Copyright Notice

DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Regression with a perceptron

Regression Problem Motivation

Regression Problem Motivation

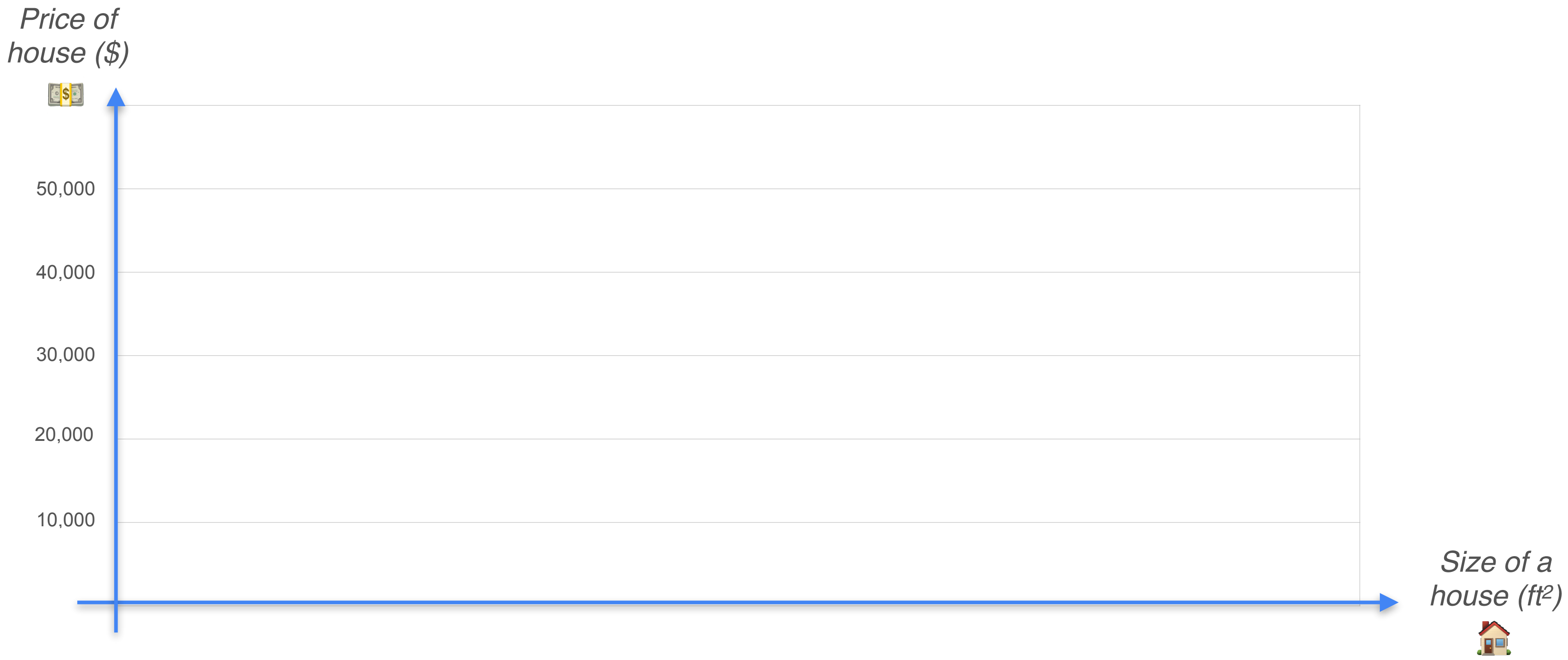
Predicting

the price of a house

from

the size of the house

Regression Problem Motivation



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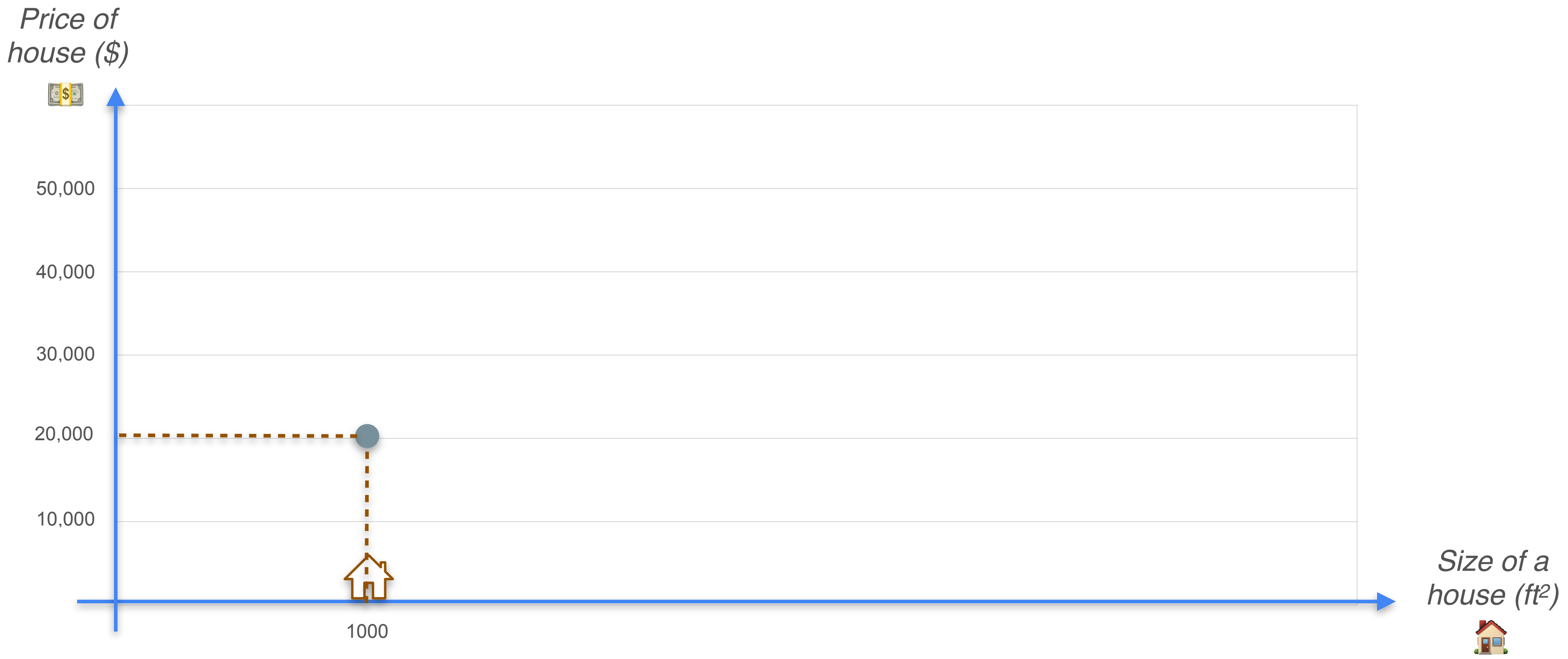
Regression Problem Motivation



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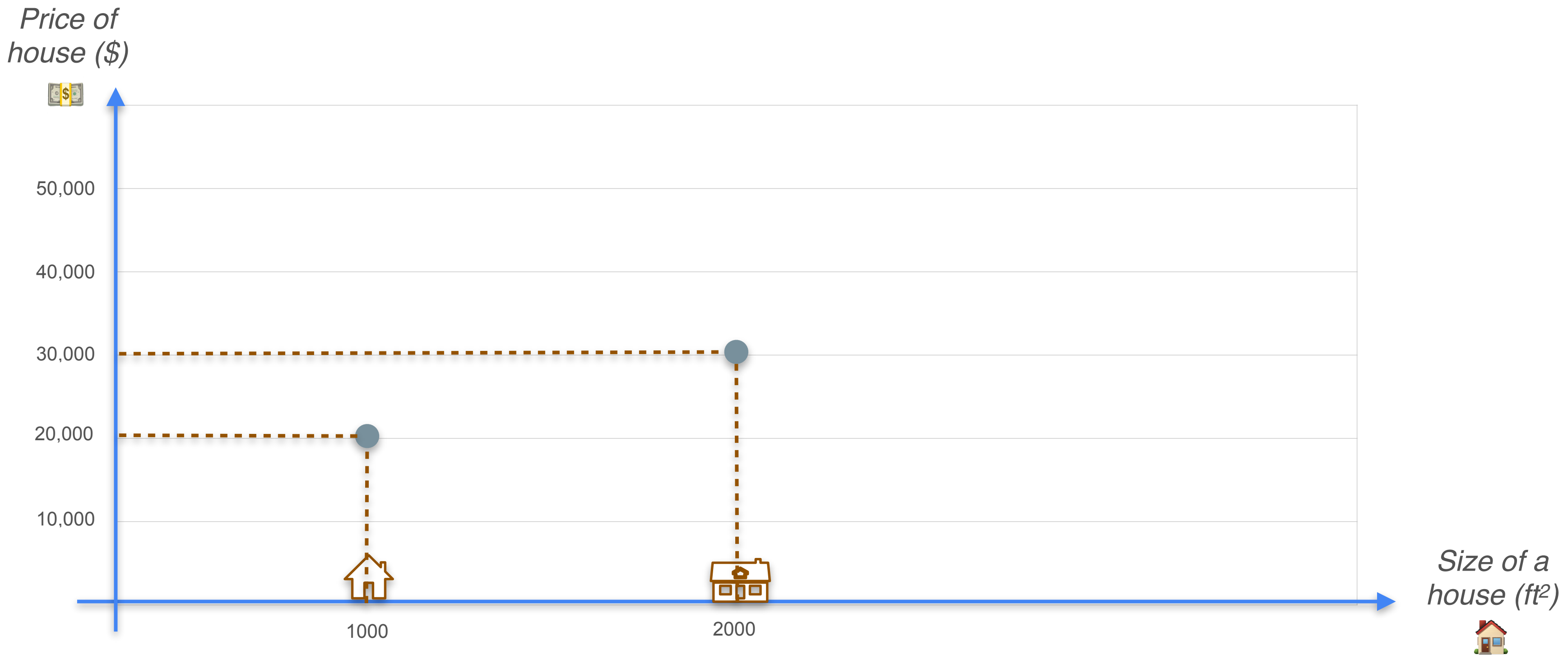
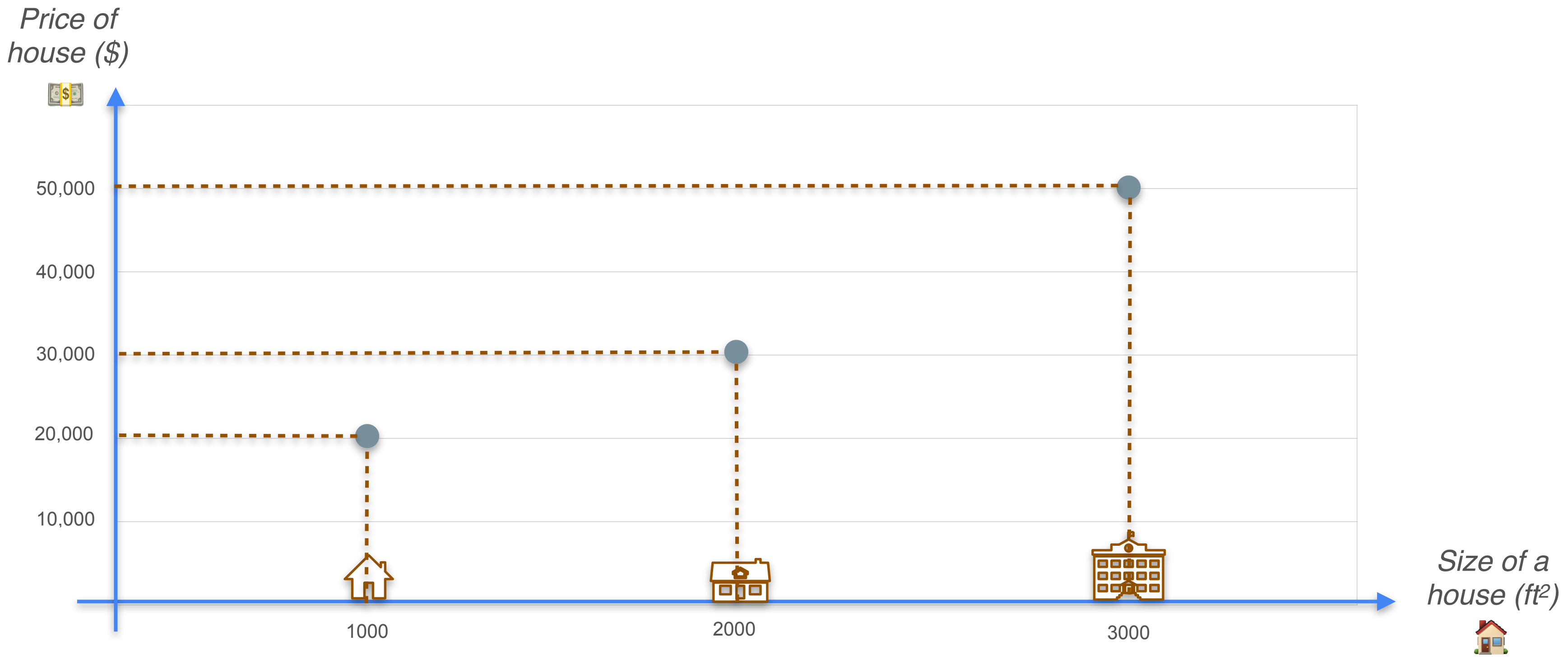
Regression Problem Motivation



Regression Problem Motivation



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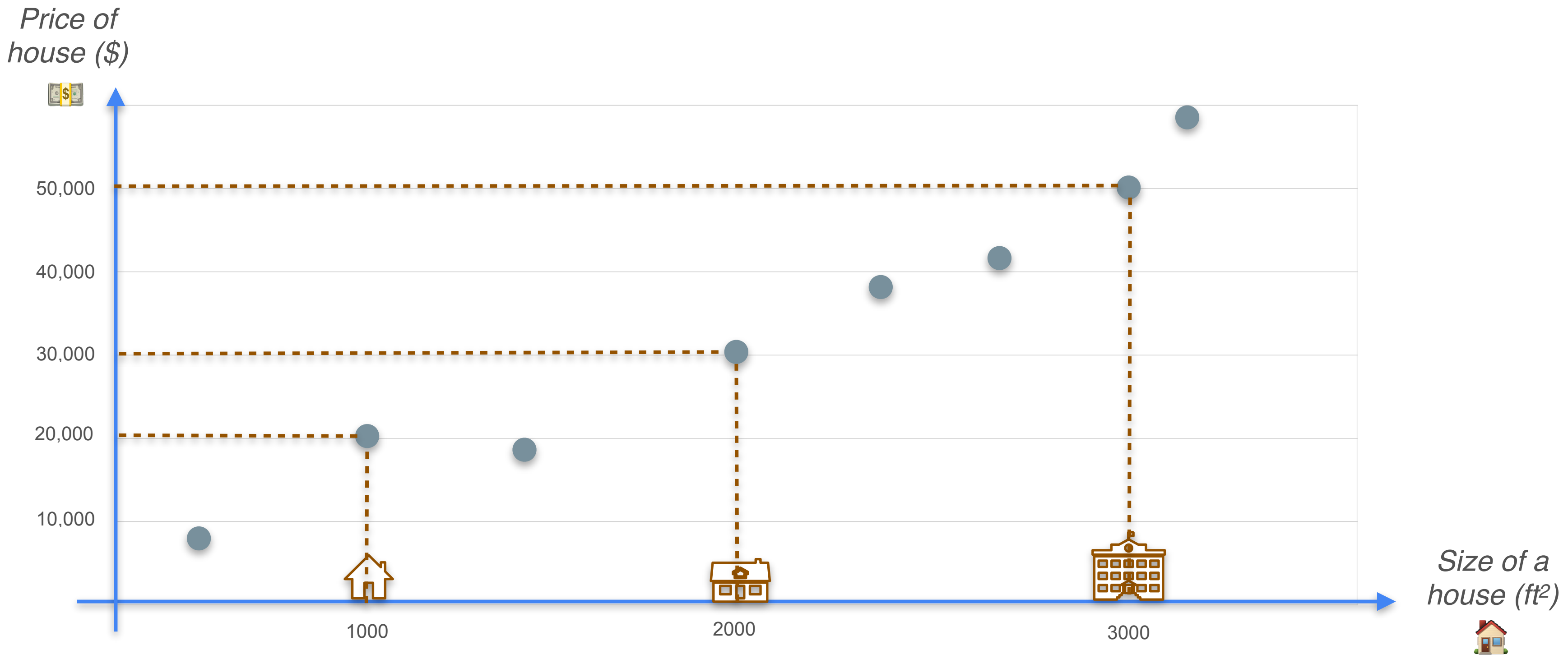

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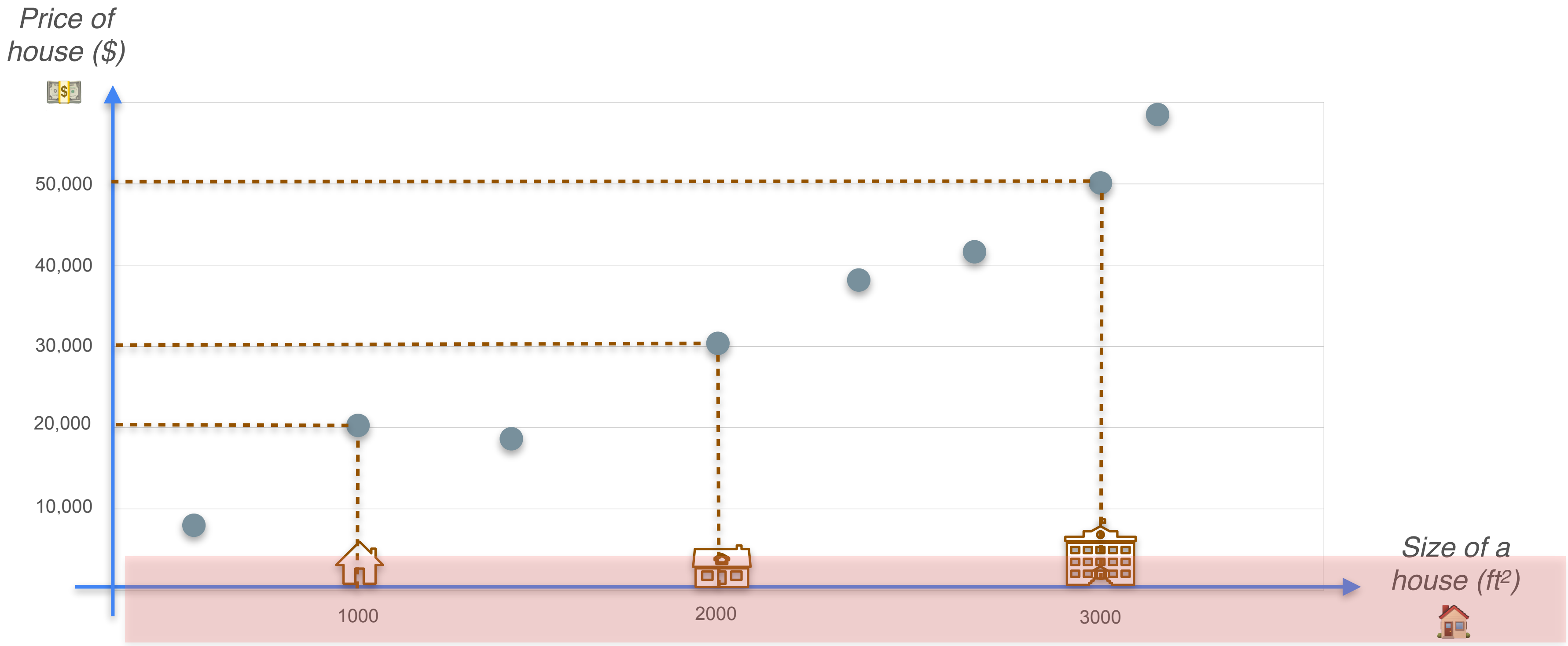

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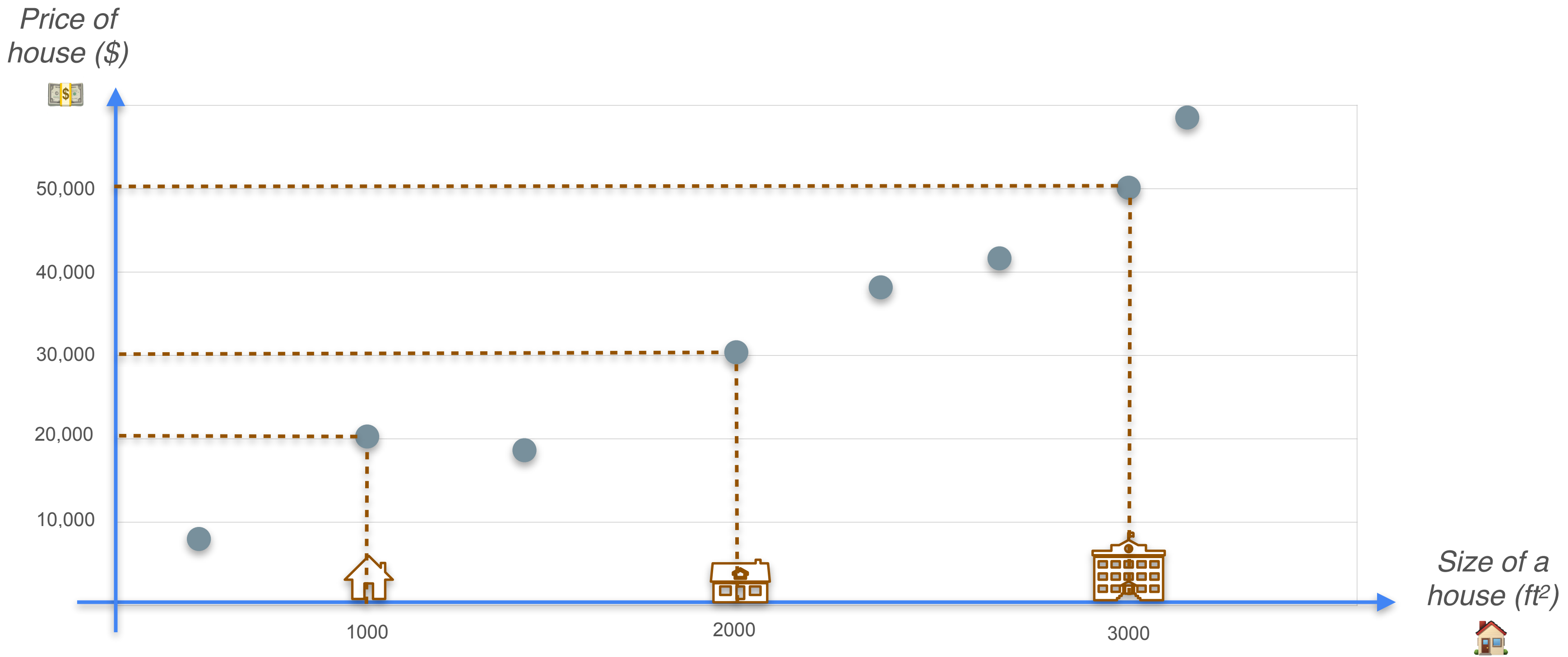
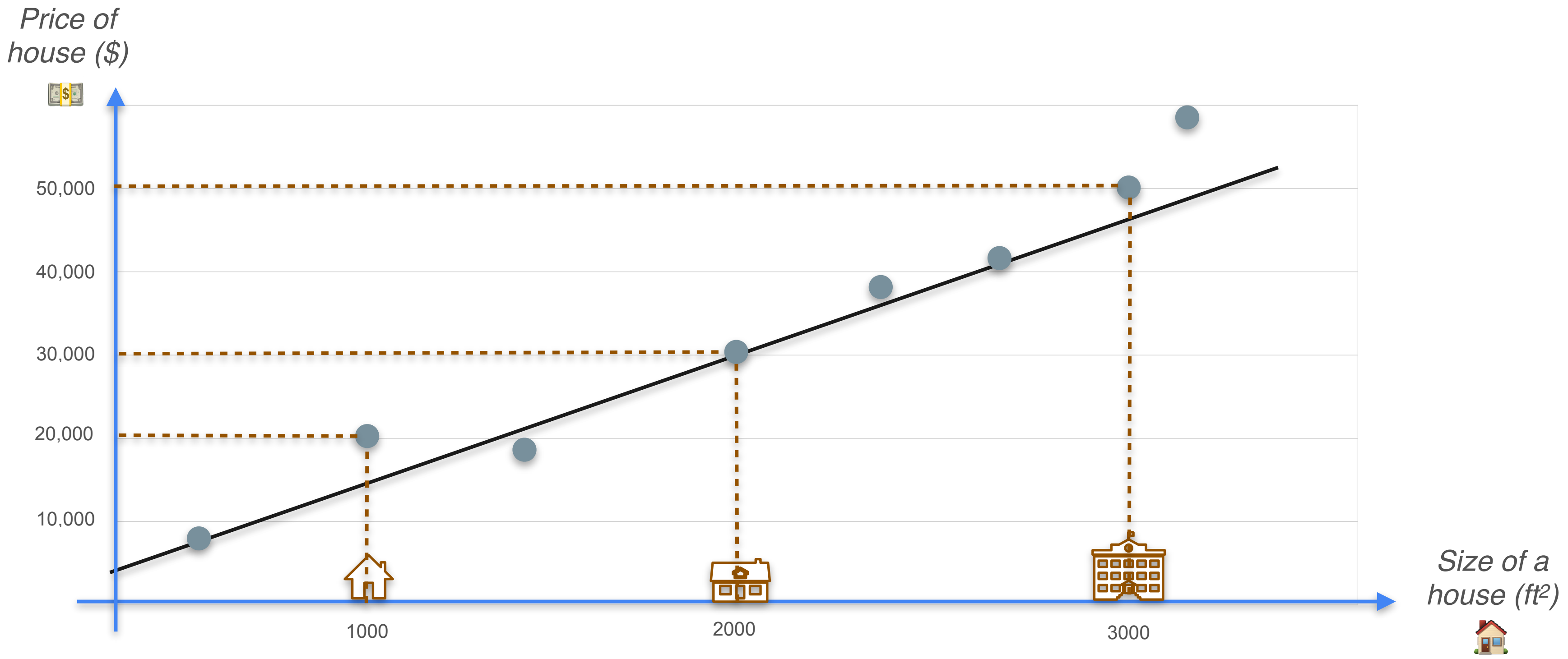
Regression Problem Motivation



Regression Problem Motivation



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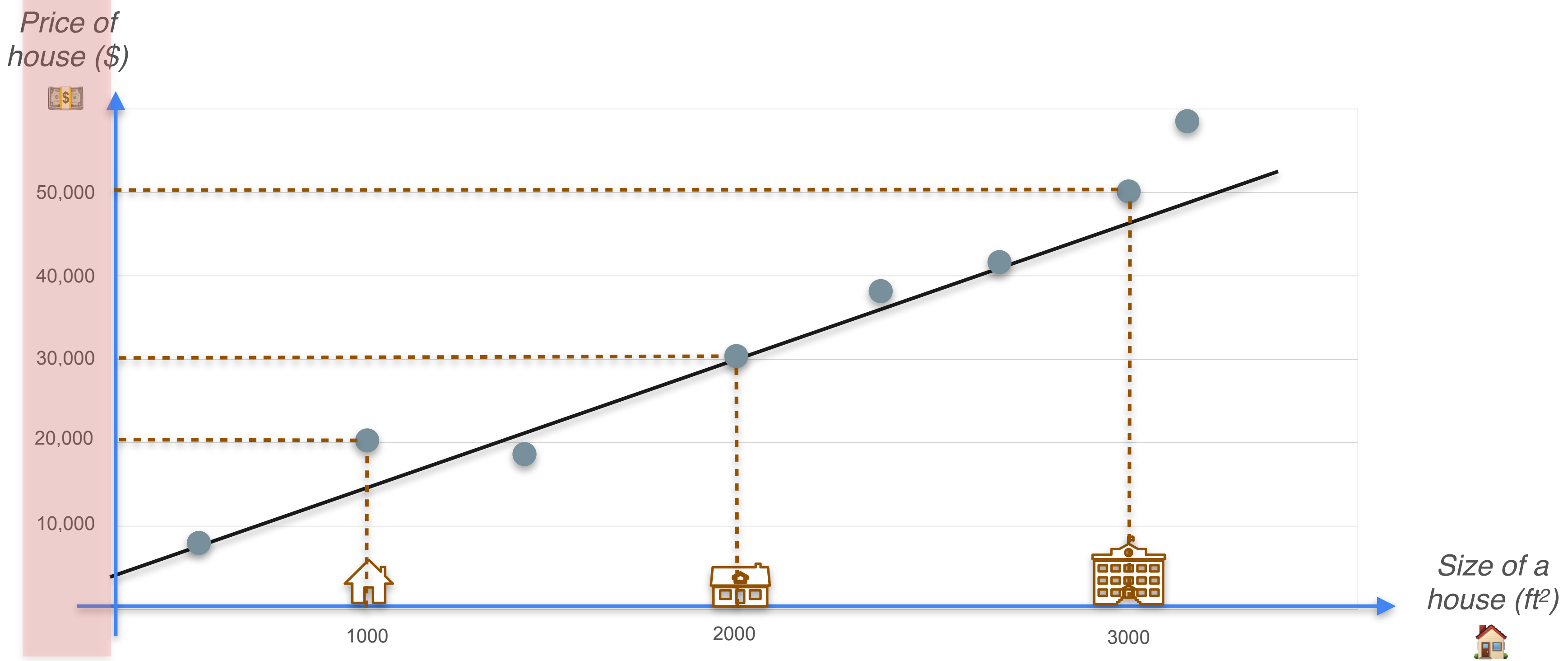

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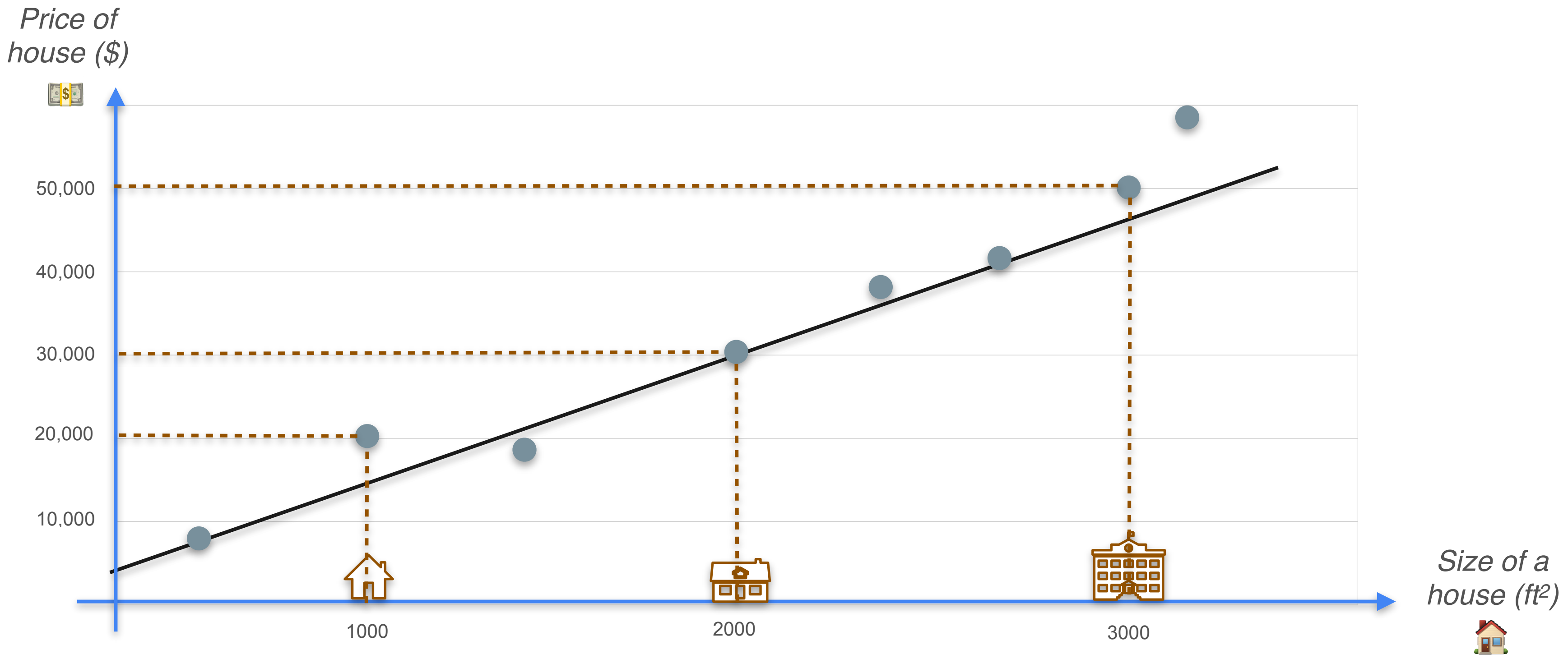


Regression With a Perceptron

	Size of a house (ft²) 🏠		*Price of house ($)* 💵
			
			
			

Regression With a Perceptron

	Size of a house (ft^2) 🏠		Price of house ($) 💵
🏠	1000ft^2		$20,000
🏫	2000ft^2		$30,000
🏢	3000ft^2		$50,000

Regression With a Perceptron

	Size of a house (ft²)	Number of rooms	Price of house ($)
	$1000ft^2$	2	$20,000
	$2000ft^2$	4	$30,000
	$3000ft^2$	7	$50,000

Regression With a Perceptron

Inputs

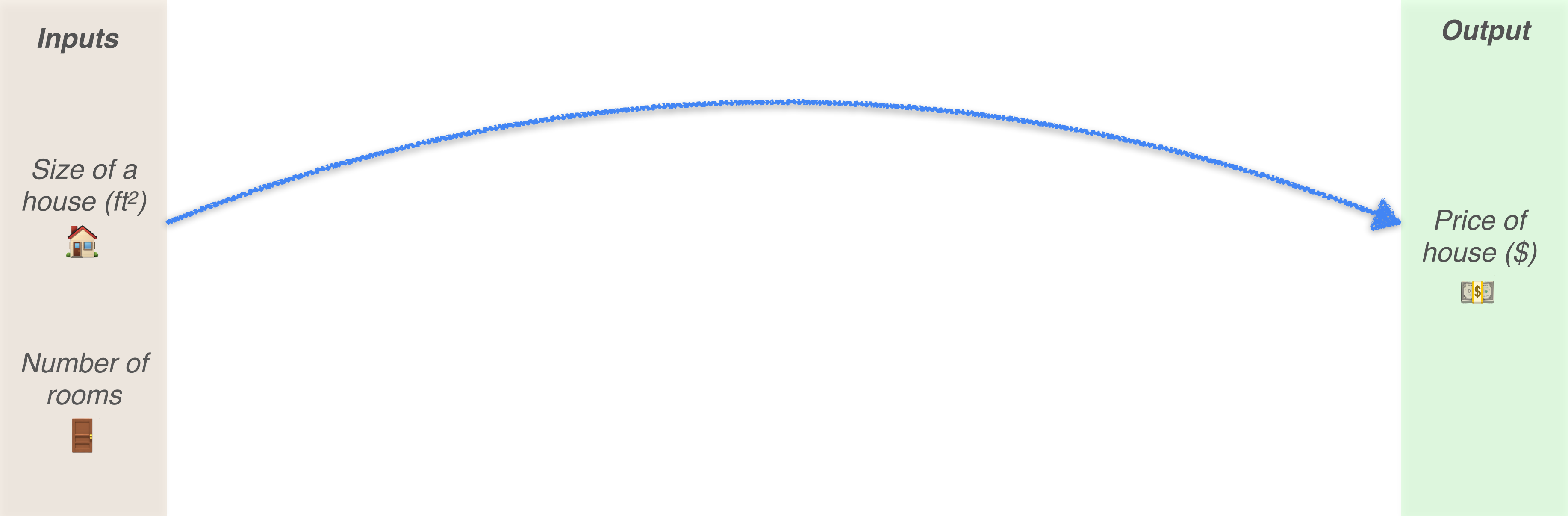
Size of a house (ft^2) 🏠

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^2) 🏠

Number of rooms 🚪

Output

Price of house ($) 💵

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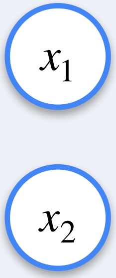
Regression With a Perceptron

Single Layer Neural Network Perceptron

Inputs

Size of a house (ft^2) 🏠

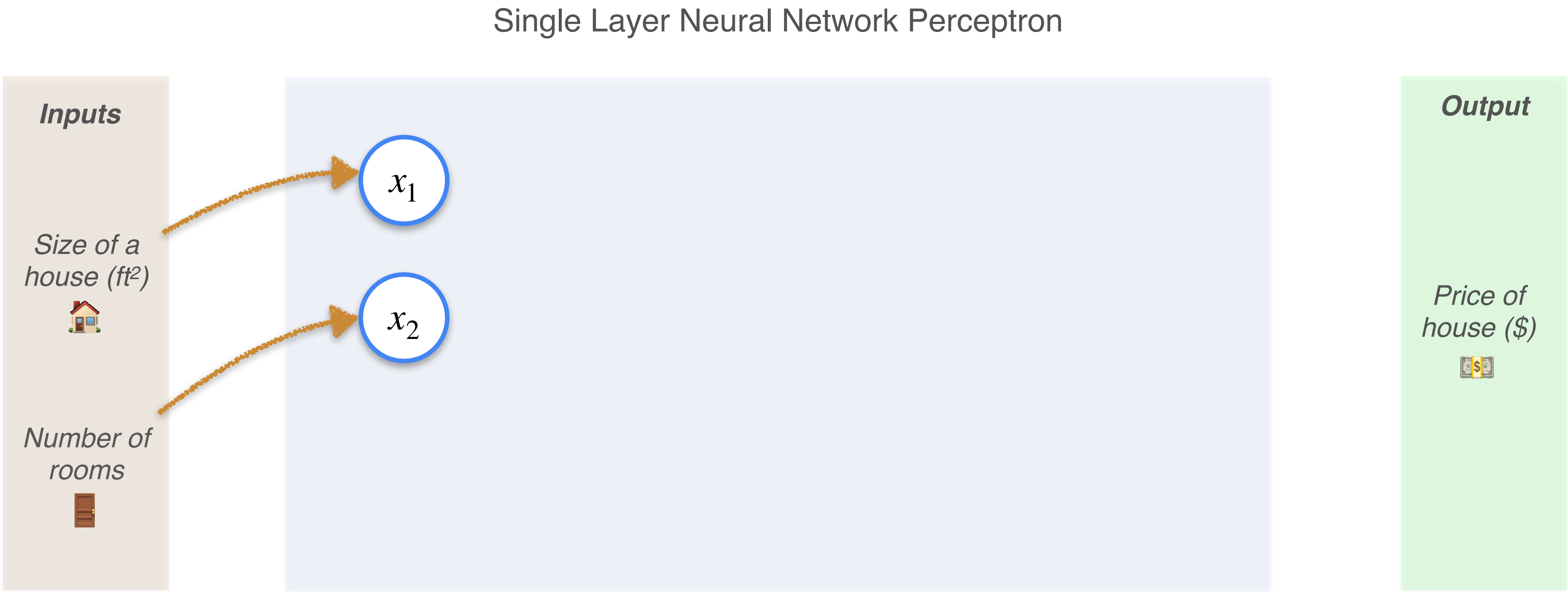
Number of rooms 🚪



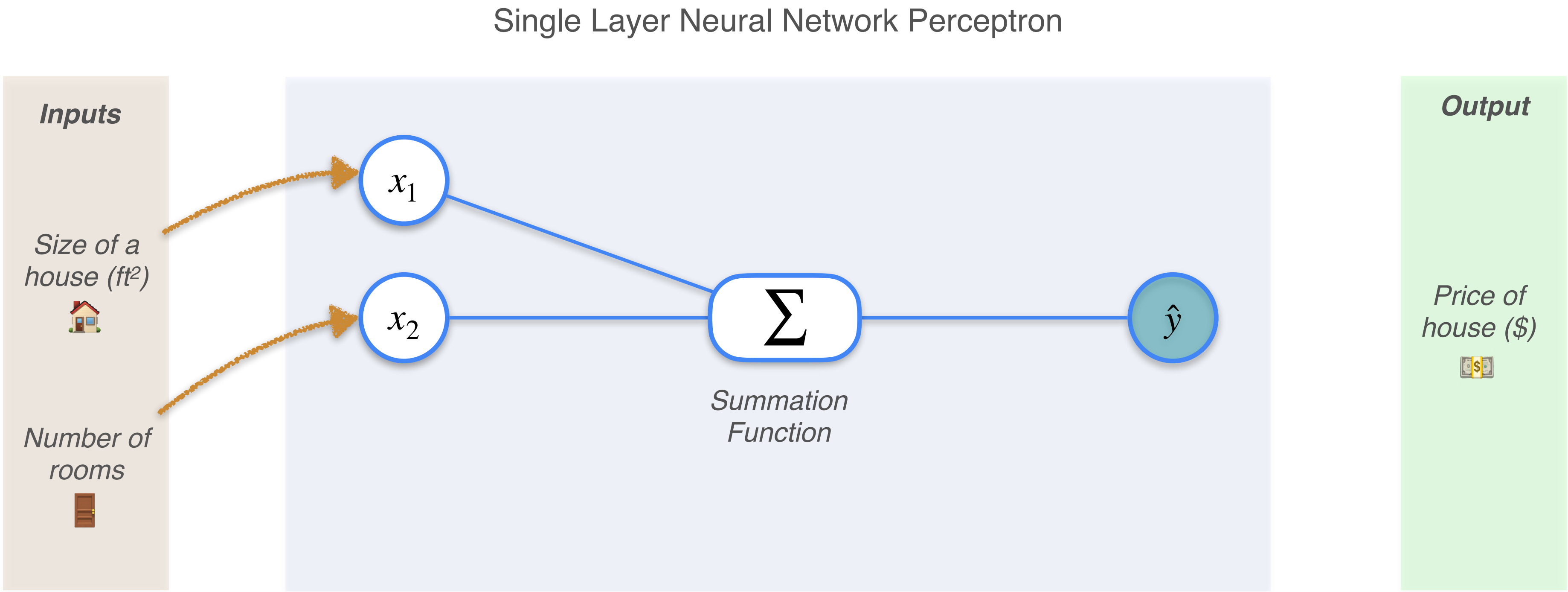
Output

Price of house (\$) 💵

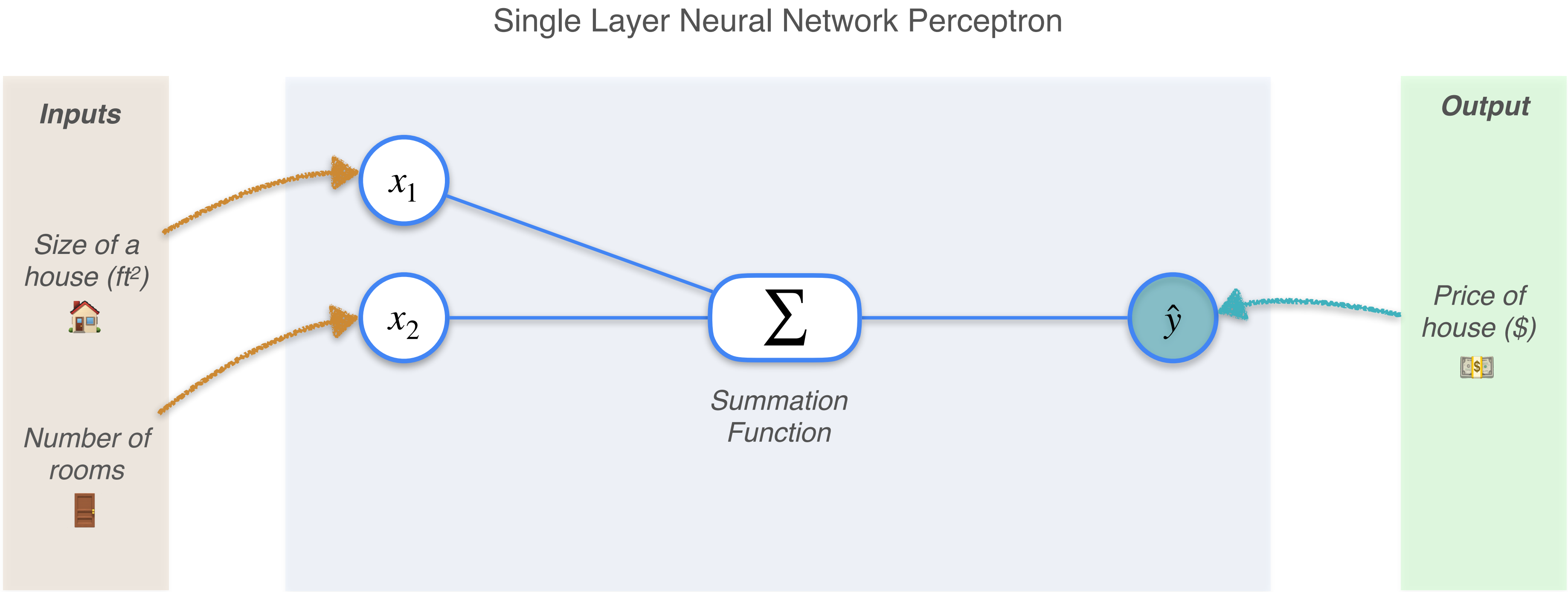
Regression With a Perceptron



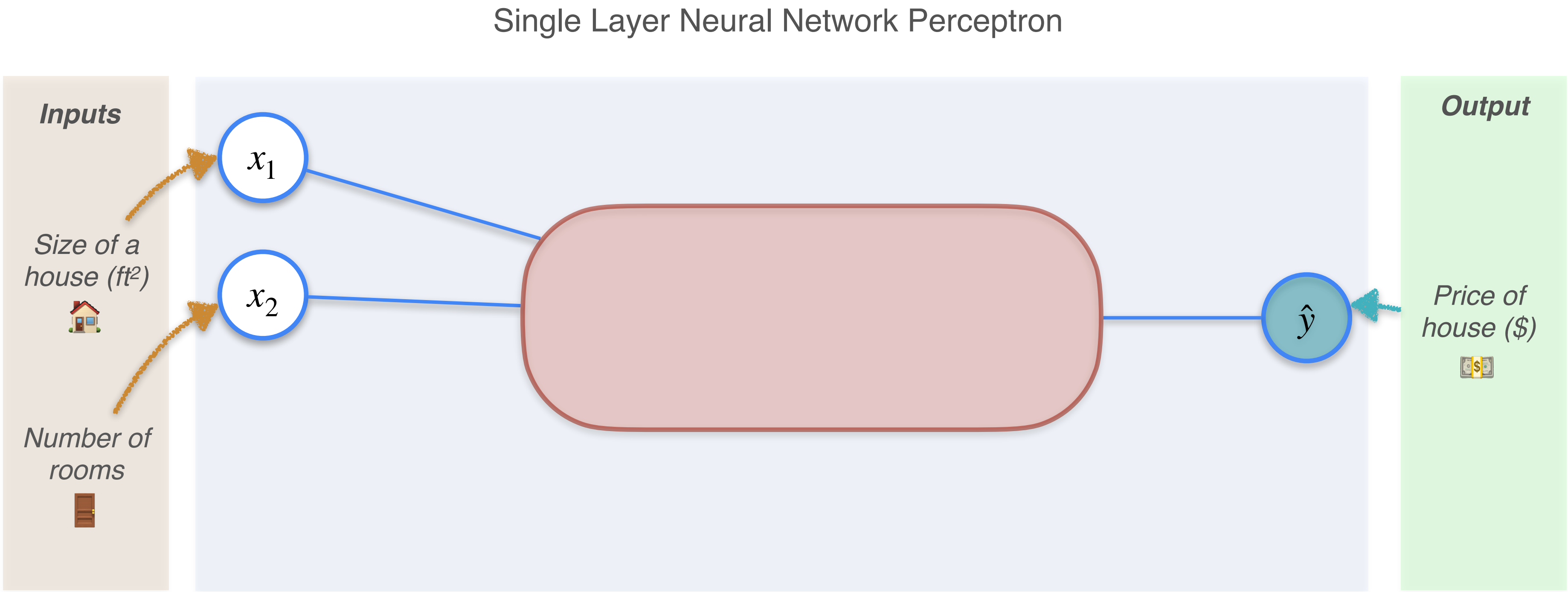
Regression With a Perceptron



Regression With a Perceptron

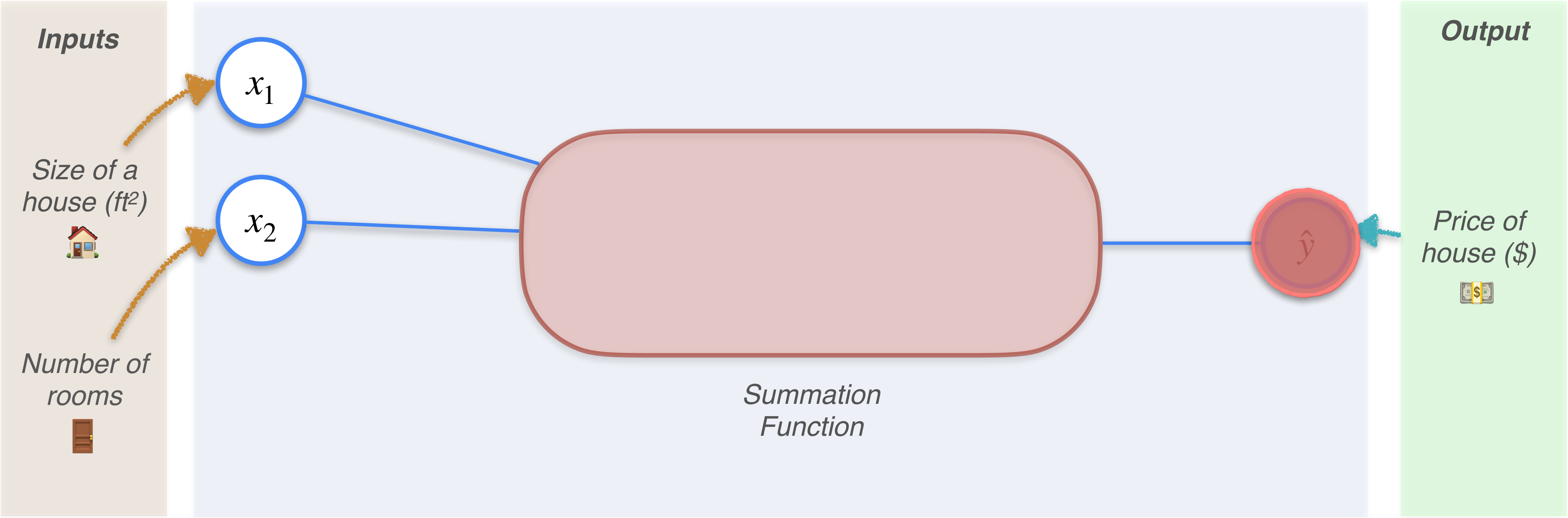


Regression With a Perceptron



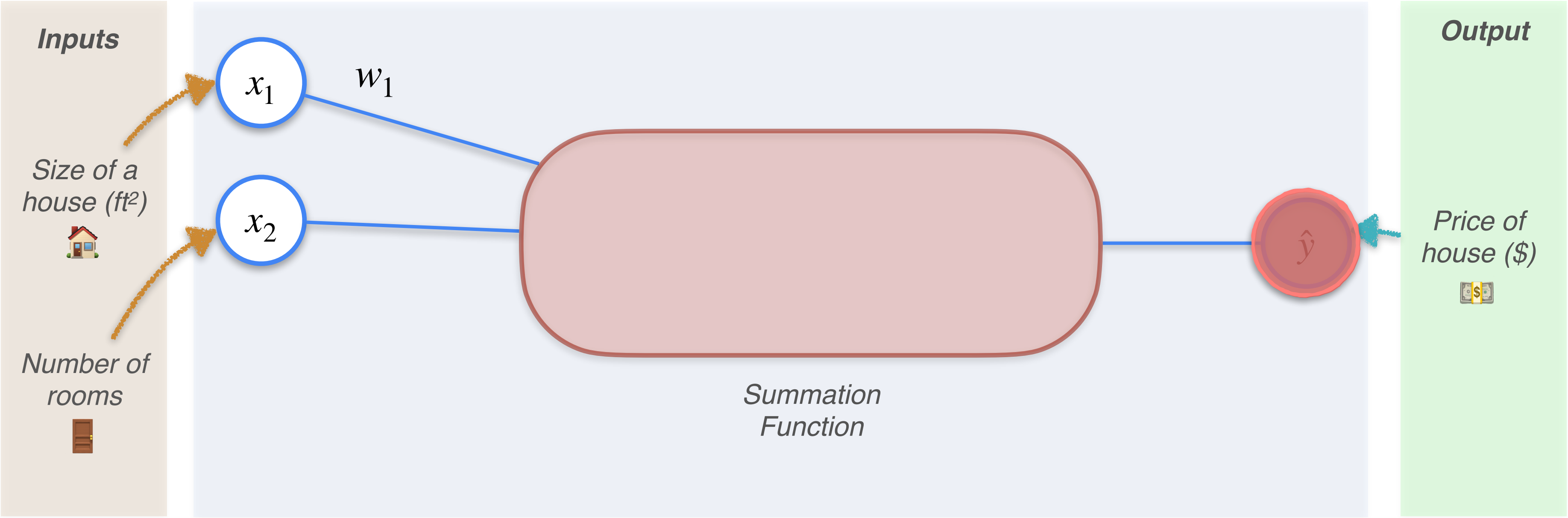
Regression With a Perceptron

Single Layer Neural Network Perceptron

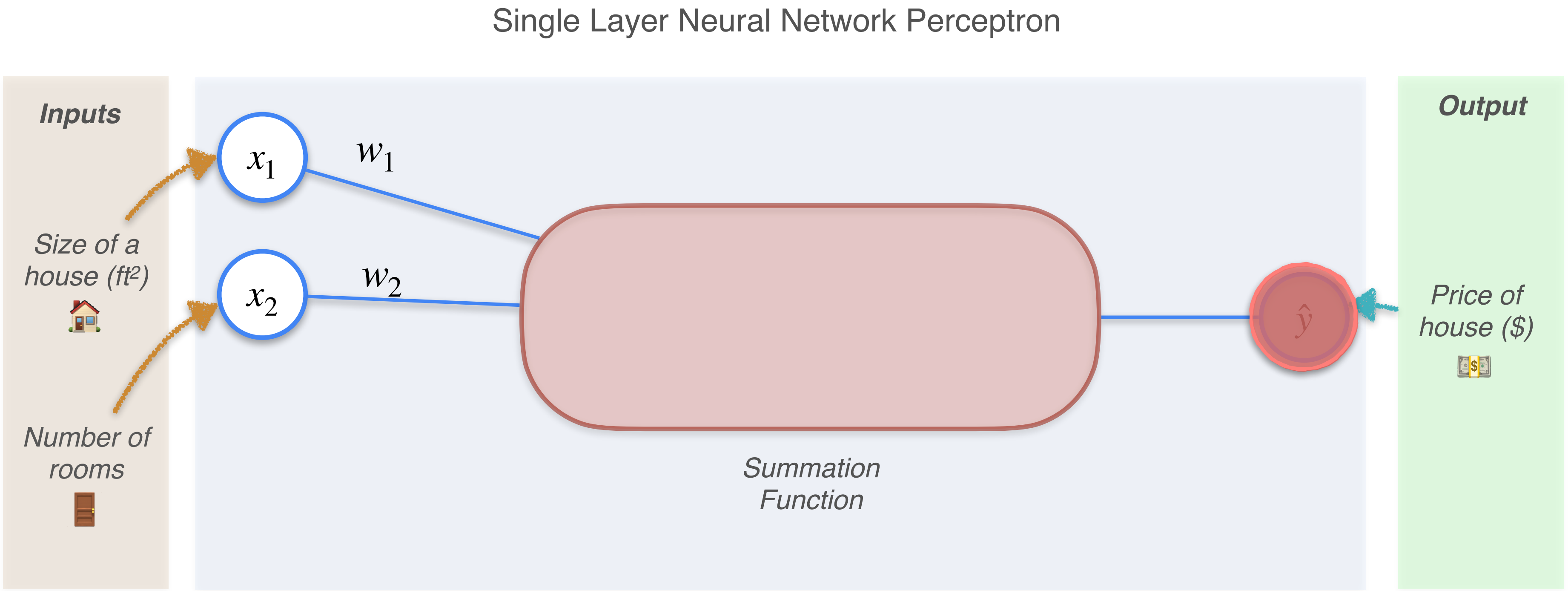


Regression With a Perceptron

Single Layer Neural Network Perceptron

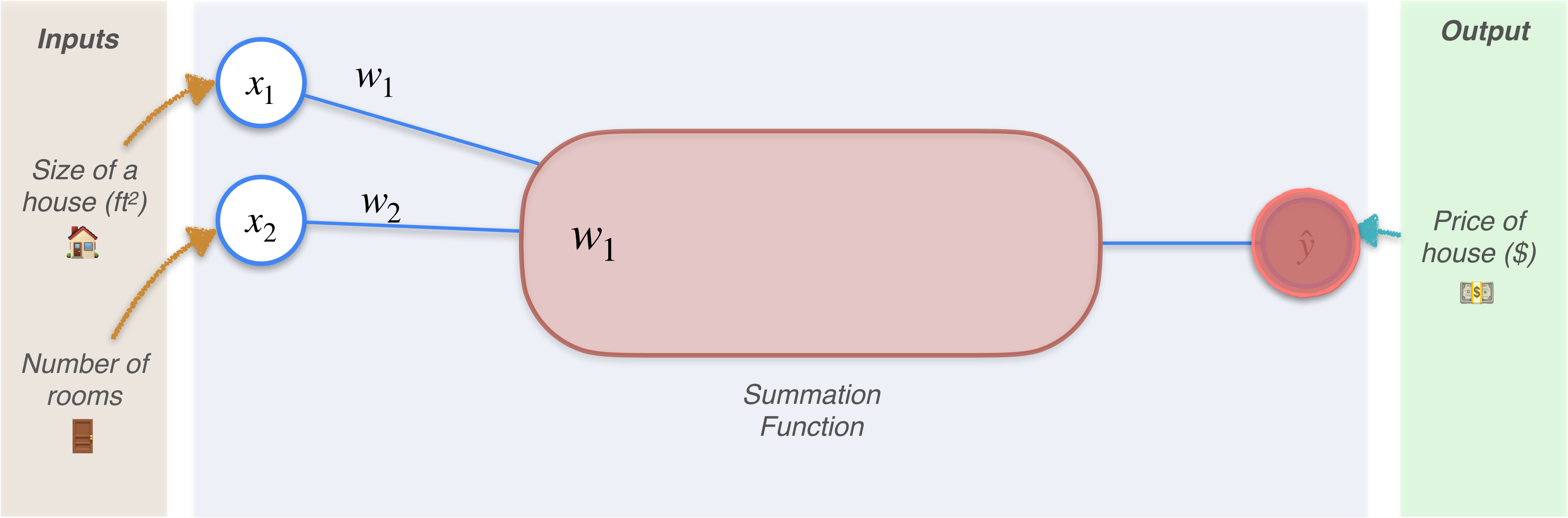


Regression With a Perceptron

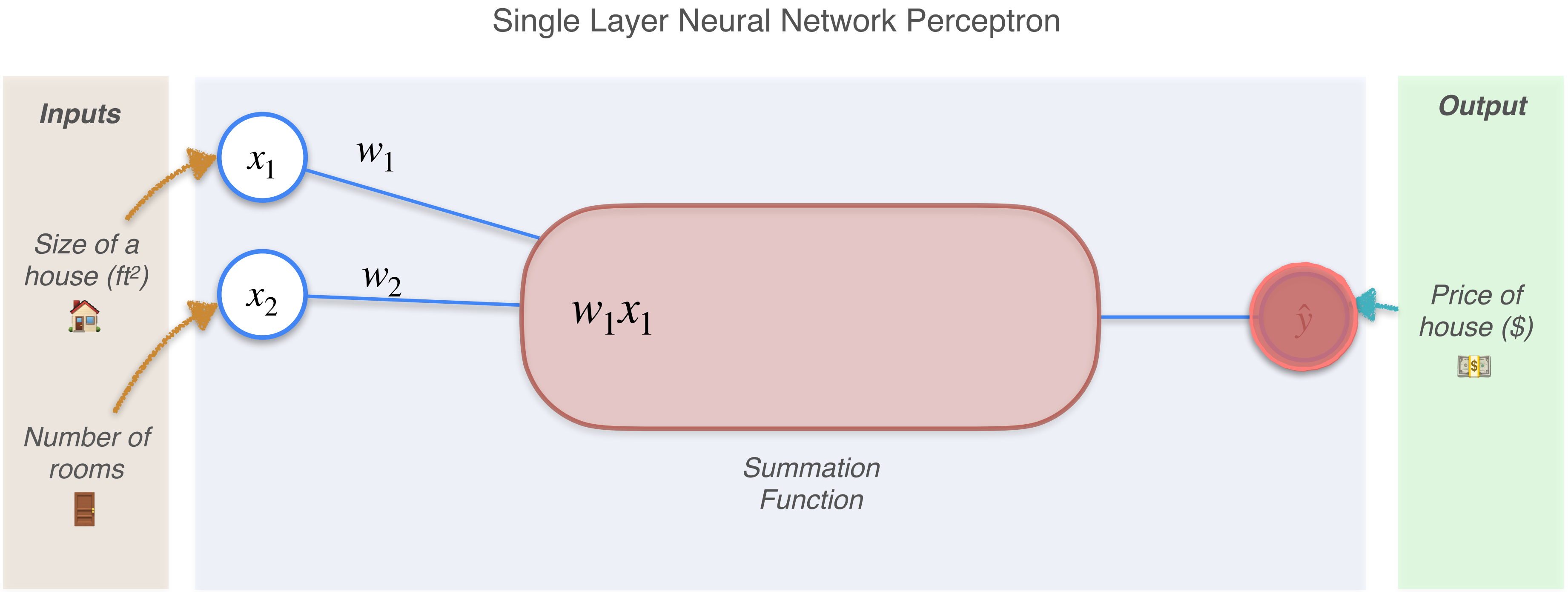


Regression With a Perceptron

Single Layer Neural Network Perceptron

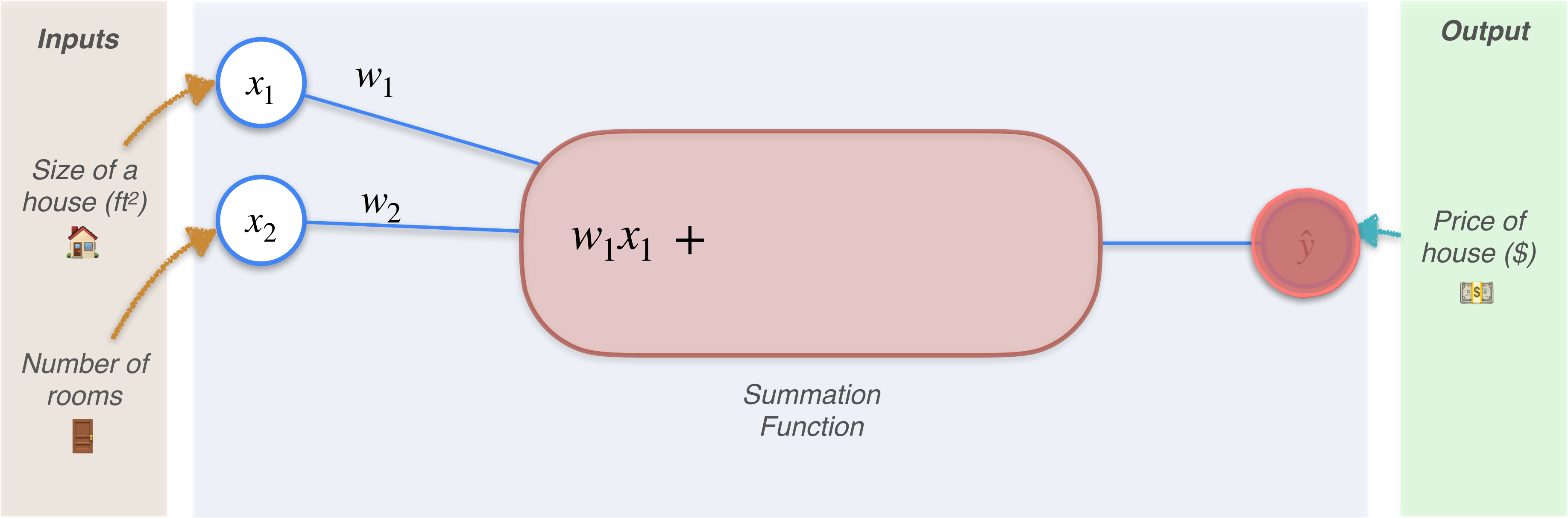


Regression With a Perceptron



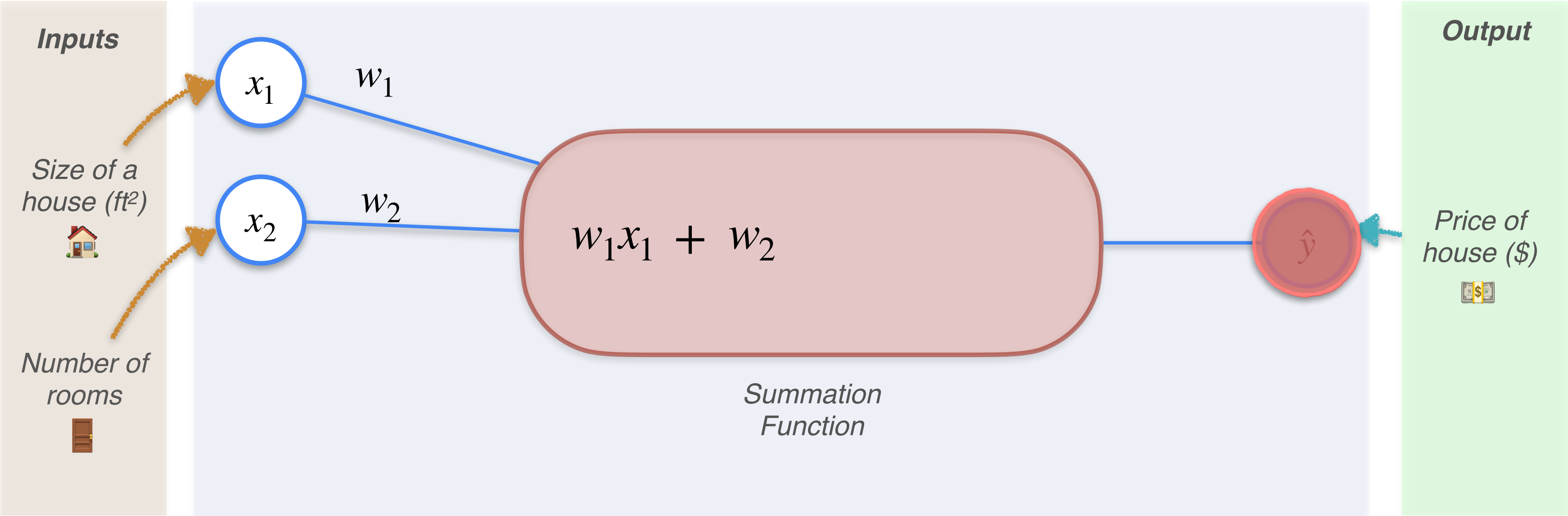
Regression With a Perceptron

Single Layer Neural Network Perceptron

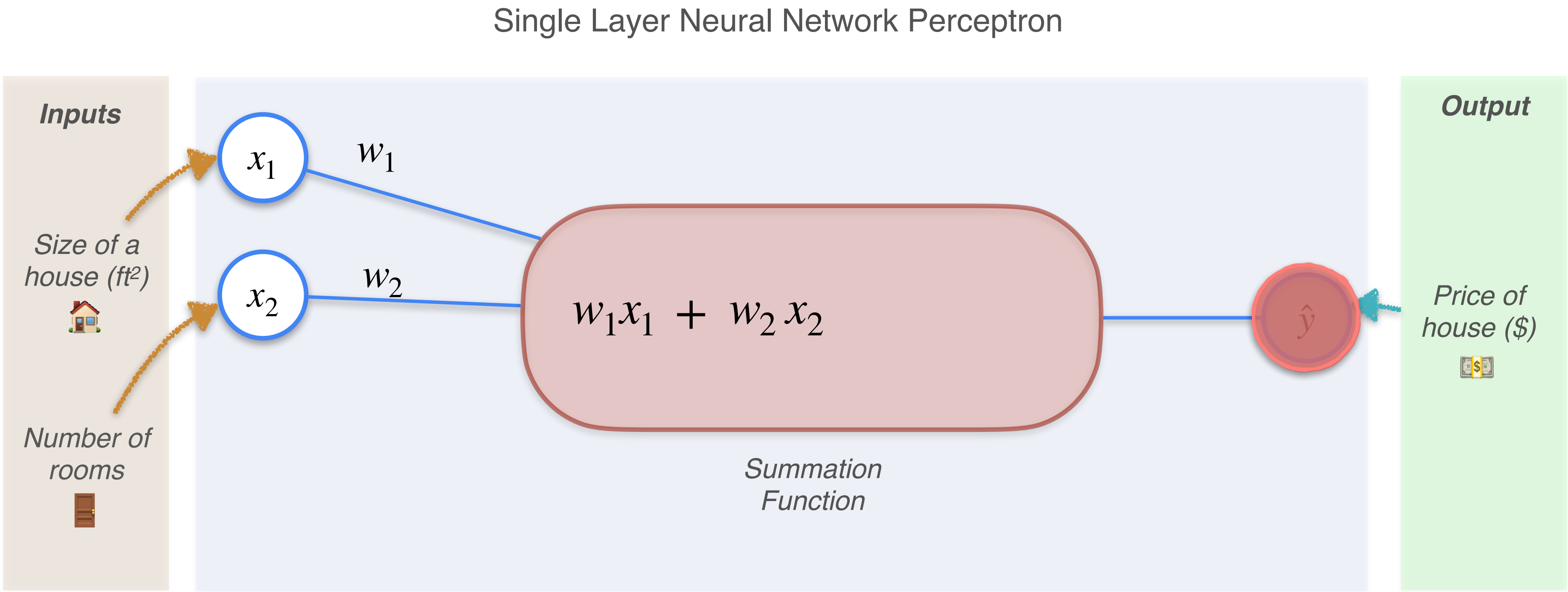


Regression With a Perceptron

Single Layer Neural Network Perceptron

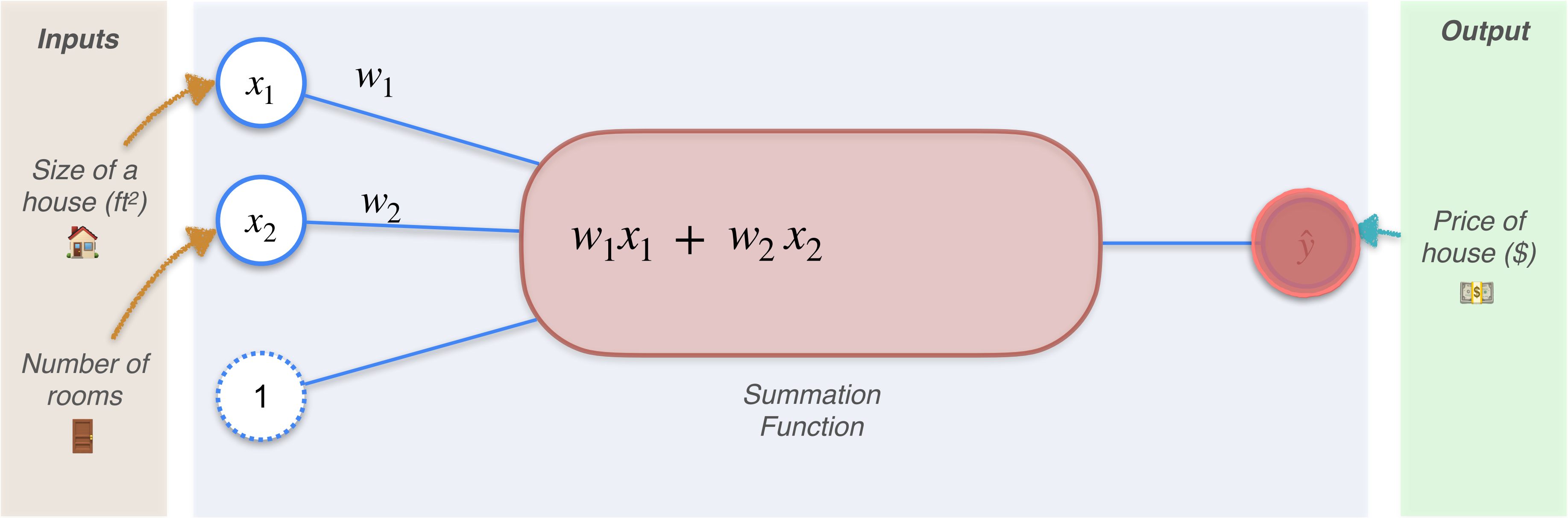


Regression With a Perceptron

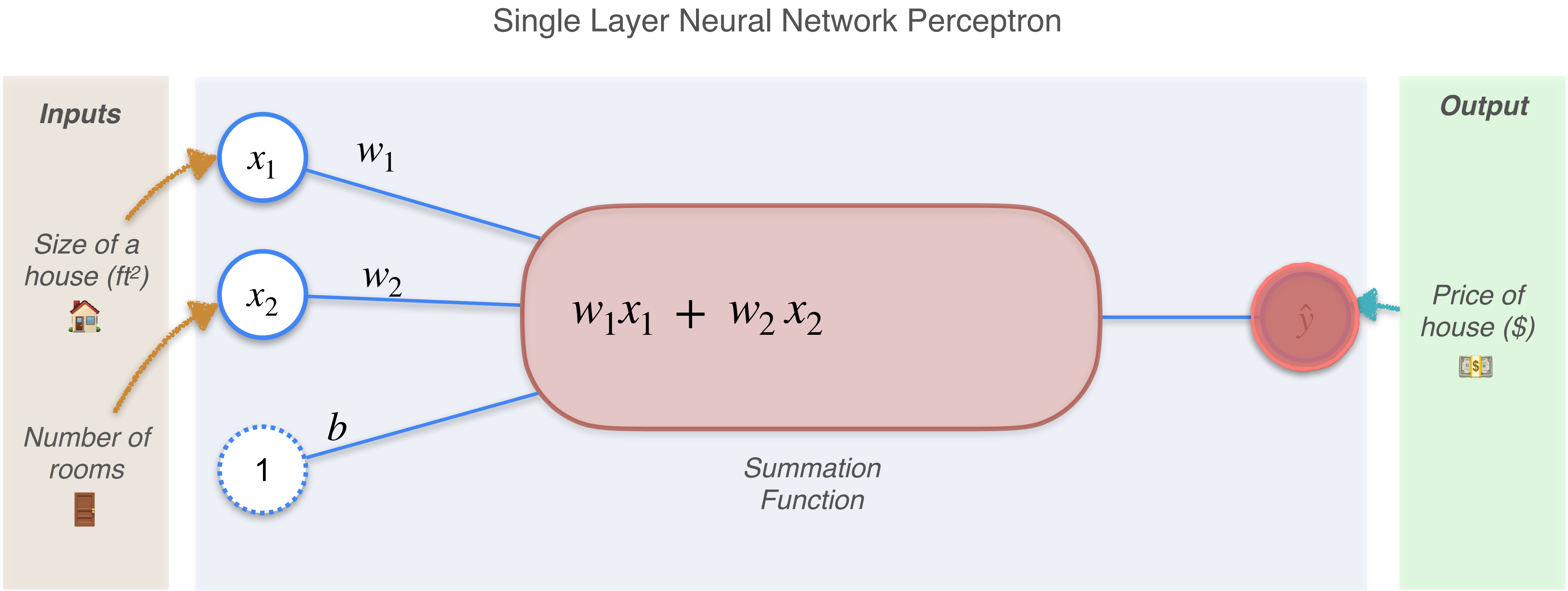


Regression With a Perceptron

Single Layer Neural Network Perceptron

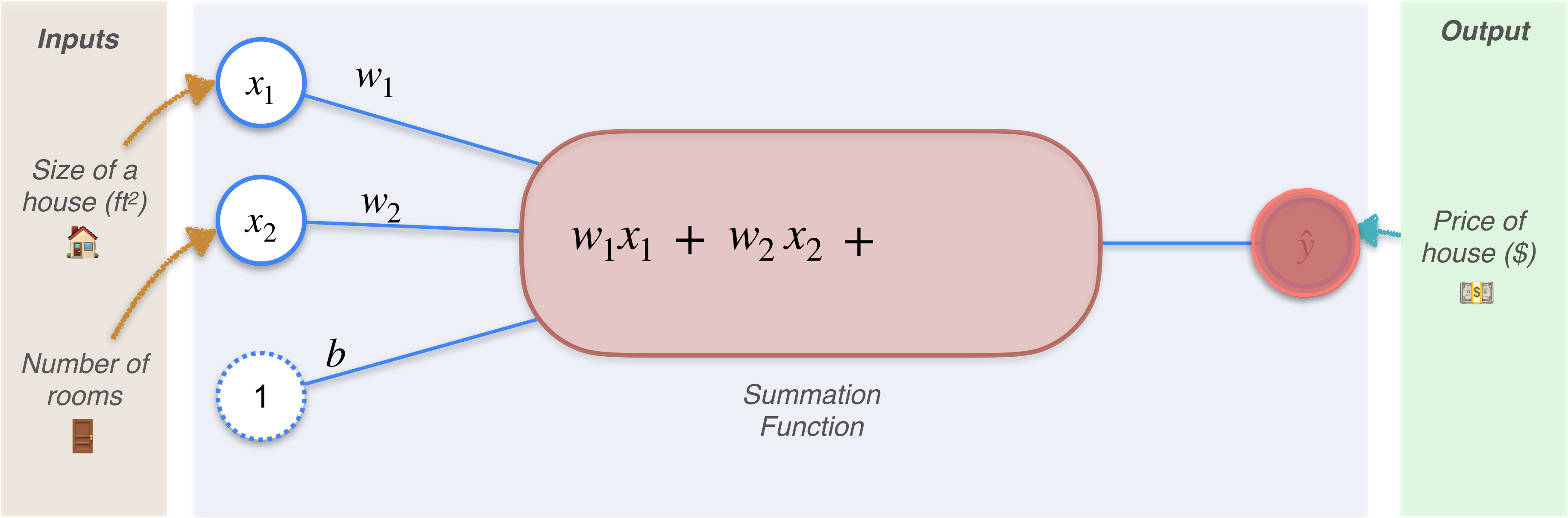


Regression With a Perceptron



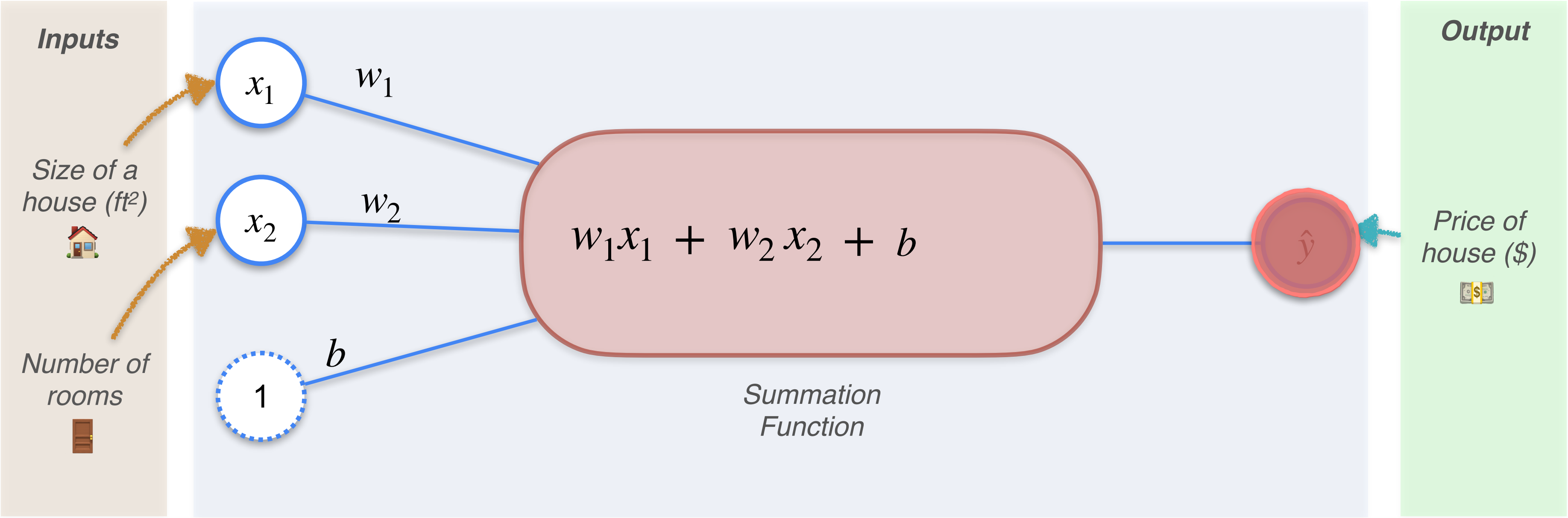
Regression With a Perceptron

Single Layer Neural Network Perceptron



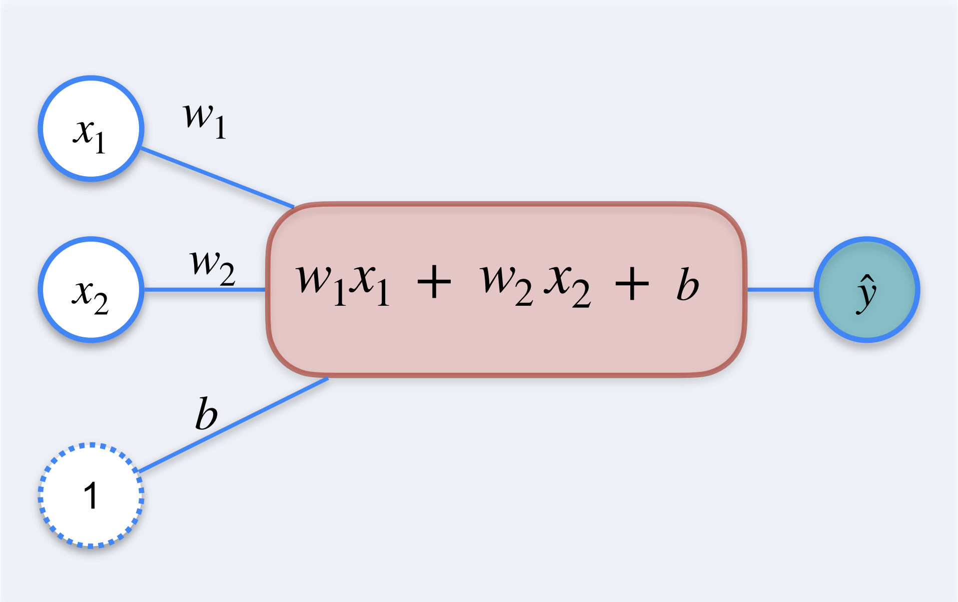
Regression With a Perceptron

Single Layer Neural Network Perceptron



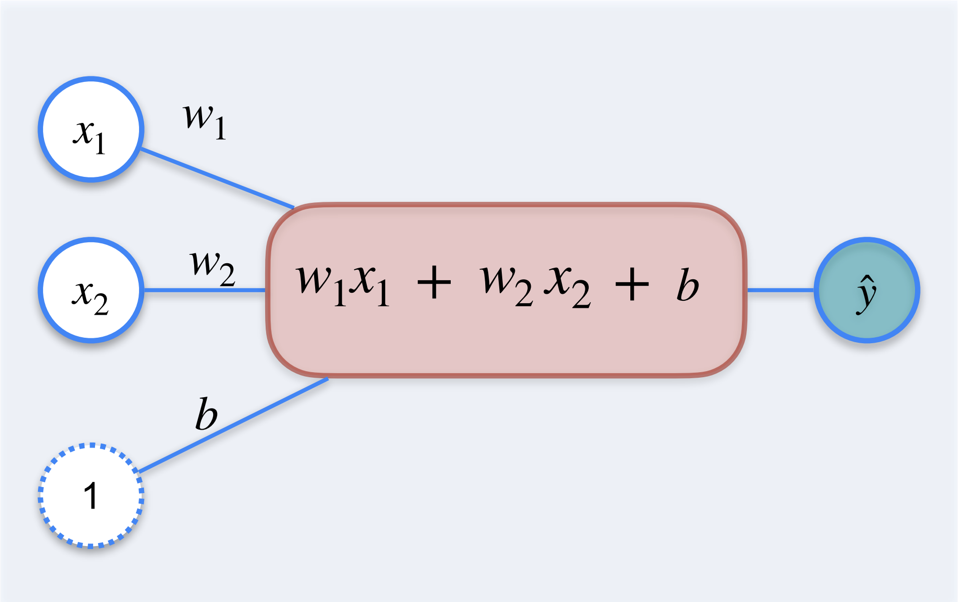
Regression With a Perceptron

Single Layer Neural Network Perceptron



Regression With a Perceptron

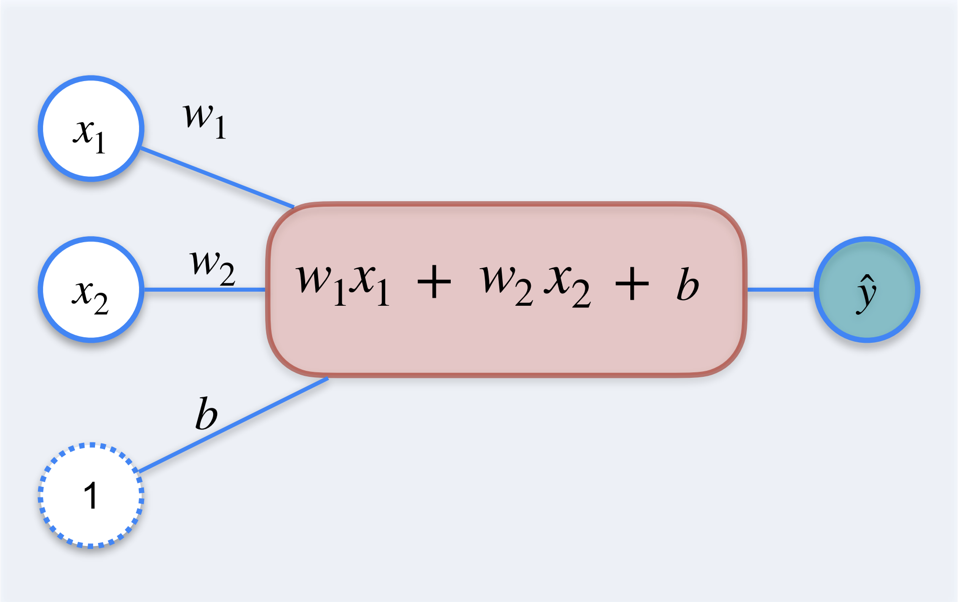
Single Layer Neural Network Perceptron



$\hat{y}$

Regression With a Perceptron

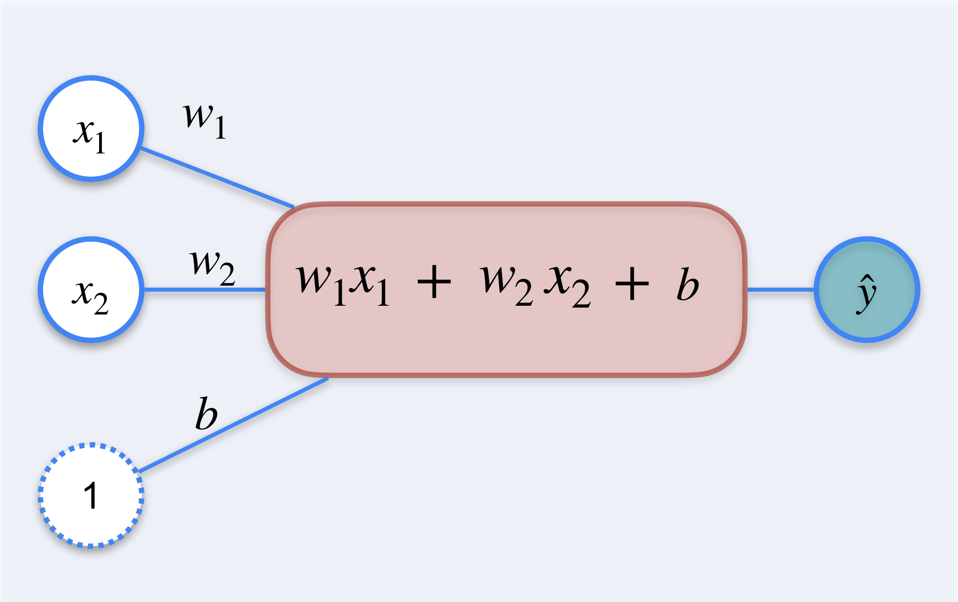
Single Layer Neural Network Perceptron



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

Regression With a Perceptron

Single Layer Neural Network Perceptron

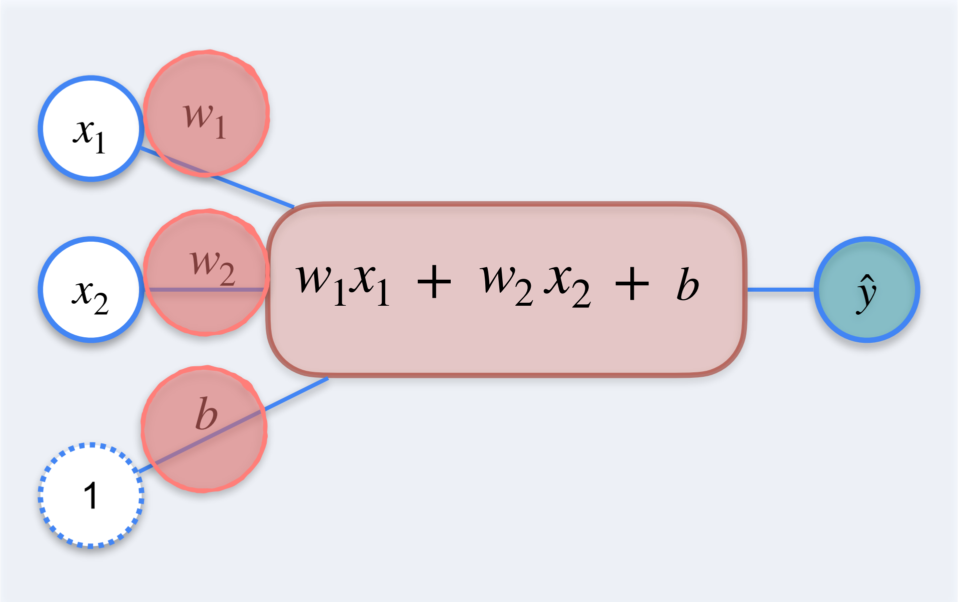


$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Main Goal:

Regression With a Perceptron

Single Layer Neural Network Perceptron

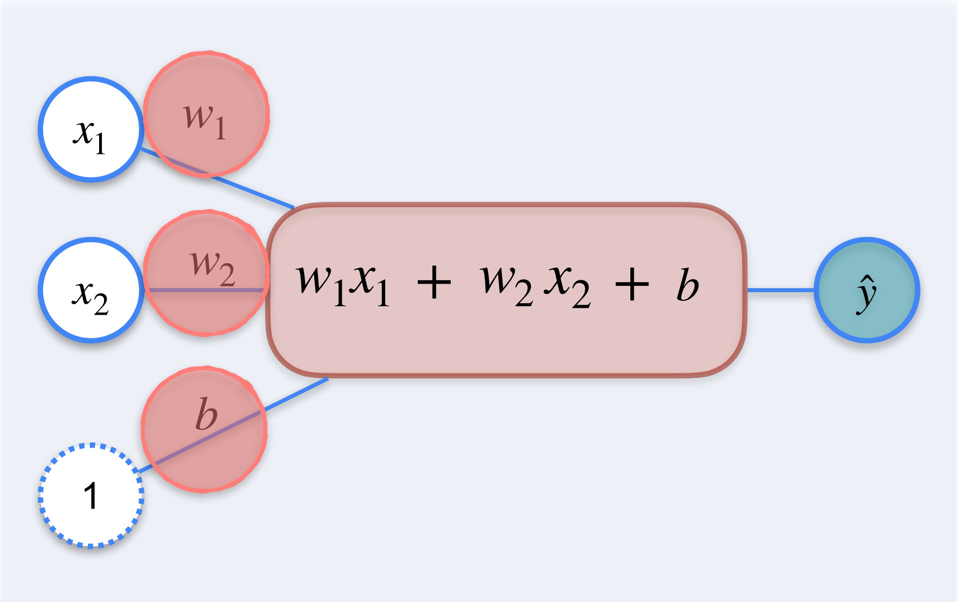


$$\hat{y} = w_1 x_1 + w_2 x_2 + b$$

Main Goal:

Regression With a Perceptron

Single Layer Neural Network Perceptron



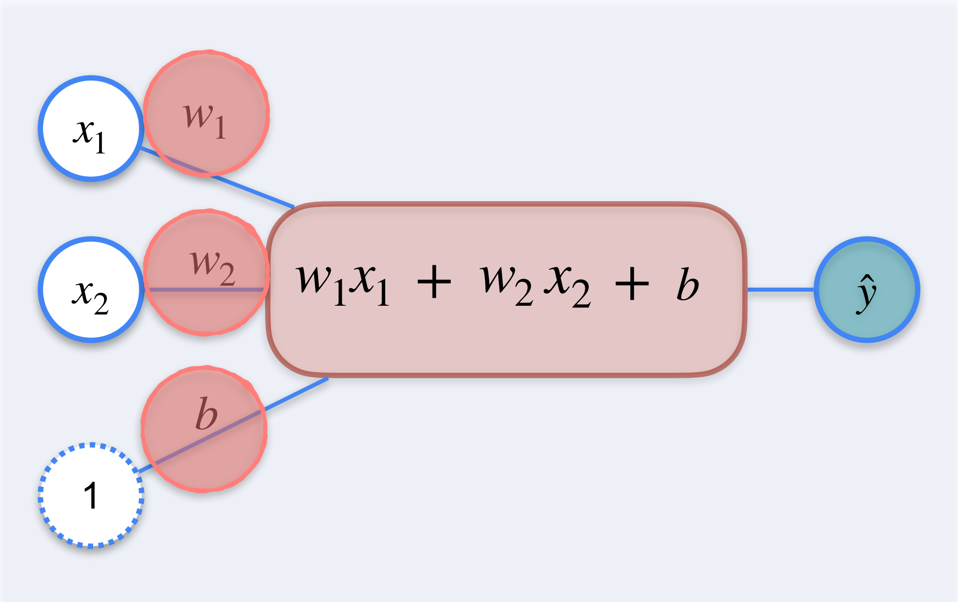
$$\hat{y} = w_1 x_1 + w_2 x_2 + b$$

Main Goal:

Find weights and bias that will optimise the predictions.

Regression With a Perceptron

Single Layer Neural Network Perceptron



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

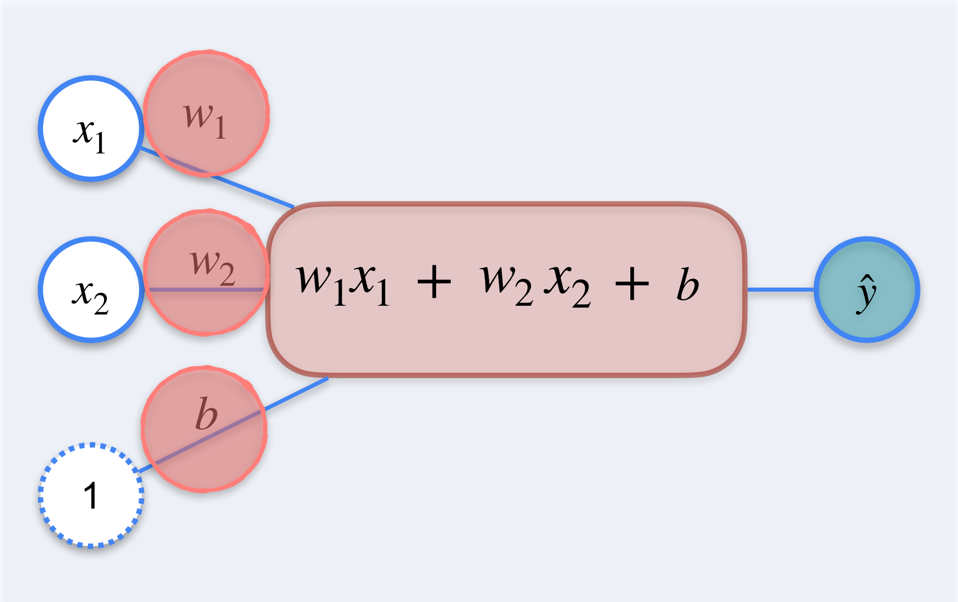
Main Goal:

Find weights and bias that will optimise the predictions.

ie. Reduce the errors in the predictions

Regression With a Perceptron

Single Layer Neural Network Perceptron



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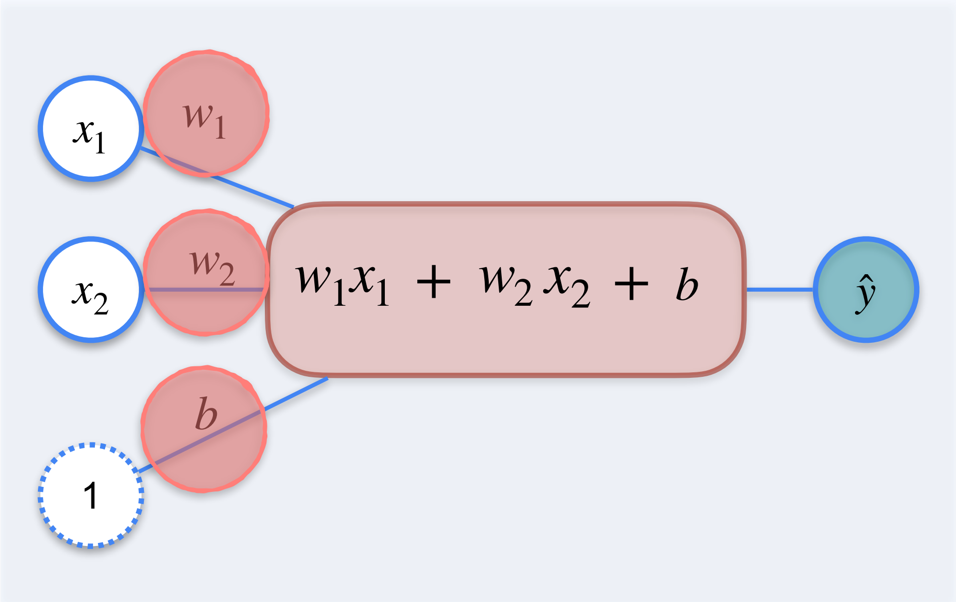
Regression With a Perceptron

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.

ie. Reduce the errors in the predictions

The Loss Function

DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Regression with a perceptron: Loss function

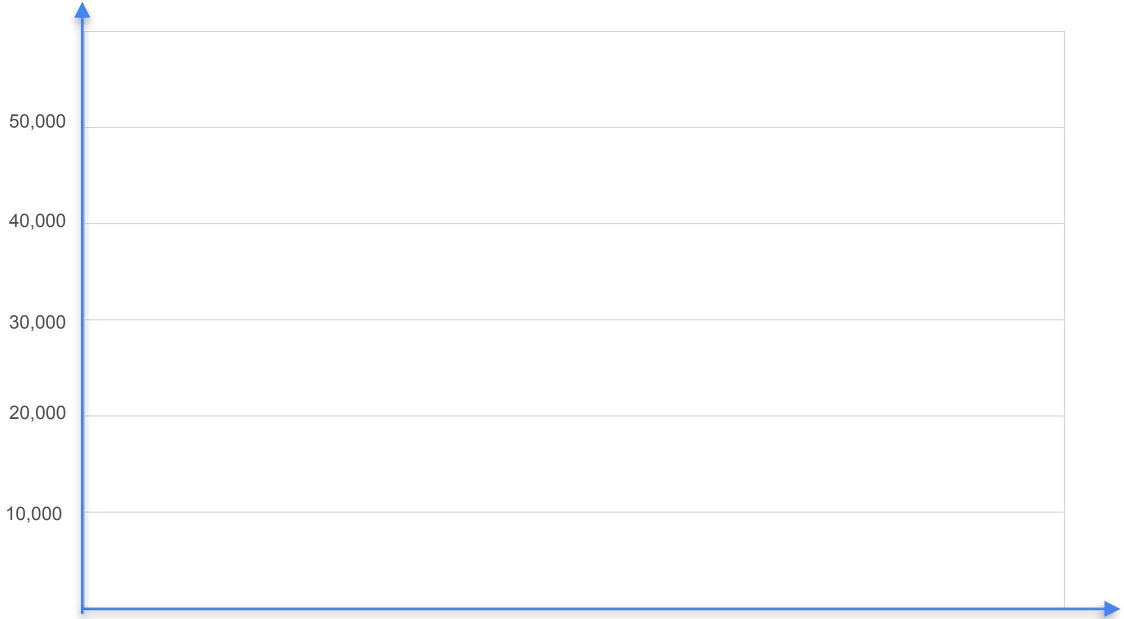
Mean Squared Error

Mean Squared Error

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

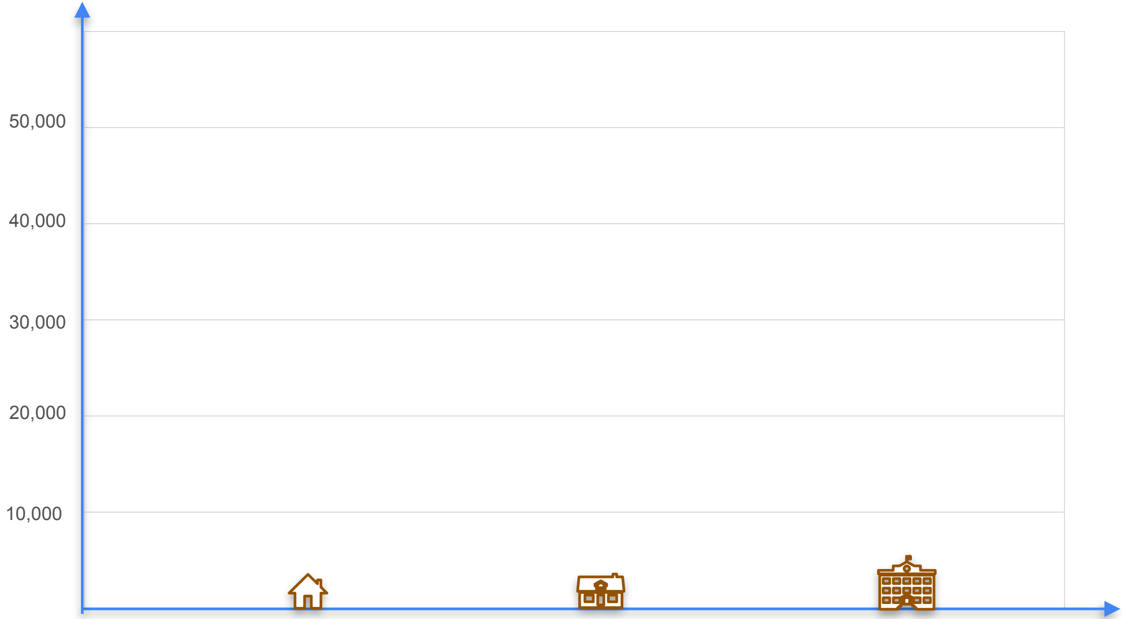
Mean Squared Error

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



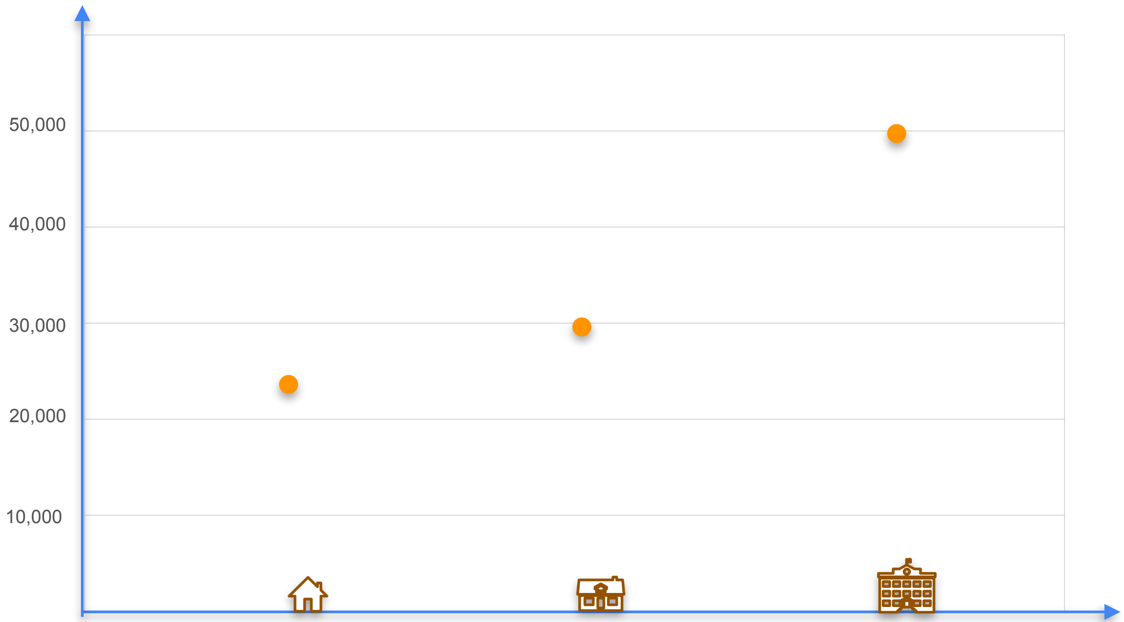
Mean Squared Error

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



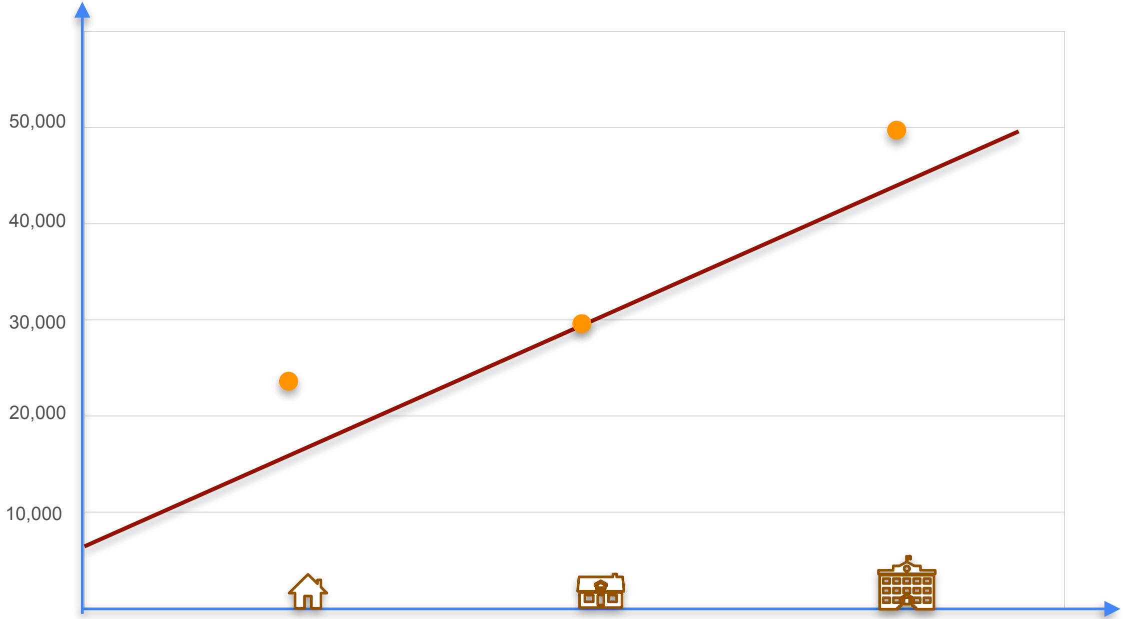
Mean Squared Error

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



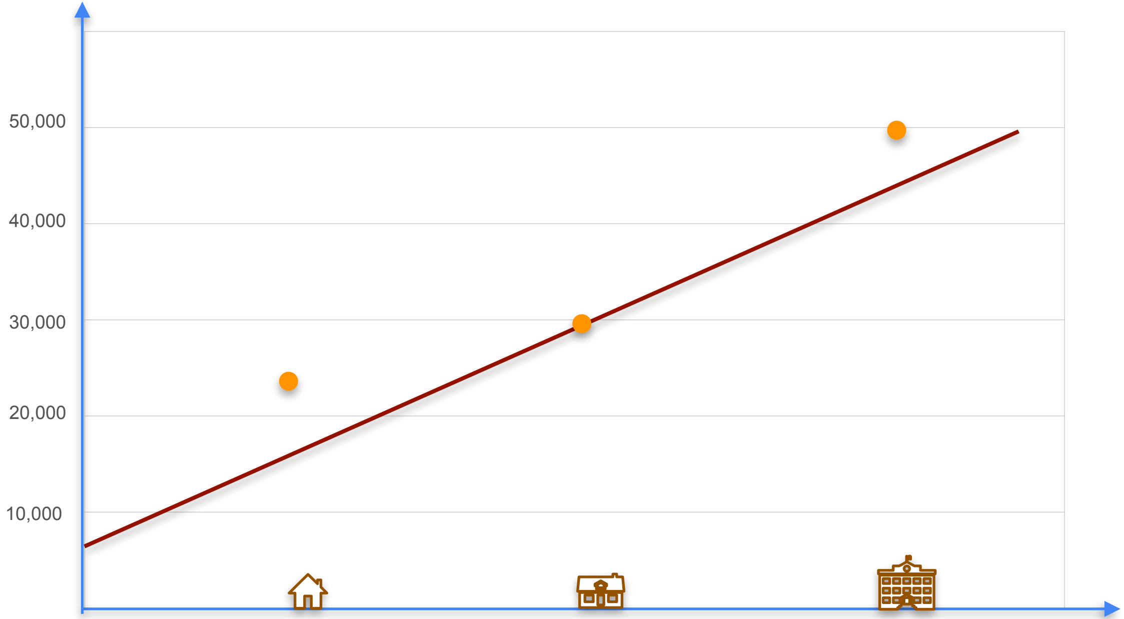
Mean Squared Error

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



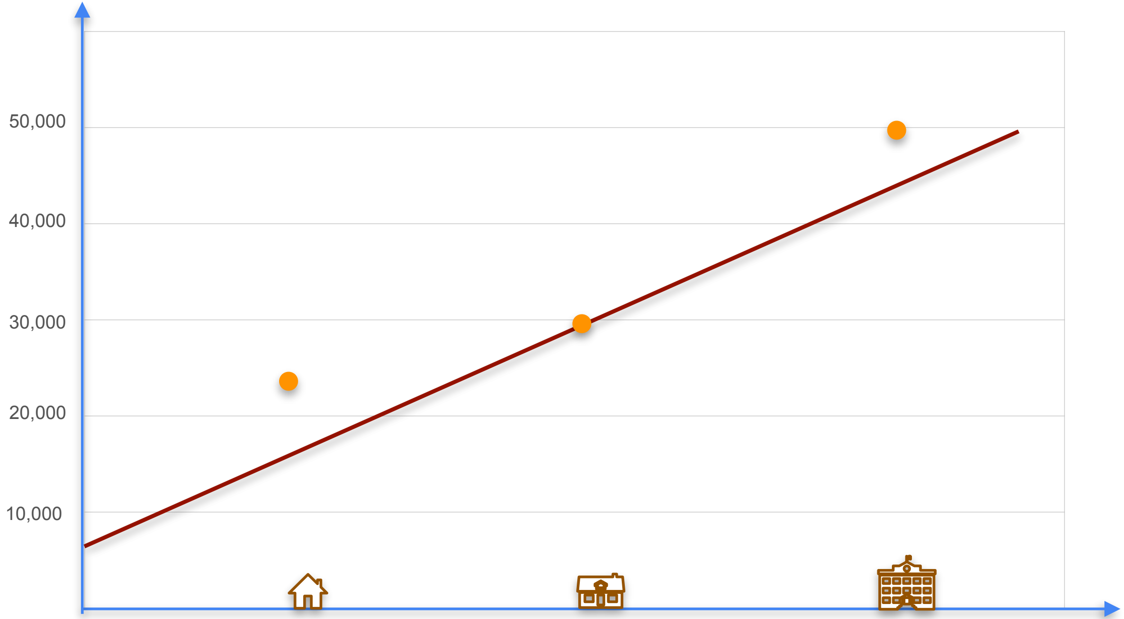
Mean Squared Error

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



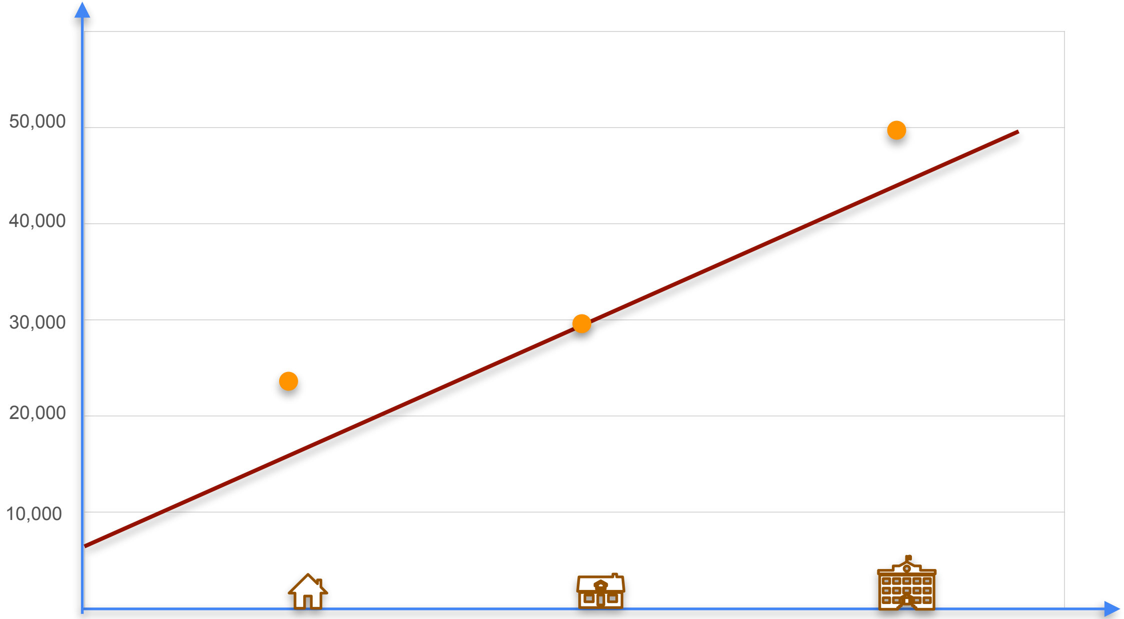
Mean Squared Error

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



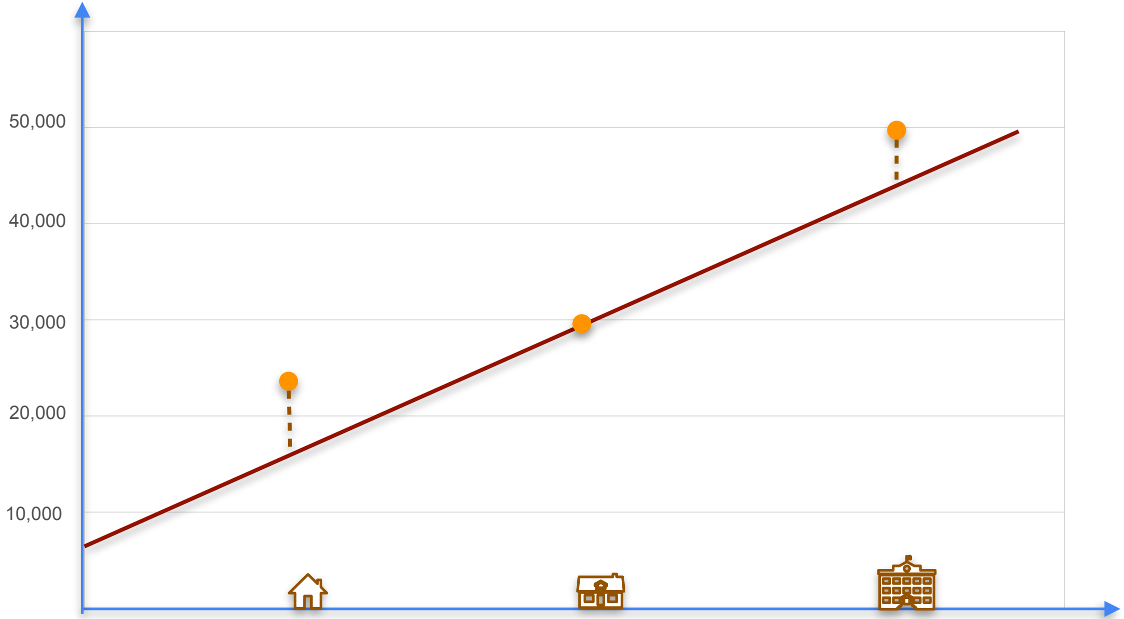
Mean Squared Error

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



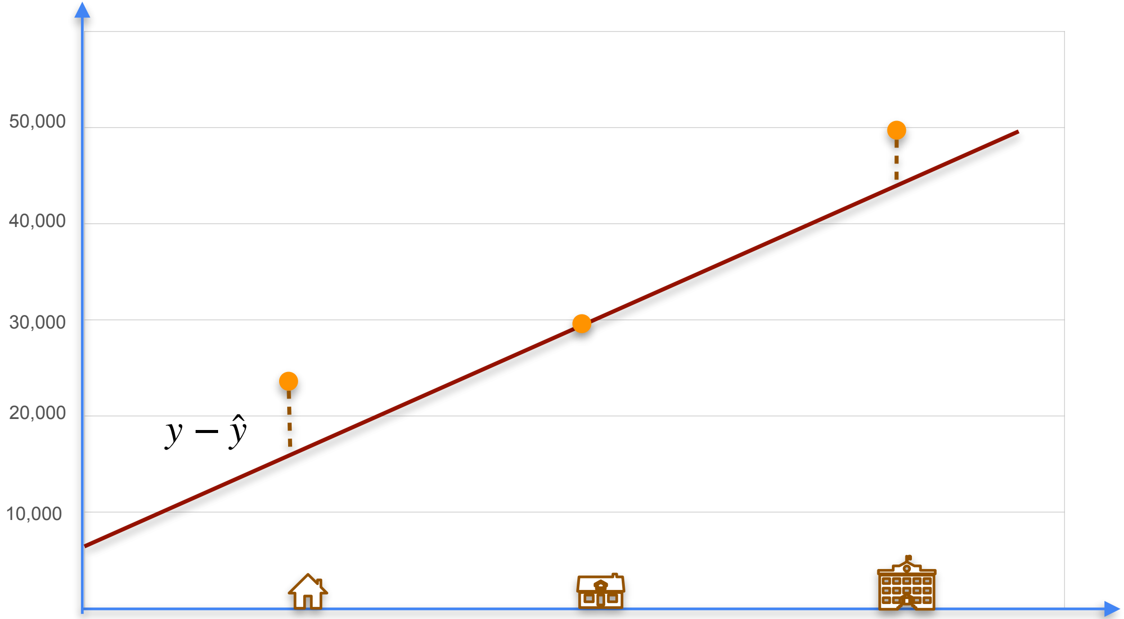
Mean Squared Error

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



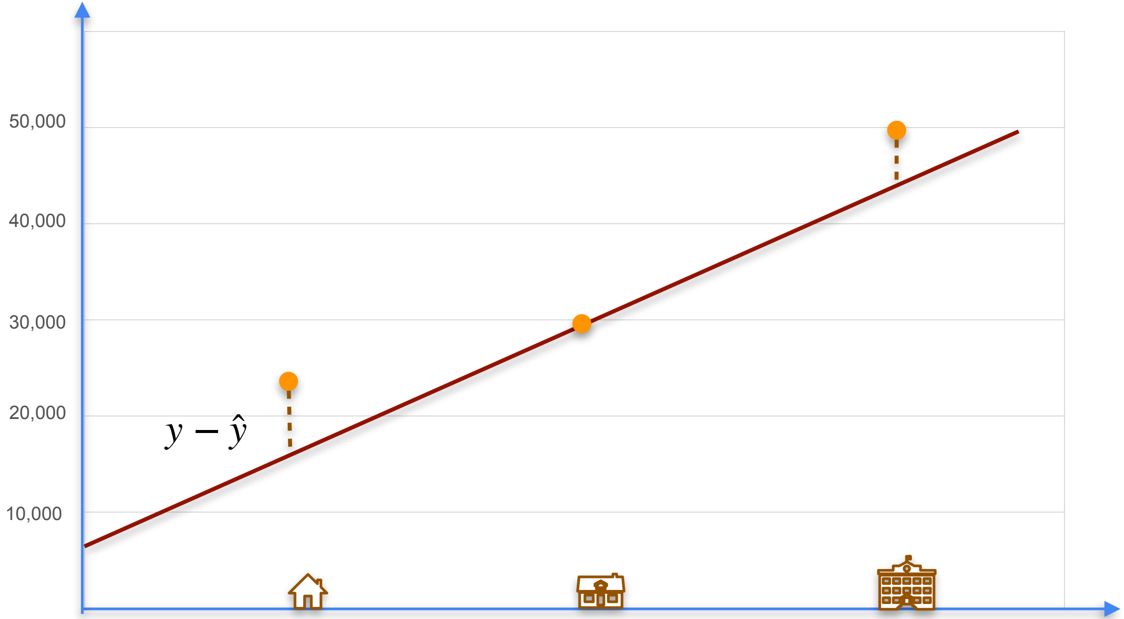
Mean Squared Error

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



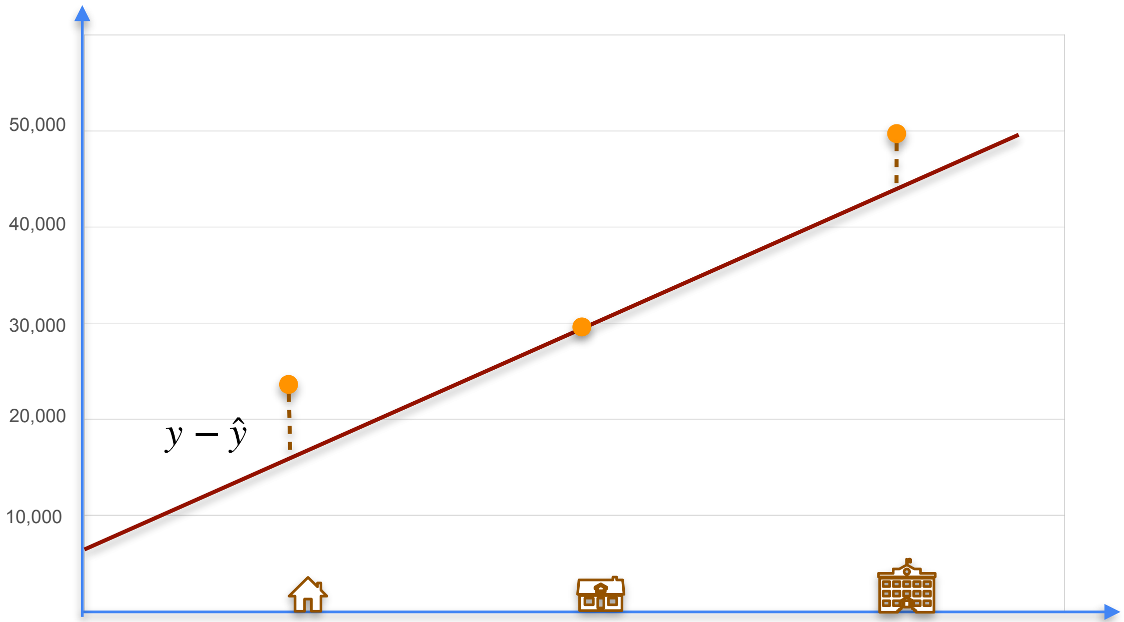
Mean Squared Error

	y	$\hat{y}$	$(y - \hat{y})^2$
	$20,000	*$15,000*	***Error***
	$30,000	*$30,000*	***Error***
	$50,000	*$45,000*	***Error***



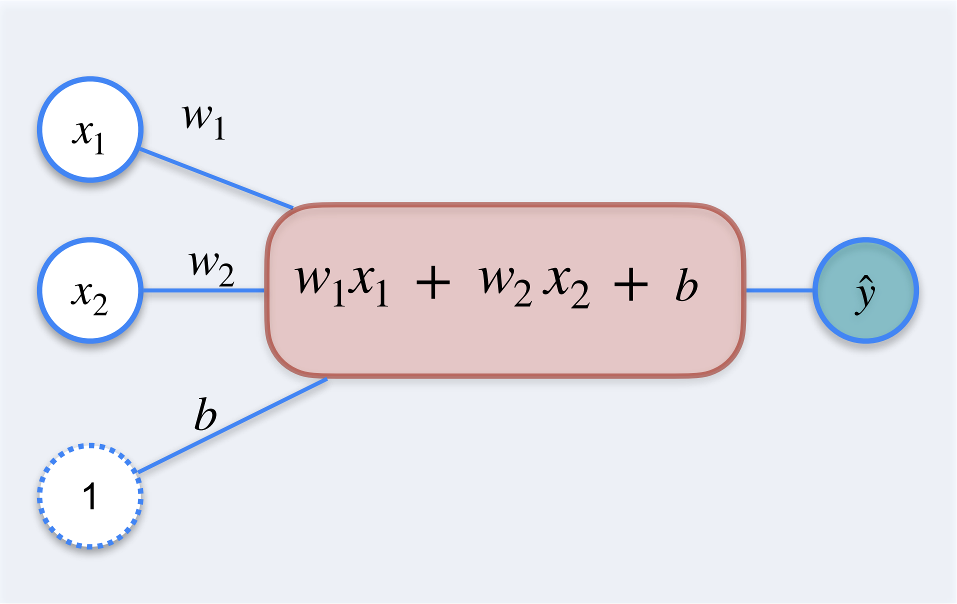
Mean Squared Error

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



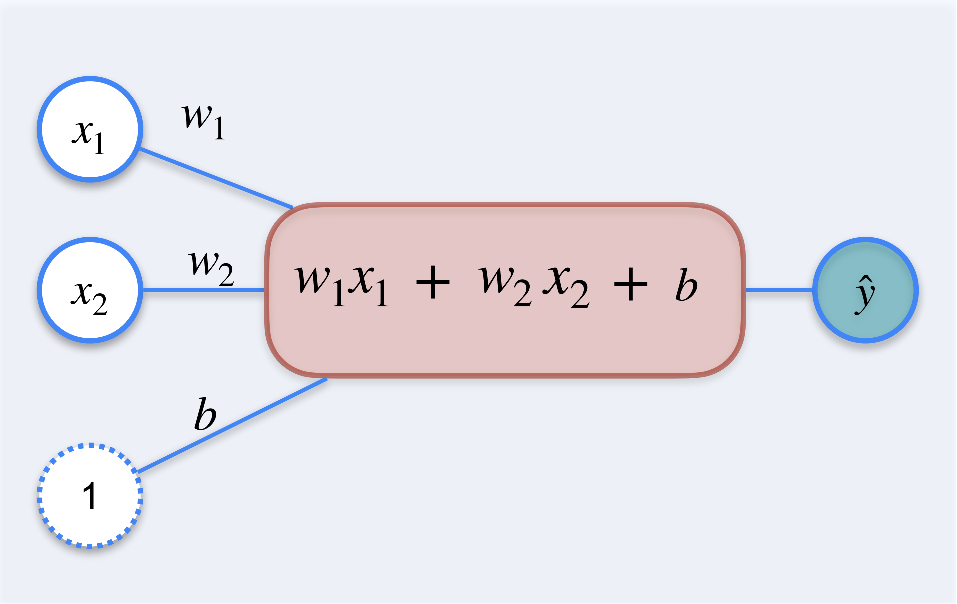
Regression With a Perceptron

Single Layer Neural Network Perceptron



Regression With a Perceptron

Single Layer Neural Network Perceptron

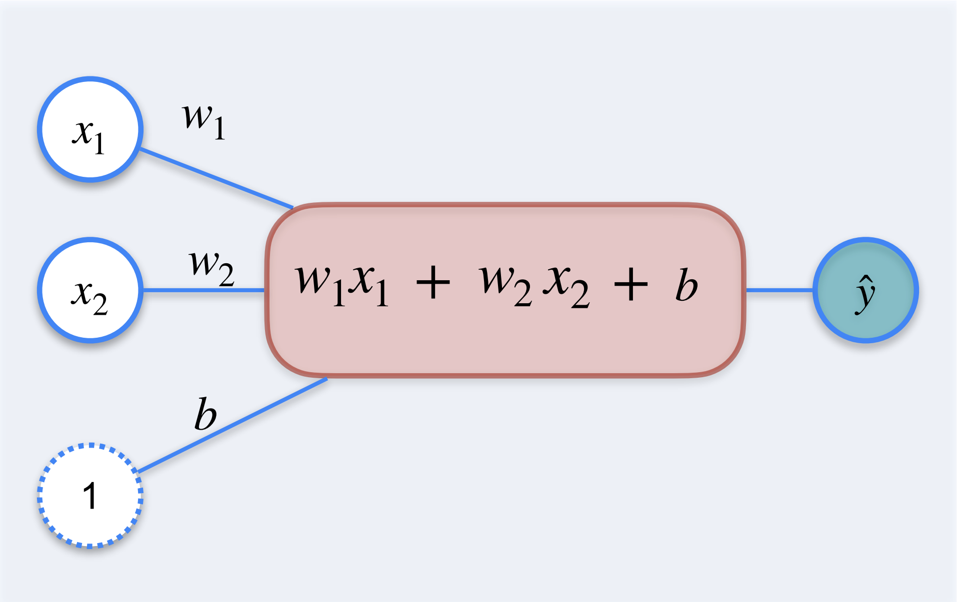


Prediction Function:

$\hat{y}$

Regression With a Perceptron

Single Layer Neural Network Perceptron

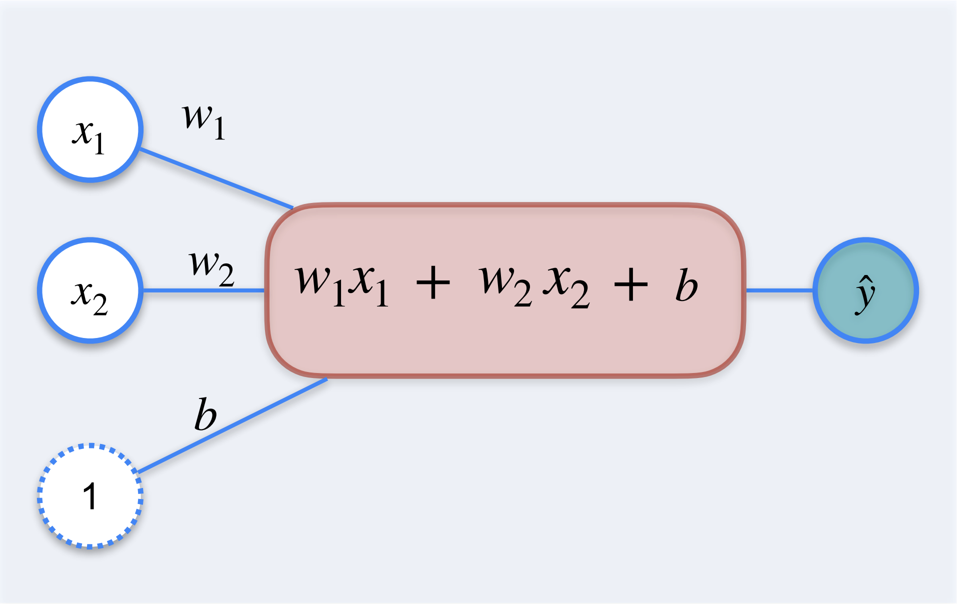


Prediction Function:

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

Regression With a Perceptron

Single Layer Neural Network Perceptron



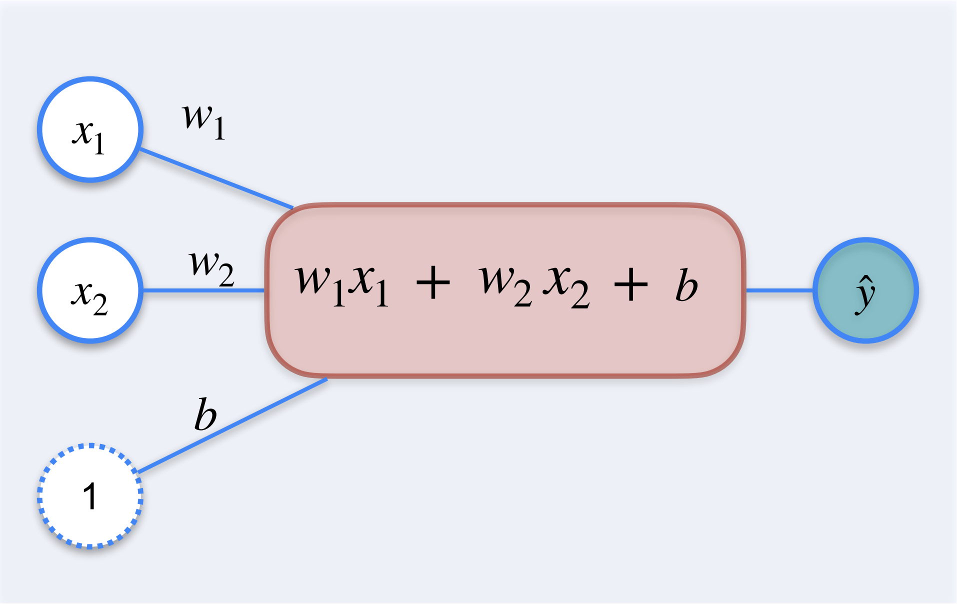
Prediction Function:

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

Loss Function:

Regression With a Perceptron

Single Layer Neural Network Perceptron



Prediction Function:

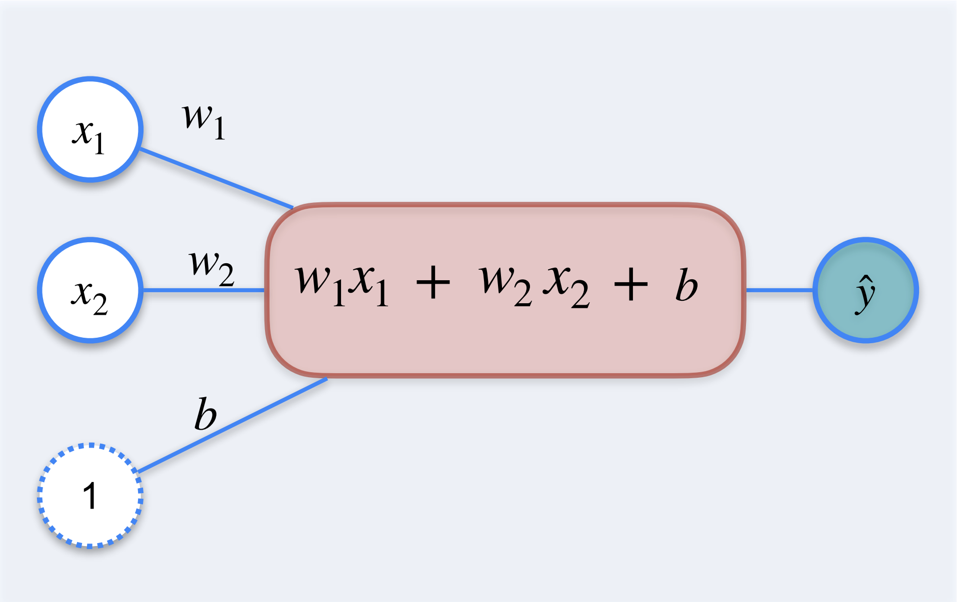
$$\hat{y} = w_1 x_1 + w_2 x_2 + b$$

Loss Function:

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

Regression With a Perceptron

Single Layer Neural Network Perceptron



Prediction Function:

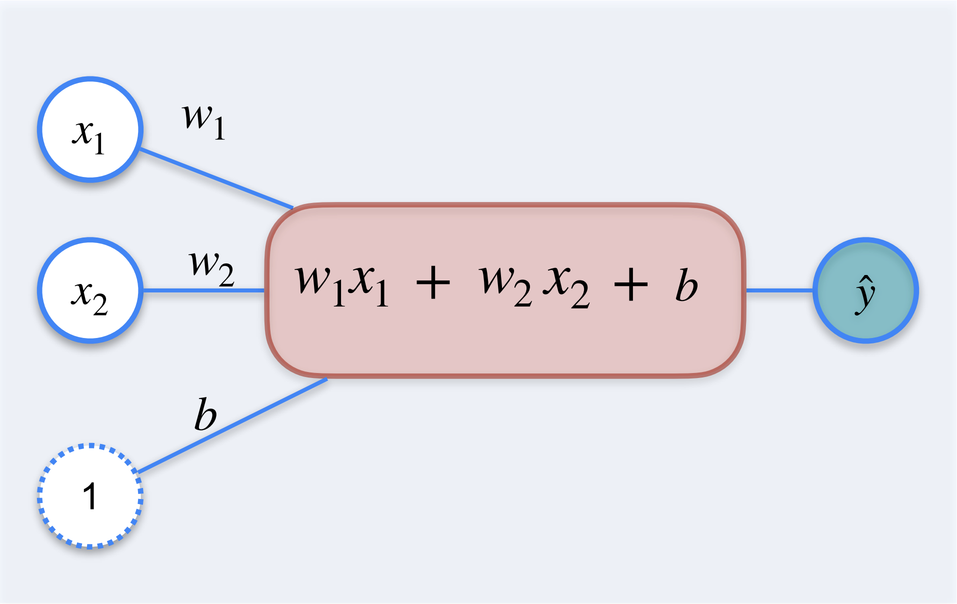
$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

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

Regression With a Perceptron

Single Layer Neural Network Perceptron



Prediction Function:

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

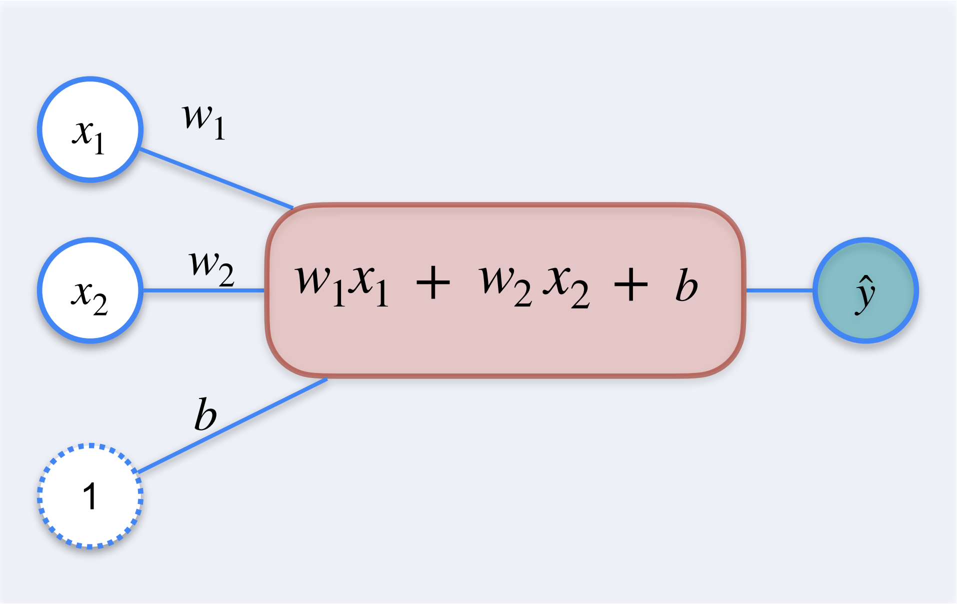
Loss Function:

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

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

Regression with a perceptron: Gradient Descent

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SUB-TASK

Find the following partial derivatives

Regression With Perceptron

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Loss Function:

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Using chain rule:

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

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

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Using chain rule:

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

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Prediction Function:

$$\hat{y} = w_1 x_1 + w_2 x_2 + b$$

Loss Function:

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

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

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

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

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

Loss Function:

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

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

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

Regression With a Perceptron

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Perform Gradient Descent

$$w_1 = w_1 - \alpha$$

Regression With a Perceptron

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

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Perform Gradient Descent

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

Regression With a Perceptron

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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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Regression With a Perceptron

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Perform Gradient Descent

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

$$w_2 = w_2 - \alpha$$

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Perform Gradient Descent

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

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

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

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

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

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

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

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

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

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

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

DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Classification with a perceptron

Classification Problem Motivation

Classification Problem Motivation

Classification Problem Motivation

Sentence			

Classification Problem Motivation

Sentence			
Aack aack aack!			

Classification Problem Motivation

Sentence			
Aack aack aack!			
Beep beep!			

Classification Problem Motivation

Sentence			
Aack aack aack!			
Beep beep!			
Aack beep beep beep!			

Classification Problem Motivation

Sentence			
Aack aack aack!			
Beep beep!			
Aack beep beep beep!			
Aack beep aack!			

DeepLearning.AI

Classification Problem Motivation

Sentence			***Mood***
Aack aack aack!			
Beep beep!			
Aack beep beep beep!			
Aack beep aack!			

Classification Problem Motivation

Sentence			*Mood*
Aack aack aack!			😊
Beep beep!			
Aack beep beep beep!			
Aack beep aack!			

Classification Problem Motivation

Sentence			Mood
Aack aack aack!			*Happy* 😊
Beep beep!			
Aack beep beep beep!			
Aack beep aack!			

Classification Problem Motivation

Sentence			Mood
Aack aack aack!			*Happy* 😊
Beep beep!			😔
Aack beep beep beep!			
Aack beep aack!			

Classification Problem Motivation

Sentence			*Mood*
Aack aack aack!			*Happy* 😊
Beep beep!			*Sad* 😔
Aack beep beep beep!			
Aack beep aack!			

Classification Problem Motivation

Sentence			Mood
Aack aack aack!			*Happy* 😊
Beep beep!			*Sad* 😔
Aack beep beep beep!			😔
Aack beep aack!			

Classification Problem Motivation

Sentence			Mood
Aack aack aack!			*Happy* 😊
Beep beep!			*Sad* 😔
Aack beep beep beep!			*Sad* 😔
Aack beep aack!			

Classification Problem Motivation

Sentence			Mood
Aack aack aack!			Happy 😊
Beep beep!			Sad 😔
Aack beep beep beep!			Sad 😔
Aack beep aack!			😊

Classification Problem Motivation

Sentence			Mood
Aack aack aack!			*Happy* 😊
Beep beep!			*Sad* 😔
Aack beep beep beep!			*Sad* 😔
Aack beep aack!			*Happy* 😊

Classification Problem Motivation

Sentence	Aack	Beep	Mood
Aack aack aack!			*Happy* 😊
Beep beep!			*Sad* 😔
Aack beep beep beep!			*Sad* 😔
Aack beep aack!			*Happy* 😊

Classification Problem Motivation

Sentence	Aack	Beep	Mood
Aack aack aack!	3		Happy 😊
Beep beep!			Sad 😔
Aack beep beep beep!			Sad 😔
Aack beep aack!			Happy 😊

Classification Problem Motivation

Sentence	Aack	Beep	Mood
Aack aack aack!	*3*	*0*	*Happy* 😊
Beep beep!			*Sad* 😔
Aack beep beep beep!			*Sad* 😔
Aack beep aack!			*Happy* 😊

Classification Problem Motivation

Sentence	Aack	Beep	Mood
Aack aack aack!	3	0	Happy 😊
Beep beep!	0		Sad 😔
Aack beep beep beep!			Sad 😔
Aack beep aack!			Happy 😊

Classification Problem Motivation

Sentence	Aack	Beep	Mood
Aack aack aack!	*3*	*0*	*Happy* 😊
Beep beep!	*0*	*2*	*Sad* 😔
Aack beep beep beep!			*Sad* 😔
Aack beep aack!			*Happy* 😊

Classification Problem Motivation

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

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!			*Happy* 😊

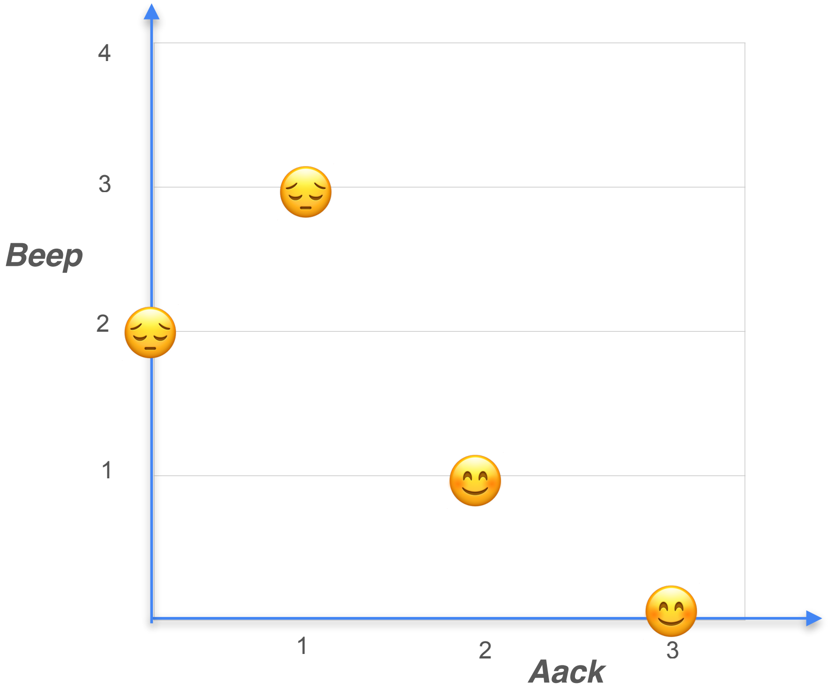
Classification Problem Motivation

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*		*Happy* 😊

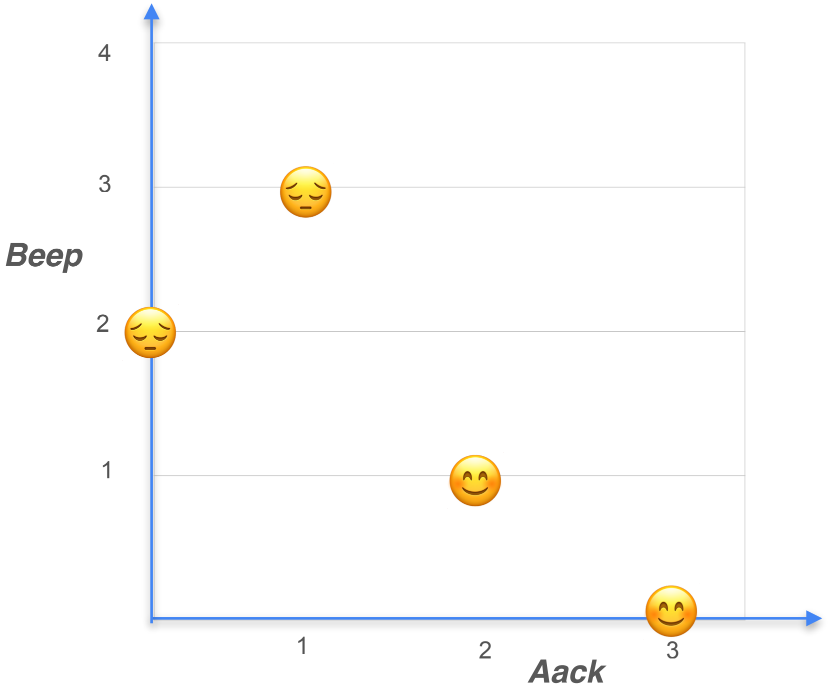
Classification Problem Motivation

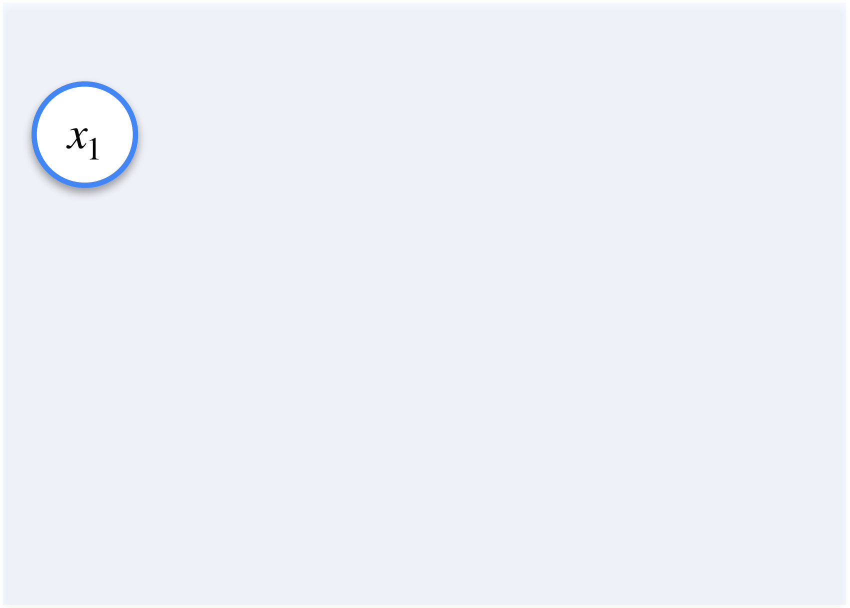
Sentence	Aack	Beep	Mood
Aack aack aack!	*3*	*0*	*Happy* 😊
Beep beep!	*0*	*2*	*Sad* 😔
Aack beep beep beep!	*1*	*3*	*Sad* 😔
Aack beep aack!	*2*	*1*	*Happy* 😊

Classification Problem Motivation

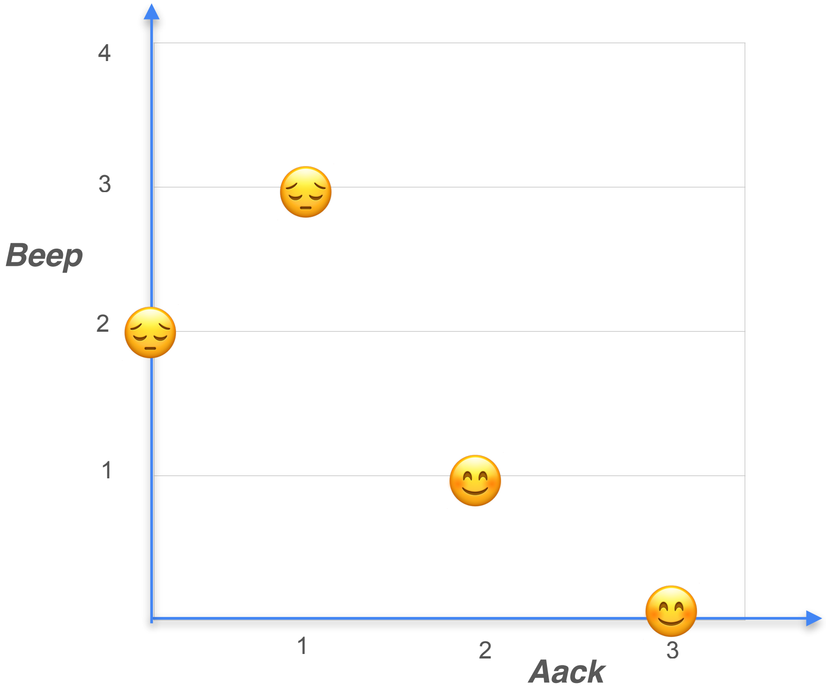


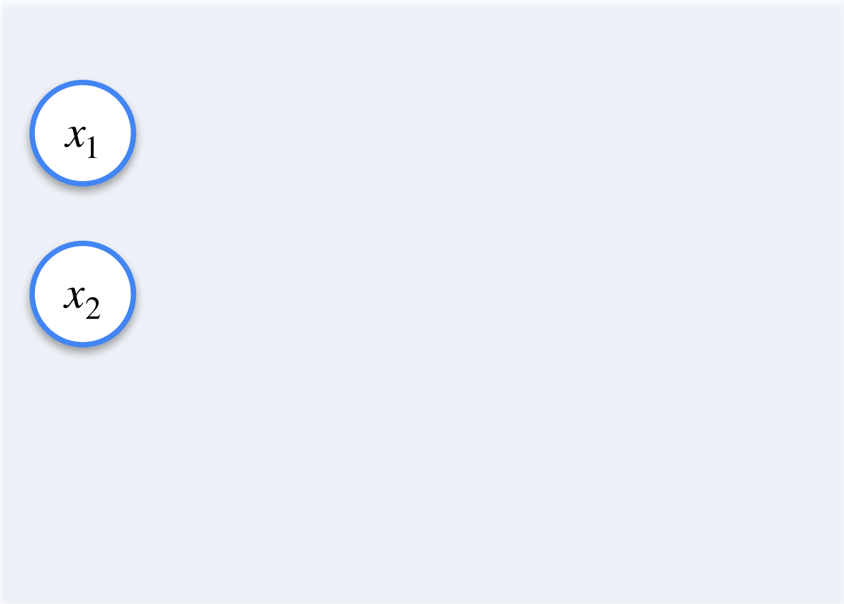
Classification Problem Motivation



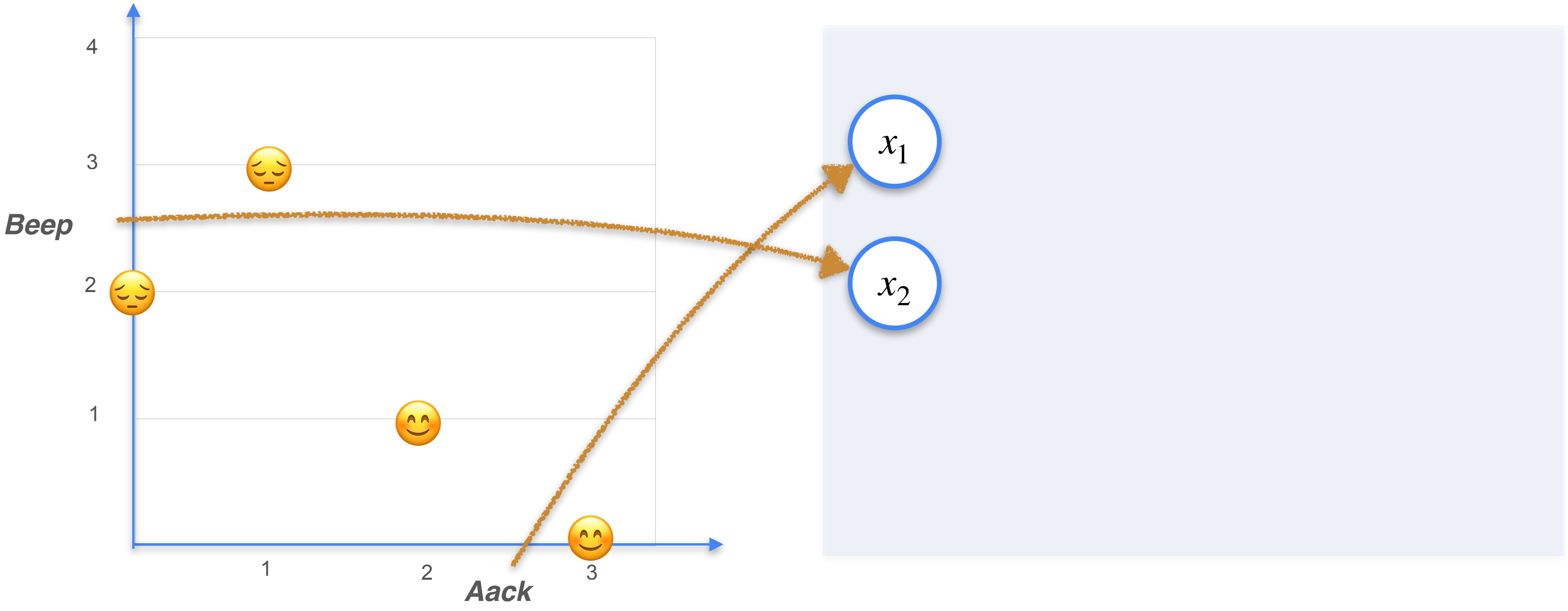


Classification Problem Motivation

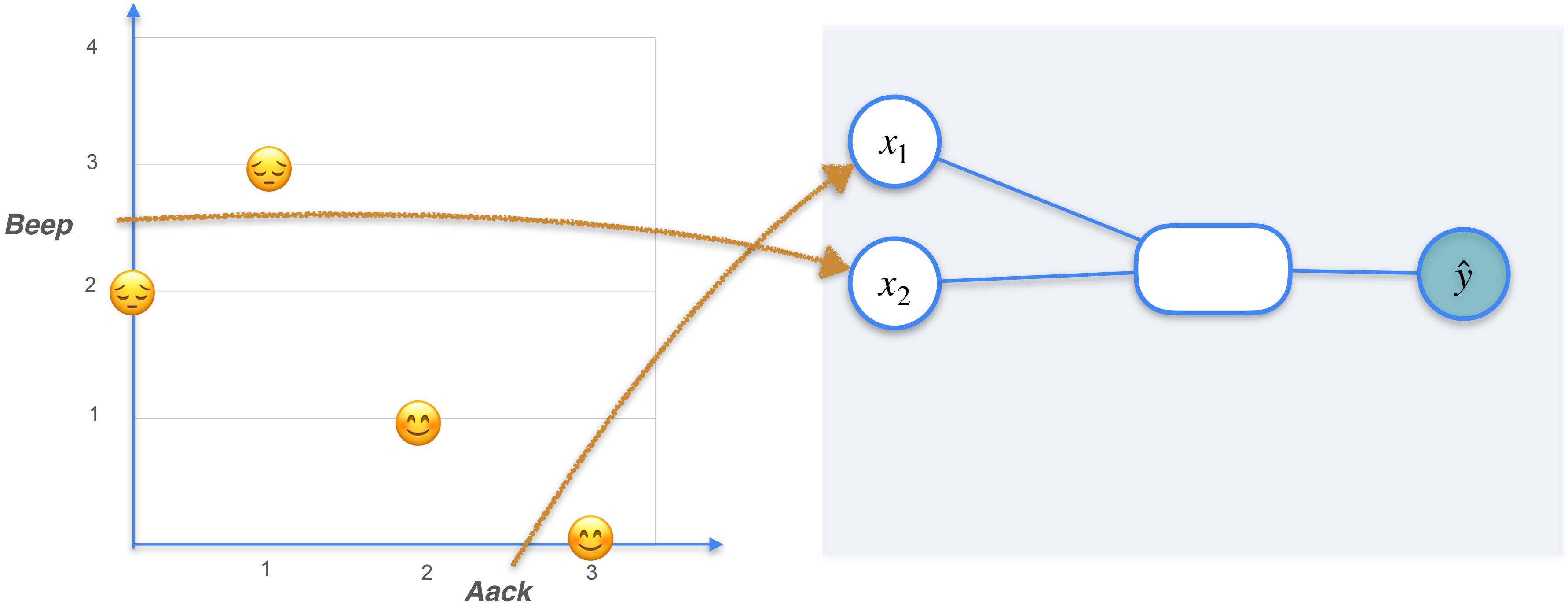




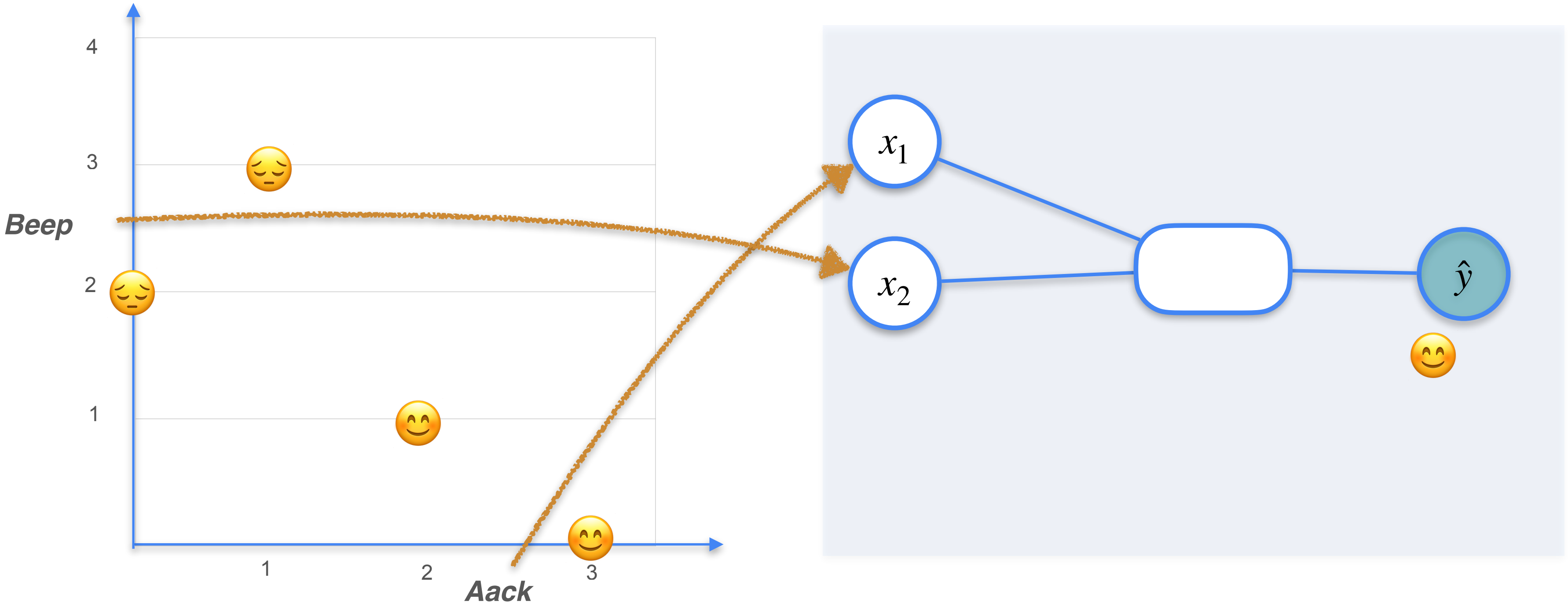
Classification Problem Motivation



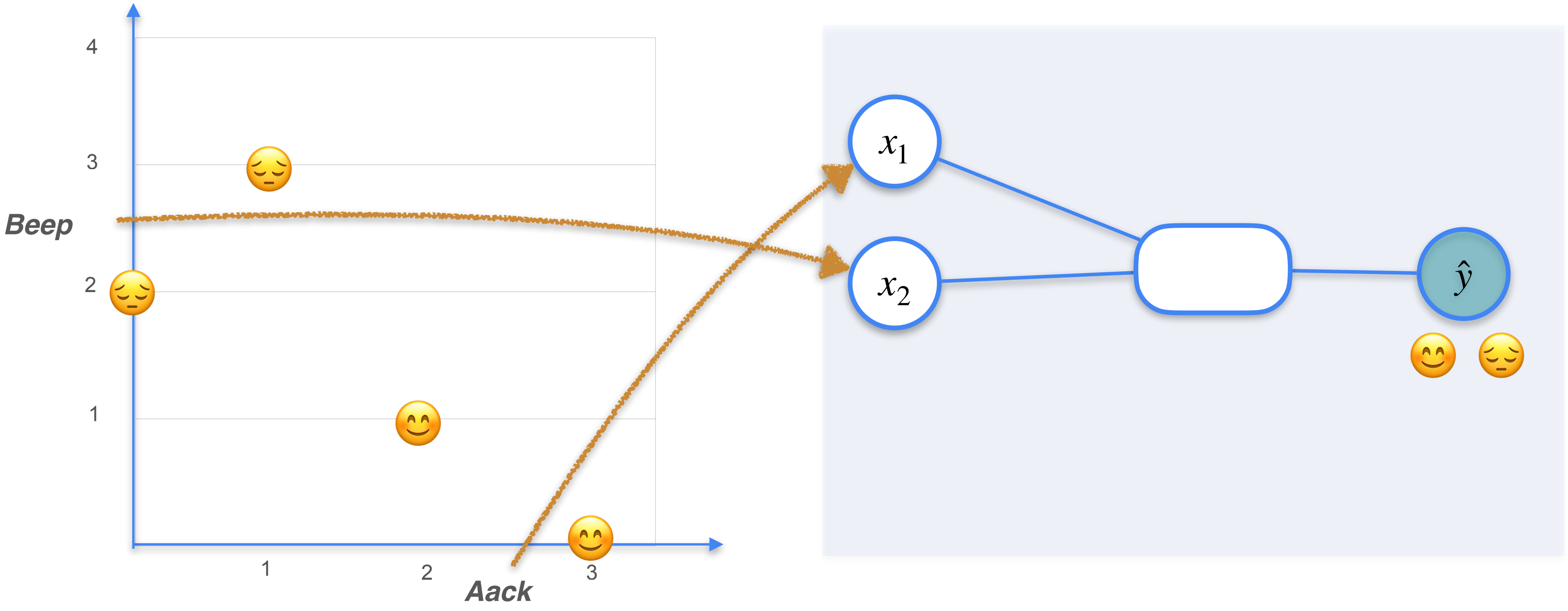
Classification Problem Motivation



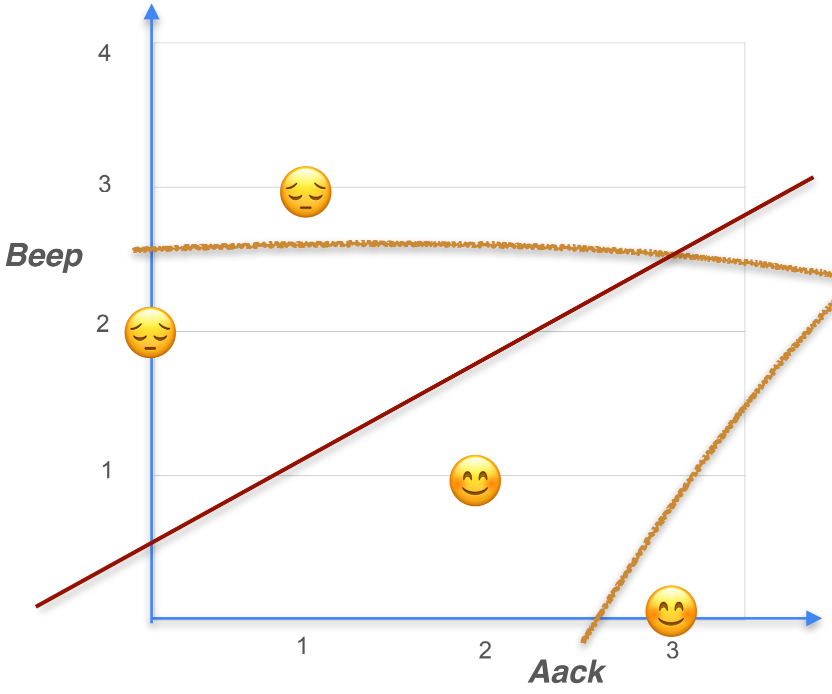
Classification Problem Motivation

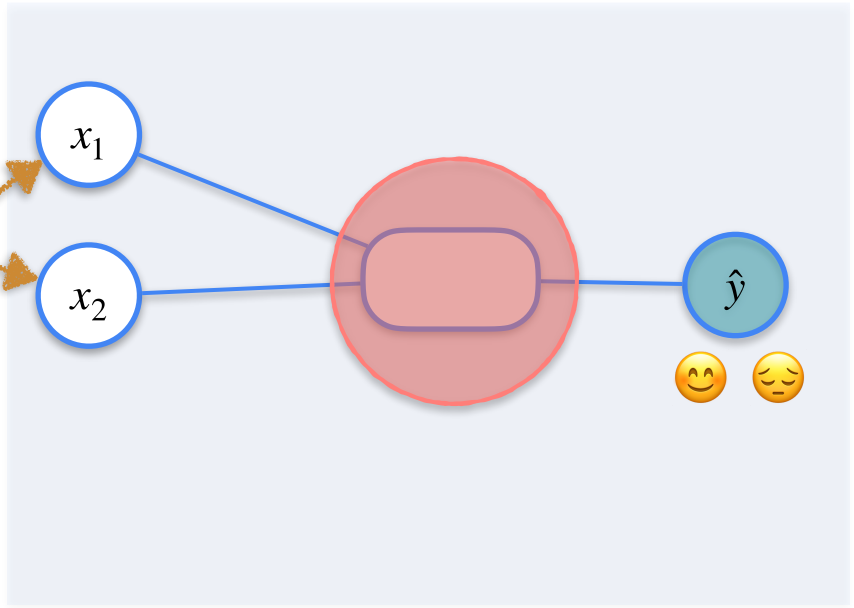


Classification Problem Motivation

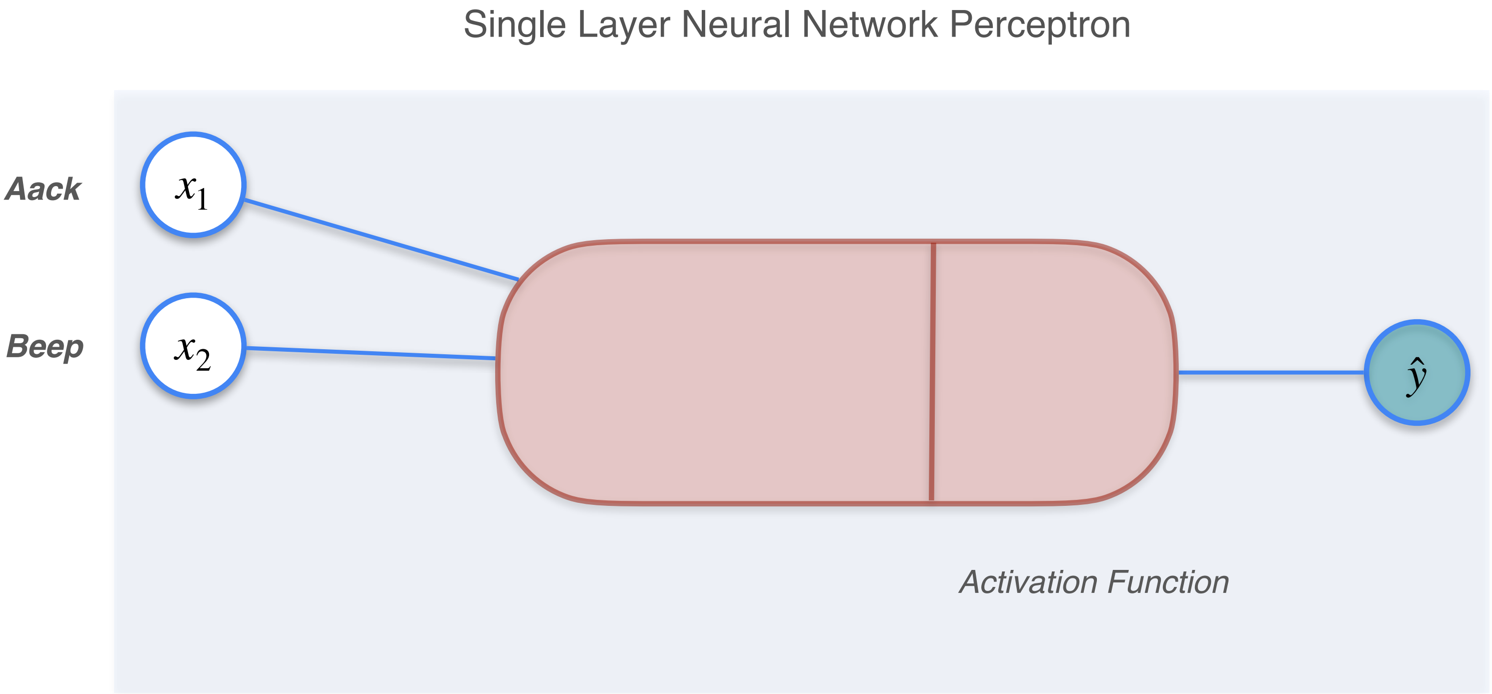


Classification Problem Motivation



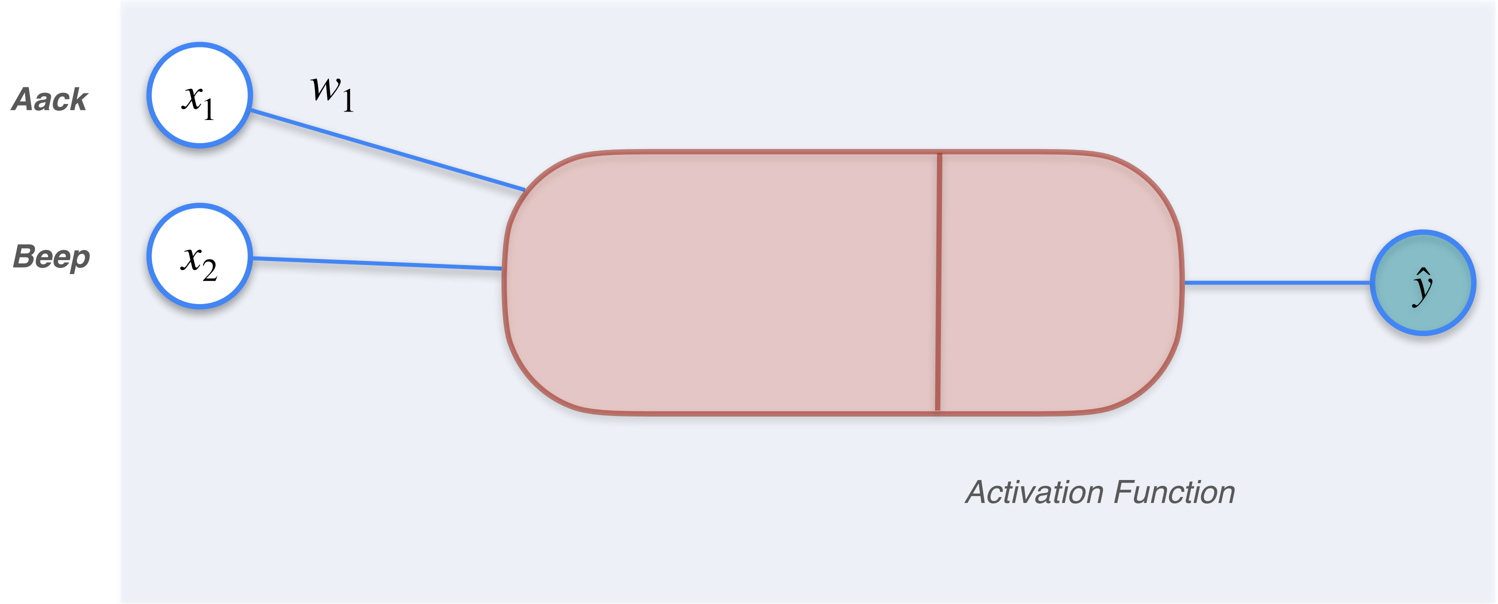


Classification With a Perceptron



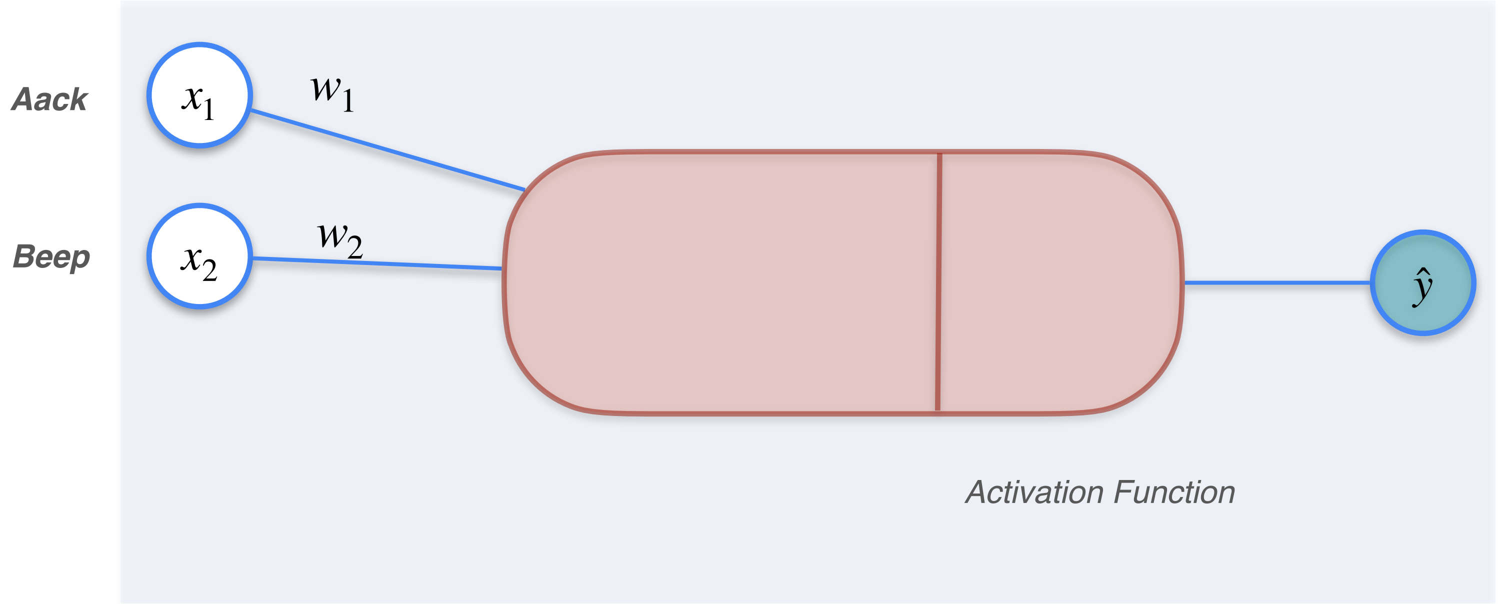
Classification With a Perceptron

Single Layer Neural Network Perceptron

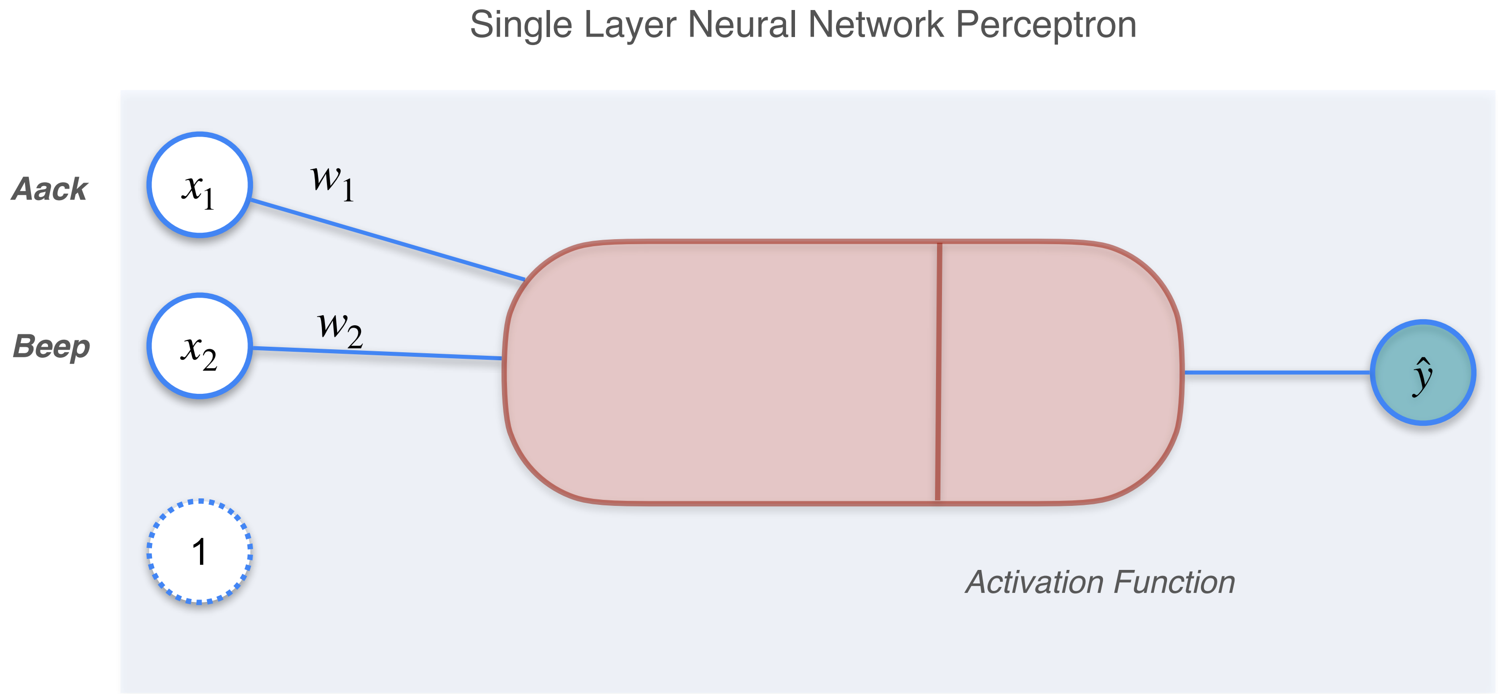


Classification With a Perceptron

Single Layer Neural Network Perceptron

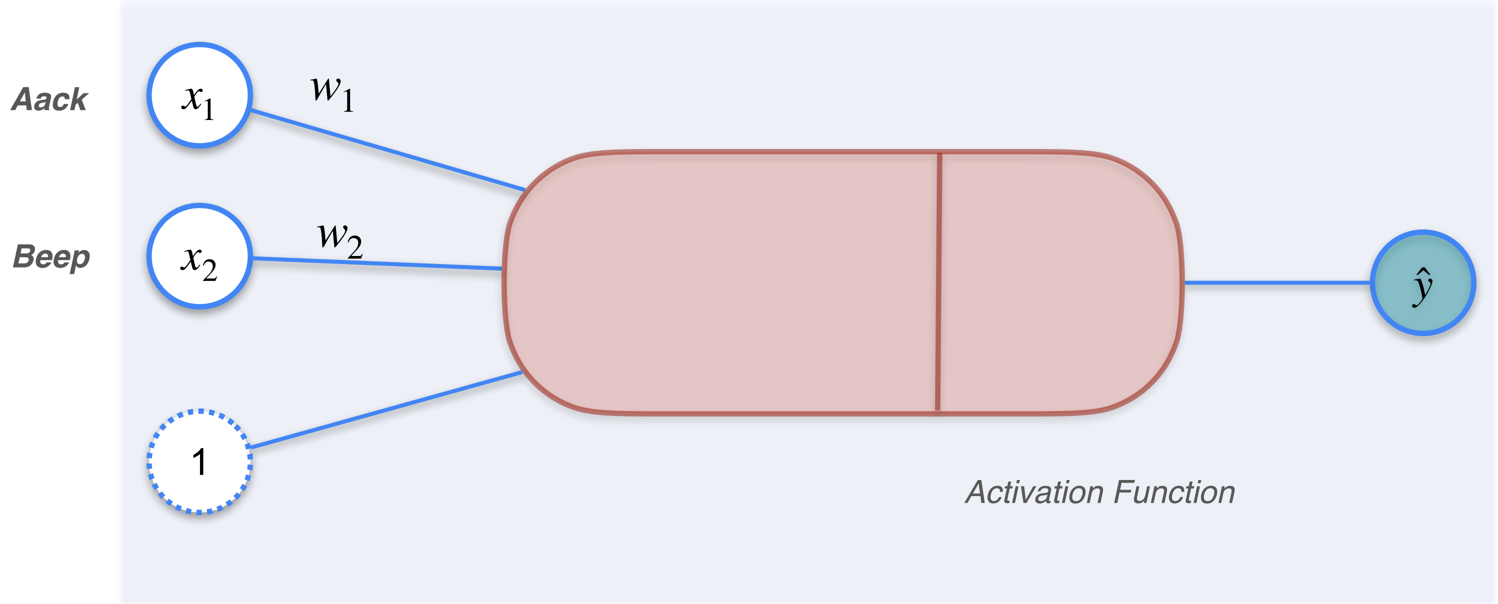


Classification With a Perceptron

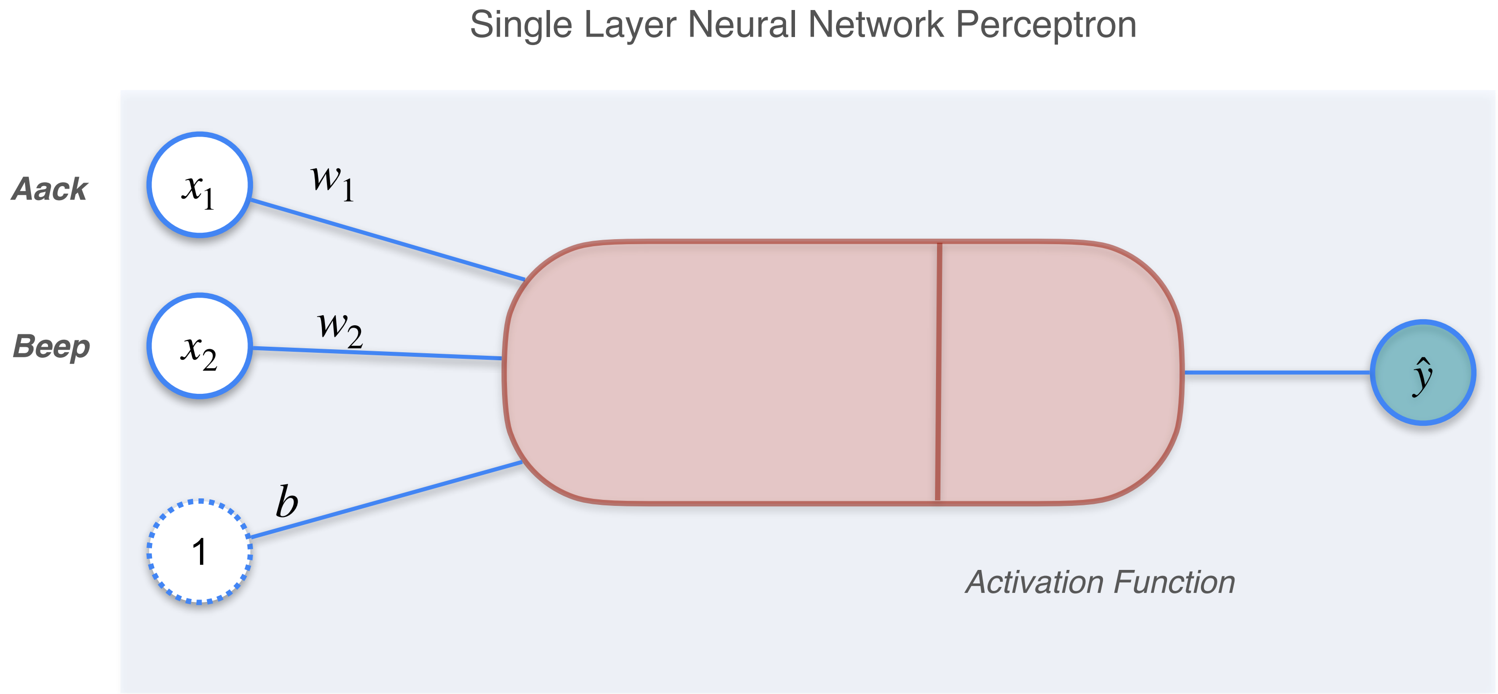


Classification With a Perceptron

Single Layer Neural Network Perceptron

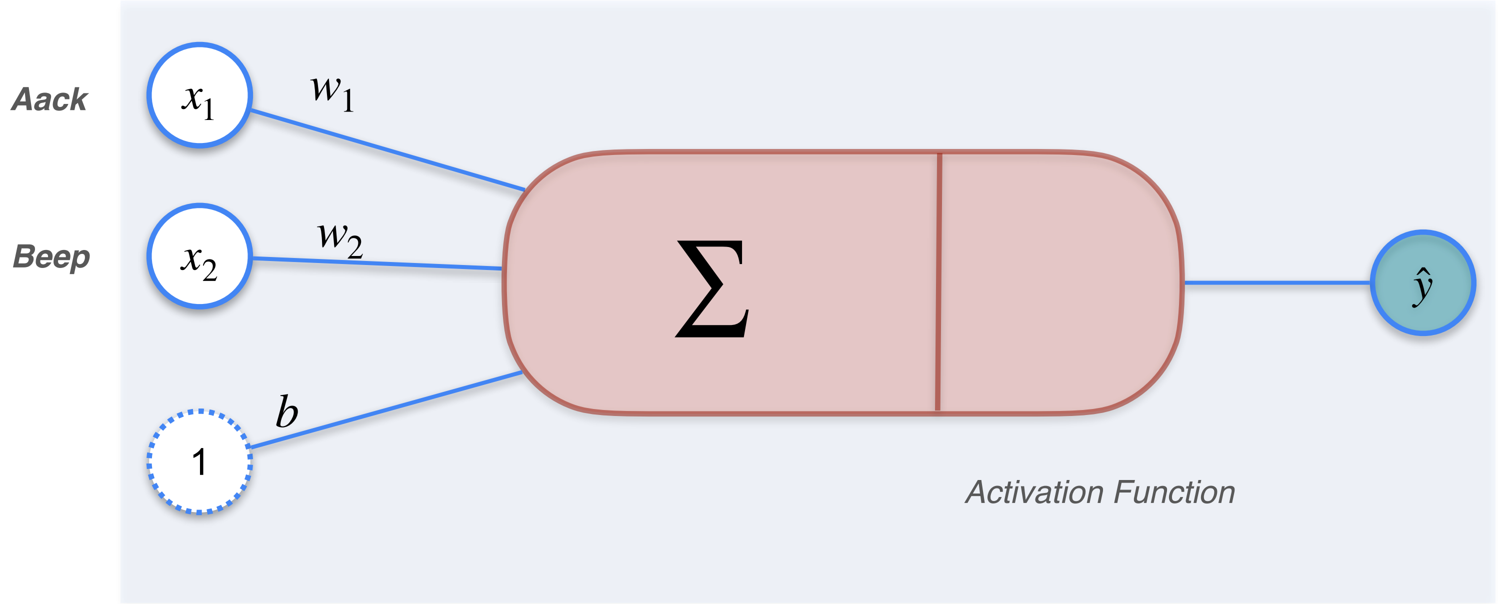


Classification With a Perceptron

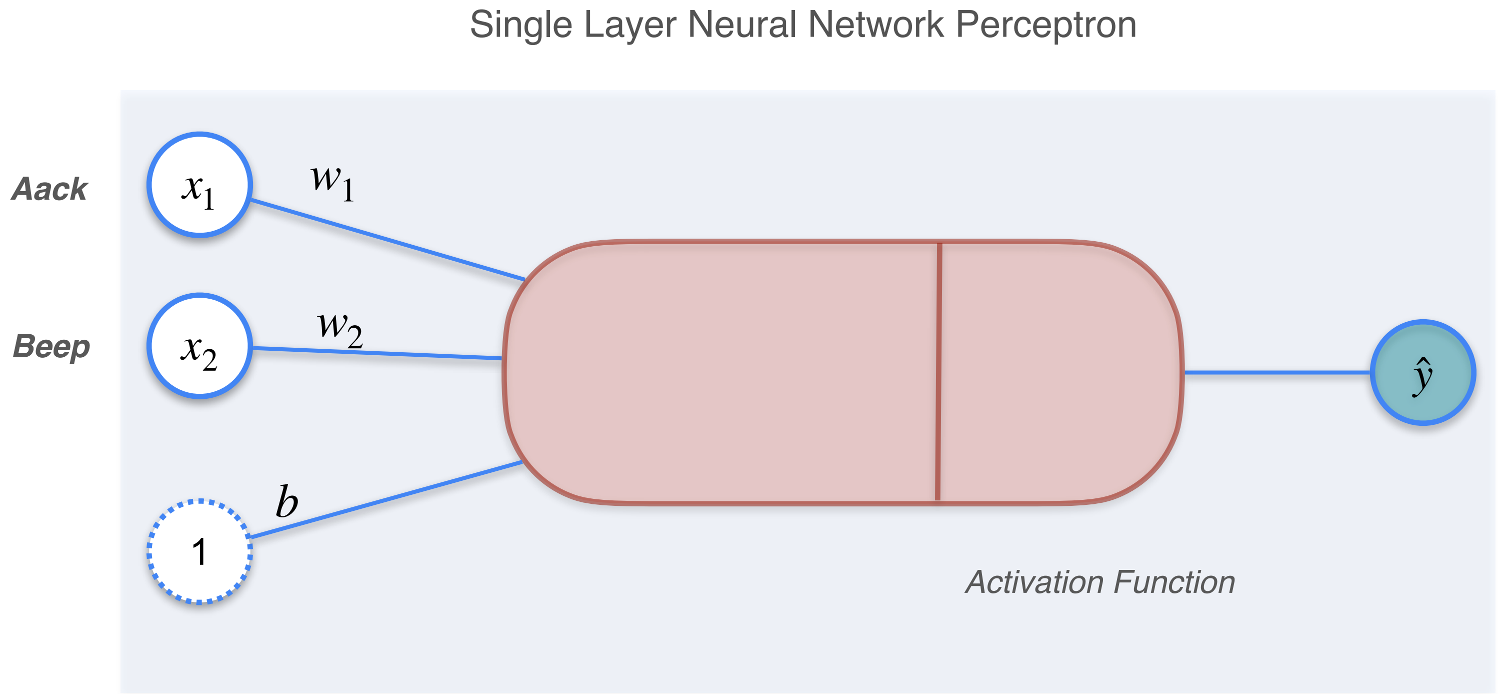


Classification With a Perceptron

Single Layer Neural Network Perceptron

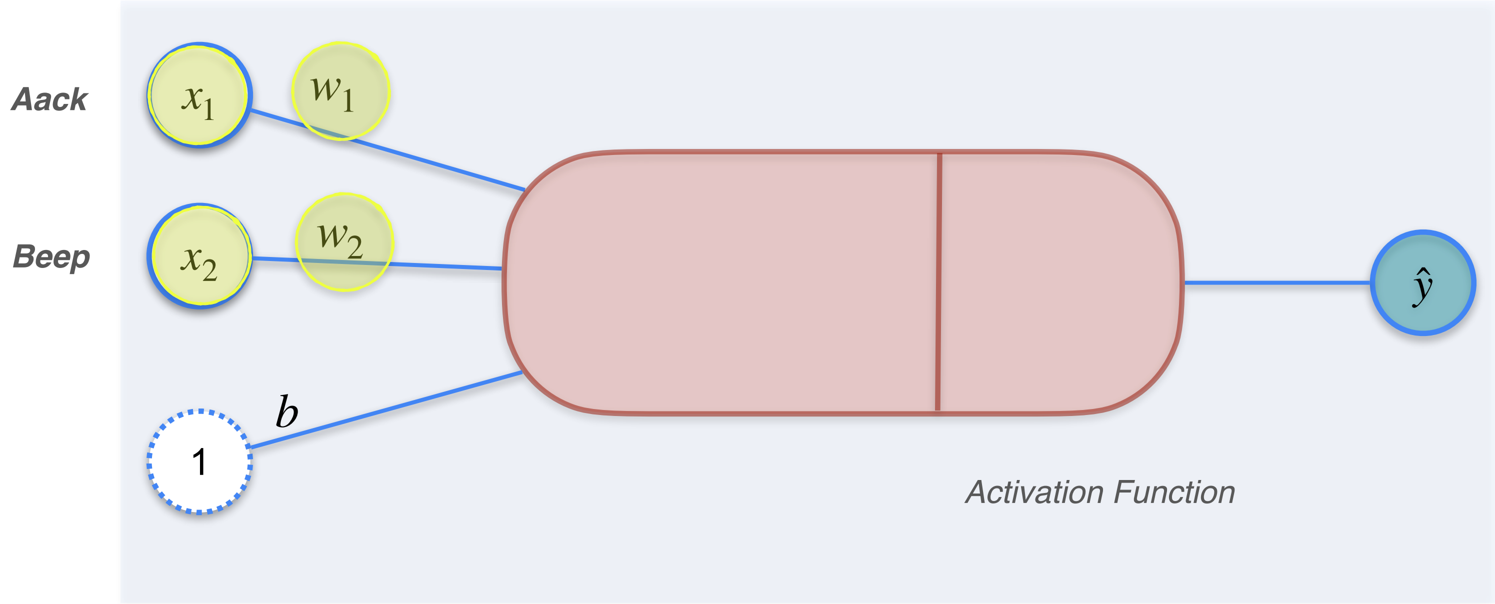


Classification With a Perceptron

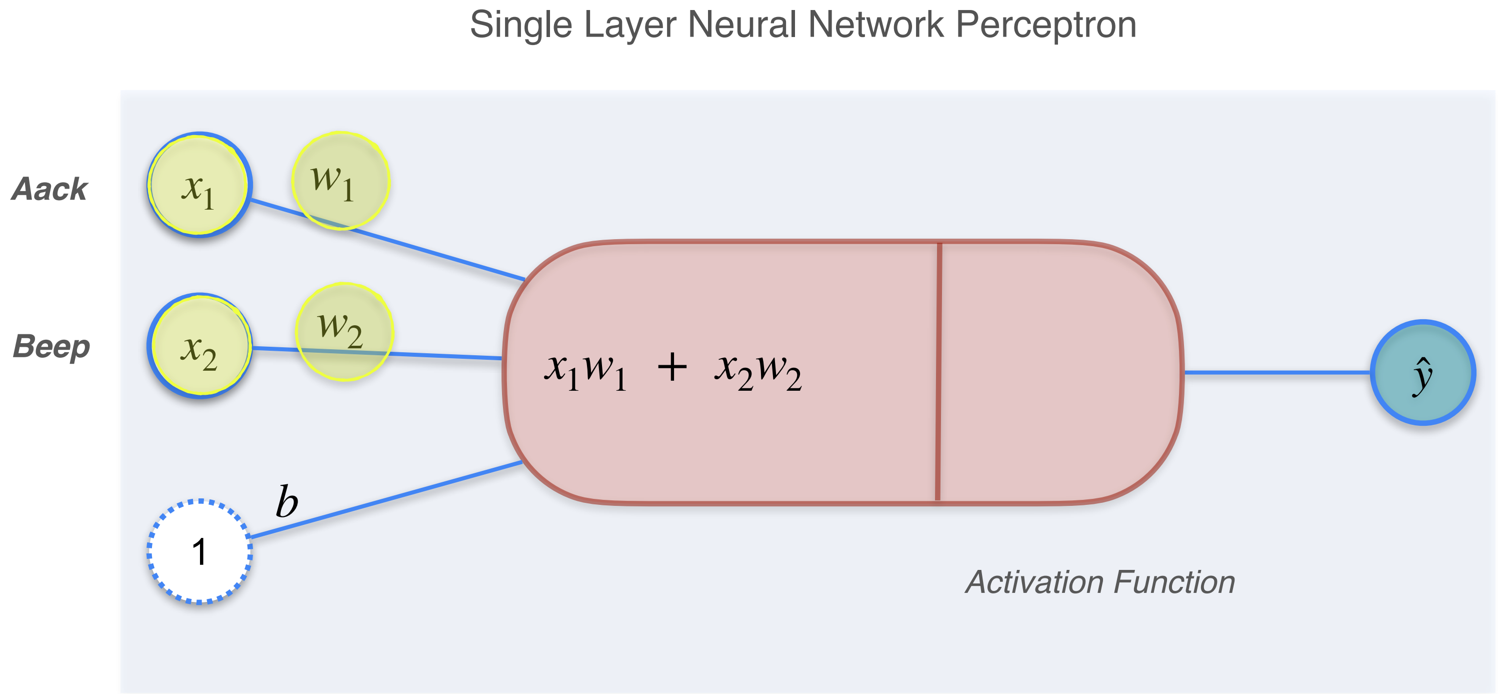


Classification With a Perceptron

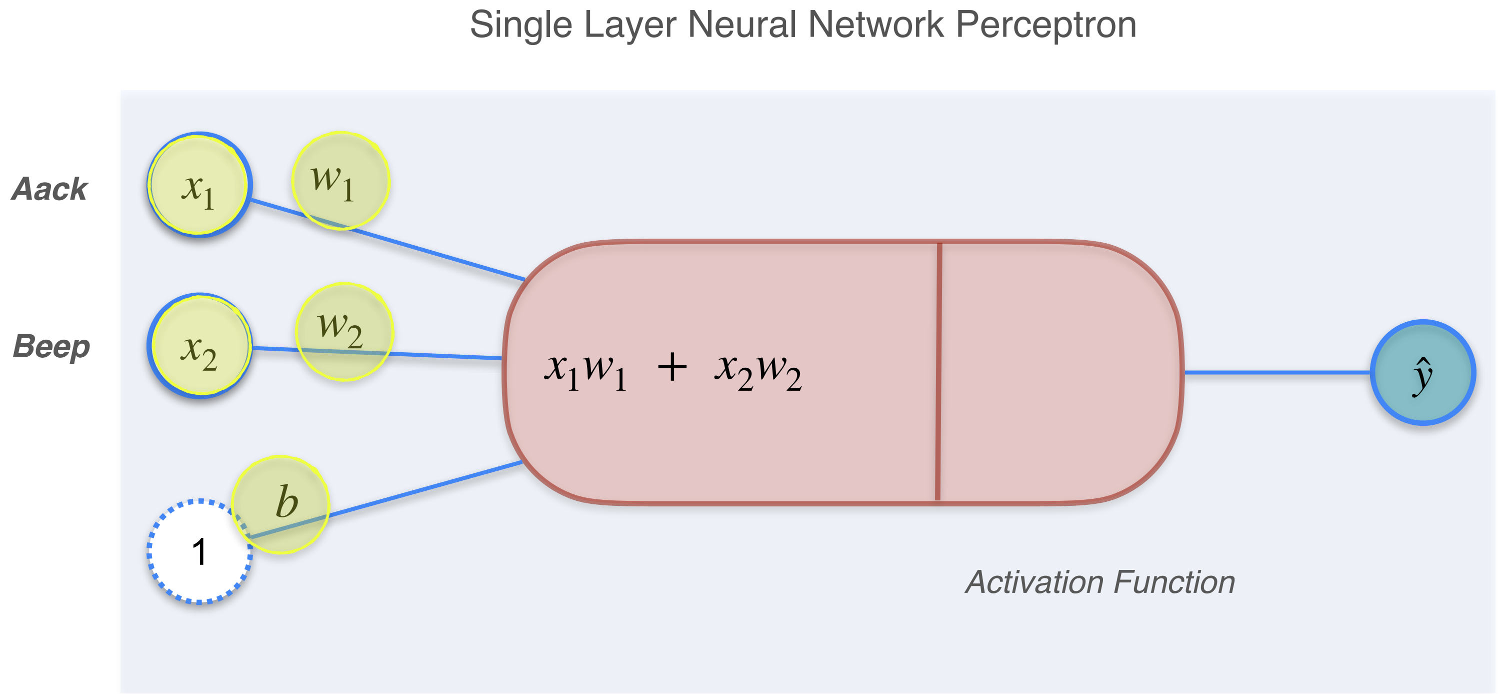
Single Layer Neural Network Perceptron



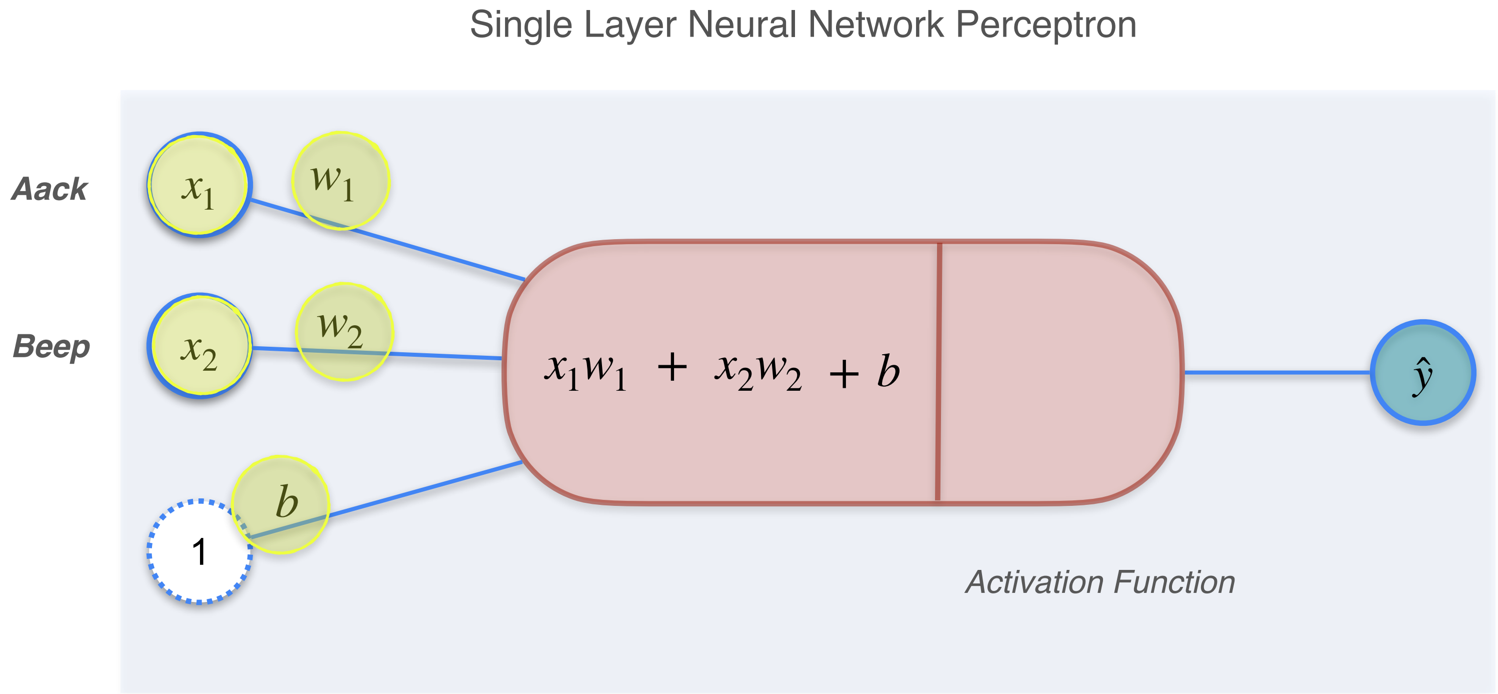
Classification With a Perceptron



Classification With a Perceptron

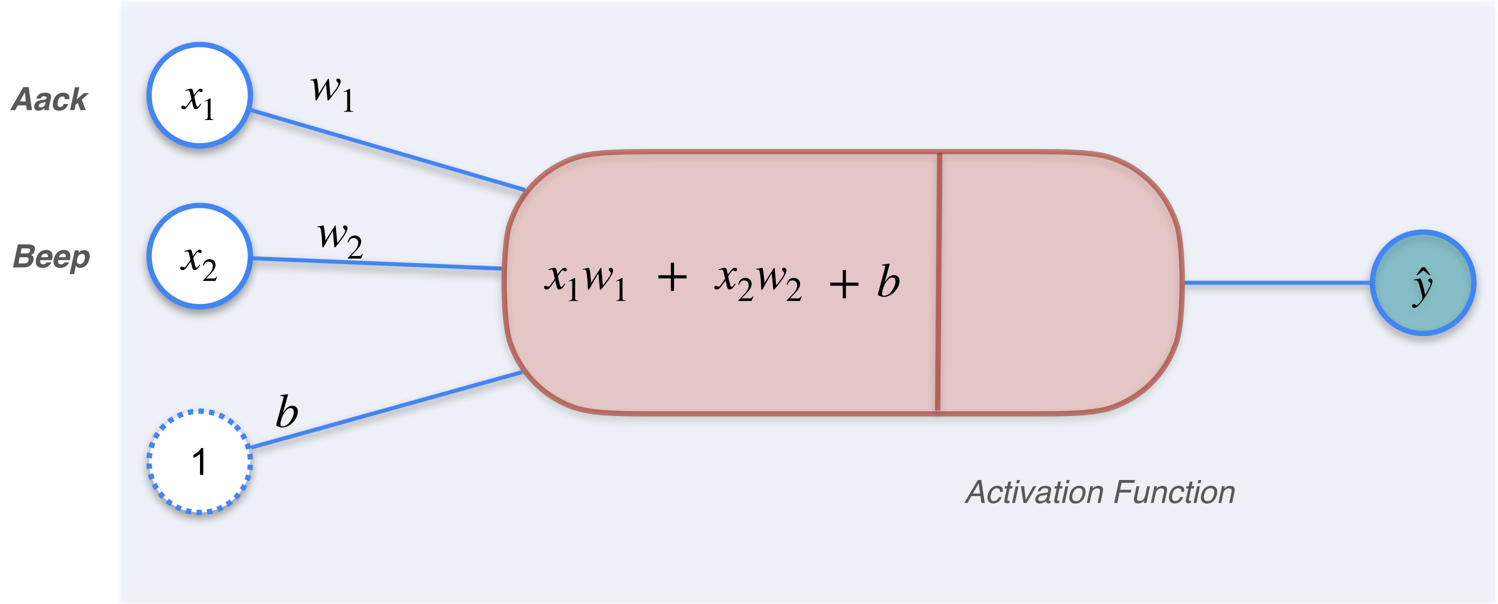


Classification With a Perceptron

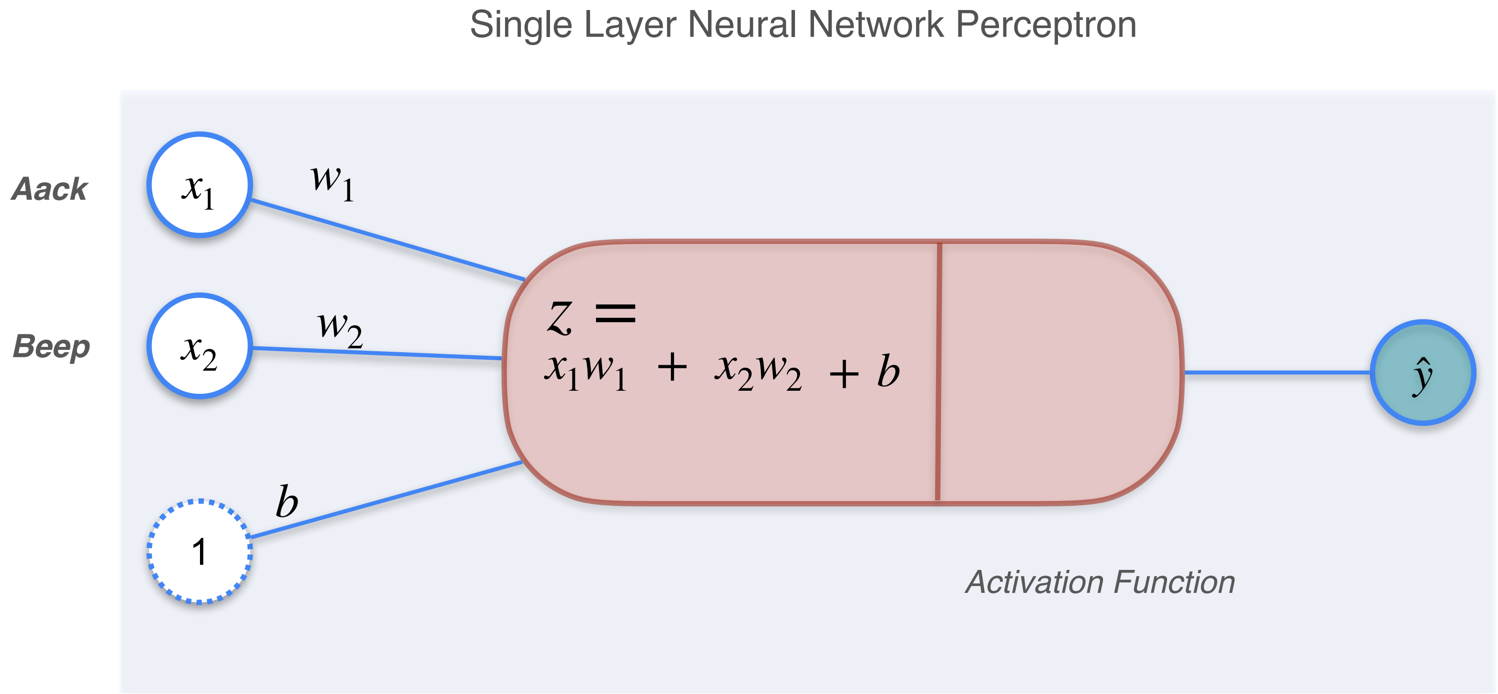


Classification With a Perceptron

Single Layer Neural Network Perceptron

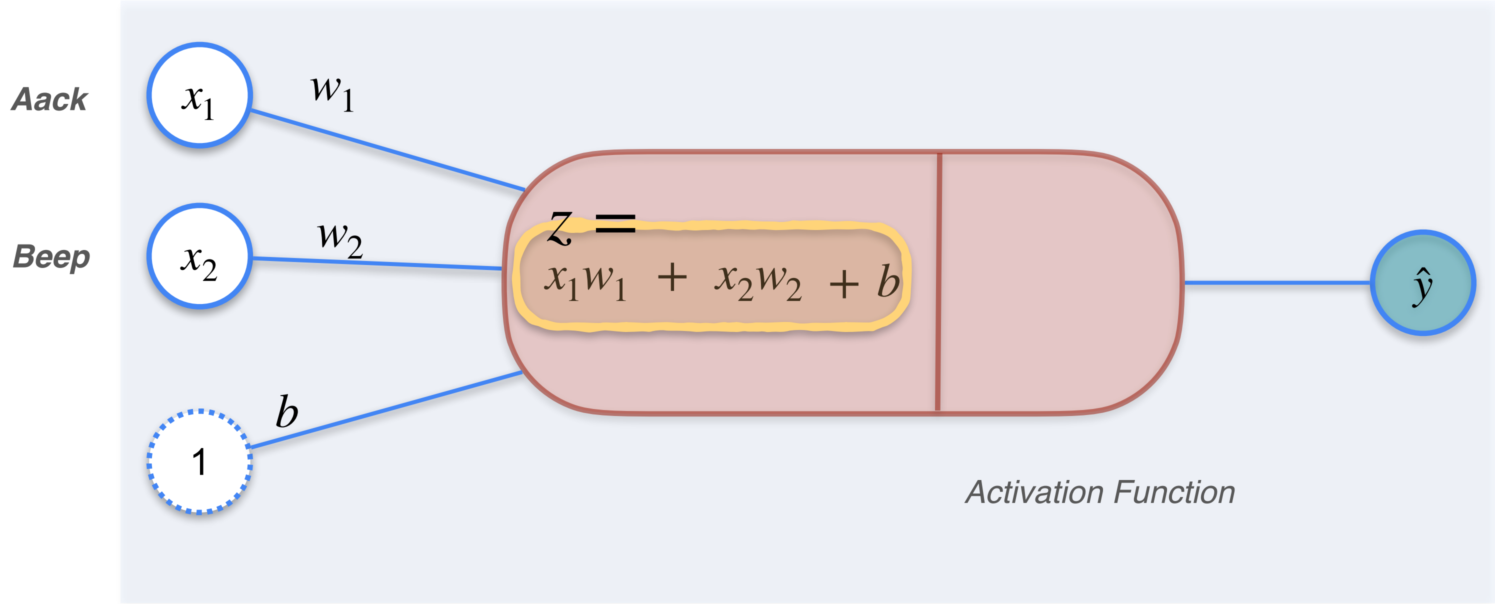


Classification With a Perceptron

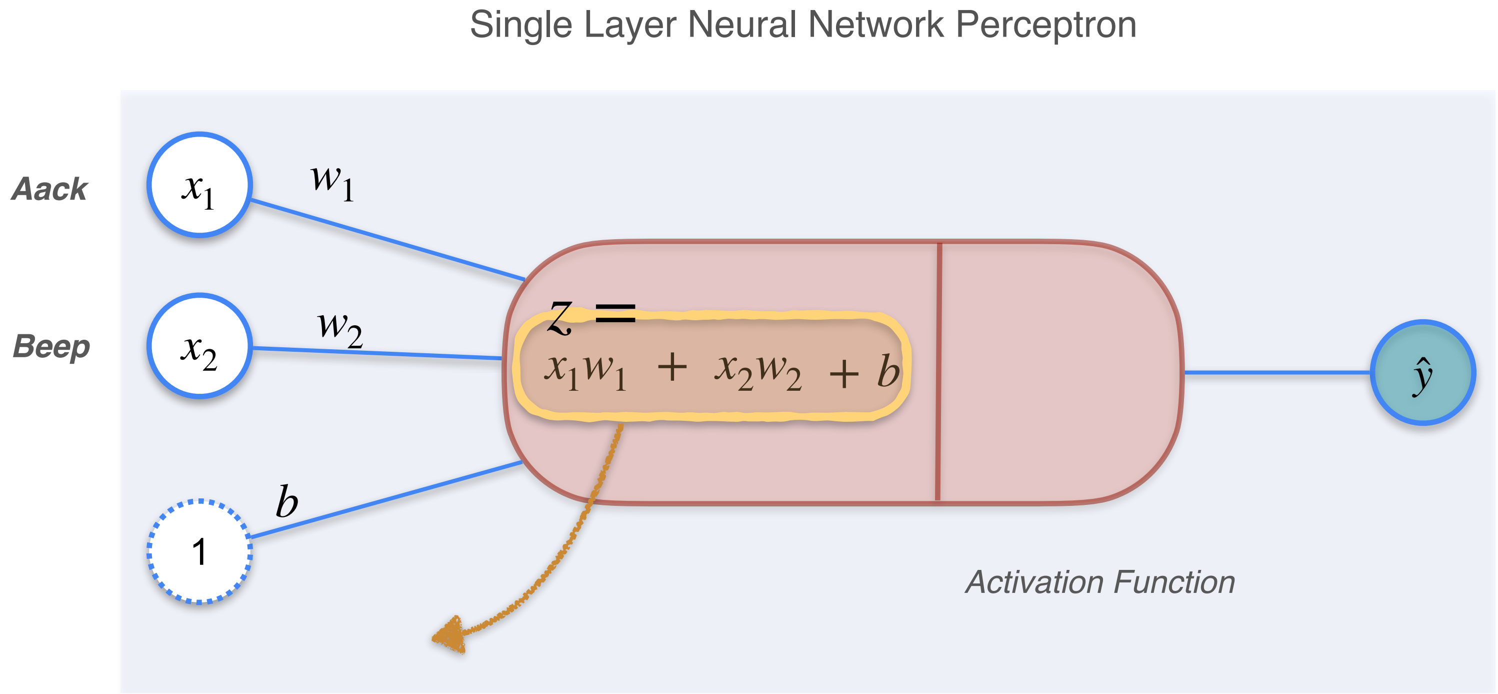


Classification With a Perceptron

Single Layer Neural Network Perceptron



Classification With a Perceptron



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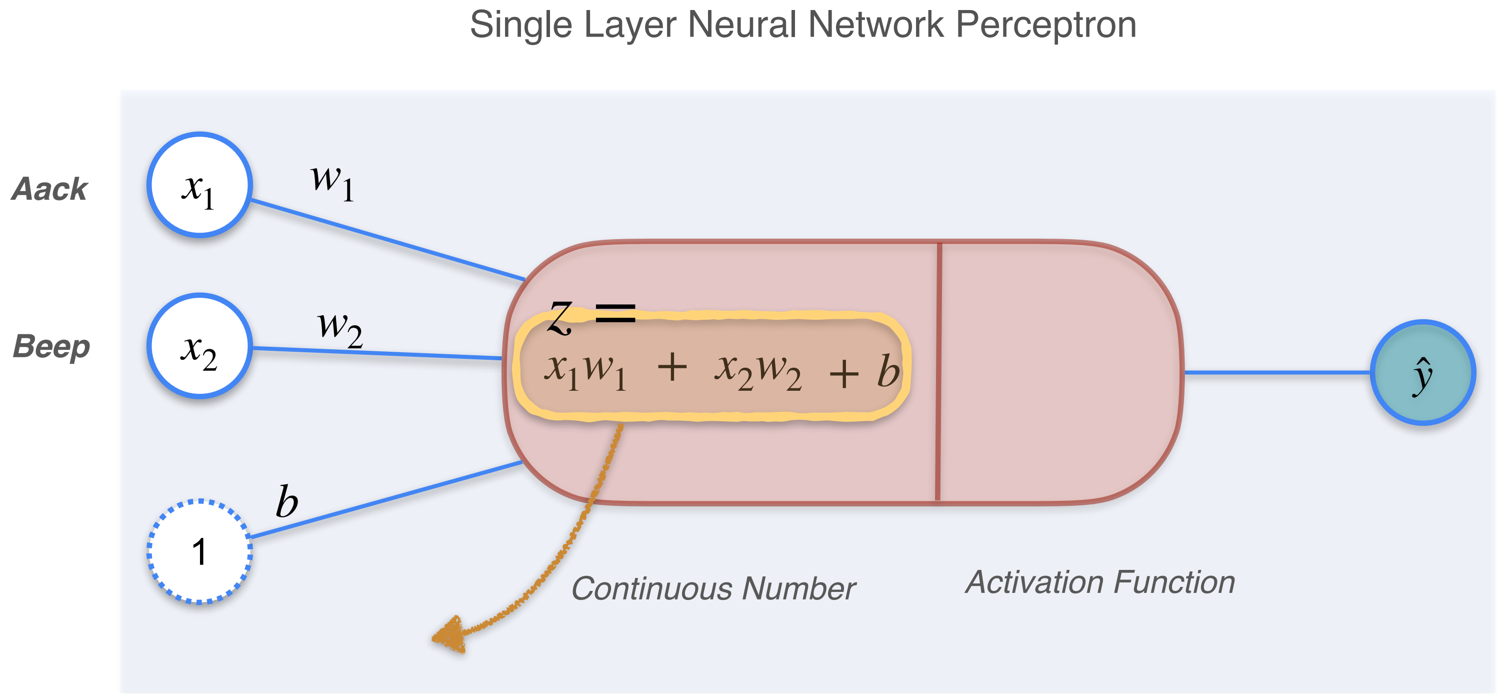
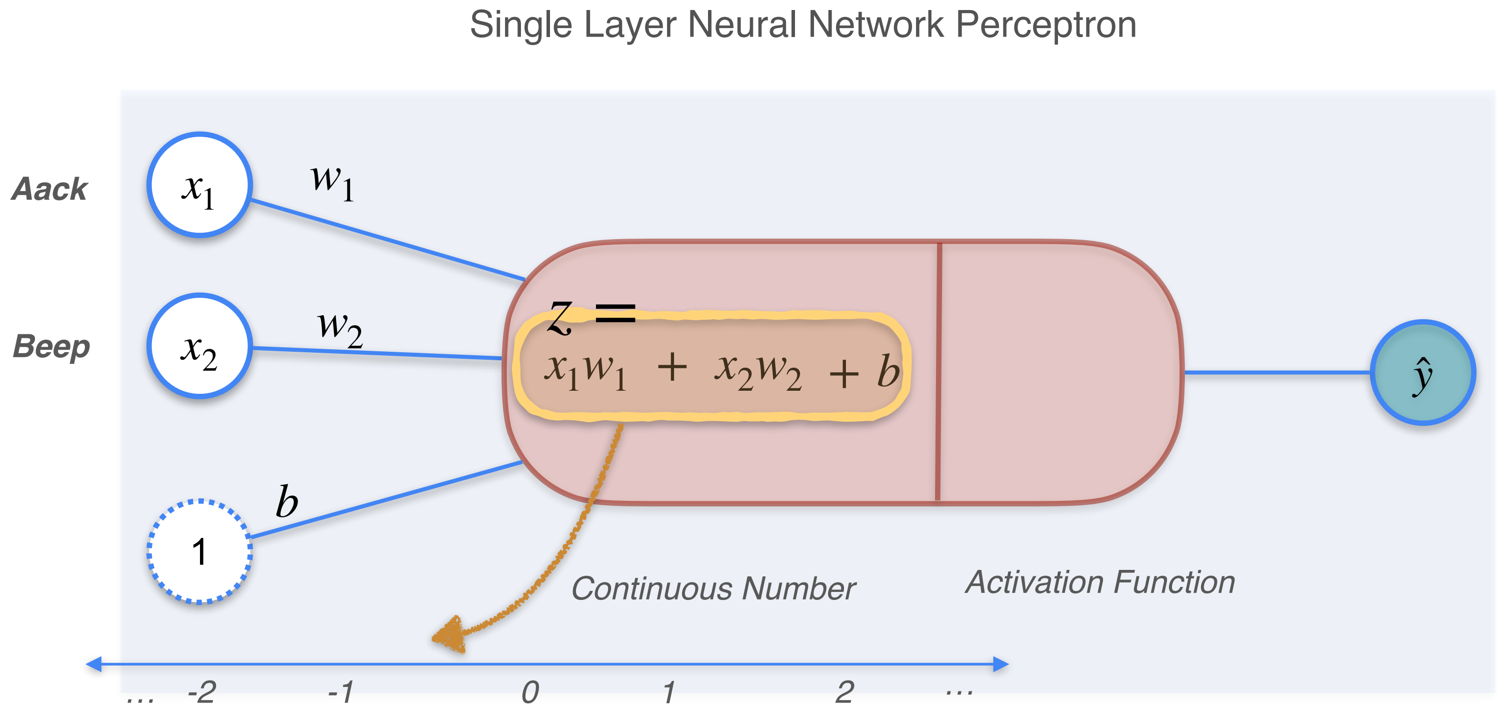
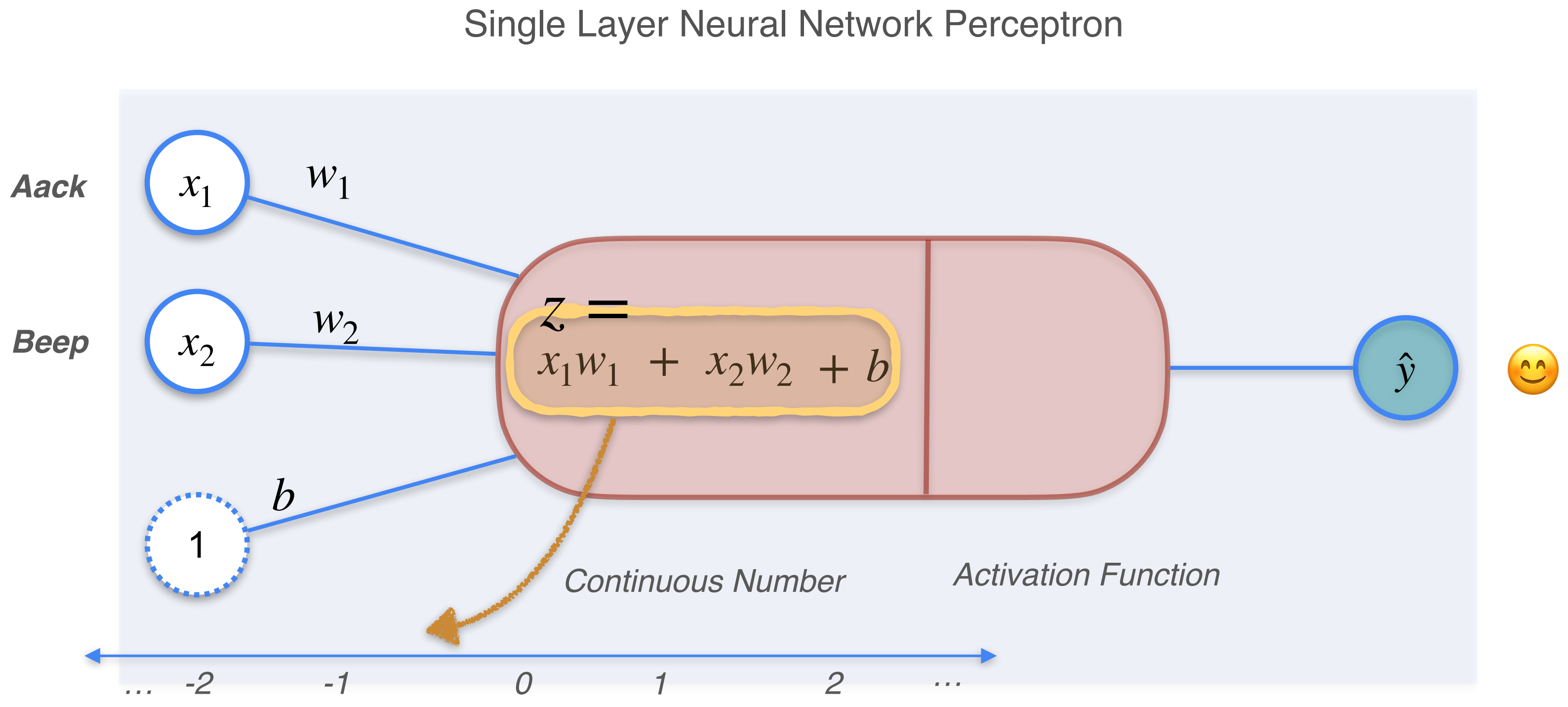
Classification With a Perceptron



