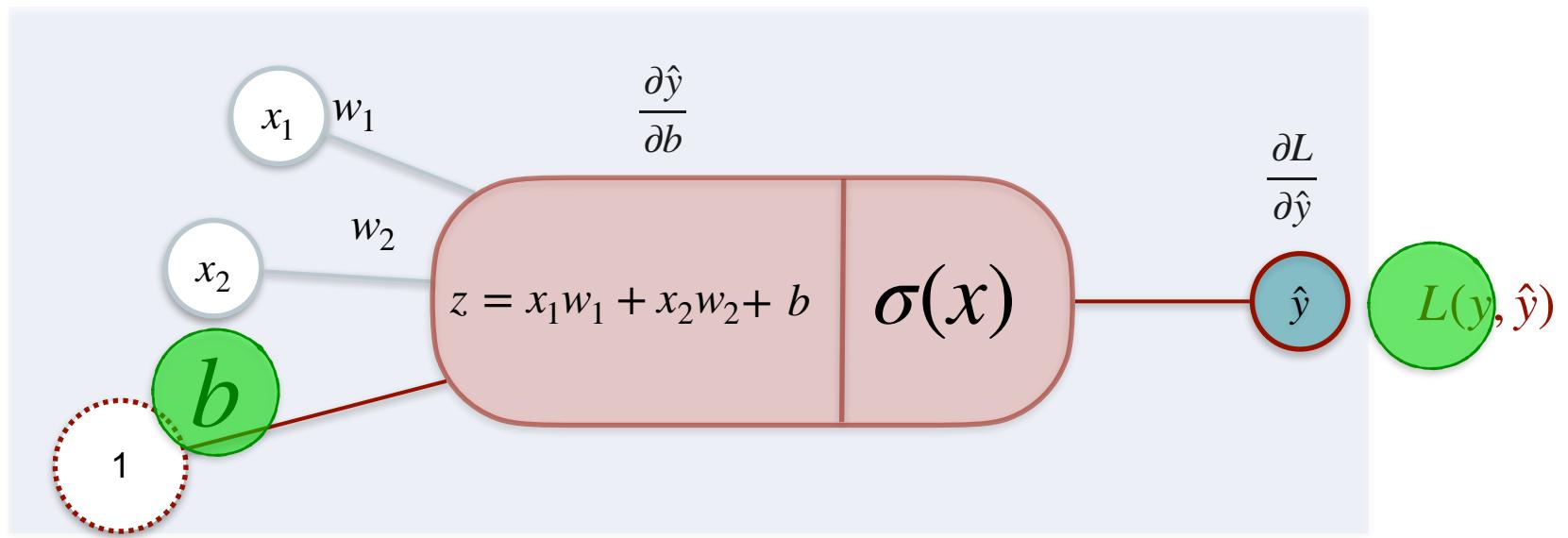
# Classification With a Perceptron



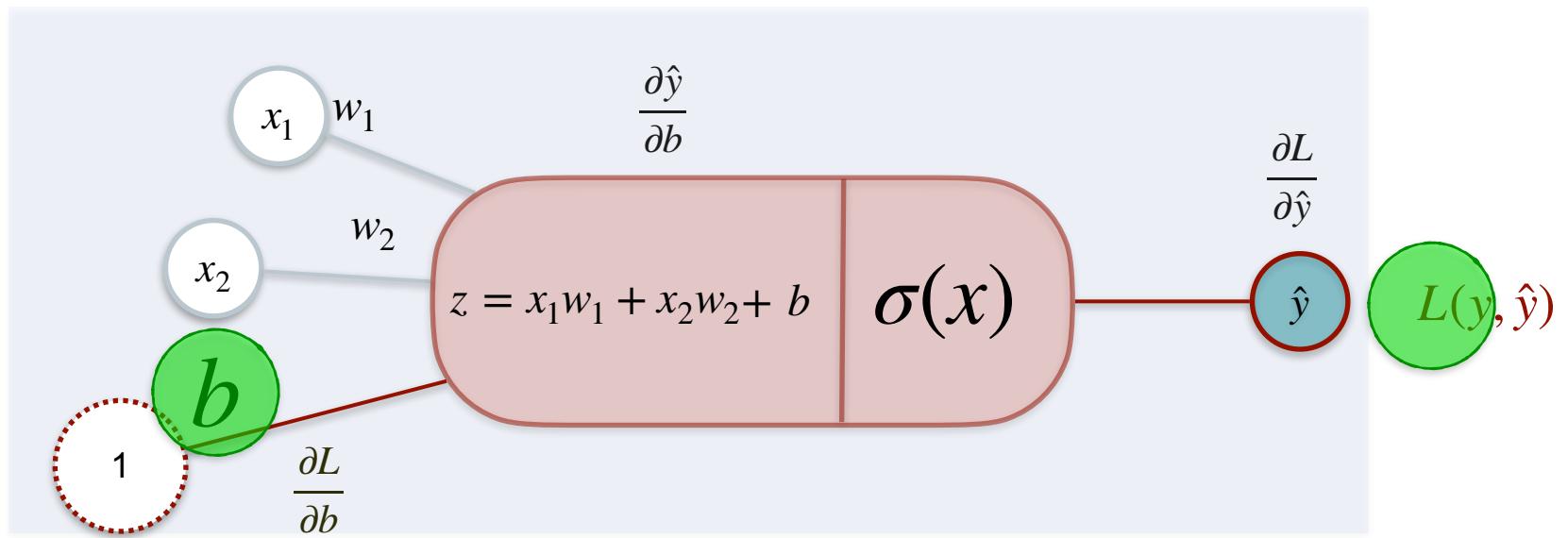
# Classification With a Perceptron



# Classification With a Perceptron

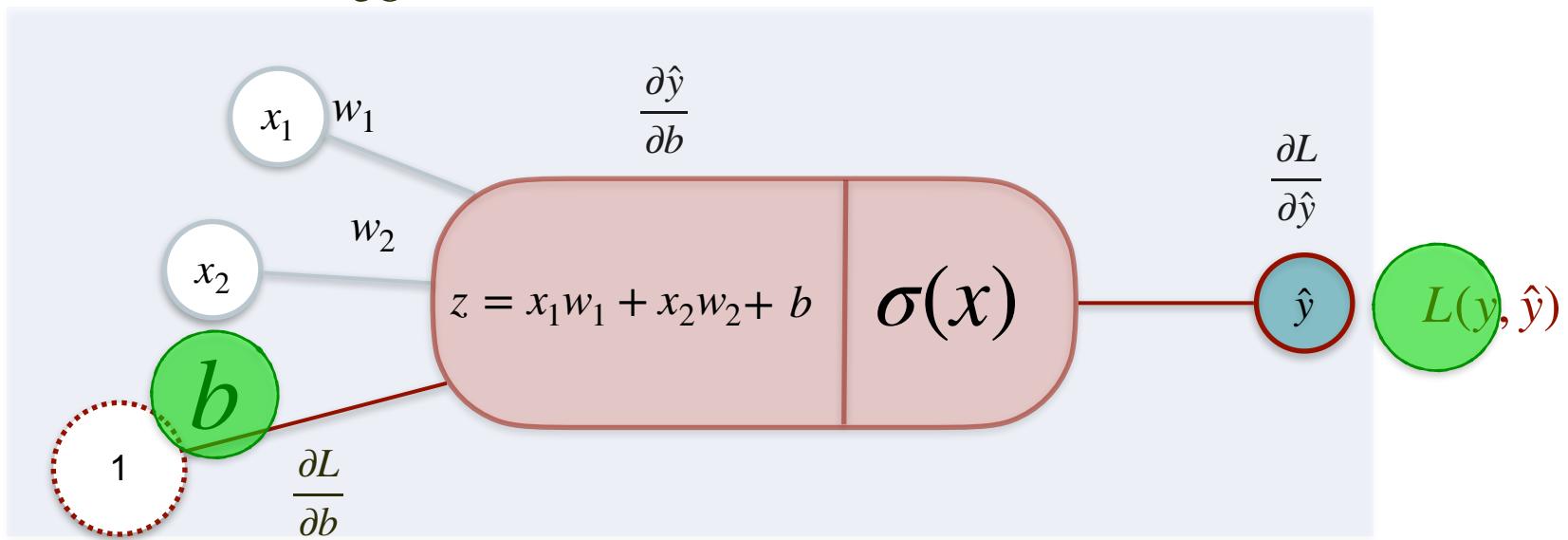


# Classification With a Perceptron



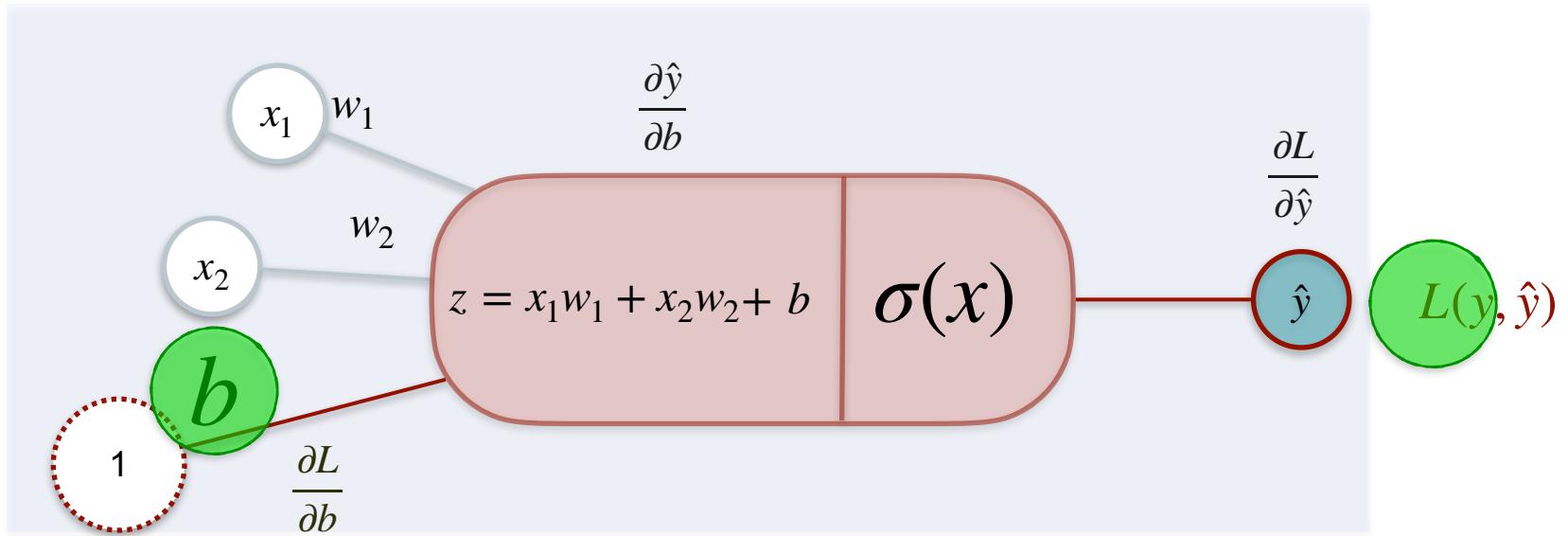
# Classification With a Perceptron

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



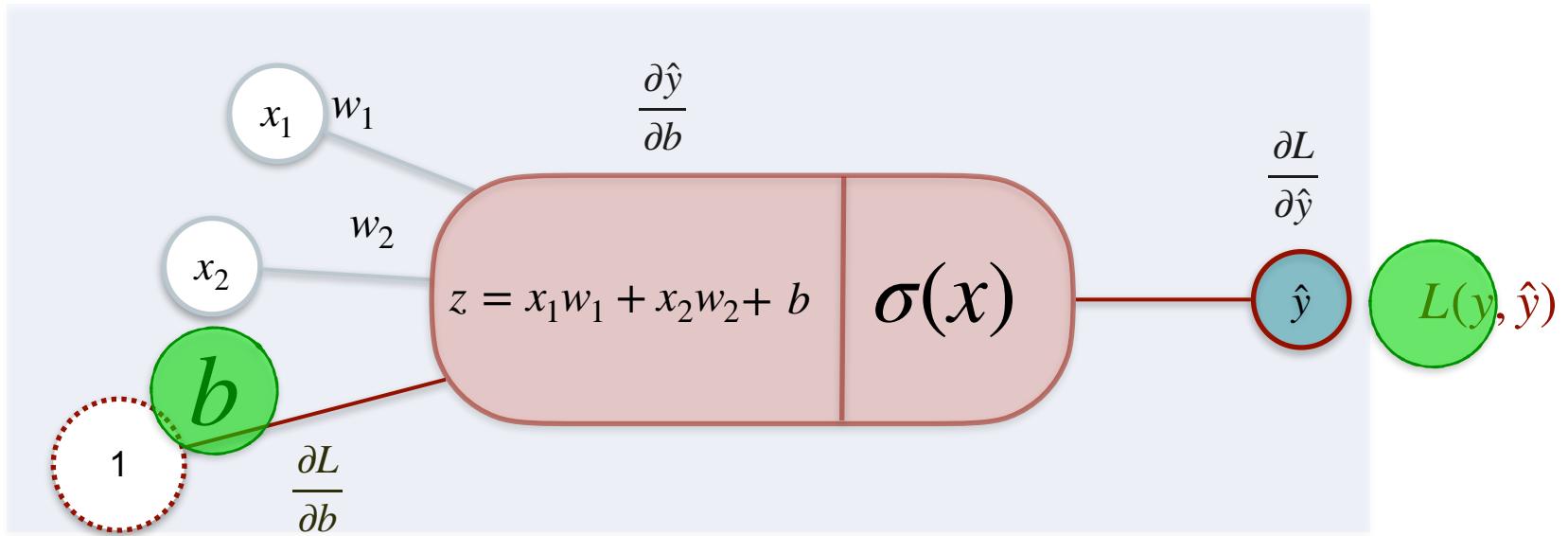
# Classification With a Perceptron

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}}$$



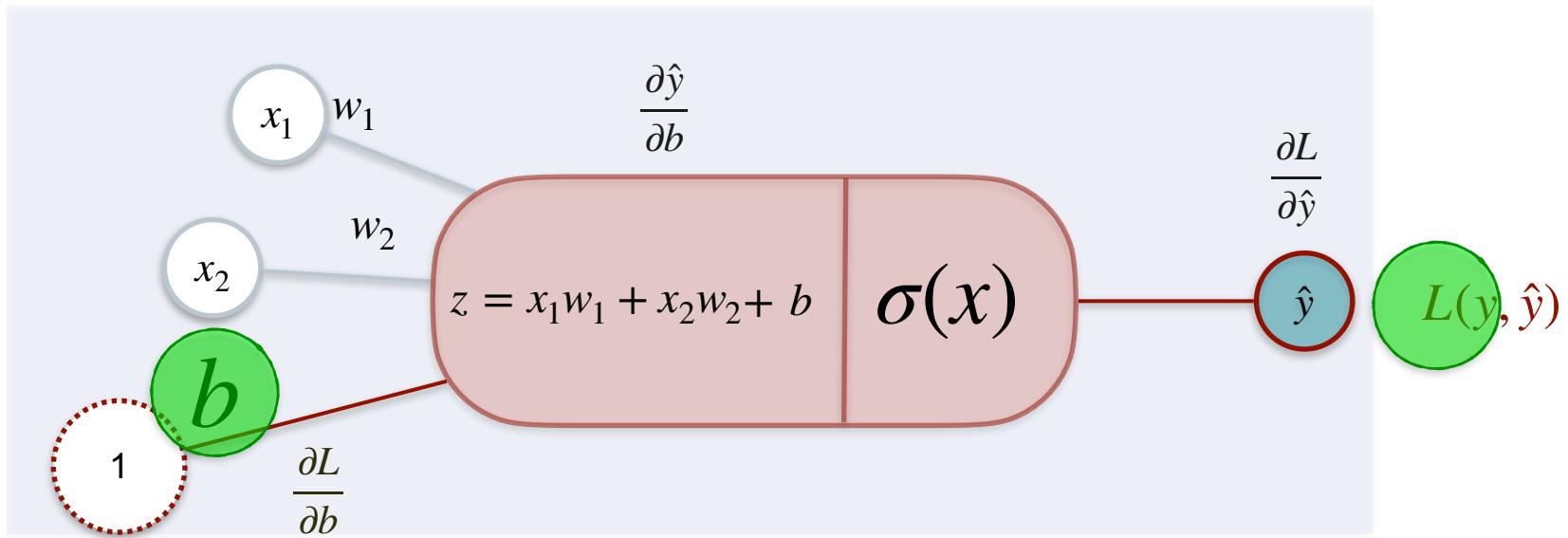
# Classification With a Perceptron

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot$$



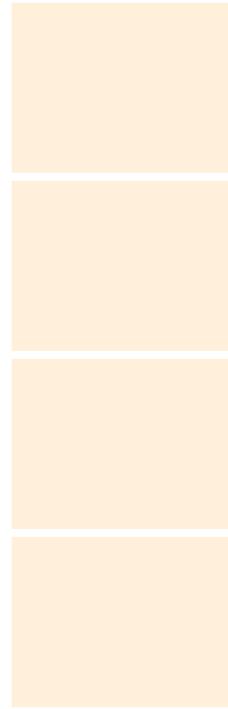
# Classification With a Perceptron

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b}$$



# Classification With a Perceptron

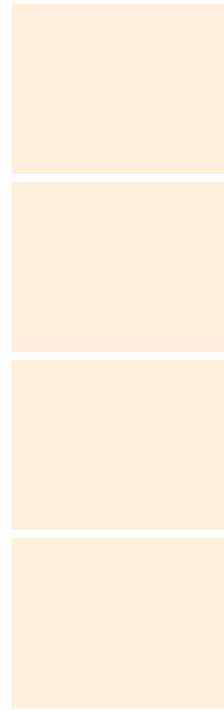
$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b}$$



# Classification With a Perceptron

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b}$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1}$$

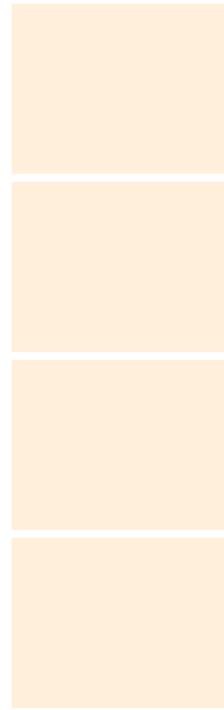


# Classification With a Perceptron

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b}$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1}$$

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# Classification With a Perceptron

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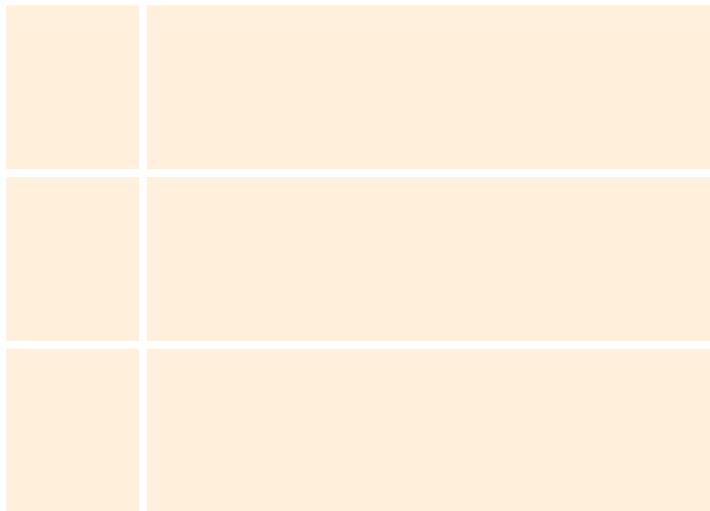
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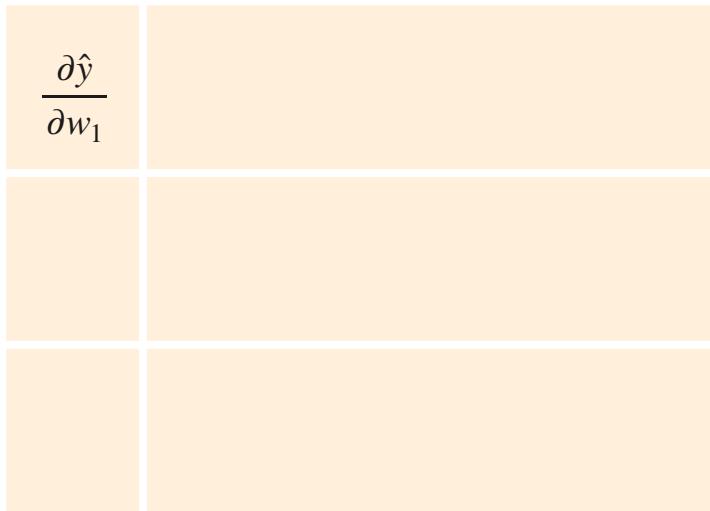
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$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$

# Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

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$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$

# Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

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$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

# Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

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$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

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$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

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# Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

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$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

# Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

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$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

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# Classification With a Perceptron

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$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

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# Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

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$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

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# Classification With a Perceptron

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

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# Classification With a Perceptron

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

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$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_2$$

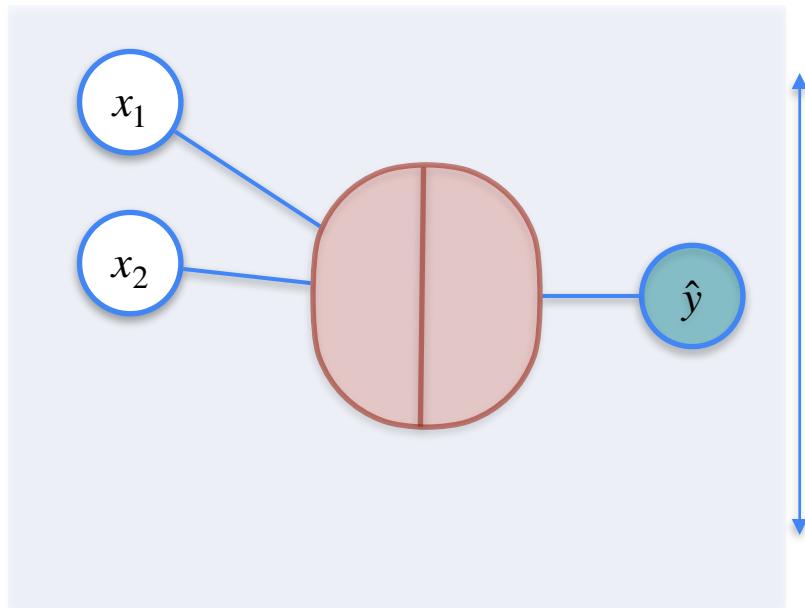
# Classification With a Perceptron

$$\frac{\partial L}{\partial b} = -(y - \hat{y})$$

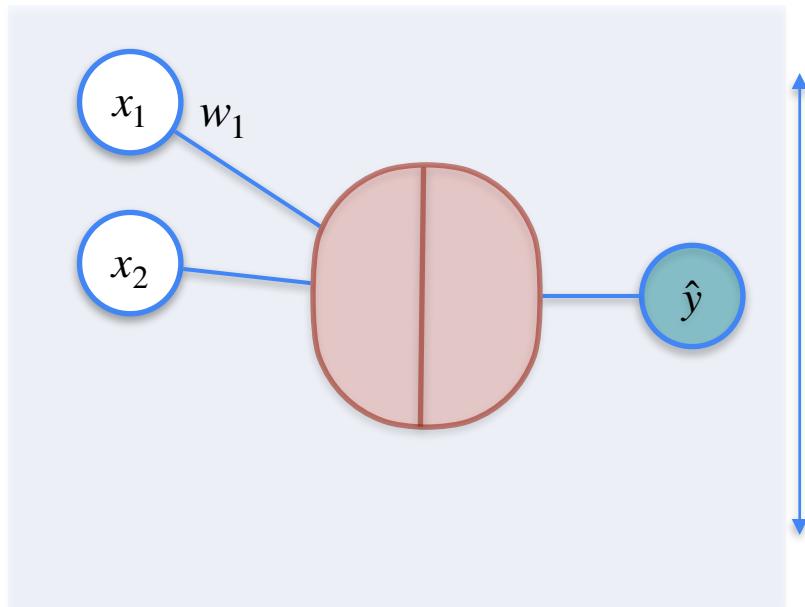
$$\frac{\partial L}{\partial w_1} = -(y - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = -(y - \hat{y})x_2$$

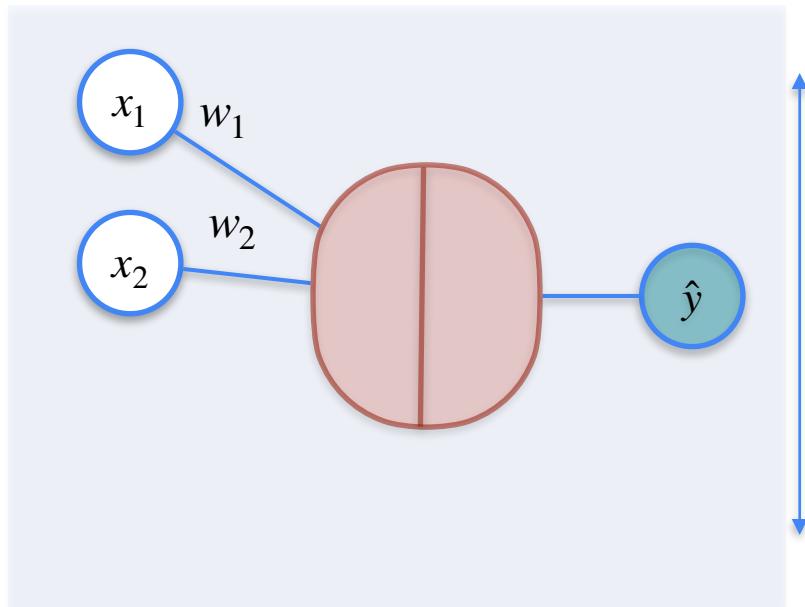
# Classification With a Perceptron



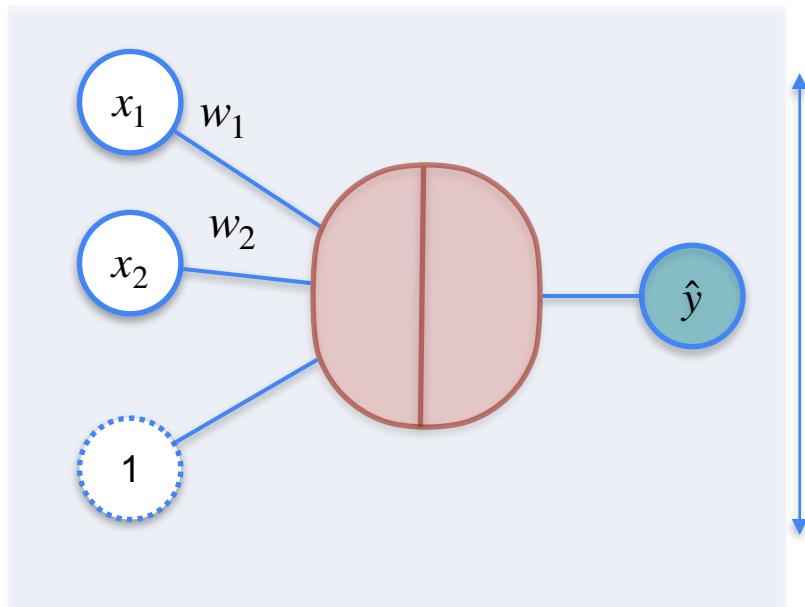
# Classification With a Perceptron



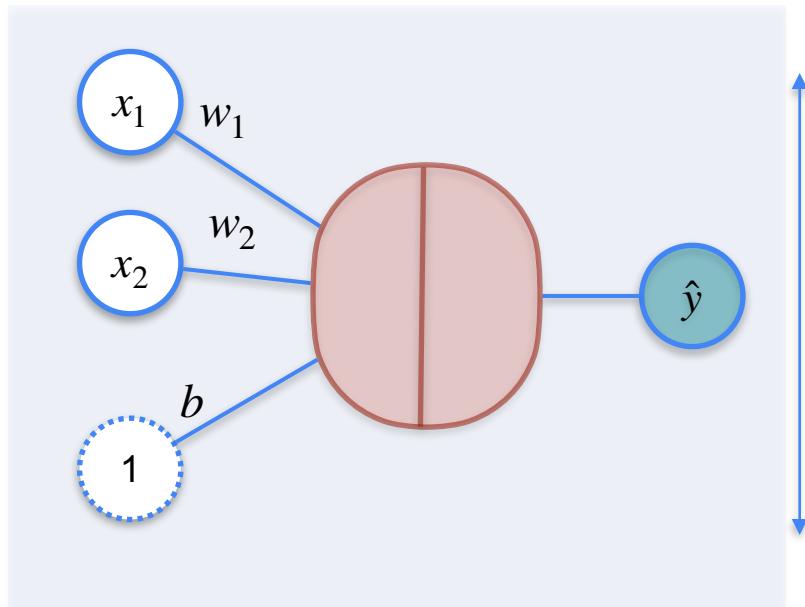
# Classification With a Perceptron



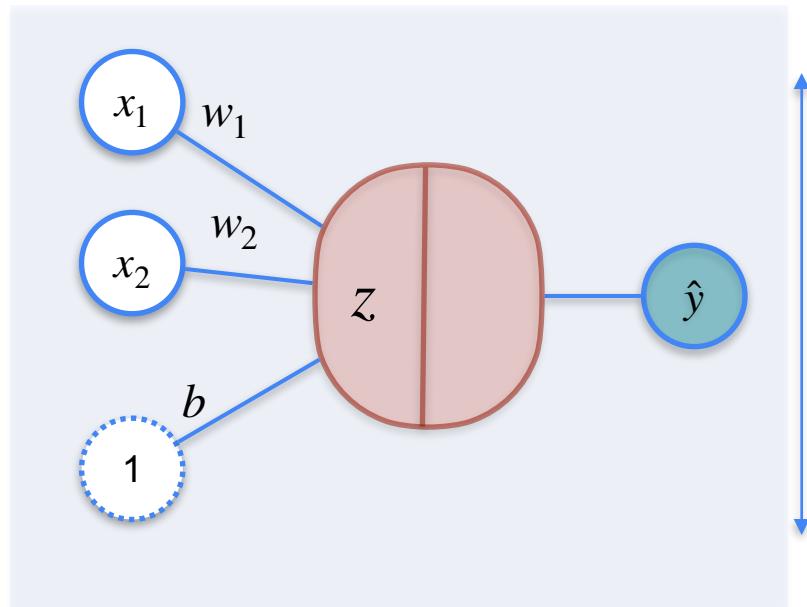
# Classification With a Perceptron



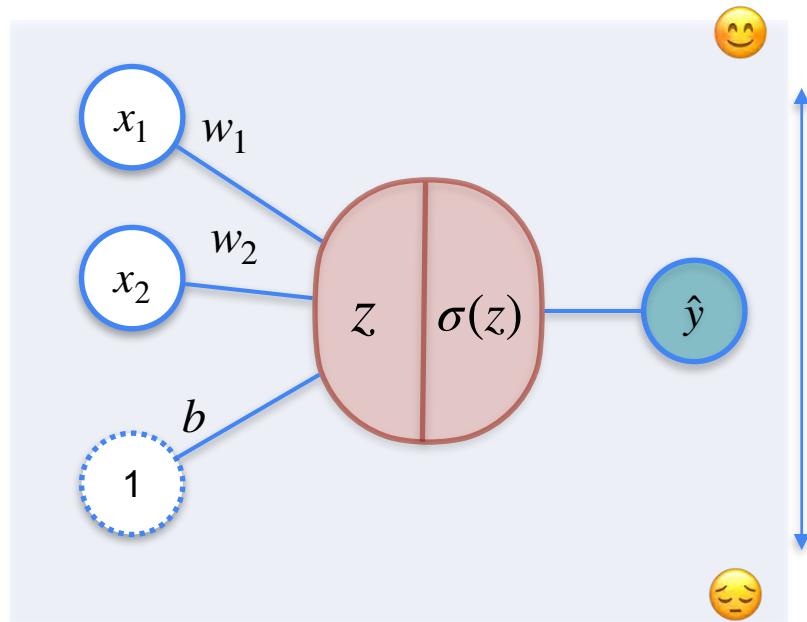
# Classification With a Perceptron



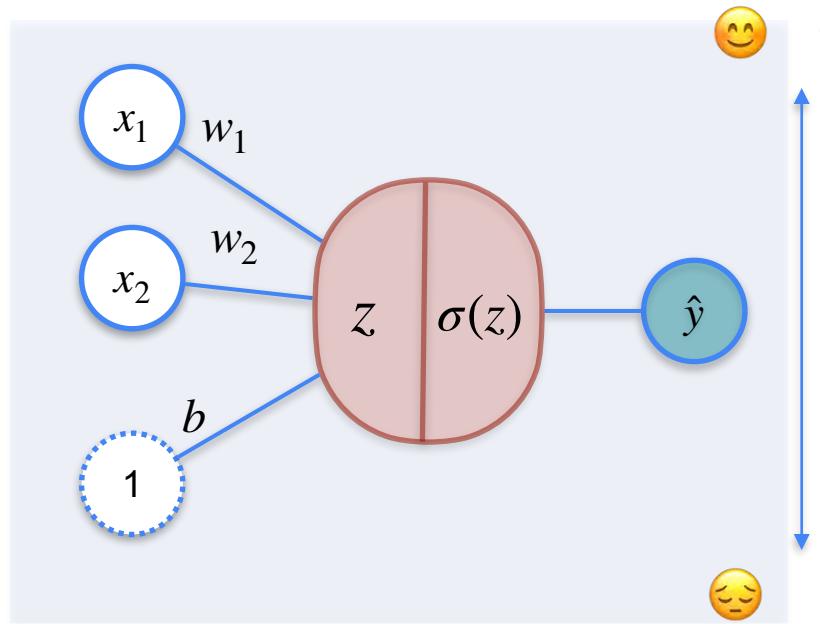
# Classification With a Perceptron



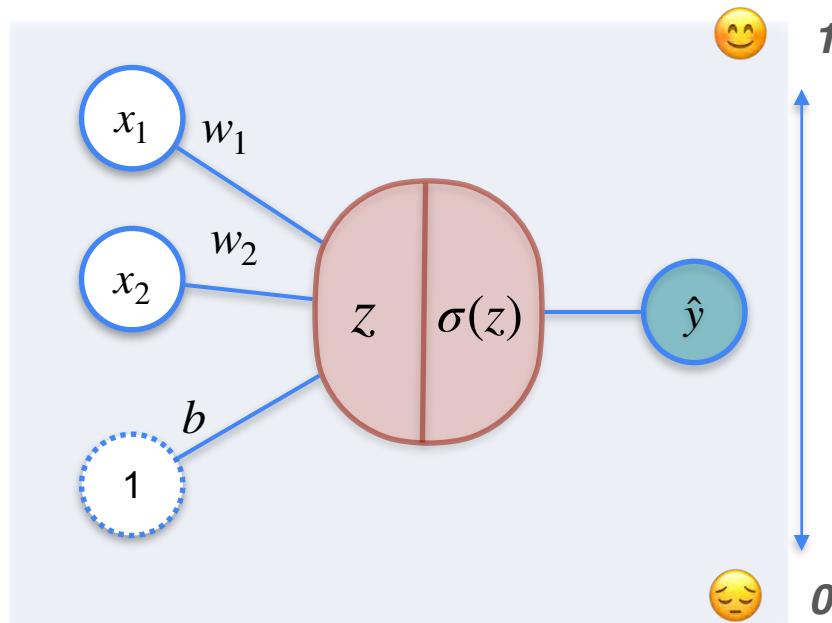
# Classification With a Perceptron



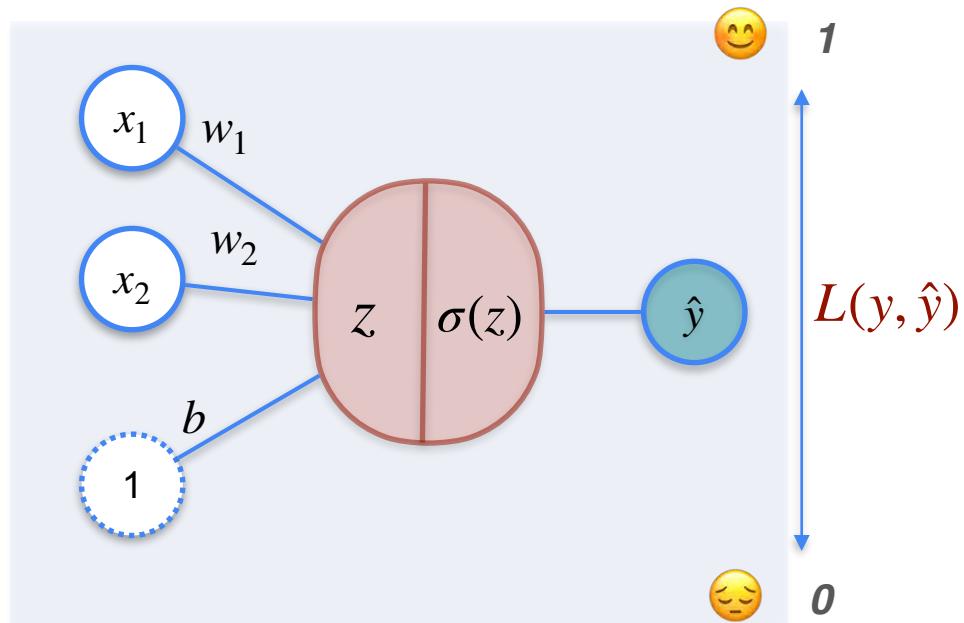
# Classification With a Perceptron



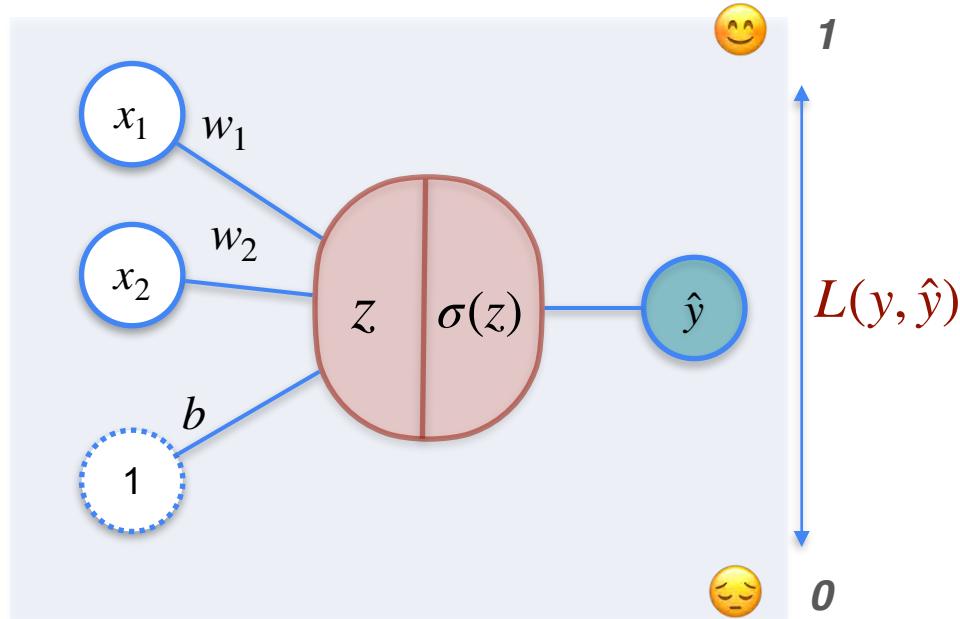
# Classification With a Perceptron



# Classification With a Perceptron

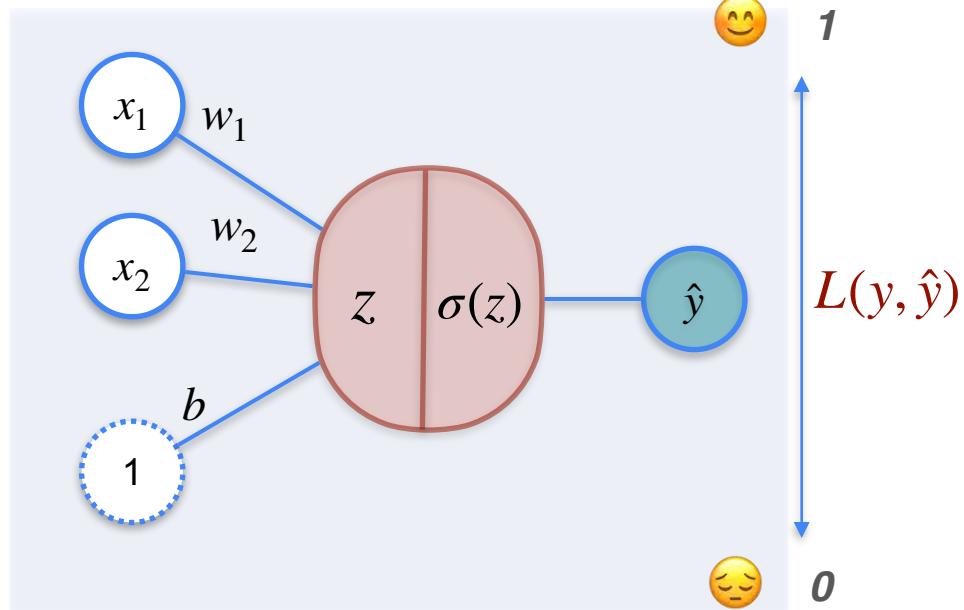


# Classification With a Perceptron



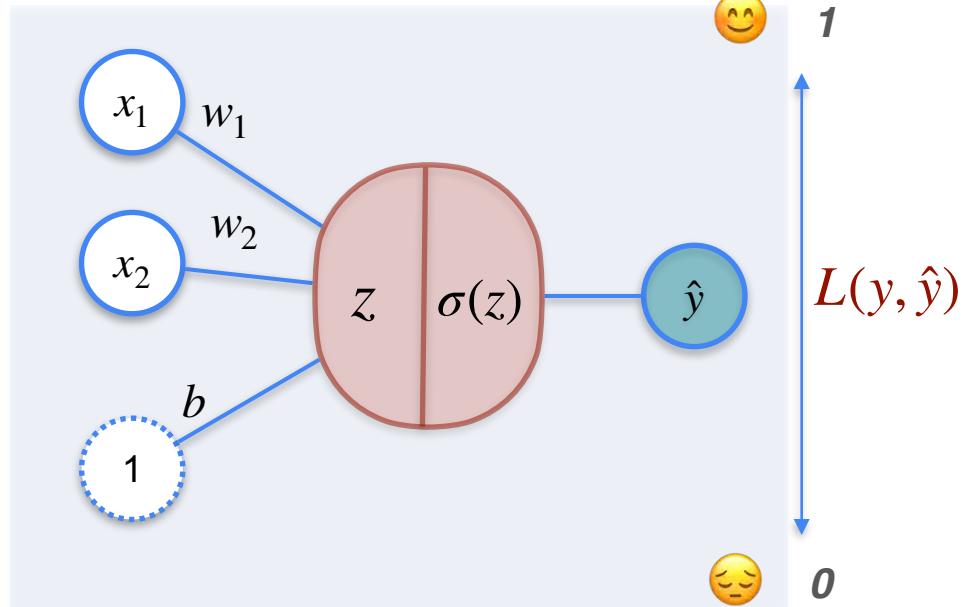
To find optimal values for:

# Classification With a Perceptron



To find optimal values for:  
 $w_1$  ,  $w_2$  ,  $b$

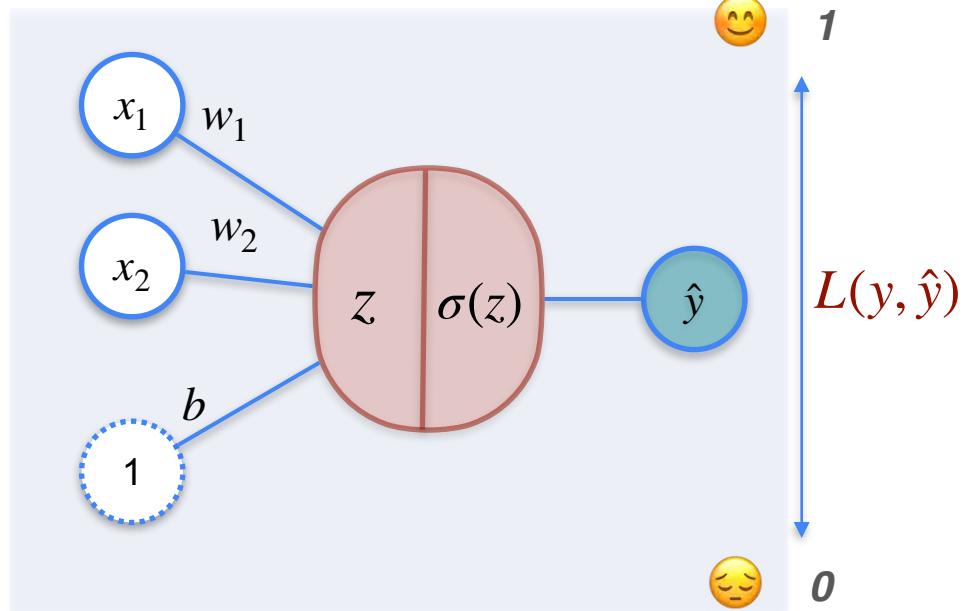
# Classification With a Perceptron



To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

# Classification With a Perceptron

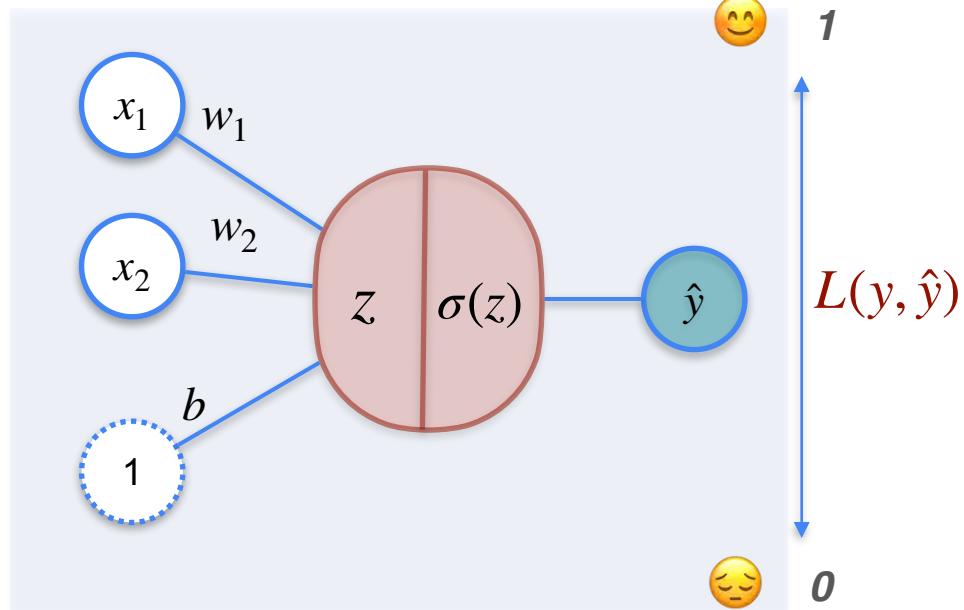


To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha \frac{\partial L}{\partial w_1}$$

# Classification With a Perceptron

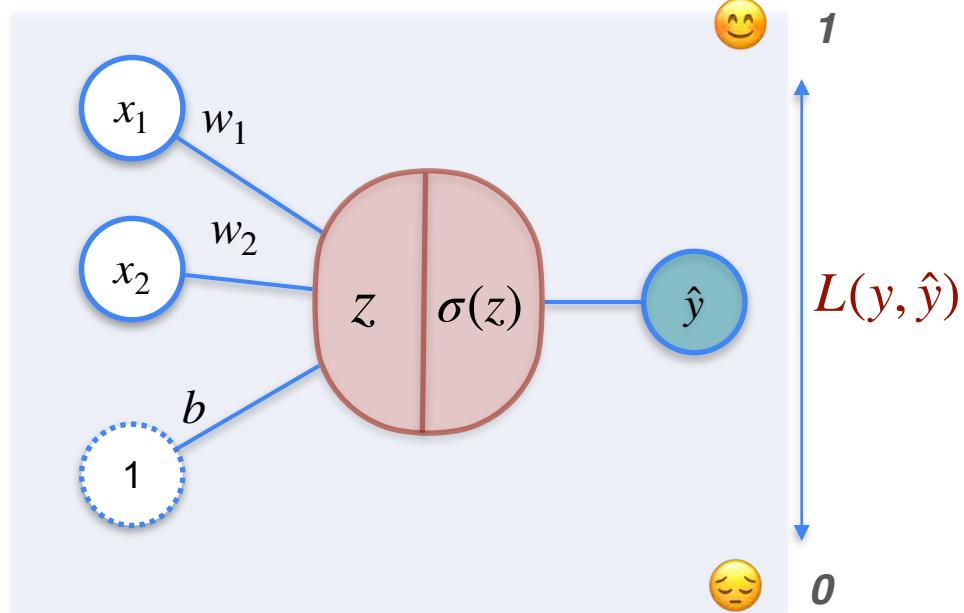


To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha$$

# Classification With a Perceptron

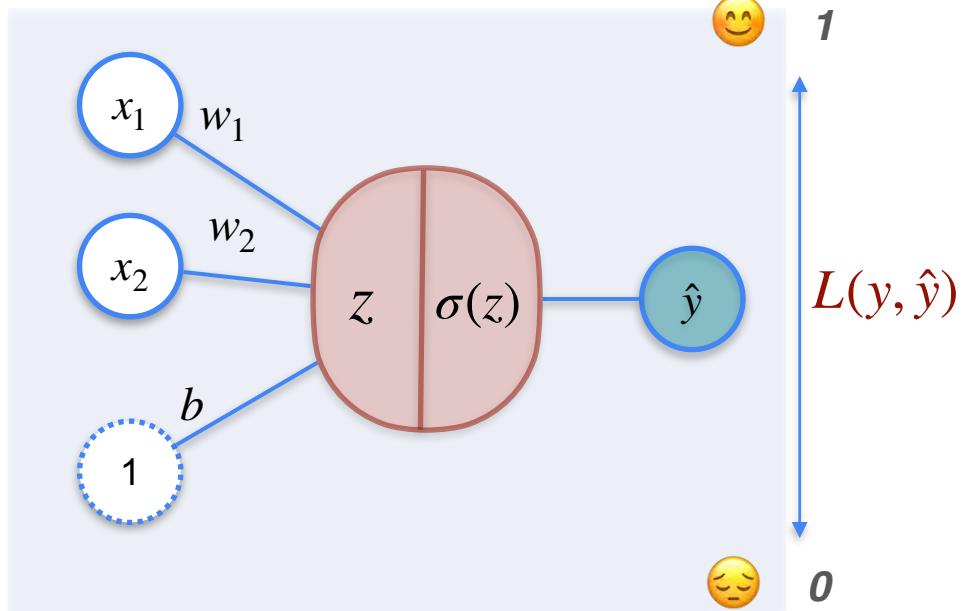


To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

# Classification With a Perceptron



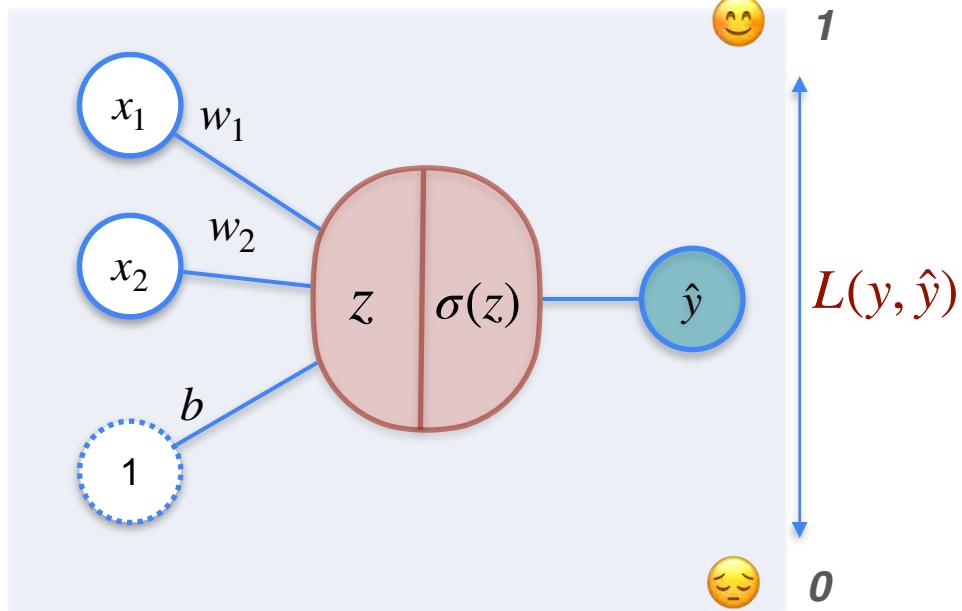
To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha \frac{\partial L}{\partial w_2}$$

# Classification With a Perceptron



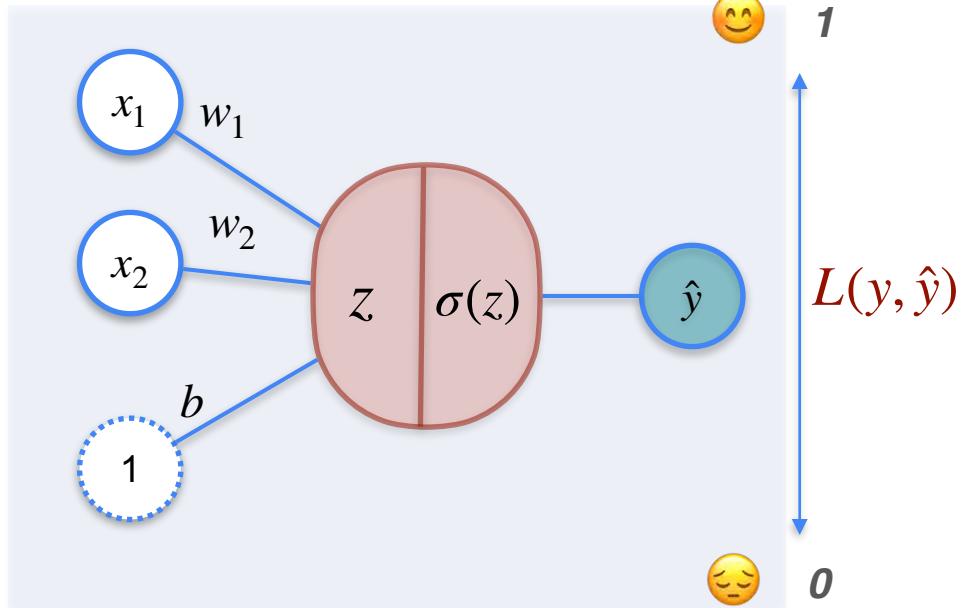
To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha$$

# Classification With a Perceptron



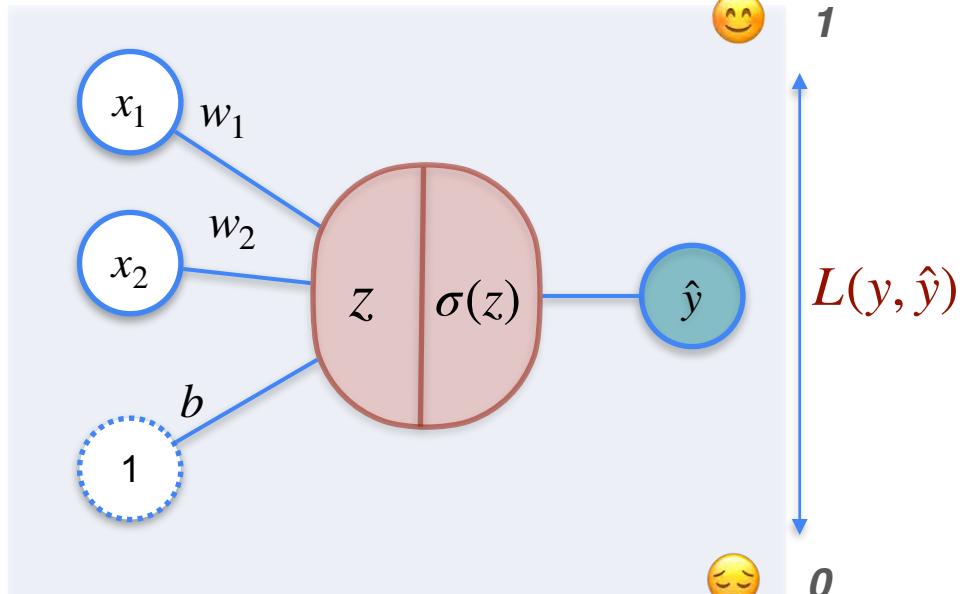
To find optimal values for:  
 $w_1, w_2, b$

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$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha(-x_2(y - \hat{y}))$$

# Classification With a Perceptron



To find optimal values for:  
 $w_1, w_2, b$

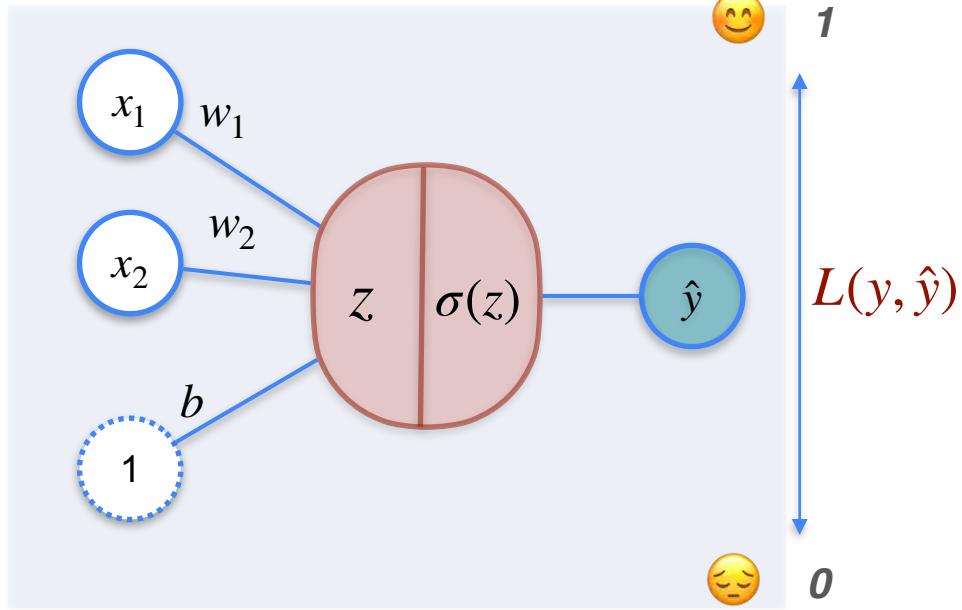
*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha(-x_2(y - \hat{y}))$$

$$b \rightarrow b - \alpha \frac{\partial L}{\partial b}$$

# Classification With a Perceptron



To find optimal values for:  
 $w_1, w_2, b$

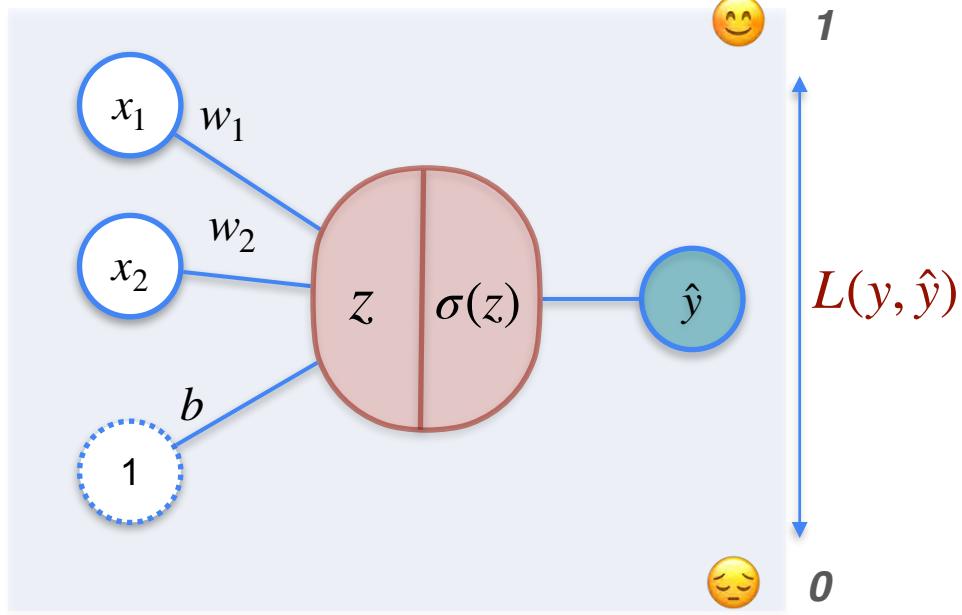
*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha(-x_2(y - \hat{y}))$$

$$b \rightarrow b - \alpha$$

# Classification With a Perceptron



To find optimal values for:  
 $w_1, w_2, b$

*You need gradient descent*

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha(-x_2(y - \hat{y}))$$

$$b \rightarrow b - \alpha(-(y - \hat{y}))$$



DeepLearning.AI

# Optimization in Neural Networks and Newton's Method

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## Classification with a Neural Network

# Classification Problem Motivation

# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊

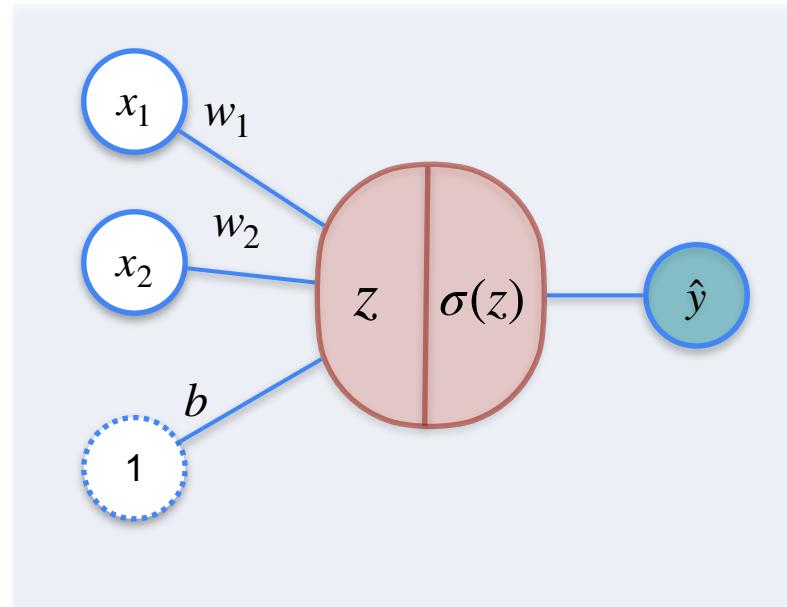
*Beep beep!*      0      2      *Sad* 😞

<i>Aack beep beep beep!</i>	1	3	<i>Sad</i> 😞
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*Aack beep aack!*      2      1      *Happy* 😊

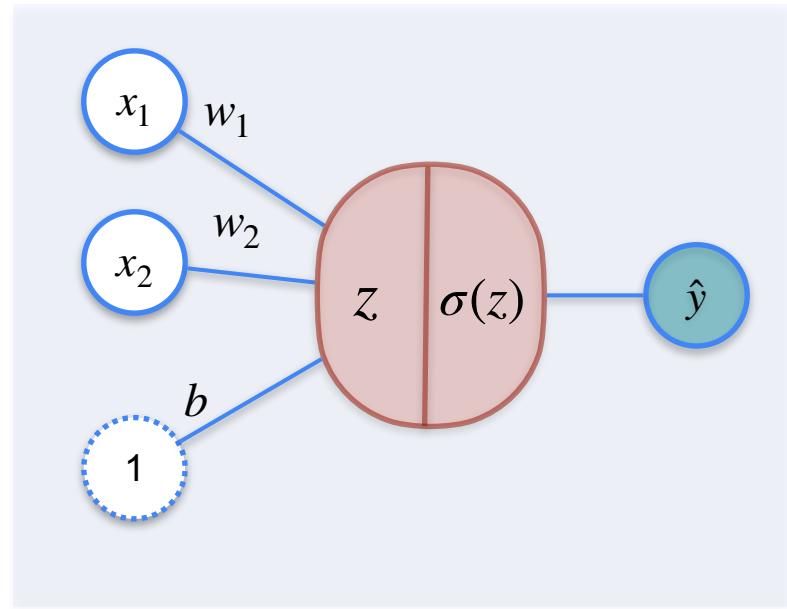
# Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊
<i>Beep beep!</i>	0	2	<i>Sad</i> 😞
<i>Aack beep beep beep!</i>	1	3	<i>Sad</i> 😞
<i>Aack beep aack!</i>	2	1	<i>Happy</i> 😊



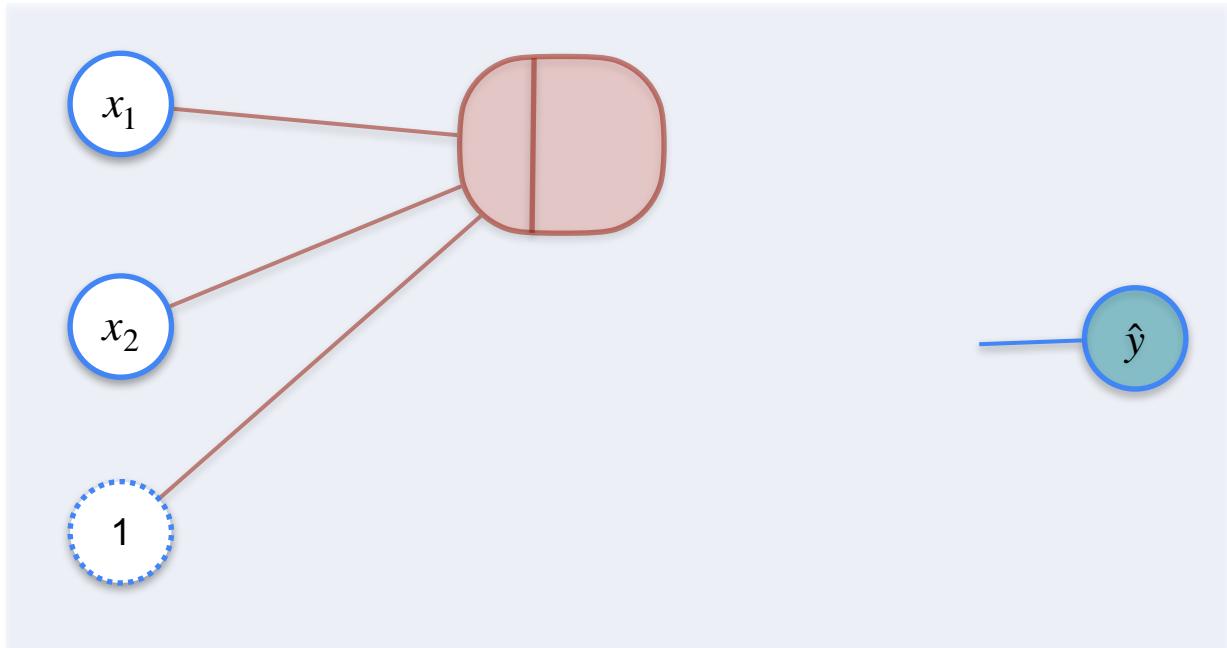
# Classification Problem Motivation

Sentence	Aack	Beep	Mood
Aack aack aack!	3	0	Happy 😊
Beep beep!	0	2	Sad 😞
Aack beep beep beep!	1	3	Sad 😞
Aack beep aack!	2	1	Happy 😊

