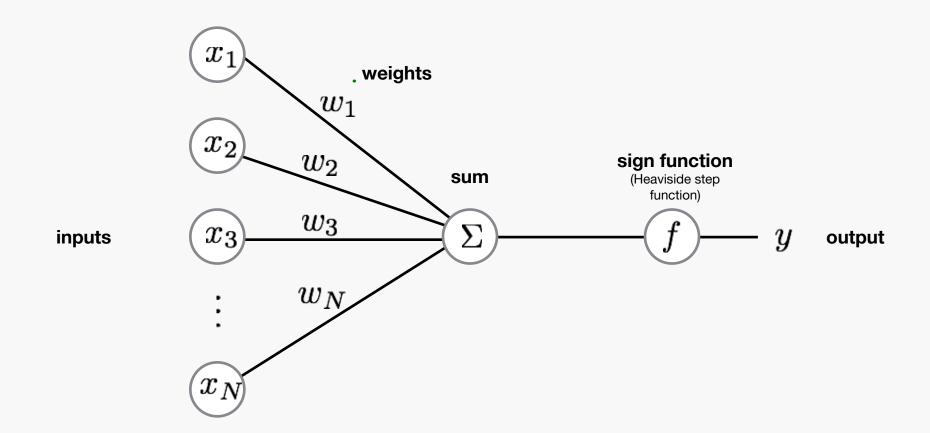
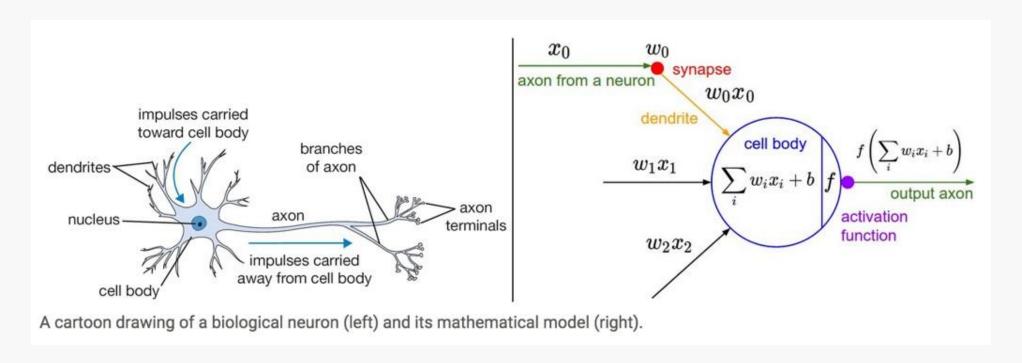
Perceptron

The Perceptron



Aside: Inspiration from Biology



Neural nets/perceptrons are loosely inspired by biology.

But they certainly are **not** a model of how the brain works, or even how neurons work.

1: **function** Perceptron Algorithm

2:
$$\boldsymbol{w}^{(0)} \leftarrow \mathbf{0}$$

3: **for**
$$t = 1, ..., T$$
 do

4:
$$extbf{RECEIVE}(oldsymbol{x}^{(t)})$$
 $extbf{x} \in \{0,1\}^N$ N-d binary vector

5:
$$\hat{y}_A^{(t)} = \operatorname*{sign}\left(\langle m{w}^{(t-1)}, m{x}^{(t)}
angle
ight)$$
 perceptron is just one line of code!

6: RECEIVE
$$(y^t)$$
 $y \in \{1, -1\}$

7:
$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

 $\mathsf{RECEIVE}(oldsymbol{x}^{(t)})$

$$\hat{y}_A^{(t)} = ext{sign}igg(\langle oldsymbol{w}^{(t-1)}, oldsymbol{x}^{(t)}
angle igg)$$

 $Receive(y^t)$

$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

initialized to 0

 $\mathsf{RECEIVE}(oldsymbol{x}^{(t)})$

$$\hat{y}_A^{(t)} = ext{sign}igg(\langle oldsymbol{w}^{(t-1)}, oldsymbol{x}^{(t)}
angleigg)$$

 $RECEIVE(y^t)$

$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

observation (1,-1)

label -1

 $\mathsf{RECEIVE}(oldsymbol{x}^{(t)})$

$$\hat{y}_A^{(t)} = ext{sign}igg(\langle oldsymbol{w}^{(t-1)}, oldsymbol{x}^{(t)}
angleigg)$$

