Lecture 7:

Deep Learning: An overview

Some slides were adapted/taken from various sources, including 3D Computer Vision of Prof. Hee, NUS, Air Lab Summer School, The Robotic Institute, CMU, Computer Vision of Prof. Mubarak Shah, UCF, Computer Vision of Prof. William Hoff, Colorado School of Mines and many more. We thankfully acknowledge them. Students are requested to use this material for their study only and **NOT** to distribute it.

Why Deep

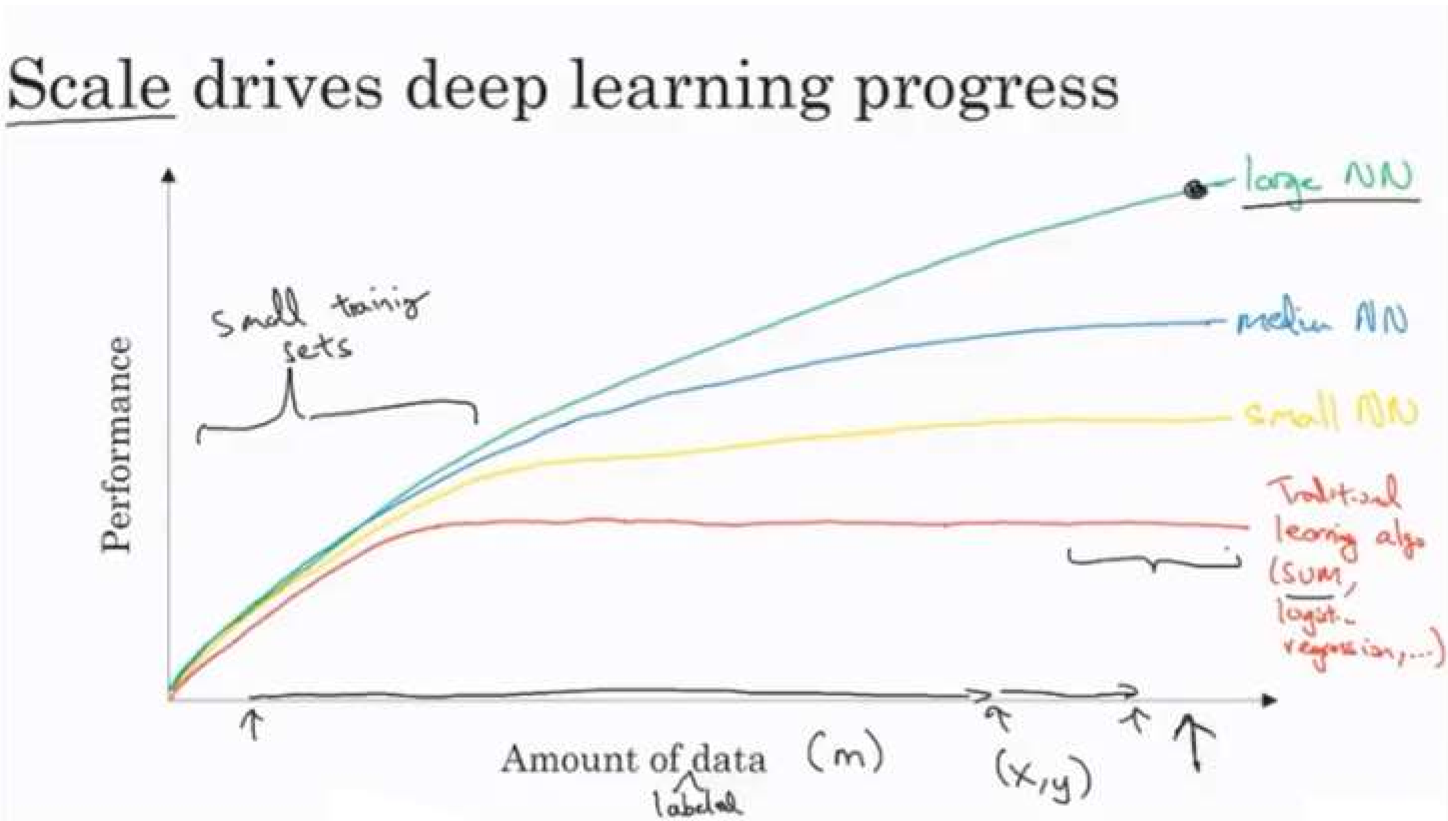

Image Source: Andrew Ng

- Data
- Computations
- Algorithm

So, 1. **what exactly is deep learning** ?

And, 2. **why is it generally better** than other methods on image, speech and certain other types of data?

So, 1. **what exactly is deep learning** ?

And, 2. **why is it generally better** than other methods on image, speech and certain other types of data?