Classification With a Perceptron

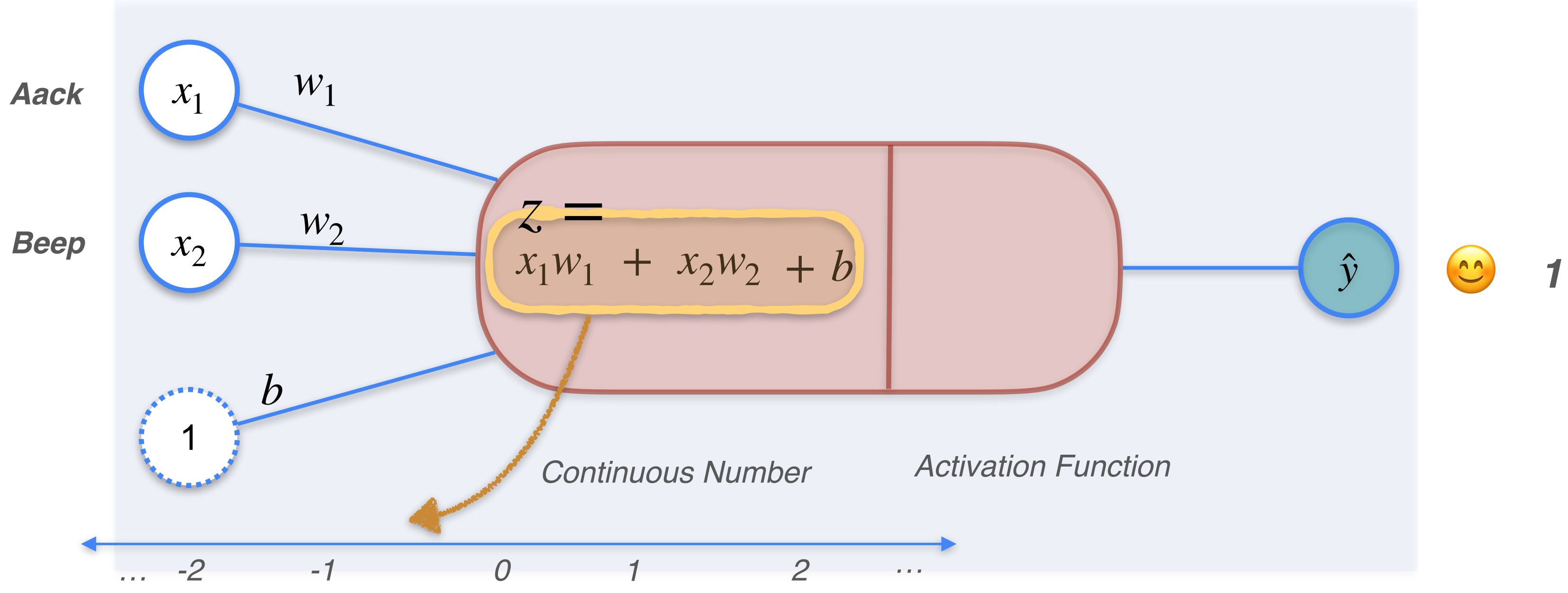


Classification With a Perceptron

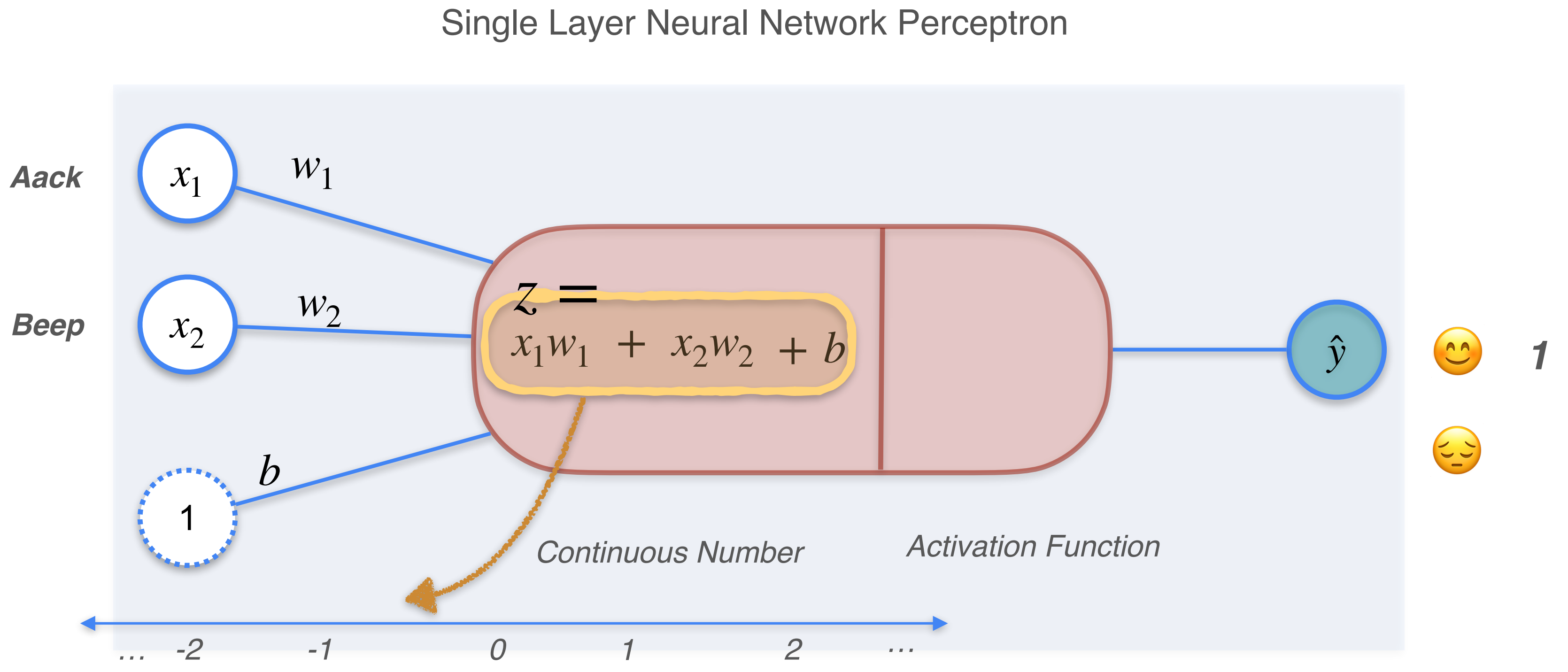


Classification With a Perceptron

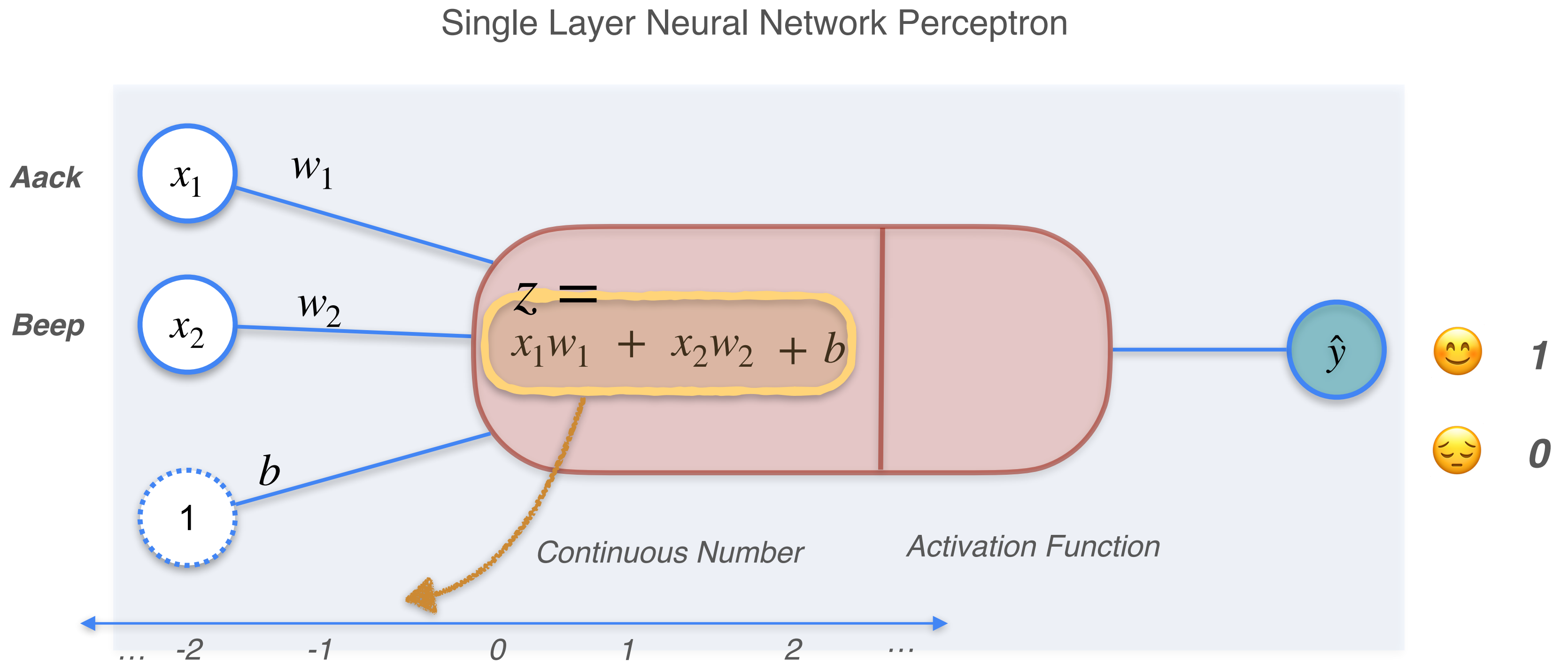
Single Layer Neural Network Perceptron



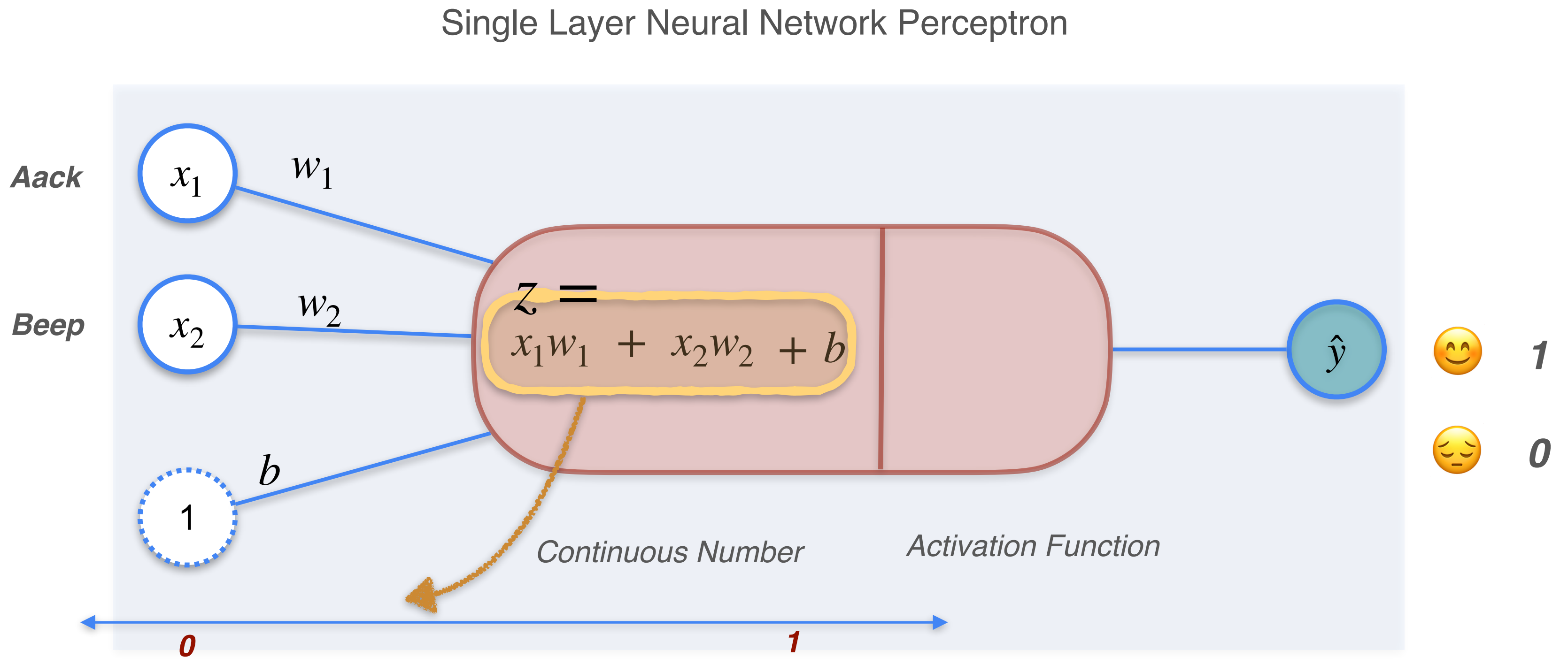
Classification With a Perceptron



Classification With a Perceptron

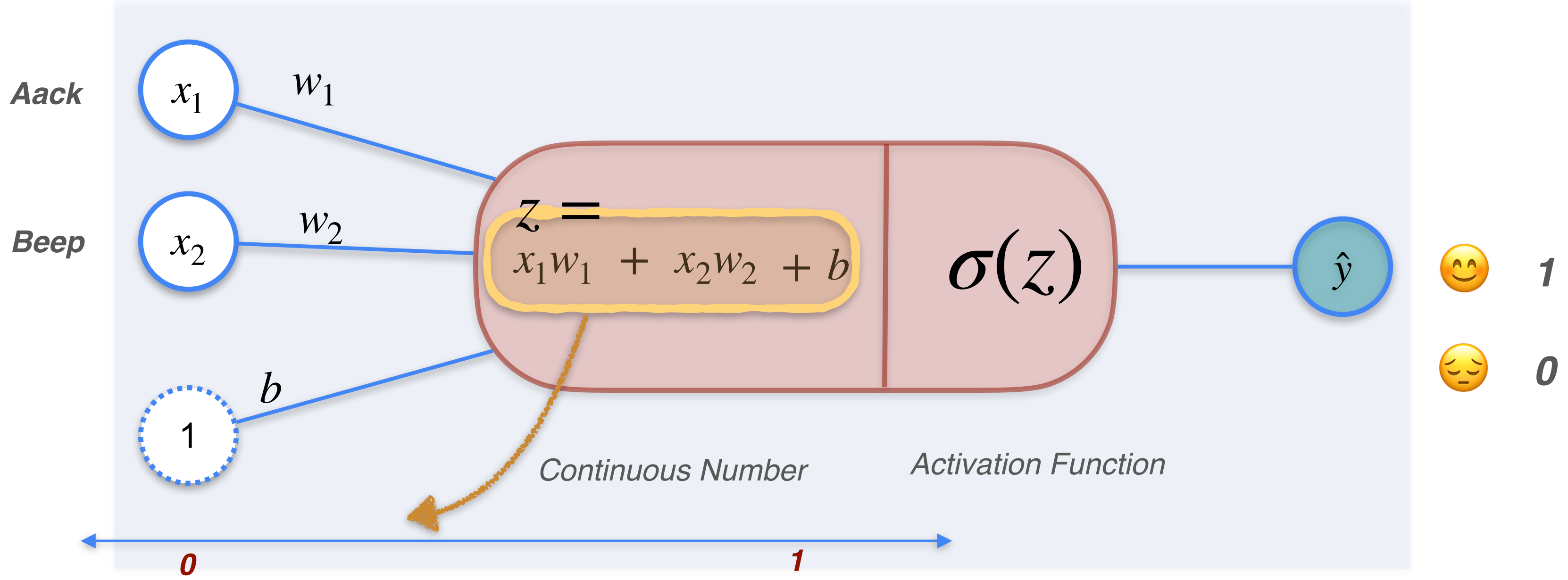


Classification With a Perceptron



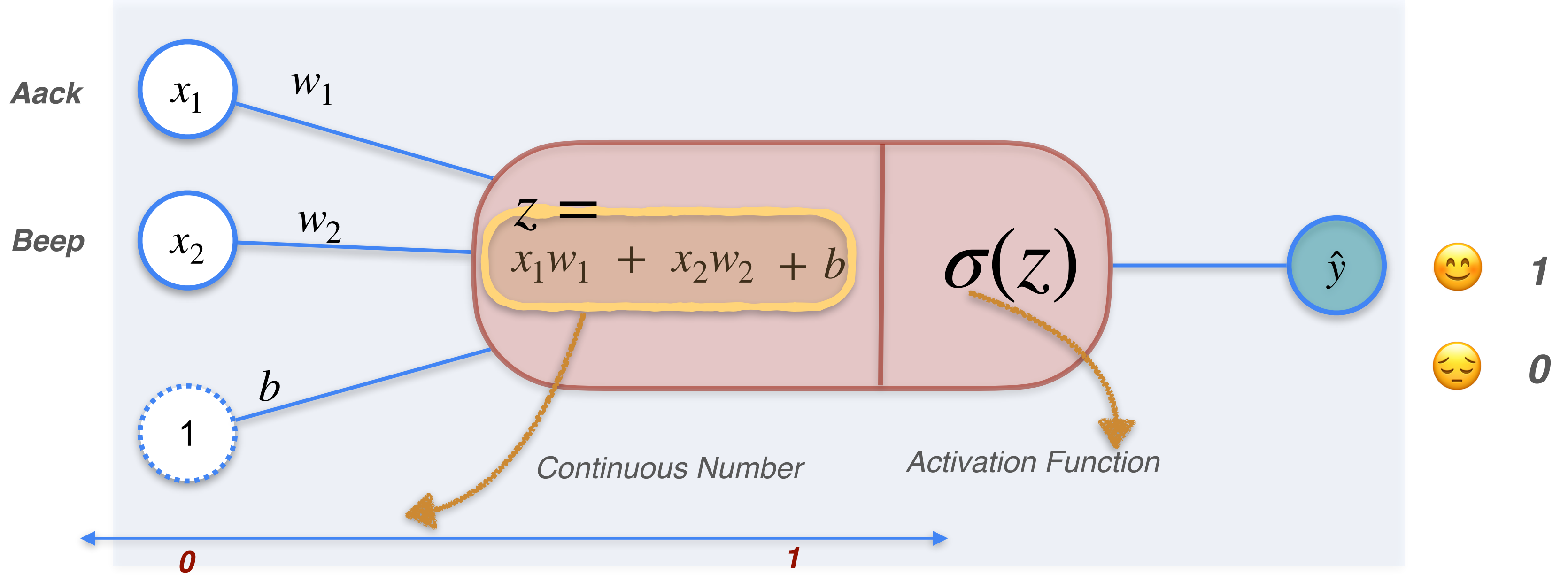
Classification With a Perceptron

Single Layer Neural Network Perceptron



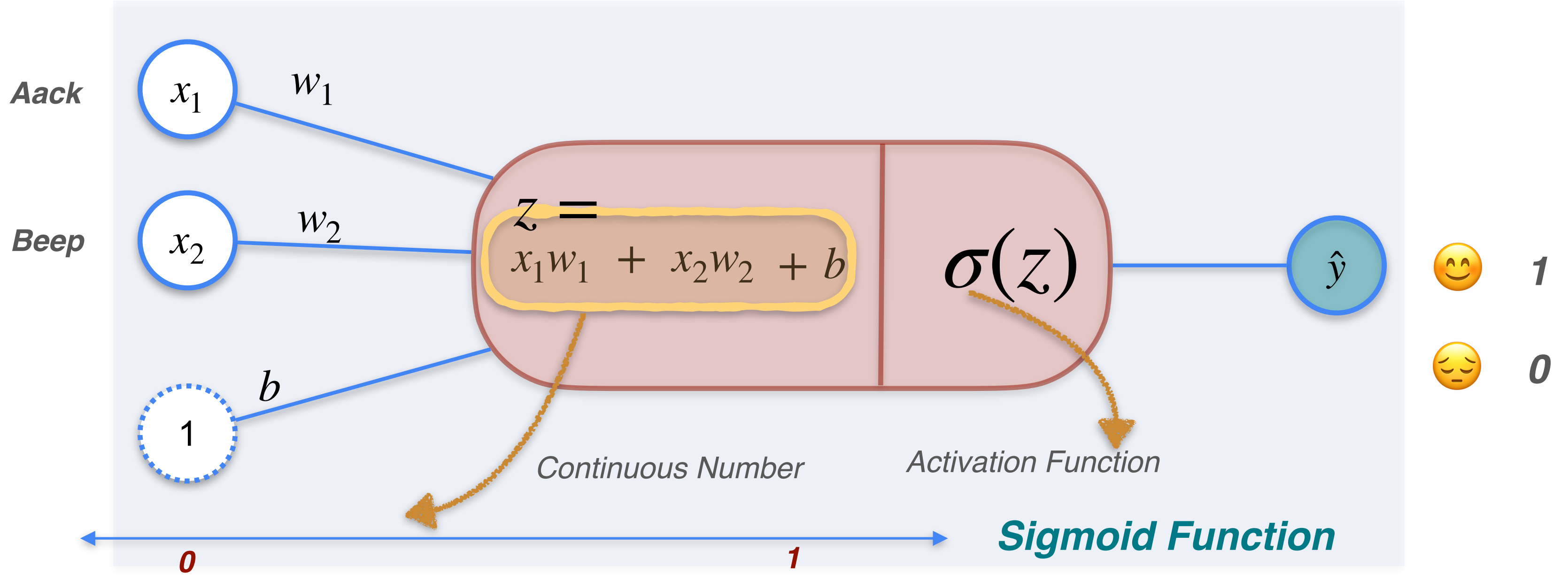
Classification With a Perceptron

Single Layer Neural Network Perceptron

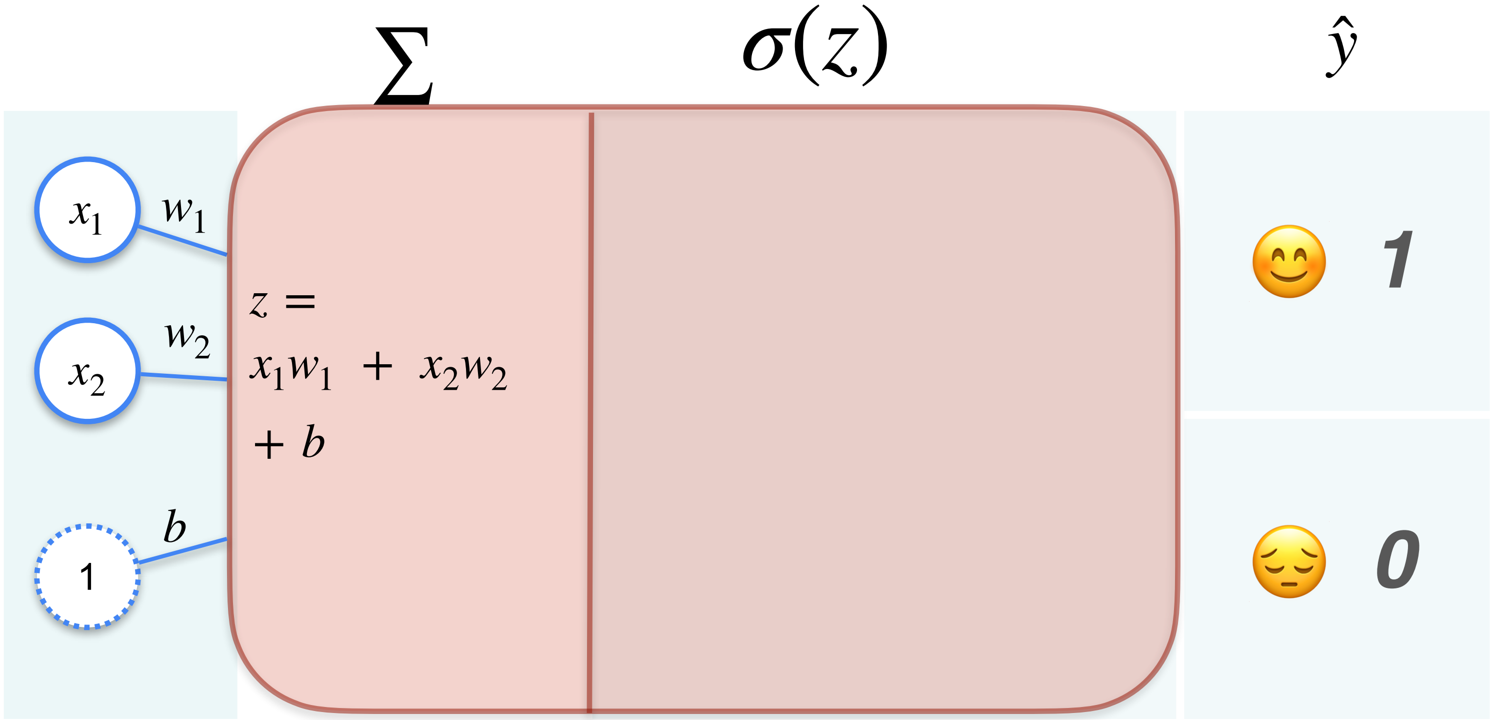


Classification With a Perceptron

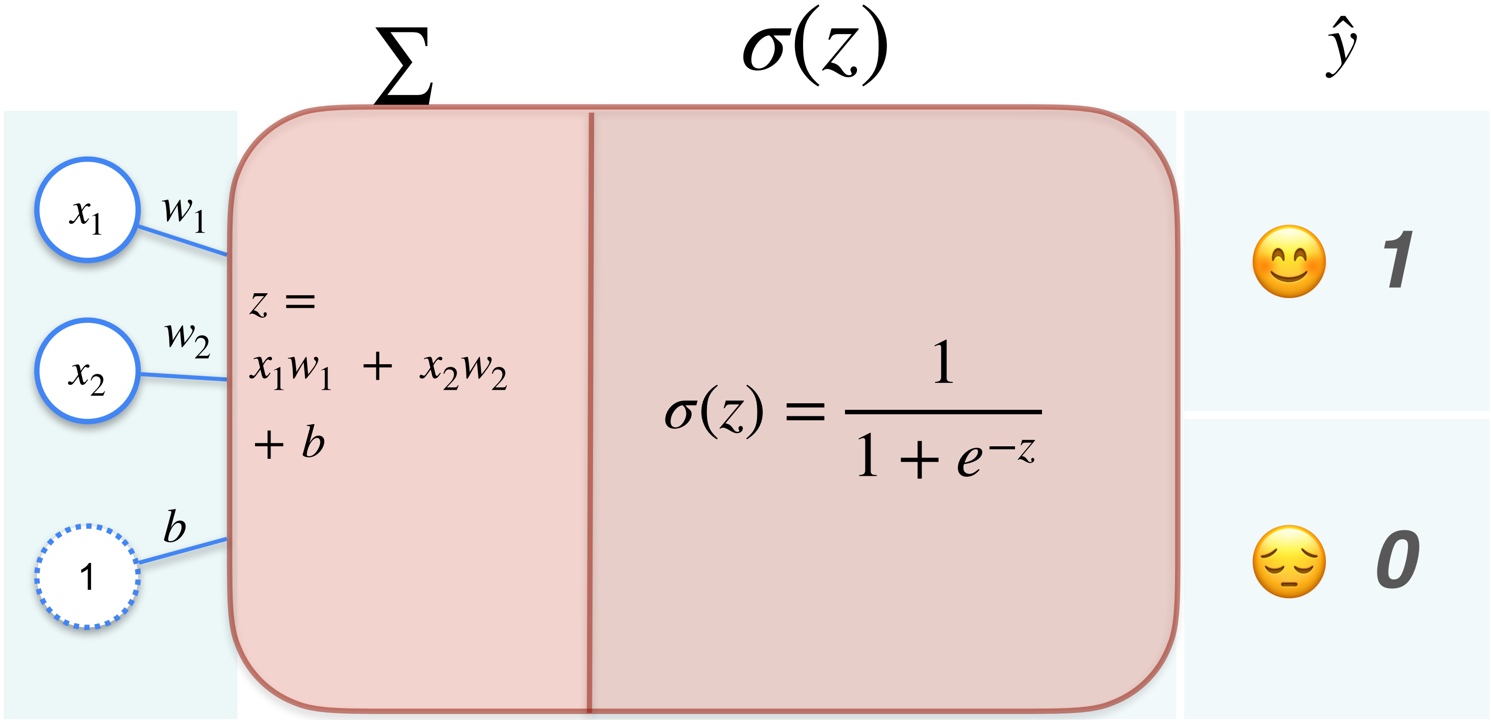
Single Layer Neural Network Perceptron



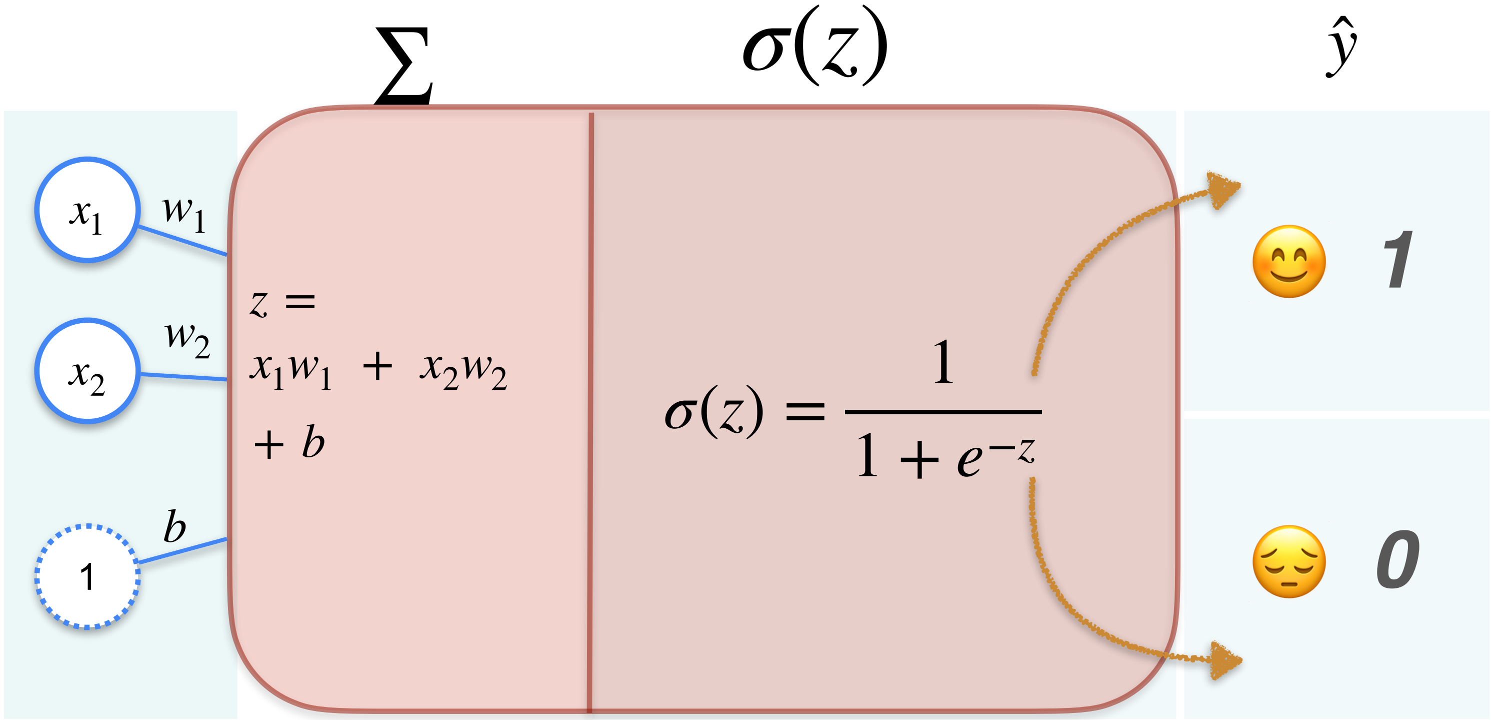
Sigmoid Function



Sigmoid Function



Sigmoid Function



Optimization in Neural Networks and Newton's Method

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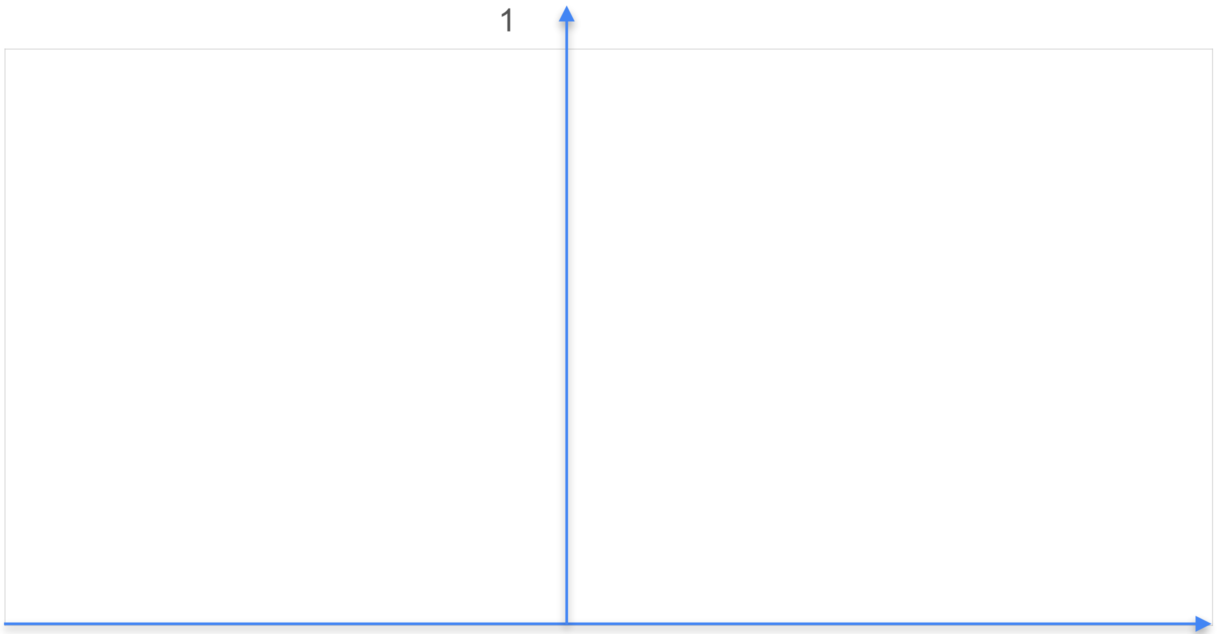
Classification with a perceptron: The sigmoid function

Sigmoid Function

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

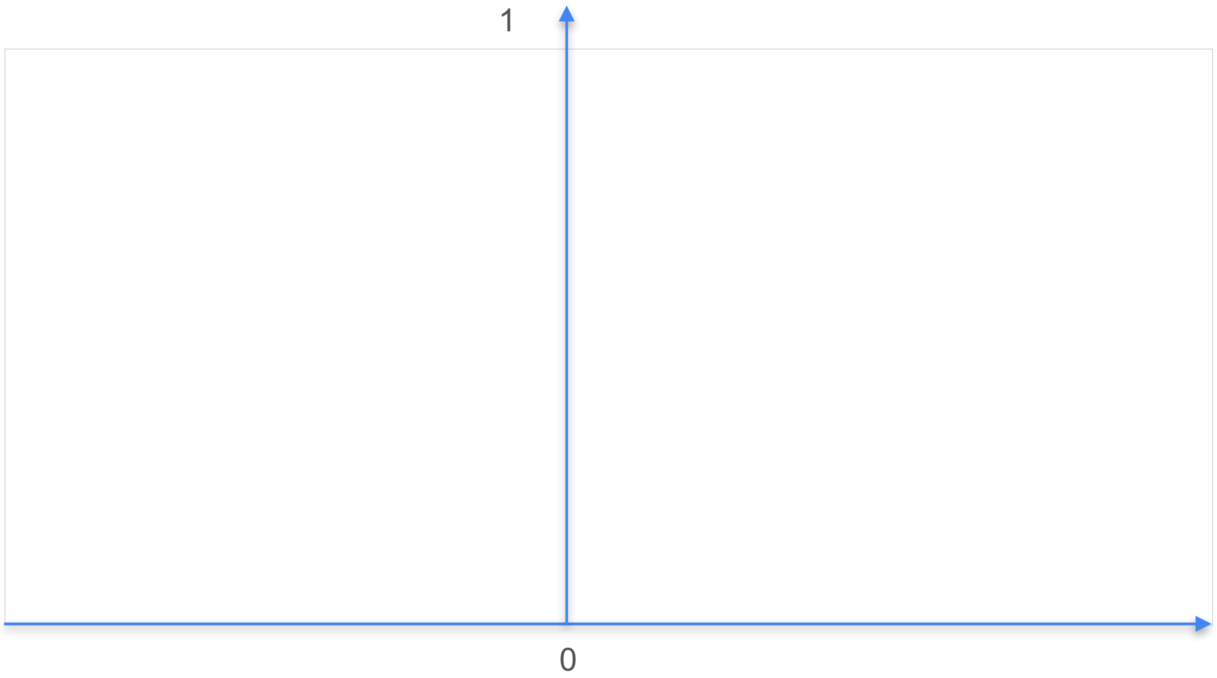
Sigmoid Function

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



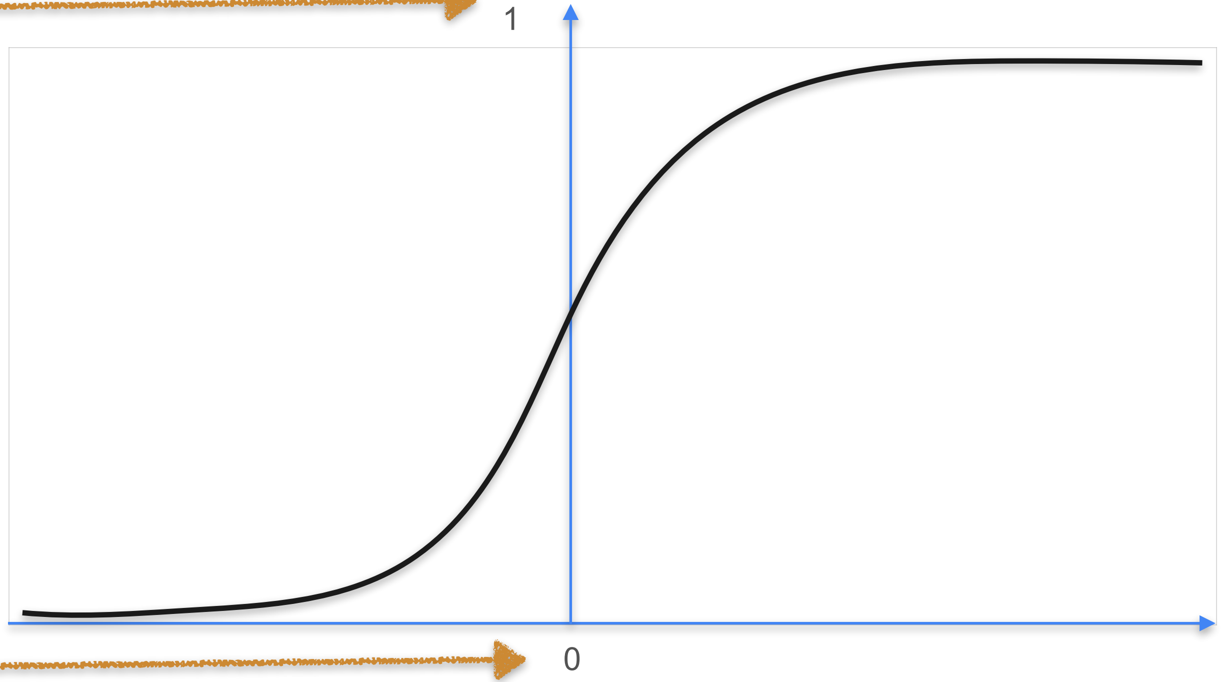
Sigmoid Function

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



Sigmoid Function

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



Derivative of a Sigmoid Function

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

$$= -1$$

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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Derivative of a Sigmoid Function

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

$$= -1$$

Derivative of a Sigmoid Function

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

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Derivative of a Sigmoid Function

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$$= -1\ (1 + e^{-z})^{-2}\ (0$$

Derivative of a Sigmoid Function

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

$$= -1\ (1+e^{-z})^{-2}\ (0\ + e^{-z}(\frac{d}{dz}(-z)))$$

Derivative of a Sigmoid Function

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Derivative of a Sigmoid Function

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$$= -1 \; (1 + e^{-z})^{-2} \; (0 + e^{-z}(\frac{d}{dz}(-z)))$$

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

Derivative of a Sigmoid Function

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Derivative of a Sigmoid Function

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Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

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

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

Derivative of a Sigmoid Function

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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Derivative of a Sigmoid Function

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

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

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

Derivative of a Sigmoid Function

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

Recall that:

Derivative of a Sigmoid Function

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

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

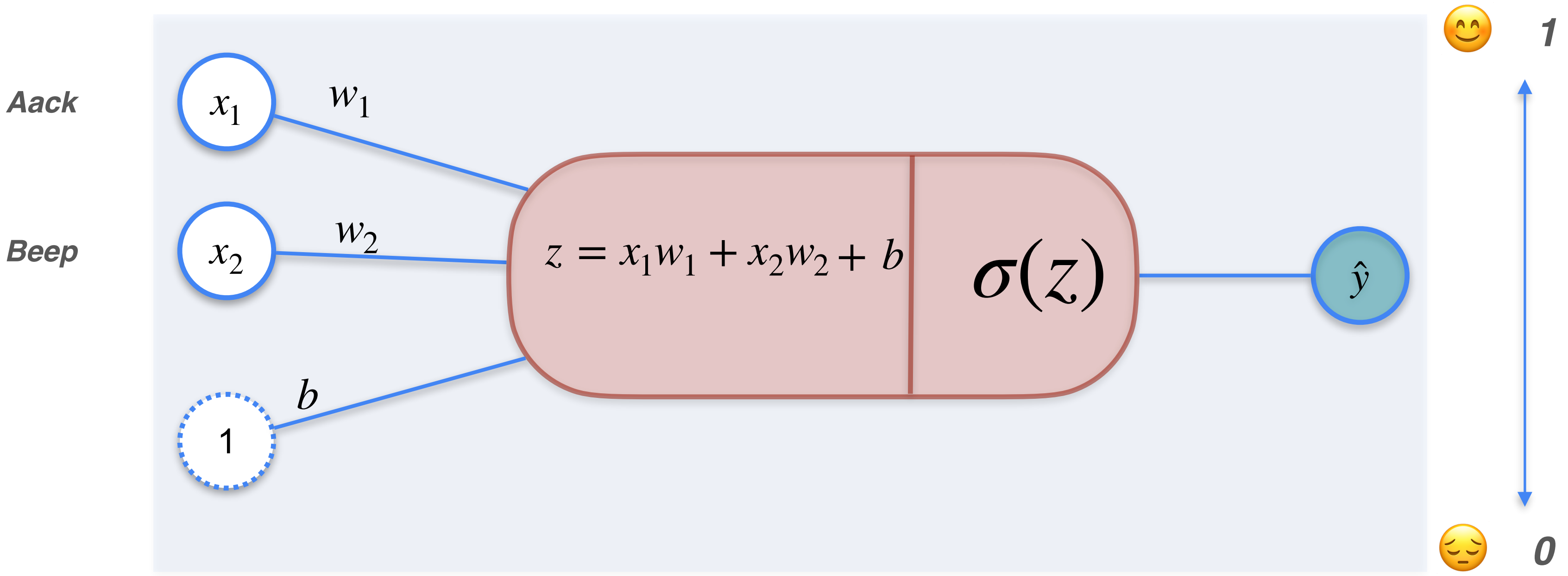
DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Classification with a perceptron: Gradient Descent

Classification With a Perceptron

Aack beep beep beep



Classification With a Perceptron

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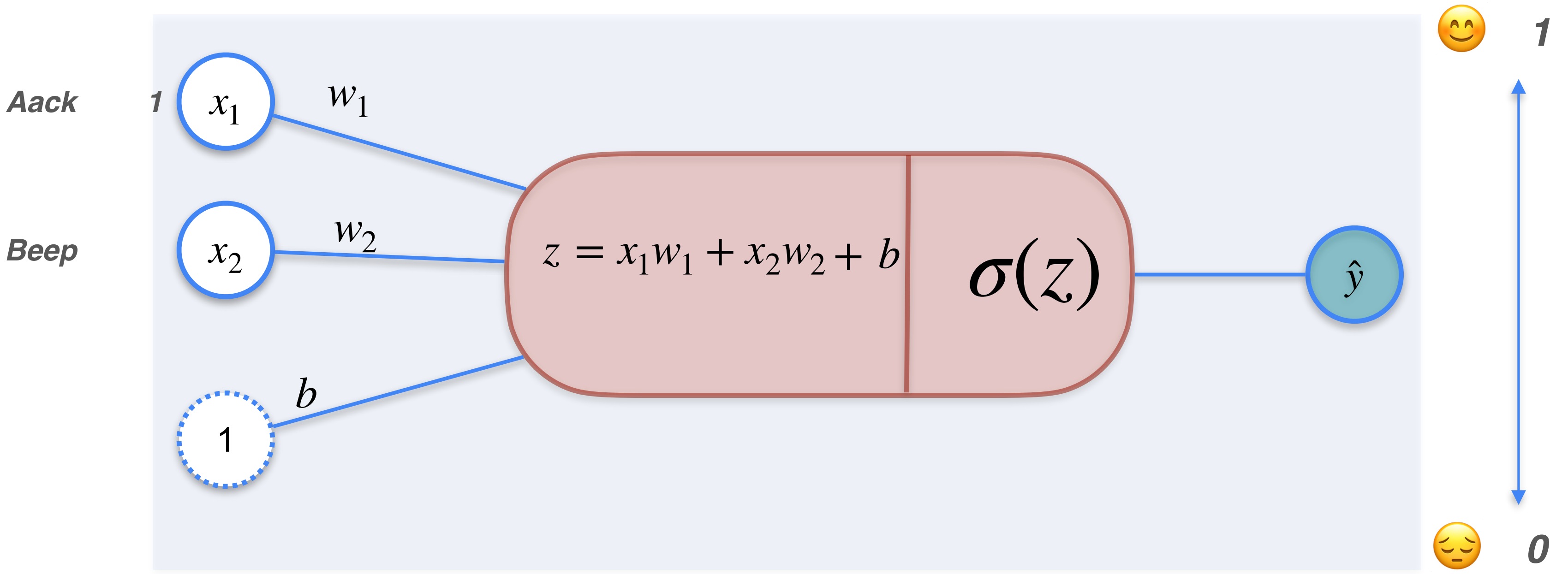

Classification With a Perceptron

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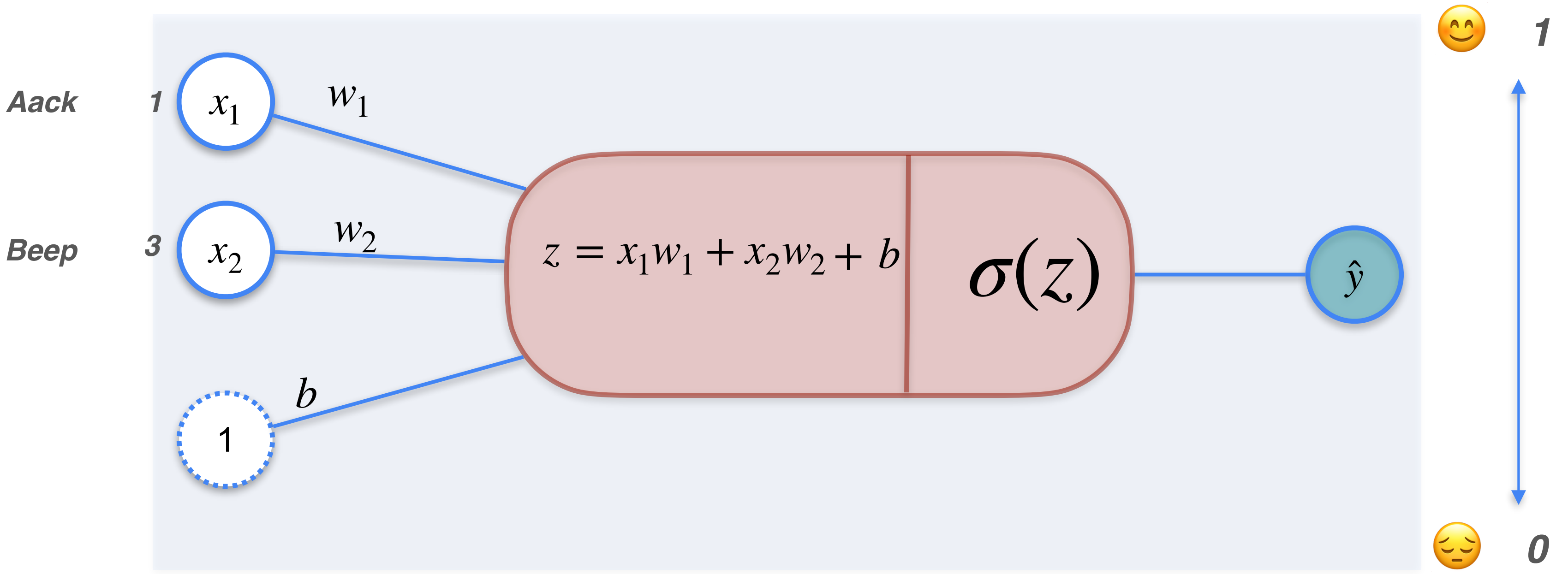

Classification With a Perceptron

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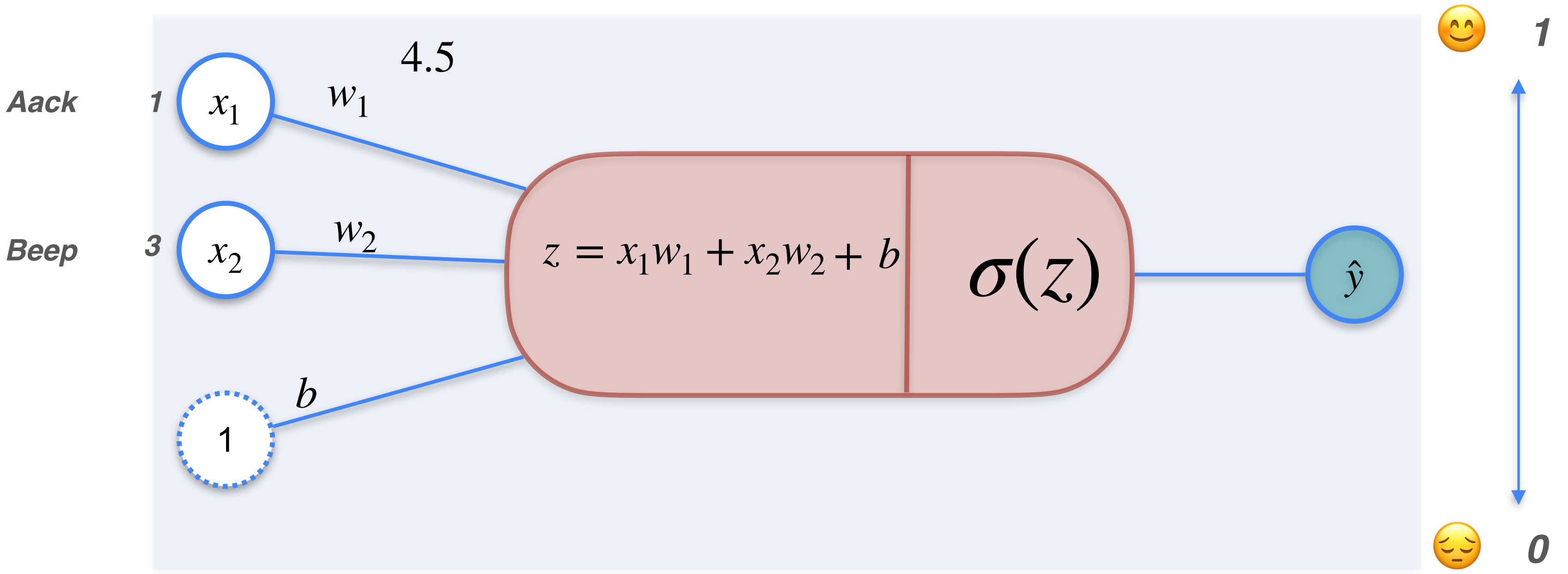

Classification With a Perceptron

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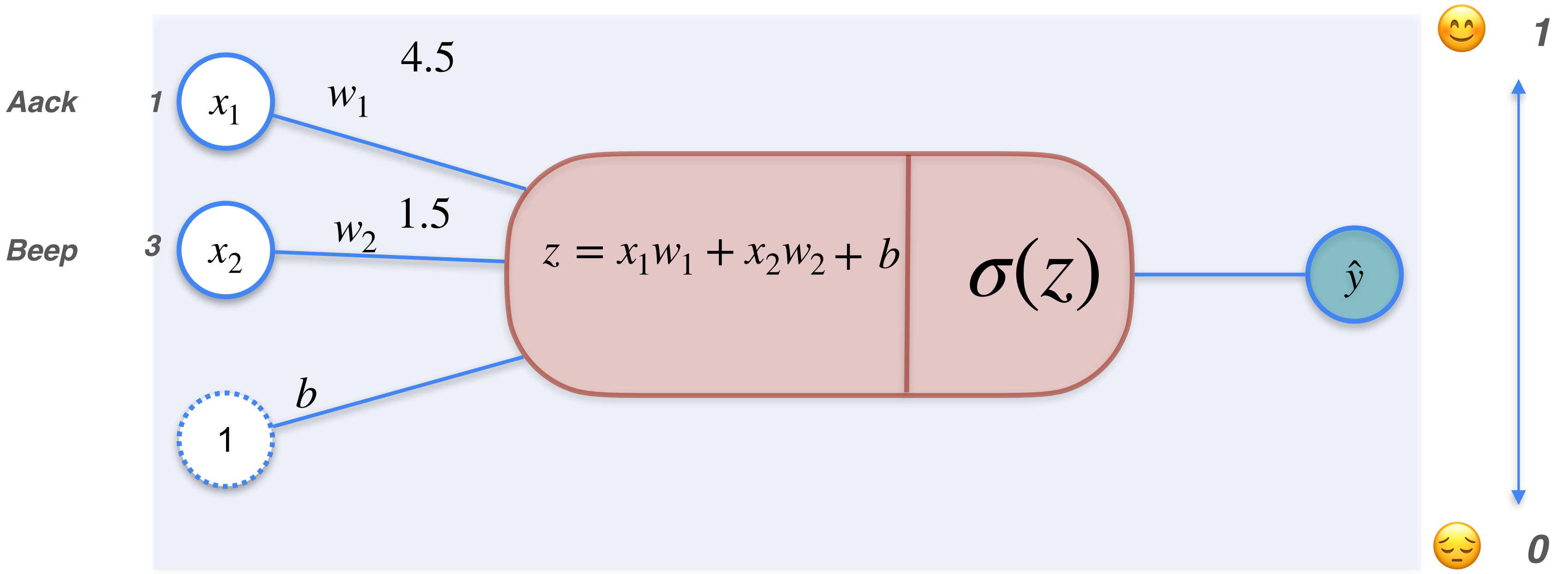

Classification With a Perceptron

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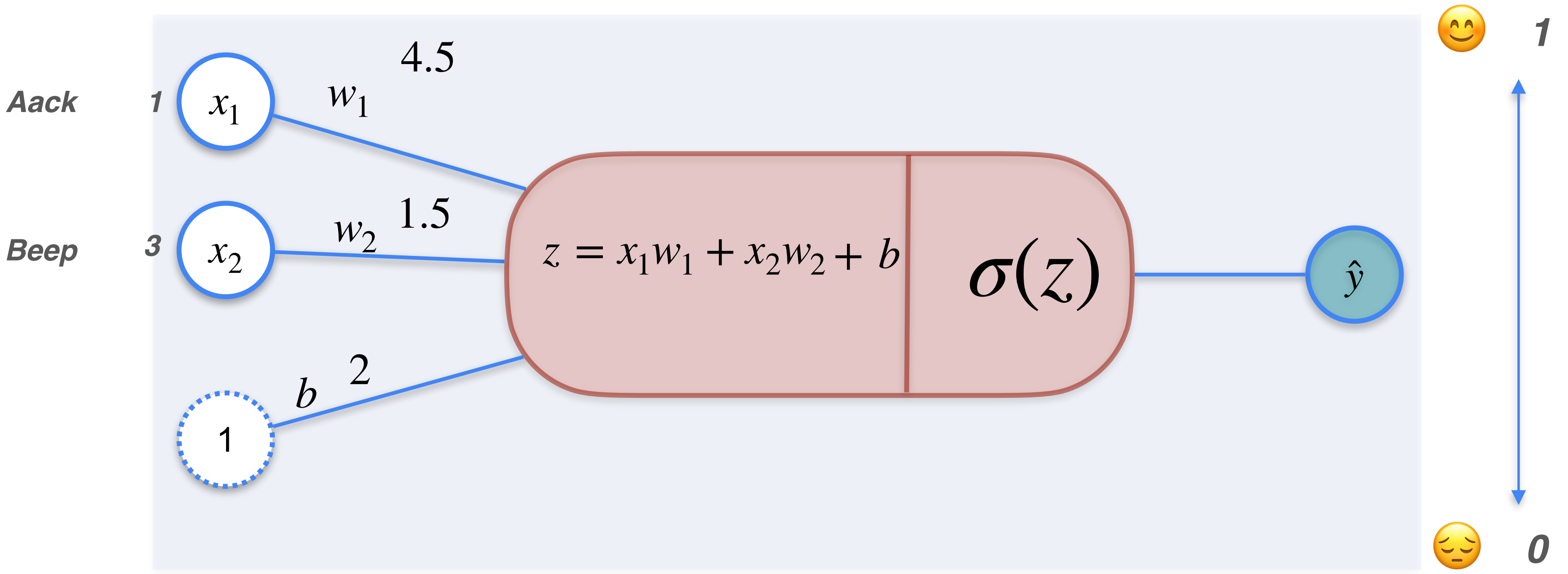

Classification With a Perceptron

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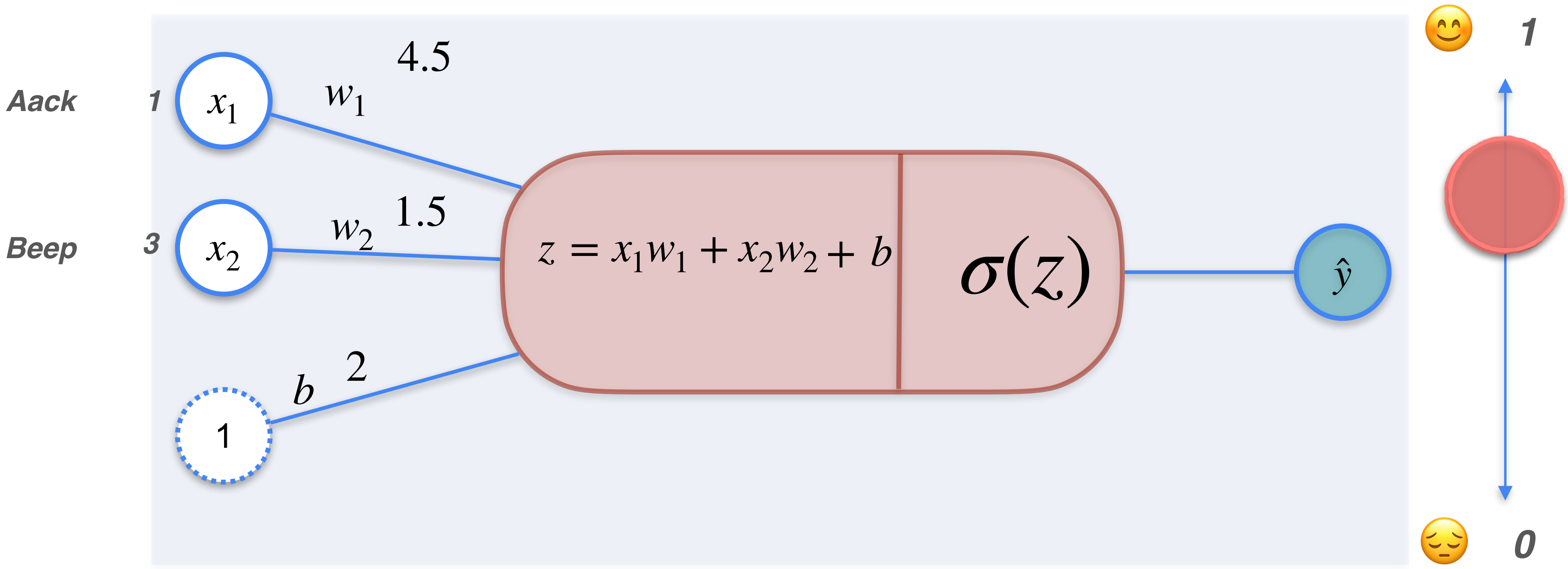

Classification With a Perceptron

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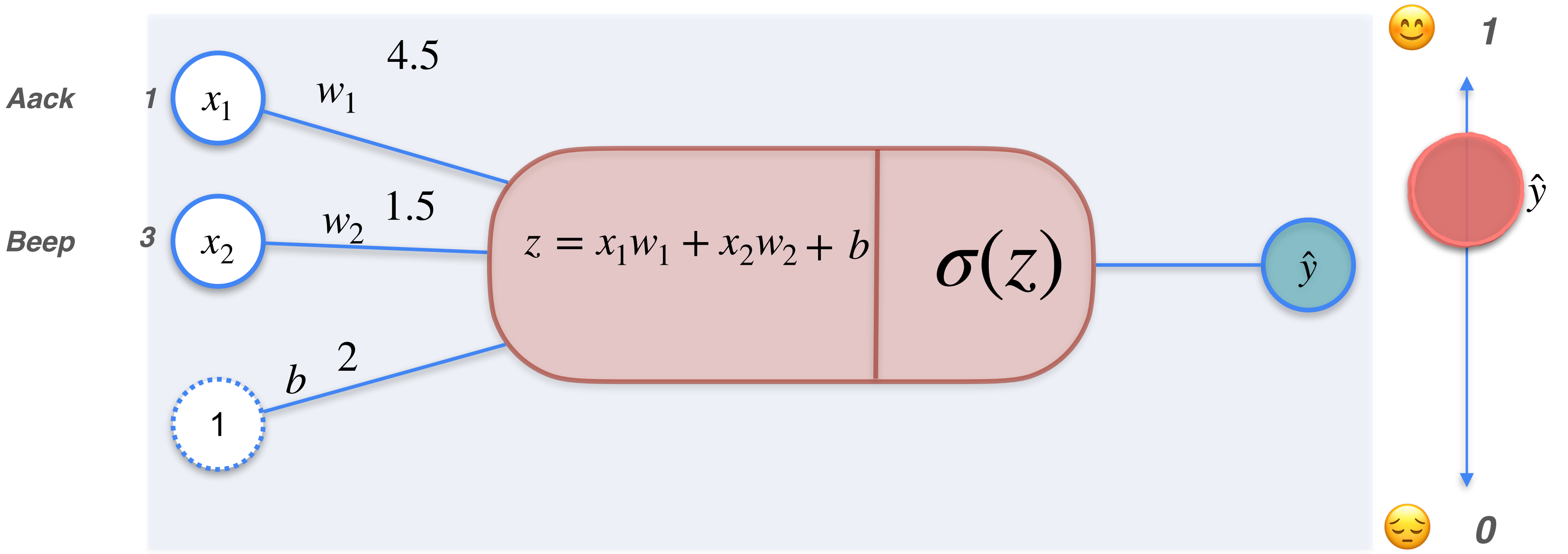

Classification With a Perceptron

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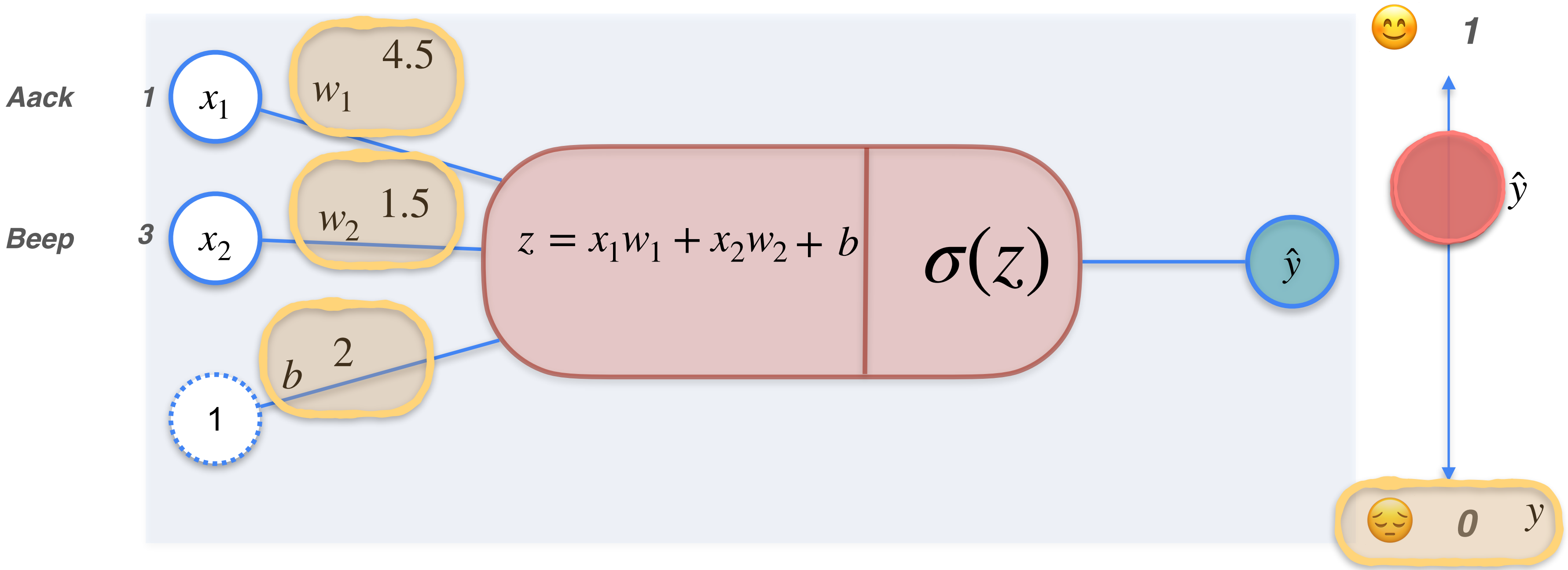

Classification With a Perceptron

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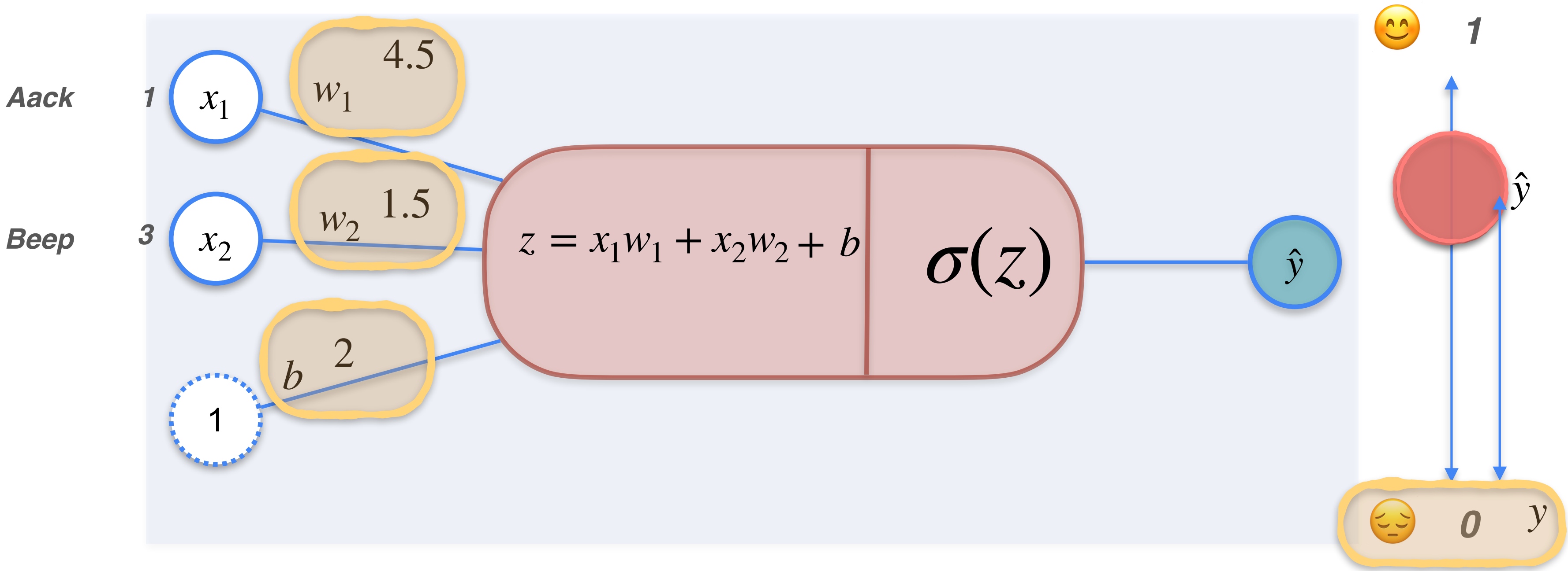

Classification With a Perceptron

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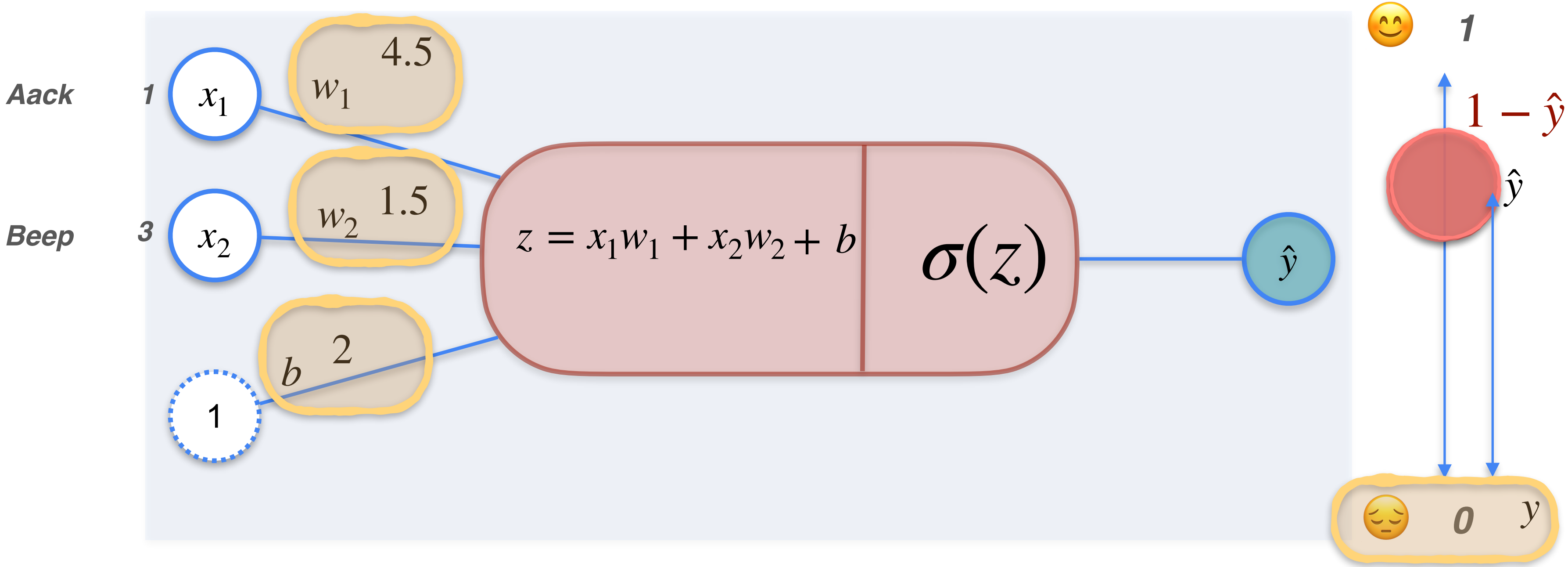

Classification With a Perceptron

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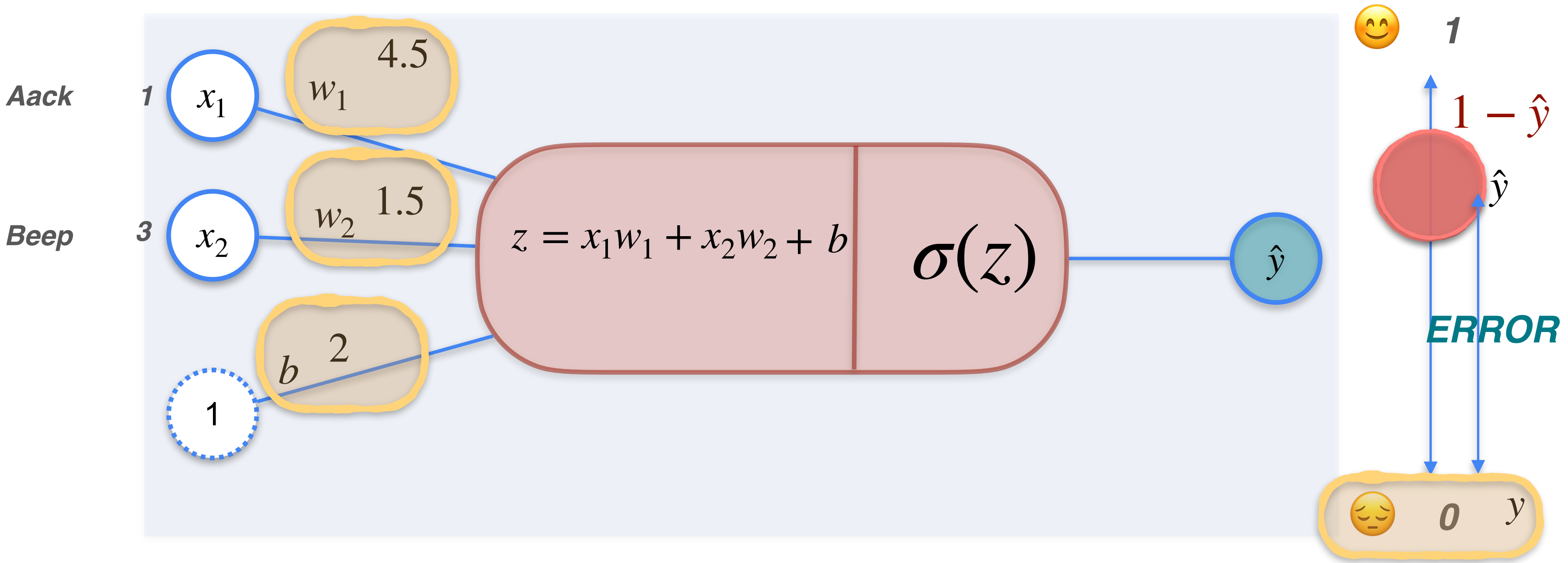
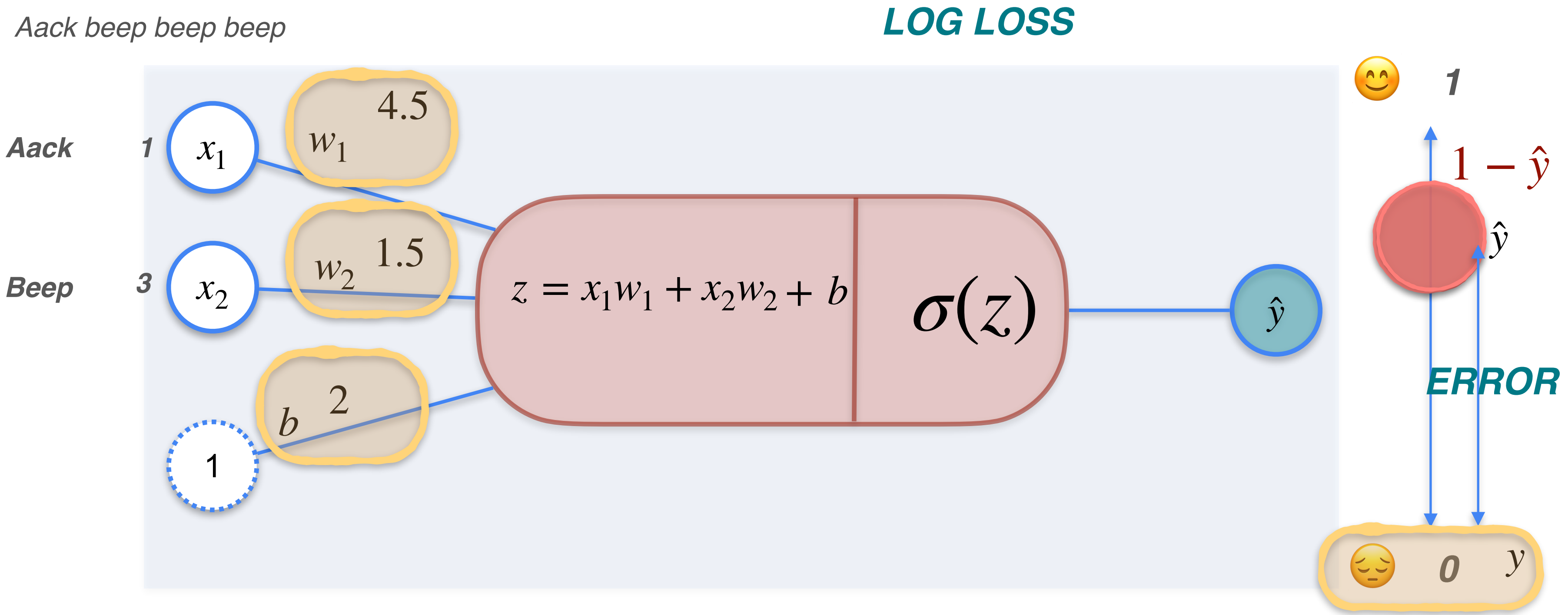


Classification With a Perceptron



Classification With a Perceptron

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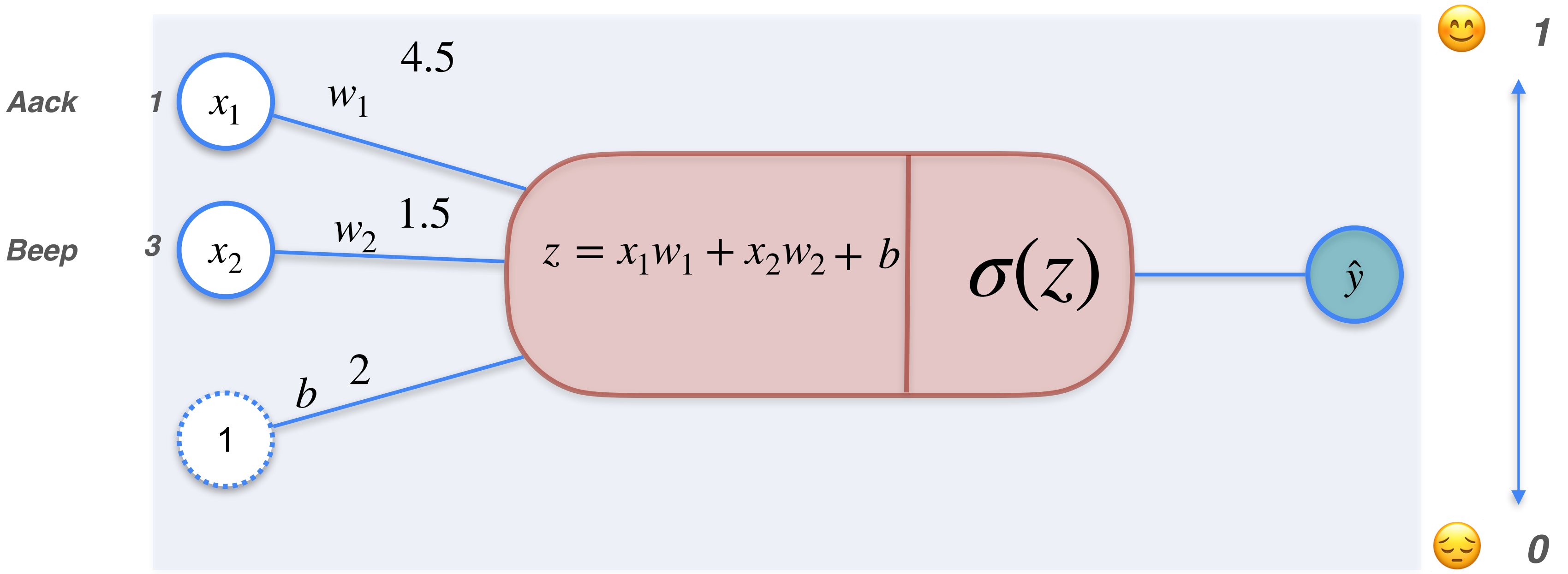
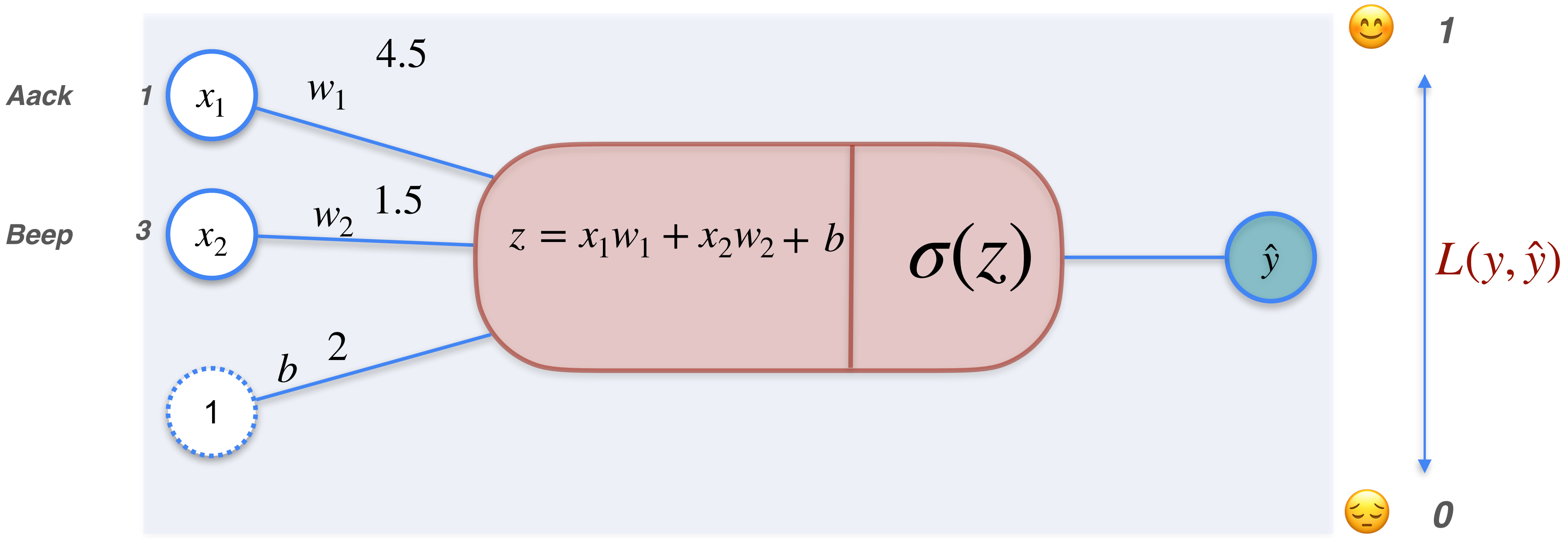


Classification With a Perceptron

Aack beep beep beep



Classification With a Perceptron

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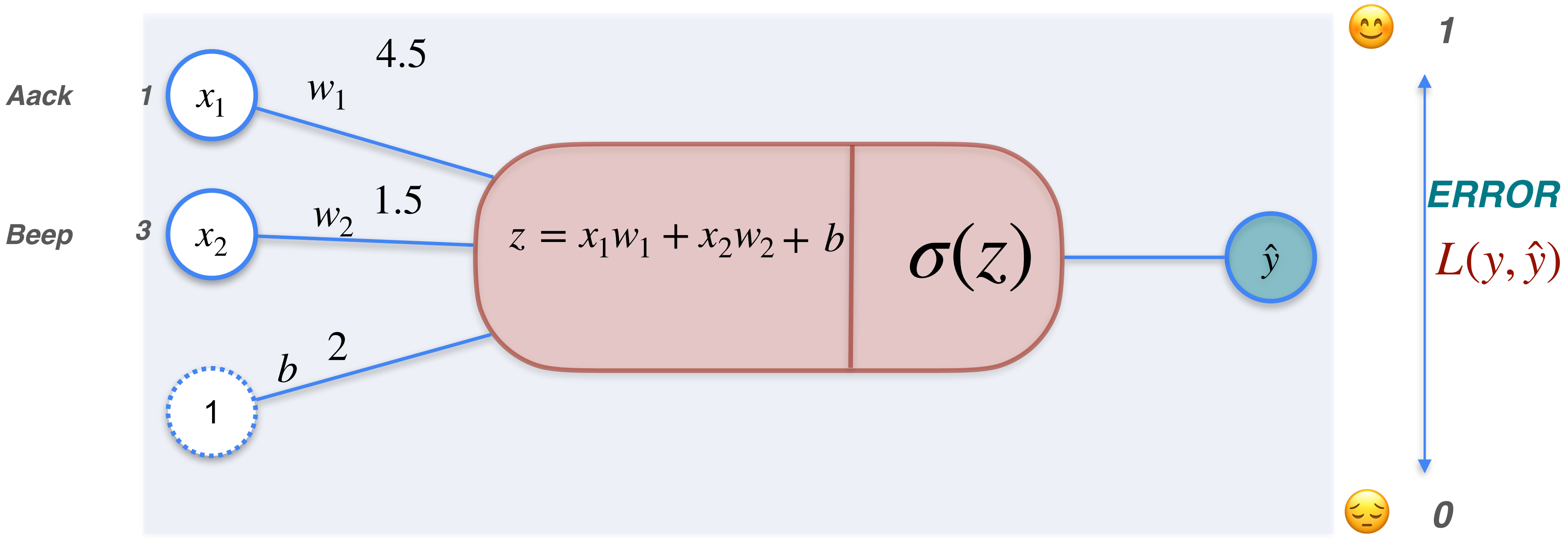
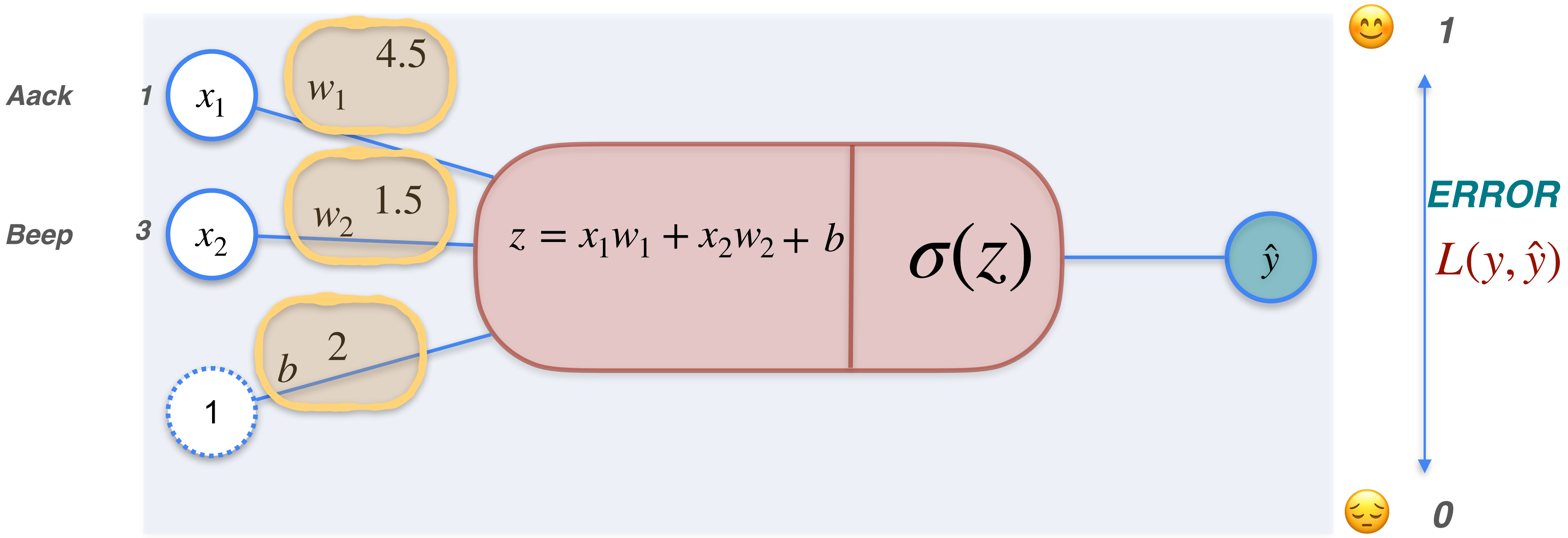


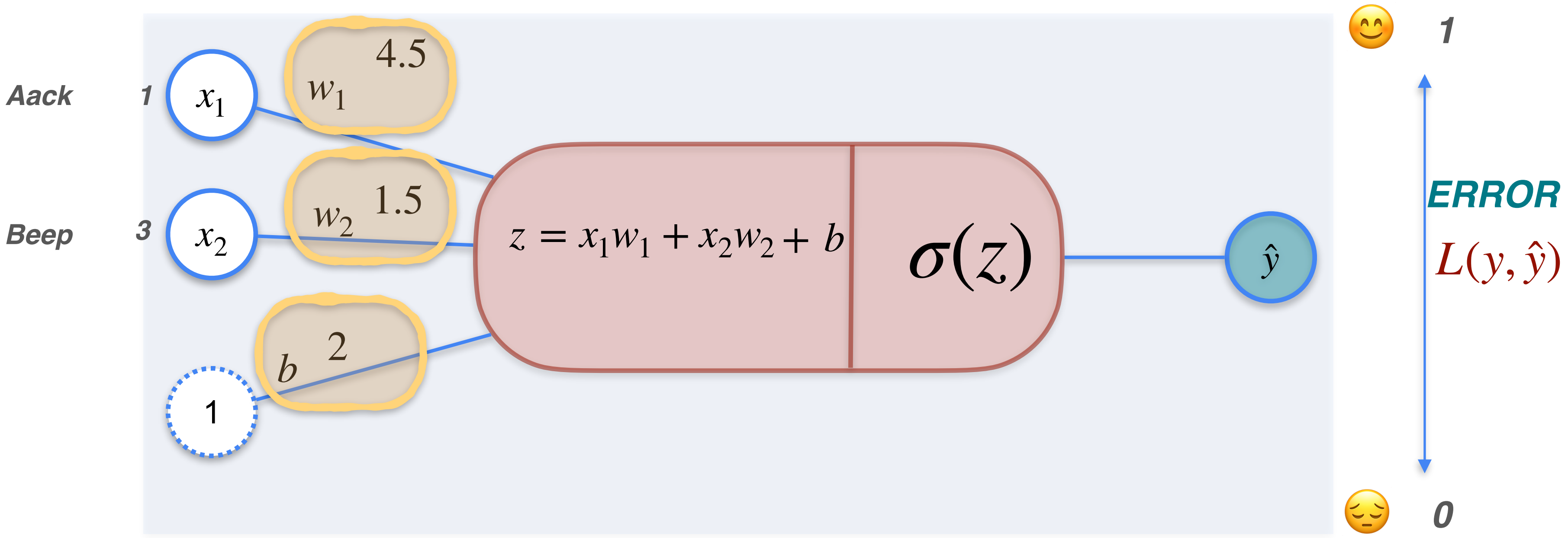
Classification With a Perceptron

Aack beep beep beep

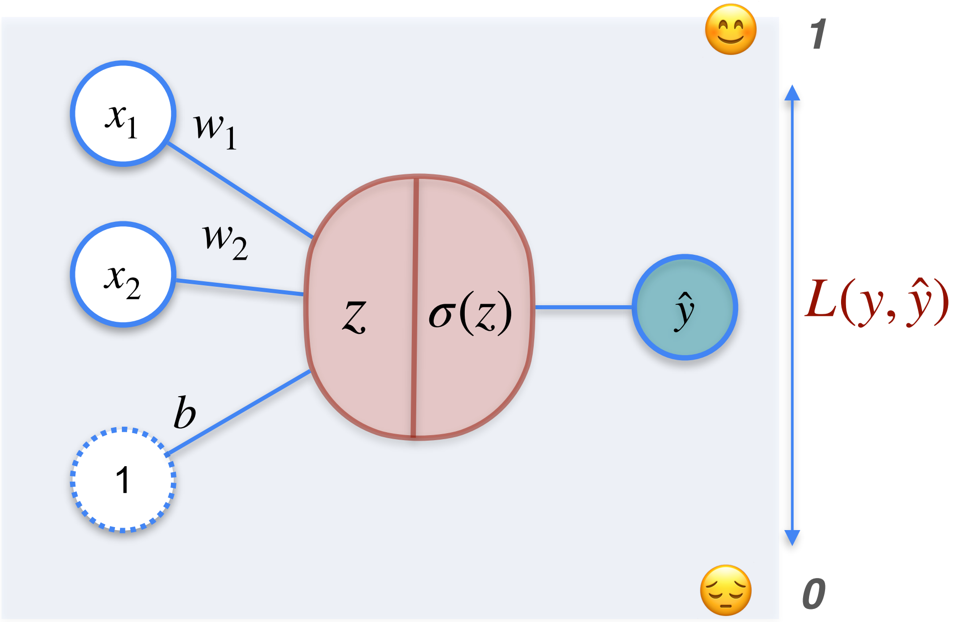


Classification With a Perceptron

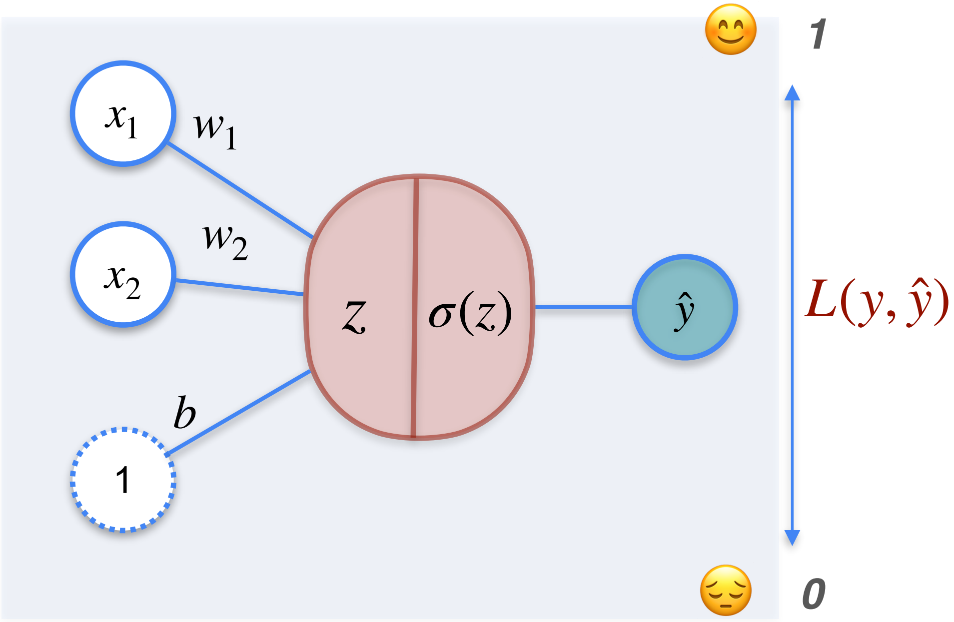
Aack beep beep beep



Classification With a Perceptron



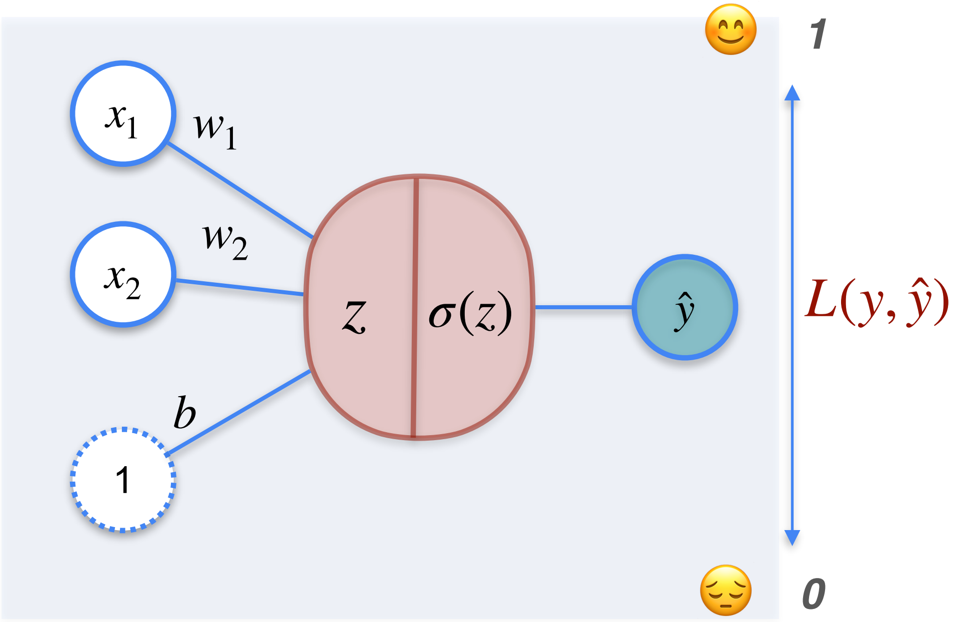
Classification With a Perceptron



Prediction Function:

$\hat{y}$

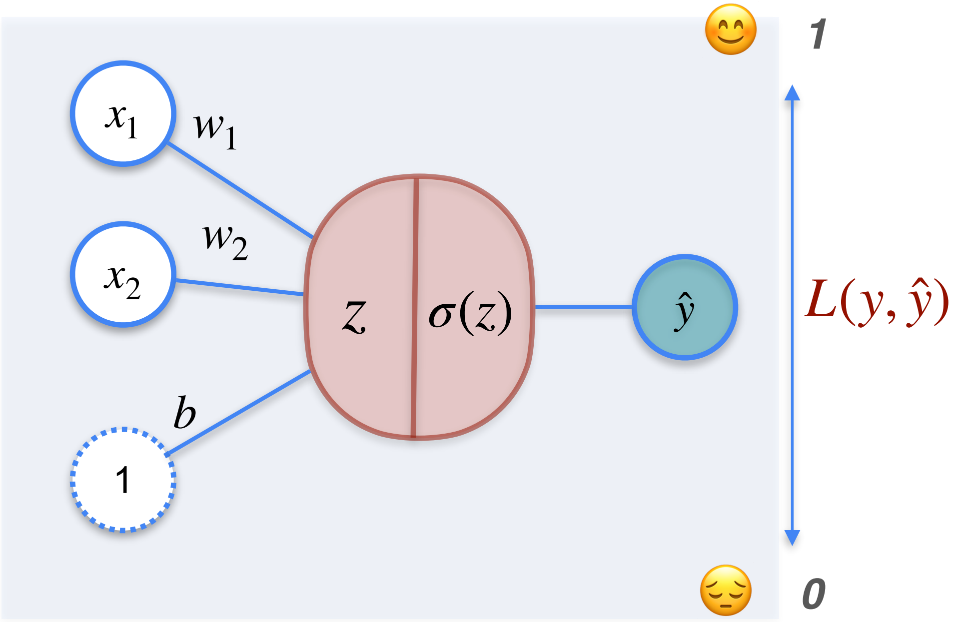
Classification With a Perceptron



Prediction Function:

$$\hat{y} = \sigma(w_1 x_1 + w_2 x_2 + b)$$

Classification With a Perceptron

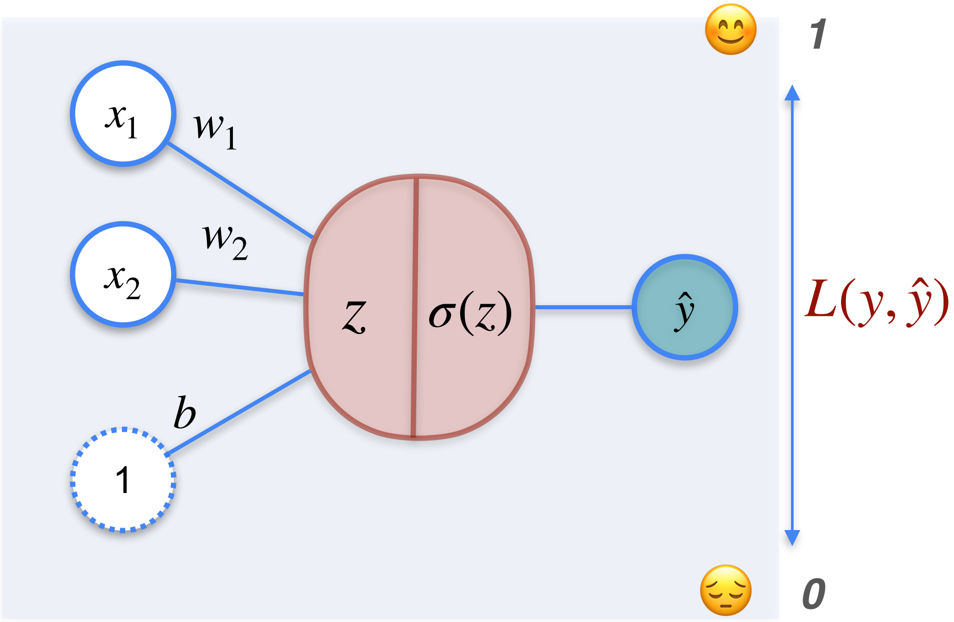


Prediction Function:

$$\hat{y} = \sigma(w_1 x_1 + w_2 x_2 + b)$$

Loss Function:

Classification With a Perceptron



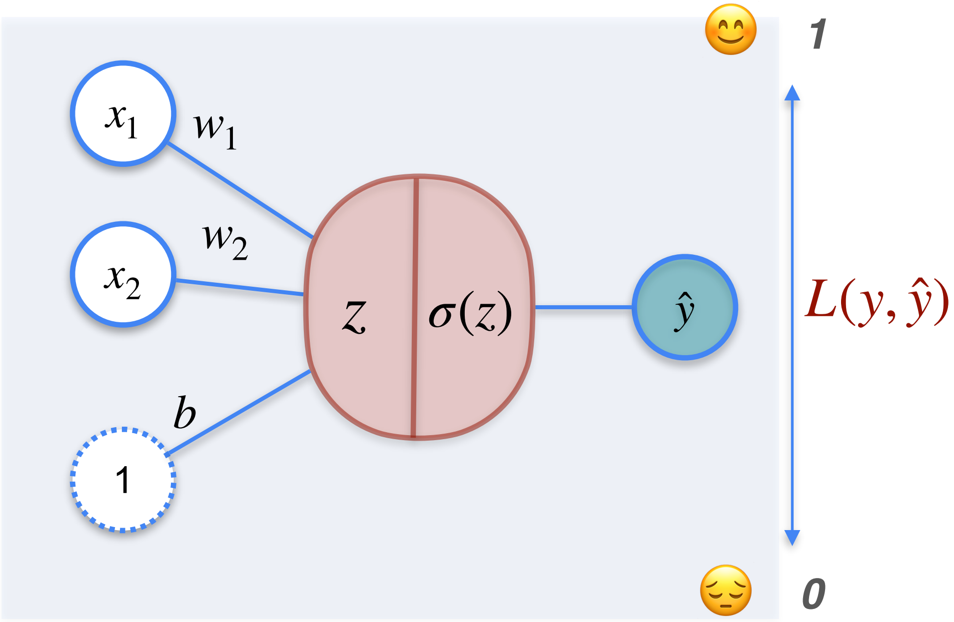
Prediction Function:

$$\hat{y} = \sigma(w_1 x_1 + w_2 x_2 + b)$$

Loss Function:

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

Classification With a Perceptron



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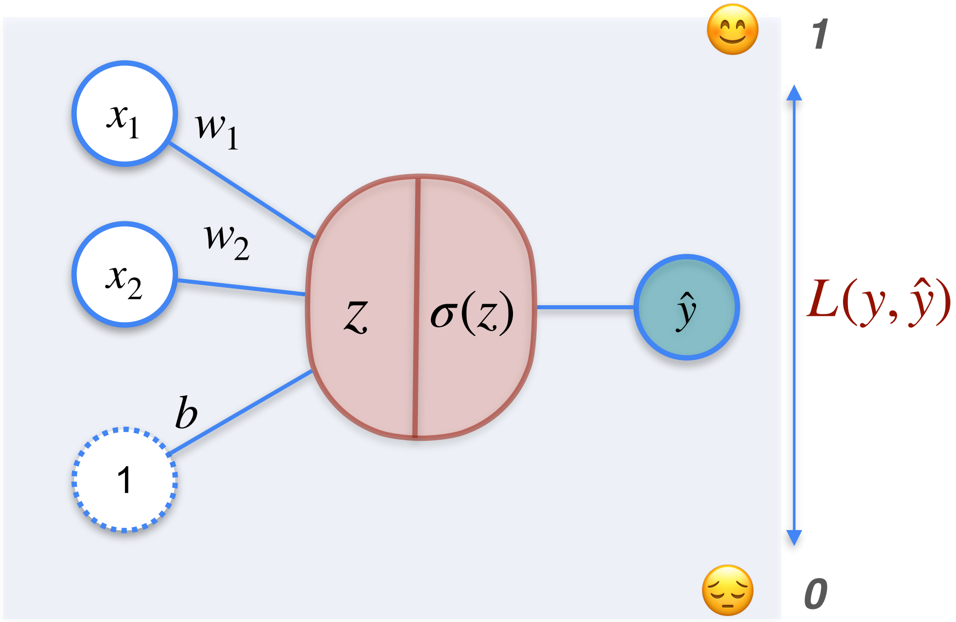
Main Goal:

Classification With a Perceptron



Prediction Function:

$$\hat{y} = \sigma(w_1 x_1 + w_2 x_2 + b)$$

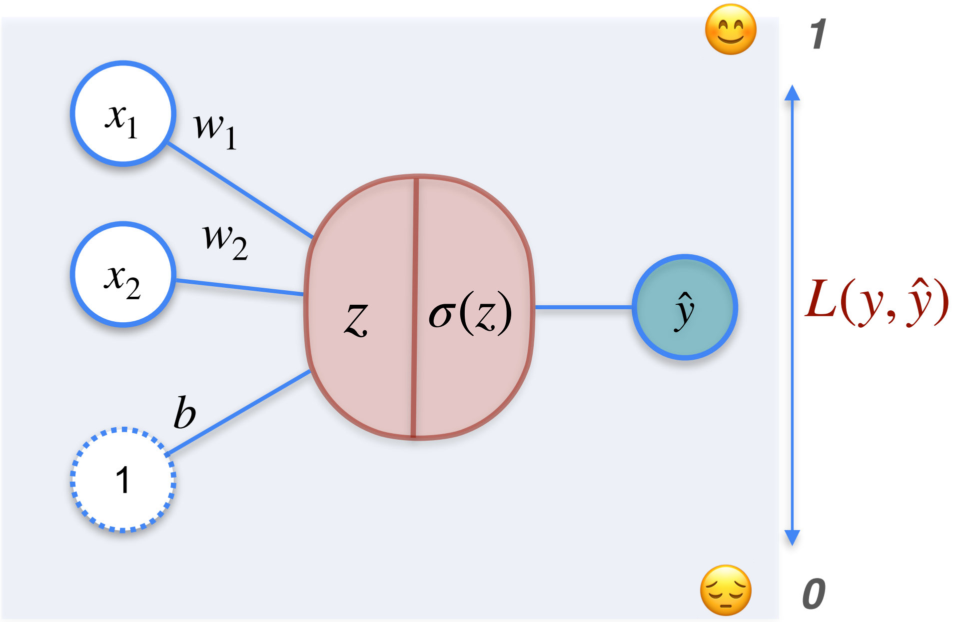
Loss Function:

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

Main Goal:

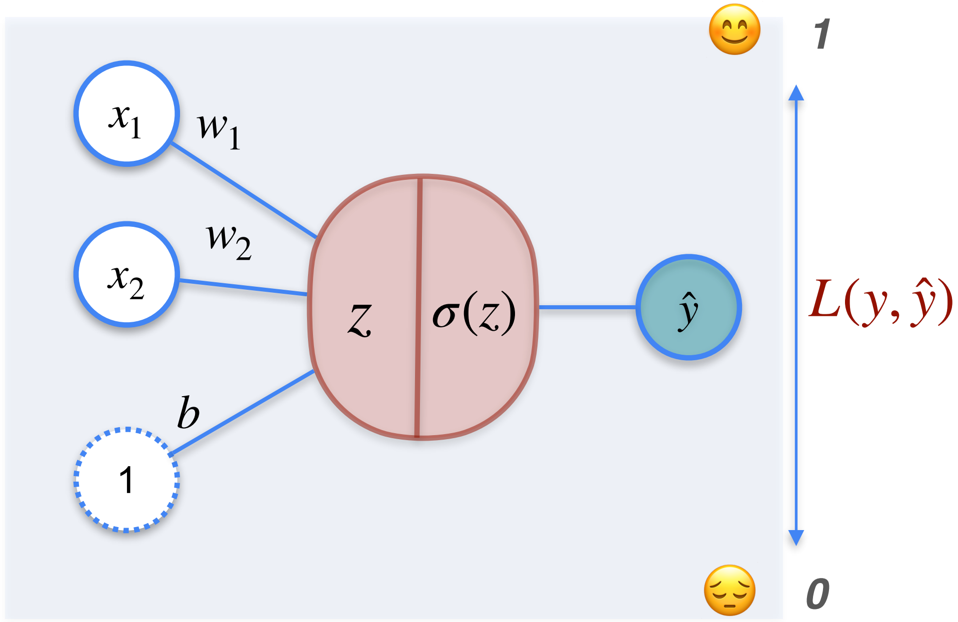
Find w_1 , w_2 , b that give $\hat{y}$ with the least error

Classification With a Perceptron

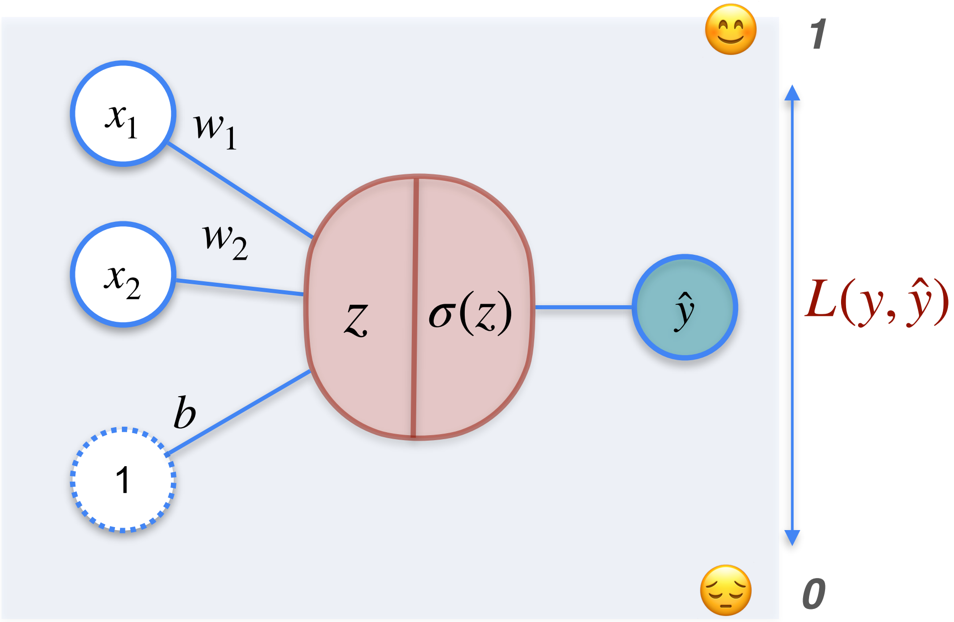


Classification With a Perceptron

To find optimal values for:



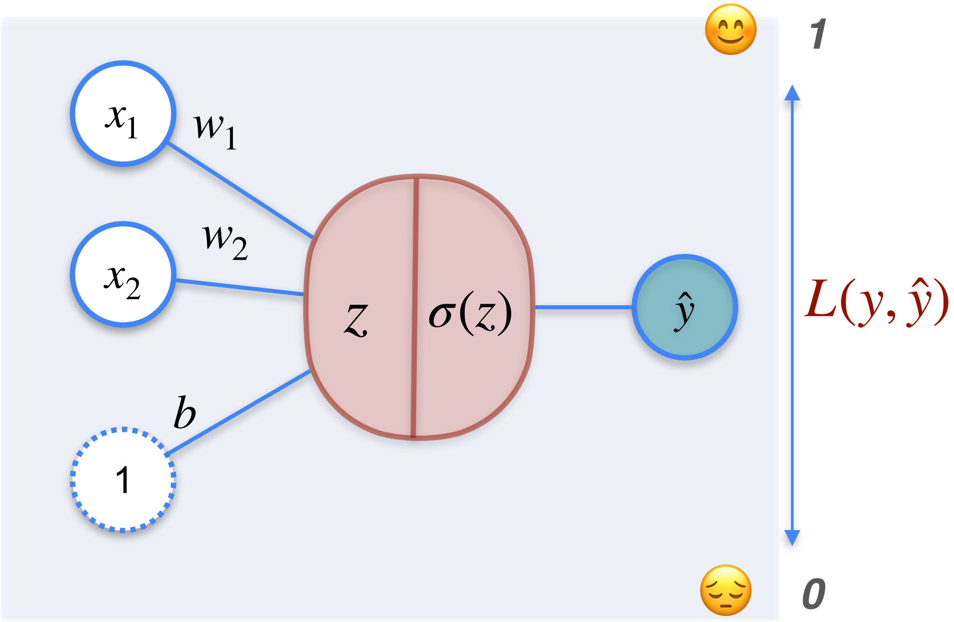
Classification With a Perceptron



To find optimal values for:

w_1 , w_2 , b

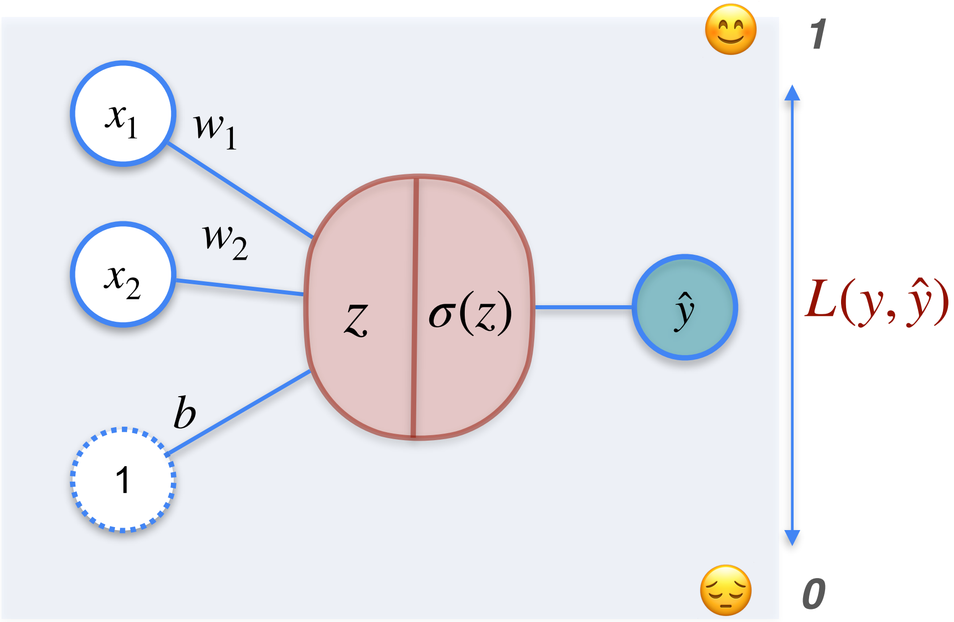
Classification With a Perceptron



To find optimal values for:
w_1 , w_2 , b

You need gradient descent

Classification With a Perceptron



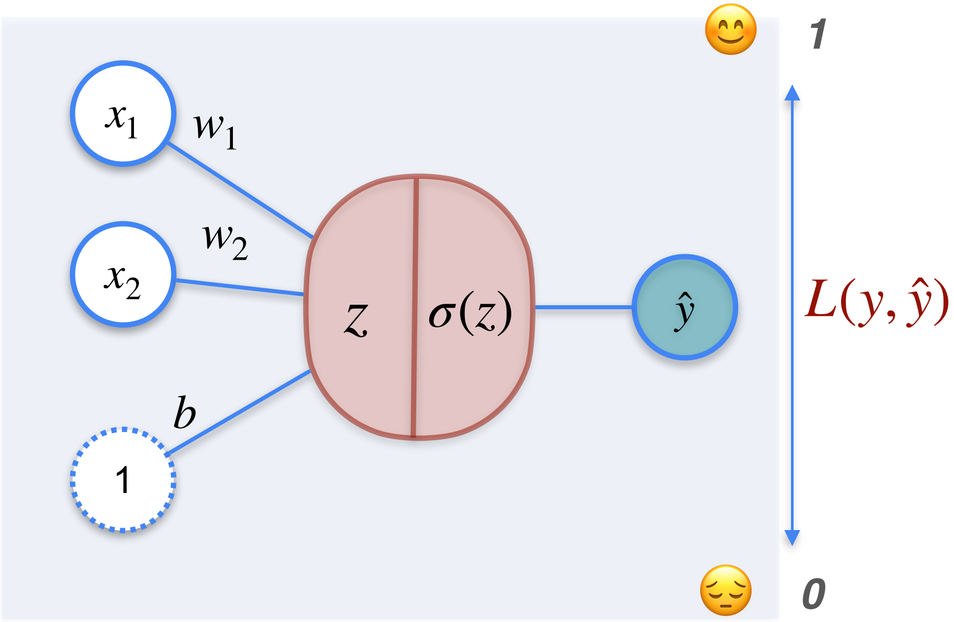
To find optimal values for:

$w_1 \ , w_2 \ , b$

You need gradient descent

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

Classification With a Perceptron



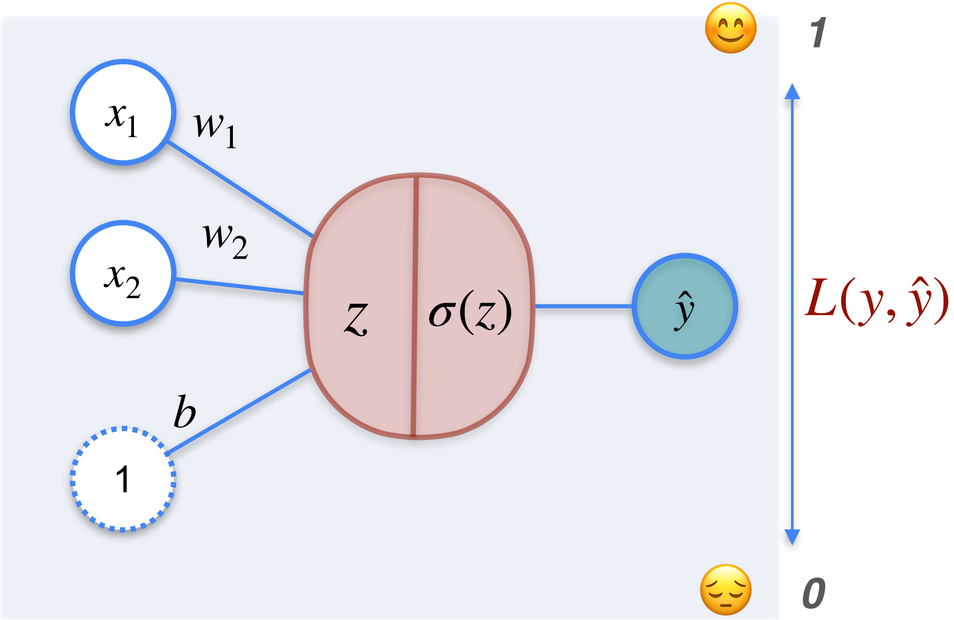
To find optimal values for:
w_1 , w_2 , b

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:

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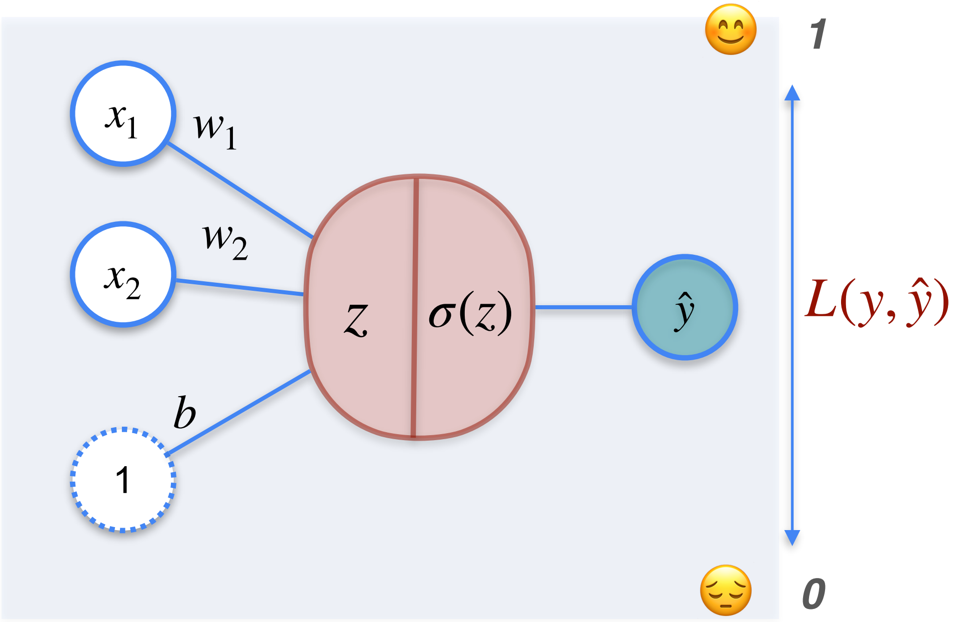
You need gradient descent

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

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

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

Classification With a Perceptron



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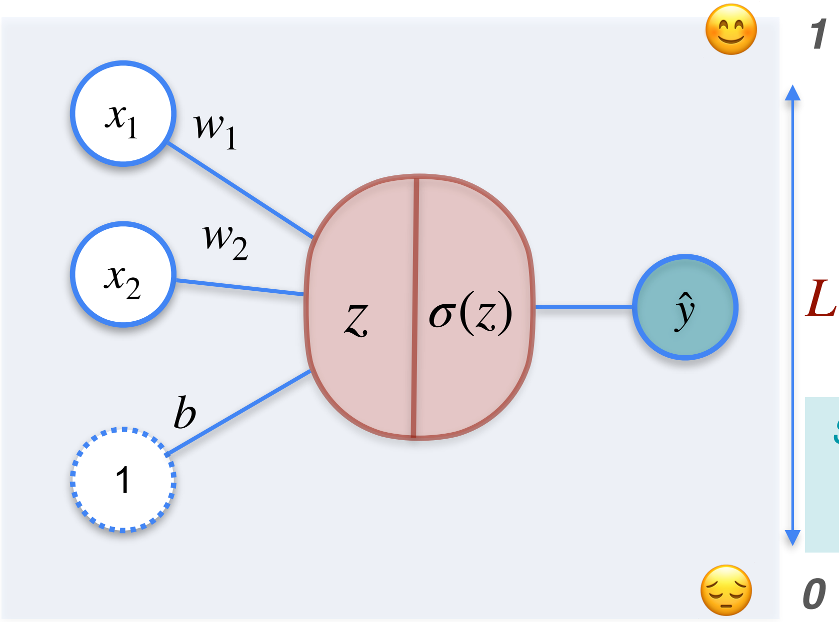
Classification With a Perceptron



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

To find optimal values for:

w_1 , w_2 , b

You need gradient descent

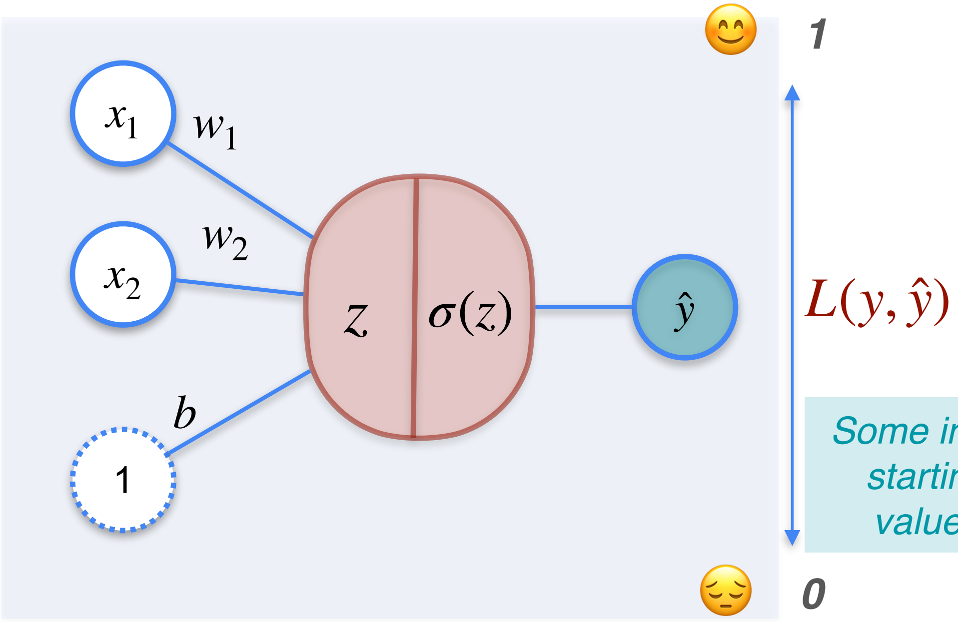
Some initial starting values

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

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

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

Classification With a Perceptron



To find optimal values for:

w_1 , w_2 , b

You need gradient descent

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

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

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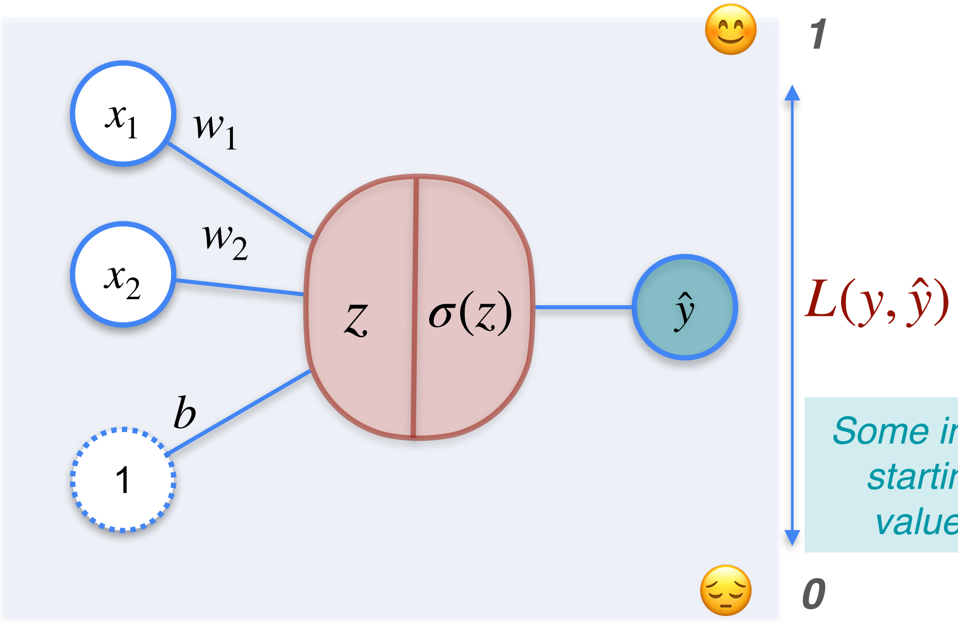
Classification With a Perceptron



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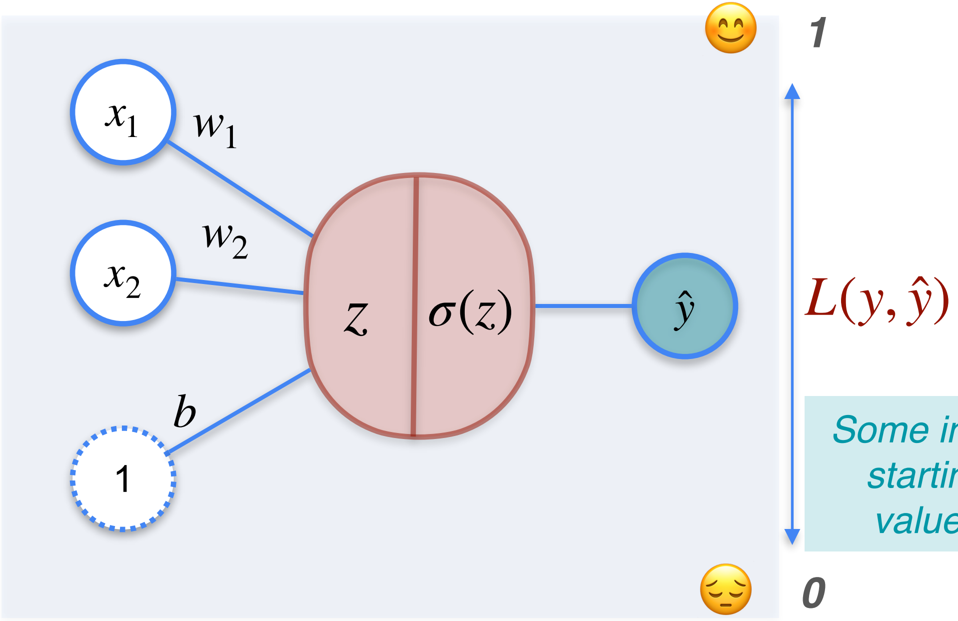
Classification With a Perceptron



To find optimal values for:

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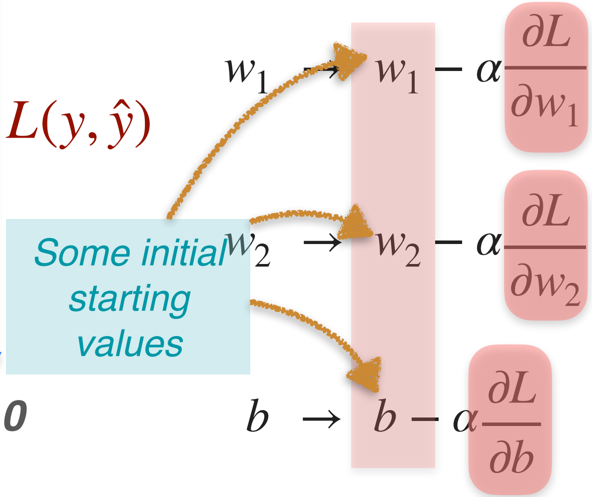
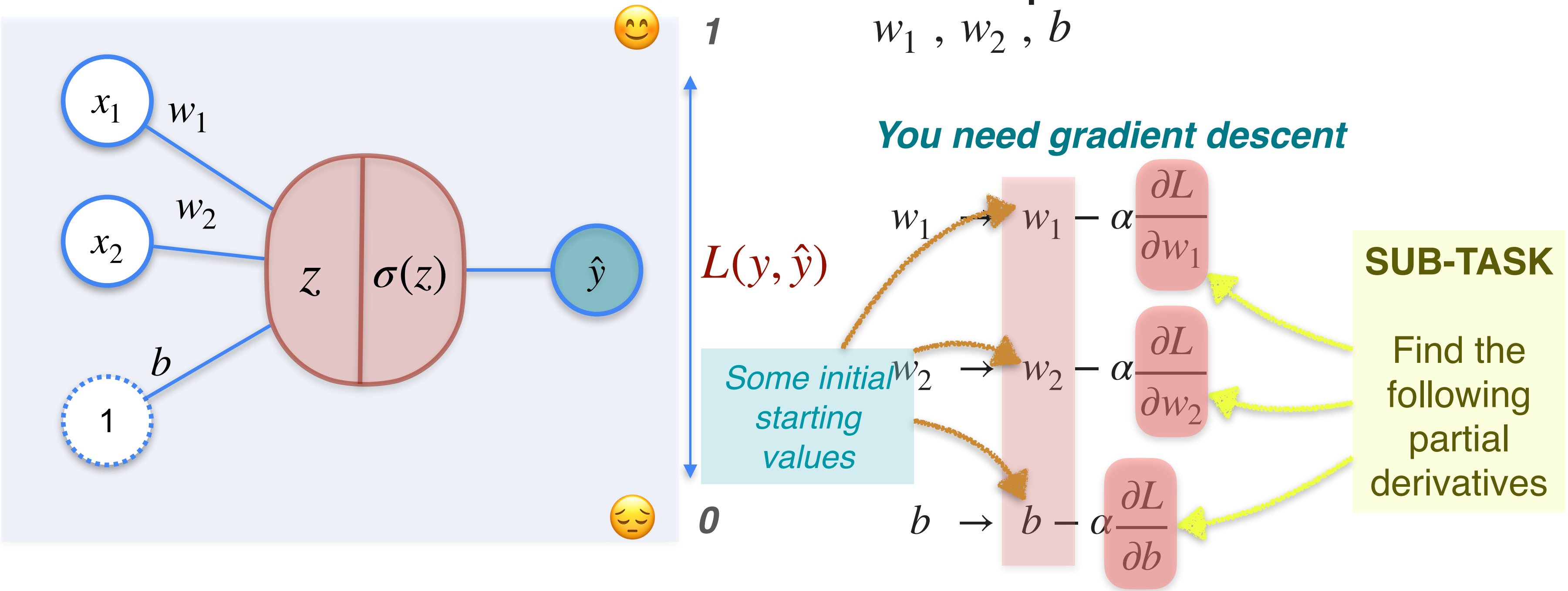


Classification With a Perceptron

To find optimal values for:

$w_1\ ,\ w_2\ ,\ b$

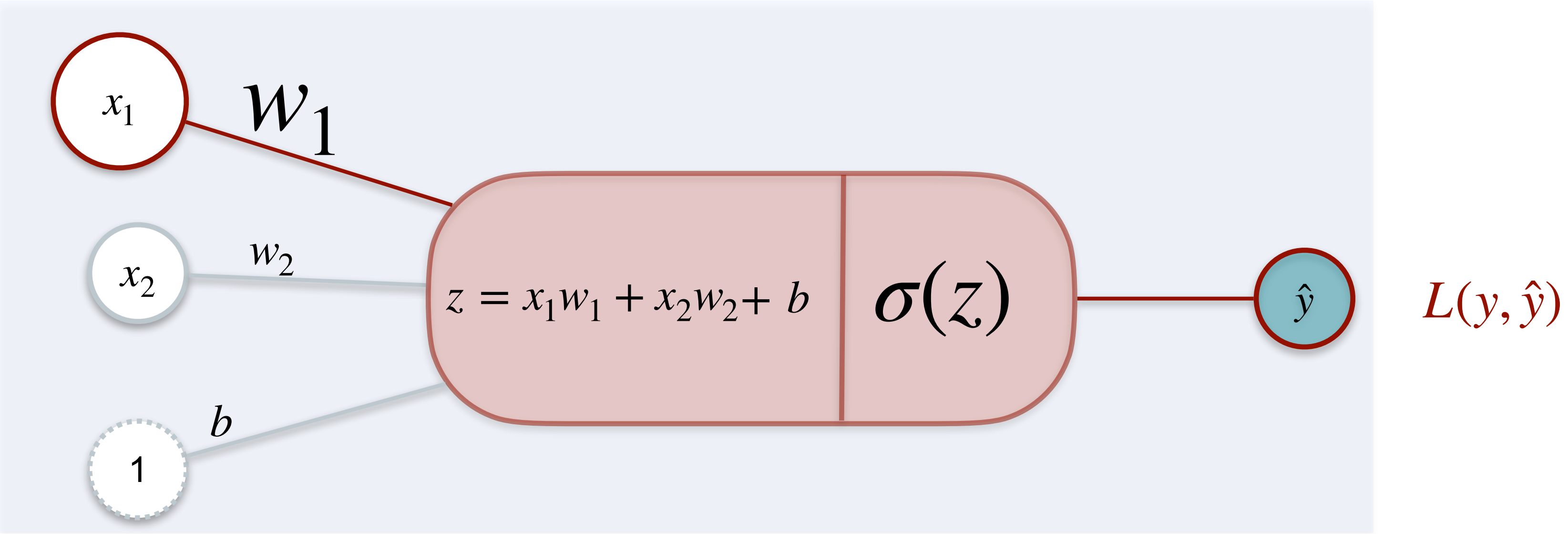


Optimization in Neural Networks and Newton's Method

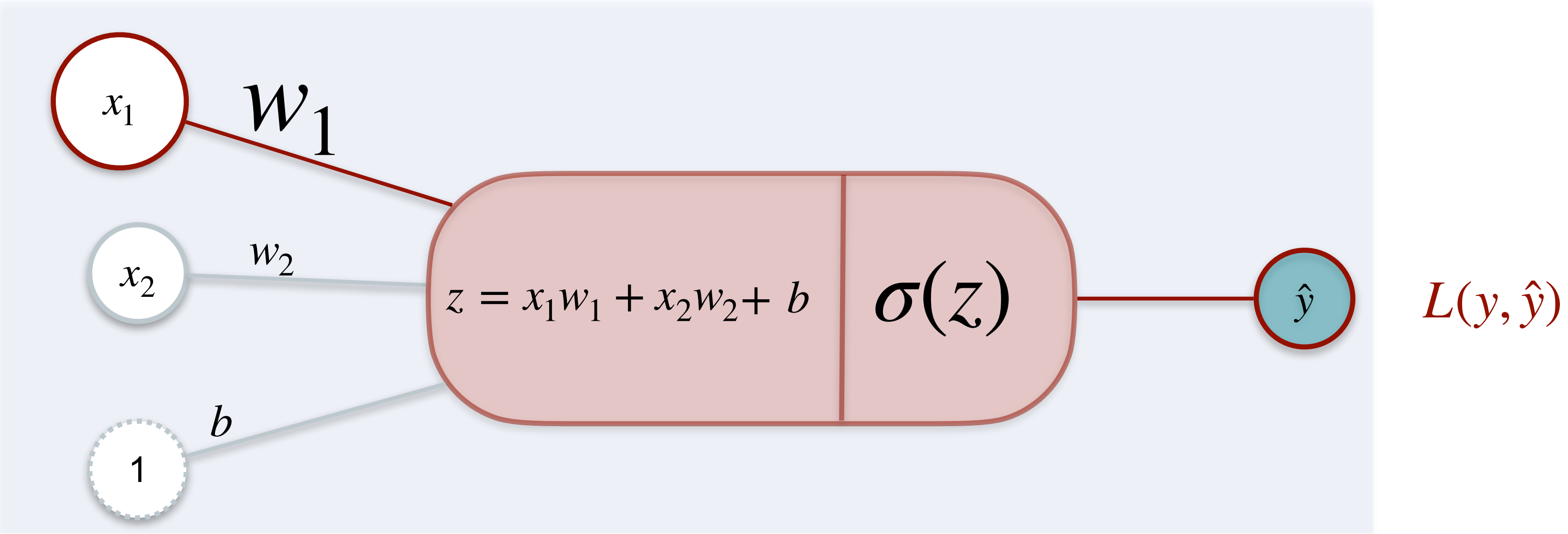
DeepLearning.AI

Classification with a perceptron: Calculating the derivatives

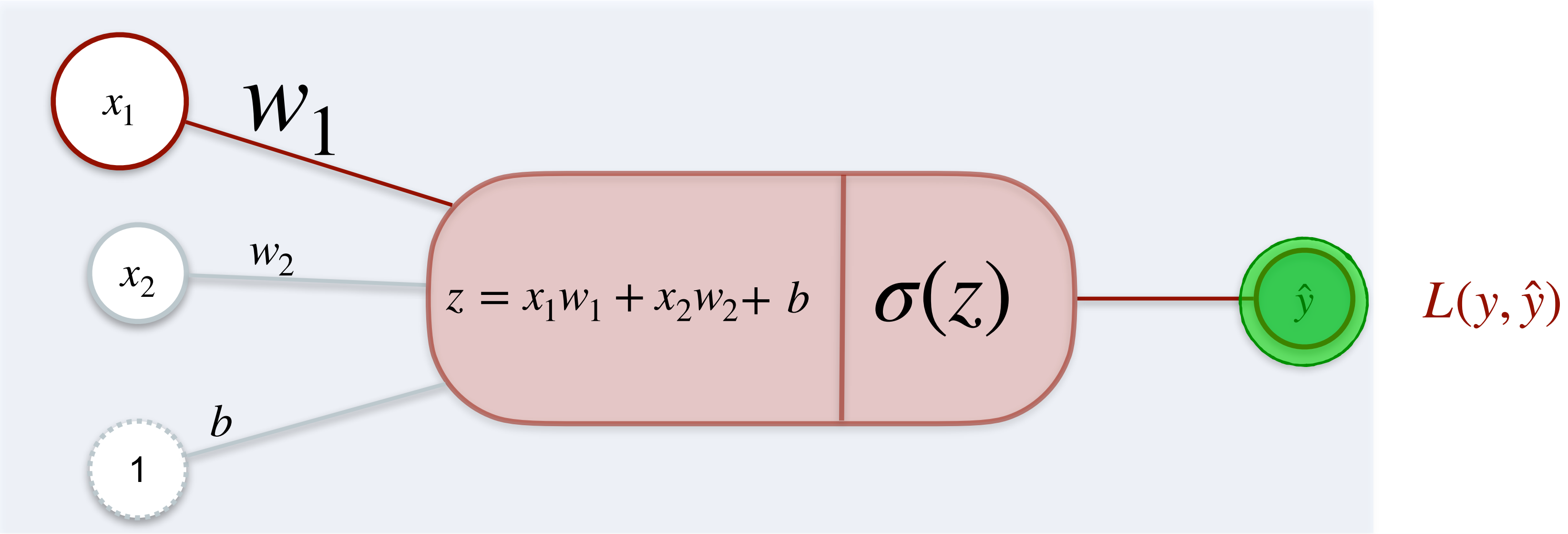
Classification With a Perceptron



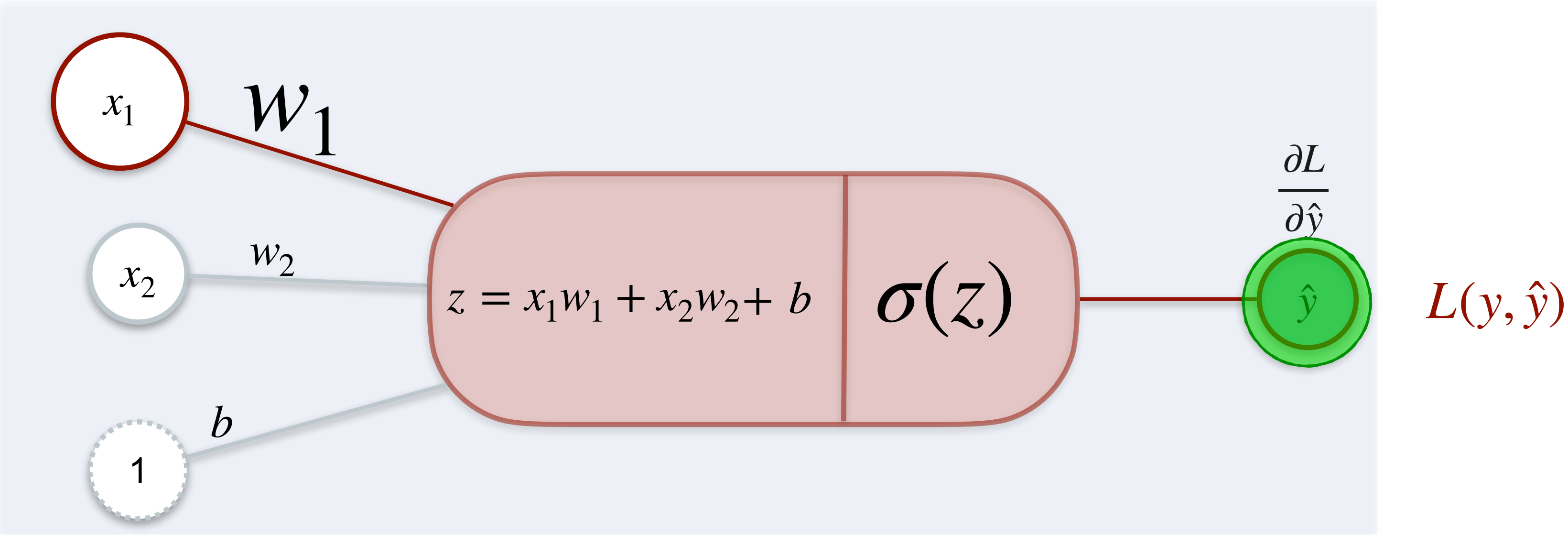
Classification With a Perceptron



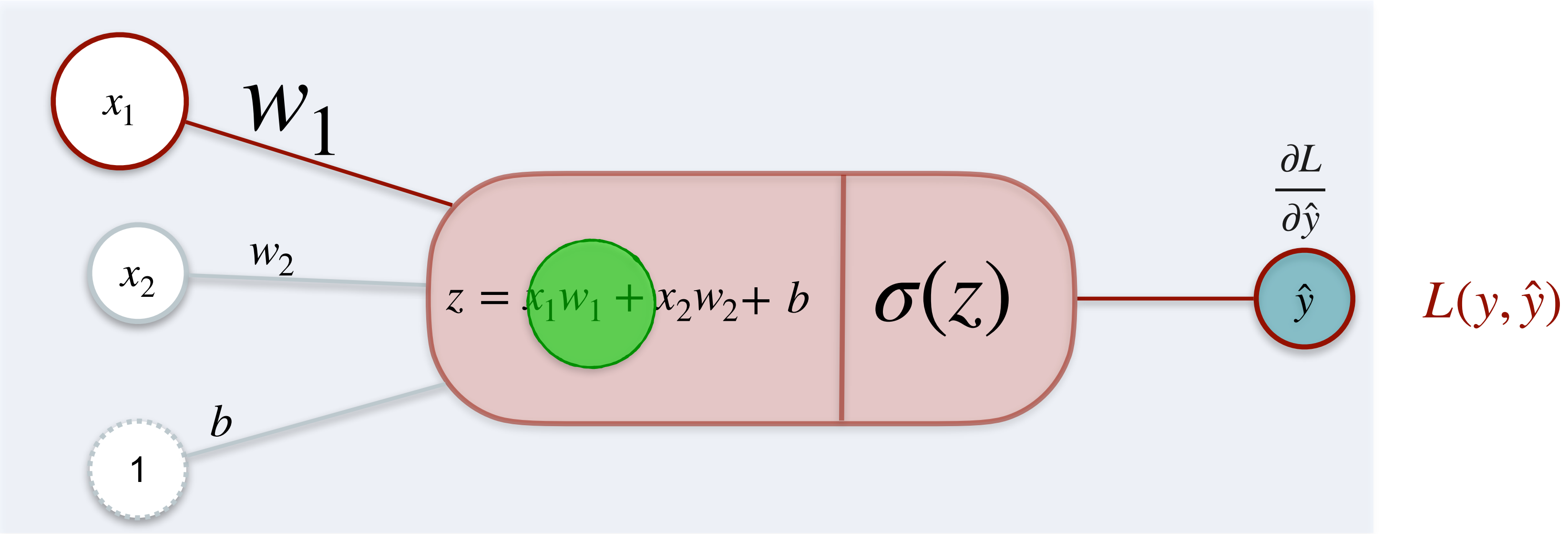
Classification With a Perceptron



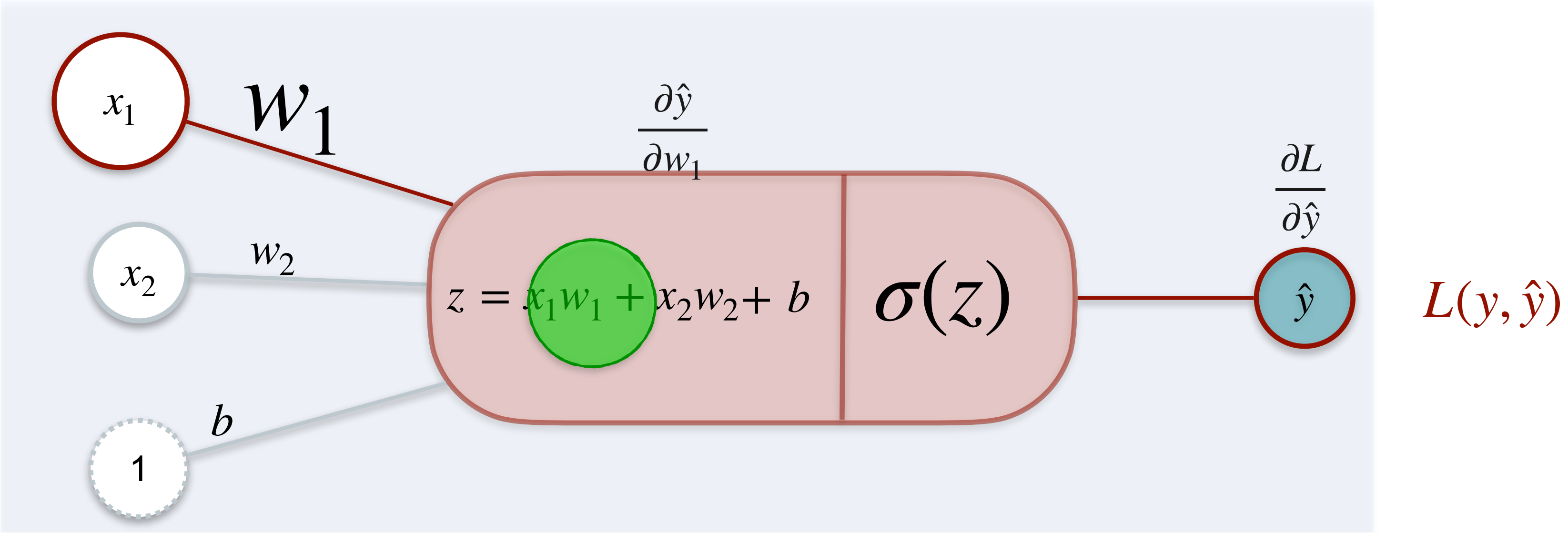
Classification With a Perceptron



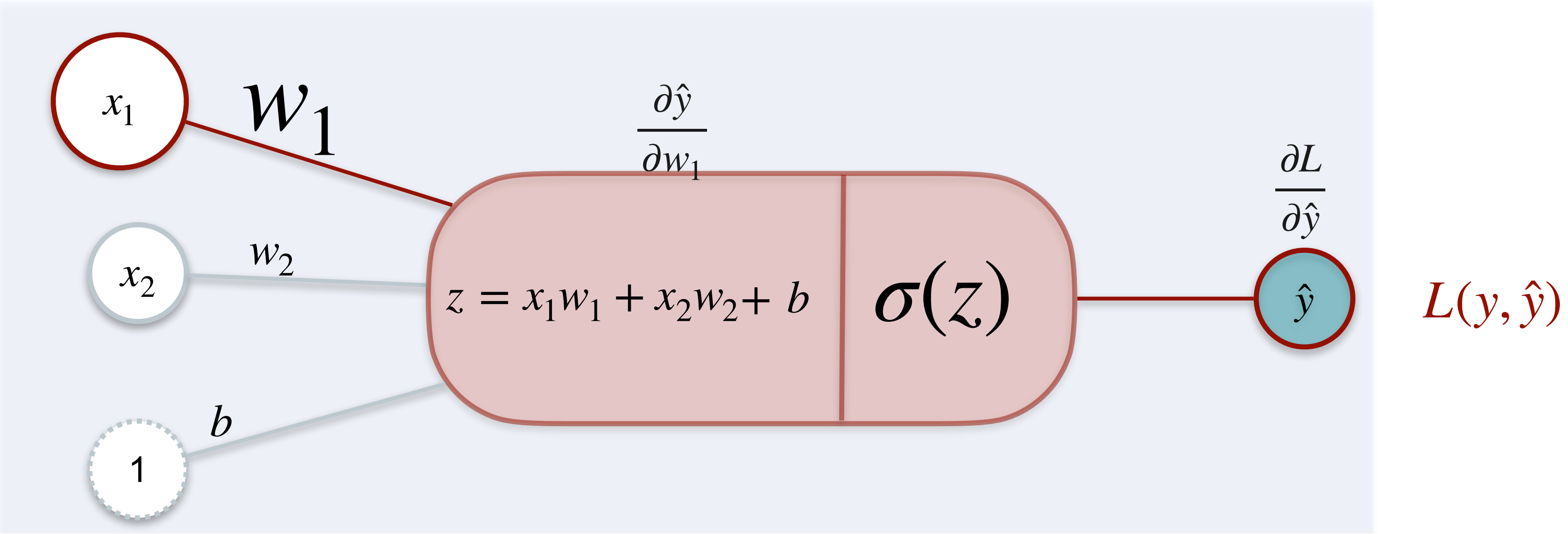
Classification With a Perceptron



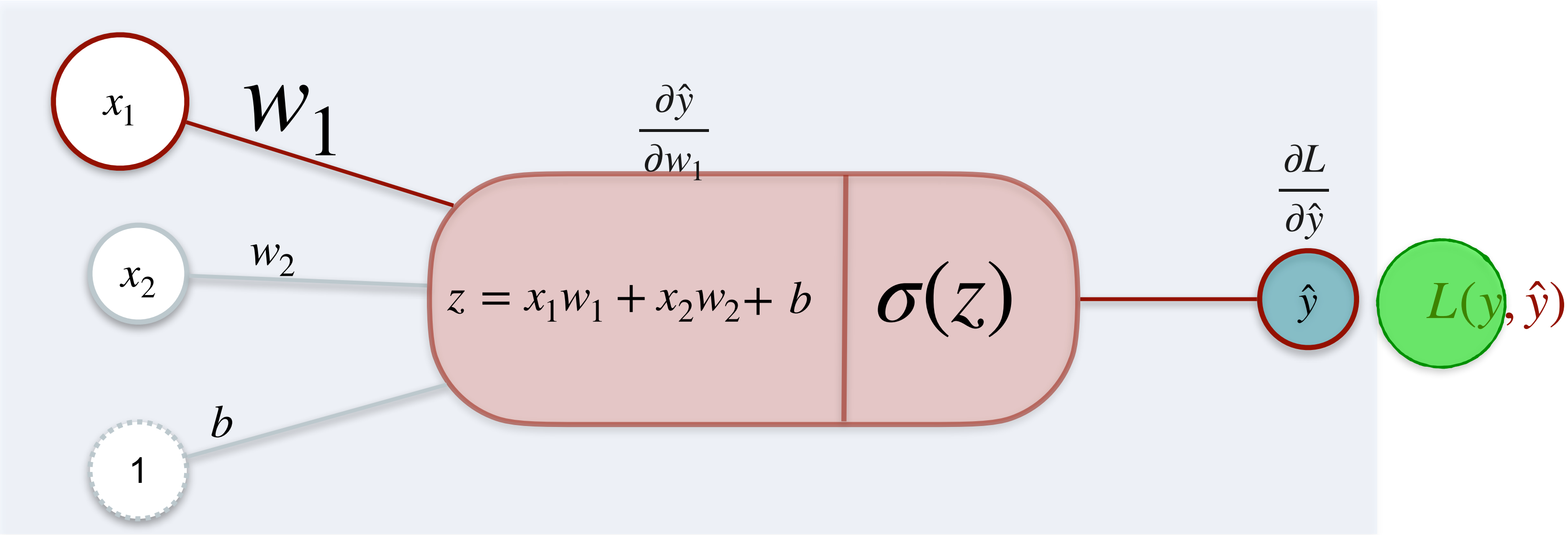
Classification With a Perceptron



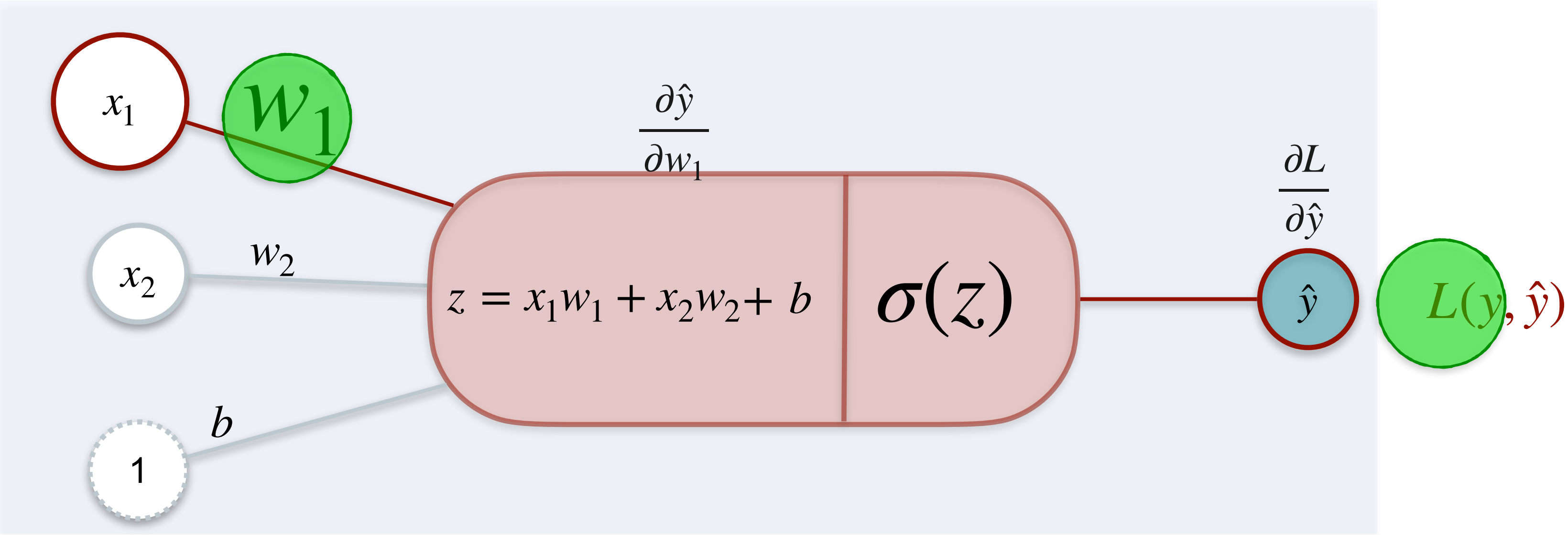
Classification With a Perceptron



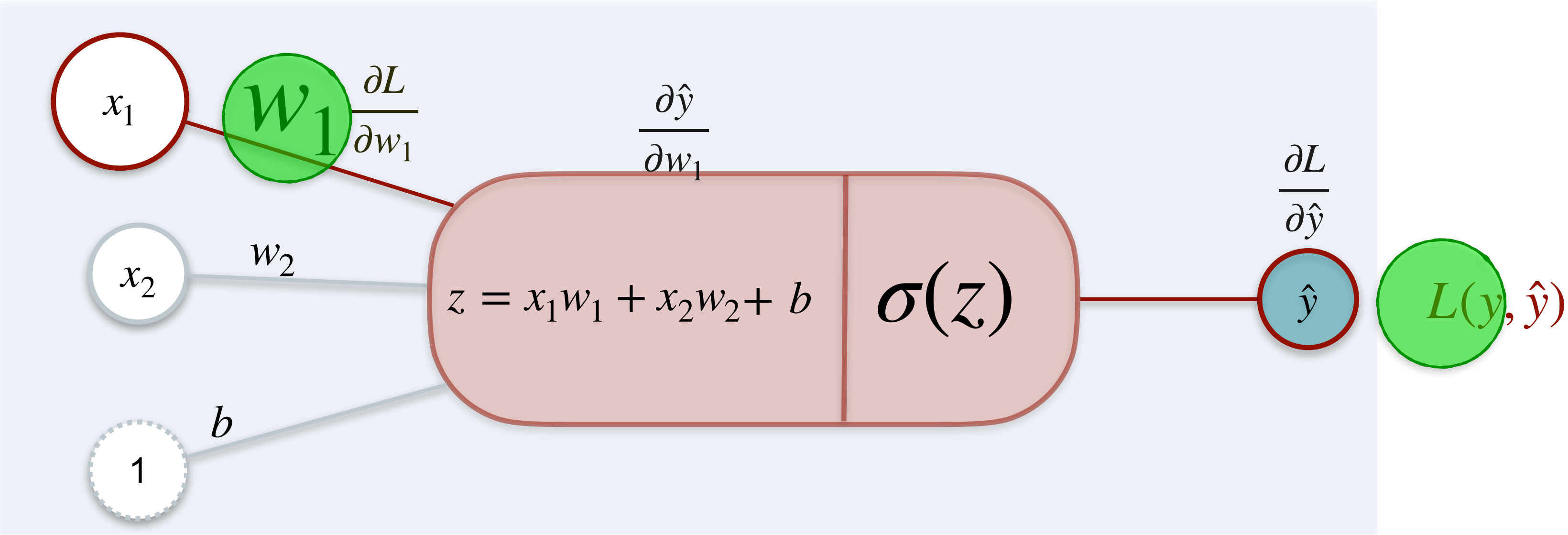
Classification With a Perceptron



Classification With a Perceptron

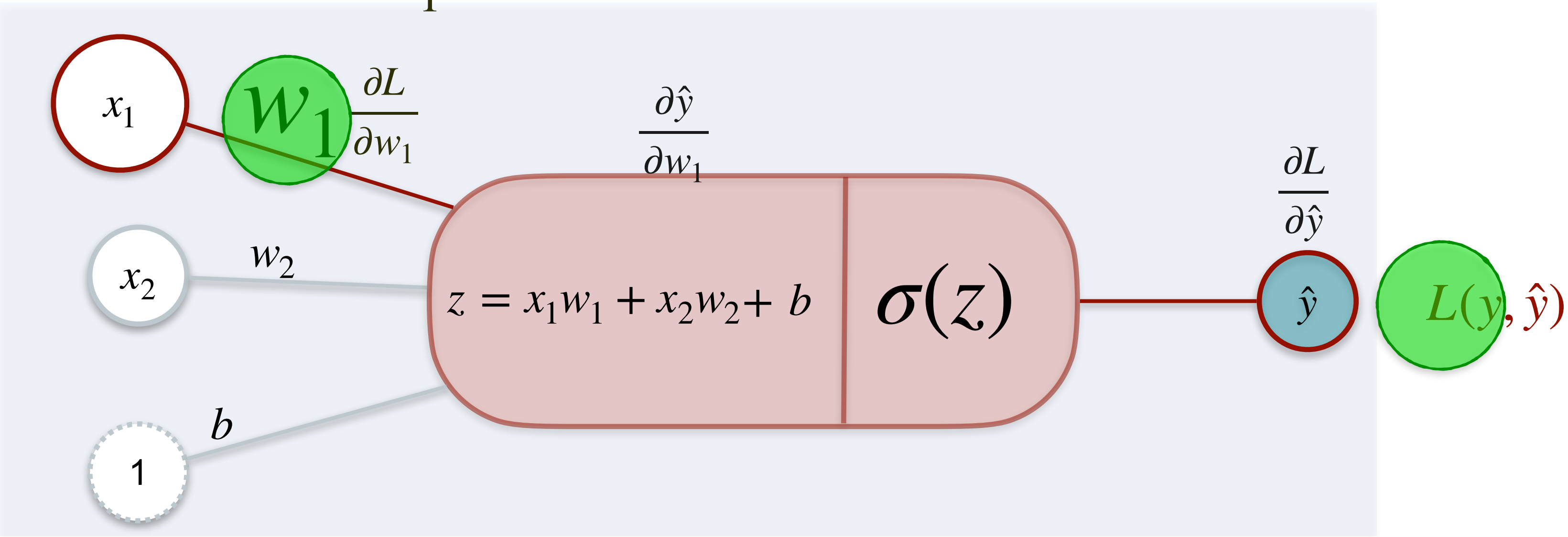


Classification With a Perceptron



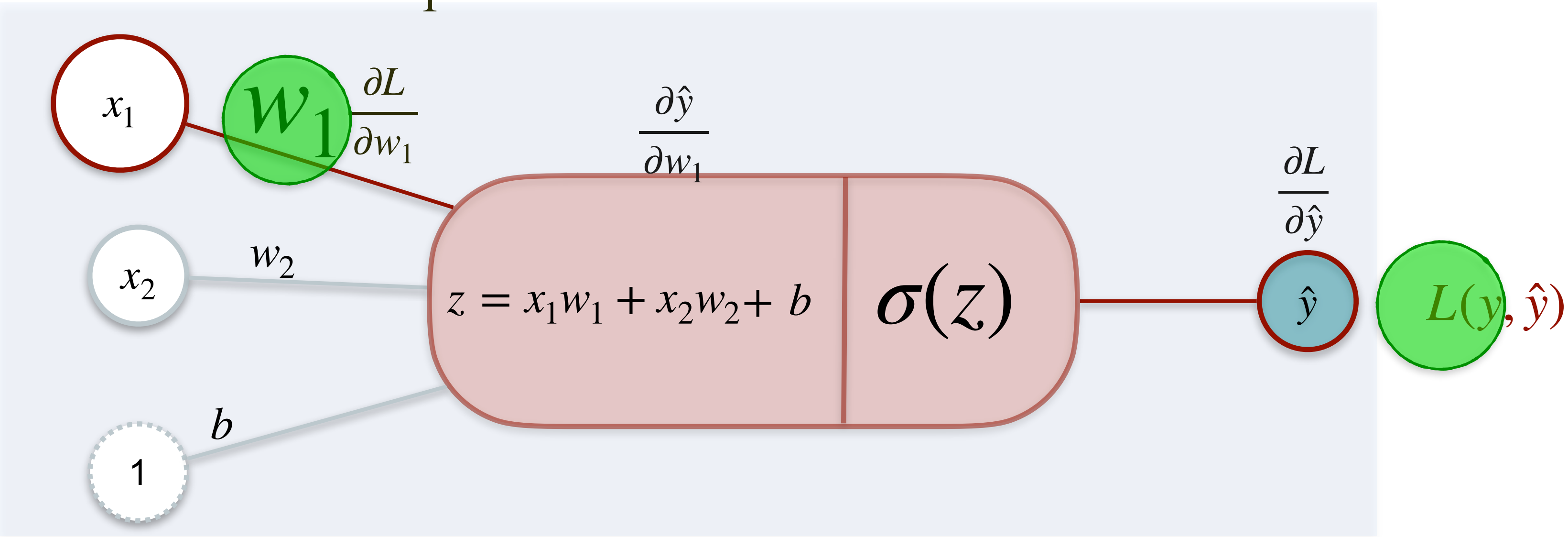
Classification With a Perceptron

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



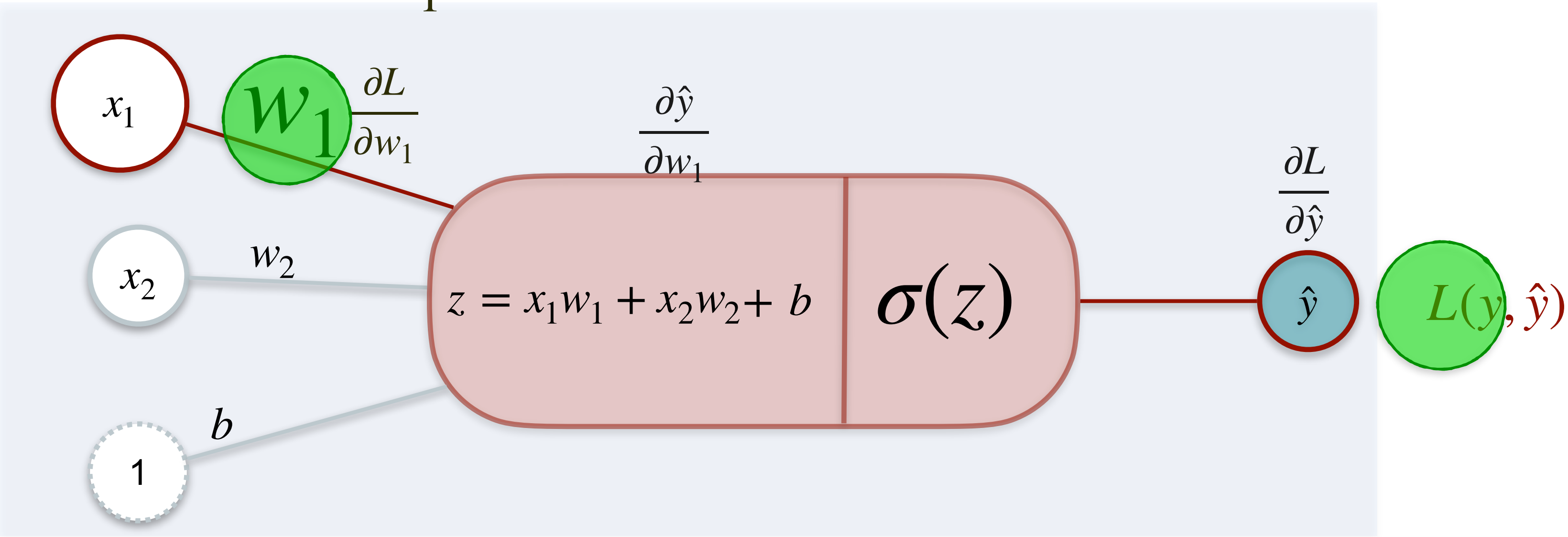
Classification With a Perceptron

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



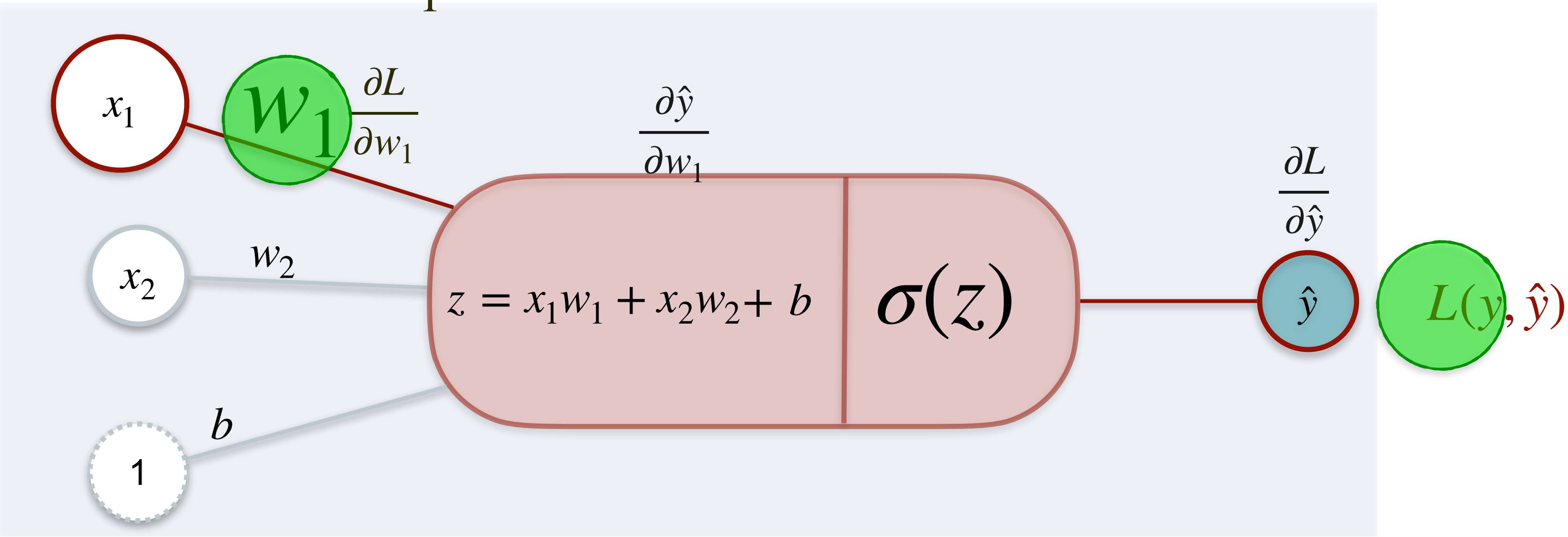
Classification With a Perceptron

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



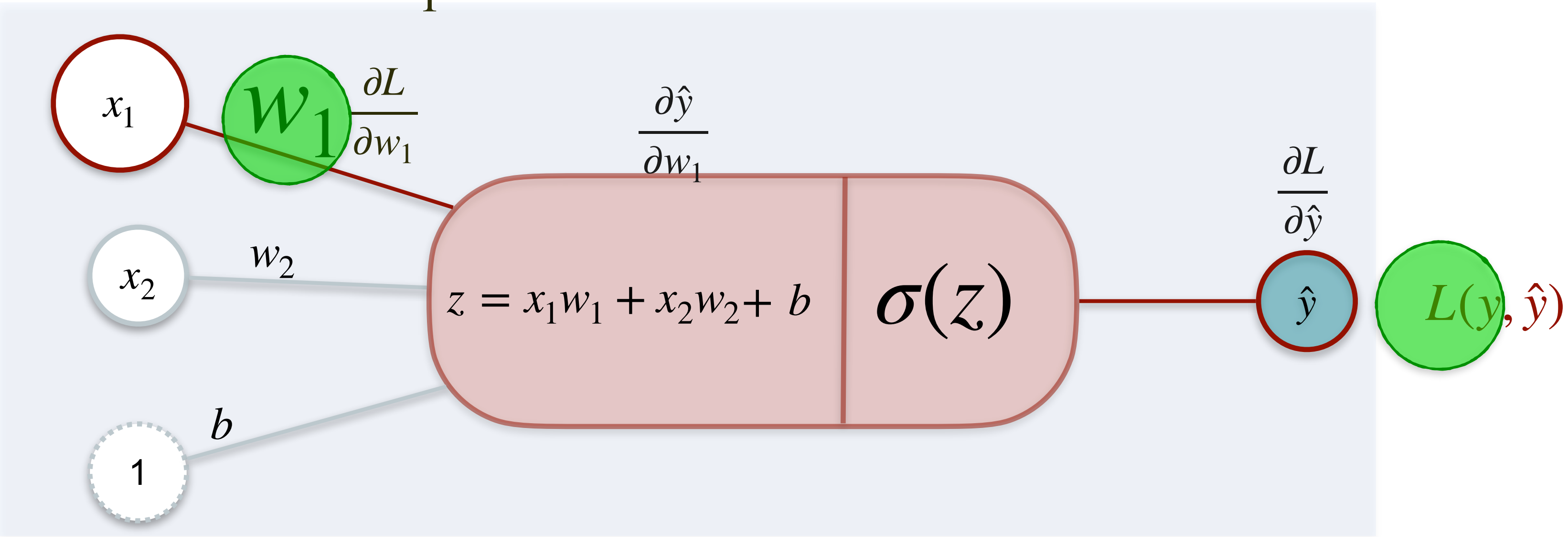
Classification With a Perceptron

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

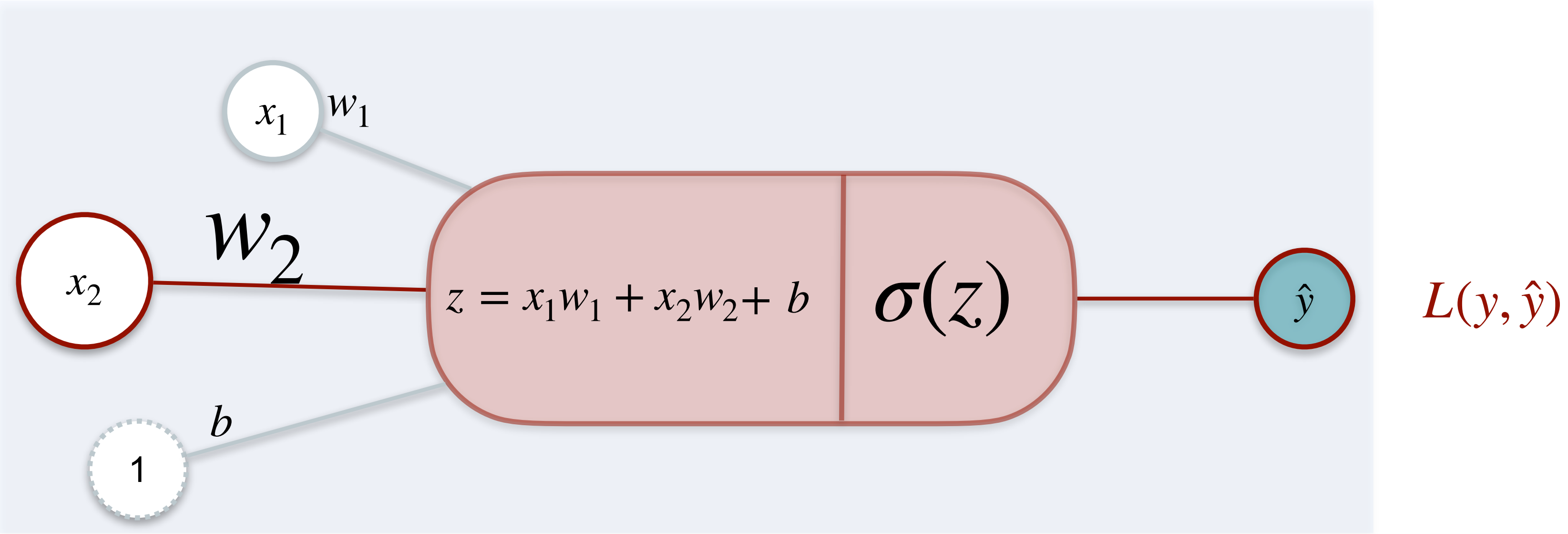


Classification With a Perceptron

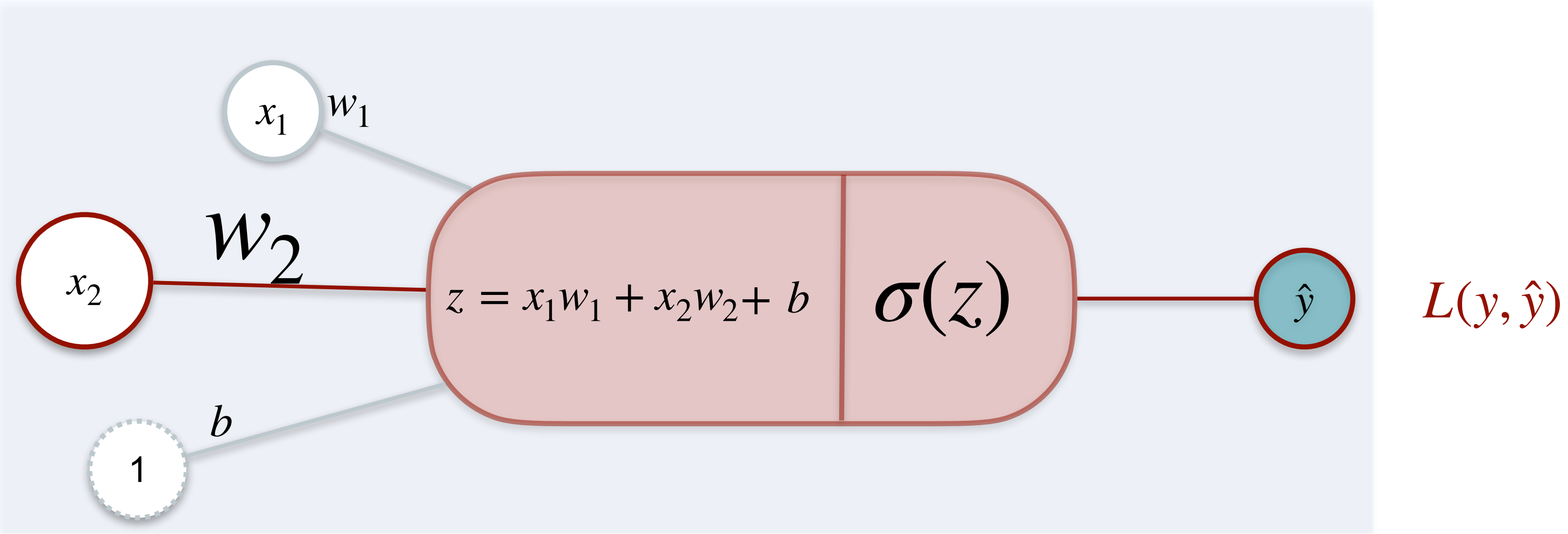
$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1}$$



Classification With a Perceptron



Classification With a Perceptron



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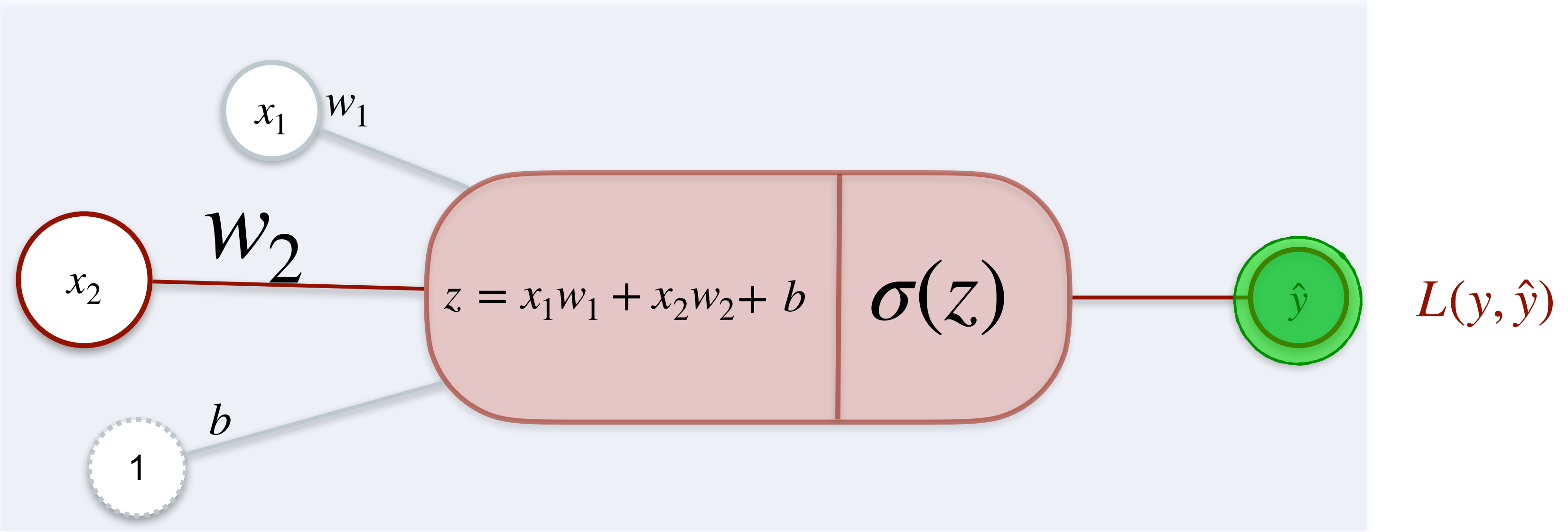
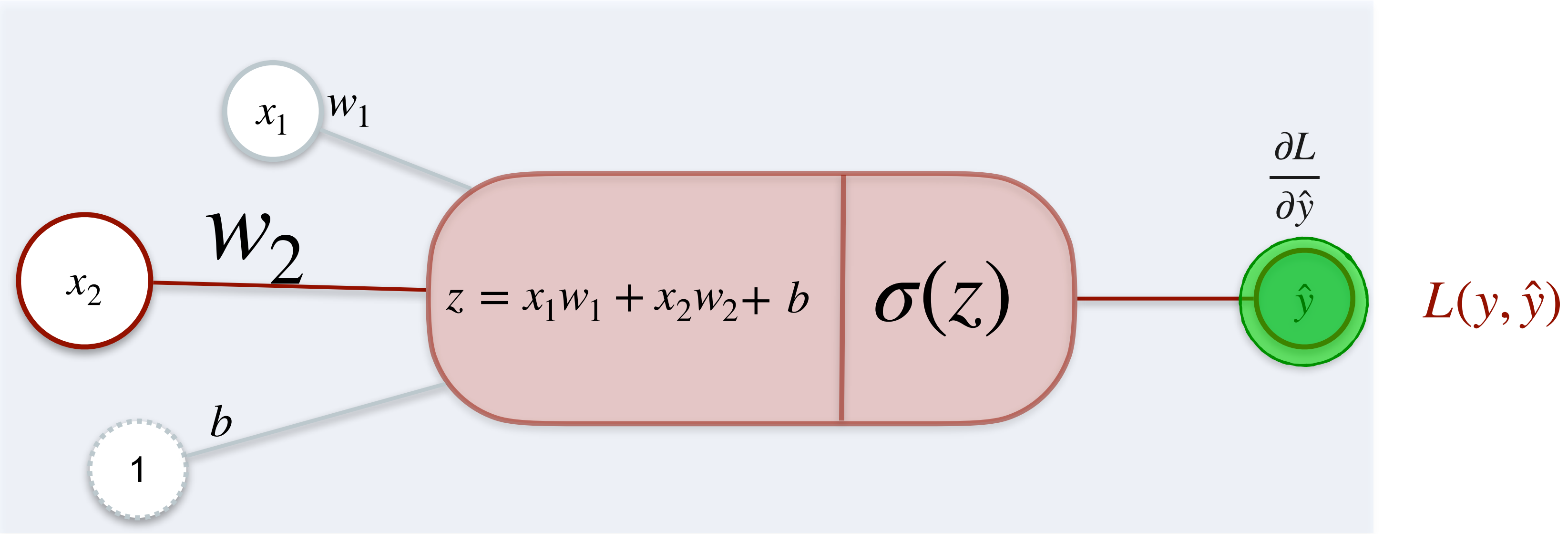
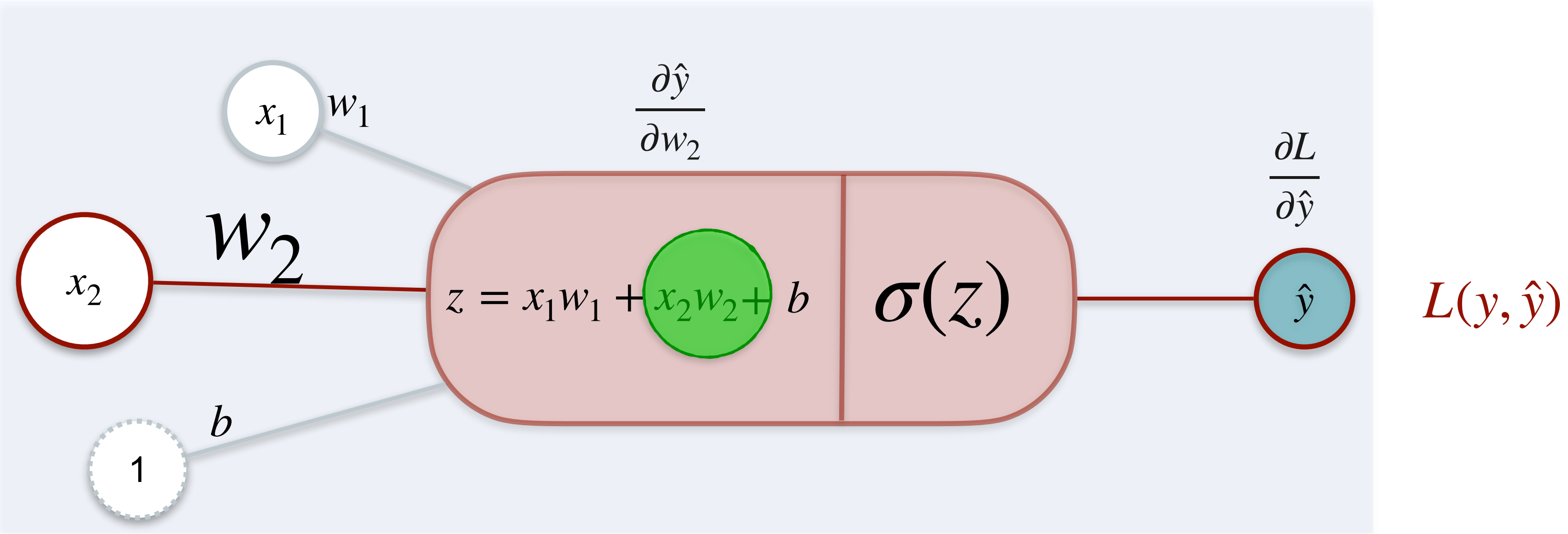


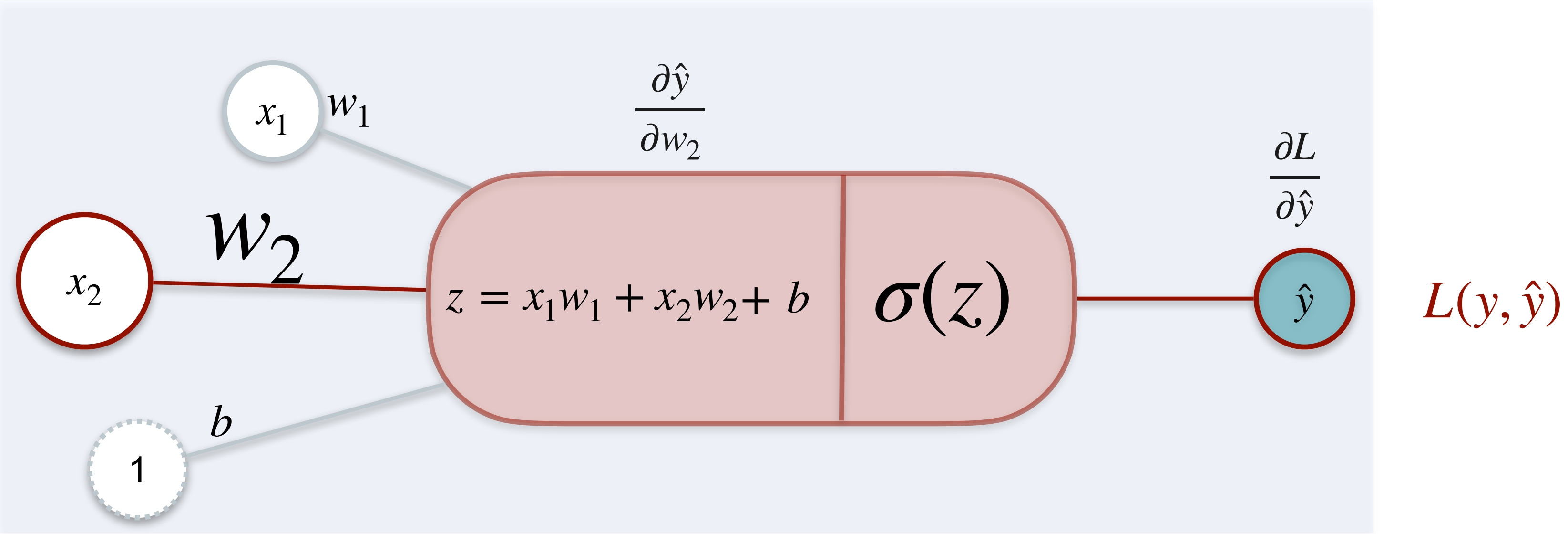
Classification With a Perceptron



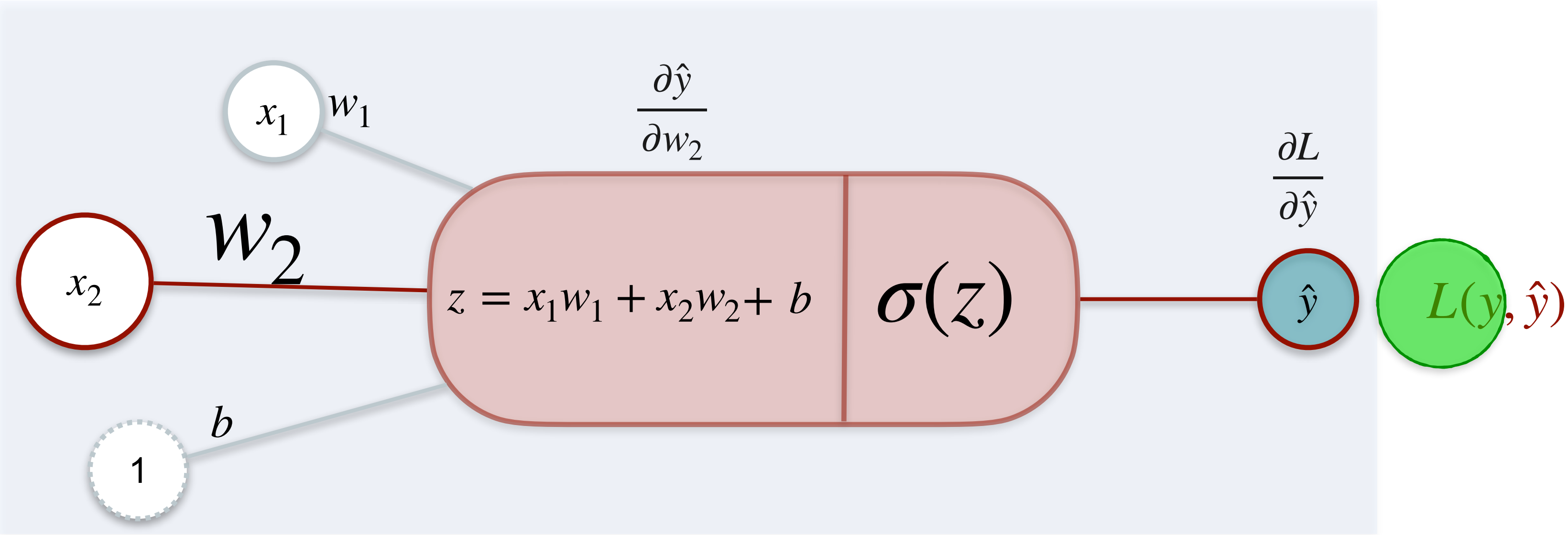
Classification With a Perceptron



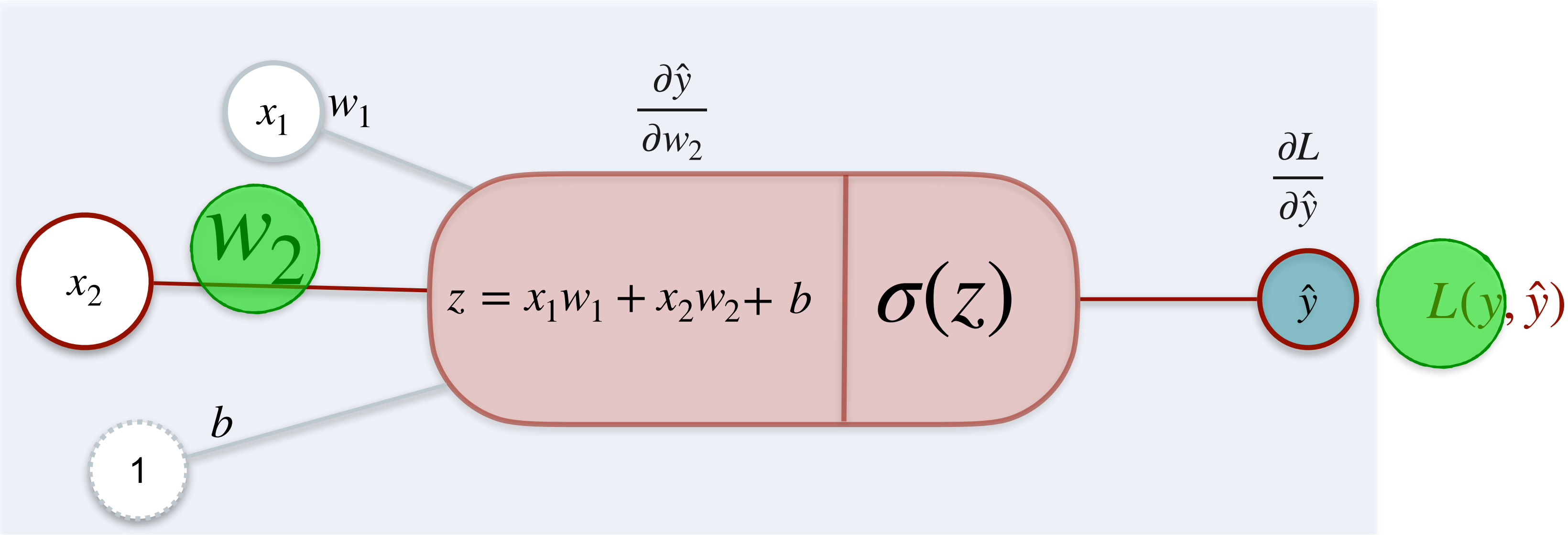
Classification With a Perceptron



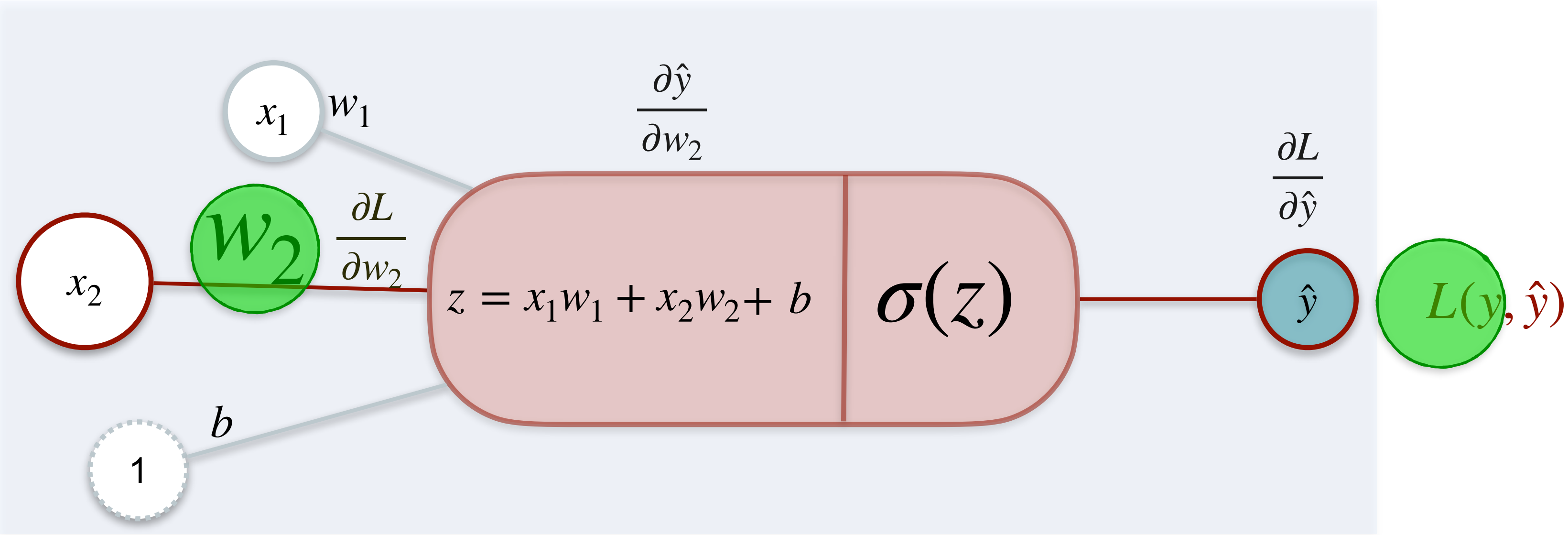
Classification With a Perceptron



Classification With a Perceptron

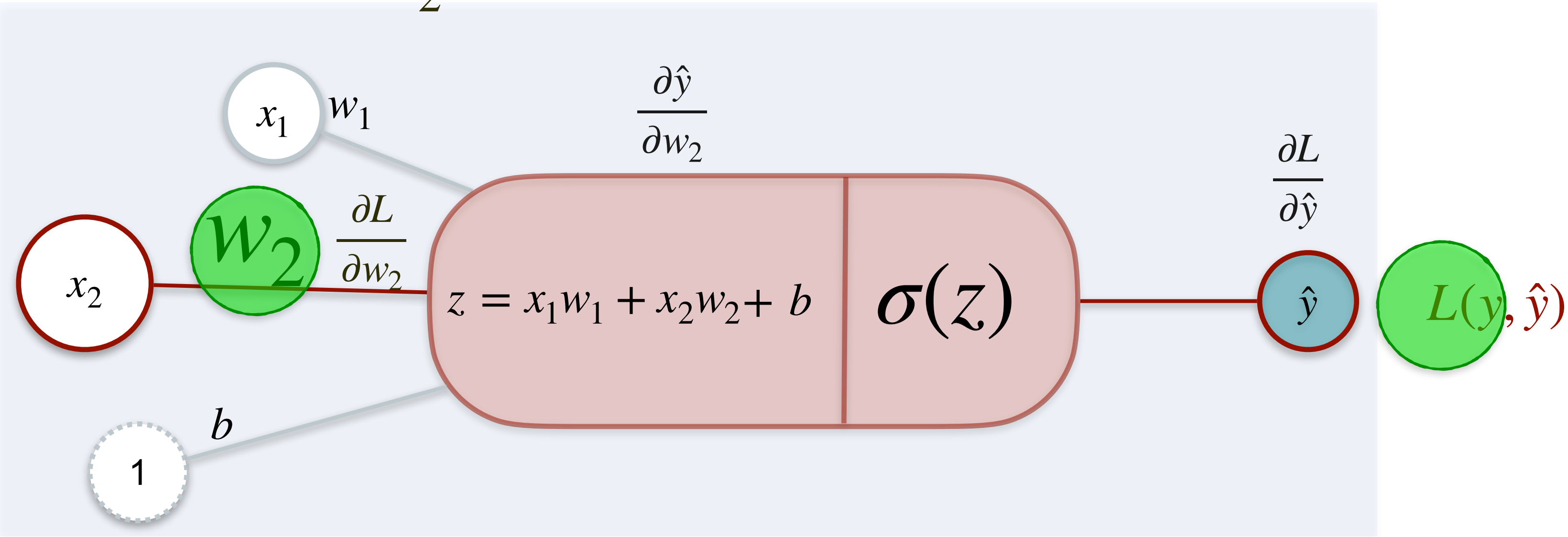


Classification With a Perceptron

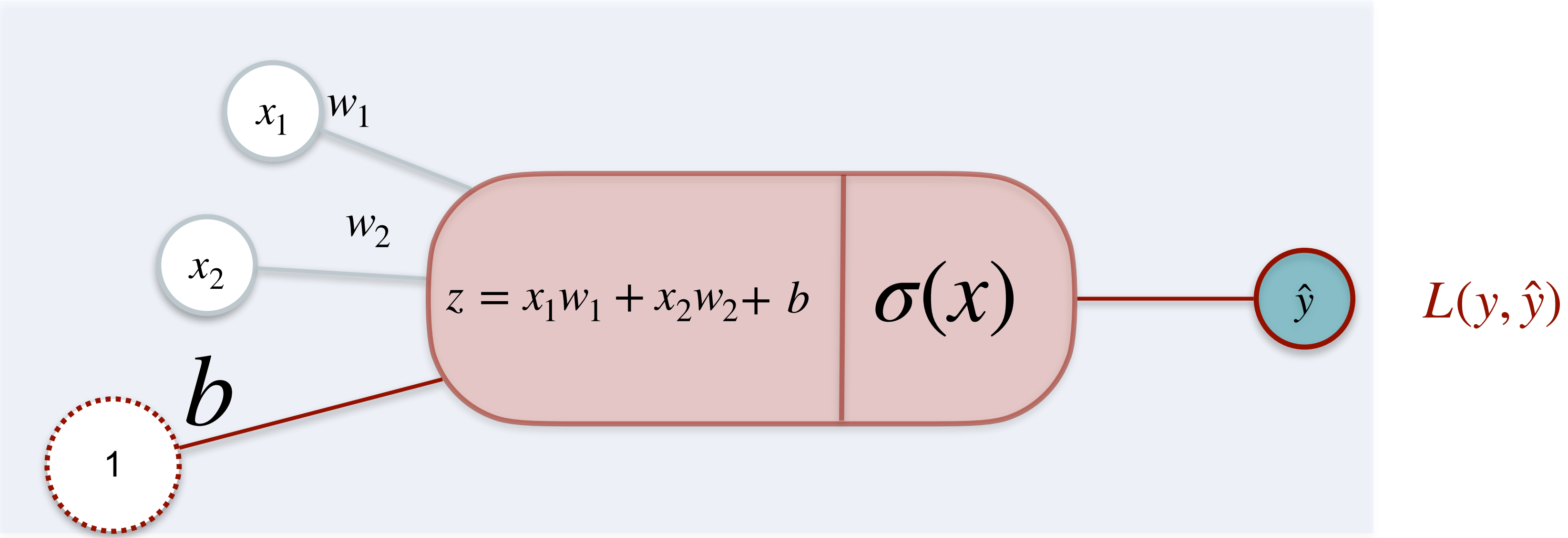


Classification With a Perceptron

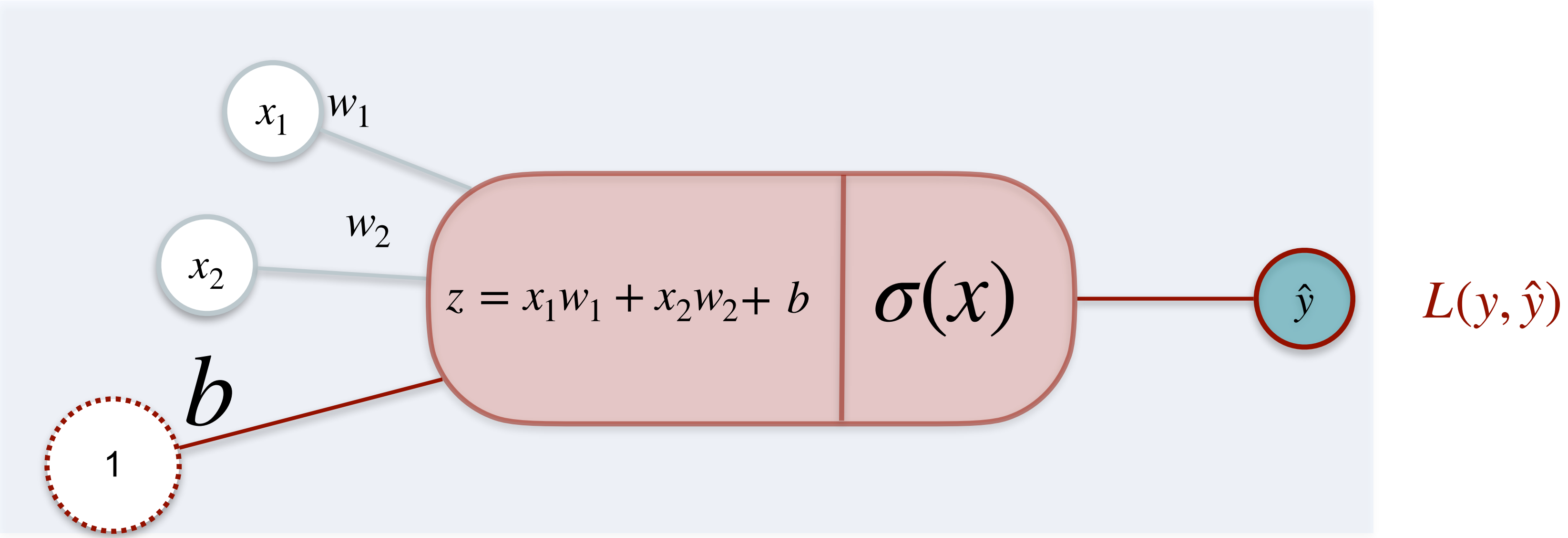
$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$



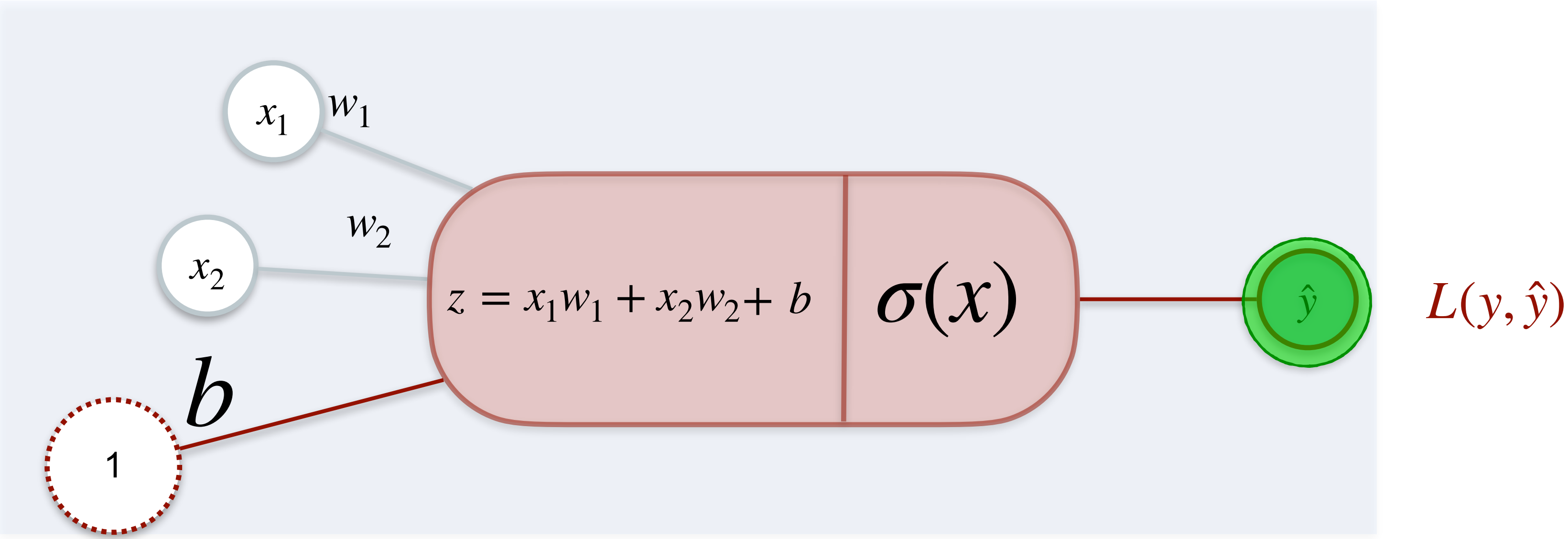
Classification With a Perceptron



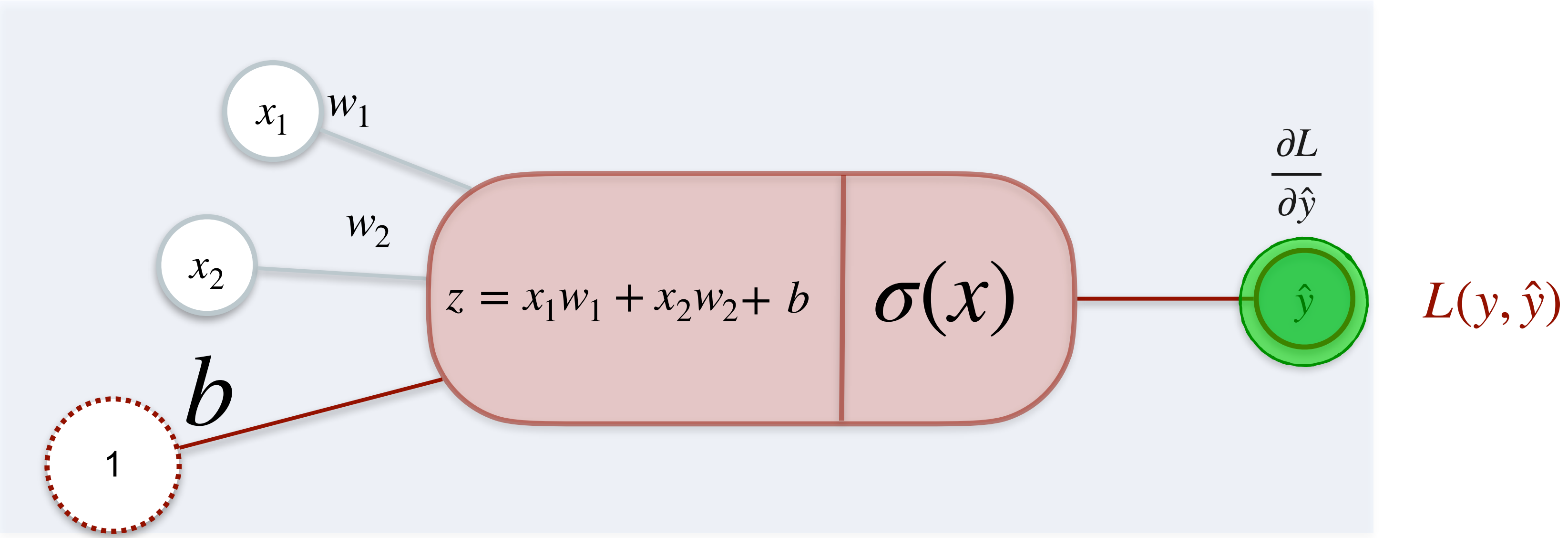
Classification With a Perceptron



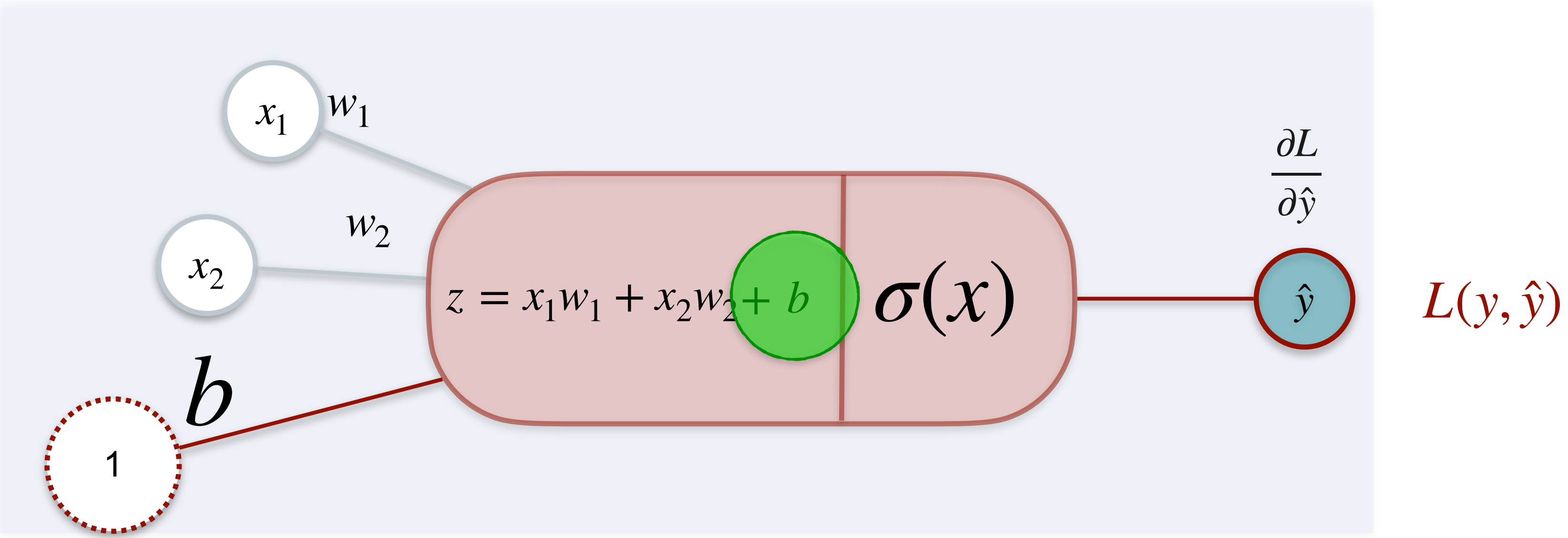
Classification With a Perceptron



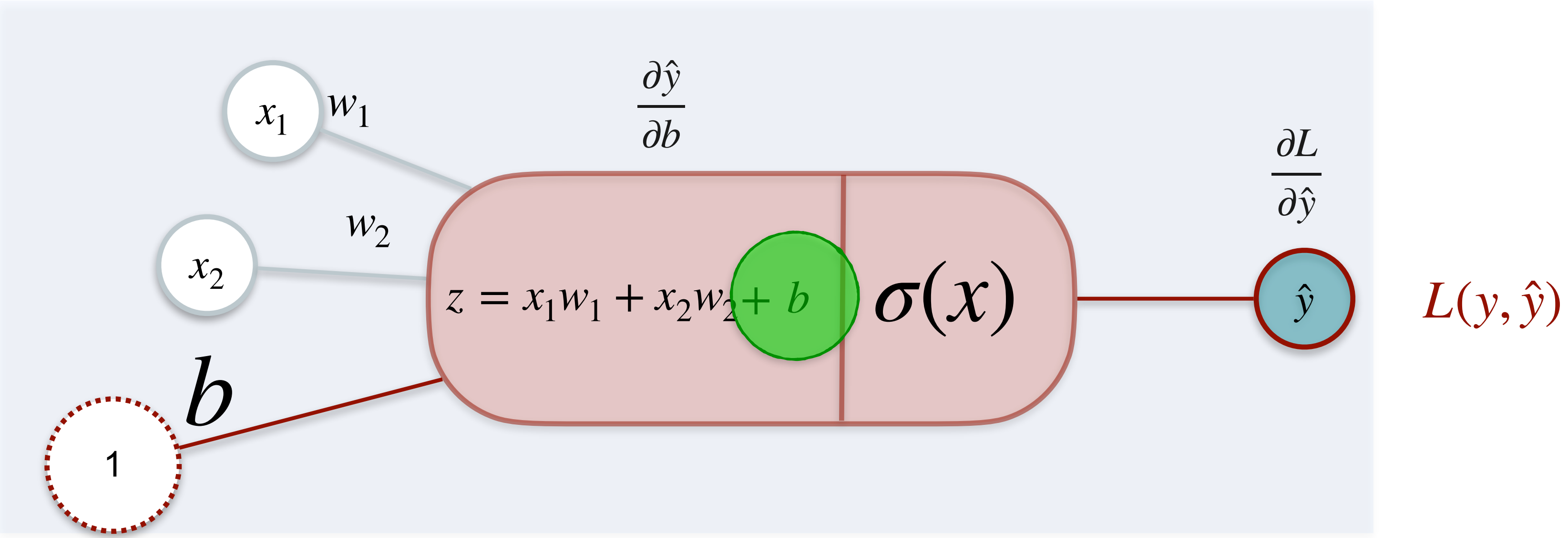
Classification With a Perceptron



Classification With a Perceptron



Classification With a Perceptron



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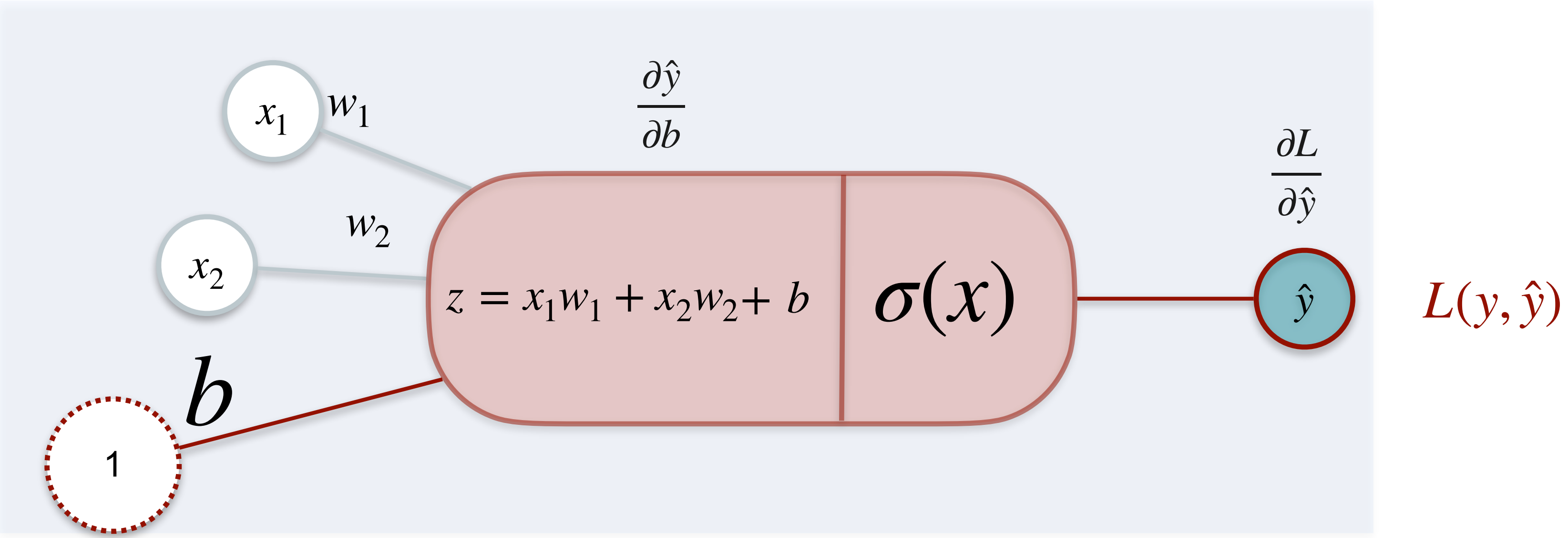

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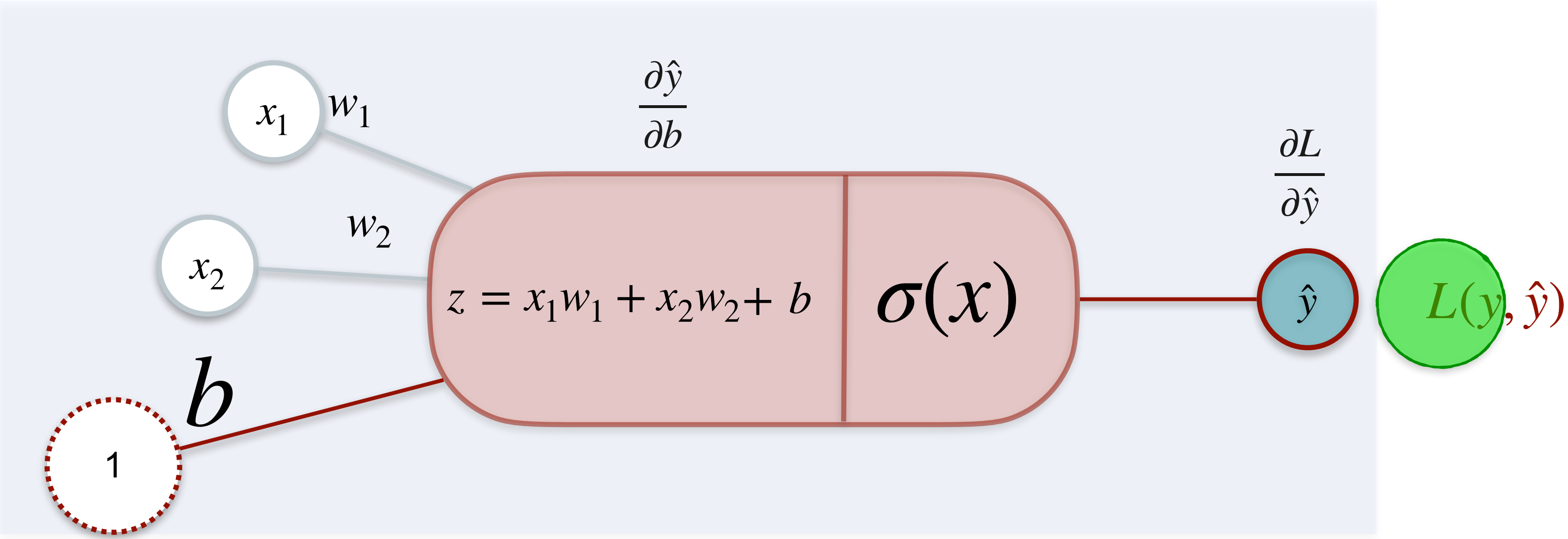

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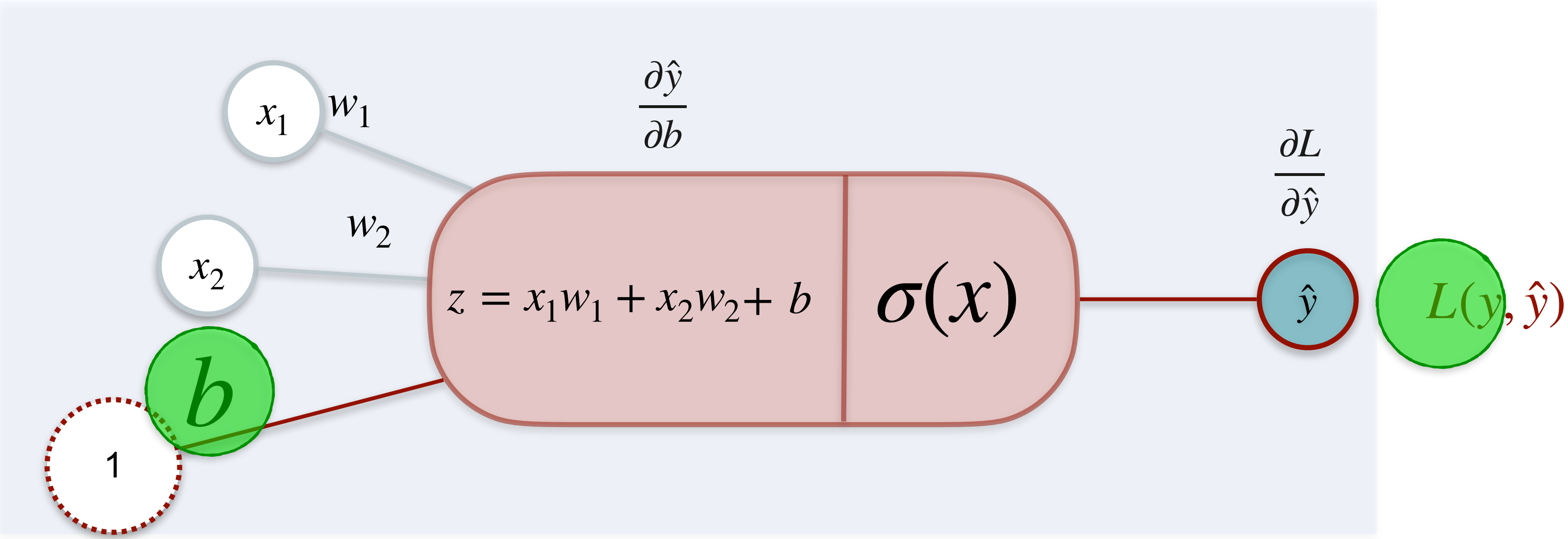
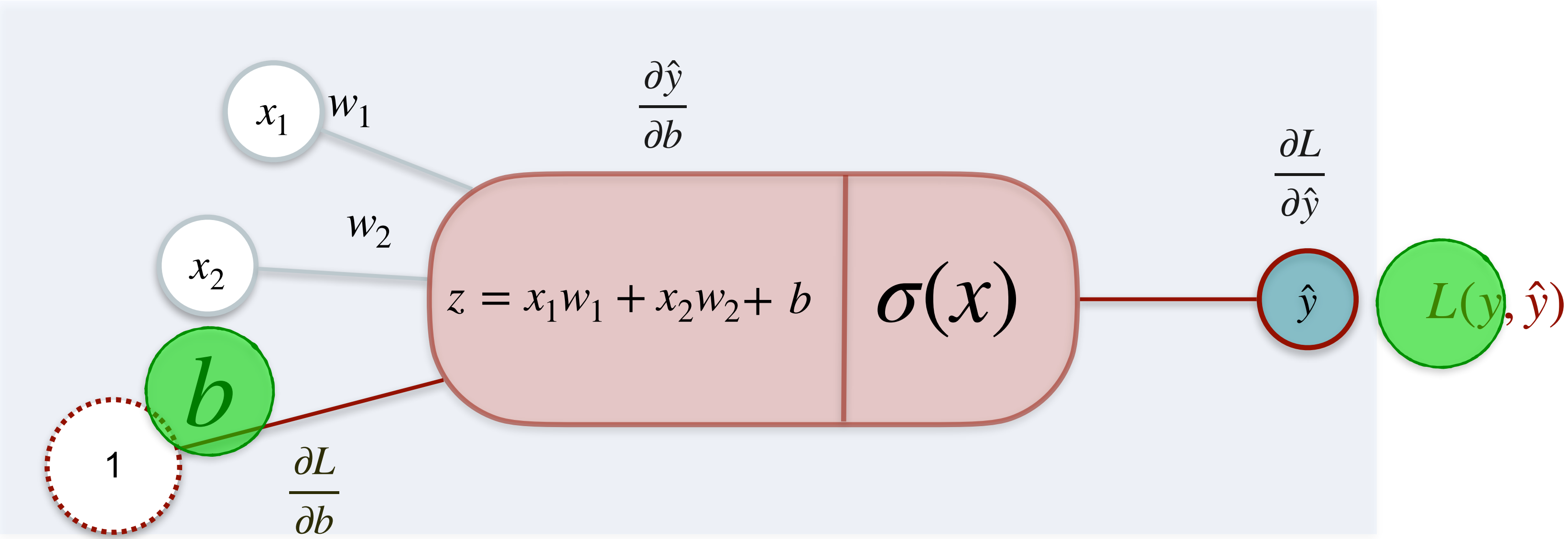
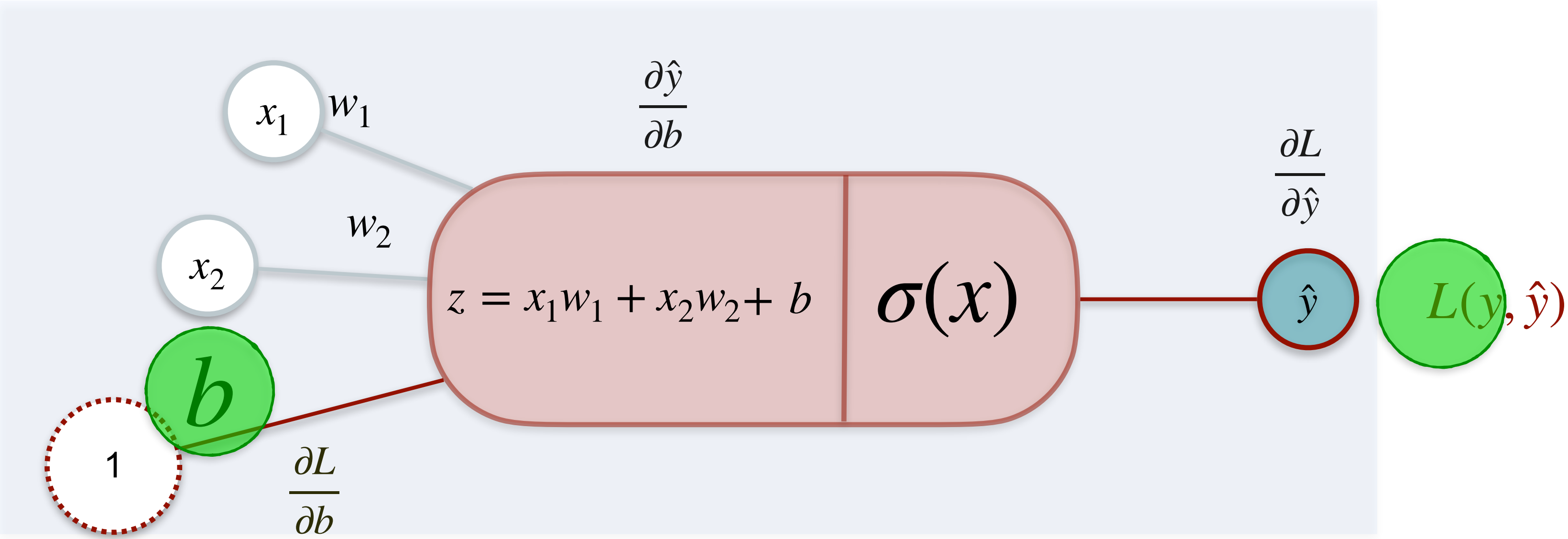


Classification With a Perceptron



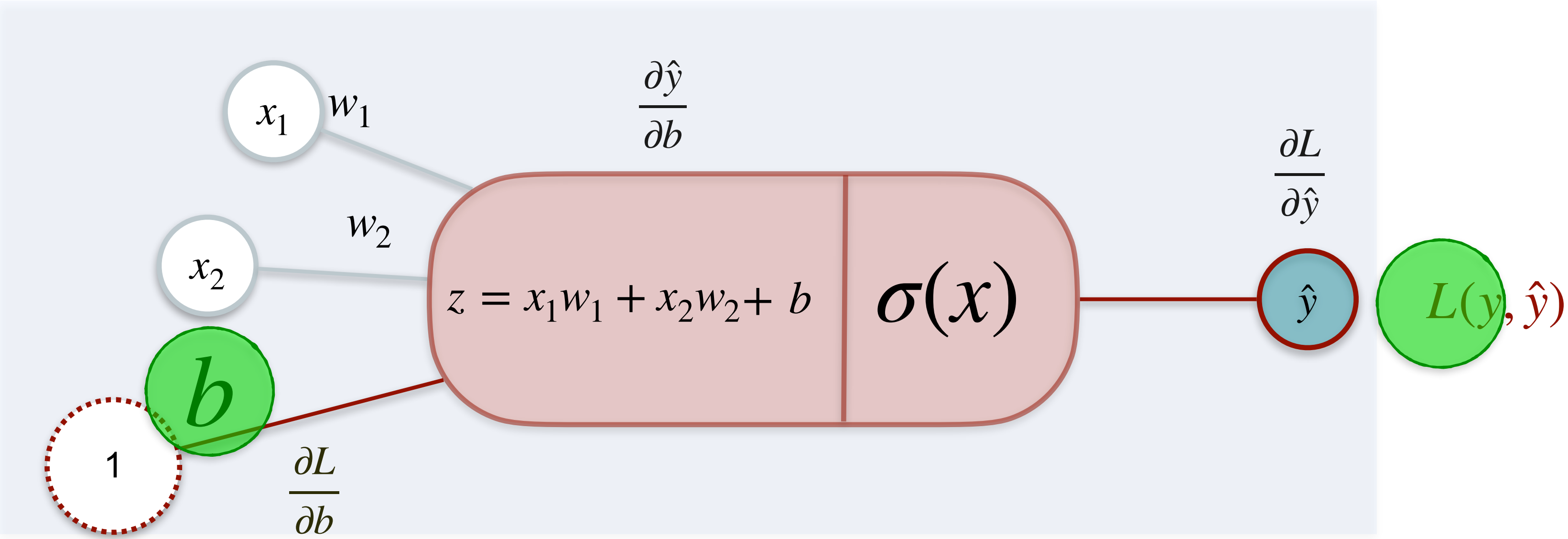
Classification With a Perceptron

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



Classification With a Perceptron

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



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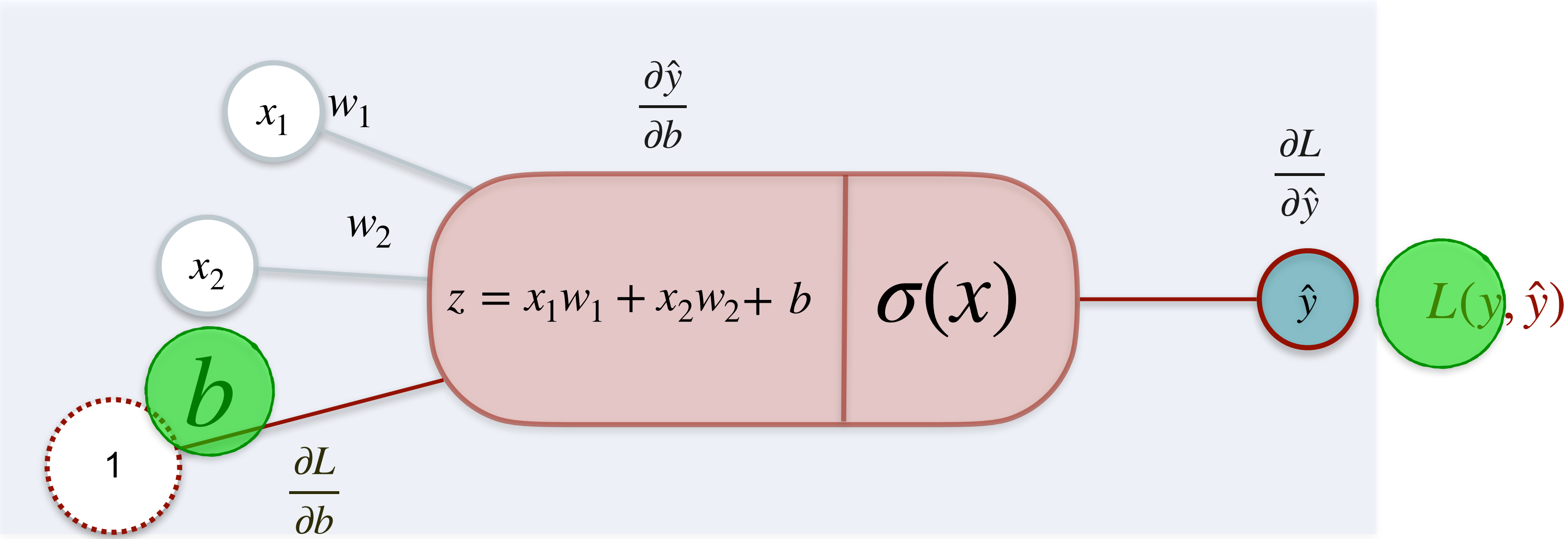
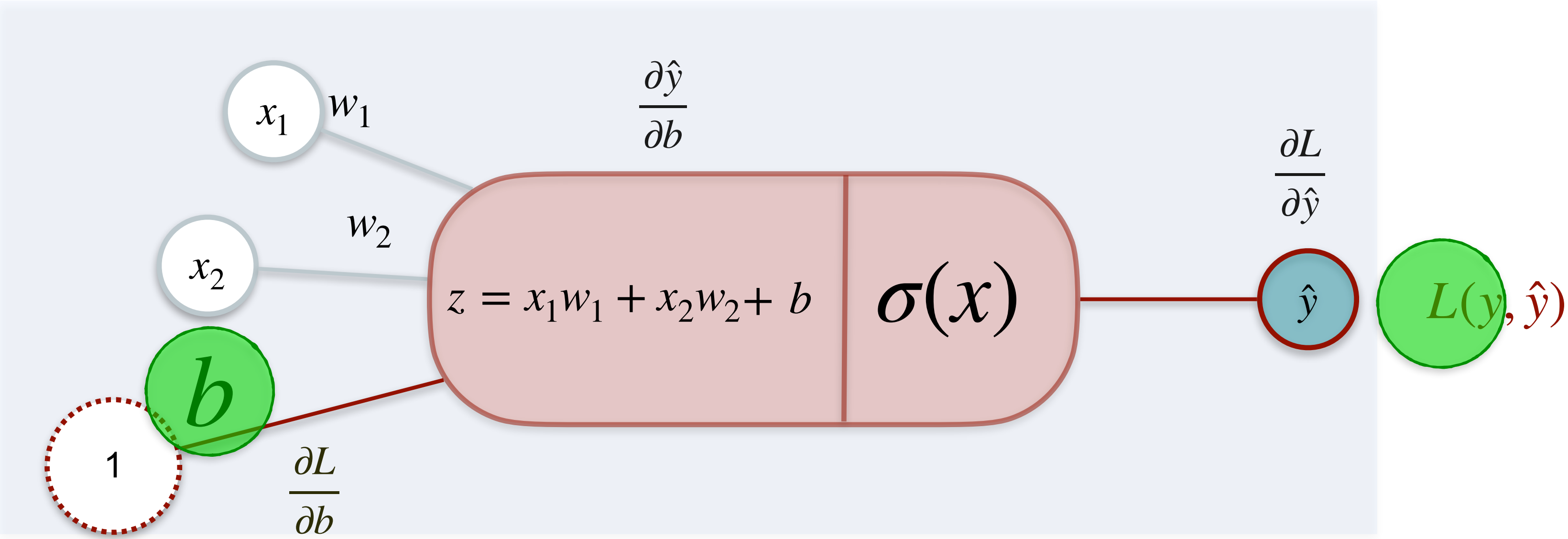


