



DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Regression with a perceptron

Regression Problem Motivation

Regression Problem Motivation

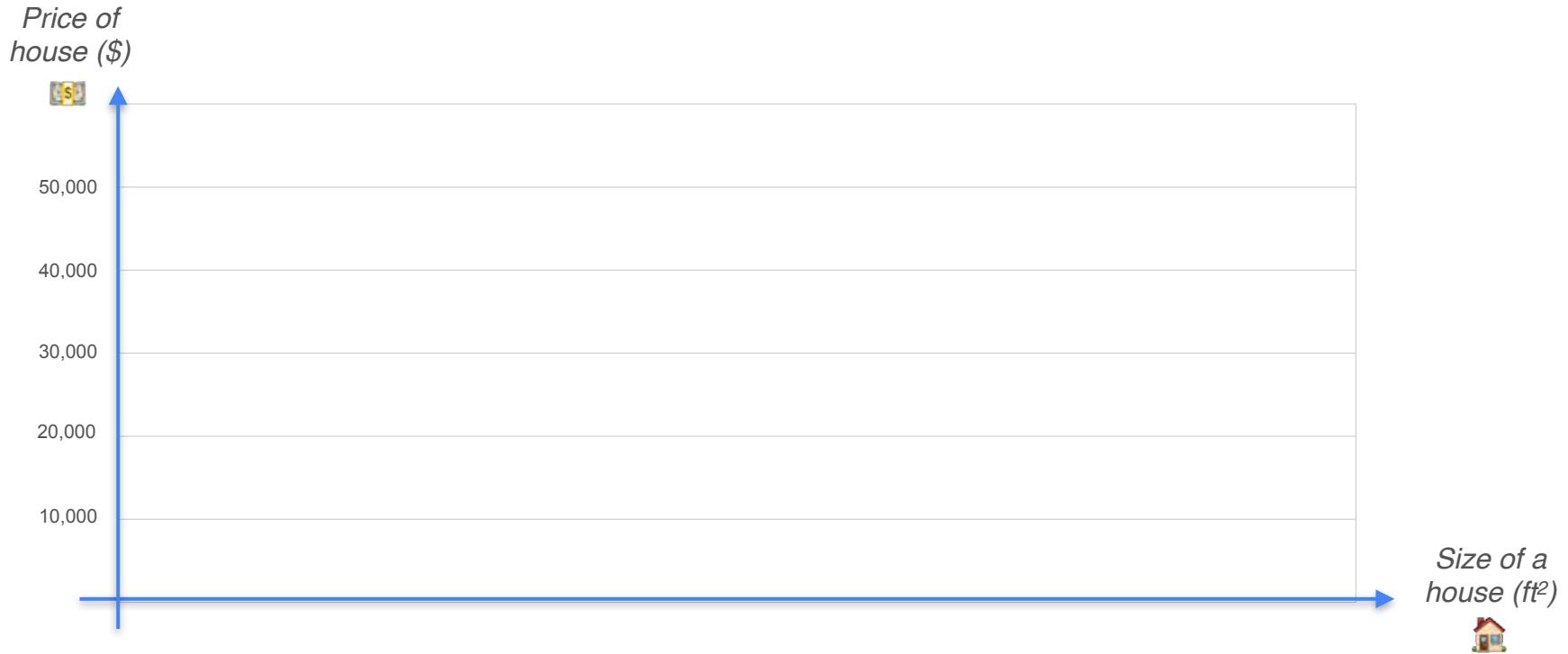
Predicting

the price of a house

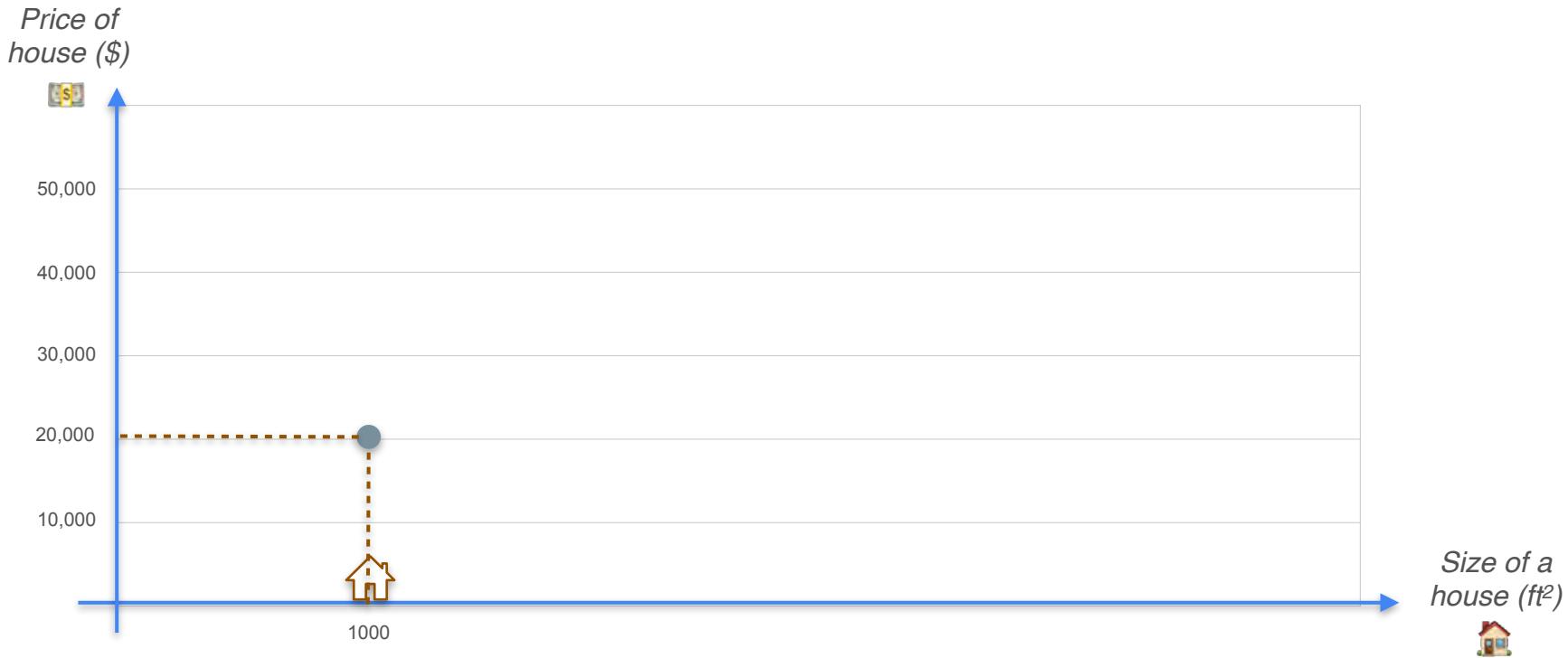
from

the size of the house

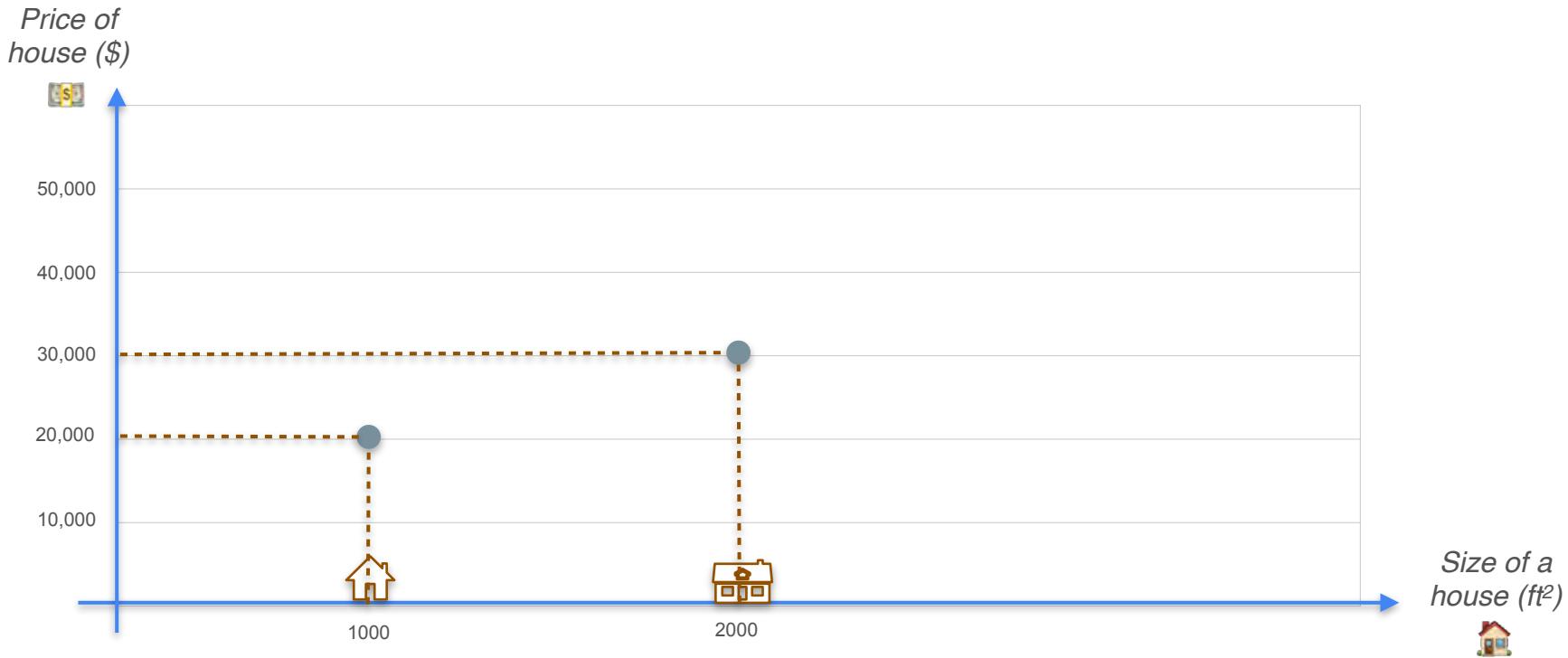
Regression Problem Motivation



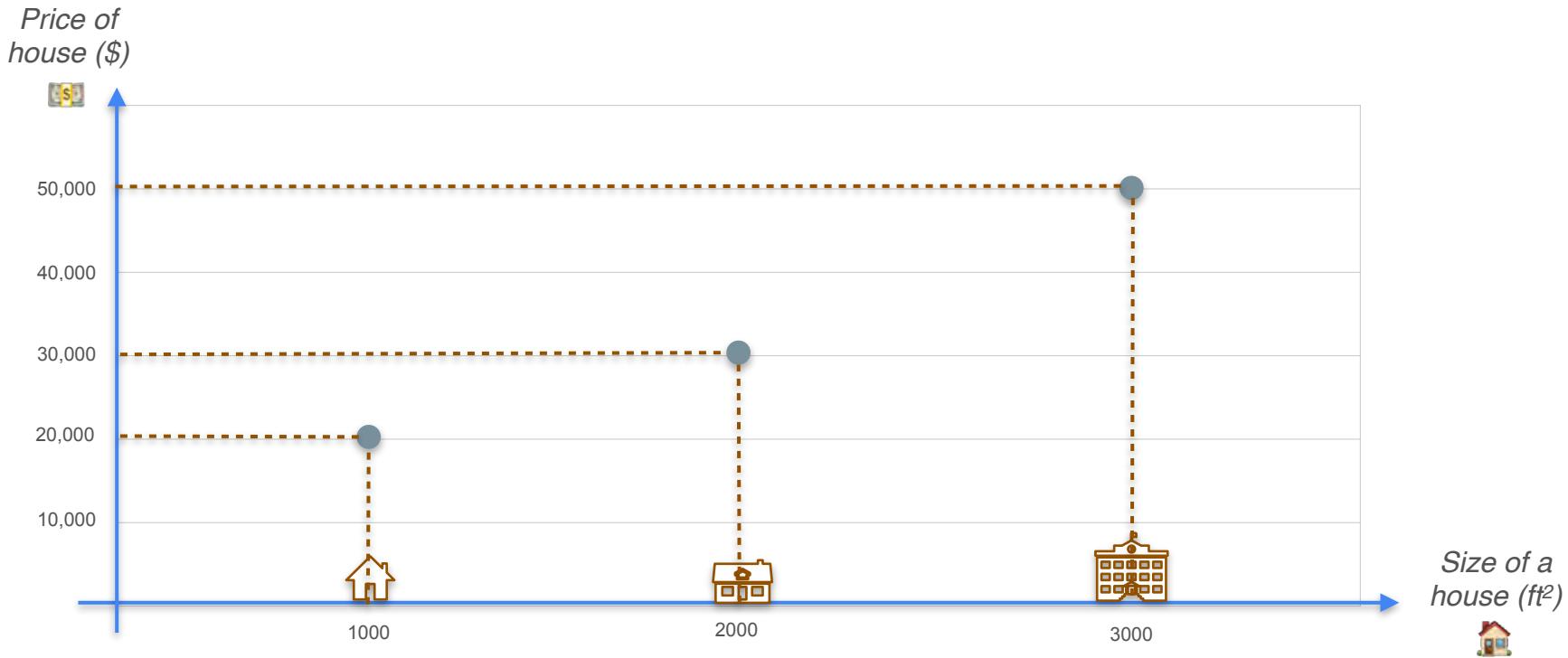
Regression Problem Motivation



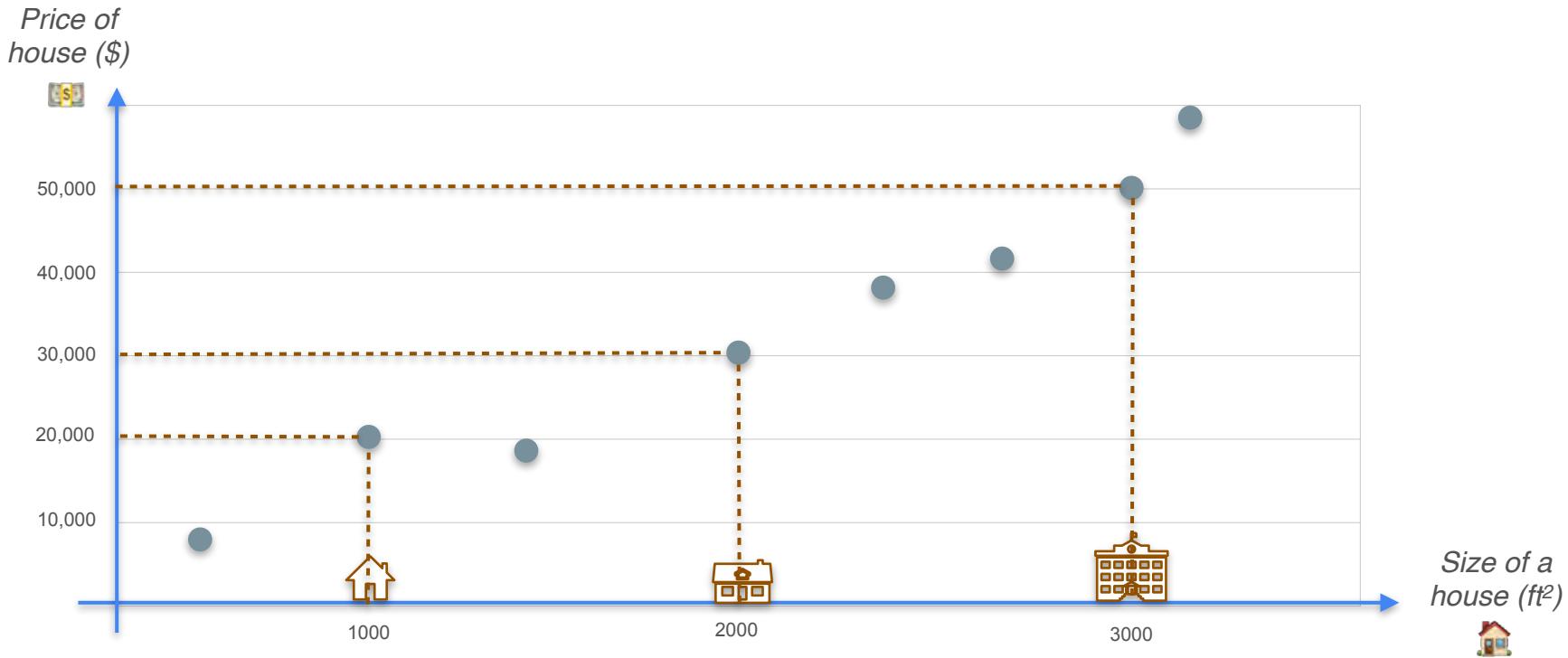
Regression Problem Motivation



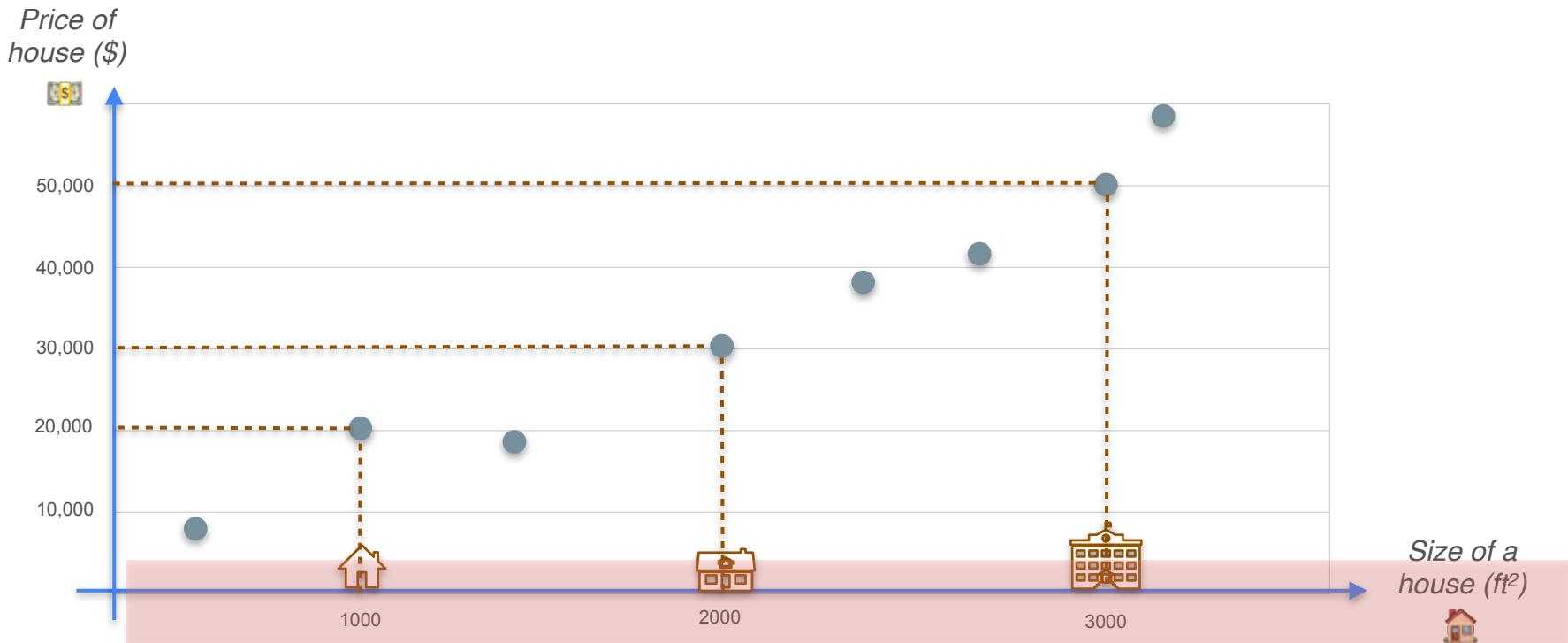
Regression Problem Motivation



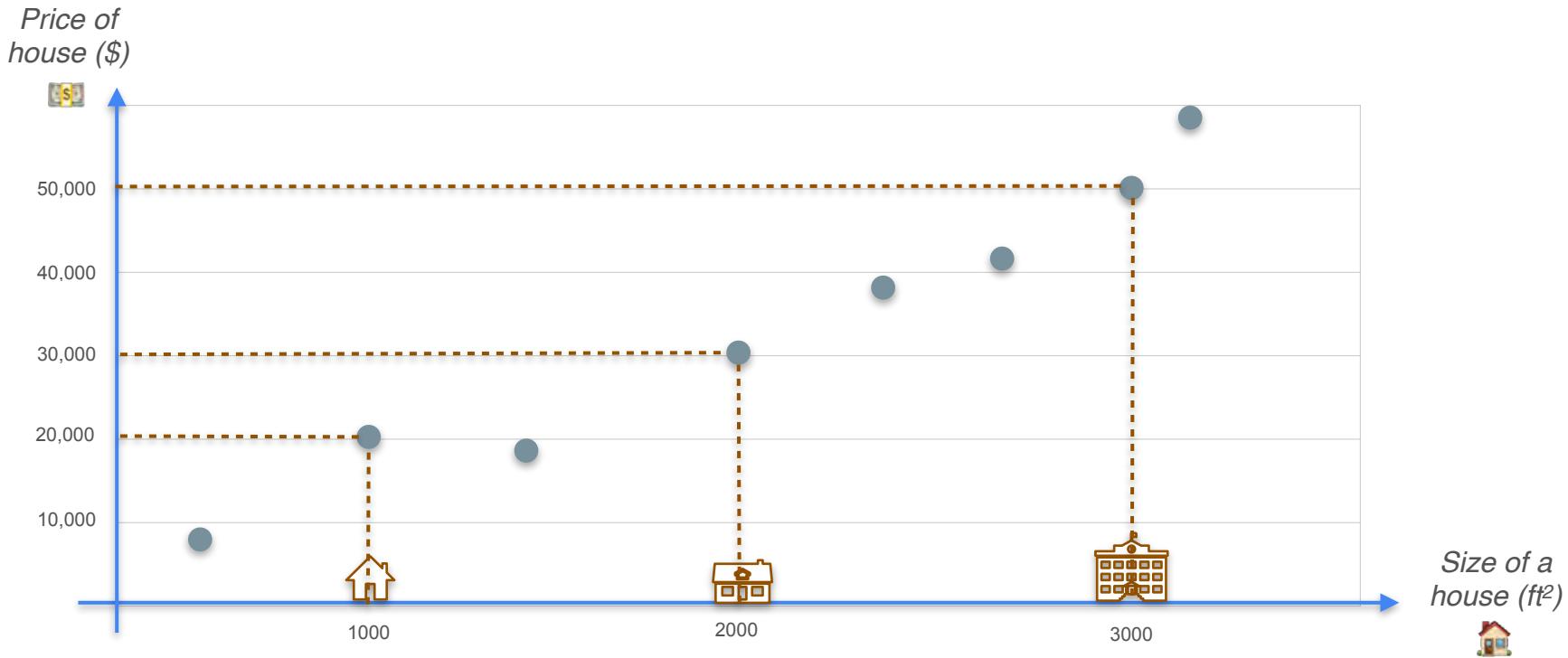
Regression Problem Motivation



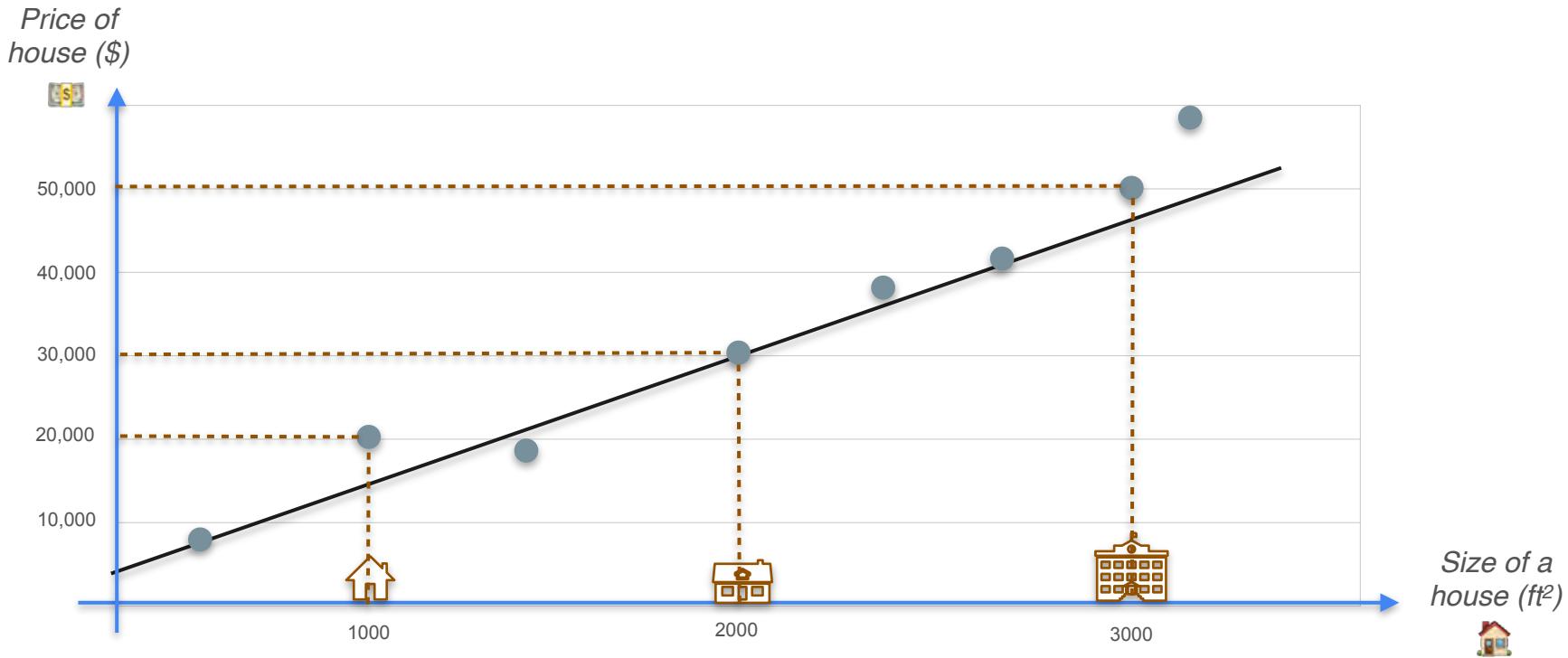
Regression Problem Motivation



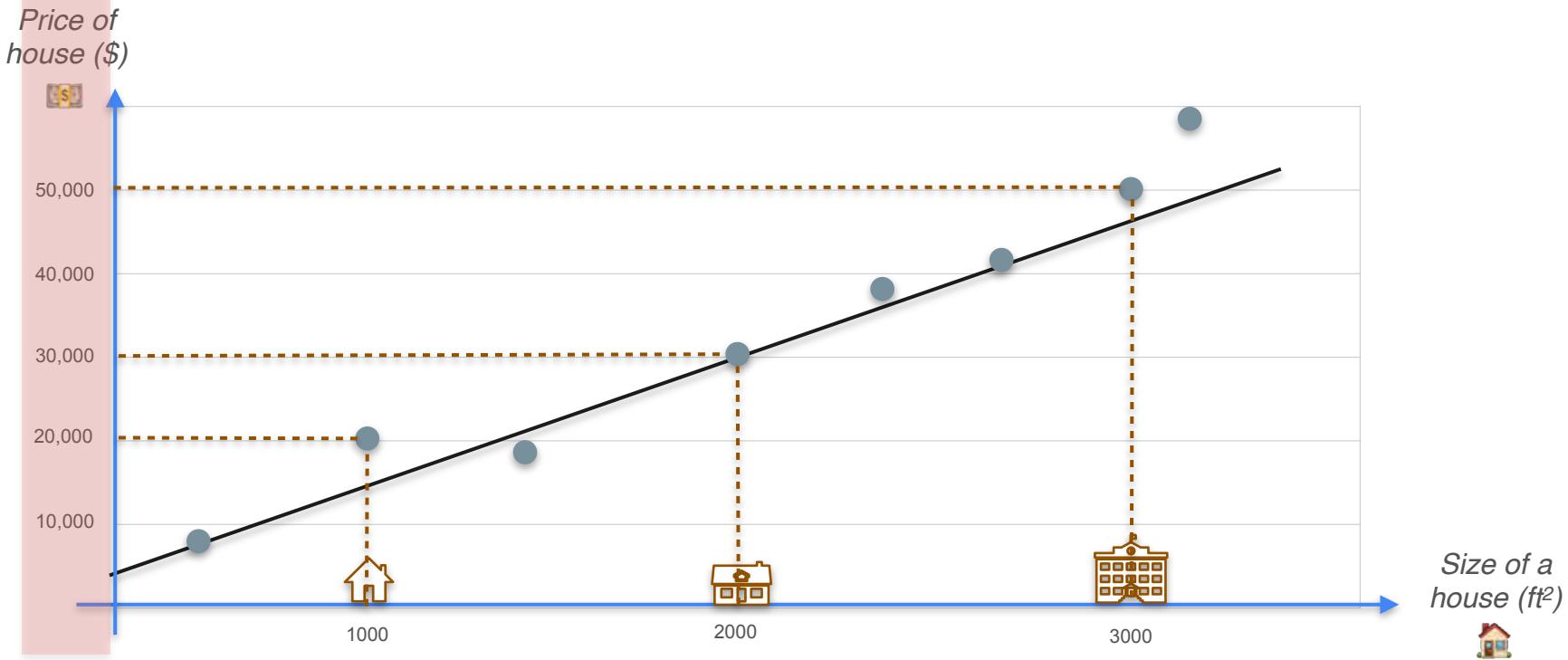
Regression Problem Motivation



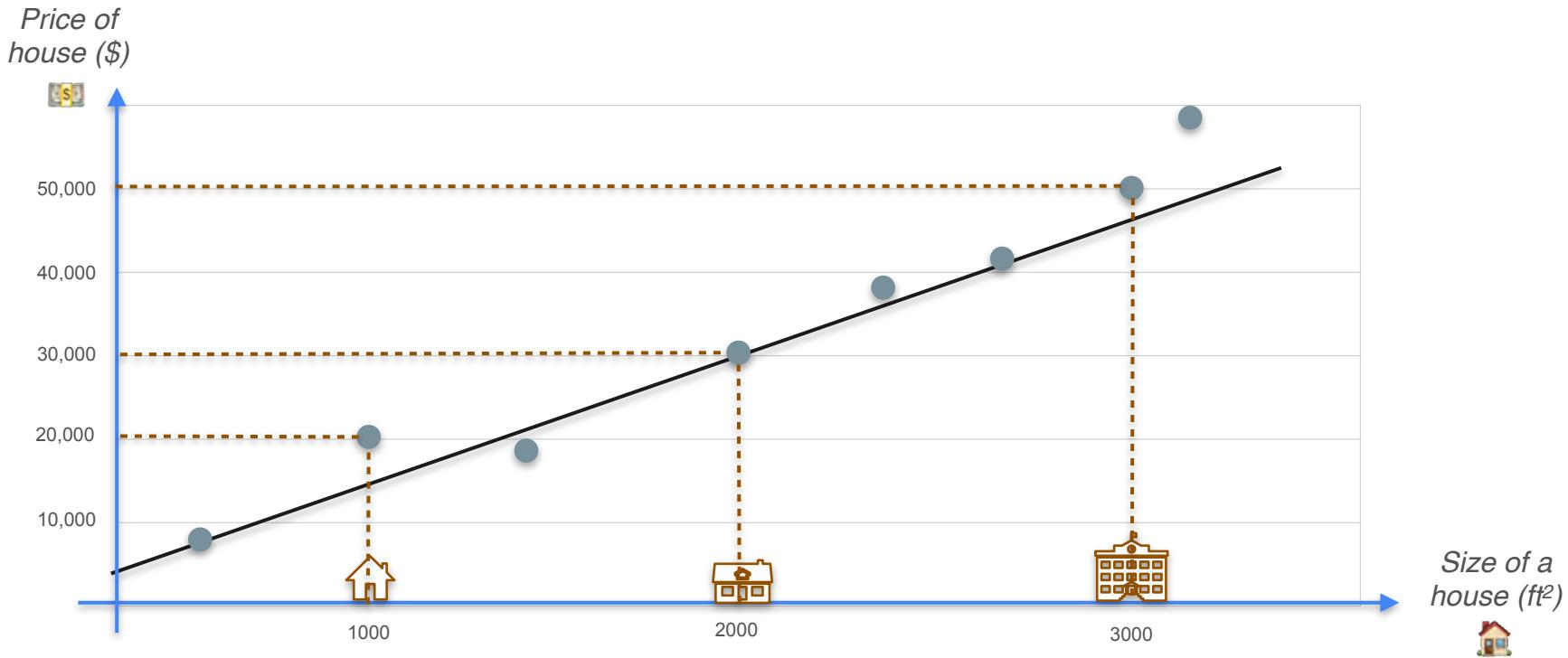
Regression Problem Motivation



Regression Problem Motivation



Regression Problem Motivation



Regression With a Perceptron

	<i>Size of a house (ft²)</i> 		<i>Price of house (\$)</i> 
			
			
			

Regression With a Perceptron

	<i>Size of a house (ft²)</i> 		<i>Price of house (\$)</i> 
	1000ft^2		\$20,000
	2000ft^2		\$30,000
	3000ft^2		\$50,000

Regression With a Perceptron

	<i>Size of a house (ft²)</i> 	<i>Number of rooms</i> 	<i>Price of house (\$)</i> 
	1000ft ²	2	\$20,000
	2000ft ²	4	\$30,000
	3000ft ²	7	\$50,000

Regression With a Perceptron

Inputs

*Size of a
house (ft²)*



*Number of
rooms*

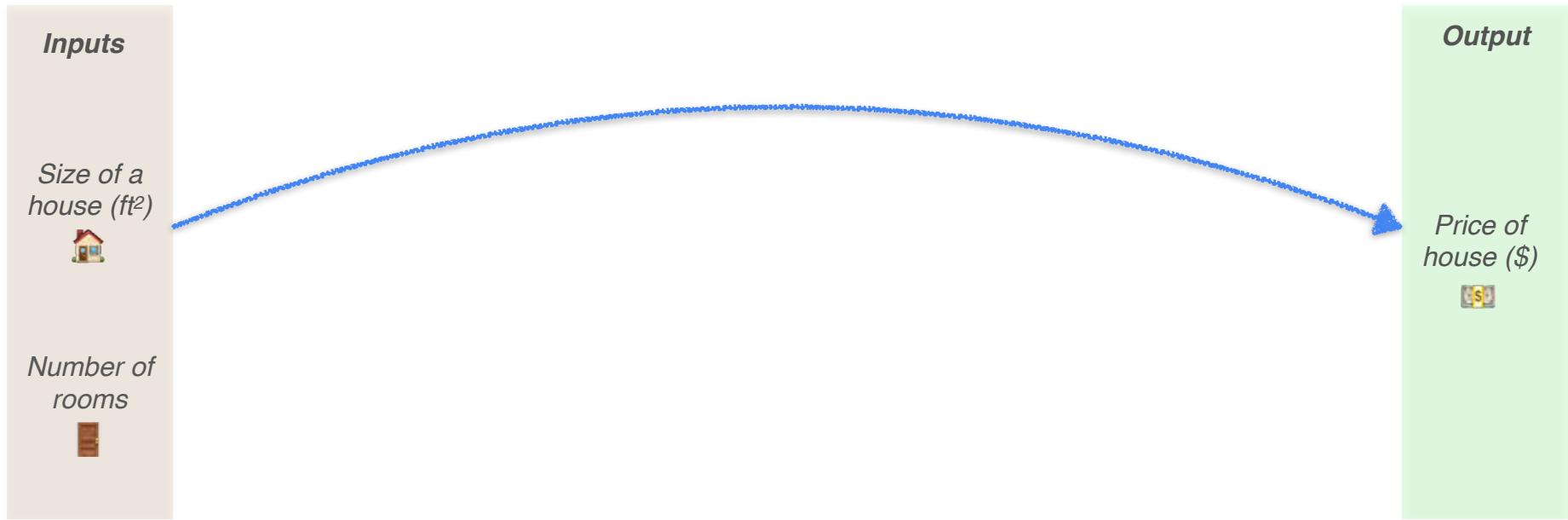


Output

*Price of
house (\$)*



Regression With a Perceptron



Regression With a Perceptron

Single Layer Neural Network Perceptron

Inputs

*Size of a
house (ft²)*



*Number of
rooms*



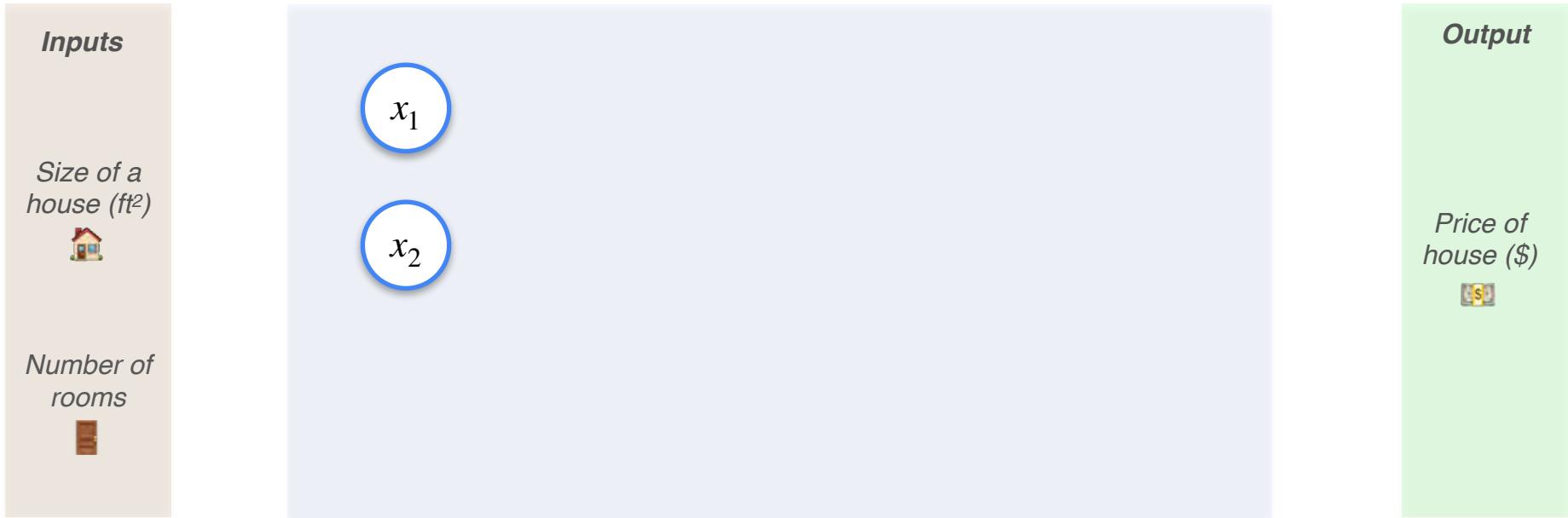
Output

*Price of
house (\$)*



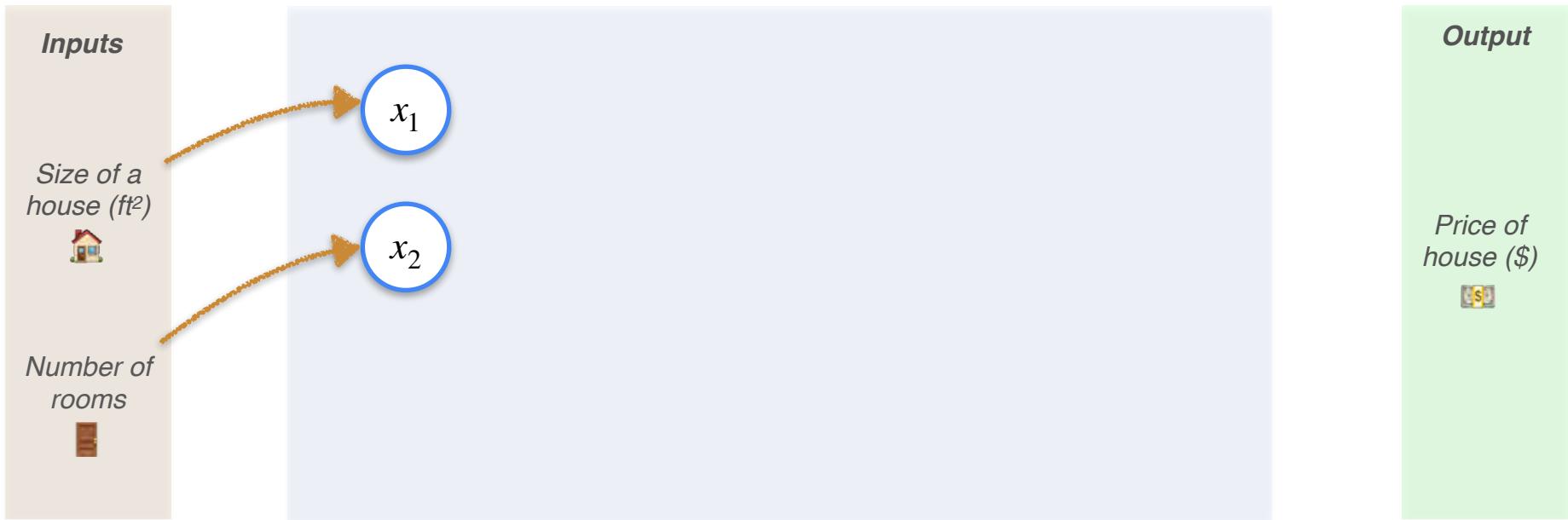
Regression With a Perceptron

Single Layer Neural Network Perceptron



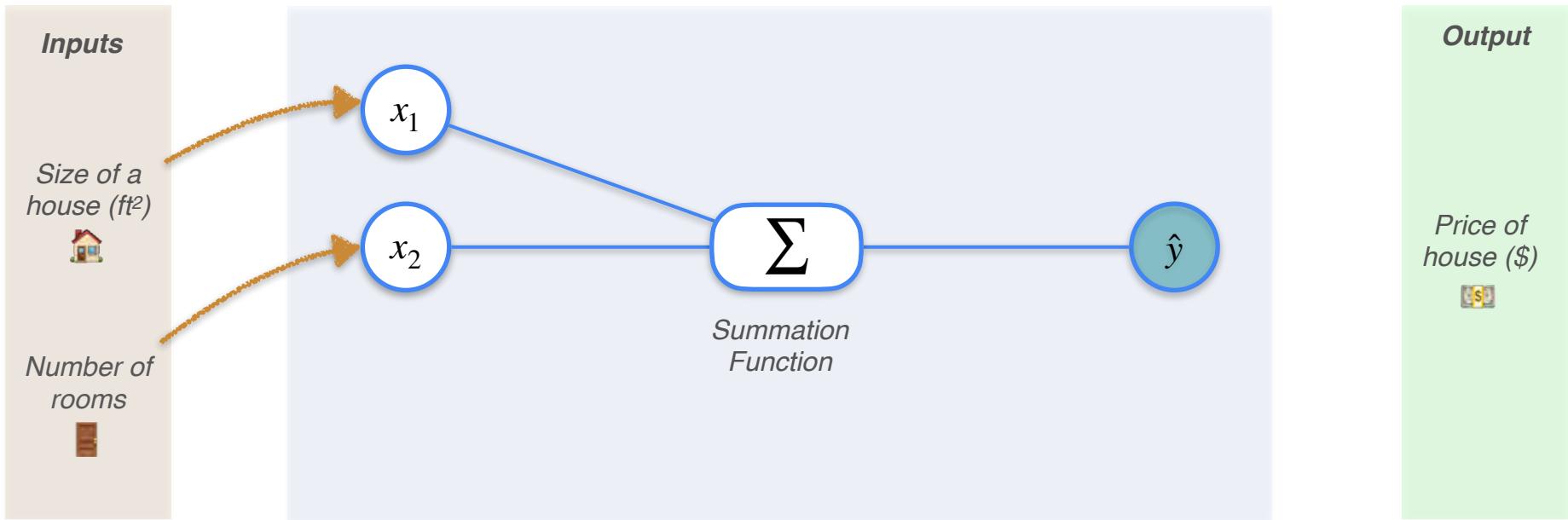
Regression With a Perceptron

Single Layer Neural Network Perceptron



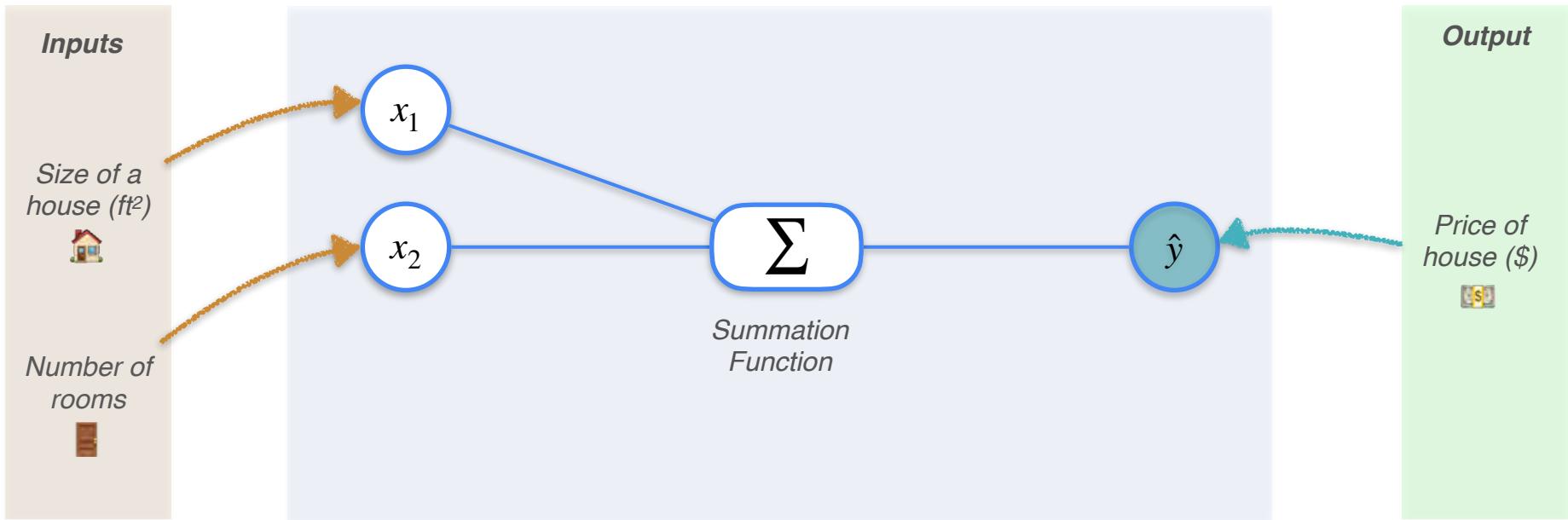
Regression With a Perceptron

Single Layer Neural Network Perceptron



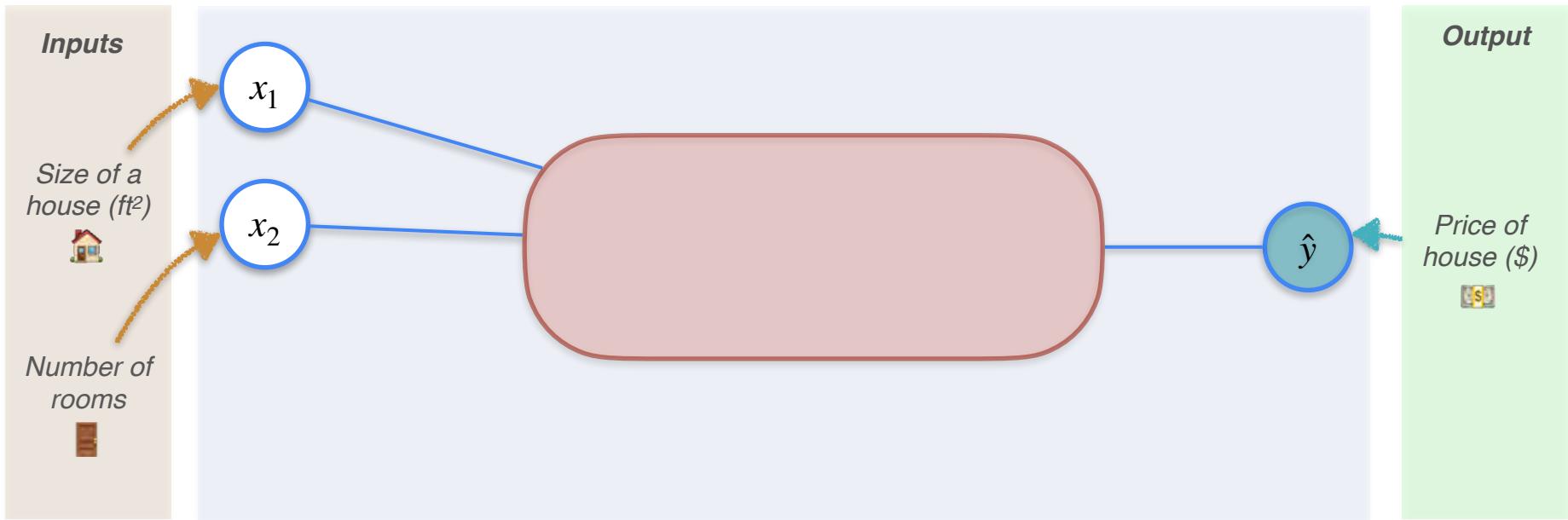
Regression With a Perceptron

Single Layer Neural Network Perceptron



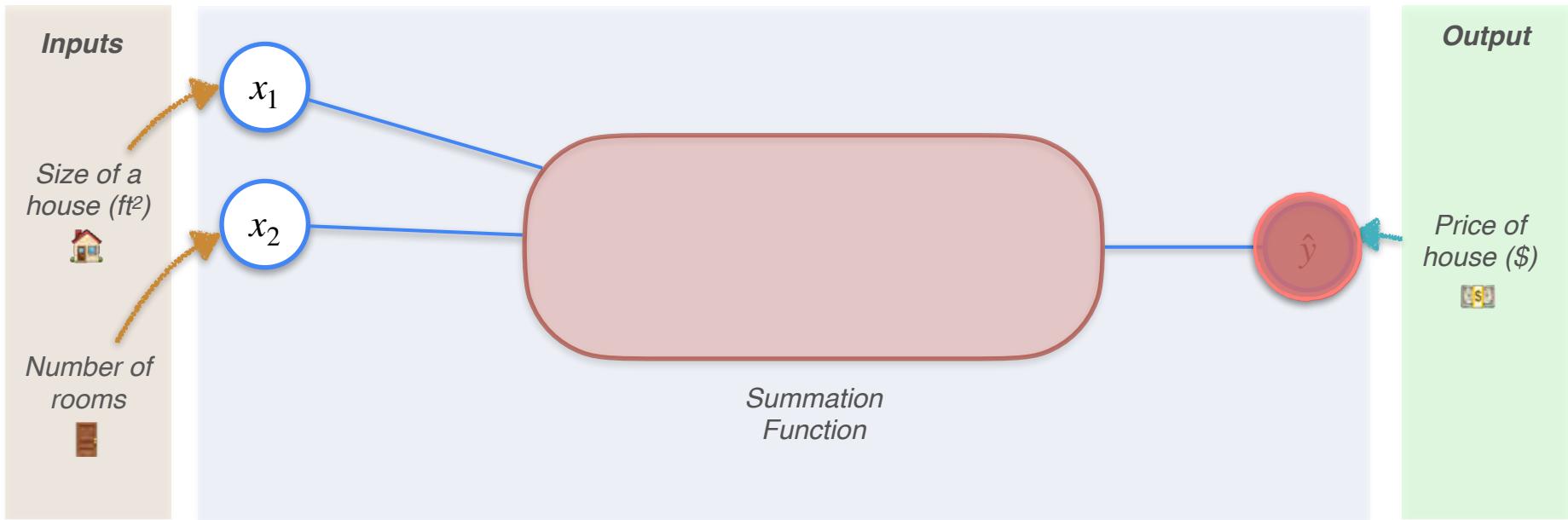
Regression With a Perceptron

Single Layer Neural Network Perceptron



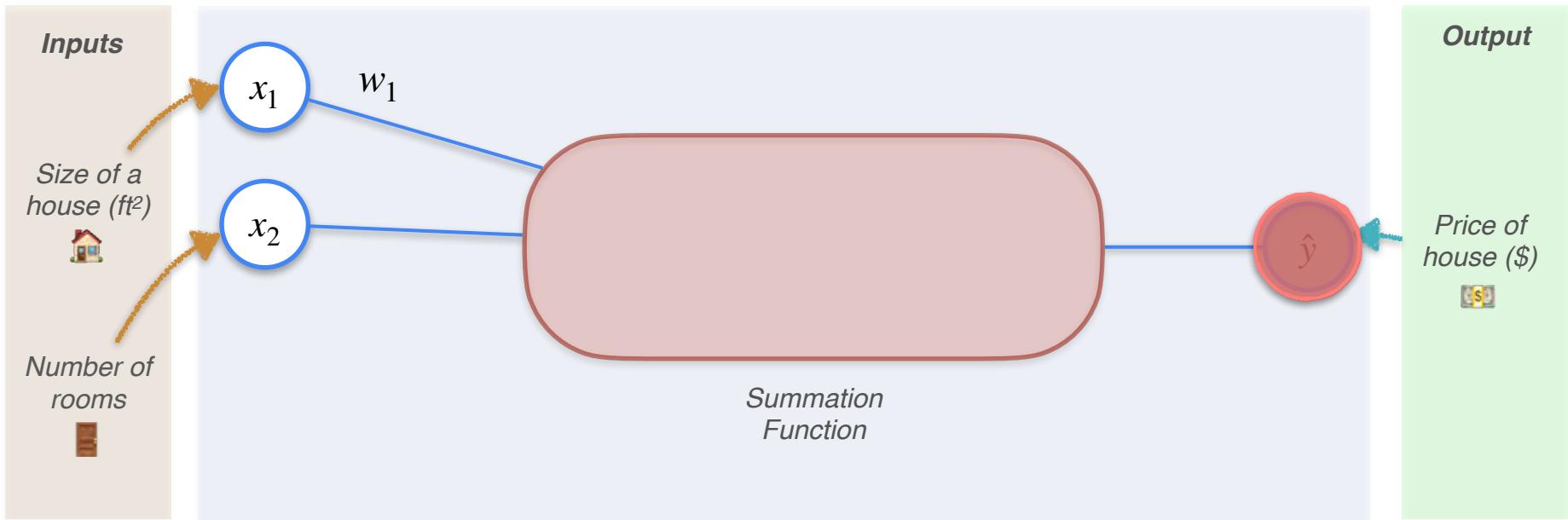
Regression With a Perceptron

Single Layer Neural Network Perceptron



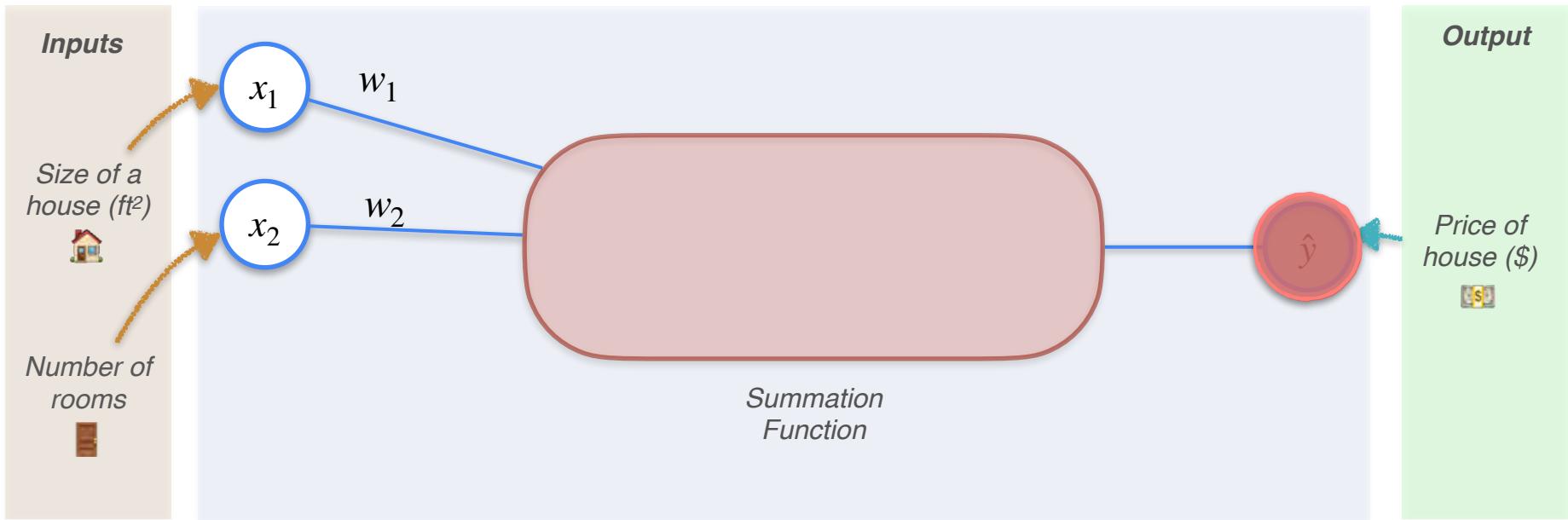
Regression With a Perceptron

Single Layer Neural Network Perceptron



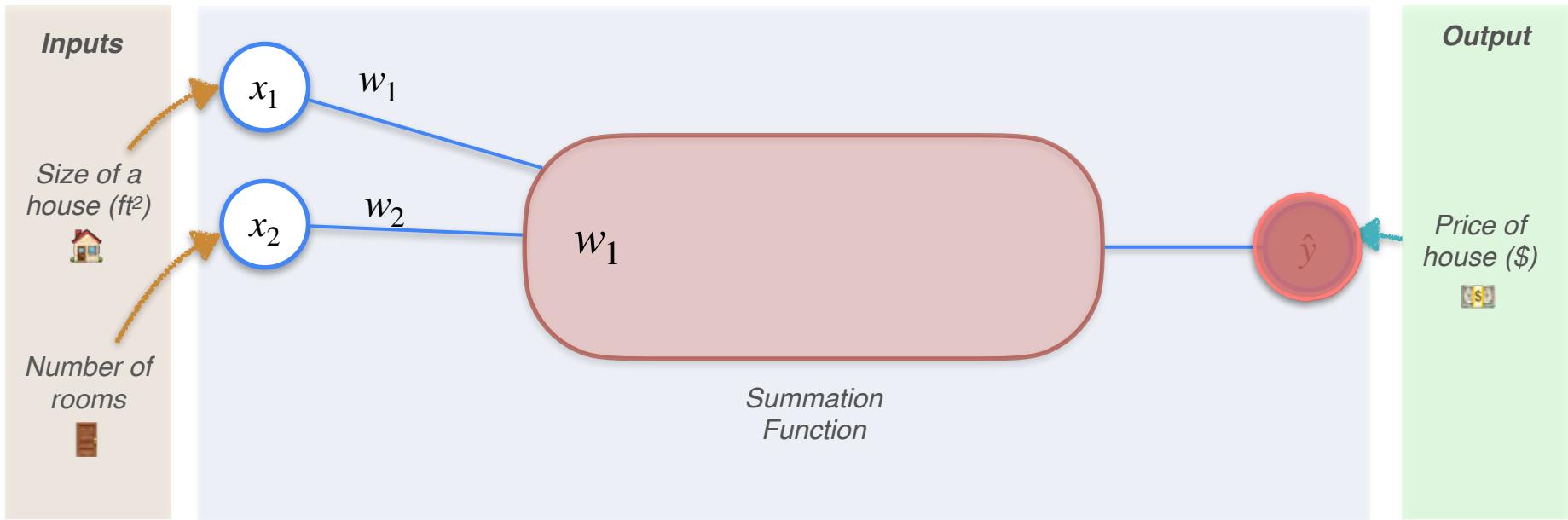
Regression With a Perceptron

Single Layer Neural Network Perceptron



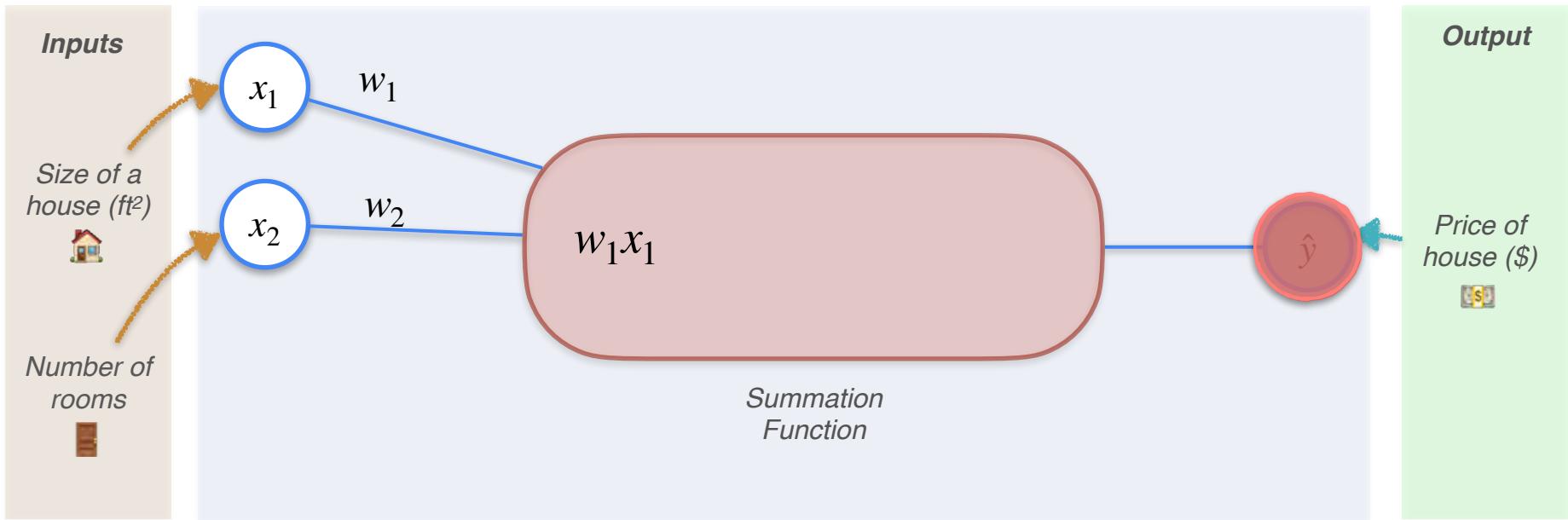
Regression With a Perceptron

Single Layer Neural Network Perceptron



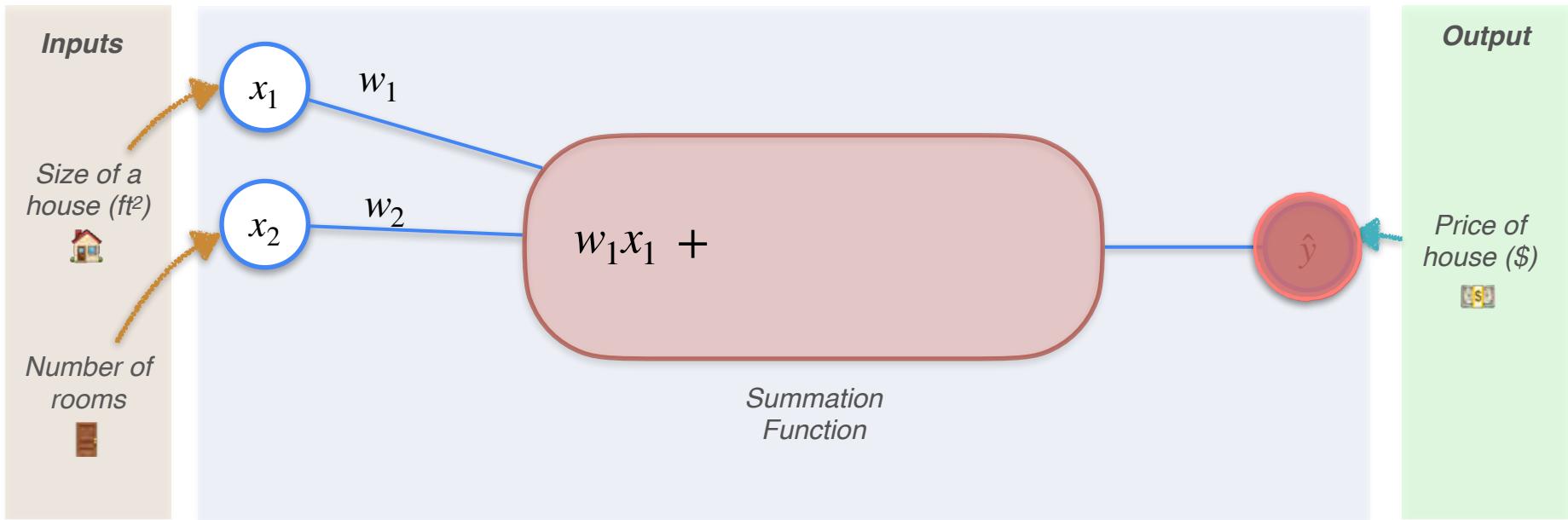
Regression With a Perceptron

Single Layer Neural Network Perceptron



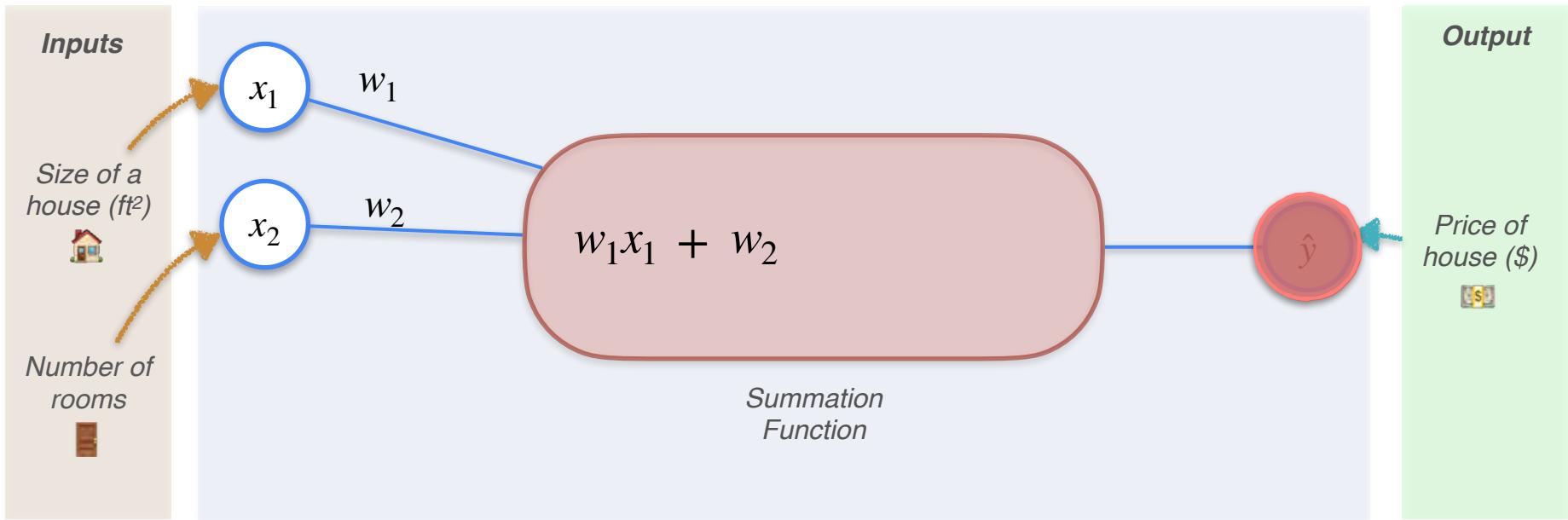
Regression With a Perceptron

Single Layer Neural Network Perceptron



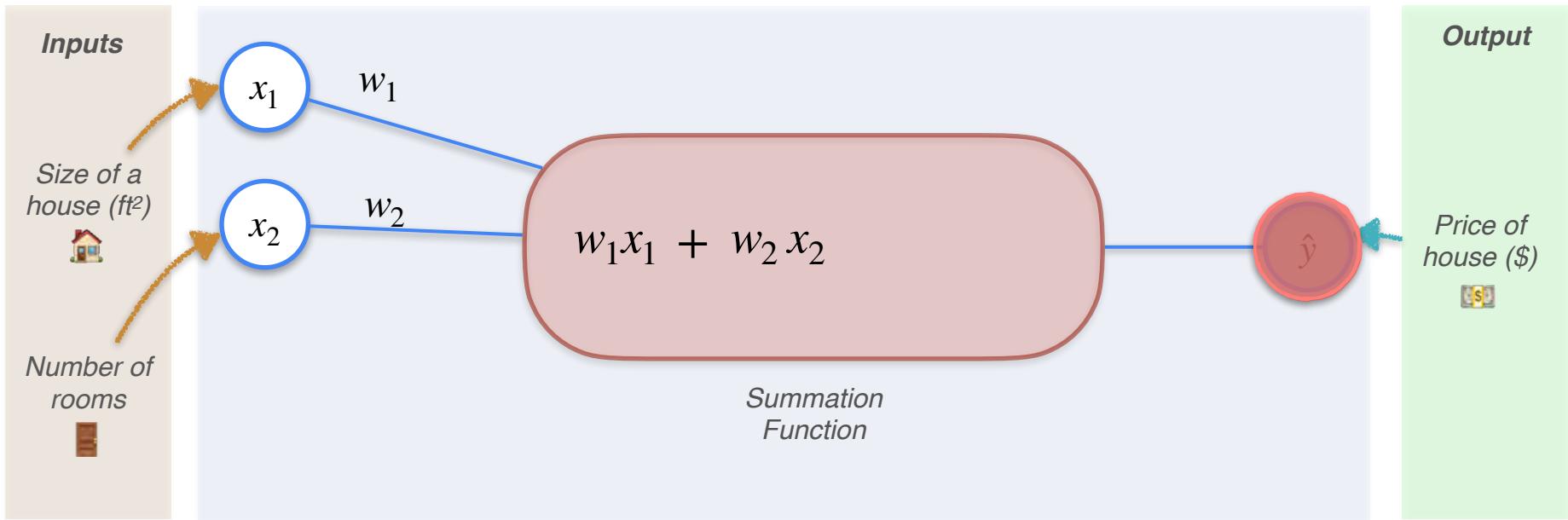
Regression With a Perceptron

Single Layer Neural Network Perceptron



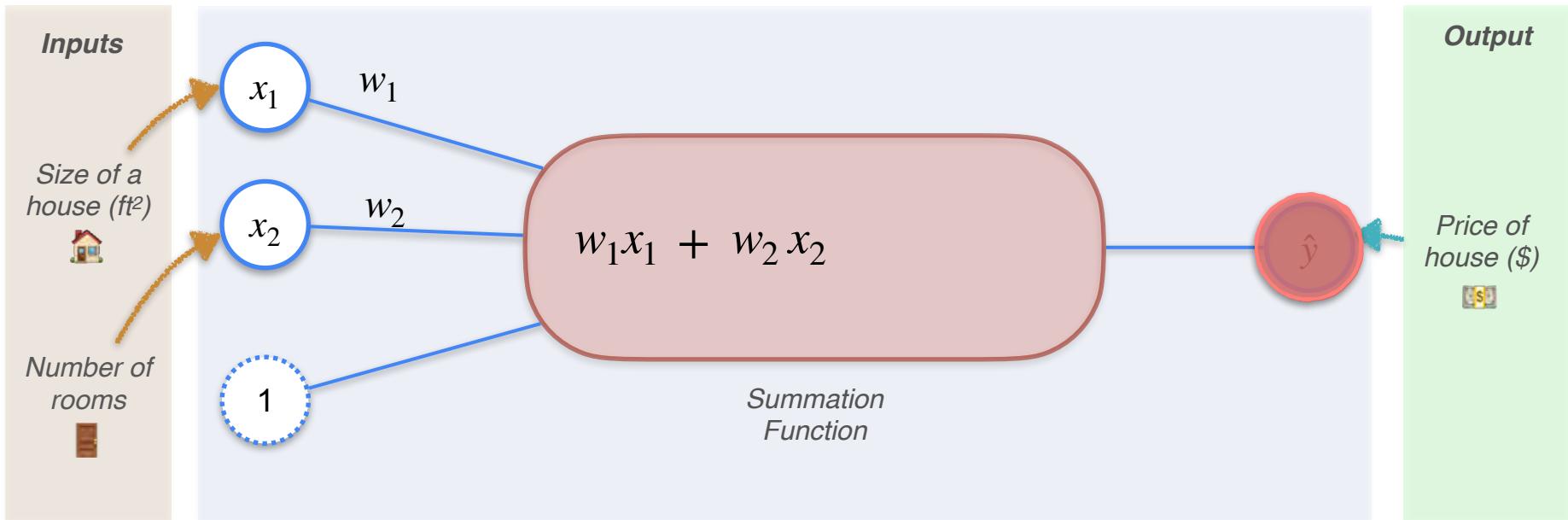
Regression With a Perceptron

Single Layer Neural Network Perceptron



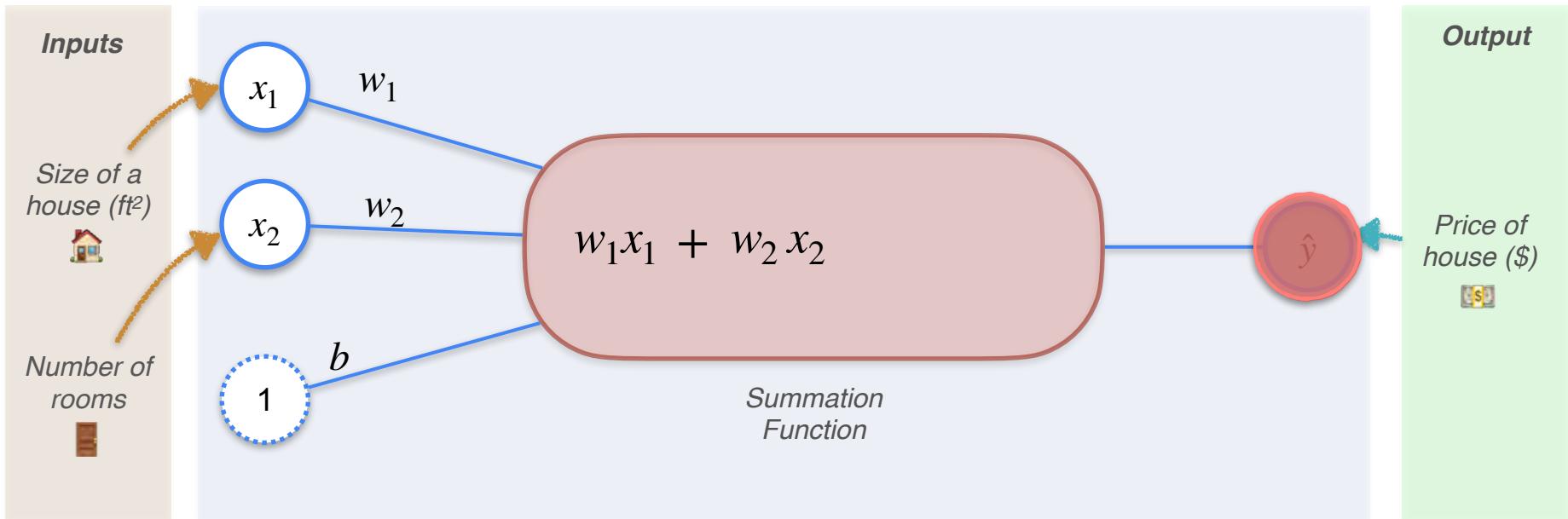
Regression With a Perceptron

Single Layer Neural Network Perceptron



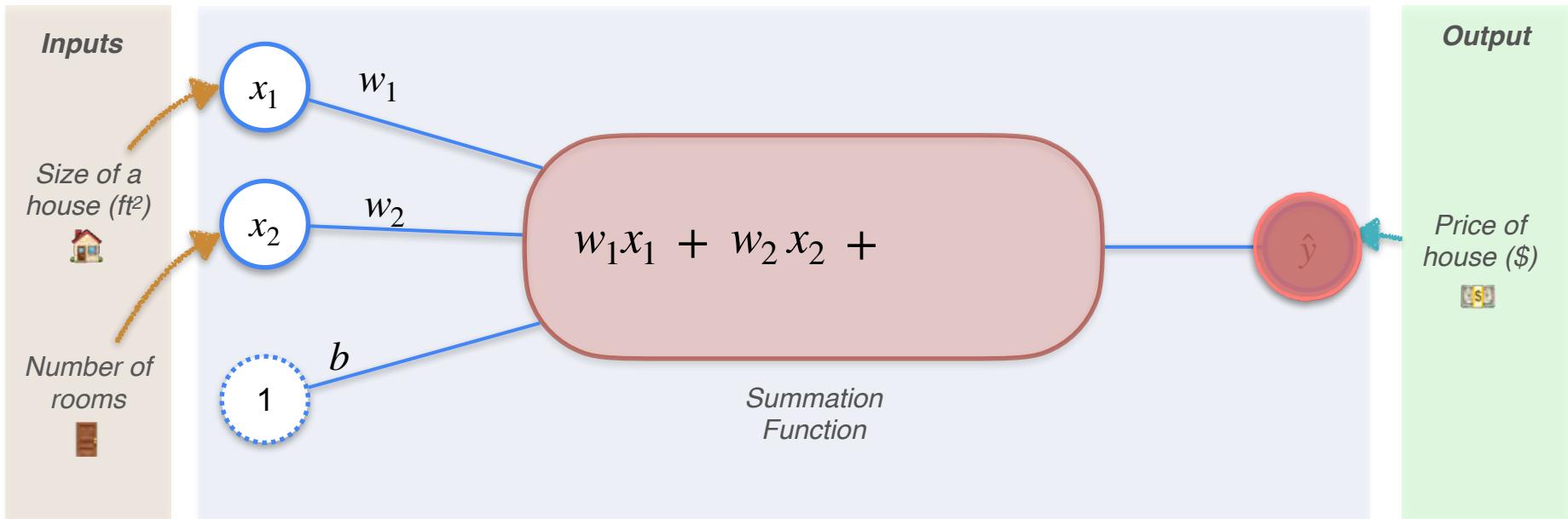
Regression With a Perceptron

Single Layer Neural Network Perceptron



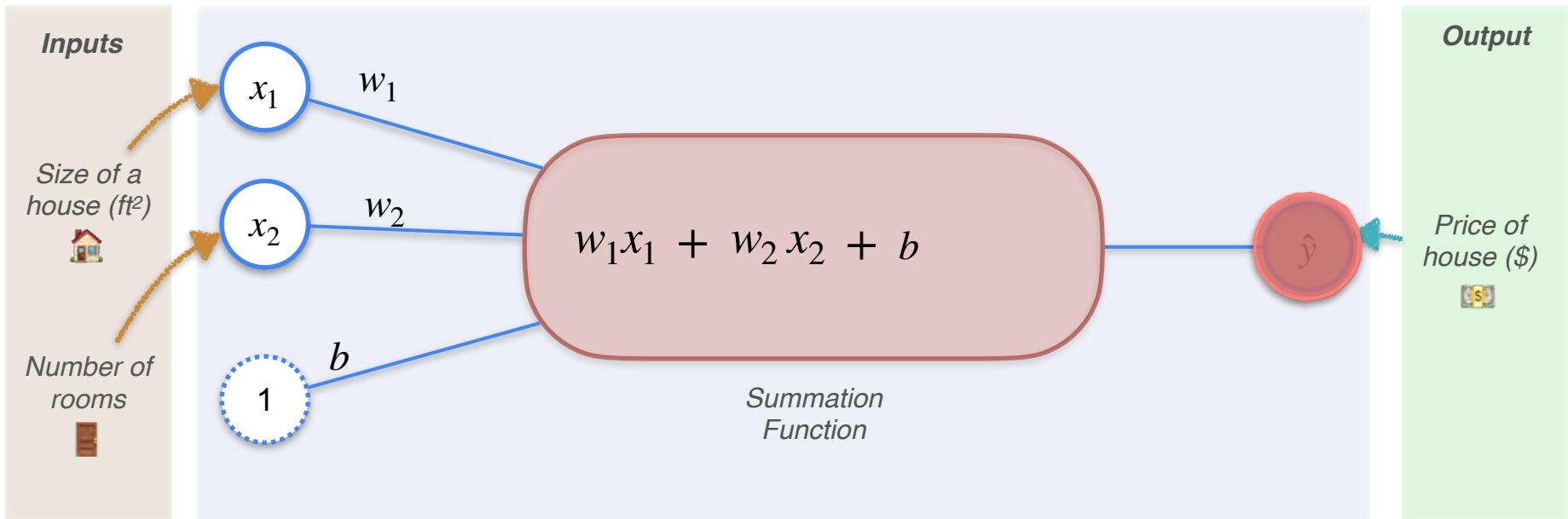
Regression With a Perceptron

Single Layer Neural Network Perceptron



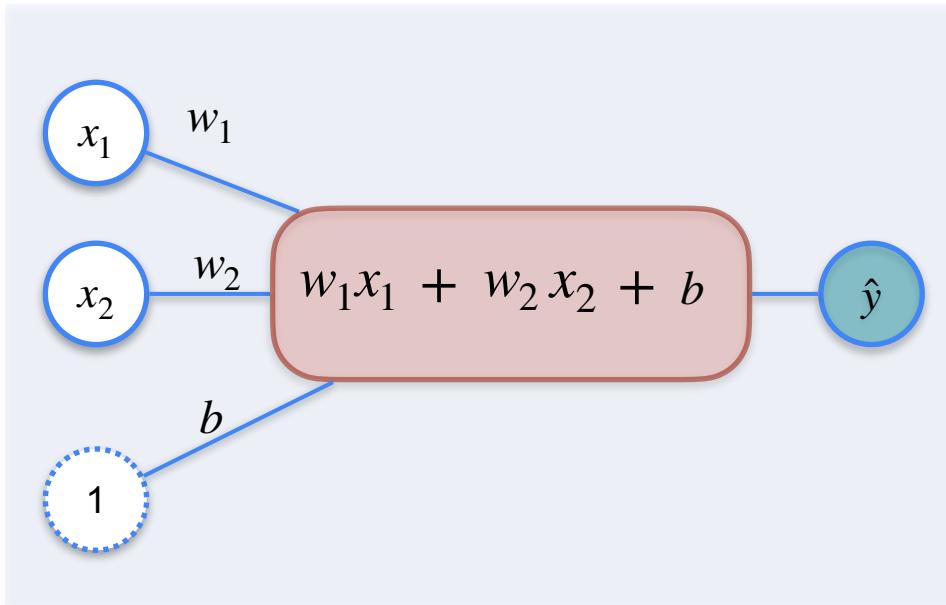
Regression With a Perceptron

Single Layer Neural Network Perceptron



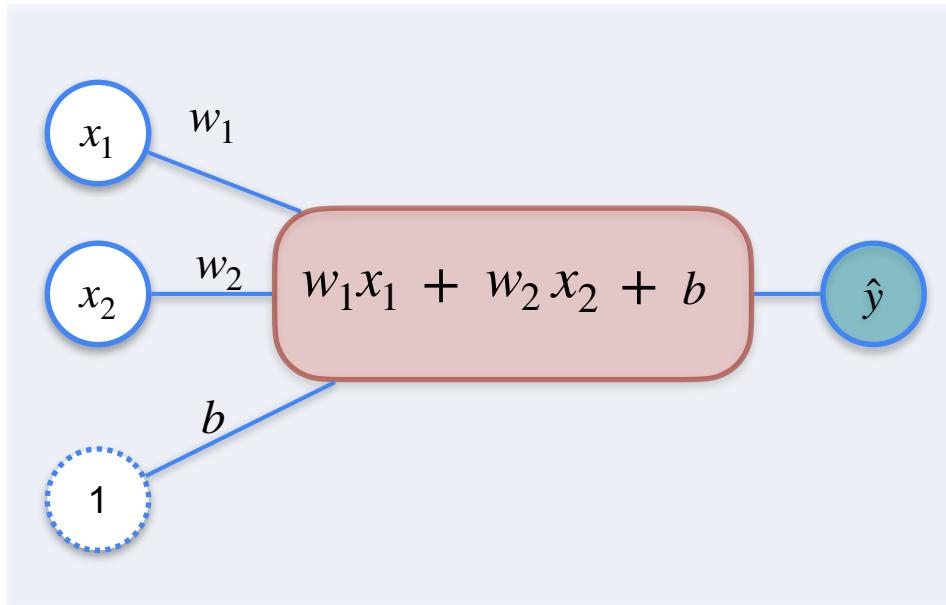
Regression With a Perceptron

Single Layer Neural Network Perceptron



Regression With a Perceptron

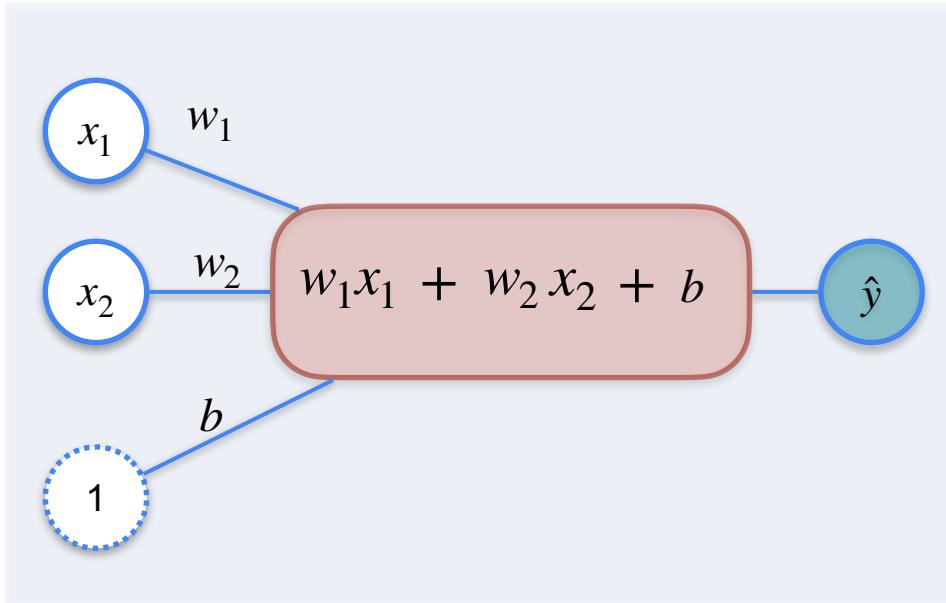
Single Layer Neural Network Perceptron



\hat{y}

Regression With a Perceptron

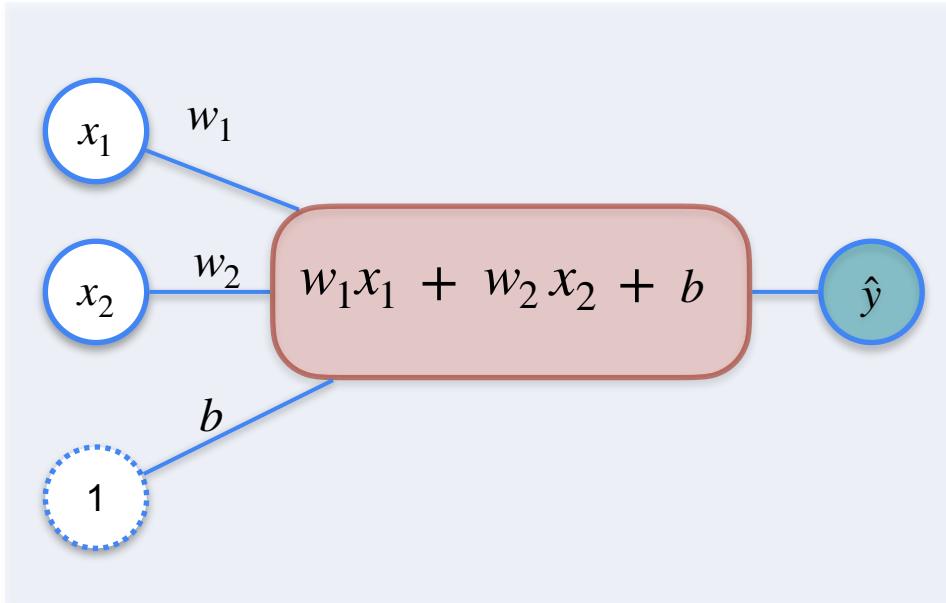
Single Layer Neural Network Perceptron



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

Regression With a Perceptron

Single Layer Neural Network Perceptron

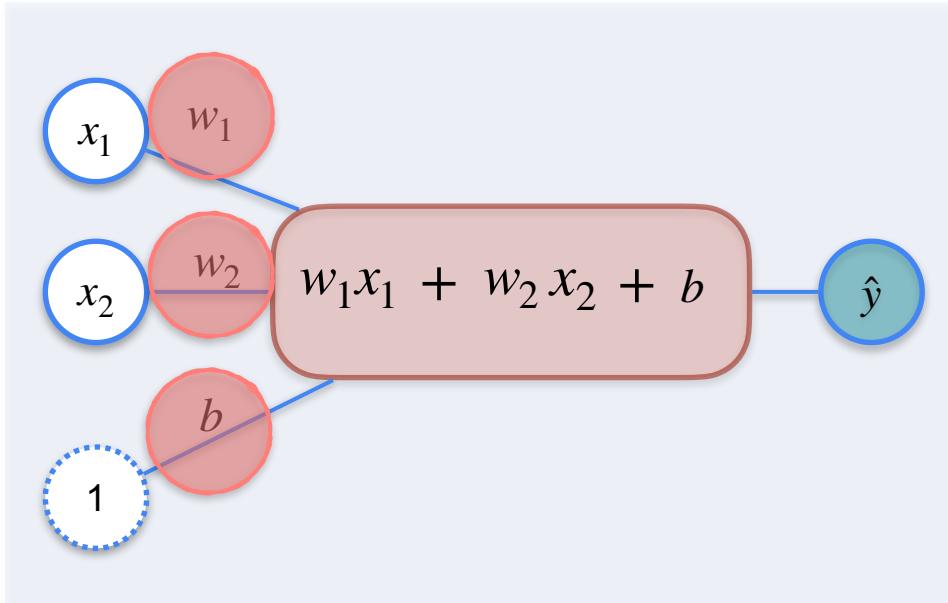


$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Main Goal:

Regression With a Perceptron

Single Layer Neural Network Perceptron

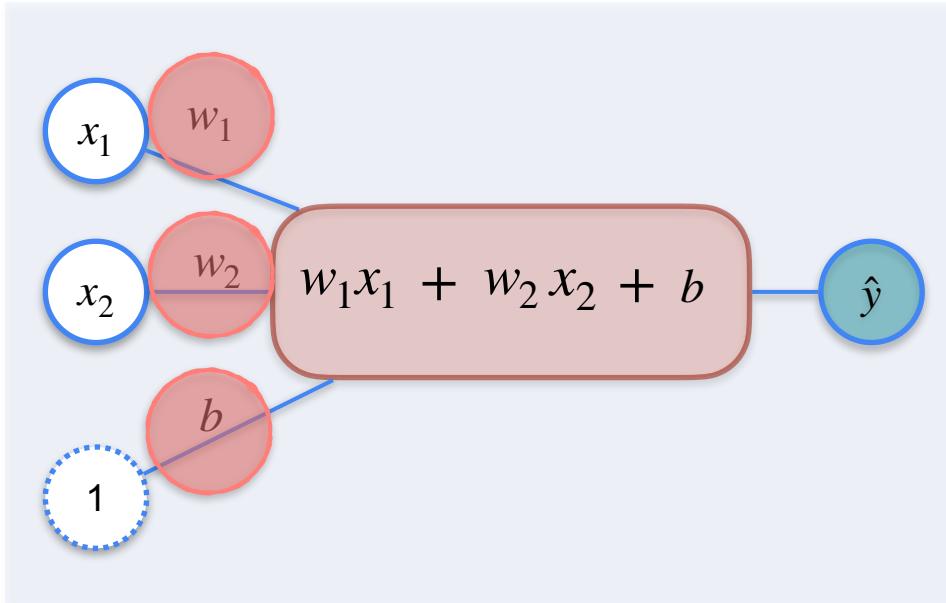


$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Main Goal:

Regression With a Perceptron

Single Layer Neural Network Perceptron



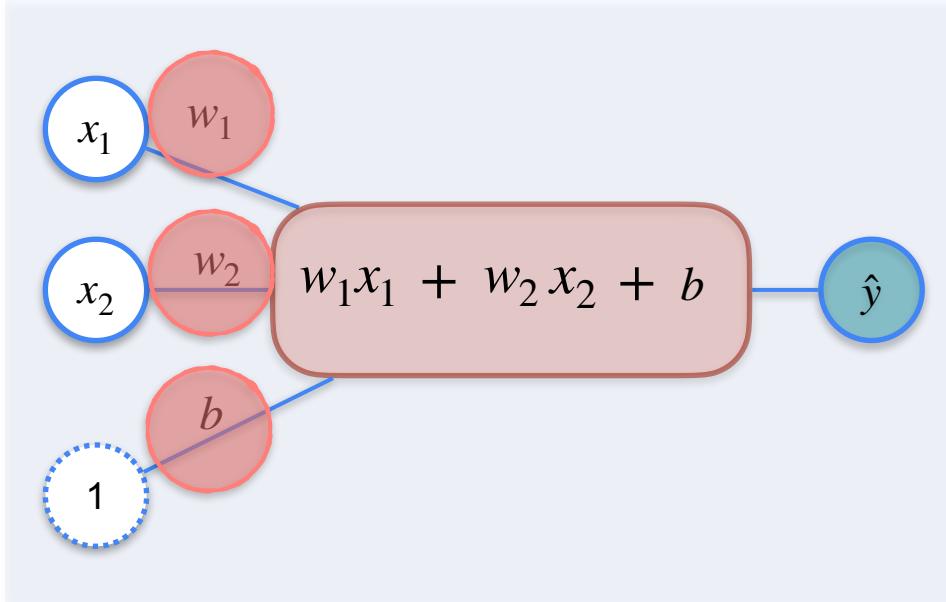
$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Main Goal:

Find weights and bias that will optimise the predictions.

Regression With a Perceptron

Single Layer Neural Network Perceptron



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

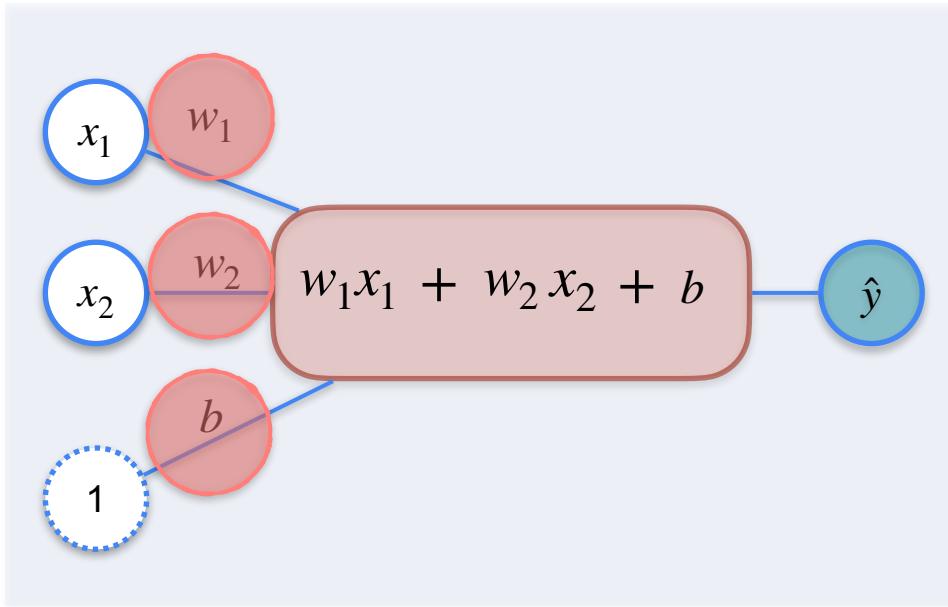
Main Goal:

Find weights and bias that will optimise the predictions.

i.e. Reduce the errors in the predictions

Regression With a Perceptron

Single Layer Neural Network Perceptron



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

Main Goal:

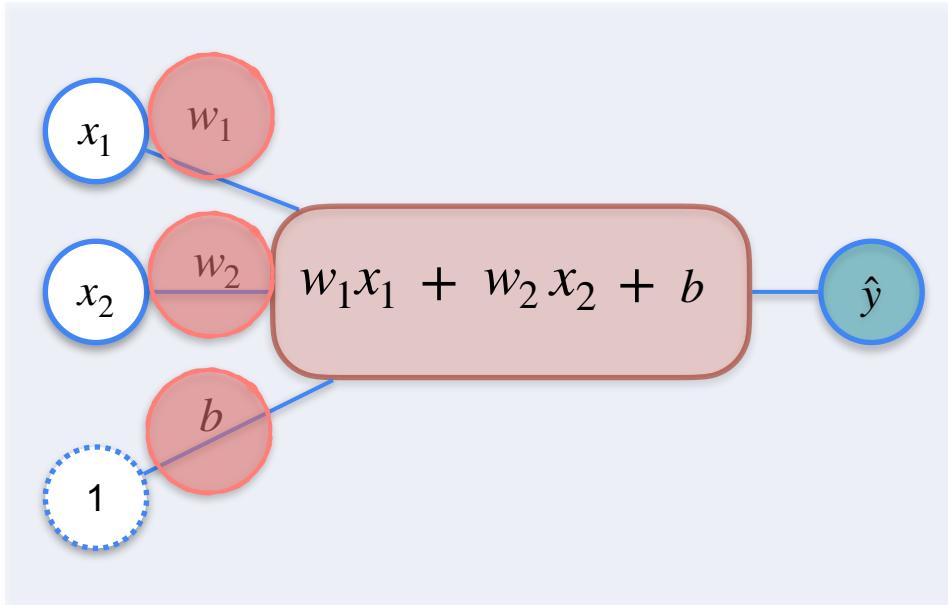
Find weights and bias that will optimise the predictions.

i.e. Reduce the errors in the predictions



Regression With a Perceptron

Single Layer Neural Network Perceptron



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

Main Goal:

Find weights and bias that will optimise the predictions.

i.e. Reduce the errors in the predictions



**The
Loss
Function**



DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Regression with a perceptron: Loss function

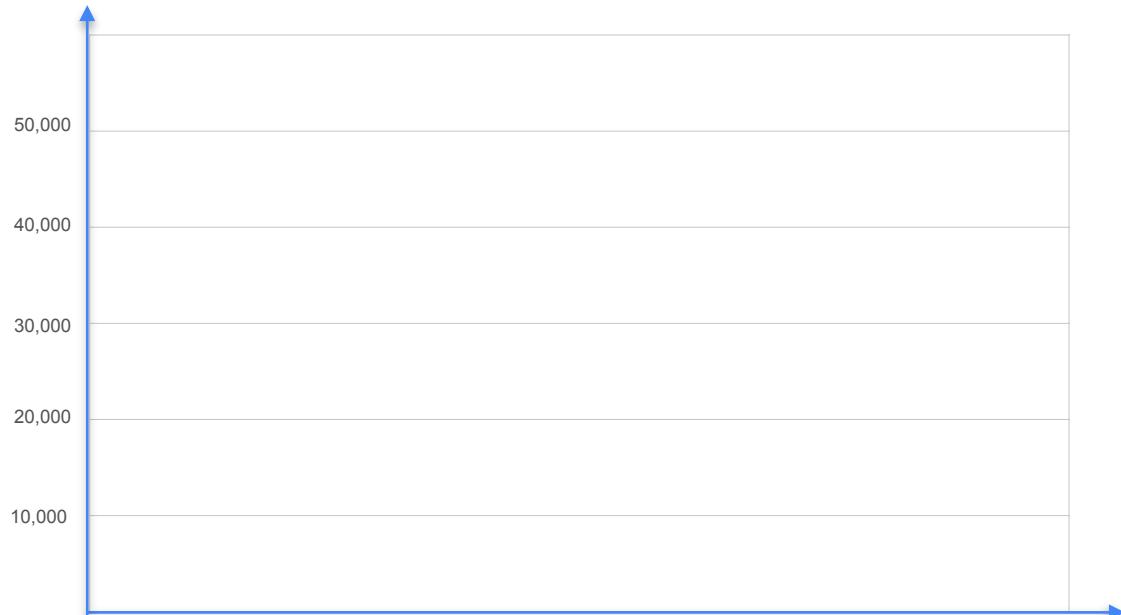
Mean Squared Error

Mean Squared Error

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

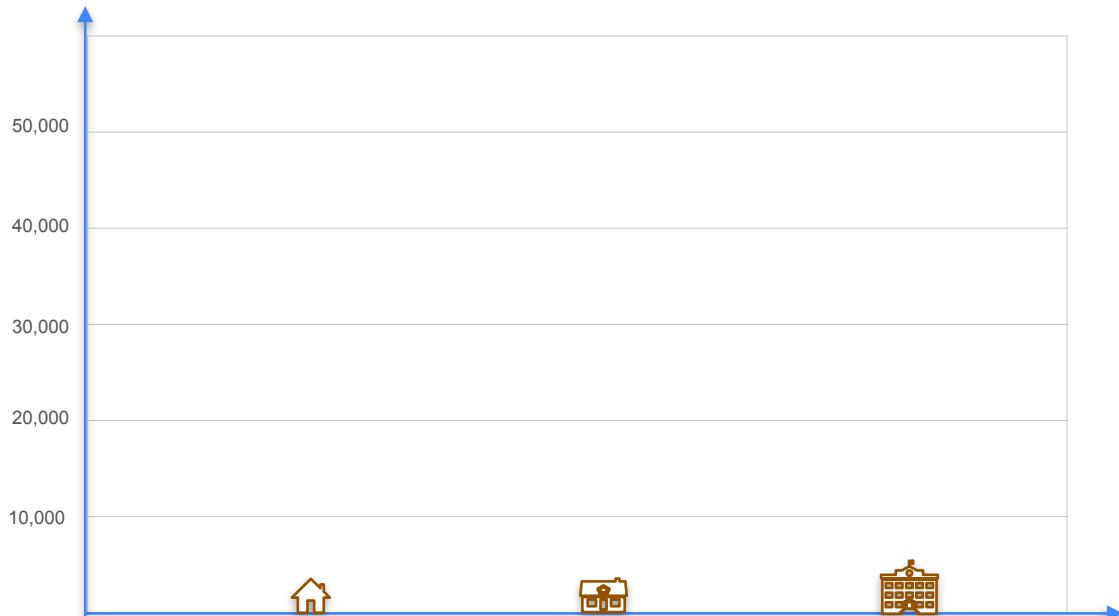
Mean Squared Error

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



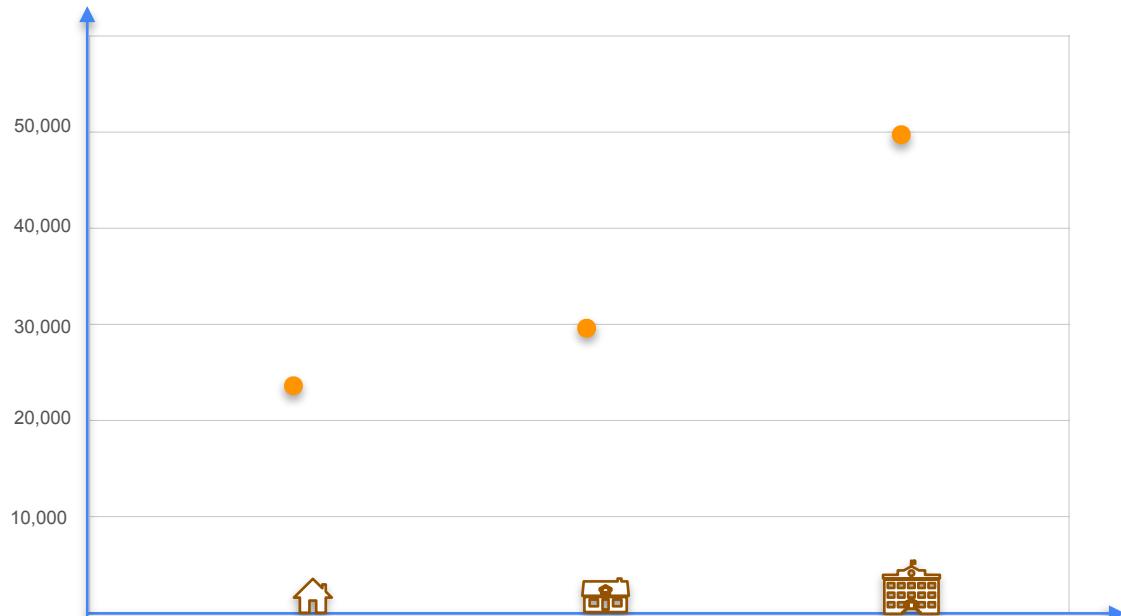
Mean Squared Error

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



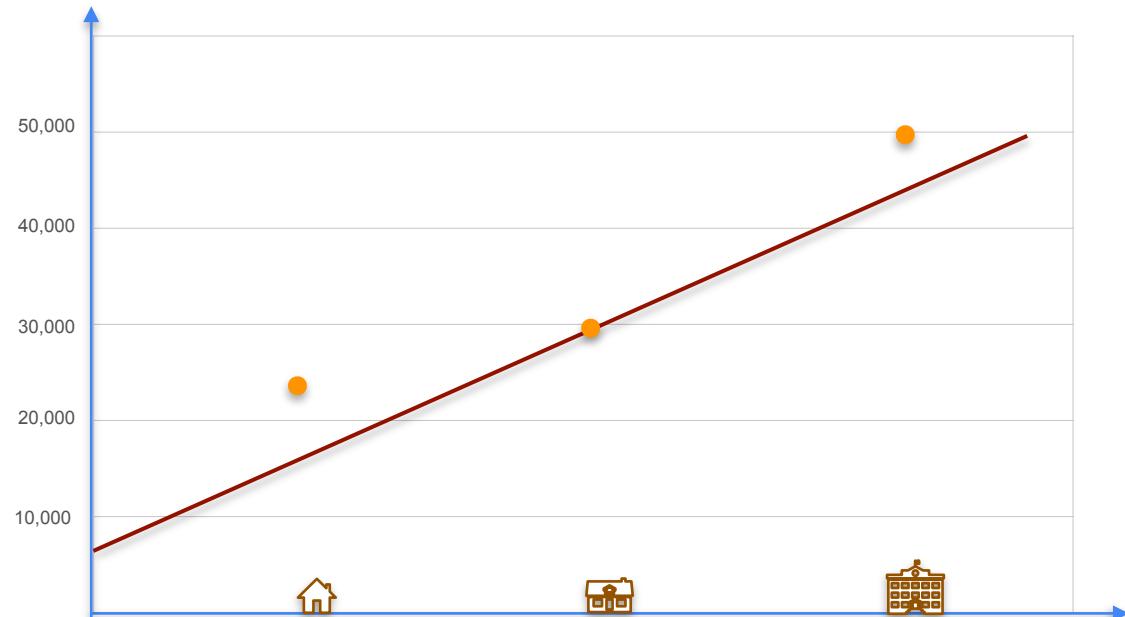
Mean Squared Error

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



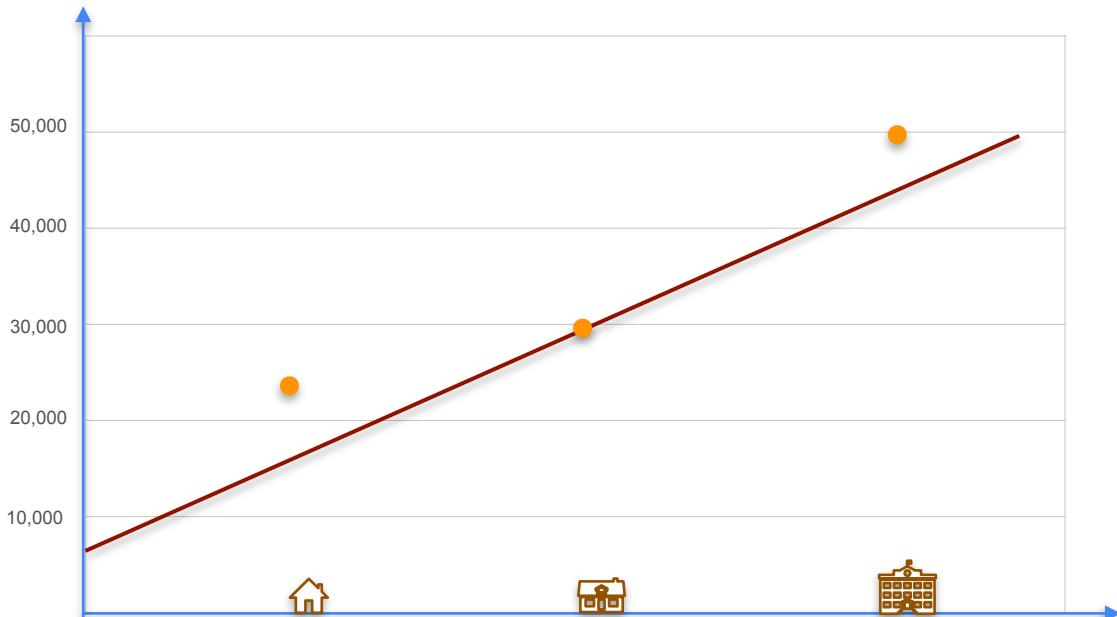
Mean Squared Error

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



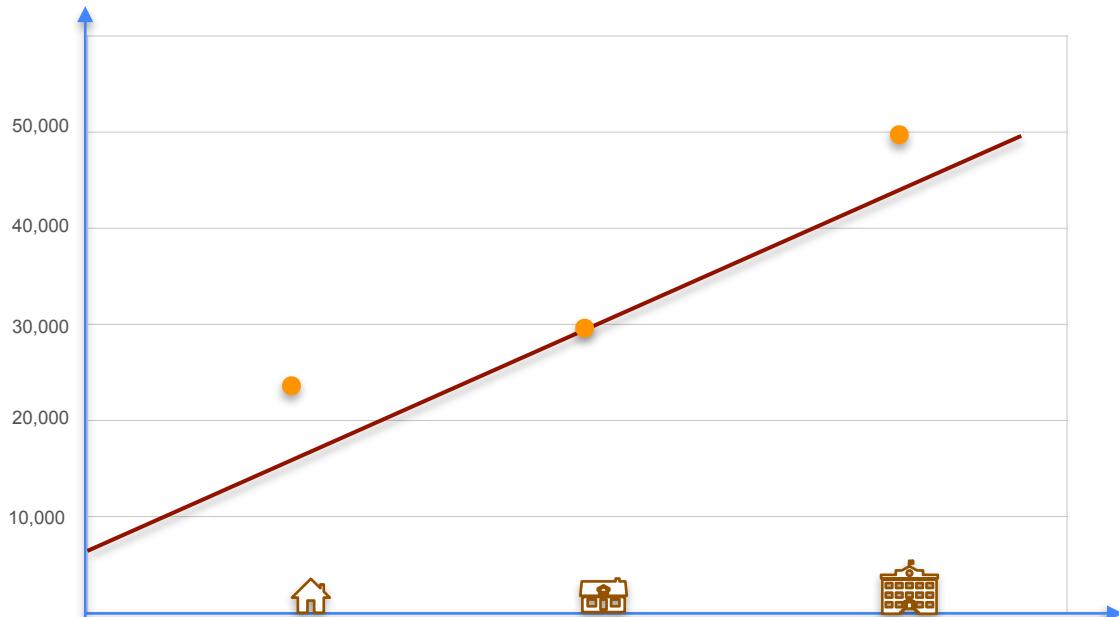
Mean Squared Error

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



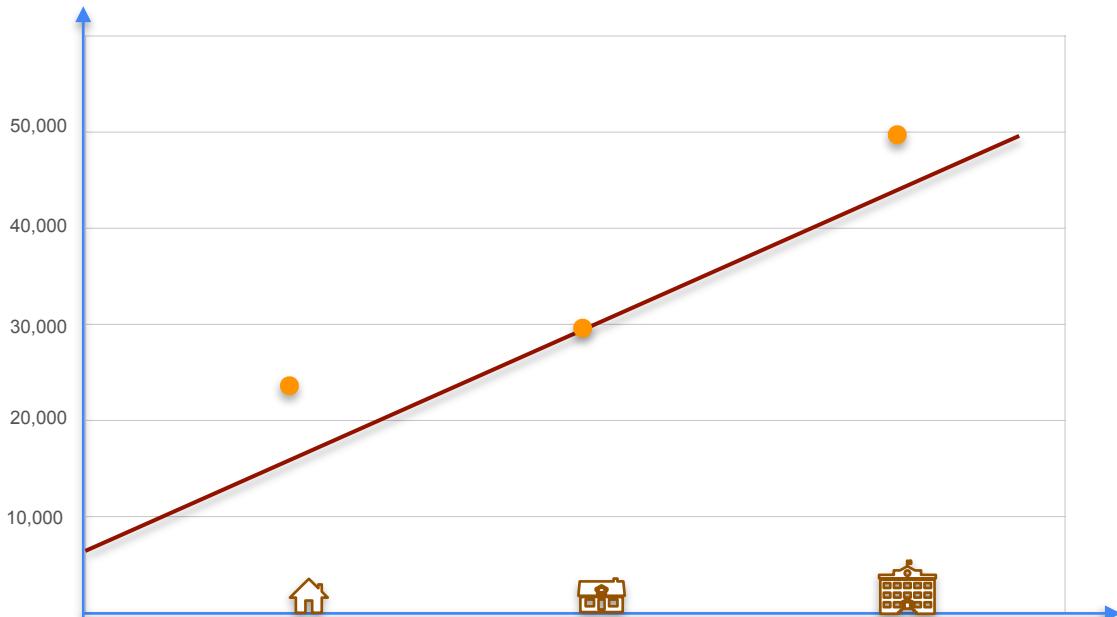
Mean Squared Error

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



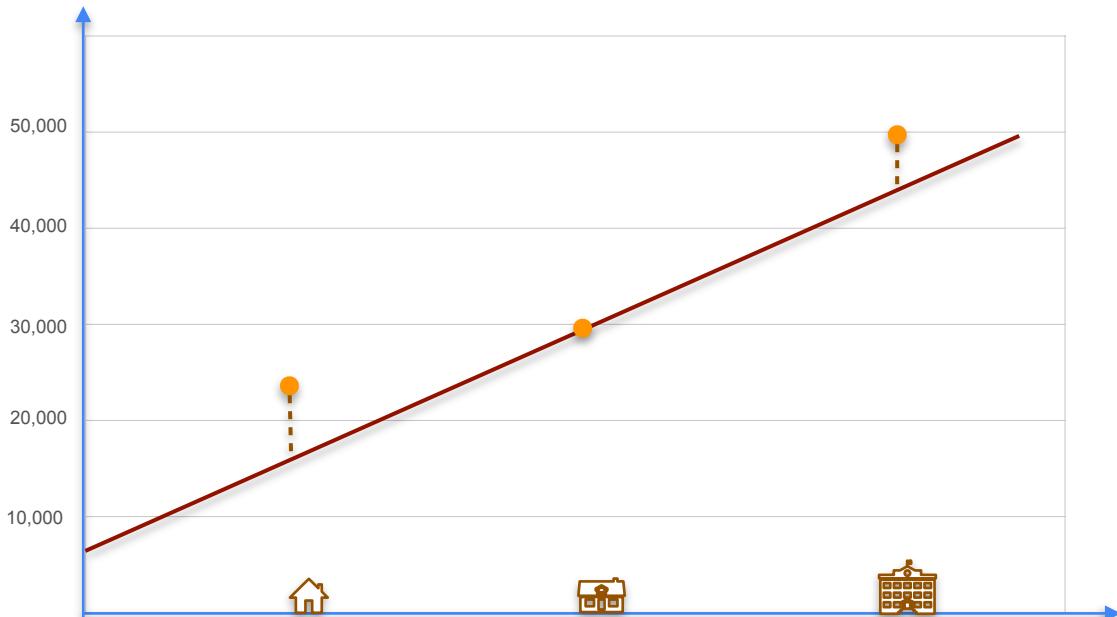
Mean Squared Error

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



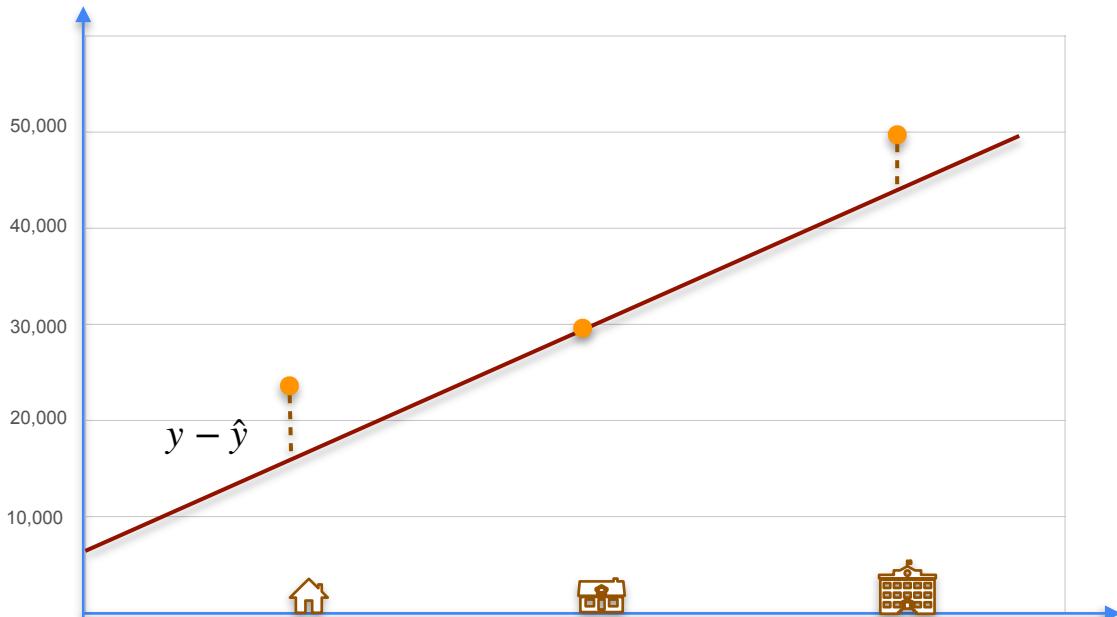
Mean Squared Error

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



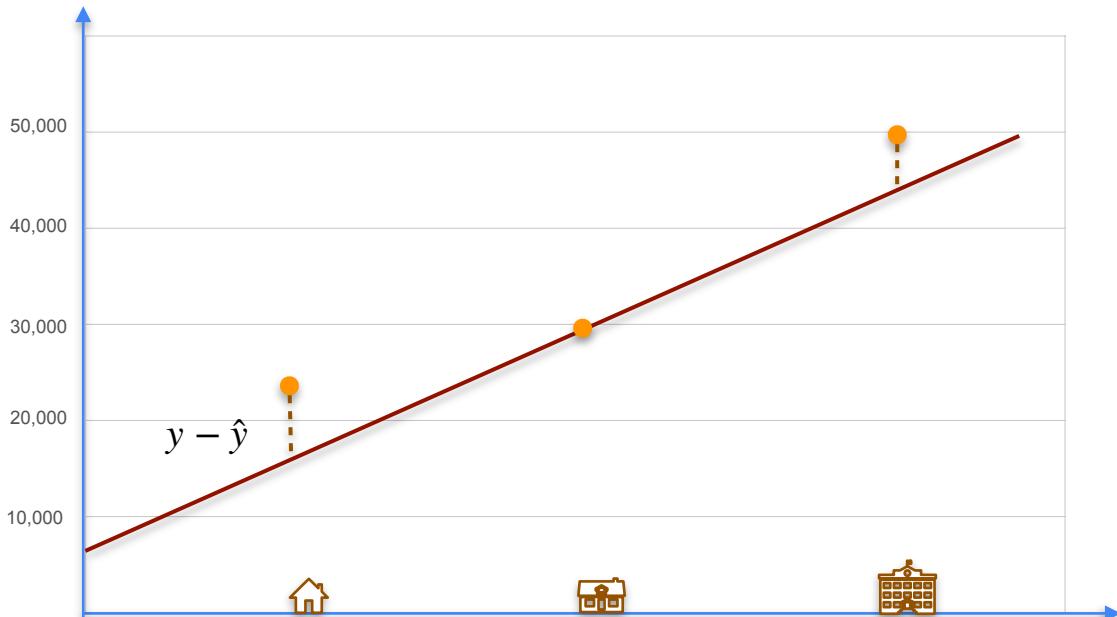
Mean Squared Error

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



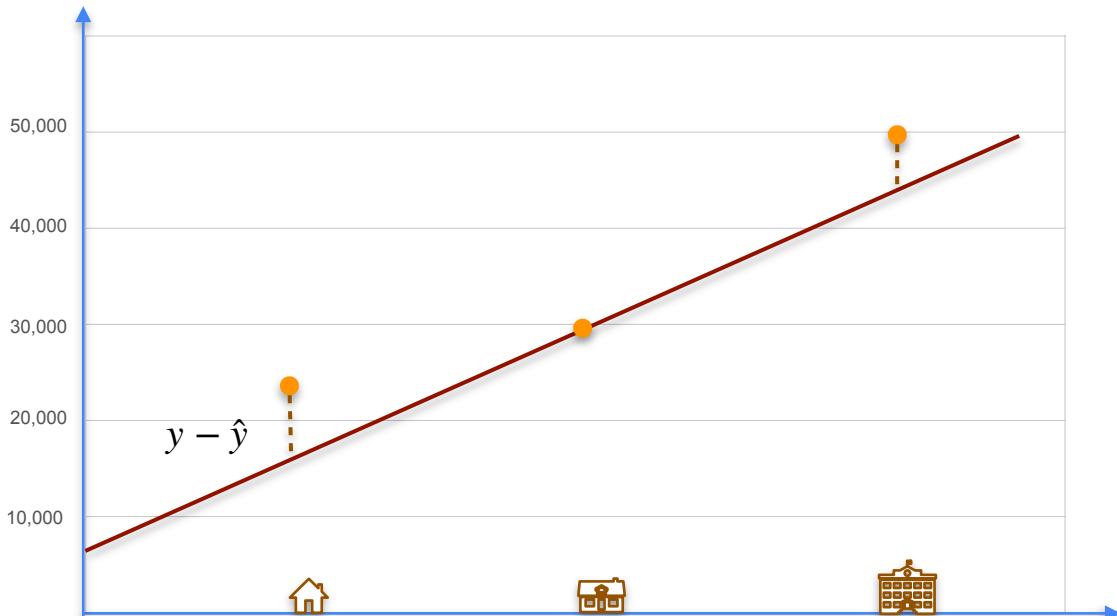
Mean Squared Error

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



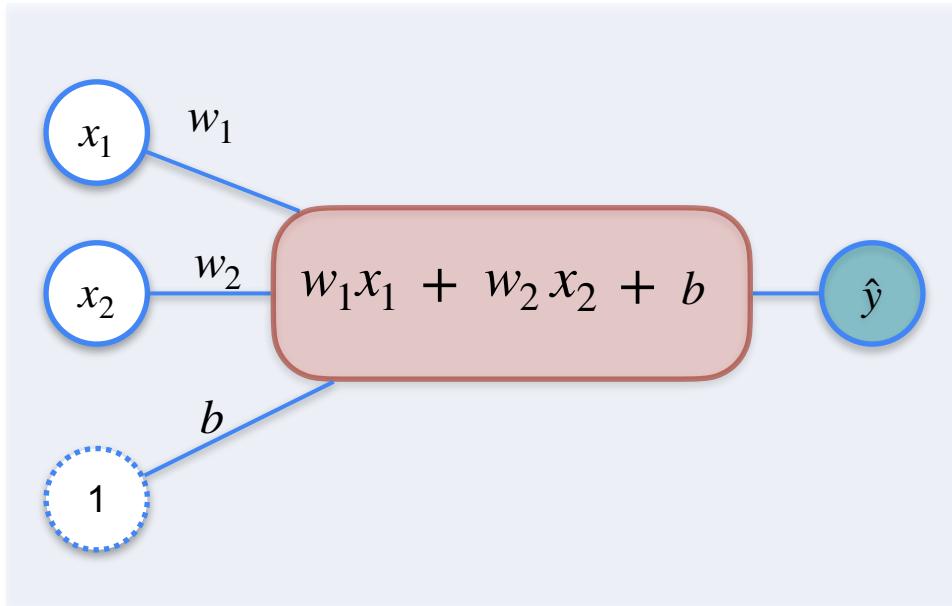
Mean Squared Error

	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



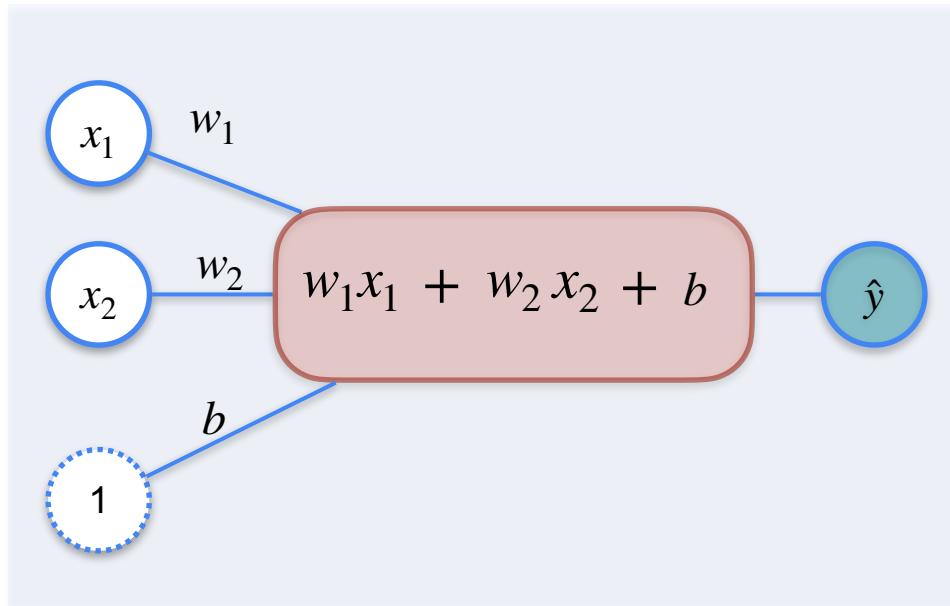
Regression With a Perceptron

Single Layer Neural Network Perceptron



Regression With a Perceptron

Single Layer Neural Network Perceptron

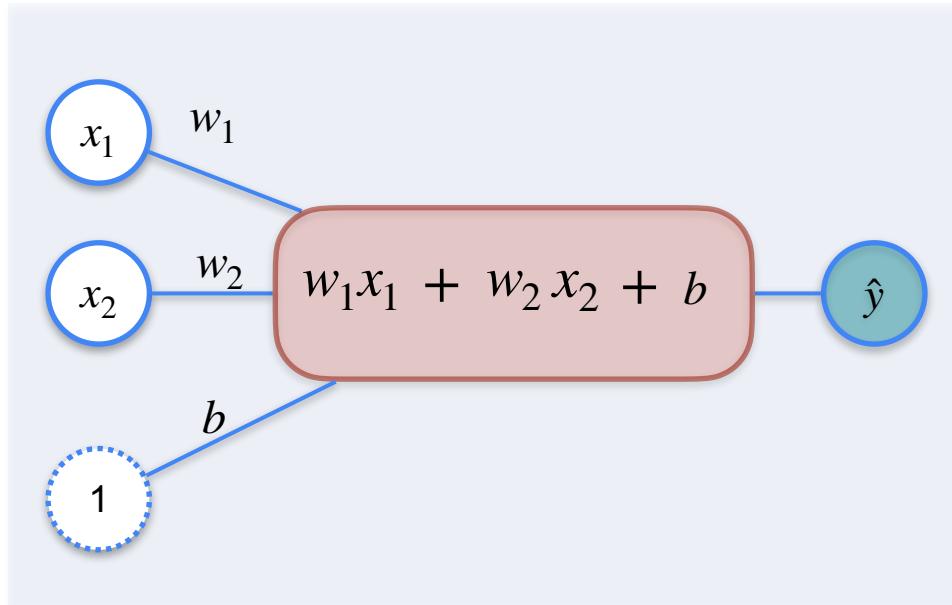


Prediction Function:

$$\hat{y}$$

Regression With a Perceptron

Single Layer Neural Network Perceptron

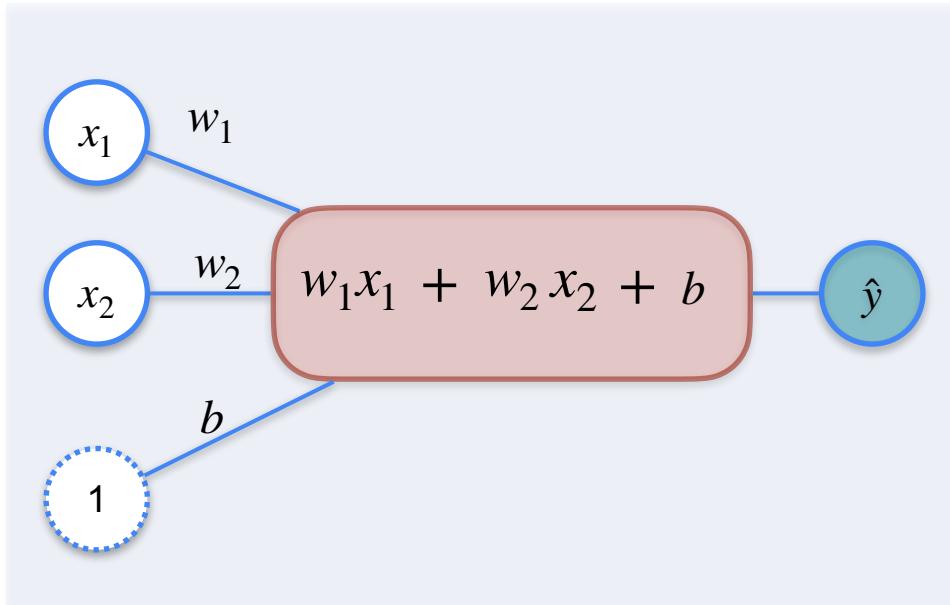


Prediction Function:

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

Regression With a Perceptron

Single Layer Neural Network Perceptron



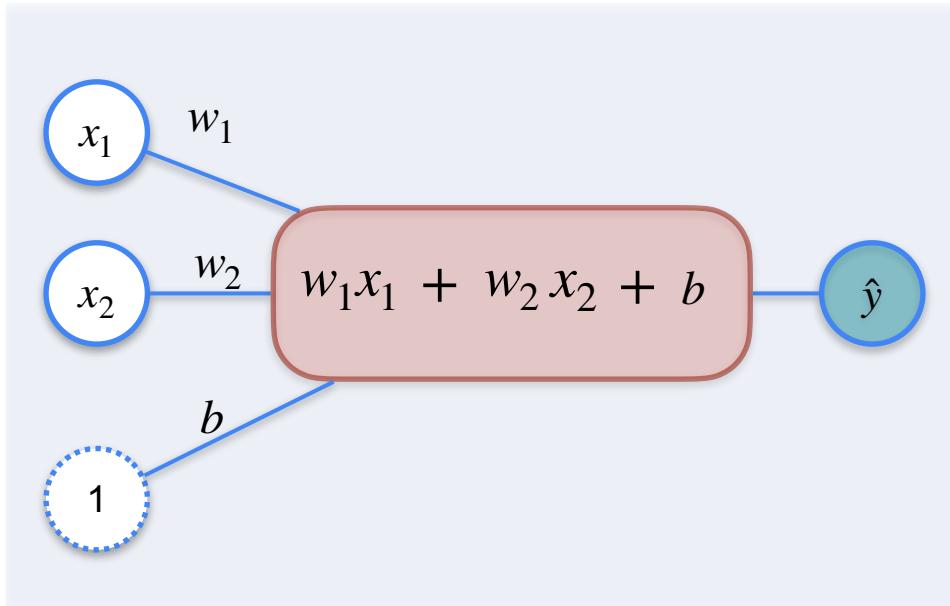
Prediction Function:

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

Loss Function:

Regression With a Perceptron

Single Layer Neural Network Perceptron



Prediction Function:

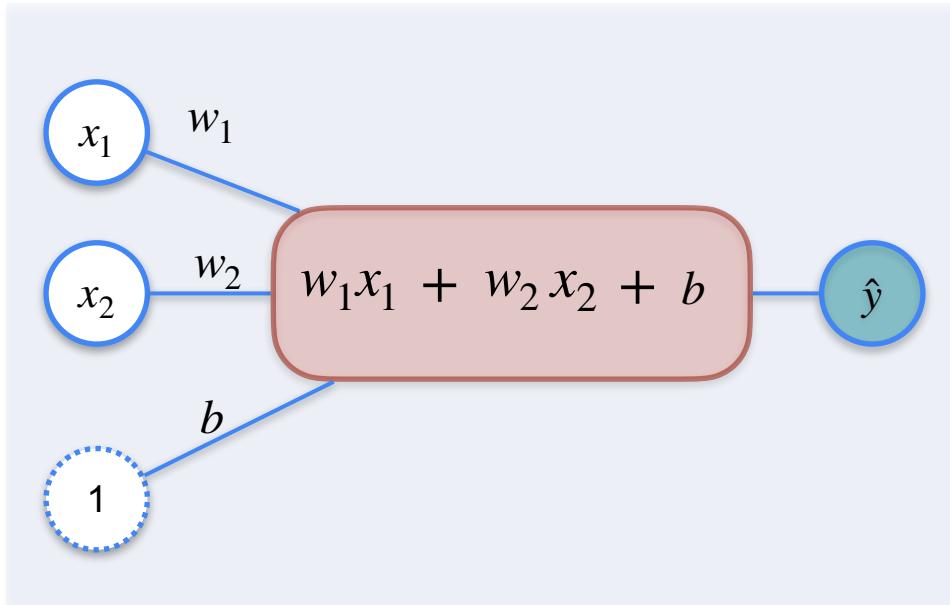
$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

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

Regression With a Perceptron

Single Layer Neural Network Perceptron



Prediction Function:

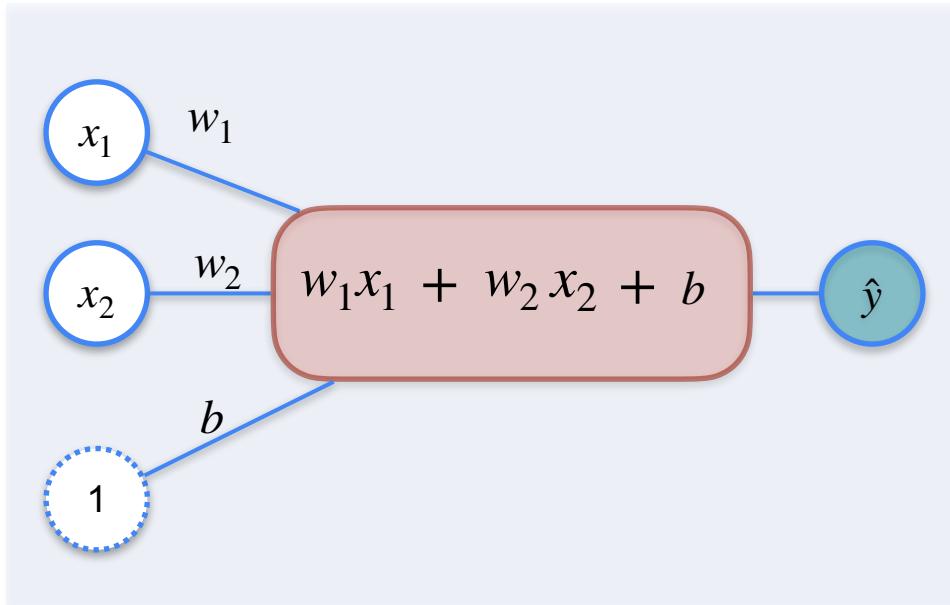
$$\hat{y} = w_1x_1 + w_2x_2 + b$$

Loss Function:

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

Regression With a Perceptron

Single Layer Neural Network Perceptron



Prediction Function:

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

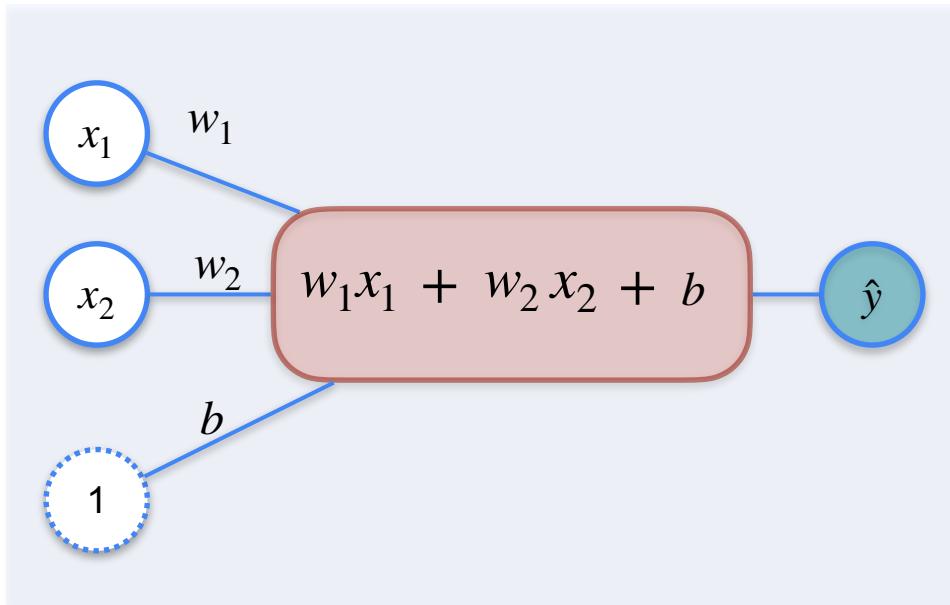
Loss Function:

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

Main Goal:

Regression With a Perceptron

Single Layer Neural Network Perceptron



Prediction Function:

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

Loss Function:

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

Main Goal:

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



DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Regression with a perceptron: Gradient Descent

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

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

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

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

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

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

To find optimal values for:

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

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

To find optimal values for:

$$w_1, w_2, b$$

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

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

To find optimal values for:

$$w_1, w_2, b$$

You need gradient descent

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

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

To find optimal values for:

$$w_1, w_2, b$$

You need gradient descent

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

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

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

To find optimal values for:

$$w_1, w_2, b$$

You need gradient descent

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

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

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

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

To find optimal values for:

$$w_1, w_2, b$$

You need gradient descent

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

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

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

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

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

To find optimal values for:

$$w_1, w_2, b$$

You need gradient descent

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

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

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

Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

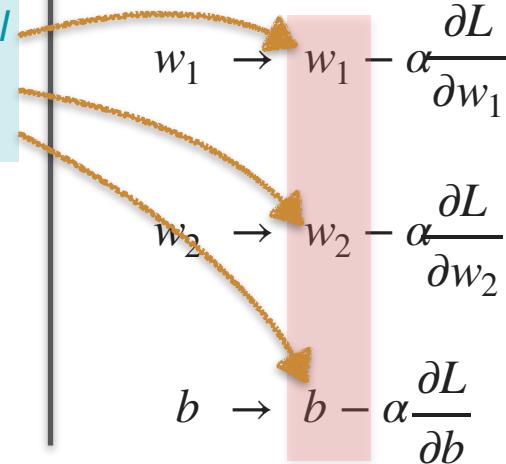
Find w_1, w_2, b that give \hat{y} with the least error

To find optimal values for:

$$w_1, w_2, b$$

You need gradient descent

Some initial starting values



Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

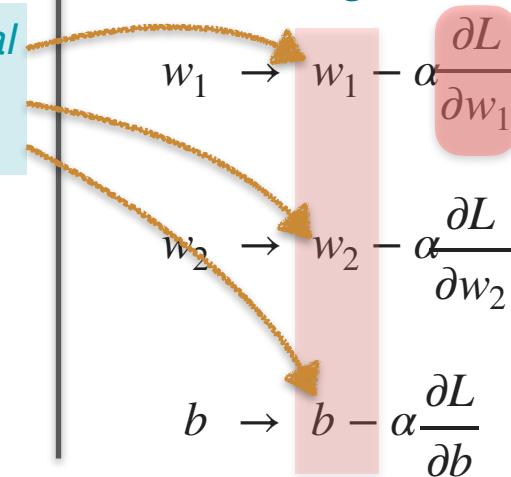
Find w_1, w_2, b that give \hat{y} with the least error

To find optimal values for:

$$w_1, w_2, b$$

You need gradient descent

Some initial starting values



Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

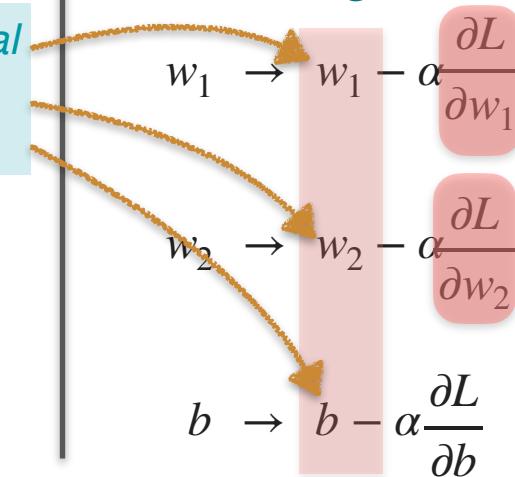
Find w_1, w_2, b that give \hat{y} with the least error

To find optimal values for:

$$w_1, w_2, b$$

You need gradient descent

Some initial starting values



Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

Main Goal:

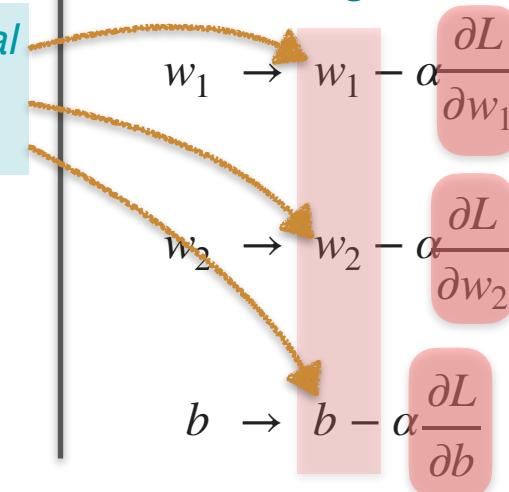
Find w_1, w_2, b that give \hat{y} with the least error

To find optimal values for:

$$w_1, w_2, b$$

You need gradient descent

Some initial starting values



Regression With a Perceptron

Prediction Function:

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

Loss Function:

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

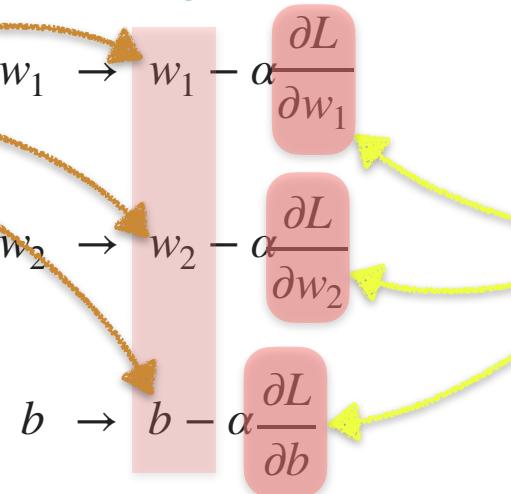
Main Goal:

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

Some initial starting values

To find optimal values for:
 w_1, w_2, b

You need gradient descent



SUB-TASK

Find the following partial derivatives

Regression With Perceptron

Prediction Function:

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

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

Loss Function:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

Using chain rule:

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

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

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

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

$\frac{\partial L}{\partial \hat{y}}$	$= -(y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	$= 1$
$\frac{\partial \hat{y}}{\partial w_1}$	$= x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

$\frac{\partial L}{\partial \hat{y}}$	$= -(y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	$= 1$
$\frac{\partial \hat{y}}{\partial w_1}$	$= x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

$\frac{\partial L}{\partial \hat{y}}$	$= -(y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	$= 1$
$\frac{\partial \hat{y}}{\partial w_1}$	$= x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

$\frac{\partial L}{\partial \hat{y}}$	$= -(y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	$= 1$
$\frac{\partial \hat{y}}{\partial w_1}$	$= x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

$\frac{\partial L}{\partial \hat{y}}$	$= -(y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	$= 1$
$\frac{\partial \hat{y}}{\partial w_1}$	$= x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	$= x_2$

Regression With Perceptron

Prediction Function:

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

Loss Function:

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

$\frac{\partial L}{\partial \hat{y}}$	$= -(y - \hat{y})$
$\frac{\partial \hat{y}}{\partial b}$	$= 1$
$\frac{\partial \hat{y}}{\partial w_1}$	$= x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	$= x_2$

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

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

Regression With Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial \hat{y}}{\partial w_1} = x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = x_2$$

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

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

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

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

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

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

Regression With a Perceptron

Main Goal:

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

Regression With a Perceptron

Main Goal:

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

Regression With a Perceptron

Main Goal:

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

ie. optimal values for:

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

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

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

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

Perform Gradient Descent

Regression With a Perceptron

Main Goal:

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

$$w_1 = w_1 - \alpha$$

ie. optimal values for:

w_1 , w_2 , b

Perform Gradient Descent

Regression With a Perceptron

Main Goal:

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

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

ie. optimal values for:

w_1 , w_2 , b

Perform Gradient Descent

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

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

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

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

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

$$w_2 = w_2 - \alpha$$

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

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

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

Perform Gradient Descent

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

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

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

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

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

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

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

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



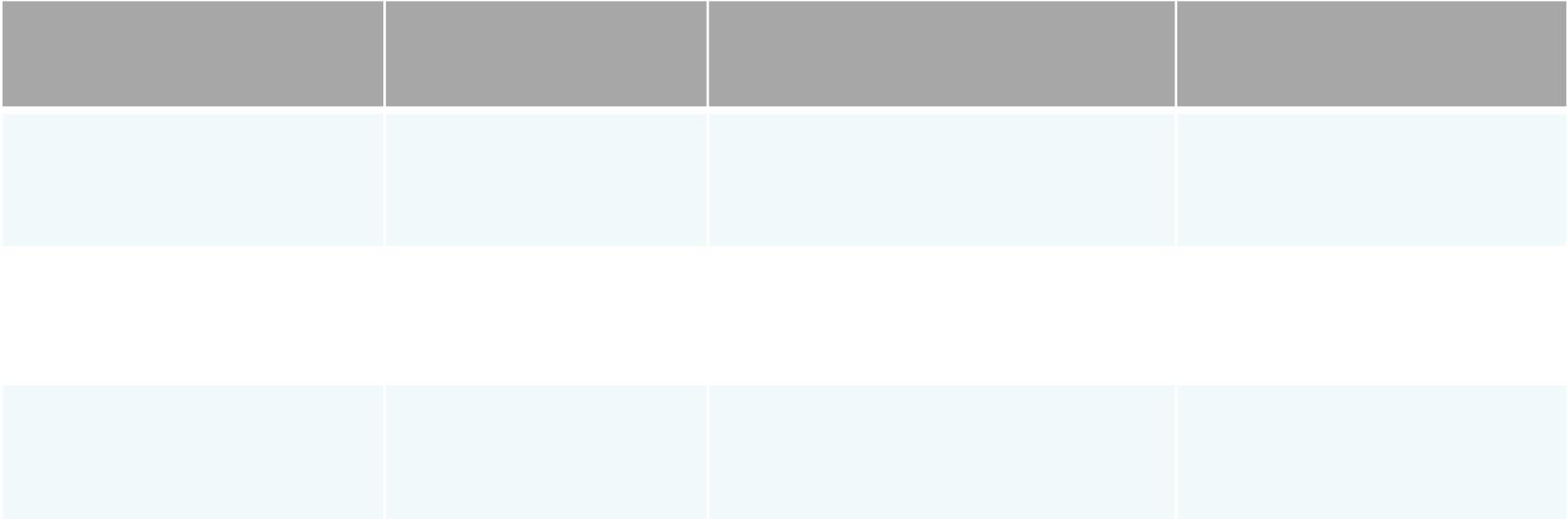
DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Classification with a perceptron

Classification Problem Motivation

Classification Problem Motivation



Classification Problem Motivation

<i>Sentence</i>			

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Beep beep!