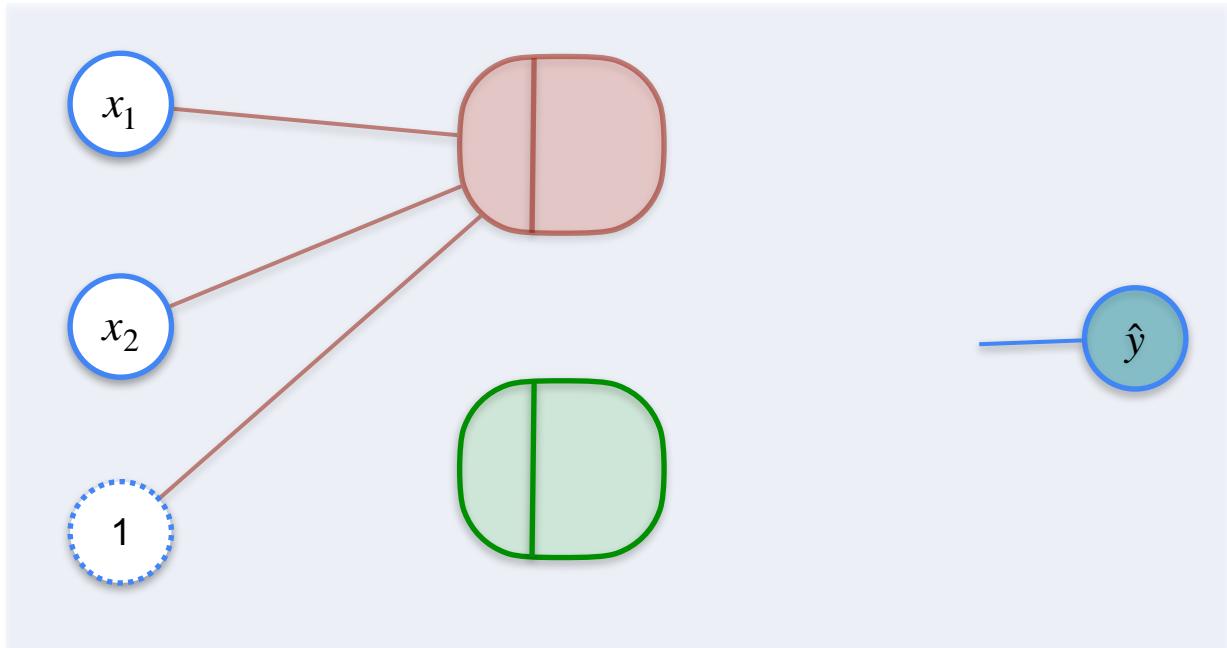


$$z = x_1 w_1 + x_2 w_2 + b$$

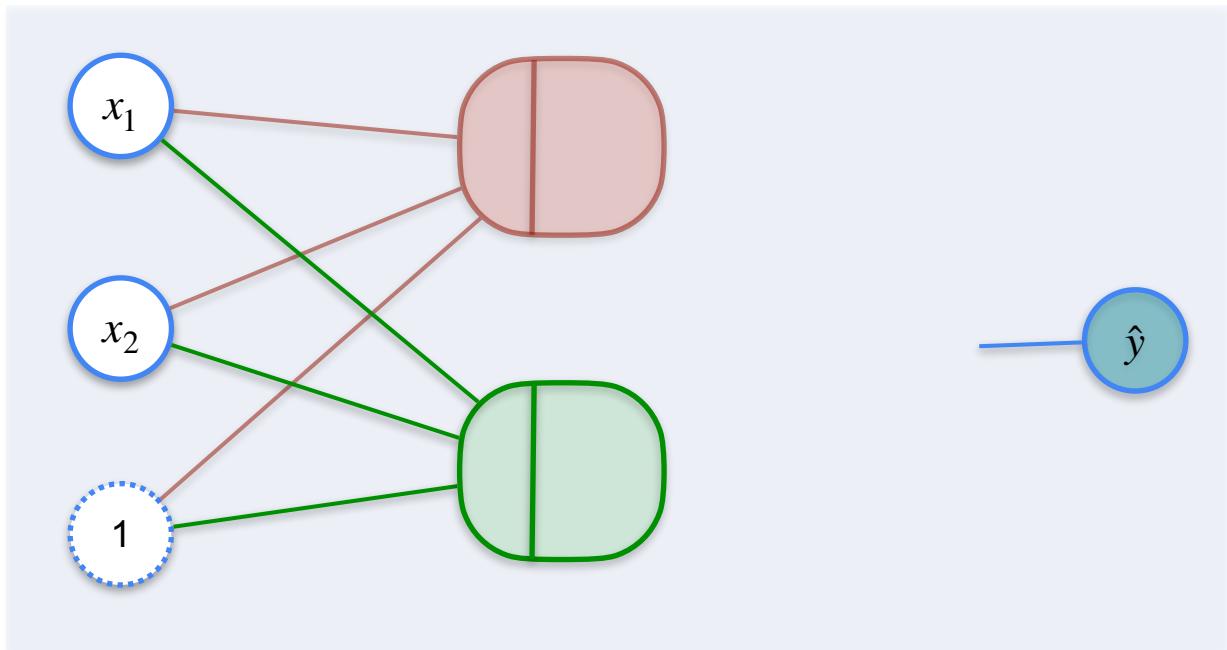
# 2,2,1 Neural Network



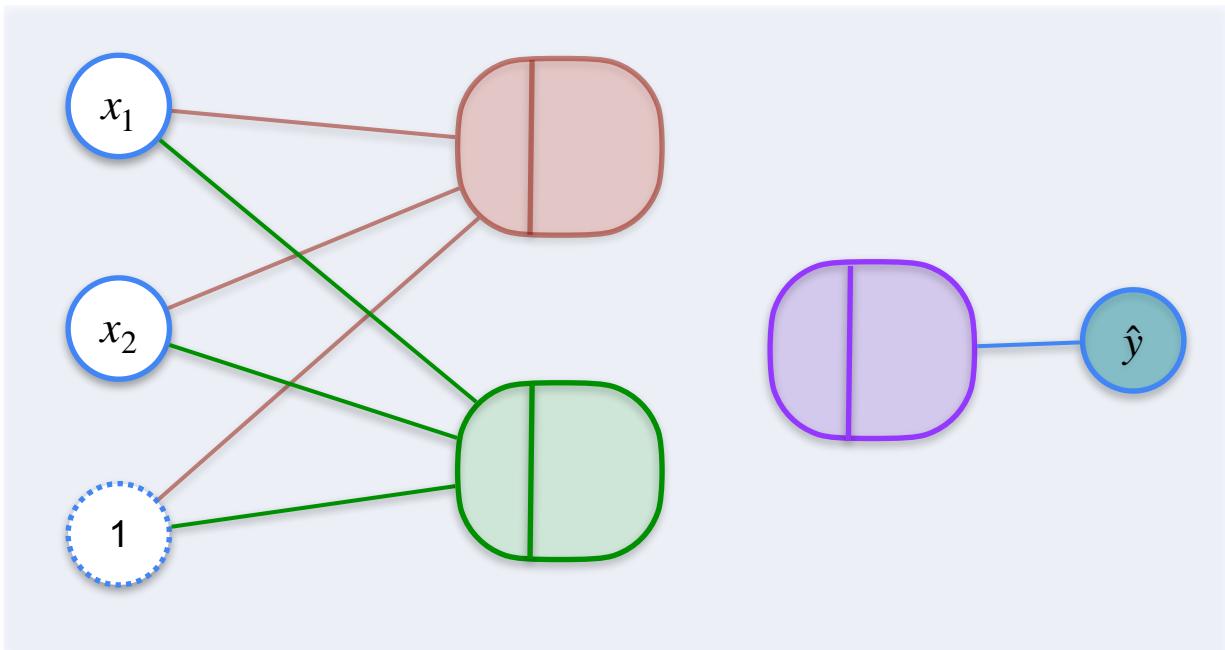
# 2,2,1 Neural Network



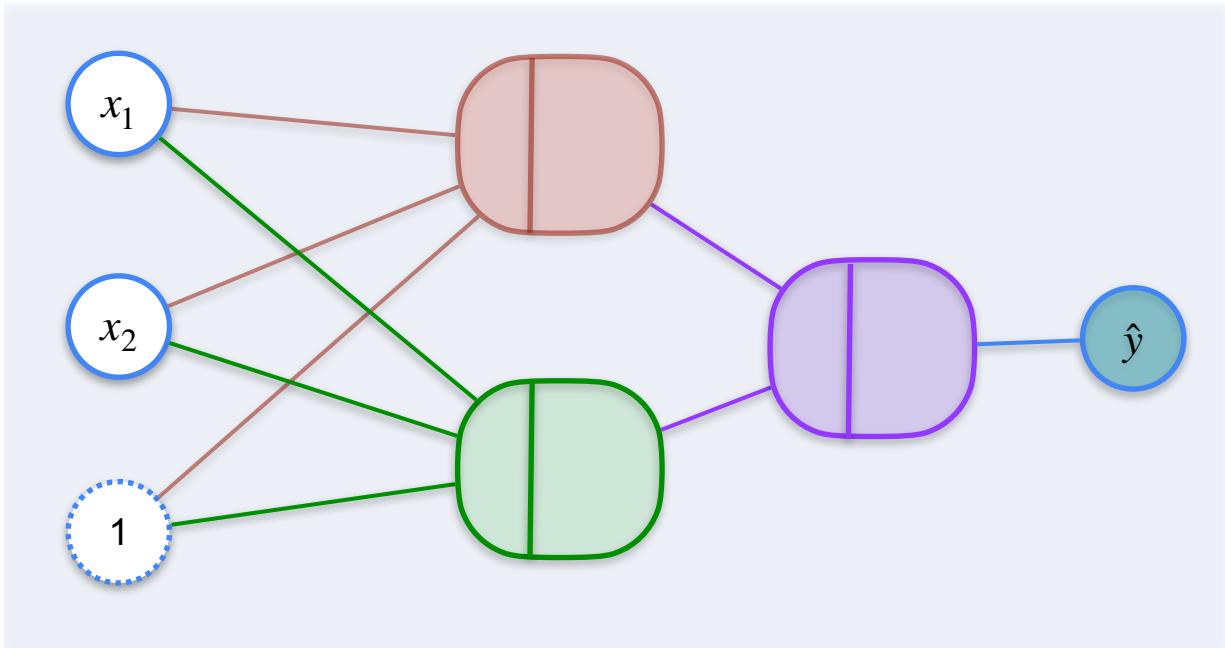
# 2,2,1 Neural Network



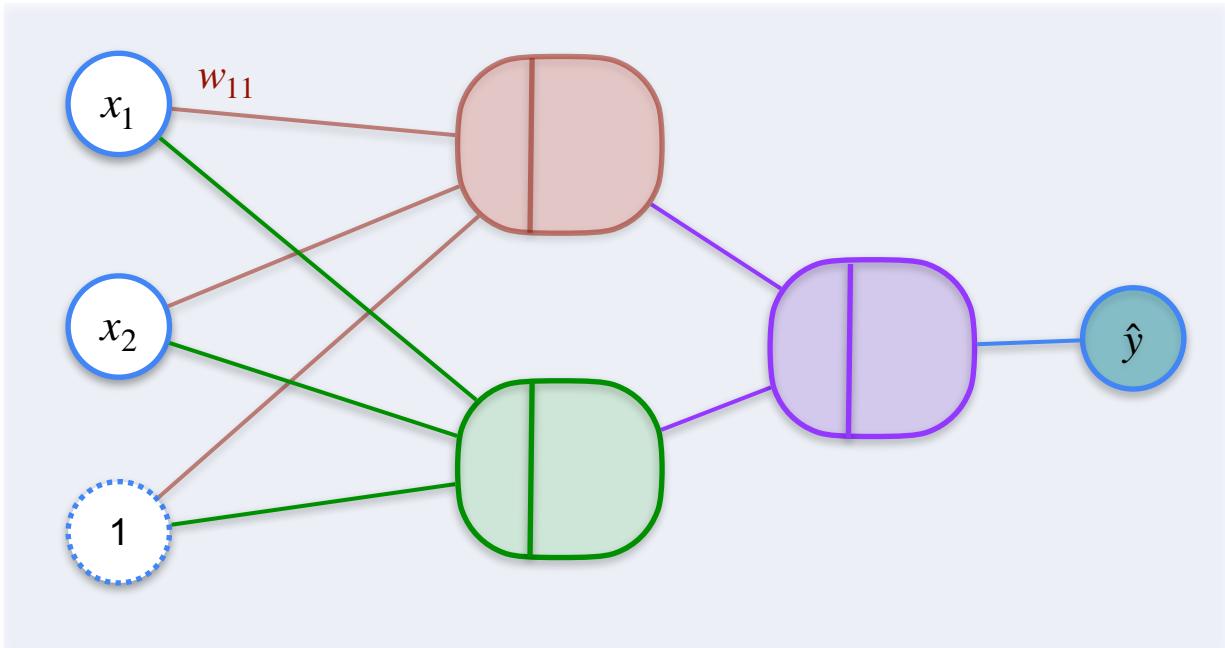
# 2,2,1 Neural Network



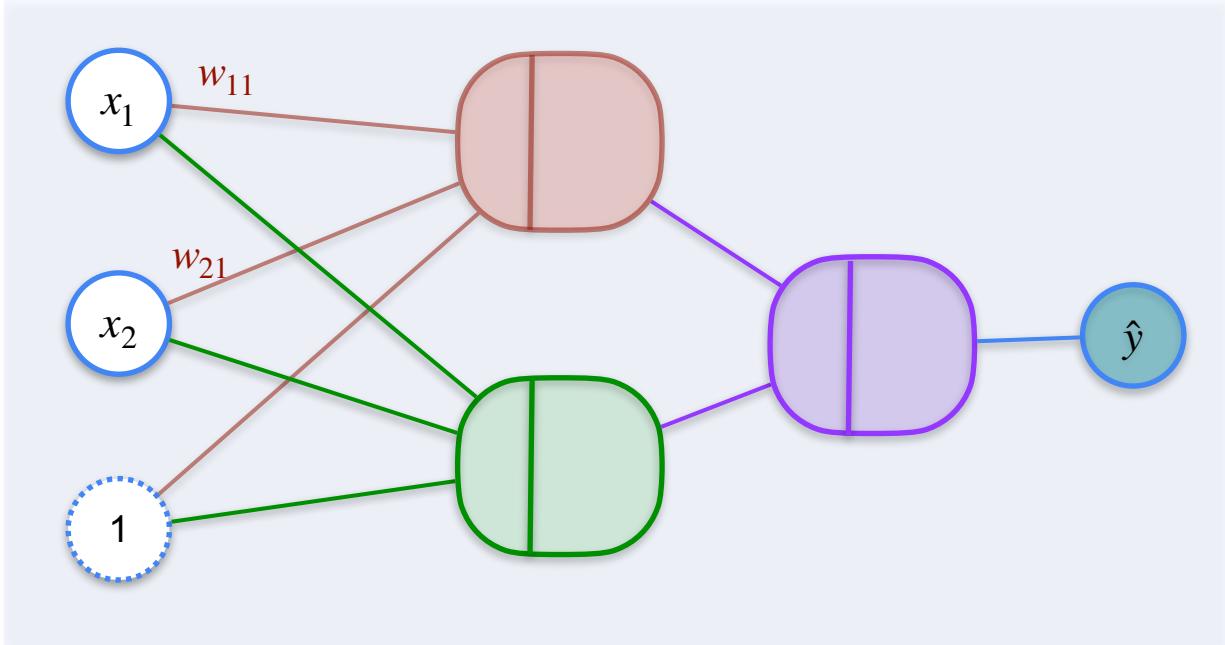
# 2,2,1 Neural Network



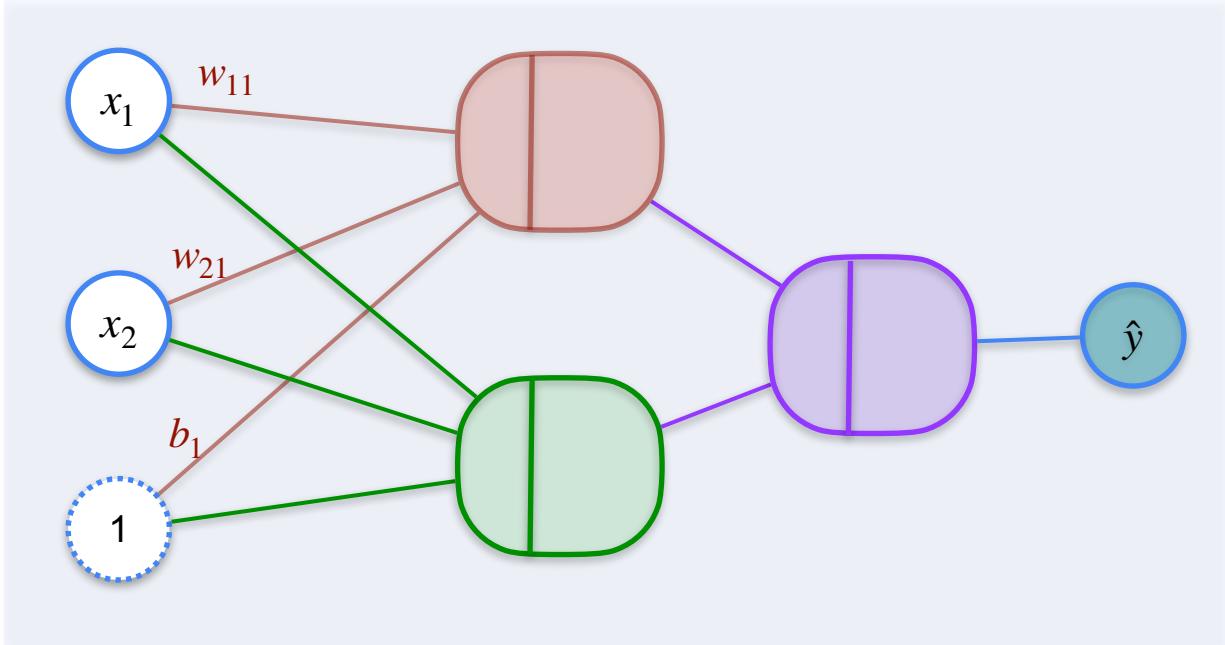
# 2,2,1 Neural Network



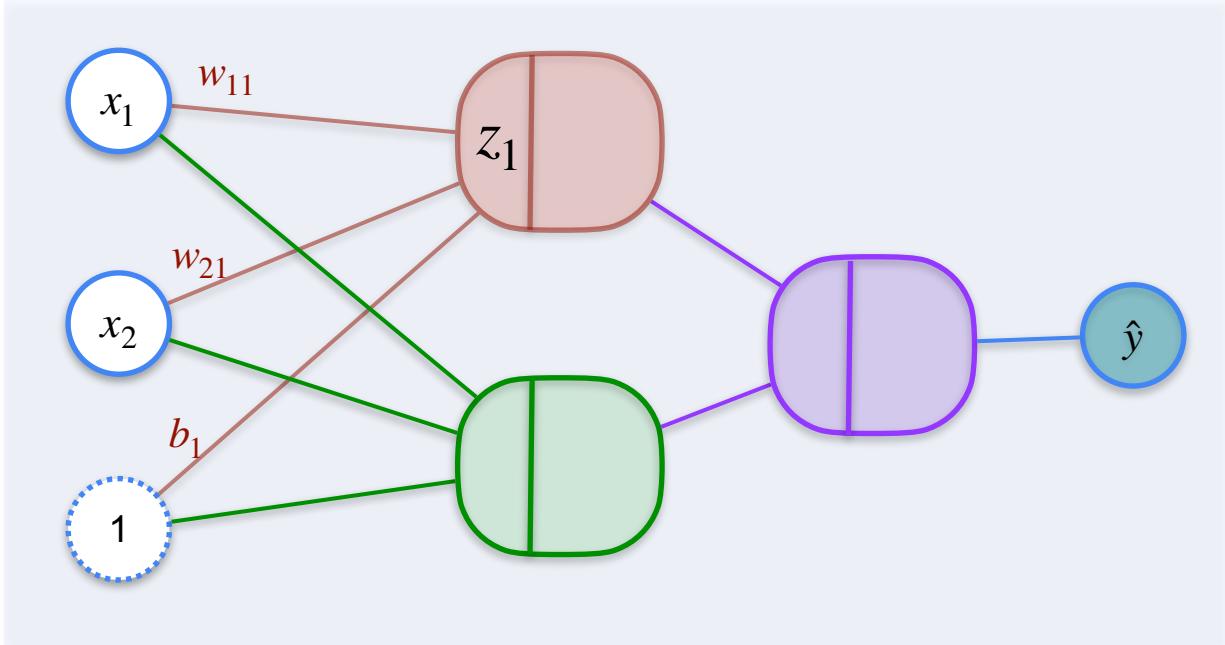
# 2,2,1 Neural Network



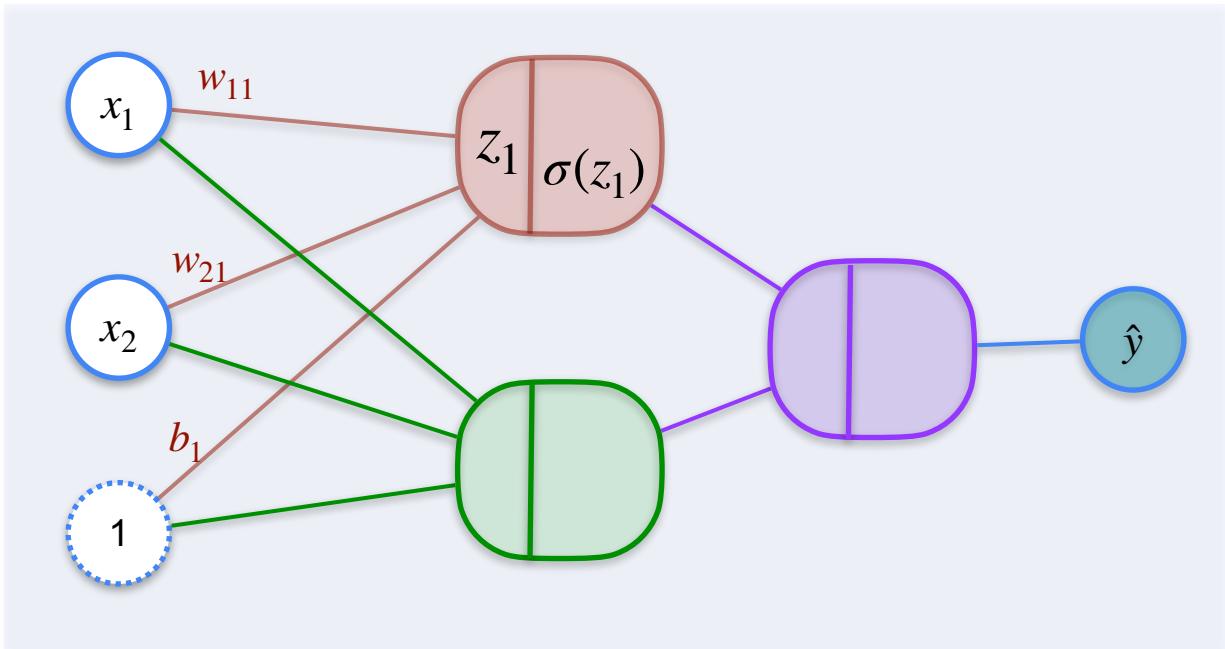
# 2,2,1 Neural Network



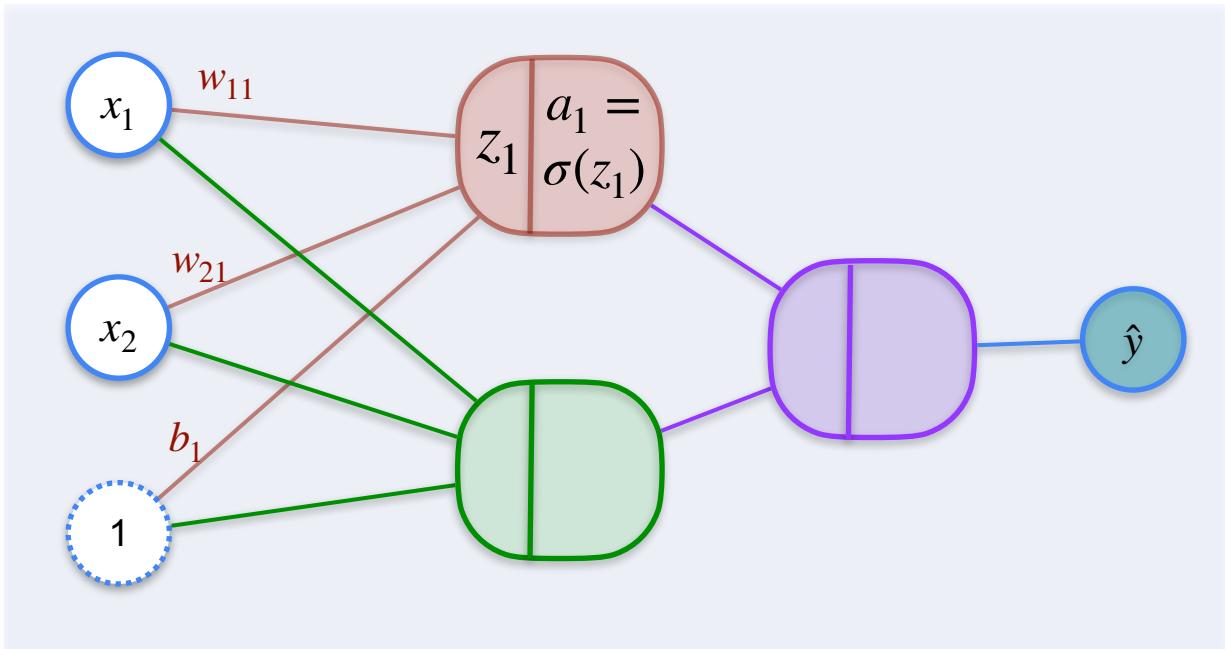
# 2,2,1 Neural Network



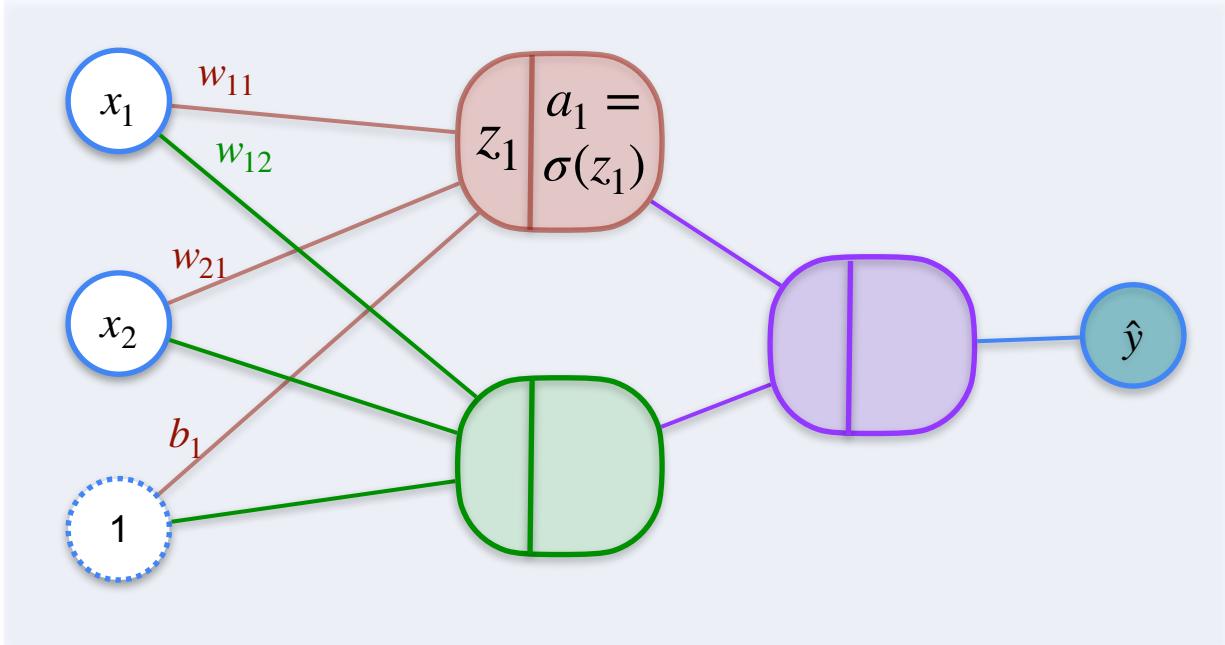
# 2,2,1 Neural Network



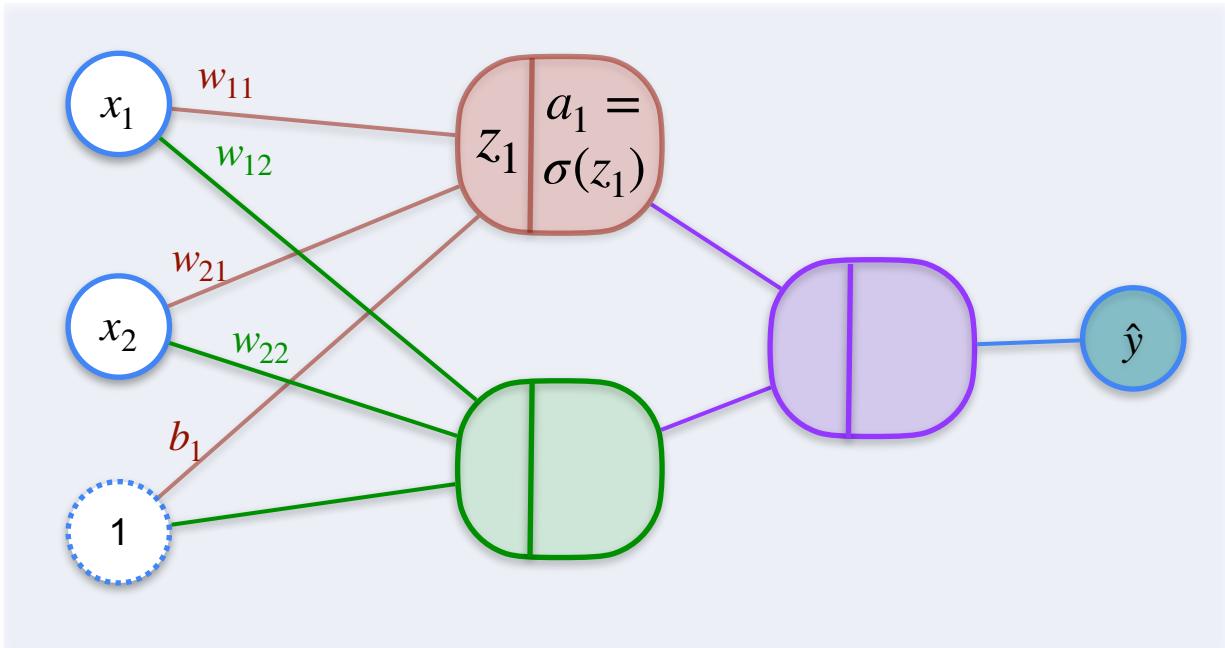
# 2,2,1 Neural Network



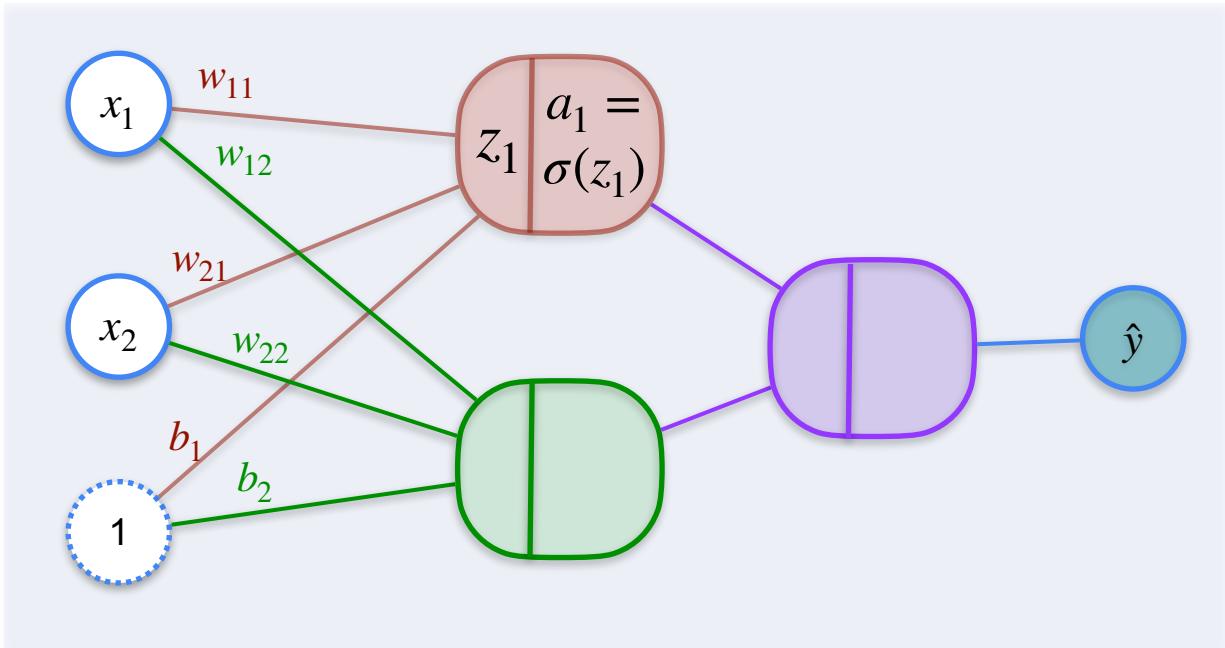
# 2,2,1 Neural Network



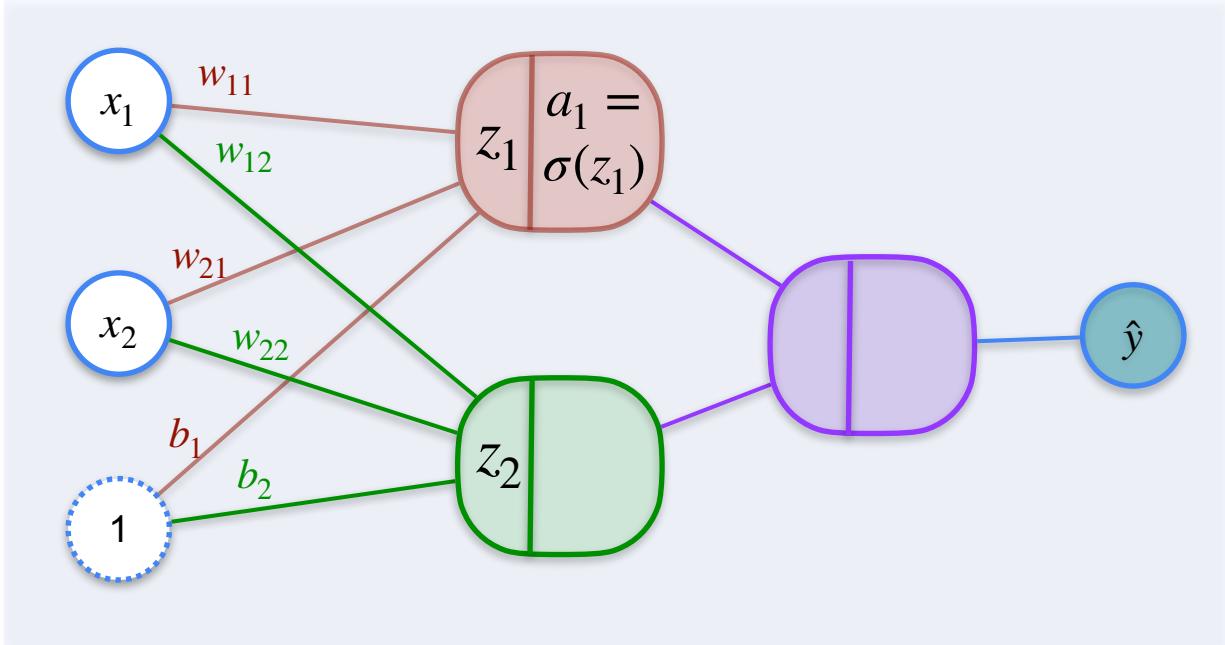
# 2,2,1 Neural Network



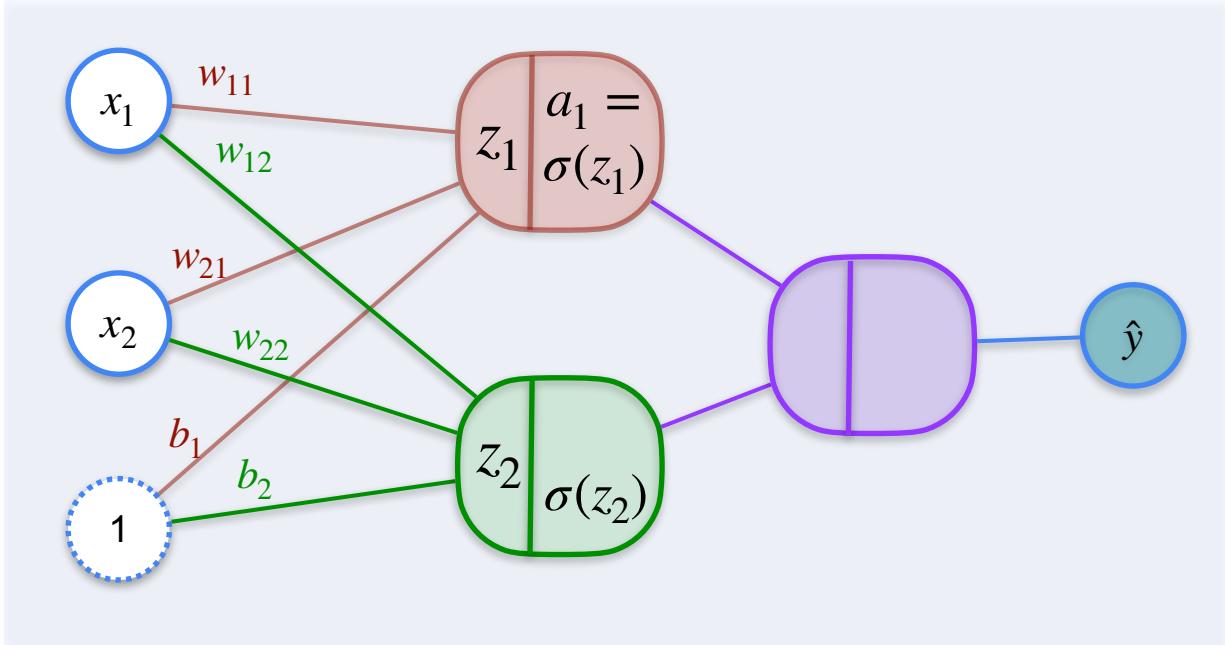
# 2,2,1 Neural Network



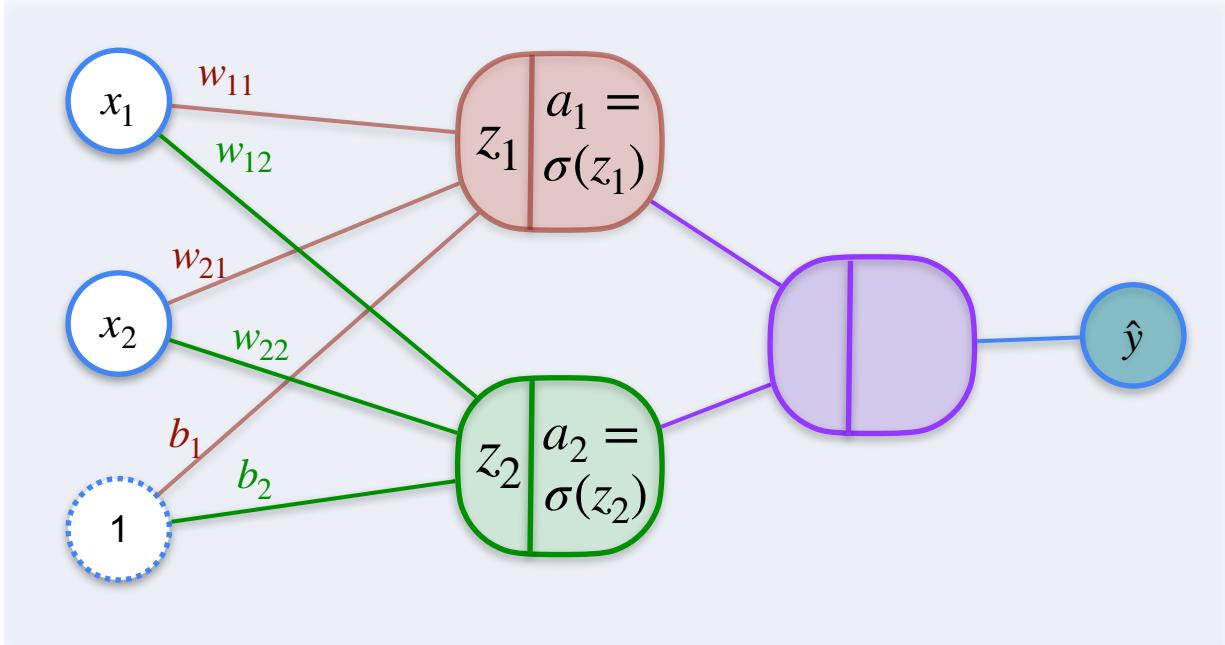
# 2,2,1 Neural Network



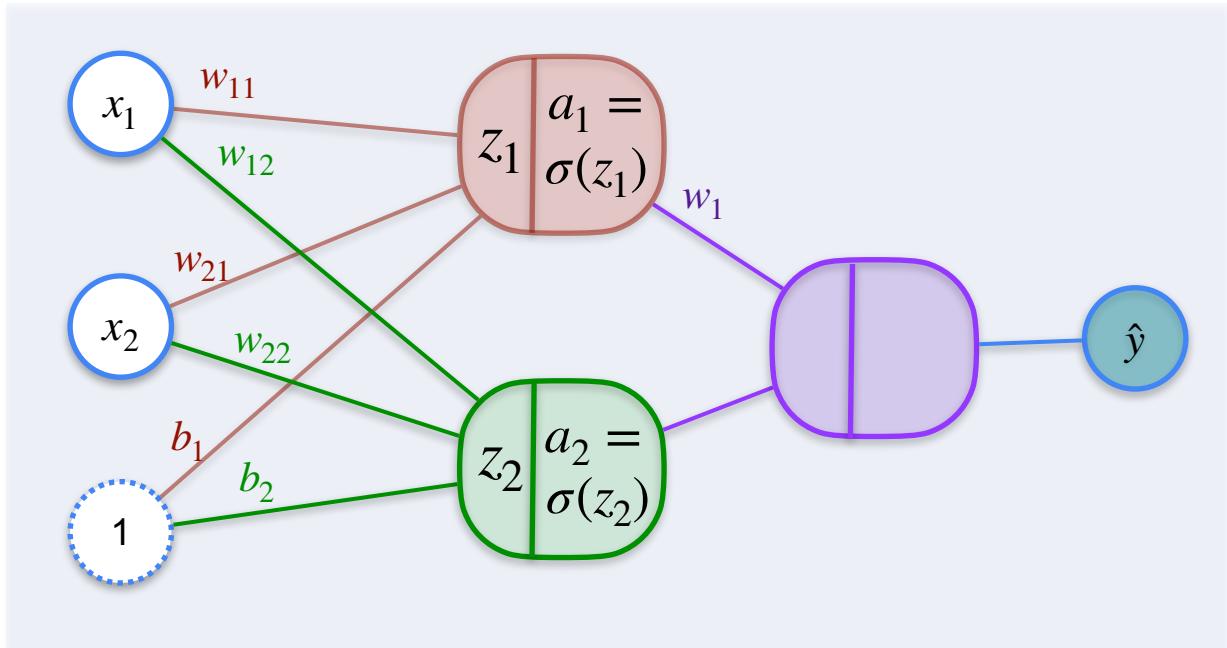
# 2,2,1 Neural Network



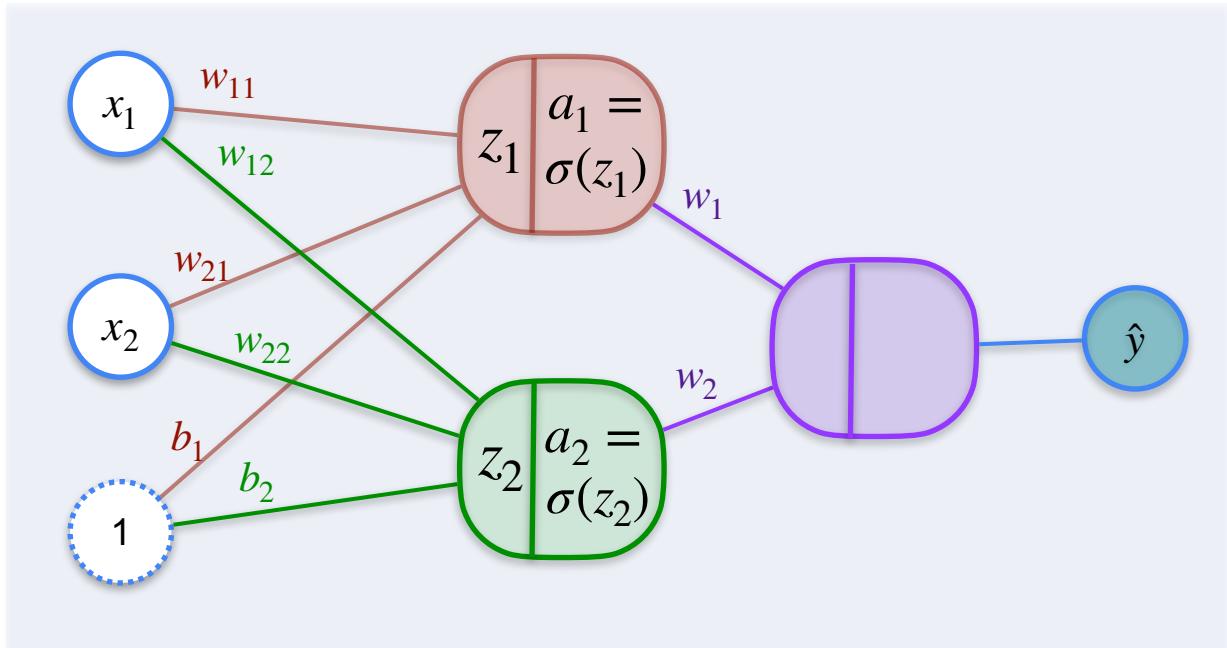
# 2,2,1 Neural Network



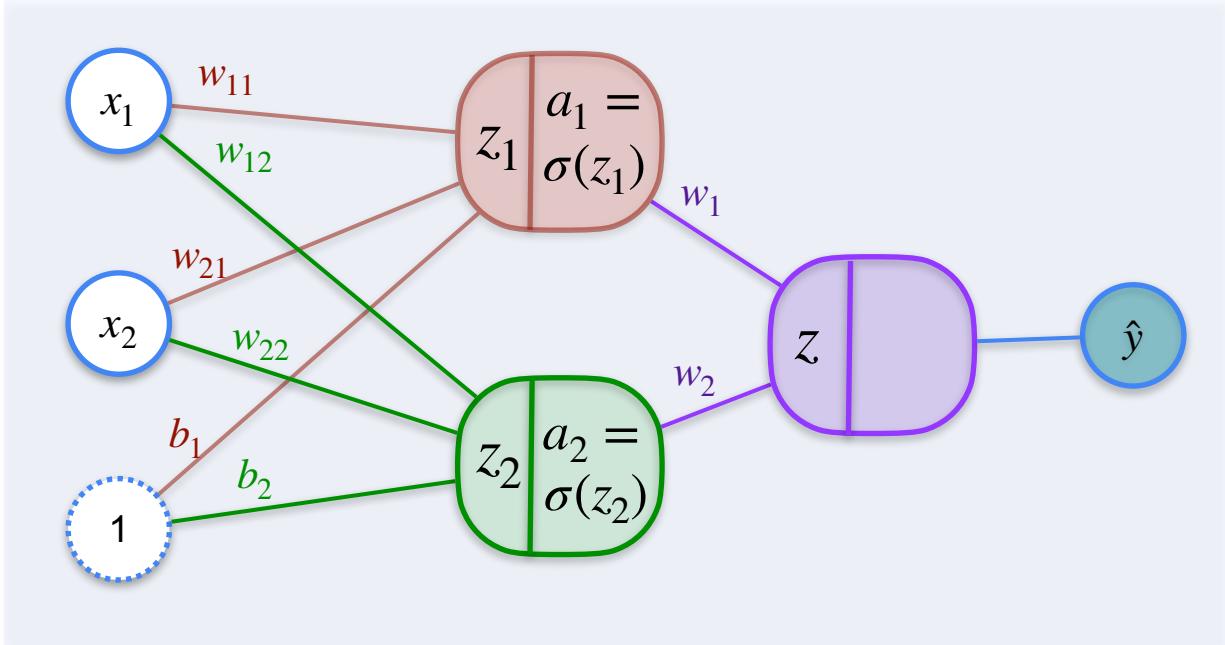
# 2,2,1 Neural Network



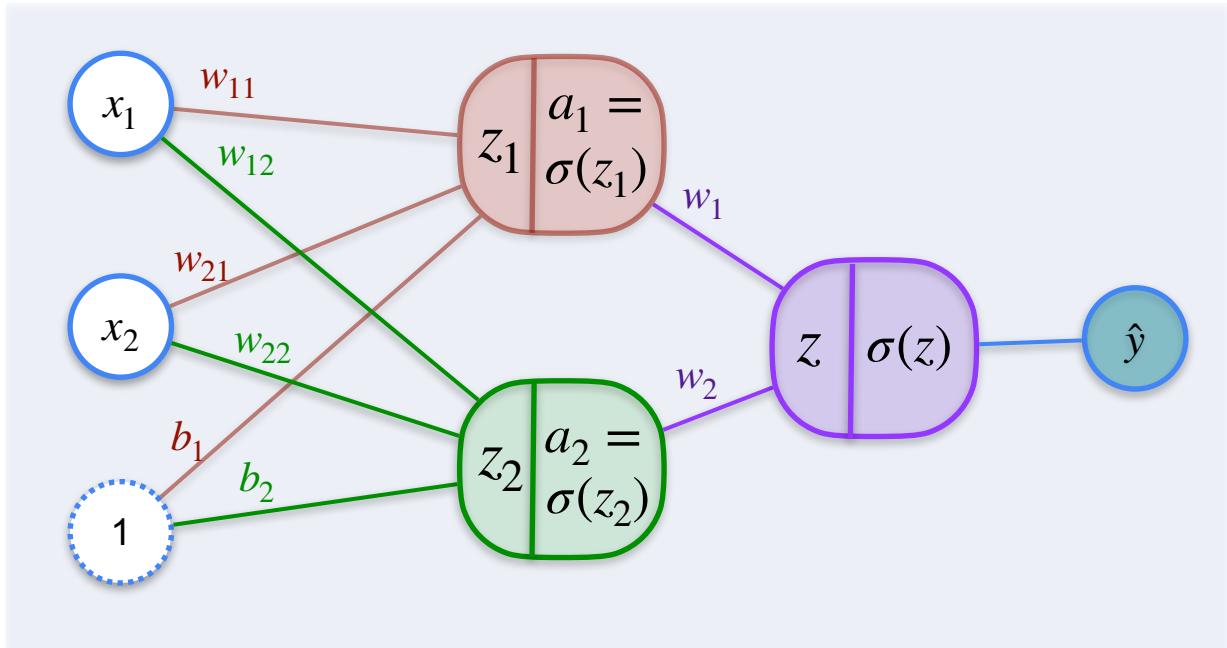
# 2,2,1 Neural Network



# 2,2,1 Neural Network



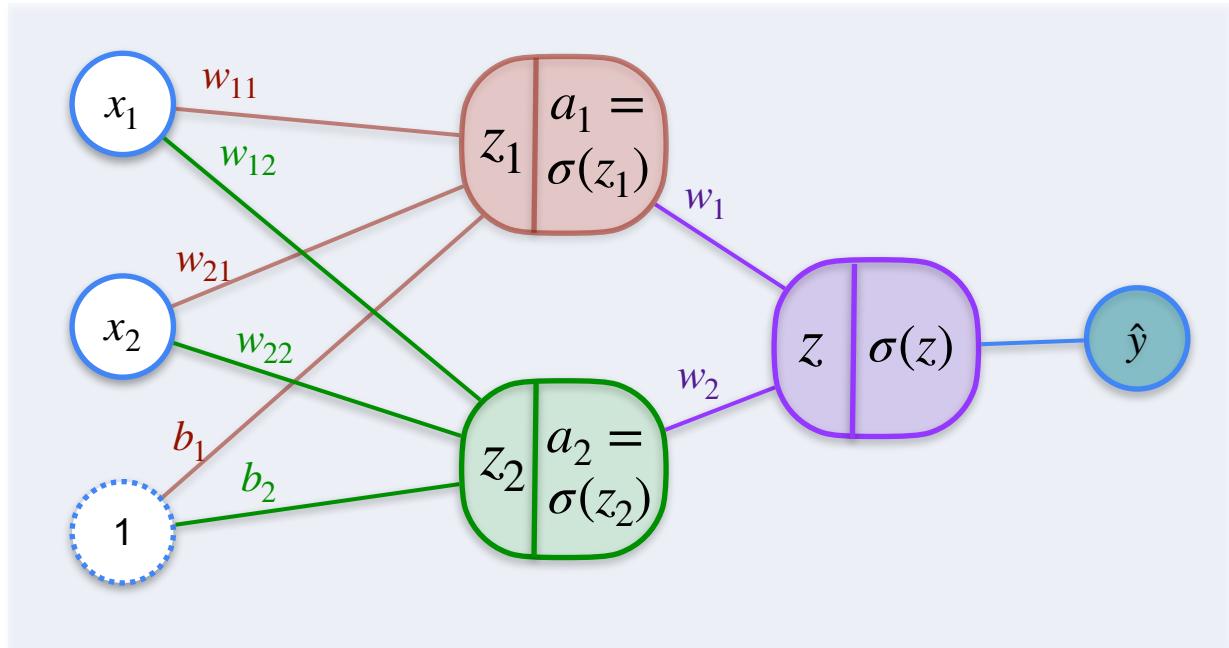
# 2,2,1 Neural Network



# 2,2,1 Neural Network

Neural network of depth 2

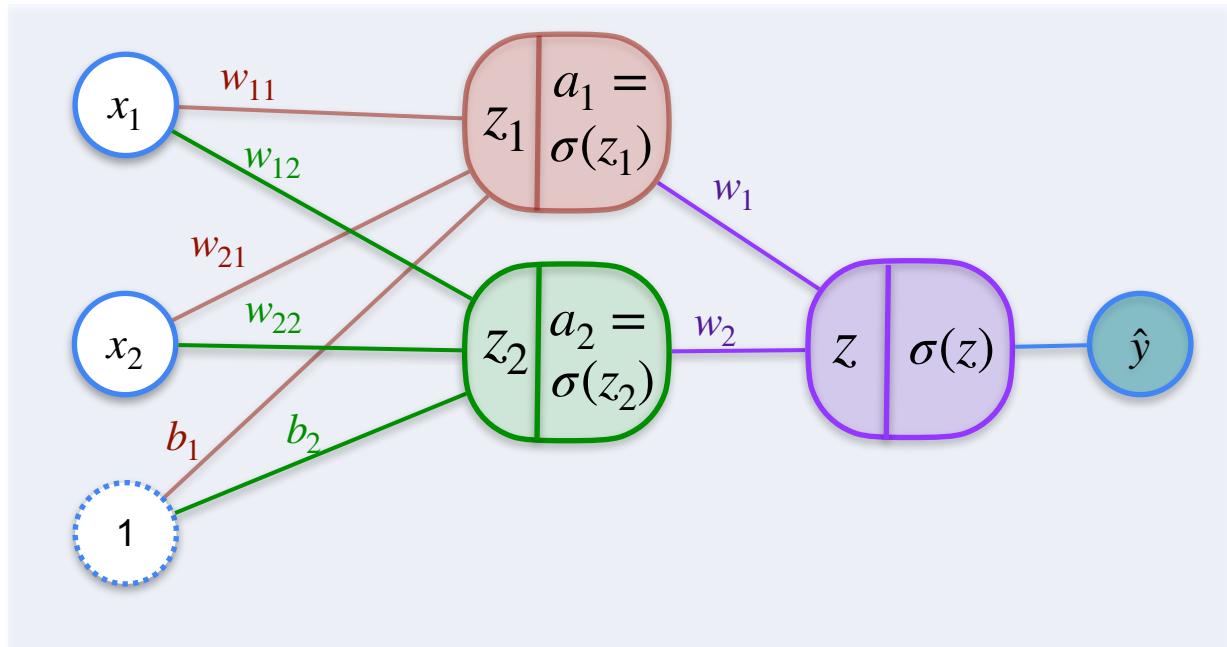
- one input layer
- one hidden layer
- one output layer



# 2,2,1 Neural Network

Neural network of depth 2

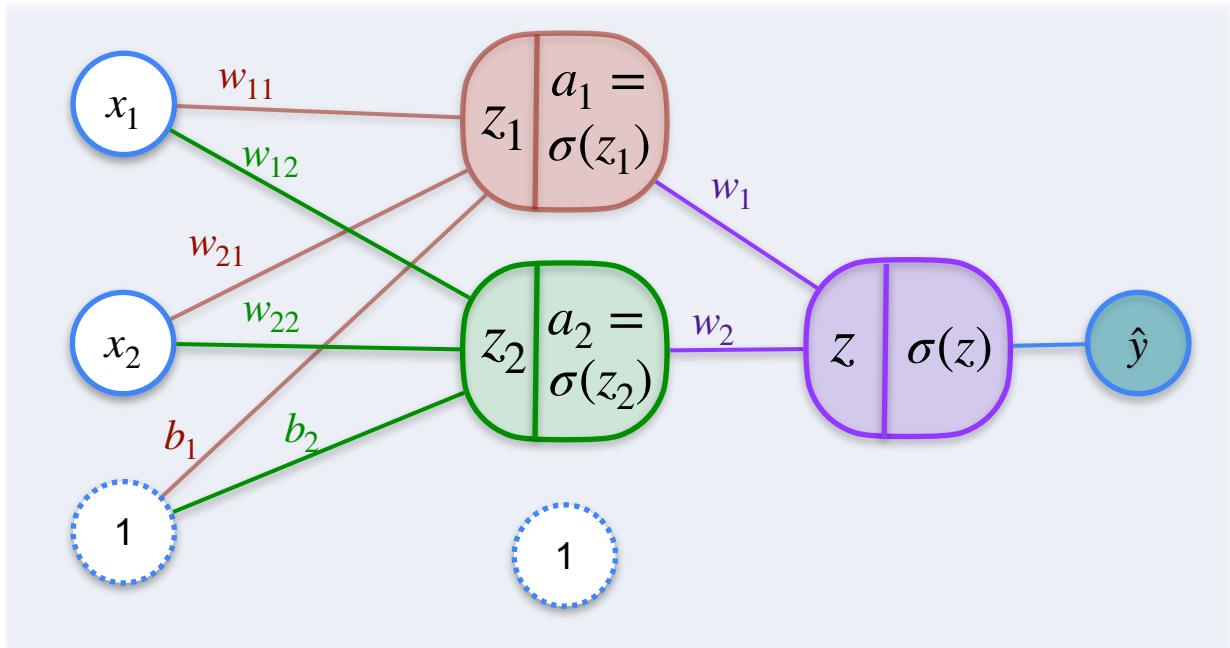
- one input layer
- one hidden layer
- one output layer



# 2,2,1 Neural Network

Neural network of depth 2

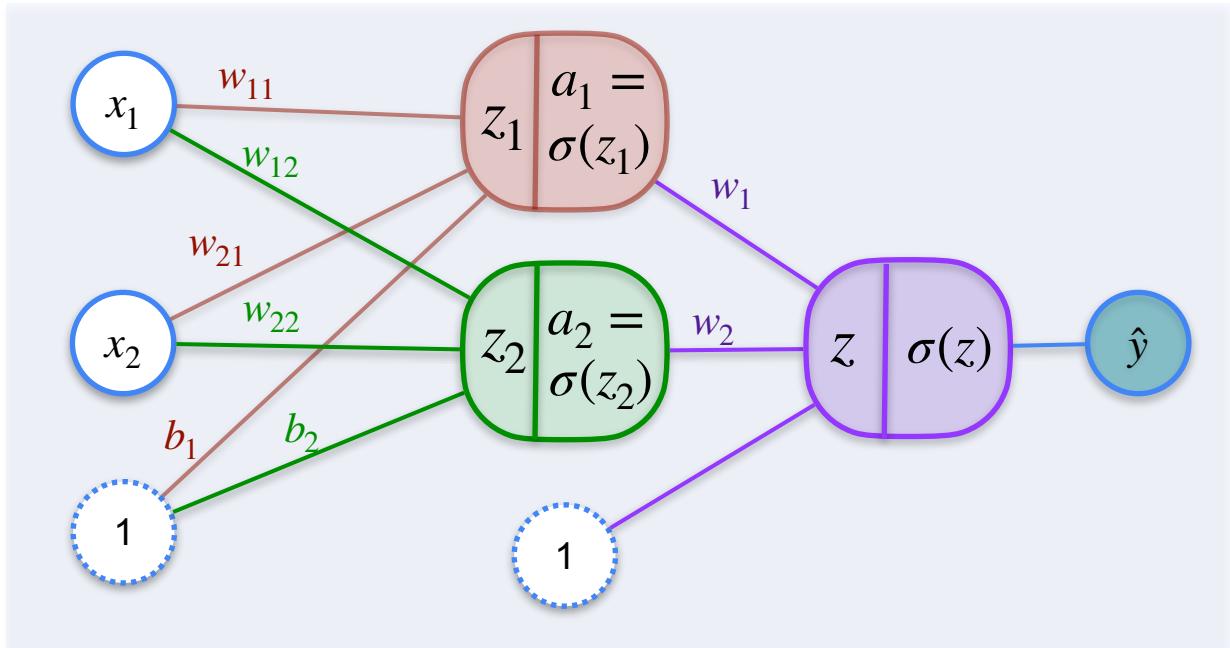
- one input layer
- one hidden layer
- one output layer



# 2,2,1 Neural Network

Neural network of depth 2

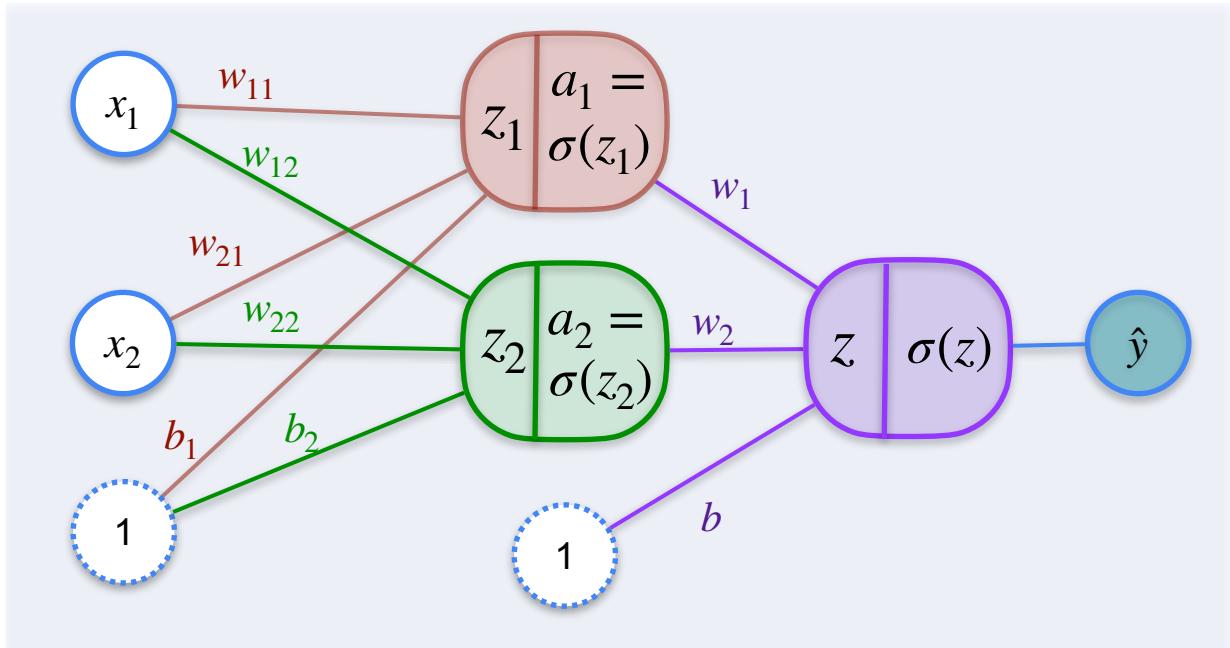
- one input layer
- one hidden layer
- one output layer



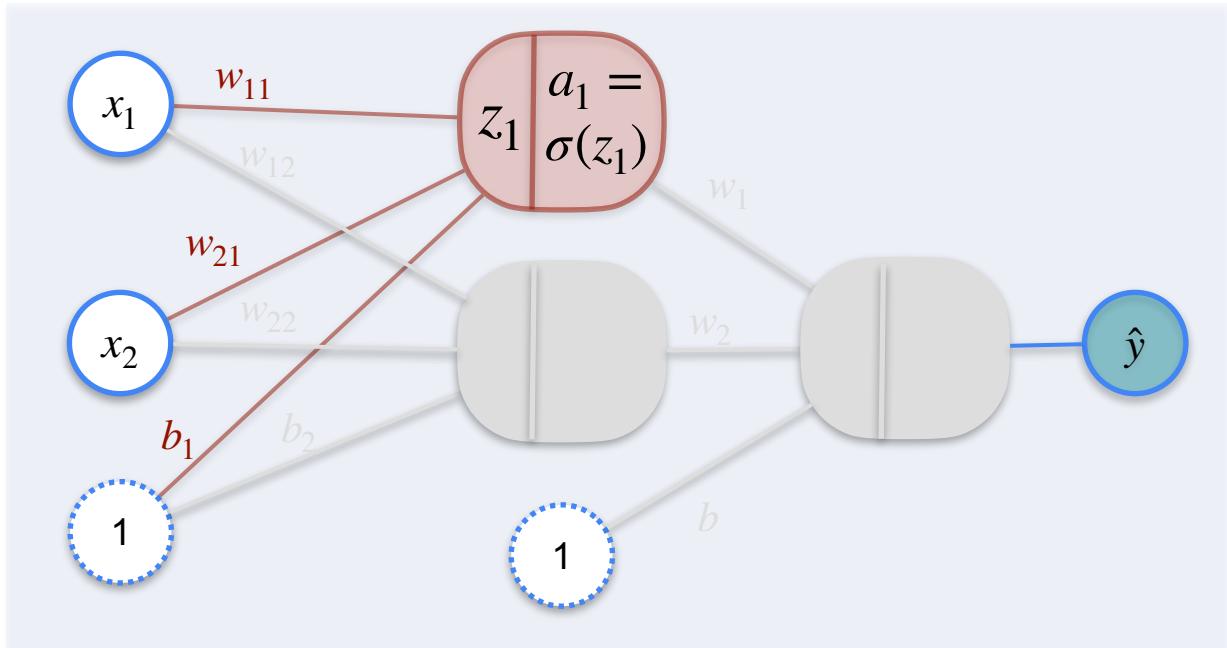
# 2,2,1 Neural Network

Neural network of depth 2

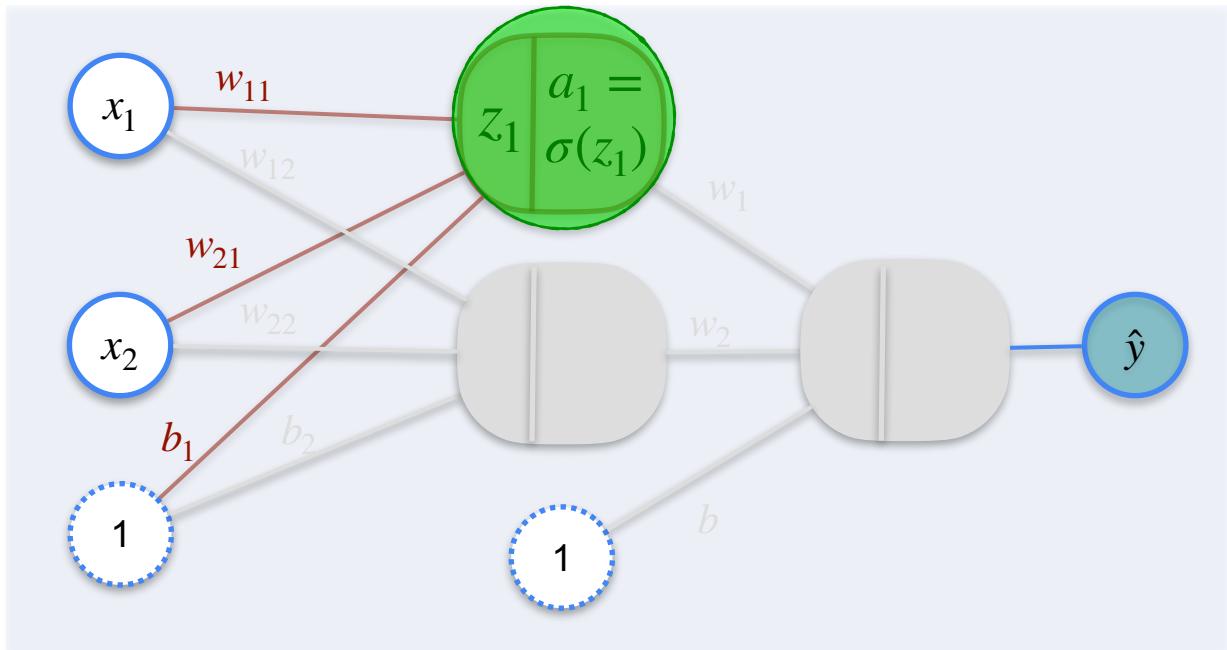
- one input layer
- one hidden layer
- one output layer



# 2,2,1 Neural Network

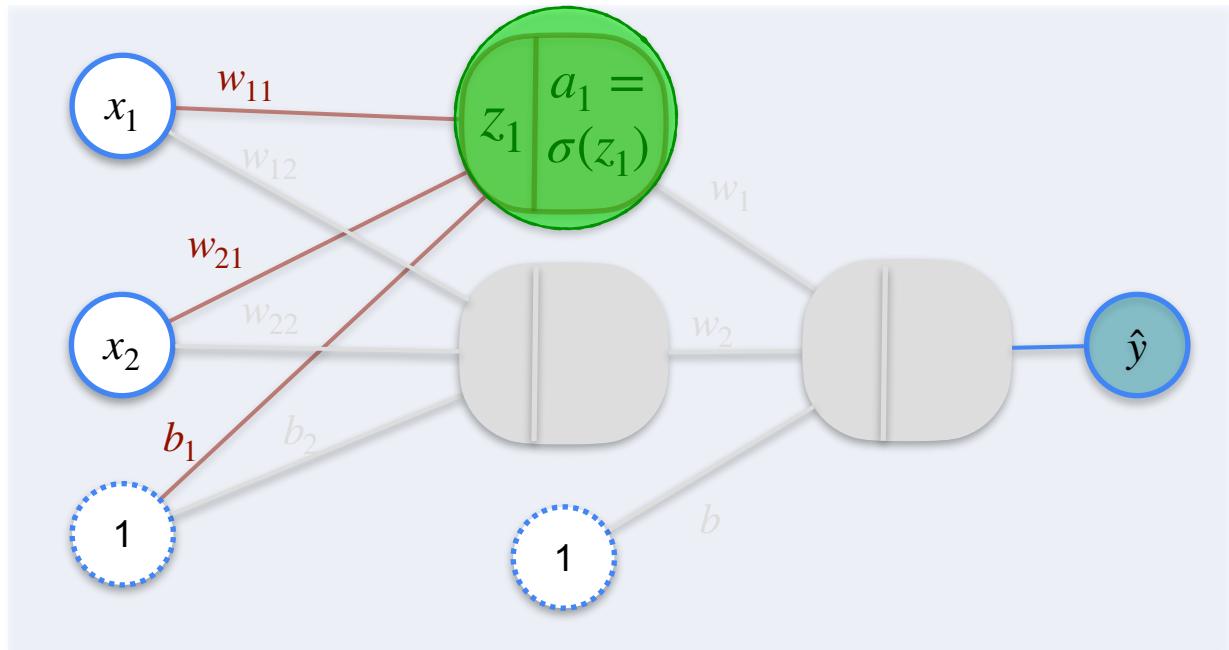


# 2,2,1 Neural Network



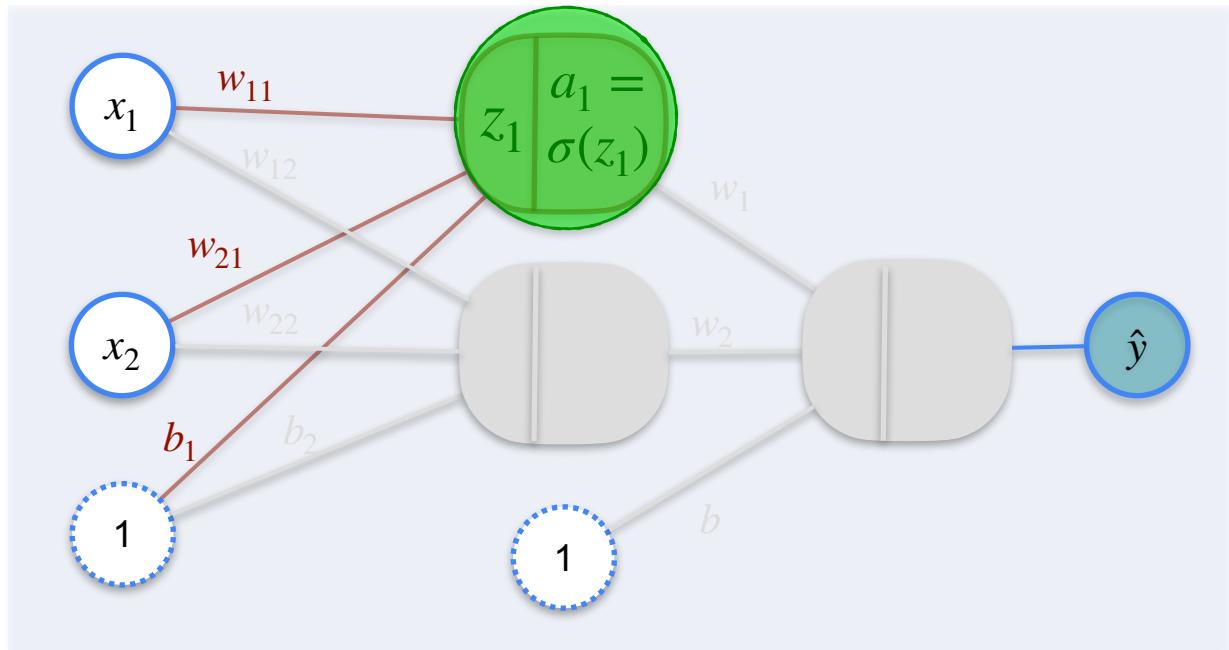
# 2,2,1 Neural Network

$a_1$



# 2,2,1 Neural Network

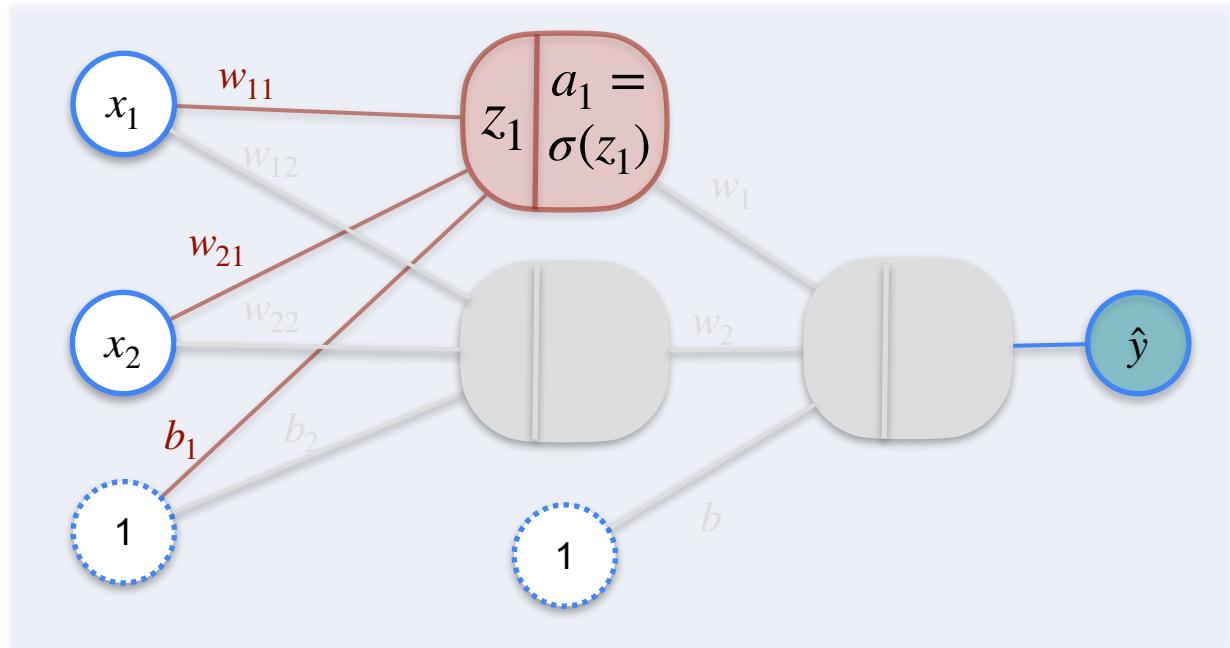
$$a_1 = \sigma(z_1)$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