Classification With a Perceptron

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



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

Classification With a Perceptron

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

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Classification With a Perceptron

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

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

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

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

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

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

Classification With a Perceptron

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

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Classification With a Perceptron

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Classification With a Perceptron

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Classification With a Perceptron

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Classification With a Perceptron

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Classification With a Perceptron

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Classification With a Perceptron

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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

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

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Classification With a Perceptron

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

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

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

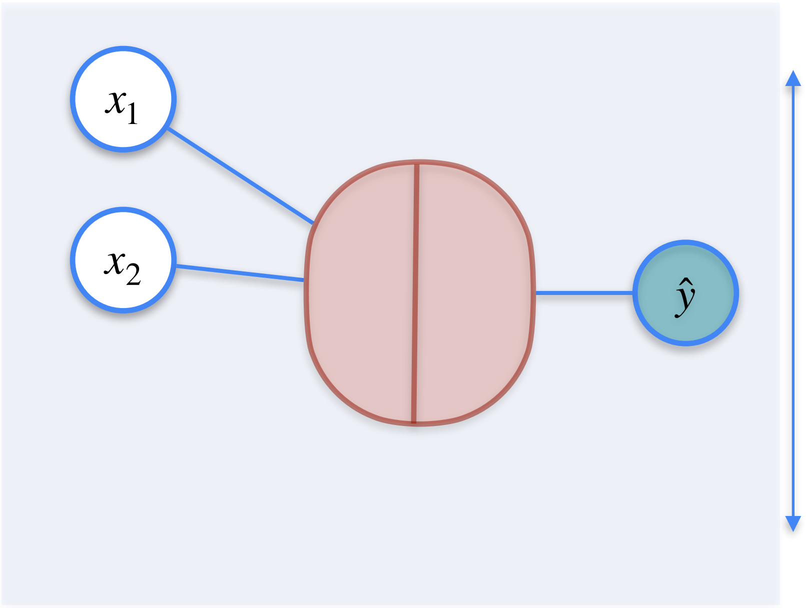
Classification With a Perceptron

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

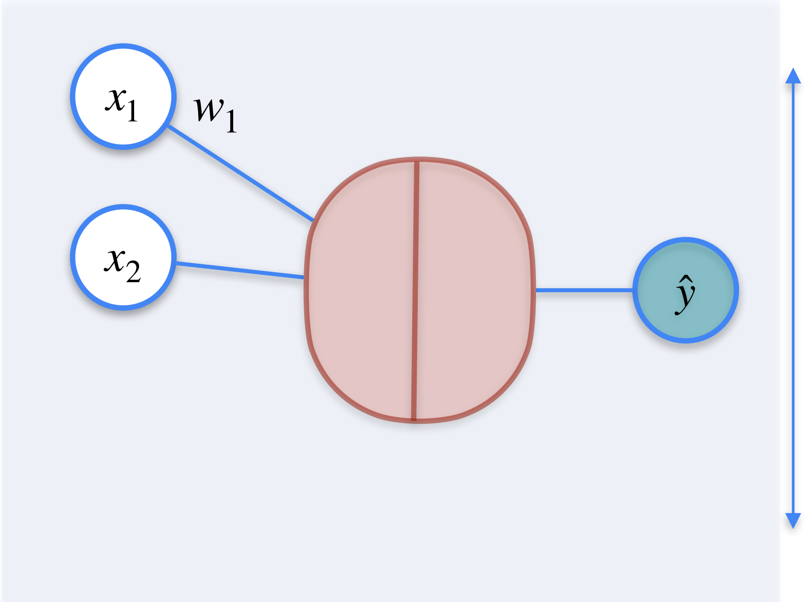
$$\frac{\partial L}{\partial w_1} = -(y - \hat{y})x_1$$

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

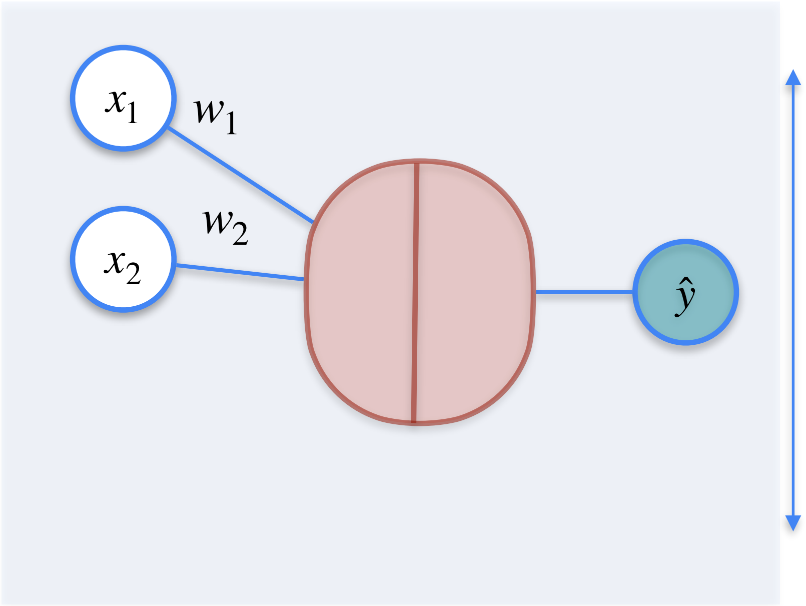
Classification With a Perceptron



Classification With a Perceptron



Classification With a Perceptron



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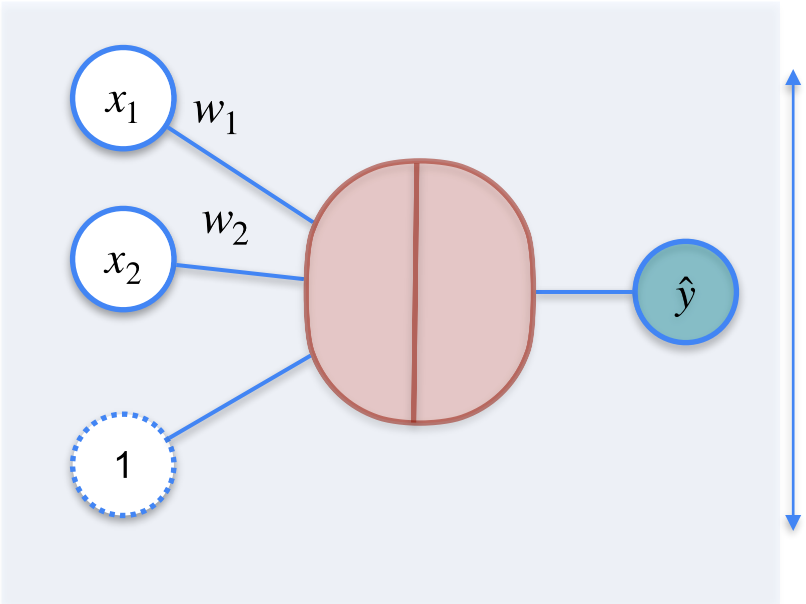
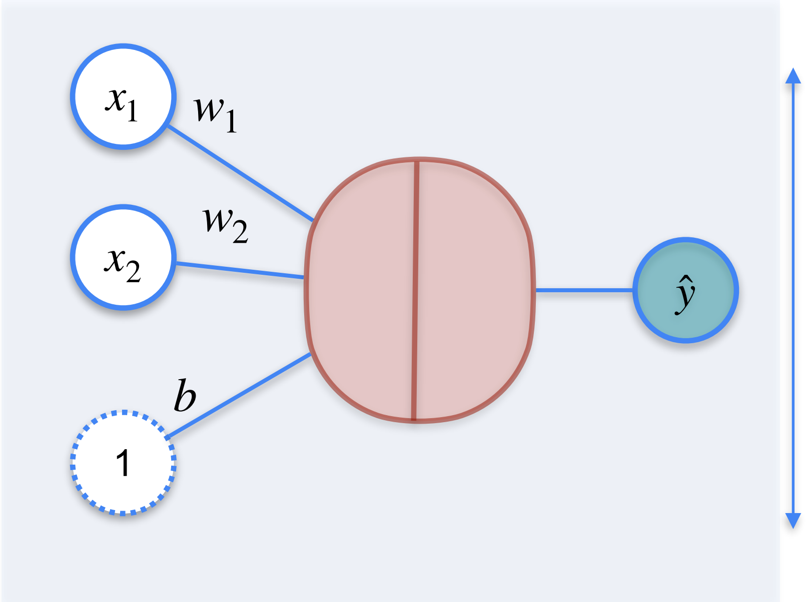
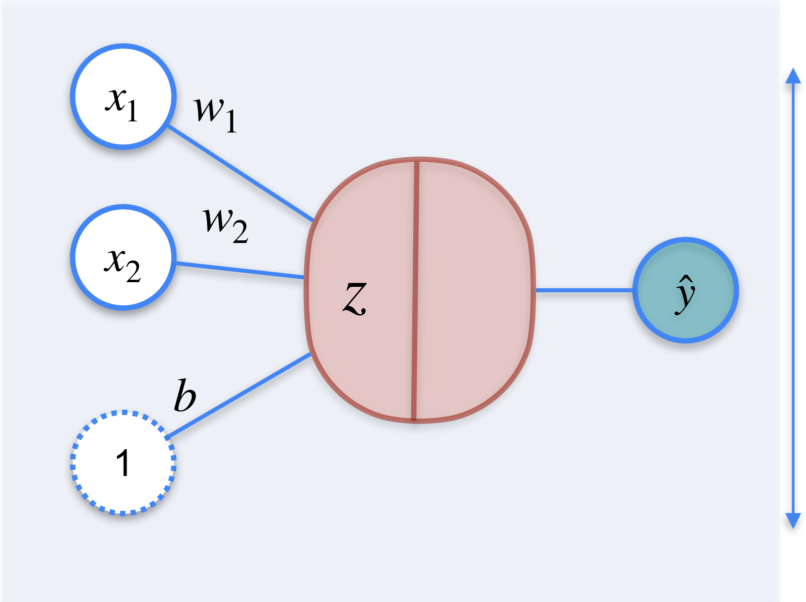
Classification With a Perceptron



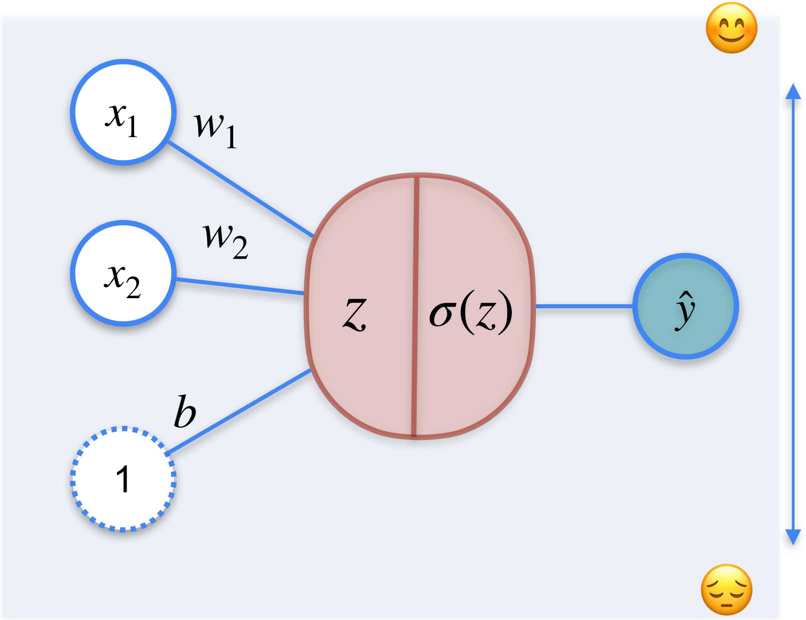
Classification With a Perceptron



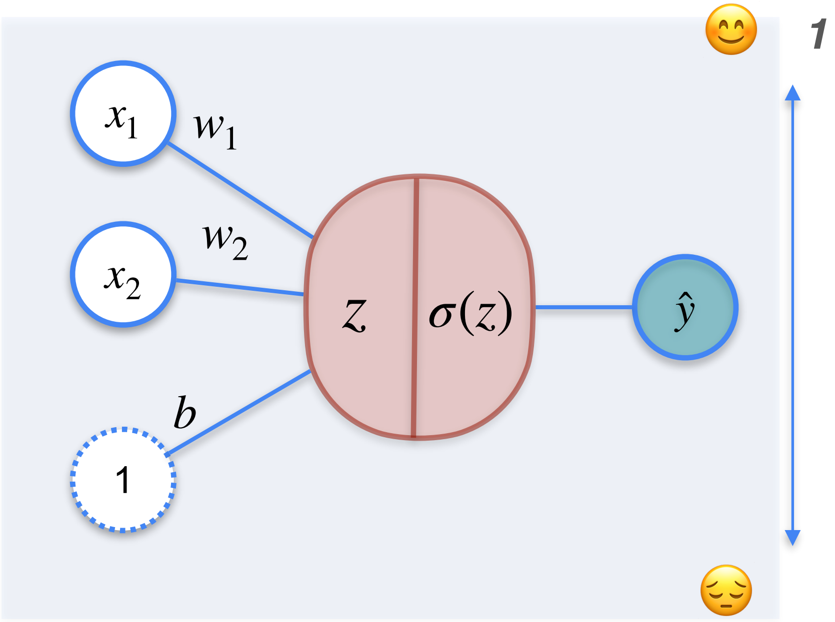
Classification With a Perceptron



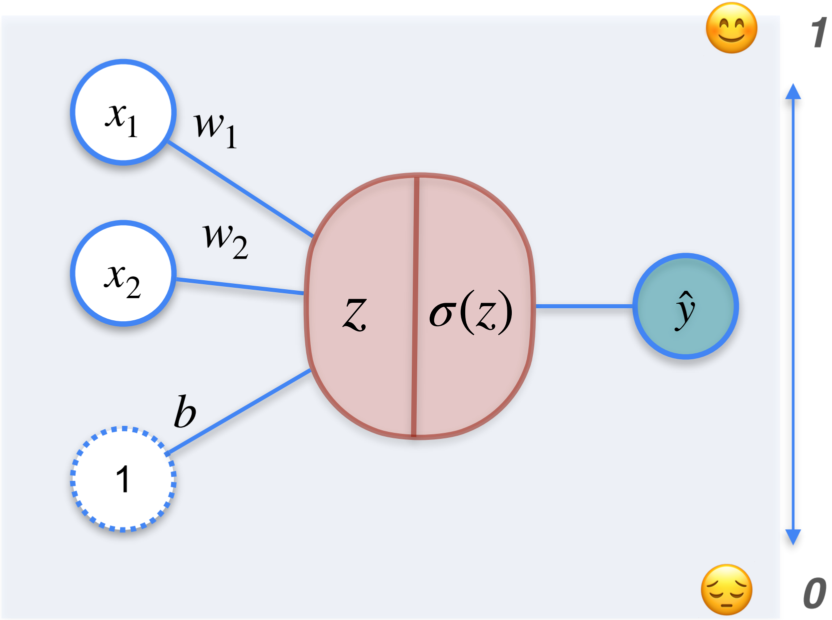
Classification With a Perceptron



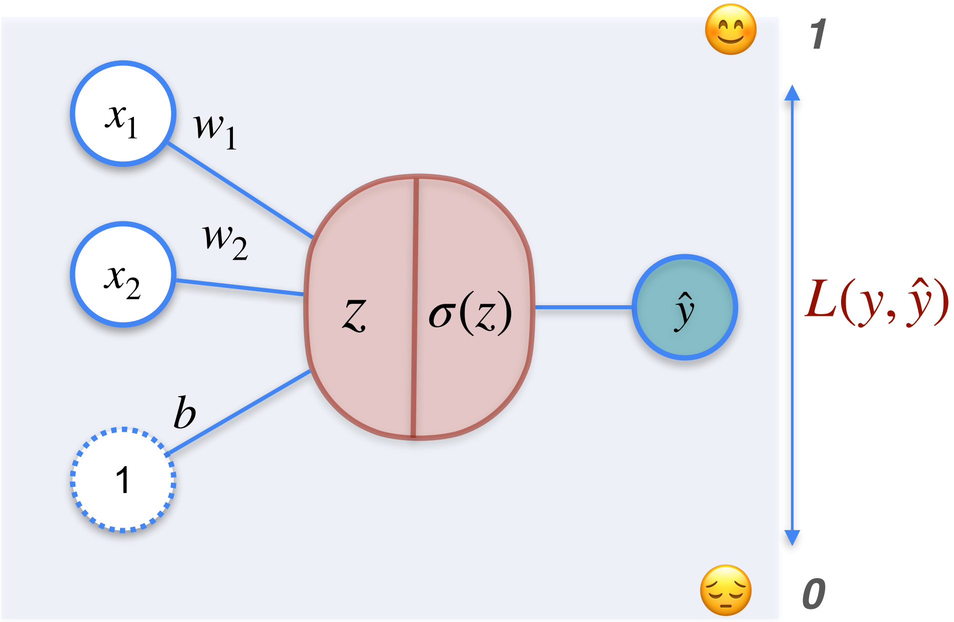
Classification With a Perceptron



Classification With a Perceptron

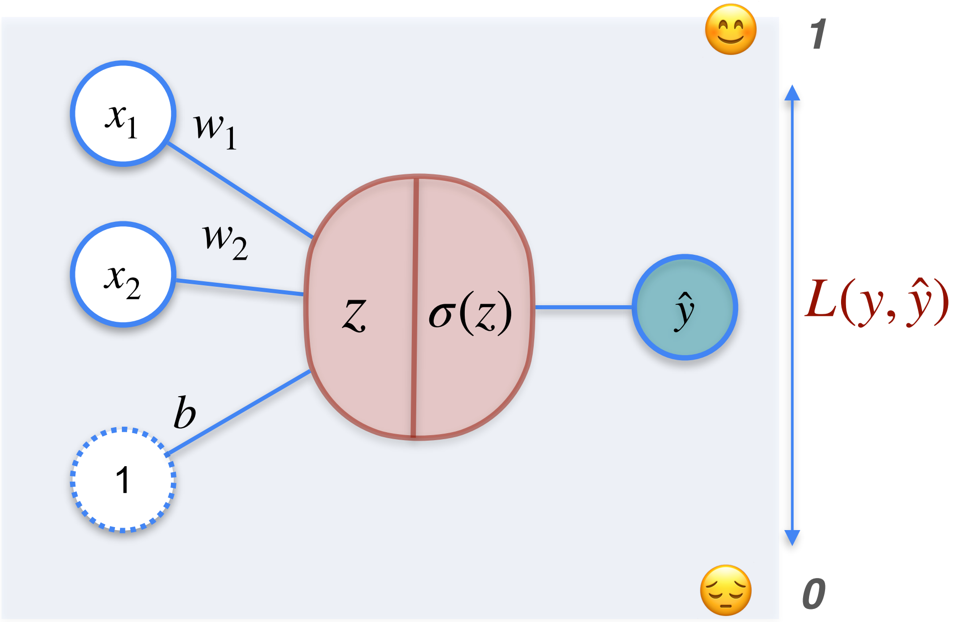


Classification With a Perceptron

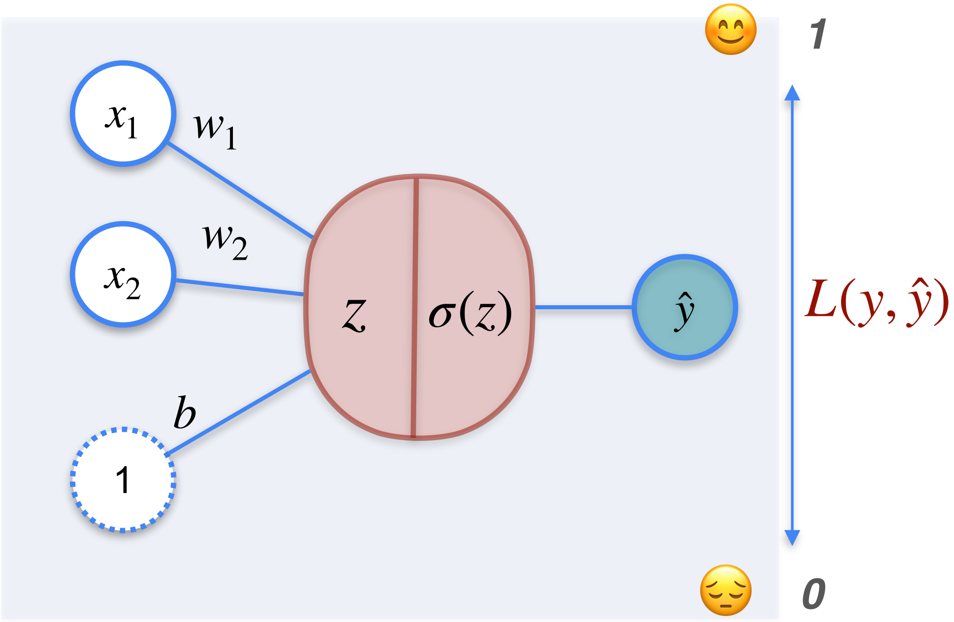


Classification With a Perceptron

To find optimal values for:



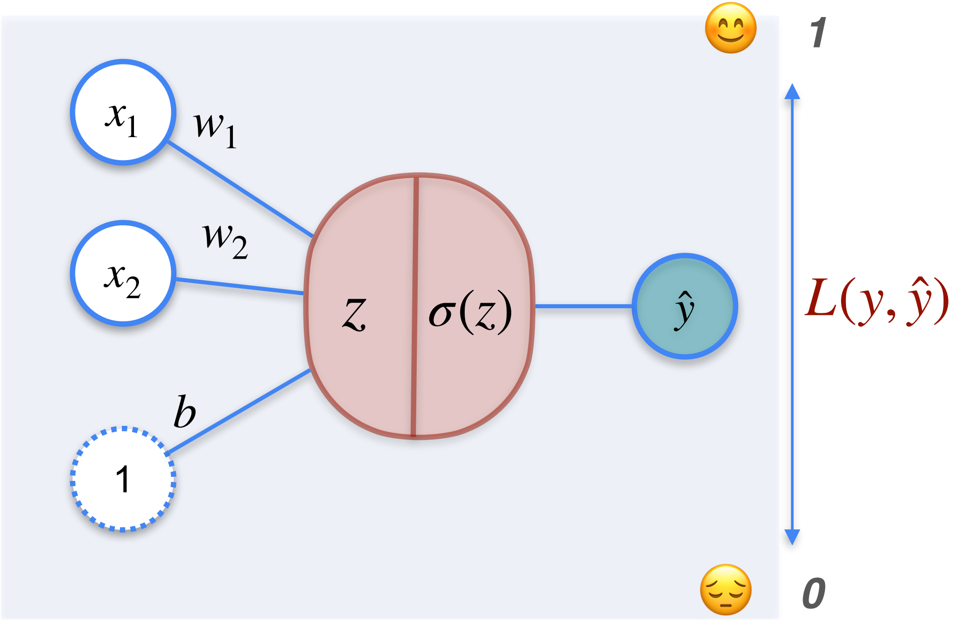
Classification With a Perceptron



To find optimal values for:

w_1 , w_2 , b

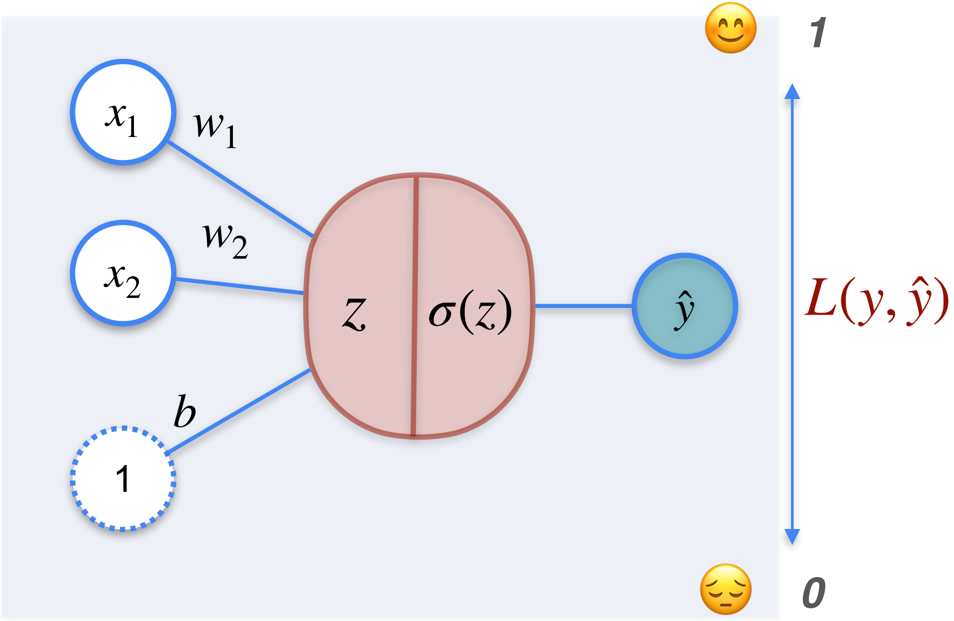
Classification With a Perceptron



To find optimal values for:
w_1 , w_2 , b

You need gradient descent

Classification With a Perceptron



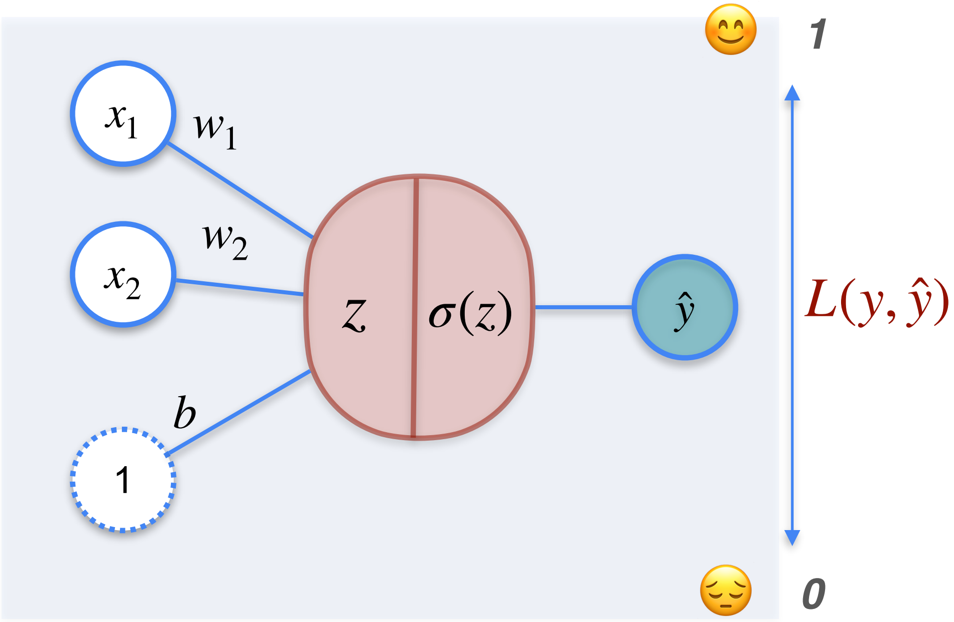
To find optimal values for:

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



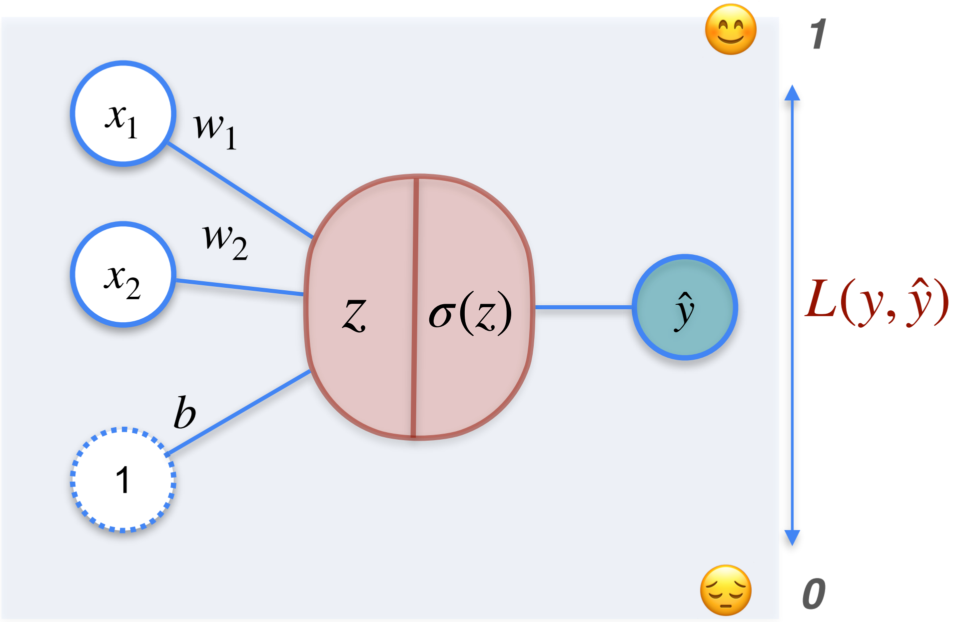
To find optimal values for:

w_1 , w_2 , b

You need gradient descent

$$w_1 \rightarrow w_1 - \alpha$$

Classification With a Perceptron



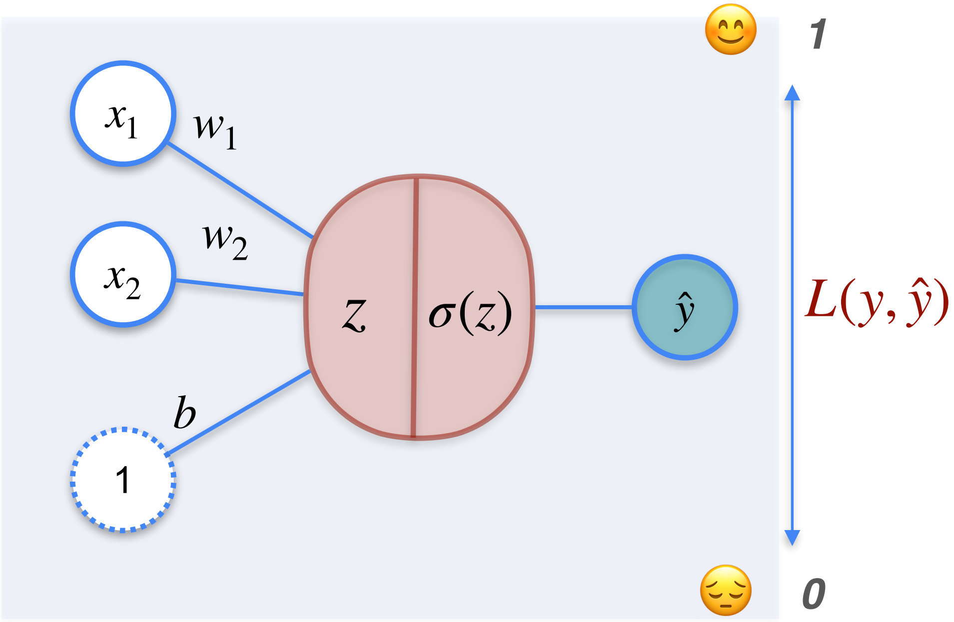
To find optimal values for:

w_1 , w_2 , b

You need gradient descent

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

Classification With a Perceptron



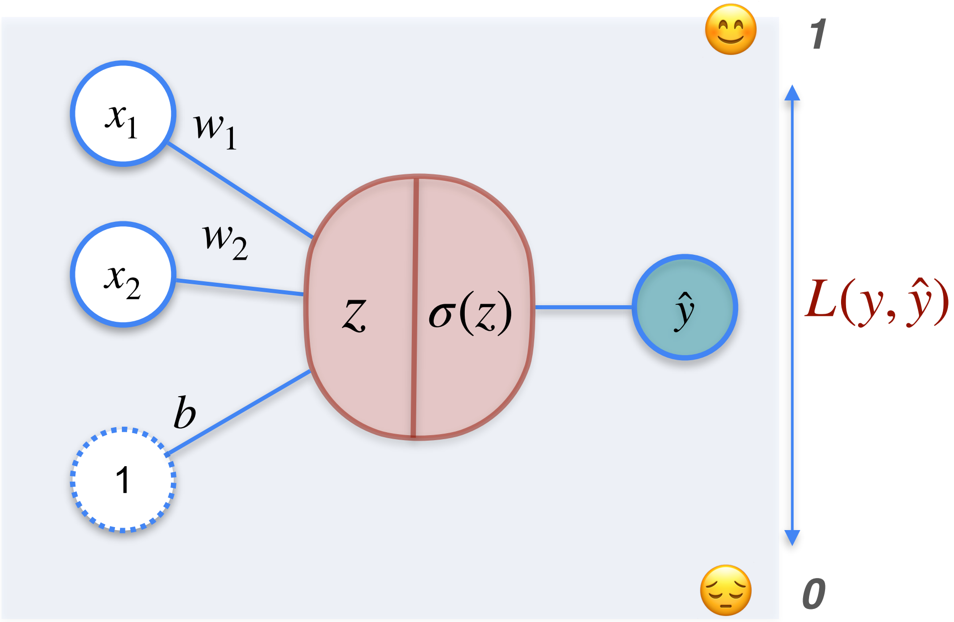
To find optimal values for:
w_1 , w_2 , b

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:

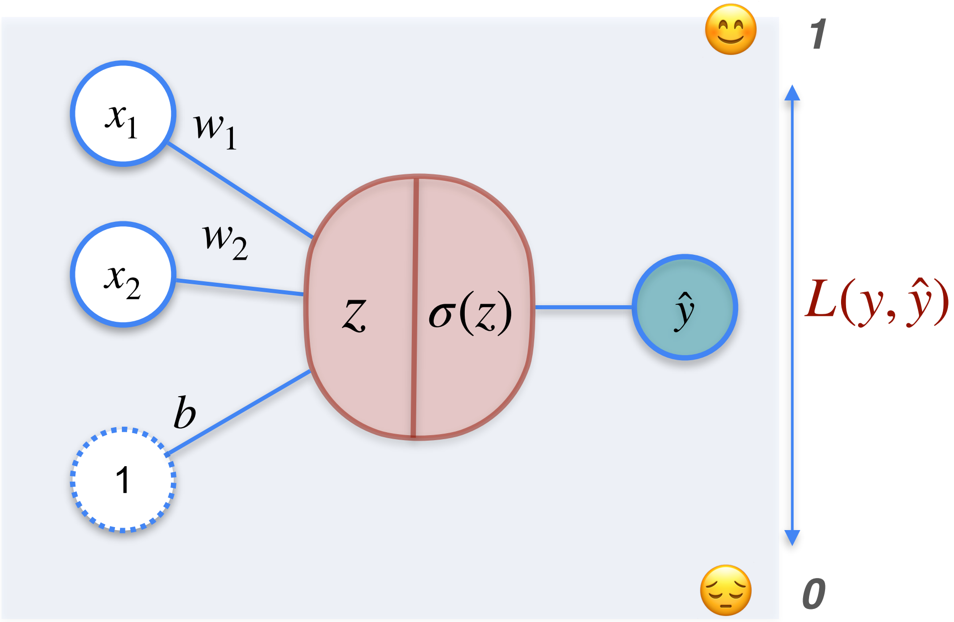
w_1 , w_2 , b

You need gradient descent

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

$$w_2 \rightarrow w_2 - \alpha$$

Classification With a Perceptron



To find optimal values for:

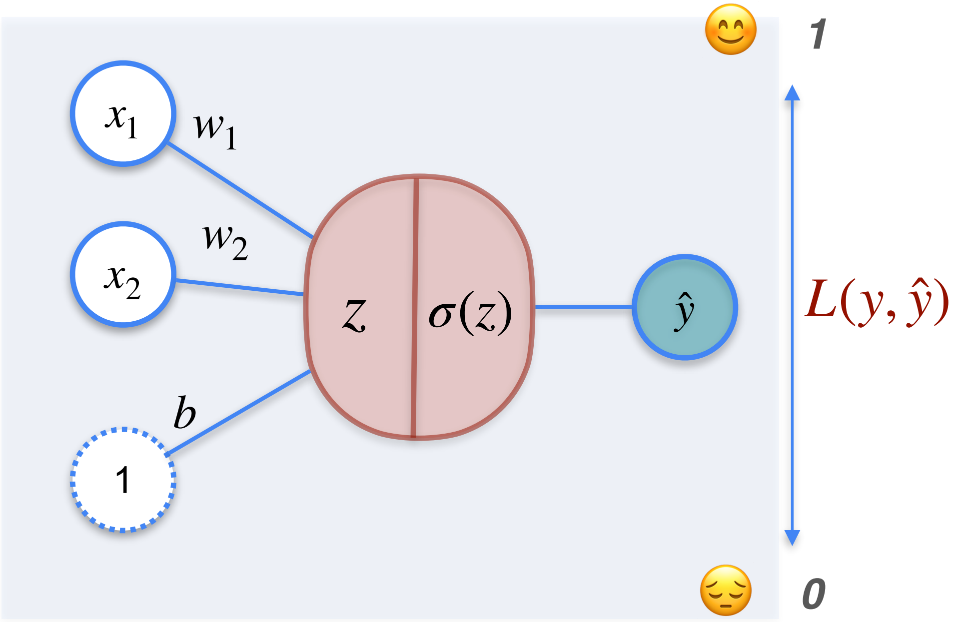
w_1 , w_2 , b

You need gradient descent

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

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

Classification With a Perceptron



To find optimal values for:
w_1 , w_2 , b

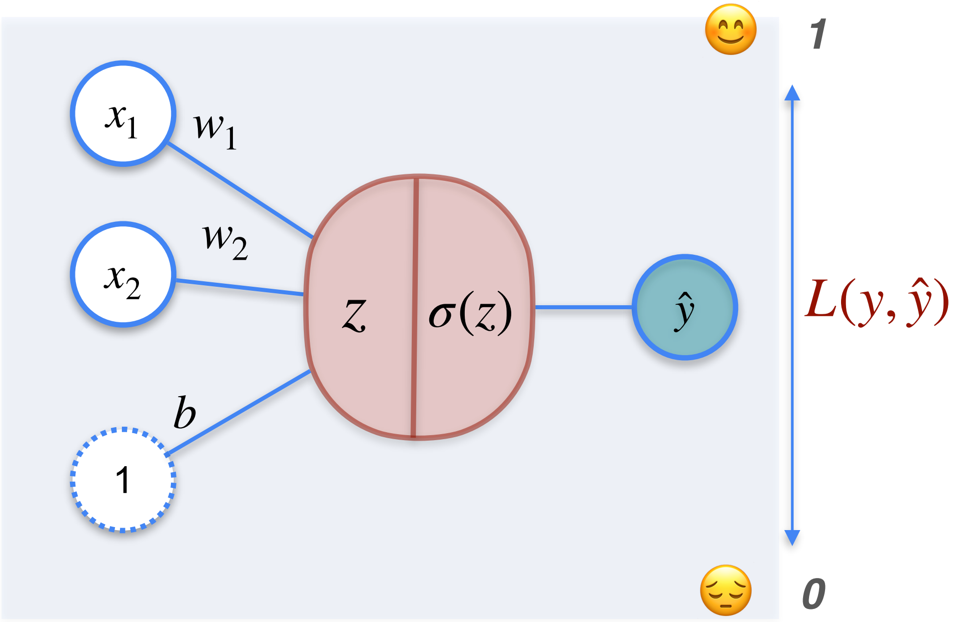
You need gradient descent

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

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

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

Classification With a Perceptron



To find optimal values for:

w_1 , w_2 , b

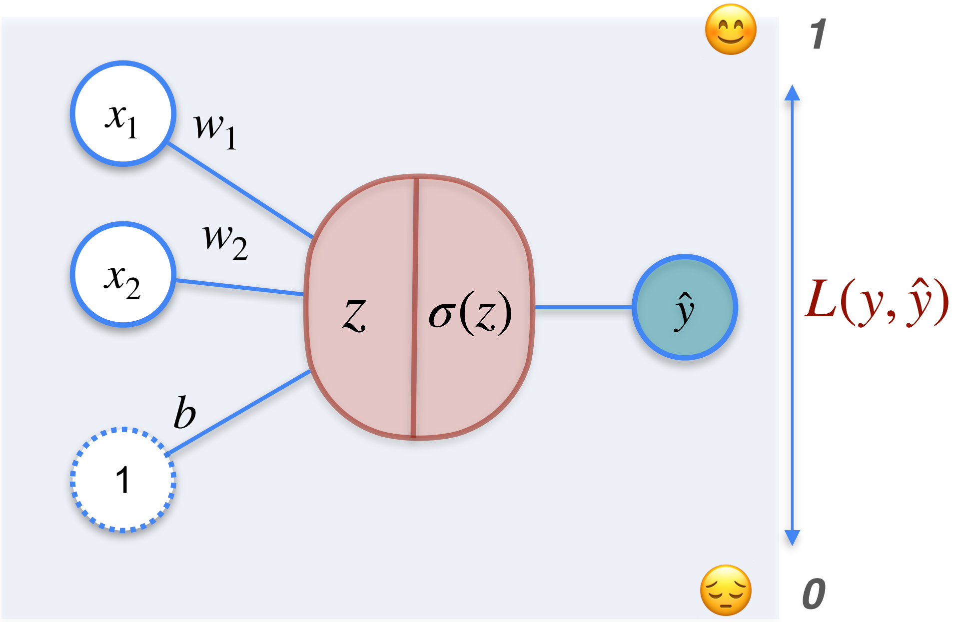
You need gradient descent

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

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

$$b \rightarrow b - \alpha$$

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

Classification with a Neural Network

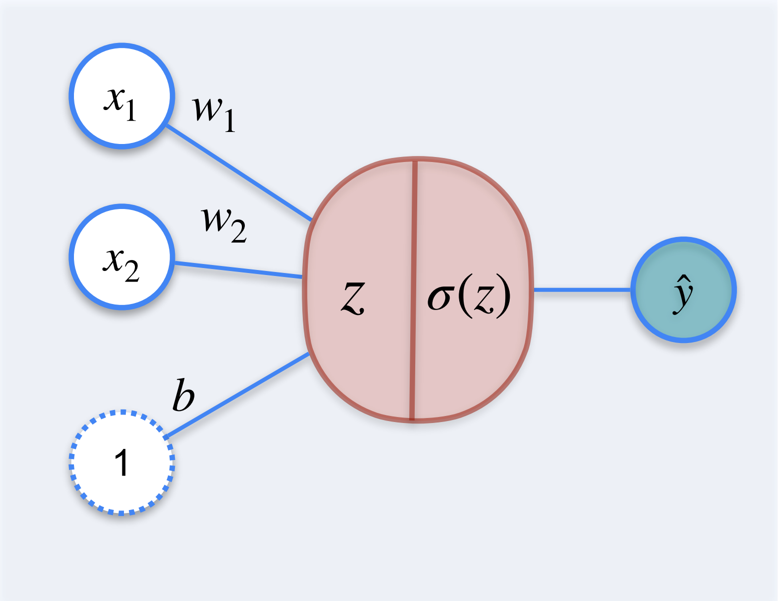
Classification Problem Motivation

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* 😊

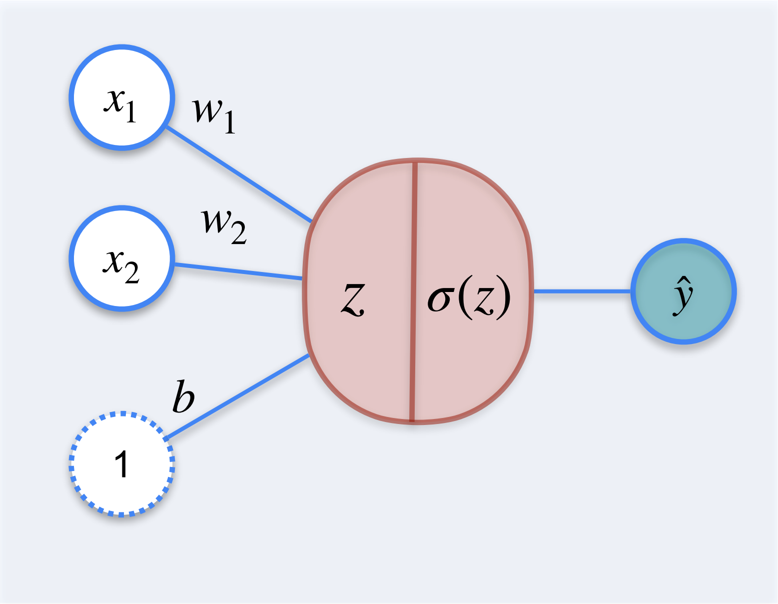
Classification Problem Motivation

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 😊



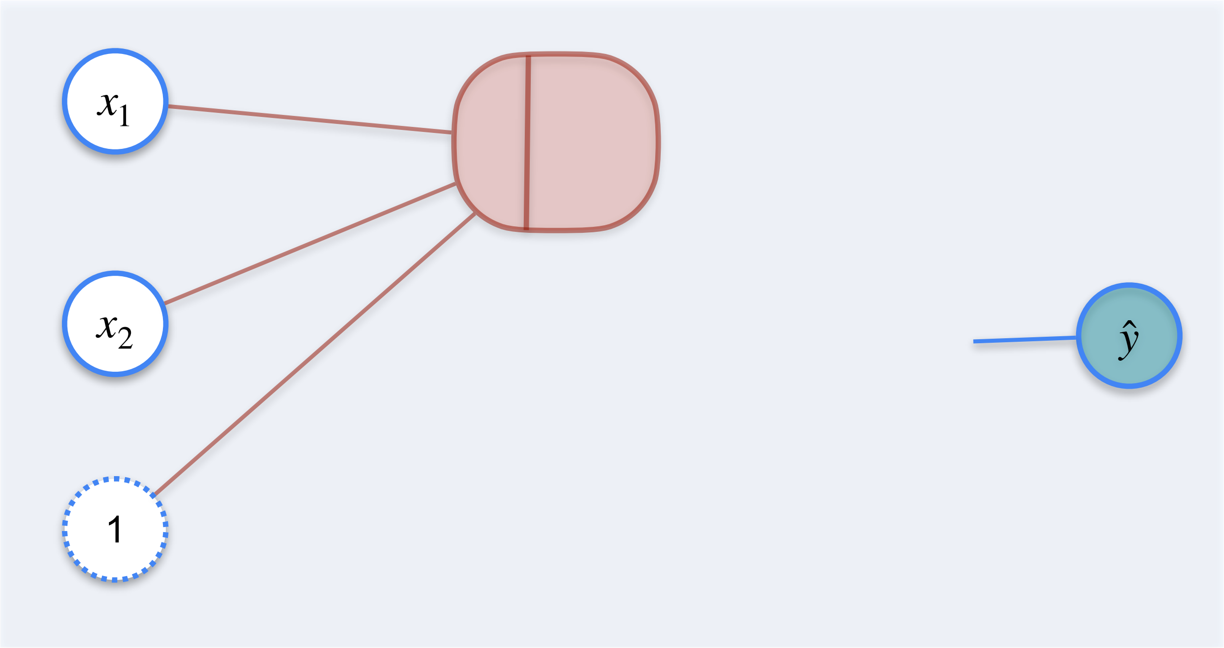
Classification Problem Motivation

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* 😊

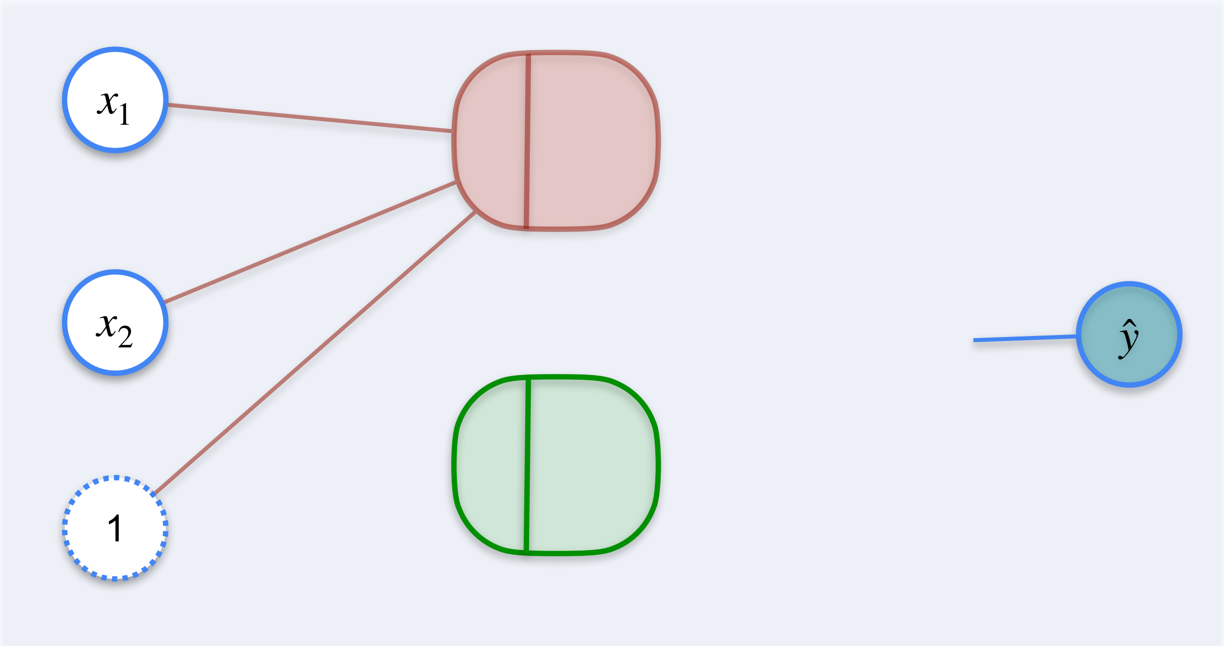


$$z = x_1 w_1 + x_2 w_2 + b$$

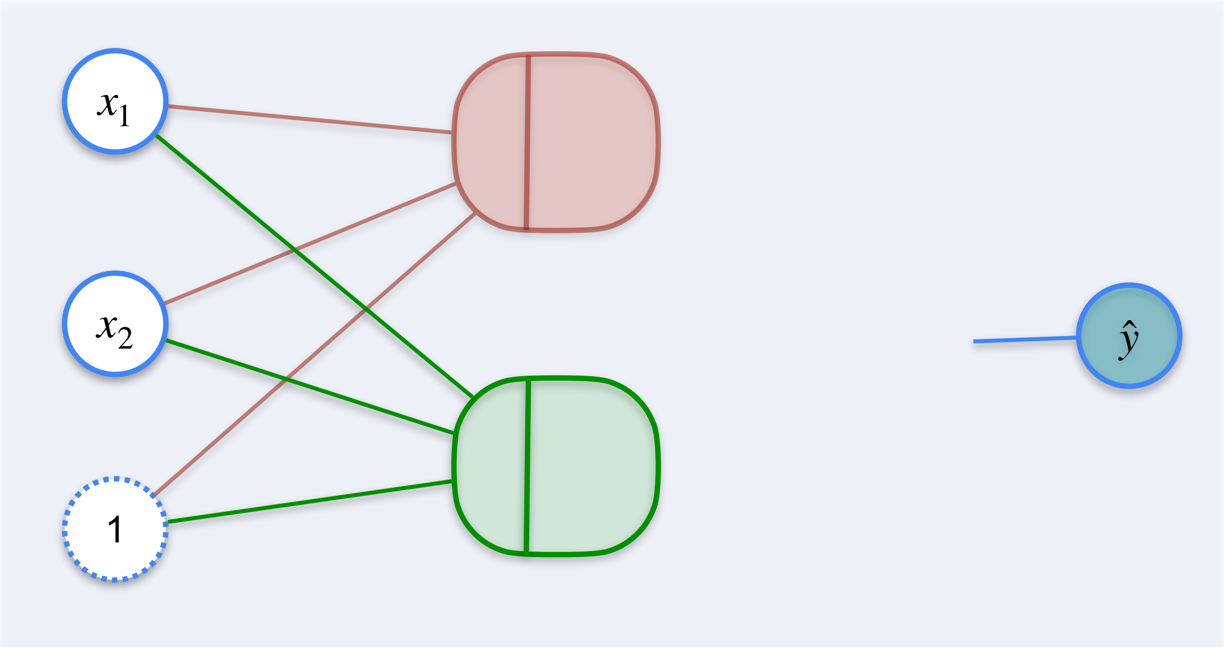
2,2,1 Neural Network



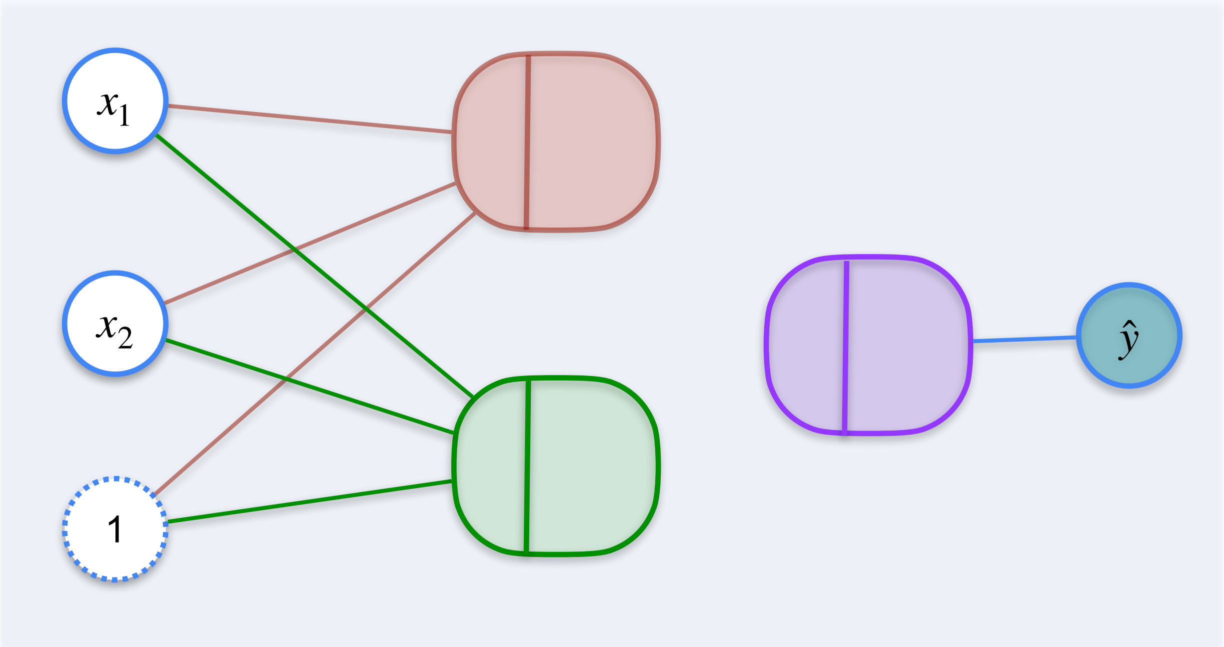
2,2,1 Neural Network



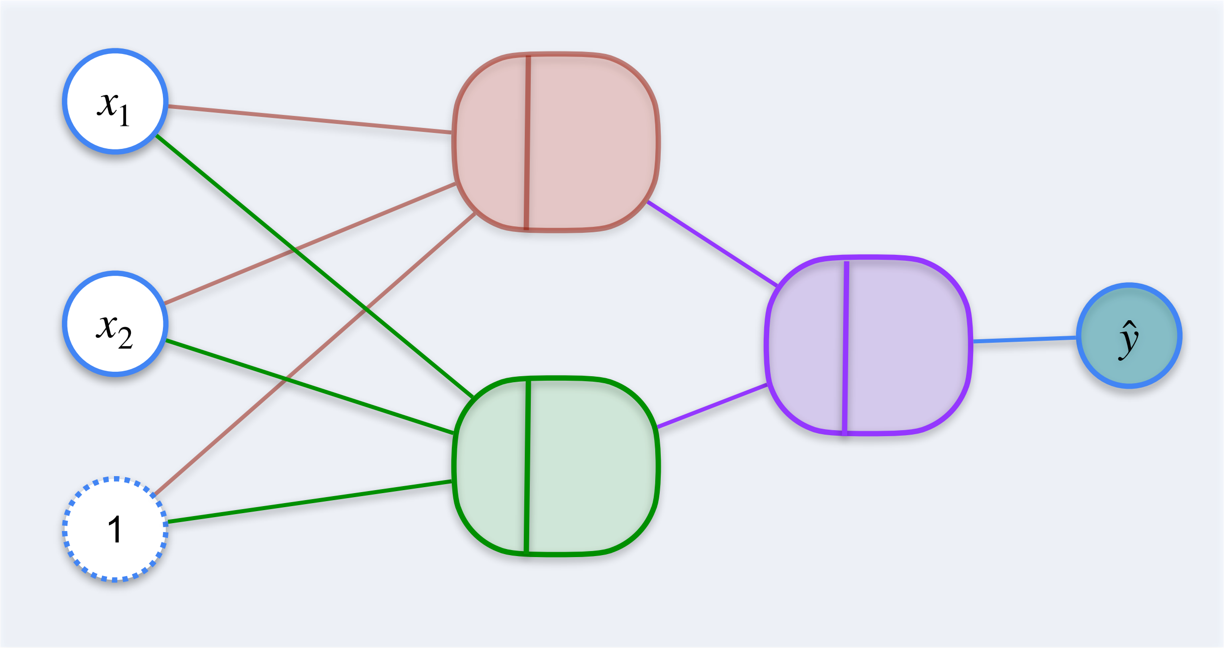
2,2,1 Neural Network



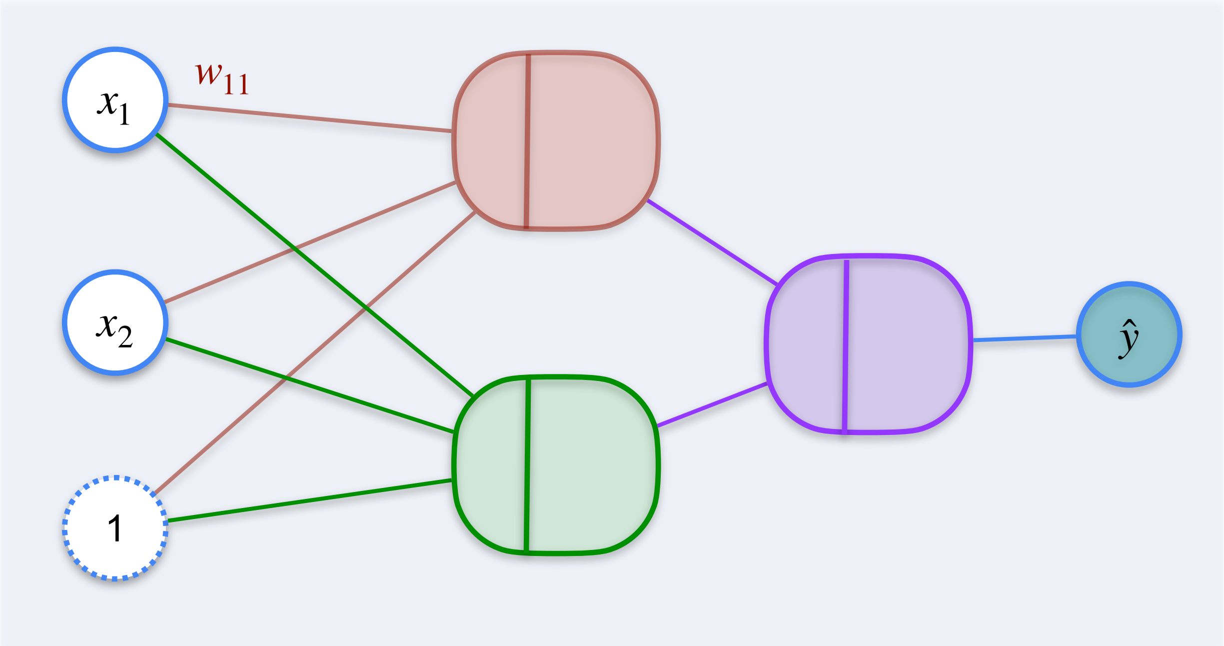
2,2,1 Neural Network



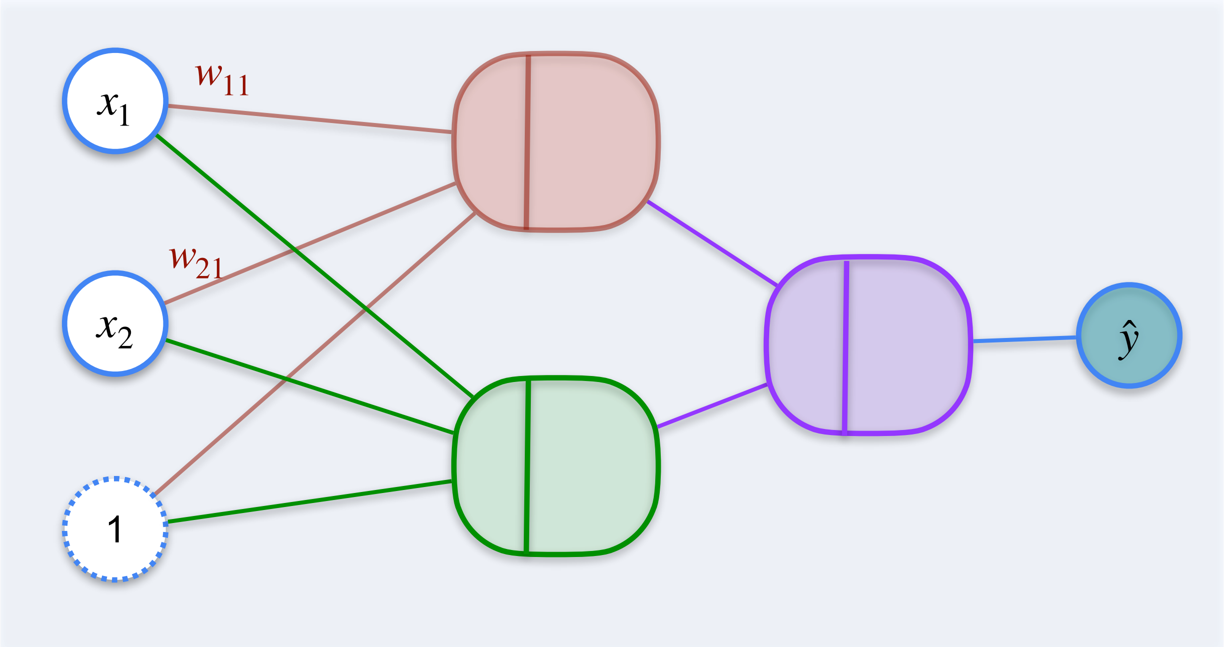
2,2,1 Neural Network



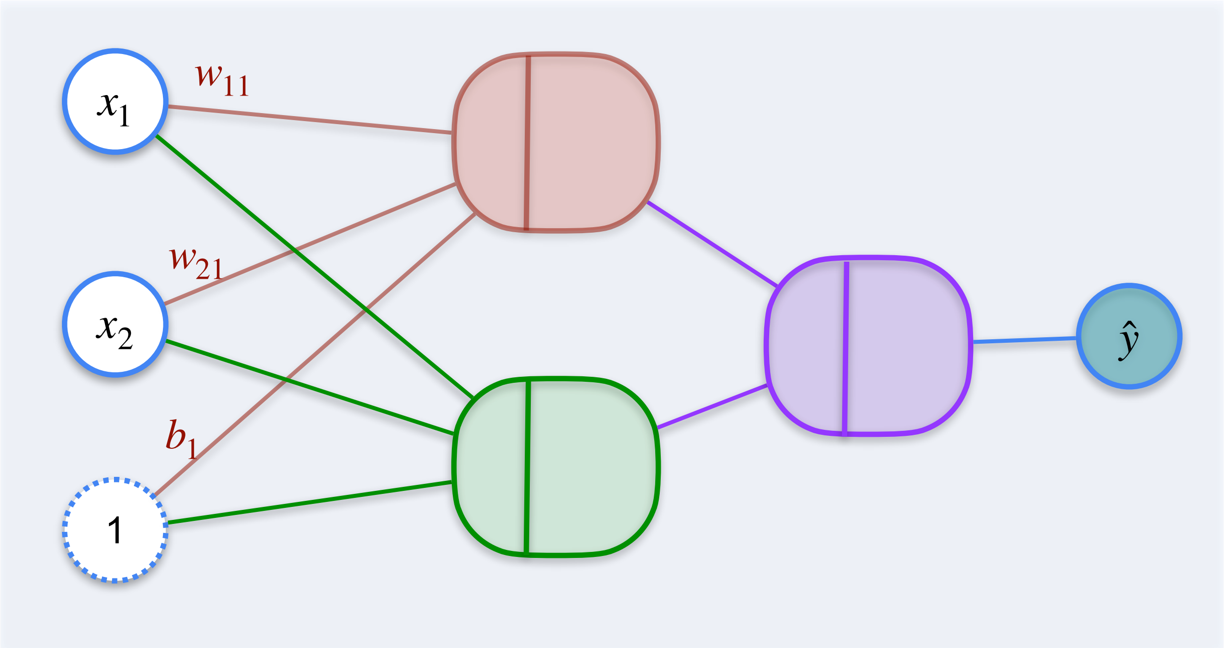
2,2,1 Neural Network



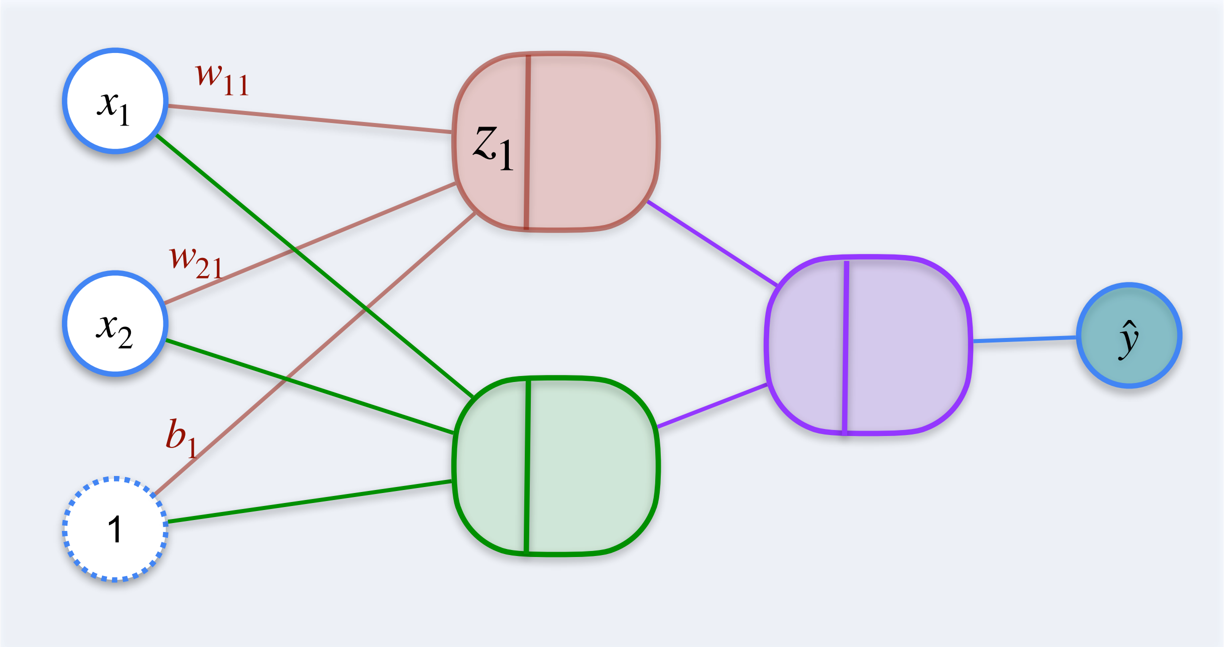
2,2,1 Neural Network



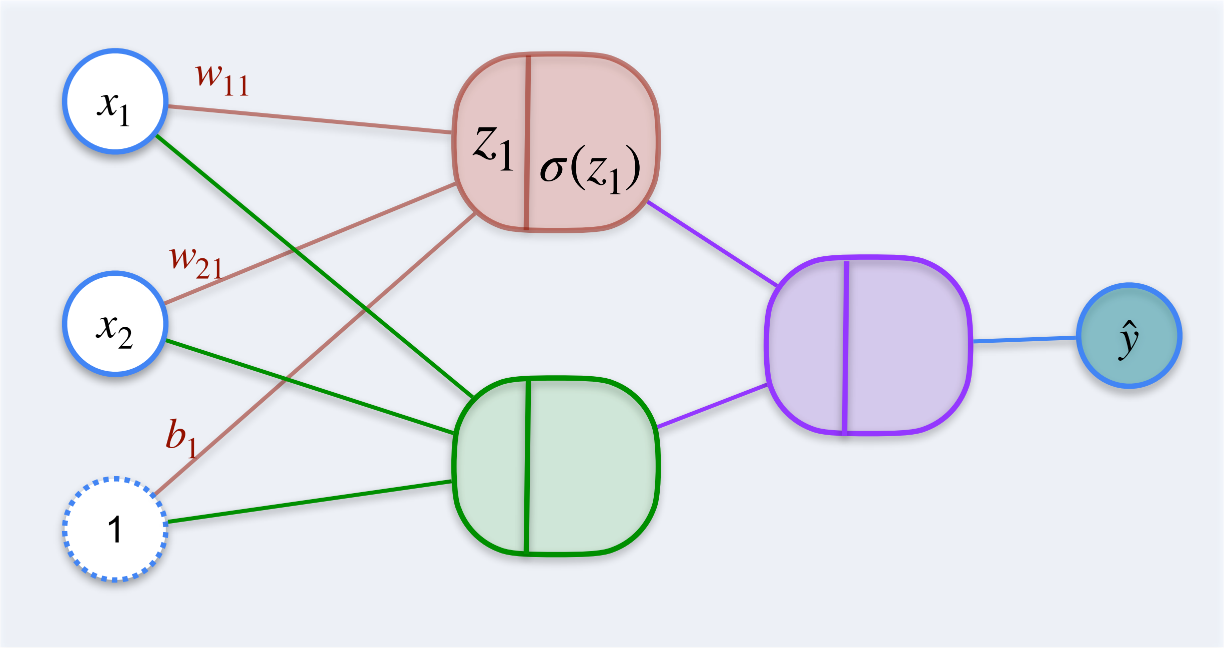
2,2,1 Neural Network



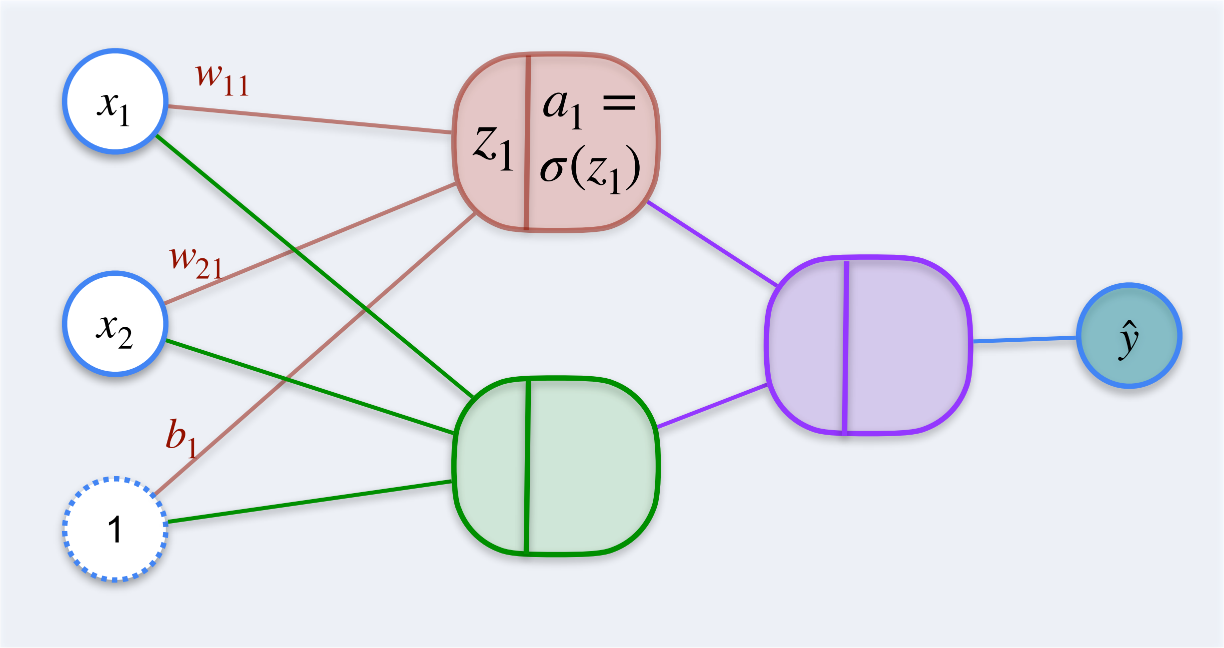
2,2,1 Neural Network



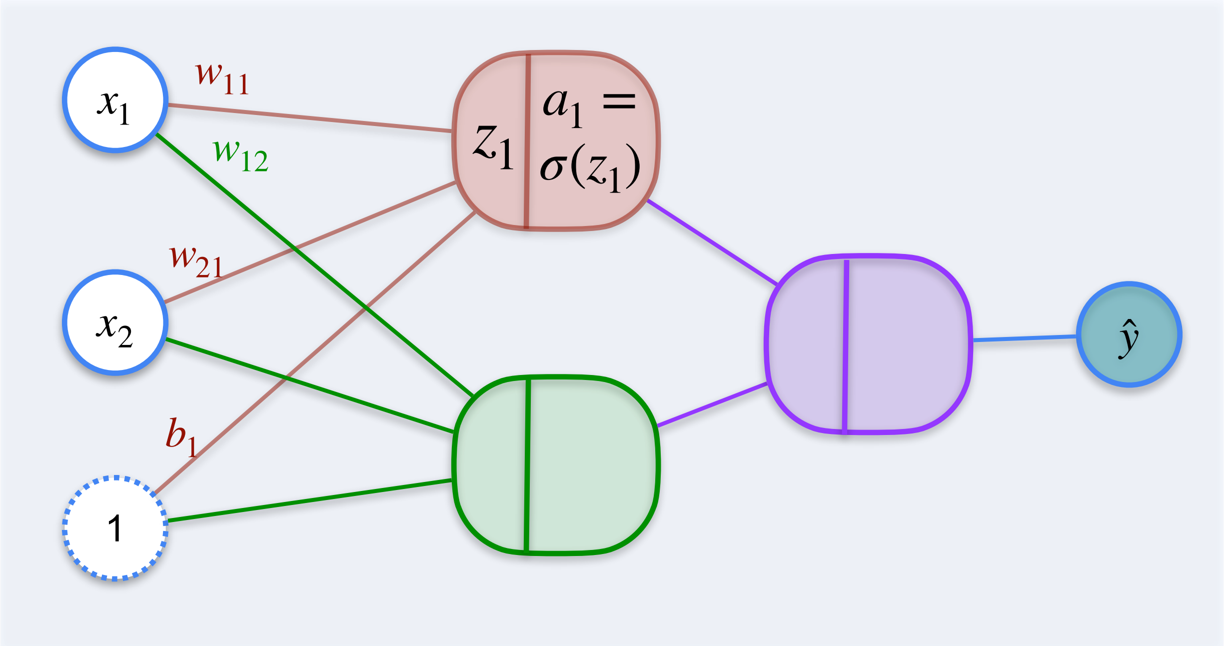
2,2,1 Neural Network



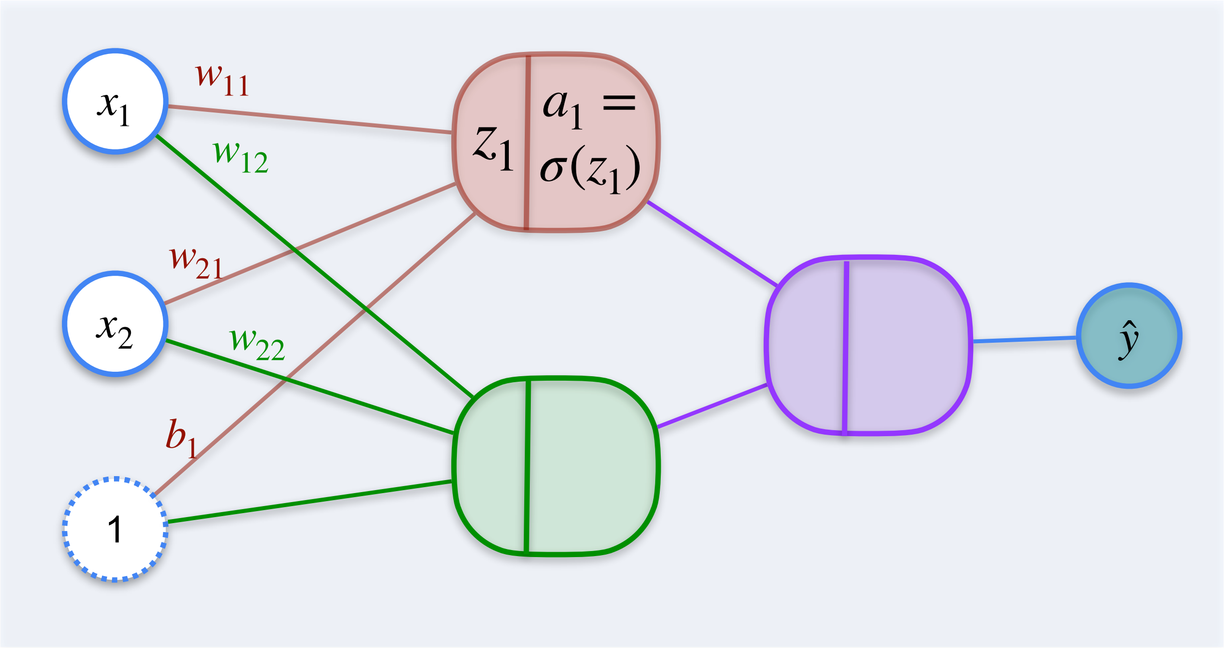
2,2,1 Neural Network



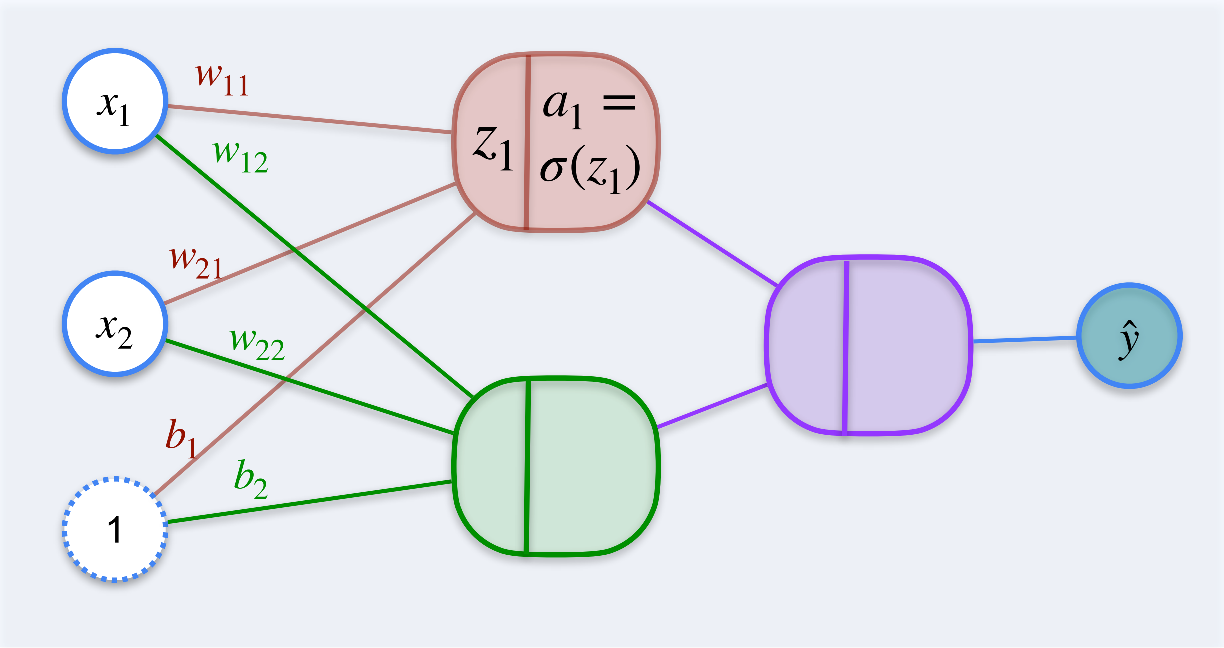
2,2,1 Neural Network



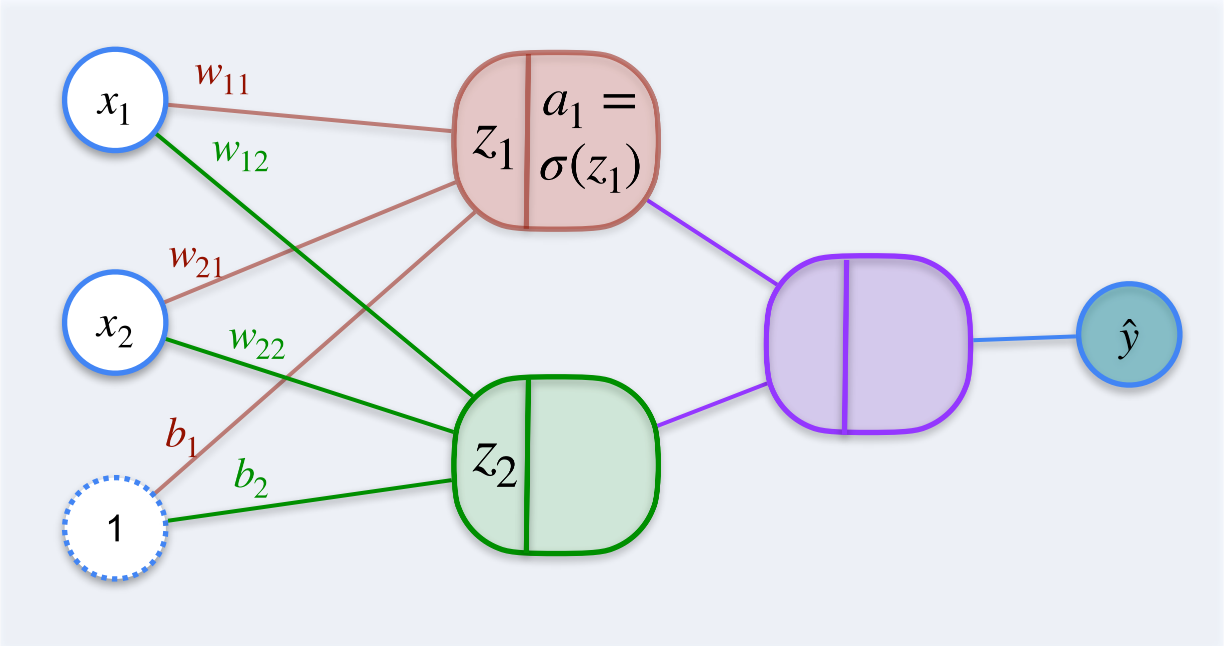
2,2,1 Neural Network



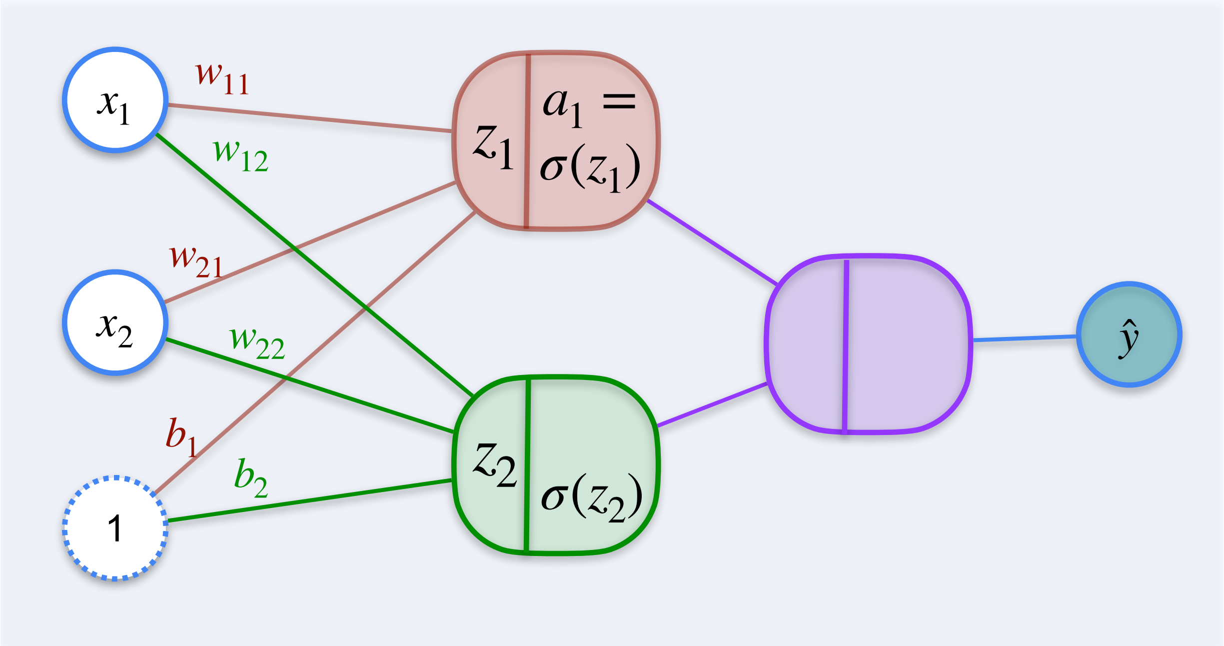
2,2,1 Neural Network



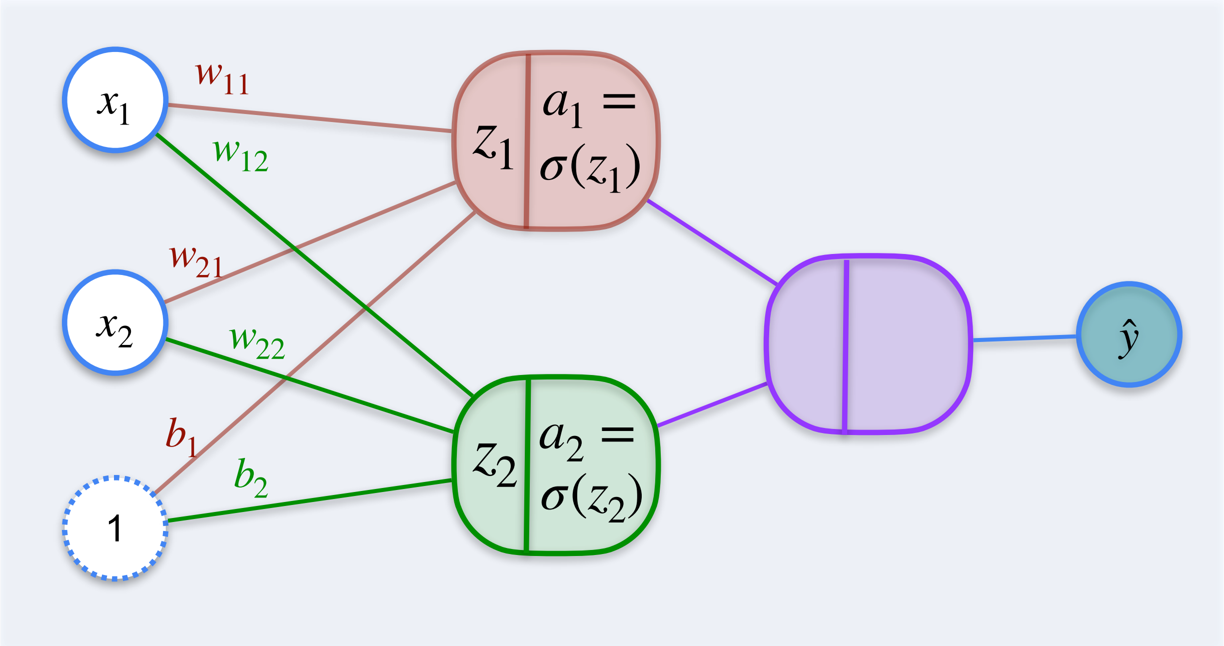
2,2,1 Neural Network



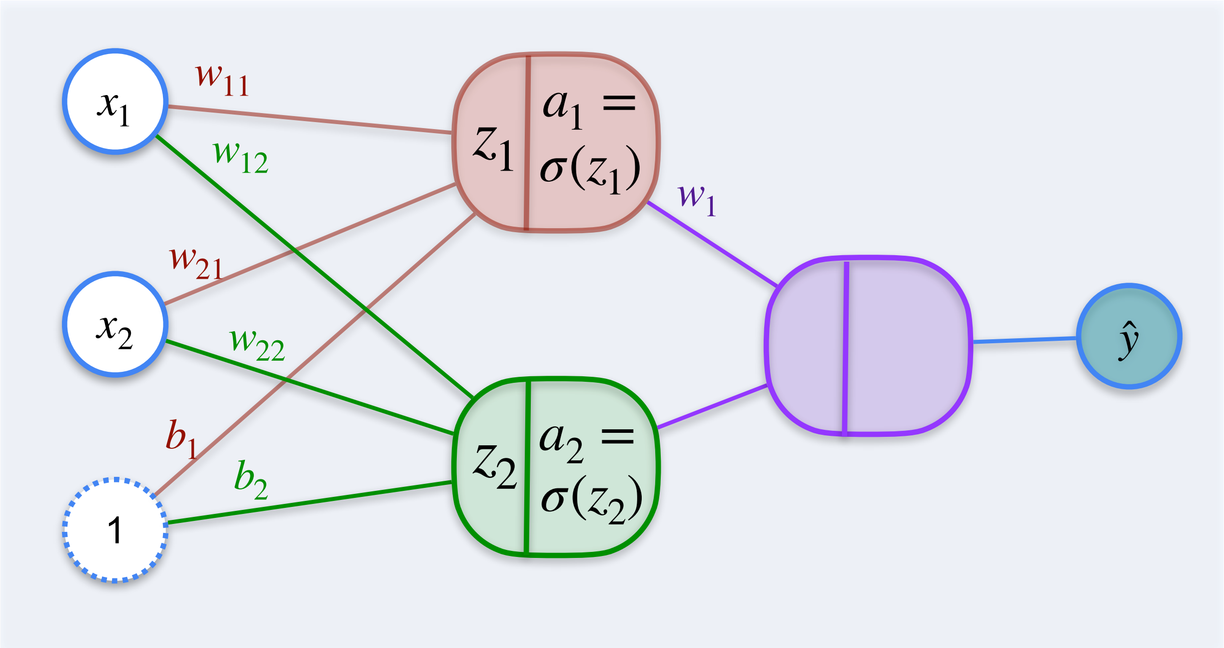
2,2,1 Neural Network



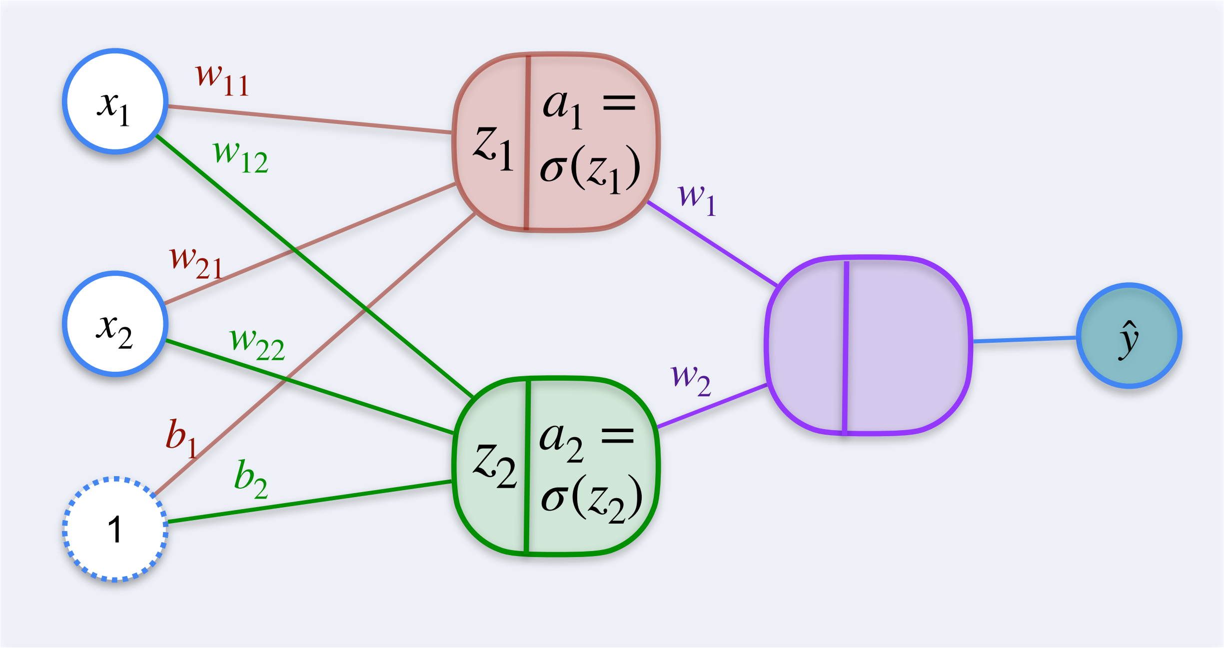
2,2,1 Neural Network



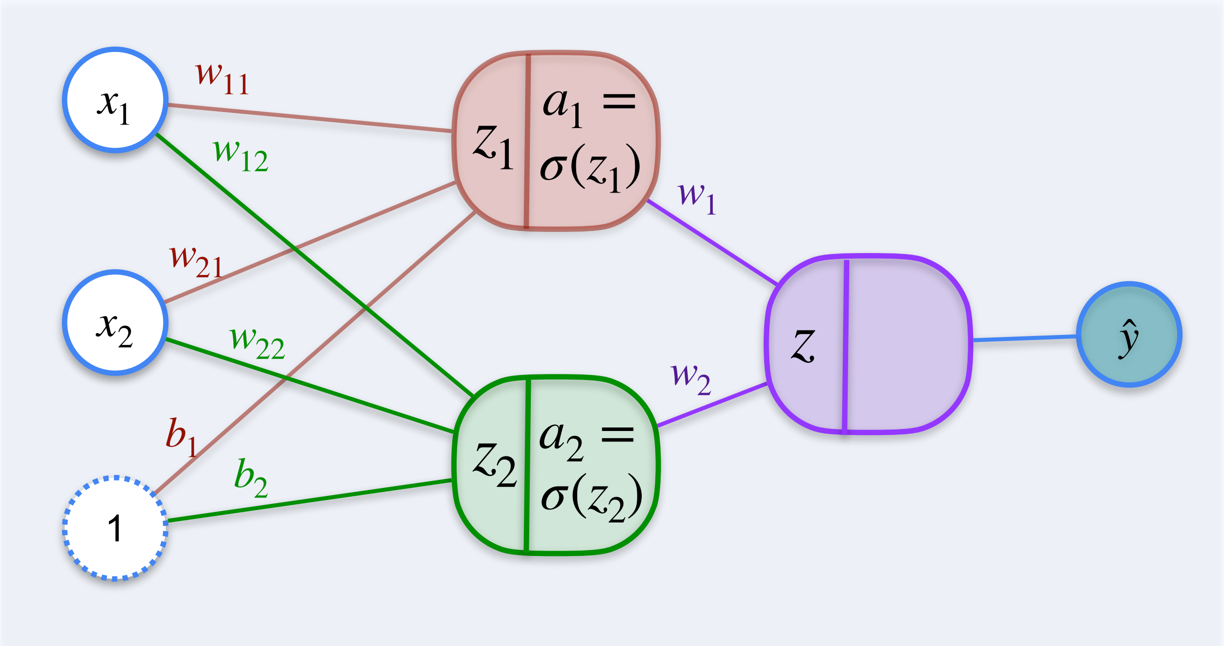
2,2,1 Neural Network



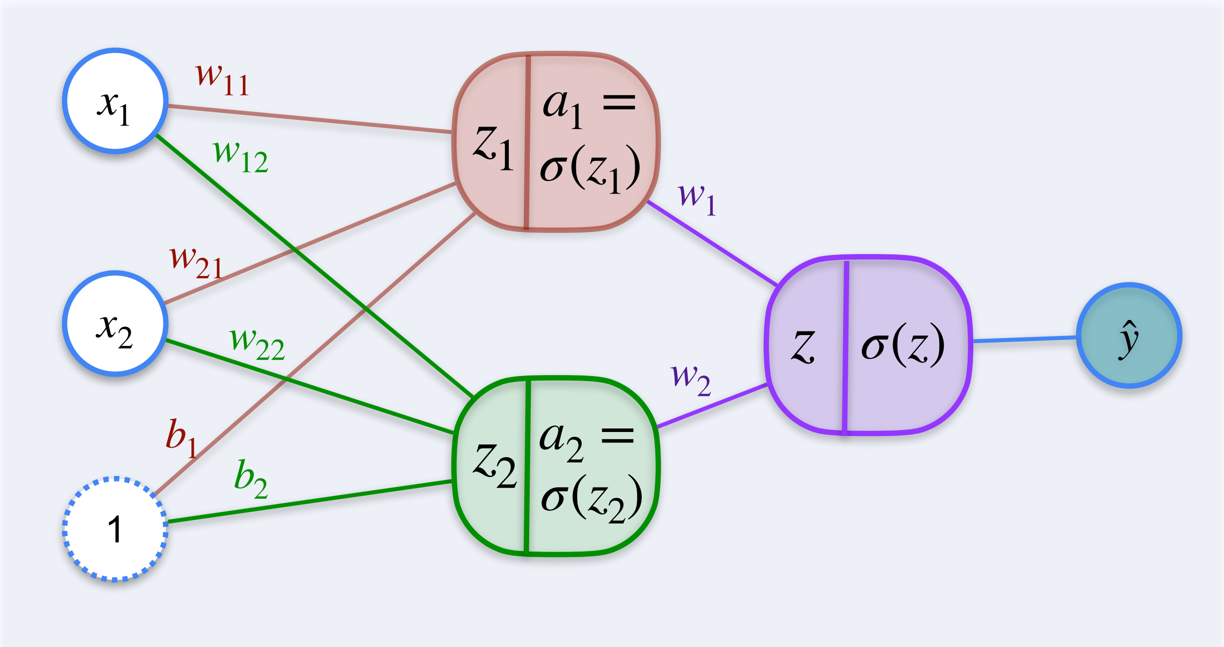
2,2,1 Neural Network



2,2,1 Neural Network



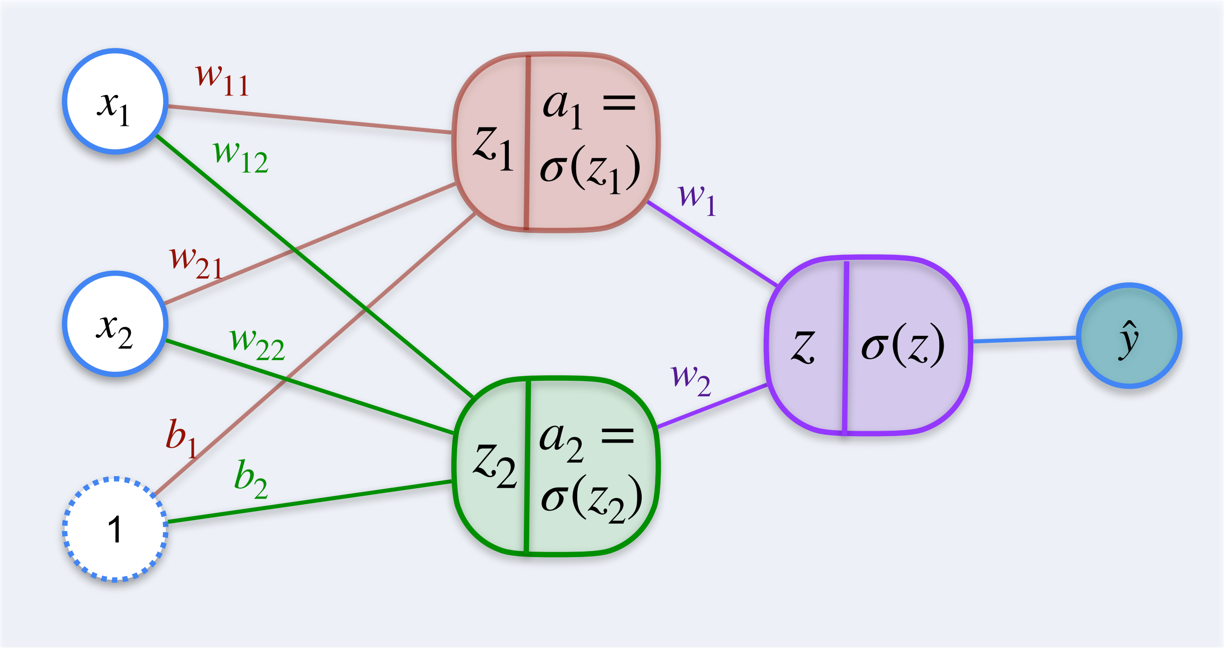
2,2,1 Neural Network



2,2,1 Neural Network

Neural network of depth 2

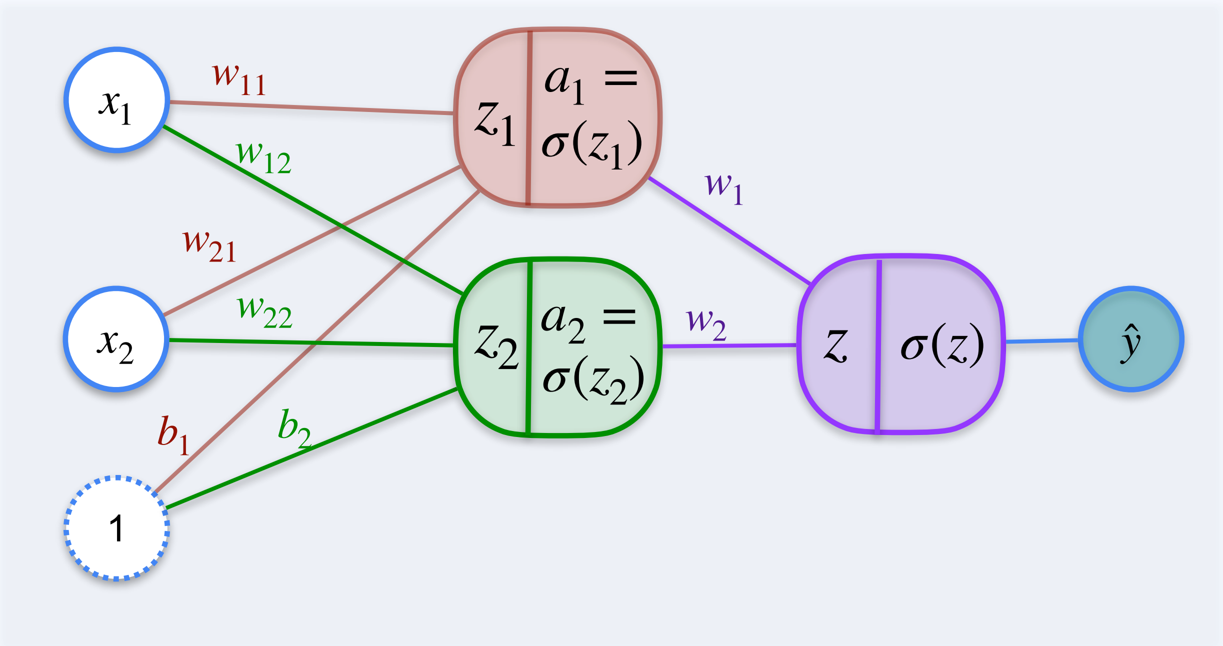
- one input layer
- one hidden layer
- one output layer



2,2,1 Neural Network

Neural network of depth 2

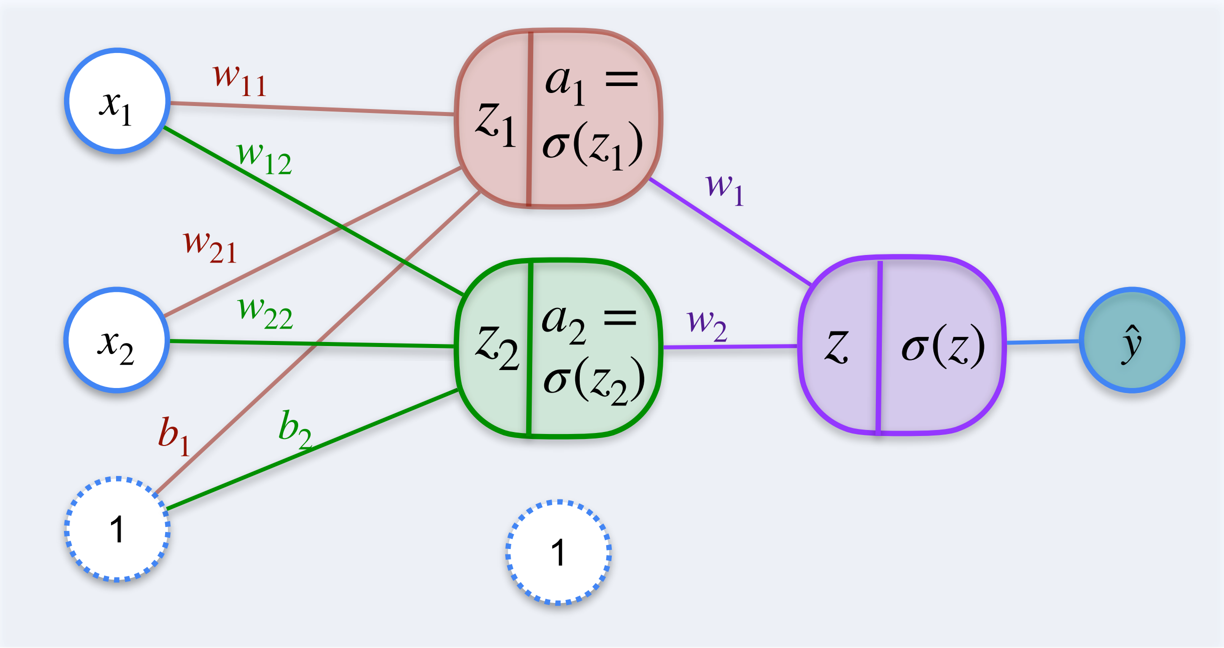
- one input layer
- one hidden layer
- one output layer



2,2,1 Neural Network

Neural network of depth 2

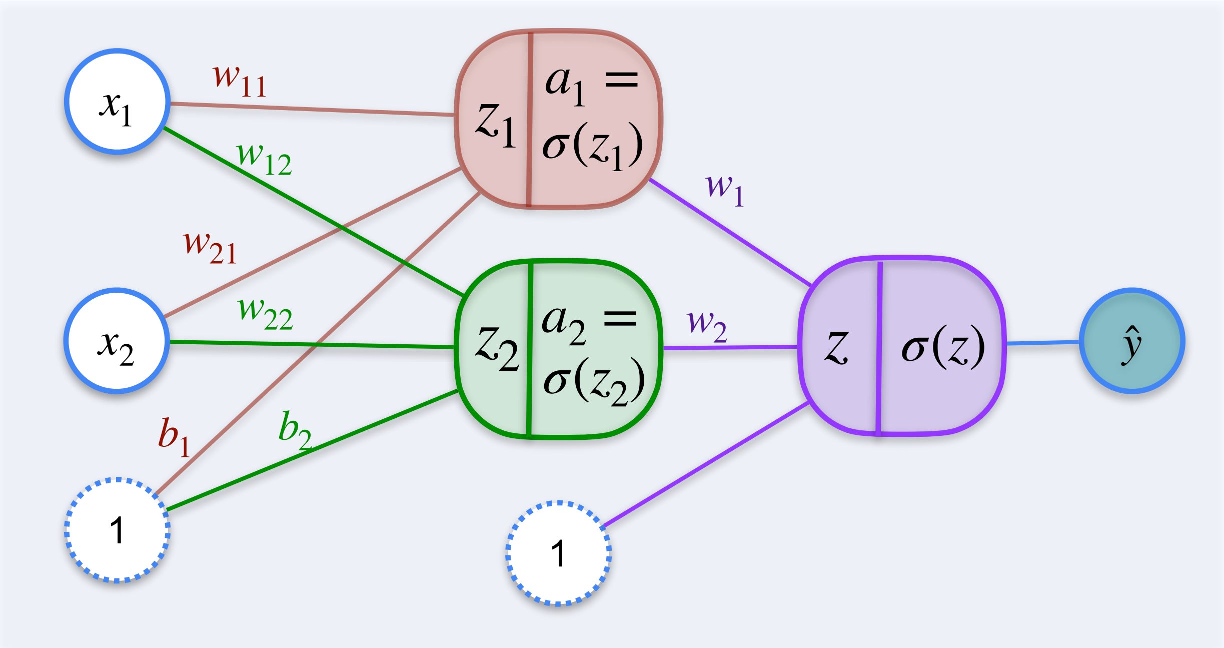
- one input layer
- one hidden layer
- one output layer



2,2,1 Neural Network

Neural network of depth 2

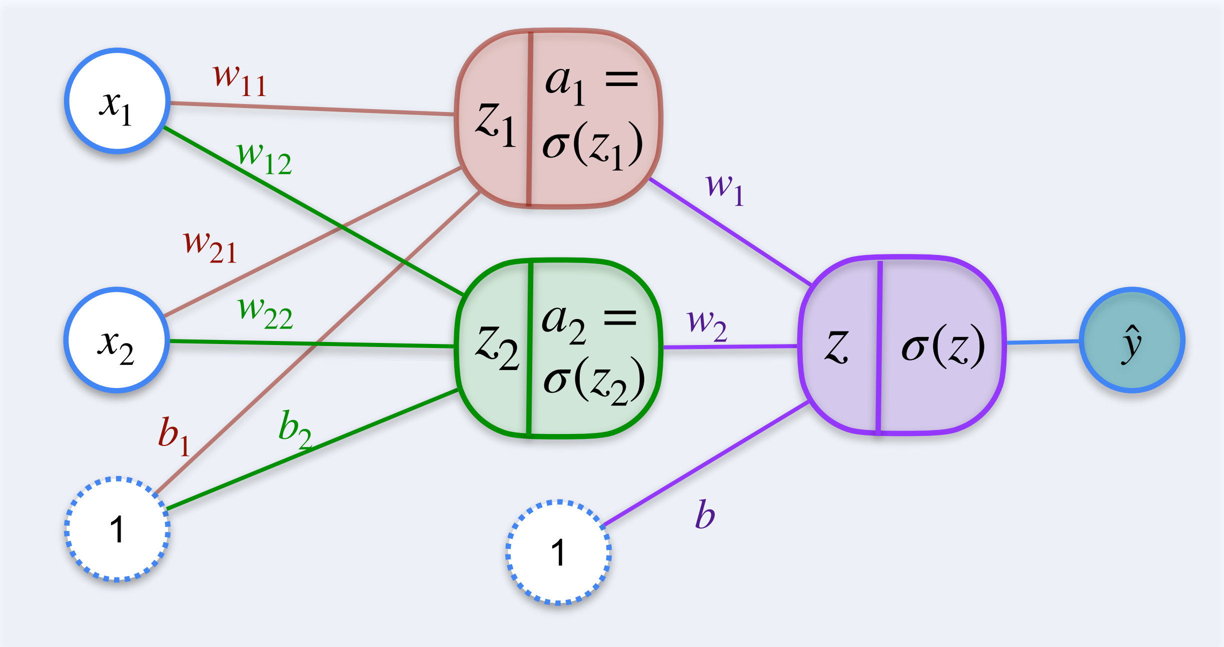
- one input layer
- one hidden layer
- one output layer



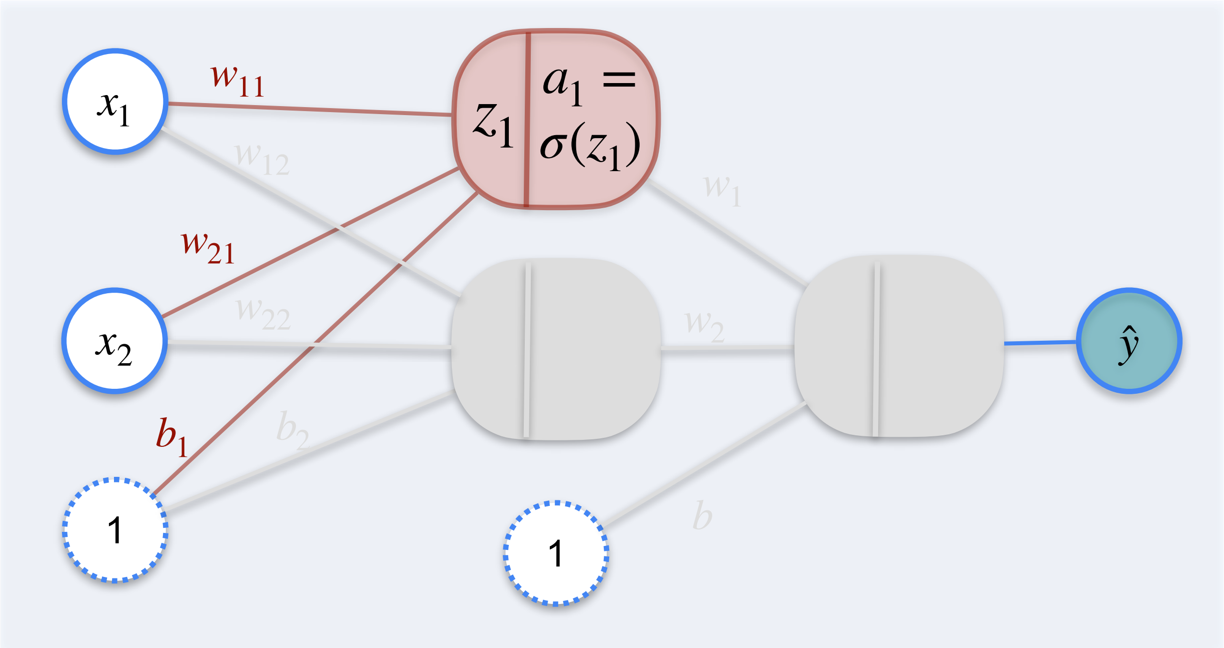
2,2,1 Neural Network

Neural network of depth 2

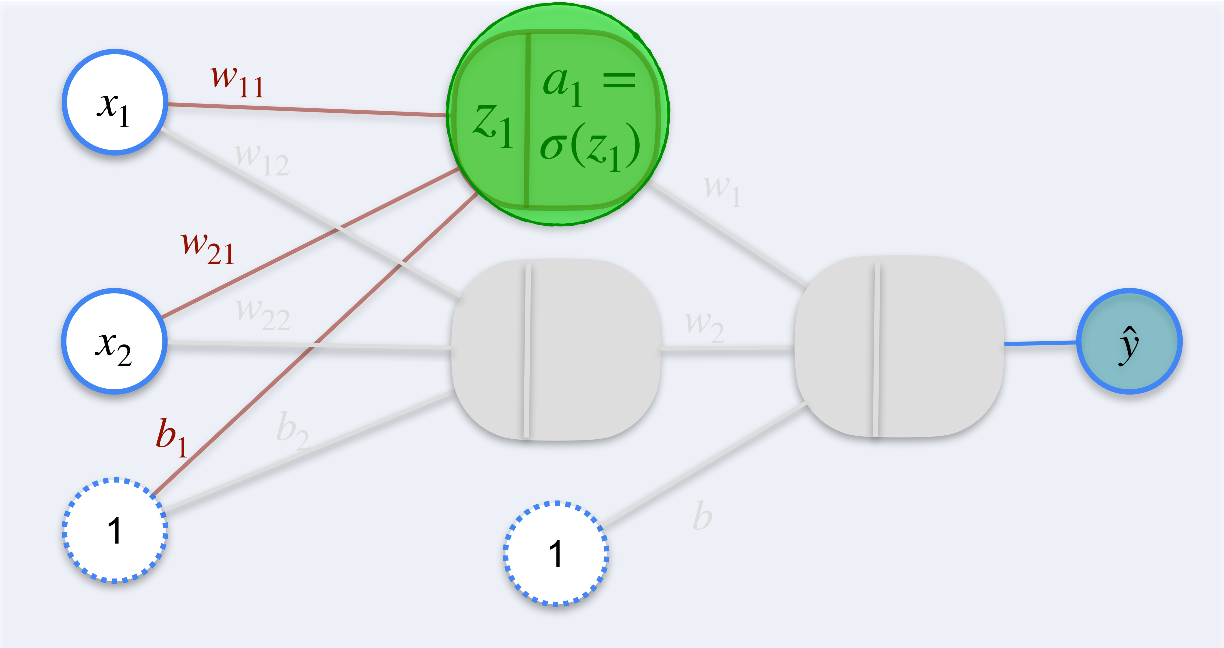
- one input layer
- one hidden layer
- one output layer



2,2,1 Neural Network

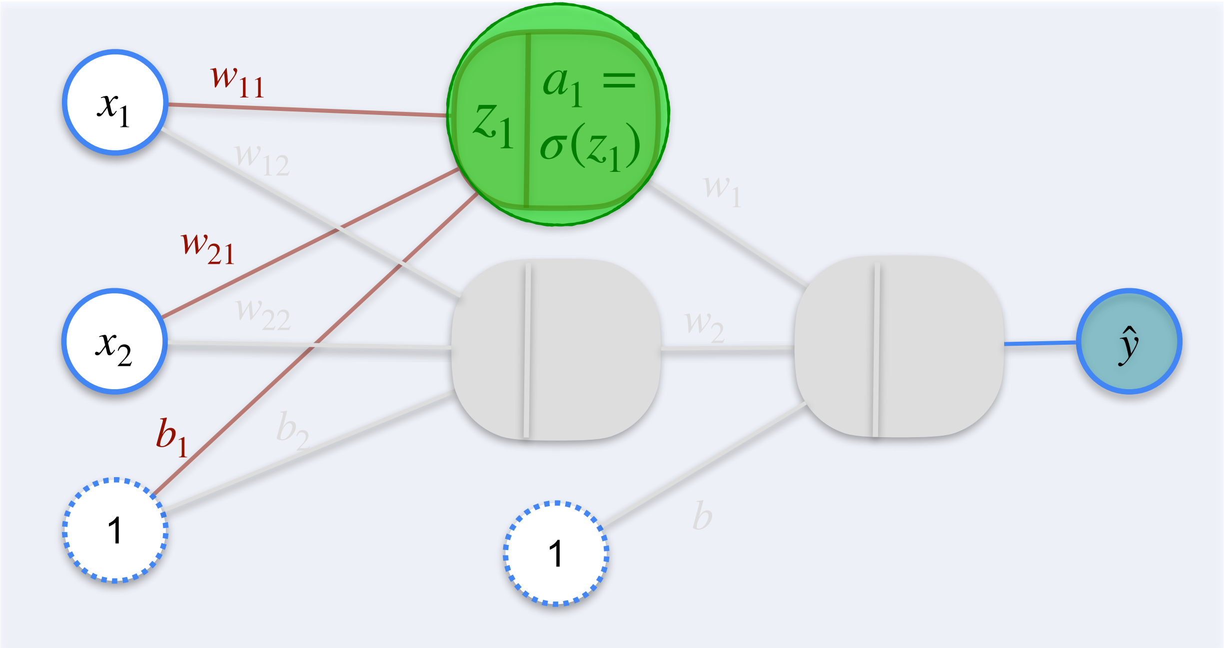


2,2,1 Neural Network



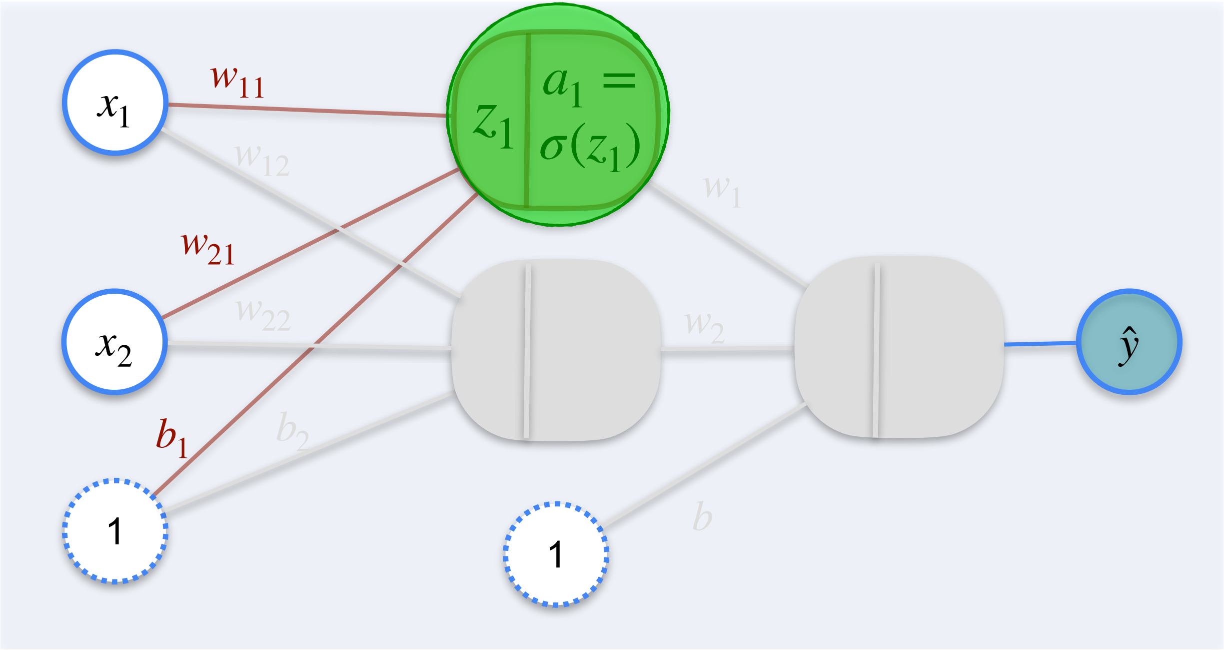
2,2,1 Neural Network

a_1



2,2,1 Neural Network

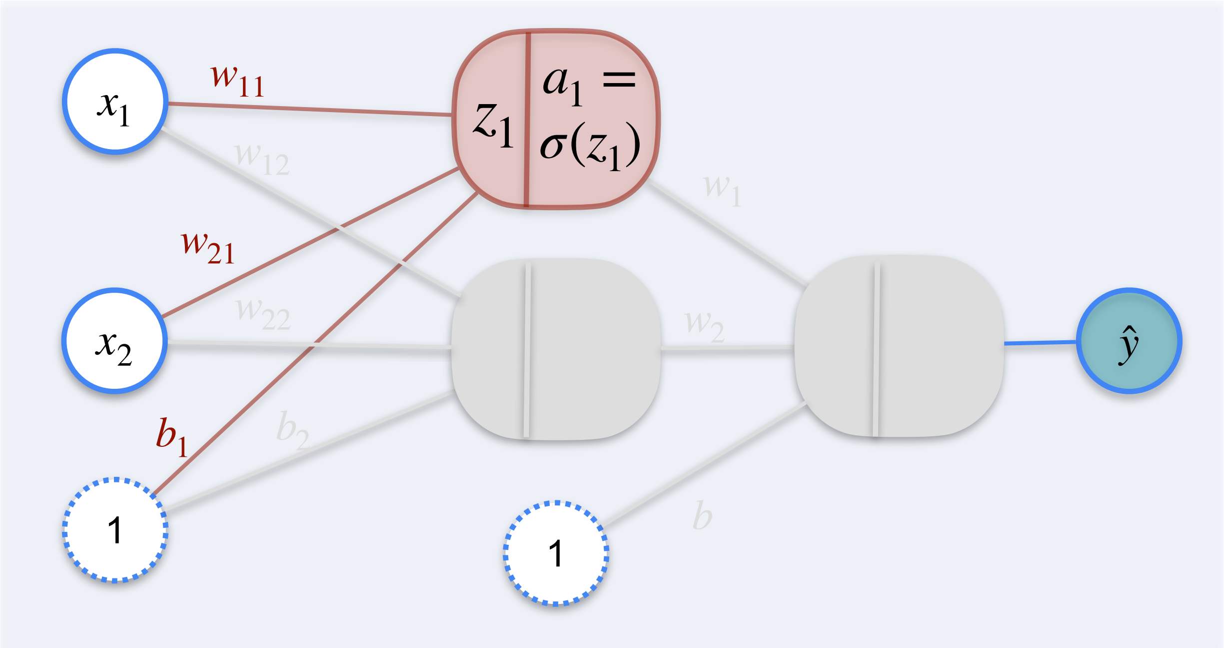
$$a_1 = \sigma(z_1)$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

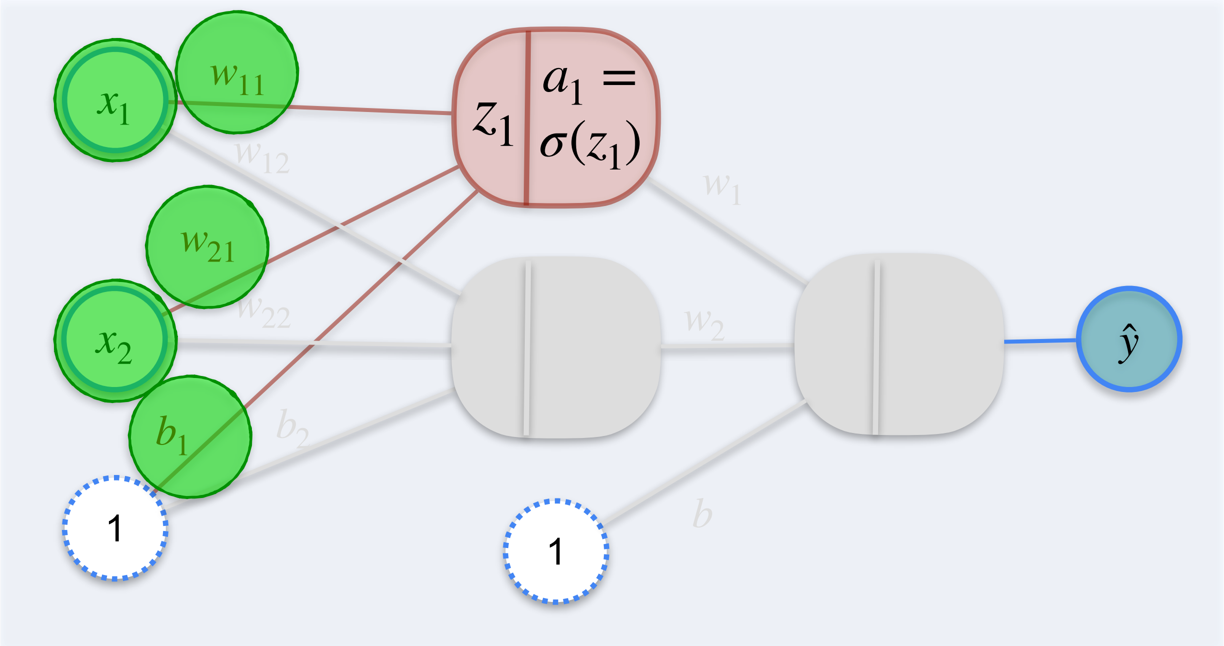
$$z_1$$



2,2,1 Neural Network

$a_1 = \sigma(z_1)$

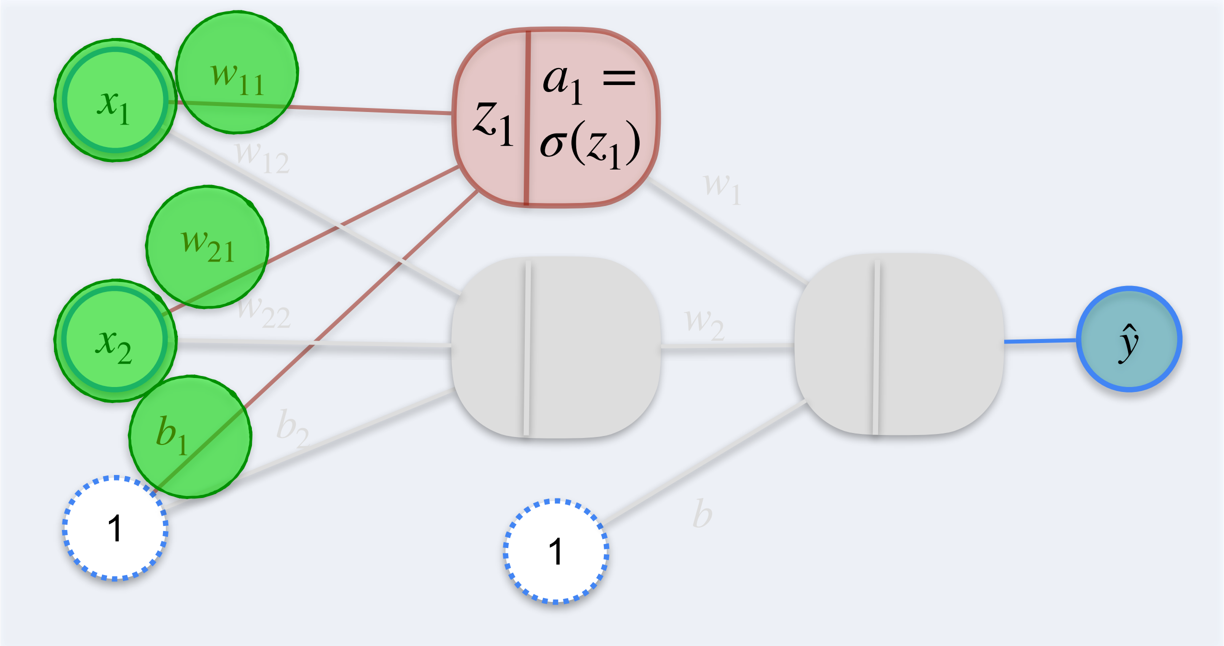
z_1



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

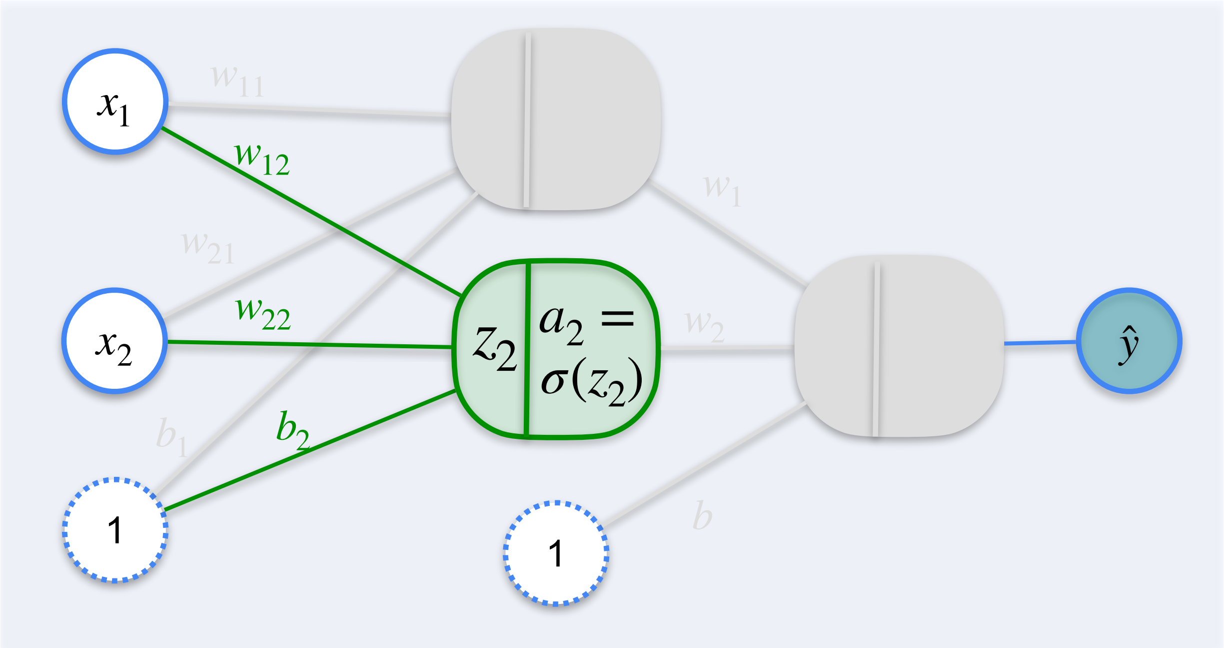
$$z_1 = x_1 w_{11} \; + \; x_2 w_{21} \; + \; b_1$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

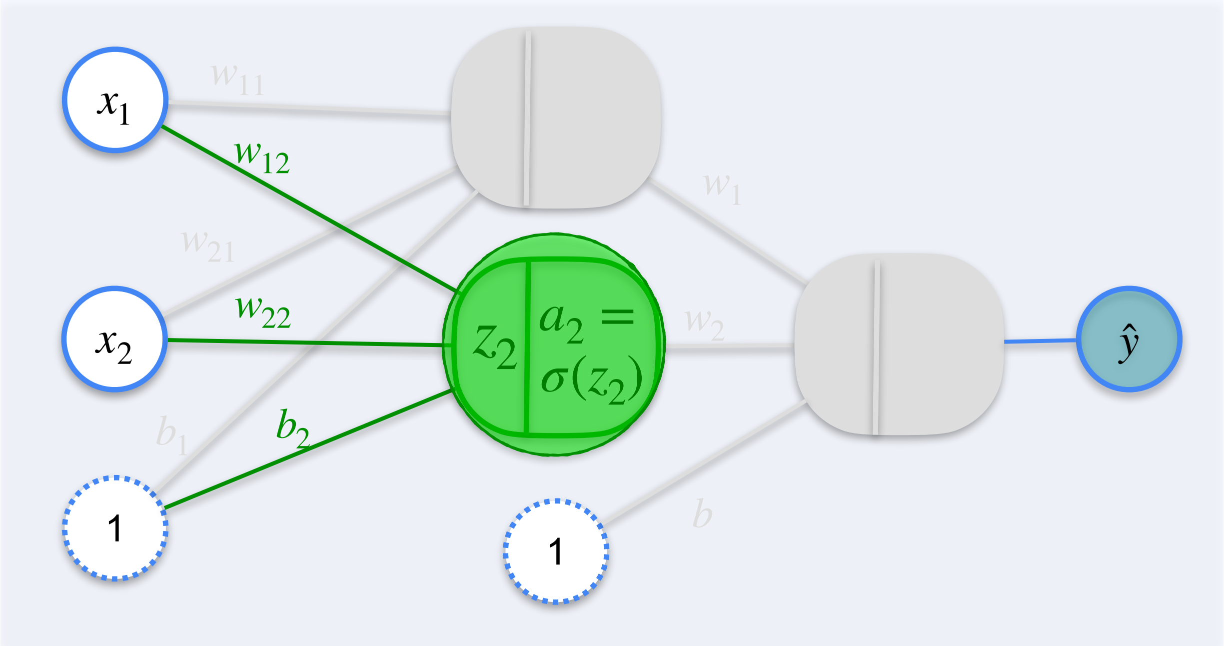
$$z_1 = x_1 w_{11} \;+\; x_2 w_{21} \;+\; b_1$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

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

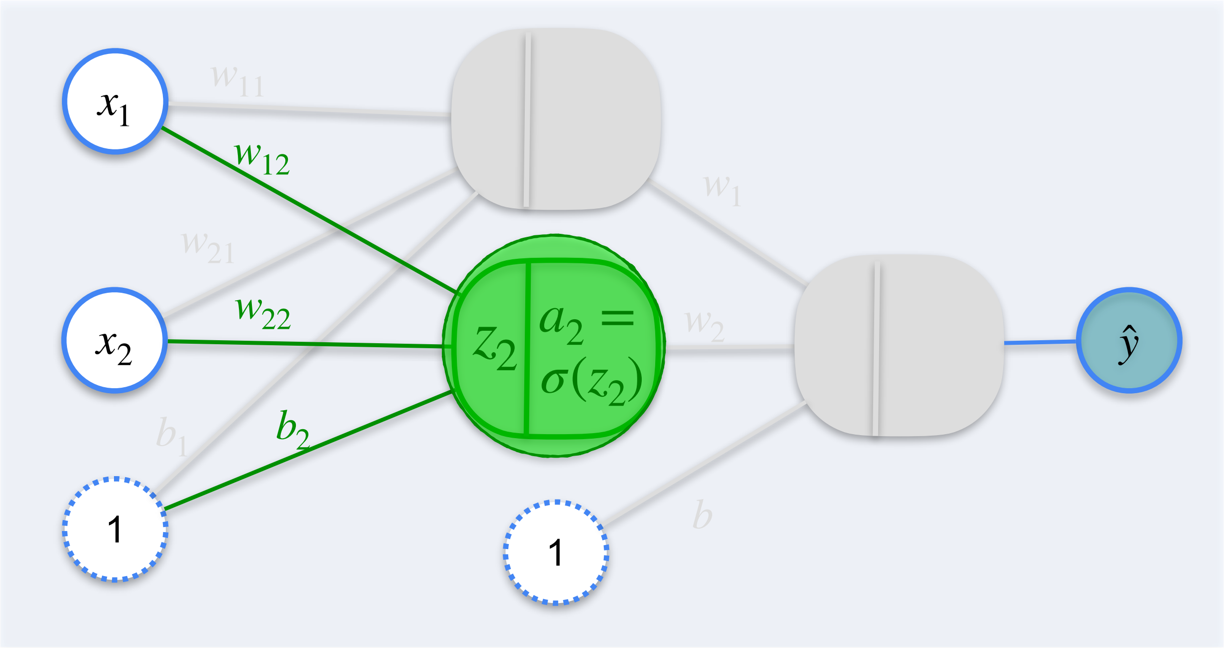


2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

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

$$a_2$$

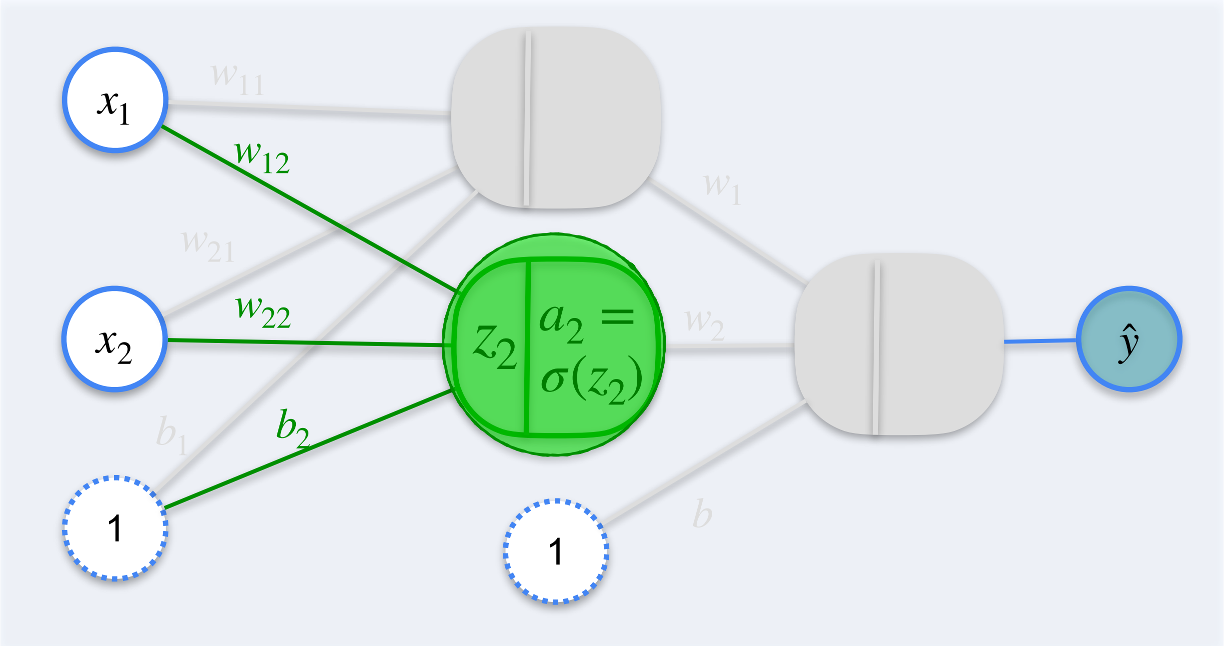


2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

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

$$a_2 = \sigma(z_2)$$



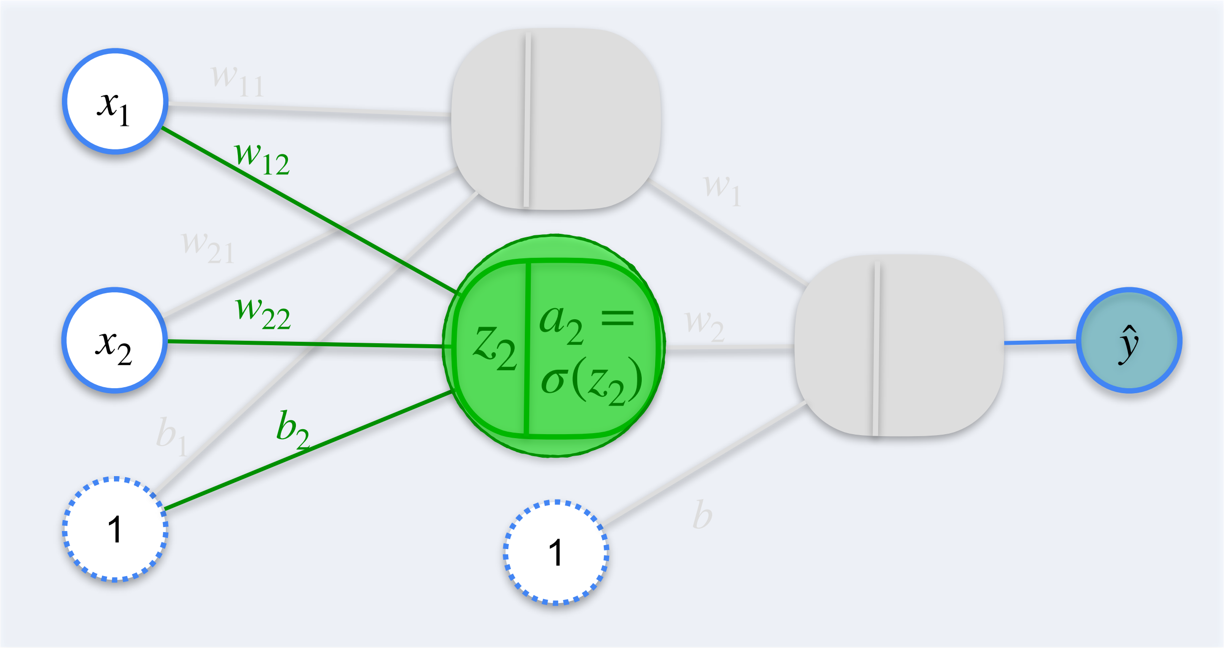
2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

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

$$a_2 = \sigma(z_2)$$

$$z_2$$



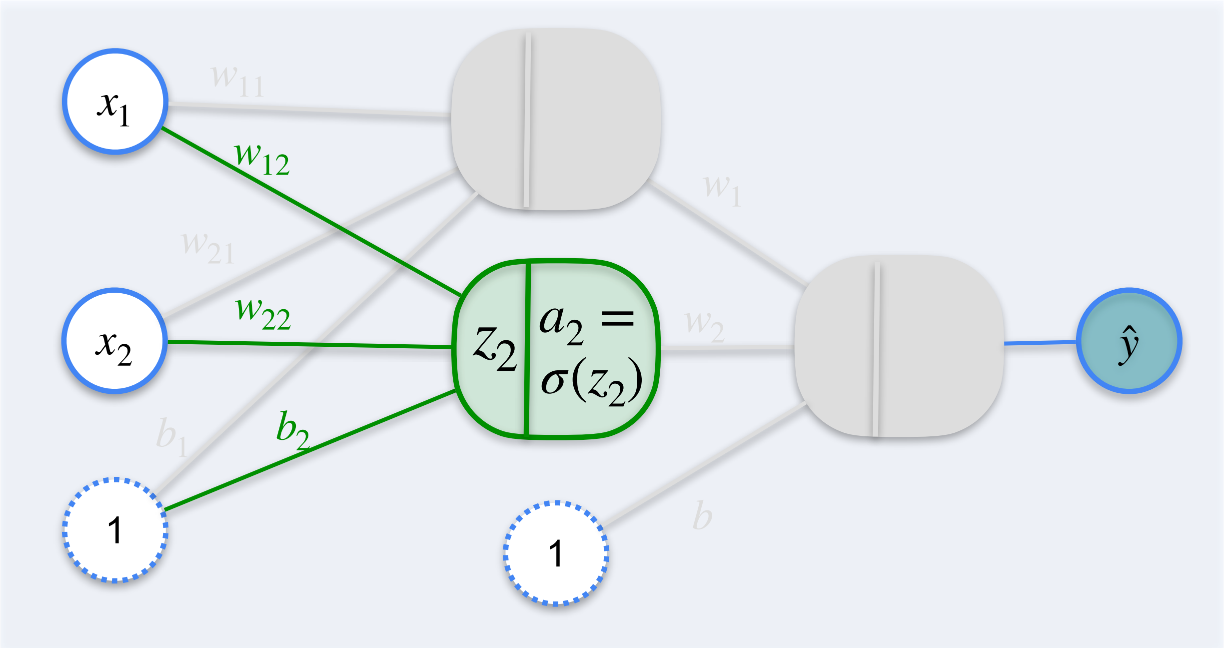
2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

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

$$a_2 = \sigma(z_2)$$

$$z_2$$



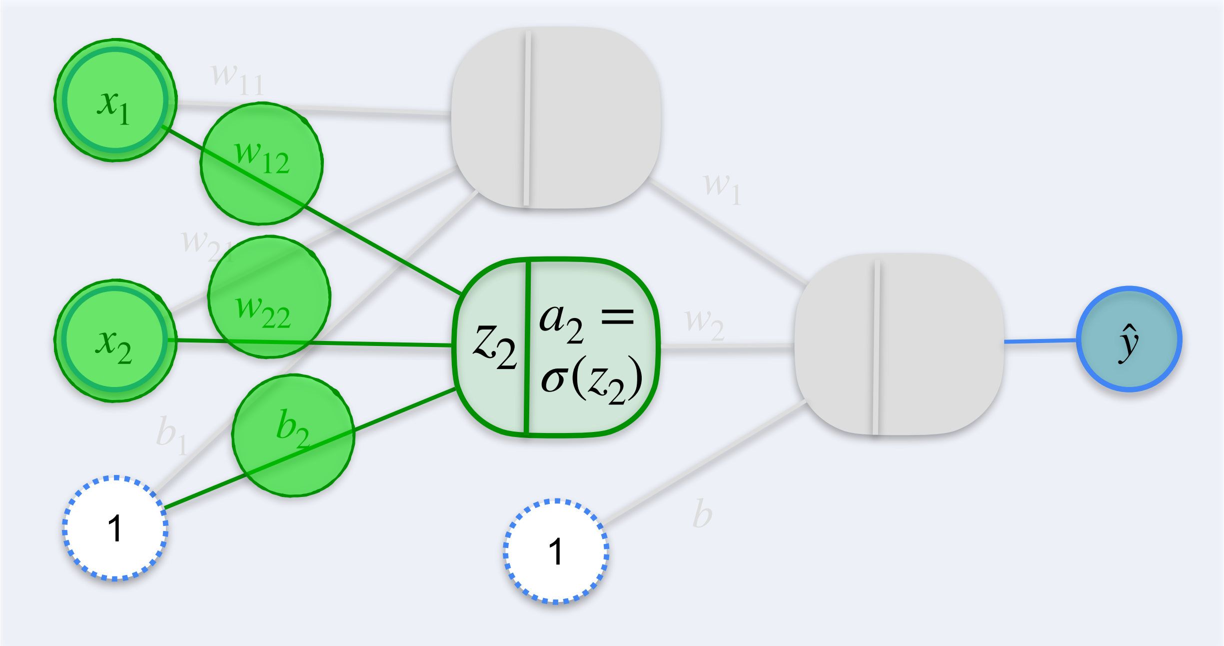
2,2,1 Neural Network

$a_1 = \sigma(z_1)$

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

$a_2 = \sigma(z_2)$

z_2



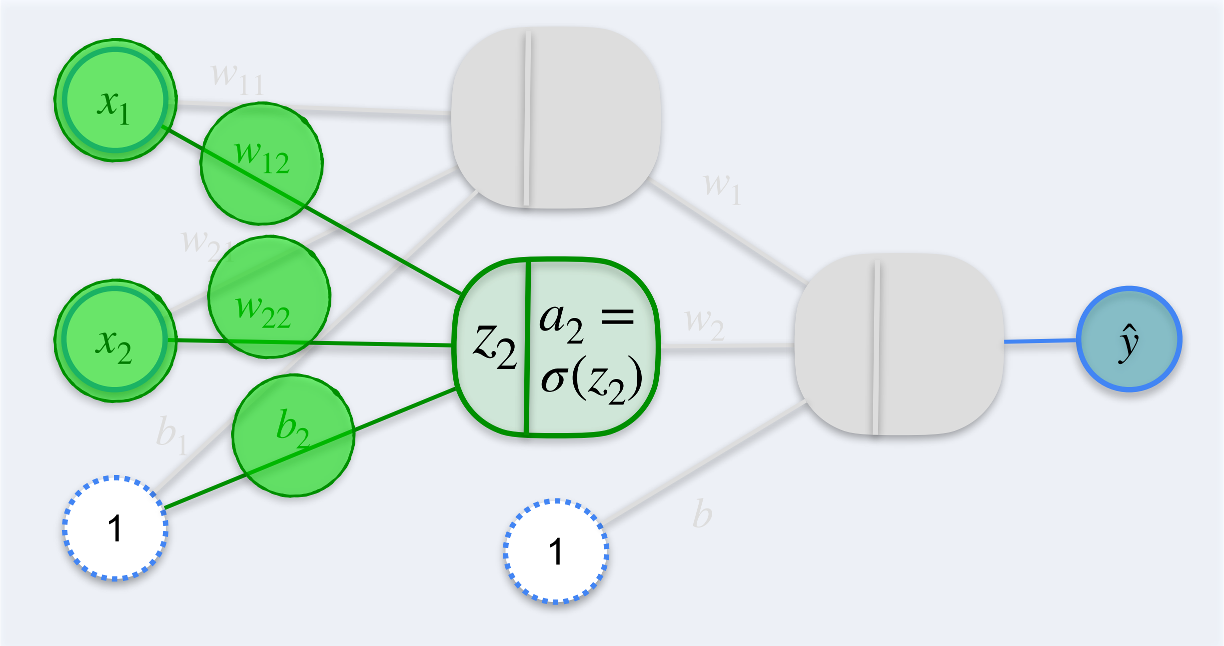
2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

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

$$a_2 = \sigma(z_2)$$

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



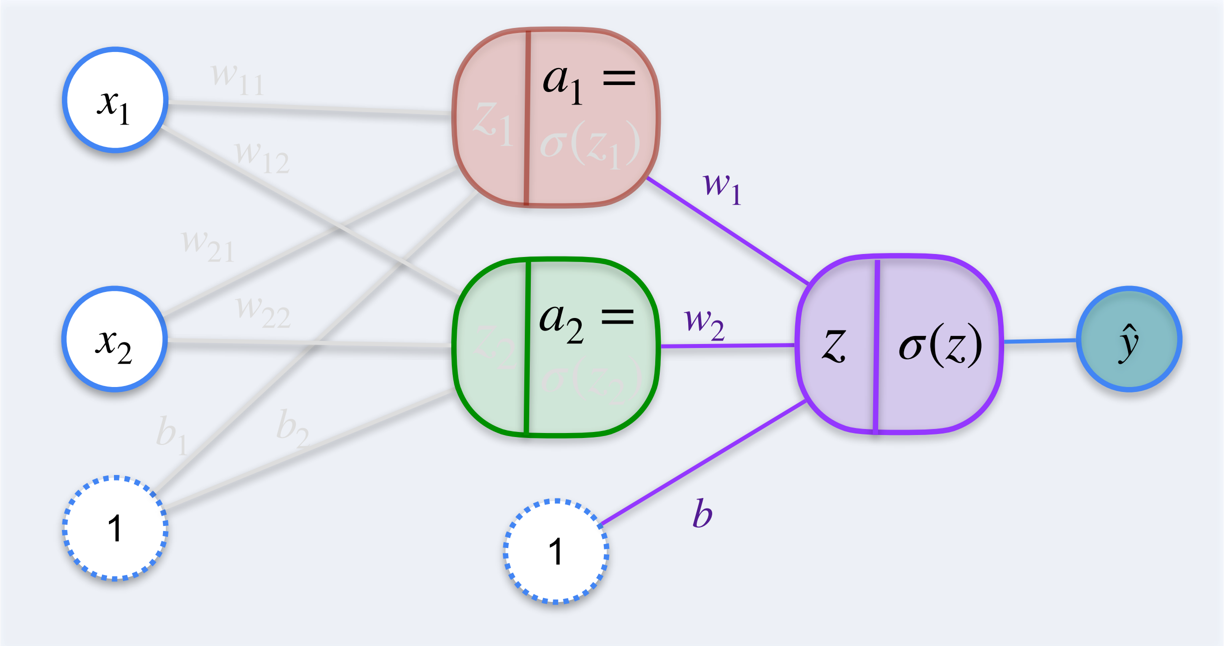
2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

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

$$a_2 = \sigma(z_2)$$

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



2,2,1 Neural Network

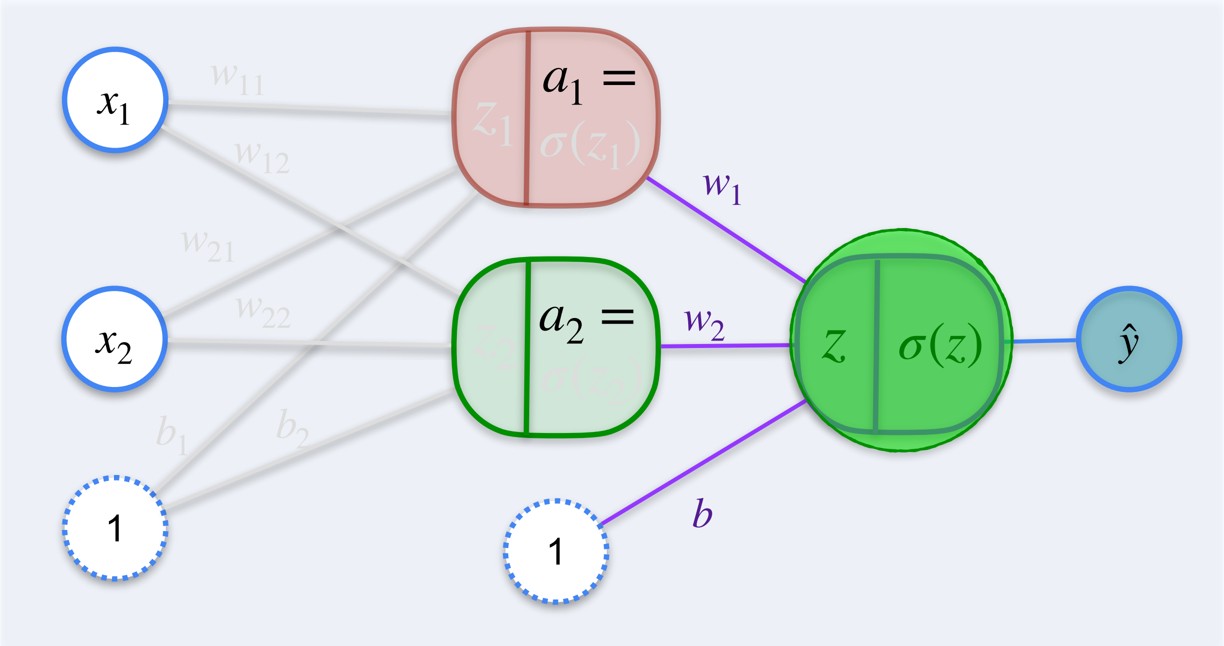
$$a_1 = \sigma(z_1)$$

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

$$a_2 = \sigma(z_2)$$

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

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



2,2,1 Neural Network

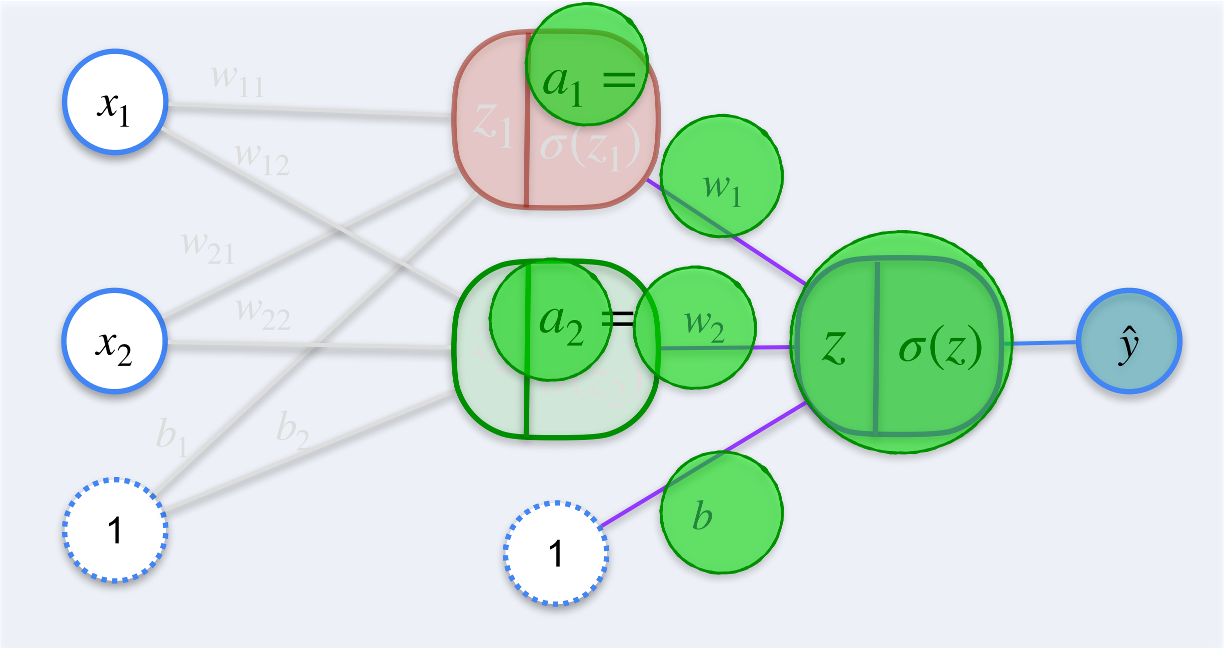
$$a_1 = \sigma(z_1)$$

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

$$a_2 = \sigma(z_2)$$

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

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



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

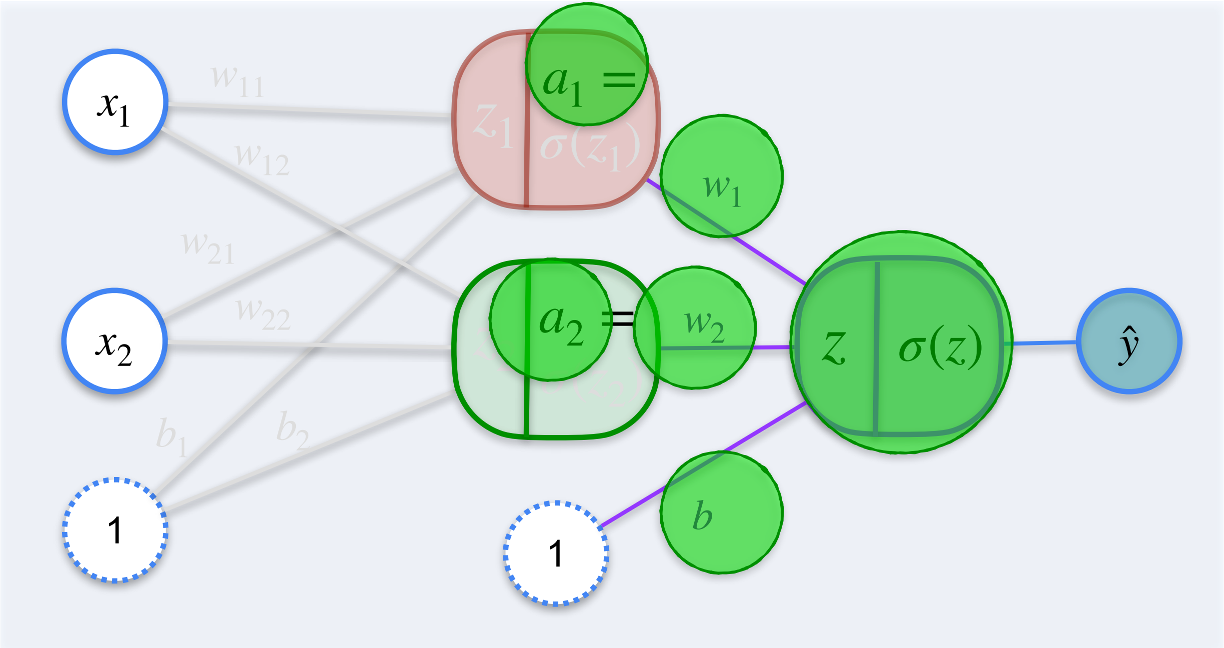
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

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

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

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



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

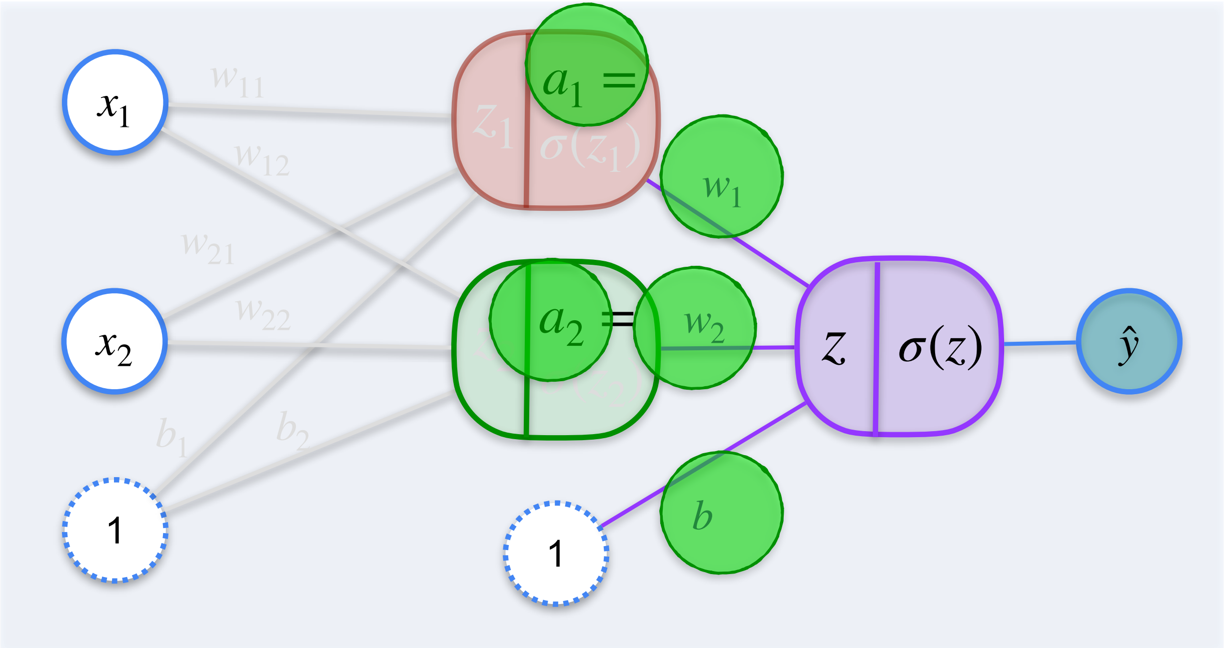
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

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

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

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



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

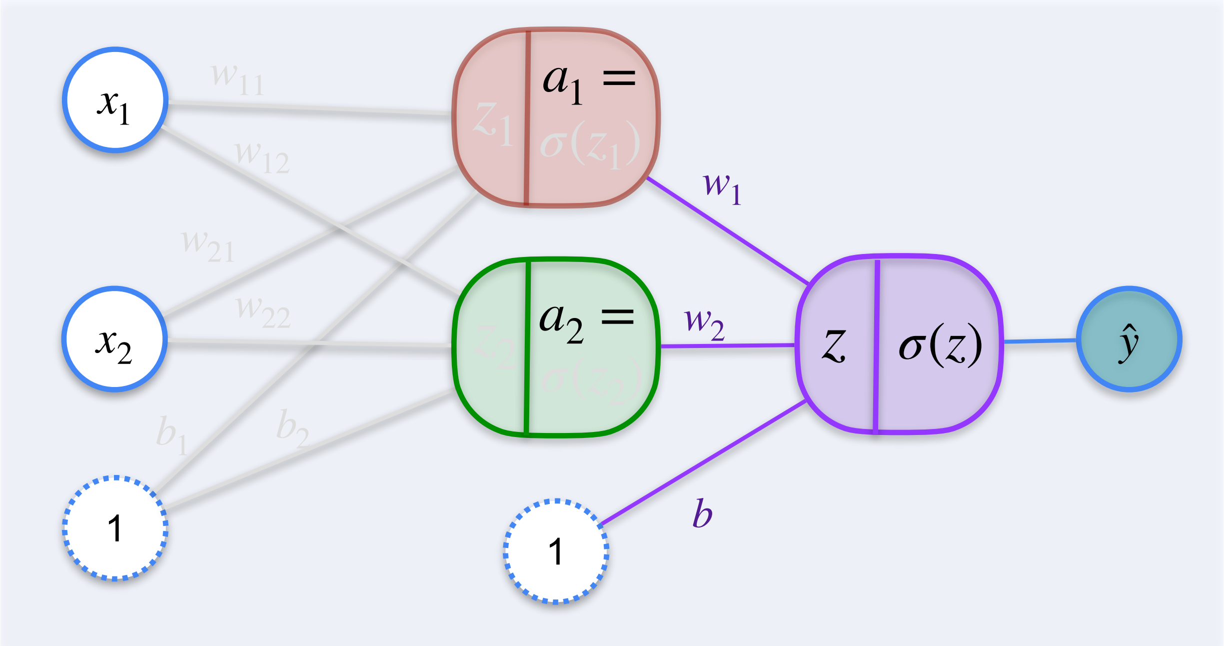
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

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

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

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



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

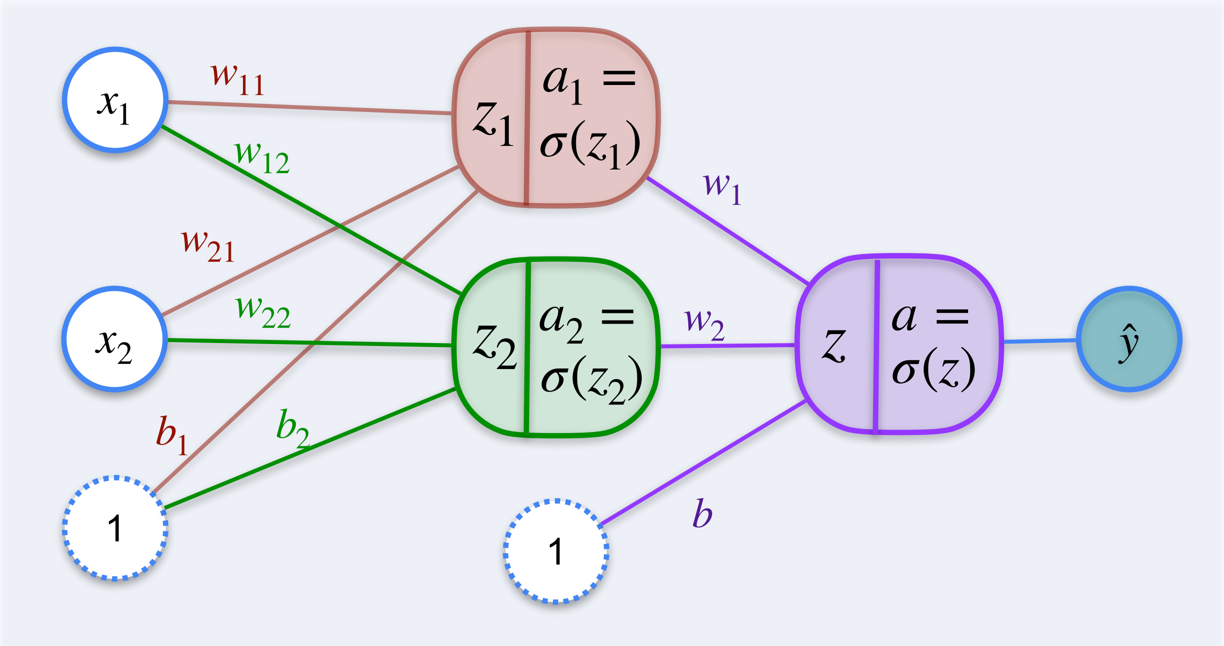
$$z_1 = x_1 w_{11} \ + \ x_2 w_{21} \ + \ b_1$$

$$a_2 = \sigma(z_2)$$

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

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

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



2,2,1 Neural Network

$a_1 = \sigma(z_1)$

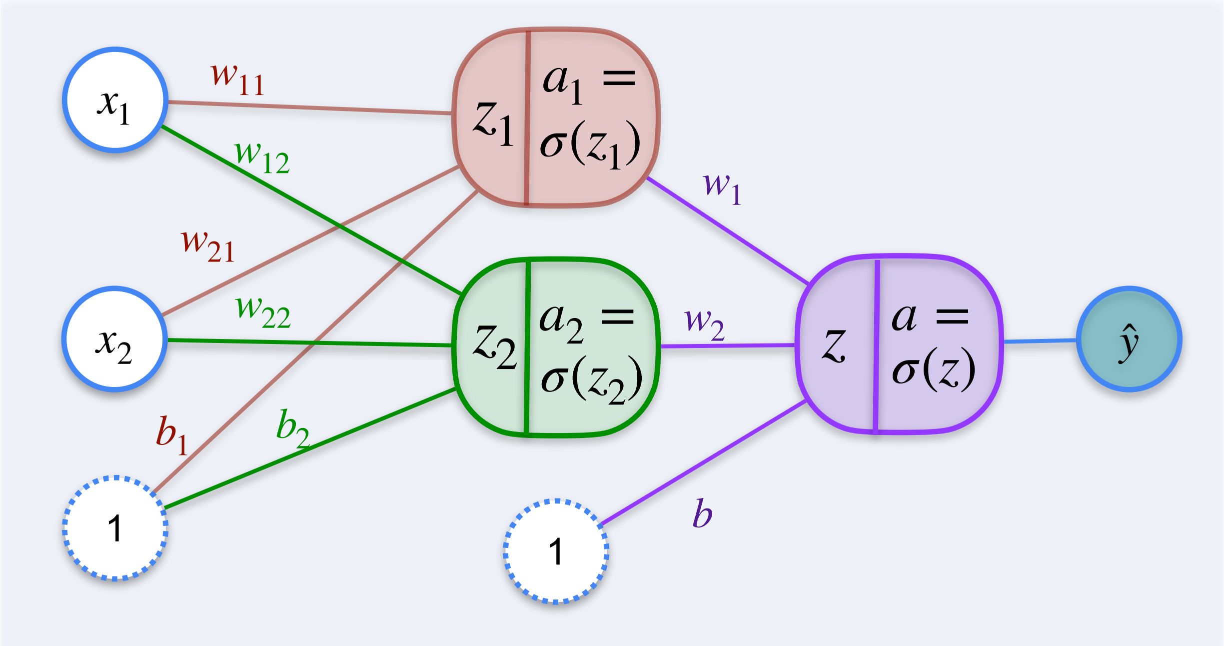
$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$

$a_2 = \sigma(z_2)$

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

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

$z = a_1 w_1 + a_2 w_2 + b$



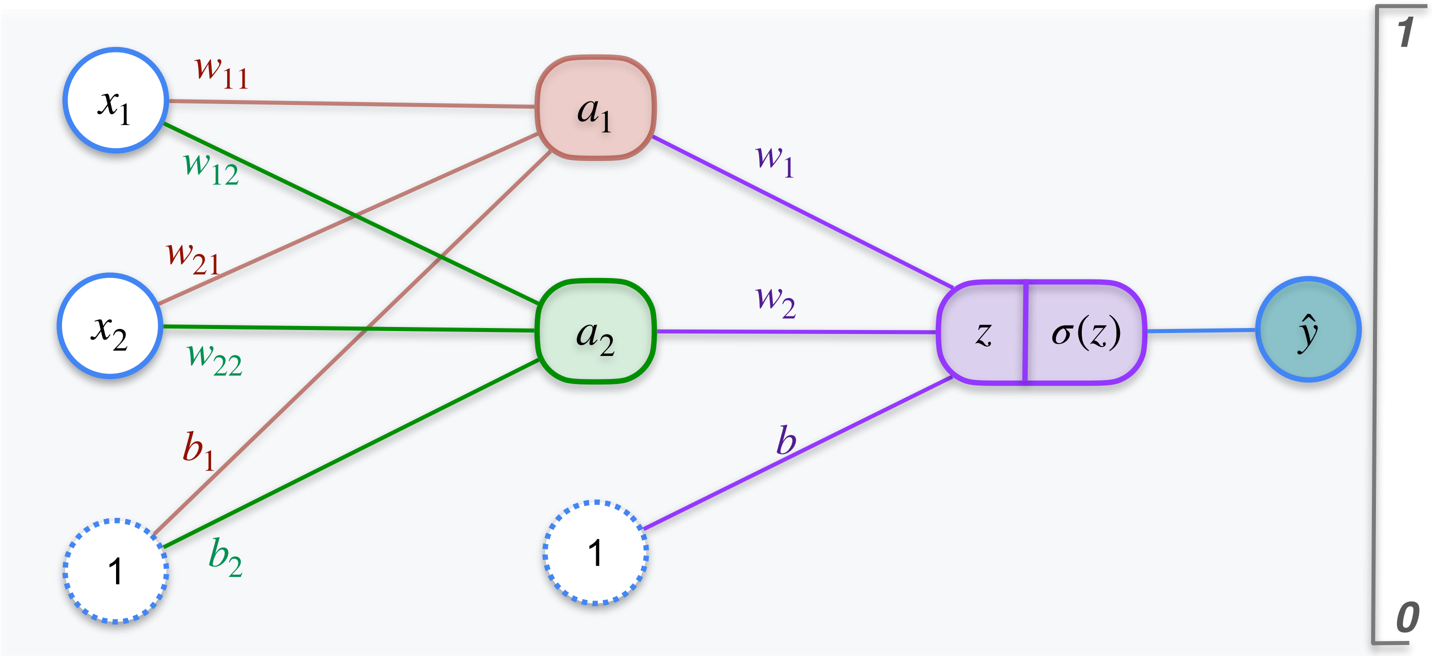
$L(y, \hat{y}) = -y log(\hat{y}) - (1 - y) log(1 - \hat{y})$

DeepLearning.AI

Optimization in Neural Networks and Newton's Method

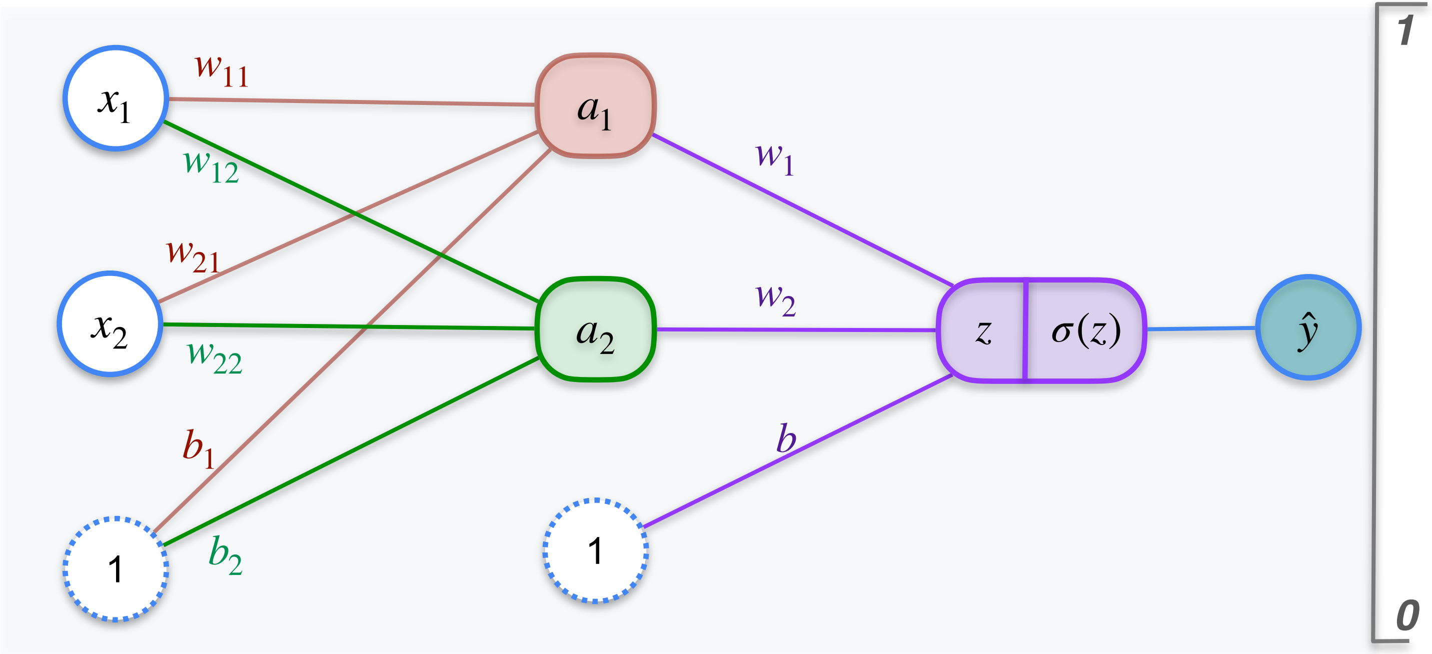
Classification with a Neural Network: Minimizing log-loss

2,2,1 Neural Network



2,2,1 Neural Network

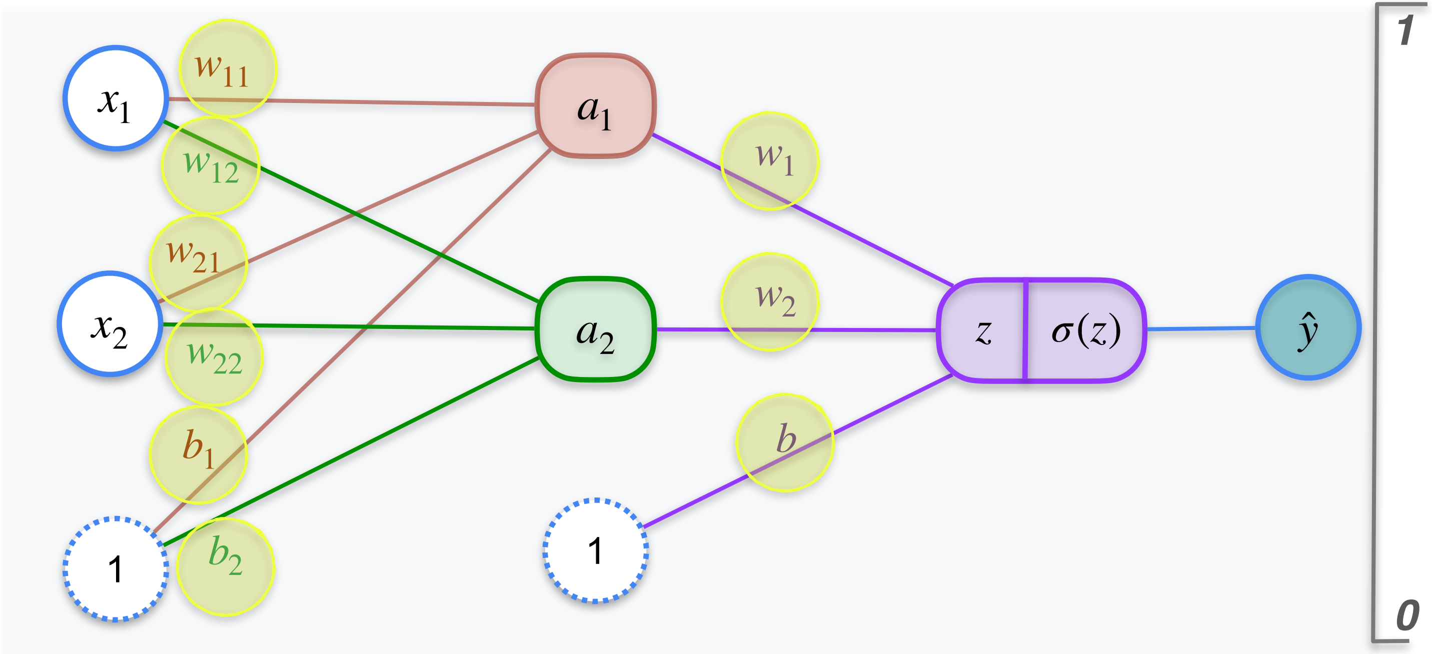
Goal



2,2,1 Neural Network

Goal

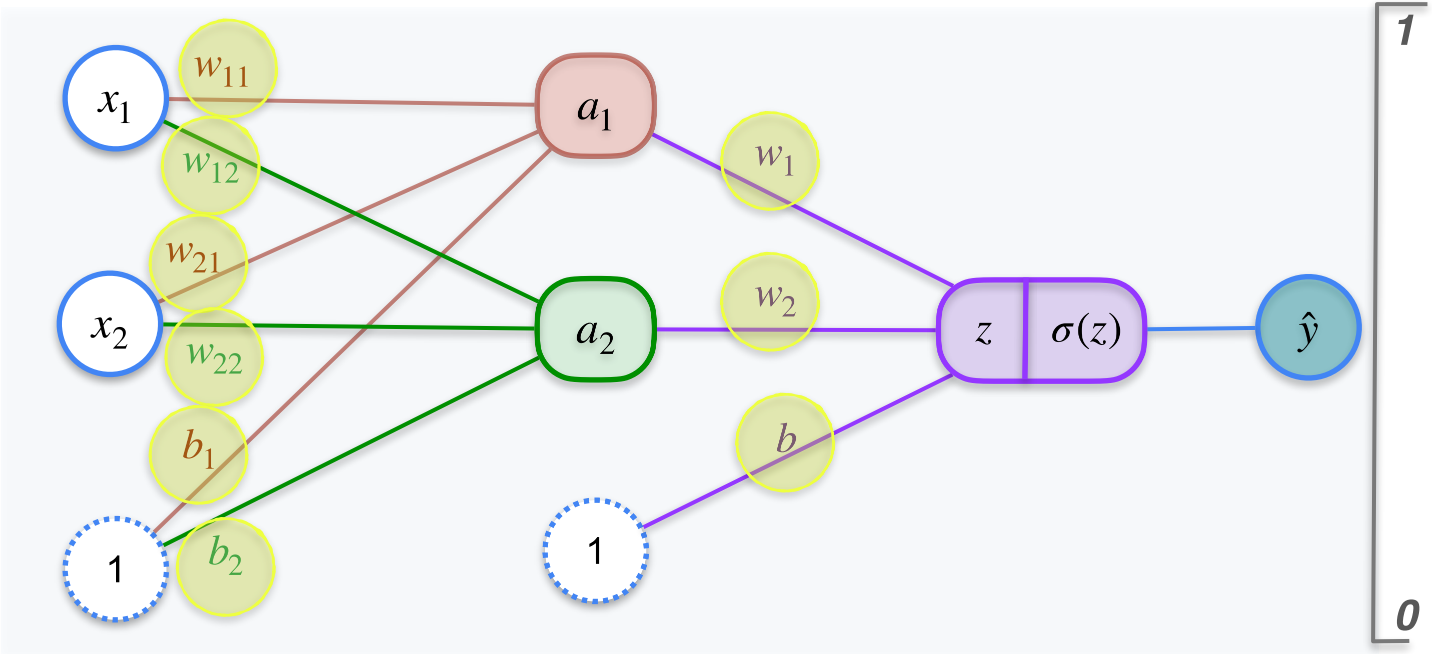
Adjust each of the highlighted weights and biases



2,2,1 Neural Network

Goal

Adjust each of the highlighted weights and biases

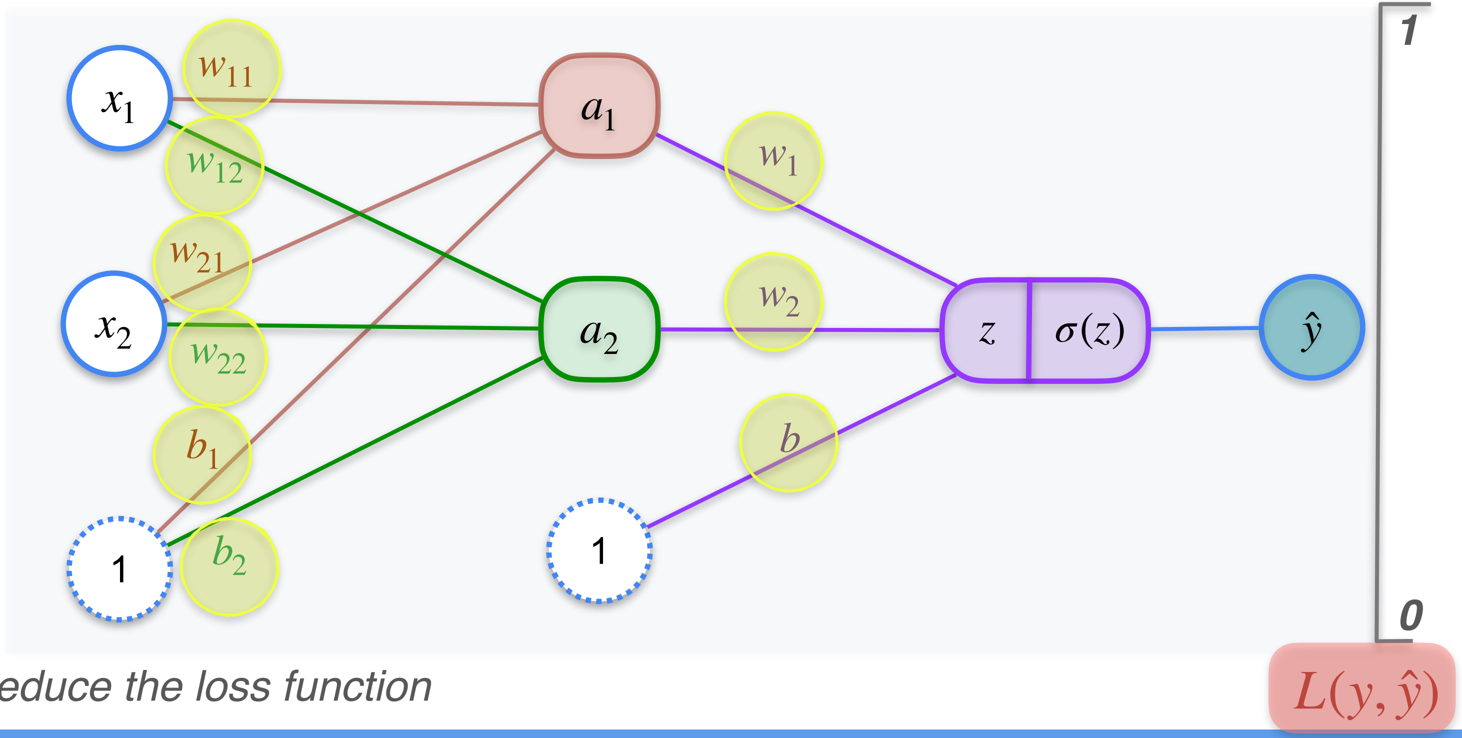


To reduce the loss function

2,2,1 Neural Network

Goal

Adjust each of the highlighted weights and biases

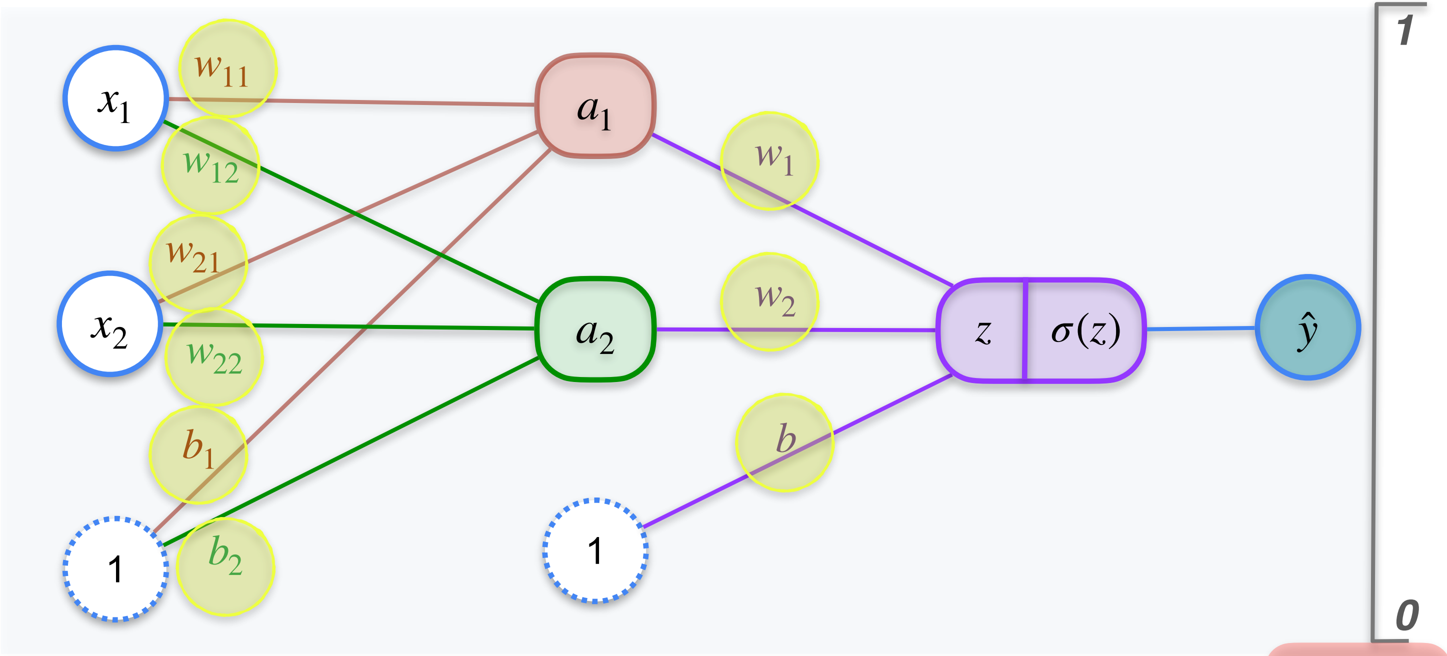


To reduce the loss function

2,2,1 Neural Network

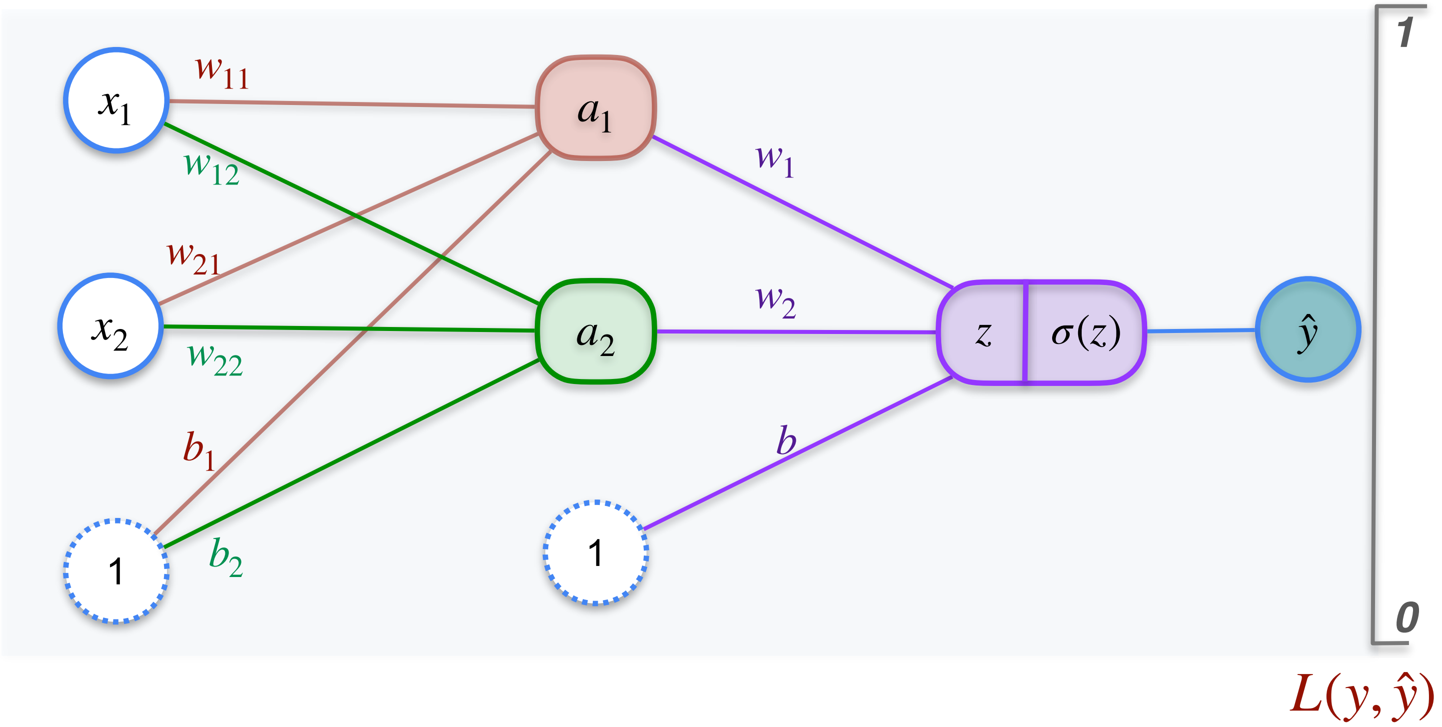
Goal

Adjust each of the highlighted weights and biases

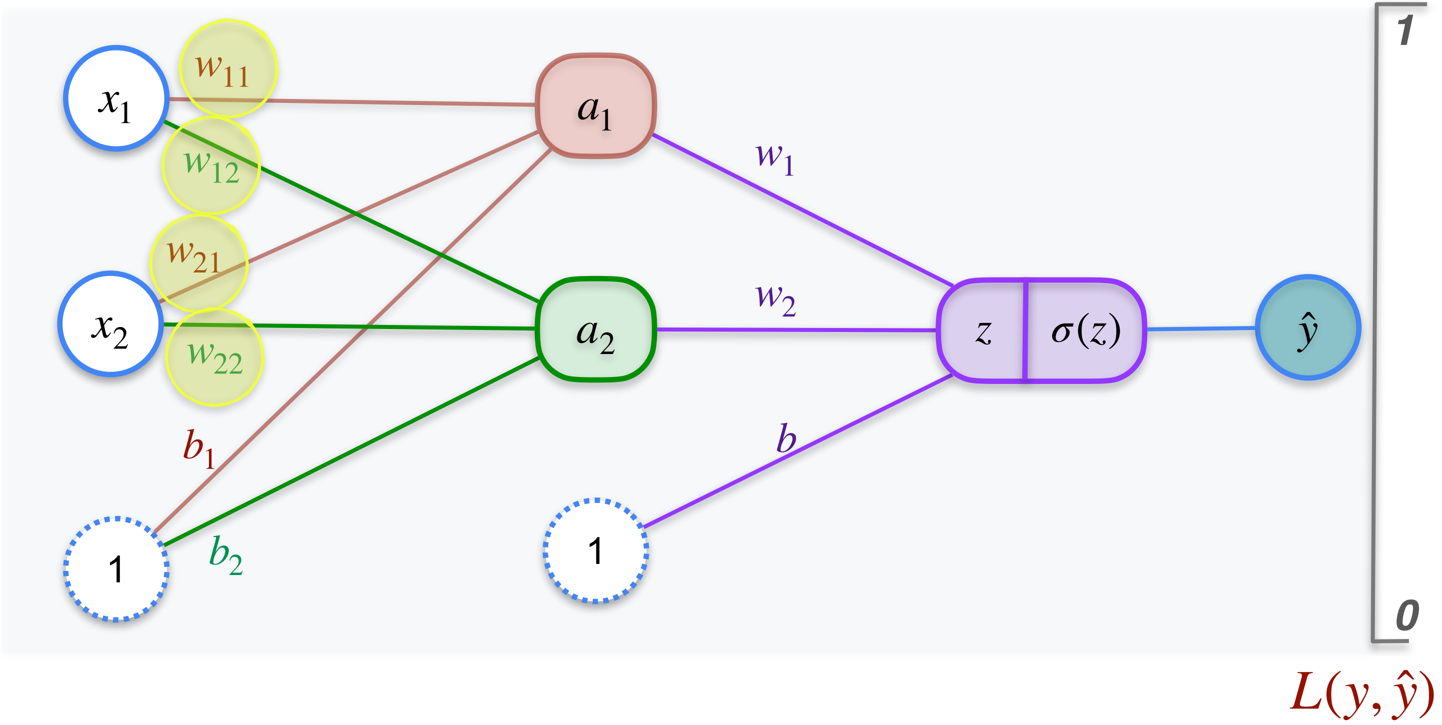


To reduce the loss function $L(y, \hat{y})$

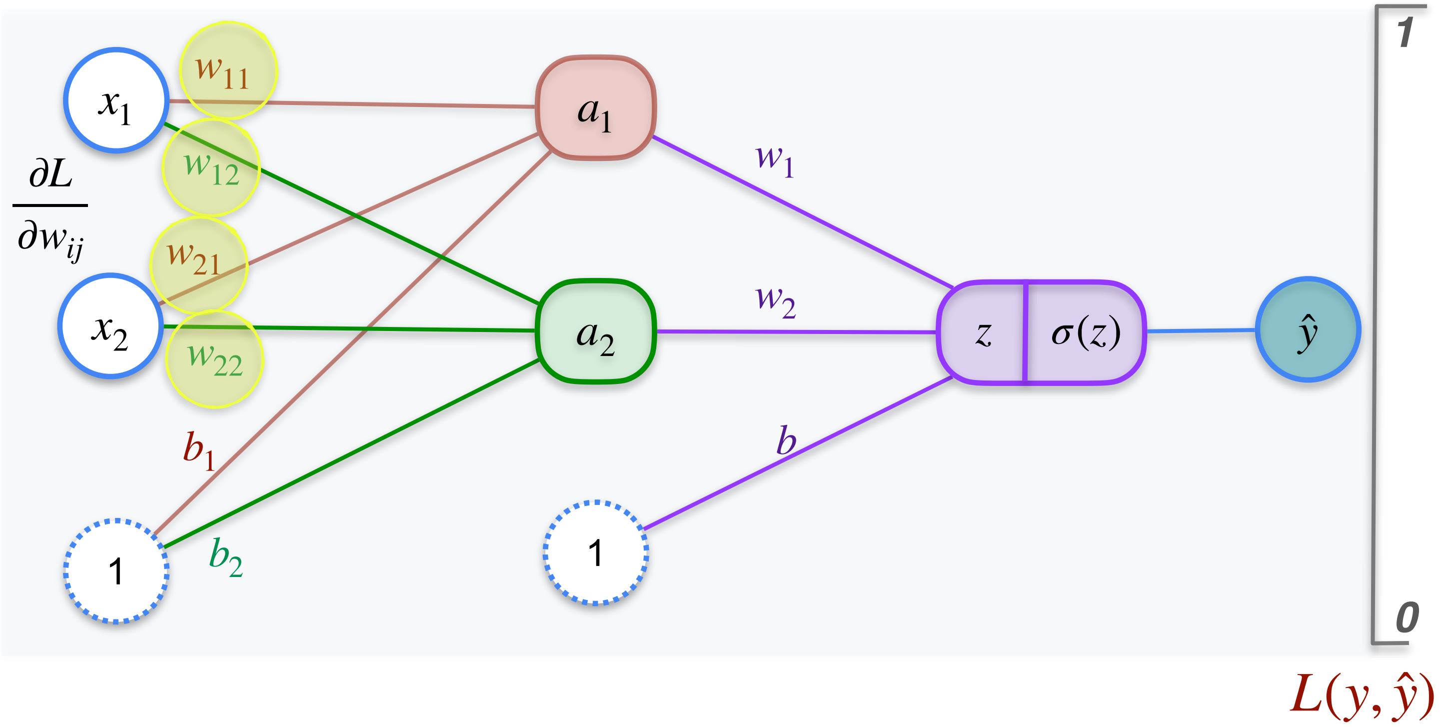
2,2,1 Neural Network



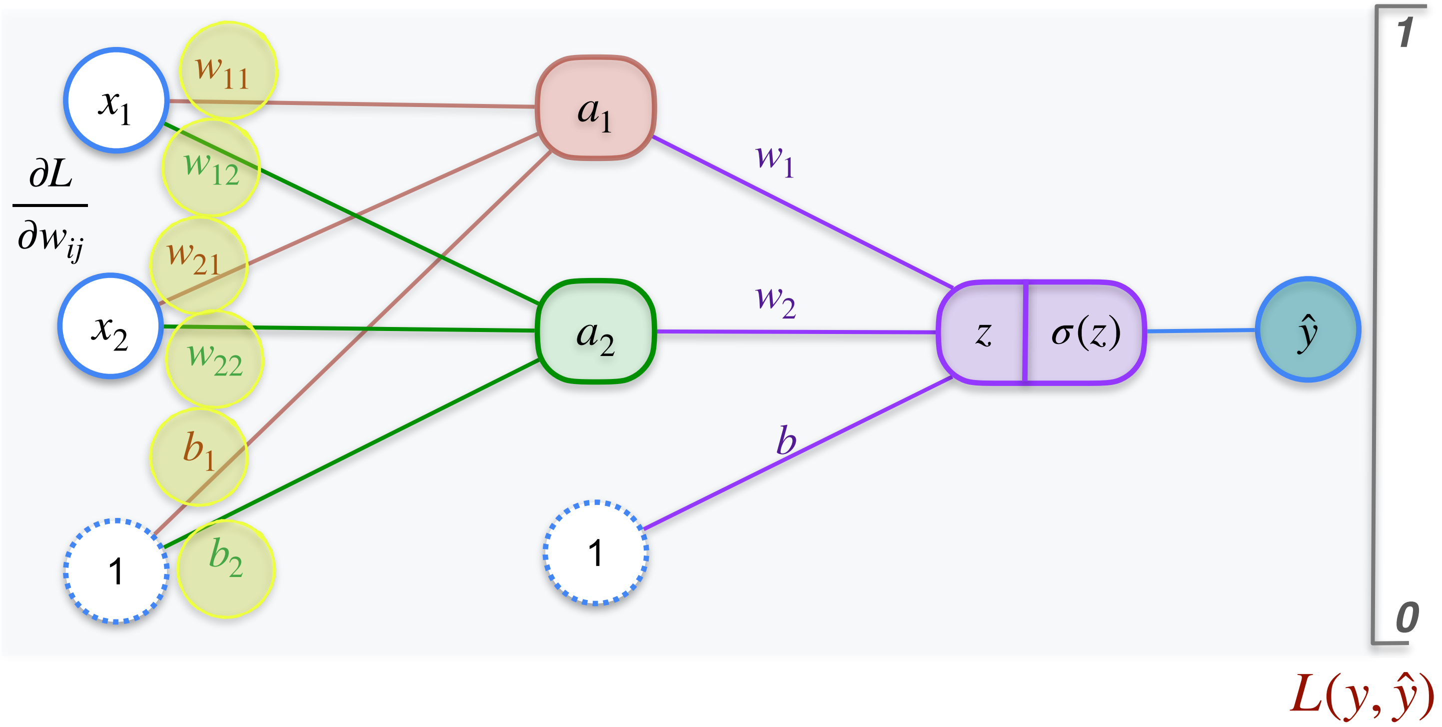
2,2,1 Neural Network



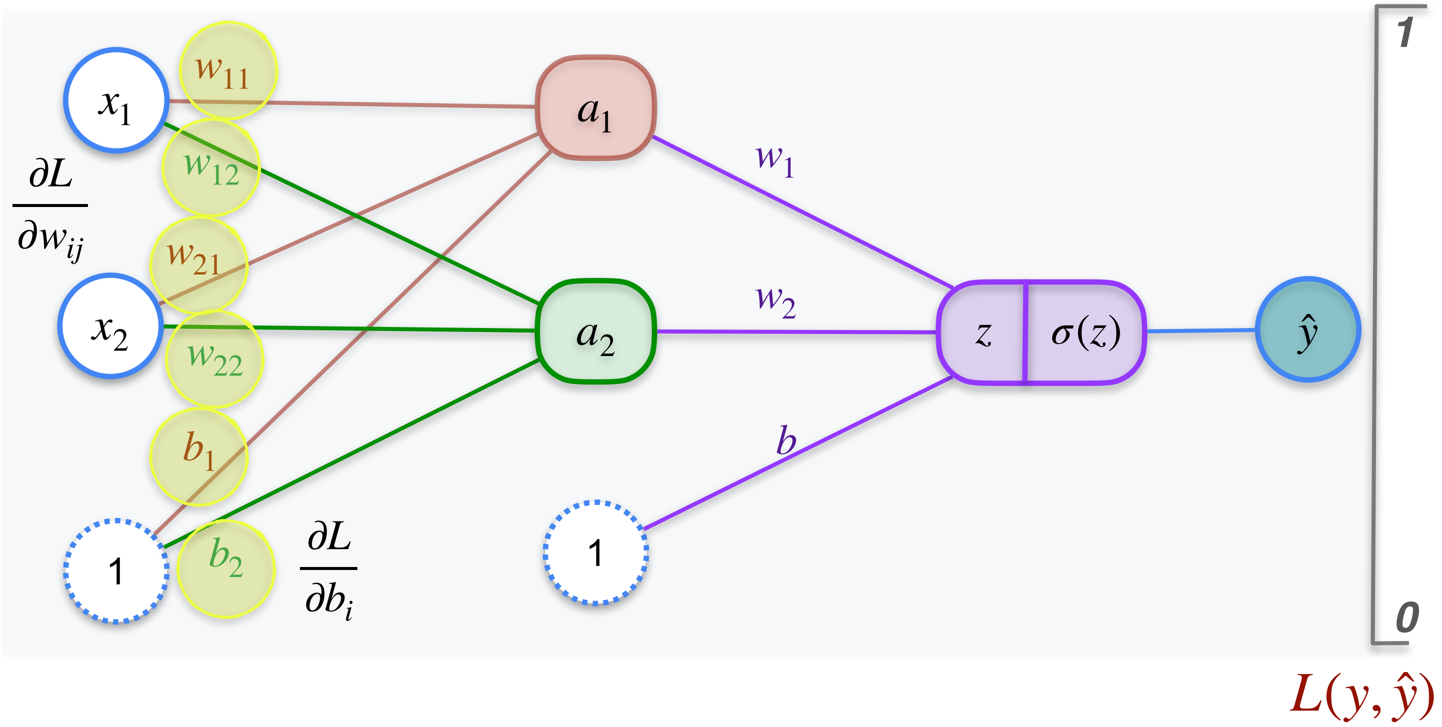
2,2,1 Neural Network



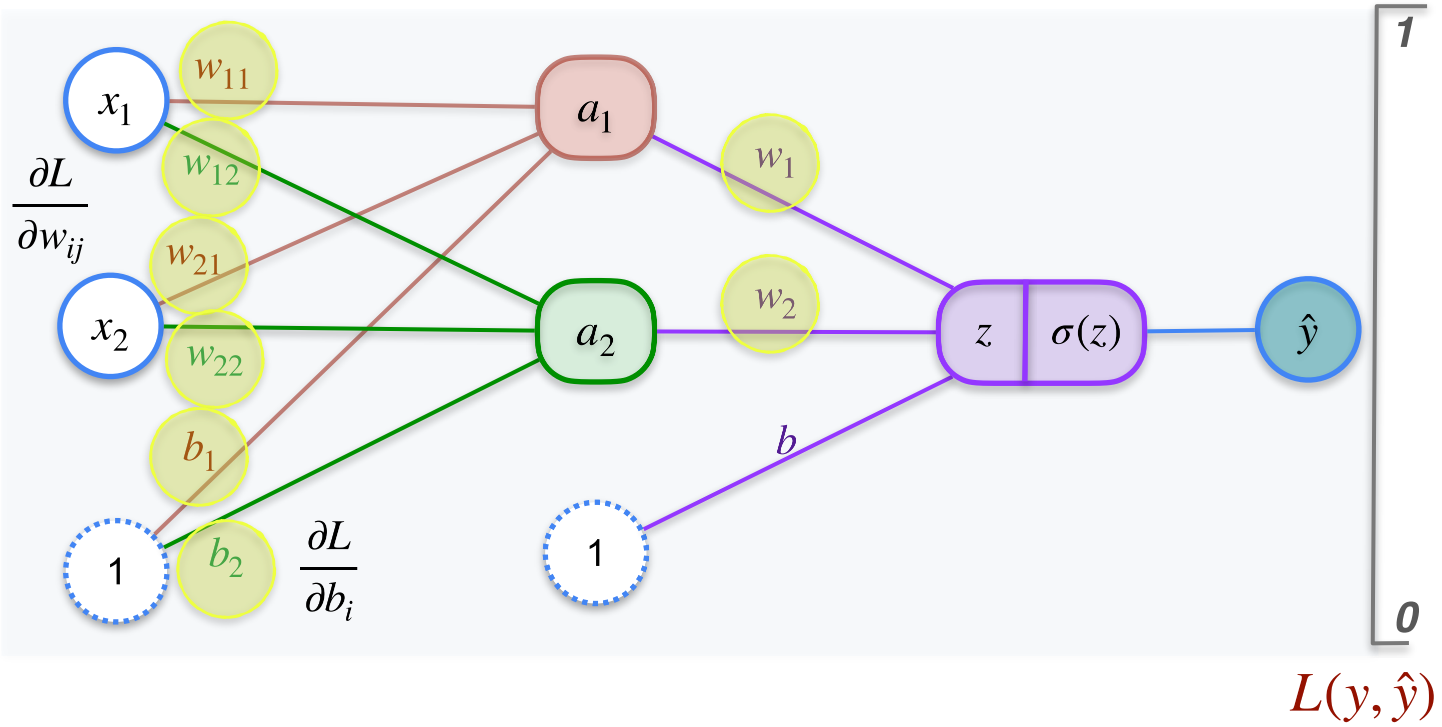
2,2,1 Neural Network



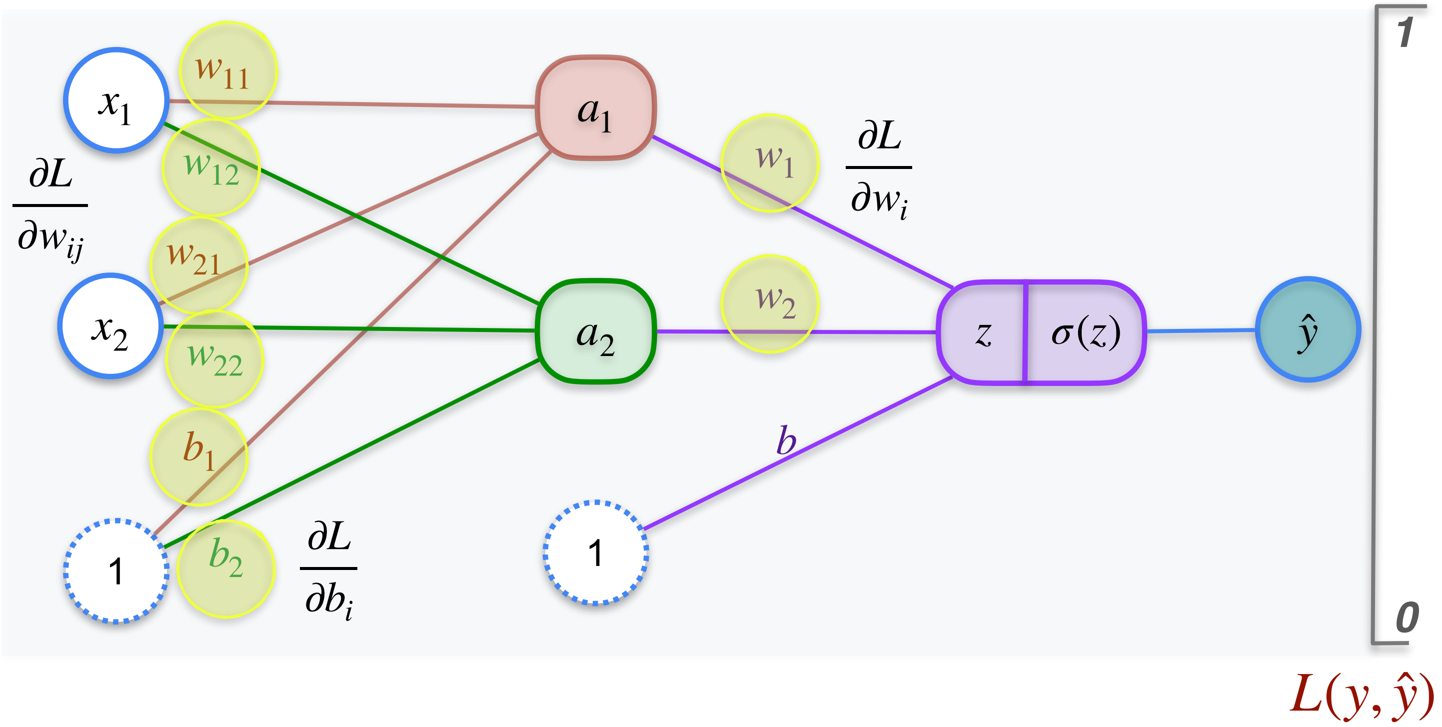
2,2,1 Neural Network



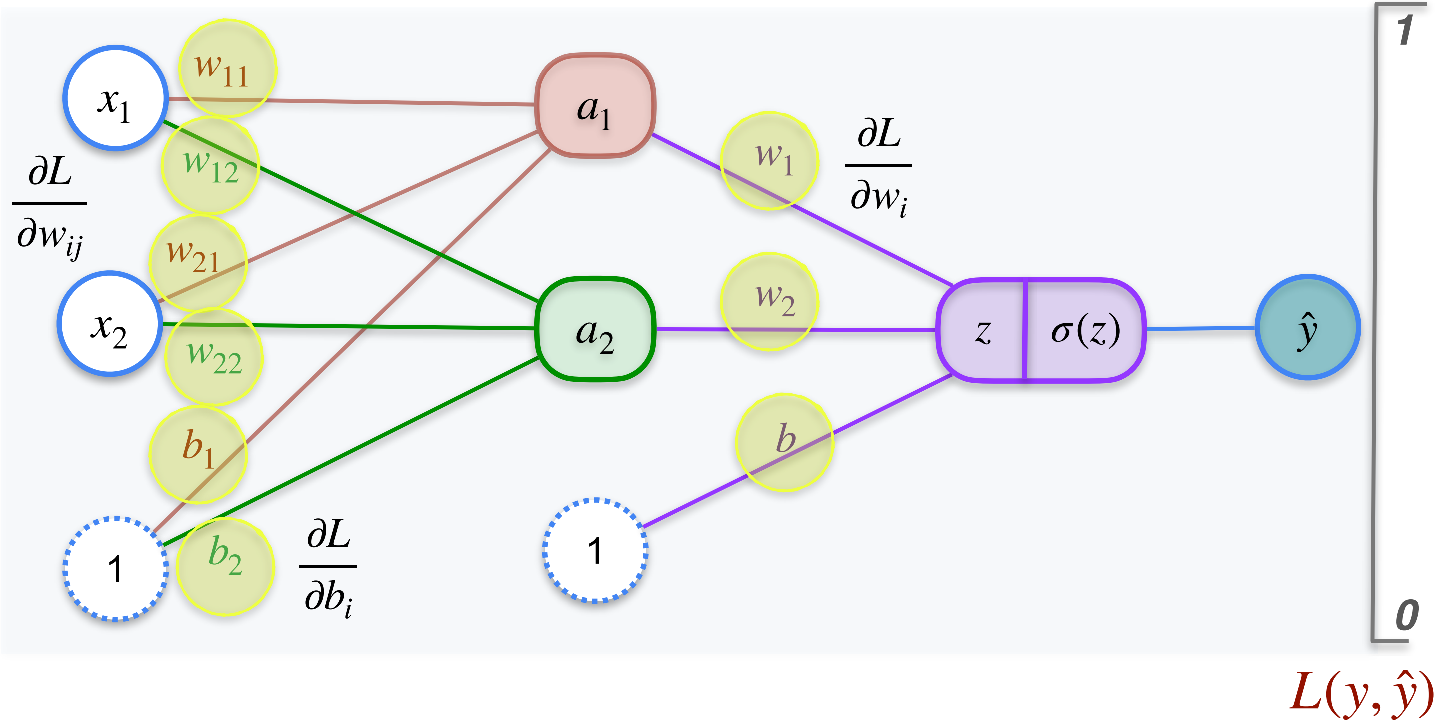
2,2,1 Neural Network



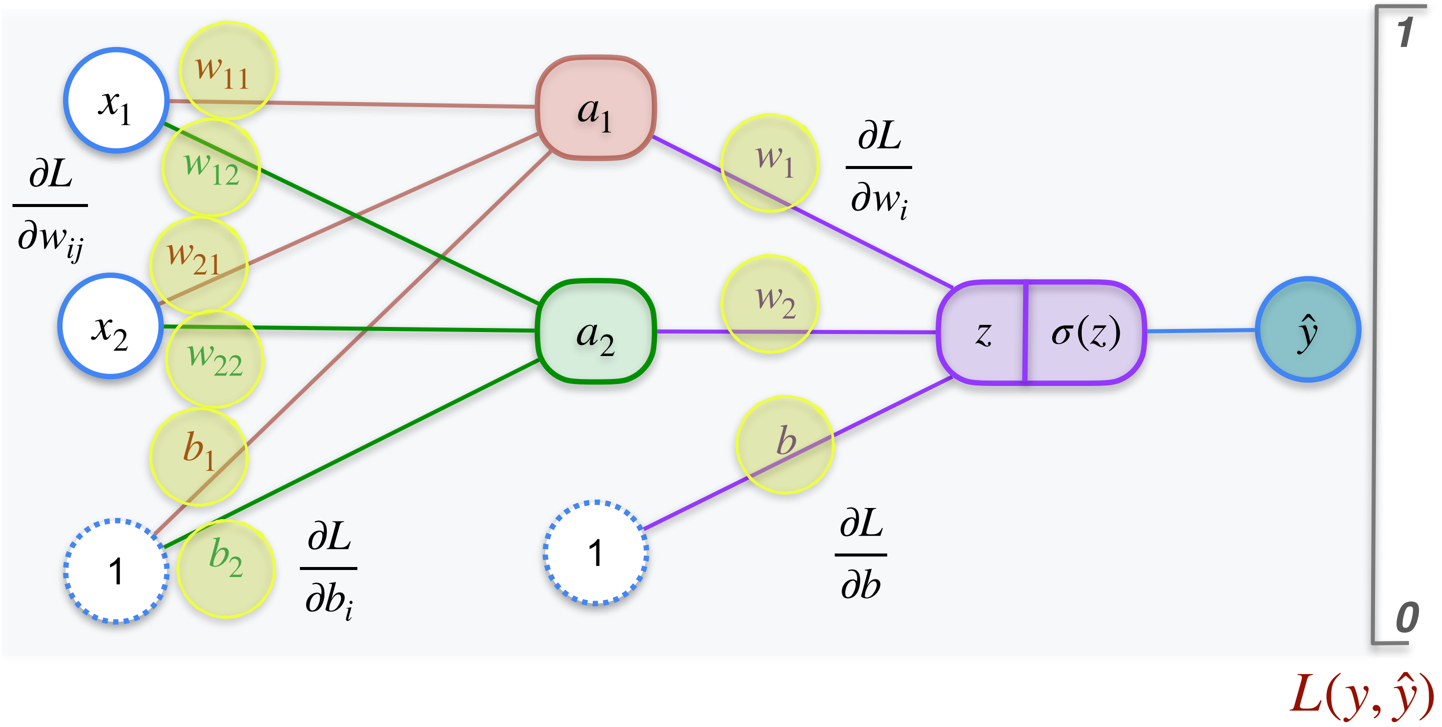
2,2,1 Neural Network



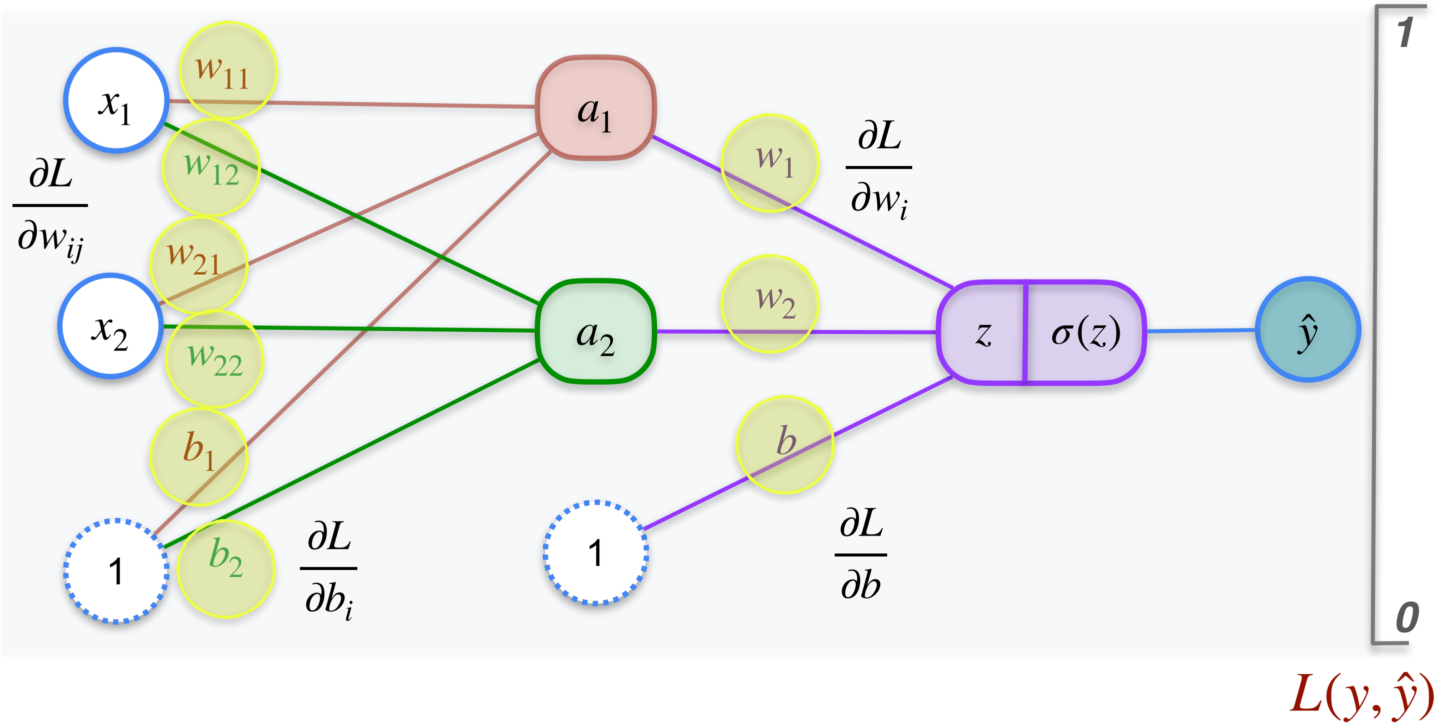
2,2,1 Neural Network



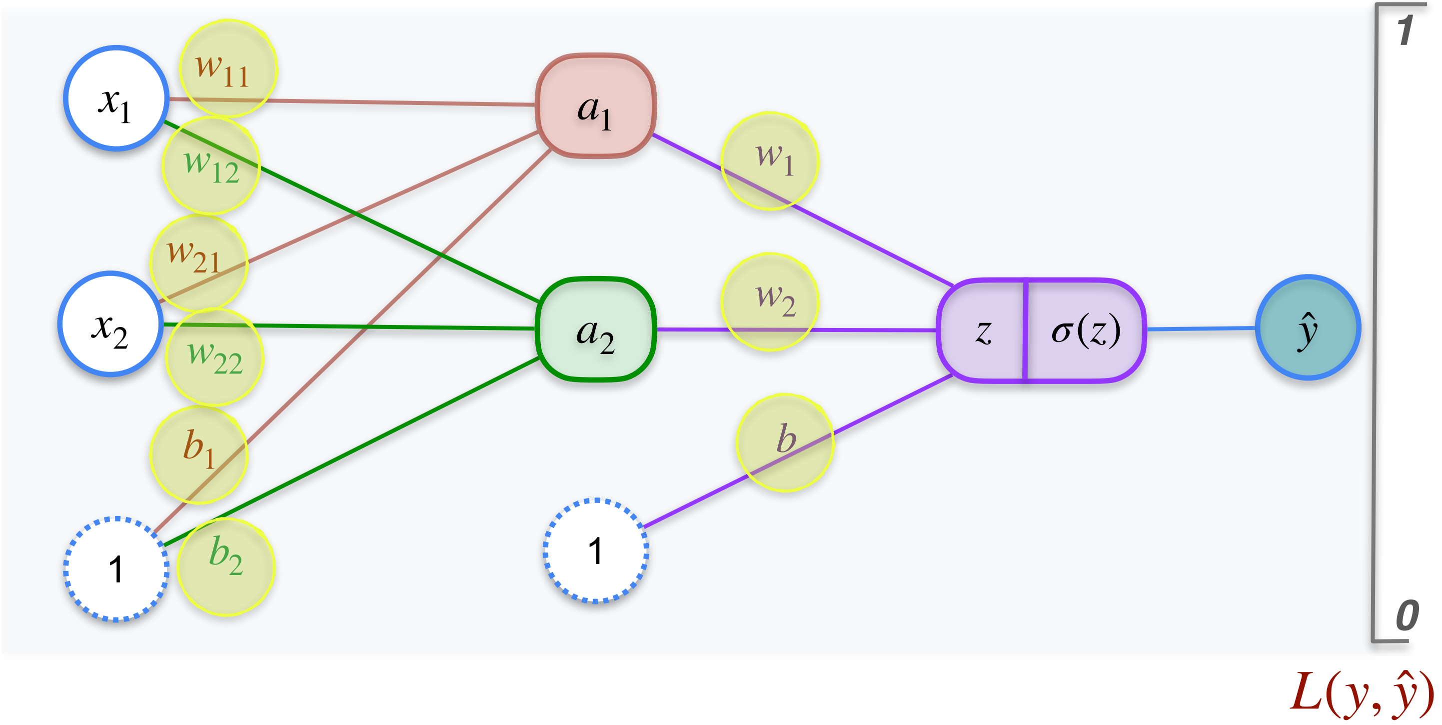
2,2,1 Neural Network



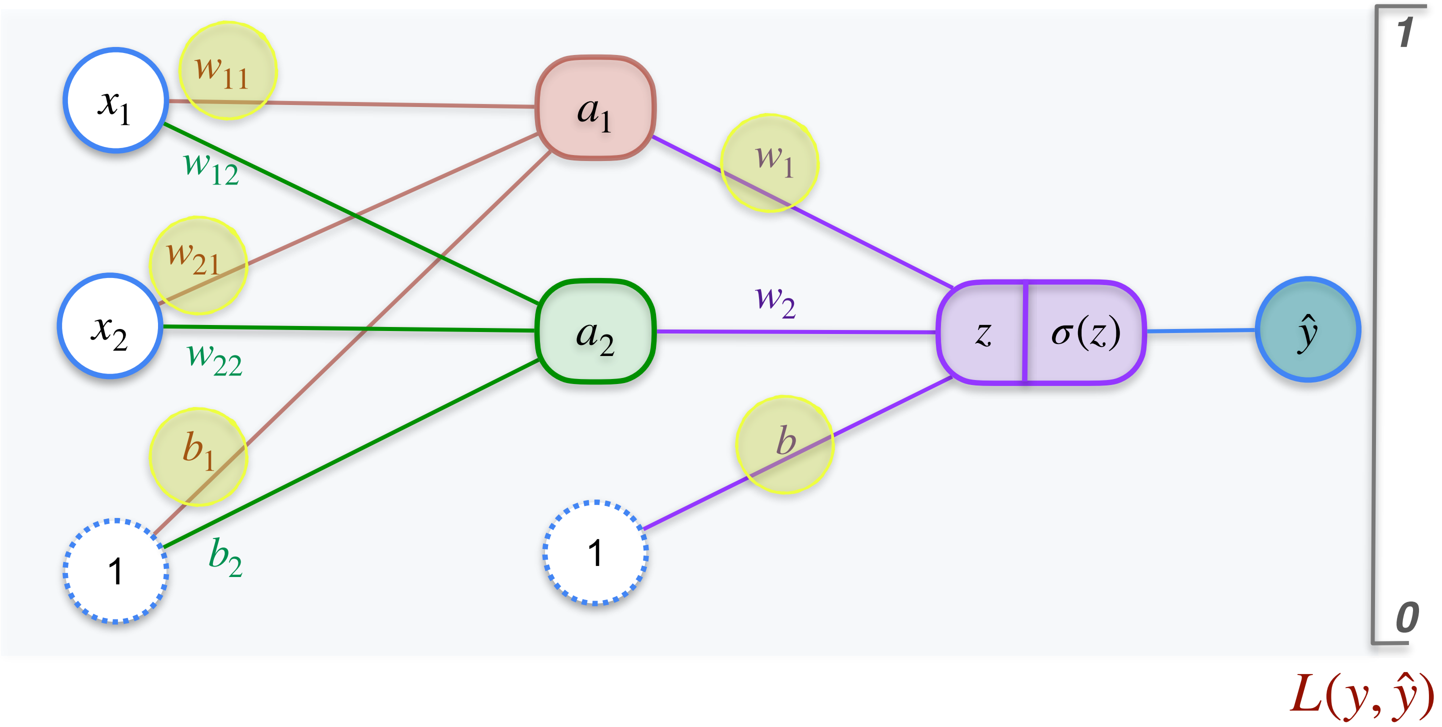
2,2,1 Neural Network



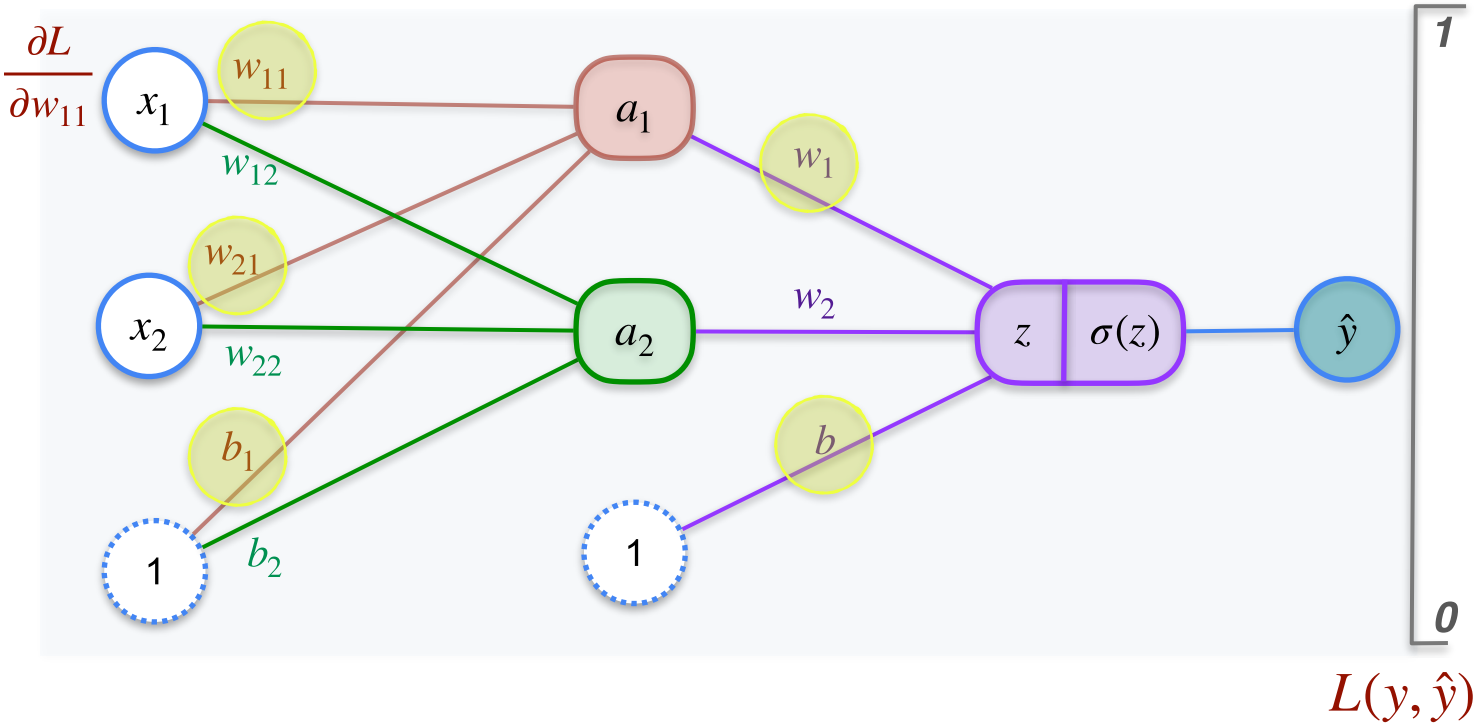
2,2,1 Neural Network



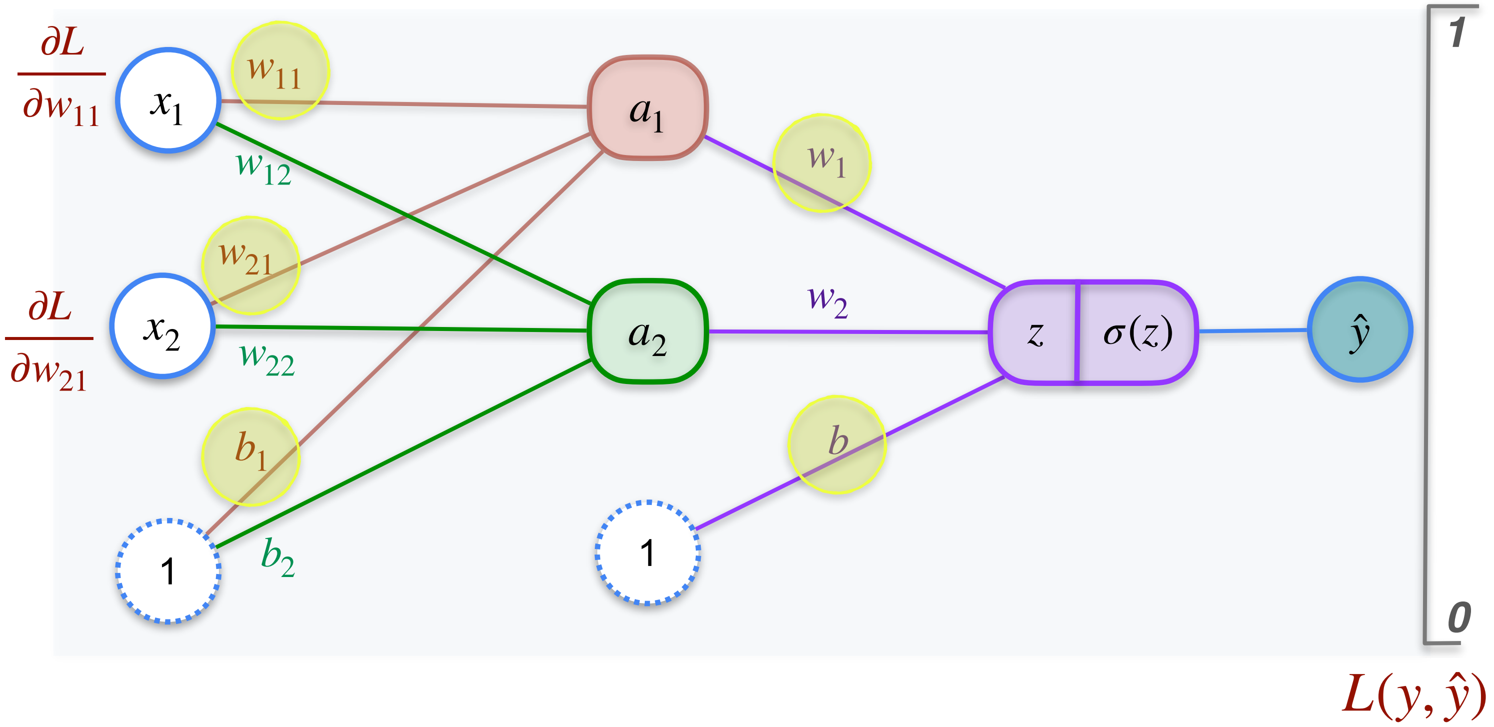
2,2,1 Neural Network



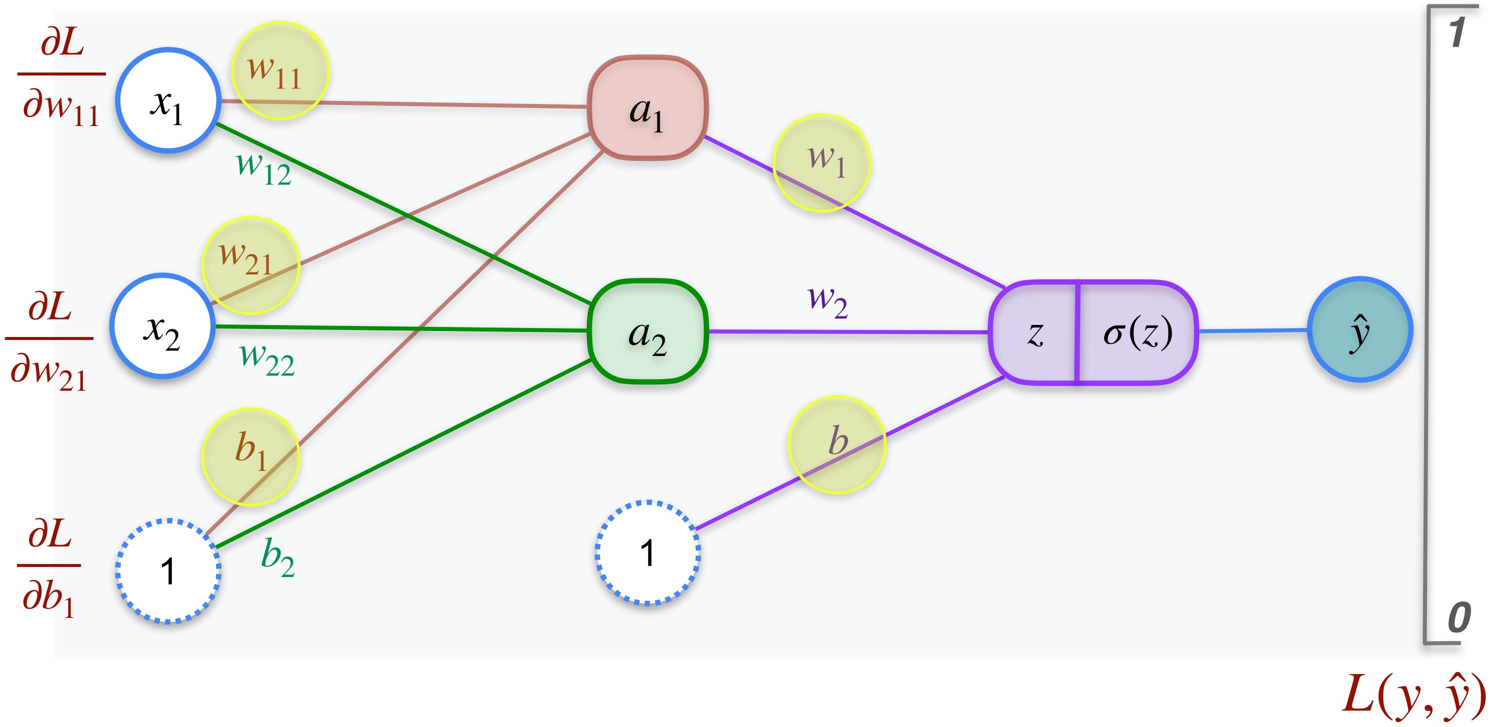
2,2,1 Neural Network



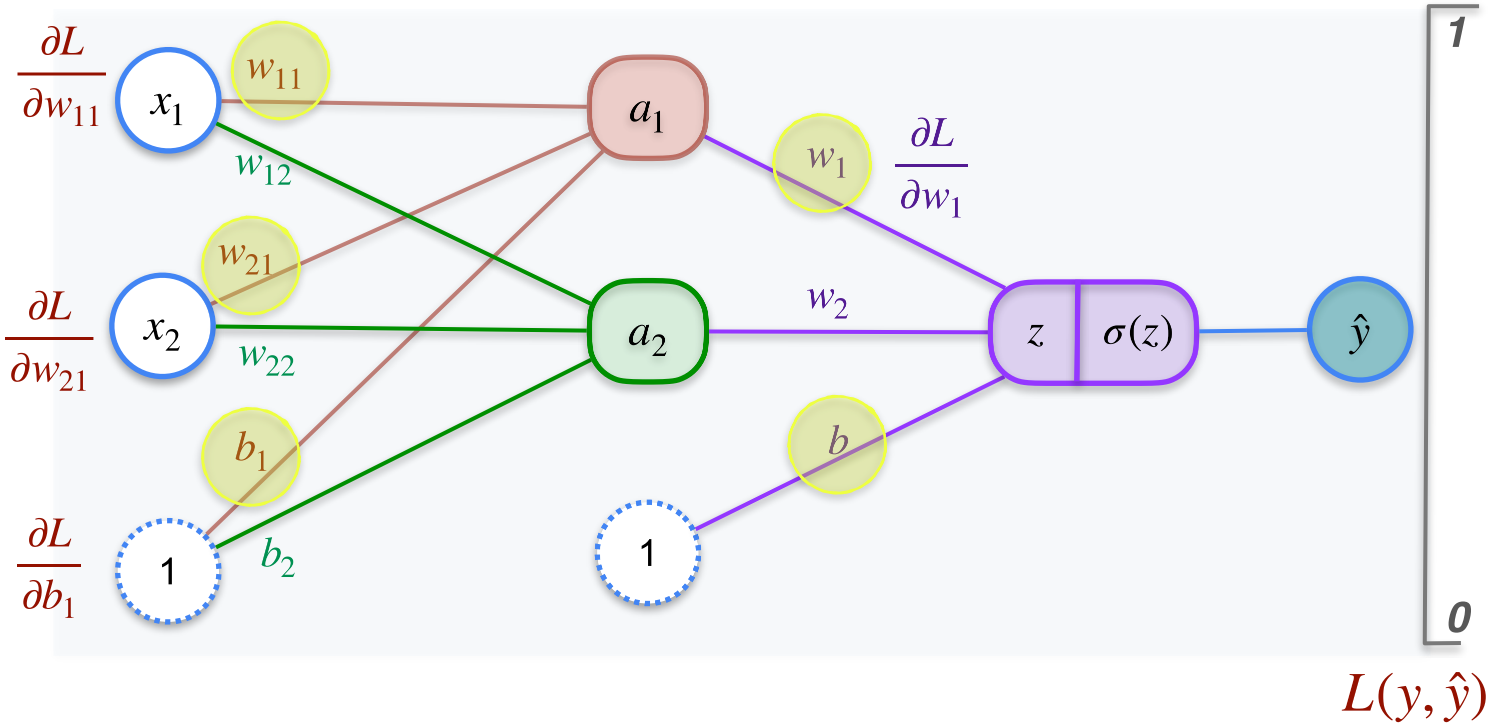
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