 $RECEIVE(y^t)$

$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

observation (1,-1)

label -1

$$\hat{y}_A^{(t)} = ext{sign}igg(\langle oldsymbol{w}^{(t-1)}, oldsymbol{x}^{(t)}
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 $\text{RECEIVE}(\boldsymbol{x}^{(t)})$

$$\hat{y}_A^{(t)} = ext{sign}igg(raket{oldsymbol{w}^{(t-1)},oldsymbol{x}^{(t)}}igg)$$

 $\mathsf{RECEIVE}(y^t)$

$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

observation (1,-1)label -1

 $ext{RECEIVE}(oldsymbol{x}^{(t)})$

$$\hat{y}_A^{(t)} = ext{sign}igg(\langle oldsymbol{w}^{(t-1)}, oldsymbol{x}^{(t)}
angleigg)$$

 $RECEIVE(y^t)$

$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

update w

$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

observation (1,-1)label -1

 $\text{RECEIVE}(\boldsymbol{x}^{(t)})$

$$\hat{y}_A^{(t)} = ext{sign}igg(\langle oldsymbol{w}^{(t-1)}, oldsymbol{x}^{(t)}
angleigg)$$

 $\mathsf{RECEIVE}(y^t)$

$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

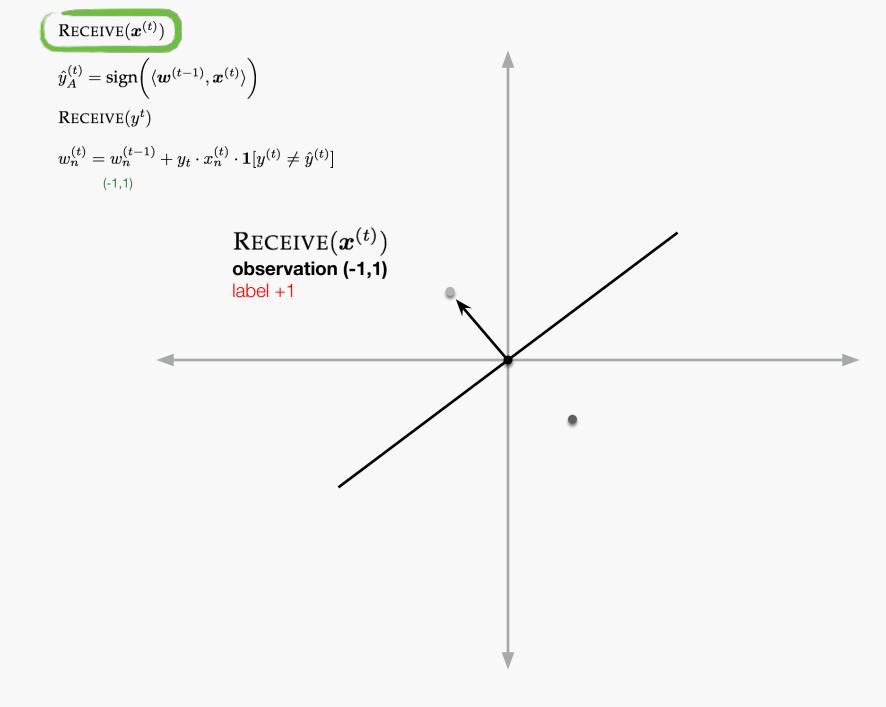
update w

no match!

$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

(-1,1) (0,0) -1 (1,-1) 1

observation (1,-1) label -1



 $\text{Receive}(\boldsymbol{x}^{(t)})$

$$\hat{y}_A^{(t)} = ext{sign}igg(\langle oldsymbol{w}^{(t-1)}, oldsymbol{x}^{(t)}
angleigg)$$

 $\mathsf{RECEIVE}(y^t)$

$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)}
eq \hat{y}^{(t)}]$$

$$\hat{y}_A^{(t)} = ext{sign}igg(raket{oldsymbol{w}^{(t-1)},oldsymbol{x}^{(t)}}{}_{ ext{ iny (-1,1)}}igg)$$

observation (-1,1) label +1

$$\begin{split} \hat{y}_A^{(t)} &= \operatorname{sign}\left(\langle \boldsymbol{w}^{(t-1)}, \boldsymbol{x}^{(t)} \rangle\right) \\ \text{RECEIVE}(y^t) \\ w_n^{(t)} &= w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}] \\ &= 1 \end{split}$$

$$\hat{y}_A^{(t)} = \operatorname{sign}\left(\langle \boldsymbol{w}^{(t-1)}, \boldsymbol{x}^{(t)} \rangle\right) \\ &= 1 \end{split}$$
 observation (-1,1) label +1

 $\text{Receive}(\boldsymbol{x}^{(t)})$

$$\hat{y}_A^{(t)} = ext{sign}igg(\langle oldsymbol{w}^{(t-1)}, oldsymbol{x}^{(t)}
angleigg)$$