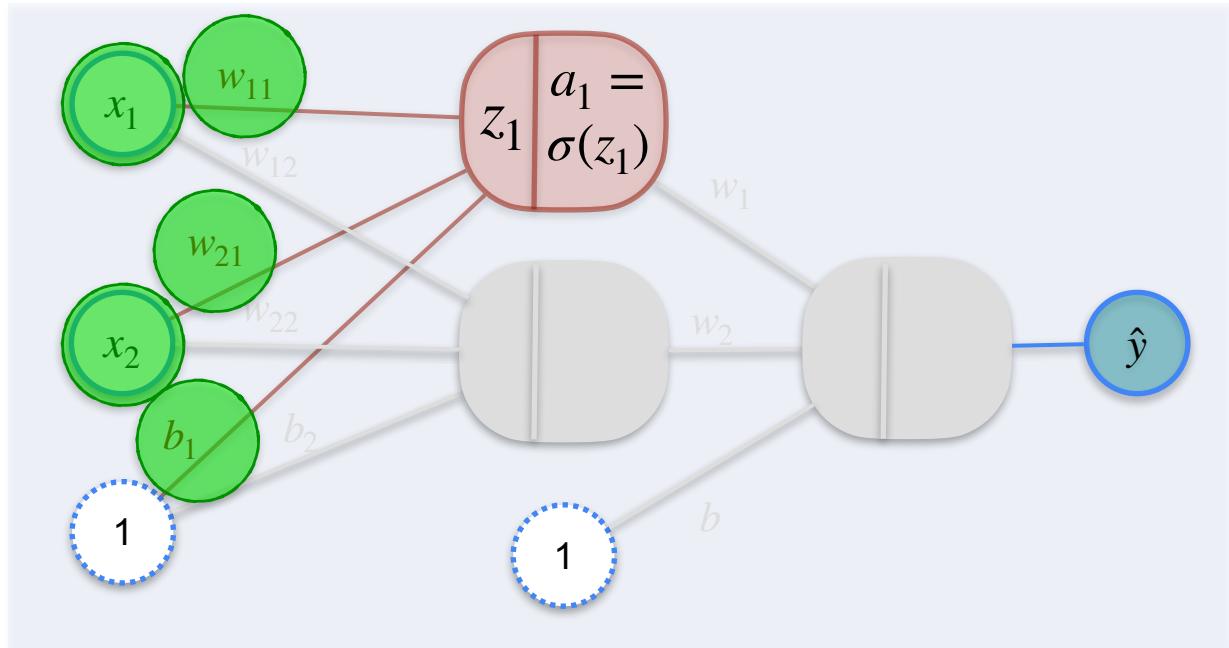
$$z_1$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

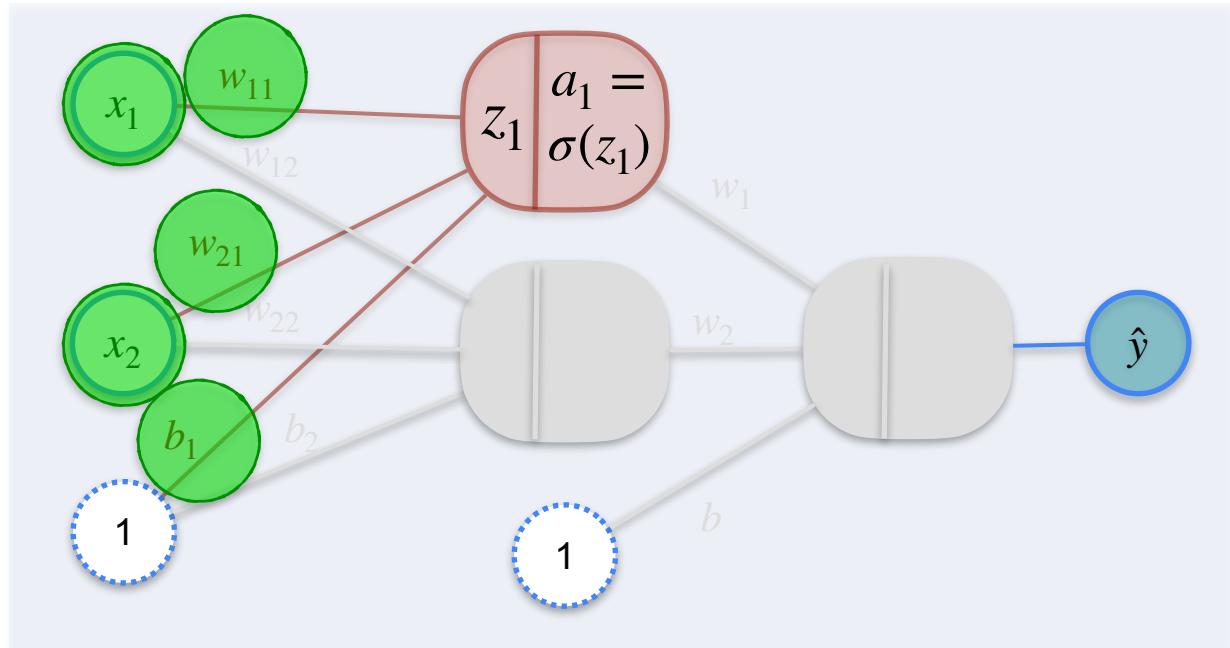
$$z_1$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

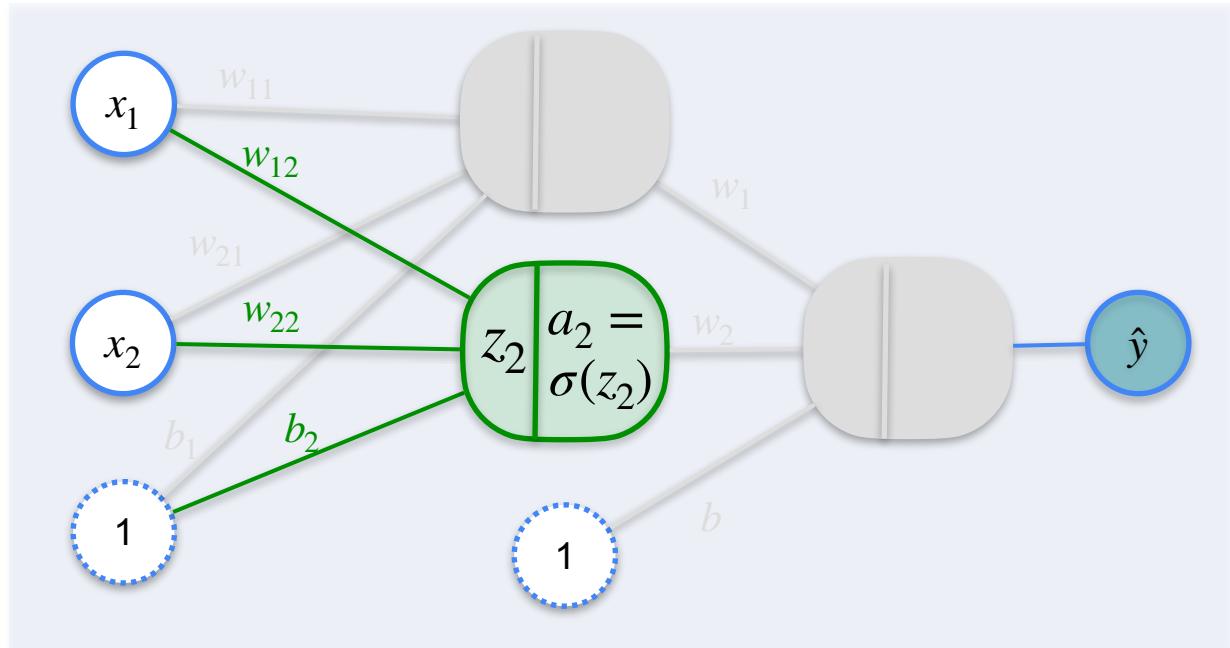
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

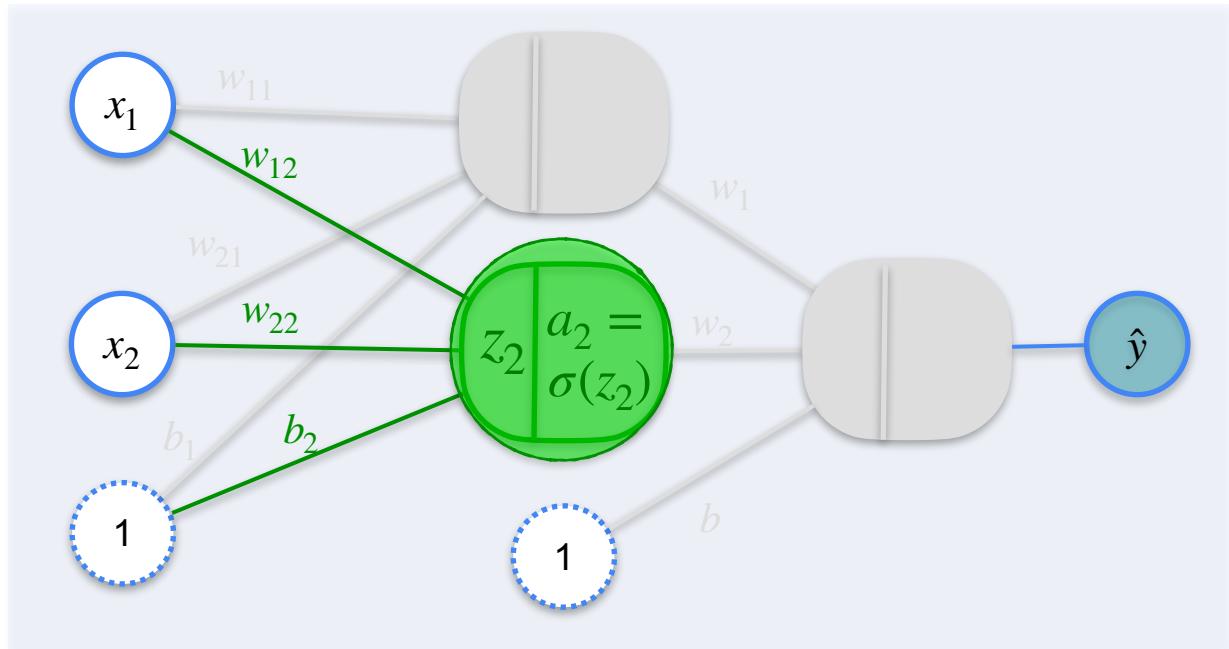
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

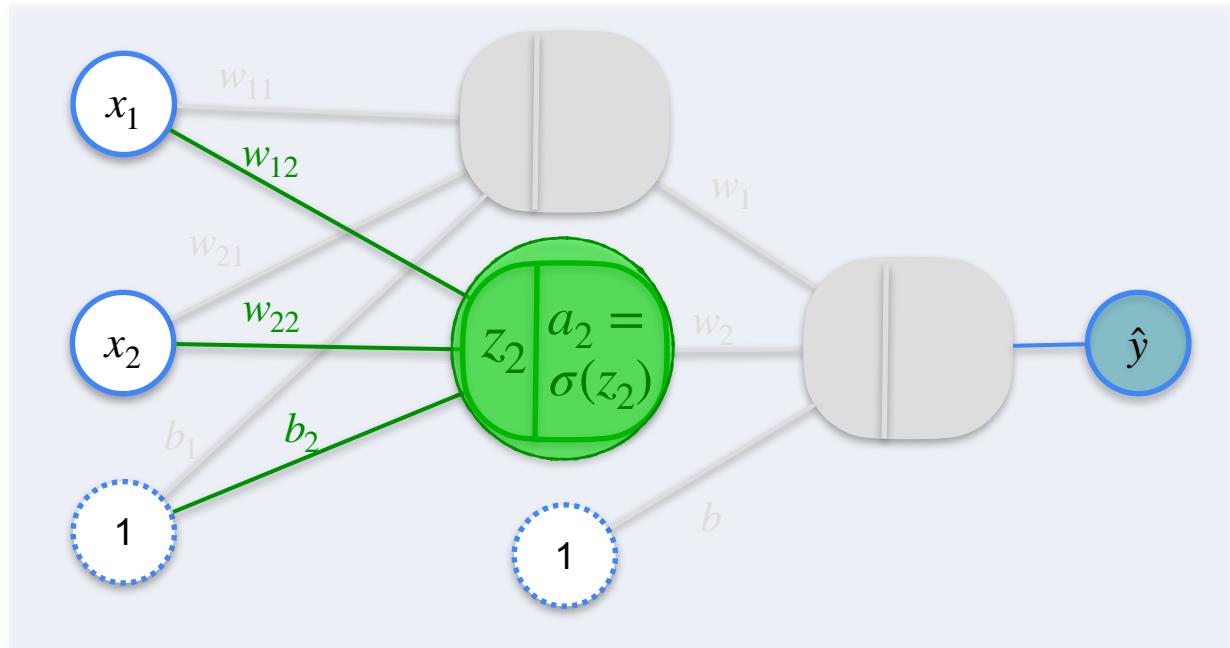


# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2$$

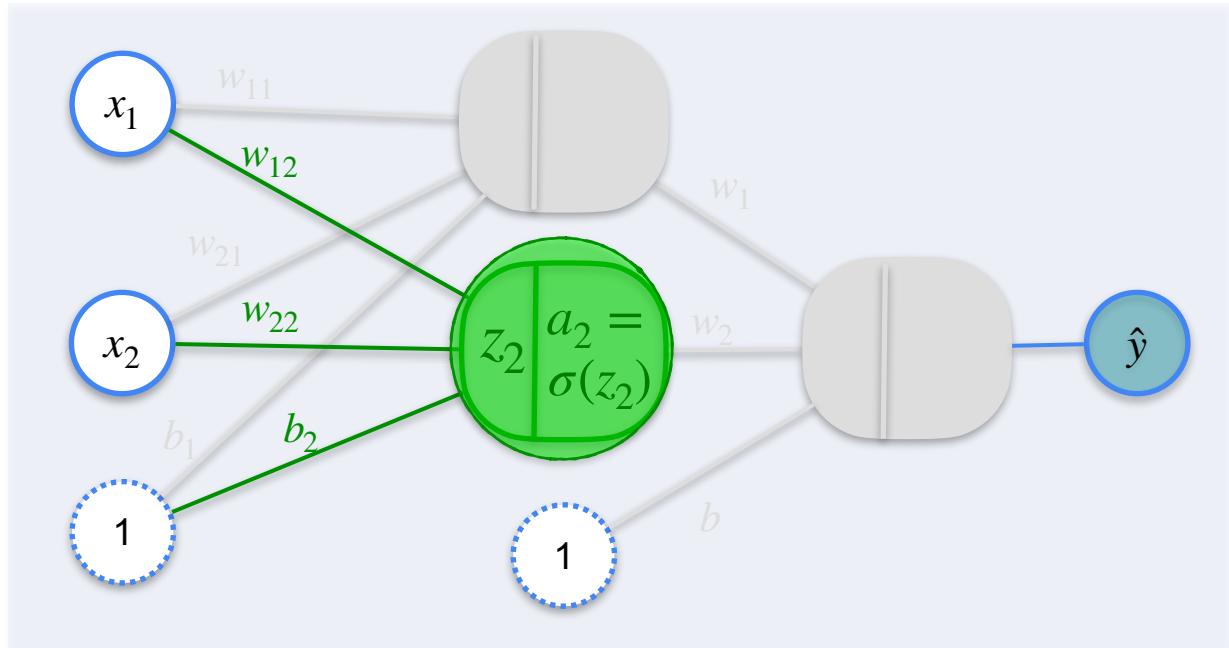


# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$



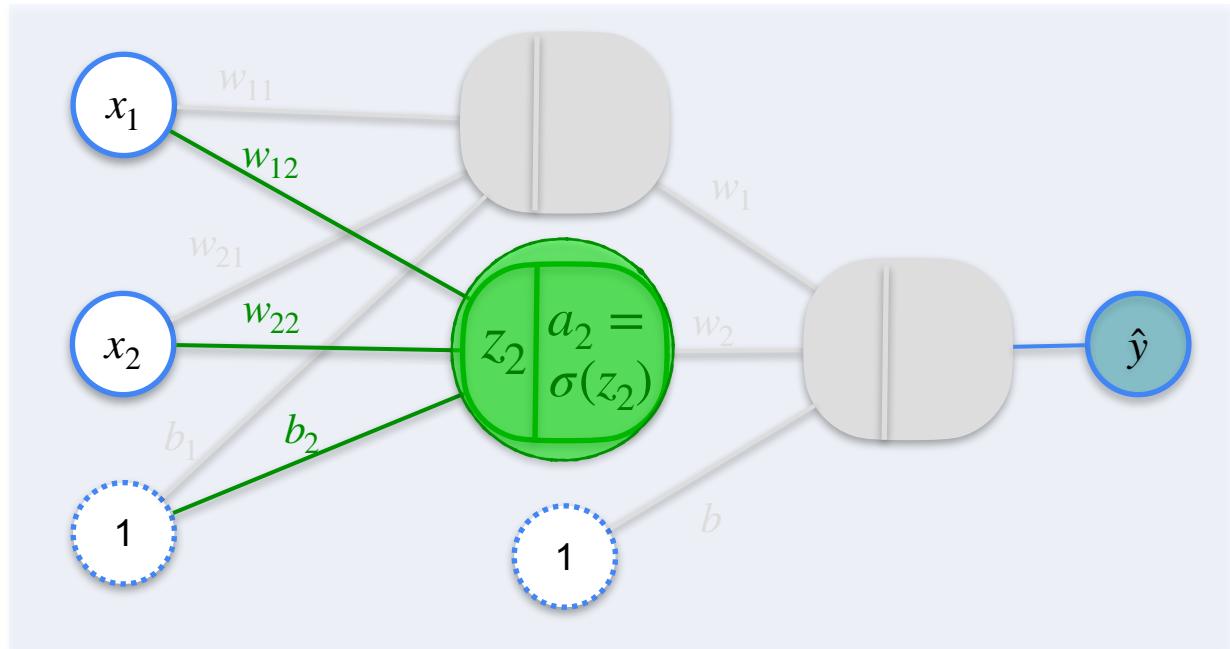
# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2$$



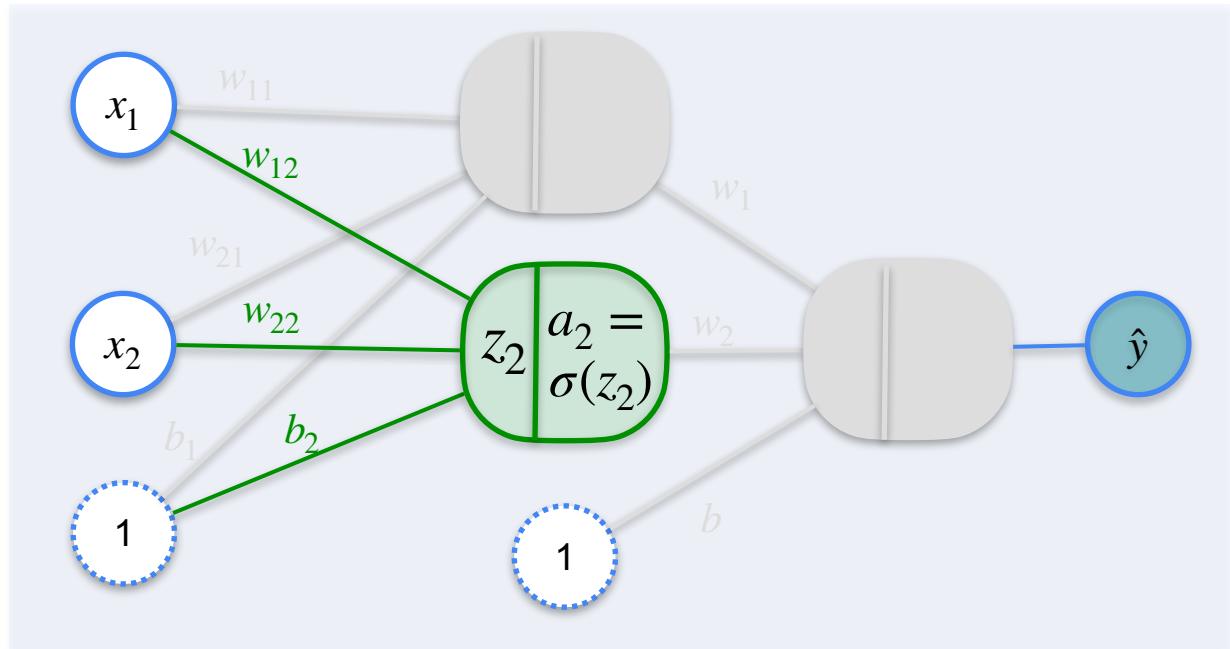
# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2$$



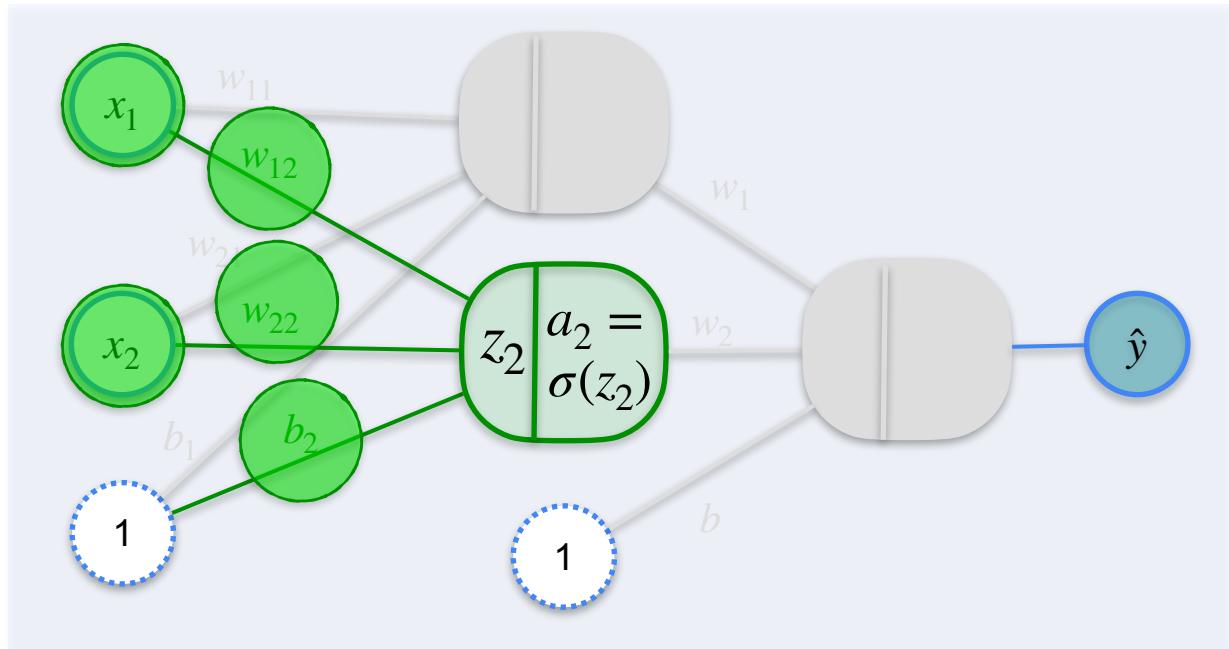
# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2$$



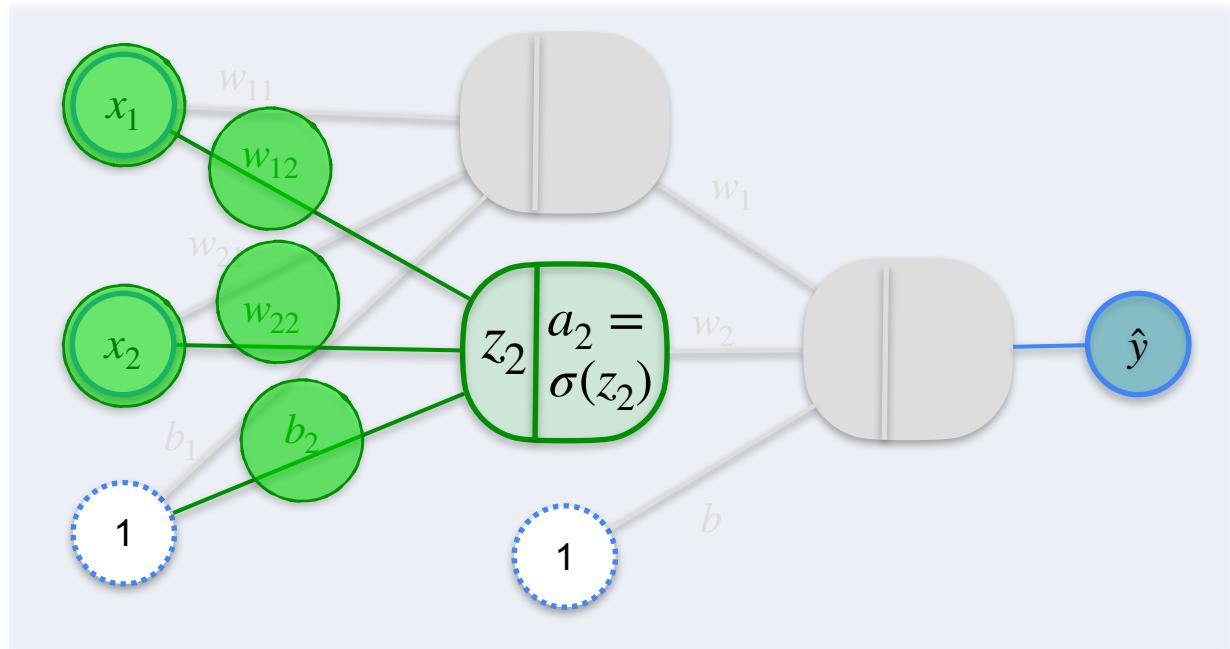
# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$



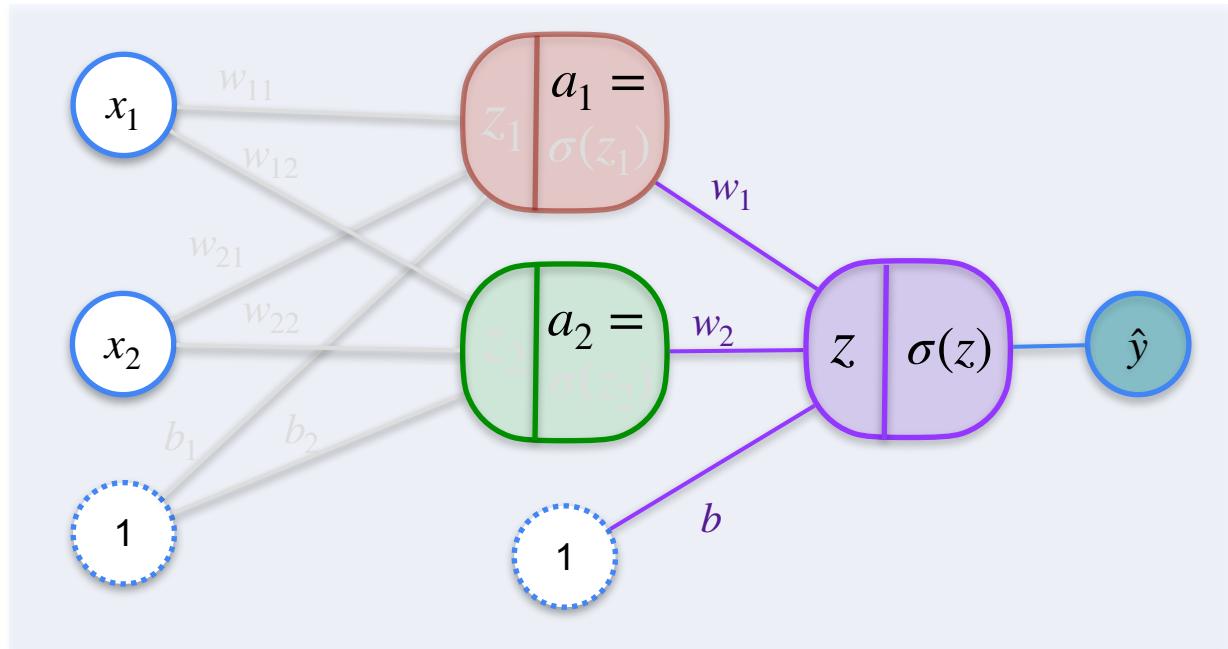
# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$



# 2,2,1 Neural Network

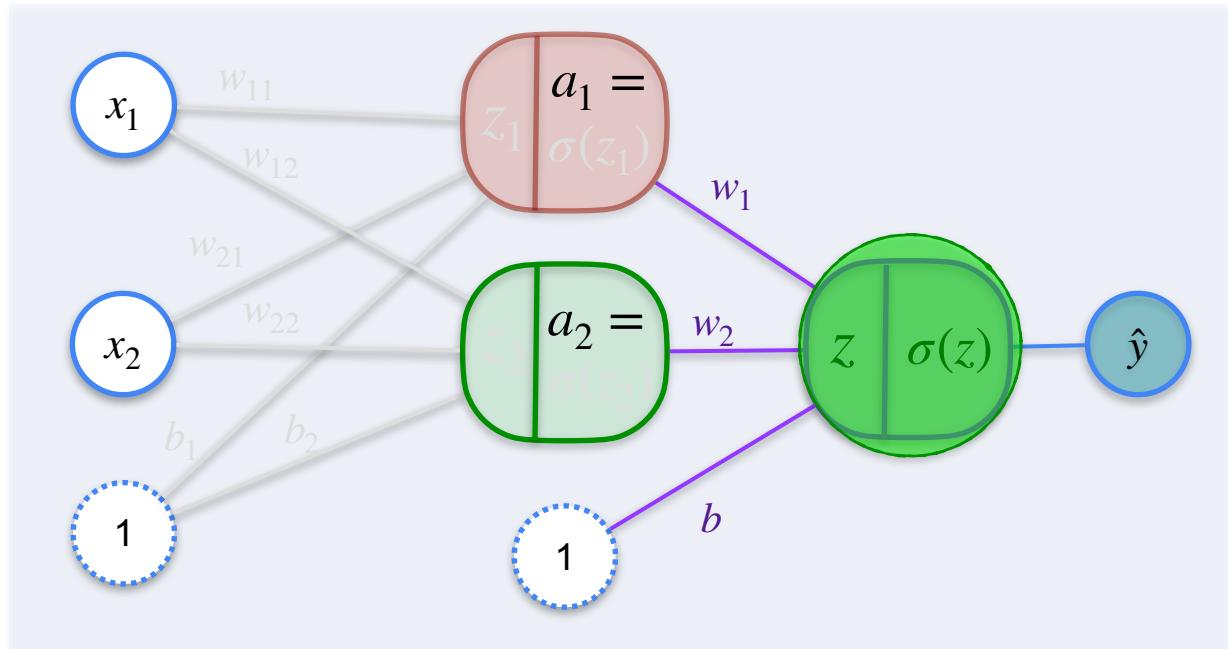
$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$



# 2,2,1 Neural Network

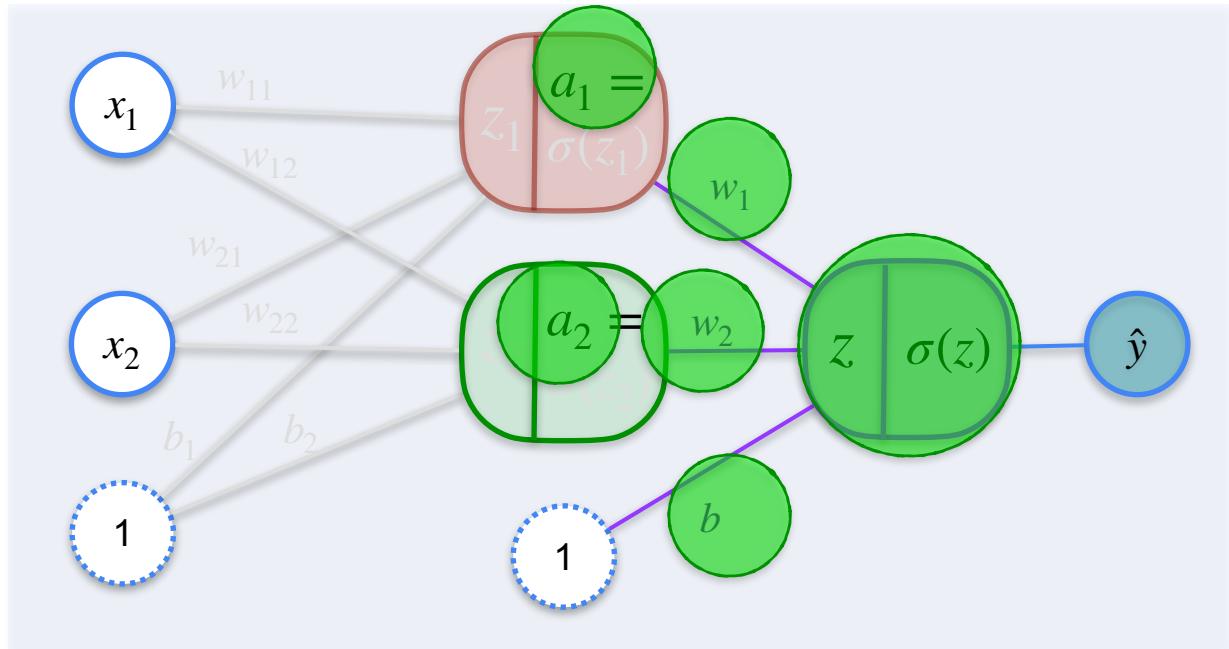
$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

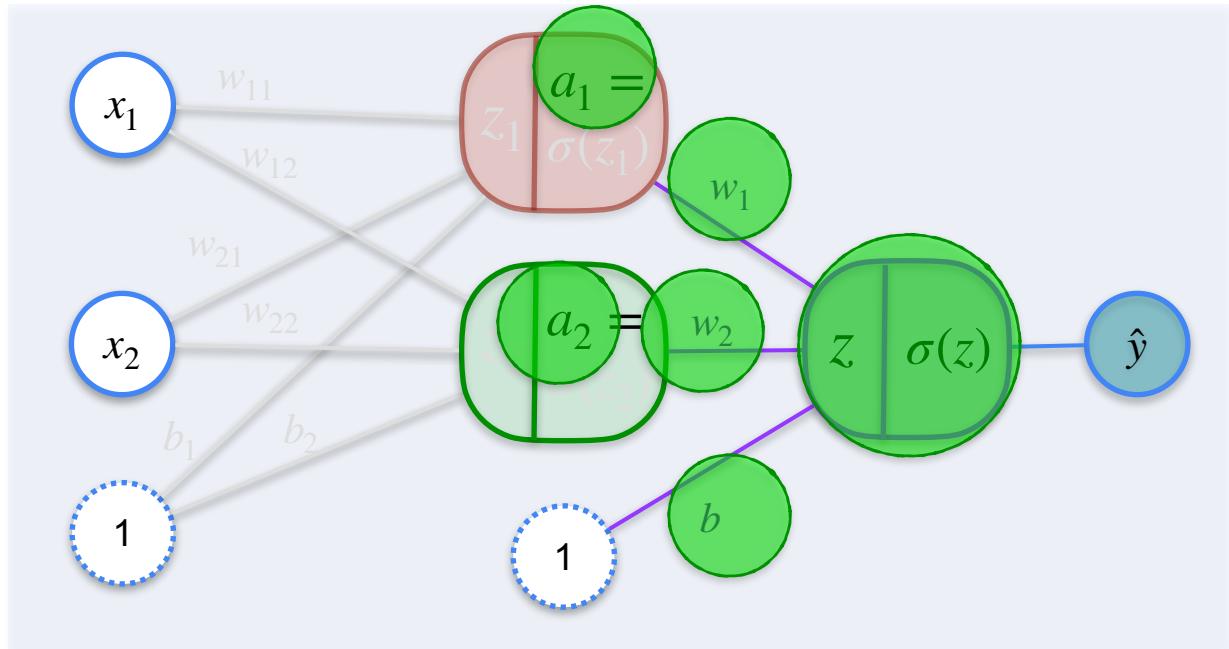
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

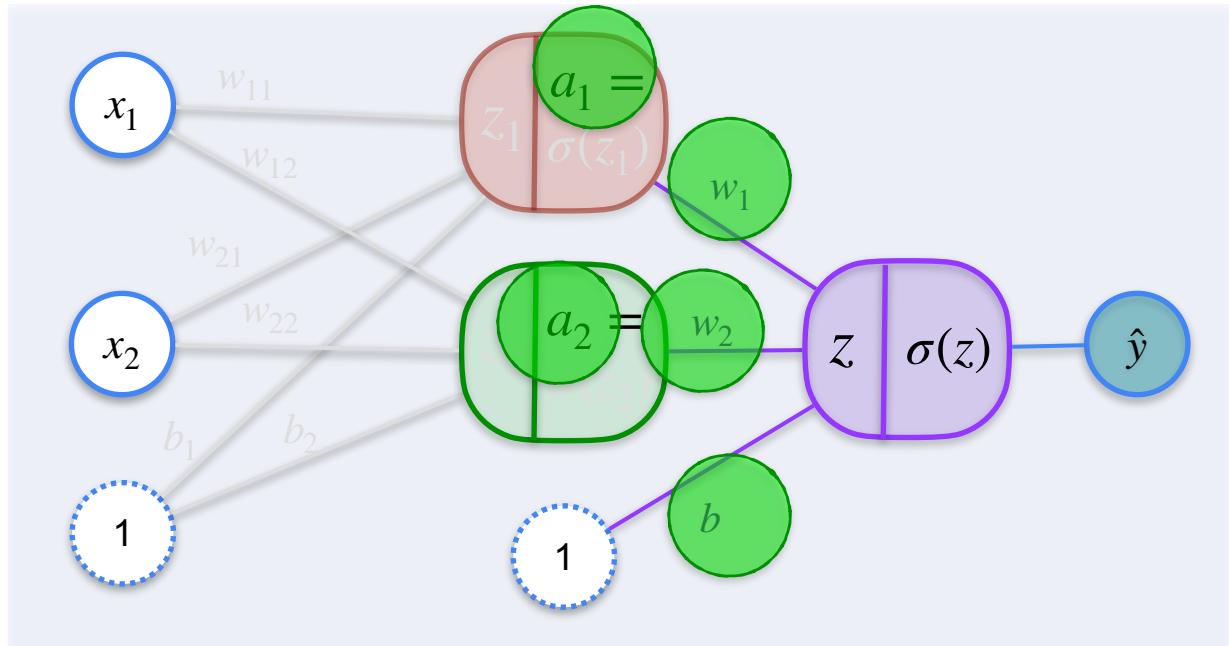
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

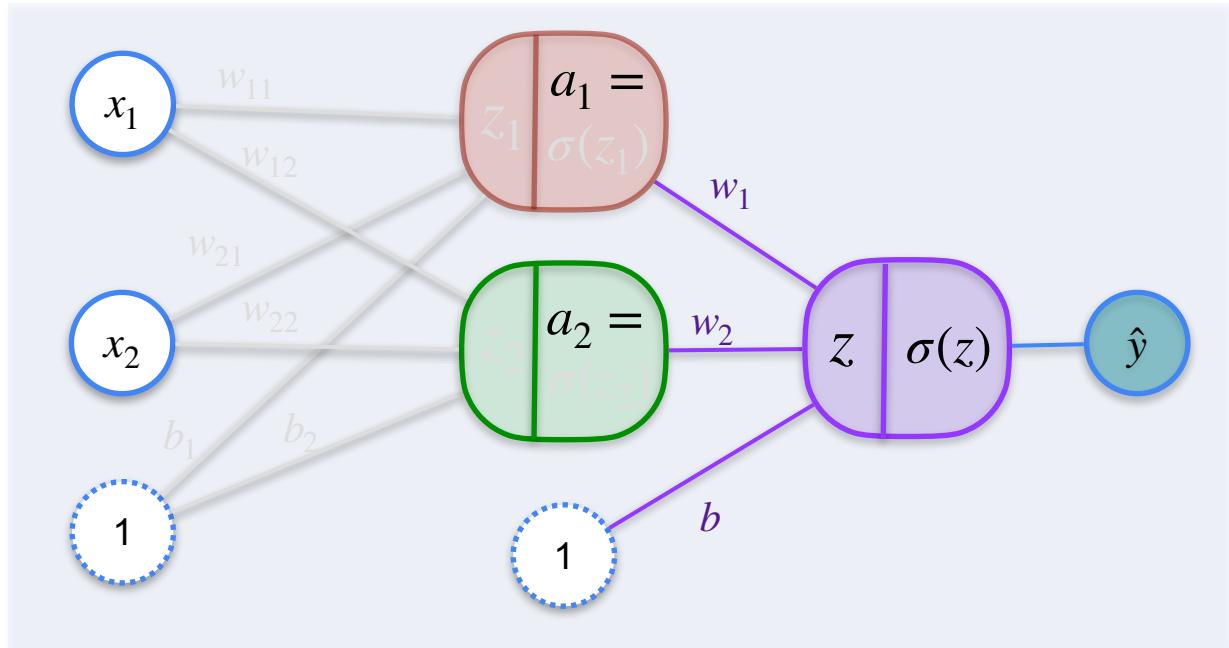
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

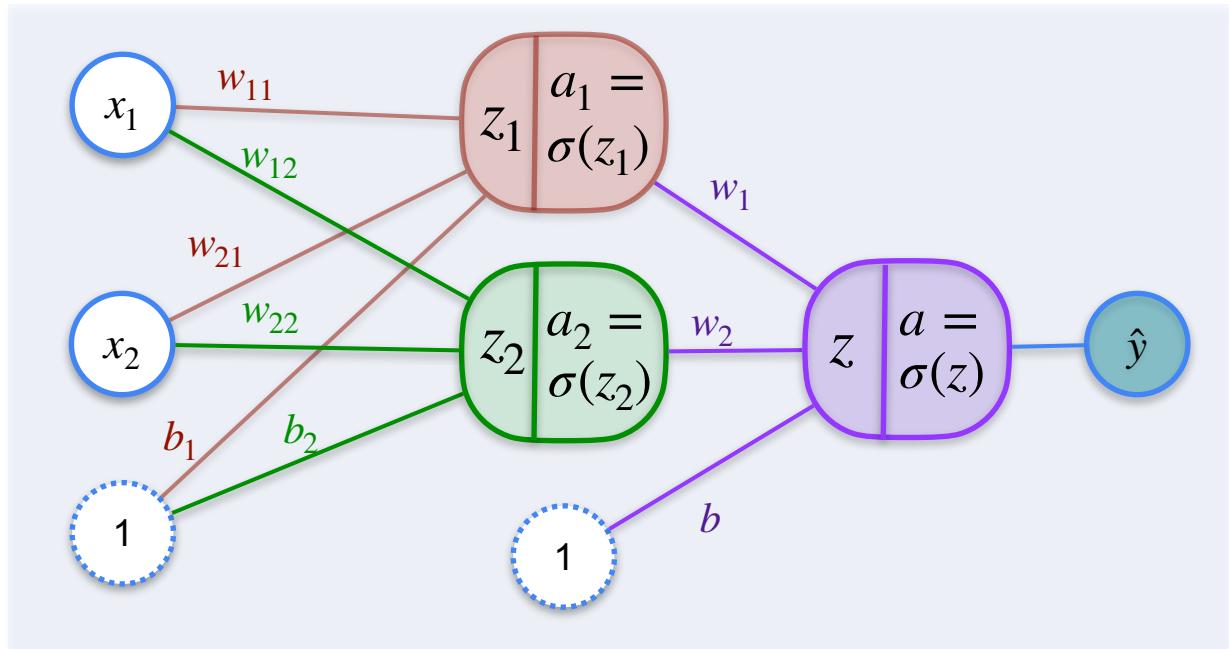
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$



# 2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

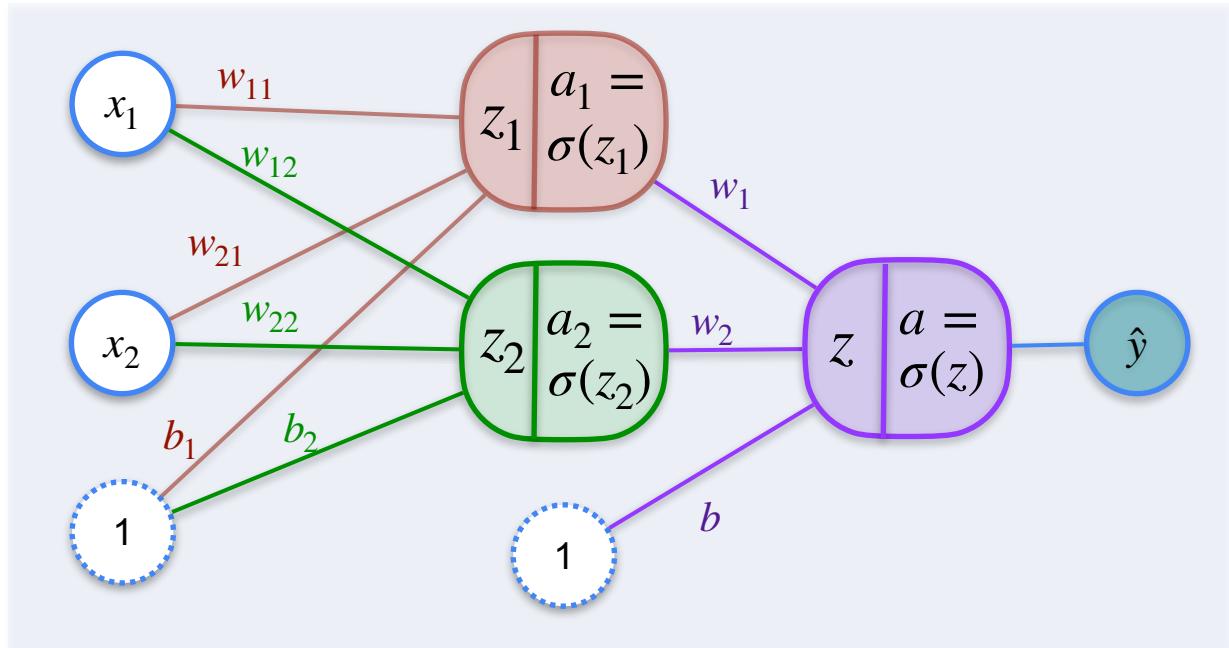
$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$





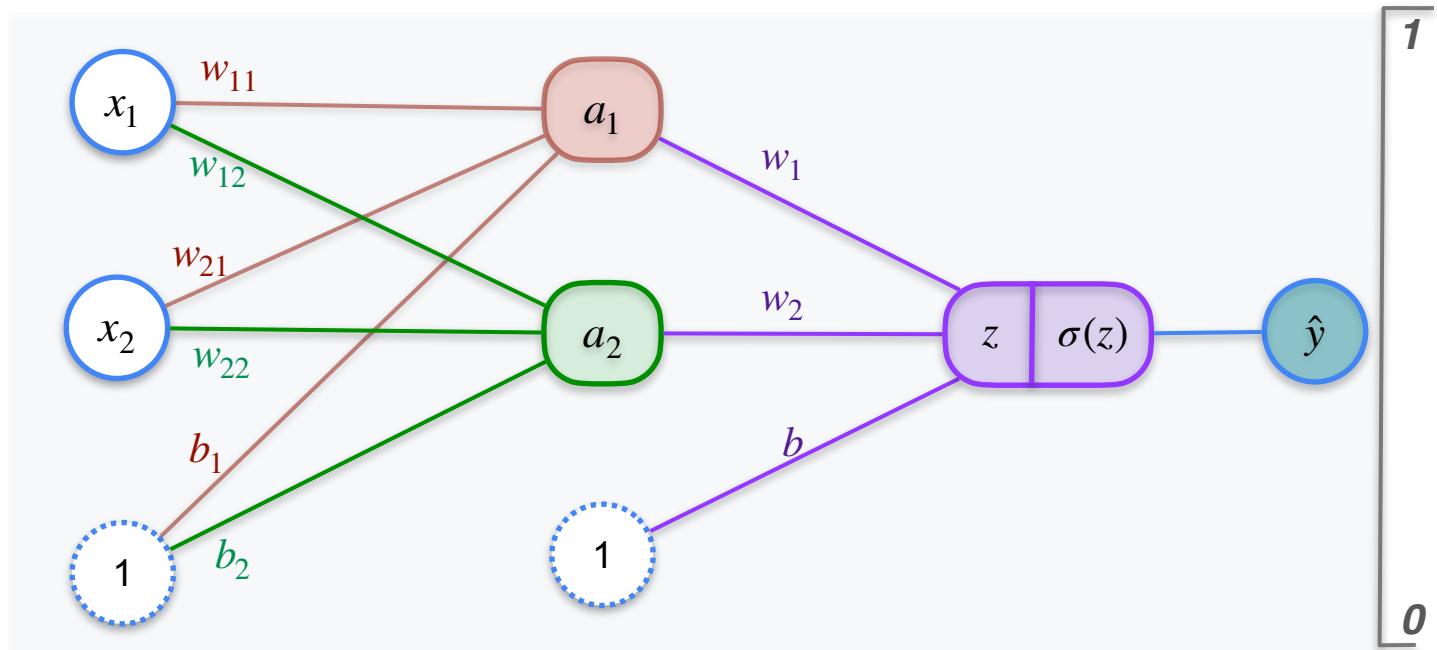
DeepLearning.AI

# Optimization in Neural Networks and Newton's Method

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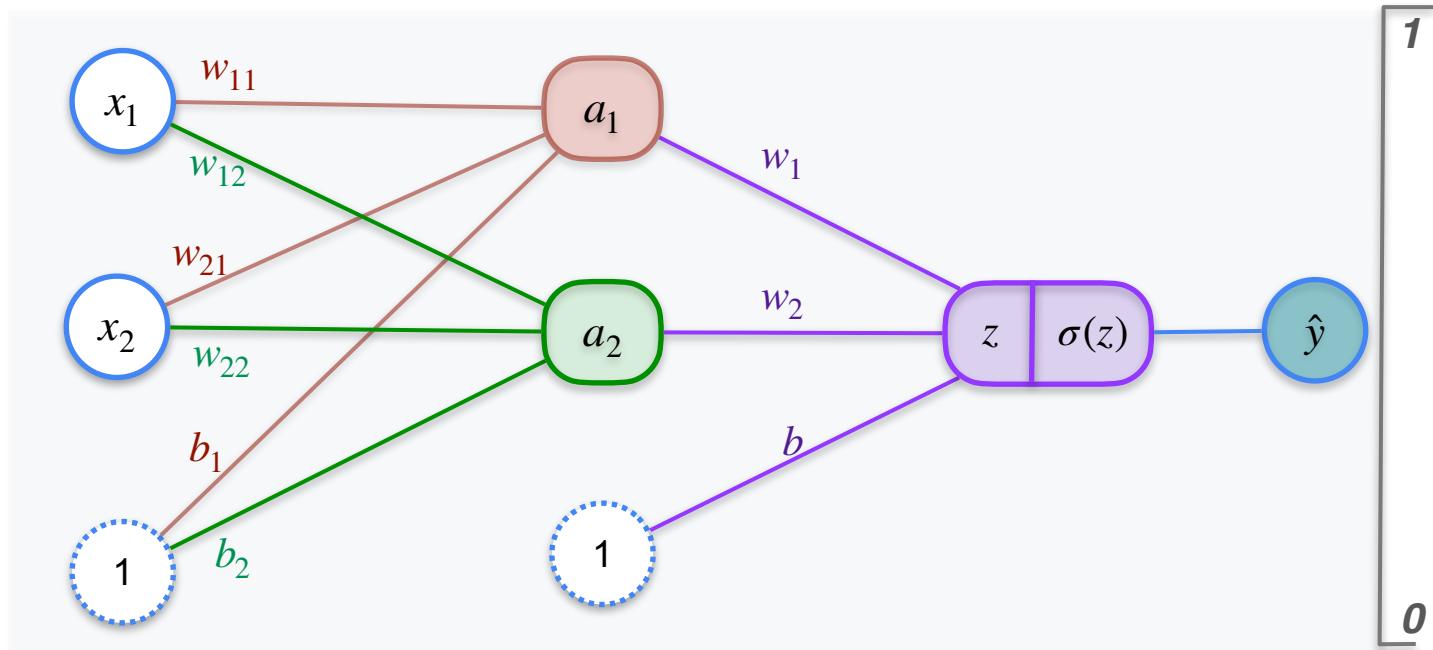
**Classification with a  
Neural Network:  
Minimizing log-loss**

# 2,2,1 Neural Network



# 2,2,1 Neural Network

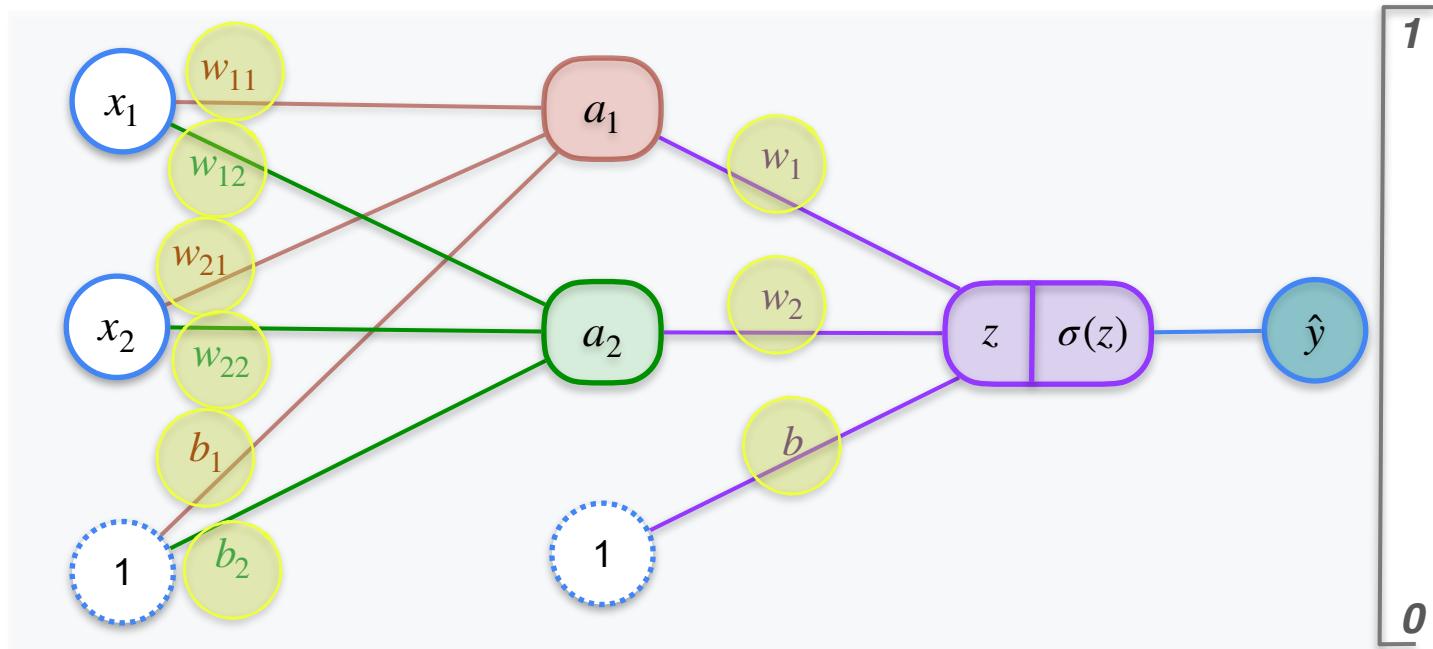
Goal



# 2,2,1 Neural Network

Goal

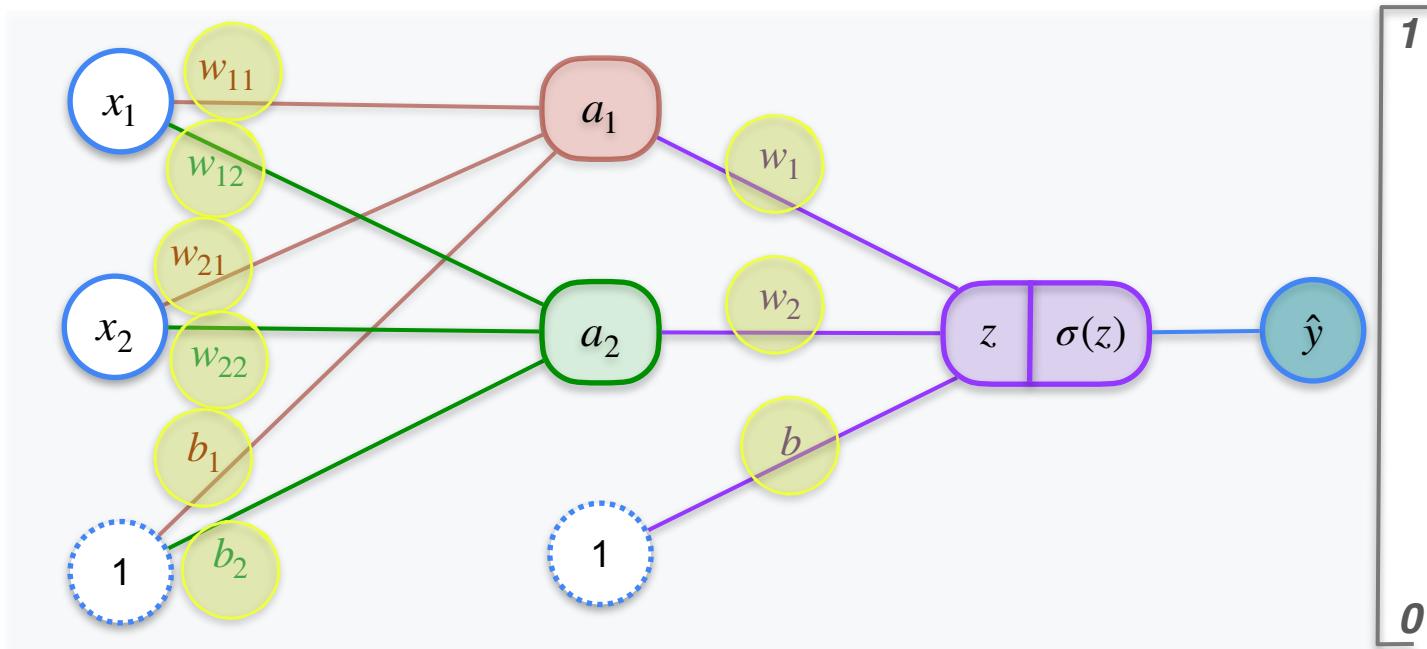
Adjust each of the highlighted weights and biases



# 2,2,1 Neural Network

Goal

Adjust each of the highlighted weights and biases

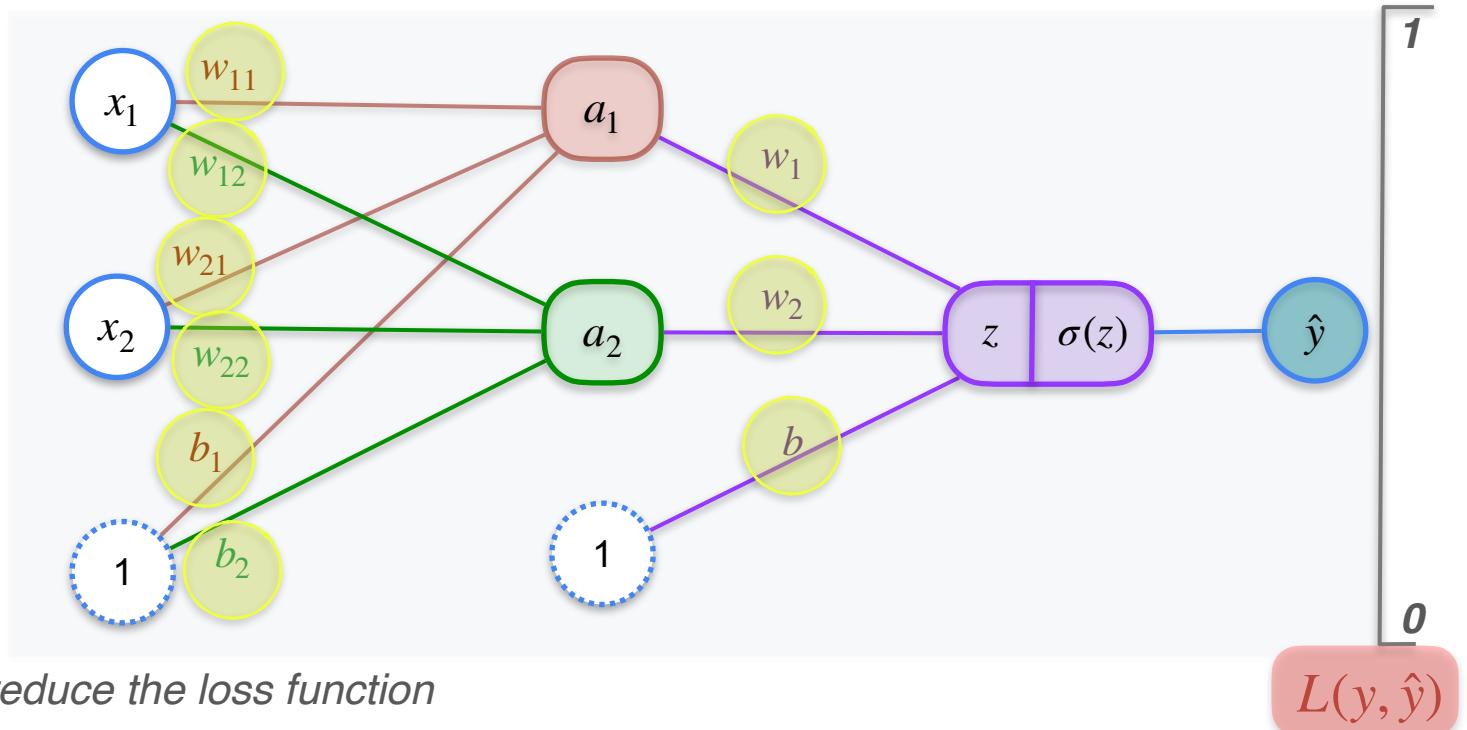


*To reduce the loss function*

# 2,2,1 Neural Network

Goal

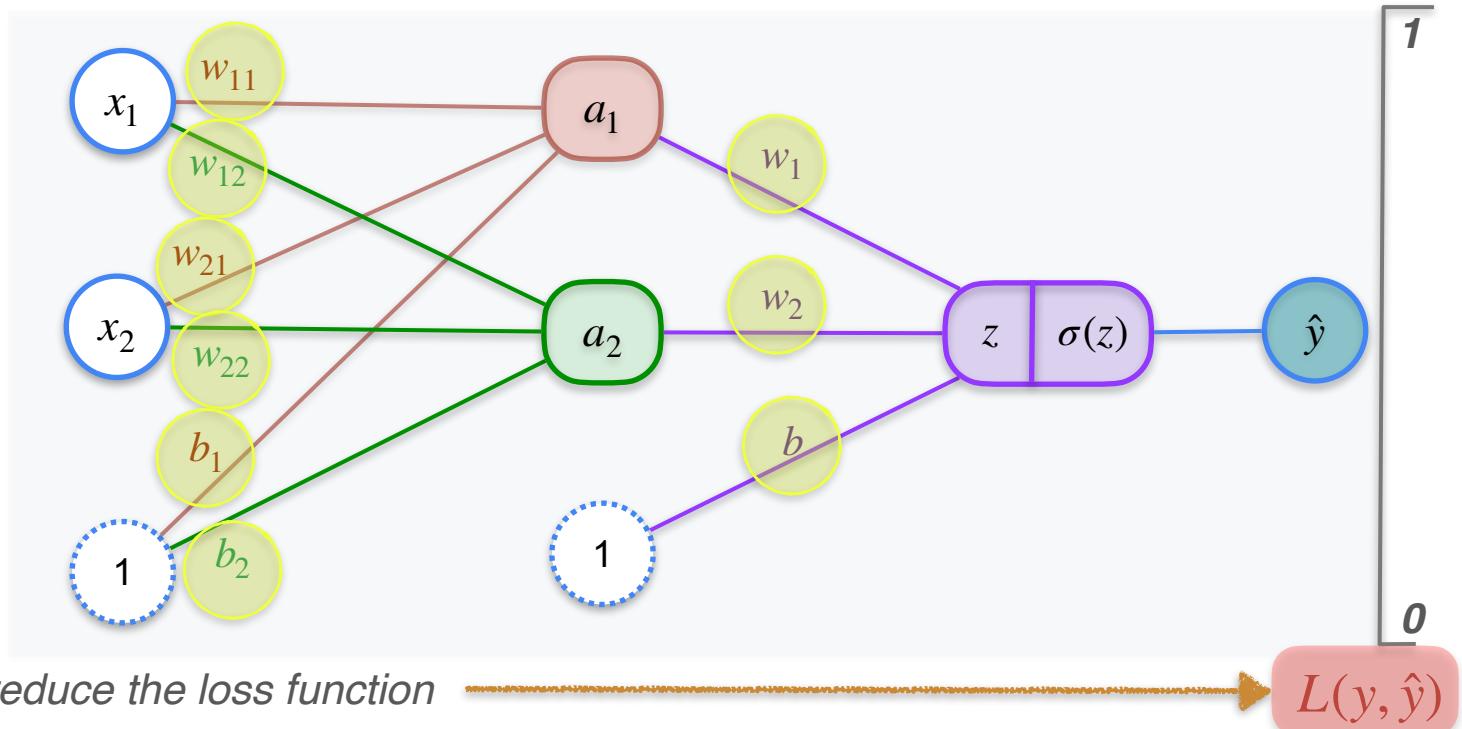
Adjust each of the highlighted weights and biases