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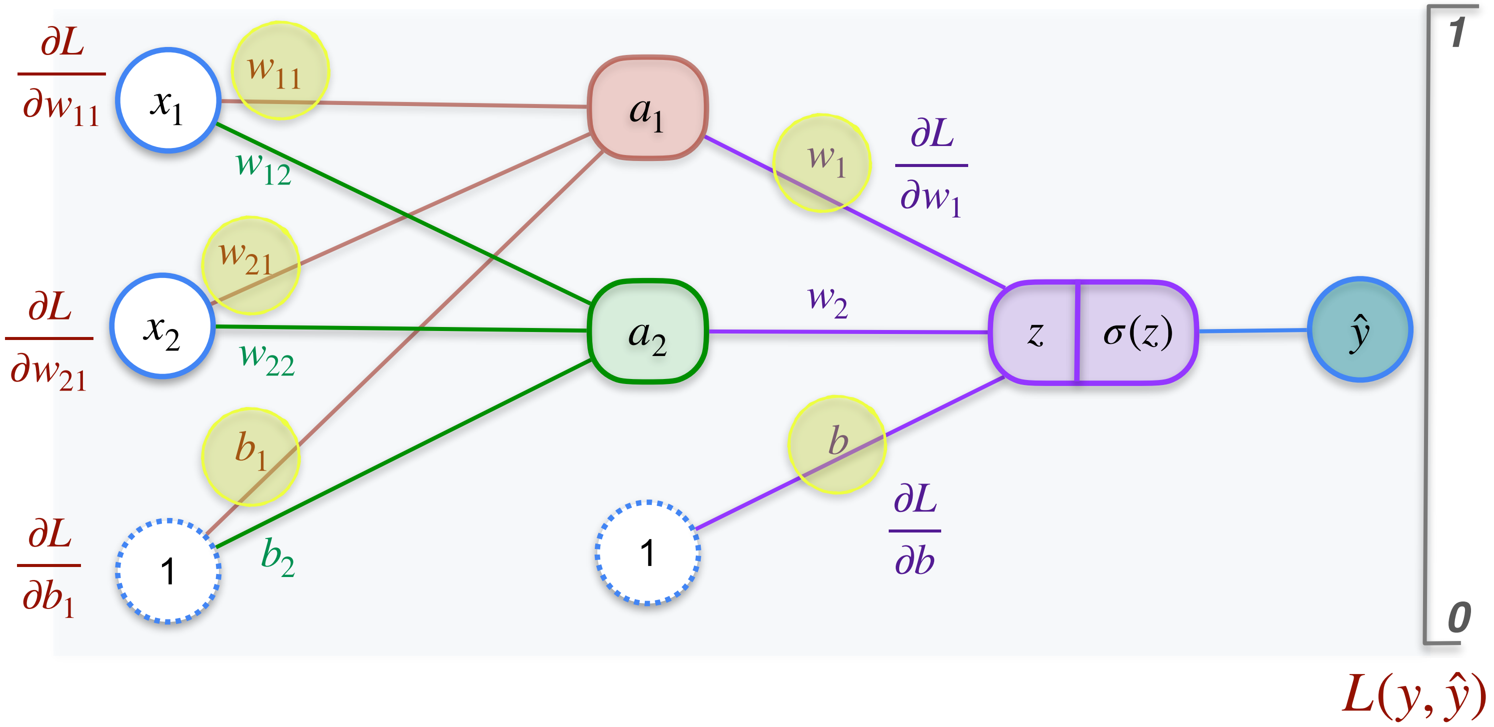
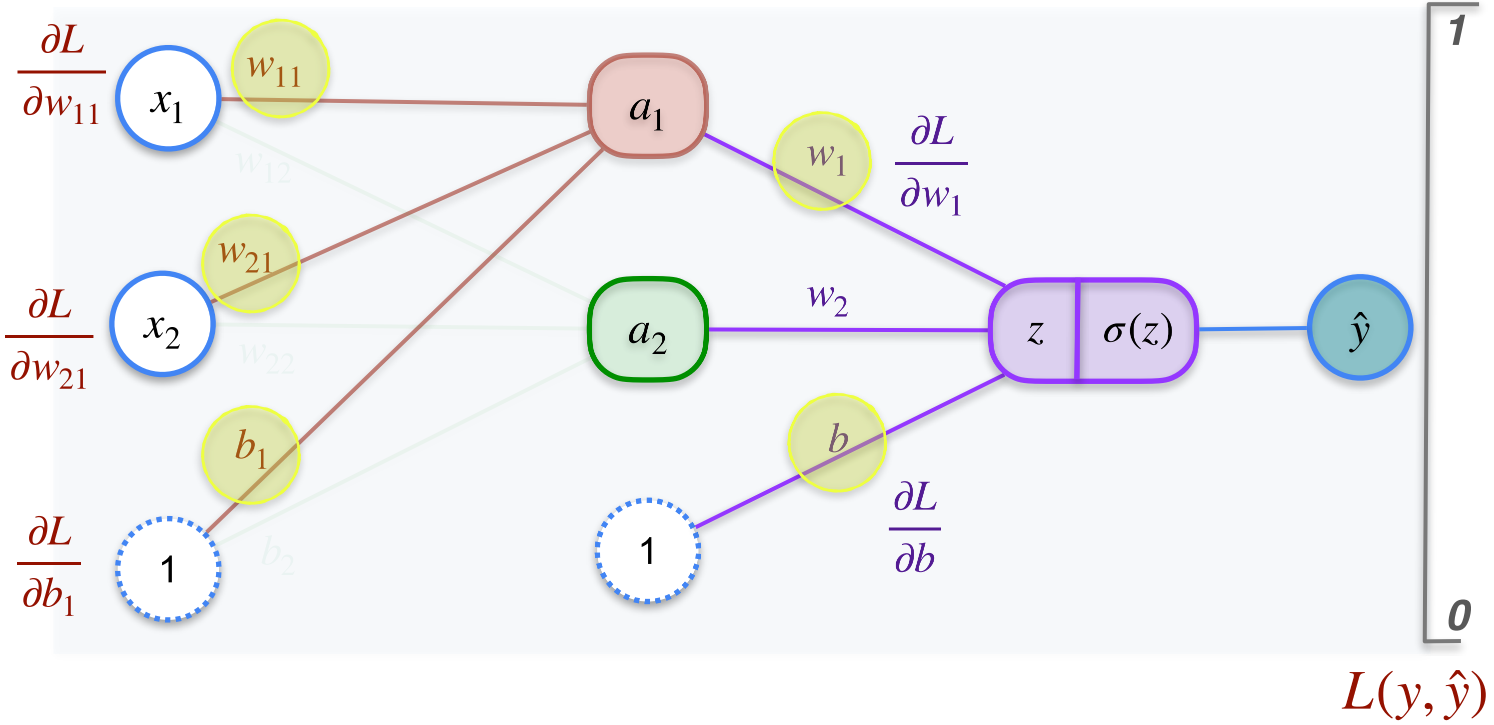
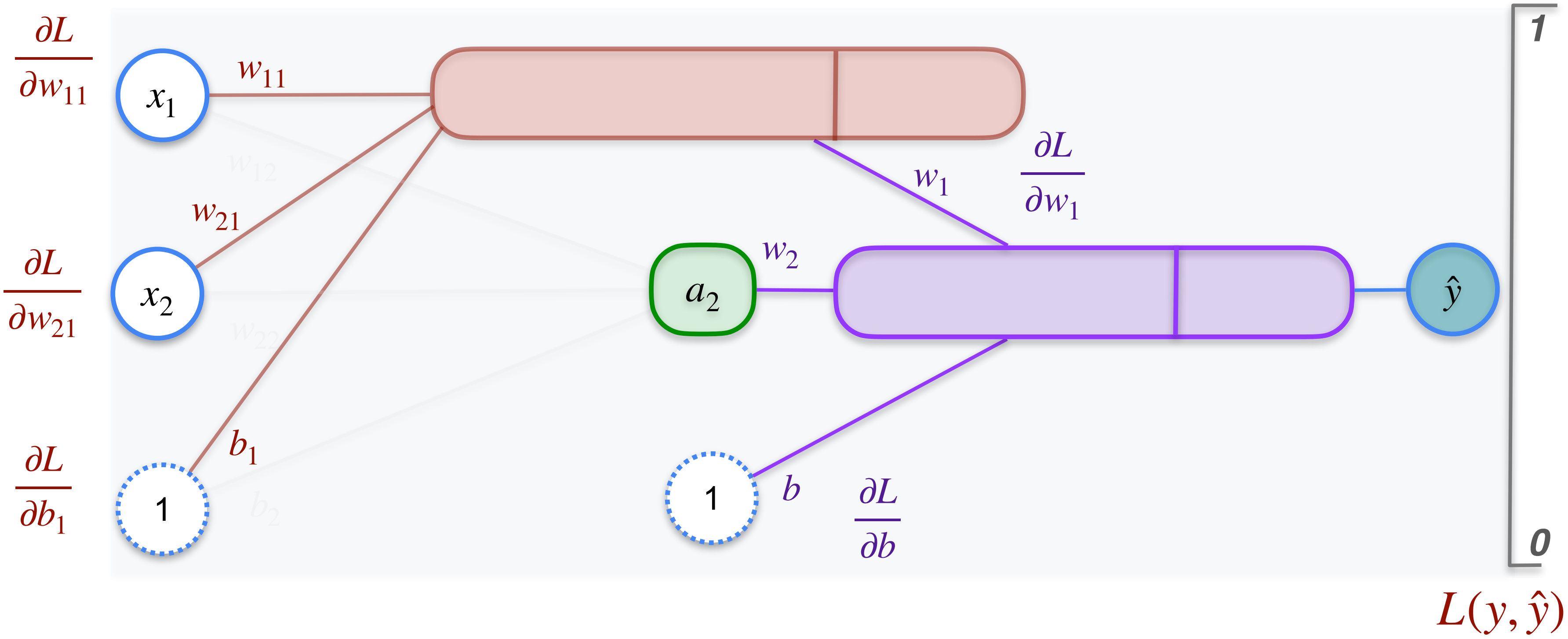
2,2,1 Neural Network



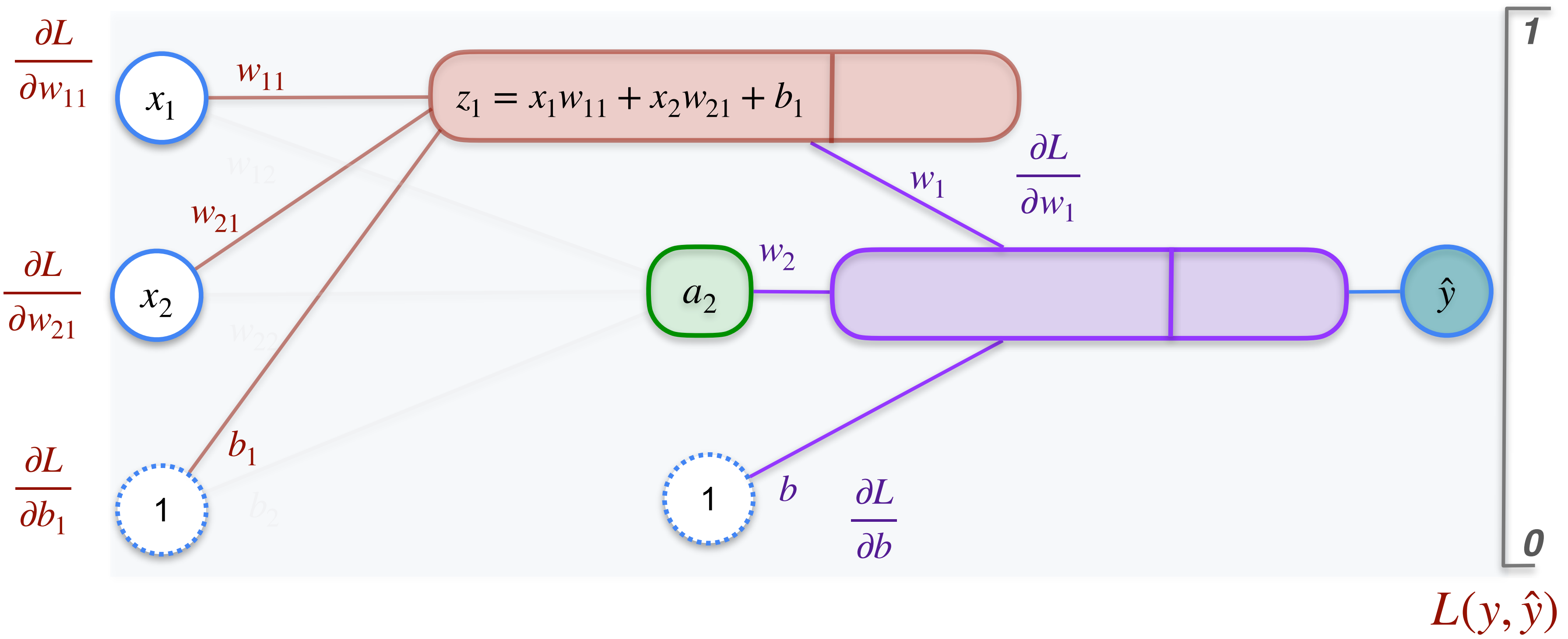
2,2,1 Neural Network



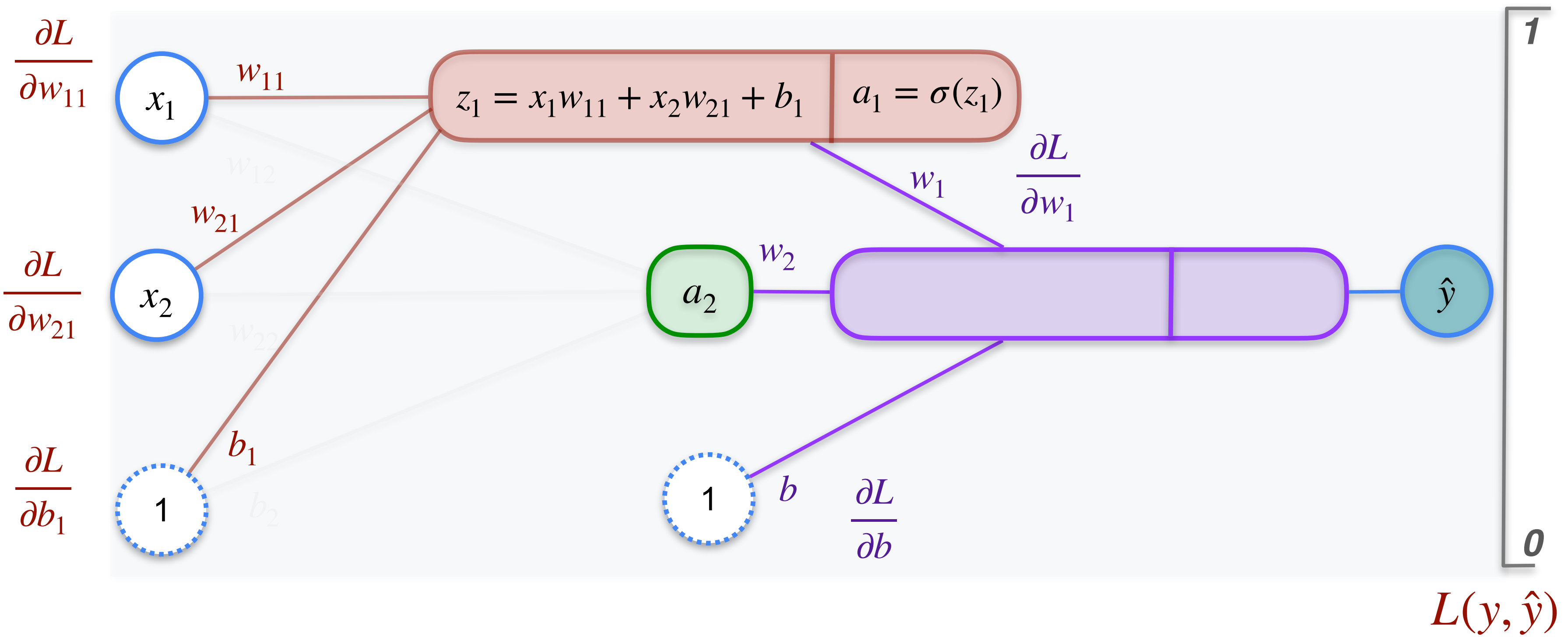
2,2,1 Neural Network



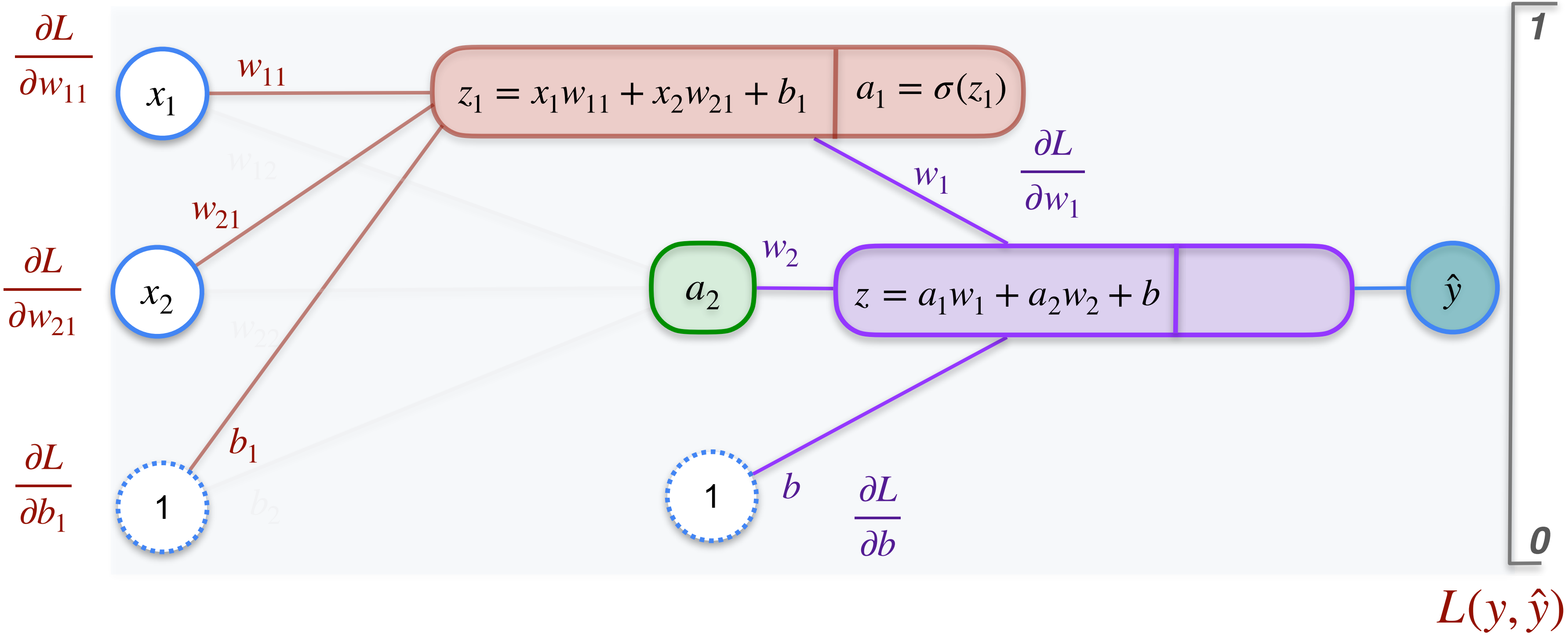
2,2,1 Neural Network



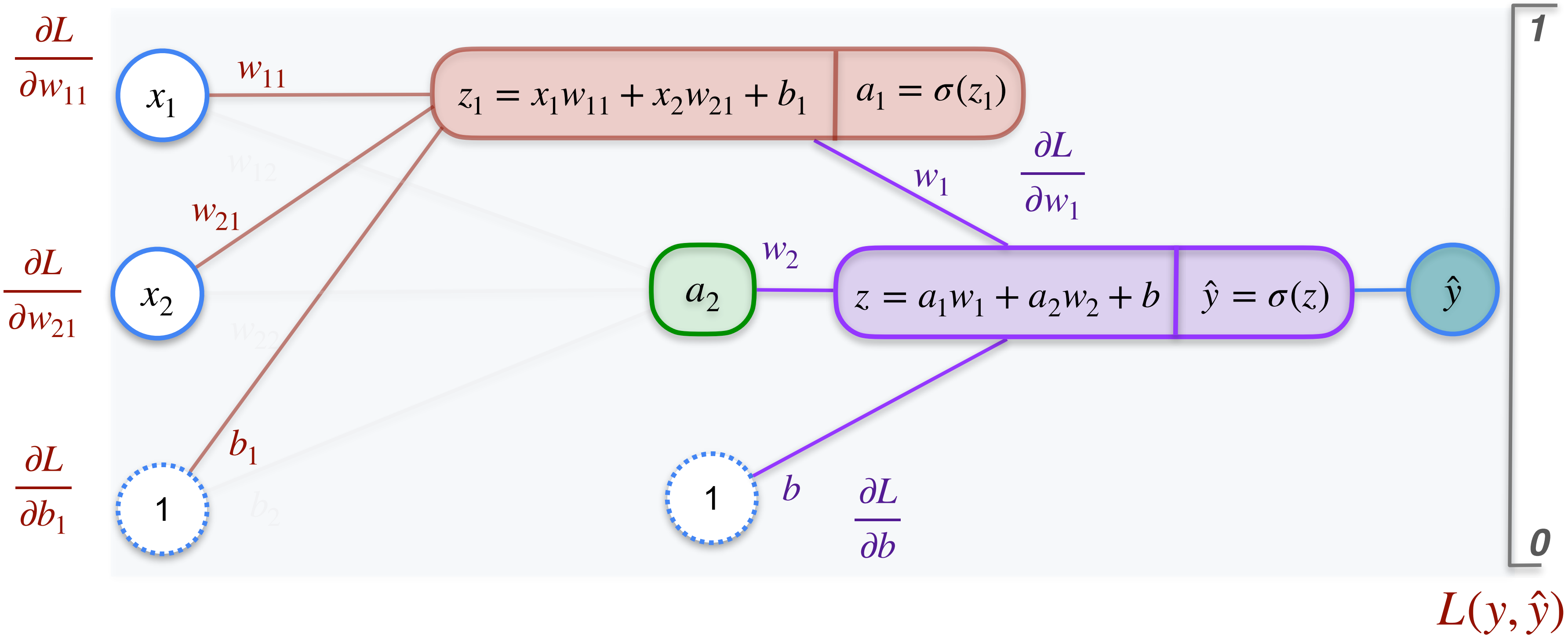
2,2,1 Neural Network



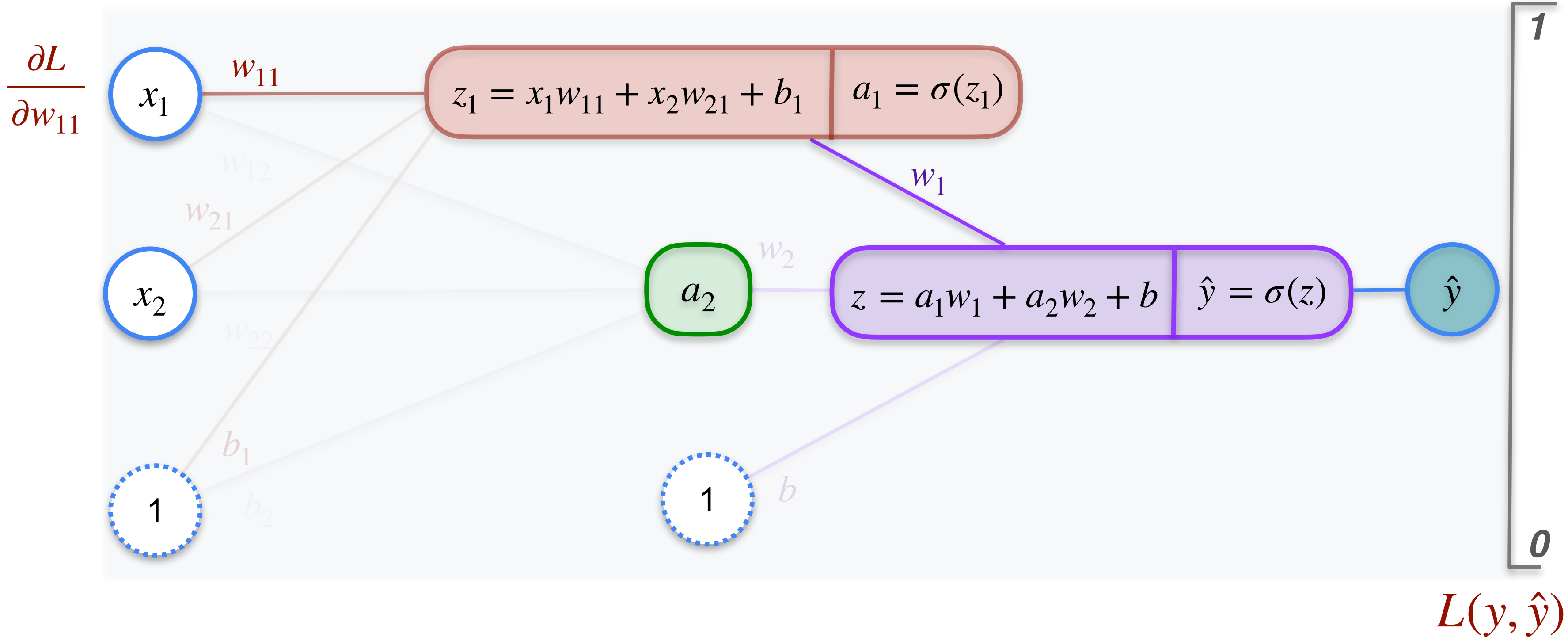
2,2,1 Neural Network



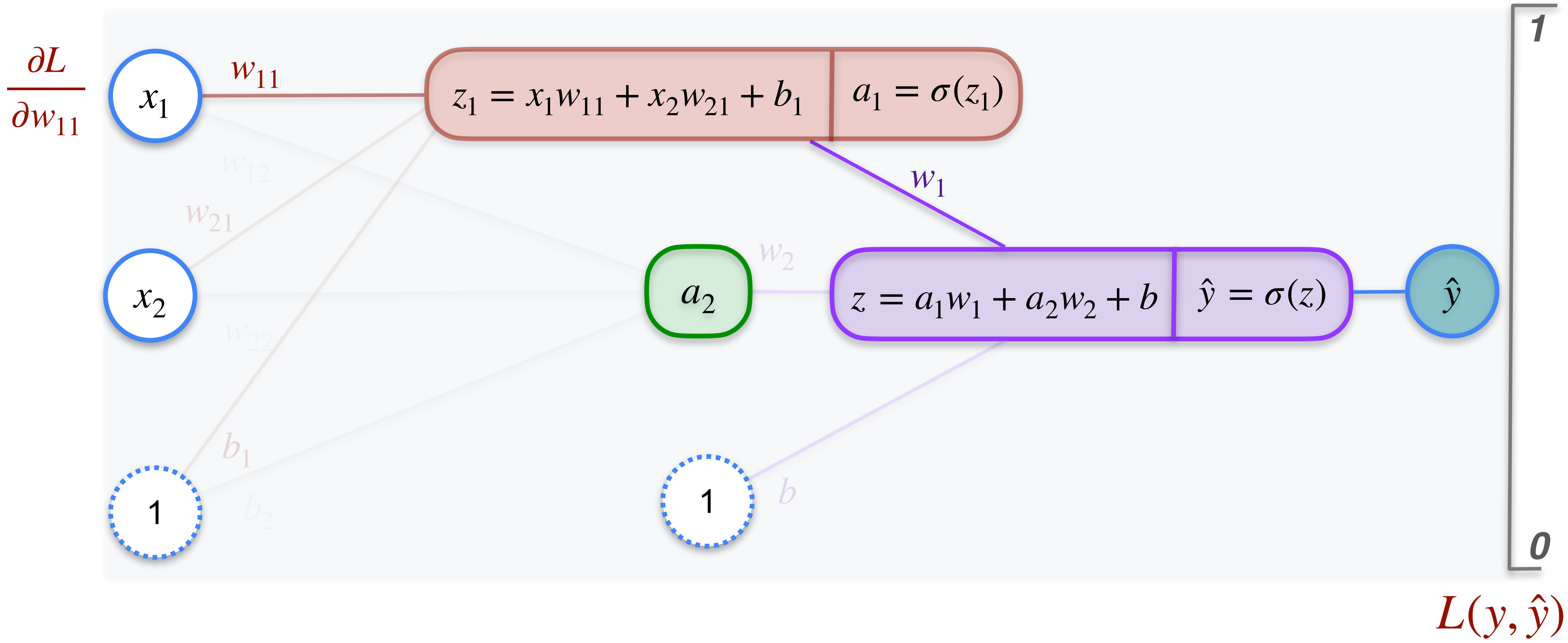
2,2,1 Neural Network



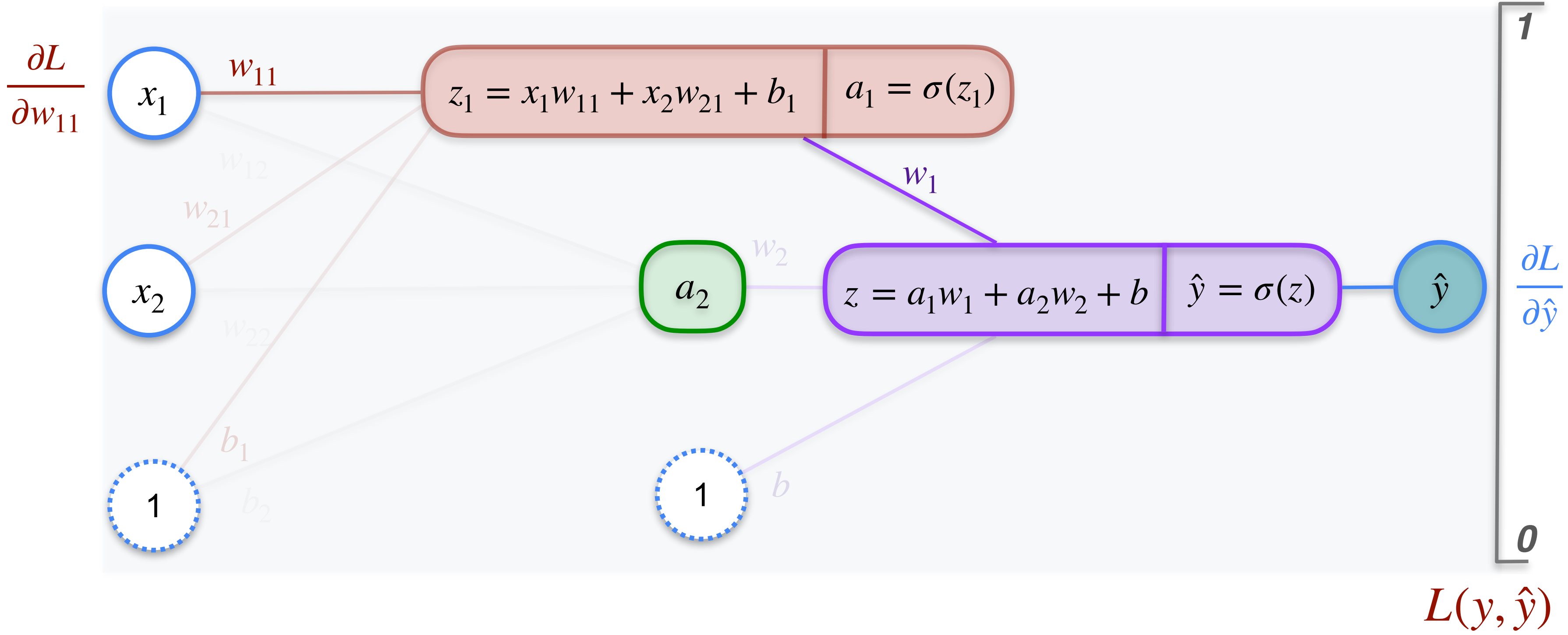
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



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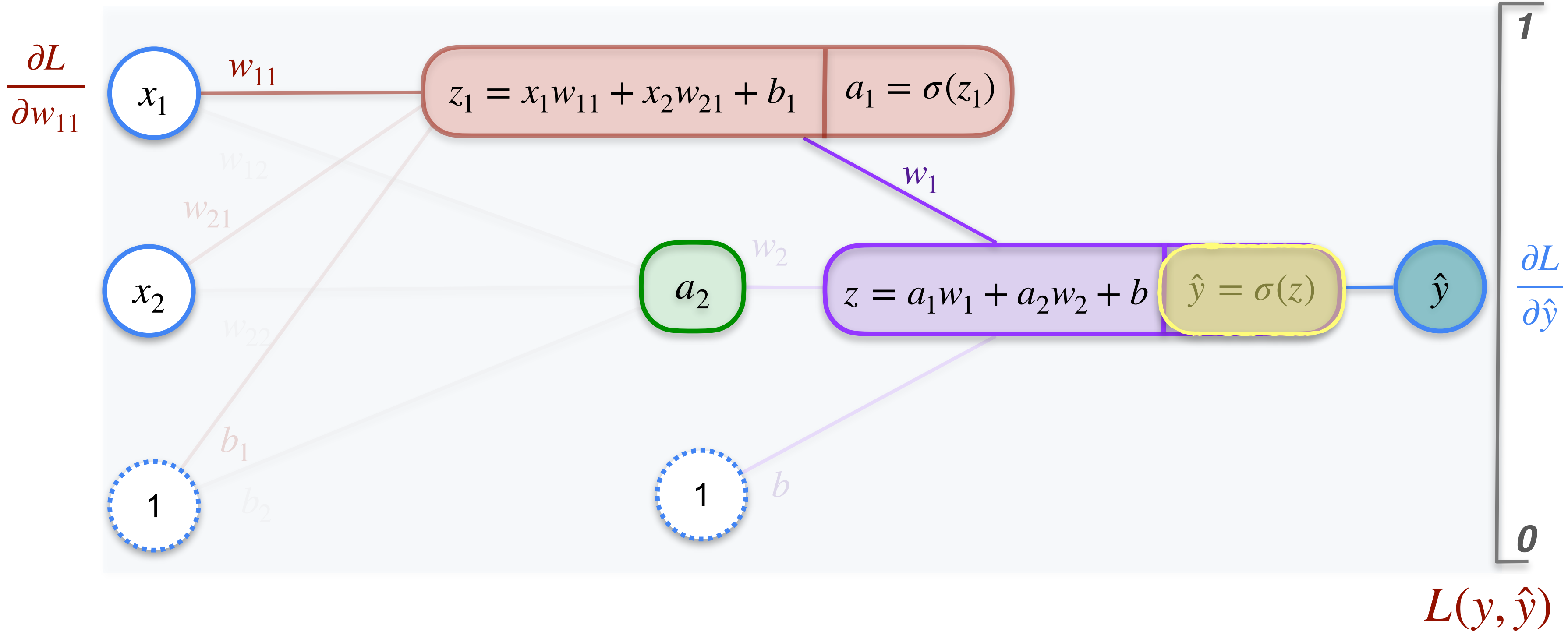
2,2,1 Neural Network



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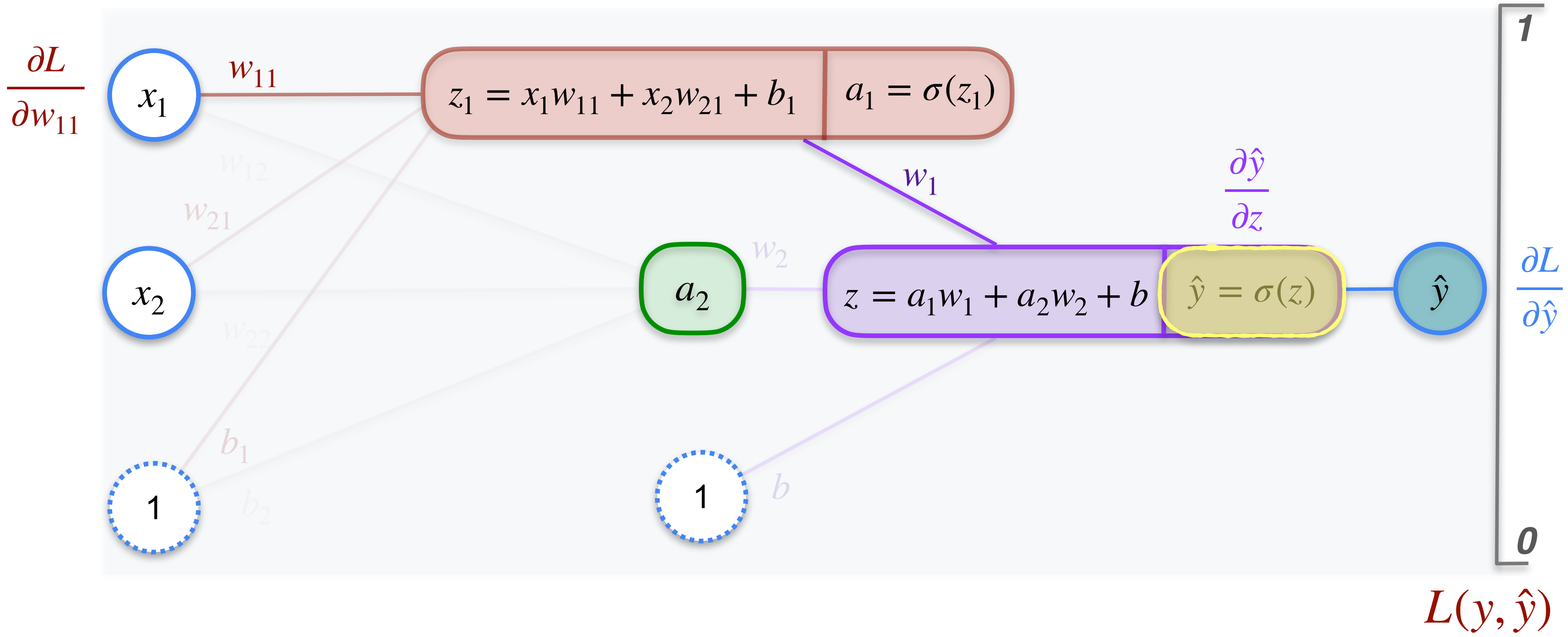
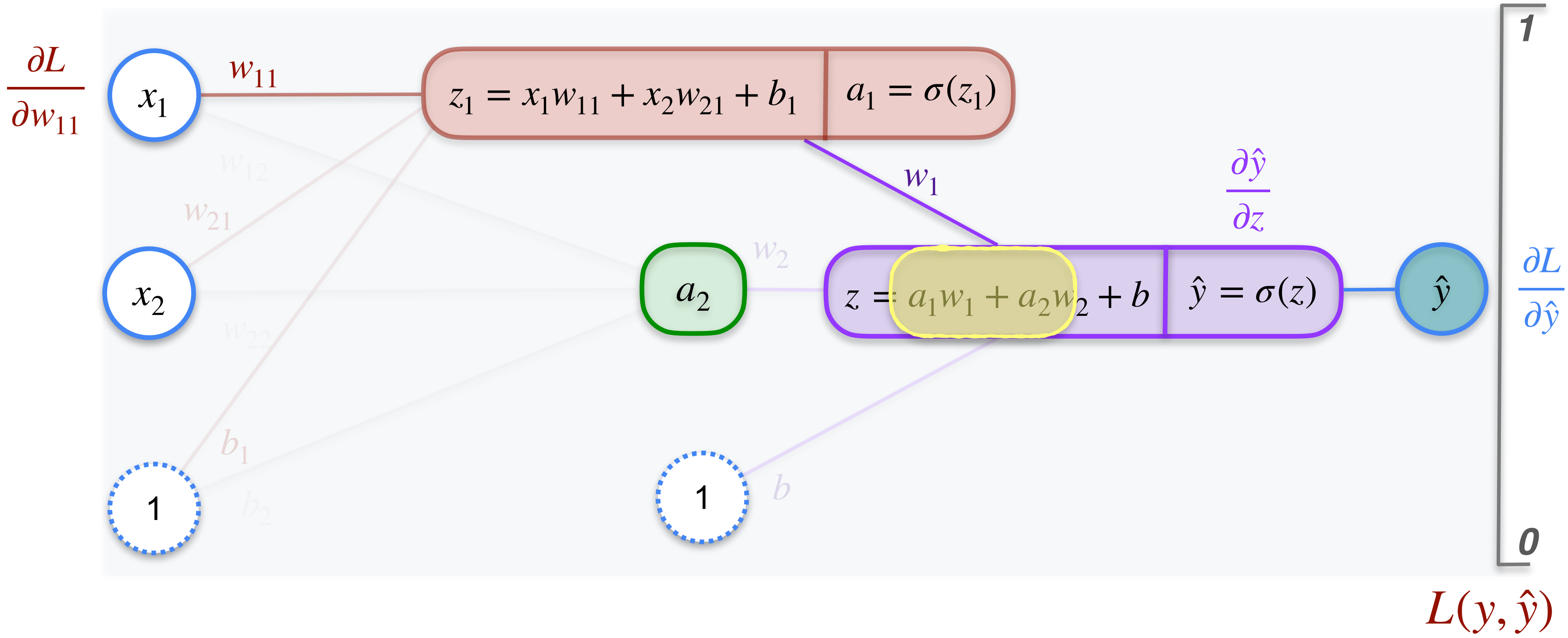
2,2,1 Neural Network



2,2,1 Neural Network



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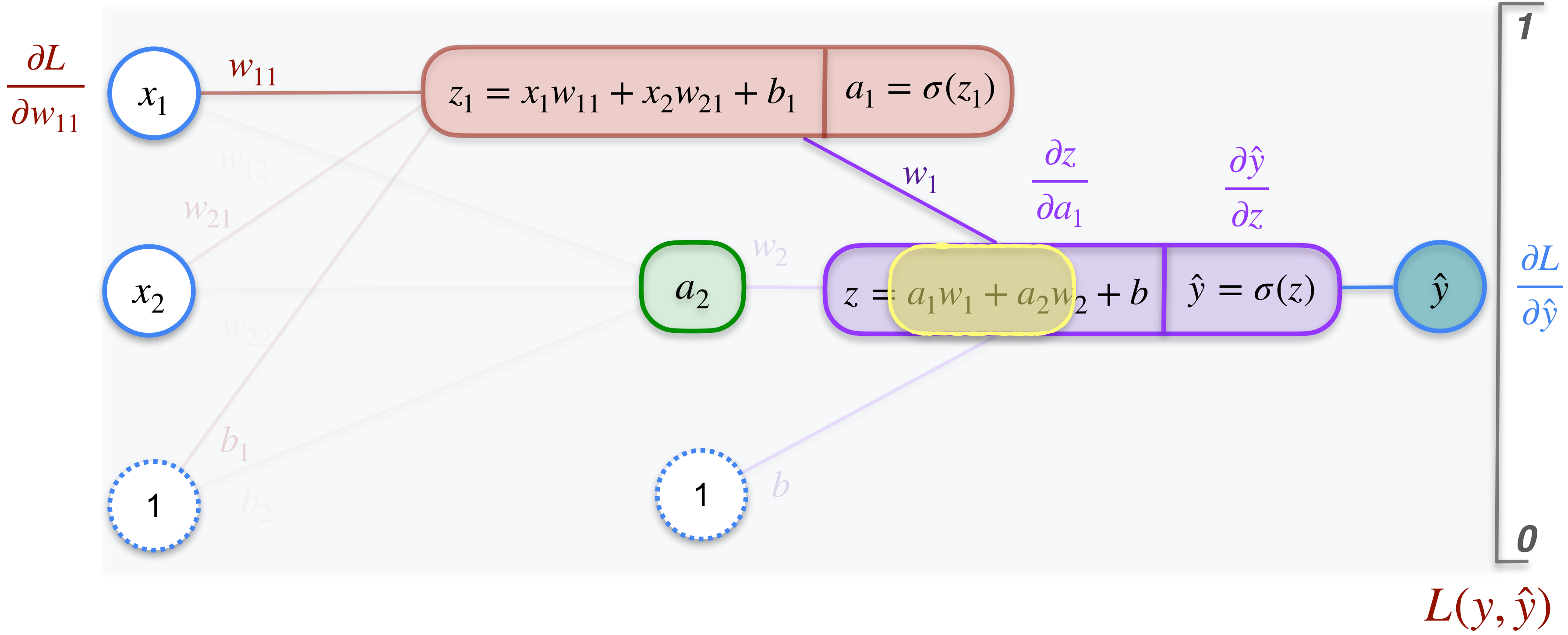
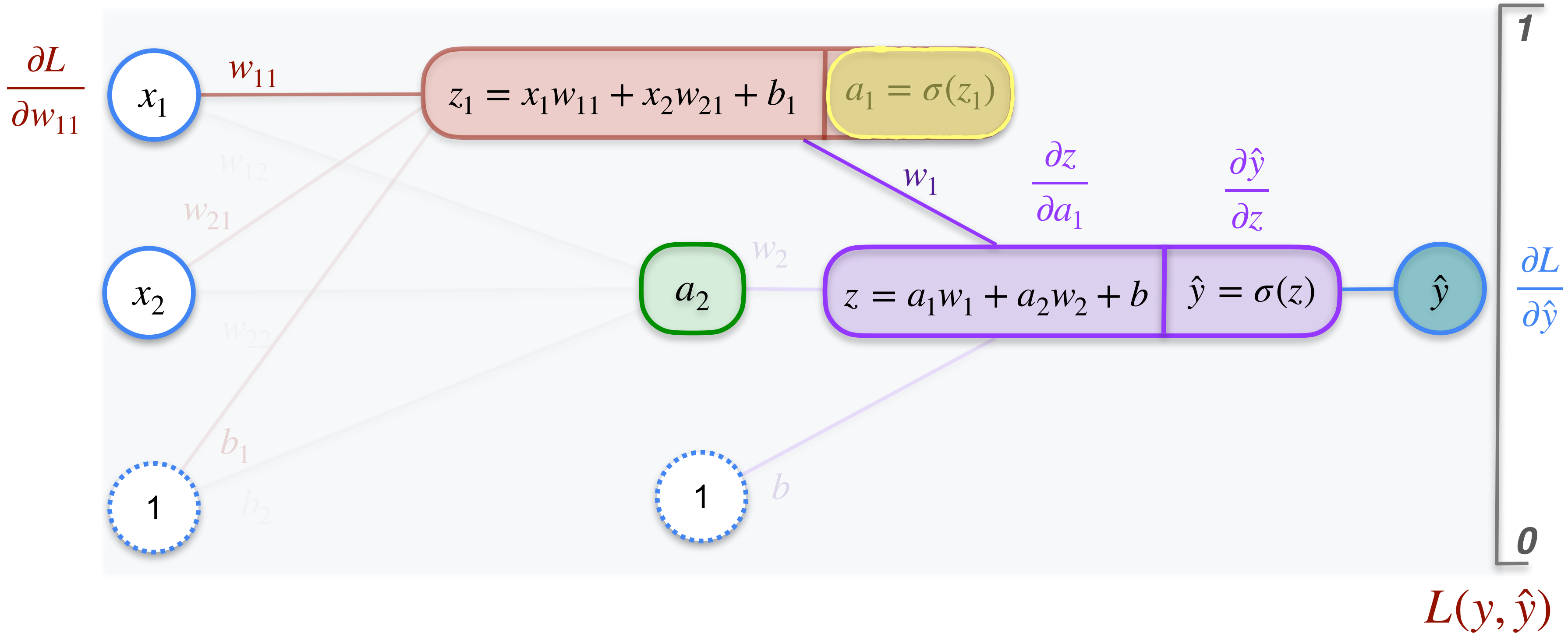
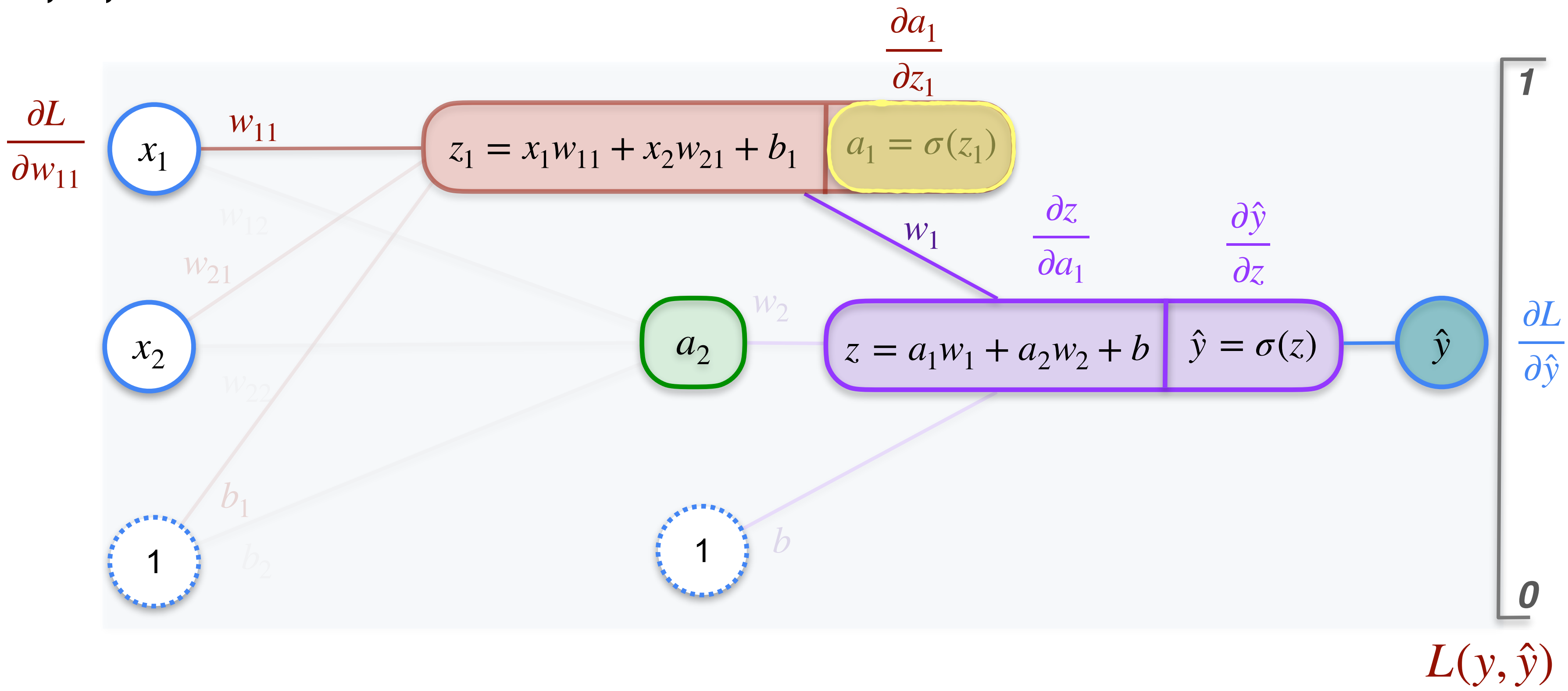
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



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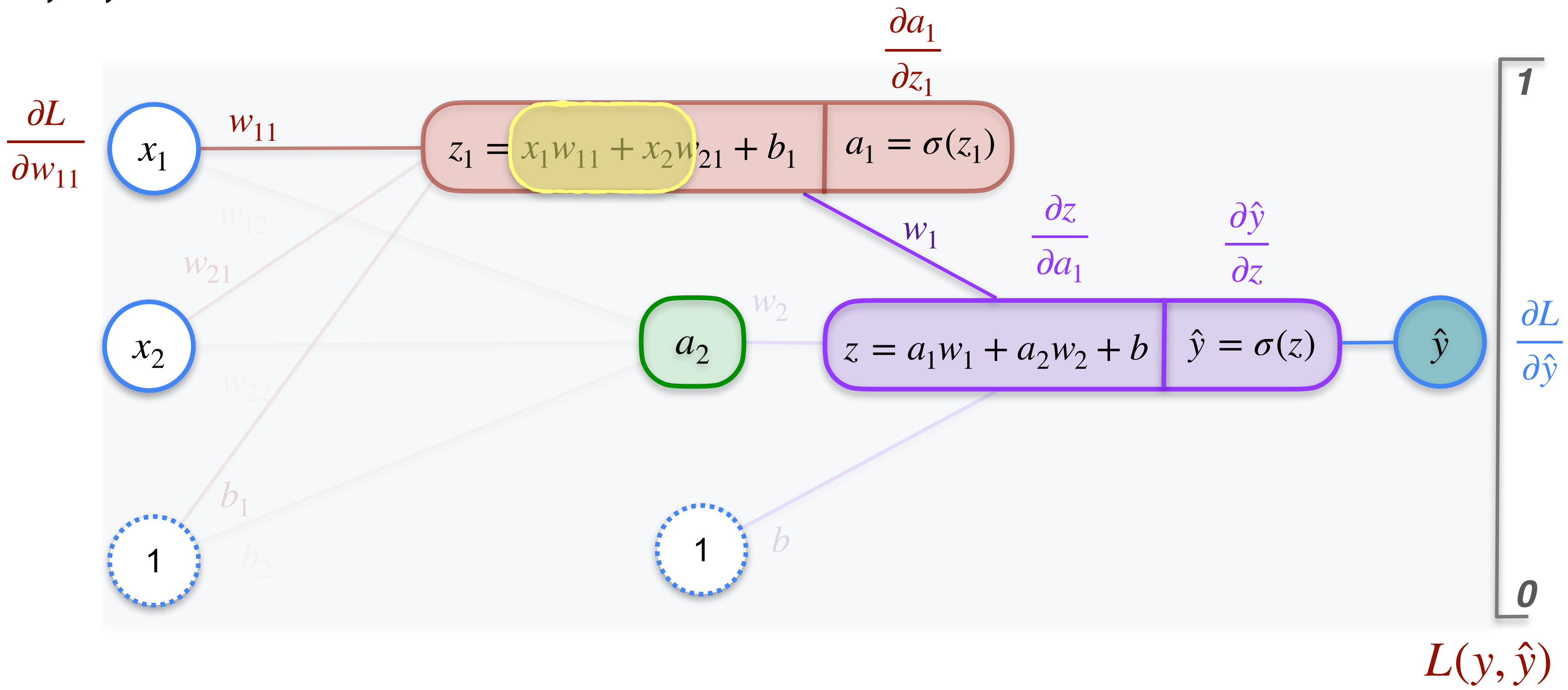
2,2,1 Neural Network



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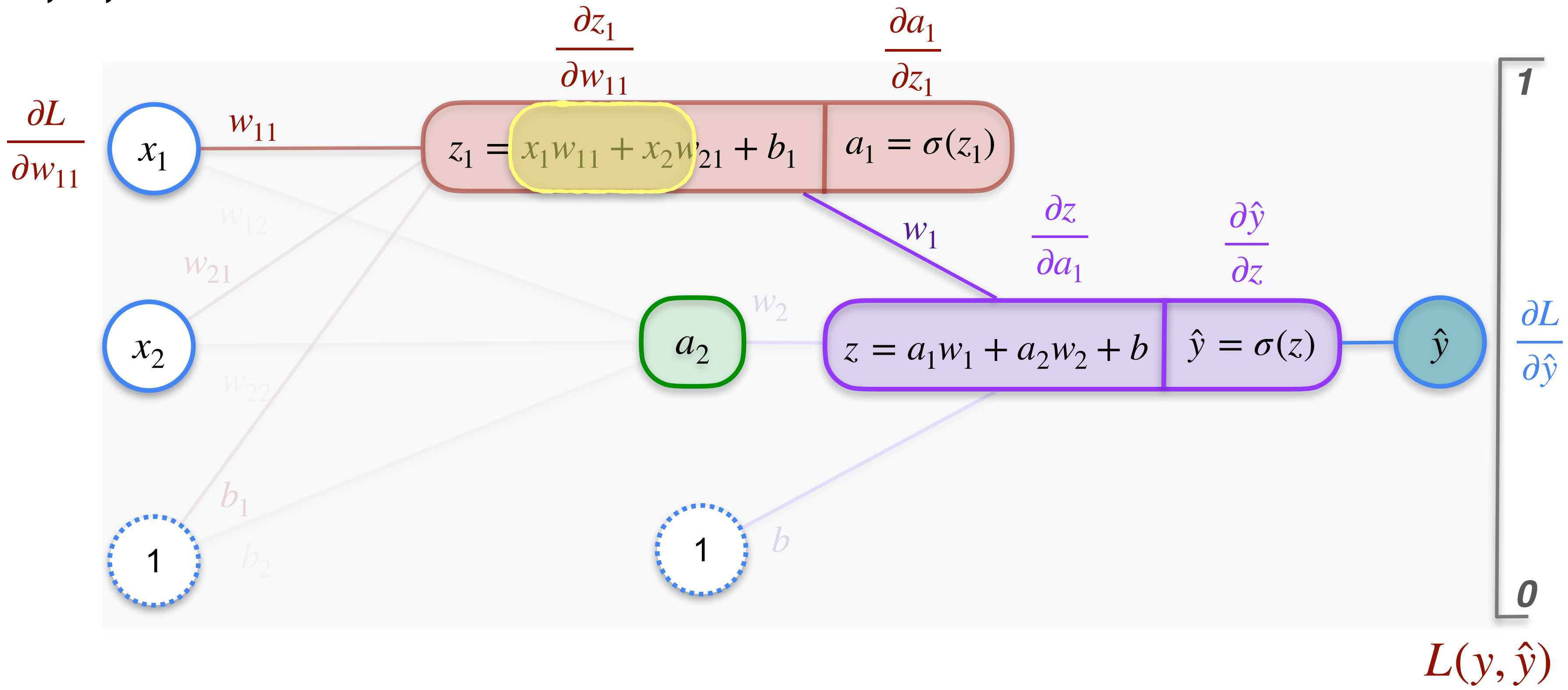
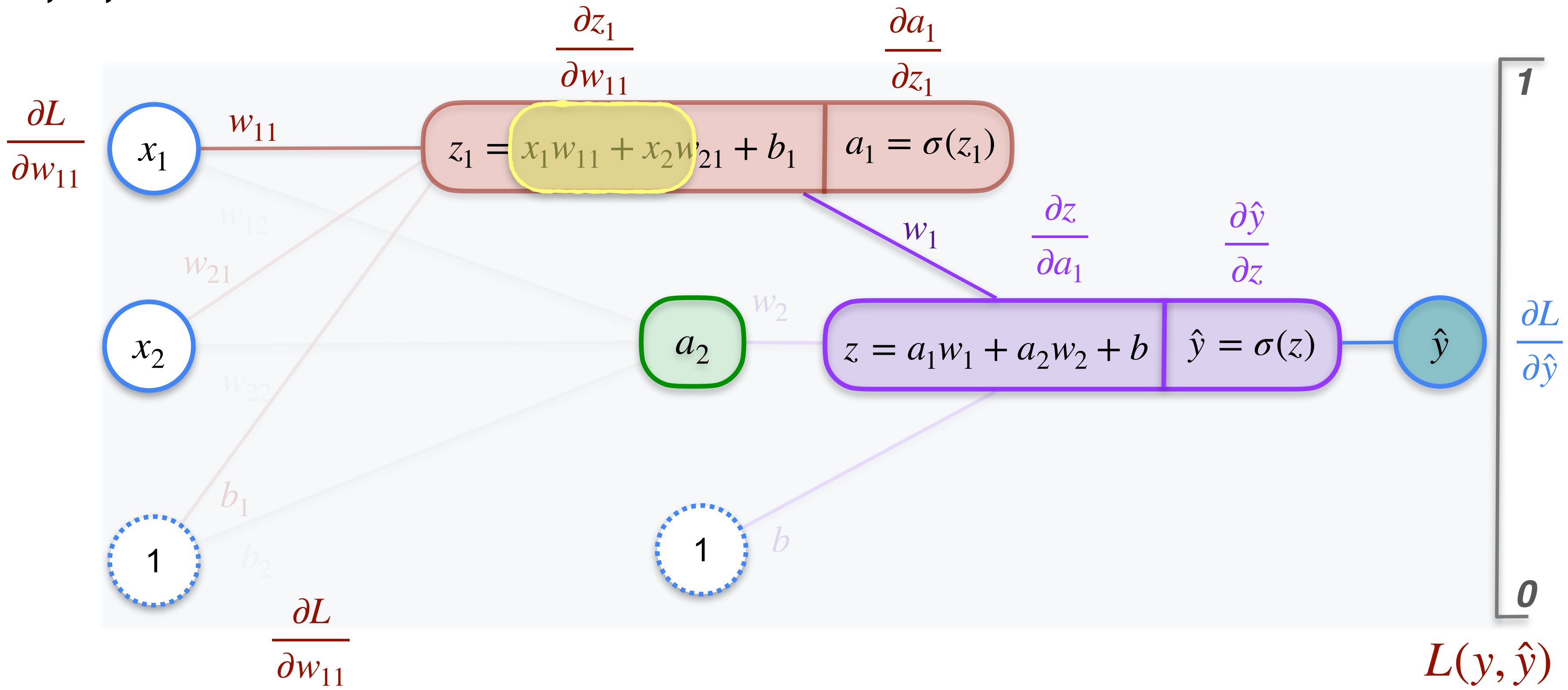
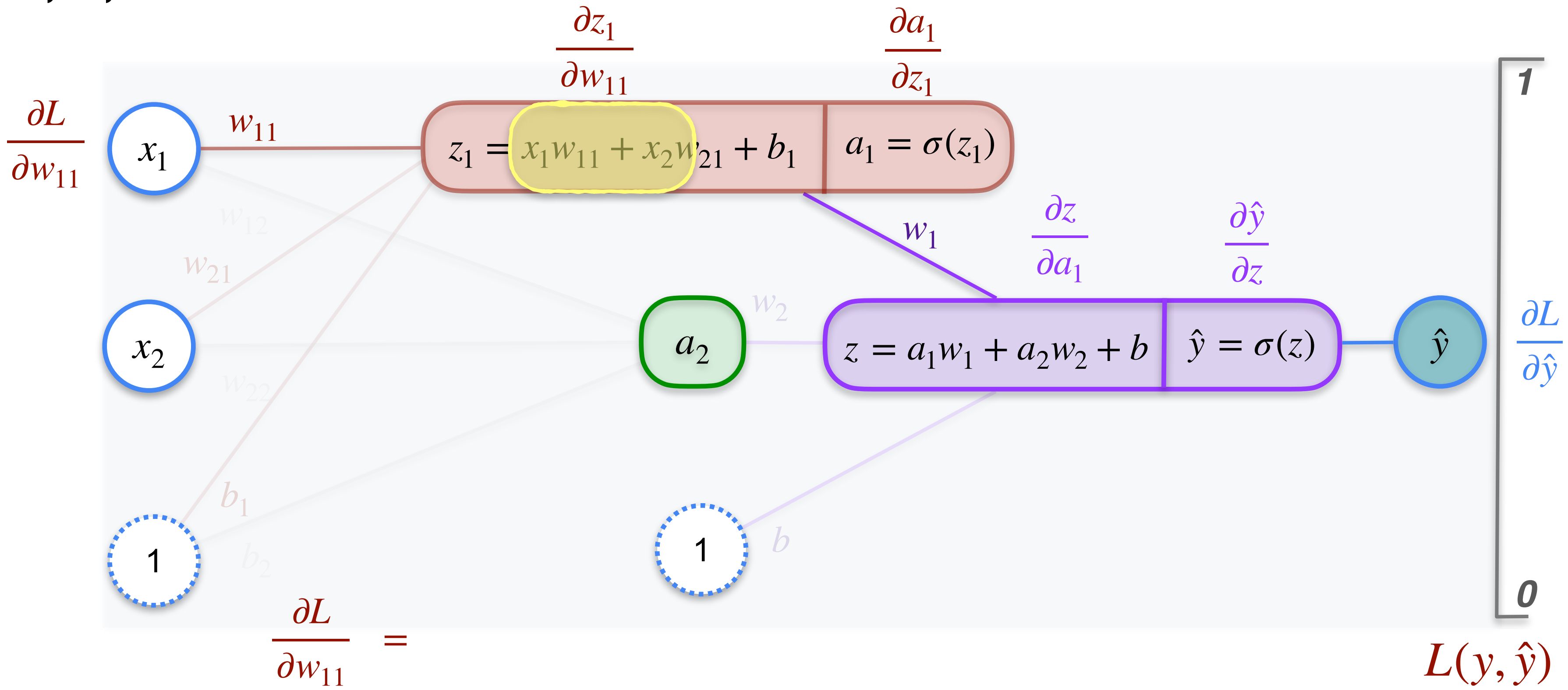


2,2,1 Neural Network

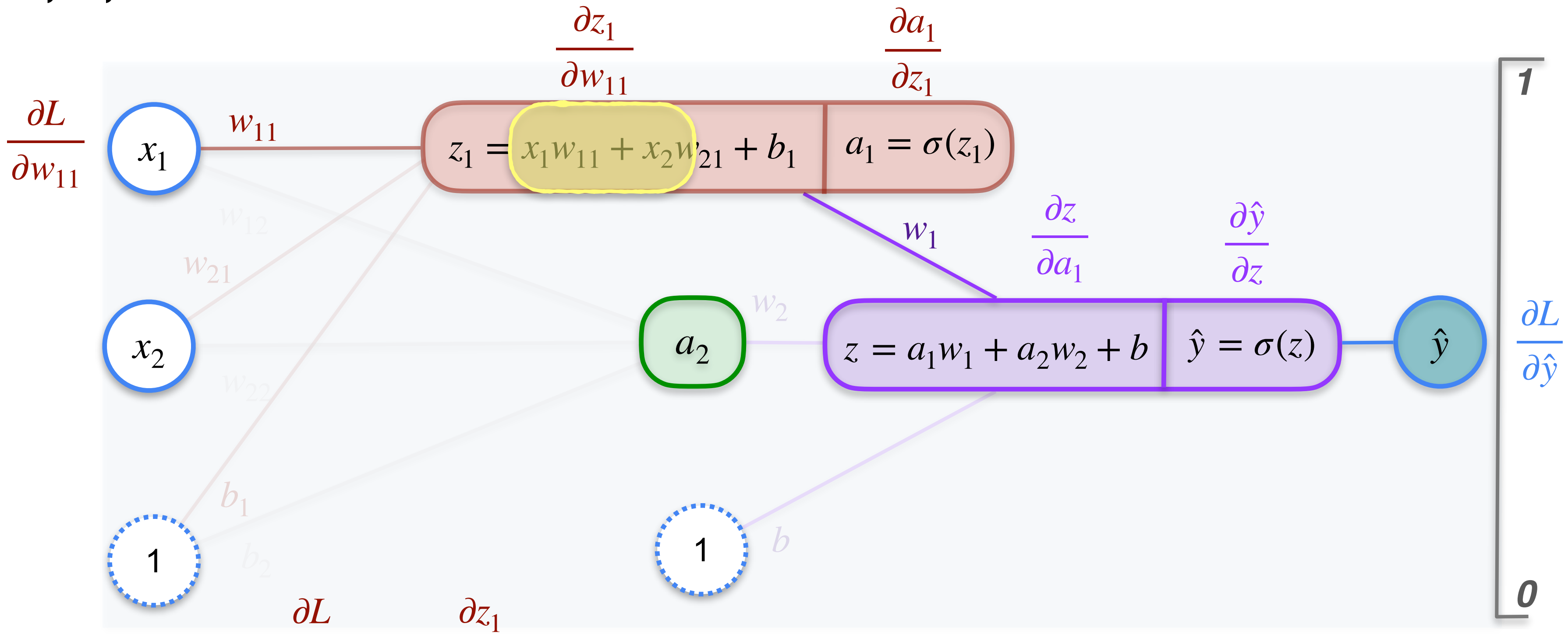


2,2,1 Neural Network



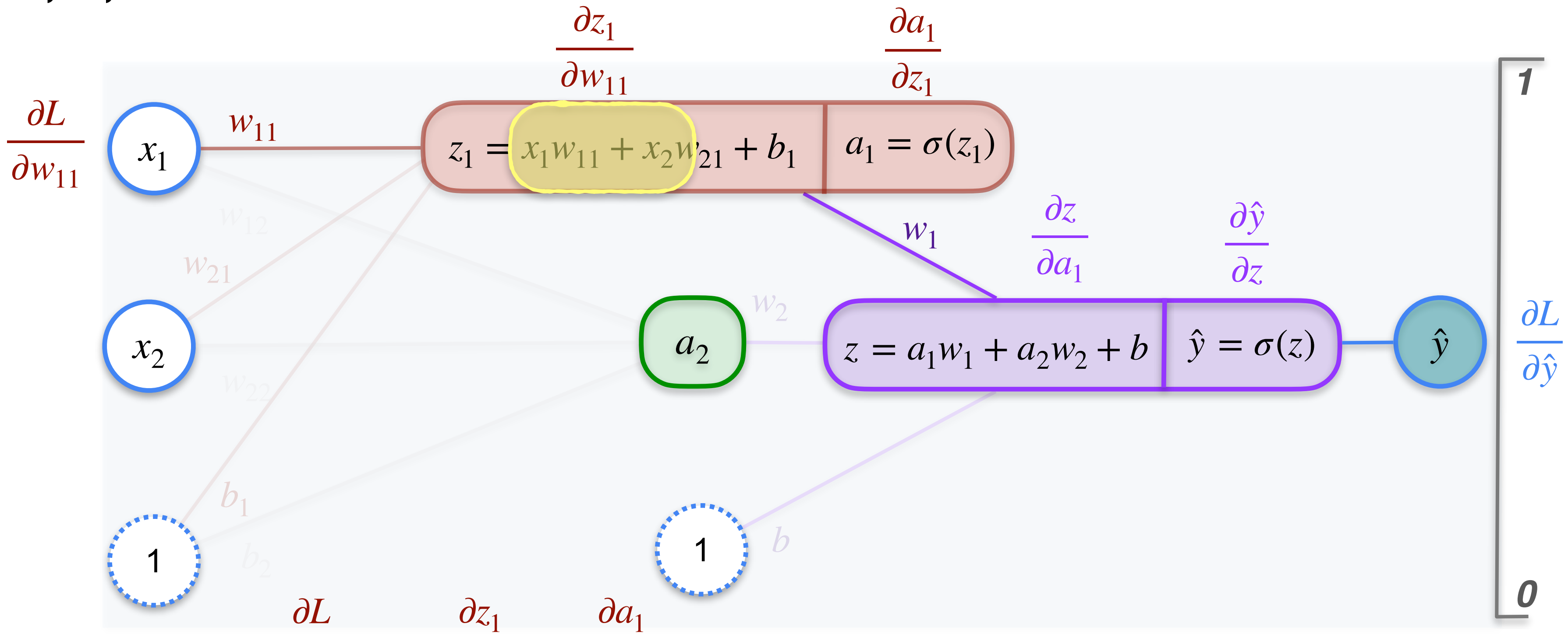
$$\frac{\partial L}{\partial w_{11}} =$$

2,2,1 Neural Network



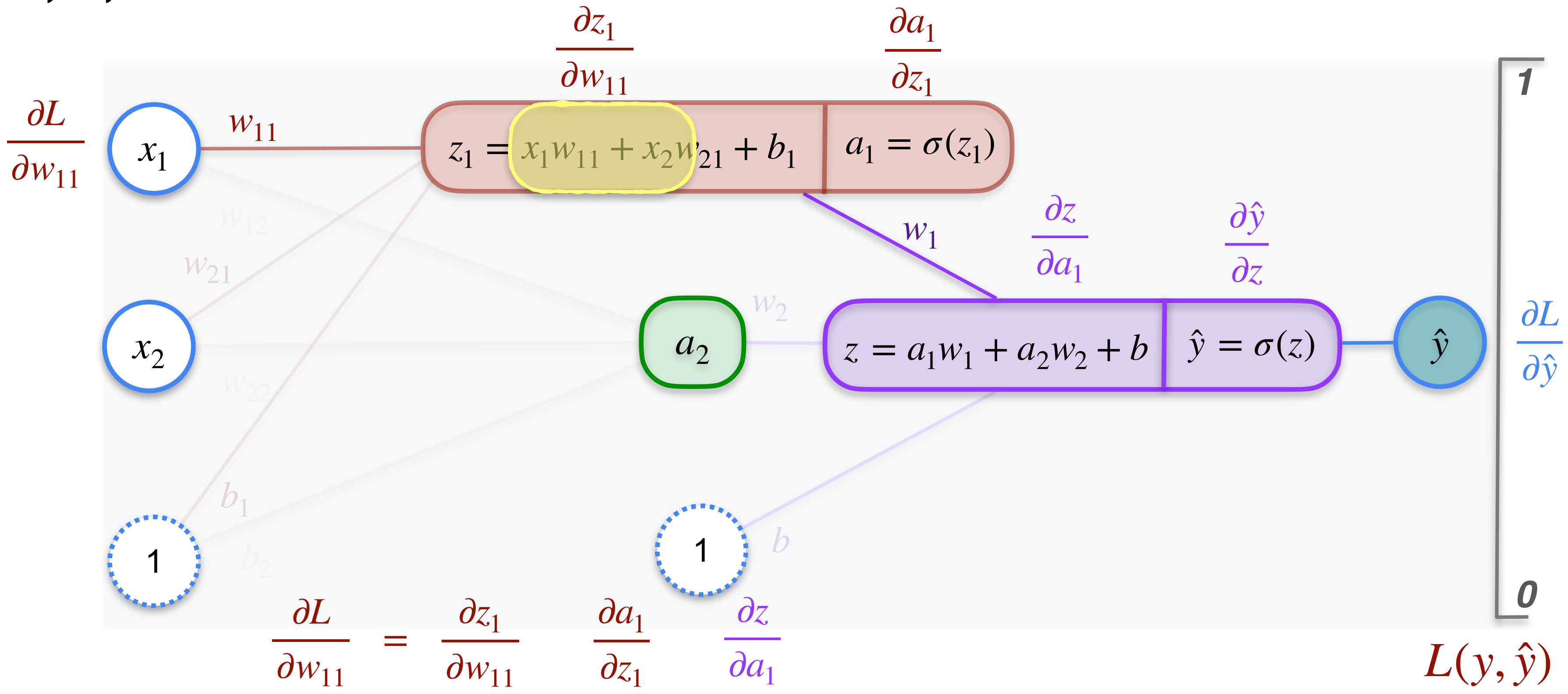
$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}}$$

2,2,1 Neural Network



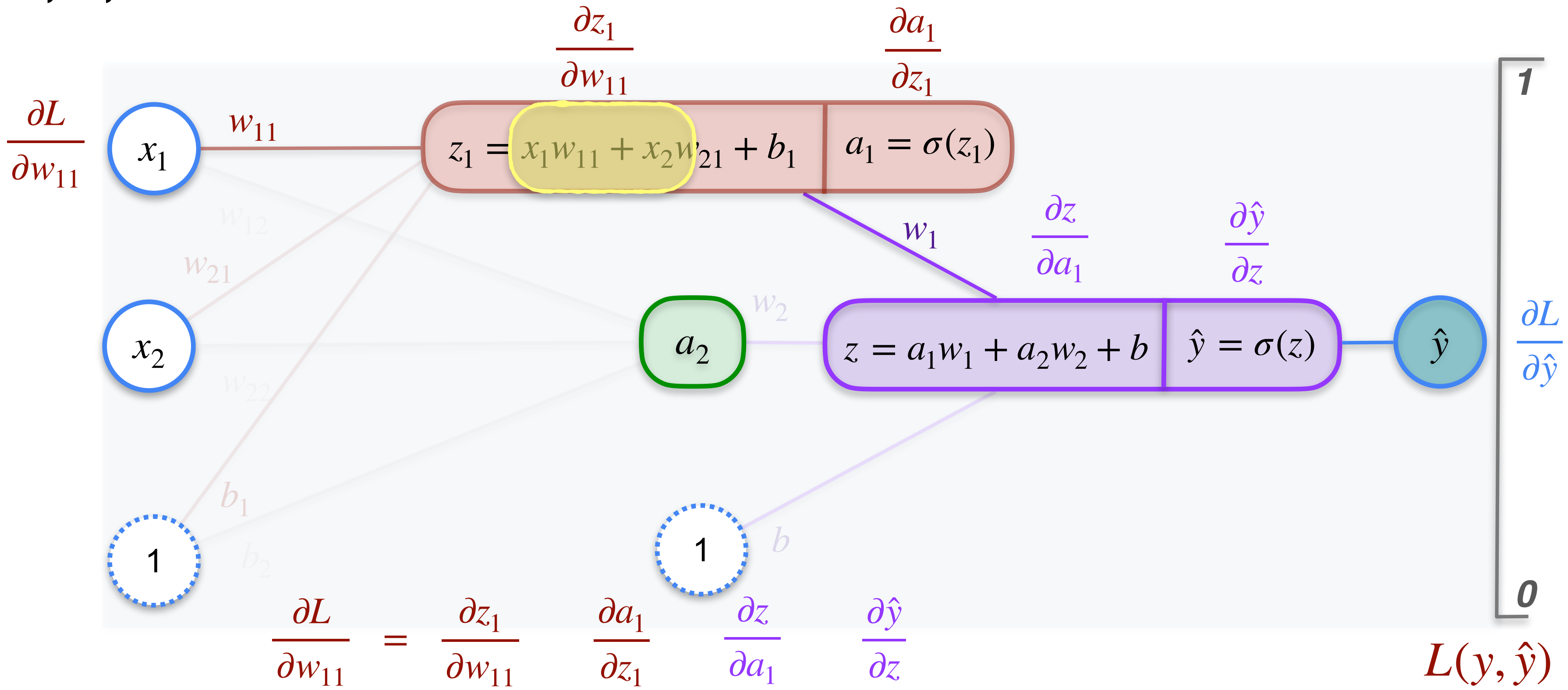
$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \quad \frac{\partial a_1}{\partial z_1}$$

2,2,1 Neural Network



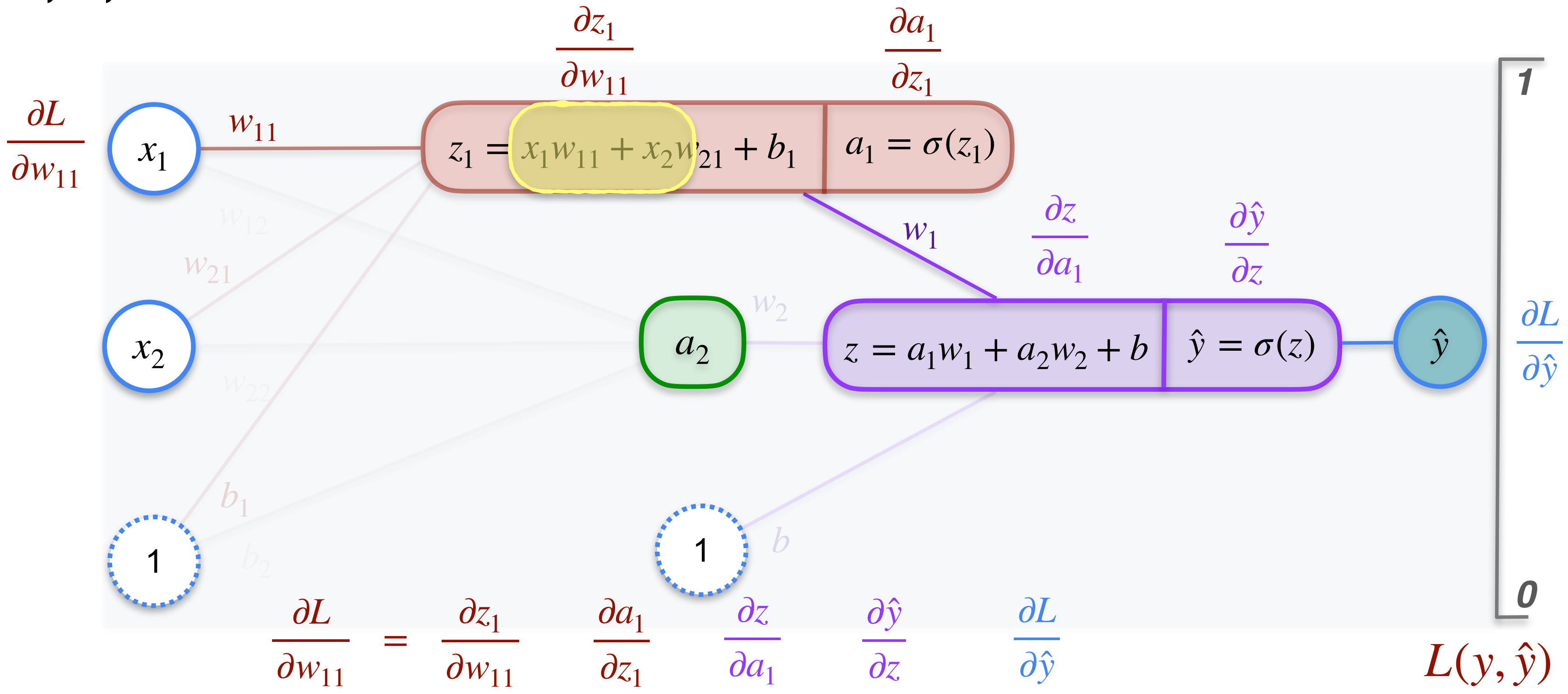
$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \quad \frac{\partial a_1}{\partial z_1} \quad \frac{\partial z}{\partial a_1}$$

2,2,1 Neural Network

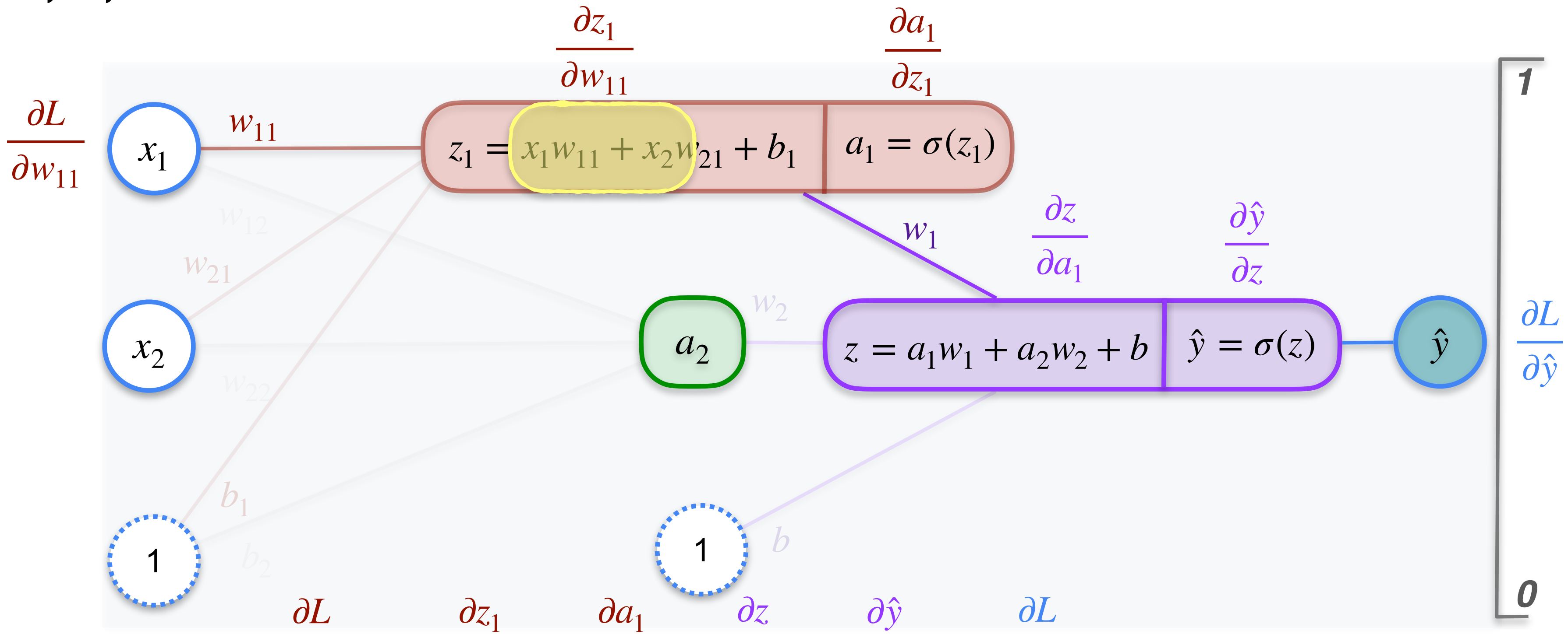


$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \quad \frac{\partial a_1}{\partial z_1} \quad \frac{\partial z}{\partial a_1} \quad \frac{\partial \hat{y}}{\partial z}$$

2,2,1 Neural Network



2,2,1 Neural Network



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

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

2,2,1 Neural Network

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

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

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

$$a_1 = \sigma(z_1)$$

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

2,2,1 Neural Network

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

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

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

$$a_1 = \sigma(z_1)$$

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

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

2,2,1 Neural Network

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

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

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

$$\frac{\partial L}{\partial w_{11}}$$

2,2,1 Neural Network

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

$$\frac{\partial L}{\partial w_{11}} =$$

2,2,1 Neural Network

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

$$\frac{\partial L}{\partial w_{11}} =$$

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

$$\frac{\partial L}{\partial w_{11}} =$$

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2,2,1 Neural Network

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

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$a_1 = \sigma(z_1)$

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

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

$$\frac{\partial L}{\partial w_{11}} = x_1$$

2,2,1 Neural Network

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

$$\frac{\partial L}{\partial w_{11}} = x_1$$

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2,2,1 Neural Network

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$$\frac{\partial L}{\partial w_{11}} = x_1$$

2,2,1 Neural Network

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

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

2,2,1 Neural Network

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

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

2,2,1 Neural Network

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

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

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2,2,1 Neural Network

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

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

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2,2,1 Neural Network

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

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

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

2,2,1 Neural Network

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

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

2,2,1 Neural Network

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

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

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

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

2,2,1 Neural Network

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

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

$z = a_1 w_1 + a_2 w_2 + b$

$a_1 = \sigma(z_1)$

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

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

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

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2,2,1 Neural Network

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$$= -x_1 w_1 a_1 (1 - a_1)(y - \hat{y})$$

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Perform gradient descent with

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

2,2,1 Neural Network

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

$$= -x_1 w_1 a_1 (1-a_1)(y \ - \ \hat{y})$$

Perform gradient descent with

$$w_{11} \ \rightarrow \ w_{11} - \alpha \frac{\partial L}{\partial w_{11}}$$

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

2,2,1 Neural Network

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$$= -x_1 w_1 a_1(1-a_1)(y - \hat{y})$$

Perform gradient descent with

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

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

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2,2,1 Neural Network

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$$= -x_1w_1a_1(1-a_1)(y - \hat{y})$$

Perform gradient descent with

$$w_{11} \rightarrow w_{11} - \alpha\text{-}x_1w_1a_1(1-a_1)(y - \hat{y})$$

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

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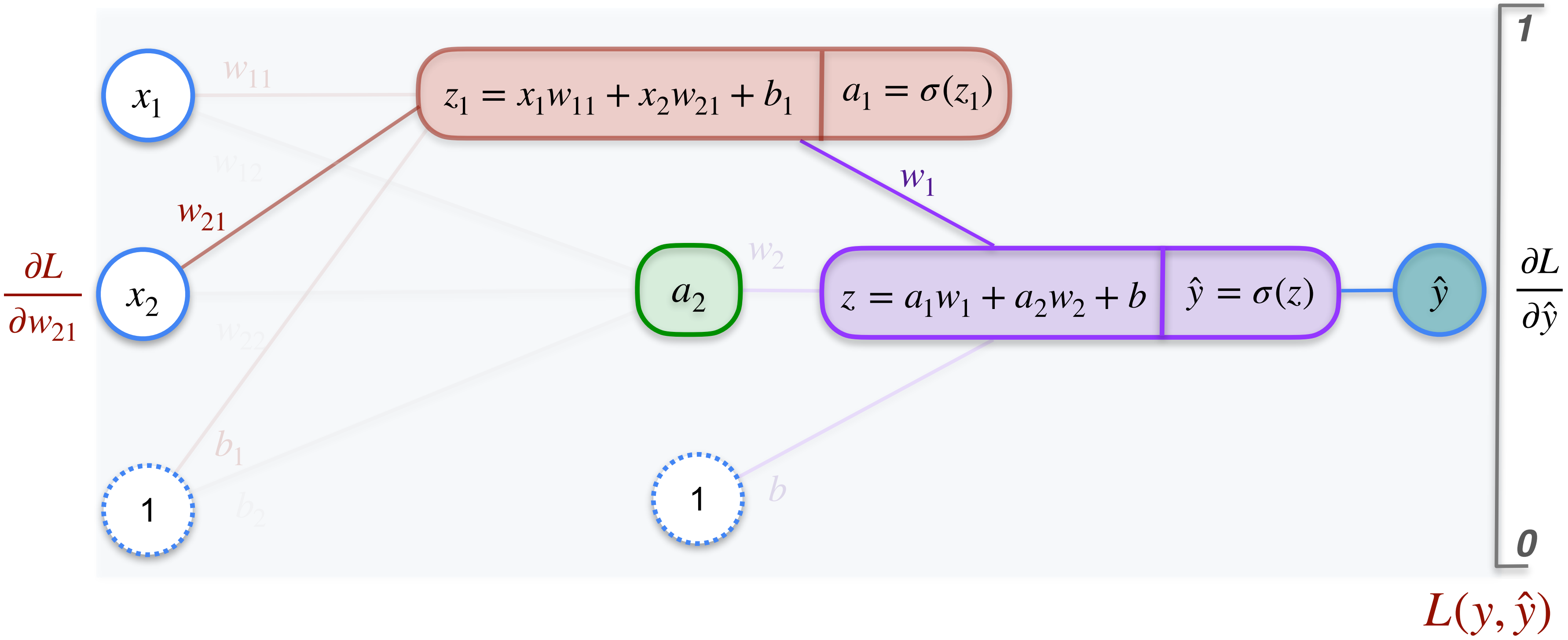
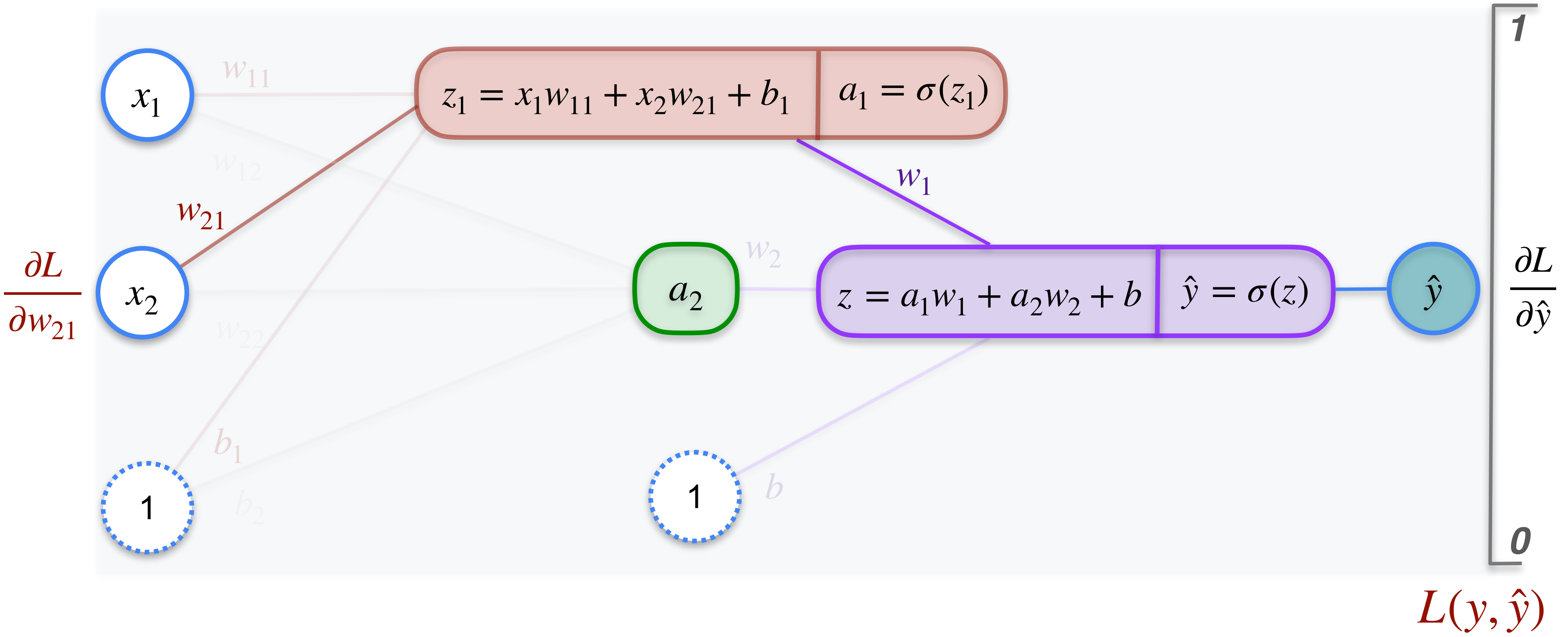
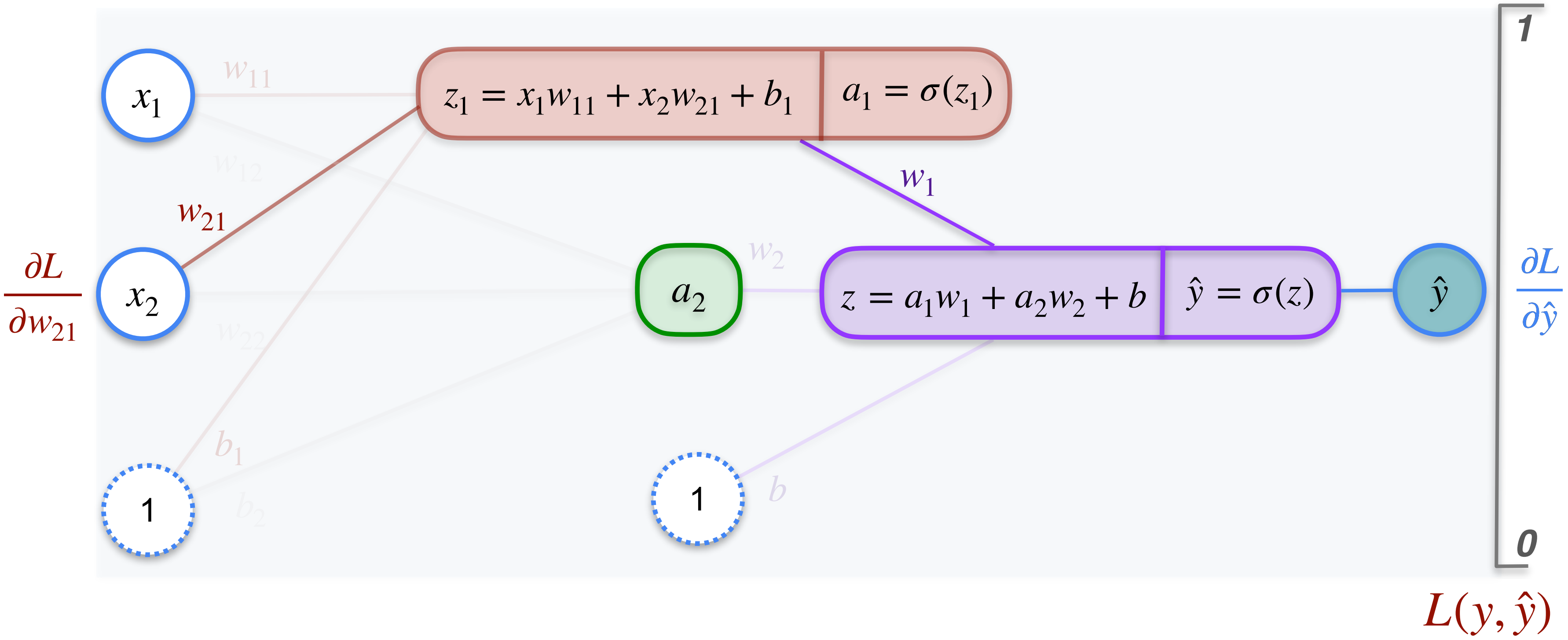
2,2,1 Neural Network



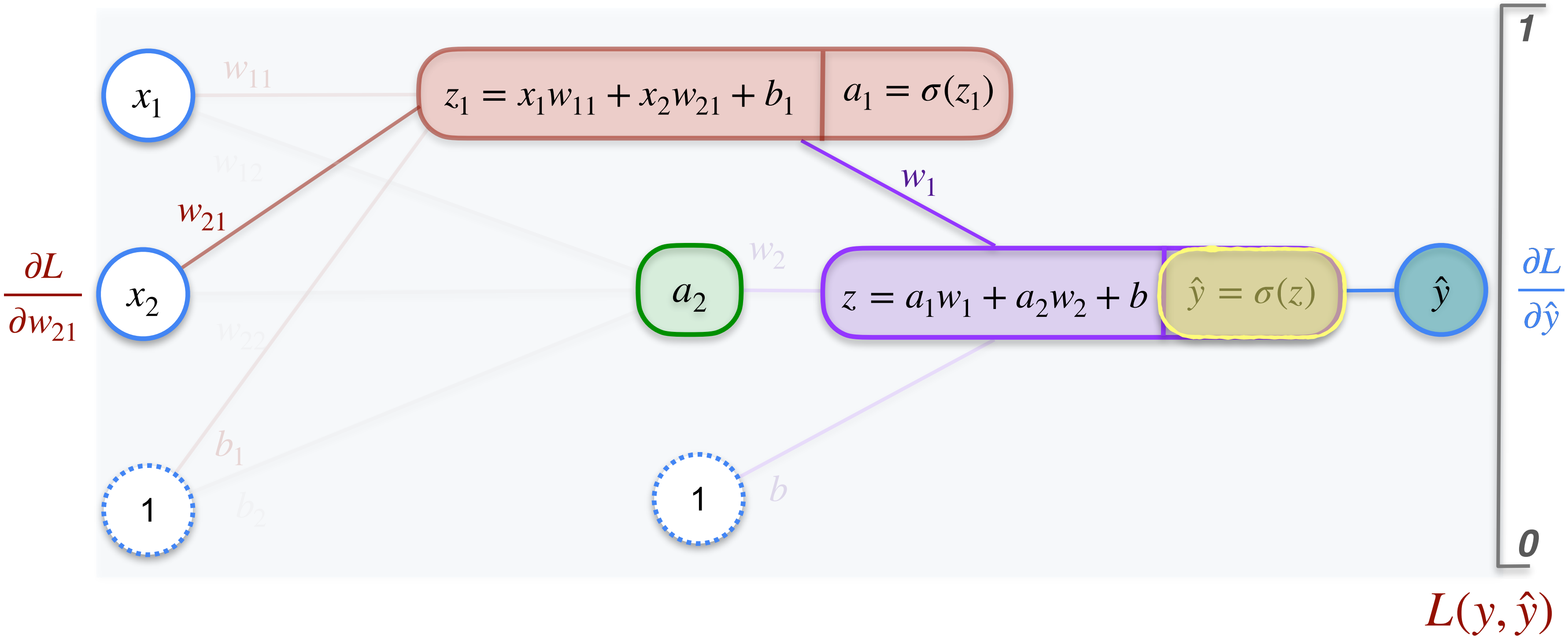
2,2,1 Neural Network



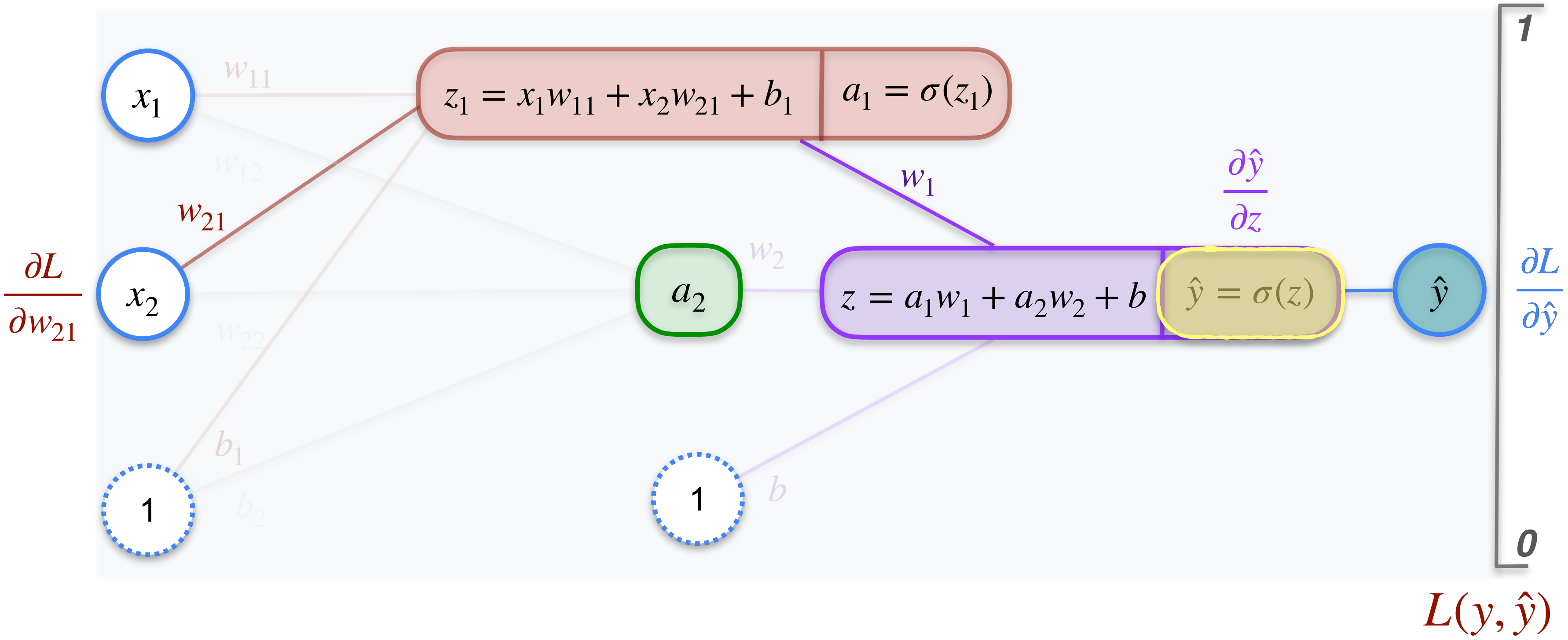
2,2,1 Neural Network



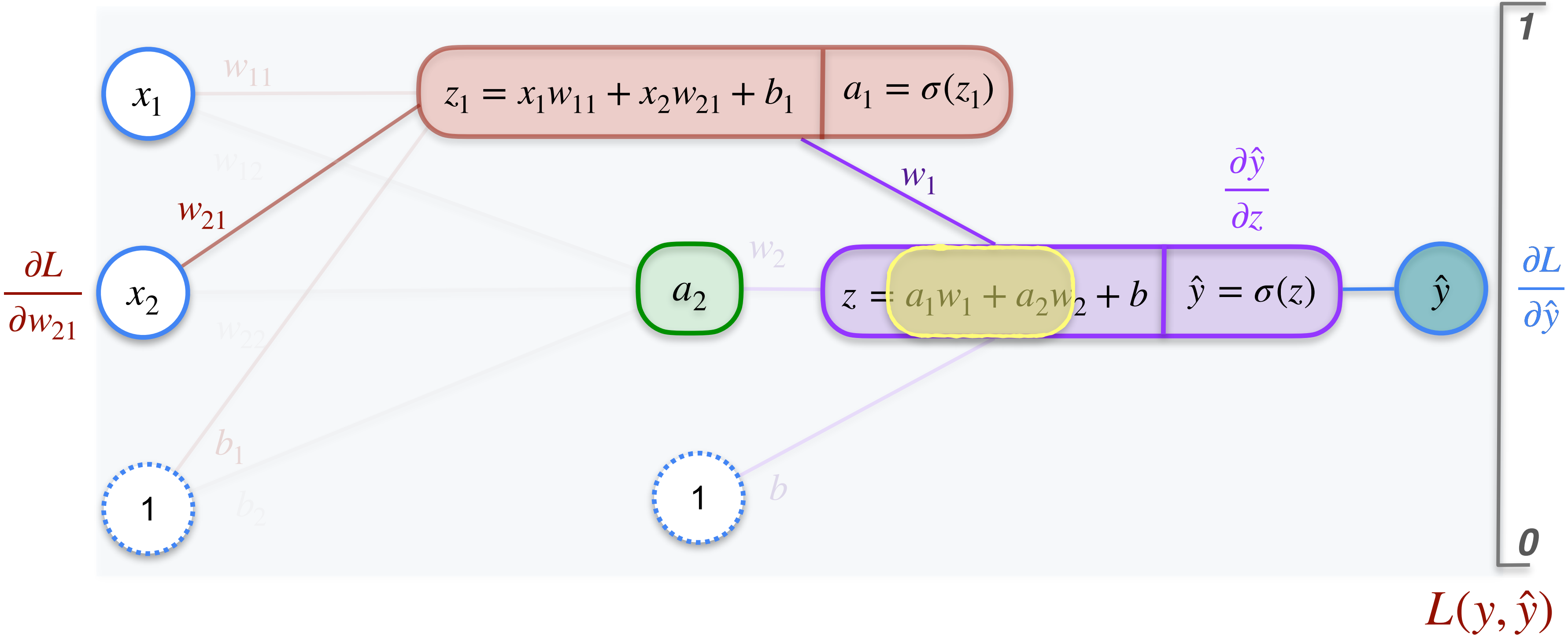
2,2,1 Neural Network



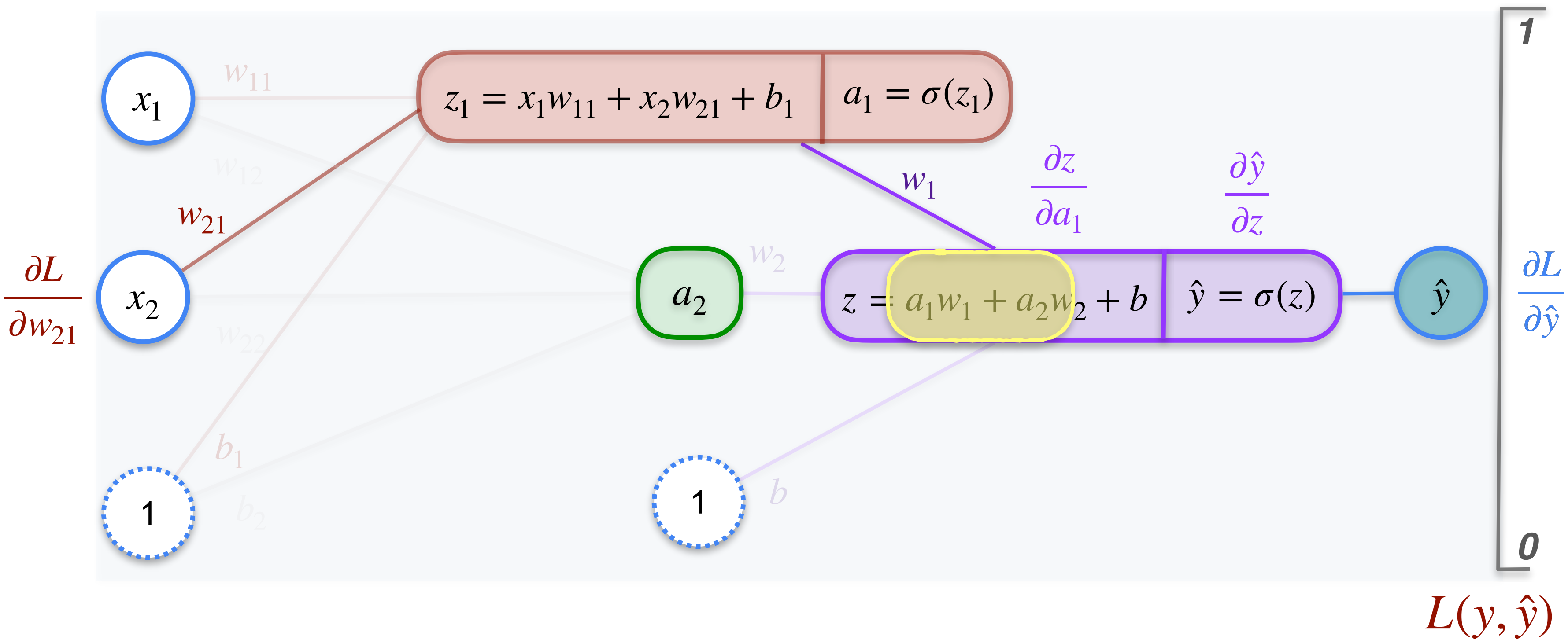
2,2,1 Neural Network



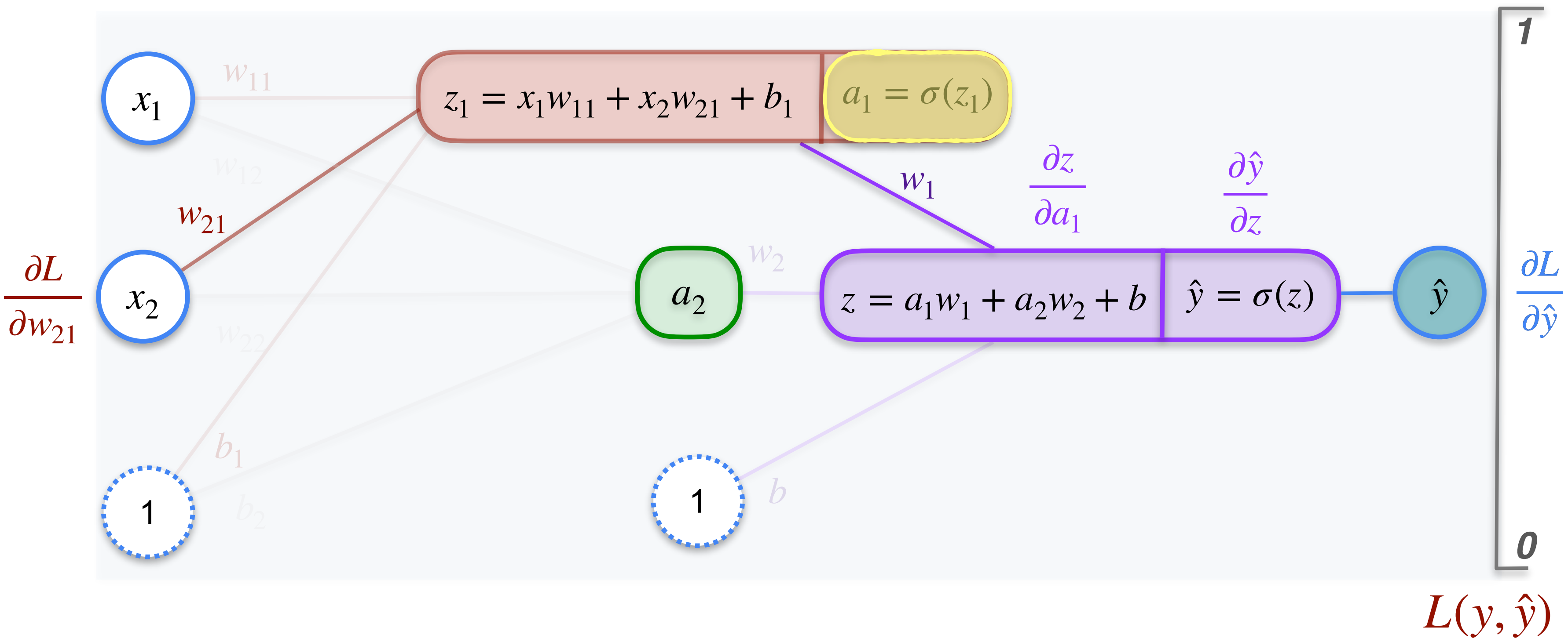
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



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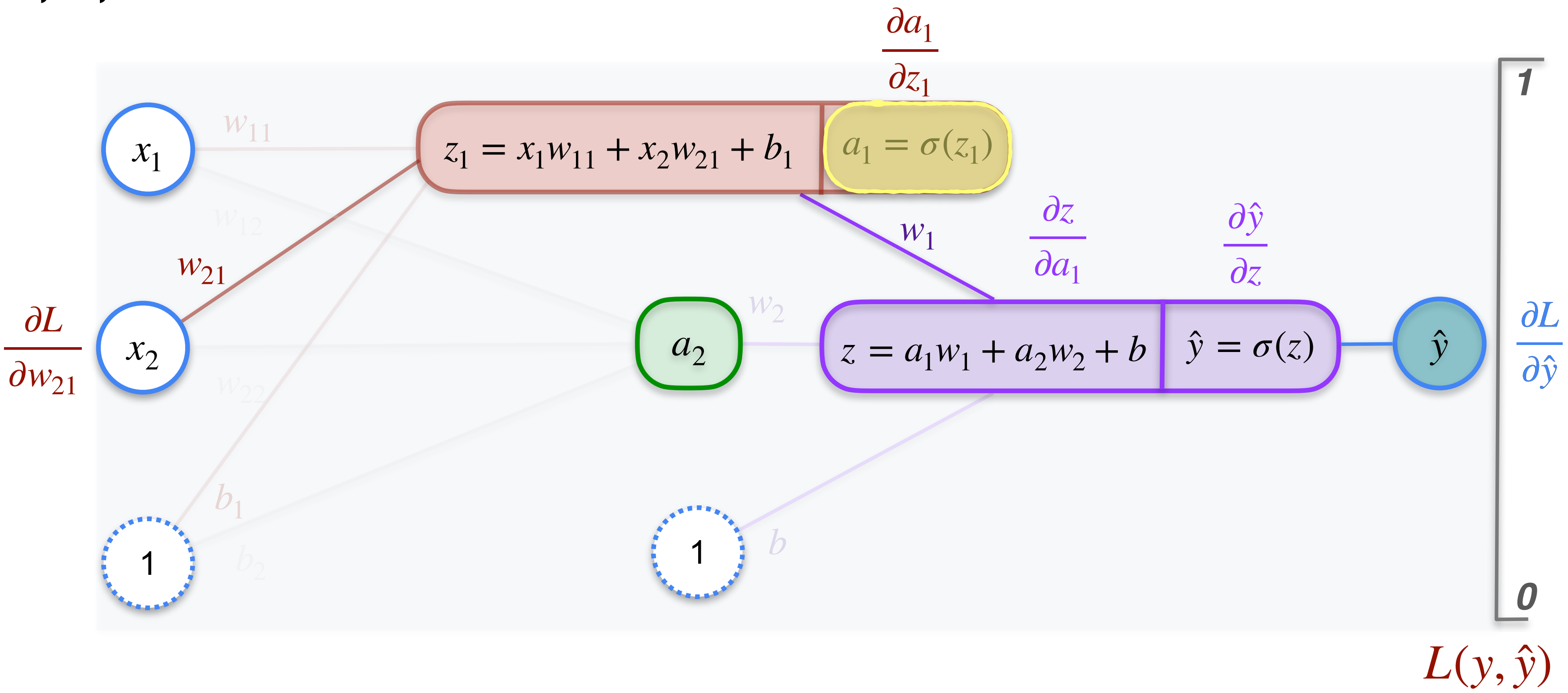
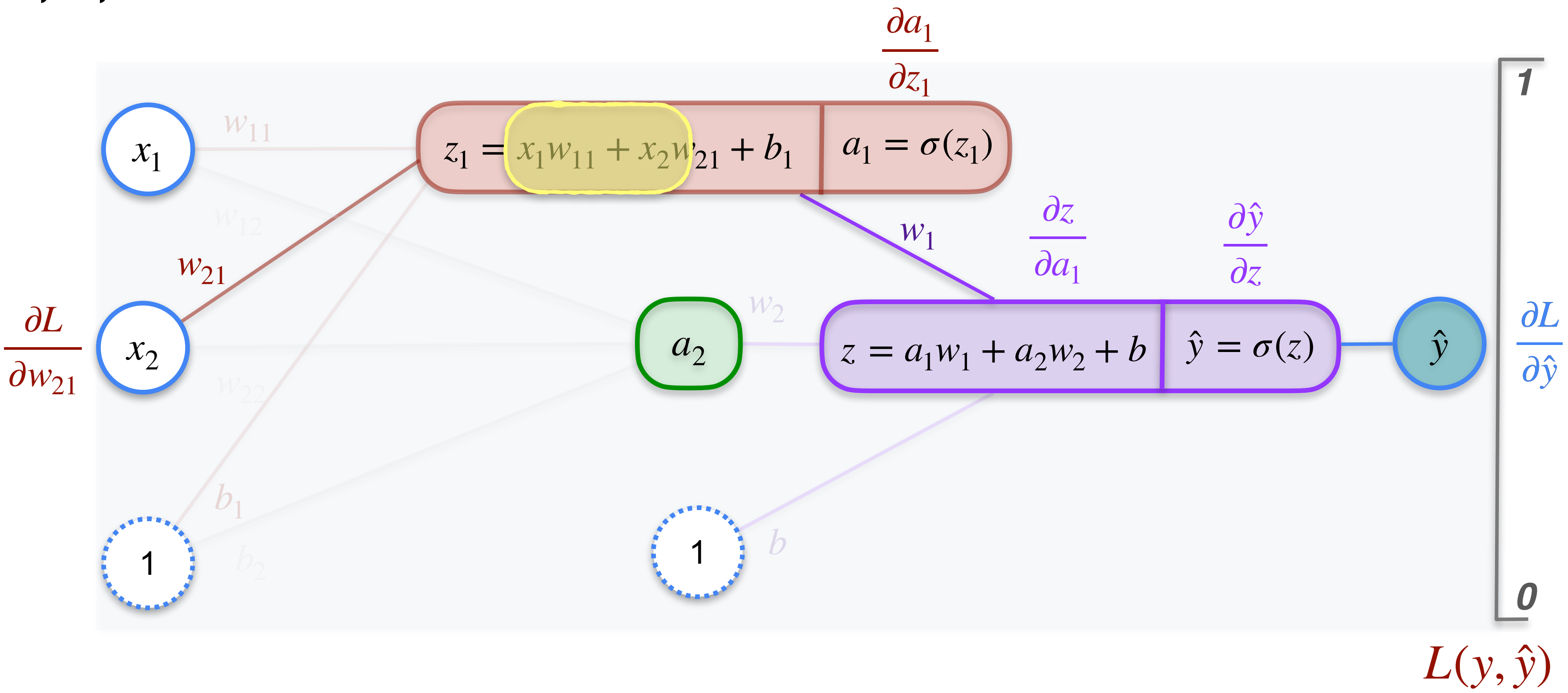
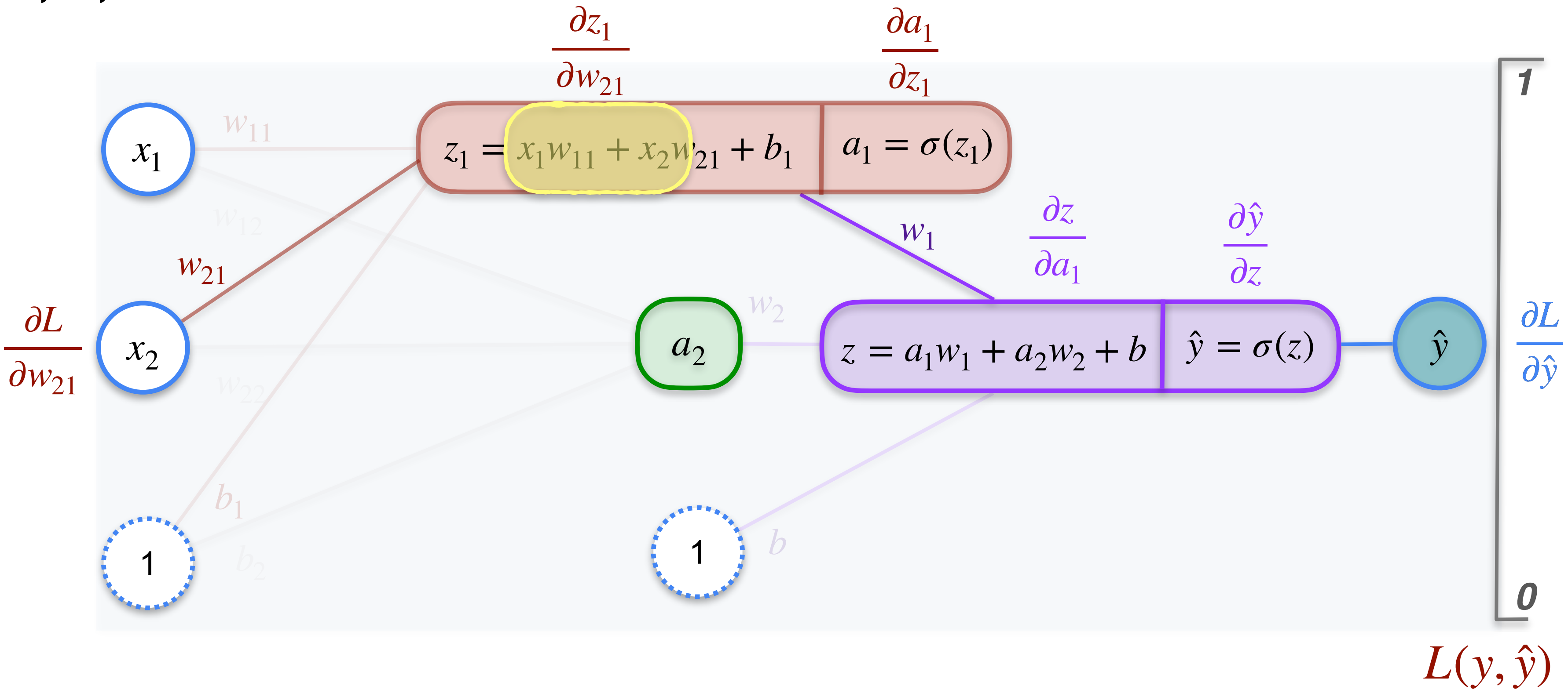
2,2,1 Neural Network



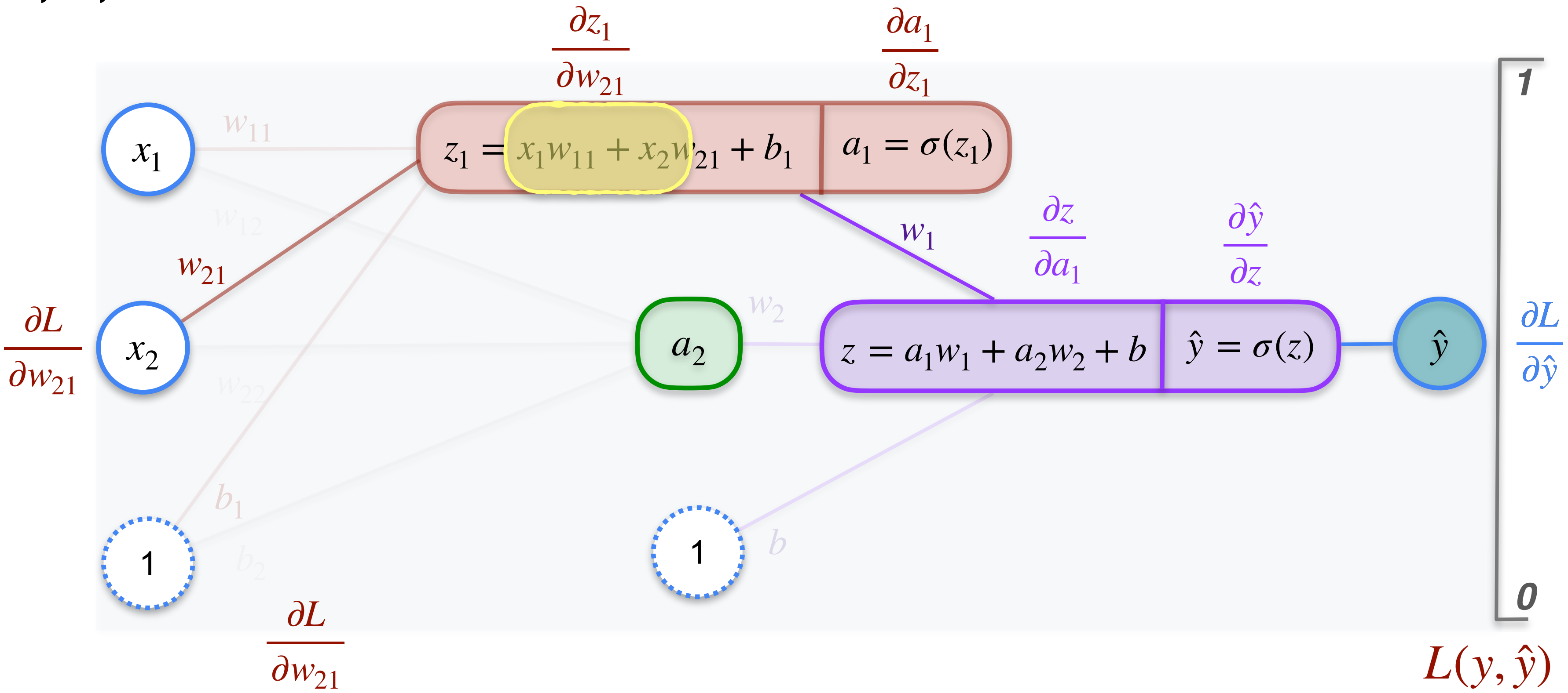
2,2,1 Neural Network



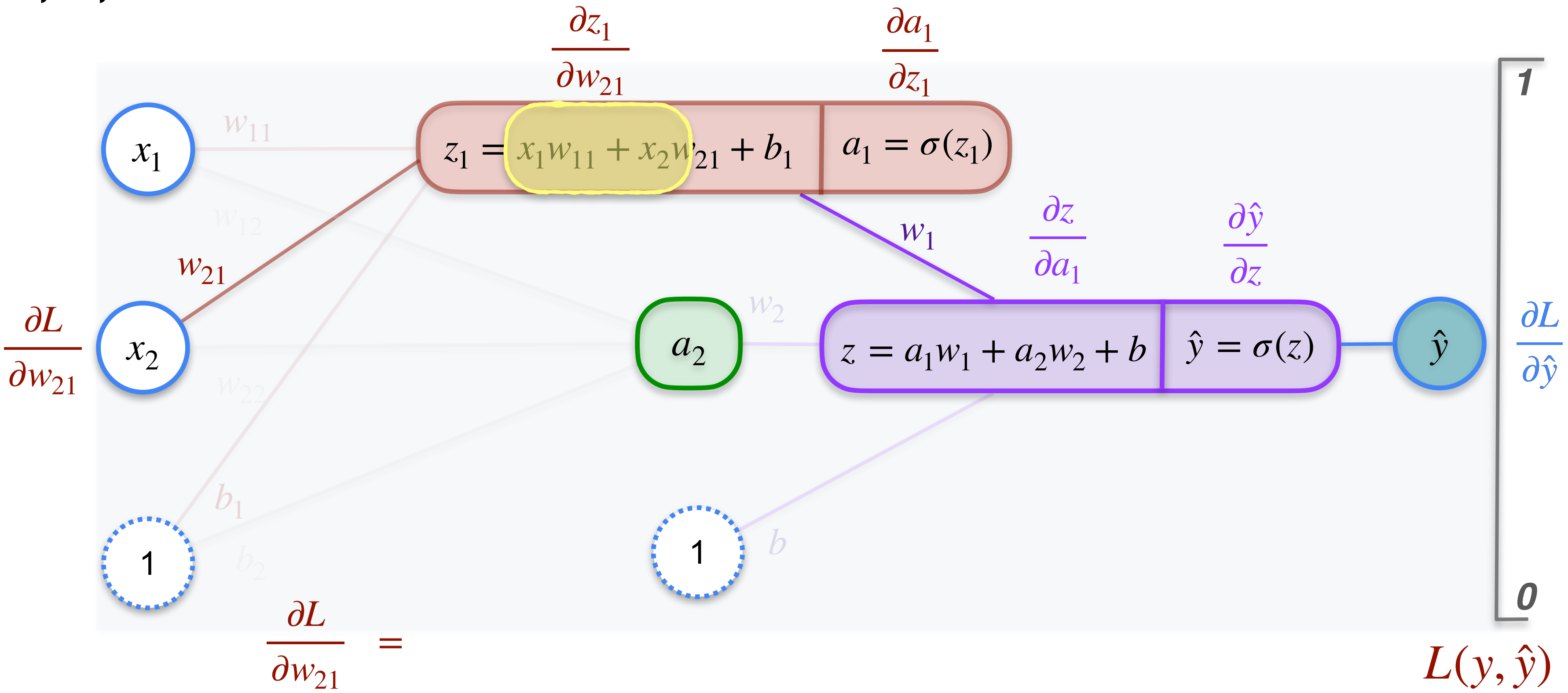
2,2,1 Neural Network



2,2,1 Neural Network

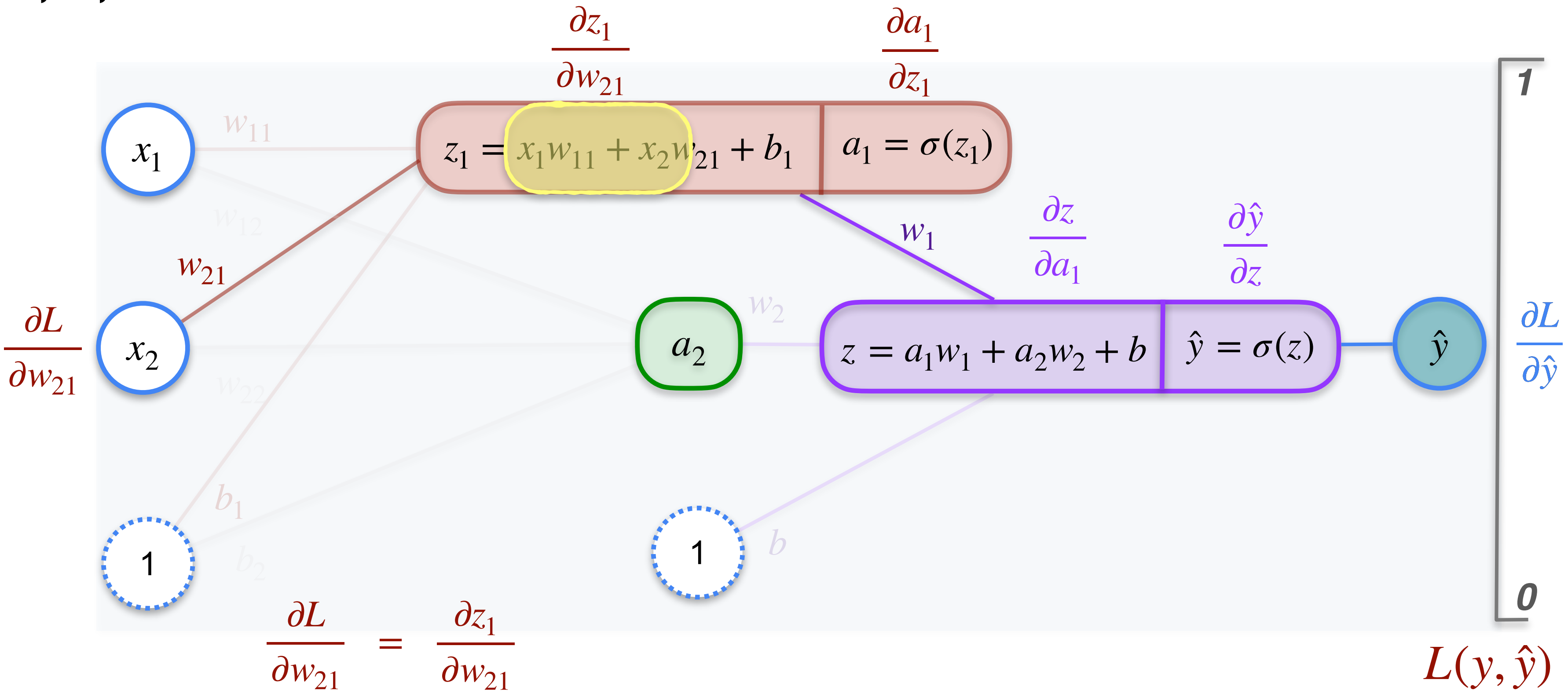


2,2,1 Neural Network

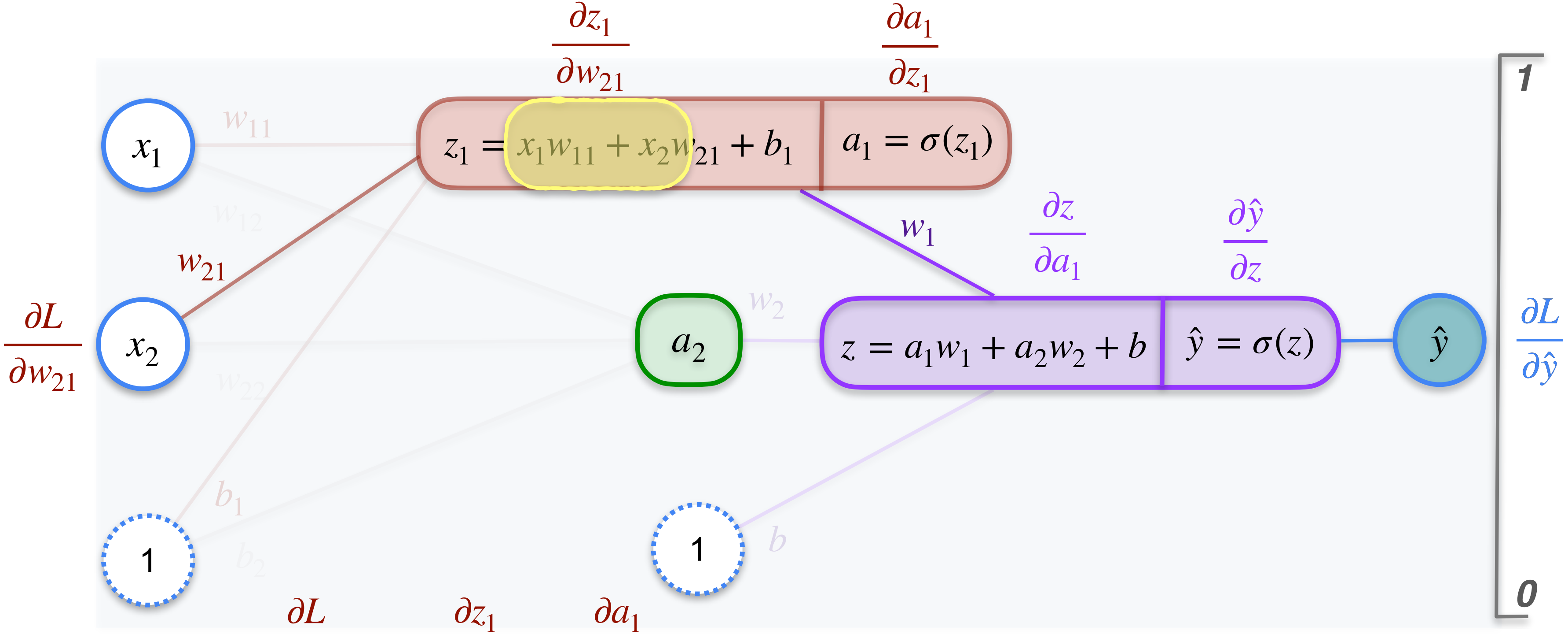


$$\frac{\partial L}{\partial w_{21}} =$$

2,2,1 Neural Network

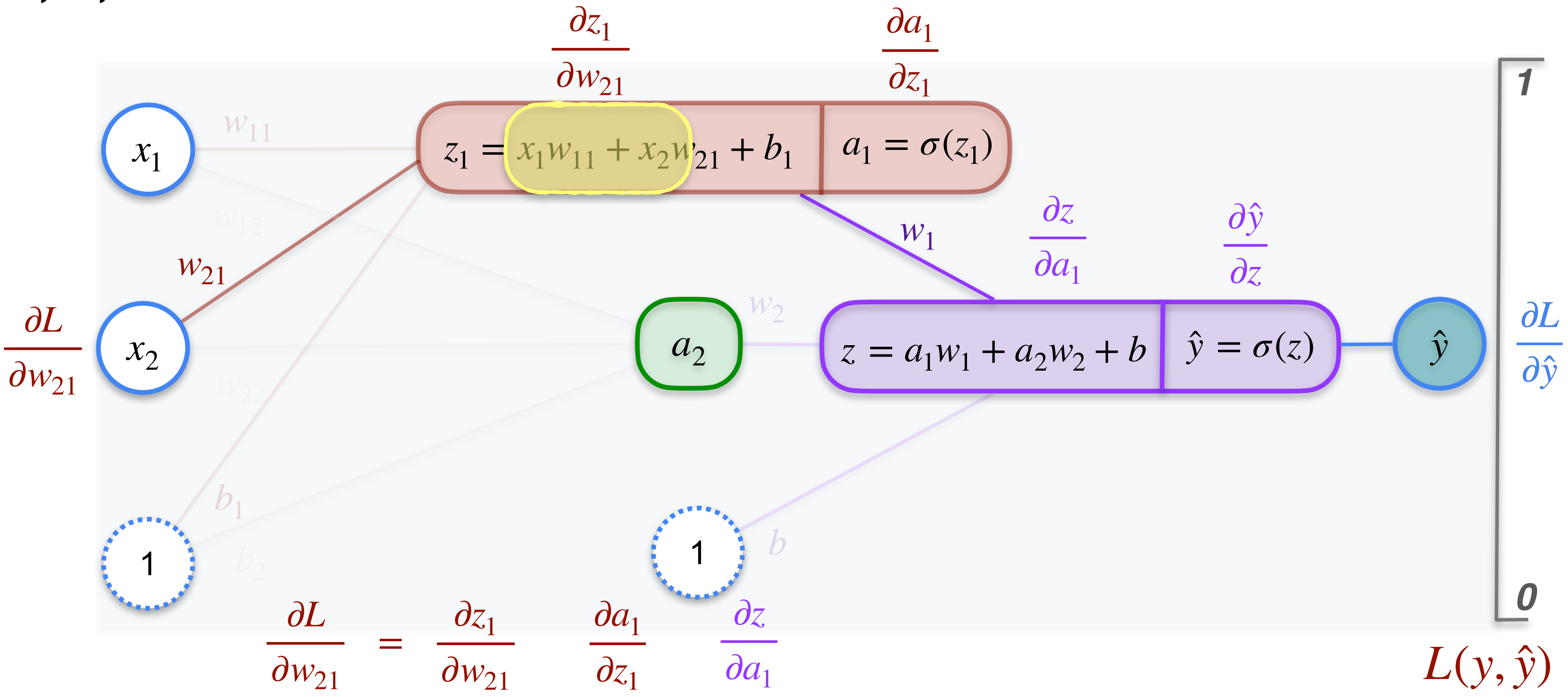


2,2,1 Neural Network

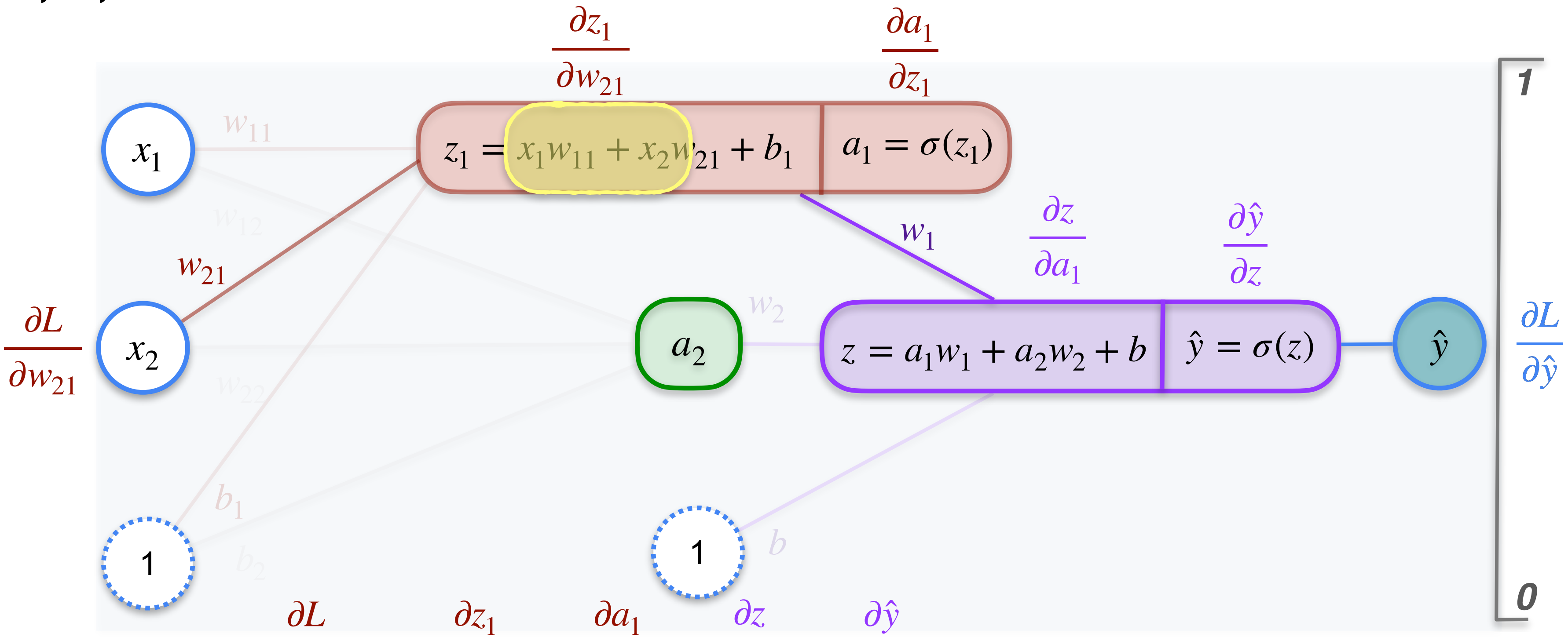


$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \quad \frac{\partial a_1}{\partial z_1}$$

2,2,1 Neural Network

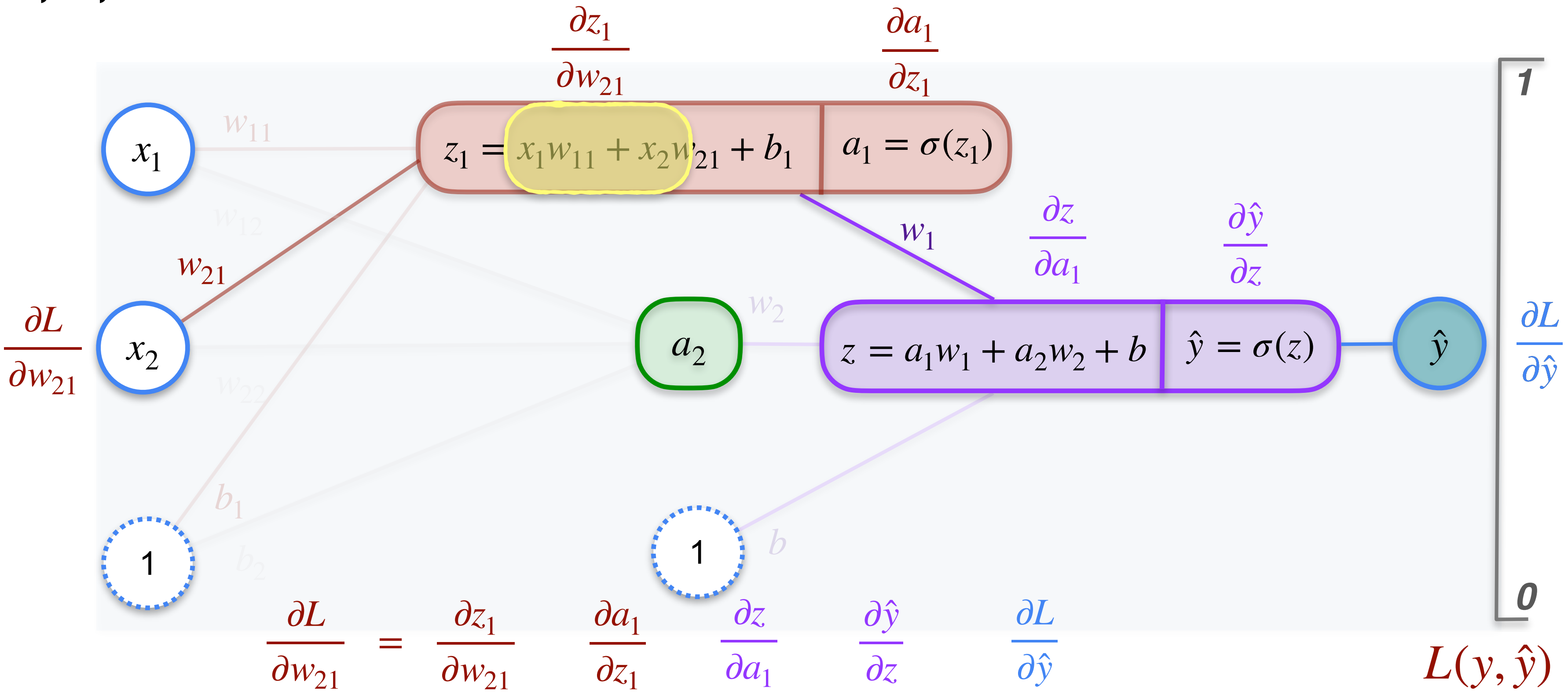


2,2,1 Neural Network



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

2,2,1 Neural Network



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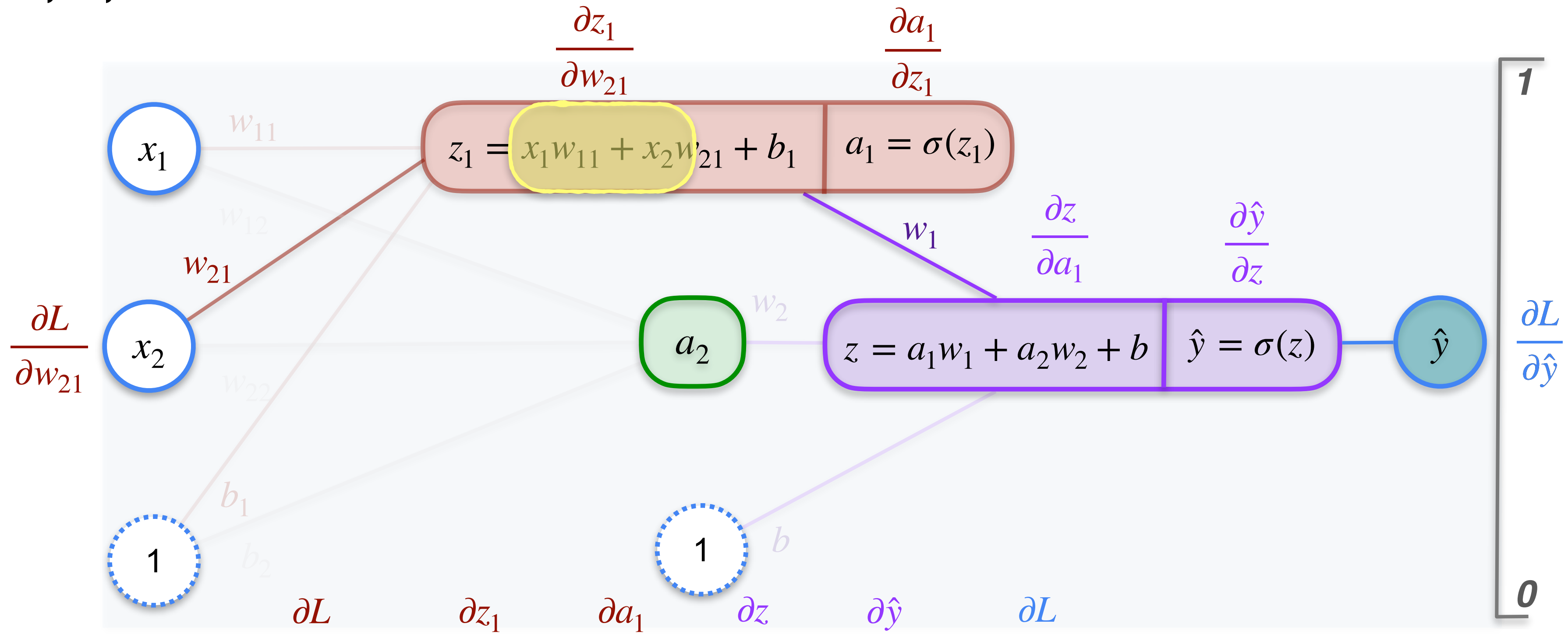
2,2,1 Neural Network



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

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$$\frac{\partial L}{\partial w_{21}}$$

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$$\frac{\partial L}{\partial w_{21}} = x_2$$

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

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2,2,1 Neural Network

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

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$z = a_1 w_1 + a_2 w_2 + b$

$a_1 = \sigma(z_1)$

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

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

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

DeepLearning.AI

2,2,1 Neural Network

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

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DeepLearning.AI

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$$= -x_2 w_1 a_1 (1-a_1)(y - \hat{y})$$

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Perform gradient descent with

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

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2,2,1 Neural Network

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$$= -x_2w_1a_1(1-a_1)(y - \hat{y})$$

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

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$$= -x_2 w_1 a_1 (1-a_1)(y - \hat{y})$$

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

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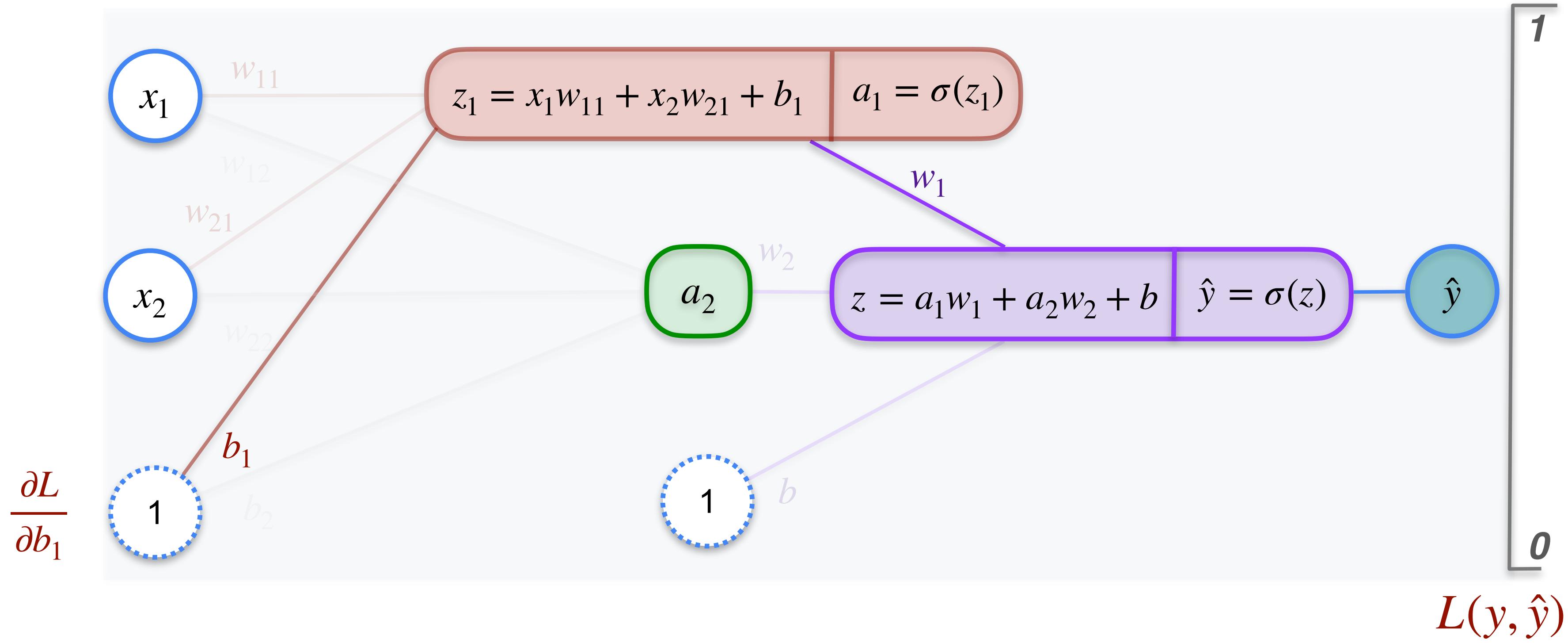
Perform gradient descent with

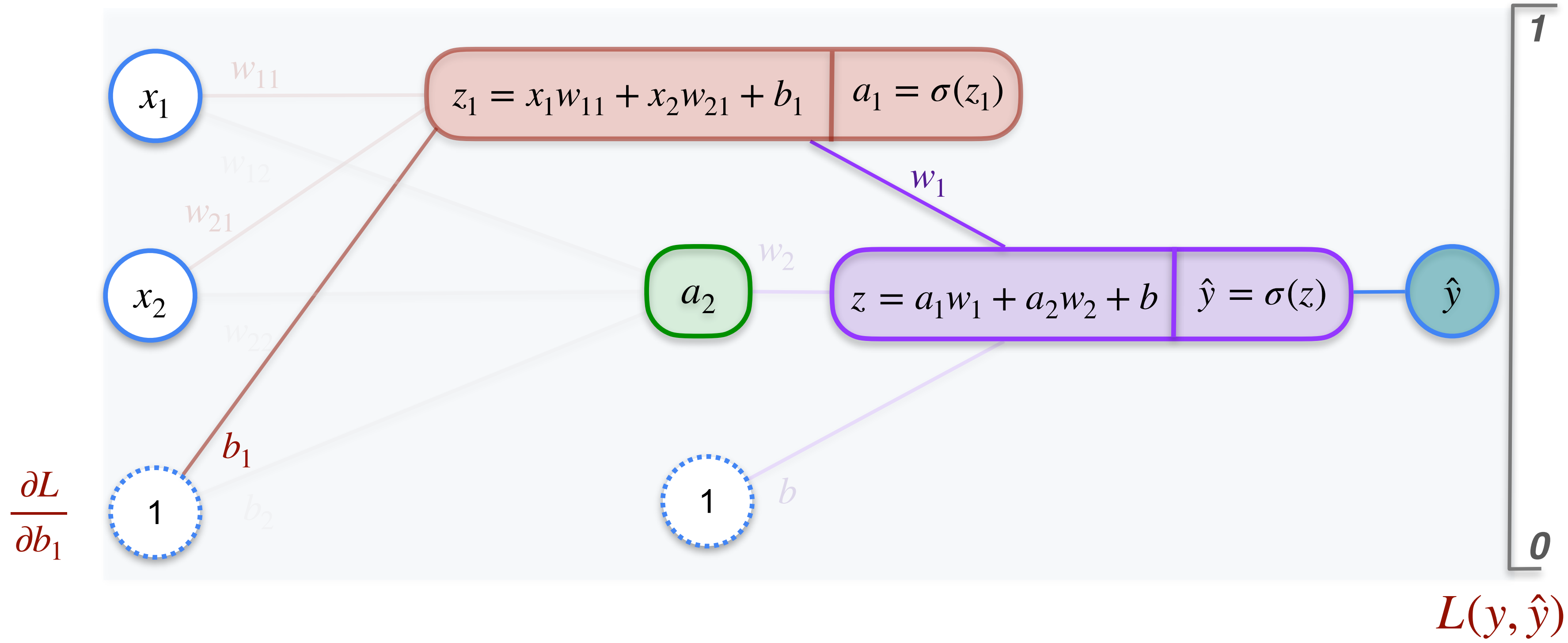
$$w_{21} \rightarrow w_{21} - \alpha \text{-} x_2 w_1 a_1 (1 - a_1)(y - \hat{y})$$

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

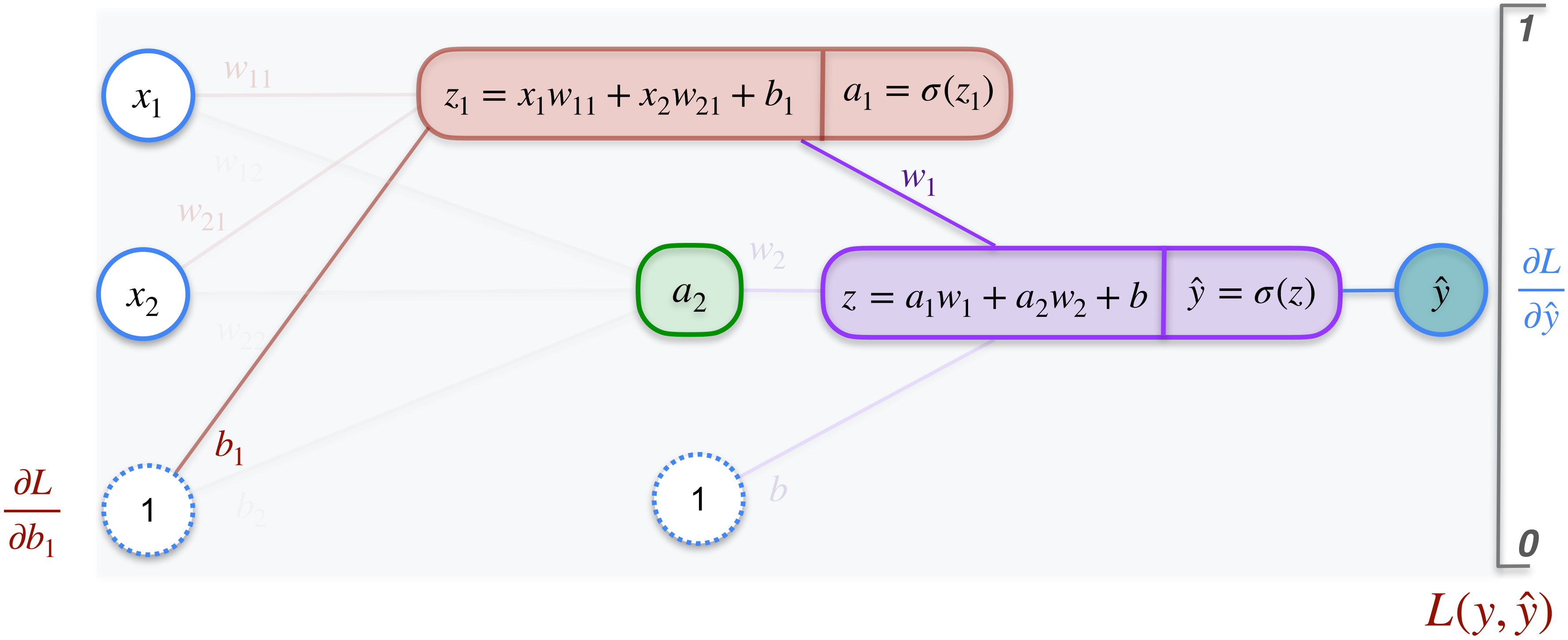
2,2,1 Neural Network



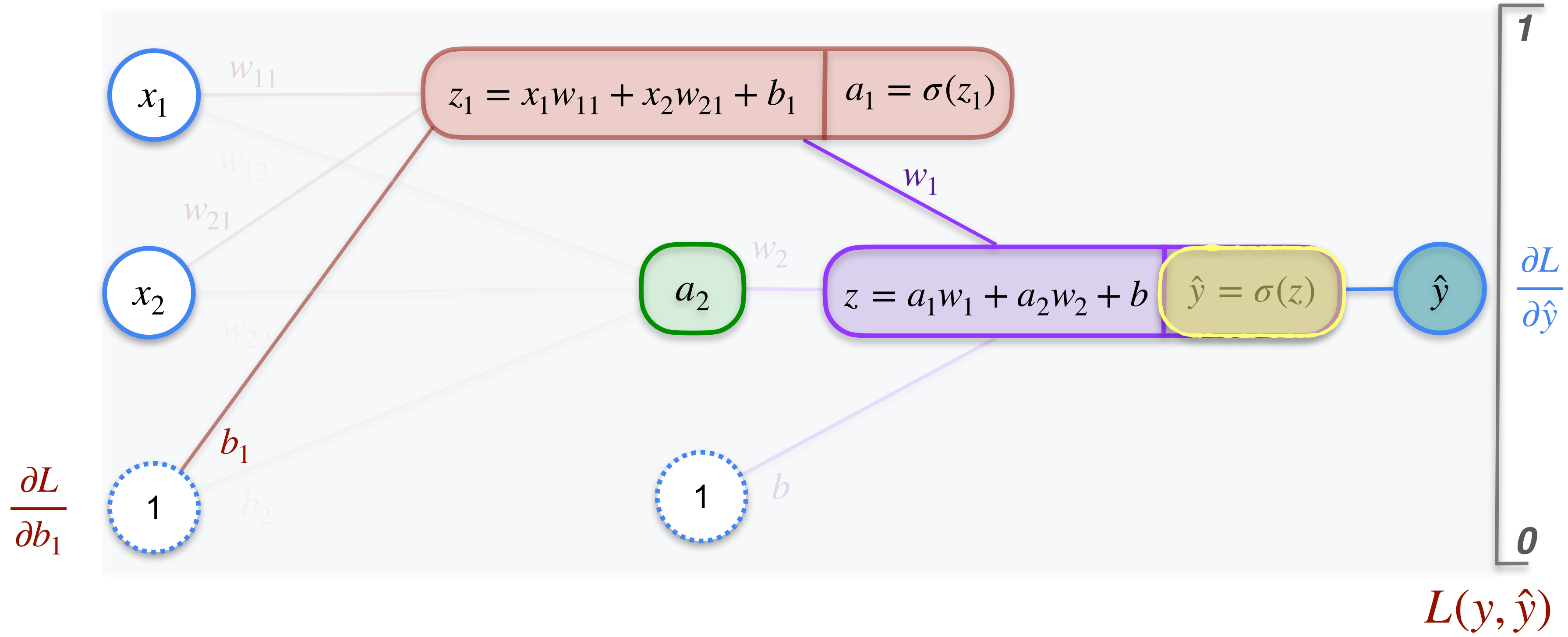
2,2,1 Neural Network



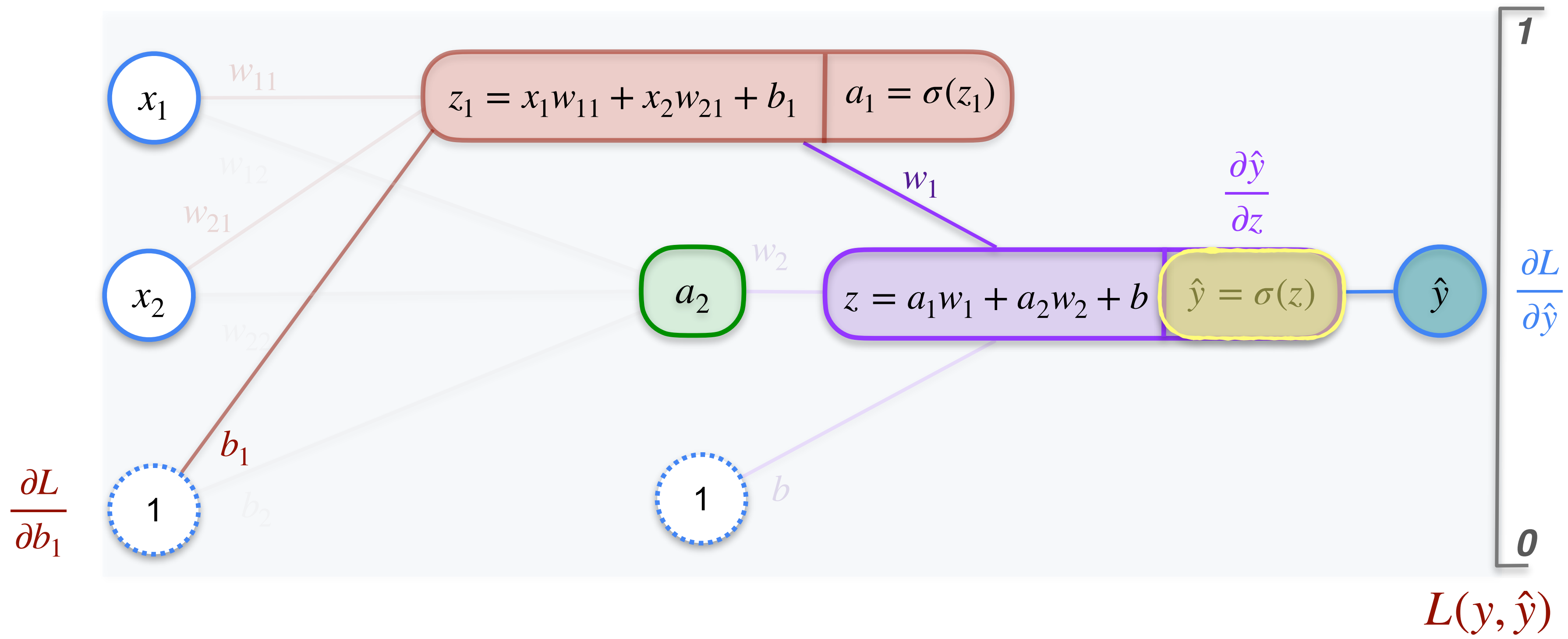
2,2,1 Neural Network



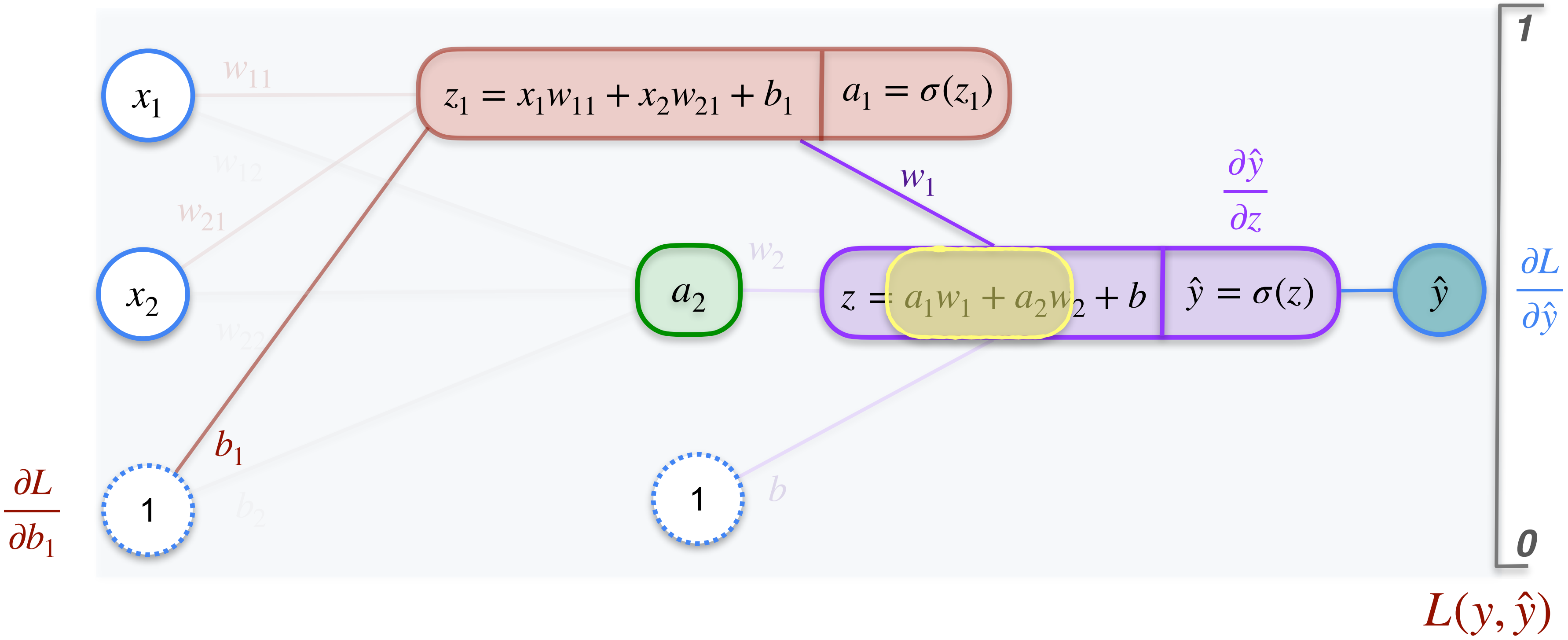
2,2,1 Neural Network



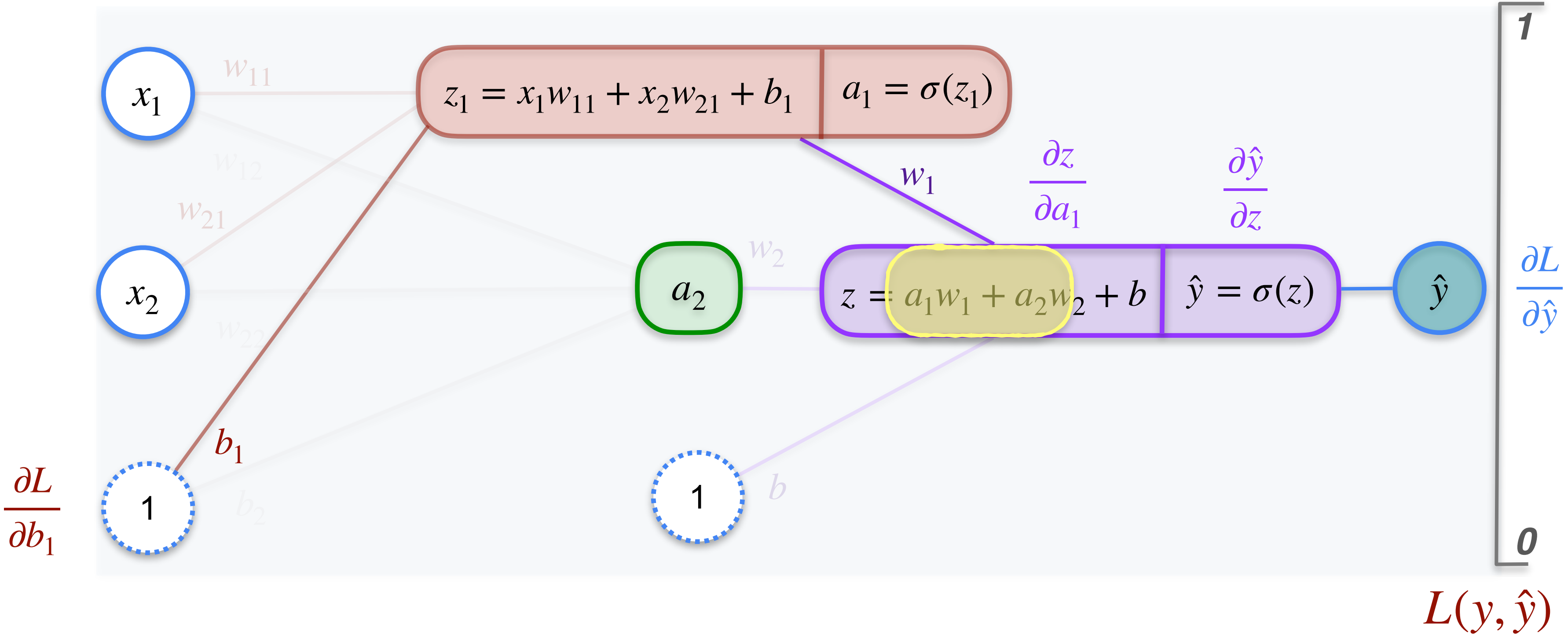
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



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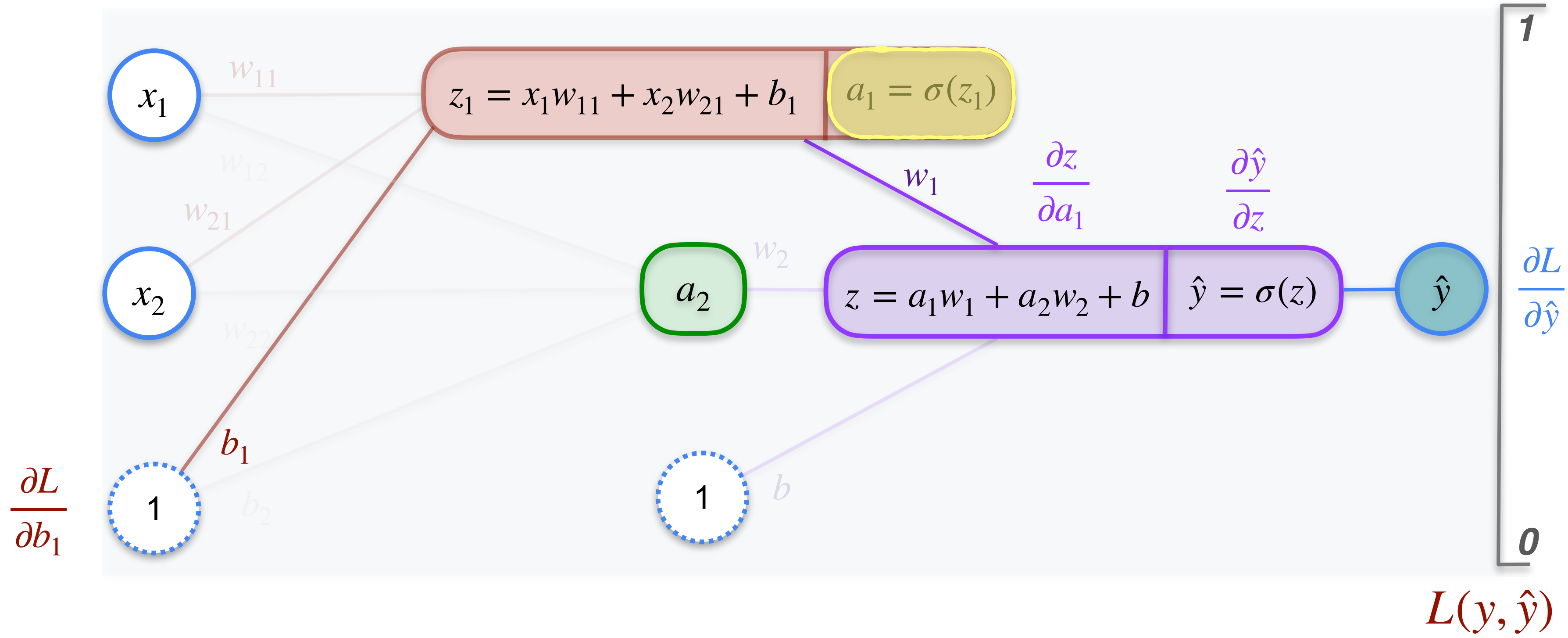
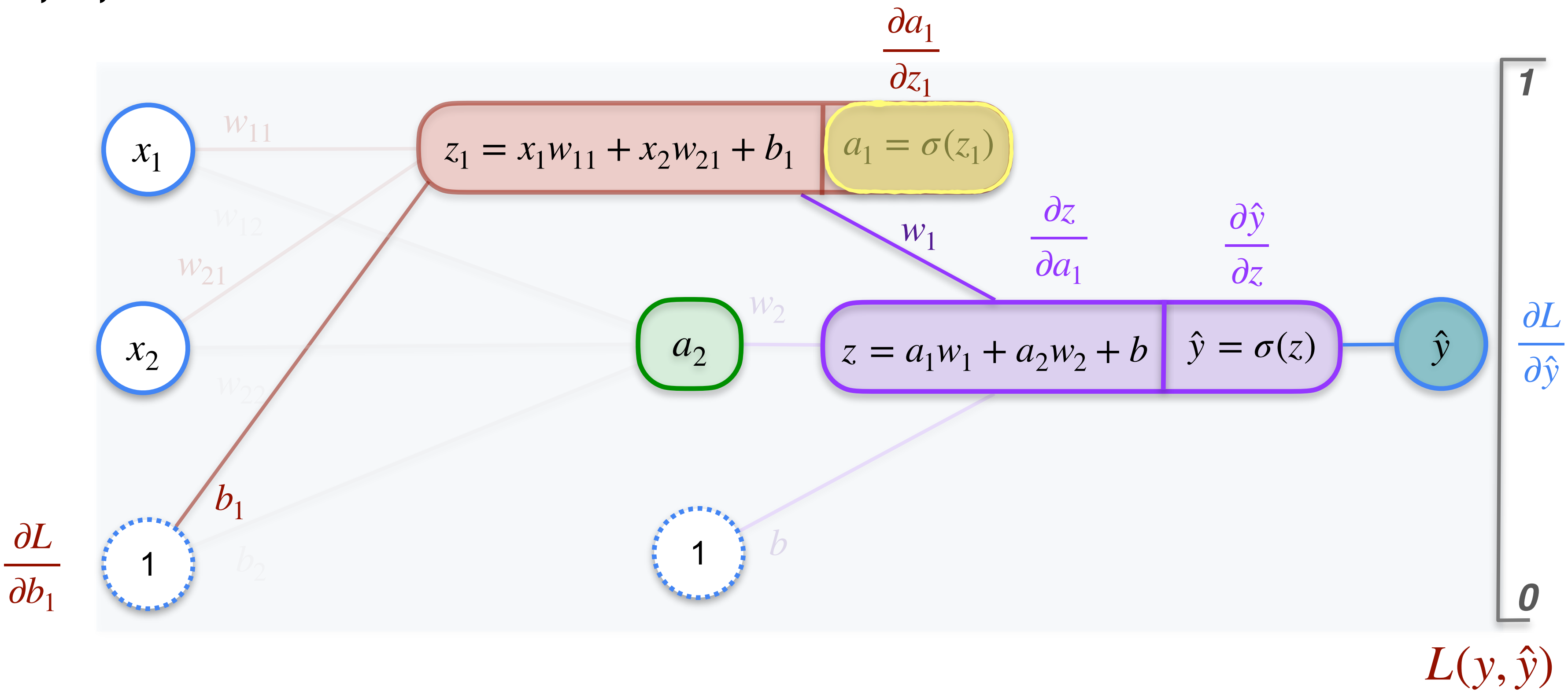
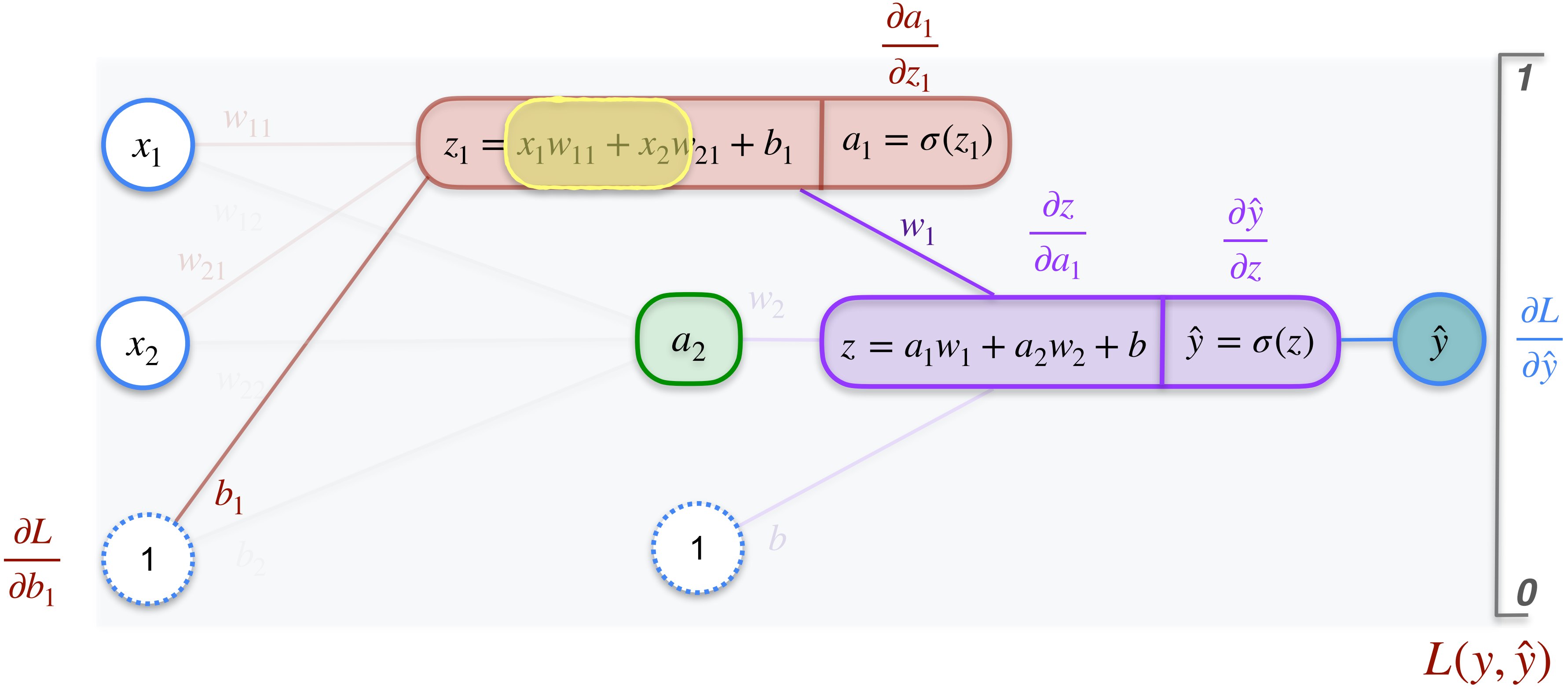
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



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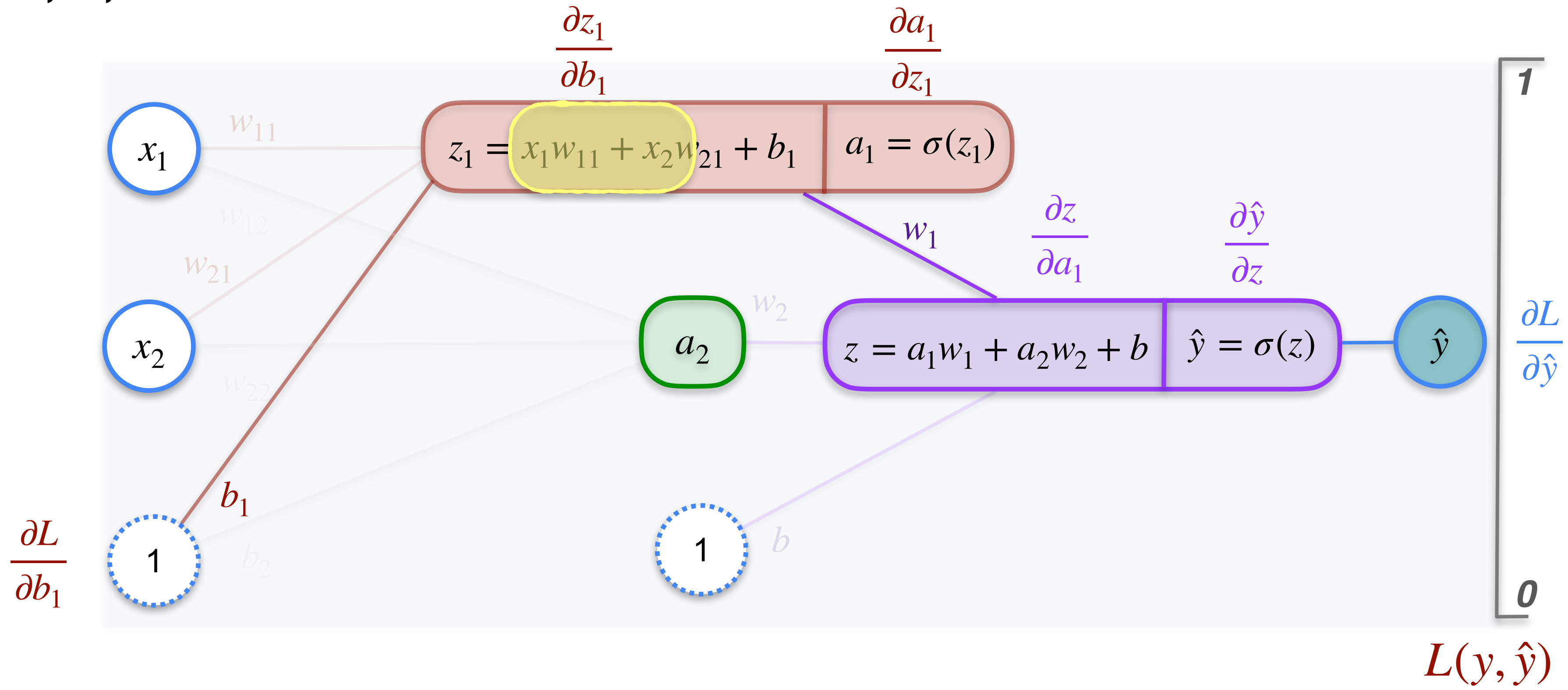
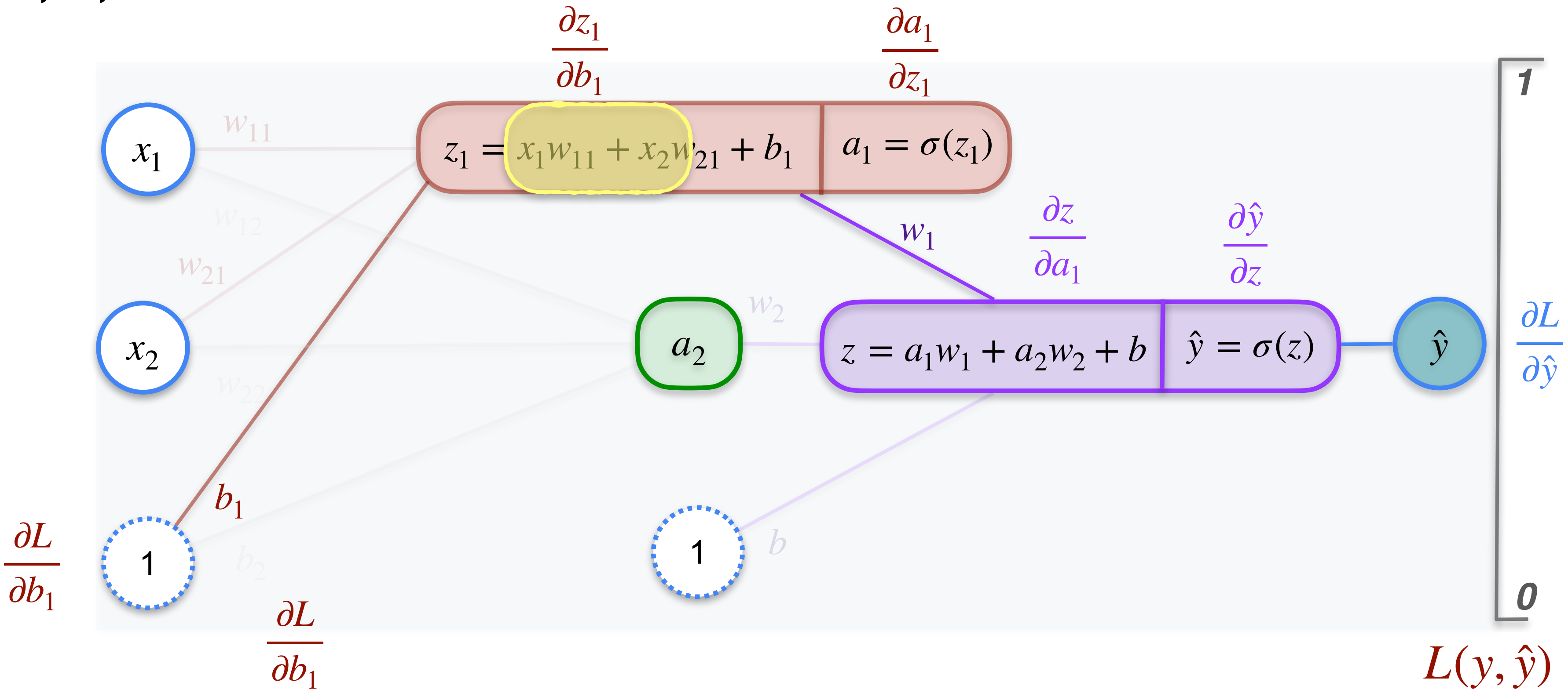
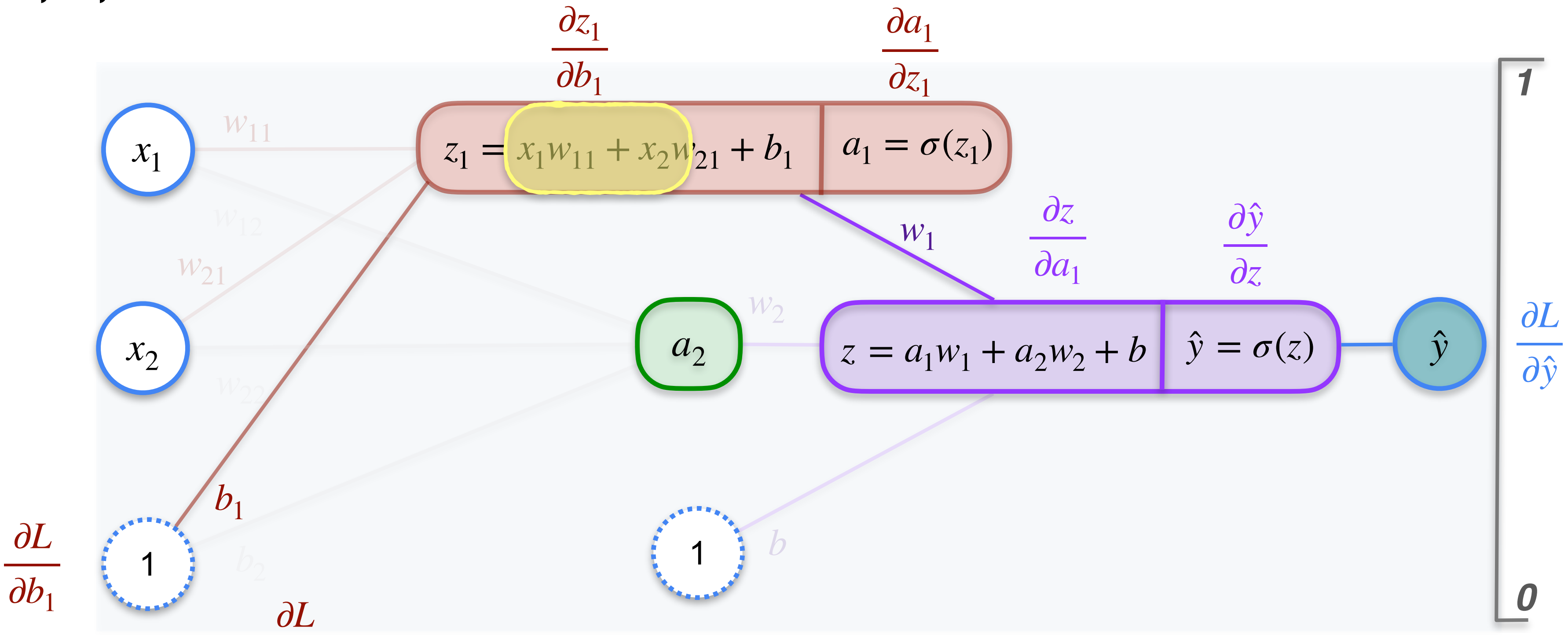
2,2,1 Neural Network



2,2,1 Neural Network

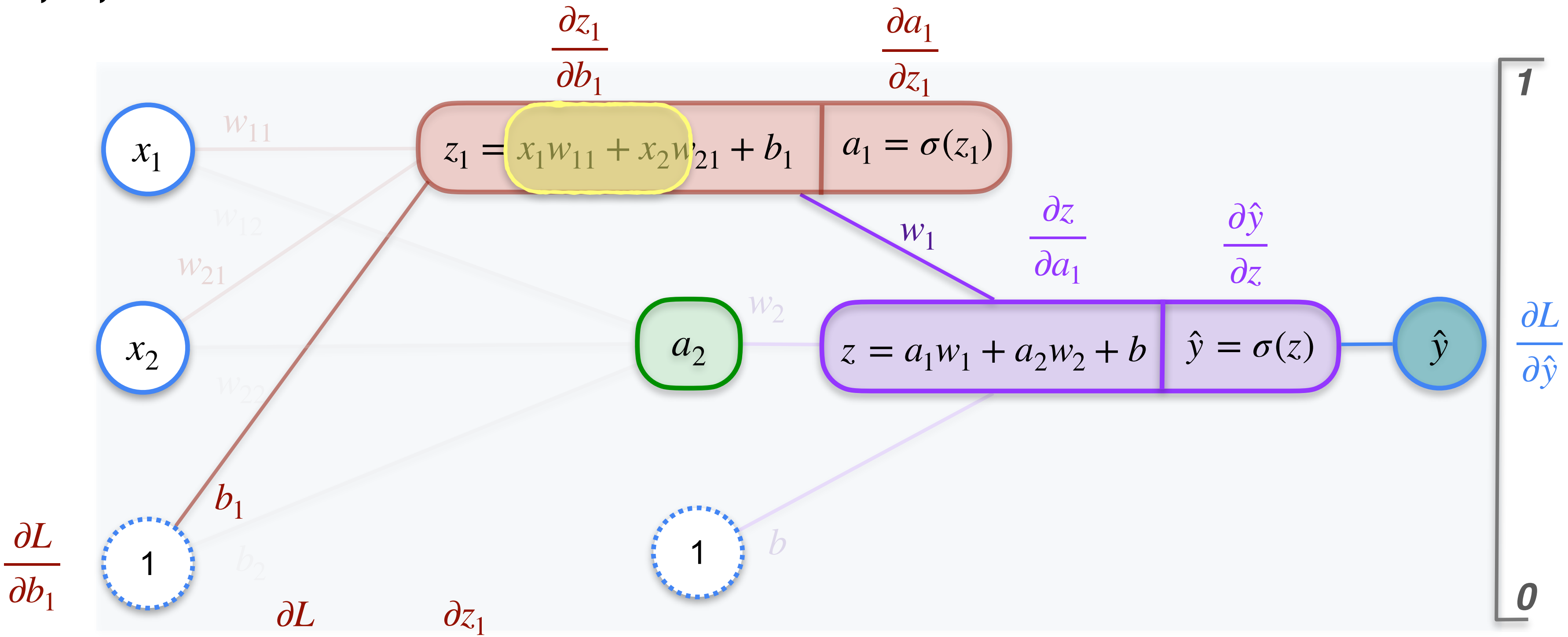


2,2,1 Neural Network



$$\frac{\partial L}{\partial b_1} =$$

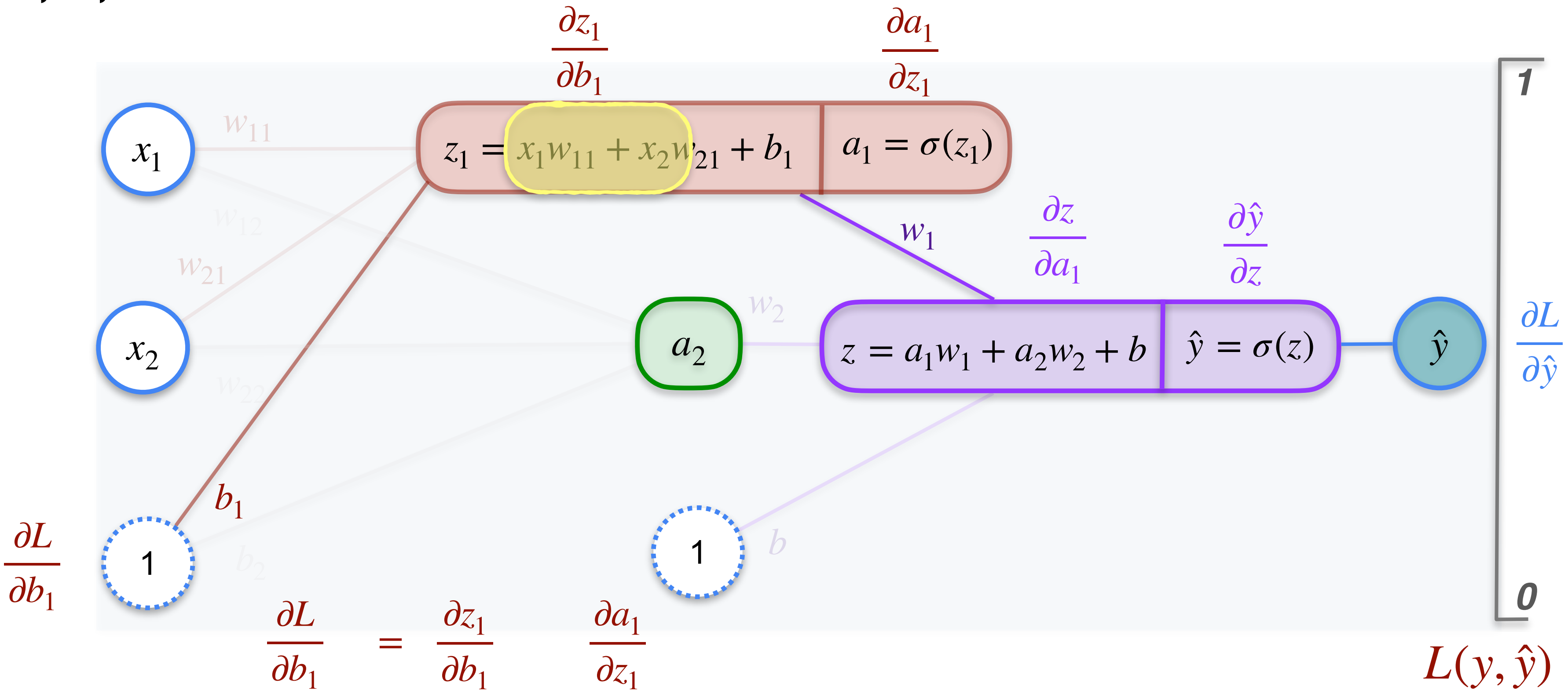
2,2,1 Neural Network



$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1}$$

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

2,2,1 Neural Network



$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \quad \frac{\partial a_1}{\partial z_1}$$

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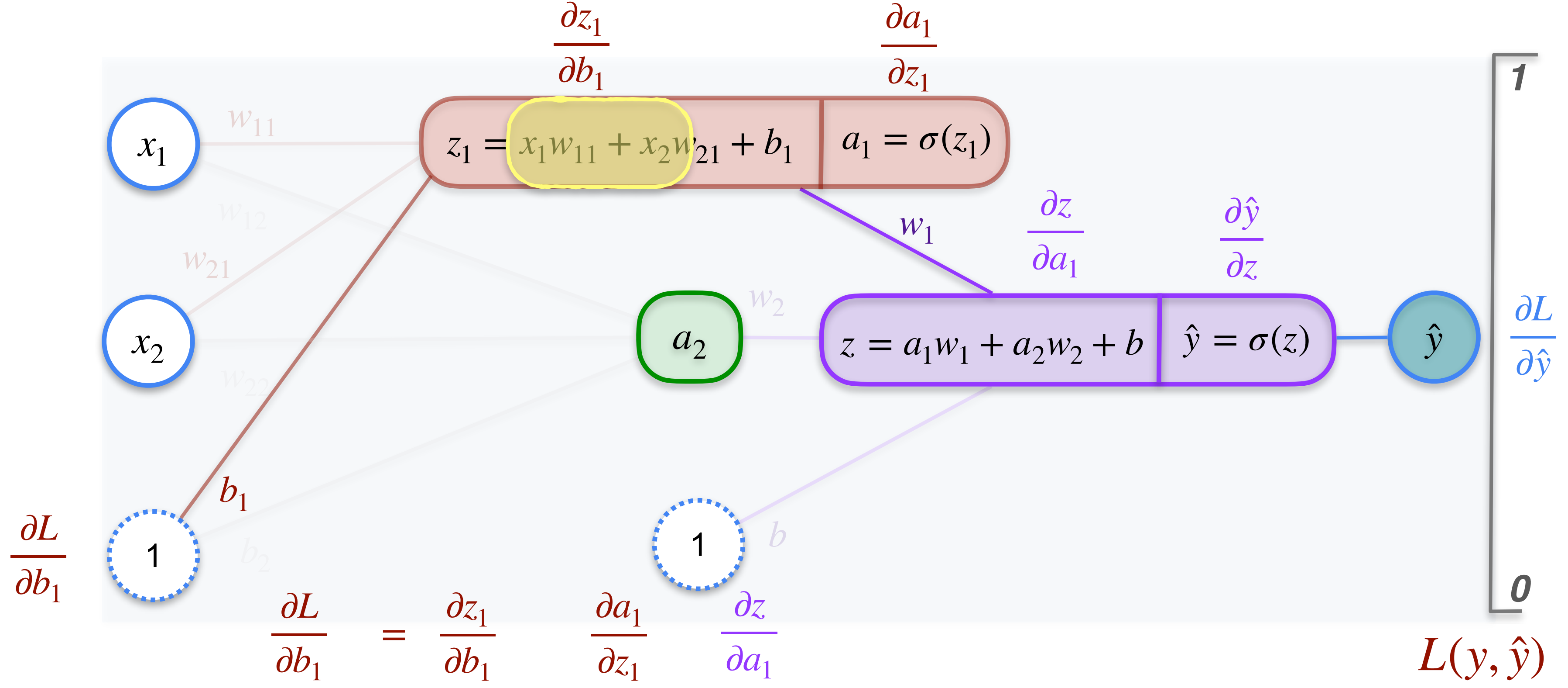
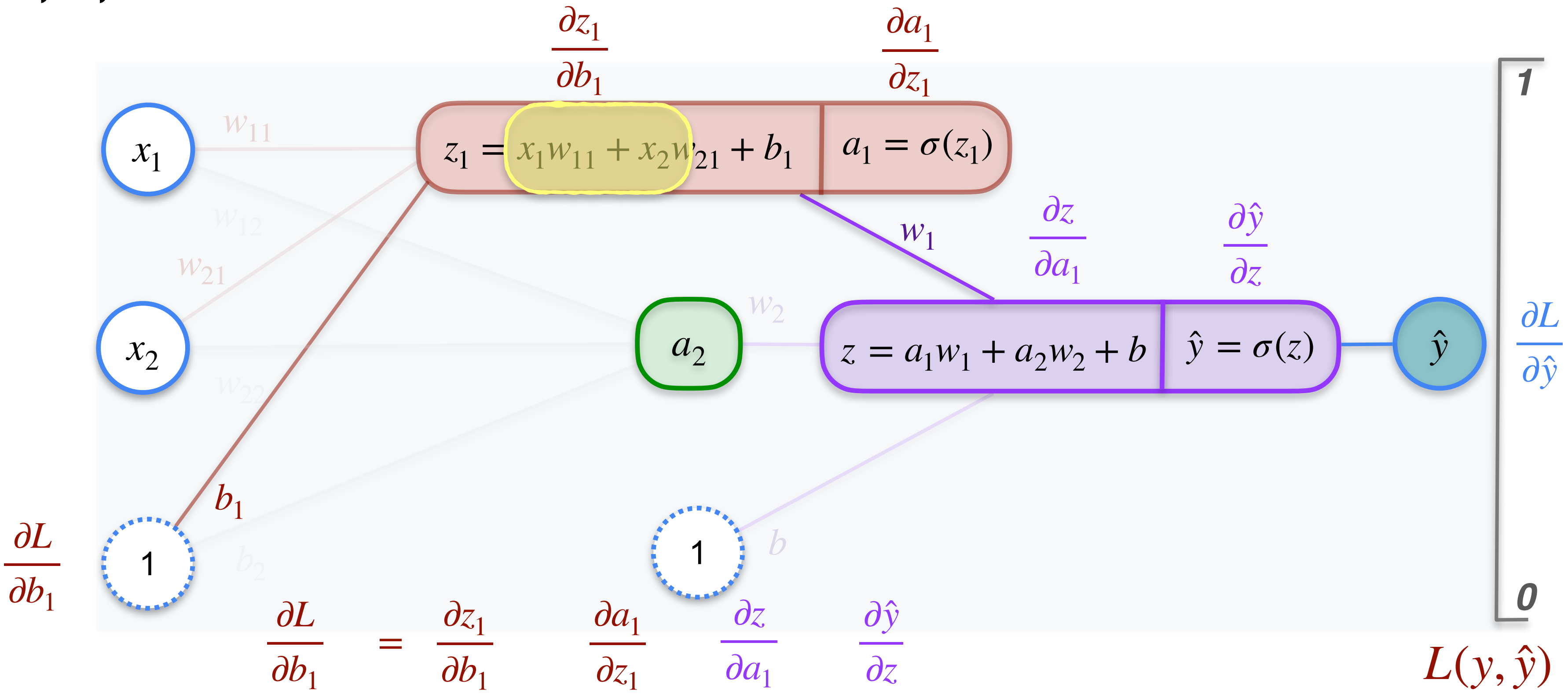
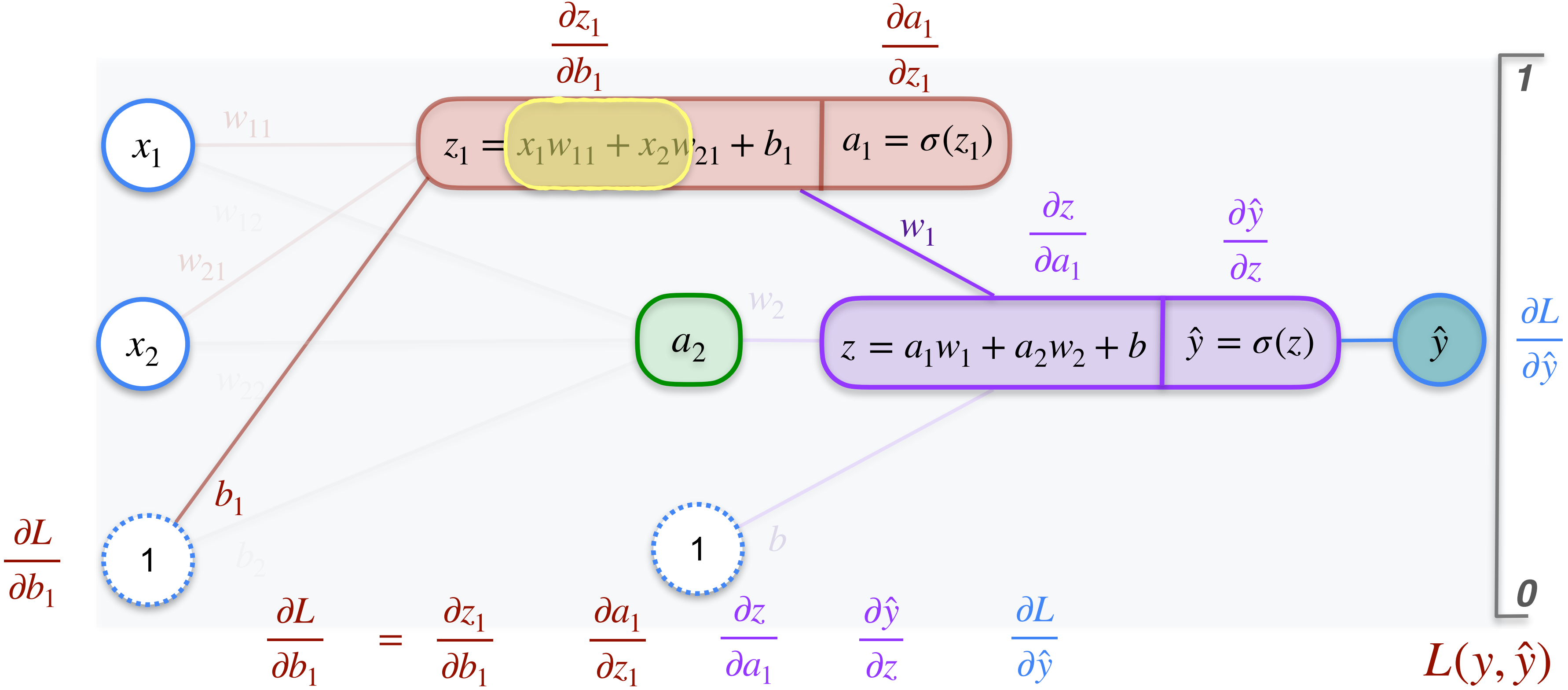
2,2,1 Neural Network



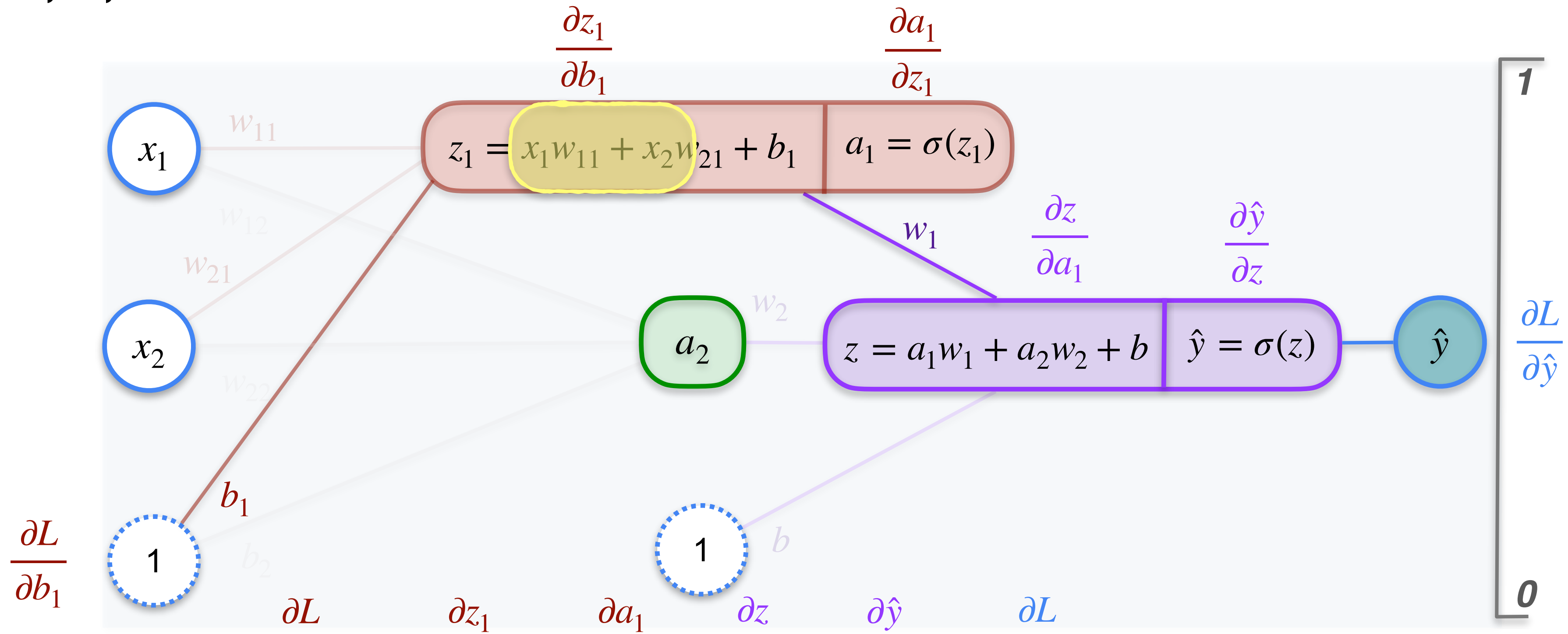
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



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

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

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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$$\frac{\partial L}{\partial b_1}$$

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2,2,1 Neural Network

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

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DeepLearning.AI

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DeepLearning.AI

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Perform gradient descent with

to find optimal value of b_1 that gives the least error

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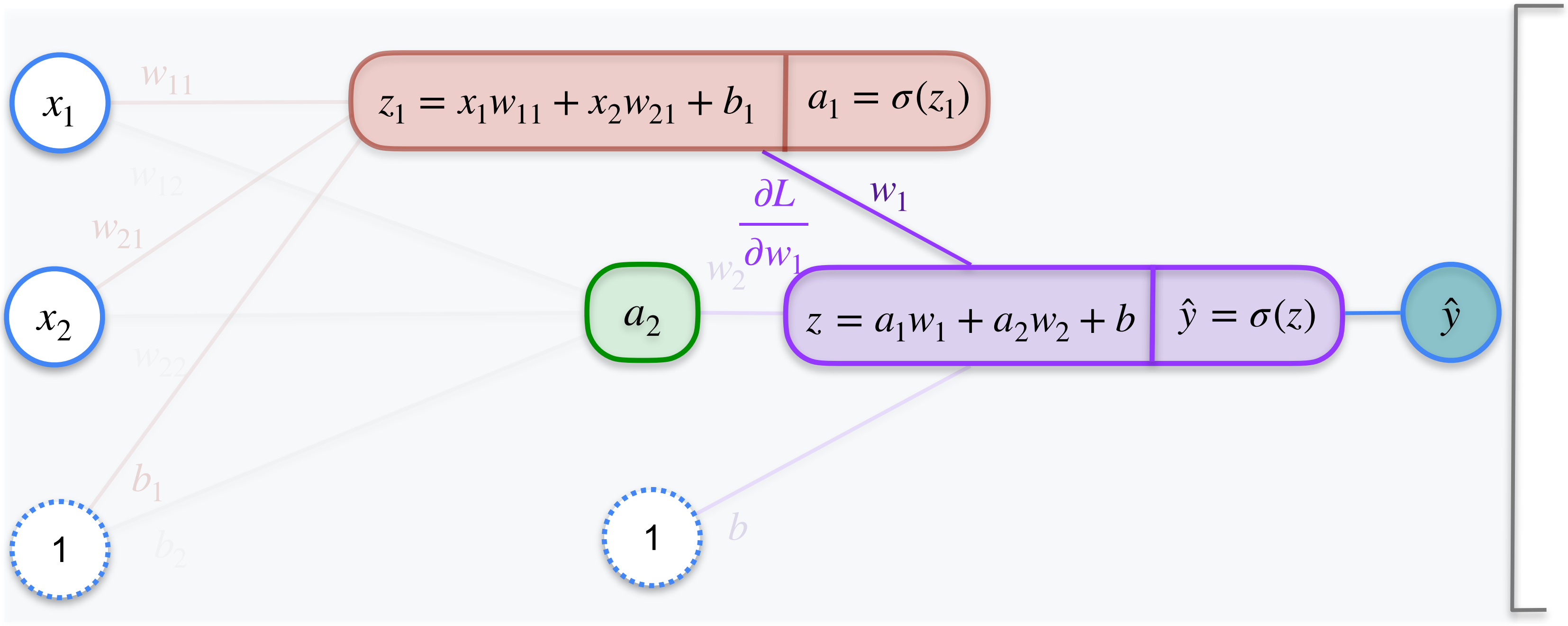
Perform gradient descent with

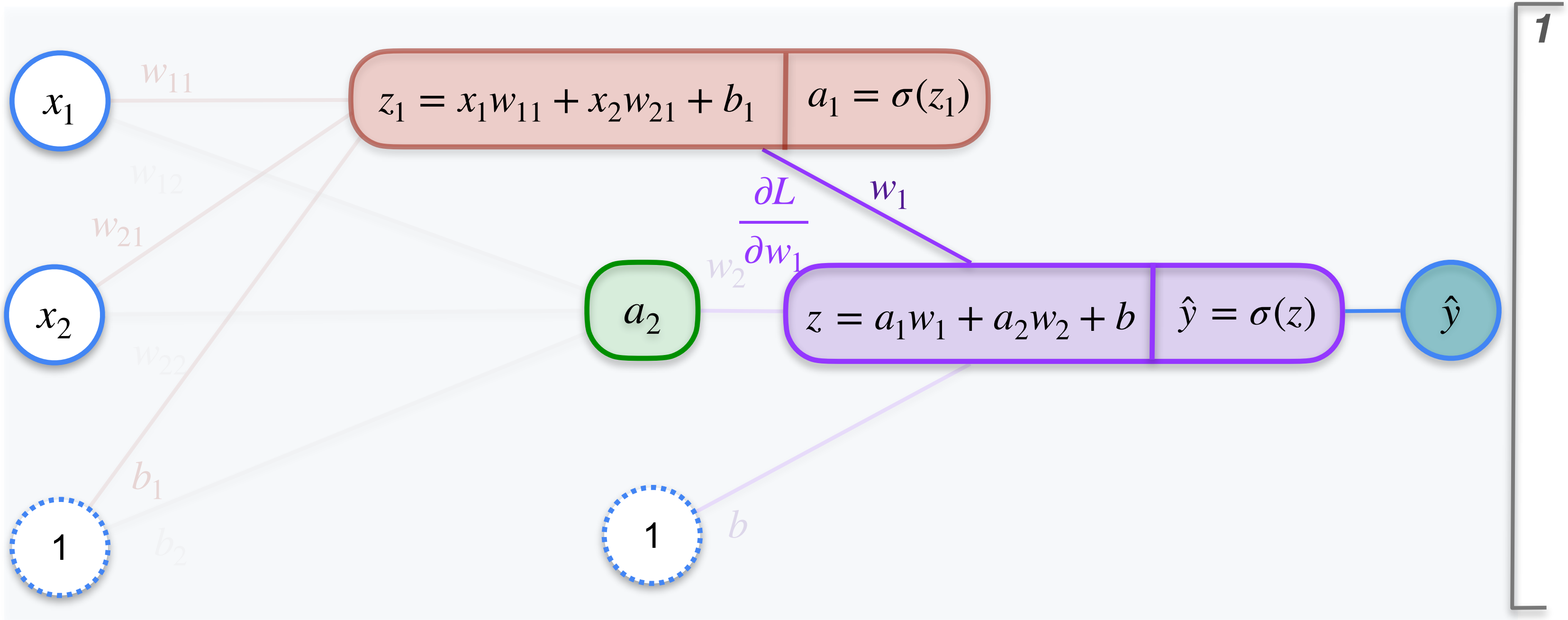
$$b_1 \rightarrow b_1 - \alpha(-w_1 a_1 (1-a_1)(y - \hat{y}))$$

to find optimal value of b_1 that gives the least error

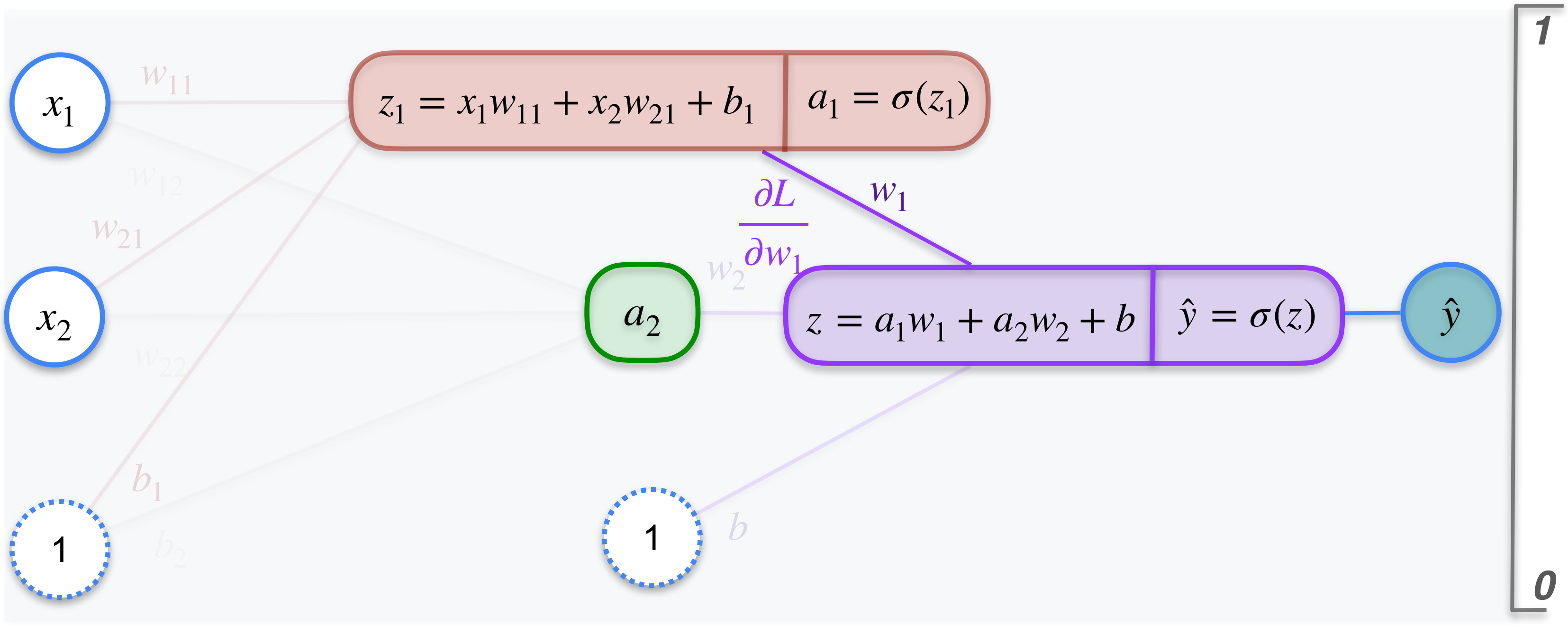
2,2,1 Neural Network



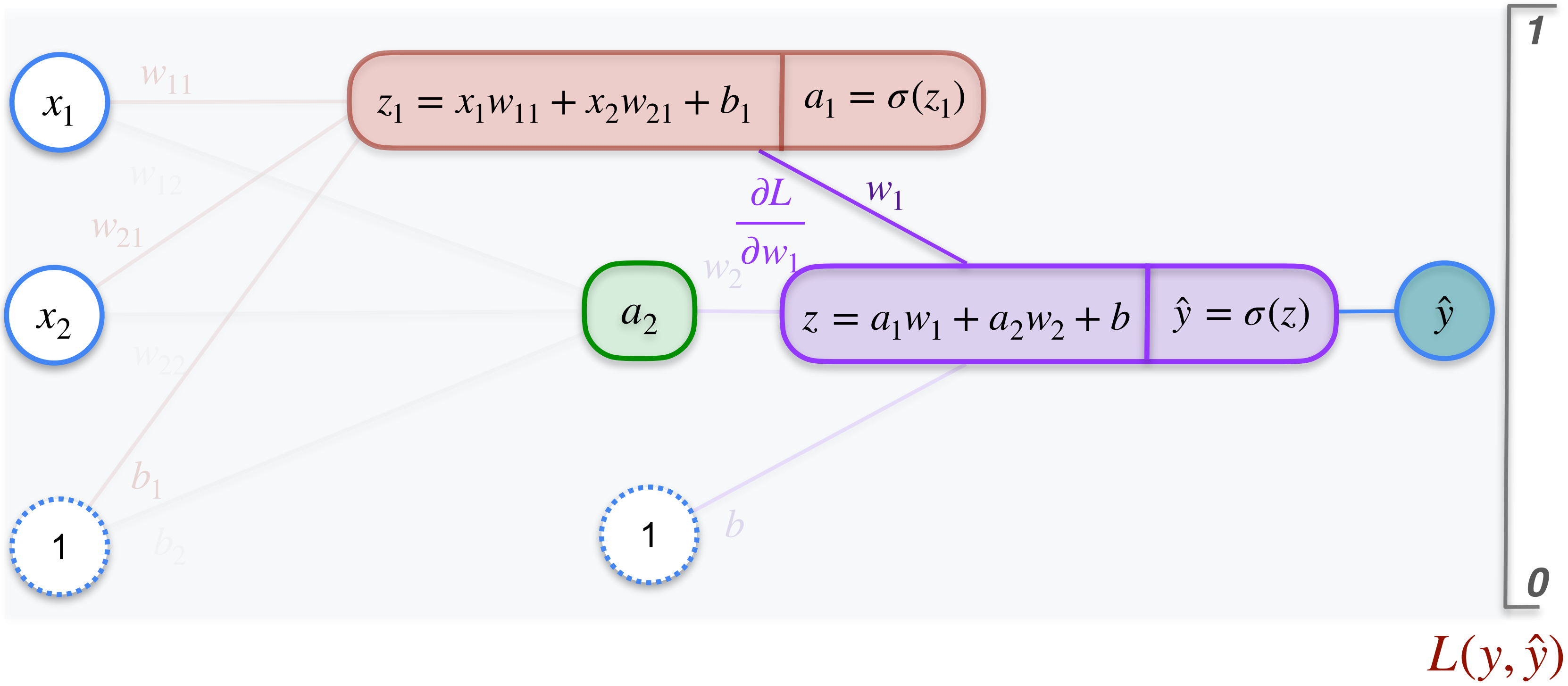
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