 $\mathsf{RECEIVE}(y^t)$

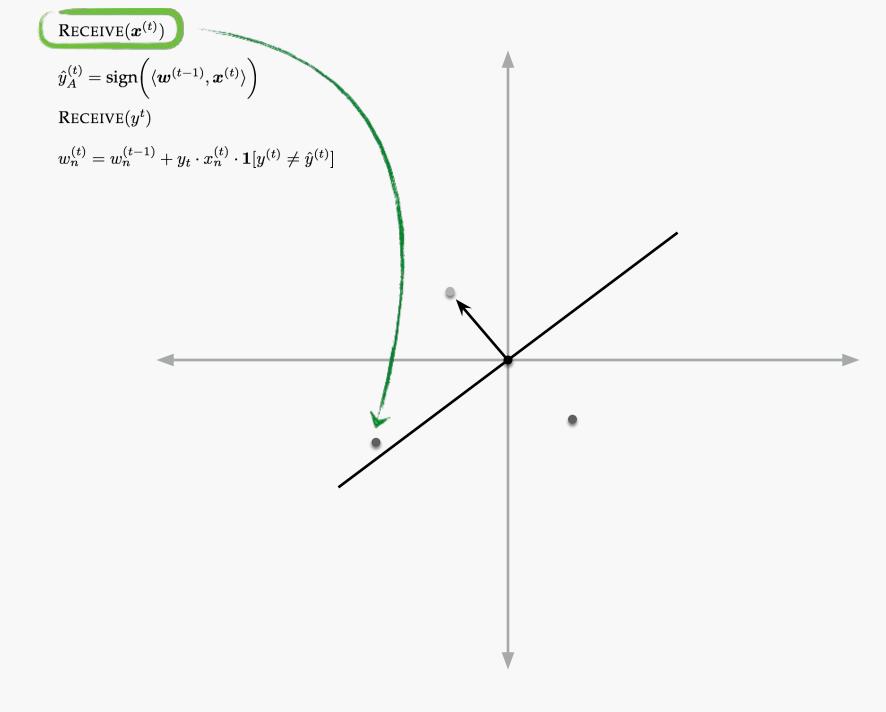
$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

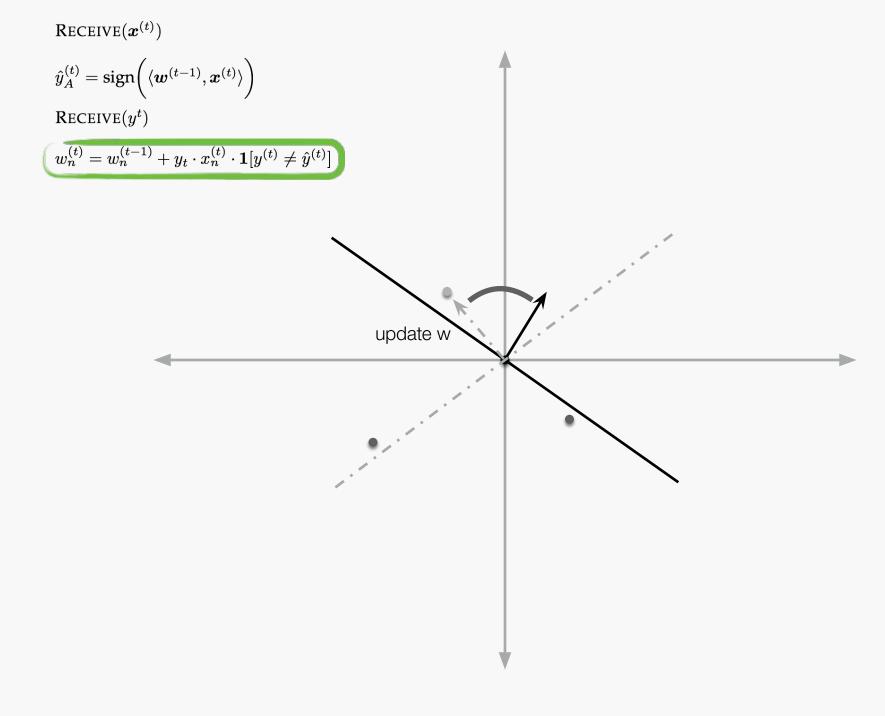
update w

match!