# 2,2,1 Neural Network

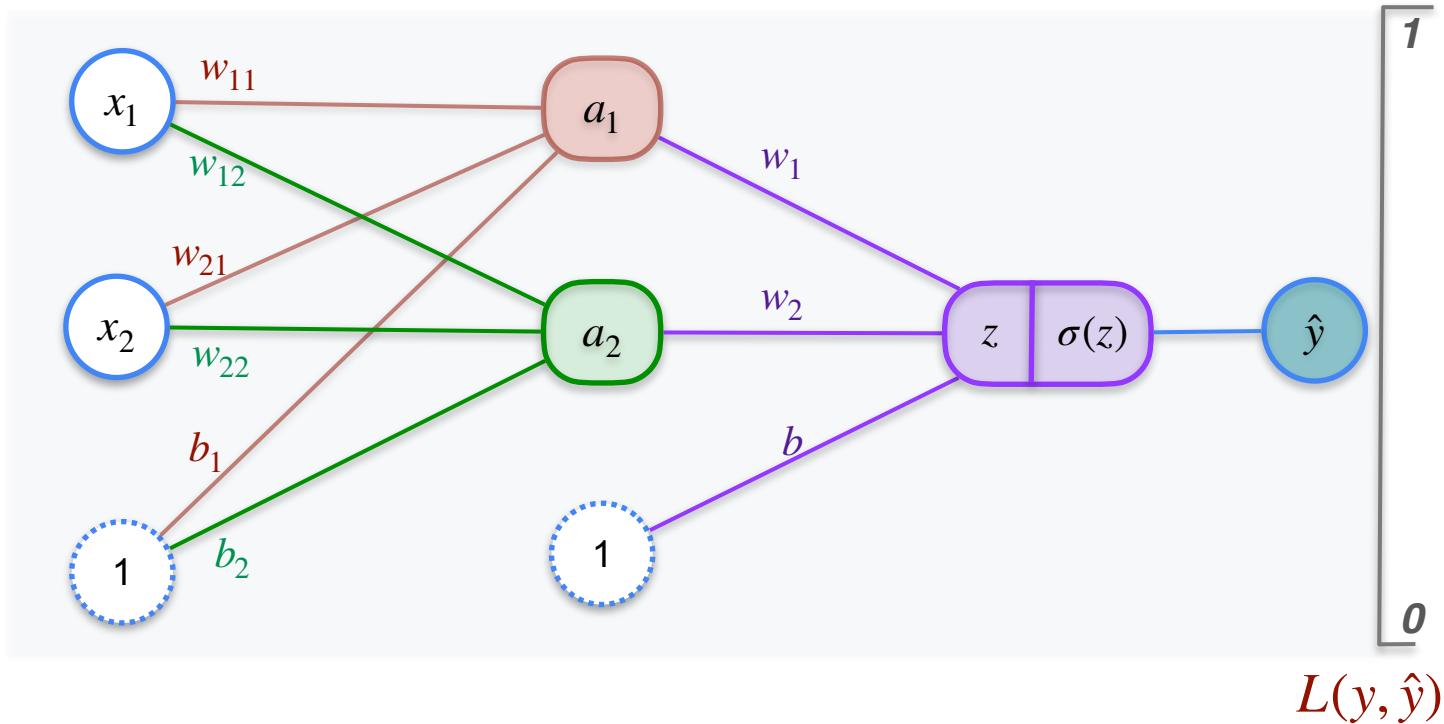
Goal

Adjust each of the highlighted weights and biases

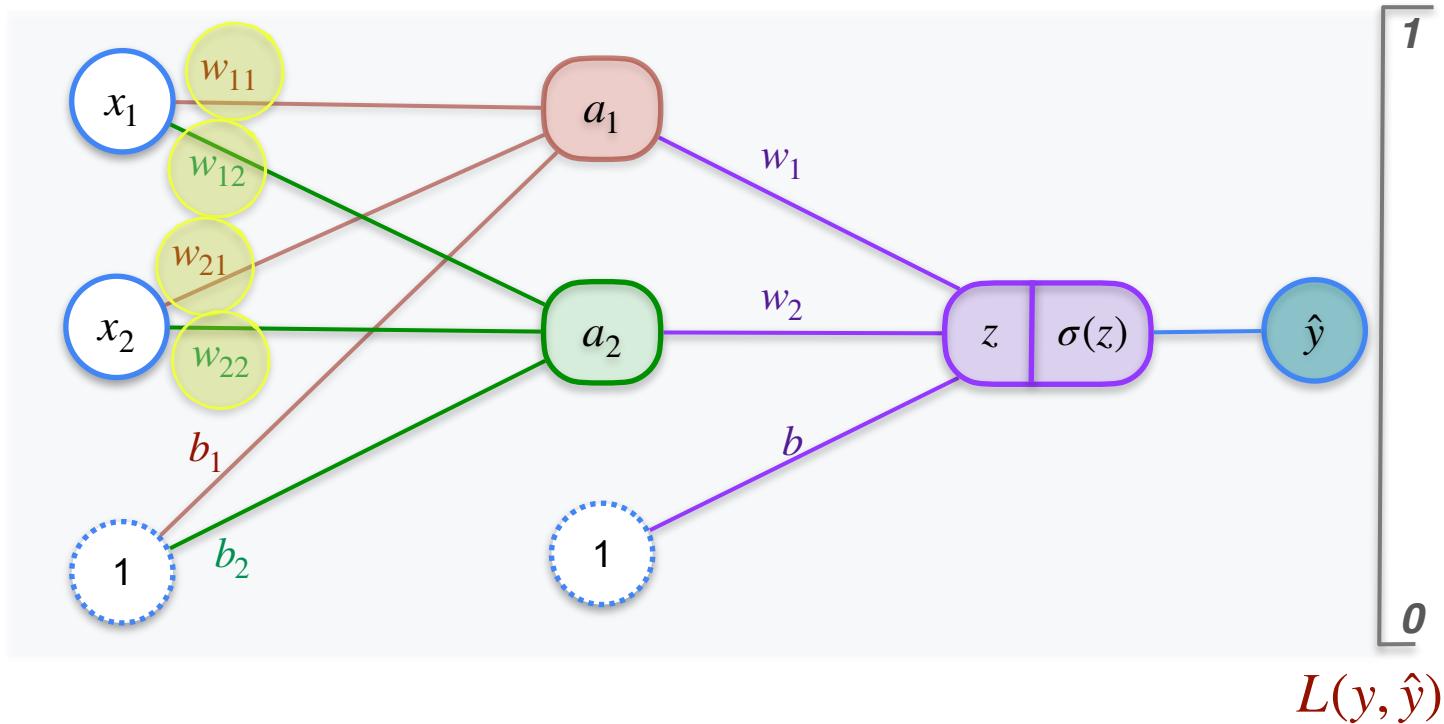


To reduce the loss function

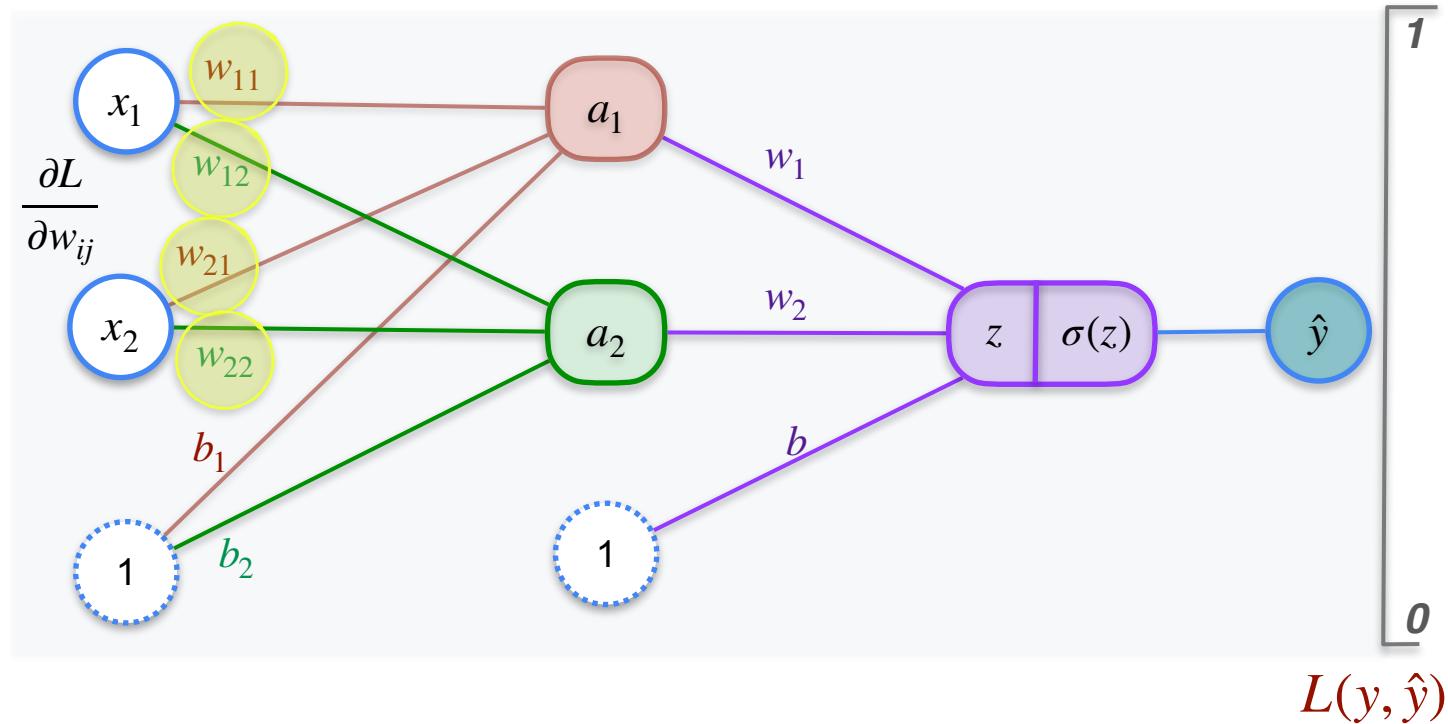
# 2,2,1 Neural Network



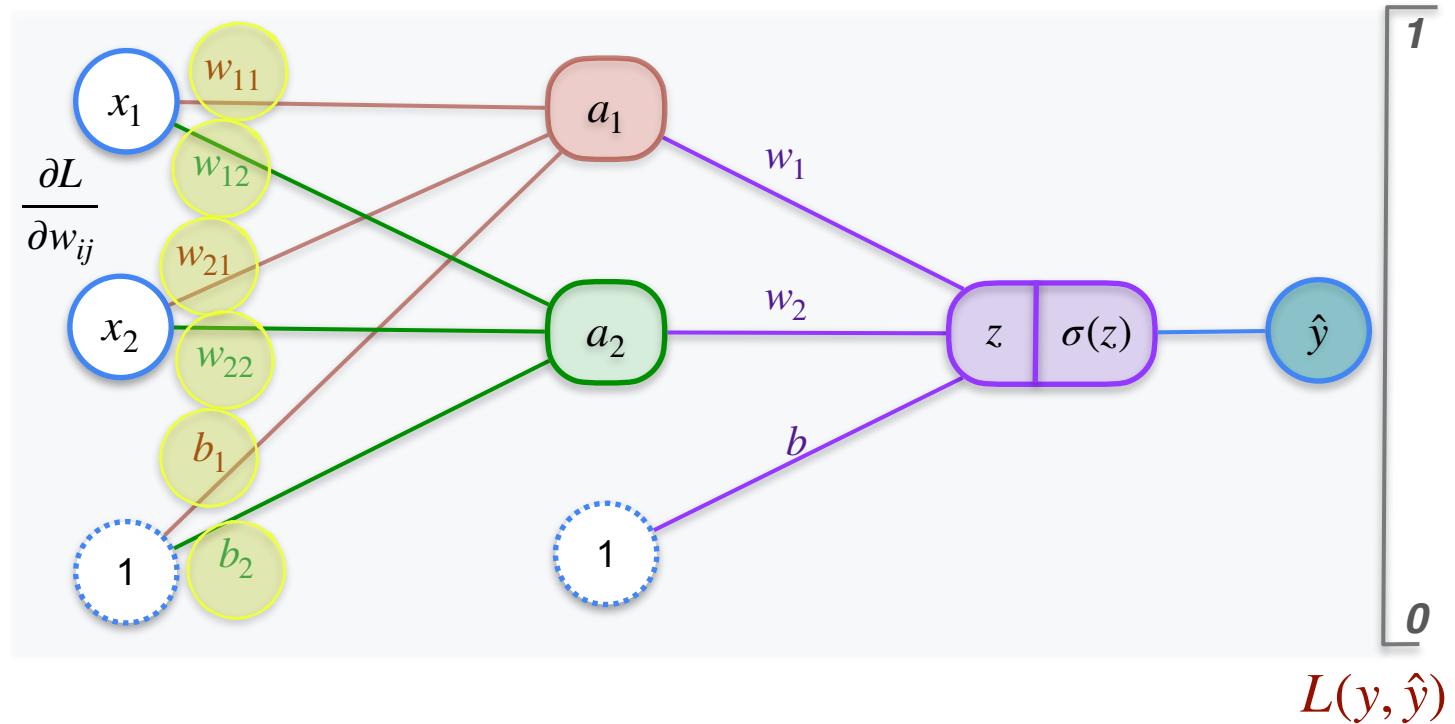
# 2,2,1 Neural Network



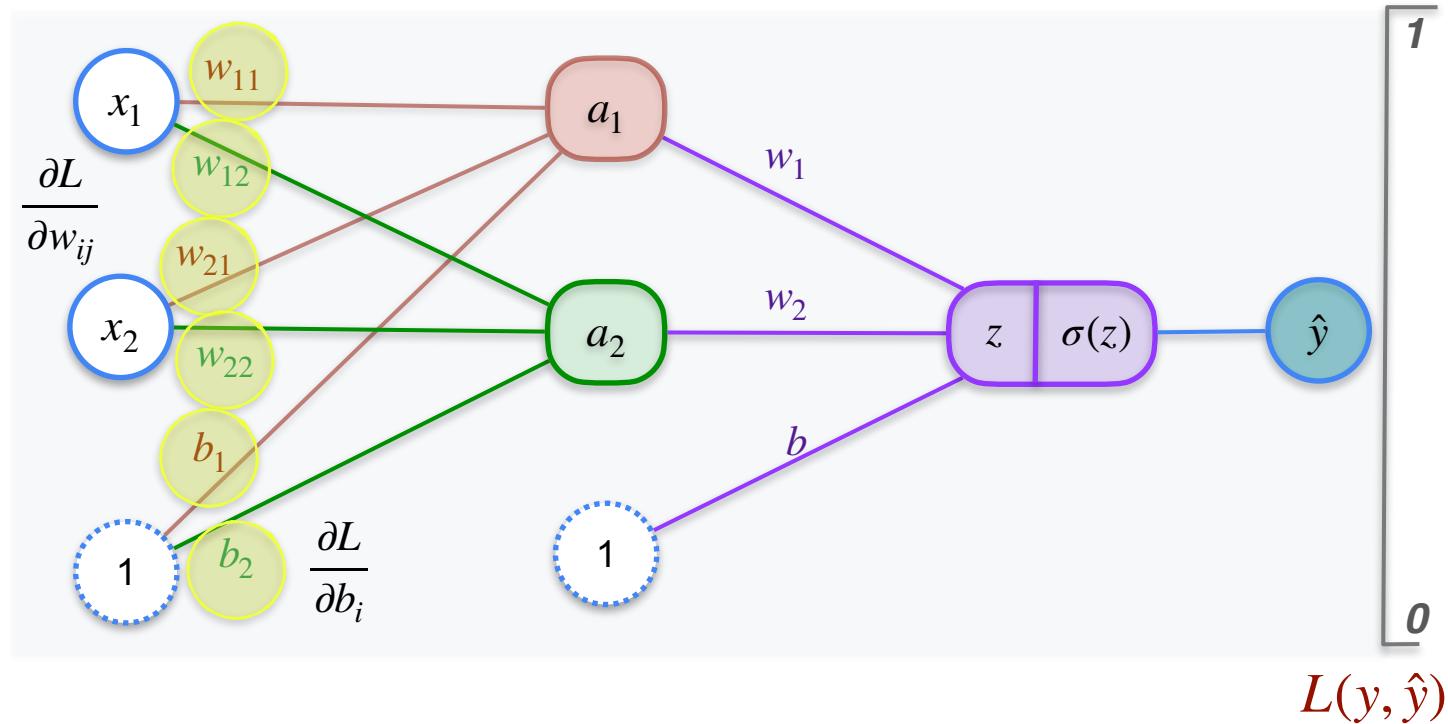
# 2,2,1 Neural Network



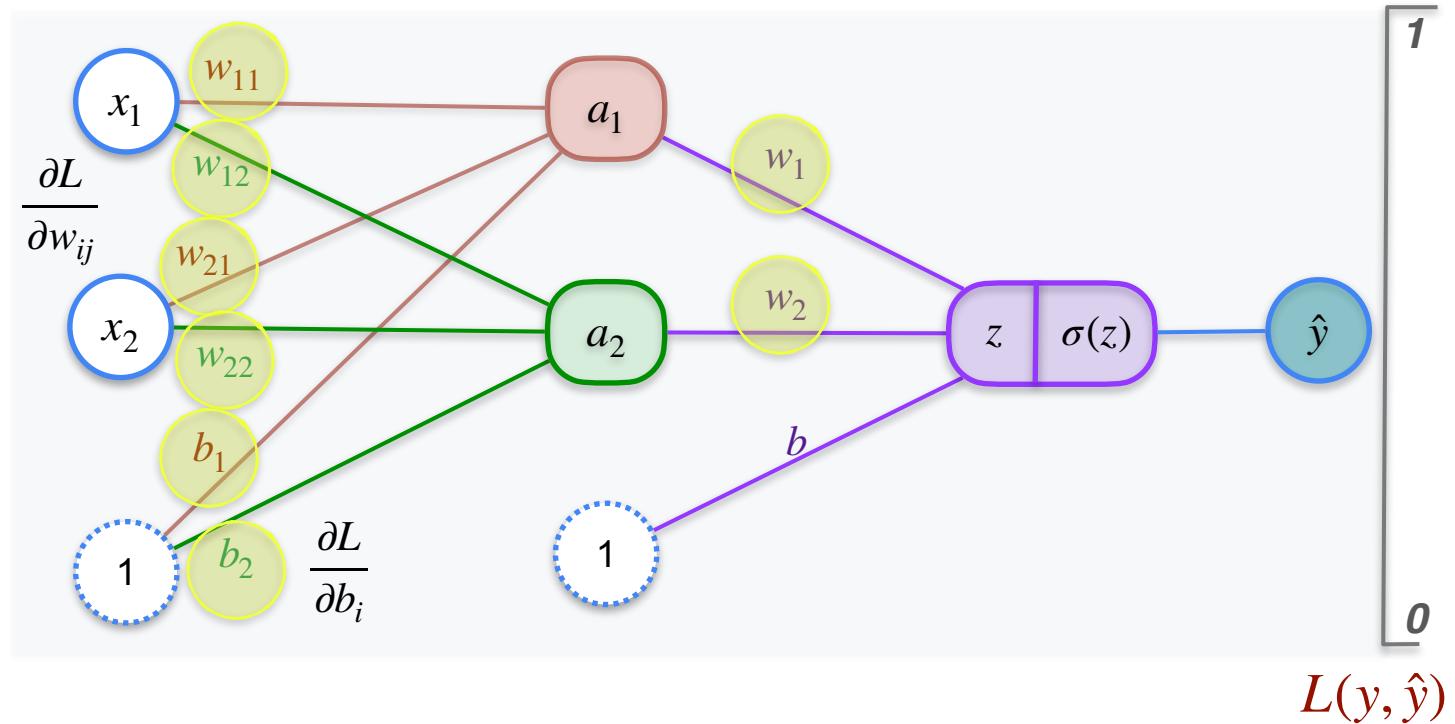
# 2,2,1 Neural Network



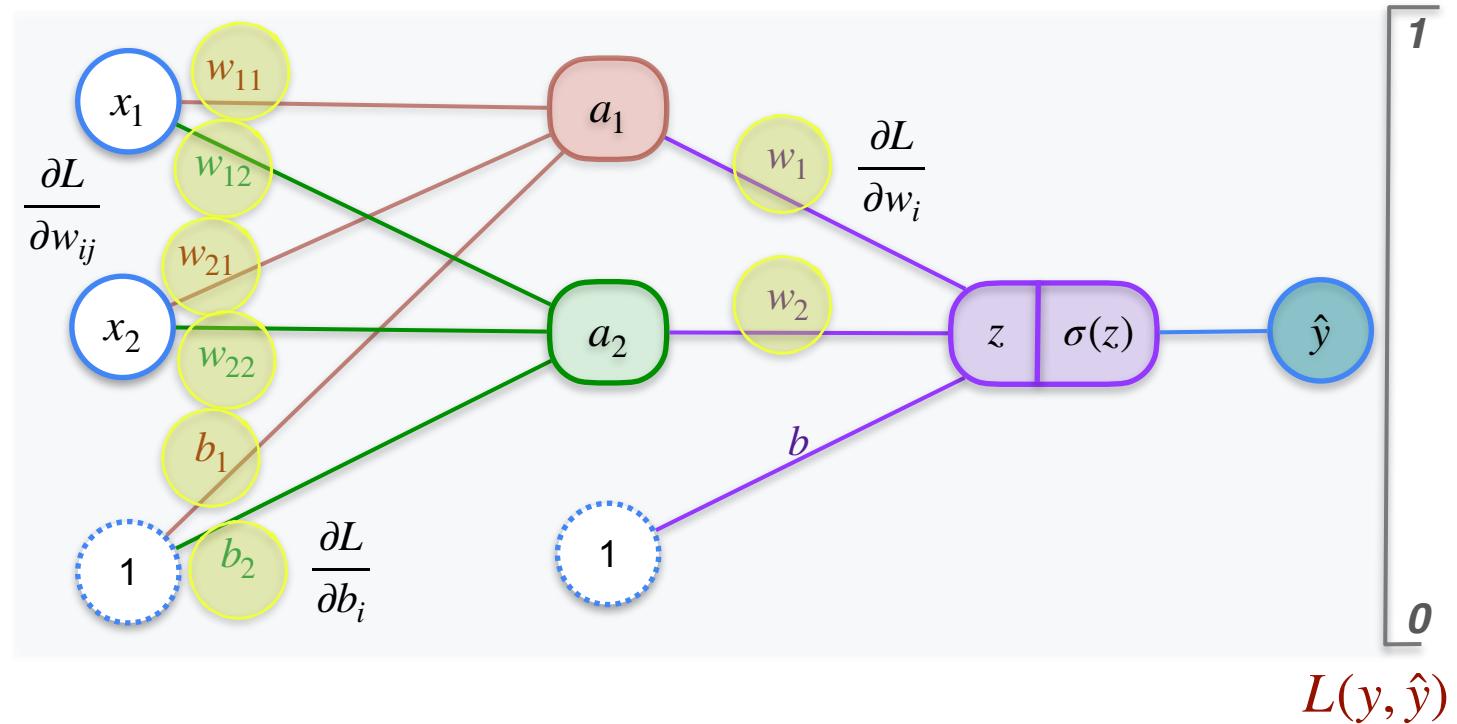
# 2,2,1 Neural Network



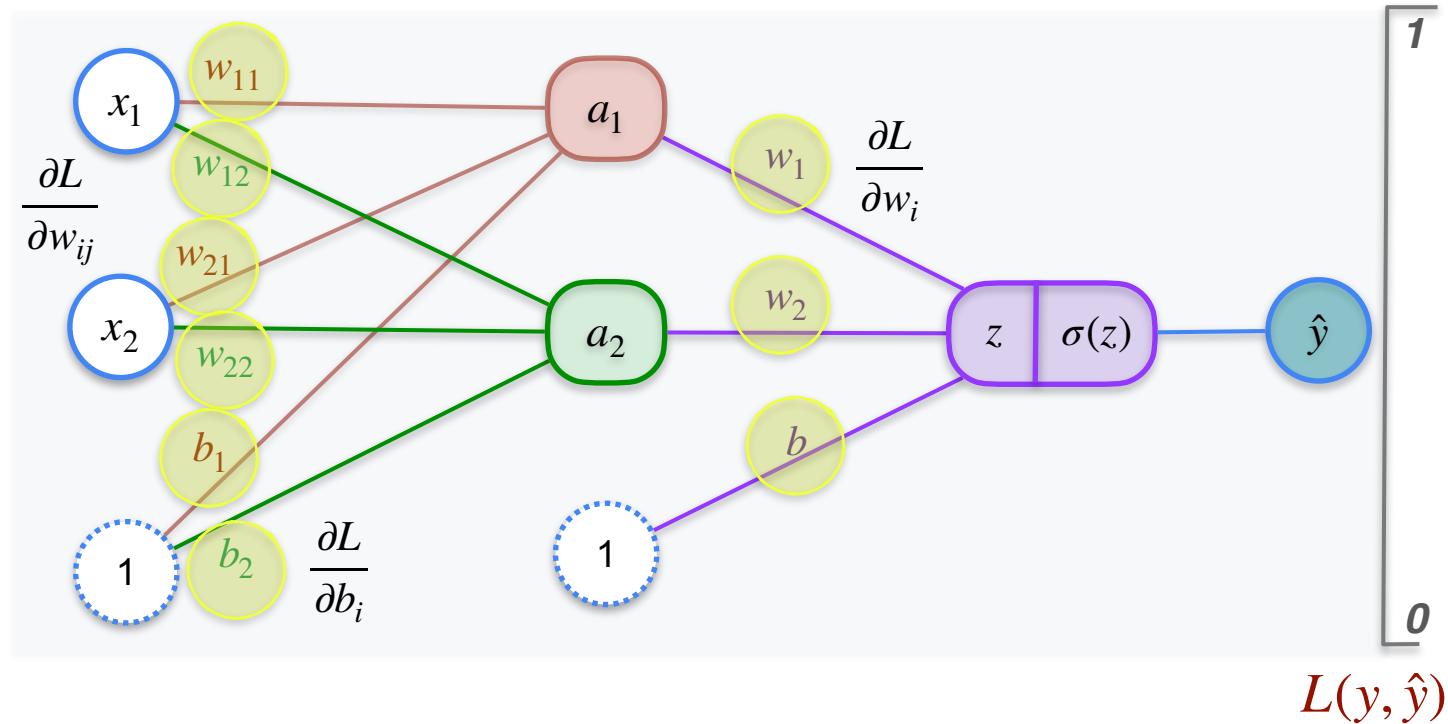
# 2,2,1 Neural Network



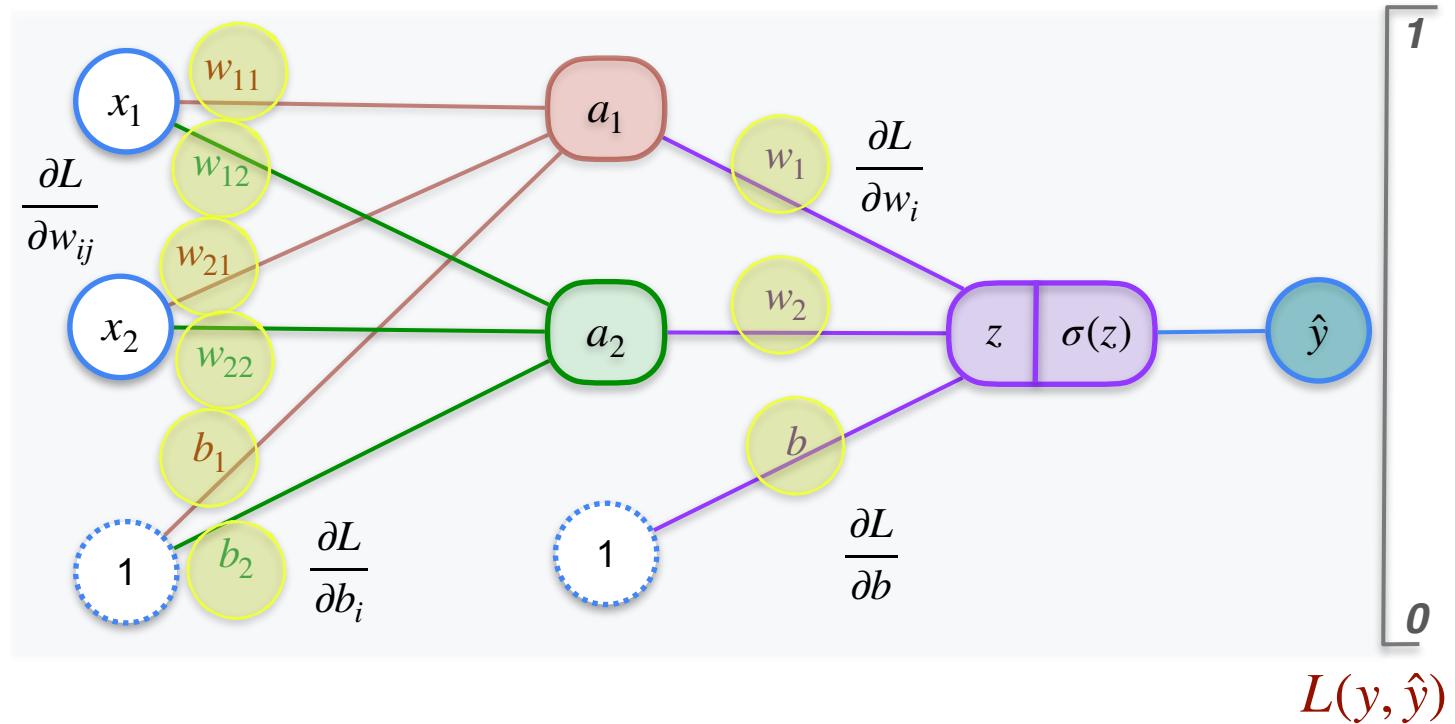
# 2,2,1 Neural Network



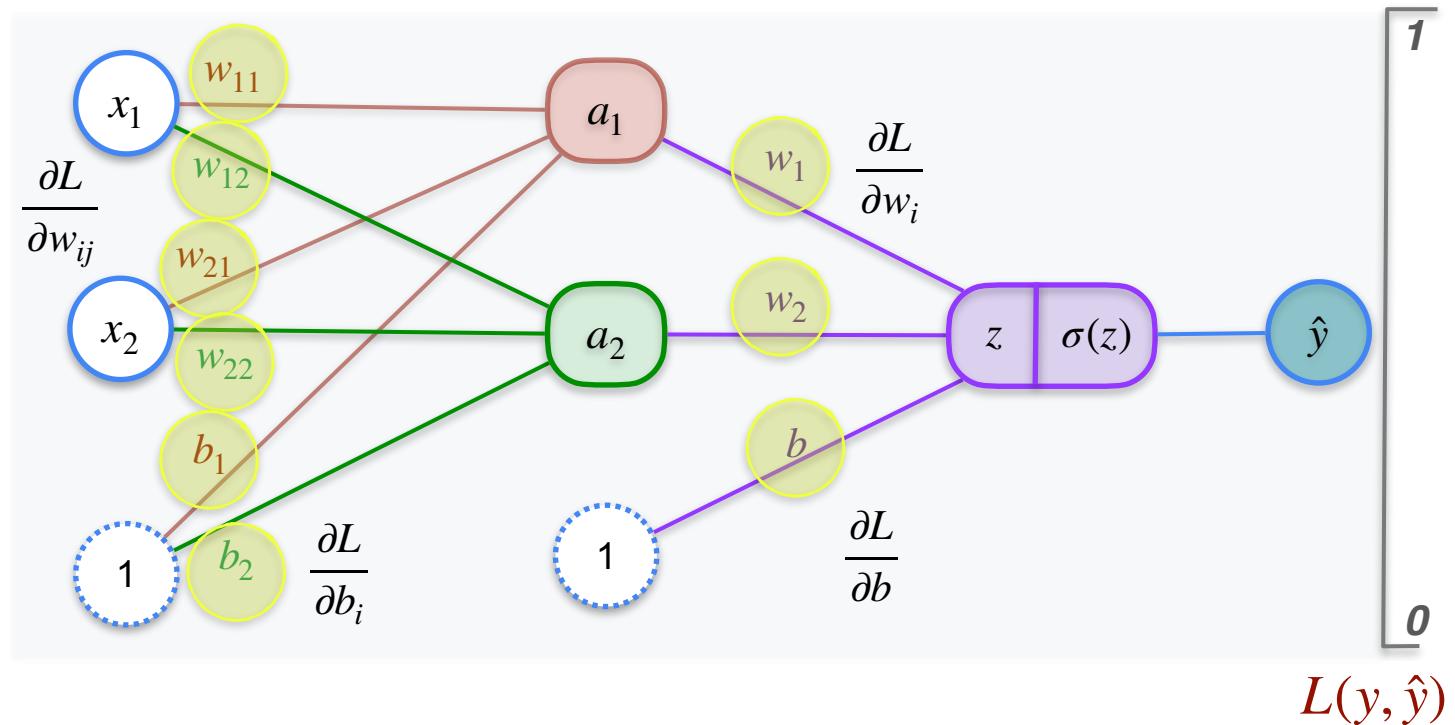
# 2,2,1 Neural Network



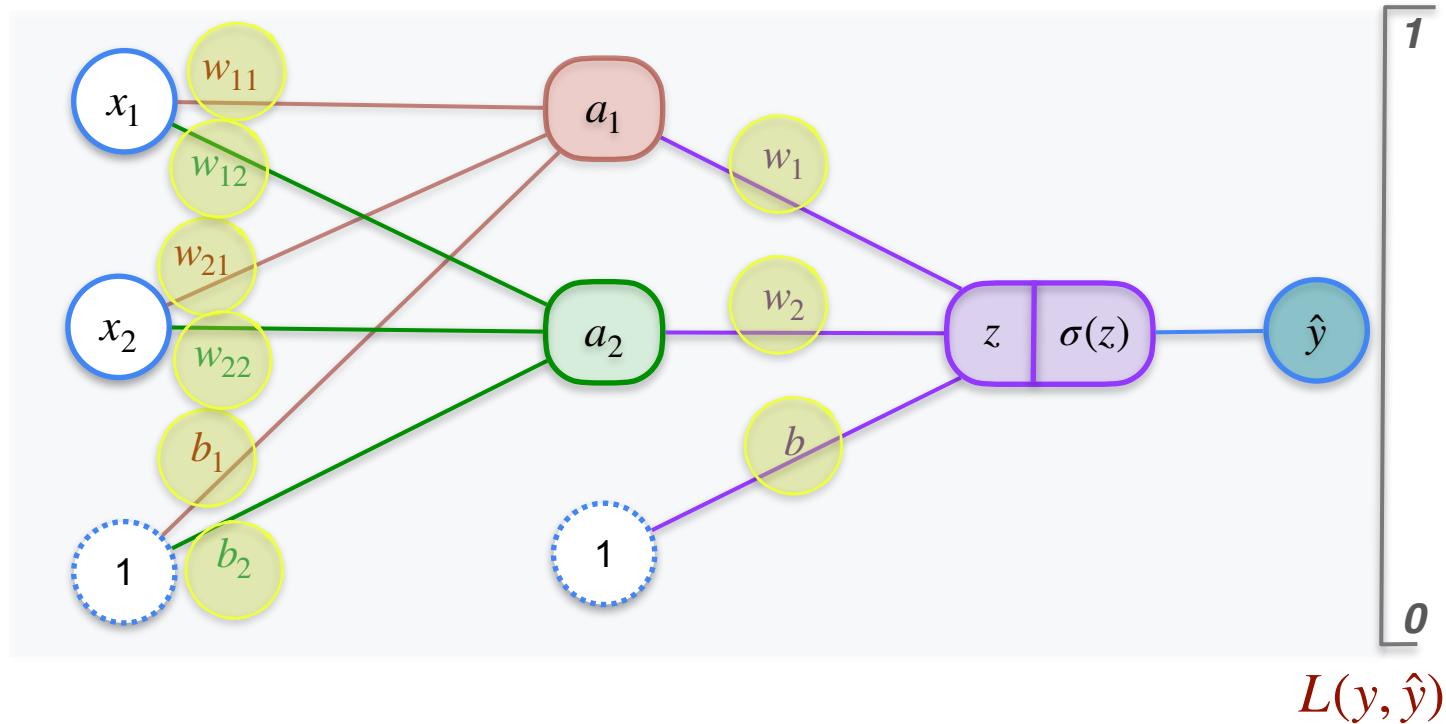
# 2,2,1 Neural Network



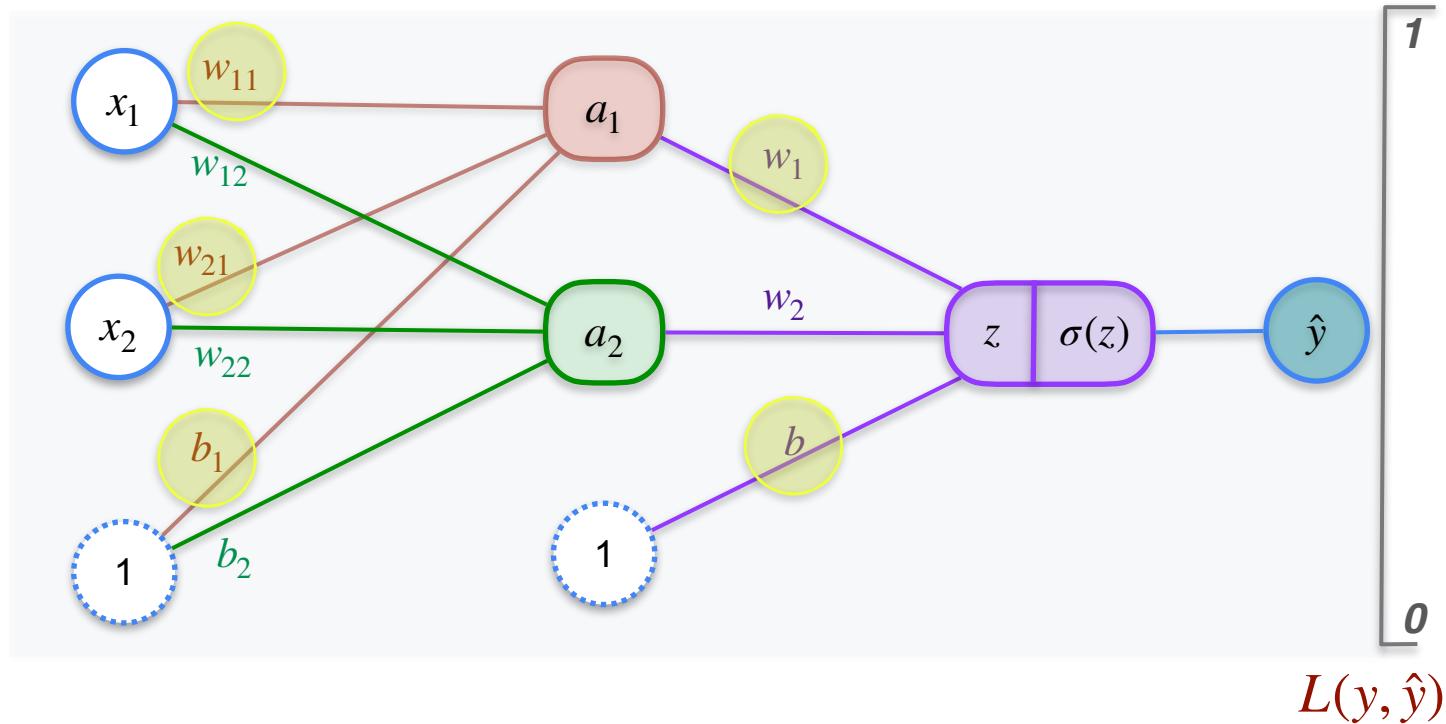
# 2,2,1 Neural Network



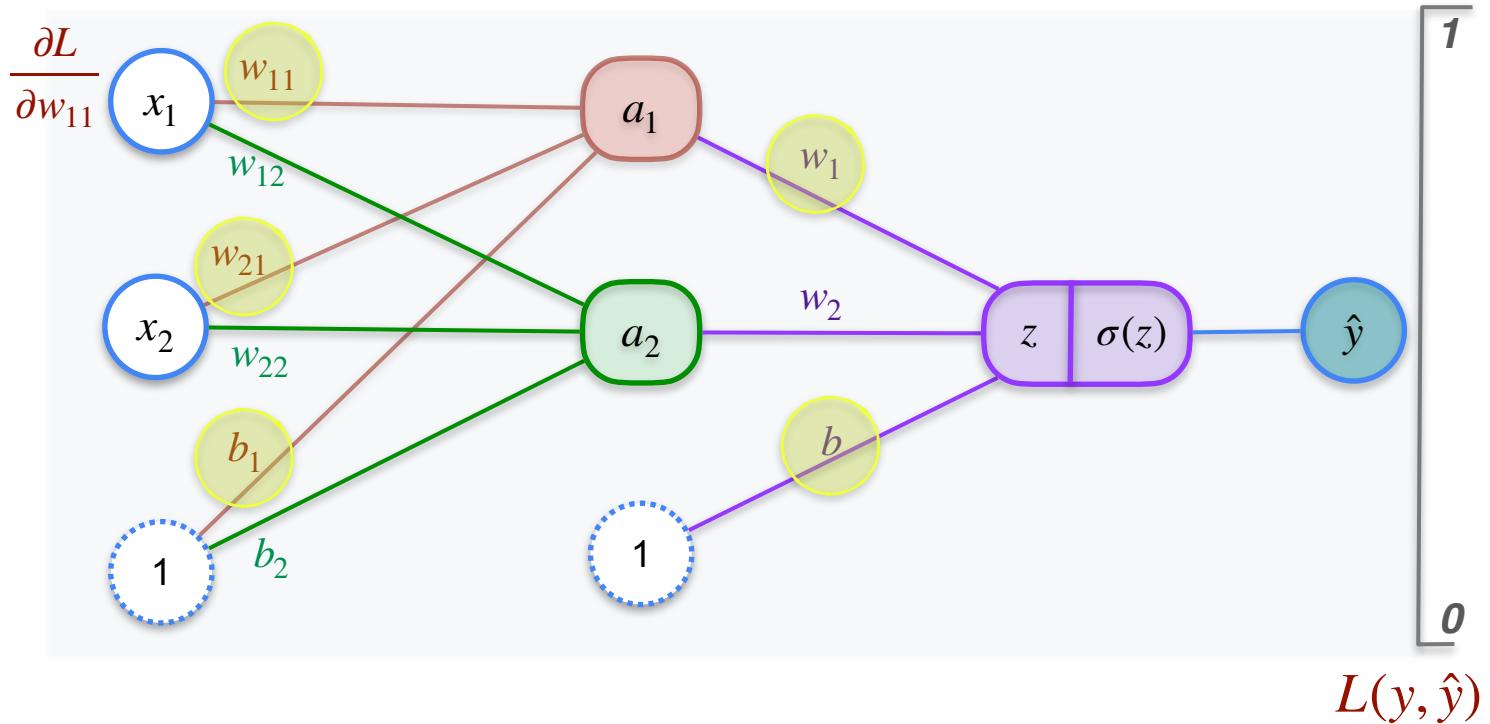
# 2,2,1 Neural Network



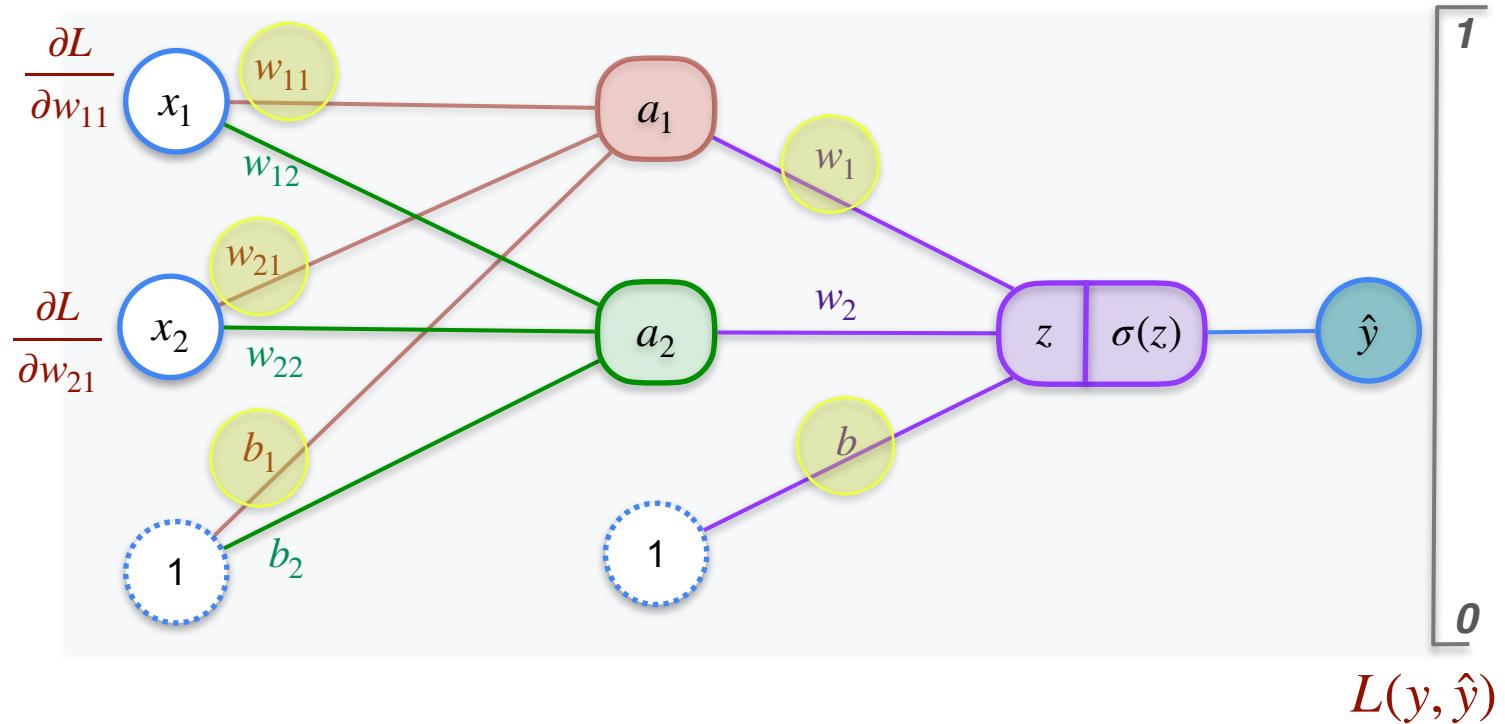
# 2,2,1 Neural Network



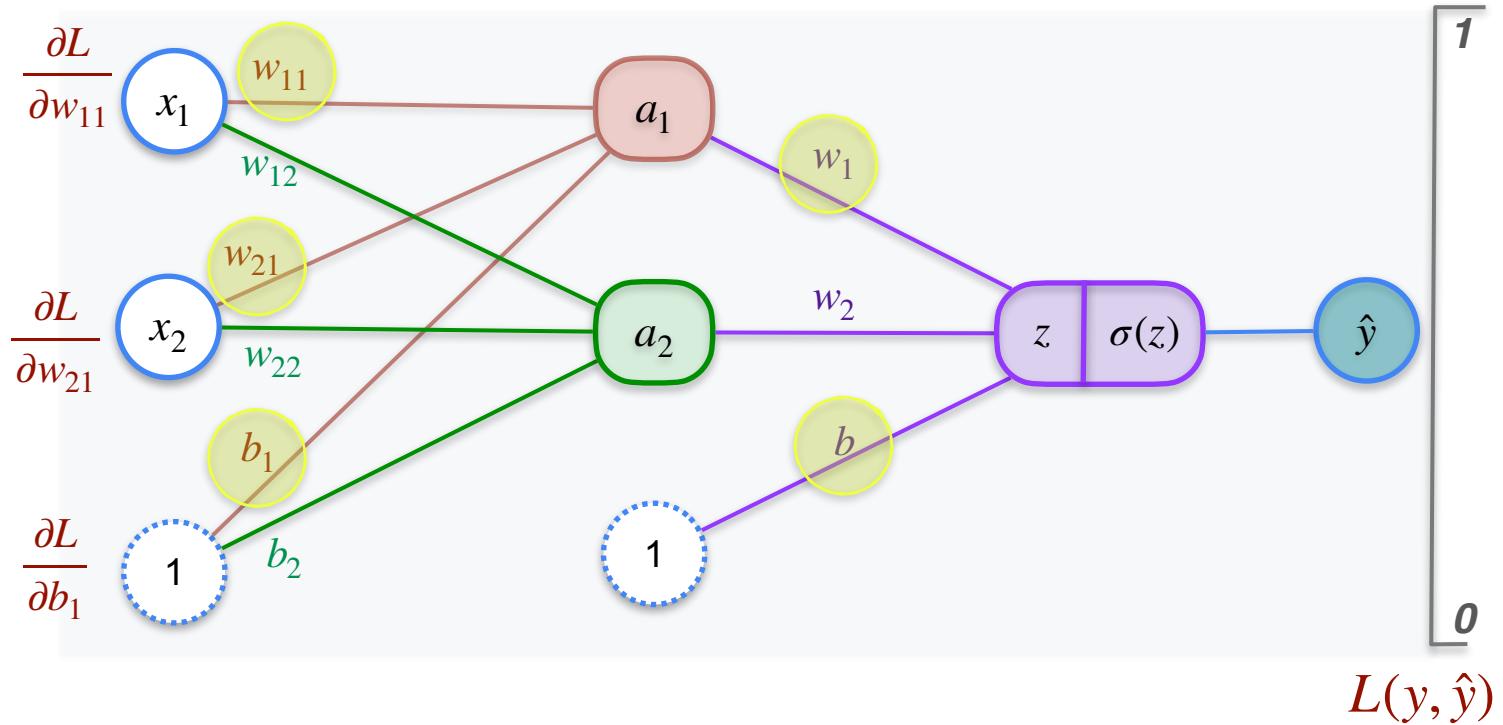
# 2,2,1 Neural Network



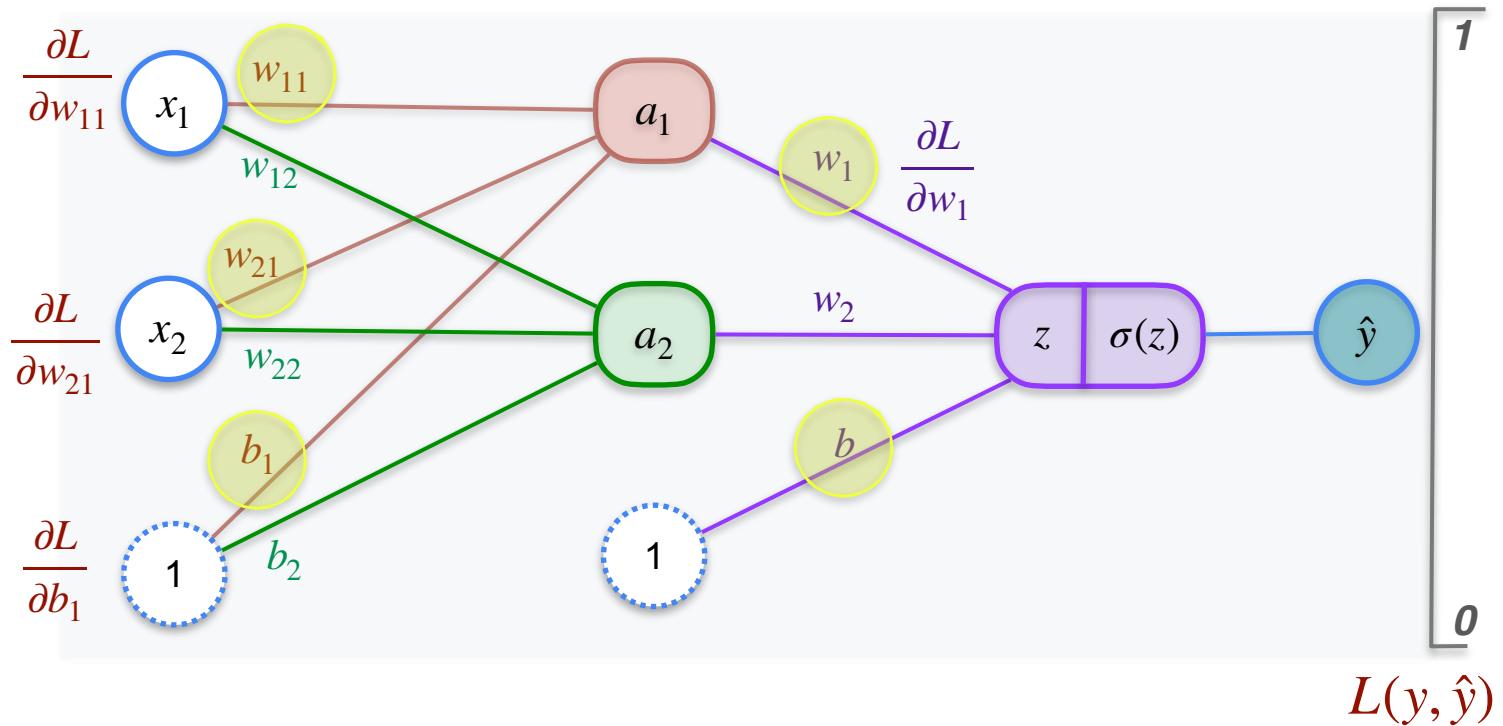
# 2,2,1 Neural Network



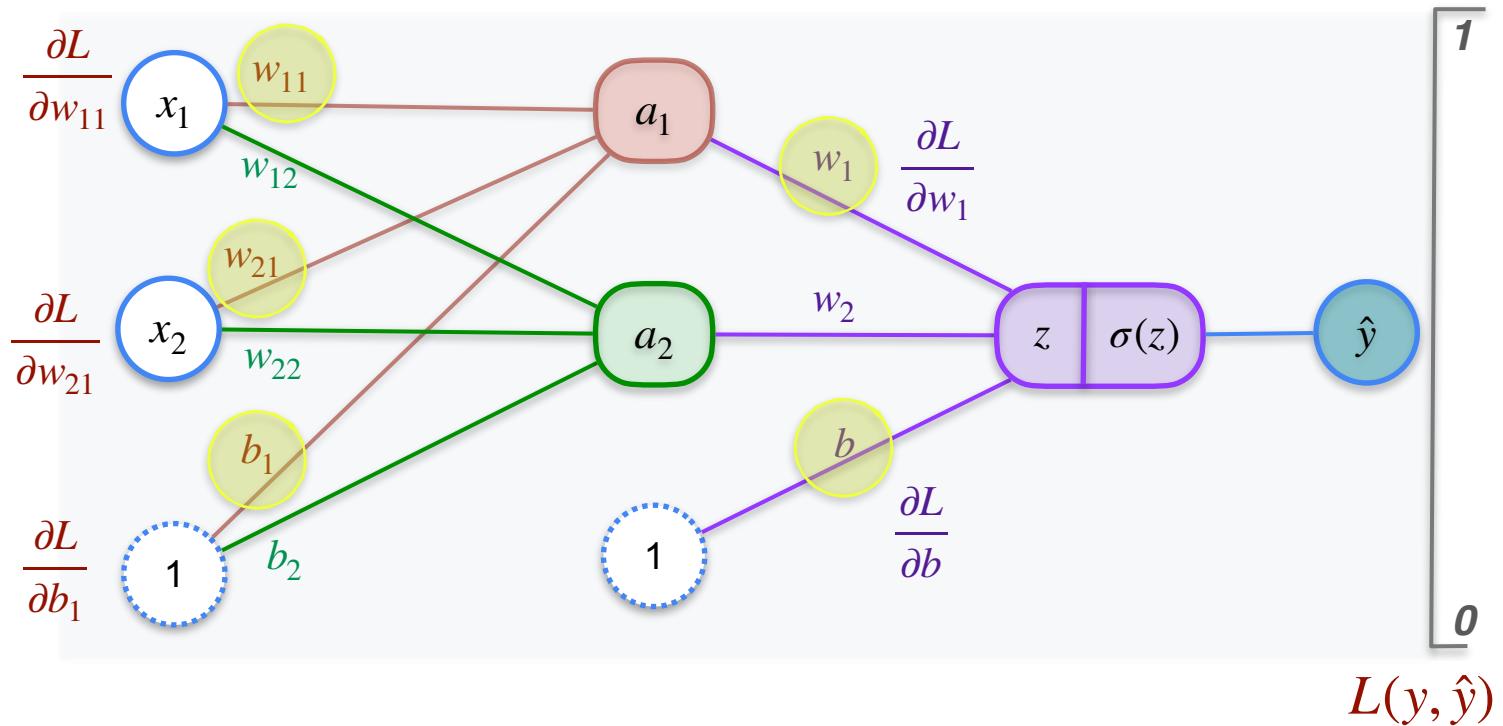
# 2,2,1 Neural Network



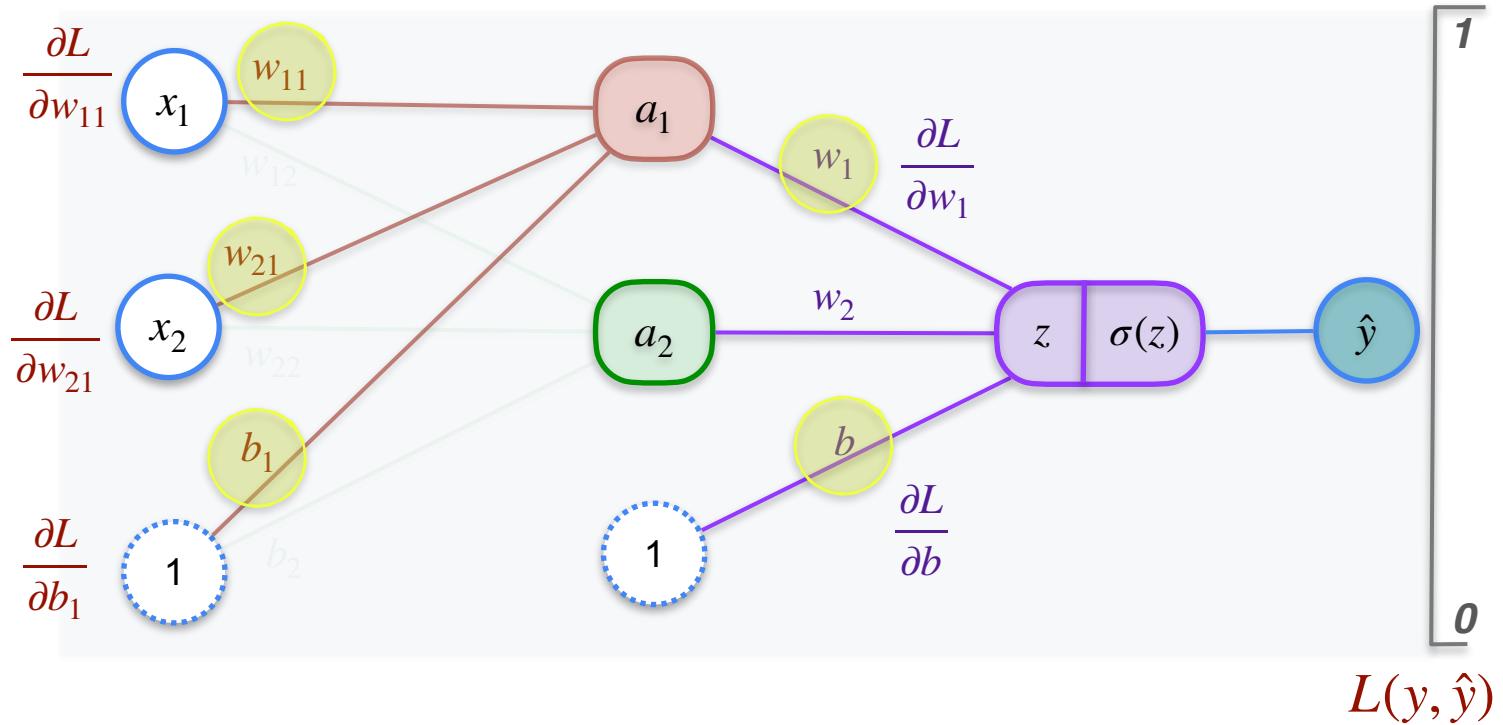
# 2,2,1 Neural Network



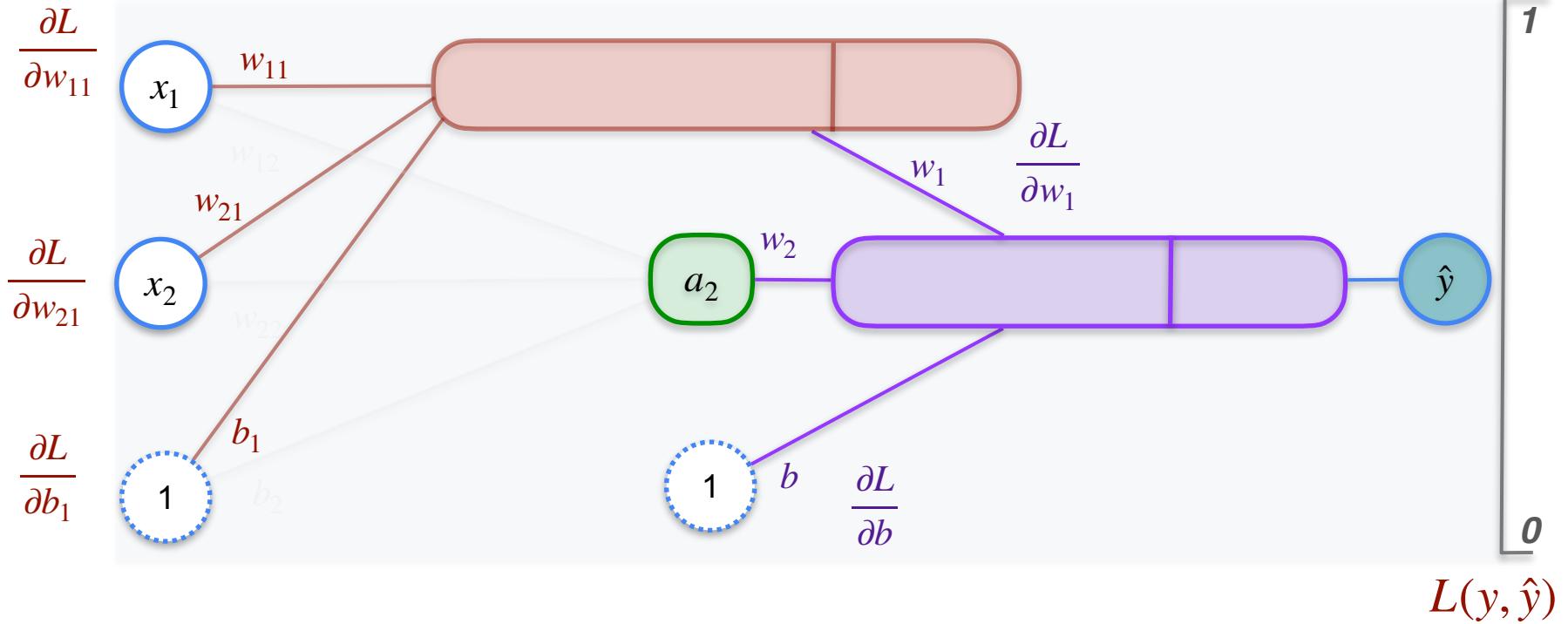
# 2,2,1 Neural Network



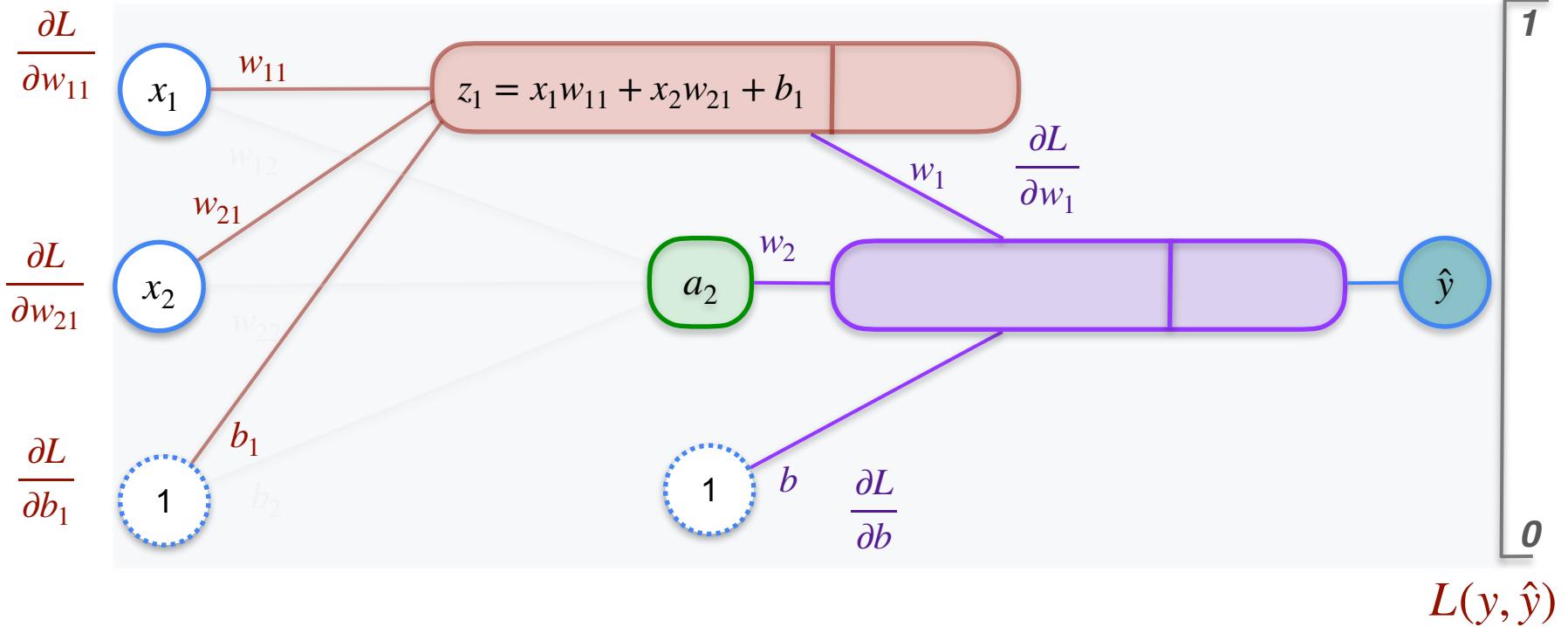
# 2,2,1 Neural Network



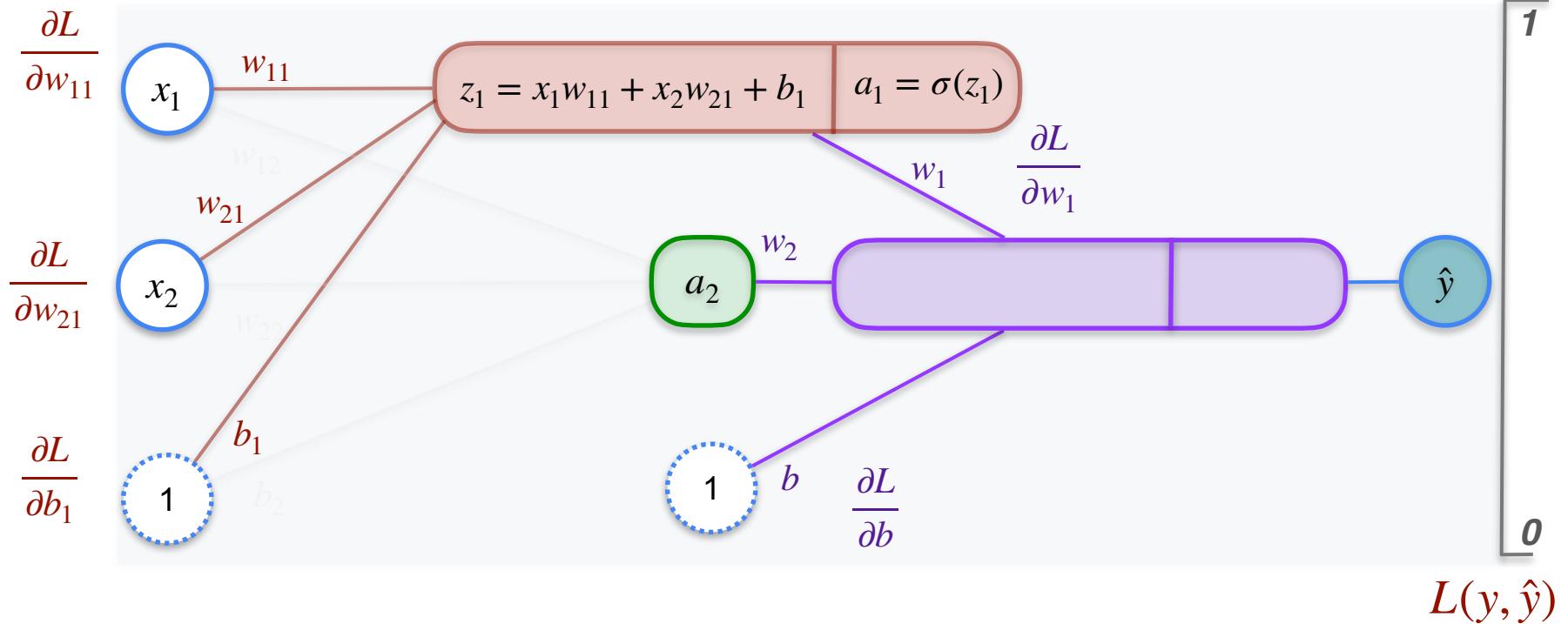
# 2,2,1 Neural Network



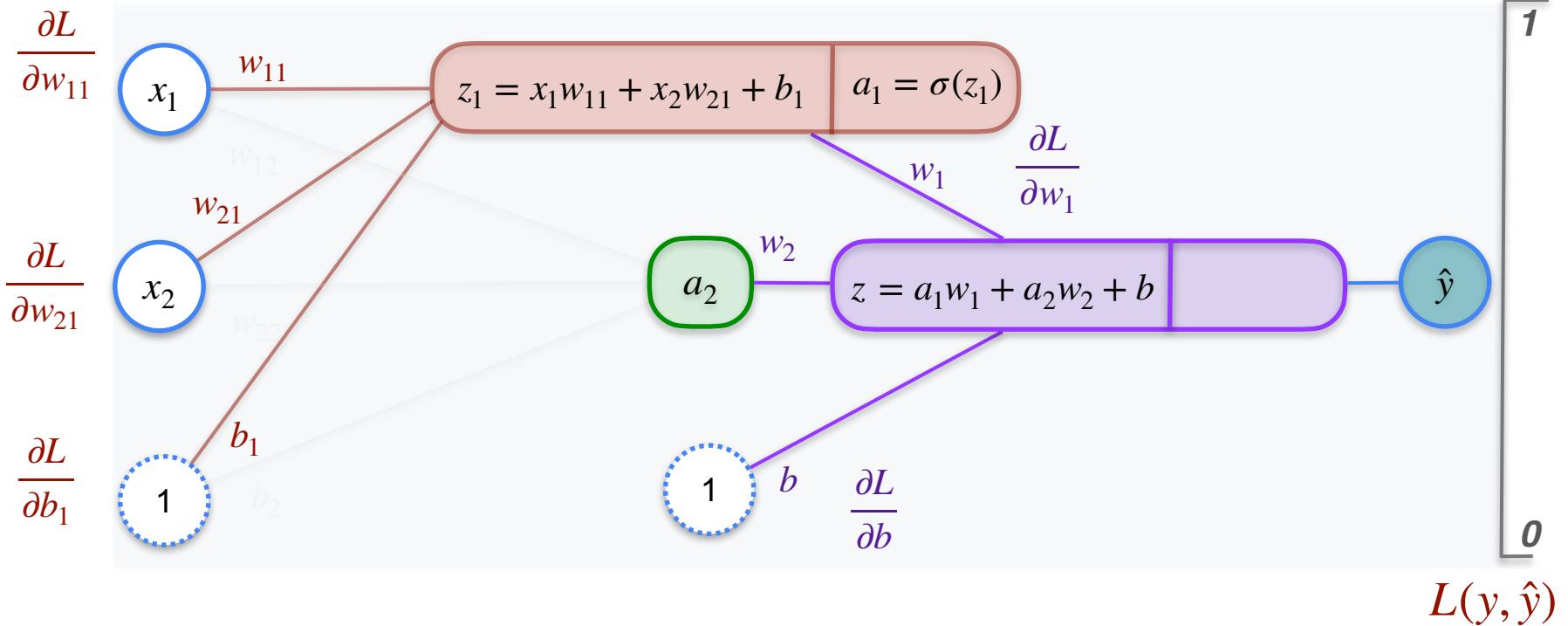
# 2,2,1 Neural Network



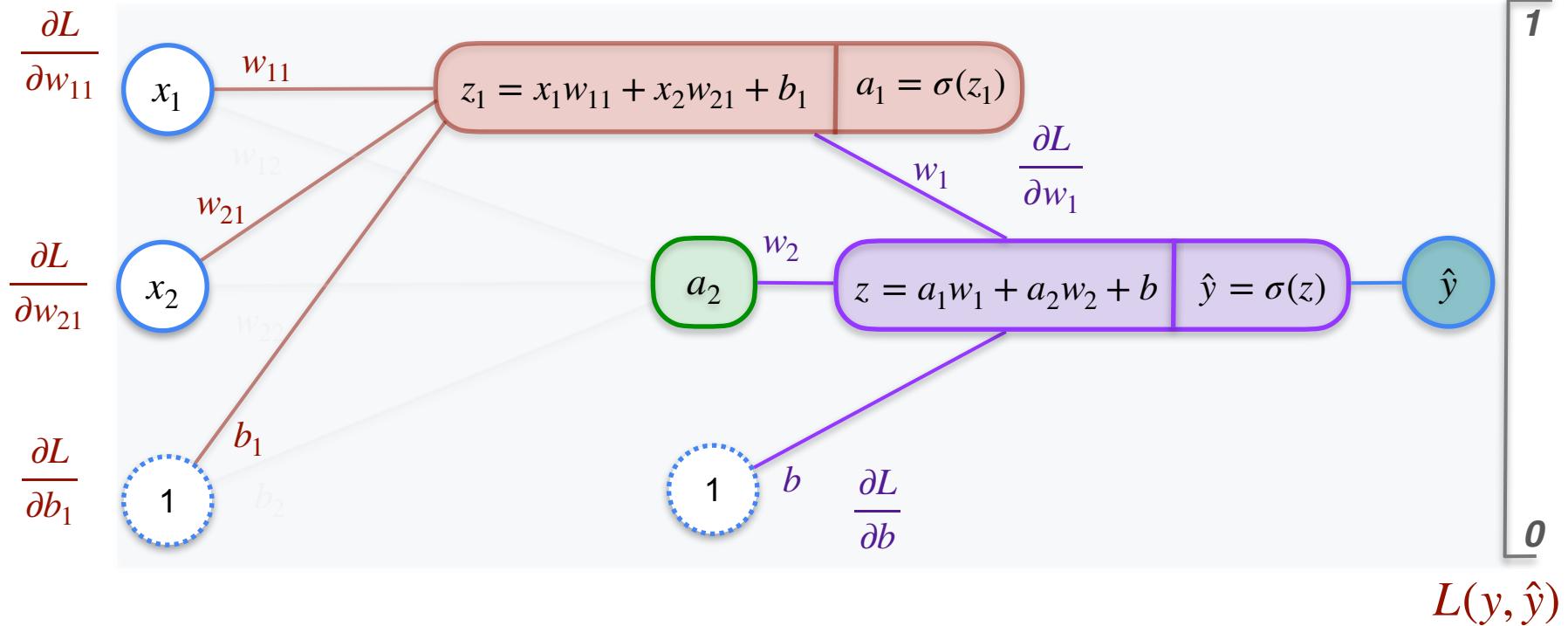
# 2,2,1 Neural Network



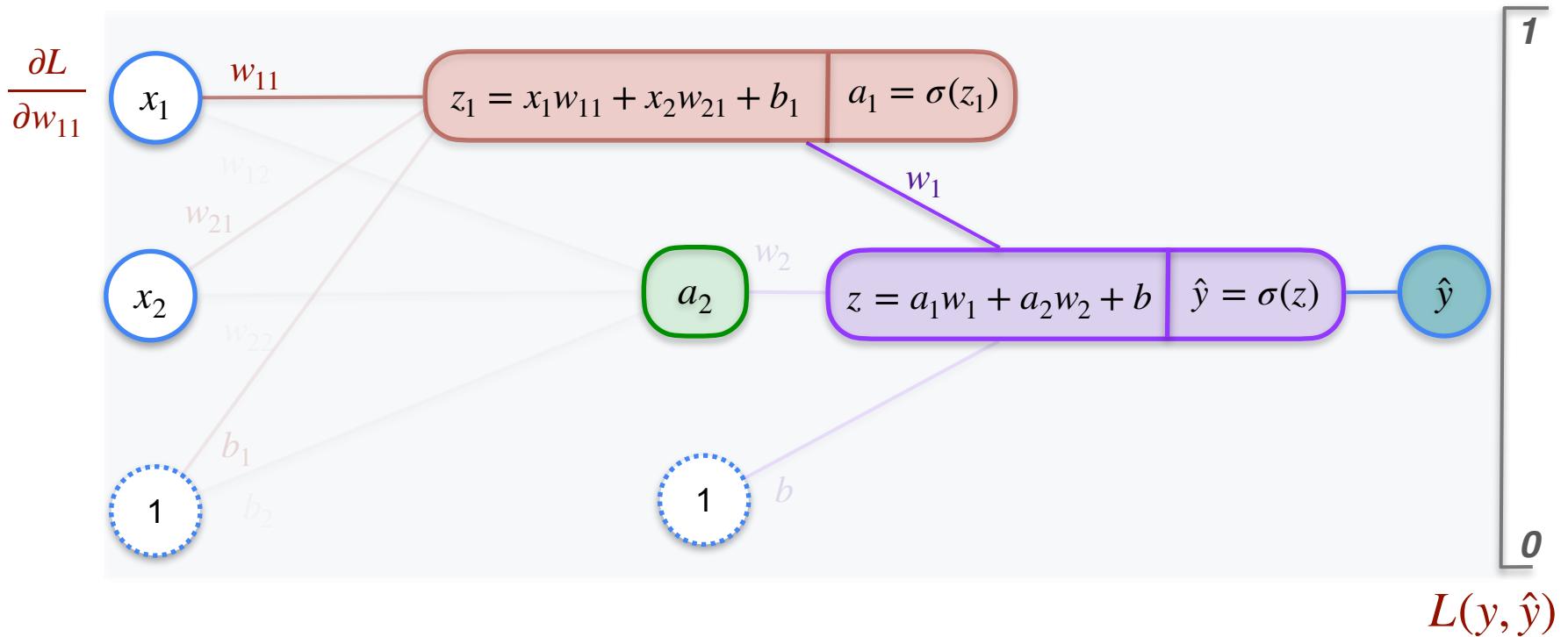
# 2,2,1 Neural Network



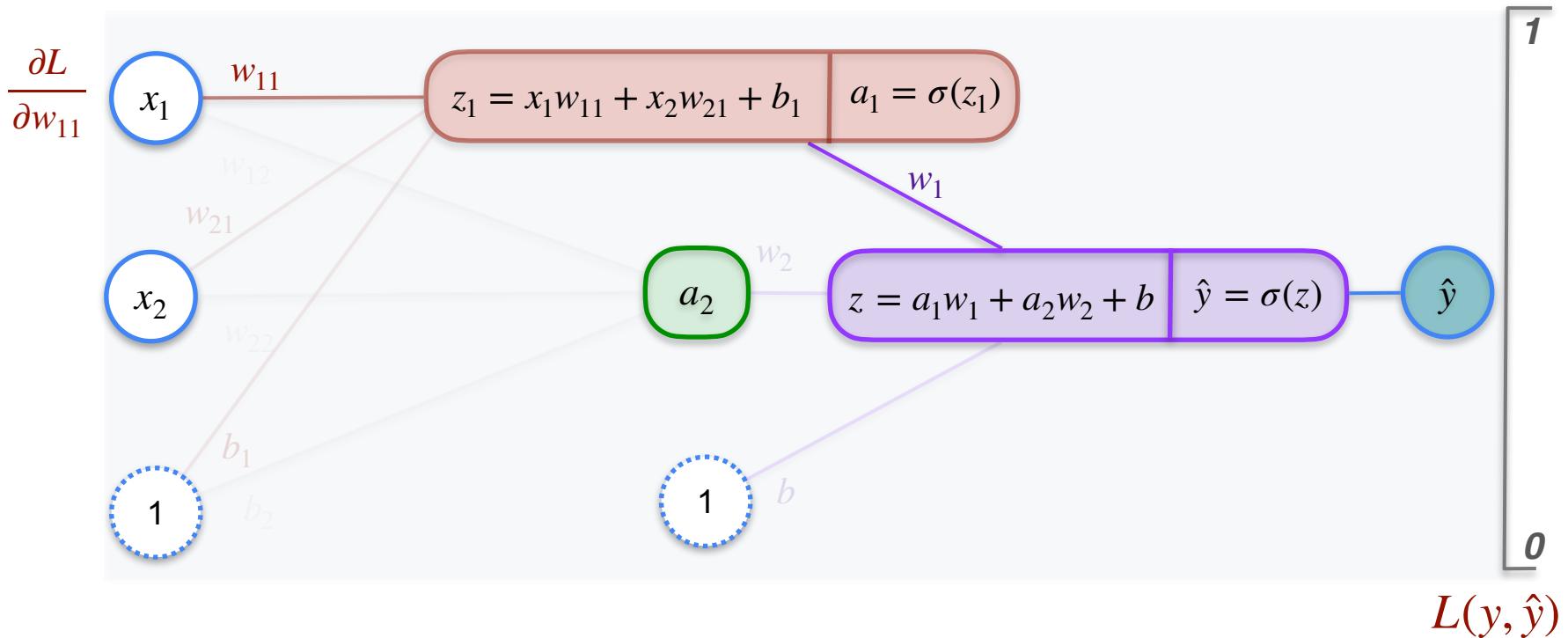
# 2,2,1 Neural Network



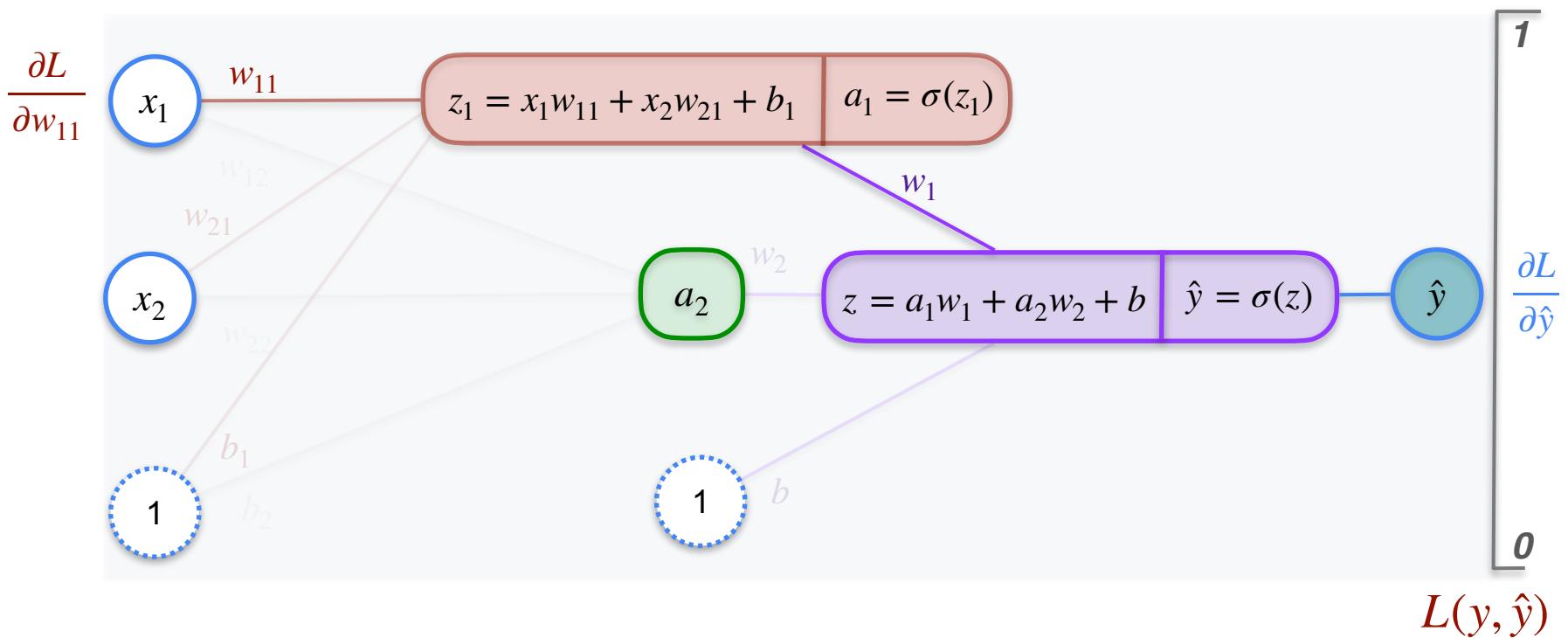
# 2,2,1 Neural Network



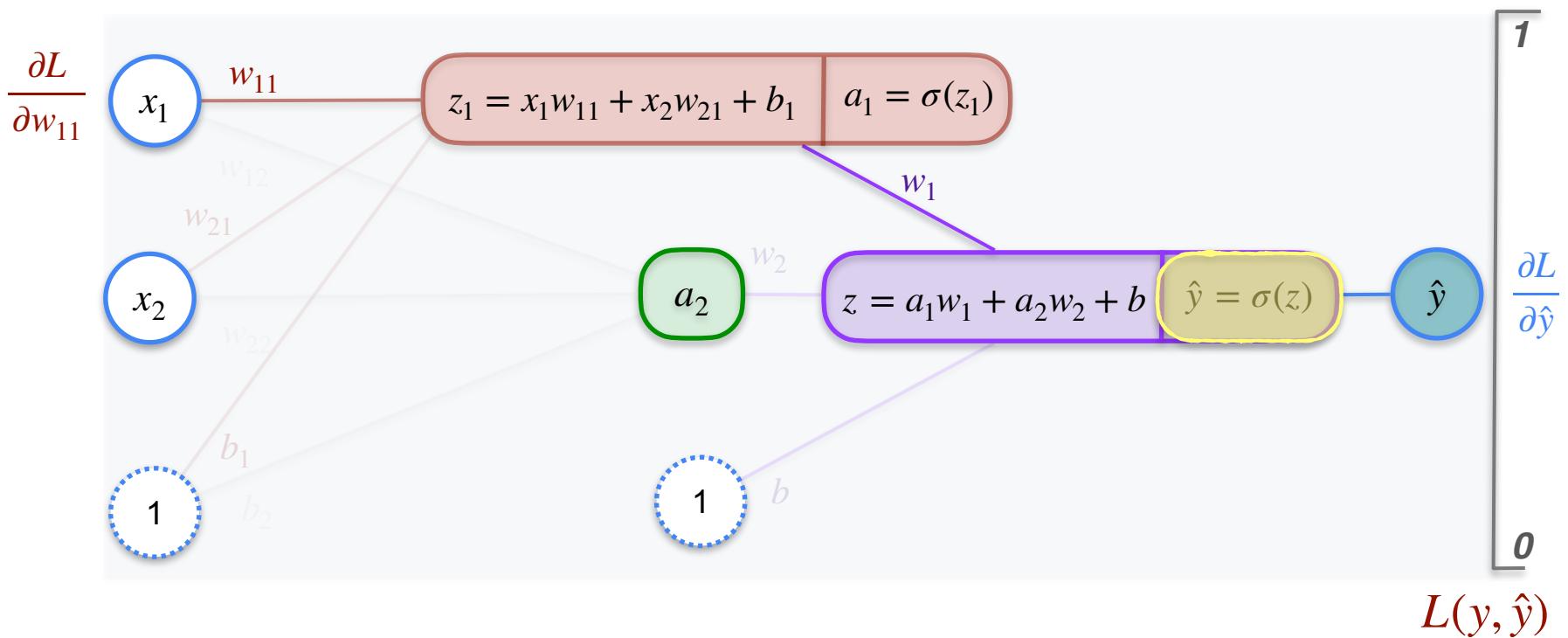
# 2,2,1 Neural Network



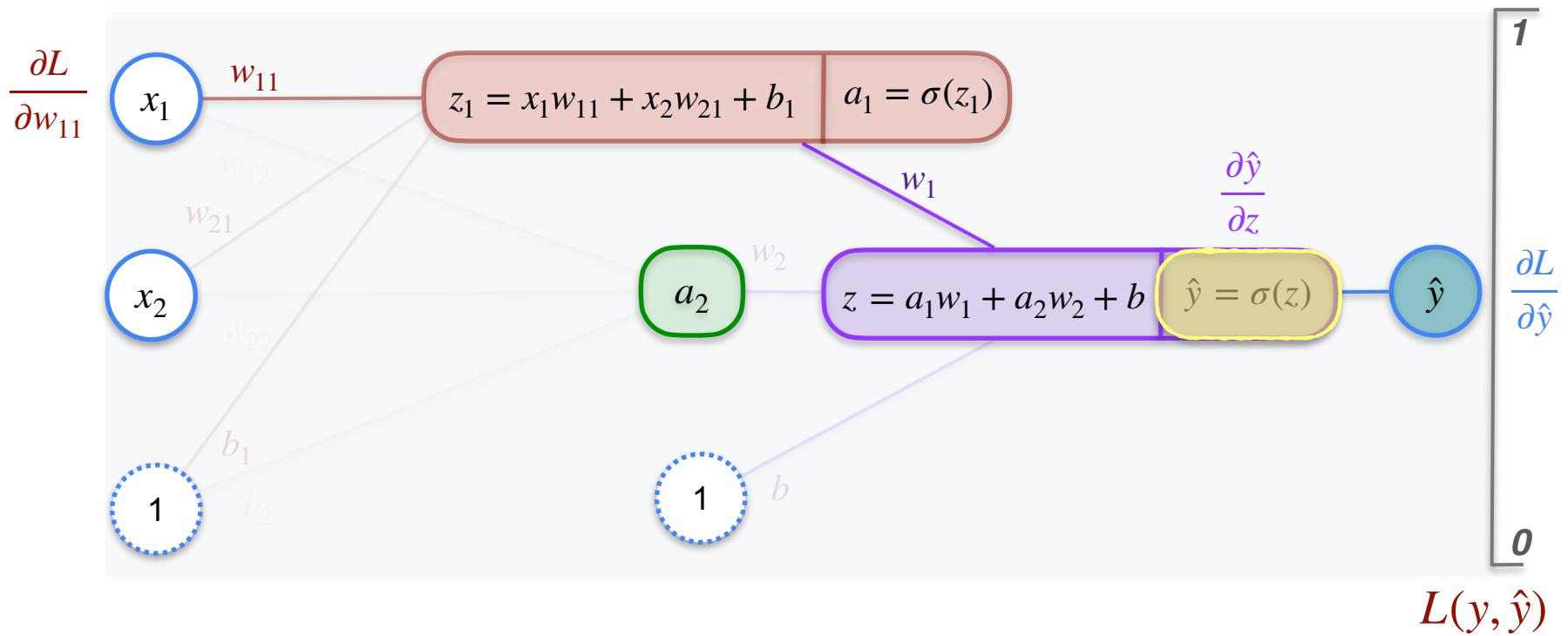
# 2,2,1 Neural Network



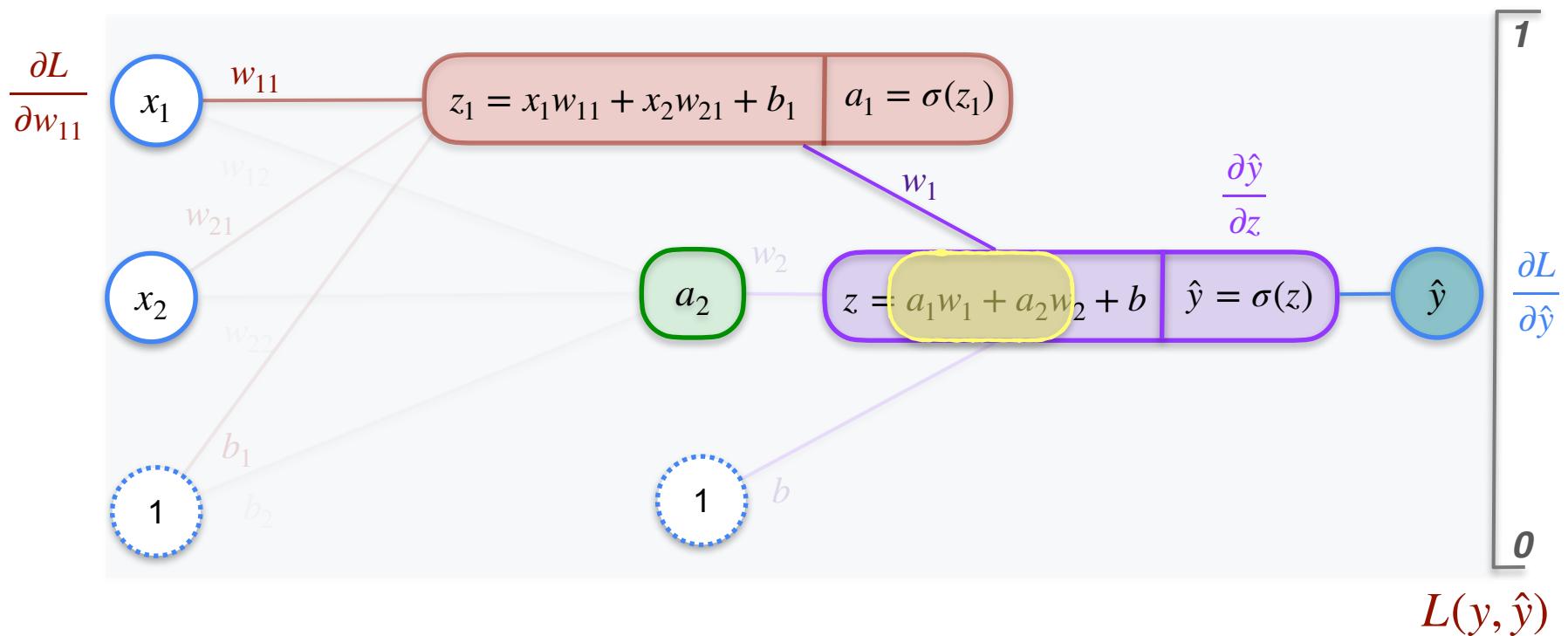
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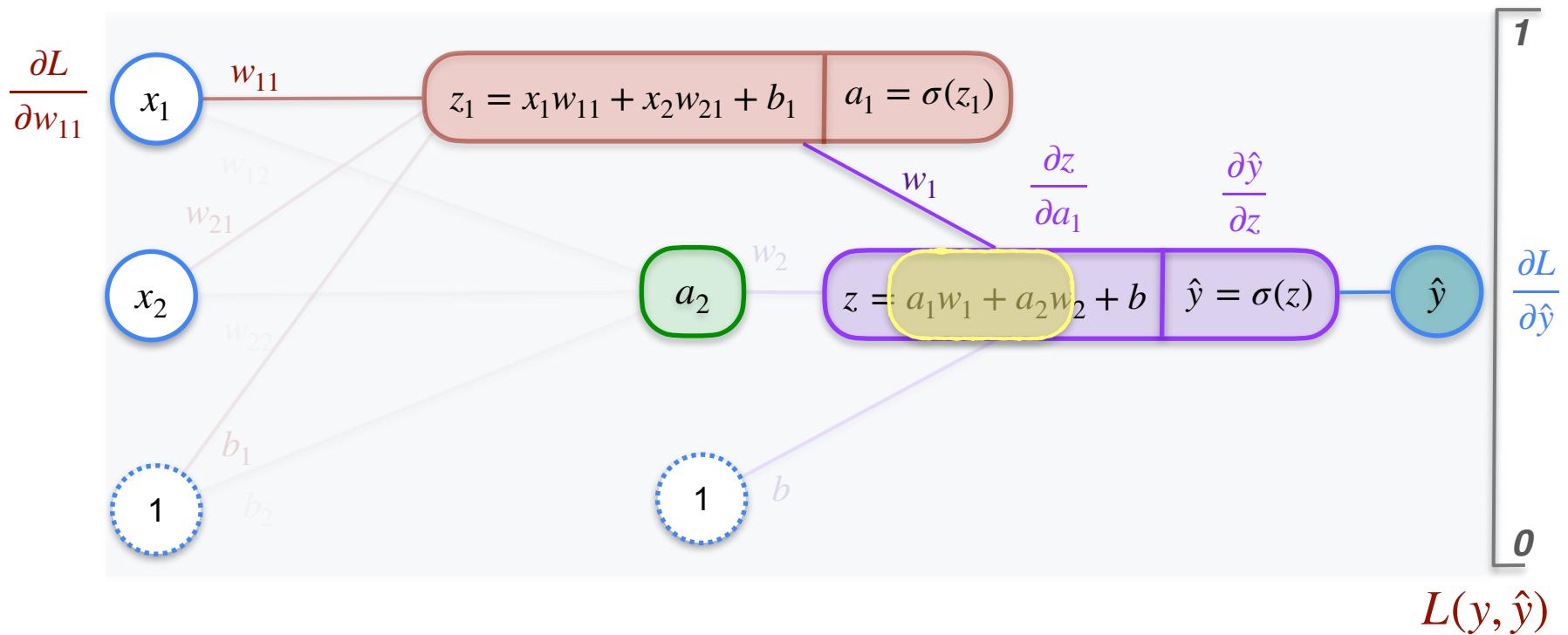
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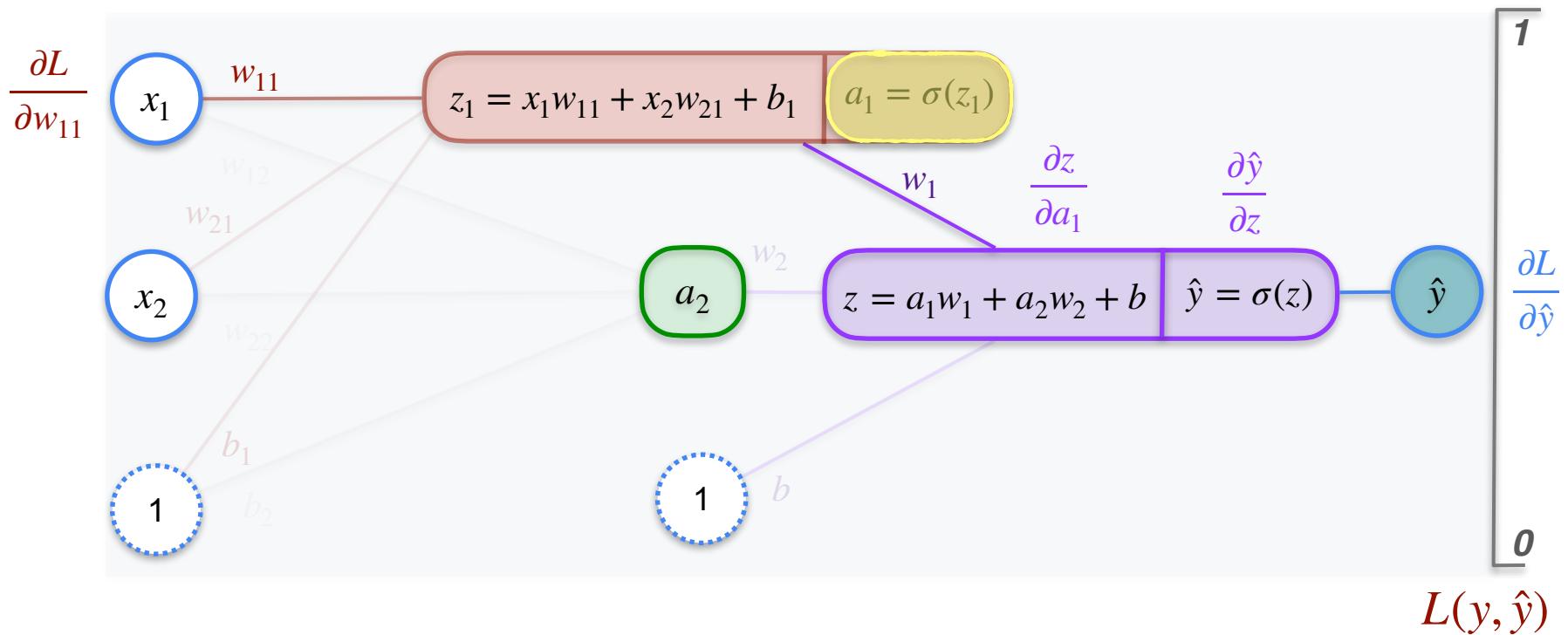
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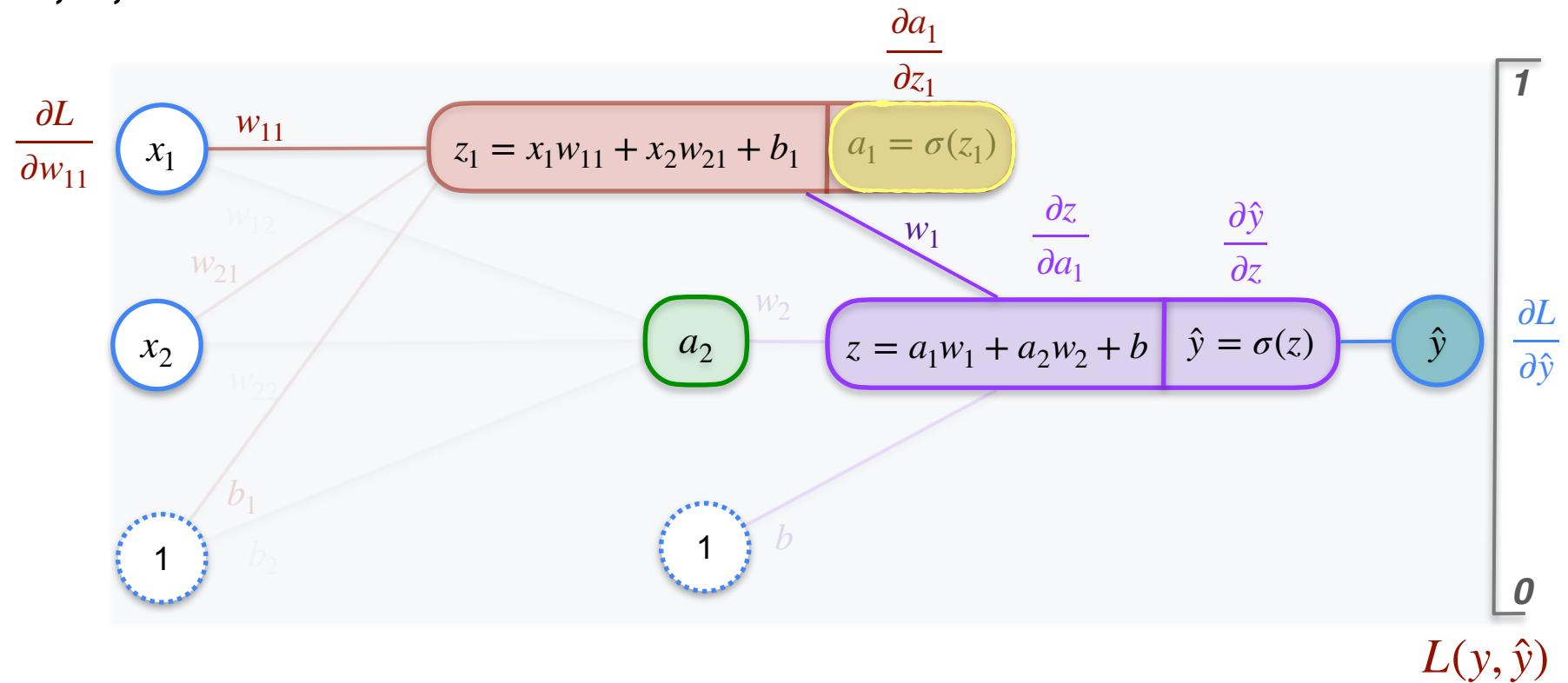
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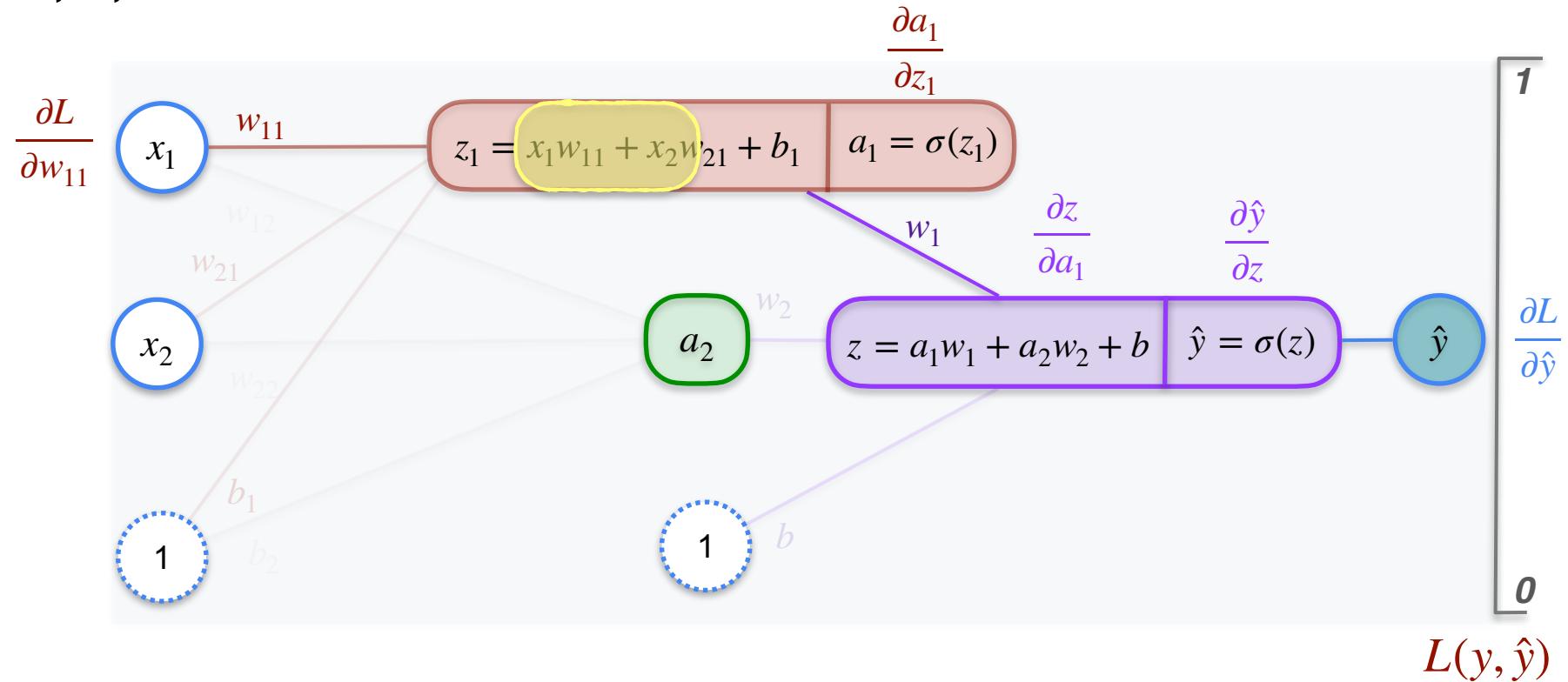
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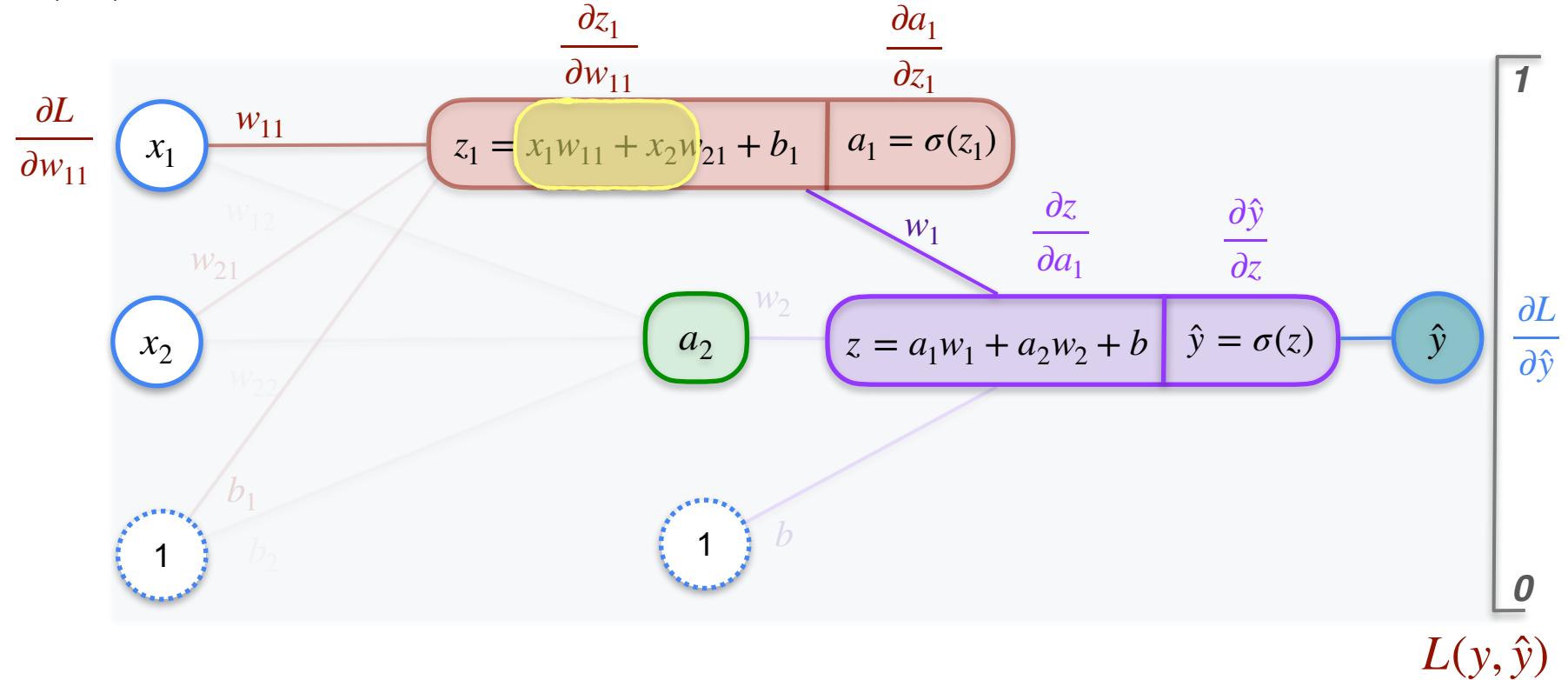
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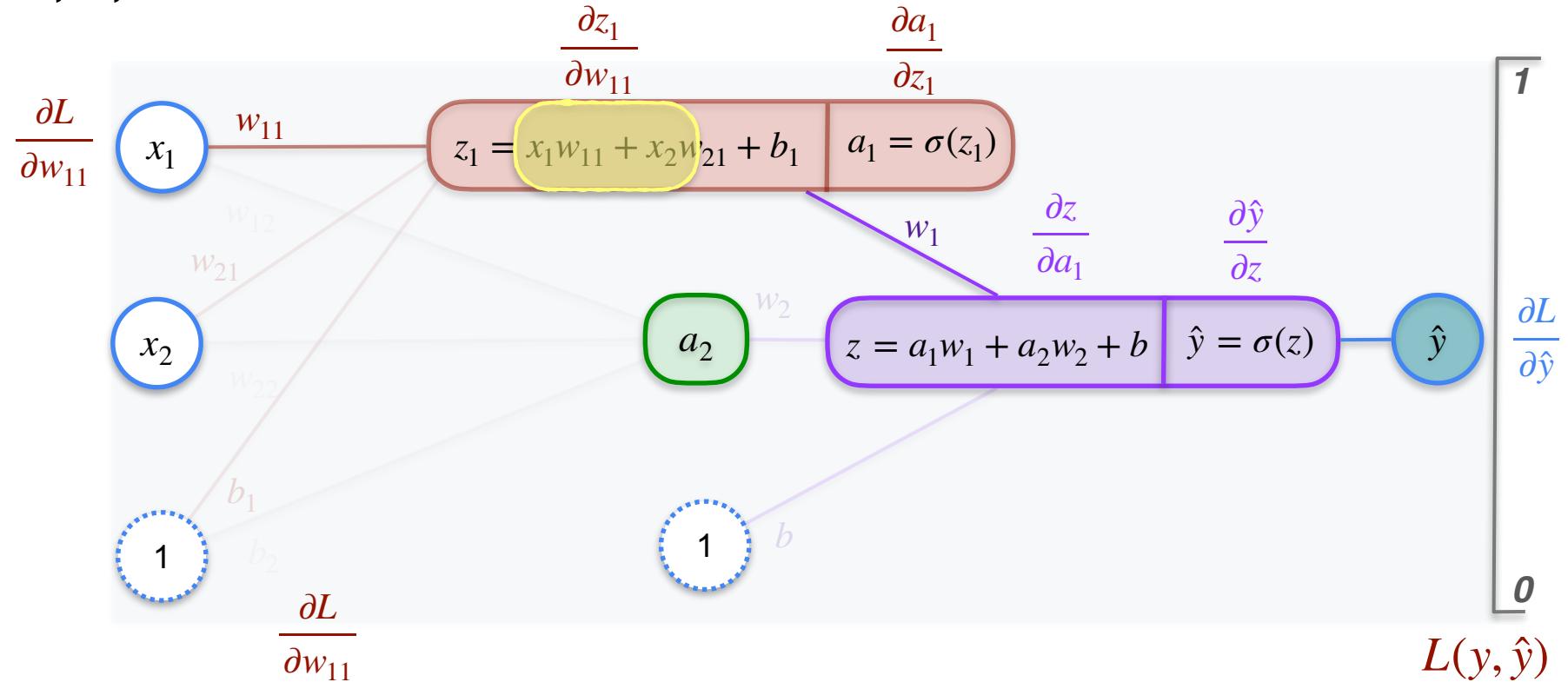
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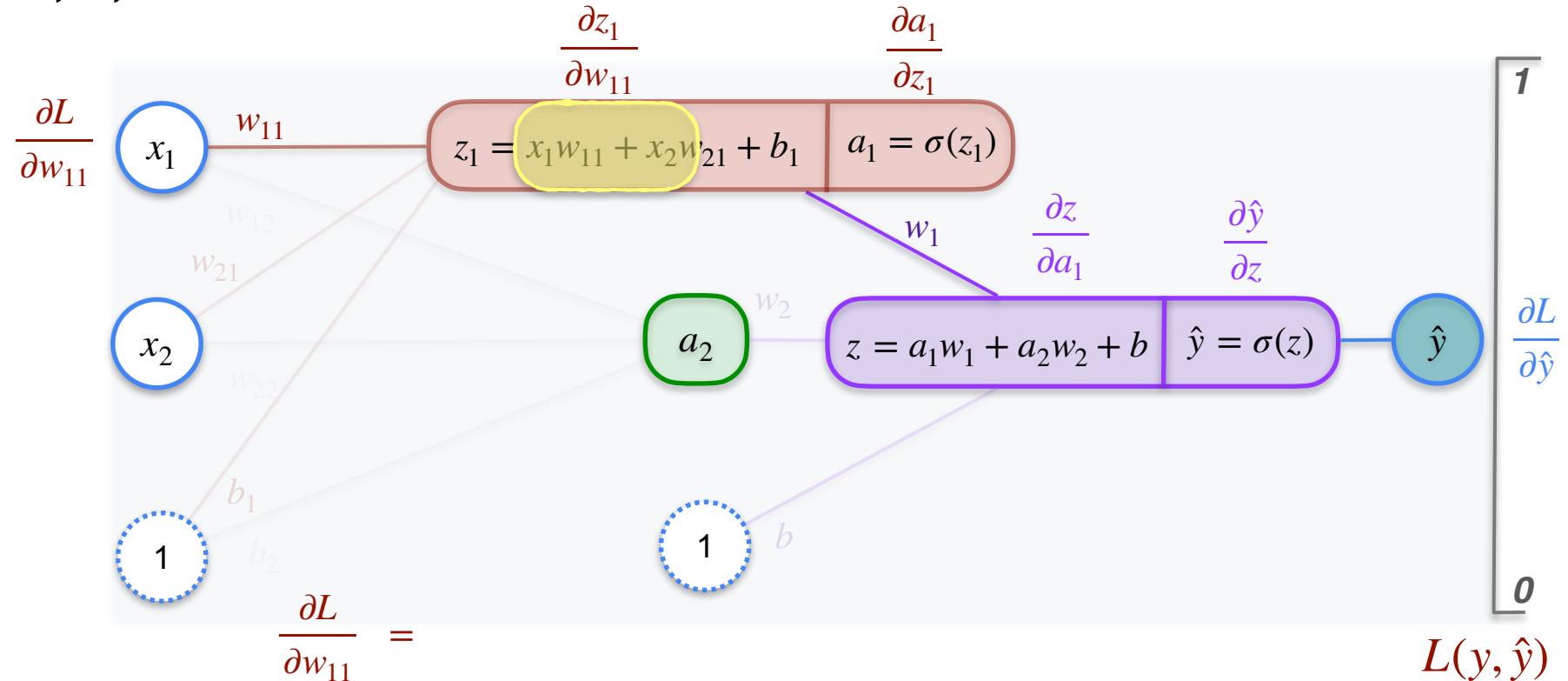