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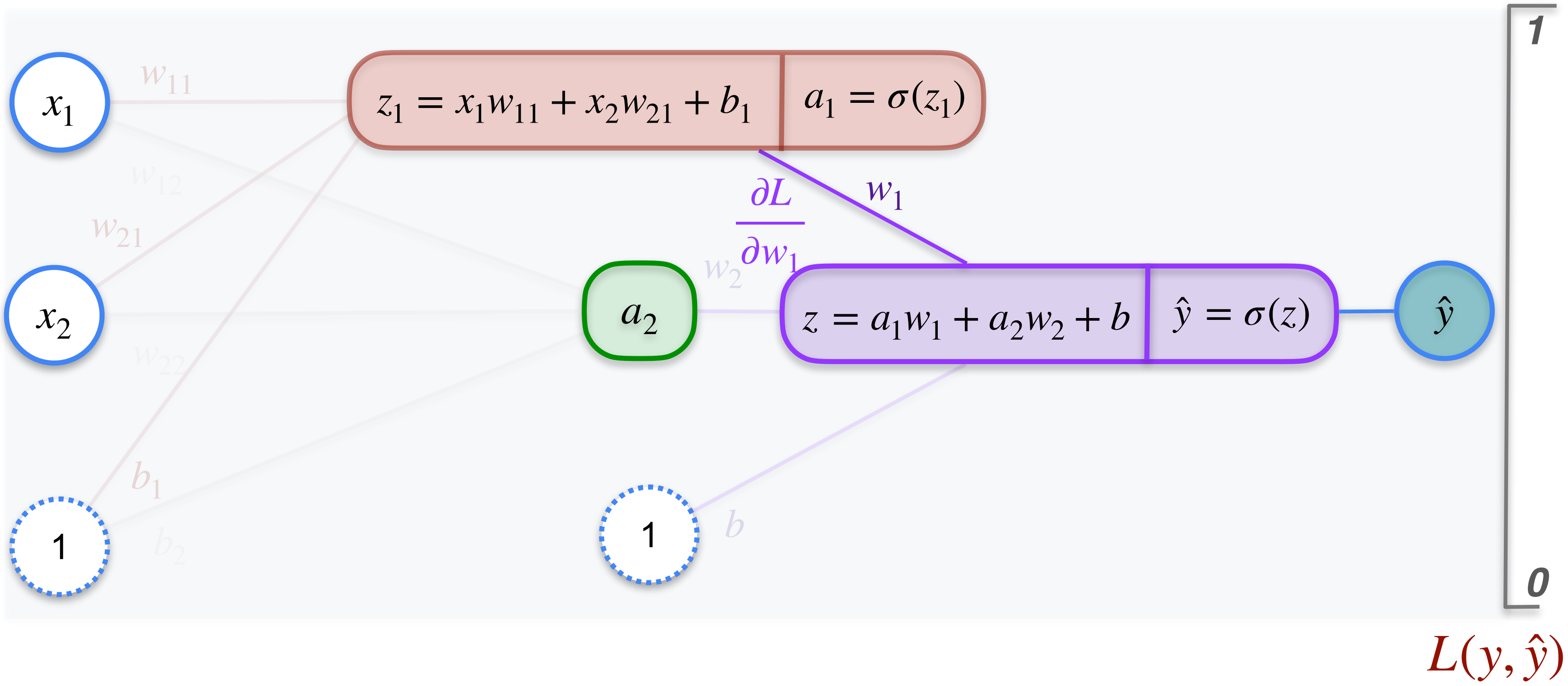

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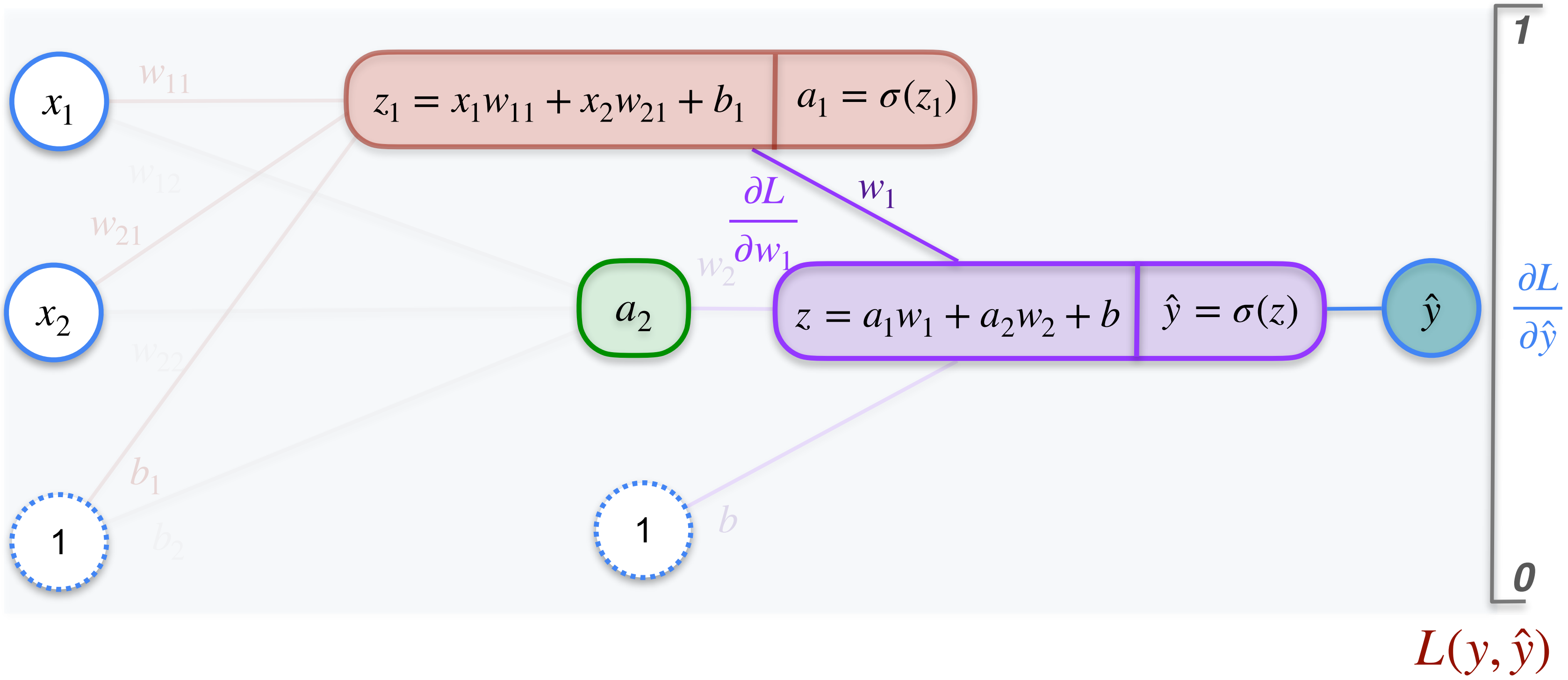
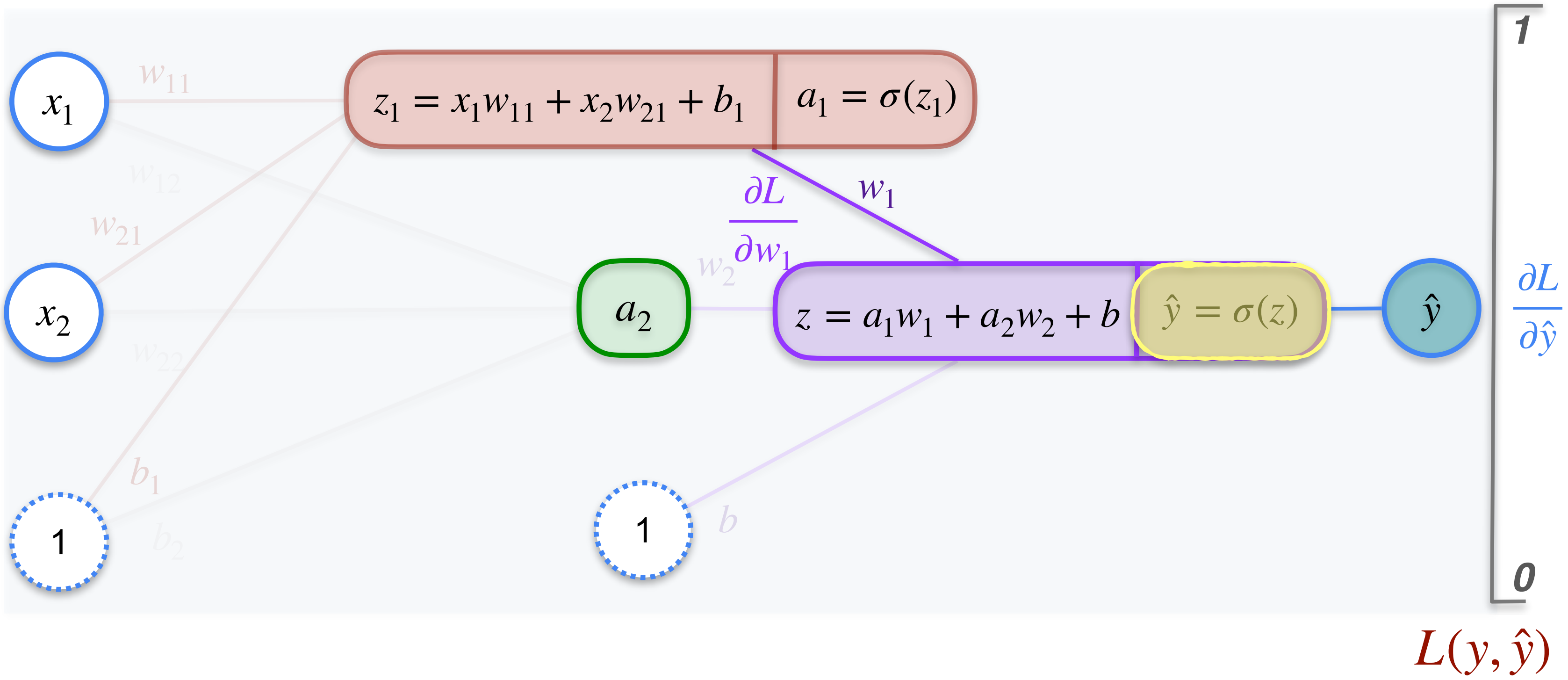


2,2,1 Neural Network



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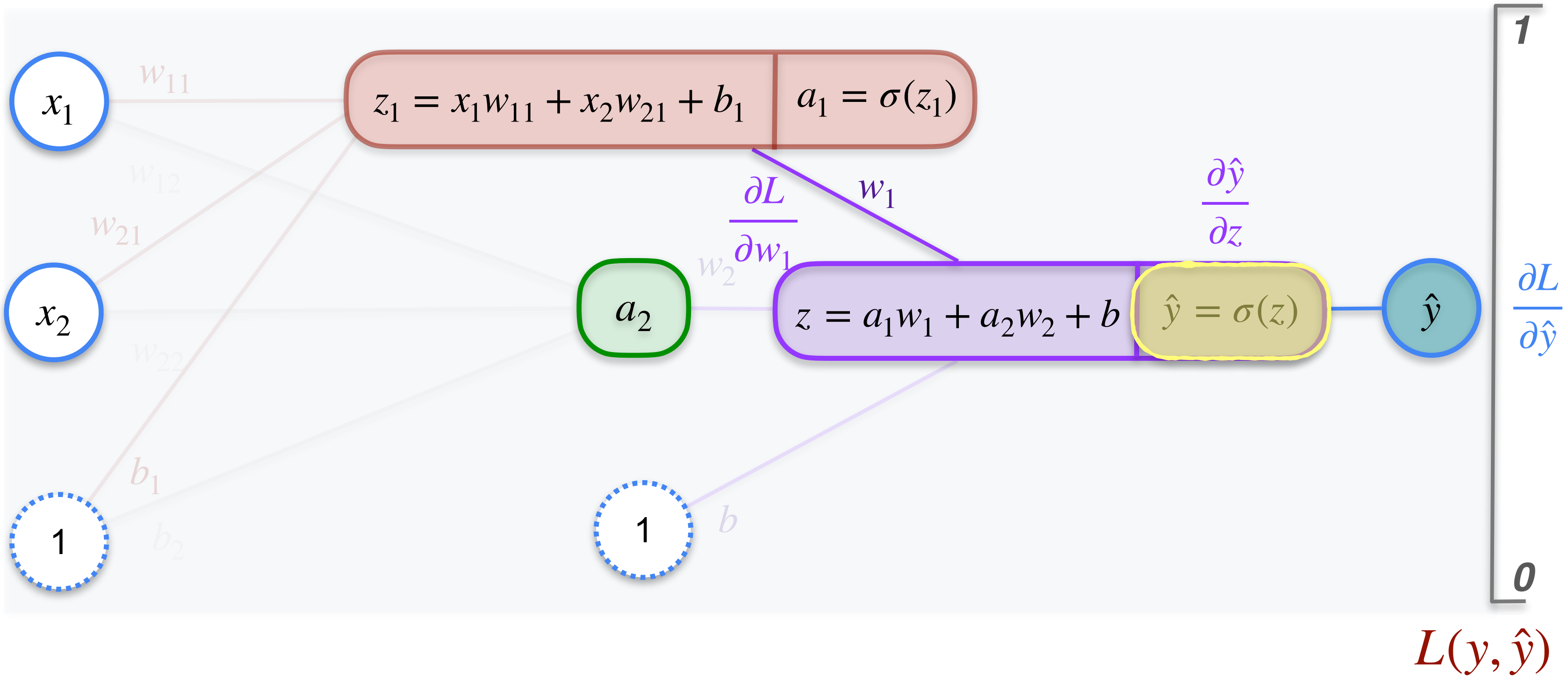
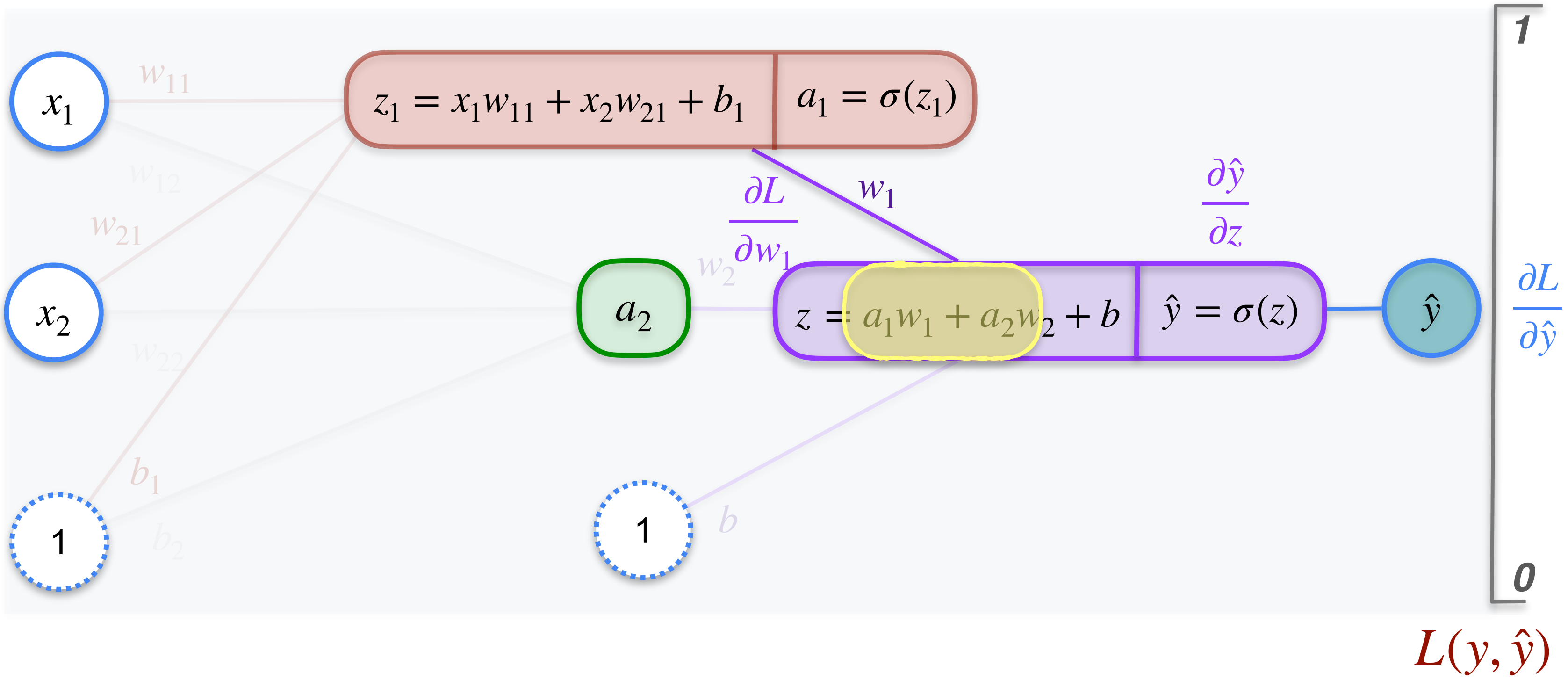


2,2,1 Neural Network



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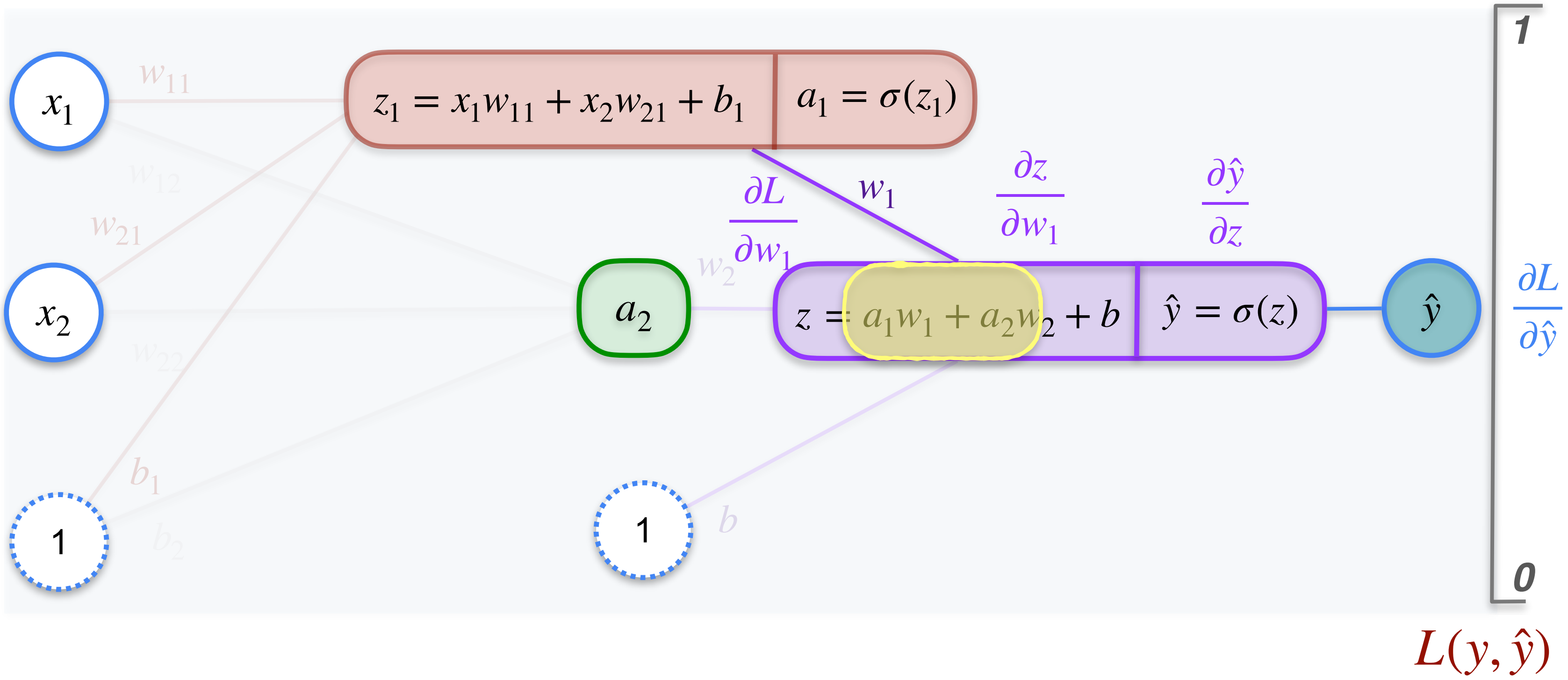

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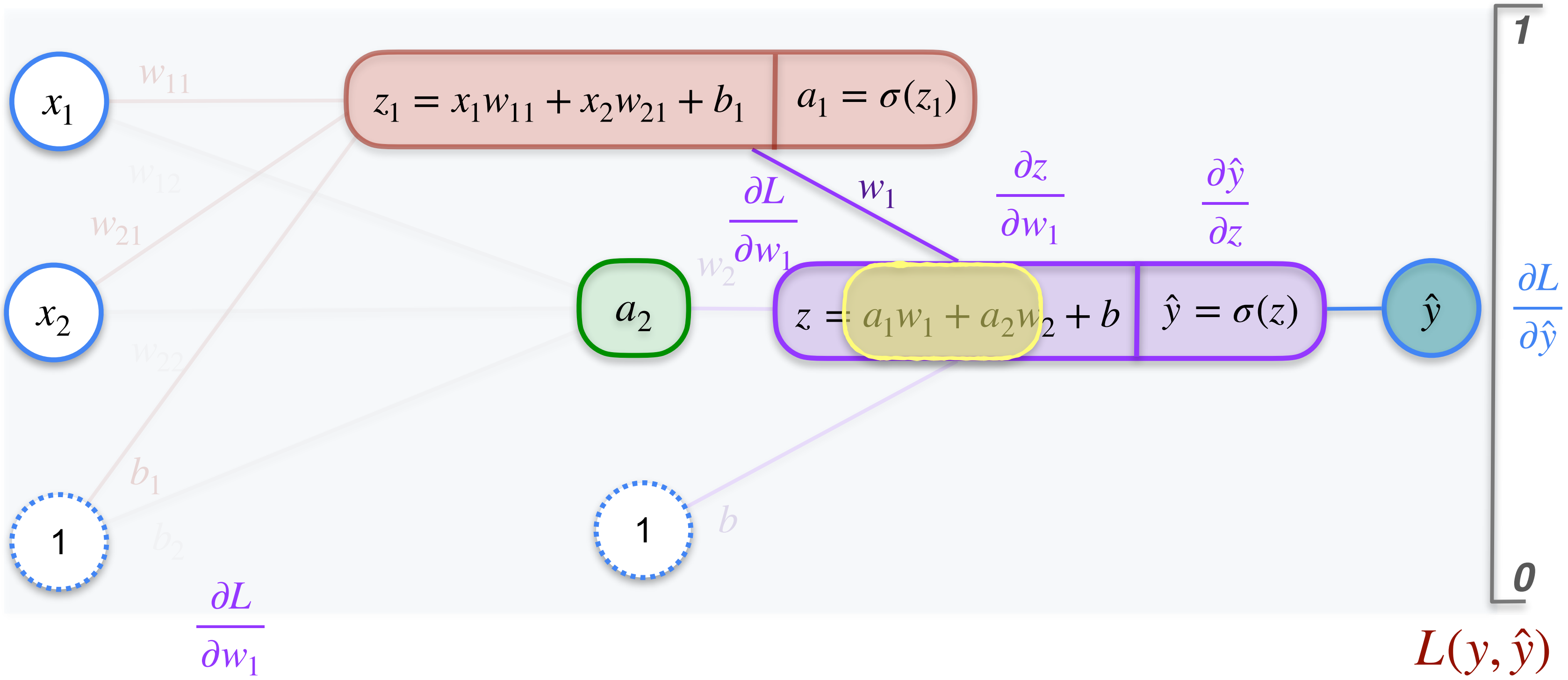

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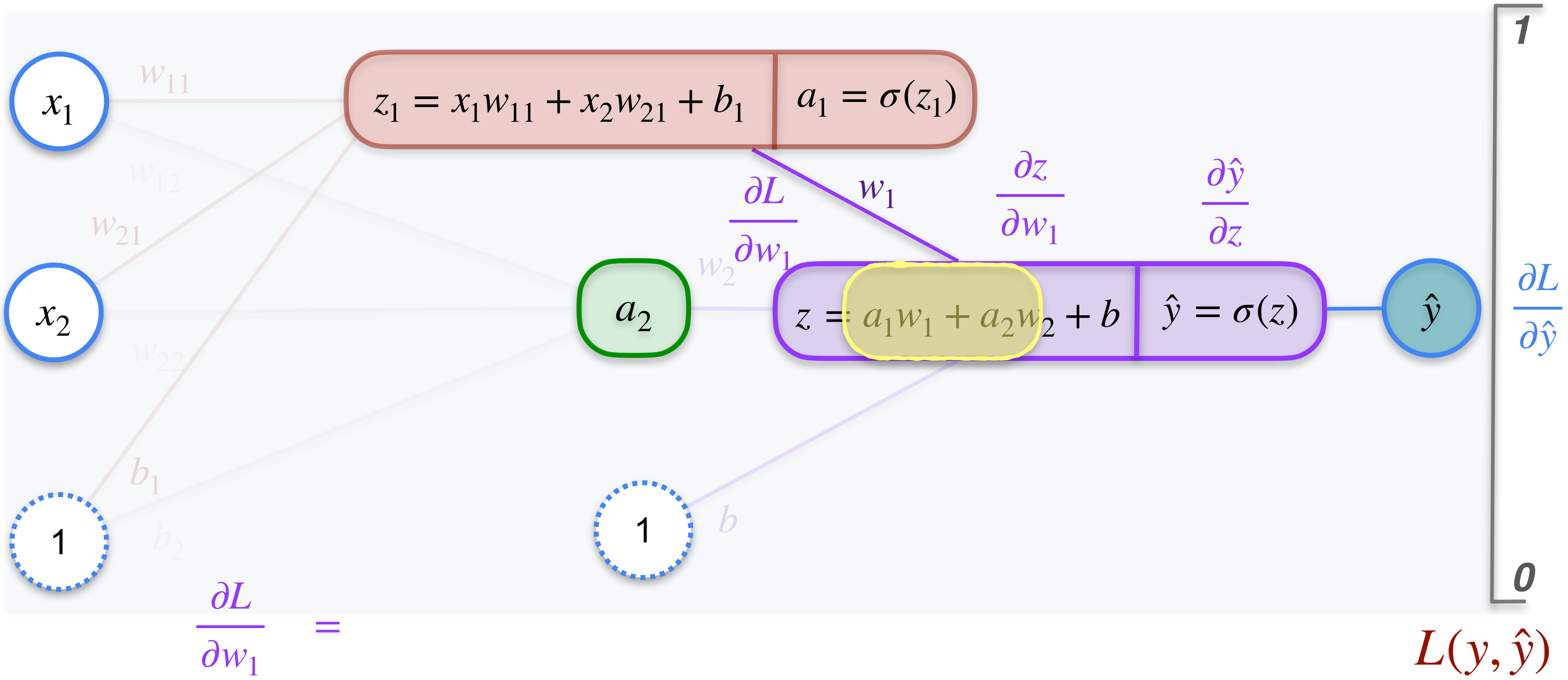
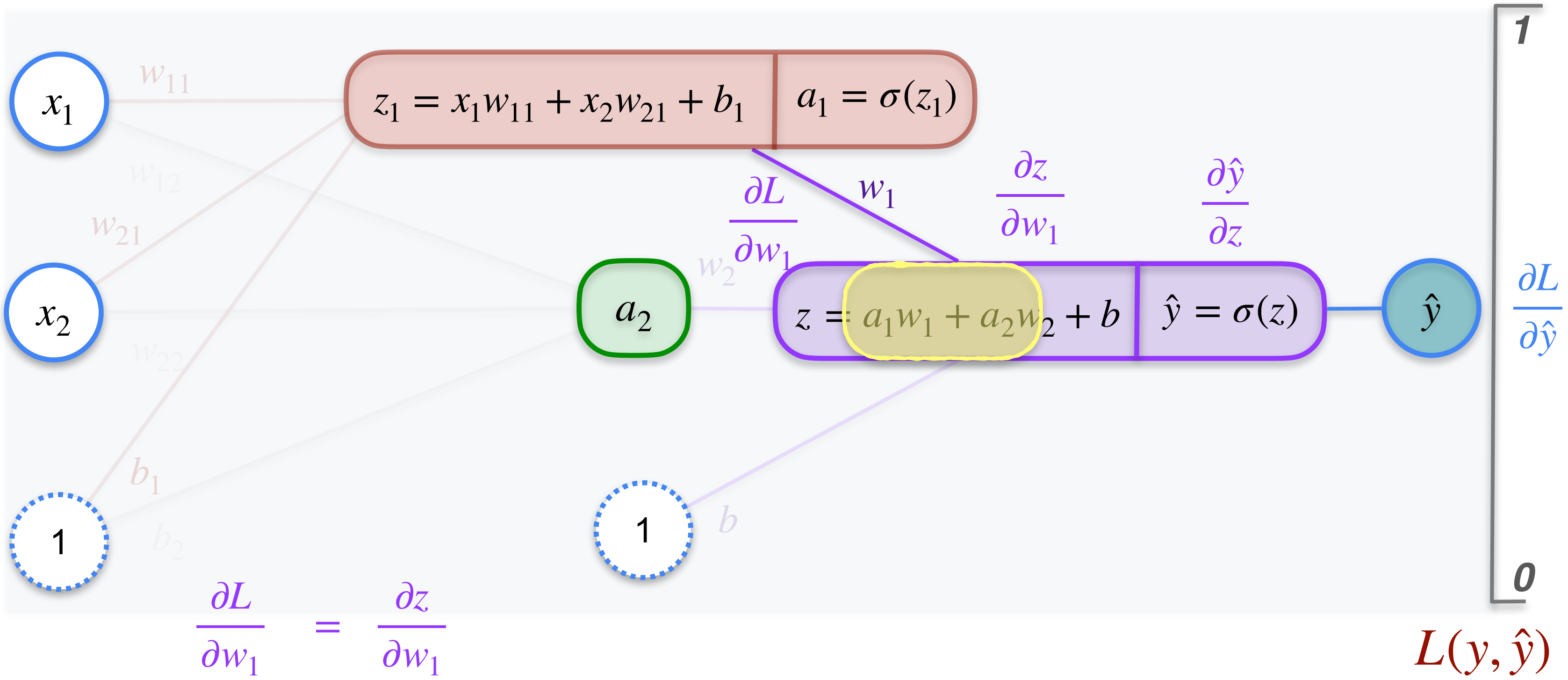


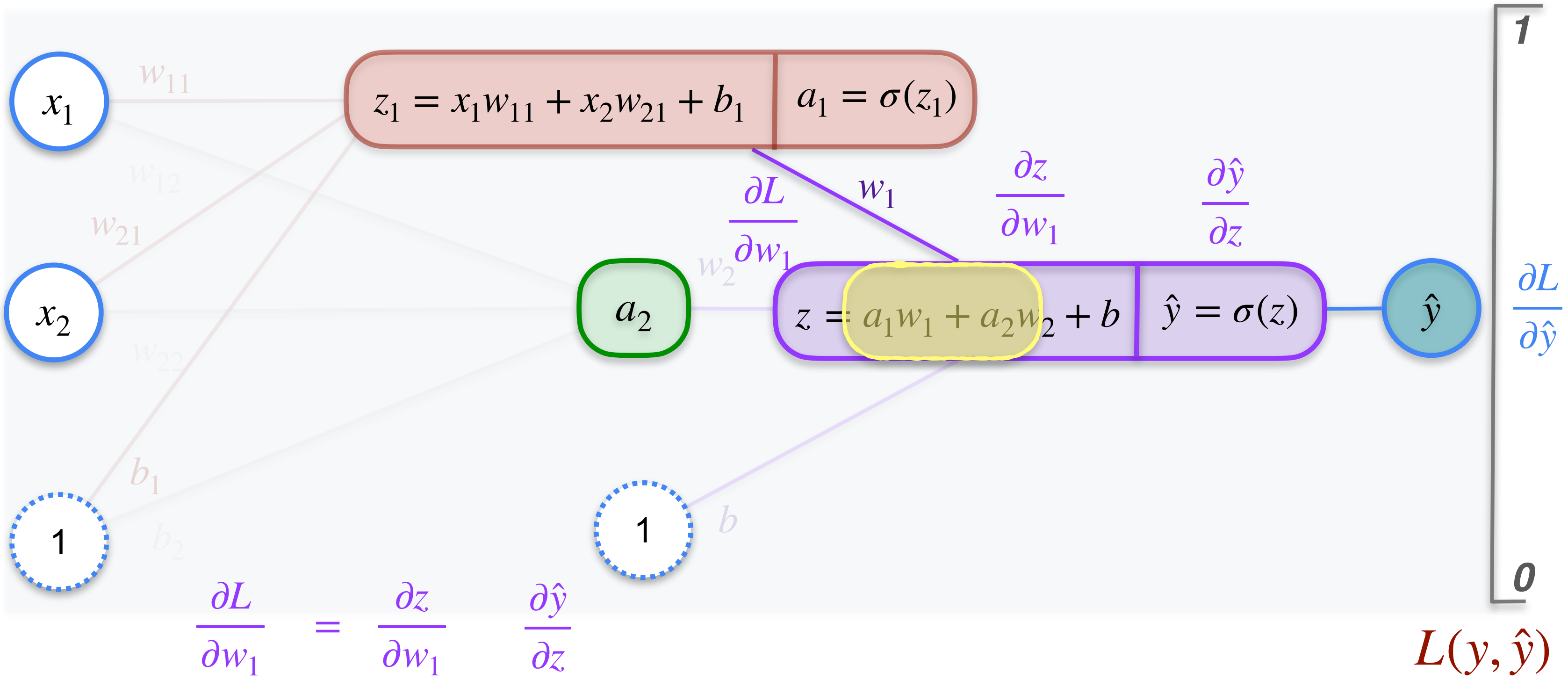
$$\frac{\partial L}{\partial w_1} =$$

2,2,1 Neural Network



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

2,2,1 Neural Network



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

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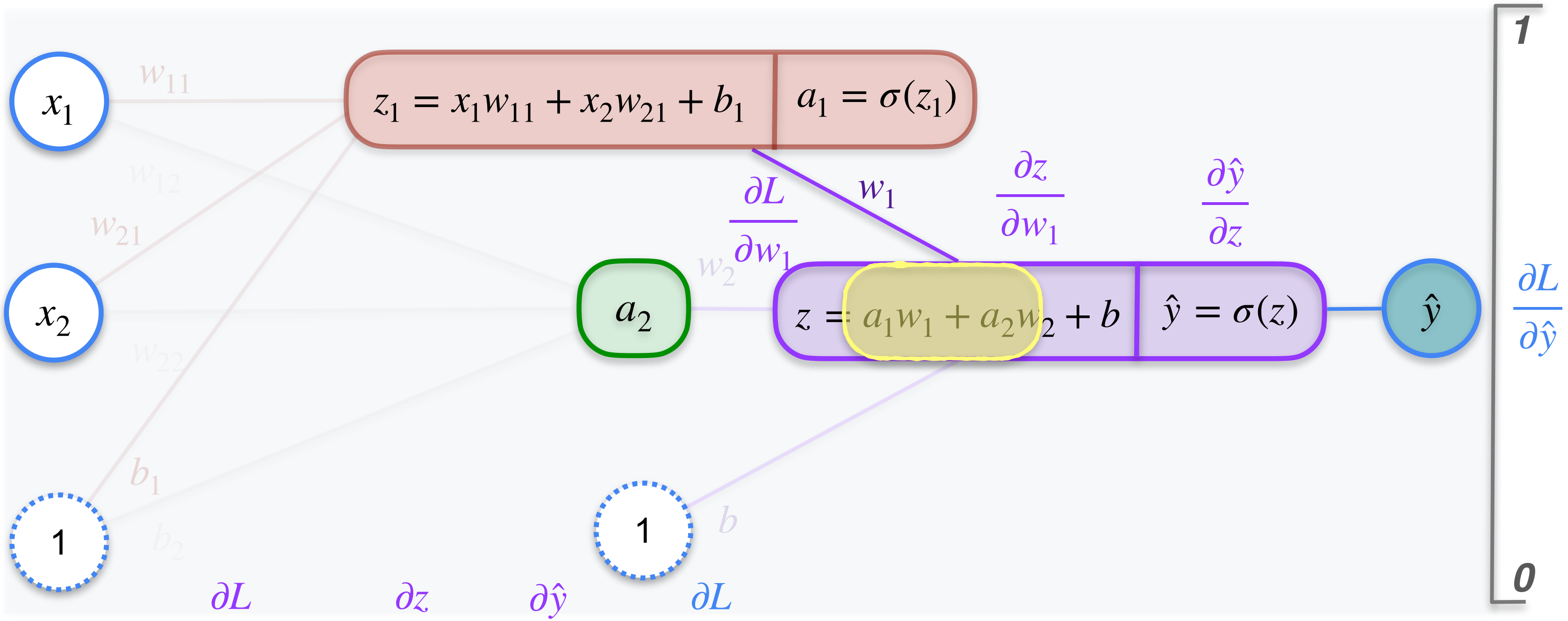

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$$\frac{\partial L}{\partial w_1} =$$

2,2,1 Neural Network

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DeepLearning.AI

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DeepLearning.AI

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to find optimal value of w_1 that gives the least error

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Perform gradient descent with

to find optimal value of w_1 that gives the least error

DeepLearning.AI

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Perform gradient descent with

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

to find optimal value of w_1 that gives the least error

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$$= -a_1(y - \hat{y})$$

Perform gradient descent with

$$w_1 \rightarrow w_1 - \alpha$$

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

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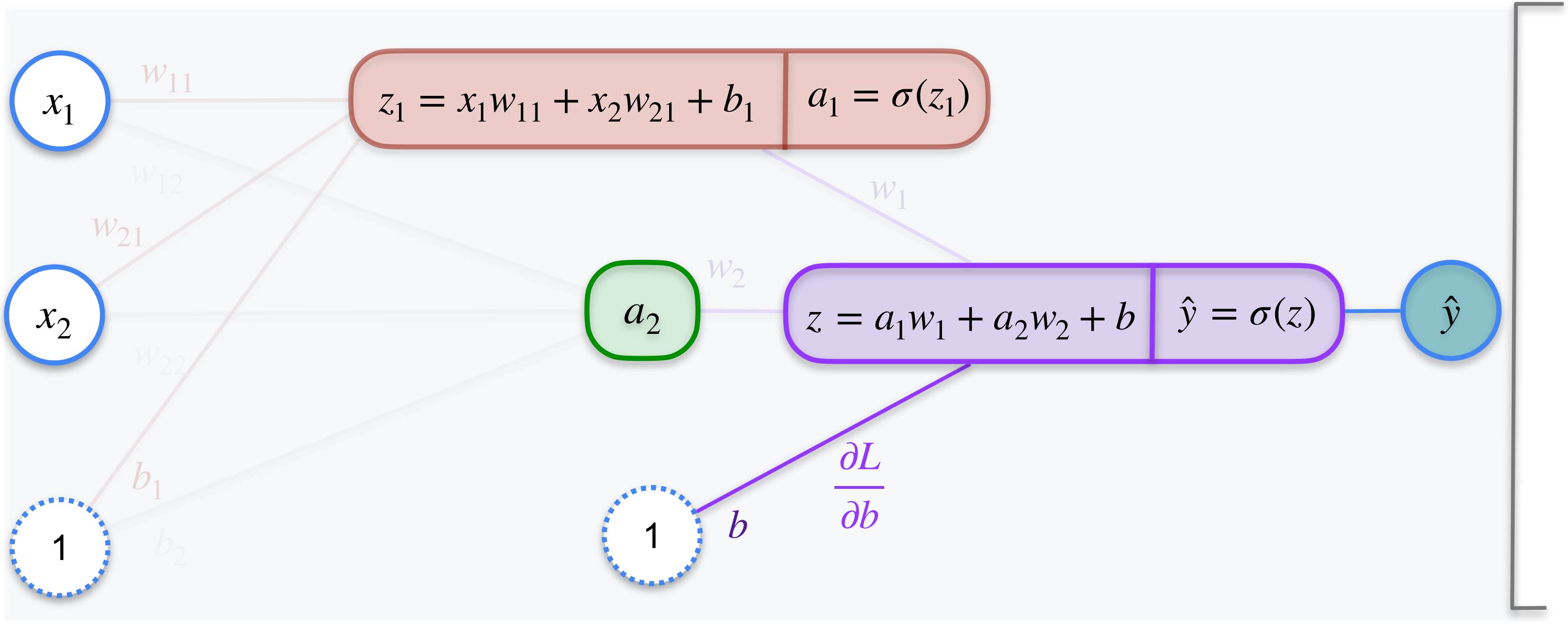
Perform gradient descent with

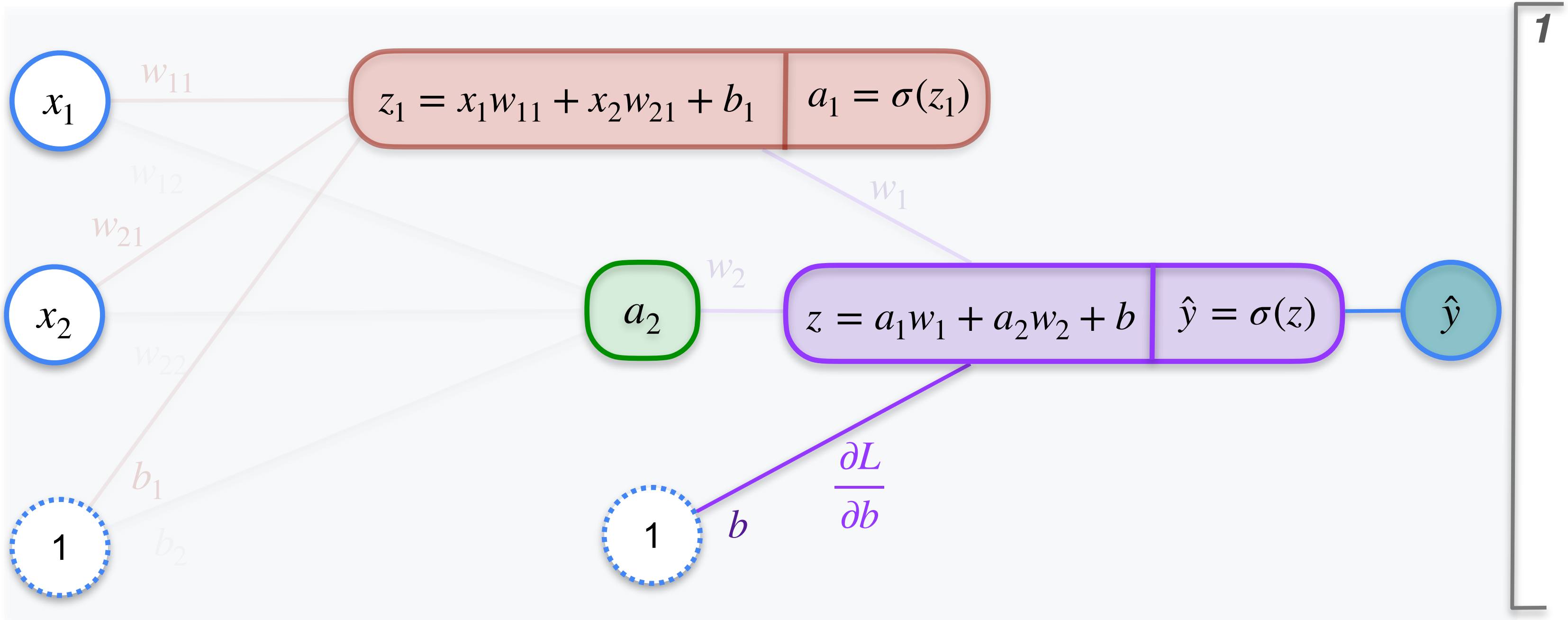
$$w_1 \to w_1 - \alpha(-a_1(y - \hat{y}))$$

to find optimal value of w_1 that gives the least error

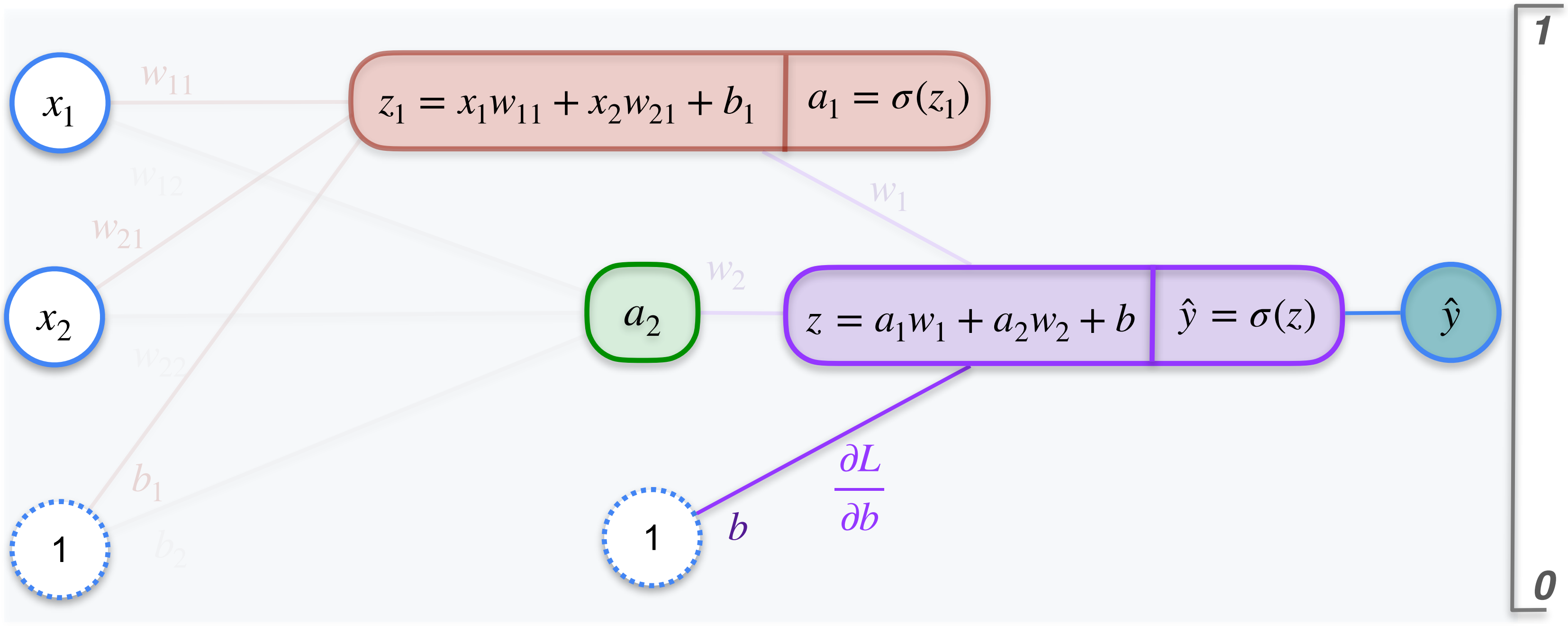
2,2,1 Neural Network



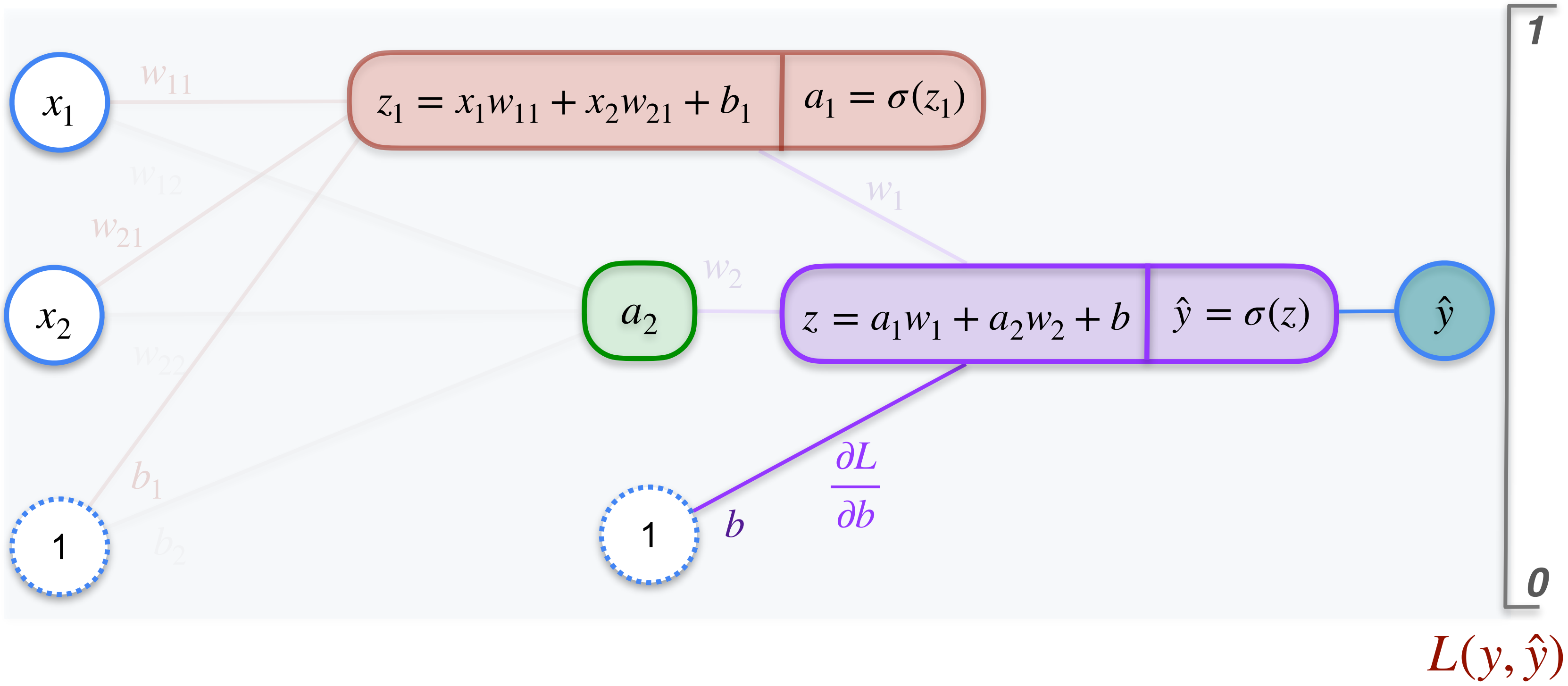
2,2,1 Neural Network



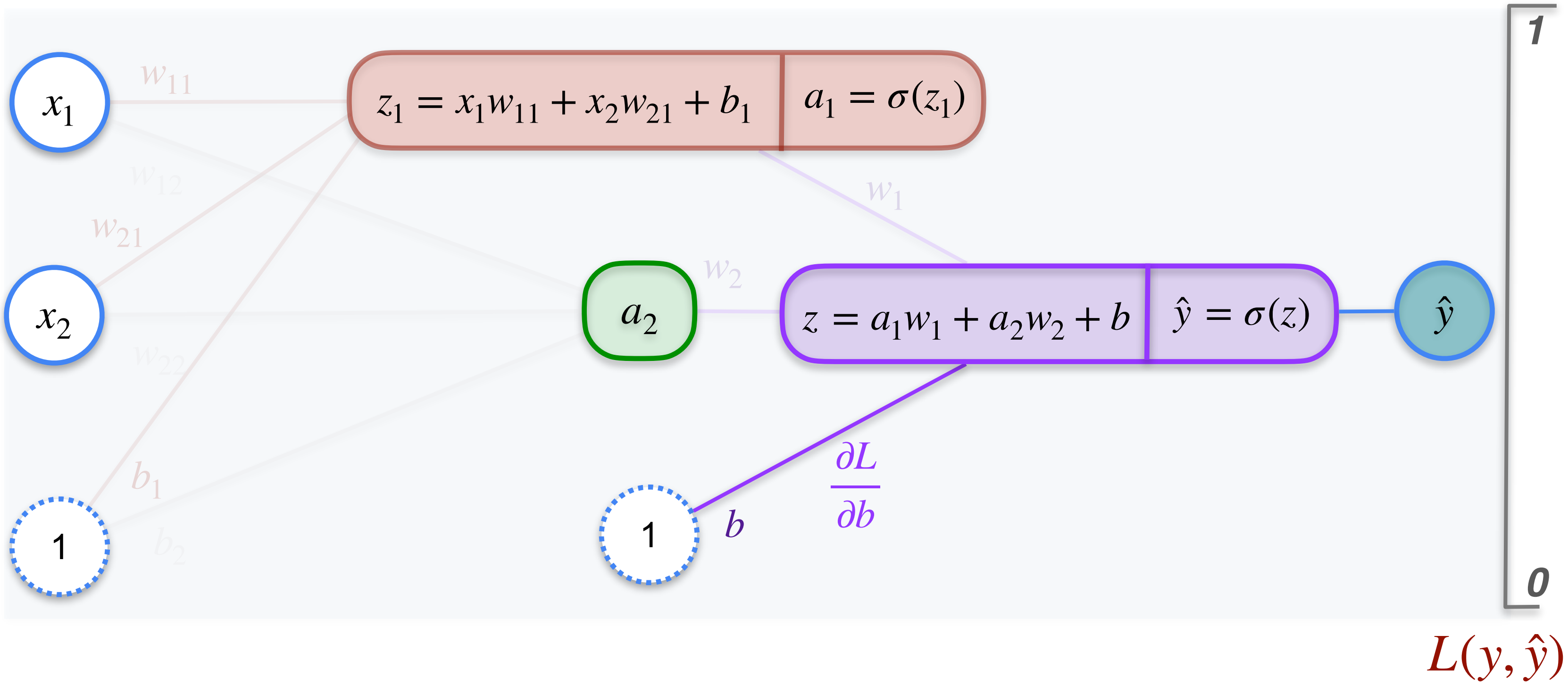
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



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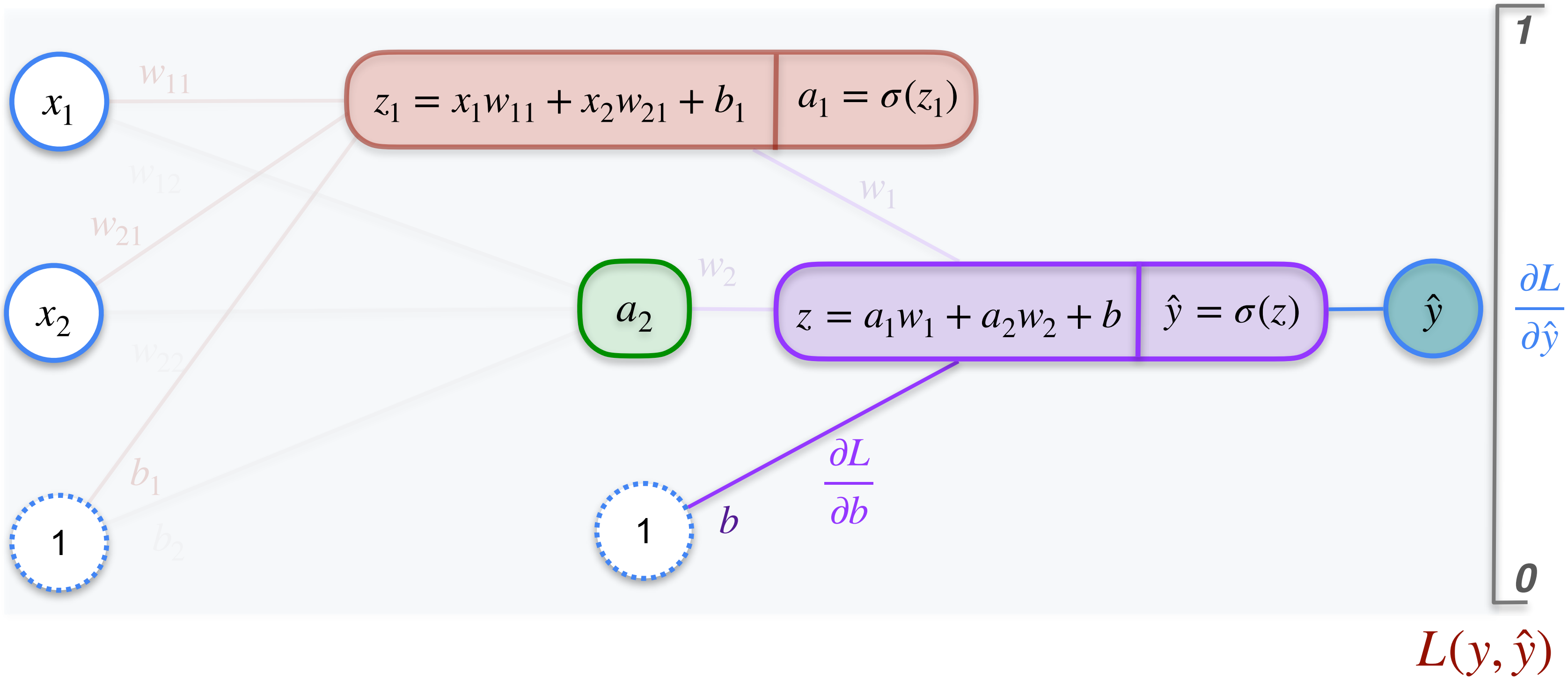
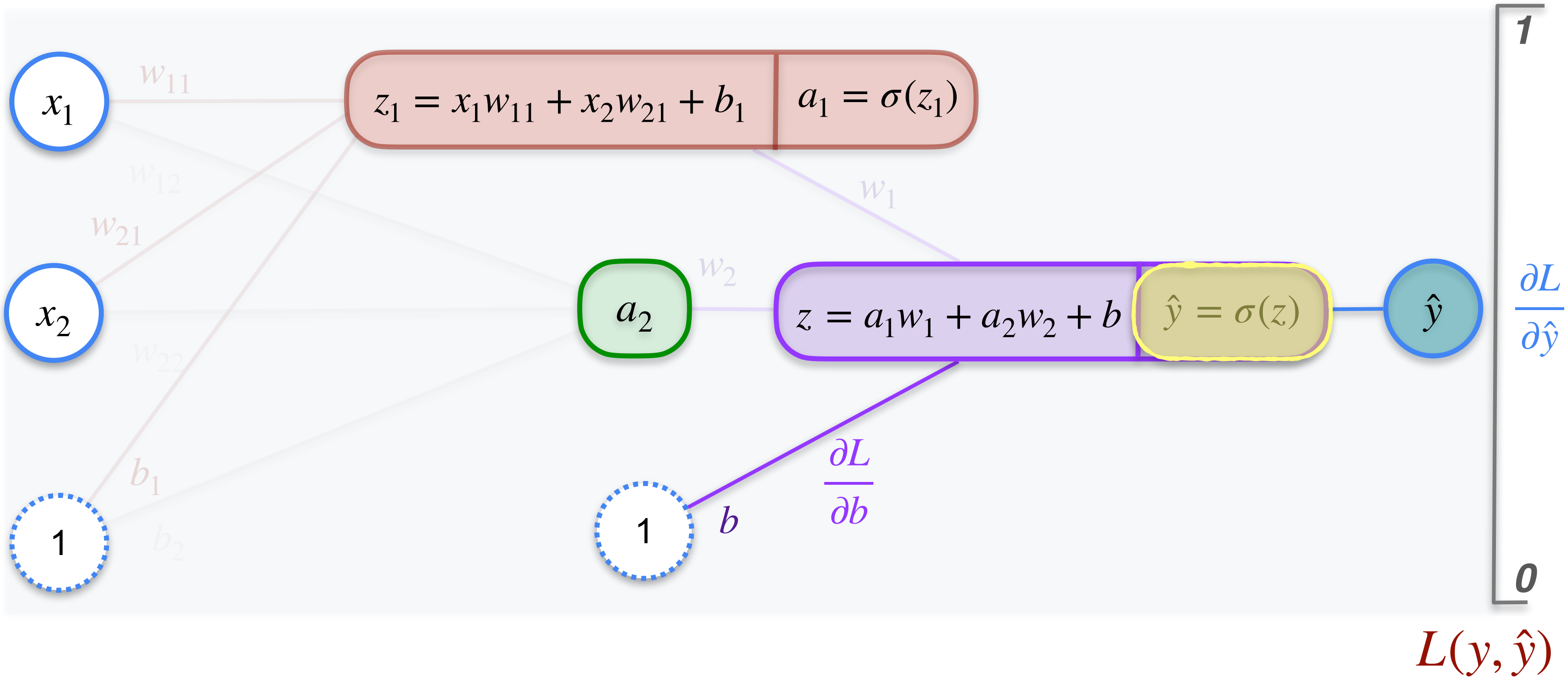
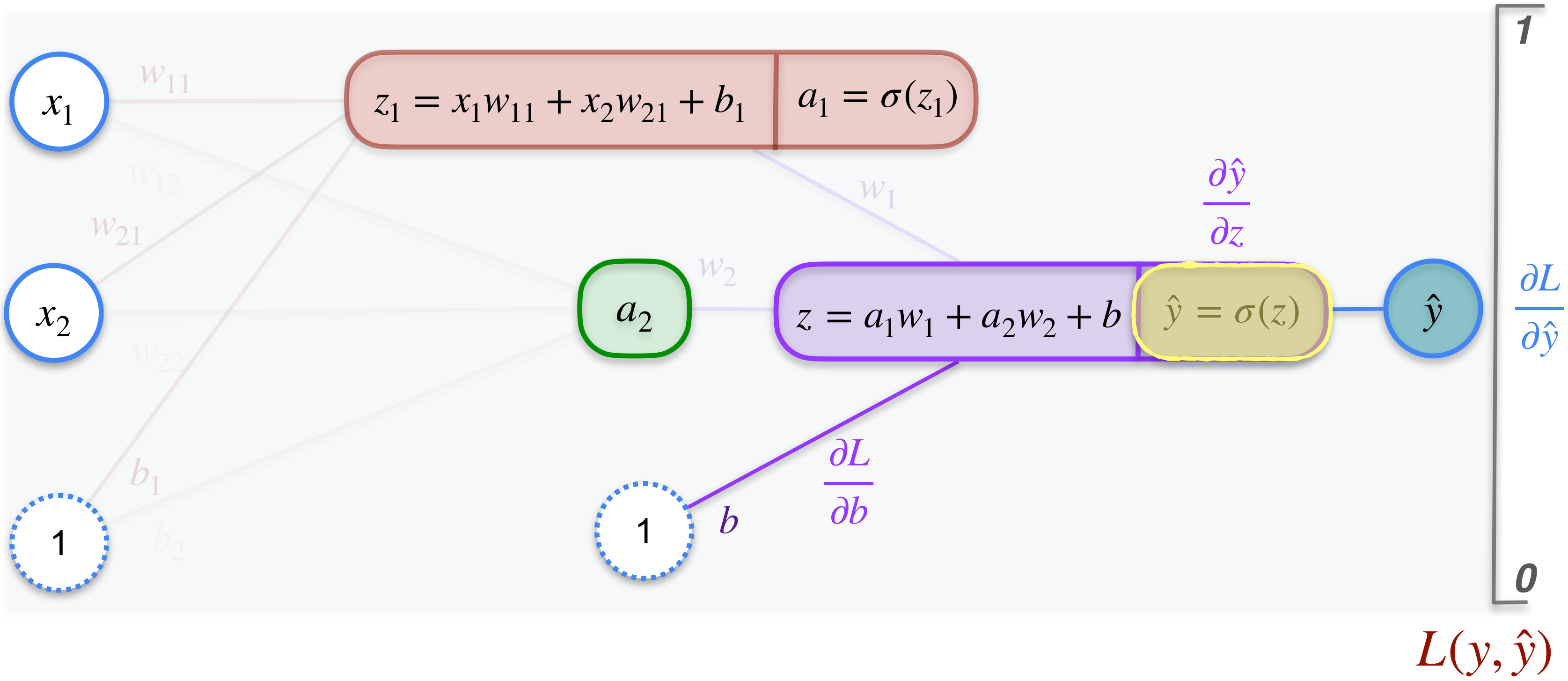


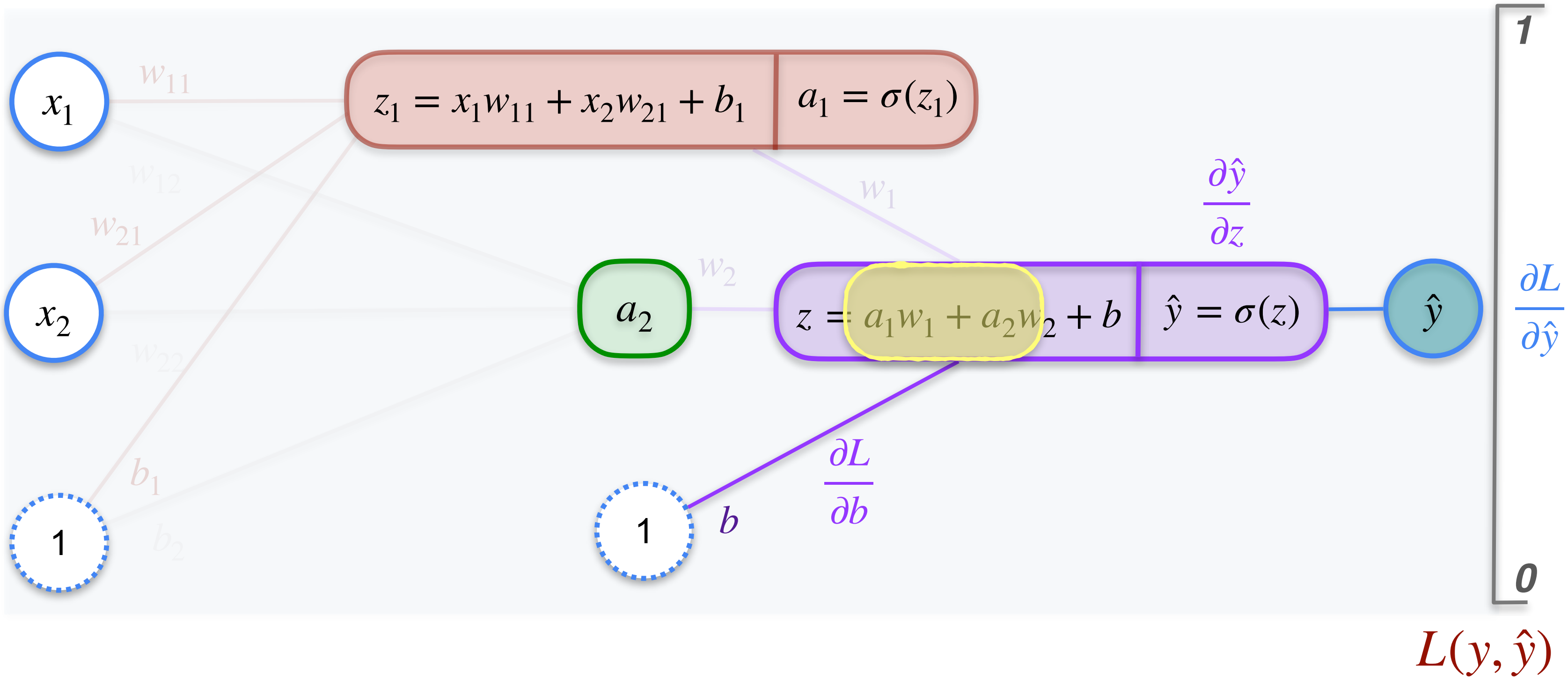
2,2,1 Neural Network



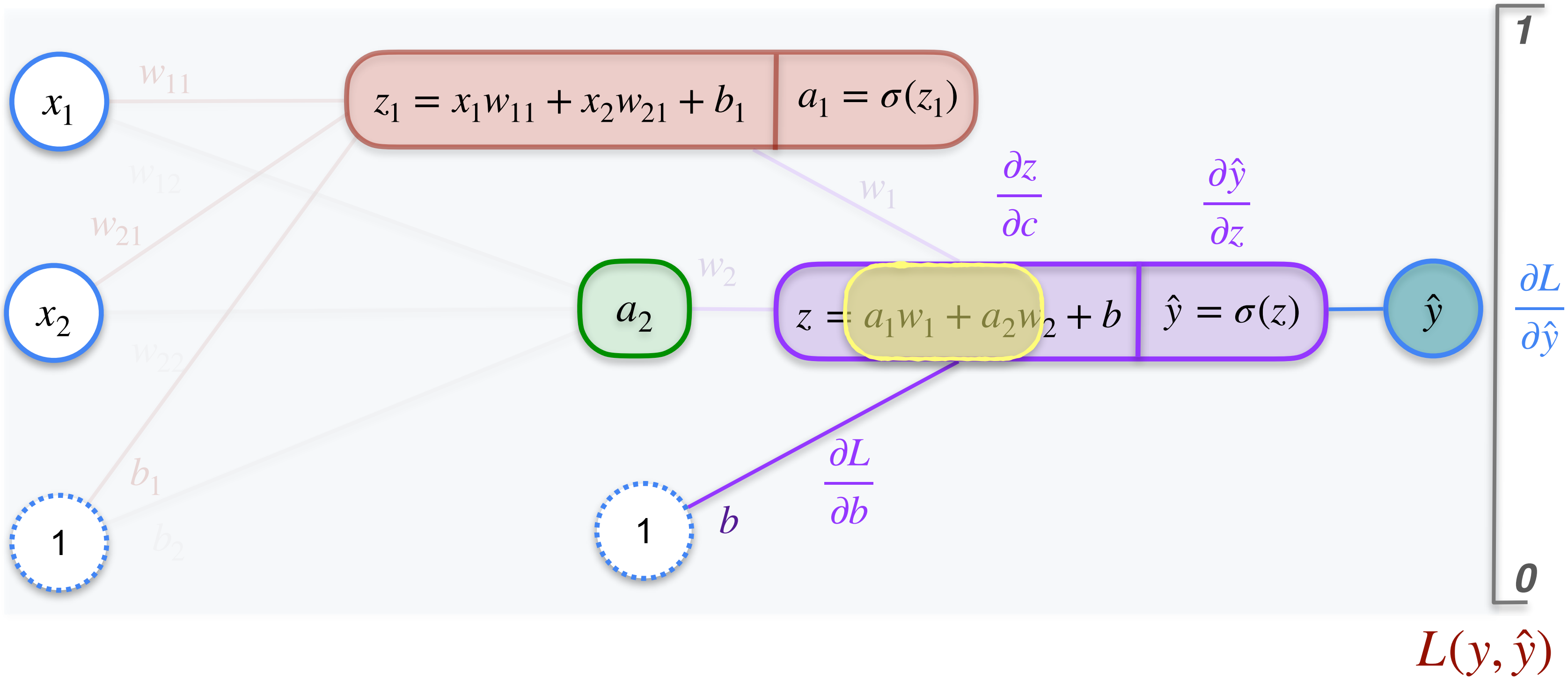
2,2,1 Neural Network



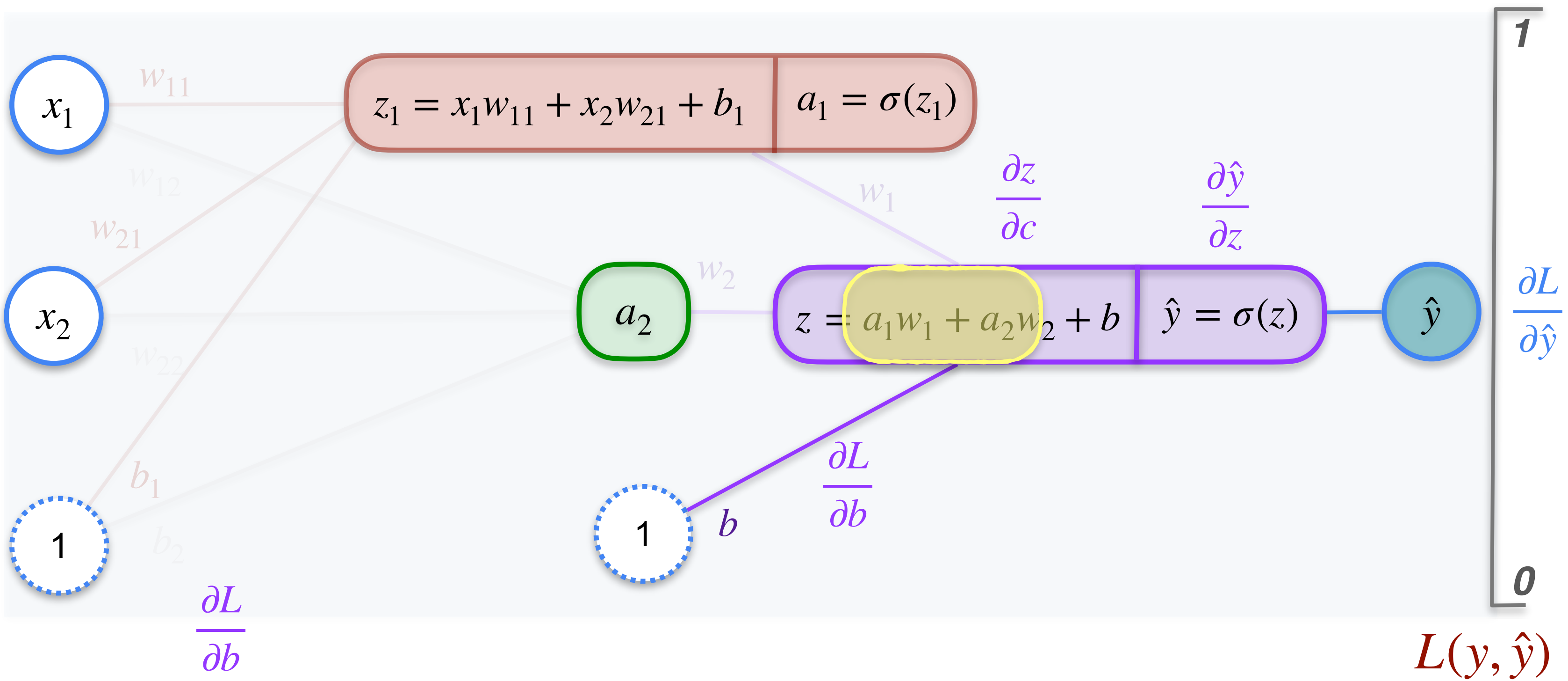
2,2,1 Neural Network



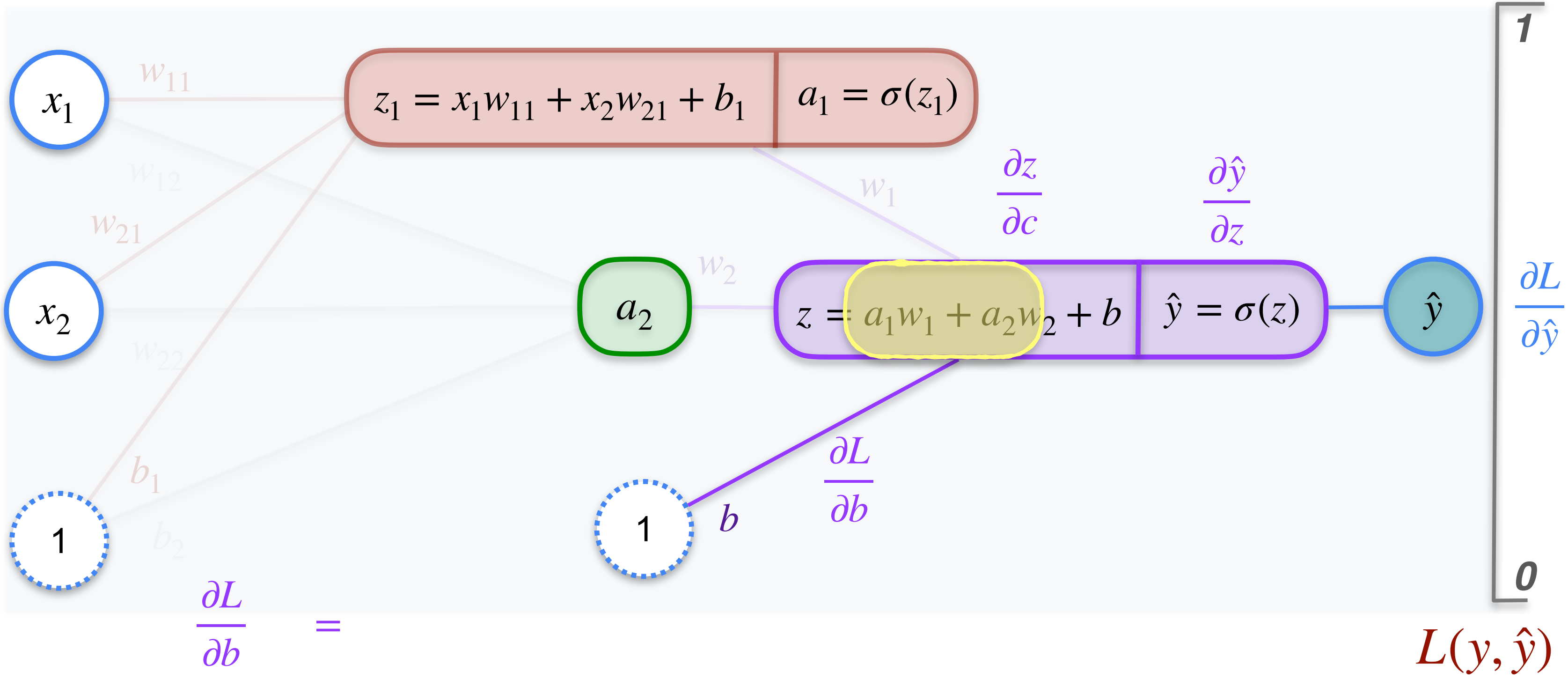
2,2,1 Neural Network



2,2,1 Neural Network

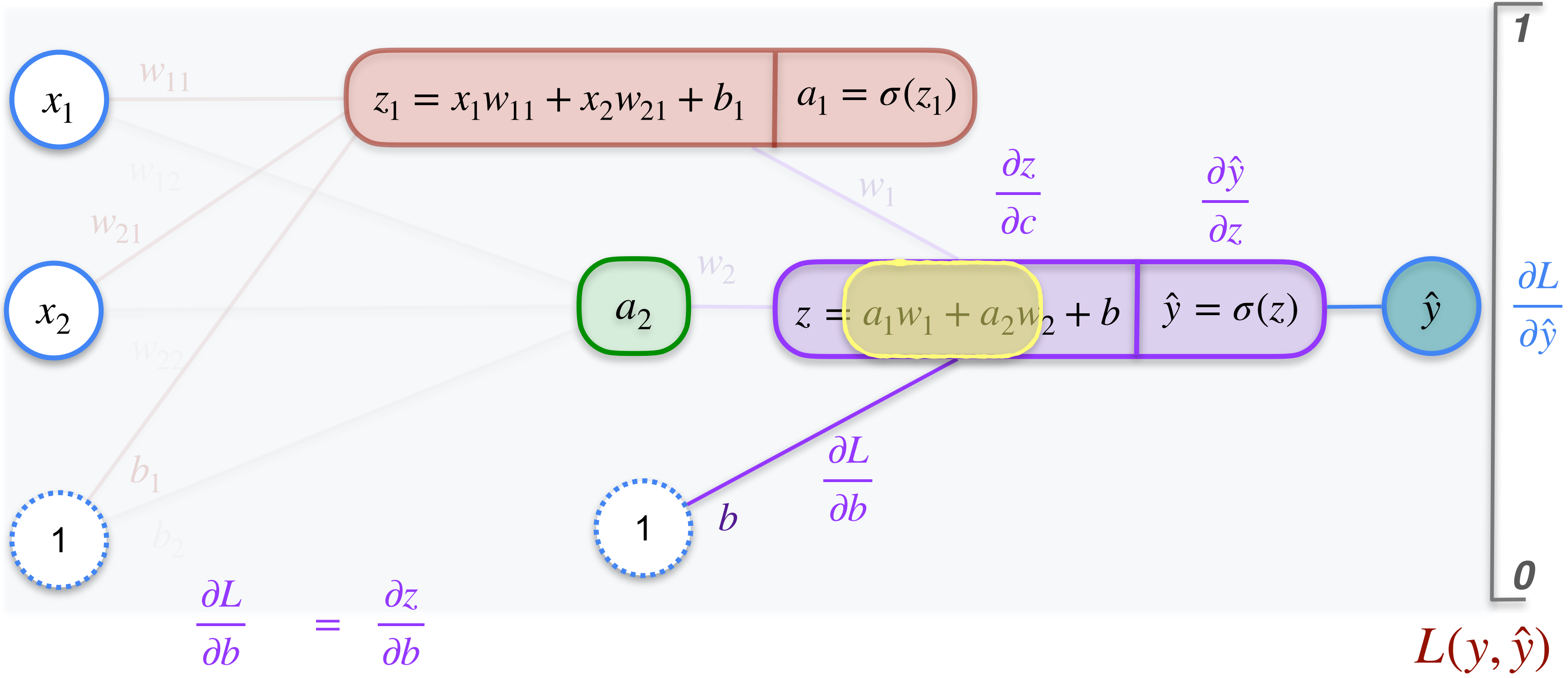


2,2,1 Neural Network



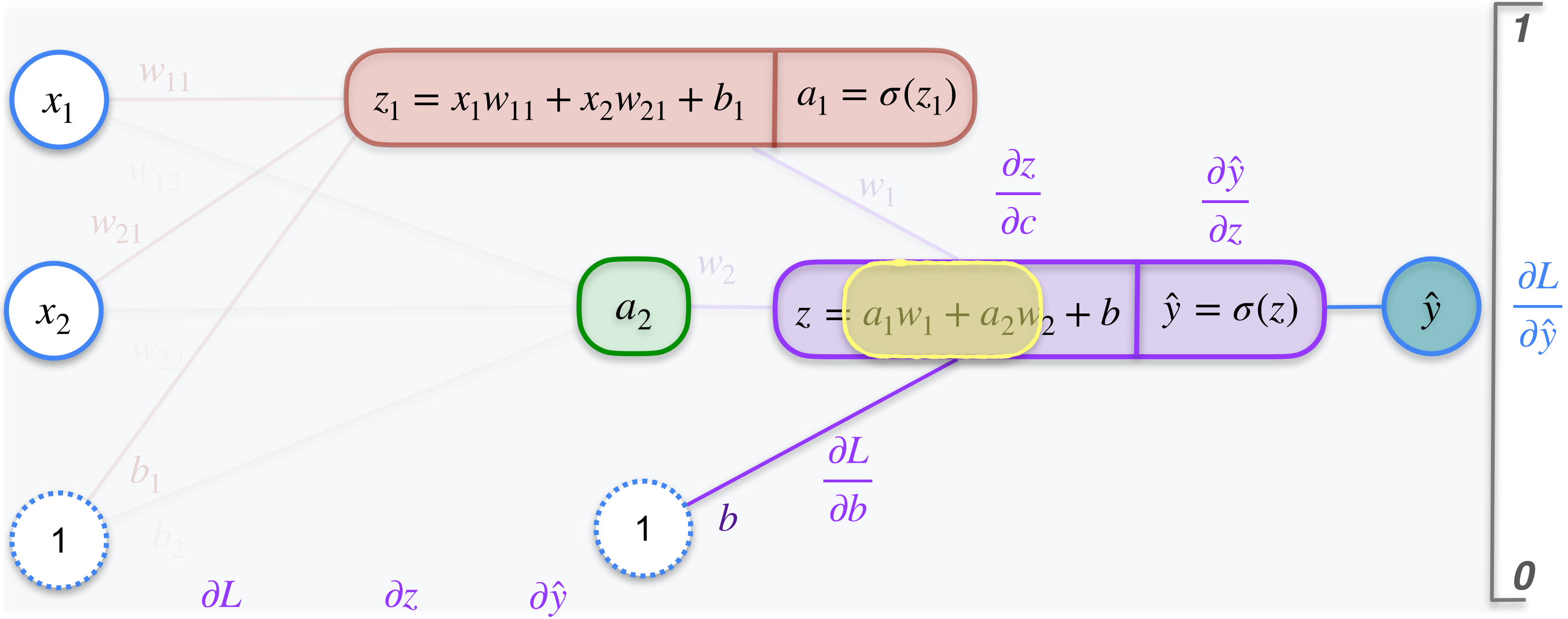
$$\frac{\partial L}{\partial b} =$$

2,2,1 Neural Network



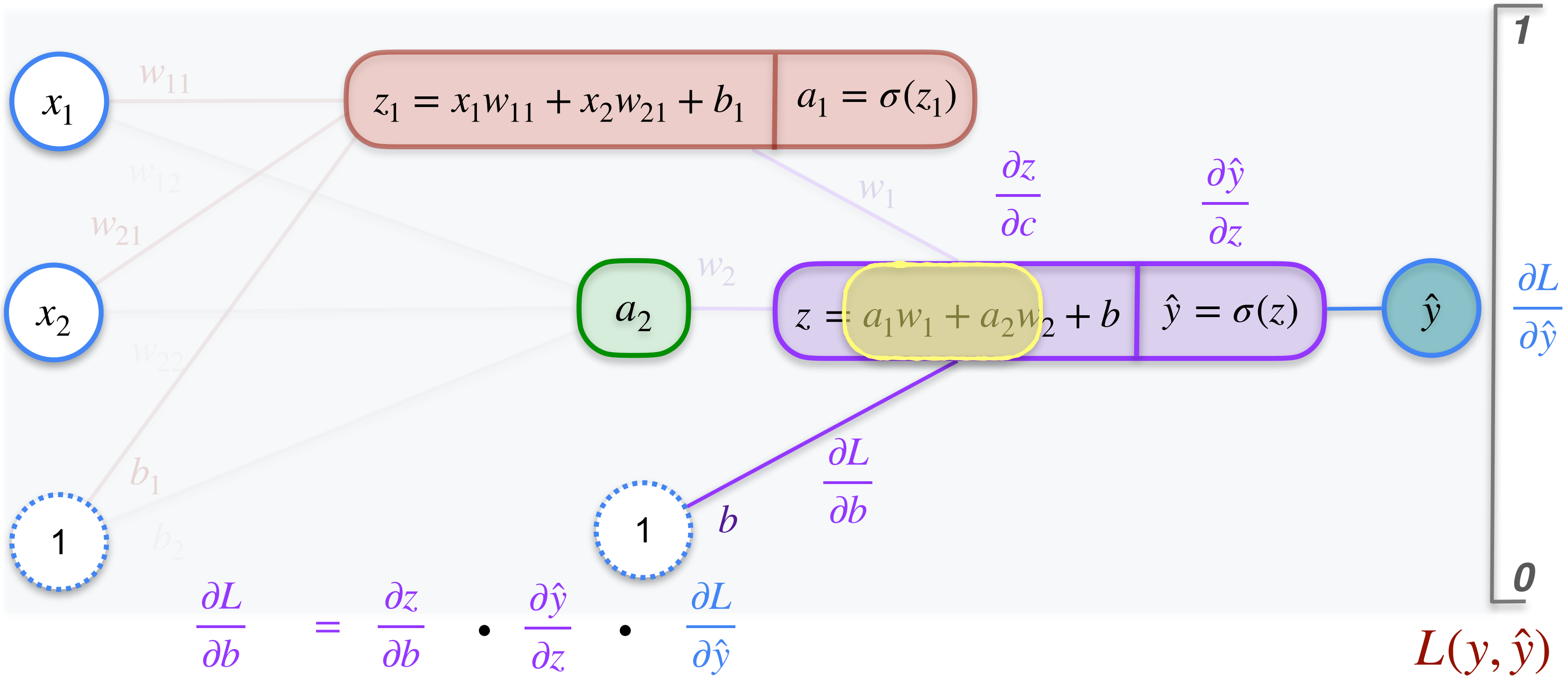
$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b}$$

2,2,1 Neural Network



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

2,2,1 Neural Network



2,2,1 Neural Network

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

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

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2,2,1 Neural Network

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to find optimal value of b that gives the least error

2,2,1 Neural Network

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

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

$$z = a_1w_1 + a_2w_2 + b$$

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

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

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

Perform gradient descent with

to find optimal value of b that gives the least error

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2,2,1 Neural Network

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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

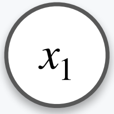
DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Gradient Descent and Backpropagation

Back Propagation Introduction

Back Propagation Introduction



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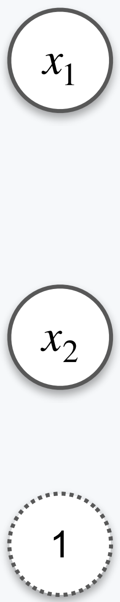

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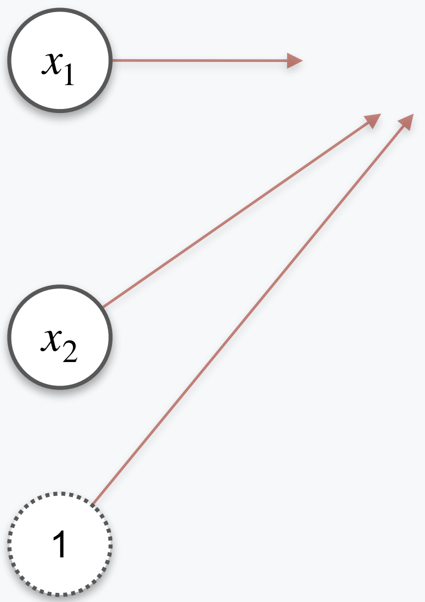

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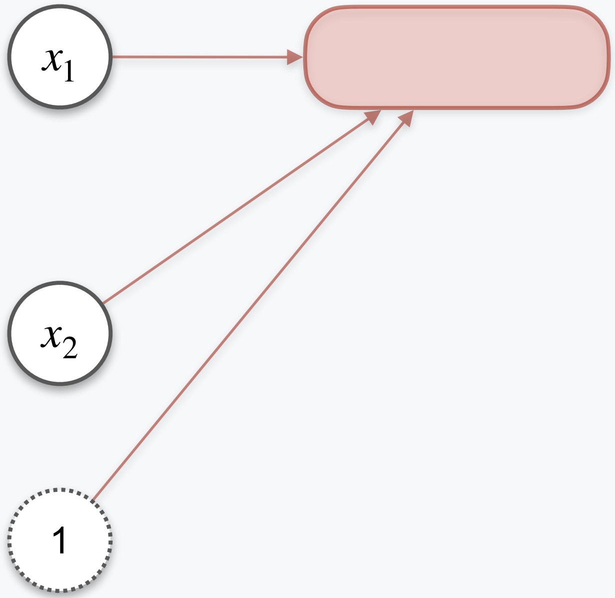

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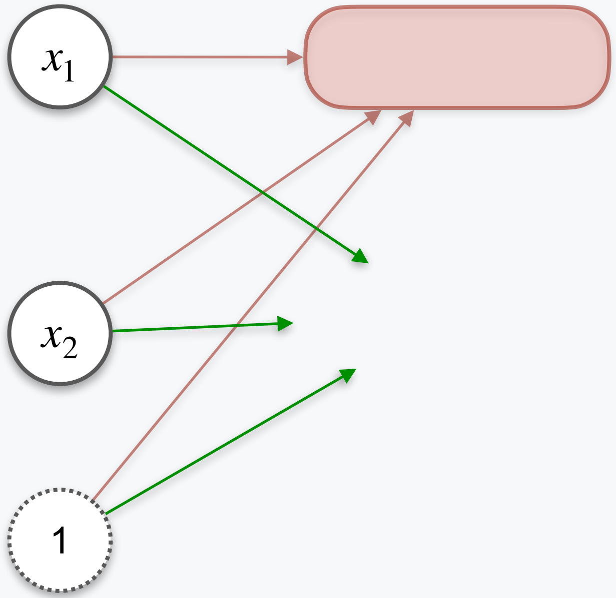

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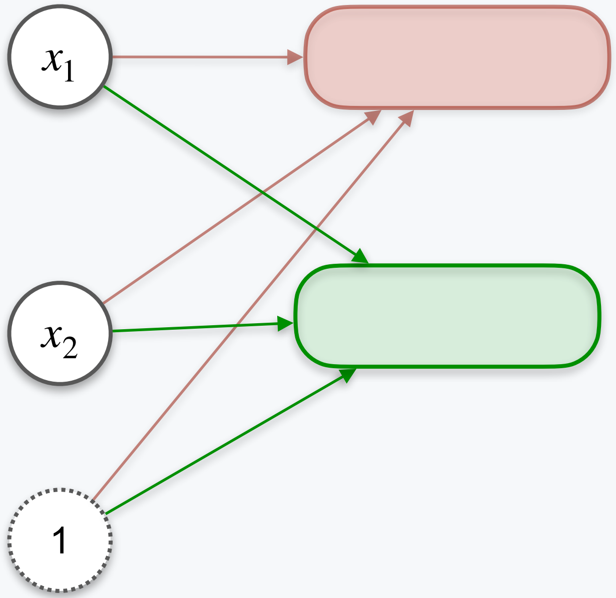

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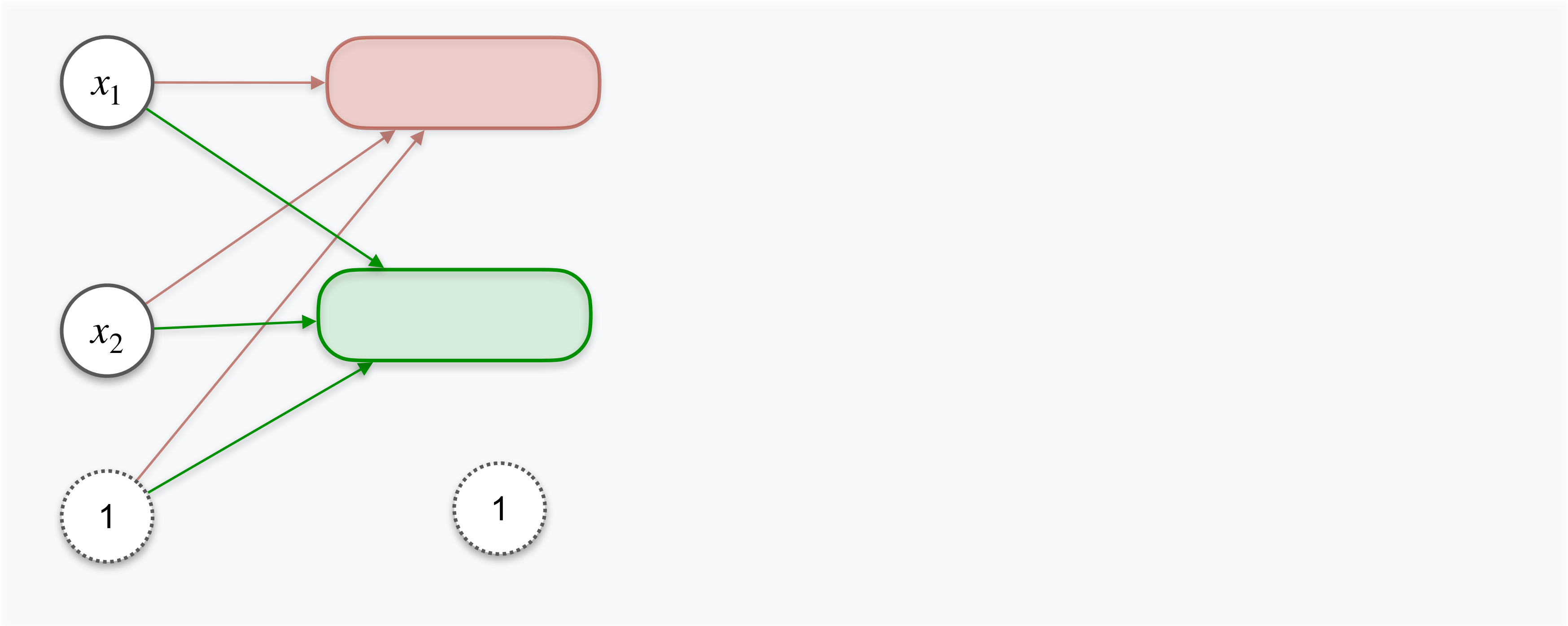

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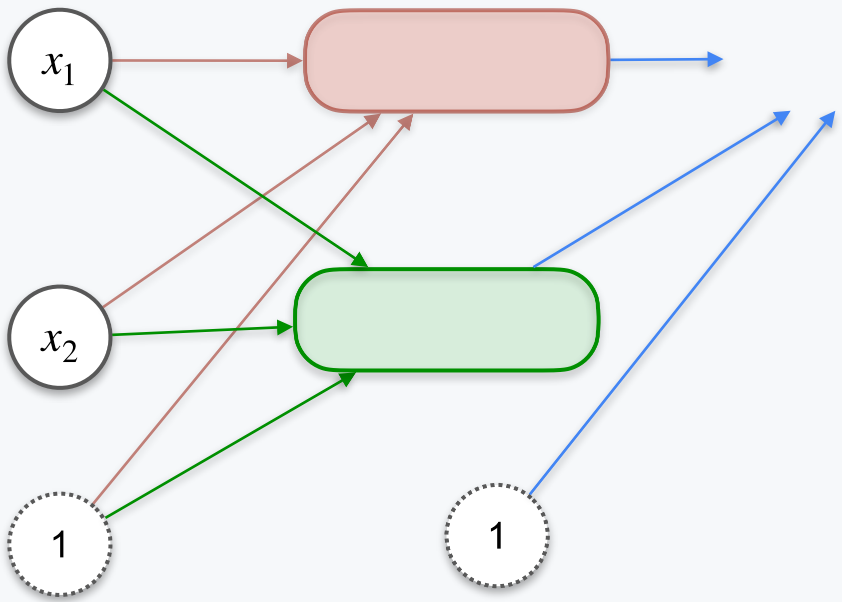

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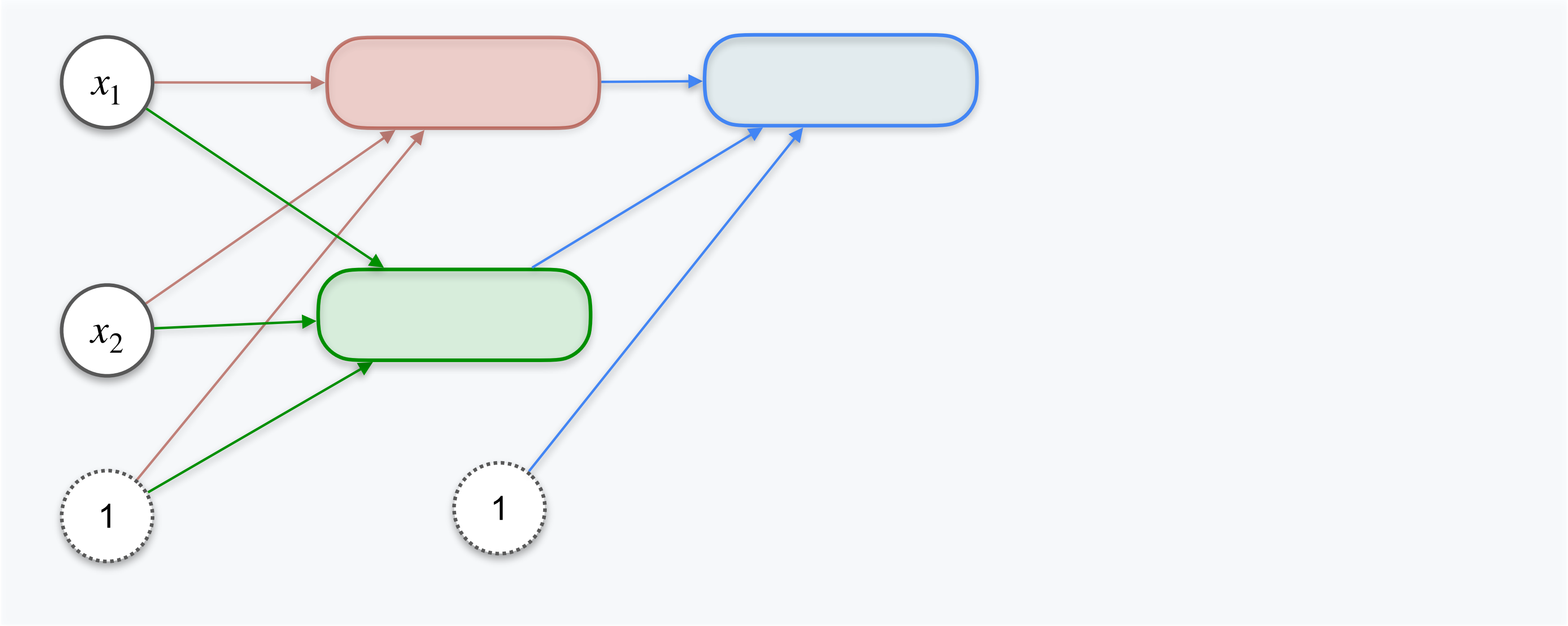

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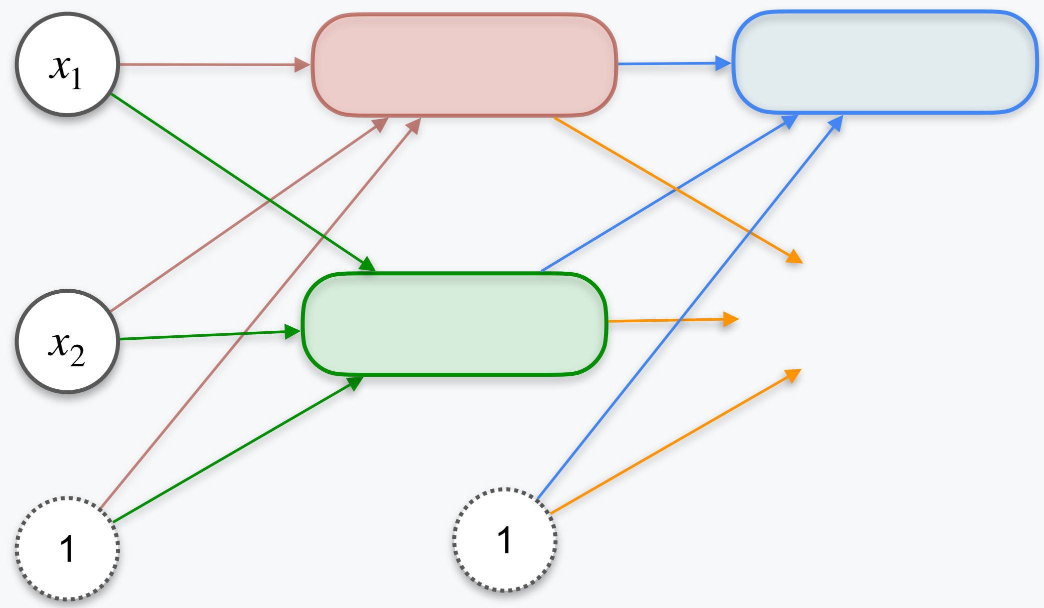

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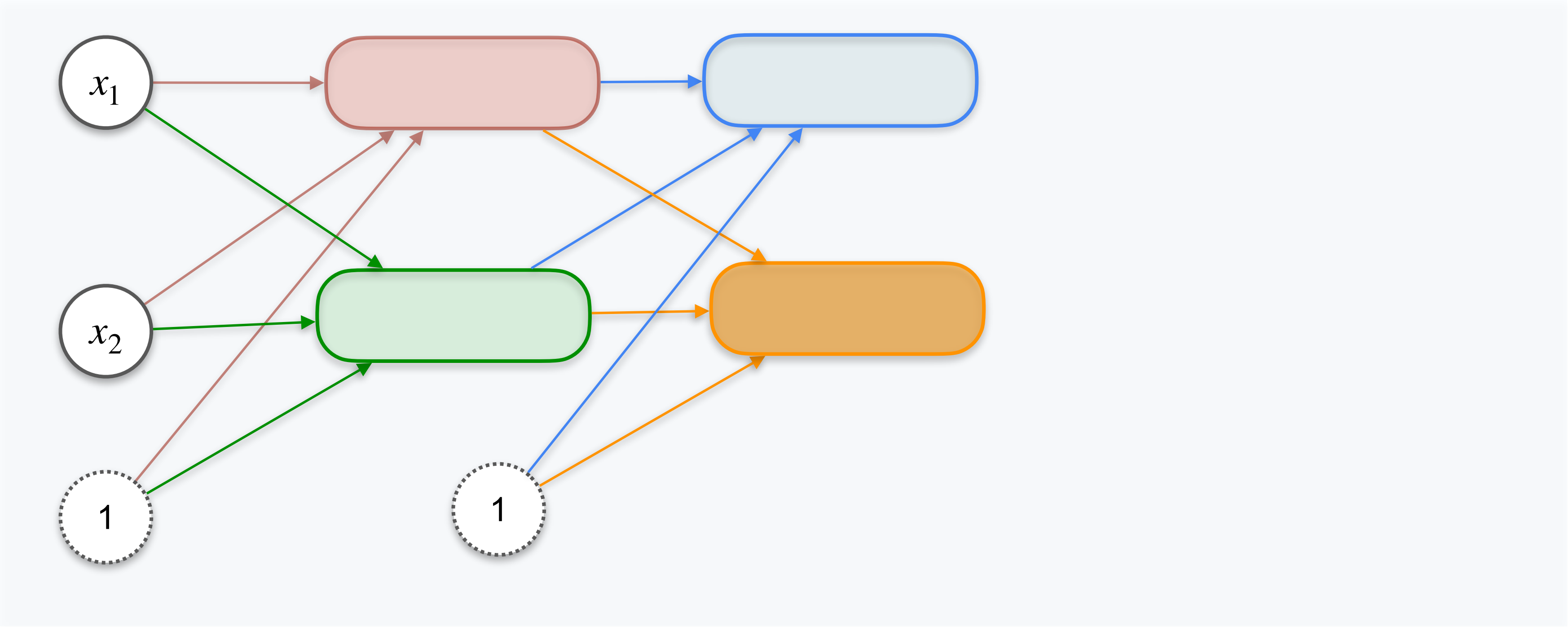

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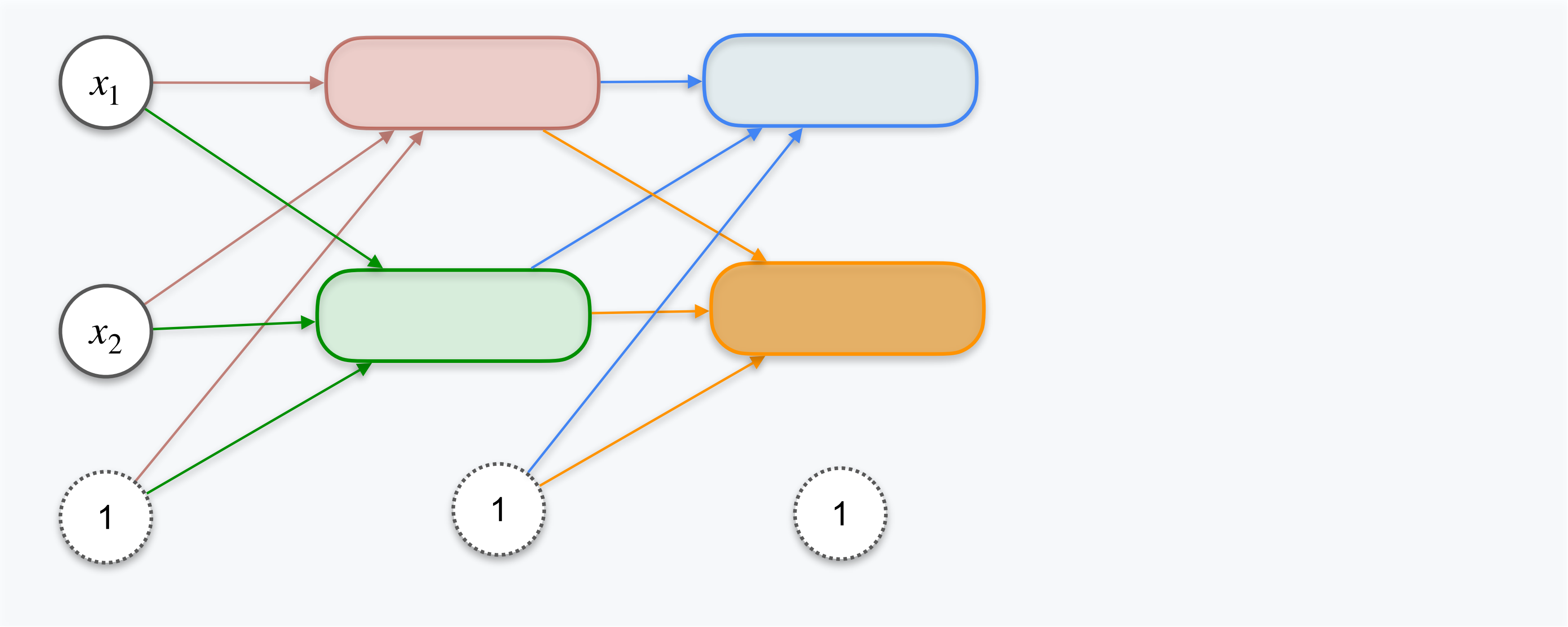

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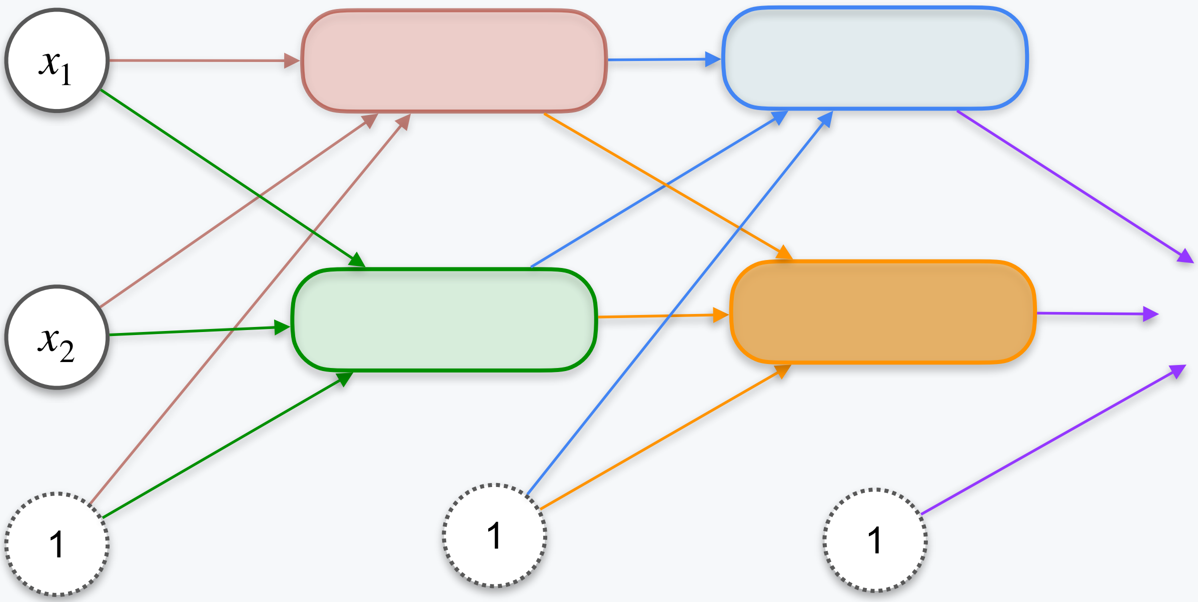

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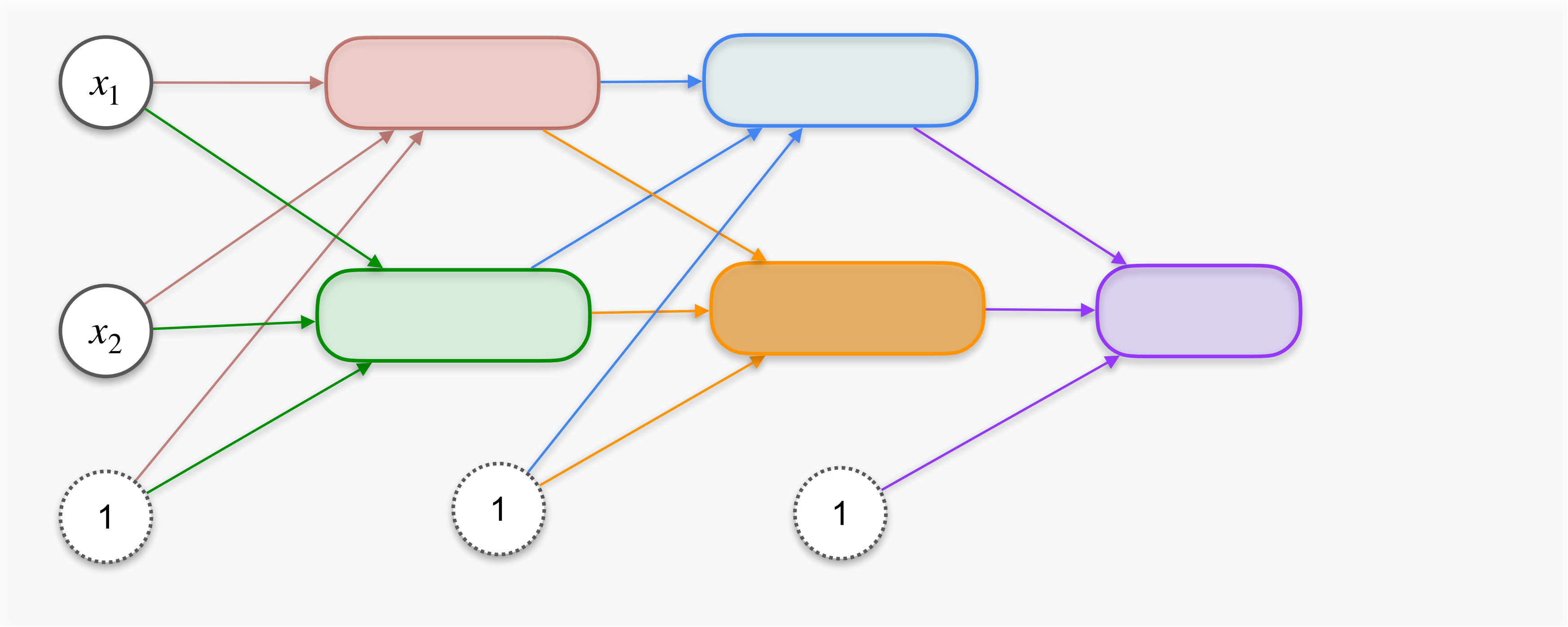

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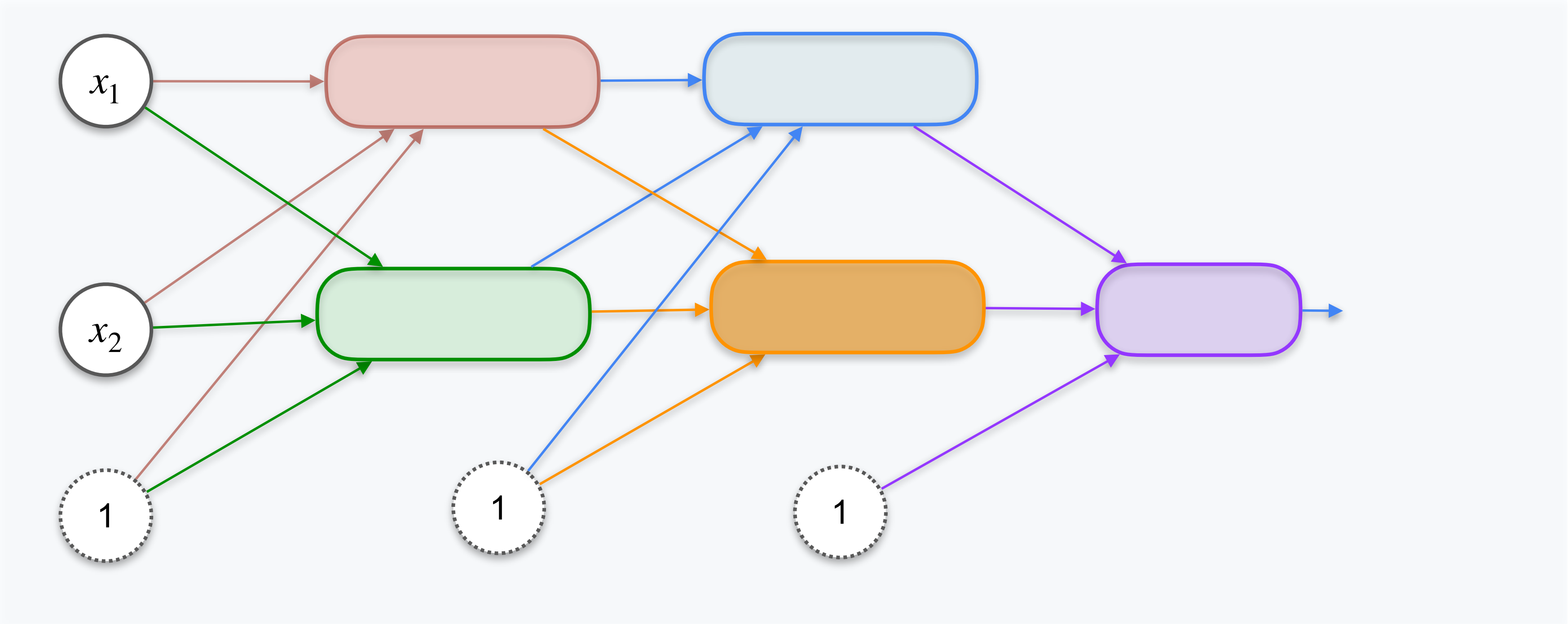

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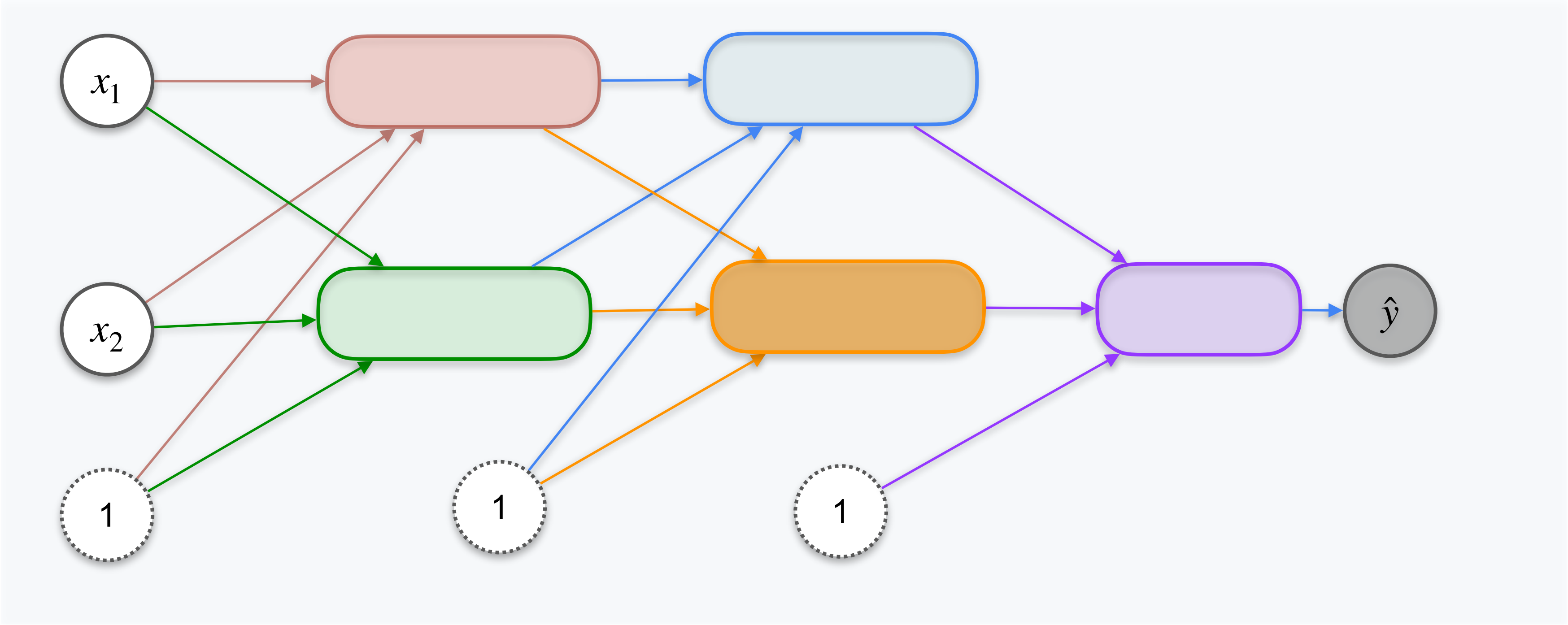

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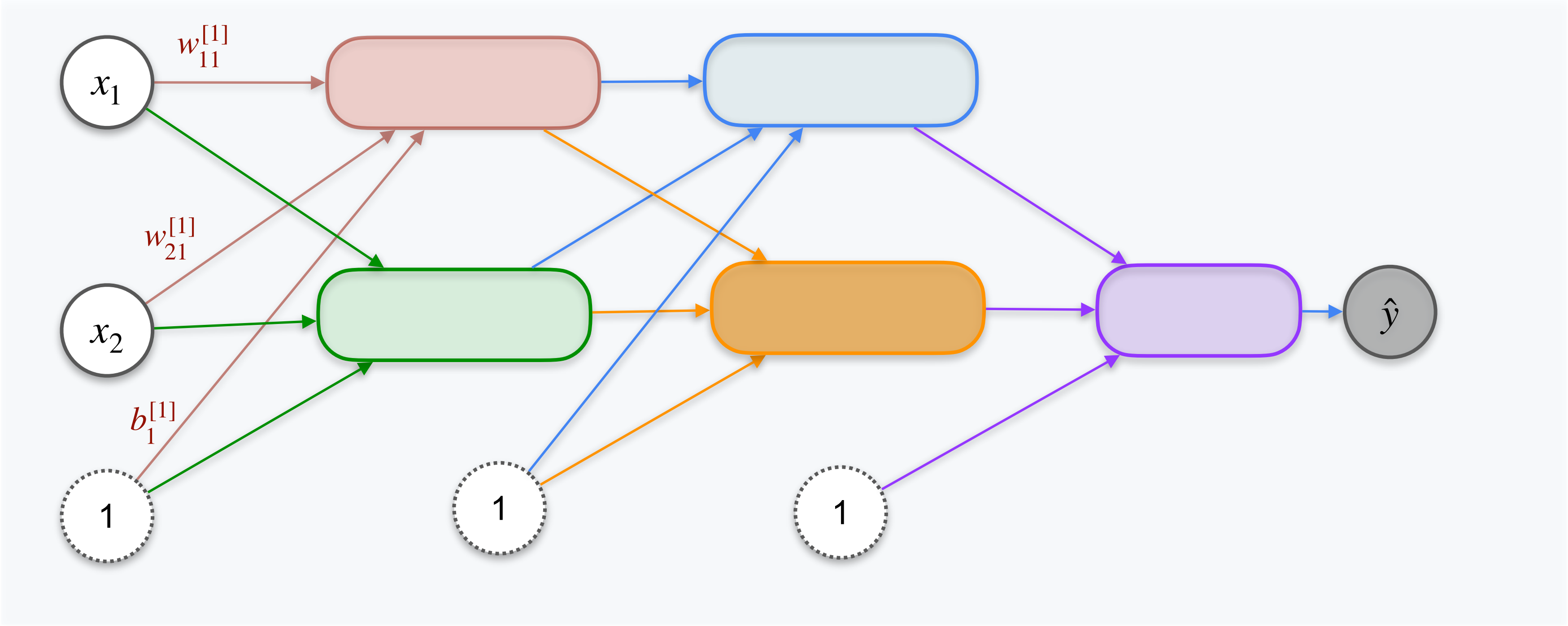

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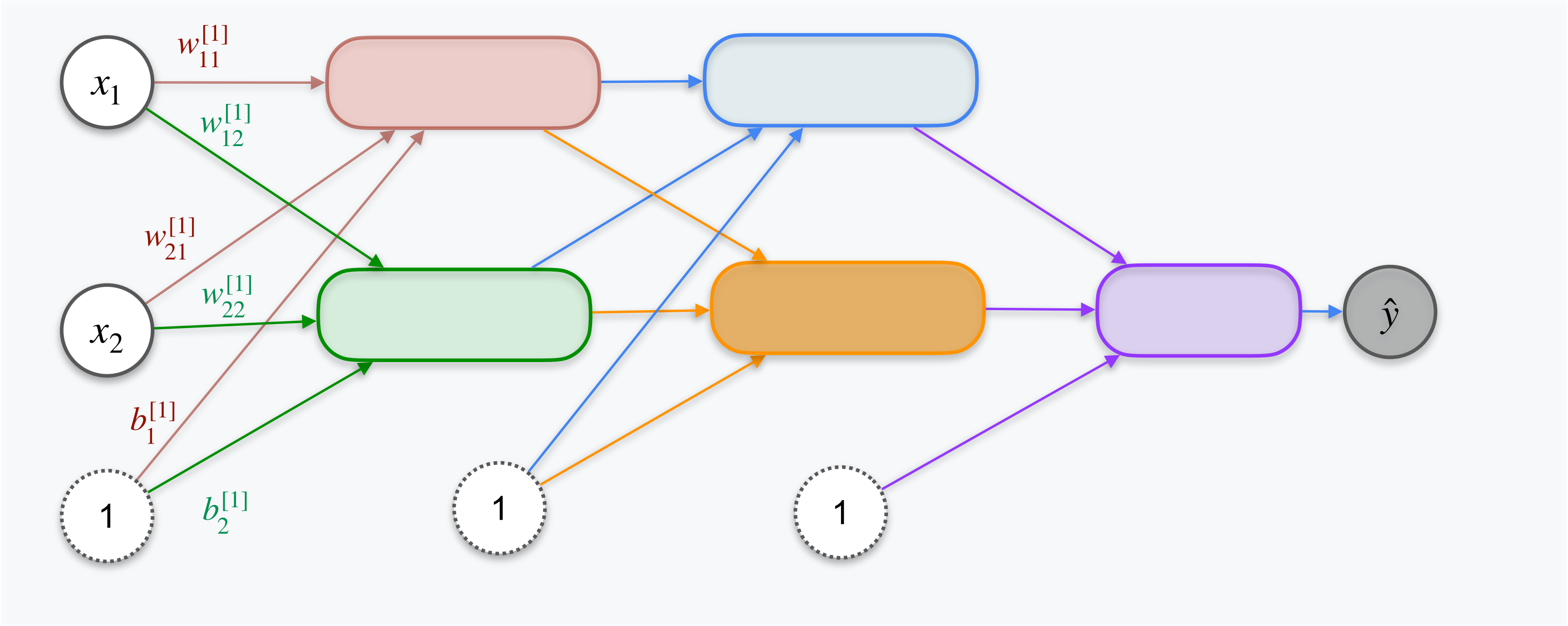

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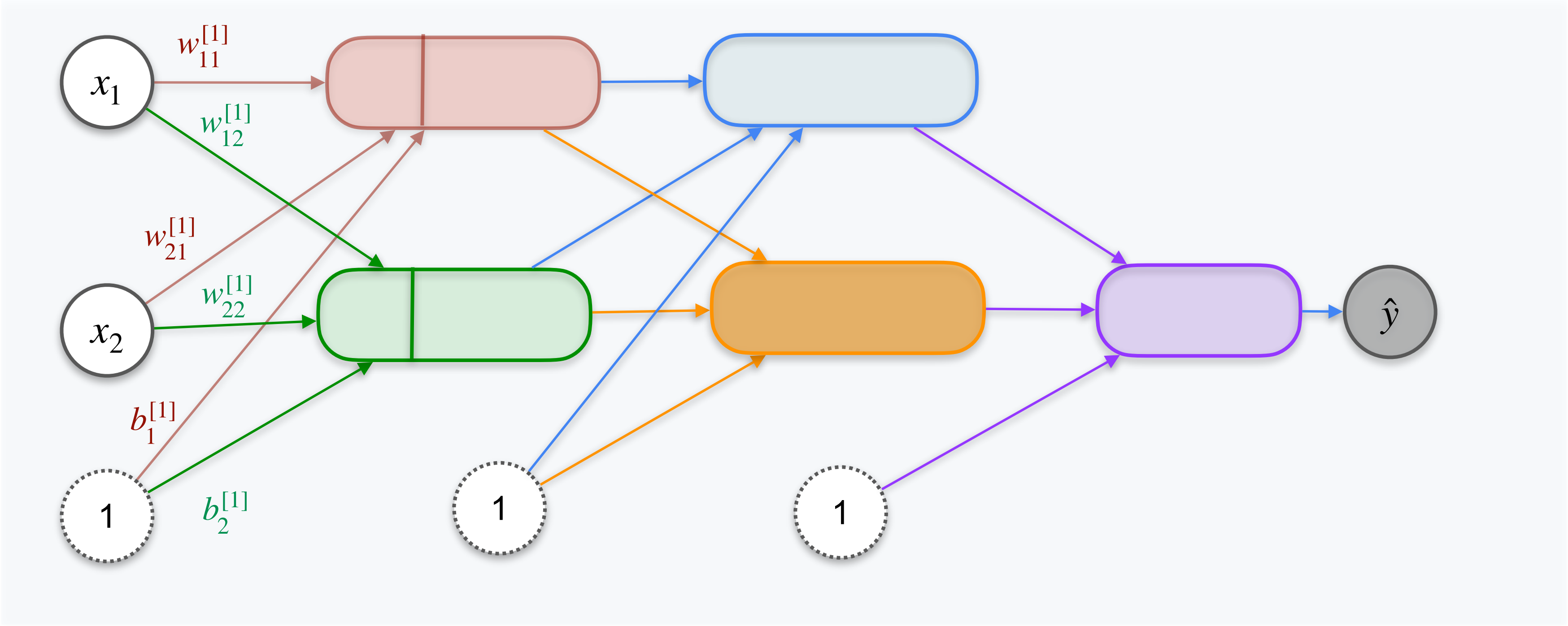

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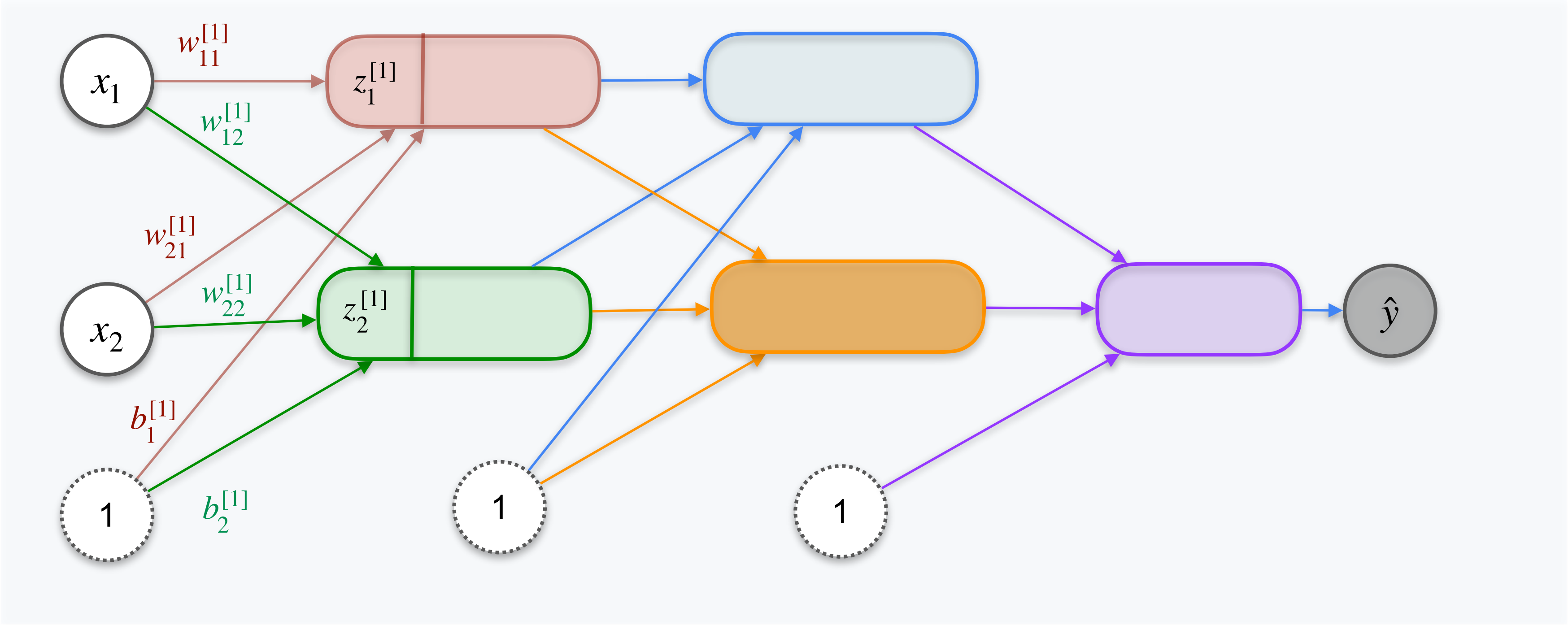

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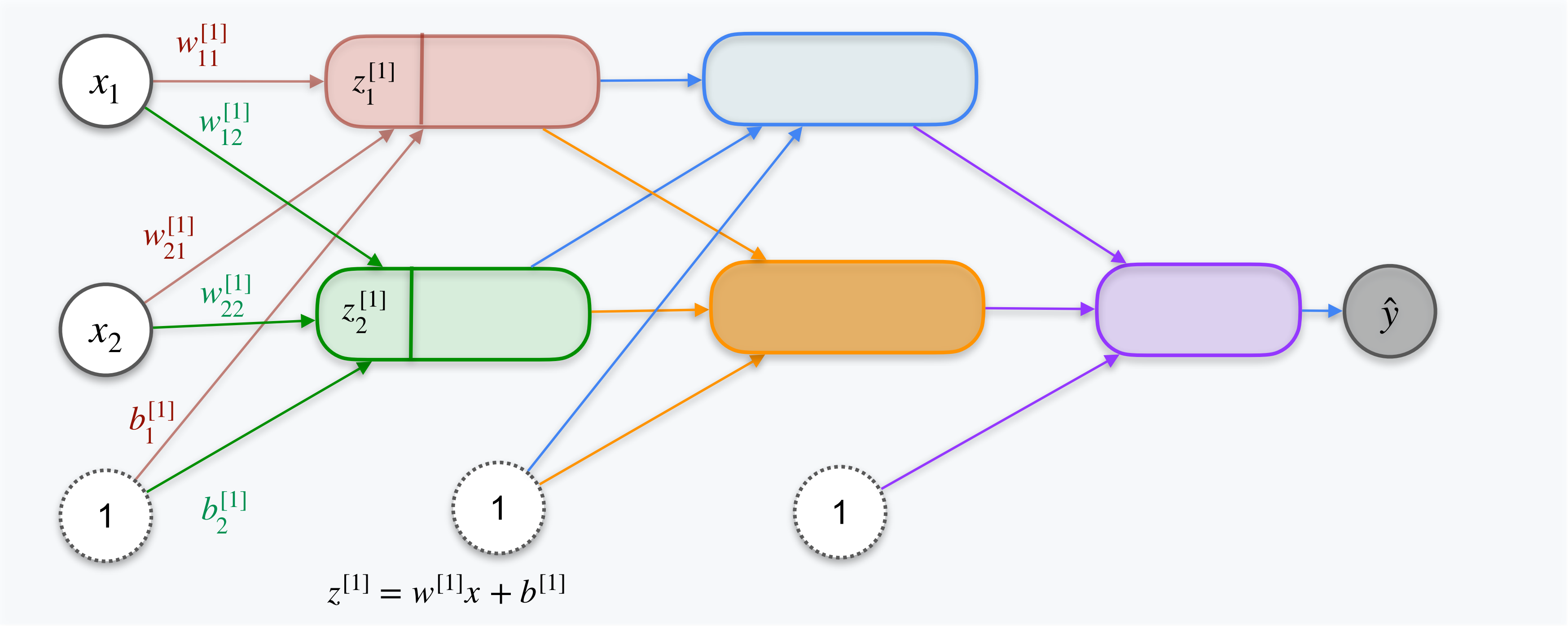

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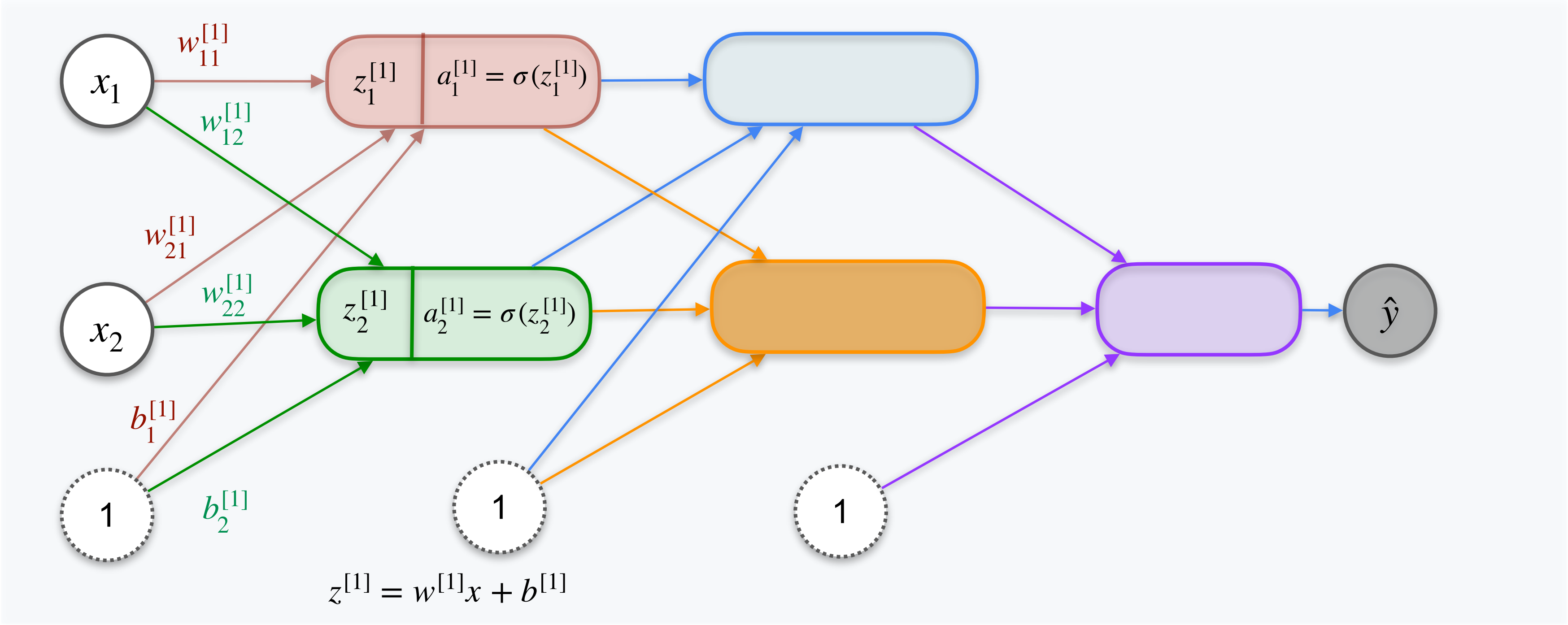

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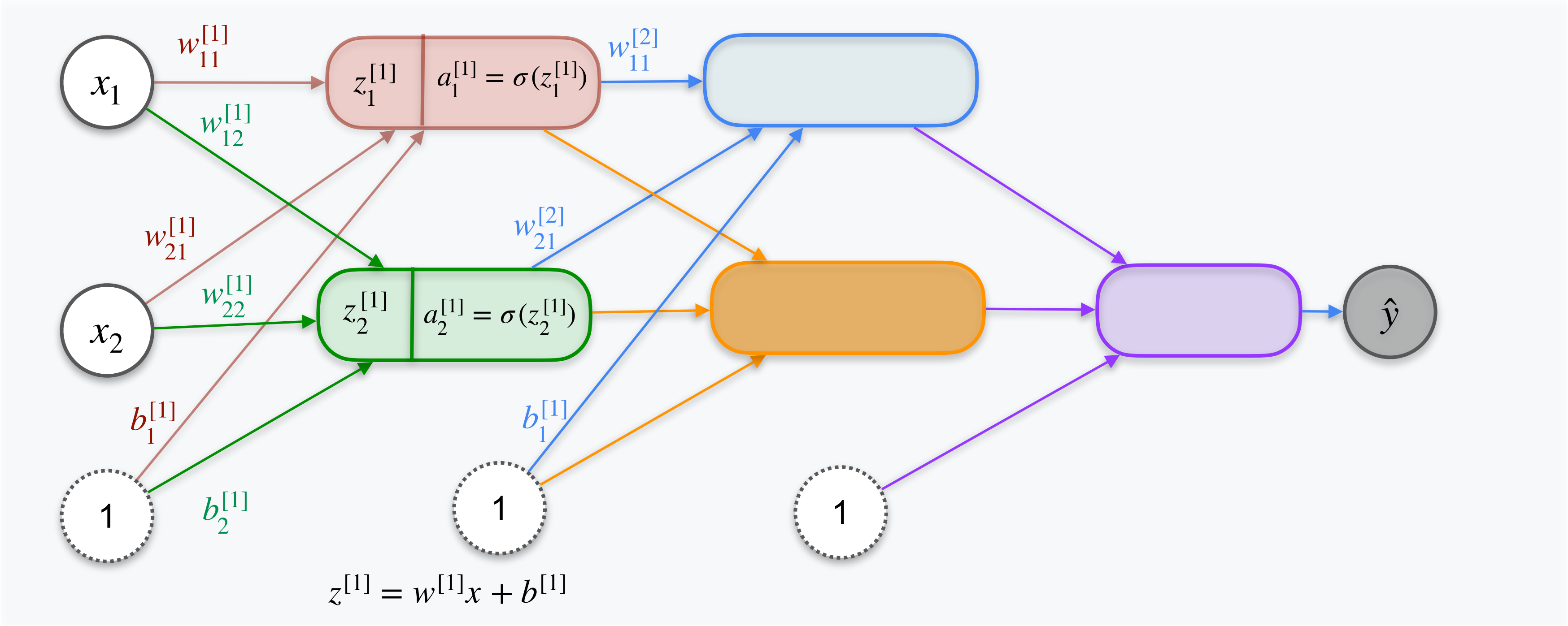

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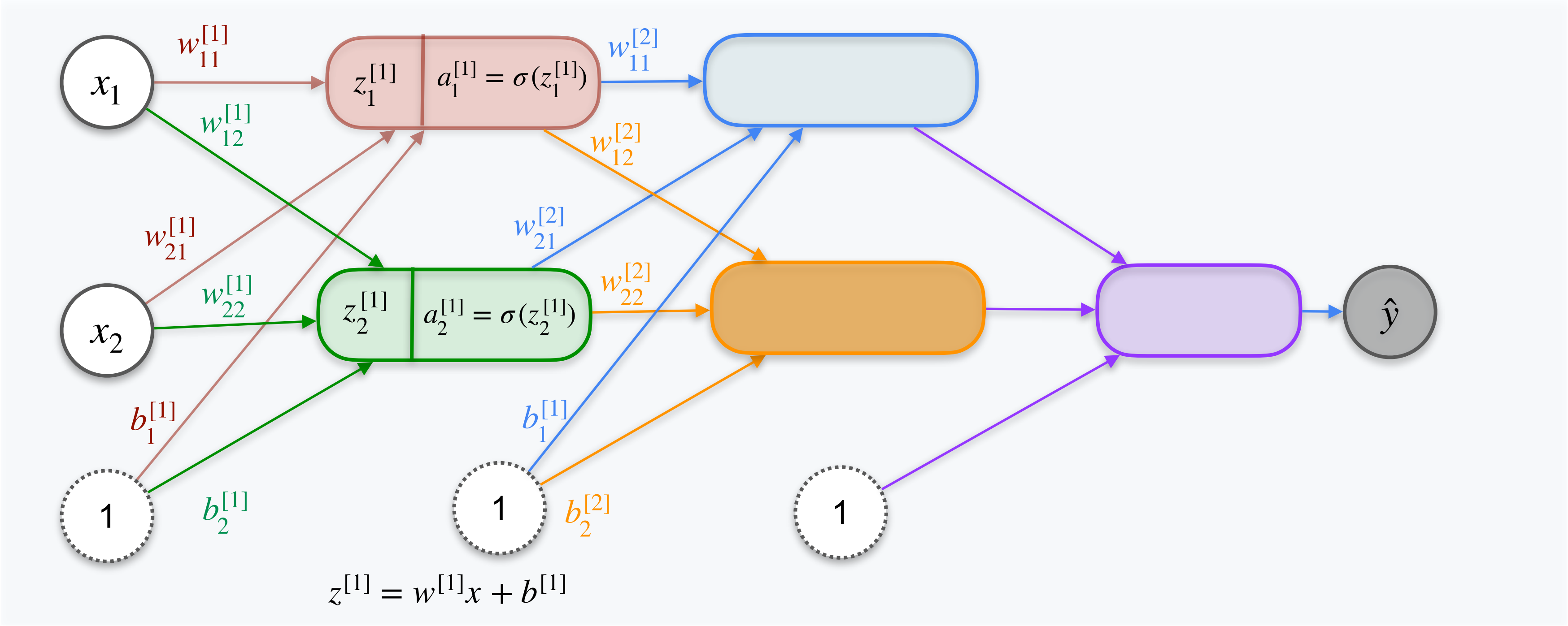

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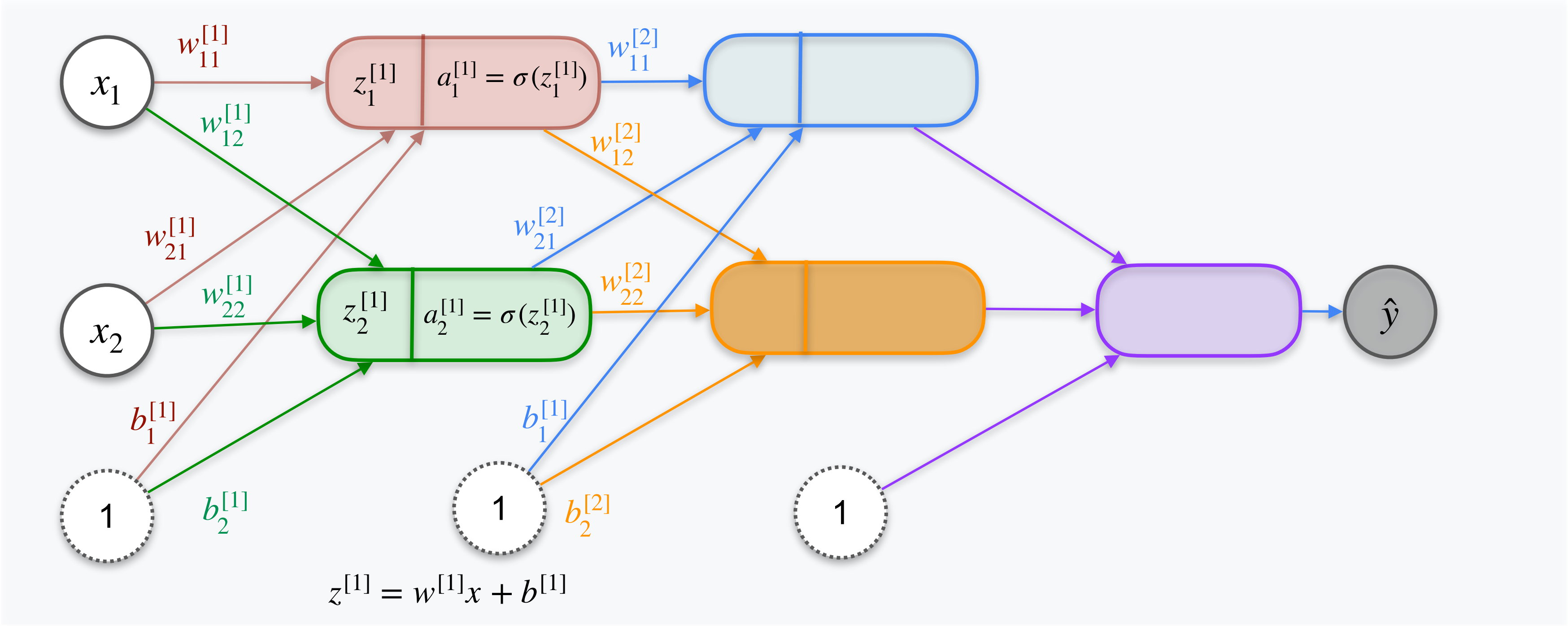

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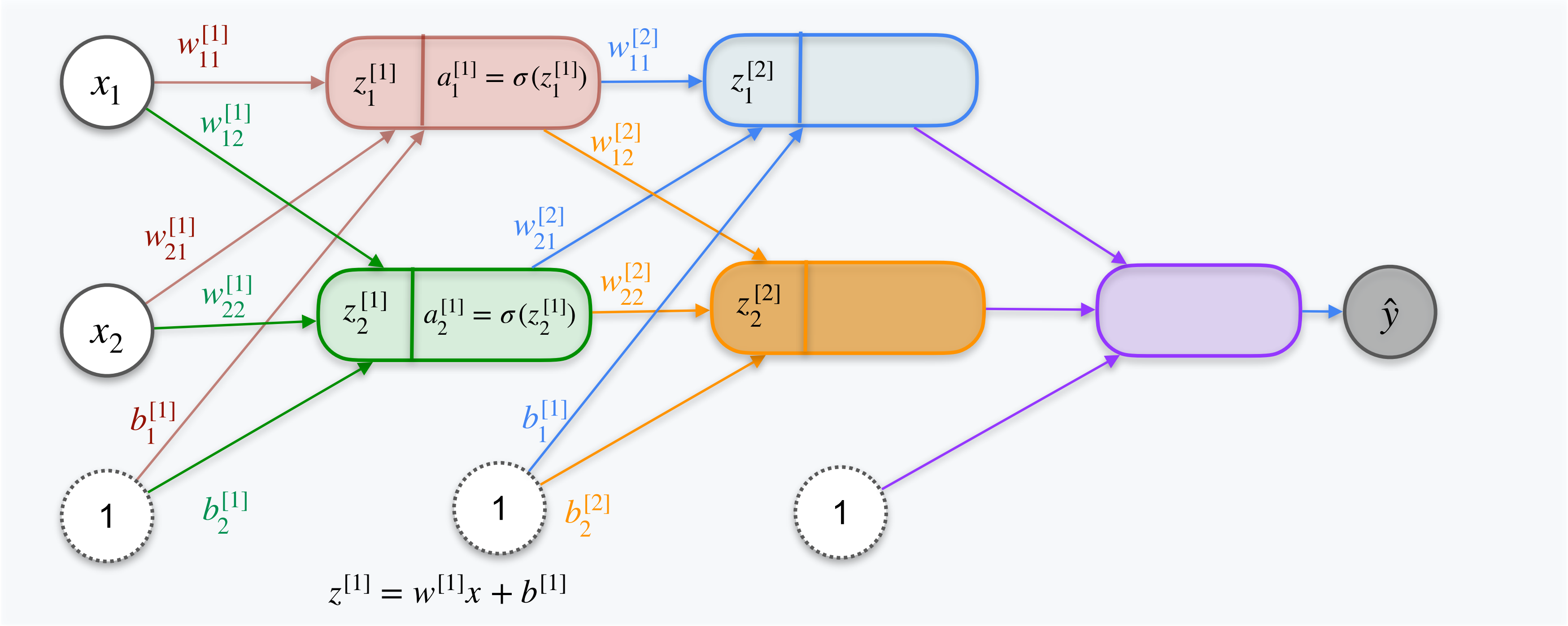

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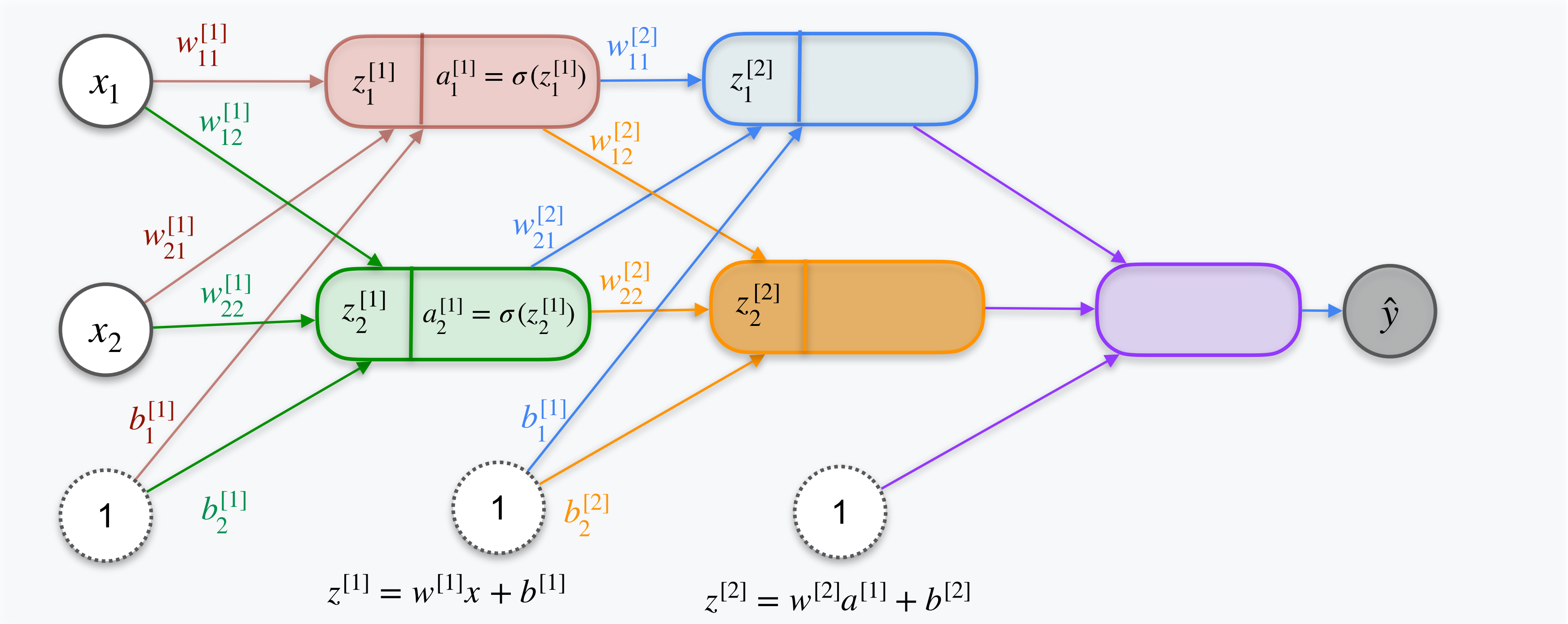

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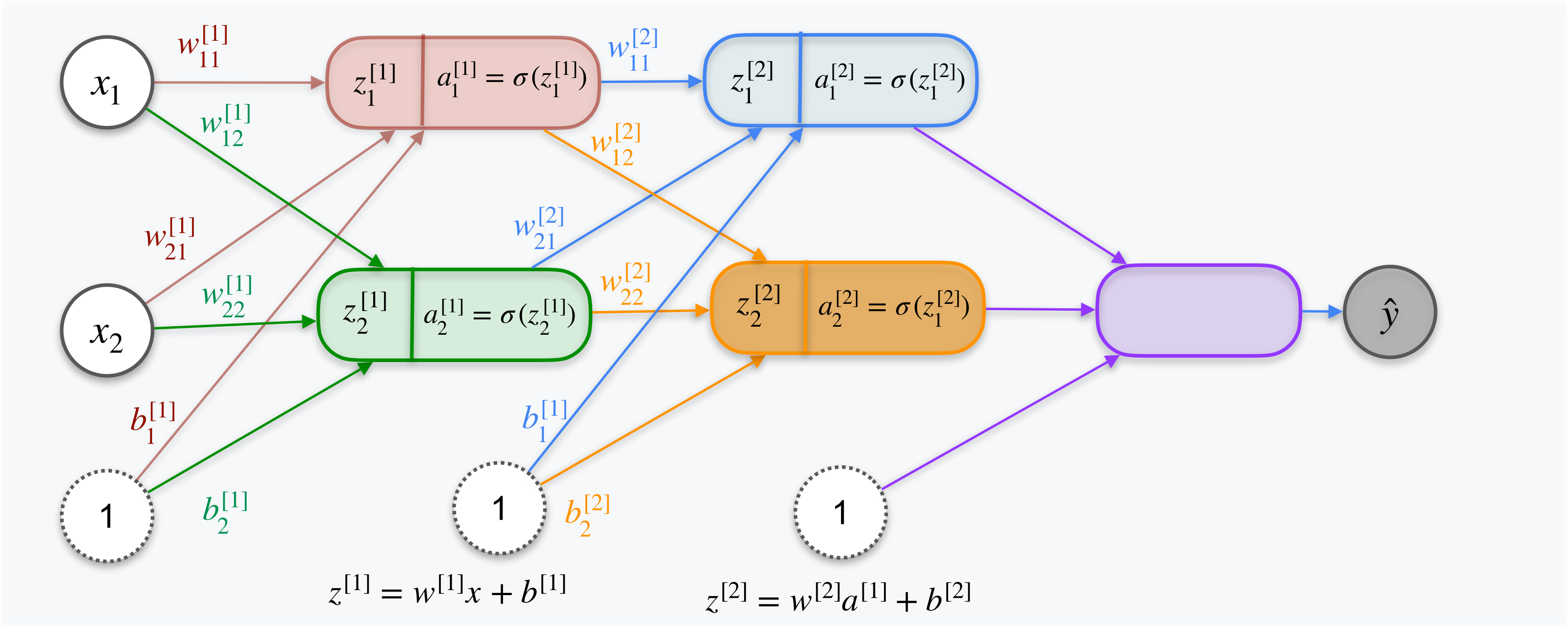

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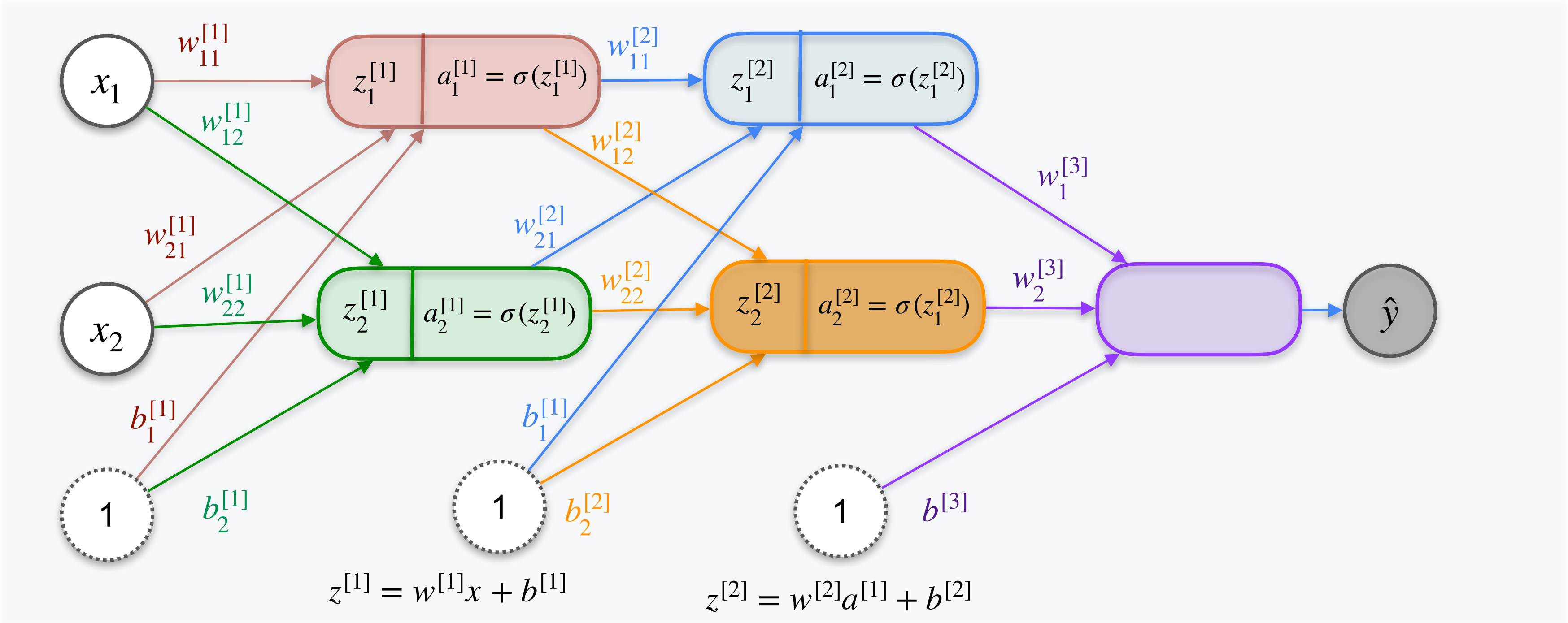

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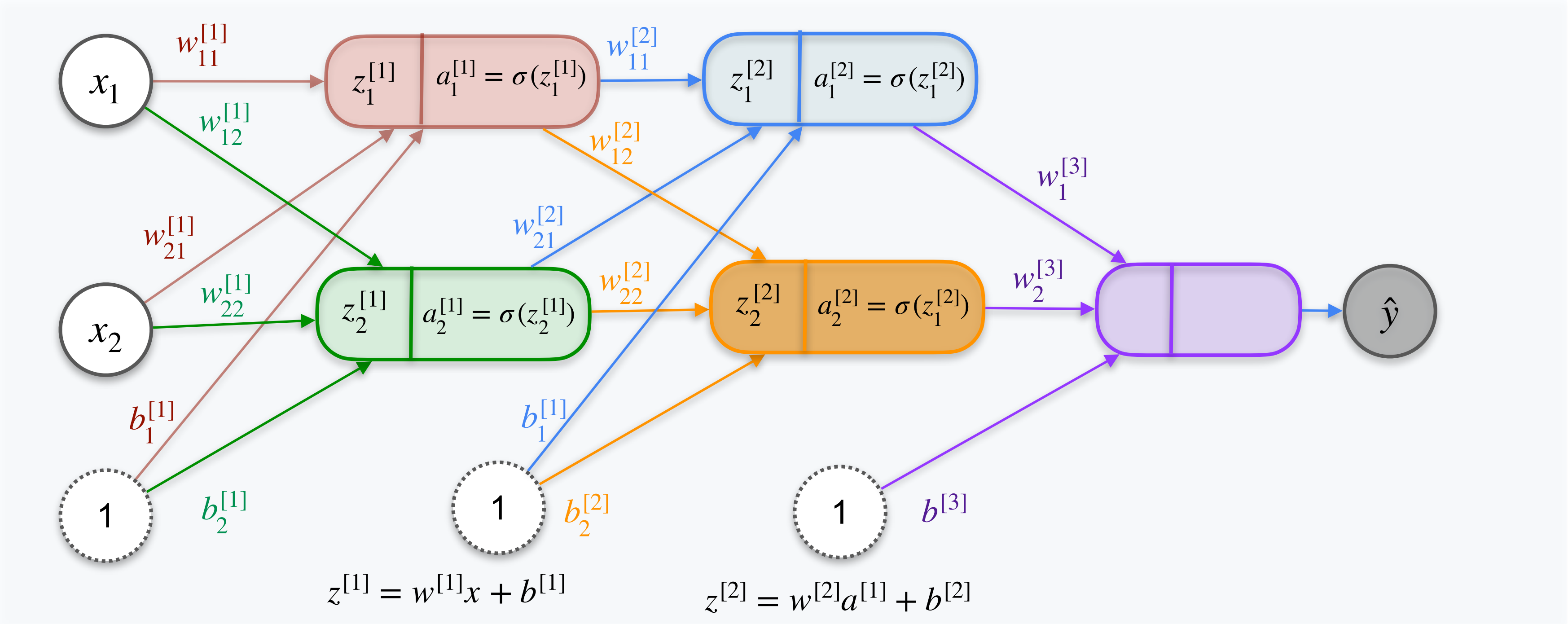

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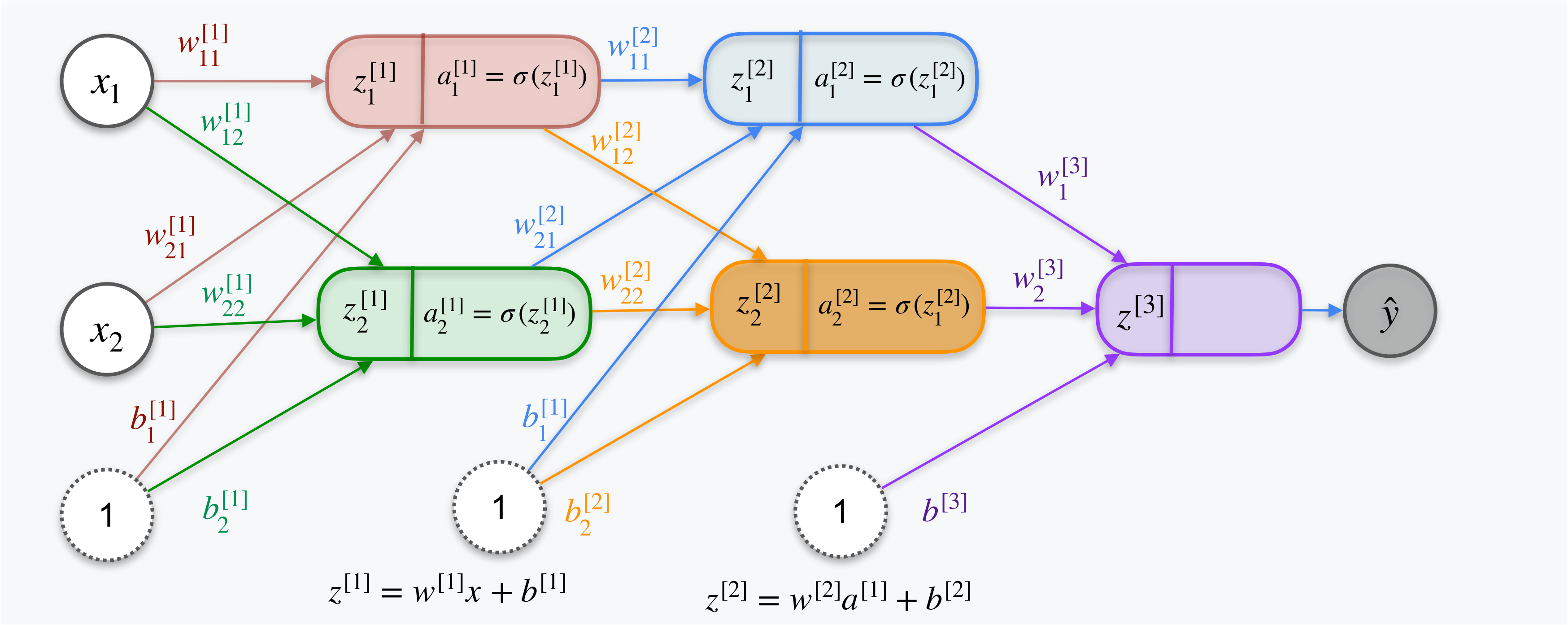

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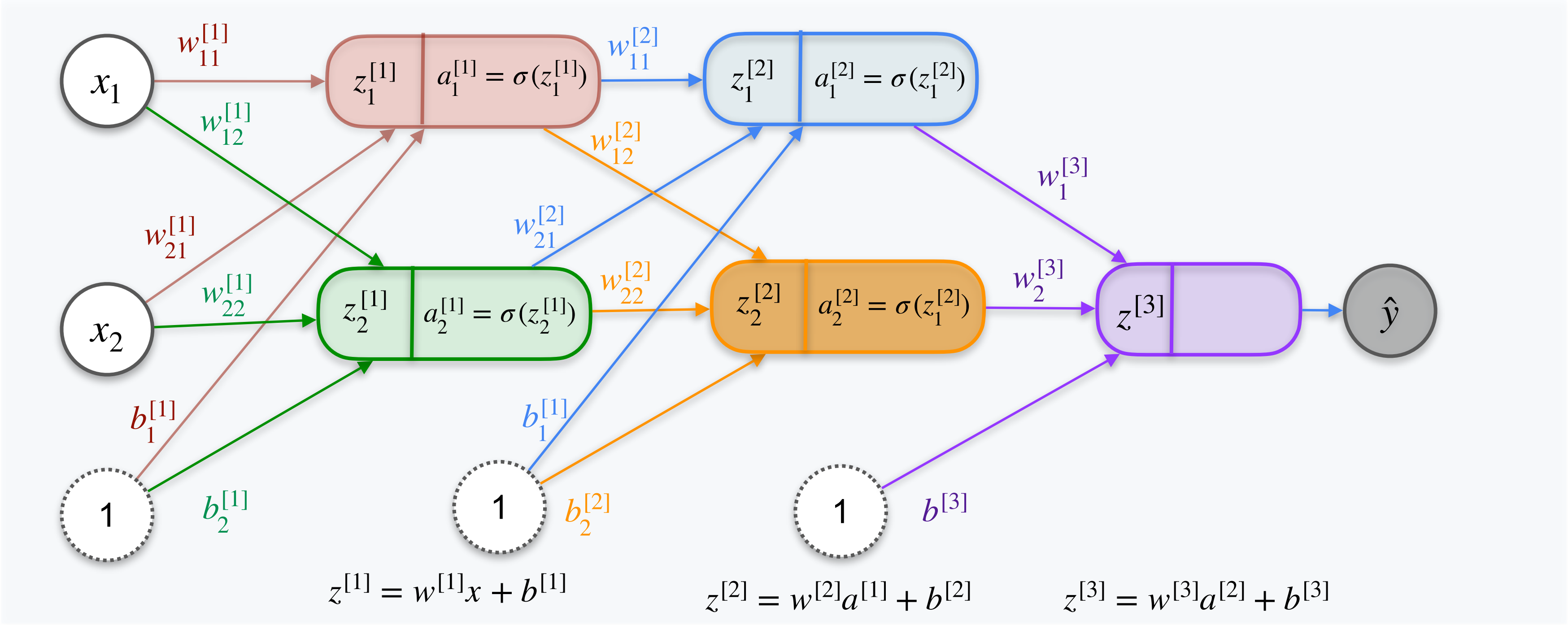

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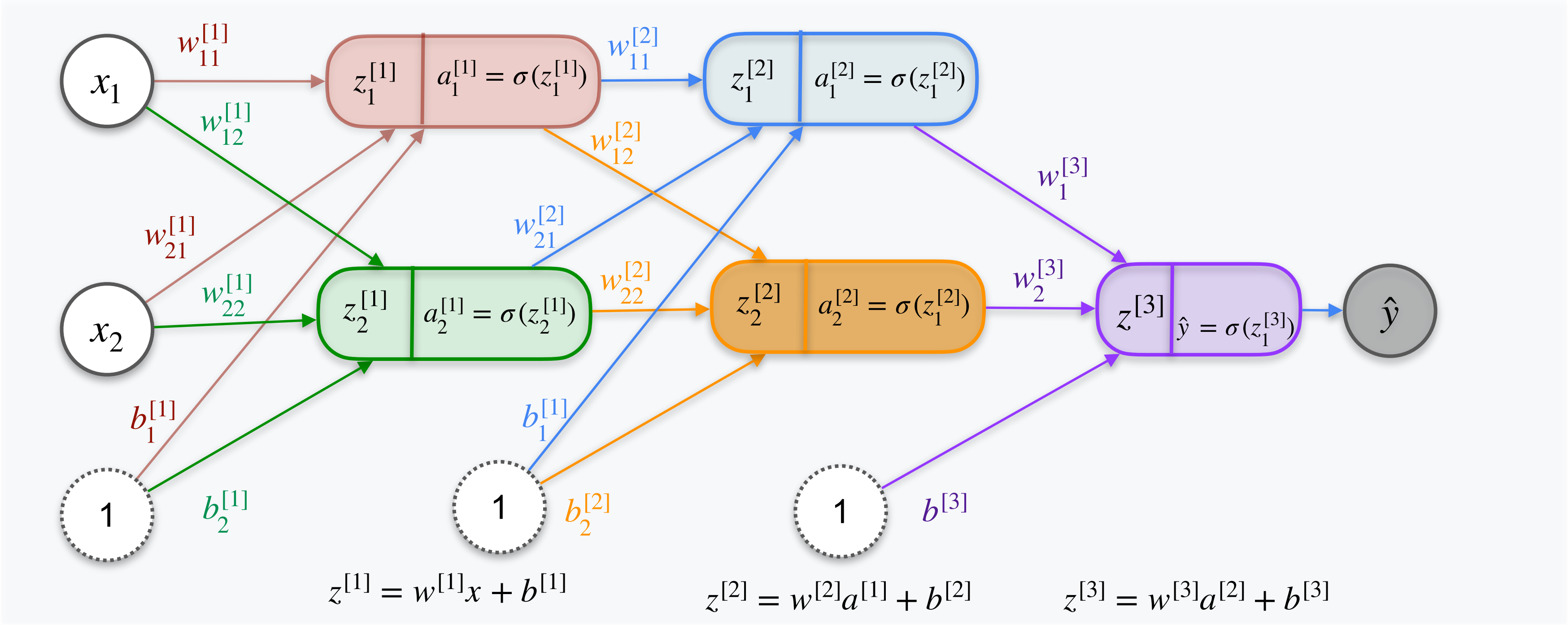

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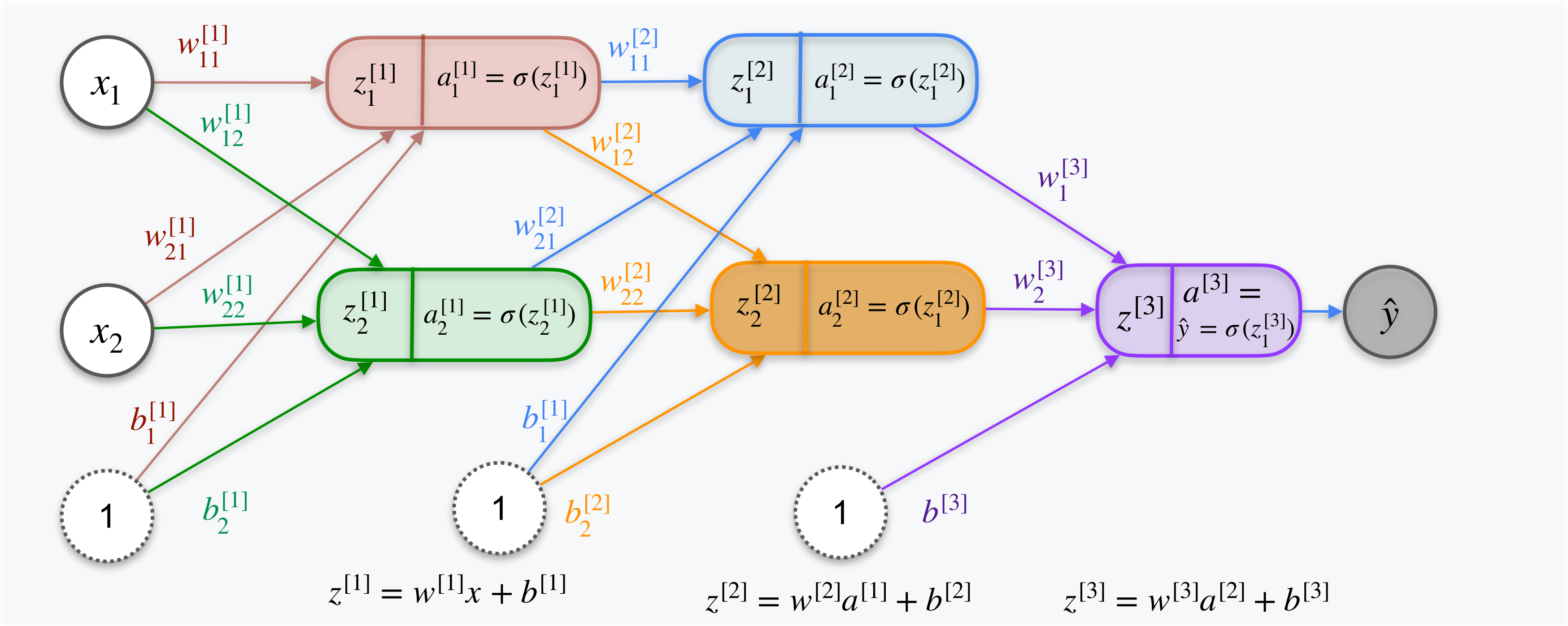

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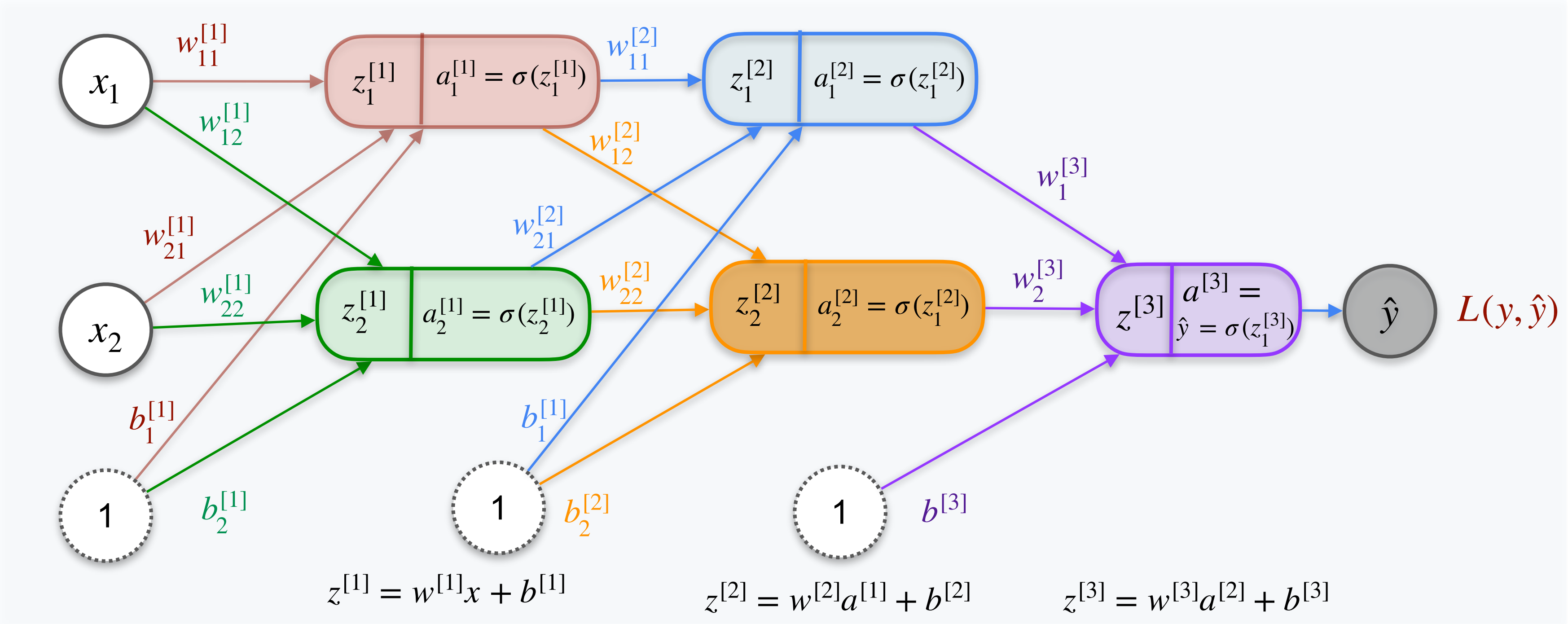

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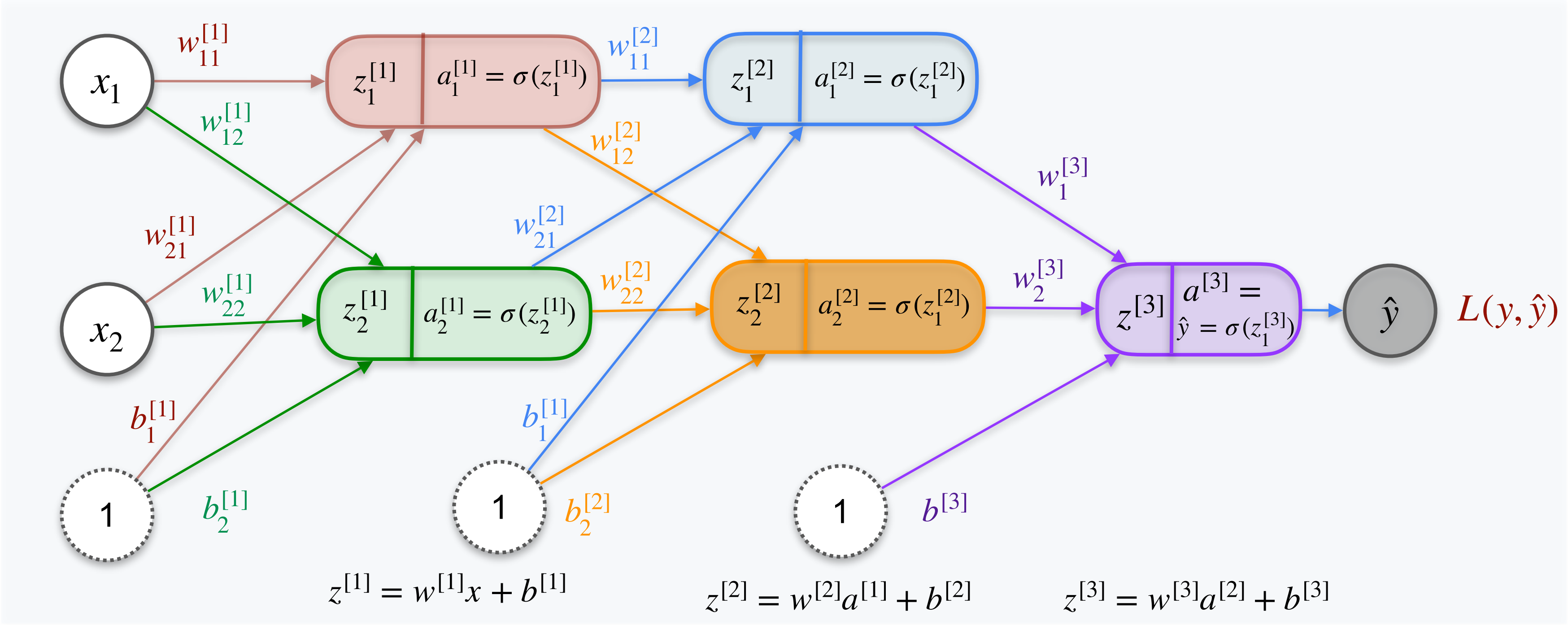

$L(y, \hat{y})$

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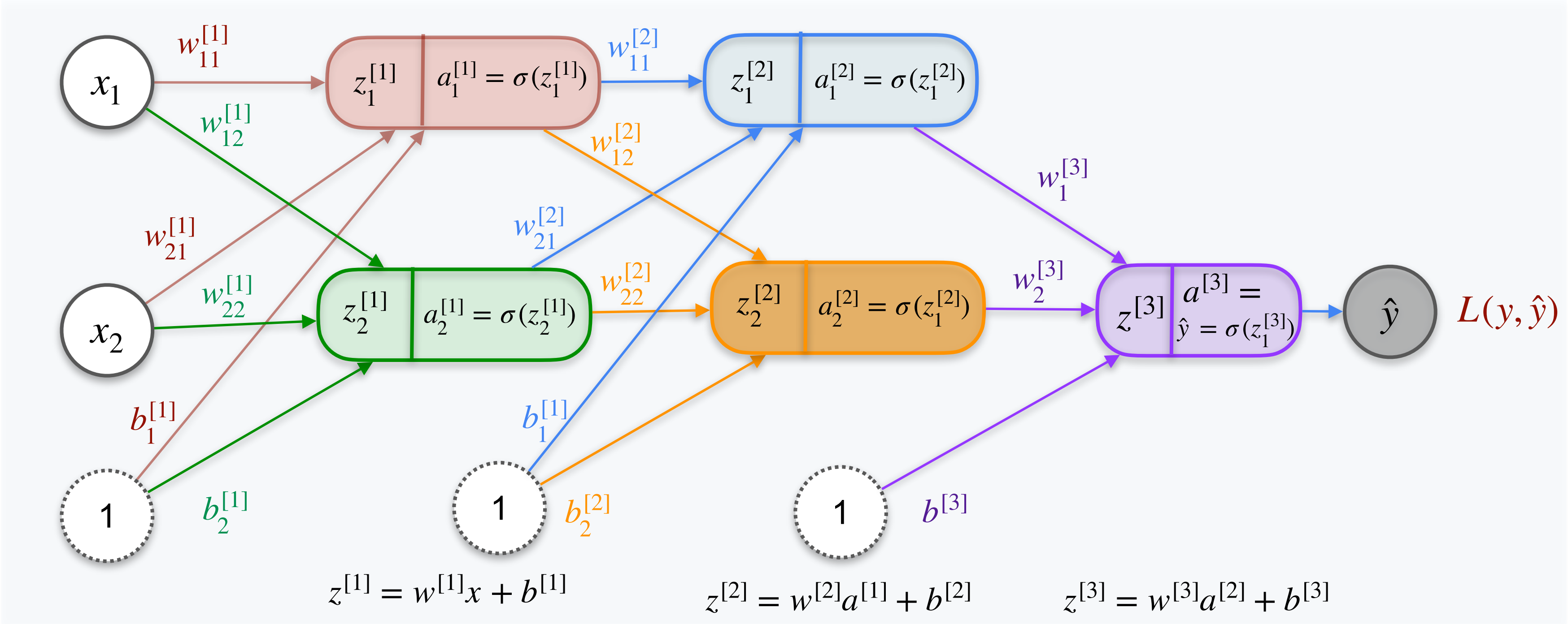

$$L(y, \hat{y}) = -y log(\hat{y}) - (1 - y) log(1 - \hat{y})$$

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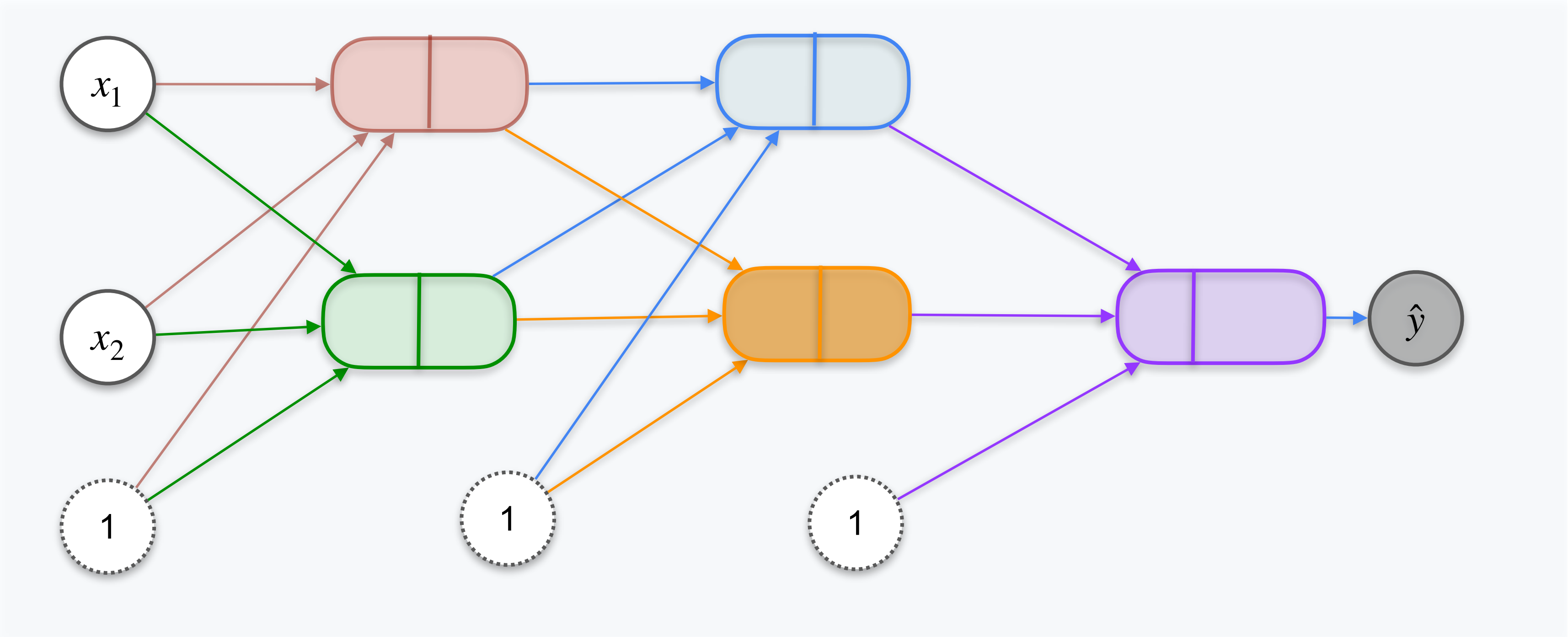

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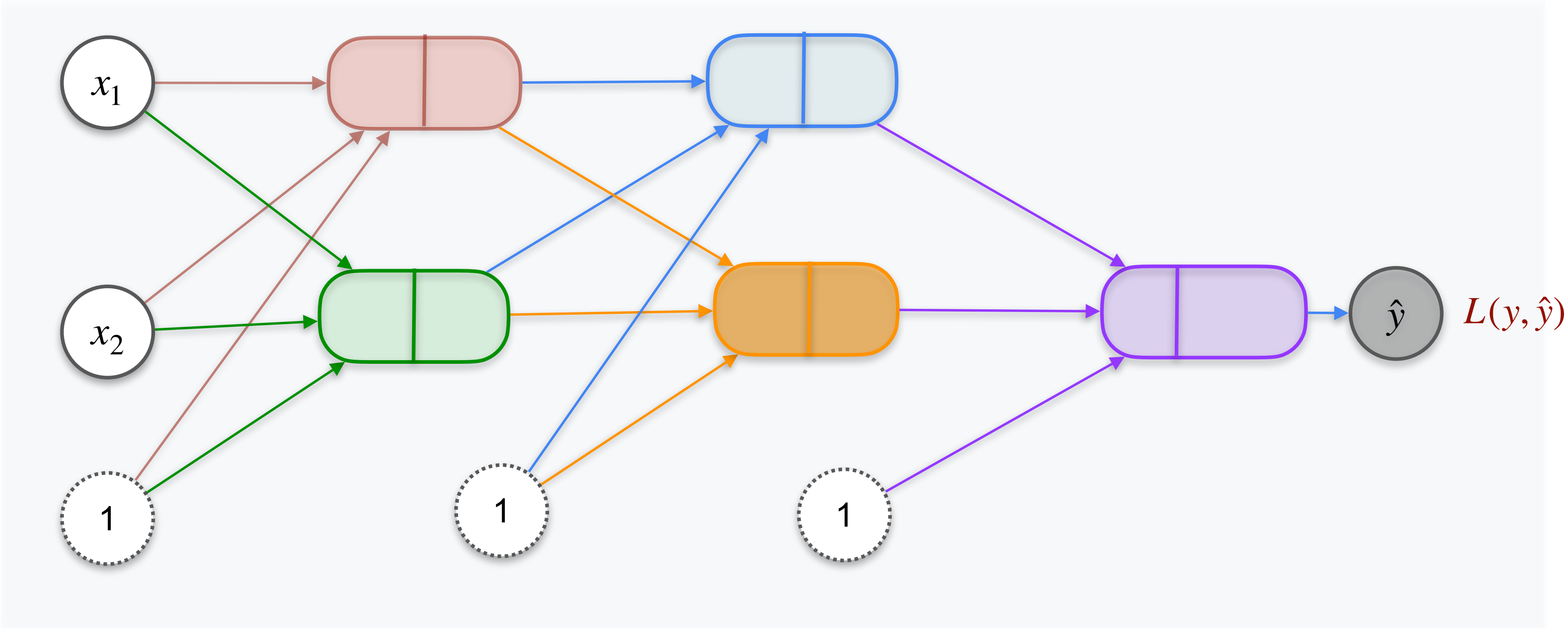

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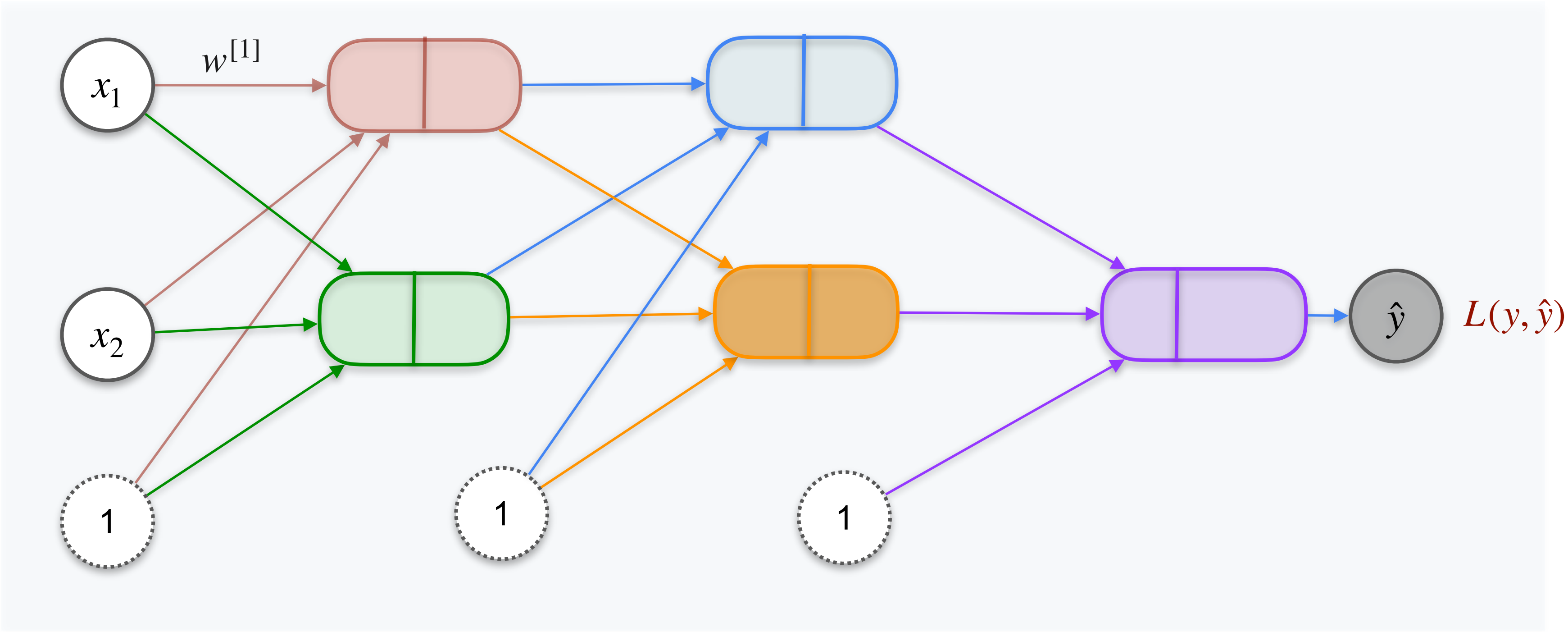

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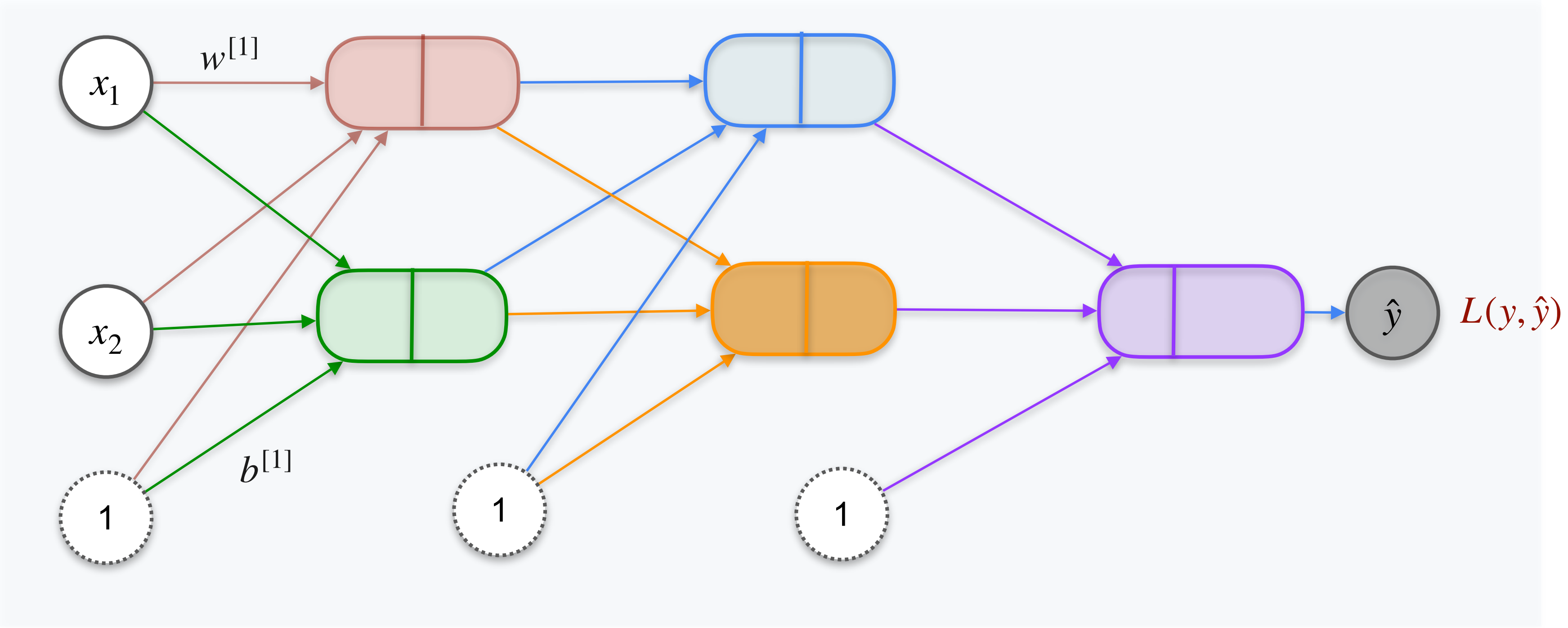

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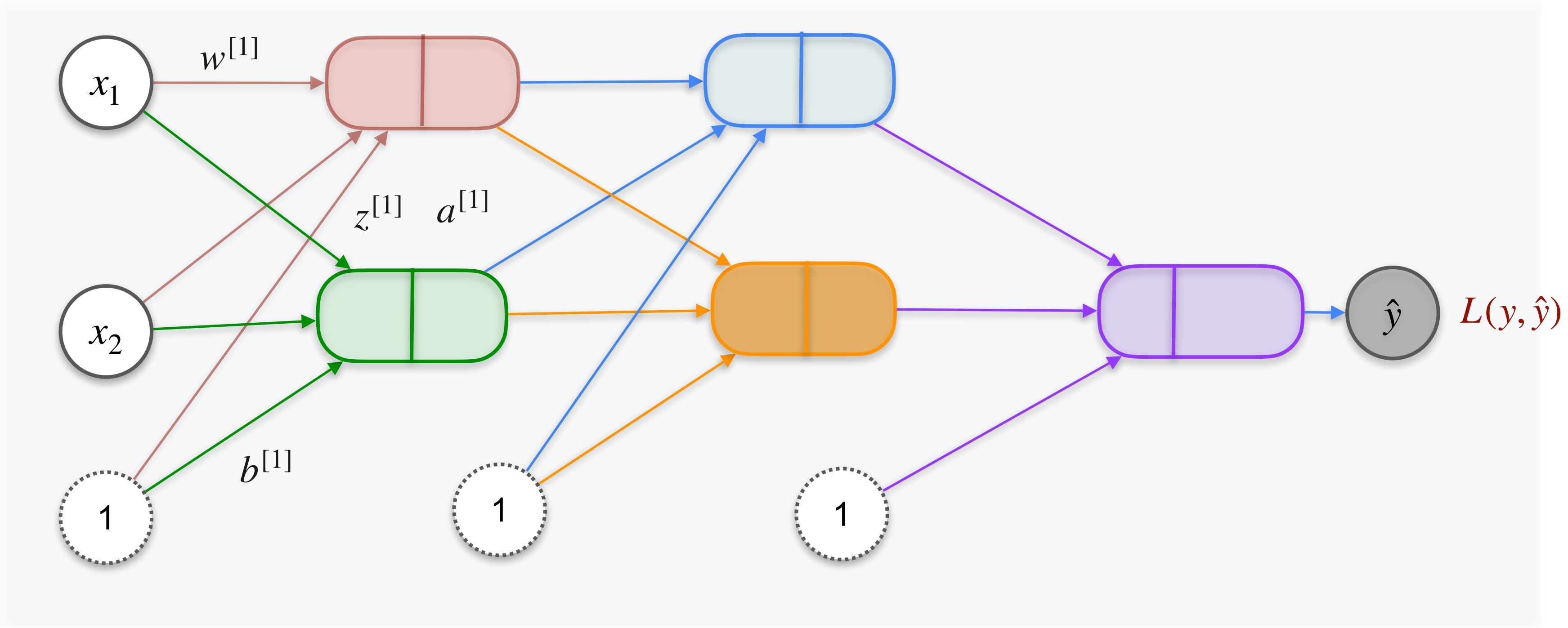

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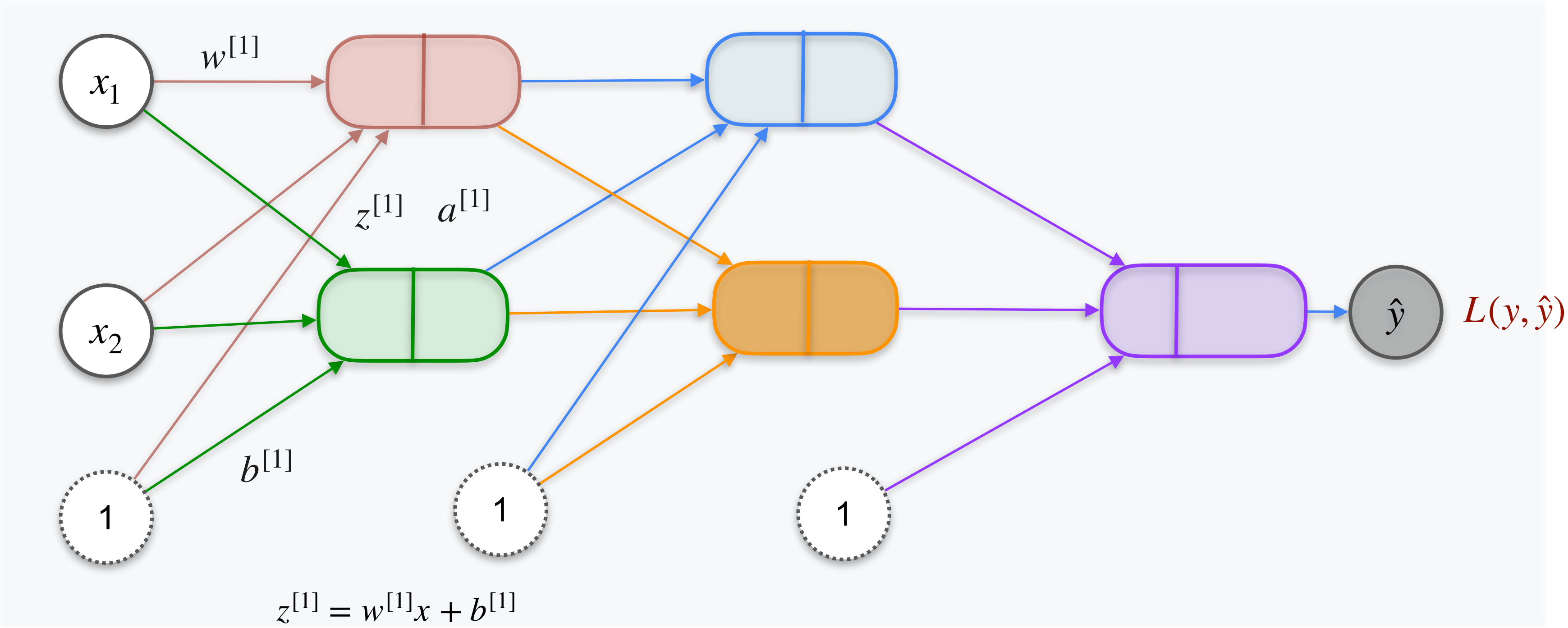

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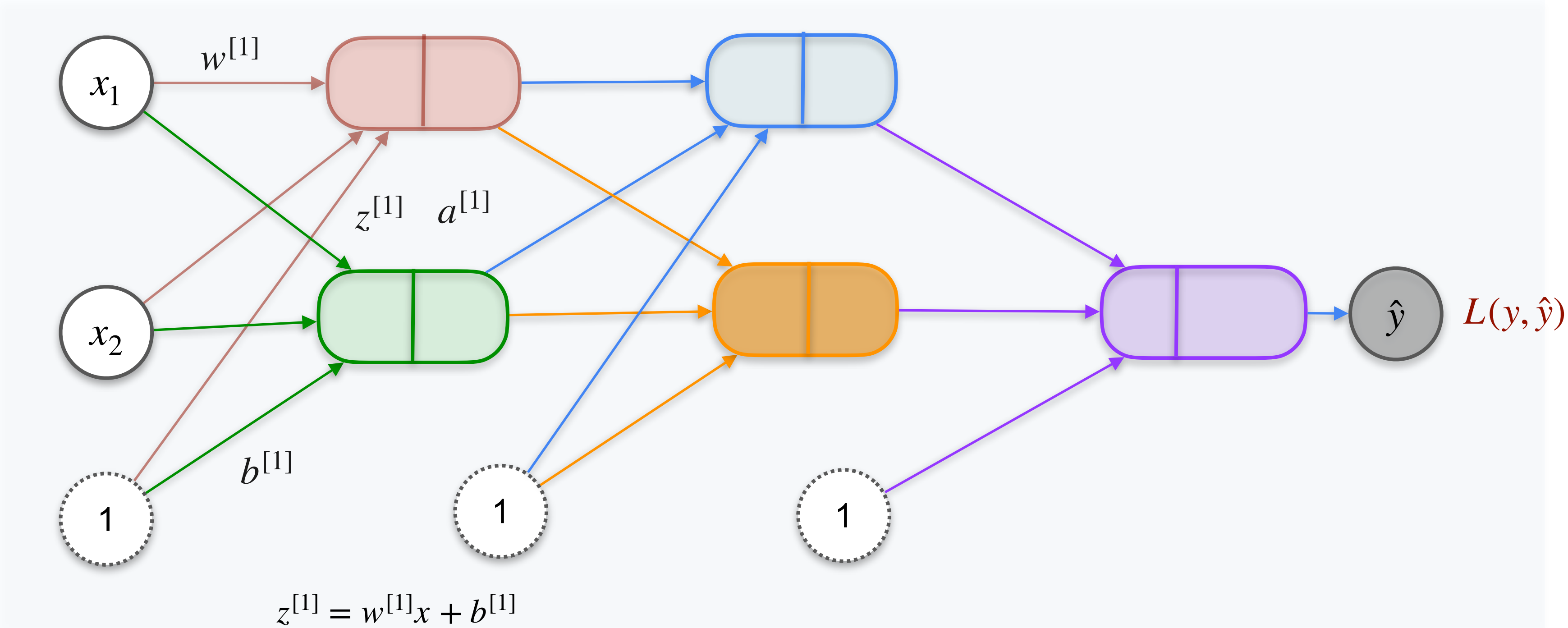

$$z^{[1]} = w^{[1]}x + b^{[1]}$$
$$a^{[1]} = \sigma(z^{[1]})$$

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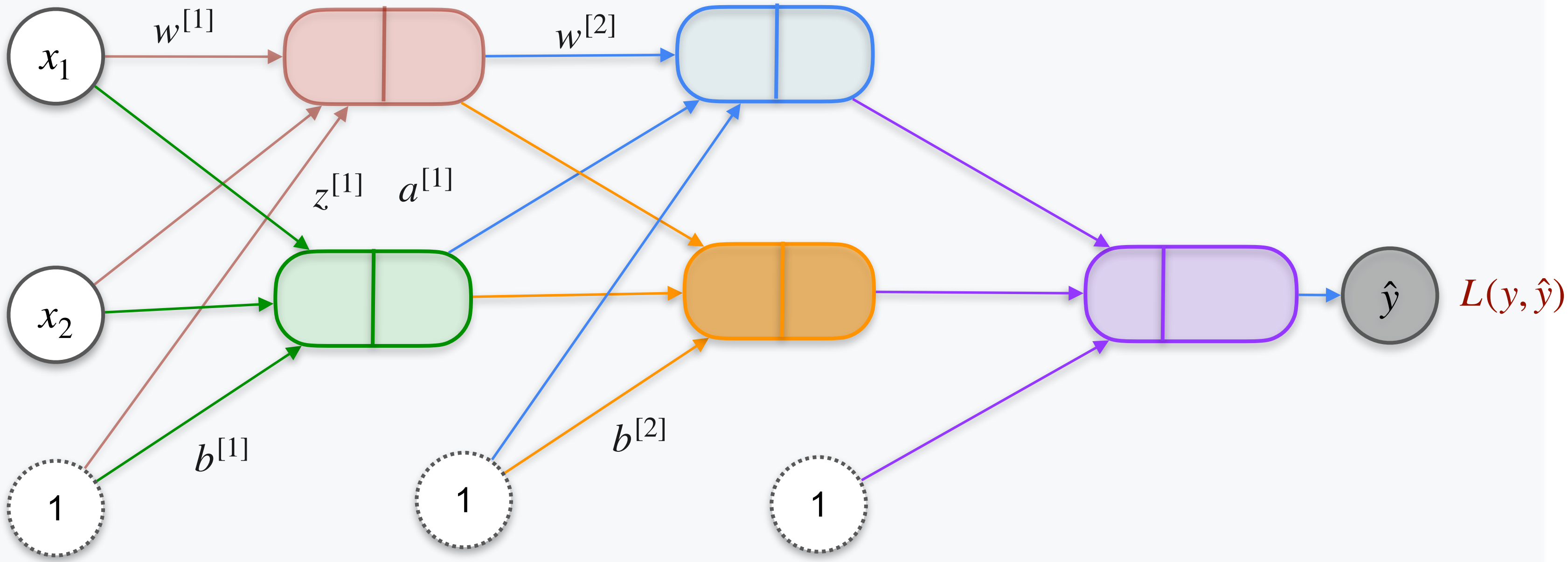

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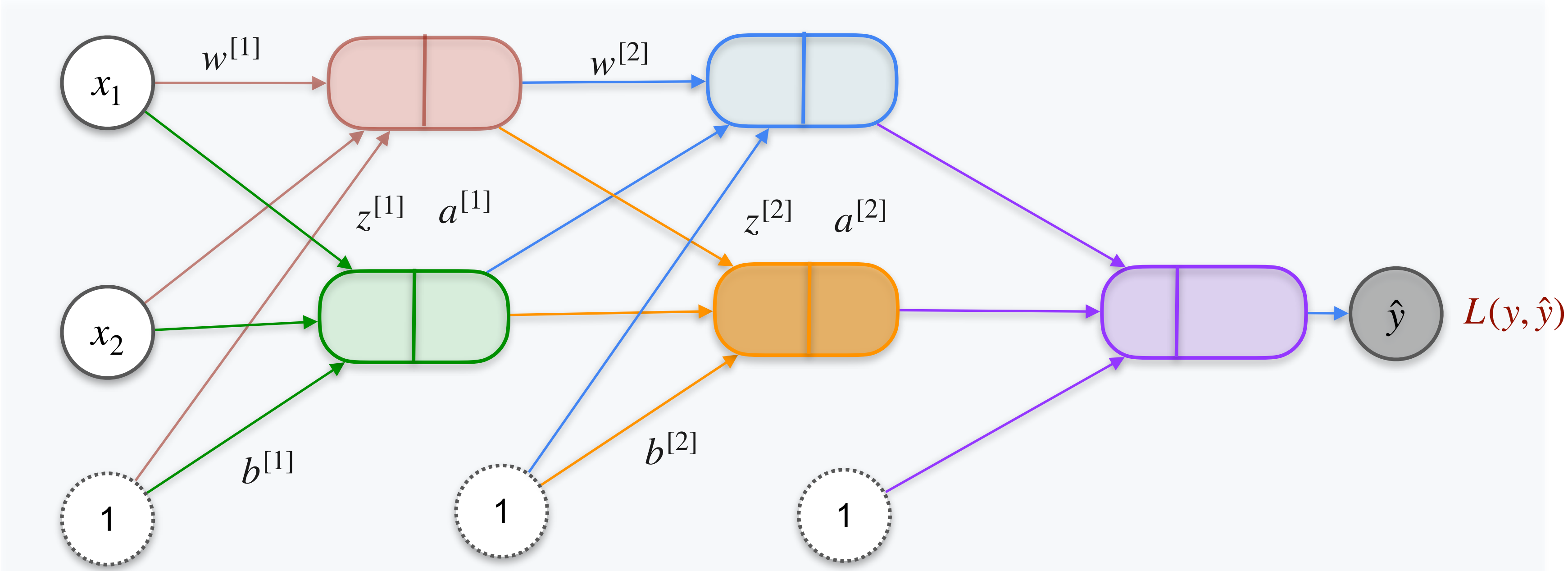

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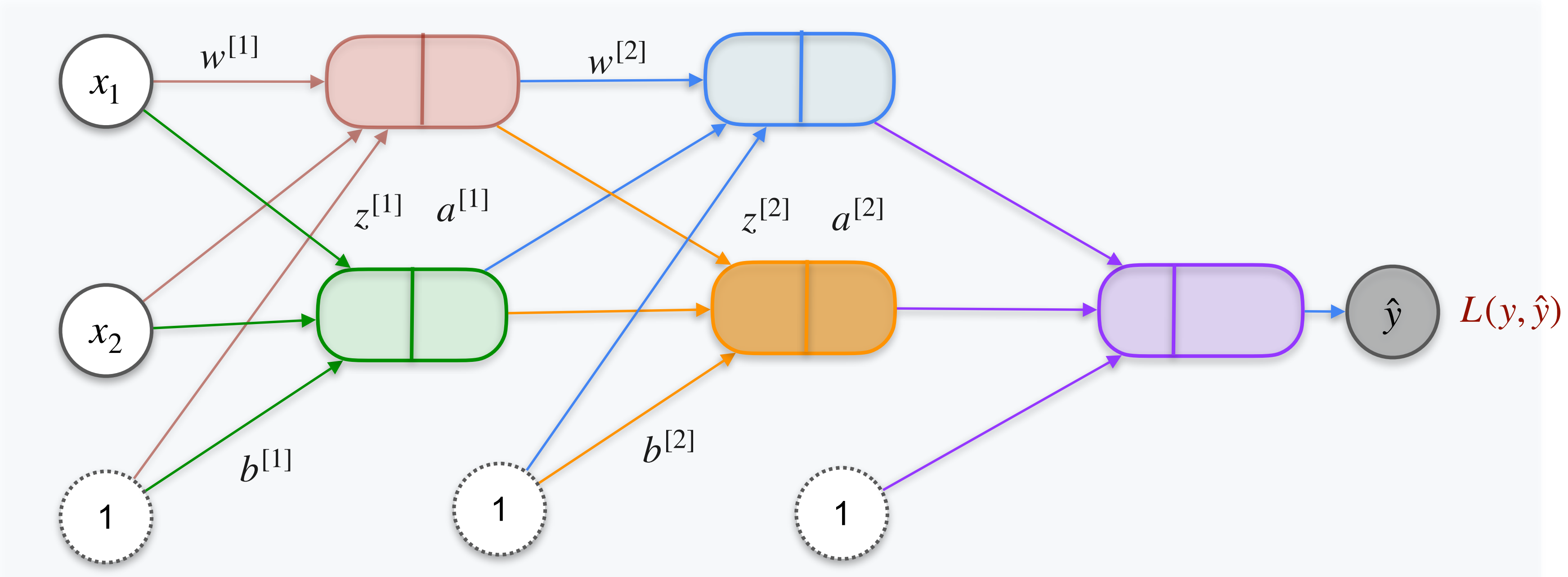

$$z^{[1]} = w^{[1]}x + b^{[1]}$$
$$a^{[1]} = \sigma(z^{[1]})$$

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

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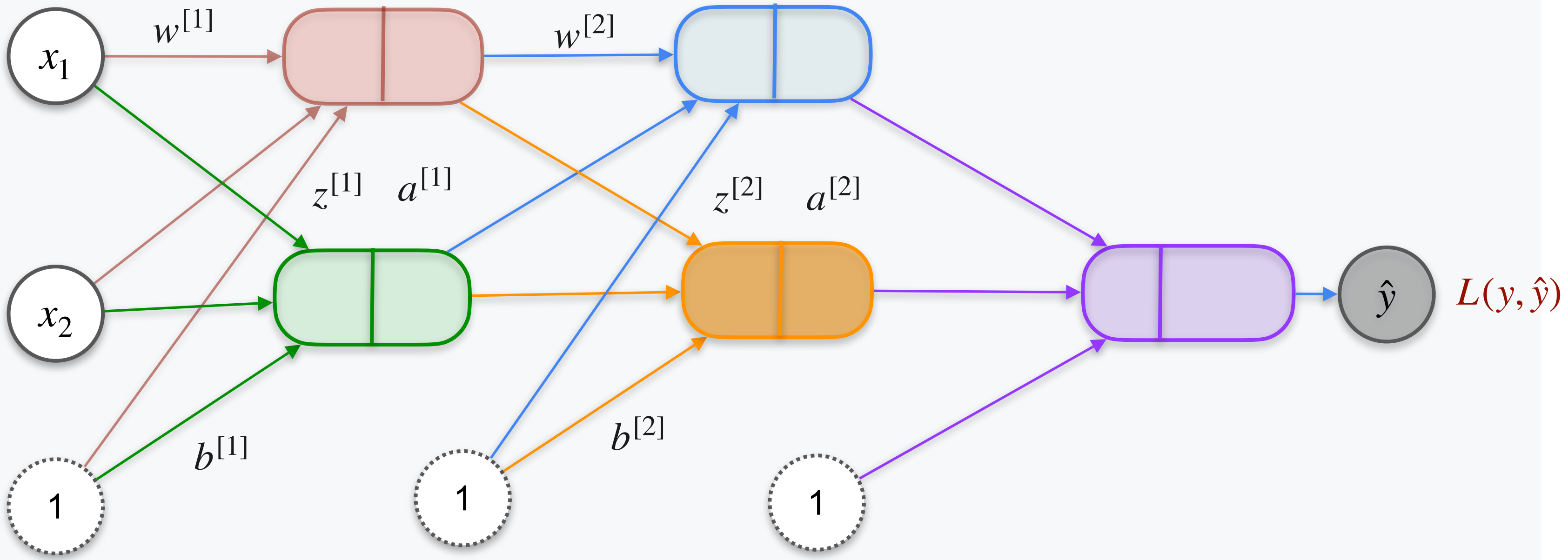

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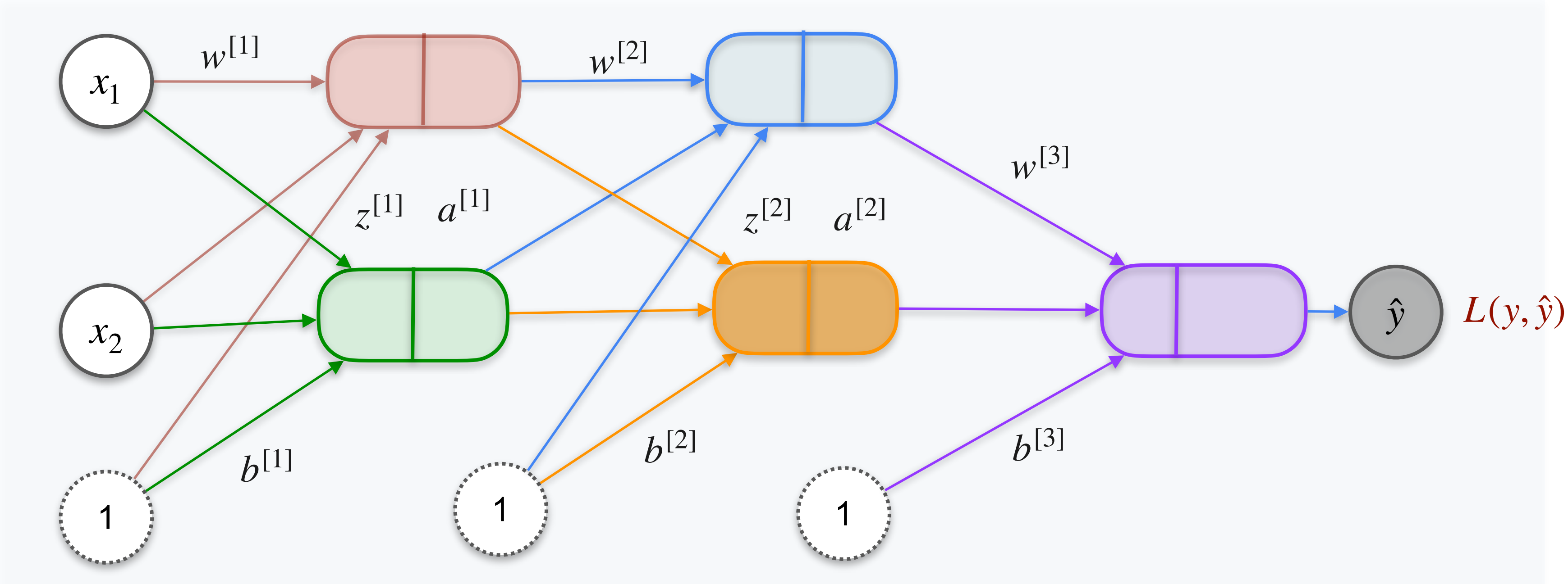

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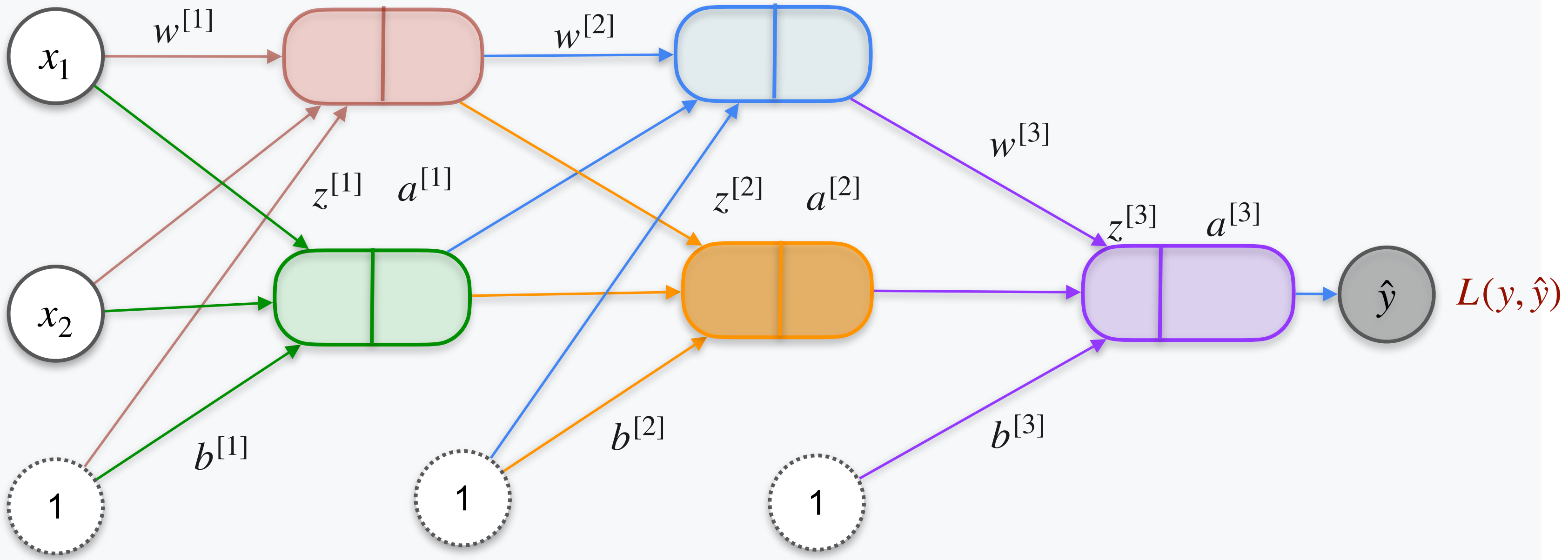

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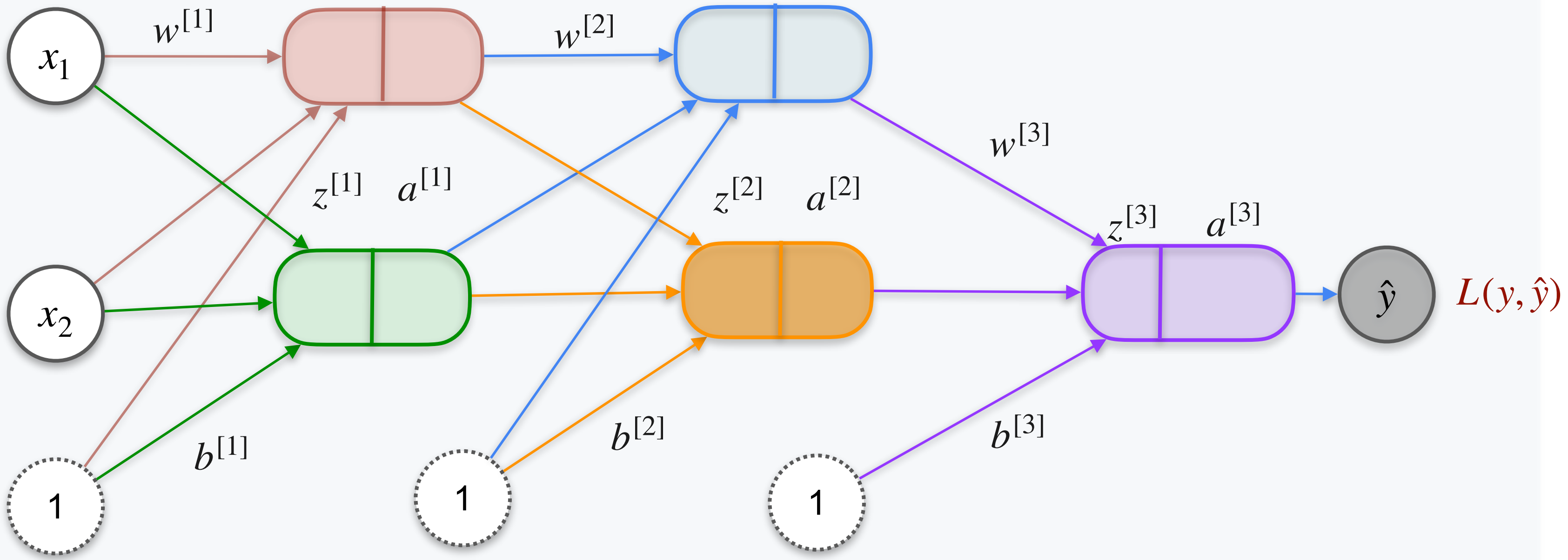

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$$a^{[2]} = \sigma(z^{[2]})$$

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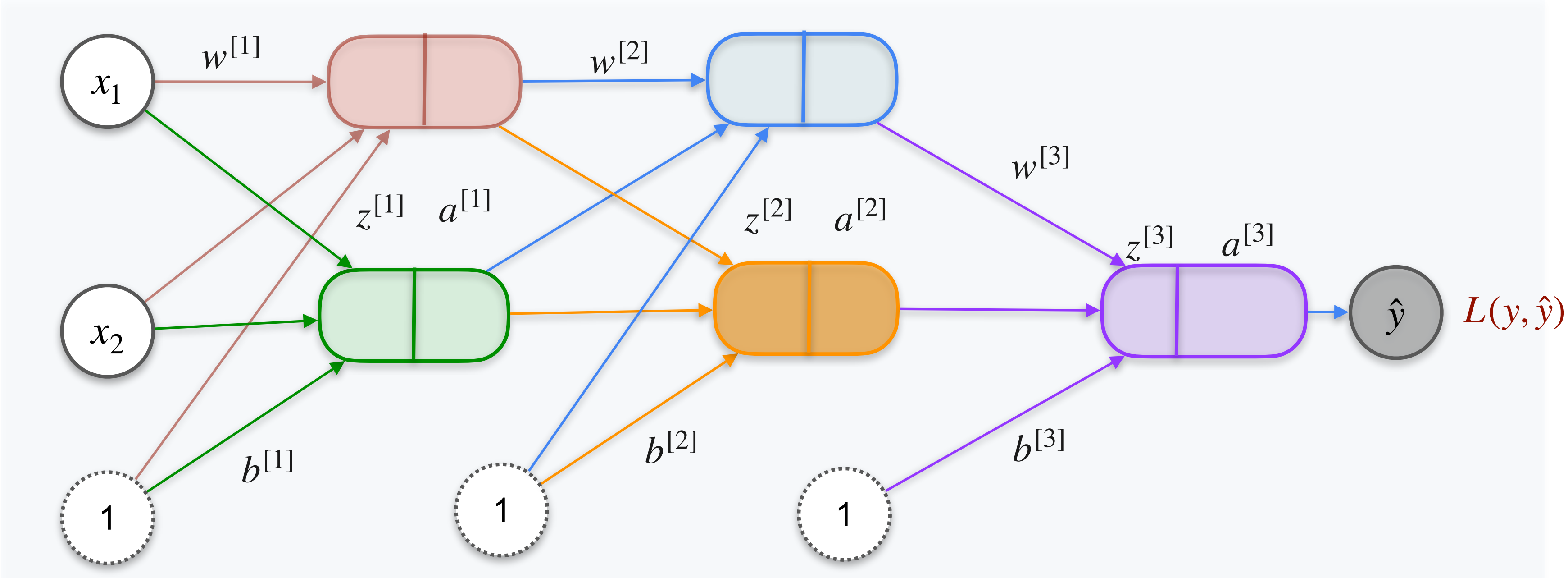

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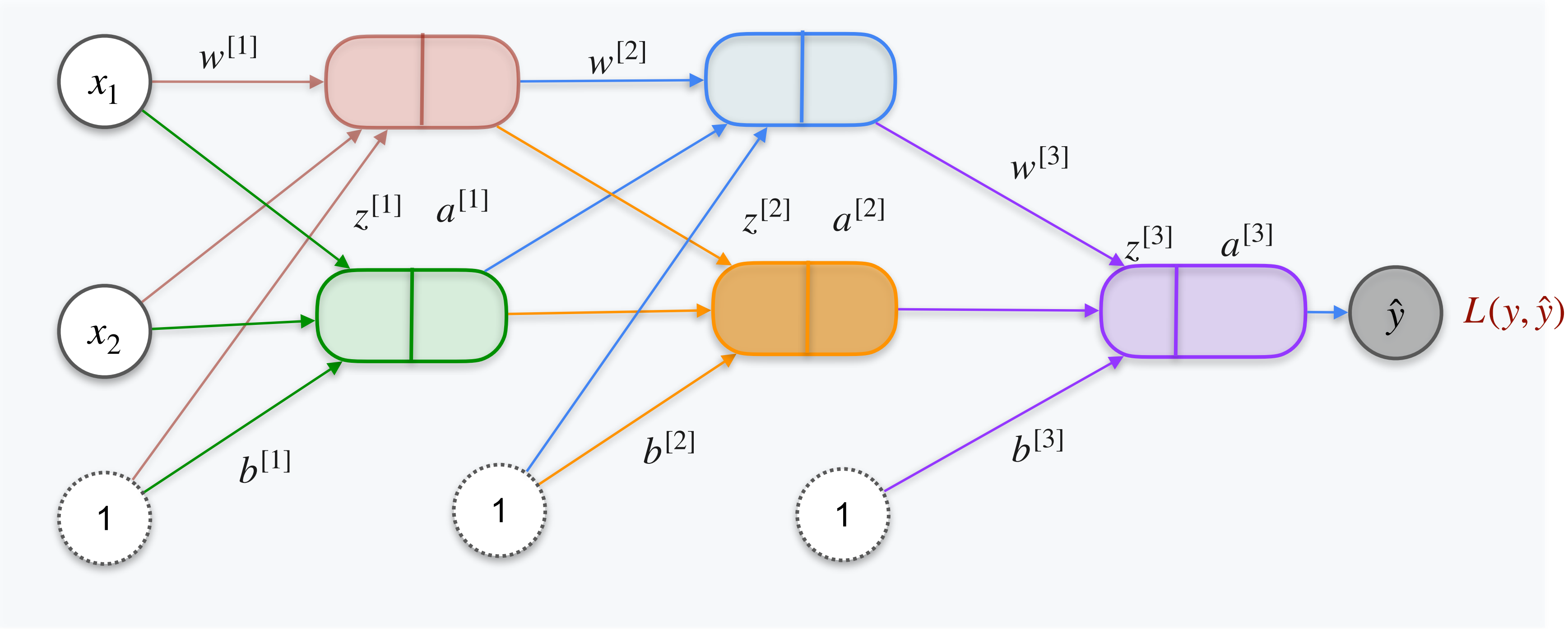

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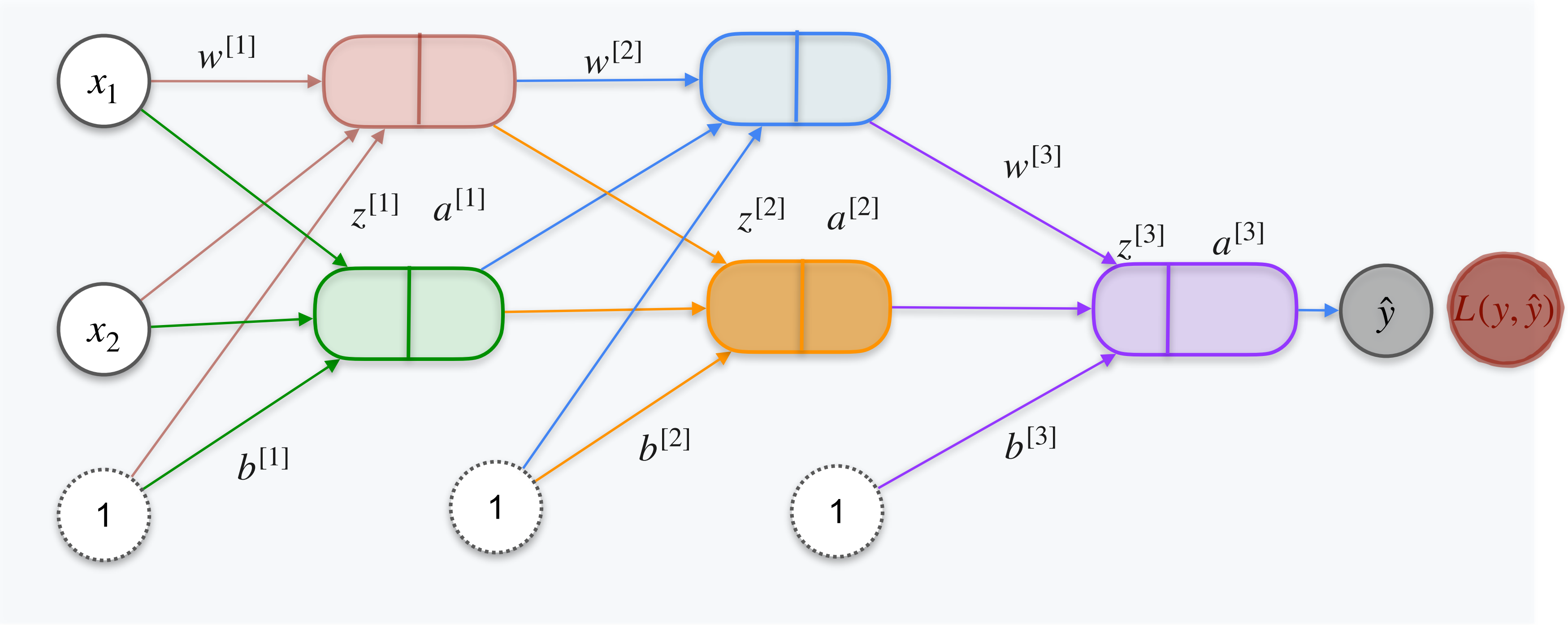