Aack beep beep beep!

Aack beep aack!

Classification Problem Motivation

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

Beep beep!

Aack beep beep beep!

Aack beep aack!

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

Classification Problem Motivation

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

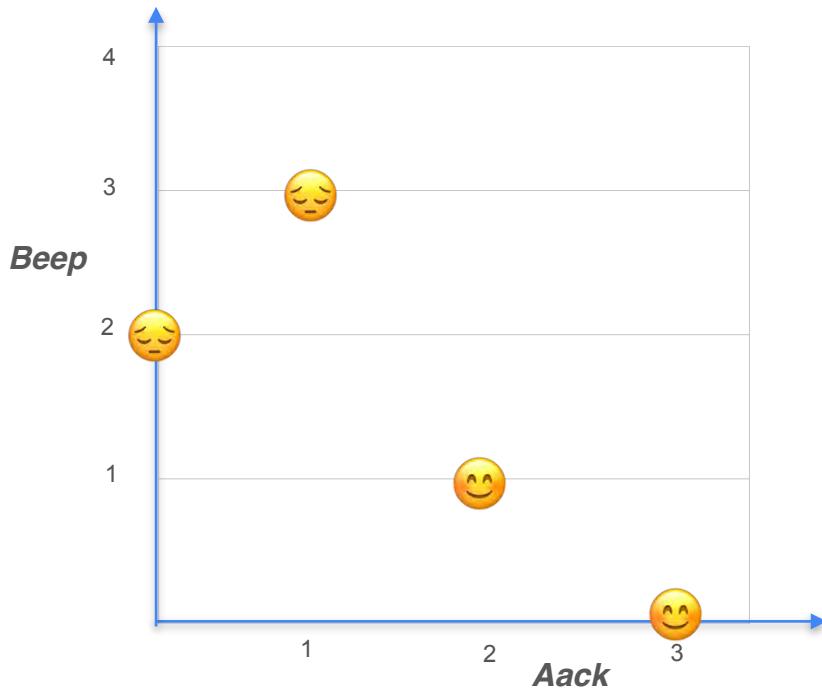
Classification Problem Motivation

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

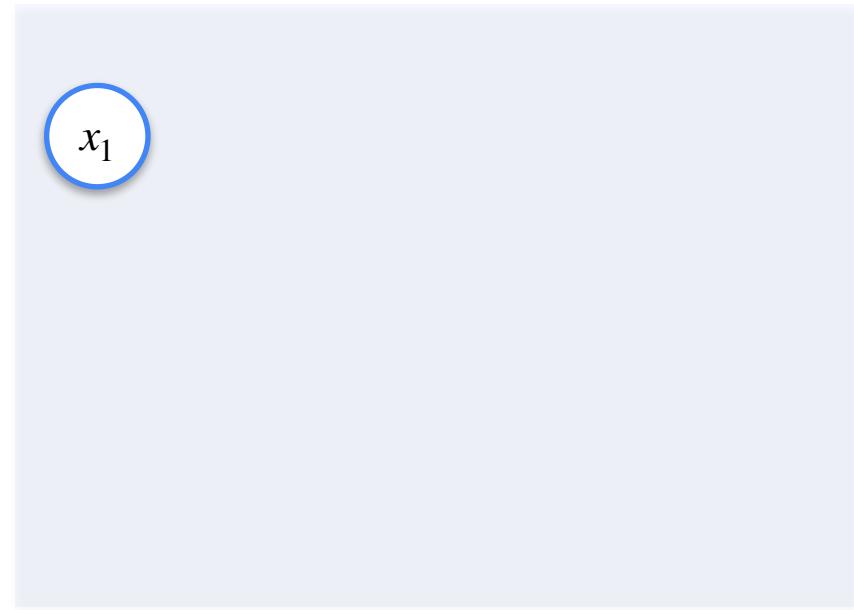
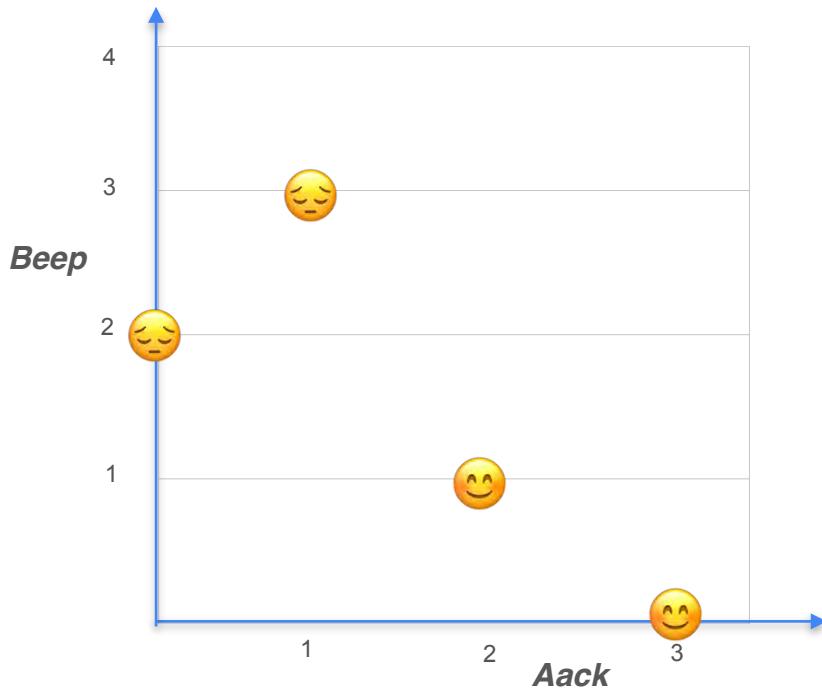
Classification Problem Motivation

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

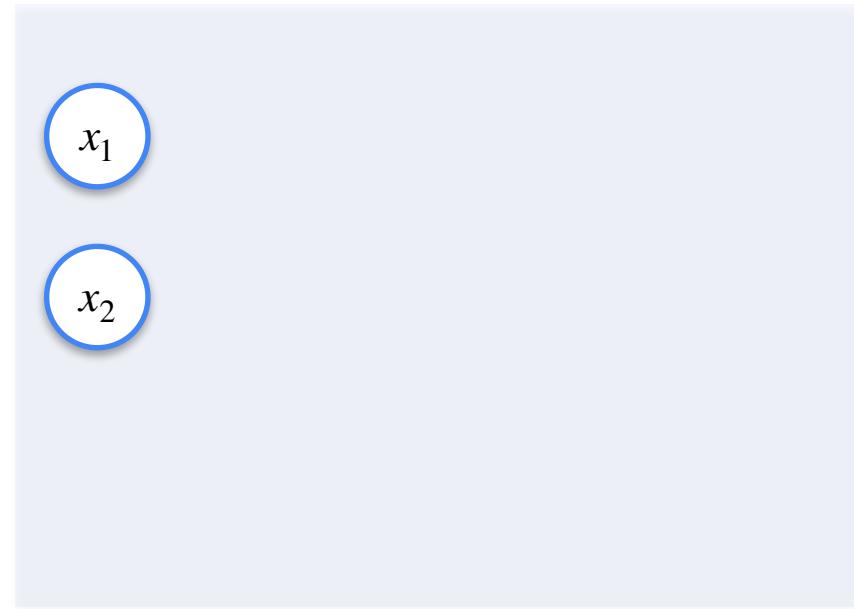
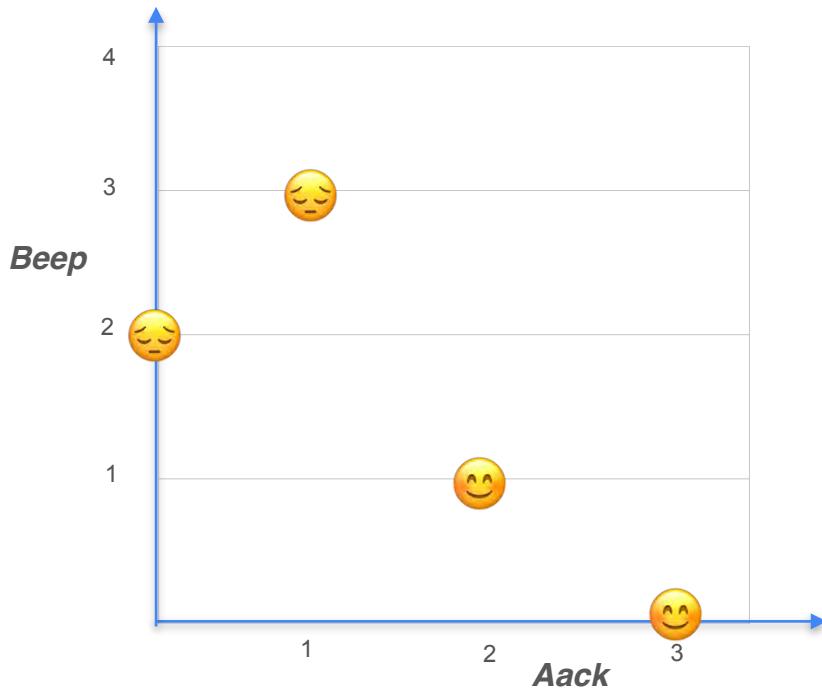
Classification Problem Motivation



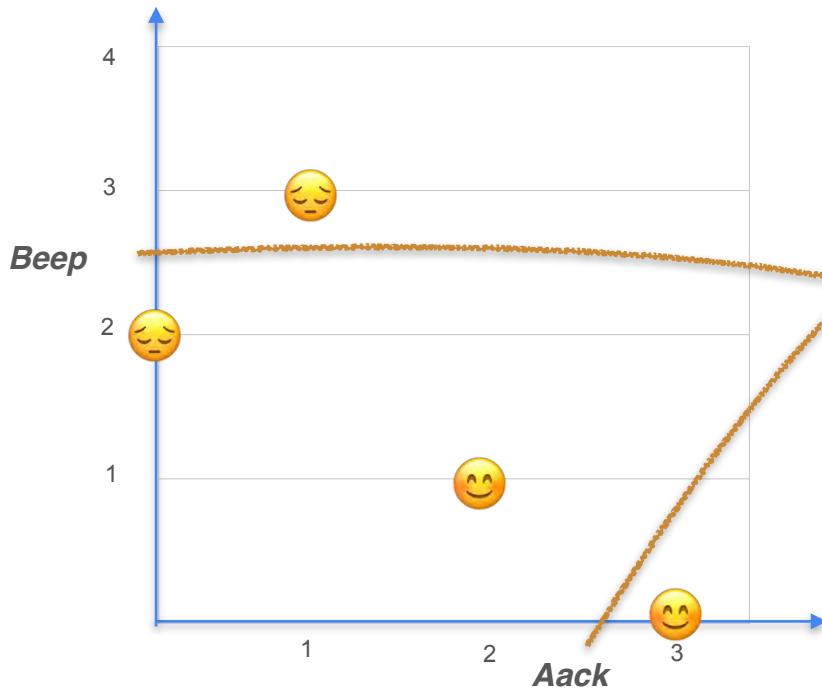
Classification Problem Motivation



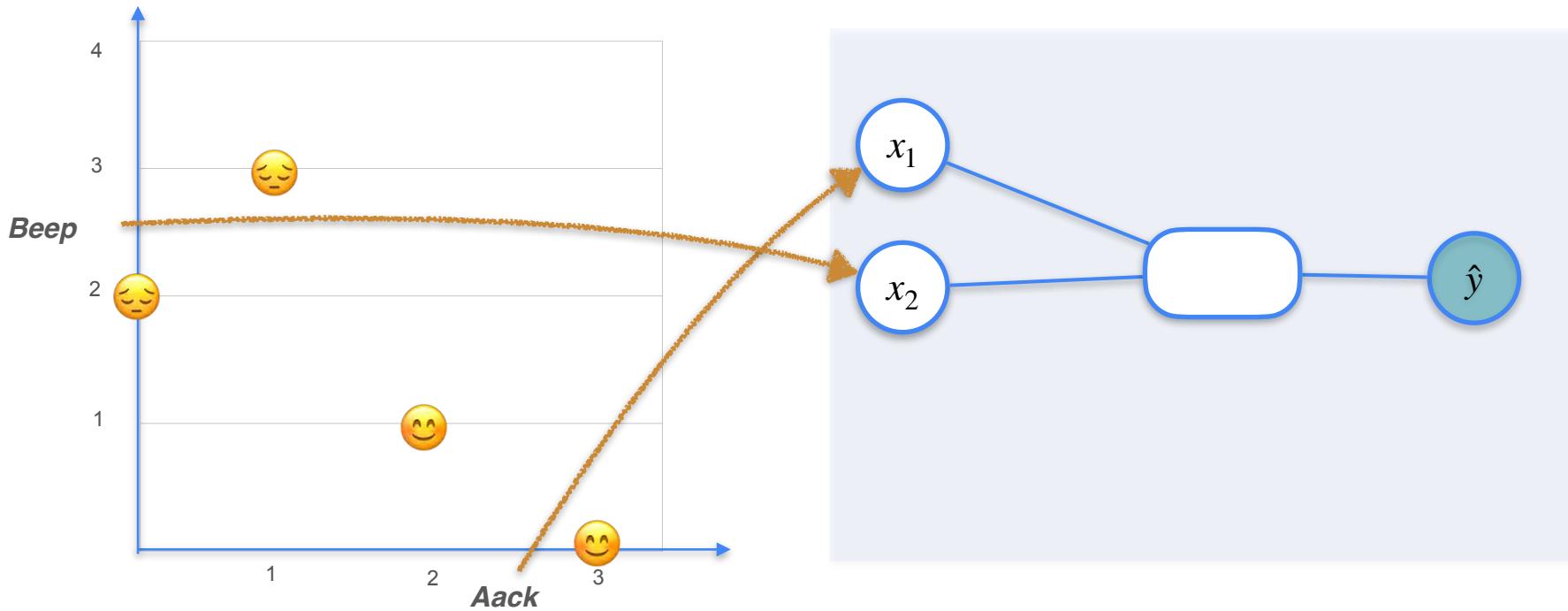
Classification Problem Motivation



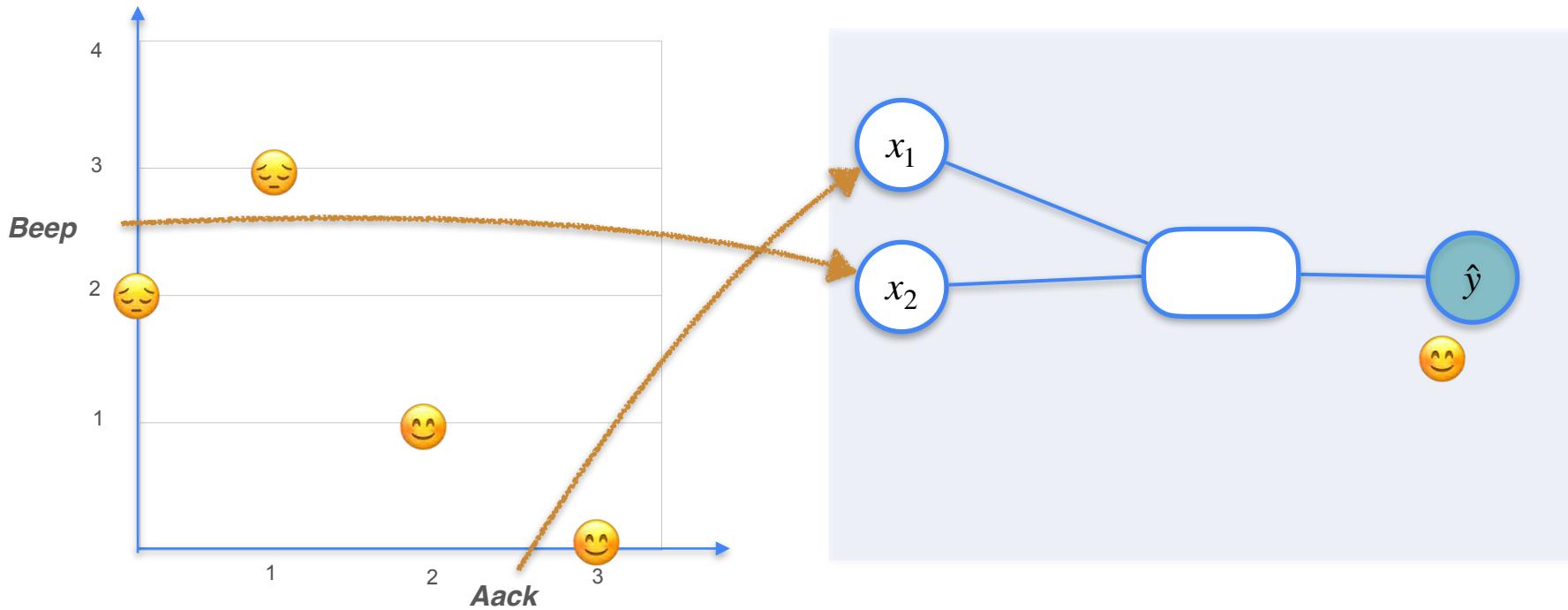
Classification Problem Motivation



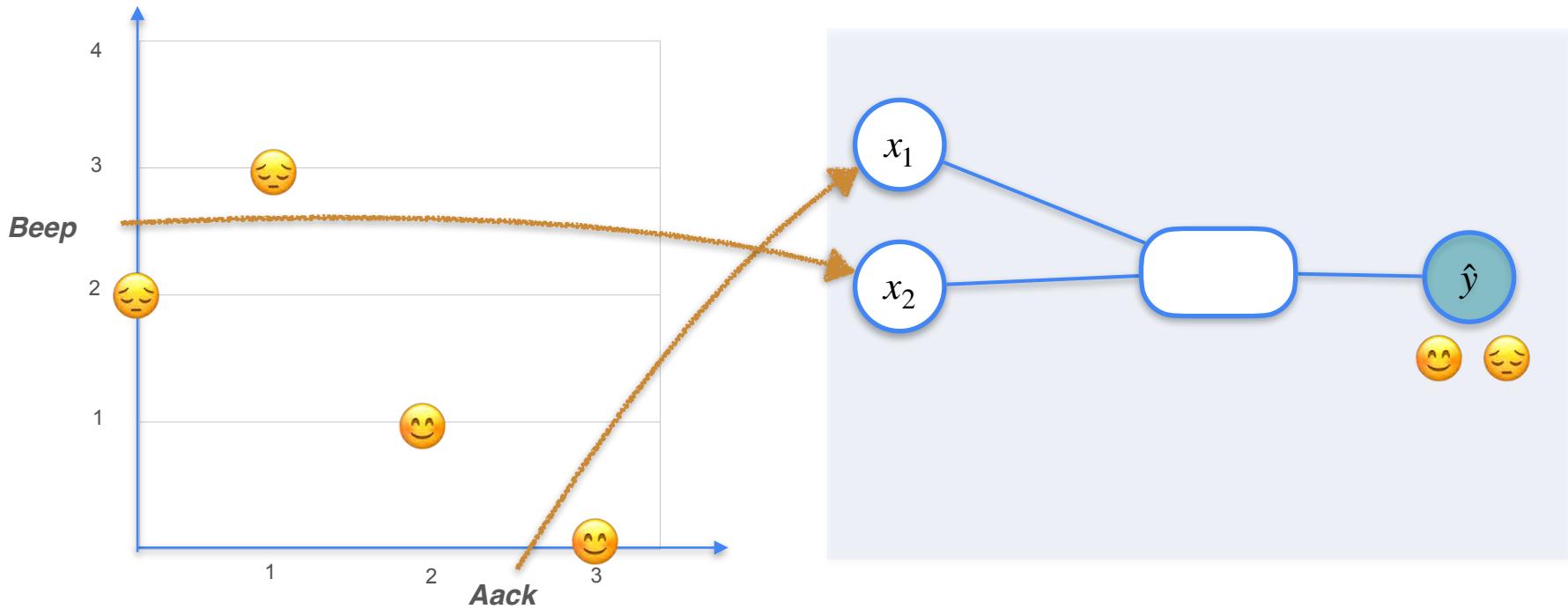
Classification Problem Motivation



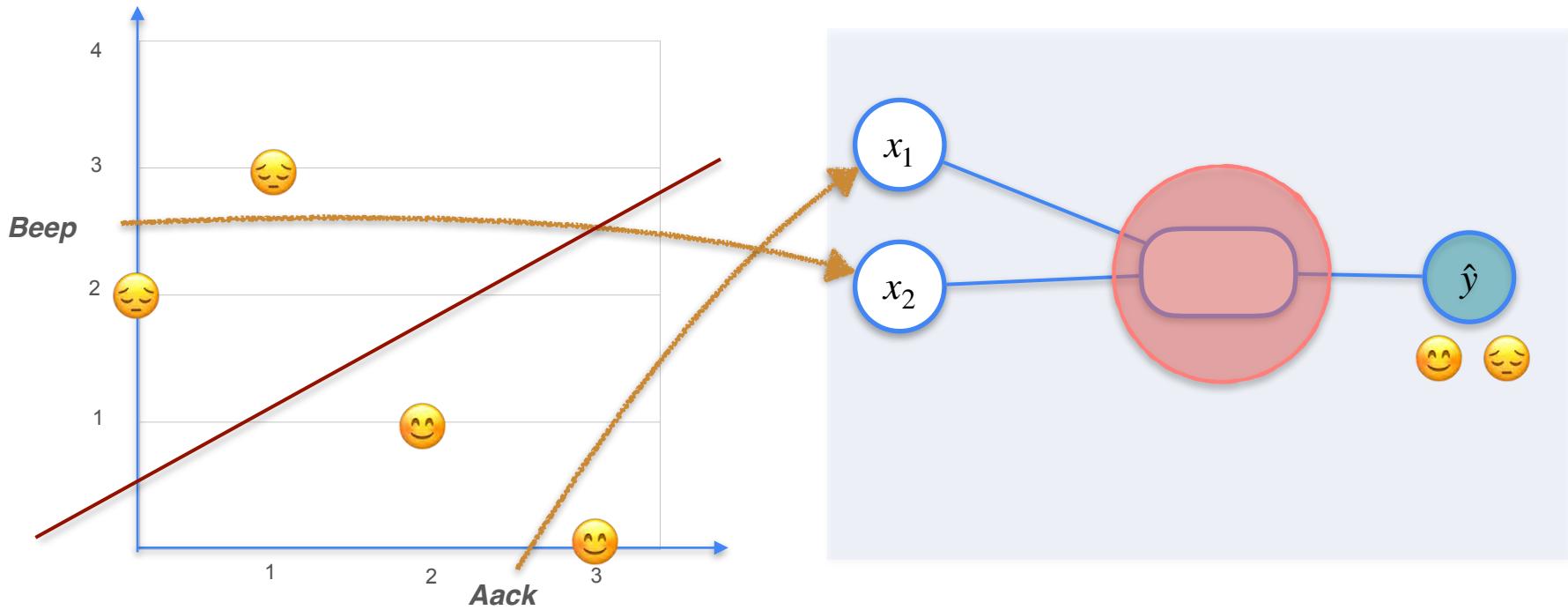
Classification Problem Motivation



Classification Problem Motivation

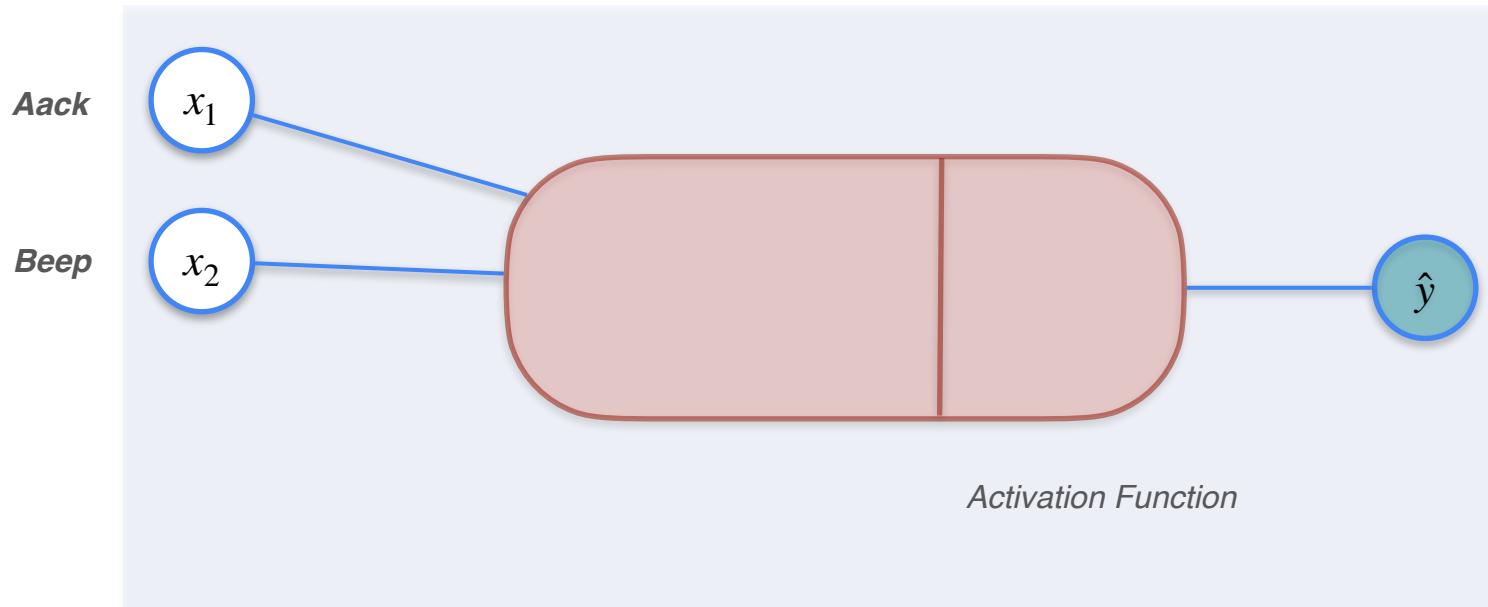


Classification Problem Motivation



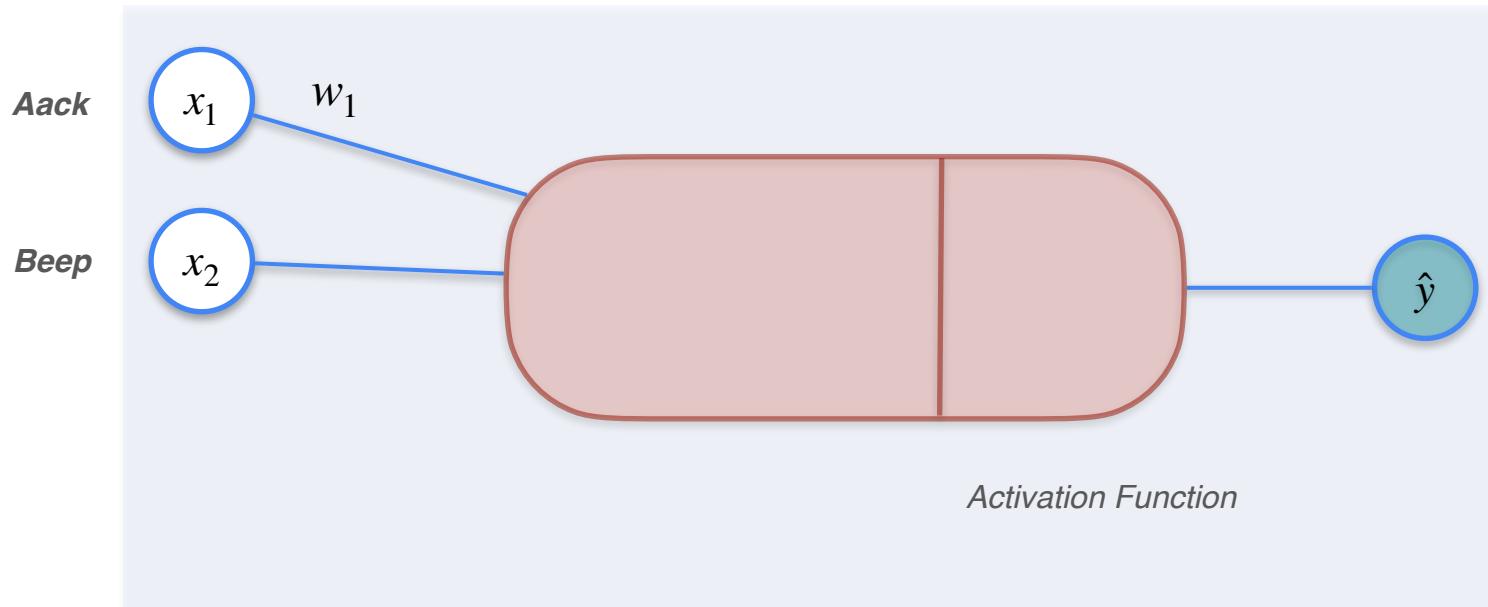
Classification With a Perceptron

Single Layer Neural Network Perceptron



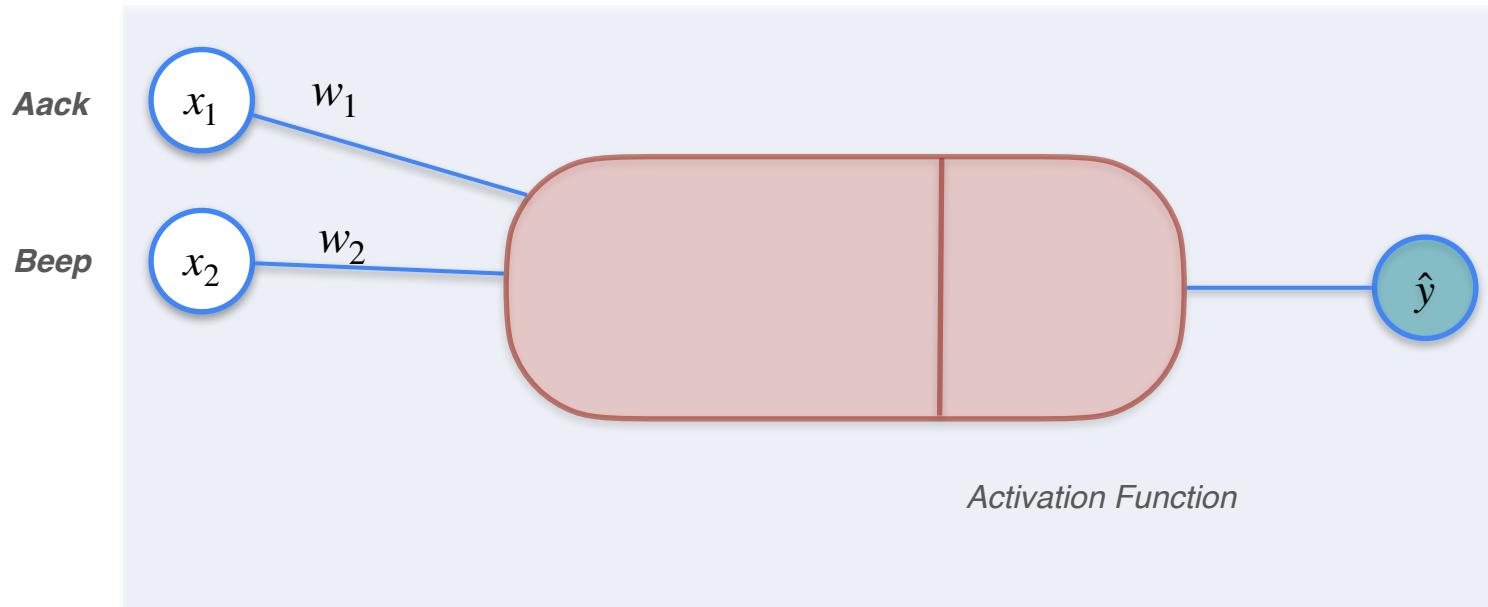
Classification With a Perceptron

Single Layer Neural Network Perceptron



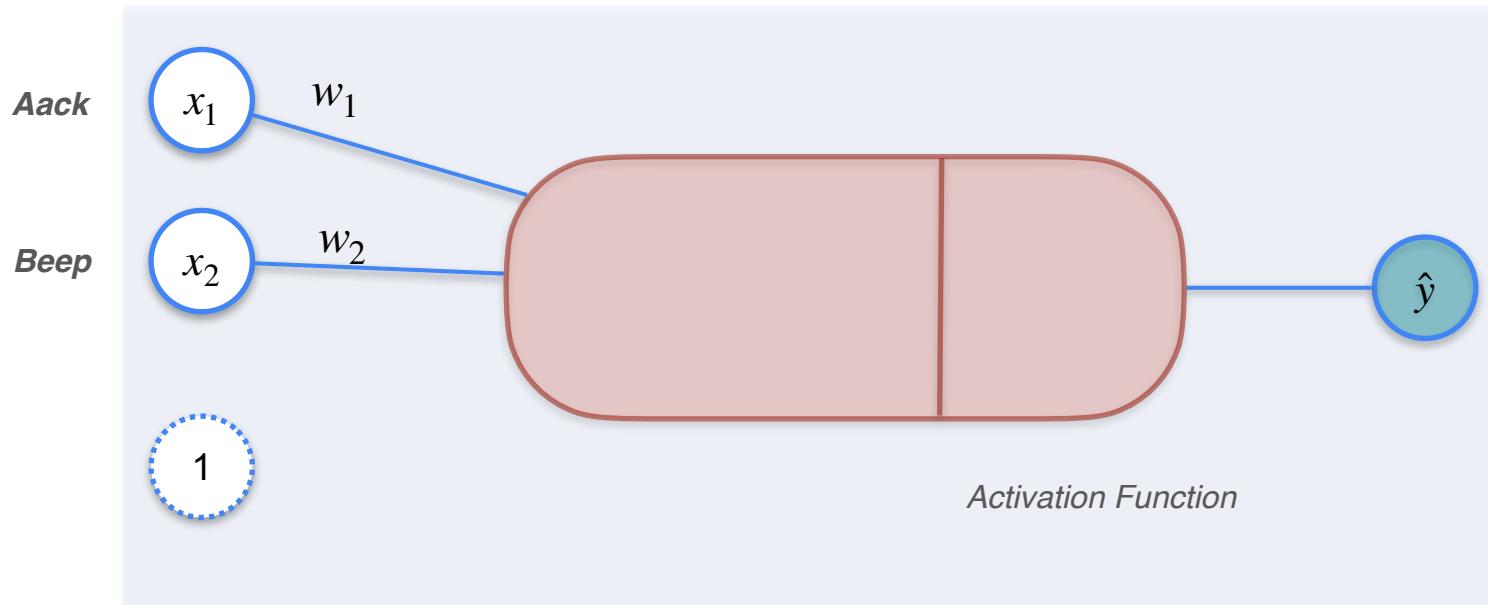
Classification With a Perceptron

Single Layer Neural Network Perceptron



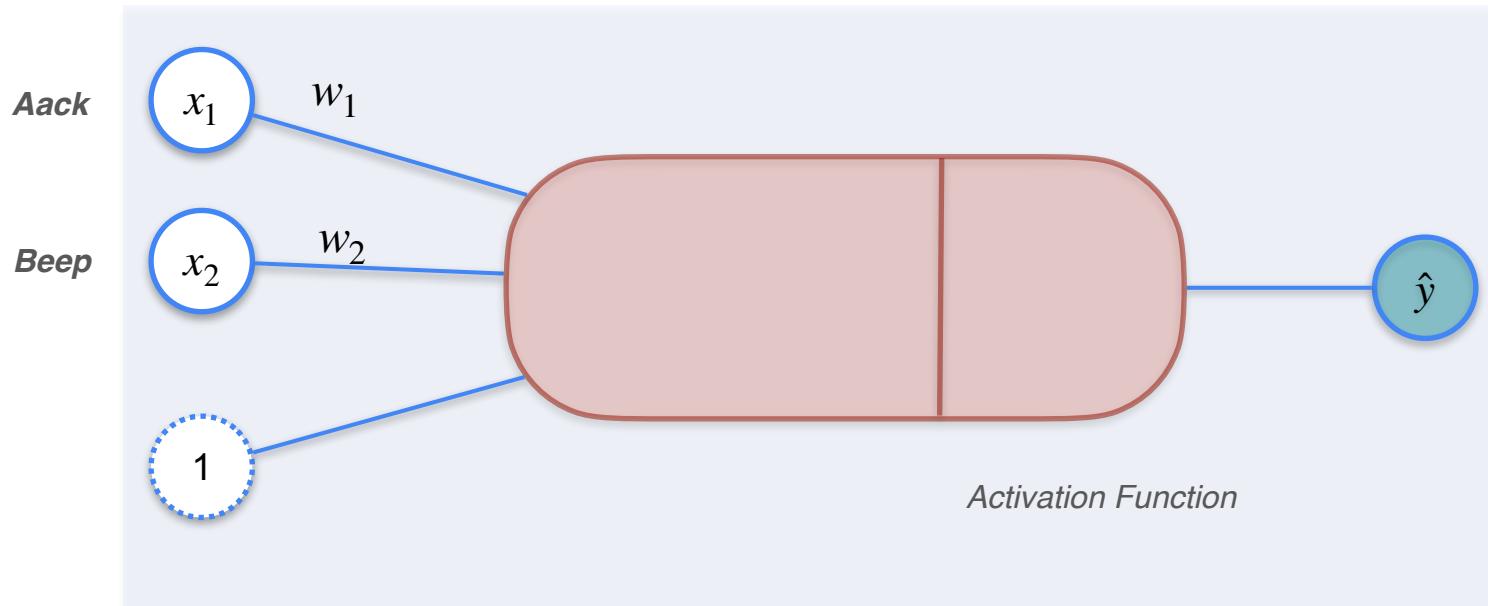
Classification With a Perceptron

Single Layer Neural Network Perceptron



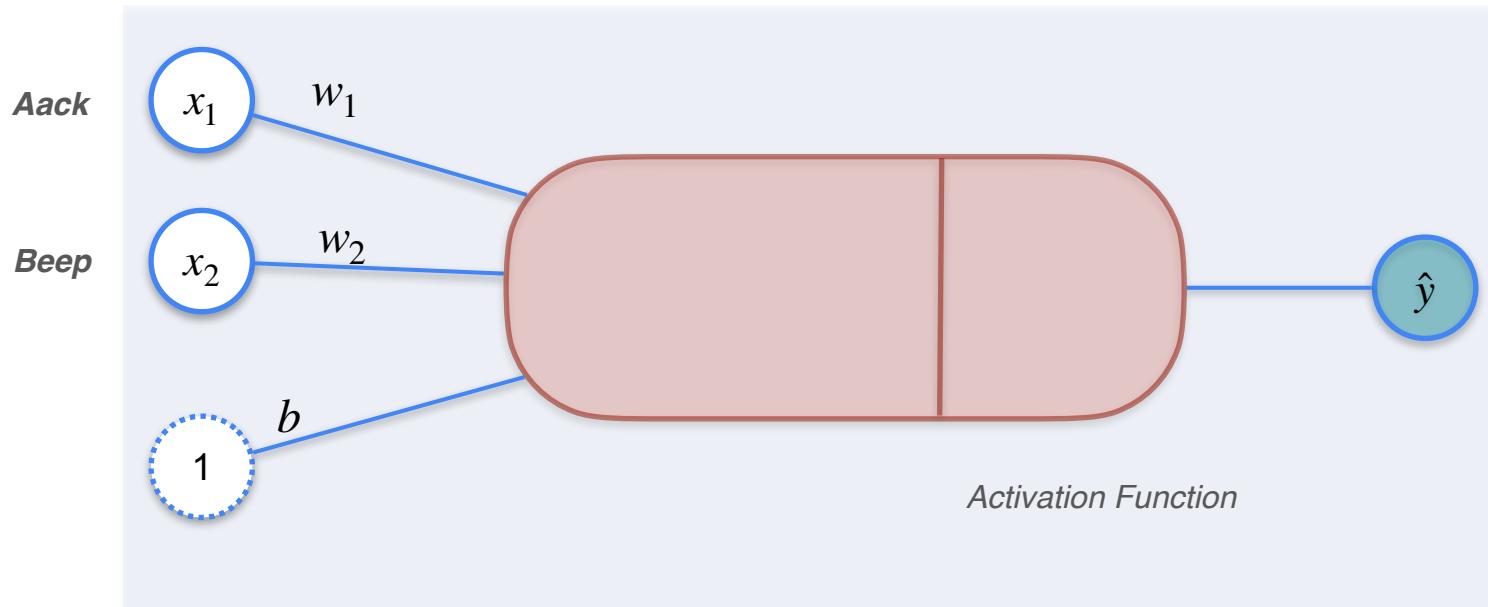
Classification With a Perceptron

Single Layer Neural Network Perceptron



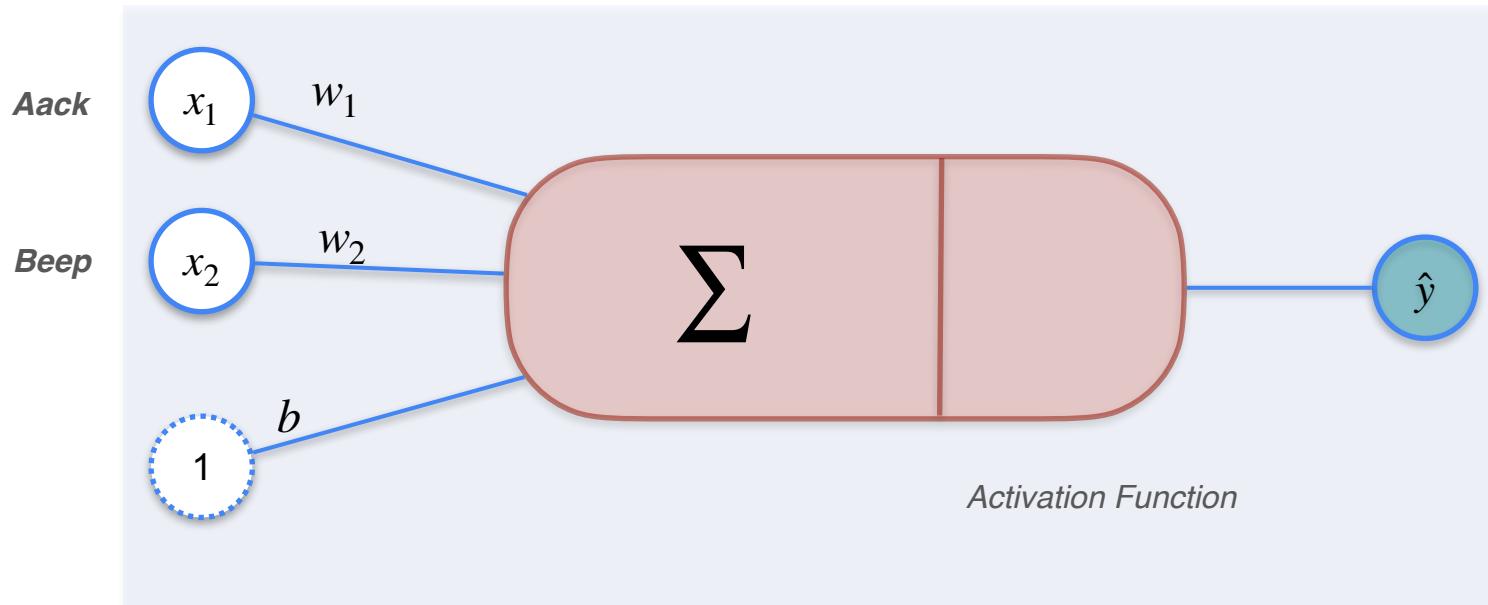
Classification With a Perceptron

Single Layer Neural Network Perceptron



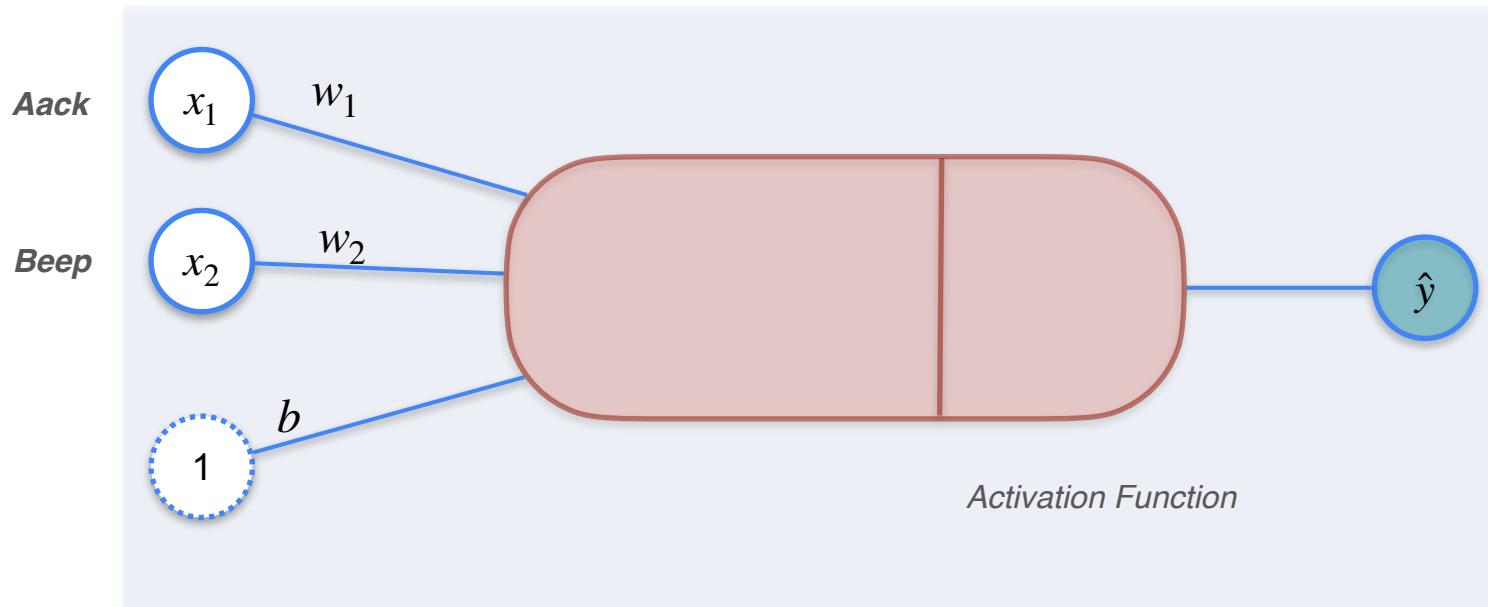
Classification With a Perceptron

Single Layer Neural Network Perceptron



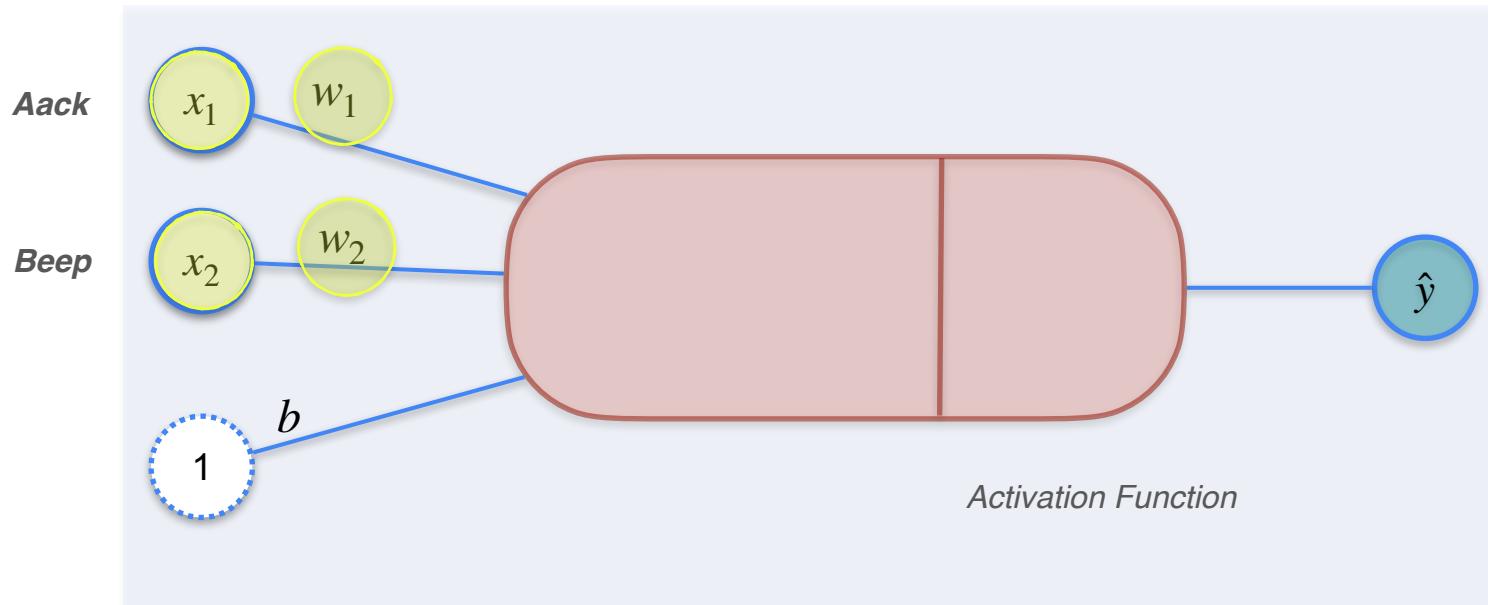
Classification With a Perceptron

Single Layer Neural Network Perceptron



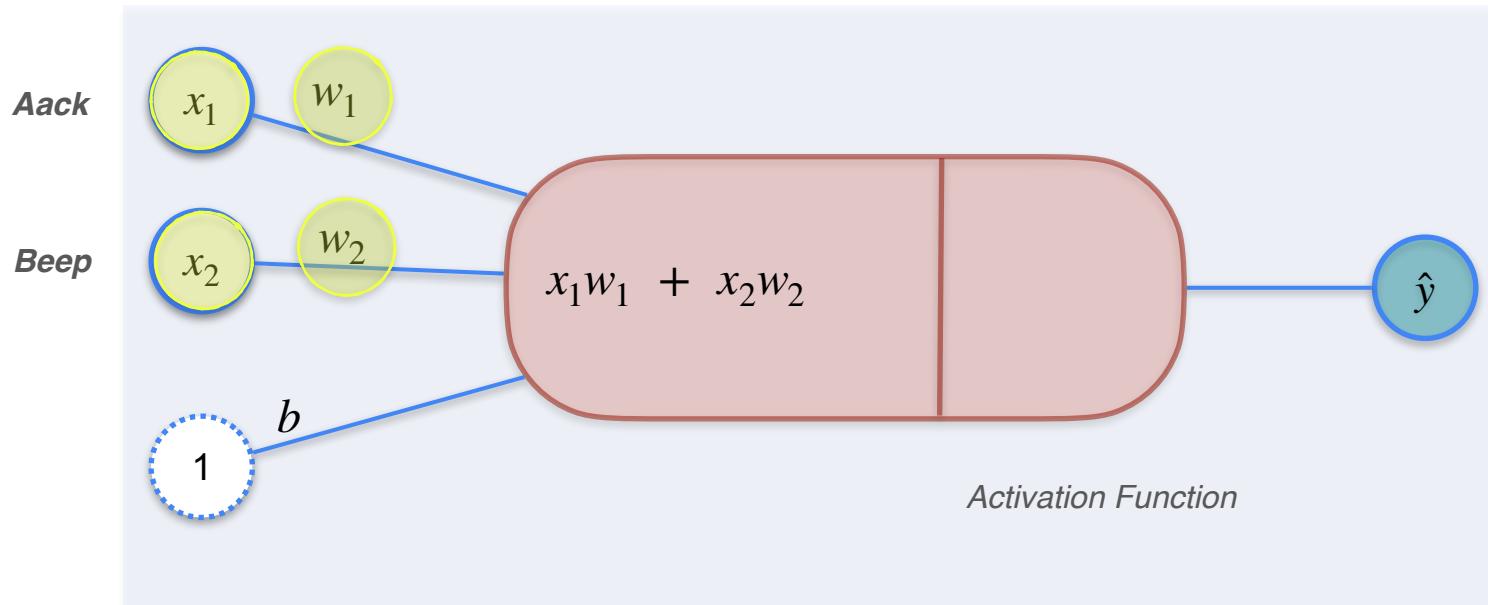
Classification With a Perceptron

Single Layer Neural Network Perceptron



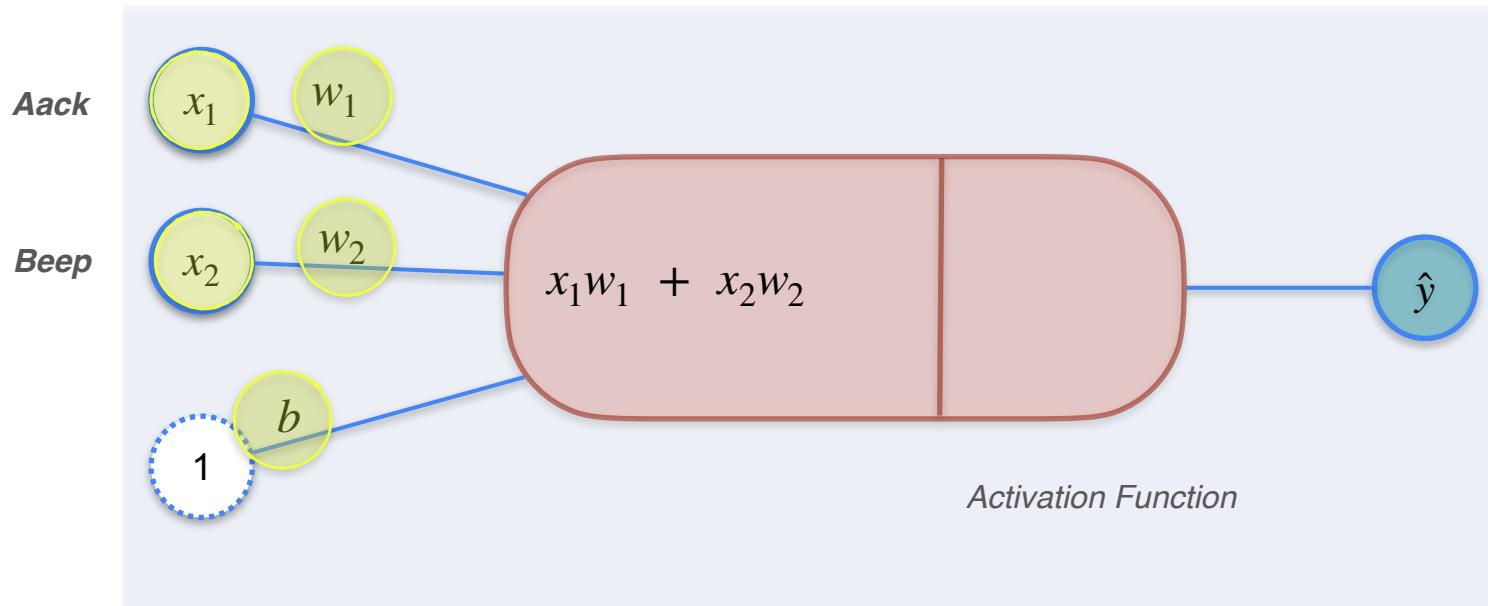
Classification With a Perceptron

Single Layer Neural Network Perceptron



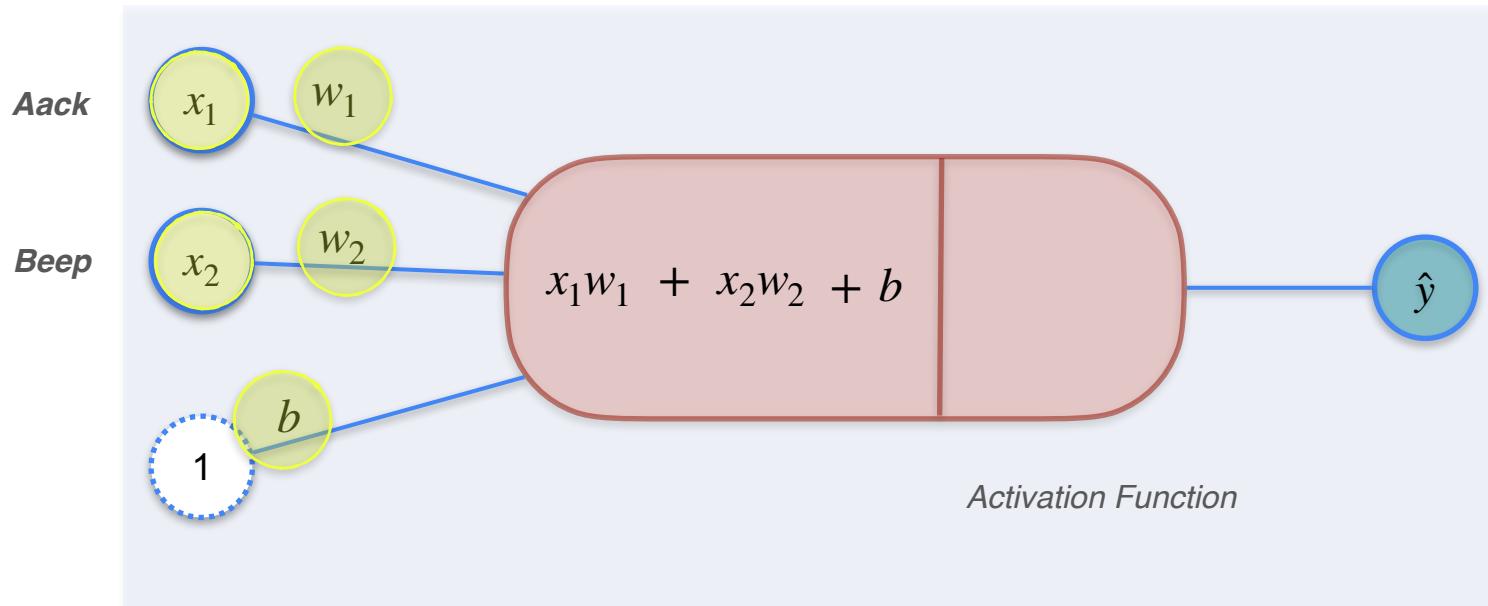
Classification With a Perceptron

Single Layer Neural Network Perceptron



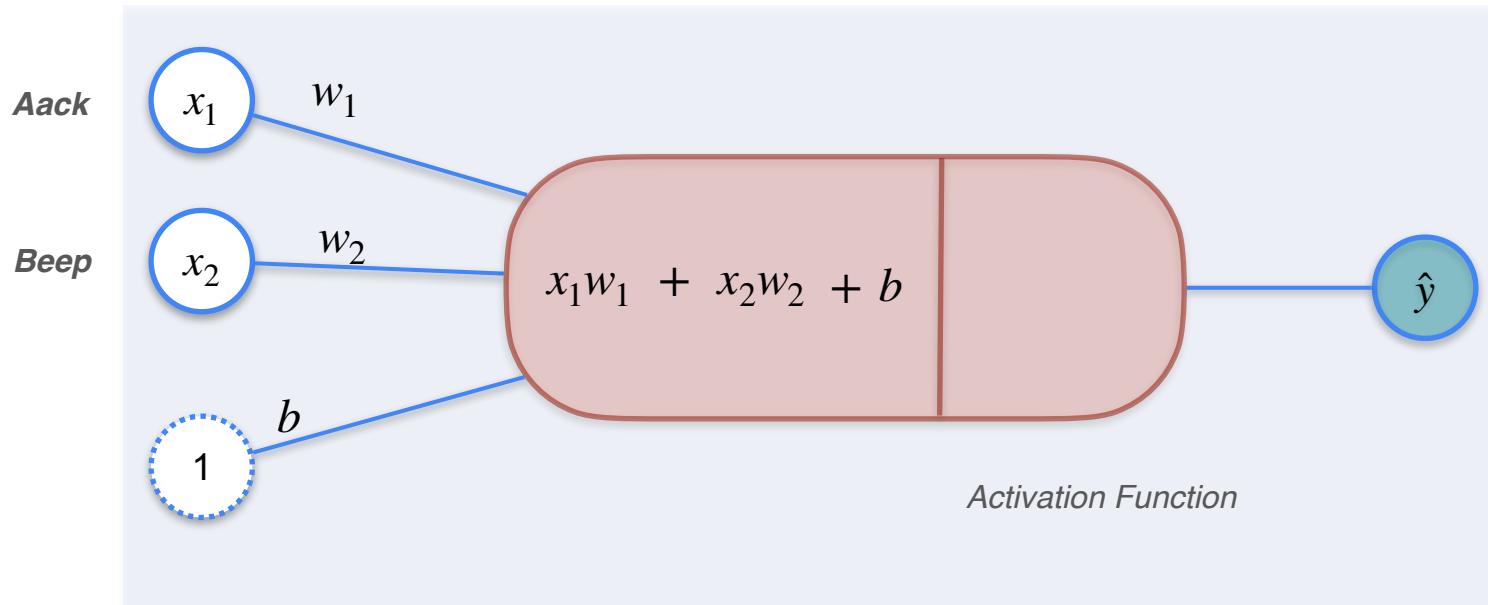
Classification With a Perceptron

Single Layer Neural Network Perceptron



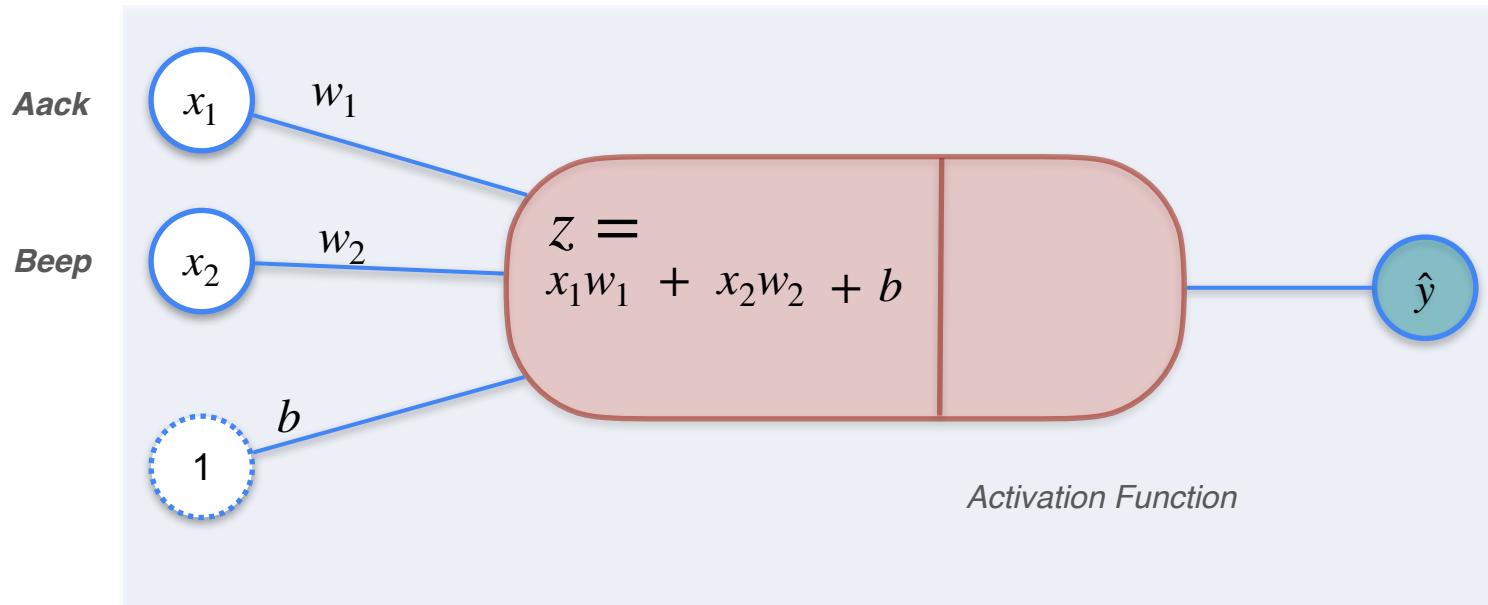
Classification With a Perceptron

Single Layer Neural Network Perceptron



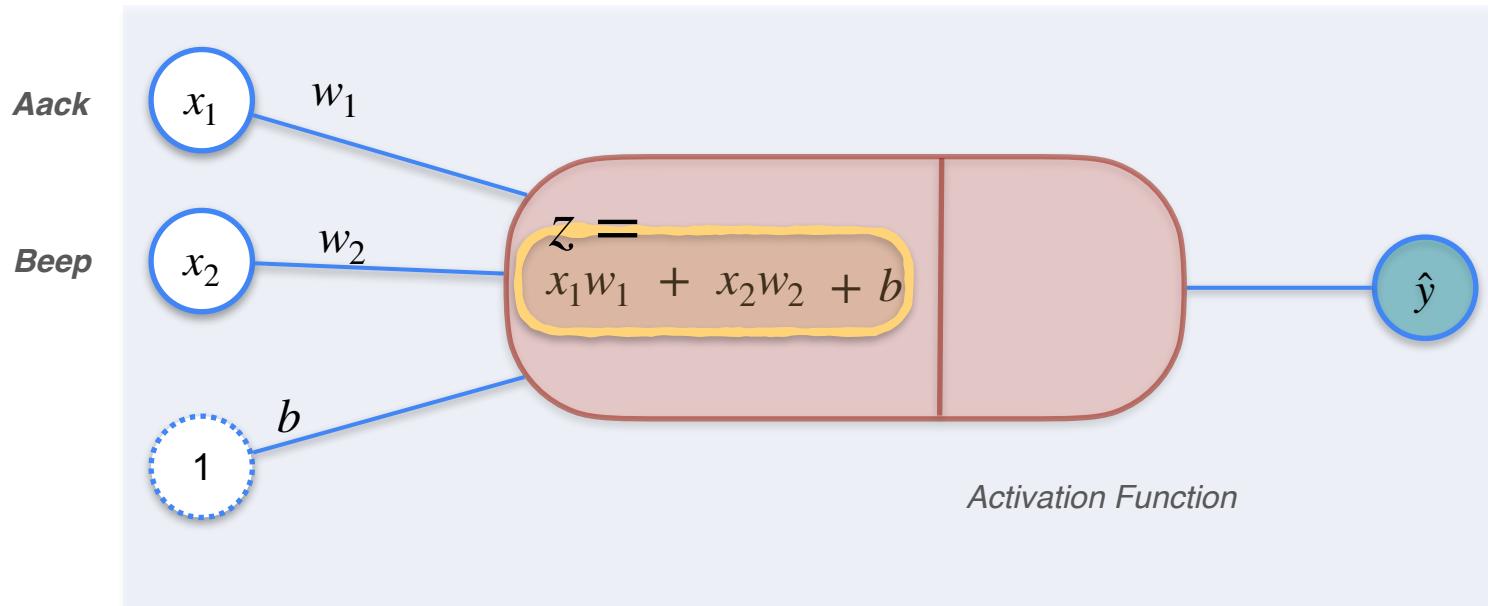
Classification With a Perceptron

Single Layer Neural Network Perceptron



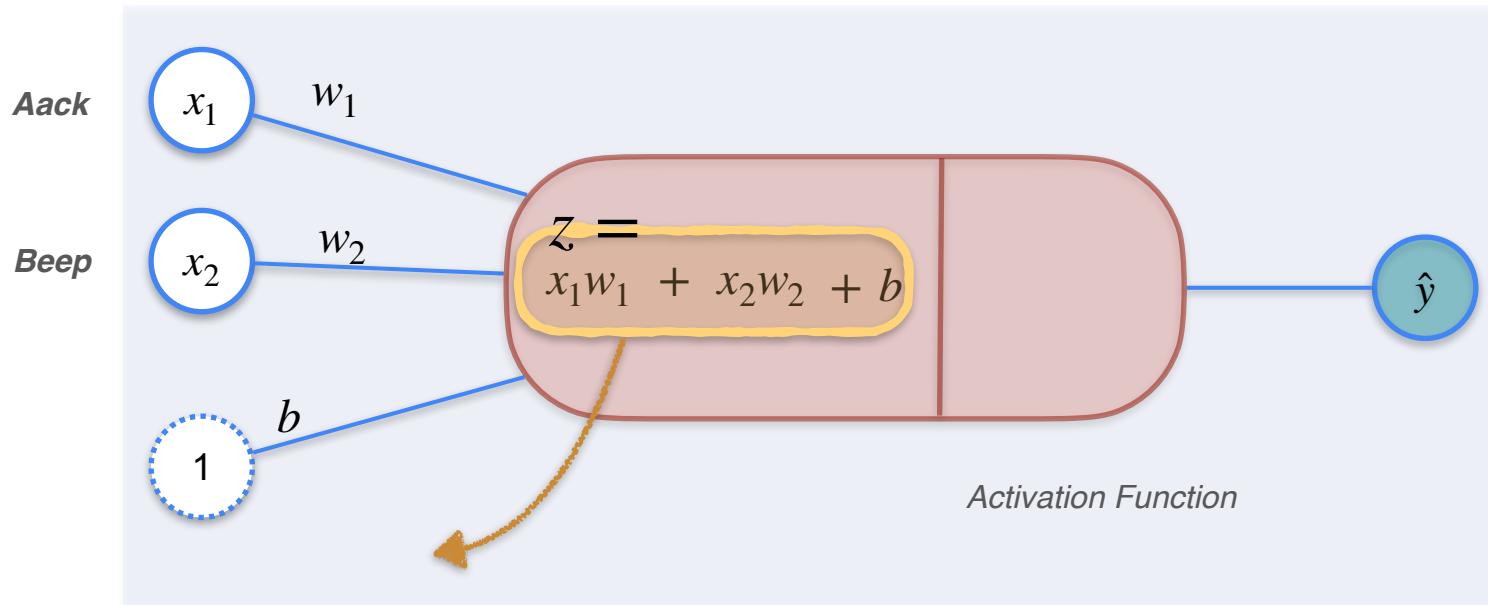
Classification With a Perceptron

Single Layer Neural Network Perceptron



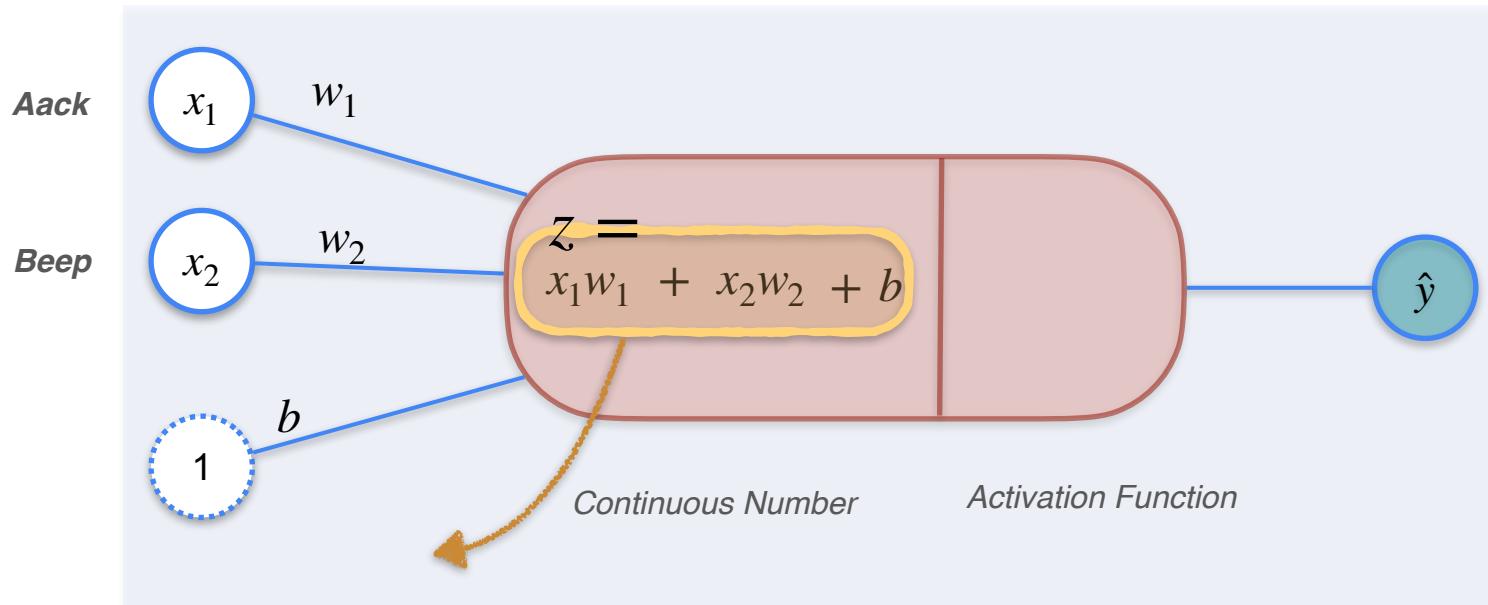
Classification With a Perceptron

Single Layer Neural Network Perceptron



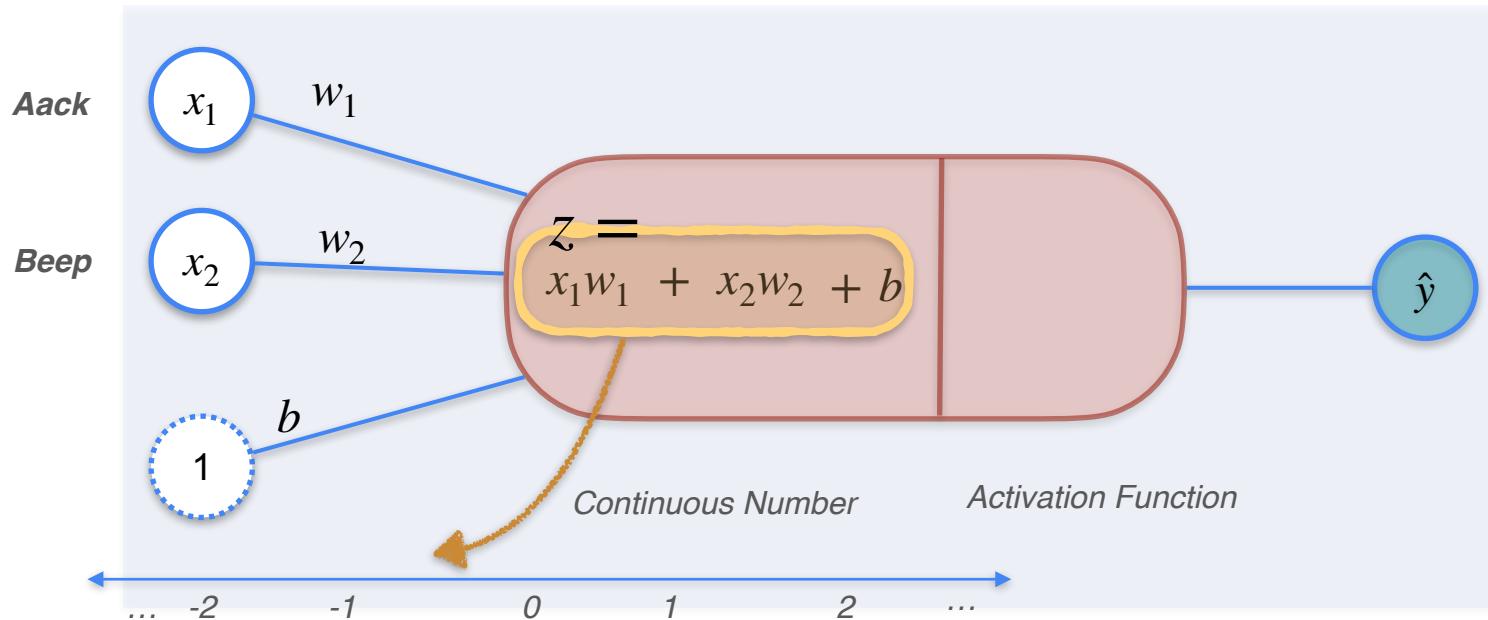
Classification With a Perceptron

Single Layer Neural Network Perceptron



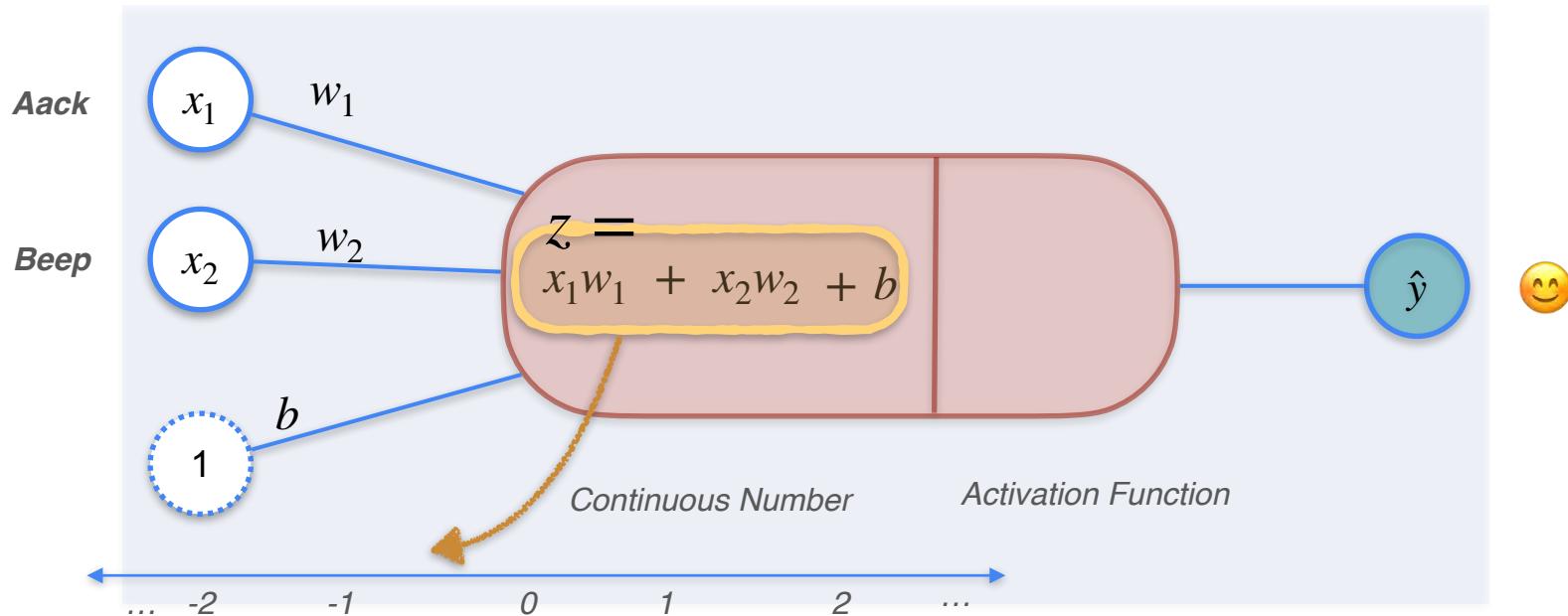
Classification With a Perceptron

Single Layer Neural Network Perceptron



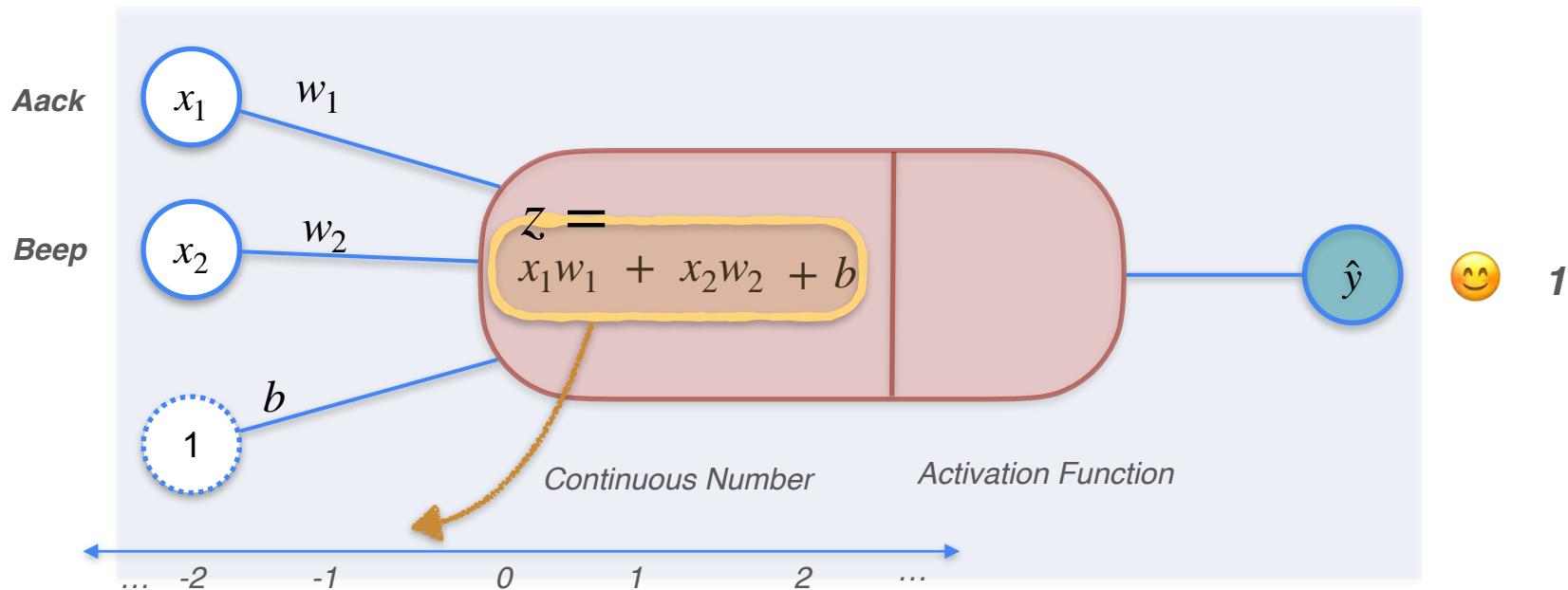
Classification With a Perceptron

Single Layer Neural Network Perceptron



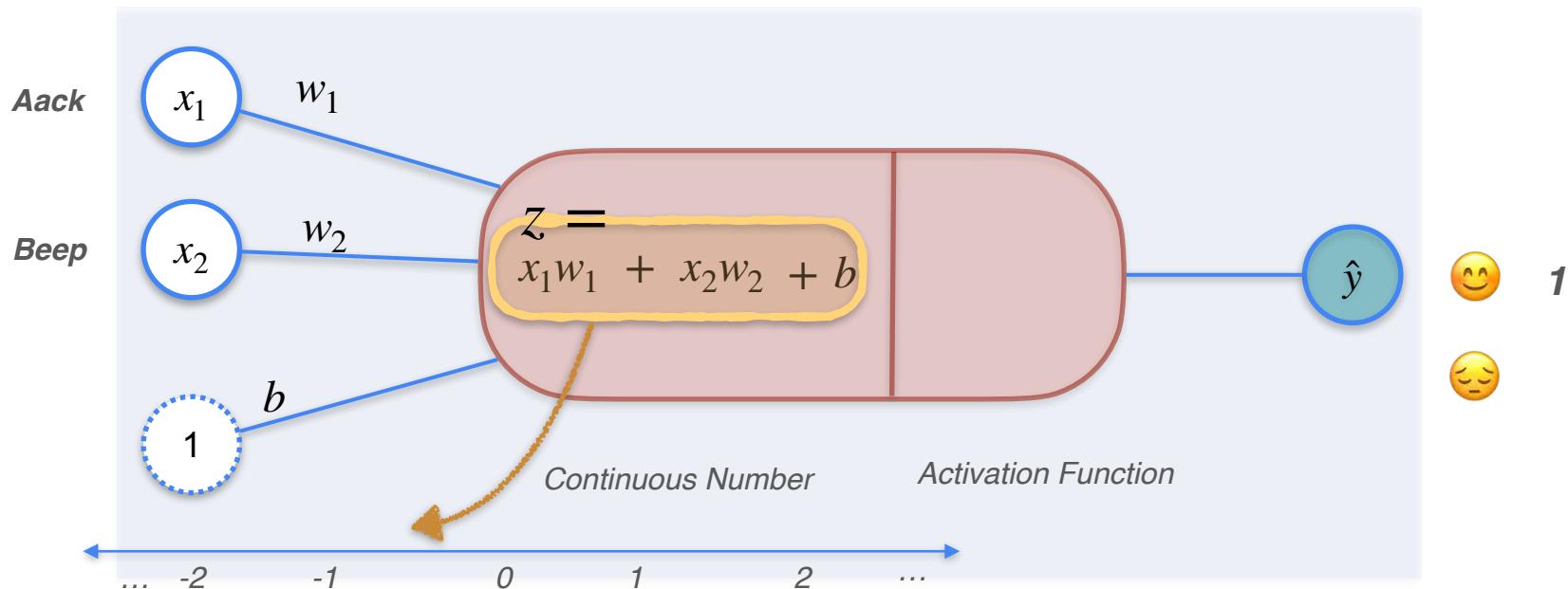
Classification With a Perceptron

Single Layer Neural Network Perceptron



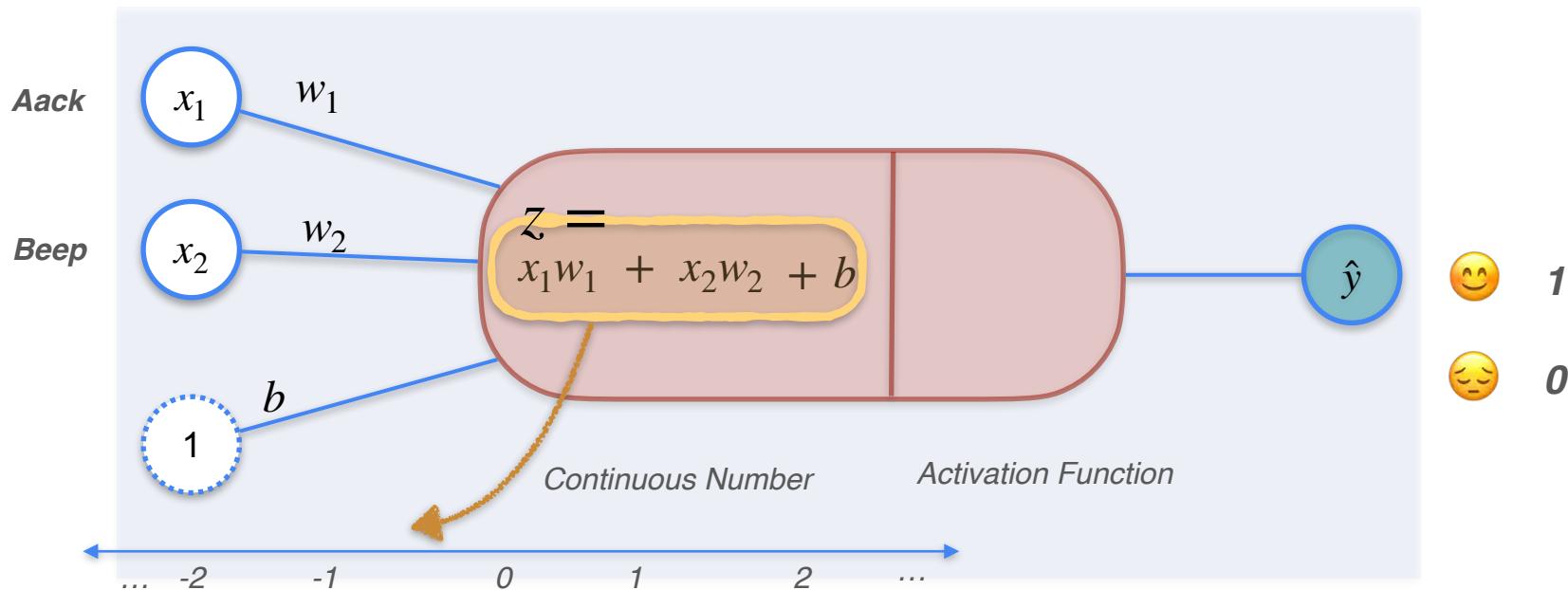
Classification With a Perceptron

Single Layer Neural Network Perceptron



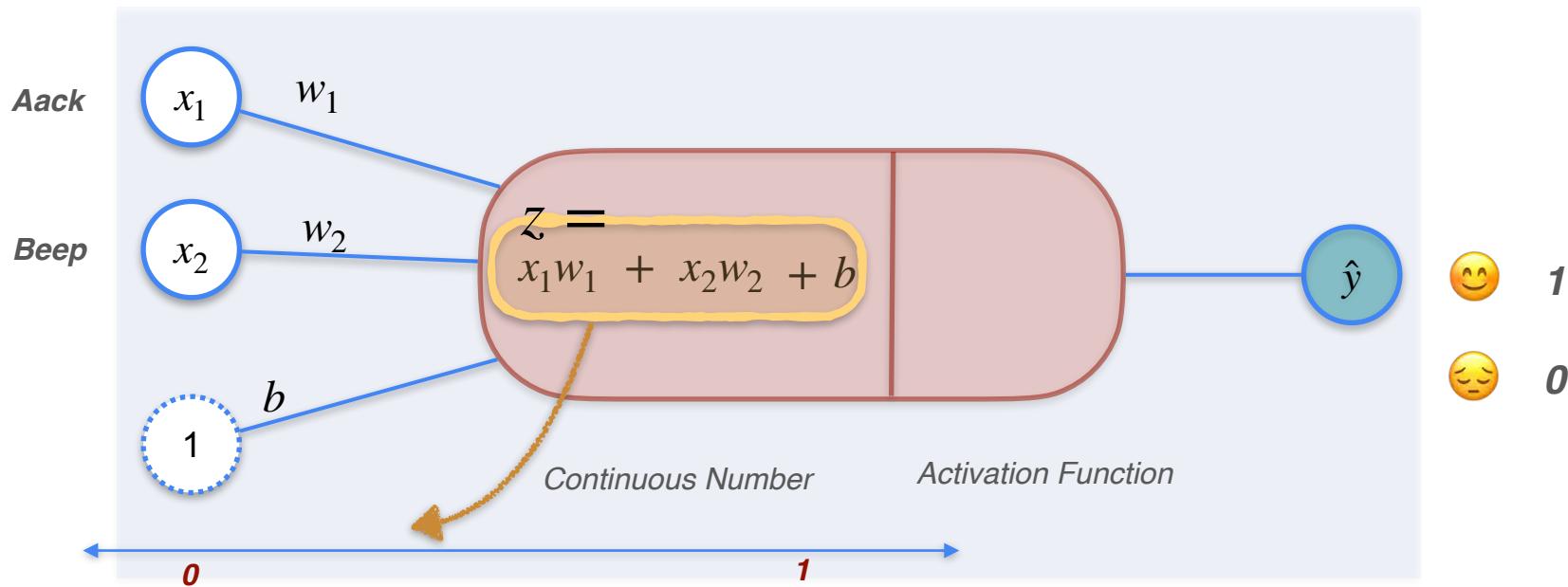
Classification With a Perceptron

Single Layer Neural Network Perceptron



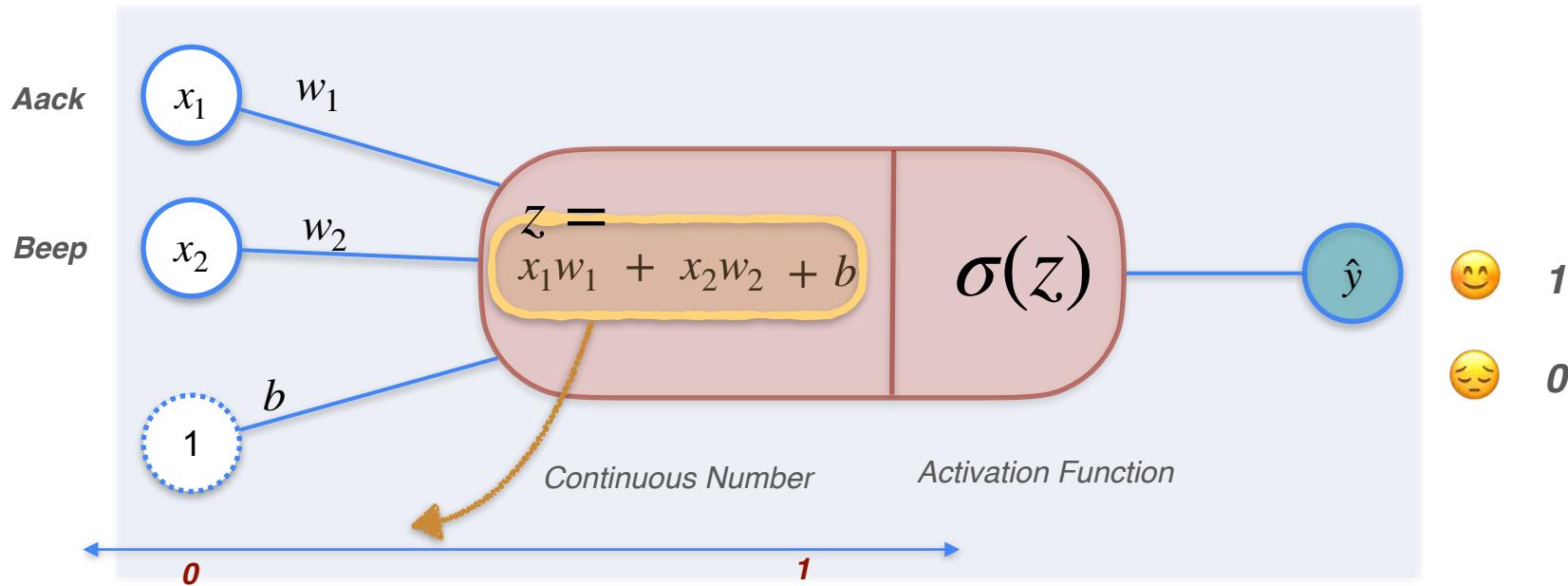
Classification With a Perceptron

Single Layer Neural Network Perceptron



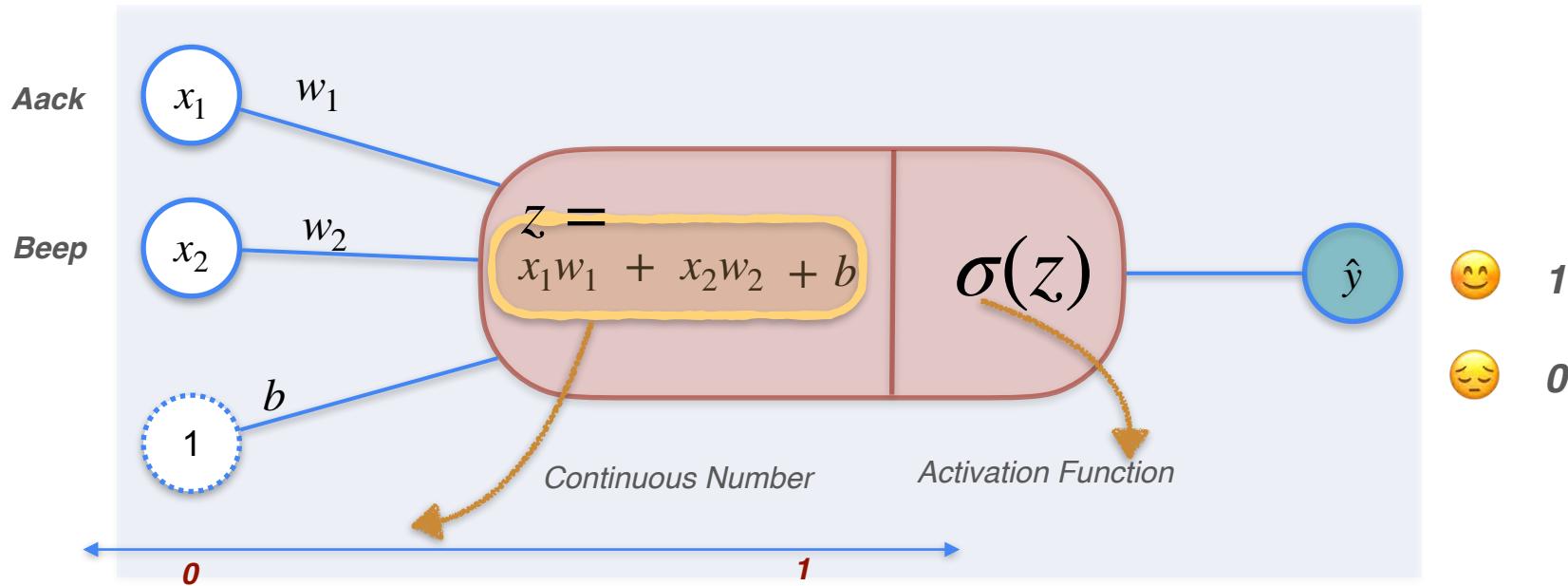
Classification With a Perceptron

Single Layer Neural Network Perceptron



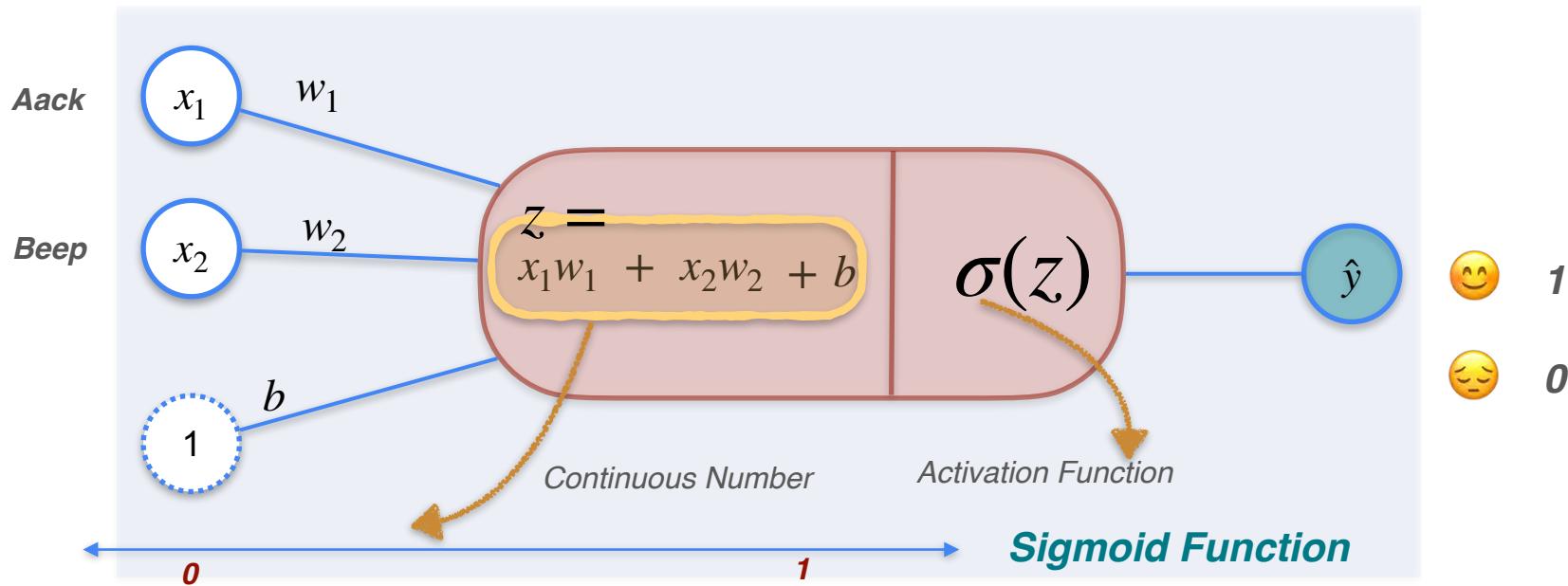
Classification With a Perceptron

Single Layer Neural Network Perceptron

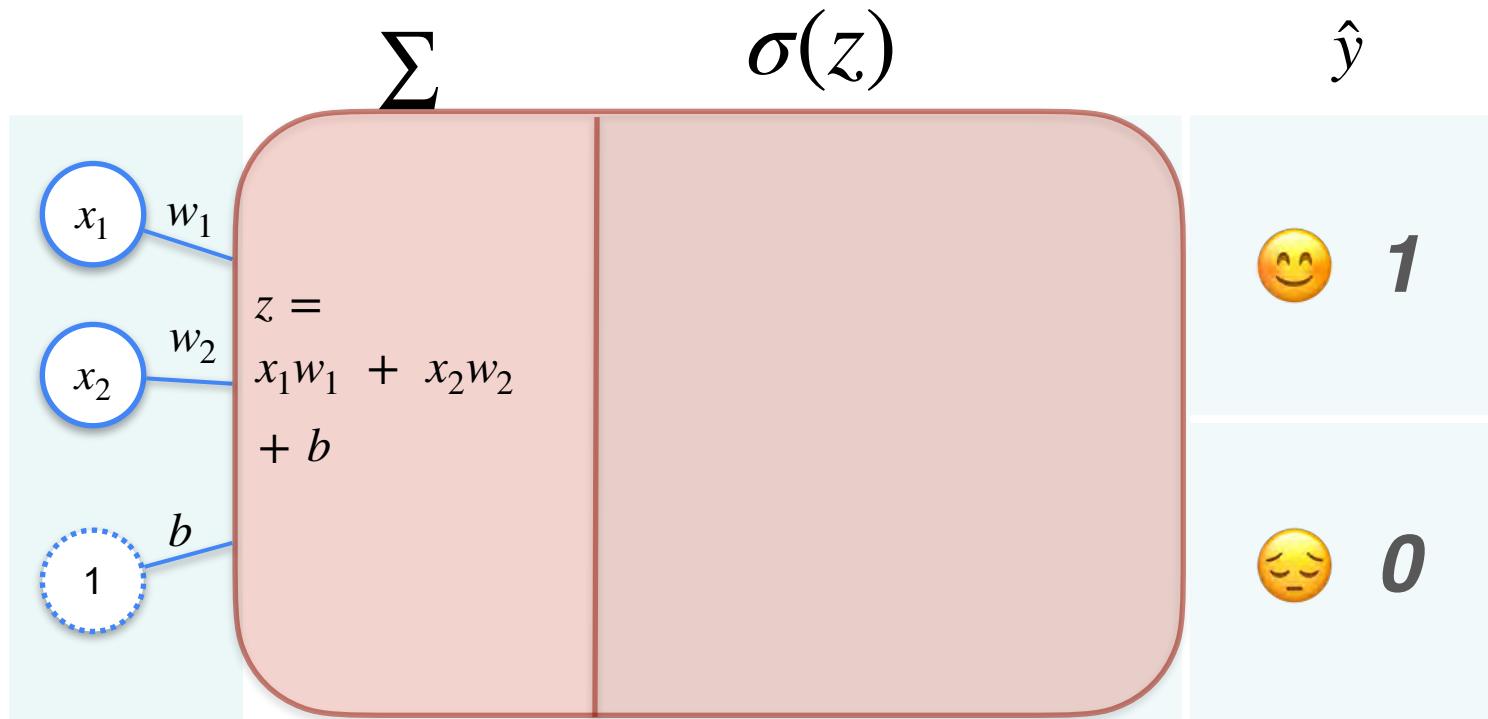


Classification With a Perceptron

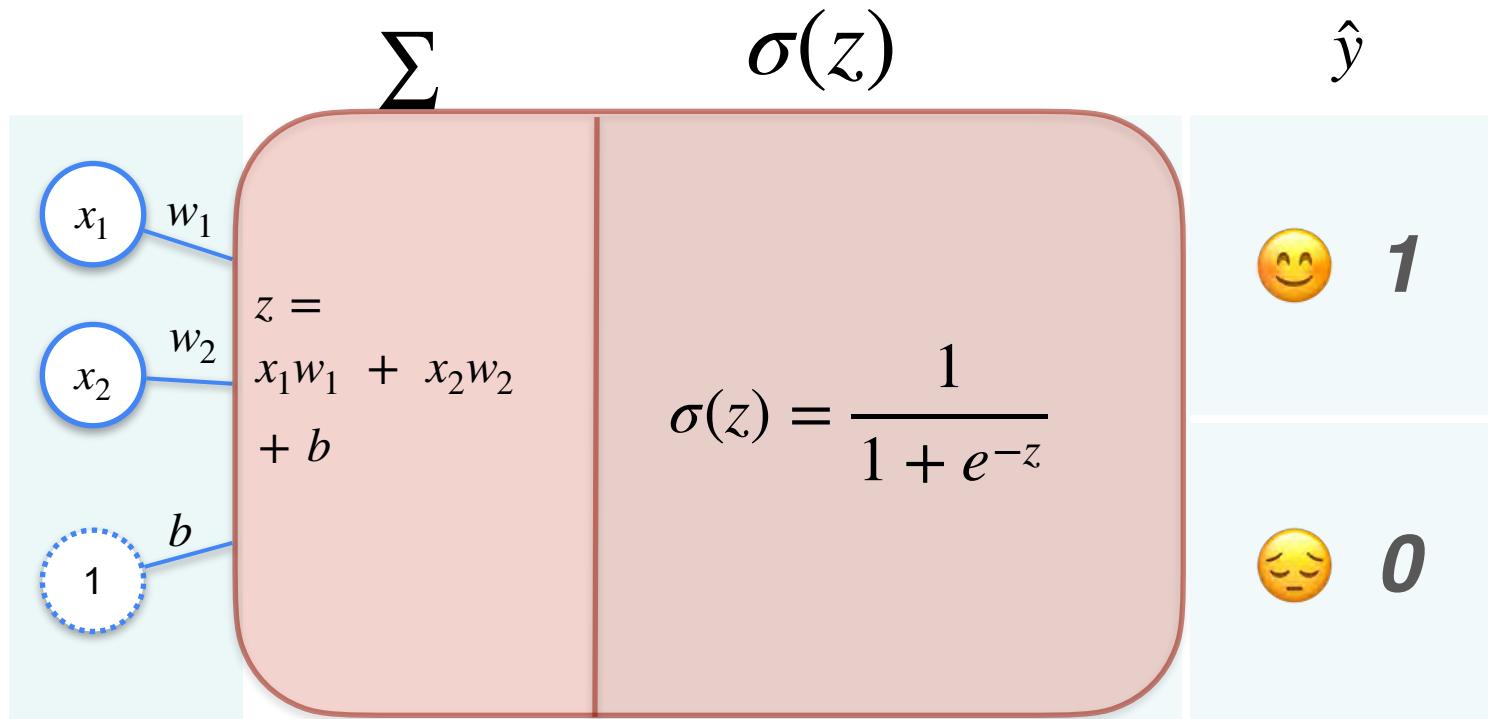
Single Layer Neural Network Perceptron



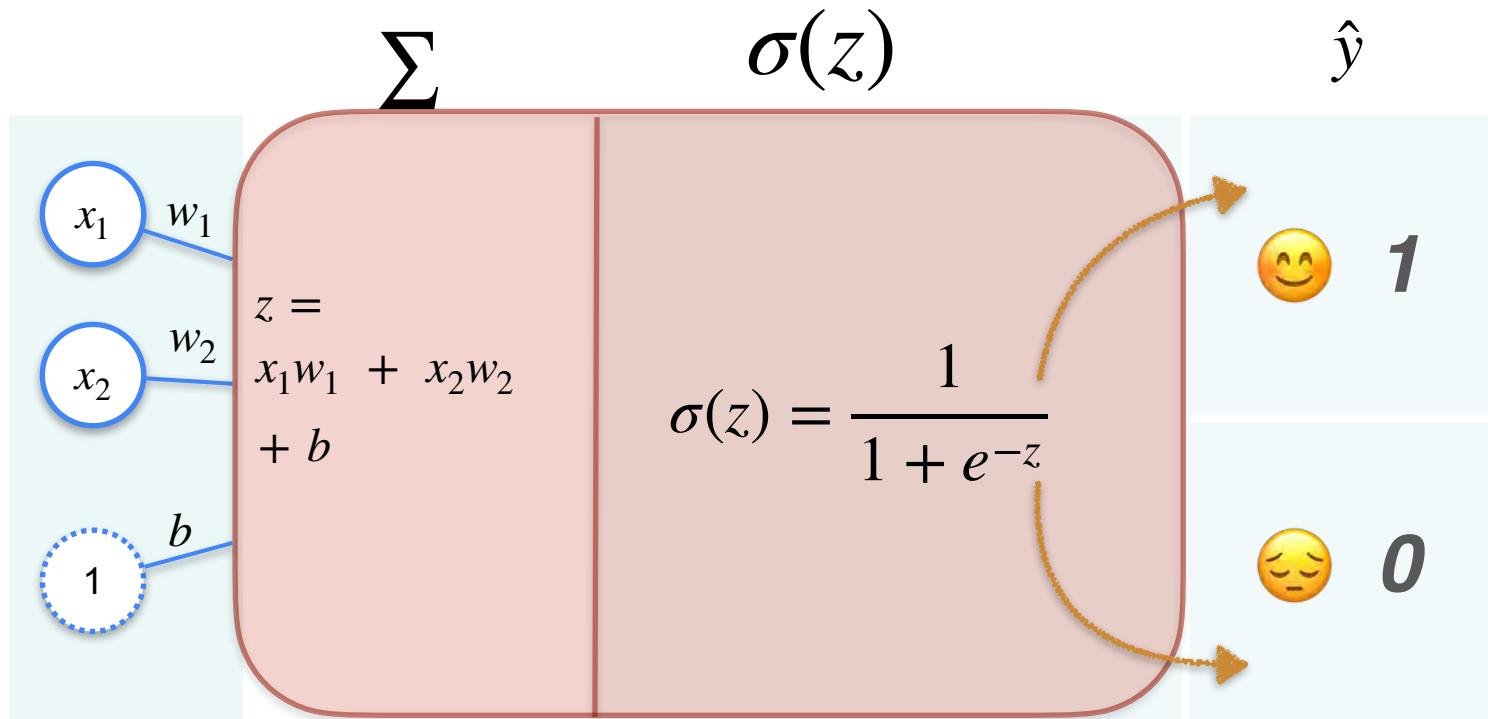
Sigmoid Function



Sigmoid Function



Sigmoid Function





DeepLearning.AI

Optimization in Neural Networks and Newton's Method

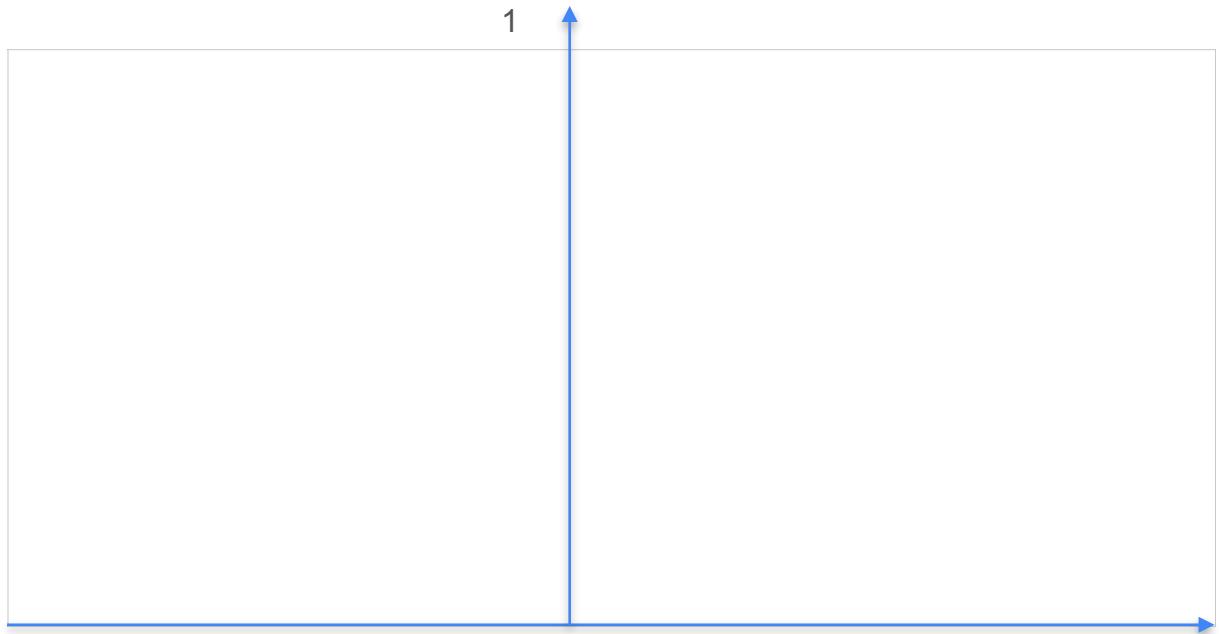
**Classification with a
perceptron:
The sigmoid function**