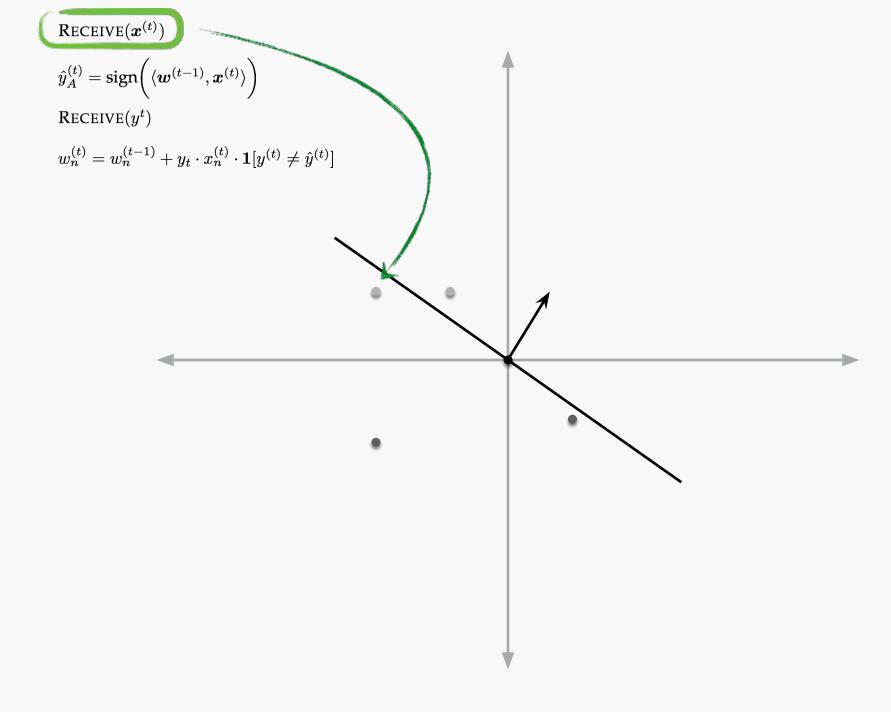
$$w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$$

update w





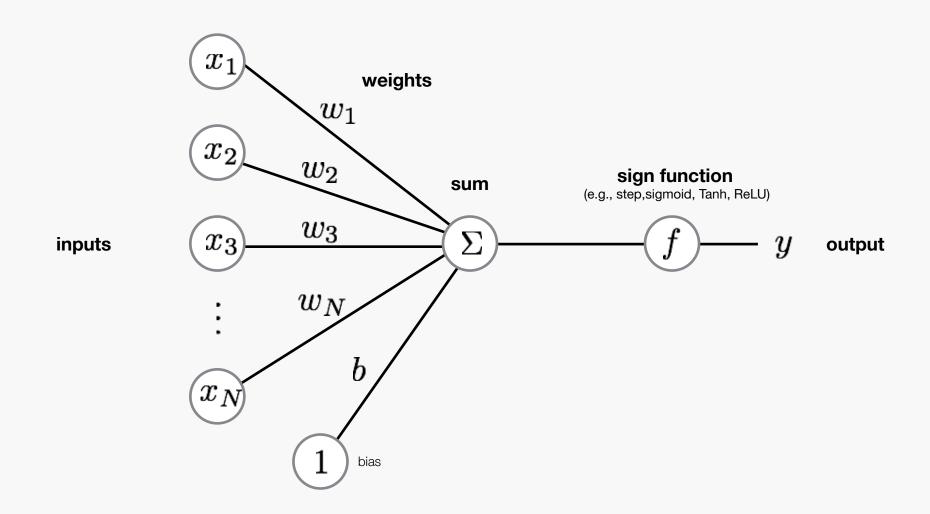
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angle igg)$ $Receive(y^t)$ $w_n^{(t)} = w_n^{(t-1)} + y_t \cdot x_n^{(t)} \cdot \mathbf{1}[y^{(t)} \neq \hat{y}^{(t)}]$ update w