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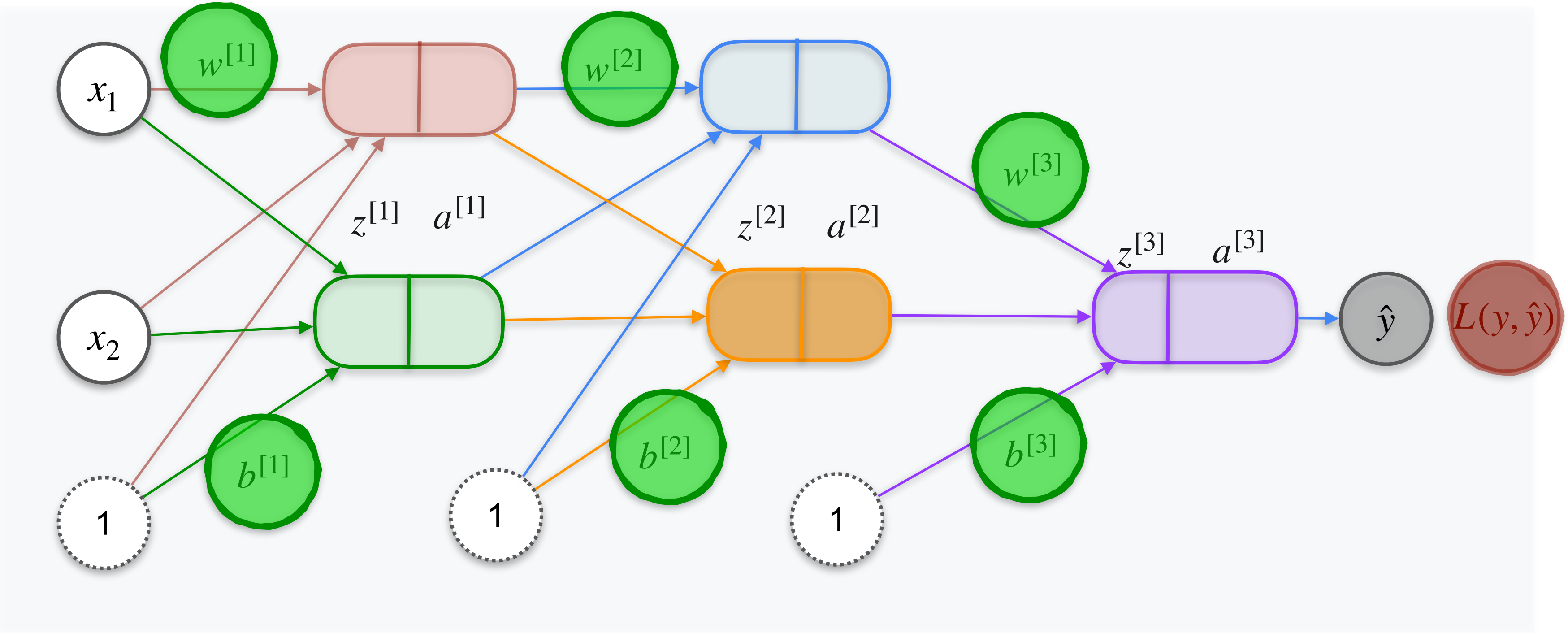

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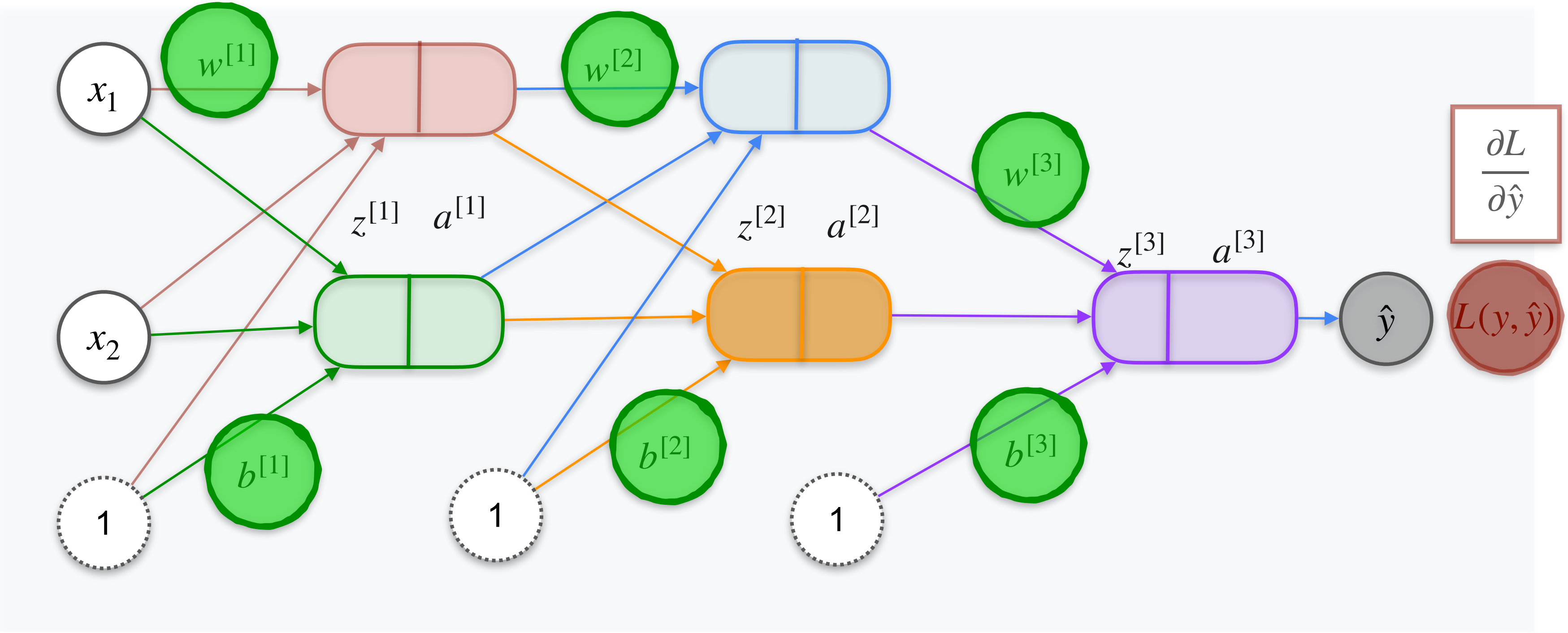

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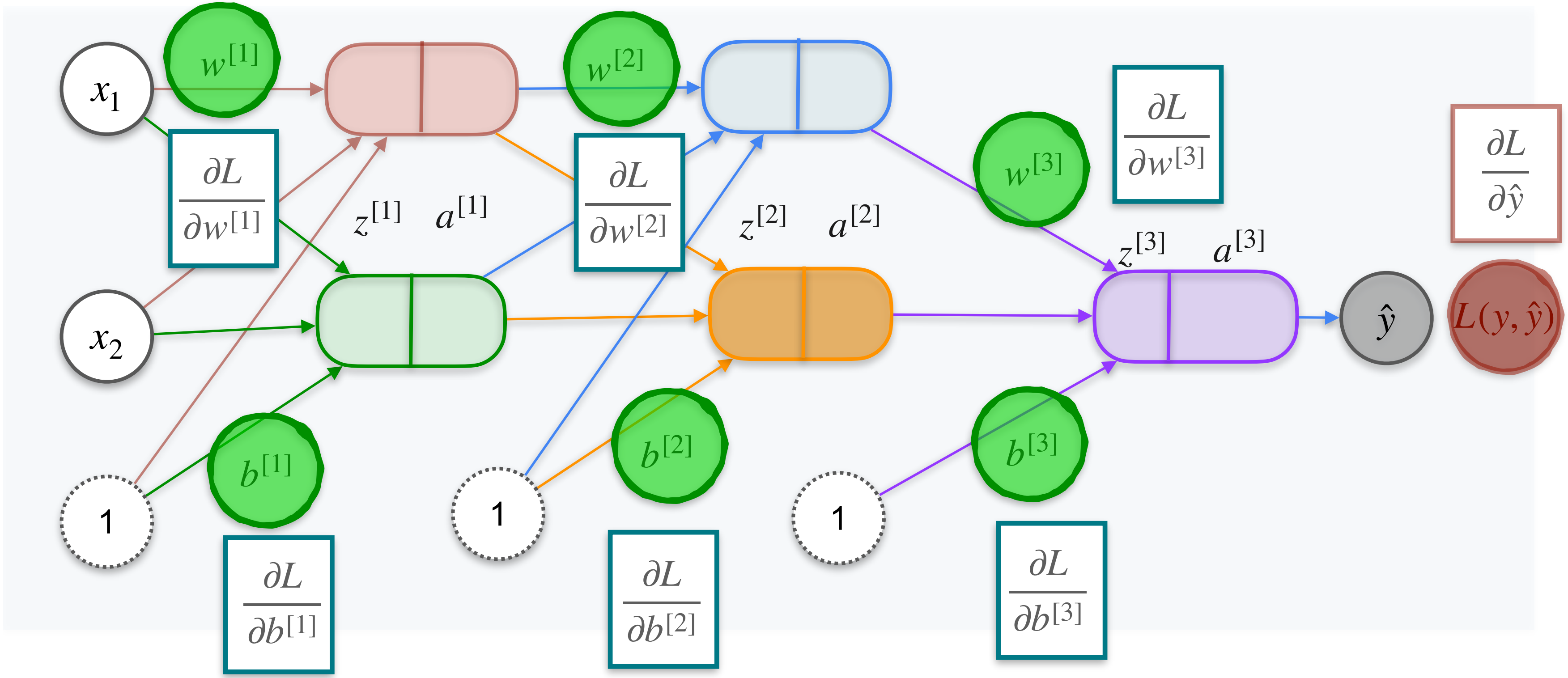

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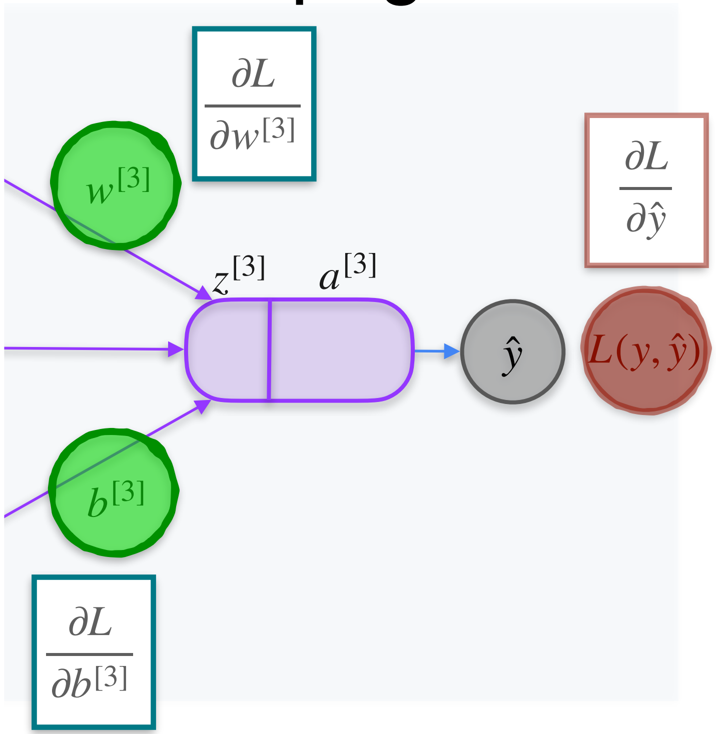

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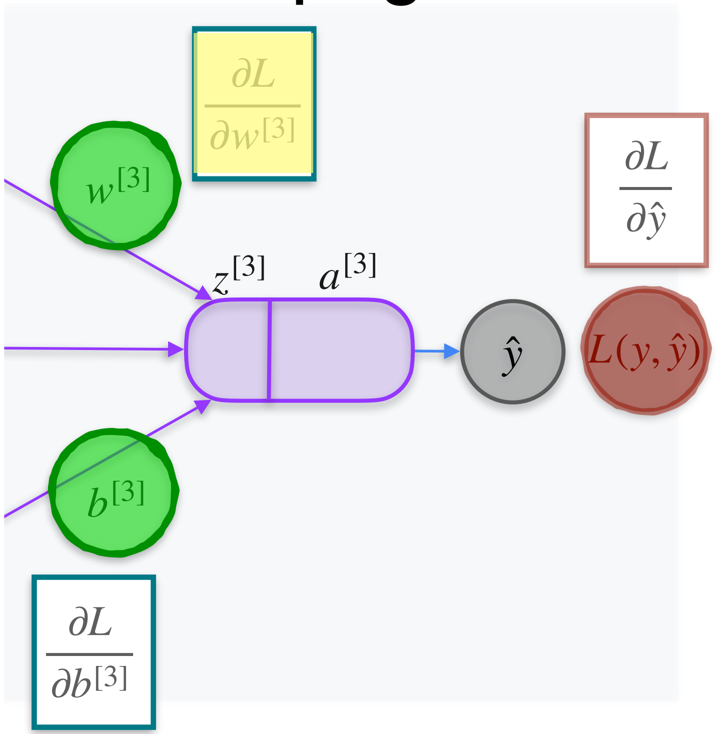

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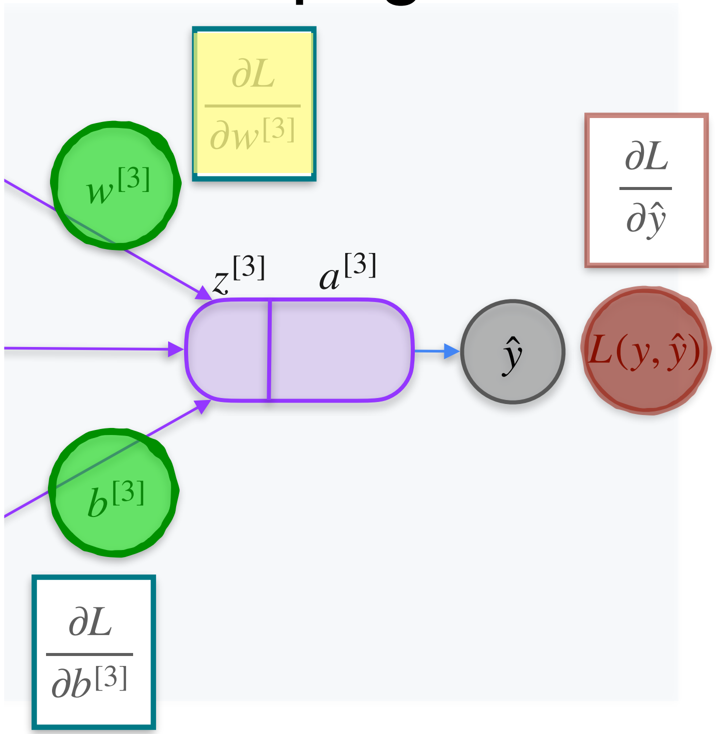
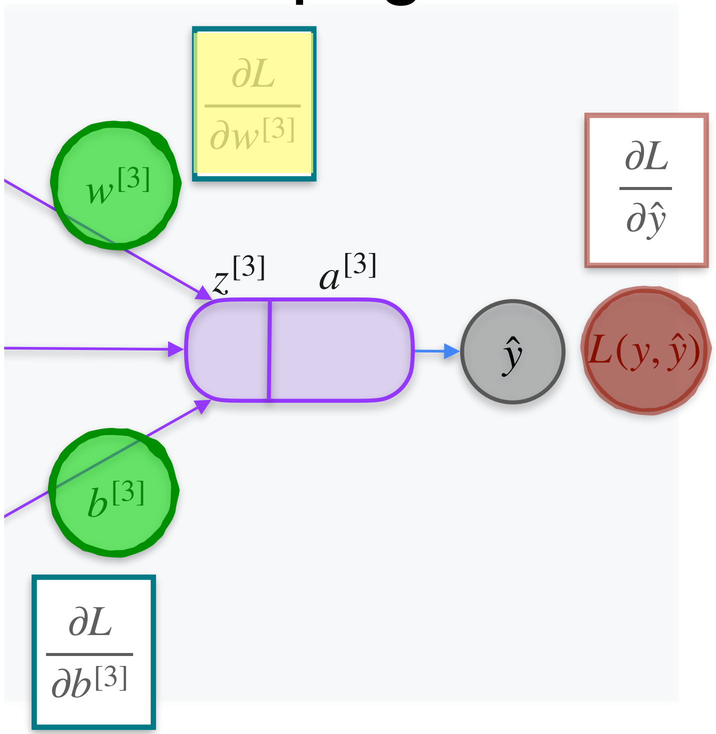


$$\frac{\partial L}{\partial w^{[3]}}$$

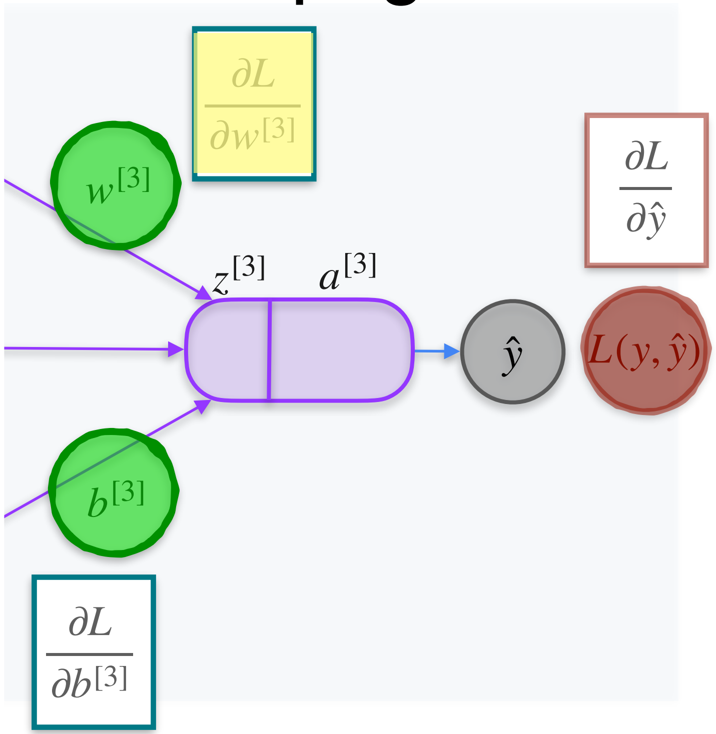
Back Propagation Introduction



$$\frac{\partial L}{\partial w^{[3]}}$$

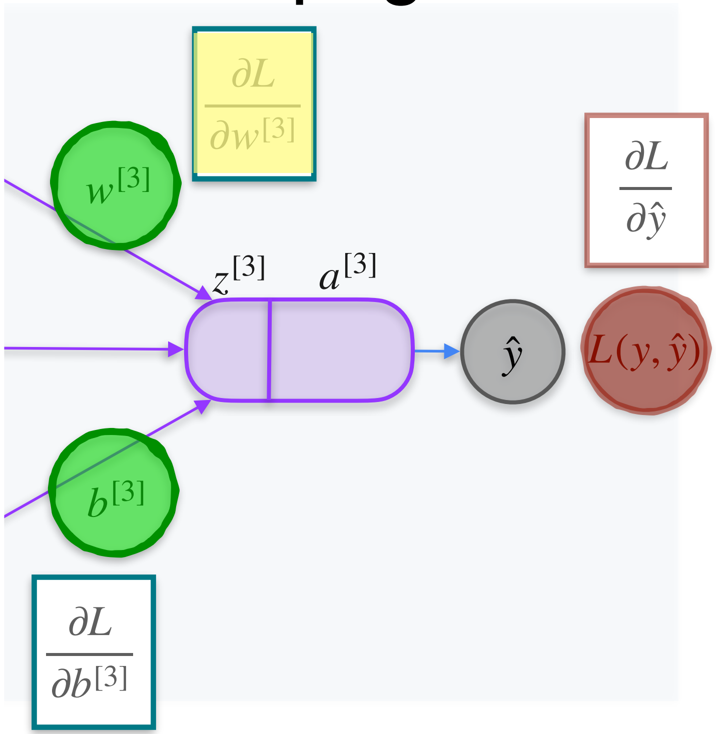
$$\frac{\partial L}{\partial a^{[3]}}$$

Back Propagation Introduction



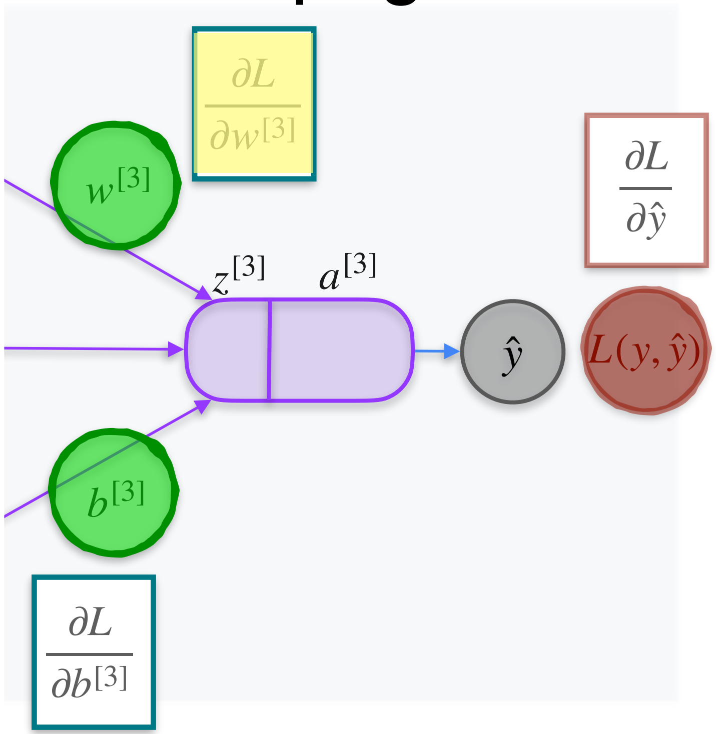
$$\frac{\partial L}{\partial w^{[3]}} \qquad \frac{\partial a^{[3]}}{\partial z^{[3]}} \qquad \frac{\partial L}{\partial a^{[3]}}$$

Back Propagation Introduction



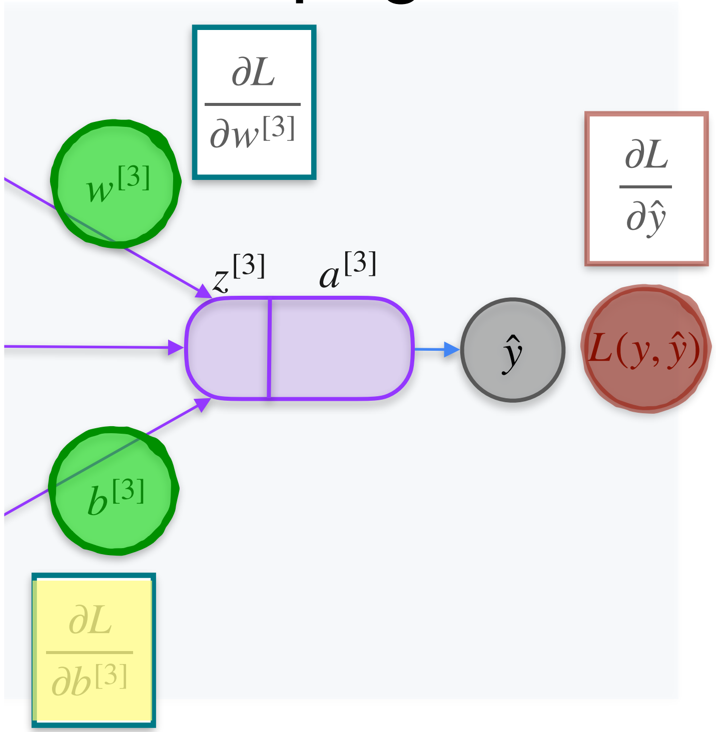
$$\frac{\partial L}{\partial w^{[3]}} \quad \frac{\partial z^{[3]}}{\partial w^{[3]}} \quad \frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

Back Propagation Introduction



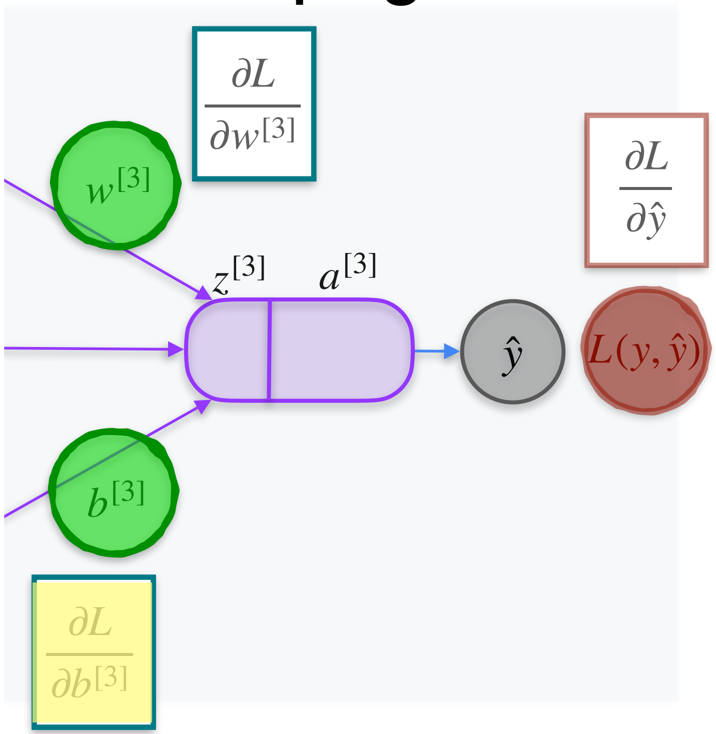
$$\boxed{\frac{\partial L}{\partial w^{[3]}}} = \boxed{\frac{\partial z^{[3]}}{\partial w^{[3]}}} \cdot \boxed{\frac{\partial a^{[3]}}{\partial z^{[3]}}} \cdot \boxed{\frac{\partial L}{\partial a^{[3]}}}$$

Back Propagation Introduction



$$\frac{\partial L}{\partial w^{[3]}} = \frac{\partial z^{[3]}}{\partial w^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial L}{\partial a^{[3]}}$$

Back Propagation Introduction



$$\frac{\partial L}{\partial w^{[3]}} = \frac{\partial z^{[3]}}{\partial w^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial L}{\partial a^{[3]}}$$

$$\frac{\partial L}{\partial b^{[3]}}$$

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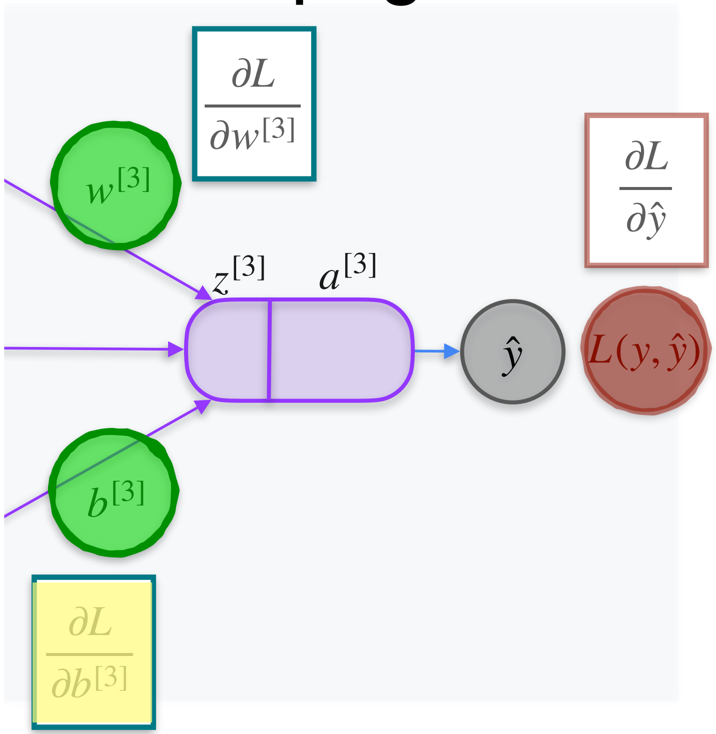
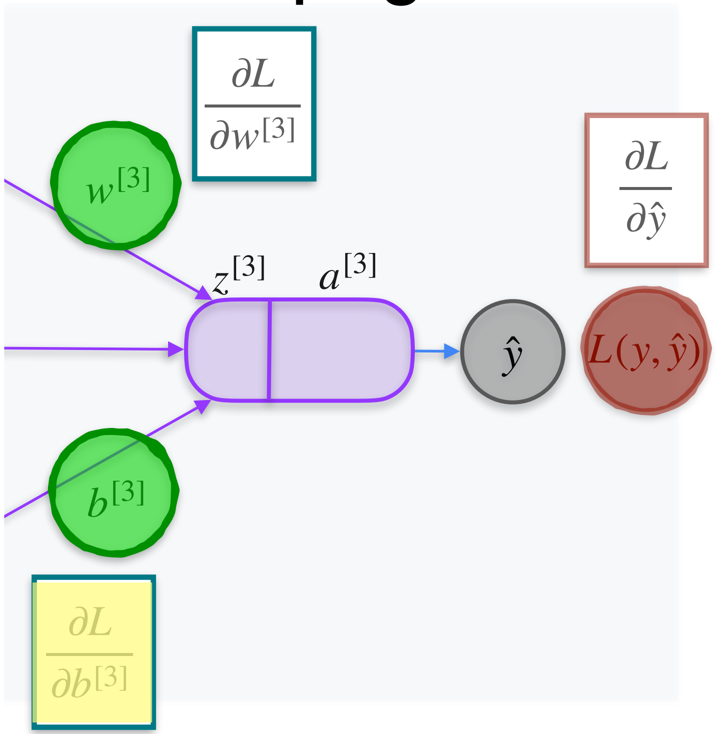


$$\frac{\partial L}{\partial w^{[3]}} = \frac{\partial z^{[3]}}{\partial w^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial L}{\partial a^{[3]}}$$

$$\frac{\partial L}{\partial b^{[3]}} \qquad \frac{\partial z^{[3]}}{\partial b^{[3]}} \quad \frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

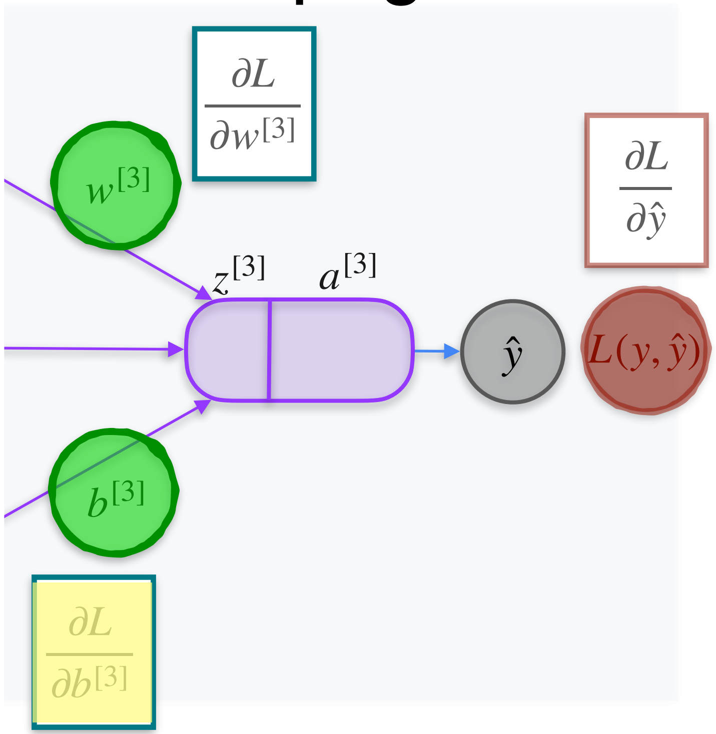
Back Propagation Introduction



$$\frac{\partial L}{\partial w^{[3]}} = \frac{\partial z^{[3]}}{\partial w^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial L}{\partial a^{[3]}}$$

$$\frac{\partial L}{\partial b^{[3]}} = \frac{\partial z^{[3]}}{\partial b^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial L}{\partial a^{[3]}}$$

Back Propagation Introduction

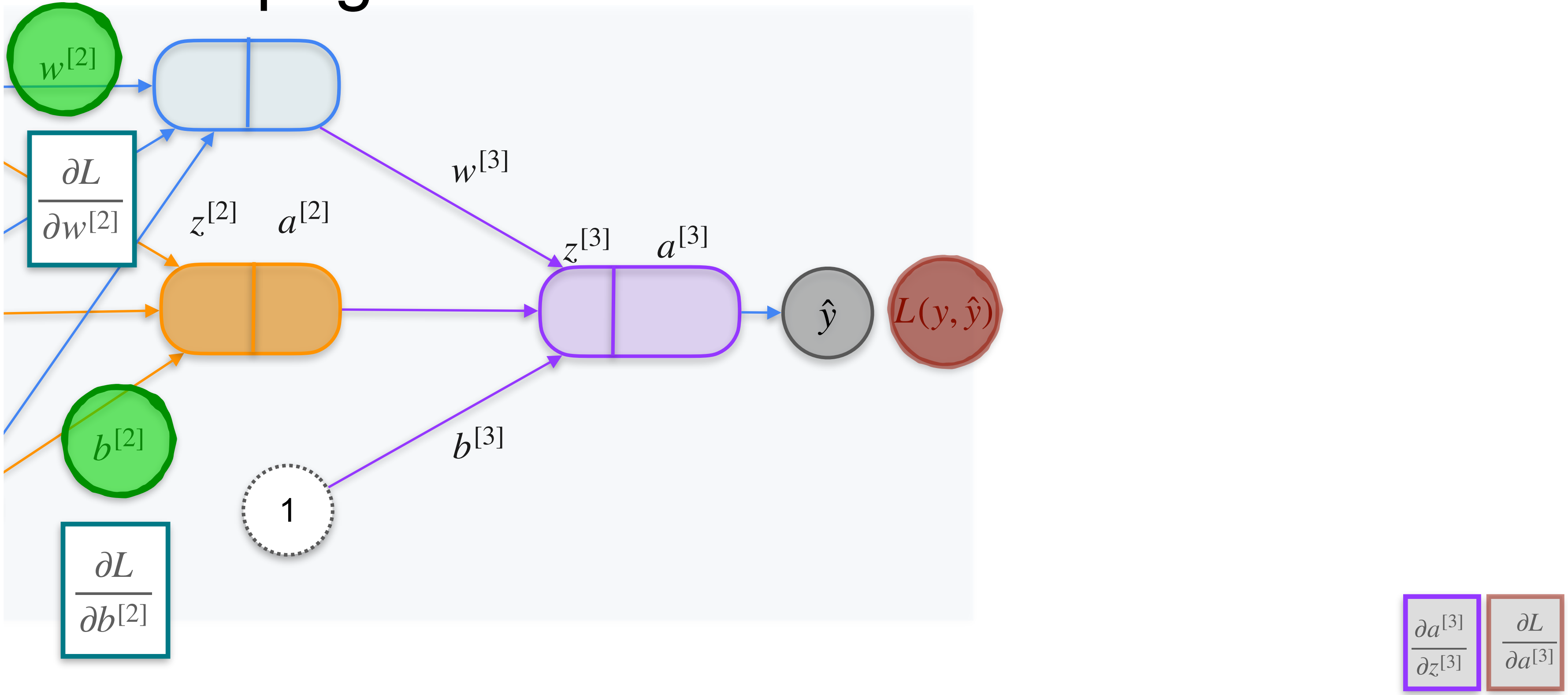


$$\frac{\partial L}{\partial w^{[3]}} = \frac{\partial z^{[3]}}{\partial w^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial L}{\partial a^{[3]}}$$

$$\frac{\partial L}{\partial b^{[3]}} = \frac{\partial z^{[3]}}{\partial b^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial L}{\partial a^{[3]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

Back Propagation Introduction



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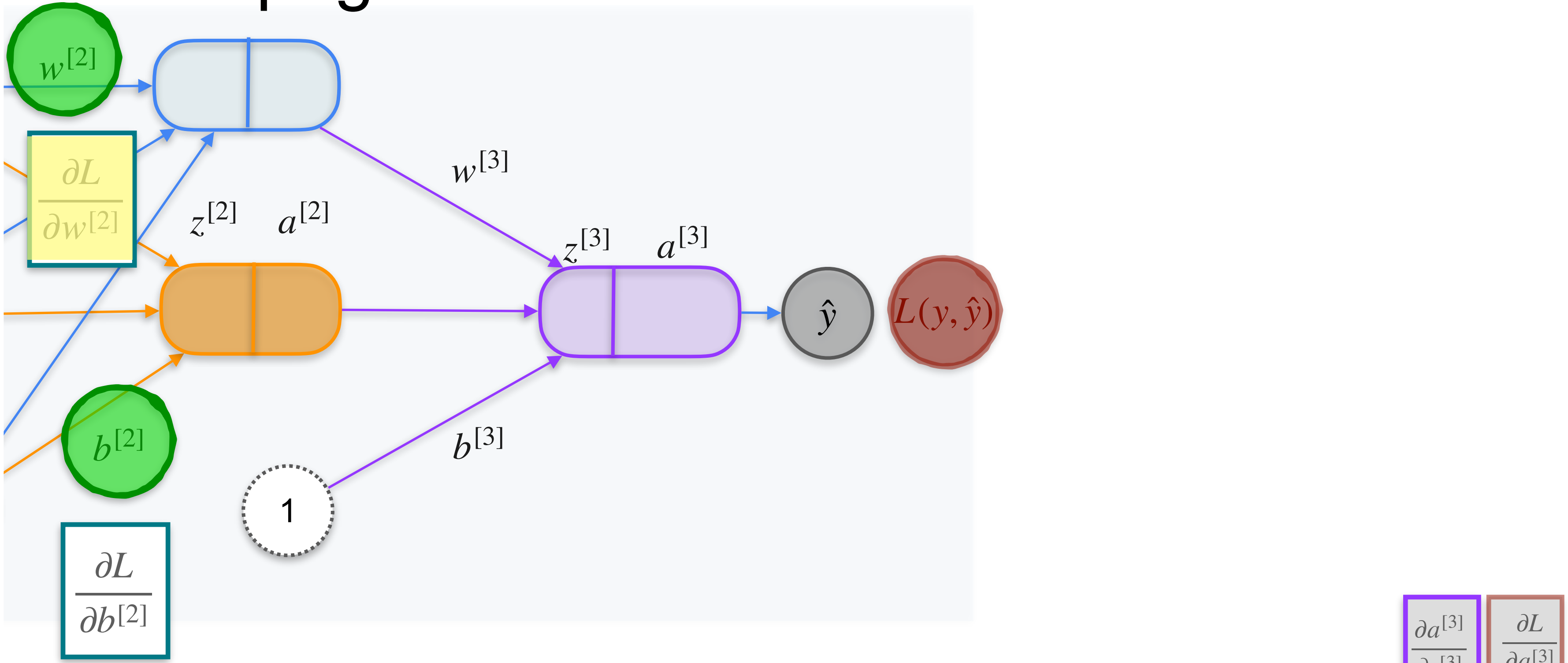

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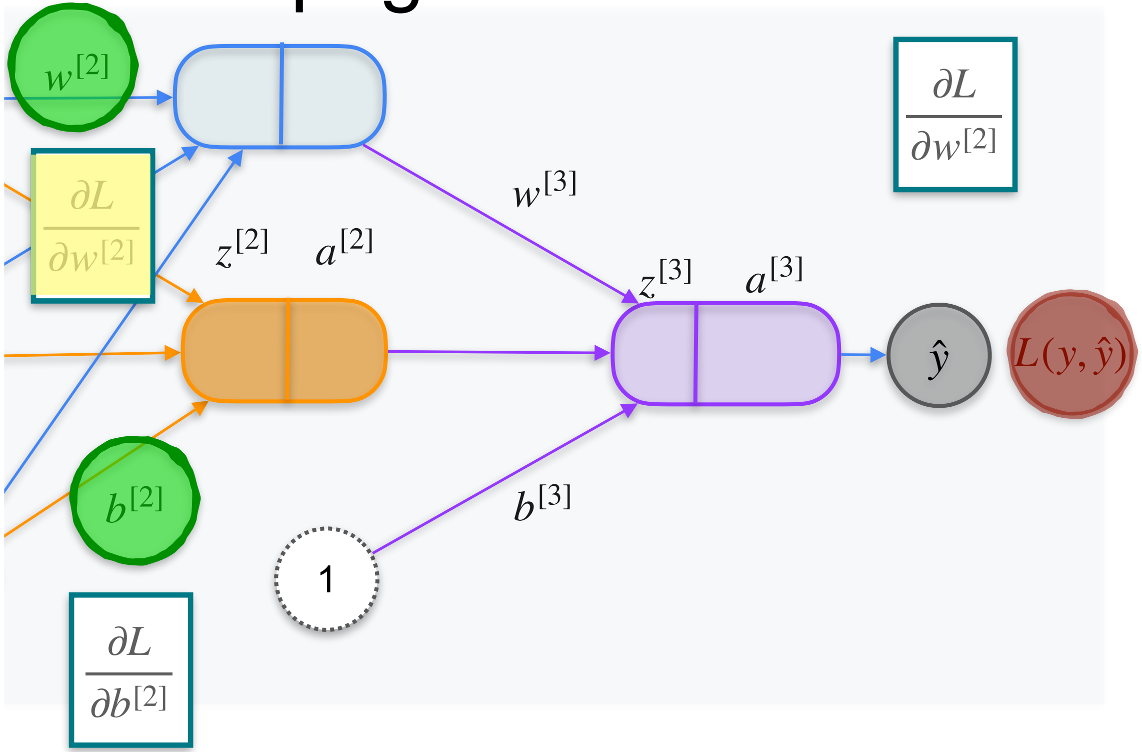

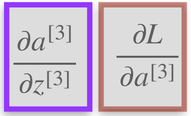

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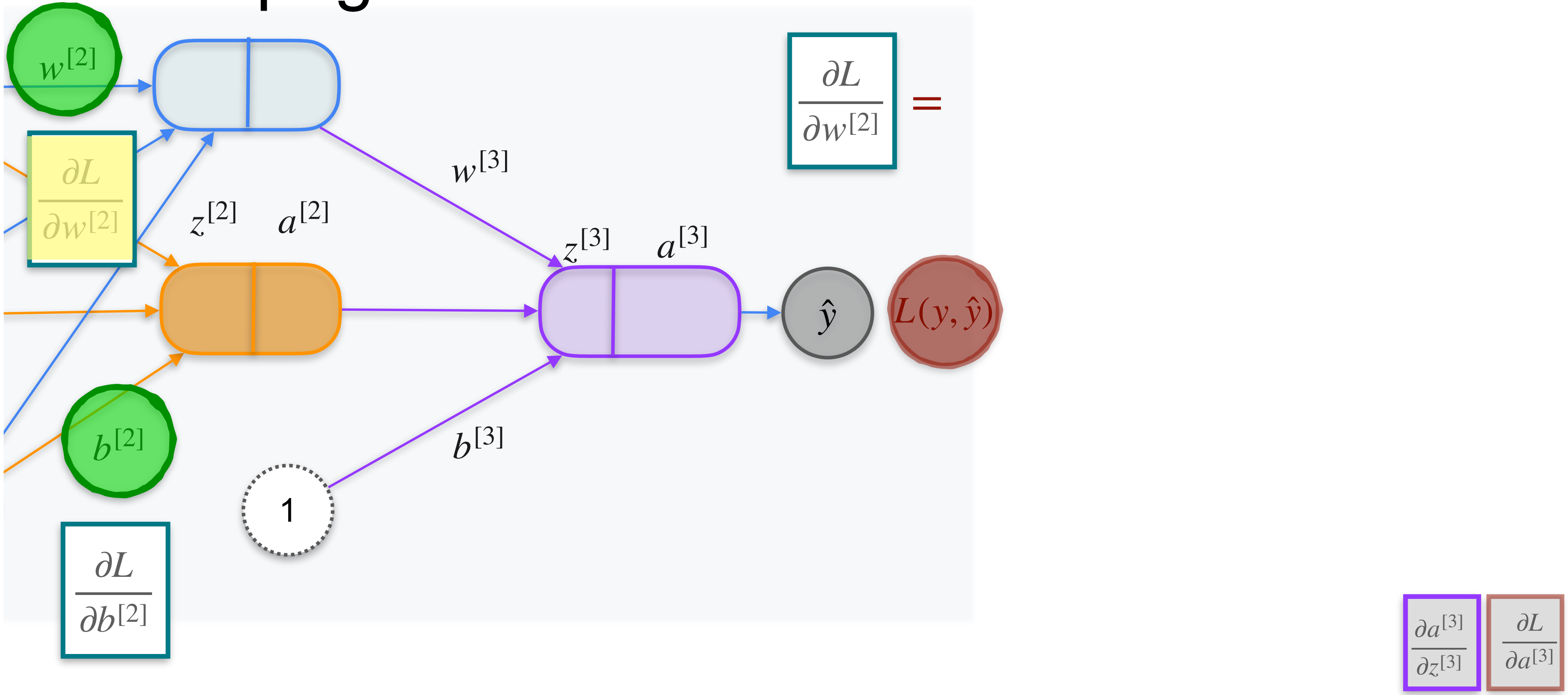

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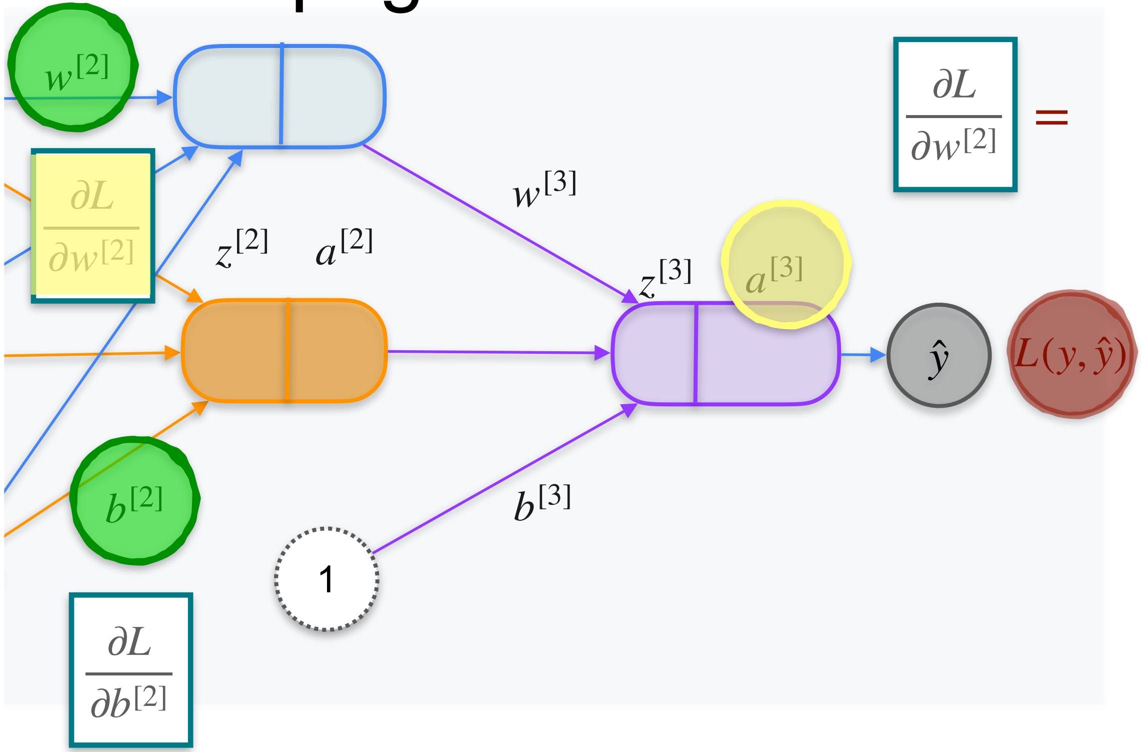

$\frac{\partial L}{\partial w^{[2]}} =$

$\frac{\partial a^{[3]}}{\partial z^{[3]}}$ $\frac{\partial L}{\partial a^{[3]}}$

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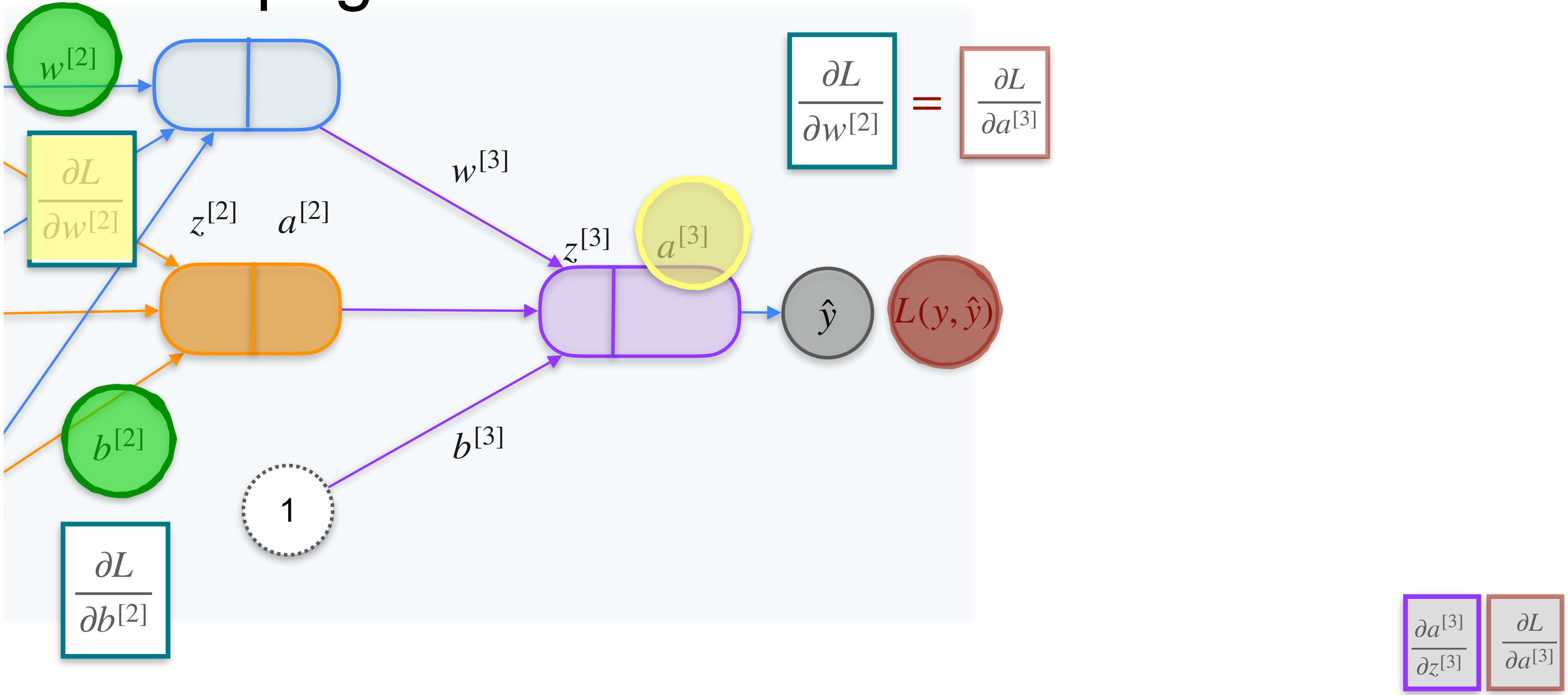

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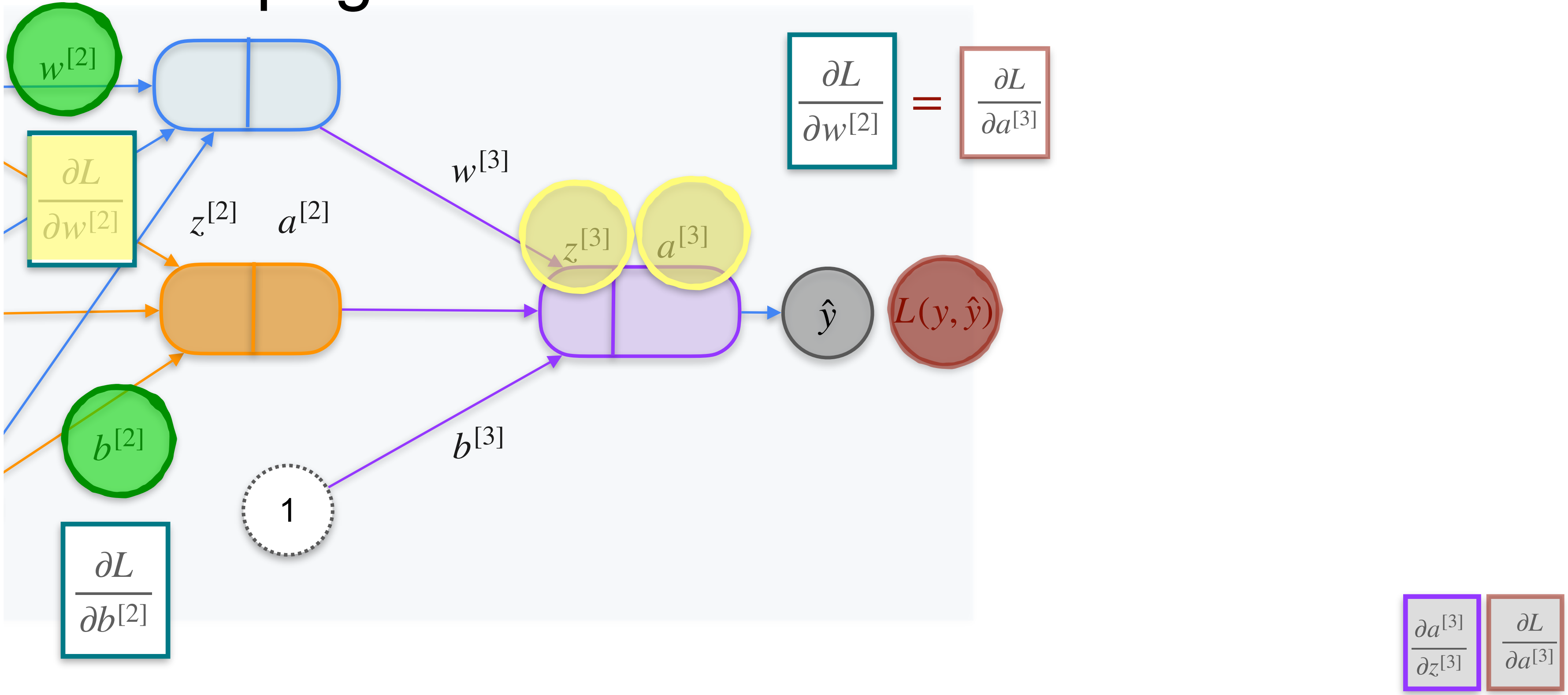

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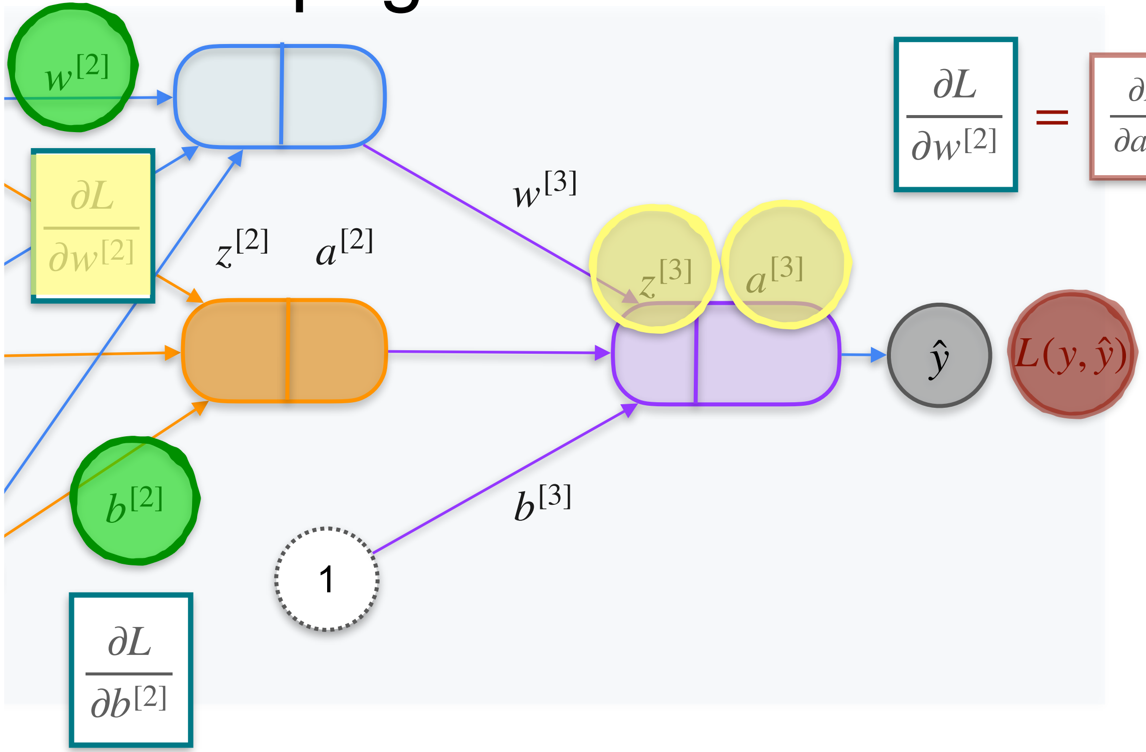
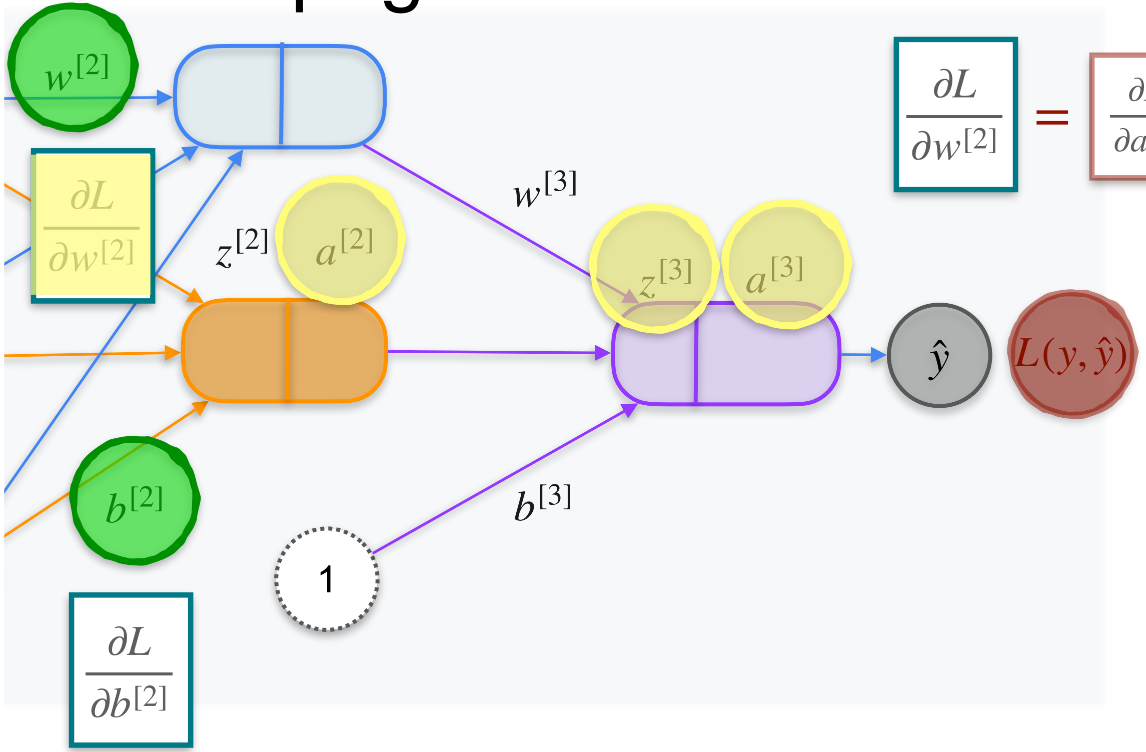


$$\boxed{\frac{\partial L}{\partial w^{[2]}}} = \boxed{\frac{\partial L}{\partial a^{[3]}}} \boxed{\frac{\partial a^{[3]}}{\partial z^{[3]}}}$$

$$\boxed{\frac{\partial a^{[3]}}{\partial z^{[3]}}} \boxed{\frac{\partial L}{\partial a^{[3]}}}$$

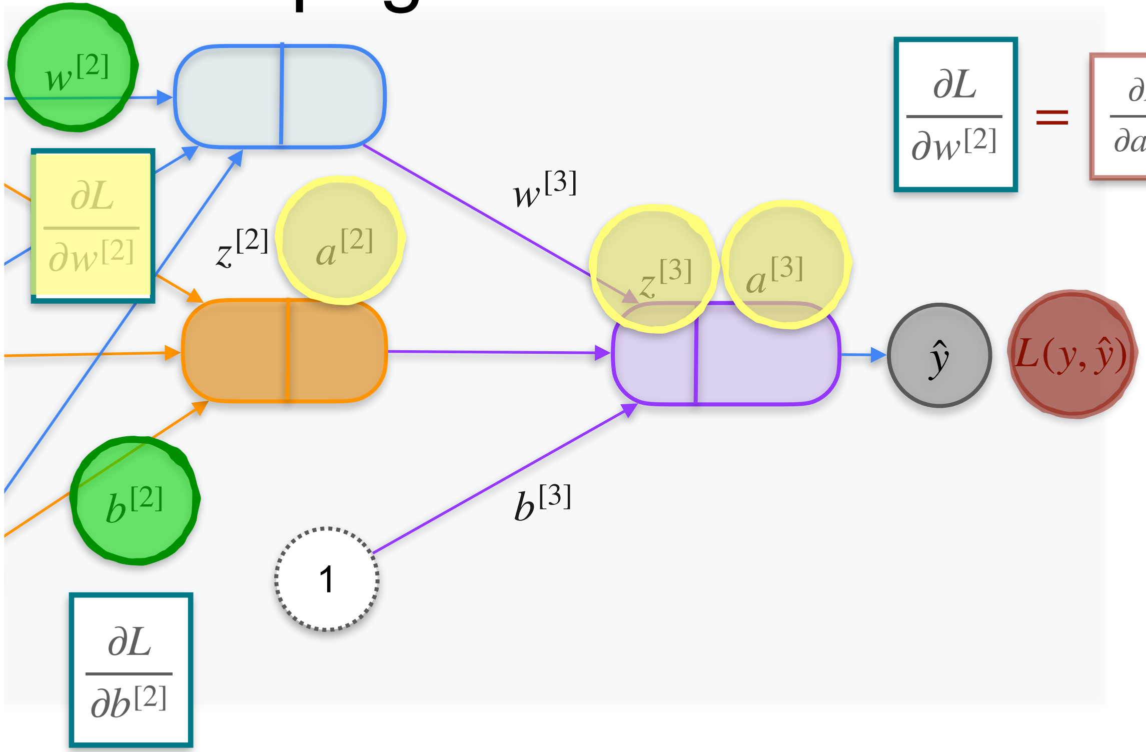
Back Propagation Introduction



$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \quad \frac{\partial a^{[3]}}{\partial z^{[3]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

Back Propagation Introduction



$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \; \frac{\partial a^{[3]}}{\partial z^{[3]}} \; \frac{\partial z^{[3]}}{\partial a^{[2]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \; \frac{\partial L}{\partial a^{[3]}}$$

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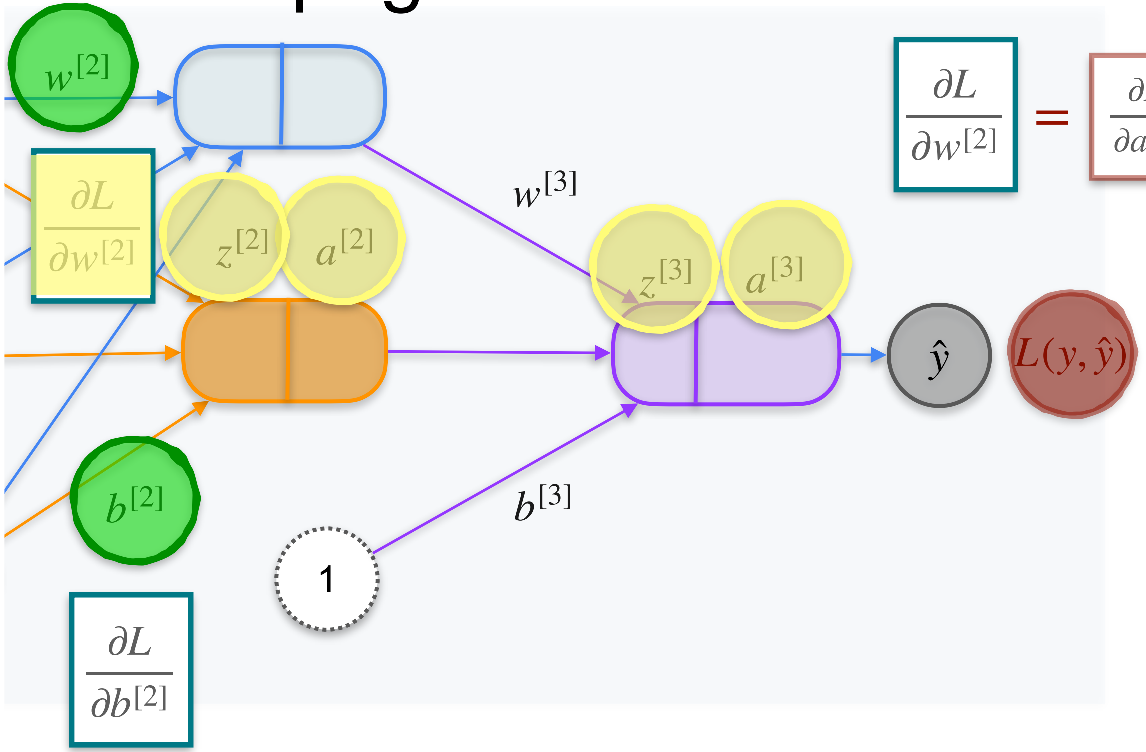
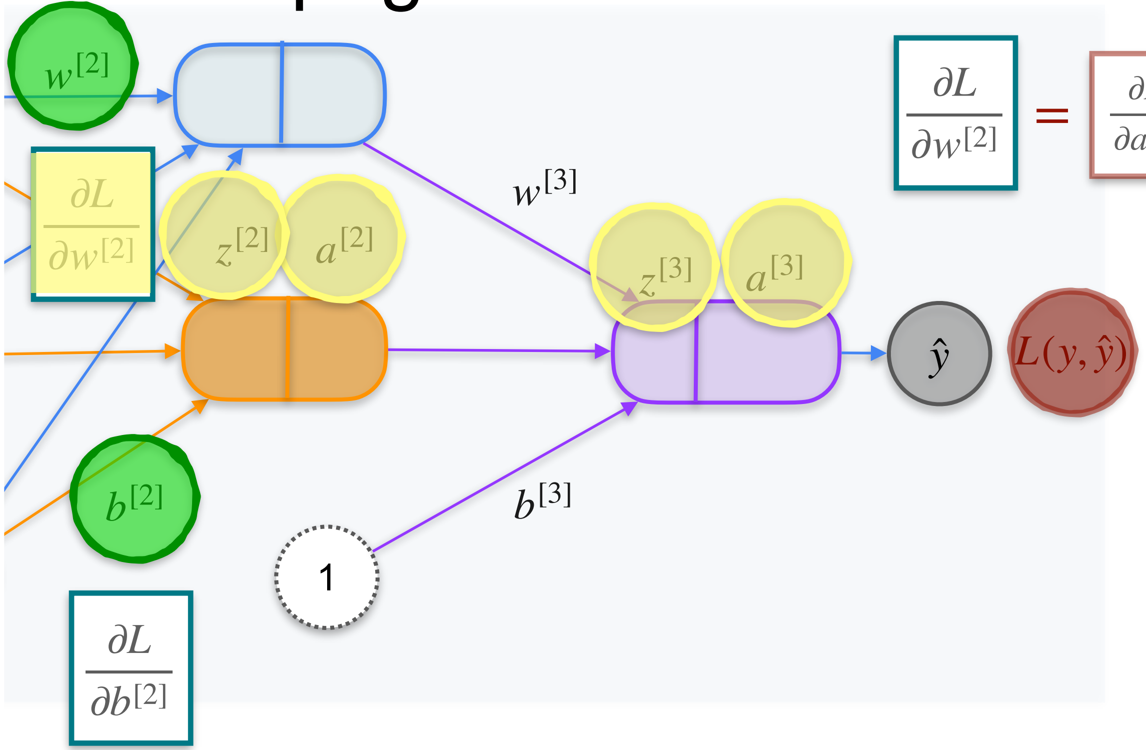


$$\boxed{\frac{\partial L}{\partial w^{[2]}}} = \boxed{\frac{\partial L}{\partial a^{[3]}}}\ \boxed{\frac{\partial a^{[3]}}{\partial z^{[3]}}}\ \boxed{\frac{\partial z^{[3]}}{\partial a^{[2]}}}$$

$$\boxed{\frac{\partial a^{[3]}}{\partial z^{[3]}}}\ \boxed{\frac{\partial L}{\partial a^{[3]}}}$$

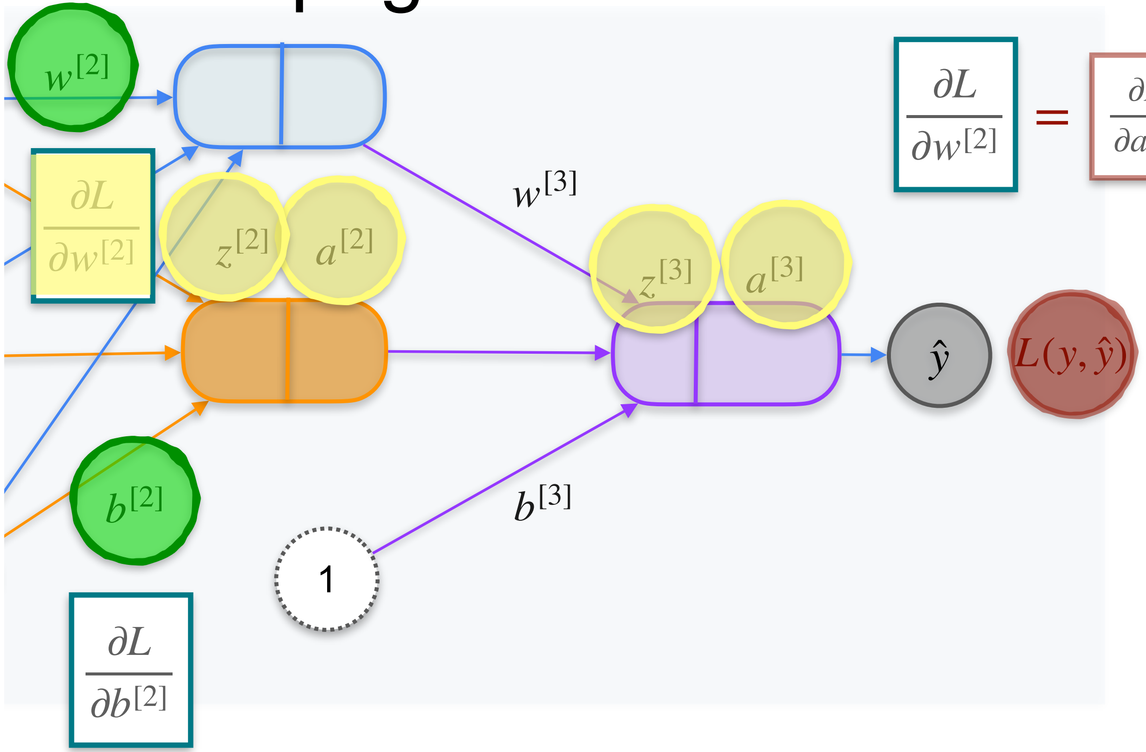
Back Propagation Introduction



$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \frac{\partial a^{[3]}}{\partial z^{[3]}} \frac{\partial z^{[3]}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

Back Propagation Introduction



$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \frac{\partial a^{[3]}}{\partial z^{[3]}} \frac{\partial z^{[3]}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

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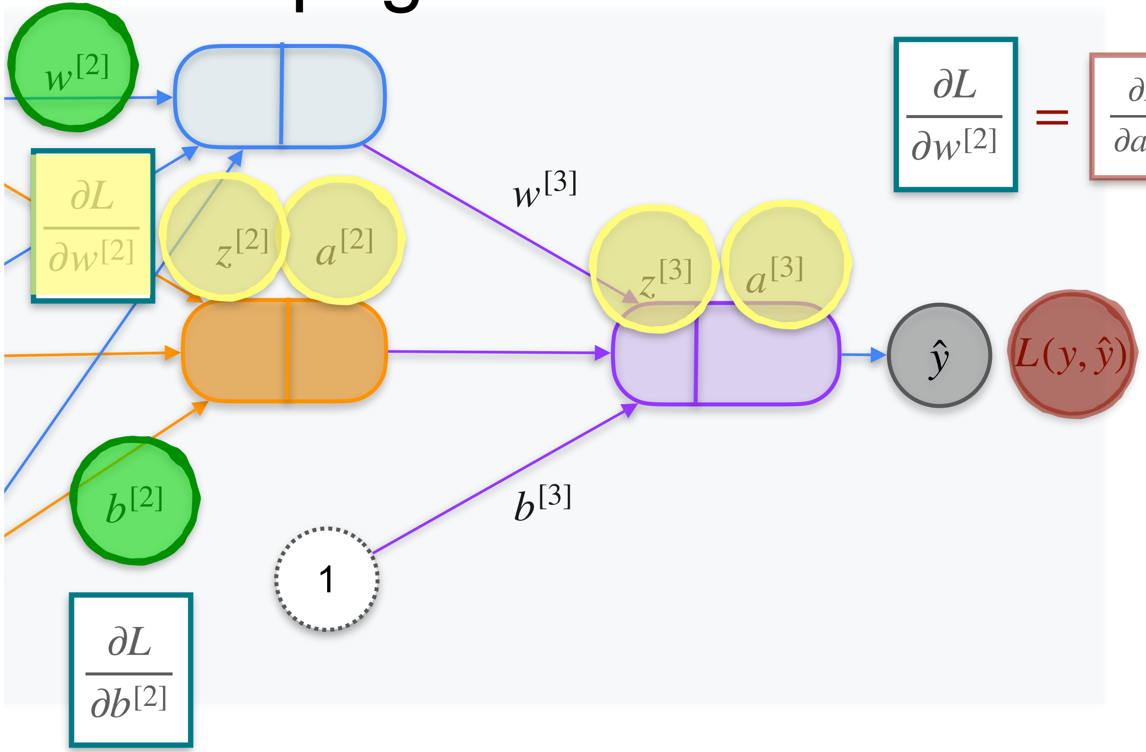

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$\frac{\partial a^{[3]}}{\partial z^{[3]}}$ $\frac{\partial L}{\partial a^{[3]}}$

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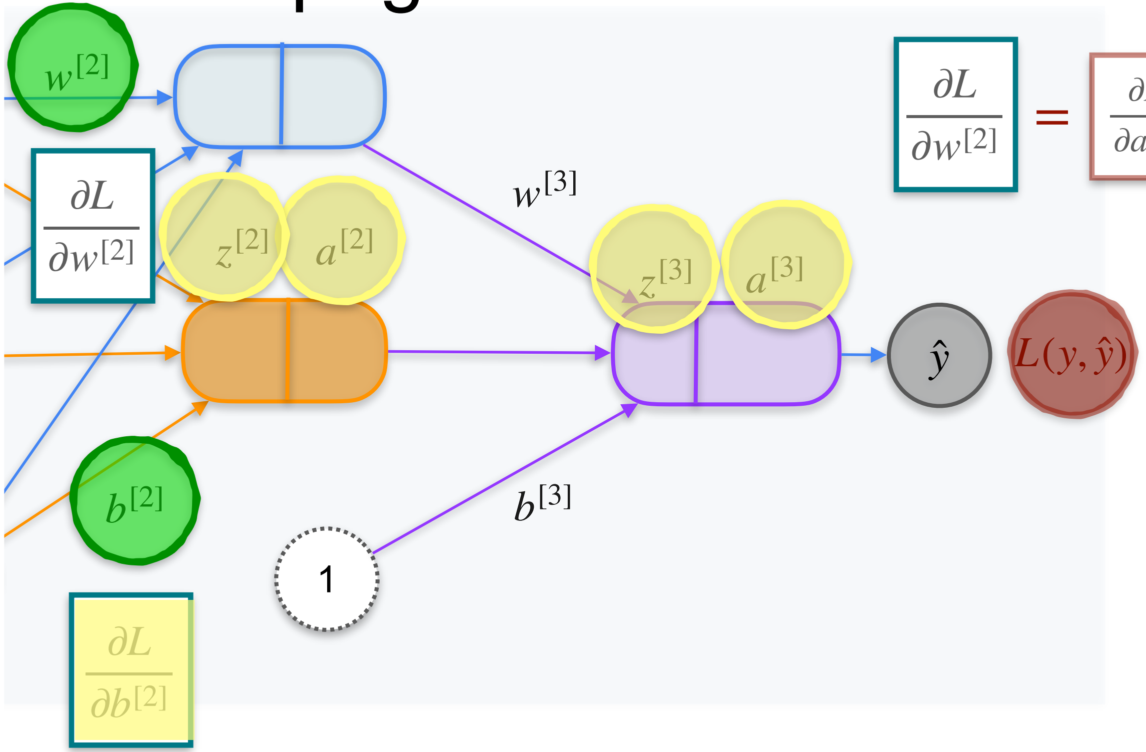

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$\frac{\partial a^{[3]}}{\partial z^{[3]}}$ $\frac{\partial L}{\partial a^{[3]}}$

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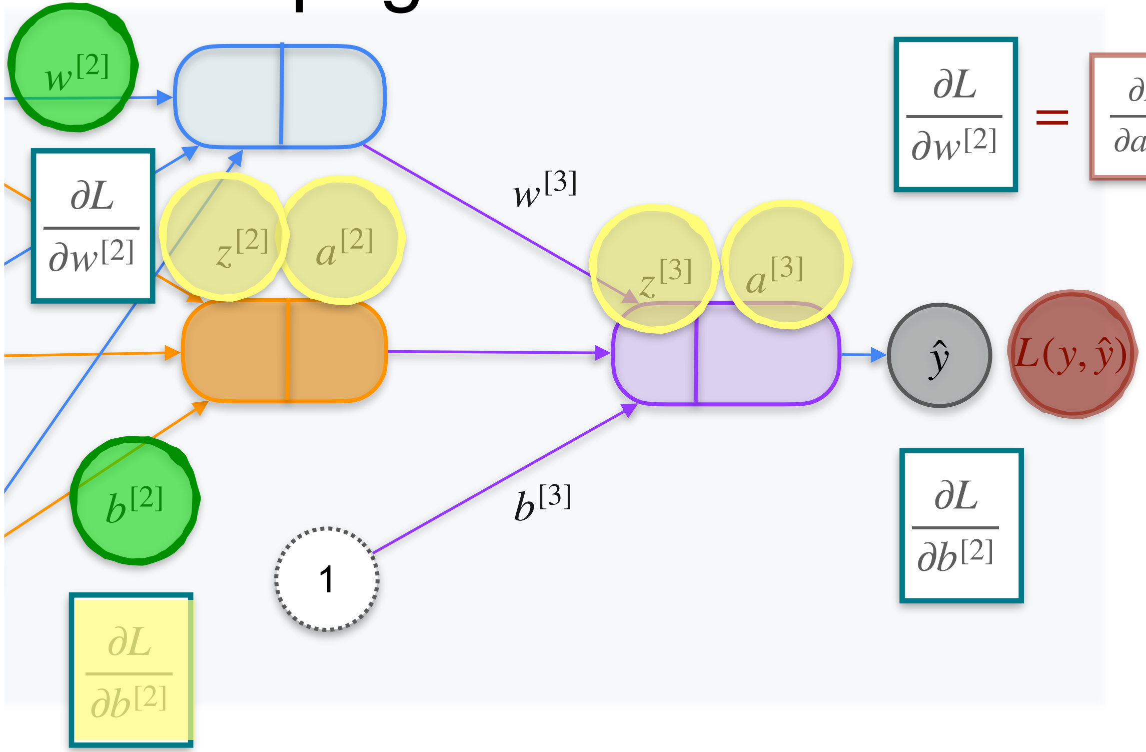

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$\frac{\partial a^{[3]}}{\partial z^{[3]}}$ $\frac{\partial L}{\partial a^{[3]}}$

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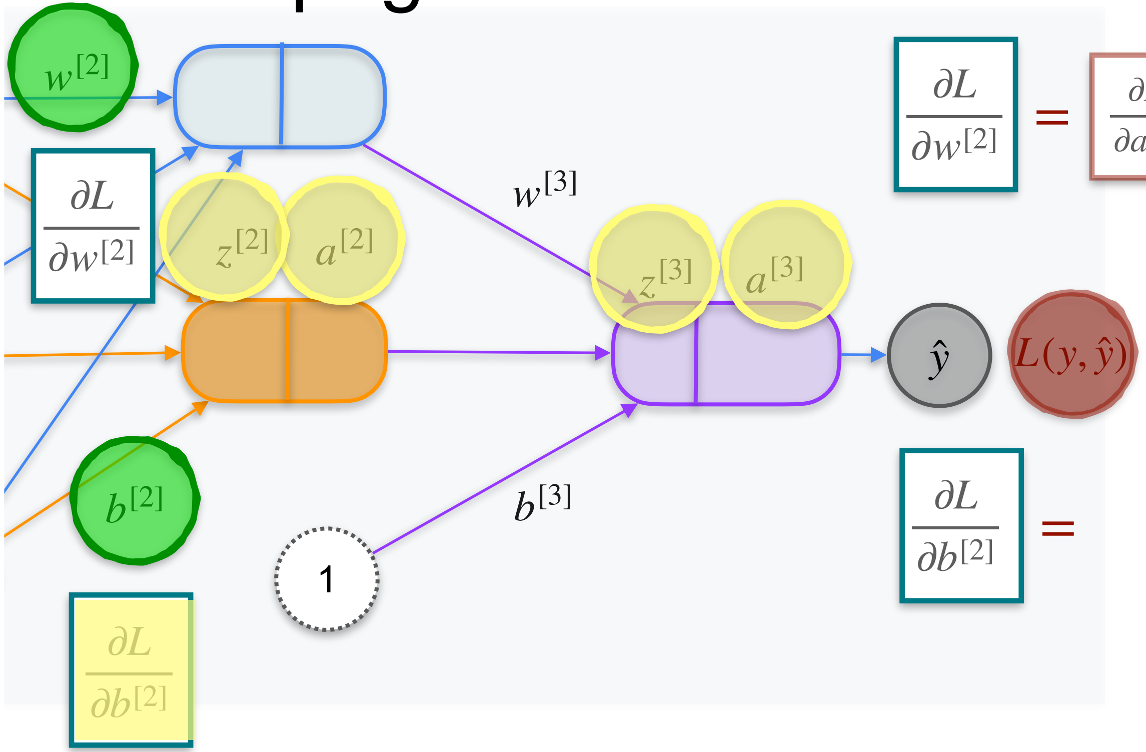

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial L}{\partial b^{[2]}} =$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

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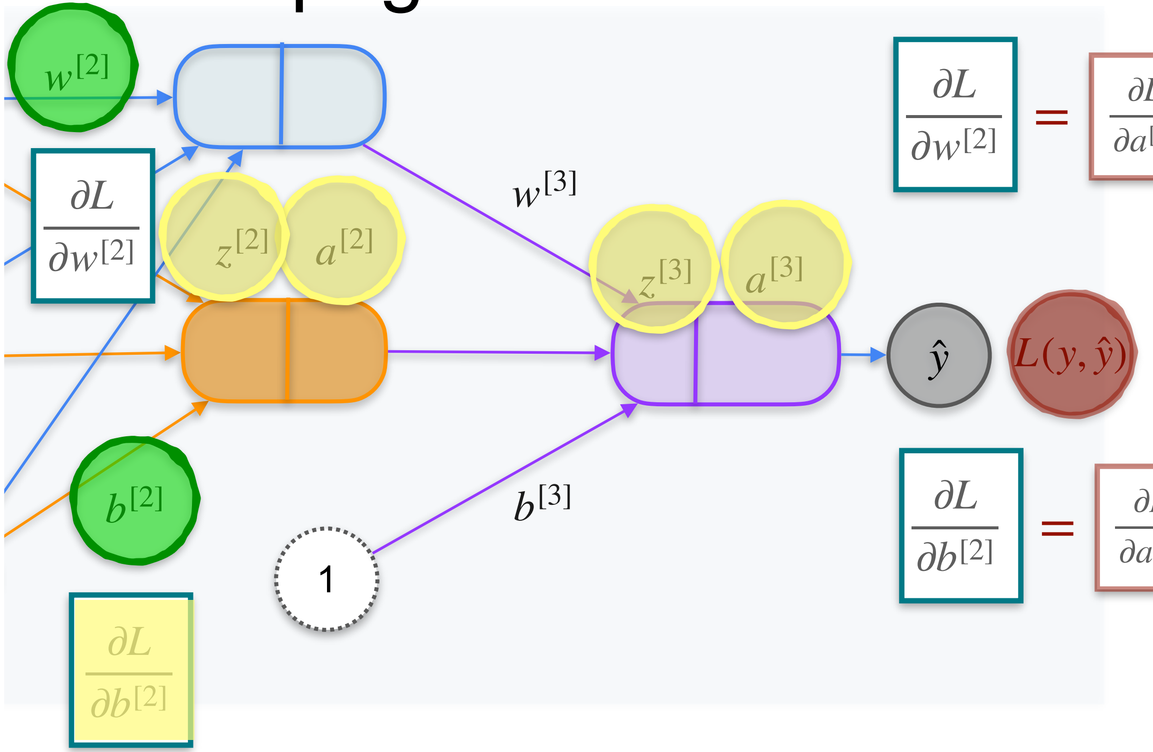

$$\boxed{\frac{\partial L}{\partial w^{[2]}}} = \boxed{\frac{\partial L}{\partial a^{[3]}}} \cdot \boxed{\frac{\partial a^{[3]}}{\partial z^{[3]}}} \cdot \boxed{\frac{\partial z^{[3]}}{\partial a^{[2]}}} \cdot \boxed{\frac{\partial a^{[2]}}{\partial z^{[2]}}} \cdot \boxed{\frac{\partial z^{[2]}}{\partial w^{[2]}}}$$

$$\boxed{\frac{\partial L}{\partial b^{[2]}}} = \boxed{\frac{\partial L}{\partial a^{[3]}}}$$

$$\boxed{\frac{\partial a^{[3]}}{\partial z^{[3]}}} \quad \boxed{\frac{\partial L}{\partial a^{[3]}}}$$

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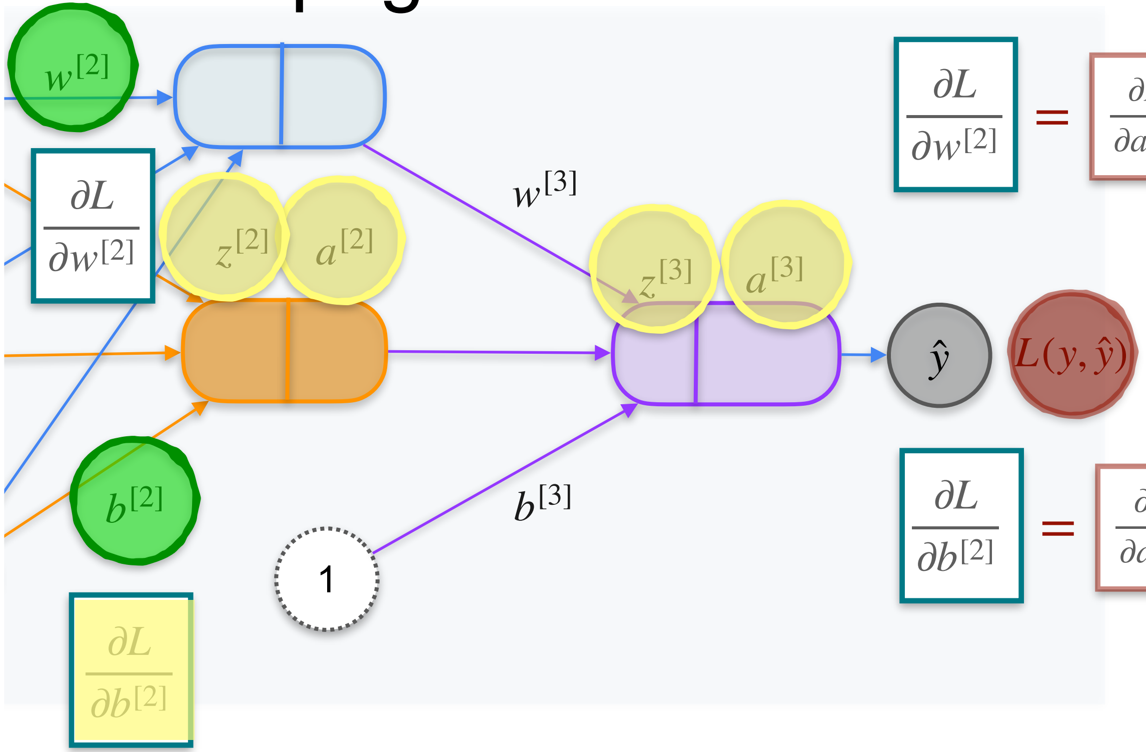

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial L}{\partial b^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \quad \frac{\partial a^{[3]}}{\partial z^{[3]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

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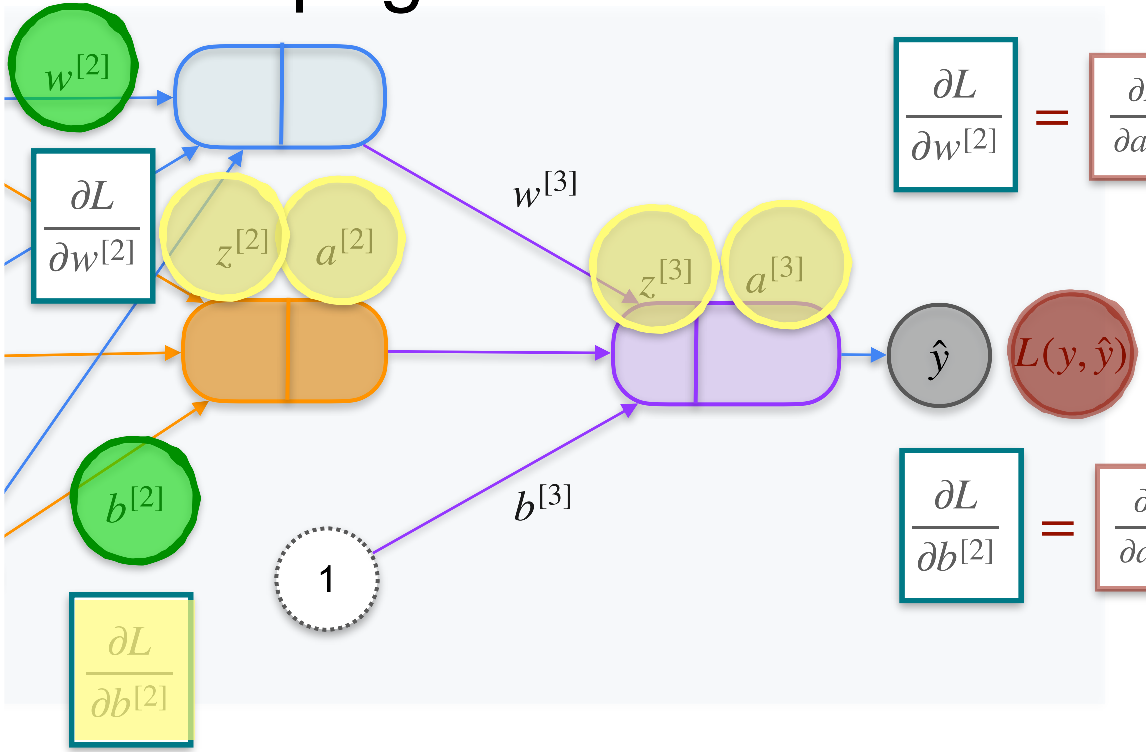

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial L}{\partial b^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \quad \frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial z^{[3]}}{\partial a^{[2]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

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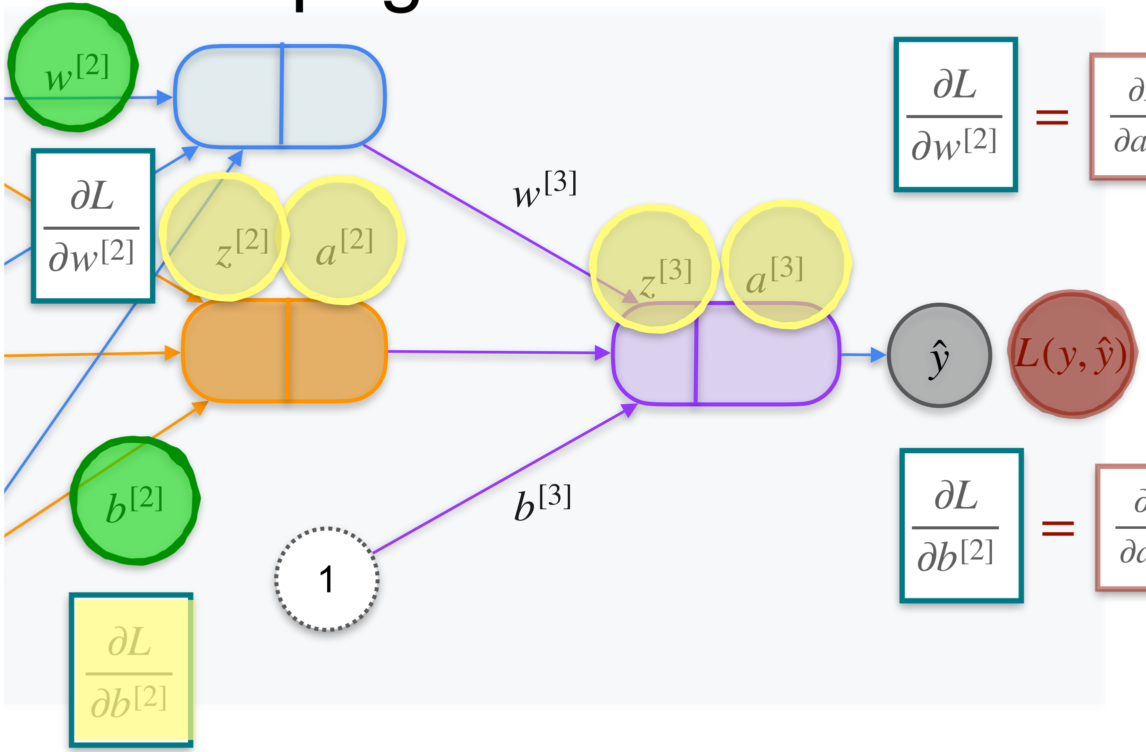

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial L}{\partial b^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \quad \frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial z^{[3]}}{\partial a^{[2]}} \quad \frac{\partial a^{[2]}}{\partial z^{[2]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

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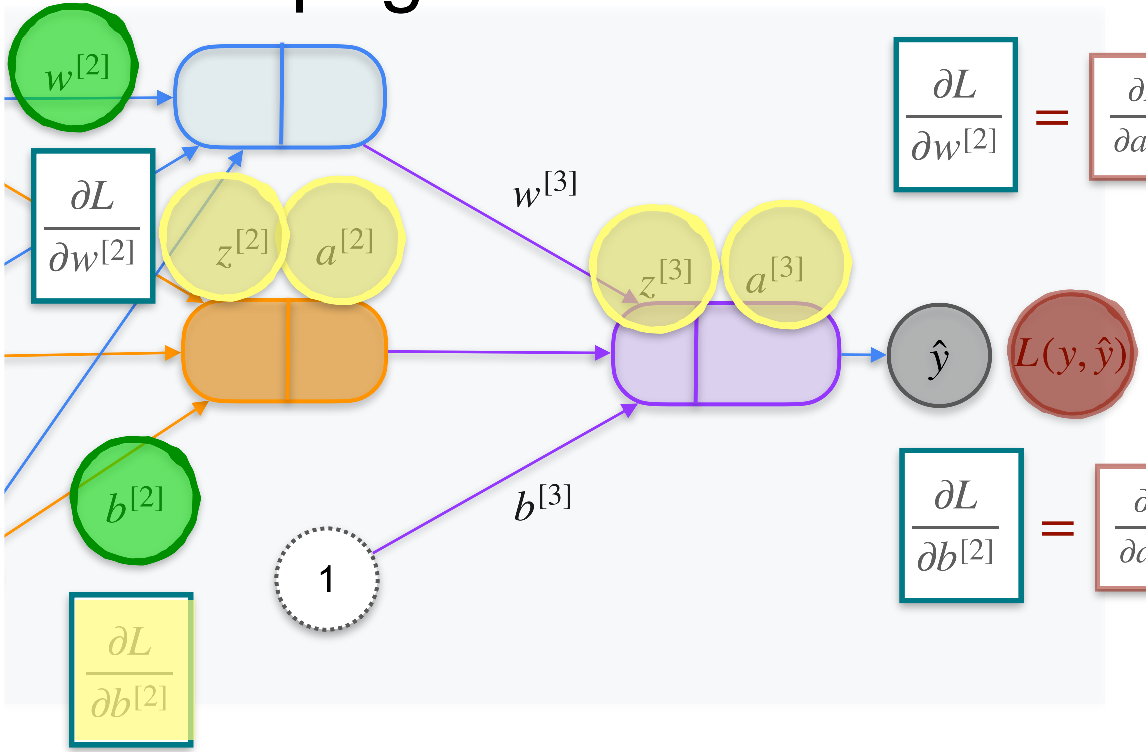

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial L}{\partial b^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \quad \frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial z^{[3]}}{\partial a^{[2]}} \quad \frac{\partial a^{[2]}}{\partial z^{[2]}} \quad \frac{\partial z^{[2]}}{\partial b^{[2]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

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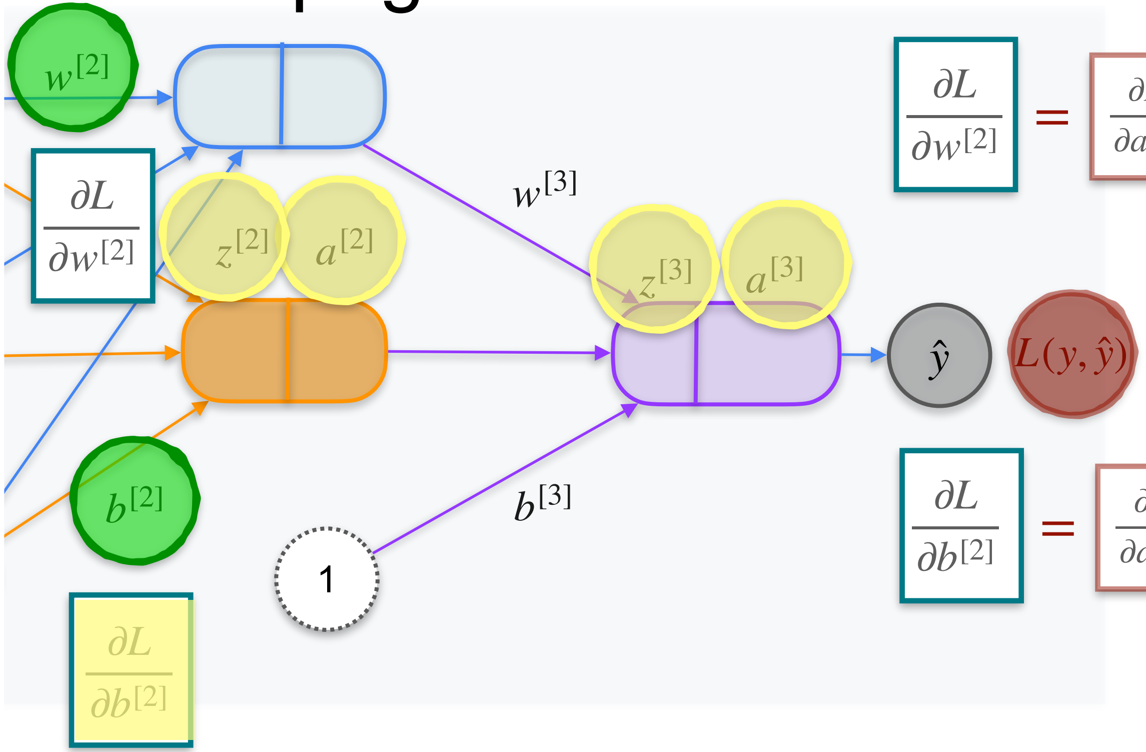

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial L}{\partial b^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial b^{[2]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

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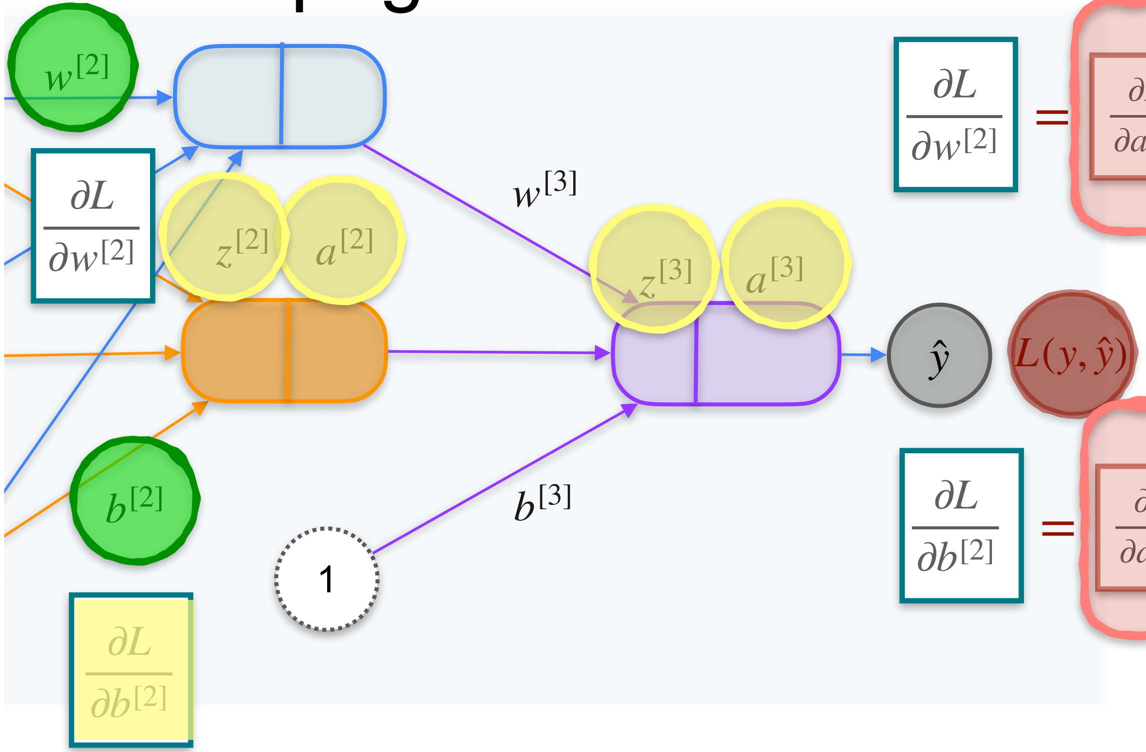

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial L}{\partial b^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial b^{[2]}}$$

$\frac{\partial a^{[3]}}{\partial z^{[3]}}$ $\frac{\partial L}{\partial a^{[3]}}$

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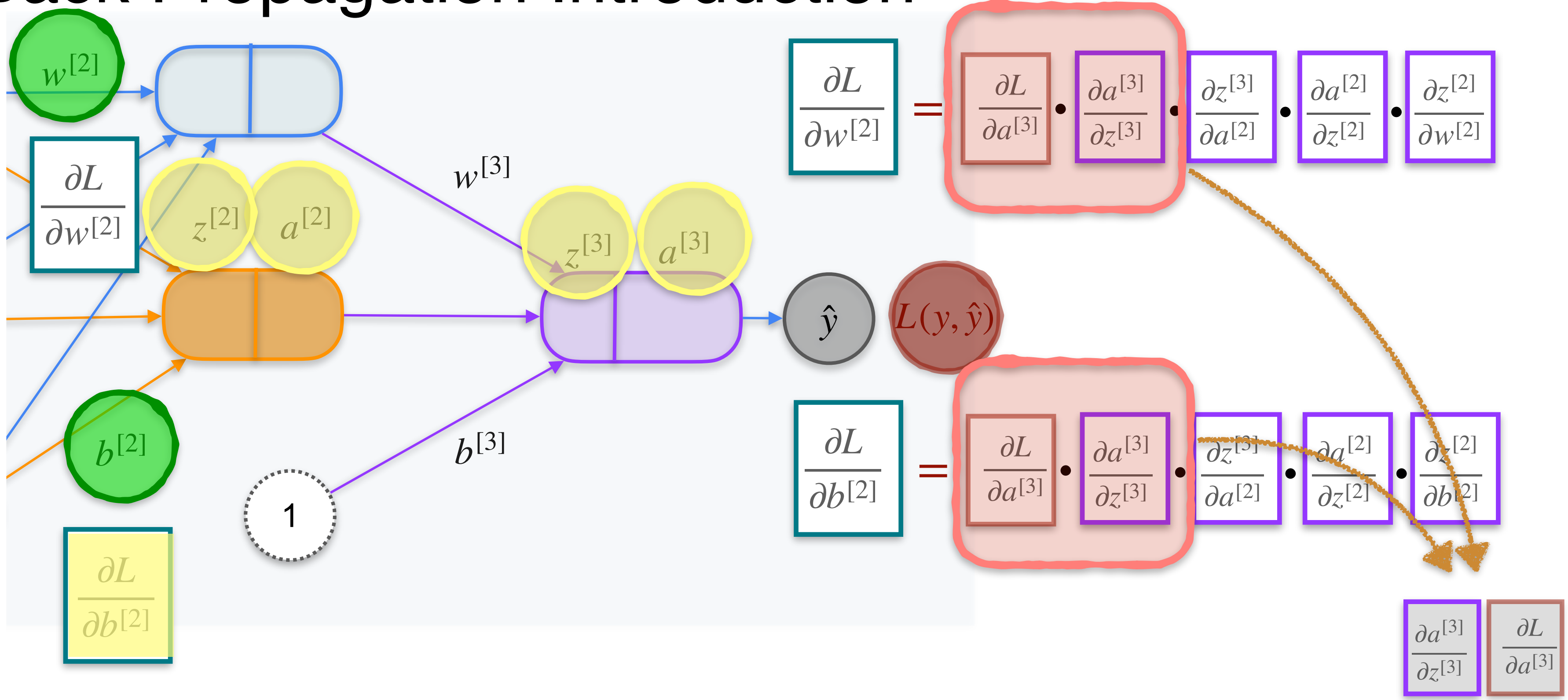

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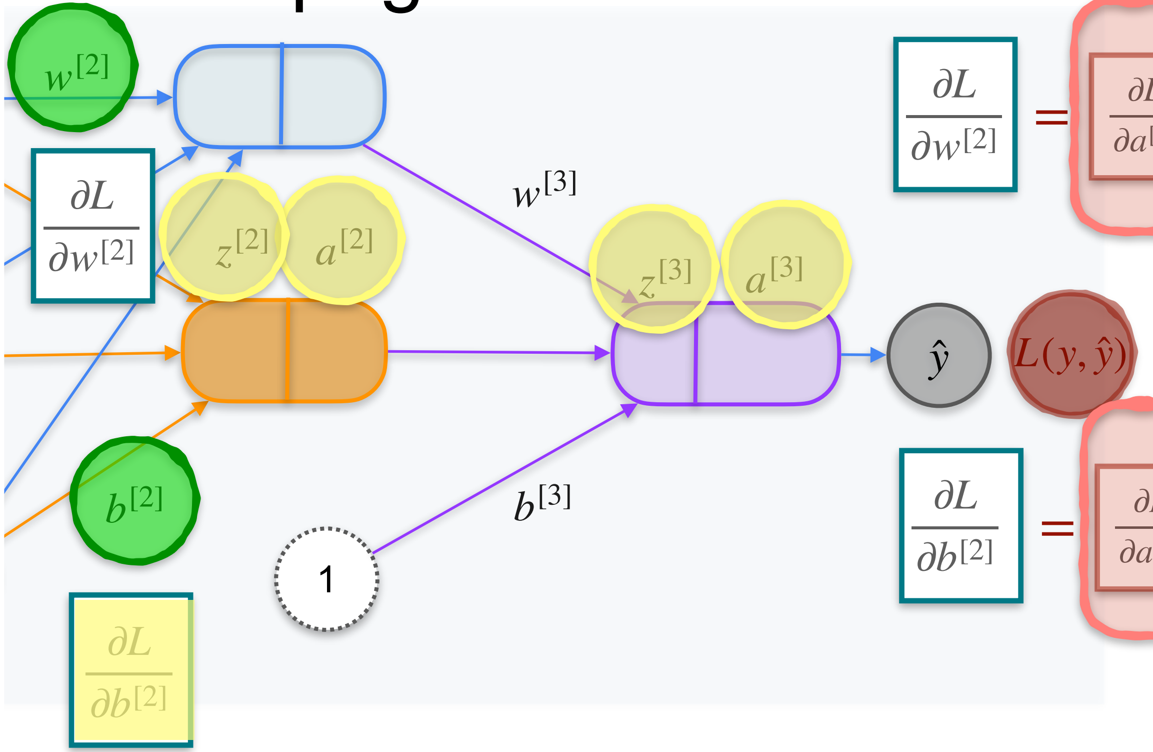

$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial w^{[2]}}$$

$$\frac{\partial L}{\partial b^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial b^{[2]}}$$

$$\frac{\partial a^{[3]}}{\partial z^{[3]}} \quad \frac{\partial L}{\partial a^{[3]}}$$

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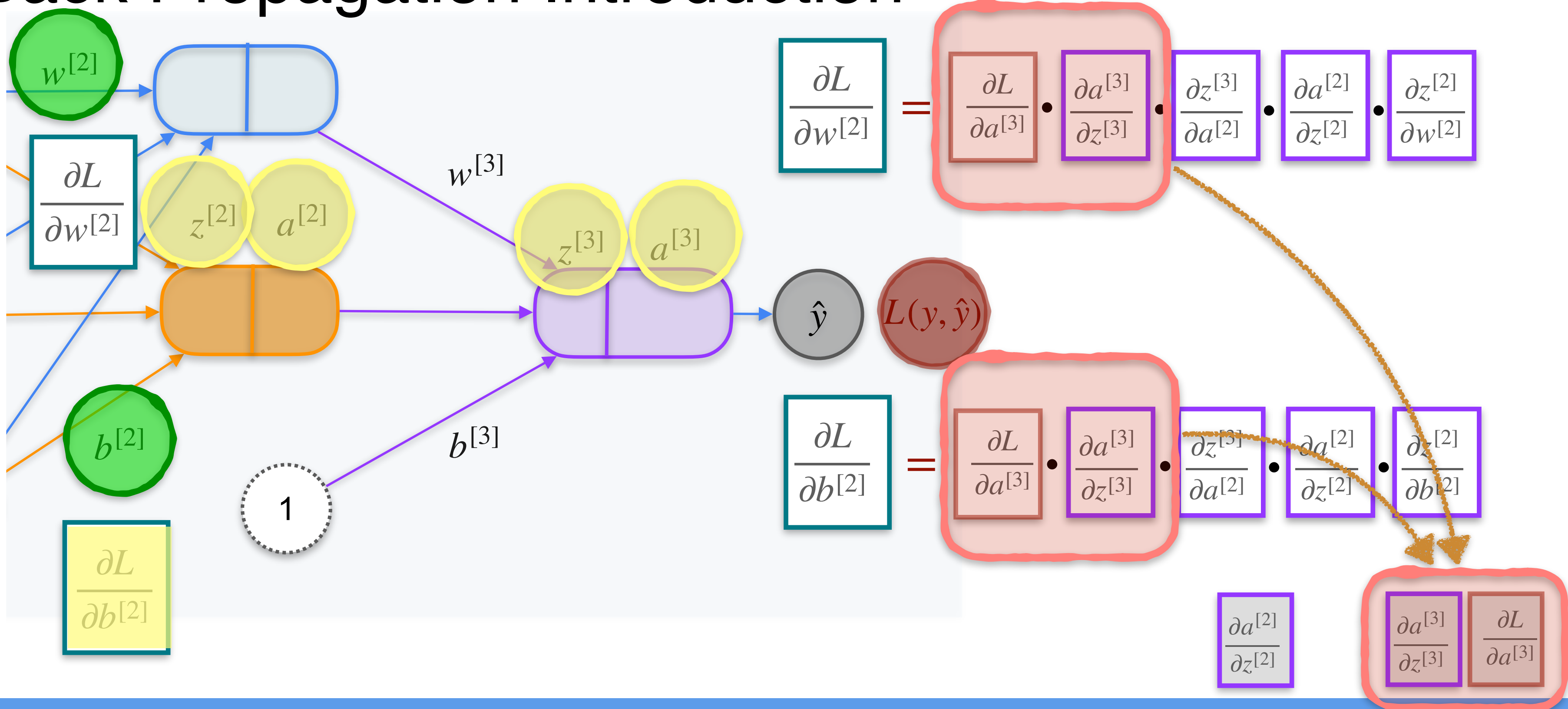

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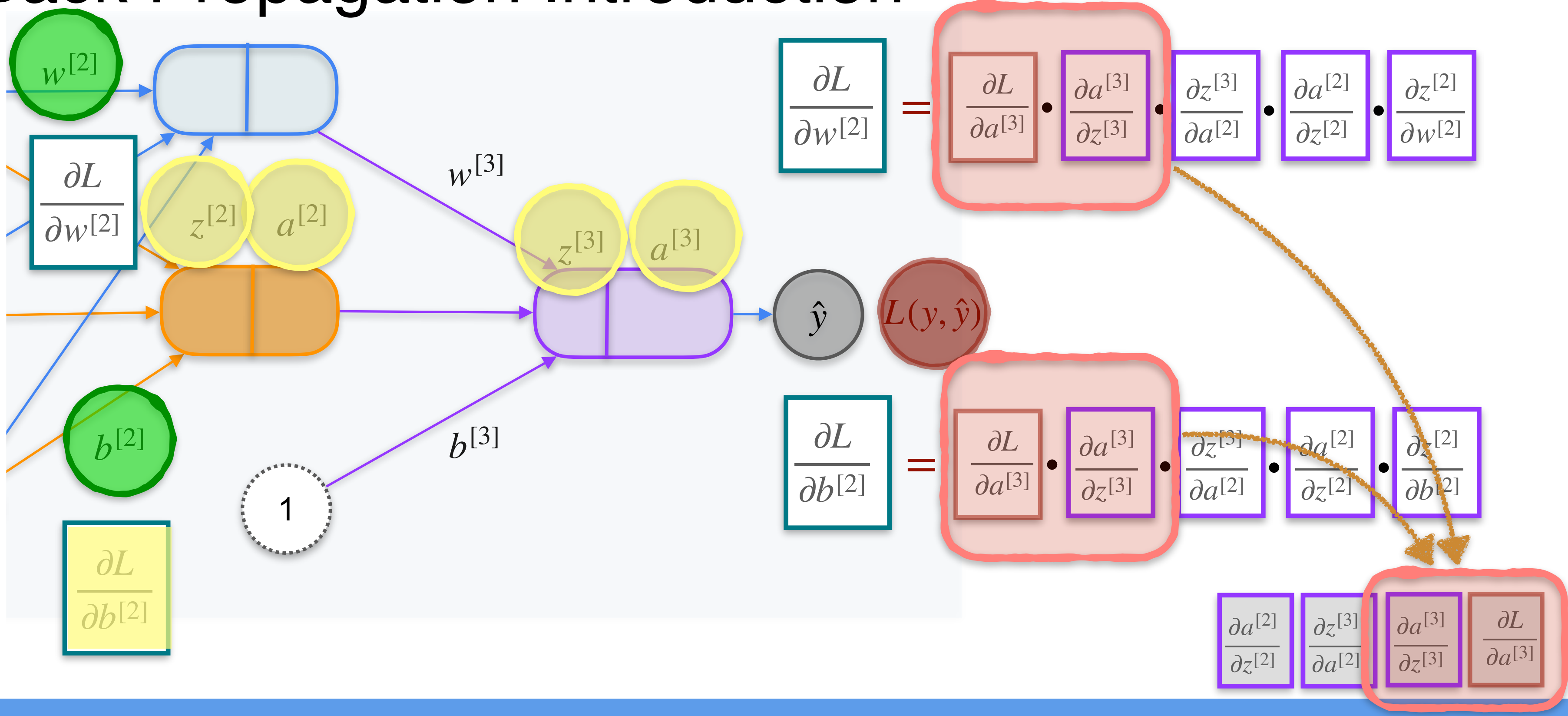

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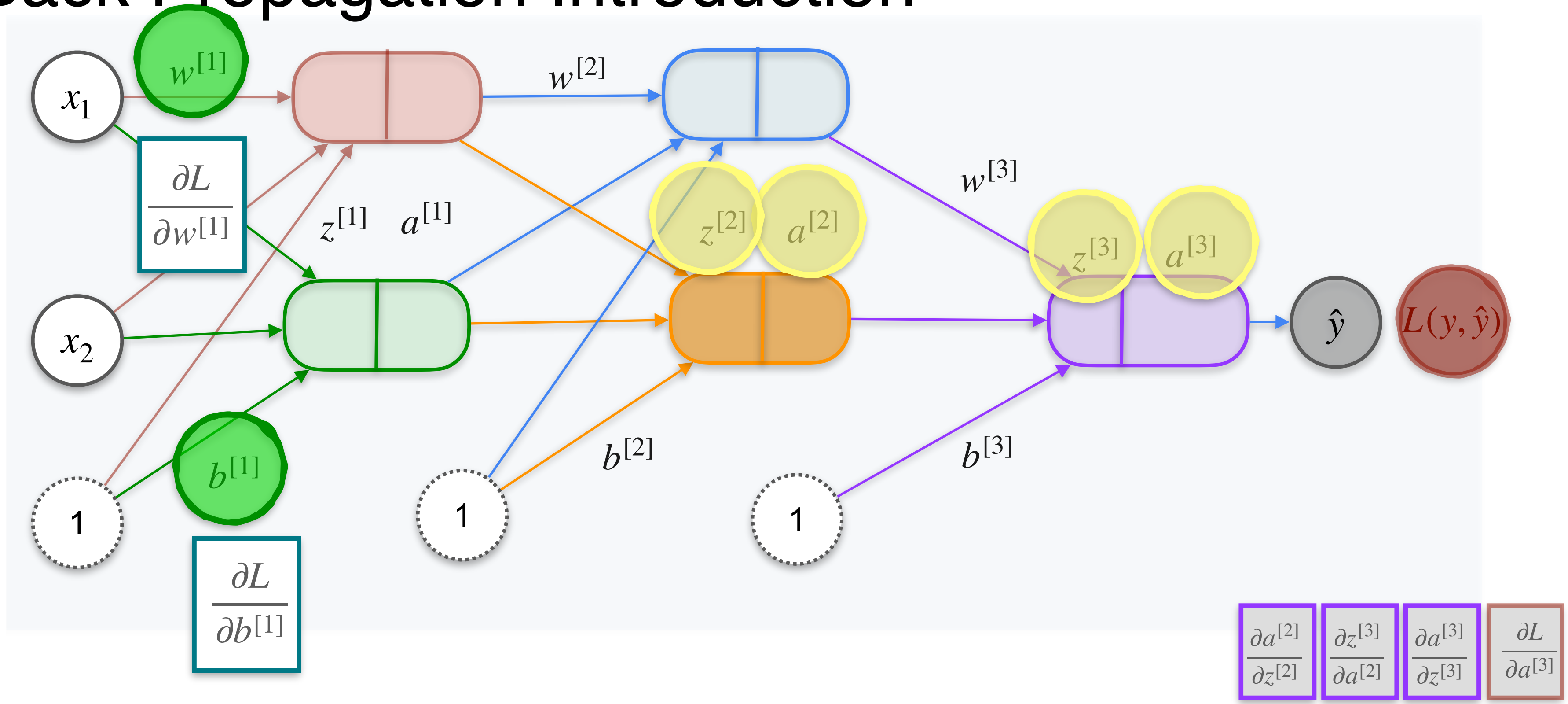

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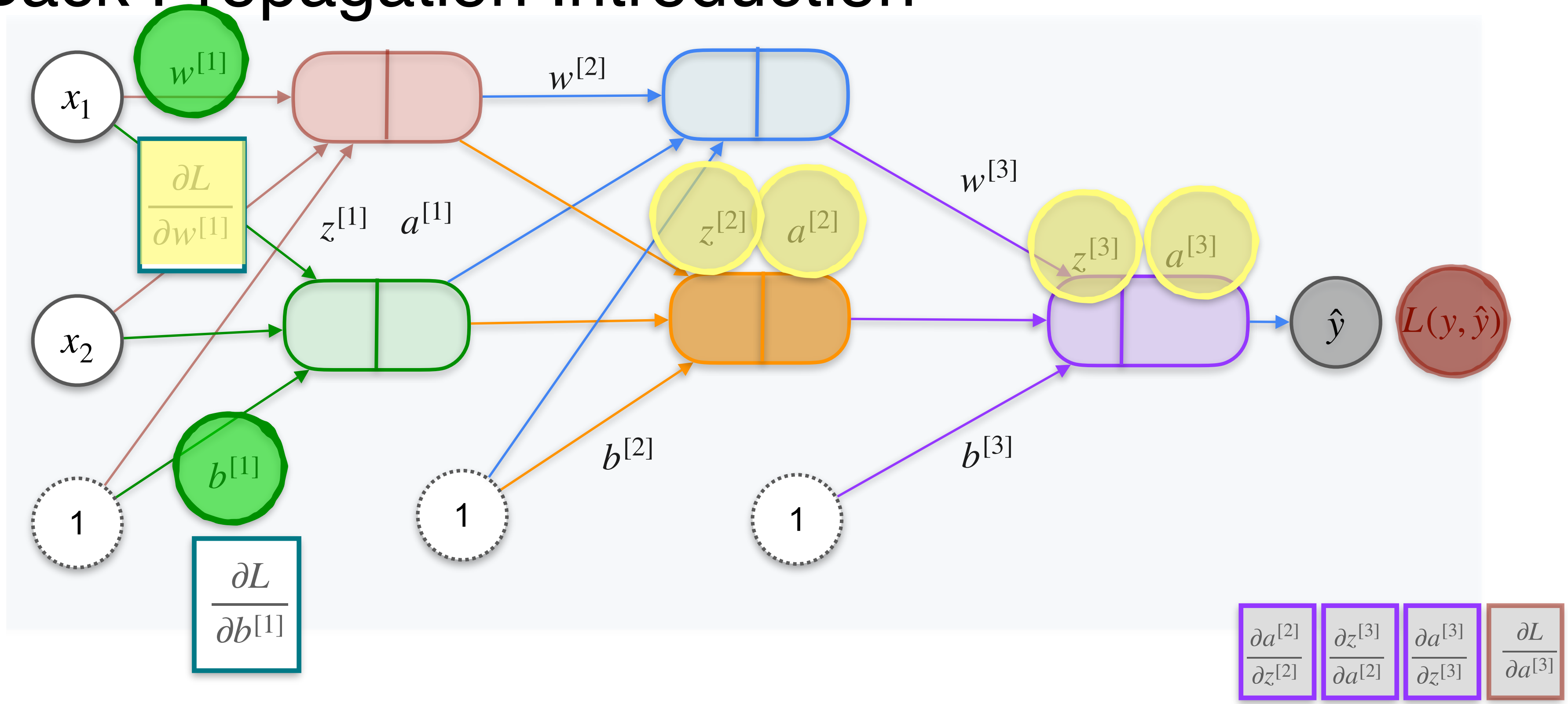

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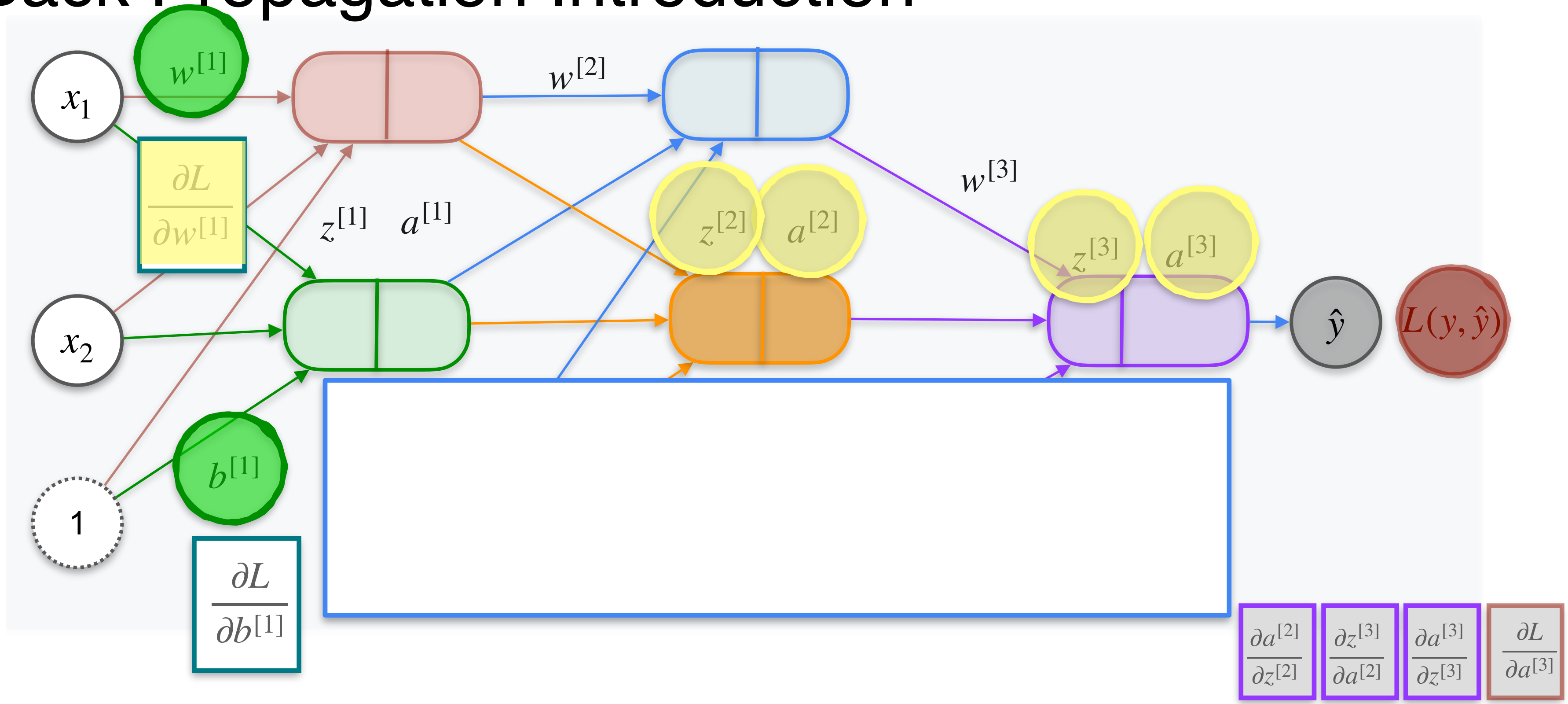

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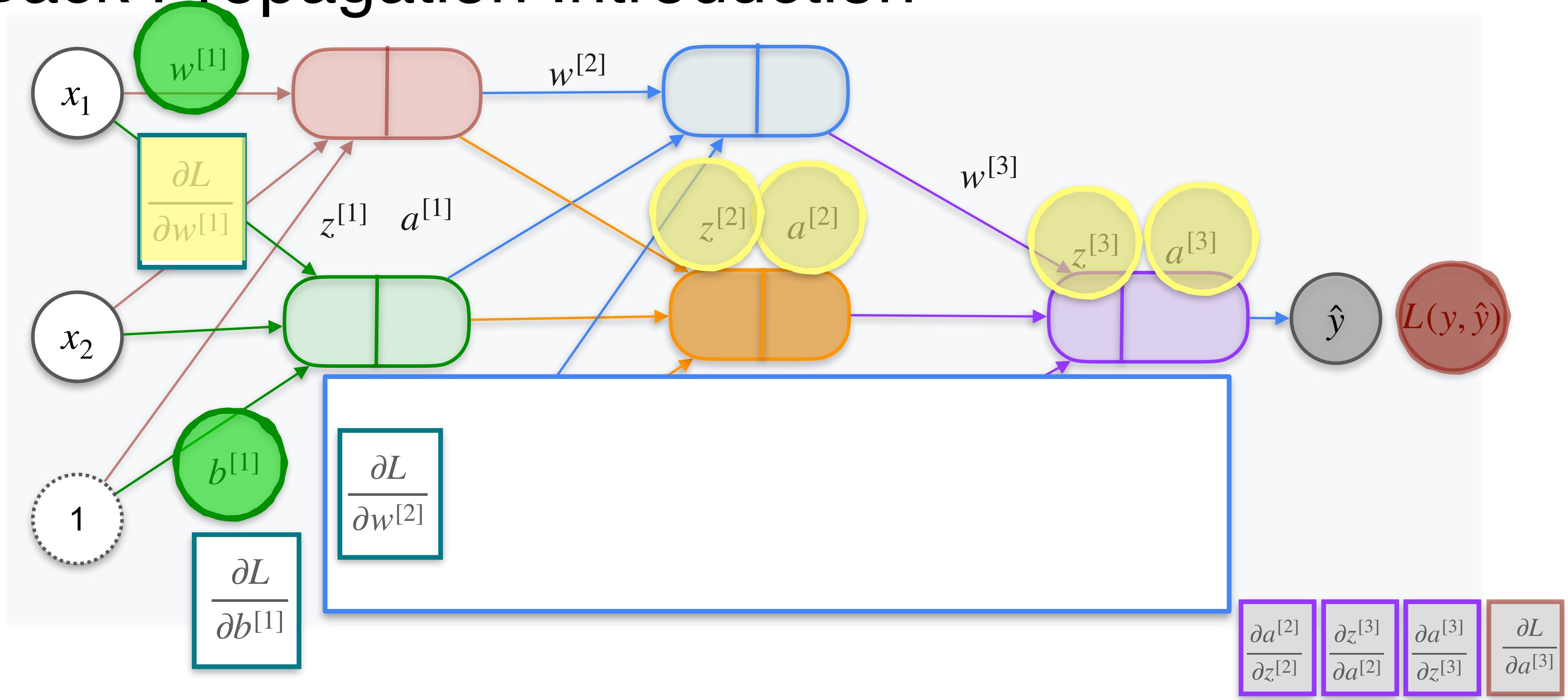

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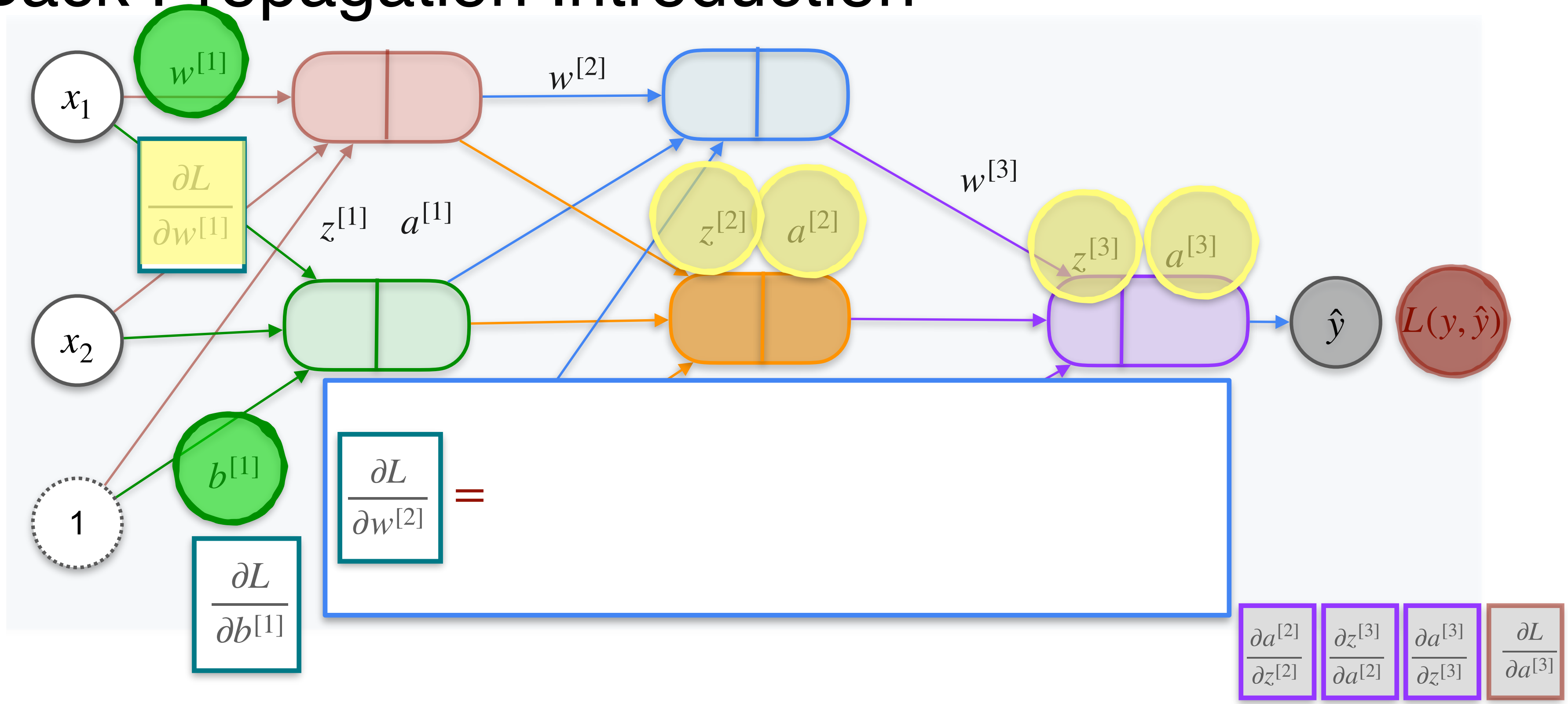

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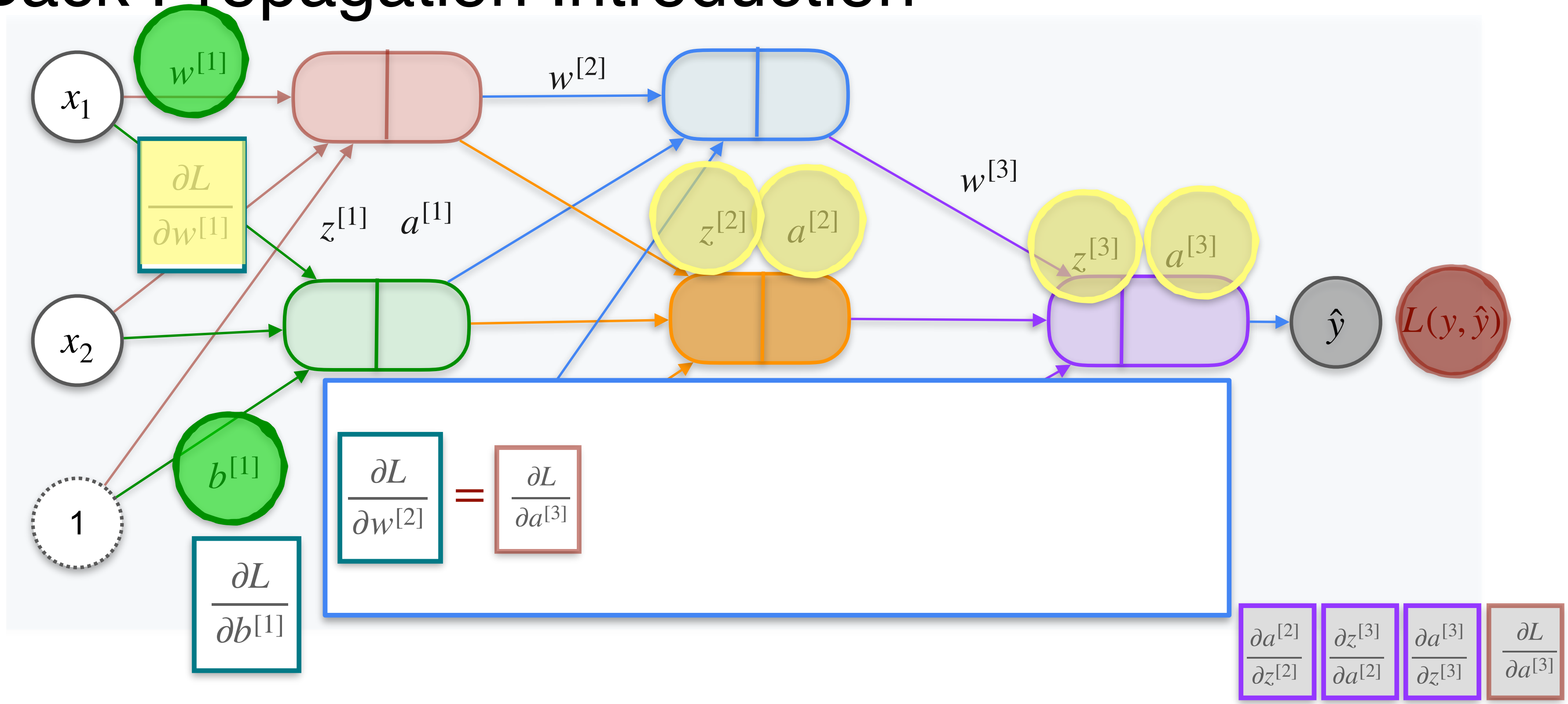

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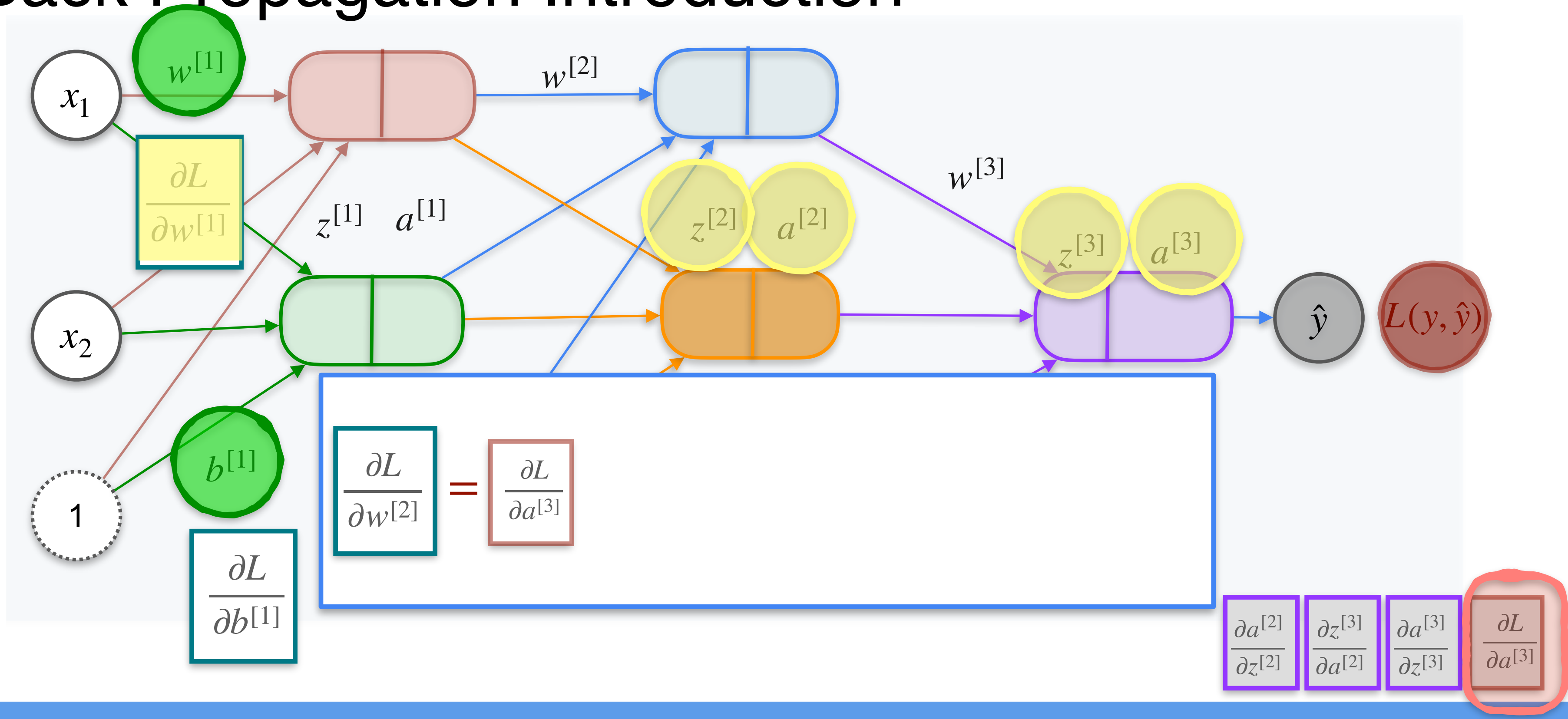

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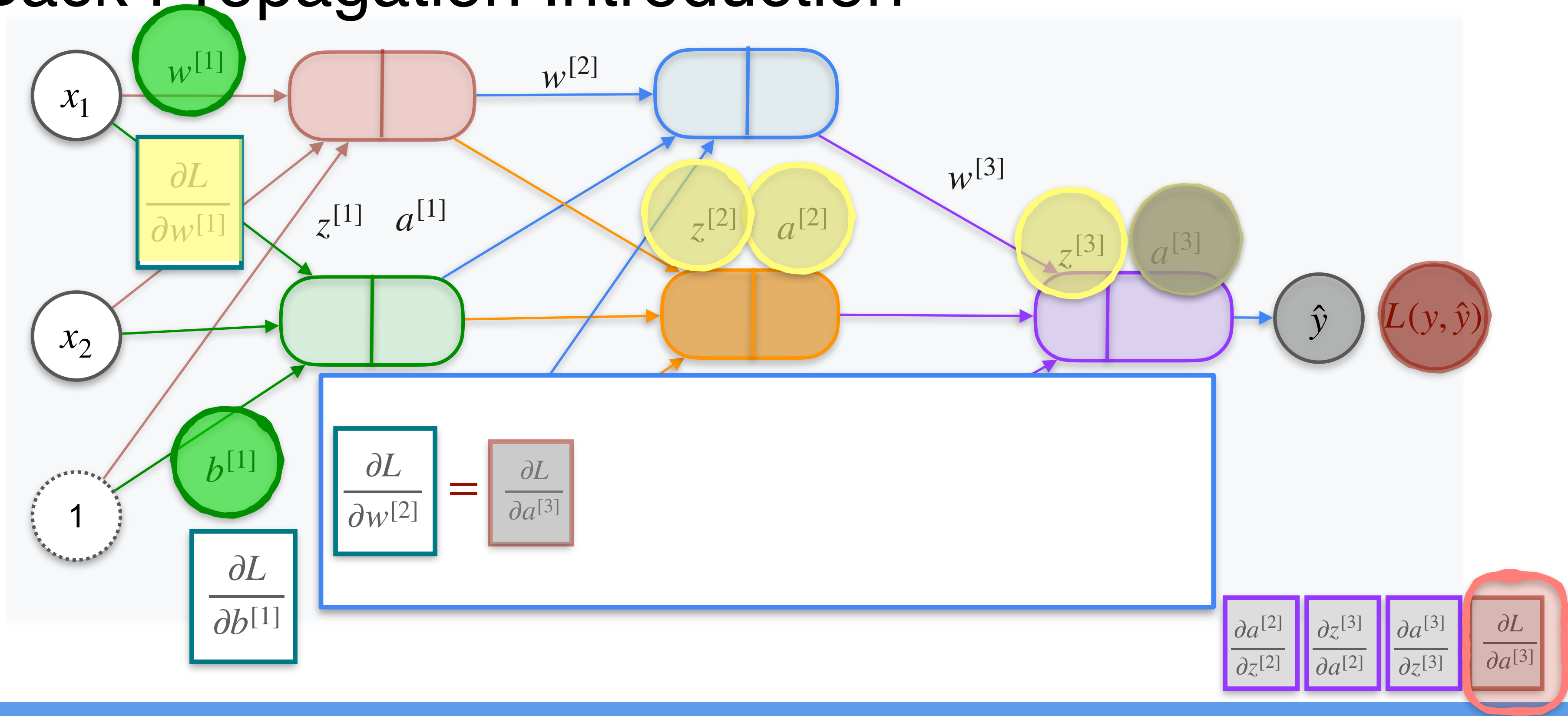
Back Propagation Introduction



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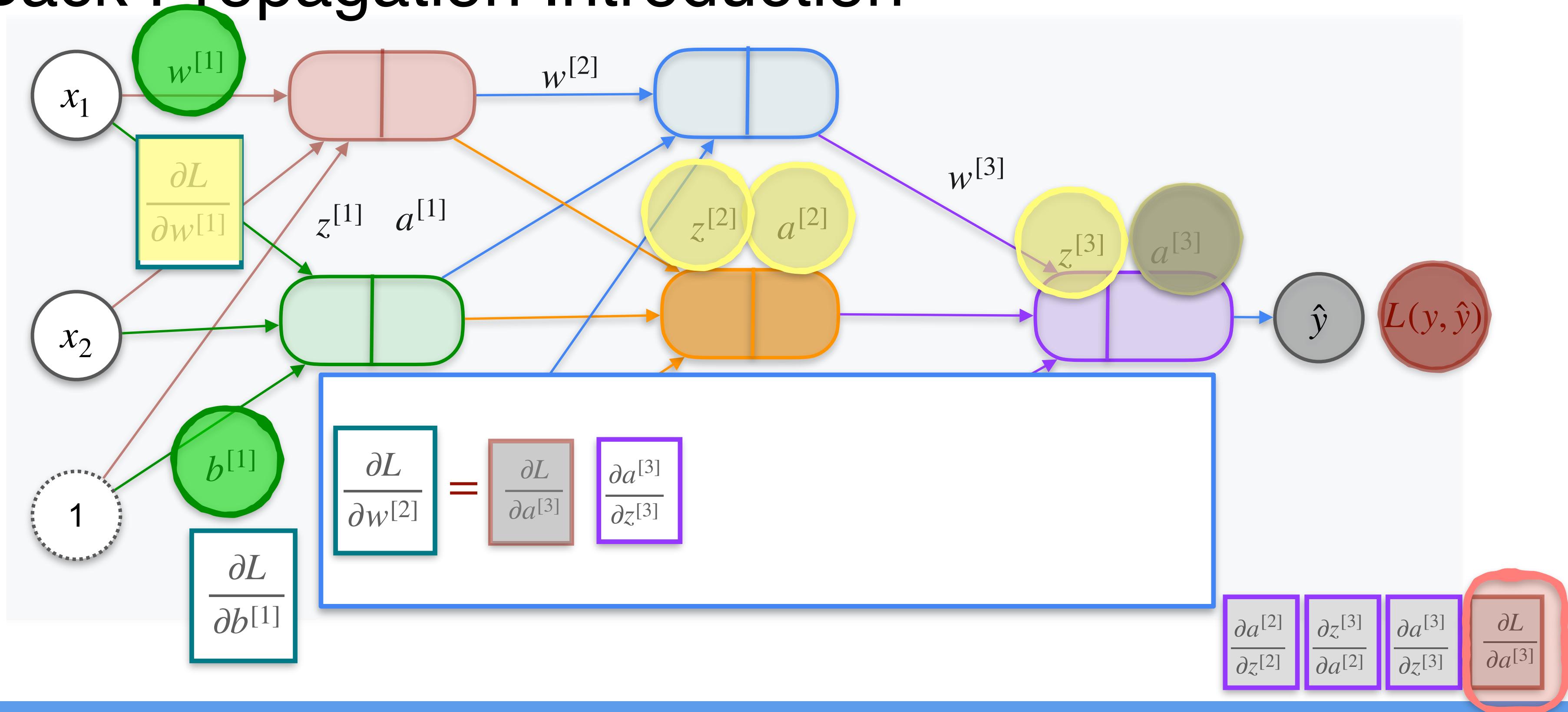

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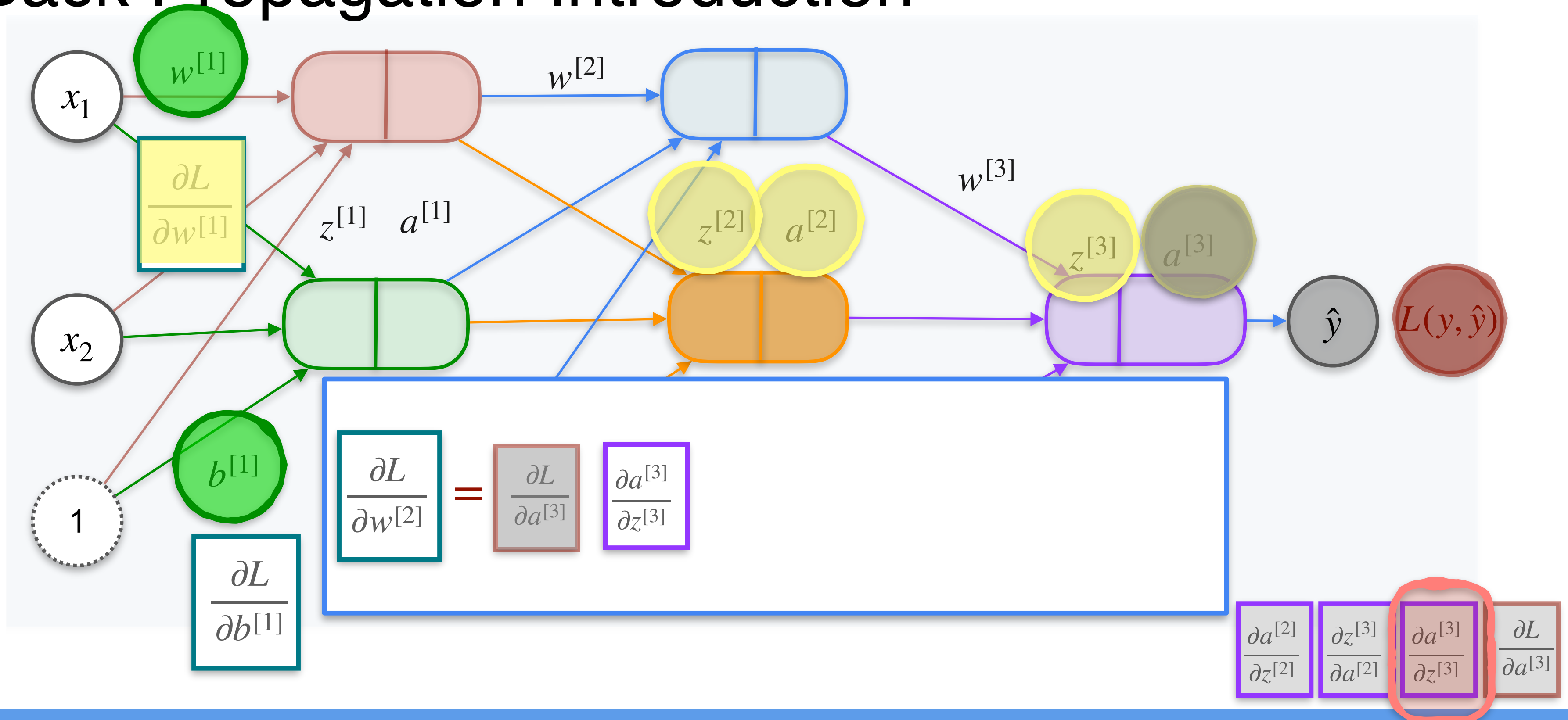

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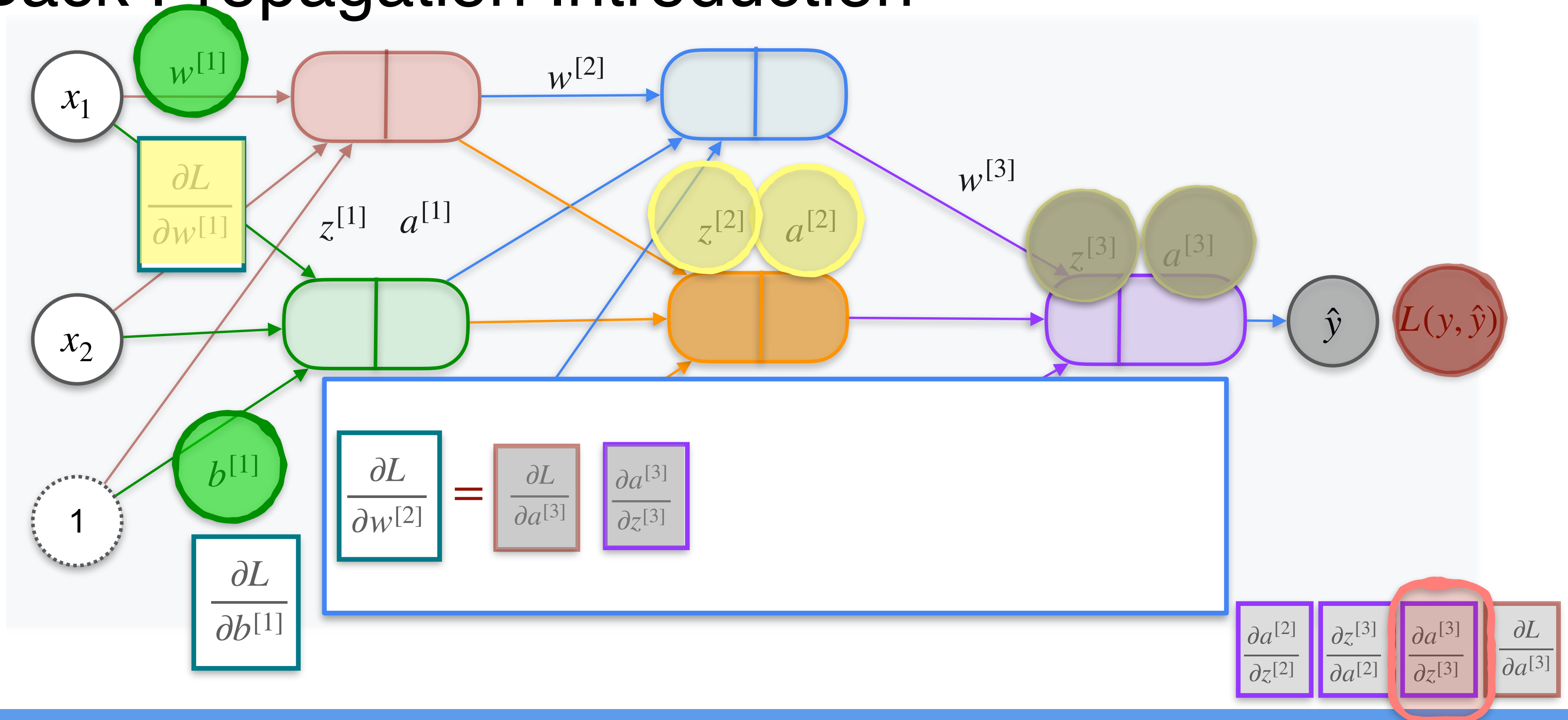

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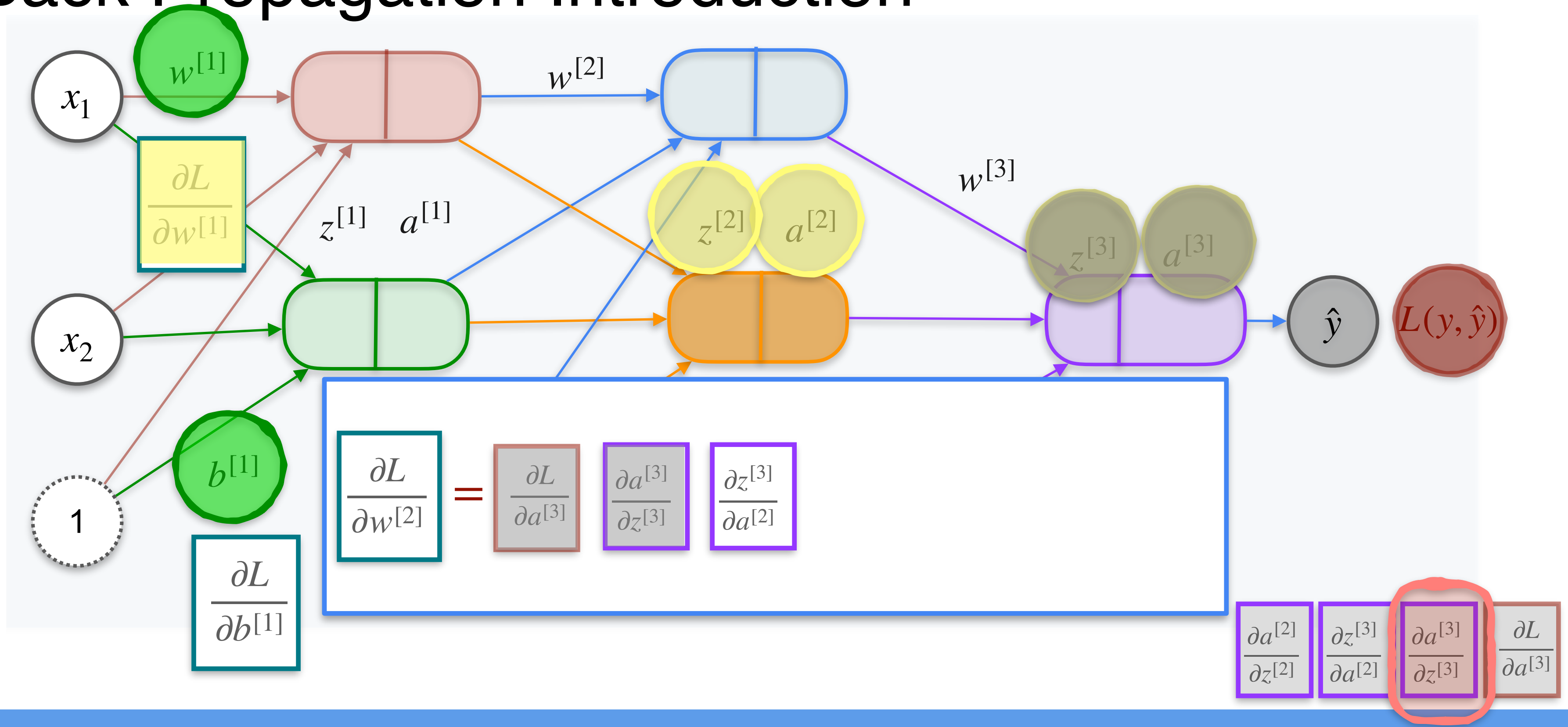

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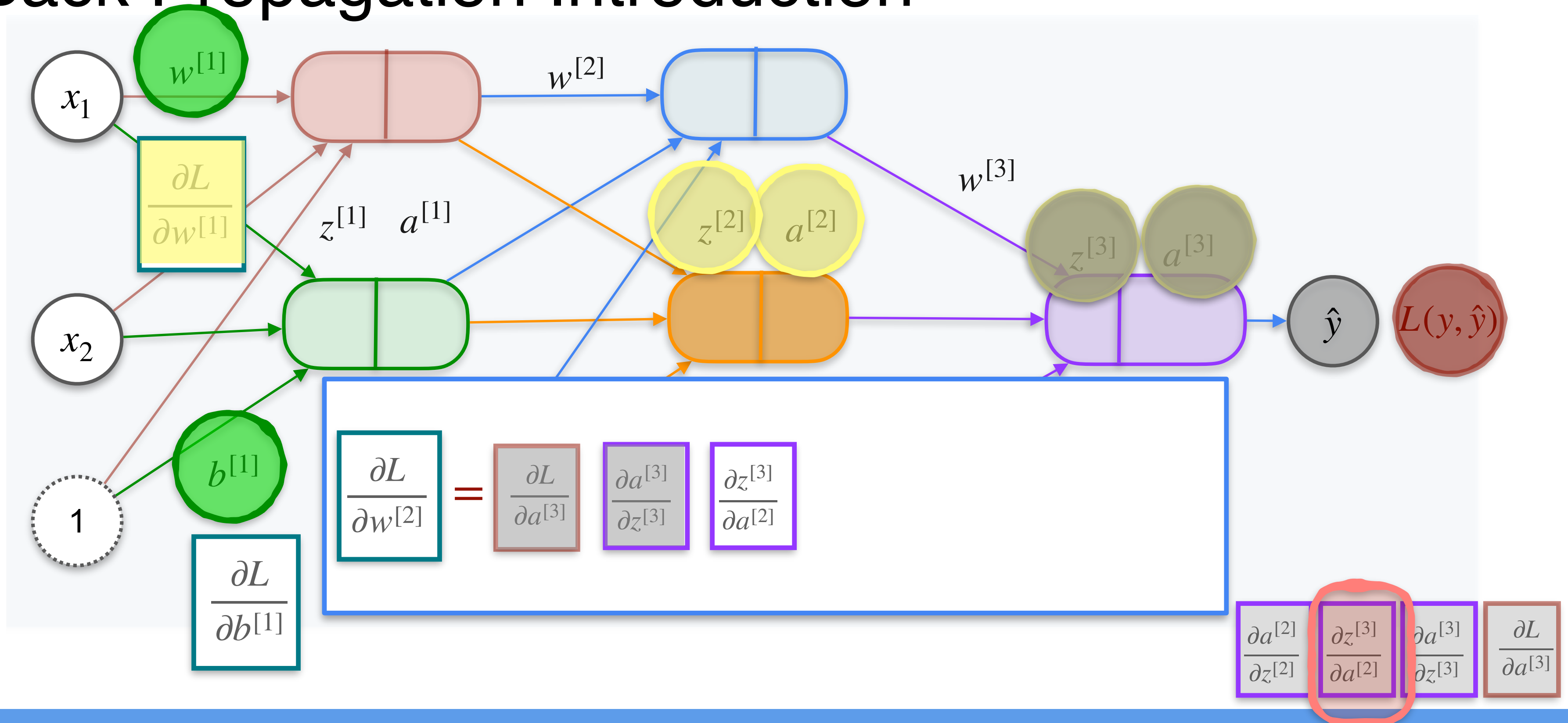

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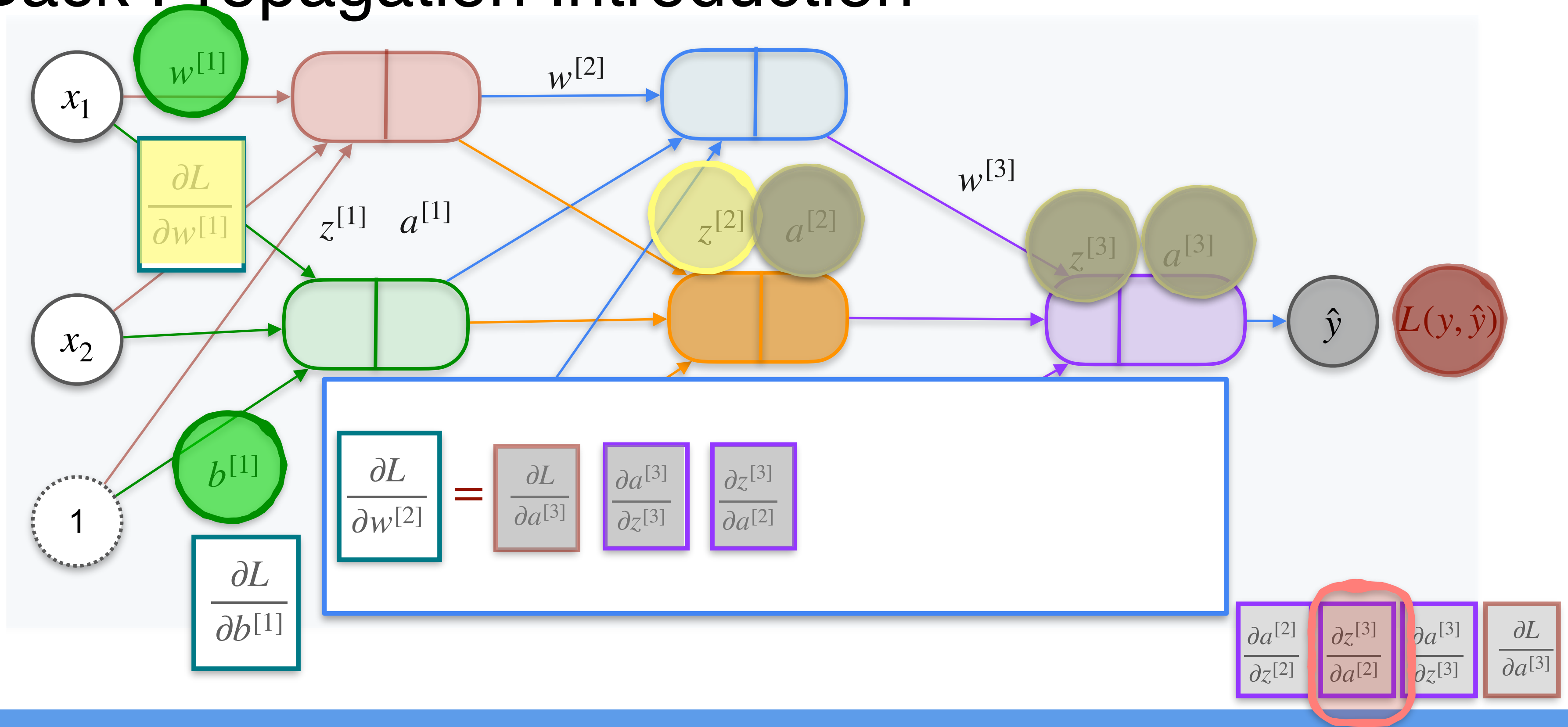

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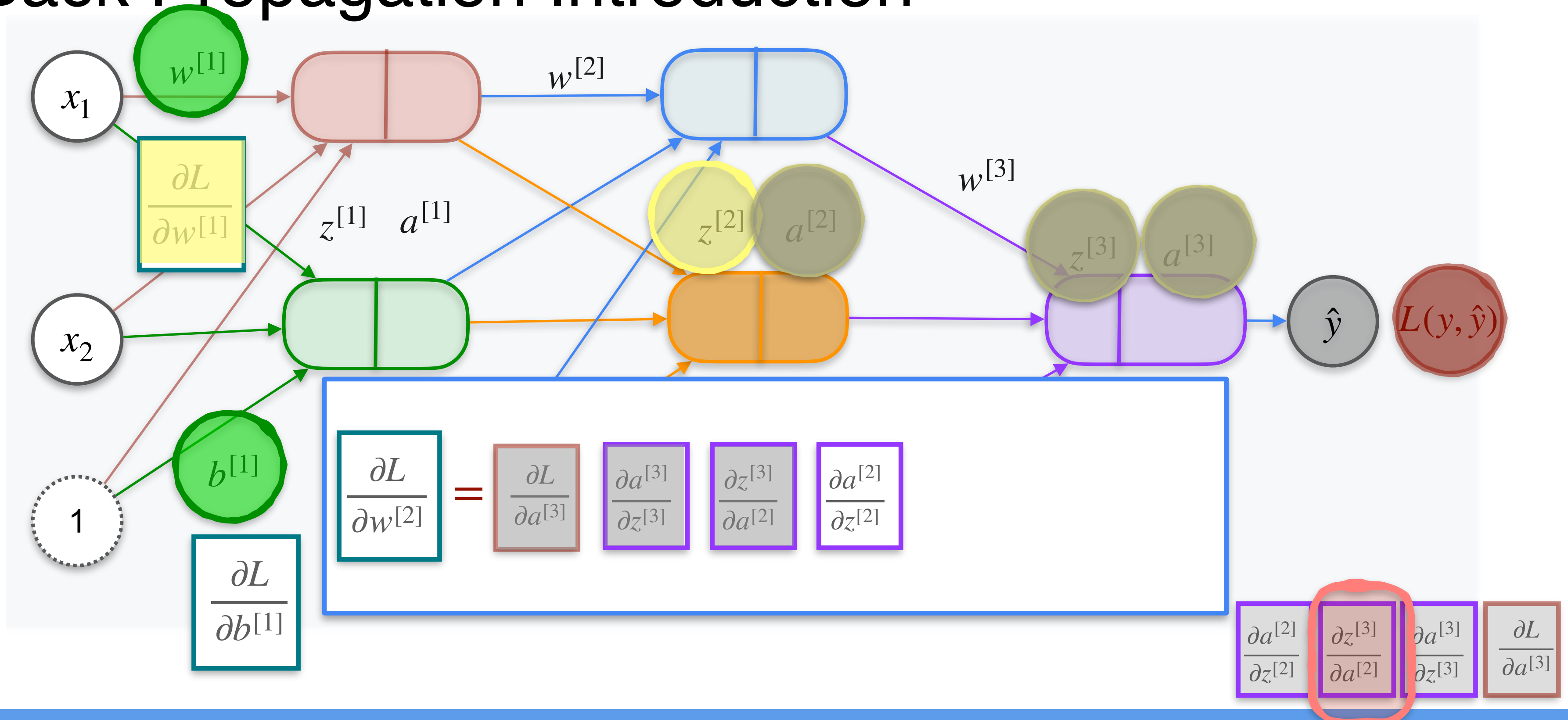

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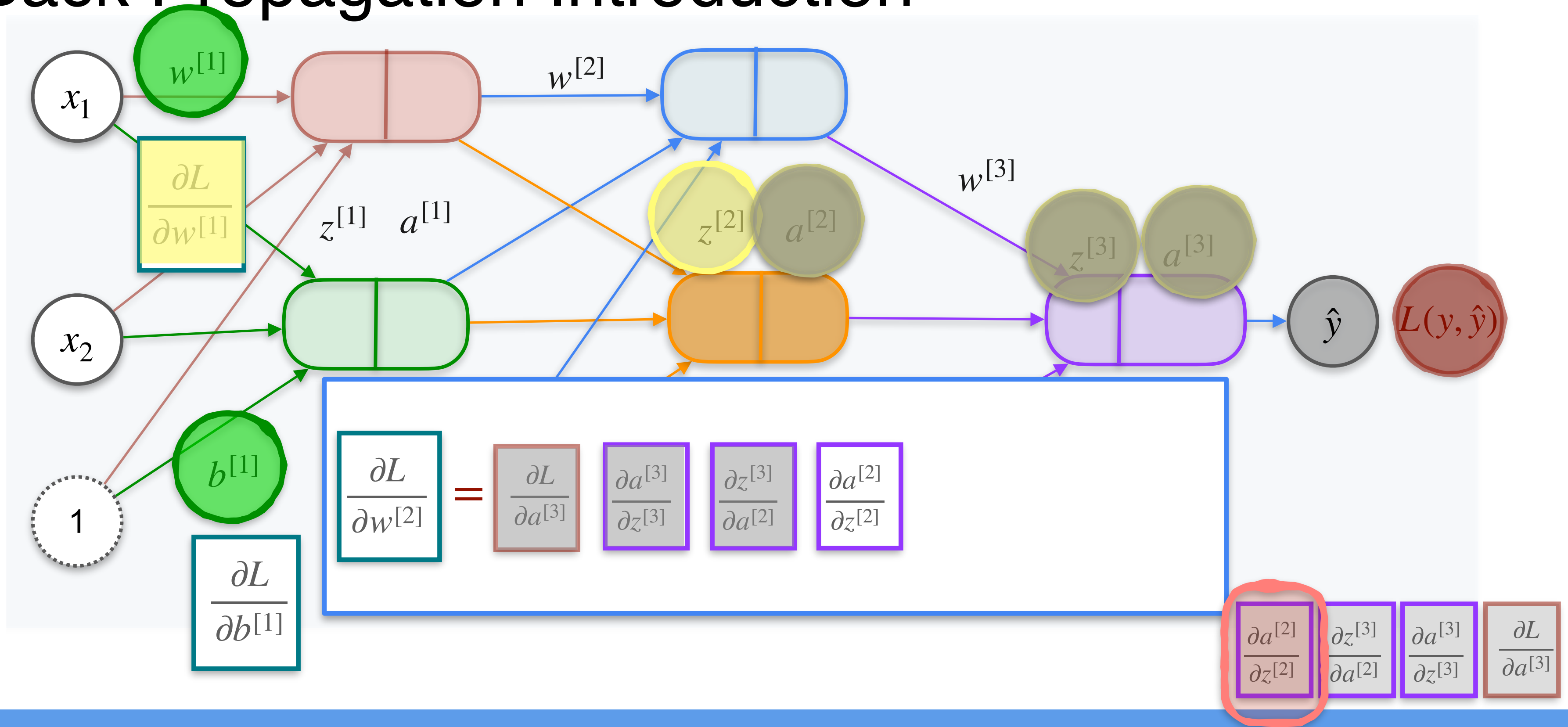

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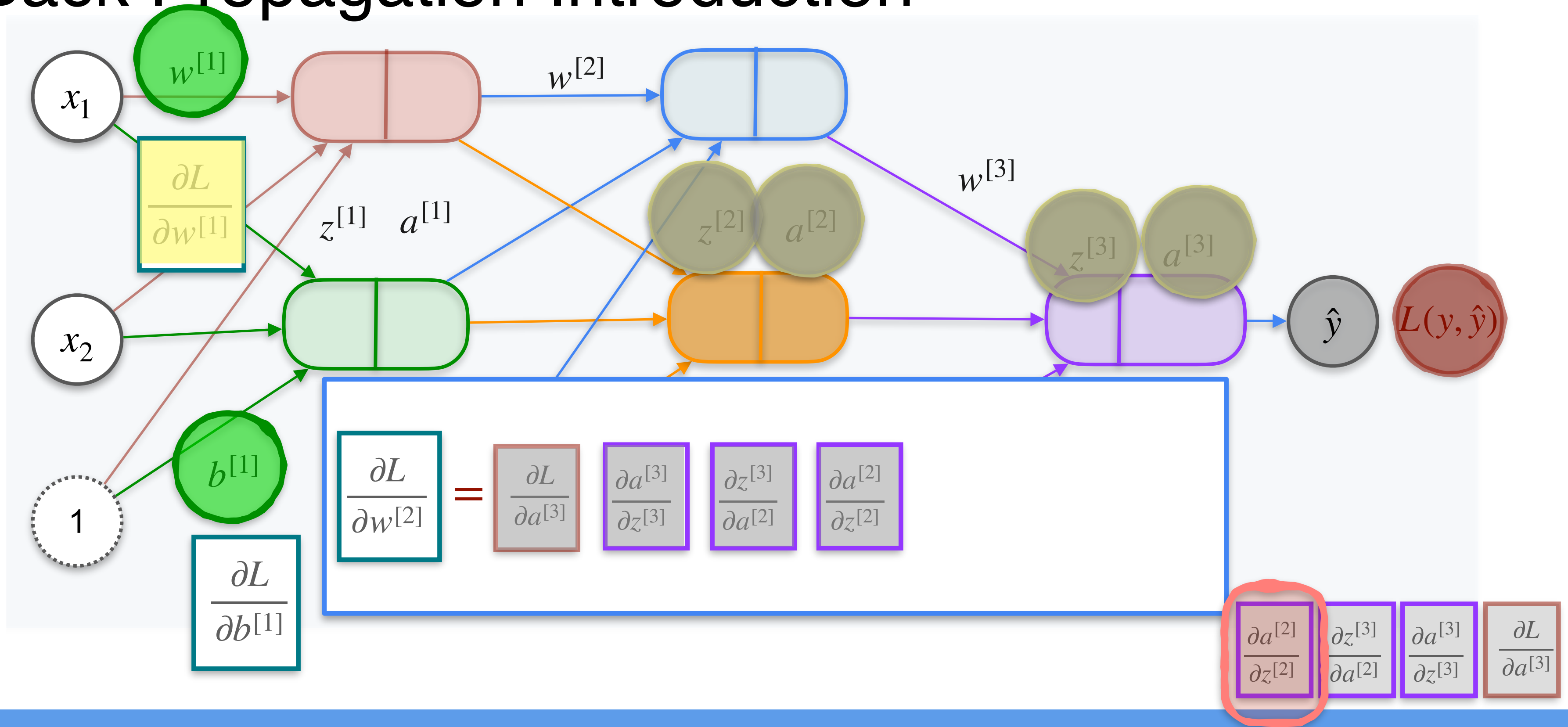

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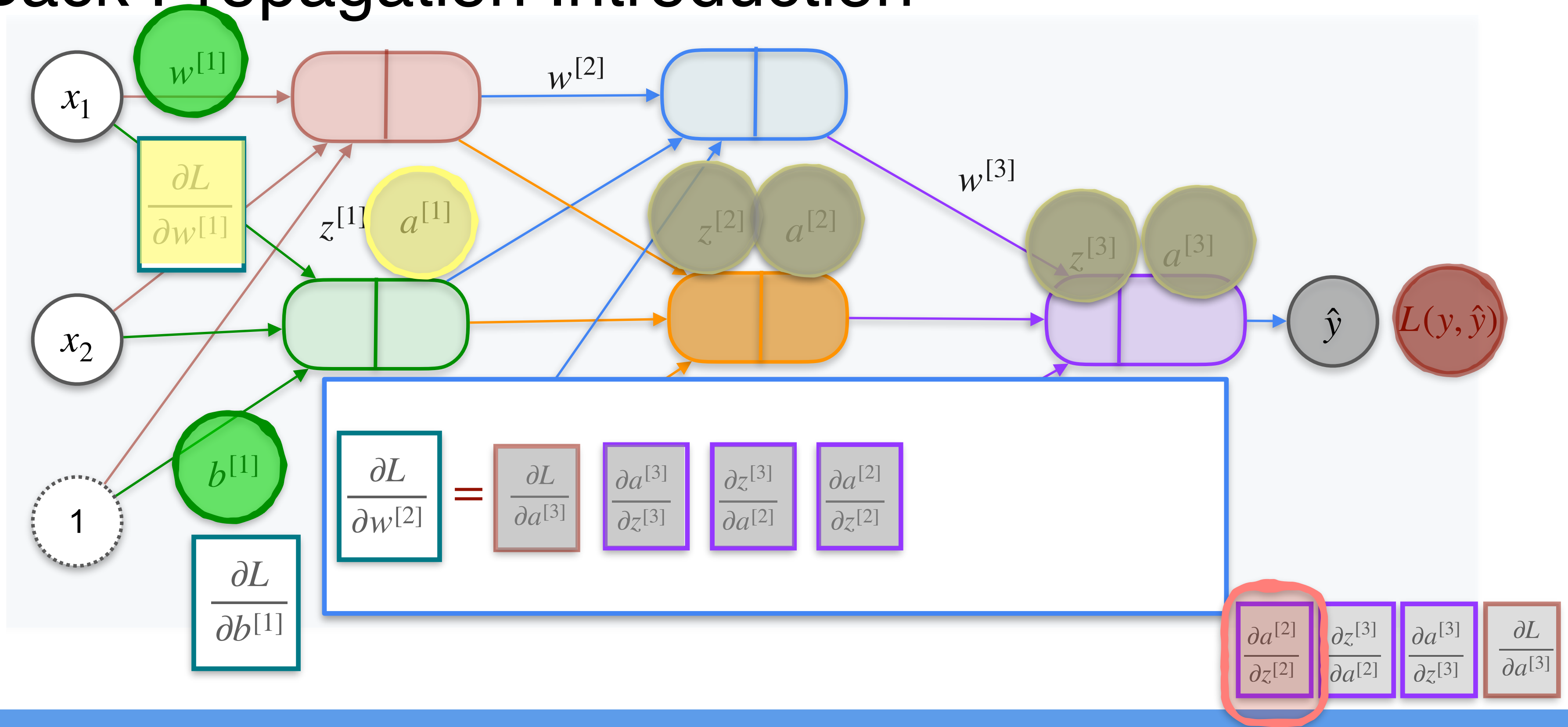

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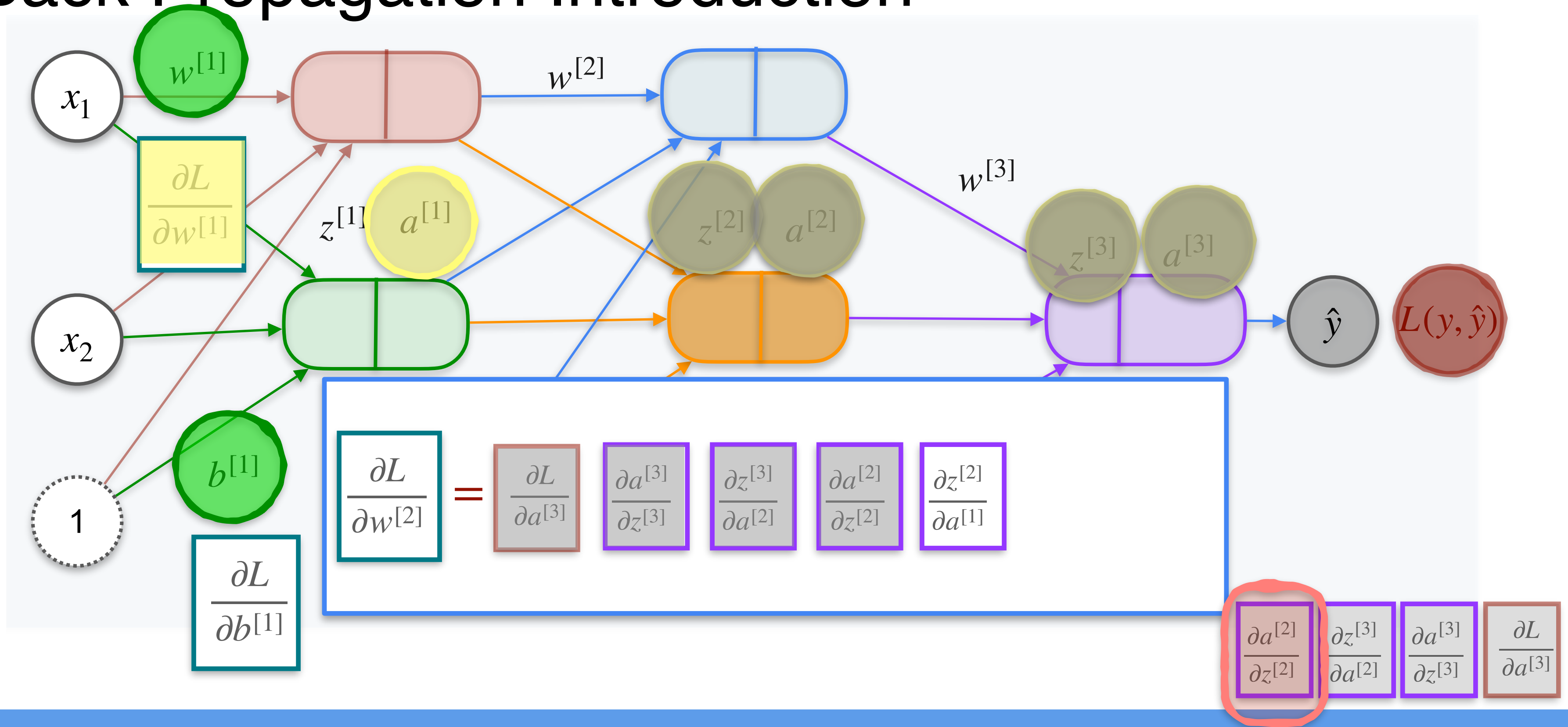

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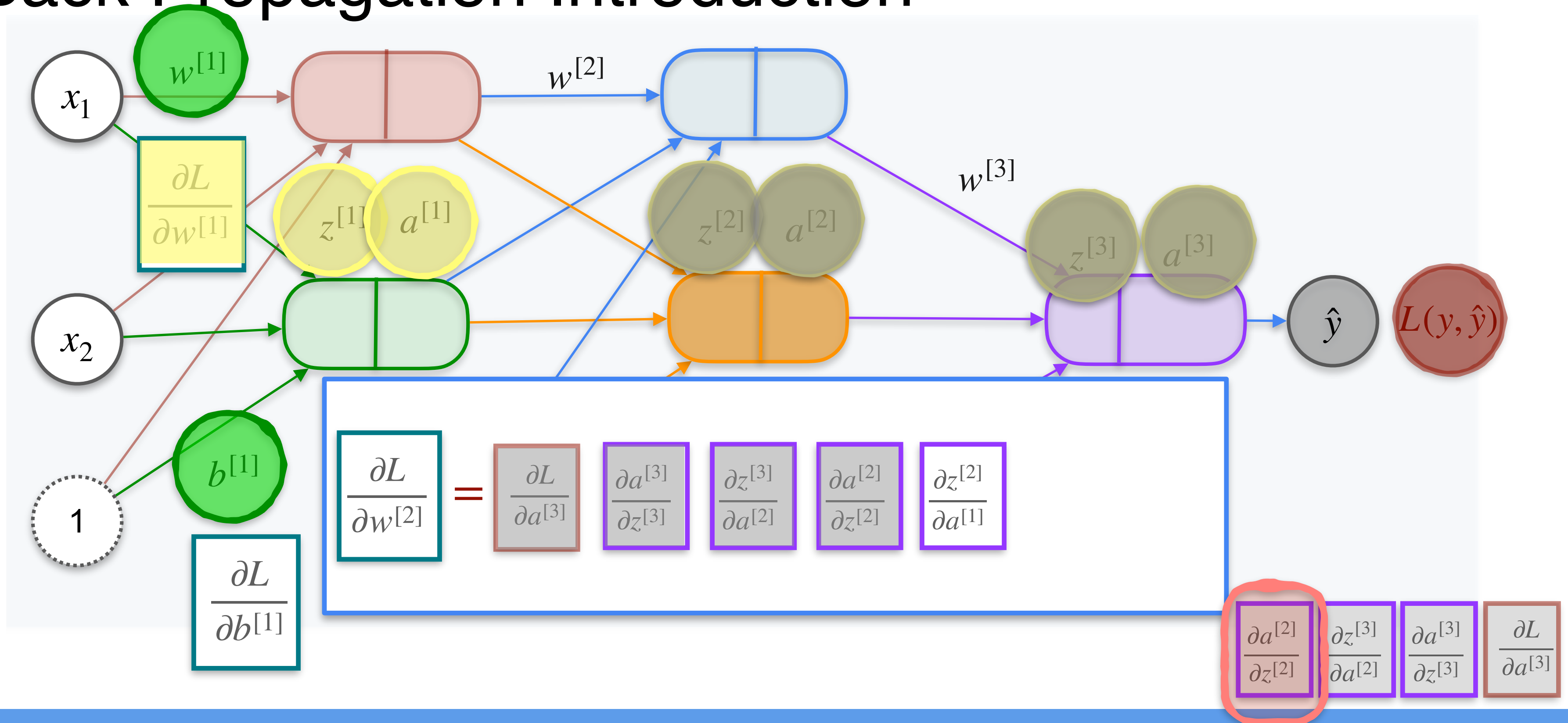

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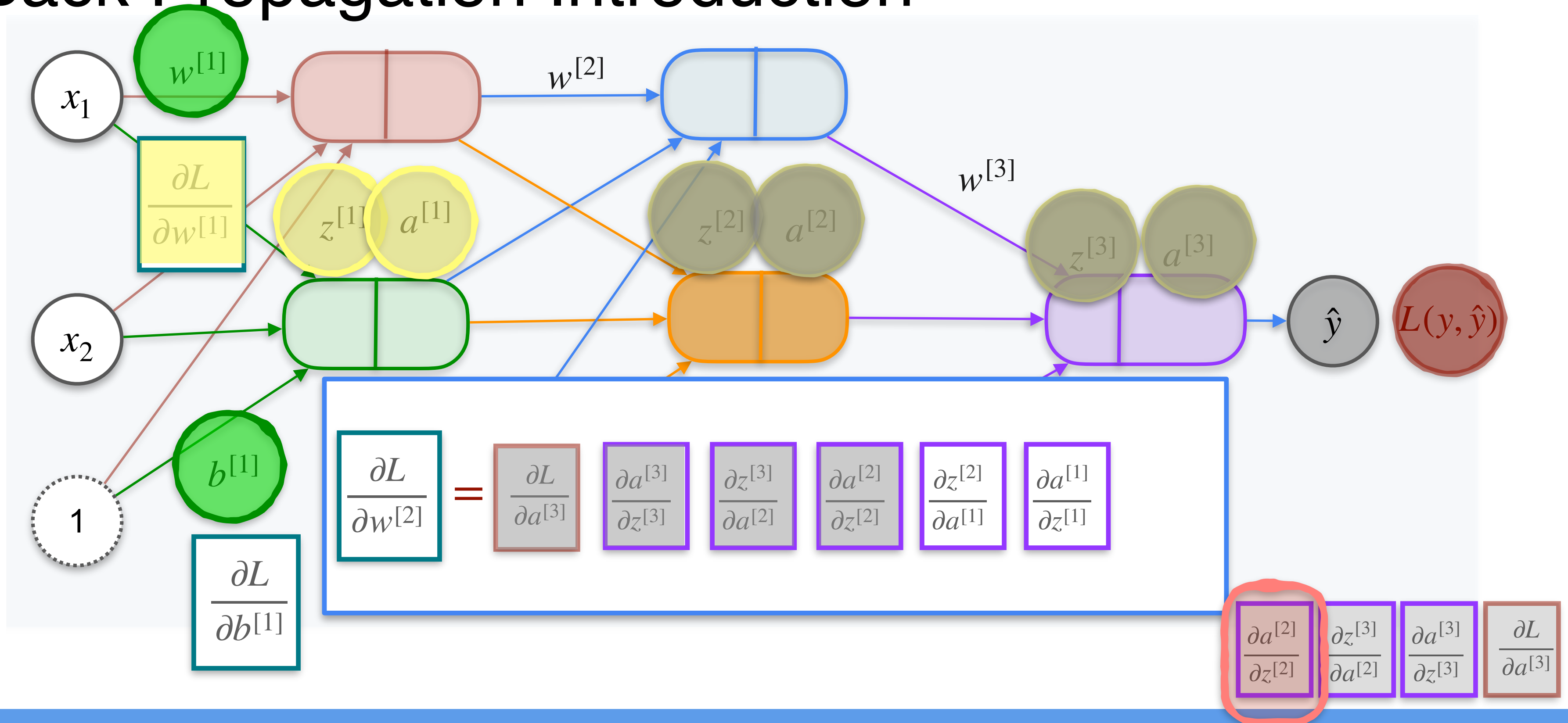

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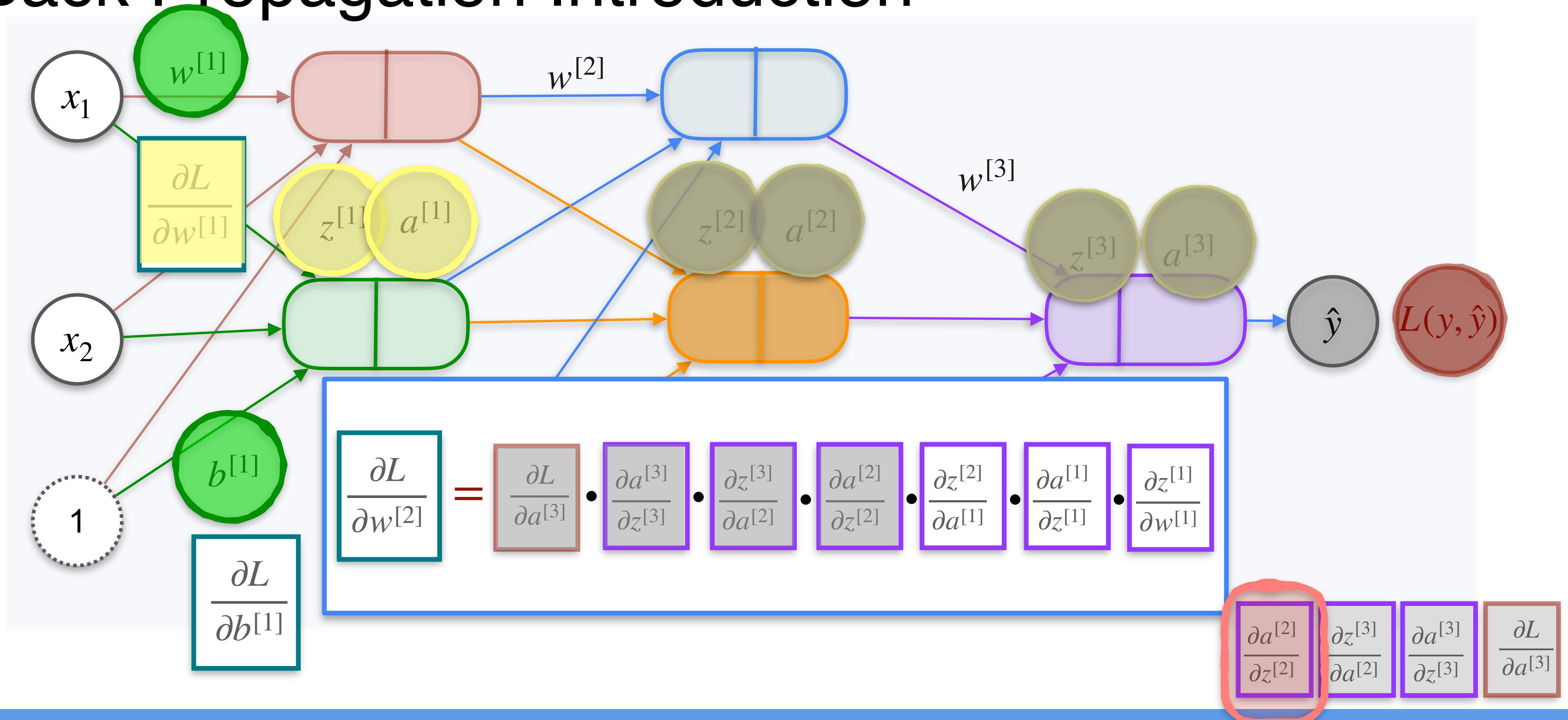


$$\frac{\partial L}{\partial w^{[2]}} = \frac{\partial L}{\partial a^{[3]}} \cdot \frac{\partial a^{[3]}}{\partial z^{[3]}} \cdot \frac{\partial z^{[3]}}{\partial a^{[2]}} \cdot \frac{\partial a^{[2]}}{\partial z^{[2]}} \cdot \frac{\partial z^{[2]}}{\partial a^{[1]}} \cdot \frac{\partial a^{[1]}}{\partial z^{[1]}} \cdot \frac{\partial z^{[1]}}{\partial w^{[1]}}$$

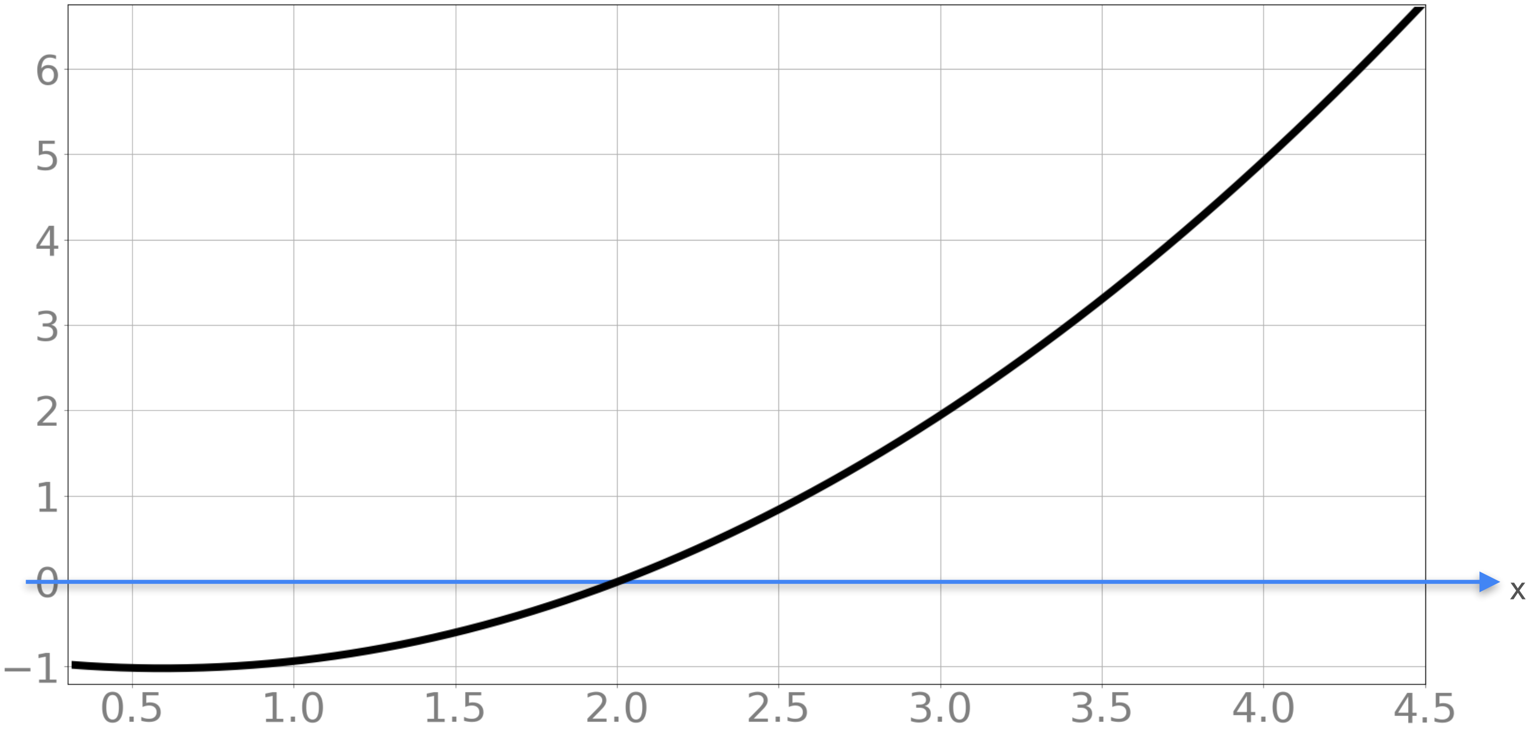
Optimization in Neural Networks and Newton's Method

DeepLearning.AI

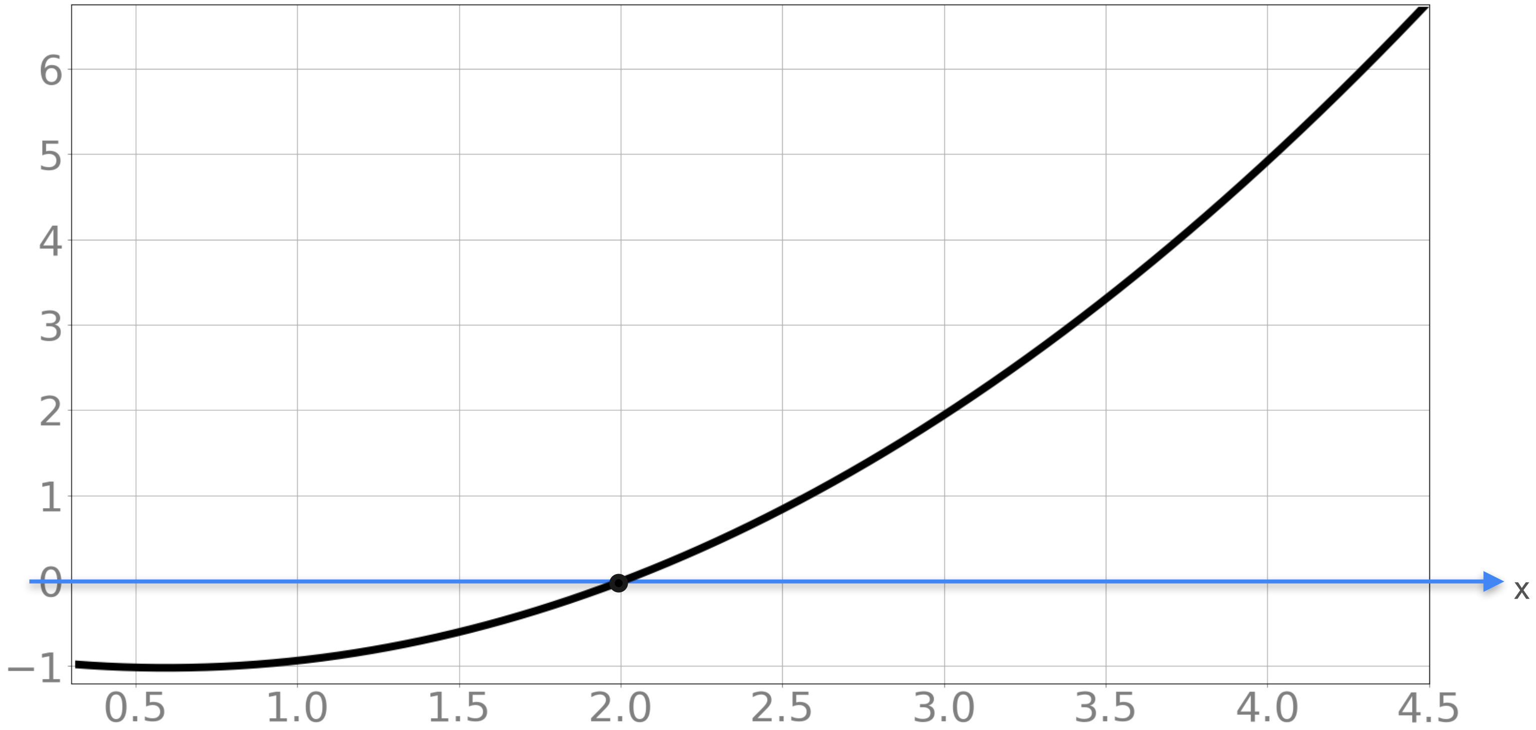
Newton's method

Newton’s Method

Newton's Method



Newton’s Method



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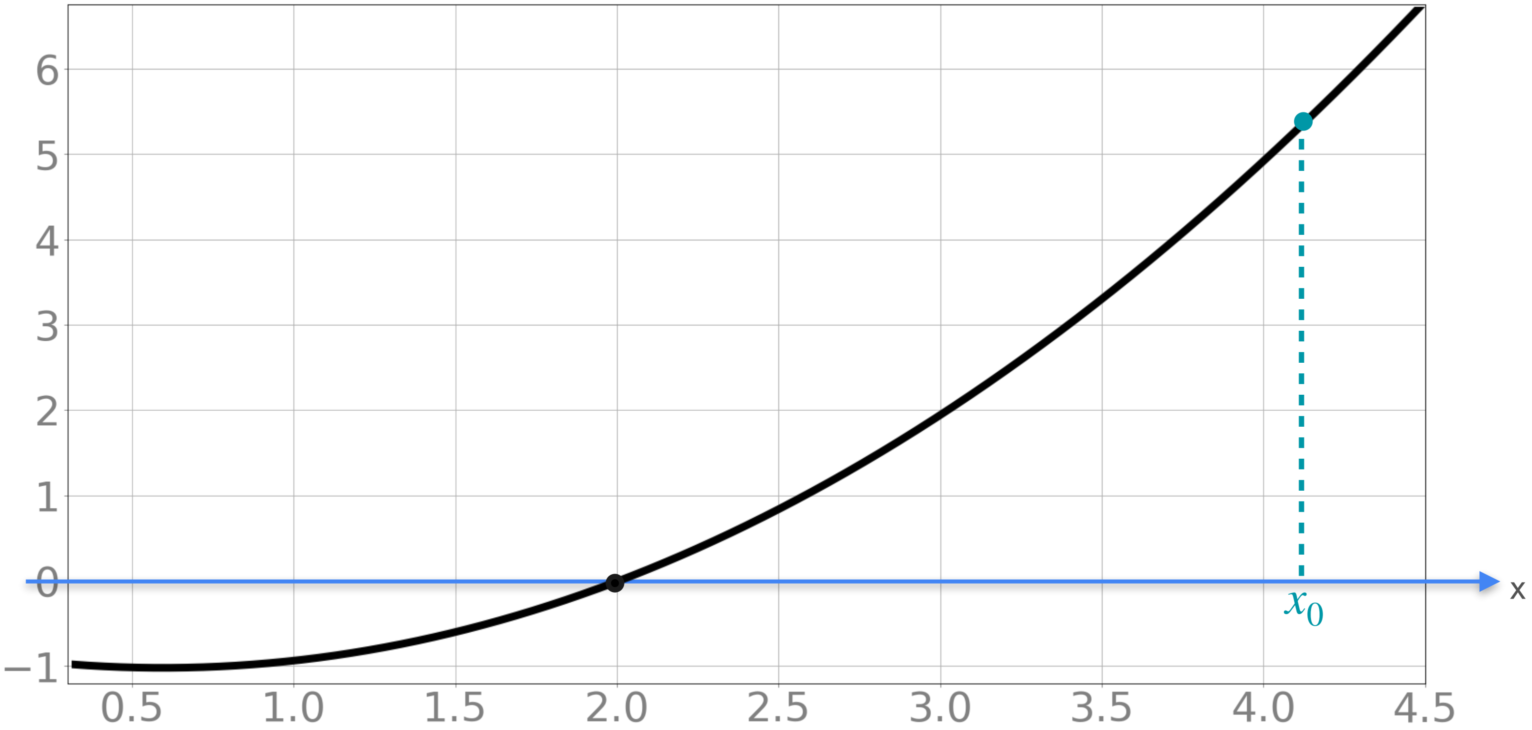

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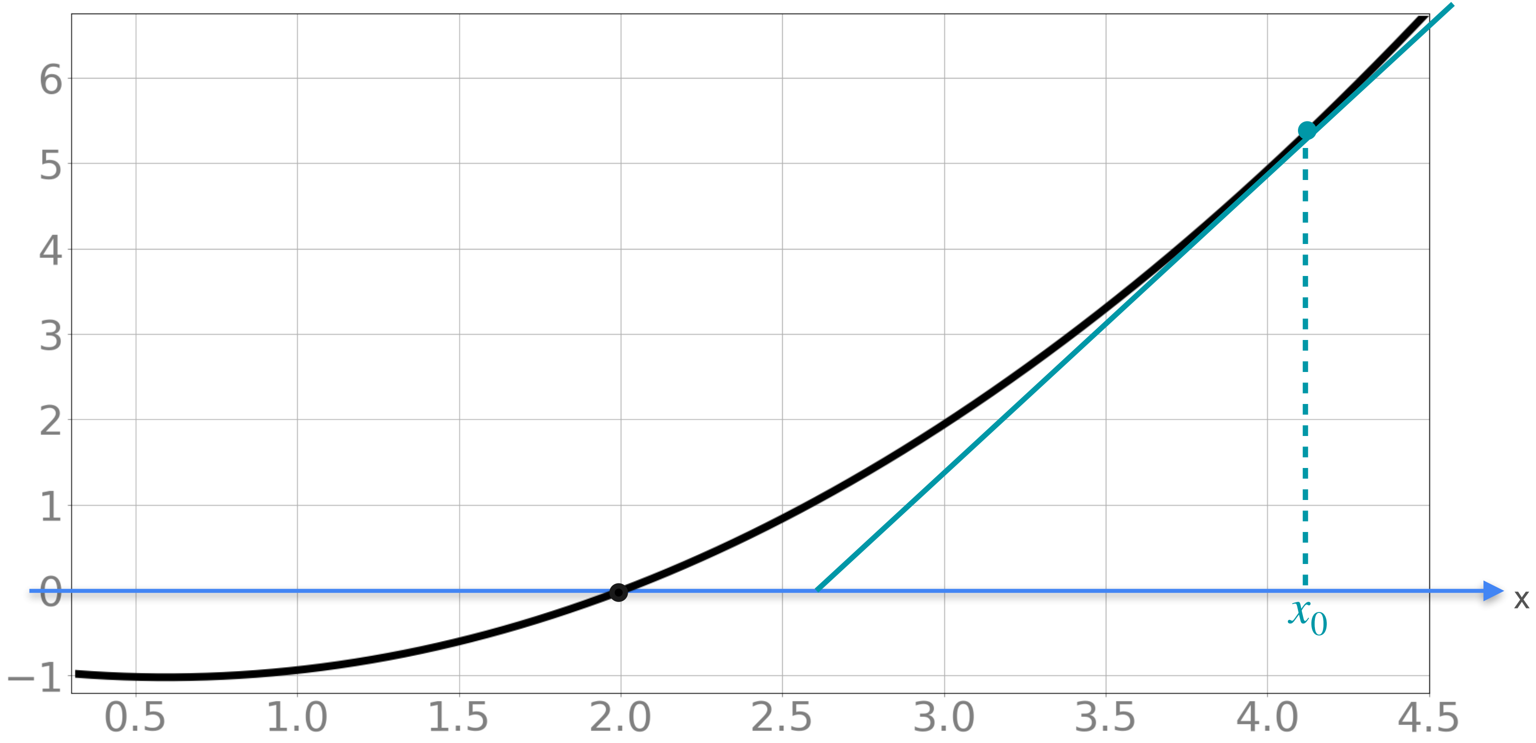
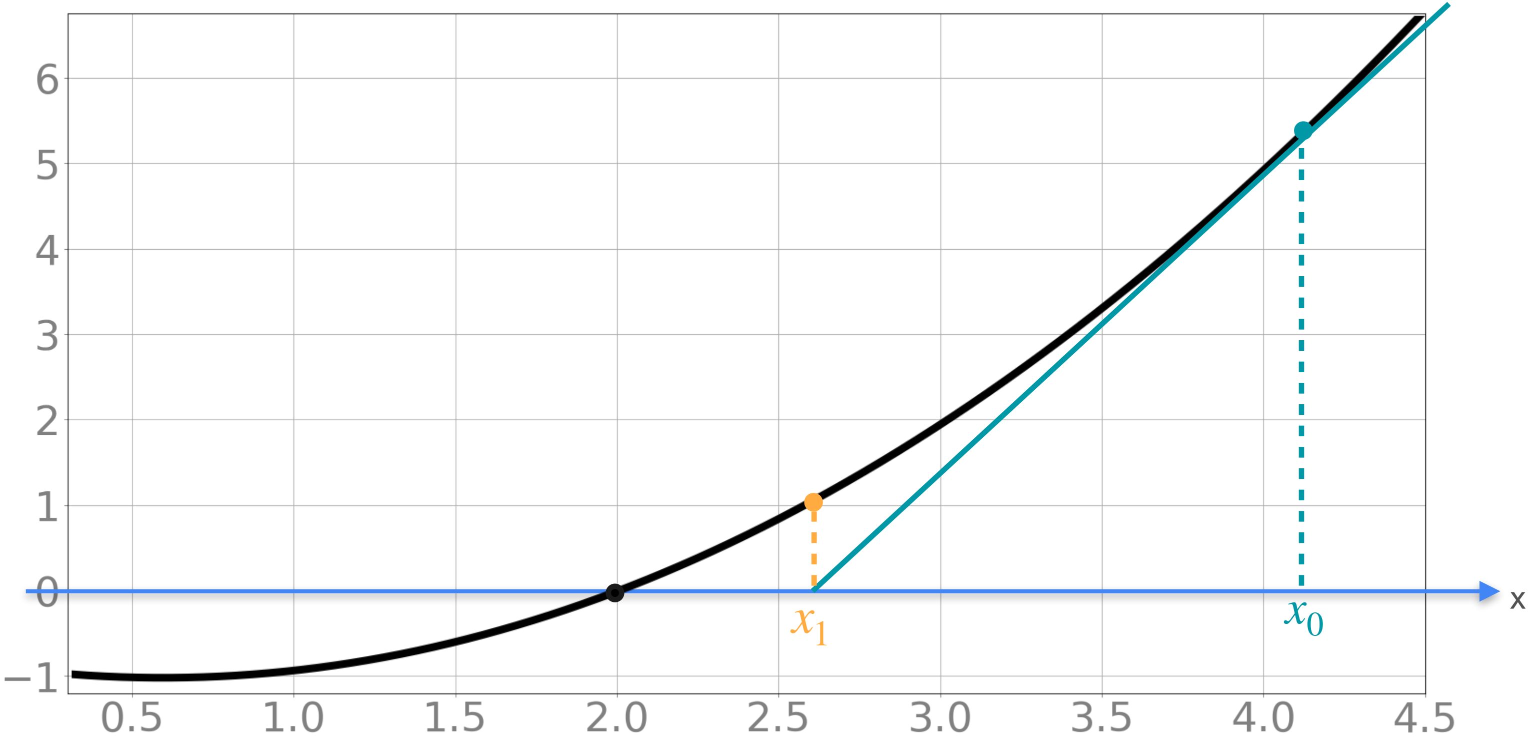


Newton's Method



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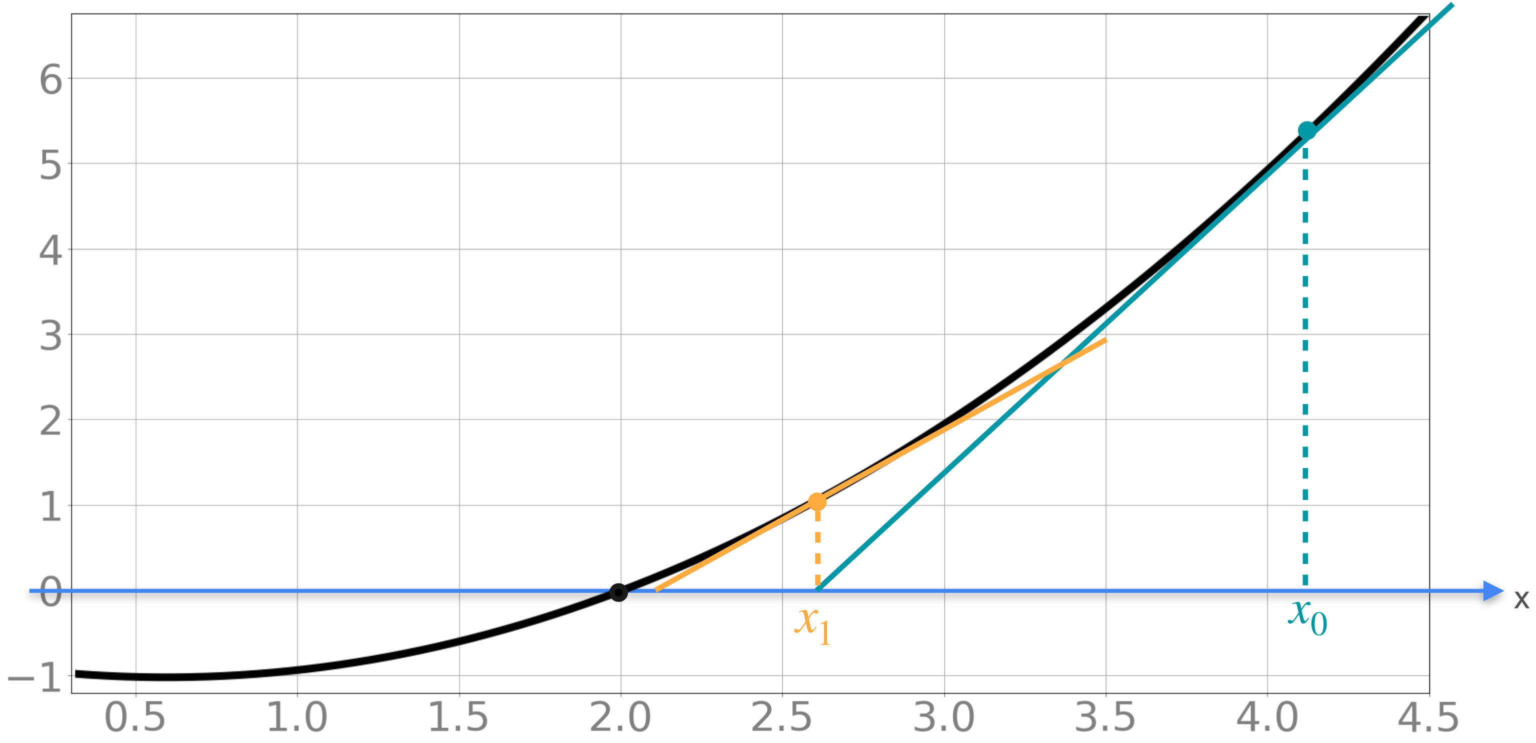
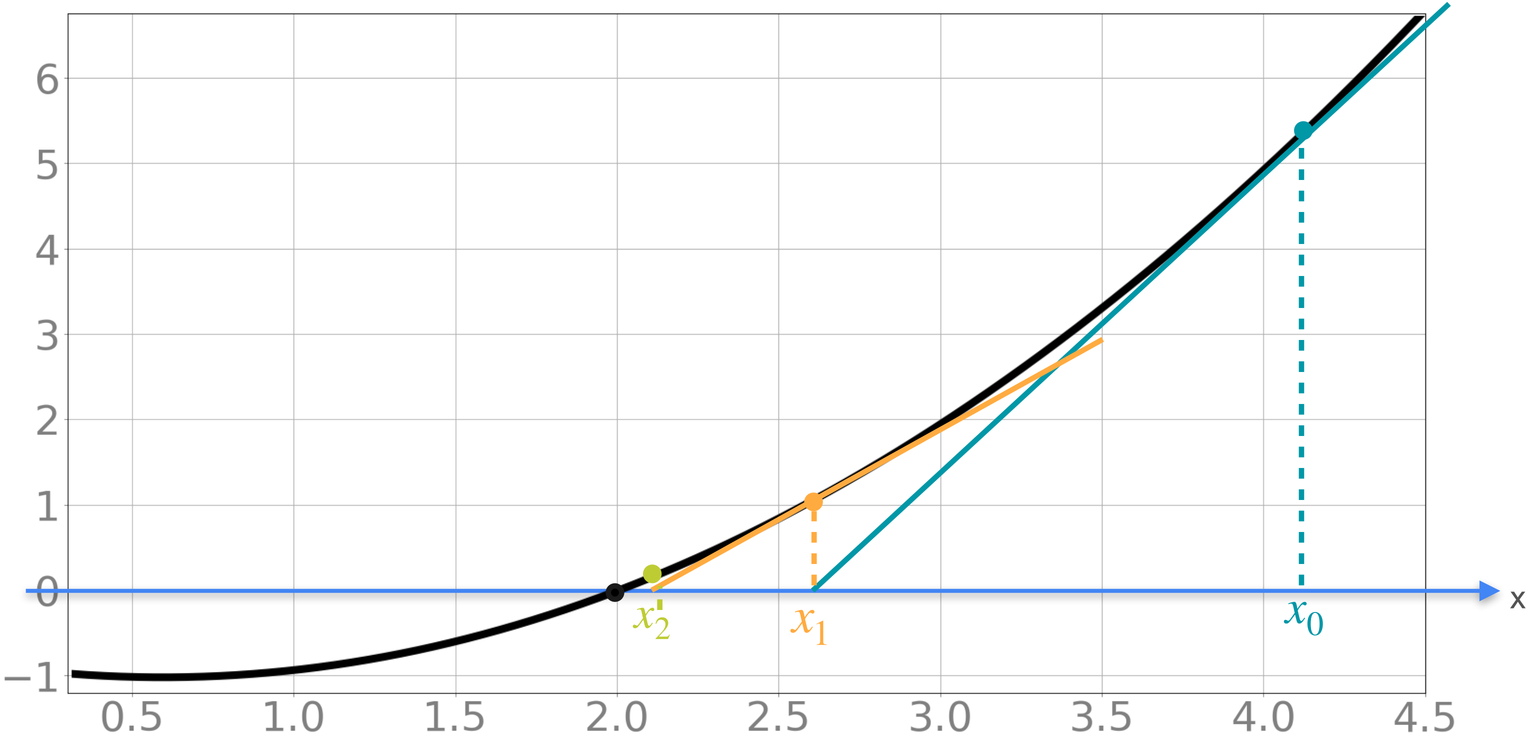
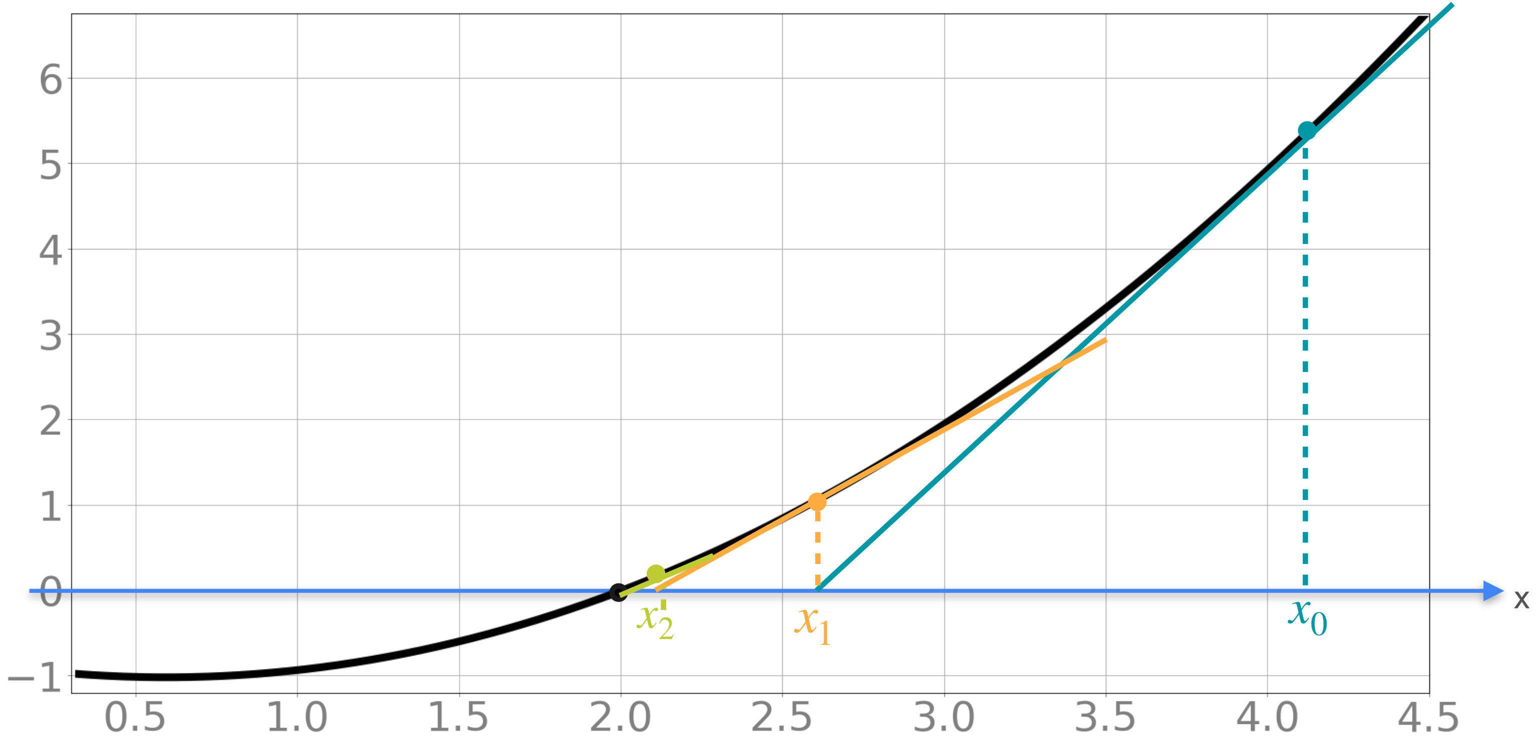
Newton's Method



Newton’s Method



Newton's Method



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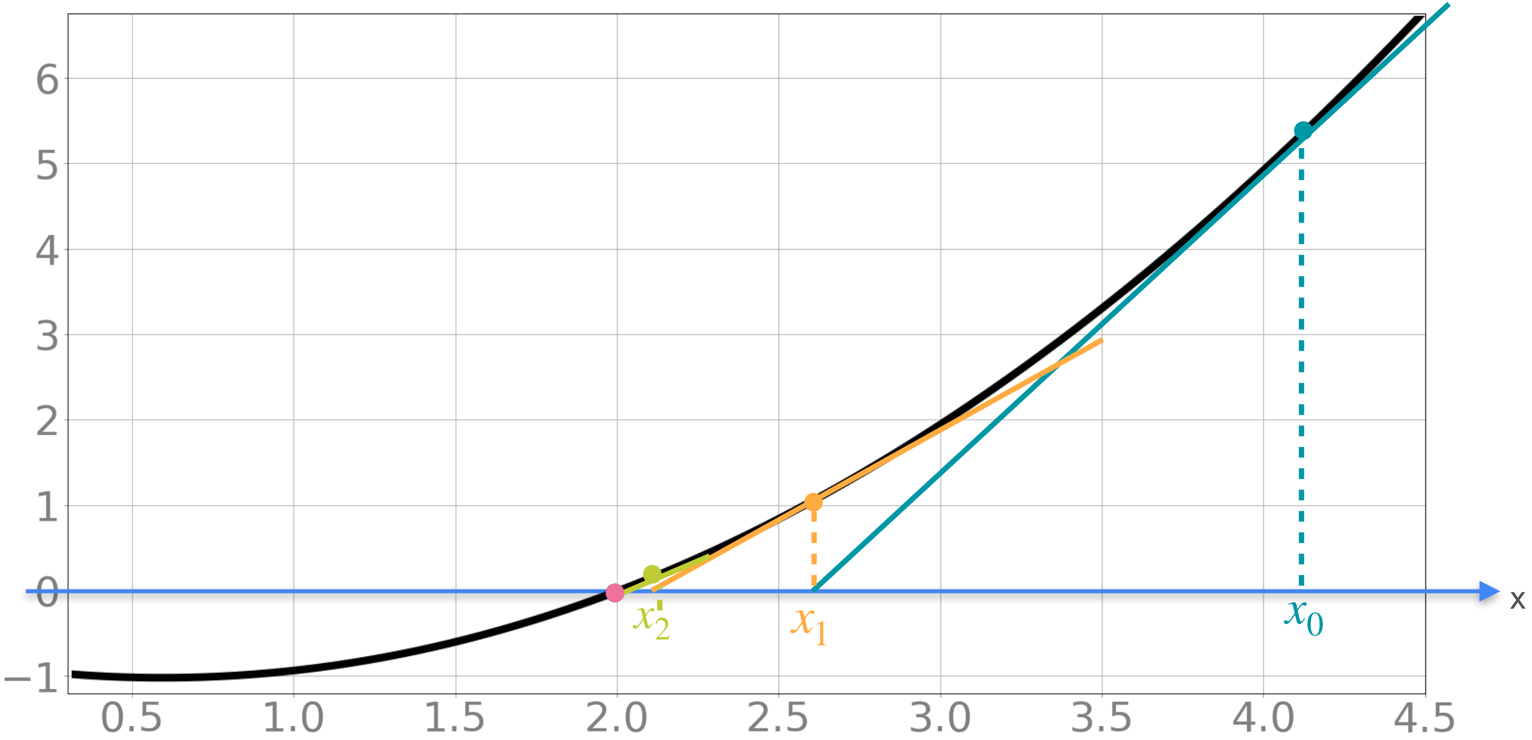
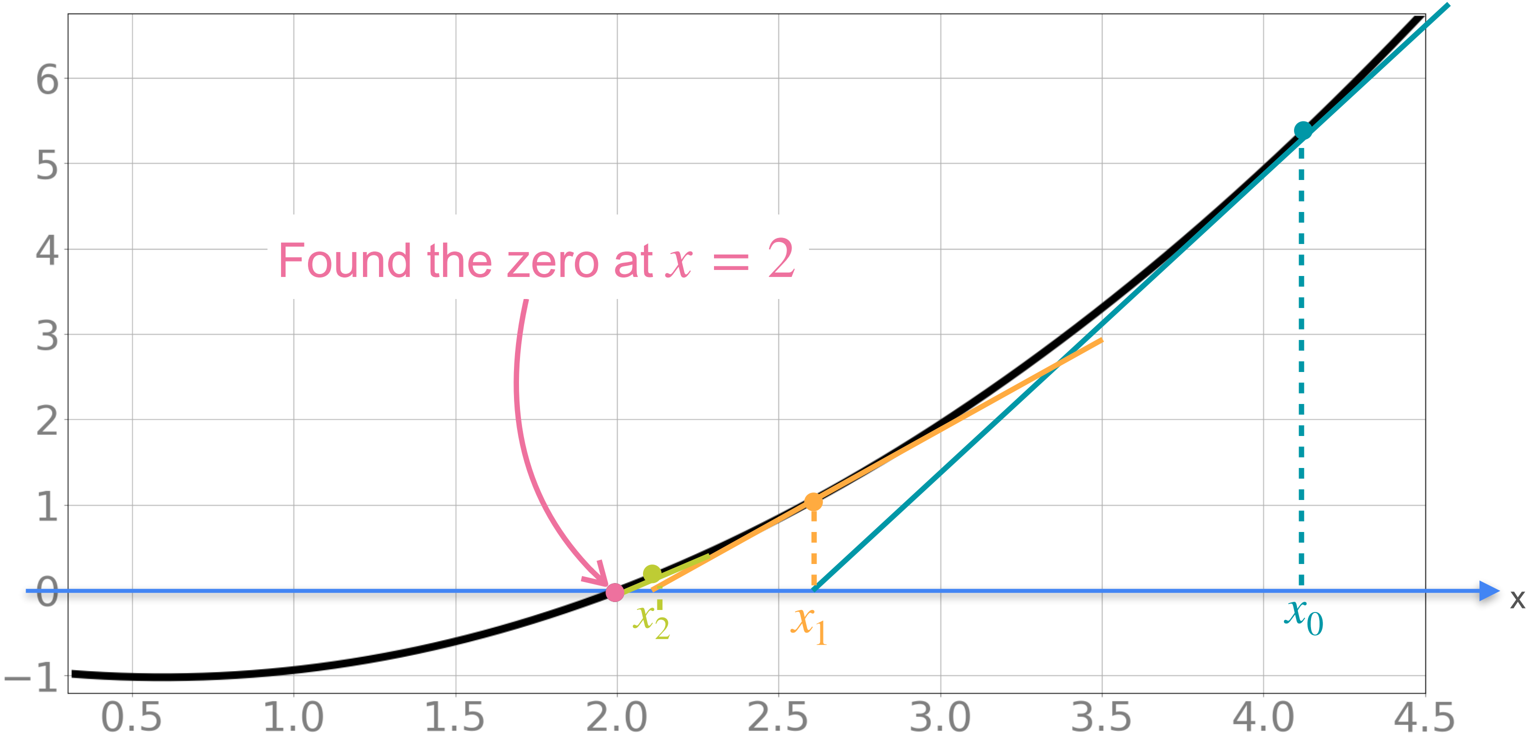


Newton's Method



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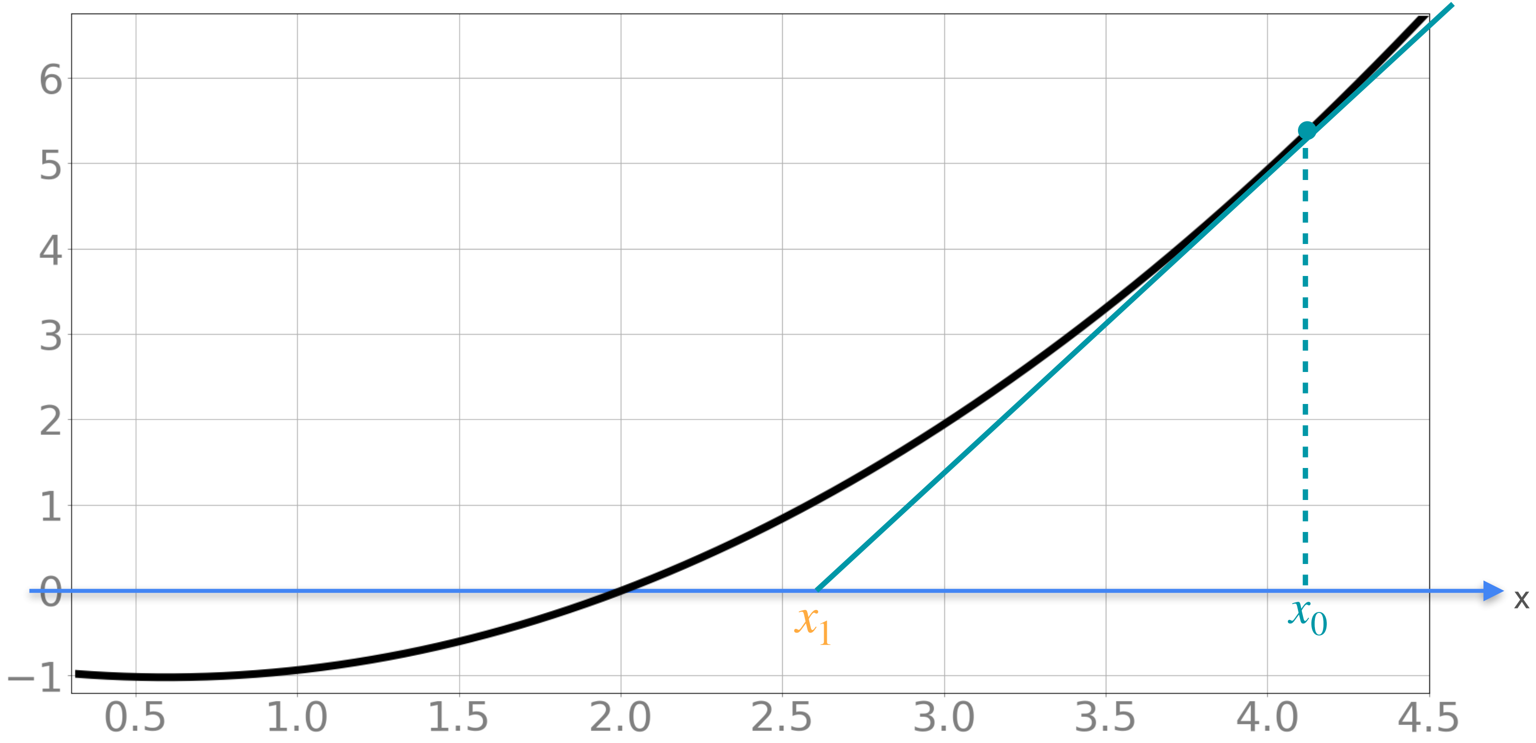

