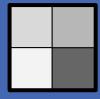
How neural networks work

Brandon Rohrer

A four pixel camera



Categorize images





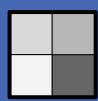
vertical



diagonal







Categorize images solid vertical diagonal horizontal

Categorize images

solid



vertical



diagonal





Categorize images

solid



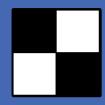
vertical



diagonal







Simple rules can't do it









diagonal





Simple rules can't do it

solid





vertical

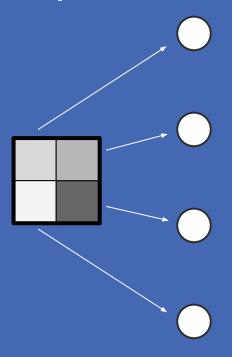


diagonal

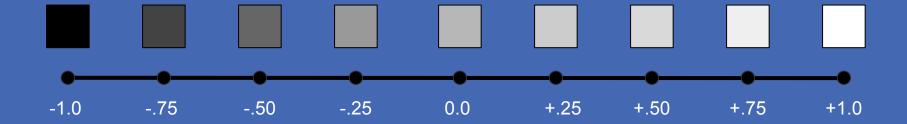




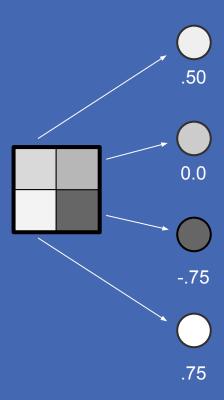
Input neurons



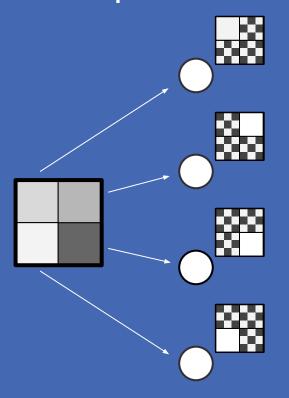
Pixel brightness



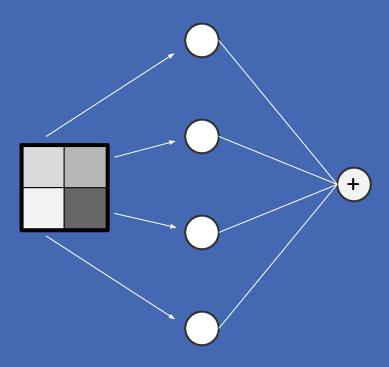
Input vector



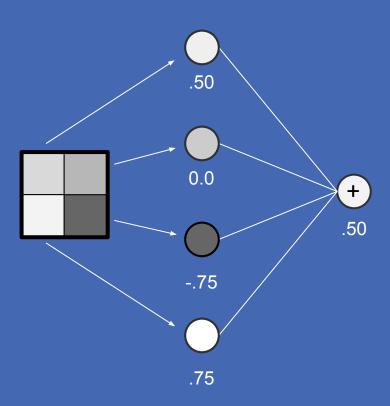
Receptive fields



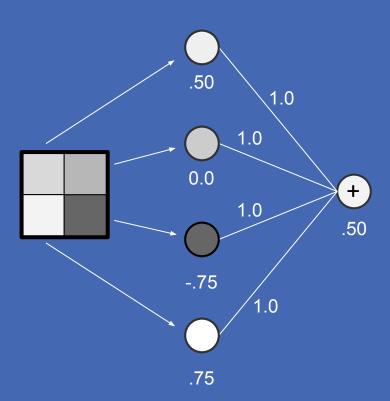
A neuron



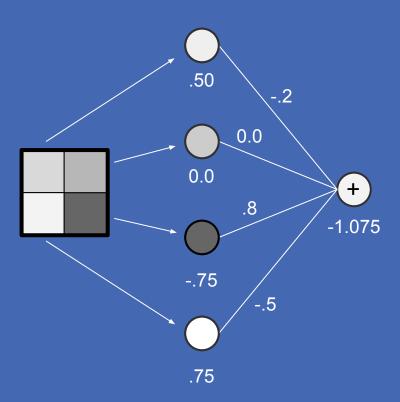