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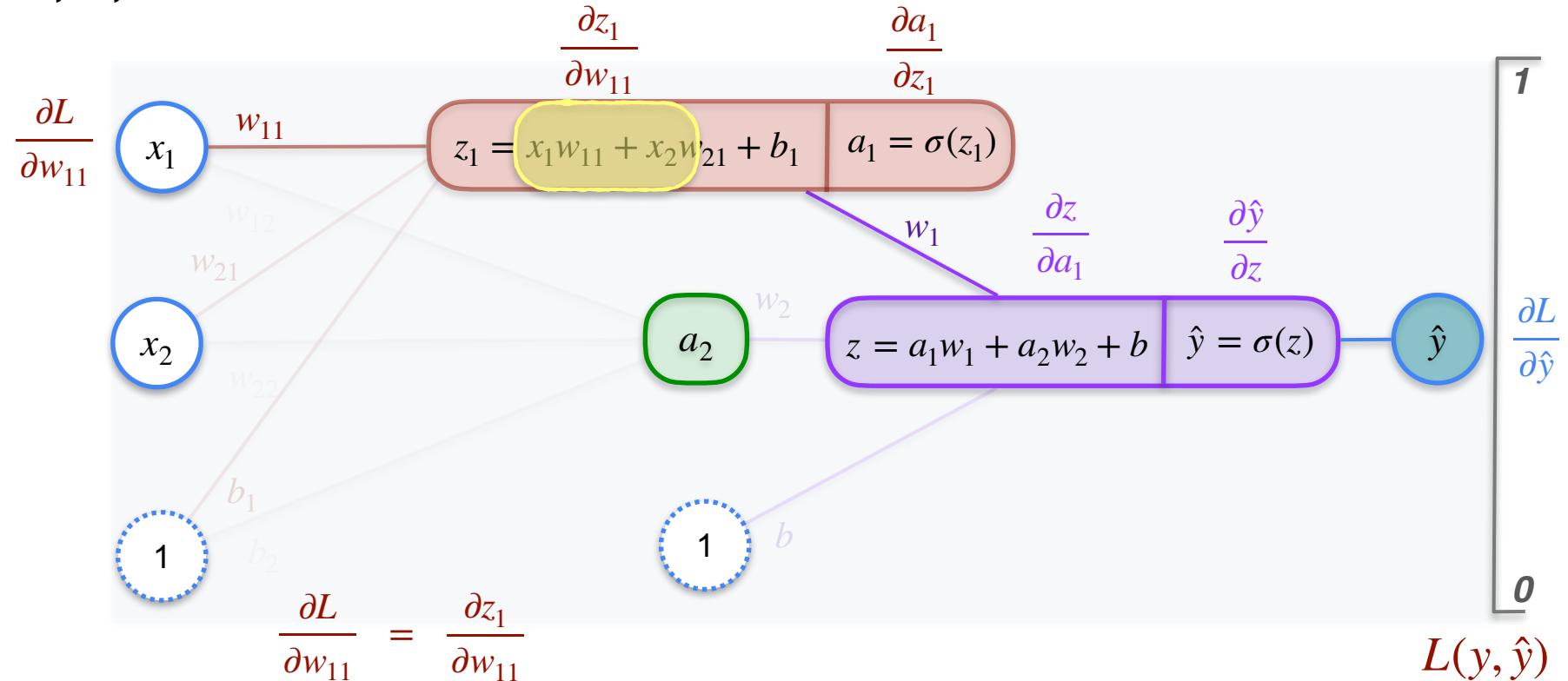
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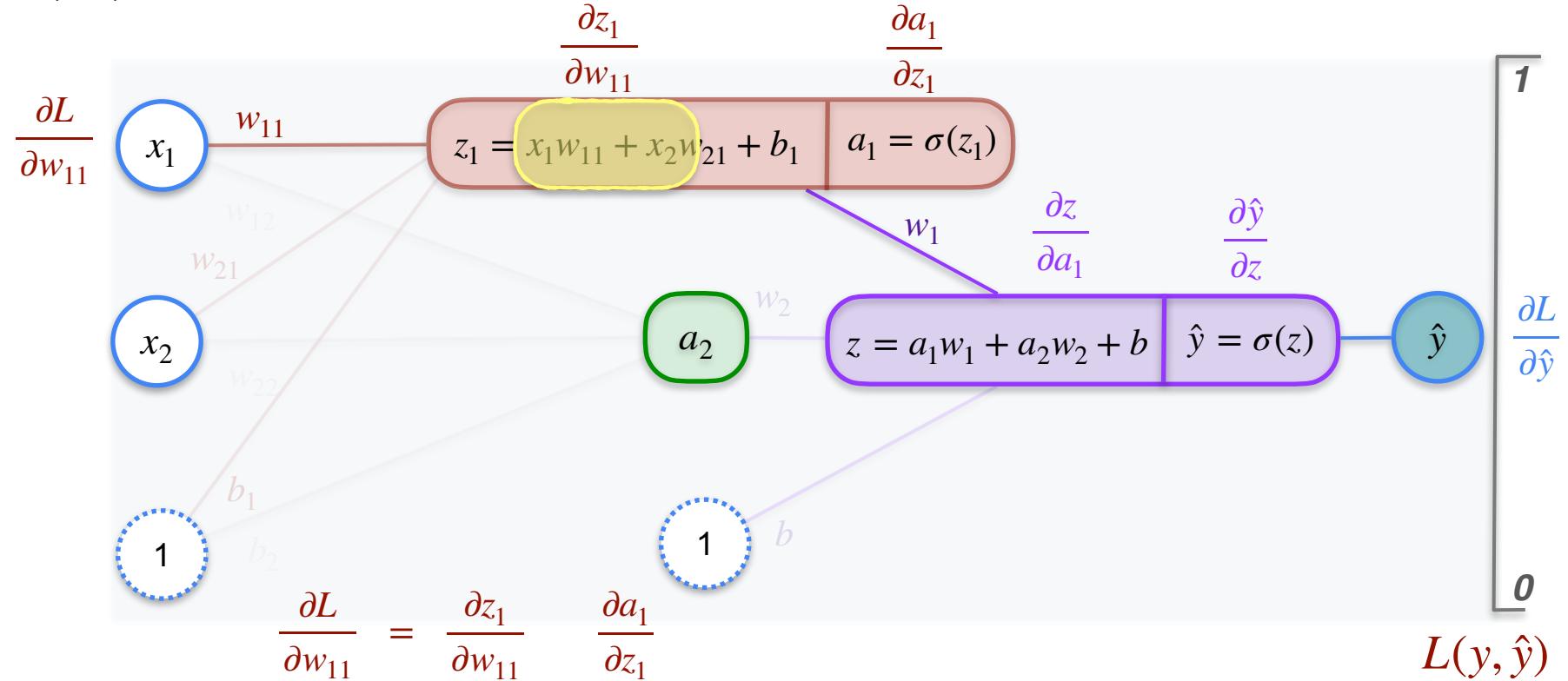
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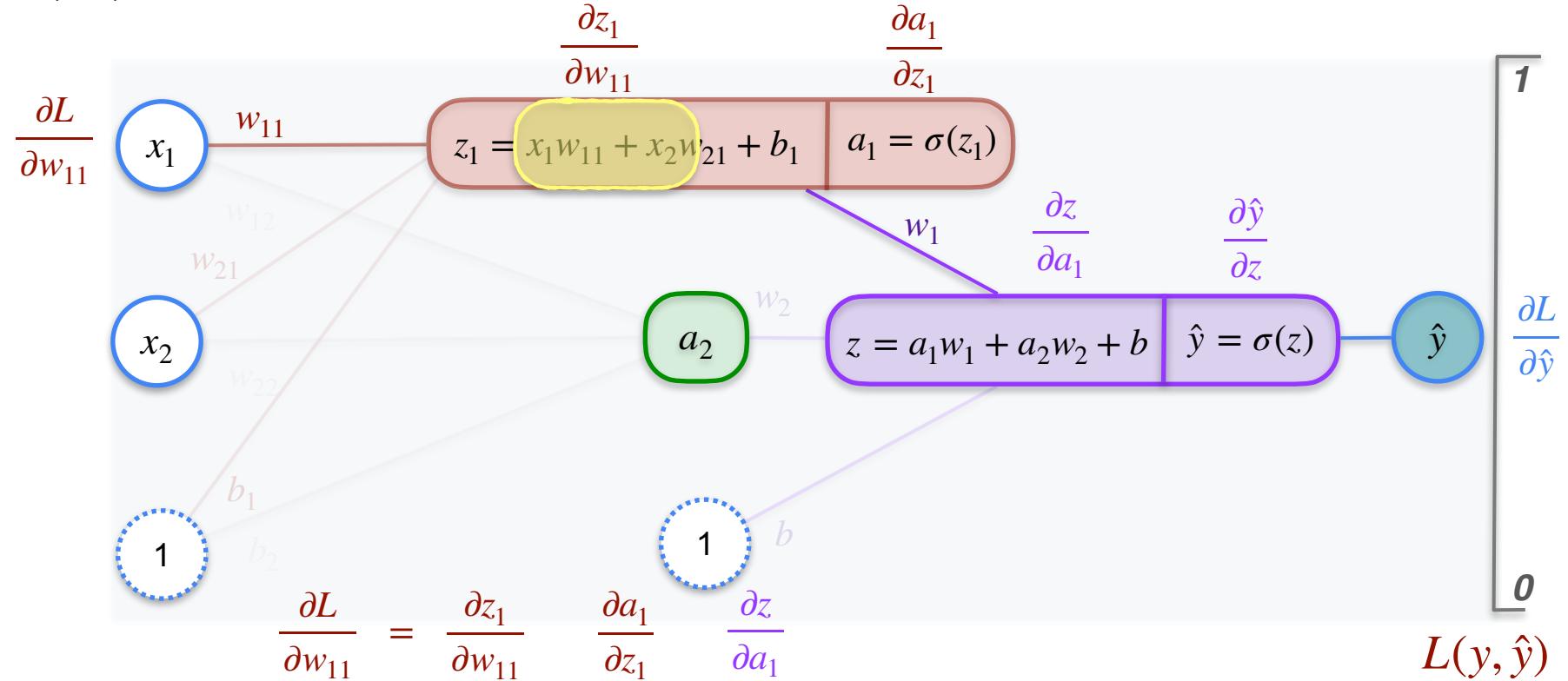
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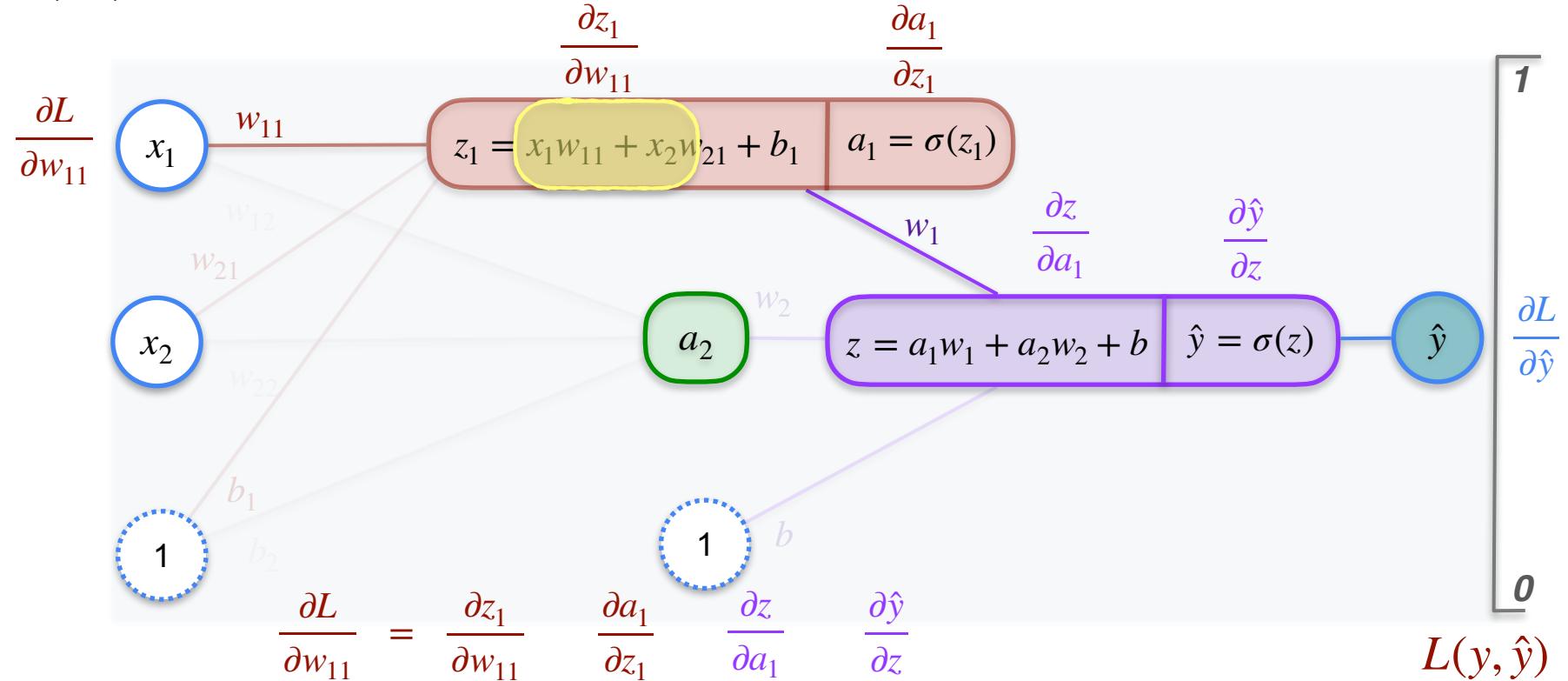
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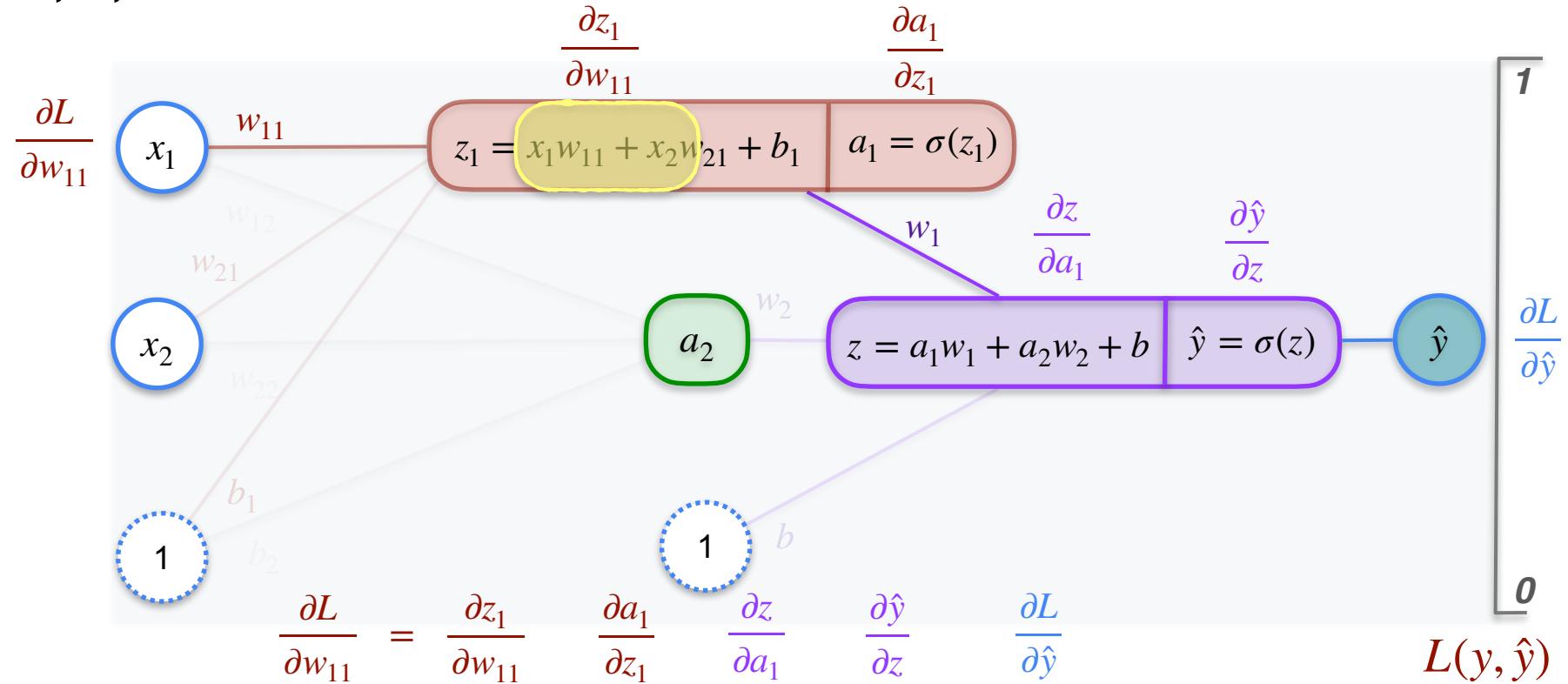
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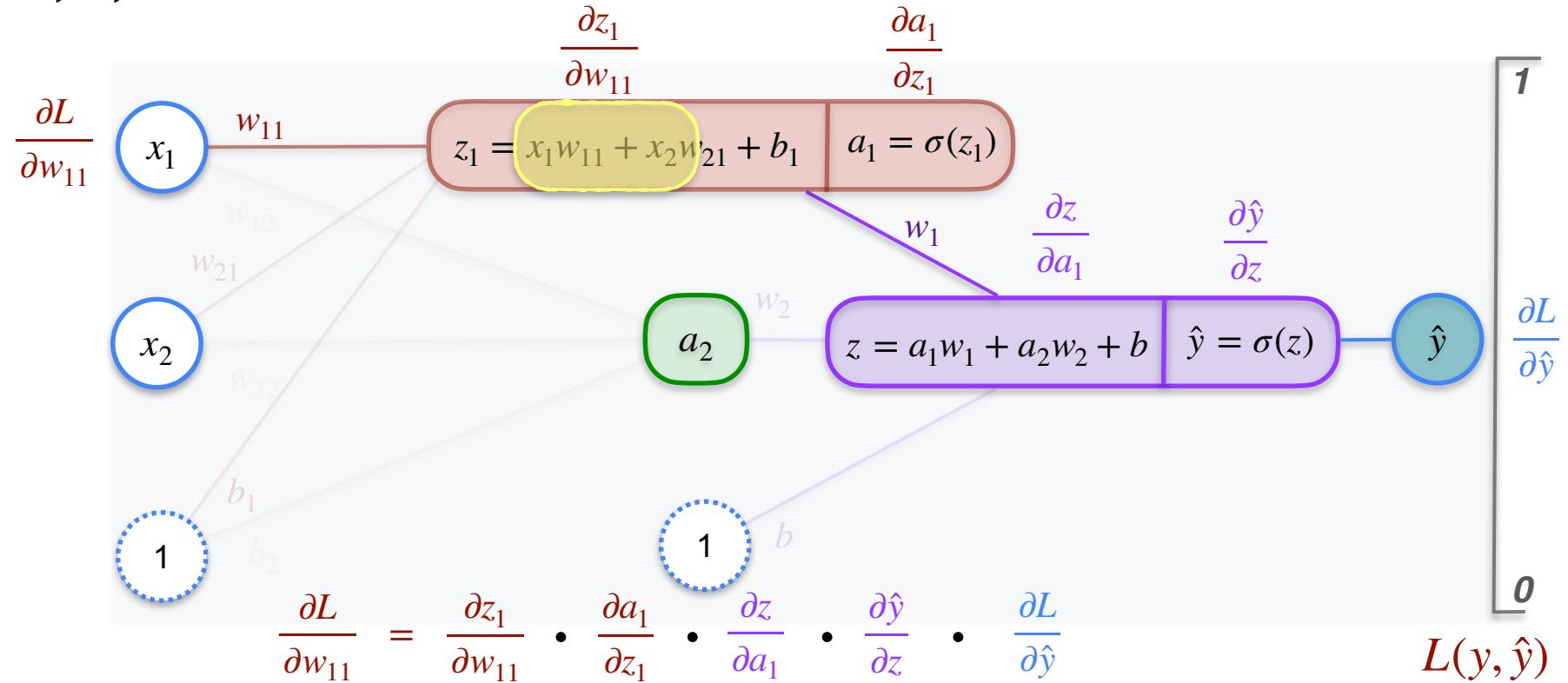
# 2,2,1 Neural Network



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# 2,2,1 Neural Network



# 2,2,1 Neural Network

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \bullet \frac{\partial a_1}{\partial z_1} \bullet \frac{\partial z}{\partial a_1} \bullet \frac{\partial \hat{y}}{\partial z} \bullet \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

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$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1 - a_1)$$

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$$\frac{\partial L}{\partial w_{11}} = x_1 \quad a_1(1-a_1) \quad w_1 \quad \hat{y}(1-\hat{y}) \quad \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

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*Perform gradient descent with*

*to find optimal  
value of  $w_{11}$  that  
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$$w_{11} \rightarrow w_{11} - \alpha \frac{\partial L}{\partial w_{11}}$$

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$$\begin{aligned}\frac{\partial L}{\partial w_{11}} &= \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{11}} &= x_1 \cdot a_1 (1 - a_1) \cdot w_1 \cdot \cancel{\hat{y}(1 - \hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1 - \hat{y})}} \\ &= -x_1 w_1 a_1 (1 - a_1) (y - \hat{y})\end{aligned}$$

*Perform gradient descent with*

$$w_{11} \rightarrow w_{11} - \alpha$$

*to find optimal value of  $w_{11}$  that gives the least error*

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

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$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

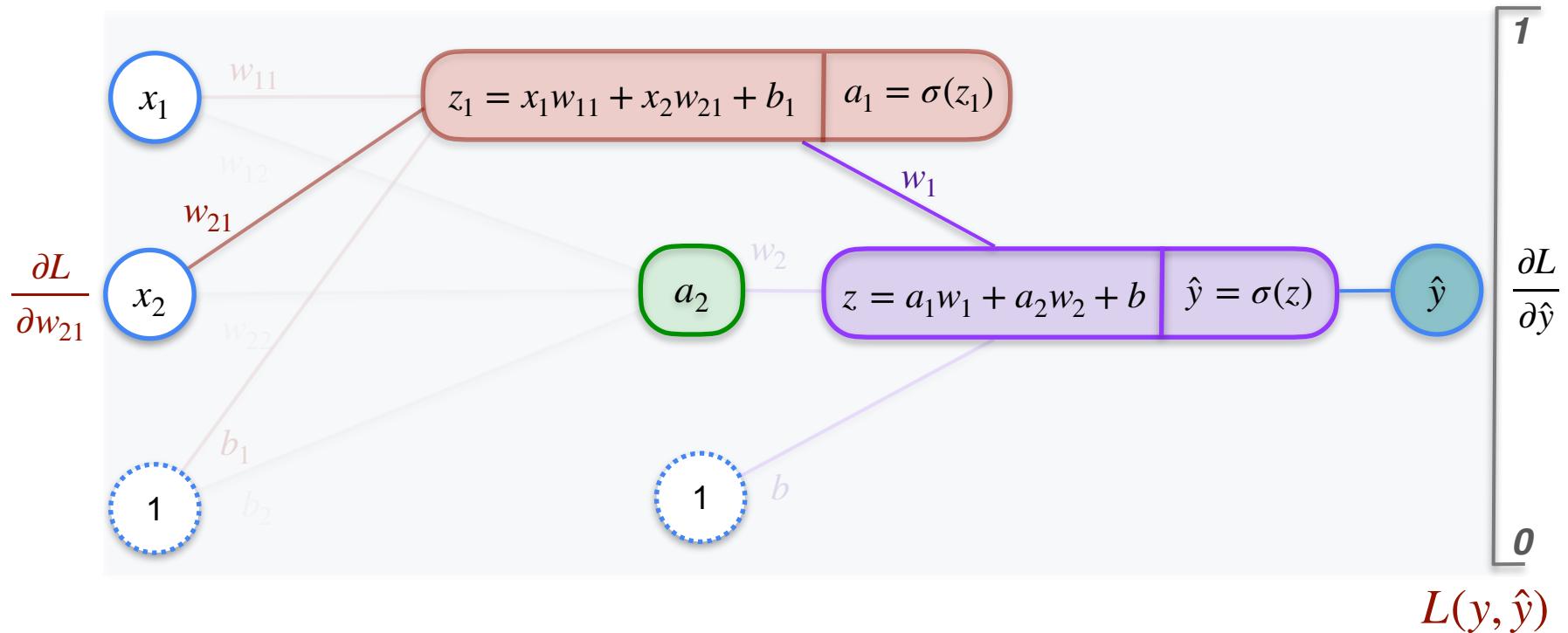
$$\begin{aligned}\frac{\partial L}{\partial w_{11}} &= \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{11}} &= x_1 \cdot a_1 (1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -x_1 w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

*Perform gradient descent with*

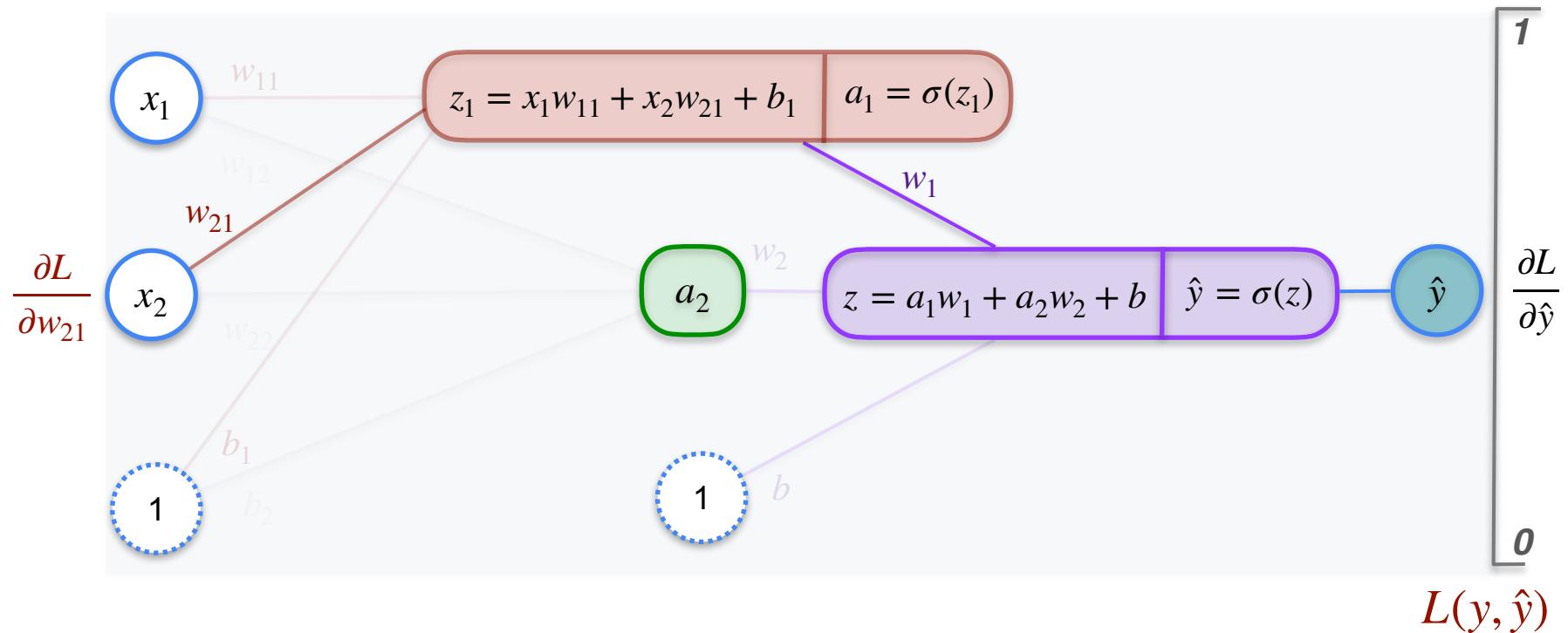
$$w_{11} \rightarrow w_{11} - \alpha \cdot x_1 w_1 a_1 (1-a_1) (y - \hat{y})$$