Sigmoid Function

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

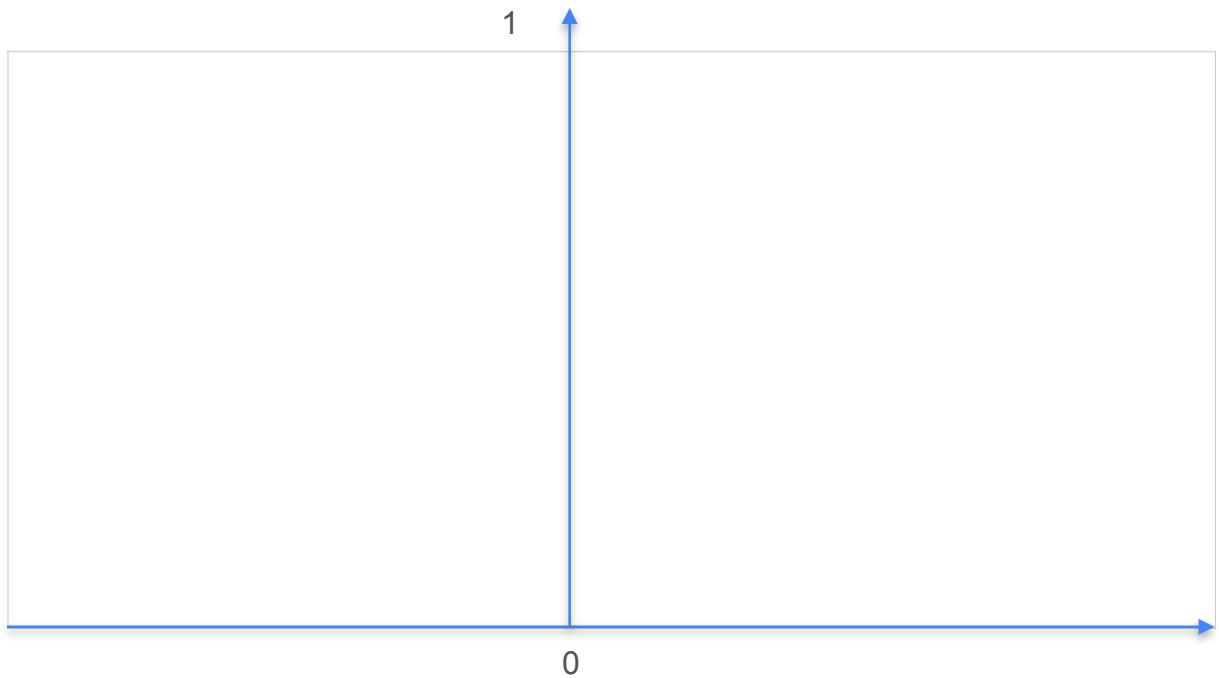
Sigmoid Function

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



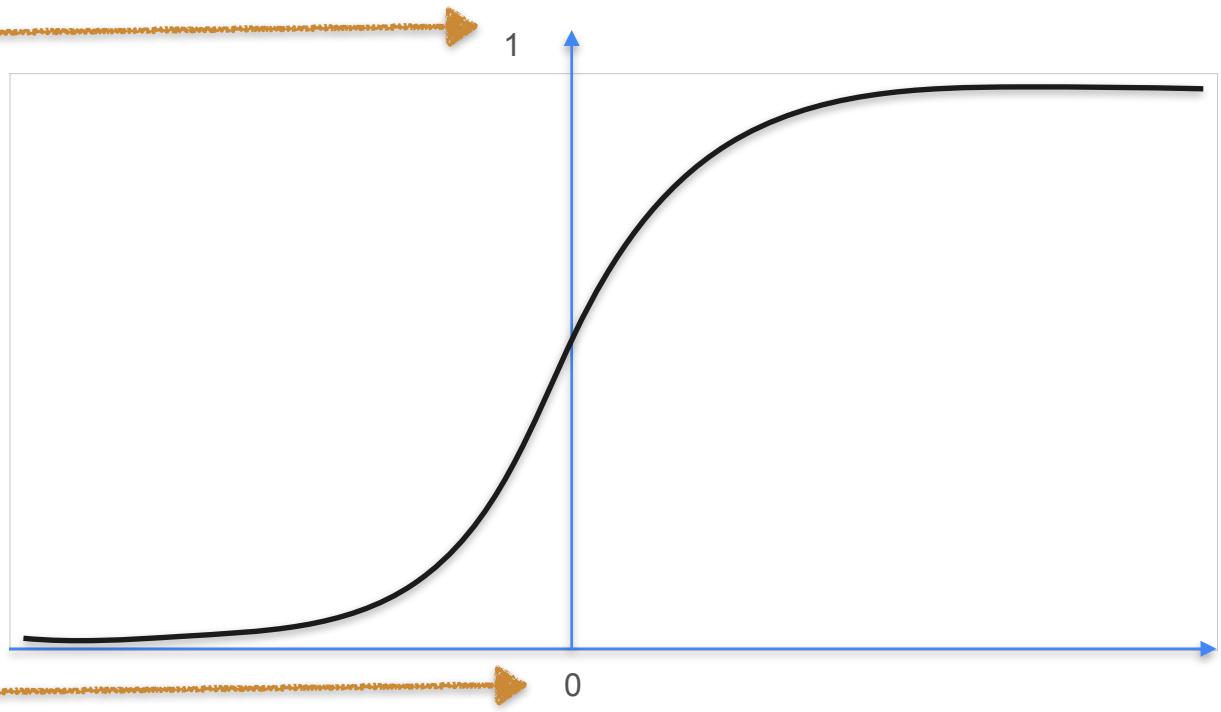
Sigmoid Function

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



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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

$$= -1$$

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

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

$$\begin{aligned}\frac{d}{dz}\sigma(z) &= -1 \ (1 + e^{-z})^{-1-1} \ (\frac{d}{dz}(1 + e^{-z})) \\ &= -1 \ (1 + e^{-z})^{-2} \ (\frac{d}{dz}(1) + \frac{d}{dz}(e^{-z})) \\ &= -1 \ (1 + e^{-z})^{-2} \ (0\end{aligned}$$

Derivative of a Sigmoid Function

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

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

$$= -1$$

Derivative of a Sigmoid Function

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

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

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

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

Derivative of a Sigmoid Function

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

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

Recall that:

Derivative of a Sigmoid Function

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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

Derivative of a Sigmoid Function

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

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

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

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



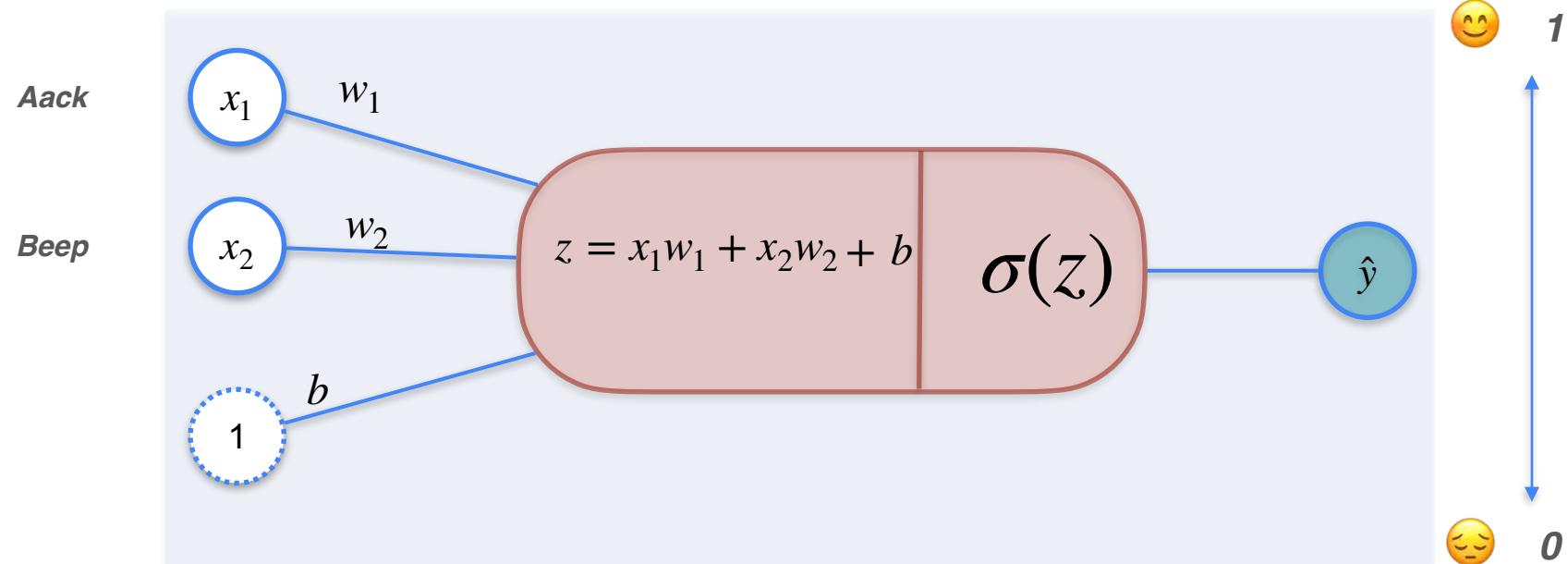
DeepLearning.AI

Optimization in Neural Networks and Newton's Method

**Classification with a
perceptron:
Gradient Descent**

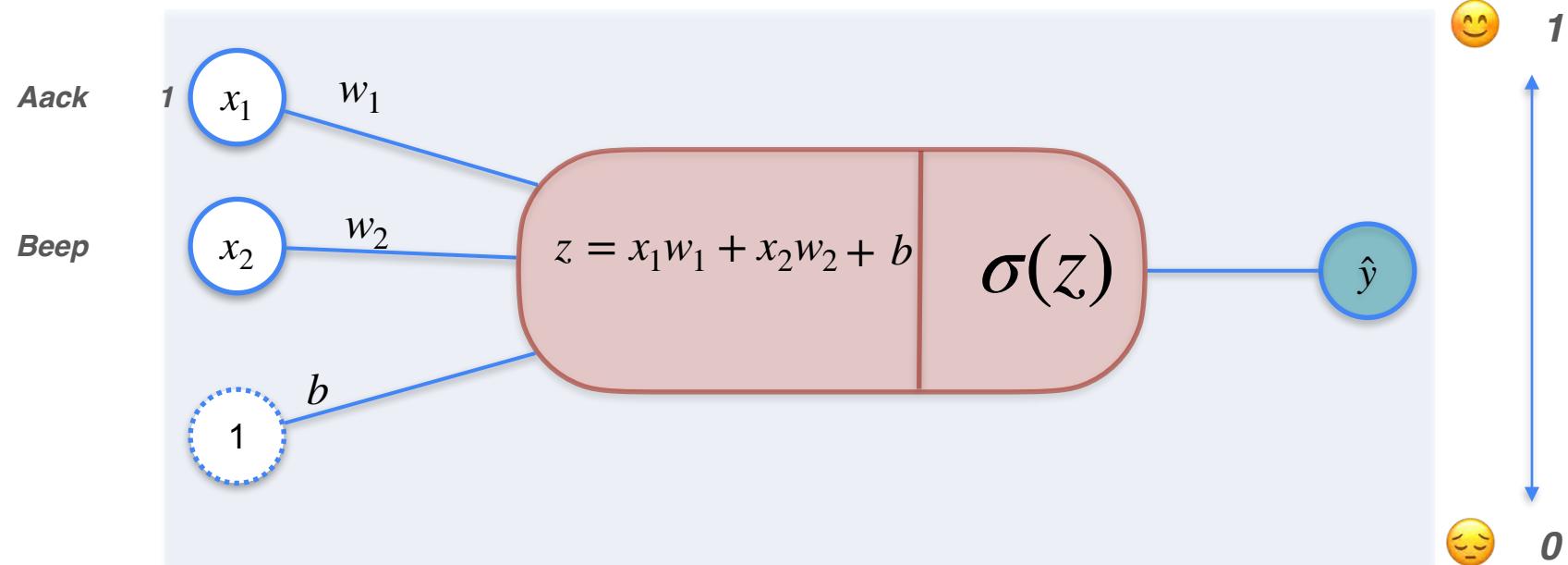
Classification With a Perceptron

Aack beep beep beep



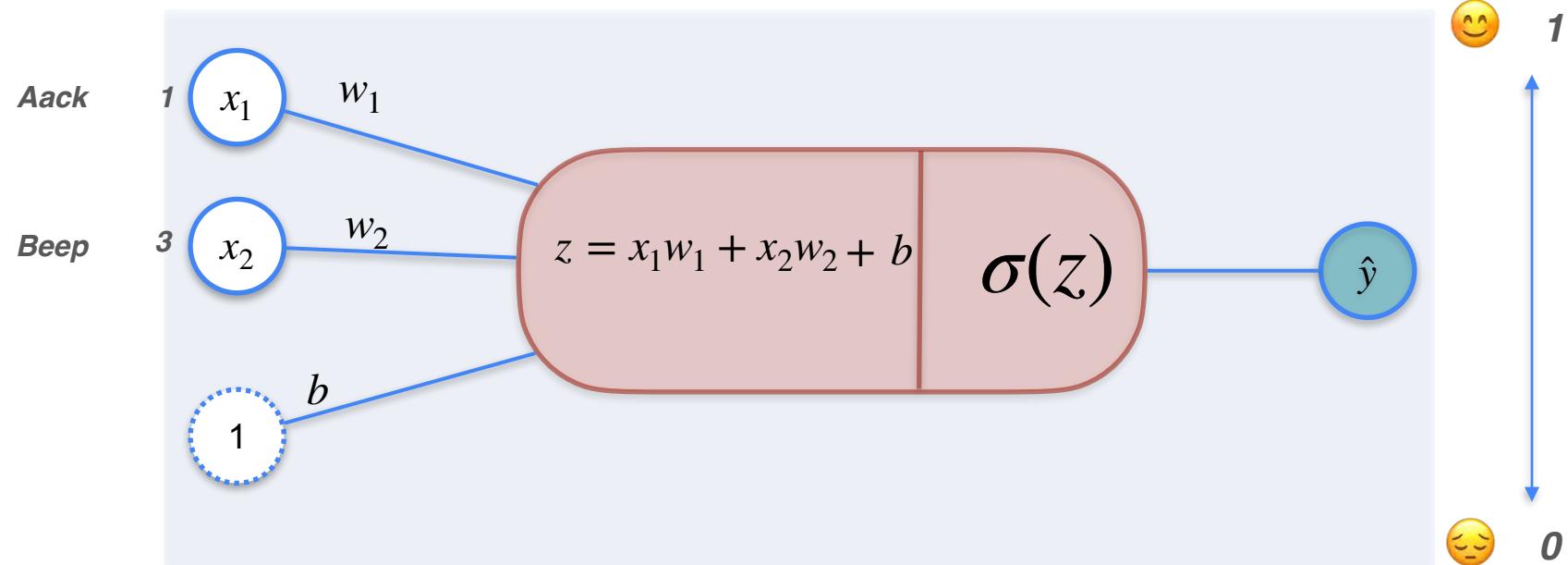
Classification With a Perceptron

Aack beep beep beep



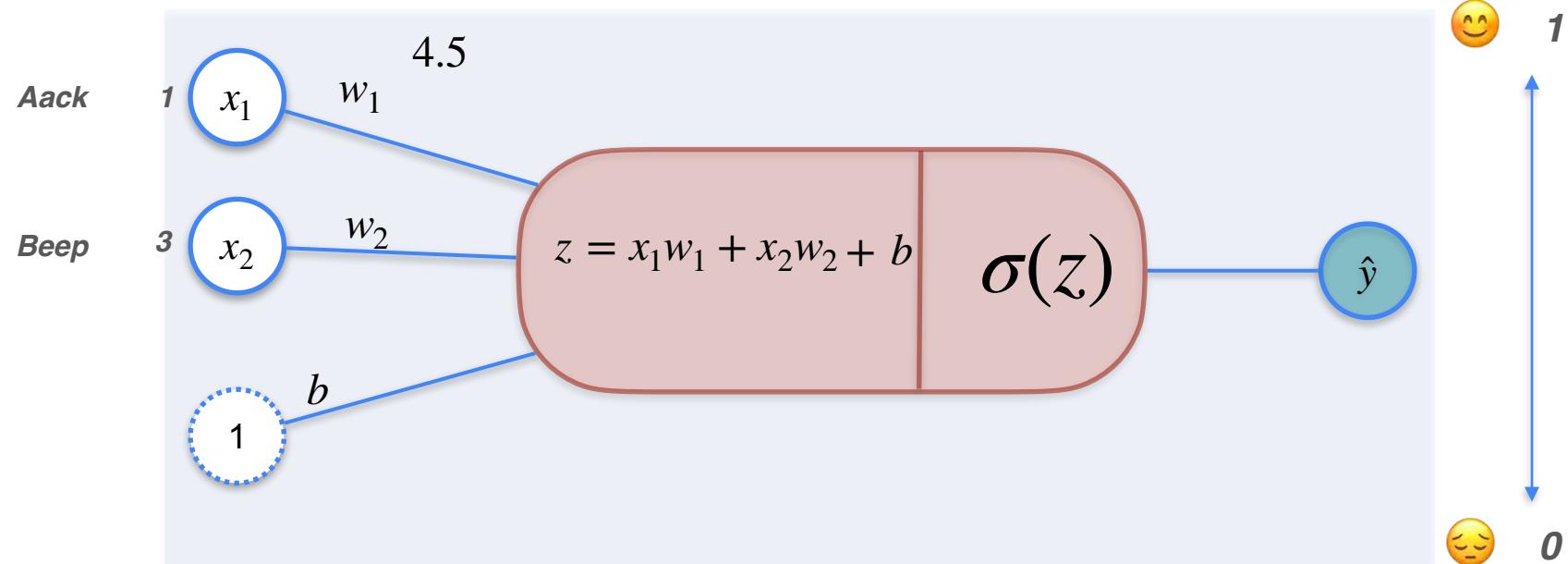
Classification With a Perceptron

Aack beep beep beep



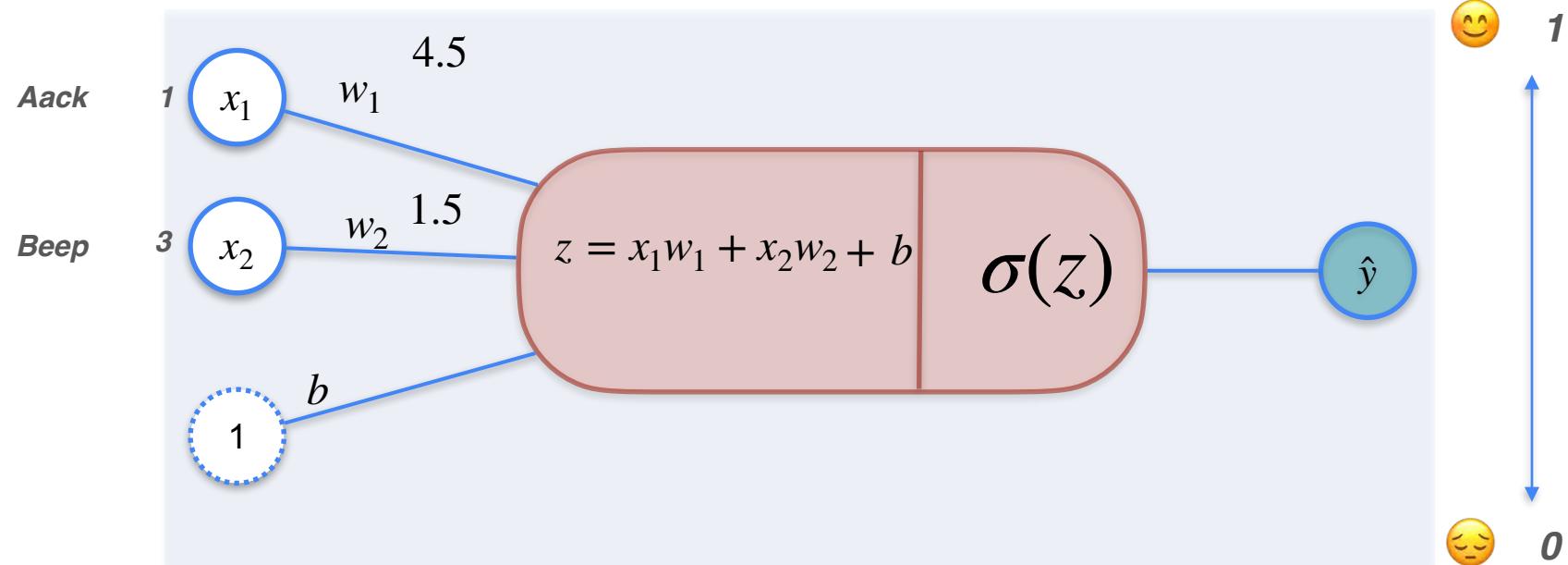
Classification With a Perceptron

Aack beep beep beep



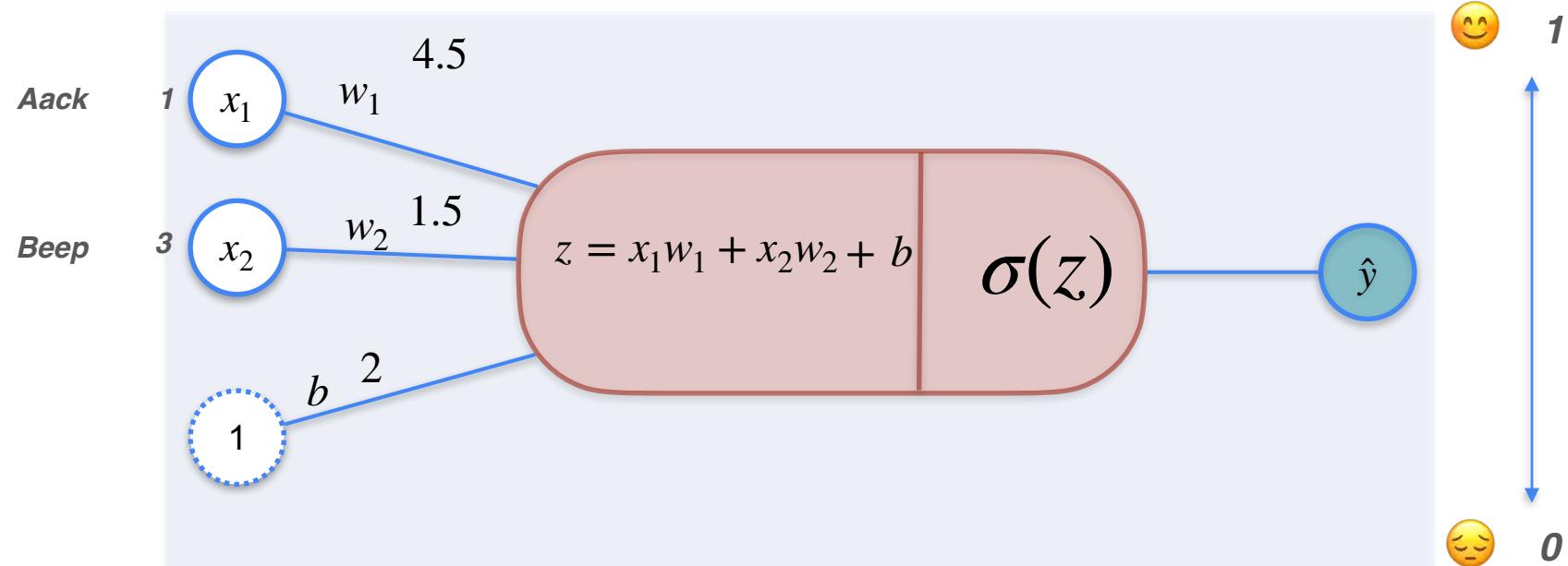
Classification With a Perceptron

Aack beep beep beep



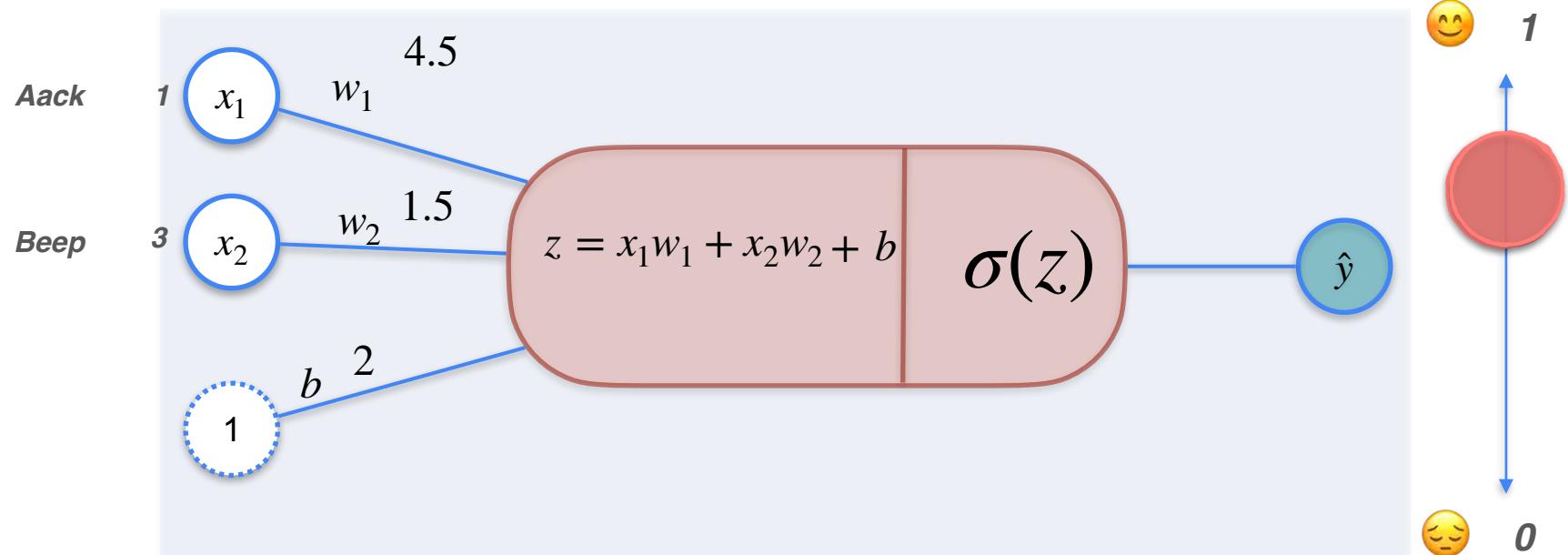
Classification With a Perceptron

Aack beep beep beep



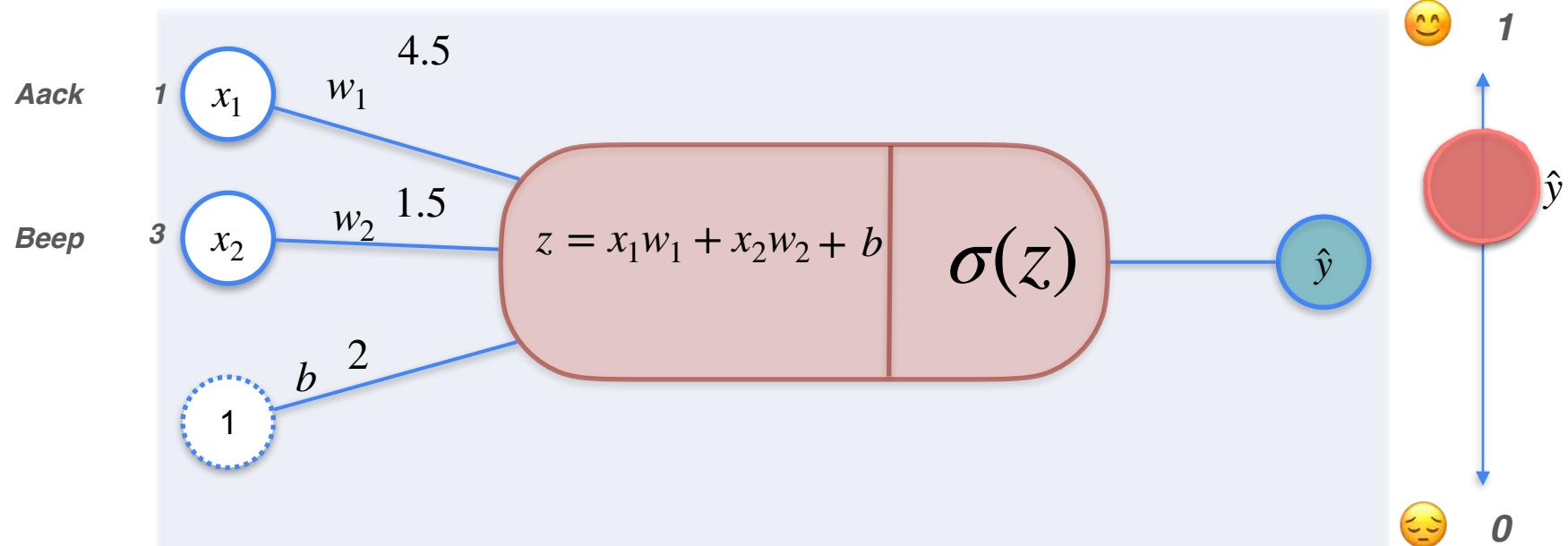
Classification With a Perceptron

Aack beep beep beep



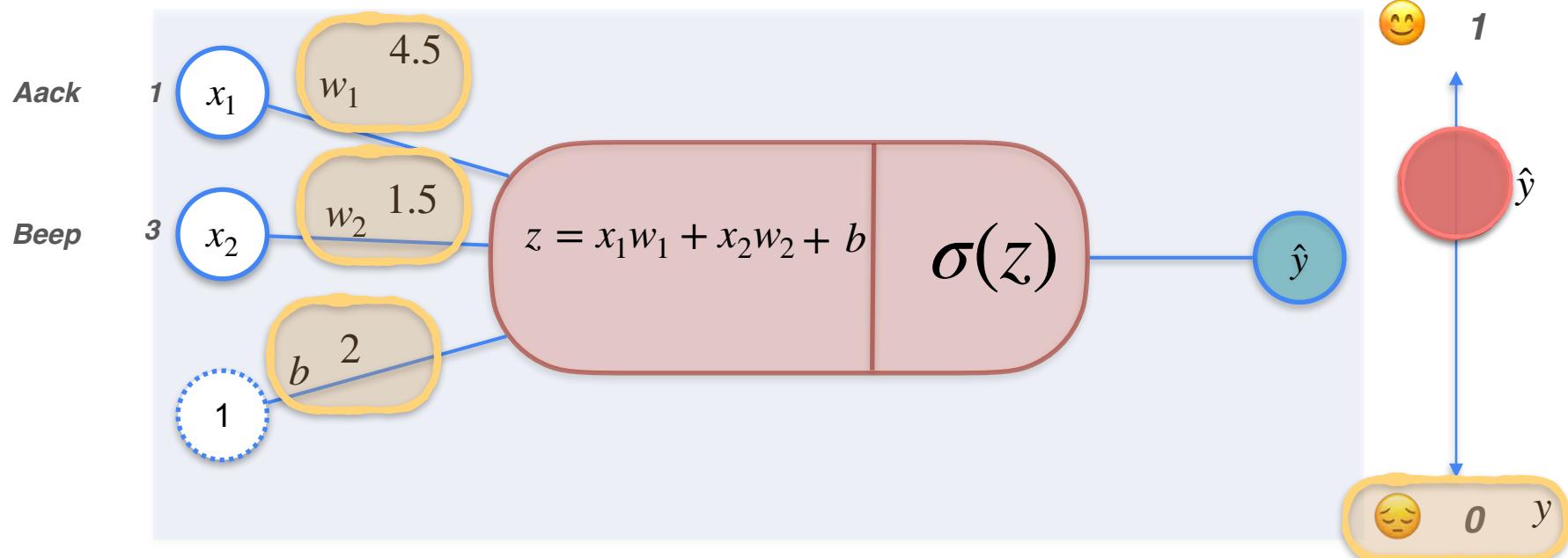
Classification With a Perceptron

Aack beep beep beep



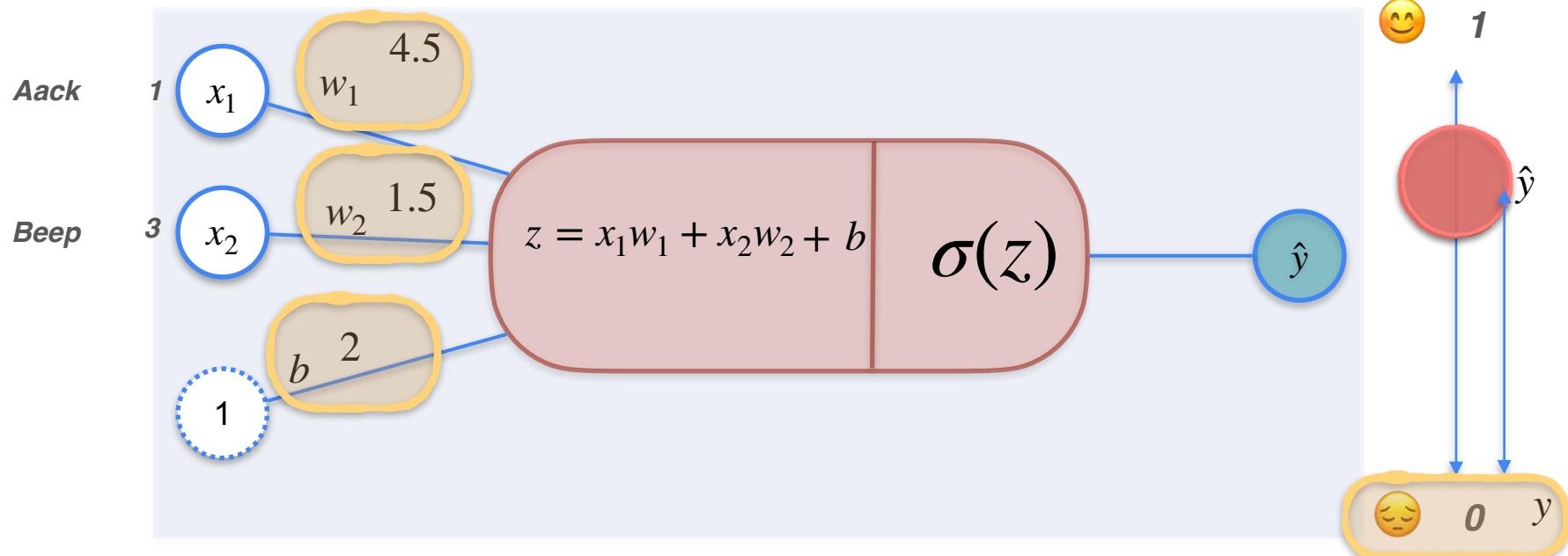
Classification With a Perceptron

Aack beep beep beep



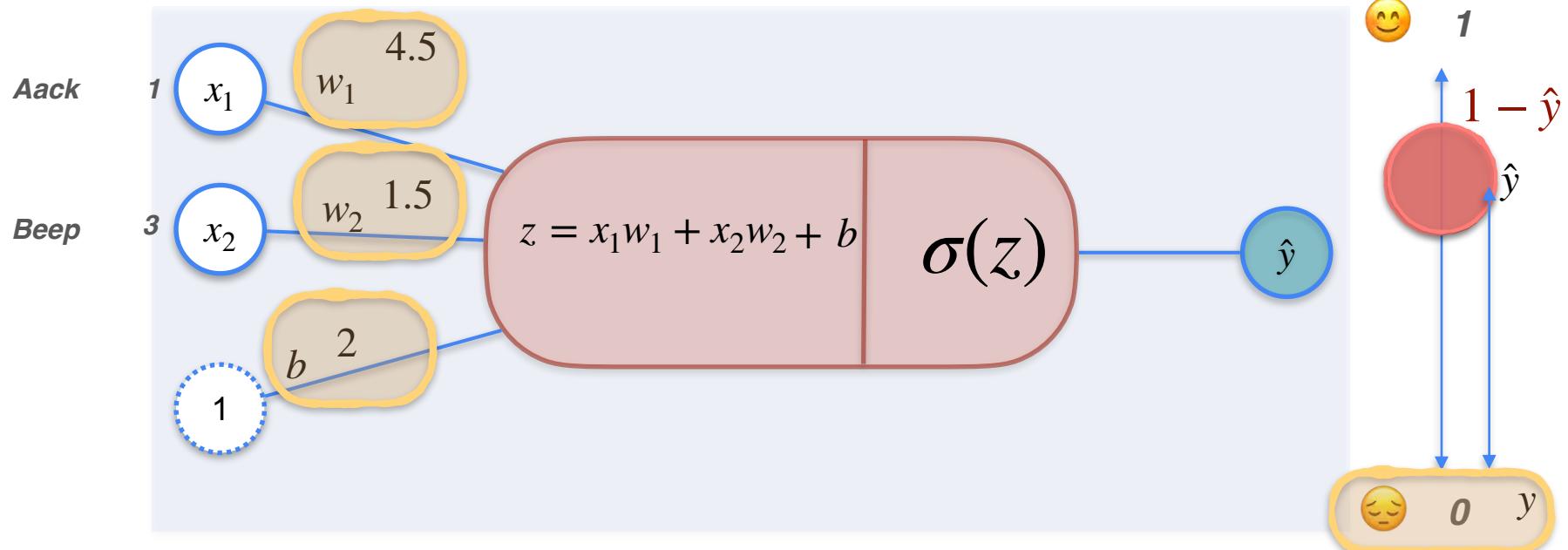
Classification With a Perceptron

Aack beep beep beep



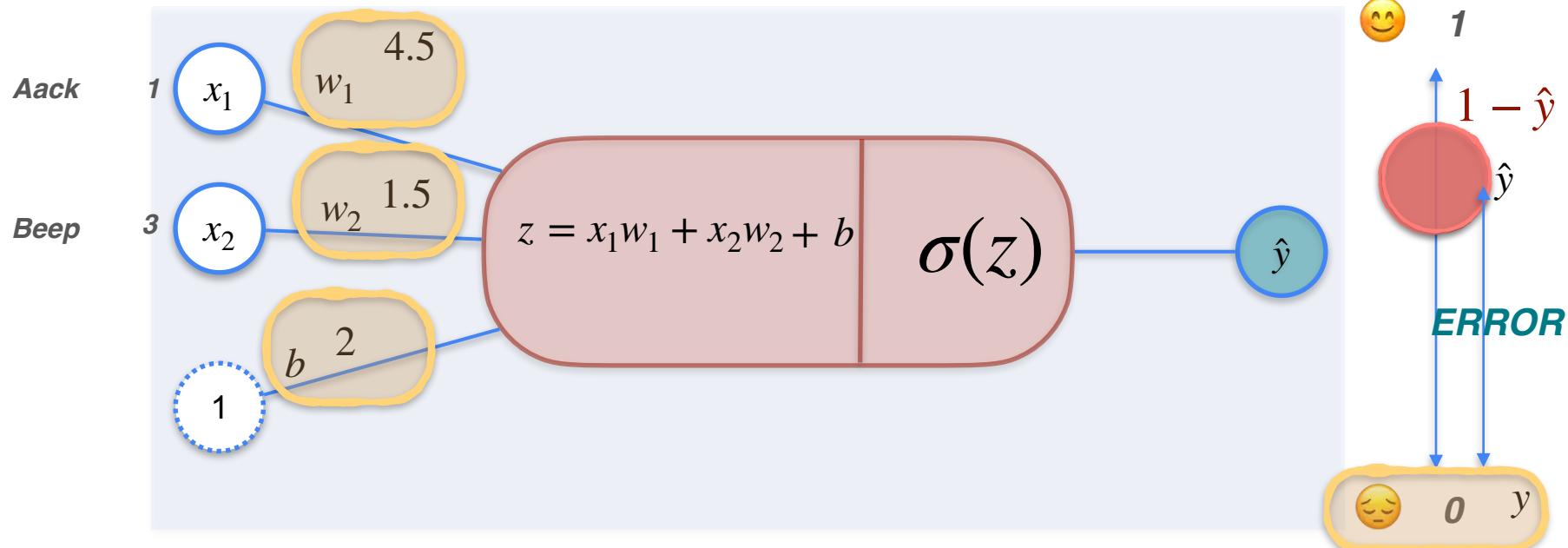
Classification With a Perceptron

Aack beep beep beep



Classification With a Perceptron

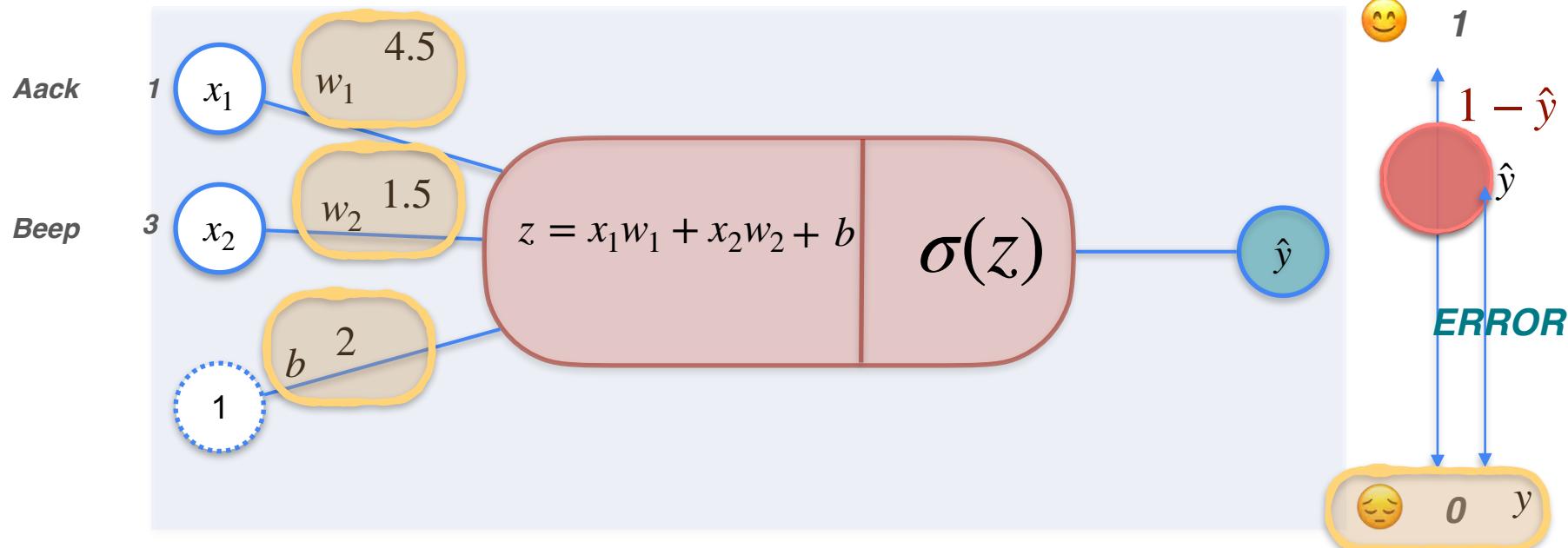
Aack beep beep beep



Classification With a Perceptron

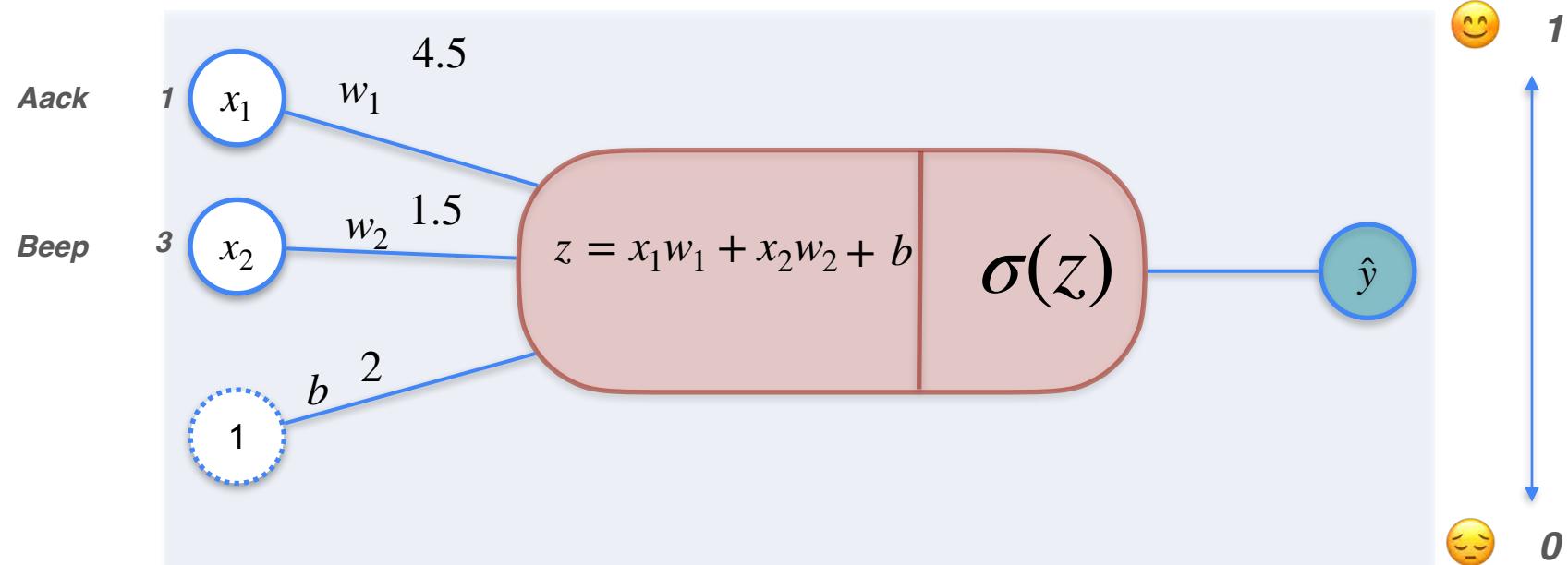
Aack beep beep beep

LOG LOSS



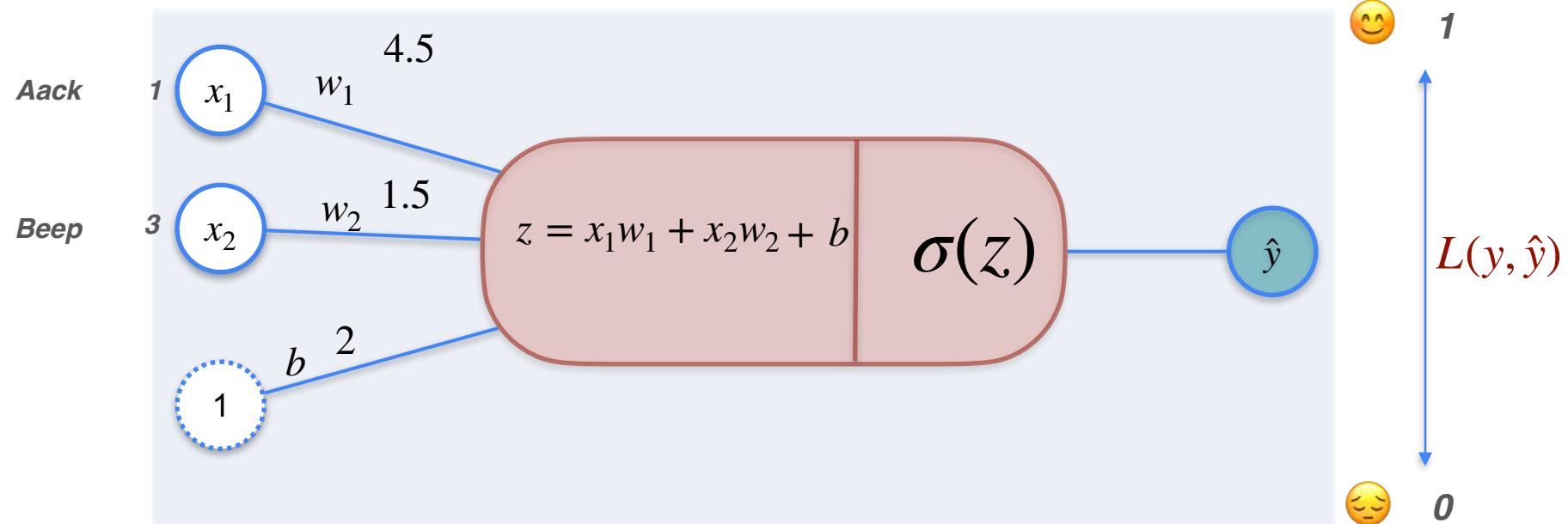
Classification With a Perceptron

Aack beep beep beep



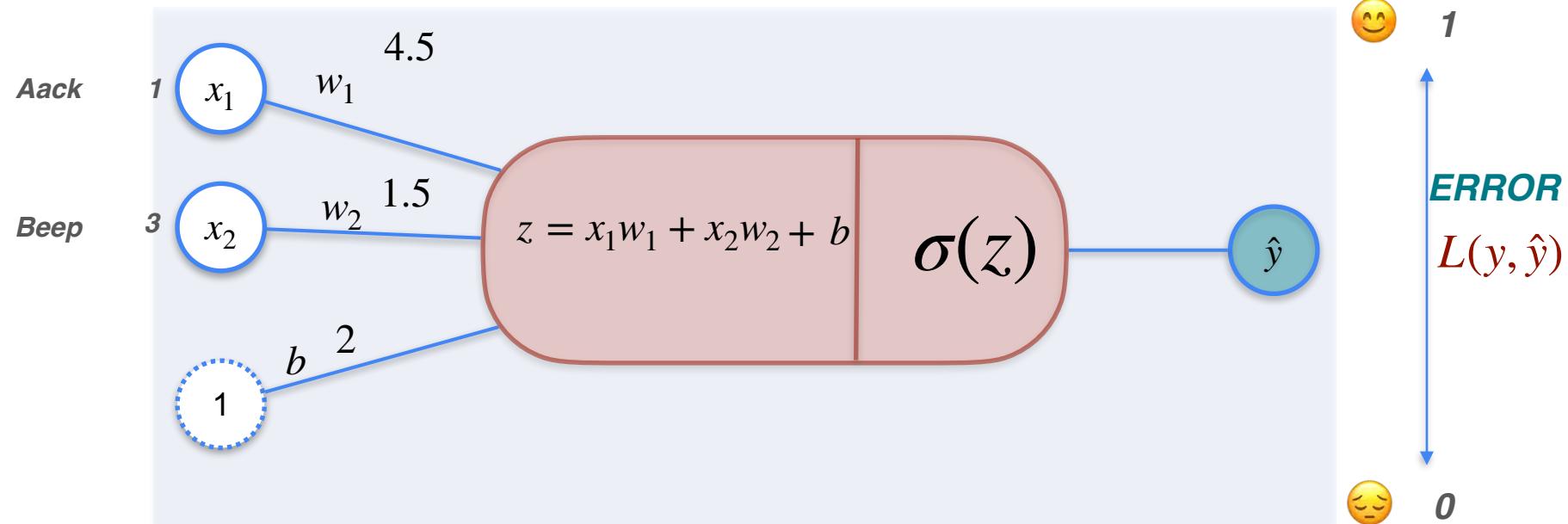
Classification With a Perceptron

Aack beep beep beep



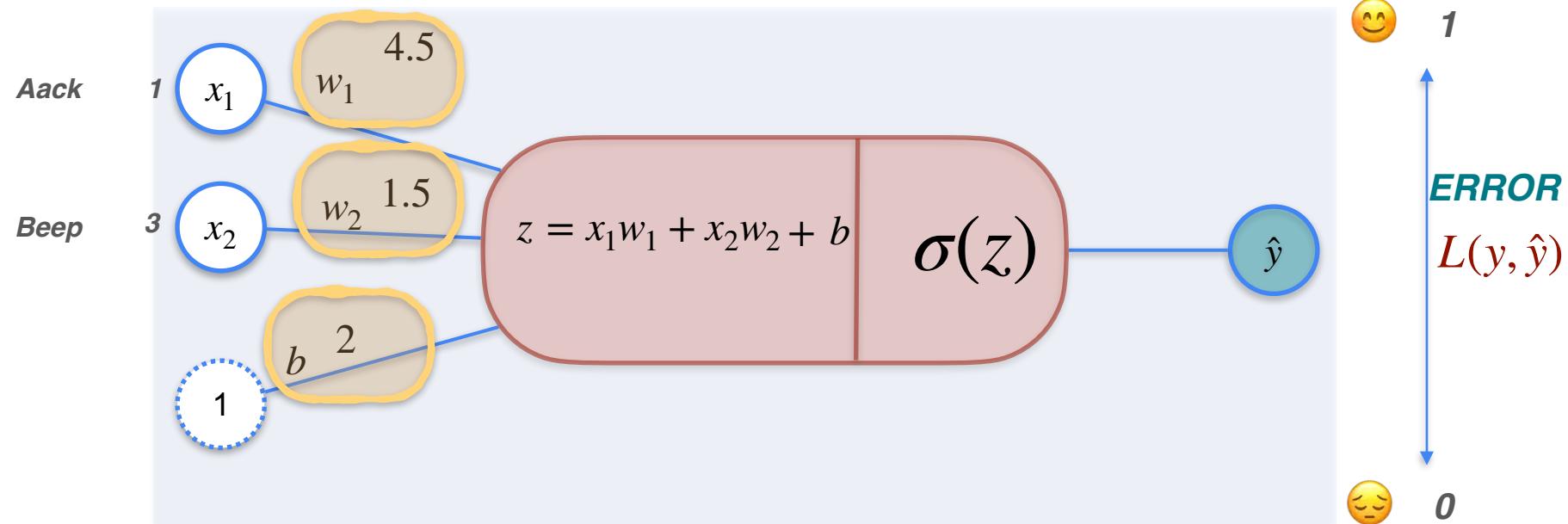
Classification With a Perceptron

Aack beep beep beep



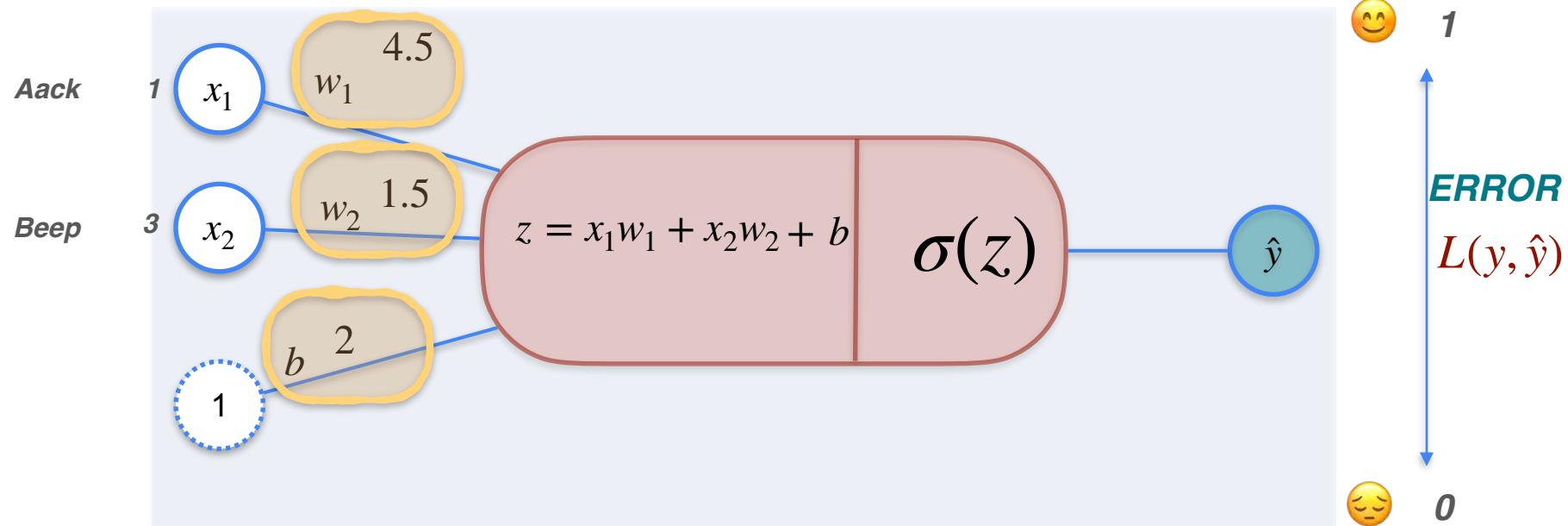
Classification With a Perceptron

Aack beep beep beep

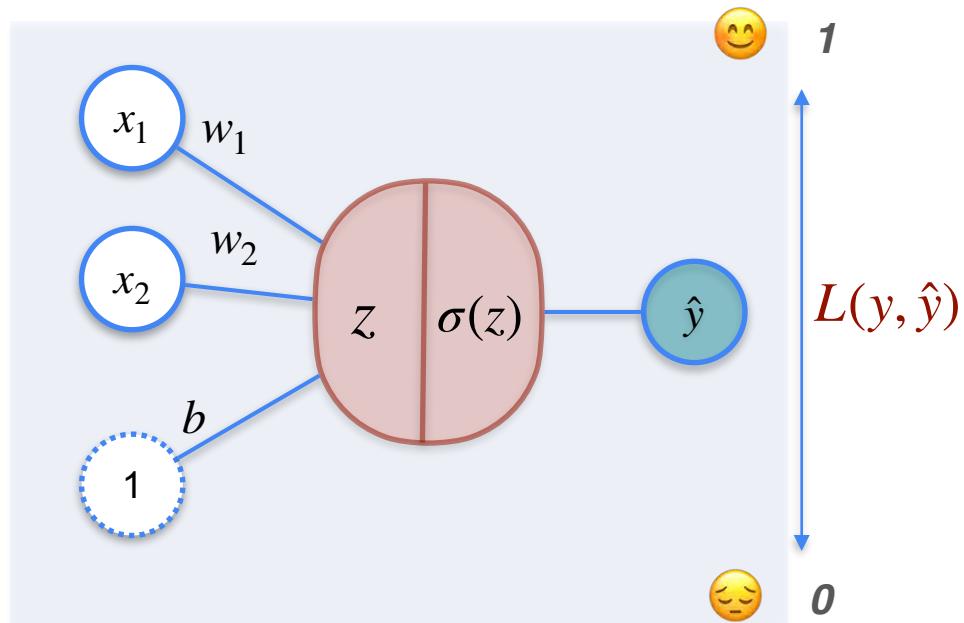


Classification With a Perceptron

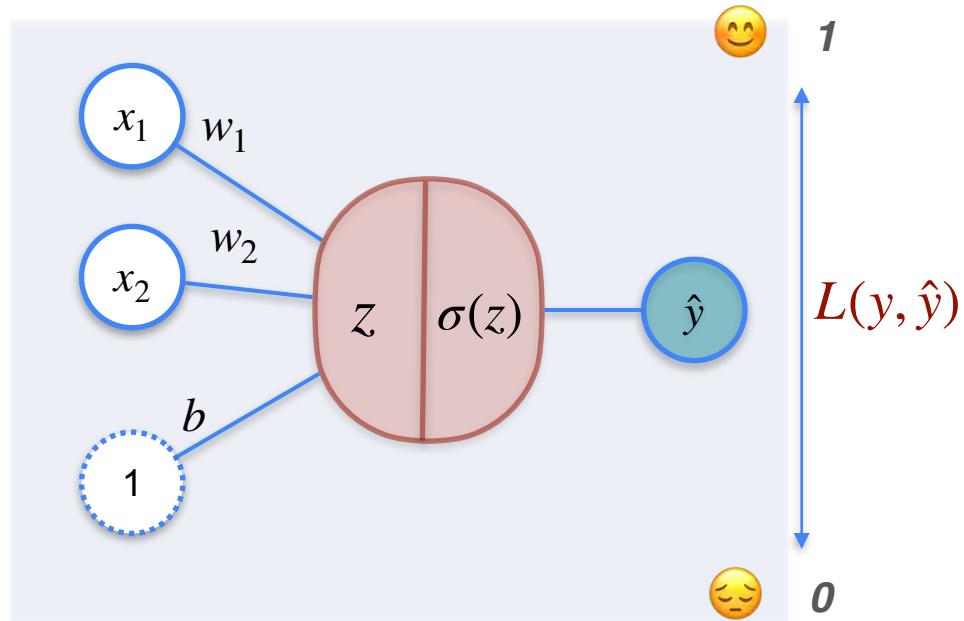
Aack beep beep beep



Classification With a Perceptron

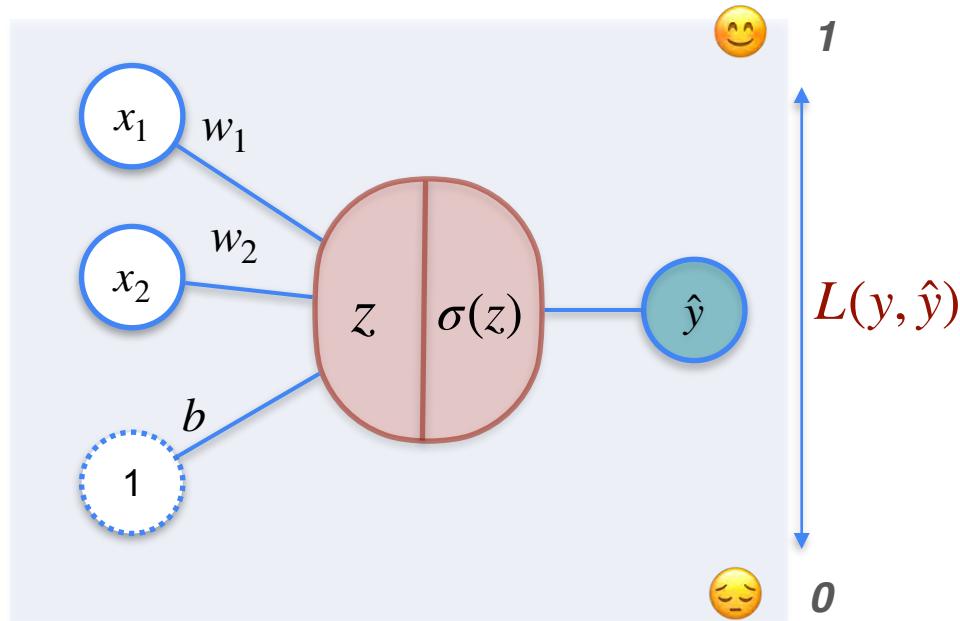


Classification With a Perceptron



Prediction Function:

Classification With a Perceptron

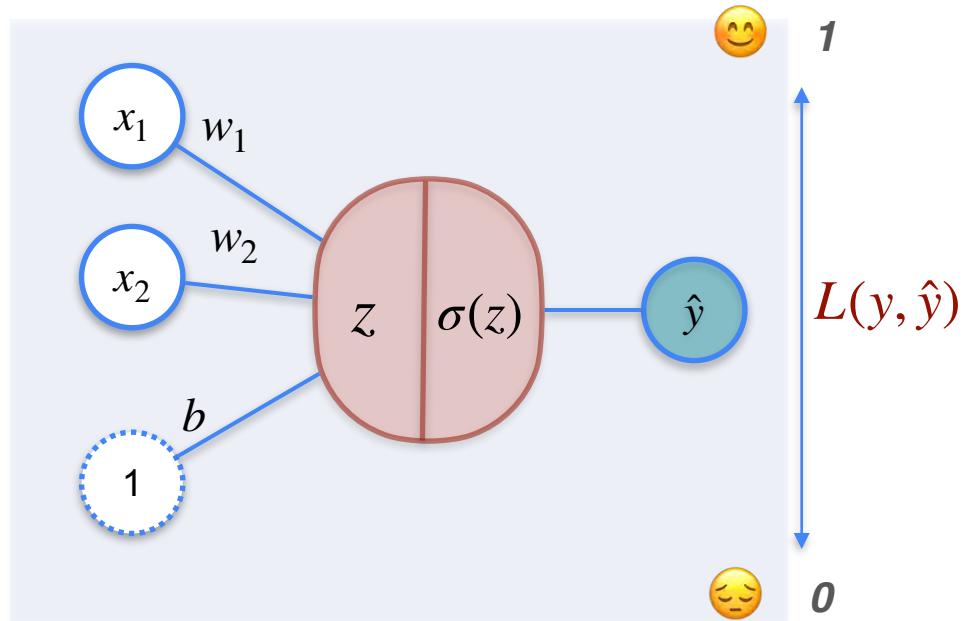


Prediction Function:

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

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

Classification With a Perceptron



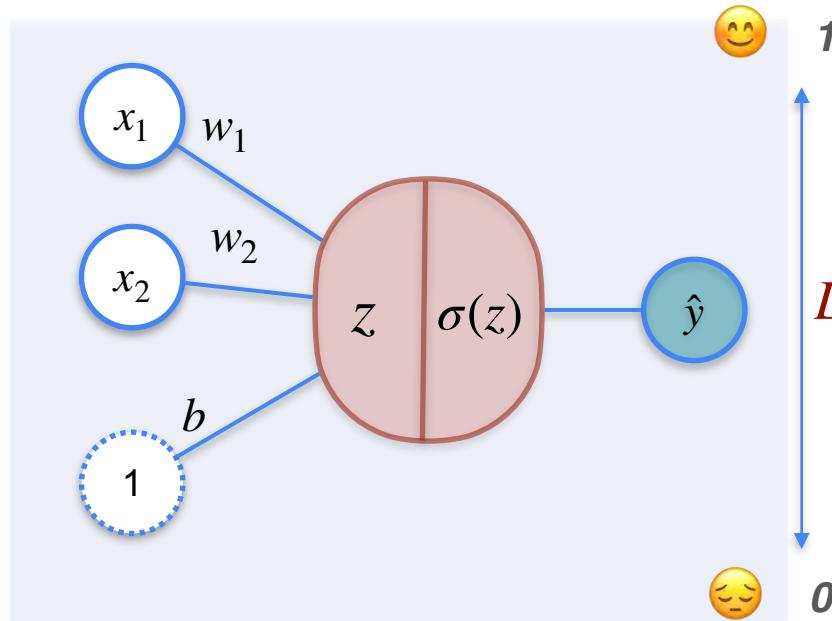
Prediction Function:

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

Loss Function:

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

Classification With a Perceptron



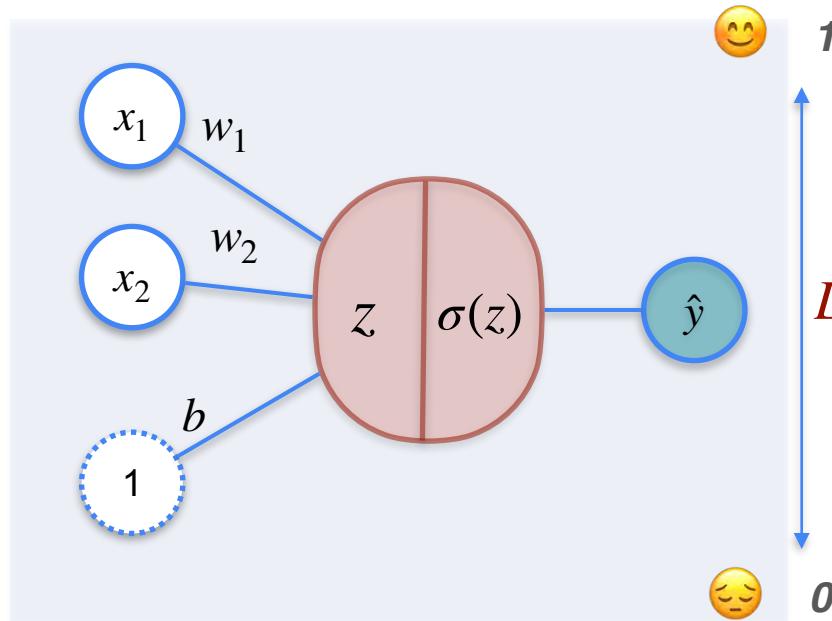
Prediction Function:

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

Loss Function:

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

Classification With a Perceptron



Prediction Function:

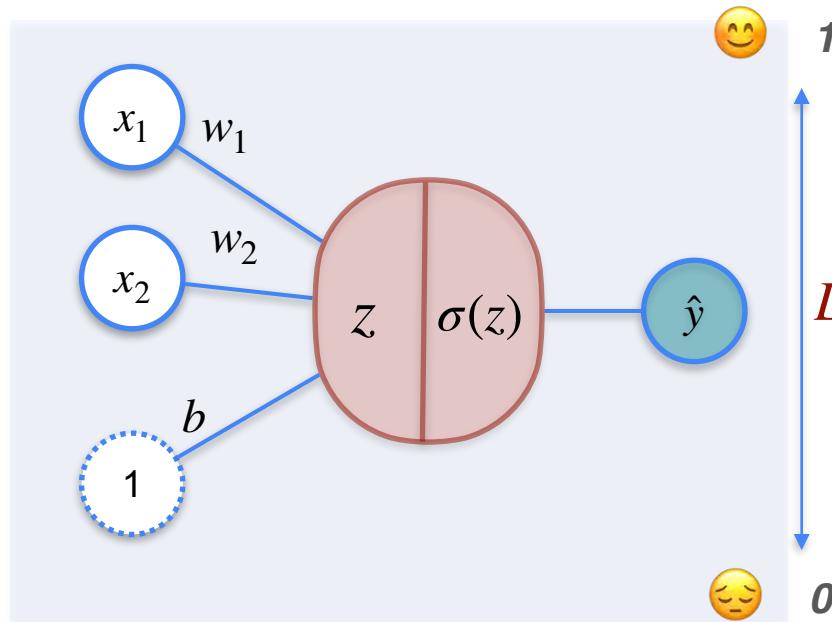
$$\hat{y} = \sigma(w_1x_1 + w_2x_2 + b)$$

Loss Function:

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

Main Goal:

Classification With a Perceptron



Prediction Function:

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

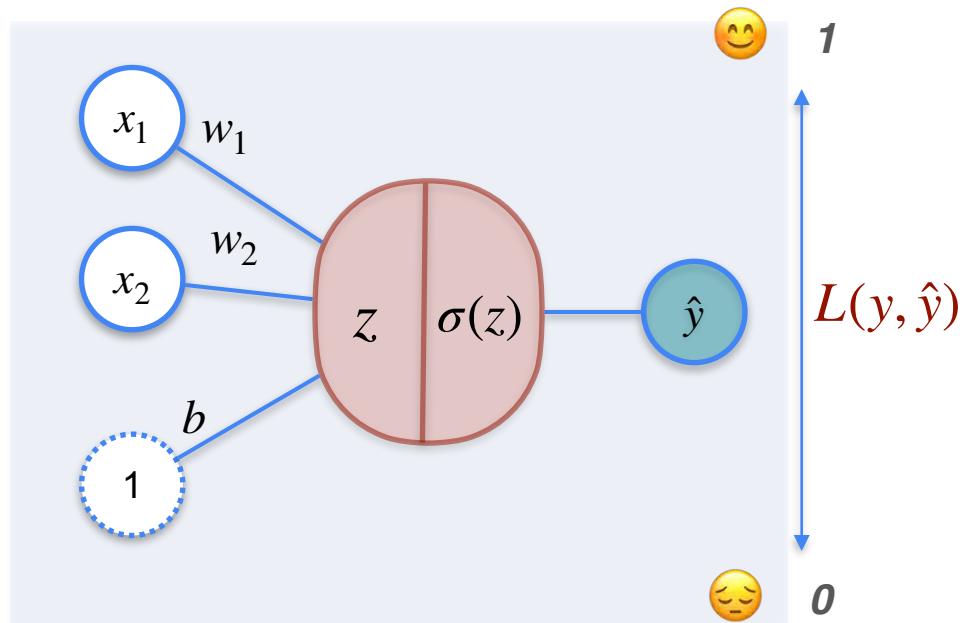
Loss Function:

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

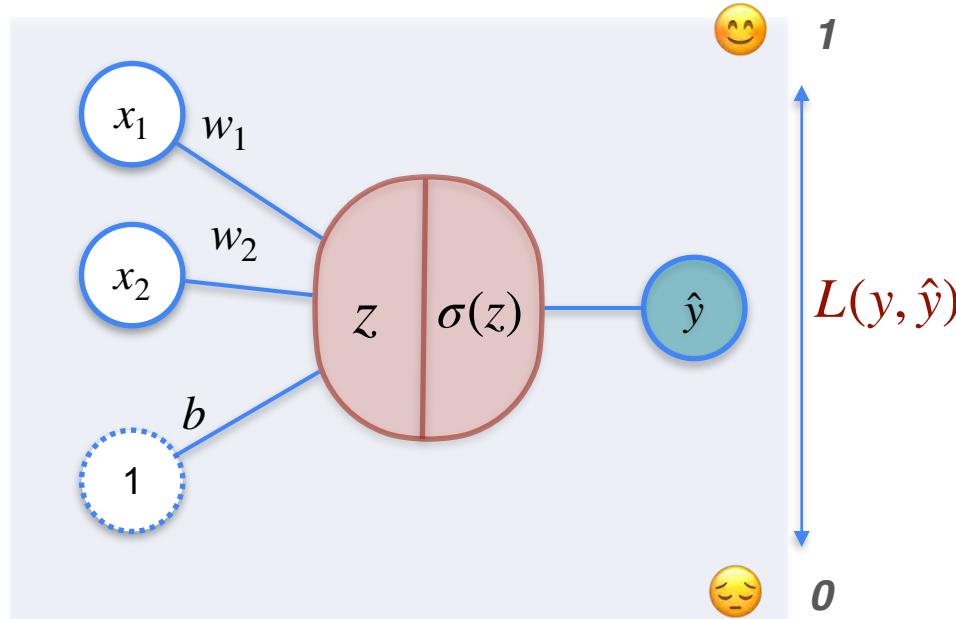
Main Goal:

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

Classification With a Perceptron

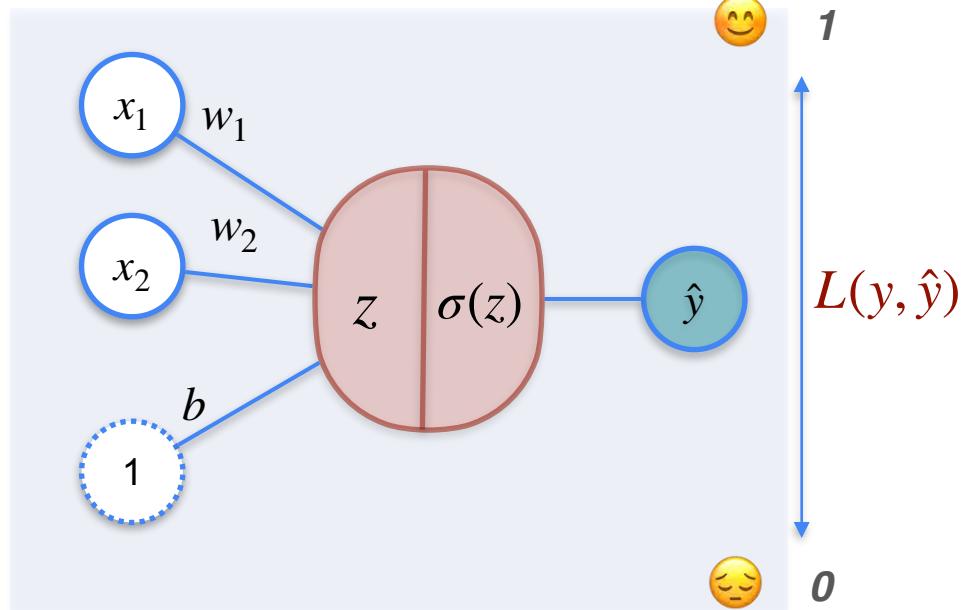


Classification With a Perceptron



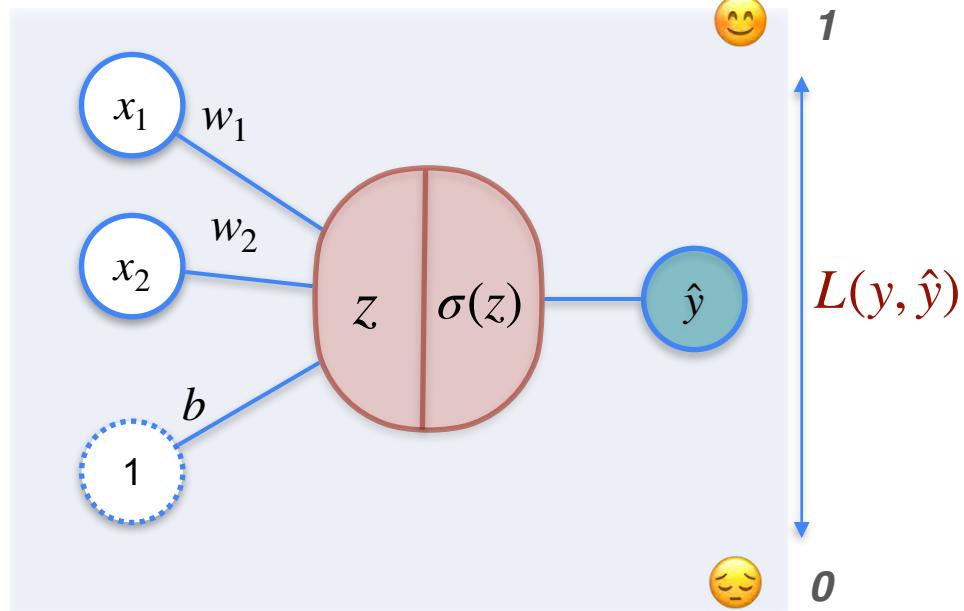
To find optimal values for:

Classification With a Perceptron



To find optimal values for:
 w_1 , w_2 , b

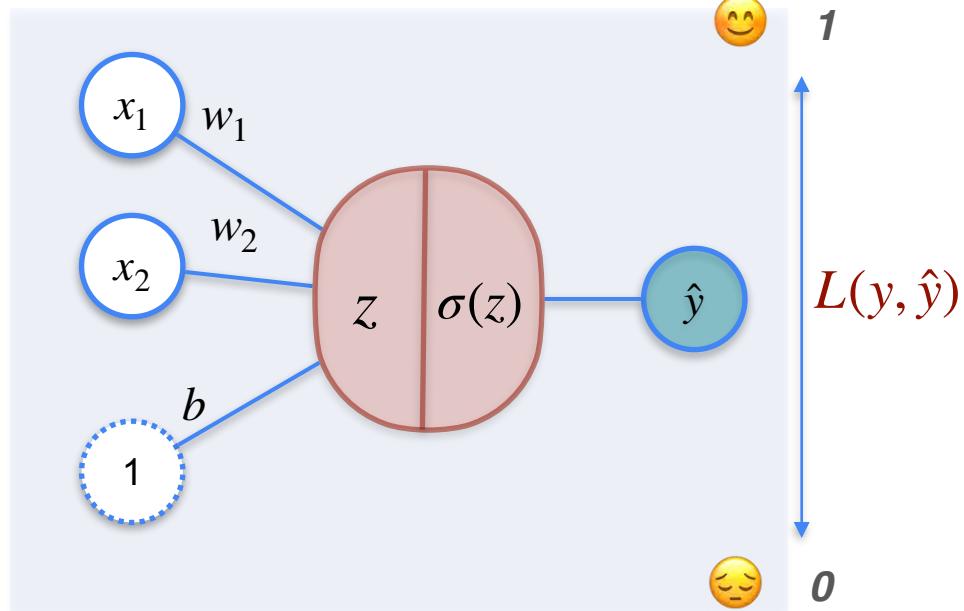
Classification With a Perceptron



To find optimal values for:
 w_1 , w_2 , b

You need gradient descent

Classification With a Perceptron

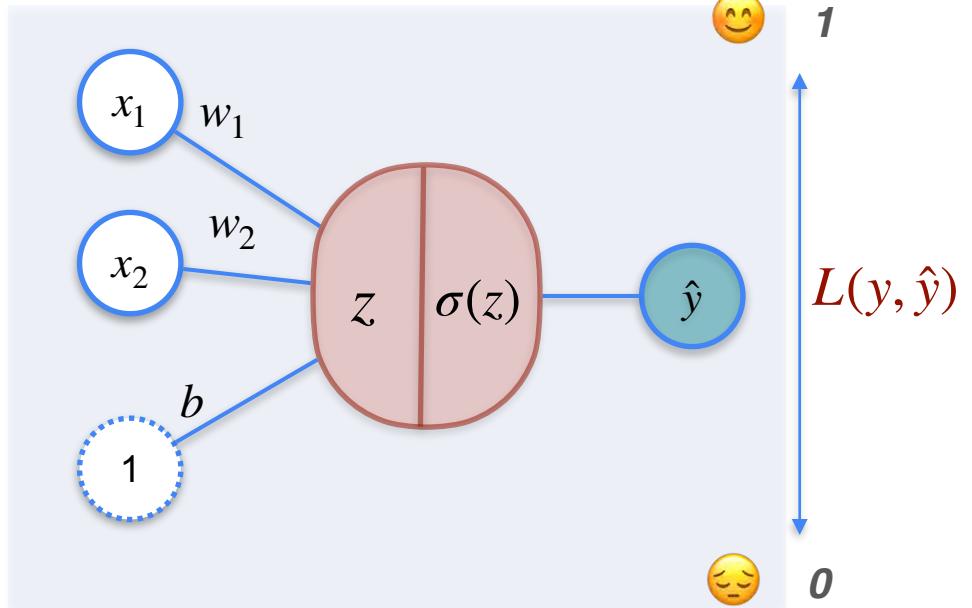


To find optimal values for:
 w_1, w_2, b

You need gradient descent

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

Classification With a Perceptron



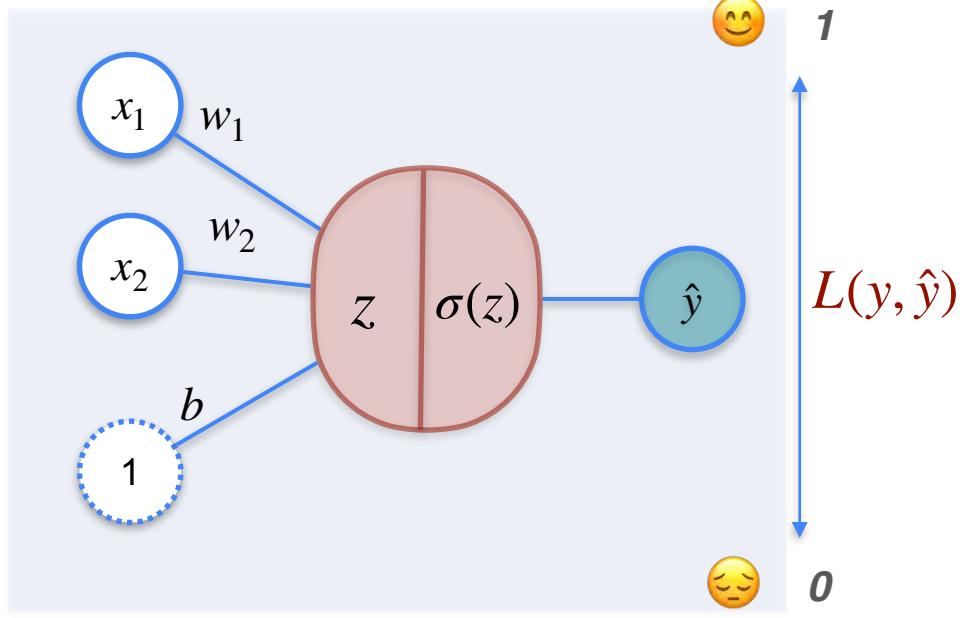
To find optimal values for:
 w_1, w_2, b

You need gradient descent

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

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

Classification With a Perceptron



To find optimal values for:
 w_1, w_2, b

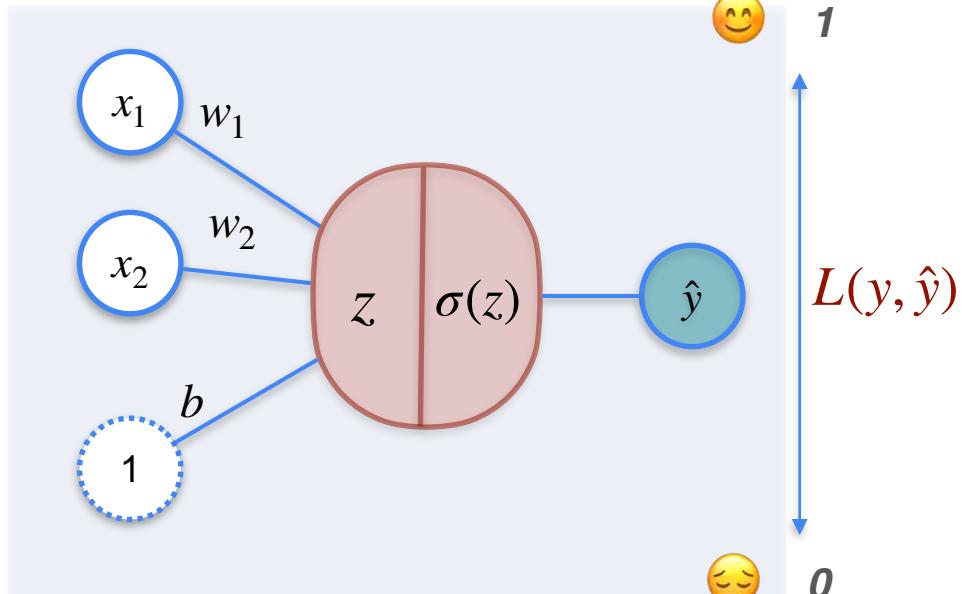
You need gradient descent

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

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

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

Classification With a Perceptron



To find optimal values for:
 w_1, w_2, b

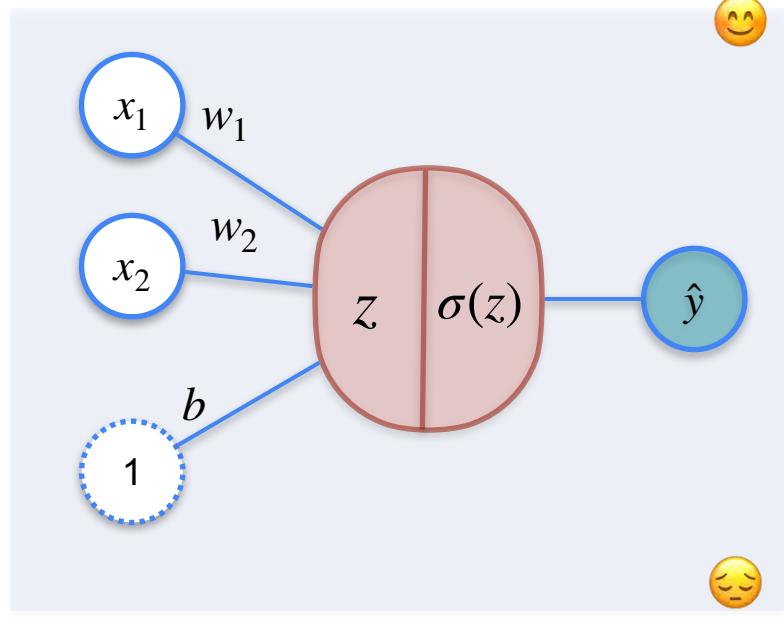
You need gradient descent

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

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

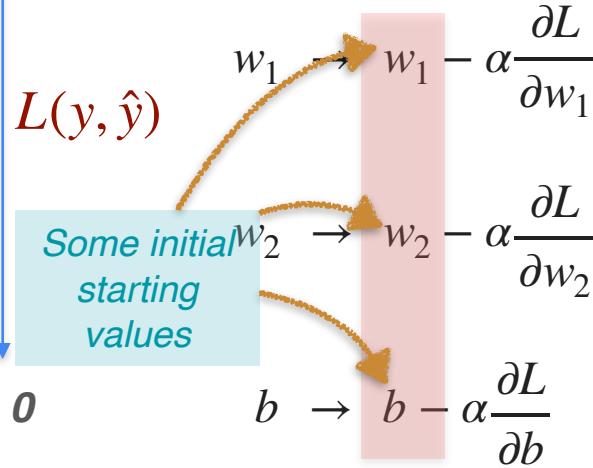
$$b \rightarrow b - \alpha \frac{\partial L}{\partial b}$$

Classification With a Perceptron

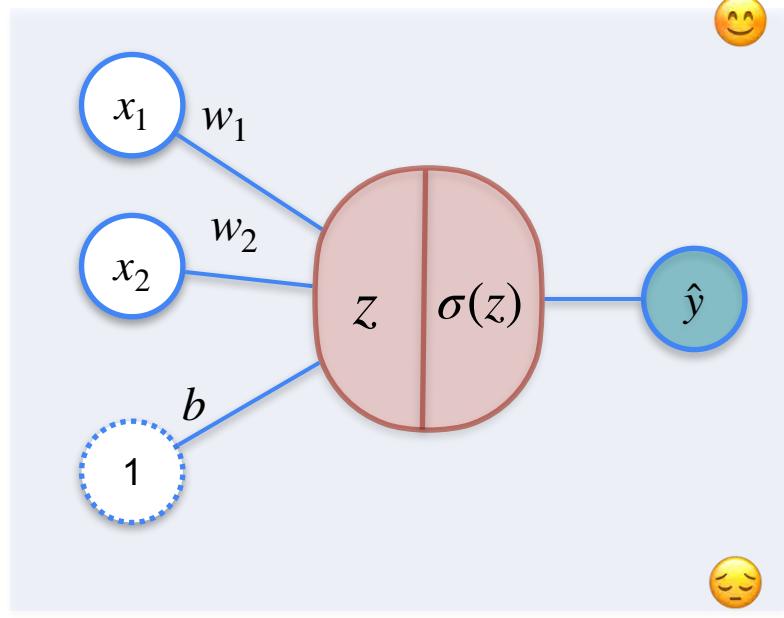


To find optimal values for:
 w_1 , w_2 , b

You need gradient descent

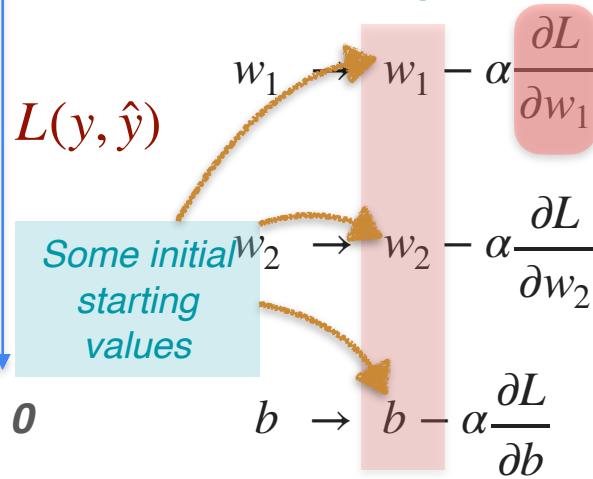


Classification With a Perceptron

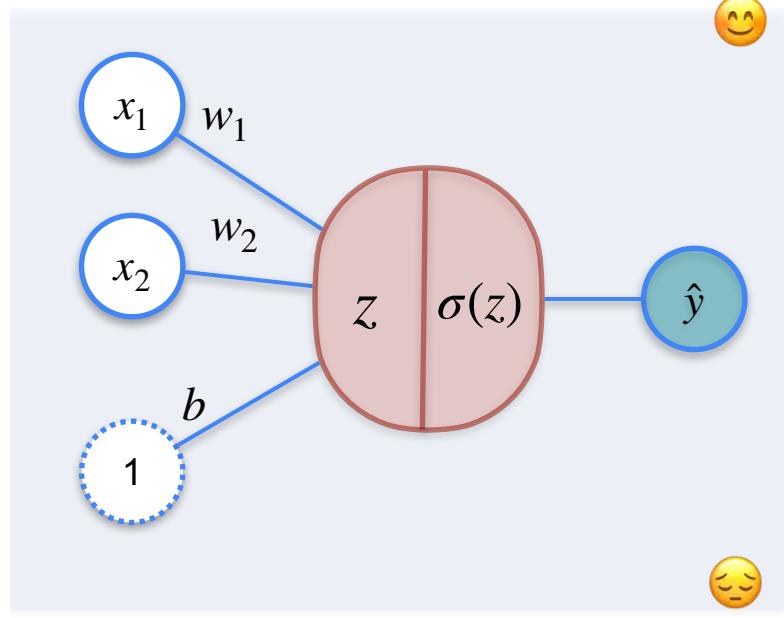


To find optimal values for:
 w_1, w_2, b

You need gradient descent

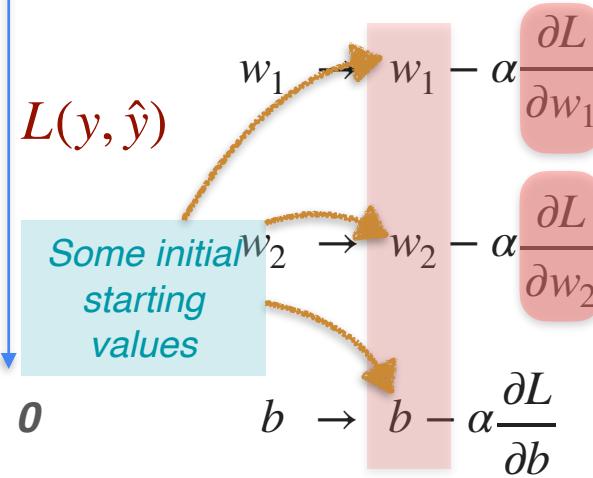


Classification With a Perceptron

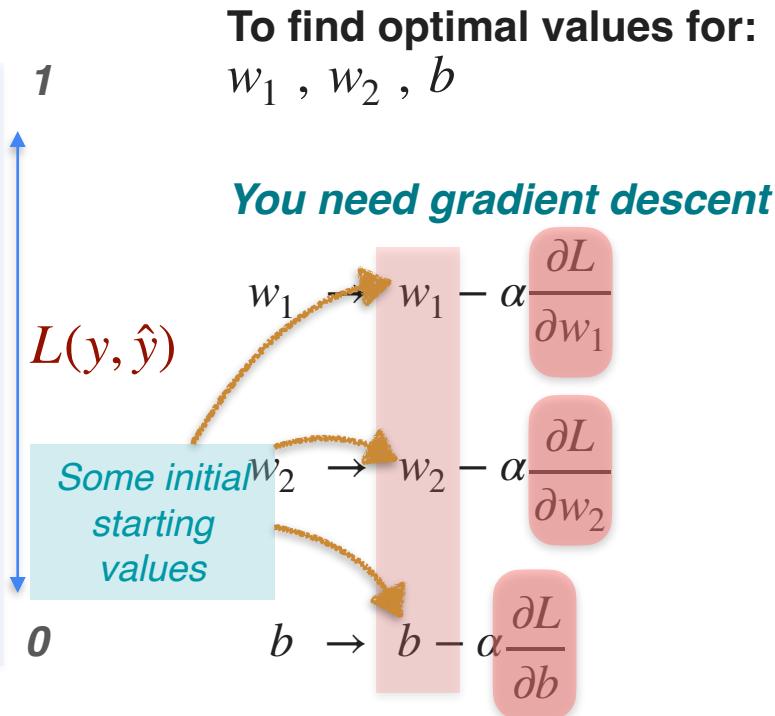
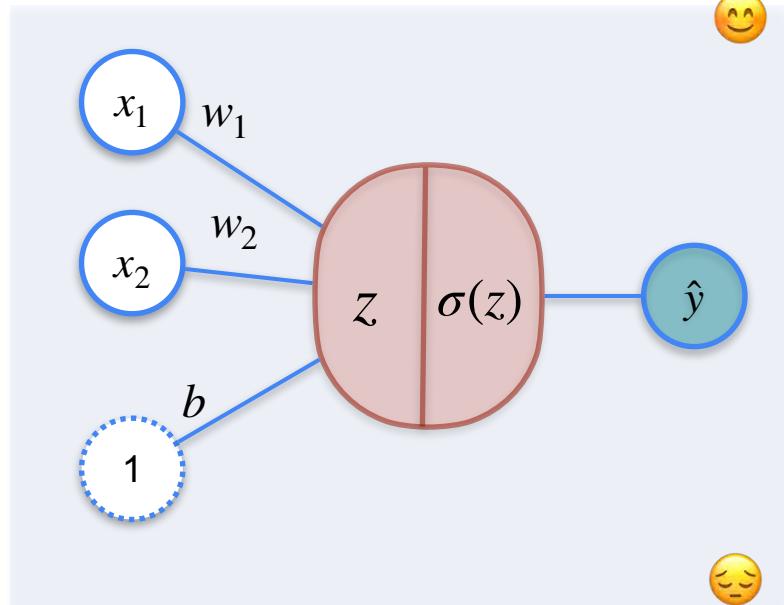


To find optimal values for:
 w_1, w_2, b

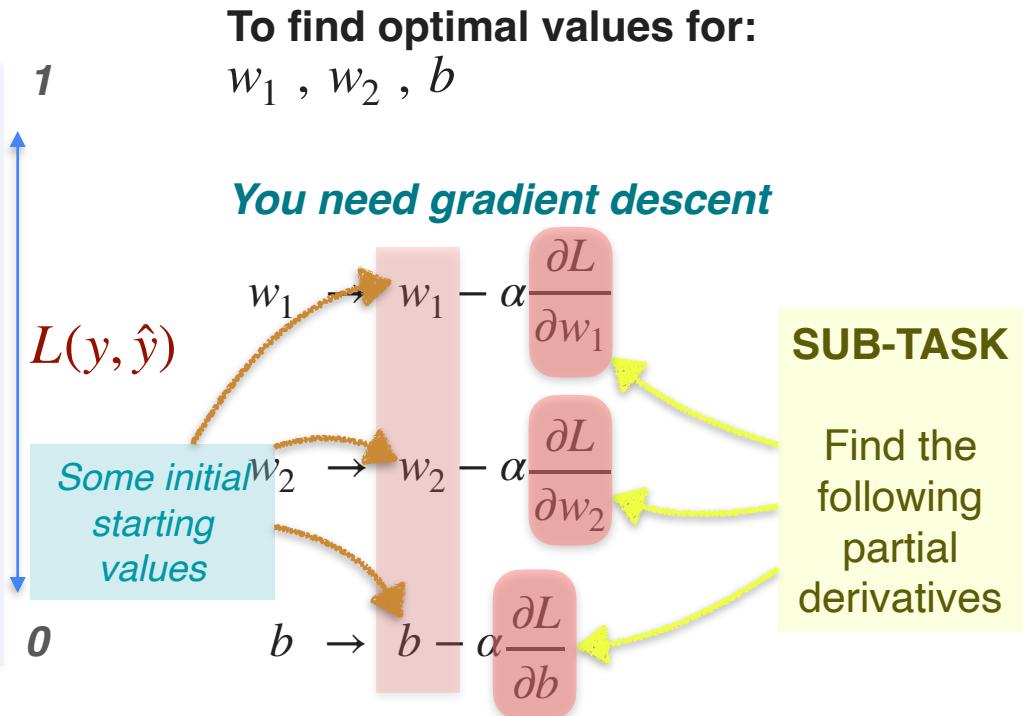
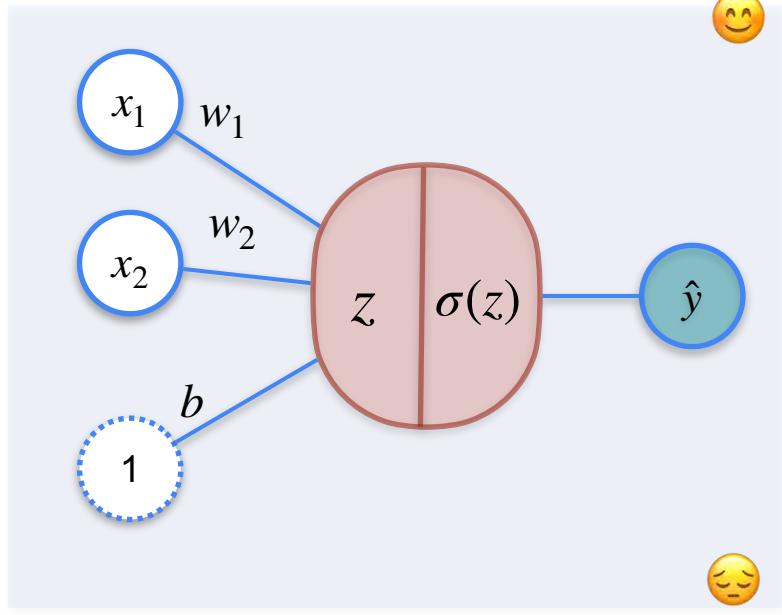
You need gradient descent



Classification With a Perceptron



Classification With a Perceptron



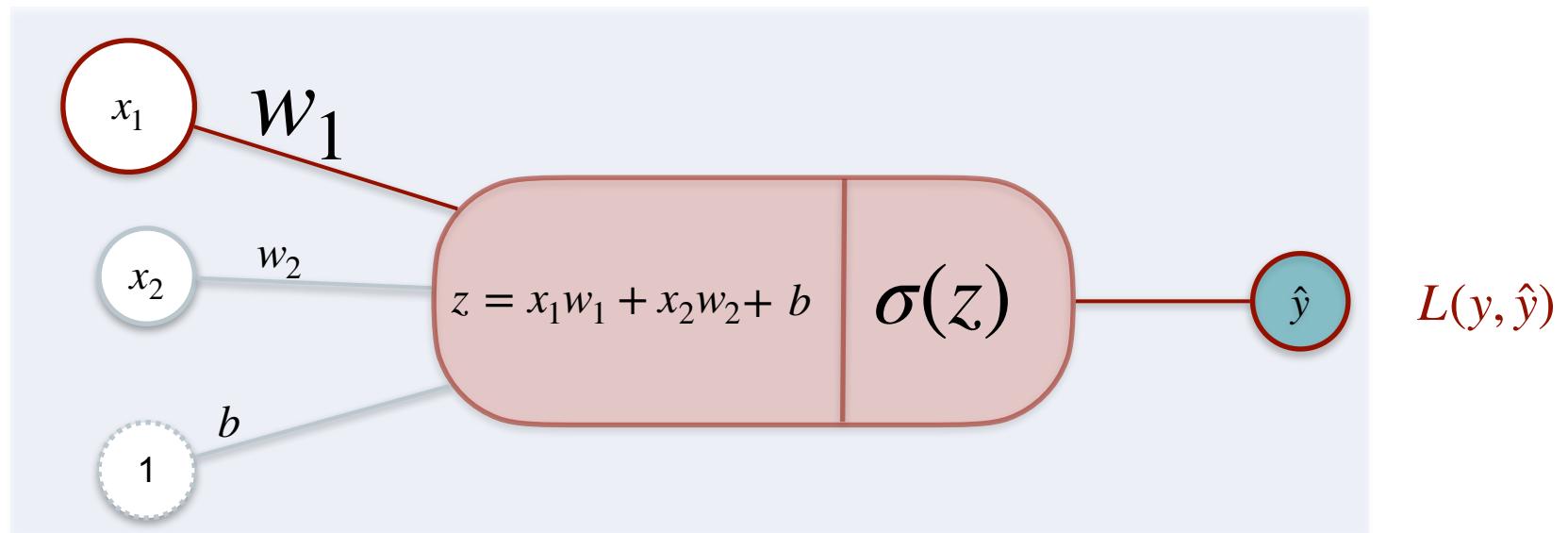


DeepLearning.AI

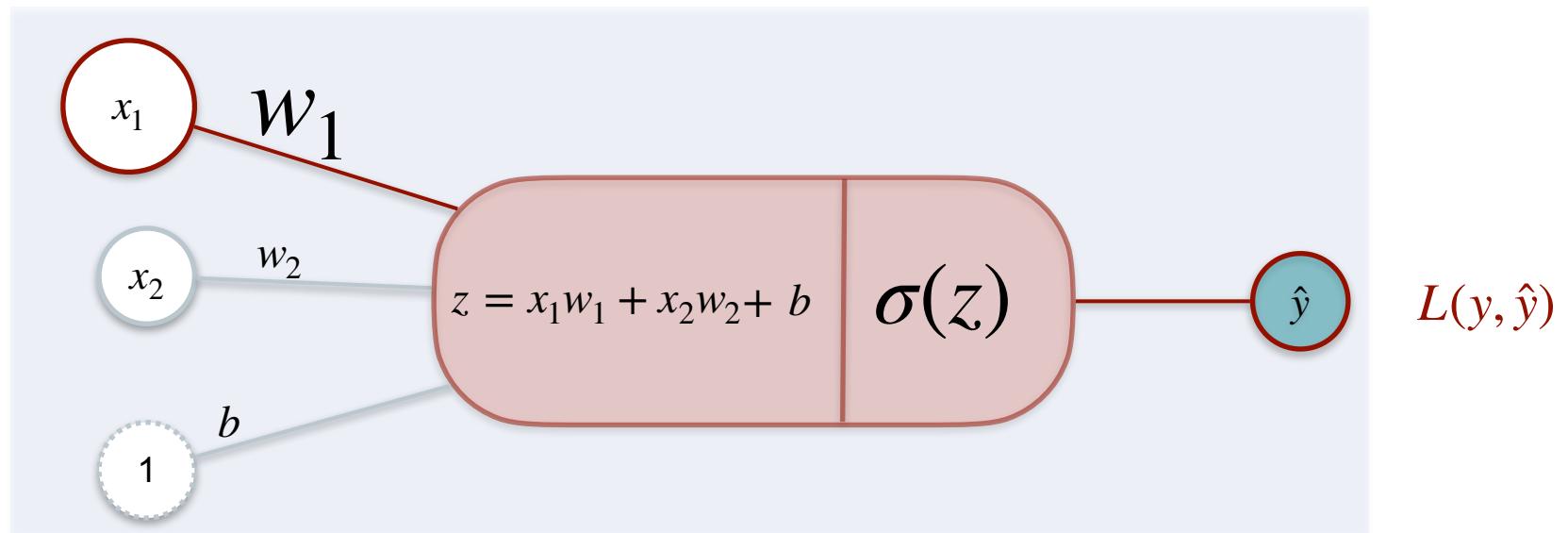
Optimization in Neural Networks and Newton's Method

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

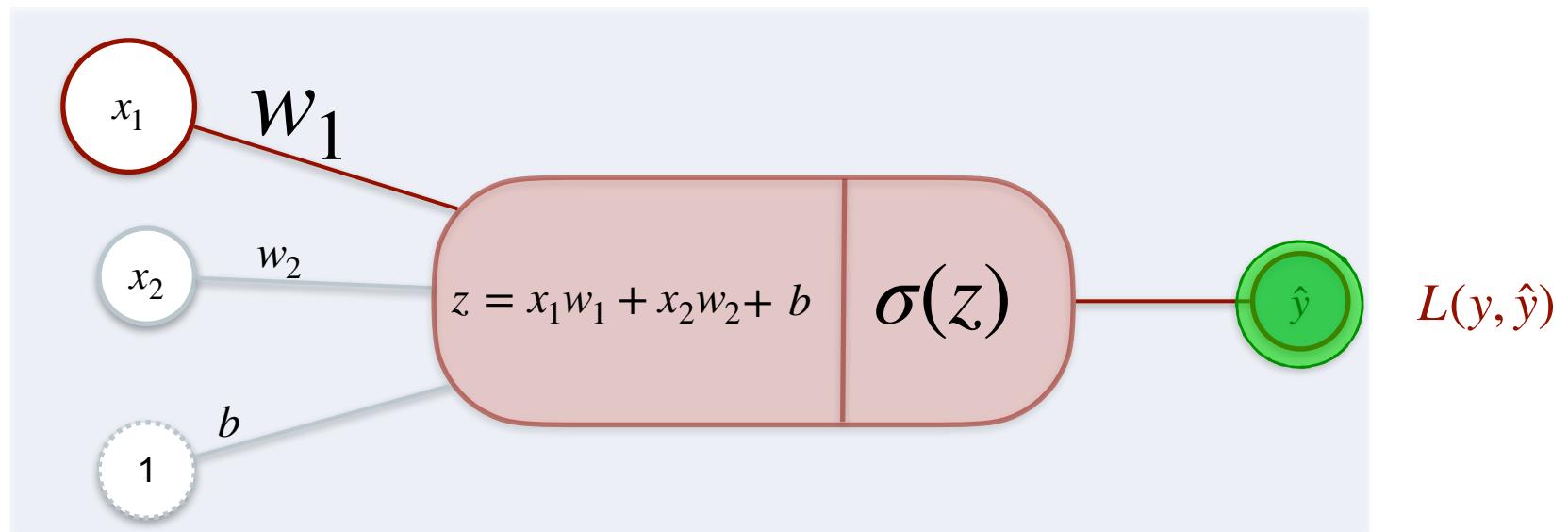
Classification With a Perceptron



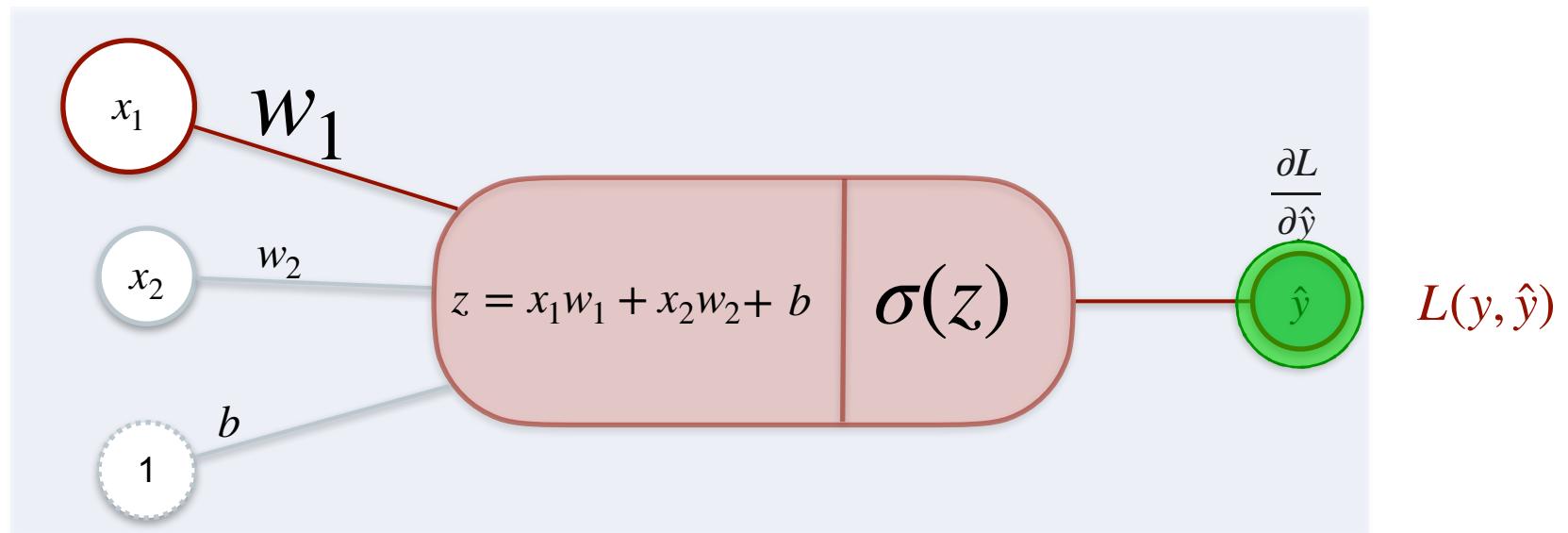
Classification With a Perceptron



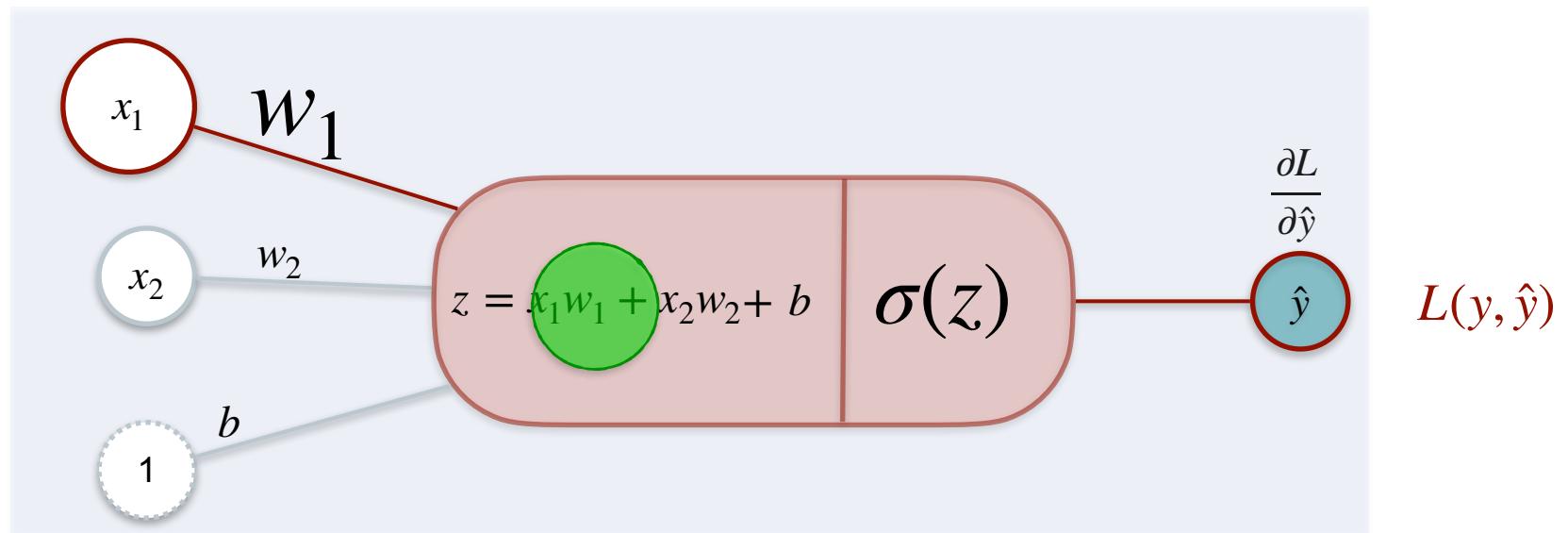
Classification With a Perceptron



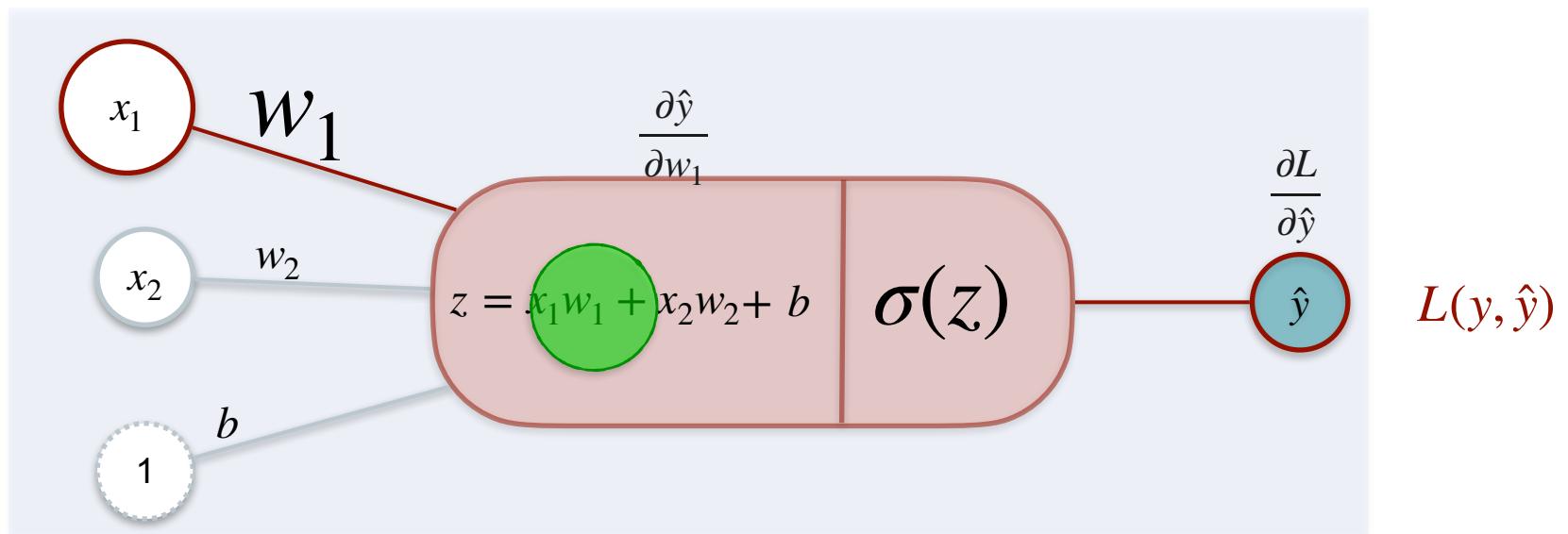
Classification With a Perceptron



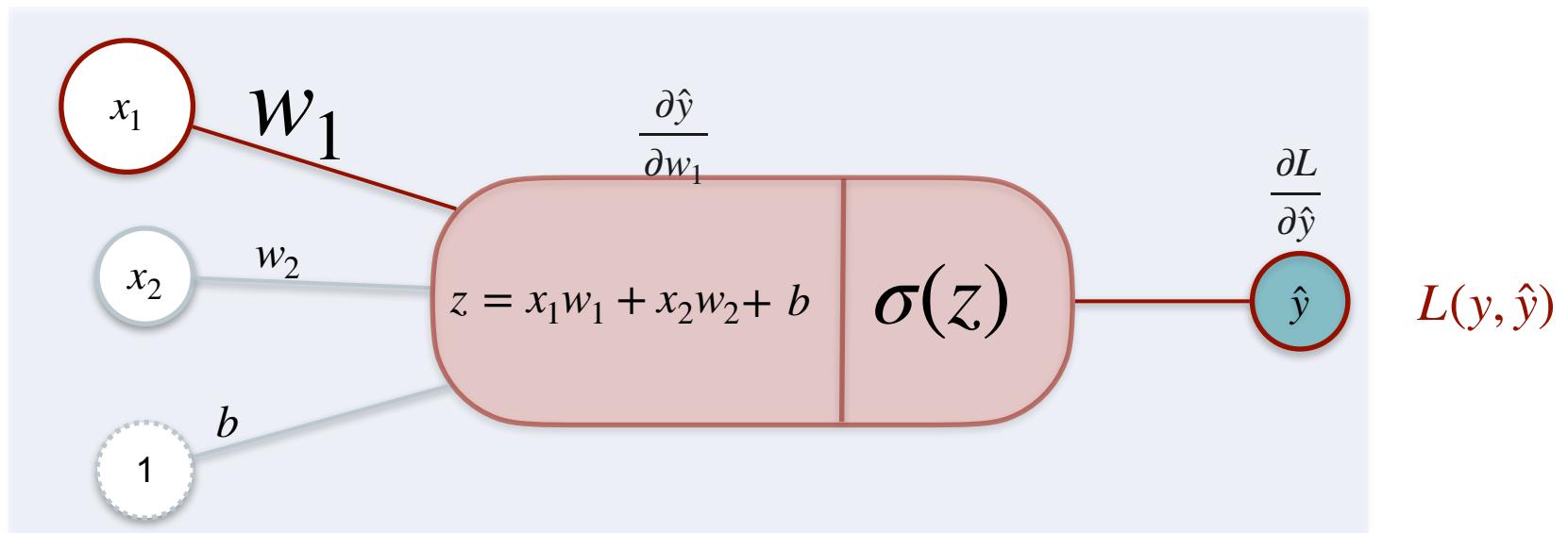
Classification With a Perceptron



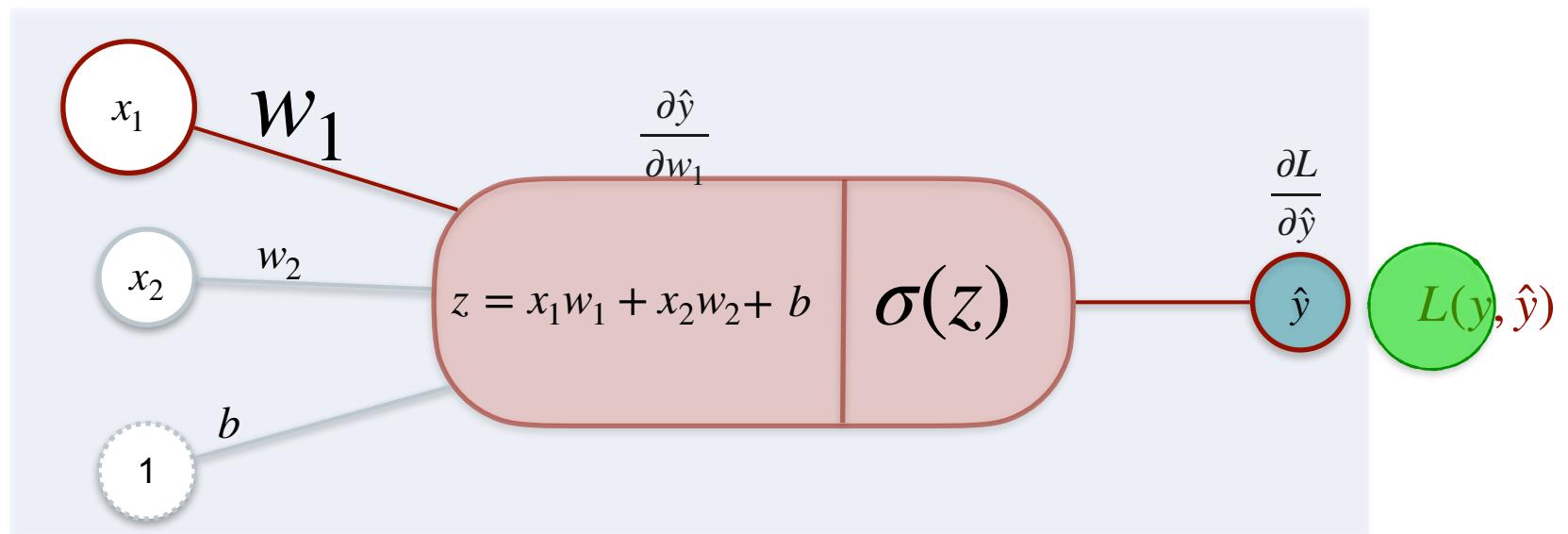
Classification With a Perceptron



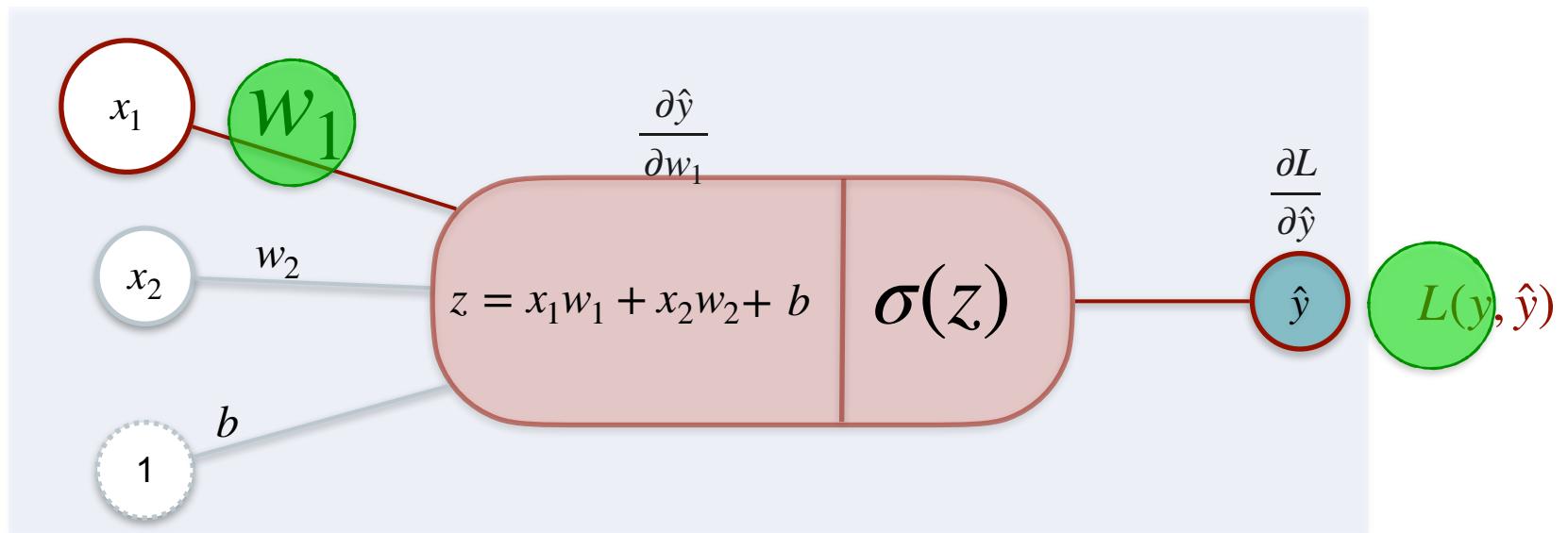
Classification With a Perceptron



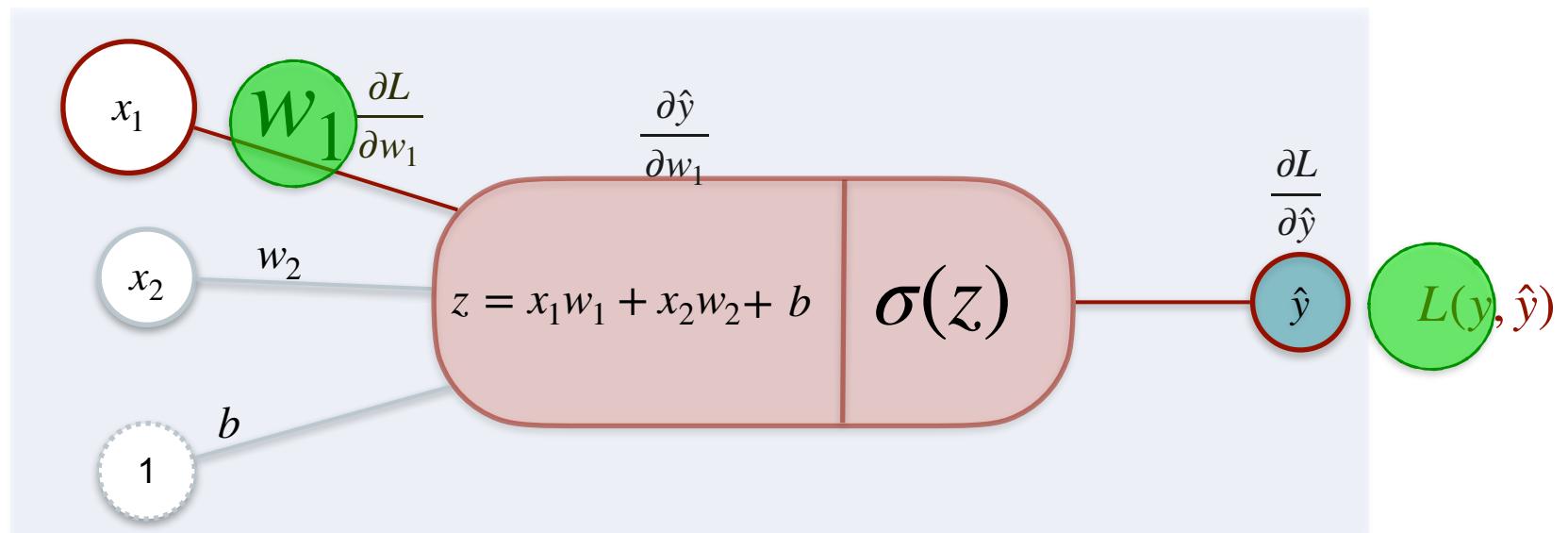
Classification With a Perceptron



Classification With a Perceptron

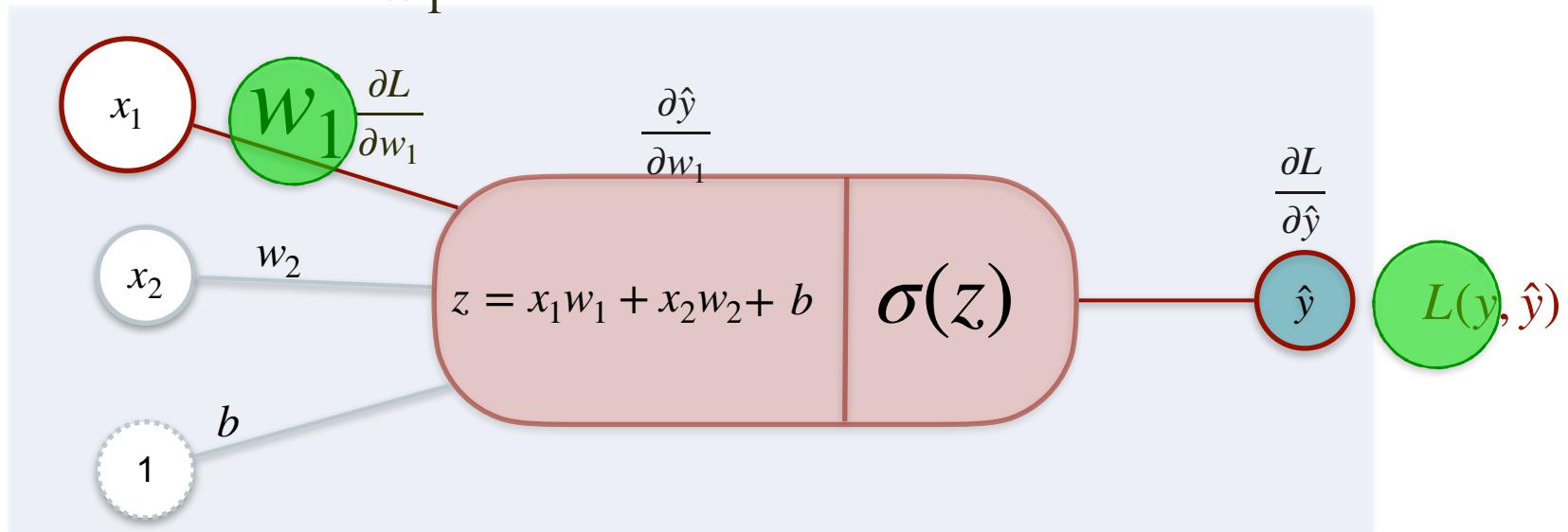


Classification With a Perceptron



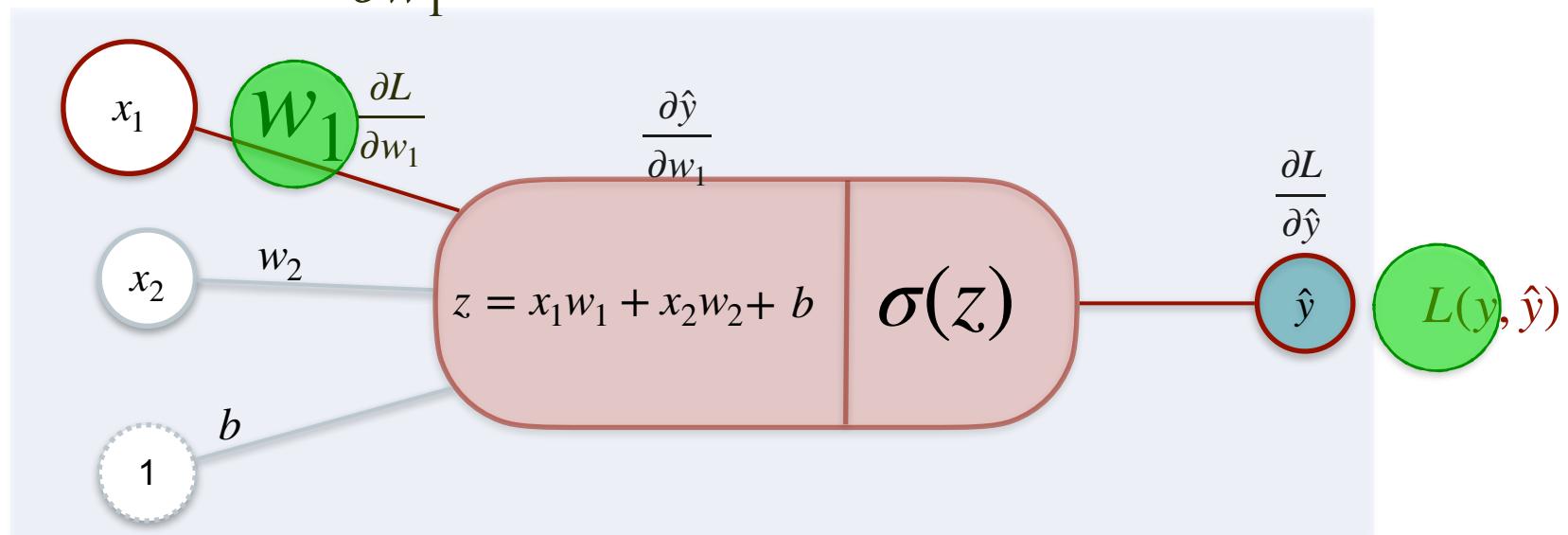
Classification With a Perceptron

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



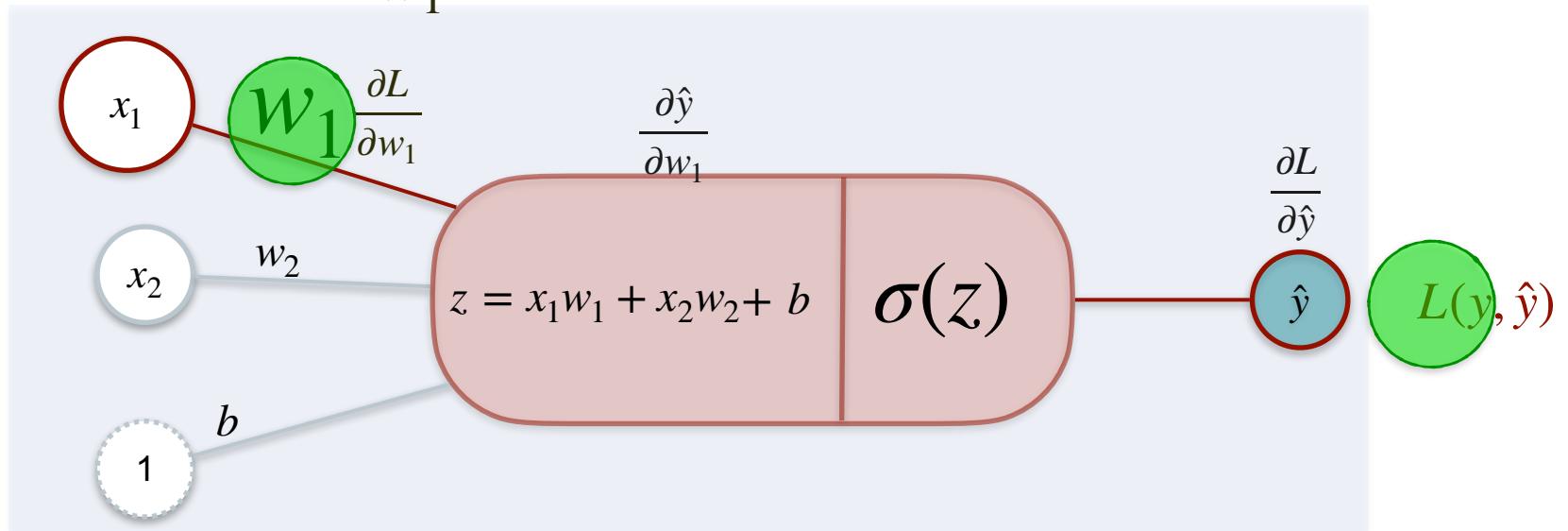
Classification With a Perceptron

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



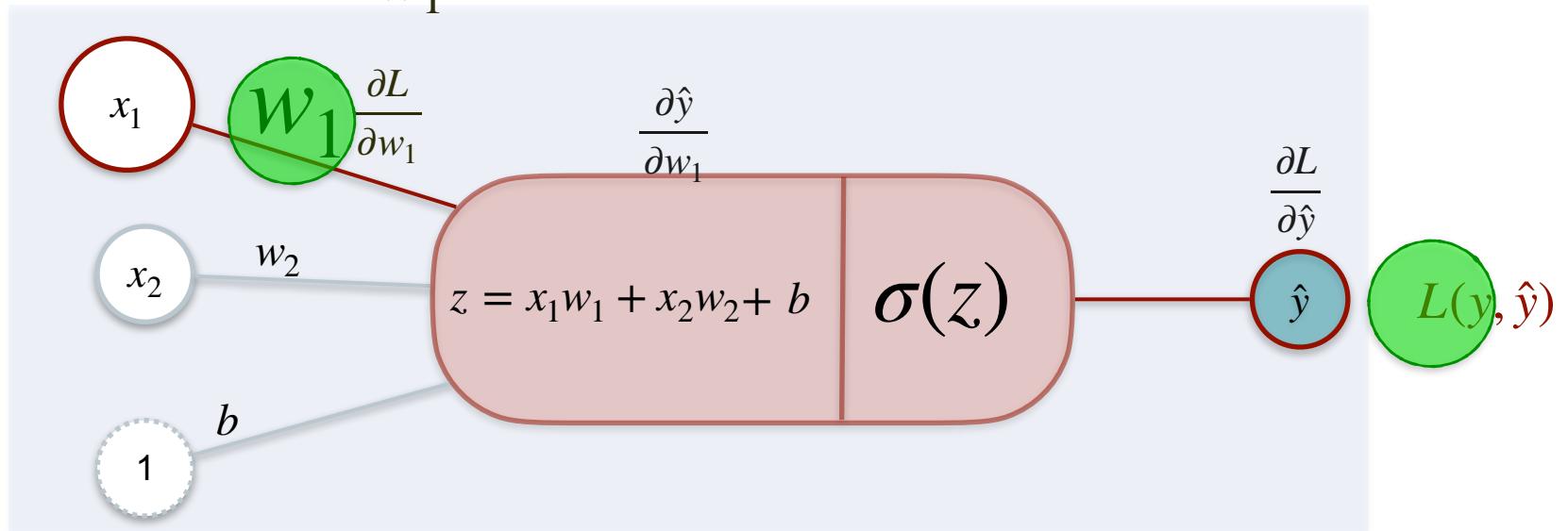
Classification With a Perceptron

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



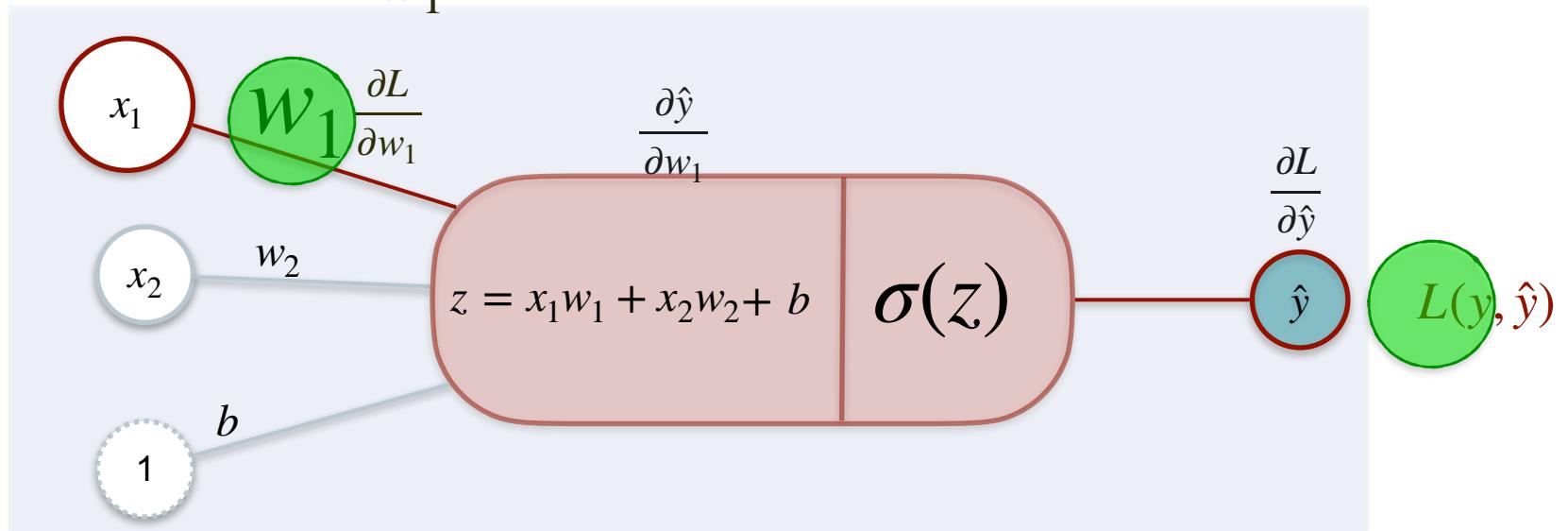
Classification With a Perceptron

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

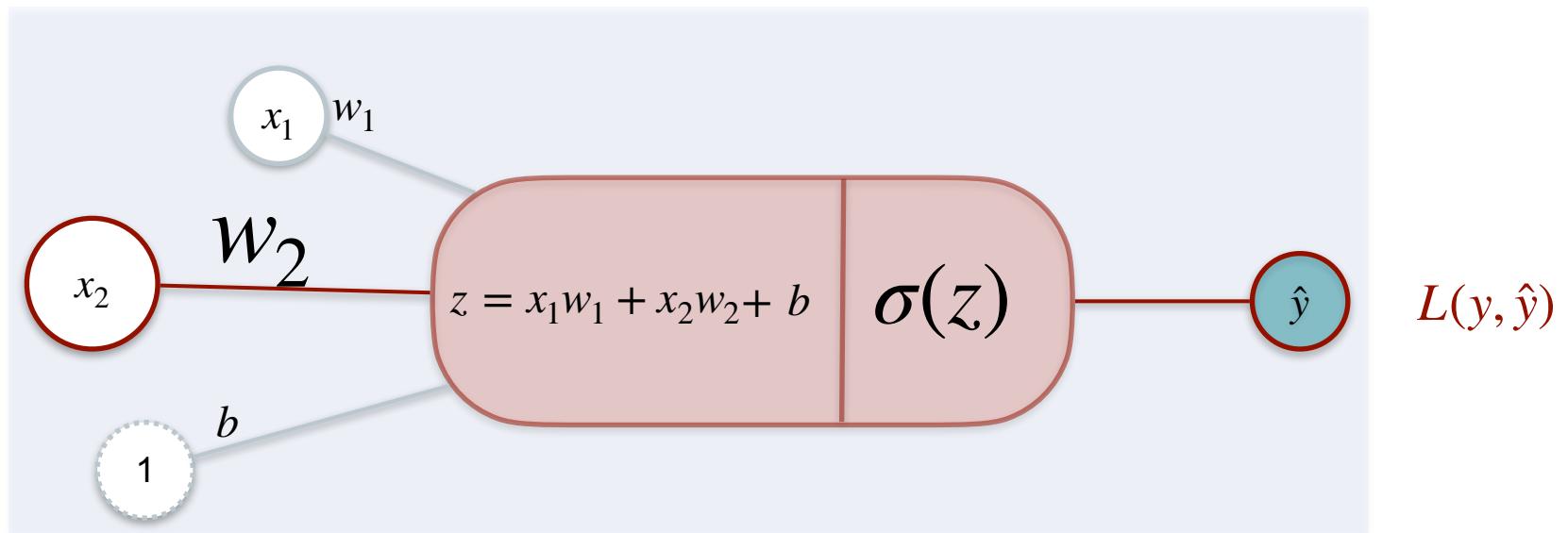


Classification With a Perceptron

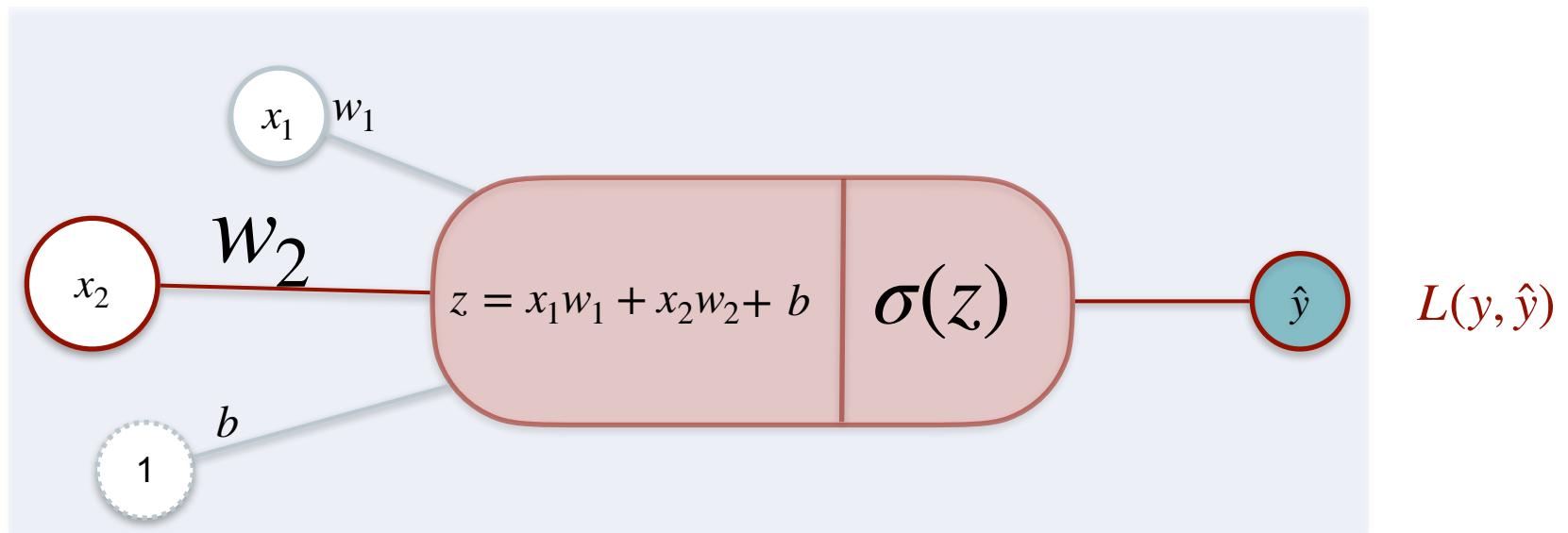
$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1}$$