Sum all the inputs



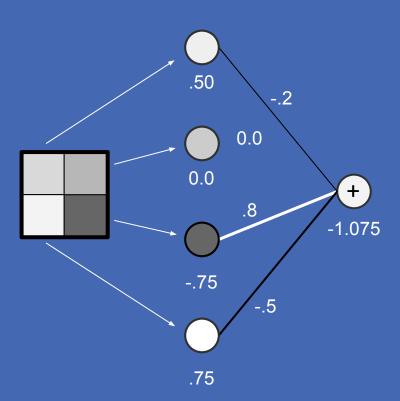
Weights



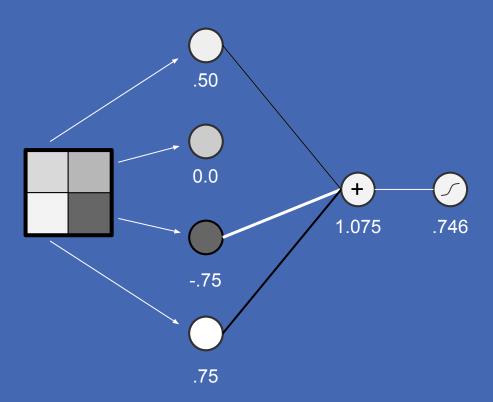
Weights



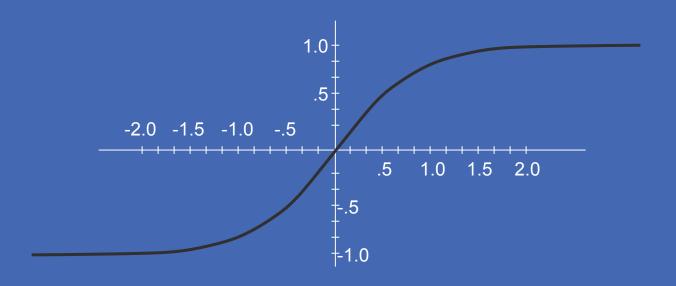
Weights



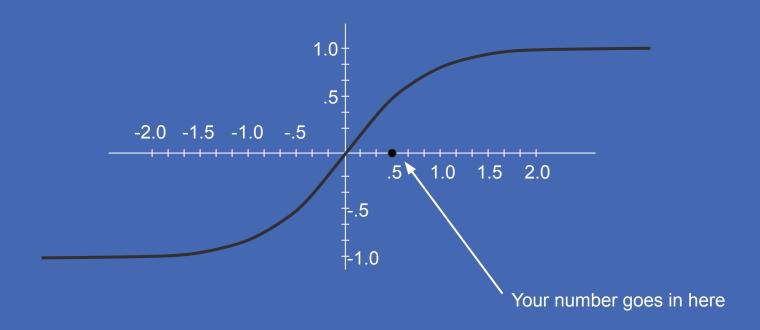
Squash the result



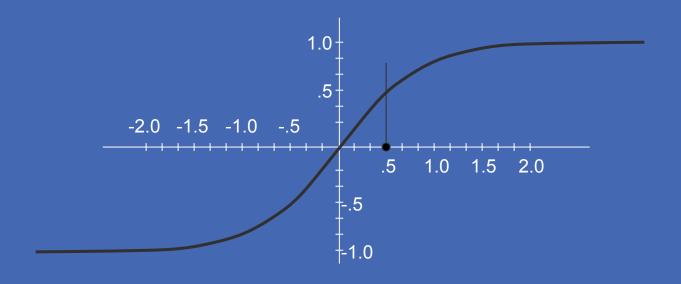




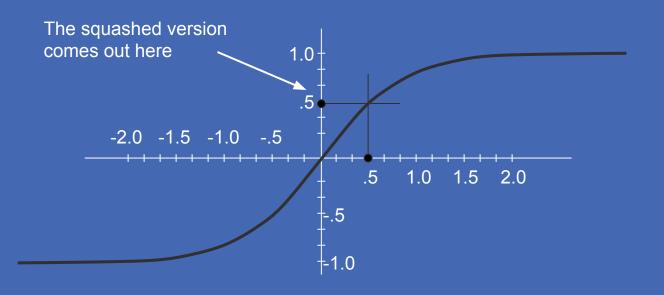




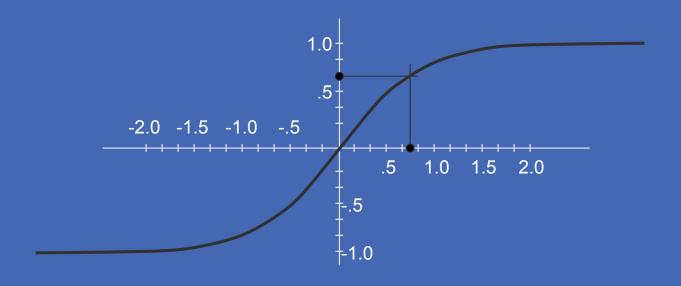




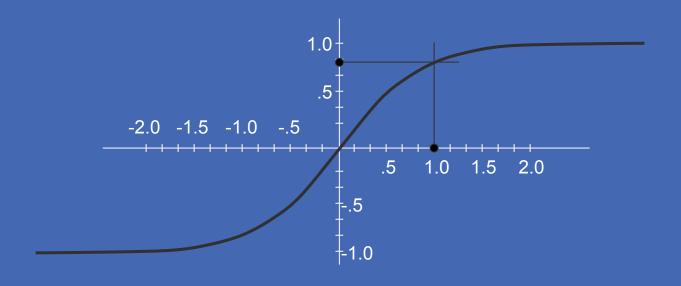




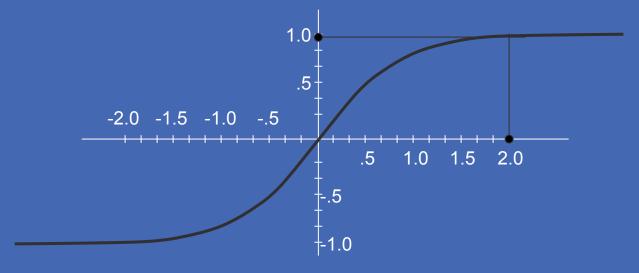




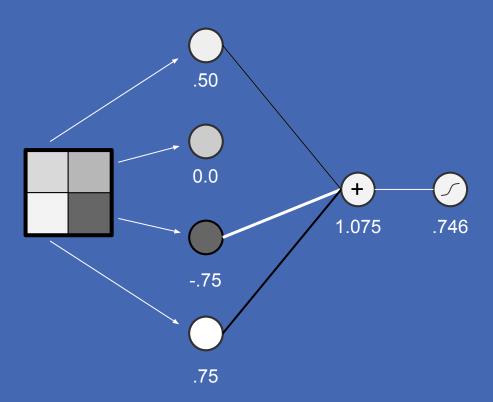




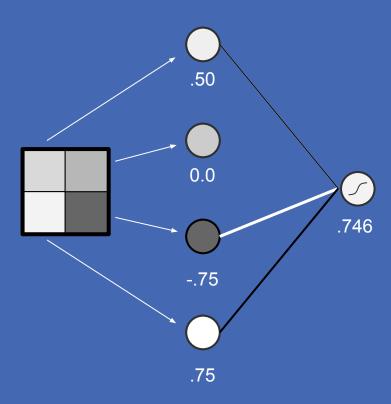
No matter what you start with, the answer stays between -1 and 1.



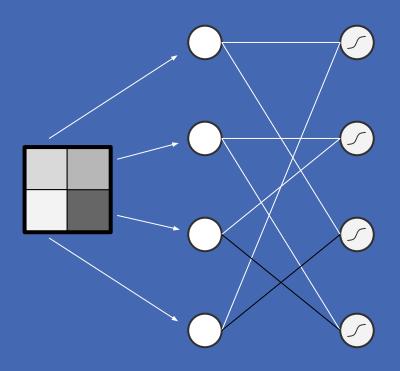
Squash the result



Weighted sum-and-squash neuron

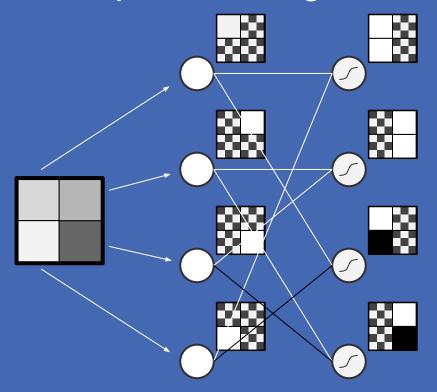


Make lots of neurons, identical except for weights

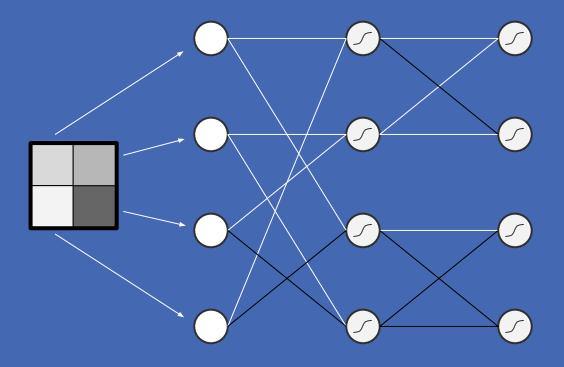


To keep our picture clear, weights will either be 1.0 (white) -1.0 (black) or 0.0 (missing)