*to find optimal value of  $w_{11}$  that gives the least error*

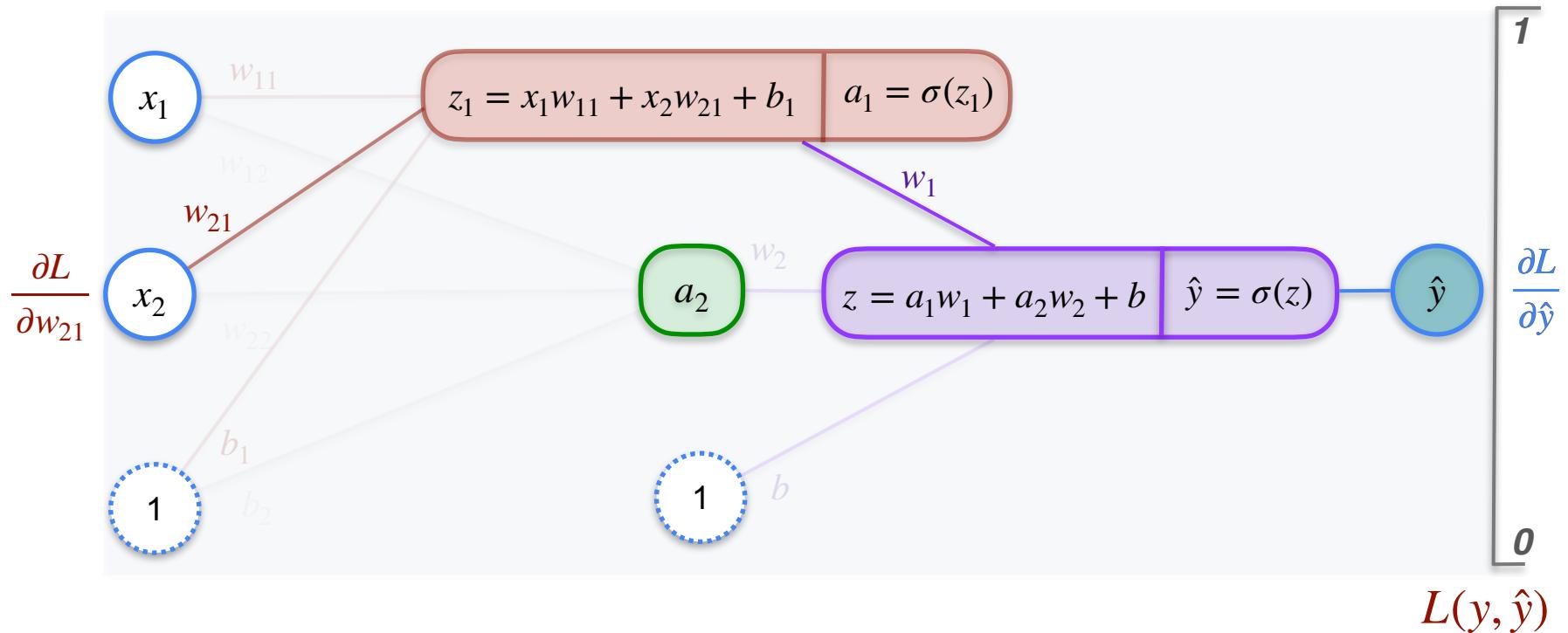
# 2,2,1 Neural Network



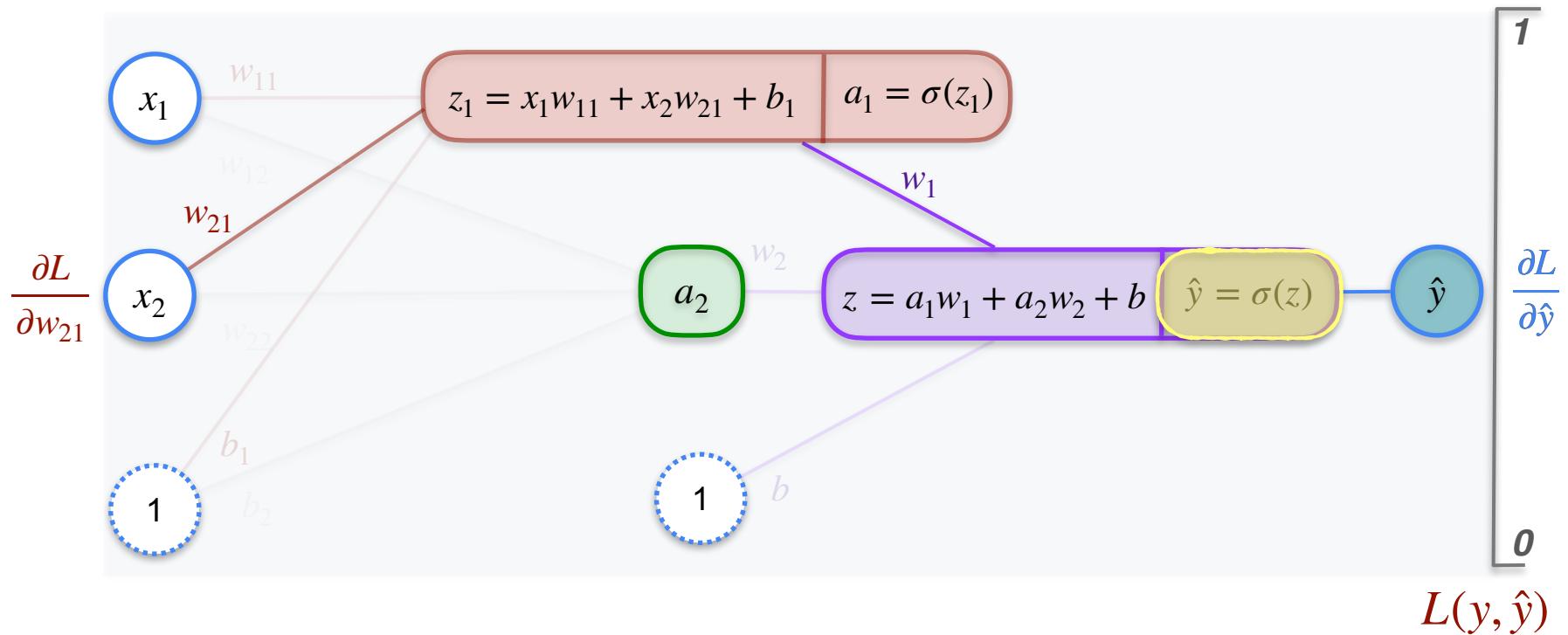
# 2,2,1 Neural Network



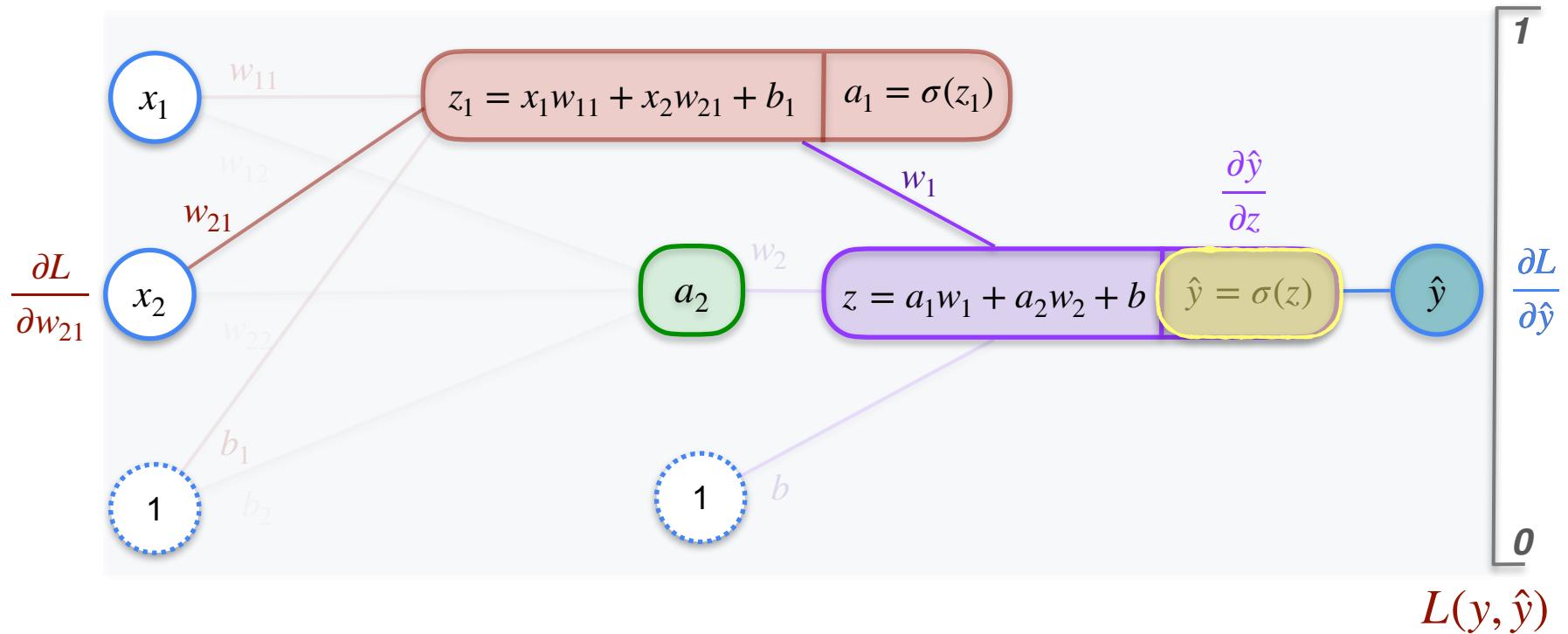
# 2,2,1 Neural Network



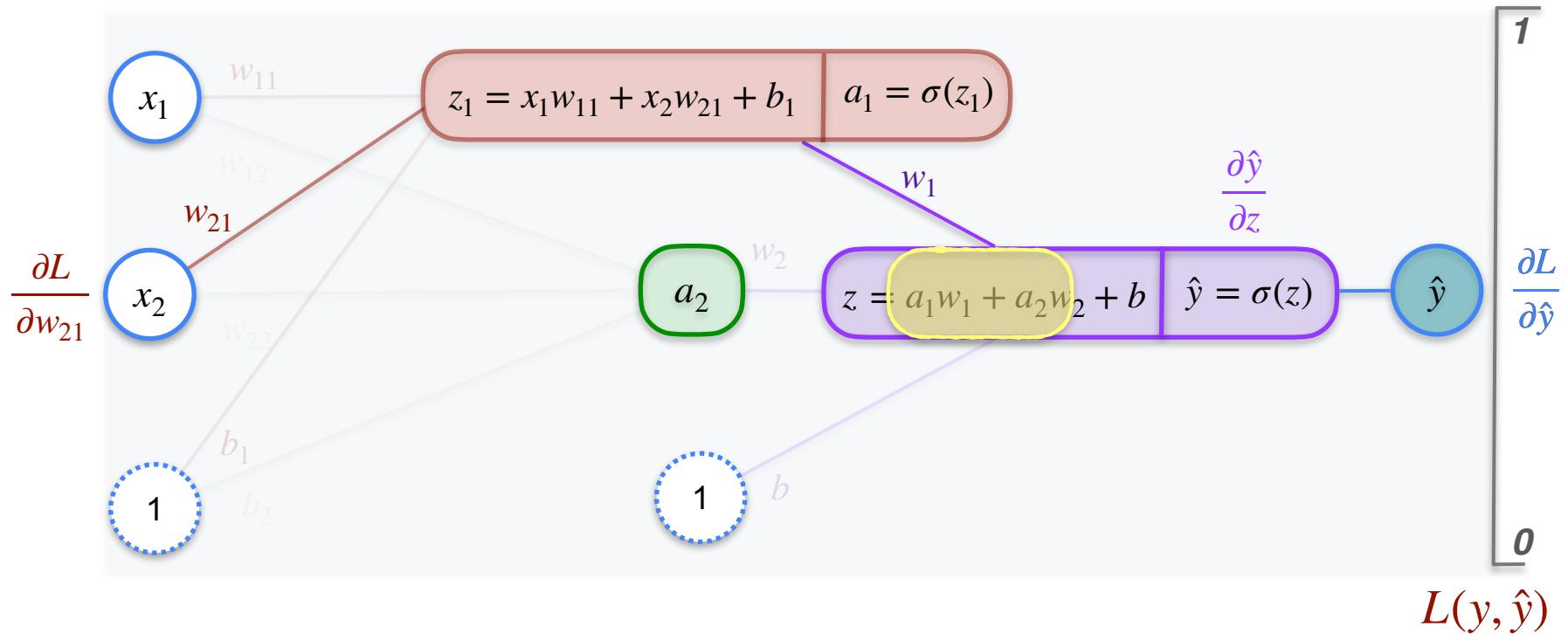
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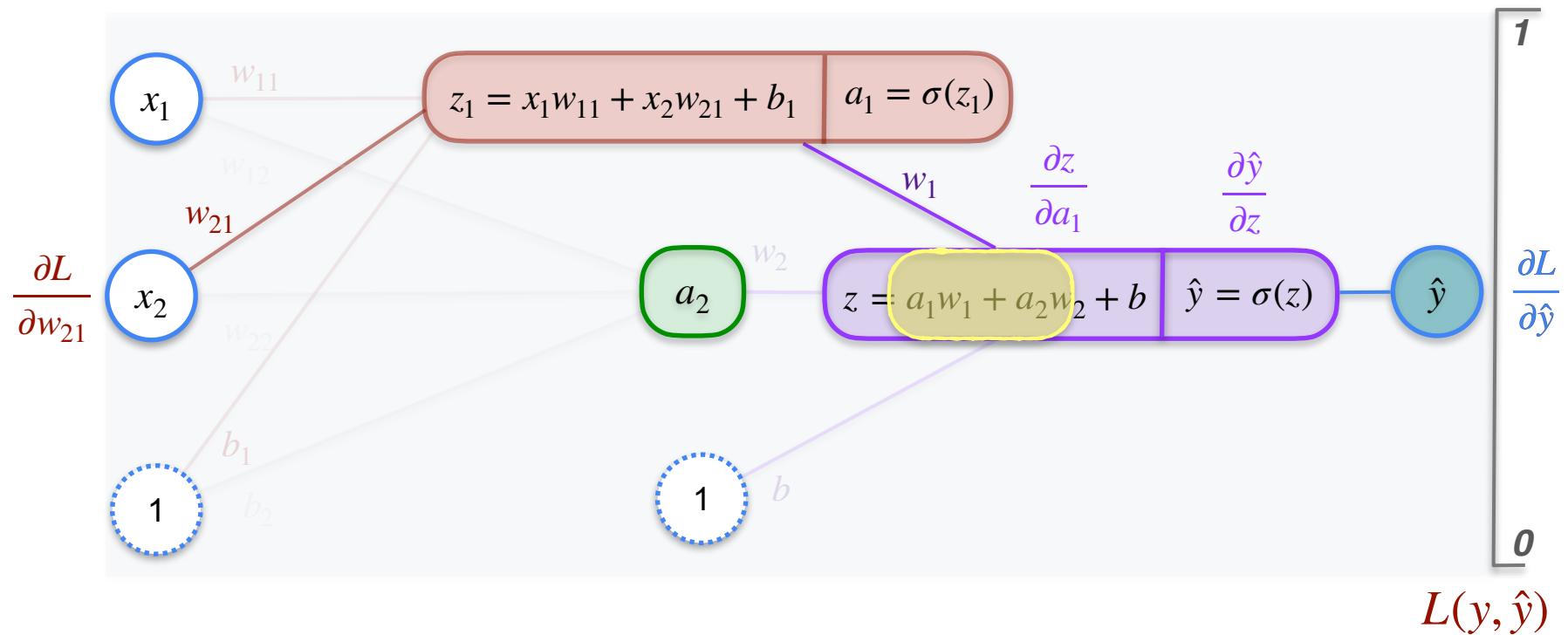
# 2,2,1 Neural Network



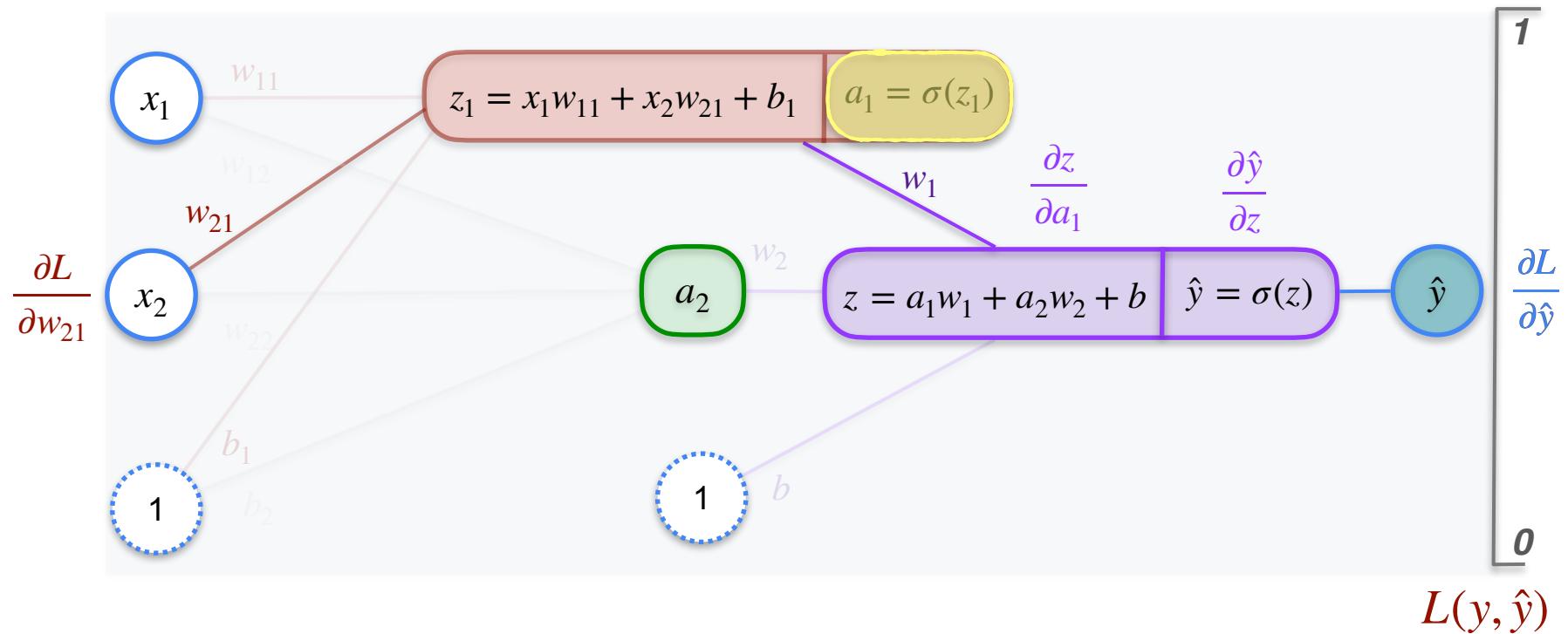
# 2,2,1 Neural Network



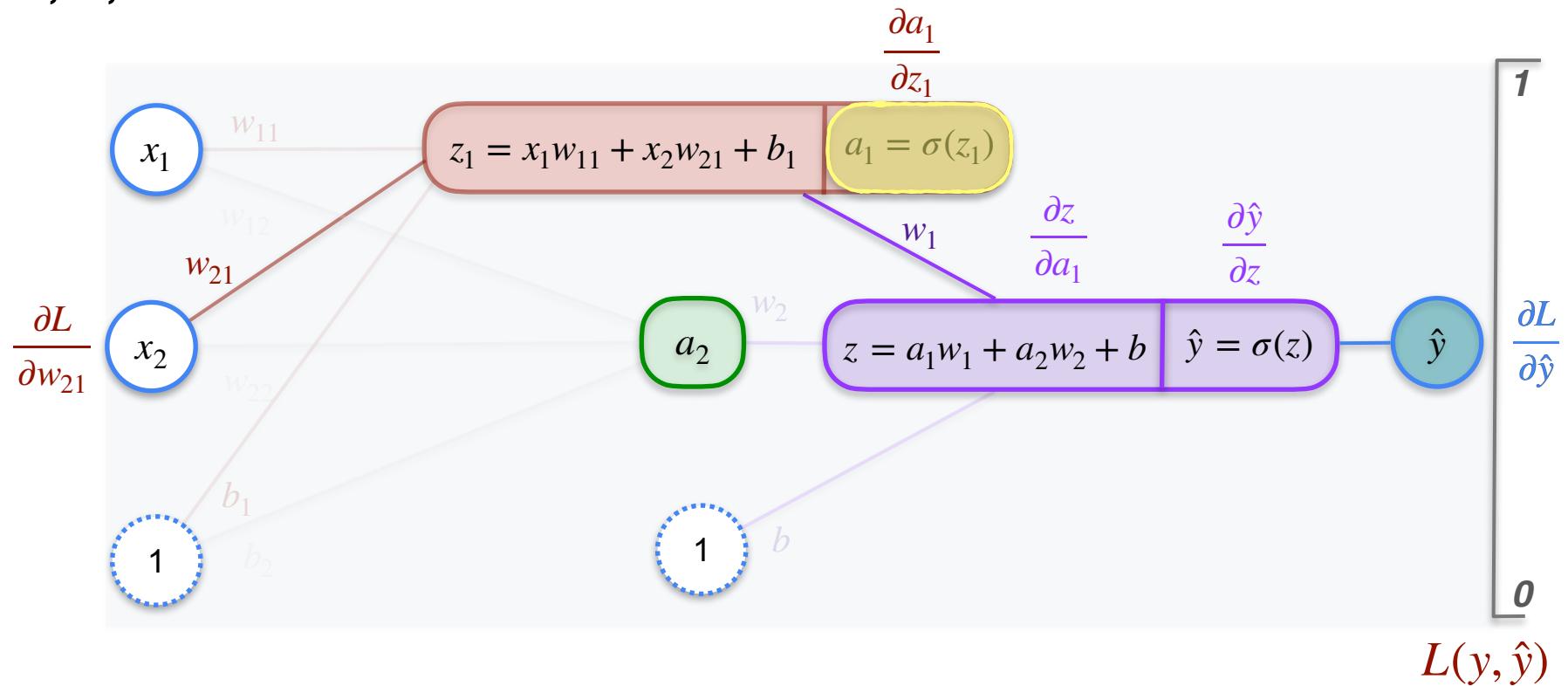
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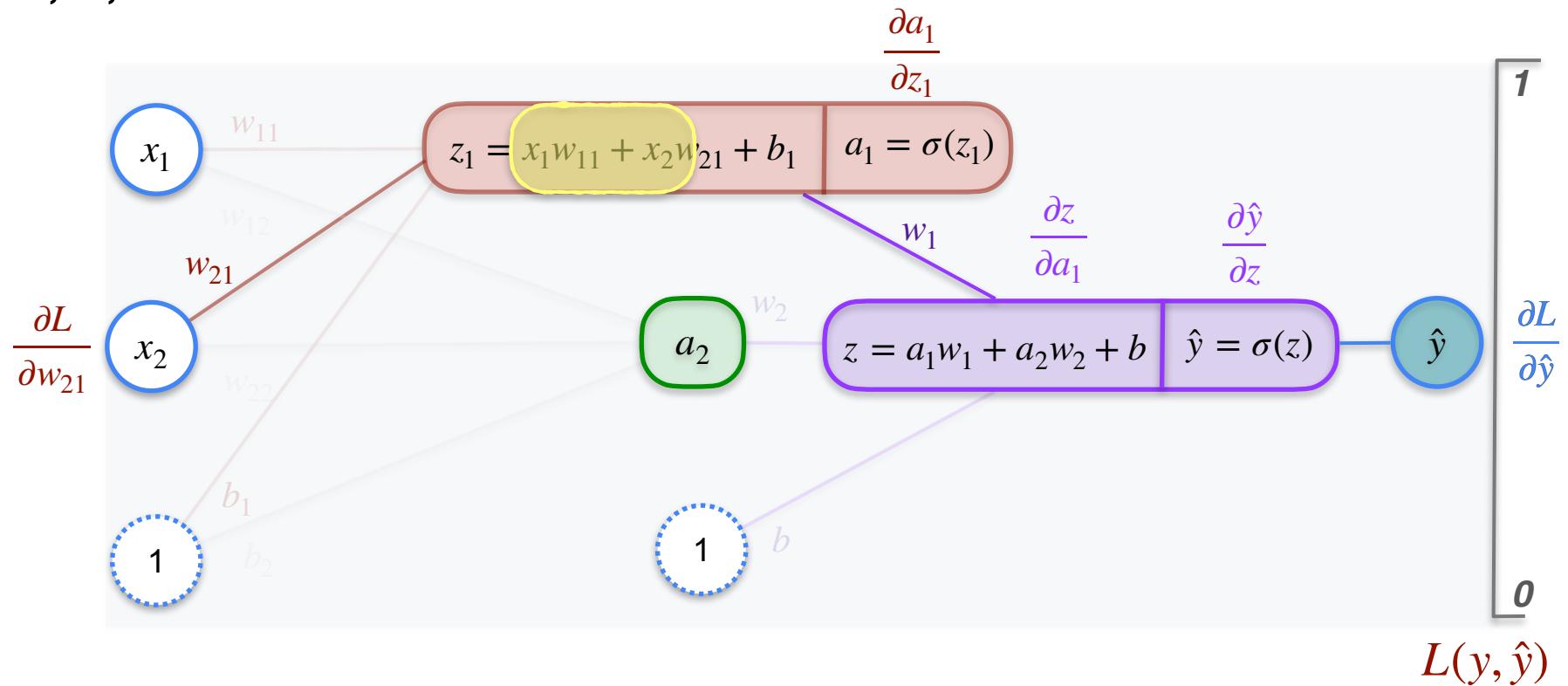
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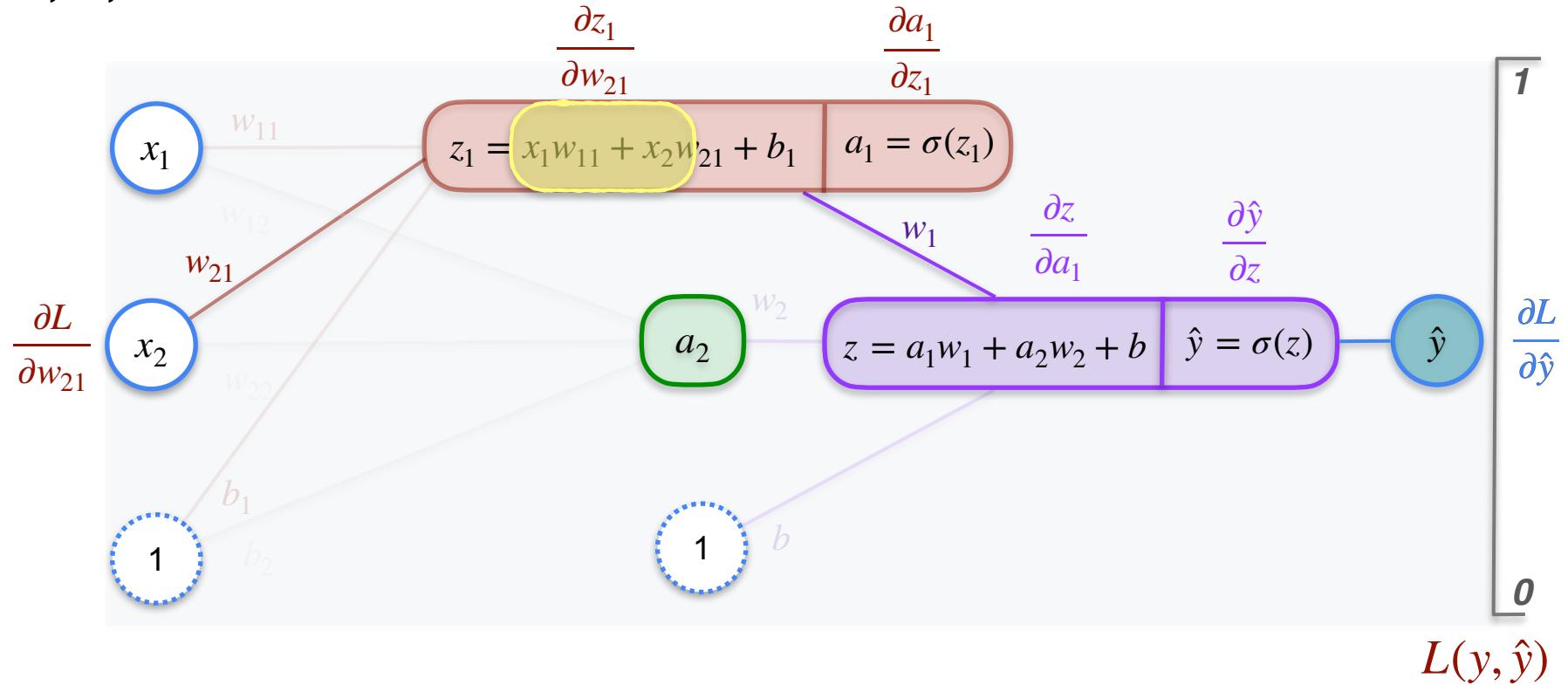
# 2,2,1 Neural Network



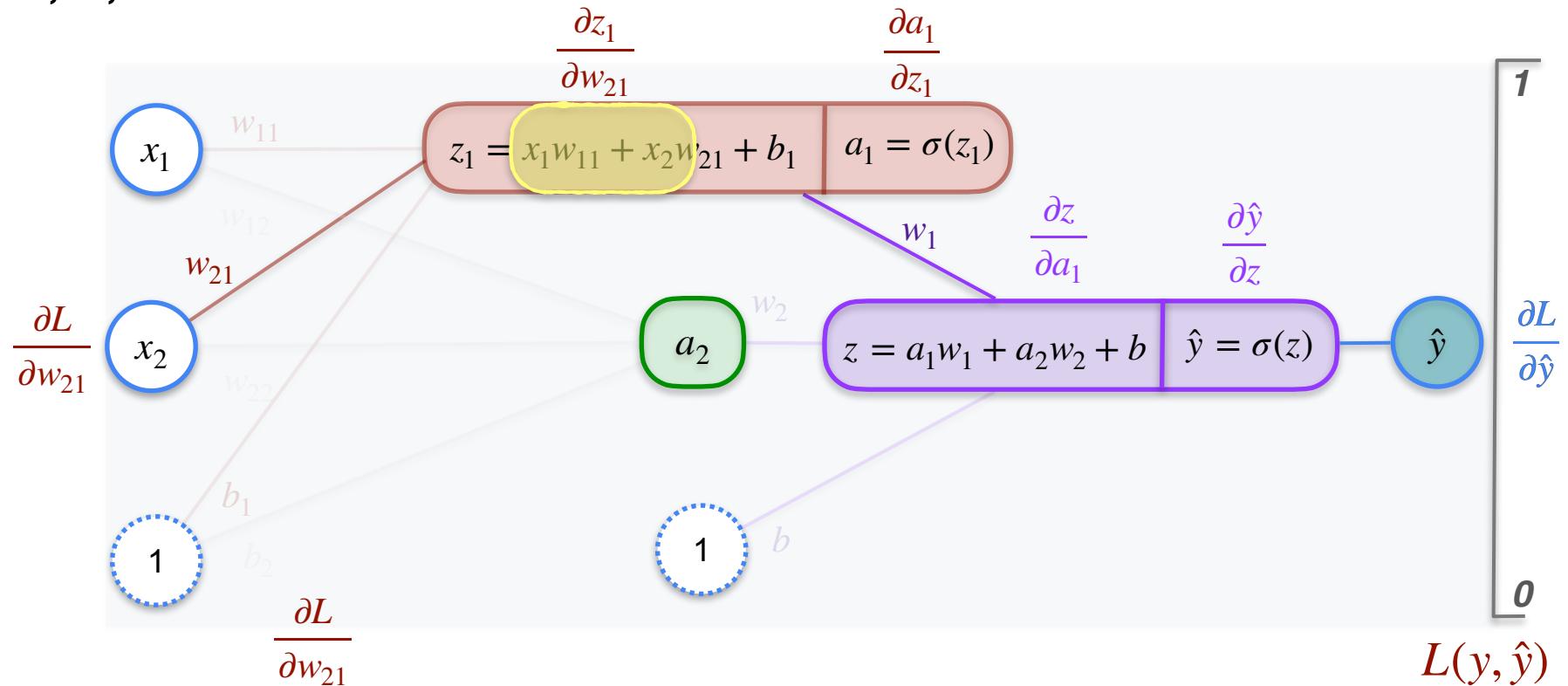
# 2,2,1 Neural Network



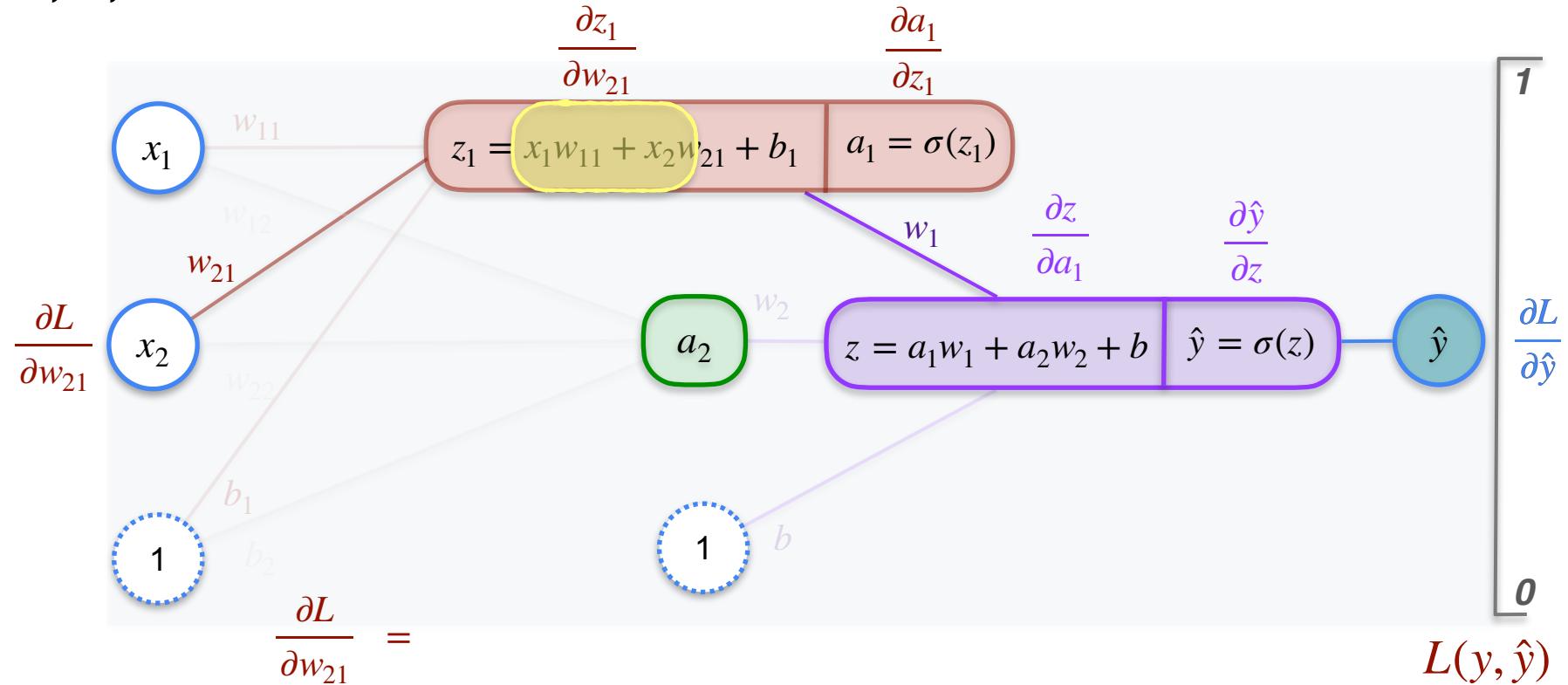
# 2,2,1 Neural Network



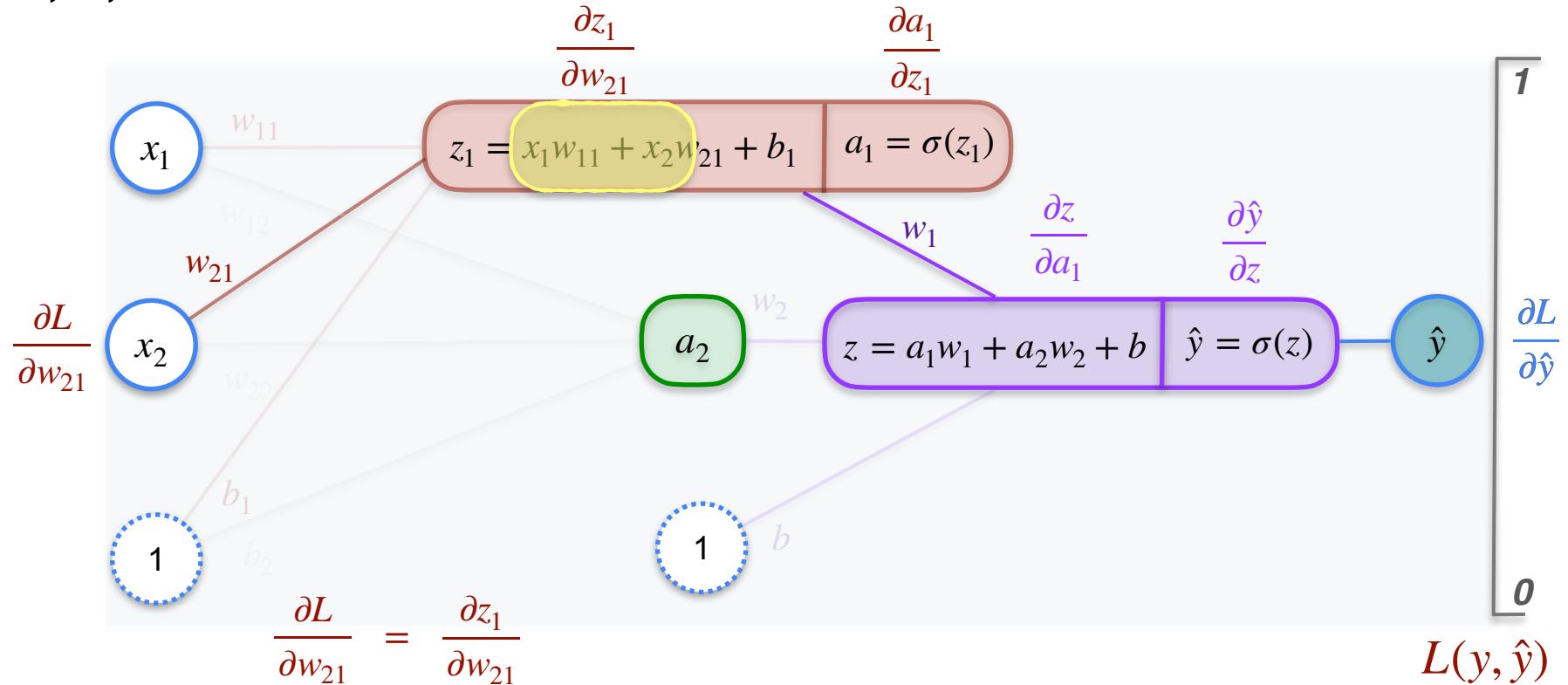
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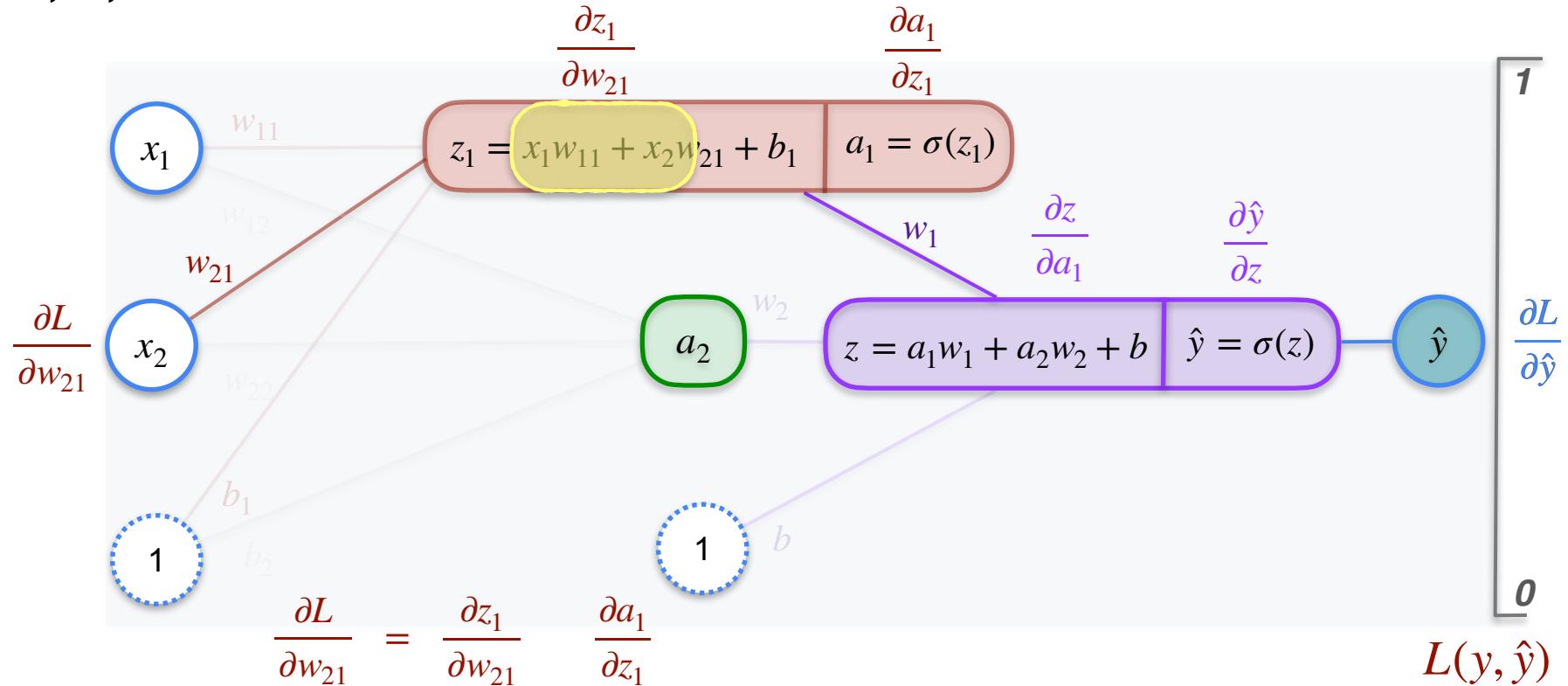
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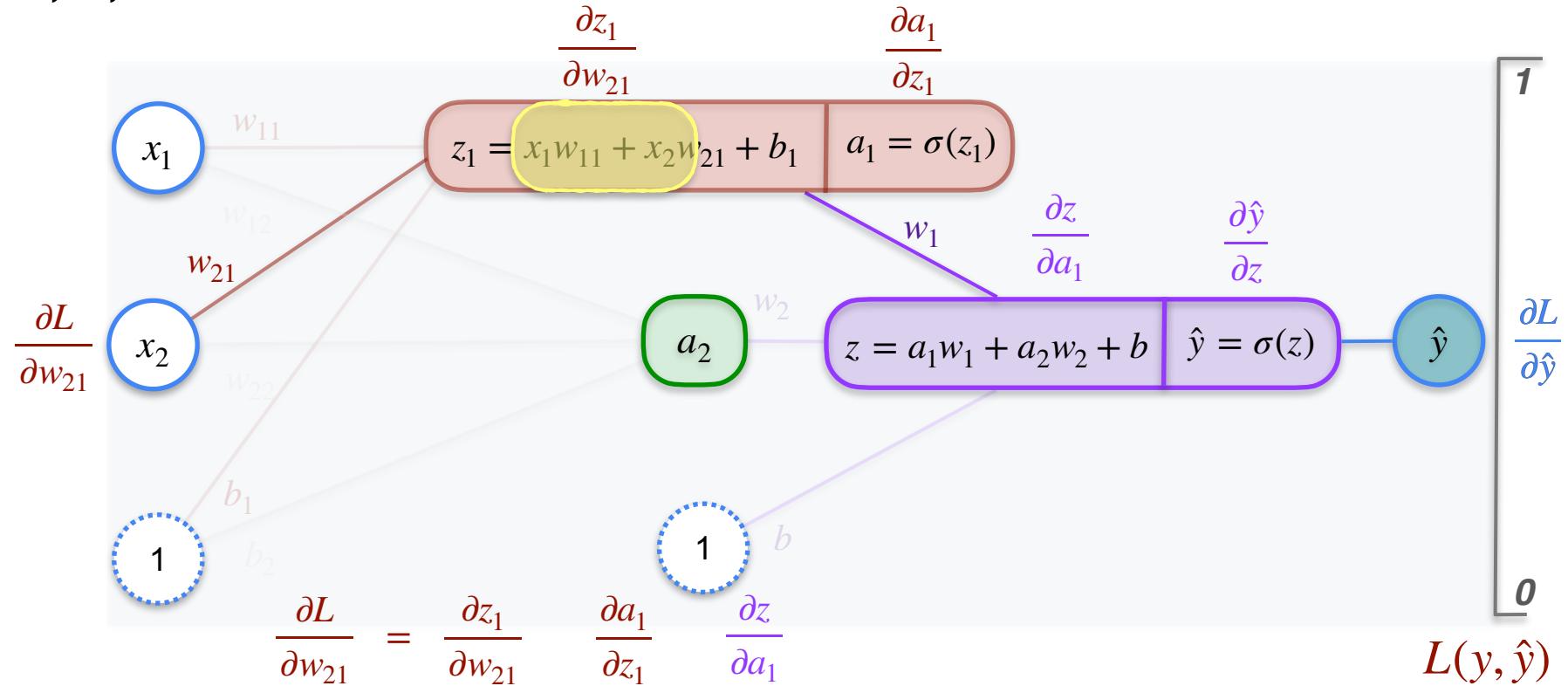
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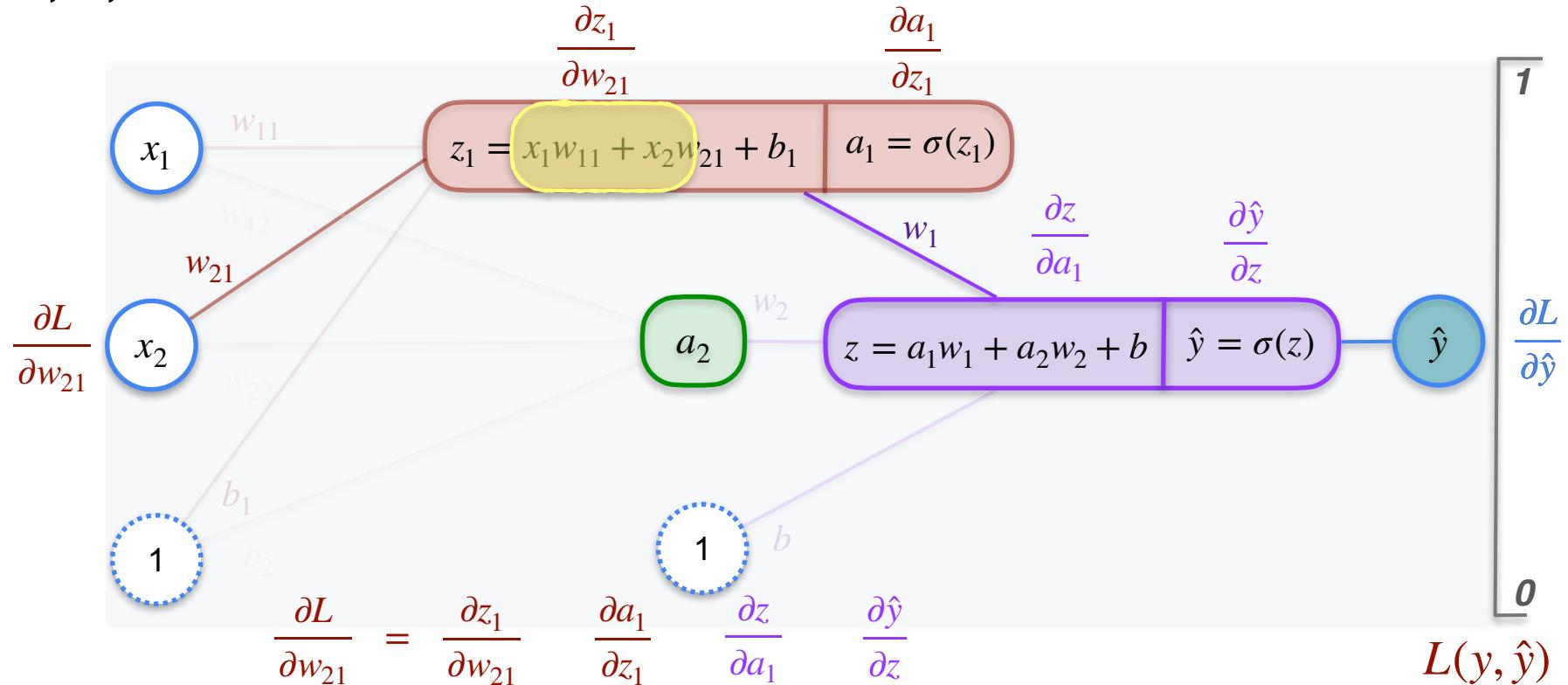
# 2,2,1 Neural Network



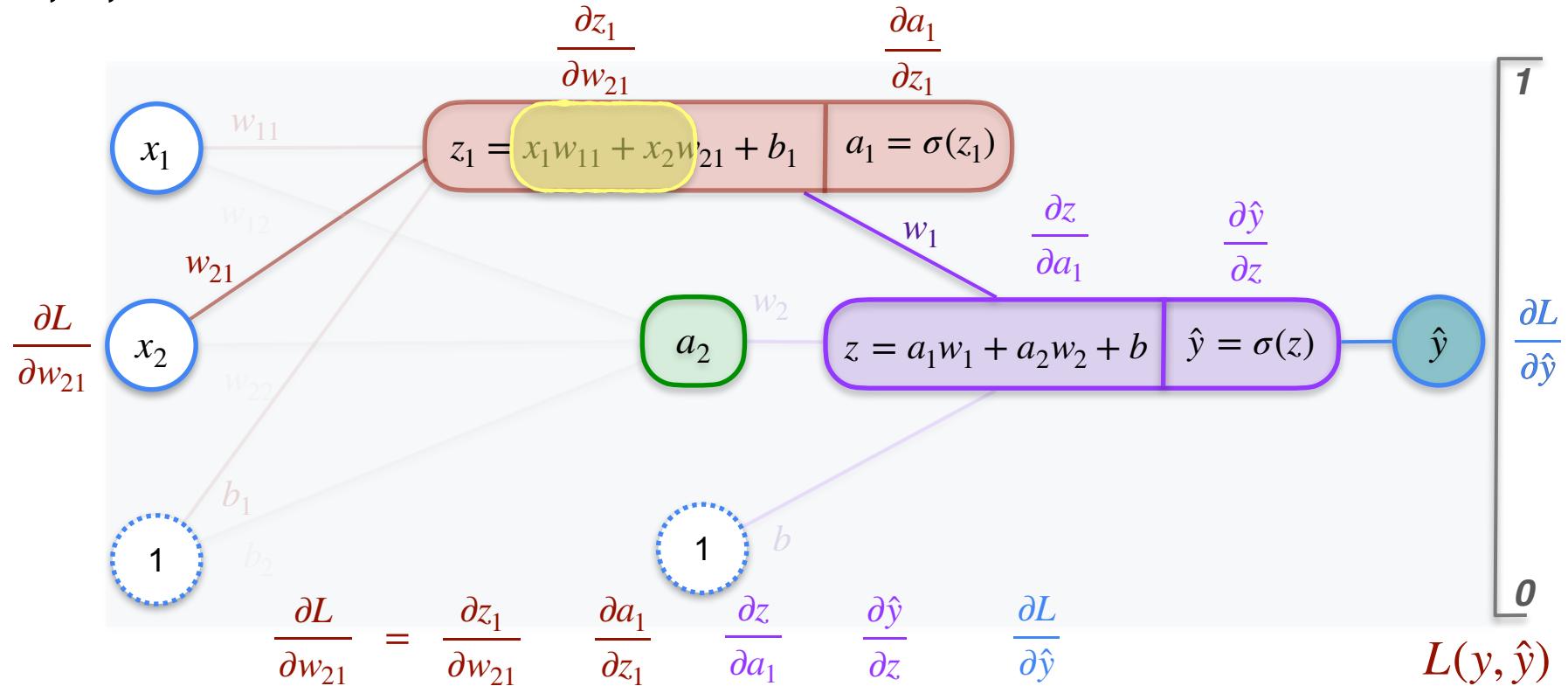
# 2,2,1 Neural Network



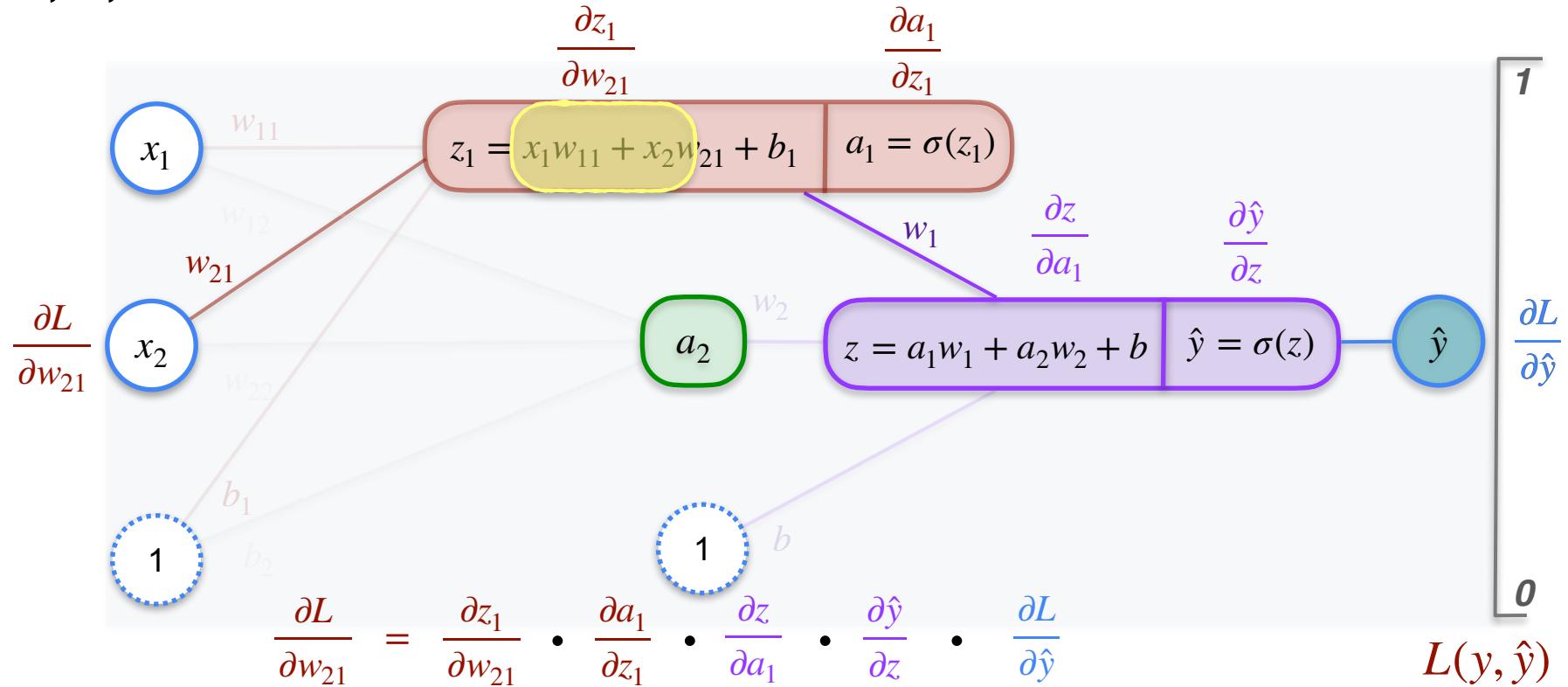
# 2,2,1 Neural Network



# 2,2,1 Neural Network



# 2,2,1 Neural Network



# 2,2,1 Neural Network

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \bullet \frac{\partial a_1}{\partial z_1} \bullet \frac{\partial z}{\partial a_1} \bullet \frac{\partial \hat{y}}{\partial z} \bullet \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

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# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

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$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1 - a_1)$$

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$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1-a_1) w_1$$

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$$\begin{aligned}\frac{\partial L}{\partial w_{21}} &= \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{21}} &= x_2 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -x_2 w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

*Perform gradient descent with*

*to find optimal  
value of  $w_{21}$  that  
gives the least error*

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

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$$\begin{aligned}\frac{\partial L}{\partial w_{21}} &= \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{21}} &= x_2 \cdot a_1 (1 - a_1) \cdot w_1 \cdot \cancel{\hat{y}(1 - \hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1 - \hat{y})}} \\ &= -x_2 w_1 a_1 (1 - a_1) (y - \hat{y})\end{aligned}$$

**Perform gradient descent with**

$$w_{21} \rightarrow w_{21} - \alpha \frac{\partial L}{\partial w_{21}}$$

**to find optimal value of  $w_{21}$  that gives the least error**

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

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*Perform gradient descent with*

$$w_{21} \rightarrow w_{21} - \alpha$$

*to find optimal value of  $w_{21}$  that gives the least error*

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

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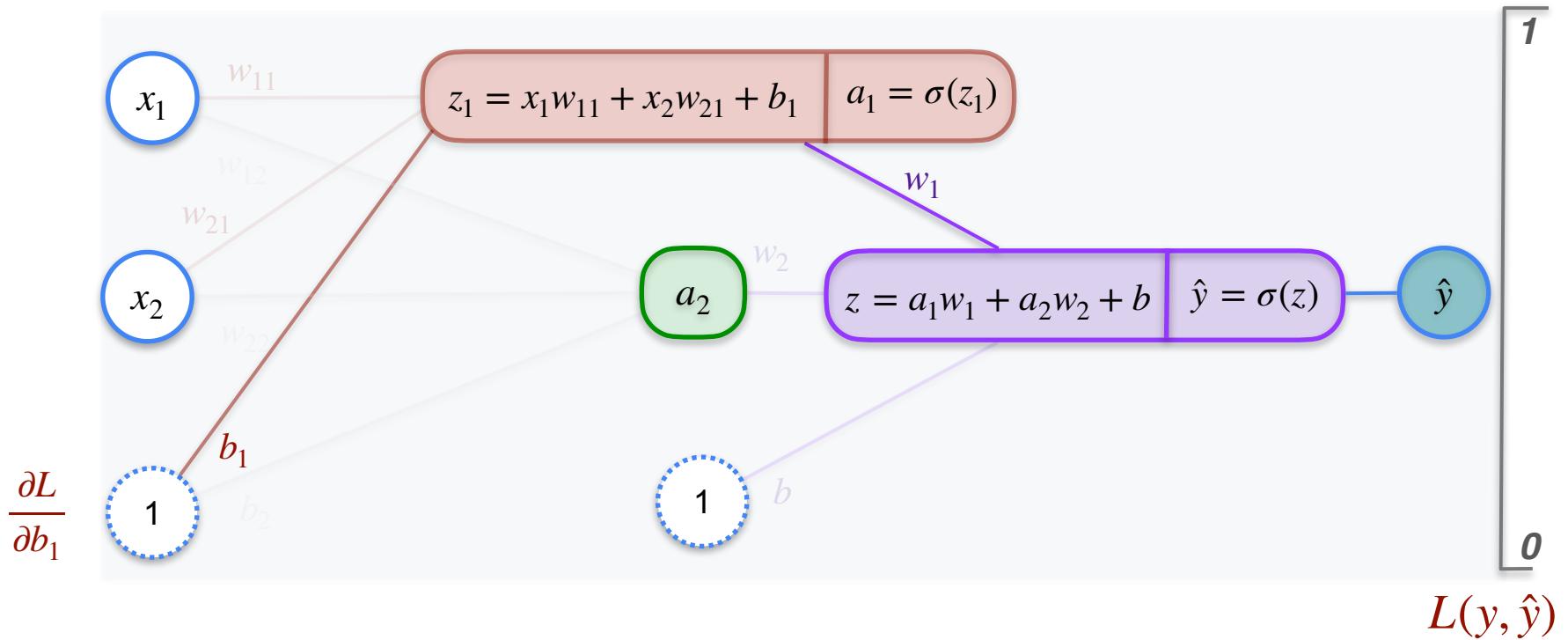
$$\begin{aligned}\frac{\partial L}{\partial w_{21}} &= \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{21}} &= x_2 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -x_2 w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

*Perform gradient descent with*

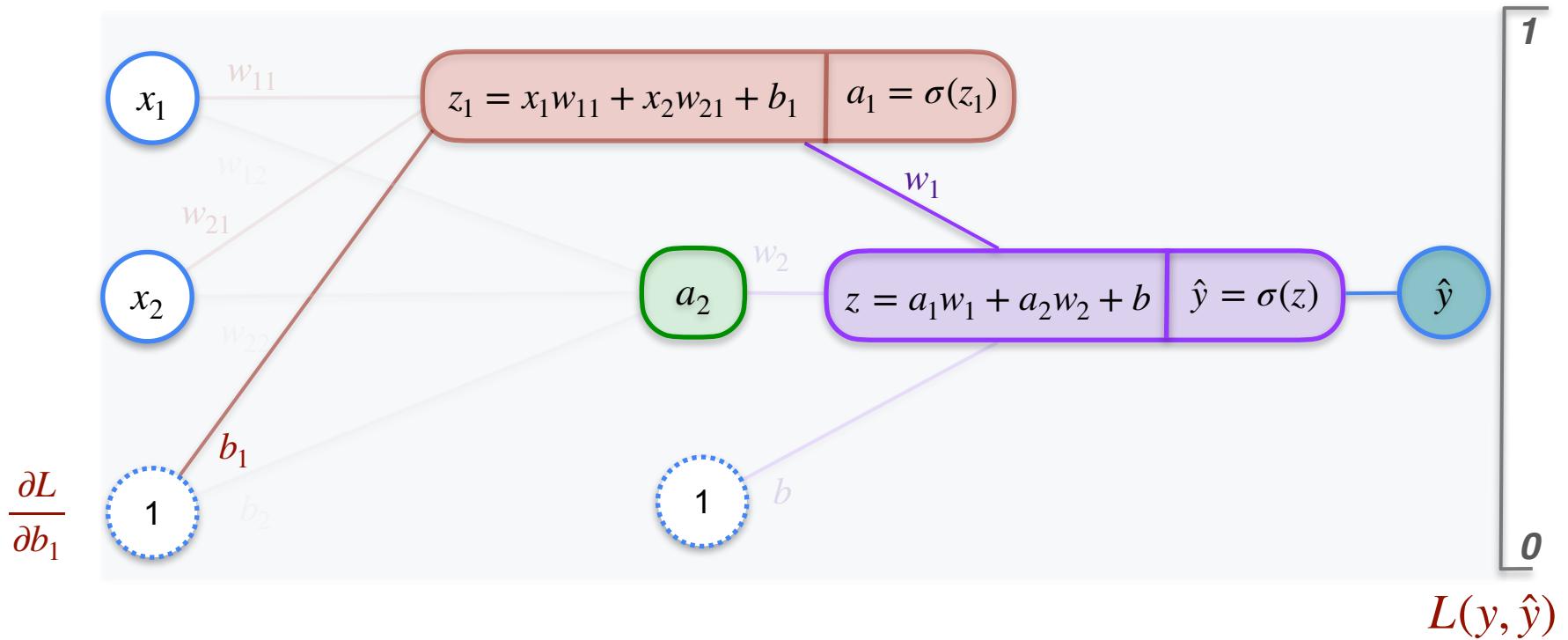
$$w_{21} \rightarrow w_{21} - \alpha \cdot x_2 w_1 a_1 (1-a_1) (y - \hat{y})$$

*to find optimal value of  $w_{21}$  that gives the least error*

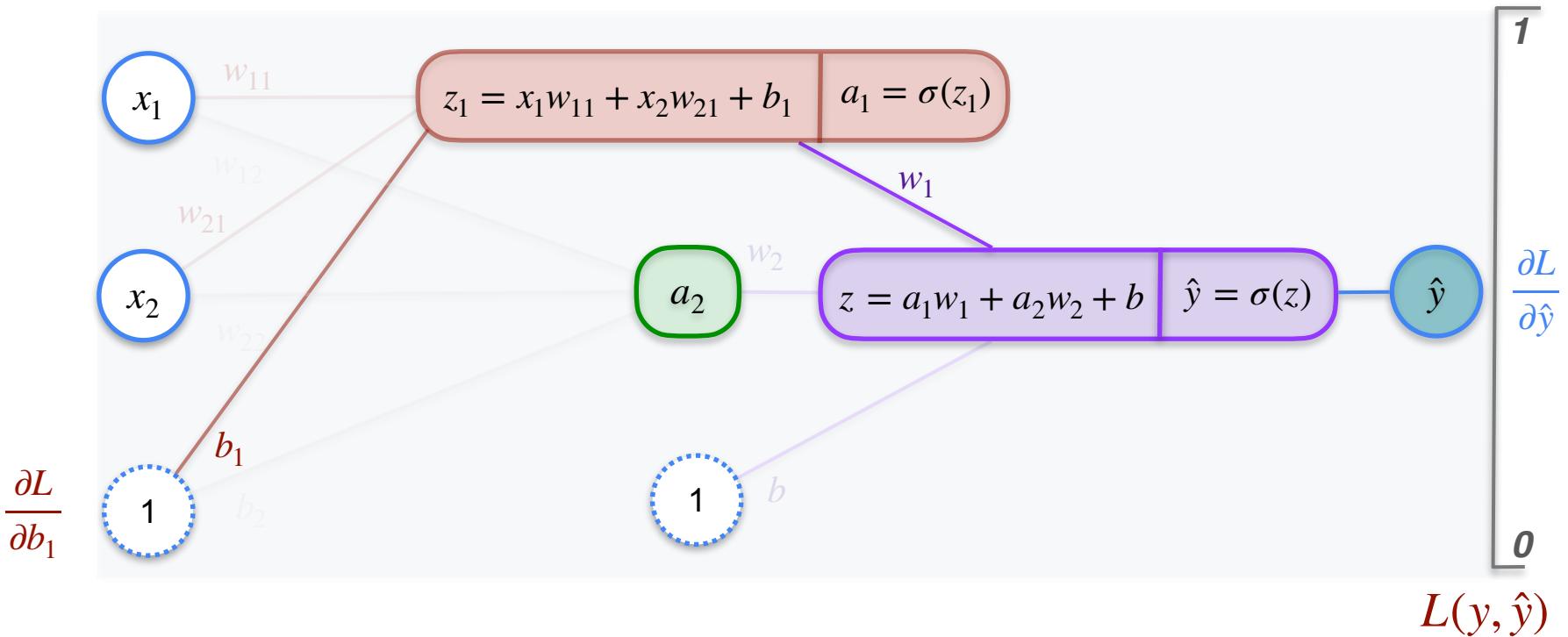
# 2,2,1 Neural Network



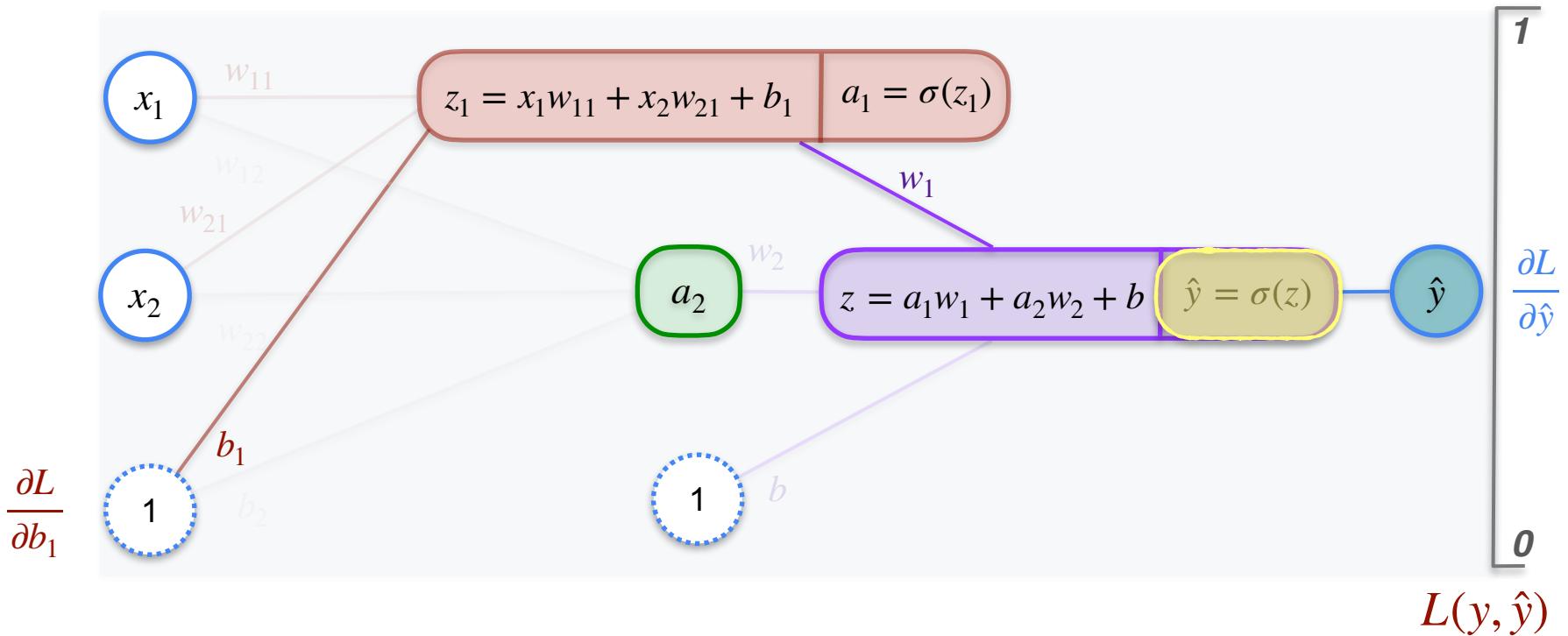
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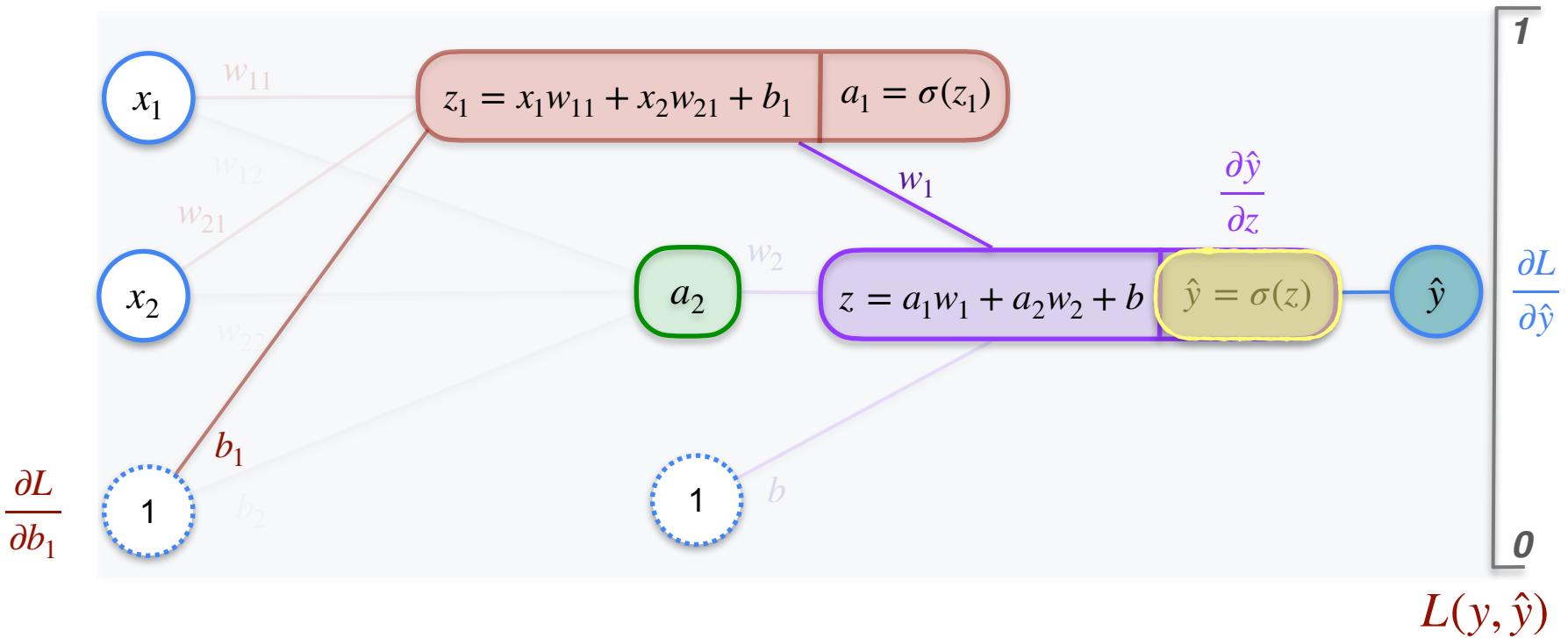
# 2,2,1 Neural Network