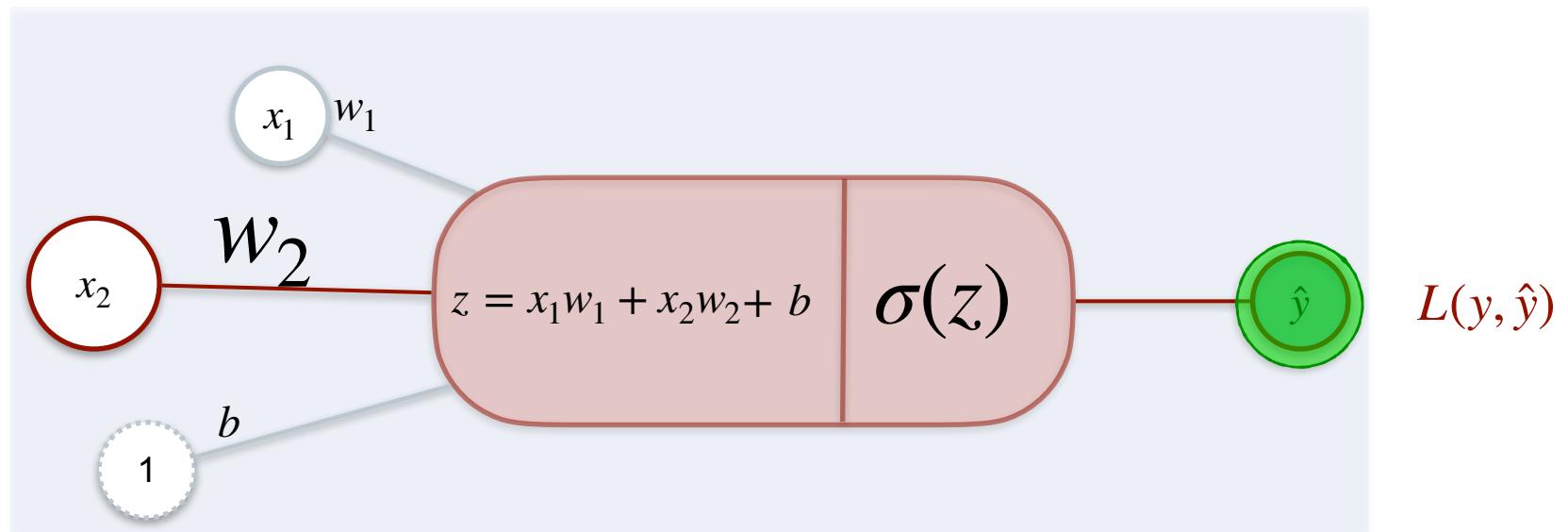
Classification With a Perceptron



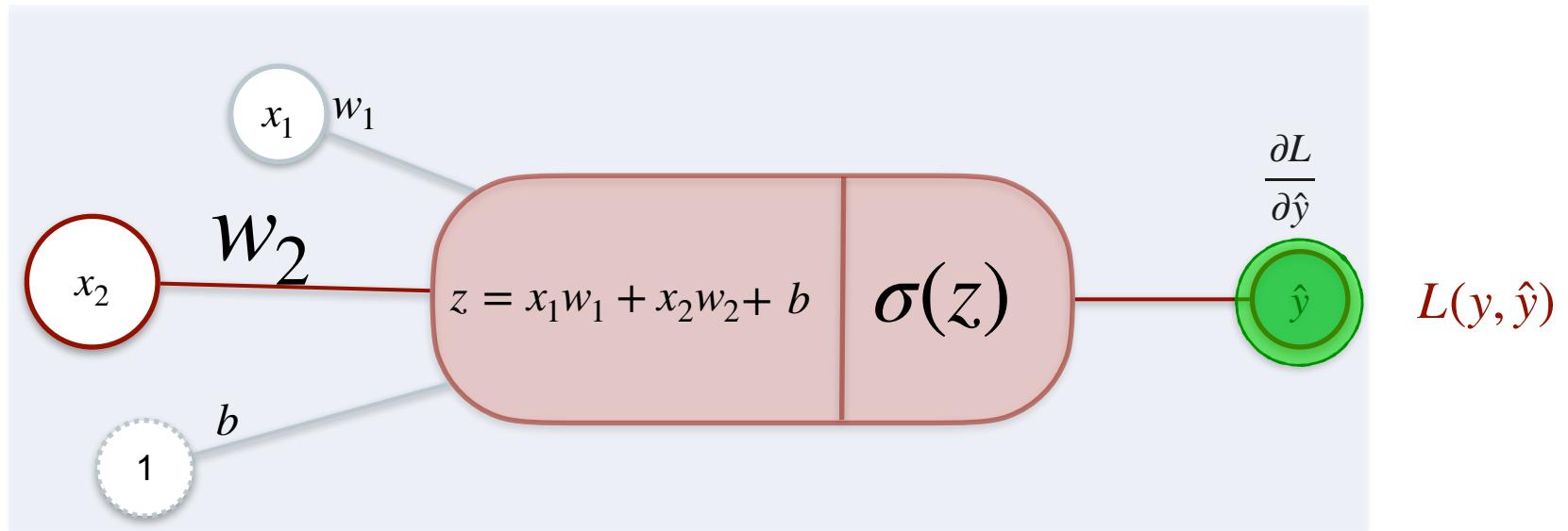
Classification With a Perceptron



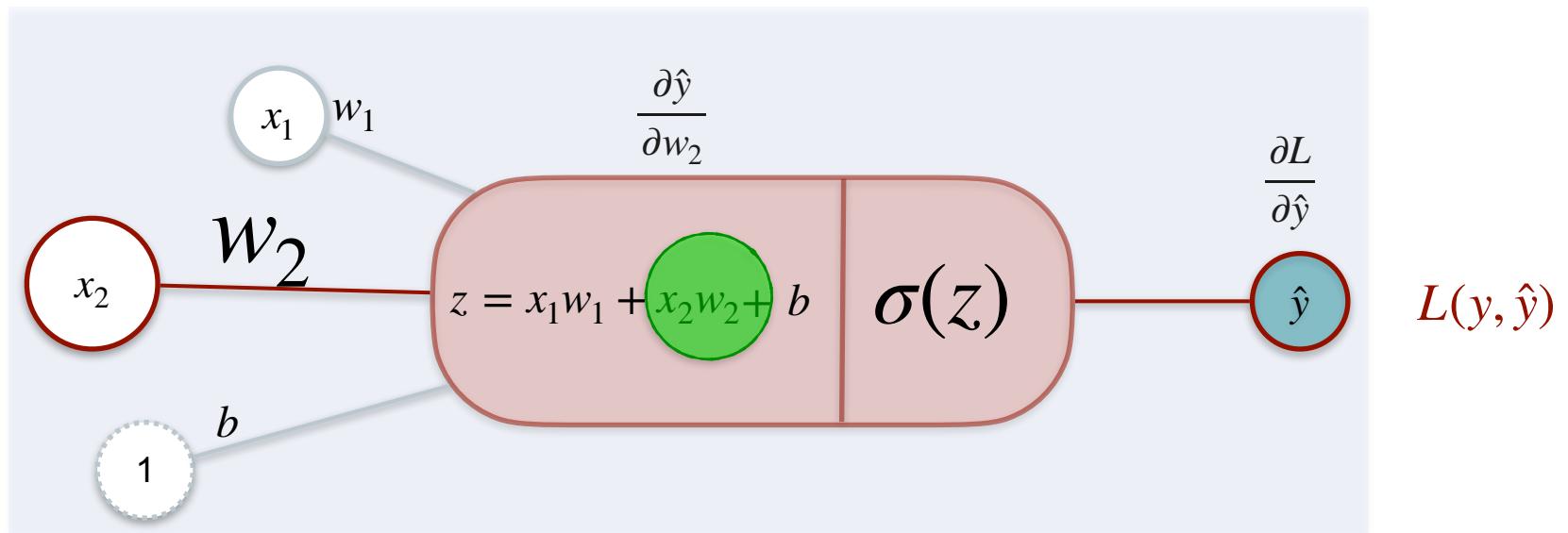
Classification With a Perceptron



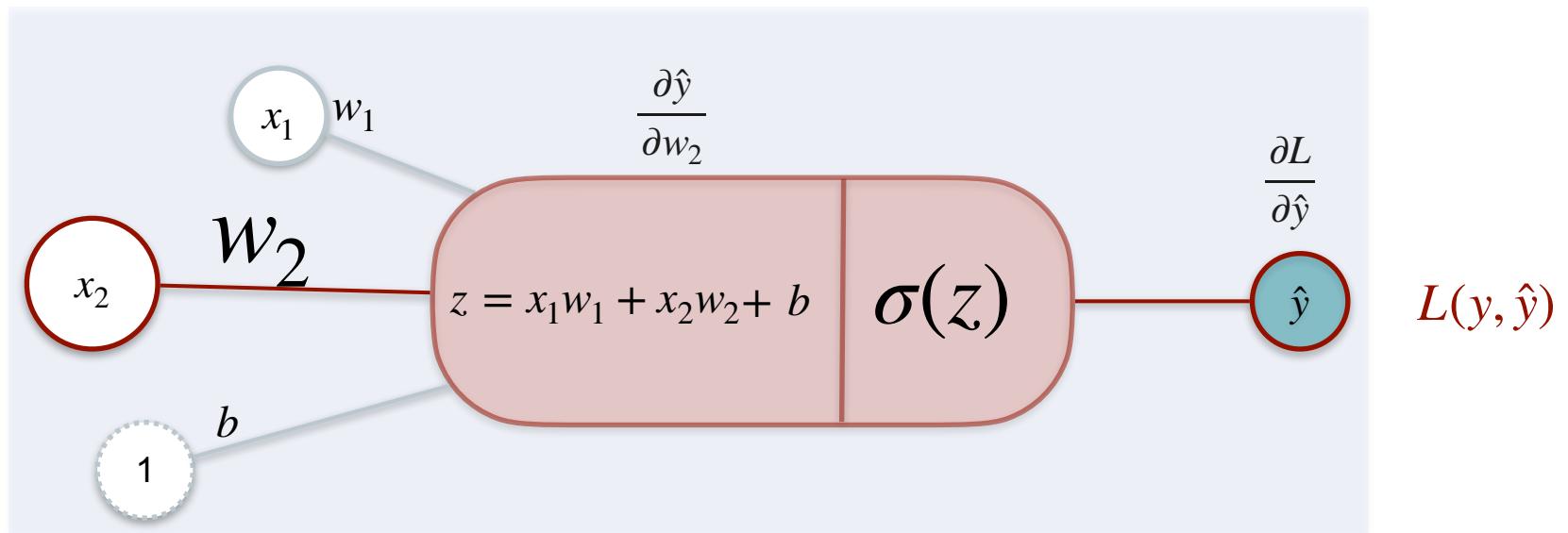
Classification With a Perceptron



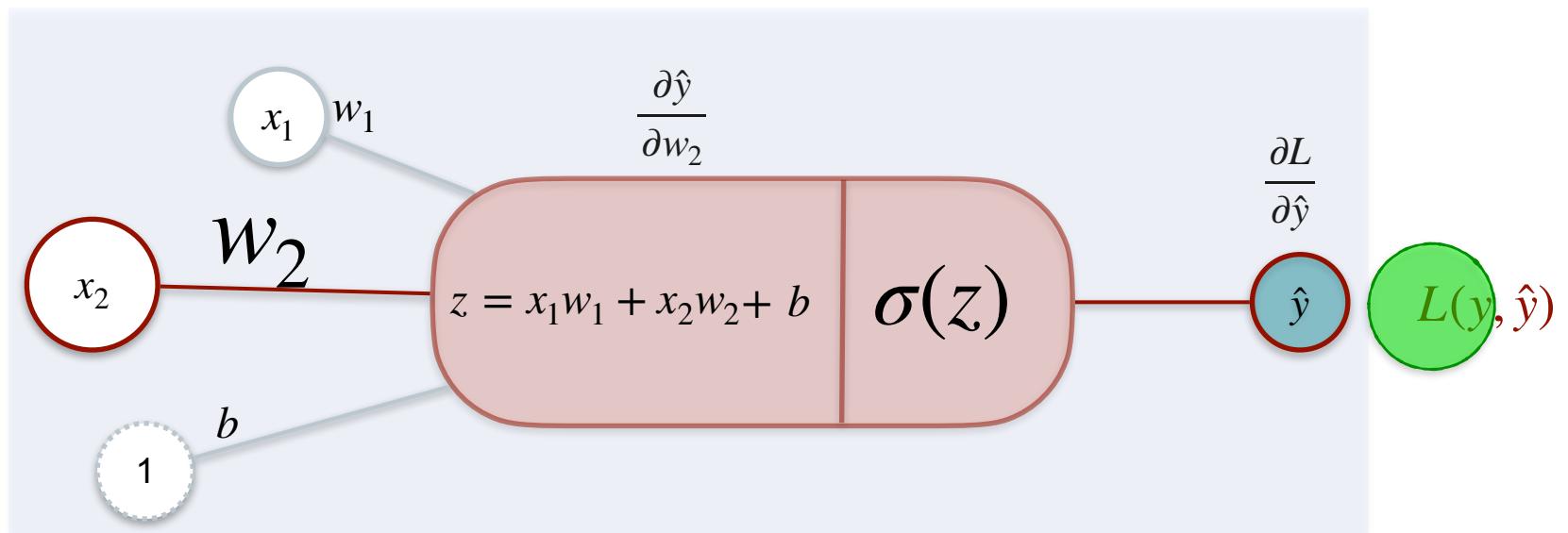
Classification With a Perceptron



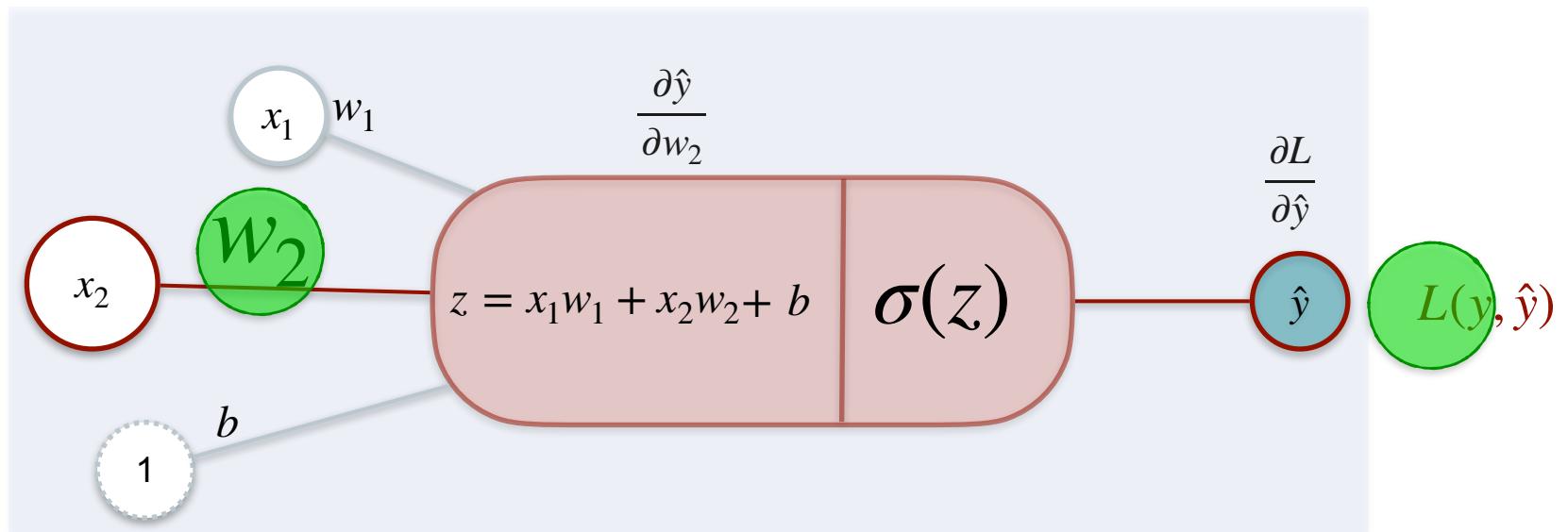
Classification With a Perceptron



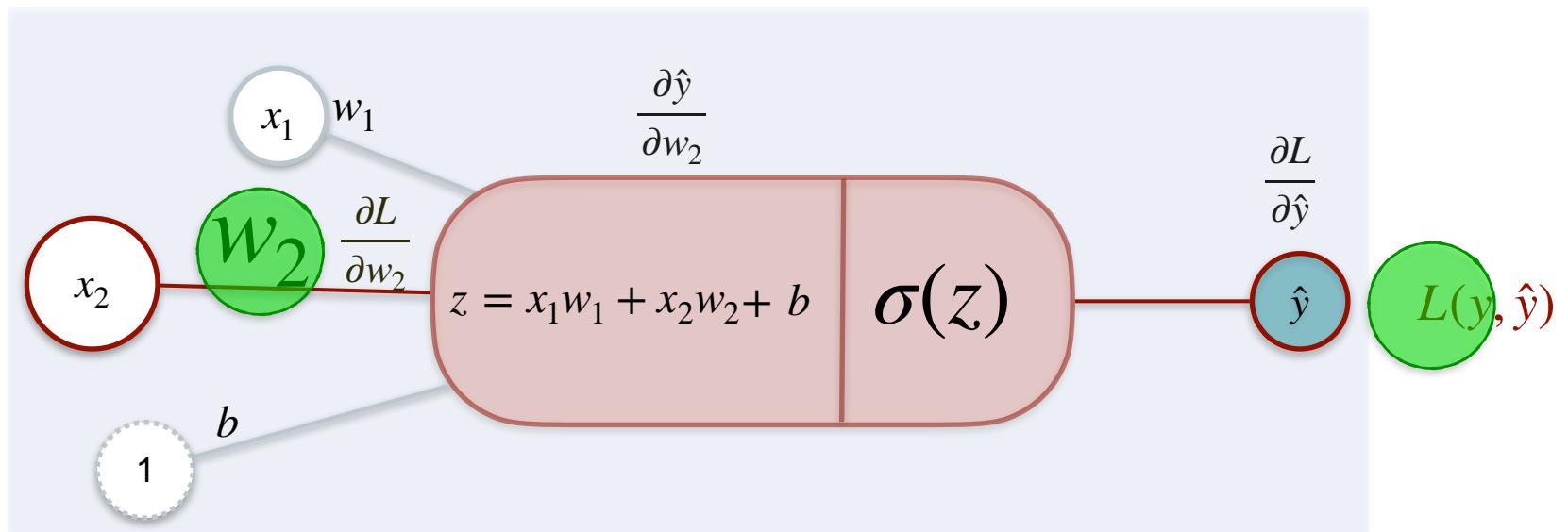
Classification With a Perceptron



Classification With a Perceptron

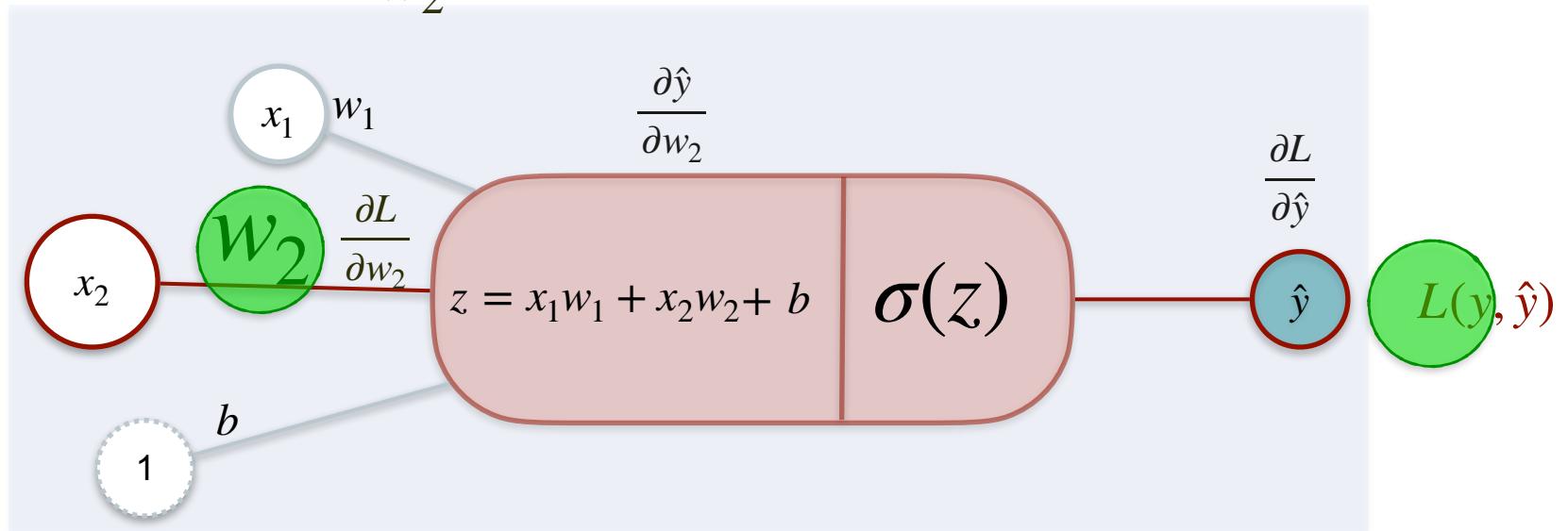


Classification With a Perceptron

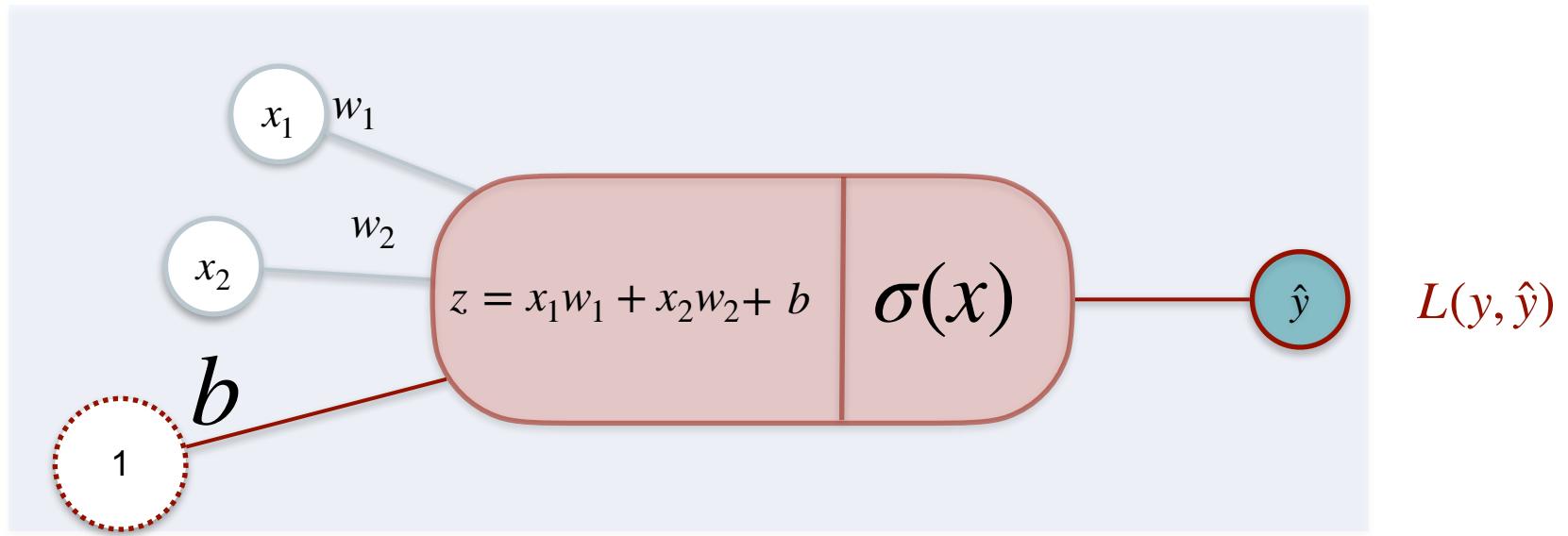


Classification With a Perceptron

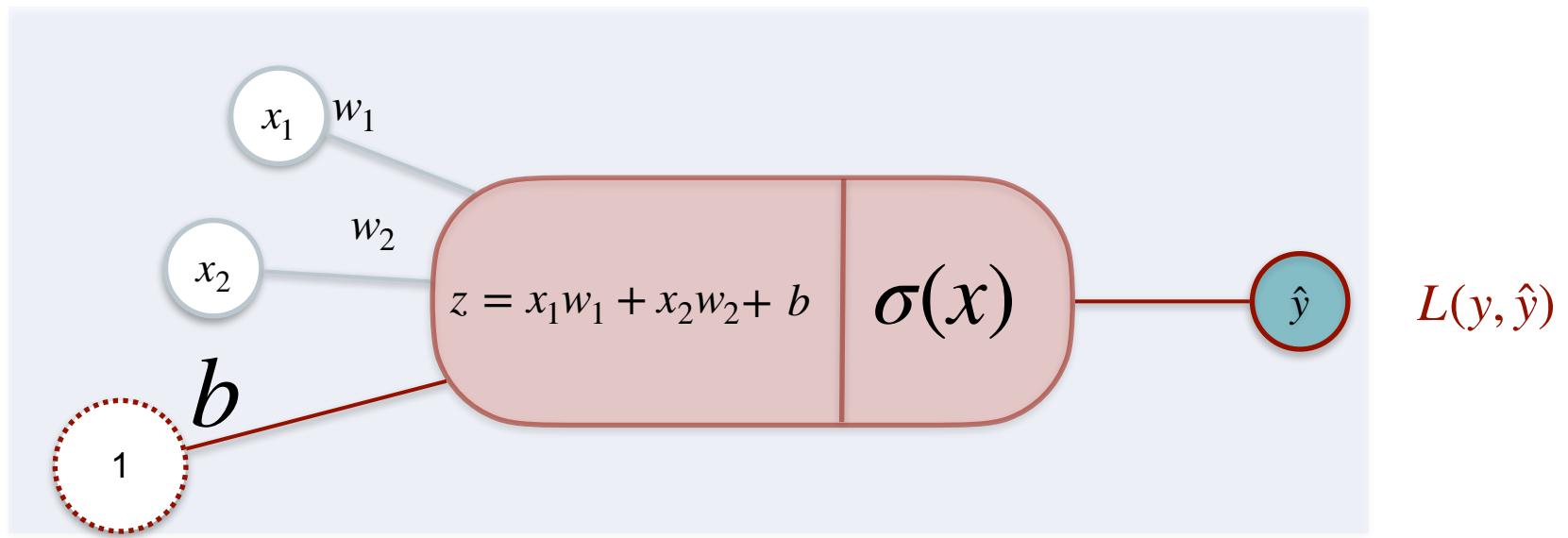
$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$



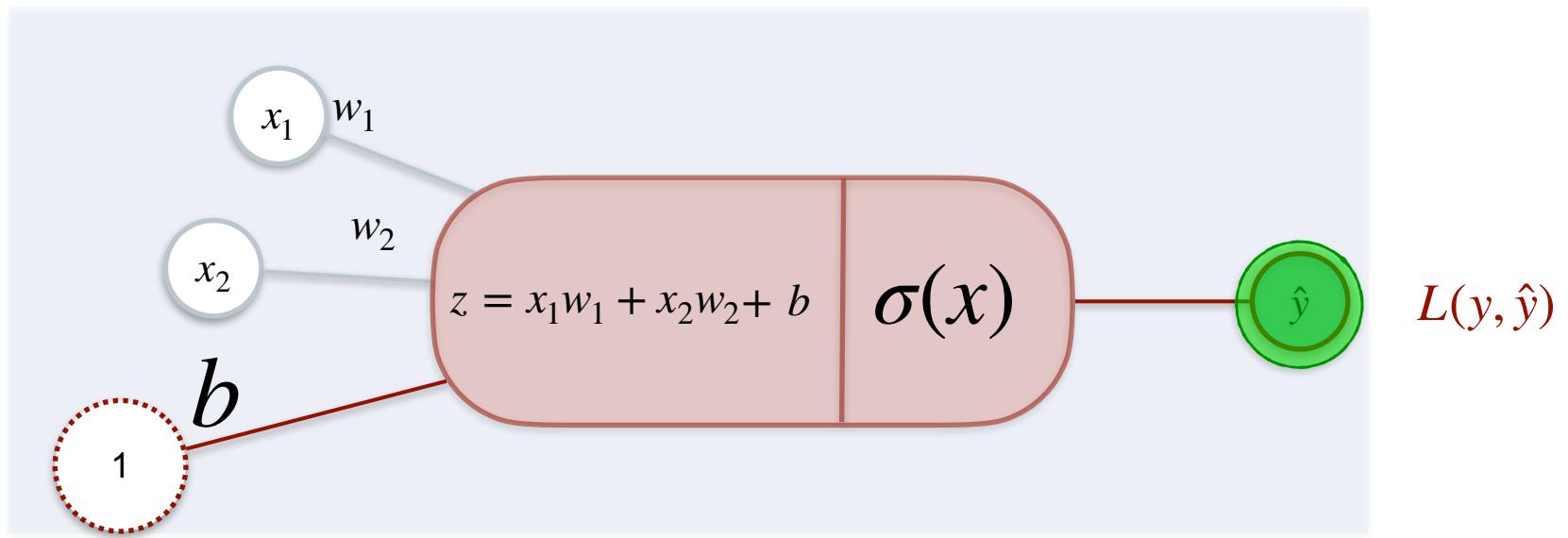
Classification With a Perceptron



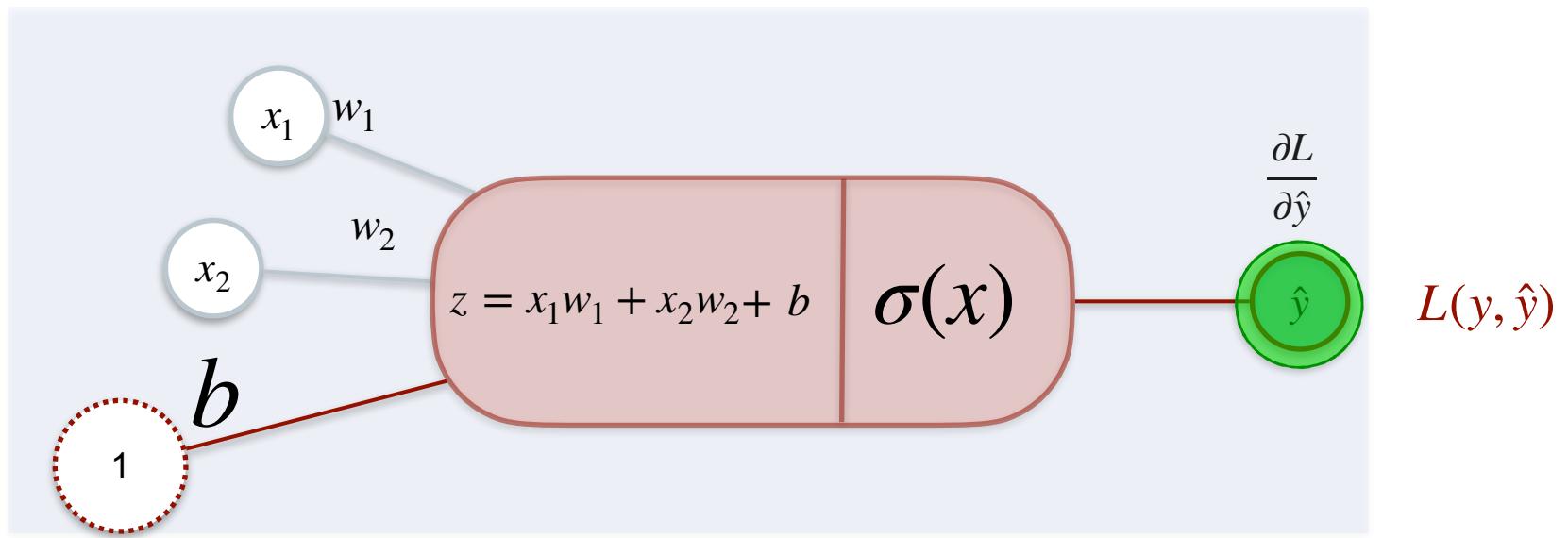
Classification With a Perceptron



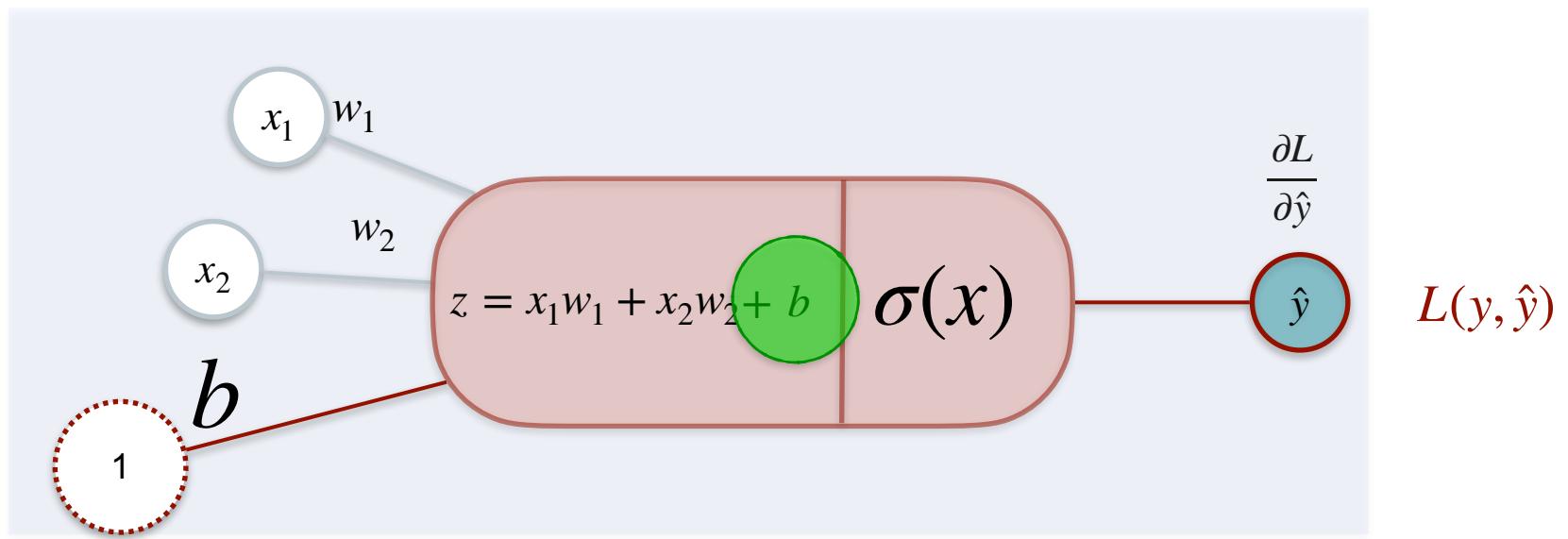
Classification With a Perceptron



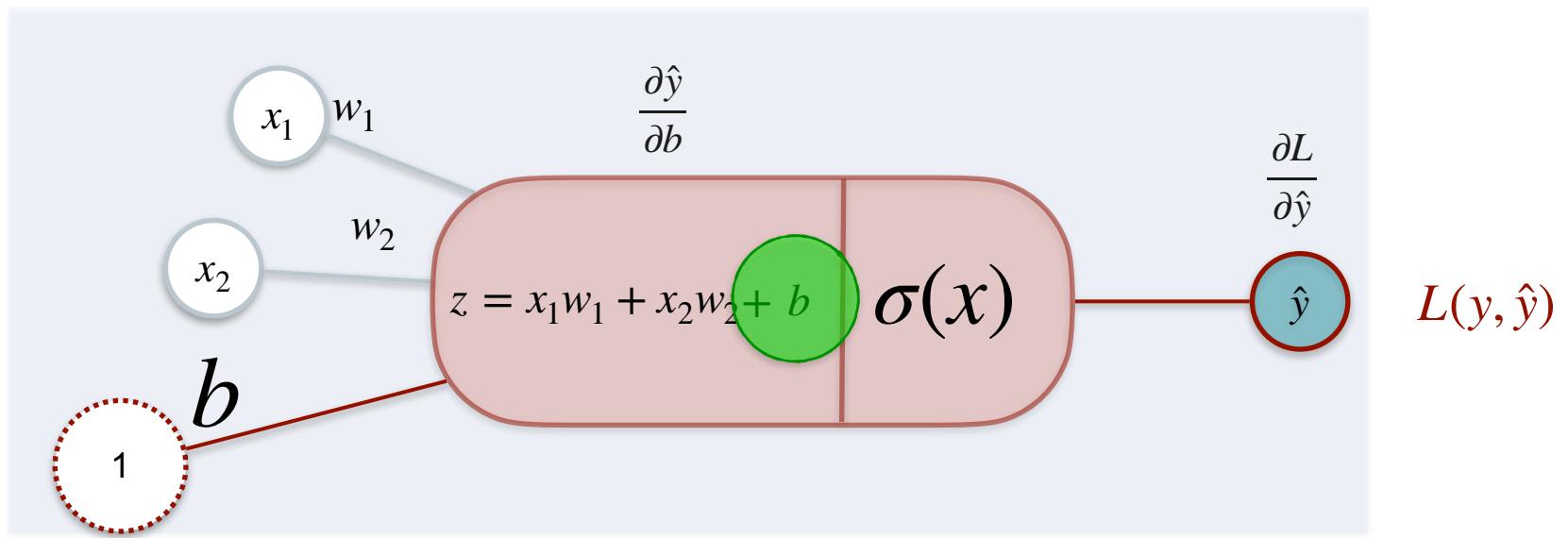
Classification With a Perceptron



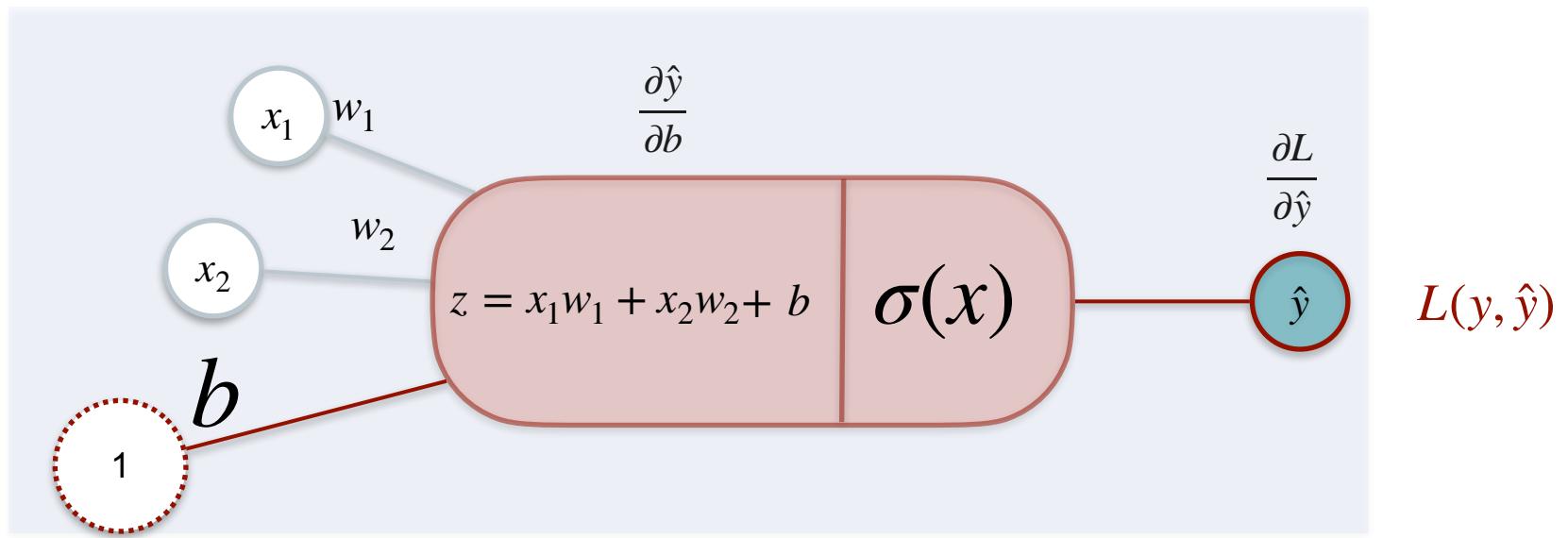
Classification With a Perceptron



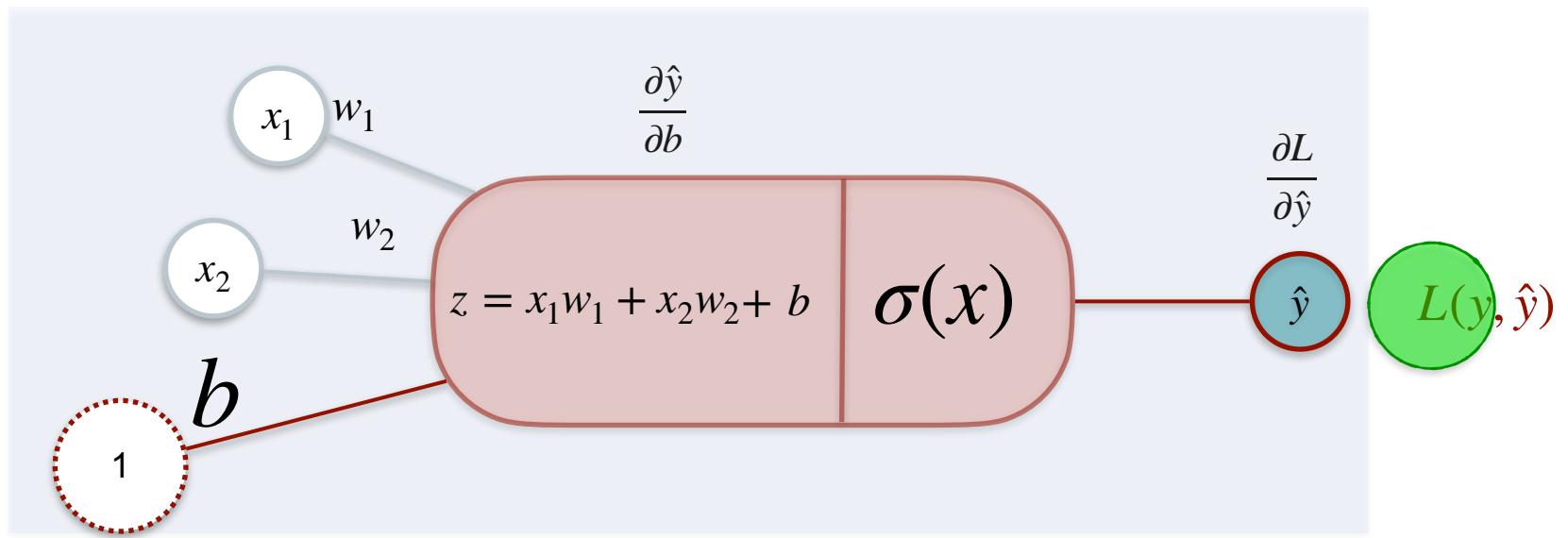
Classification With a Perceptron



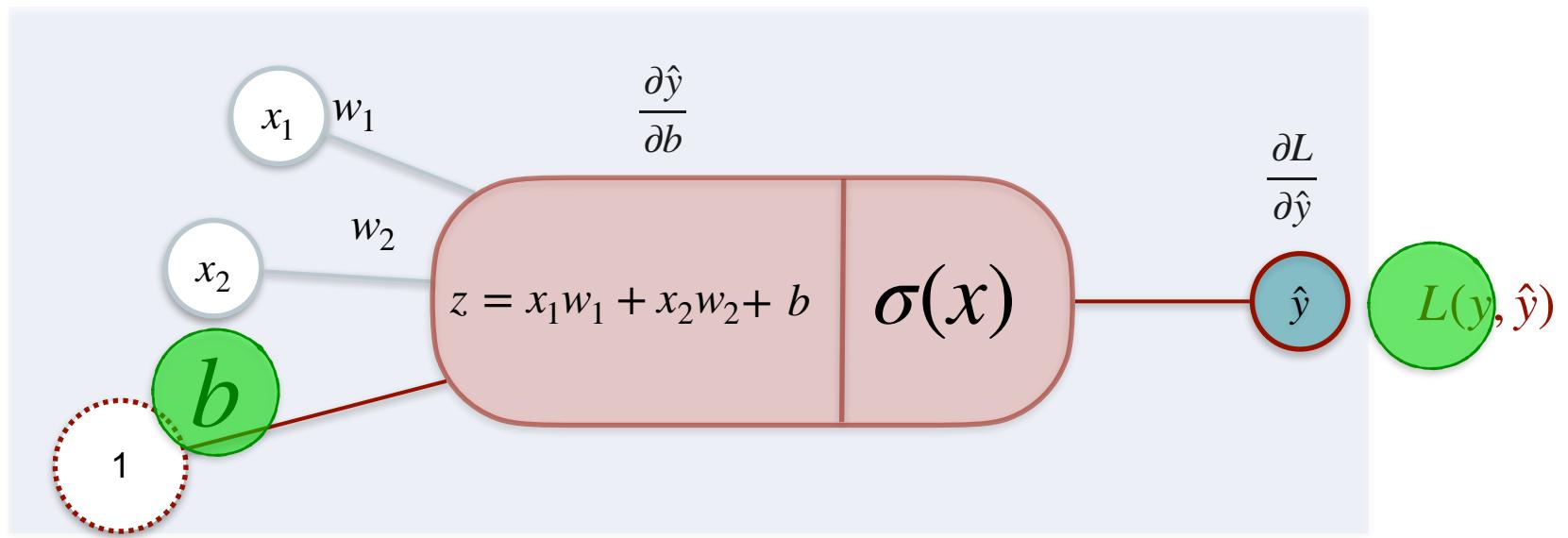
Classification With a Perceptron



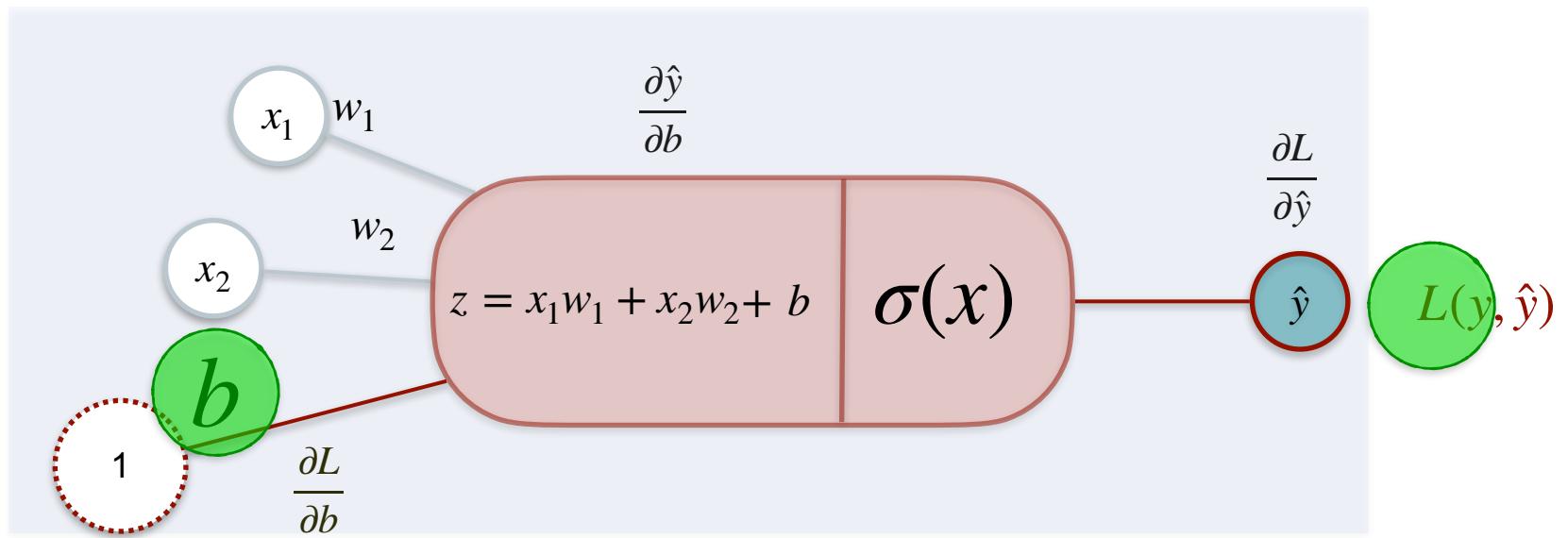
Classification With a Perceptron



Classification With a Perceptron

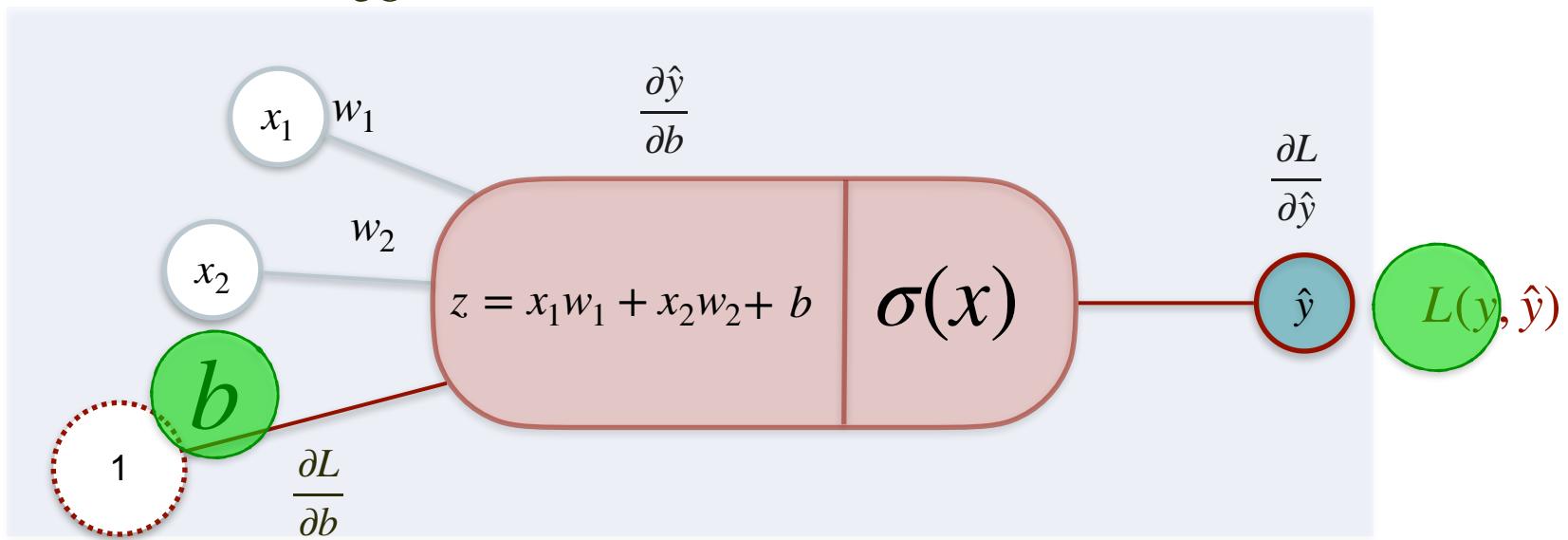


Classification With a Perceptron



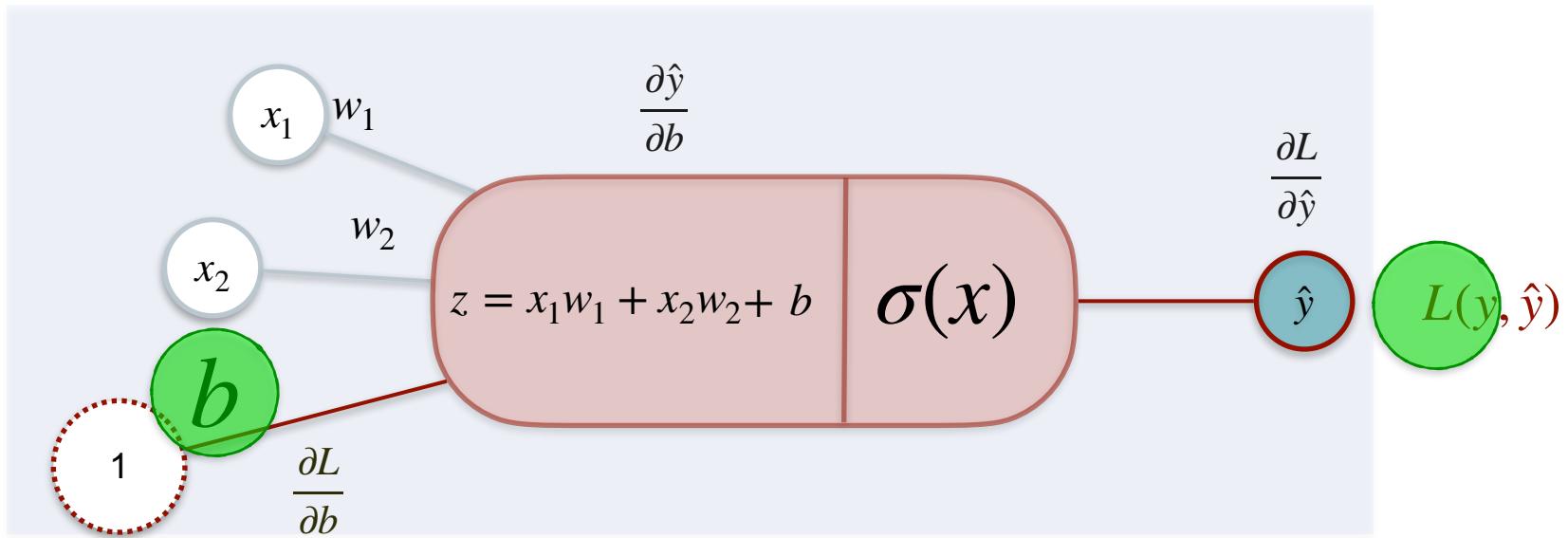
Classification With a Perceptron

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



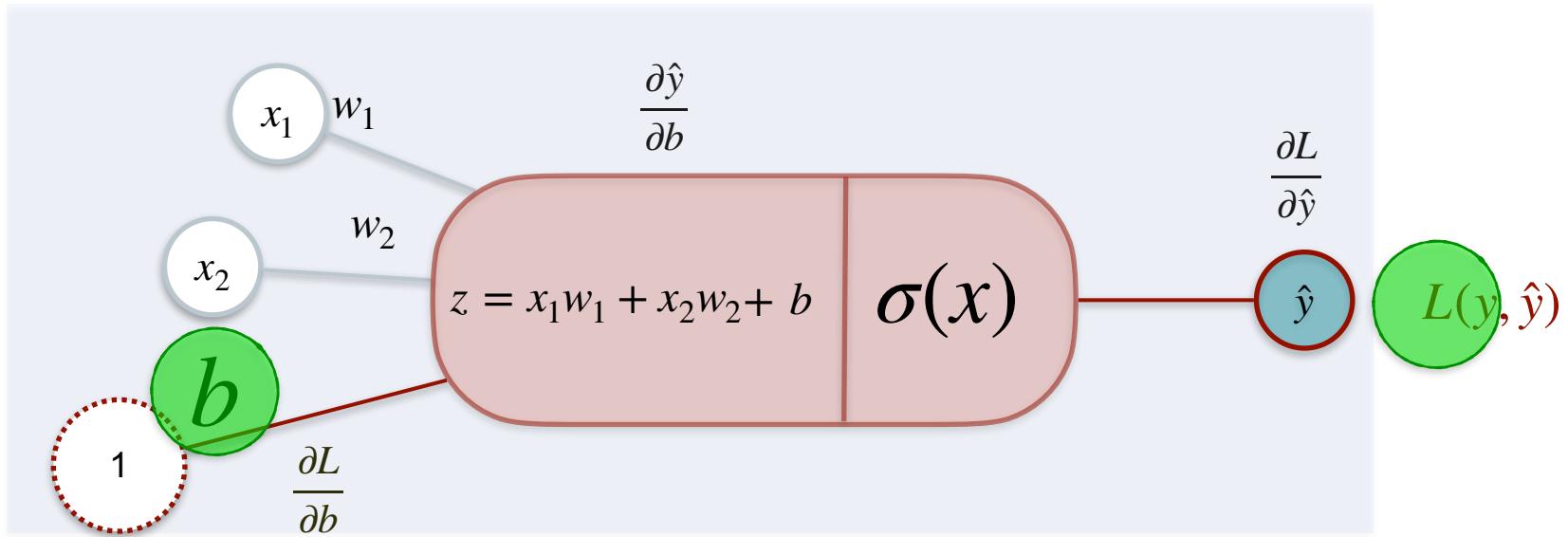
Classification With a Perceptron

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



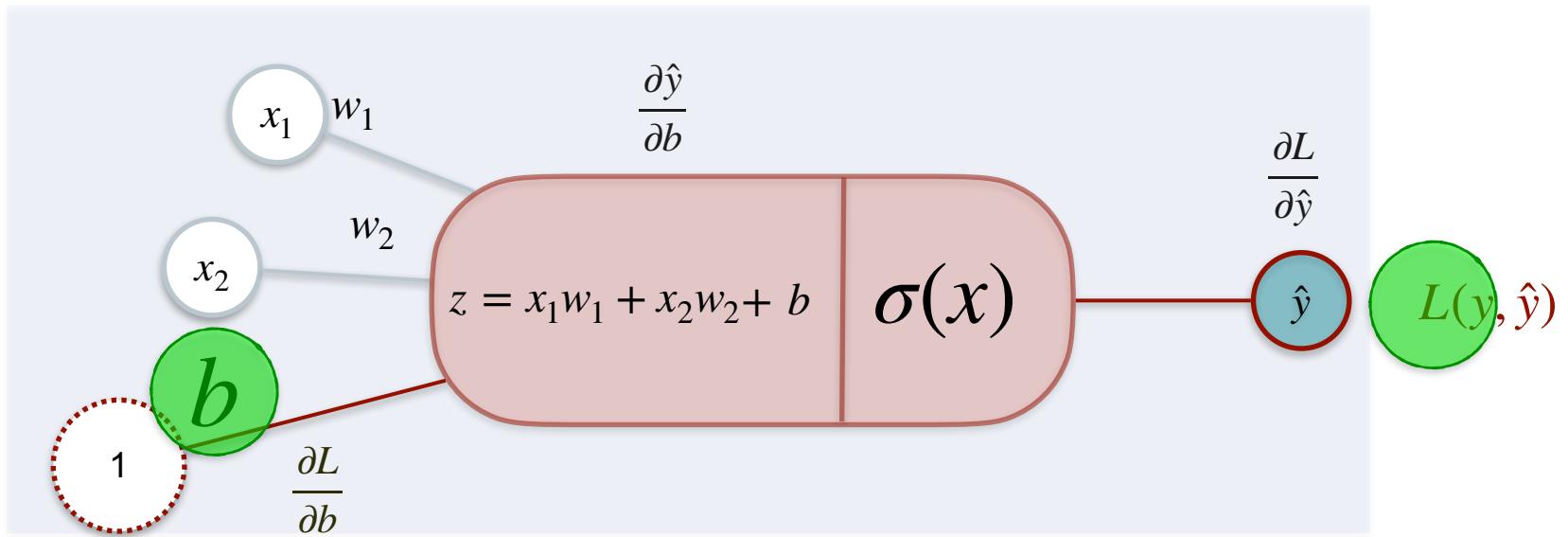
Classification With a Perceptron

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



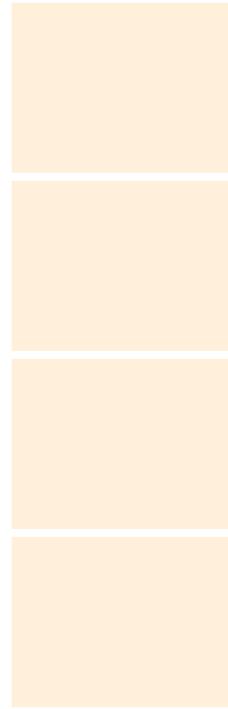
Classification With a Perceptron

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



Classification With a Perceptron

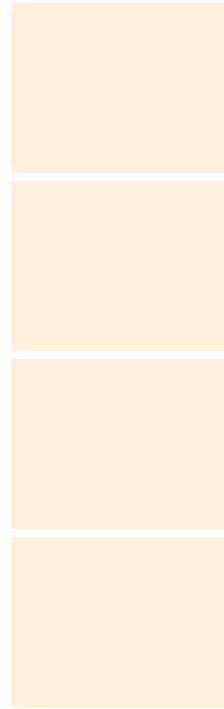
$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b}$$



Classification With a Perceptron

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

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

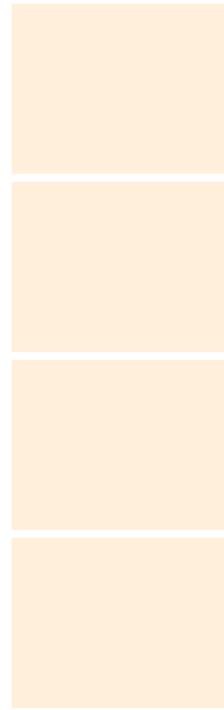


Classification With a Perceptron

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

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

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



Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

?

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

Classification With a Perceptron

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

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

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

Classification With a Perceptron

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

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

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

Classification With a Perceptron

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

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

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

Classification With a Perceptron

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

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

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

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

Classification With a Perceptron

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

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

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

$$= \frac{-y + \cancel{y\hat{y}} + \hat{y} - y\hat{y}}{\hat{y}(1 - \hat{y})}$$

Classification With a Perceptron

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

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

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

$$= \frac{-y + \cancel{y\hat{y}} + \hat{y} - \cancel{y\hat{y}}}{\hat{y}(1 - \hat{y})}$$

Classification With a Perceptron

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

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

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

$$= \frac{-y + \cancel{y\hat{y}} + \hat{y} - \cancel{y\hat{y}}}{\hat{y}(1 - \hat{y})}$$

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

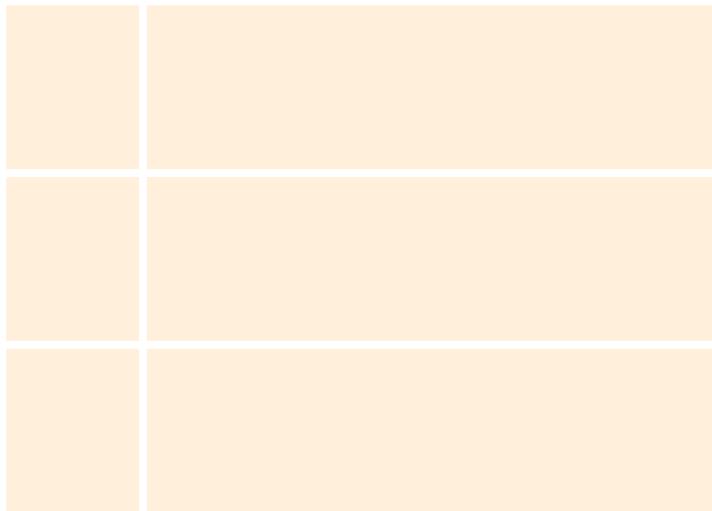
Classification With a Perceptron

Classification With a Perceptron

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

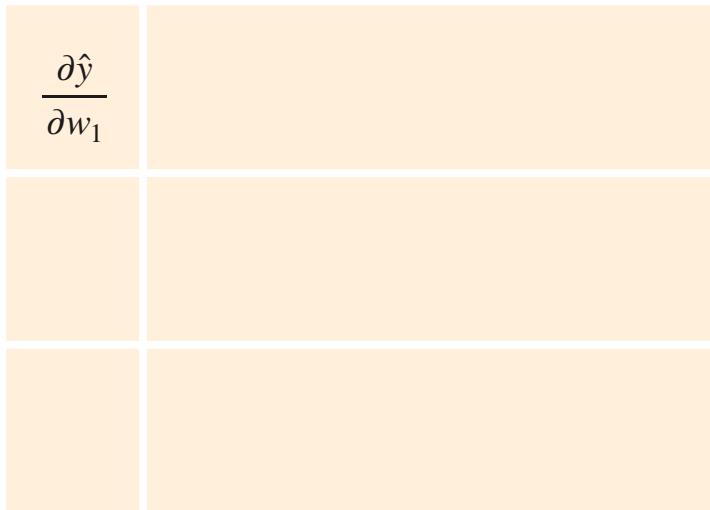
Classification With a Perceptron

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



Classification With a Perceptron

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



Classification With a Perceptron

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

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

Classification With a Perceptron

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

$\frac{\partial \hat{y}}{\partial w_1}$	$= \hat{y}(1 - \hat{y})x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	

Classification With a Perceptron

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

$\frac{\partial \hat{y}}{\partial w_1}$	$= \hat{y}(1 - \hat{y})x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	$= \hat{y}(1 - \hat{y})x_2$

Classification With a Perceptron

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

$\frac{\partial \hat{y}}{\partial w_1}$	$= \hat{y}(1 - \hat{y})x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	$= \hat{y}(1 - \hat{y})x_2$
$\frac{\partial \hat{y}}{\partial b}$	

Classification With a Perceptron

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

$\frac{\partial \hat{y}}{\partial w_1}$	$= \hat{y}(1 - \hat{y})x_1$
$\frac{\partial \hat{y}}{\partial w_2}$	$= \hat{y}(1 - \hat{y})x_2$
$\frac{\partial \hat{y}}{\partial b}$	$= \hat{y}(1 - \hat{y})$

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

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

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

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

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

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

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

Classification With a Perceptron

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

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_2$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_2$$

Classification With a Perceptron

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})}$$

$$\frac{\partial \hat{y}}{\partial b} = \hat{y}(1 - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w_1} = \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial \hat{y}}{\partial w_2} = \hat{y}(1 - \hat{y})x_2$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_2$$

Classification With a Perceptron

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_2$$

Classification With a Perceptron

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} = \frac{-(y - \hat{y})}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})x_2$$

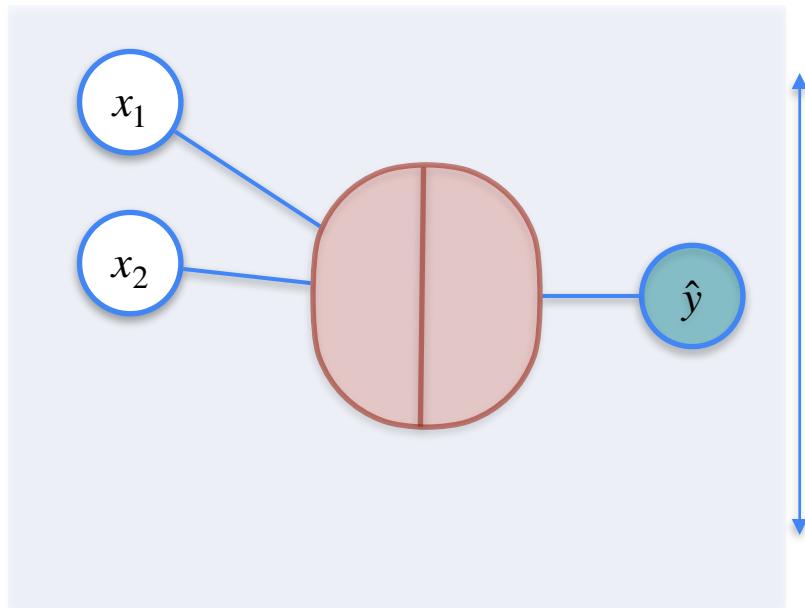
Classification With a Perceptron

$$\frac{\partial L}{\partial b} = -(y - \hat{y})$$

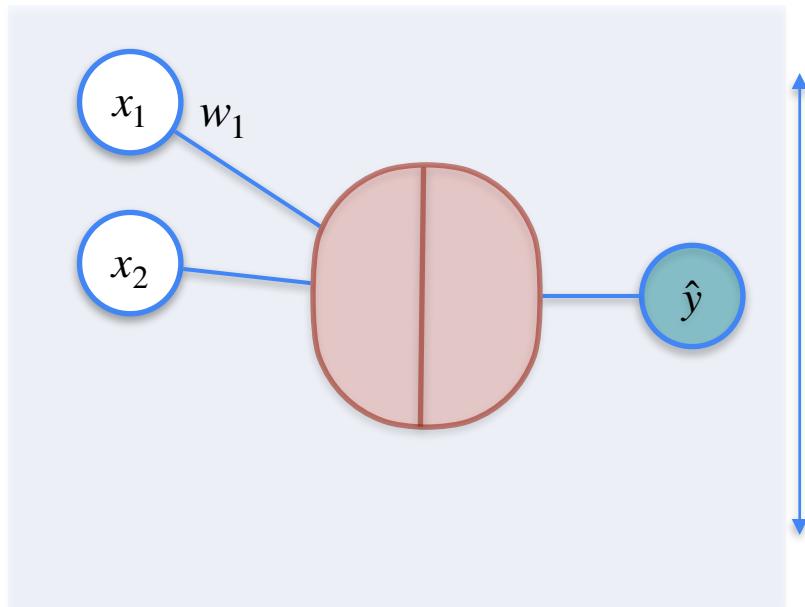
$$\frac{\partial L}{\partial w_1} = -(y - \hat{y})x_1$$

$$\frac{\partial L}{\partial w_2} = -(y - \hat{y})x_2$$

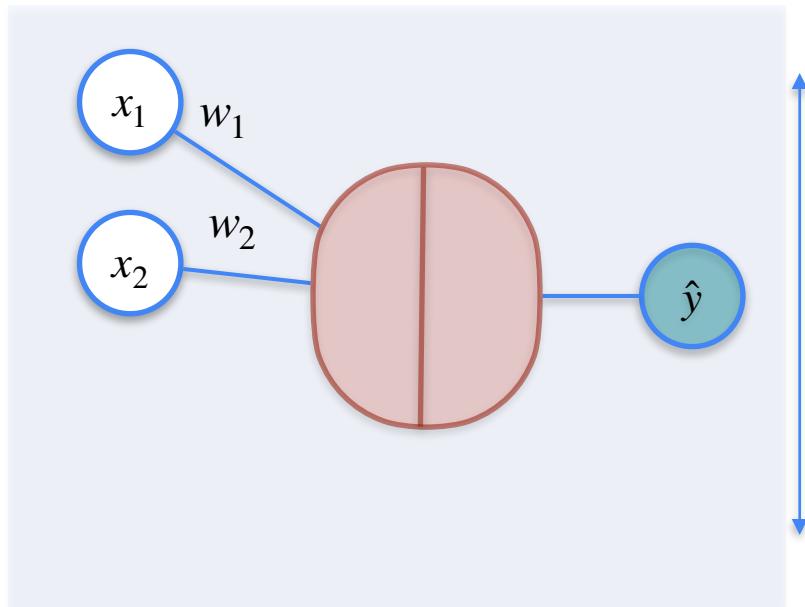
Classification With a Perceptron



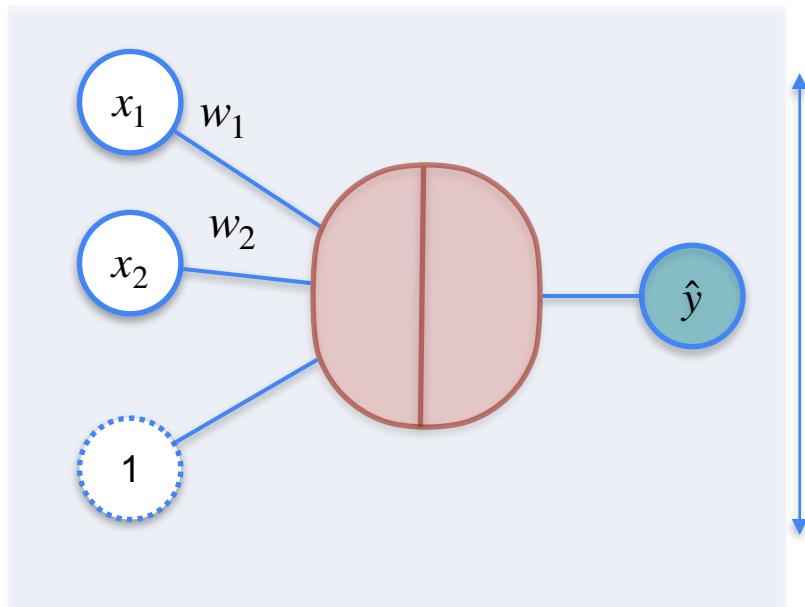
Classification With a Perceptron



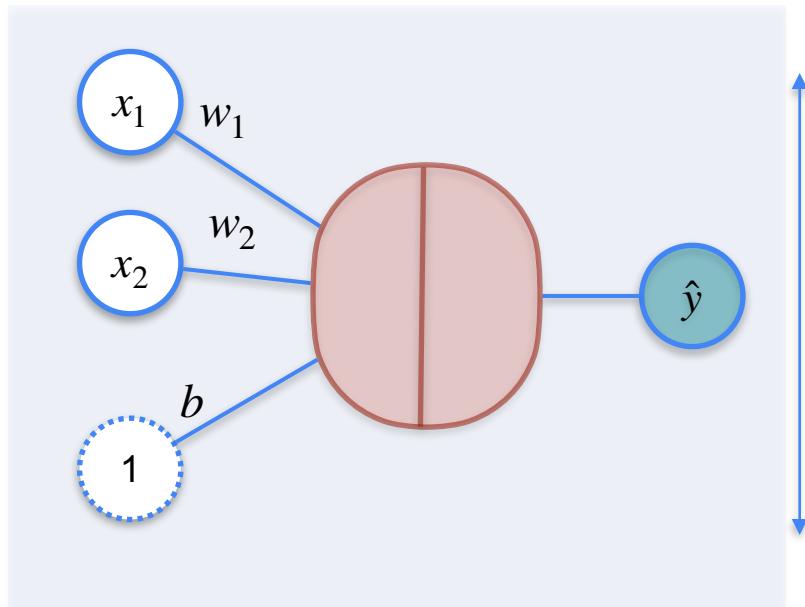
Classification With a Perceptron



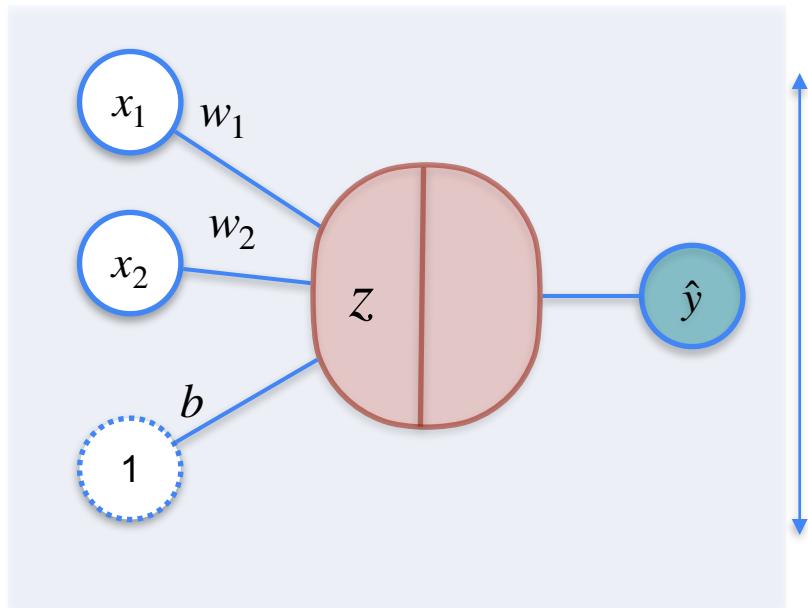
Classification With a Perceptron



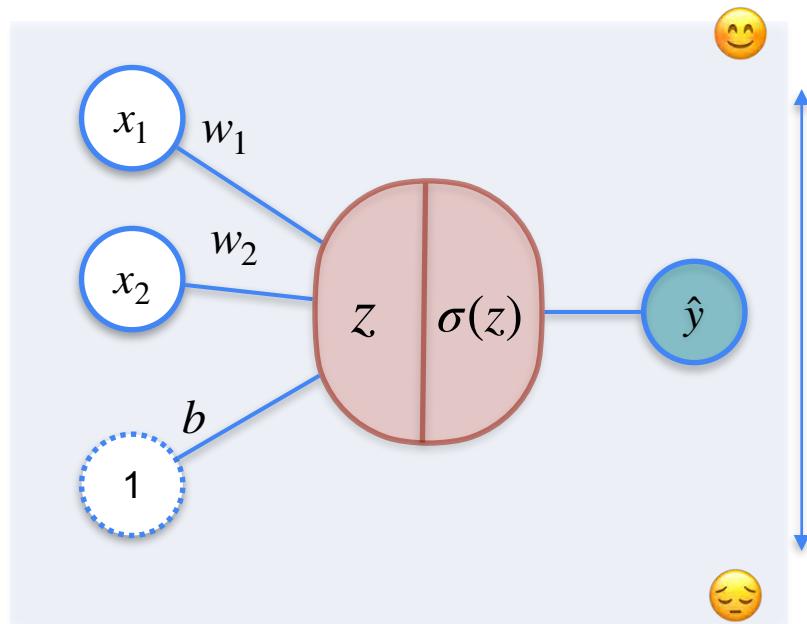
Classification With a Perceptron



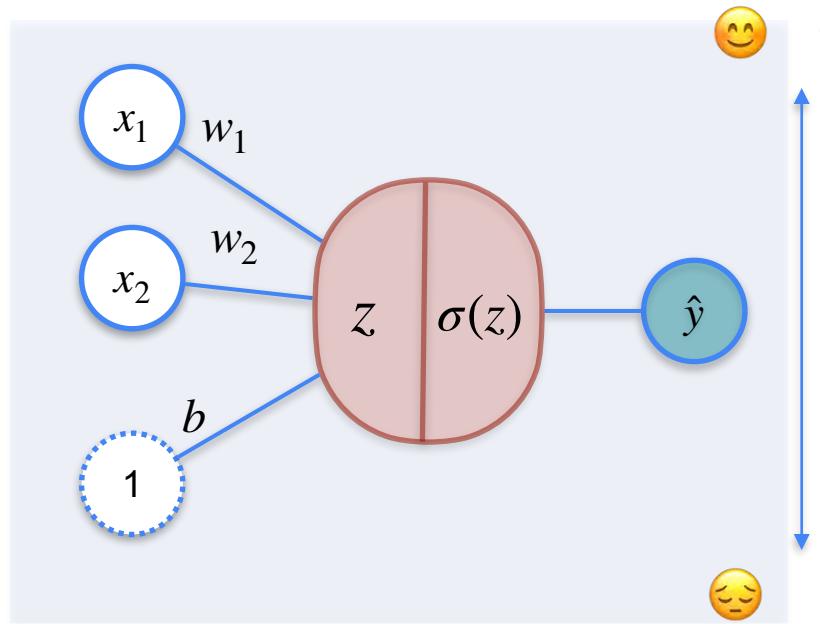
Classification With a Perceptron



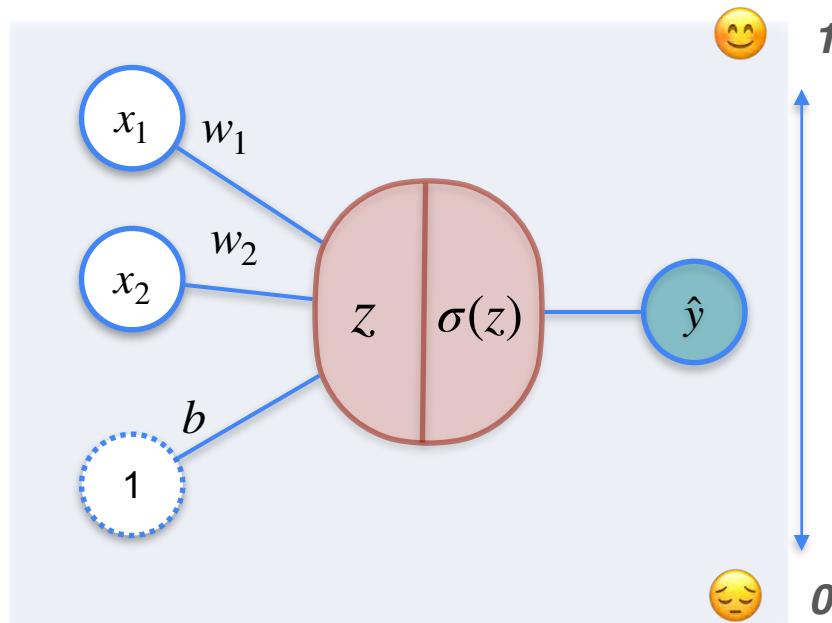
Classification With a Perceptron



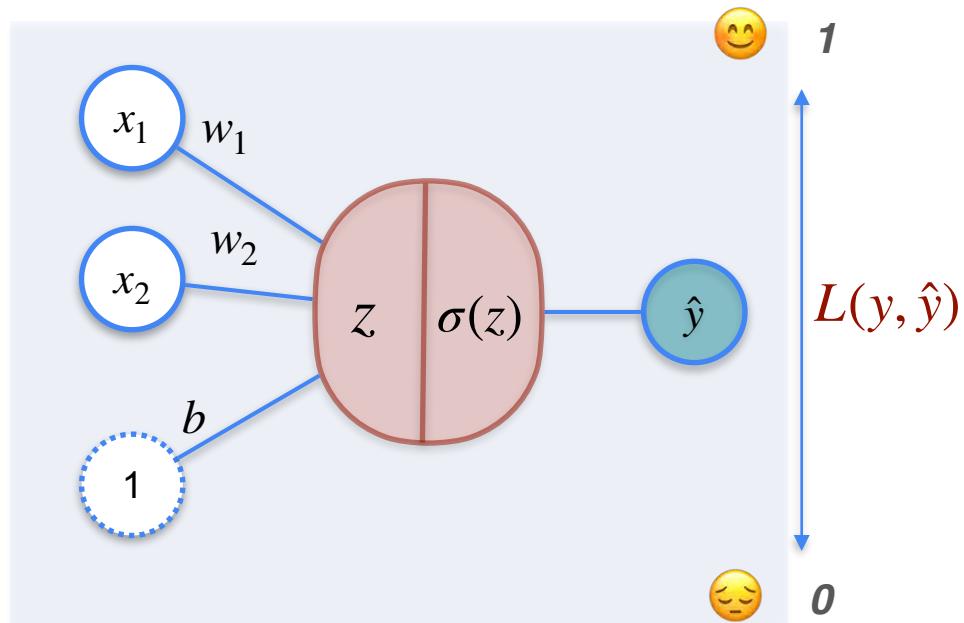
Classification With a Perceptron



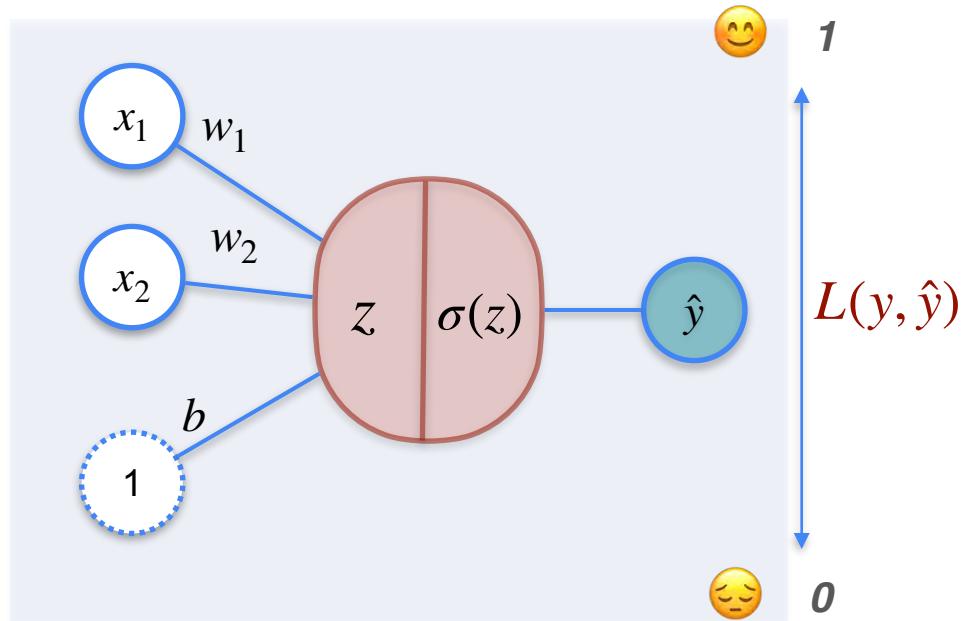
Classification With a Perceptron



Classification With a Perceptron

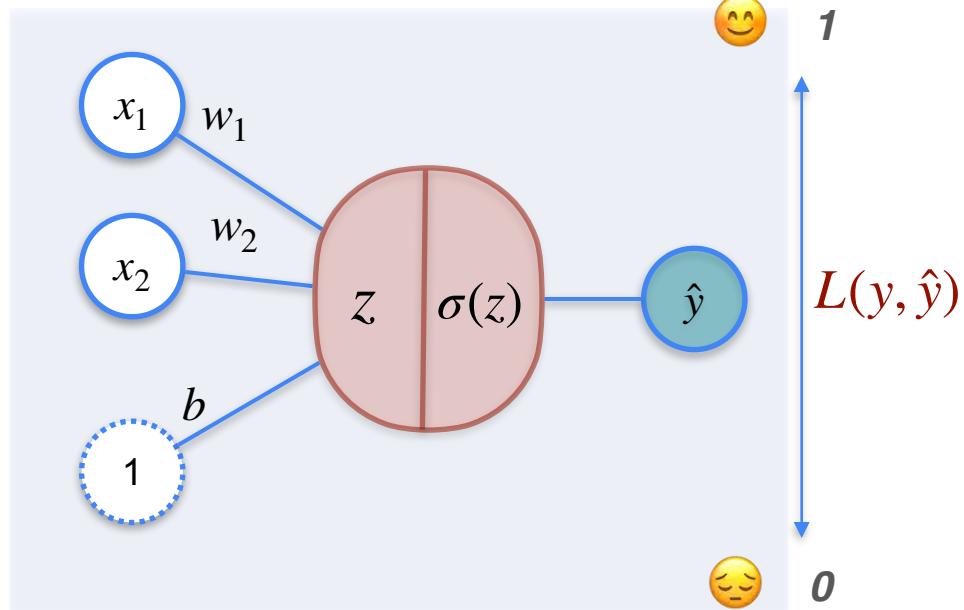


Classification With a Perceptron



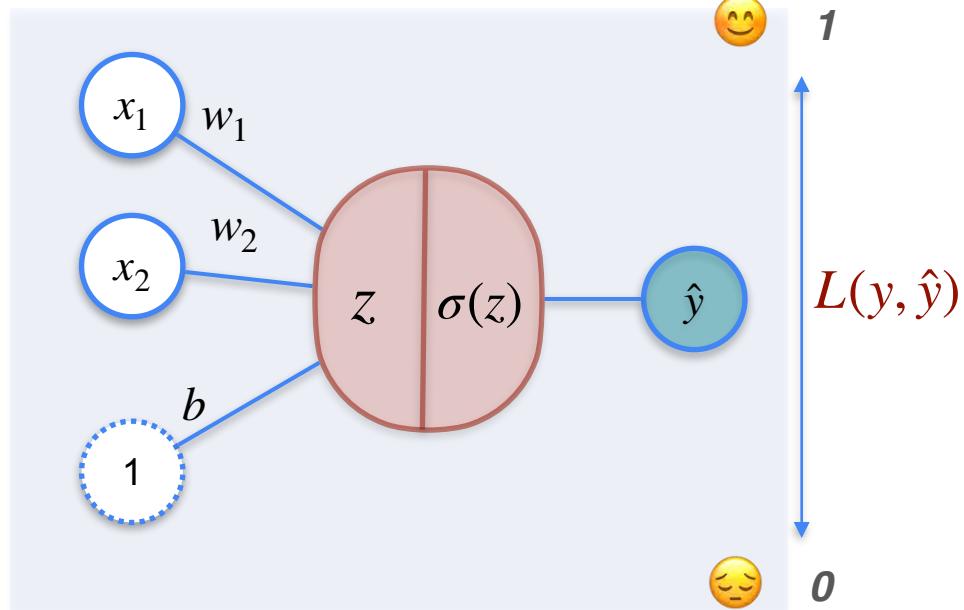
To find optimal values for:

Classification With a Perceptron



To find optimal values for:
 w_1 , w_2 , b

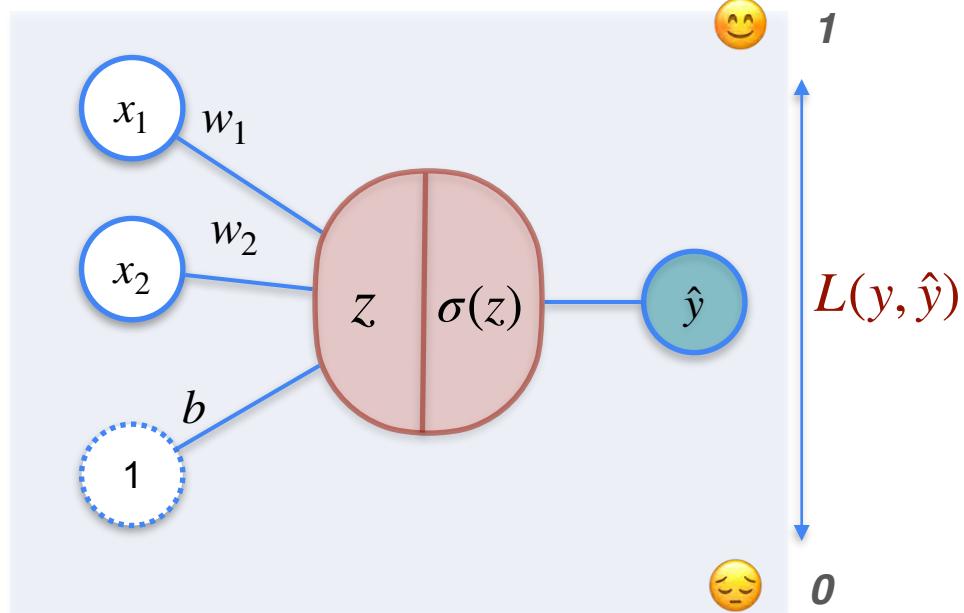
Classification With a Perceptron



To find optimal values for:
 w_1, w_2, b

You need gradient descent

Classification With a Perceptron

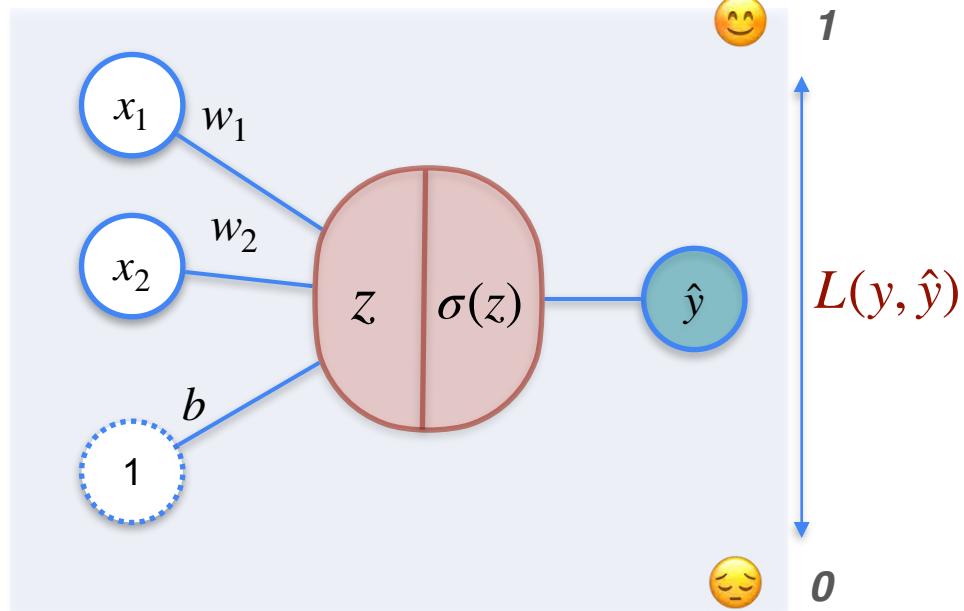


To find optimal values for:
 w_1 , w_2 , b

You need gradient descent

$$w_1 \rightarrow w_1 - \alpha \frac{\partial L}{\partial w_1}$$

Classification With a Perceptron

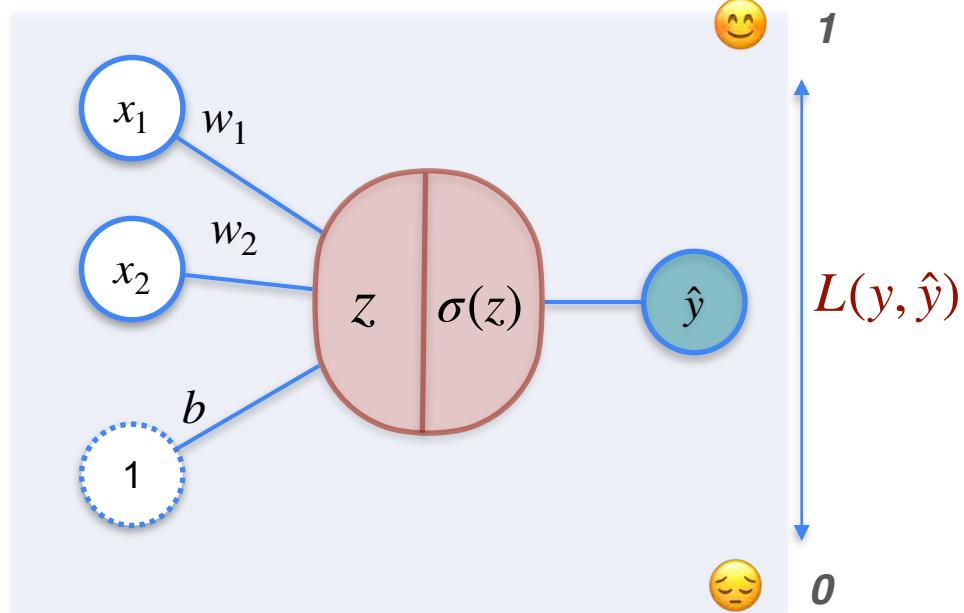


To find optimal values for:
 w_1, w_2, b

You need gradient descent

$$w_1 \rightarrow w_1 - \alpha$$

Classification With a Perceptron

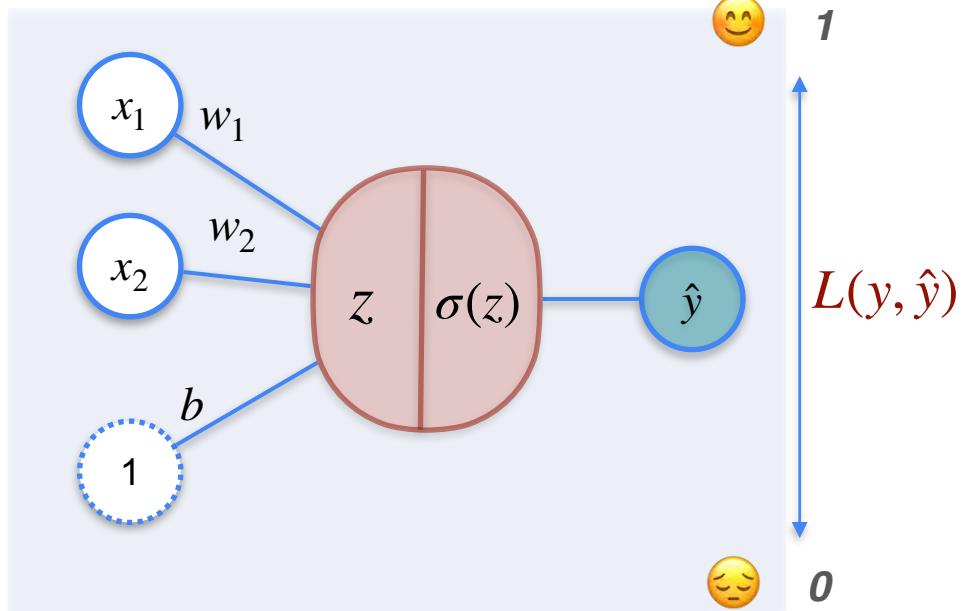


To find optimal values for:
 w_1, w_2, b

You need gradient descent

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

Classification With a Perceptron



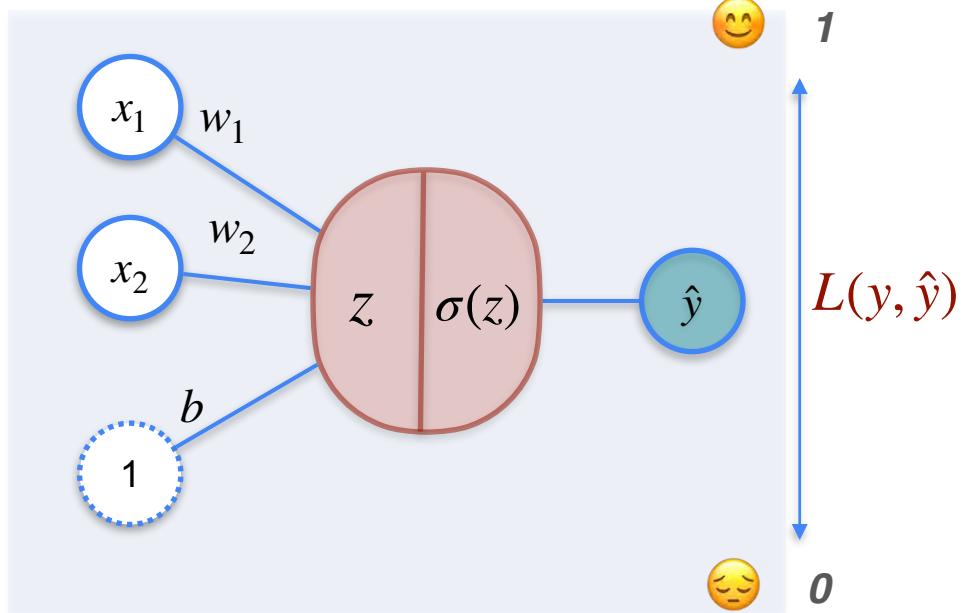
To find optimal values for:
 w_1, w_2, b

You need gradient descent

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha \frac{\partial L}{\partial w_2}$$

Classification With a Perceptron



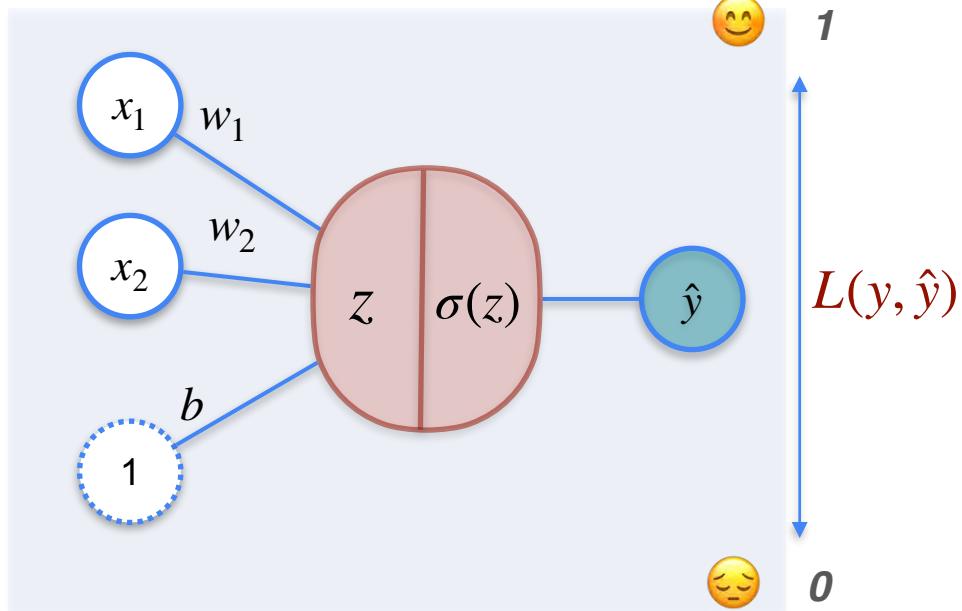
To find optimal values for:
 w_1, w_2, b

You need gradient descent

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha$$

Classification With a Perceptron



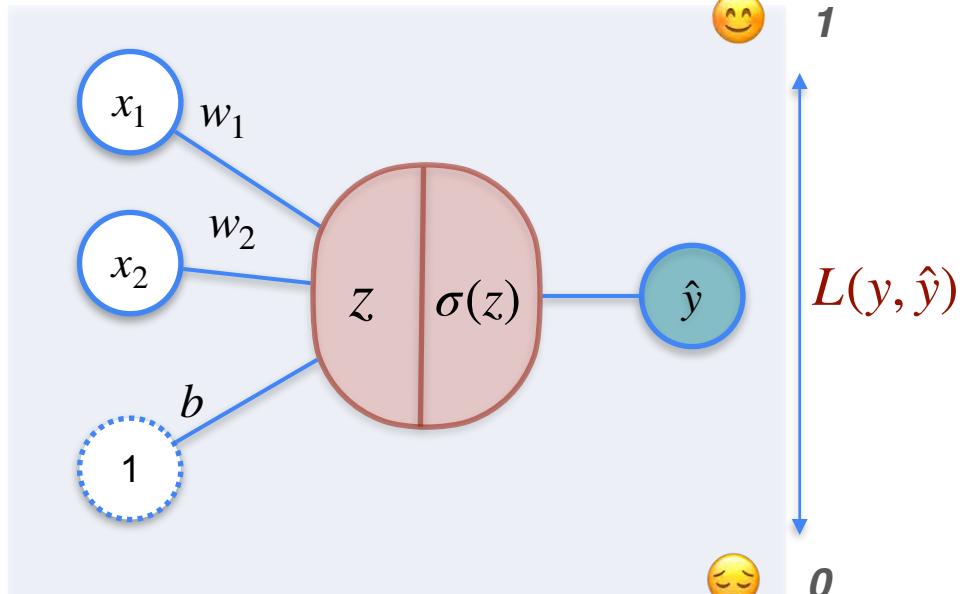
To find optimal values for:
 w_1, w_2, b

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

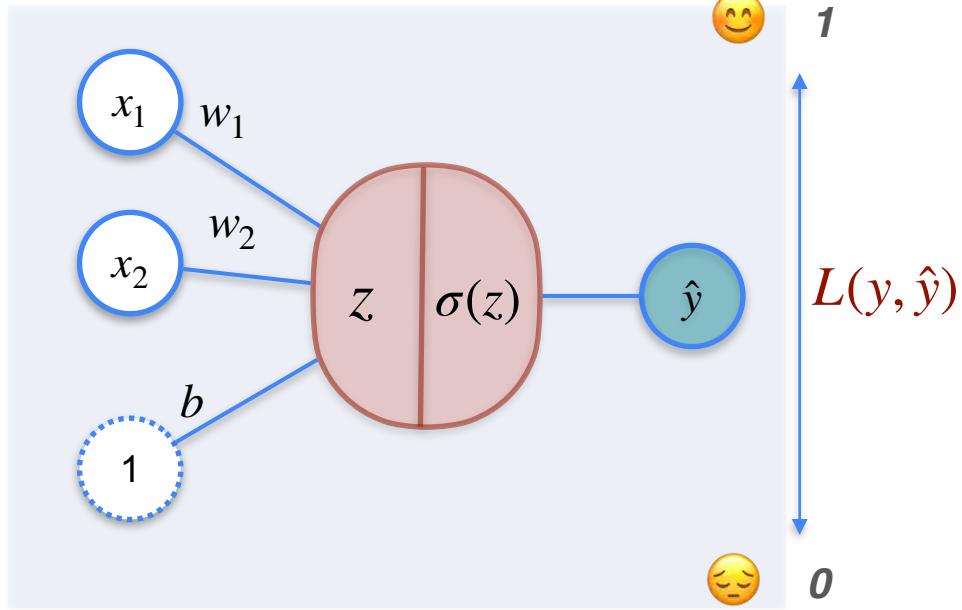
You need gradient descent

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha(-x_2(y - \hat{y}))$$

$$b \rightarrow b - \alpha \frac{\partial L}{\partial b}$$

Classification With a Perceptron



To find optimal values for:
 w_1, w_2, b

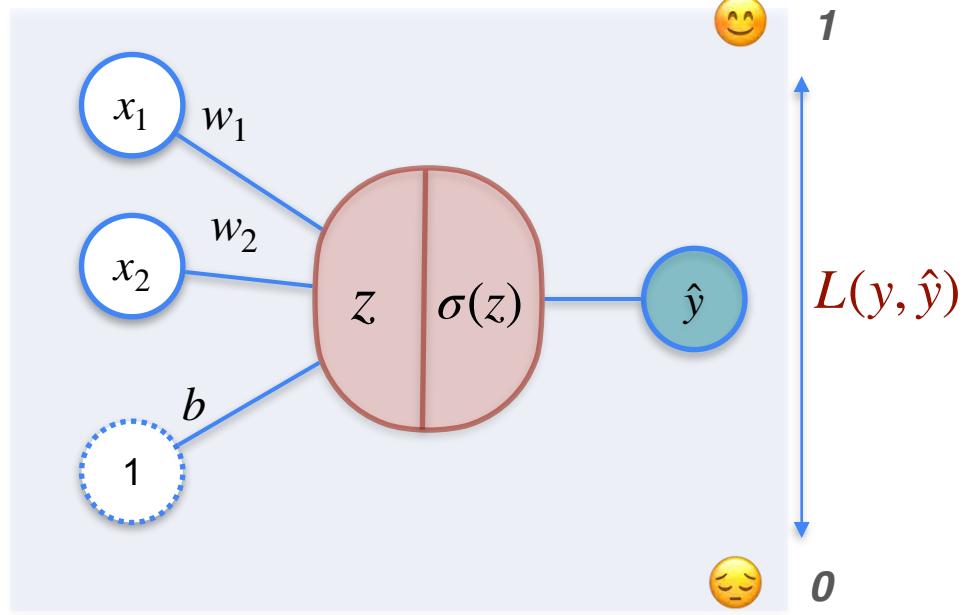
You need gradient descent

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha(-x_2(y - \hat{y}))$$

$$b \rightarrow b - \alpha$$

Classification With a Perceptron



To find optimal values for:
 w_1, w_2, b

You need gradient descent

$$w_1 \rightarrow w_1 - \alpha(-x_1(y - \hat{y}))$$

$$w_2 \rightarrow w_2 - \alpha(-x_2(y - \hat{y}))$$

$$b \rightarrow b - \alpha(-(y - \hat{y}))$$



DeepLearning.AI

Optimization in Neural Networks and Newton's Method

Classification with a Neural Network

Classification Problem Motivation

Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊

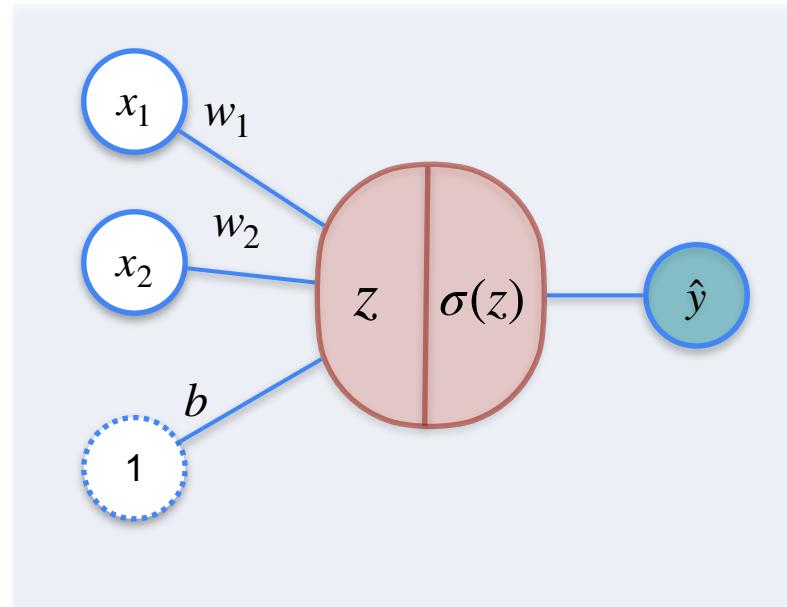
Beep beep! 0 2 *Sad* 😞

<i>Aack beep beep beep!</i>	1	3	<i>Sad</i> 😞
-----------------------------	---	---	--------------

Aack beep aack! 2 1 *Happy* 😊

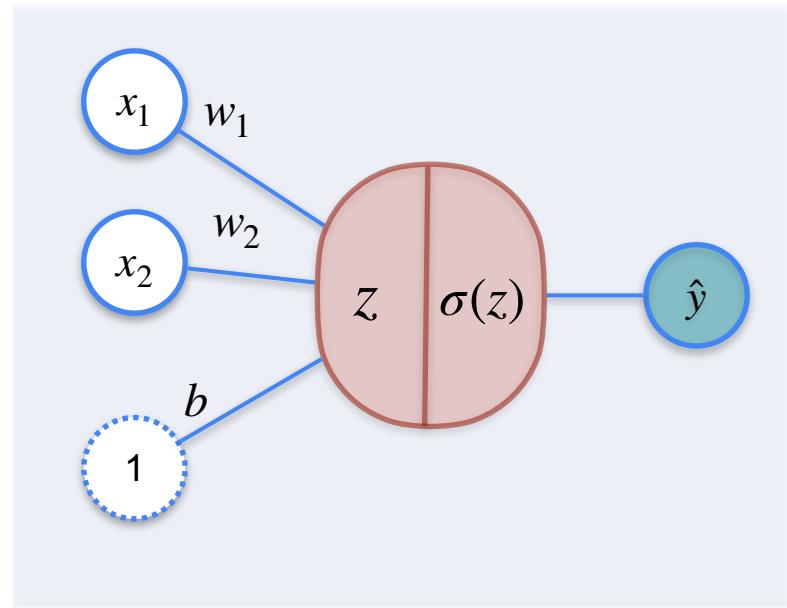
Classification Problem Motivation

<i>Sentence</i>	<i>Aack</i>	<i>Beep</i>	<i>Mood</i>
<i>Aack aack aack!</i>	3	0	<i>Happy</i> 😊
<i>Beep beep!</i>	0	2	<i>Sad</i> 😞
<i>Aack beep beep beep!</i>	1	3	<i>Sad</i> 😞
<i>Aack beep aack!</i>	2	1	<i>Happy</i> 😊