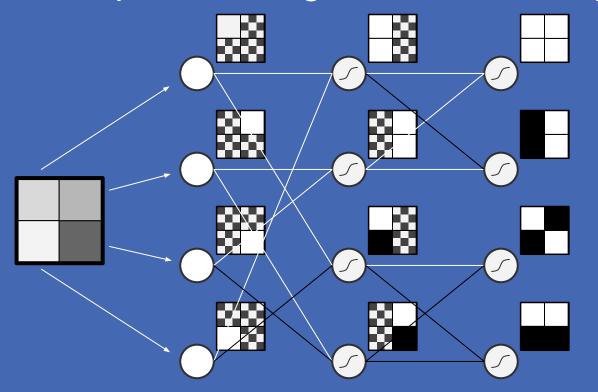
Receptive fields get more complex

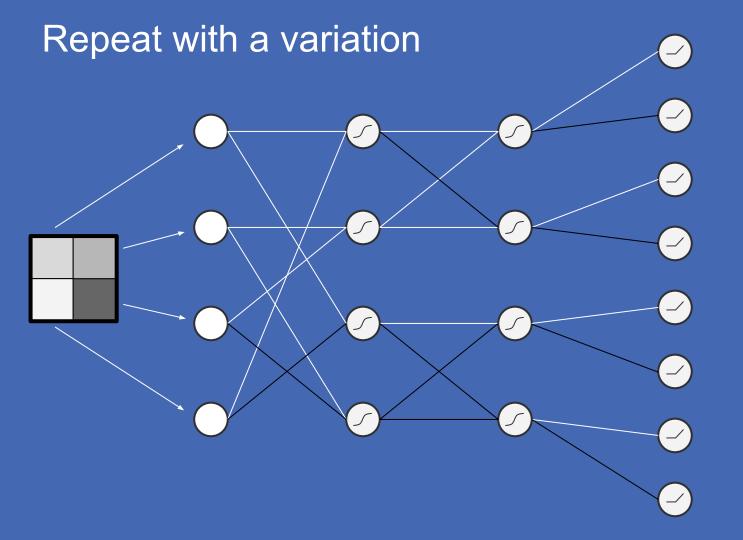


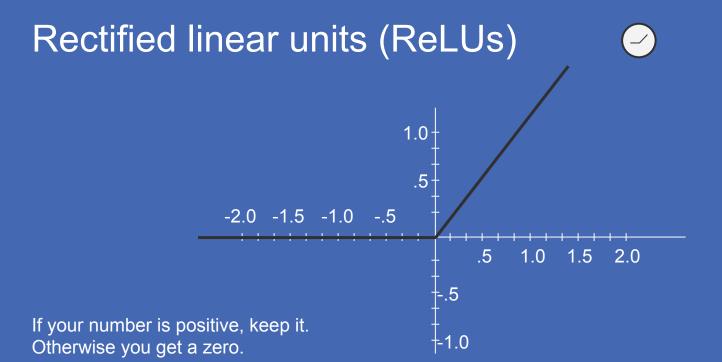
Repeat for additional layers

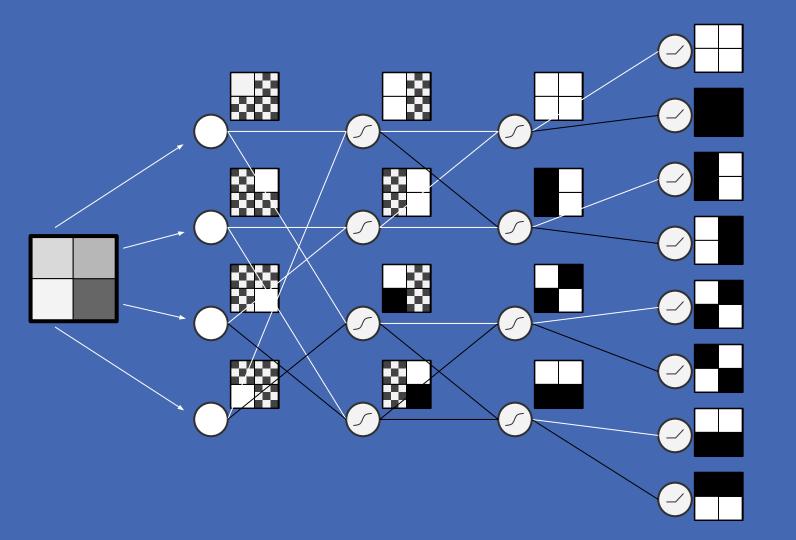


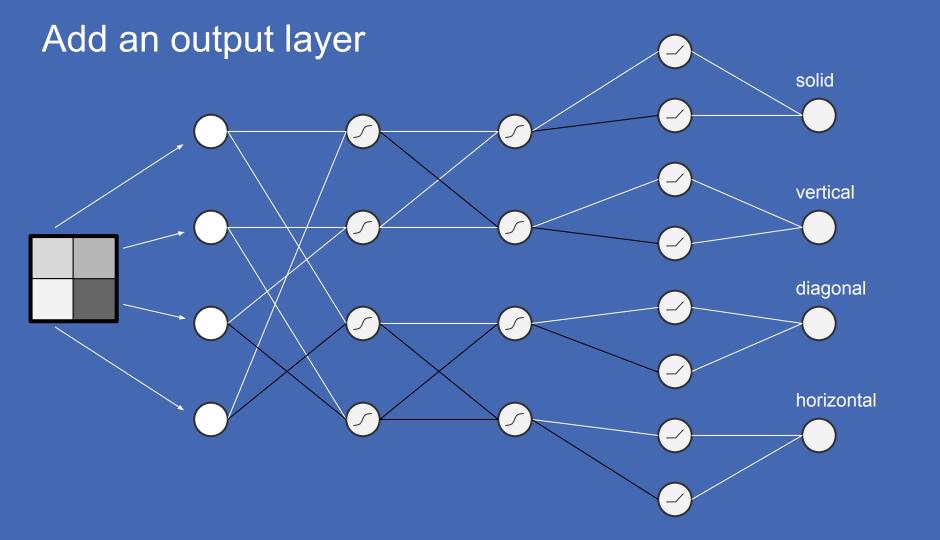
Receptive fields get still more complex

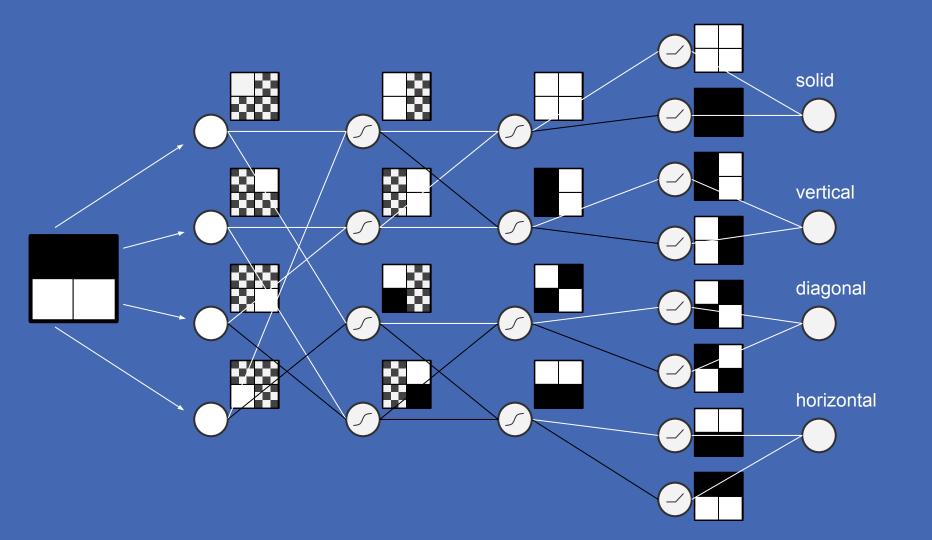