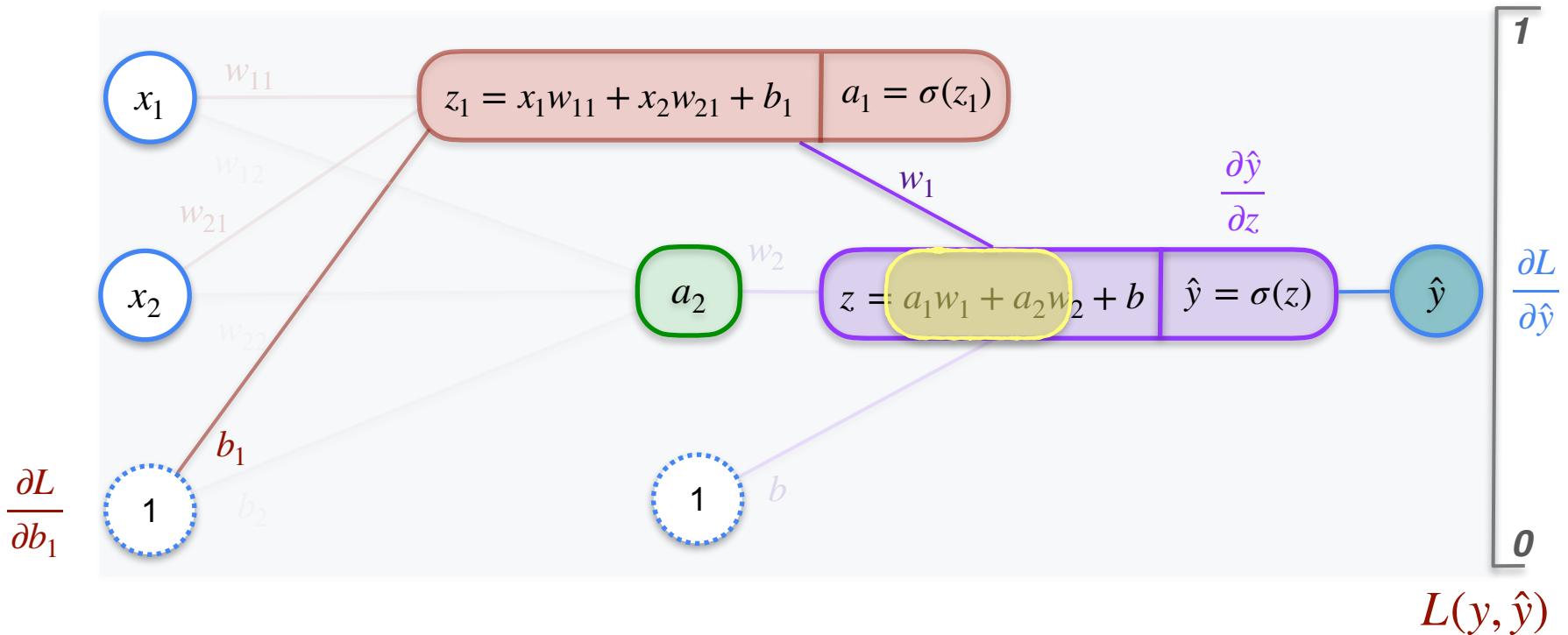
# 2,2,1 Neural Network



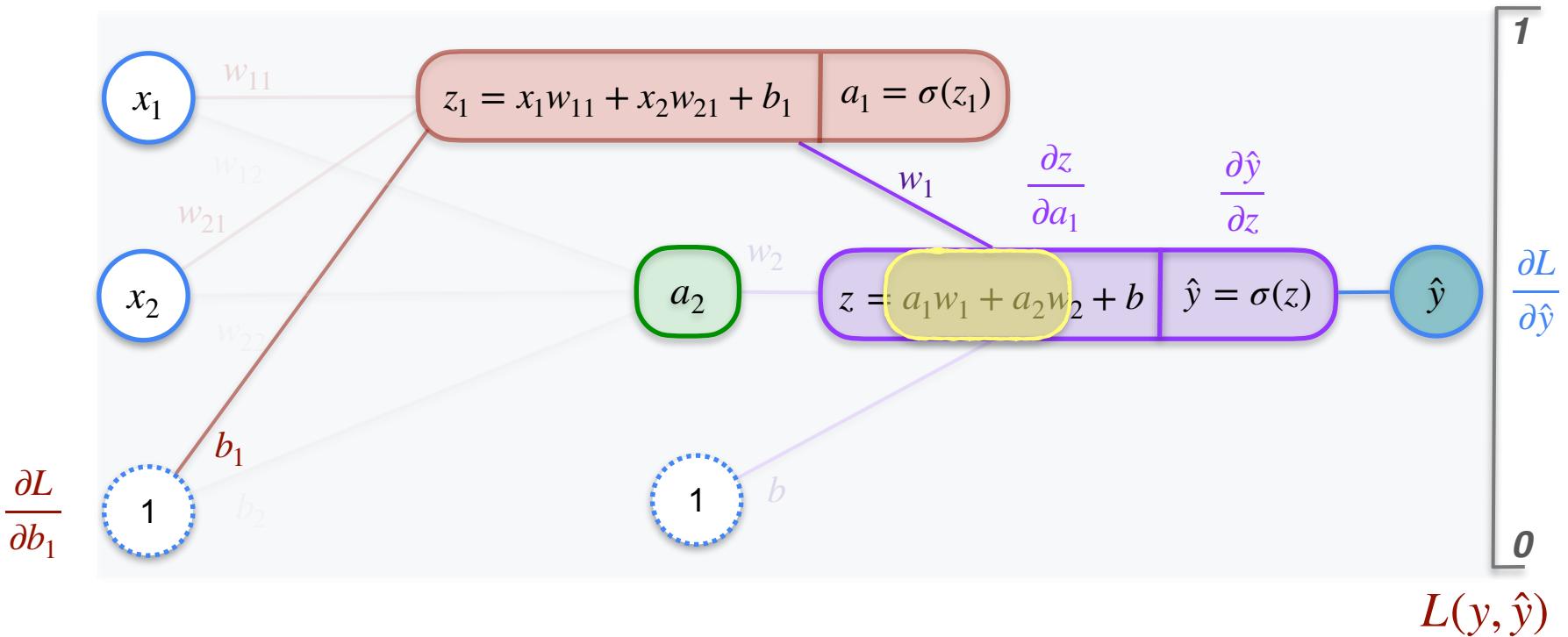
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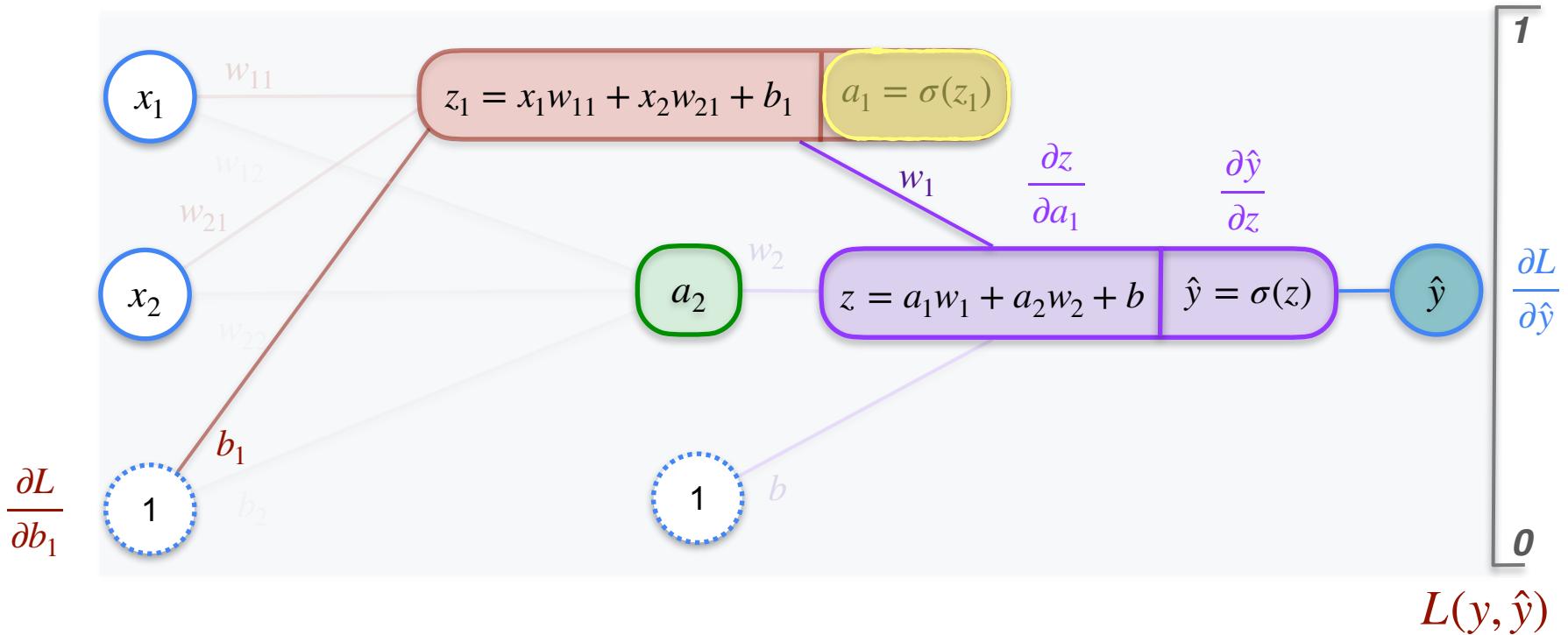
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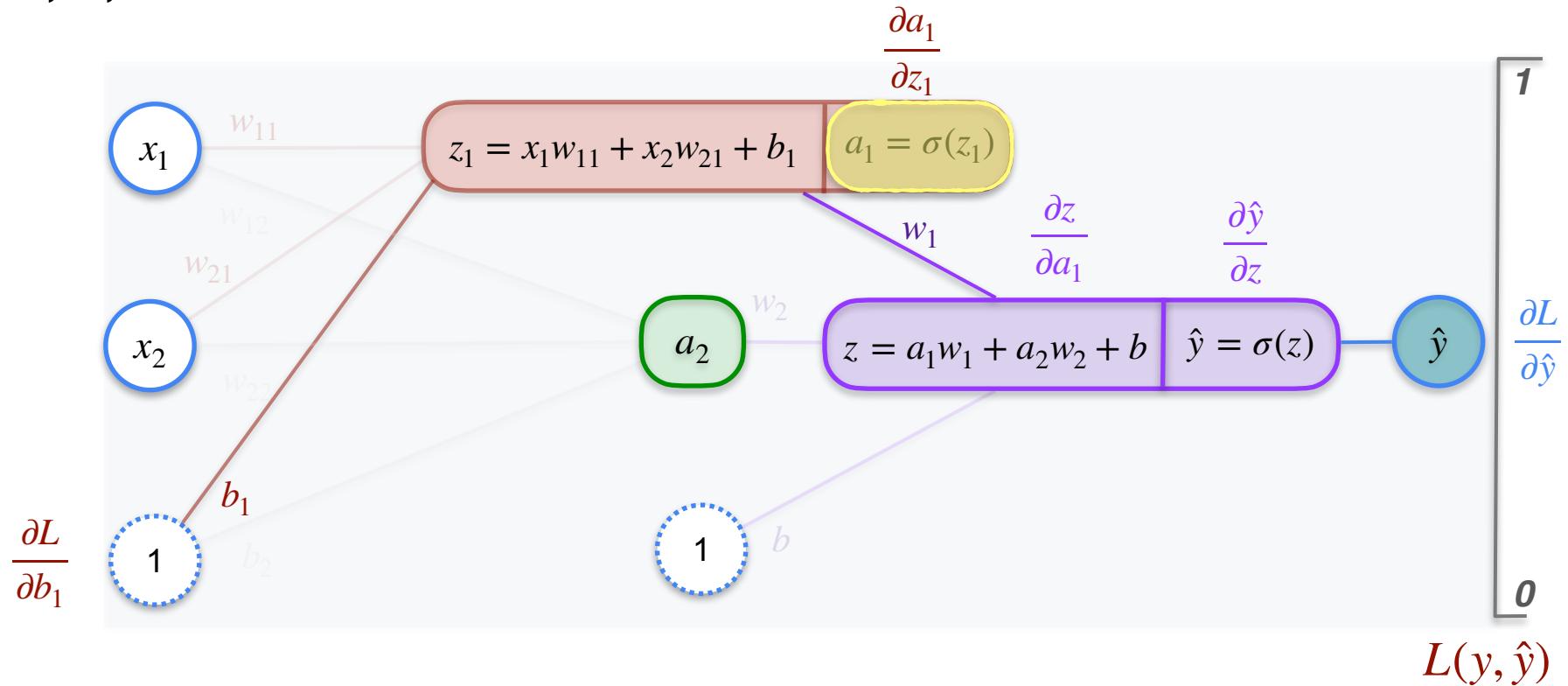
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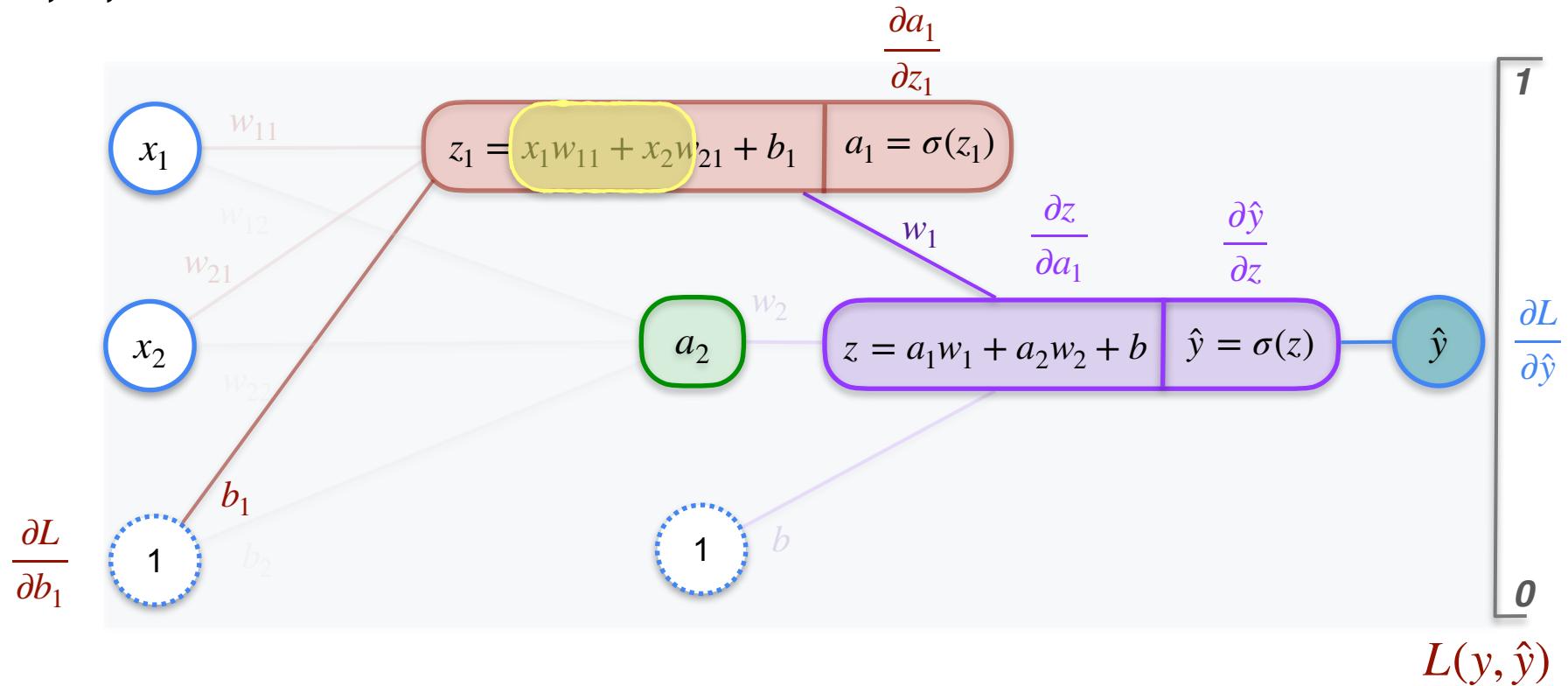
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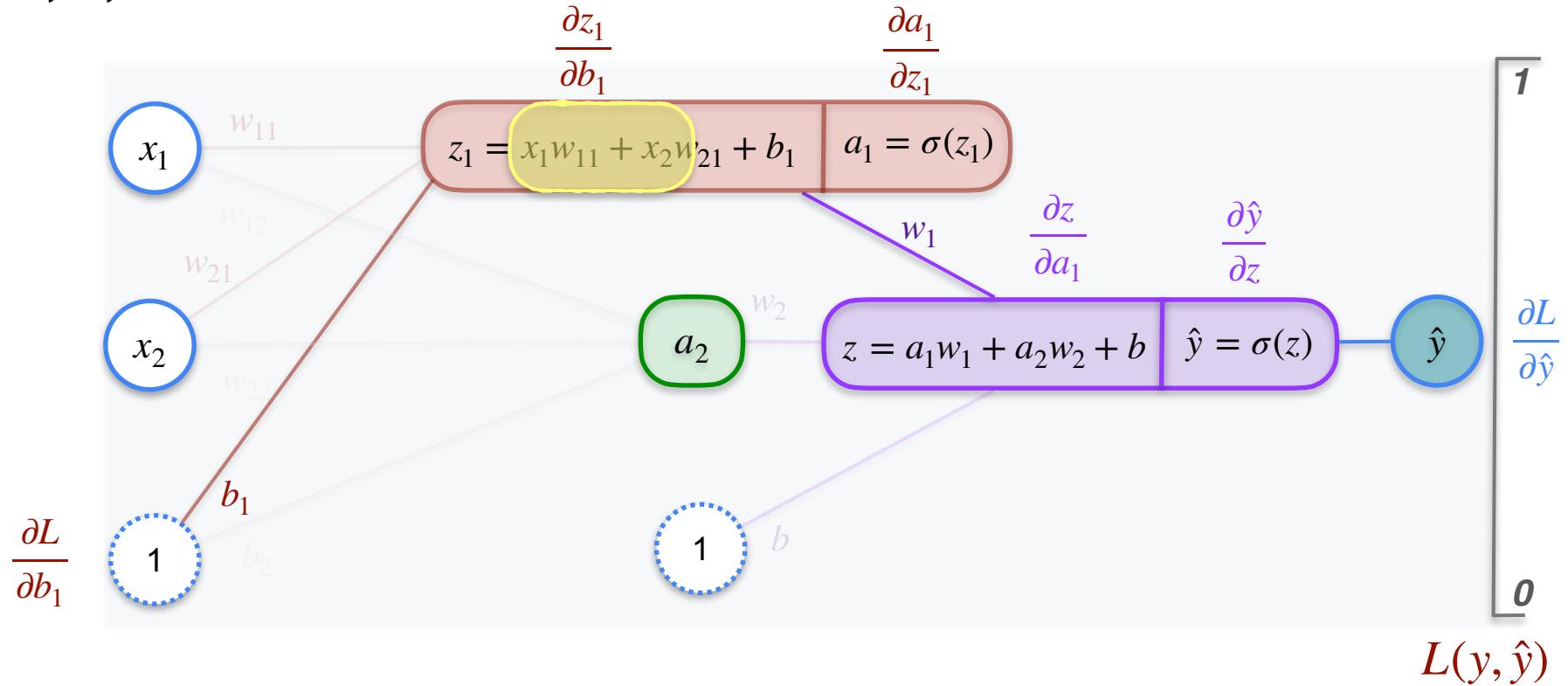
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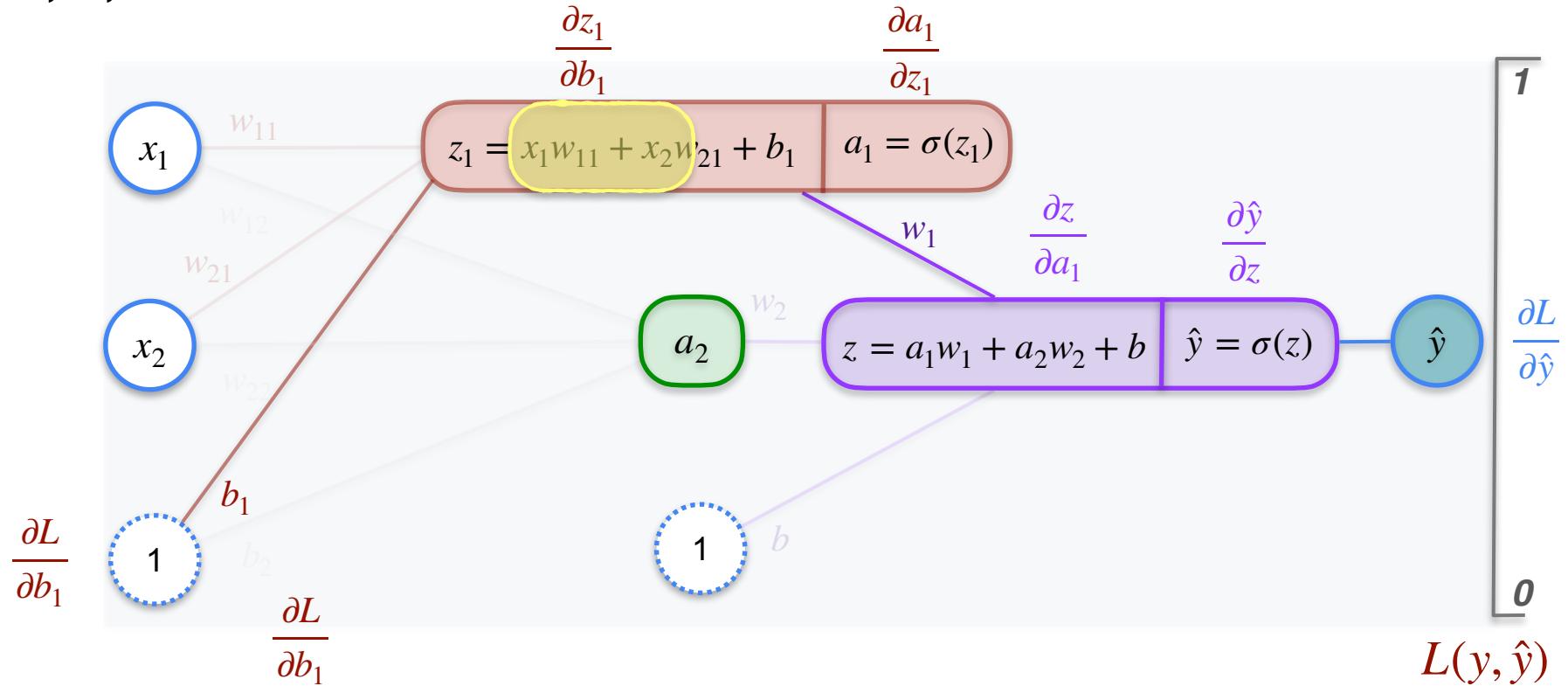
# 2,2,1 Neural Network



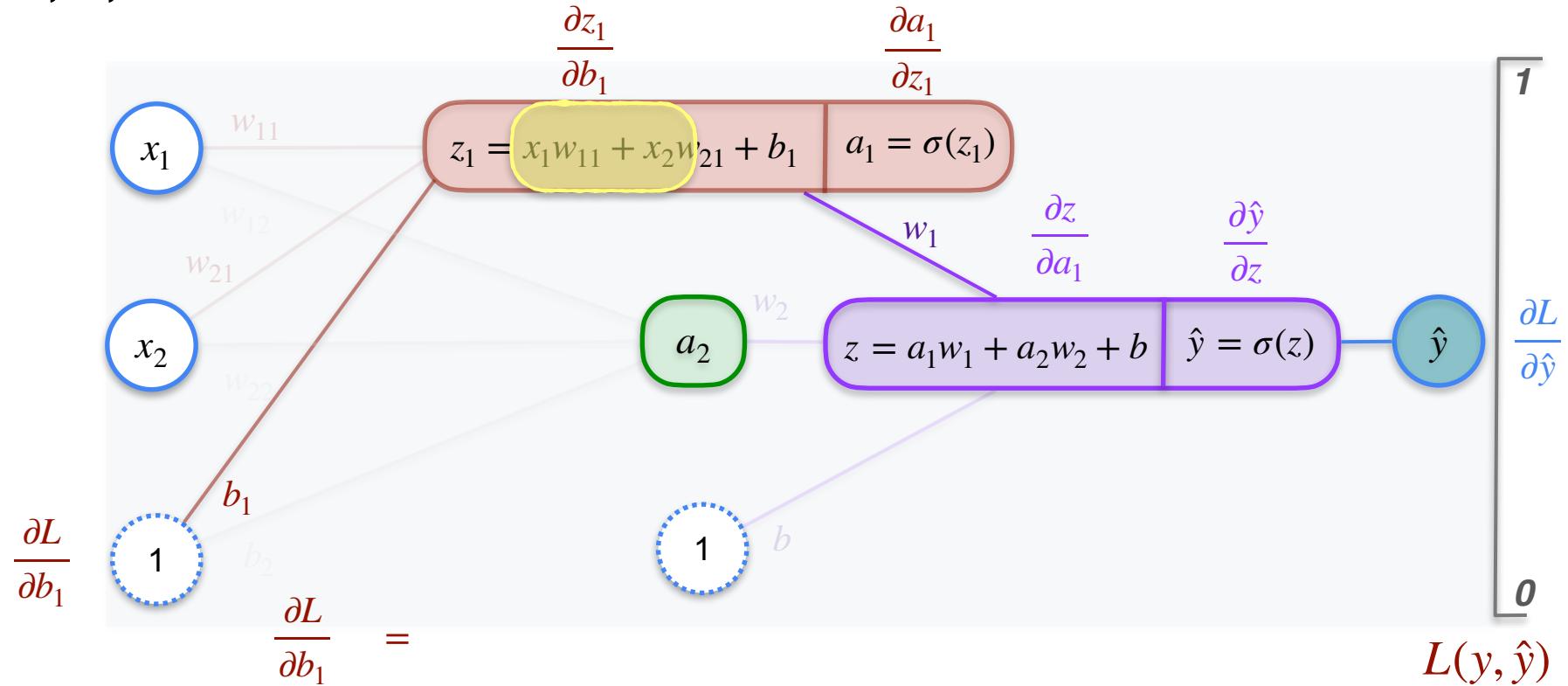
# 2,2,1 Neural Network



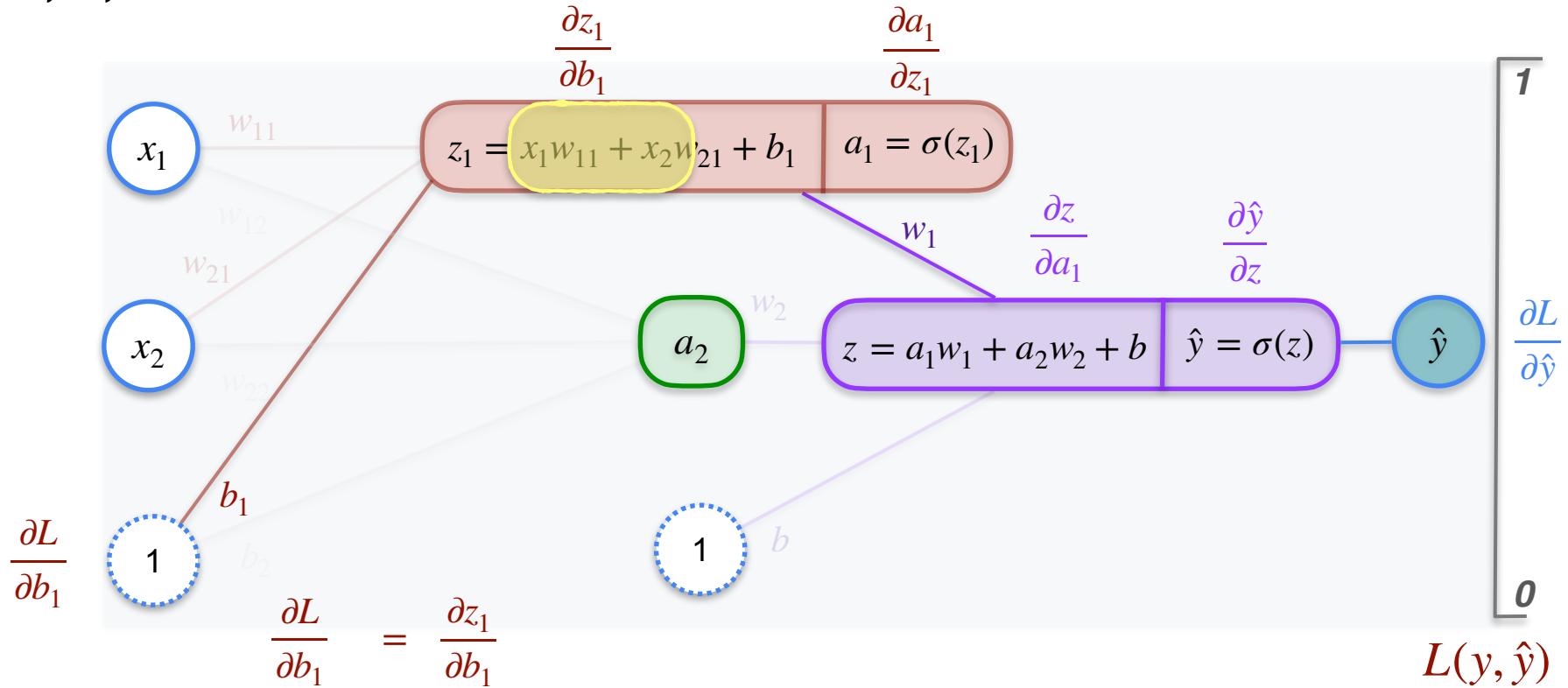
# 2,2,1 Neural Network



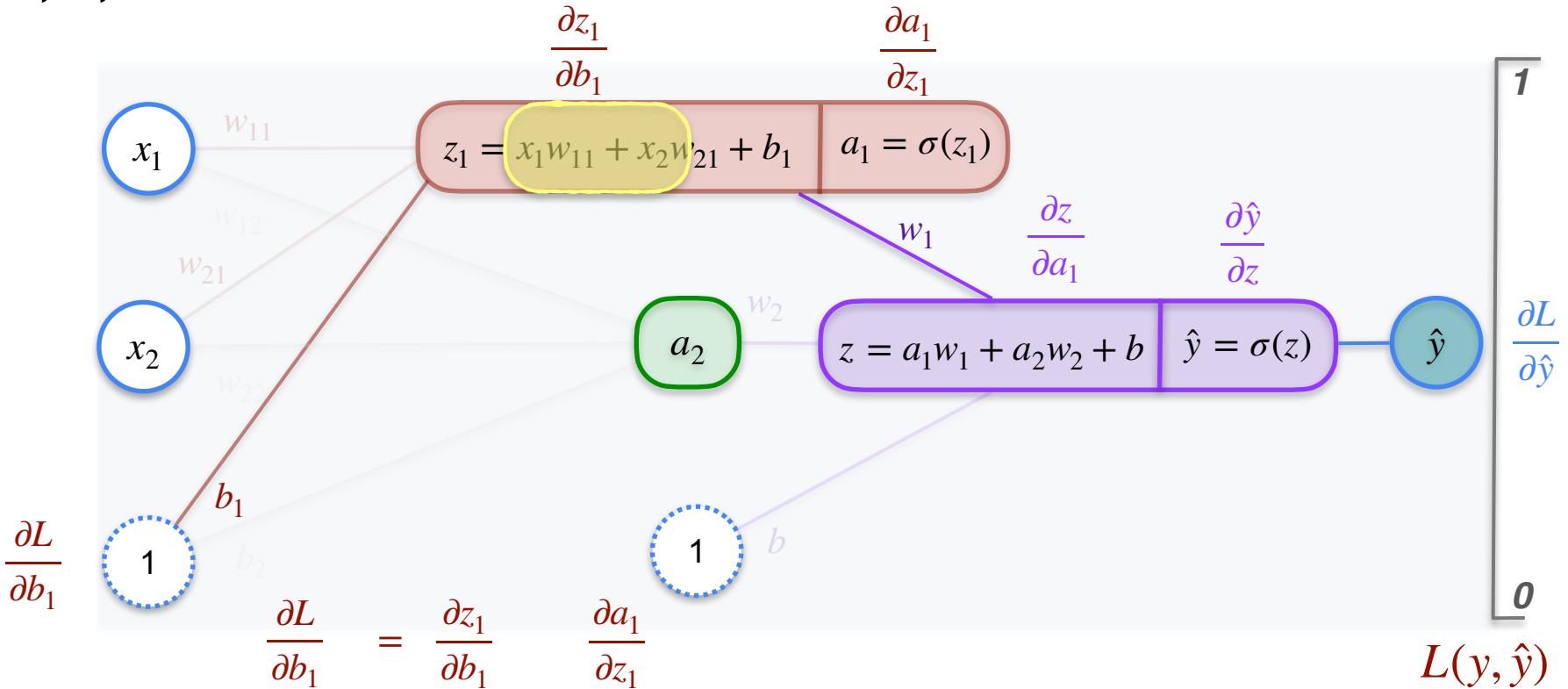
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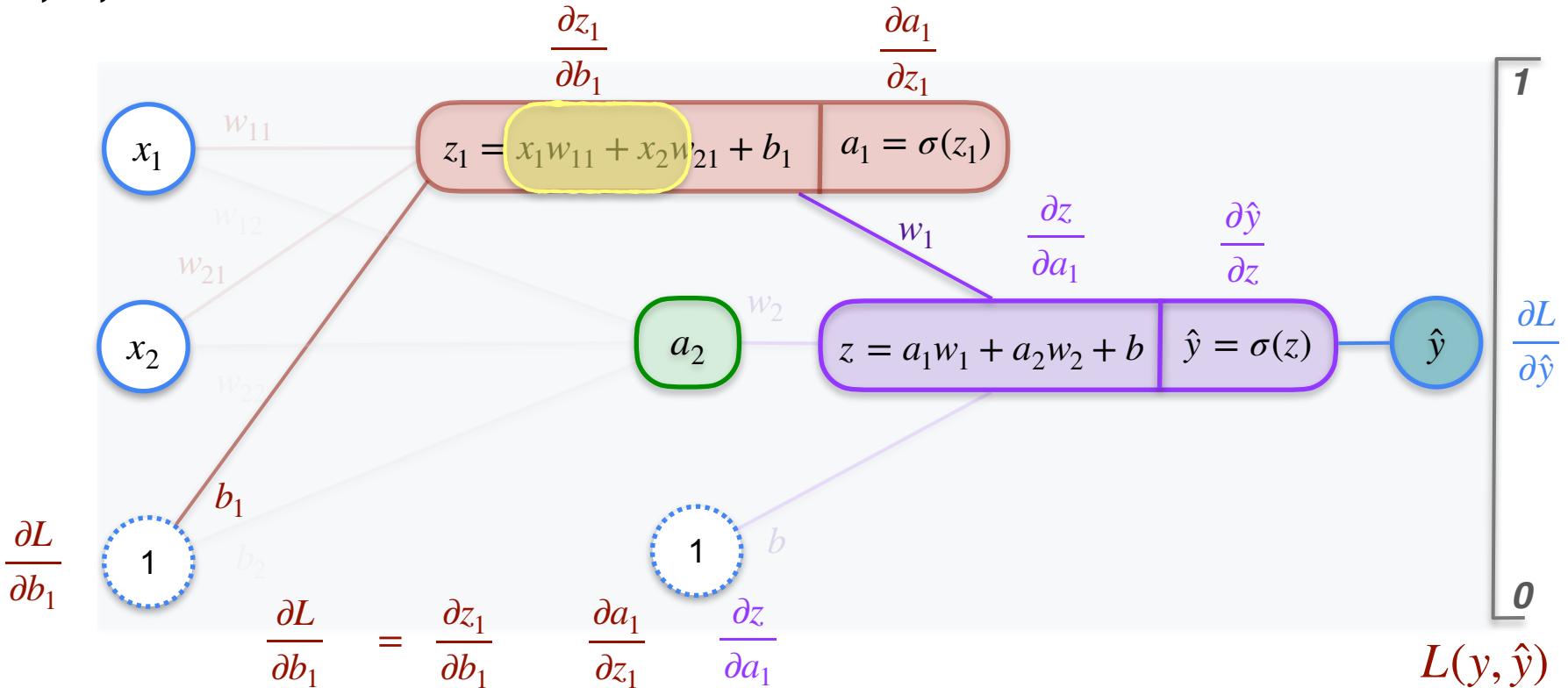
# 2,2,1 Neural Network



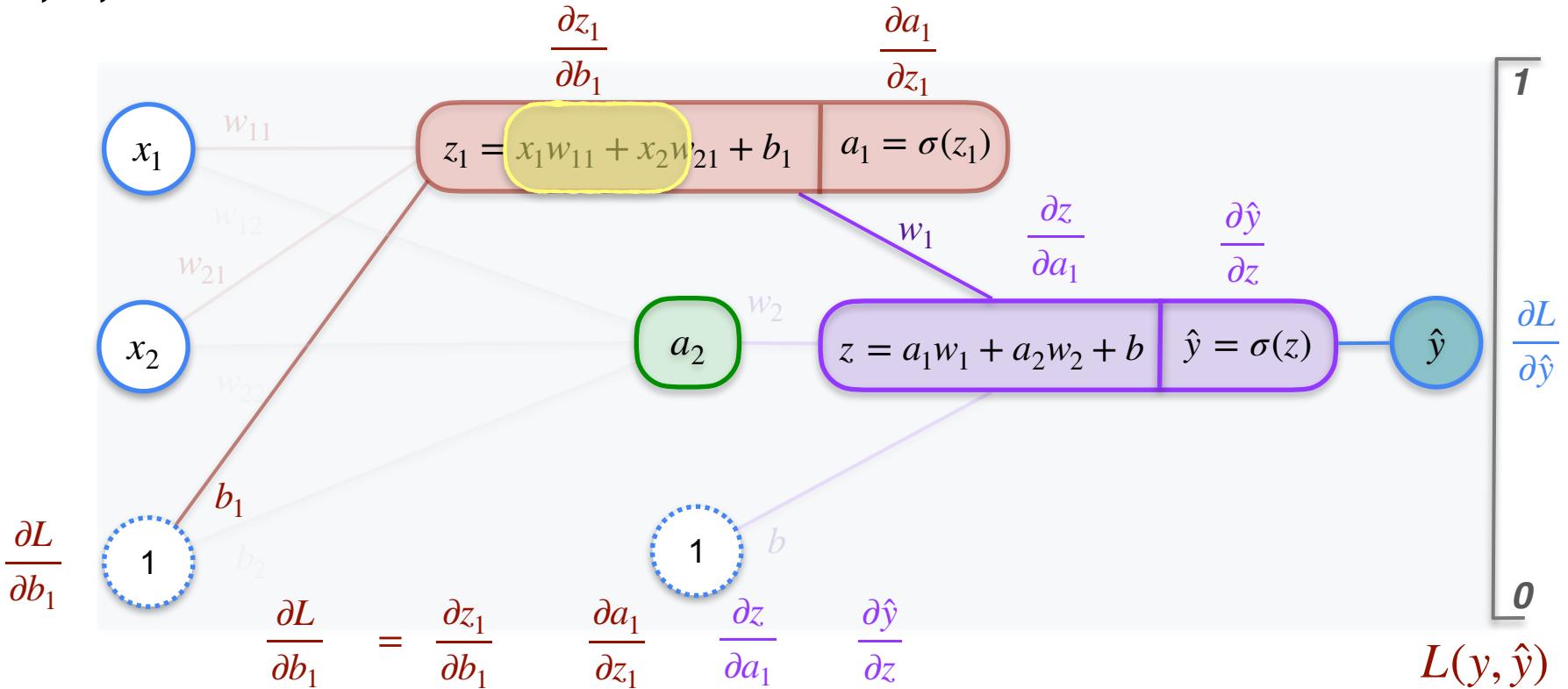
# 2,2,1 Neural Network



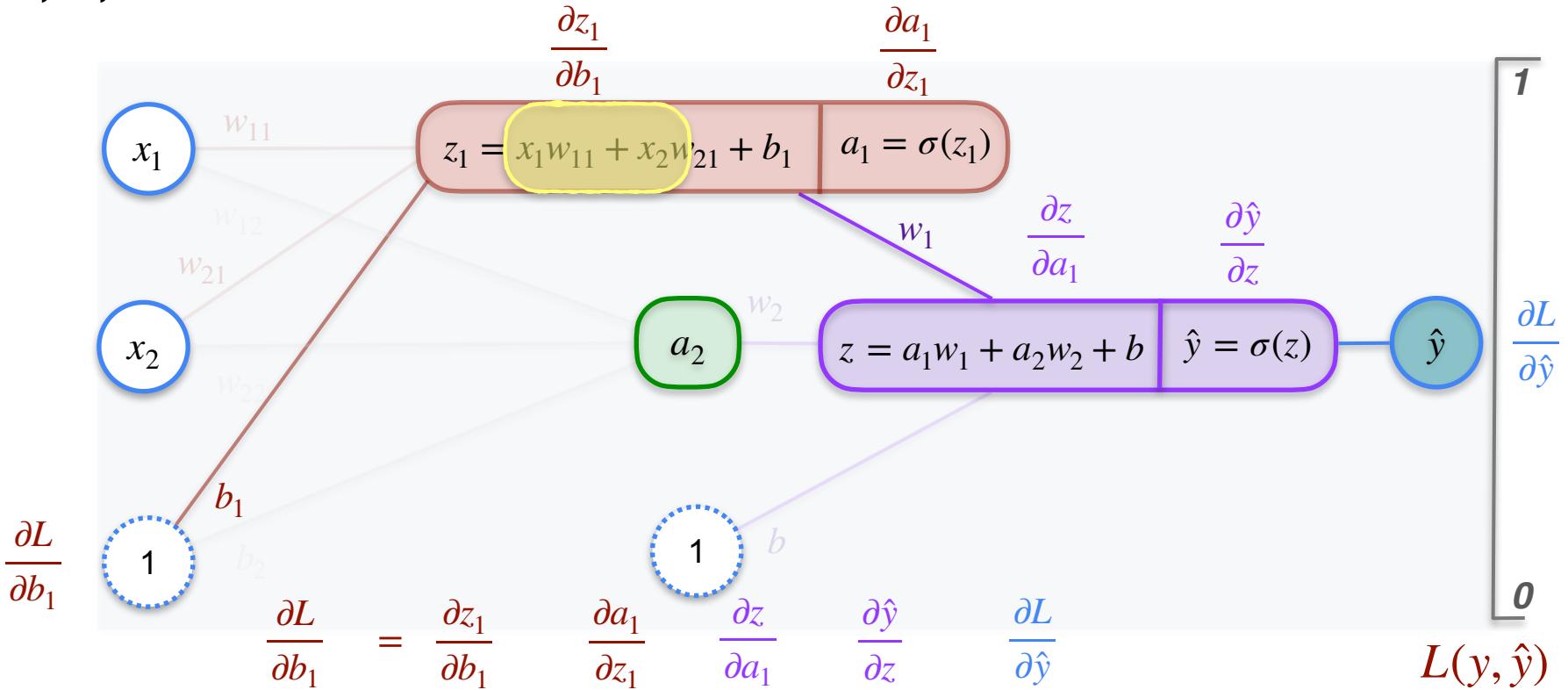
# 2,2,1 Neural Network



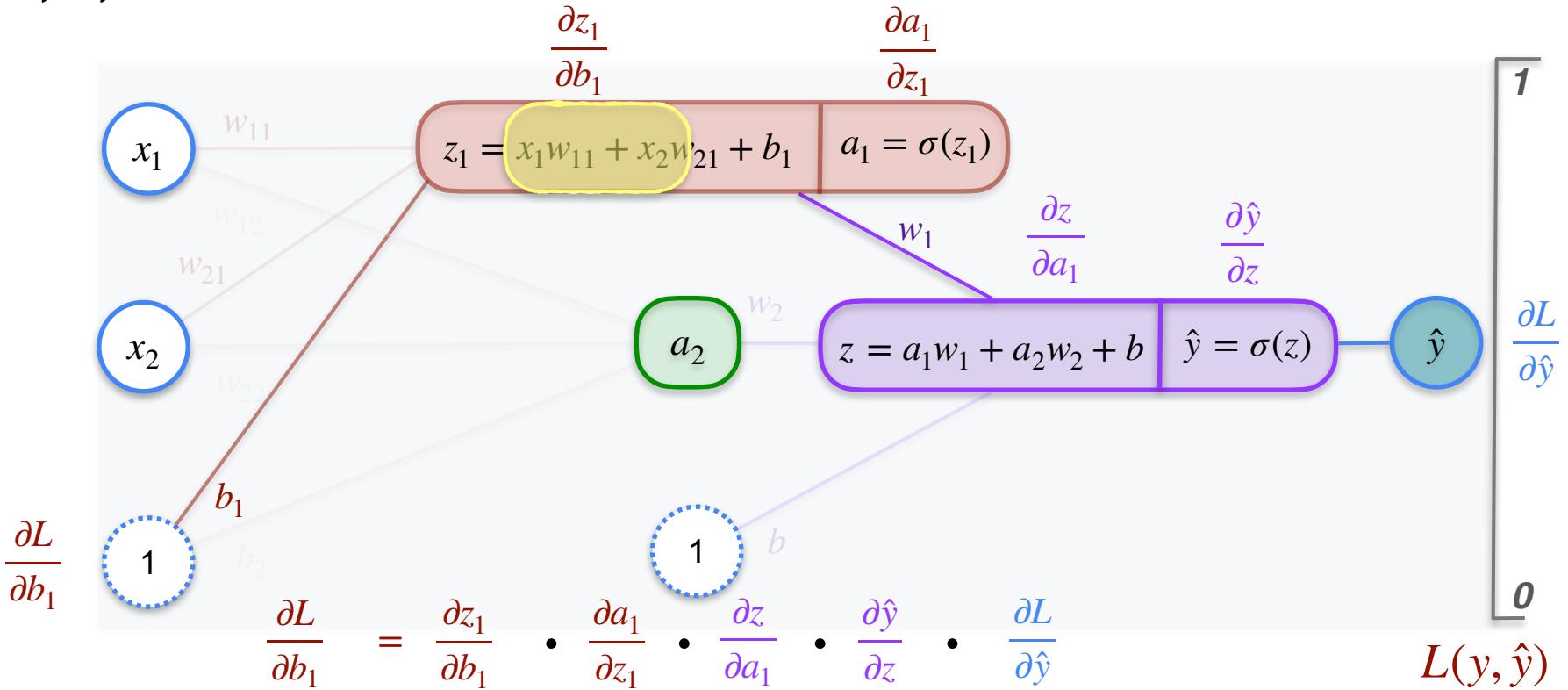
# 2,2,1 Neural Network



# 2,2,1 Neural Network



# 2,2,1 Neural Network



# 2,2,1 Neural Network

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

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# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

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$$\frac{\partial L}{\partial b_1} = 1 - a_1(1 - a_1)$$

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$$\frac{\partial L}{\partial b_1} = 1 - a_1(1 - a_1) w_1$$

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$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial b_1} = 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

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$$\begin{aligned}\frac{\partial L}{\partial b_1} &= \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial b_1} &= 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

# 2,2,1 Neural Network

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*Perform gradient descent with*

*to find optimal  
value of  $b_1$  that  
gives the least error*

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

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**Perform gradient descent with**

$$b_1 \rightarrow b_1 - \alpha \frac{\partial L}{\partial b_1}$$

**to find optimal value of  $b_1$  that gives the least error**

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

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# 2,2,1 Neural Network

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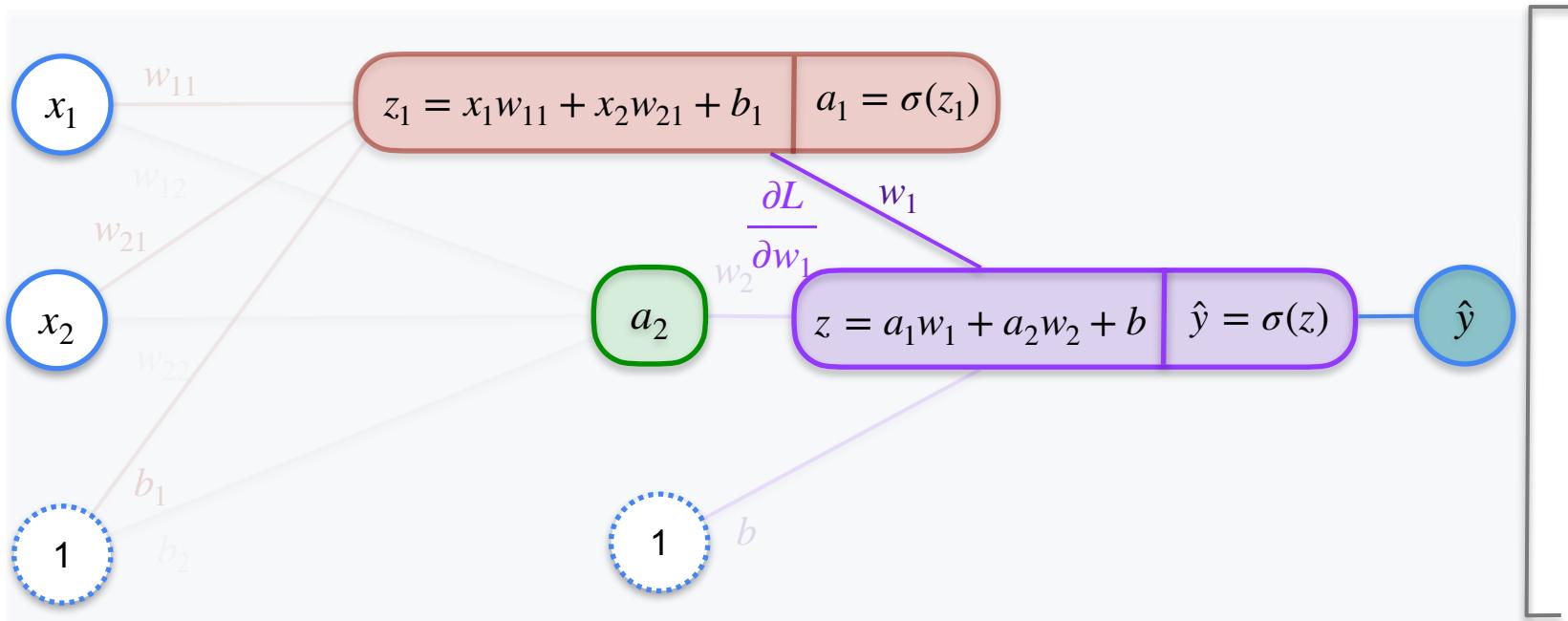
$$\begin{aligned}\frac{\partial L}{\partial b_1} &= \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial b_1} &= 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

*Perform gradient descent with*

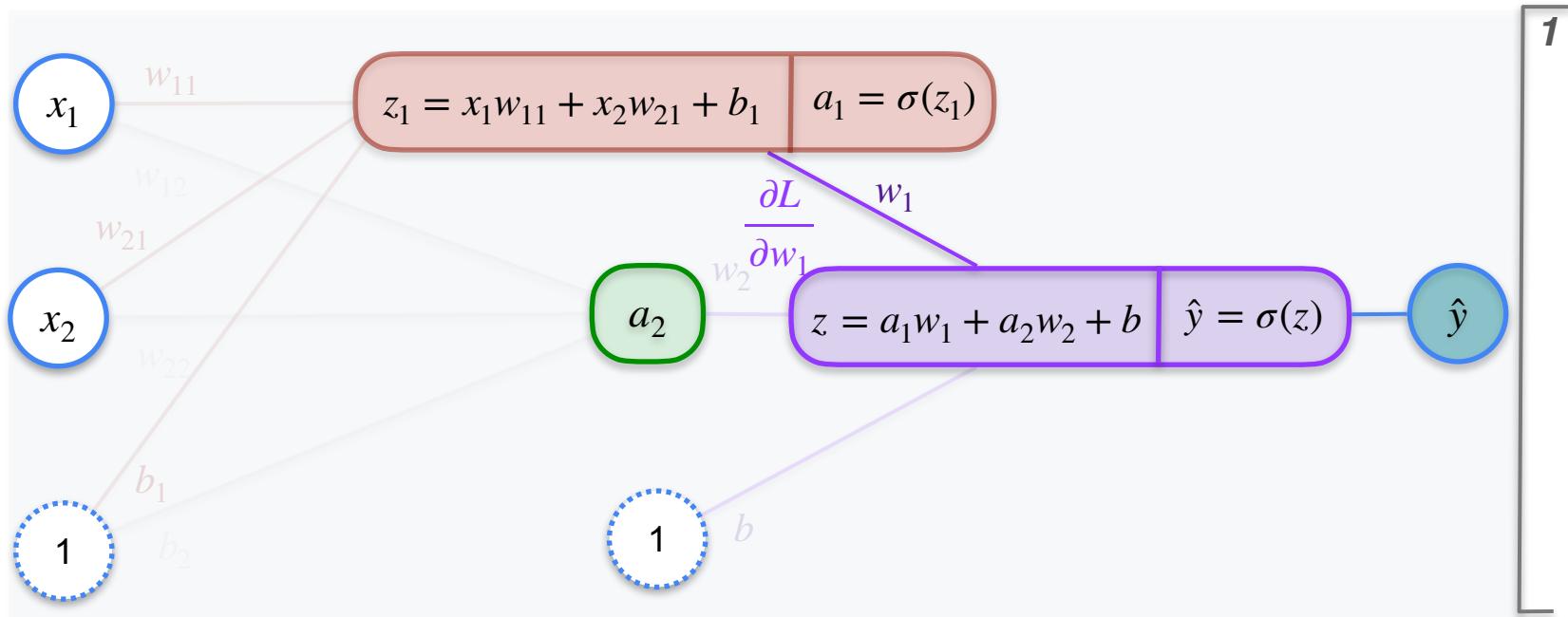
$$b_1 \rightarrow b_1 - \alpha (-w_1 a_1 (1-a_1) (y - \hat{y}))$$

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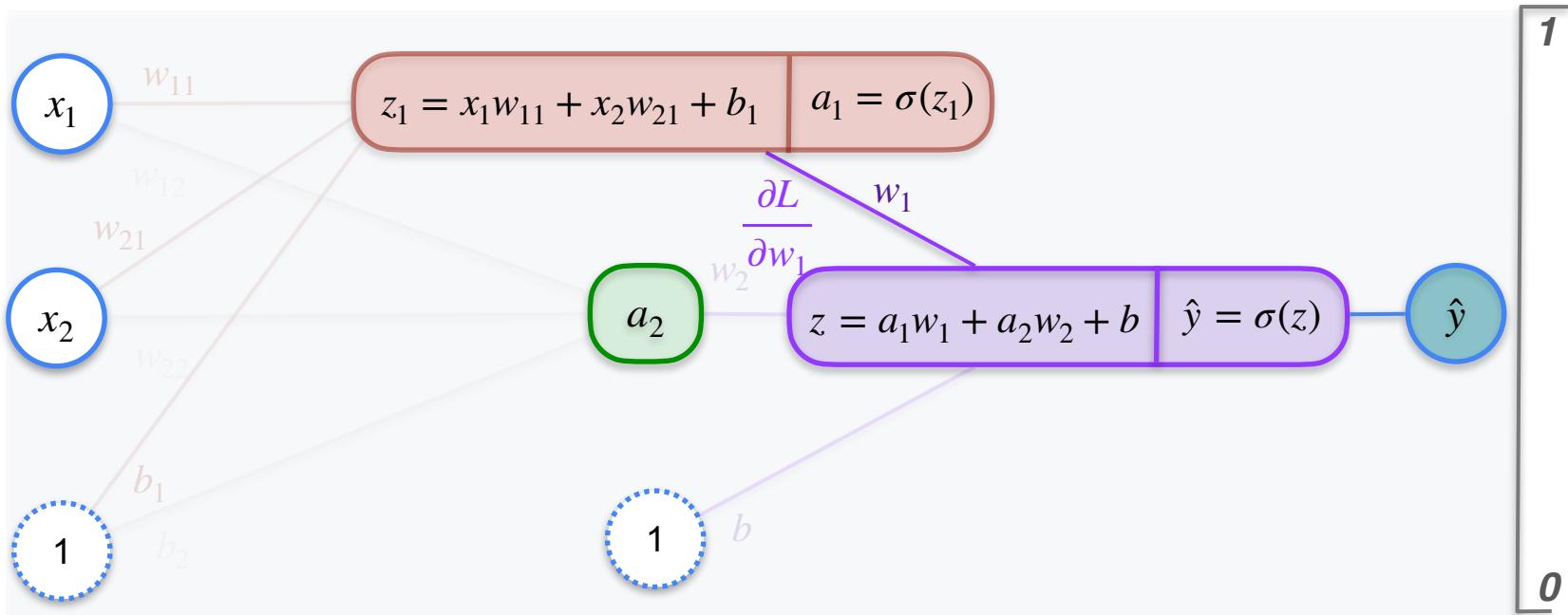
# 2,2,1 Neural Network



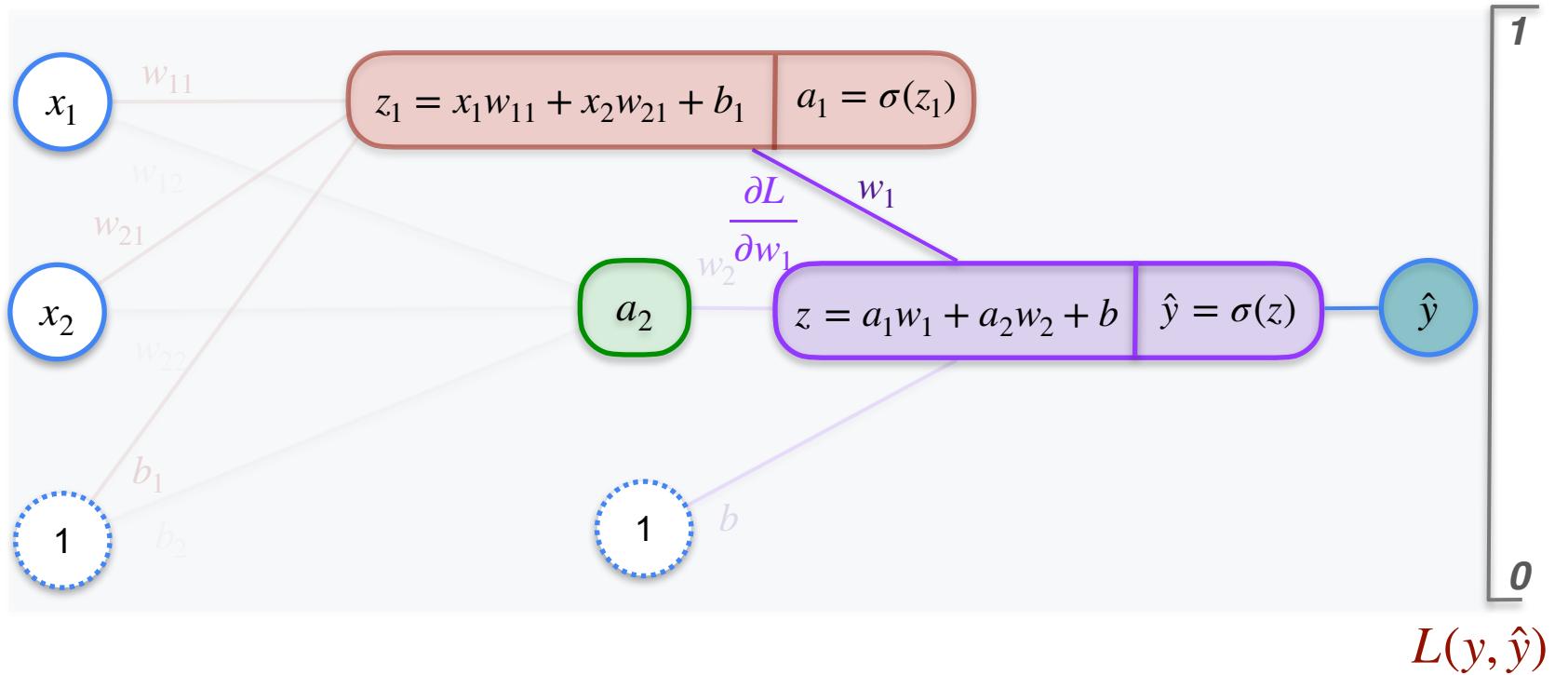
# 2,2,1 Neural Network



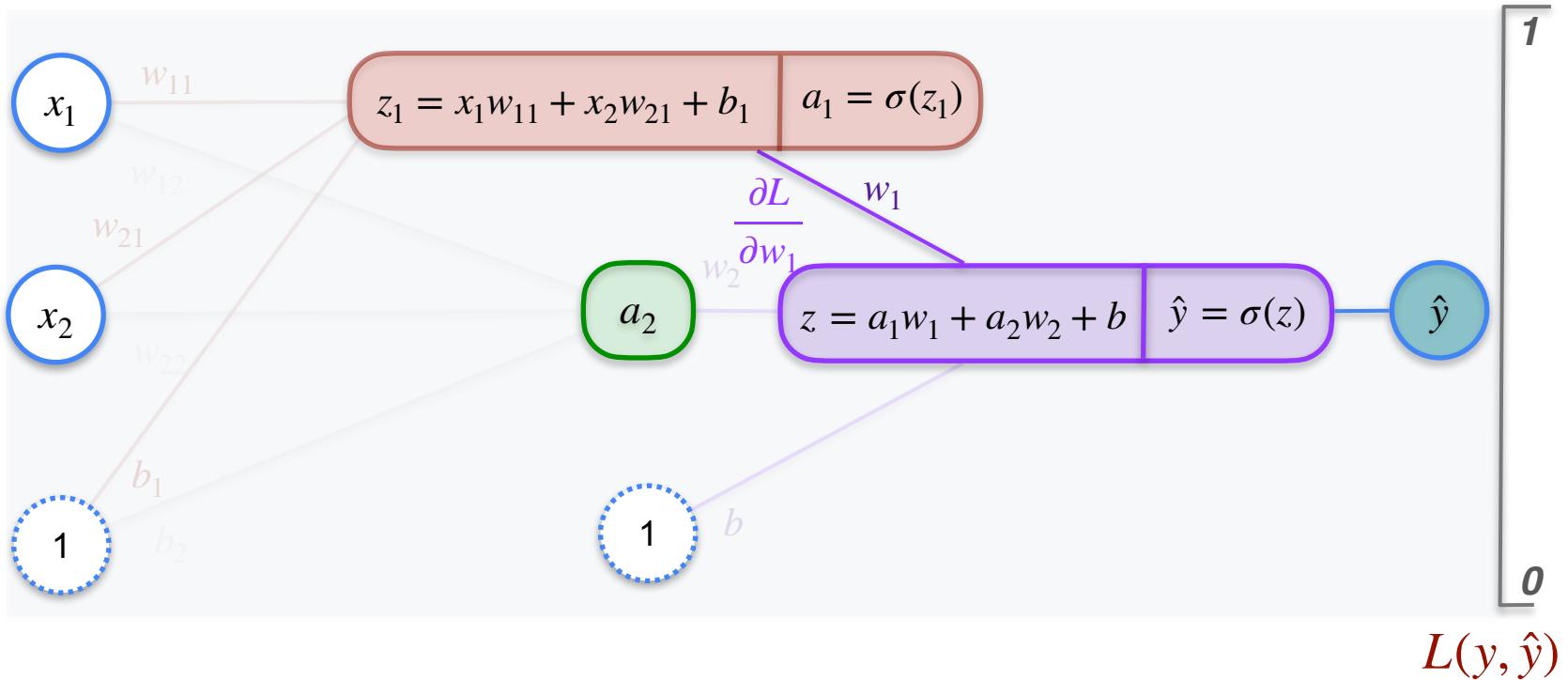
# 2,2,1 Neural Network



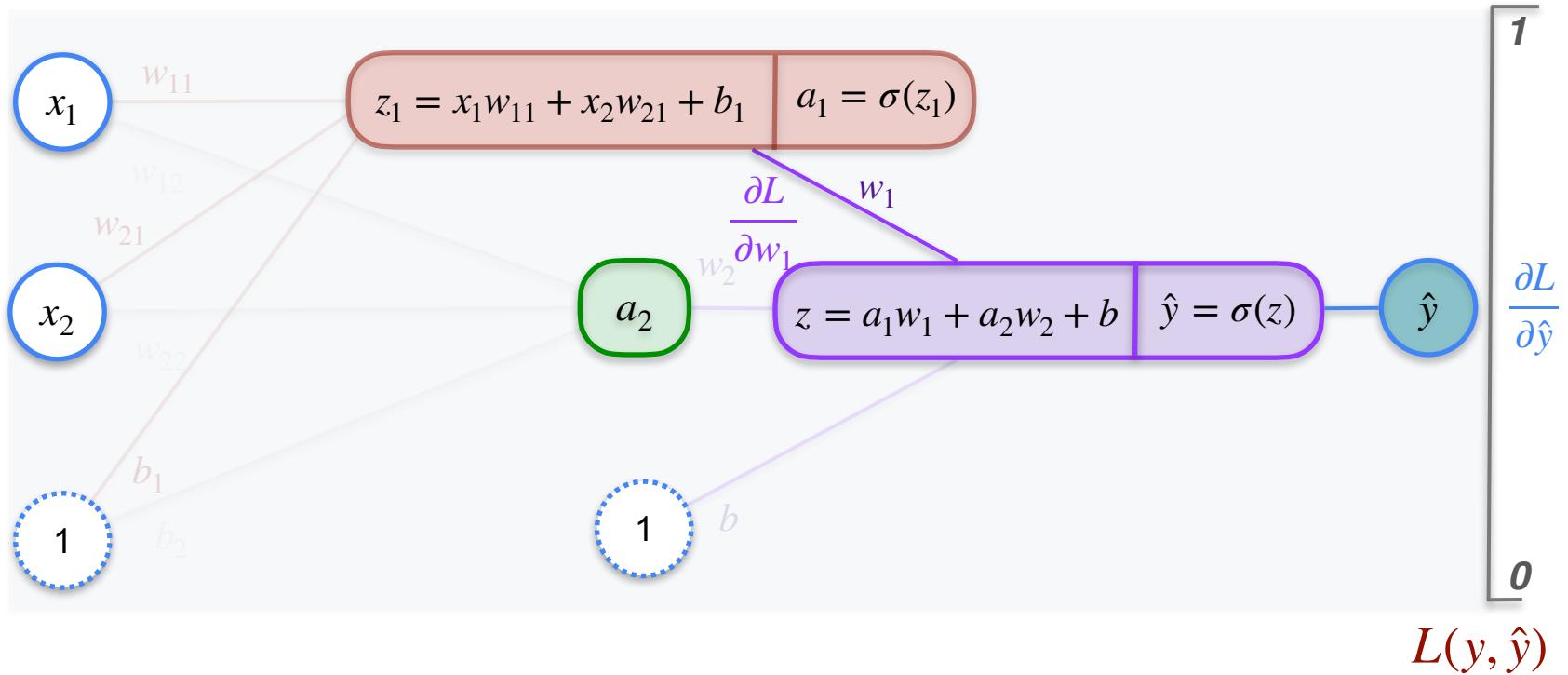
# 2,2,1 Neural Network



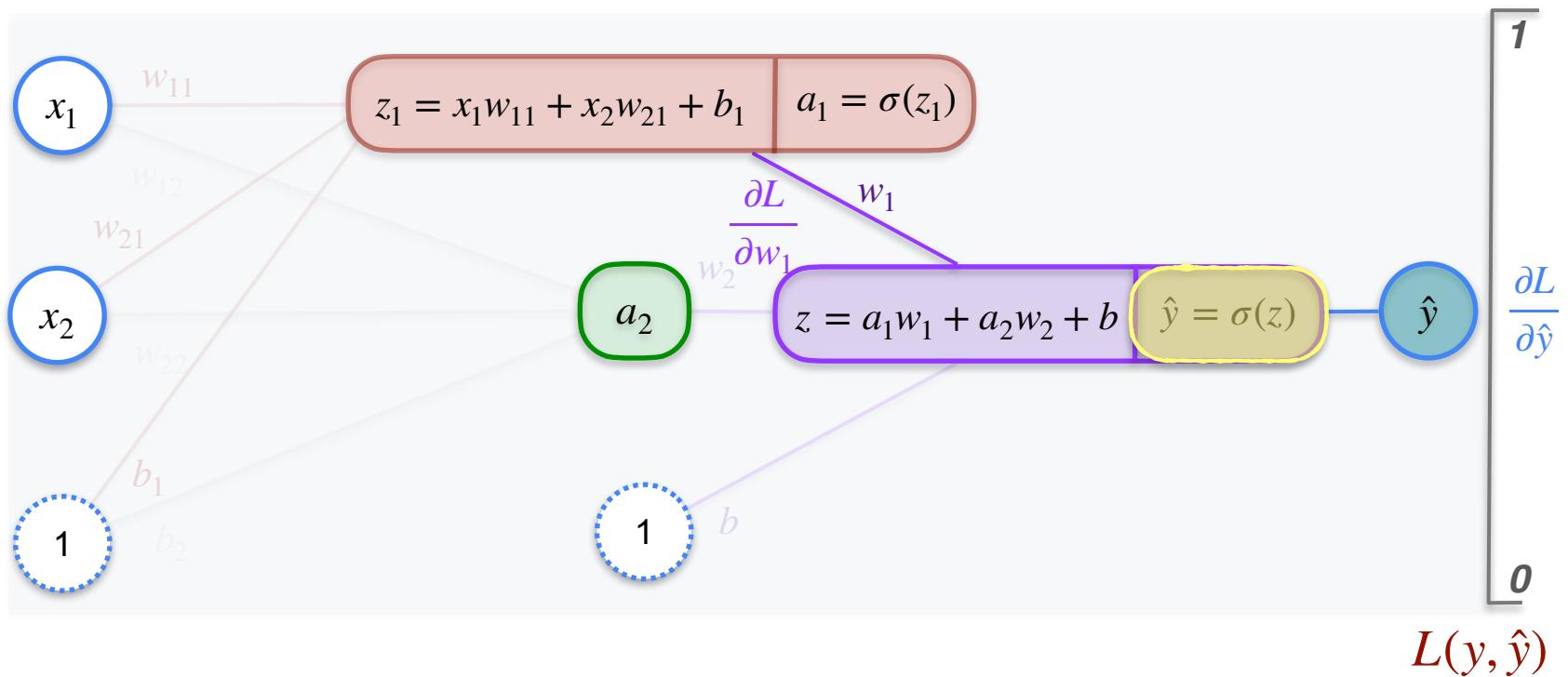
# 2,2,1 Neural Network



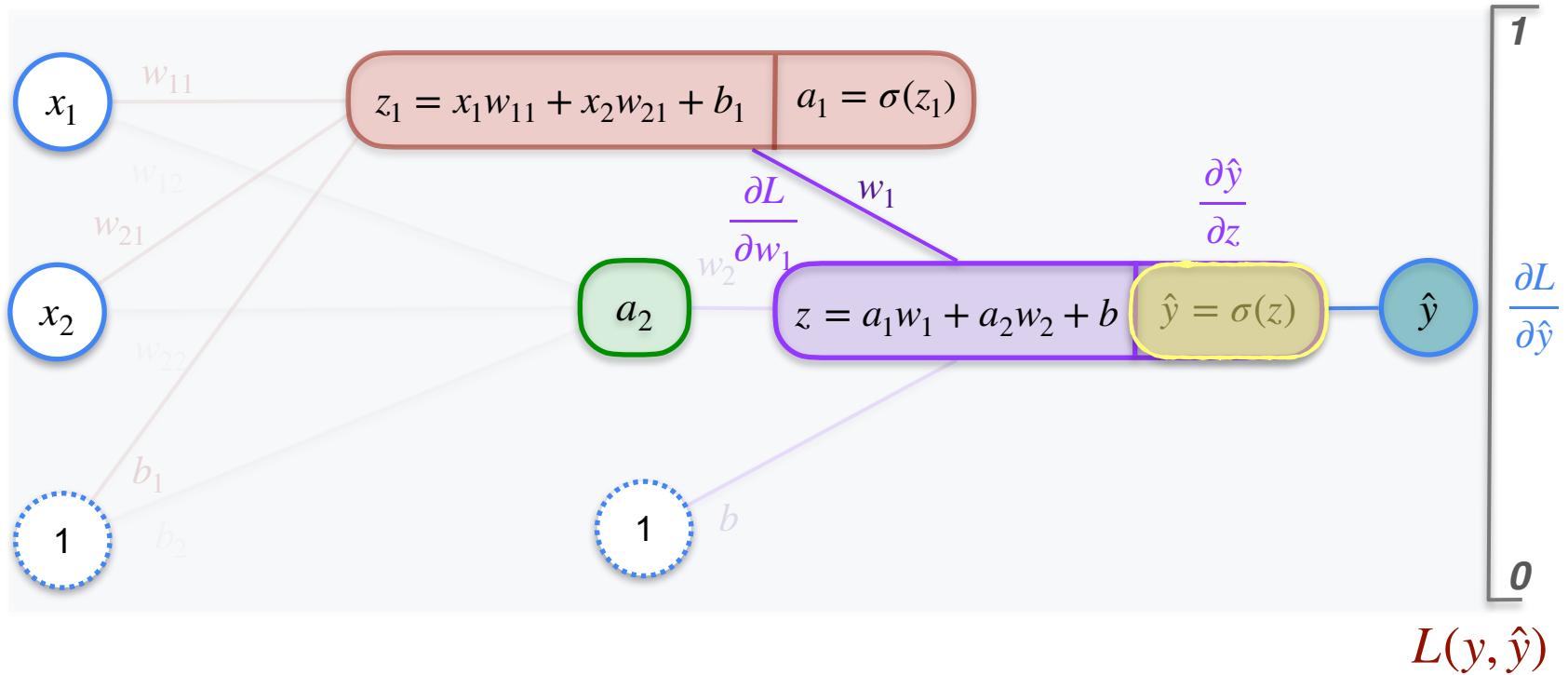
# 2,2,1 Neural Network



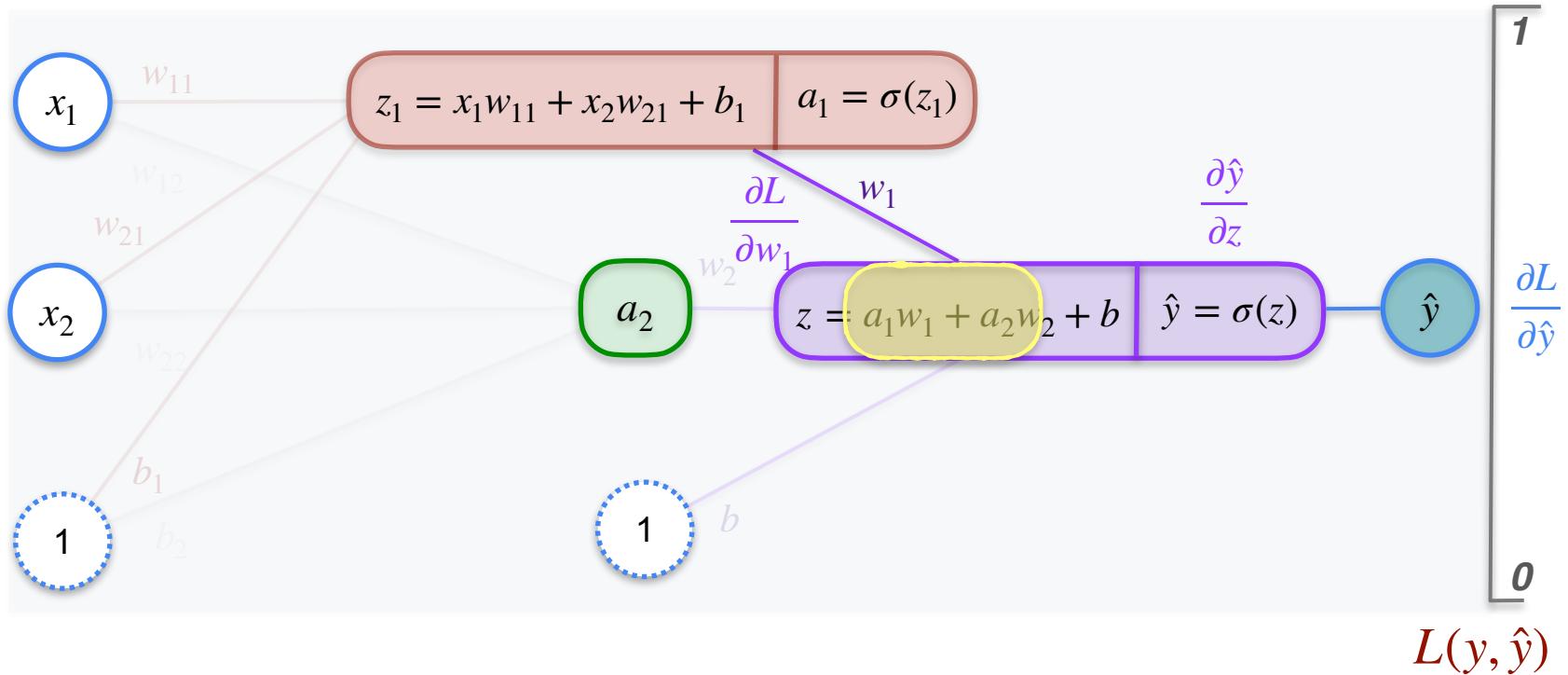
# 2,2,1 Neural Network



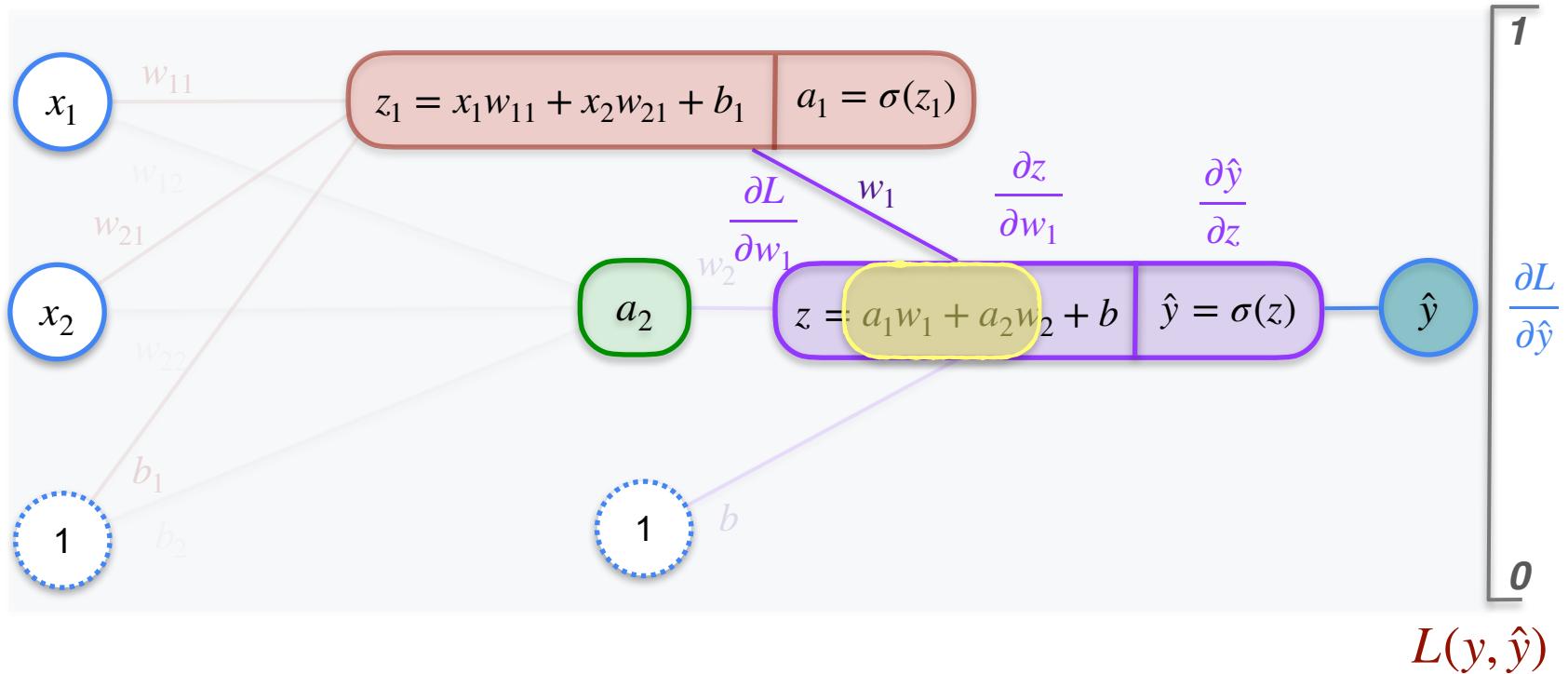
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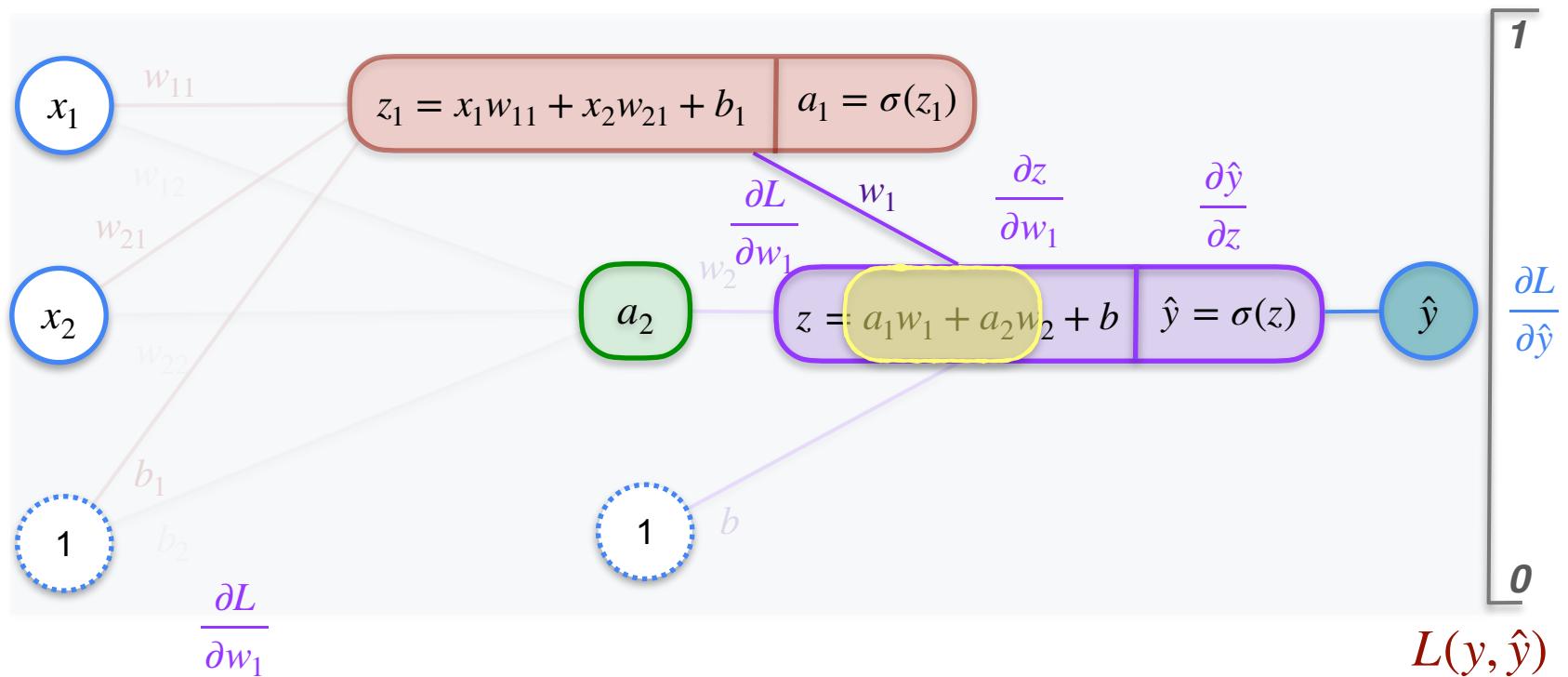
# 2,2,1 Neural Network