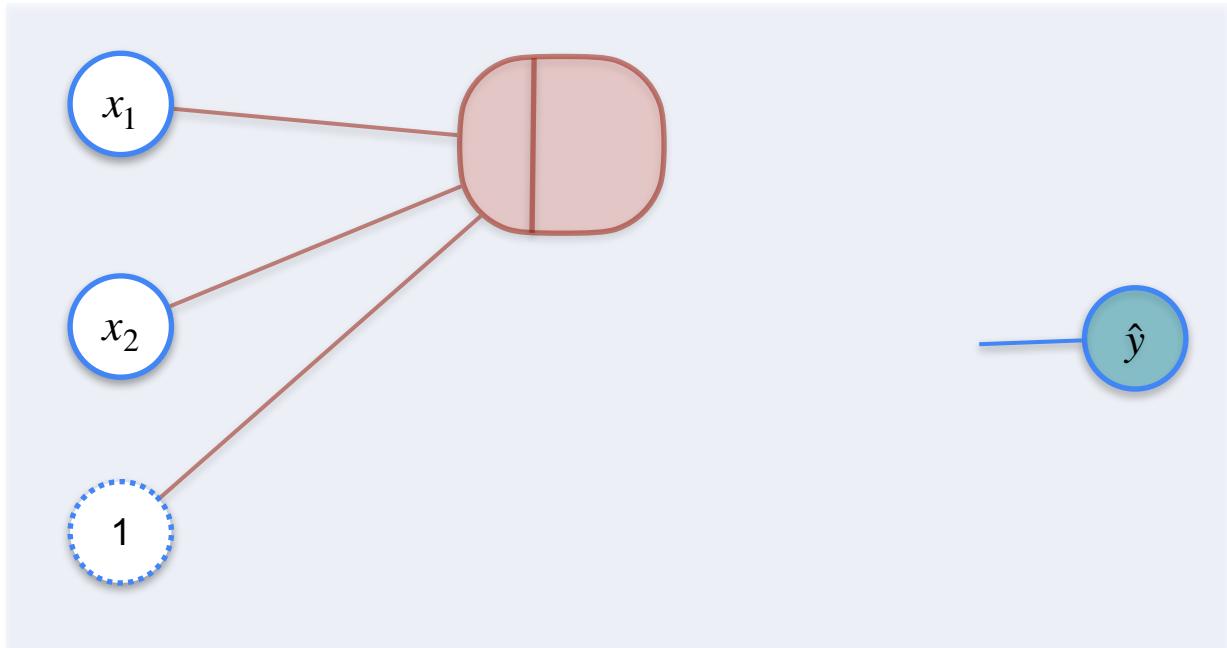
Classification Problem Motivation

Sentence	Aack	Beep	Mood
Aack aack aack!	3	0	Happy 😊
Beep beep!	0	2	Sad 😞
Aack beep beep beep!	1	3	Sad 😞
Aack beep aack!	2	1	Happy 😊

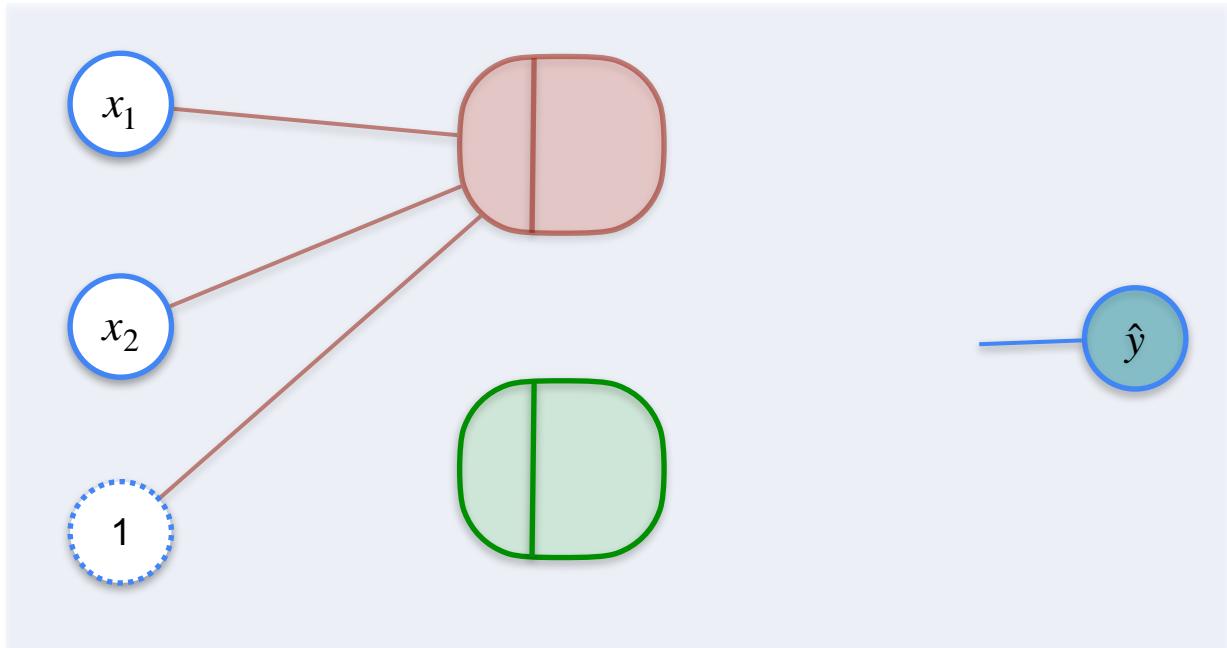


$$z = x_1 w_1 + x_2 w_2 + b$$

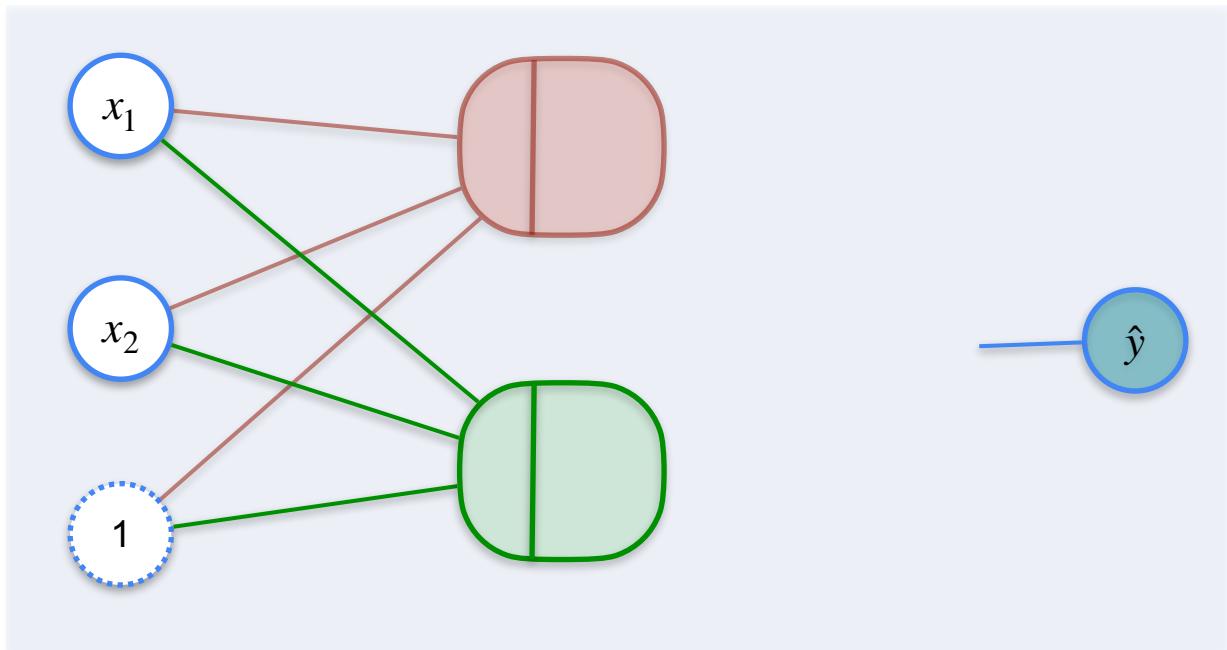
2,2,1 Neural Network



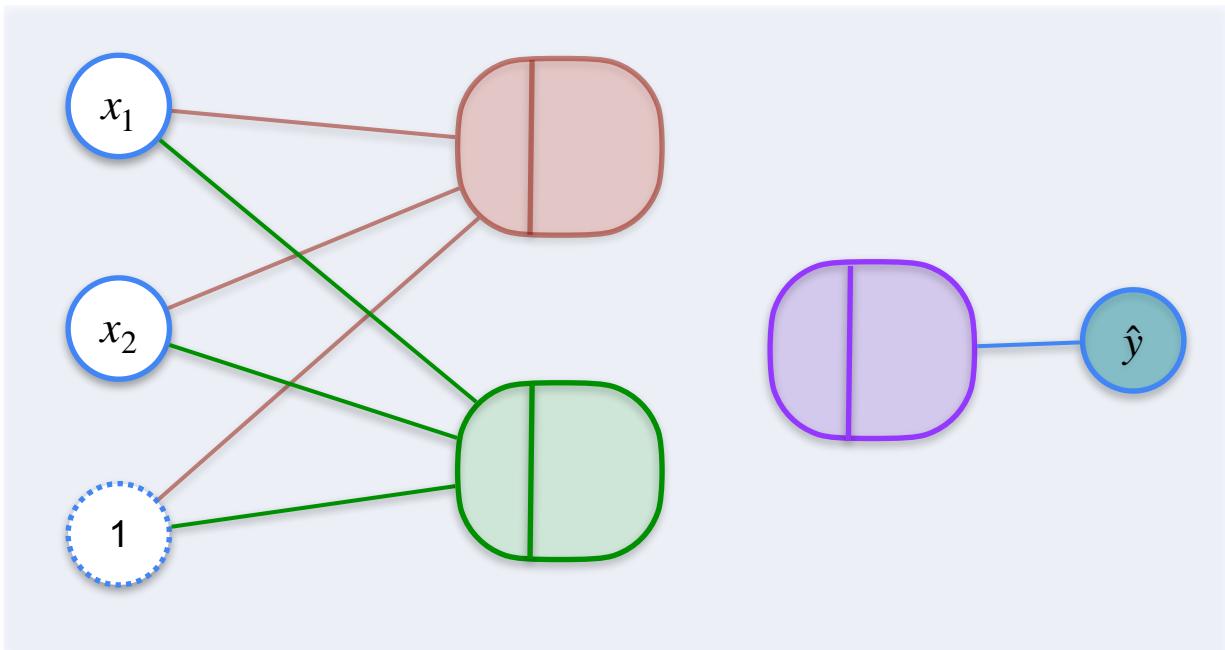
2,2,1 Neural Network



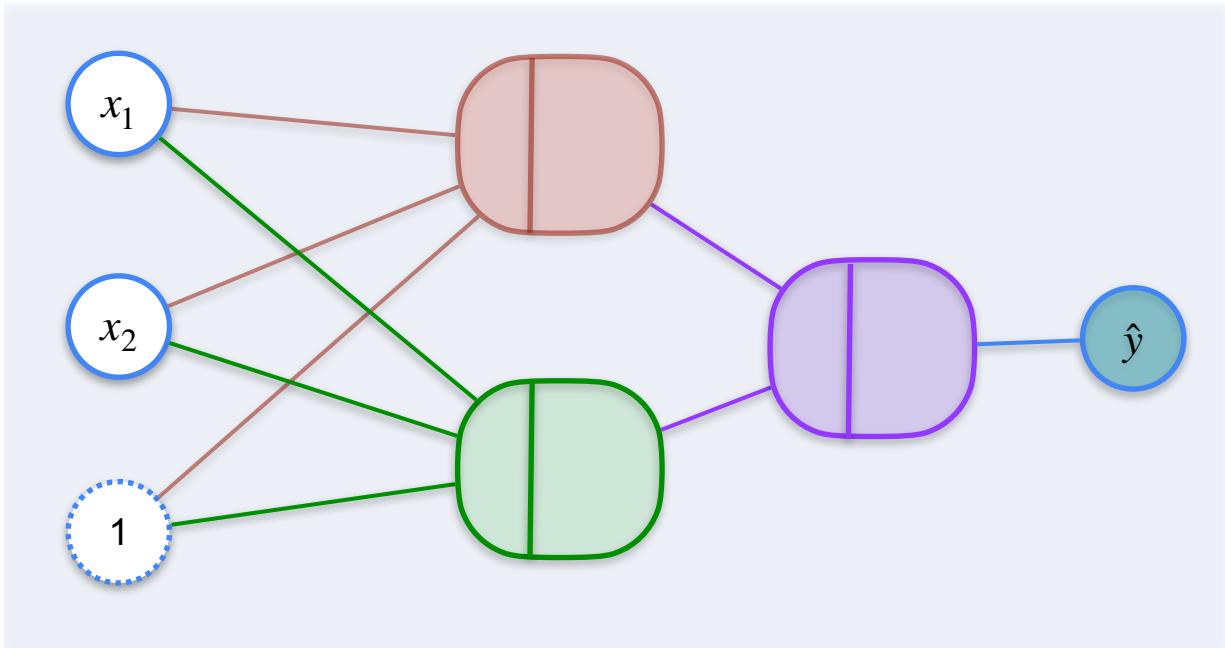
2,2,1 Neural Network



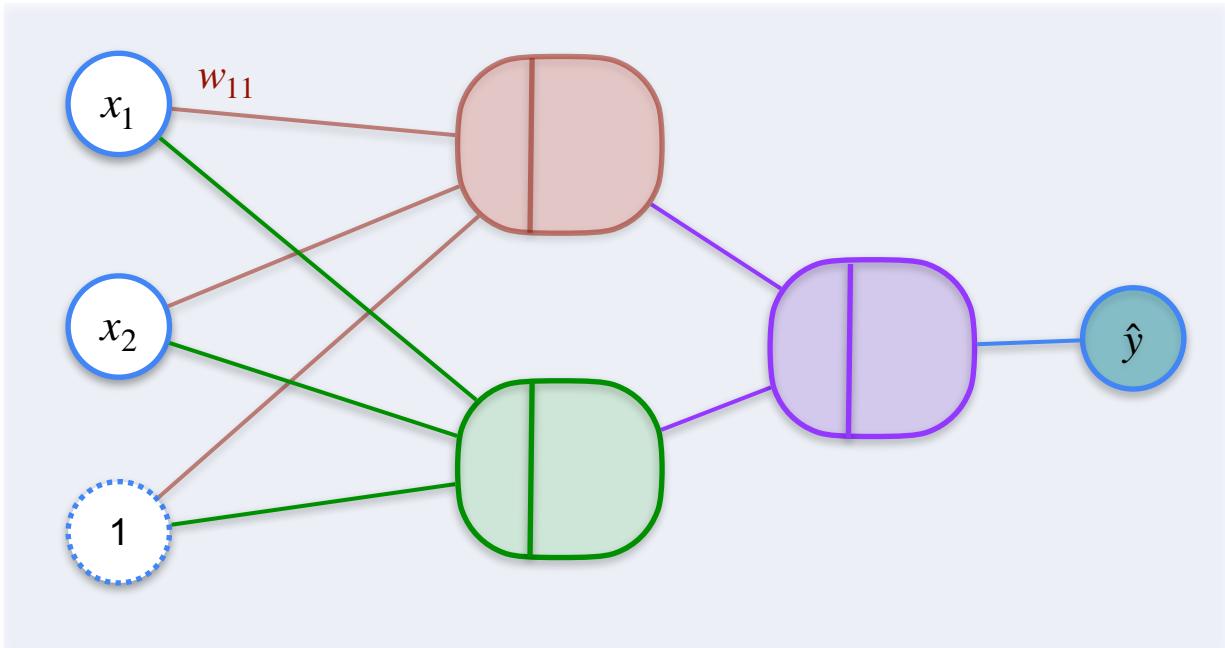
2,2,1 Neural Network



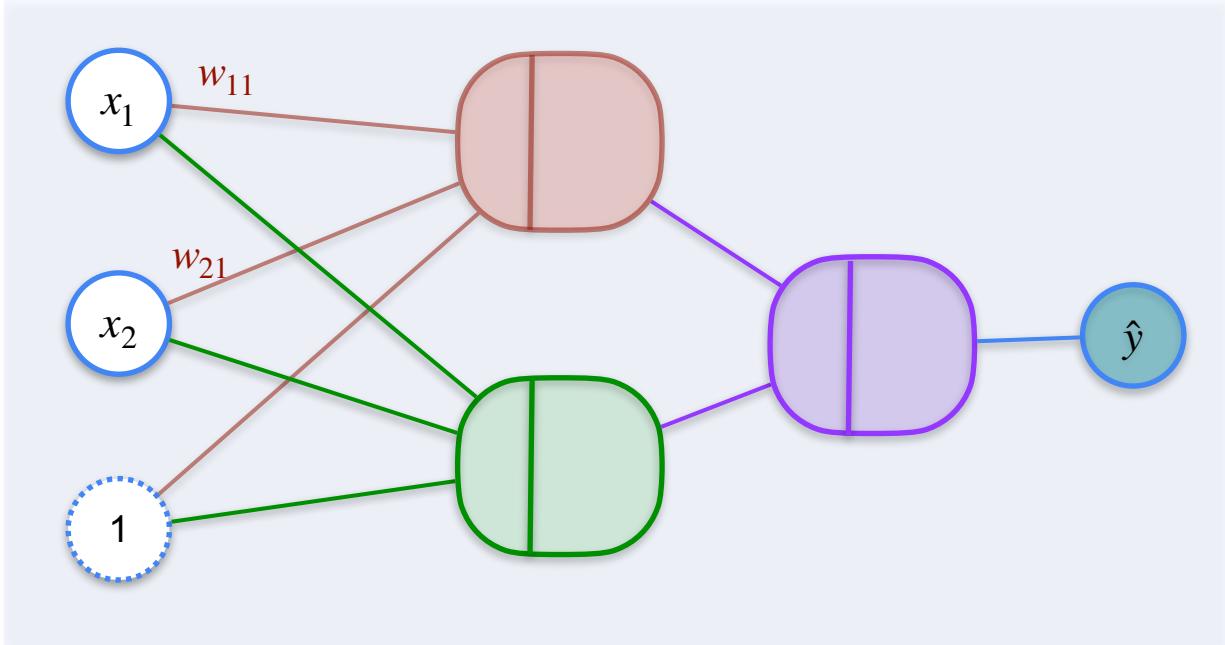
2,2,1 Neural Network



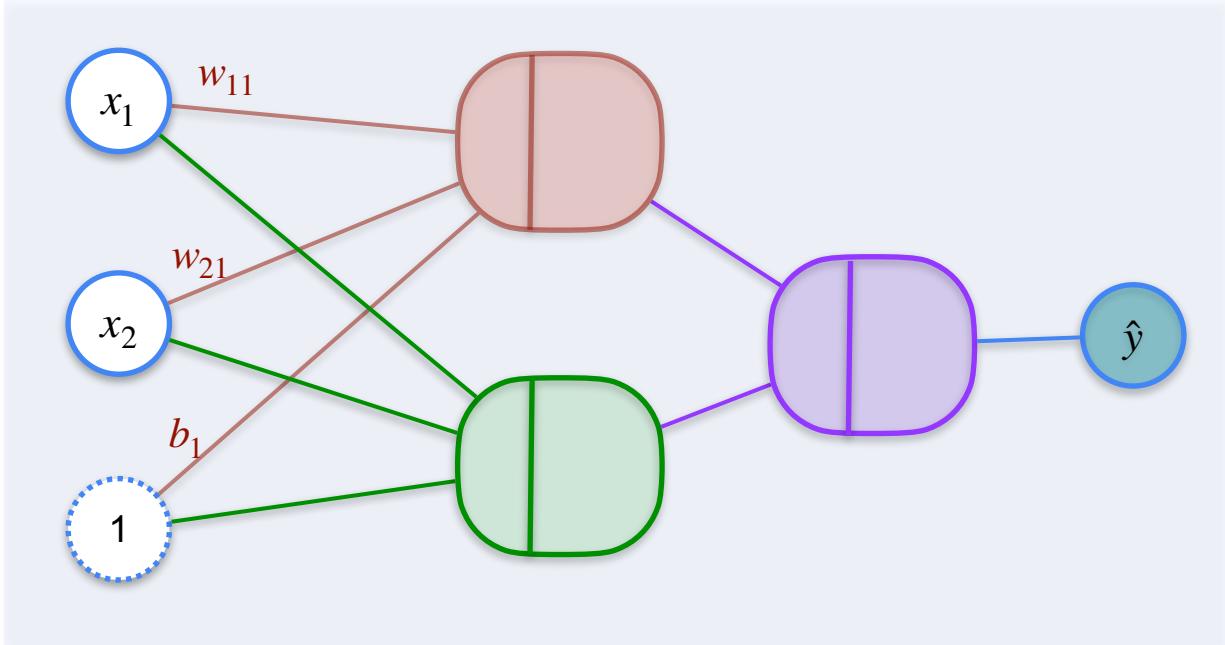
2,2,1 Neural Network



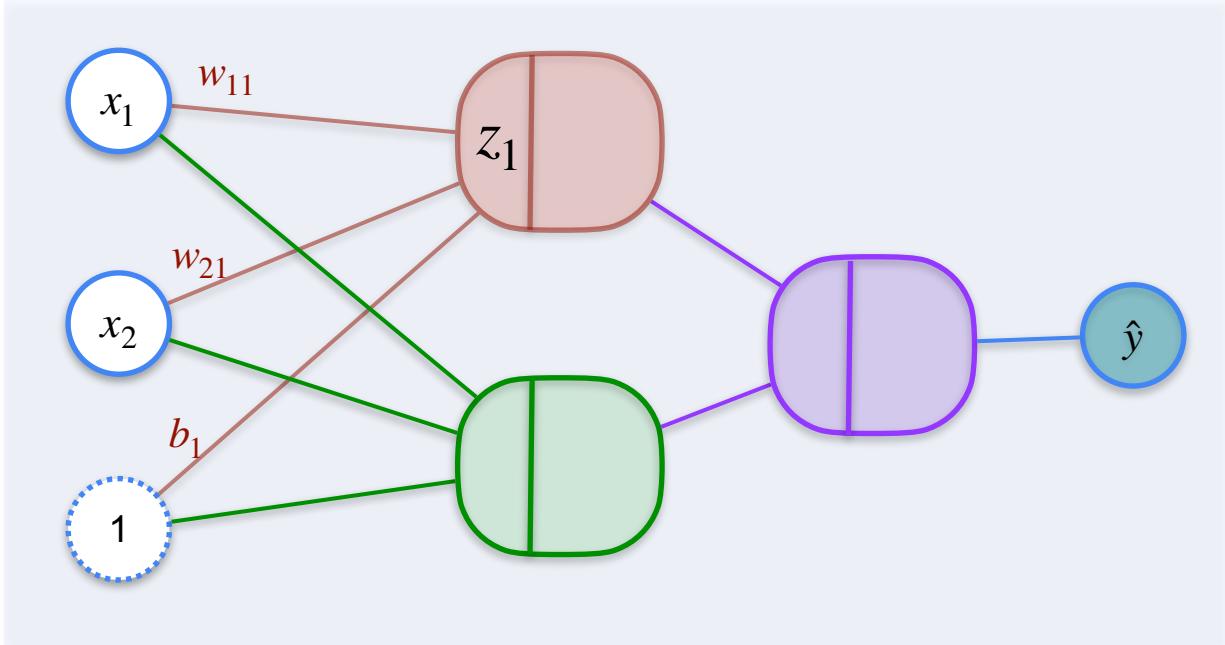
2,2,1 Neural Network



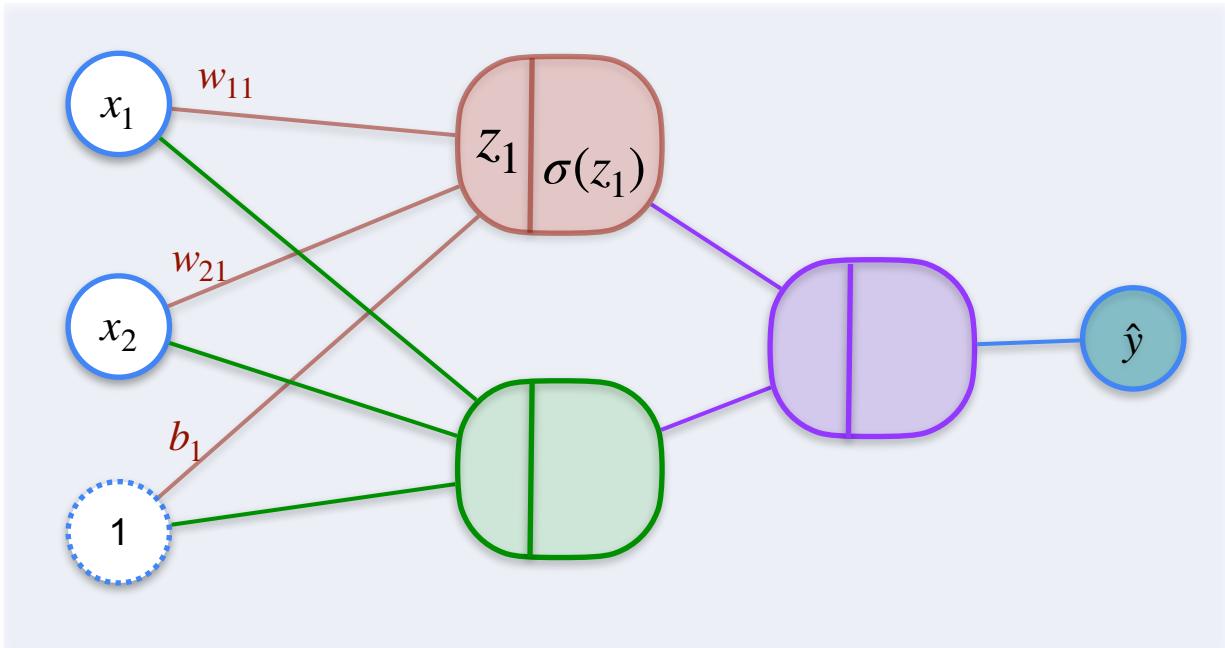
2,2,1 Neural Network



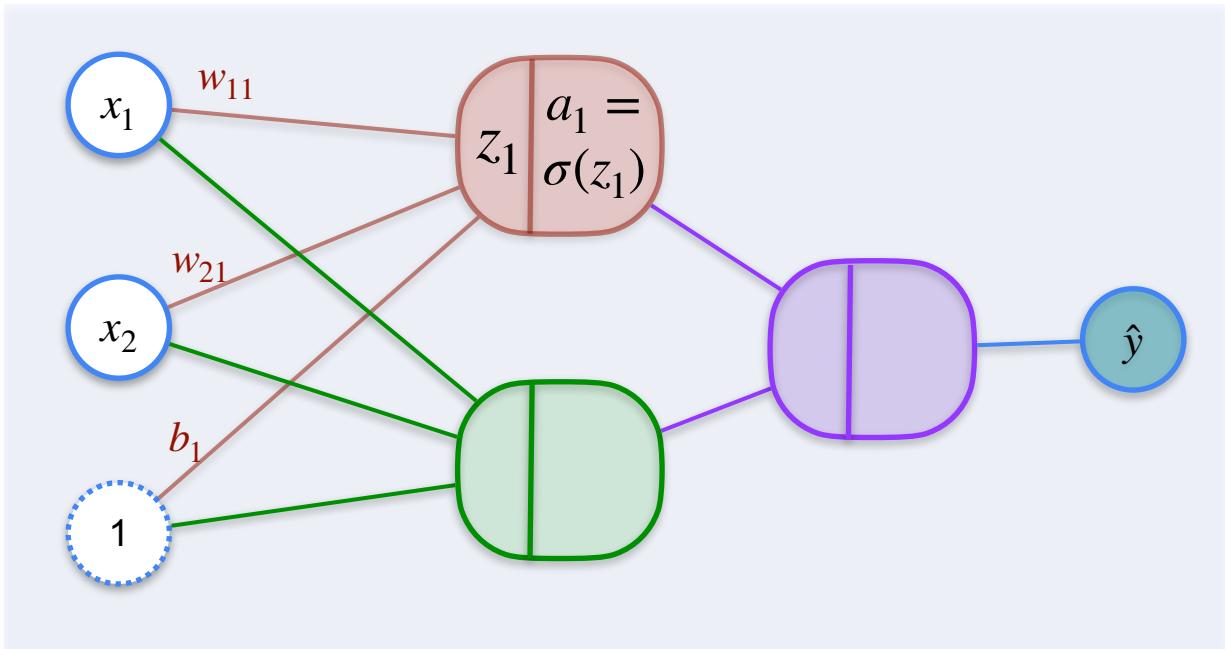
2,2,1 Neural Network



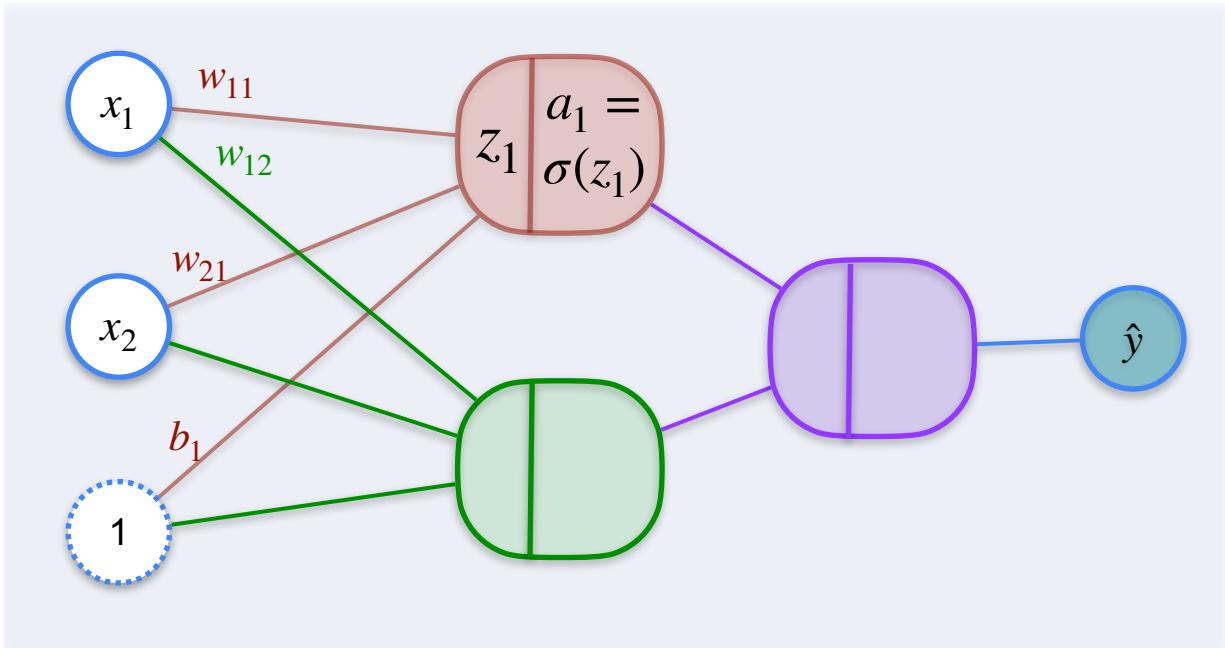
2,2,1 Neural Network



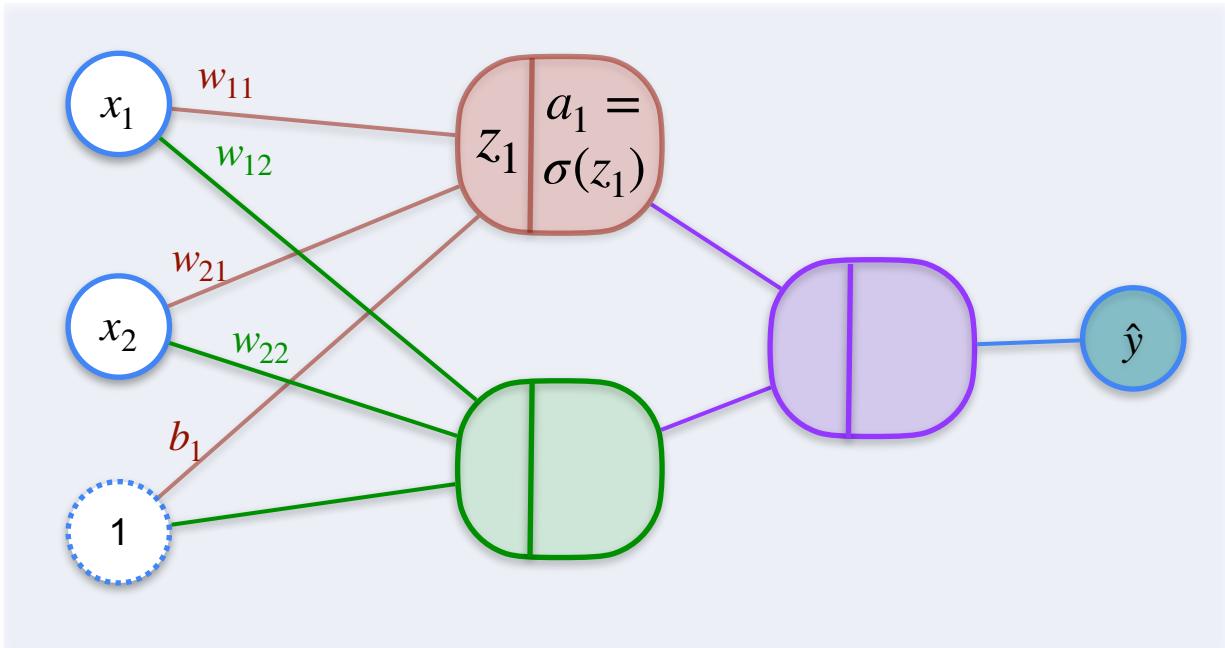
2,2,1 Neural Network



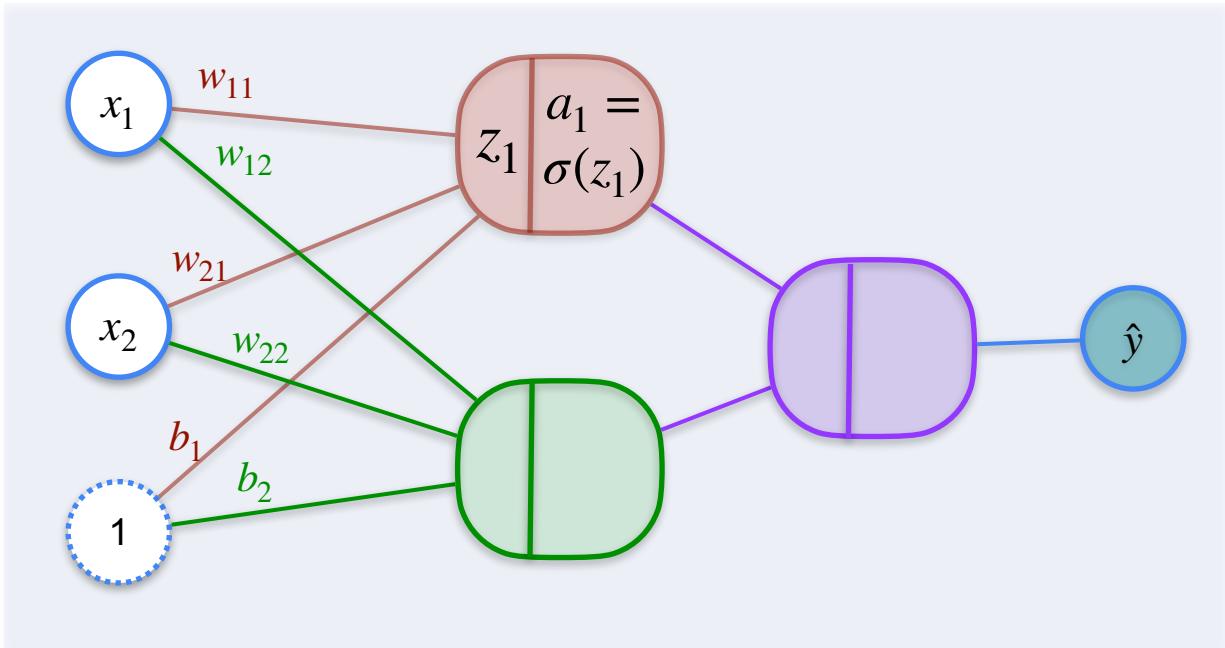
2,2,1 Neural Network



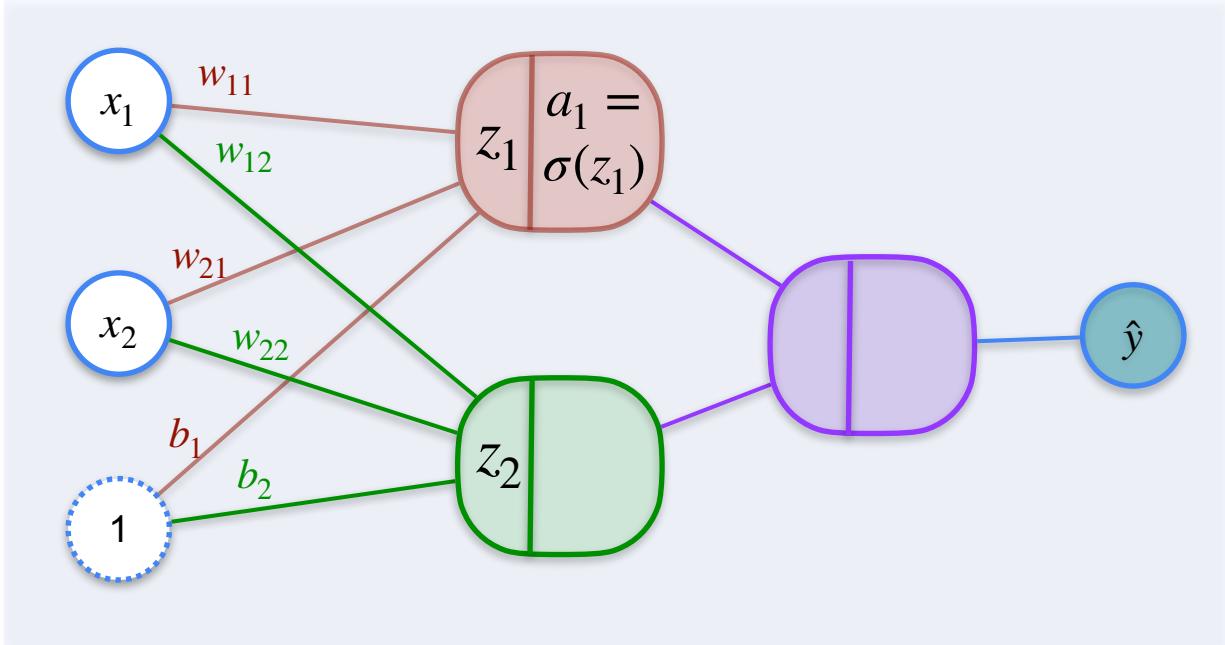
2,2,1 Neural Network



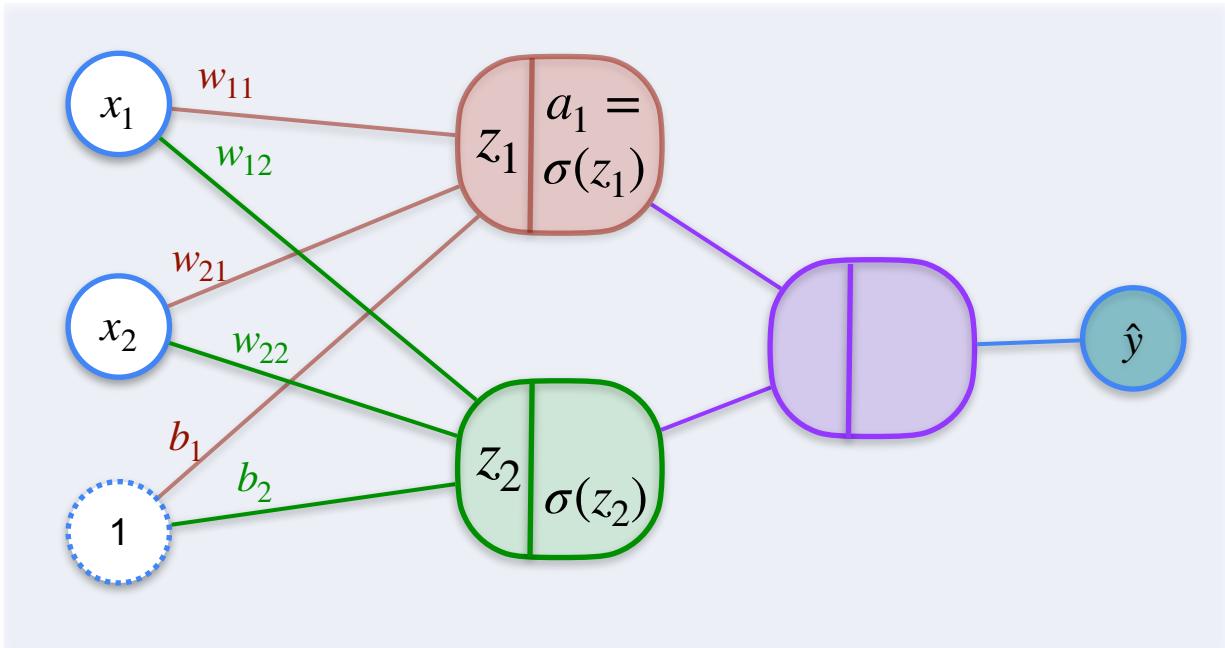
2,2,1 Neural Network



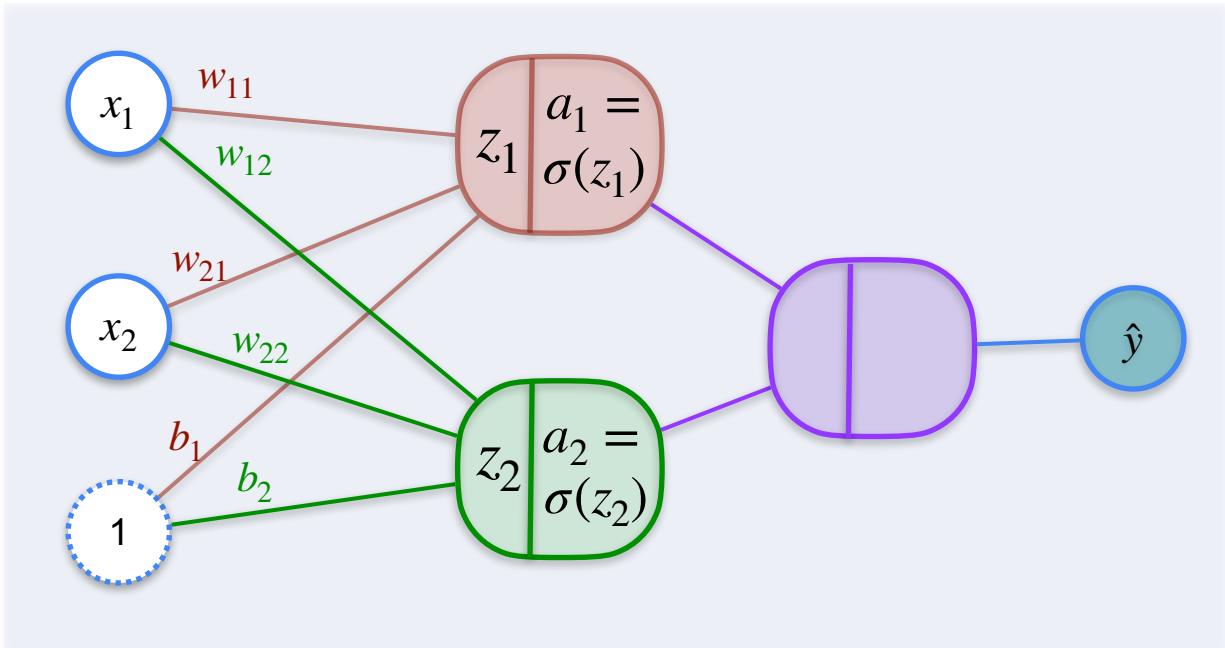
2,2,1 Neural Network



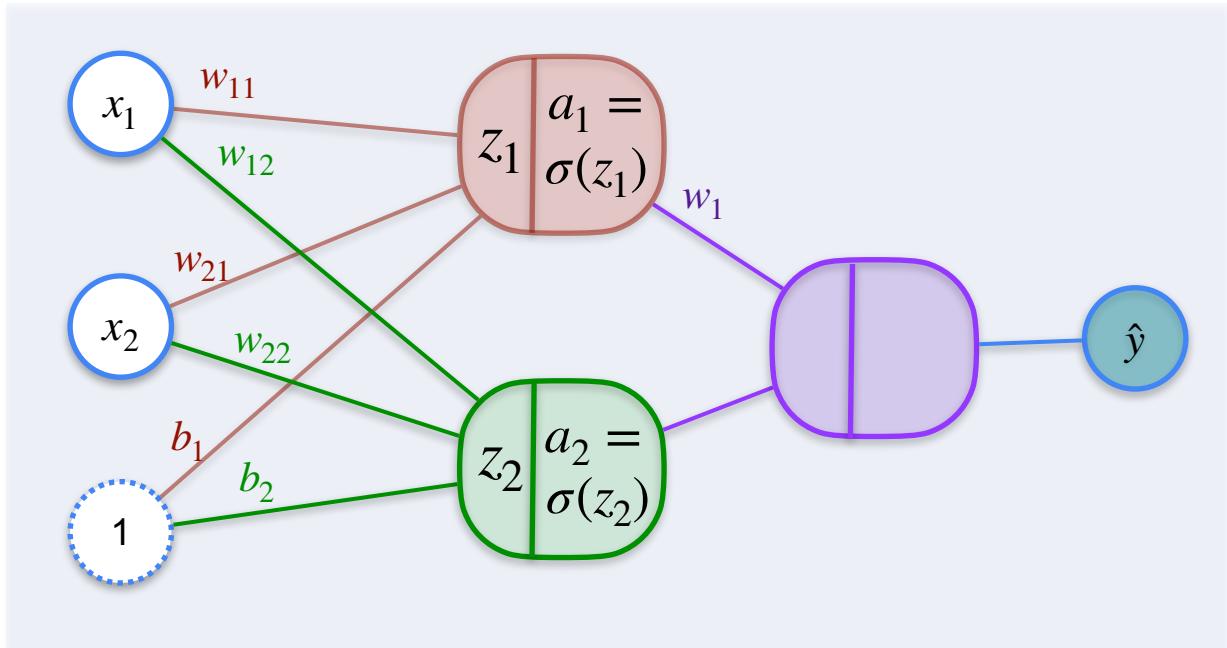
2,2,1 Neural Network



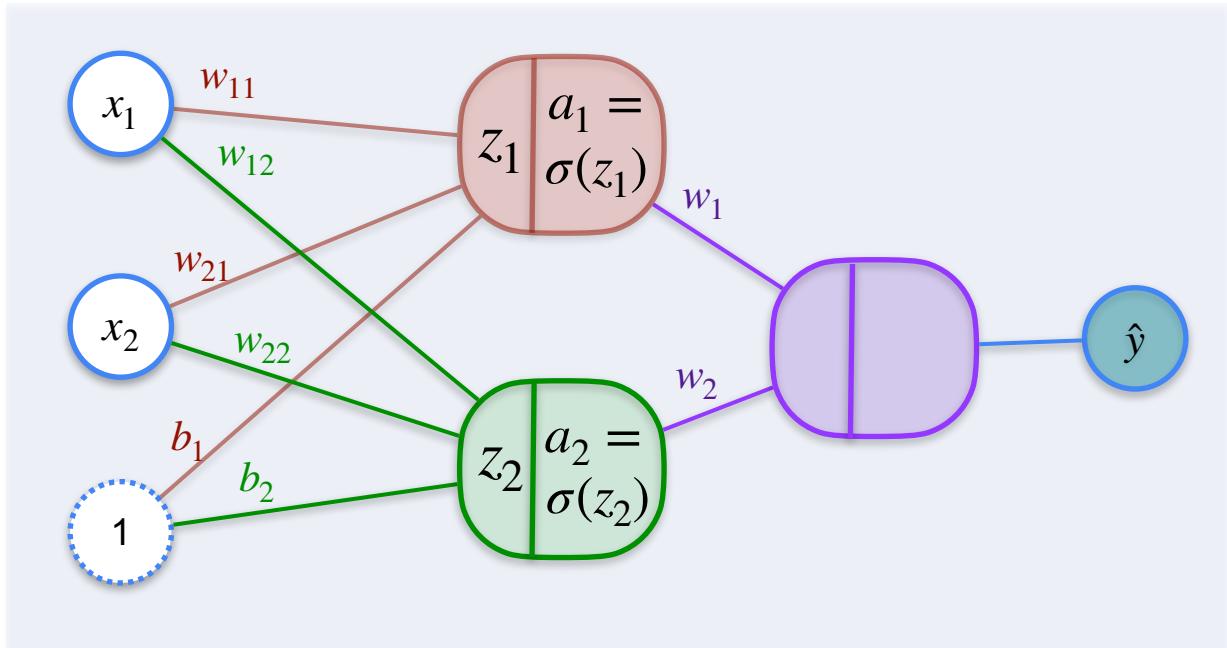
2,2,1 Neural Network



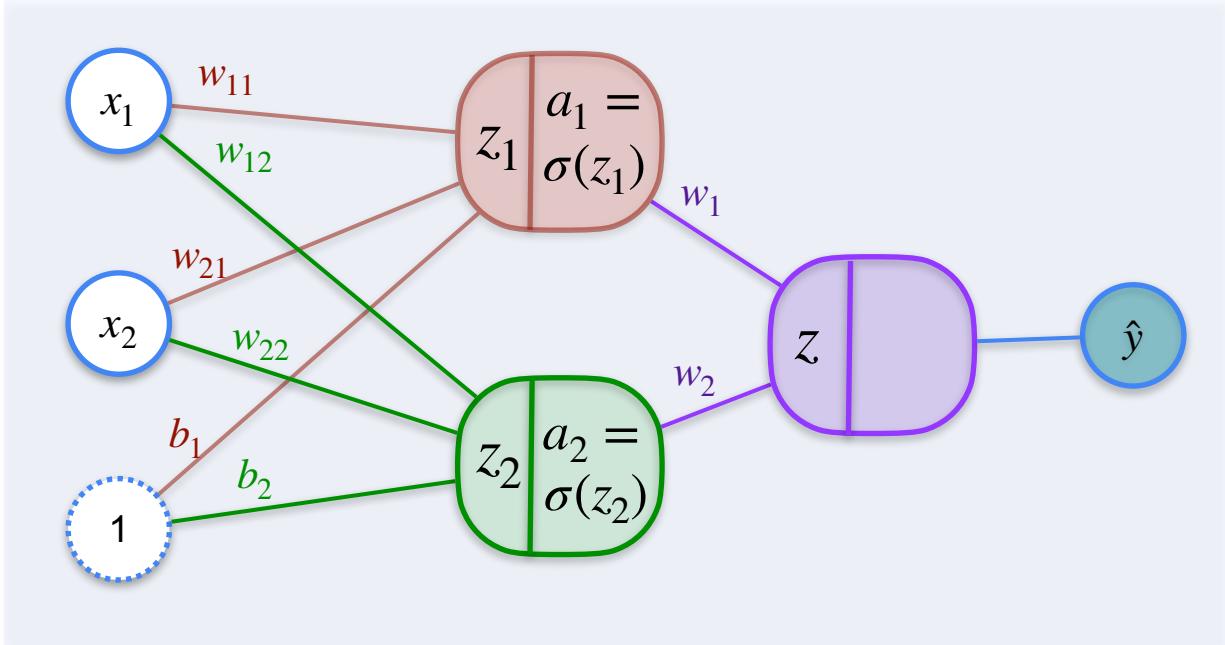
2,2,1 Neural Network



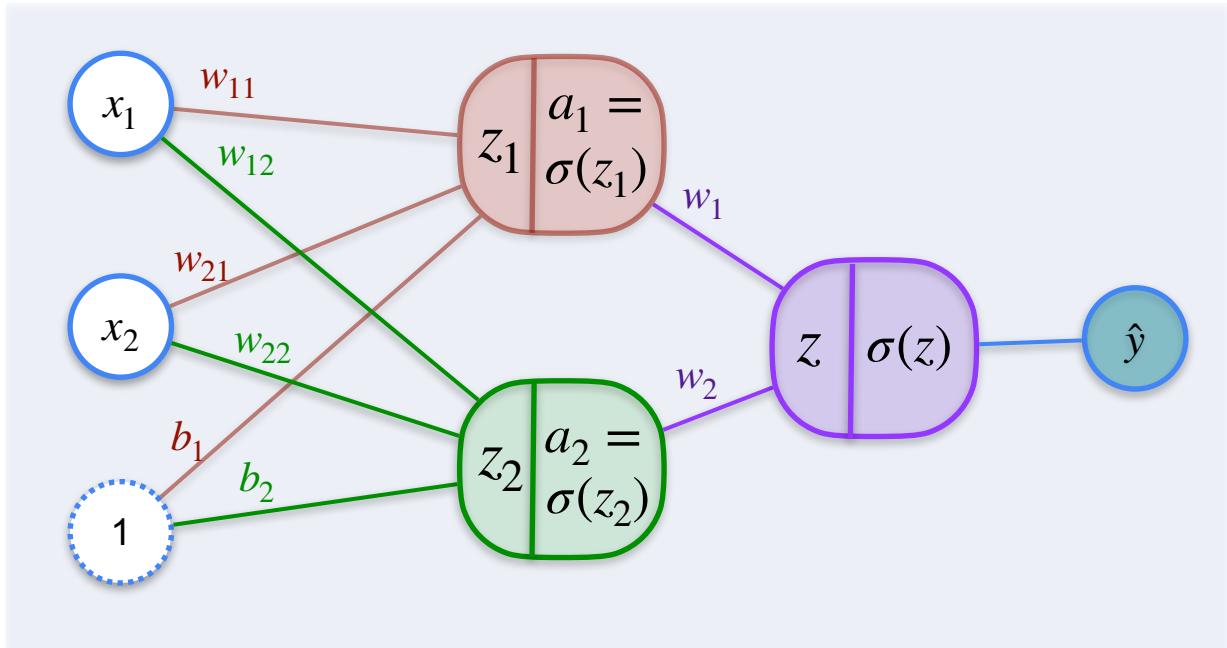
2,2,1 Neural Network



2,2,1 Neural Network



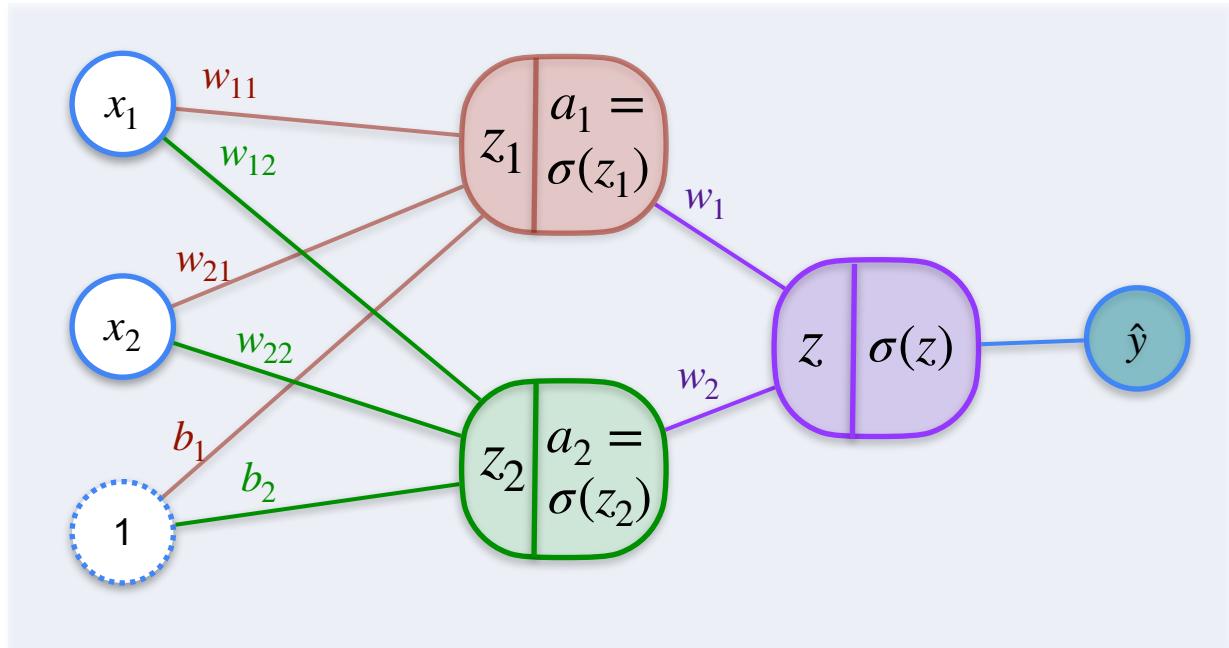
2,2,1 Neural Network



2,2,1 Neural Network

Neural network of depth 2

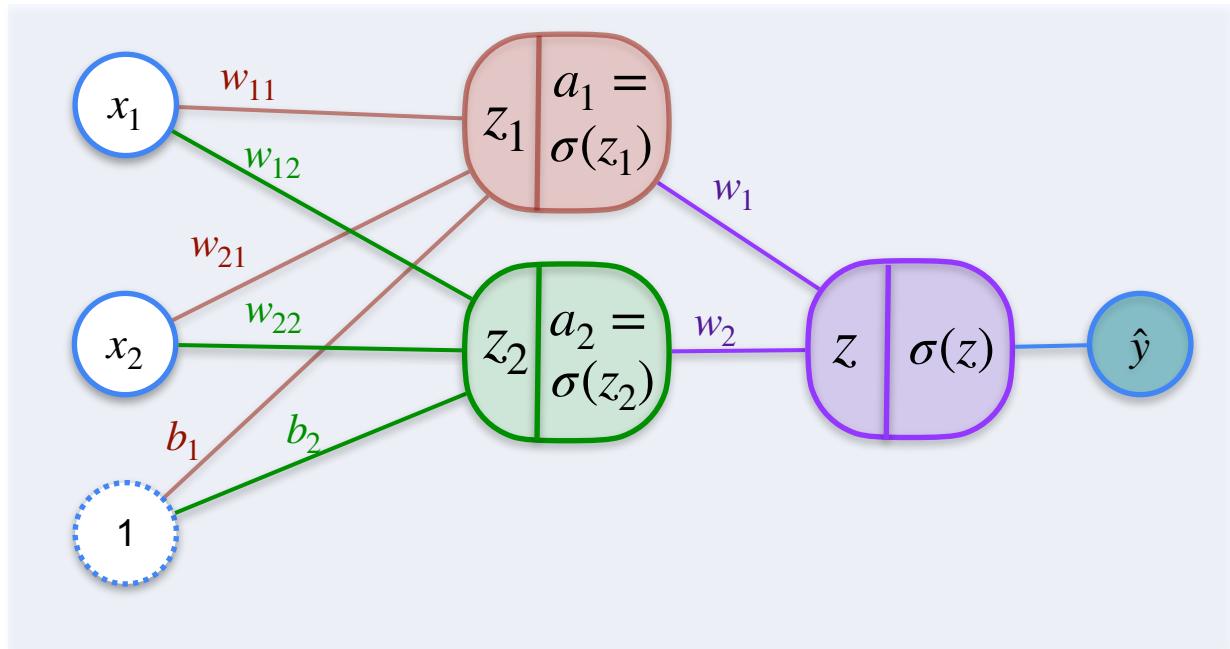
- one input layer
- one hidden layer
- one output layer



2,2,1 Neural Network

Neural network of depth 2

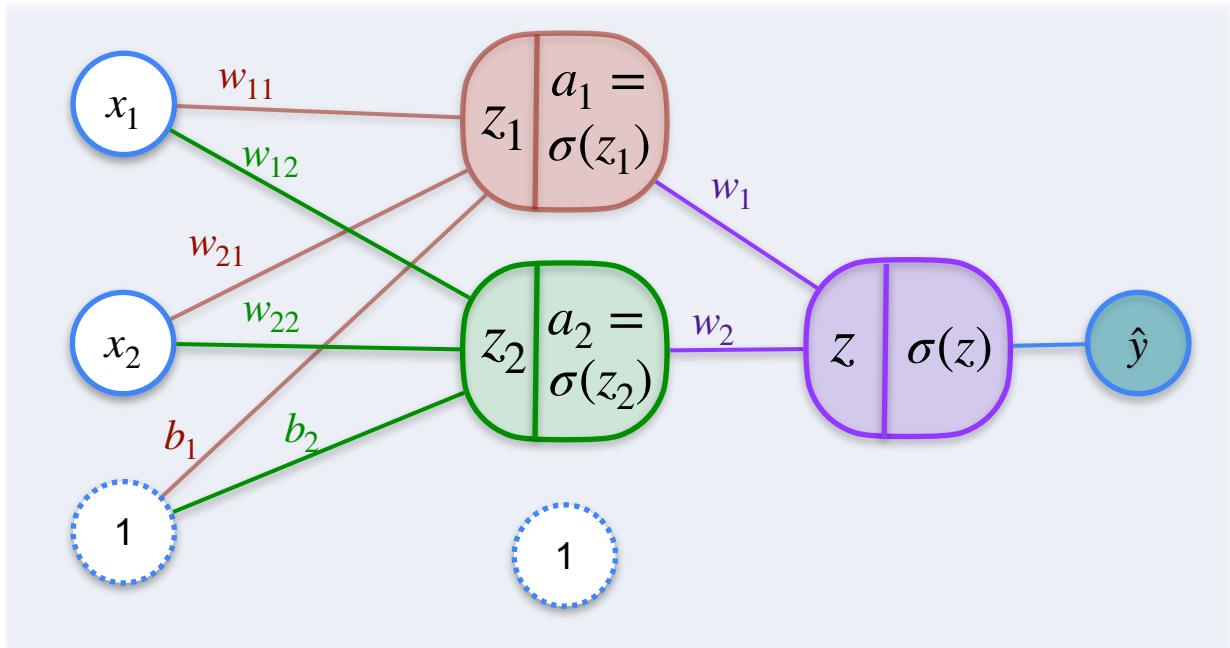
- one input layer
- one hidden layer
- one output layer



2,2,1 Neural Network

Neural network of depth 2

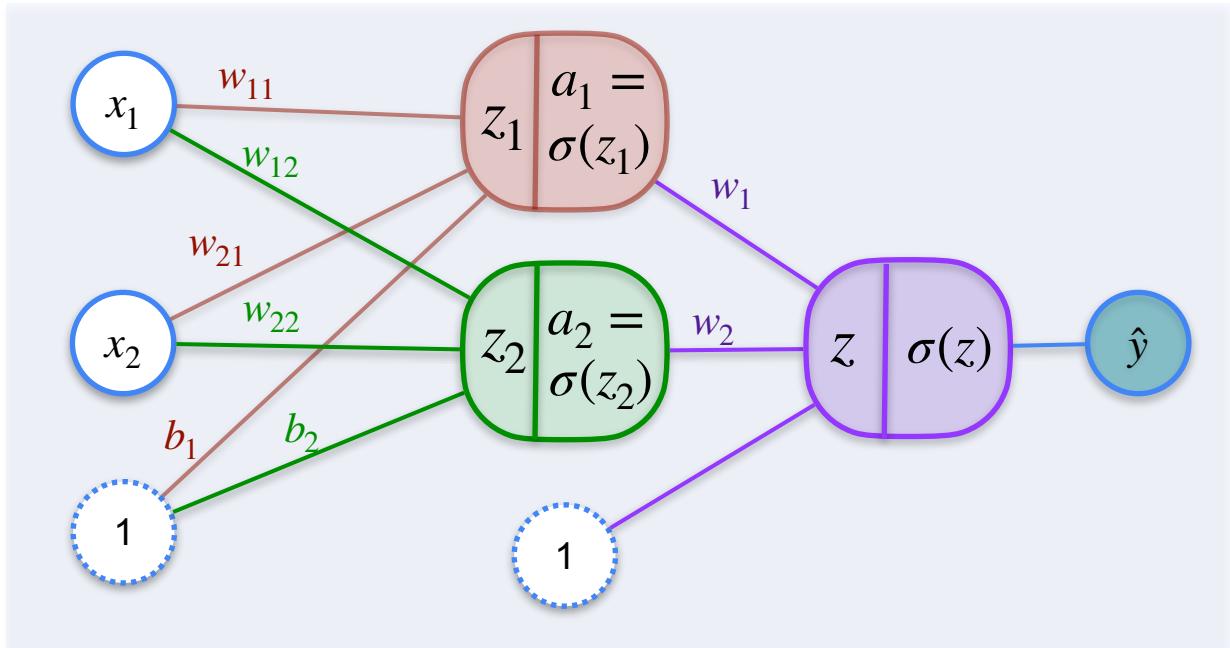
- one input layer
- one hidden layer
- one output layer



2,2,1 Neural Network

Neural network of depth 2

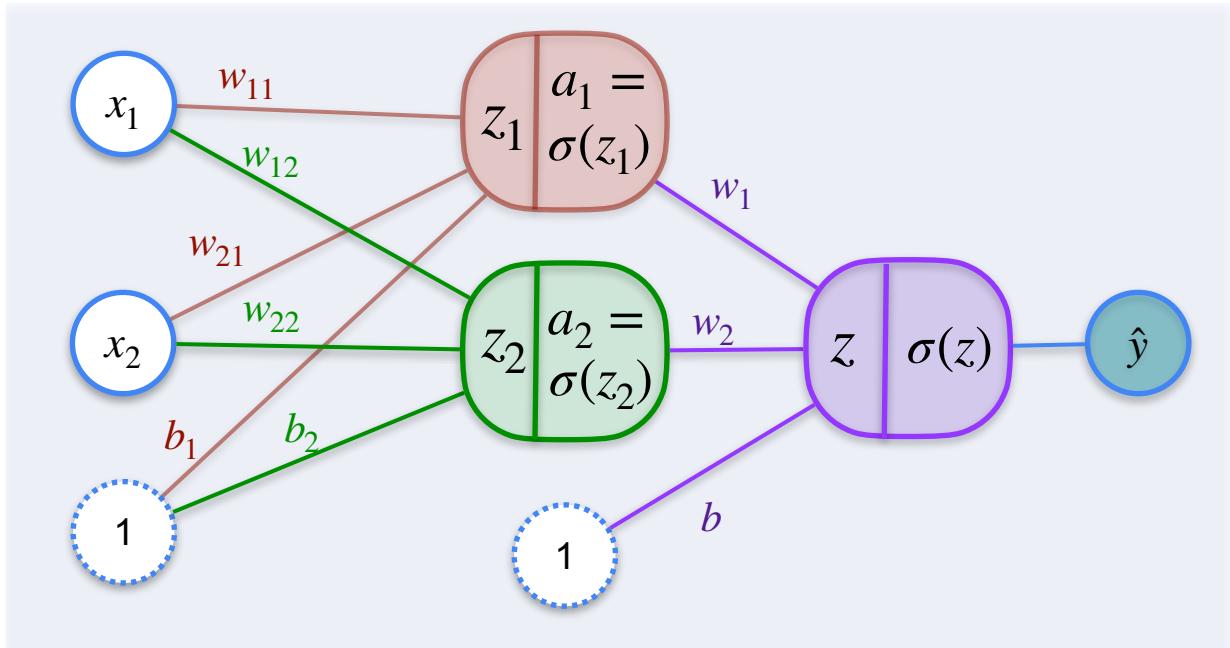
- one input layer
- one hidden layer
- one output layer



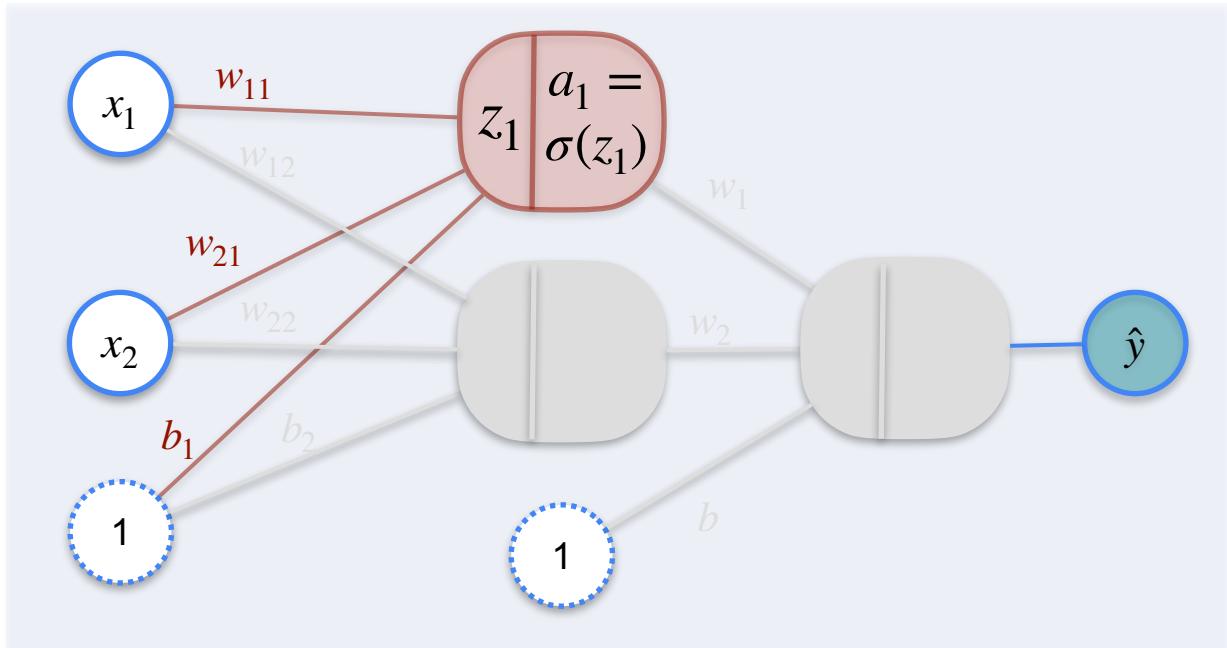
2,2,1 Neural Network

Neural network of depth 2

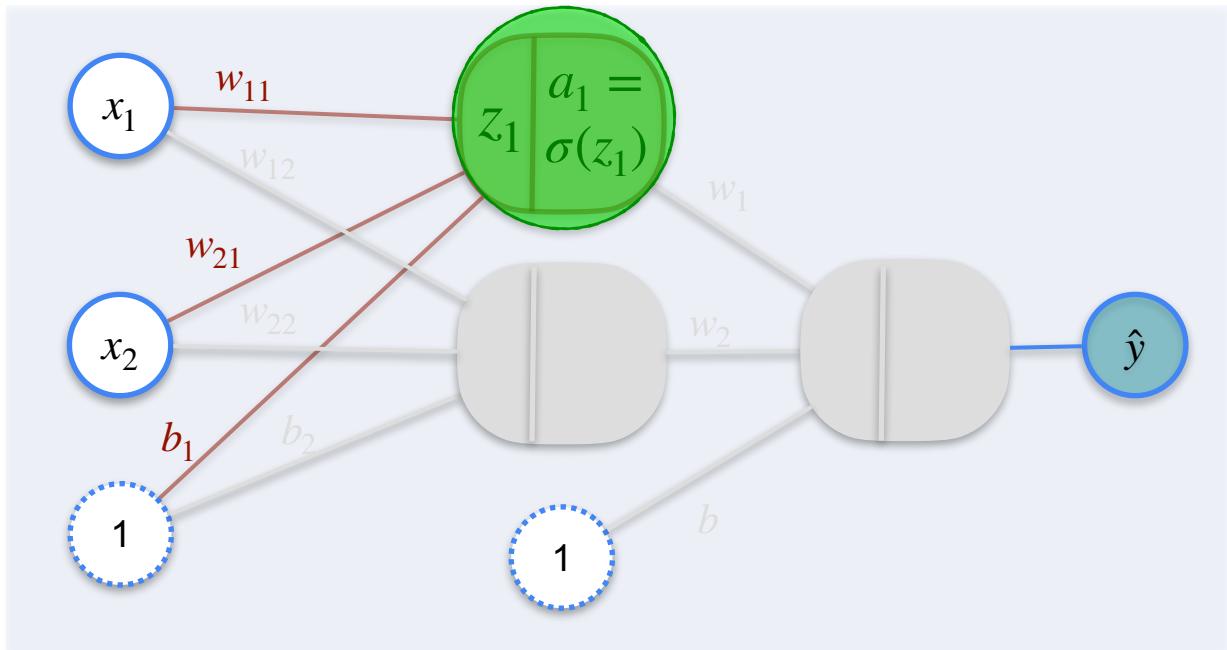
- one input layer
- one hidden layer
- one output layer



2,2,1 Neural Network

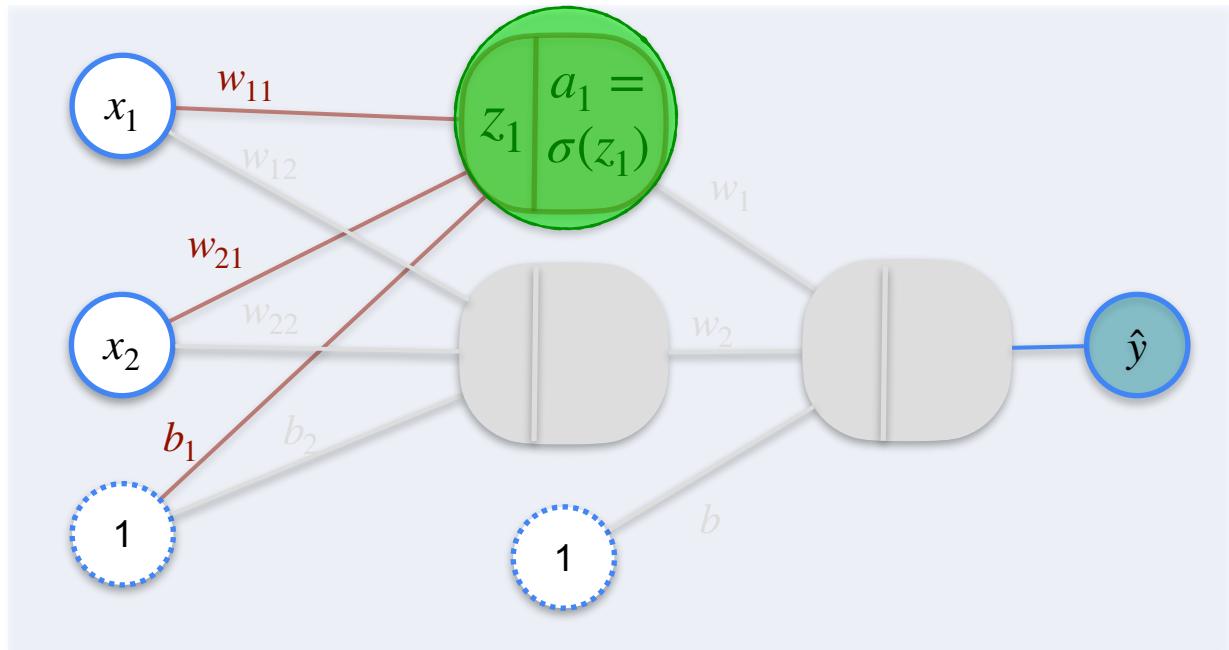


2,2,1 Neural Network



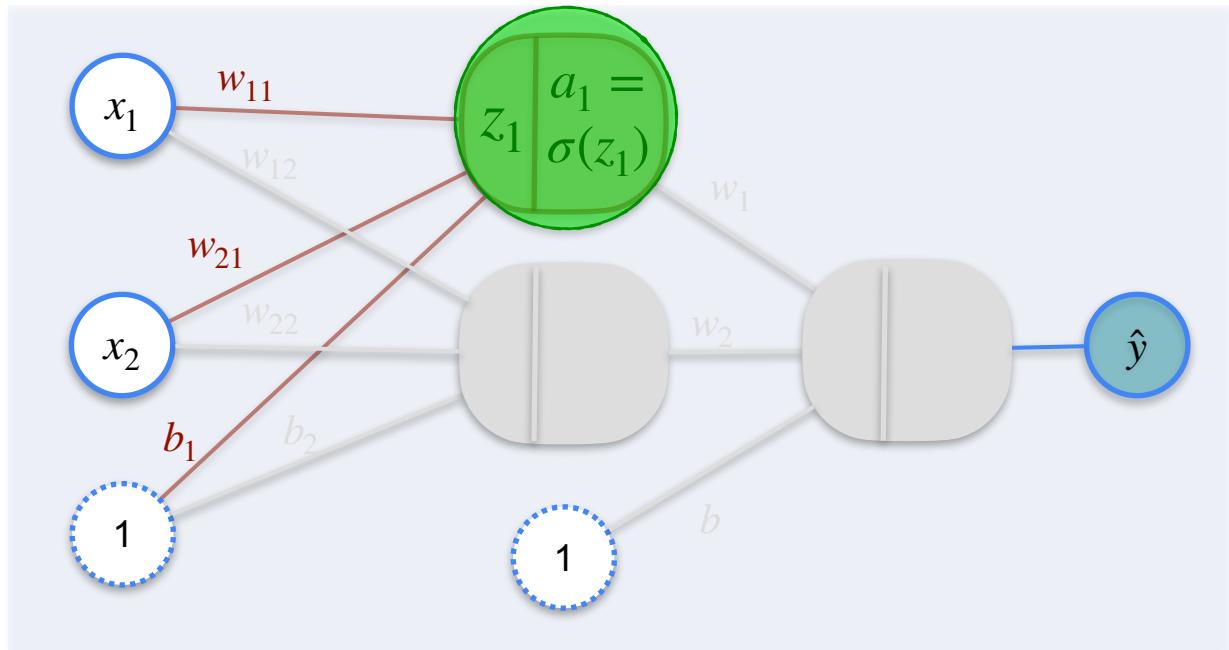
2,2,1 Neural Network

a_1



2,2,1 Neural Network

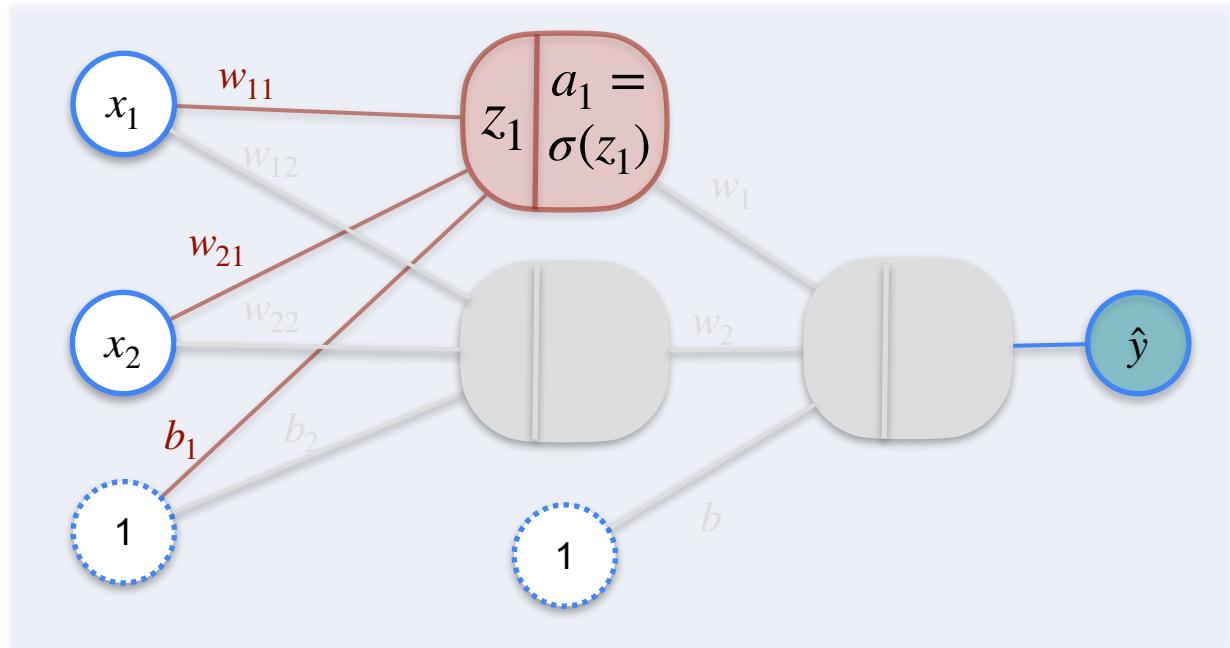
$$a_1 = \sigma(z_1)$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

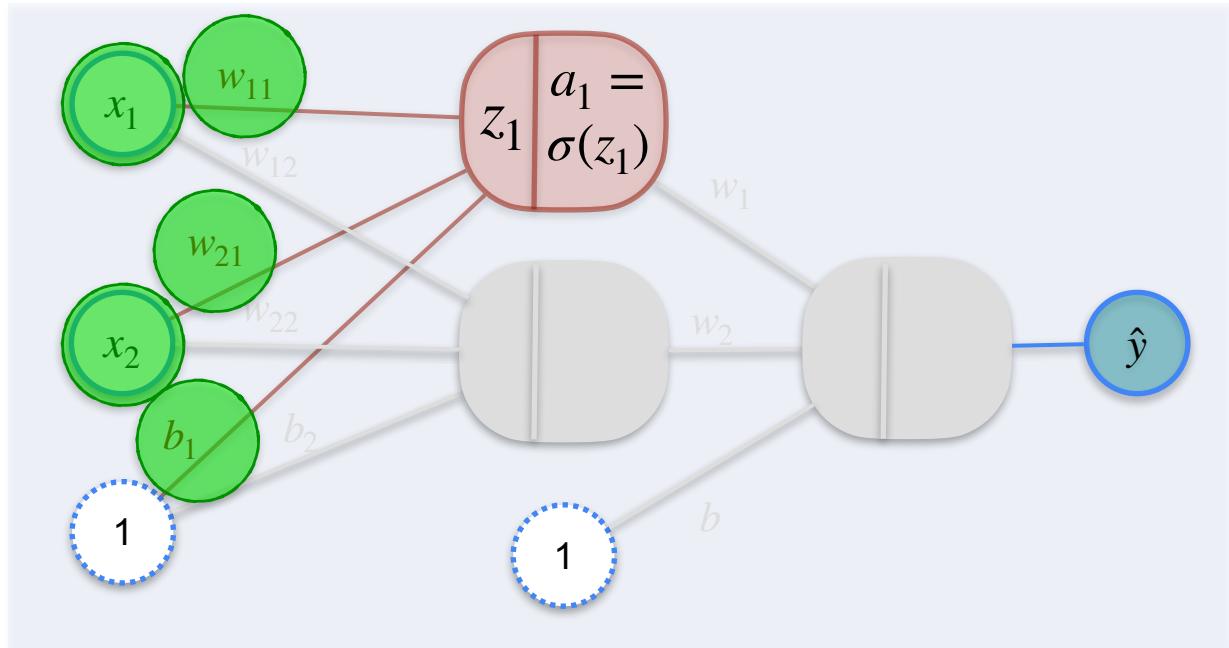
$$z_1$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

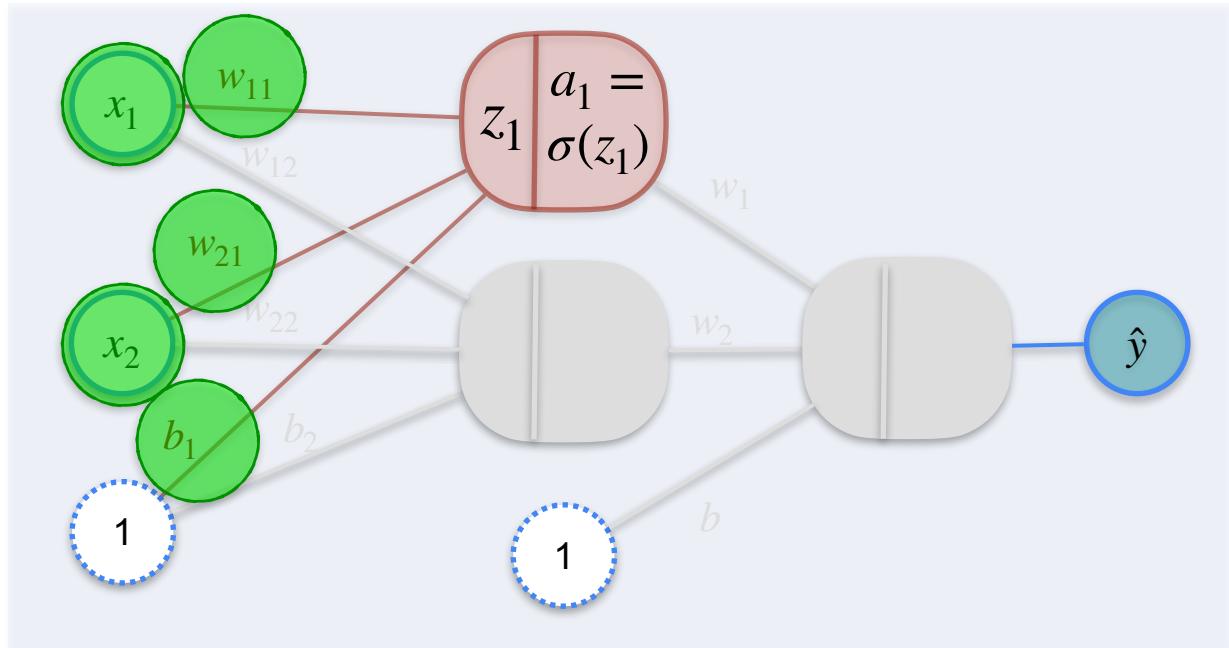
$$z_1$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

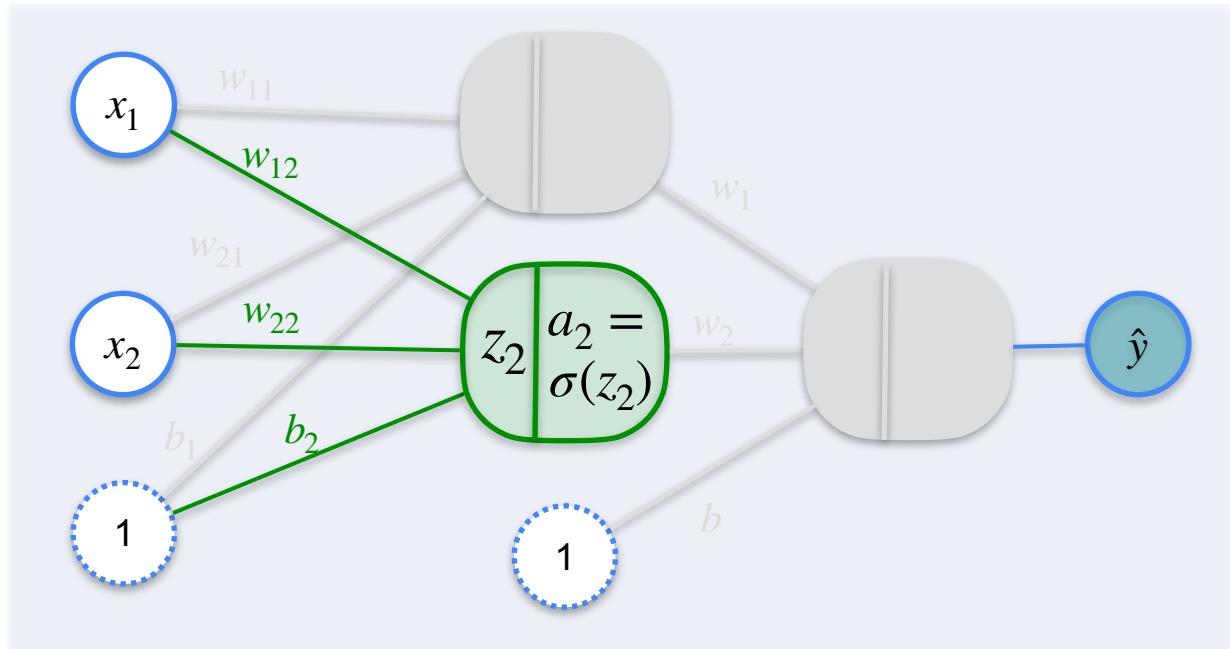
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

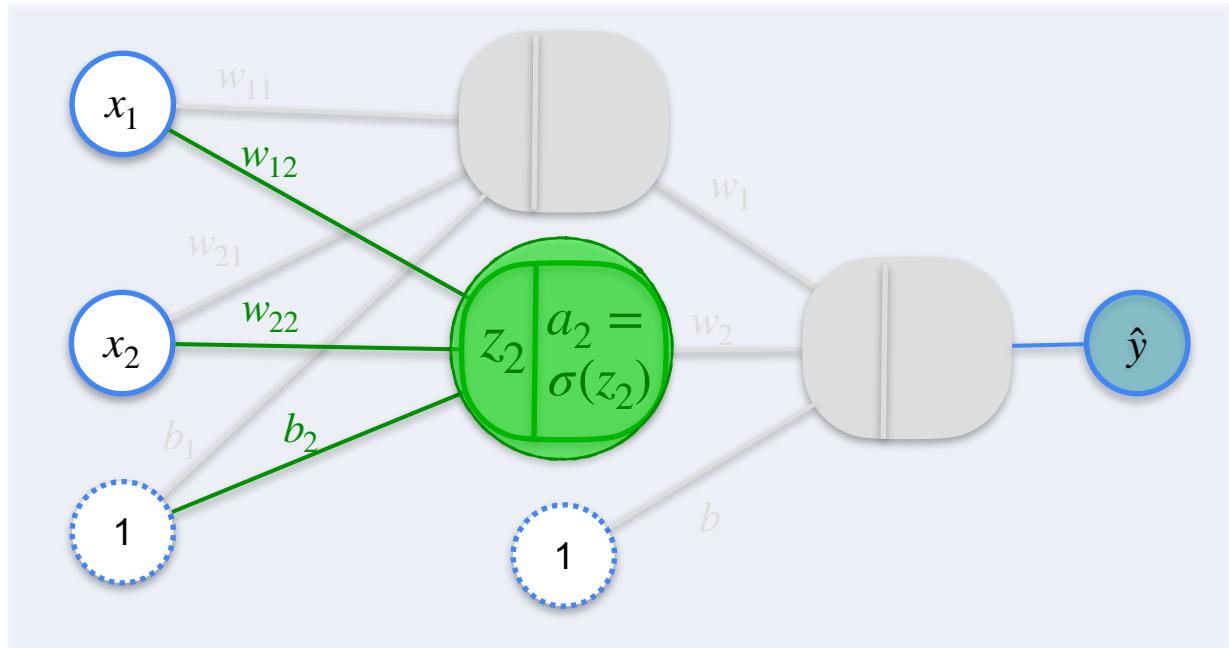
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

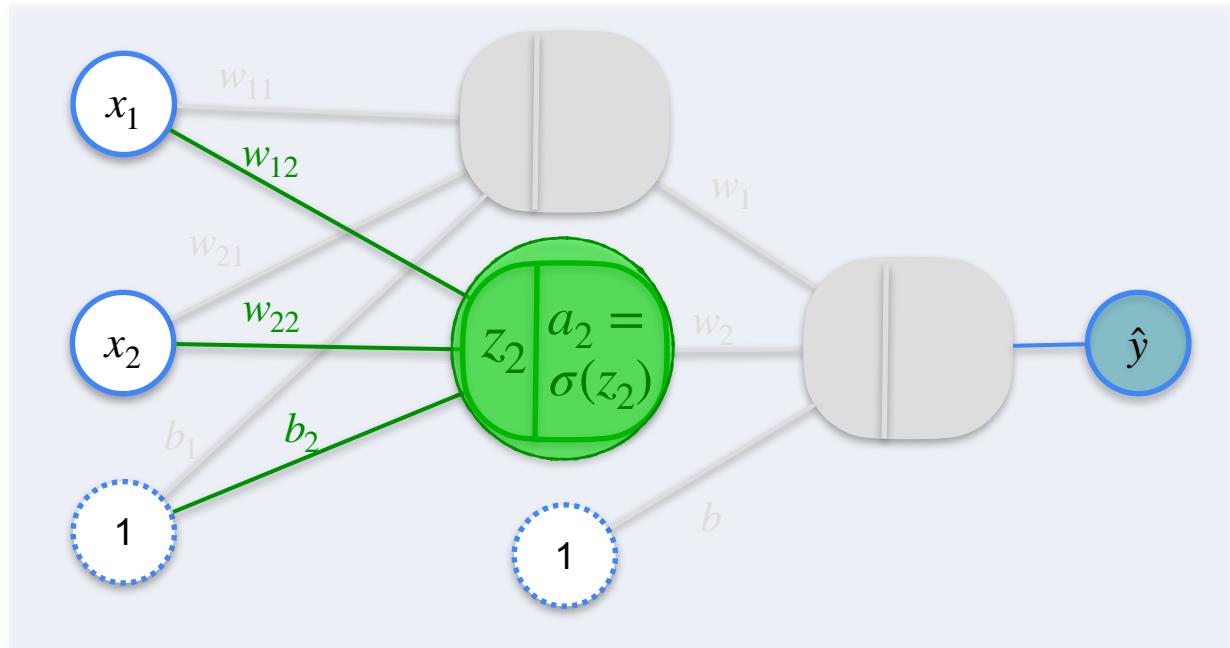


2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2$$

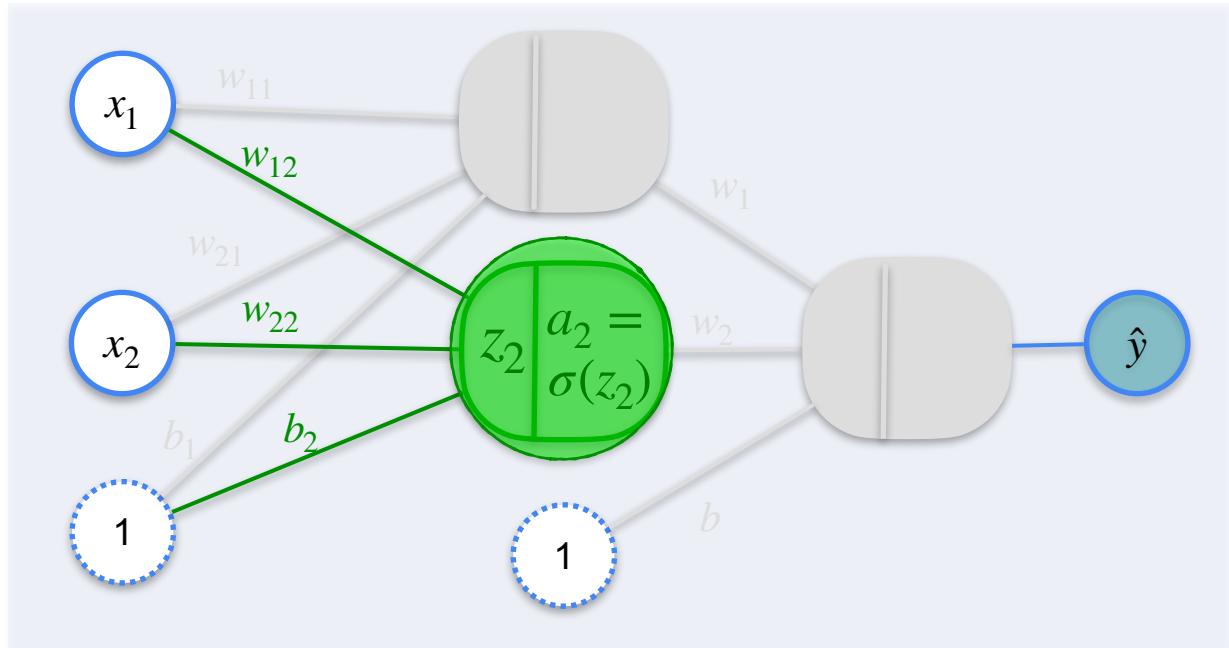


2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$



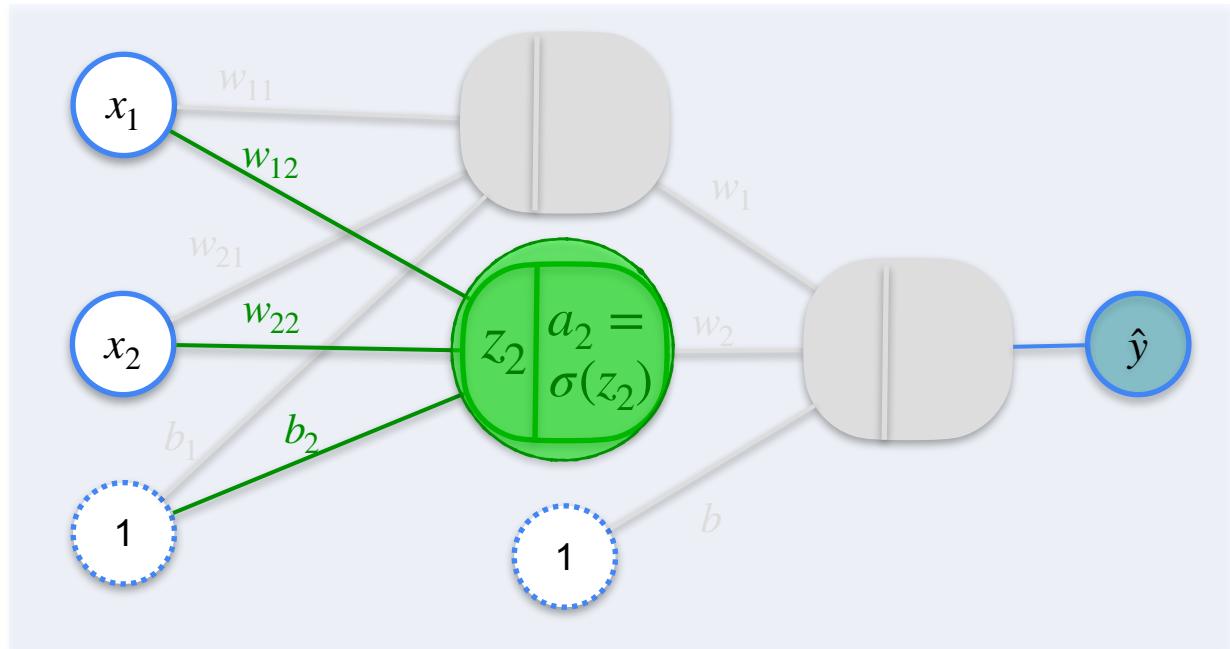
2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2$$



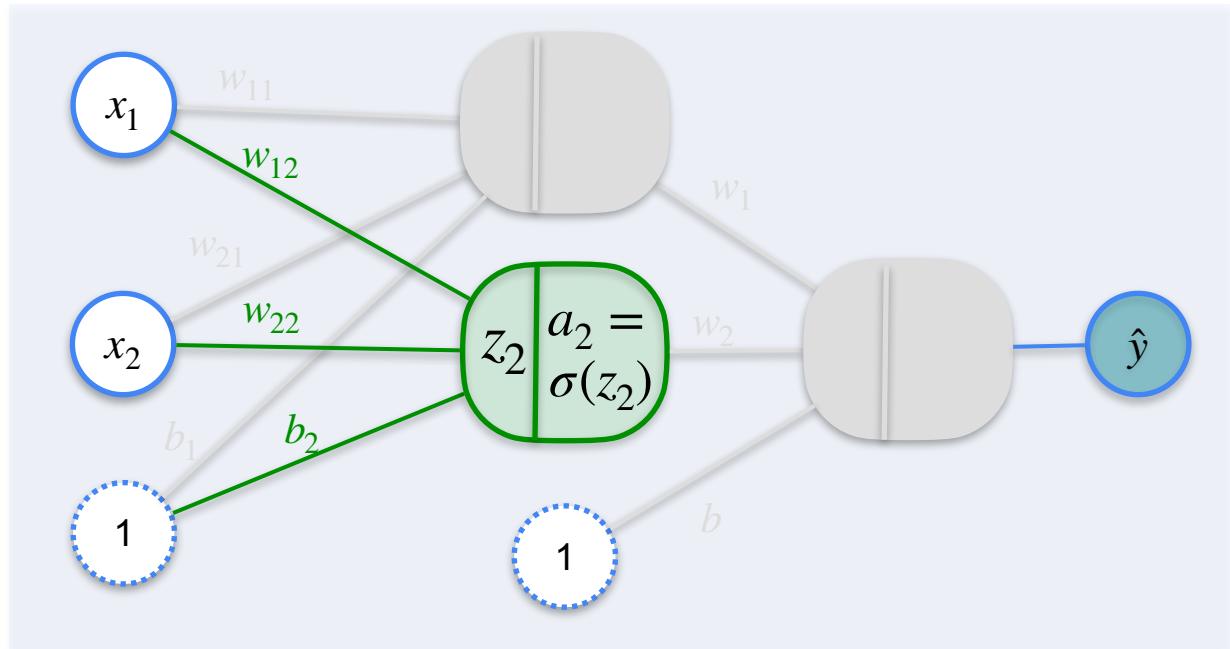
2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2$$



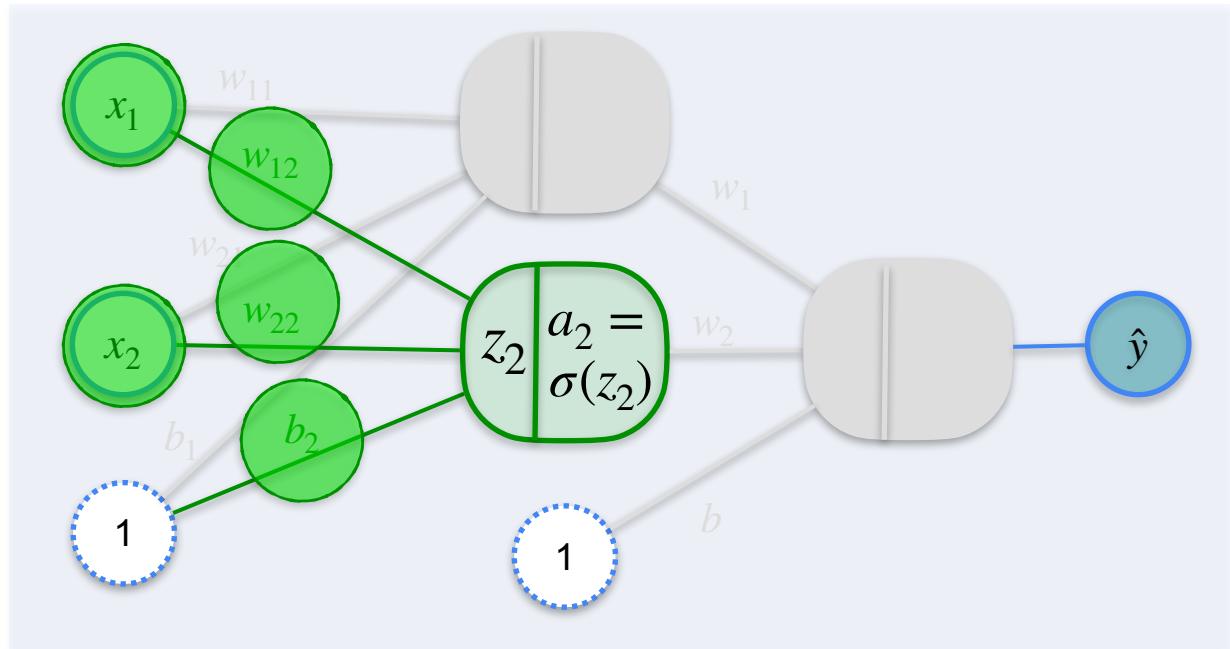
2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2$$



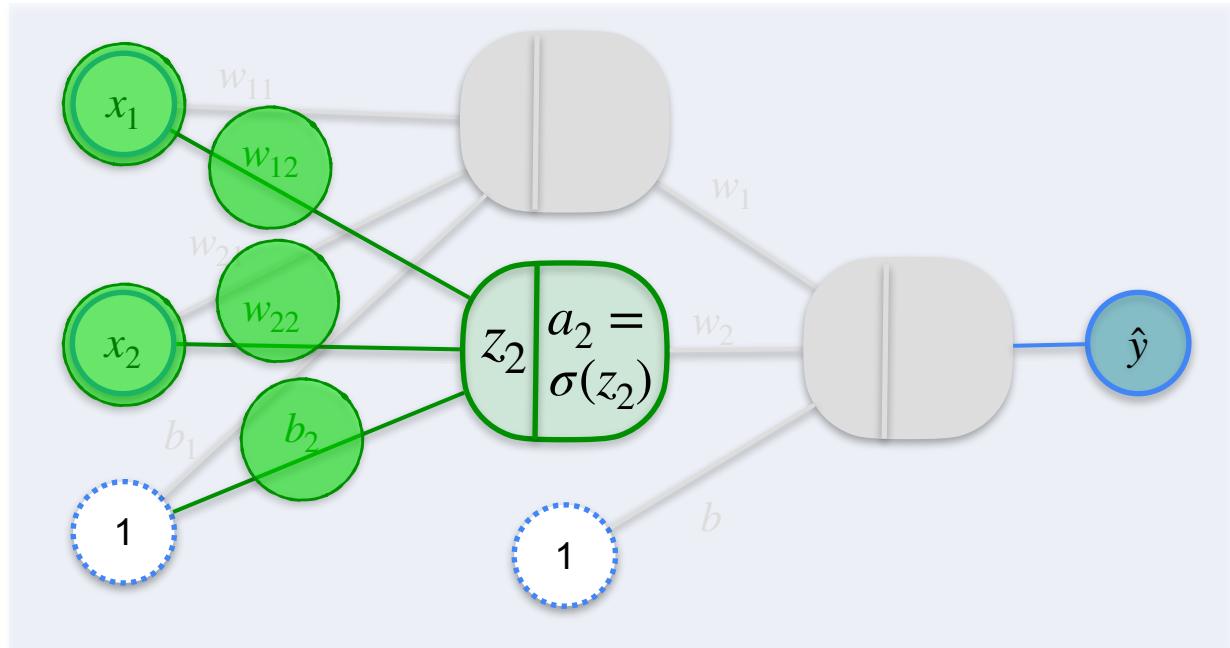
2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$



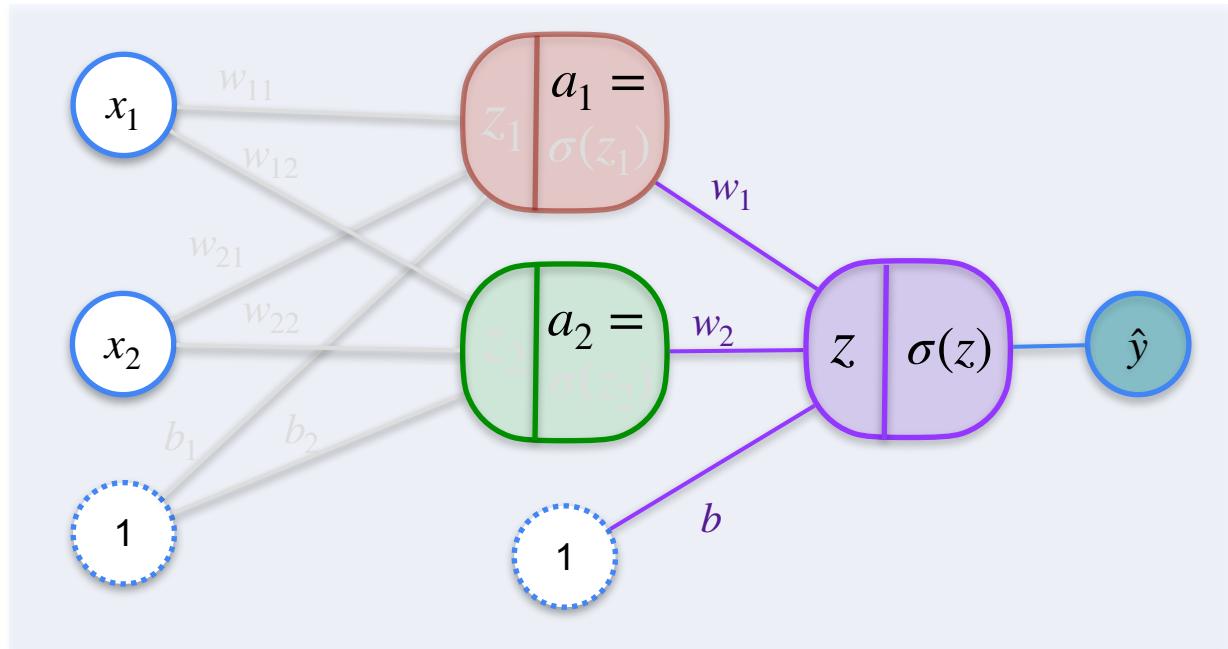
2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$



2,2,1 Neural Network

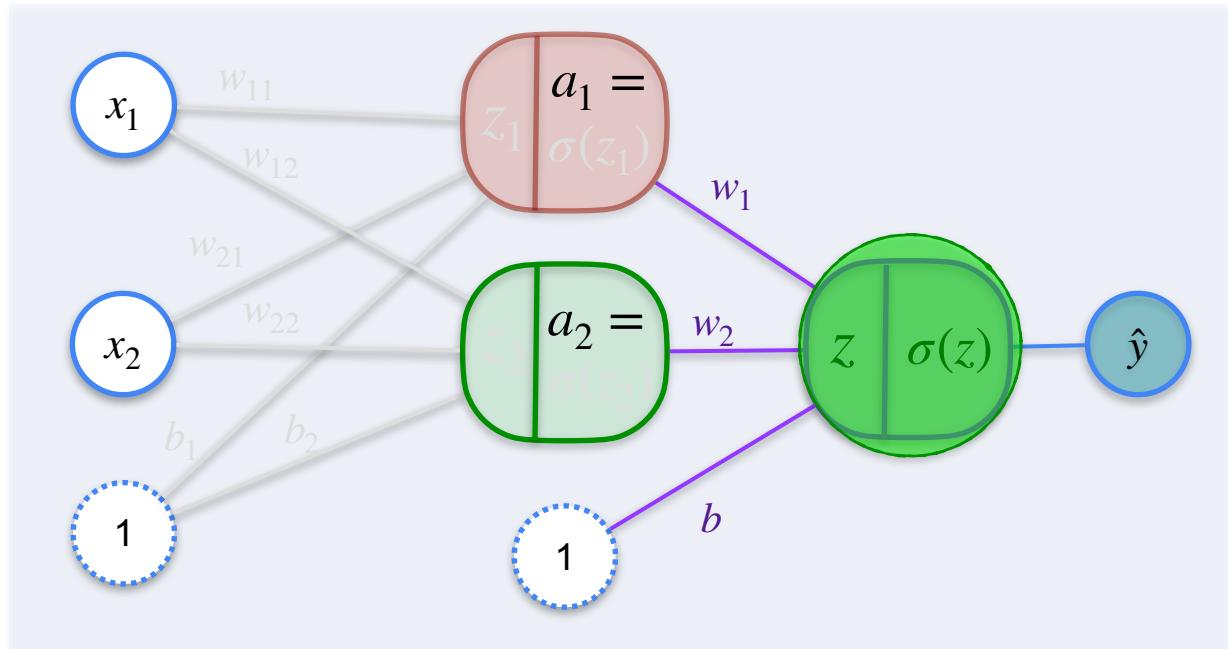
$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$



2,2,1 Neural Network

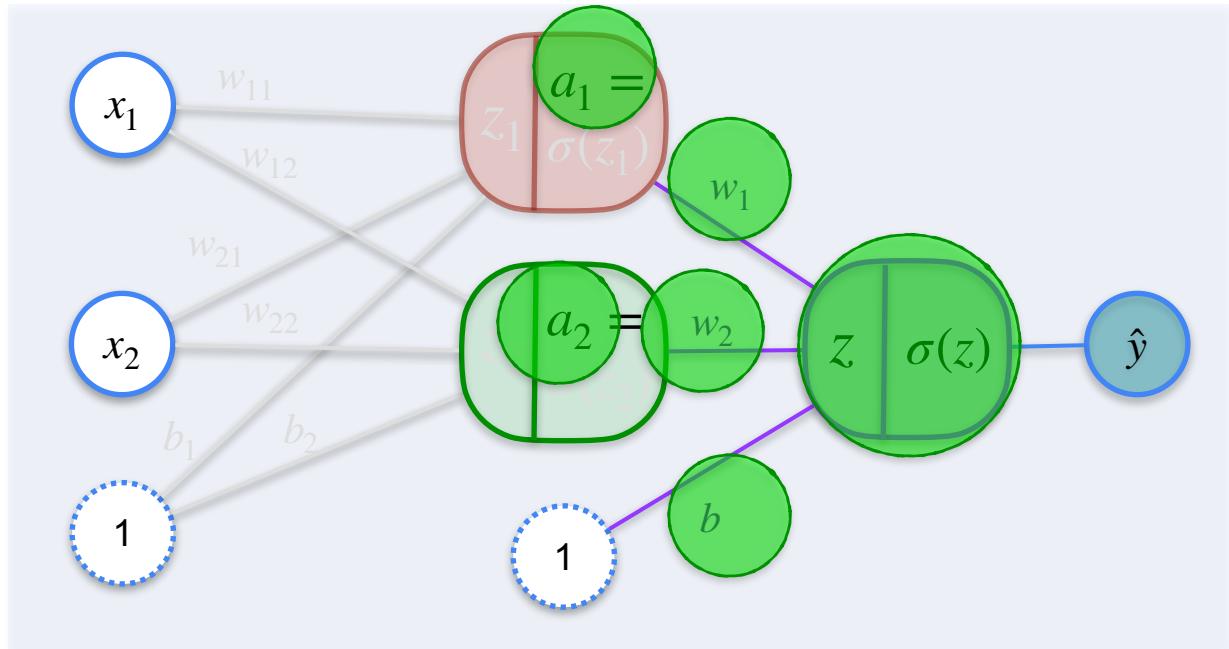
$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

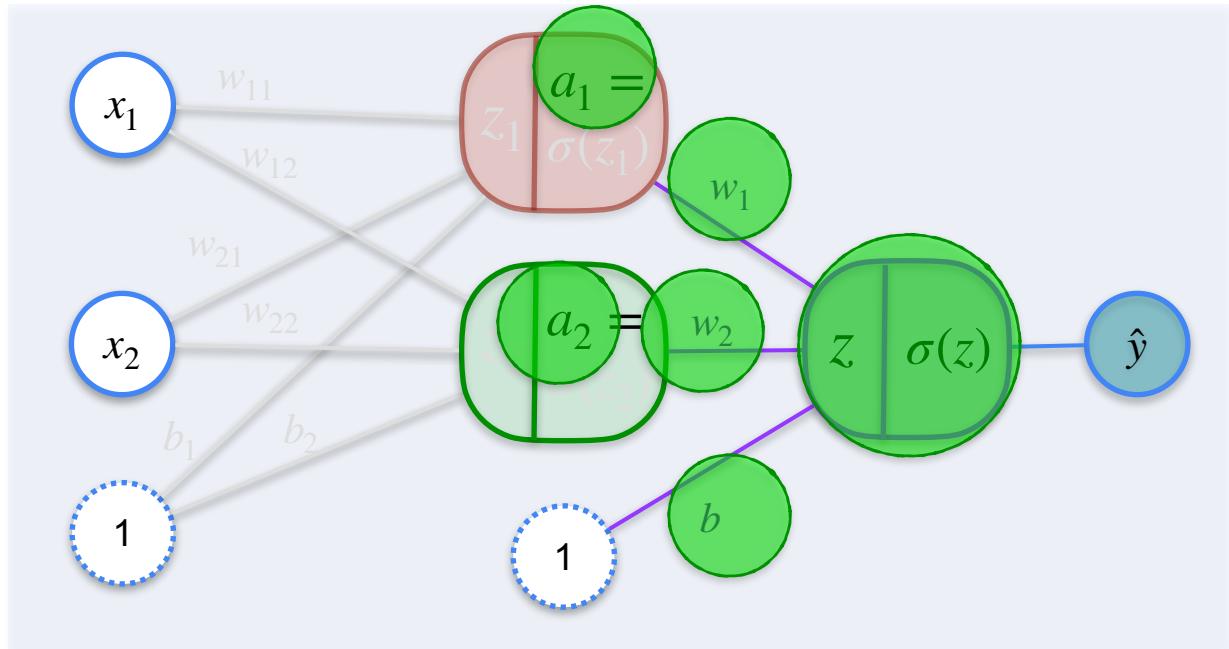
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

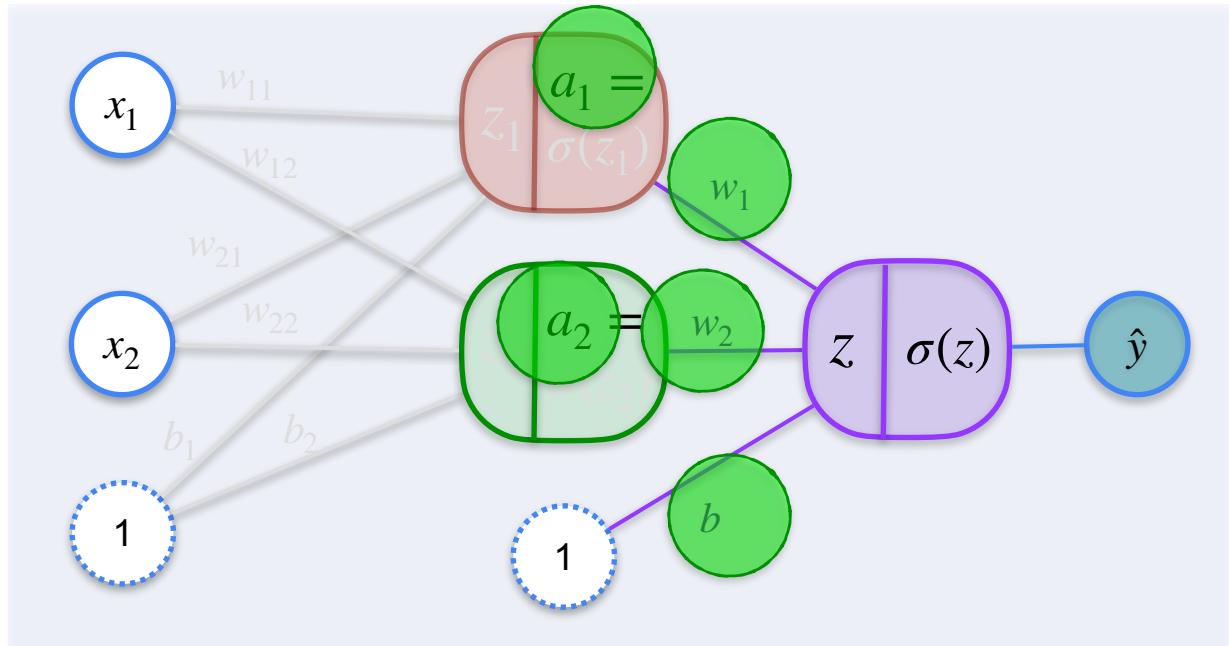
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

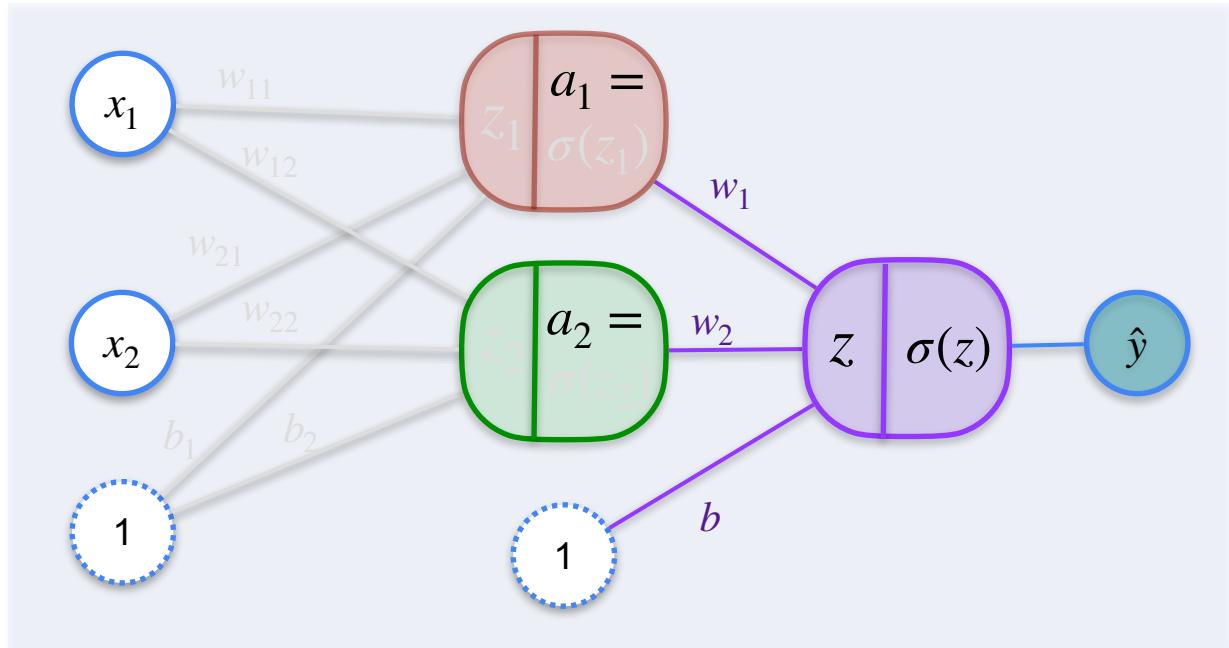
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

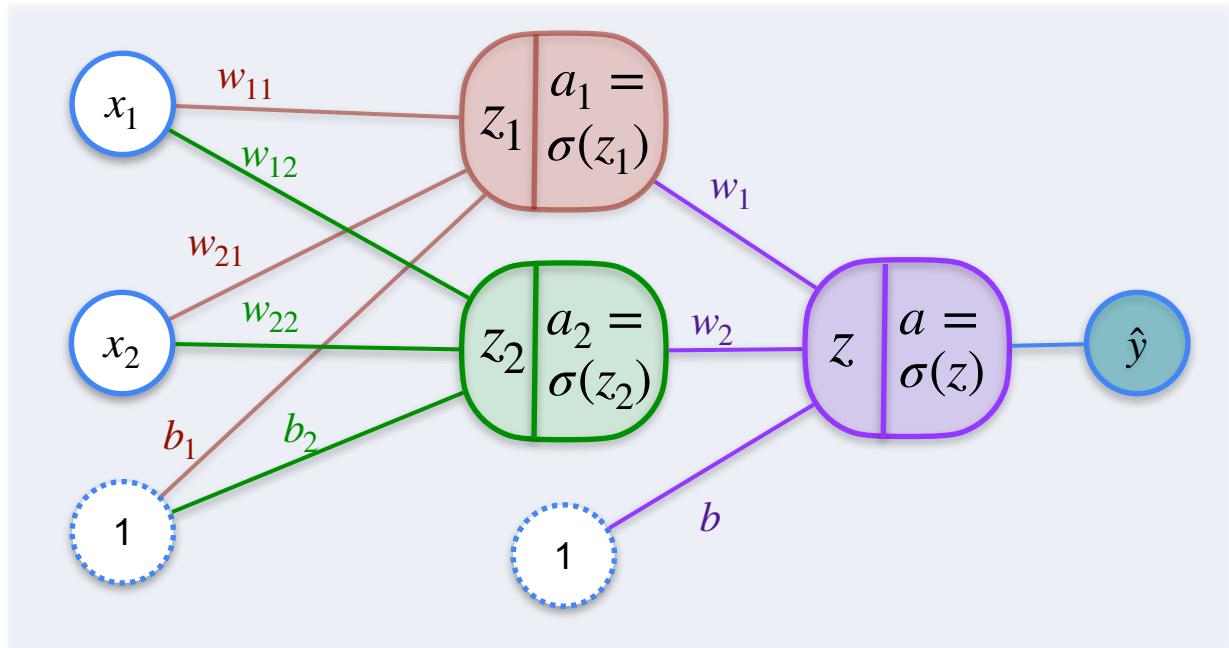
$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$



2,2,1 Neural Network

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

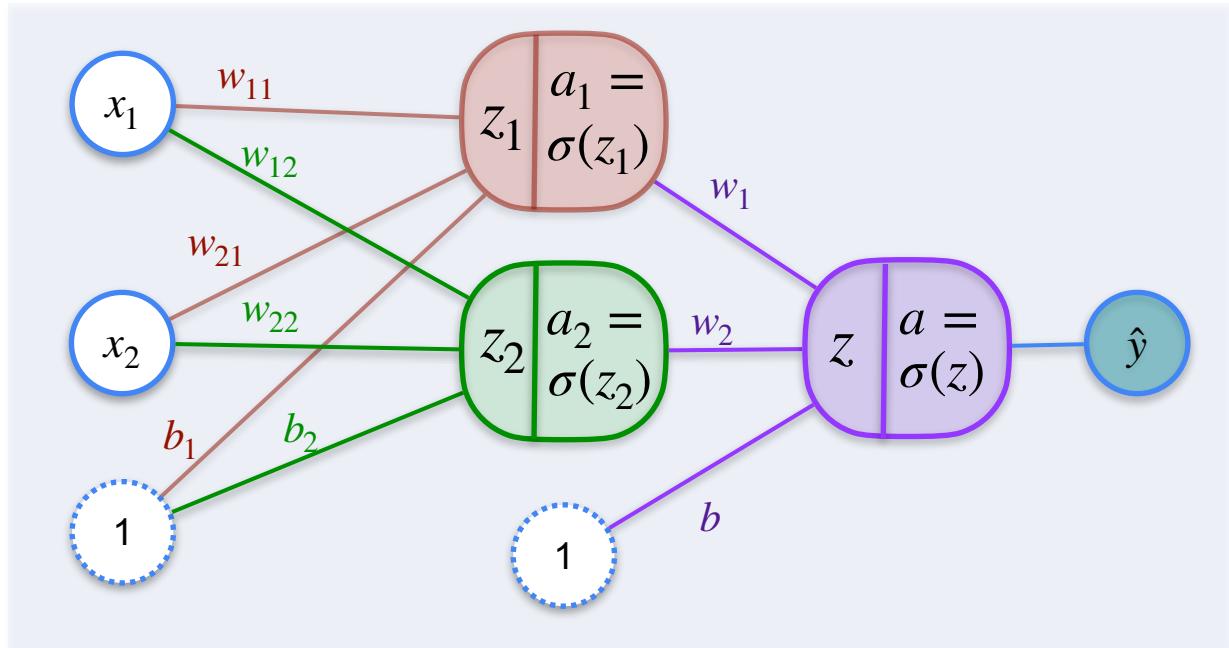
$$a_2 = \sigma(z_2)$$

$$z_2 = x_1 w_{12} + x_2 w_{22} + b_2$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$



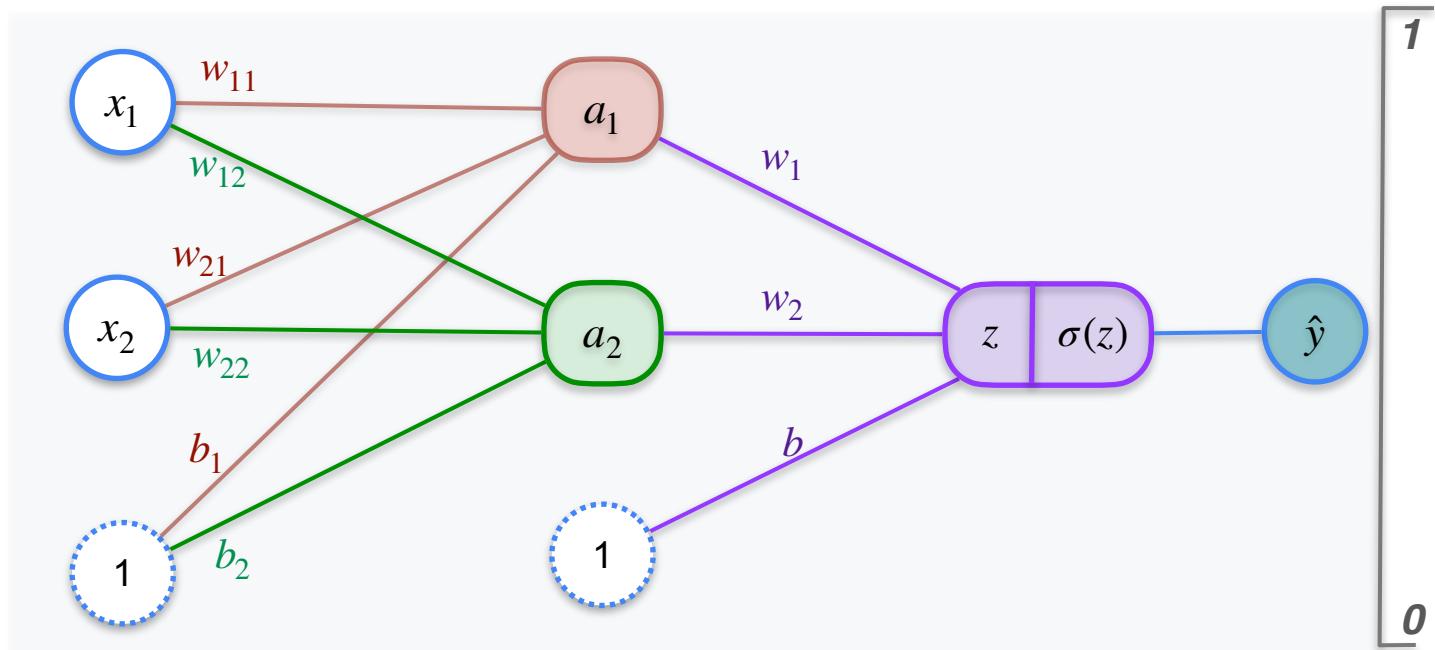


DeepLearning.AI

Optimization in Neural Networks and Newton's Method

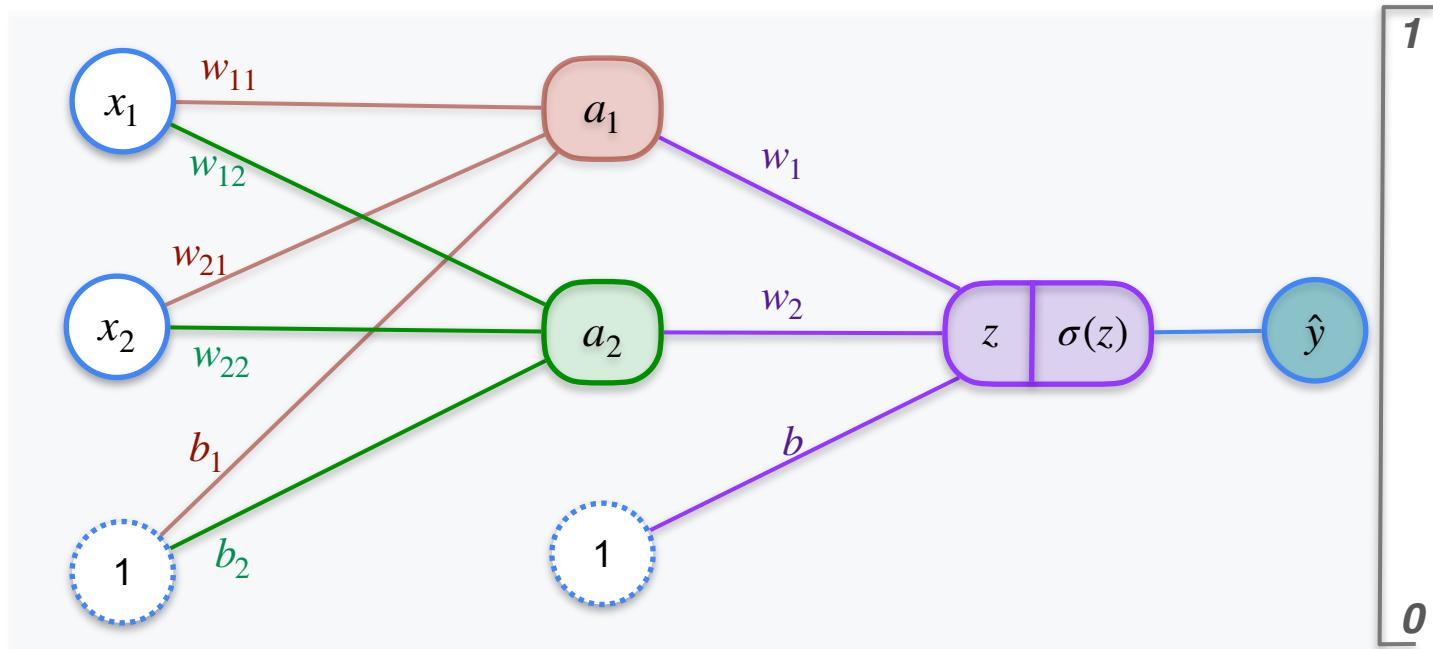
**Classification with a
Neural Network:
Minimizing log-loss**