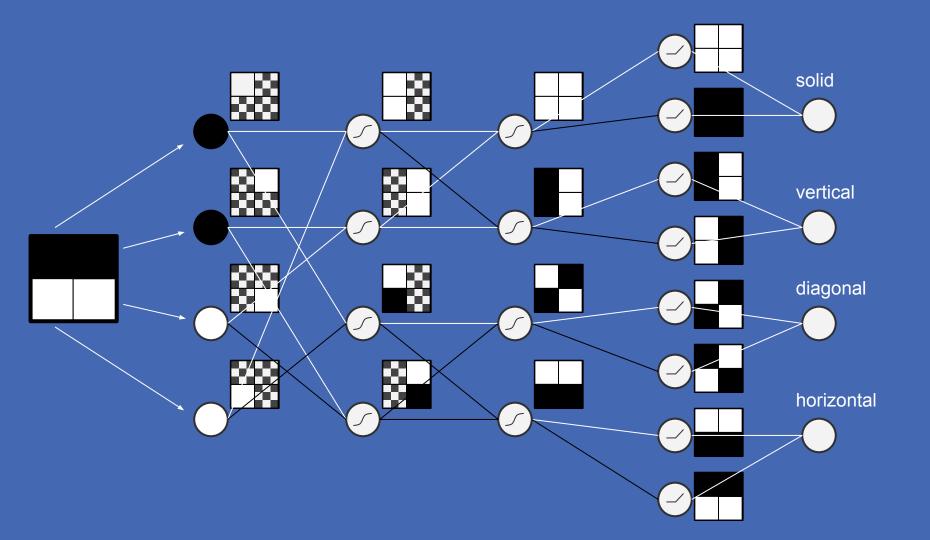


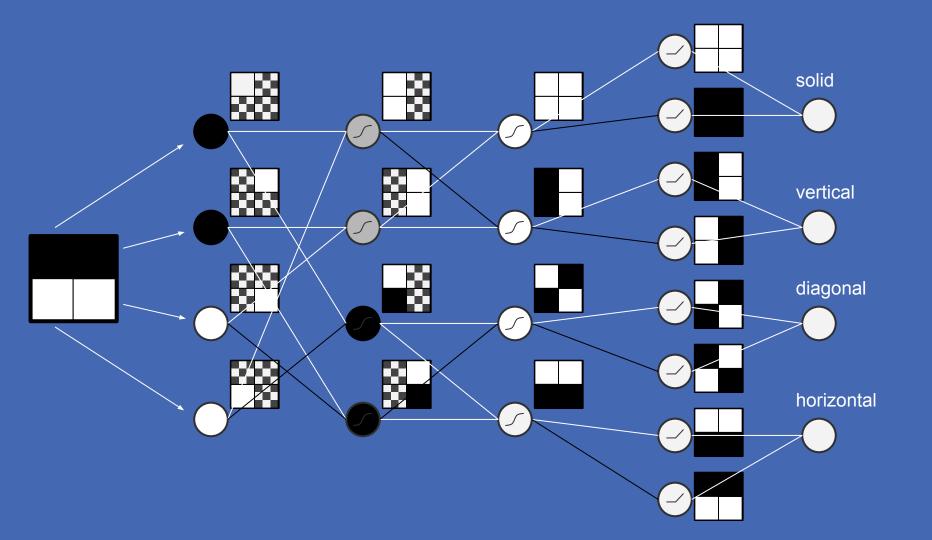


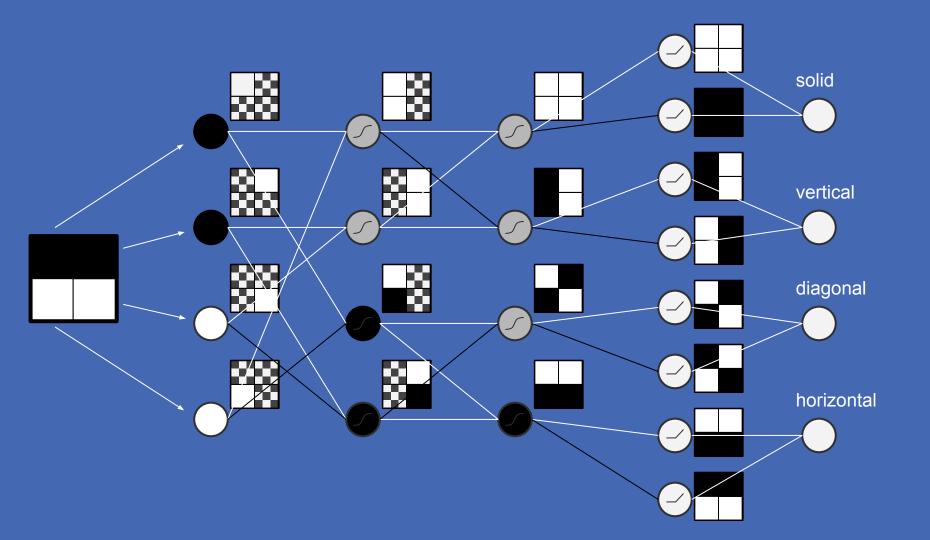


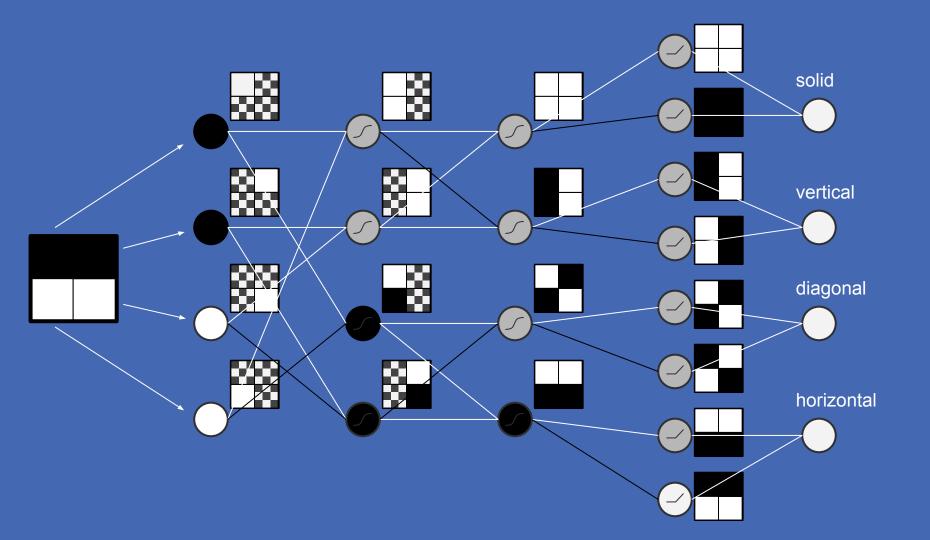


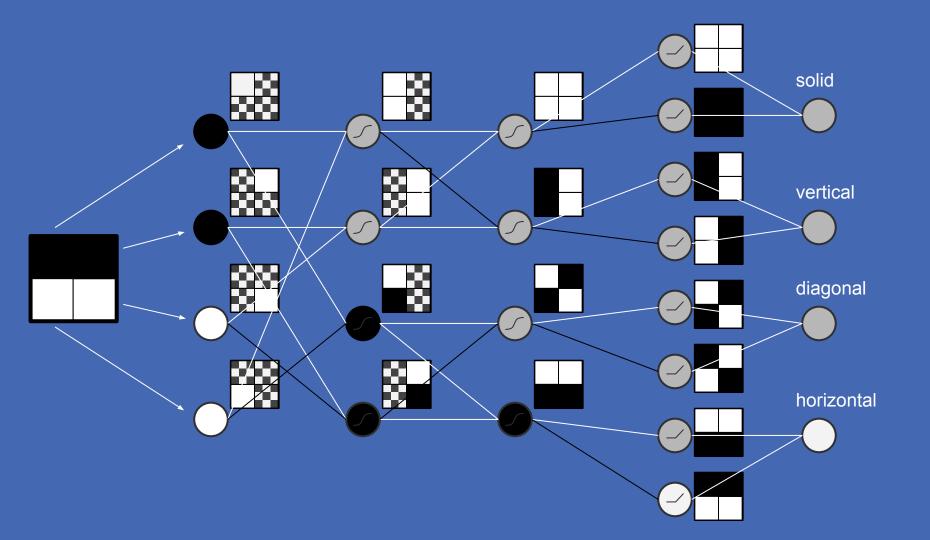


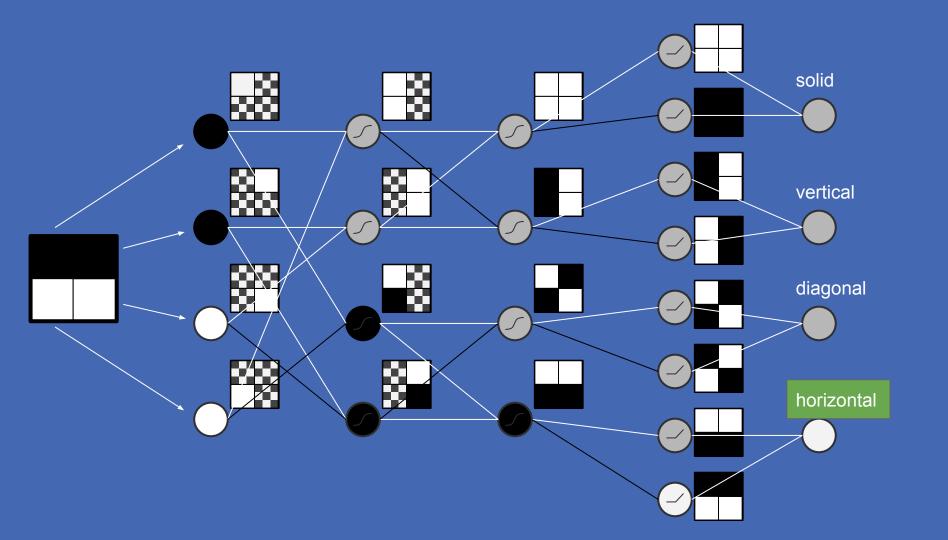












truth 0.

solid





0.

vertical

diagonal

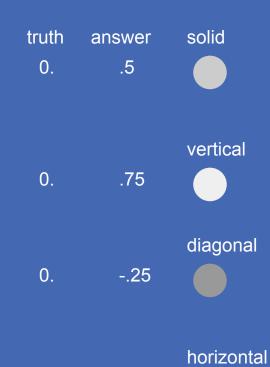
0.

horizontal

1.