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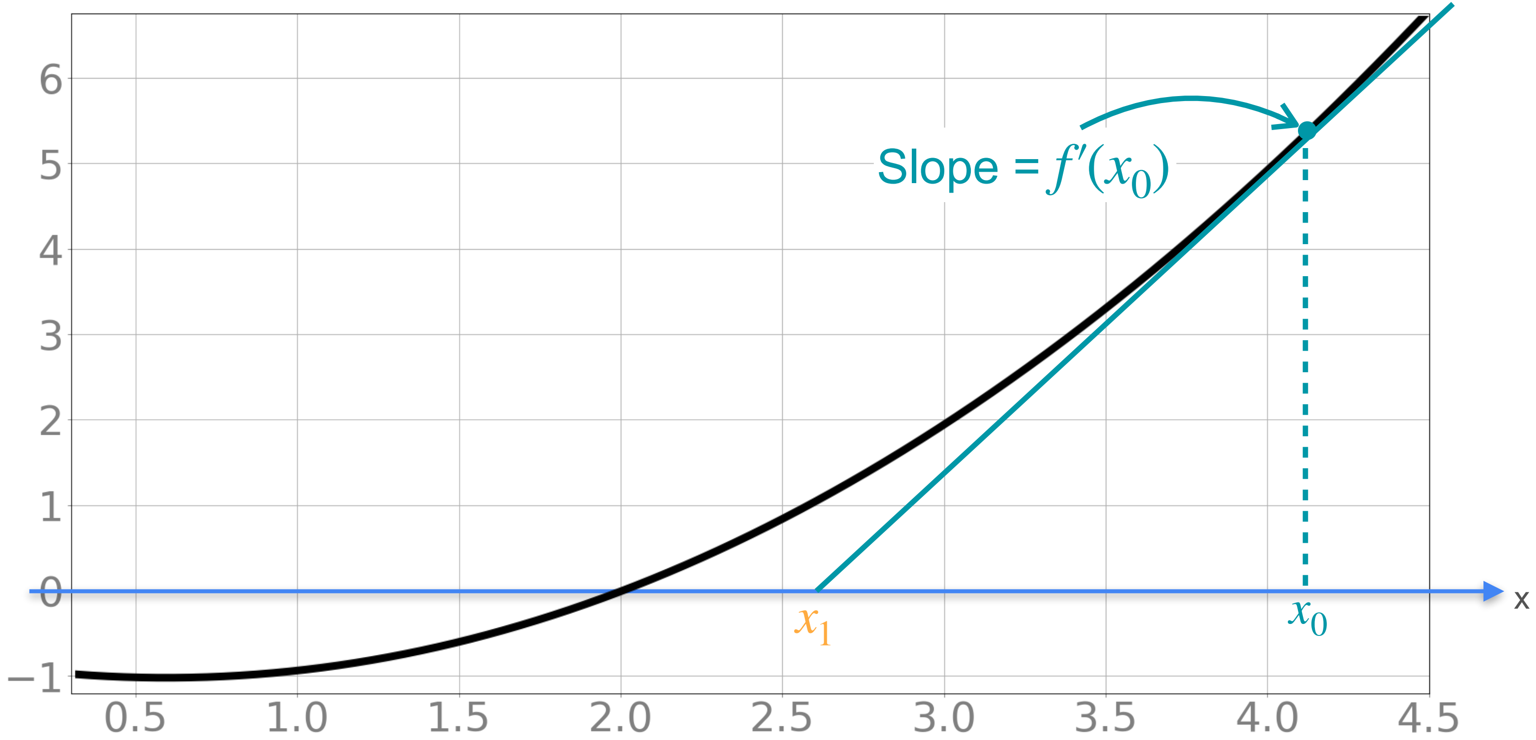

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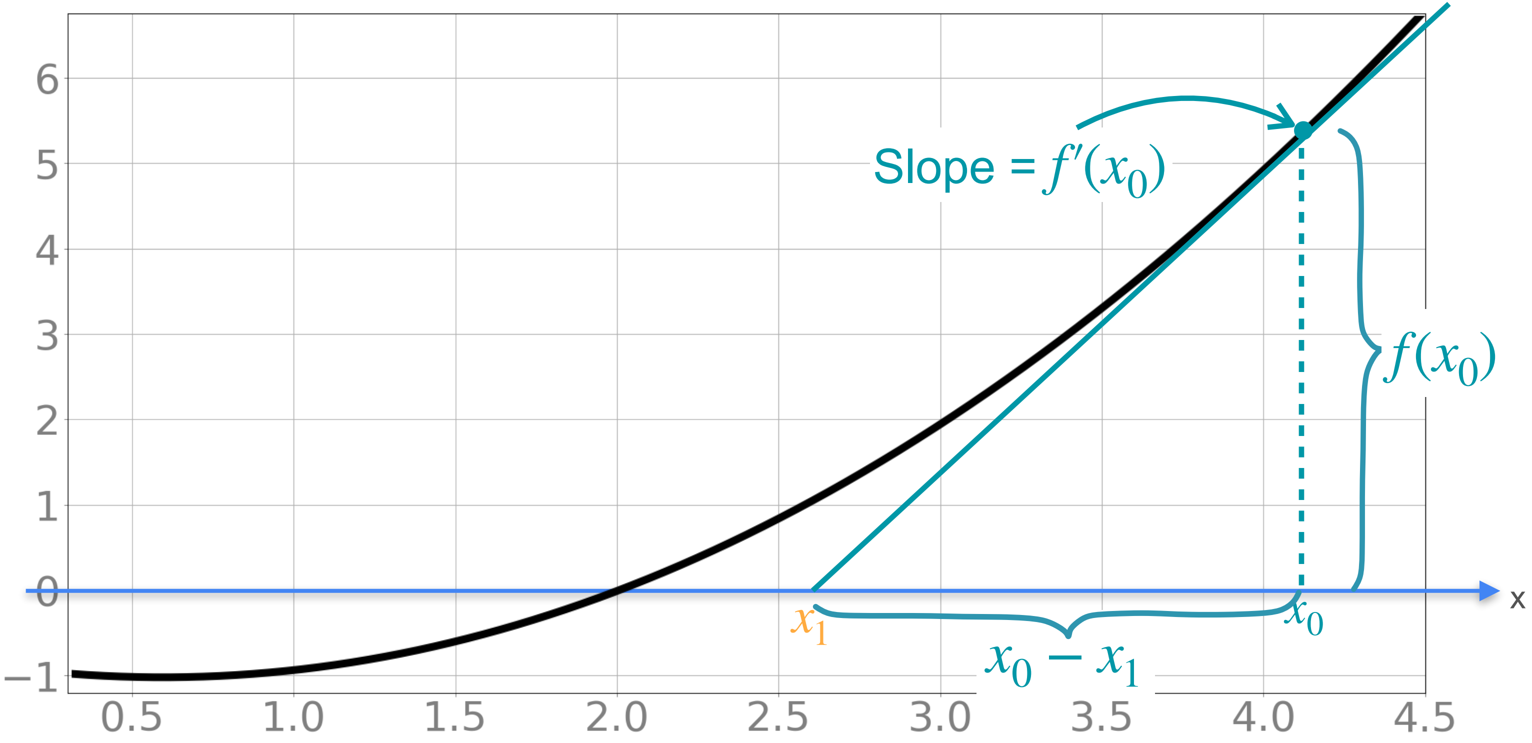
Update Approximation



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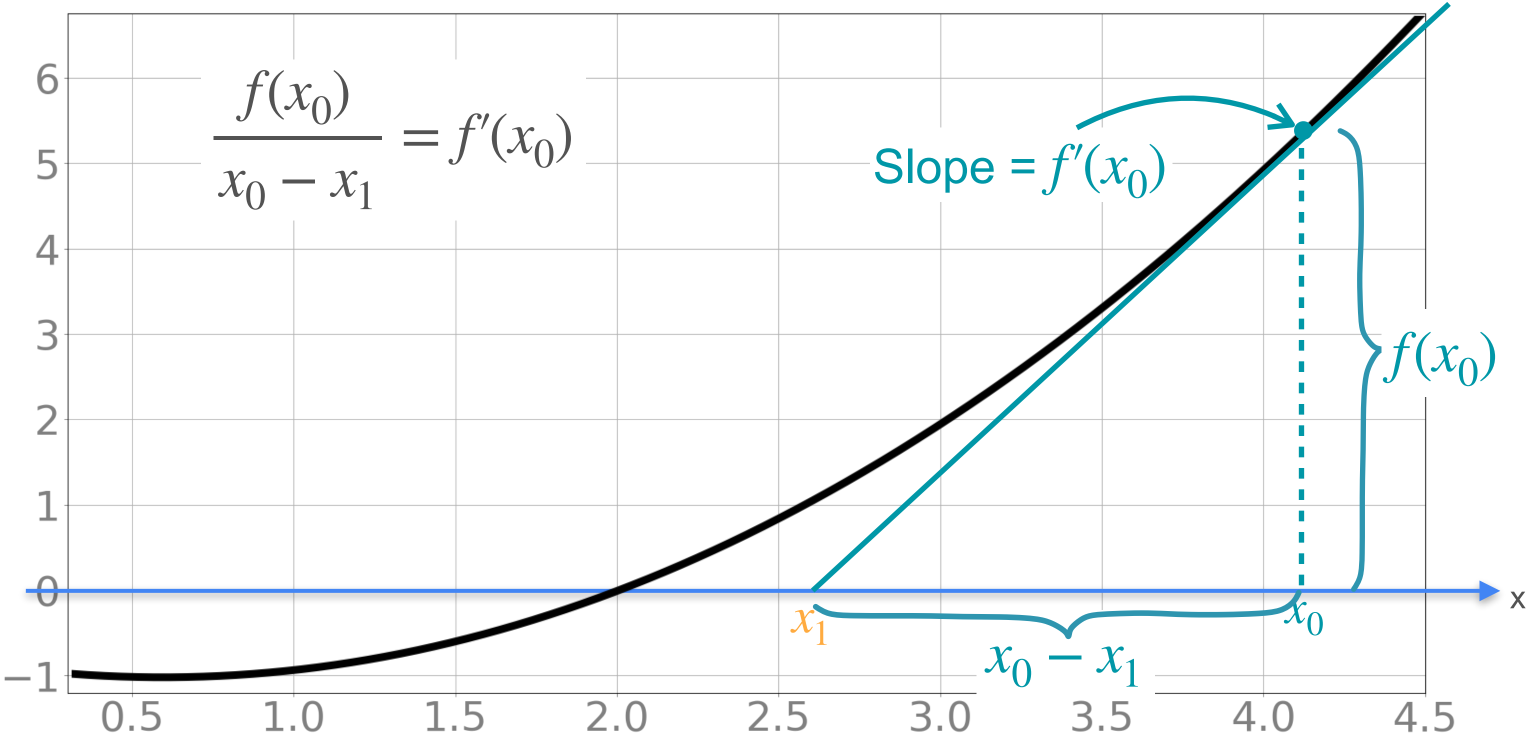

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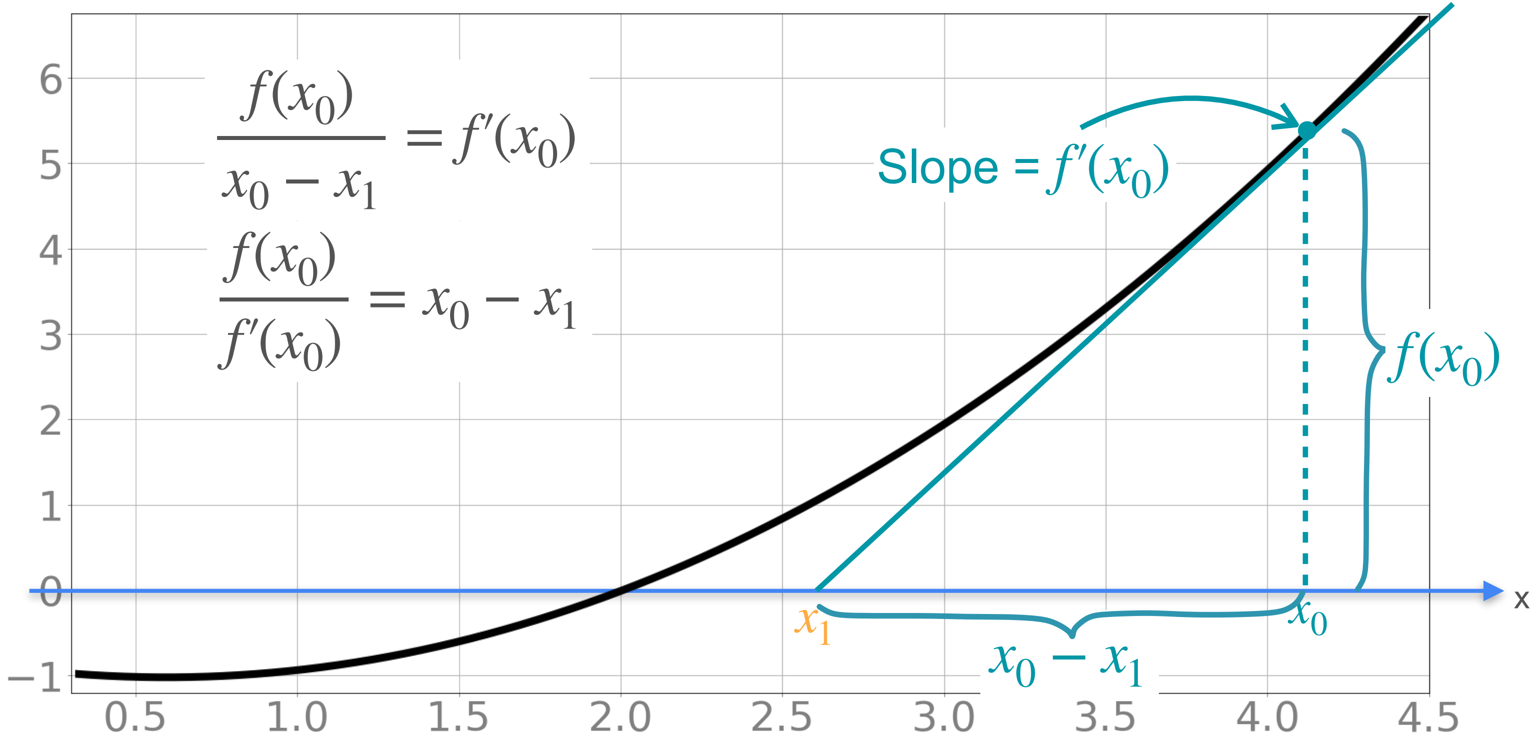

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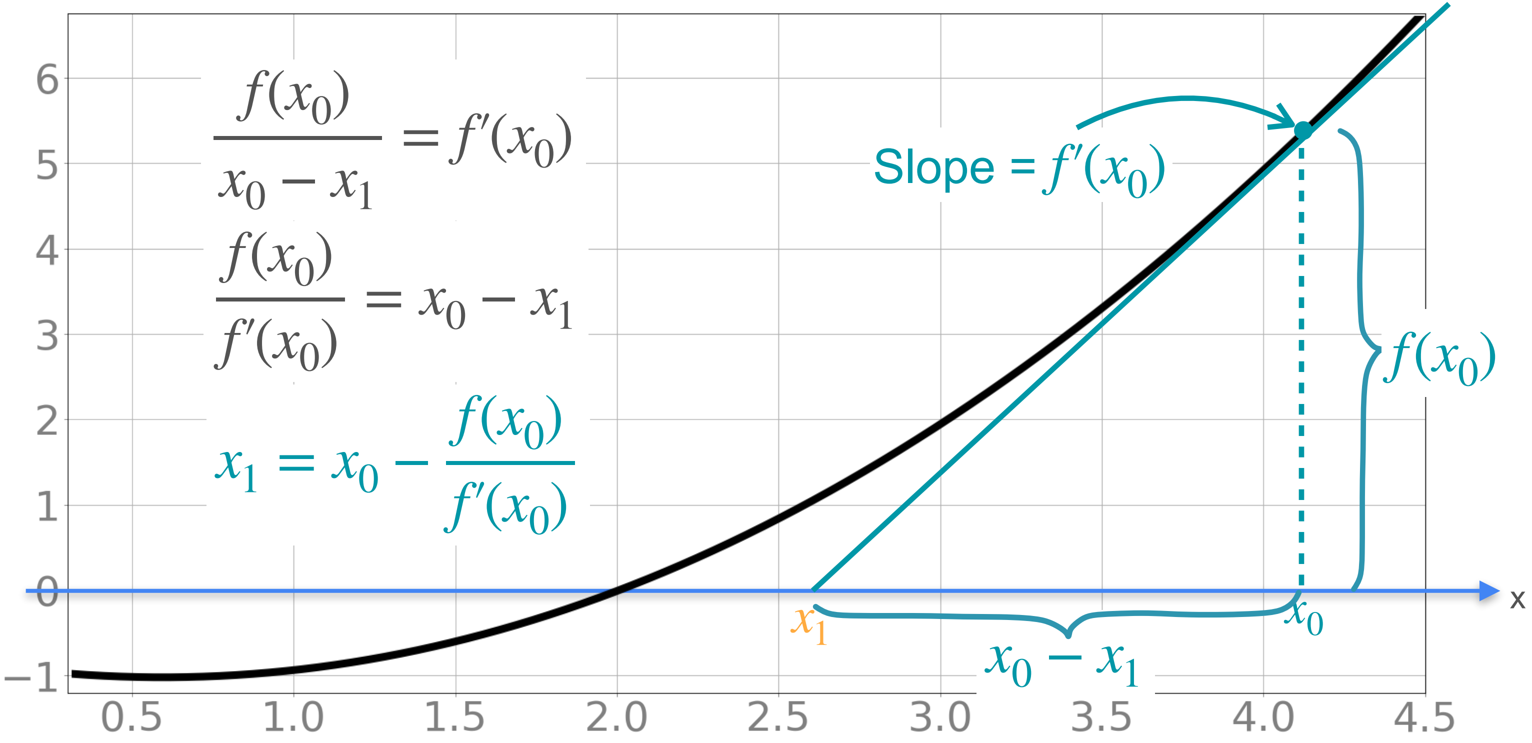

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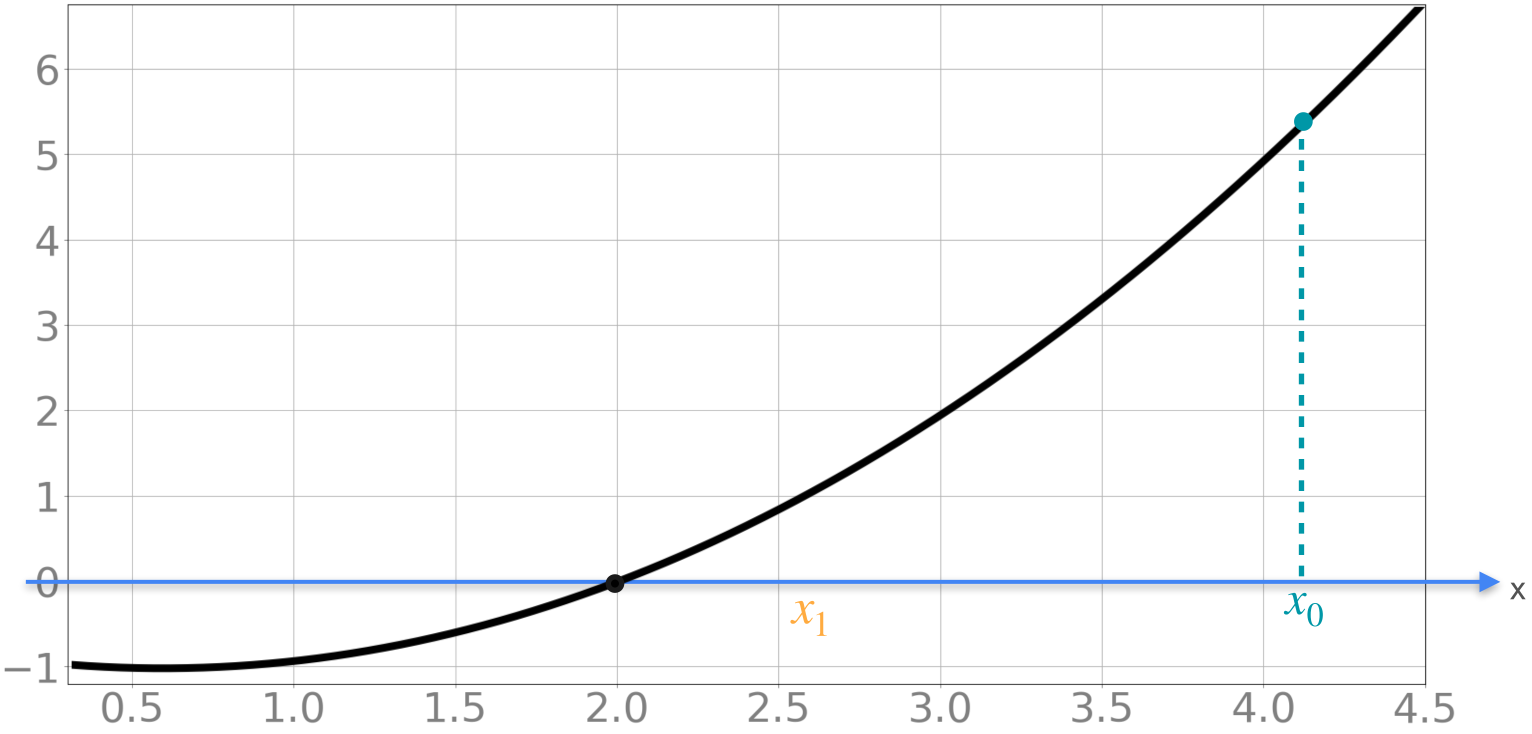

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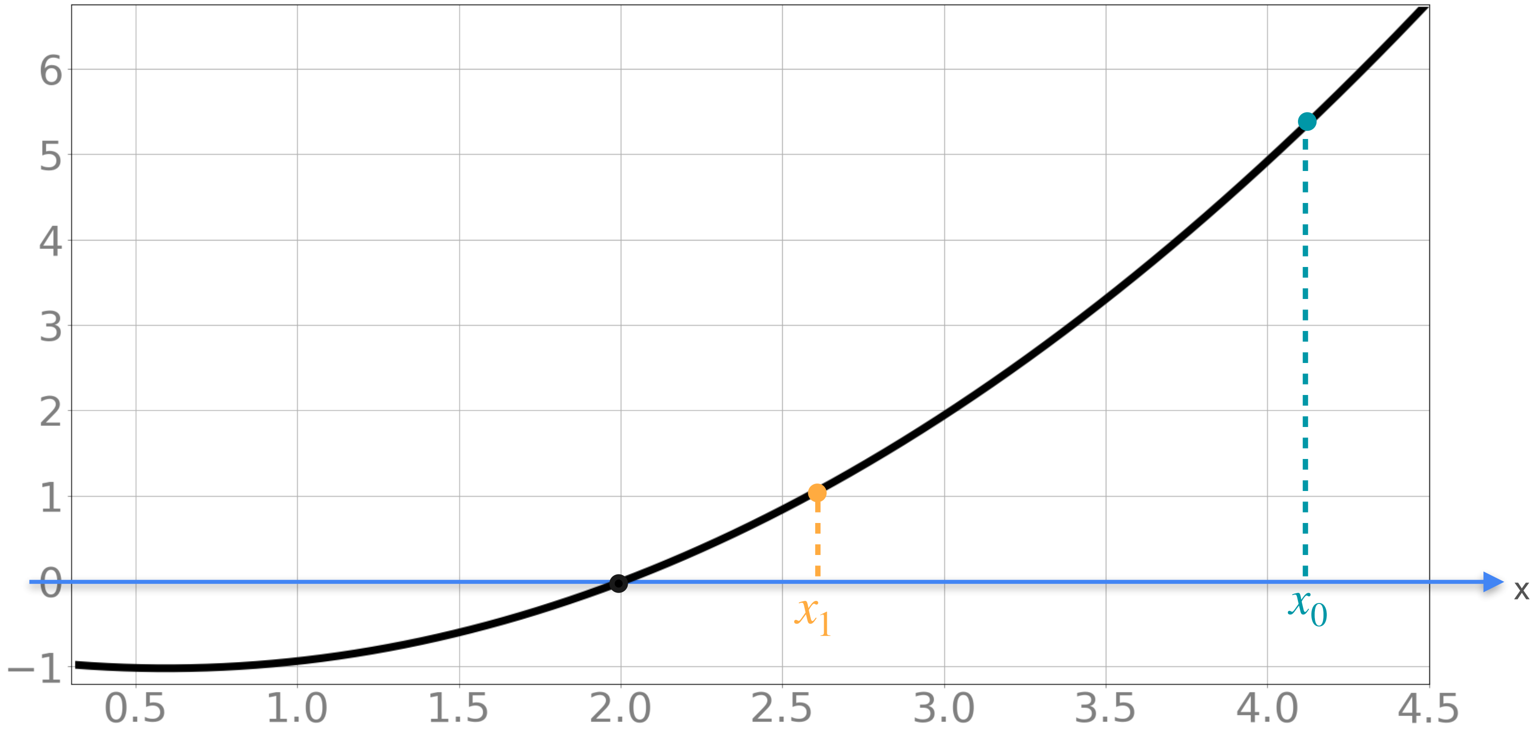

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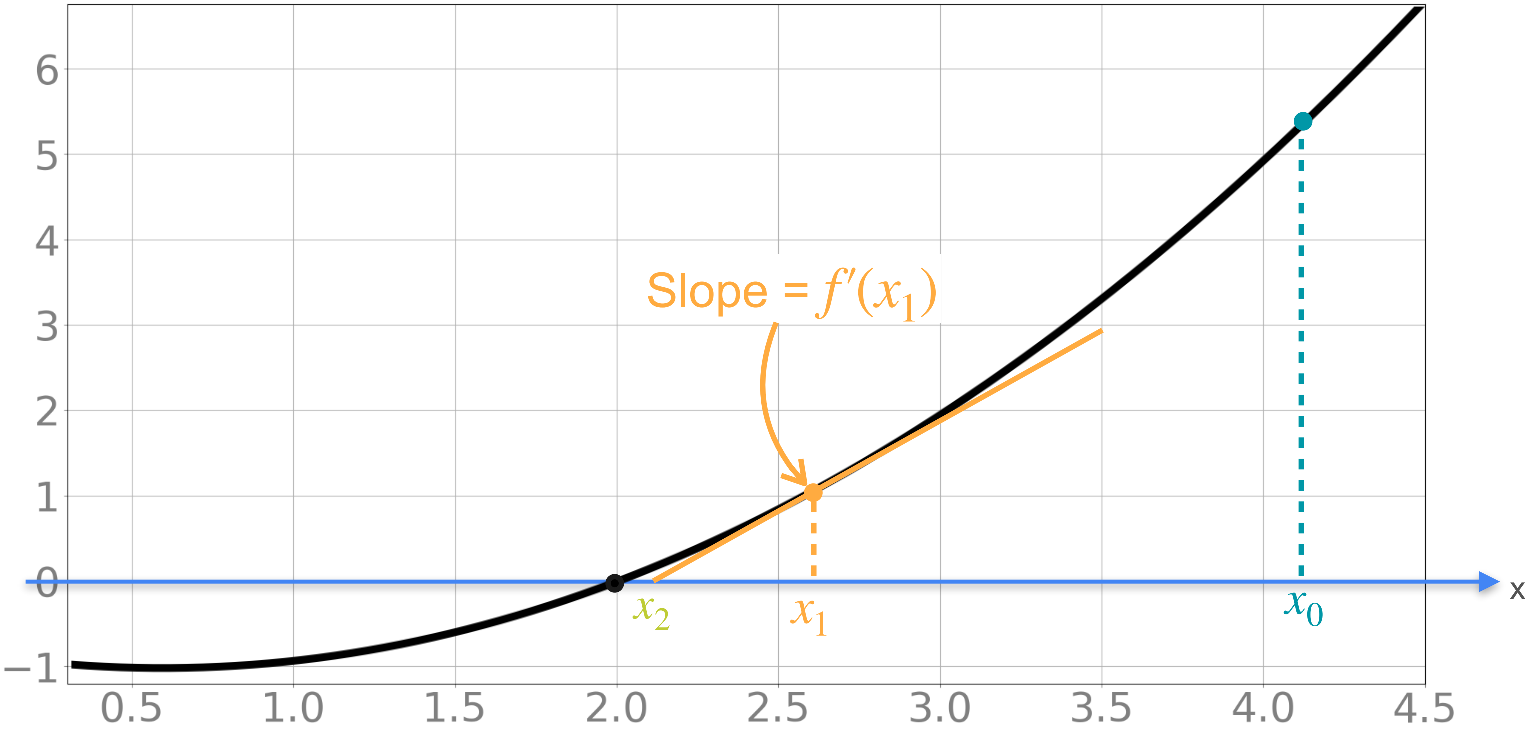

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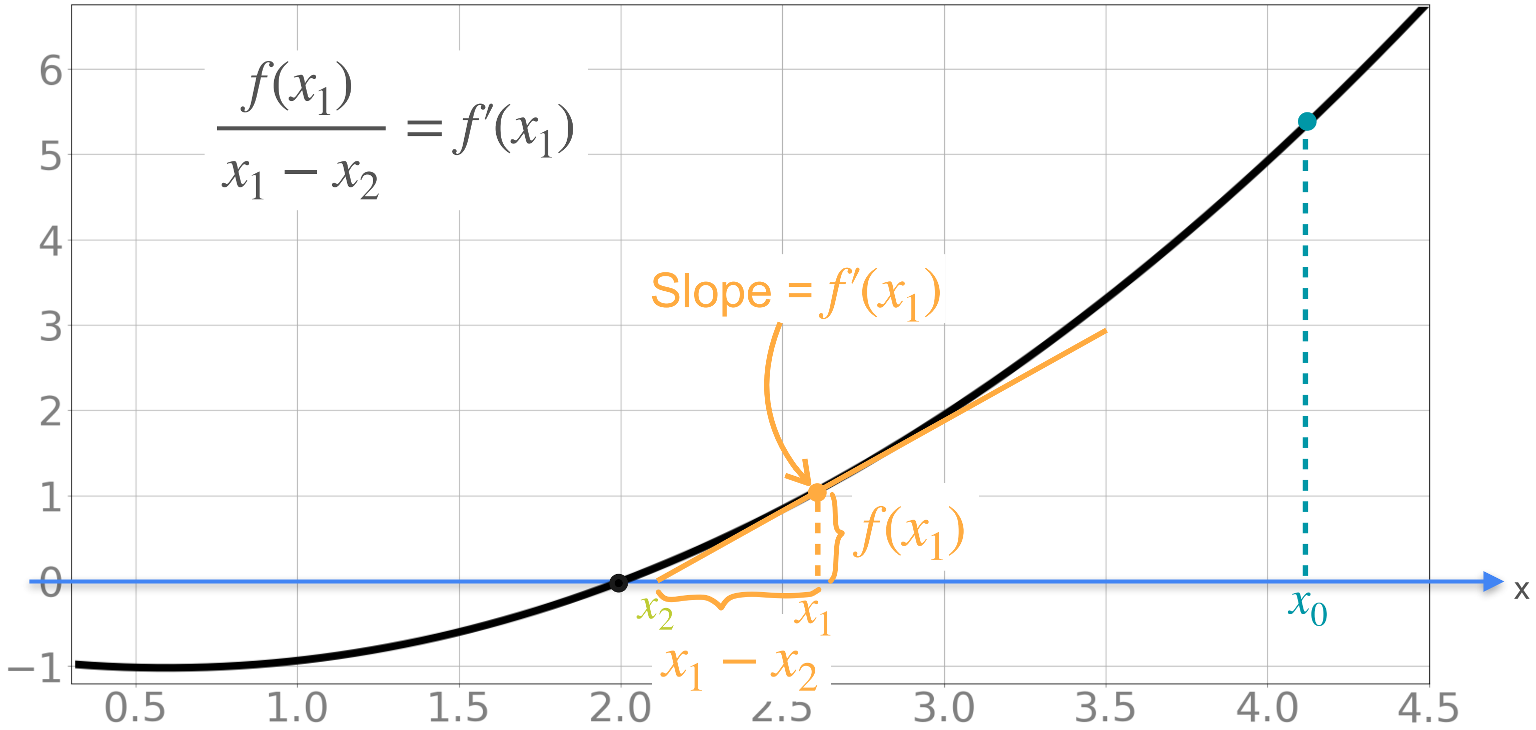

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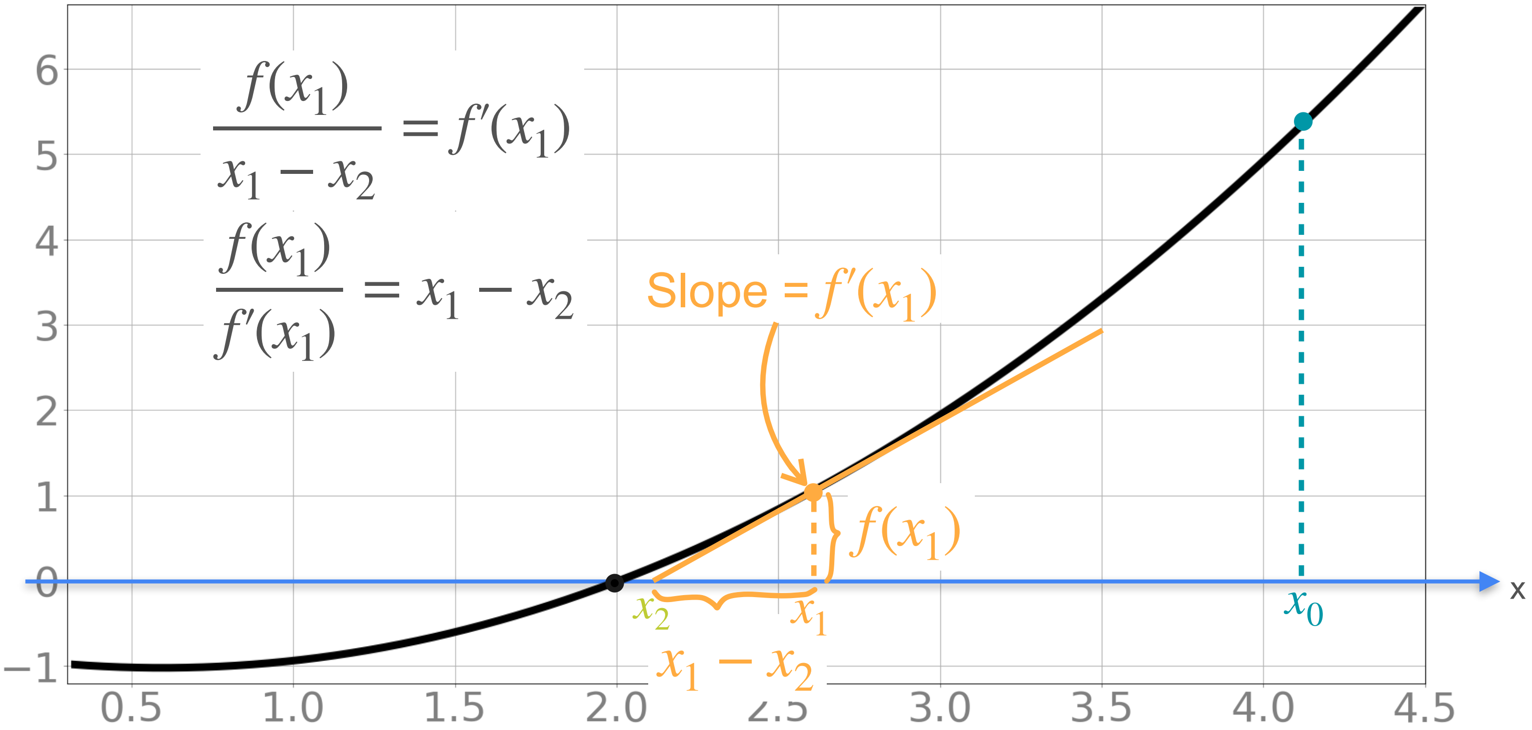

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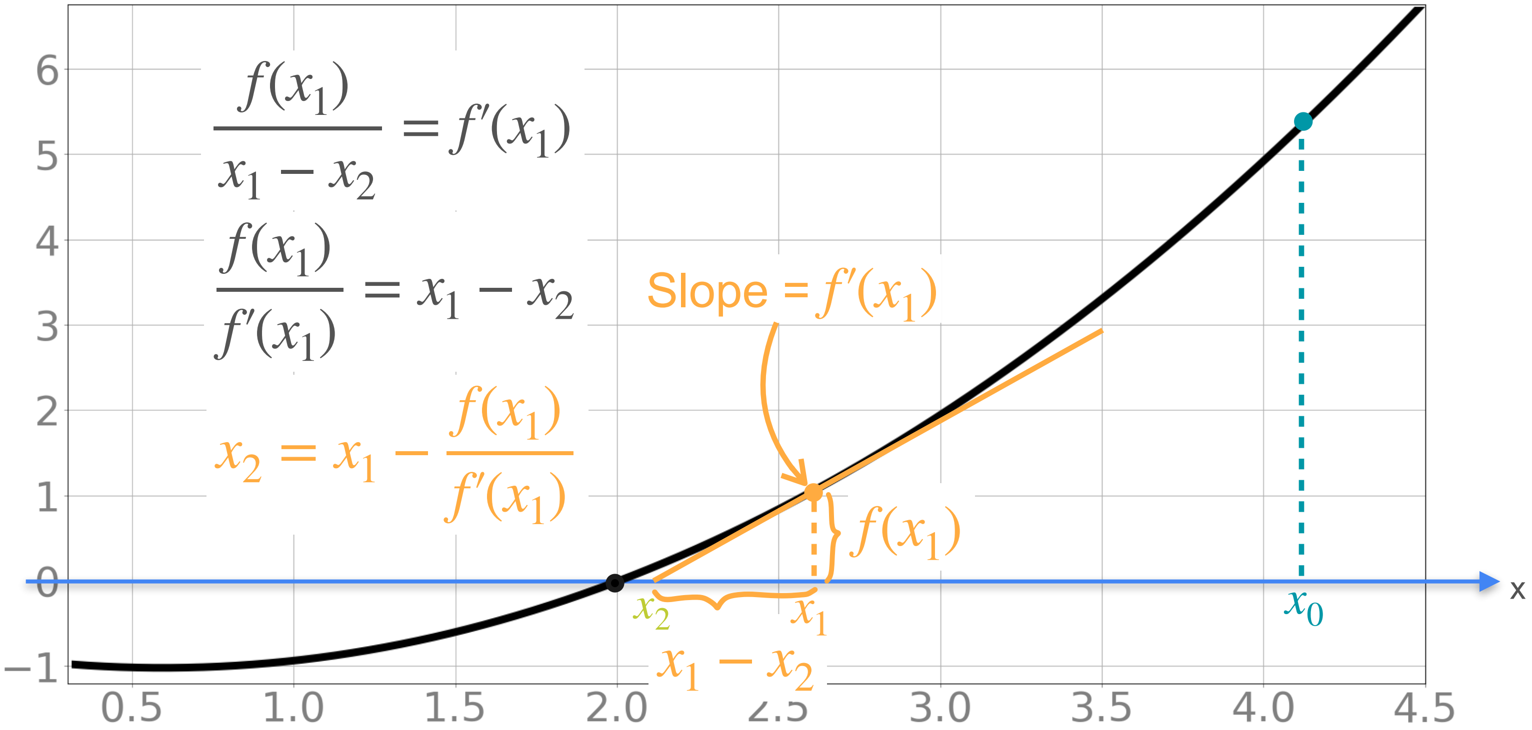

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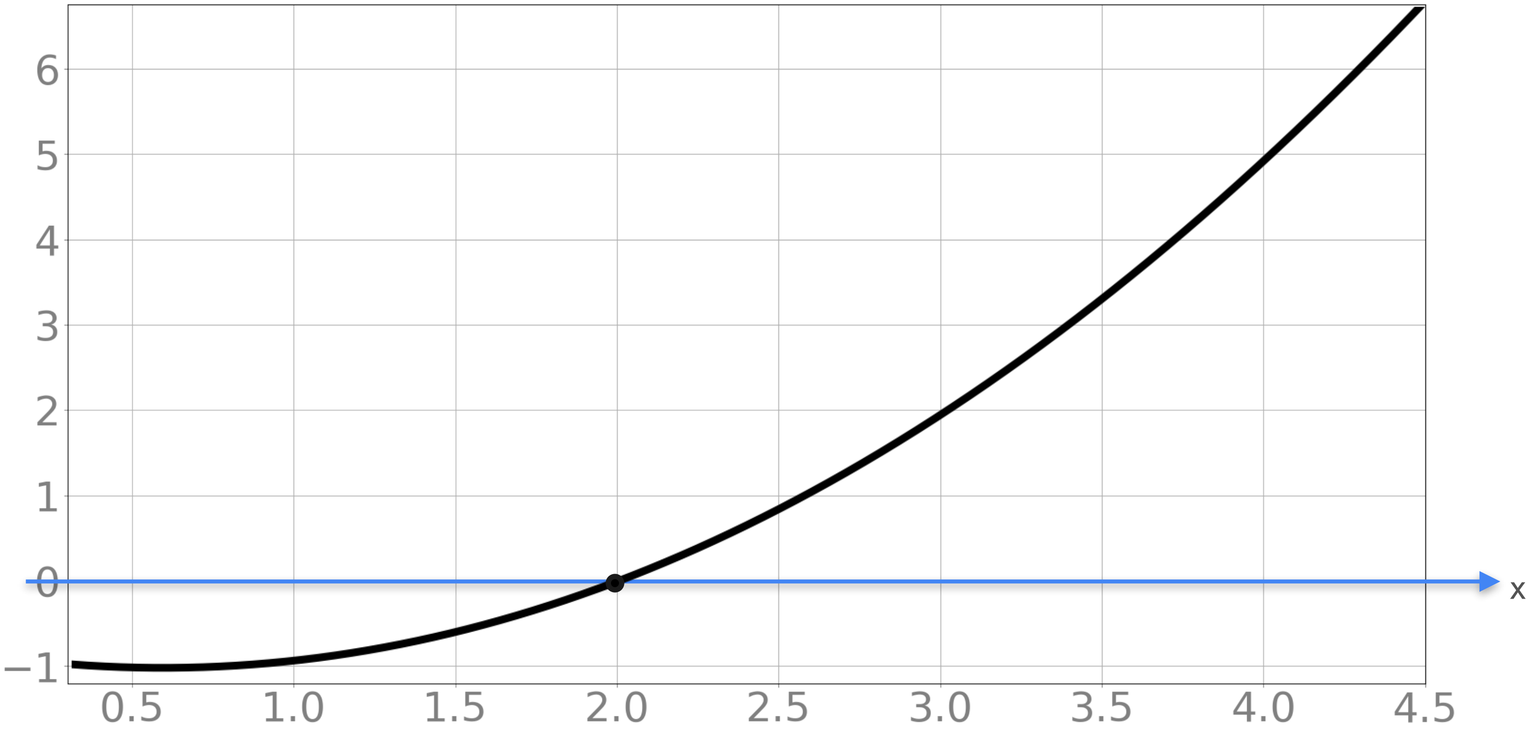

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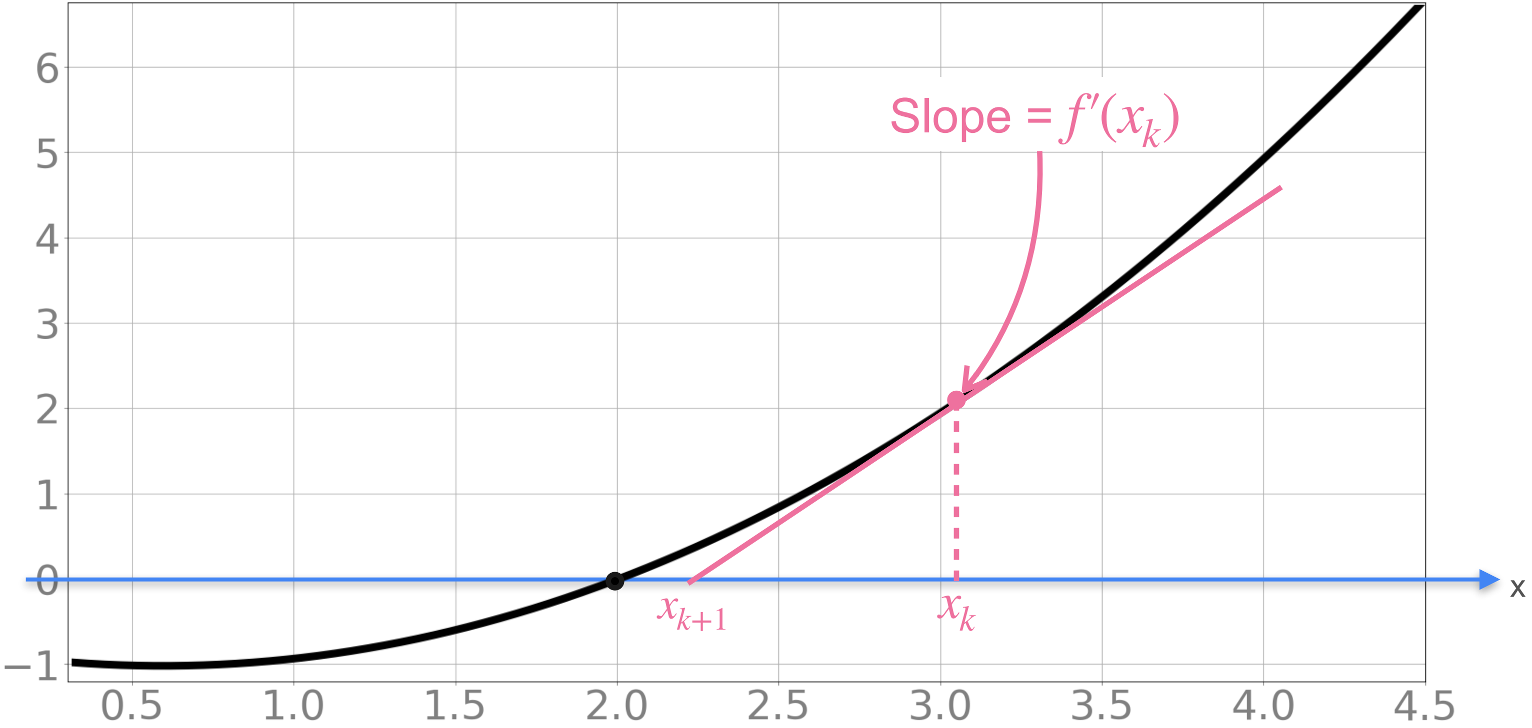

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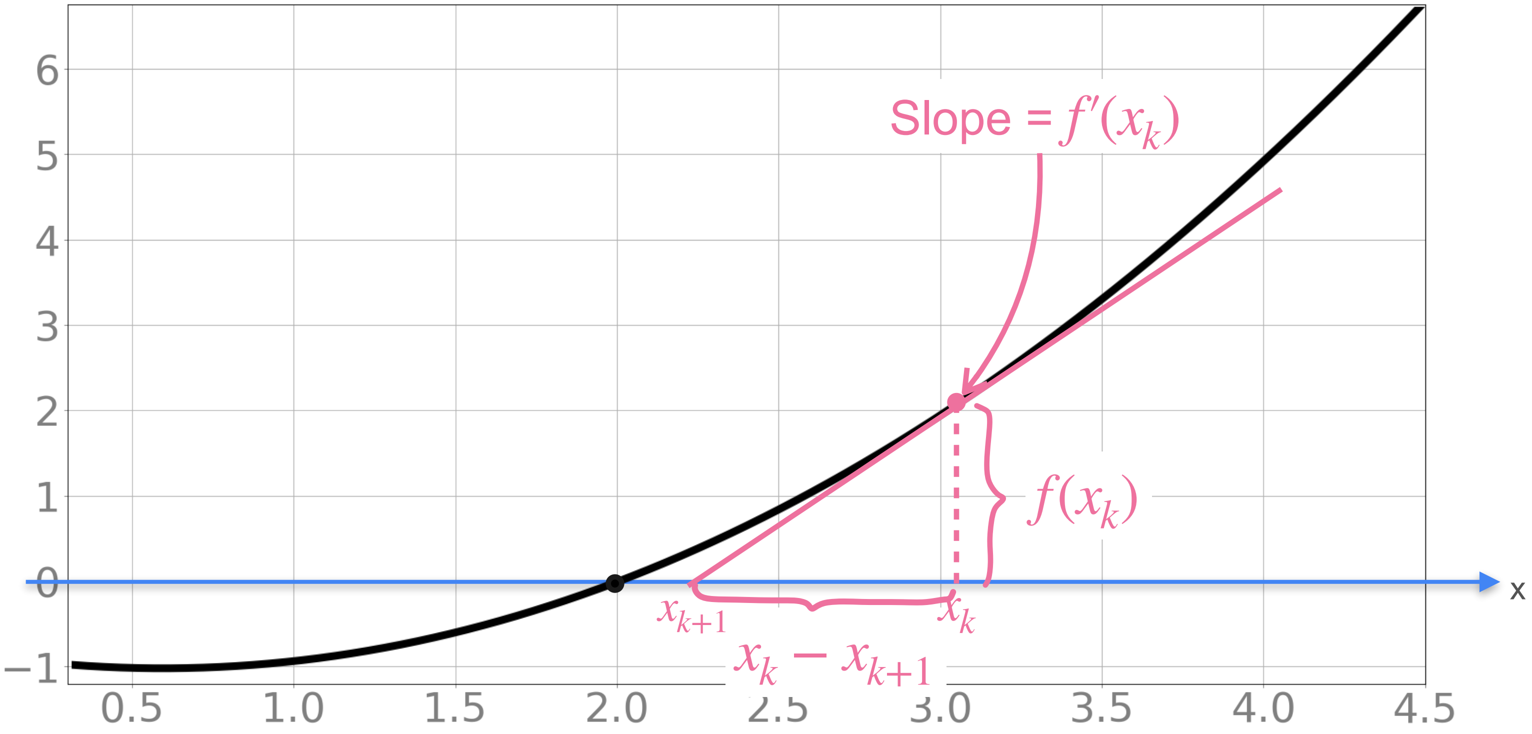
Update Approximation



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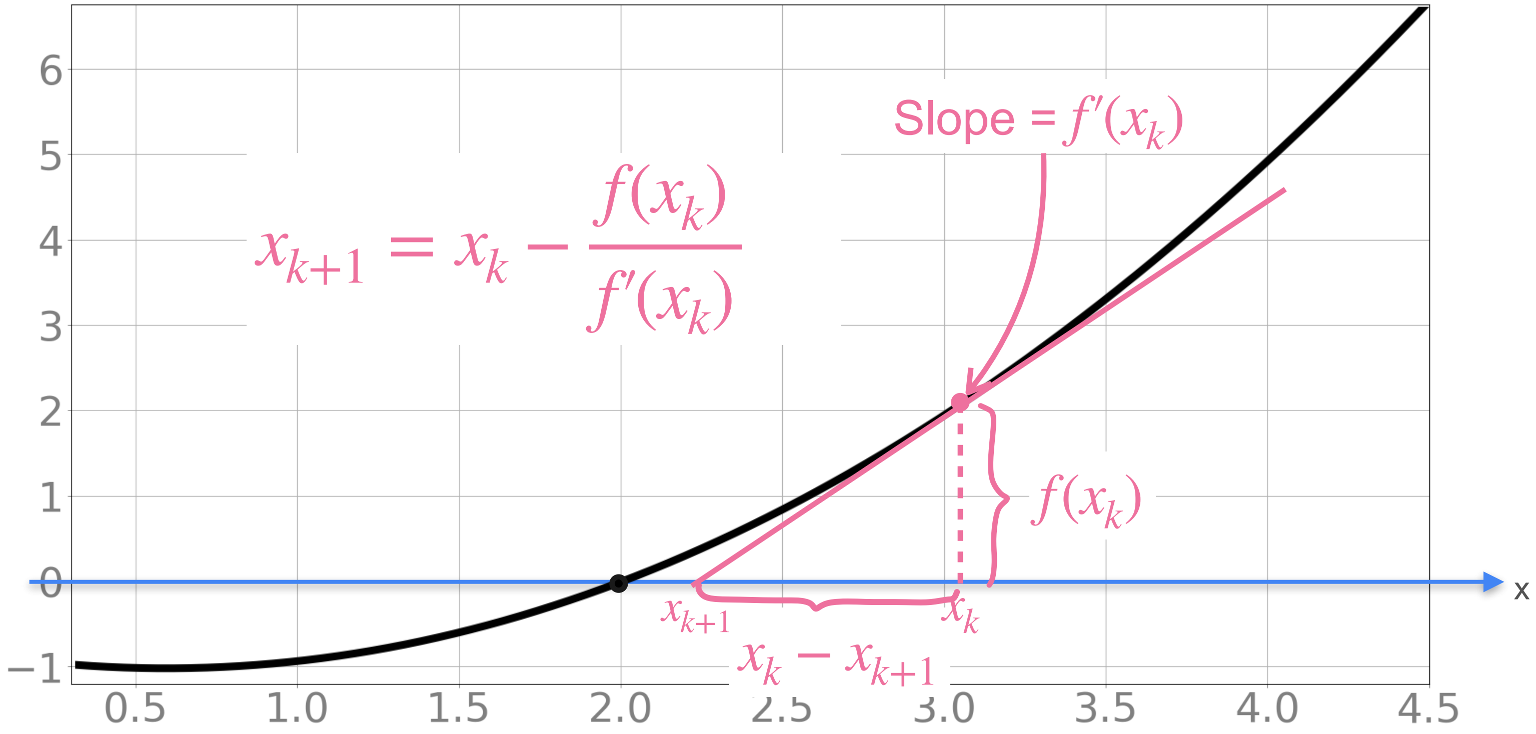

Newton’s Method for Optimization

Newton’s Method for Optimization

Newton’s Method for Optimization

Newton’s method

Goal: find a zero of $f(x)$

Newton's Method for Optimization

Newton's method

Goal: find a zero of $f(x)$

NM for Optimization

Goal: minimize $g(x) \Rightarrow$ find zeros of $g'(x)$

Newton's Method for Optimization

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NM for Optimization

Goal: minimize $g(x) \Rightarrow$ find zeros of $g'(x)$

$f(x) \mapsto g'(x)$ $\quad$ $f'(x) \mapsto (g'(x))'$

Newton's Method for Optimization

Newton's method

Goal: find a zero of $f(x)$

1) Start with some x_0

NM for Optimization

Goal: minimize $g(x) \Rightarrow$ find zeros of $g'(x)$

$f(x) \mapsto g'(x) \qquad f'(x) \mapsto (g'(x))'$

1) Start with some x_0

Newton’s Method for Optimization

Newton’s method

Goal: find a zero of $f(x)$

1) Start with some x_0

2) Update:

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

NM for Optimization

Goal: minimize $g(x)$ $\Longrightarrow$ find zeros of $g'(x)$

$f(x) \mapsto g'(x)$ $\qquad$ $f'(x) \mapsto (g'(x))'$

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Newton's Method for Optimization

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NM for Optimization

Goal: minimize $g(x) \Rightarrow$ find zeros of $g'(x)$

$$f(x) \mapsto g'(x) \qquad f'(x) \mapsto (g'(x))'$$

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2) Update:

$$x_{k+1} = x_k - \frac{g'(x_k)}{(g'(x_k))'}$$

Newton's Method for Optimization

Newton's method

Goal: find a zero of $f(x)$

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2) Update:

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

3) Repeat 2) until you find the root.

NM for Optimization

Goal: minimize $g(x) \Rightarrow$ find zeros of $g'(x)$

$f(x) \mapsto g'(x) \qquad f'(x) \mapsto (g'(x))'$

1) Start with some x_0

2) Update:

$$x_{k+1} = x_k - \frac{g'(x_k)}{(g'(x_k))'}$$

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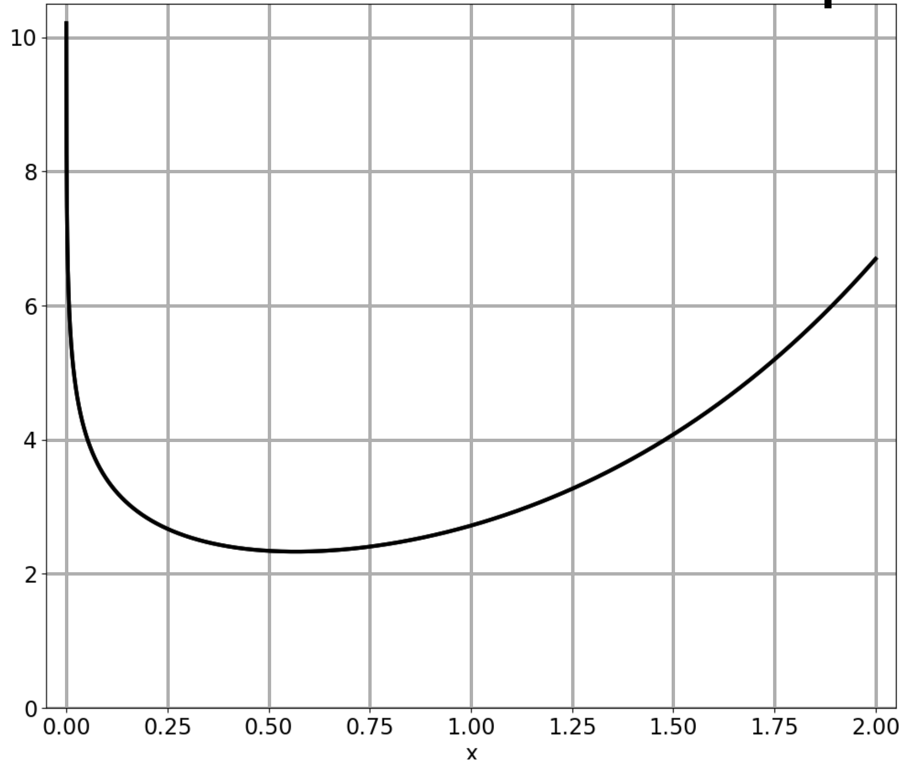
Optimization in Neural Networks and Newton's Method

DeepLearning.AI

Newton's method: An example

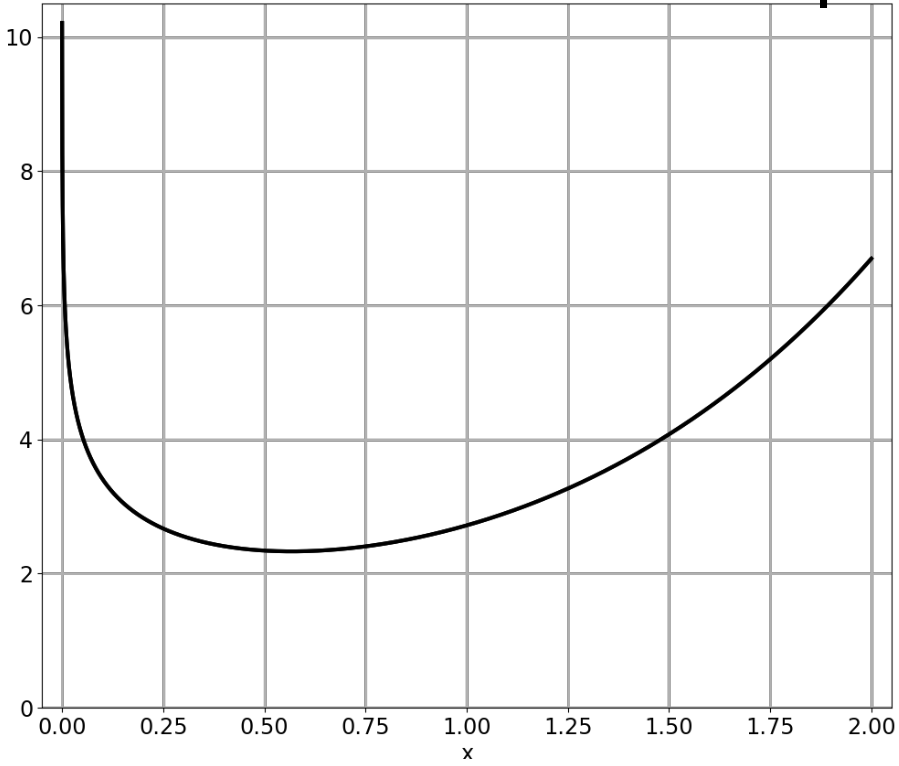
Newton’s Method for Optimization

Newton's Method for Optimization



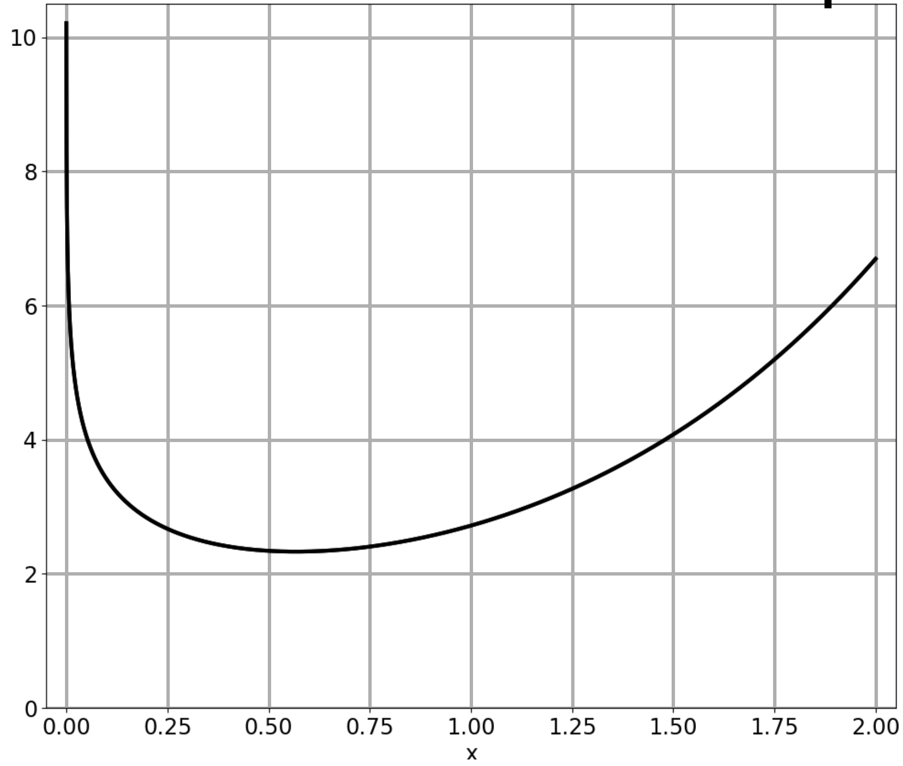
$$g(x) = e^x - \log(x)$$

Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

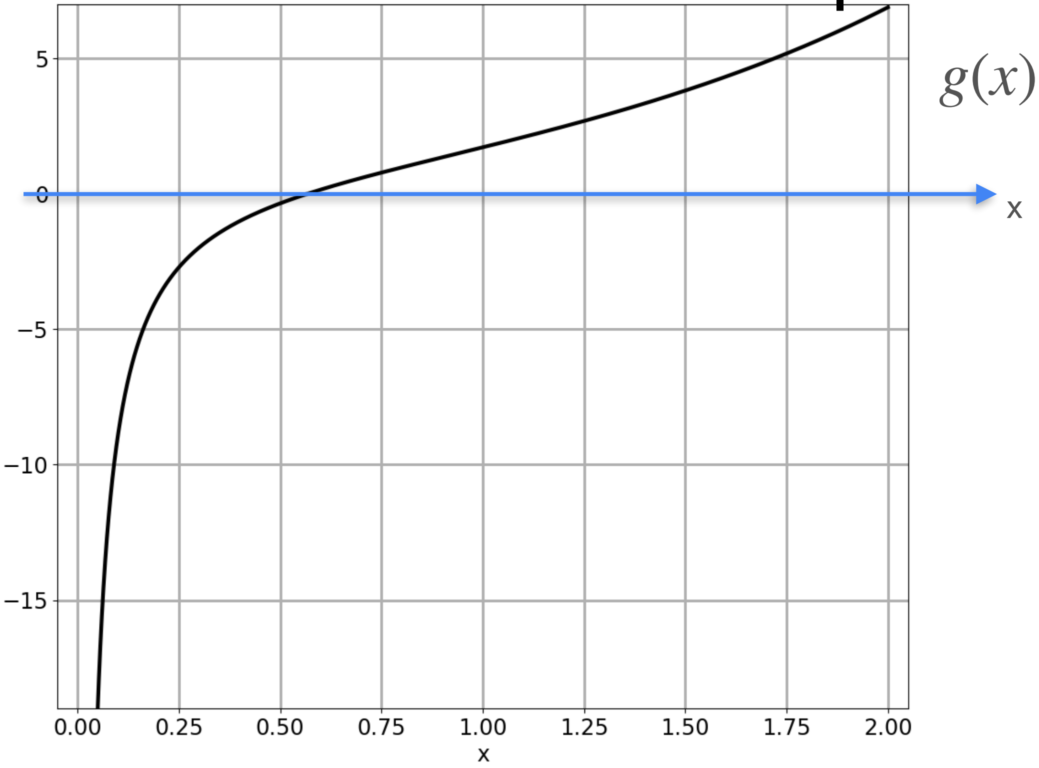
Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

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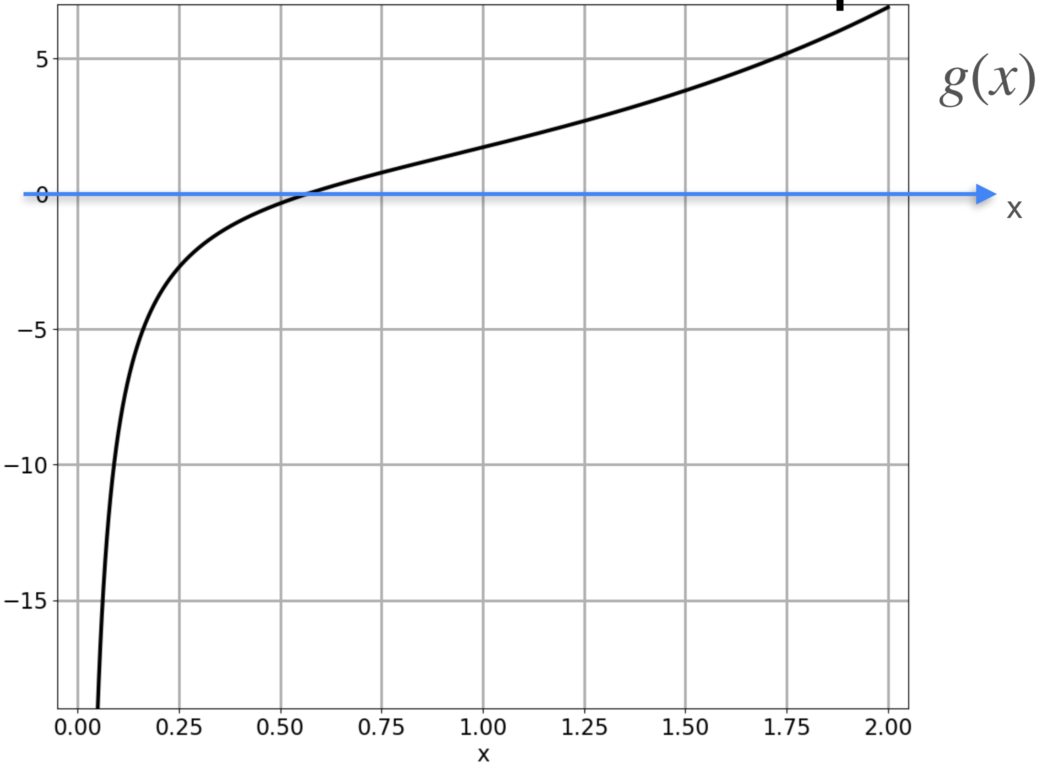
Newton's Method for Optimization

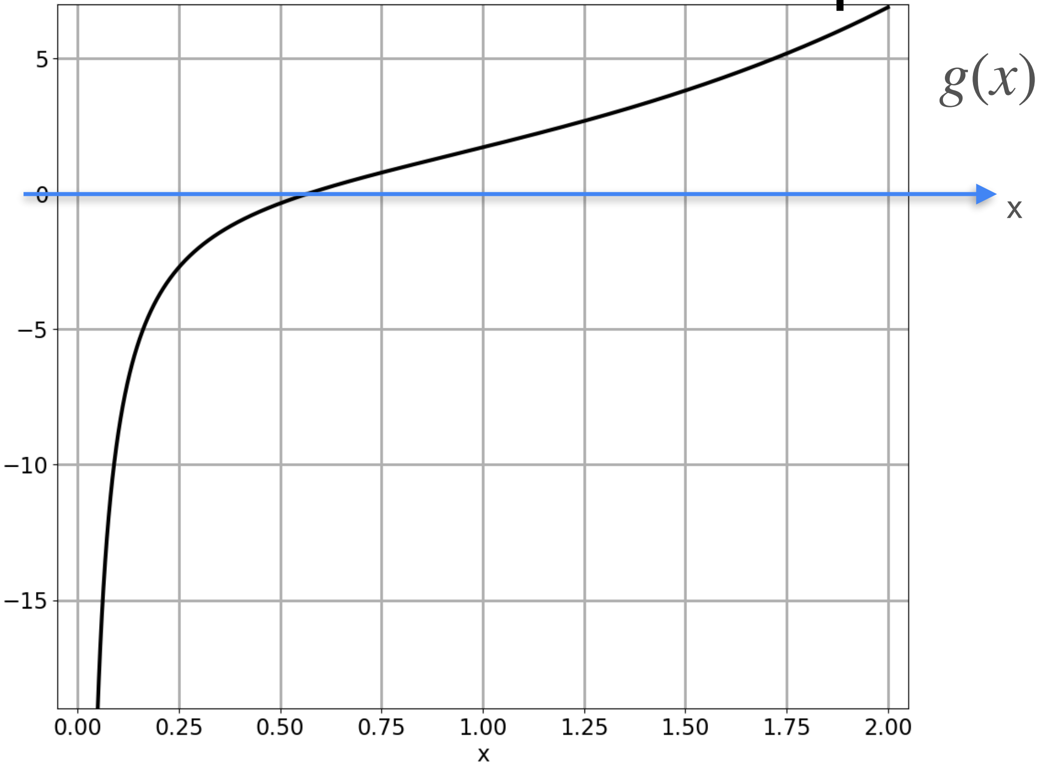


$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

Newton's Method for Optimization

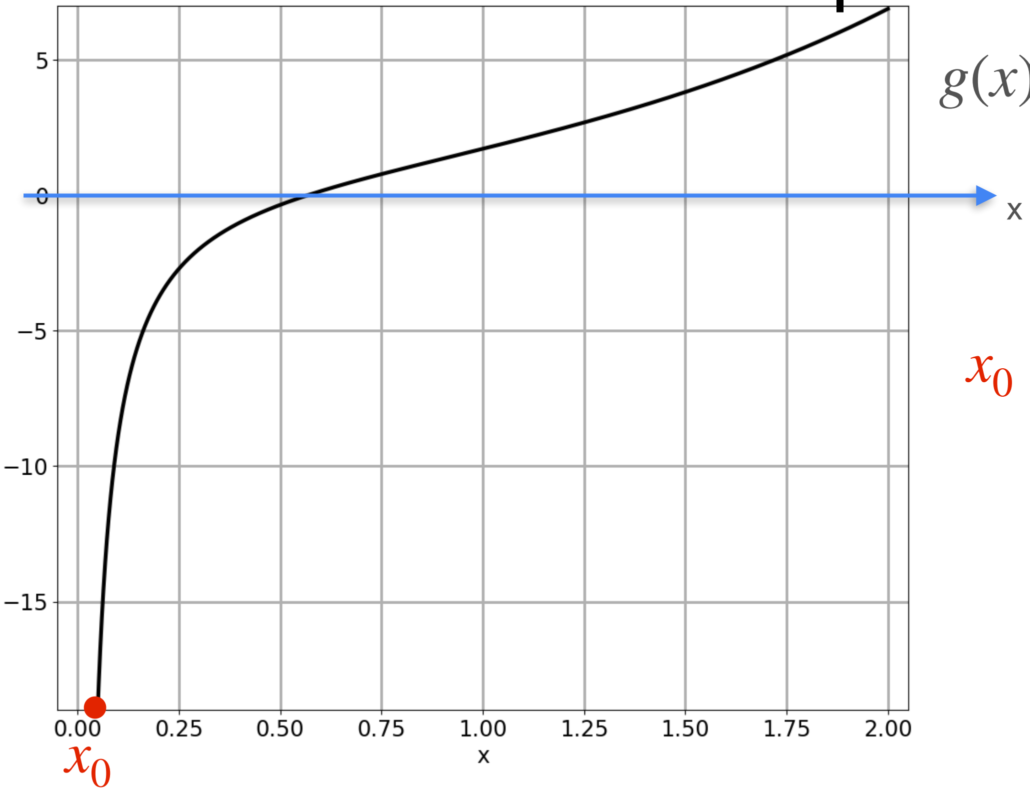


$$g(x) = e^x - \log(x) \qquad \overbrace{g'(x) = e^x - 1/x}^{f(x)}$$

Minimum: $x^* = 0.5671$

$$\underbrace{(g'(x))' = e^x + \frac{1}{x^2}}_{f'(x)}$$

Newton's Method for Optimization



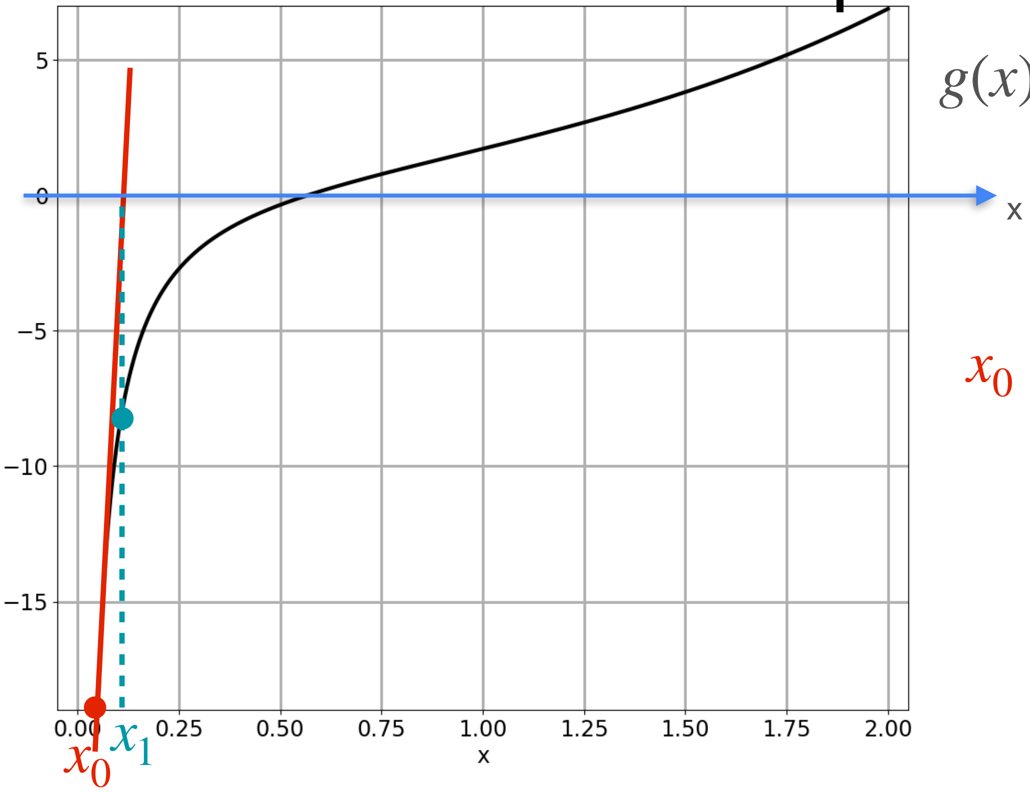
$$g(x) = e^x - \log(x) \qquad \overbrace{g'(x) = e^x - 1/x}^{f(x)}$$

Minimum: $x^* = 0.5671$

$$\underbrace{(g'(x))' = e^x + \frac{1}{x^2}}_{f'(x)}$$

$x_0 = 0.05$

Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad \overbrace{g'(x) = e^x - 1/x}^{f(x)}$$

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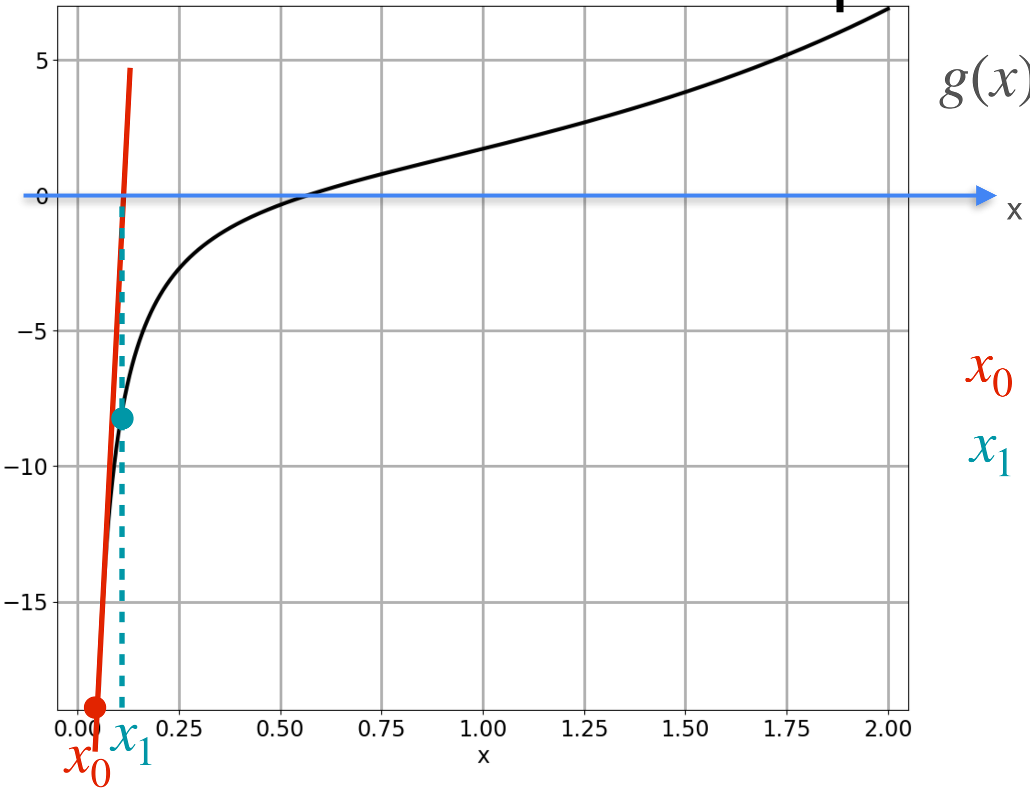
Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad \overbrace{g'(x) = e^x - 1/x}^{f(x)}$$

Minimum: $x^* = 0.5671$

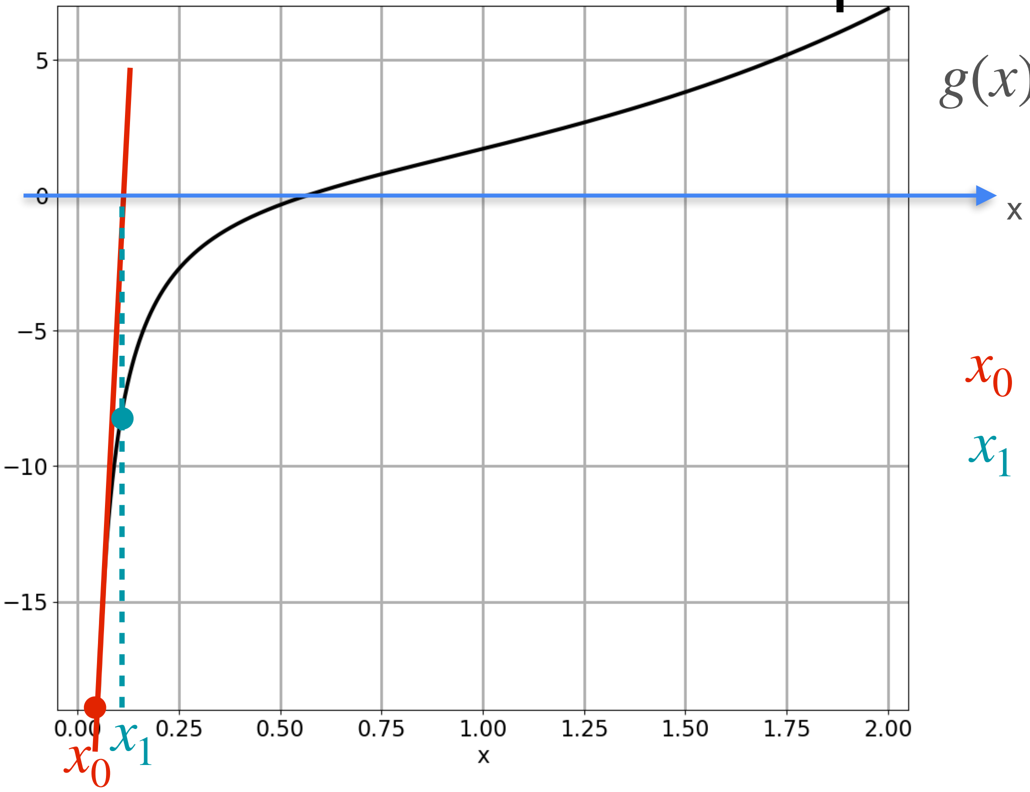
$$\underbrace{(g'(x))' = e^x + \frac{1}{x^2}}_{f'(x)}$$

$$x_0 = 0.05$$

$$x_1 = x_0 - \frac{g'(x_0)}{(g'(x_0))'}$$

$$= 0.05 - \frac{\left(e^{0.05} - \frac{1}{0.05}\right)}{\left(e^{0.05} + \frac{1}{0.05^2}\right)}$$

Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad \underbrace{g'(x) = e^x - 1/x}_{f(x)}$$

Minimum: $x^* = 0.5671$

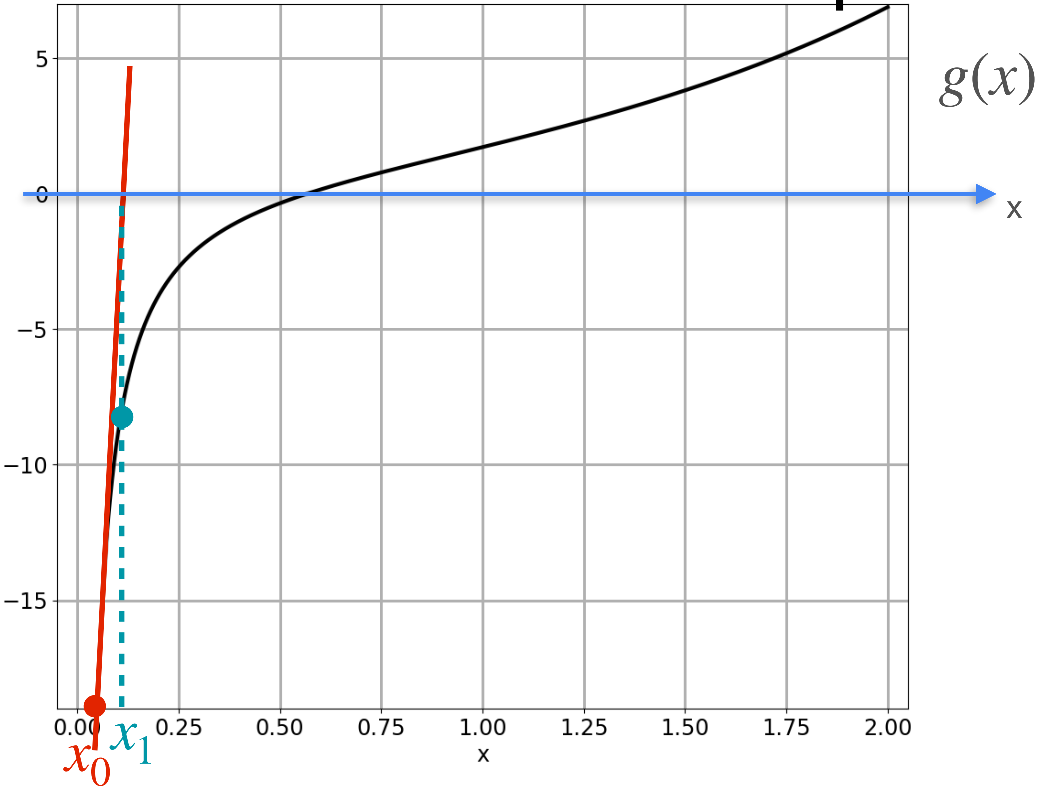
$$\underbrace{(g'(x))' = e^x + \frac{1}{x^2}}_{f'(x)}$$

$$x_0 = 0.05$$

$$x_1 = x_0 - \frac{g'(x_0)}{(g'(x_0))'}$$

$$= 0.05 - \frac{\left(e^{0.05} - \frac{1}{0.05}\right)}{\left(e^{0.05} + \frac{1}{0.05^2}\right)} = 0.097$$

Newton's Method for Optimization

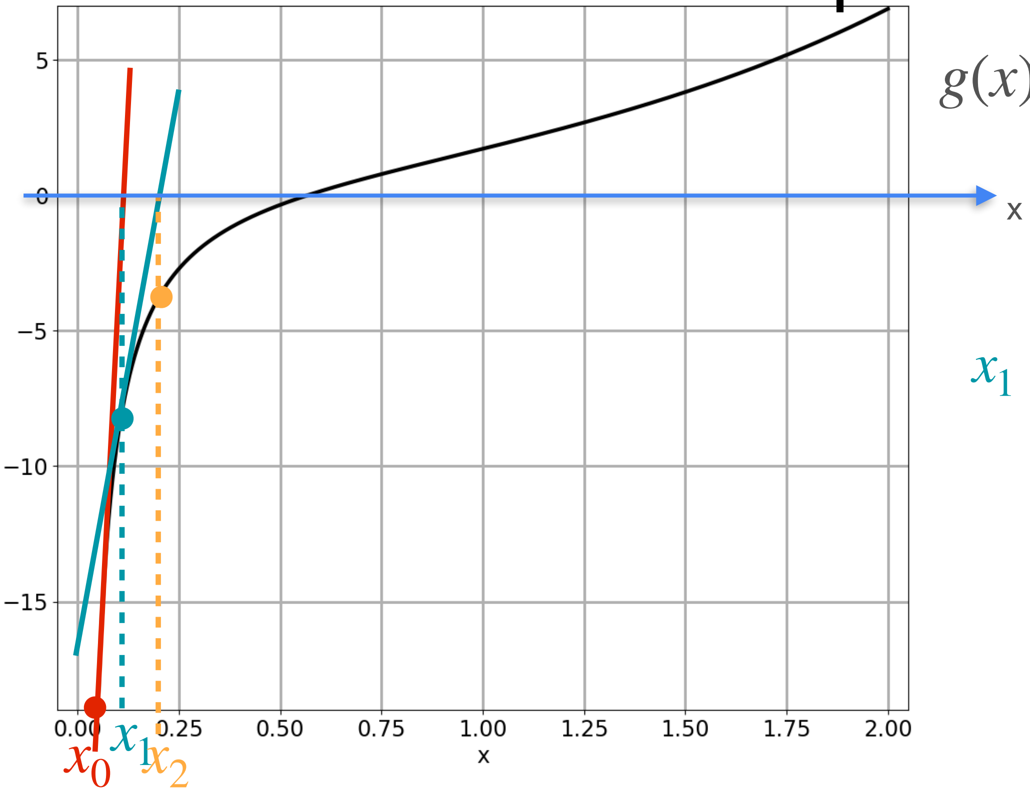


$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

Newton's Method for Optimization



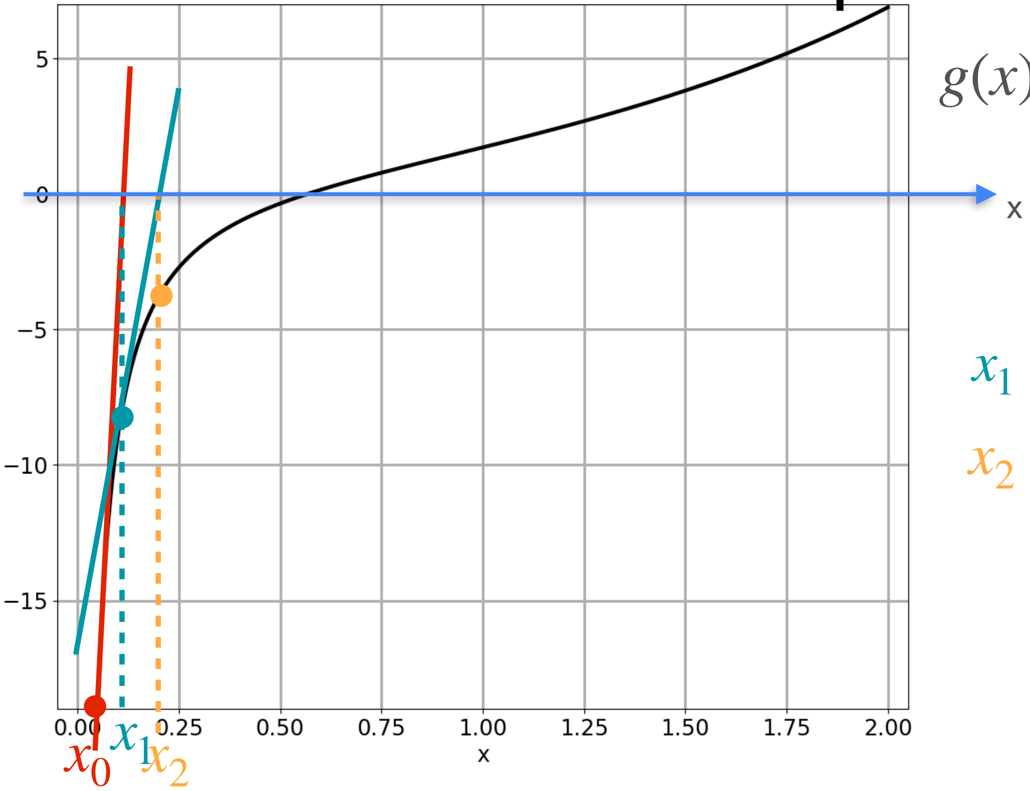
$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_1 = 0.097$

Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

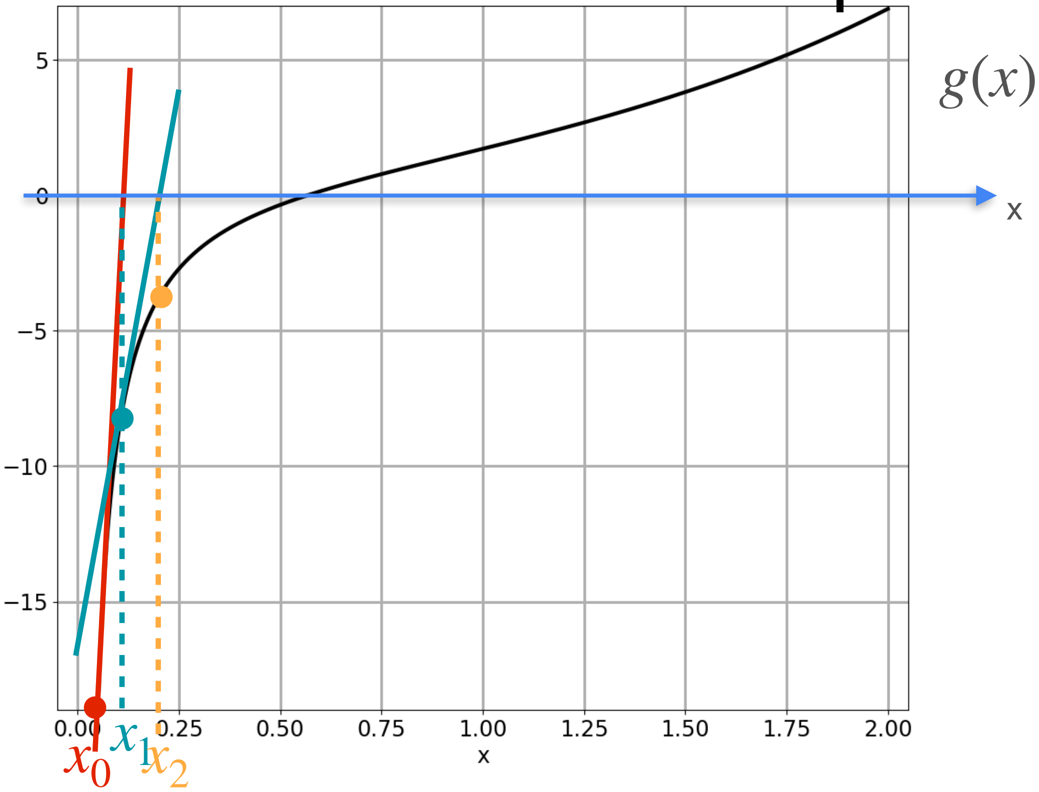
$$(g'(x))' = e^x + \frac{1}{x^2}$$

$$x_1 = 0.097$$

$$x_2 = x_1 - \frac{g'(x_1)}{(g'(x_1))'}$$

$$= 0.097 - \frac{\left(e^{0.097} - \frac{1}{0.097}\right)}{\left(e^{0.097} + \frac{1}{0.097^2}\right)} = 0.183$$

Newton's Method for Optimization

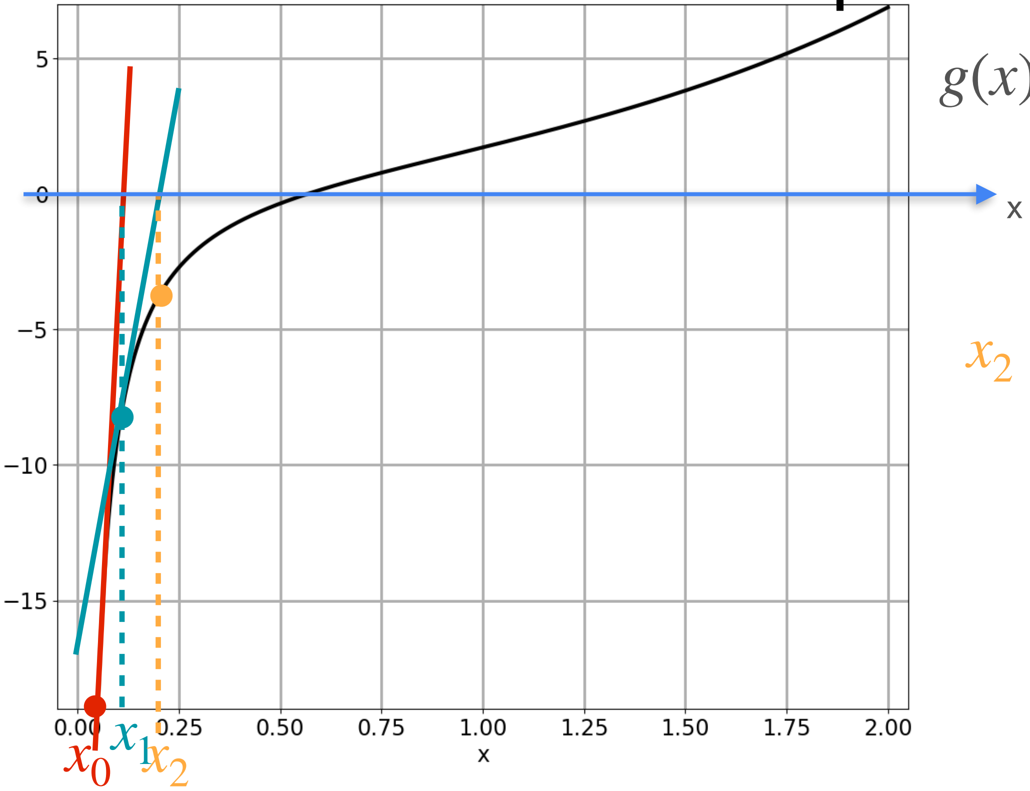


$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

Newton’s Method for Optimization



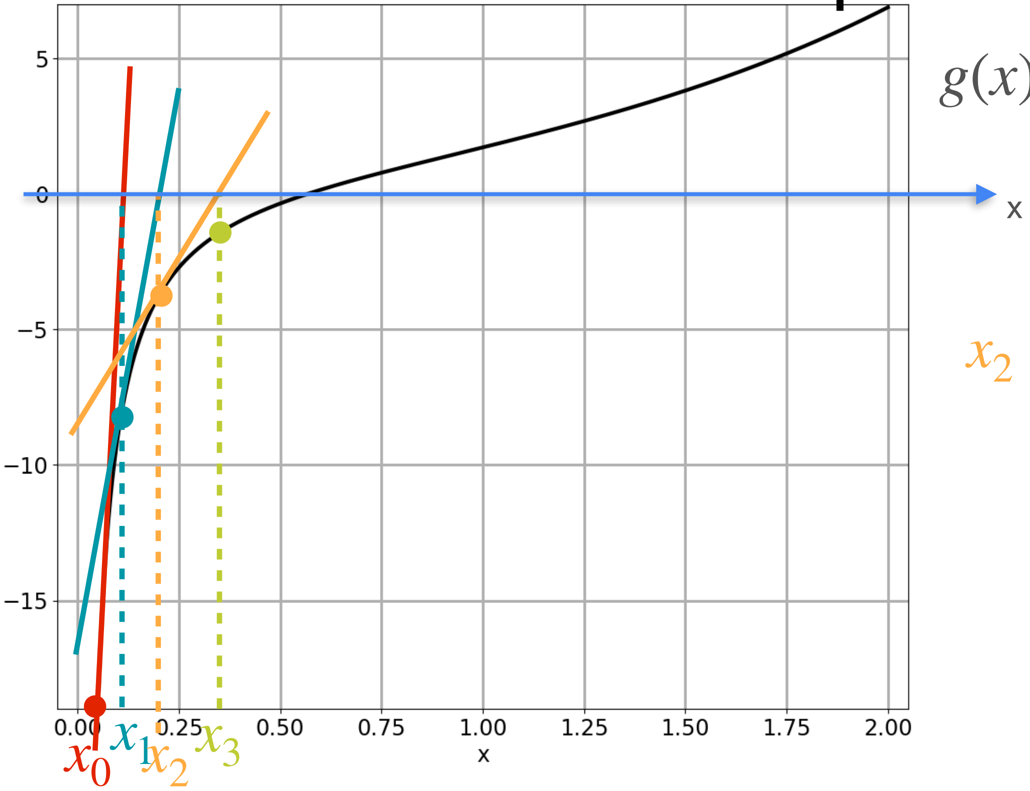
$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_2 = 0.183$

Newton's Method for Optimization



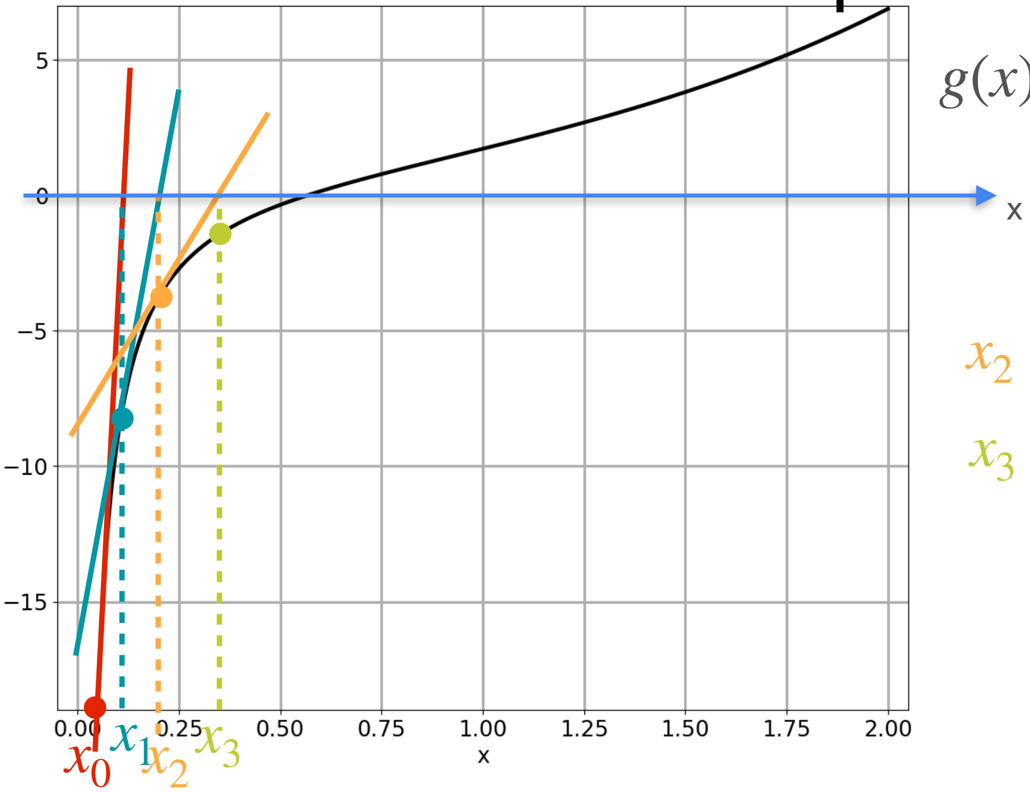
$g(x) = e^x - \log(x)$ $\quad g'(x) = e^x - 1/x$

Minimum: $x^* = 0.5671$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_2 = 0.183$

Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

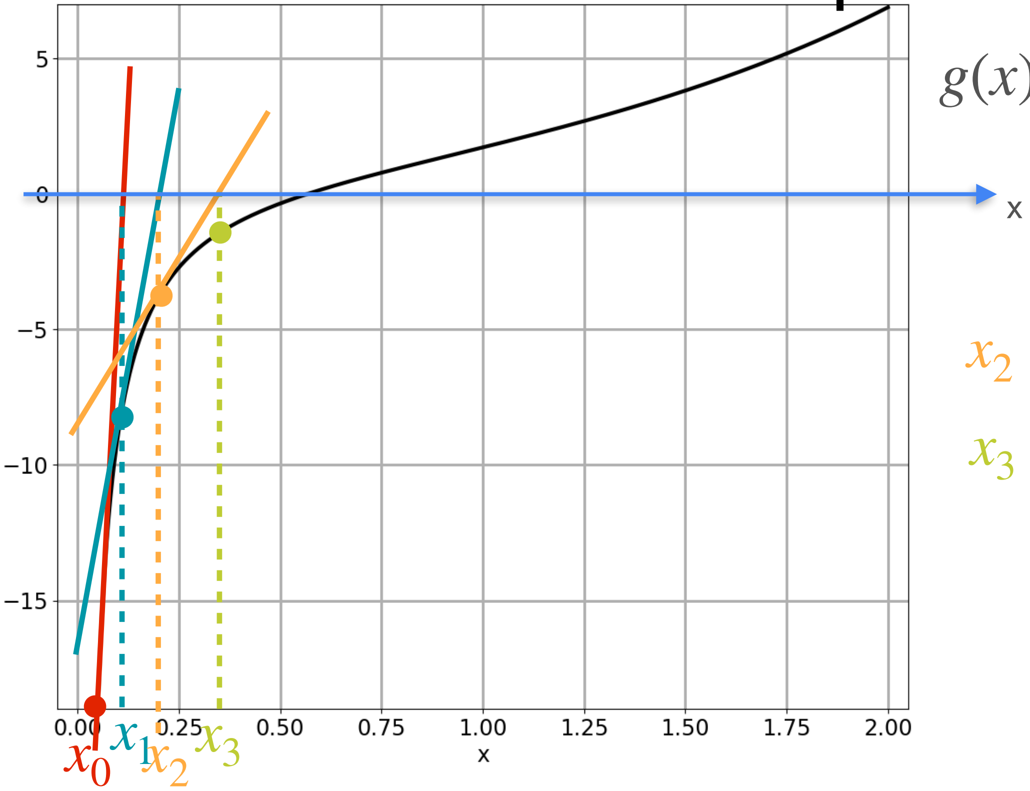
$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_2 = 0.183$

$$x_3 = x_2 - \frac{g'(x_2)}{(g'(x_2))'}$$

$$= 0.183 - \frac{\left(e^{0.183} - \frac{1}{0.183}\right)}{\left(e^{0.183} + \frac{1}{0.183^2}\right)}$$

Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

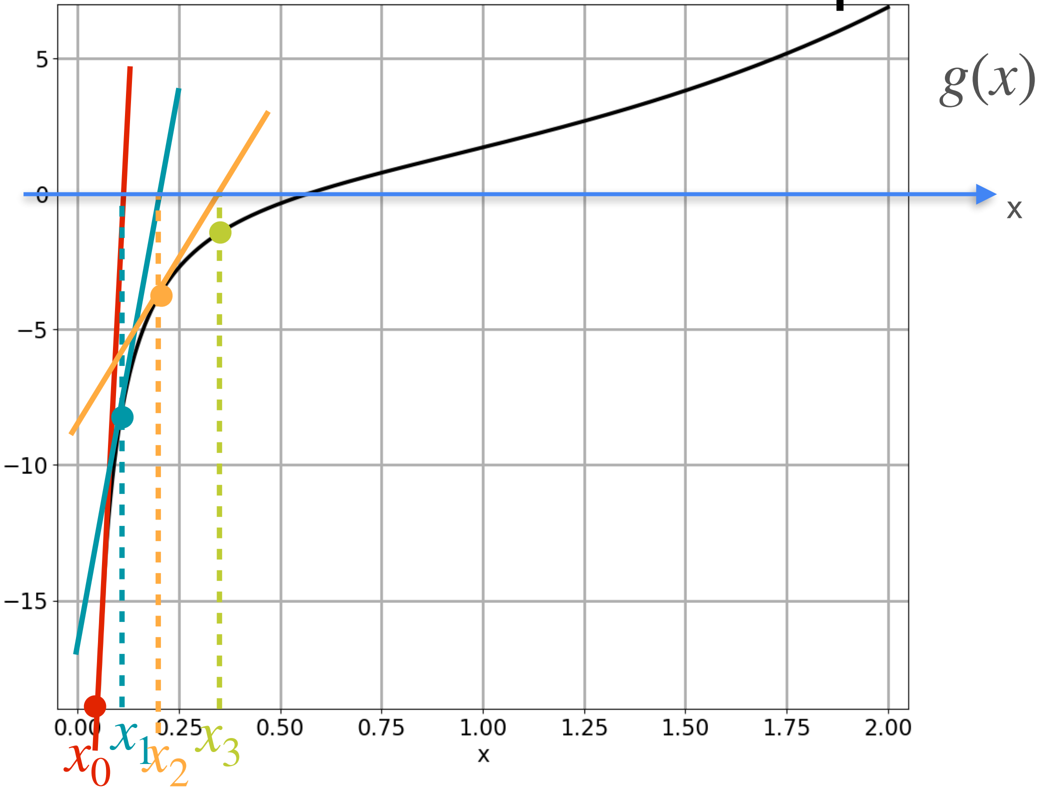
$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_2 = 0.183$

$$x_3 = x_2 - \frac{g'(x_2)}{(g'(x_2))'}$$

$$= 0.183 - \frac{\left(e^{0.183} - \frac{1}{0.183}\right)}{\left(e^{0.183} + \frac{1}{0.183^2}\right)} = 0.320$$

Newton's Method for Optimization

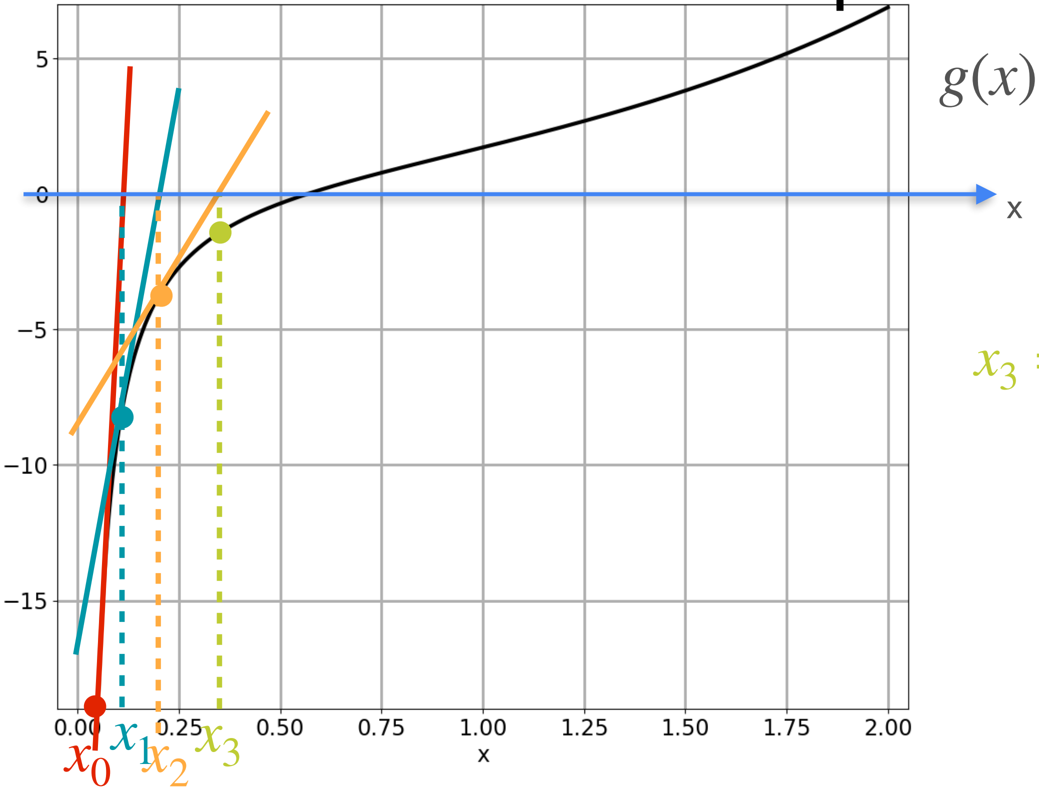


$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

Newton's Method for Optimization



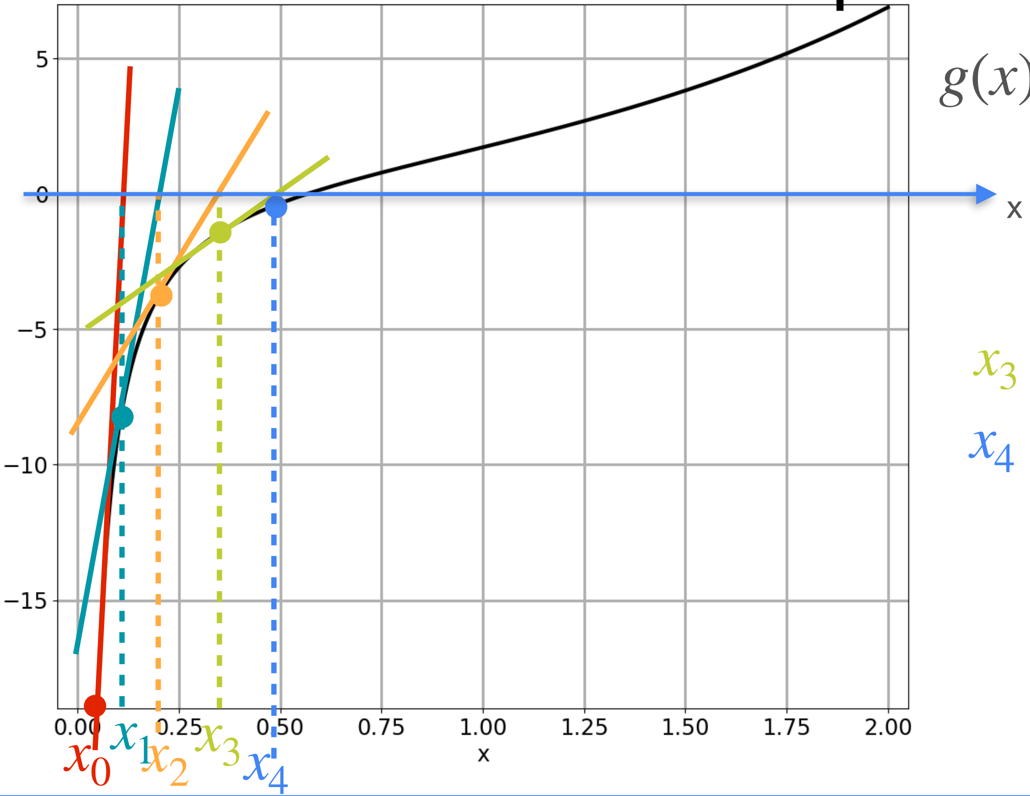
$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_3 = 0.320$

Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

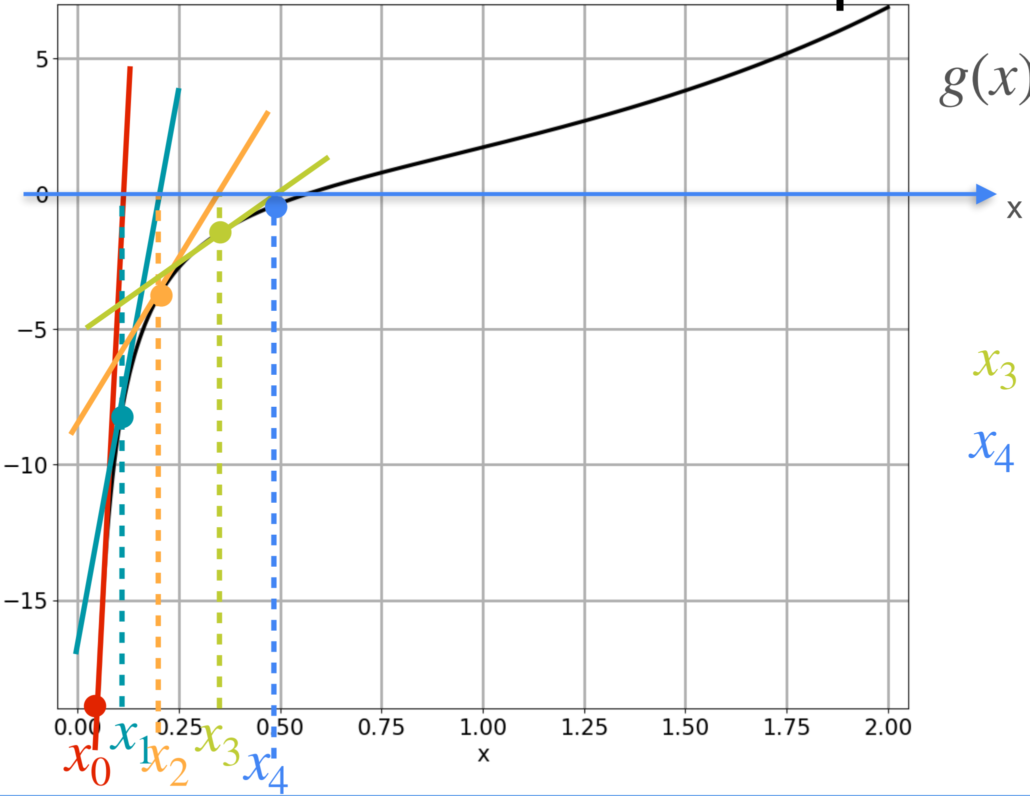
$$(g'(x))' = e^x + \frac{1}{x^2}$$

$$x_3 = 0.320$$

$$x_4 = x_3 - \frac{g'(x_3)}{(g'(x_3))'}$$

$$= 0.320 - \frac{\left(e^{0.320} - \frac{1}{0.320}\right)}{\left(e^{0.320} + \frac{1}{0.320^2}\right)}$$

Newton's Method for Optimization



$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

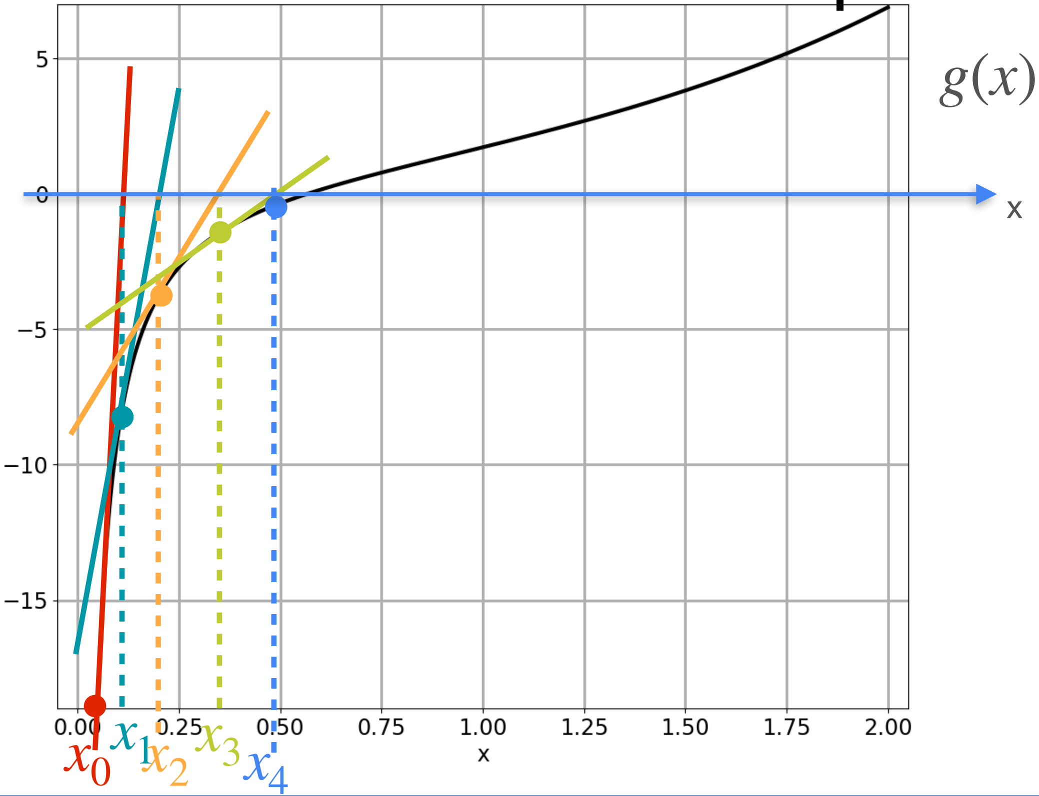
$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_3 = 0.320$

$$x_4 = x_3 - \frac{g'(x_3)}{(g'(x_3))'}$$

$$= 0.320 - \frac{\left(e^{0.320} - \frac{1}{0.320}\right)}{\left(e^{0.320} + \frac{1}{0.320^2}\right)} = 0.477$$

Newton's Method for Optimization

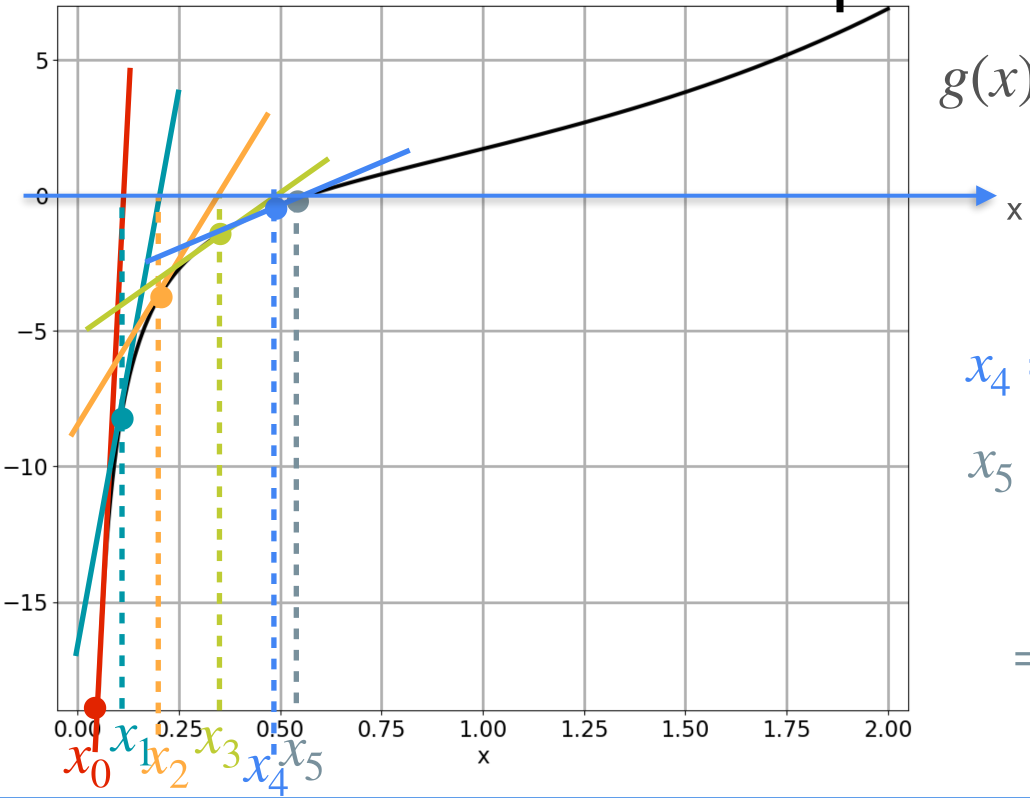


$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.5671$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

Newton's Method for Optimization



$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$

Minimum: $x^* = 0.5671$

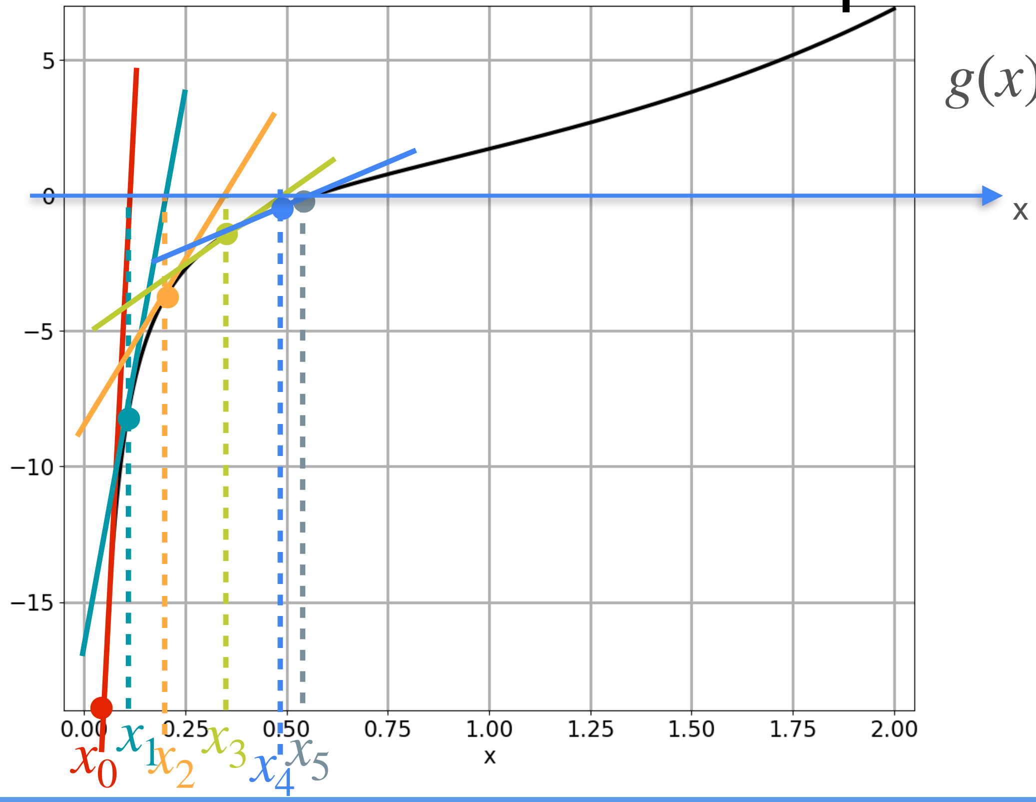
$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_4 = 0.477$

$$x_5 = x_4 - \frac{g'(x_4)}{(g'(x_4))'}$$

$$= 0.447 - \frac{\left(e^{0.447} - \frac{1}{0.447}\right)}{\left(e^{0.447} + \frac{1}{0.447^2}\right)} = 0.558$$

Newton's Method for Optimization

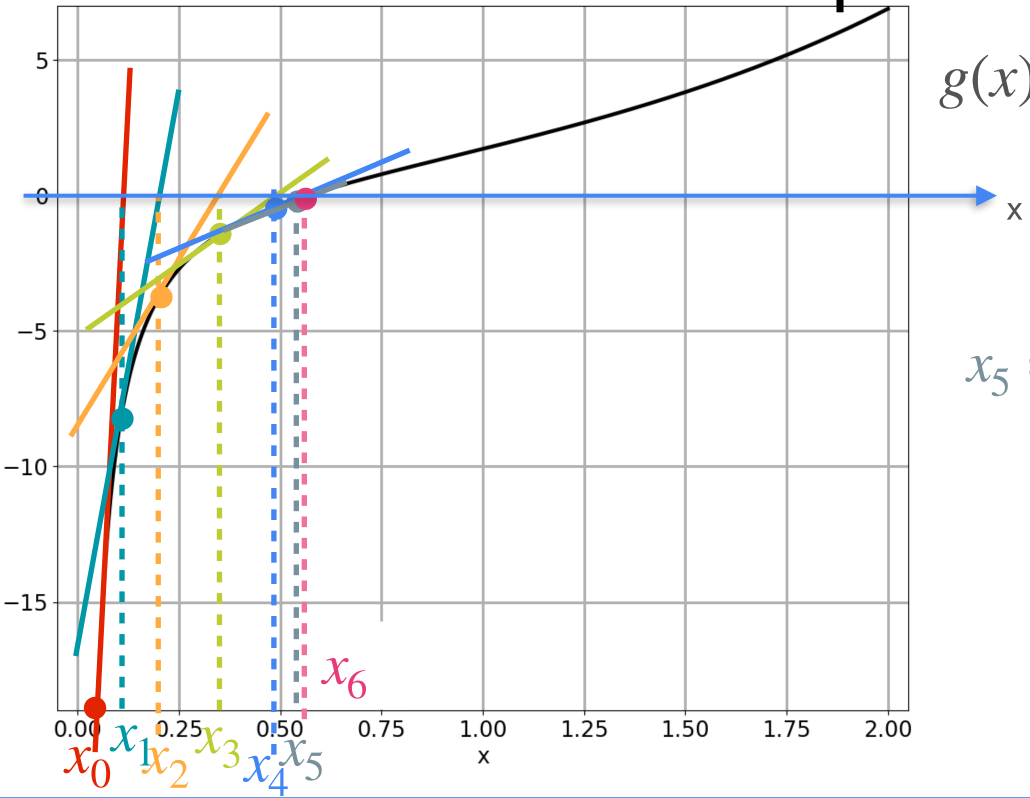


$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.567$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

Newton's Method for Optimization



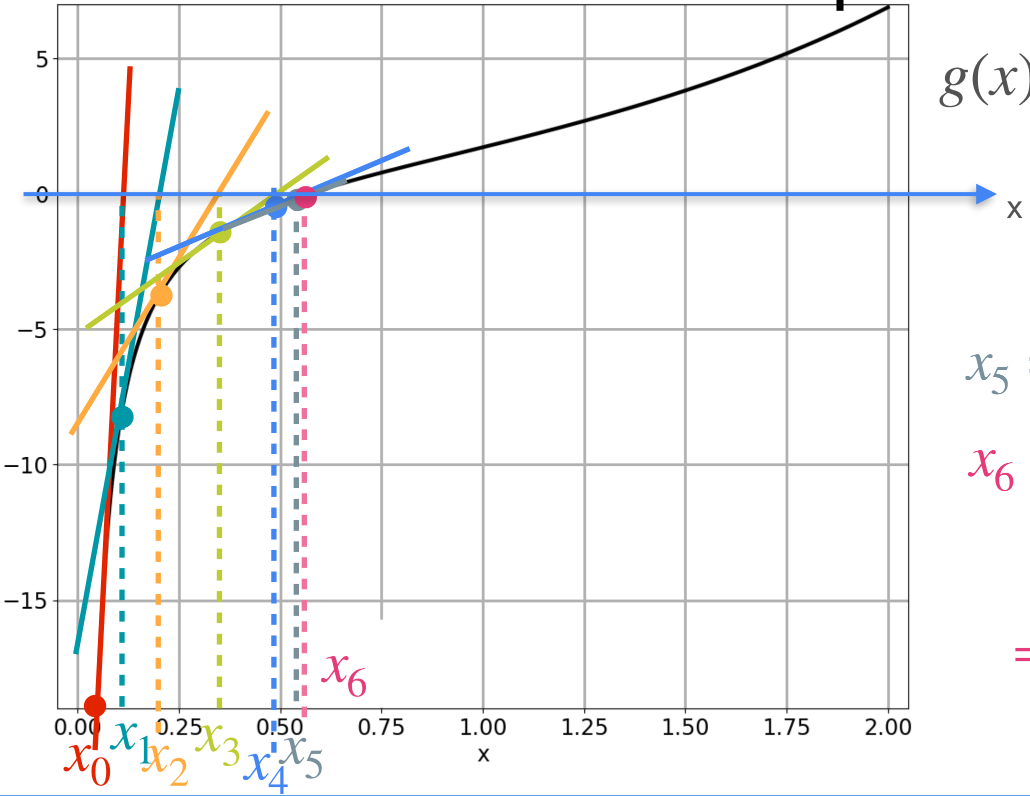
$$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$$

Minimum: $x^* = 0.567$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_5 = 0.558$

Newton's Method for Optimization



$g(x) = e^x - \log(x) \qquad g'(x) = e^x - 1/x$

Minimum: $x^* = 0.567$

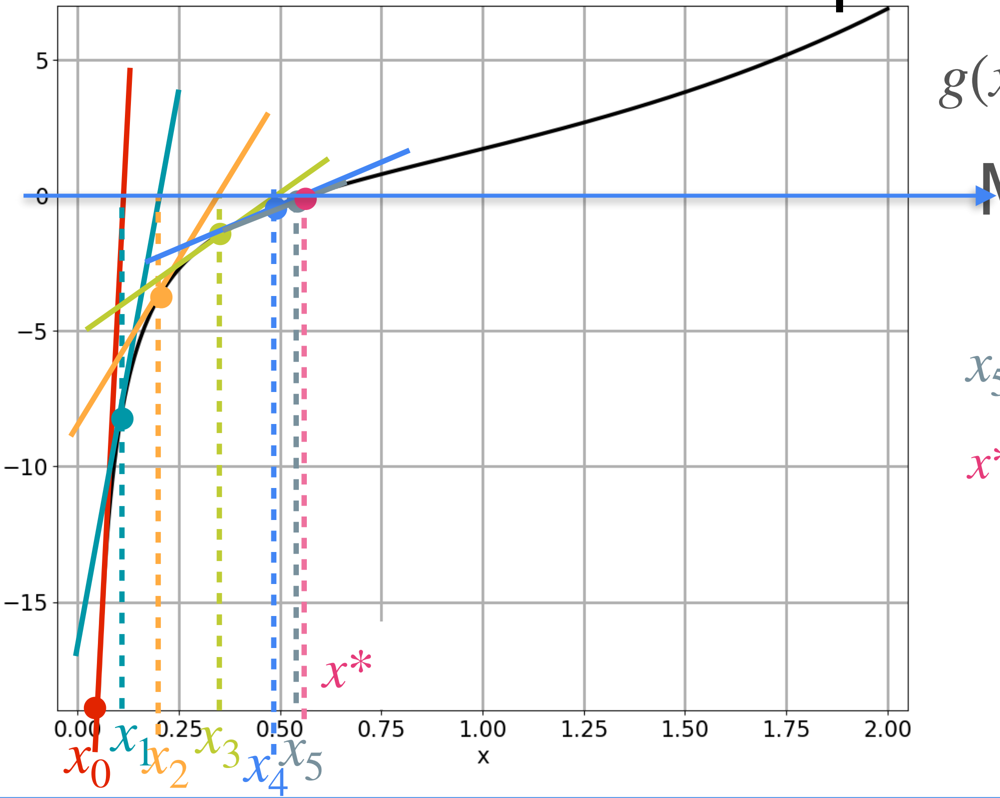
$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_5 = 0.558$

$$x_6 = x_5 - \frac{g'(x_5)}{(g'(x_5))'}$$

$$= 0.558 - \frac{\left(e^{0.558} - \frac{1}{0.558}\right)}{\left(e^{0.558} + \frac{1}{0.558^2}\right)}$$

Newton's Method for Optimization



$g(x) = e^x - \log(x)$ $\quad g'(x) = e^x - 1/x$

Minimum: $x^* = 0.567$

$$(g'(x))' = e^x + \frac{1}{x^2}$$

$x_5 = 0.558$

$$x^* = x_5 - \frac{g'(x_5)}{(g'(x_5))'}$$

$$= 0.558 - \frac{\left(e^{0.558} - \frac{1}{0.558}\right)}{\left(e^{0.558} + \frac{1}{0.558^2}\right)} = 0.567$$

Optimization in Neural Networks and Newton's Method

DeepLearning.AI

The second derivative

Second Derivative

Second Derivative

Newton's method:

Second Derivative

Newton's method: $$x_{k+1} = x_k - \frac{g'(x_k)}{(g'(x_k))'}$$

Second Derivative

Newton's method: $x_{k+1} = x_k - \dfrac{g'(x_k)}{\boxed{(g'(x_k))'}}$??

Second Derivative

Newton's method: $x_{k+1} = x_k - \dfrac{g'(x_k)}{\boxed{(g'(x_k))'}}$??

Second derivative

Second Derivative

Newton's method: $$x_{k+1} = x_k - \frac{g'(x_k)}{\boxed{(g'(x_k))'}}$$??

Second derivative

Leibniz notation: $$\frac{d^2 f(x)}{dx^2} = \frac{d}{dx}\left(\frac{df(x)}{dx}\right)$$

Second Derivative

Newton's method: $$x_{k+1} = x_k - \frac{g'(x_k)}{\boxed{(g'(x_k))'}}\ ??$$

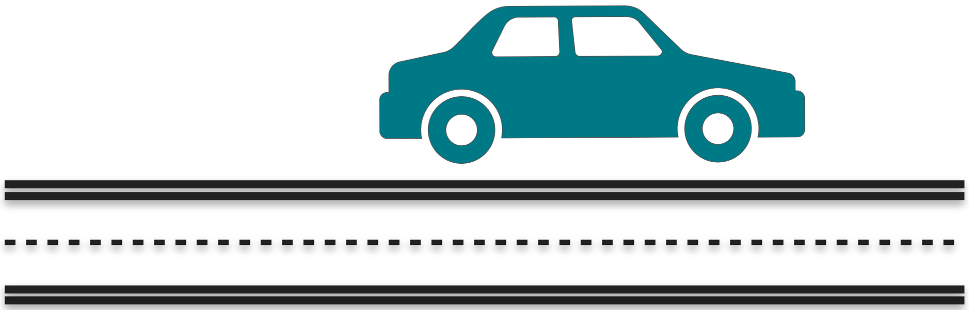
Second derivative

Leibniz notation: $$\frac{d^2 f(x)}{dx^2} = \frac{d}{dx}\left(\frac{df(x)}{dx}\right)$$

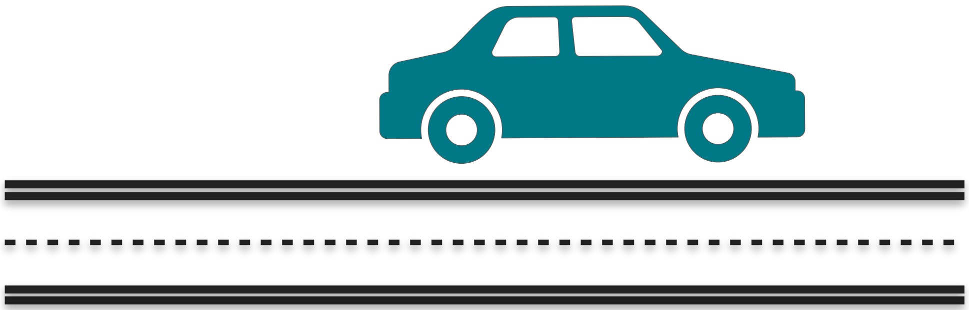
Lagrange notation: $f''(x)$

Understanding Second Derivative

Understanding Second Derivative

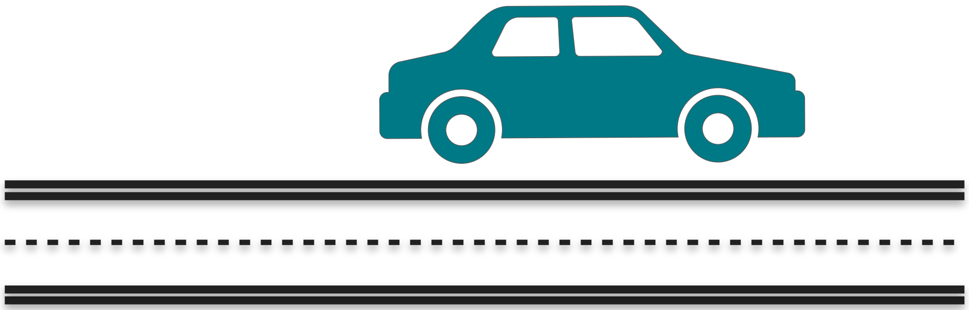


Understanding Second Derivative



x Distance

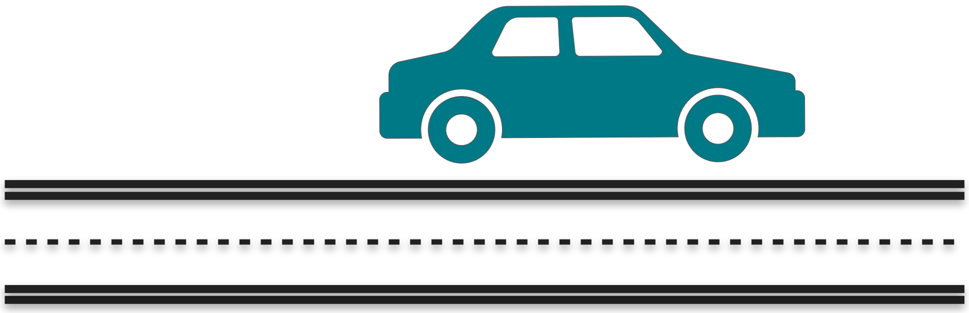
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

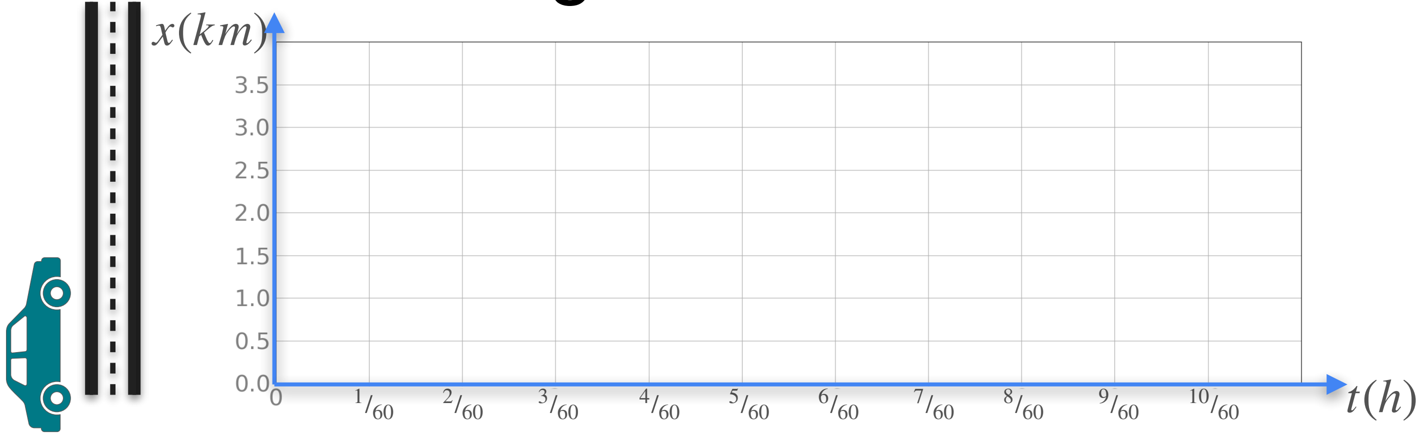
Understanding Second Derivative



x	Distance	
v	Velocity	$\frac{dx}{dt}$
a	Acceleration	$\frac{dv}{dt} = \frac{d^2x}{dt^2}$

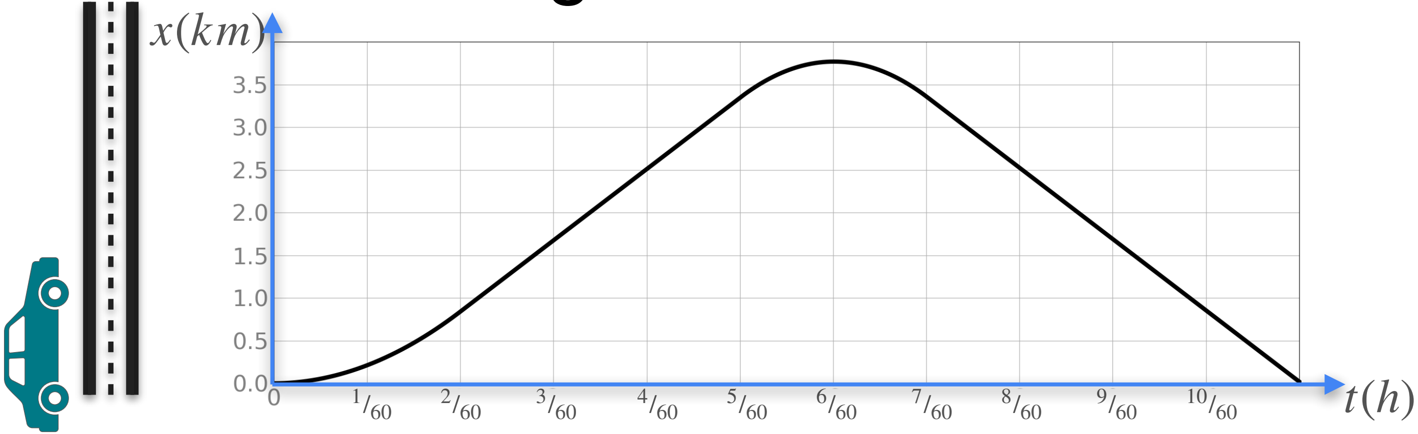
Understanding Second Derivative

Understanding Second Derivative



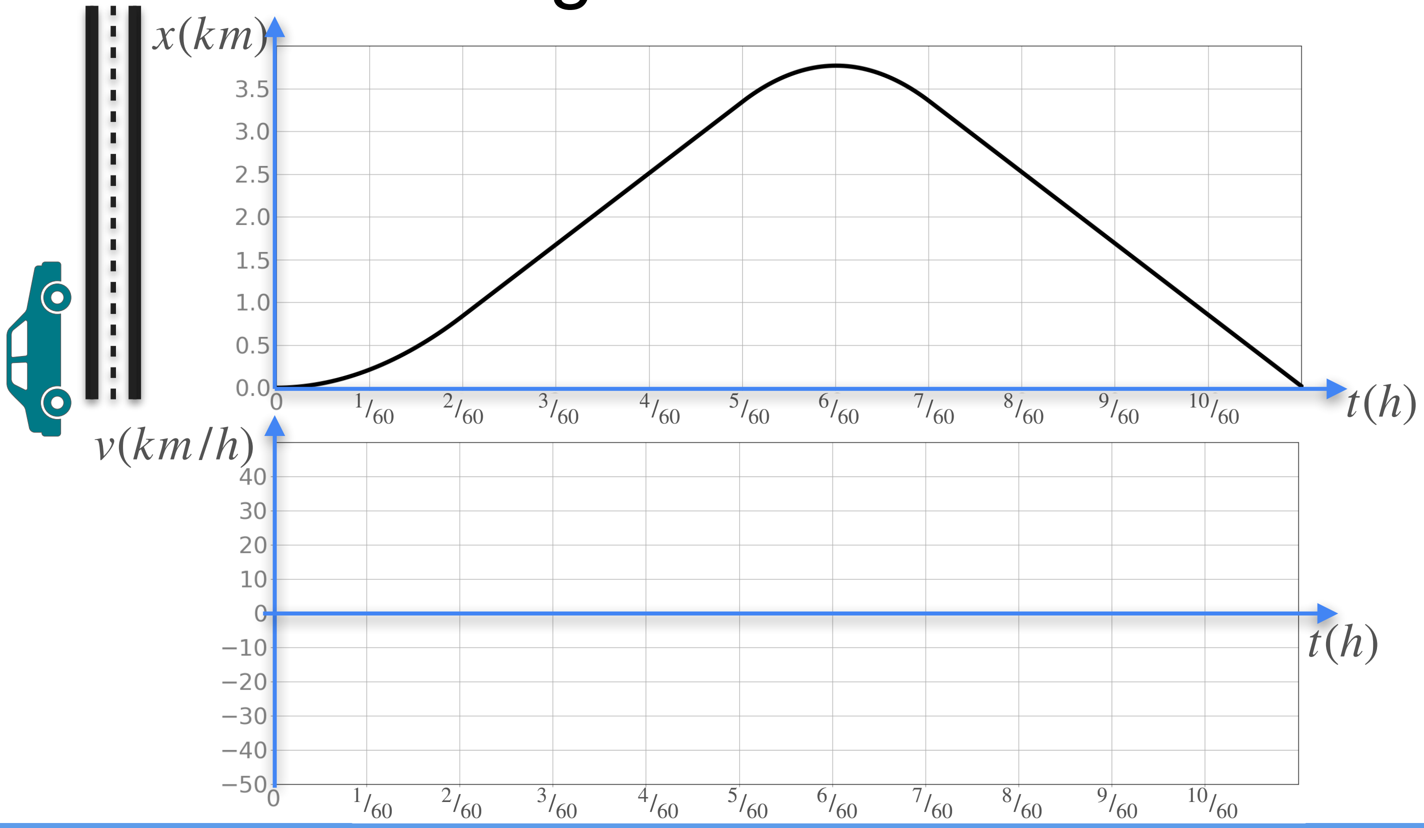
x Distance

Understanding Second Derivative



x Distance

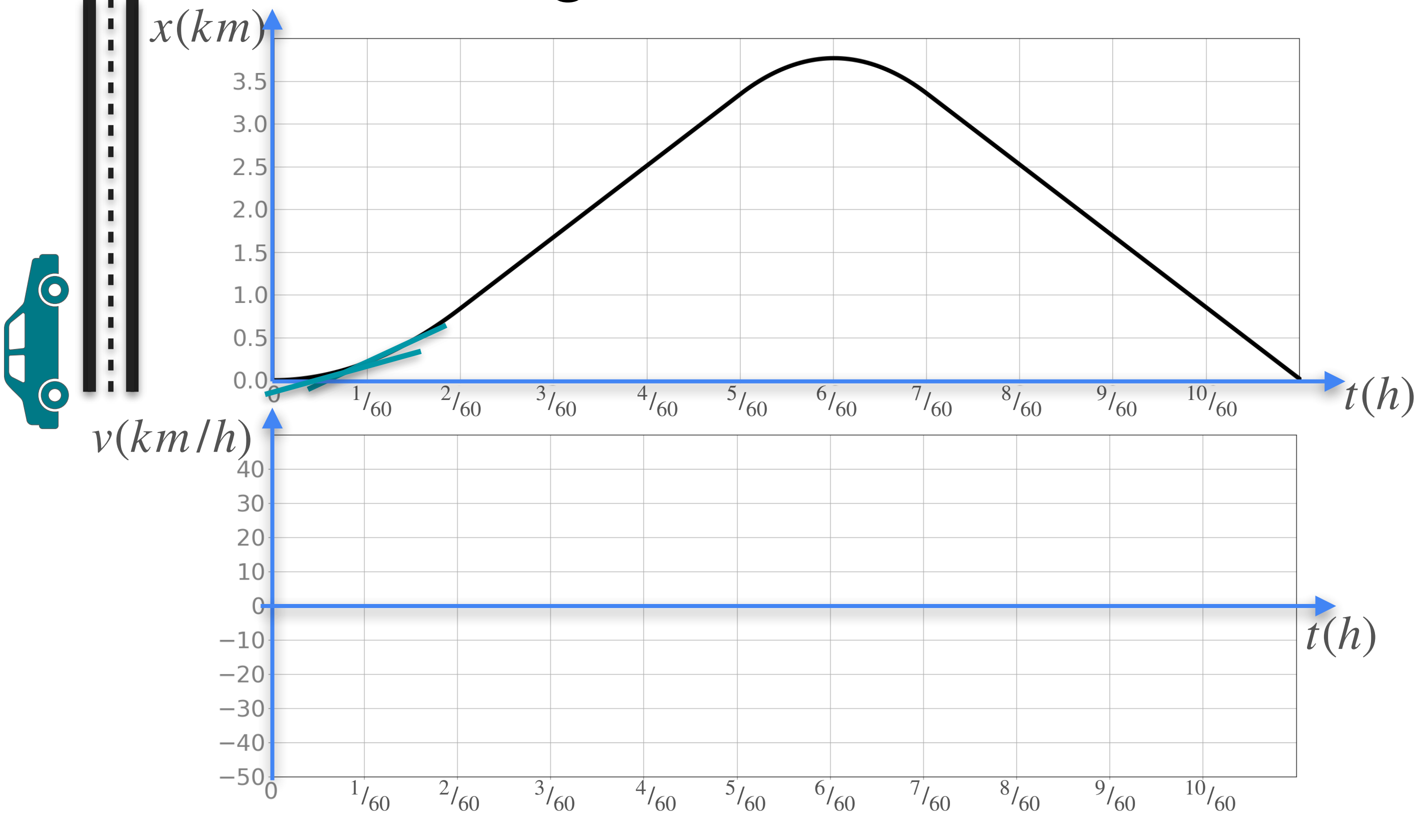
Understanding Second Derivative



x Distance

v Velocity $\dfrac{dx}{dt}$

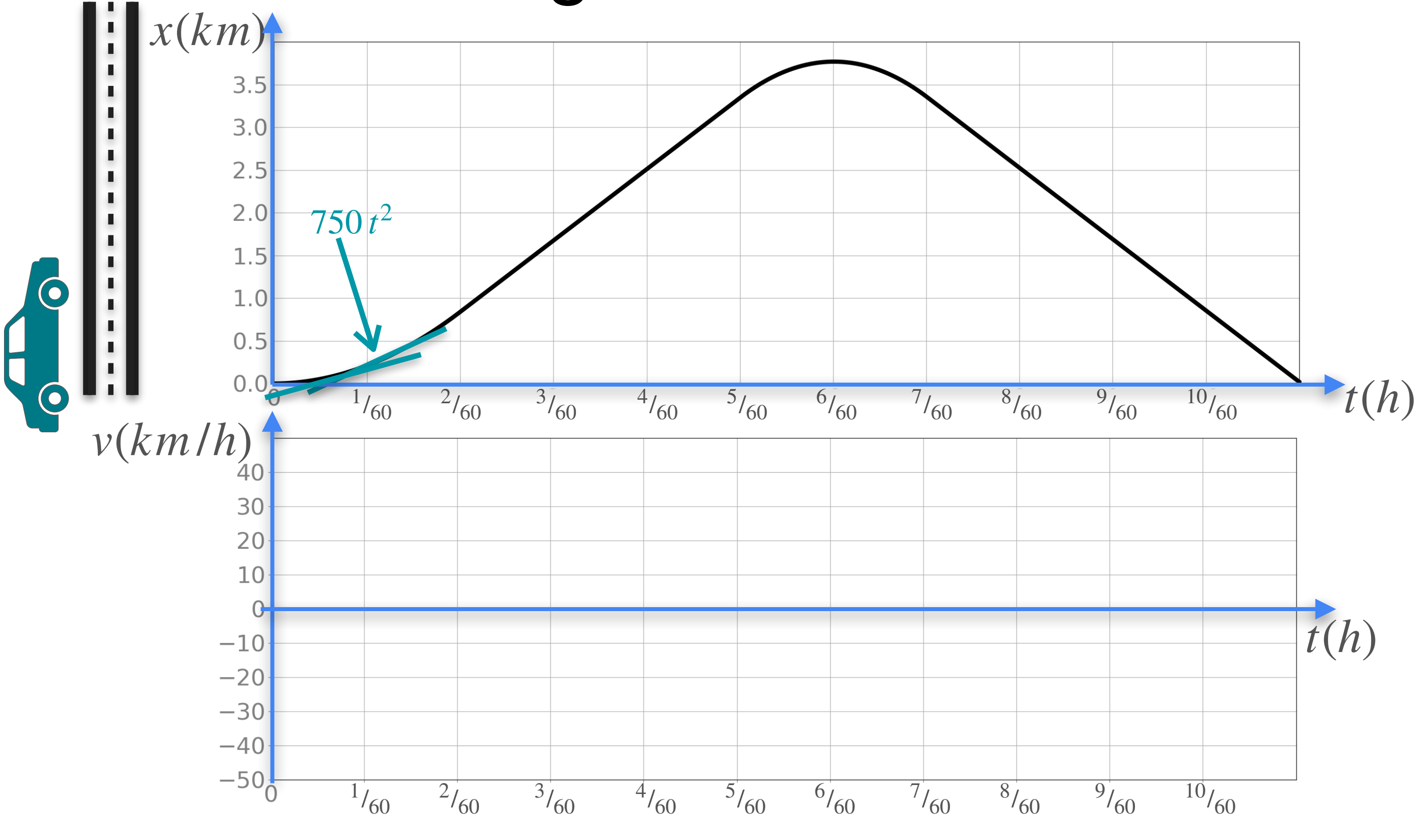
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

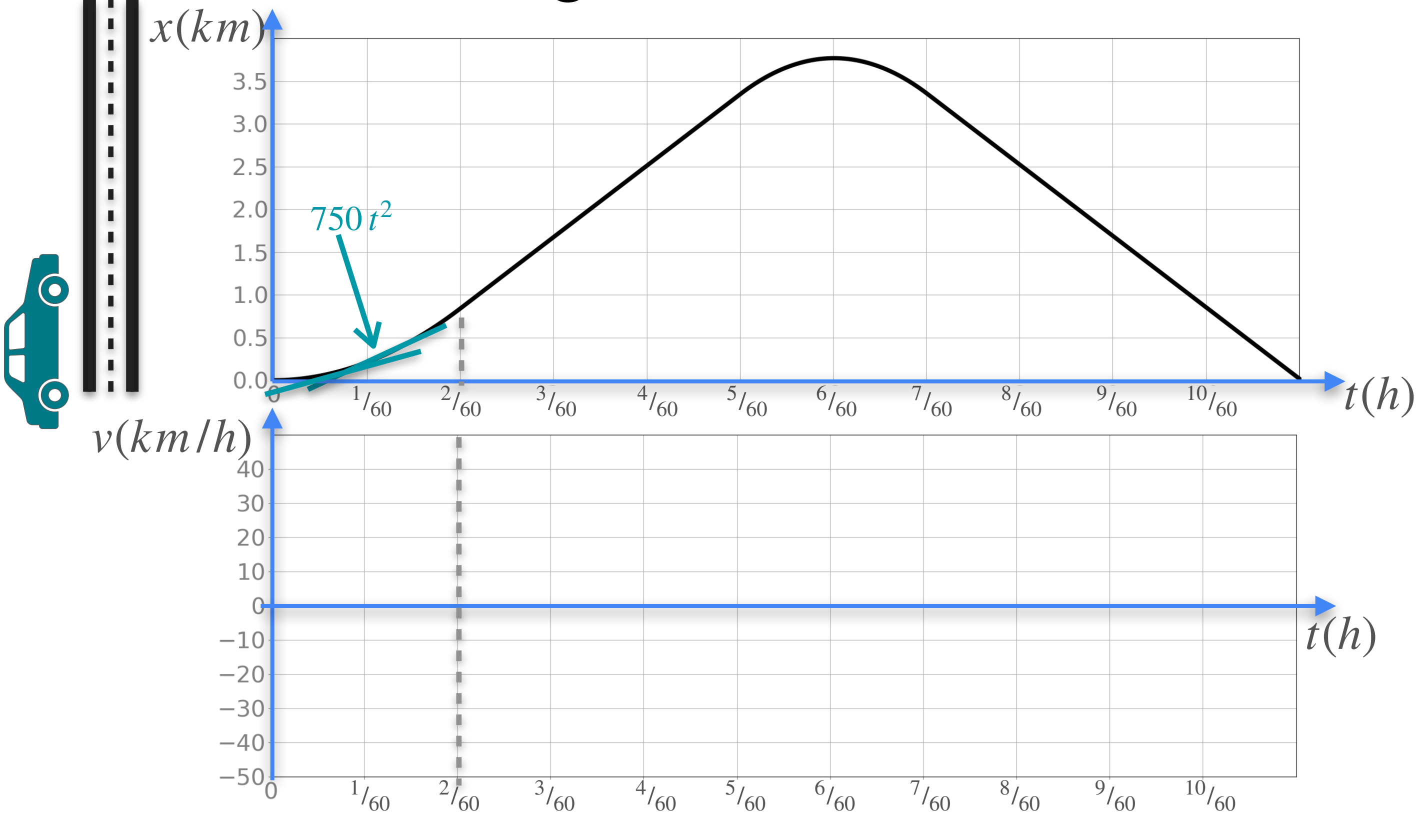
Understanding Second Derivative



x Distance

v Velocity $\dfrac{dx}{dt}$

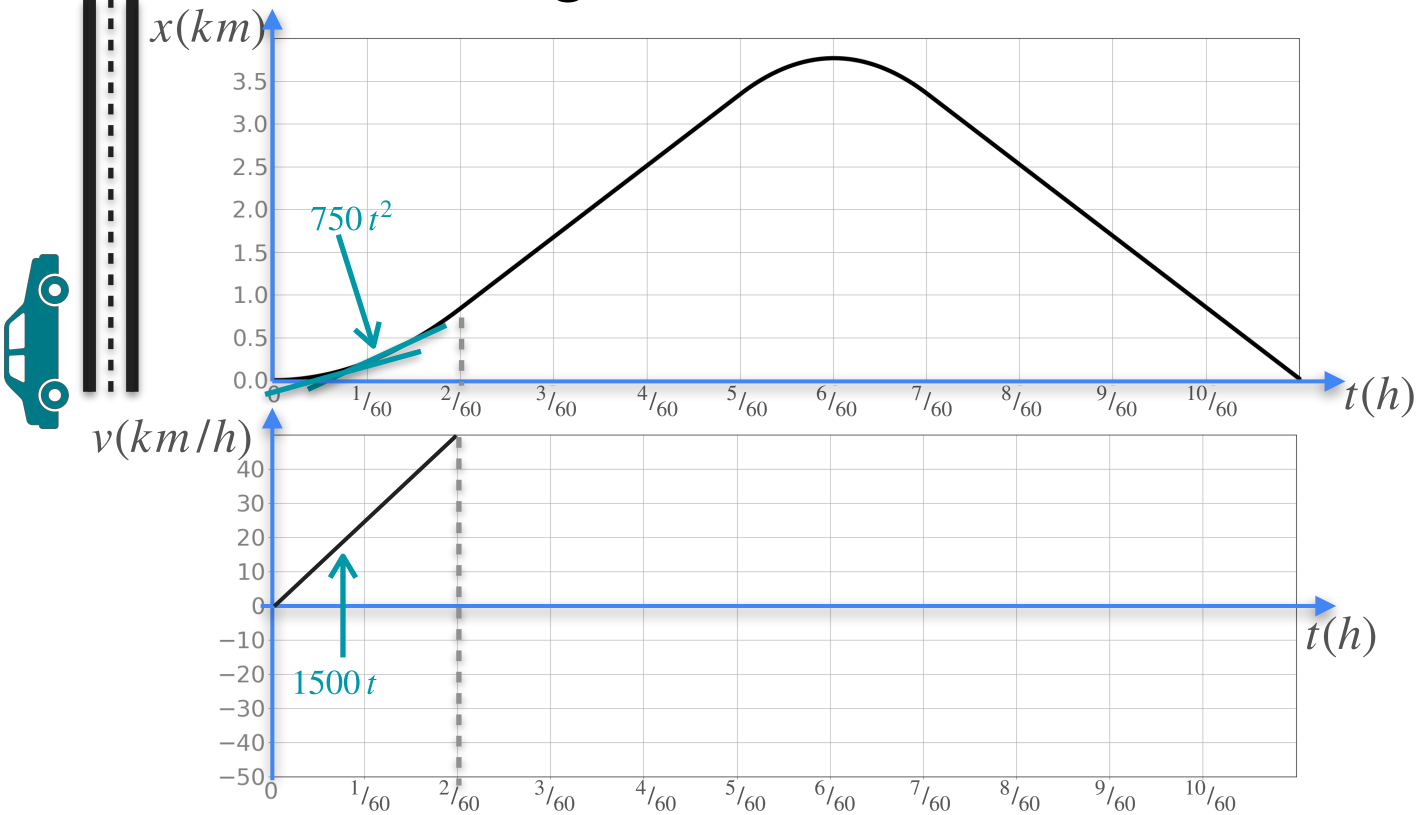
Understanding Second Derivative



x Distance

v Velocity $\dfrac{dx}{dt}$

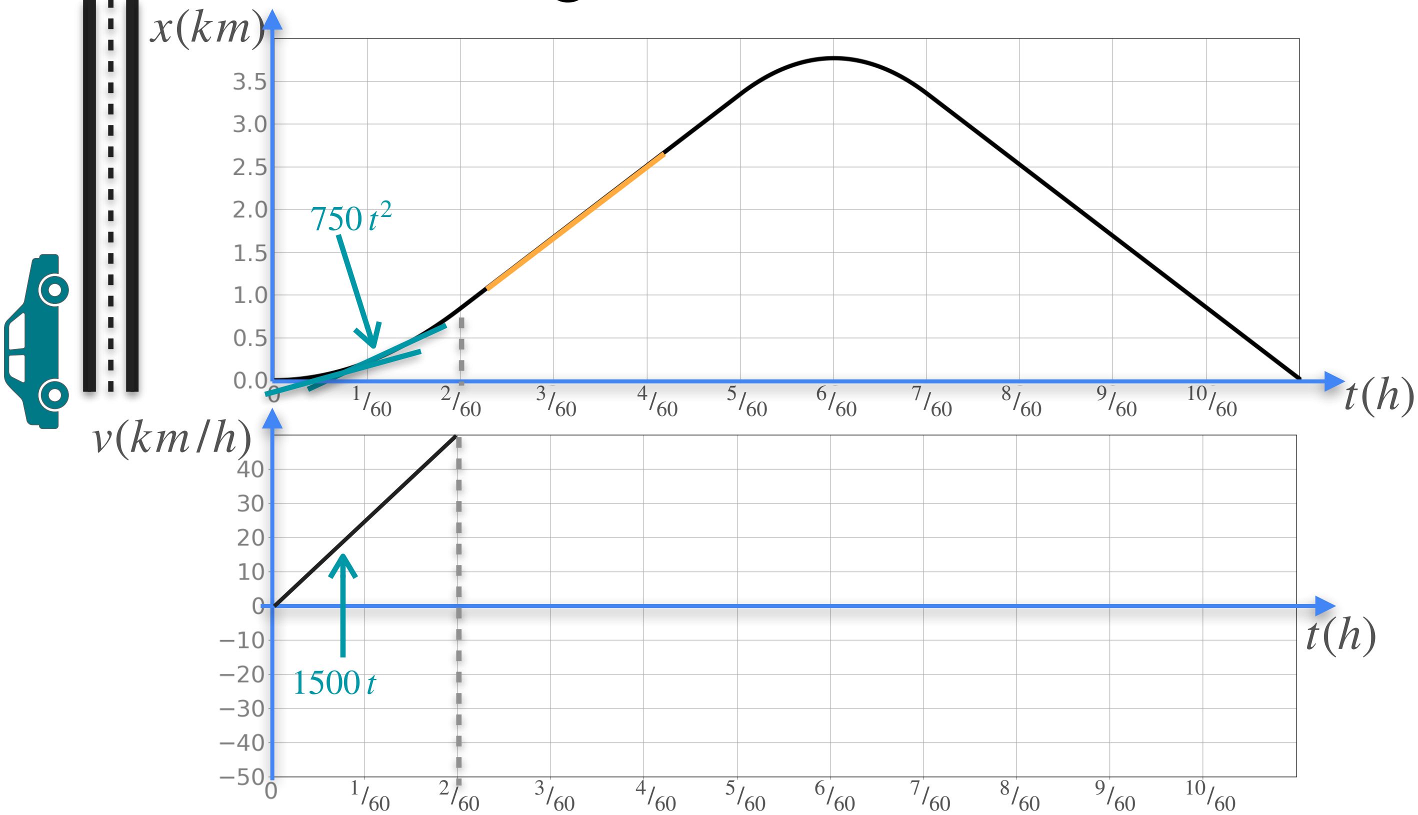
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

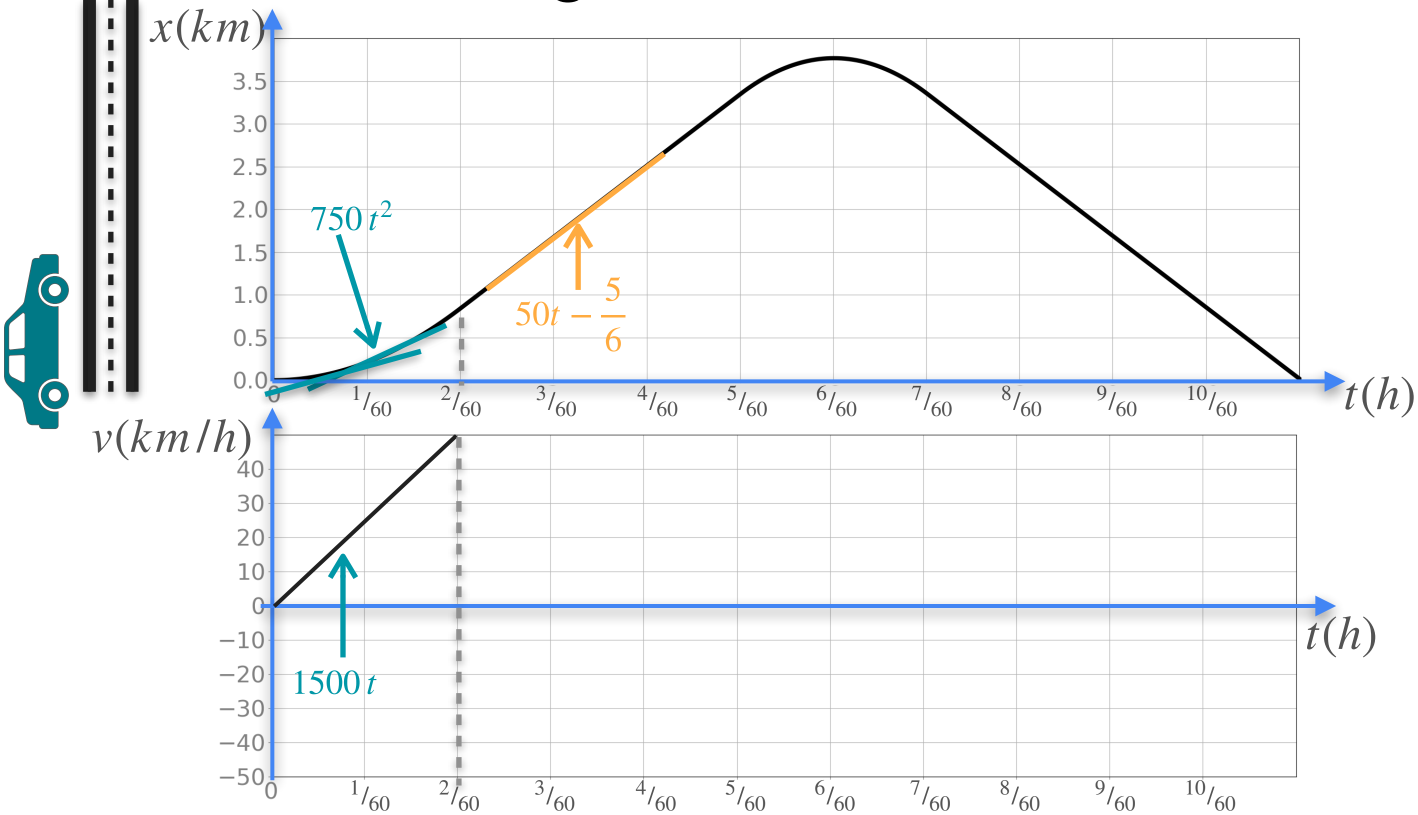
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

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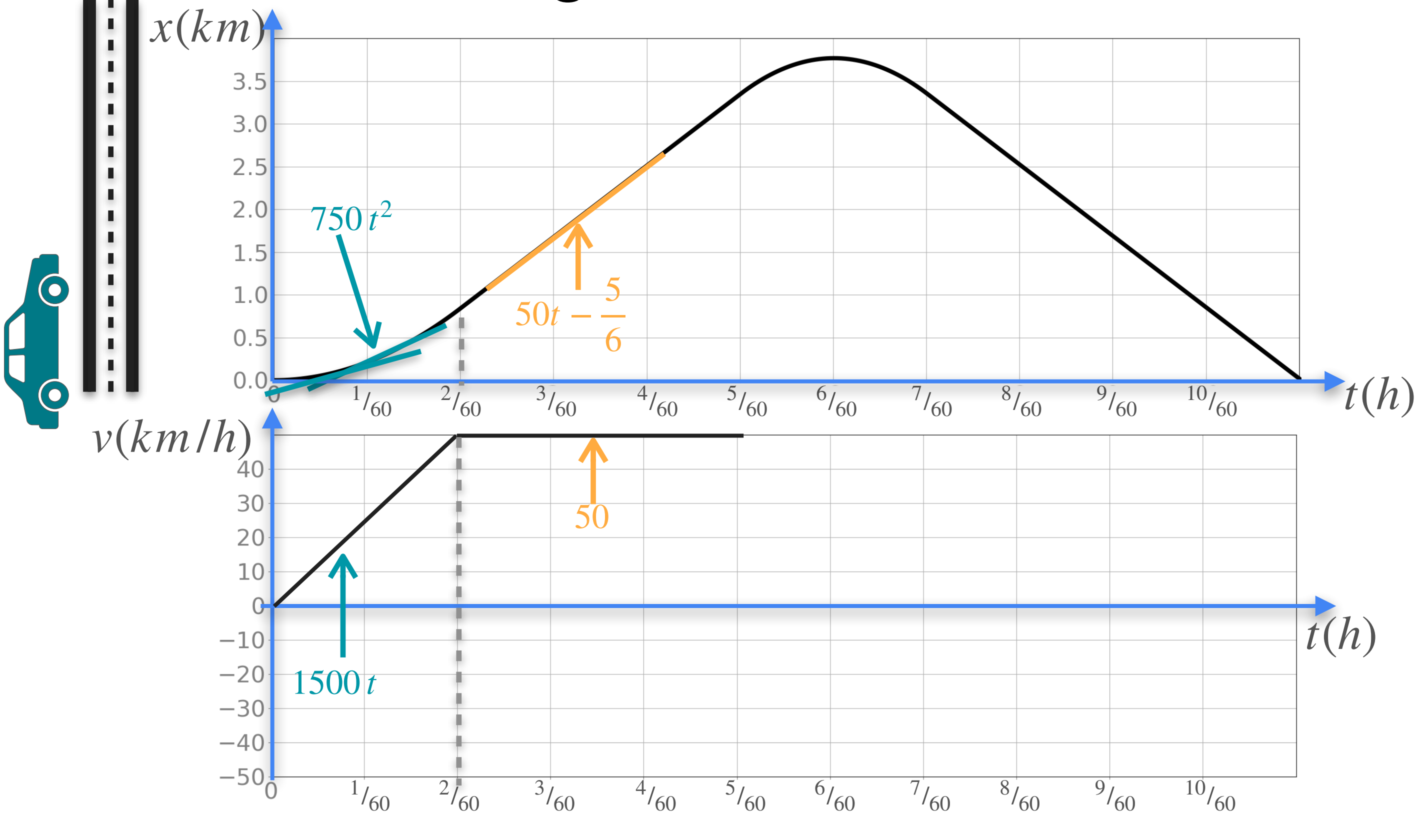
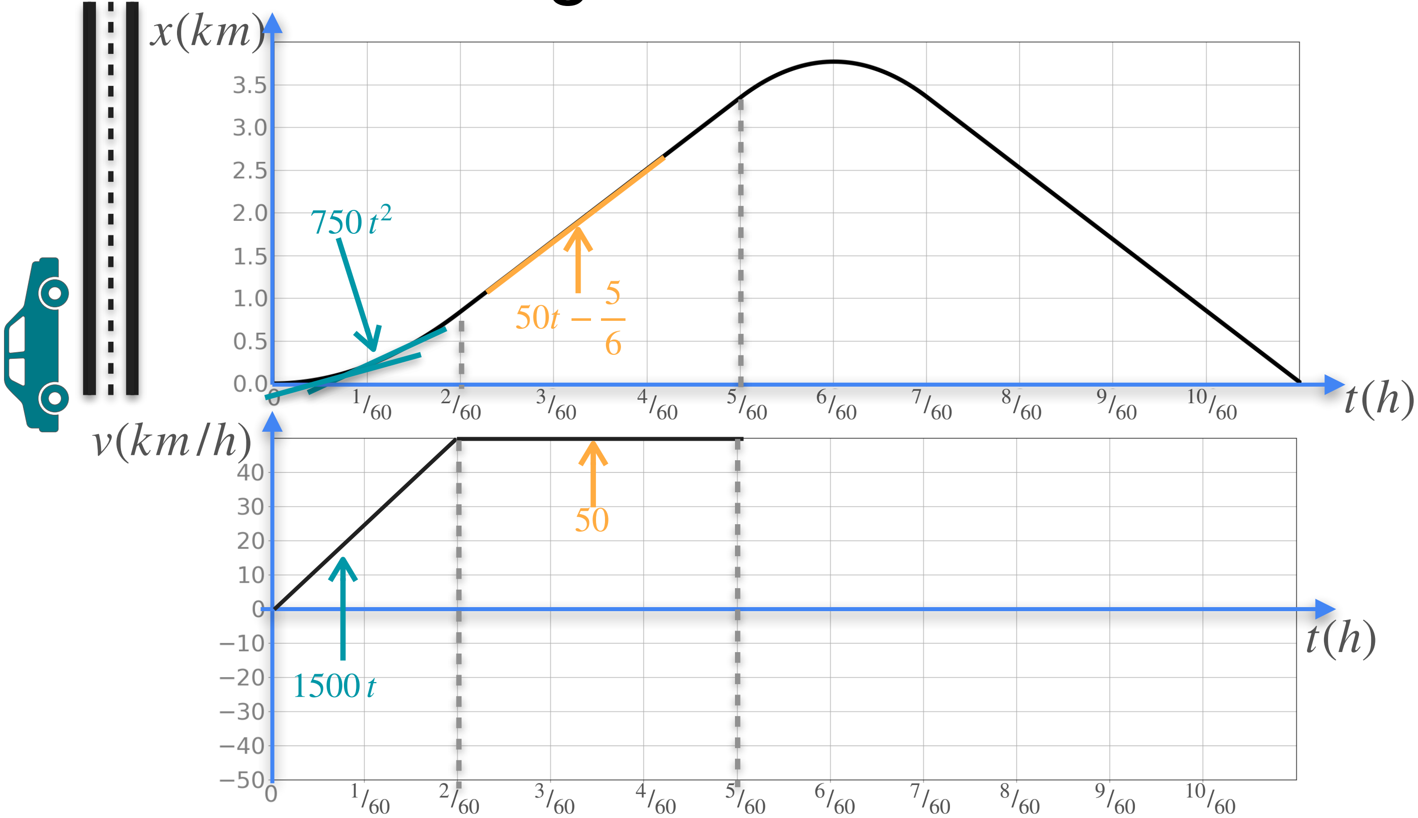
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

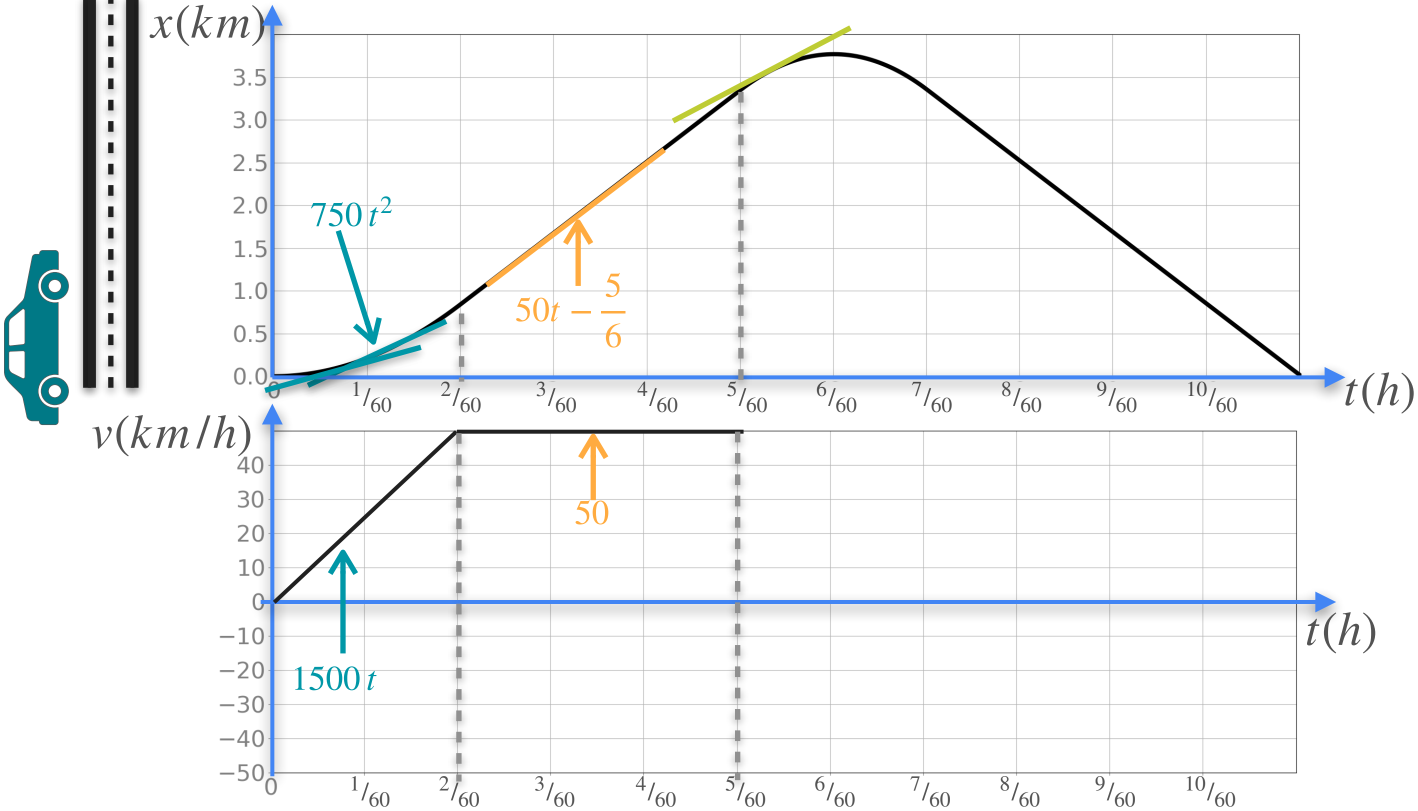
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

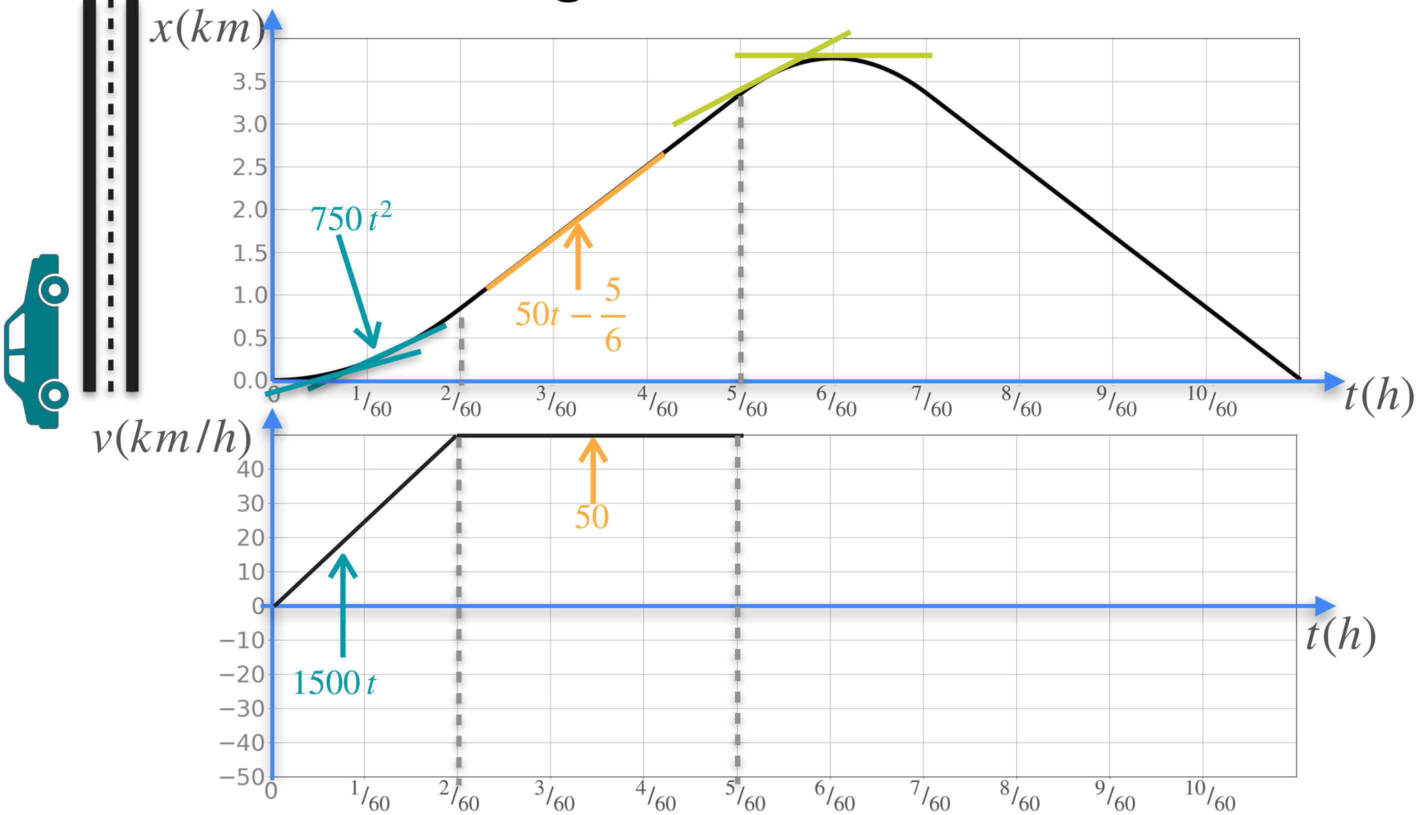
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

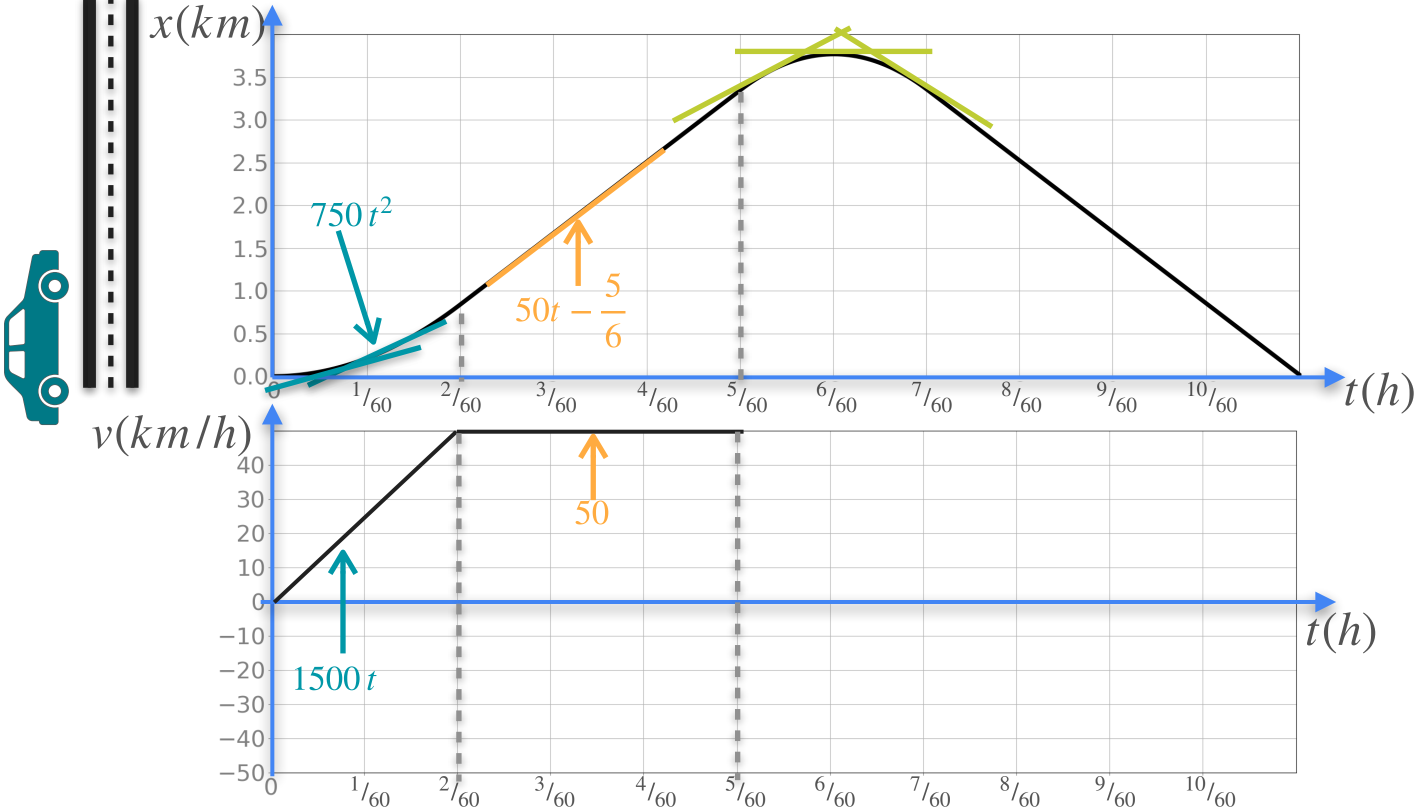
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

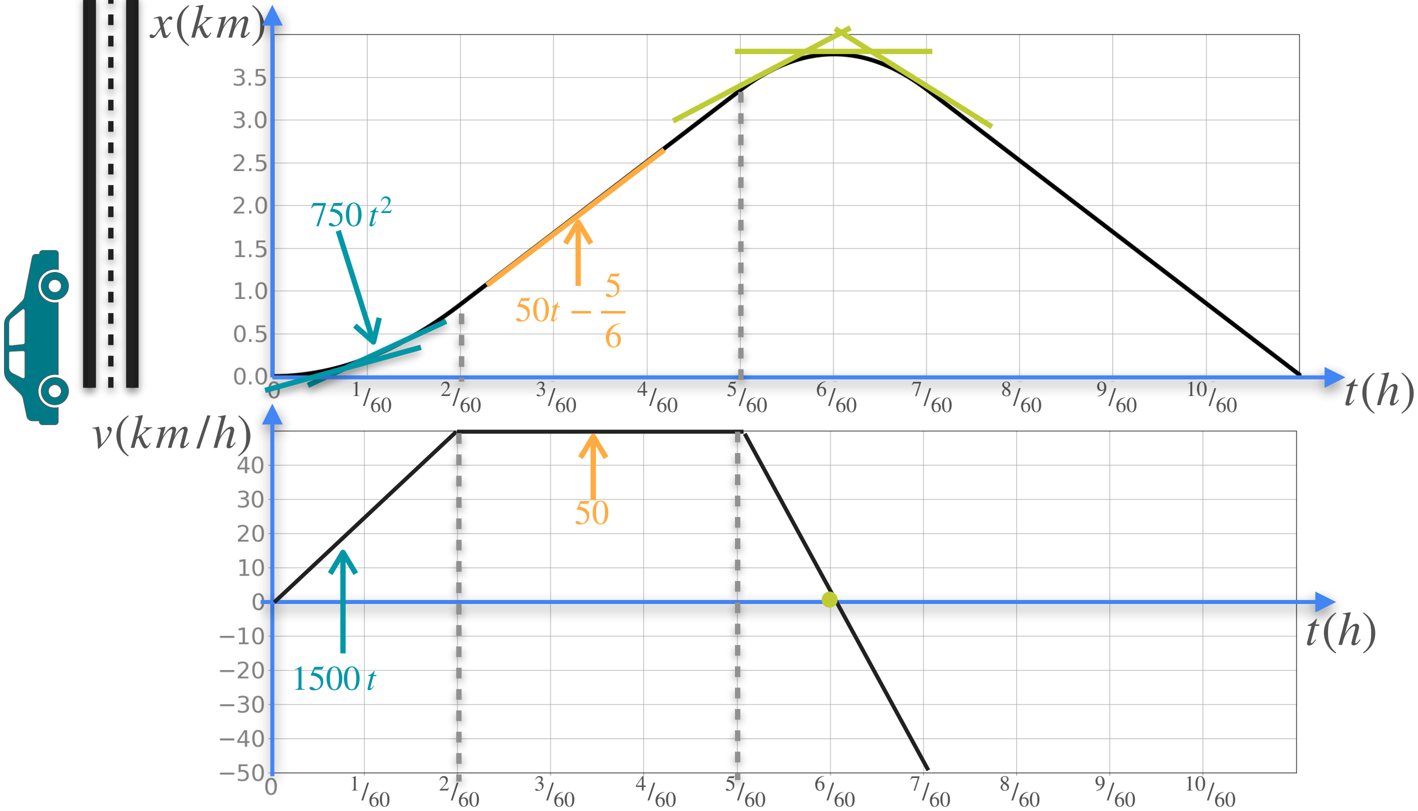
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

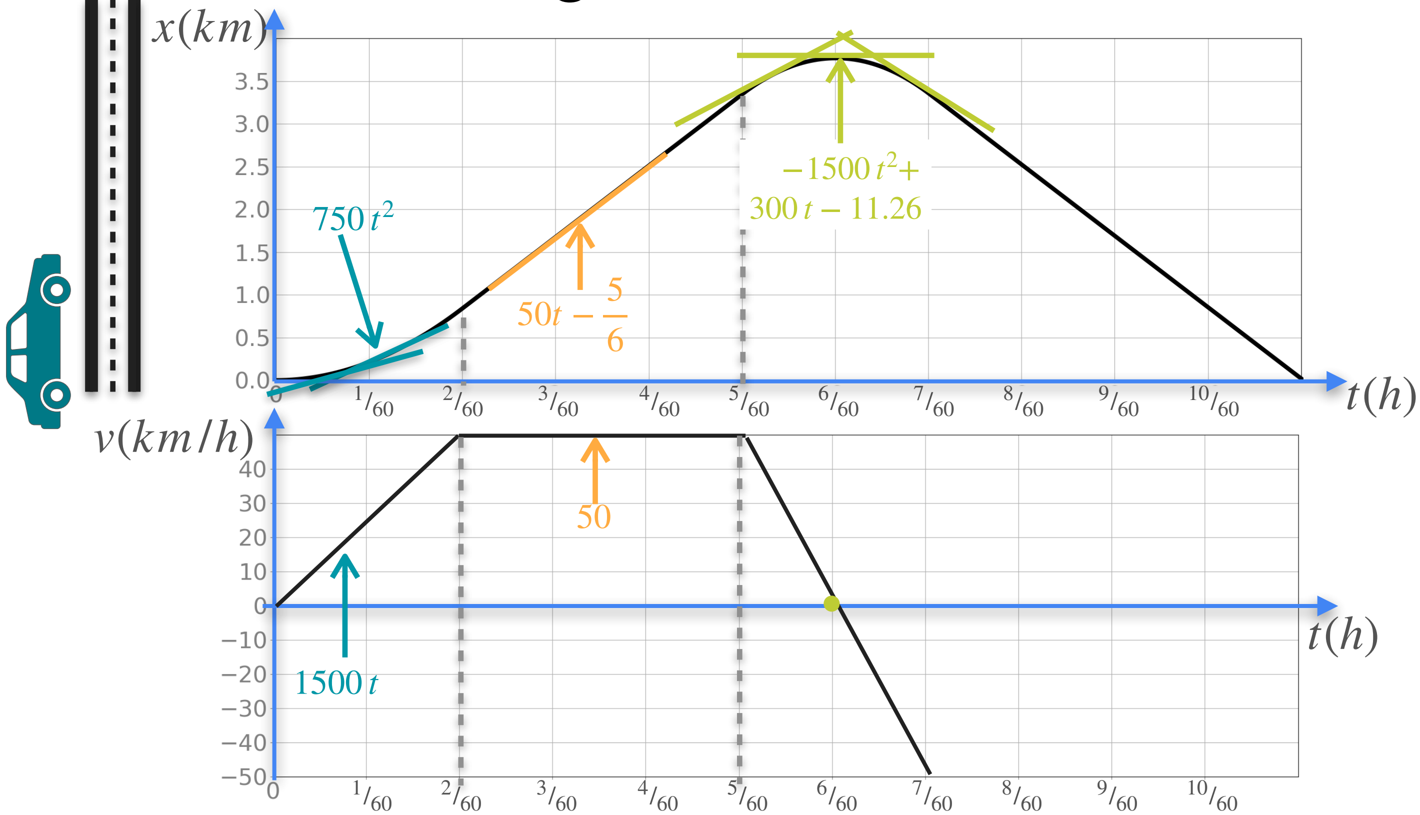
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

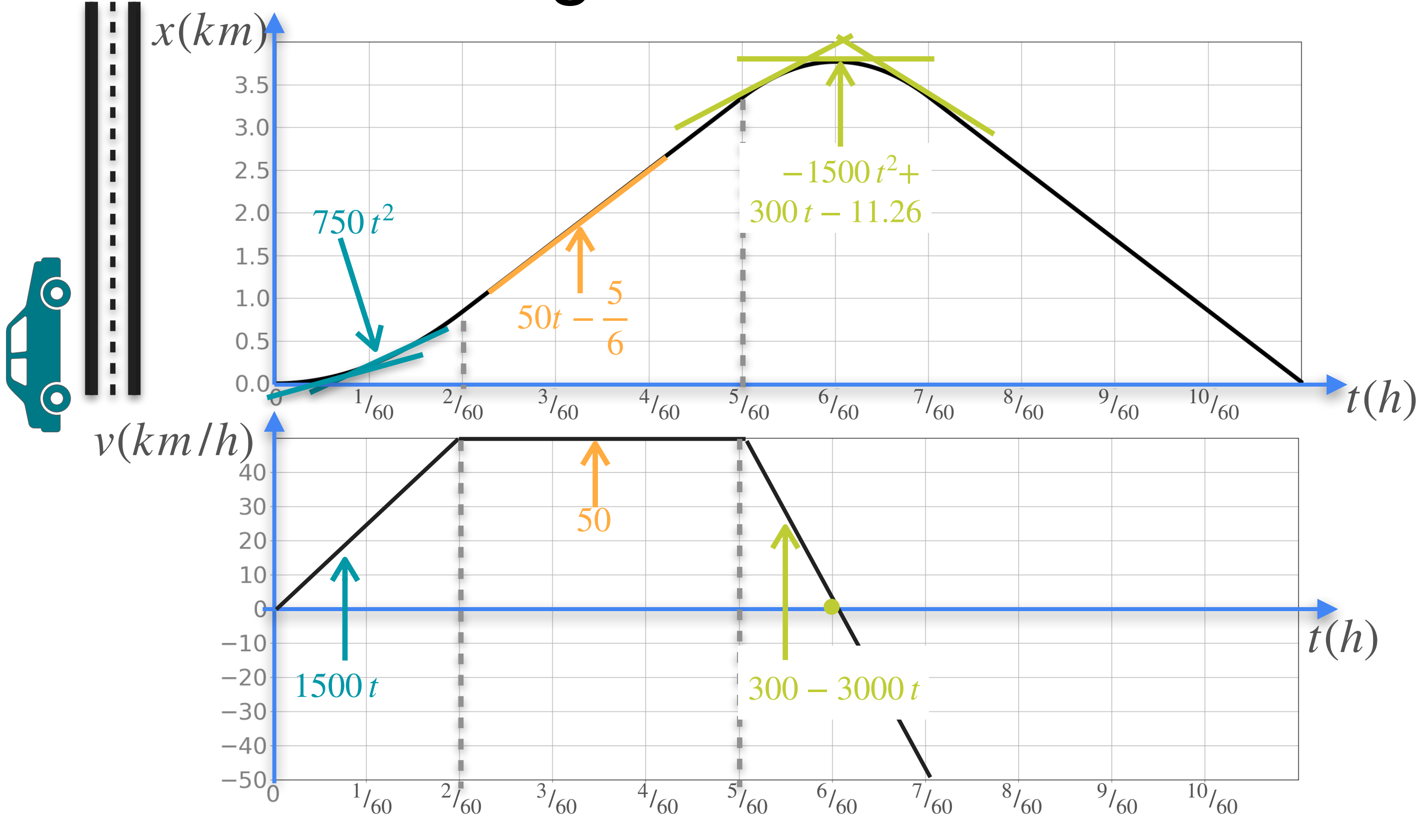
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

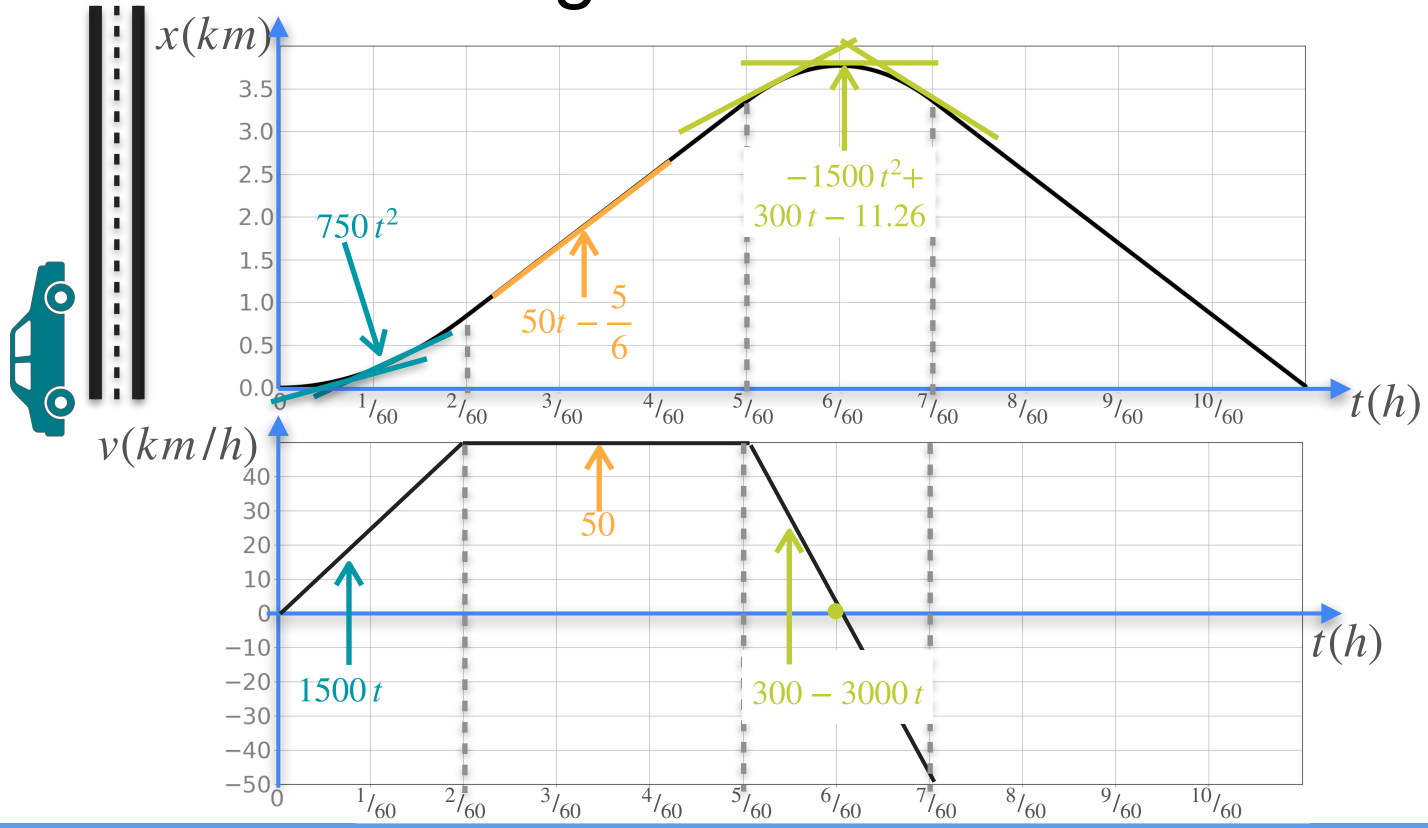
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

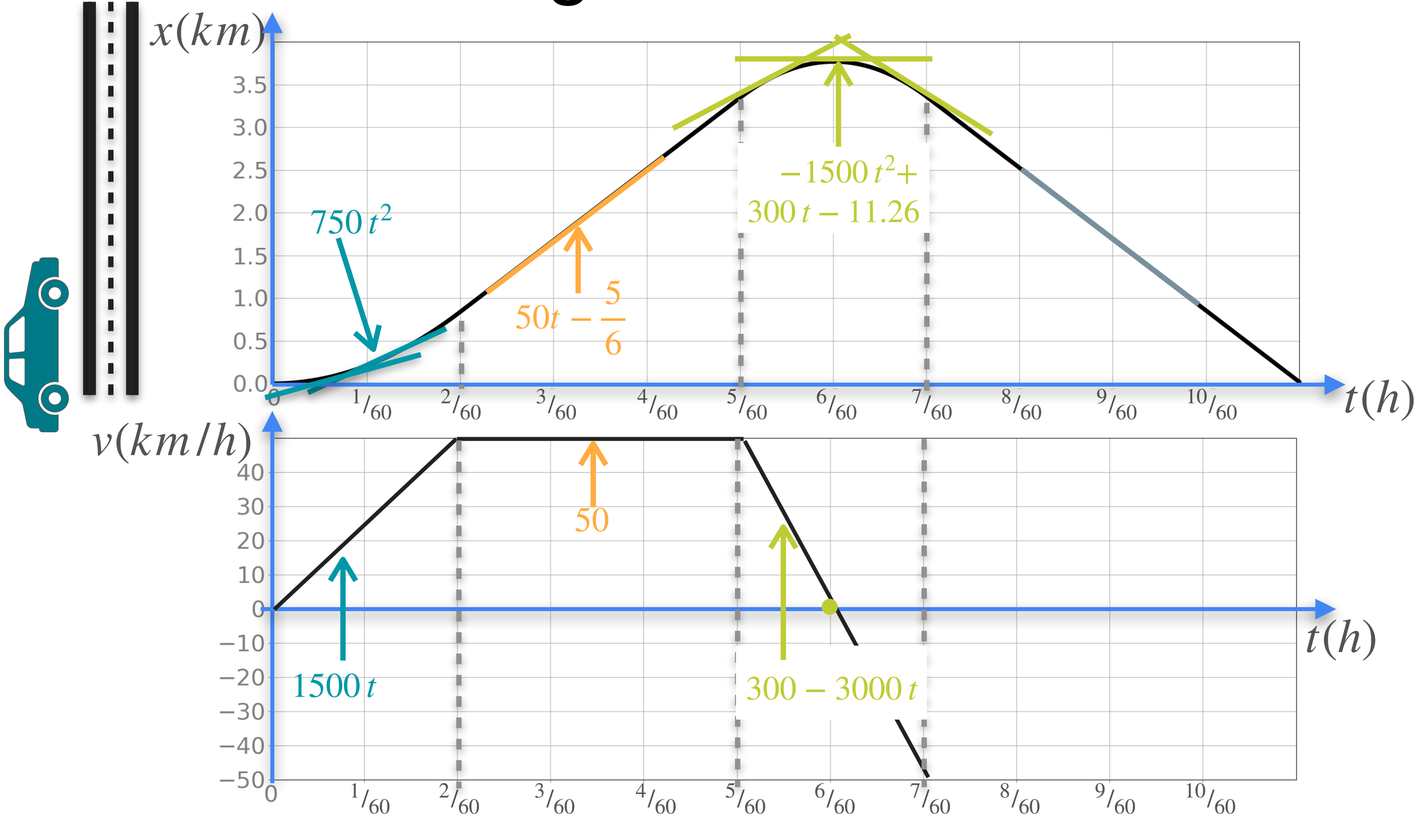
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

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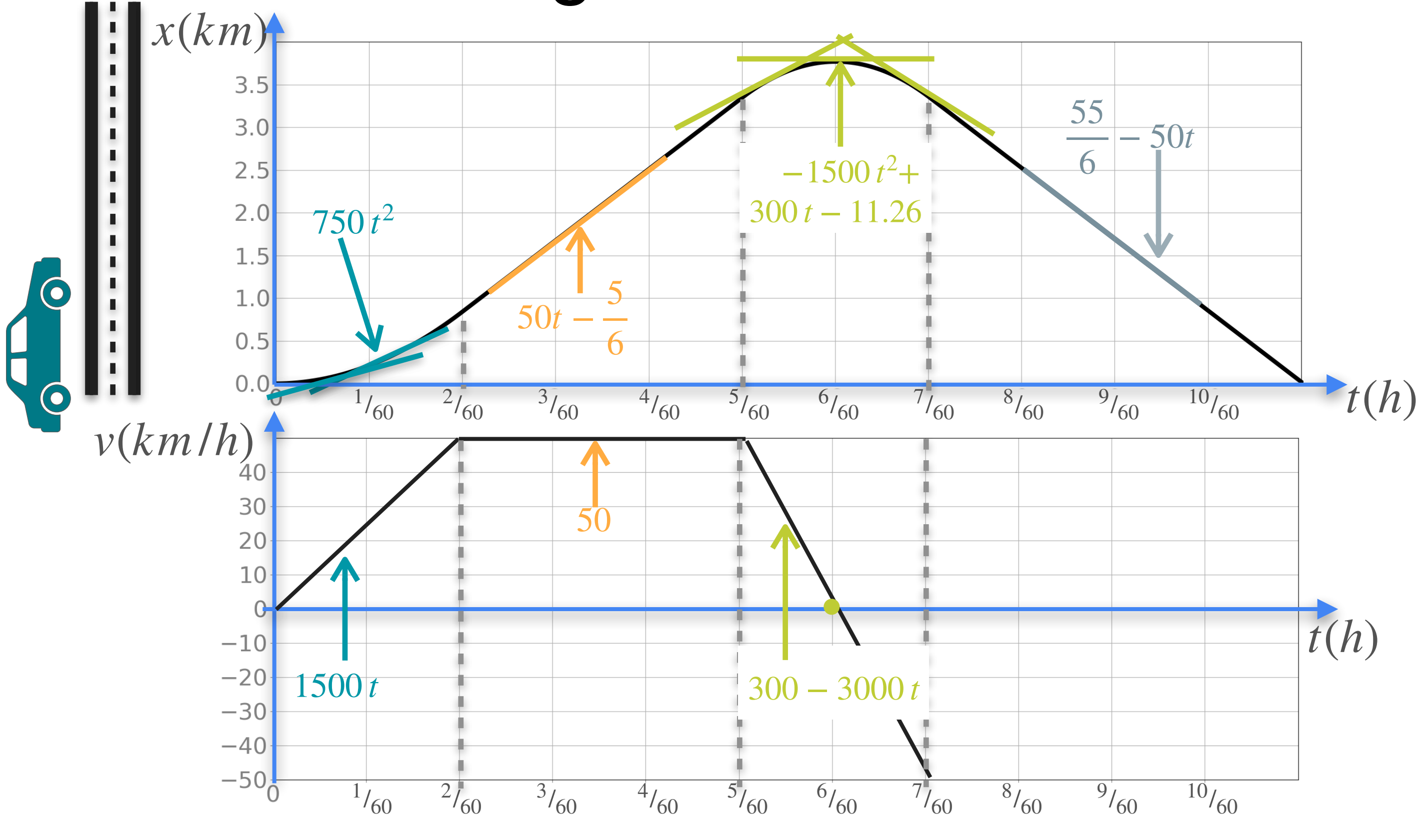
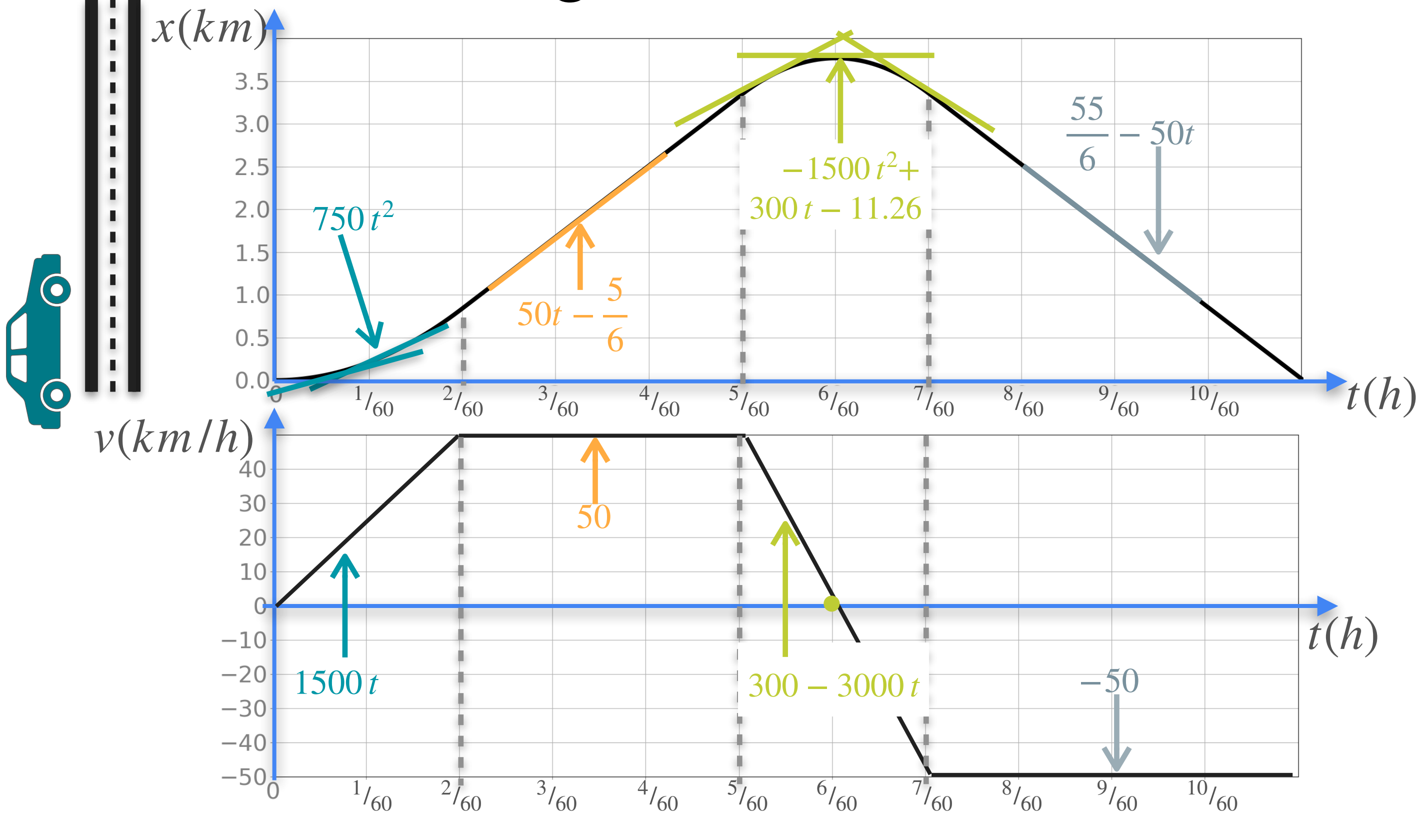
Understanding Second Derivative



x Distance

v Velocity $\frac{dx}{dt}$

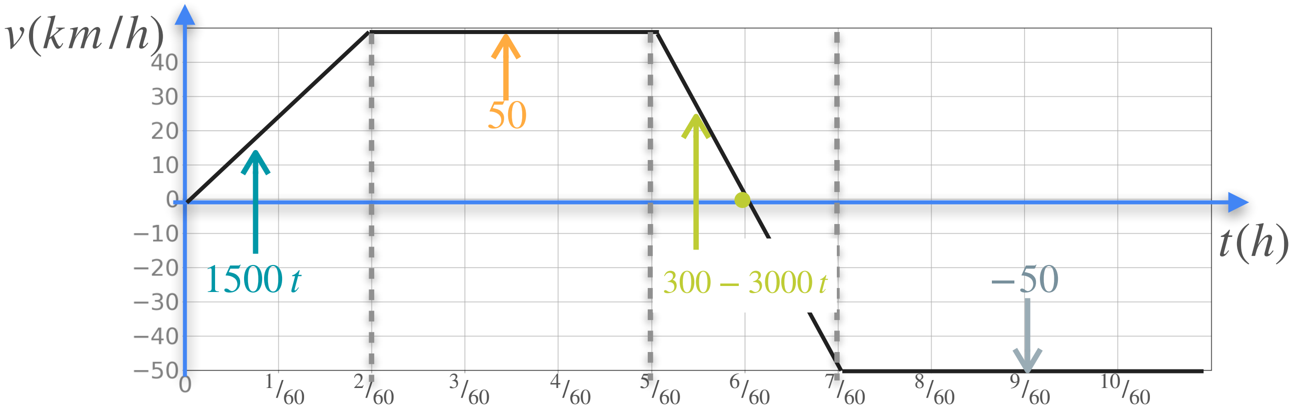
Understanding Second Derivative



x Distance

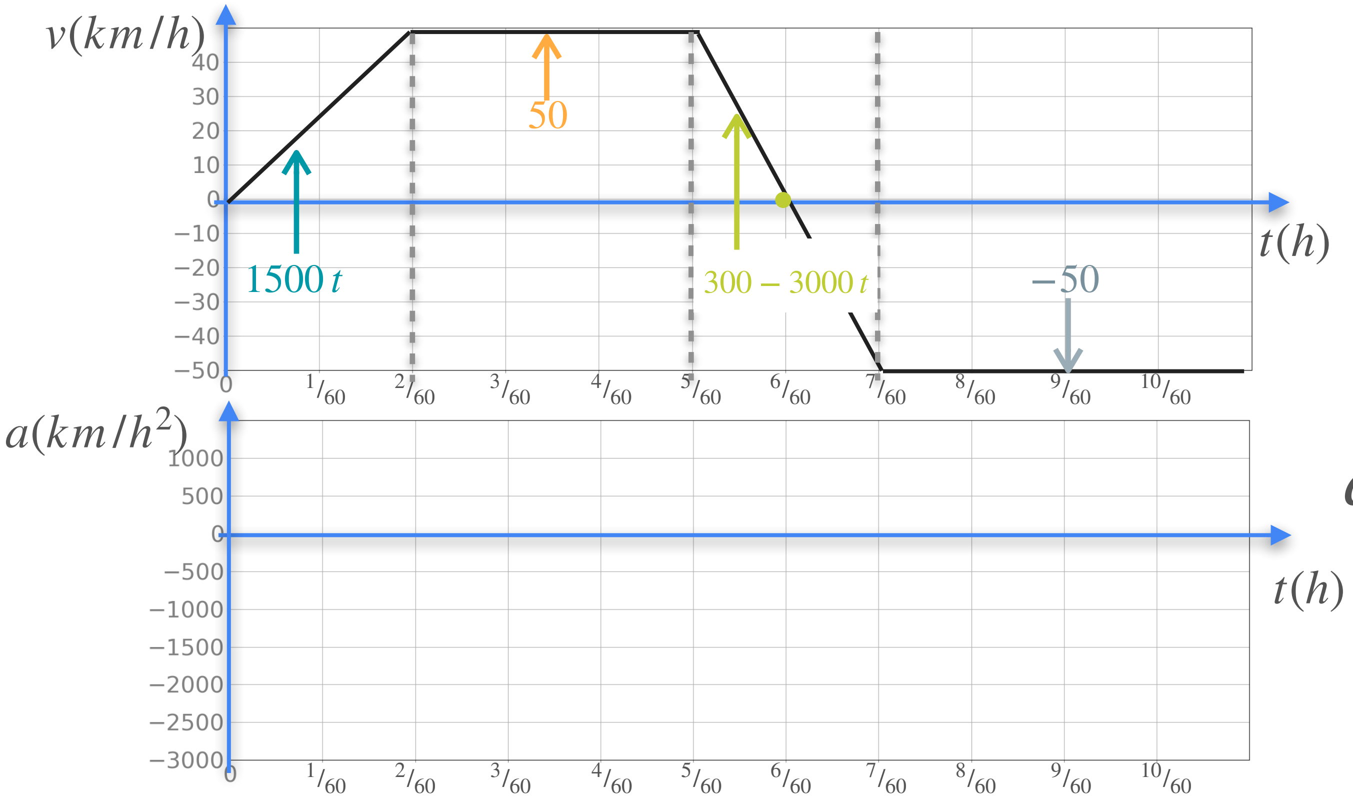
v Velocity $\frac{dx}{dt}$

Understanding Second Derivative



v Velocity $\frac{dx}{dt}$

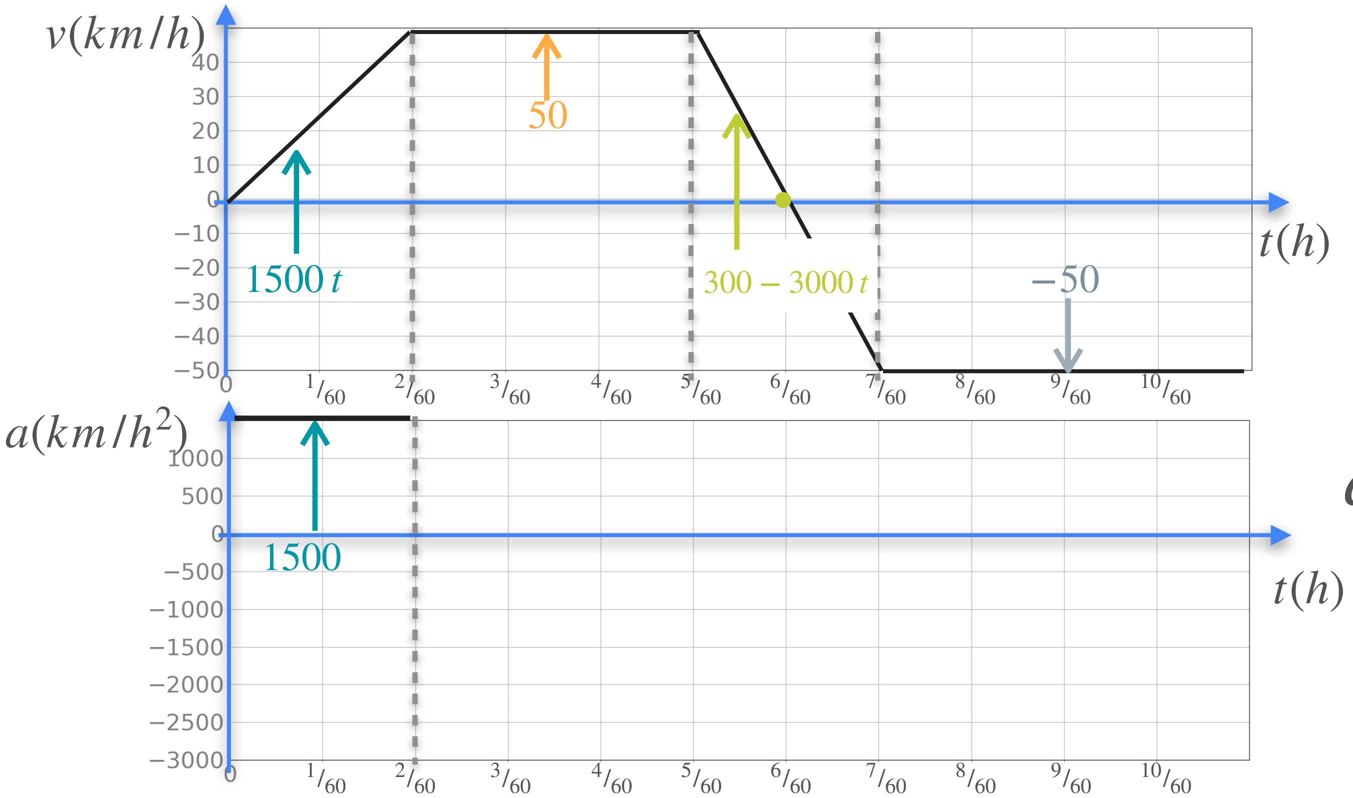
Understanding Second Derivative



v Velocity $\dfrac{dx}{dt}$

a Acceleration $\dfrac{dv}{dt}$

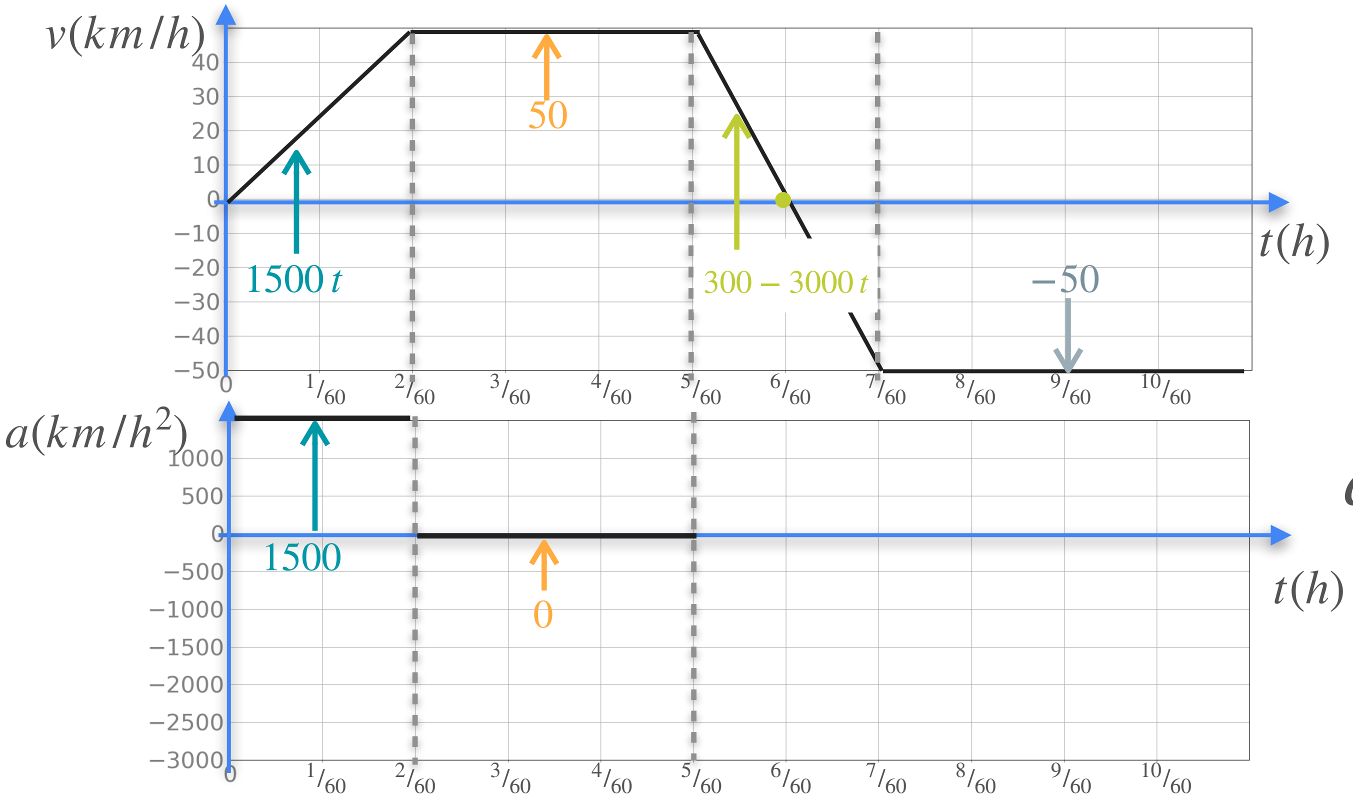
Understanding Second Derivative



v Velocity $\dfrac{dx}{dt}$

a Acceleration $\dfrac{dv}{dt}$

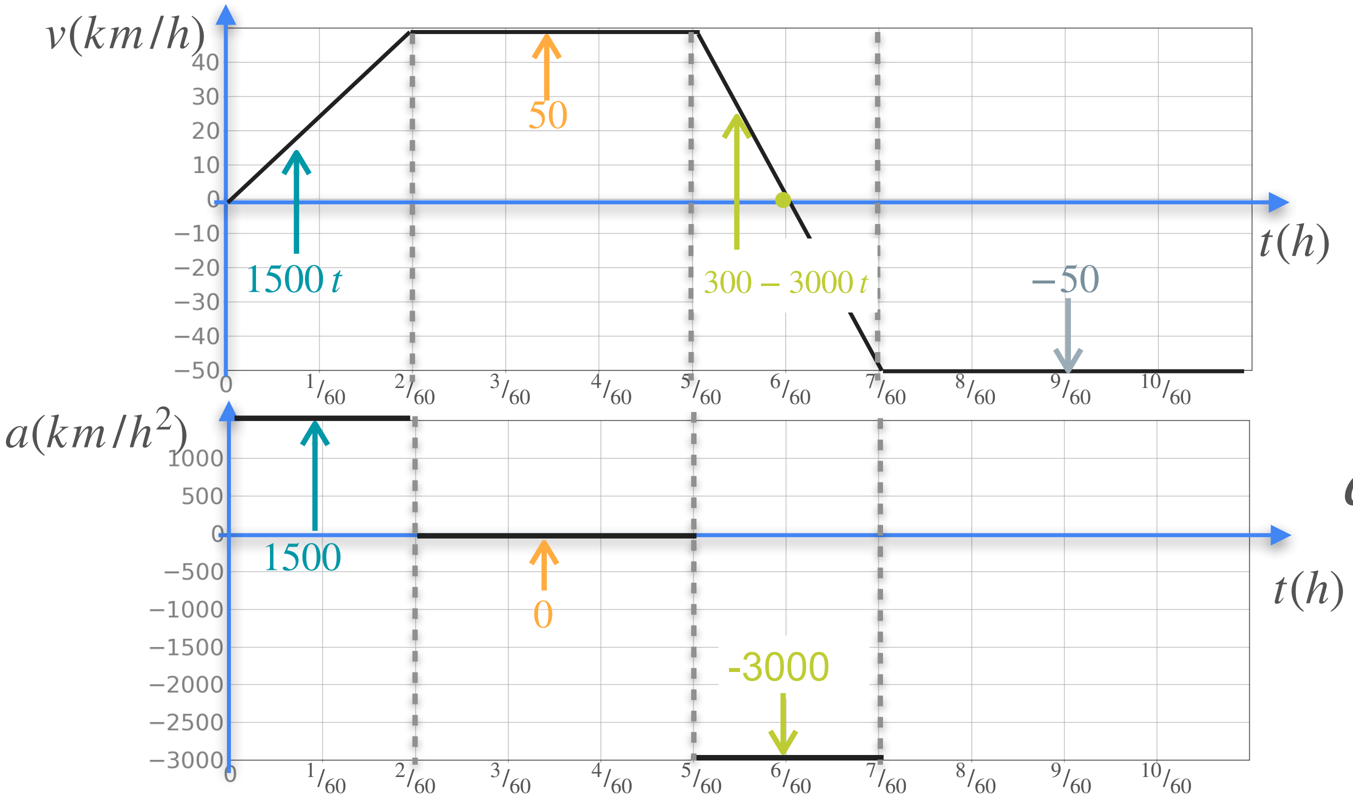
Understanding Second Derivative



v Velocity $\frac{dx}{dt}$

a Acceleration $\frac{dv}{dt}$

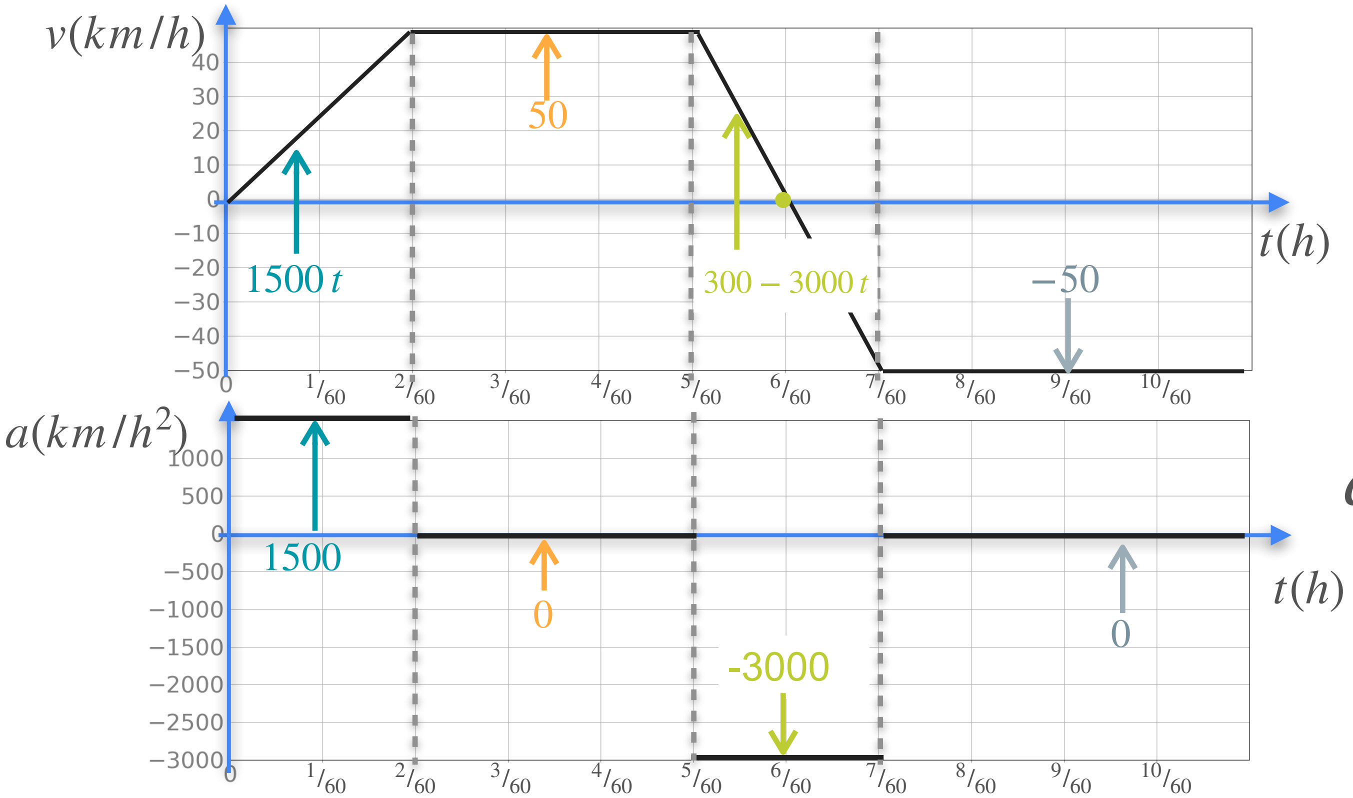
Understanding Second Derivative



v Velocity $\frac{dx}{dt}$

a Acceleration $\frac{dv}{dt}$

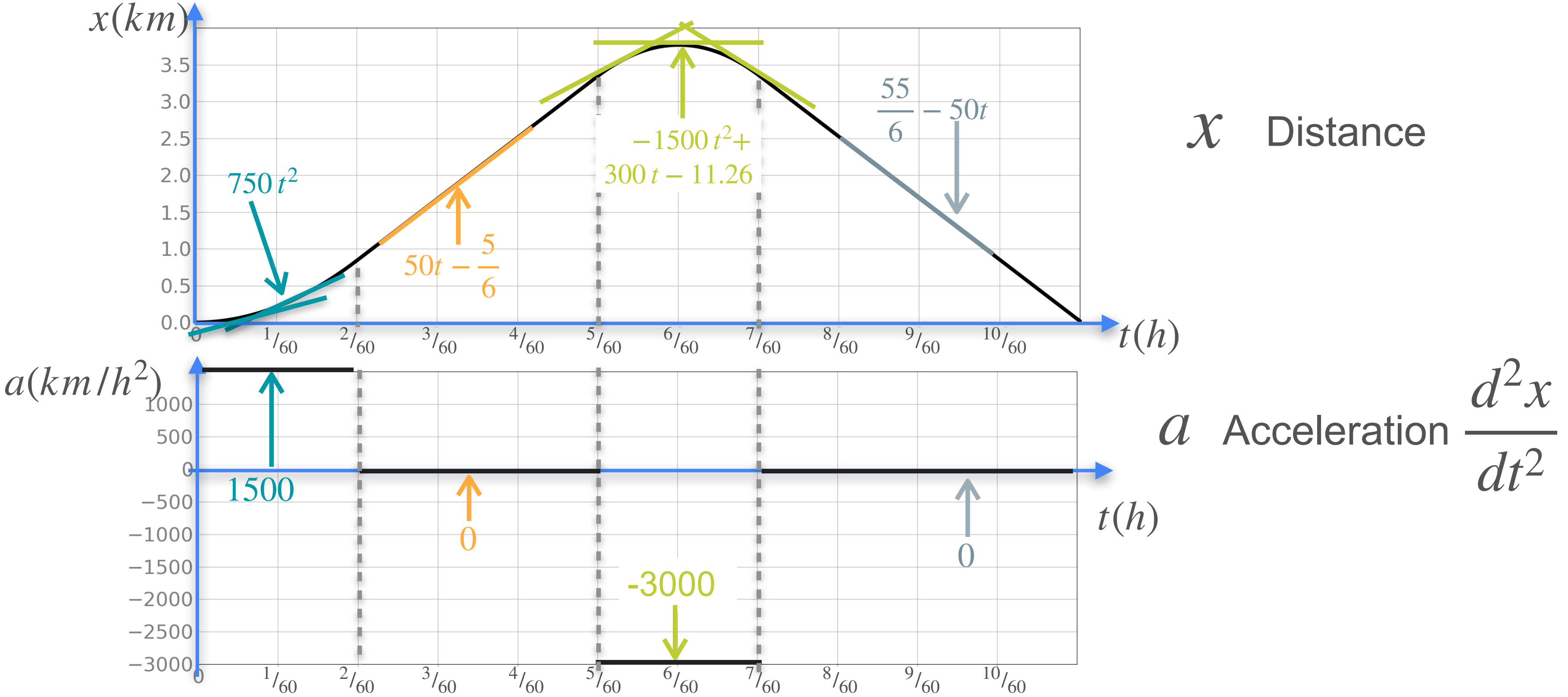
Understanding Second Derivative



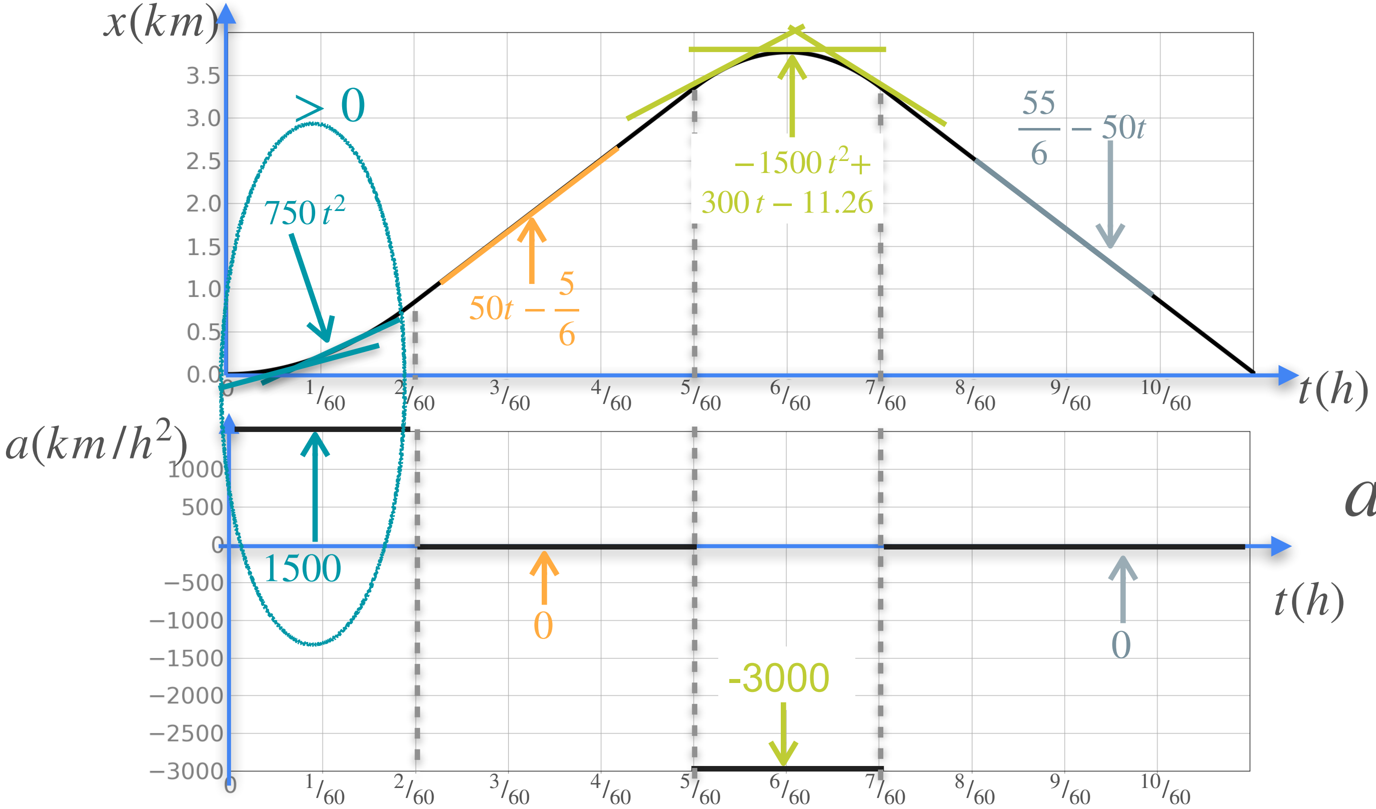
v Velocity $\frac{dx}{dt}$

a Acceleration $\frac{dv}{dt}$

Understanding Second Derivative



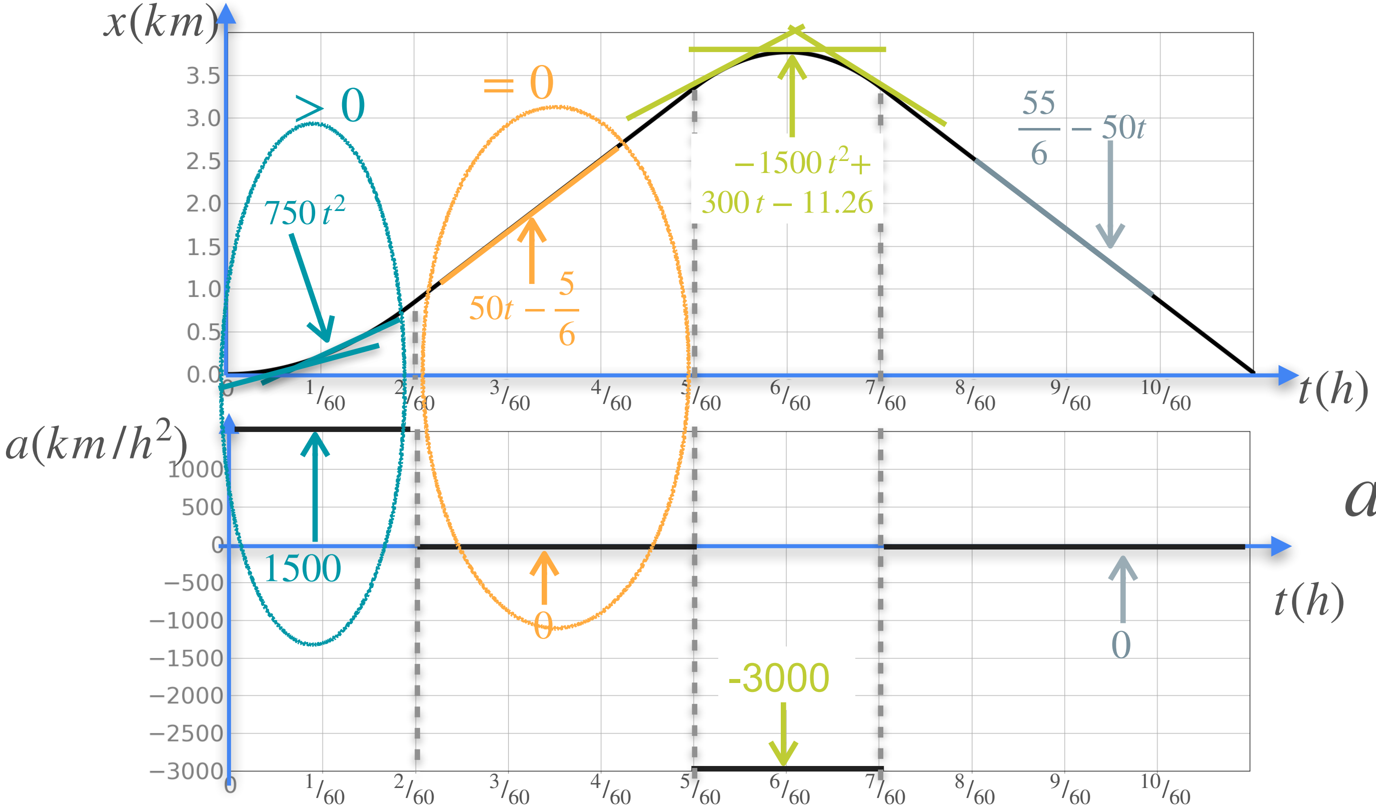
Understanding Second Derivative



x Distance

a Acceleration $\dfrac{d^2x}{dt^2}$

Understanding Second Derivative



x Distance

a Acceleration $\frac{d^2x}{dt^2}$

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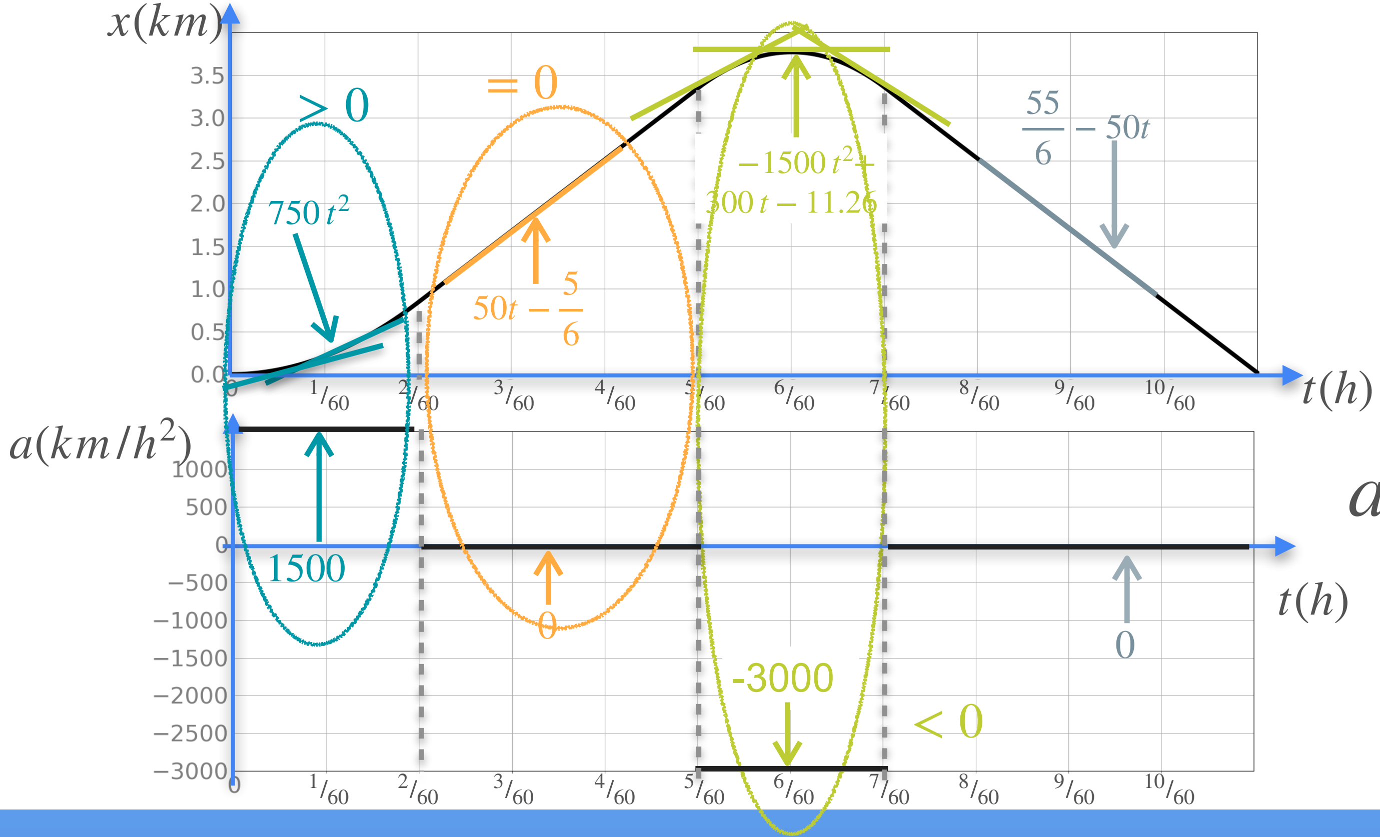
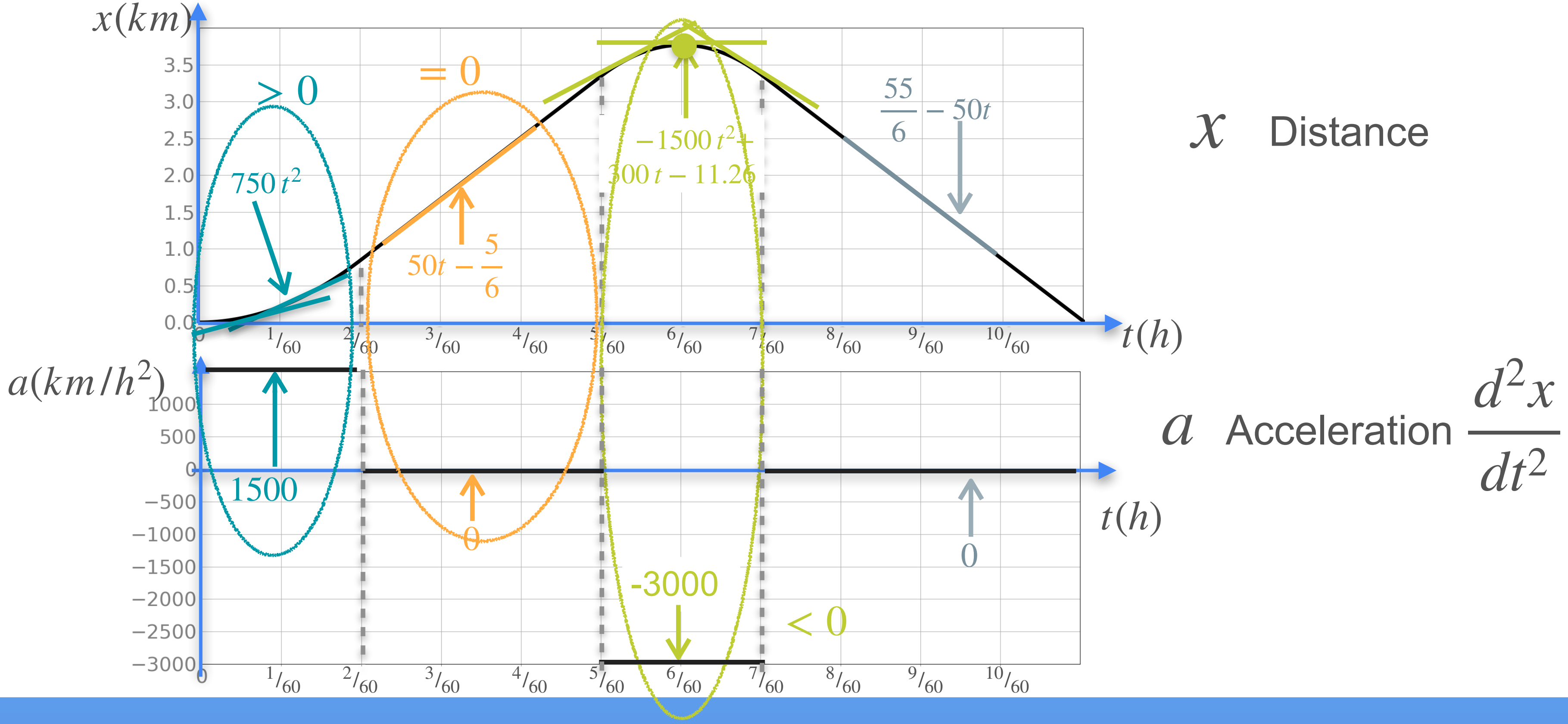
Understanding Second Derivative