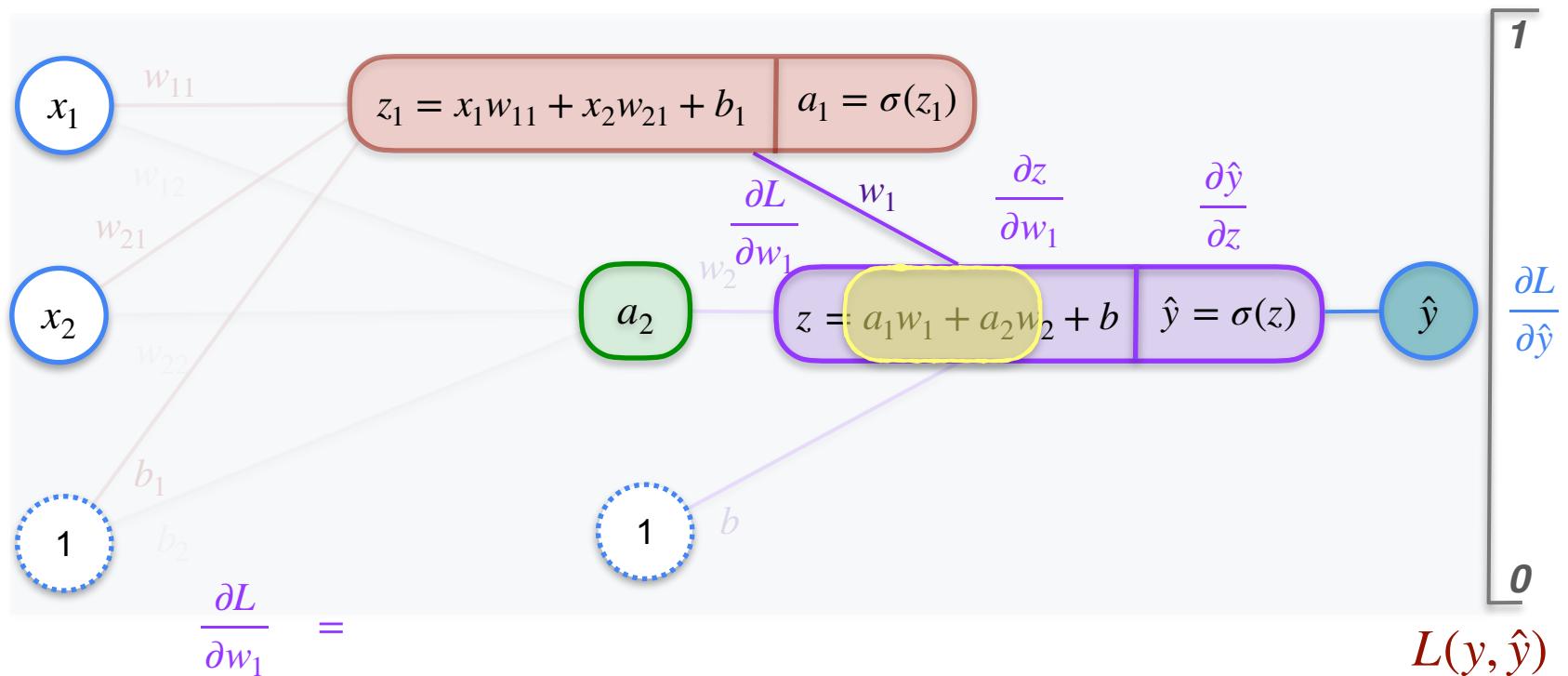
# 2,2,1 Neural Network



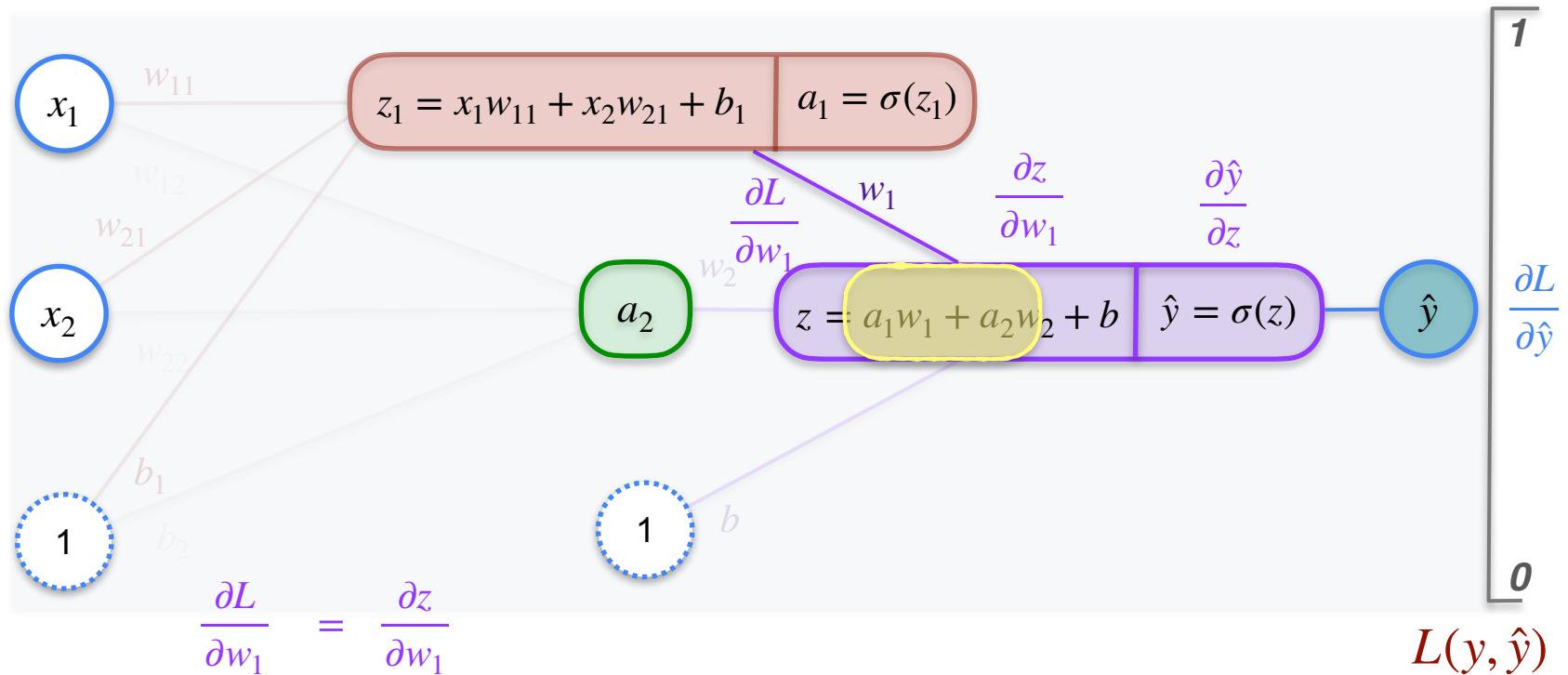
# 2,2,1 Neural Network



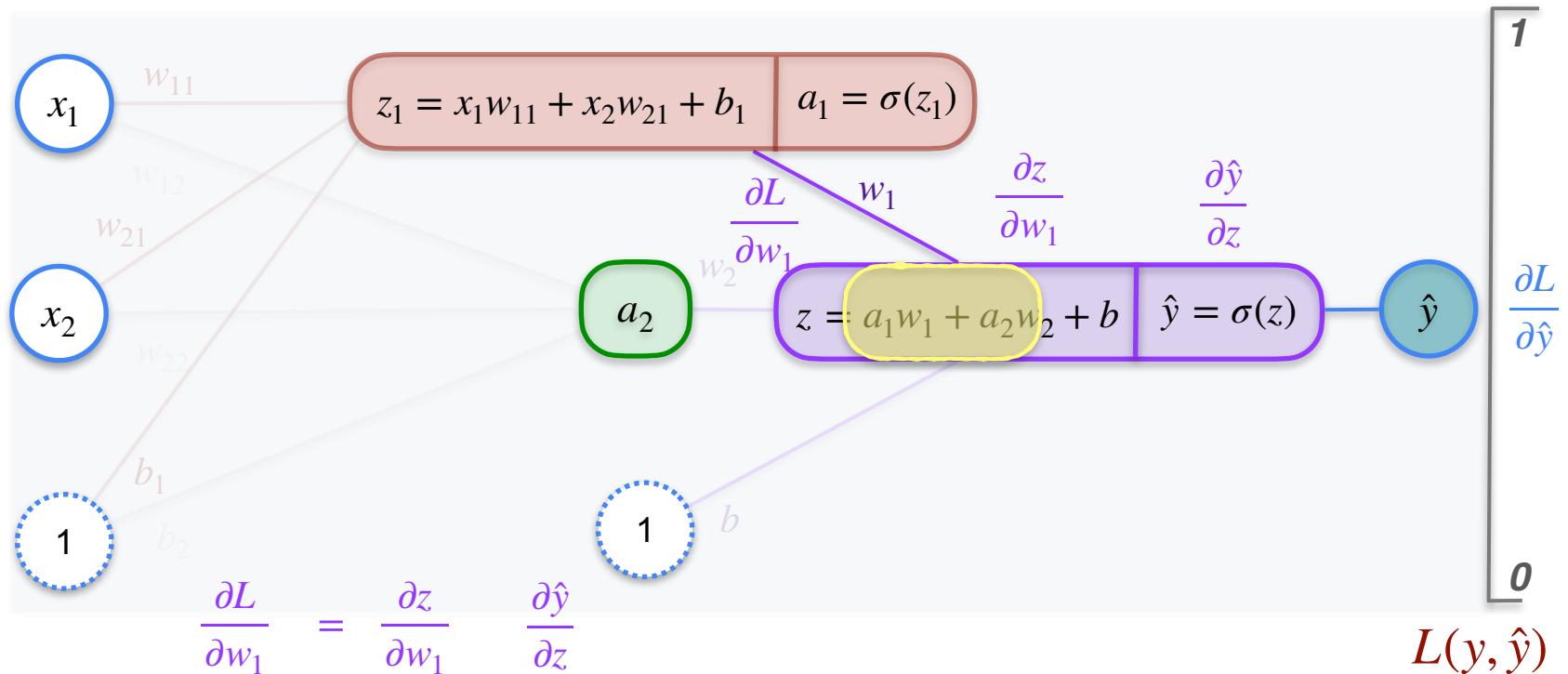
# 2,2,1 Neural Network



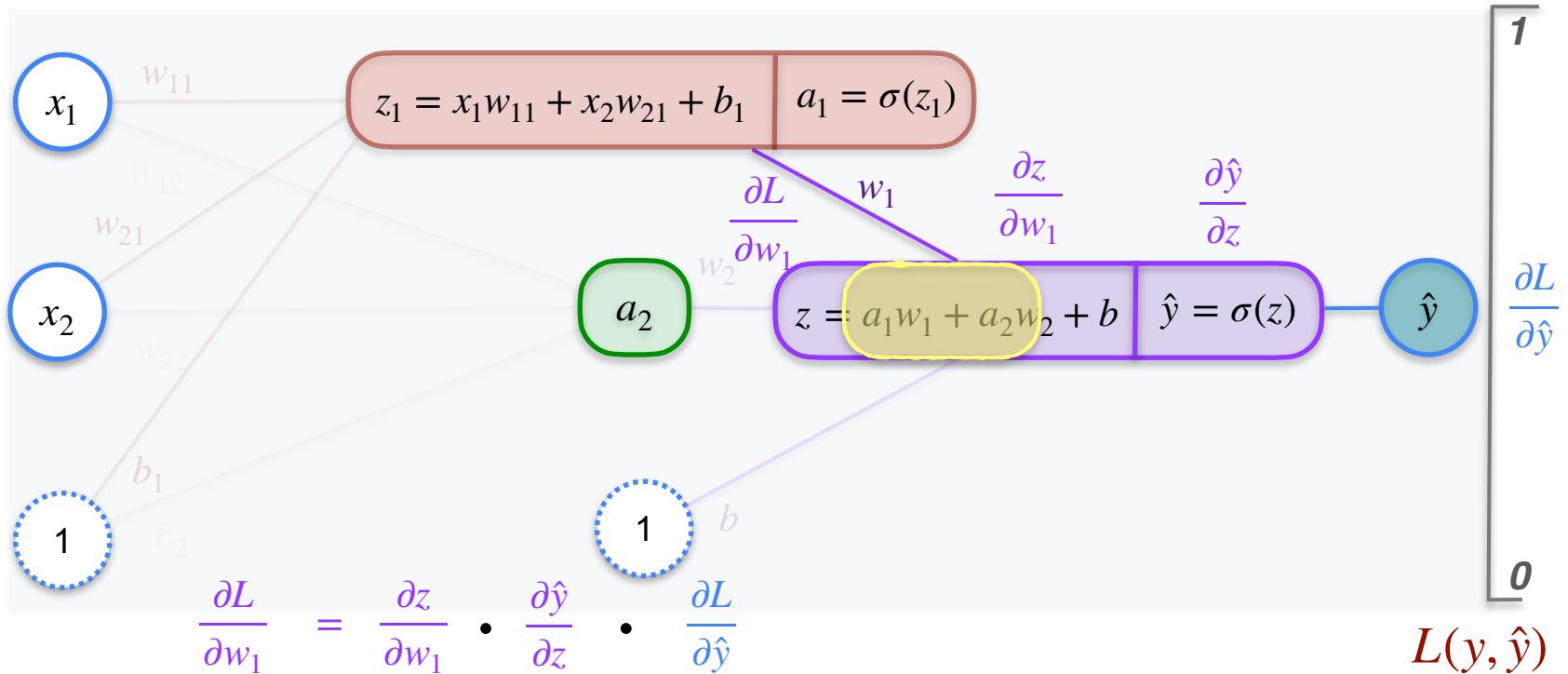
# 2,2,1 Neural Network



# 2,2,1 Neural Network



# 2,2,1 Neural Network



# 2,2,1 Neural Network

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1w_1 + a_2w_2 + b$$

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

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

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*to find optimal value of  $w_1$  that gives the least error*

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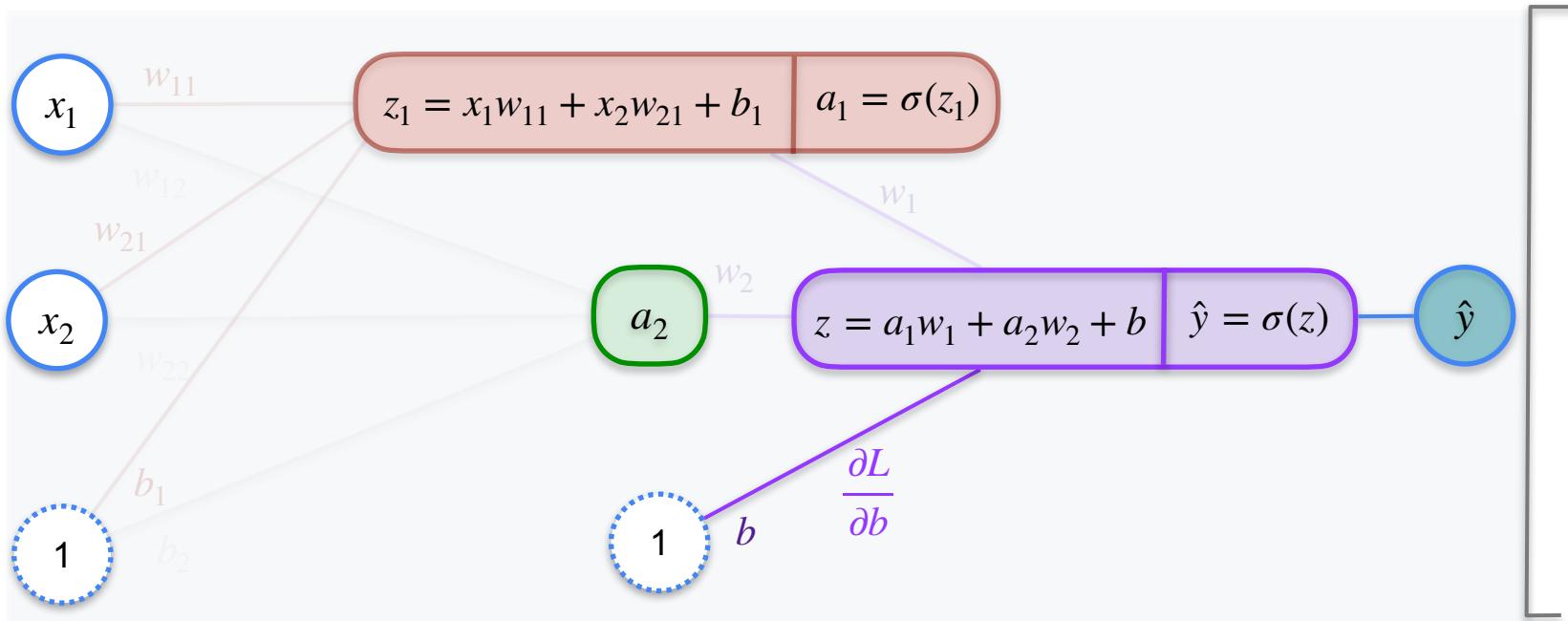
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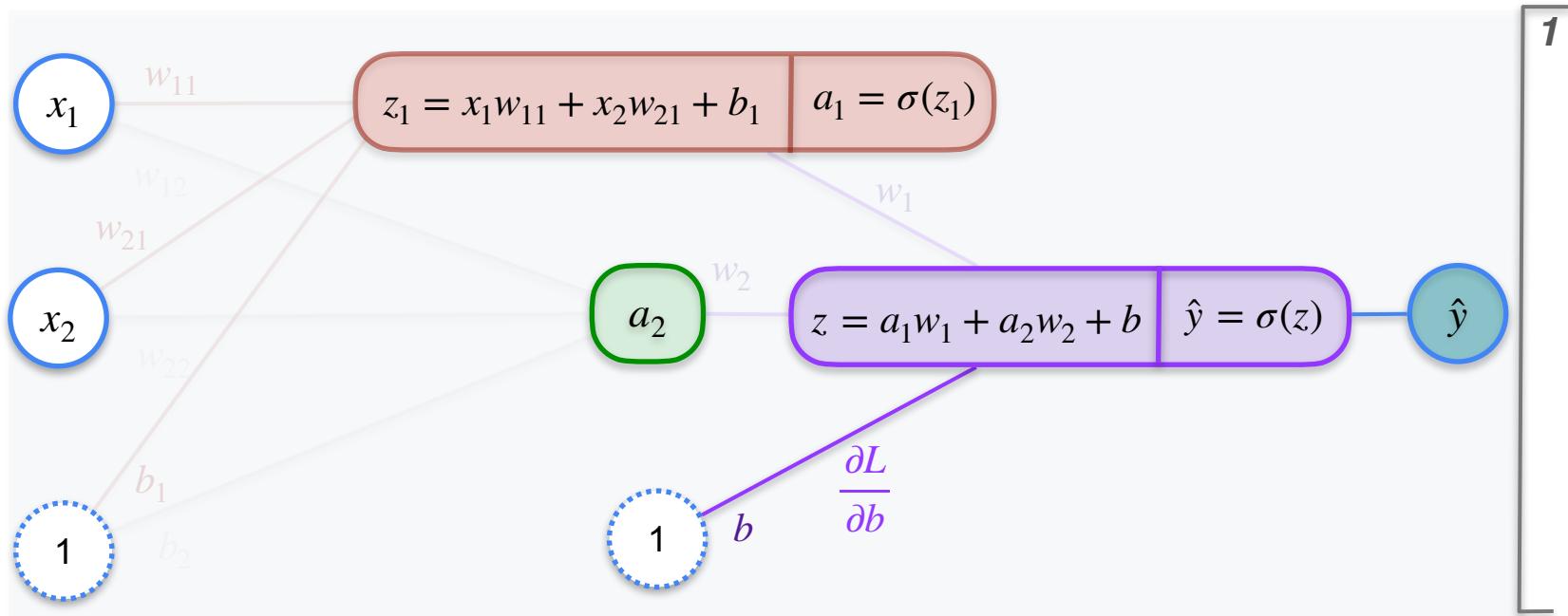
$$w_1 \rightarrow w_1 - \alpha(-a_1(y - \hat{y}))$$

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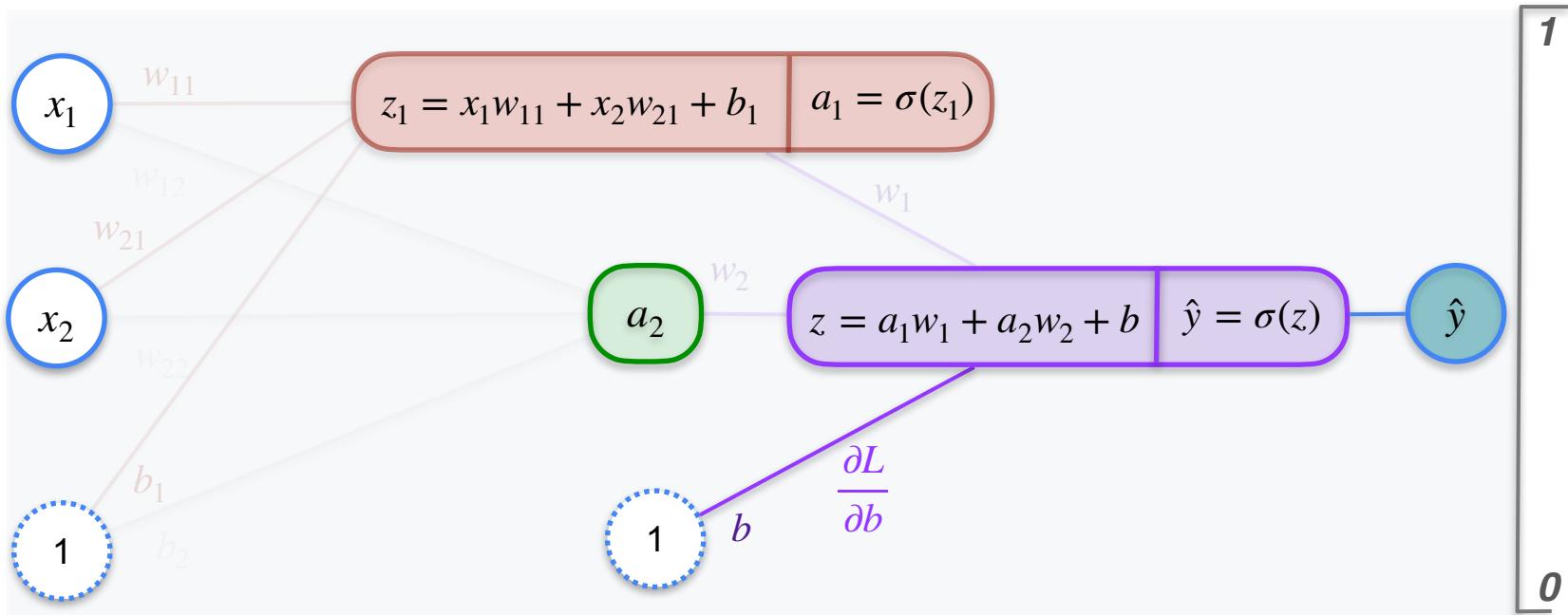
# 2,2,1 Neural Network



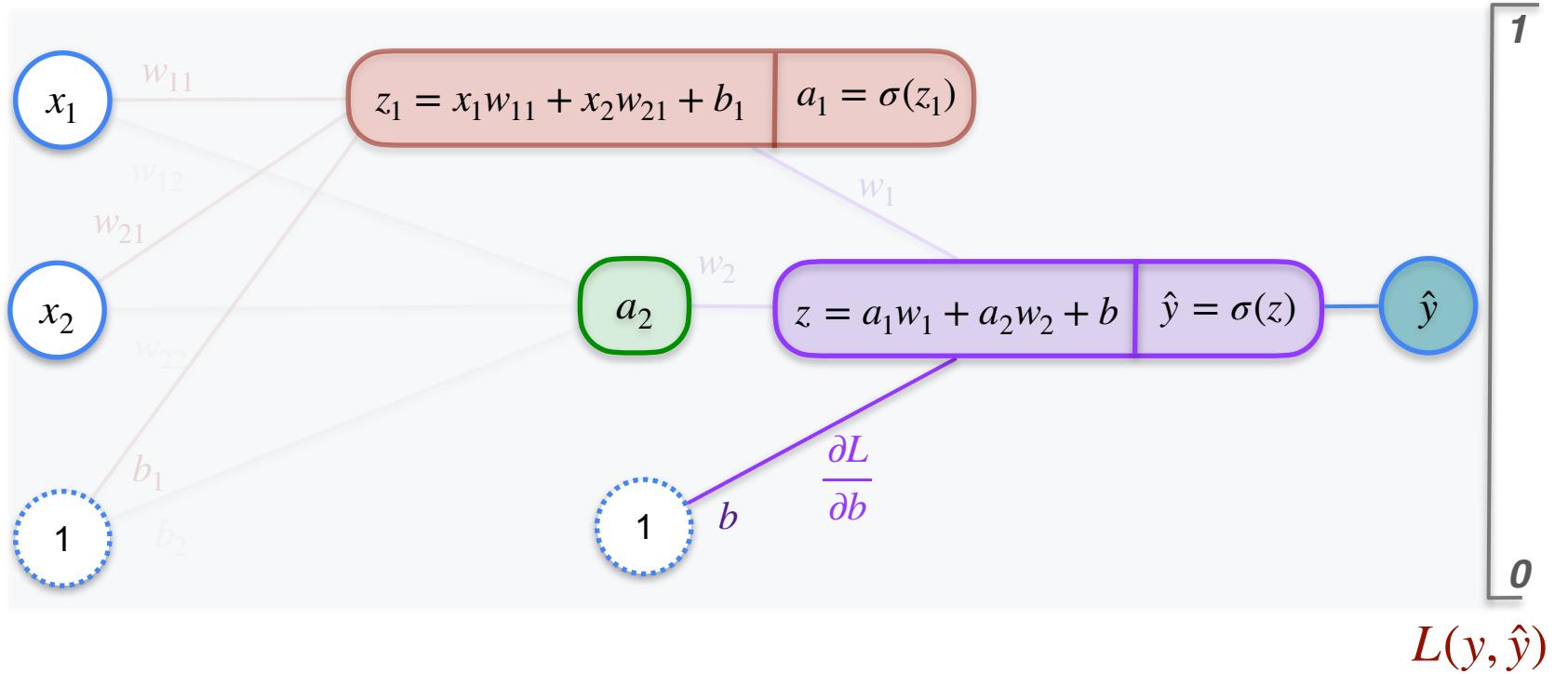
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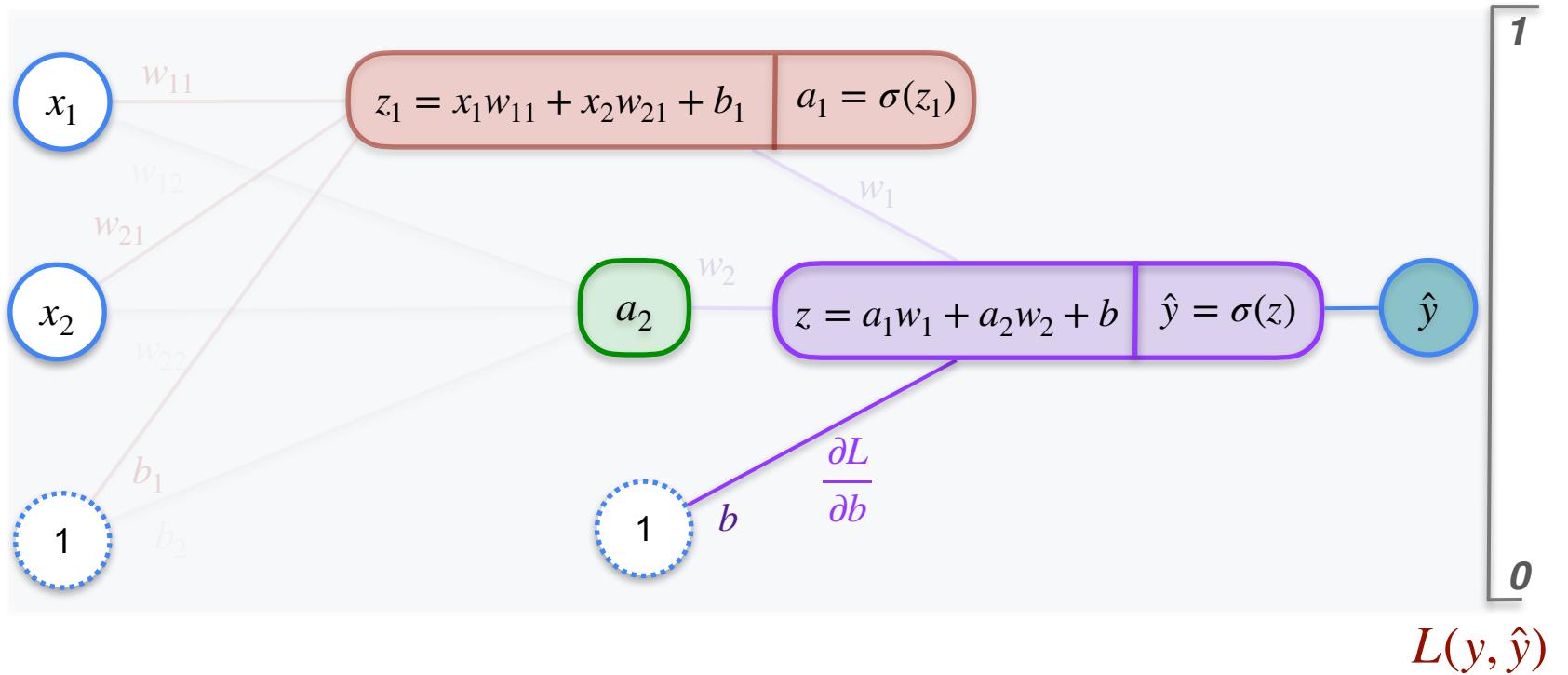
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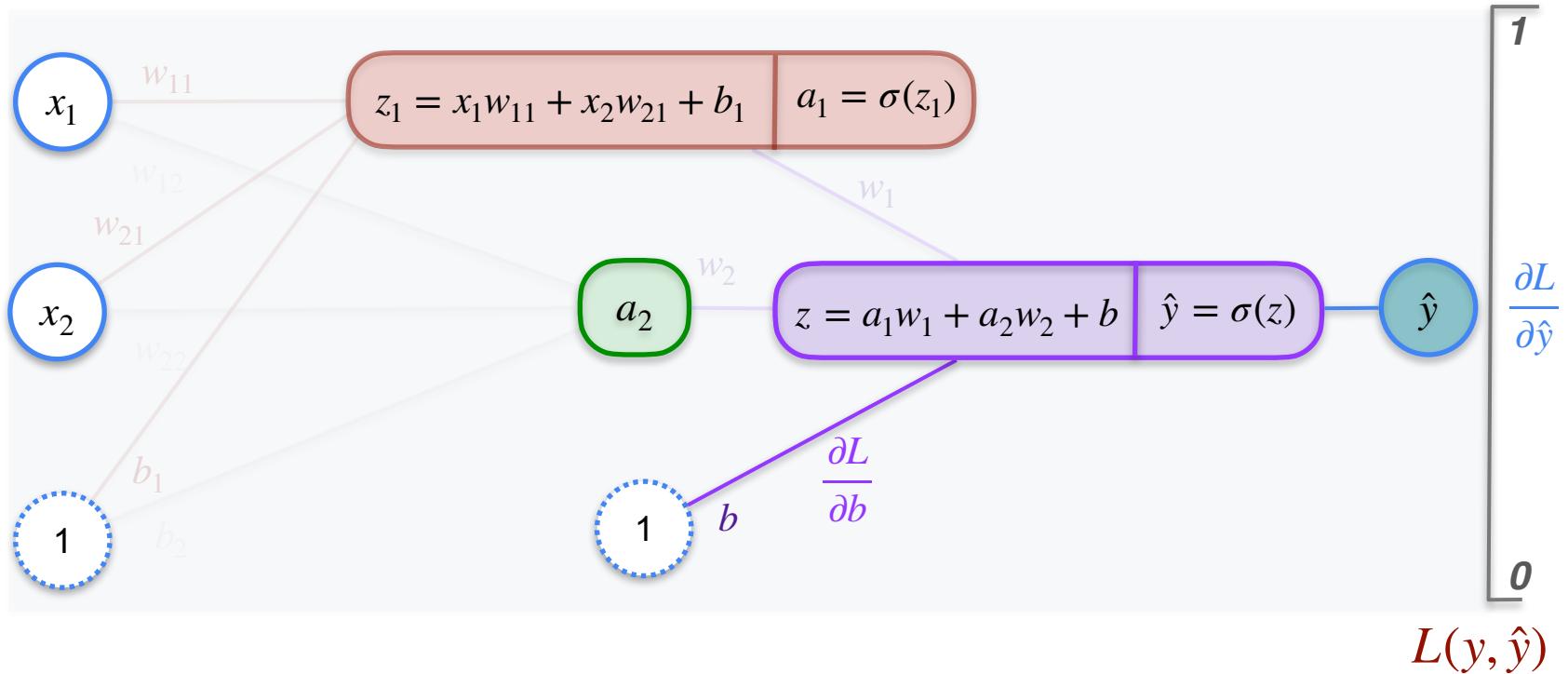
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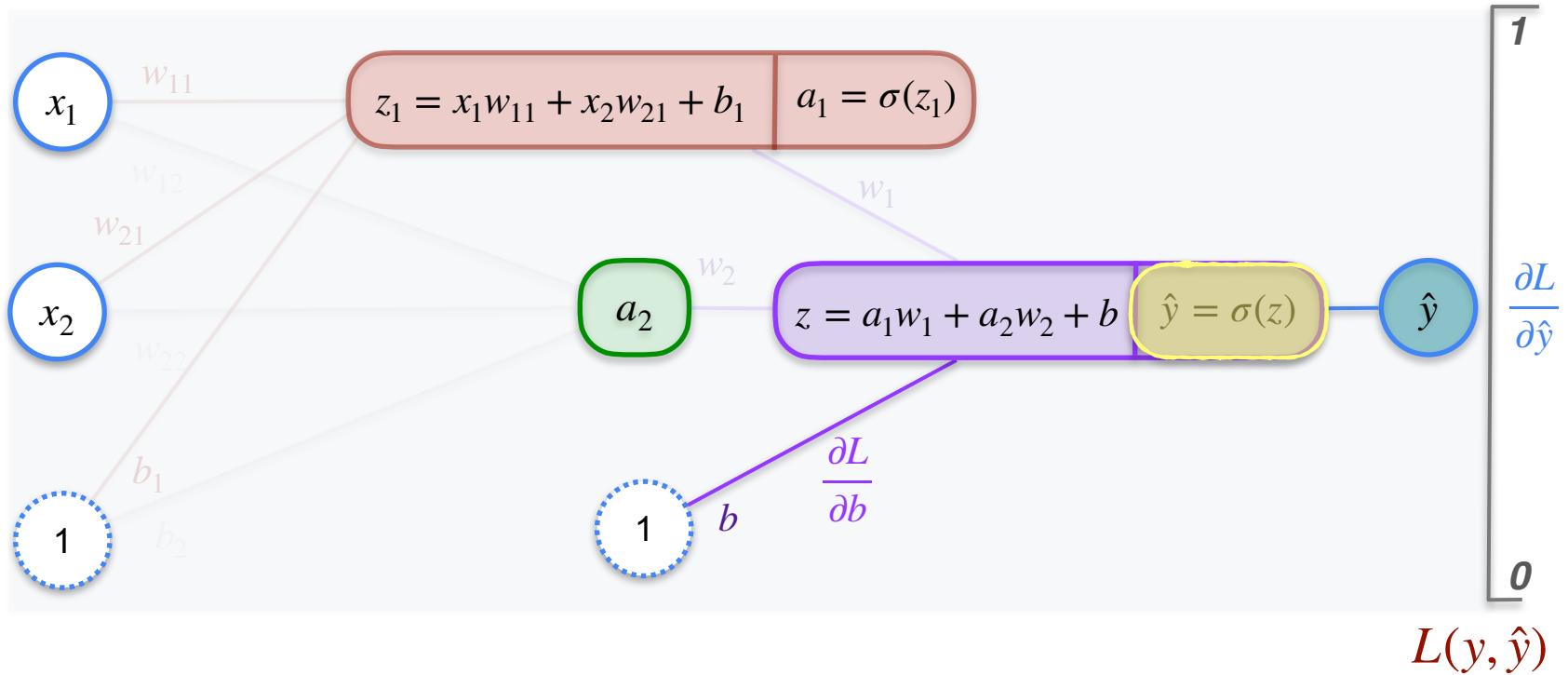
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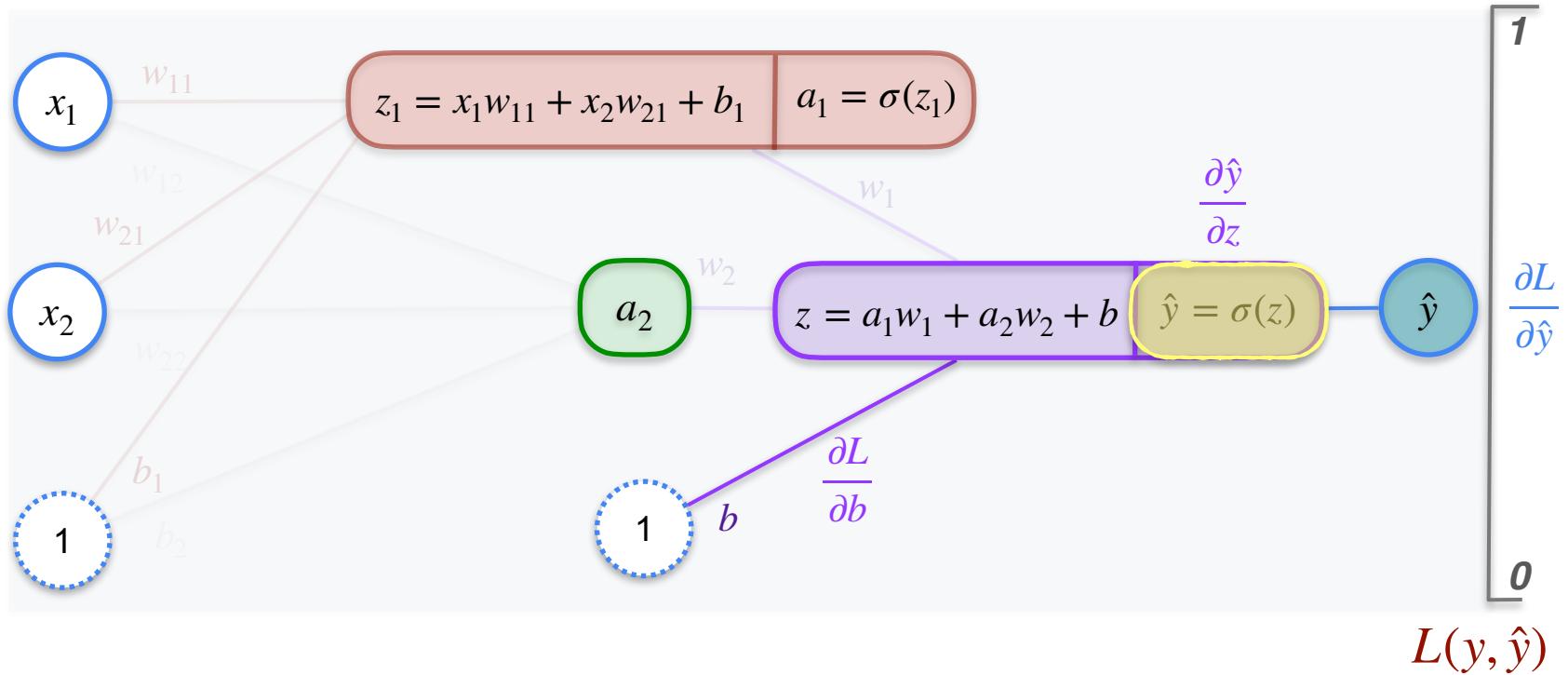
# 2,2,1 Neural Network



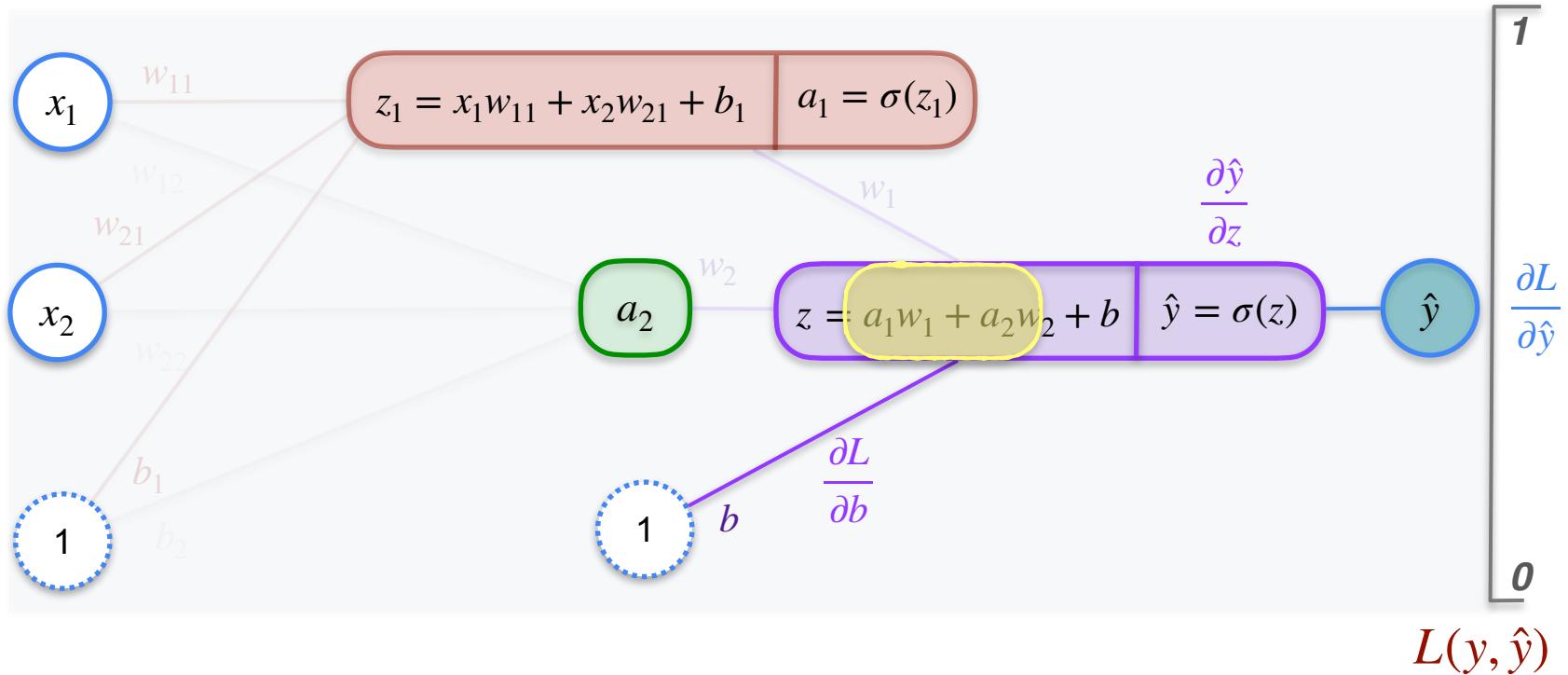
# 2,2,1 Neural Network



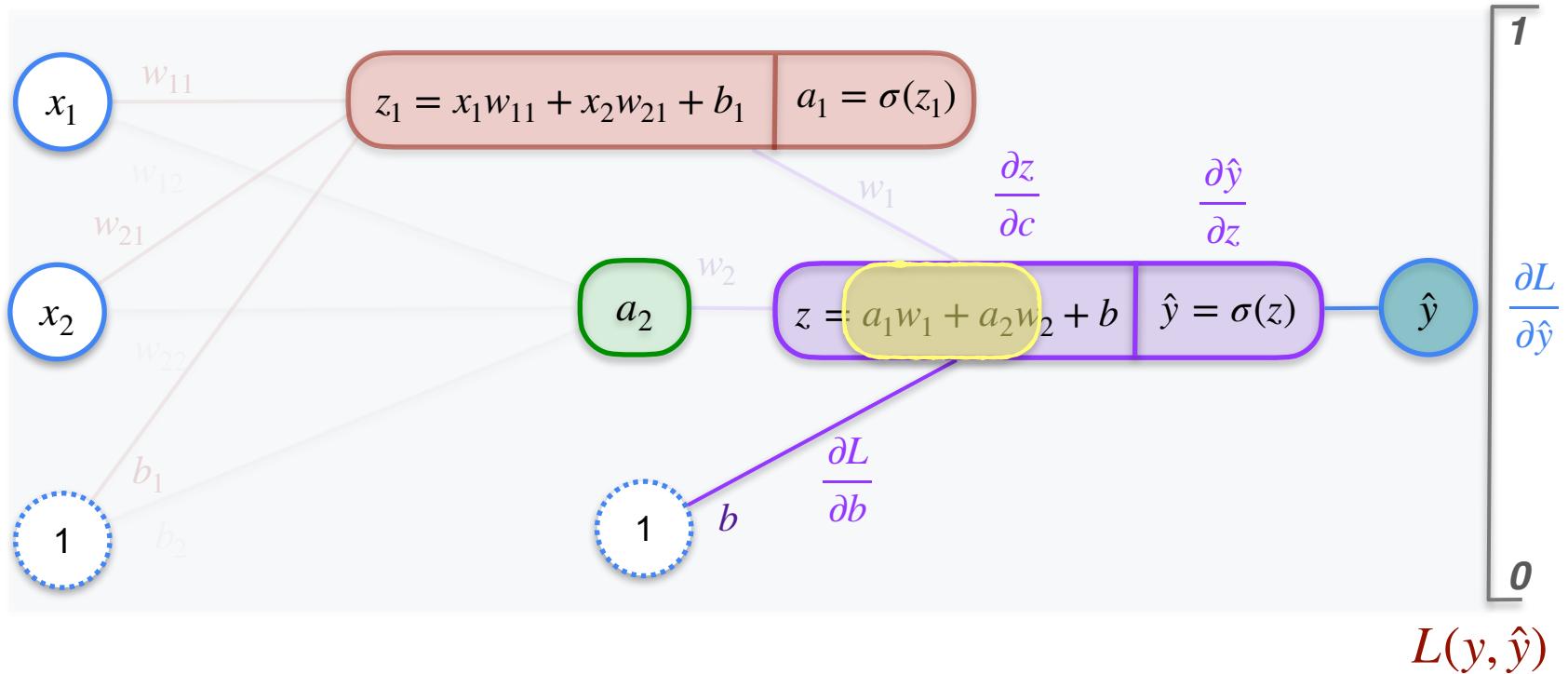
# 2,2,1 Neural Network



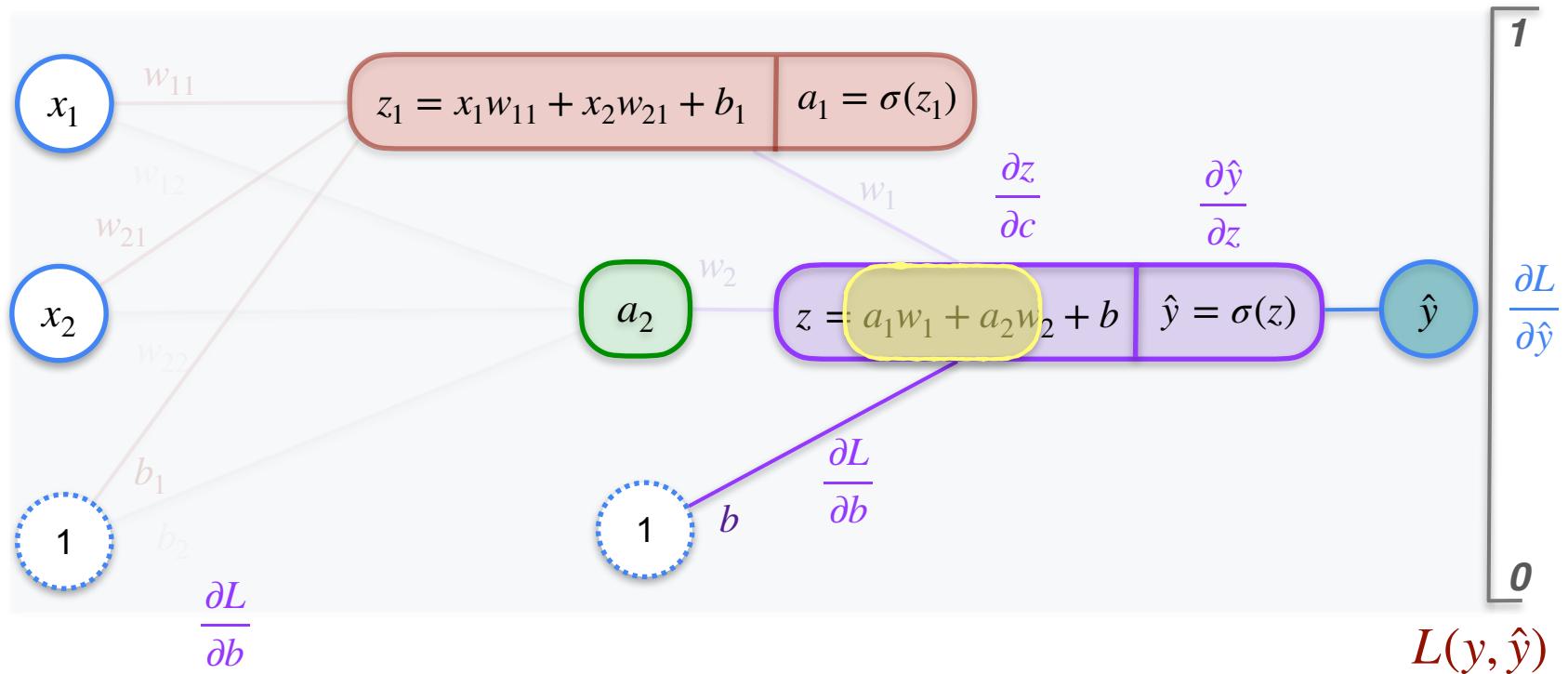
# 2,2,1 Neural Network



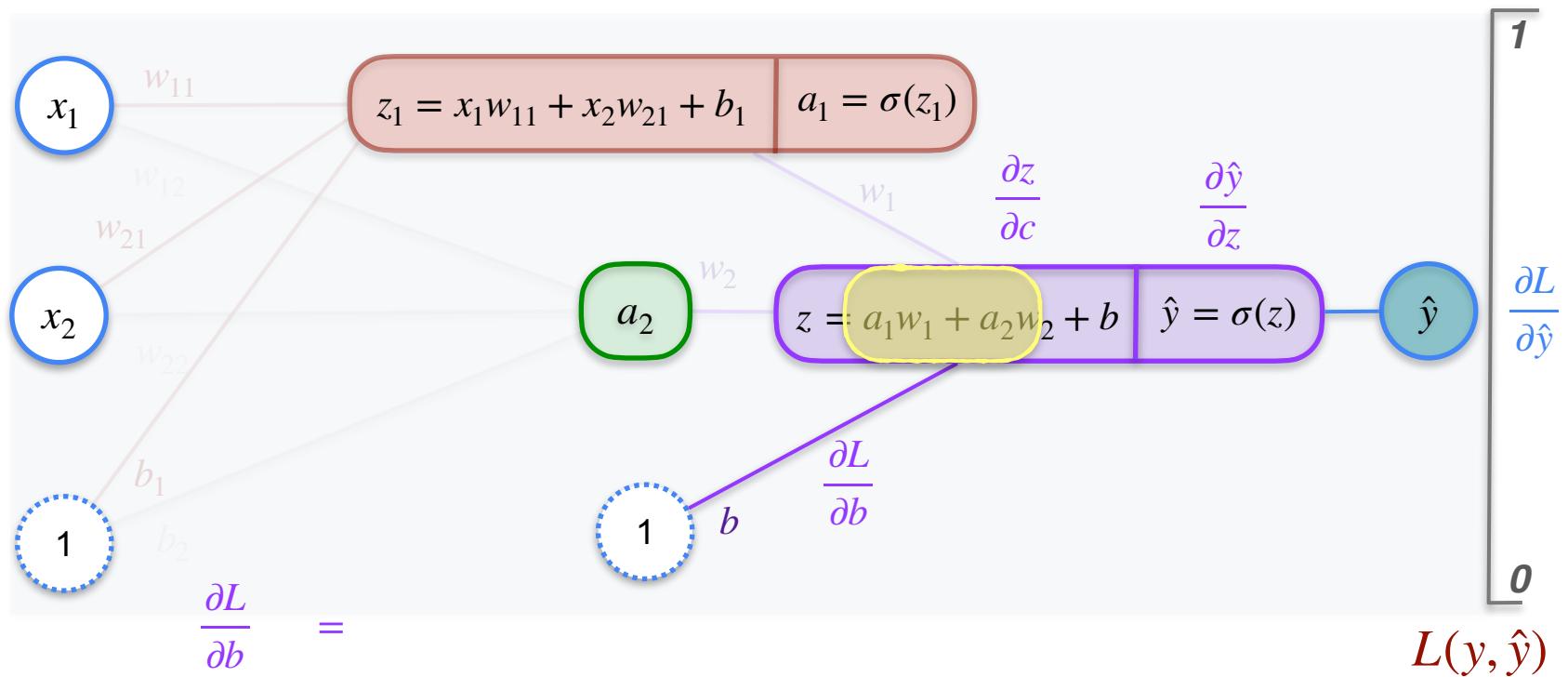
# 2,2,1 Neural Network



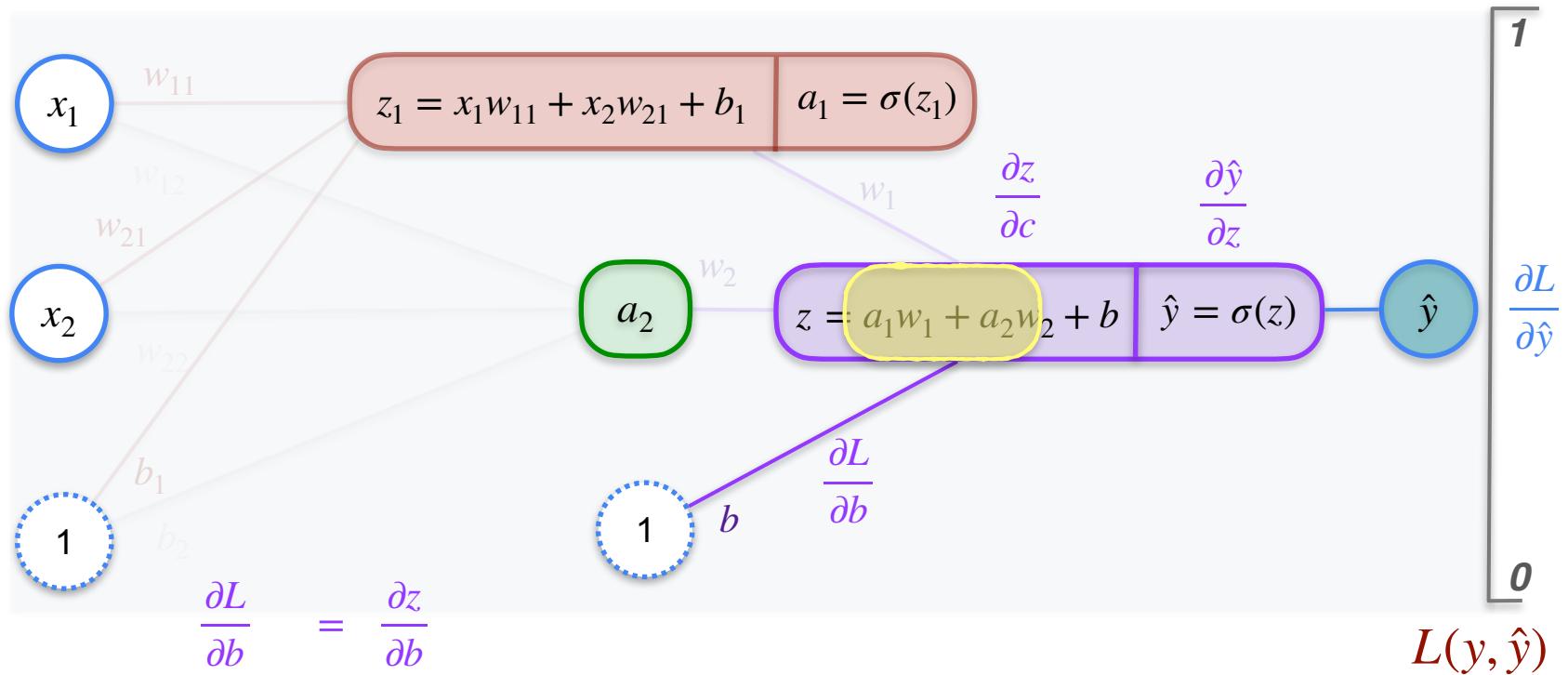
# 2,2,1 Neural Network



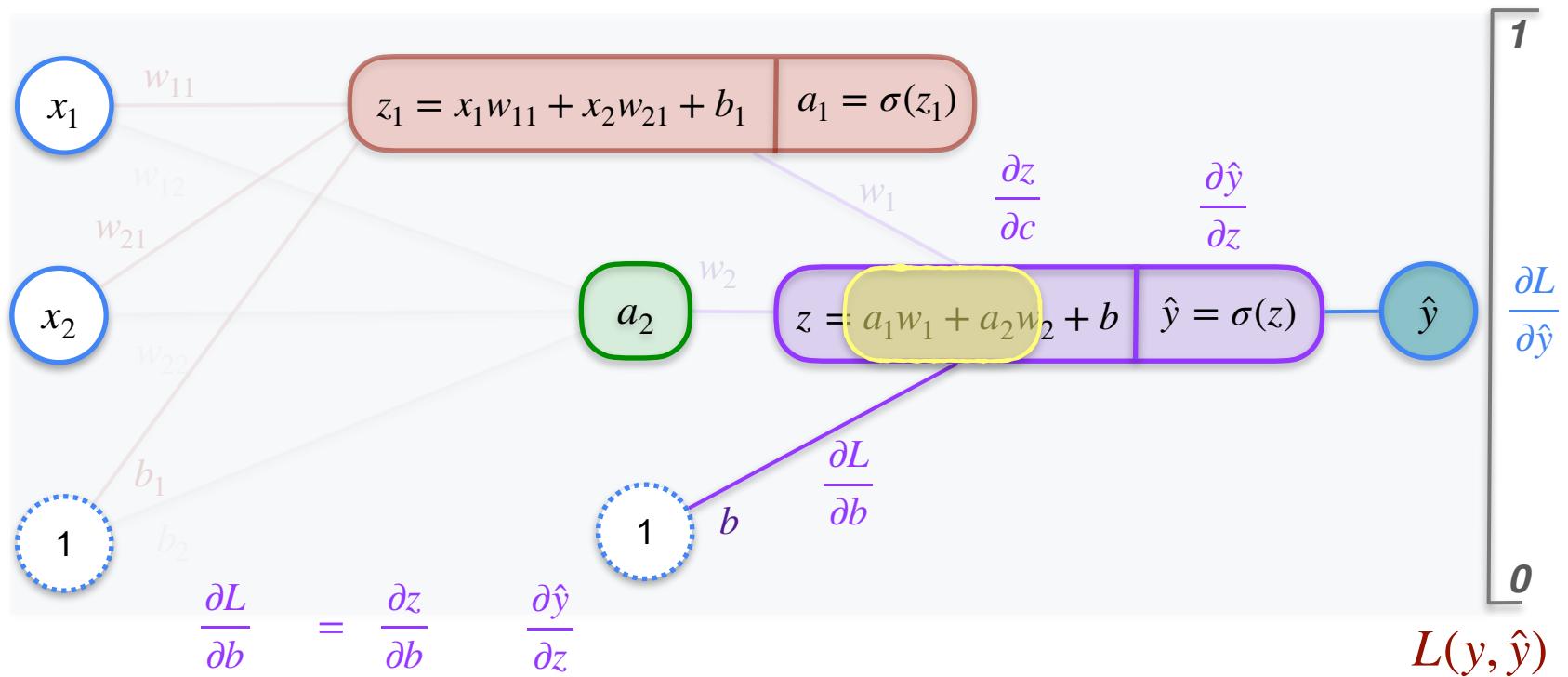
# 2,2,1 Neural Network



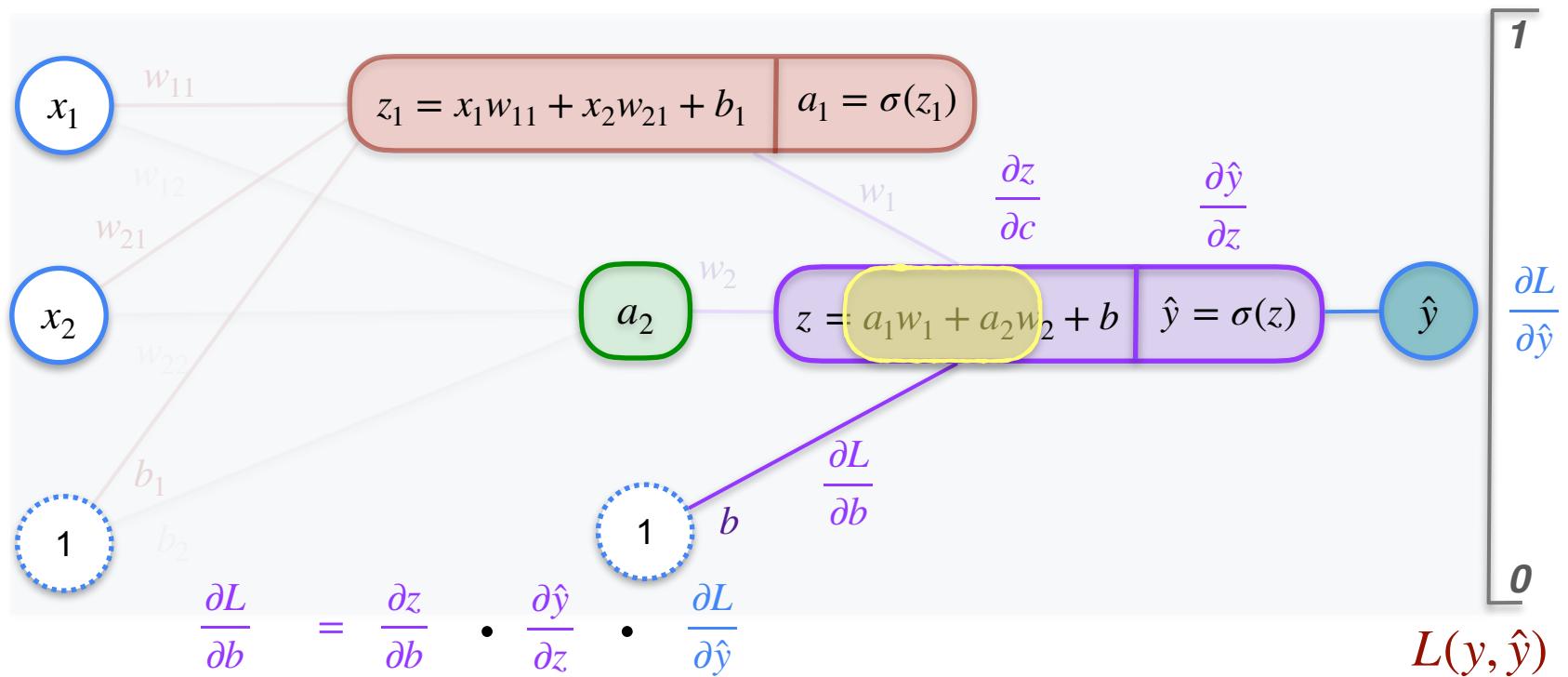
# 2,2,1 Neural Network



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# 2,2,1 Neural Network



# 2,2,1 Neural Network

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1w_1 + a_2w_2 + b$$

# 2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

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*to find optimal value of  $b$  that gives the least error*

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*Perform gradient descent with*

$$b \rightarrow b - \alpha \frac{\partial L}{\partial b}$$

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$$= -(y - \hat{y})$$

*Perform gradient descent with*

$$b \rightarrow b - \alpha(-(y - \hat{y}))$$

*to find optimal value of  $b$  that gives the least error*