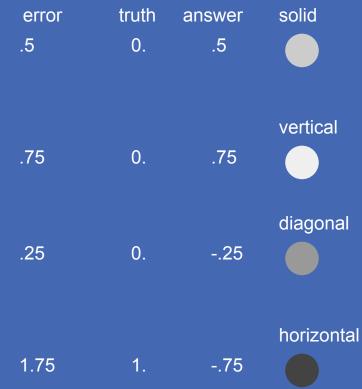






-.75





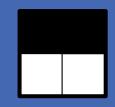




answer .5







.75

0.

.75



vertical

.25

0.

-.25



diagonal





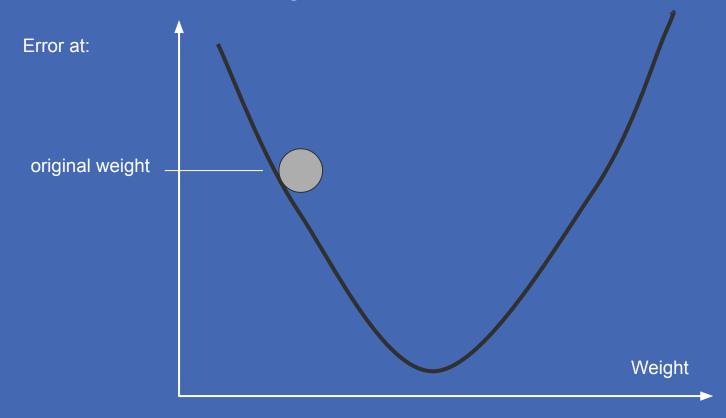
3.25

1.75

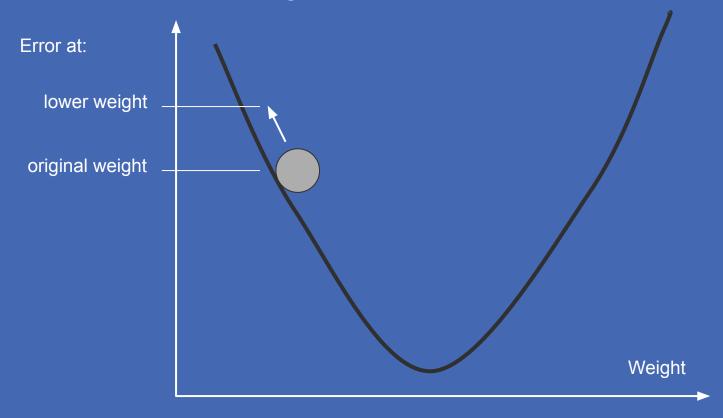
-.75



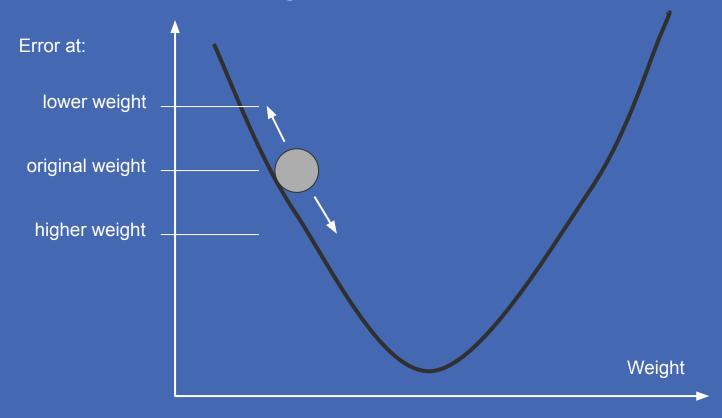
Learn all the weights: Gradient descent



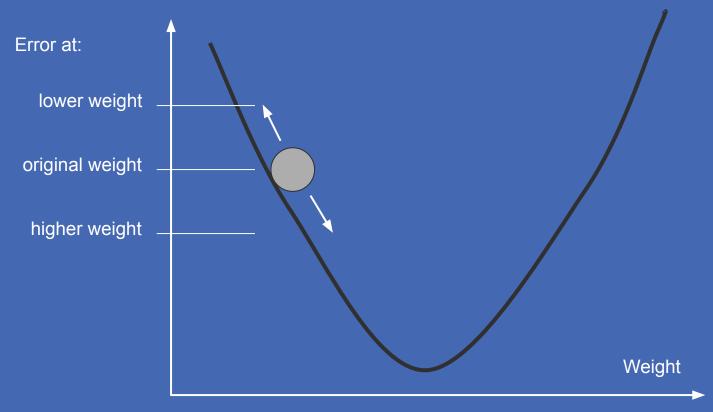
Learn all the weights: Gradient descent



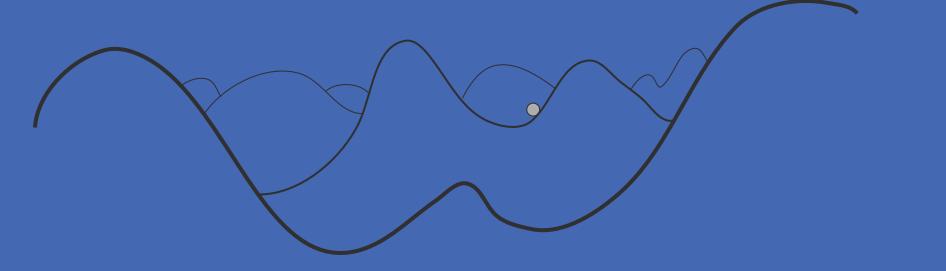
Learn all the weights: Gradient descent



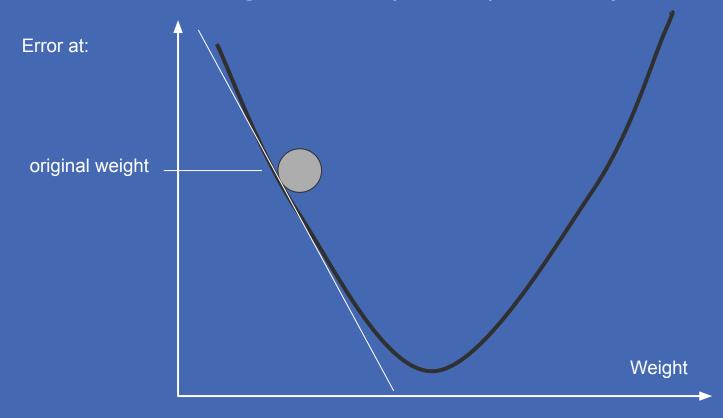
Numerically calculating the gradient is expensive