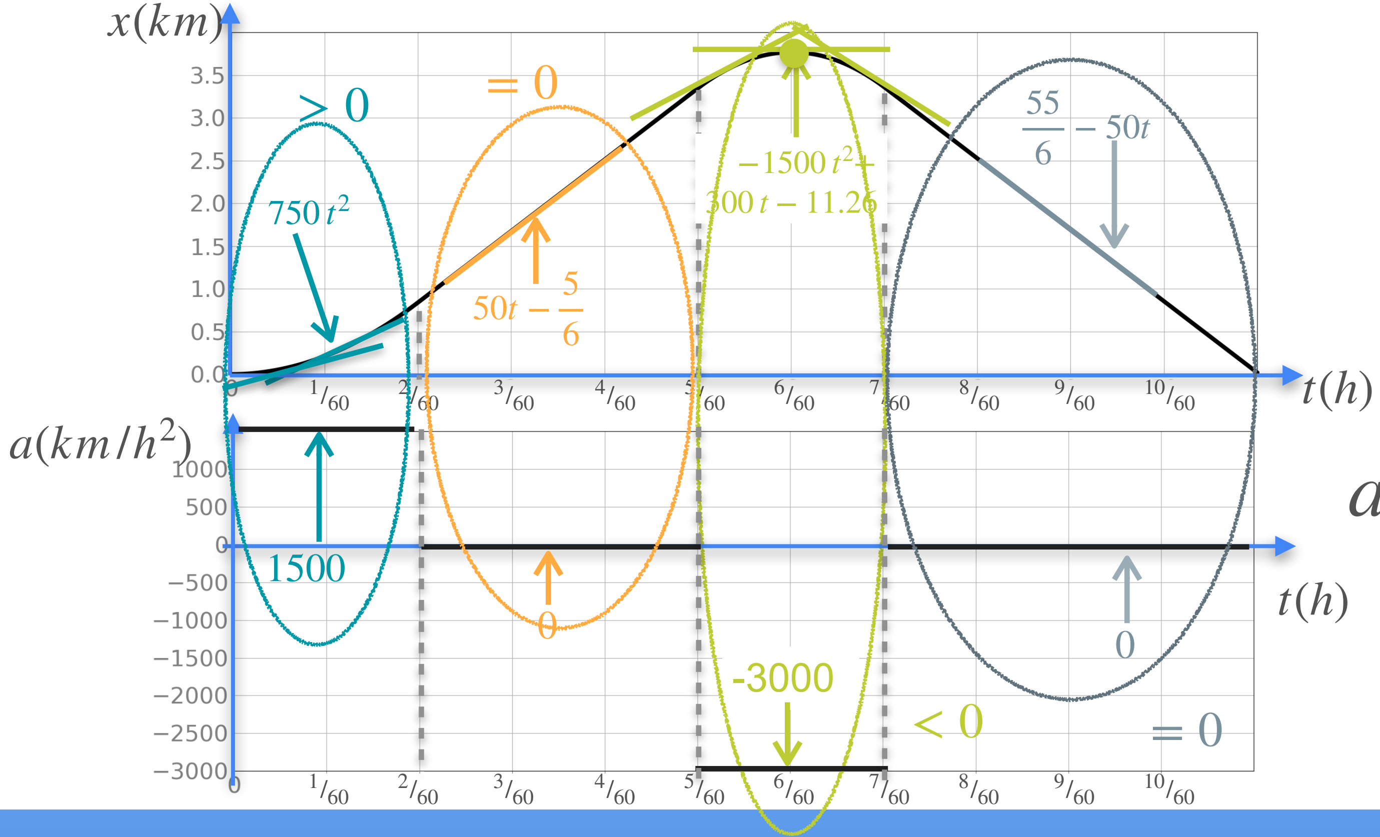
x Distance

a Acceleration $\frac{d^2x}{dt^2}$

Understanding Second Derivative



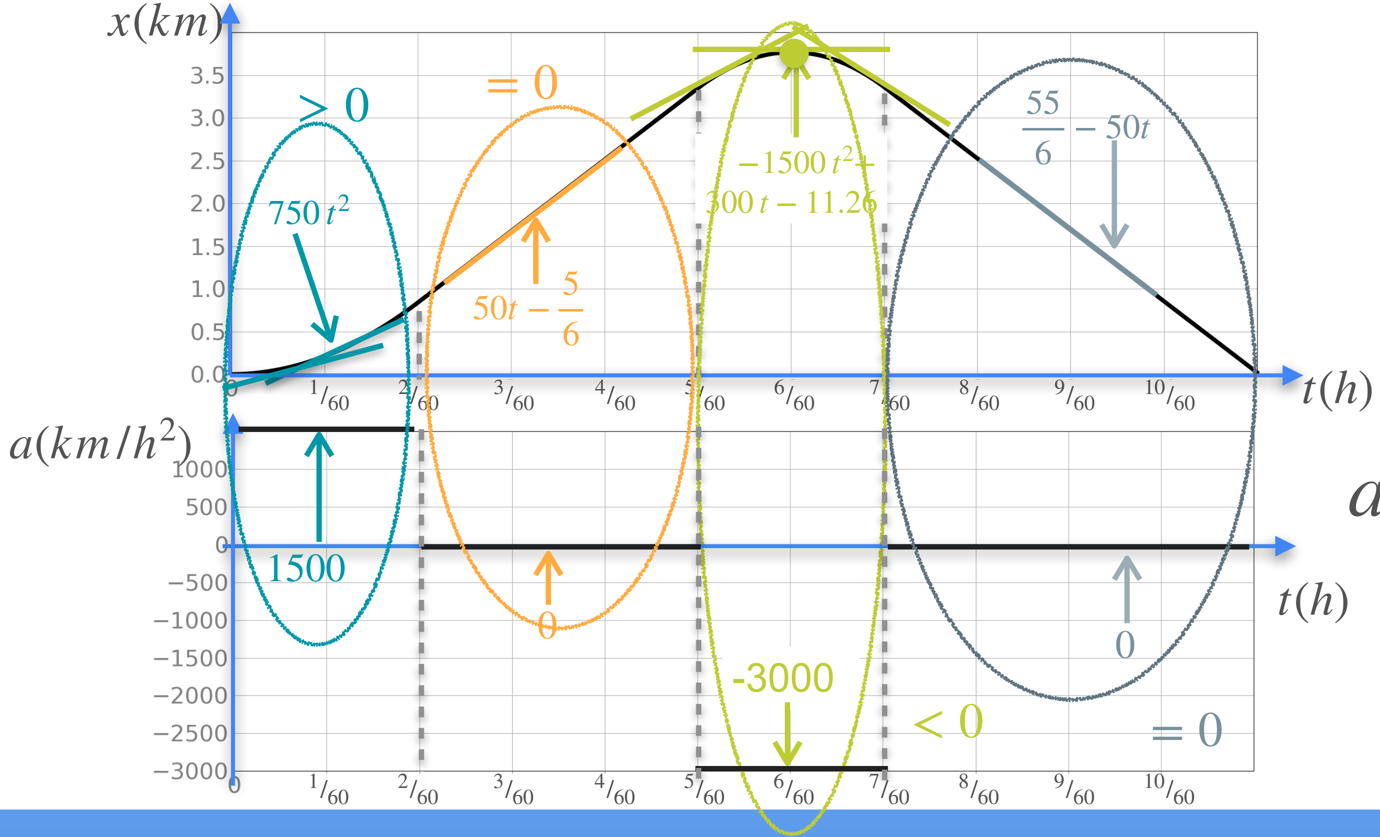
Understanding Second Derivative



x Distance

a Acceleration $\frac{d^2x}{dt^2}$

Understanding Second Derivative



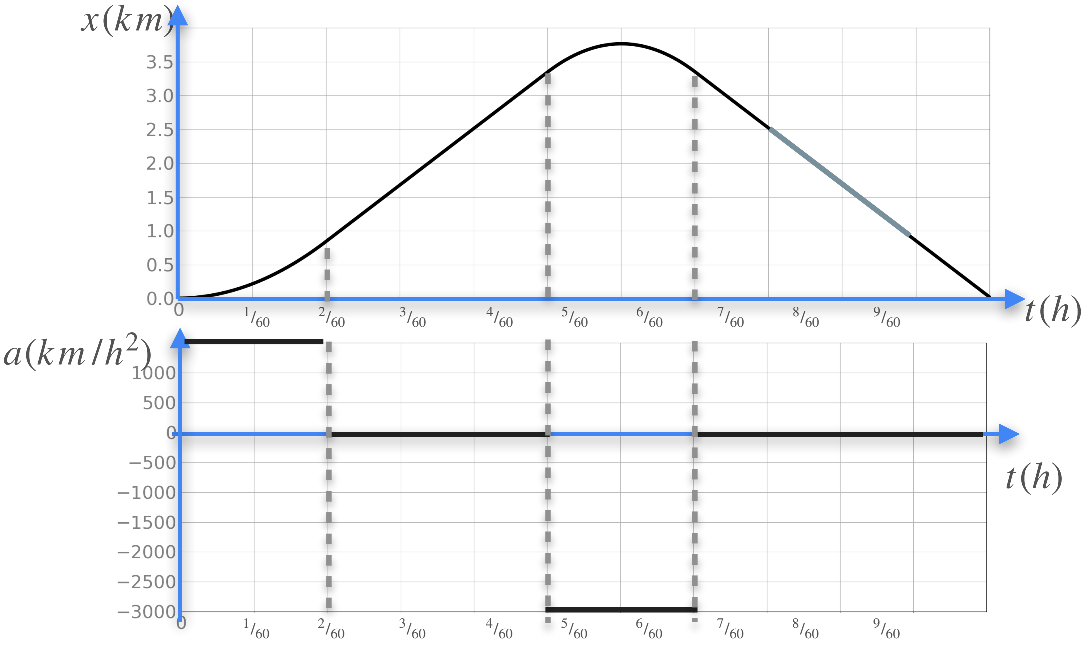
x Distance

Second derivative tells us about the curvature

a Acceleration $\frac{d^2x}{dt^2}$

Curvature

Curvature

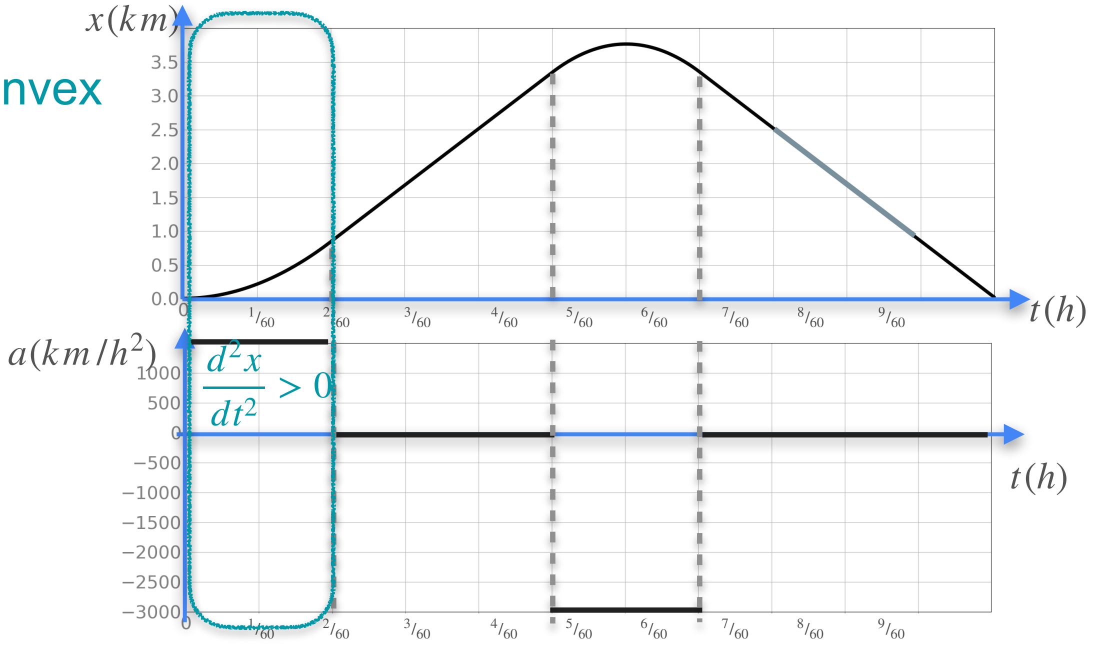


$x(km)$
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1/60
2/60
3/60
4/60
5/60
6/60
7/60
8/60
9/60
$t(h)$
$a(km/h^2)$
1000
500
0
−500
−1000
−1500
−2000
−2500
−3000
0
1/60
2/60
3/60
4/60
5/60
6/60
7/60
8/60
9/60
$t(h)$

Curvature

$$\frac{d^2x}{dt^2} > 0$$

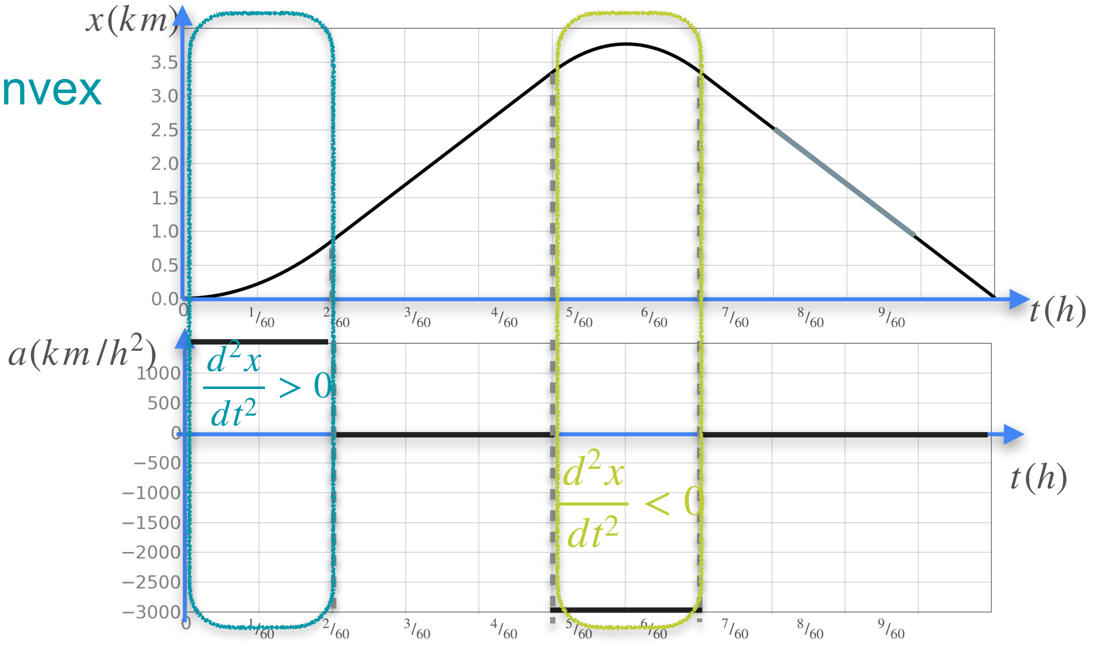
Concave up or convex



Curvature

$$\frac{d^2x}{dt^2} > 0$$ Concave up or convex

$$\frac{d^2x}{dt^2} < 0$$ Concave down

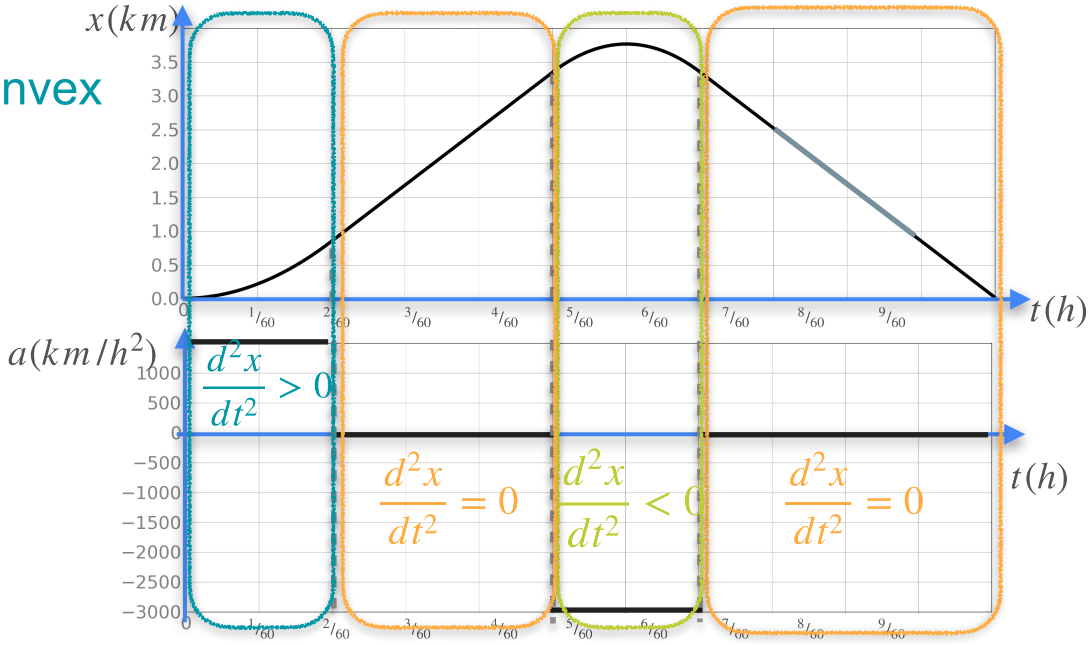


Curvature

$$\frac{d^2x}{dt^2} > 0$$ Concave up or convex

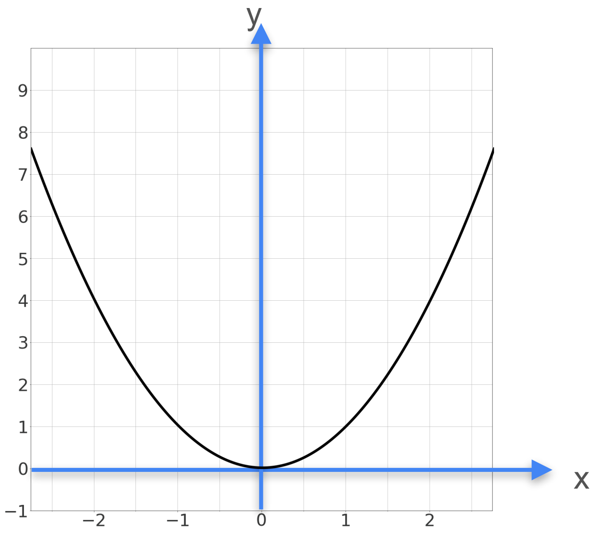
$$\frac{d^2x}{dt^2} < 0$$ Concave down

$$\frac{d^2x}{dt^2} = 0$$ Need more information

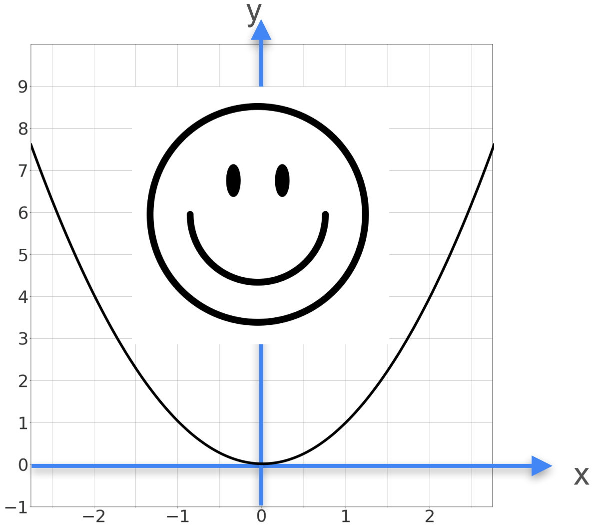


Curvature

Curvature



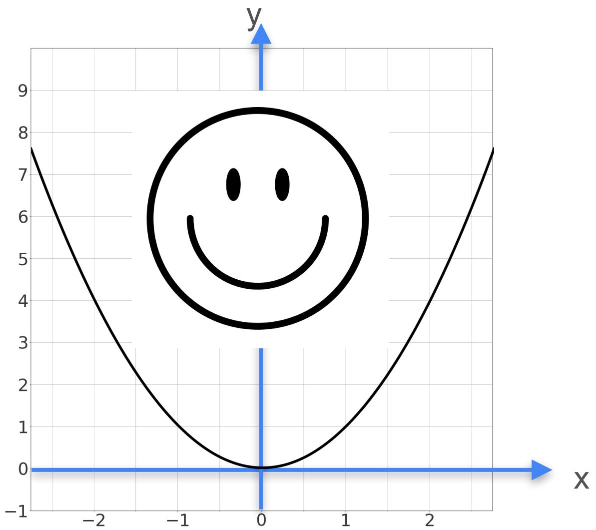
Curvature



Concave up or convex

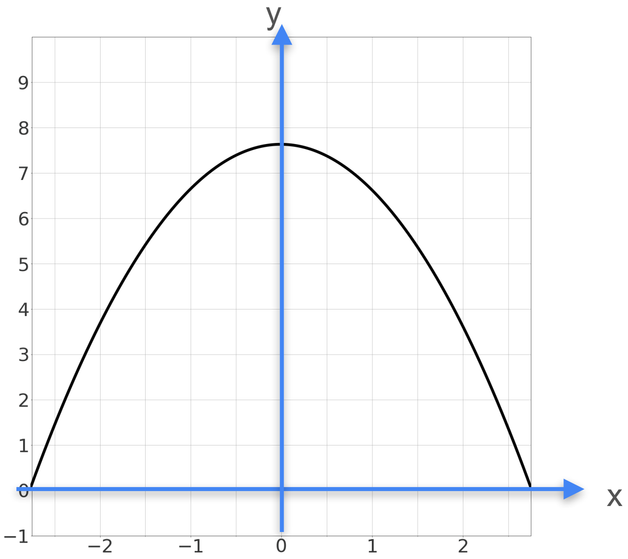
$$f''(0) > 0$$

Curvature

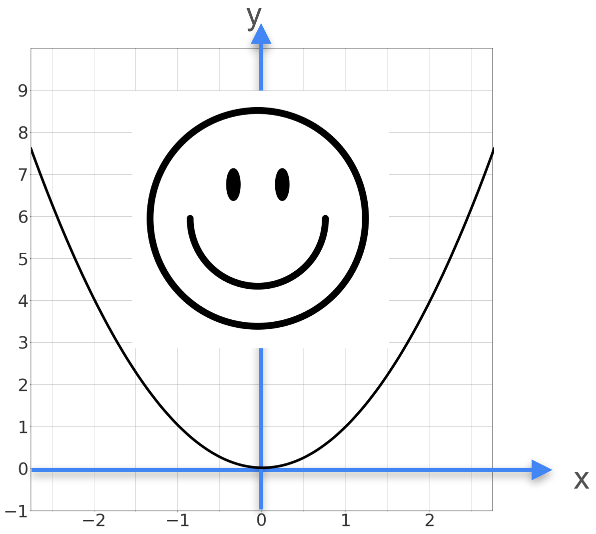


Concave up or convex

$$f''(0) > 0$$

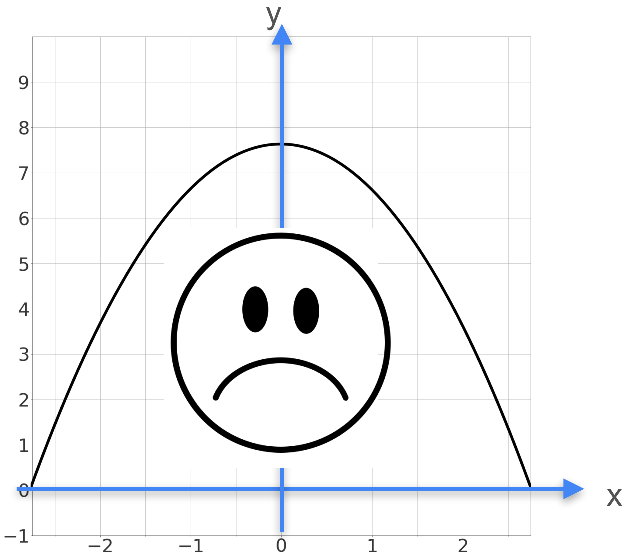


Curvature



Concave up or convex

$$f''(0) > 0$$



Concave down

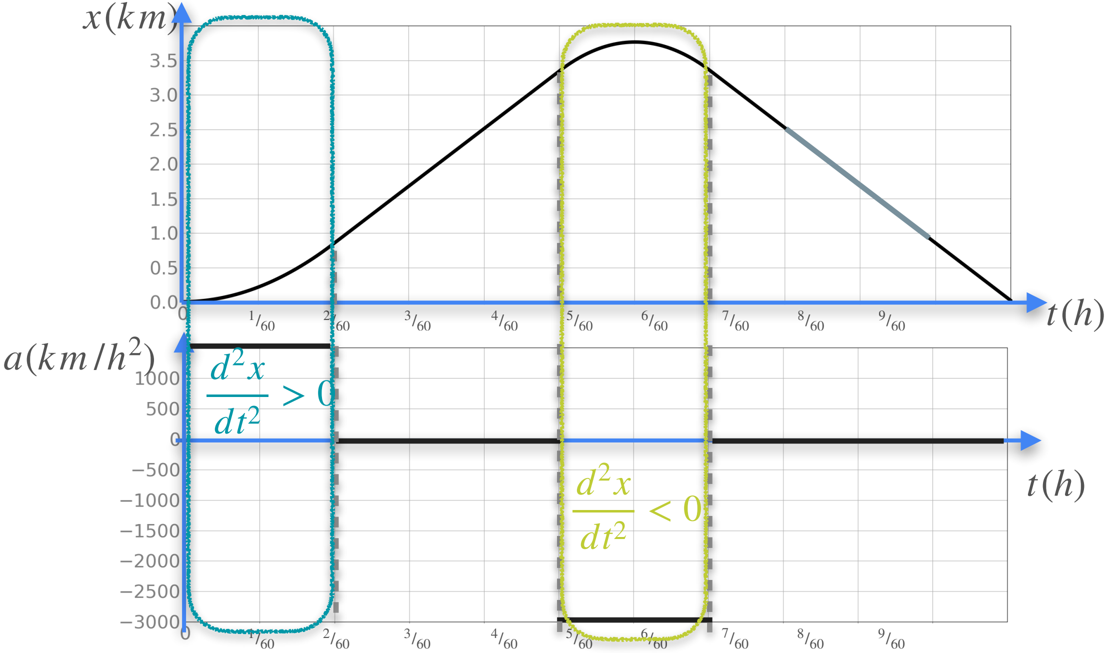
$$f''(0) < 0$$

Second Derivative and Optimization

$$\frac{d^2x}{dt^2} > 0$$

$$\frac{d^2x}{dt^2} < 0$$

$$\frac{d^2x}{dt^2} = 0$$

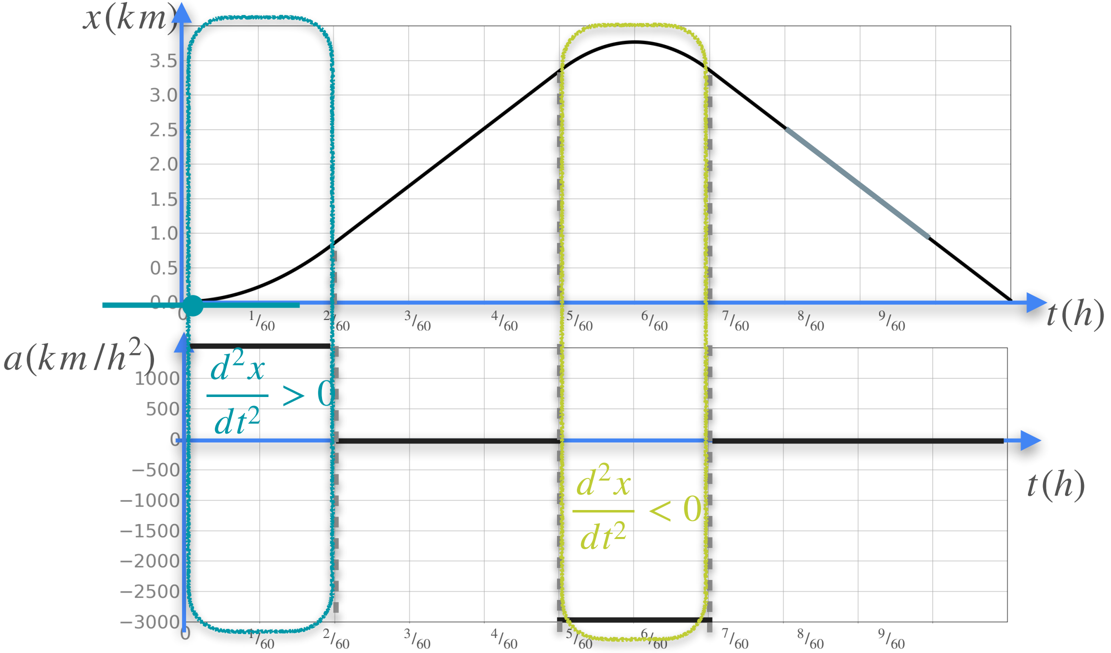


Second Derivative and Optimization

$$\frac{d^2x}{dt^2} > 0$$ (Local) Minimum

$$\frac{d^2x}{dt^2} < 0$$

$$\frac{d^2x}{dt^2} = 0$$

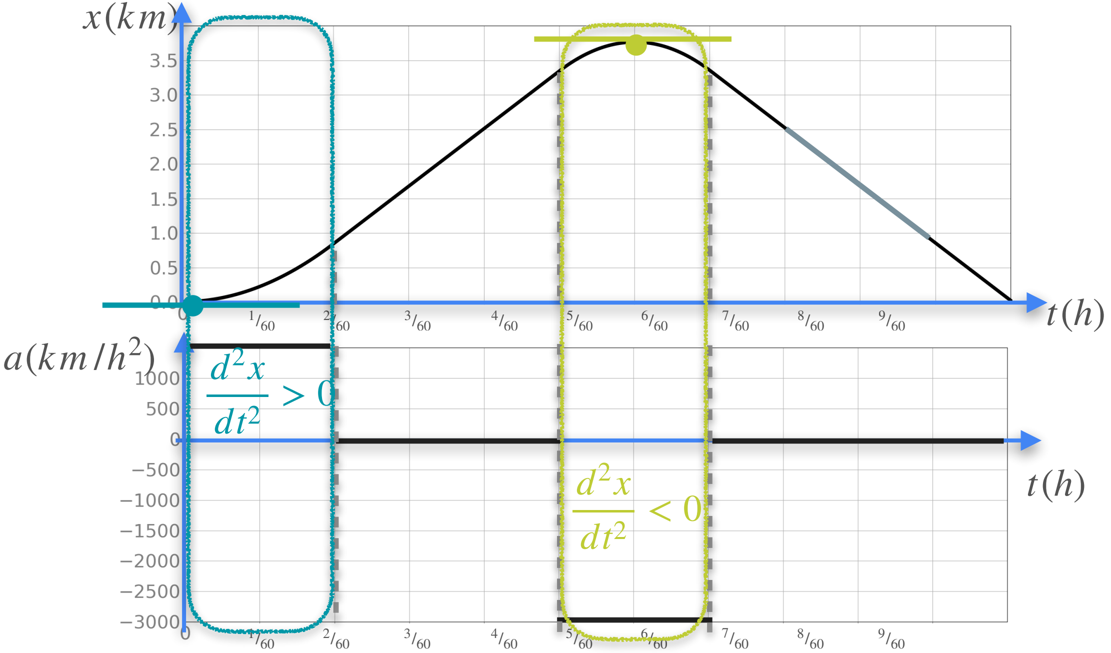


Second Derivative and Optimization

$$\frac{d^2x}{dt^2} > 0$$ (Local) Minimum

$$\frac{d^2x}{dt^2} < 0$$ (Local) maximum

$$\frac{d^2x}{dt^2} = 0$$

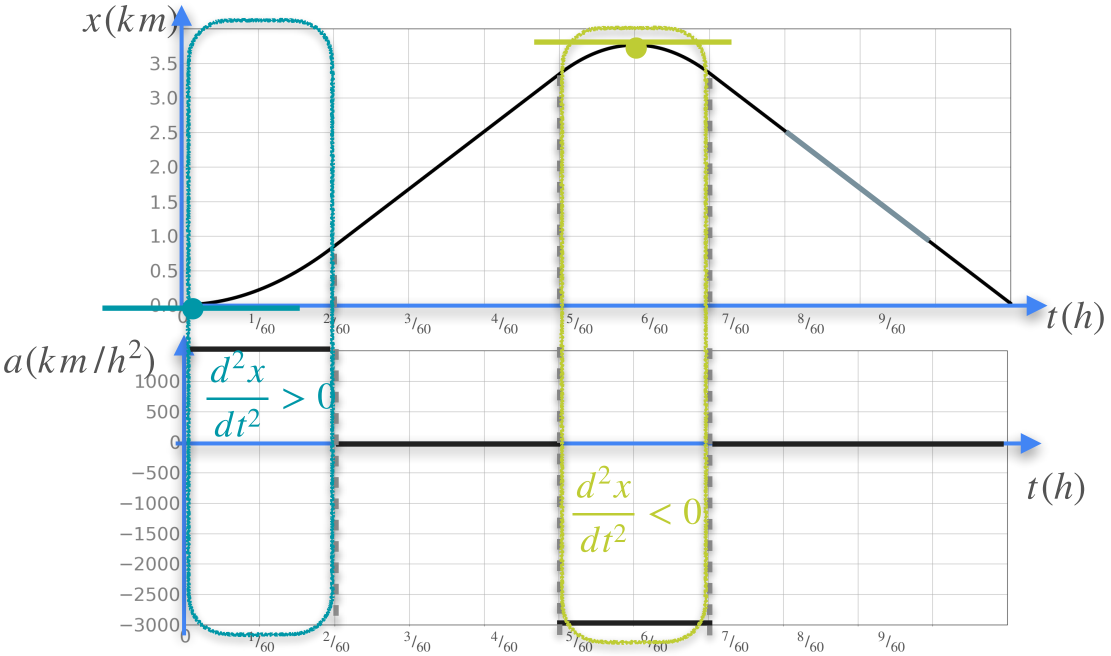


Second Derivative and Optimization

$$\frac{d^2x}{dt^2} > 0$$ (Local) Minimum

$$\frac{d^2x}{dt^2} < 0$$ (Local) maximum

$$\frac{d^2x}{dt^2} = 0$$ Inconclusive



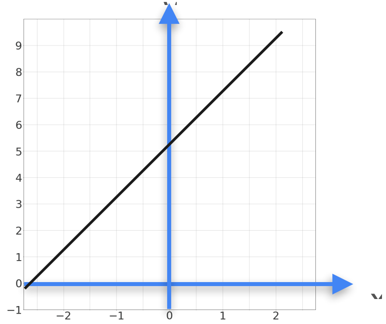
Curvature

First derivative

Second derivative

Curvature

First derivative



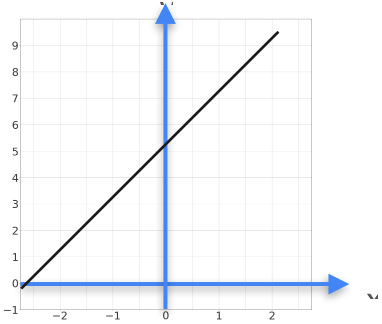
Increasing

$$f'(0) > 0$$

Second derivative

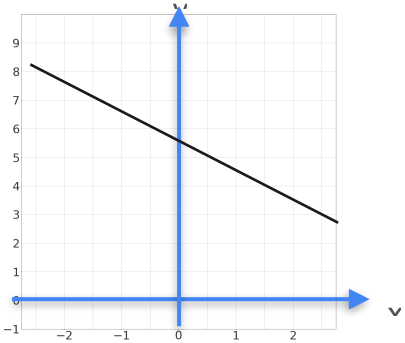
Curvature

First derivative



Increasing

$$f'(0) > 0$$



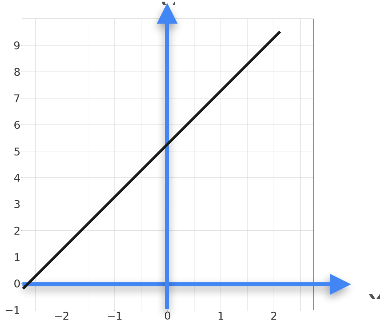
Decreasing

$$f'(0) < 0$$

Second derivative

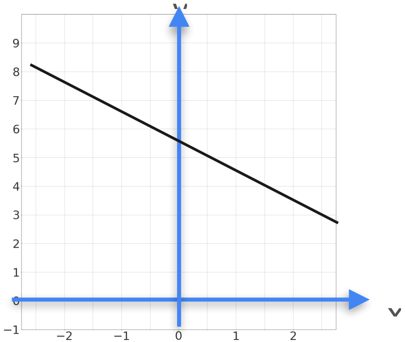
Curvature

First derivative



Increasing

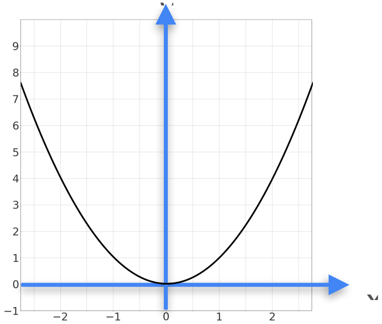
$$f'(0) > 0$$



Decreasing

$$f'(0) < 0$$

Second derivative

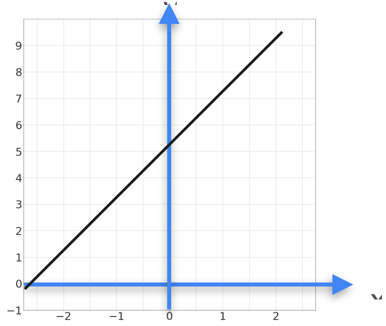


Concave up

$$f''(0) > 0$$

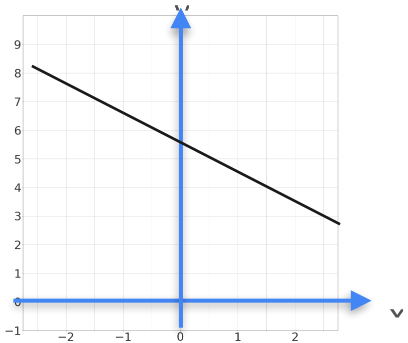
Curvature

First derivative



Increasing

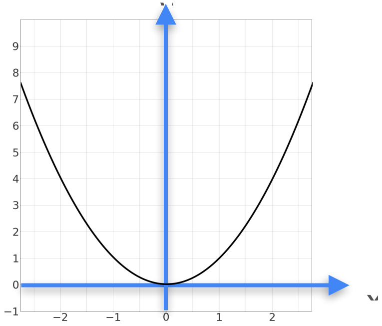
$$f'(0) > 0$$



Decreasing

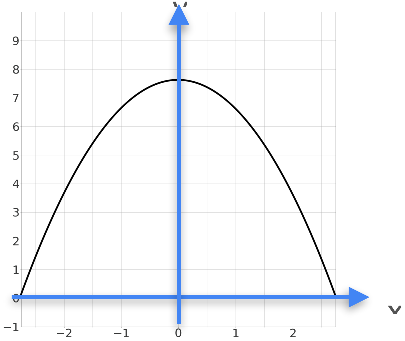
$$f'(0) < 0$$

Second derivative



Concave up

$$f''(0) > 0$$



Concave down

$$f''(0) < 0$$

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Optimization in Neural Networks and Newton's Method

The Hessian

Second Derivative

Second Derivative

	1 variable	2 variables

Second Derivative

	1 variable	2 variables
Function	$f(x)$	

Second Derivative

	1 variable	2 variables
Function	$f(x)$	$f(x, y)$

Second Derivative

	1 variable	2 variables
Function	$f(x)$	$f(x, y)$
First derivative	$f'(x)$ Rate of change of $f(x)$	

Second Derivative

	1 variable		2 variables	
Function	$f(x)$		$f(x, y)$	
First derivative	$f'(x)$	Rate of change of $f(x)$	$f_x(x, y)$	Rate of change w.r.t x

Second Derivative

	1 variable		2 variables	
Function	$f(x)$		$f(x, y)$	
First derivative	$f'(x)$	Rate of change of $f(x)$	$f_x(x, y)$	Rate of change w.r.t x
			$f_y(x, y)$	Rate of change w.r.t y

Second Derivative

	1 variable	2 variables
Function	$f(x)$	$f(x, y)$
First derivative	$f'(x)$ Rate of change of $f(x)$	$f_x(x, y)$ Rate of change w.r.t x $f_y(x, y)$ Rate of change w.r.t y $\nabla f = \begin{bmatrix} f_x(x, y) \\ f_y(x, y) \end{bmatrix}$

Second Derivative

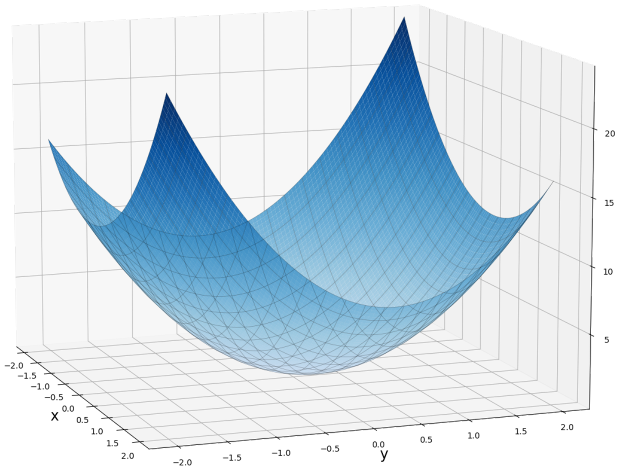
	1 variable	2 variables
Function	$f(x)$	$f(x, y)$
First derivative	$f'(x)$ Rate of change of $f(x)$	$f_x(x, y)$ Rate of change w.r.t x $f_y(x, y)$ Rate of change w.r.t y $\nabla f = \begin{bmatrix} f_x(x, y) \\ f_y(x, y) \end{bmatrix}$
Second derivative	$f''(x)$ Rate of change of the rate of change of $f(x)$	

Second Derivative

	1 variable		2 variables	
Function	$f(x)$		$f(x,y)$	
First derivative	$f'(x)$	Rate of change of $f(x)$	$f_x(x,y)$	Rate of change w.r.t x
			$f_y(x,y)$	Rate of change w.r.t y
			$\nabla f = \begin{bmatrix} f_x(x,y) \\ f_y(x,y) \end{bmatrix}$	
Second derivative	$f''(x)$	Rate of change of the rate of change of $f(x)$	???	

Second Derivative

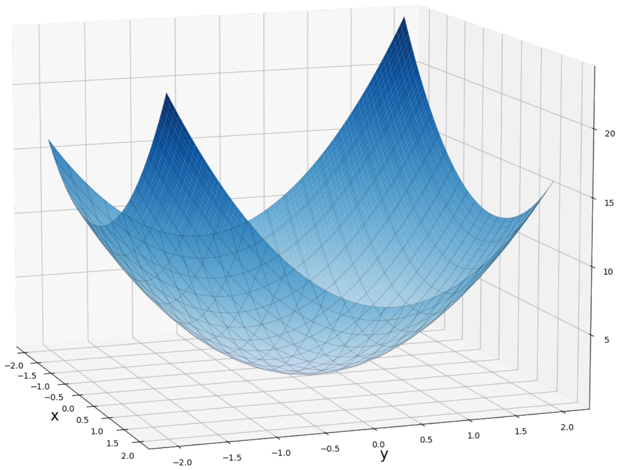
Second Derivative



$$f(x, y) =$$

$$2x^2 + 3y^2 - xy$$

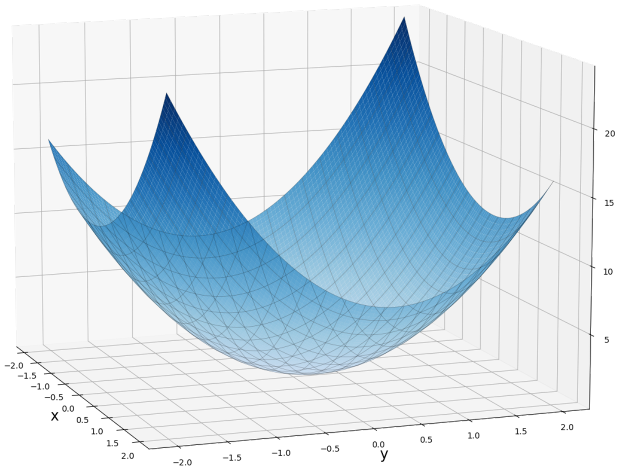
Second Derivative



$$f(x, y) =$$

$$2x^2 + 3y^2 - xy \xrightarrow{x} 4x - y$$

Second Derivative



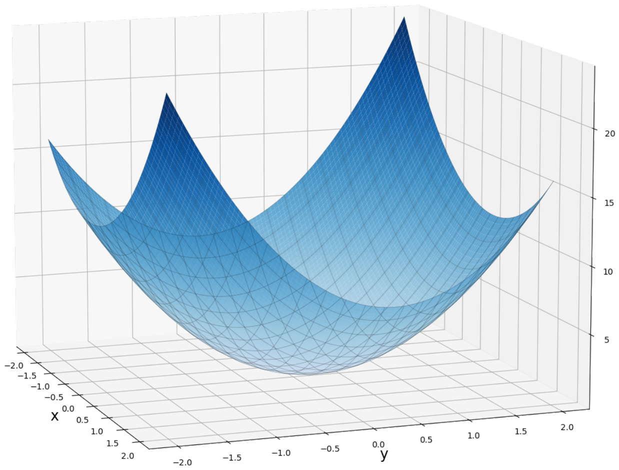
$f(x, y) =$

$2x^2 + 3y^2 - xy$

$\xrightarrow{x} 4x - y$

$\xrightarrow{y} 6y - x$

Second Derivative

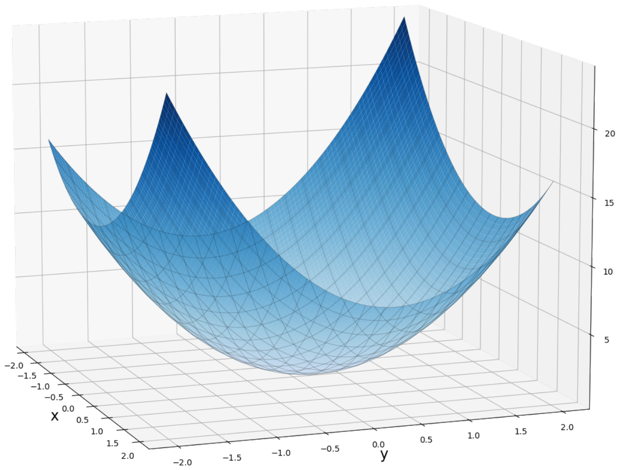


$$f(x, y) = 2x^2 + 3y^2 - xy \xrightarrow{x} 4x - y \xrightarrow{x} 4$$

Rate of change of $f'_x(x, y)$ w.r.t x

$$f(x, y) = 2x^2 + 3y^2 - xy \xrightarrow{y} 6y - x$$

Second Derivative



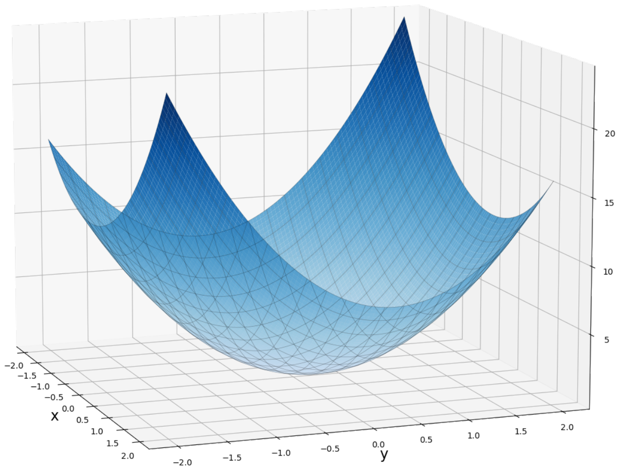
$$f(x, y) = 2x^2 + 3y^2 - xy$$

$$\begin{tikzcd}
 & & 4 \\
 & 4x - y \arrow[ur, "x"] \arrow[dr, "y"'] & \\
2x^2 + 3y^2 - xy \arrow[ur, "x"] \arrow[dr, "y"'] & & -1 \\
 & 6y - x &
\end{tikzcd}$$

Rate of change of $f'_x(x, y)$ w.r.t x

Rate of change of $f'_x(x, y)$ w.r.t y

Second Derivative



$f(x, y) =$

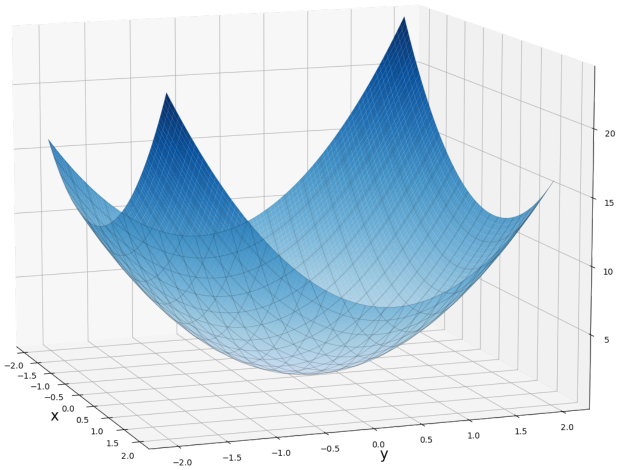
$2x^2 + 3y^2 - xy$

$\xrightarrow{x}$ $4x - y$ $\xrightarrow{x}$ 4 Rate of change of $f'_x(x, y)$ w.r.t x

$4x - y$ $\xrightarrow{y}$ -1 Rate of change of $f'_x(x, y)$ w.r.t y

$\xrightarrow{y}$ $6y - x$ $\xrightarrow{x}$ -1 Rate of change of $f'_y(x, y)$ w.r.t x

Second Derivative



$$f(x,y) = 2x^2 + 3y^2 - xy$$

$$f(x,y) \xrightarrow{x} 4x - y \qquad f(x,y) \xrightarrow{y} 6y - x$$

$$4x - y \xrightarrow{x} 4$$

Rate of change of $f'_x(x,y)$ w.r.t x

$$4x - y \xrightarrow{y} -1$$

Rate of change of $f'_x(x,y)$ w.r.t y

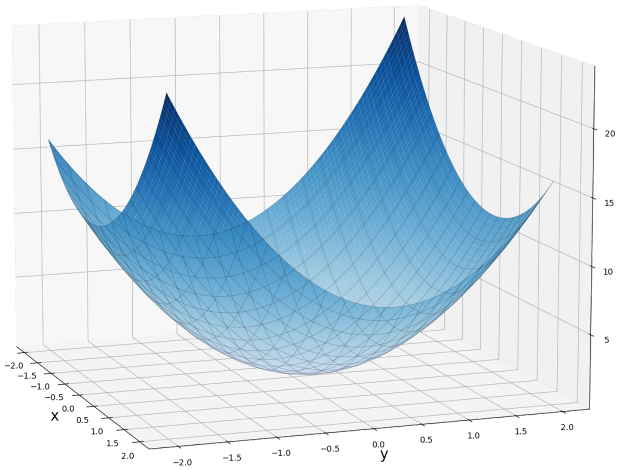
$$6y - x \xrightarrow{x} -1$$

Rate of change of $f'_y(x,y)$ w.r.t x

$$6y - x \xrightarrow{y} 6$$

Rate of change of $f'_y(x,y)$ w.r.t y

Second Derivative



$$
\begin{tikzcd}
 & & 4 \\
 & 4x - y \arrow[ur, "x"] \arrow[dr, "y"'] & \\
 & & -1 \\
f(x,y) = 2x^2 + 3y^2 - xy \arrow[uur, "x"] \arrow[ddr, "y"'] & & \\
 & & -1 \\
 & 6y - x \arrow[ur, "x"] \arrow[dr, "y"'] & \\
 & & 6
\end{tikzcd}
$$

Rate of change of $f'_x(x, y)$ w.r.t x

Rate of change of $f'_x(x, y)$ w.r.t y

Rate of change of $f'_y(x, y)$ w.r.t x

Rate of change of $f'_y(x, y)$ w.r.t y

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What Do These Mean?

Rate of change of
$f_x(x, y)$ w.r.t x

Rate of change of
$f_y(x, y)$ w.r.t y

Rate of change of
$f_x(x, y)$ w.r.t y

Rate of change of
$f_y(x, y)$ w.r.t x

What Do These Mean?

Rate of change of $f_x(x, y)$ w.r.t x

Rate of change of $f_y(x, y)$ w.r.t y

Change in the change in the function w.r.t tiny changes in x and y

Rate of change of $f_x(x, y)$ w.r.t y

Rate of change of $f_y(x, y)$ w.r.t x

What Do These Mean?

Rate of change of $f_x(x, y)$ w.r.t x

Rate of change of $f_y(x, y)$ w.r.t y

Change in the change in the function w.r.t tiny changes in x and y

Same idea as with one variable!

Rate of change of $f_x(x, y)$ w.r.t y

Rate of change of $f_y(x, y)$ w.r.t x

1. Change in the slope along one coordinate axis w.r.t tiny changes along an orthogonal coordinate axis

What Do These Mean?

Rate of change of $f_x(x, y)$ w.r.t x

Rate of change of $f_y(x, y)$ w.r.t y

Change in the change in the function w.r.t tiny changes in x and y

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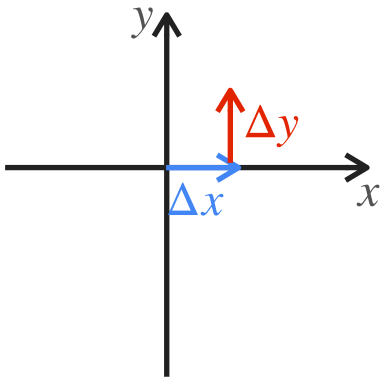
Rate of change of $f_x(x, y)$ w.r.t y

Rate of change of $f_y(x, y)$ w.r.t x

1. Change in the slope along one coordinate axis w.r.t tiny changes along an orthogonal coordinate axis



What Do These Mean?

Rate of change of $f_x(x, y)$ w.r.t x

Rate of change of $f_y(x, y)$ w.r.t y

Change in the change in the function w.r.t tiny changes in x and y

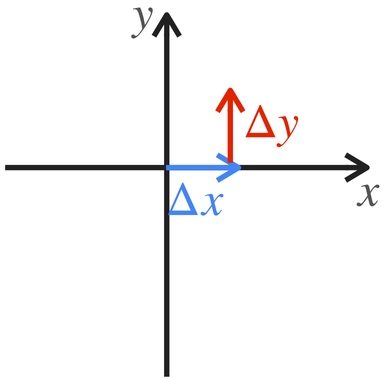
Same idea as with one variable!

Rate of change of $f_x(x, y)$ w.r.t y

Rate of change of $f_y(x, y)$ w.r.t x

1. Change in the slope along one coordinate axis w.r.t tiny changes along an orthogonal coordinate axis

2. They are the same!



What Do These Mean?

Rate of change of $f_x(x, y)$ w.r.t x

Rate of change of $f_y(x, y)$ w.r.t y

Change in the change in the function w.r.t tiny changes in x and y

Same idea as with one variable!

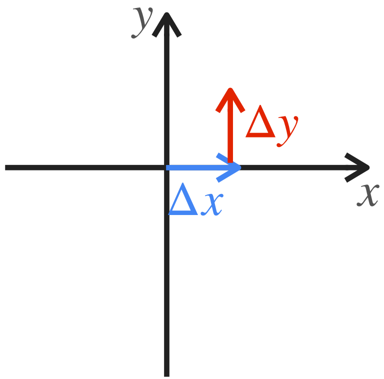
Rate of change of $f_x(x, y)$ w.r.t y

Rate of change of $f_y(x, y)$ w.r.t x

1. Change in the slope along one coordinate axis w.r.t tiny changes along an orthogonal coordinate axis

2. They are the same!

(In most cases)



Notation

Rate of change of $f'_x(x, y)$ w.r.t x

Rate of change of $f'_y(x, y)$ w.r.t y

Rate of change of $f'_x(x, y)$ w.r.t y

Rate of change of $f'_y(x, y)$ w.r.t x

Notation

Leibniz's notation

Rate of change of
$f'_x(x, y)$ w.r.t x

Rate of change of
$f'_y(x, y)$ w.r.t y

Rate of change of
$f'_x(x, y)$ w.r.t y

Rate of change of
$f'_y(x, y)$ w.r.t x

Notation

	Leibniz's notation
Rate of change of $f'_x(x, y)$ w.r.t x	$\frac{\partial^2 f}{\partial x^2}$
Rate of change of $f'_y(x, y)$ w.r.t y	$\frac{\partial^2 f}{\partial y^2}$
Rate of change of $f'_x(x, y)$ w.r.t y	
Rate of change of $f'_y(x, y)$ w.r.t x	

Notation

	Leibniz's notation
Rate of change of $f'_x(x, y)$ w.r.t x	$\dfrac{\partial^2 f}{\partial x^2}$
Rate of change of $f'_y(x, y)$ w.r.t y	$\dfrac{\partial^2 f}{\partial y^2}$
Rate of change of $f'_x(x, y)$ w.r.t y	$\dfrac{\partial^2 f}{\partial x \partial y}$
Rate of change of $f'_y(x, y)$ w.r.t x	$\dfrac{\partial^2 f}{\partial y \partial x}$

Notation

	Leibniz's notation	Lagrange's notation
Rate of change of $f'_x(x, y)$ w.r.t x	$\dfrac{\partial^2 f}{\partial x^2}$	
Rate of change of $f'_y(x, y)$ w.r.t y	$\dfrac{\partial^2 f}{\partial y^2}$	
Rate of change of $f'_x(x, y)$ w.r.t y	$\dfrac{\partial^2 f}{\partial x \partial y}$	
Rate of change of $f'_y(x, y)$ w.r.t x	$\dfrac{\partial^2 f}{\partial y \partial x}$	

Notation

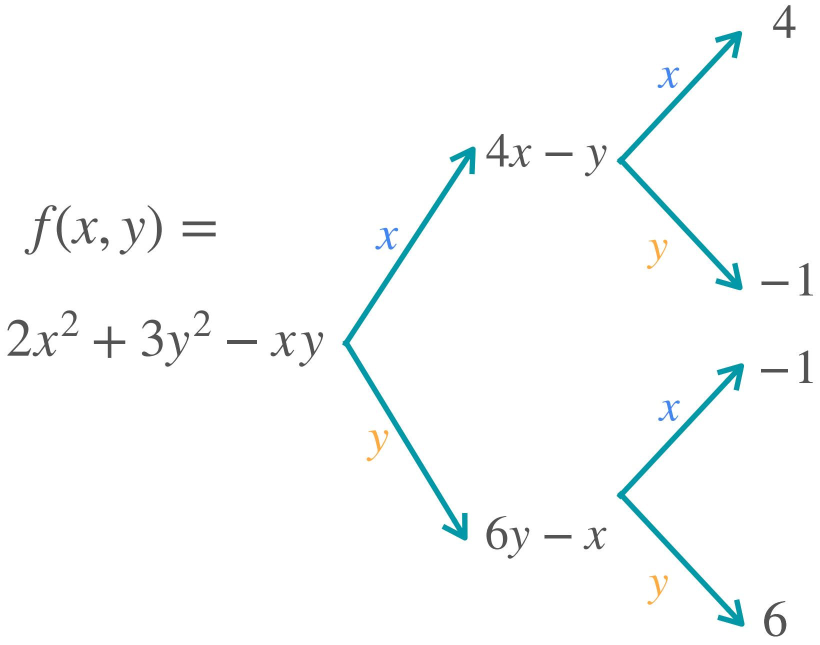
	Leibniz's notation	Lagrange's notation
Rate of change of $f'_x(x, y)$ w.r.t x	$\frac{\partial^2 f}{\partial x^2}$	$f_{xx}(x, y)$
Rate of change of $f'_y(x, y)$ w.r.t y	$\frac{\partial^2 f}{\partial y^2}$	$f_{yy}(x, y)$
Rate of change of $f'_x(x, y)$ w.r.t y	$\frac{\partial^2 f}{\partial x \partial y}$	
Rate of change of $f'_y(x, y)$ w.r.t x	$\frac{\partial^2 f}{\partial y \partial x}$	

Notation

	Leibniz's notation	Lagrange's notation
Rate of change of $f'_x(x, y)$ w.r.t x	$\dfrac{\partial^2 f}{\partial x^2}$	$f_{xx}(x, y)$
Rate of change of $f'_y(x, y)$ w.r.t y	$\dfrac{\partial^2 f}{\partial y^2}$	$f_{yy}(x, y)$
Rate of change of $f'_x(x, y)$ w.r.t y	$\dfrac{\partial^2 f}{\partial x \partial y}$	$f_{xy}(x, y)$
Rate of change of $f'_y(x, y)$ w.r.t x	$\dfrac{\partial^2 f}{\partial y \partial x}$	$f_{yx}(x, y)$

Hessian Matrix

Hessian Matrix



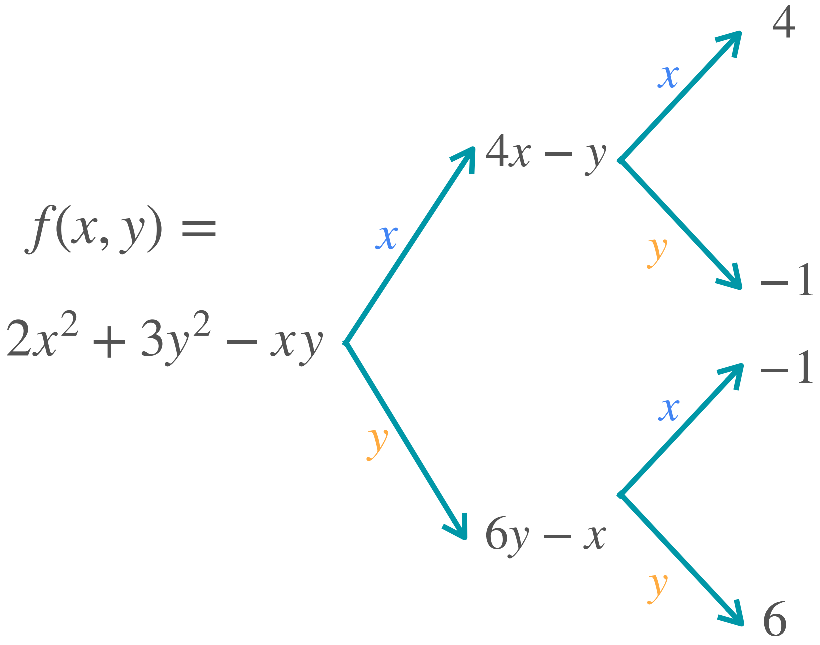
Hessian Matrix

$f(x, y) =$

$$\begin{tikzcd}
 & & 4 \\
 & 4x - y \arrow[ur, "x"] \arrow[dr, "y"] & \\
 & & -1 \\
2x^2 + 3y^2 - xy \arrow[uur, "x"] \arrow[ddr, "y"] & & \\
 & & -1 \\
 & 6y - x \arrow[ur, "x"] \arrow[dr, "y"] & \\
 & & 6
\end{tikzcd}$$

$$\begin{matrix} 4 \\ -1 \end{matrix}$$

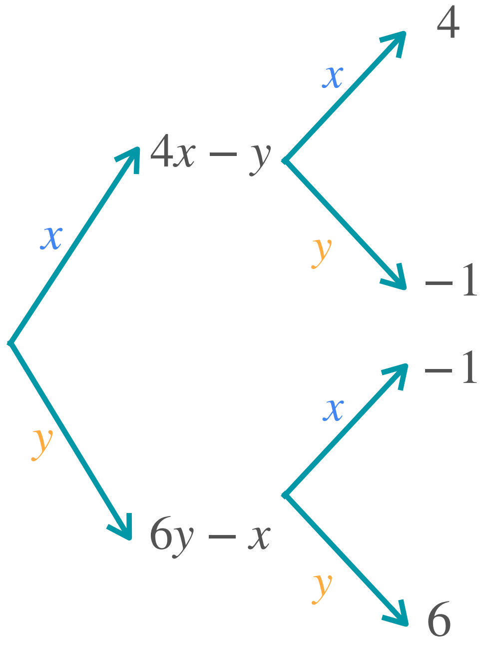
Hessian Matrix



$$\nabla f_x = \begin{bmatrix} 4 \\ -1 \end{bmatrix}$$

Hessian Matrix

$$f(x, y) = 2x^2 + 3y^2 - xy$$



$$\nabla f_x = \begin{bmatrix} 4 \\ -1 \end{bmatrix} \qquad \begin{matrix} -1 \\ 6 \end{matrix}$$

Hessian Matrix

$$
\begin{tikzcd}
 & & 4 \\
 & 4x-y \arrow[ur, "x"] \arrow[dr, "y"'] & \\
 & & -1 \\
f(x,y) = 2x^2+3y^2-xy \arrow[uur, "x"] \arrow[ddr, "y"'] & & \\
 & & -1 \\
 & 6y-x \arrow[ur, "x"] \arrow[dr, "y"'] & \\
 & & 6
\end{tikzcd}
$$

$$\nabla f_x = \begin{bmatrix} 4 \\ -1 \end{bmatrix} \qquad \nabla f_y = \begin{bmatrix} -1 \\ 6 \end{bmatrix}$$

Hessian Matrix

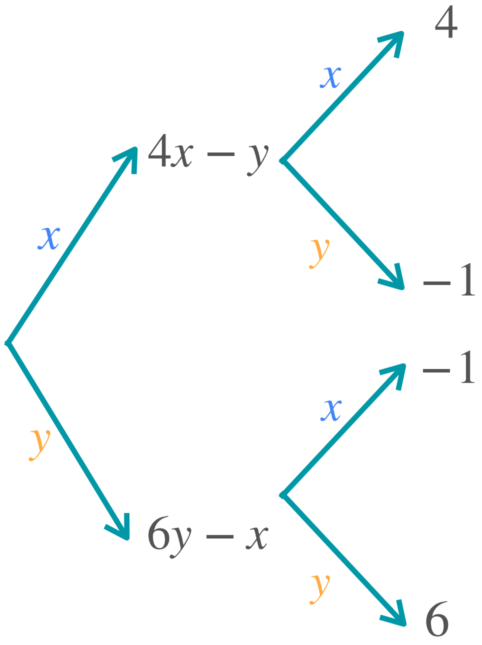
$$
\begin{tikzcd}
 & & 4 \\
 & 4x - y \arrow[ur, "x"] \arrow[dr, "y"'] & \\
 & & -1 \\
\begin{array}{c} f(x, y) = \\ 2x^2 + 3y^2 - xy \end{array} \arrow[uur, "x"] \arrow[ddr, "y"'] & & \\
 & & -1 \\
 & 6y - x \arrow[ur, "x"] \arrow[dr, "y"'] & \\
 & & 6
\end{tikzcd}
$$

$$\nabla f_x = \begin{bmatrix} 4 \\ -1 \end{bmatrix} \qquad \nabla f_y = \begin{bmatrix} -1 \\ 6 \end{bmatrix}$$

$$\begin{matrix} 4 & -1 \\ -1 & 6 \end{matrix}$$

Hessian Matrix

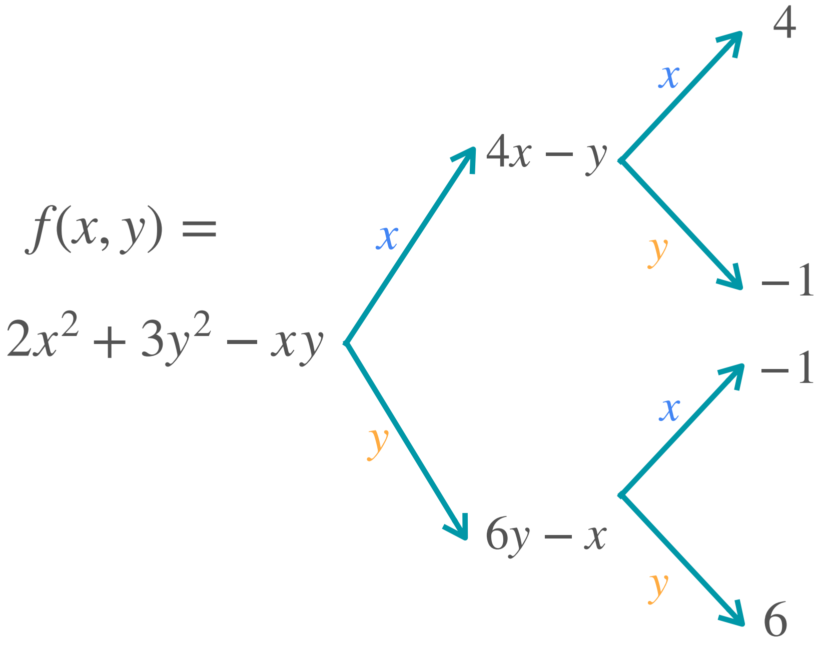
$$f(x, y) = 2x^2 + 3y^2 - xy$$



$$\nabla f_x = \begin{bmatrix} 4 \\ -1 \end{bmatrix} \qquad \nabla f_y = \begin{bmatrix} -1 \\ 6 \end{bmatrix}$$

$$\begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix} = \begin{bmatrix} \nabla f_x{}^T \\ \nabla f_y{}^T \end{bmatrix}$$

Hessian Matrix



$$\nabla f_x = \begin{bmatrix} 4 \\ -1 \end{bmatrix} \qquad \nabla f_y = \begin{bmatrix} -1 \\ 6 \end{bmatrix}$$

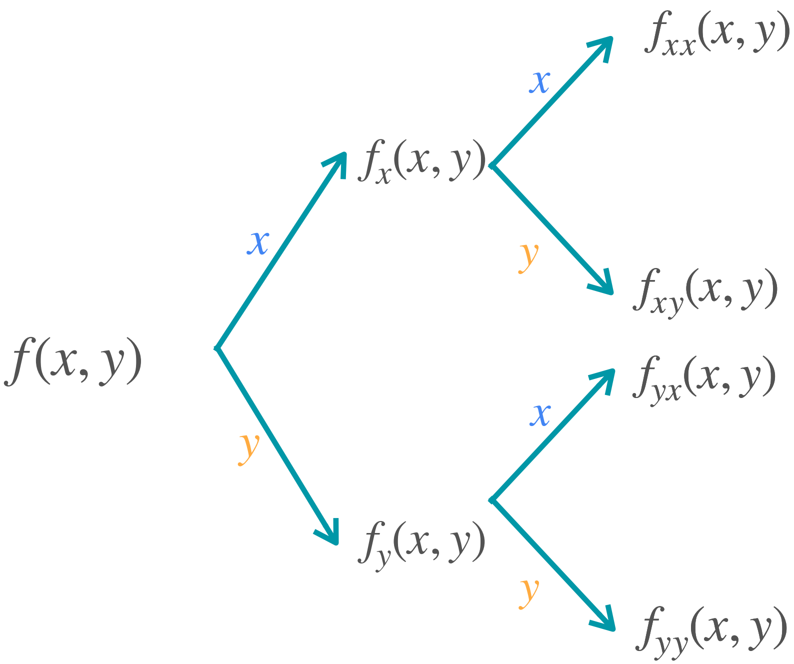
$$H = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix} = \begin{bmatrix} \nabla {f_x}^T \\ \nabla {f_y}^T \end{bmatrix}$$

Hessian matrix

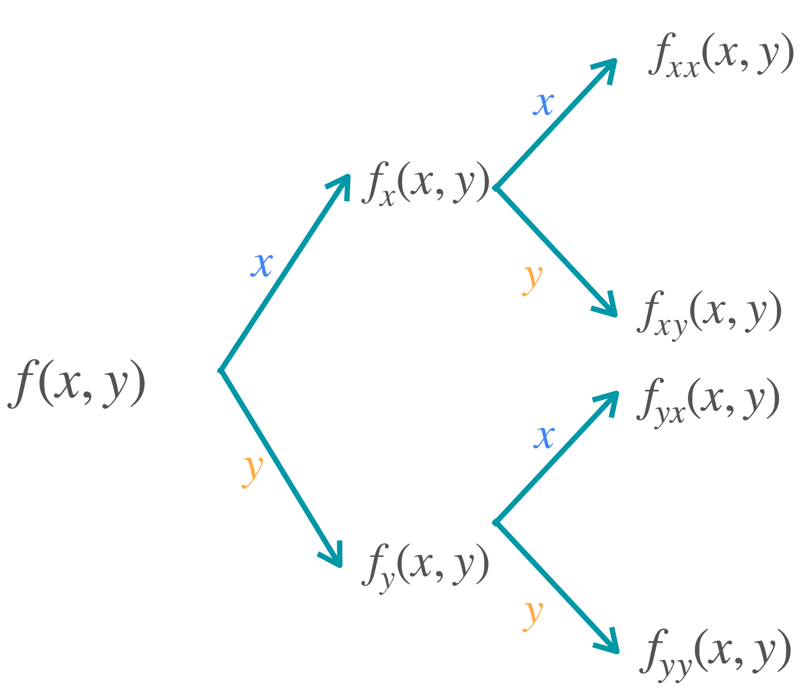
All information about second derivatives

Hessian Matrix - General Case

Hessian Matrix - General Case



Hessian Matrix - General Case



$f_{xx}(x, y)$

$f_{xy}(x, y)$

Hessian Matrix - General Case

$$
\begin{tikzcd}
 & & f_{xx}(x, y) \\
 & f_x(x, y) \arrow[ur, "x"] \arrow[dr, "y"'] & \\
f(x, y) \arrow[ur, "x"] \arrow[ddr, "y"'] & & f_{xy}(x, y) \\
 & & f_{yx}(x, y) \\
 & f_y(x, y) \arrow[ur, "x"] \arrow[dr, "y"'] & \\
 & & f_{yy}(x, y)
\end{tikzcd}
$$

$$\nabla f_x = \begin{bmatrix} f_{xx}(x, y) \\ f_{xy}(x, y) \end{bmatrix}$$

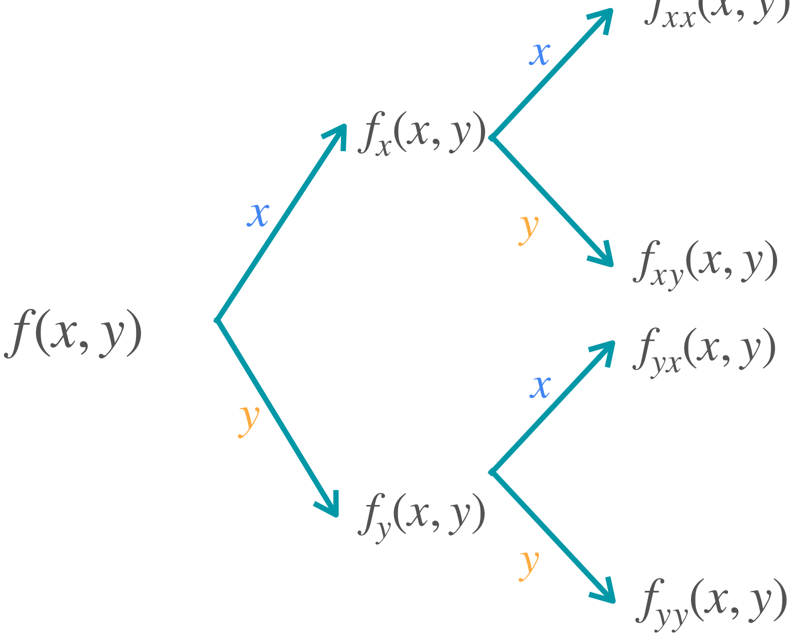
Hessian Matrix - General Case

$$
\begin{tikzcd}
 & & f_{xx}(x,y) \\
 & f_x(x,y) \arrow[ur, "x"] \arrow[dr, "y"'] & \\
 & & f_{xy}(x,y) \\
f(x,y) \arrow[uur, "x"] \arrow[ddr, "y"'] & & \\
 & & f_{yx}(x,y) \\
 & f_y(x,y) \arrow[ur, "x"] \arrow[dr, "y"'] & \\
 & & f_{yy}(x,y)
\end{tikzcd}
$$

$$\nabla f_x = \begin{bmatrix} f_{xx}(x,y) \\ f_{xy}(x,y) \end{bmatrix}$$

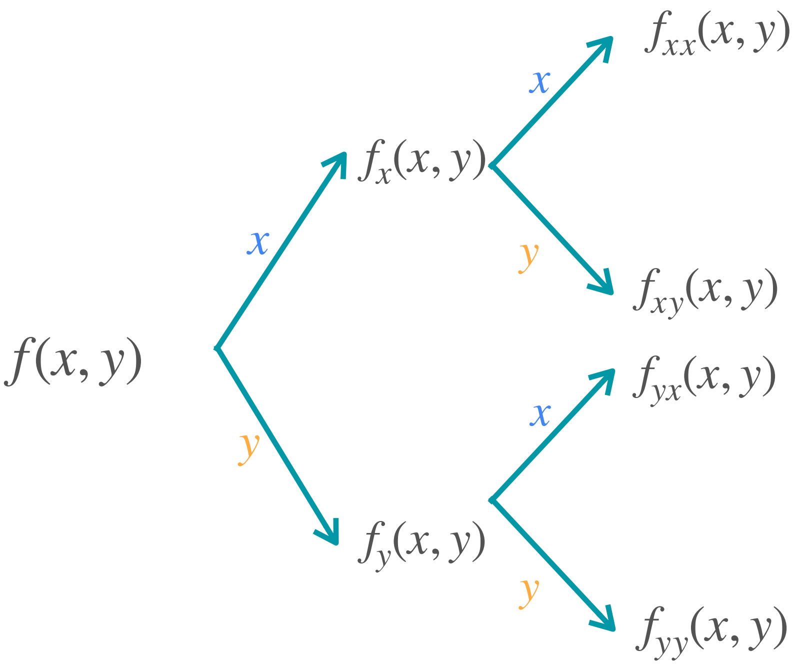
$$\begin{matrix} f_{yx}(x,y) \\ f_{yy}(x,y) \end{matrix}$$

Hessian Matrix - General Case



$$\nabla f_x = \begin{bmatrix} f_{xx}(x, y) \\ f_{xy}(x, y) \end{bmatrix} \qquad \nabla f_y' = \begin{bmatrix} f_{yx}(x, y) \\ f_{yy}(x, y) \end{bmatrix}$$

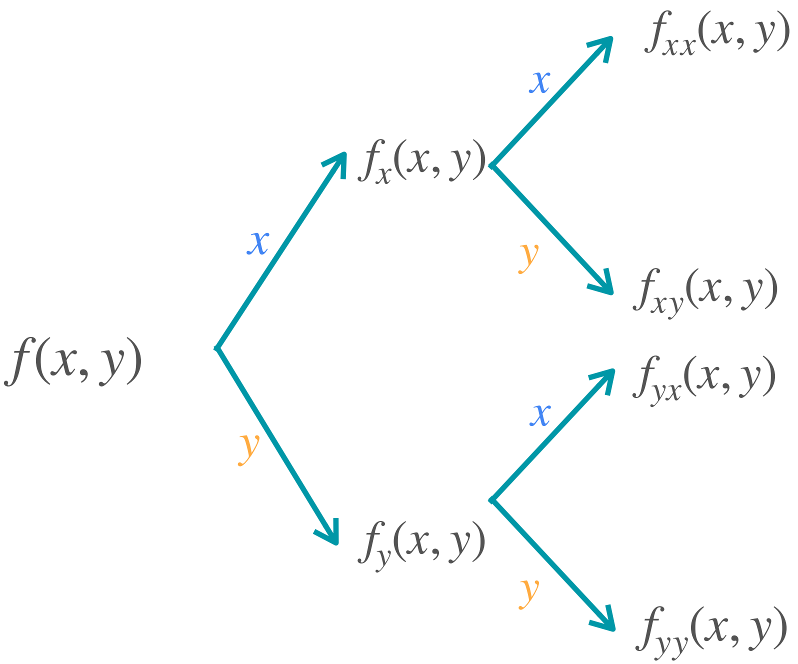
Hessian Matrix - General Case



$$\nabla f_x = \begin{bmatrix} f_{xx}(x, y) \\ f_{xy}(x, y) \end{bmatrix} \qquad \nabla f_y' = \begin{bmatrix} f_{yx}(x, y) \\ f_{yy}(x, y) \end{bmatrix}$$

$$\begin{matrix} f_{xx}(x, y) & f_{xy}(x, y) \\ f_{yx}(x, y) & f_{yy}(x, y) \end{matrix}$$

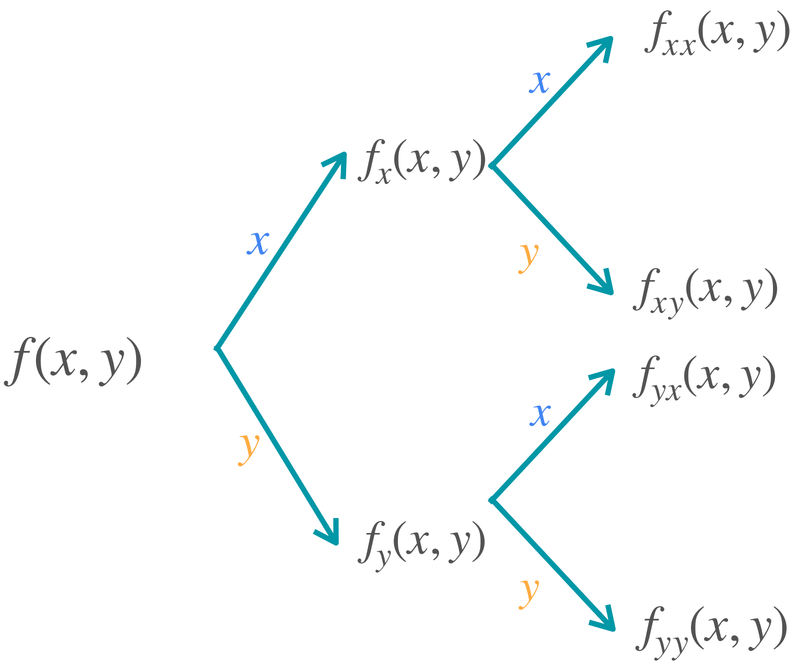
Hessian Matrix - General Case



$$\nabla f_x = \begin{bmatrix} f_{xx}(x, y) \\ f_{xy}(x, y) \end{bmatrix} \qquad \nabla f'_y = \begin{bmatrix} f_{yx}(x, y) \\ f_{yy}(x, y) \end{bmatrix}$$

$$\begin{bmatrix} f_{xx}(x, y) & f_{xy}(x, y) \\ f_{yx}(x, y) & f_{yy}(x, y) \end{bmatrix} = \begin{bmatrix} \nabla f_x^{\,T} \\ \nabla f_y^{\,T} \end{bmatrix}$$

Hessian Matrix - General Case



$$\nabla f_x = \begin{bmatrix} f_{xx}(x, y) \\ f_{xy}(x, y) \end{bmatrix} \qquad \nabla f'_y = \begin{bmatrix} f_{yx}(x, y) \\ f_{yy}(x, y) \end{bmatrix}$$

$$H = \begin{bmatrix} f_{xx}(x, y) & f_{xy}(x, y) \\ f_{yx}(x, y) & f_{yy}(x, y) \end{bmatrix} = \begin{bmatrix} \nabla f_x{}^T \\ \nabla f_y{}^T \end{bmatrix}$$

Hessian matrix

All information about second derivatives

Second Derivative

Second Derivative

	1 variable		2 variables
Function	$f(x)$		$f(x, y)$
First derivative	$f'(x)$	Rate of change of $f(x)$	$f_x(x, y)$ Rate of change w.r.t x $f_y(x, y)$ Rate of change w.r.t y $\nabla f = \begin{bmatrix} f_x(x, y) \\ f_y(x, y) \end{bmatrix}$
Second derivative	$f''(x)$	Rate of change of the rate of change of $f(x)$	

Second Derivative

	1 variable		2 variables	
Function	$f(x)$		$f(x, y)$	
First derivative	$f'(x)$	Rate of change of $f(x)$	$f_x(x, y)$	Rate of change w.r.t x
			$f_y(x, y)$	Rate of change w.r.t y
			$\nabla f = \begin{bmatrix} f_x(x, y) \\ f_y(x, y) \end{bmatrix}$	
Second derivative	$f''(x)$	Rate of change of the rate of change of $f(x)$	$H(x, y) = \begin{bmatrix} f_{xx}(x, y) & f_{xy}(x, y) \\ f_{yx}(x, y) & f_{yy}(x, y) \end{bmatrix}$	

DeepLearning.AI

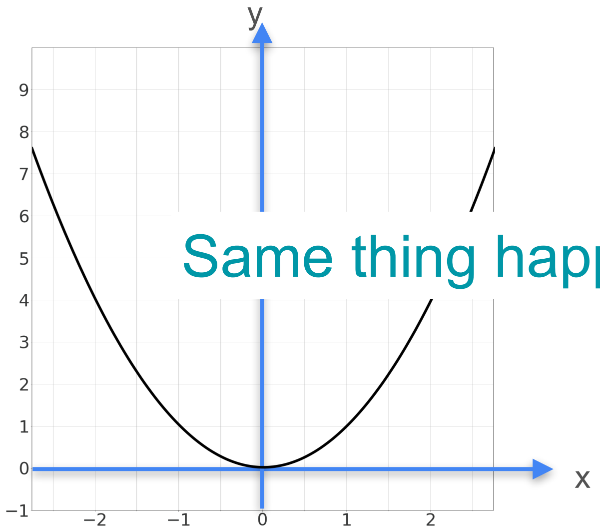
Optimization in Neural Networks and Newton's Method

Hessians and concavity

Remember…

Same thing happens for many variables!

Remember...

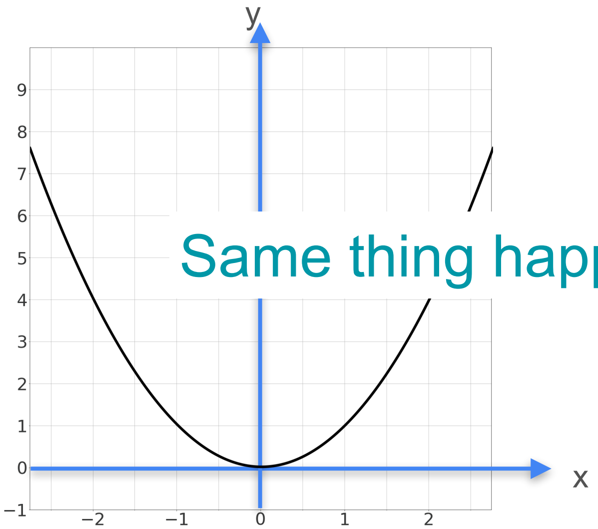


Same thing happens for many variables!

Concave up or convex

$$f''(0) > 0$$

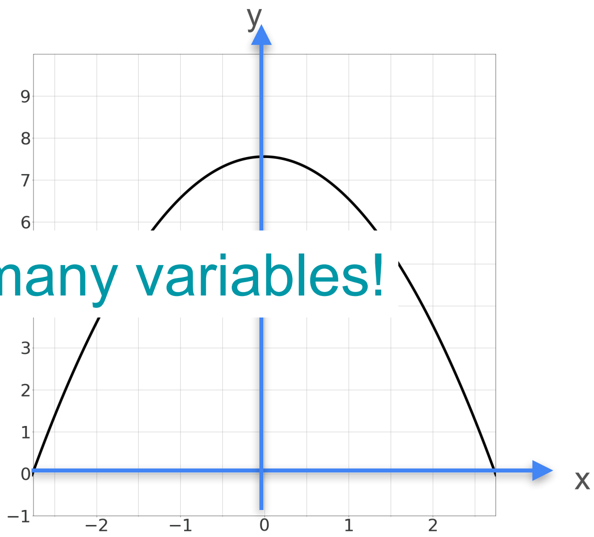
Remember…



Concave up or convex

$$f''(0) > 0$$

Same thing happens for many variables!

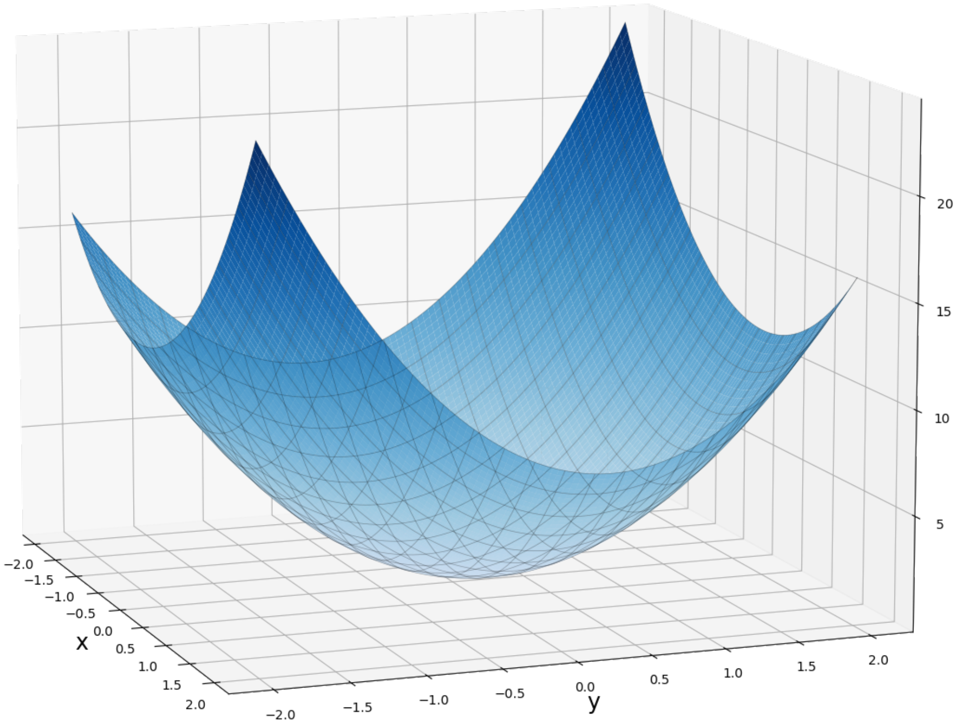


Concave down

$$f''(0) < 0$$

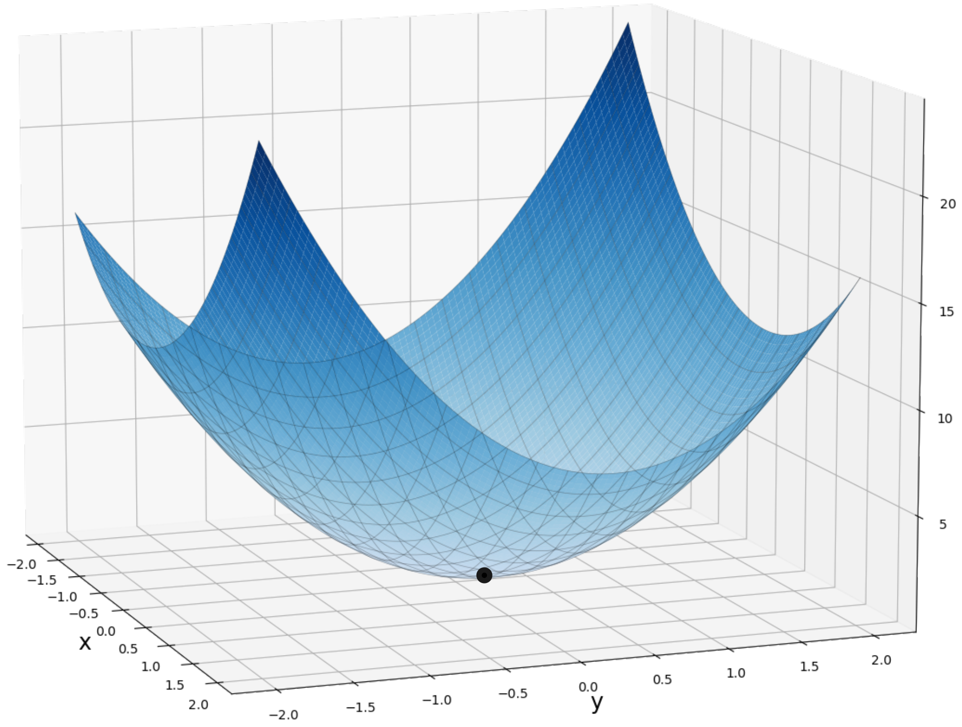
Concave Up

Concave Up



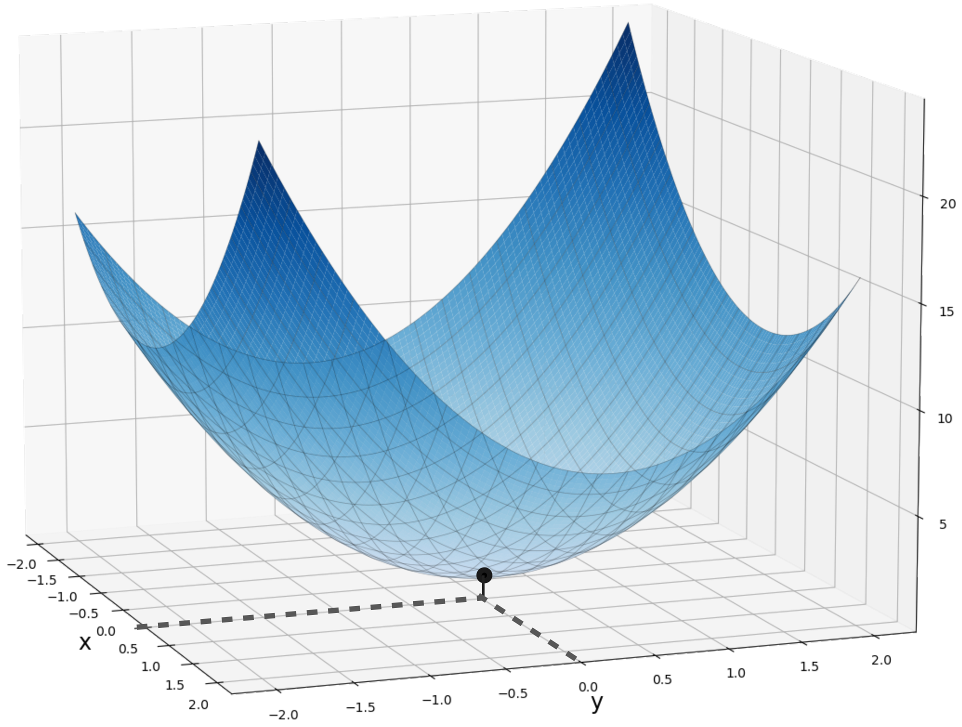
$$f(x, y) = 2x^2 + 3y^2 - xy$$

Concave Up



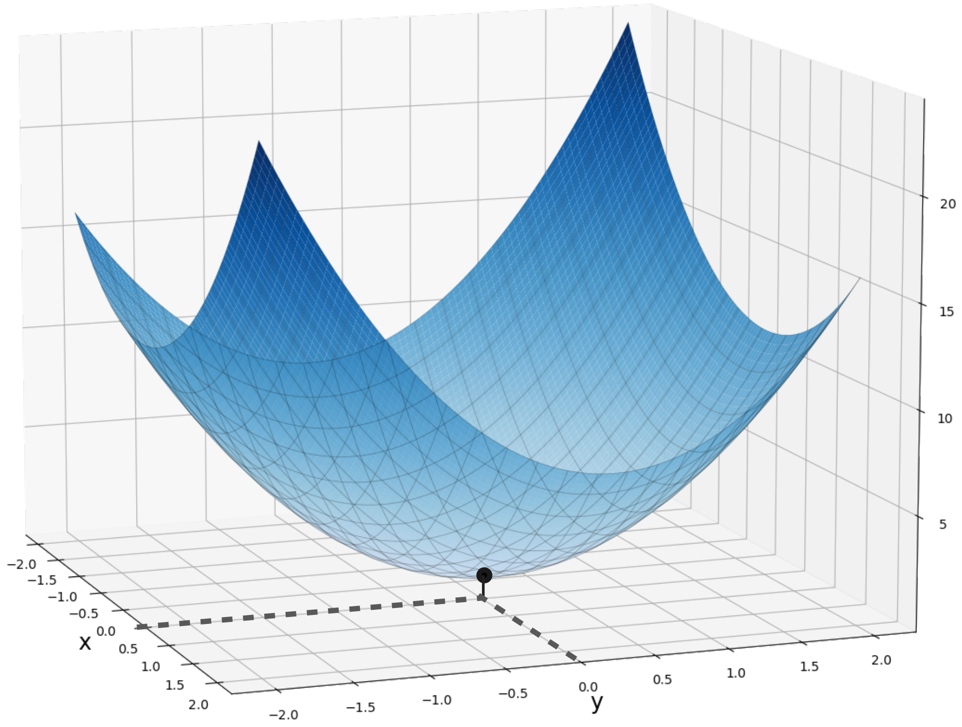
$$f(x, y) = 2x^2 + 3y^2 - xy$$

Concave Up



$$f(x, y) = 2x^2 + 3y^2 - xy$$

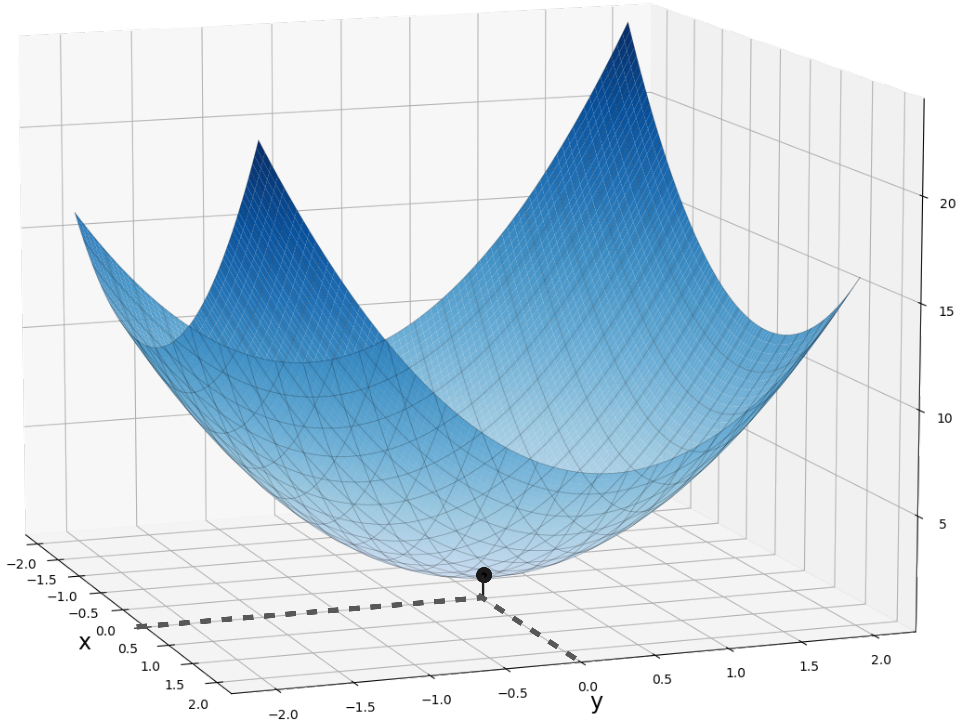
Concave Up



$$f(x, y) = 2x^2 + 3y^2 - xy$$

$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

Concave Up

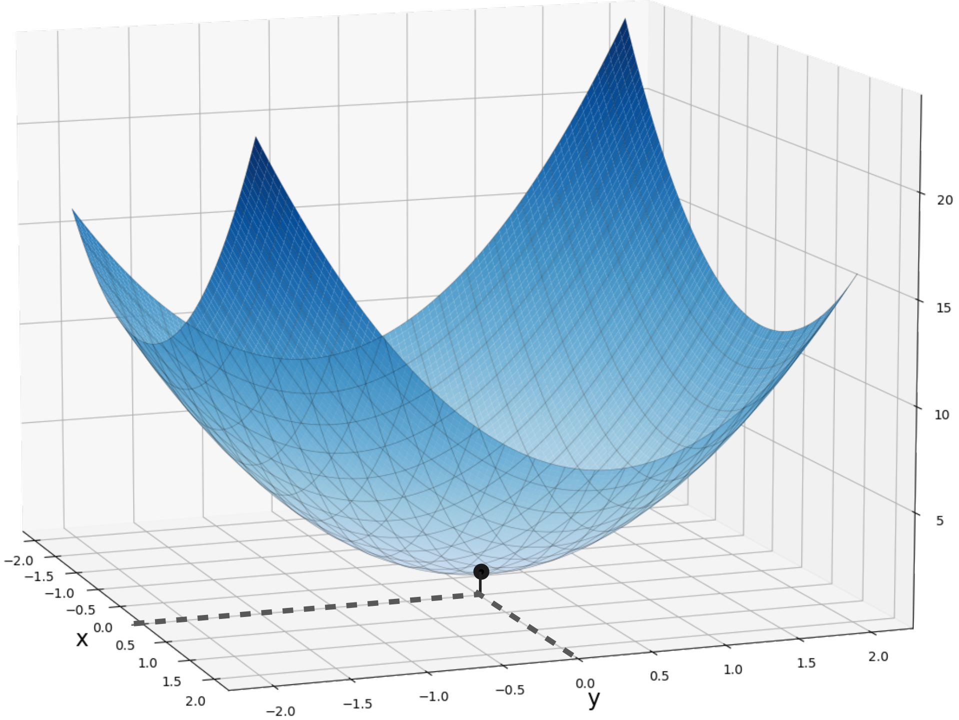


$$f(x, y) = 2x^2 + 3y^2 - xy$$

$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) =$$

Concave Up

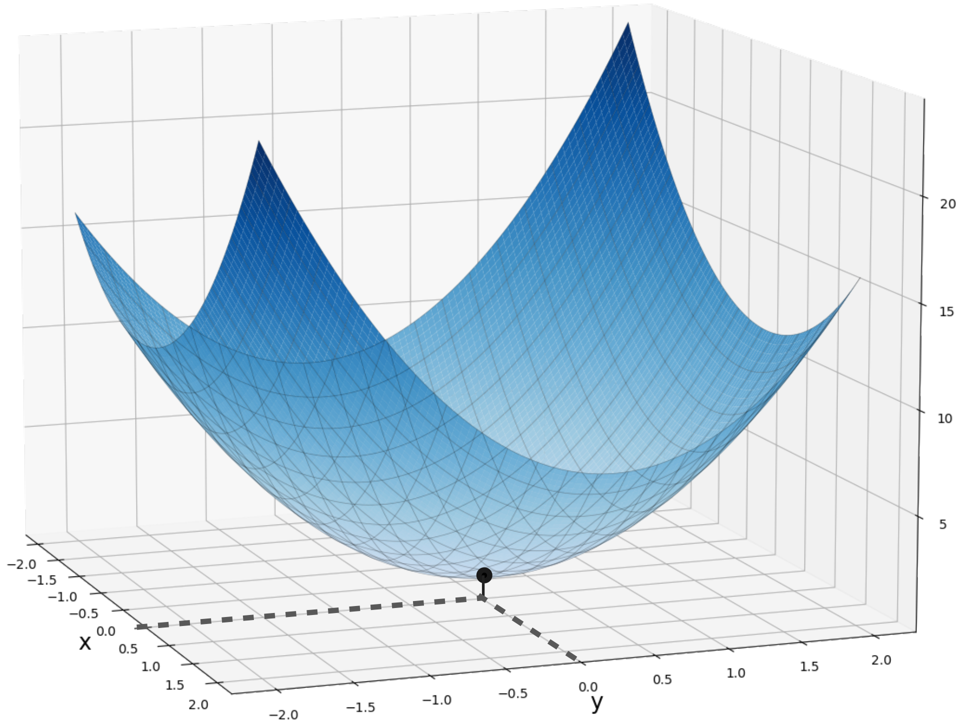


$$f(x, y) = 2x^2 + 3y^2 - xy$$

$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) = \det\left(\begin{bmatrix} 4-\lambda & -1 \\ -1 & 6-\lambda \end{bmatrix}\right)$$

Concave Up



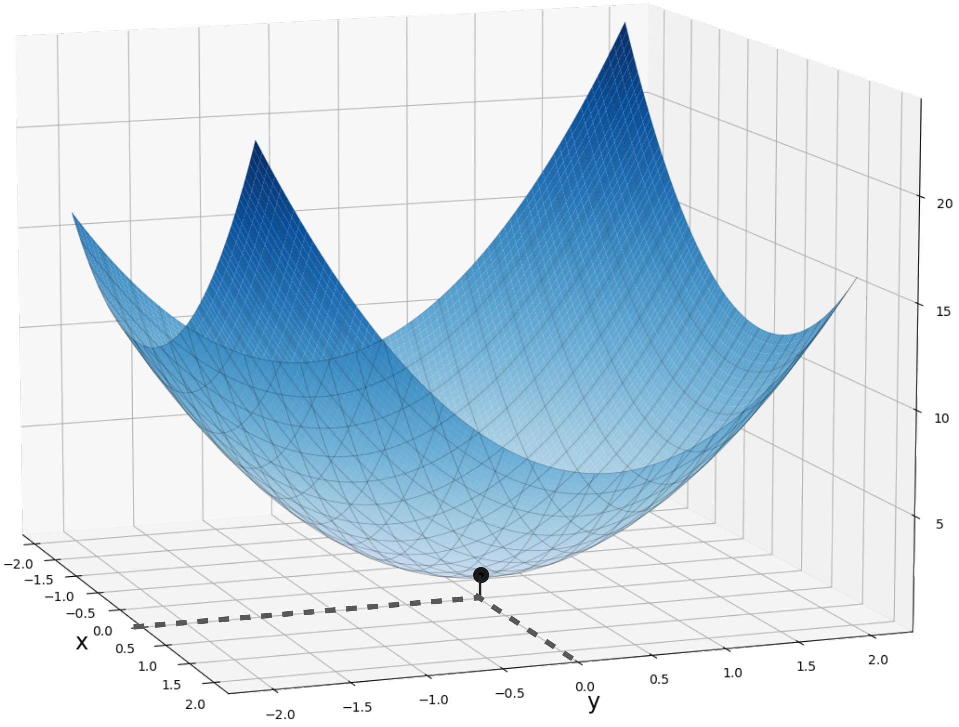
$$f(x, y) = 2x^2 + 3y^2 - xy$$

$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) = \det\left(\begin{bmatrix} 4-\lambda & -1 \\ -1 & 6-\lambda \end{bmatrix}\right)$$

$$= (4-\lambda)(6-\lambda) - (-1)(-1)$$

Concave Up



$$f(x,y) = 2x^2 + 3y^2 - xy$$

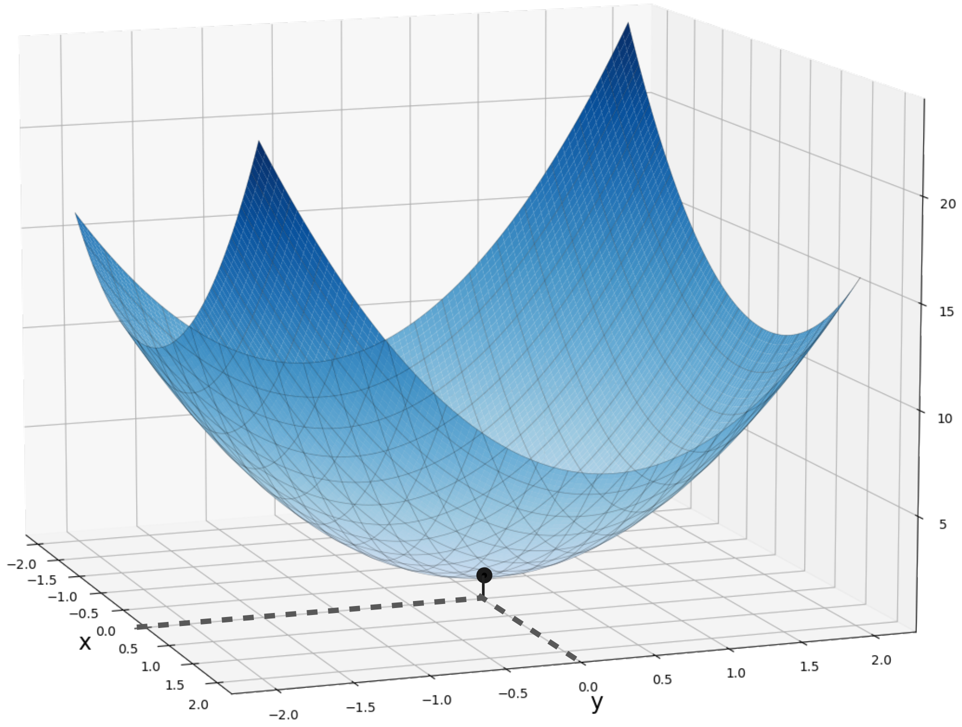
$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) = \det\left(\begin{bmatrix} 4-\lambda & -1 \\ -1 & 6-\lambda \end{bmatrix}\right)$$

$$= (4-\lambda)(6-\lambda) - (-1)(-1)$$

$$= \lambda^2 - 10\lambda + 23$$

Concave Up



$$f(x, y) = 2x^2 + 3y^2 - xy$$

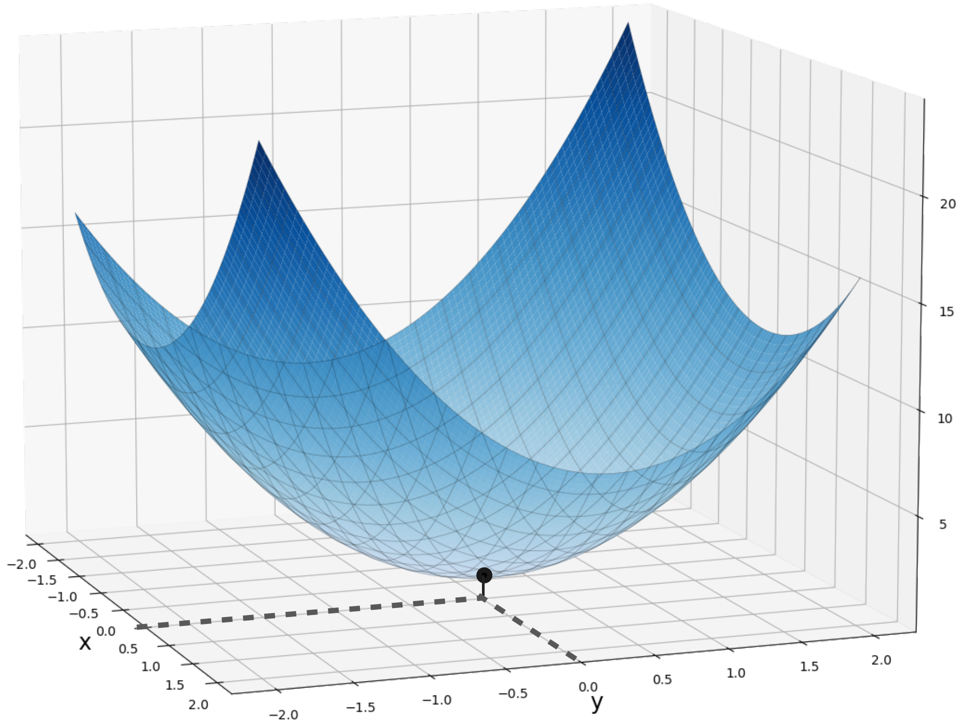
$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) = \det\left(\begin{bmatrix} 4-\lambda & -1 \\ -1 & 6-\lambda \end{bmatrix}\right)$$

$$= (4-\lambda)(6-\lambda) - (-1)(-1)$$

$$= \lambda^2 - 10\lambda + 23 \rightarrow \lambda_1 = 6.41$$

Concave Up



$$f(x, y) = 2x^2 + 3y^2 - xy$$

$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) = \det\left(\begin{bmatrix} 4-\lambda & -1 \\ -1 & 6-\lambda \end{bmatrix}\right)$$

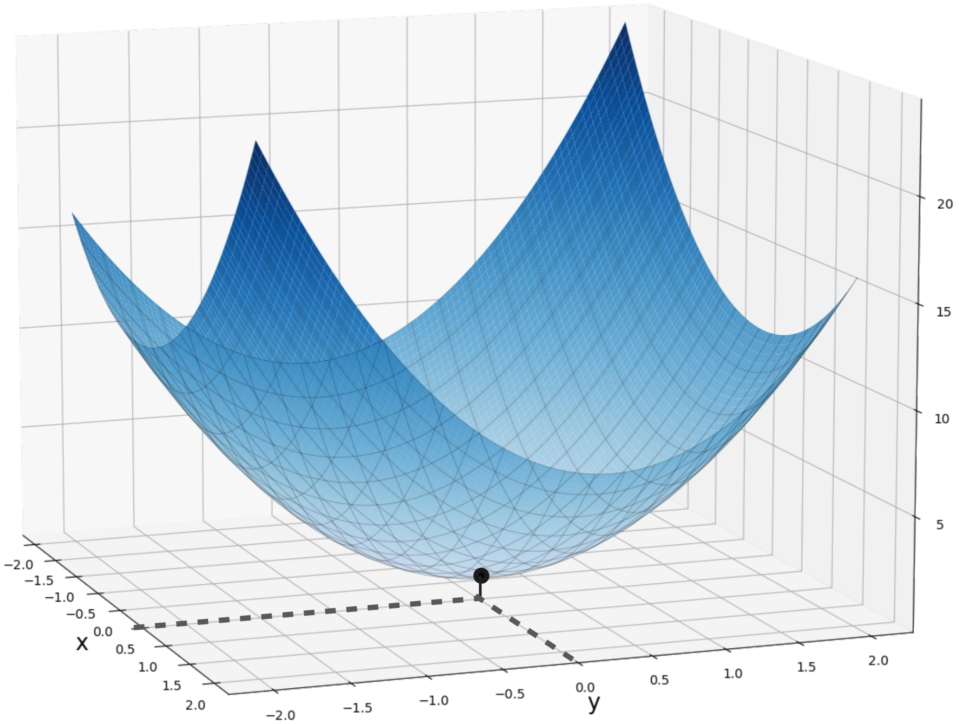
$$= (4-\lambda)(6-\lambda) - (-1)(-1)$$

$$= \lambda^2 - 10\lambda + 23$$

$$\lambda_1 = 6.41$$

$$\lambda_2 = 3.59$$

Concave Up



$$f(x, y) = 2x^2 + 3y^2 - xy$$

$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) = \det\left(\begin{bmatrix} 4-\lambda & -1 \\ -1 & 6-\lambda \end{bmatrix}\right)$$

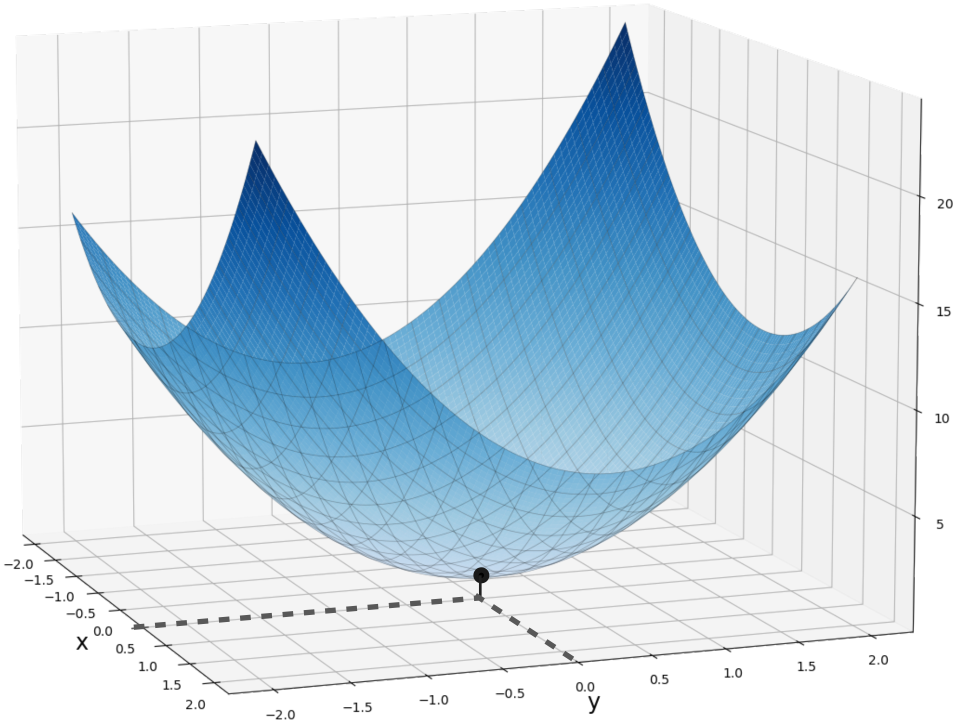
$$= (4-\lambda)(6-\lambda) - (-1)(-1)$$

$$= \lambda^2 - 10\lambda + 23$$

$$\boxed{\begin{matrix} \lambda_1 = 6.41 \\ \lambda_2 = 3.59 \end{matrix}}$$

> 0

Concave Up



$$f(x, y) = 2x^2 + 3y^2 - xy$$

$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) = \det\left(\begin{bmatrix} 4-\lambda & -1 \\ -1 & 6-\lambda \end{bmatrix}\right)$$

$$= (4-\lambda)(6-\lambda) - (-1)(-1)$$

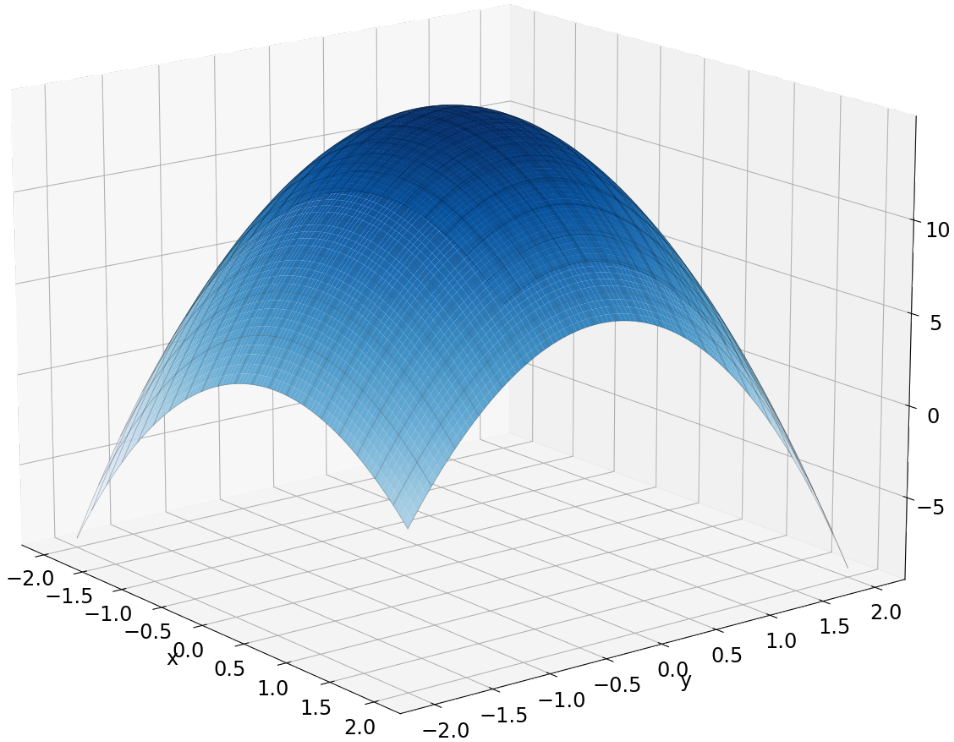
$$= \lambda^2 - 10\lambda + 23 \rightarrow \boxed{\begin{matrix} \lambda_1 = 6.41 \\ \lambda_2 = 3.59 \end{matrix}}$$

> 0

$(0,0)$ is a minimum!

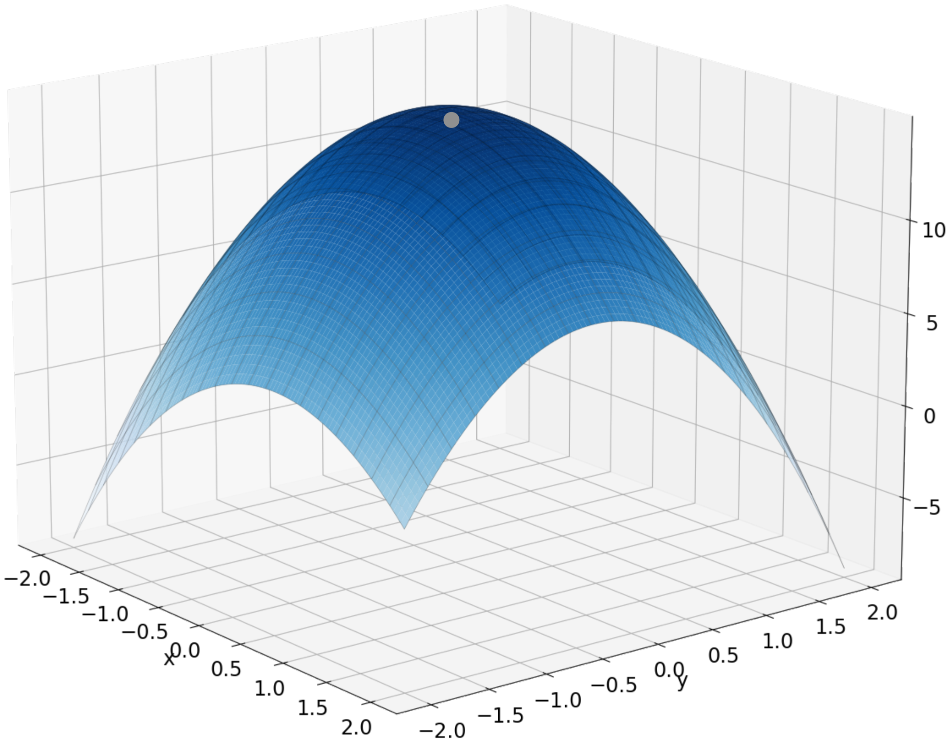
Concave Down

Concave Down



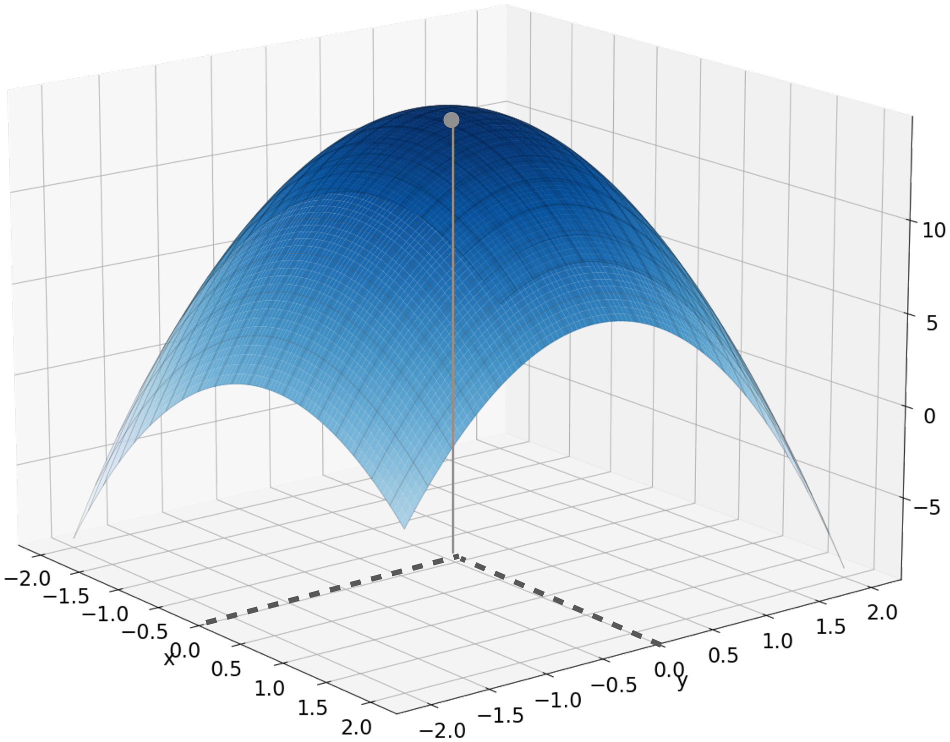
$$f(x, y) = \ -2x^2 + -3y^2 - xy + 15$$

Concave Down



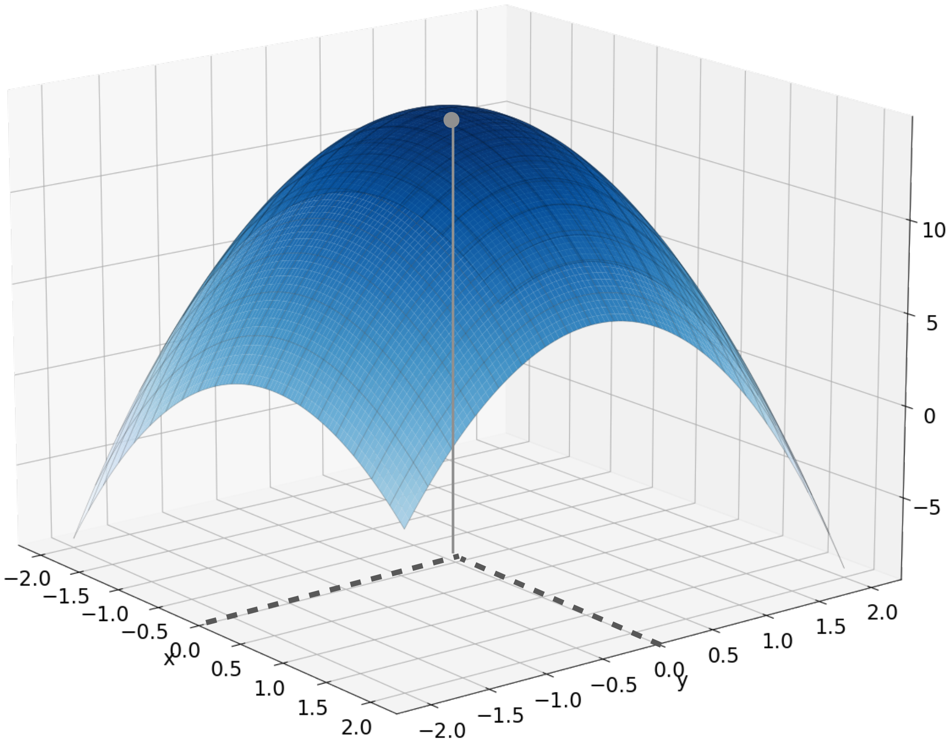
$$f(x, y) = -2x^2 + -3y^2 - xy + 15$$

Concave Down



$$f(x, y) = -2x^2 + -3y^2 - xy + 15$$

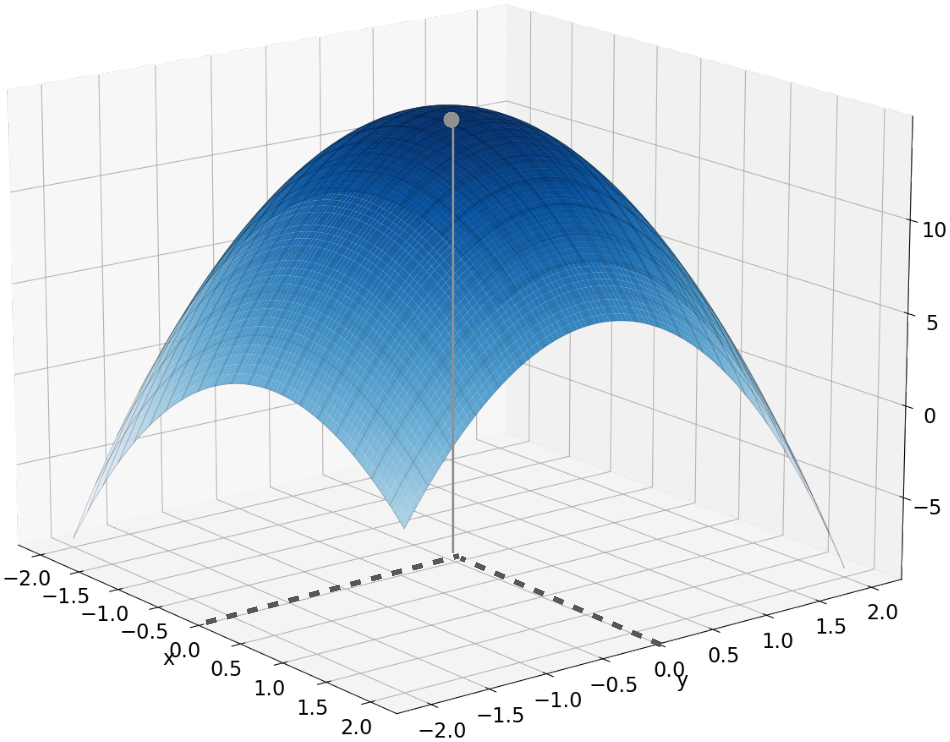
Concave Down



$$f(x, y) = -2x^2 + -3y^2 - xy + 15$$

$$\nabla f(x, y) = \begin{bmatrix} -4x - y \\ -x - 6y \end{bmatrix}$$

Concave Down

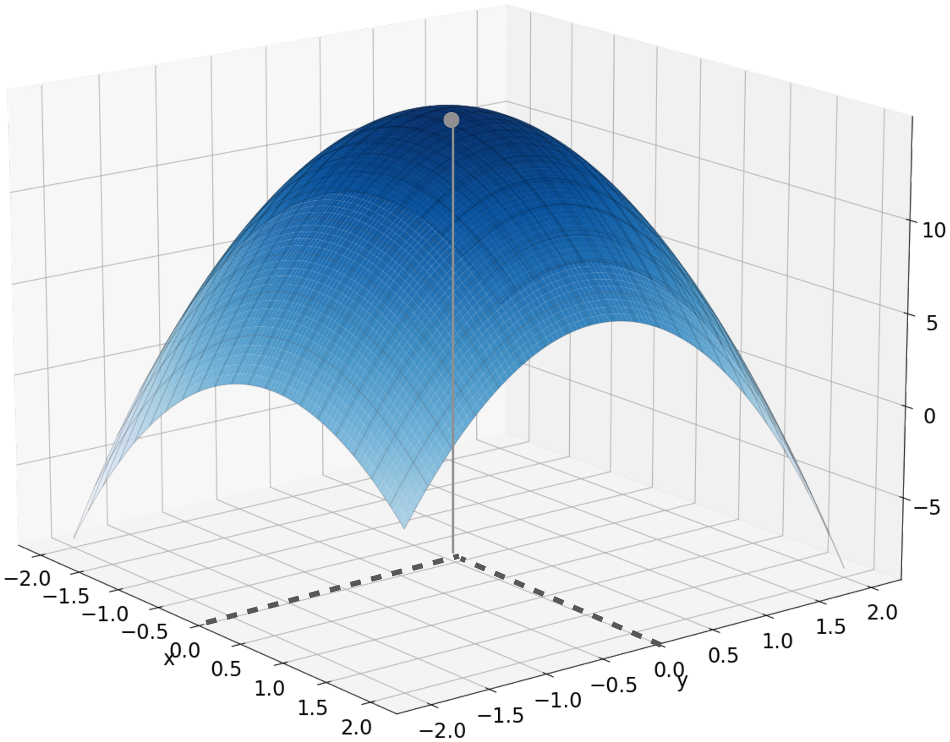


$$f(x, y) = \; -2x^2 + -3y^2 - xy + 15$$

$$\nabla f(x, y) = \begin{bmatrix} -4x - y \\ -x - 6y \end{bmatrix}$$

$$H(0,0) = \begin{bmatrix} -4 & -1 \\ -1 & -6 \end{bmatrix}$$

Concave Down



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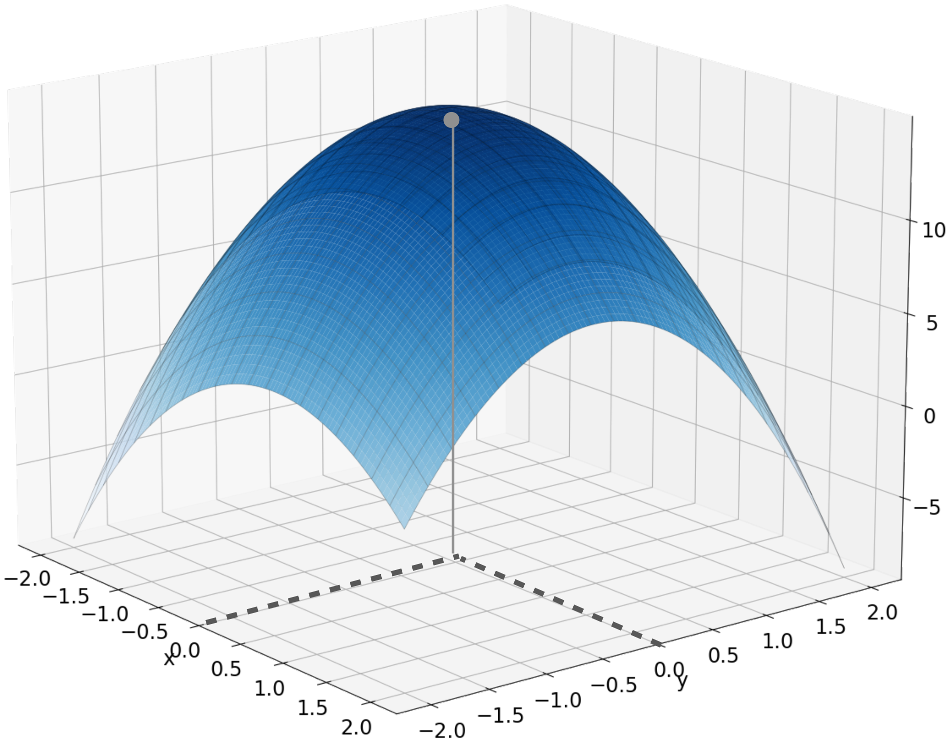
$$\det(H(0,0) - \lambda I) =$$

Concave Down



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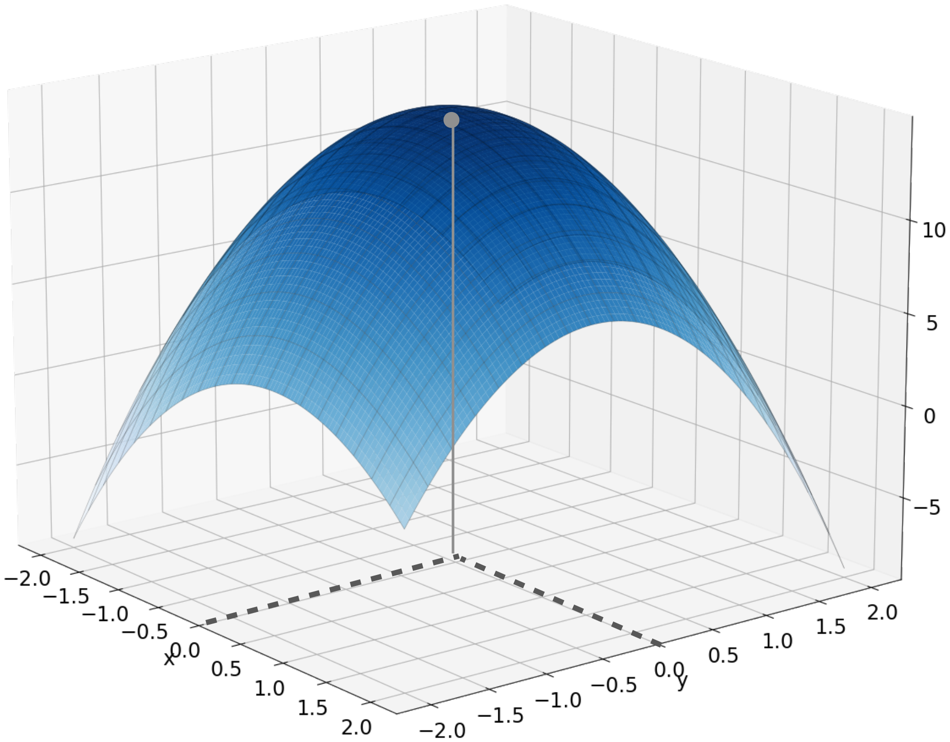
Concave Down



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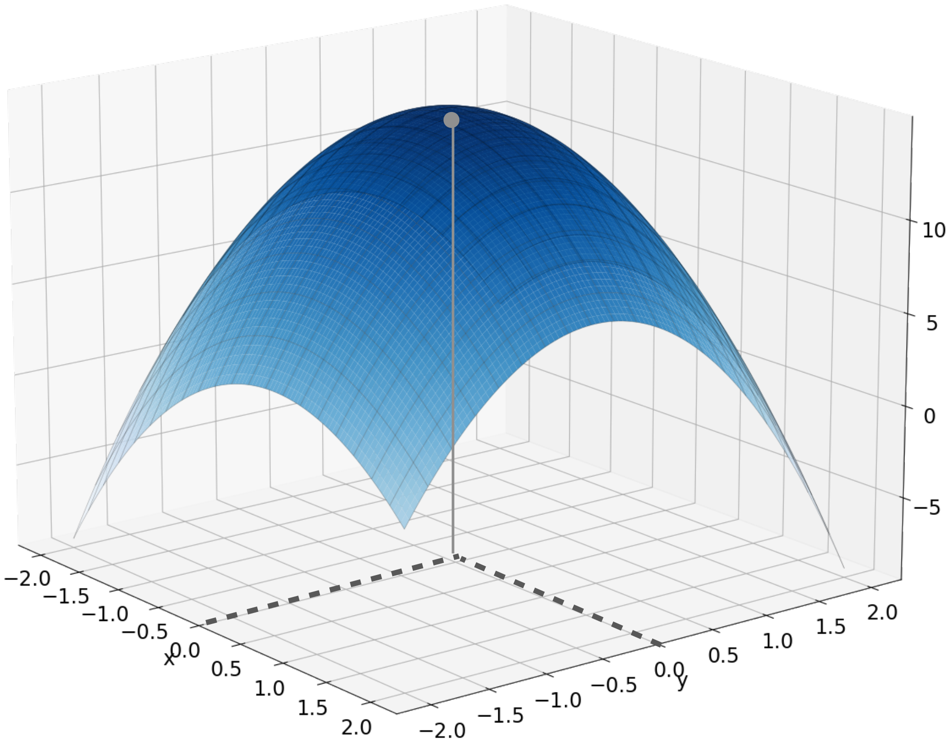
$$(-4-\lambda)(-6-\lambda) - (-1)(-1)$$

$$= \lambda^2 + 10\lambda + 23$$

Concave Down



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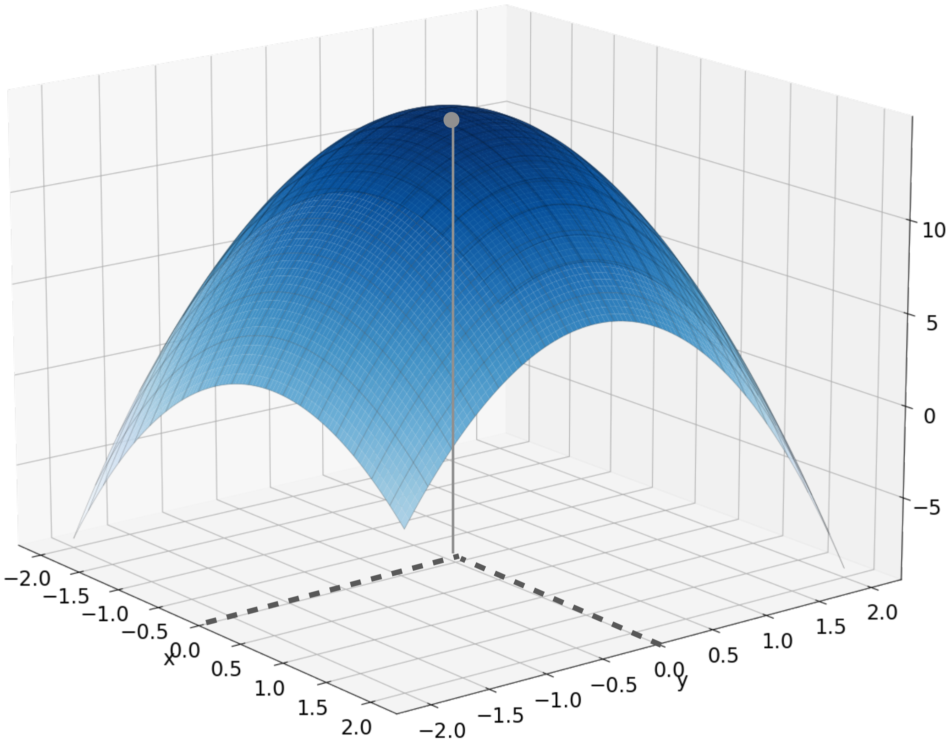
$$\det(H(0,0) - \lambda I) =$$

$$(-4 - \lambda)(-6 - \lambda) - (-1)(-1)$$

$$= \lambda^2 + 10\lambda + 23 \rightarrow \lambda_1 = -3.49$$

Concave Down



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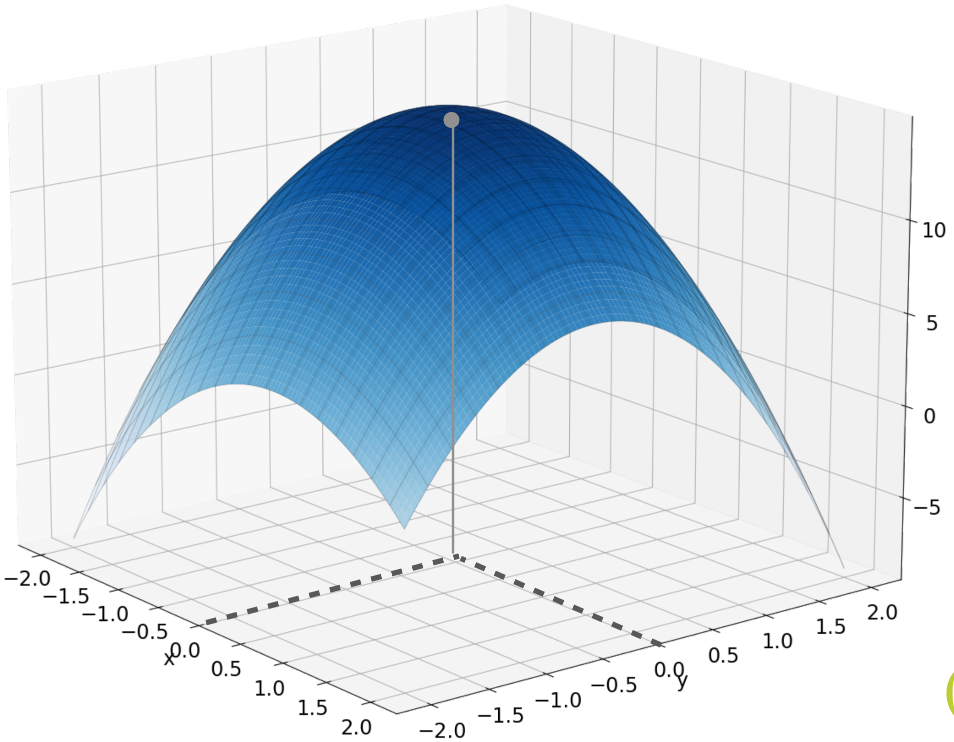
$$(-4 - \lambda)(-6 - \lambda) - (-1)(-1)$$

$$= \lambda^2 + 10\lambda + 23$$

$$\lambda_1 = -3.49$$

$$\lambda_2 = -6.41$$

Concave Down



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$$\det(H(0,0) - \lambda I) =$$

$$(-4 - \lambda)(-6 - \lambda) - (-1)(-1)$$

$$= \lambda^2 + 10\lambda + 23$$

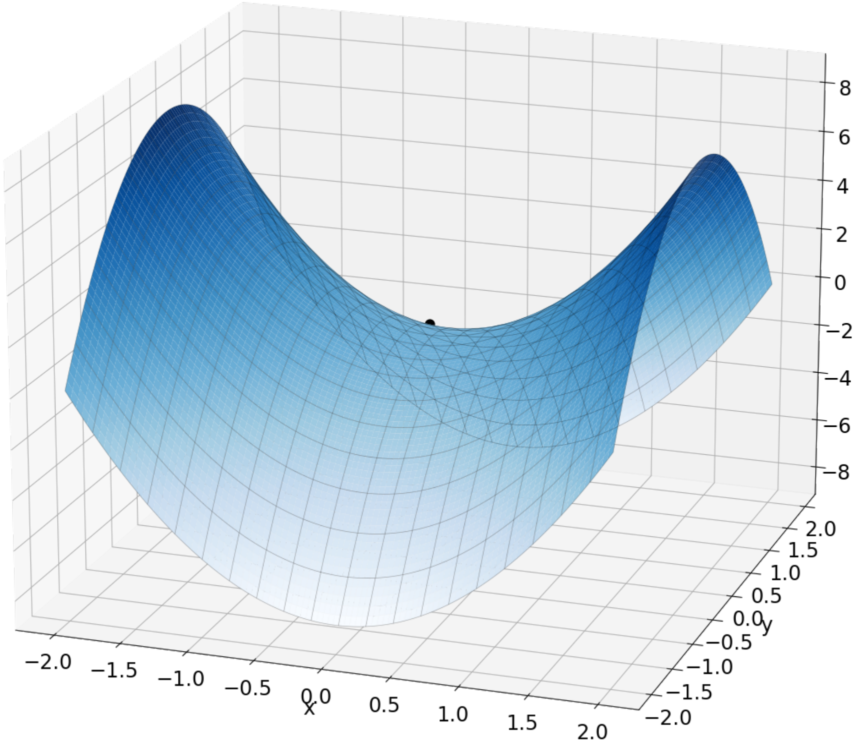
$$\boxed{\begin{aligned} \lambda_1 &= -3.49 \\ \lambda_2 &= -6.41 \end{aligned}}$$

< 0

(0,0) is a maximum!

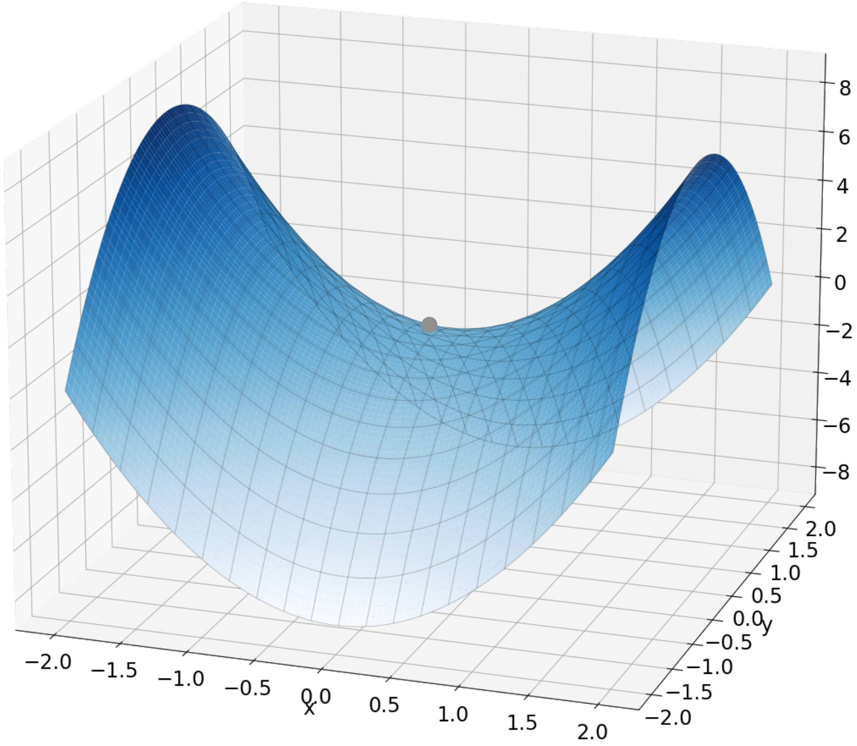
Saddle Point

Saddle Point



$$f(x, y) = 2x^2 - 2y^2$$

Saddle Point



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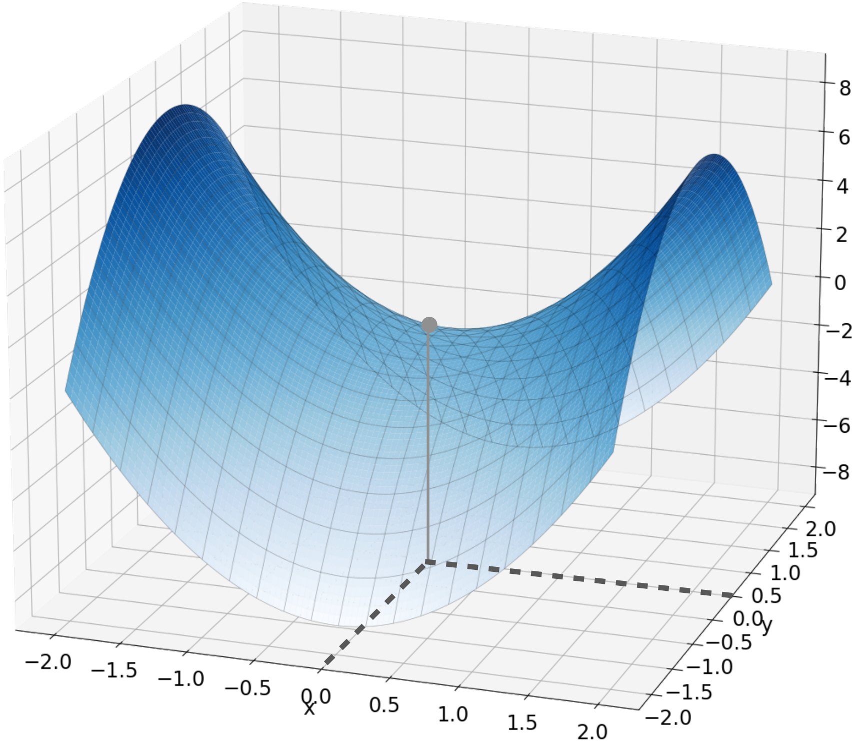

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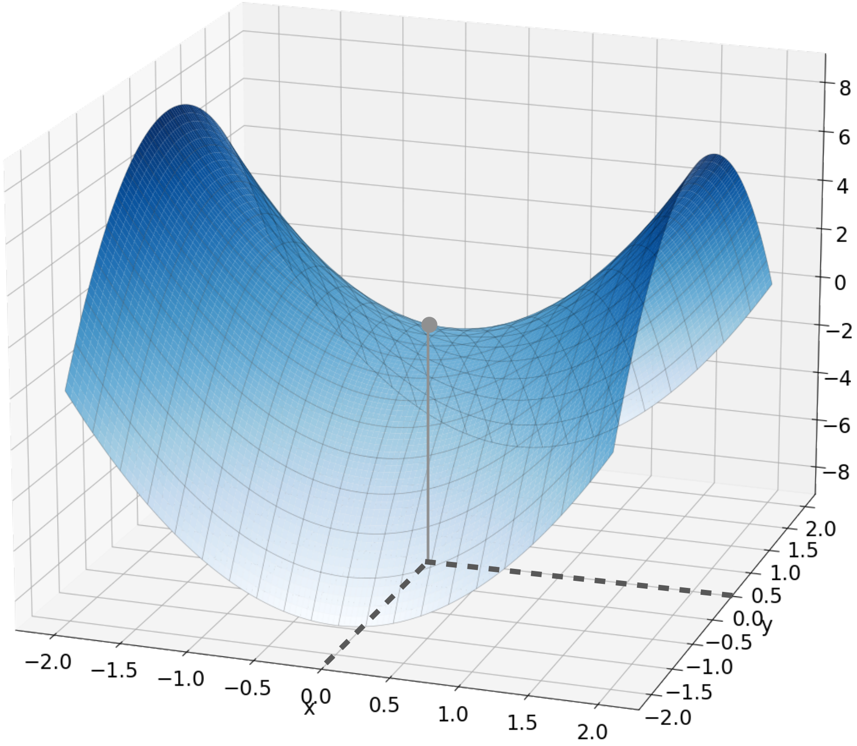
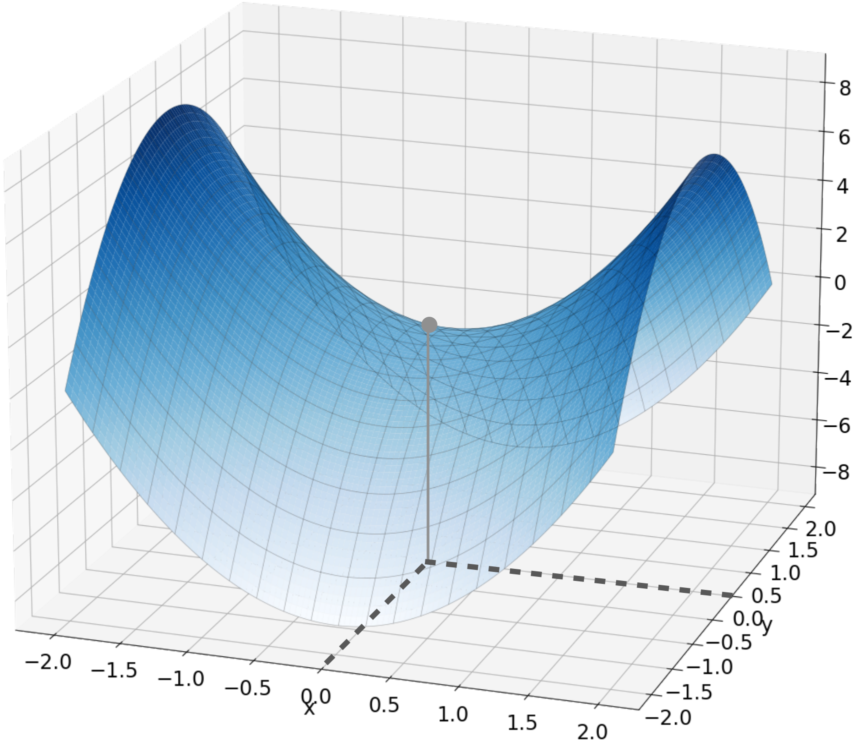
Saddle Point



$$f(x, y) = 2x^2 - 2y^2$$

$$\nabla f(x, y) = \begin{bmatrix} 4x \\ -4y \end{bmatrix}$$

Saddle Point



$$f(x, y) = 2x^2 - 2y^2$$

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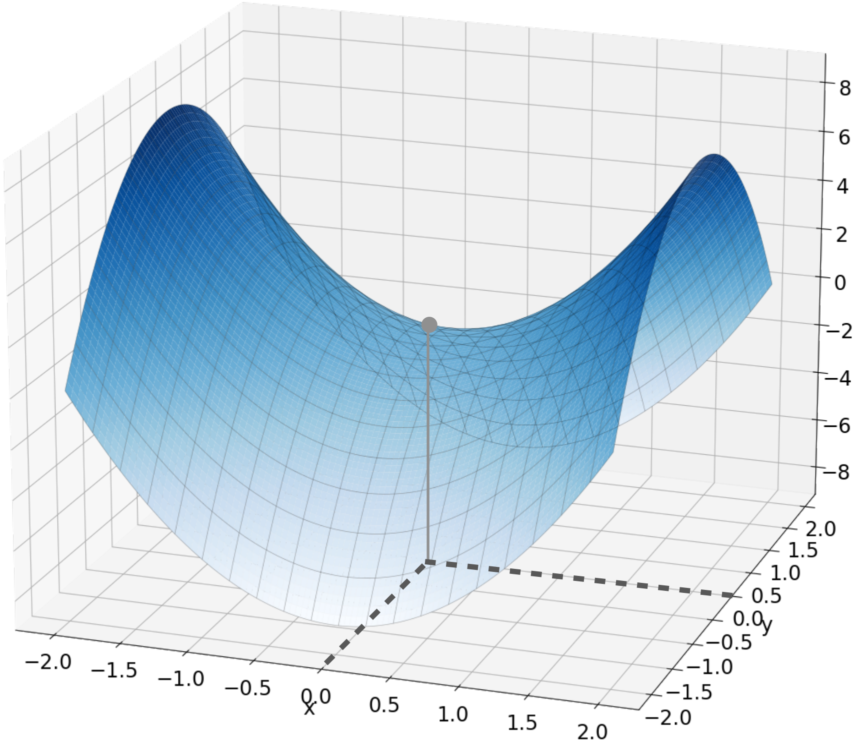
$$H(0,0) = \begin{bmatrix} 4 & 0 \\ 0 & -4 \end{bmatrix}$$

Saddle Point



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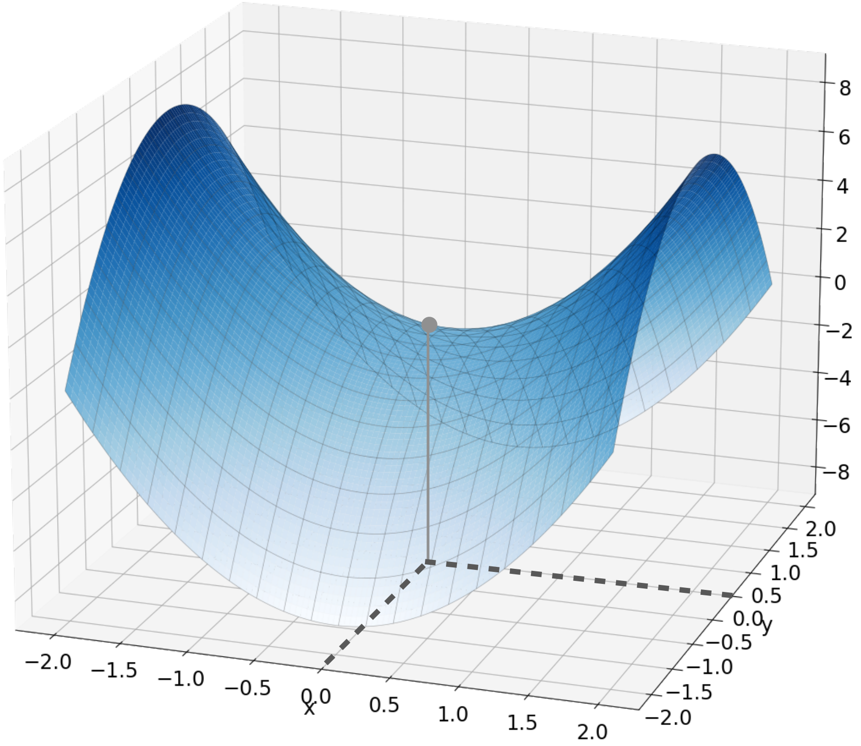
$$\det(H(0,0) - \lambda I) =$$

Saddle Point



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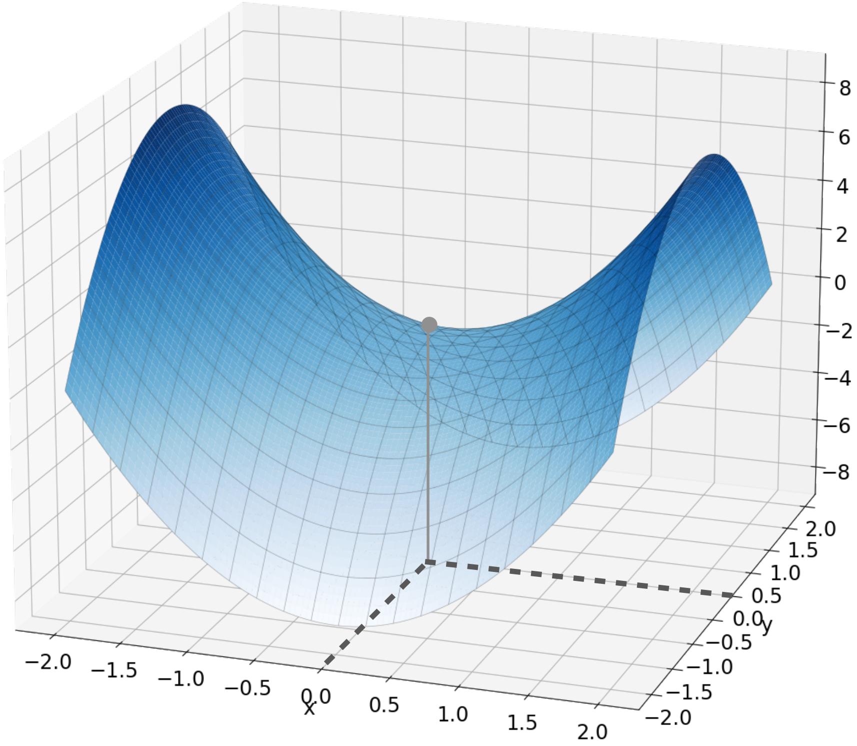
$$(4 - \lambda)(-4 - \lambda) - 0$$

$$\lambda_1 = -4$$

Saddle Point



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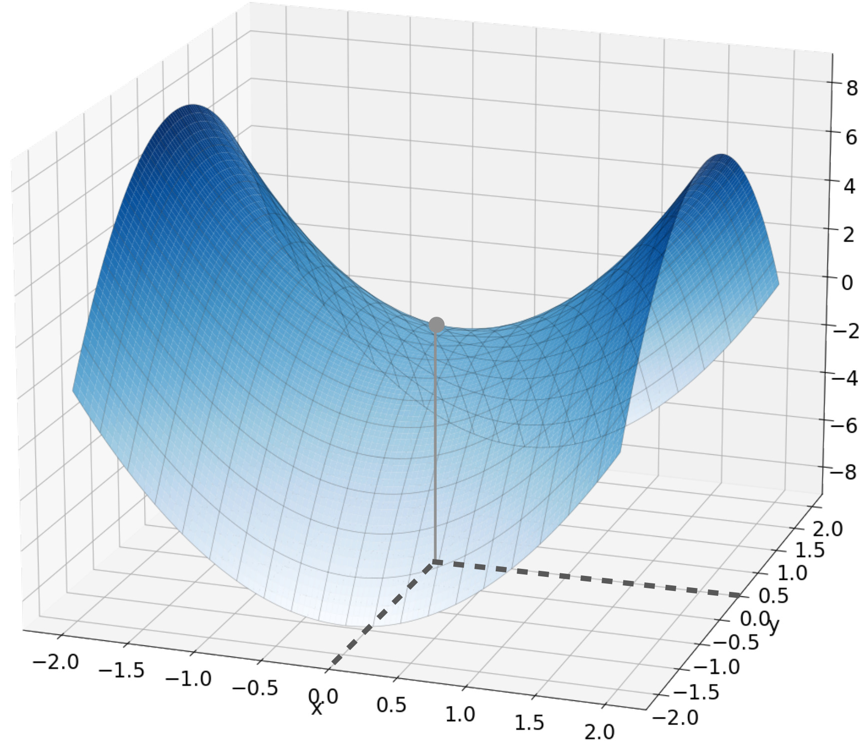
$$\det(H(0,0) - \lambda I) =$$

$$(4 - \lambda)(-4 - \lambda) - 0$$

$$\lambda_1 = -4$$

$$\lambda_2 = 4$$

Saddle Point



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$$H(0,0) = \begin{bmatrix} 4 & 0 \\ 0 & -4 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) =$$

$$(4 - \lambda)(-4 - \lambda) - 0$$

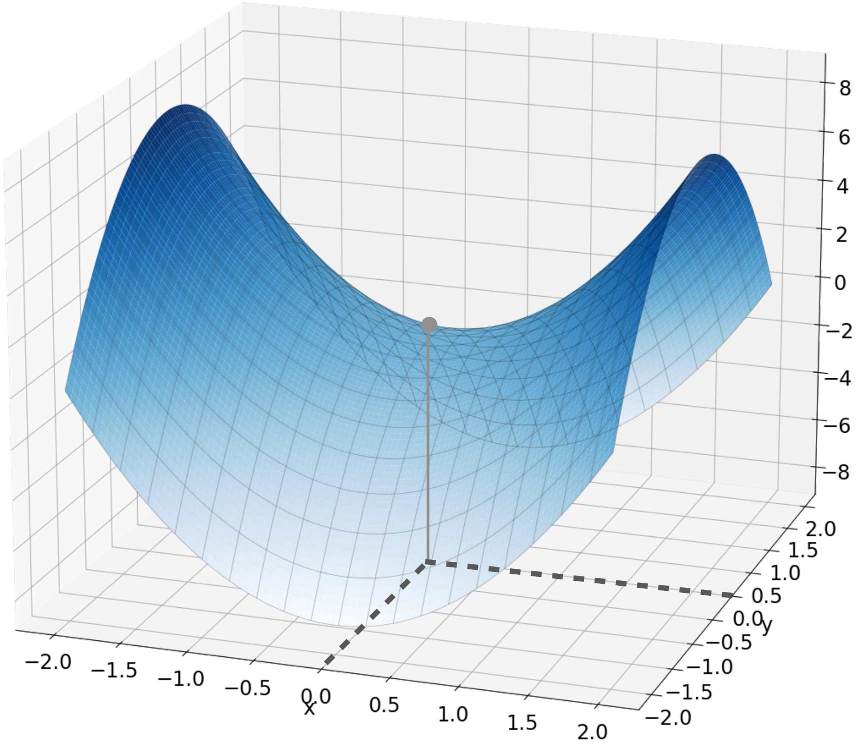
< 0

$$\boxed{\lambda_1 = -4}$$

$$\lambda_2 = 4$$

(0,0) is saddle point

Saddle Point



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$$\det(H(0,0) - \lambda I) = (4 - \lambda)(-4 - \lambda) - 0$$

< 0

$$\boxed{\lambda_1 = -4}$$

$$\boxed{\lambda_2 = 4}$$

> 0

(0,0) is saddle point

Summary

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	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$

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(Local) minima	Happy face $f''(x) > 0$		

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	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \,\&\, \lambda_2 > 0$	

Summary

	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \,\&\, \lambda_2 > 0$	All $\lambda_i > 0$

Summary

	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \; \& \; \lambda_2 > 0$	All $\lambda_i > 0$
(Local) maxima	Sad face $f''(x) < 0$		

Summary

	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \,\&\, \lambda_2 > 0$	All $\lambda_i > 0$
(Local) maxima	Sad face $f''(x) < 0$	Down paraboloid $\lambda_1 < 0 \,\&\, \lambda_2 < 0$	

Summary

	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \,\&\, \lambda_2 > 0$	All $\lambda_i > 0$
(Local) maxima	Sad face $f''(x) < 0$	Down paraboloid $\lambda_1 < 0 \,\&\, \lambda_2 < 0$	All $\lambda_i < 0$

Summary

	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \,\&\, \lambda_2 > 0$	All $\lambda_i > 0$
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Need more information	$f''(x) = 0$		

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	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \,\&\, \lambda_2 > 0$	All $\lambda_i > 0$
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Need more information	$f''(x) = 0$	Saddle point $\lambda_1 > 0 \,\&\, \lambda_2 < 0$ $\lambda_1 < 0 \,\&\, \lambda_2 > 0$	

Summary

	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \,\&\, \lambda_2 > 0$	All $\lambda_i > 0$
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Need more information	$f''(x) = 0$	Saddle point $\lambda_1 > 0 \,\&\, \lambda_2 < 0$ $\lambda_1 < 0 \,\&\, \lambda_2 > 0$ Or some $\lambda_i = 0$	

Summary

	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \ldots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \,\&\, \lambda_2 > 0$	All $\lambda_i > 0$
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Need more information	$f''(x) = 0$	Saddle point $\lambda_1 > 0 \,\&\, \lambda_2 < 0$ $\lambda_1 < 0 \,\&\, \lambda_2 > 0$ Or some $\lambda_i = 0$	Some $\lambda_i > 0$ and some $\lambda_j < 0$ OR At least one $\lambda_i = 0$

DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Newton's method for two variables

Newton’s Method

Newton’s Method

1 variable

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

Newton's Method

1 variable

$$x_{k+1} = \boxed{x_k} - \frac{f'(x_k)}{f''(x_k)}$$

Newton's Method

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Newton's Method

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Newton's Method

1 variable

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

$$x_{k+1} = x_k - f''(x_k)^{-1} f'(x_k)$$

Newton's Method

1 variable

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

$$x_{k+1} = x_k - f''(x_k)^{-1} f'(x_k)$$

2 variables

Newton's Method

1 variable

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

$$x_{k+1} = x_k - f''(x_k)^{-1} f'(x_k)$$

2 variables

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix}$$

Newton's Method

1 variable

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

$$x_{k+1} = x_k - f''(x_k)^{-1} f'(x_k)$$

2 variables

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} -$$

Newton's Method

1 variable

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

$$x_{k+1} = x_k - \boxed{f''(x_k)^{-1}} f'(x_k)$$

2 variables

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - H^{-1}(x_k, y_k)$$

Newton's Method

1 variable

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

$$x_{k+1} = x_k - f''(x_k)^{-1} f'(x_k)$$

2 variables

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - H^{-1}(x_k, y_k)\ \nabla f(x_k, y_k)$$

Newton's Method

2 variables

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - H^{-1}(x_k, y_k) \; \nabla f(x_k, y_k)$$

Newton's Method

2 variables

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - H^{-1}(x_k, y_k) \; \nabla f(x_k, y_k)$$

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Newton's Method

2 variables

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - H^{-1}(x_k, y_k) \; \nabla f(x_k, y_k)$$

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} \cancel{- \nabla f(x_k, y_k) \; H^{-1}(x_k, y_k)}$$

Newton's Method

2 variables

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - \underbrace{H^{-1}(x_k, y_k)}_{2\times 2} \underbrace{\nabla f(x_k, y_k)}_{2\times 1}$$

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - \cancel{\nabla f(x_k, y_k)\, H^{-1}(x_k, y_k)}$$

Newton's Method

2 variables

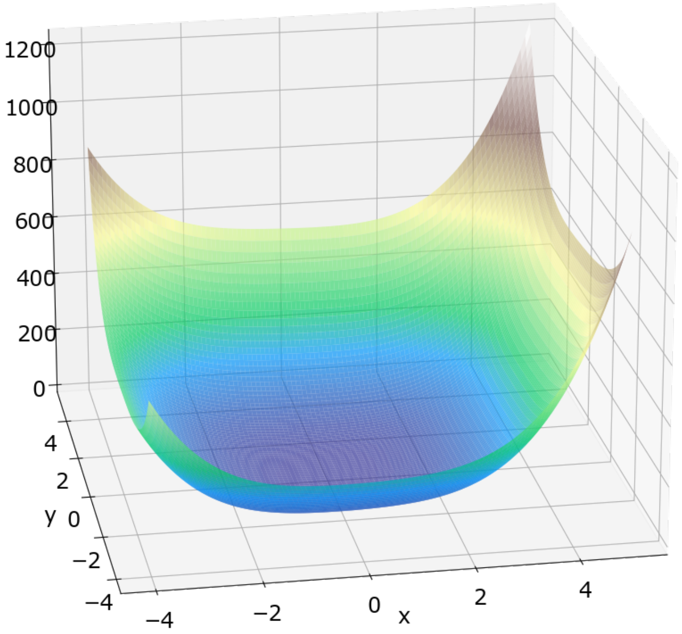
$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - \underbrace{H^{-1}(x_k, y_k)}_{2\times 2} \underbrace{\nabla f(x_k, y_k)}_{2\times 1}$$

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - \cancel{\nabla f(x_k, y_k) H^{-1}(x_k, y_k)}$$

When working with 2 variables the order is crucial!

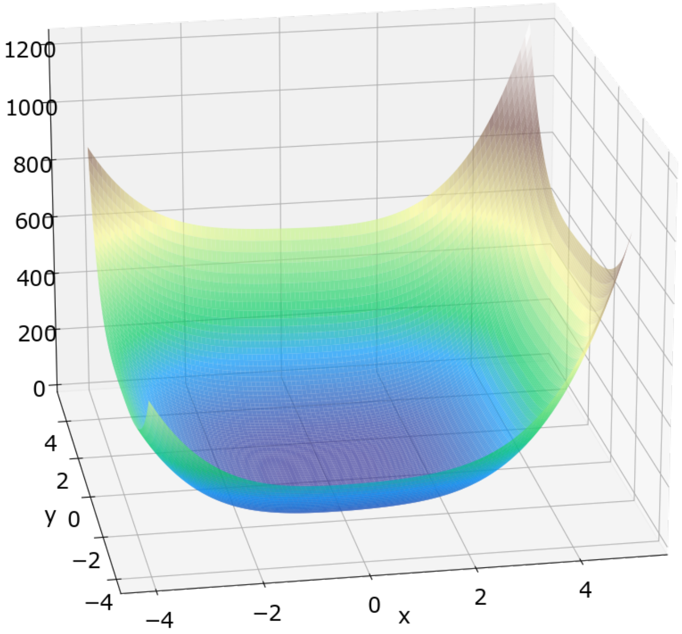
An Example

An Example



$$f(x, y) = x^4 + 0.8y^4 + 4x^2 + 2y^2 - xy - 0.2x^2y$$

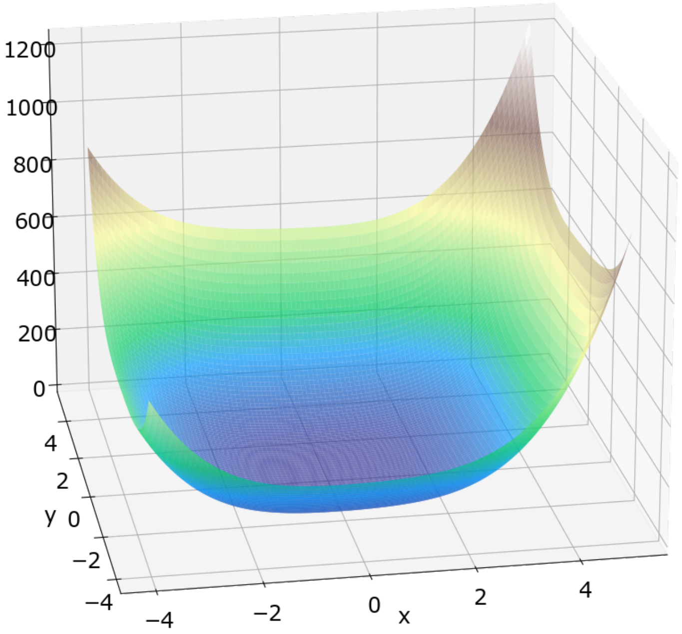
An Example



$$f(x,y) = x^4 + 0.8y^4 + 4x^2 + 2y^2 - xy - 0.2x^2y$$

$$f(x,y) \xrightarrow{x} 4x^3 + 8x - y - 0.4xy$$

An Example



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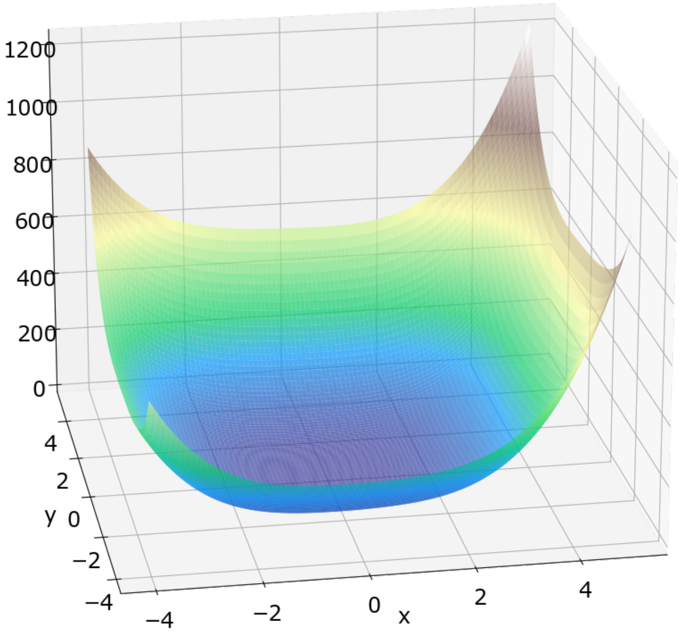
$$f(x,y) \xrightarrow{x} 4x^3 + 8x - y - 0.4xy$$

$$f(x,y) \xrightarrow{y} 3.2y^3 + 4y - x - 0.2x^2$$

An Example

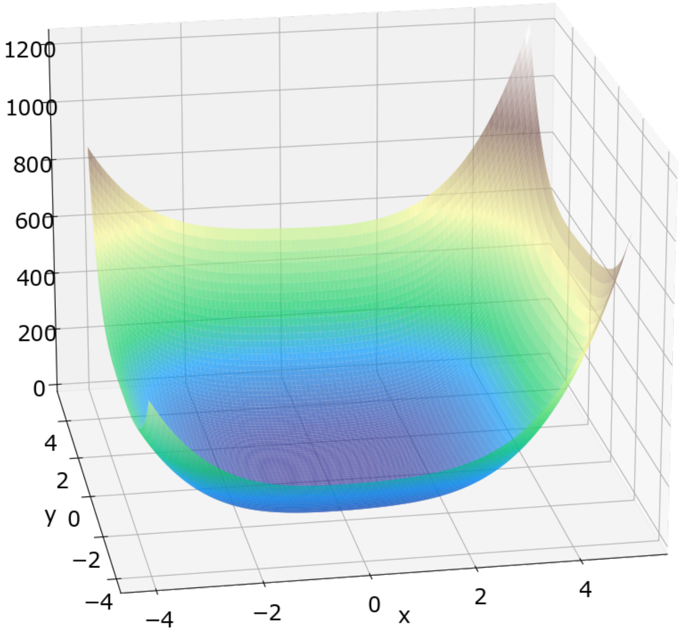


$$f(x,y) = x^4 + 0.8y^4 + 4x^2 + 2y^2 - xy - 0.2x^2y$$

$$f(x,y) \xrightarrow{x} 4x^3 + 8x - y - 0.4xy \xrightarrow{x} 12x^2 + 8 - 0.4y$$

$$f(x,y) \xrightarrow{y} 3.2y^3 + 4y - x - 0.2x^2$$

An Example



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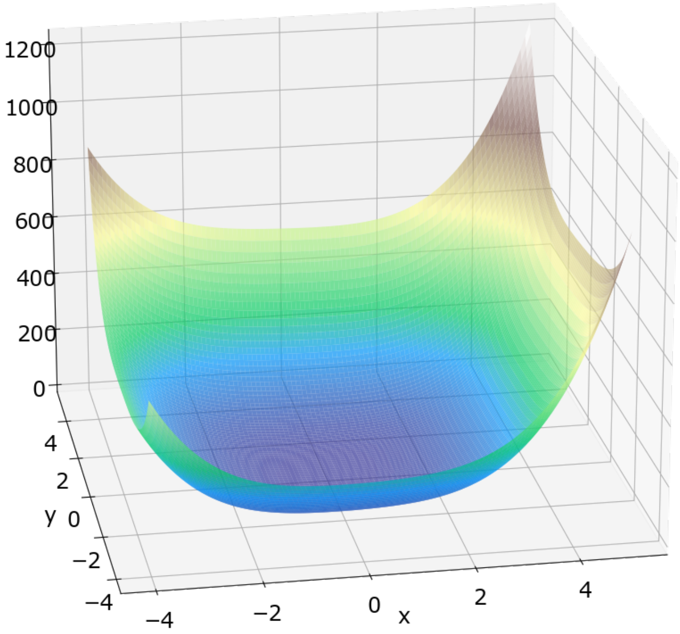
$$f(x, y) \xrightarrow{x} 4x^3 + 8x - y - 0.4xy$$

$$4x^3 + 8x - y - 0.4xy \xrightarrow{x} 12x^2 + 8 - 0.4y$$

$$4x^3 + 8x - y - 0.4xy \xrightarrow{y} -1 - 0.4x$$

$$f(x, y) \xrightarrow{y} 3.2y^3 + 4y - x - 0.2x^2$$

An Example



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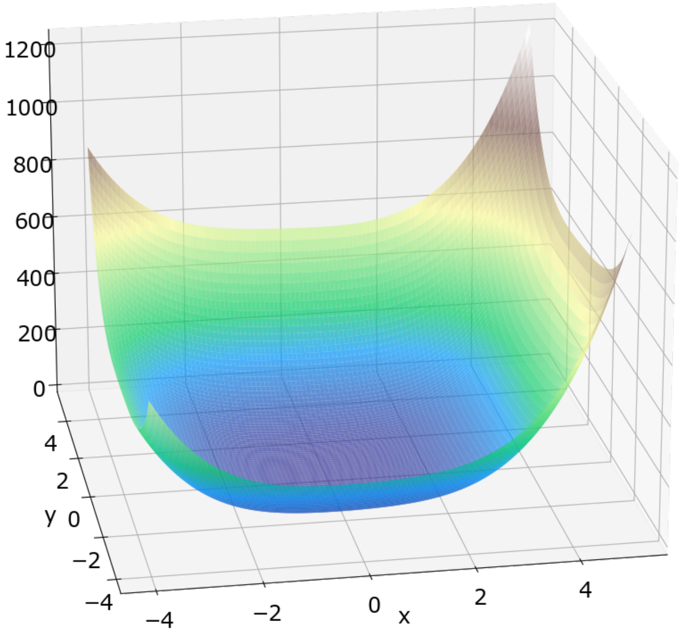
$$f(x,y) \xrightarrow{x} 4x^3 + 8x - y - 0.4xy \xrightarrow{x} 12x^2 + 8 - 0.4y$$

$$4x^3 + 8x - y - 0.4xy \xrightarrow{y} -1 - 0.4x$$

$$f(x,y) \xrightarrow{y} 3.2y^3 + 4y - x - 0.2x^2 \xrightarrow{x} -1 - 0.4x$$

An Example



$$f(x, y) = x^4 + 0.8y^4 + 4x^2 + 2y^2 - xy - 0.2x^2y$$

$$f(x,y) \xrightarrow{x} 4x^3 + 8x - y - 0.4xy \xrightarrow{x} 12x^2 + 8 - 0.4y$$

$$4x^3 + 8x - y - 0.4xy \xrightarrow{y} -1 - 0.4x$$

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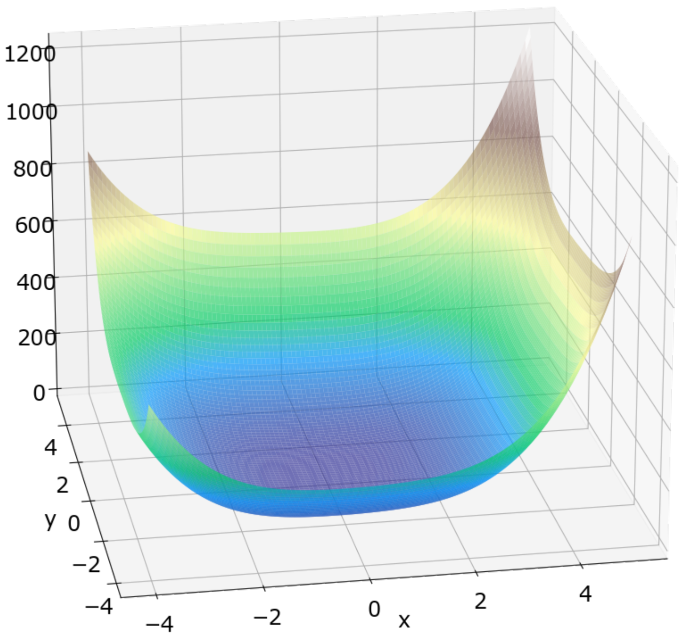
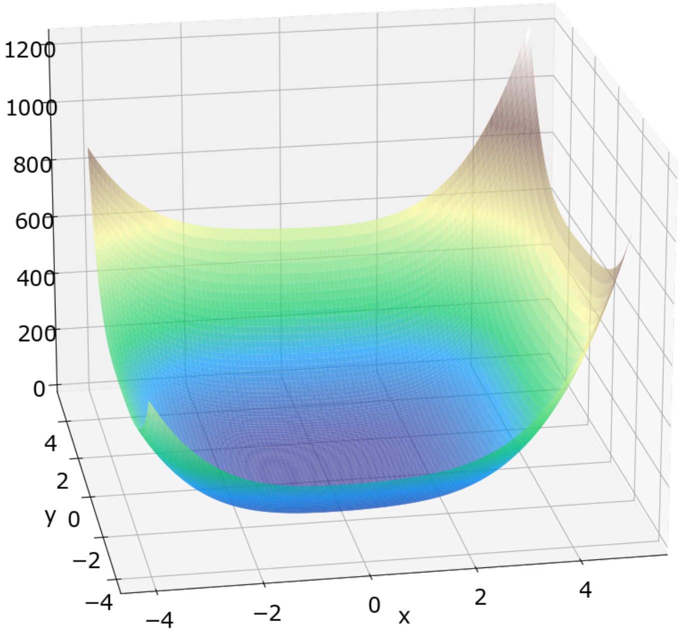
$$3.2y^3 + 4y - x - 0.2x^2 \xrightarrow{y} 9.6y^2 + 4$$

An Example



$$f(x, y) = x^4 + 0.8y^4 + 4x^2 + 2y^2 - xy - 0.2x^2y$$

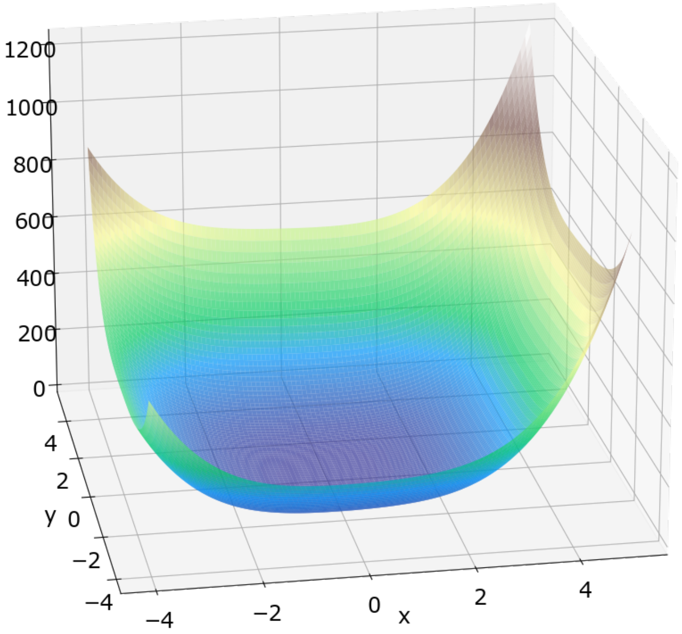
An Example



$$f(x, y) = x^4 + 0.8y^4 + 4x^2 + 2y^2 - xy - 0.2x^2y$$

$$\nabla f(x, y) = \begin{bmatrix} 4x^3 + 8x - y - 0.4xy \\ 3.2y^3 + 4y - x - 0.2x^2 \end{bmatrix}$$

An Example

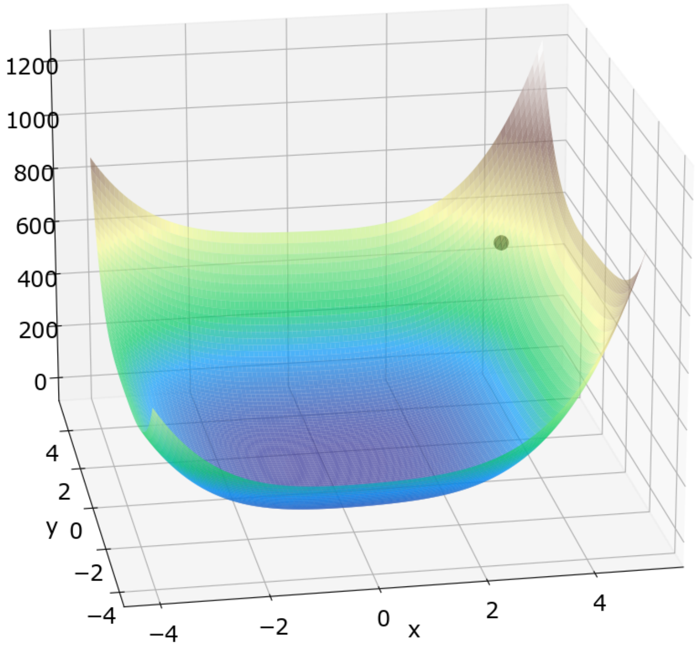


$$f(x, y) = x^4 + 0.8y^4 + 4x^2 + 2y^2 - xy - 0.2x^2y$$

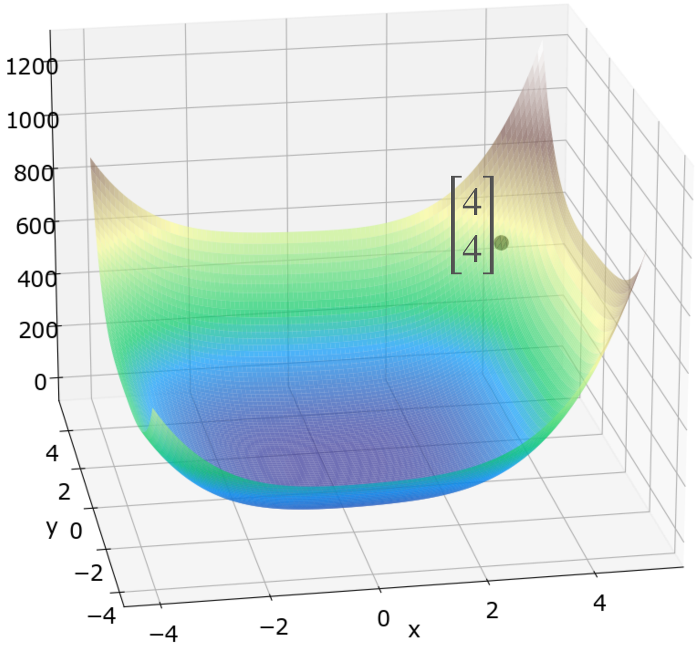
$$\nabla f(x, y) = \begin{bmatrix} 4x^3 + 8x - y - 0.4xy \\ 3.2y^3 + 4y - x - 0.2x^2 \end{bmatrix}$$

$$H(x, y) = \begin{bmatrix} 12x^2 + 8 - 0.4y & -1 - 0.4x \\ -1 - 0.4x & 9.6y^2 + 4 \end{bmatrix}$$

An Example

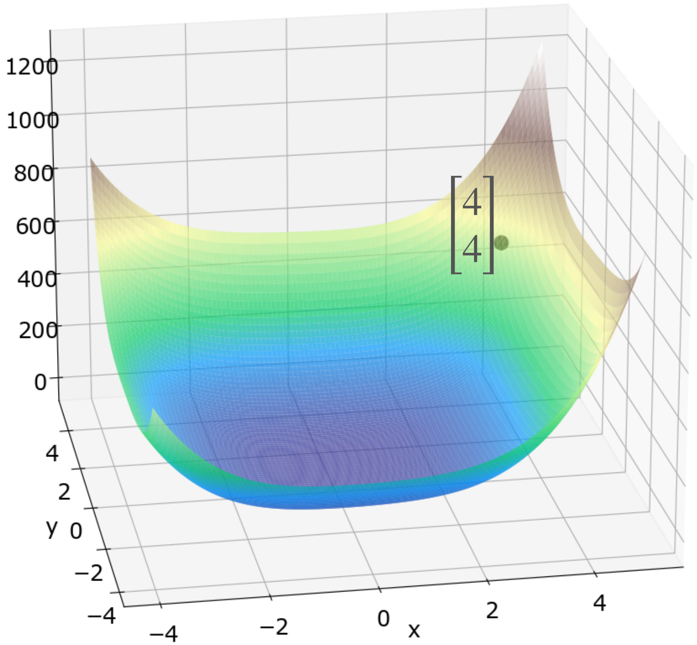


An Example



Start at some point $\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \end{bmatrix}$

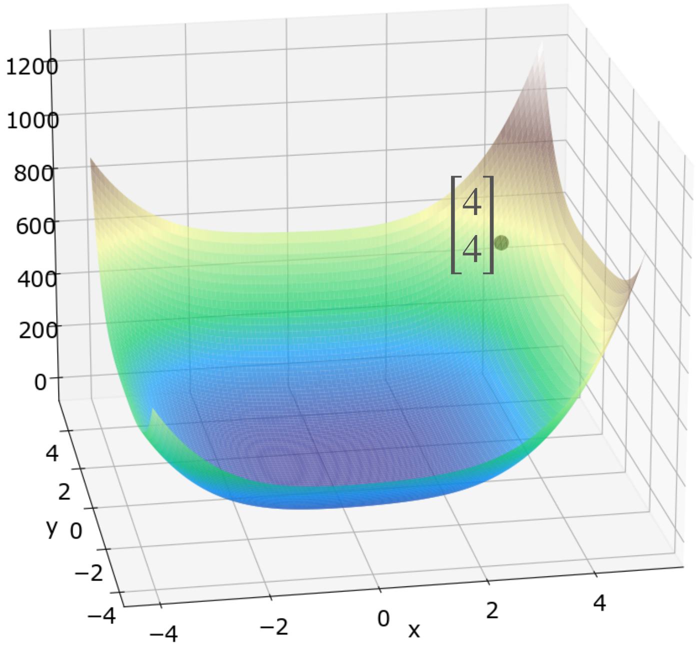
An Example



Start at some point $\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \end{bmatrix}$

$$\nabla f(4,4) = \begin{bmatrix} 277.6 \\ 213.6 \end{bmatrix}$$

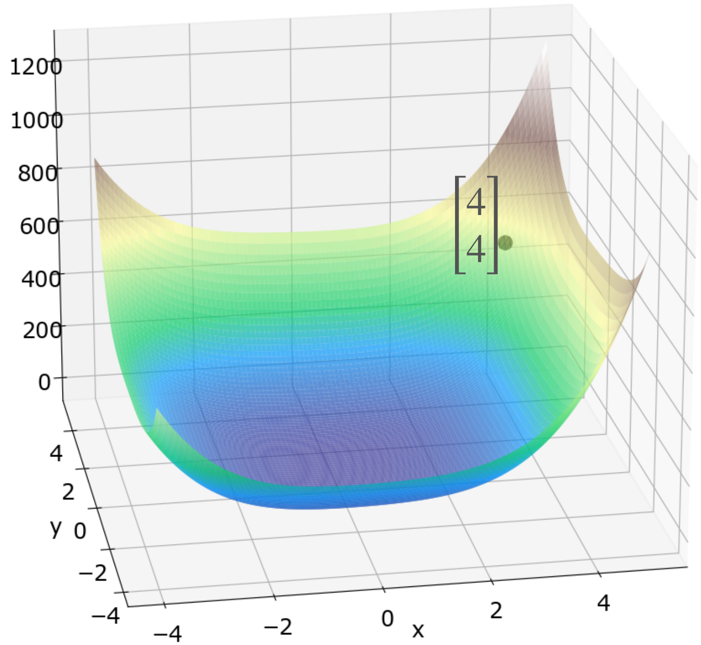
An Example



Start at some point $\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \end{bmatrix}$

$$\nabla f(4,4) = \begin{bmatrix} 277.6 \\ 213.6 \end{bmatrix} \qquad H(4,4) = \begin{bmatrix} 198.4 & -2.6 \\ -2.6 & 157.6 \end{bmatrix}$$

An Example

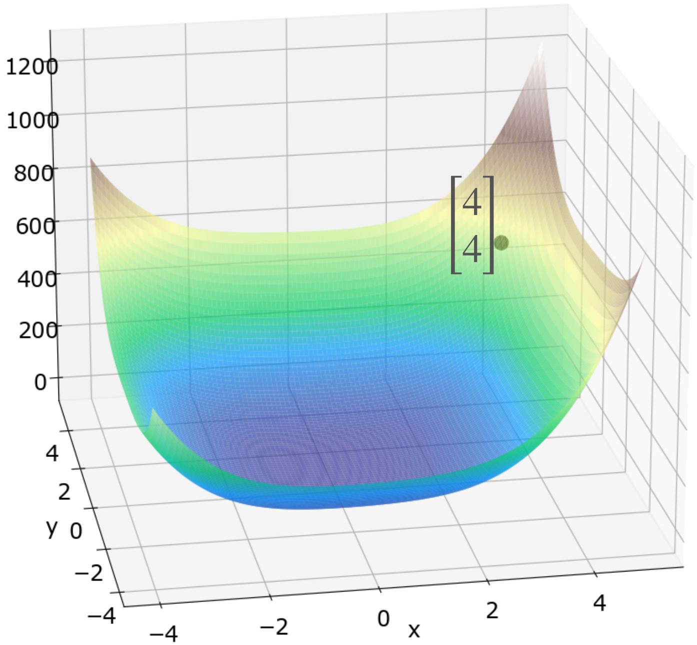


Start at some point $\begin{bmatrix}x_0\\y_0\end{bmatrix} = \begin{bmatrix}4\\4\end{bmatrix}$

$$\nabla f(4,4) = \begin{bmatrix}277.6\\213.6\end{bmatrix} \qquad H(4,4) = \begin{bmatrix}198.4 & -2.6\\-2.6 & 157.6\end{bmatrix}$$

$$\begin{bmatrix}x_1\\y_1\end{bmatrix} = \begin{bmatrix}4\\4\end{bmatrix} -$$

An Example



Start at some point $\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \end{bmatrix}$

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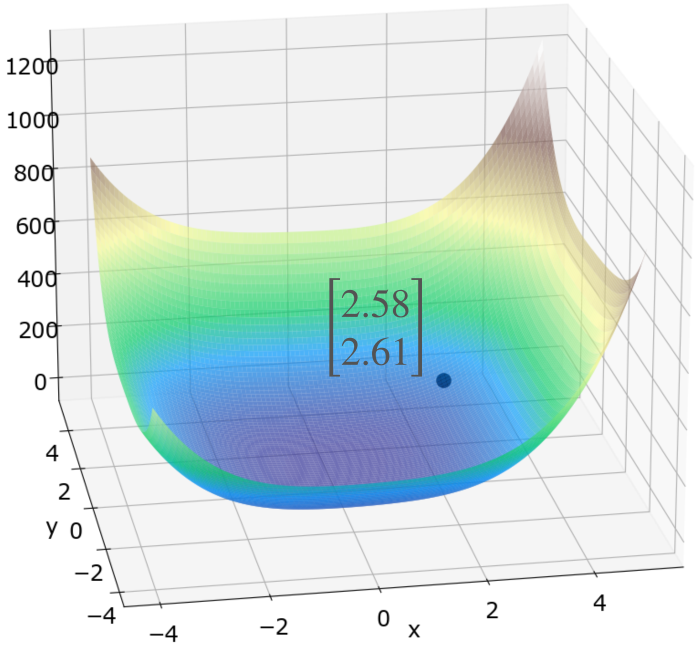
$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \end{bmatrix} - \begin{bmatrix} 198.4 & -2.6 \\ -2.6 & 157.6 \end{bmatrix}^{-1} \begin{bmatrix} 277.6 \\ 213.6 \end{bmatrix}$$

An Example



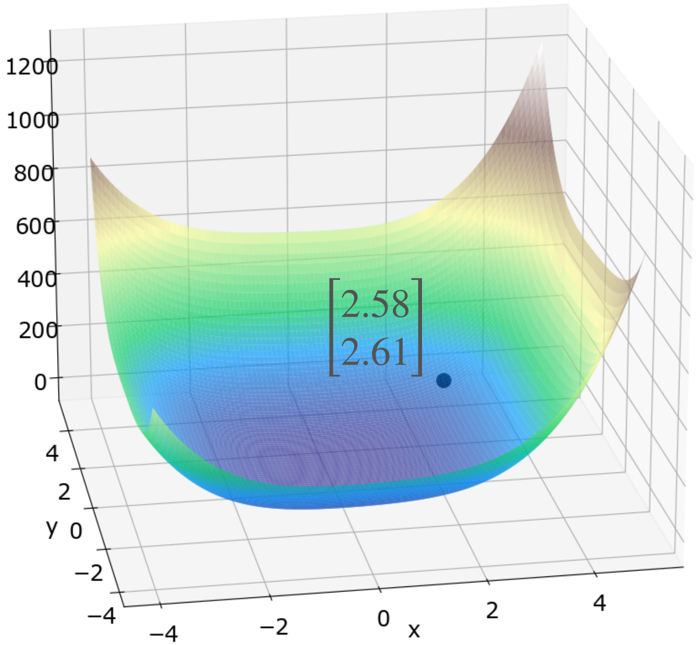
Start at some point $\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \end{bmatrix}$

$$\nabla f(4,4) = \begin{bmatrix} 277.6 \\ 213.6 \end{bmatrix} \qquad H(4,4) = \begin{bmatrix} 198.4 & -2.6 \\ -2.6 & 157.6 \end{bmatrix}$$

$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \end{bmatrix} - \begin{bmatrix} 198.4 & -2.6 \\ -2.6 & 157.6 \end{bmatrix}^{-1} \begin{bmatrix} 277.6 \\ 213.6 \end{bmatrix}$$

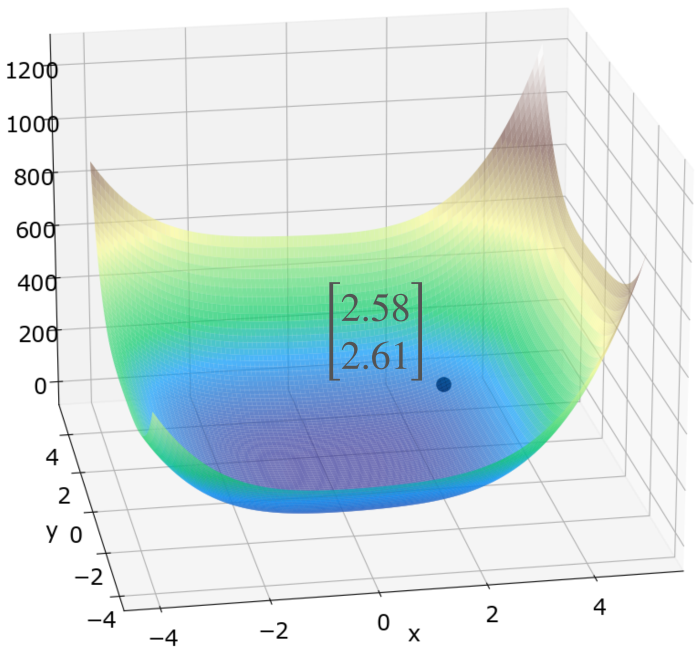
$$= \begin{bmatrix} 2.58 \\ 2.62 \end{bmatrix}$$

An Example



$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} 2.58 \\ 2.61 \end{bmatrix}$$

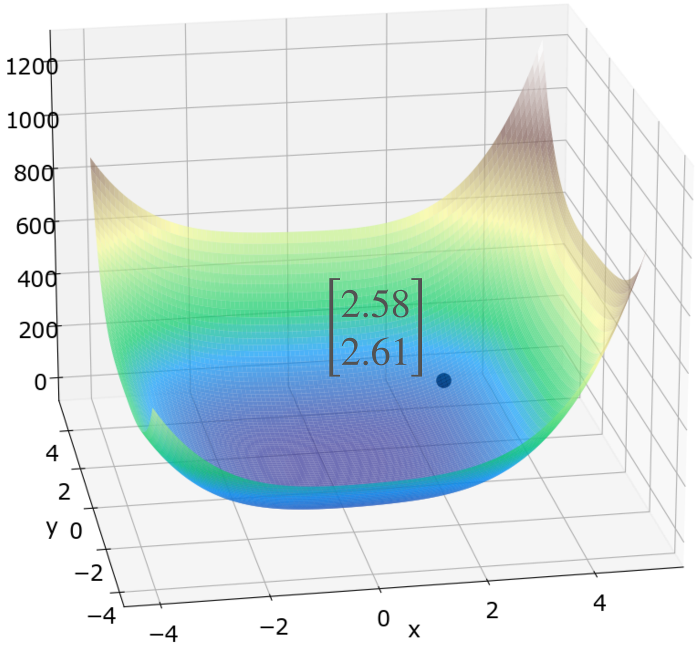
An Example



$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} 2.58 \\ 2.61 \end{bmatrix}$$

$$\nabla f(2.58, 2.61) = \begin{bmatrix} 84.25 \\ 63.4 \end{bmatrix}$$

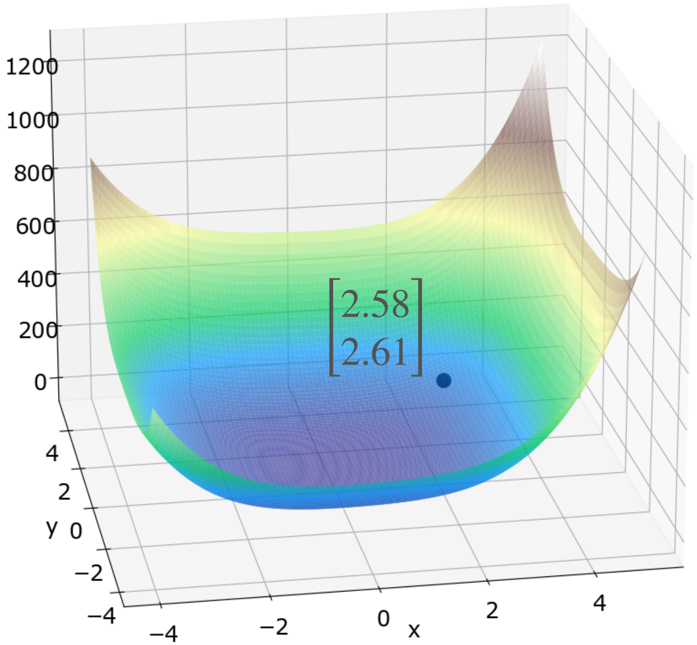
An Example



$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} 2.58 \\ 2.61 \end{bmatrix}$$

$$\nabla f(2.58, 2.61) = \begin{bmatrix} 84.25 \\ 63.4 \end{bmatrix} \quad H(2.58, 2.61) = \begin{bmatrix} 86.83 & -2.032 \\ -2.032 & 69.39 \end{bmatrix}$$

An Example

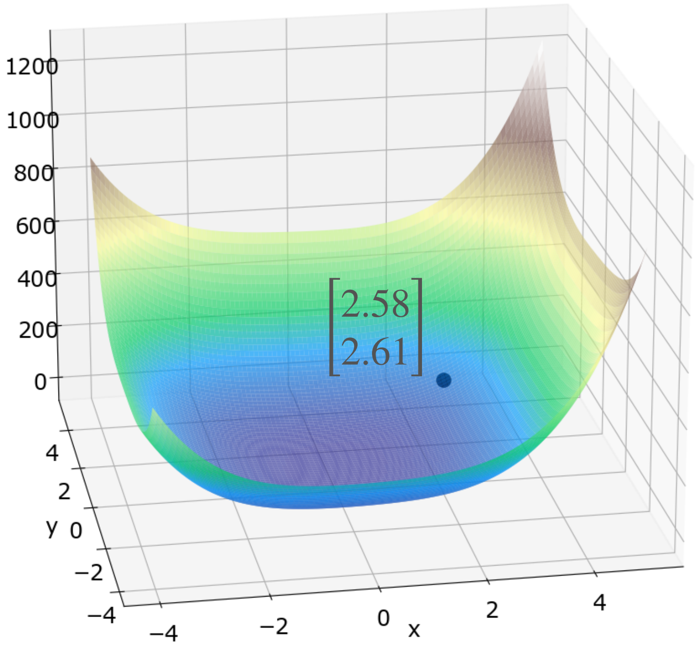


$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} 2.58 \\ 2.61 \end{bmatrix}$$

$$\nabla f(2.58, 2.61) = \begin{bmatrix} 84.25 \\ 63.4 \end{bmatrix} \quad H(2.58, 2.61) = \begin{bmatrix} 86.83 & -2.032 \\ -2.032 & 69.39 \end{bmatrix}$$

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} 2.58 \\ 2.61 \end{bmatrix} -$$

An Example

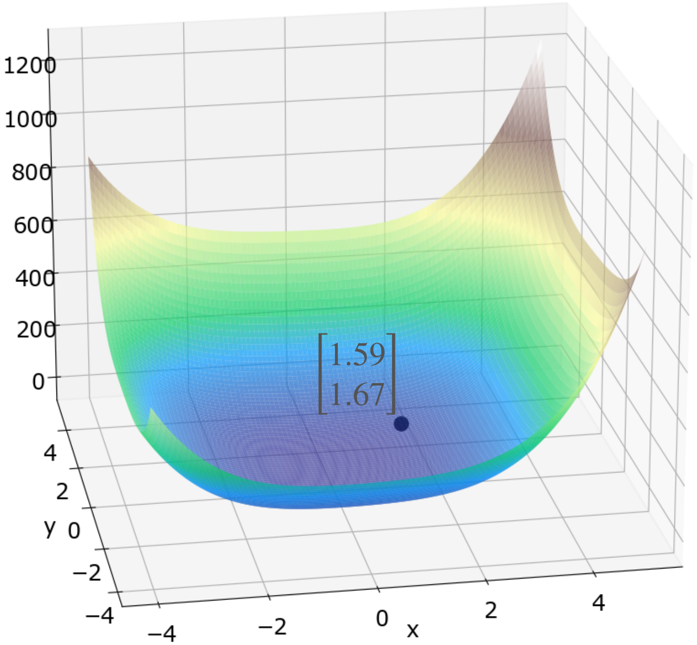


$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} 2.58 \\ 2.61 \end{bmatrix}$$

$$\nabla f(2.58, 2.61) = \begin{bmatrix} 84.25 \\ 63.4 \end{bmatrix} \quad H(2.58, 2.61) = \begin{bmatrix} 86.83 & -2.032 \\ -2.032 & 69.39 \end{bmatrix}$$

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} 2.58 \\ 2.61 \end{bmatrix} - \begin{bmatrix} 86.83 & -2.032 \\ -2.032 & 69.39 \end{bmatrix}^{-1} \begin{bmatrix} 84.25 \\ 63.4 \end{bmatrix}$$

An Example



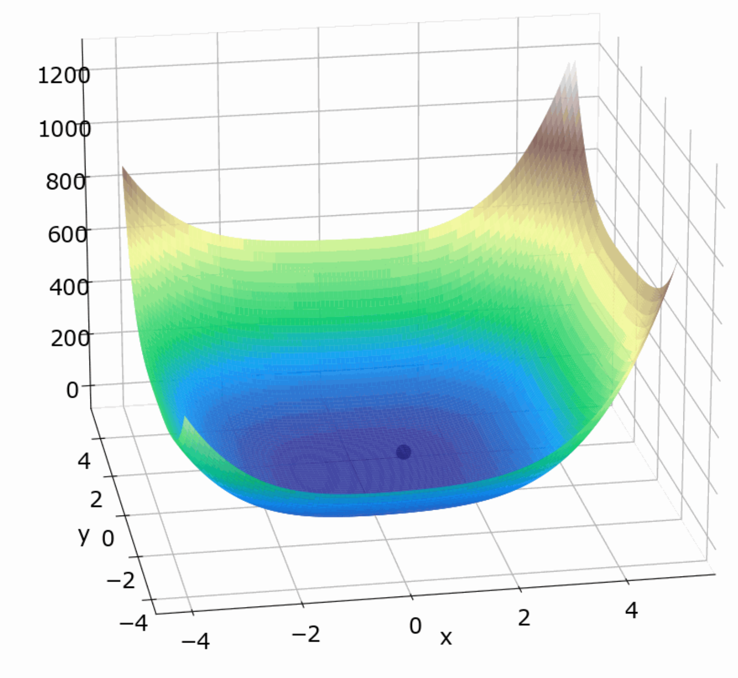
$$\begin{bmatrix}x_1\\y_1\end{bmatrix} = \begin{bmatrix}2.58\\2.61\end{bmatrix}$$

$$\nabla f(2.58,2.61) = \begin{bmatrix}84.25\\63.4\end{bmatrix} \quad H(2.58,2.61) = \begin{bmatrix}86.83 & -2.032\\-2.032 & 69.39\end{bmatrix}$$

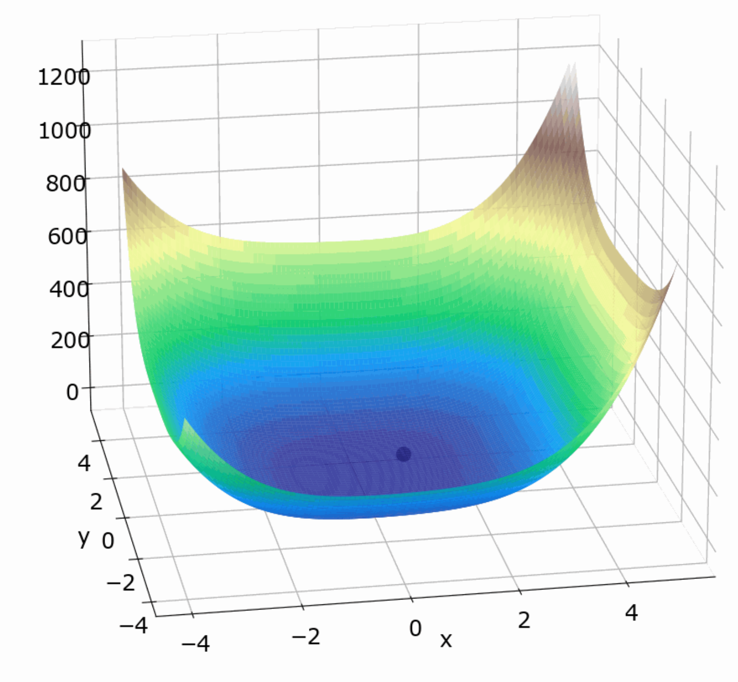
$$\begin{bmatrix}x_2\\y_2\end{bmatrix} = \begin{bmatrix}2.58\\2.61\end{bmatrix} - \begin{bmatrix}86.83 & -2.032\\-2.032 & 69.39\end{bmatrix}^{-1}\begin{bmatrix}84.25\\63.4\end{bmatrix}$$

$$= \begin{bmatrix}1.59\\1.67\end{bmatrix}$$

An Example

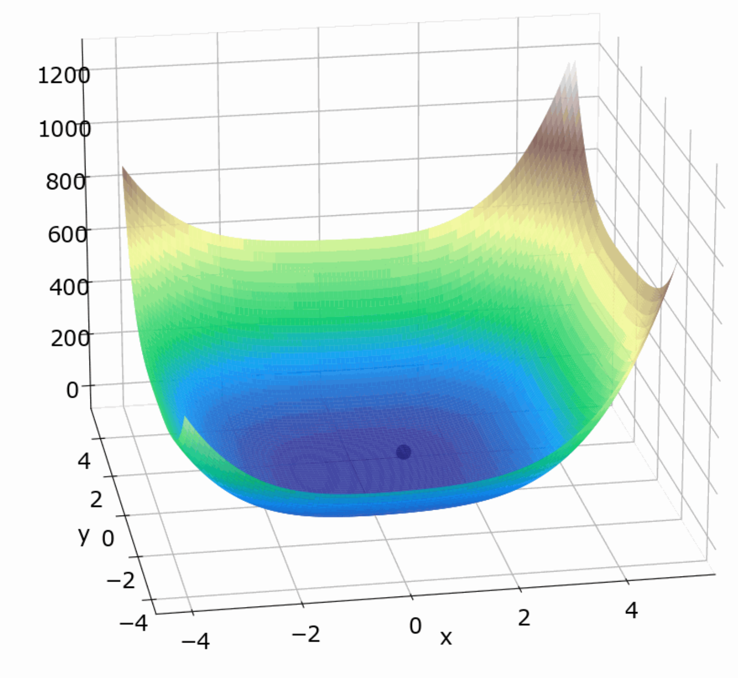


An Example



Repeat until you are close enough to the actual zero!

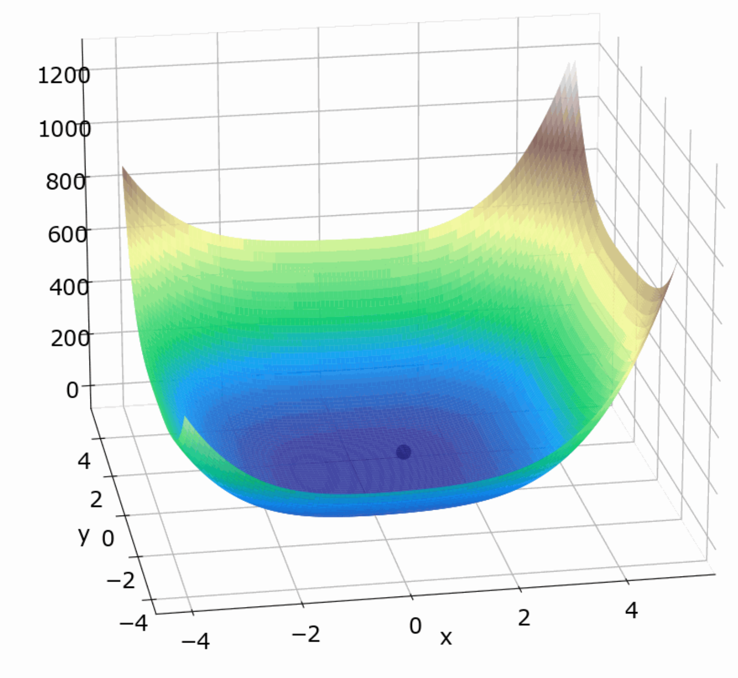
An Example



Repeat until you are close enough to the actual zero!

Needed $k = 8$ steps

An Example

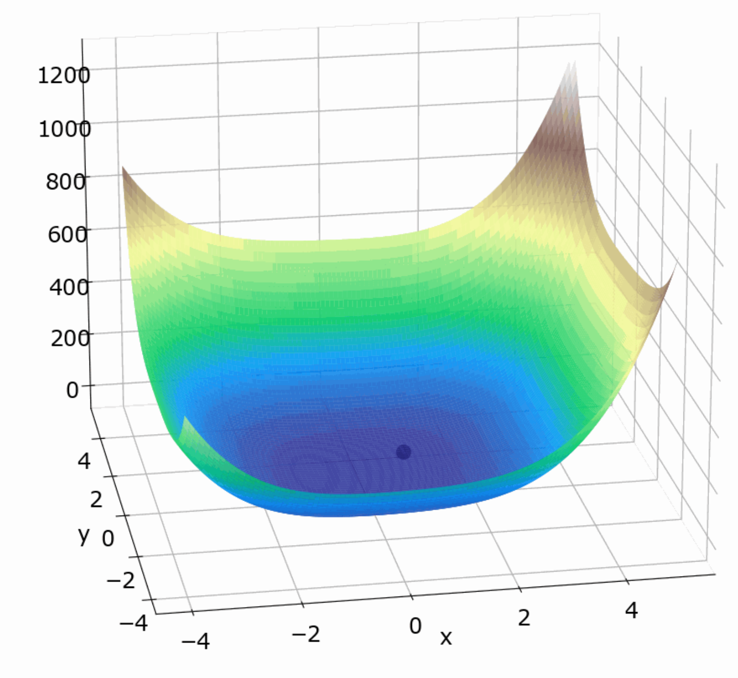


Repeat until you are close enough to the actual zero!

Needed $k = 8$ steps

$$\begin{bmatrix} x_8 \\ y_8 \end{bmatrix} = \begin{bmatrix} 4.15\ 10^{-17} \\ -2.05\ 10^{-17} \end{bmatrix}$$

An Example



Repeat until you are close enough to the actual zero!

Needed $k = 8$ steps

$$\begin{bmatrix} x_8 \\ y_8 \end{bmatrix} = \begin{bmatrix} 4.15\ 10^{-17} \\ -2.05\ 10^{-17} \end{bmatrix}$$

$$\begin{bmatrix} x^* \\ y^* \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Optimization in Neural Networks and Newton's Method

DeepLearning.AI

Conclusion