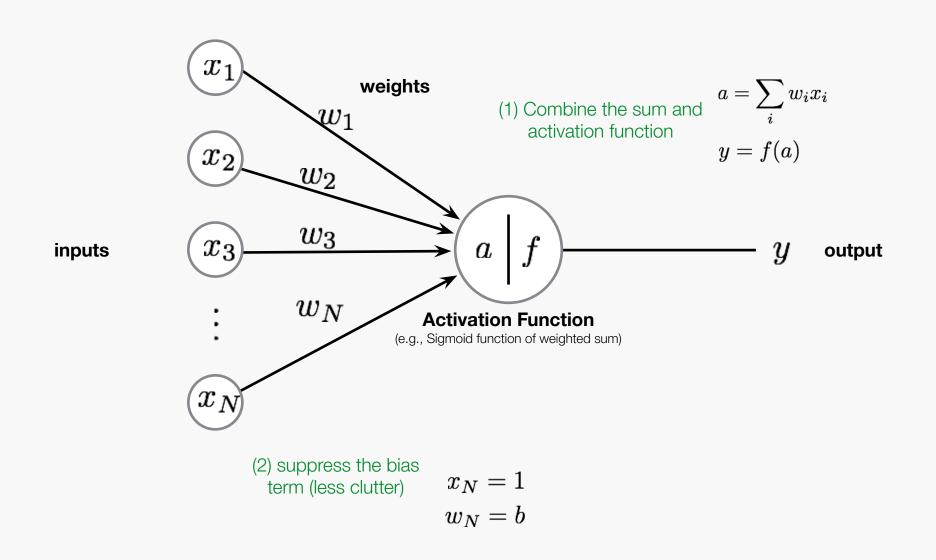
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The Perceptron



Another way to draw it...



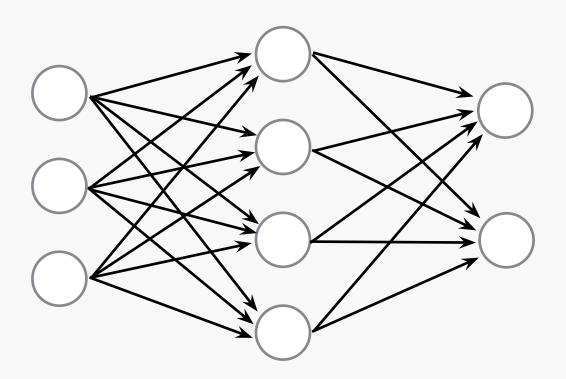
Programming the 'forward pass'

Activation function (sigmoid, logistic

```
function)
                   float f(float a)
x_1
                      return 1.0 / (1.0 + \exp(-a));
x_2
        w_2
        w_3
x_3
                                                     output
        w_N
x_N
     Perceptron function (logistic regression)
     float perceptron(vector<float> x, vector<float> w)
        float a = dot(x, w);
        return f(a);
```

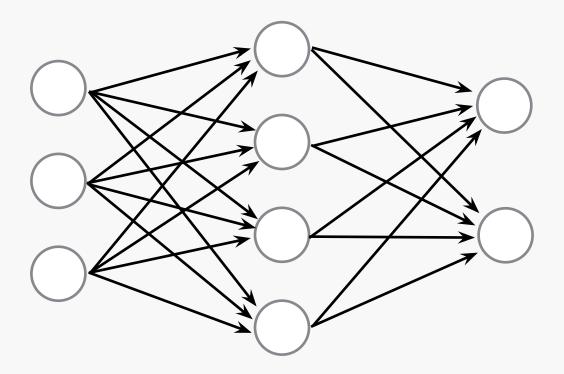
Neural networks

Connect a bunch of perceptrons together ... Neural Network

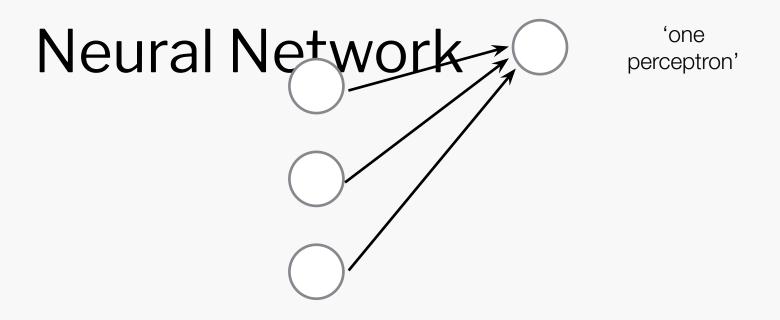


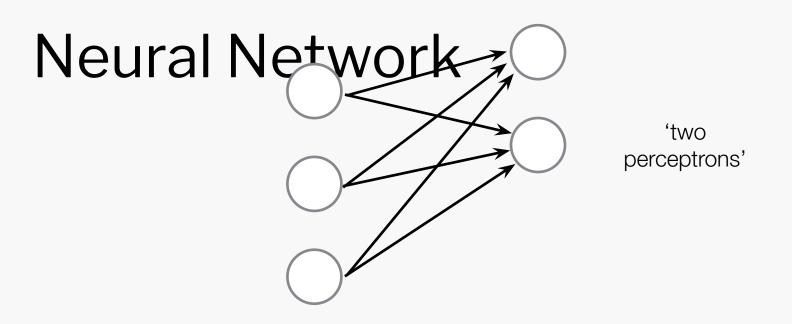
Connect a bunch of perceptrons together ... Neural Network