2,2,1 Neural Network



2,2,1 Neural Network

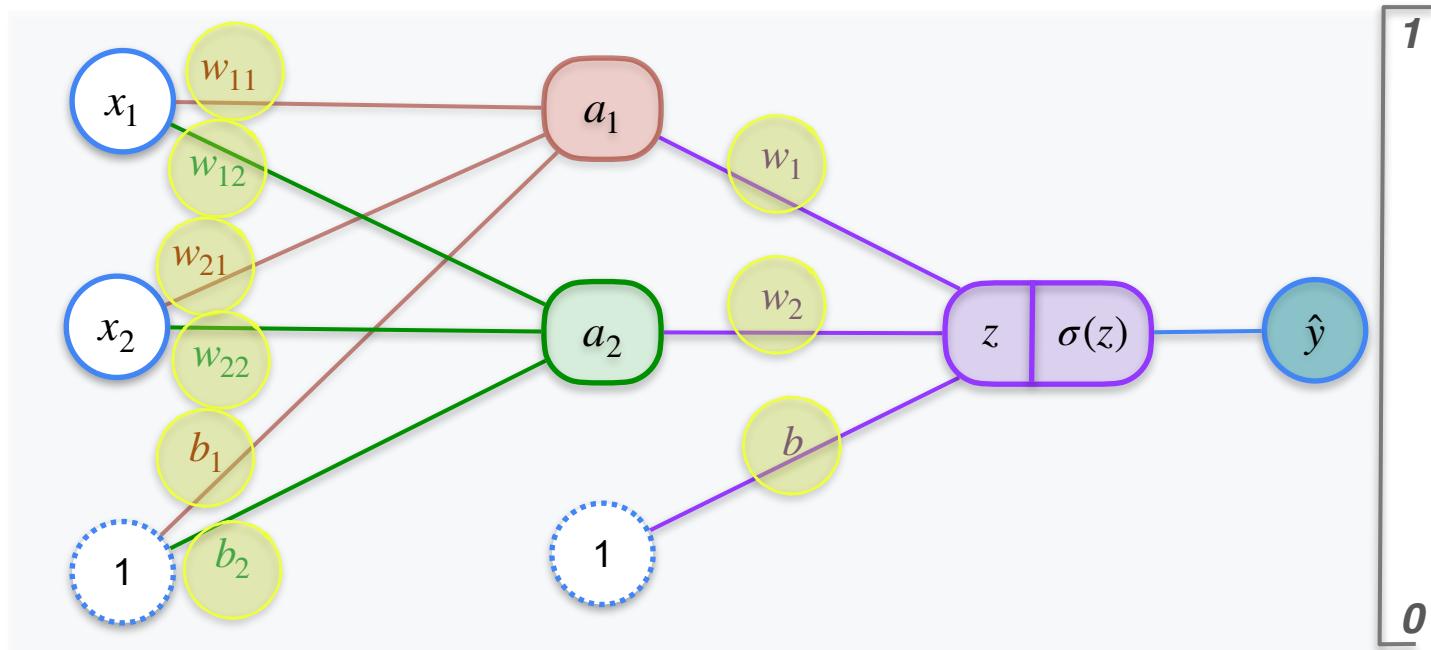
Goal



2,2,1 Neural Network

Goal

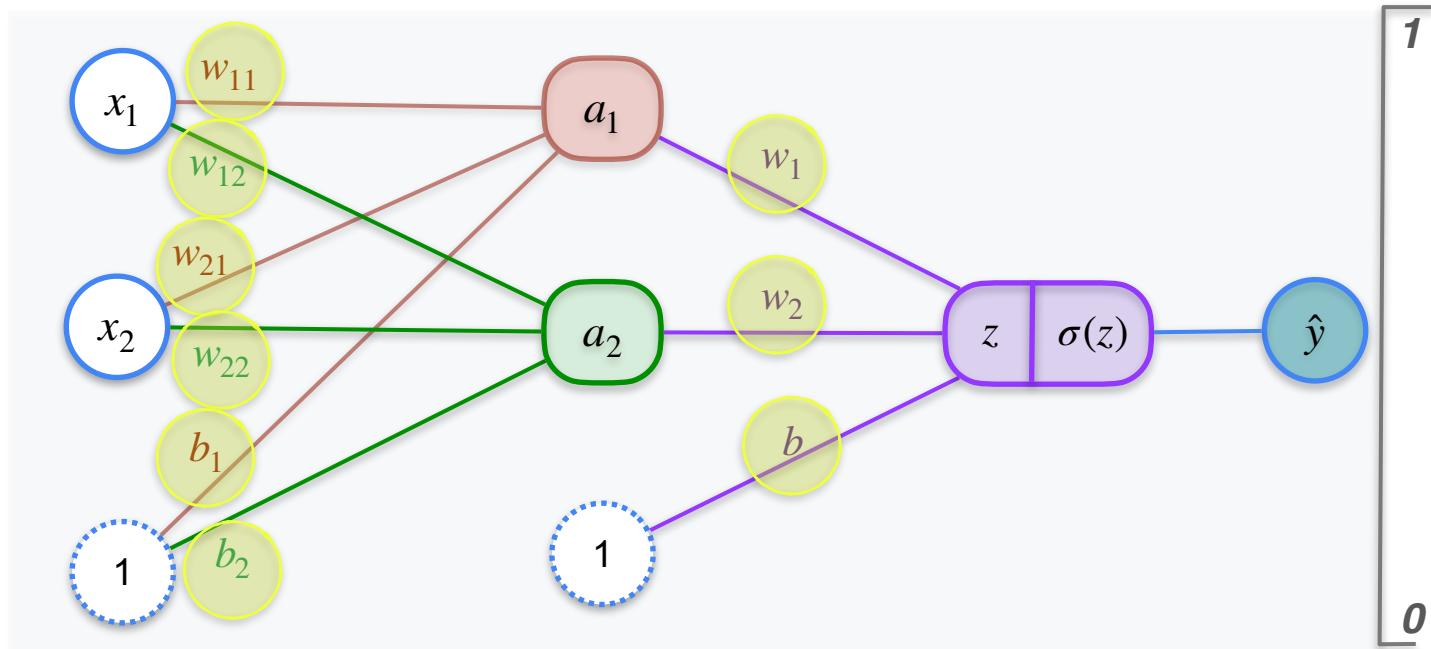
Adjust each of the highlighted weights and biases



2,2,1 Neural Network

Goal

Adjust each of the highlighted weights and biases

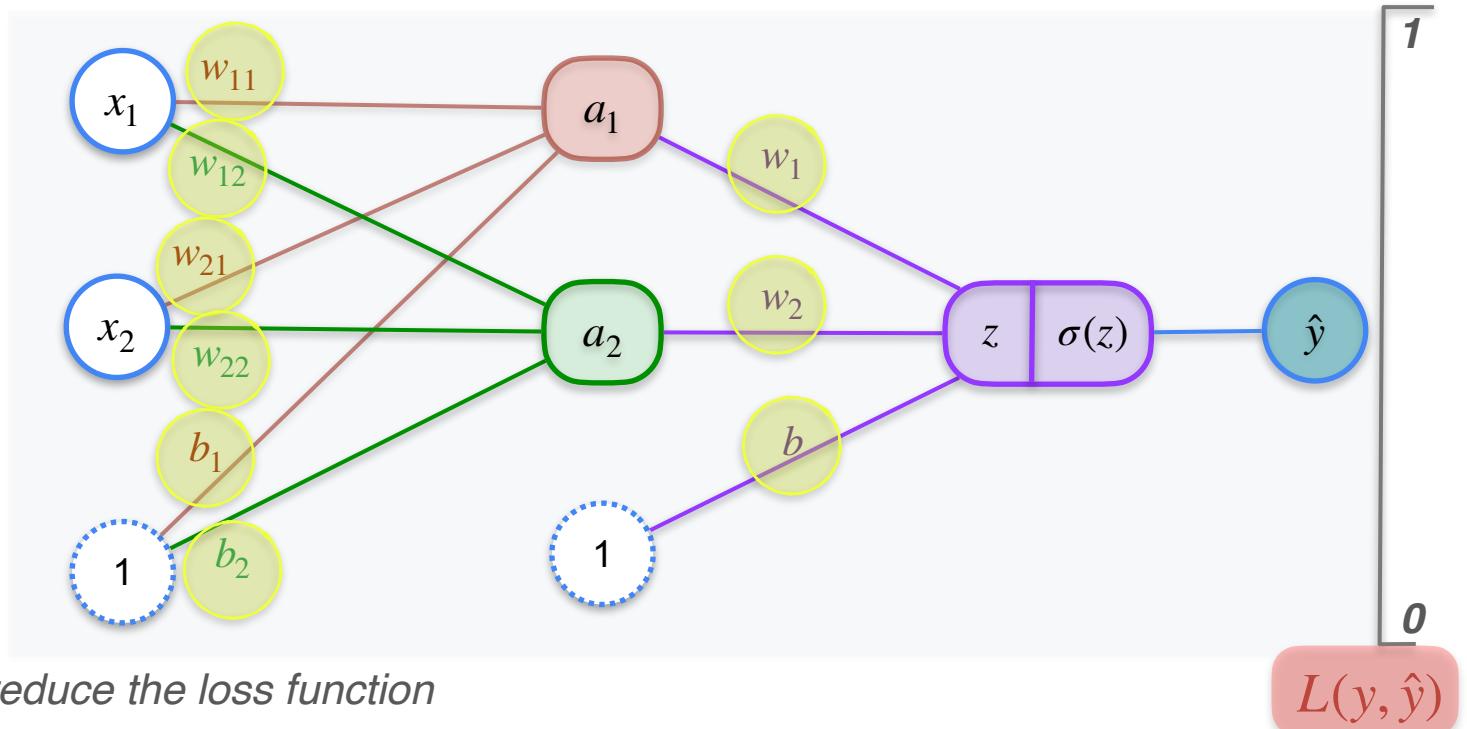


To reduce the loss function

2,2,1 Neural Network

Goal

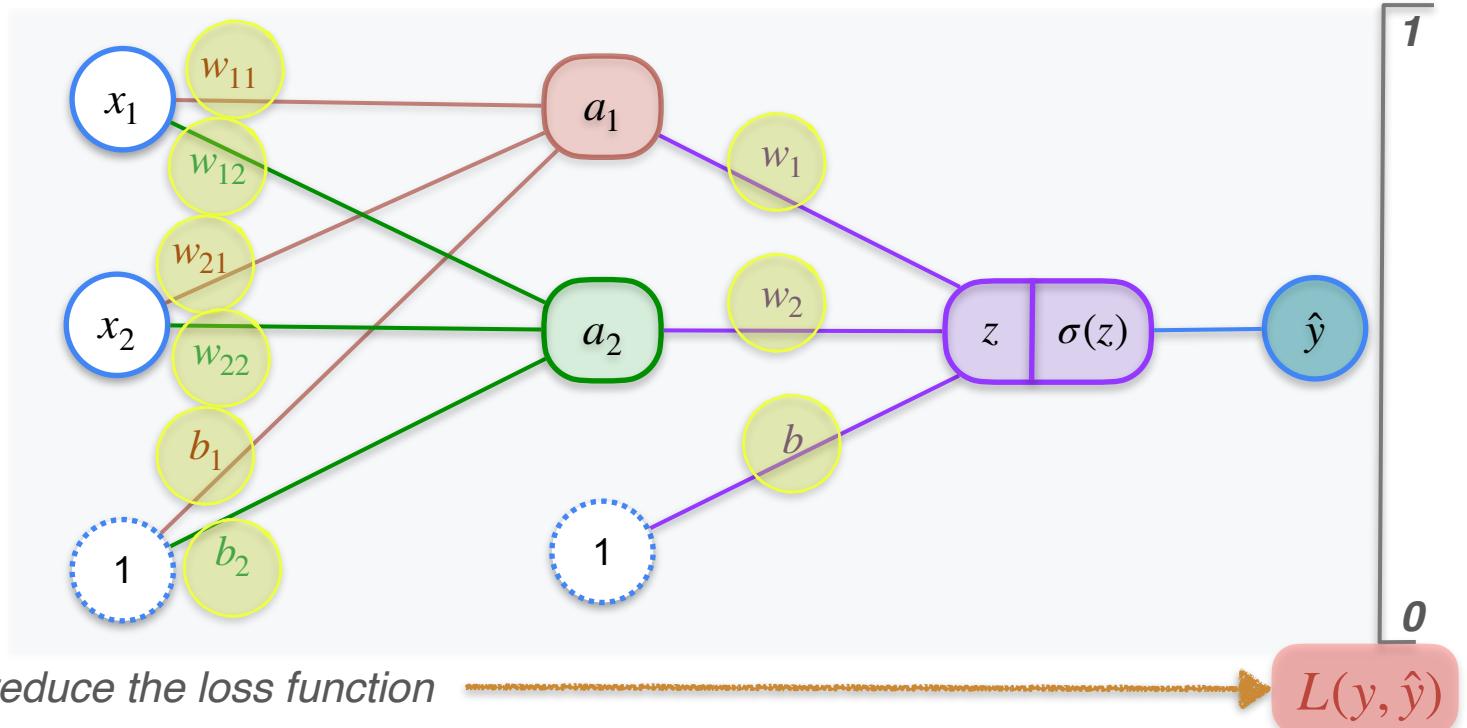
Adjust each of the highlighted weights and biases