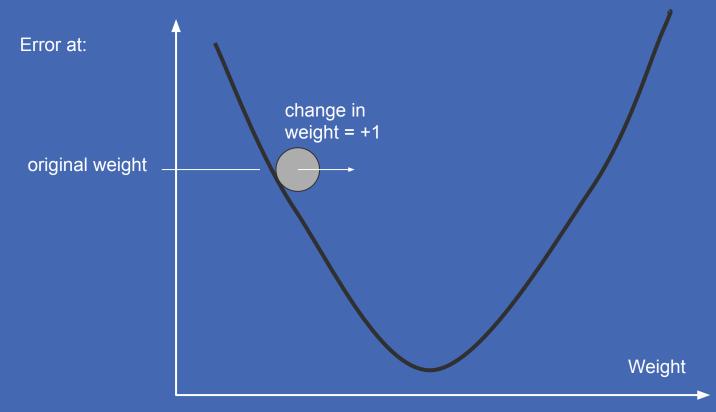


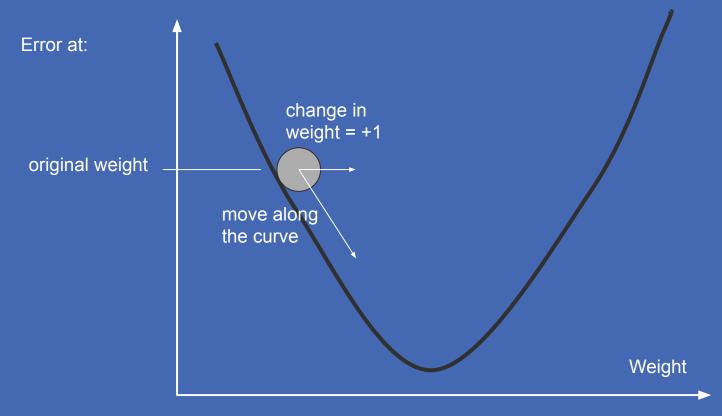
Numerically calculating the gradient is very expensive

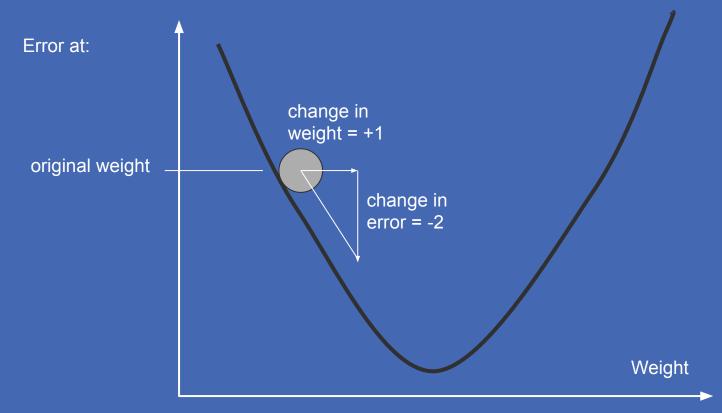


Calculate the gradient (slope) directly



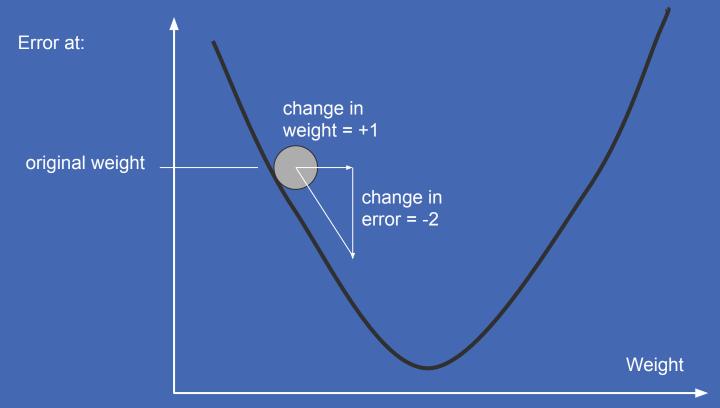


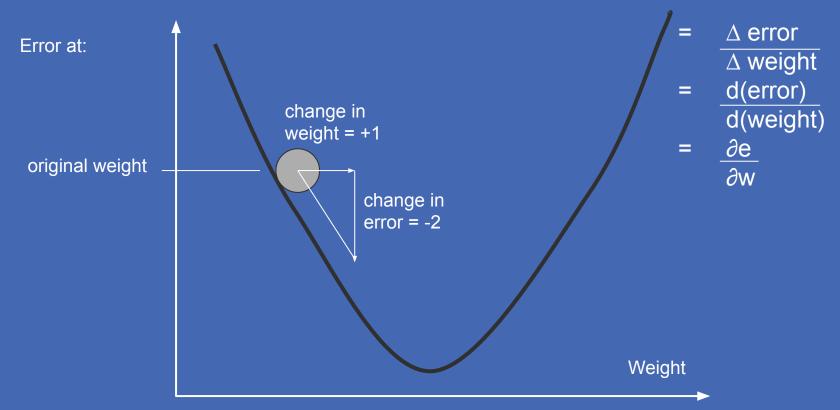






slope = change in error change in weight



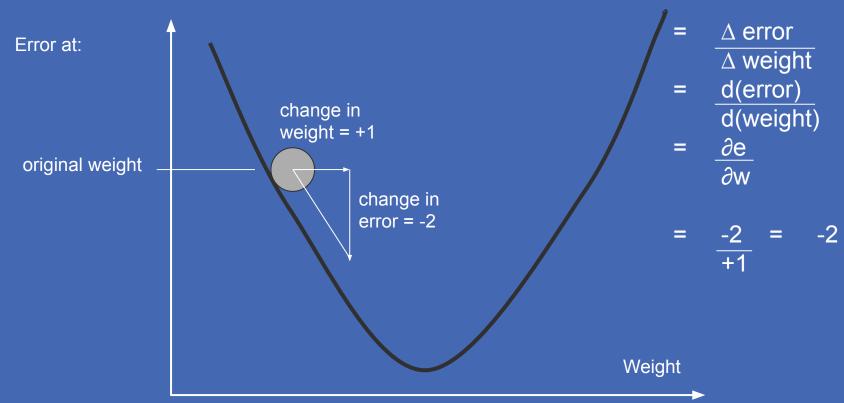


slope

Ε

change in error

change in weight

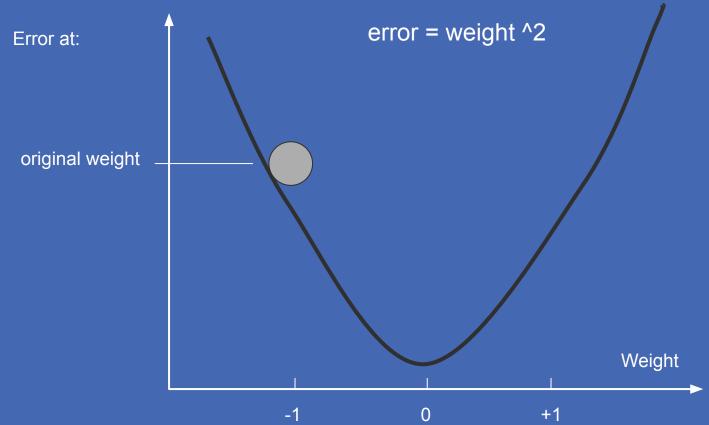


= change in error change in weight

slope

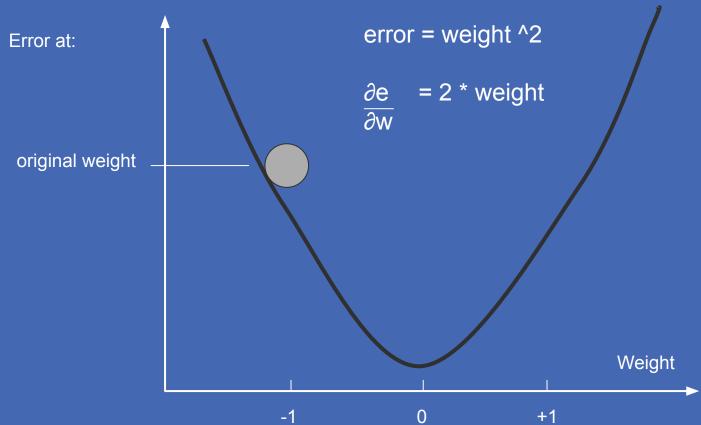


You have to know your error function. For example:



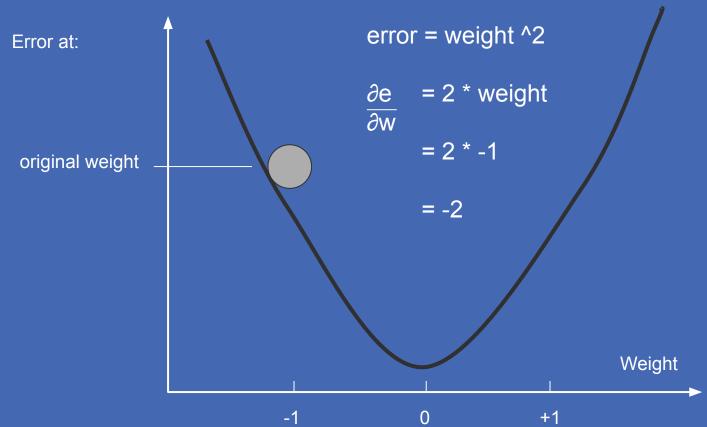


You have to know your error function. For example:

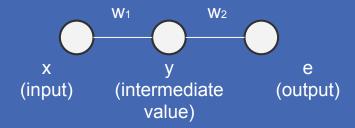




You have to know your error function. For example:

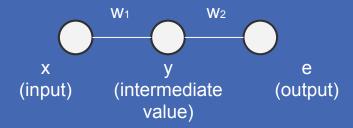


$$y = x * w_1$$



$$y = x * w_1$$

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

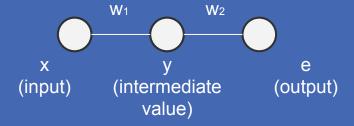


$$y = x * w_1$$

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

$$e = y * w_2$$

$$\frac{\partial e}{\partial v} = w_2$$



$$y = x * w_1$$

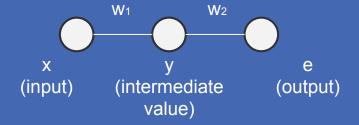
$$\frac{\partial y}{\partial w_1} = x$$

$$e = y * w_2$$

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

$$e = x * w_1 * w_2$$

$$\frac{\partial e}{\partial w_1} = x * w_2$$



$$y = x * W_{1}$$

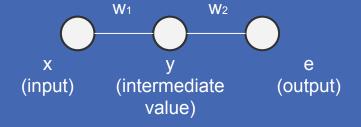
$$\frac{\partial y}{\partial W_{1}} = x$$

$$e = y * W_{2}$$

$$\frac{\partial e}{\partial y} = w_{2}$$

$$\frac{\partial e}{\partial w_{1}} = x * W_{1} * W_{2}$$

$$\frac{\partial e}{\partial W_{1}} = x * W_{2}$$



$$y = x * w_1$$

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

$$e = y * w_2$$

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

$$\frac{\partial e}{\partial w_1} = x * w_2$$

$$\frac{\partial e}{\partial w_1} = \frac{\partial y}{\partial w_1} * \frac{\partial e}{\partial y}$$

$$\frac{\partial \text{err}}{\partial \text{weight}} = \frac{\partial a}{\partial \text{weight}} \frac{\partial b}{\partial a} * \frac{\partial c}{\partial b} * \frac{\partial d}{\partial c} * \dots * \frac{\partial y}{\partial x} * \frac{\partial z}{\partial y} * \frac{\partial \text{err}}{\partial z}$$



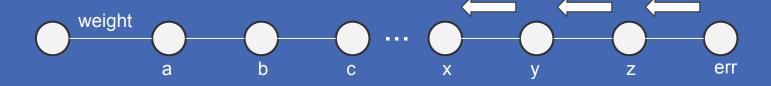
$$\frac{\partial \text{err}}{\partial \text{weight}} = \frac{\partial a}{\partial \text{weight}} \frac{\partial b}{\partial a} * \frac{\partial c}{\partial b} * \frac{\partial d}{\partial c} * \dots * \frac{\partial y}{\partial x} * \frac{\partial z}{\partial y} * \frac{\partial \text{err}}{\partial z}$$



$$\frac{\partial \text{err}}{\partial \text{weight}} = \frac{\partial a}{\partial \text{weight}} \frac{\partial b}{\partial a} * \frac{\partial c}{\partial b} * \frac{\partial d}{\partial c} * \dots * \frac{\partial y}{\partial x} * \frac{\partial z}{\partial y} * \frac{\partial \text{err}}{\partial z}$$



$$\frac{\partial \text{err}}{\partial \text{weight}} = \frac{\partial a}{\partial \text{weight}} \frac{*}{\partial a} \frac{\partial b}{\partial a} * \frac{\partial c}{\partial b} * \frac{\partial d}{\partial c} * \dots * \frac{\partial y}{\partial x} * \frac{\partial z}{\partial y} * \frac{\partial err}{\partial z}$$

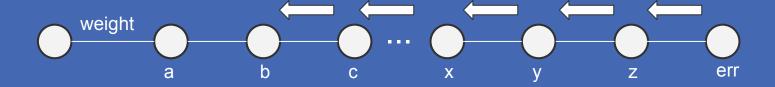


$$\frac{\partial \text{err}}{\partial \text{weight}} = \frac{\partial a}{\partial \text{weight}} \frac{\partial b}{\partial a} * \frac{\partial c}{\partial b} * \frac{\partial d}{\partial c} * \dots * \frac{\partial y}{\partial x} * \frac{\partial z}{\partial y} * \frac{\partial \text{err}}{\partial z}$$



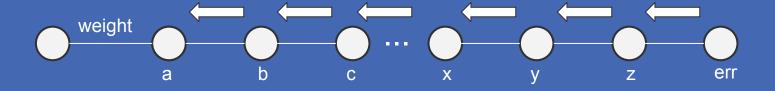
Backpropagation

$$\frac{\partial \text{err}}{\partial \text{weight}} = \frac{\partial a}{\partial \text{weight}} \frac{*}{\partial a} \frac{\partial b}{\partial b} \frac{*}{\partial c} \frac{\partial d}{\partial c} \frac{*}{\partial x} \frac{\partial d}{\partial y} \frac{*}{\partial z} \frac{\partial z}{\partial z} \frac{*}{\partial z} \frac{\partial \text{err}}{\partial z}$$



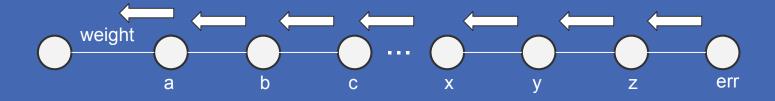
Backpropagation

$$\frac{\partial \text{err}}{\partial \text{weight}} = \frac{\partial a}{\partial \text{weight}} \frac{*}{\partial a} \frac{\partial b}{\partial c} * \frac{\partial c}{\partial c} * \frac{\partial d}{\partial c} * \dots * \frac{\partial y}{\partial x} * \frac{\partial z}{\partial y} * \frac{\partial err}{\partial z}$$

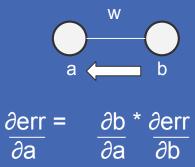


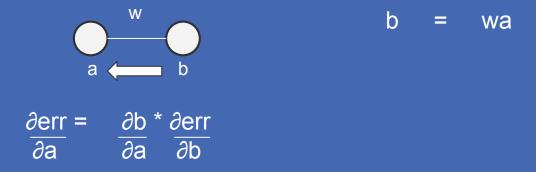
Backpropagation

$$\frac{\partial \text{err}}{\partial \text{weight}} = \frac{\partial a}{\partial \text{weight}} \frac{*}{\partial a} \frac{\partial b}{\partial c} * \frac{\partial d}{\partial c} * \dots * \frac{\partial y}{\partial x} * \frac{\partial z}{\partial y} * \frac{\partial \text{err}}{\partial z}$$