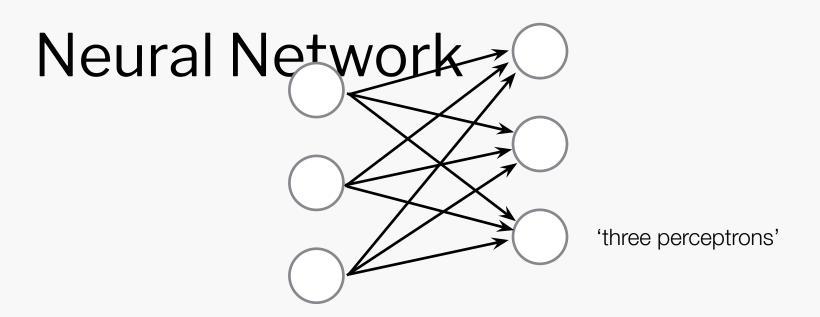
a collection of connected perceptrons



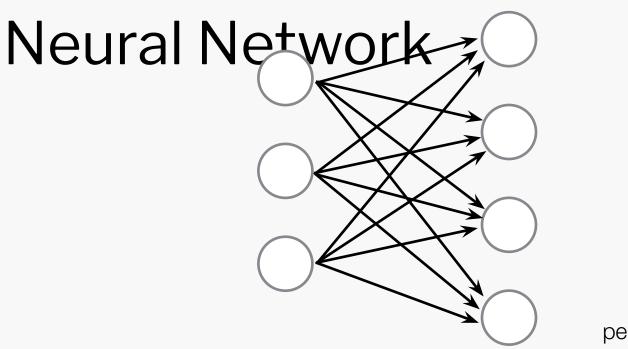
How many perceptrons in this neural network?