2,2,1 Neural Network

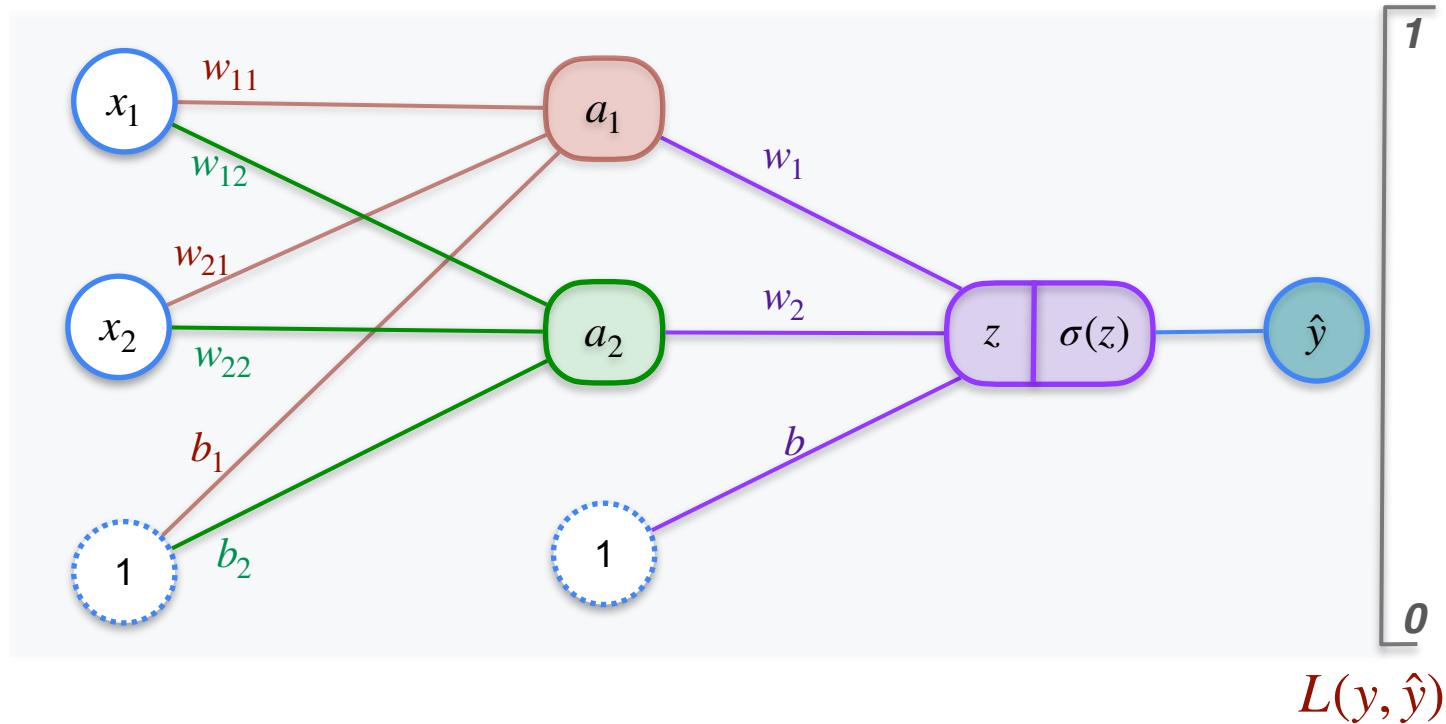
Goal

Adjust each of the highlighted weights and biases

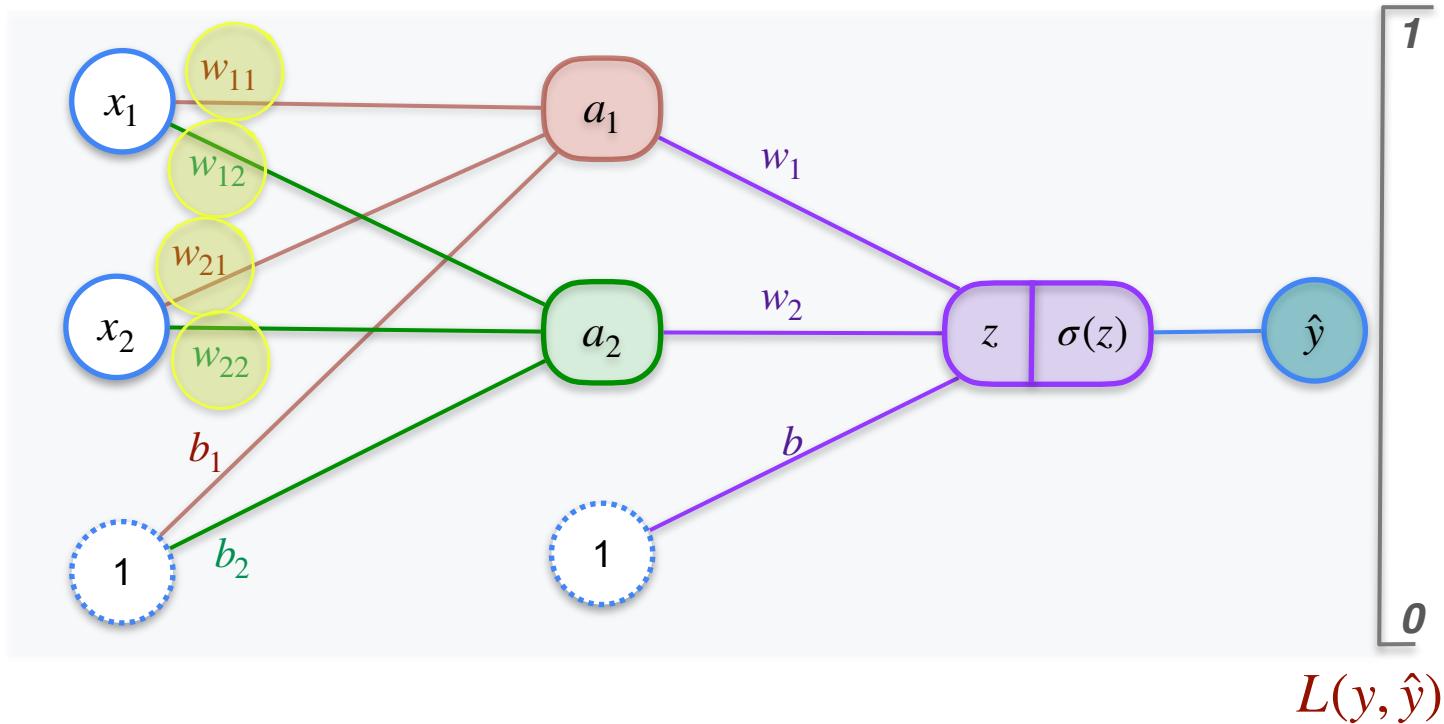


To reduce the loss function

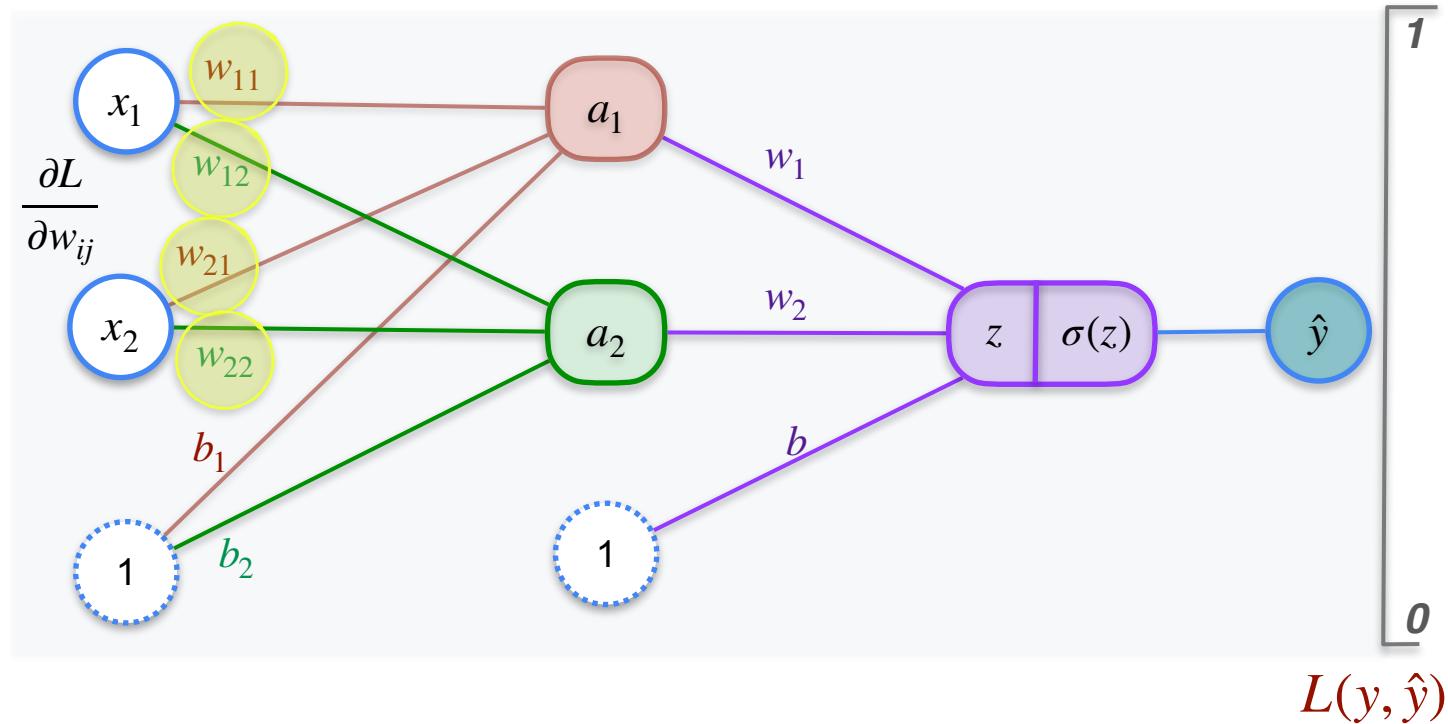
2,2,1 Neural Network



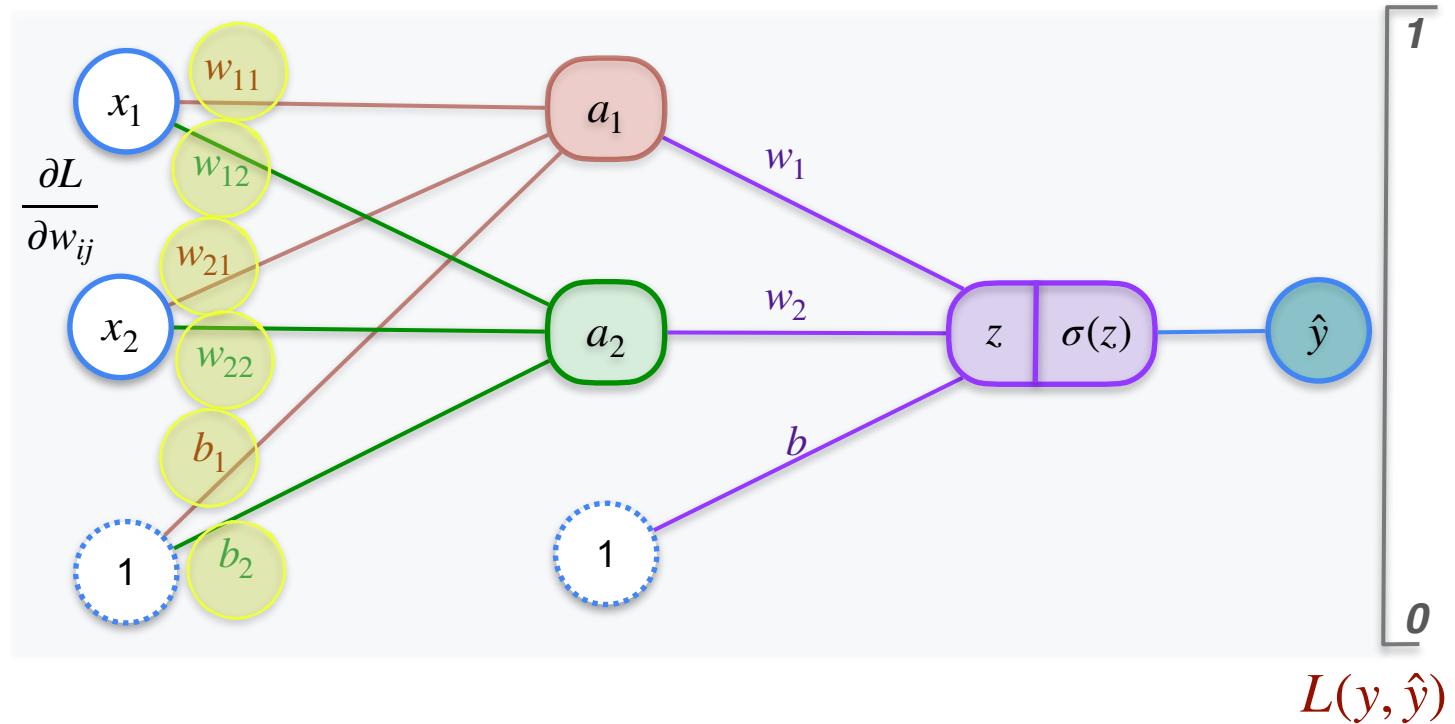
2,2,1 Neural Network



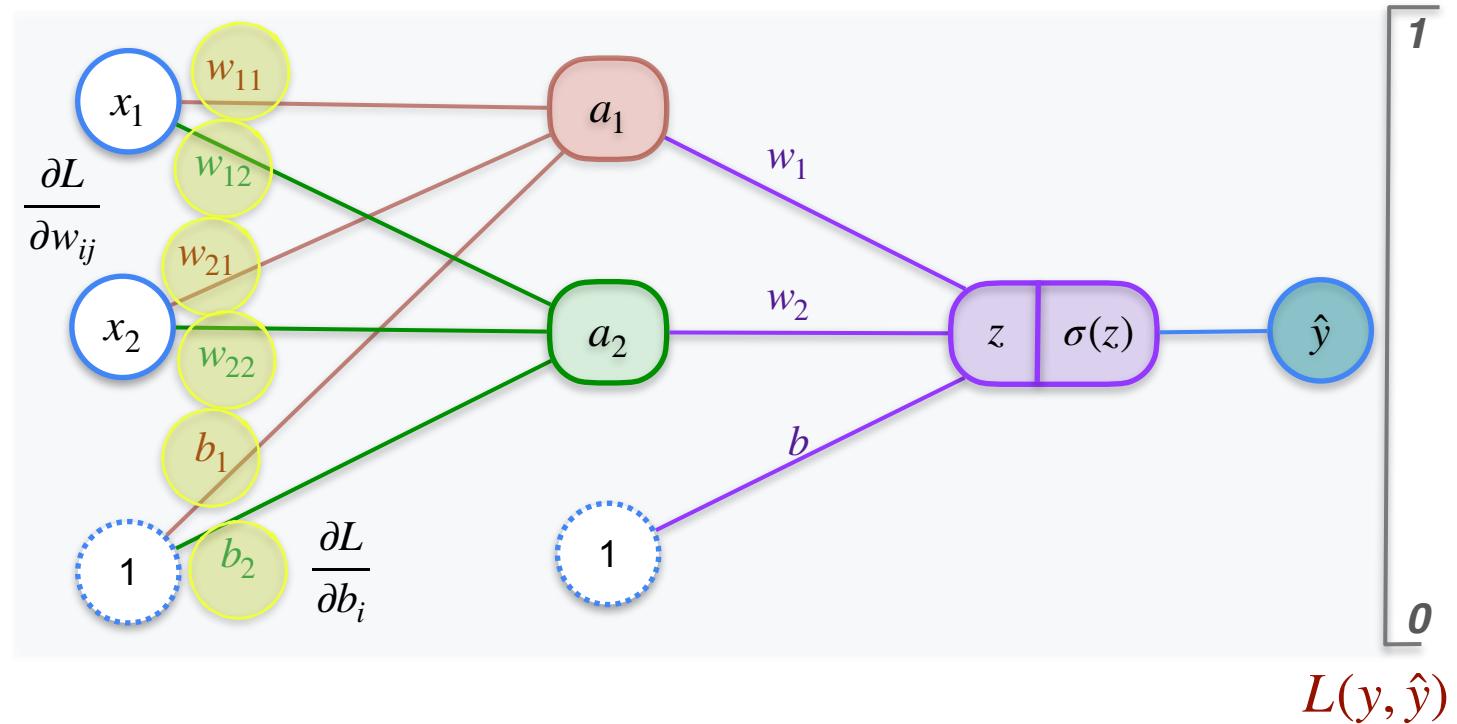
2,2,1 Neural Network



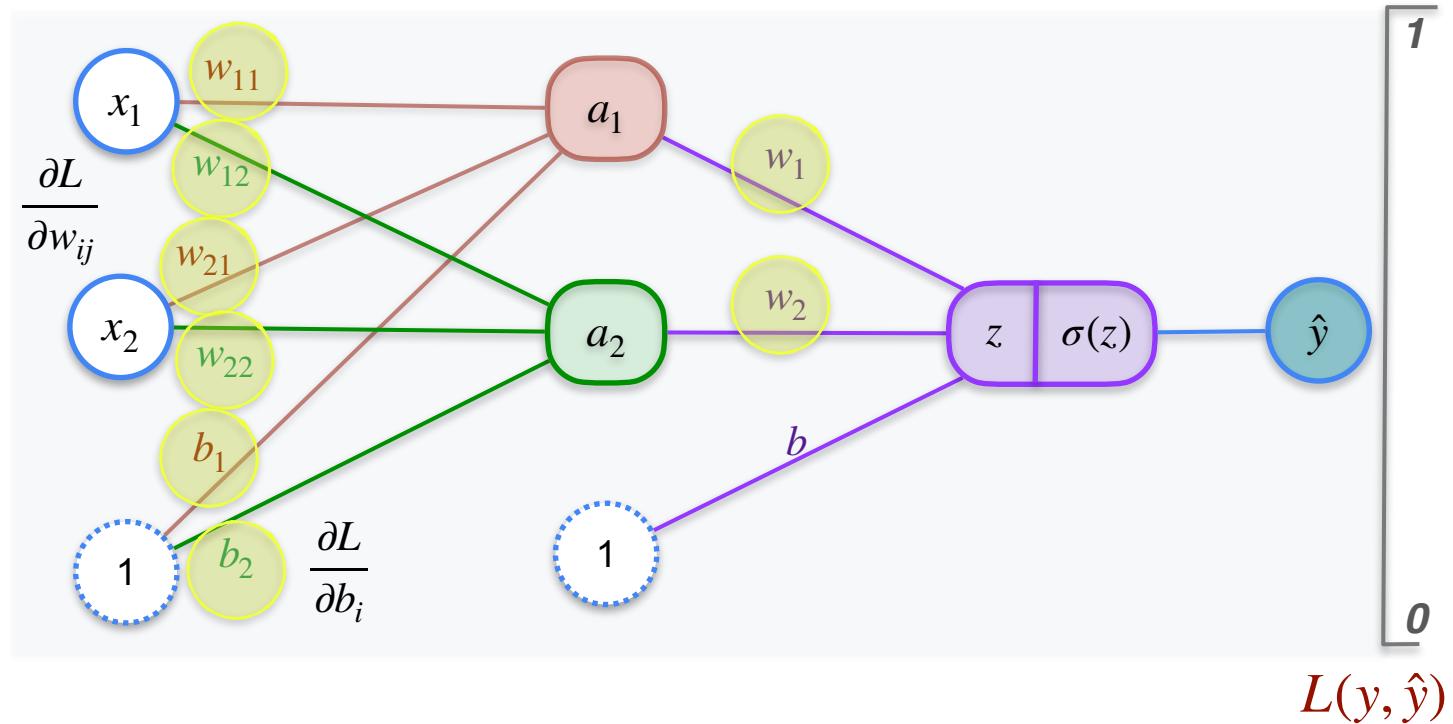
2,2,1 Neural Network



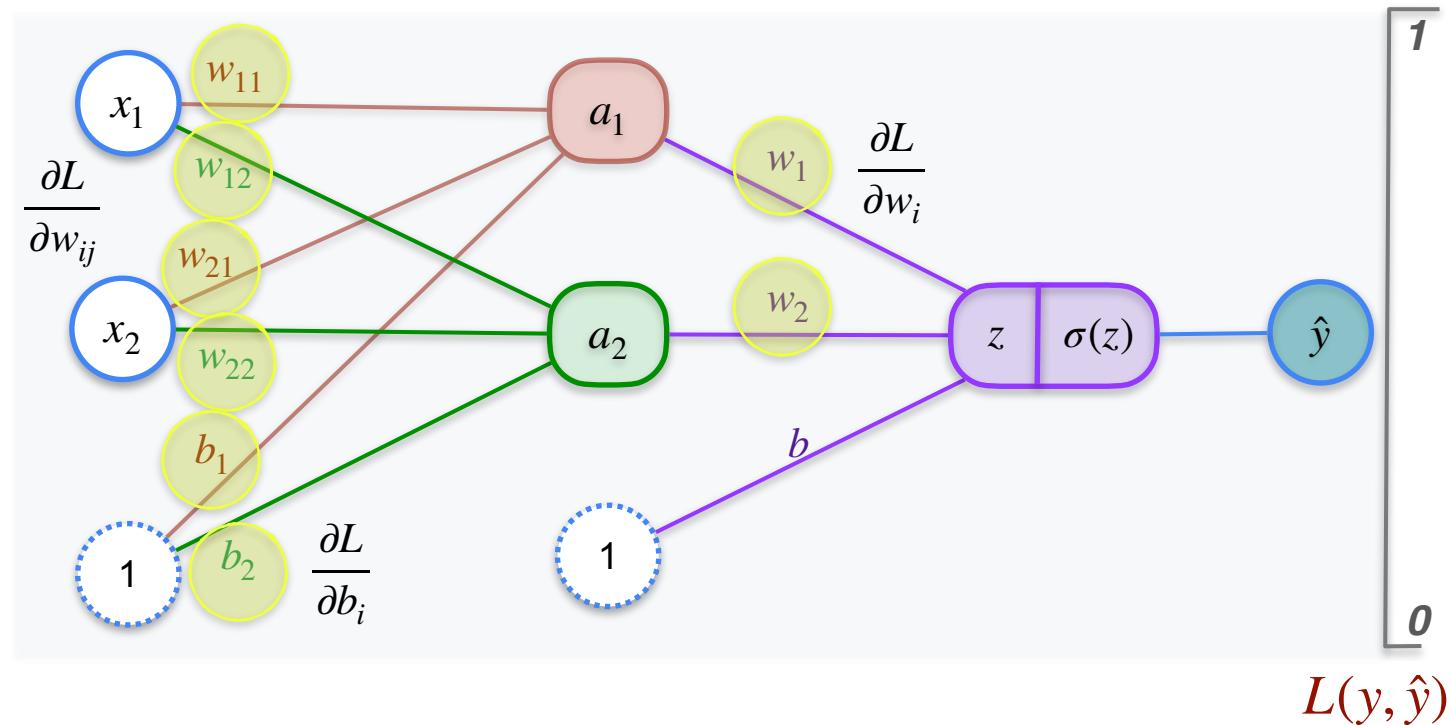
2,2,1 Neural Network



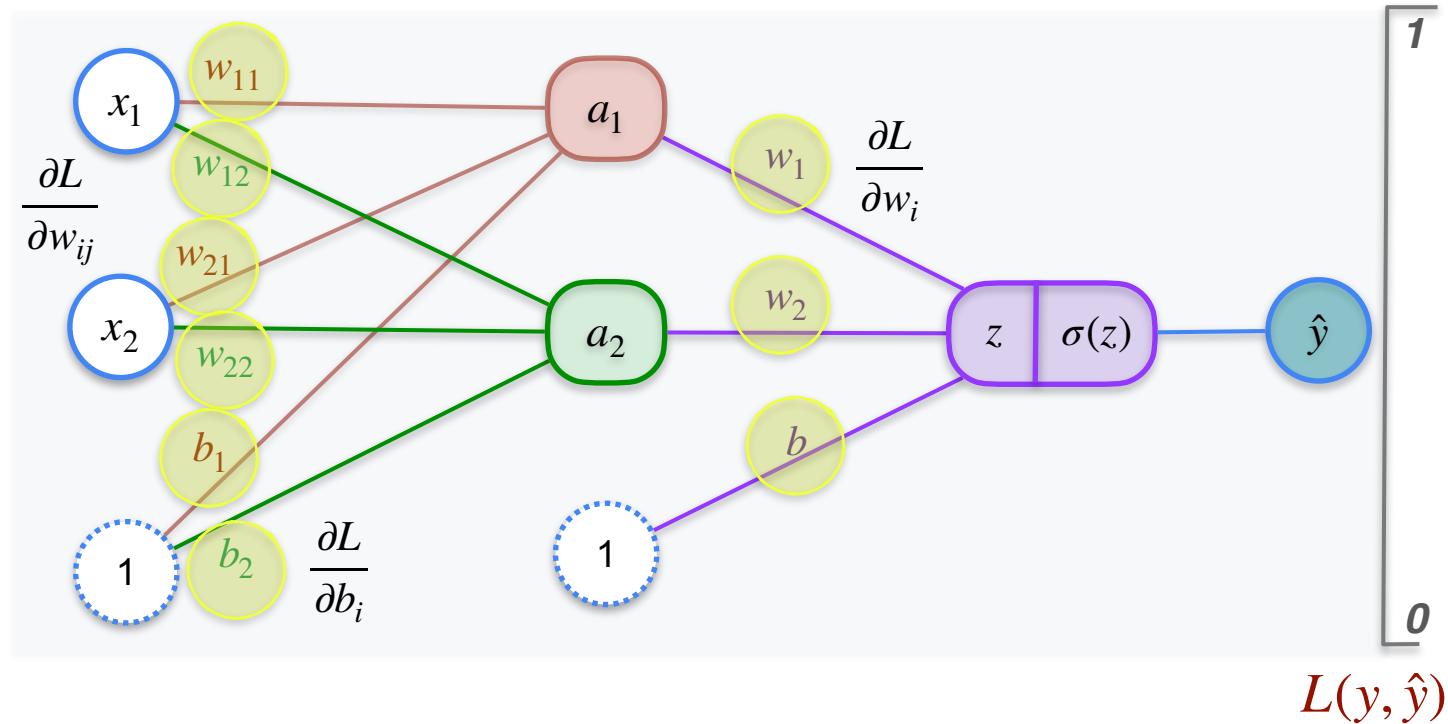
2,2,1 Neural Network



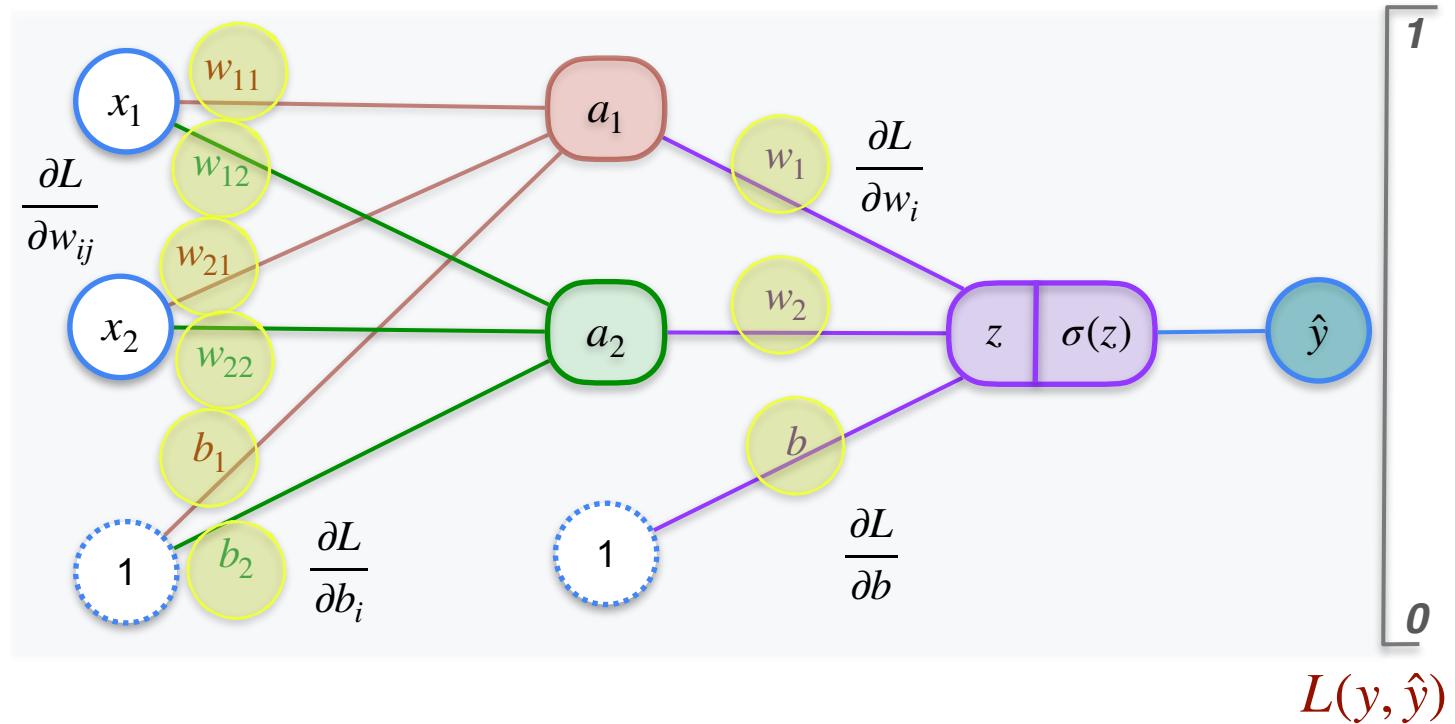
2,2,1 Neural Network



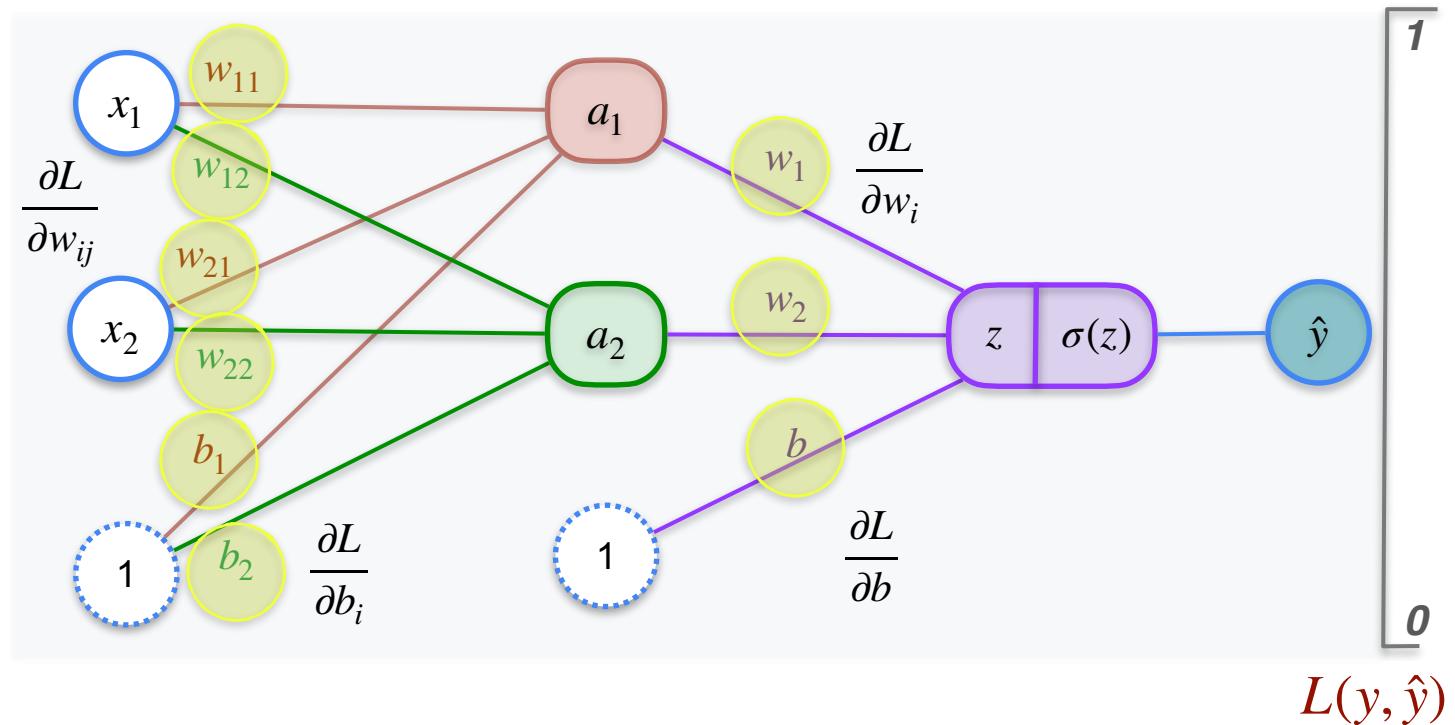
2,2,1 Neural Network



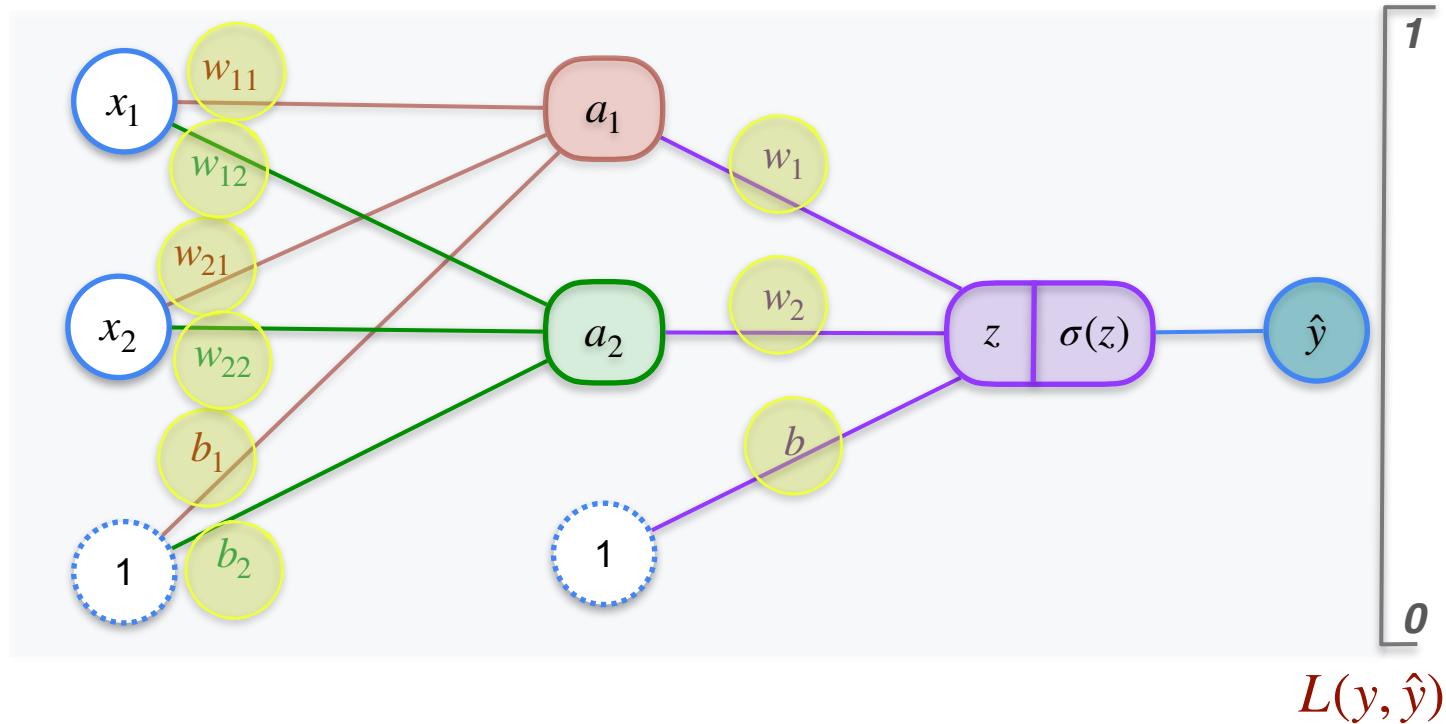
2,2,1 Neural Network



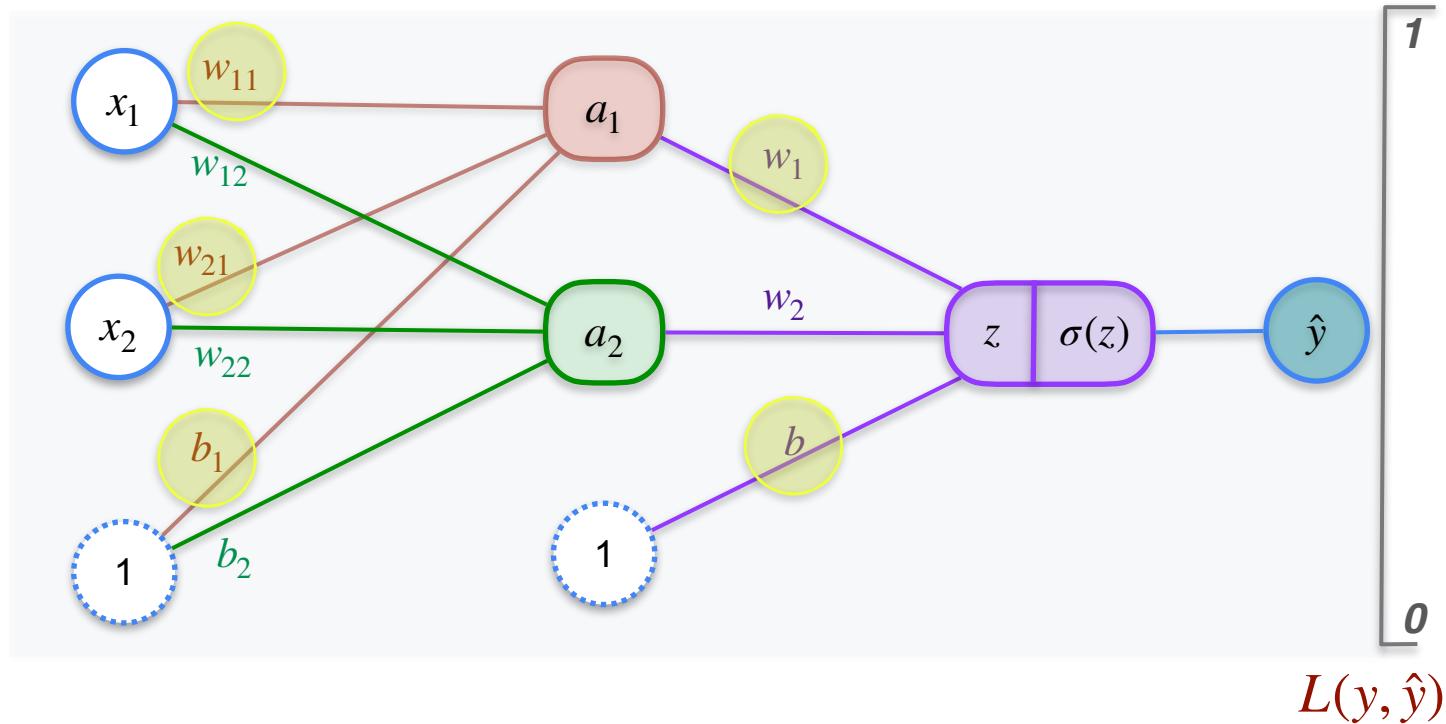
2,2,1 Neural Network



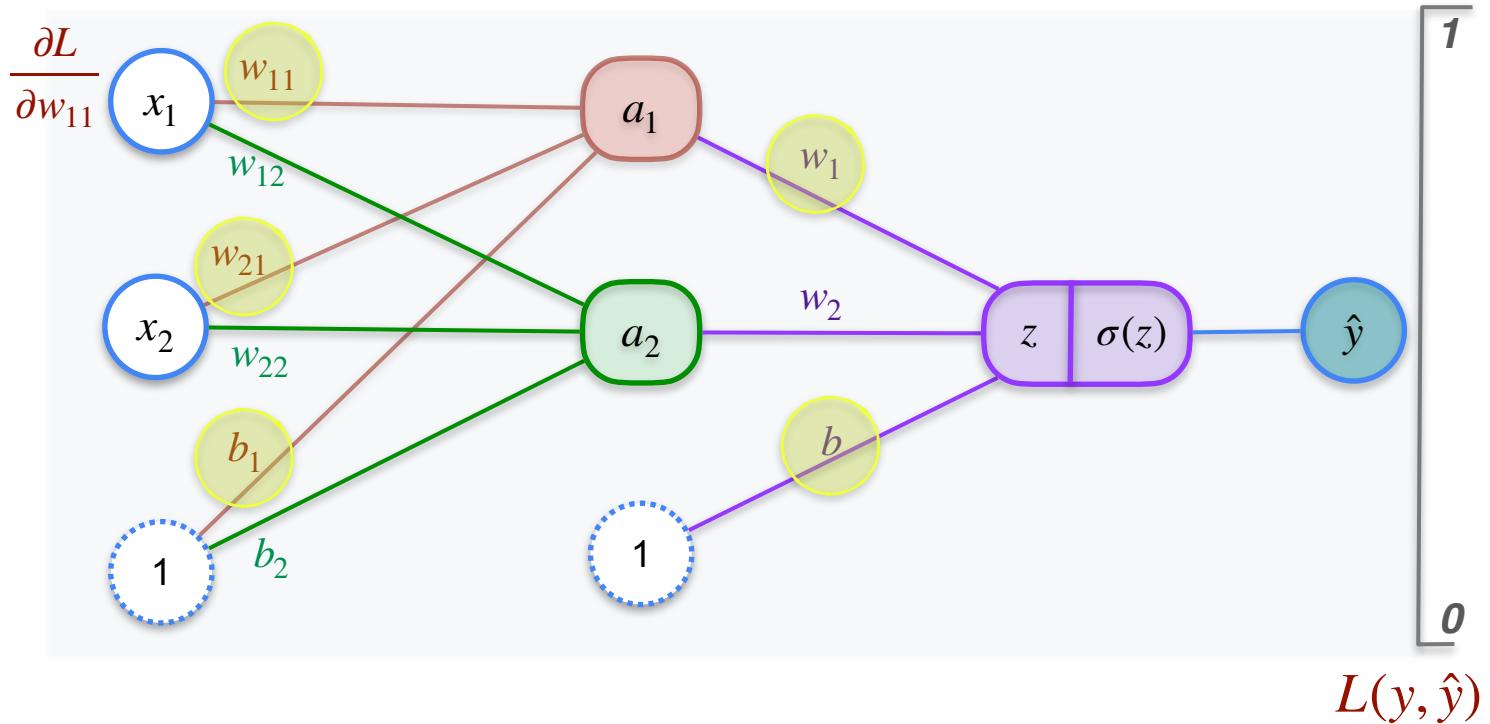
2,2,1 Neural Network



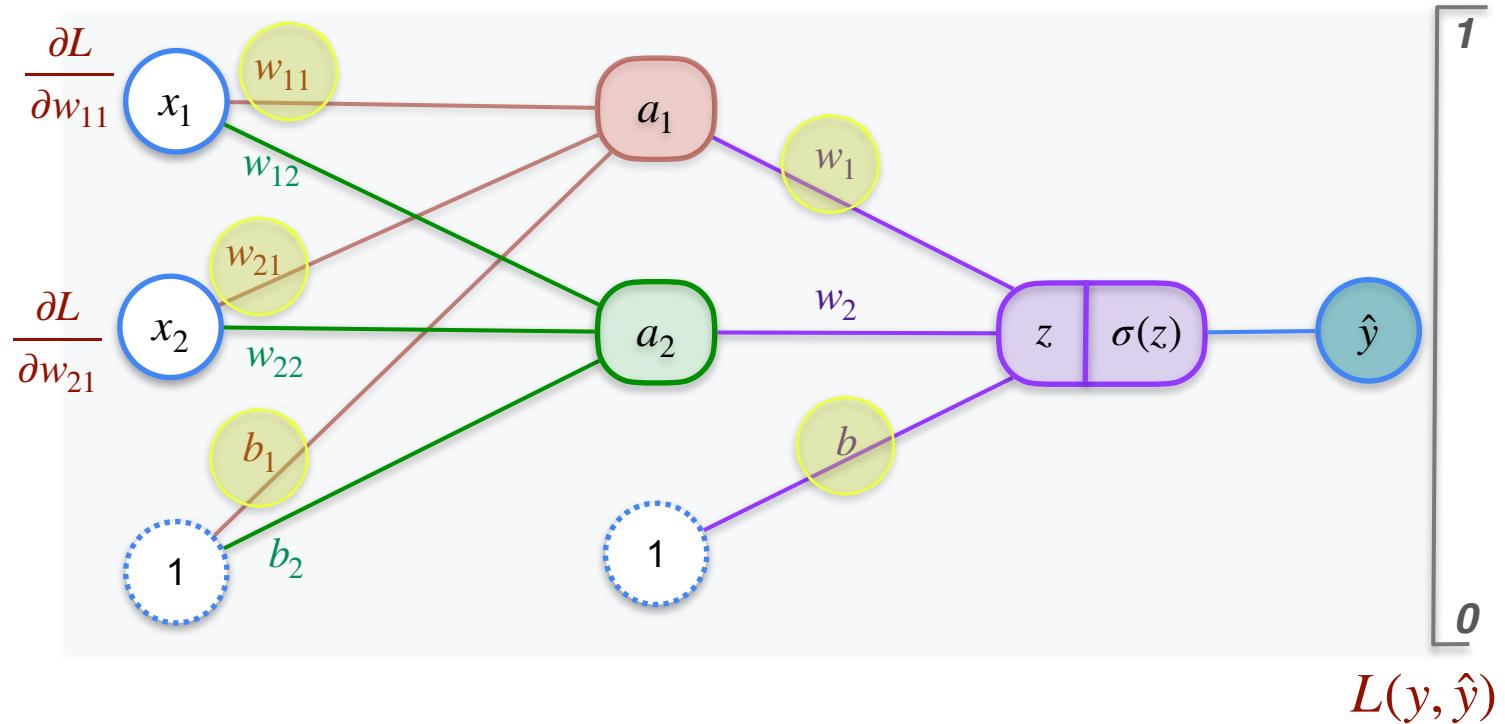
2,2,1 Neural Network



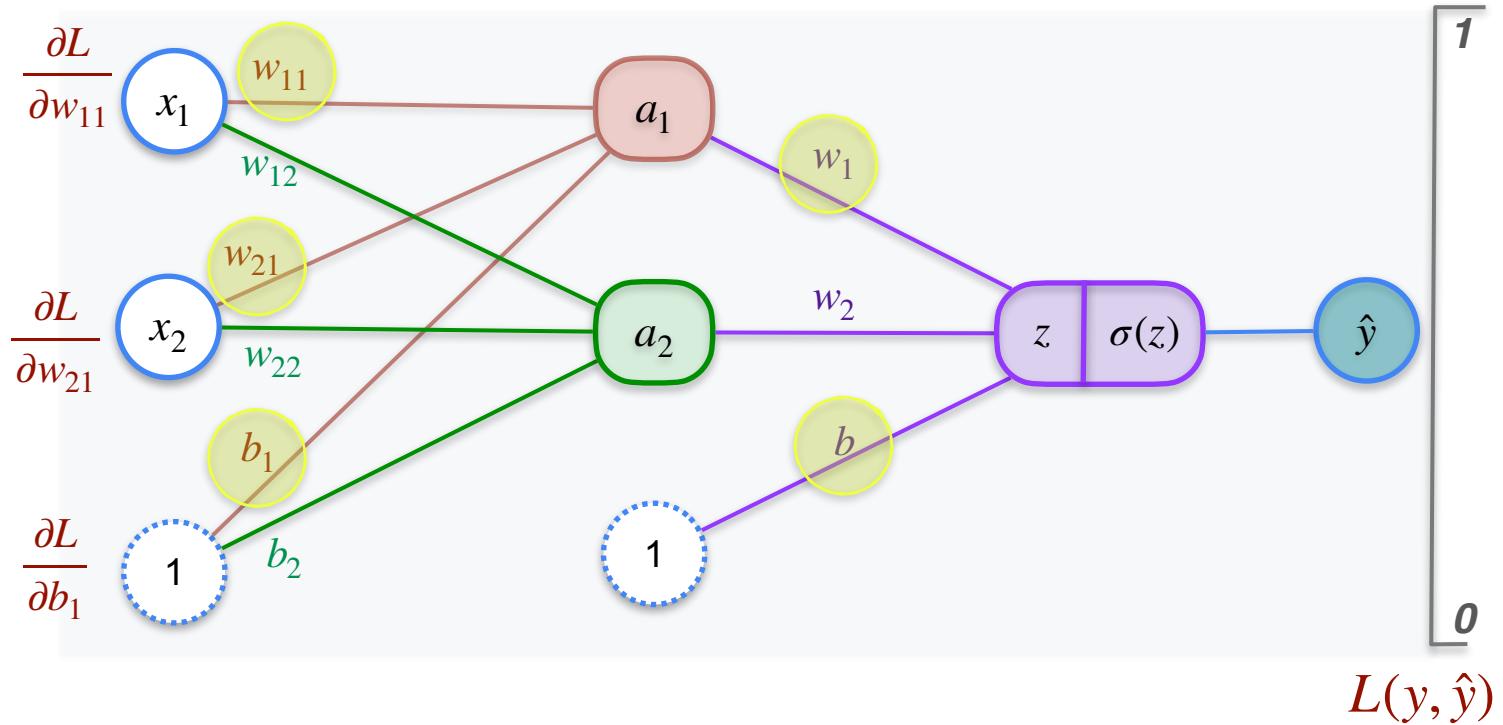
2,2,1 Neural Network



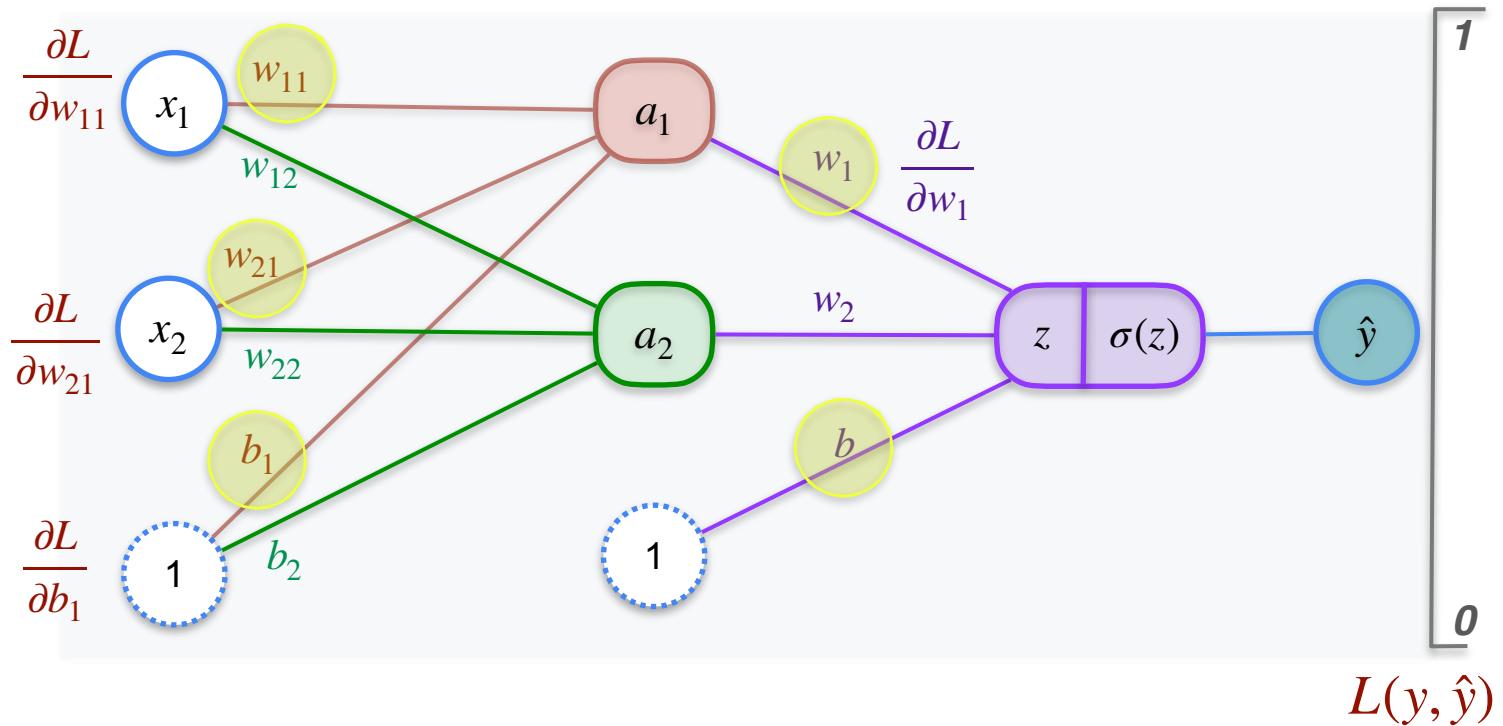
2,2,1 Neural Network



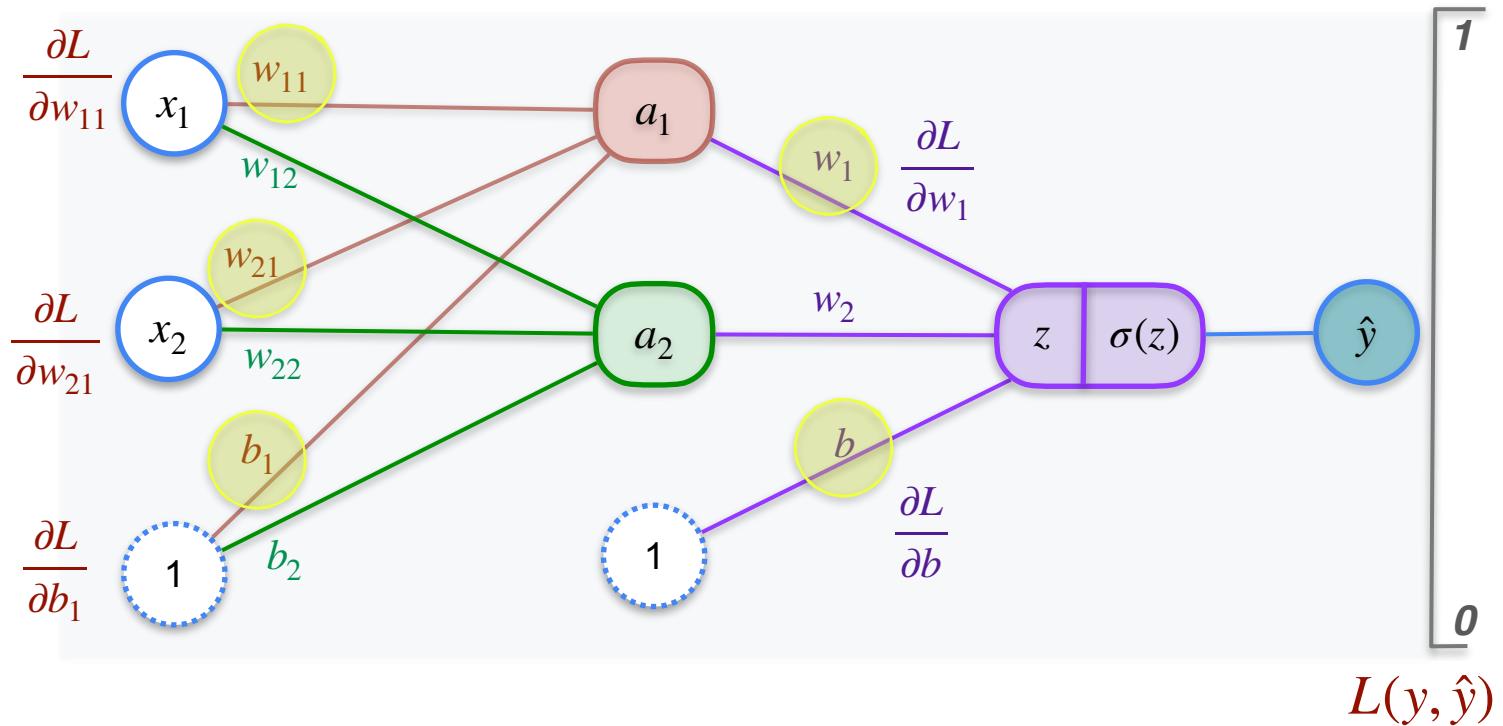
2,2,1 Neural Network



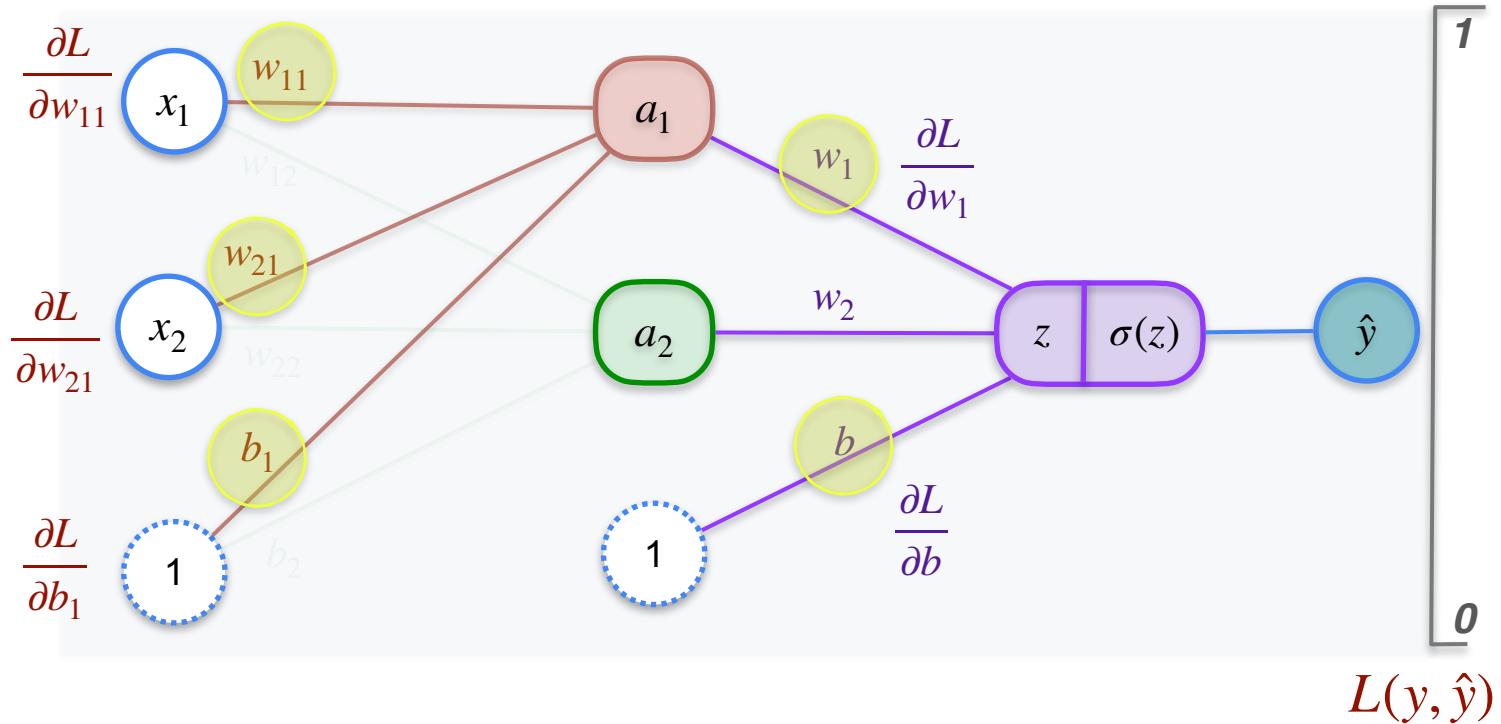
2,2,1 Neural Network



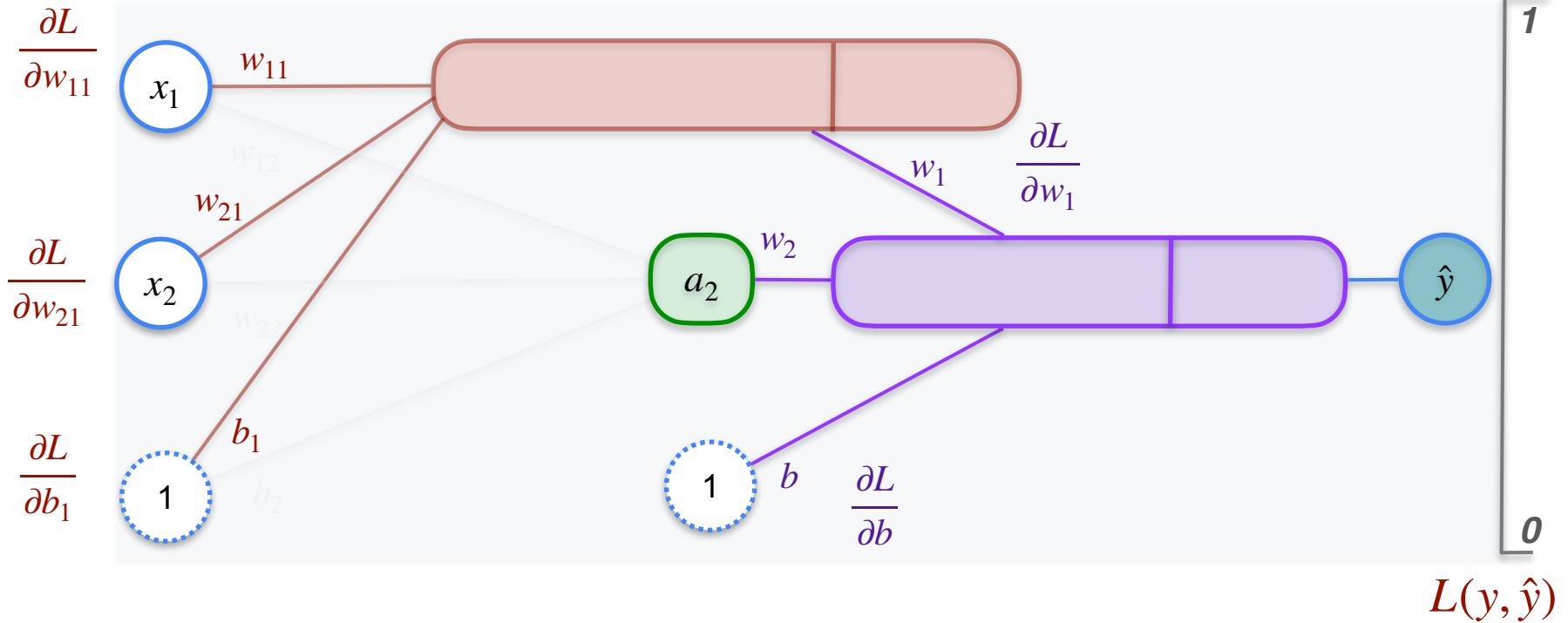
2,2,1 Neural Network



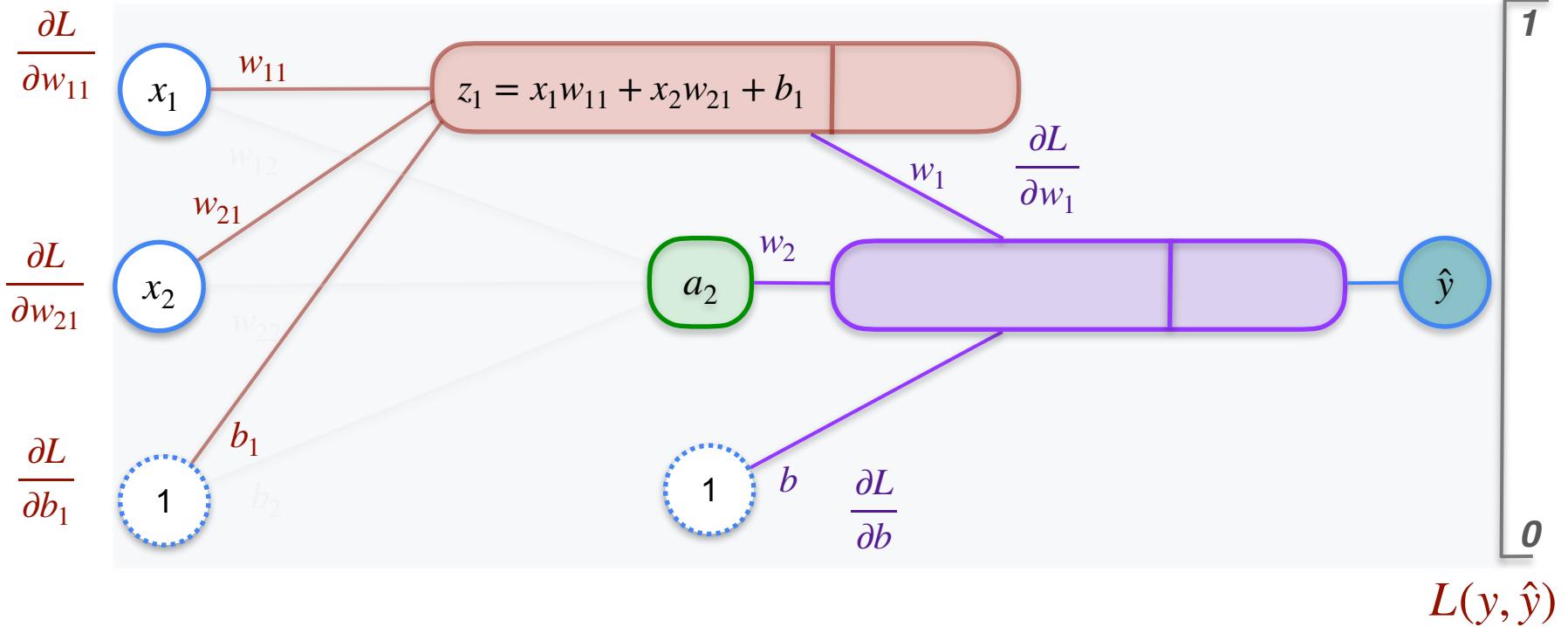
2,2,1 Neural Network



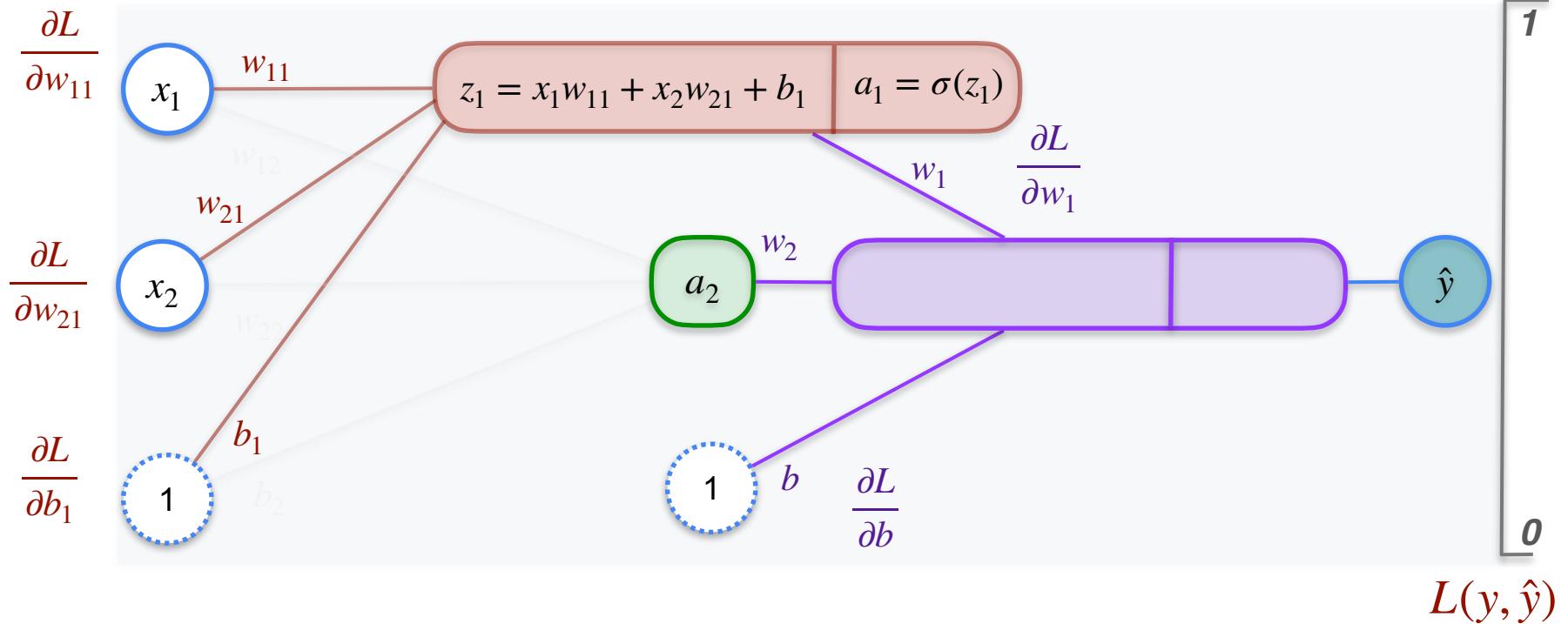
2,2,1 Neural Network



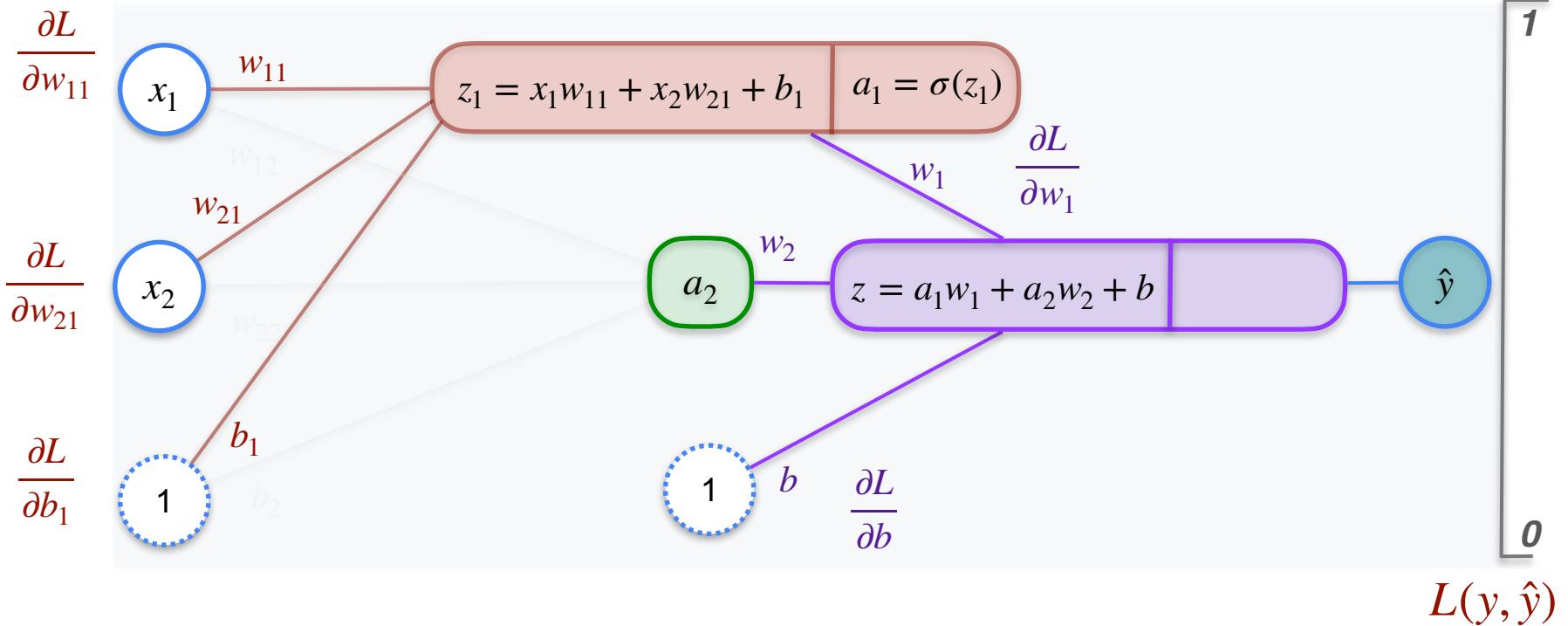
2,2,1 Neural Network



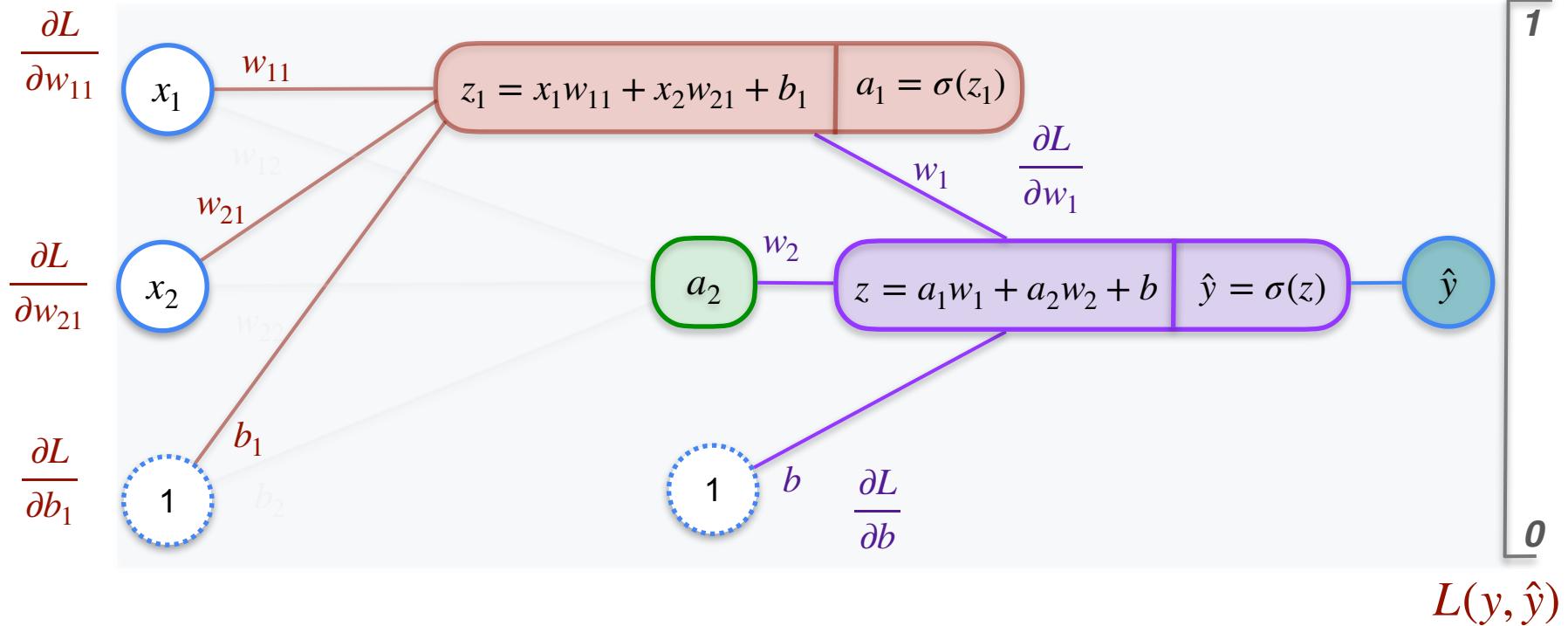
2,2,1 Neural Network



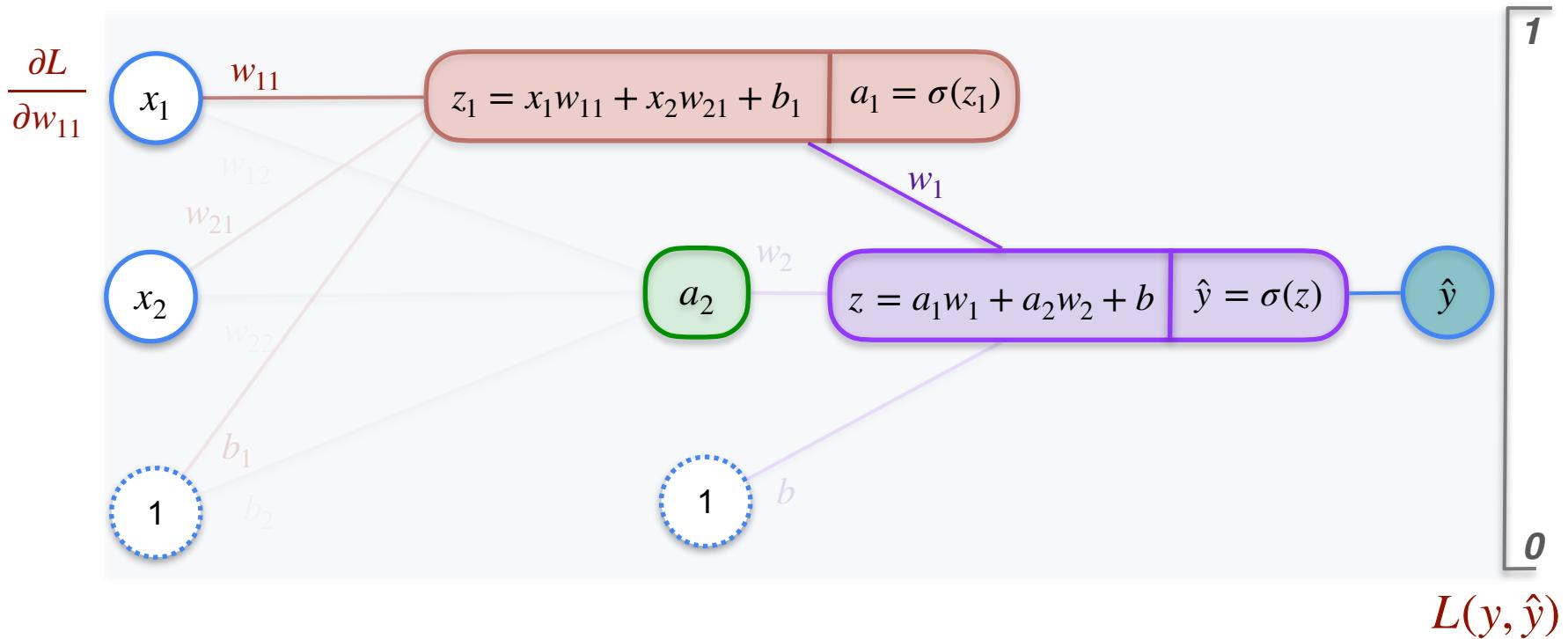
2,2,1 Neural Network



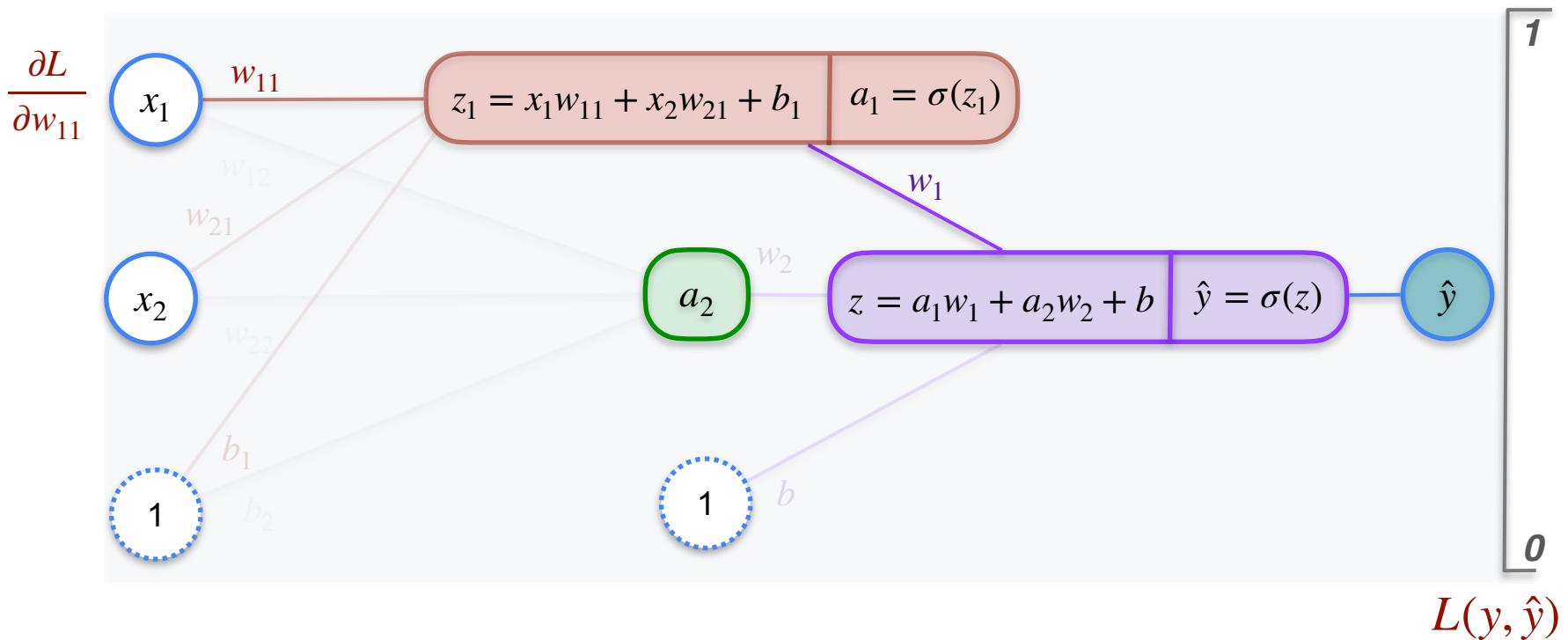
2,2,1 Neural Network



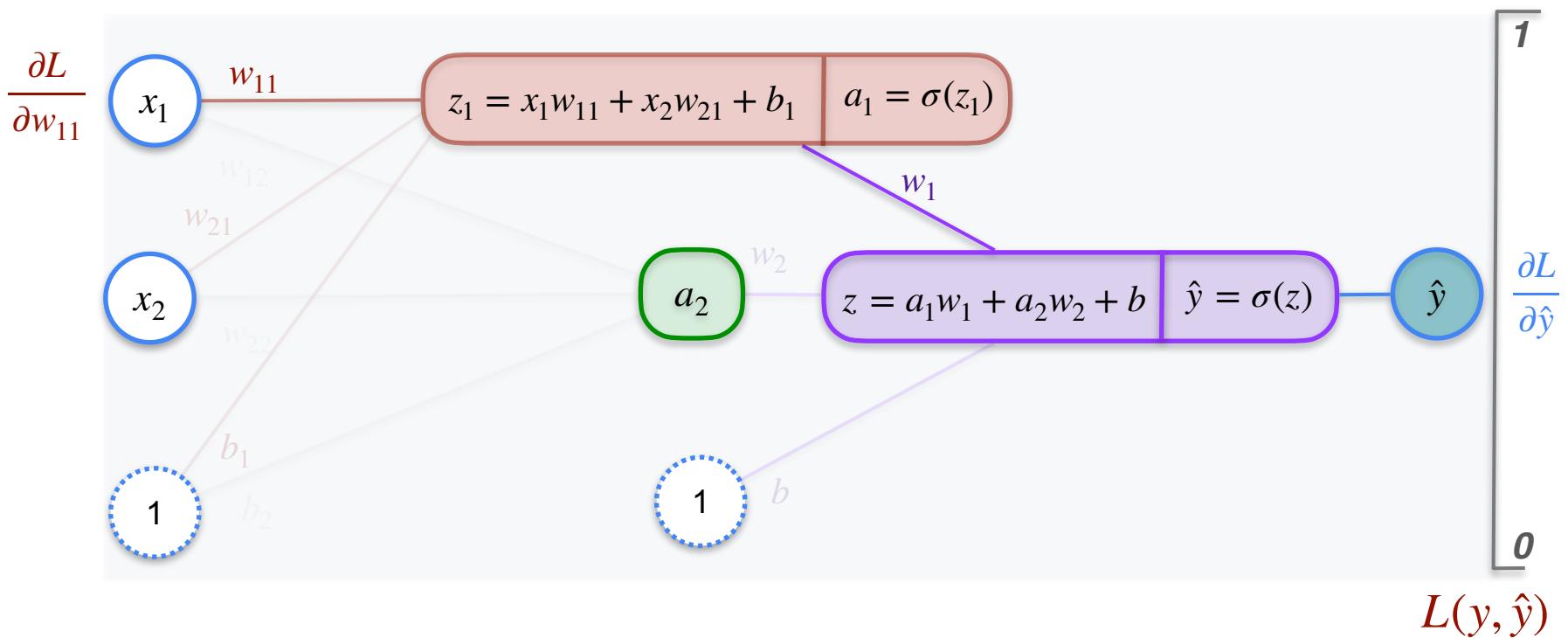
2,2,1 Neural Network



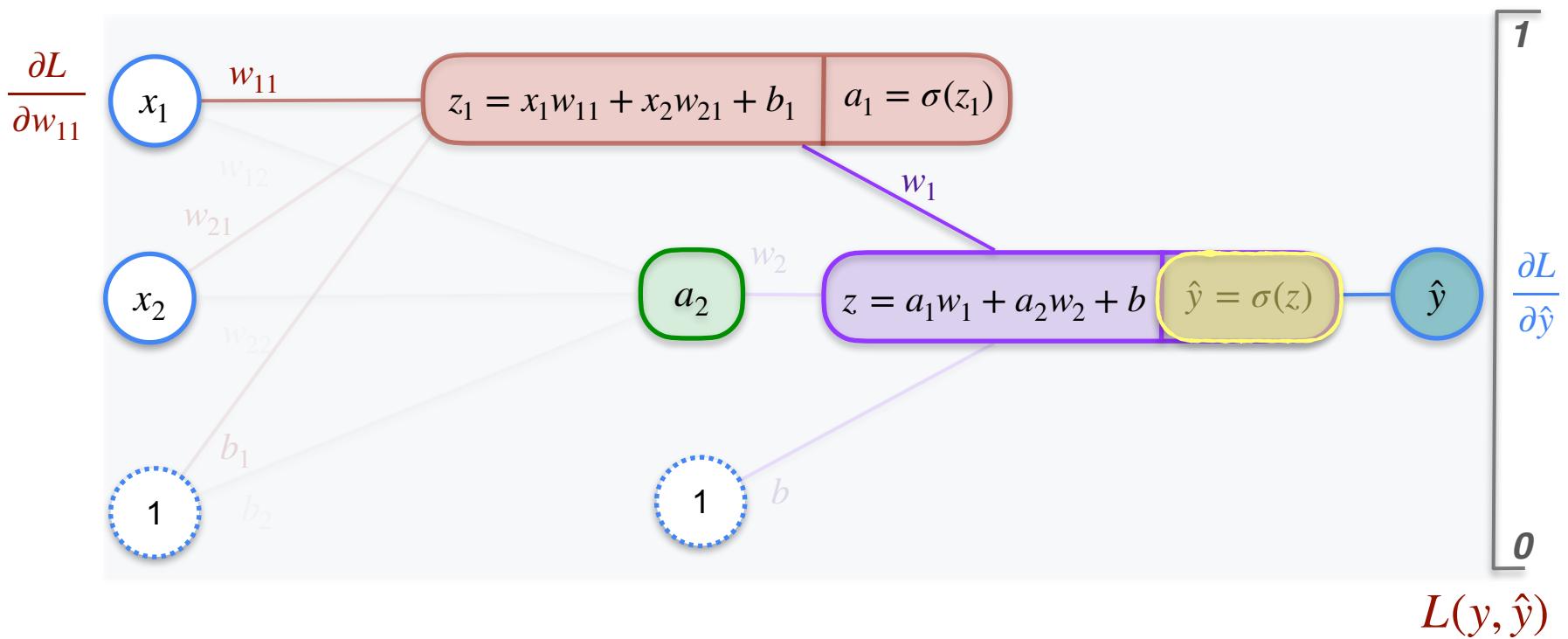
2,2,1 Neural Network



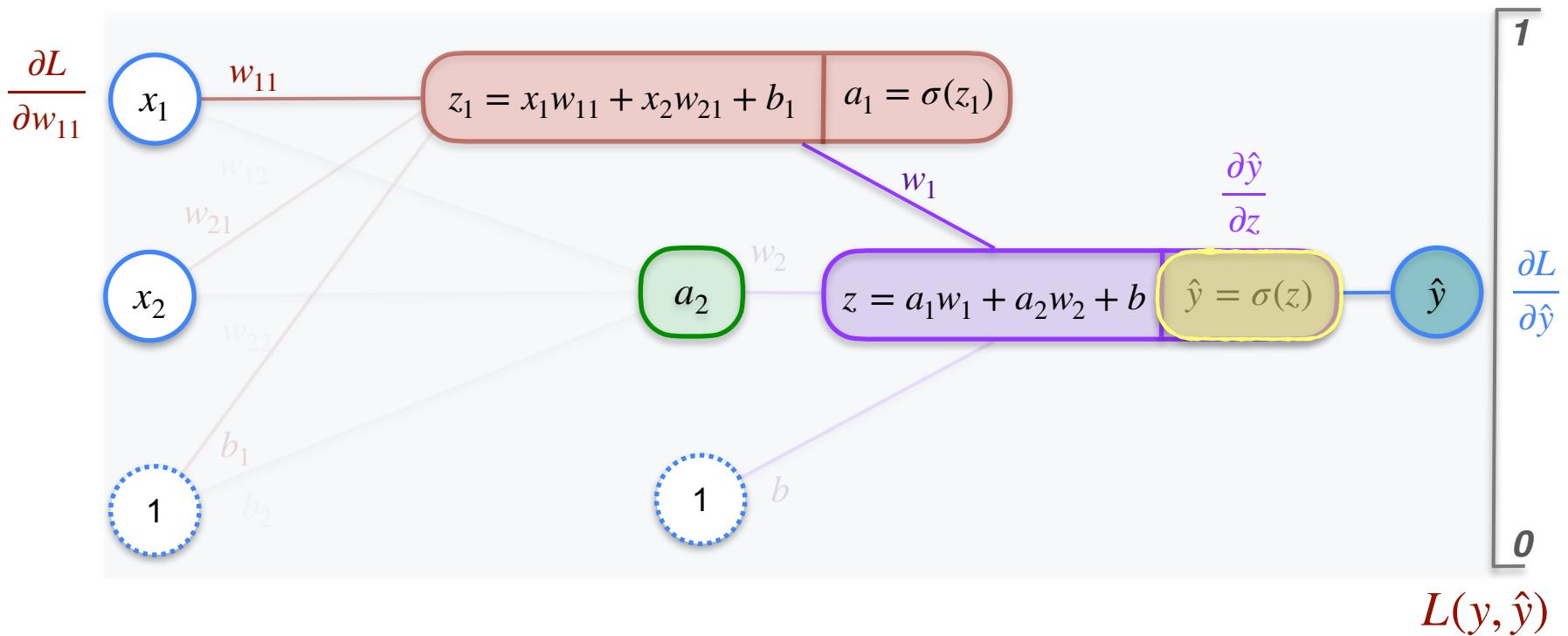
2,2,1 Neural Network



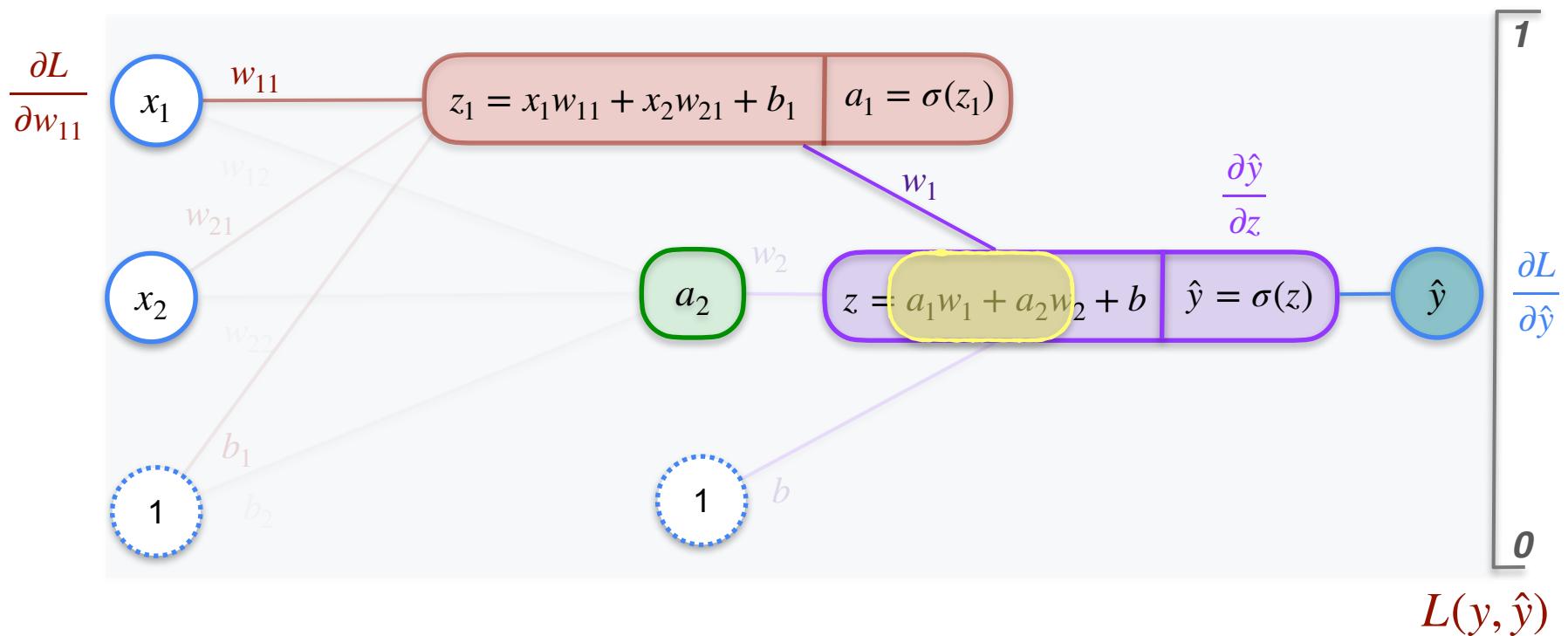
2,2,1 Neural Network



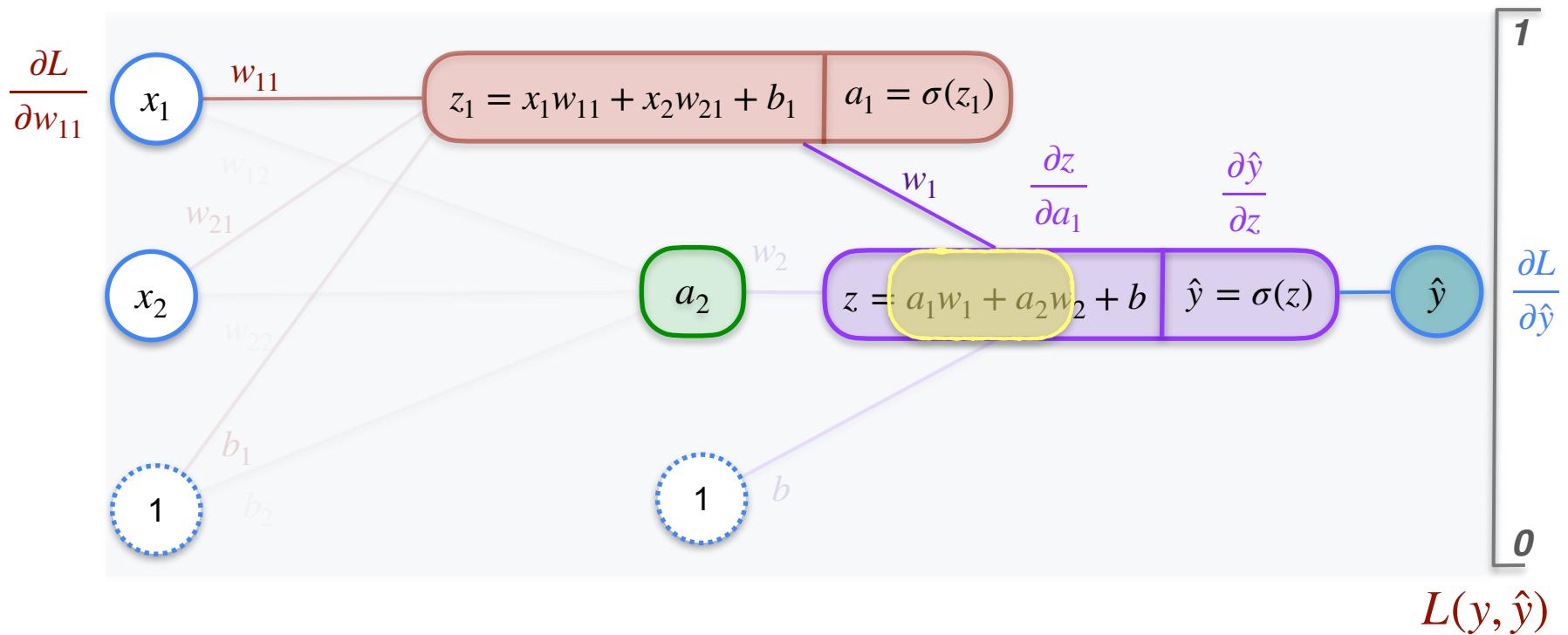
2,2,1 Neural Network



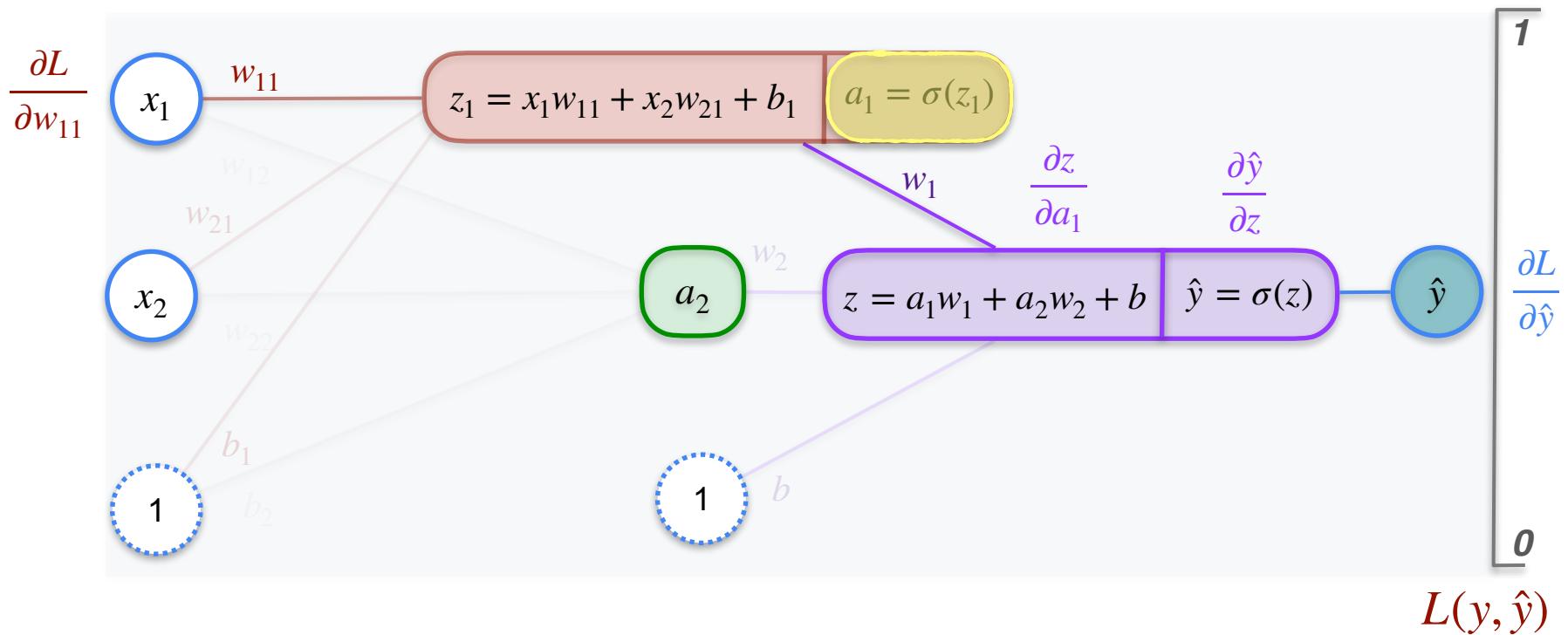
2,2,1 Neural Network



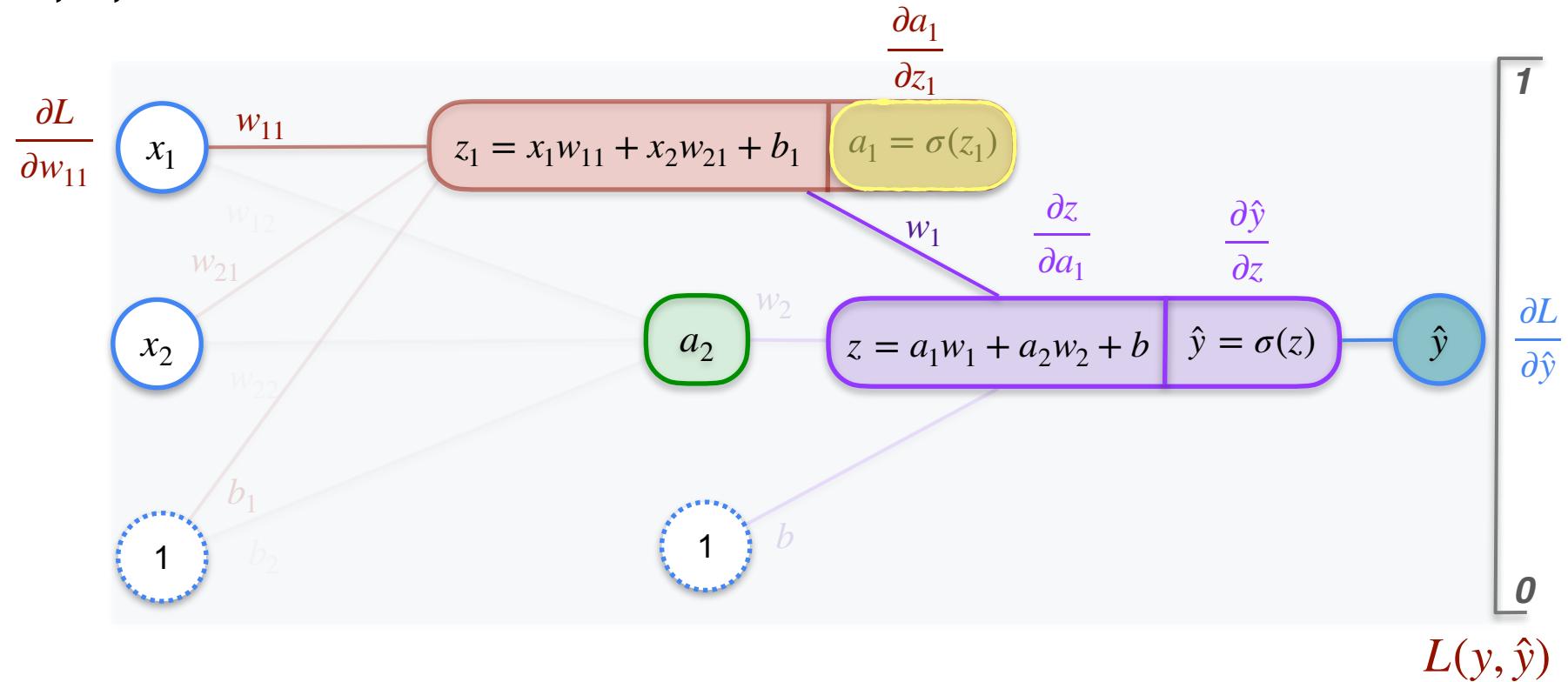
2,2,1 Neural Network



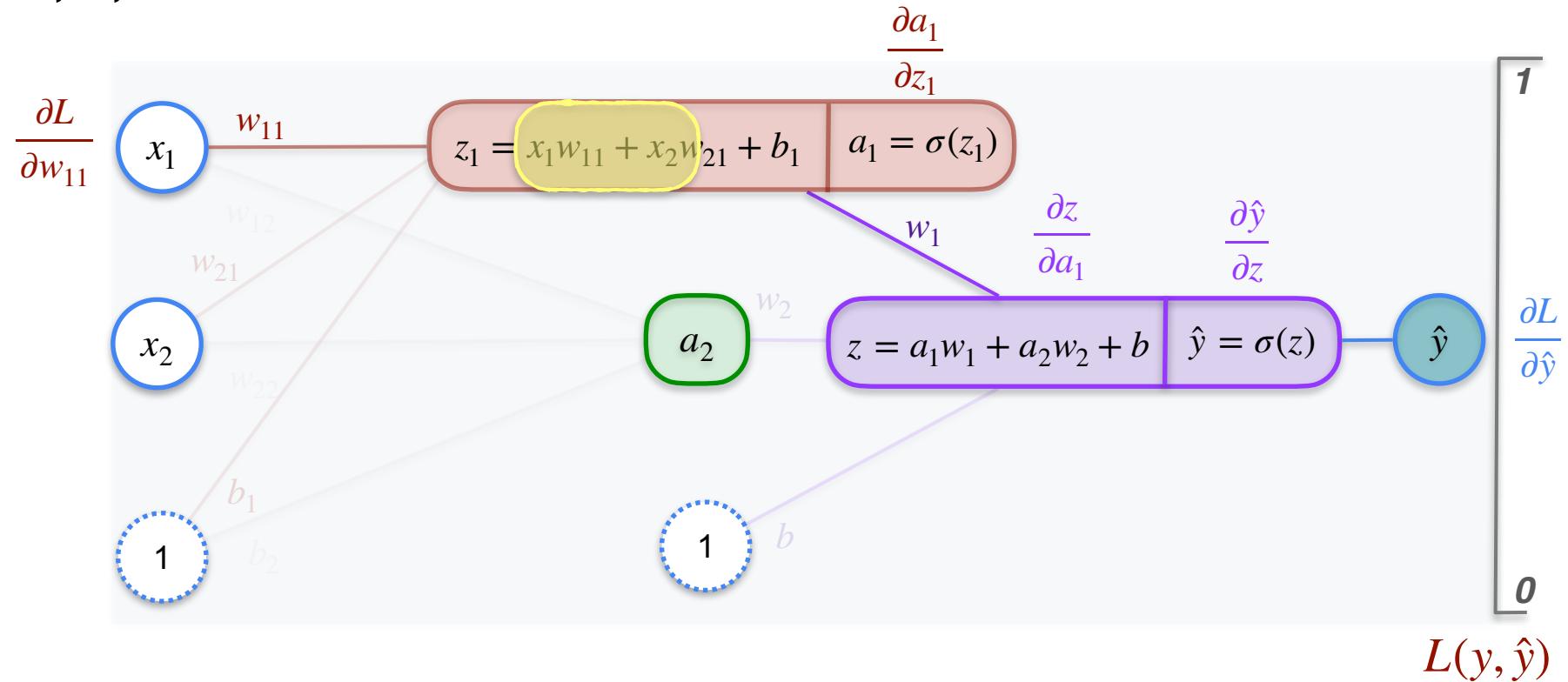
2,2,1 Neural Network



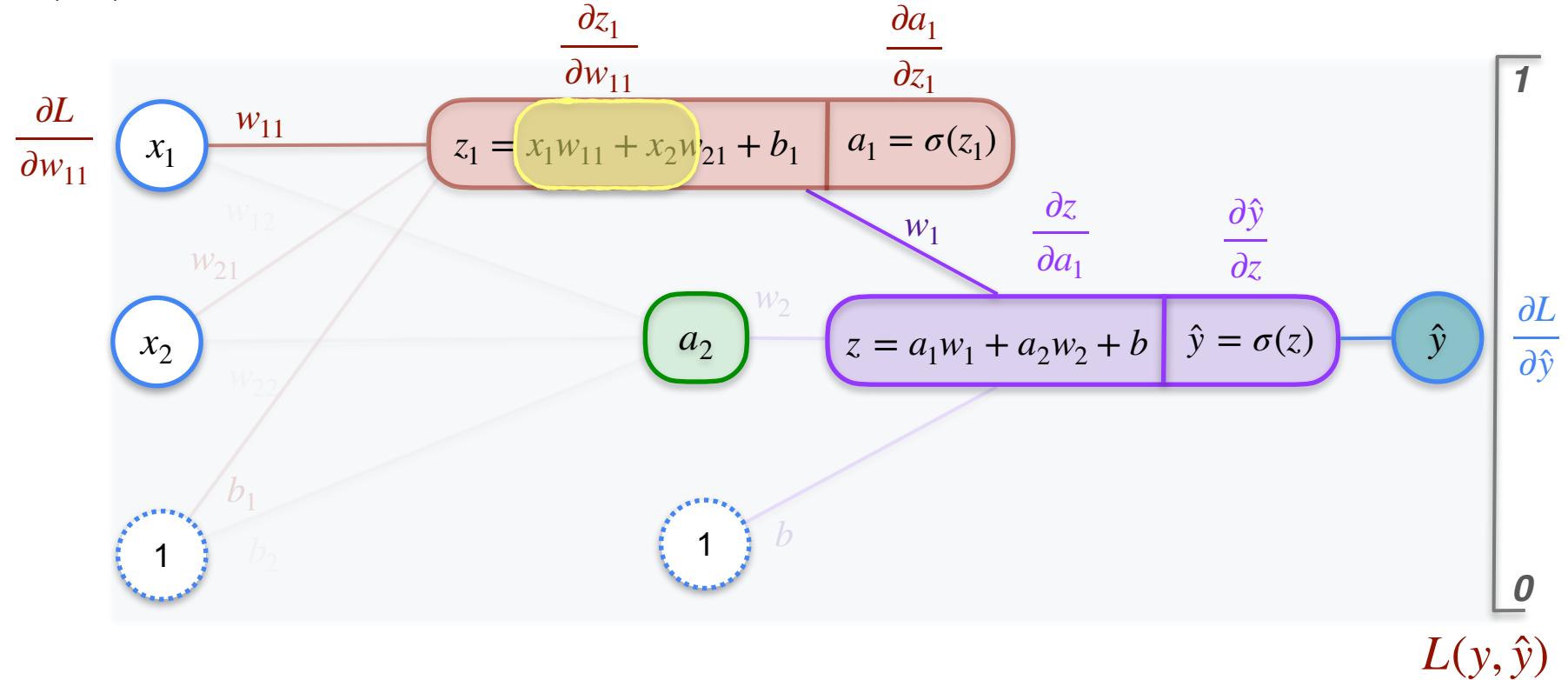
2,2,1 Neural Network



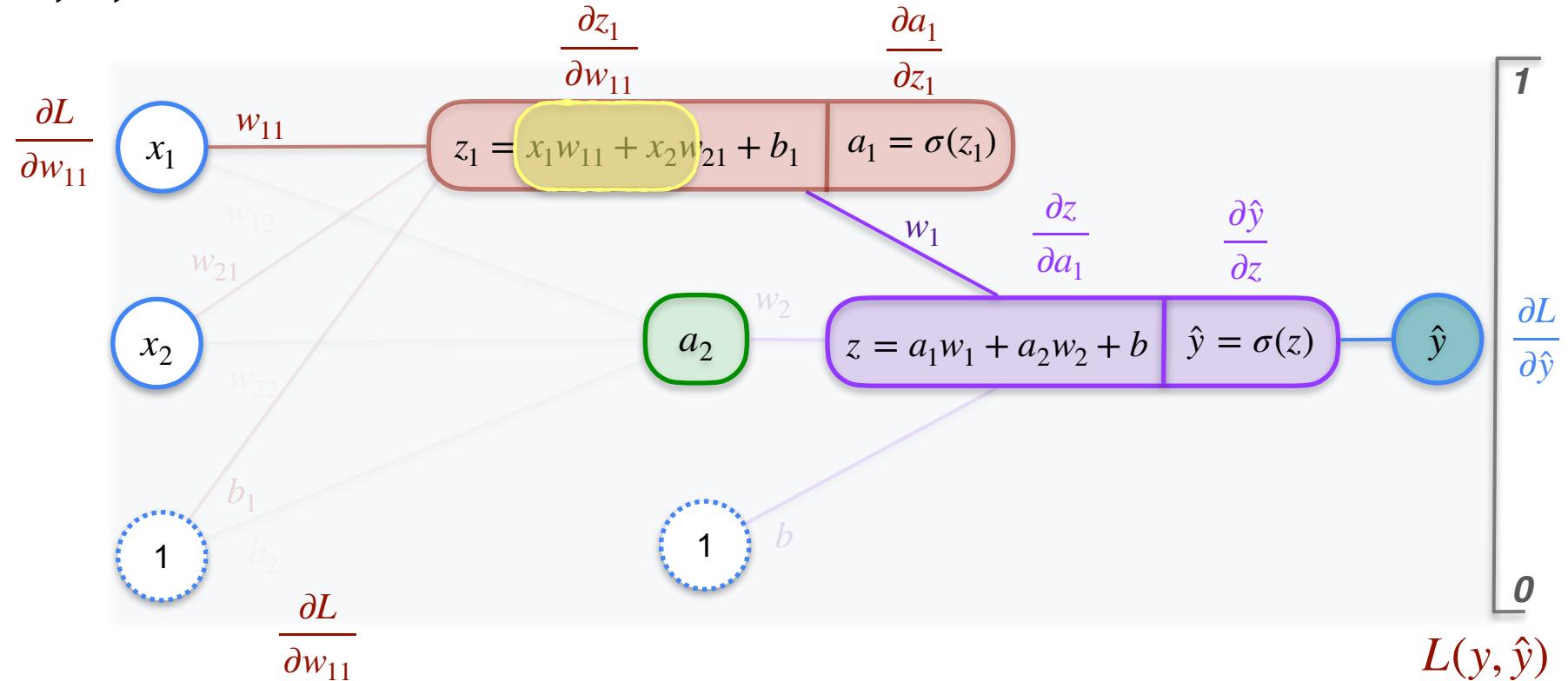
2,2,1 Neural Network



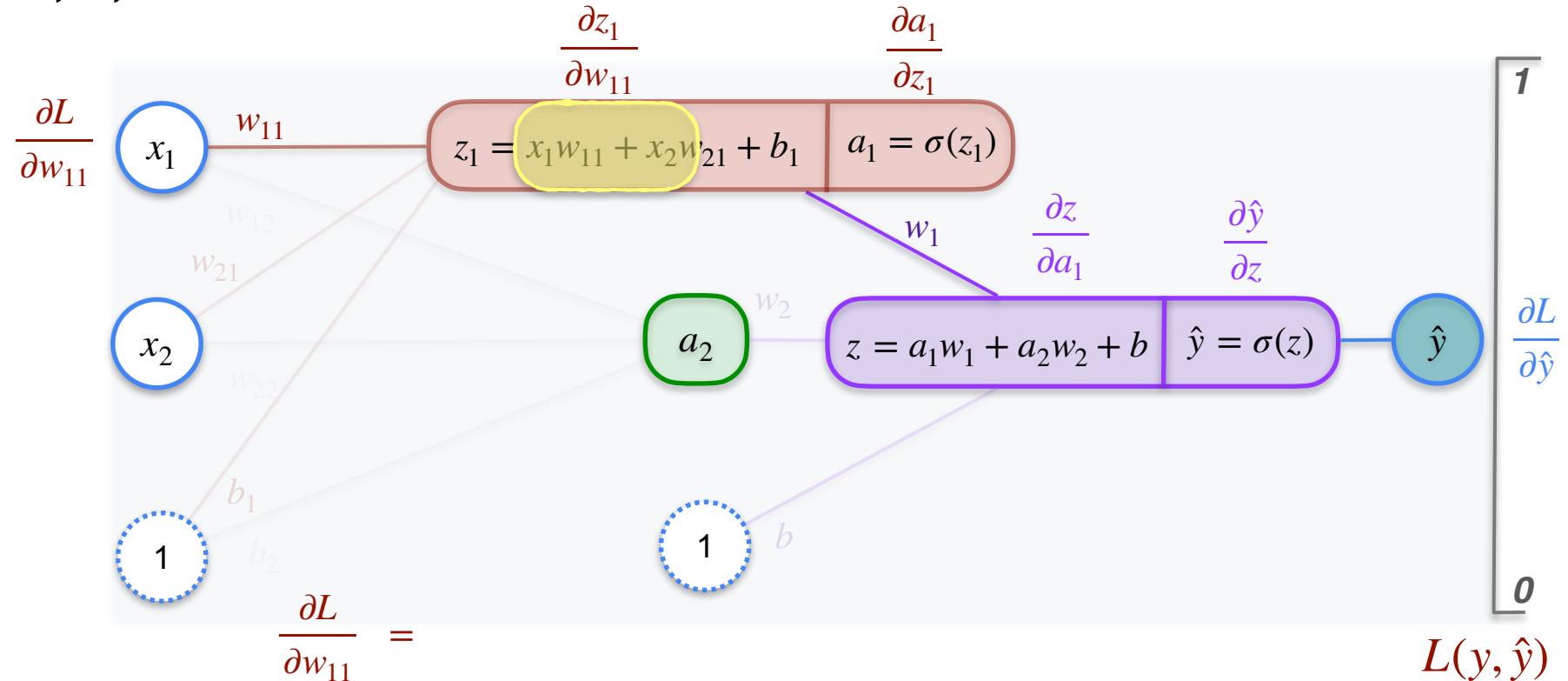
2,2,1 Neural Network



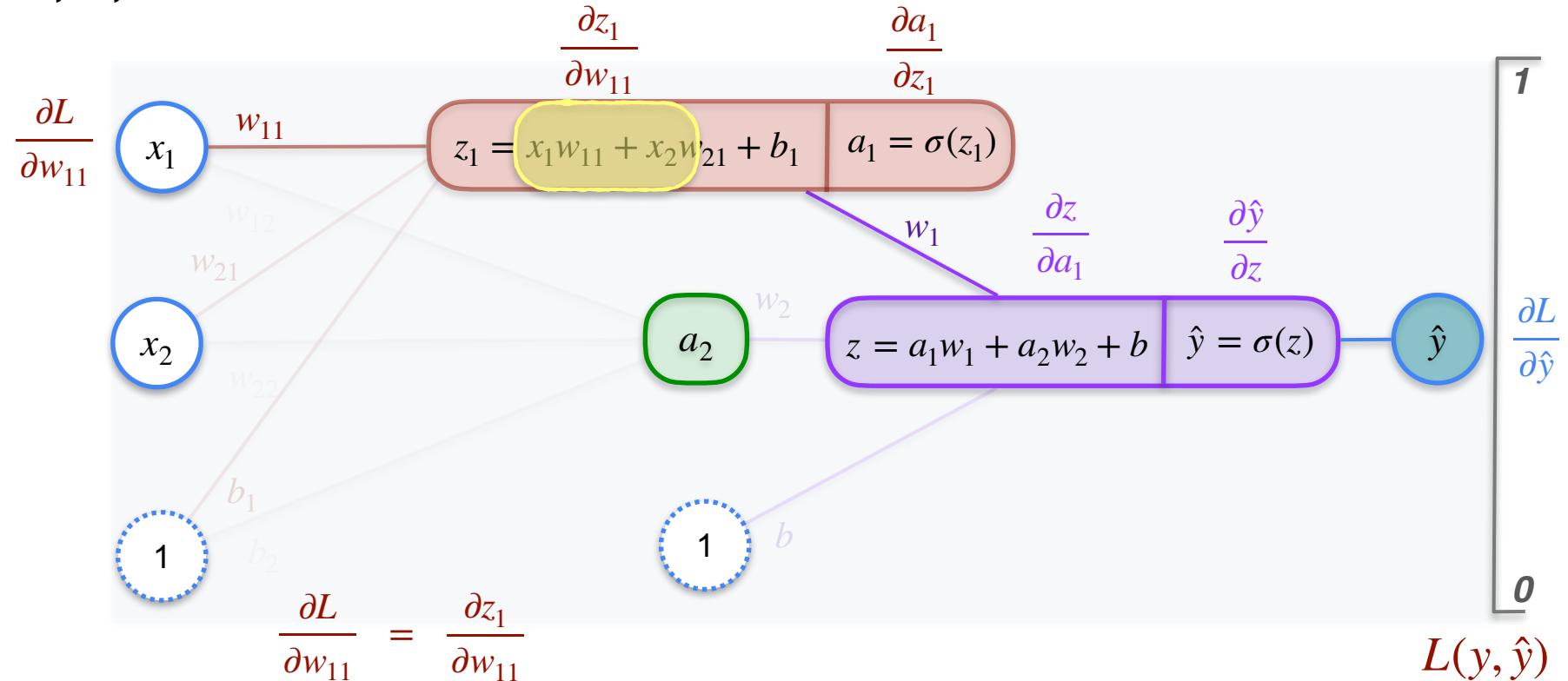
2,2,1 Neural Network



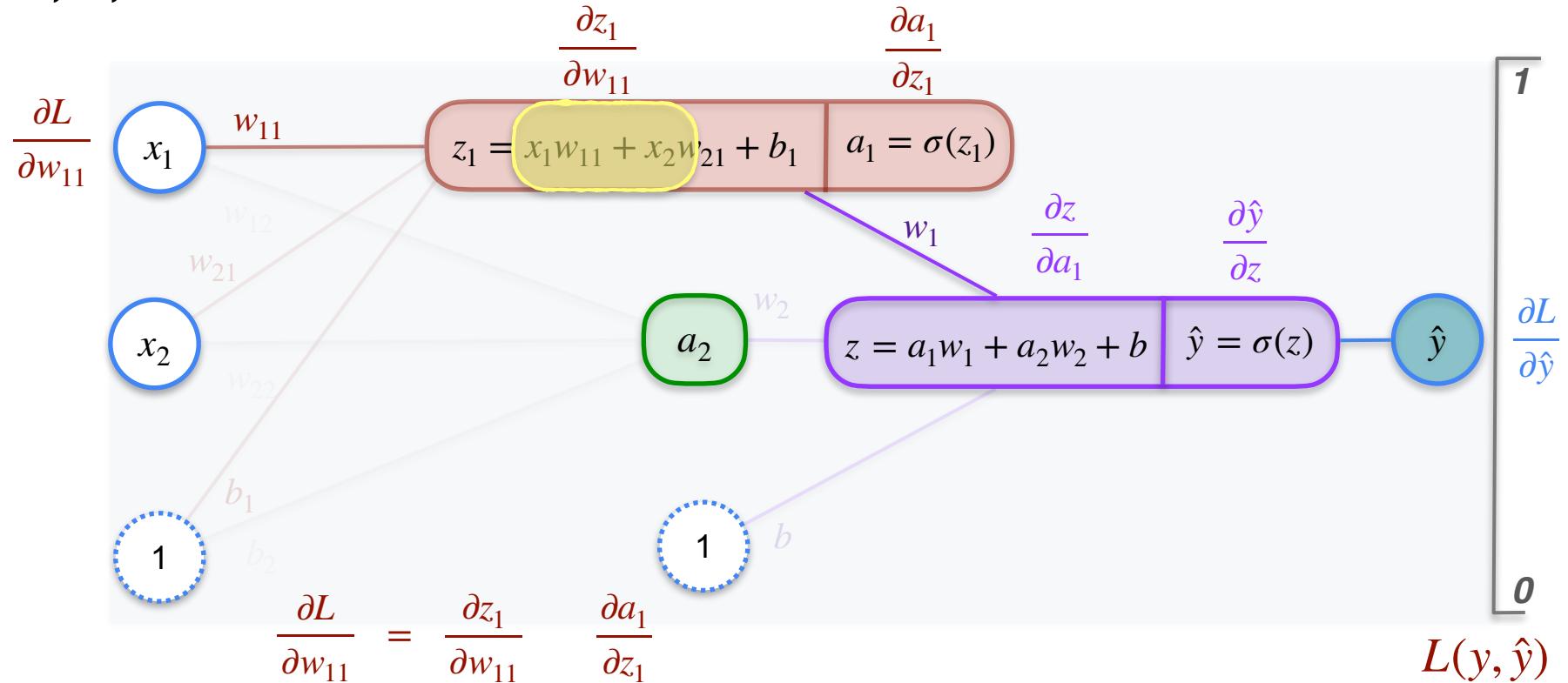
2,2,1 Neural Network



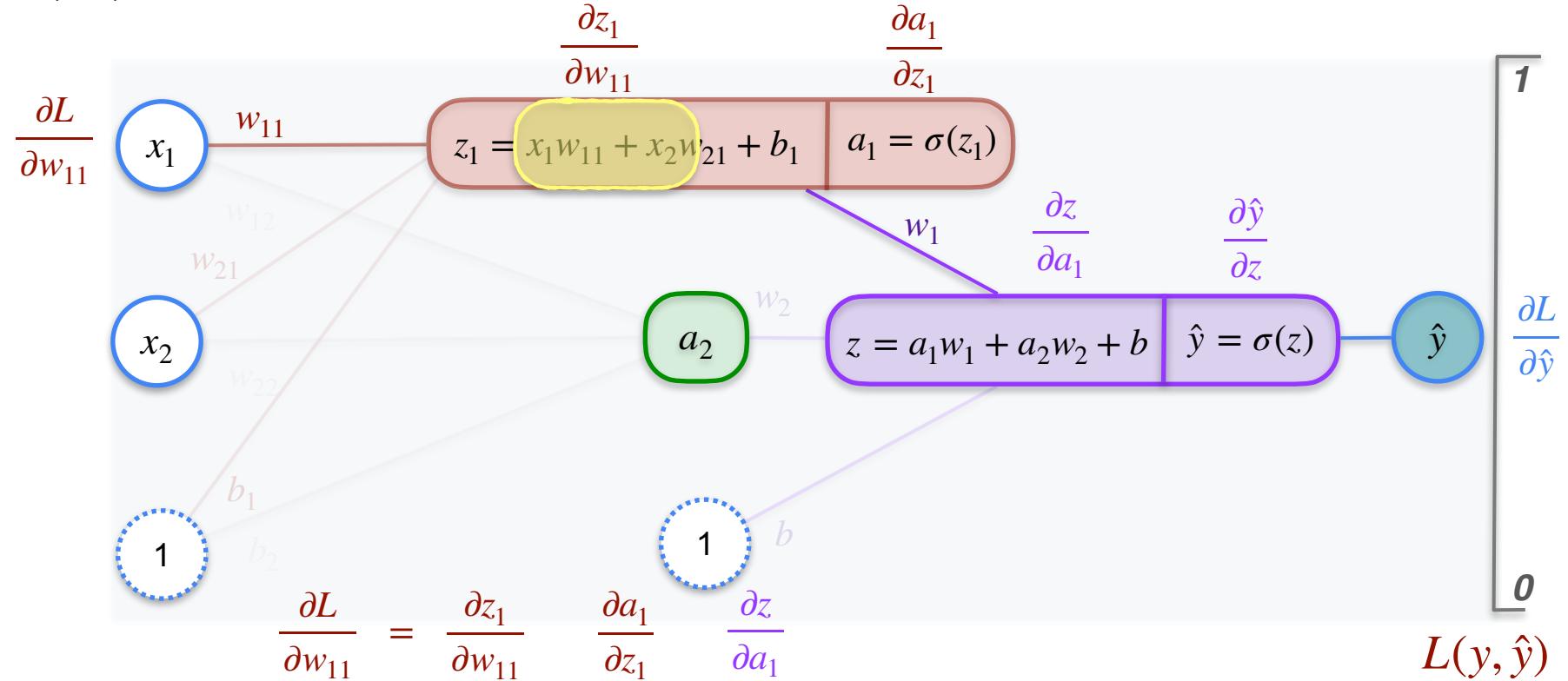
2,2,1 Neural Network



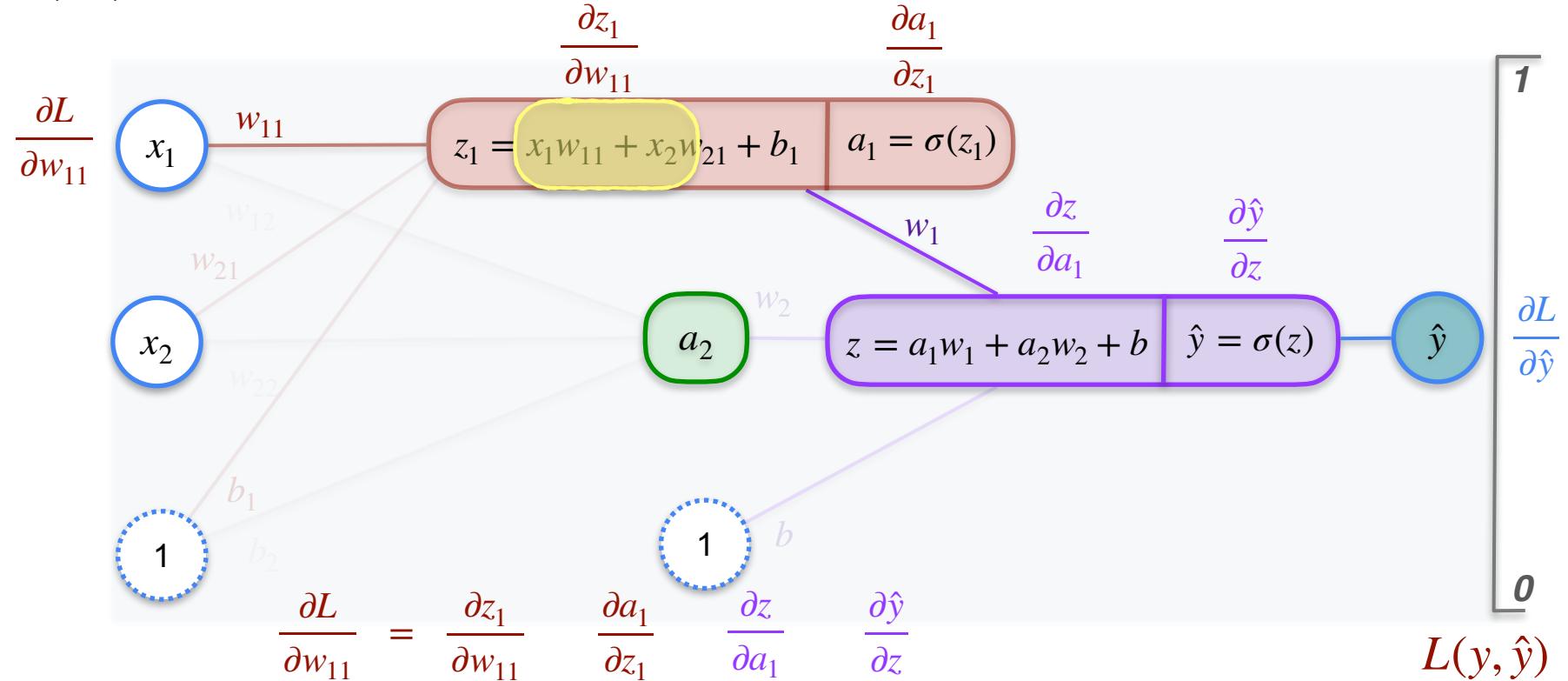
2,2,1 Neural Network



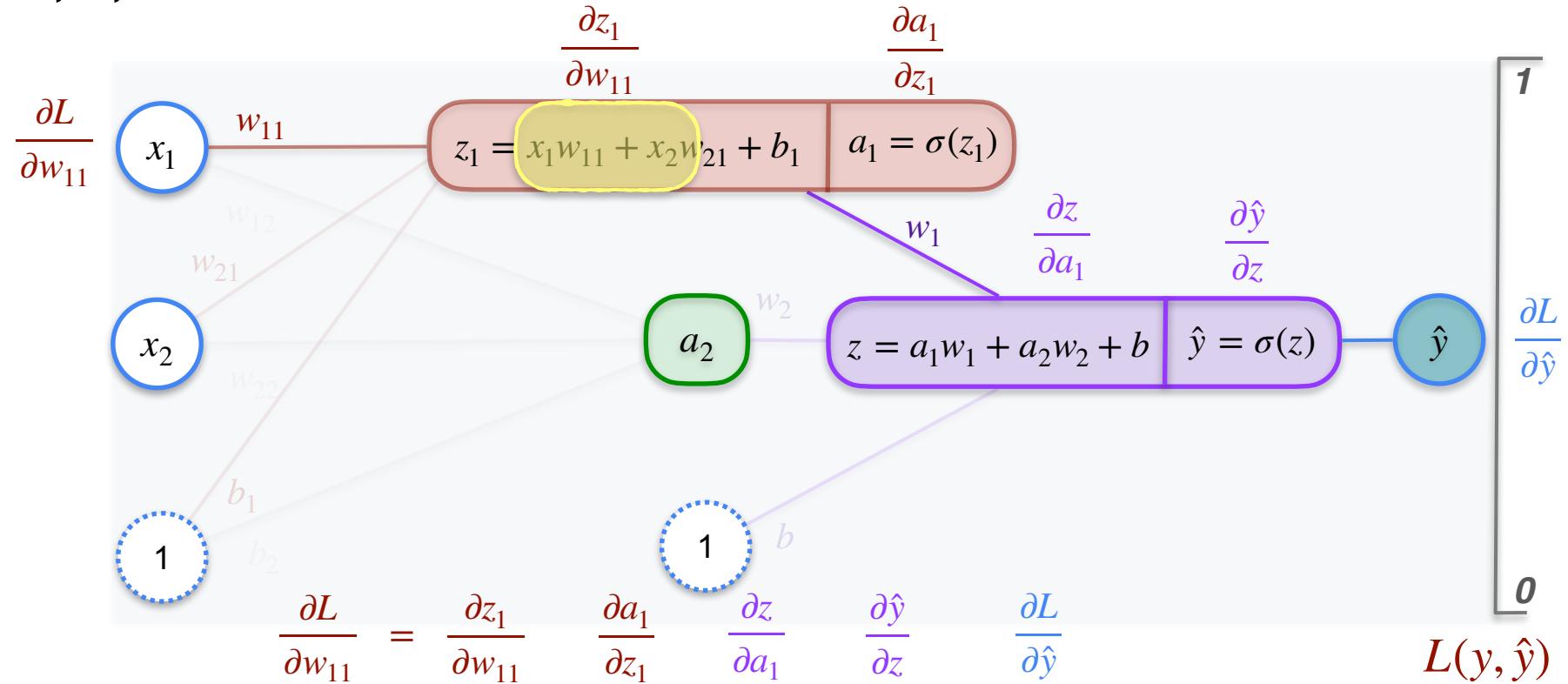
2,2,1 Neural Network



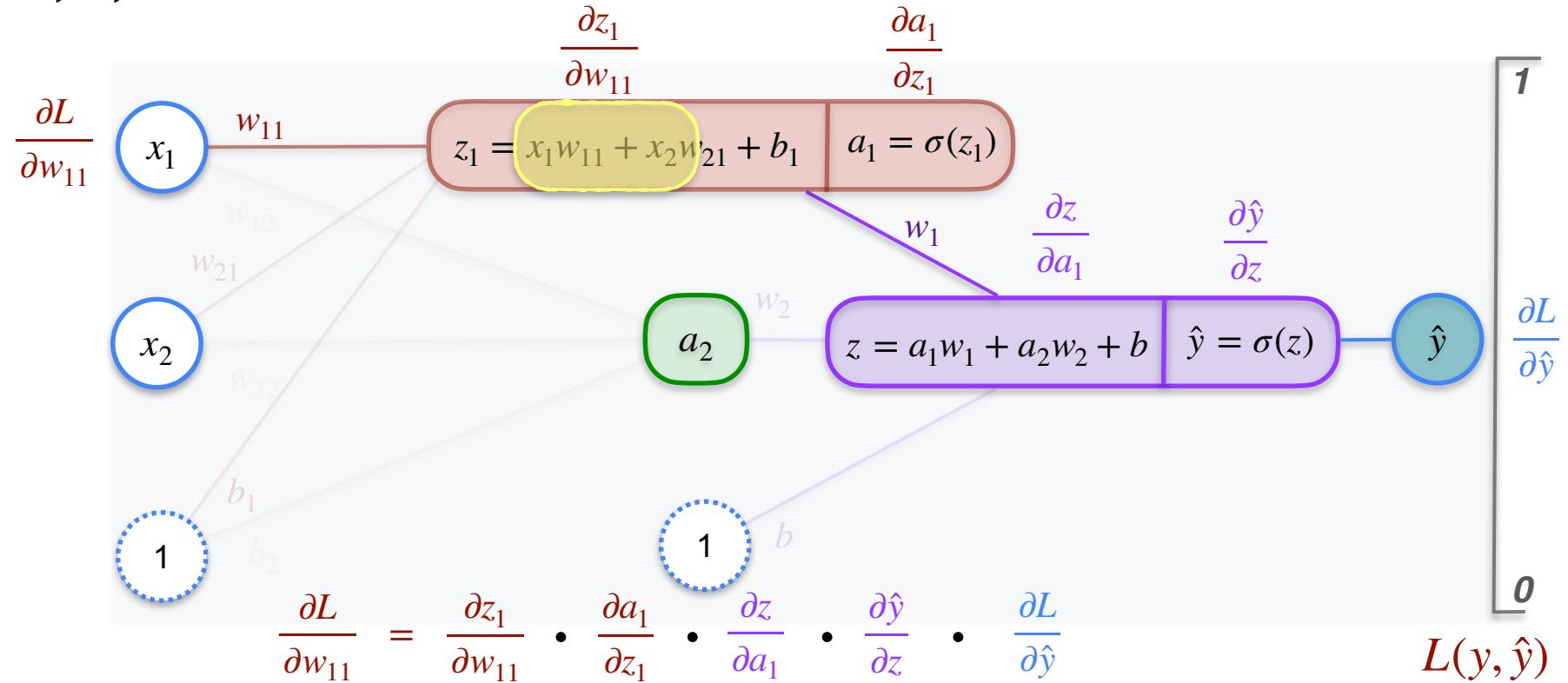
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \bullet \frac{\partial a_1}{\partial z_1} \bullet \frac{\partial z}{\partial a_1} \bullet \frac{\partial \hat{y}}{\partial z} \bullet \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_{11}}$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \boxed{\frac{\partial z_1}{\partial w_{11}}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \boxed{\frac{\partial z_1}{\partial w_{11}}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1 - a_1)$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1 - a_1)$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1 - a_1)$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1-a_1) w_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1-a_1) w_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1-a_1) w_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1-a_1) w_1 - \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1-a_1) w_1 - \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = x_1 - a_1(1-a_1) w_1 - \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial w_{11}} = x_1 \quad a_1(1-a_1) \quad w_1 \quad \hat{y}(1-\hat{y}) \quad \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial w_{11}} = x_1 \cdot a_1(1-a_1) \cdot w_1 \cdot \hat{y}(1-\hat{y}) \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial w_{11}} = x_1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{11}} = \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{11}} = x_1 \cdot a_1 (1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial w_{11}} &= \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{11}} &= x_1 \cdot a_1 (1 - a_1) \cdot w_1 \cdot \cancel{\hat{y}(1 - \hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1 - \hat{y})}} \\ &= -x_1 w_1 a_1 (1 - a_1) (y - \hat{y})\end{aligned}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial w_{11}} &= \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{11}} &= x_1 \cdot a_1 (1 - a_1) \cdot w_1 \cdot \cancel{\hat{y}(1 - \hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1 - \hat{y})}} \\ &= -x_1 w_1 a_1 (1 - a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

*to find optimal
value of w_{11} that
gives the least error*

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial w_{11}} &= \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{11}} &= x_1 \cdot a_1 (1 - a_1) \cdot w_1 \cdot \cancel{\hat{y}(1 - \hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1 - \hat{y})}} \\ &= -x_1 w_1 a_1 (1 - a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

$$w_{11} \rightarrow w_{11} - \alpha \frac{\partial L}{\partial w_{11}}$$

to find optimal value of w_{11} that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial w_{11}} &= \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{11}} &= x_1 \cdot a_1 (1 - a_1) \cdot w_1 \cdot \cancel{\hat{y}(1 - \hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1 - \hat{y})}} \\ &= -x_1 w_1 a_1 (1 - a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

$$w_{11} \rightarrow w_{11} - \alpha$$

to find optimal value of w_{11} that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

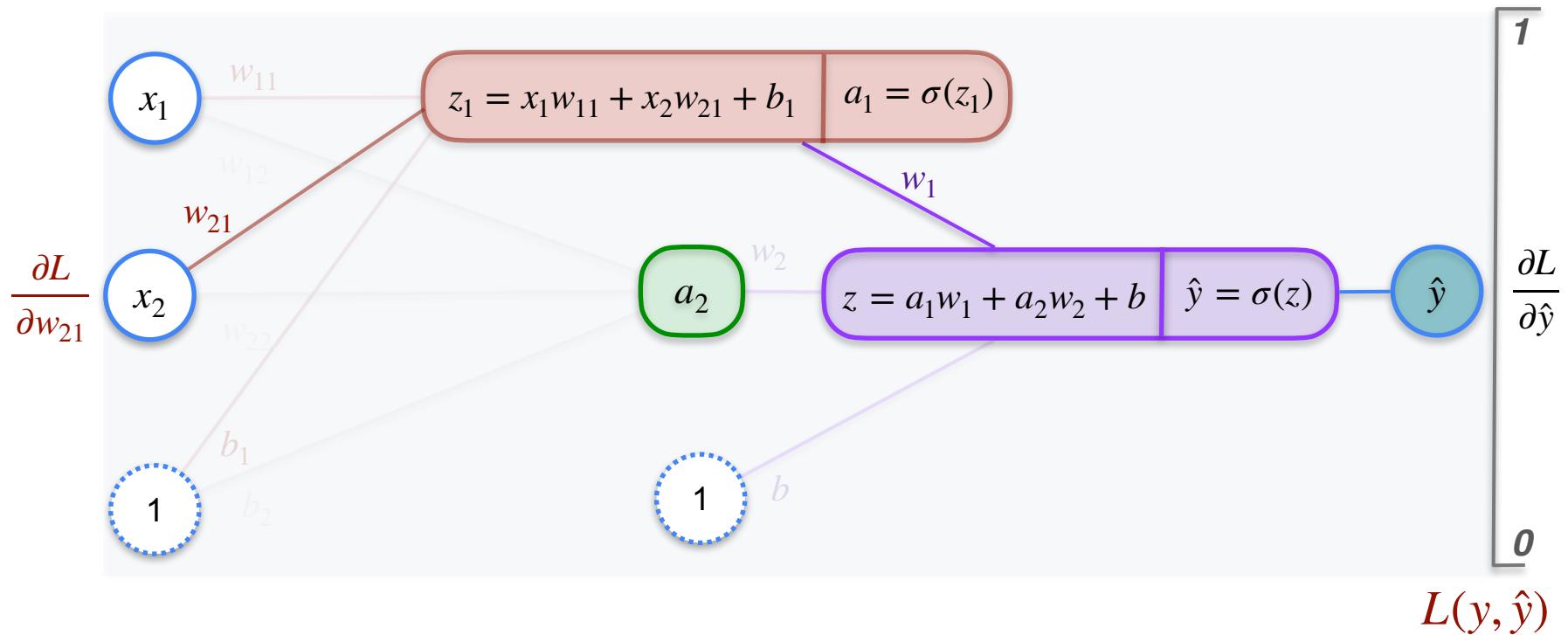
$$\begin{aligned}\frac{\partial L}{\partial w_{11}} &= \frac{\partial z_1}{\partial w_{11}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{11}} &= x_1 \cdot a_1 (1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -x_1 w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

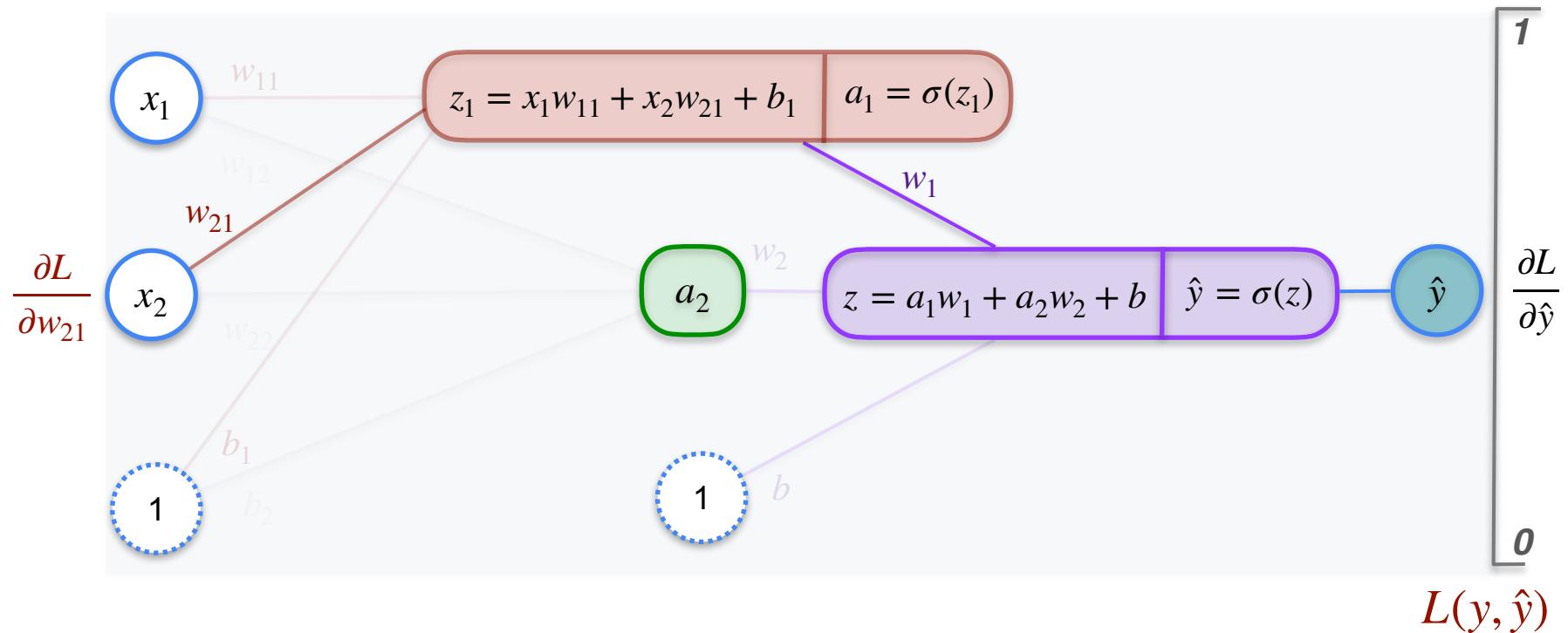
$$w_{11} \rightarrow w_{11} - \alpha \cdot x_1 w_1 a_1 (1-a_1) (y - \hat{y})$$

to find optimal value of w_{11} that gives the least error

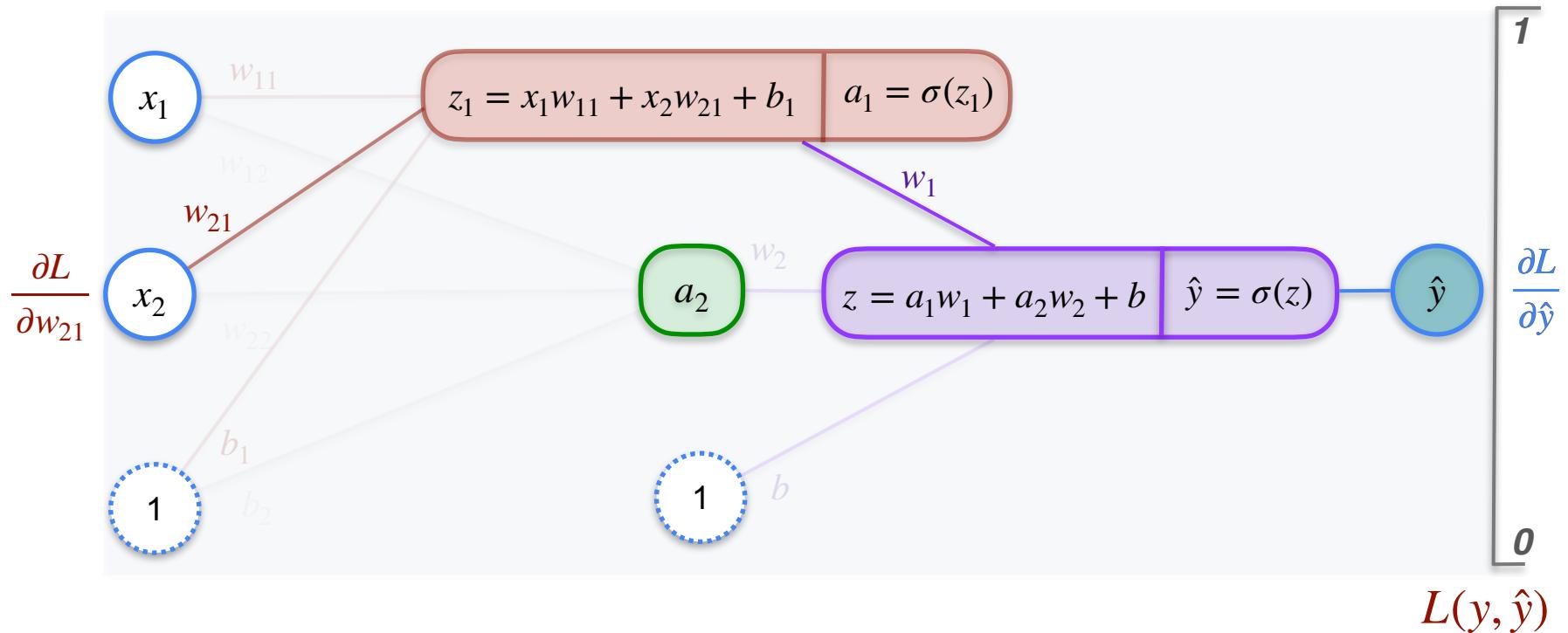
2,2,1 Neural Network



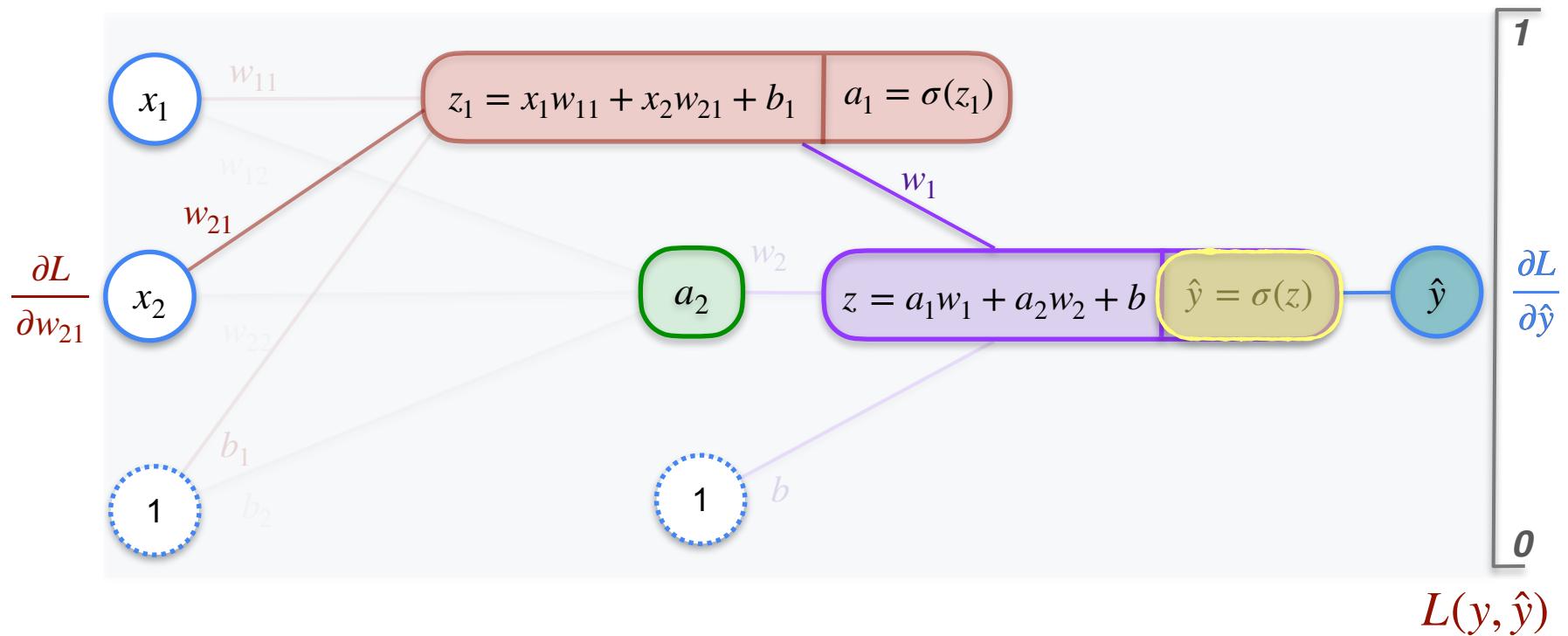
2,2,1 Neural Network



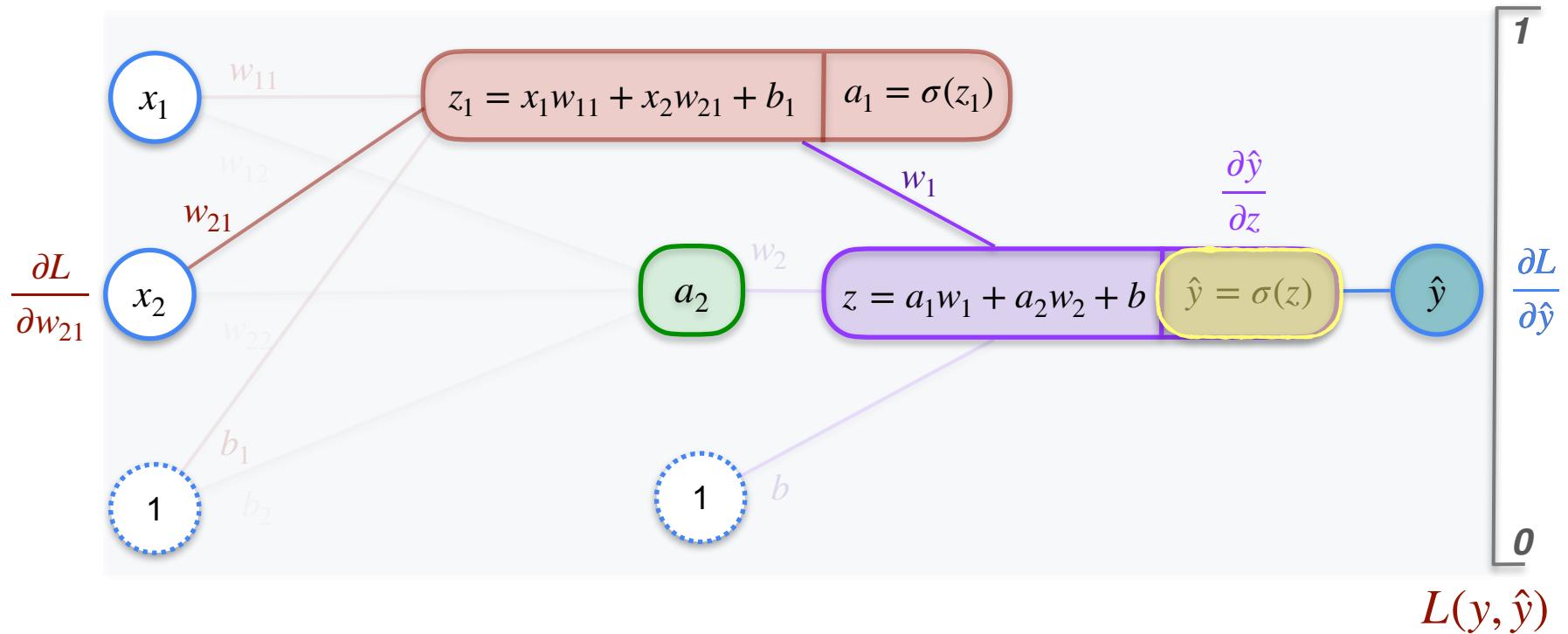
2,2,1 Neural Network



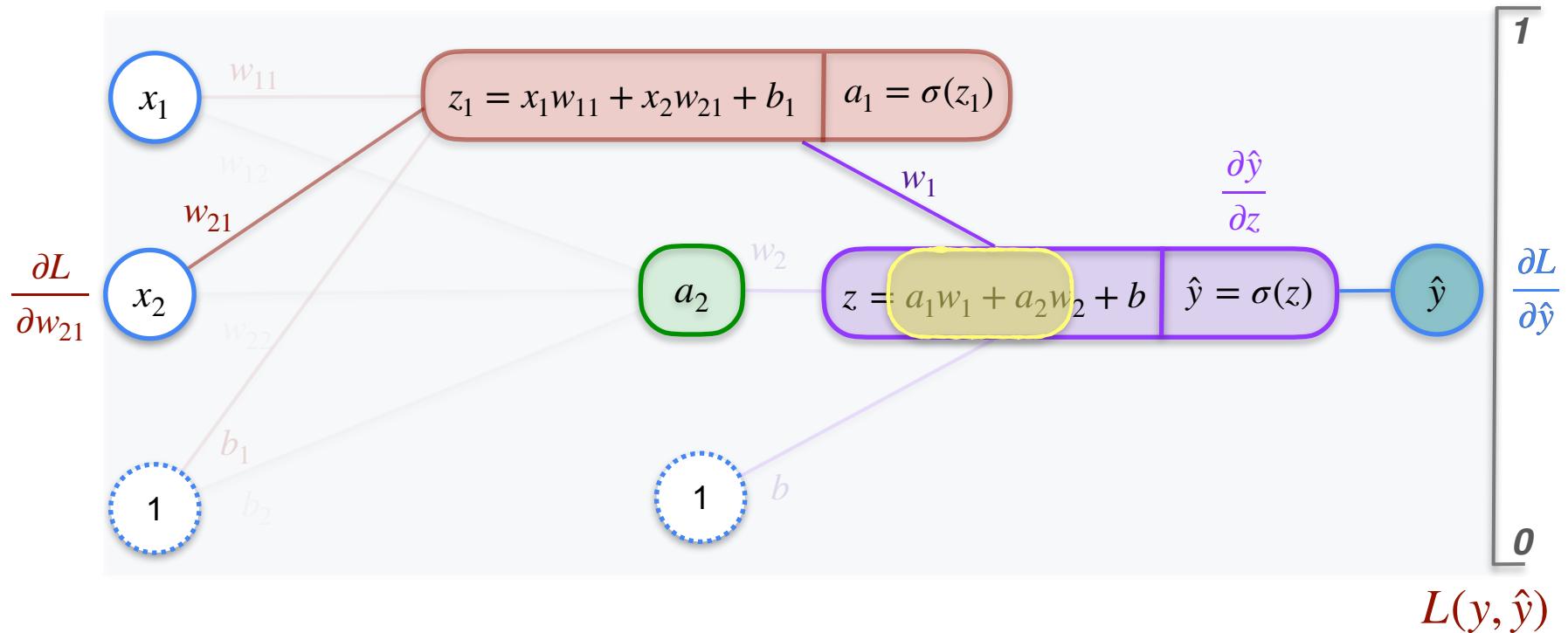
2,2,1 Neural Network



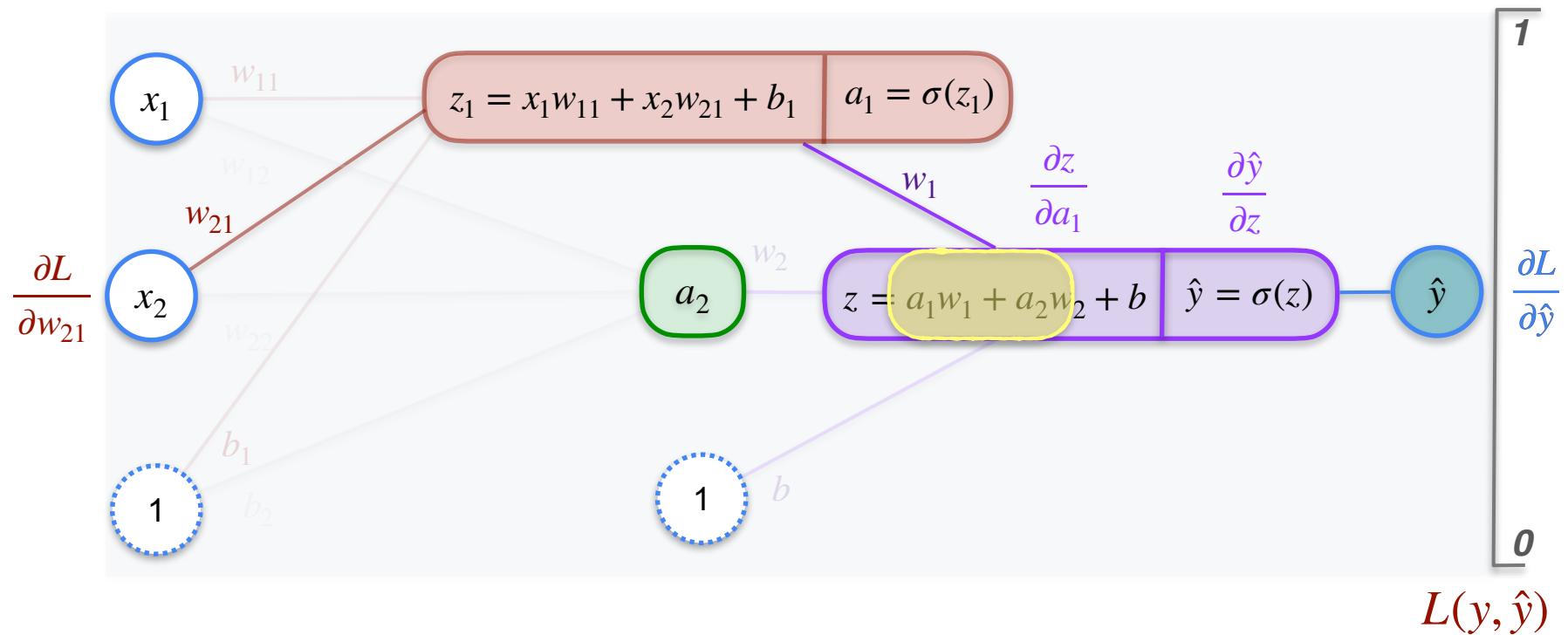
2,2,1 Neural Network



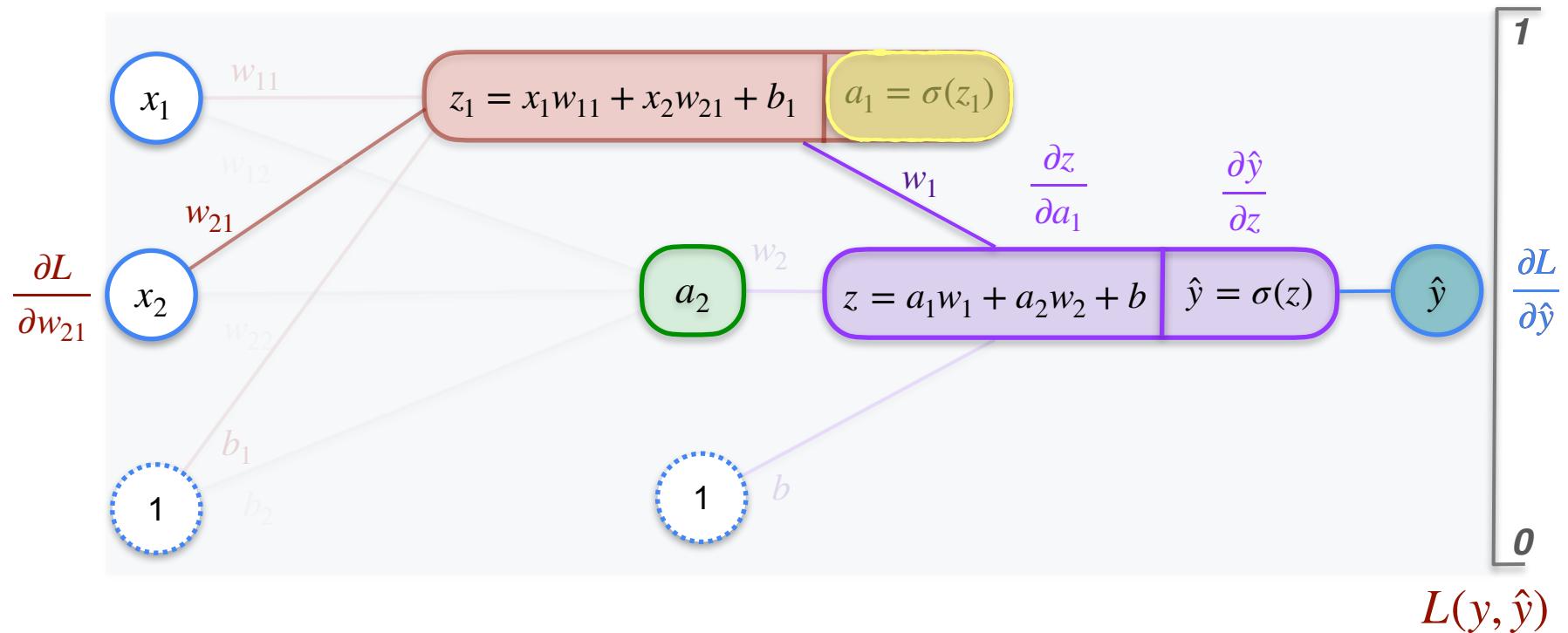
2,2,1 Neural Network



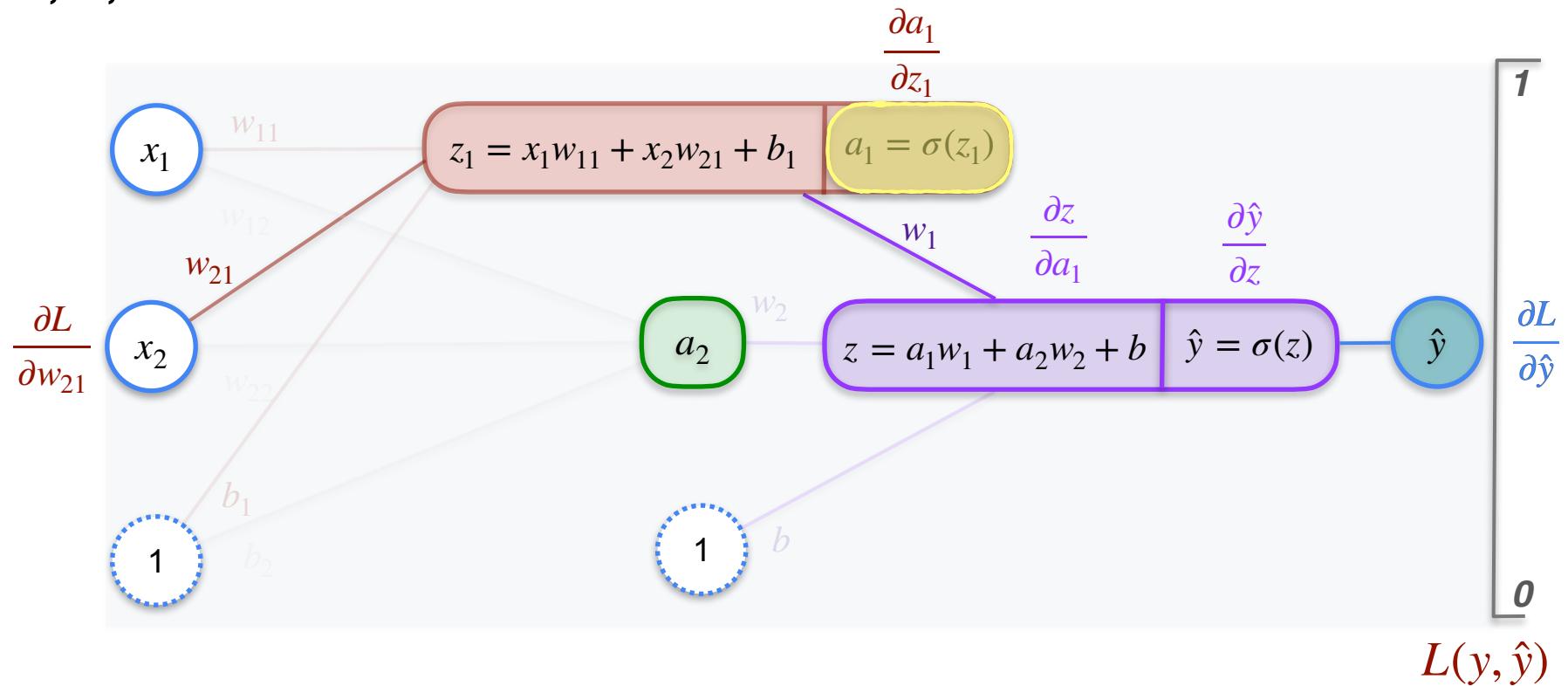
2,2,1 Neural Network



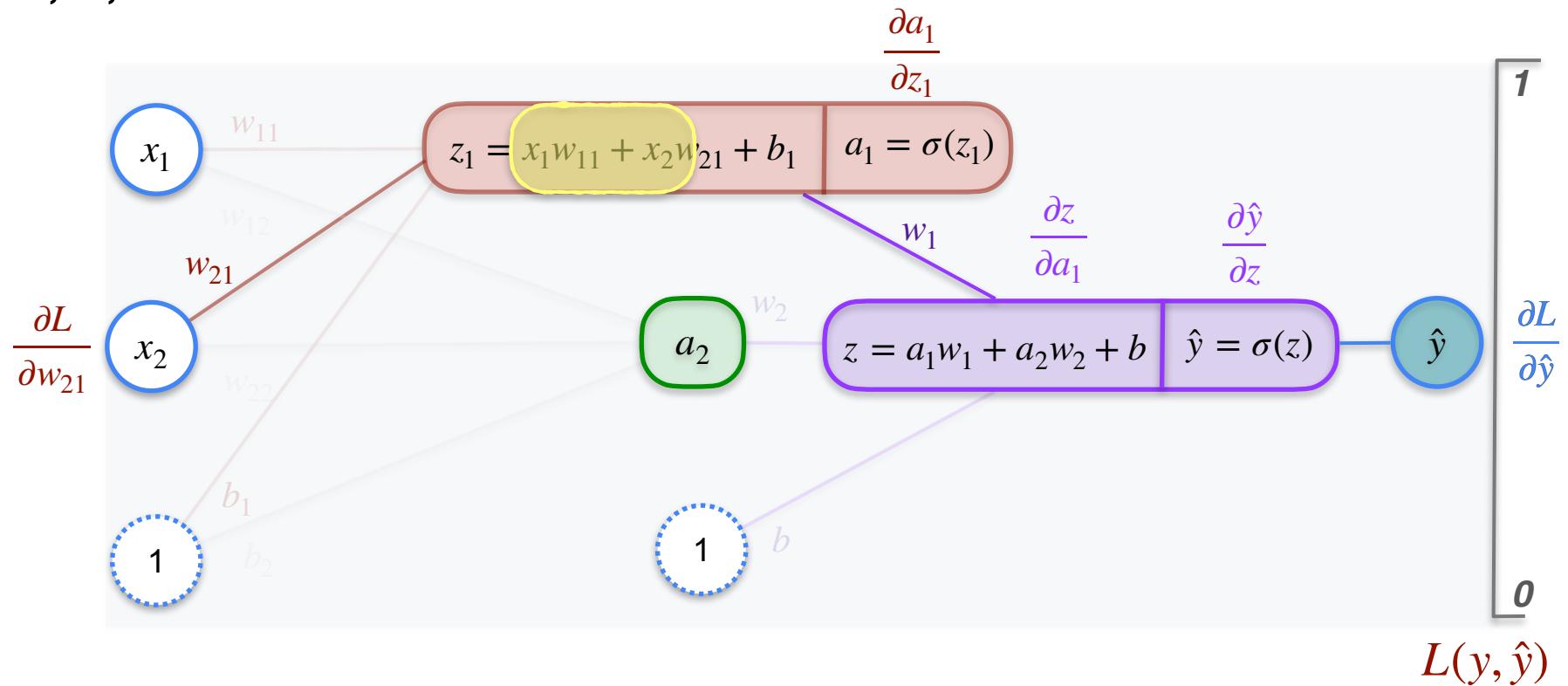
2,2,1 Neural Network



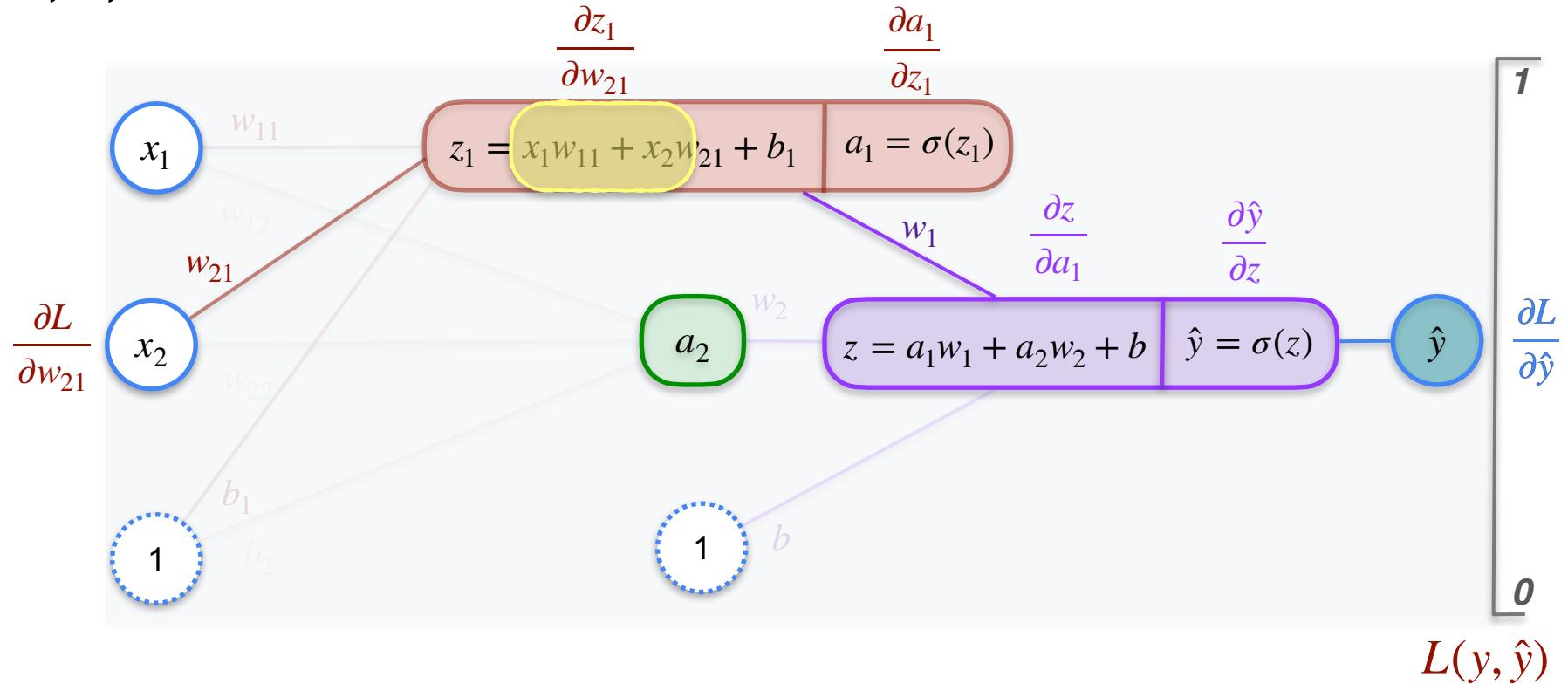
2,2,1 Neural Network



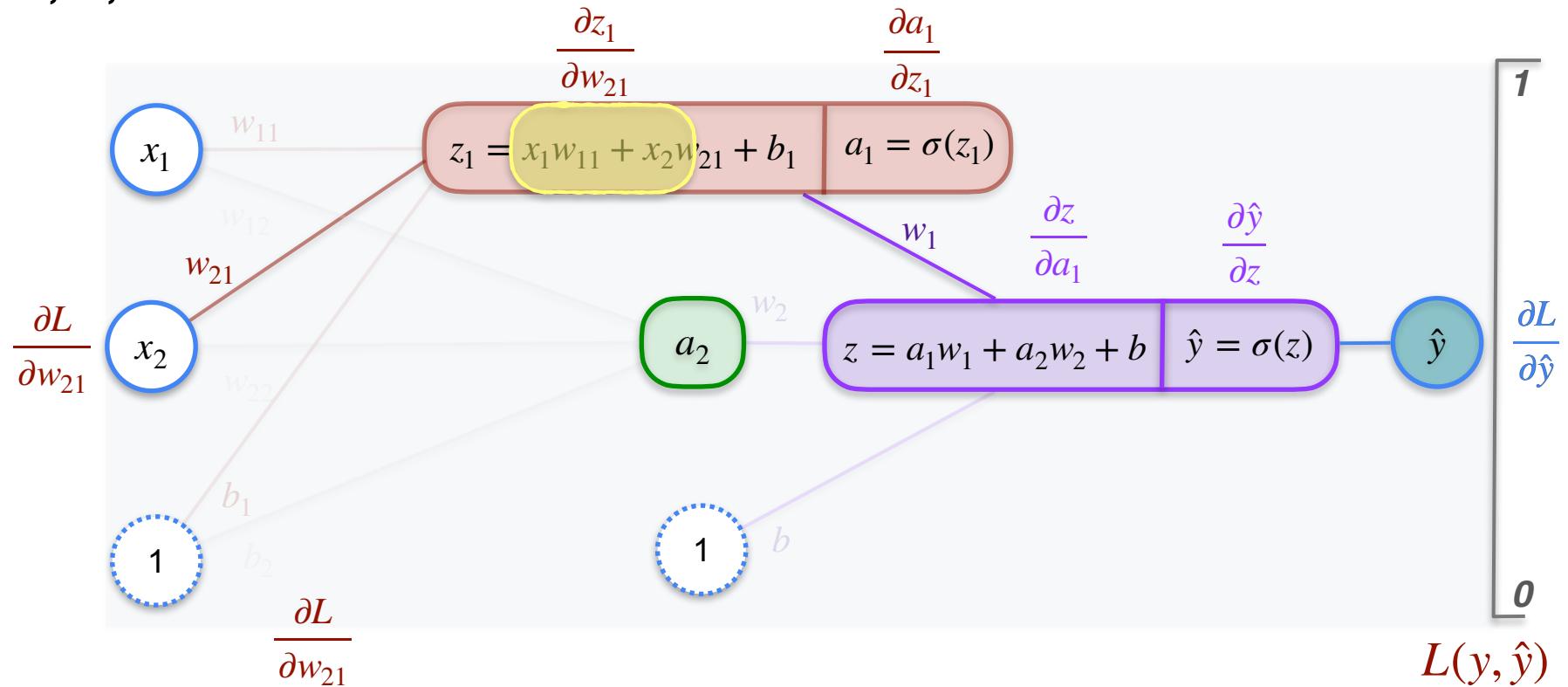
2,2,1 Neural Network



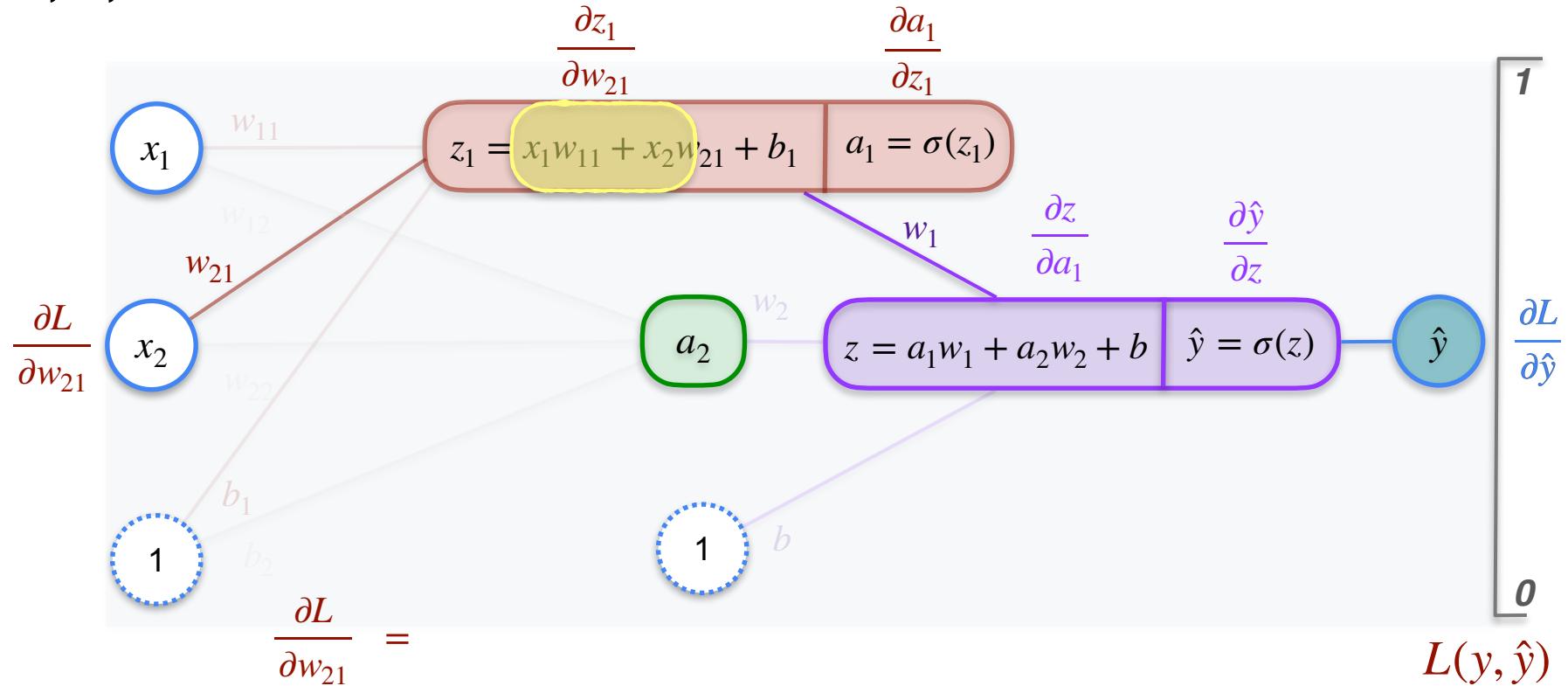
2,2,1 Neural Network



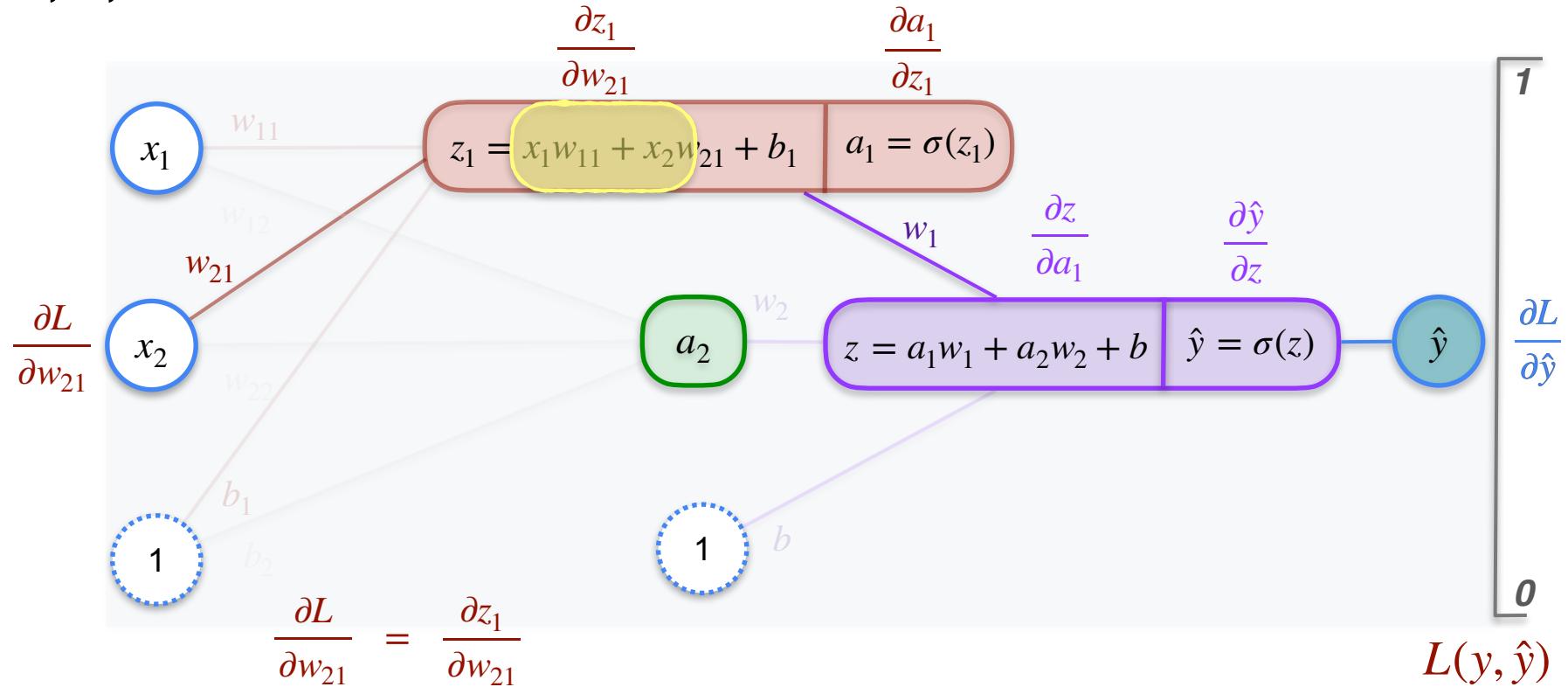
2,2,1 Neural Network



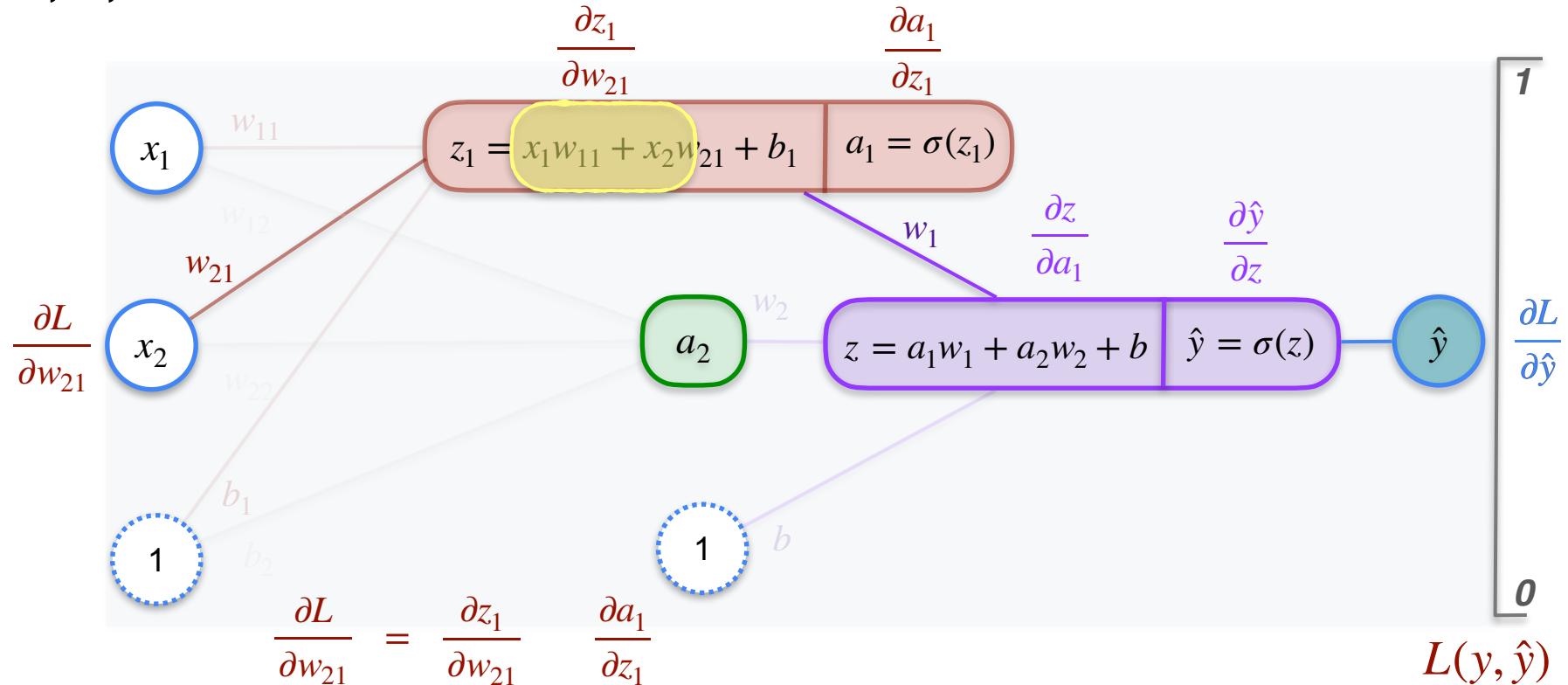
2,2,1 Neural Network



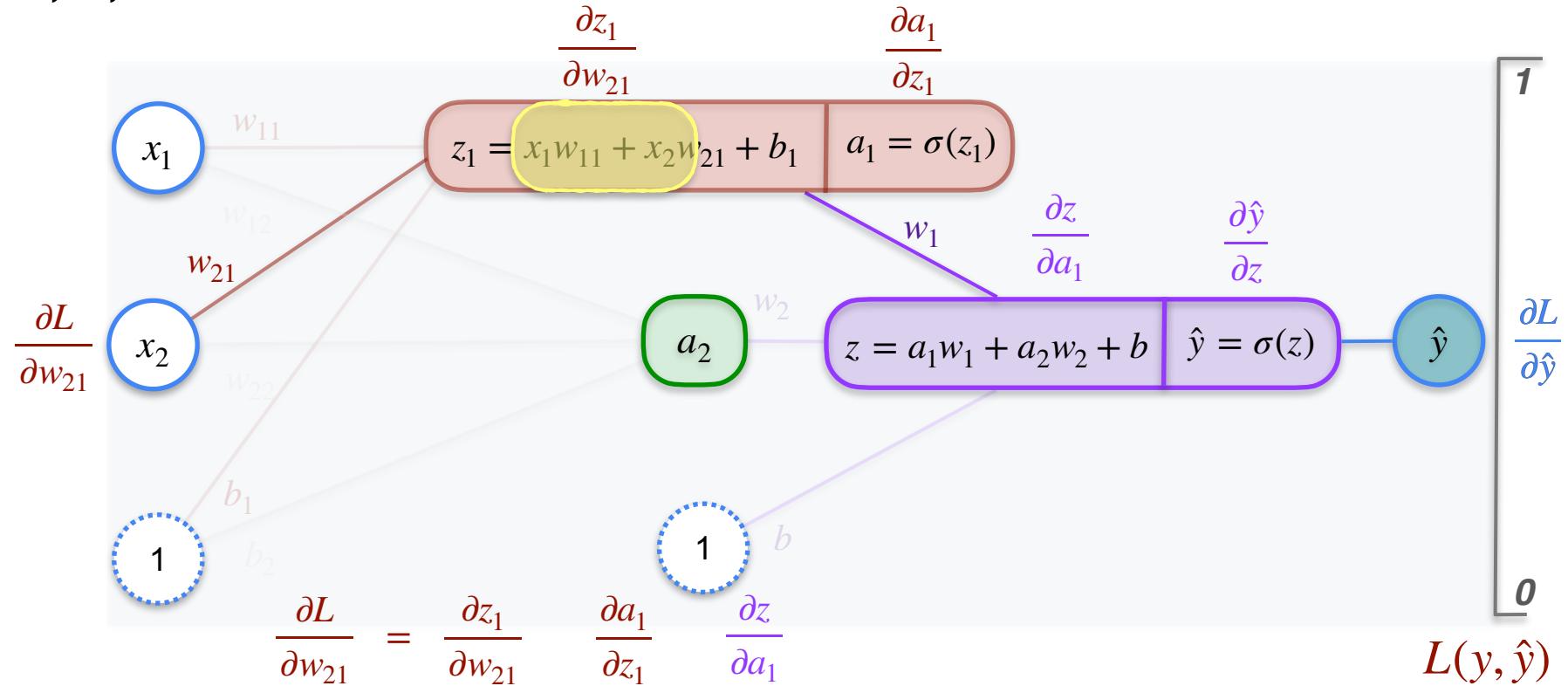
2,2,1 Neural Network



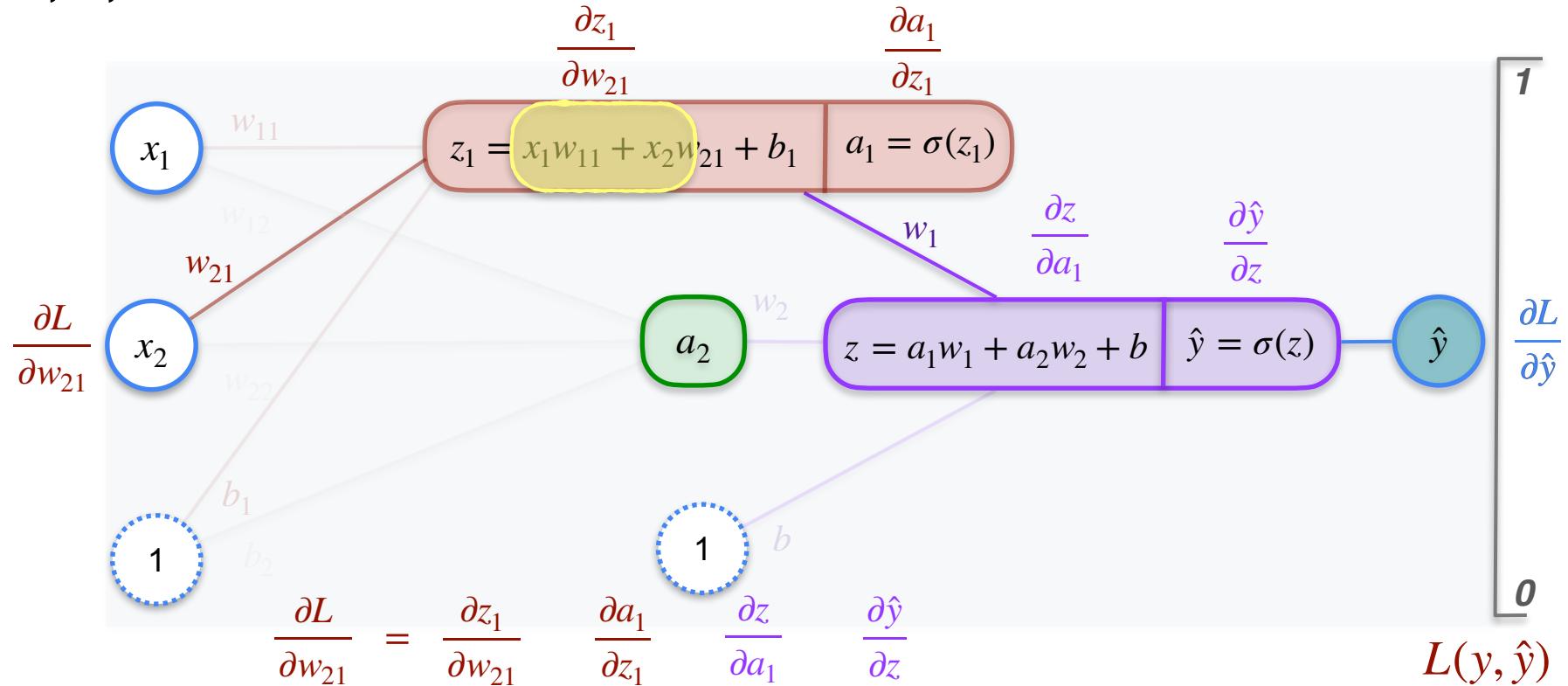
2,2,1 Neural Network



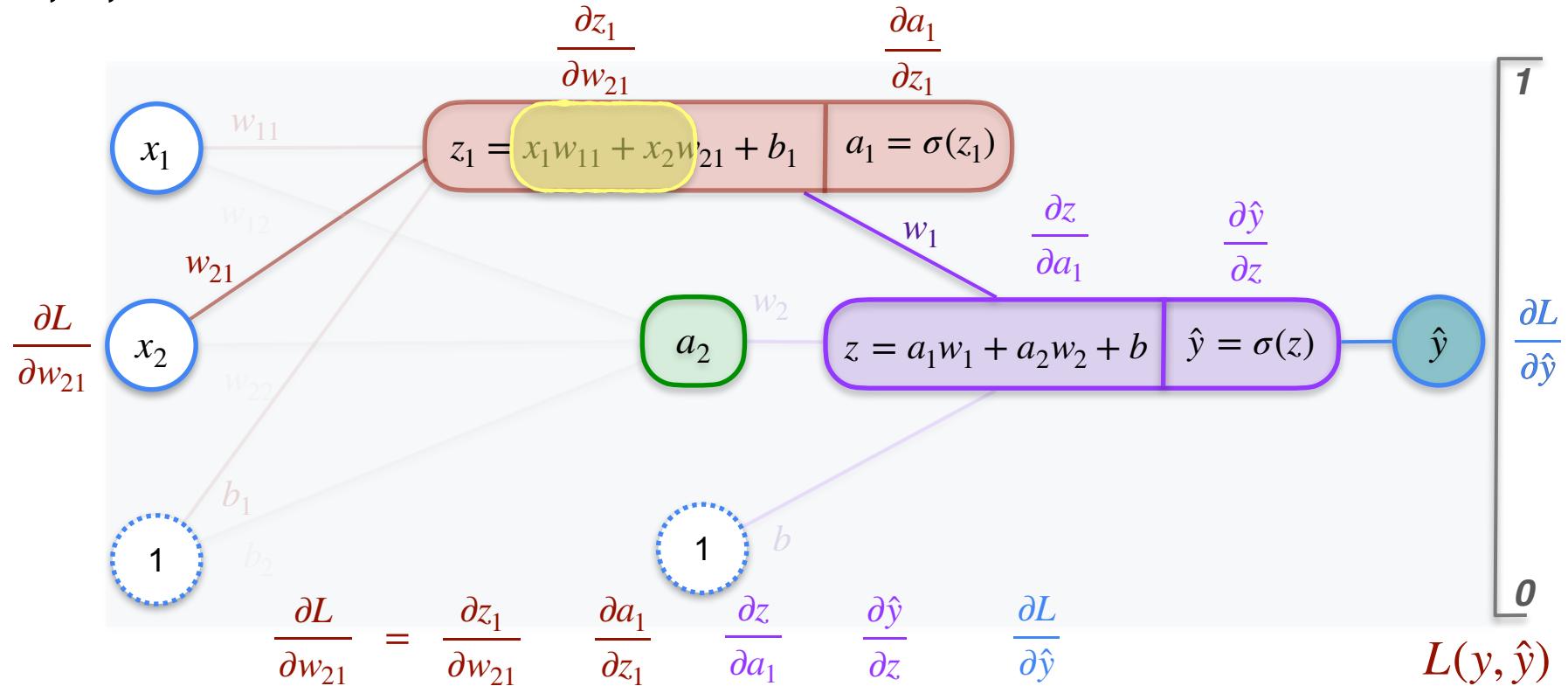
2,2,1 Neural Network



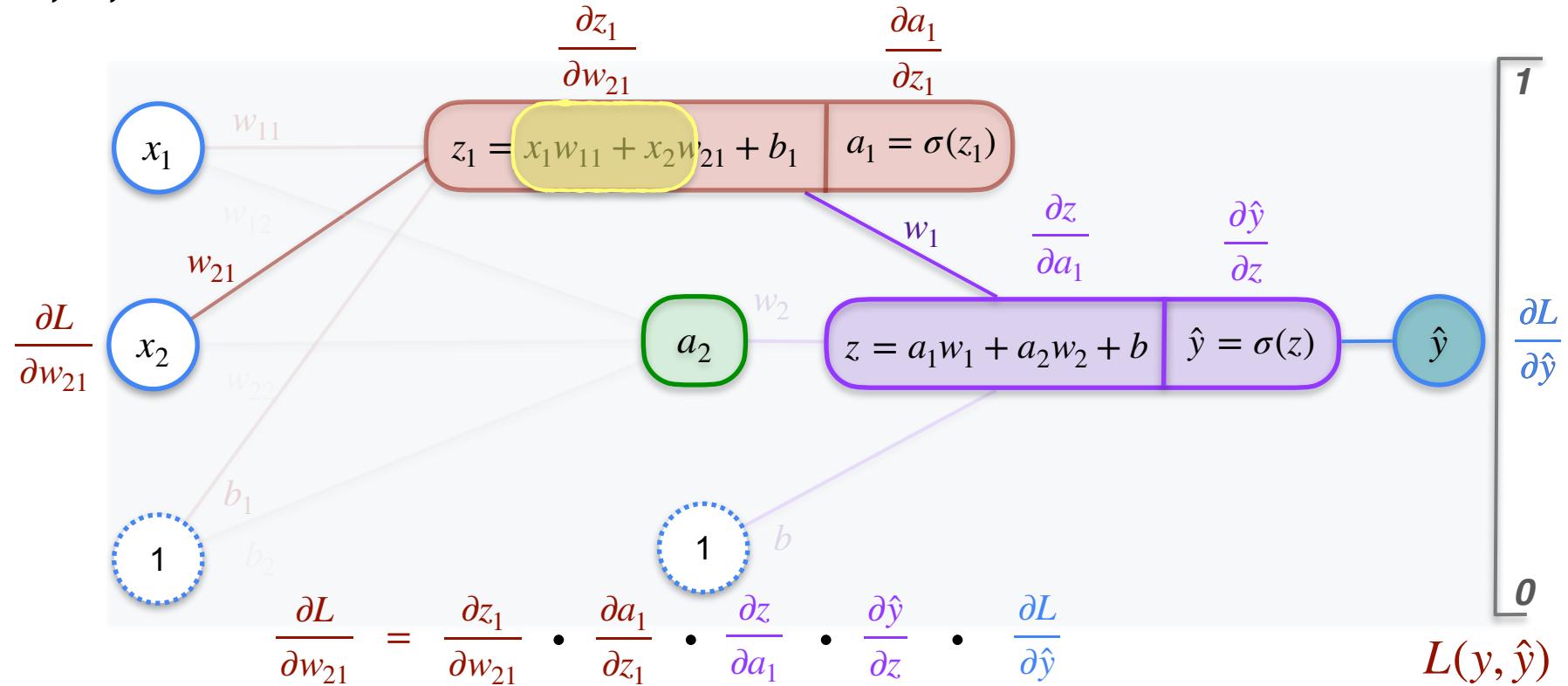
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_{21}}$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \boxed{\frac{\partial z_1}{\partial w_{21}}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \boxed{\frac{\partial z_1}{\partial w_{21}}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1 - a_1)$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1 - a_1)$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1 - a_1)$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1-a_1) w_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1-a_1) w_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1-a_1) w_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1-a_1) w_1 - \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2 \quad a_1(1-a_1) \quad w_1 \quad \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = x_2 - a_1(1-a_1) w_1 - \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial w_{21}} = x_2 \quad a_1(1-a_1) \quad w_1 \quad \hat{y}(1-\hat{y}) \quad \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial w_{21}} = x_2 \cdot a_1(1-a_1) \cdot w_1 \cdot \hat{y}(1-\hat{y}) \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial w_{21}} = x_2 \cdot a_1 (1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial w_{21}} = \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_{21}} = x_2 \cdot a_1 (1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial w_{21}} &= \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{21}} &= x_2 \cdot a_1 (1 - a_1) \cdot w_1 \cdot \cancel{\hat{y}(1 - \hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1 - \hat{y})}} \\ &= -x_2 w_1 a_1 (1 - a_1) (y - \hat{y})\end{aligned}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial w_{21}} &= \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{21}} &= x_2 \cdot a_1 (1 - a_1) \cdot w_1 \cdot \cancel{\hat{y}(1 - \hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1 - \hat{y})}} \\ &= -x_2 w_1 a_1 (1 - a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

*to find optimal
value of w_{21} that
gives the least error*

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial w_{21}} &= \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{21}} &= x_2 \cdot a_1 (1 - a_1) \cdot w_1 \cdot \cancel{\hat{y}(1 - \hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1 - \hat{y})}} \\ &= -x_2 w_1 a_1 (1 - a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

$$w_{21} \rightarrow w_{21} - \alpha \frac{\partial L}{\partial w_{21}}$$

to find optimal value of w_{21} that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial w_{21}} &= \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{21}} &= x_2 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -x_2 w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

$$w_{21} \rightarrow w_{21} - \alpha$$

to find optimal value of w_{21} that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

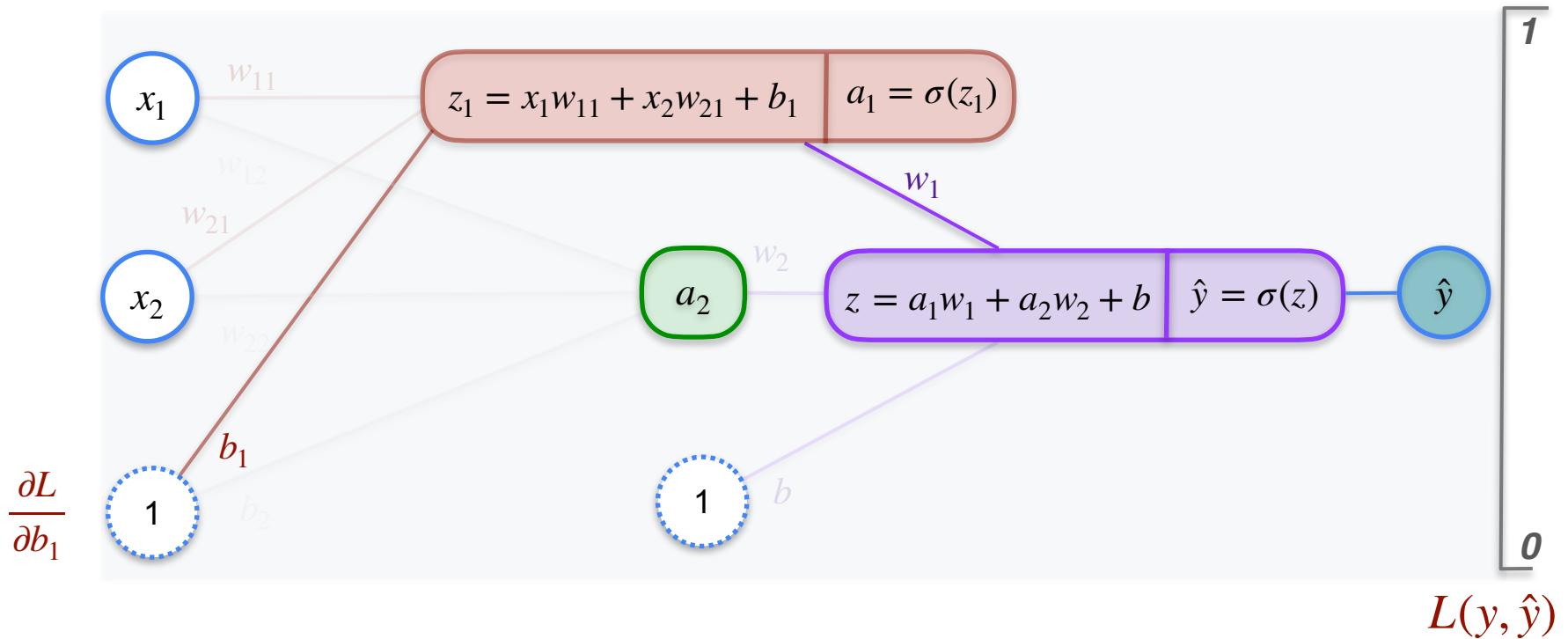
$$\begin{aligned}\frac{\partial L}{\partial w_{21}} &= \frac{\partial z_1}{\partial w_{21}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_{21}} &= x_2 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -x_2 w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

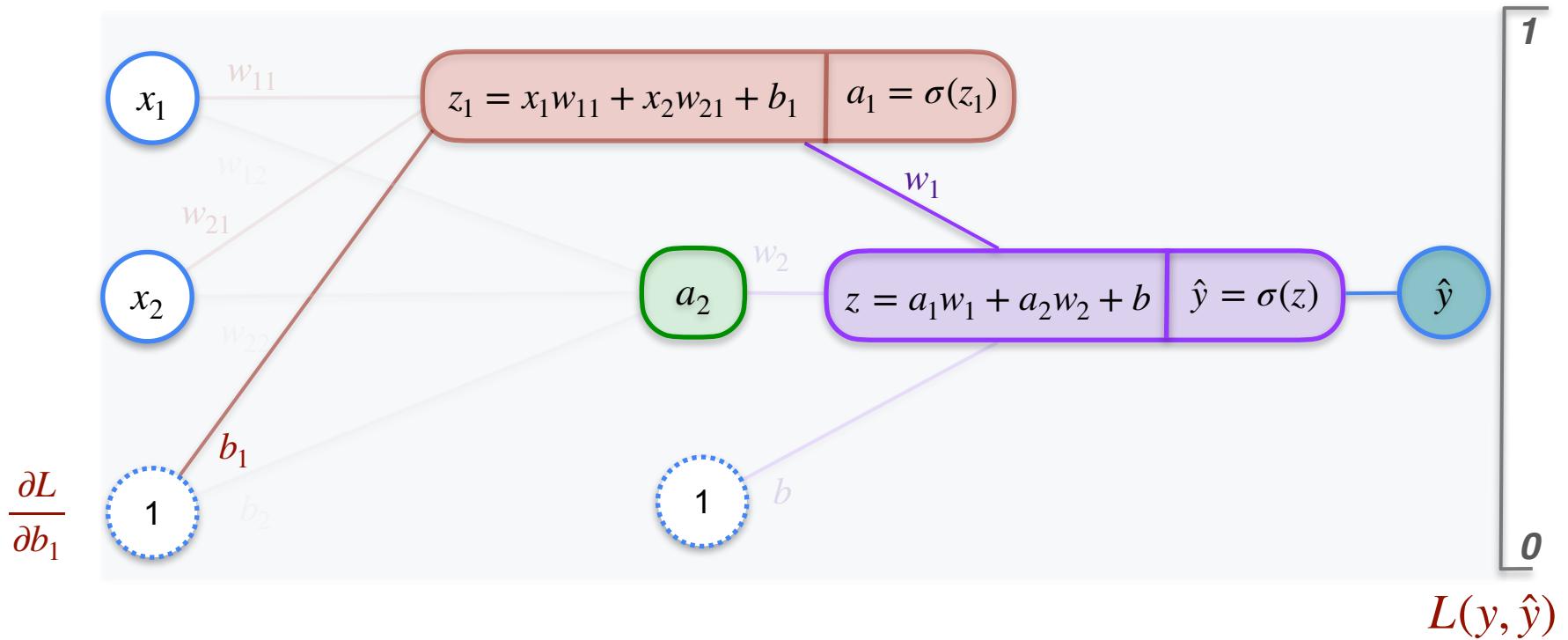
$$w_{21} \rightarrow w_{21} - \alpha \cdot x_2 w_1 a_1 (1-a_1) (y - \hat{y})$$