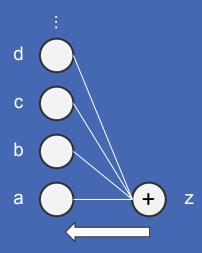


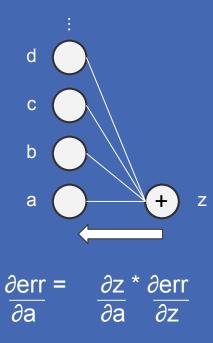


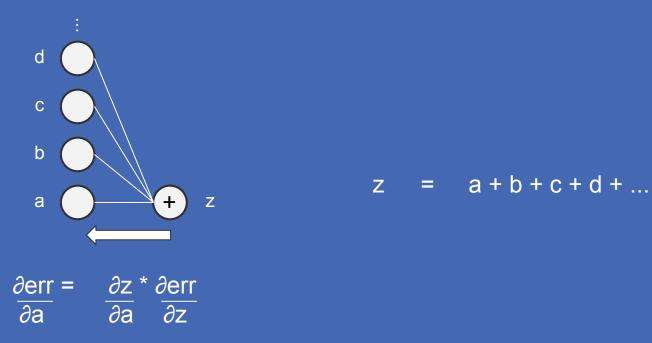


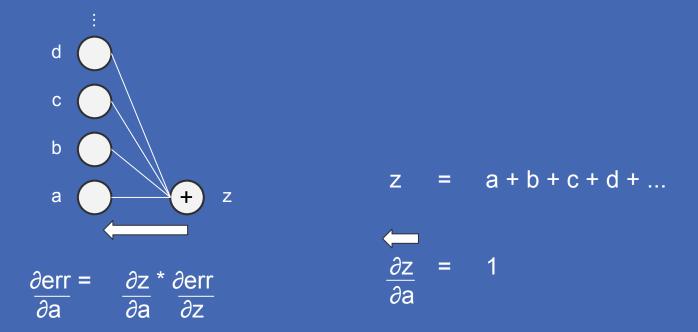


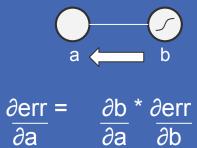




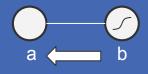






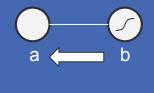


$$b = \frac{1}{1 + e^{-a}}$$



$$\frac{\partial \text{err}}{\partial a} = \frac{\partial b}{\partial a} * \frac{\partial \text{err}}{\partial b}$$

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

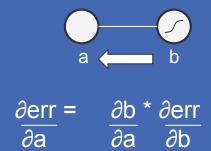


$$\frac{\partial \text{err}}{\partial a} = \frac{\partial b}{\partial a} * \frac{\partial \text{err}}{\partial b}$$

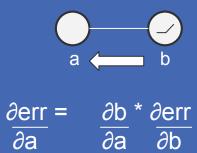
$$b = \frac{1}{1 + e^{-a}}$$
$$= \sigma(a)$$

Because math is beautiful / dumb luck:

$$\frac{\partial b}{\partial a} = \sigma(a) * (1 - \sigma(a))$$



Backpropagation challenge: ReLU



Backpropagation challenge: ReLU

$$\frac{\partial}{\partial a} = \frac{\partial}{\partial a} * \frac{\partial}{\partial b}$$

$$\frac{\partial}{\partial a} = \frac{\partial}{\partial a} * \frac{\partial}{\partial b} * \frac{\partial}{\partial b}$$

$$b = a, a > 0$$

= 0, otherwise

Backpropagation challenge: ReLU

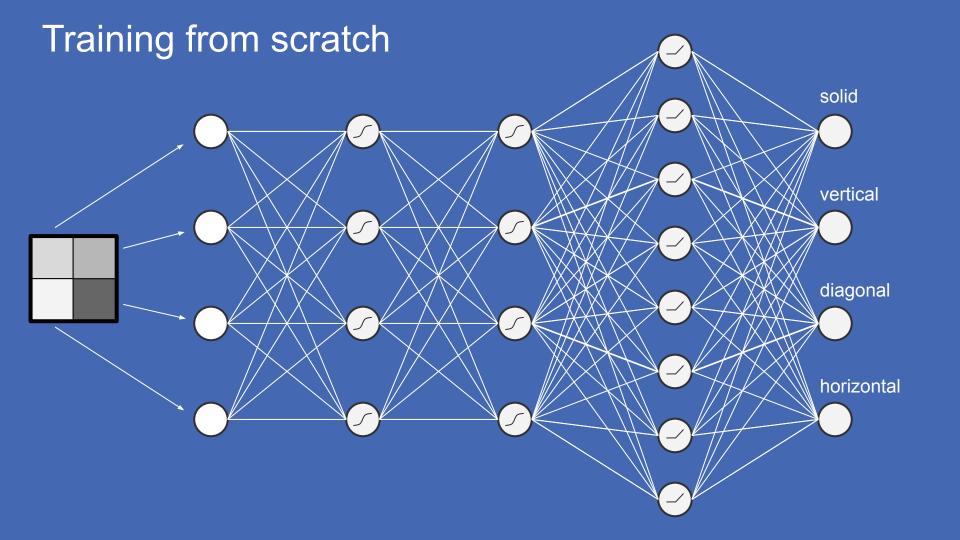
$$\frac{\partial err}{\partial a} = \frac{\partial b}{\partial a} * \frac{\partial err}{\partial b}$$

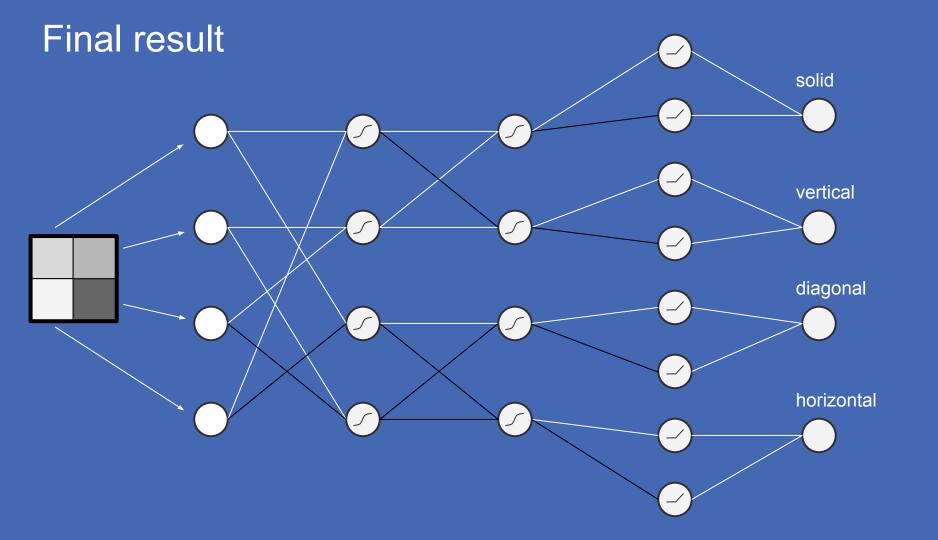
$$= 0, \text{ otherwise}$$

$$\frac{\partial b}{\partial a} = 1, a > 0$$

$$0, \text{ otherwise}$$

b = a, a > 0





Advanced topics

Bias neurons

Dropout

Backpropagation details

Andrej Karpathy's Stanford CS231 lecture

Backpropagation gotchas

Andrej Karpathy's article <u>"Yes you should understand backprop"</u>

Tips and tricks

Nikolas Markou's article "The Black Magic of Deep Learning"

Data Science and Robots Blog

For more How it Works:

How Deep Learning works

How Convolutional Neural Networks work

How Bayes Law works

How data science works

How linear regression works

These slides

https://docs.google.com/presentation/d/1AAEFCgC0Ja7QEl3-wmuvlizbvaE-aQRksc7-W8LR2GY/edit?usp=sharing