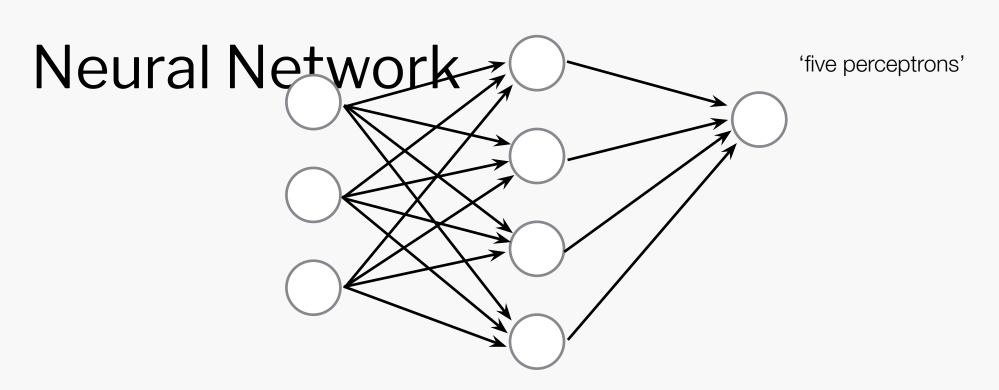


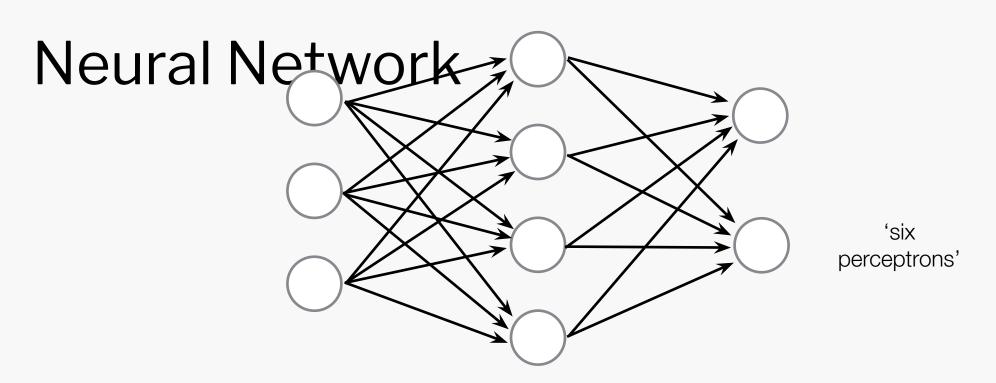


a collection of connected perceptrons



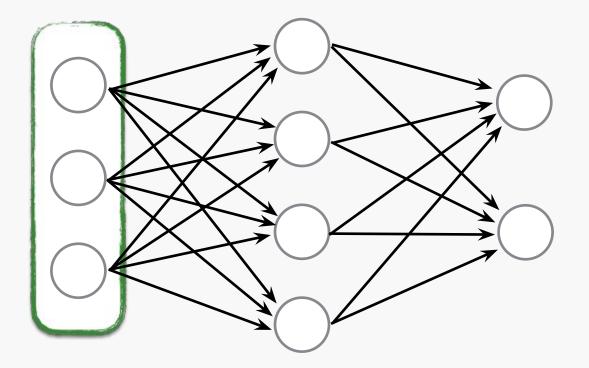
'four perceptrons'



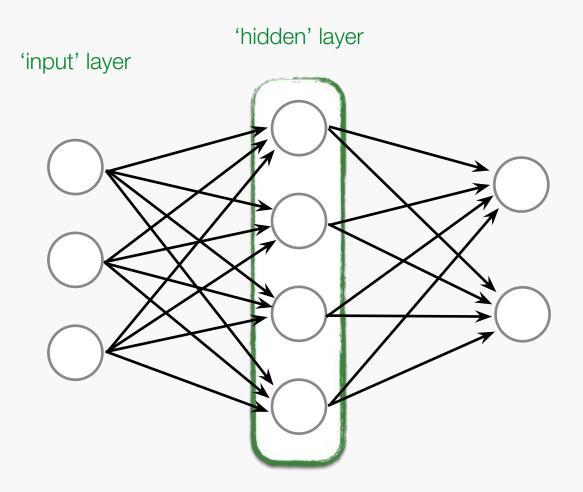


Some terminology...

'input' layer

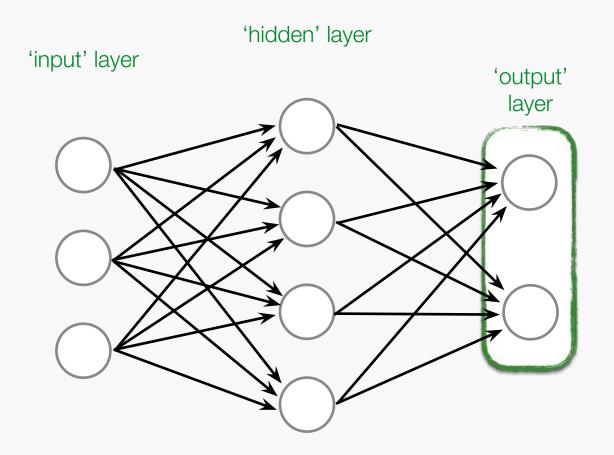


Some terminology...

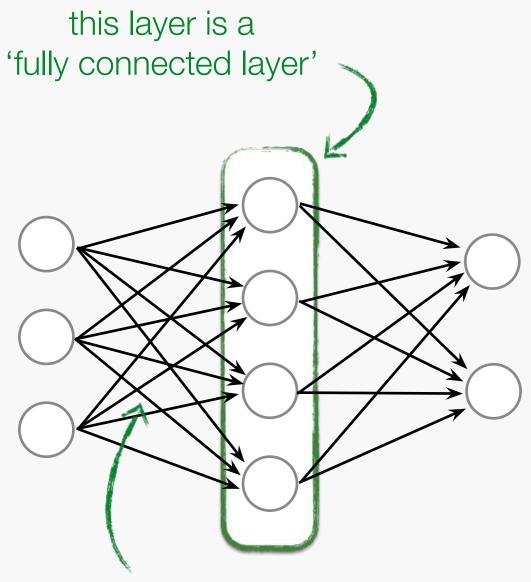


...also called a **Multi-layer Perceptron** (MLP)

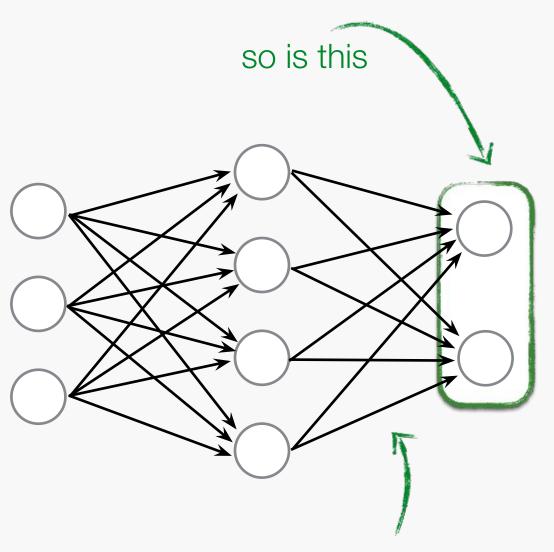
Some terminology...