to find optimal value of w_{21} that gives the least error

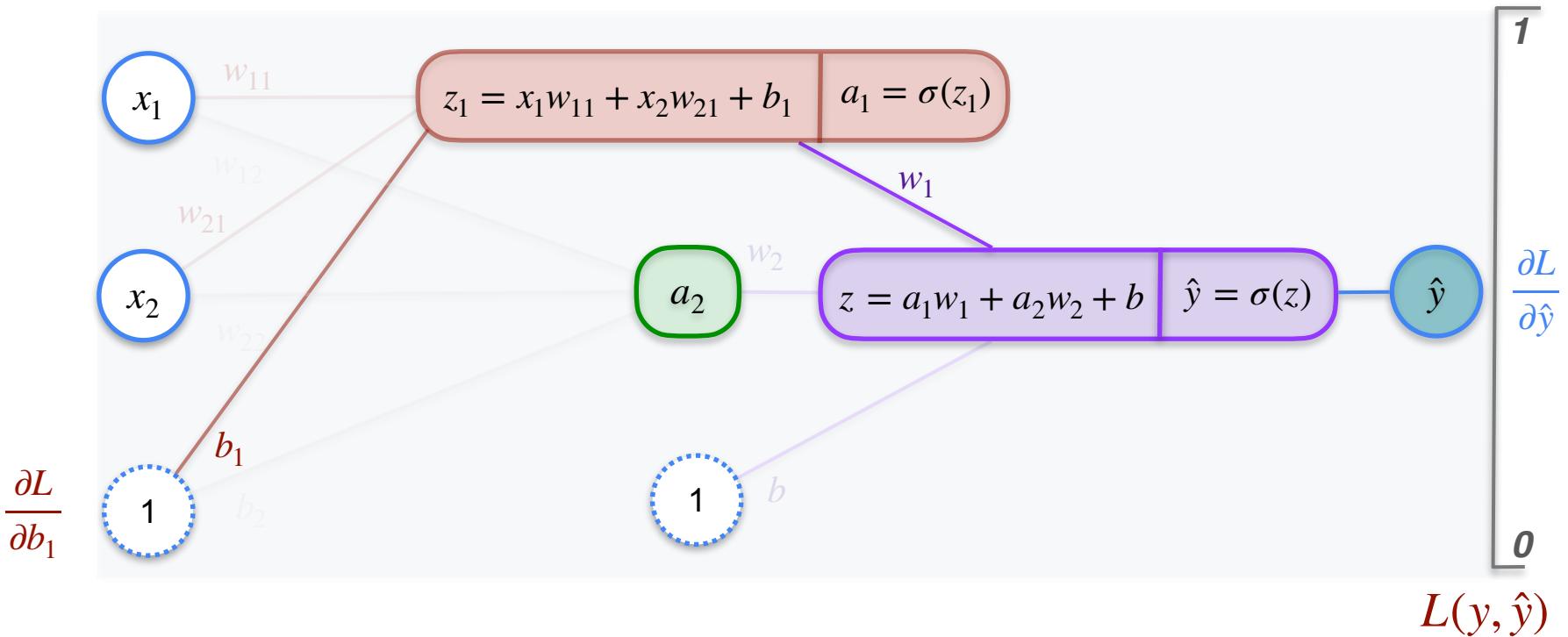
2,2,1 Neural Network



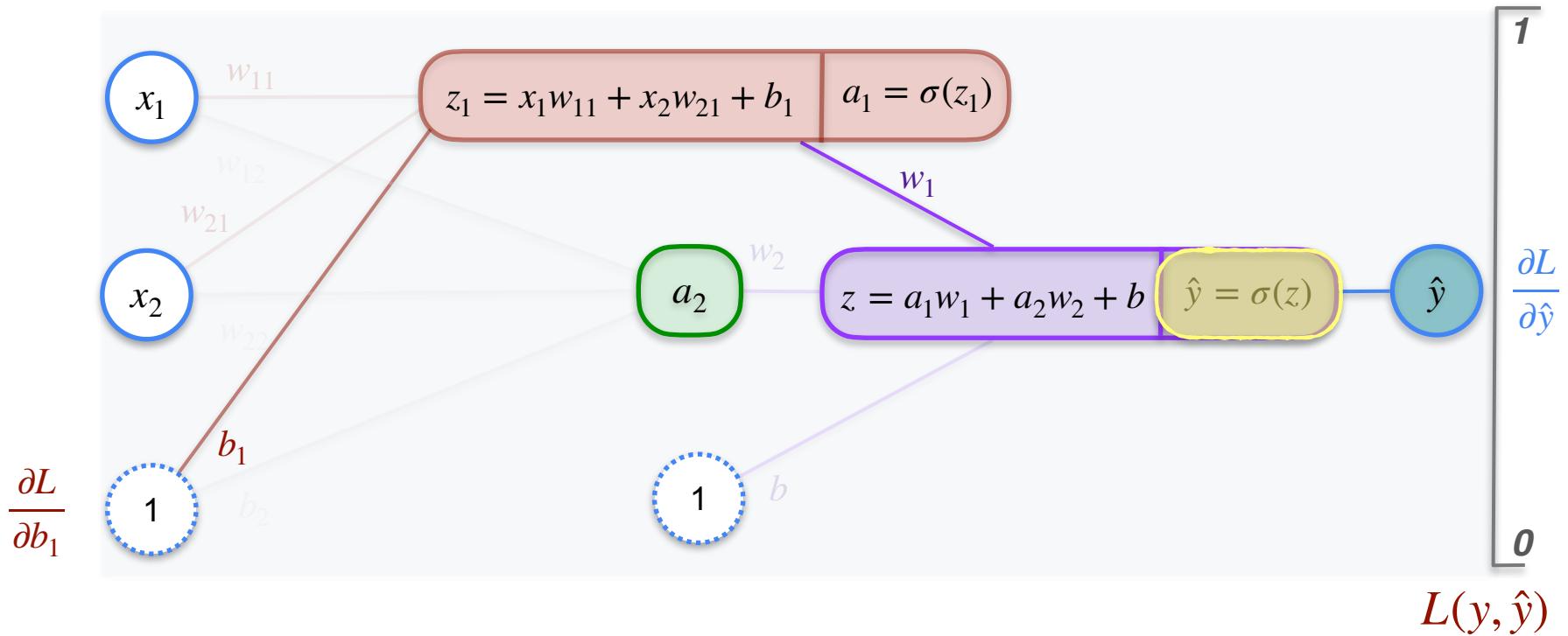
2,2,1 Neural Network



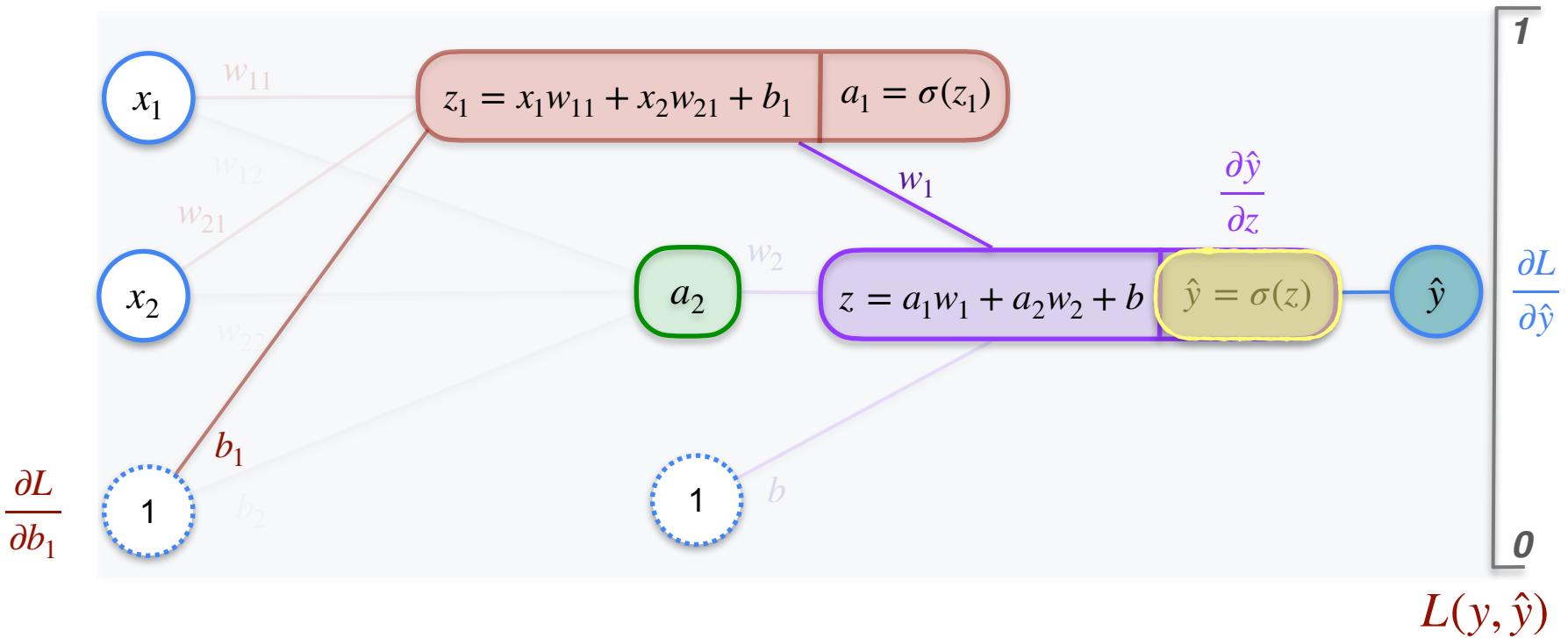
2,2,1 Neural Network



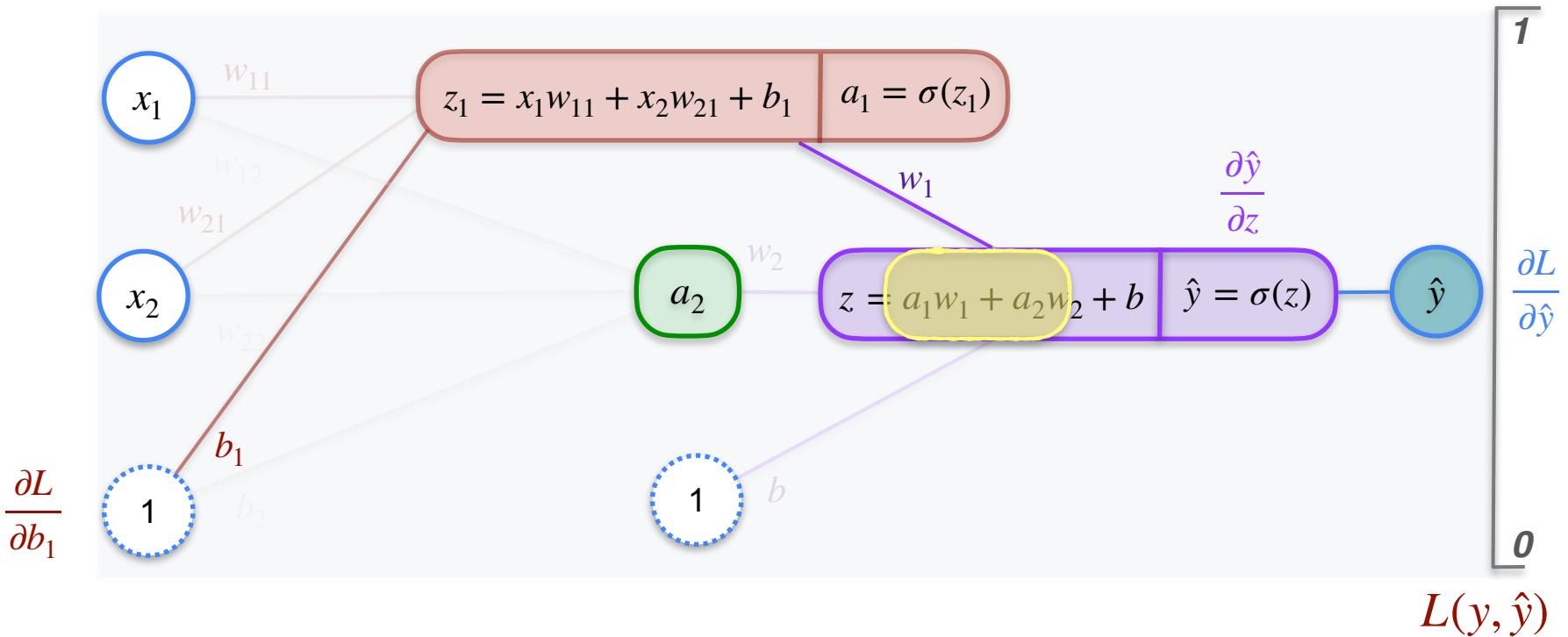
2,2,1 Neural Network



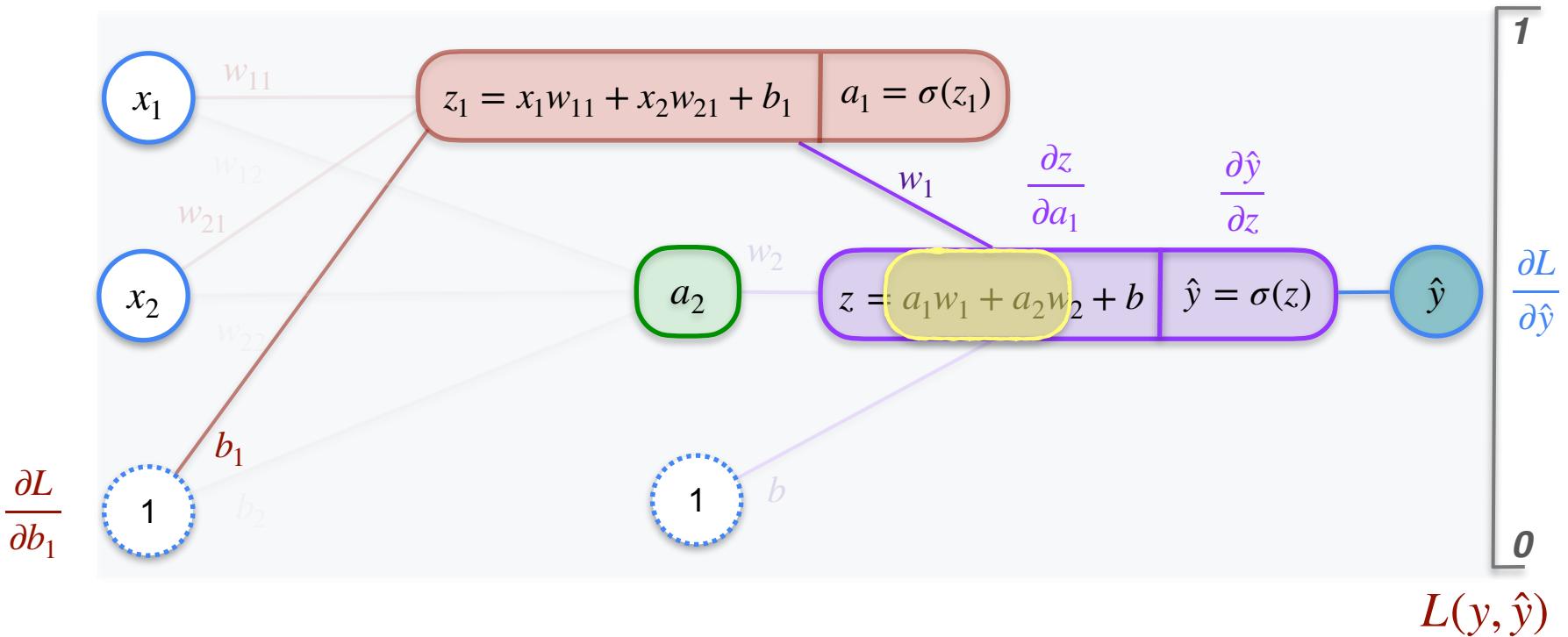
2,2,1 Neural Network



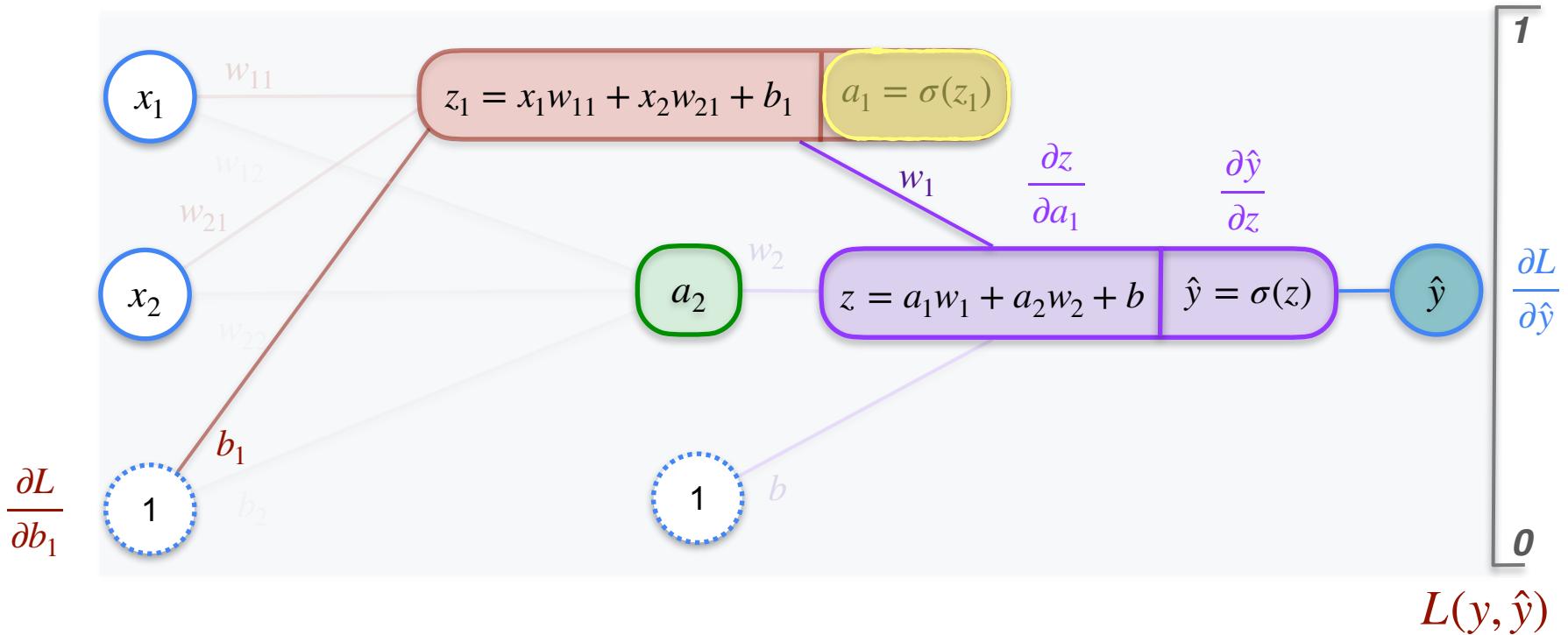
2,2,1 Neural Network



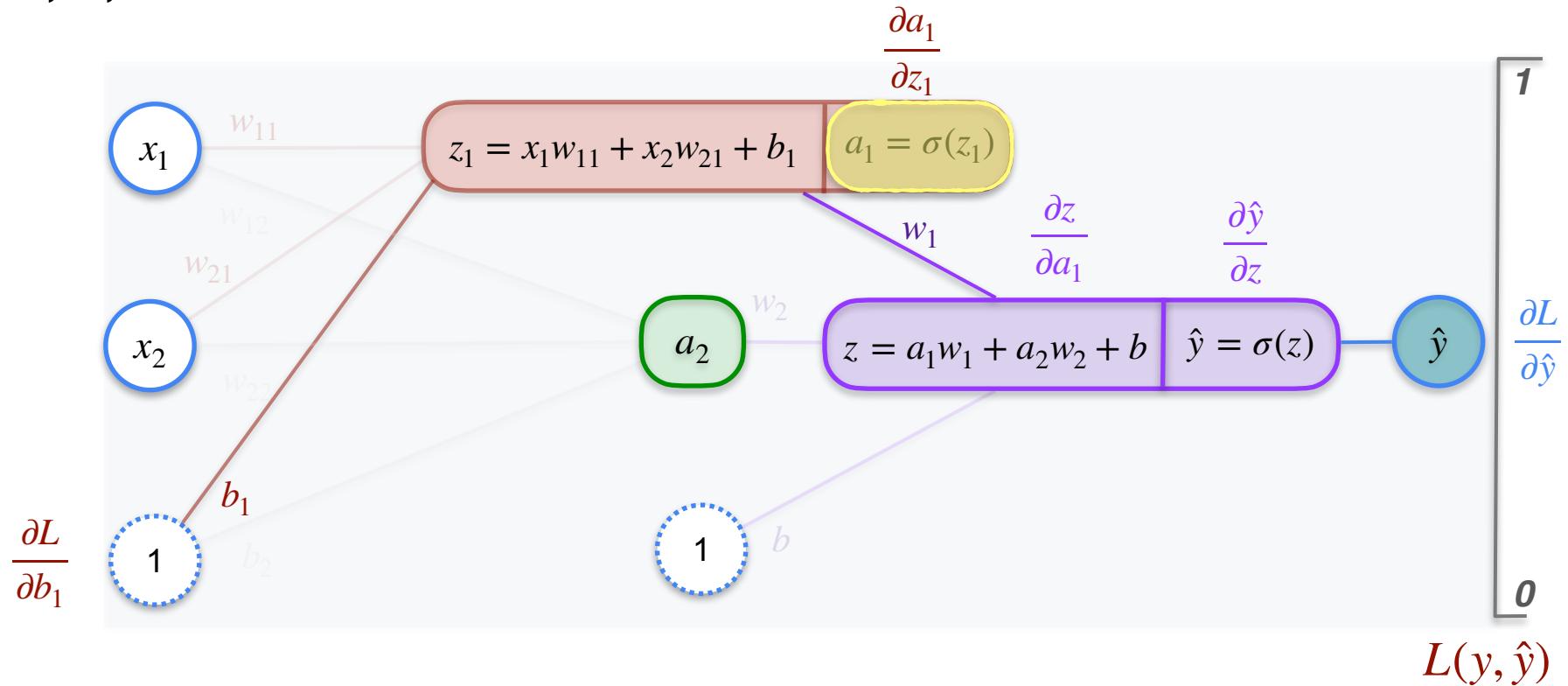
2,2,1 Neural Network



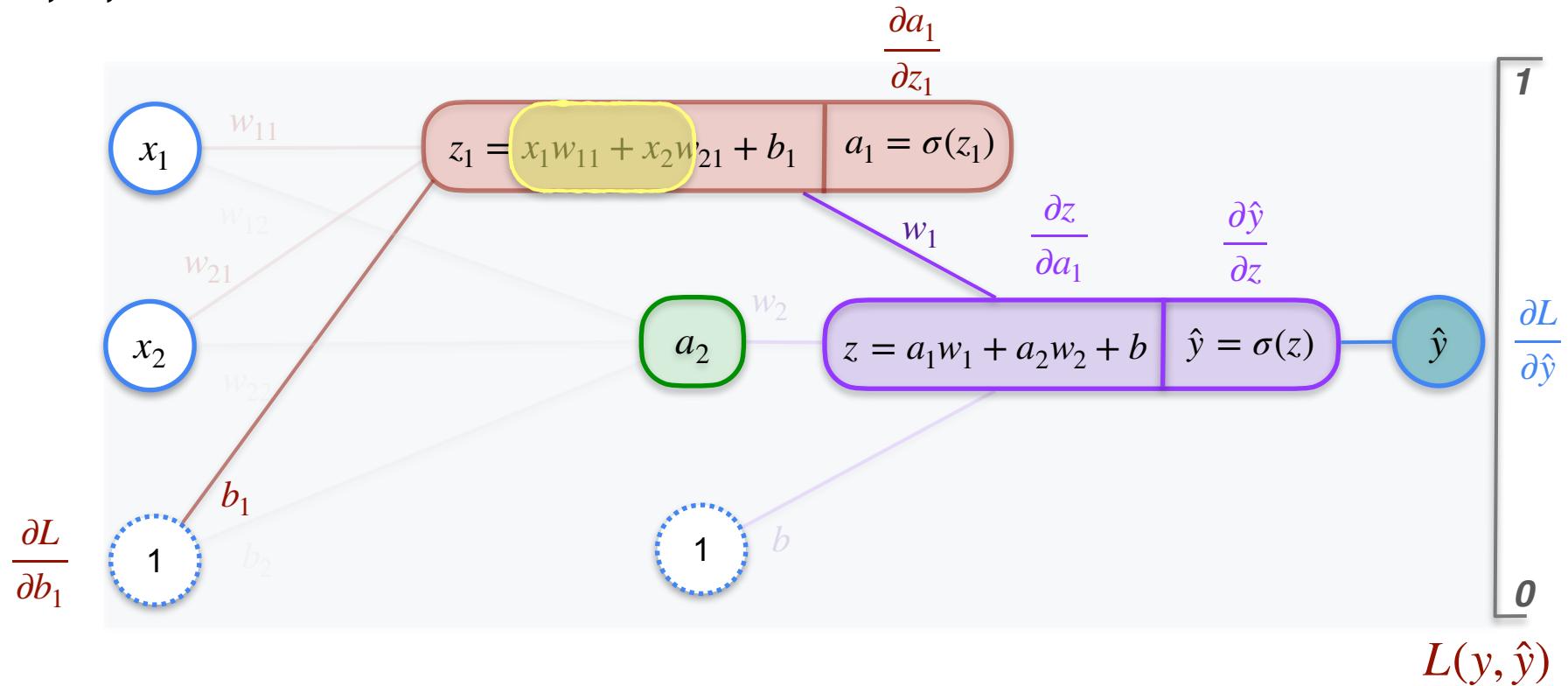
2,2,1 Neural Network



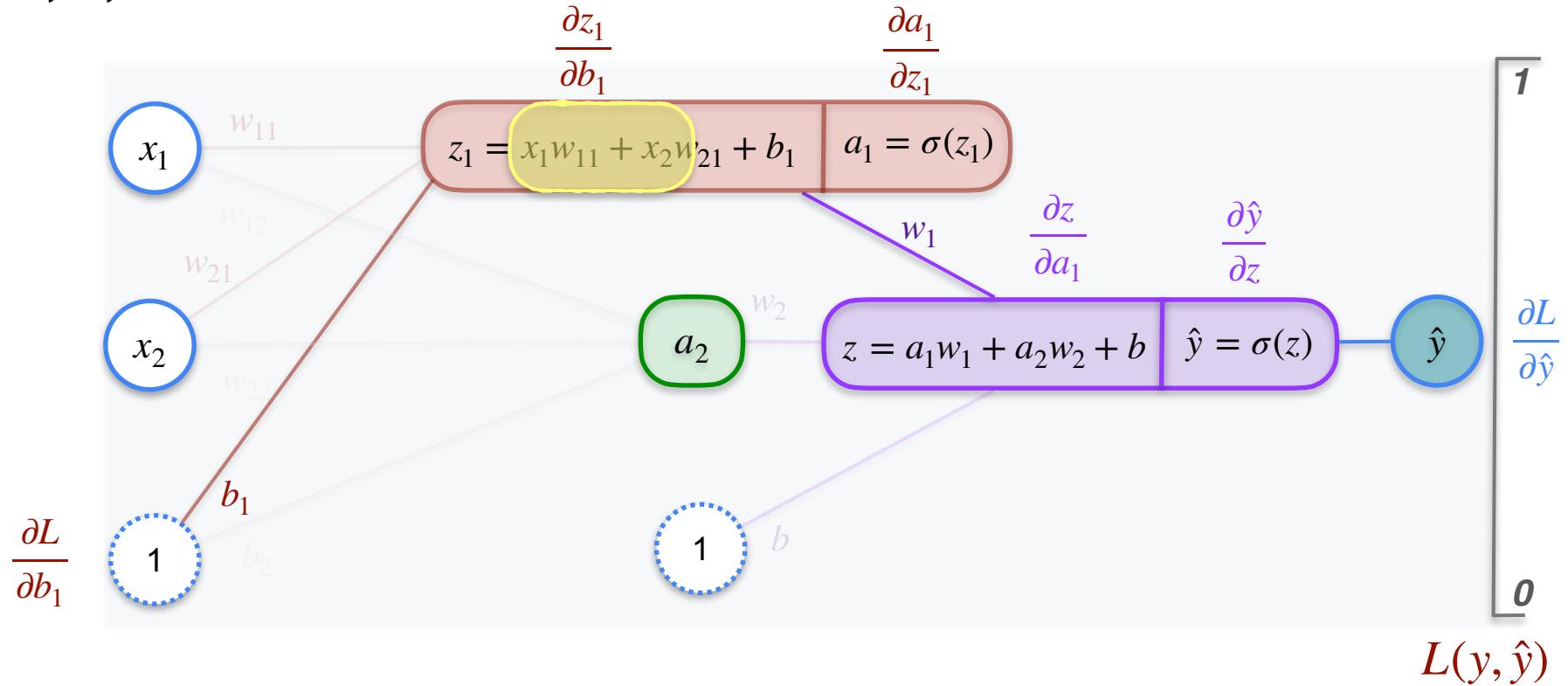
2,2,1 Neural Network



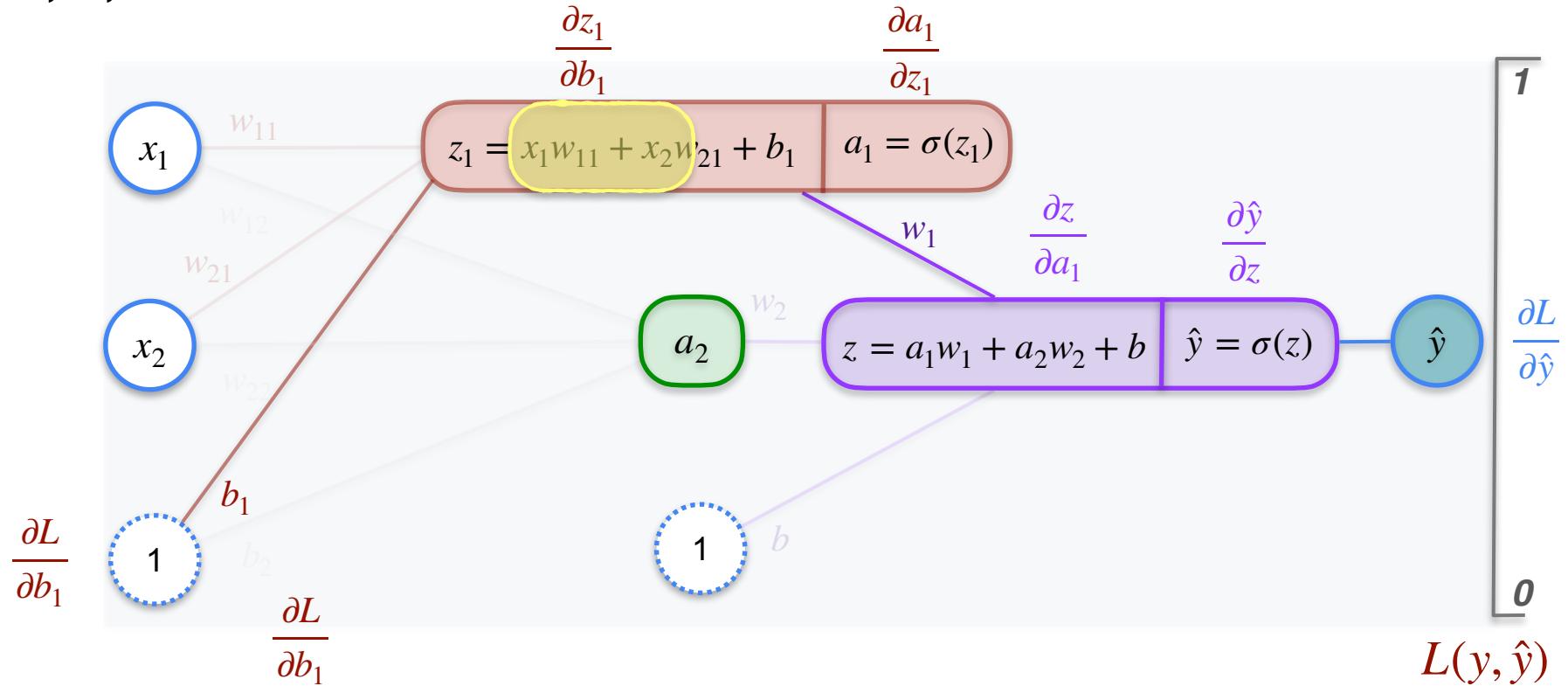
2,2,1 Neural Network



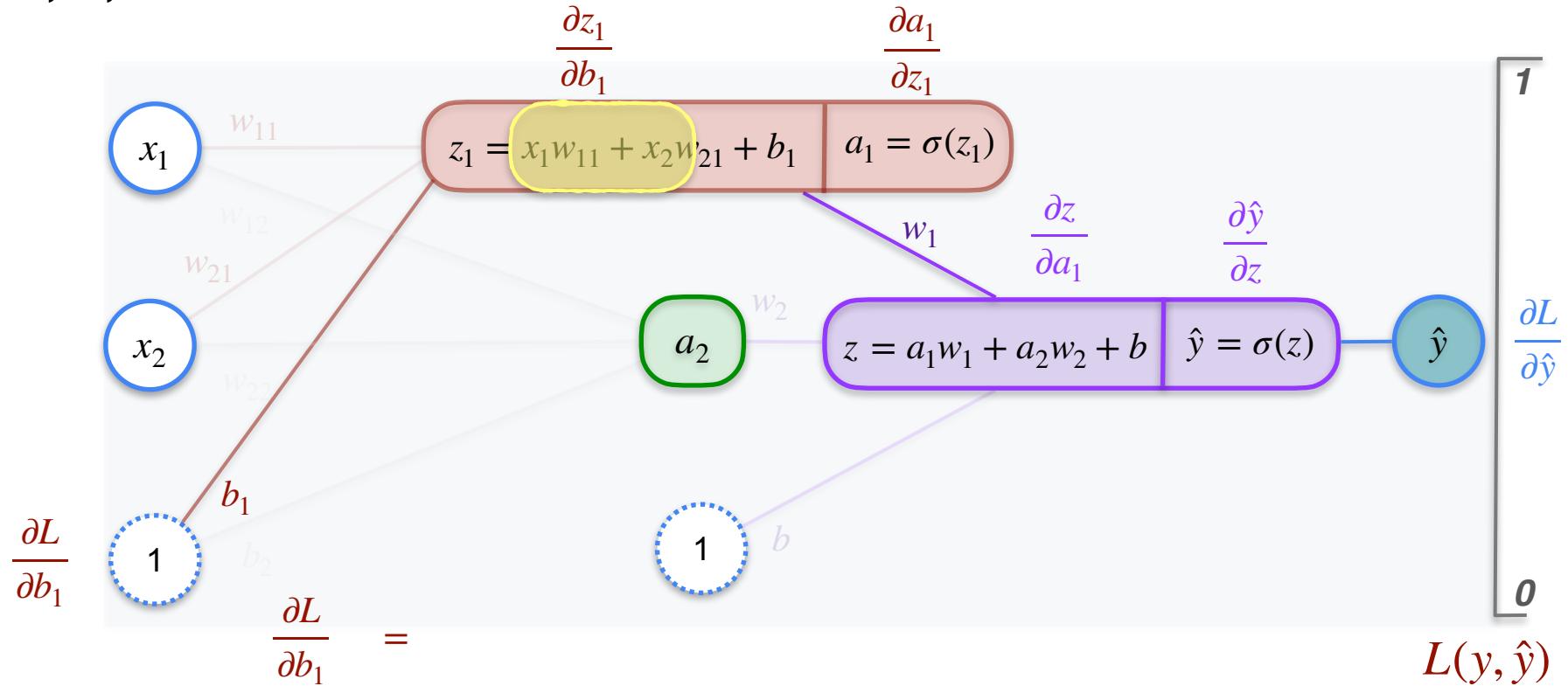
2,2,1 Neural Network



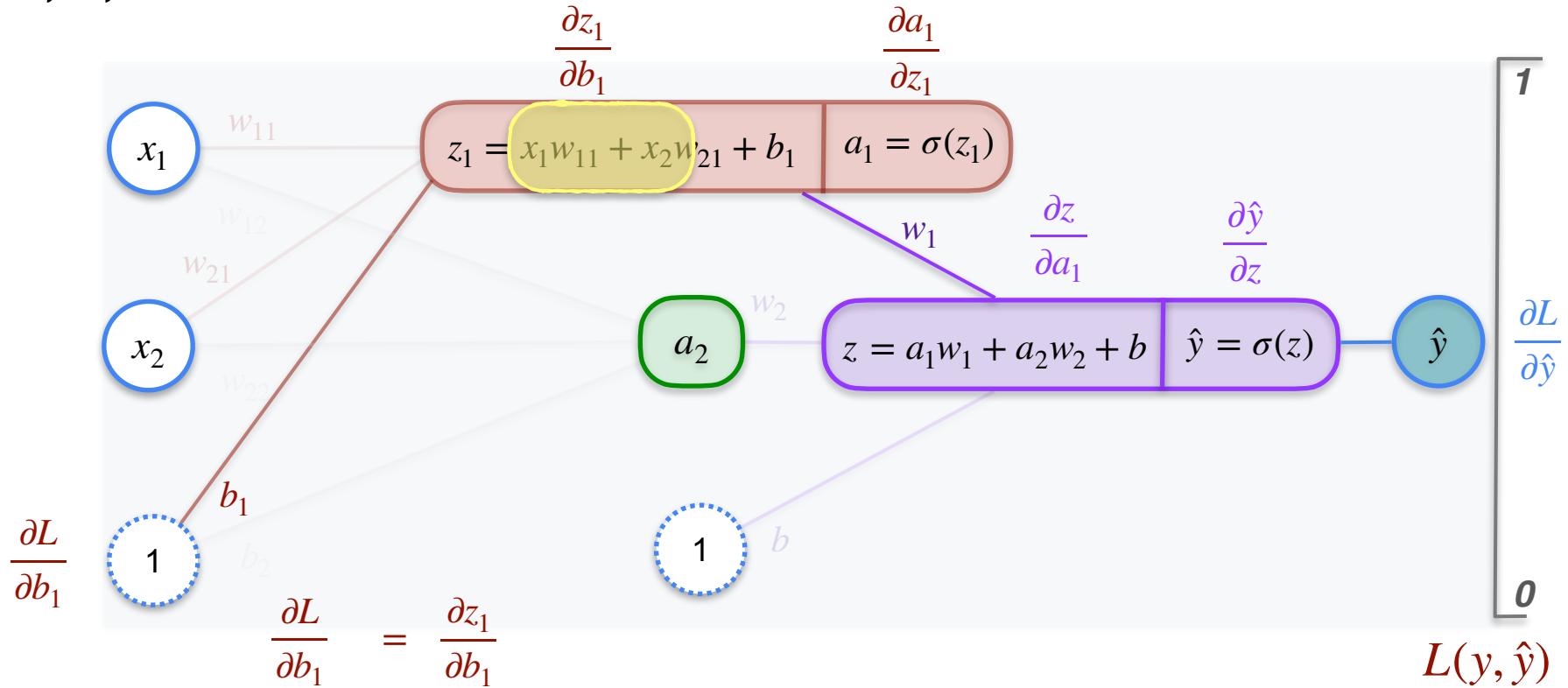
2,2,1 Neural Network



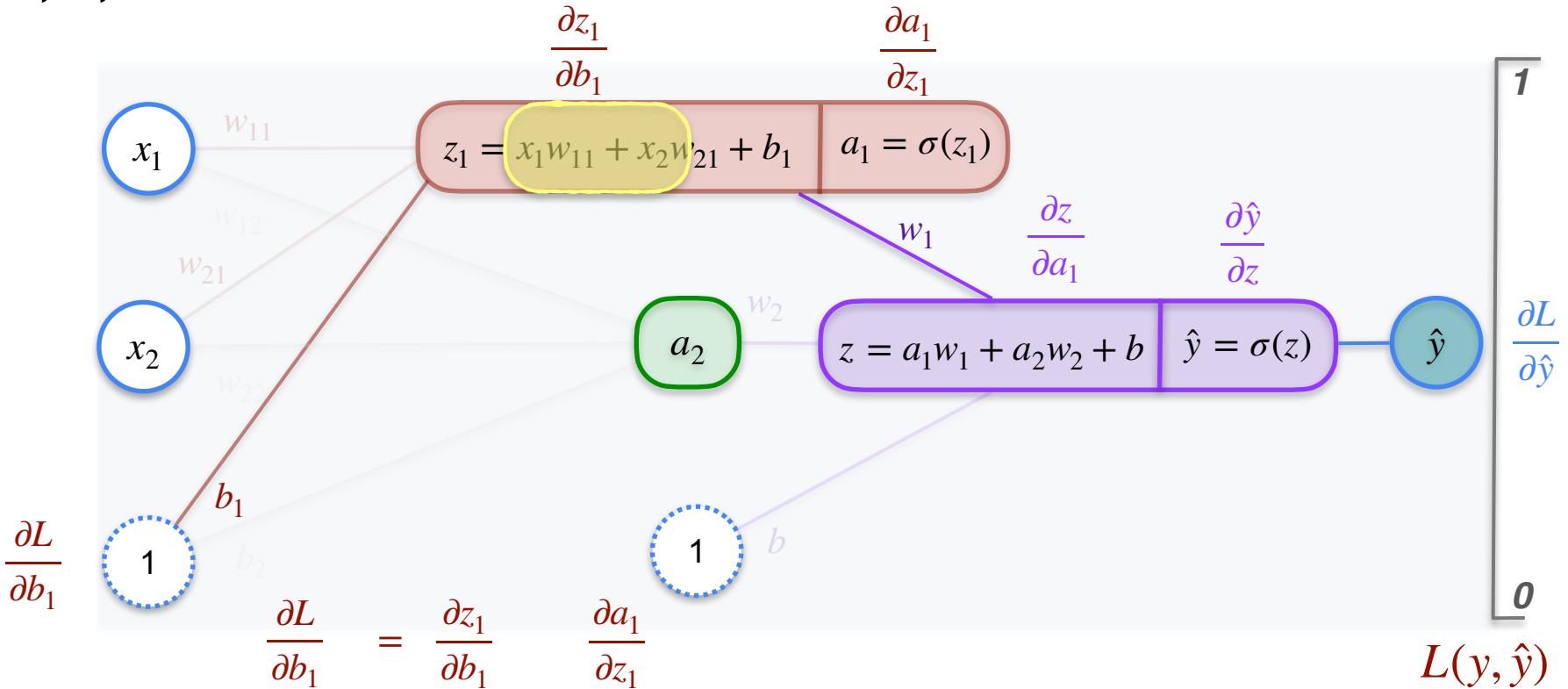
2,2,1 Neural Network



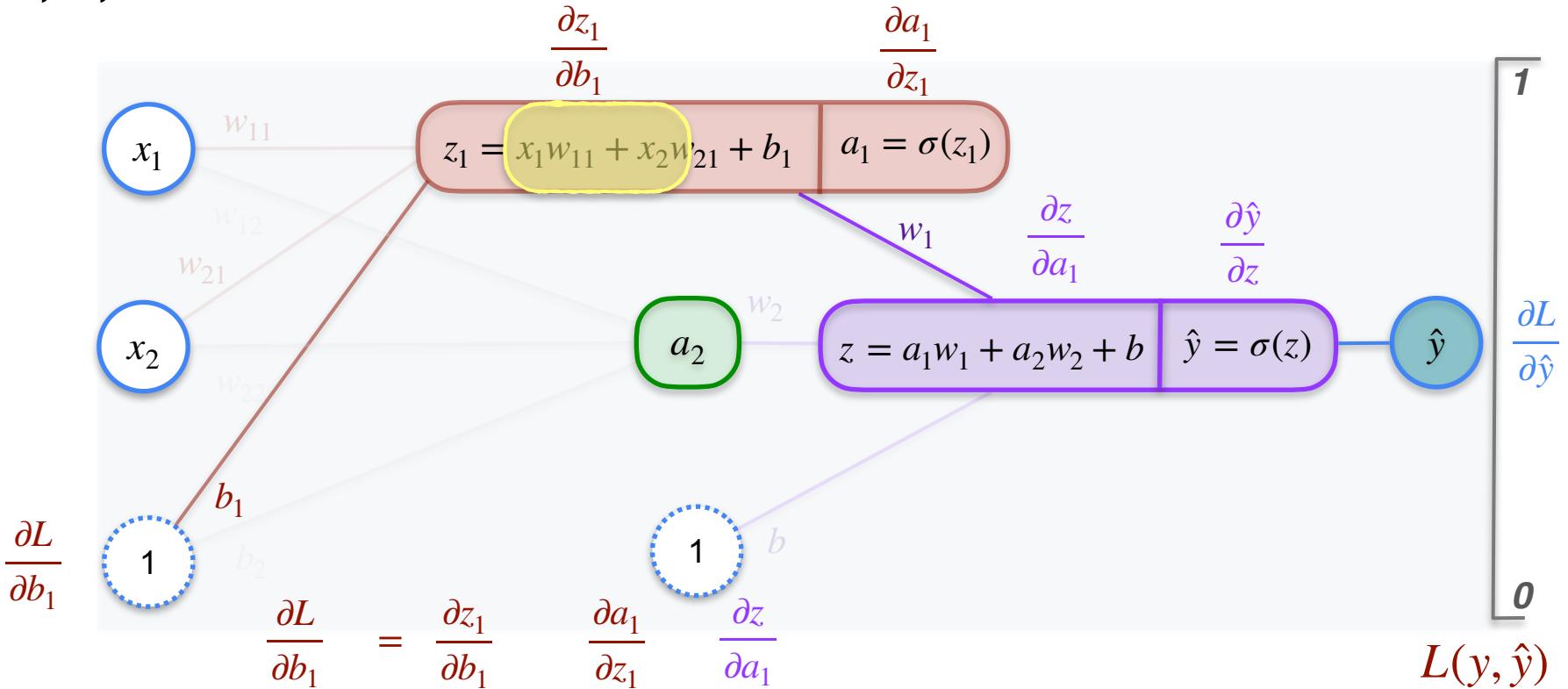
2,2,1 Neural Network



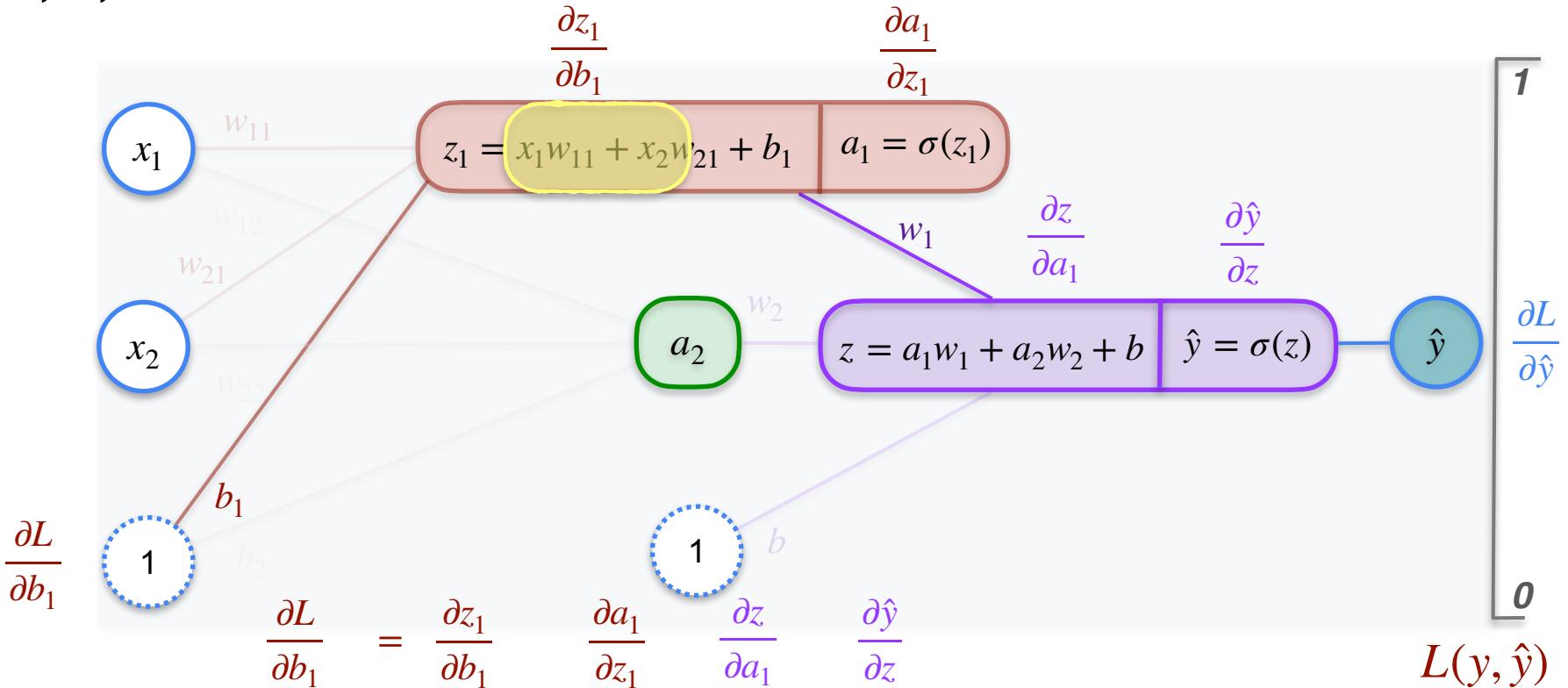
2,2,1 Neural Network



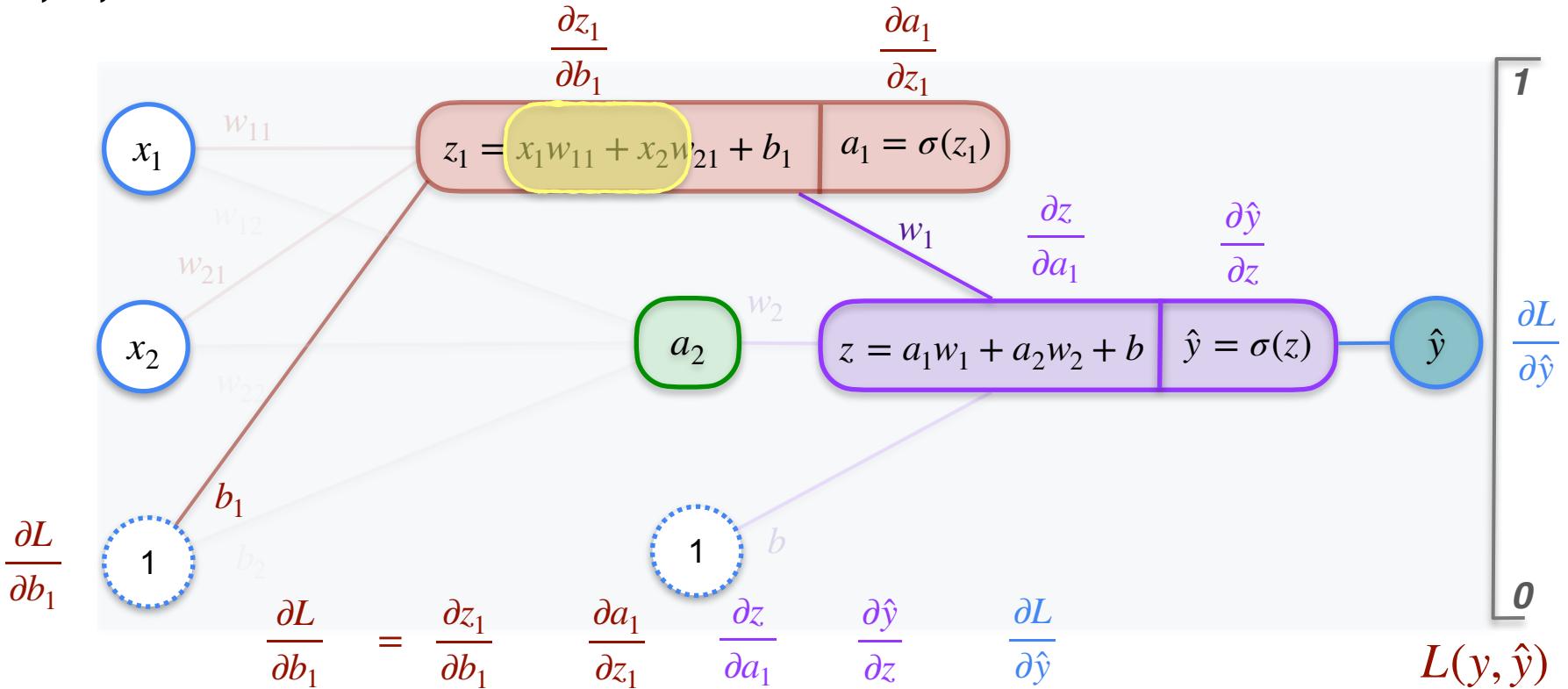
2,2,1 Neural Network



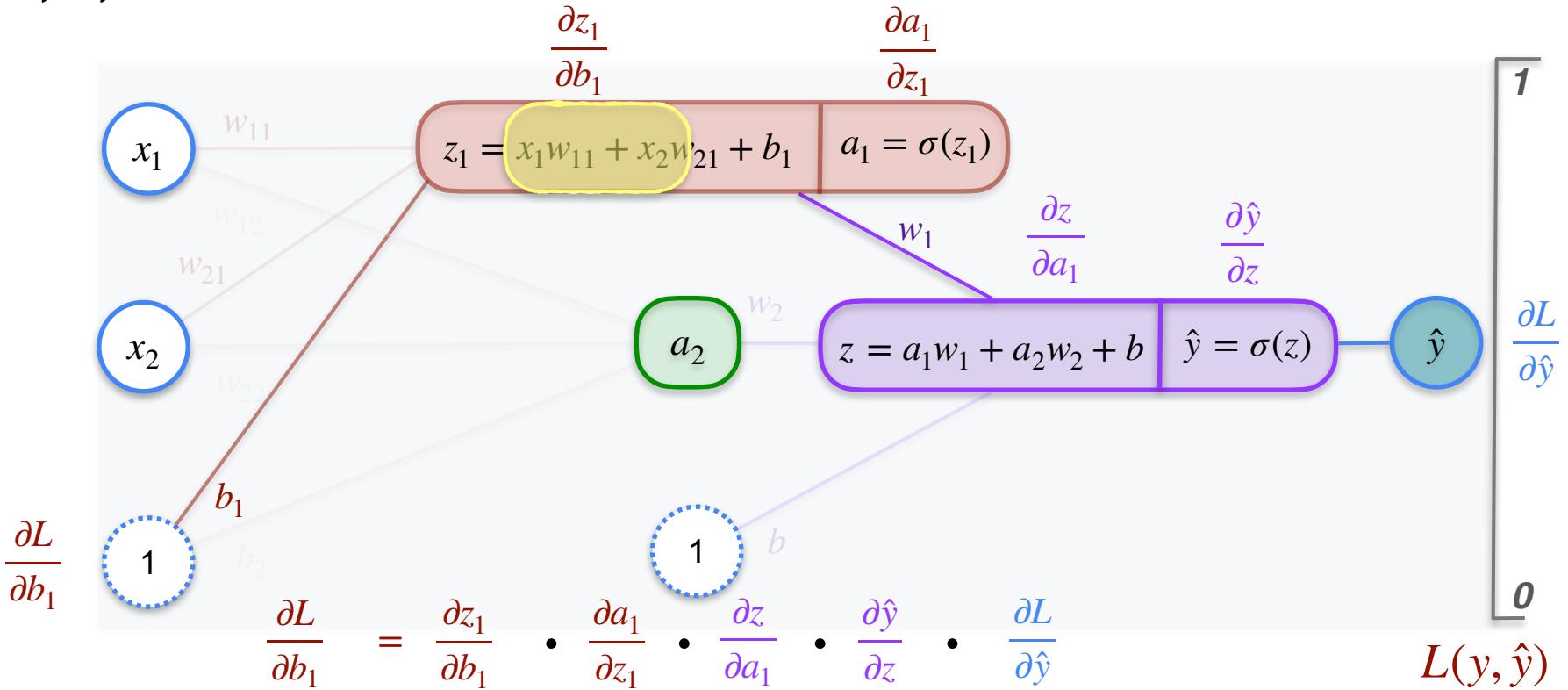
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b_1}$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b_1} =$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \boxed{\frac{\partial z_1}{\partial b_1}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \boxed{\frac{\partial z_1}{\partial b_1}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \boxed{\frac{\partial z_1}{\partial b_1}} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$\frac{\partial L}{\partial b_1} = 1$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1 - a_1(1 - a_1)$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1 - a_1(1 - a_1)$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1 - a_1(1 - a_1)$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1 - a_1(1 - a_1) w_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1 - a_1(1 - a_1) w_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1 - a_1(1 - a_1) w_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1 - a_1(1-a_1) w_1 \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b_1} = 1 - a_1(1-a_1) w_1 \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b_1} = 1 - a_1(1-a_1) w_1 \hat{y}(1-\hat{y})$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial b_1} = 1 - a_1(1-a_1) w_1 \hat{y}(1-\hat{y}) \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial b_1} = 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \hat{y}(1-\hat{y}) \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial b_1} = 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$
$$\frac{\partial L}{\partial b_1} = 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial b_1} &= \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial b_1} &= 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial b_1} &= \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial b_1} &= 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

*to find optimal
value of b_1 that
gives the least error*

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial b_1} &= \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial b_1} &= 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

$$b_1 \rightarrow b_1 - \alpha \frac{\partial L}{\partial b_1}$$

to find optimal value of b_1 that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

$$\begin{aligned}\frac{\partial L}{\partial b_1} &= \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial b_1} &= 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

$$b_1 \rightarrow b_1 - \alpha$$

to find optimal value of b_1 that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$a_1 = \sigma(z_1)$$

$$z_1 = x_1 w_{11} + x_2 w_{21} + b_1$$

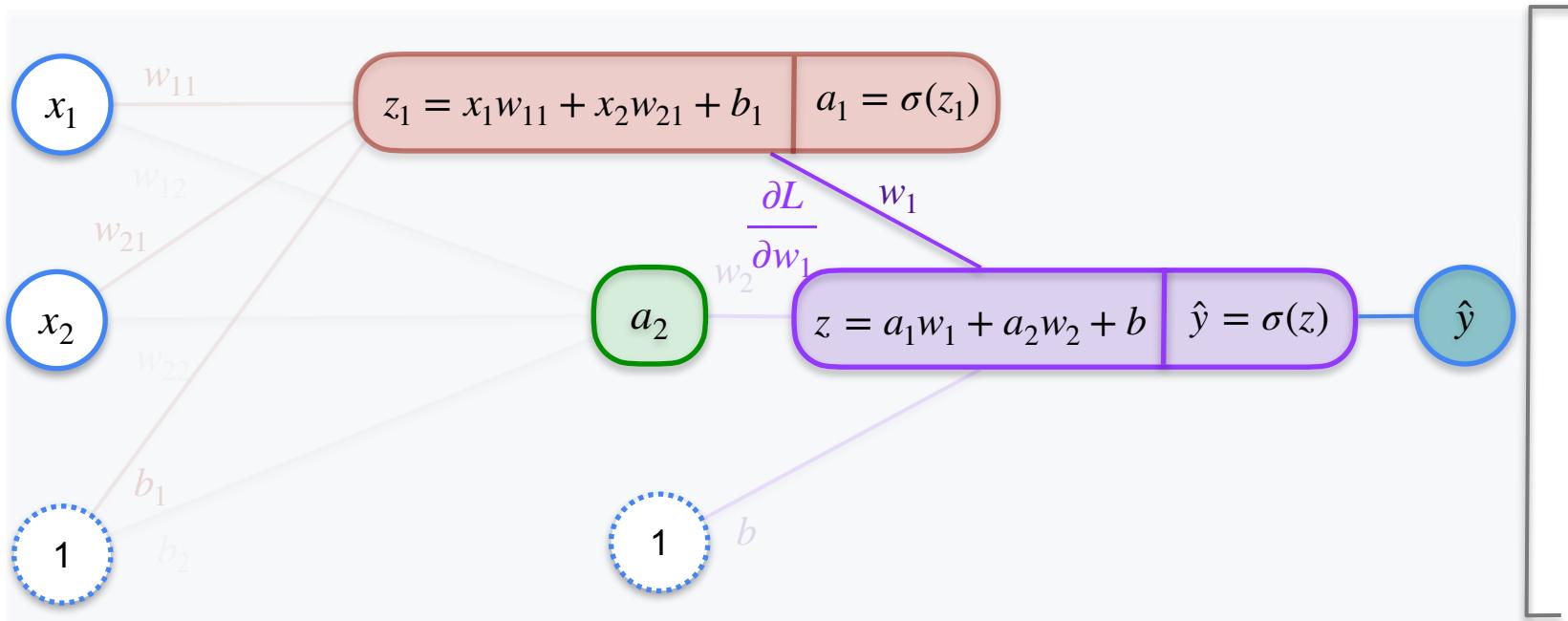
$$\begin{aligned}\frac{\partial L}{\partial b_1} &= \frac{\partial z_1}{\partial b_1} \cdot \frac{\partial a_1}{\partial z_1} \cdot \frac{\partial z}{\partial a_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial b_1} &= 1 \cdot a_1(1-a_1) \cdot w_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -w_1 a_1 (1-a_1) (y - \hat{y})\end{aligned}$$

Perform gradient descent with

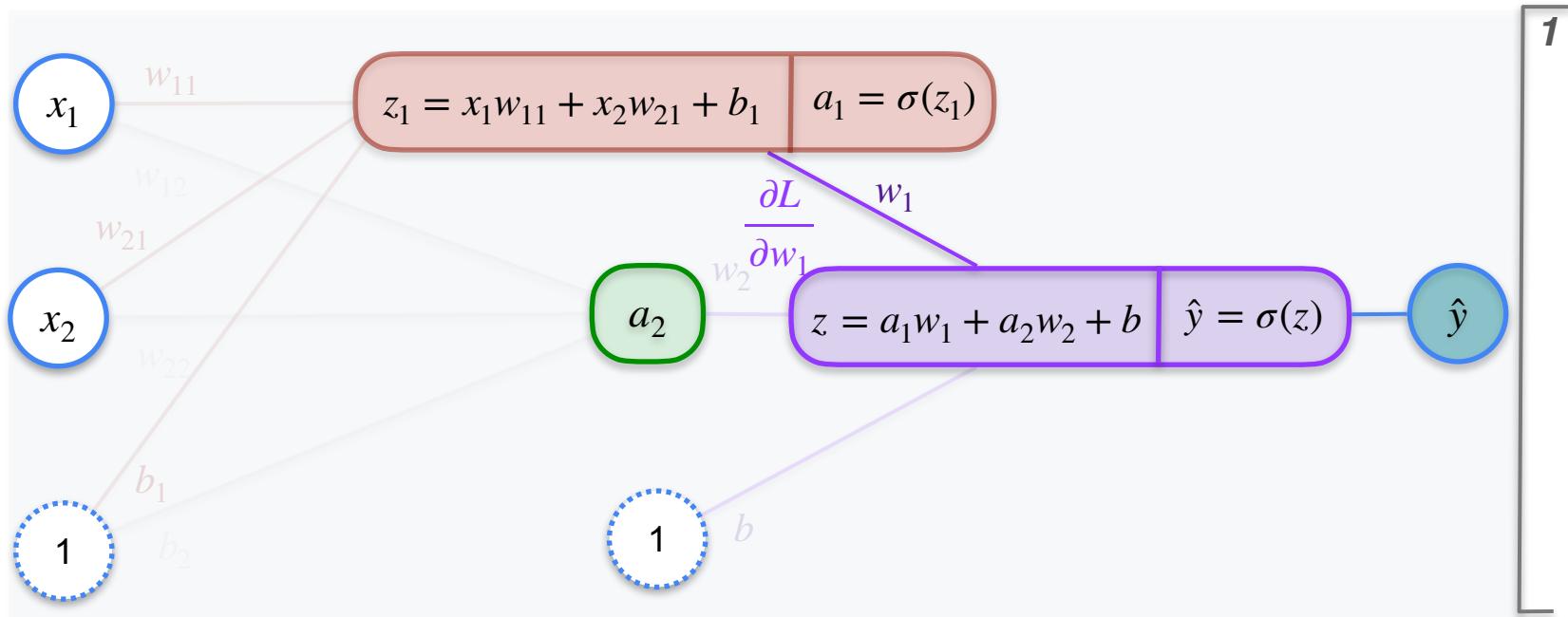
$$b_1 \rightarrow b_1 - \alpha (-w_1 a_1 (1-a_1) (y - \hat{y}))$$

to find optimal value of b_1 that gives the least error

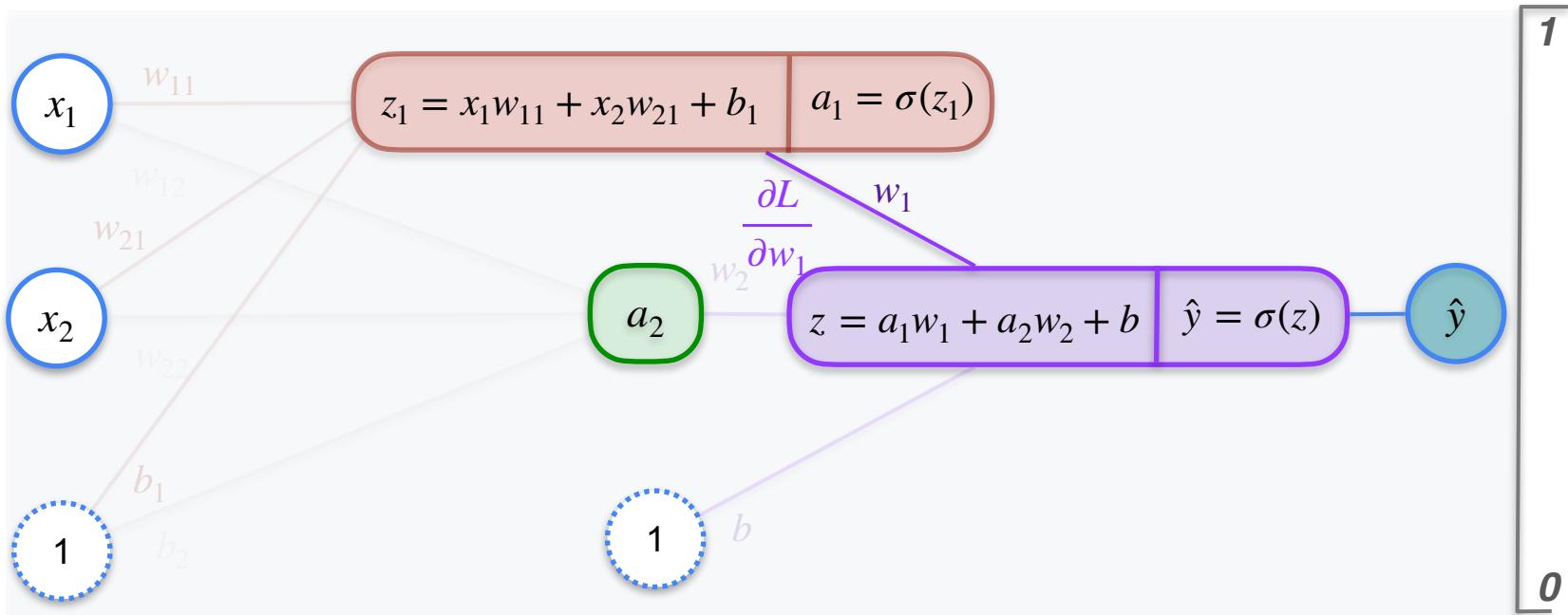
2,2,1 Neural Network



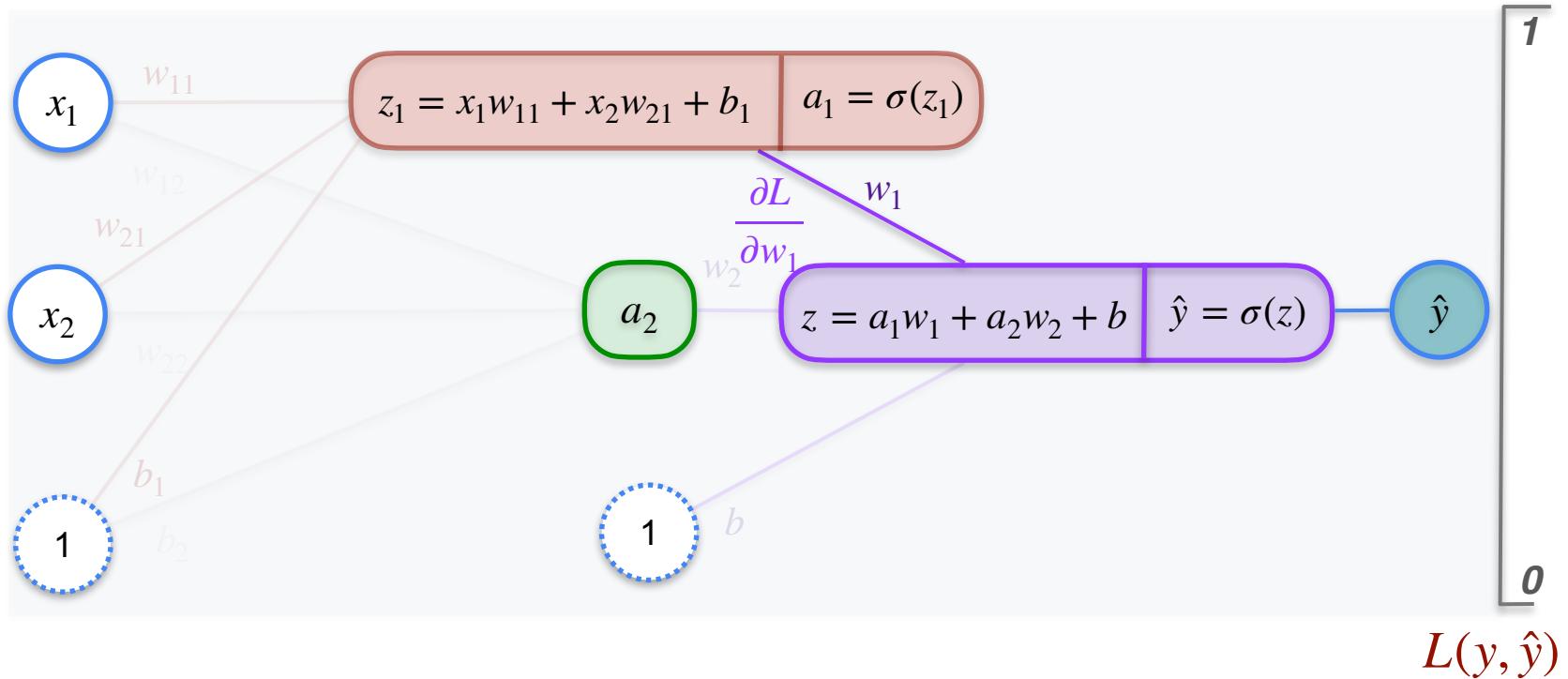
2,2,1 Neural Network



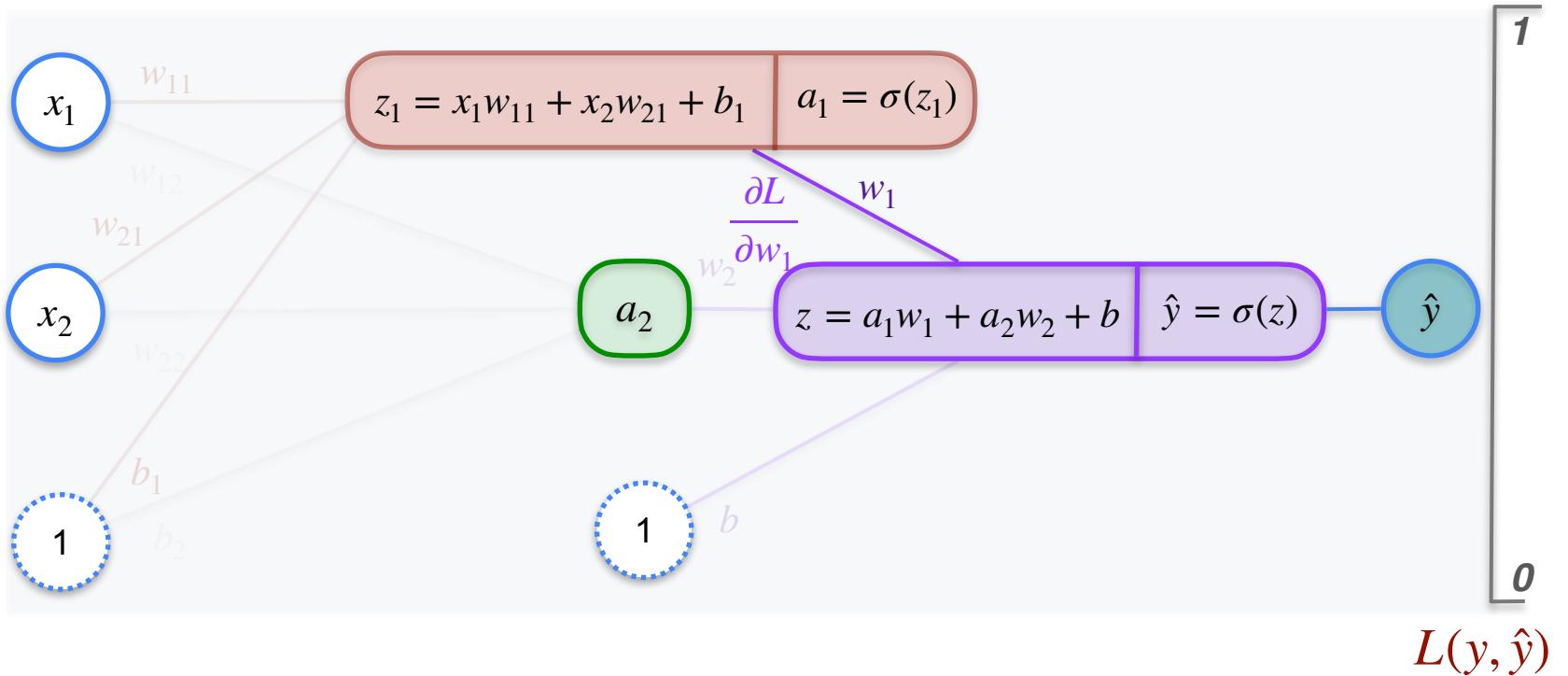
2,2,1 Neural Network



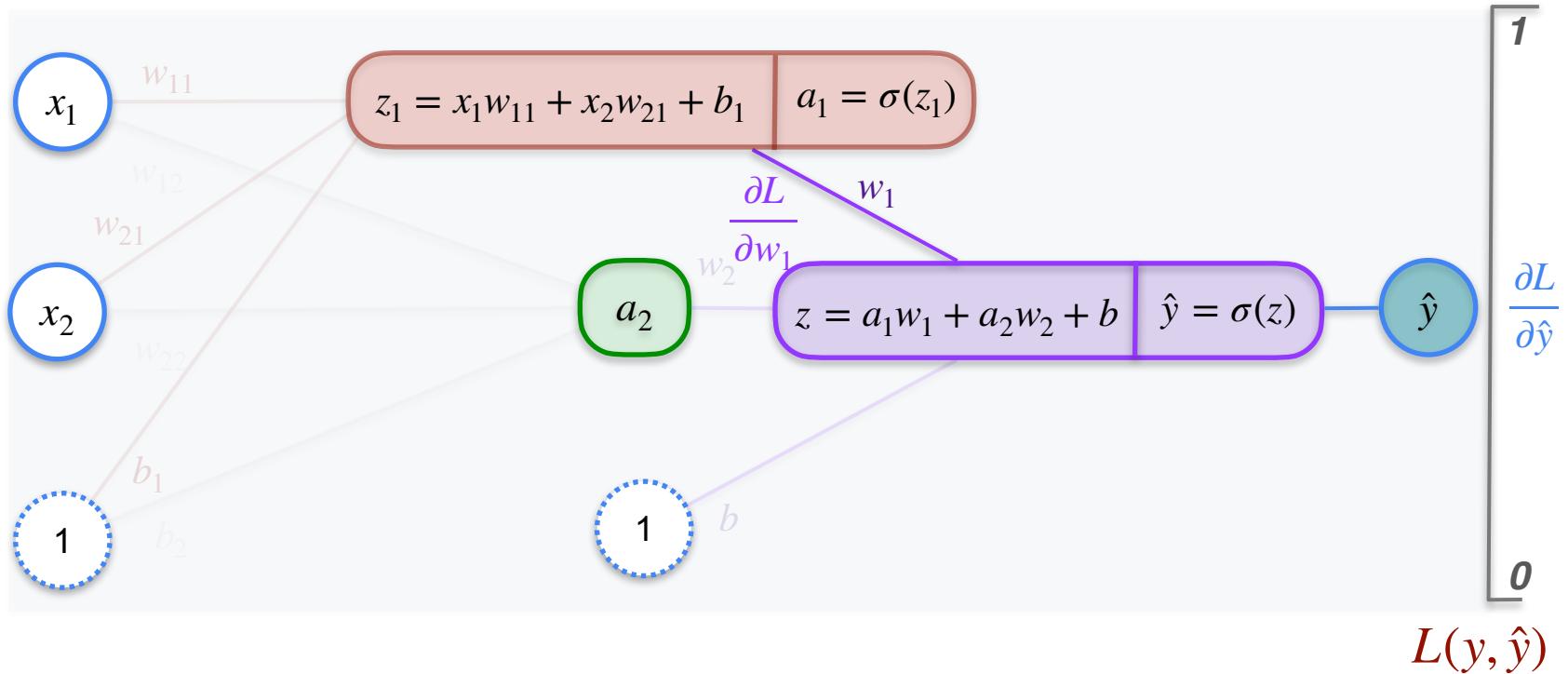
2,2,1 Neural Network



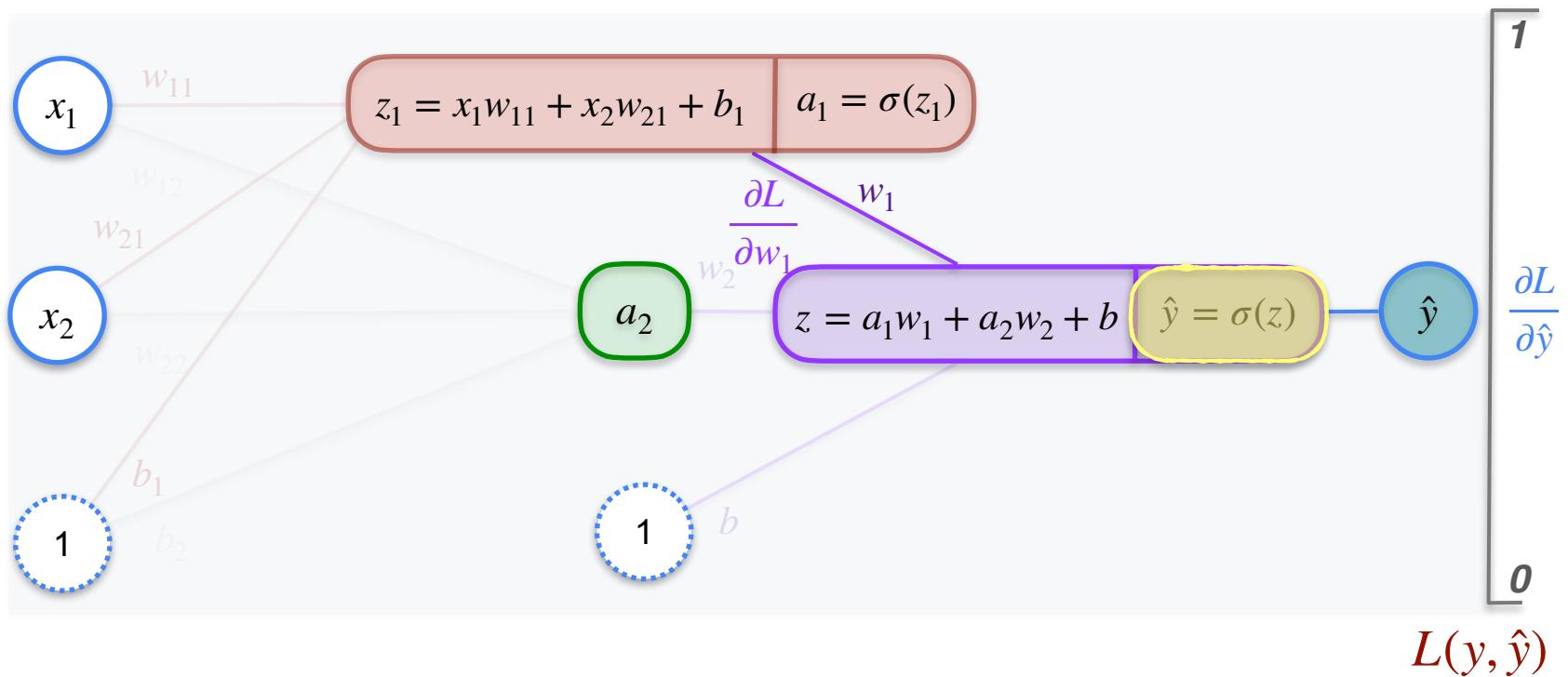
2,2,1 Neural Network



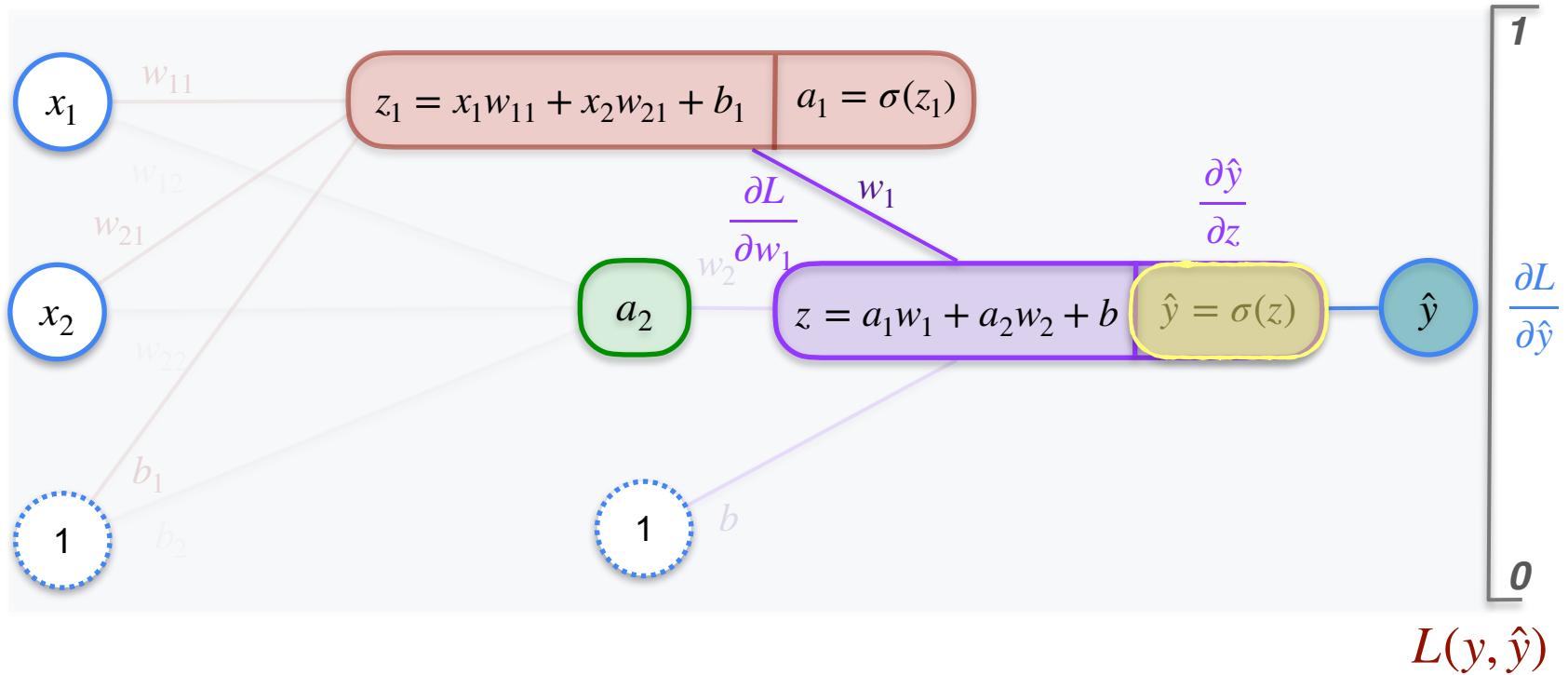
2,2,1 Neural Network



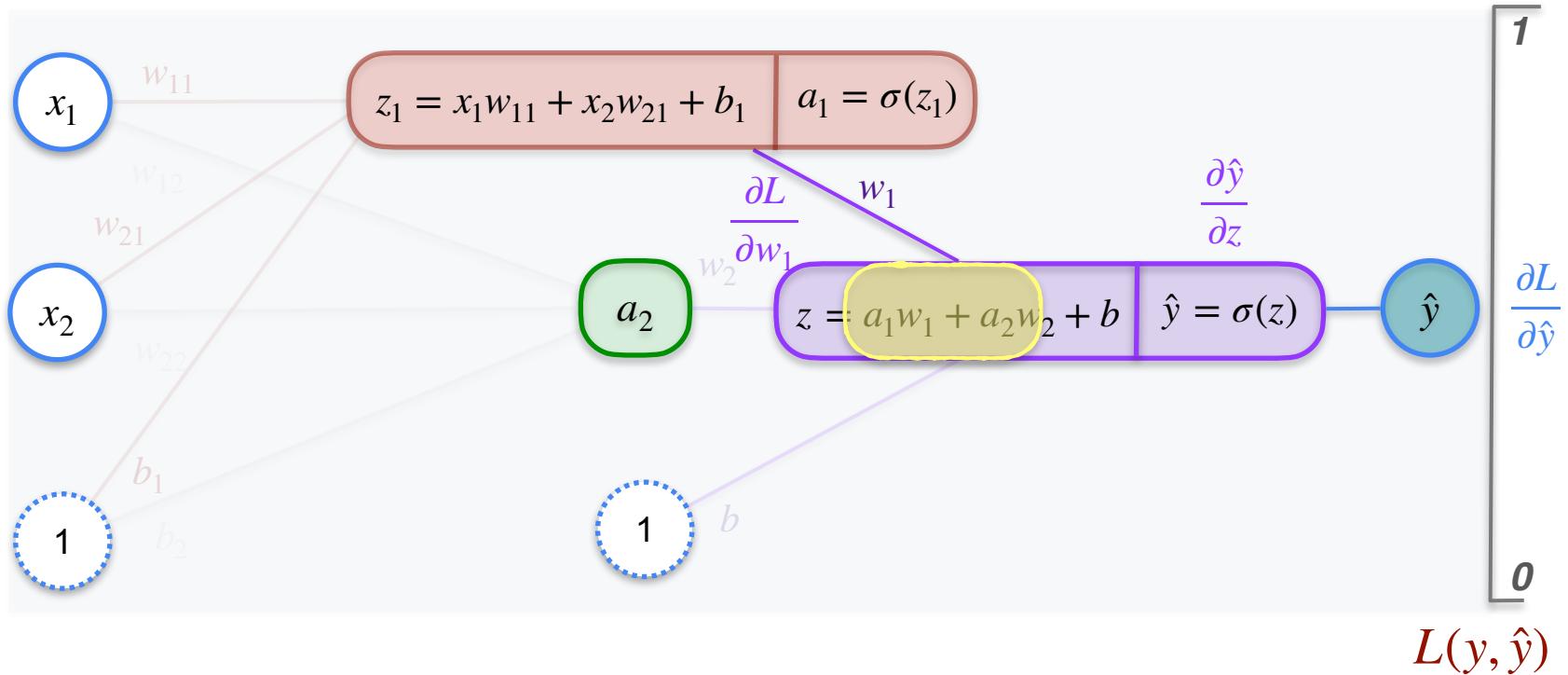
2,2,1 Neural Network



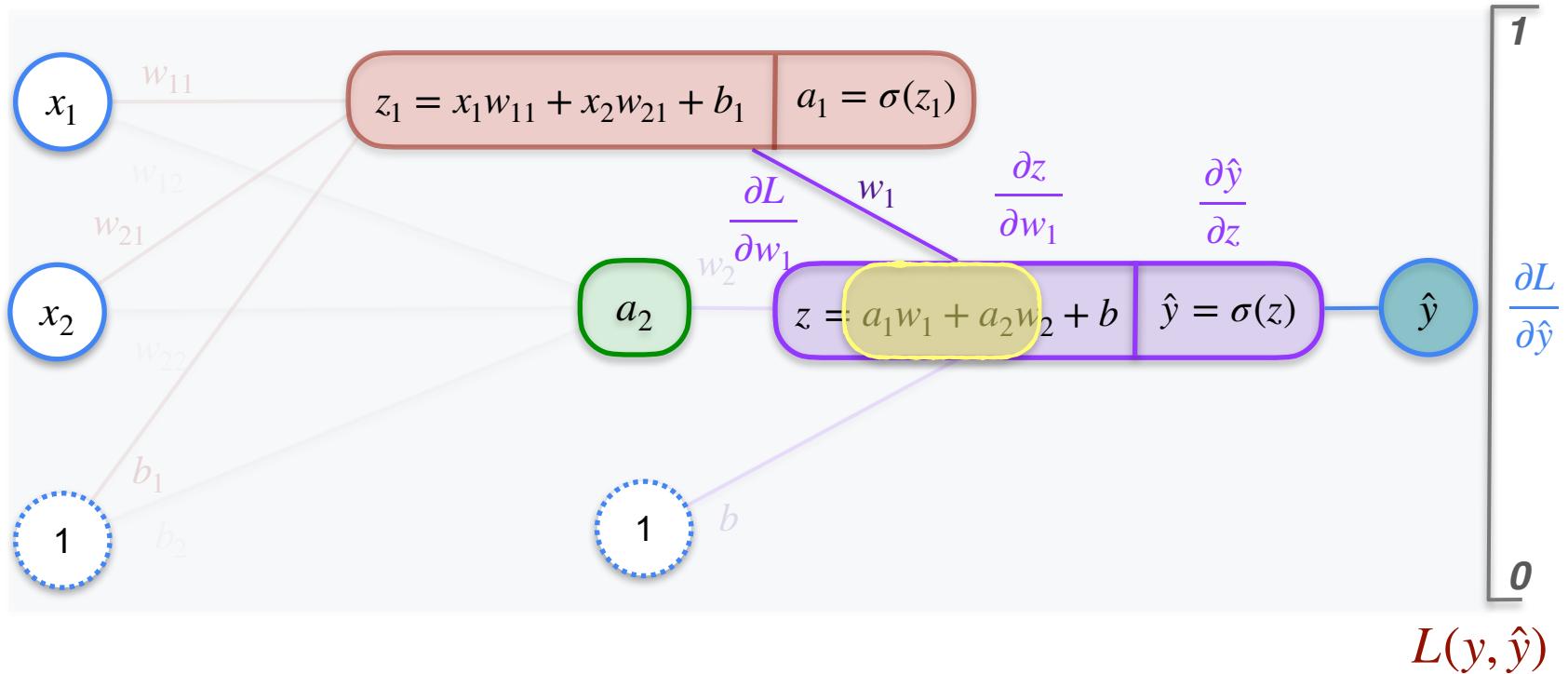
2,2,1 Neural Network



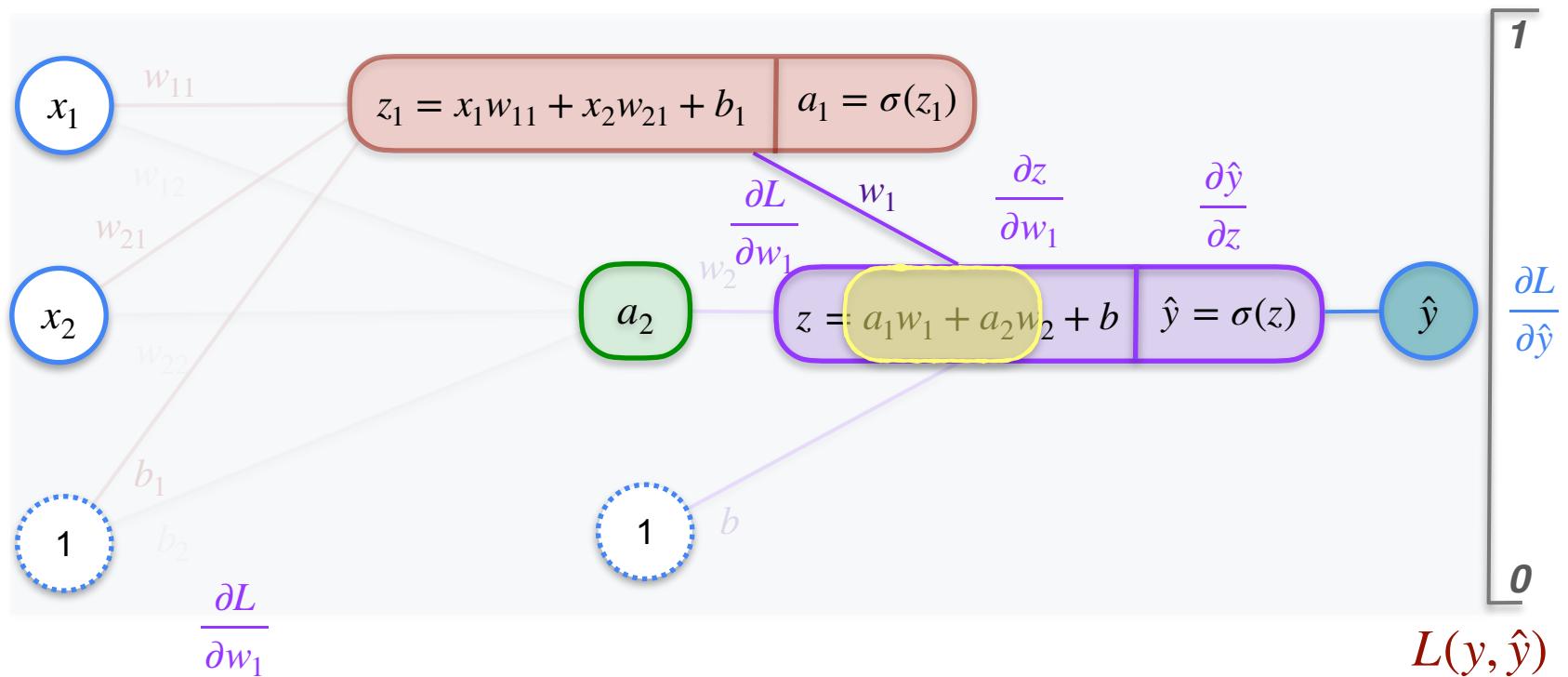
2,2,1 Neural Network



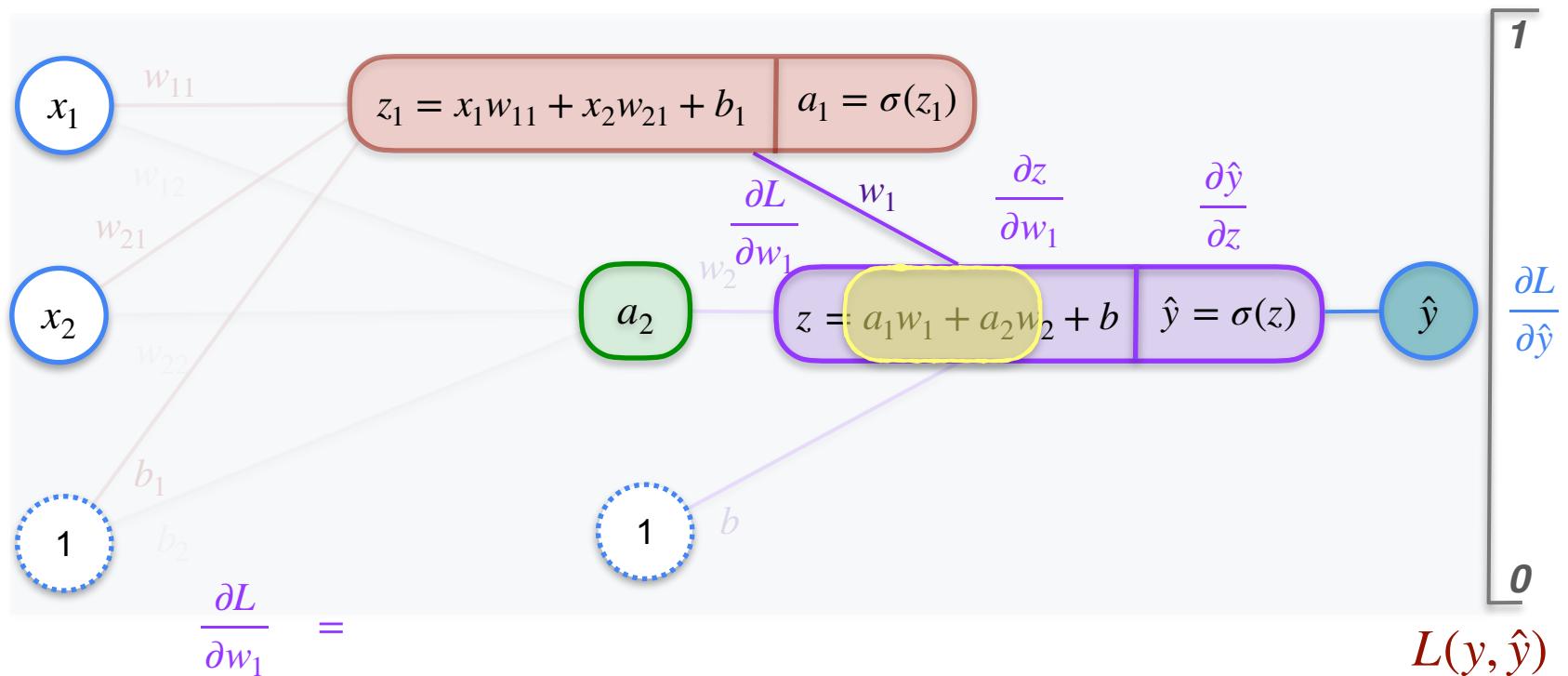
2,2,1 Neural Network



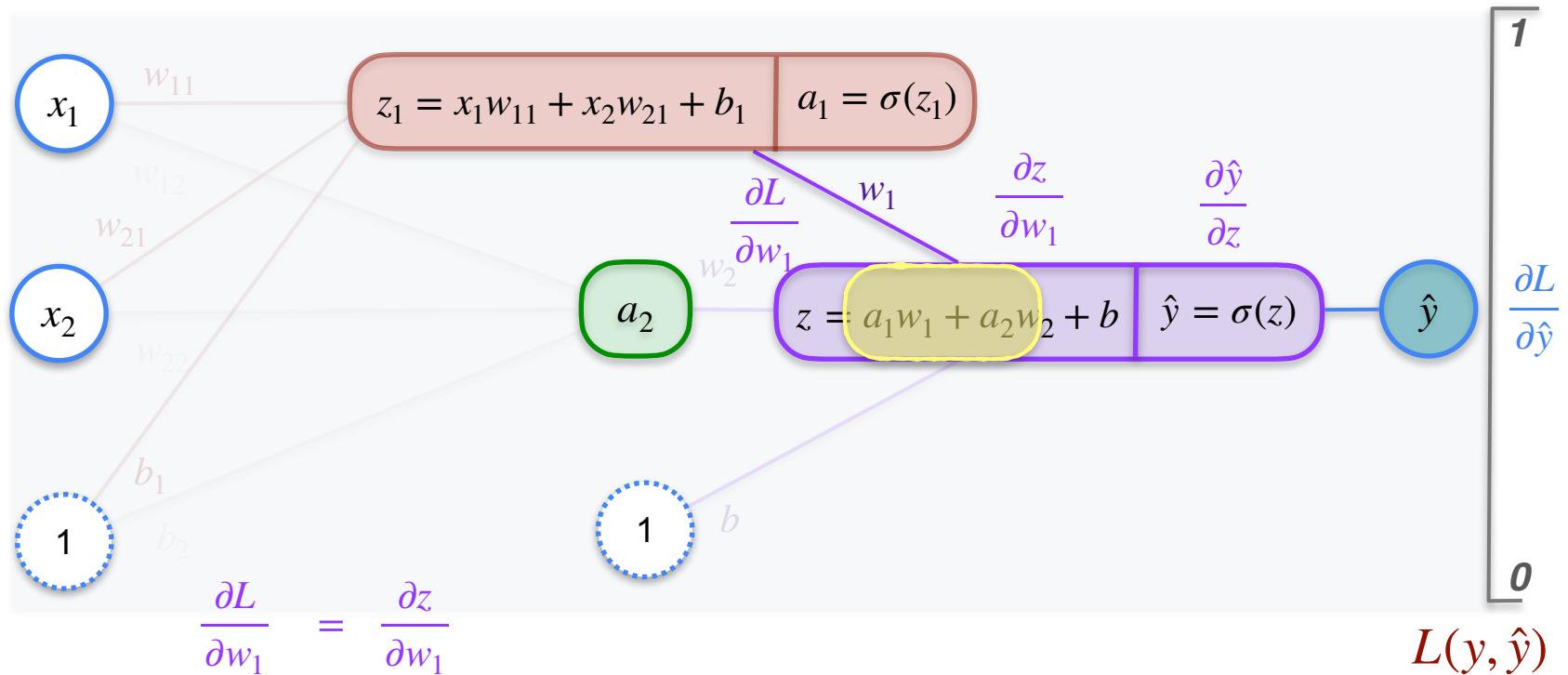
2,2,1 Neural Network



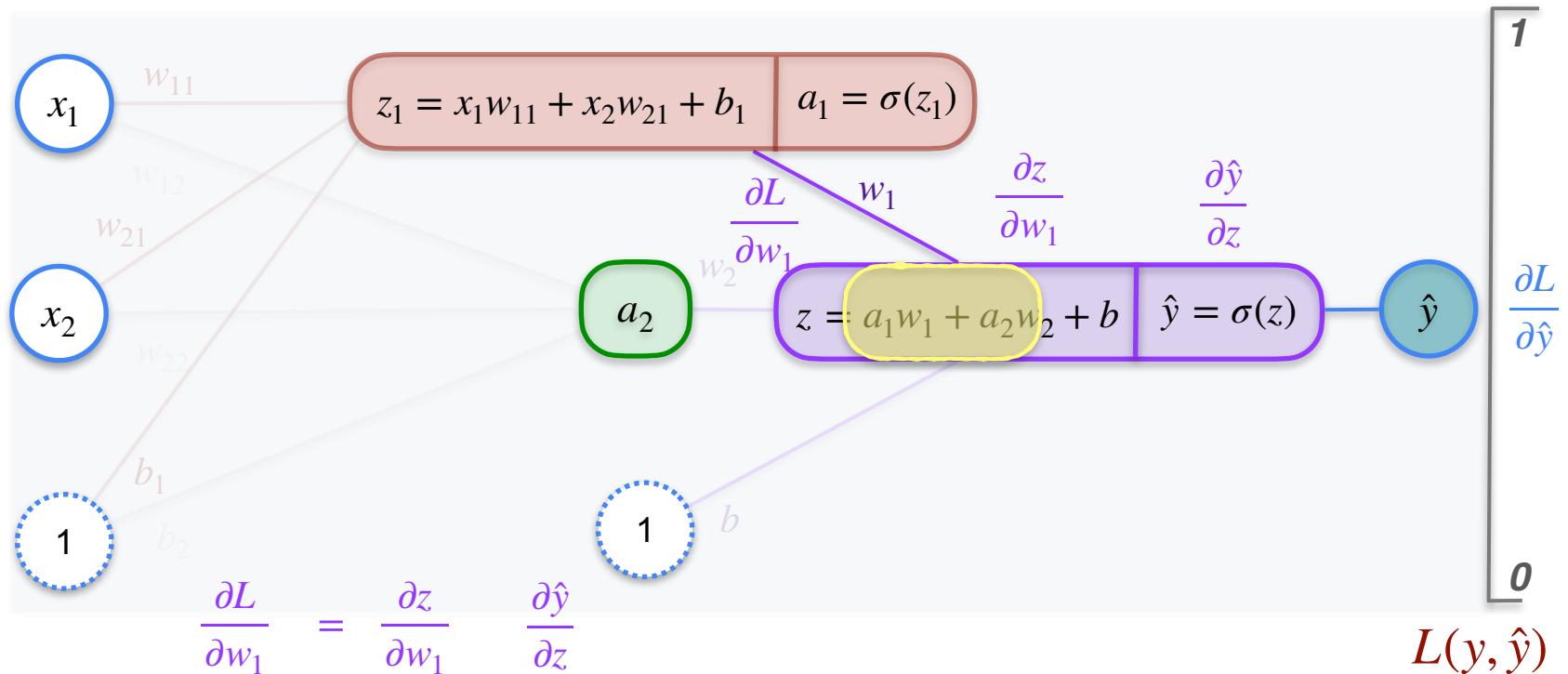
2,2,1 Neural Network



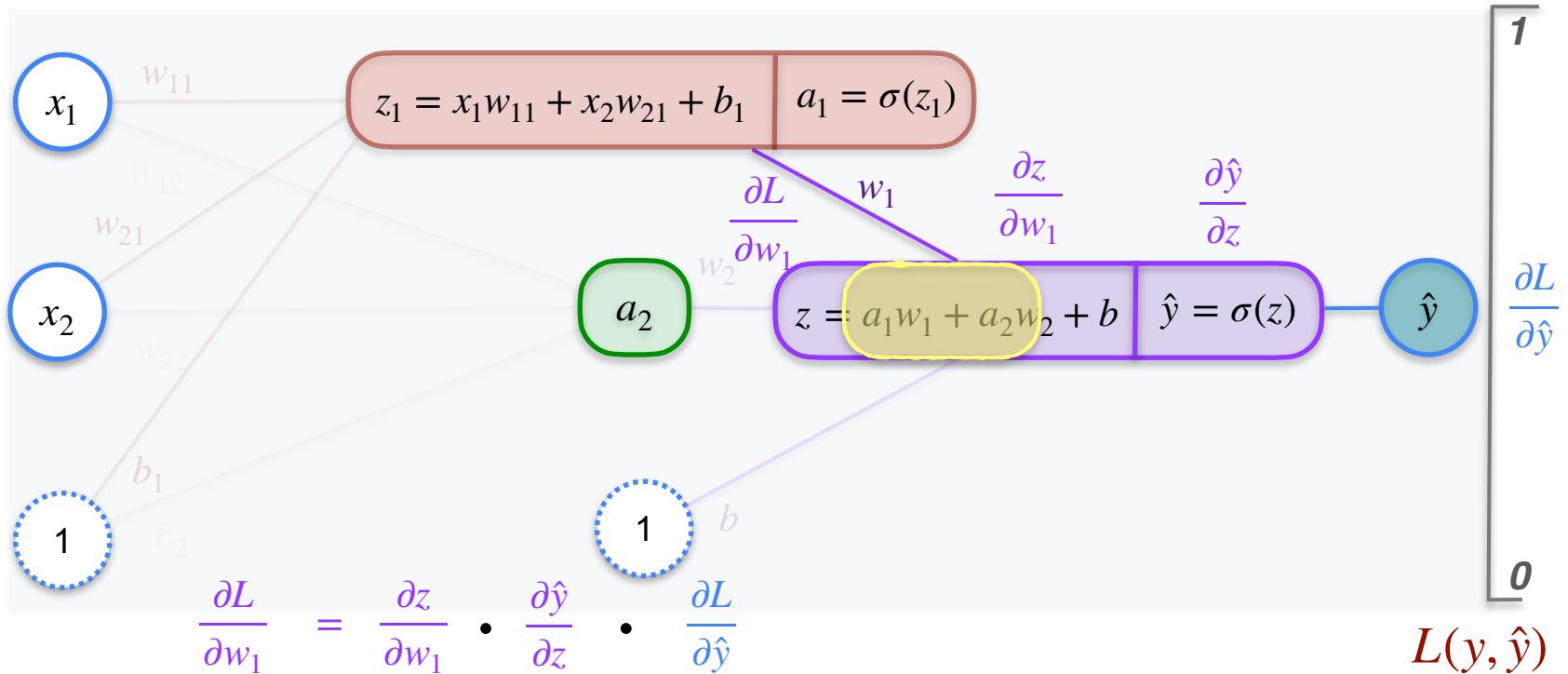
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1w_1 + a_2w_2 + b$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_1} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = \boxed{\frac{\partial z}{\partial w_1}} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_1} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_1} = a_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_1} = a_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_1} = a_1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_1} = a_1 \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial w_1} = a_1 \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = a_1 \hat{y}(1-\hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = a_1 \hat{y}(1-\hat{y}) \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = a_1 \cdot \hat{y}(1-\hat{y}) \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = a_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = a_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial w_1} = a_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

$$= -a_1(y - \hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\begin{aligned}\frac{\partial L}{\partial w_1} &= \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_1} &= a_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -a_1(y - \hat{y})\end{aligned}$$

to find optimal value of w_1 that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\begin{aligned}\frac{\partial L}{\partial w_1} &= \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_1} &= a_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -a_1(y - \hat{y})\end{aligned}$$

Perform gradient descent with

*to find optimal
value of w_1 that
gives the least error*

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\begin{aligned}\frac{\partial L}{\partial w_1} &= \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_1} &= a_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -a_1(y - \hat{y})\end{aligned}$$

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

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\begin{aligned}\frac{\partial L}{\partial w_1} &= \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_1} &= a_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -a_1(y - \hat{y})\end{aligned}$$

Perform gradient descent with

$$w_1 \rightarrow w_1 - \alpha$$

to find optimal value of w_1 that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

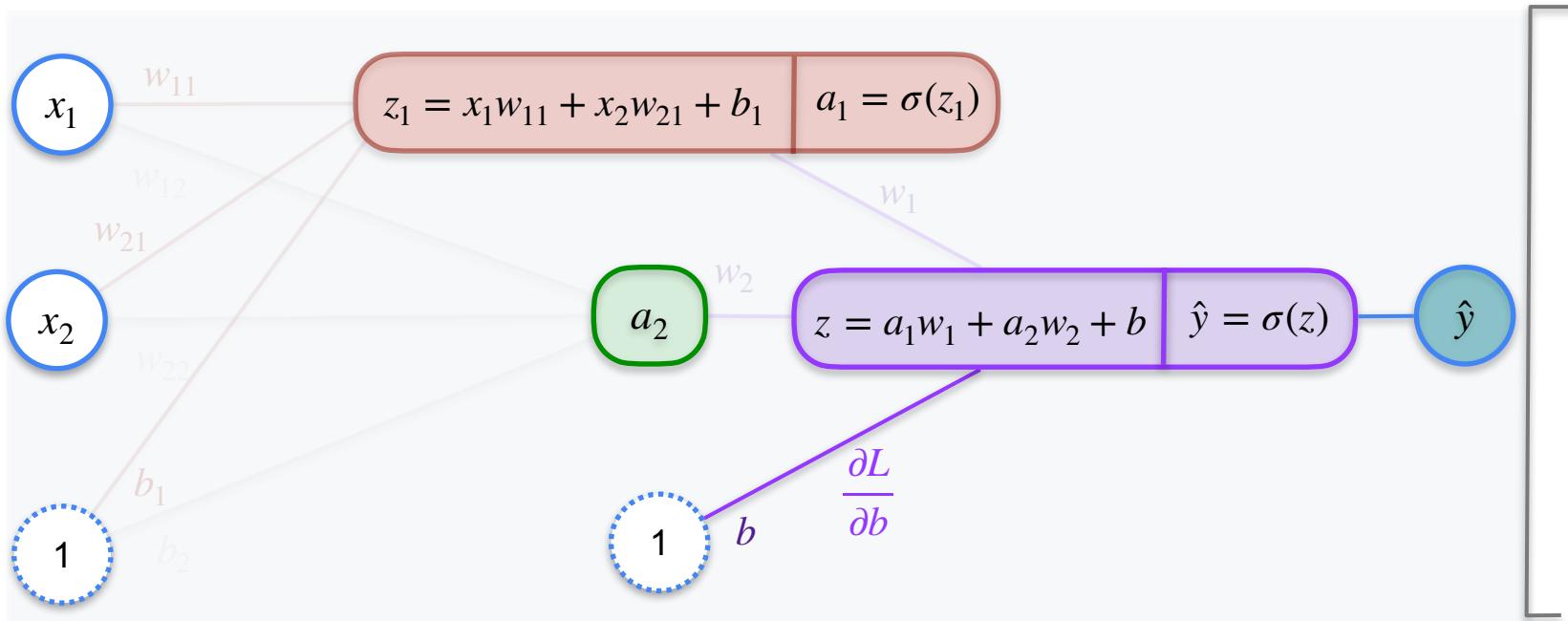
$$\begin{aligned}\frac{\partial L}{\partial w_1} &= \frac{\partial z}{\partial w_1} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}} \\ \frac{\partial L}{\partial w_1} &= a_1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}} \\ &= -a_1(y - \hat{y})\end{aligned}$$

Perform gradient descent with

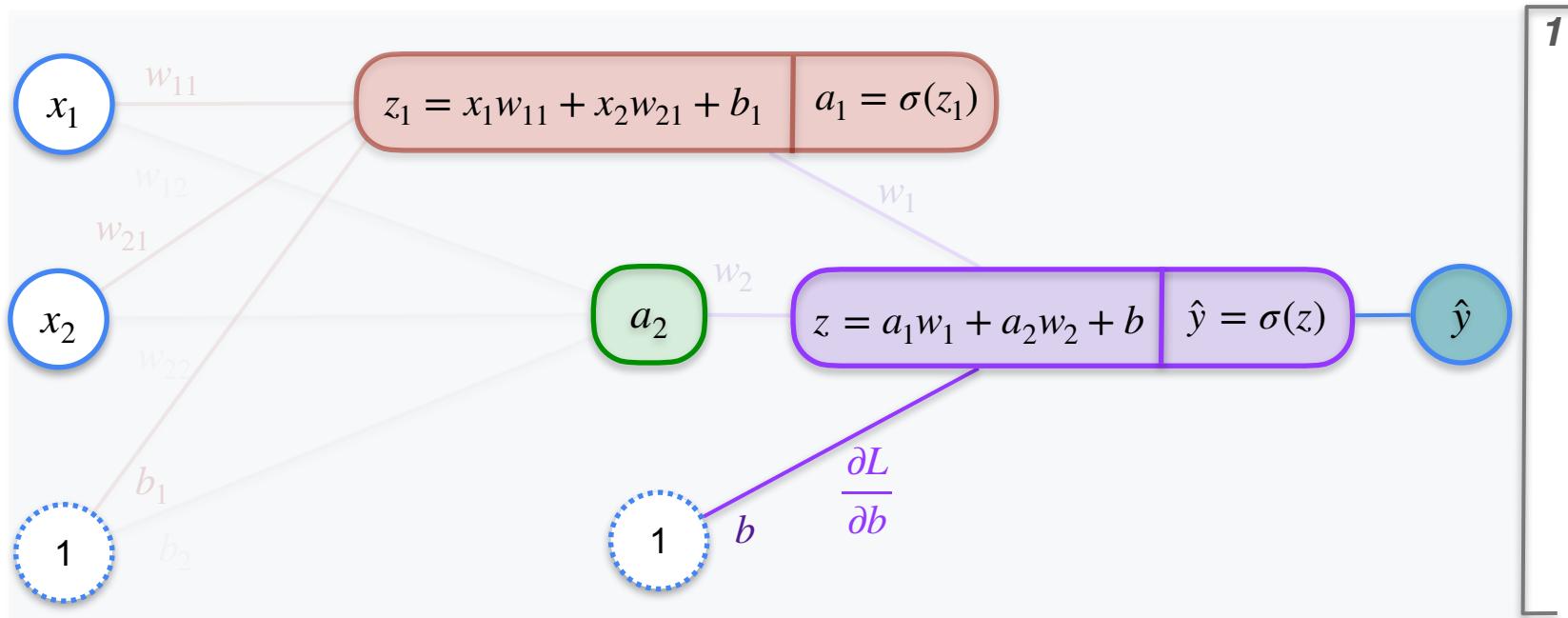
$$w_1 \rightarrow w_1 - \alpha(-a_1(y - \hat{y}))$$

to find optimal value of w_1 that gives the least error

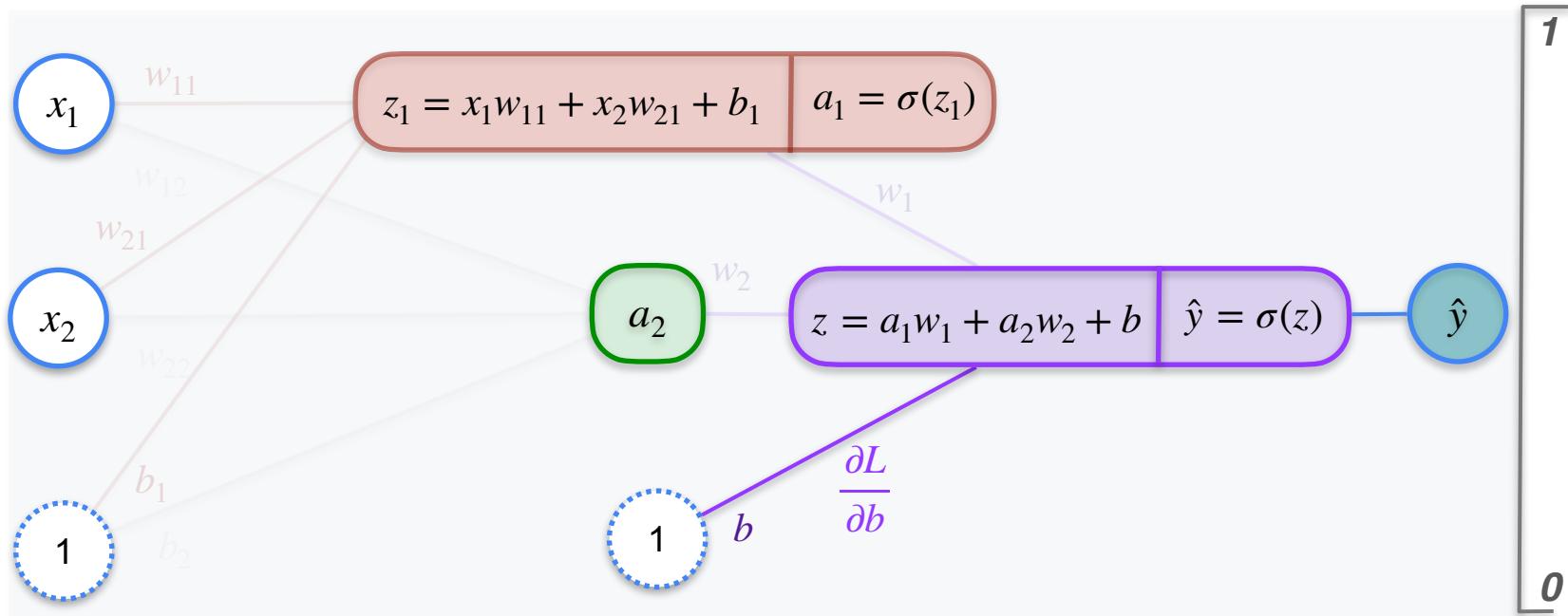
2,2,1 Neural Network



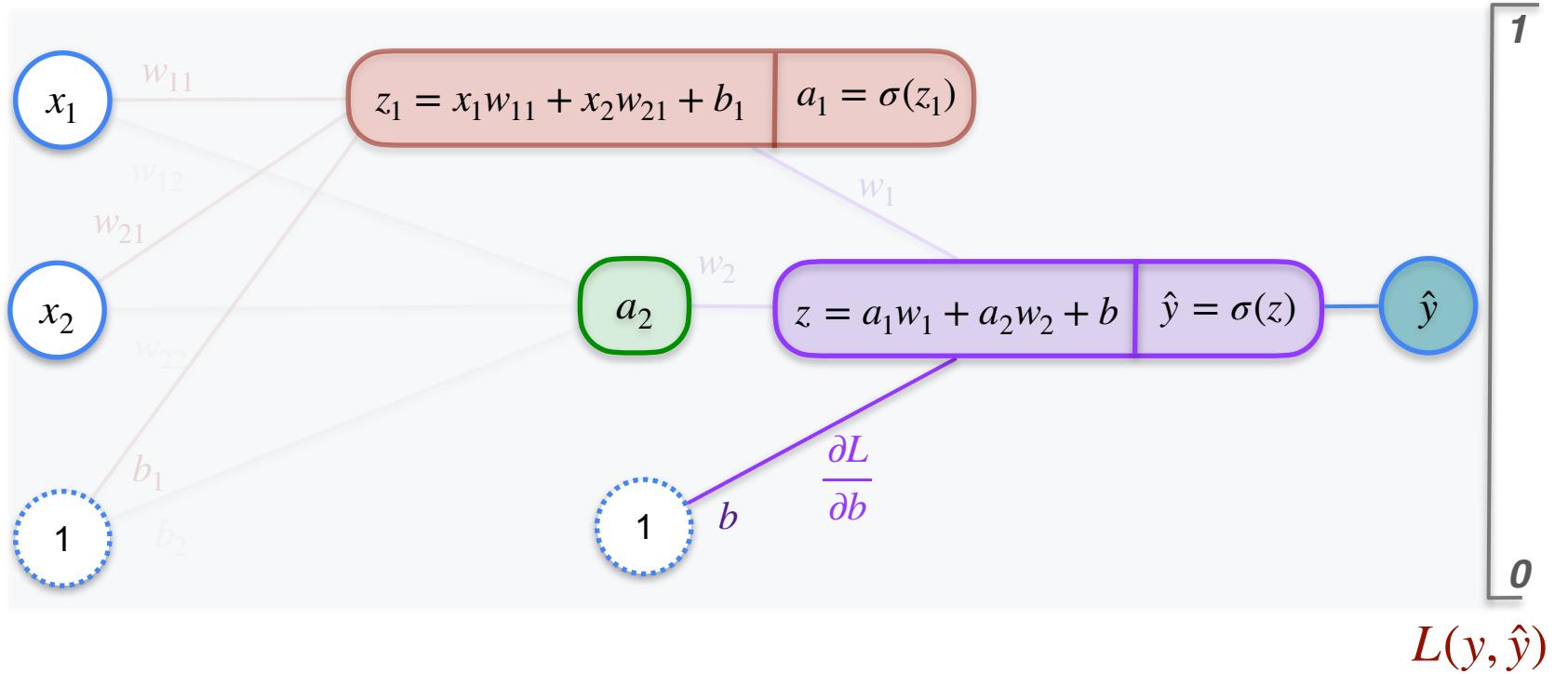
2,2,1 Neural Network



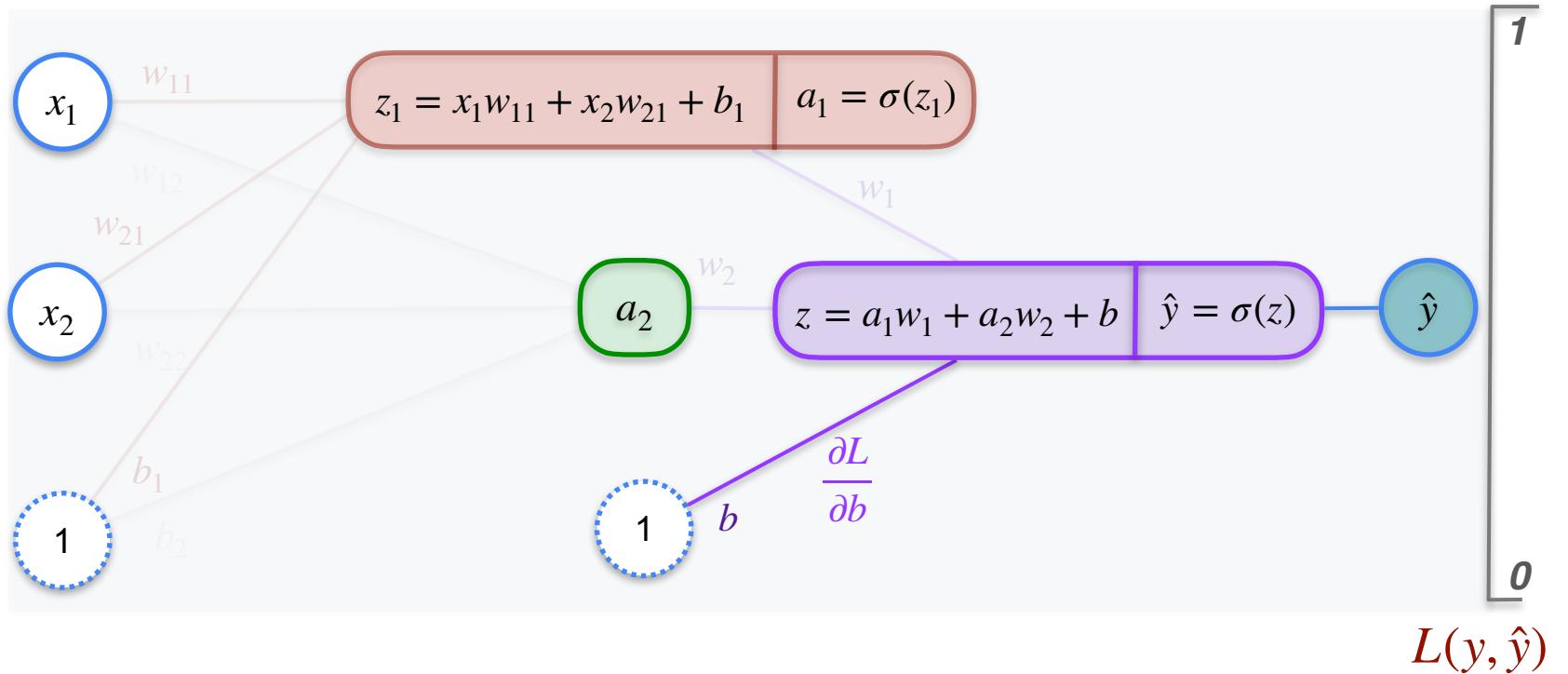
2,2,1 Neural Network



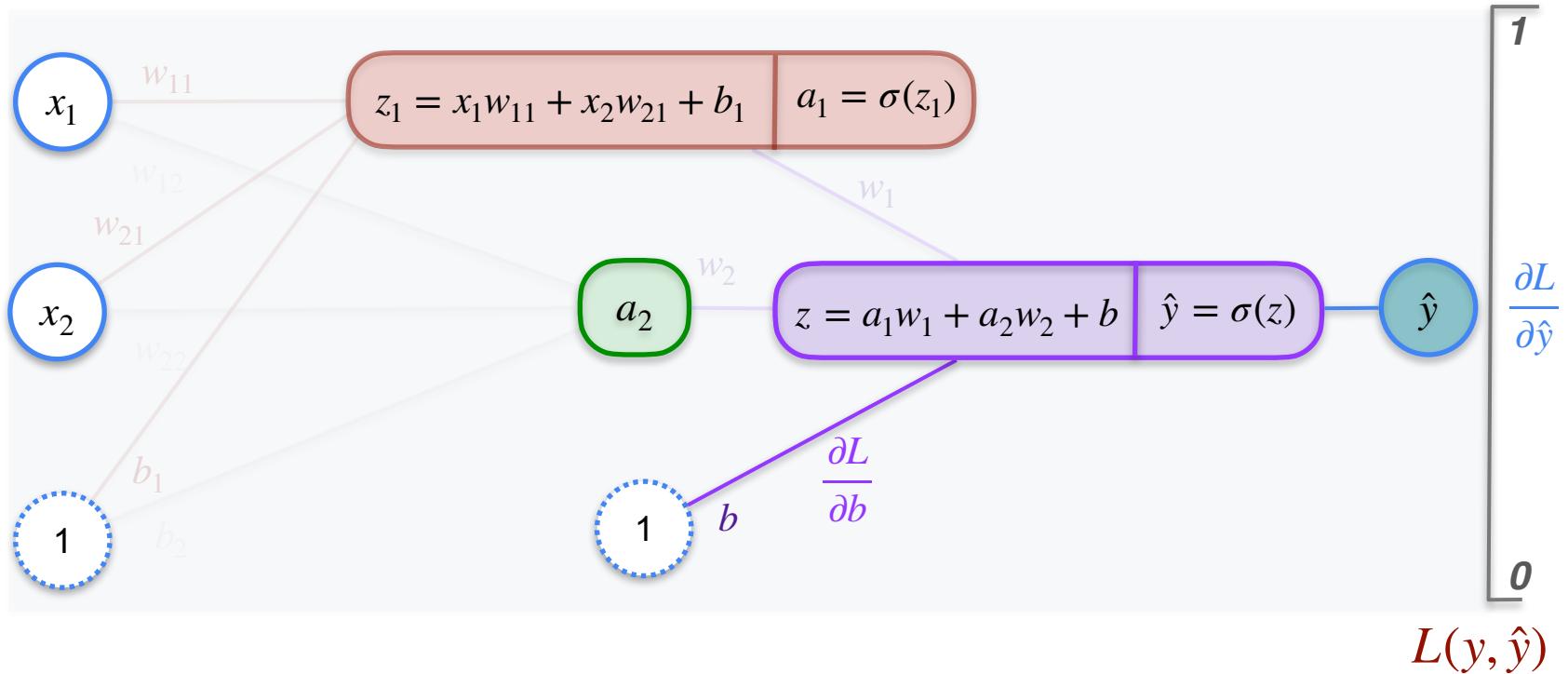
2,2,1 Neural Network



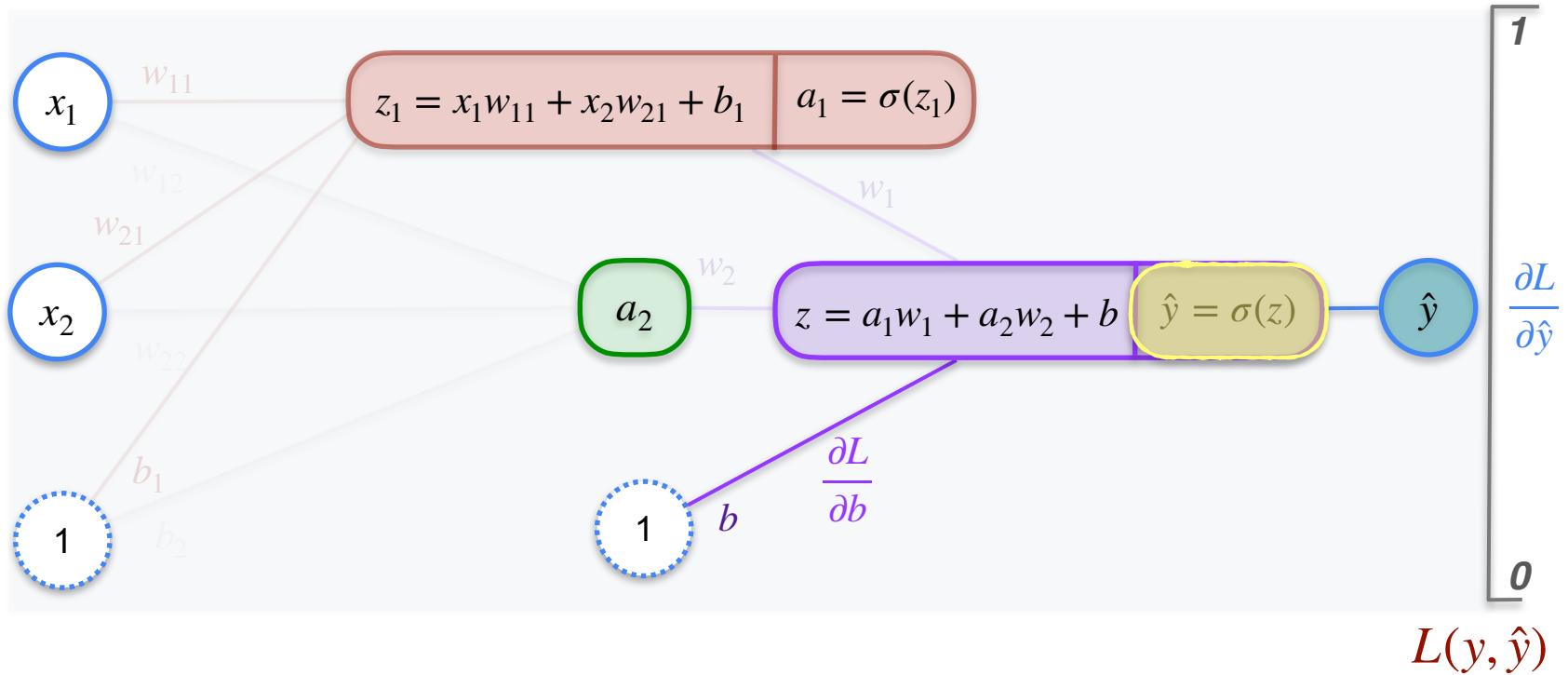
2,2,1 Neural Network



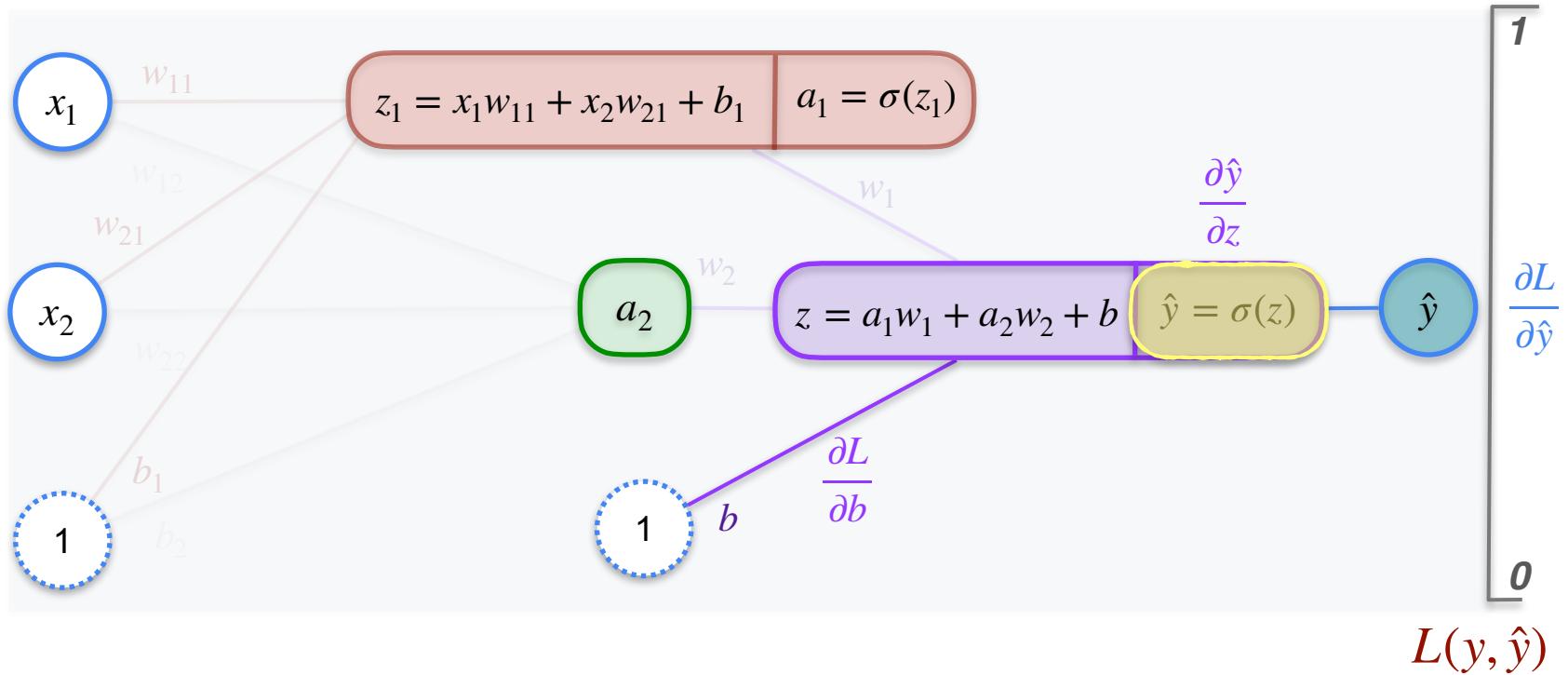
2,2,1 Neural Network



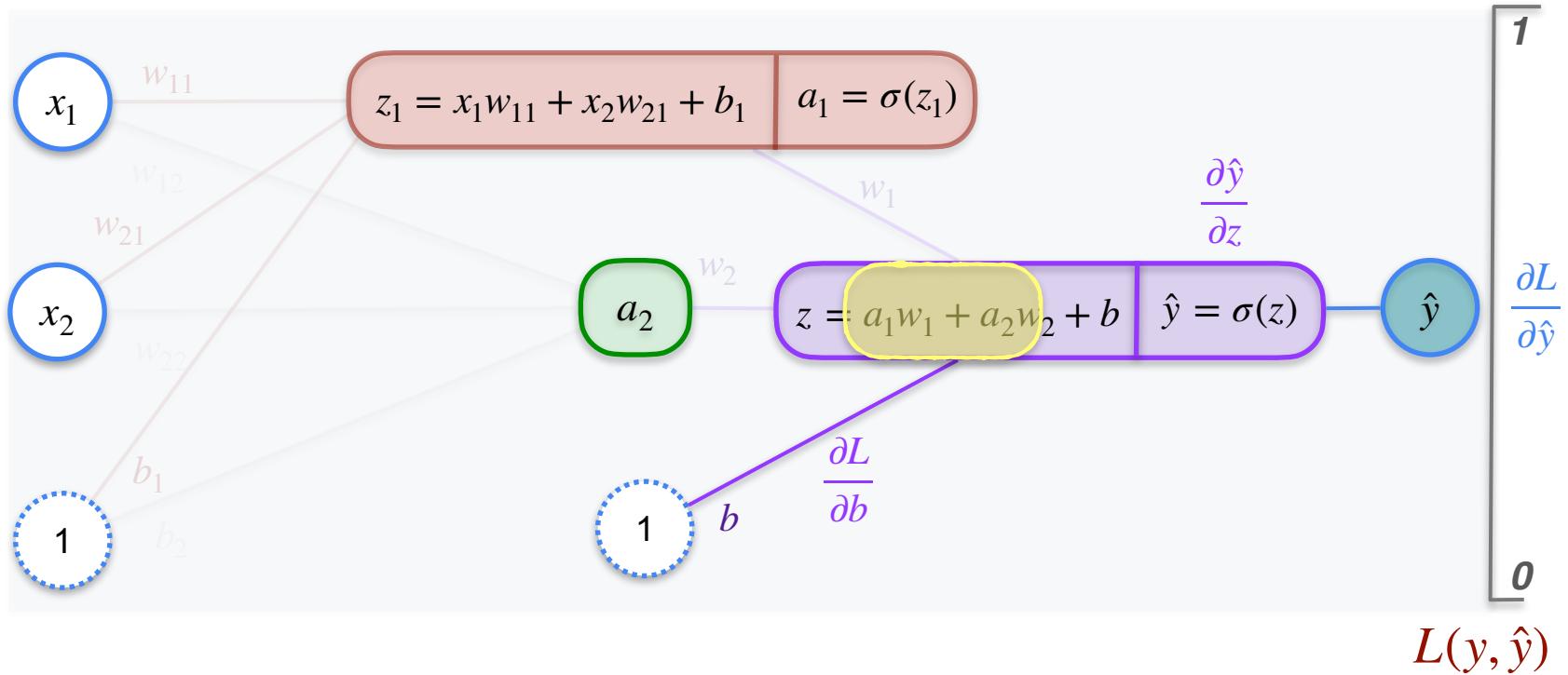
2,2,1 Neural Network



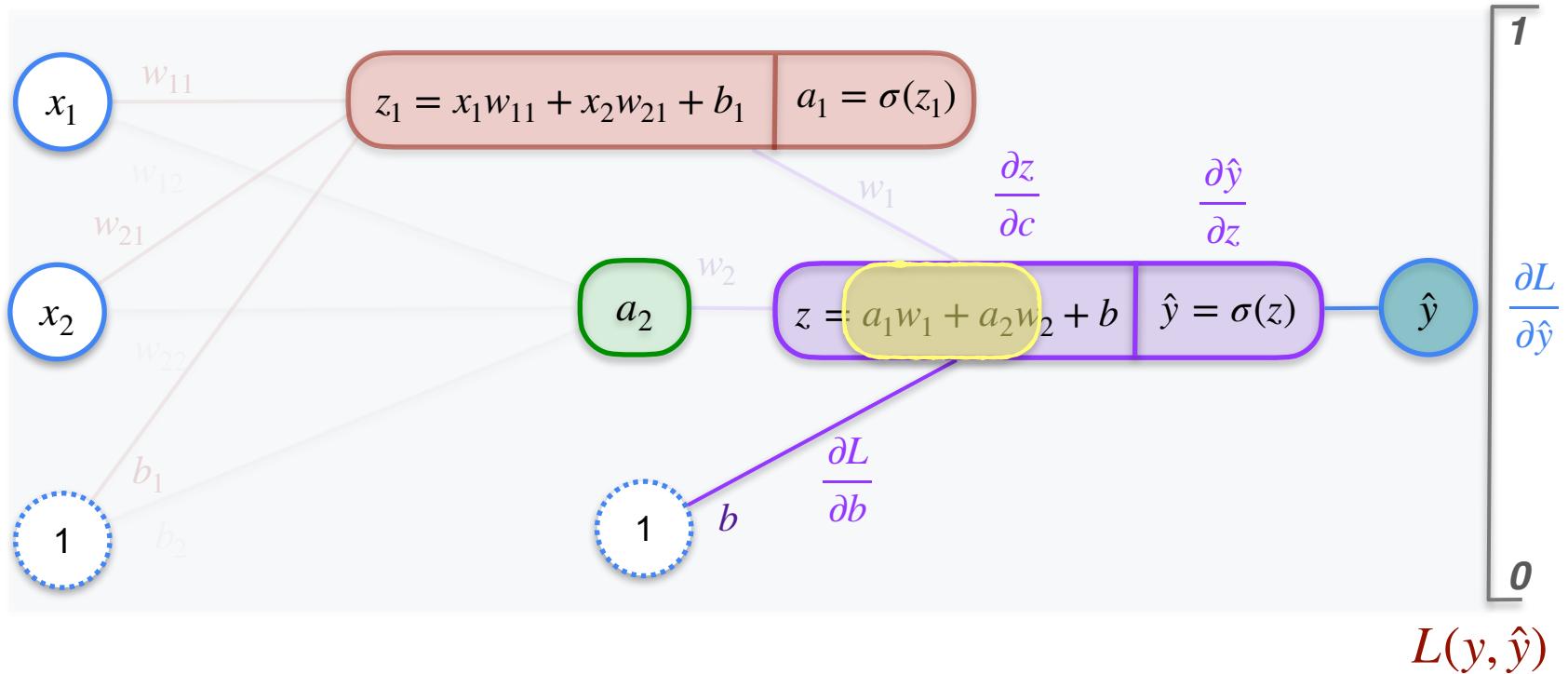
2,2,1 Neural Network



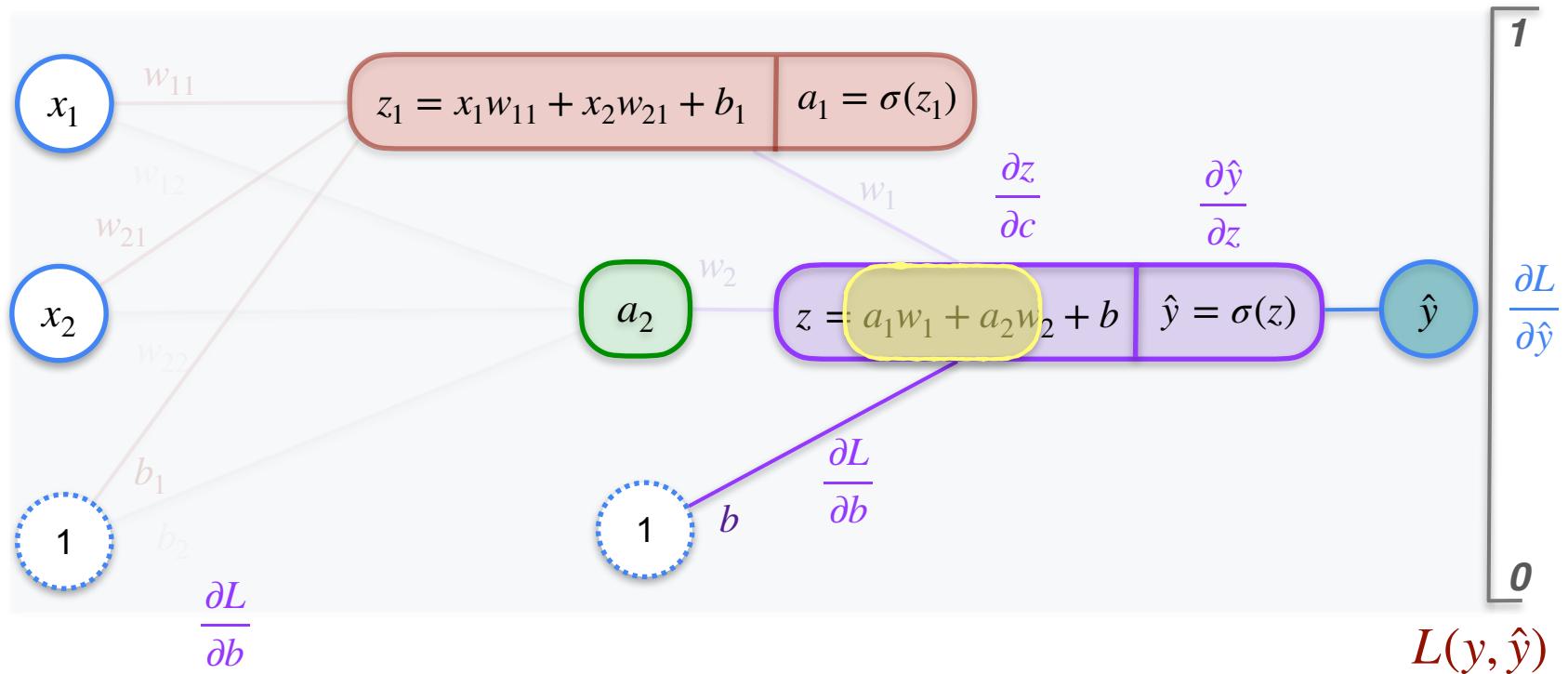
2,2,1 Neural Network



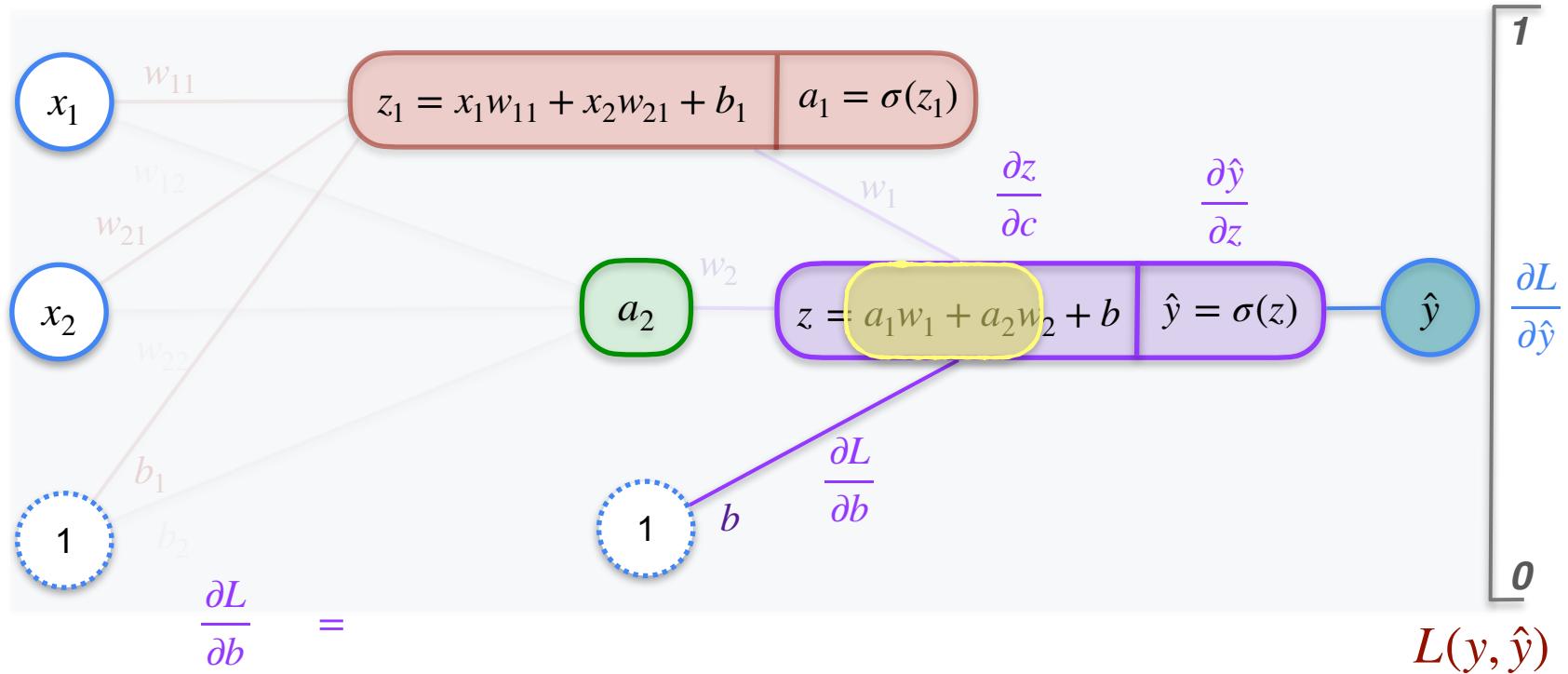
2,2,1 Neural Network



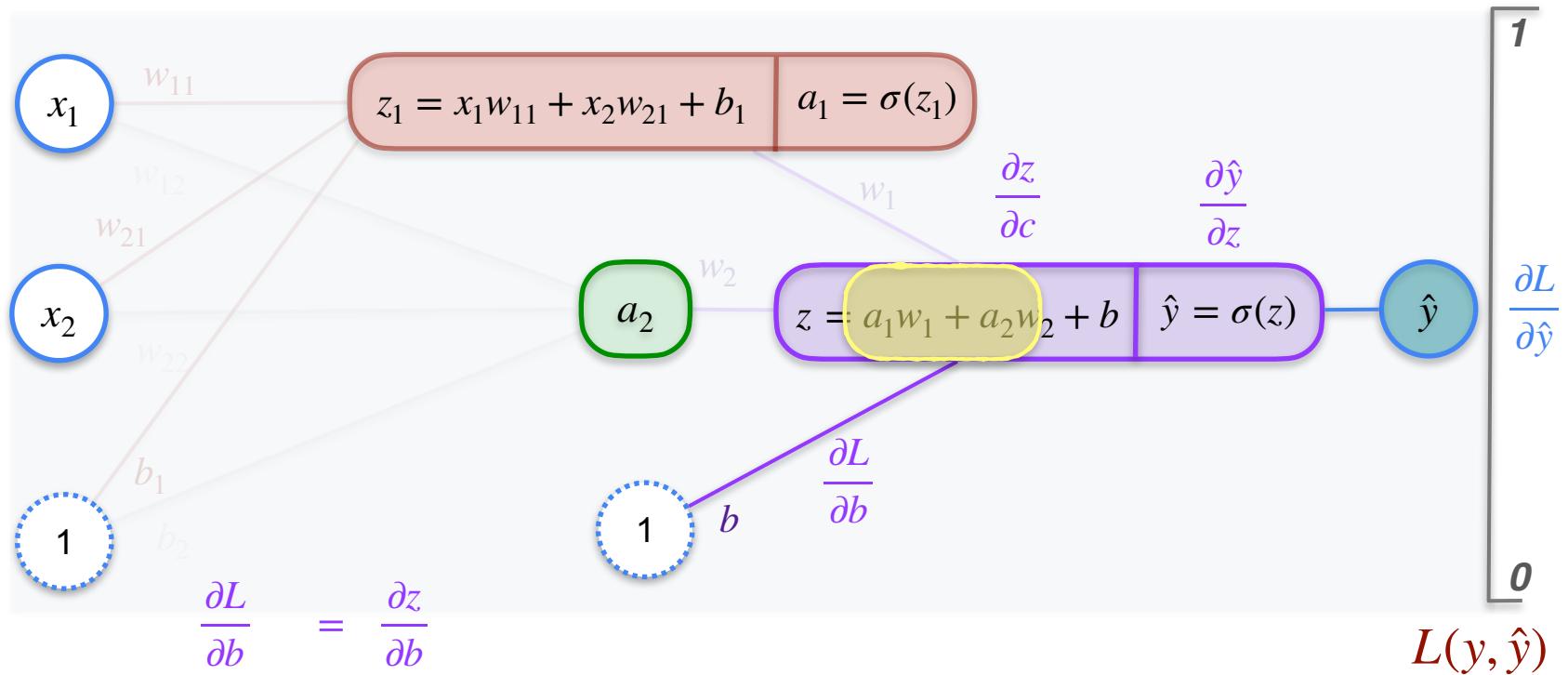
2,2,1 Neural Network



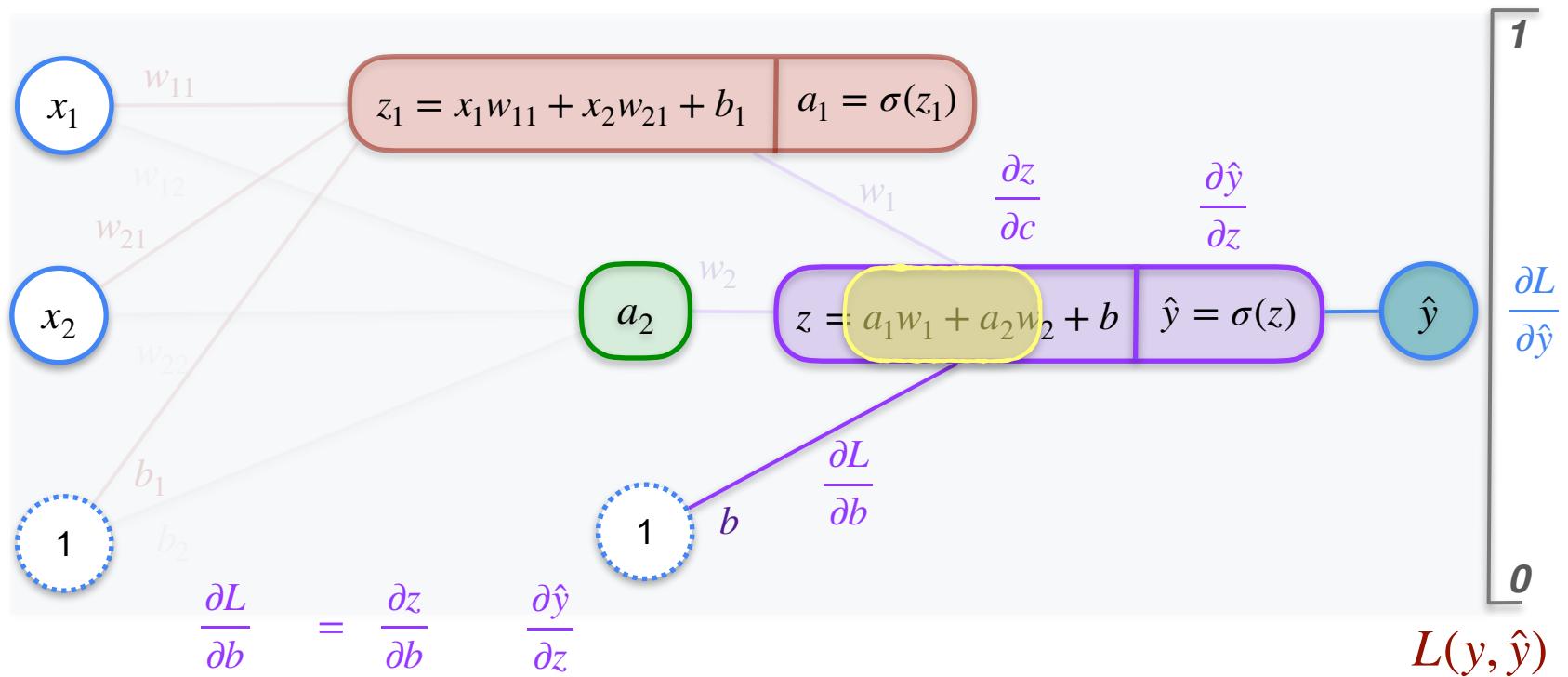
2,2,1 Neural Network



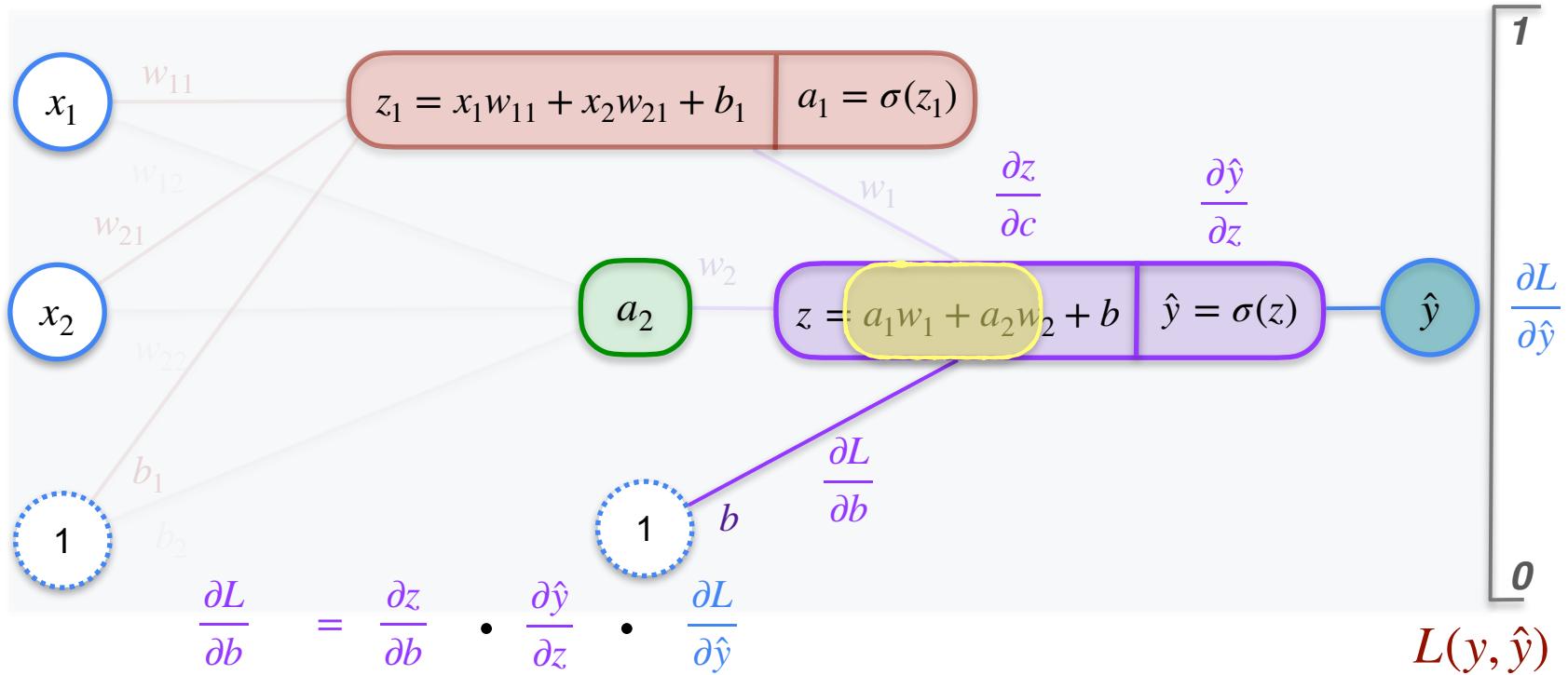
2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network



2,2,1 Neural Network

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1w_1 + a_2w_2 + b$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y}) \quad \frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b} =$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b} = 1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b} = 1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b} = 1$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b} = 1 - \hat{y}(1 - \hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\frac{\partial L}{\partial b} = 1 - \hat{y}(1 - \hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 - \hat{y}(1 - \hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 - \hat{y}(1-\hat{y}) \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1w_1 + a_2w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 \cdot \hat{y}(1-\hat{y}) \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\hat{y}(1-\hat{y})}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

$$= -(y - \hat{y})$$

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

$$= -(y - \hat{y})$$

to find optimal value of b that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

$$= -(y - \hat{y})$$

Perform gradient descent with

*to find optimal
value of b that gives
the least error*

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

$$= -(y - \hat{y})$$

Perform gradient descent with

$$b \rightarrow b - \alpha \frac{\partial L}{\partial b}$$

to find optimal value of b that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

$$= -(y - \hat{y})$$

Perform gradient descent with

$$b \rightarrow b - \alpha$$

to find optimal value of b that gives the least error

2,2,1 Neural Network

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

$$\frac{\partial L}{\partial b} = \frac{\partial z}{\partial b} \cdot \frac{\partial \hat{y}}{\partial z} \cdot \frac{\partial L}{\partial \hat{y}}$$

$$\hat{y} = \sigma(z)$$

$$z = a_1 w_1 + a_2 w_2 + b$$

$$\frac{\partial L}{\partial b} = 1 \cdot \cancel{\hat{y}(1-\hat{y})} \cdot \frac{-(y - \hat{y})}{\cancel{\hat{y}(1-\hat{y})}}$$

$$= -(y - \hat{y})$$

Perform gradient descent with

$$b \rightarrow b - \alpha(-(y - \hat{y}))$$

to find optimal value of b that gives the least error