...also called a **Multi-layer Perceptron** (MLP)

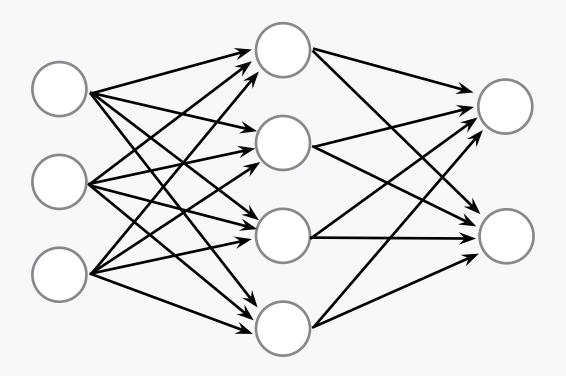


all pairwise neurons between layers are connected



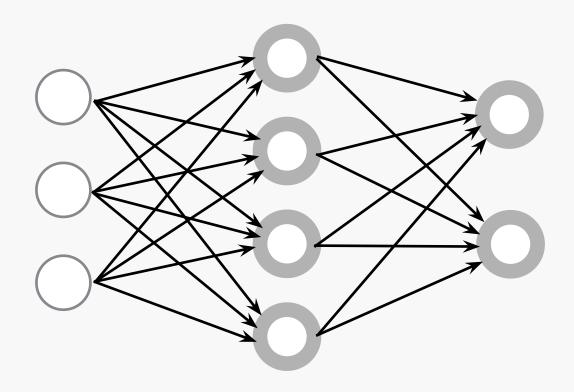
all pairwise neurons between layers are connected

How many weights (edges)?



$$4 + 2 = 6$$

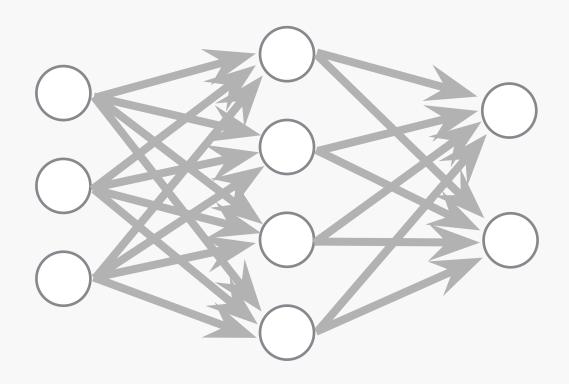
How many weights (edges)?



$$4 + 2 = 6$$

How many weights (edges)?

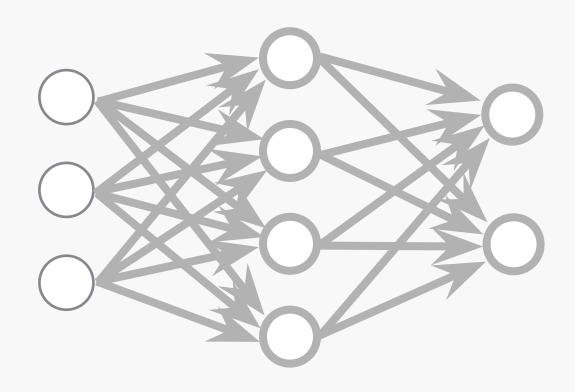
$$(3 \times 4) + (4 \times 2) = 20$$



$$4 + 2 = 6$$

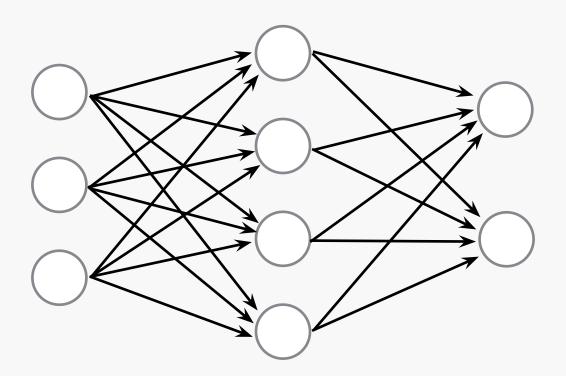
How many weights (edges)?

$$(3 \times 4) + (4 \times 2) = 20$$



$$20 + 4 + 2 =$$

performance usually tops out at 2-3 layers, deeper networks don't really improve performance...



...with the exception of **convolutional** networks for images