The short answers

1. **'Deep Learning' means** using a **neural network** with **several layers of nodes** between input and output

2. **the series of layers between input & output do feature identification and processing in a series of stages, just as our brains seem to.**

hmmm… OK, but:

3. **multilayer neural networks have been around for 25 years. What's actually new?**

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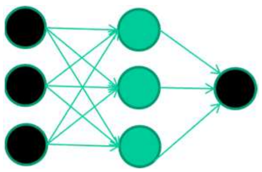
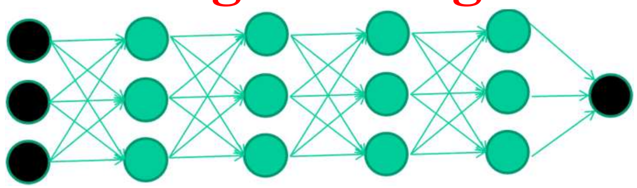
3. **multilayer neural networks have been around for 25 years. What's actually new?**

we have always had good algorithms for learning the weights in networks with 1 hidden layer



but these algorithms are not good at learning the weights for networks with more hidden layers

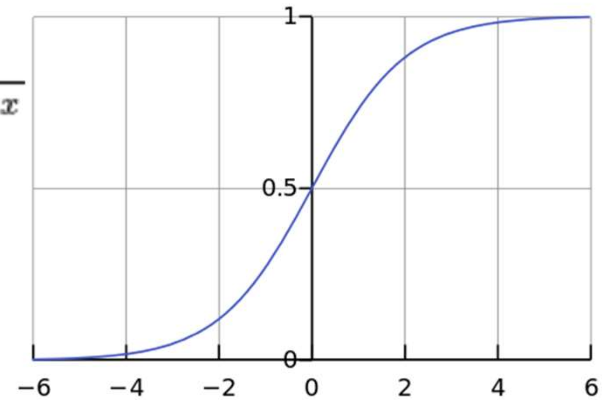


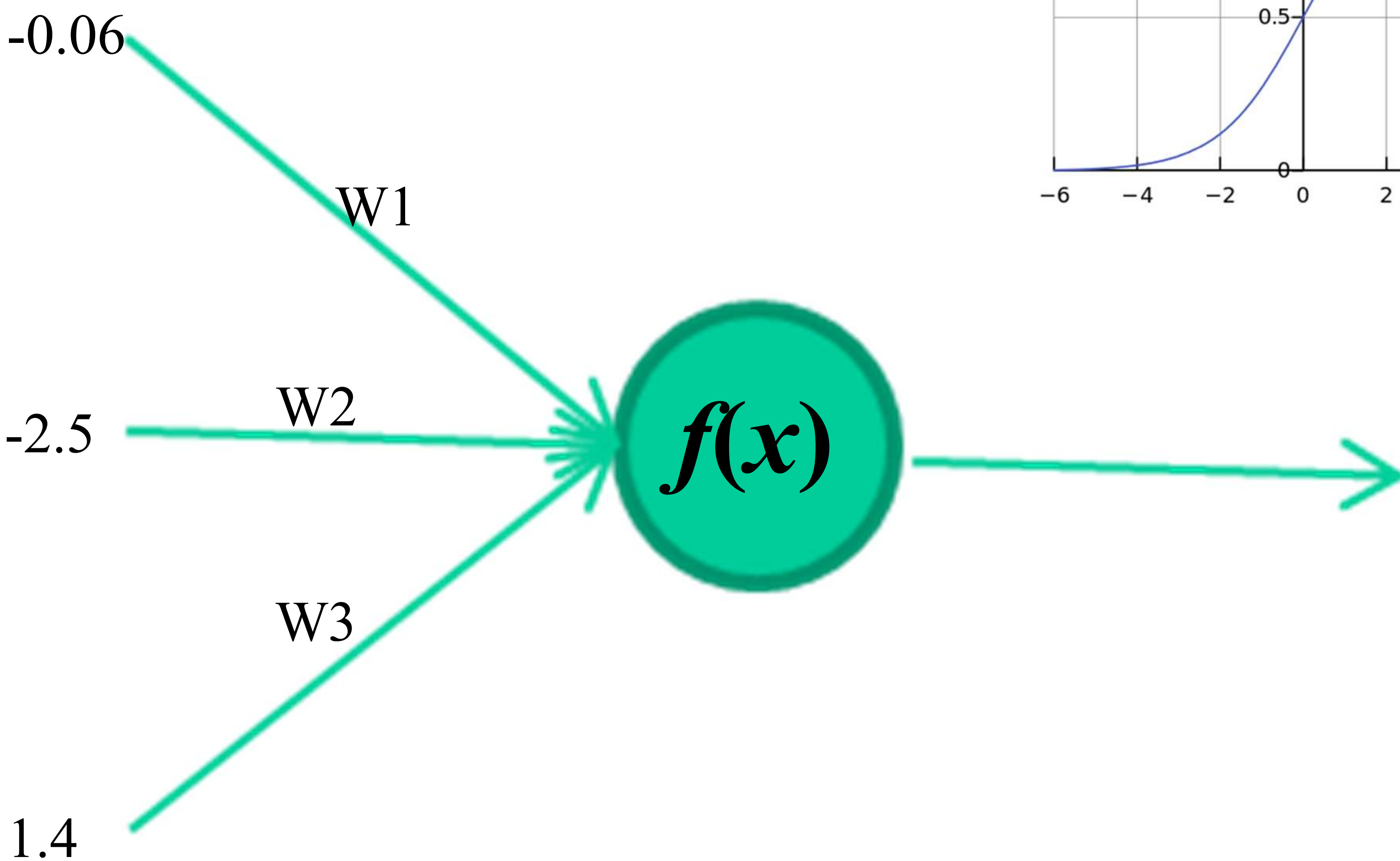
what's new is: <u>**algorithms for training many-layer networks**</u>

longer answers

1. reminder/quick-explanation of how neural network weights are learned;
2. the idea of **unsupervised feature learning** (why 'intermediate features' are important for difficult classification tasks, and how NNs seem to naturally learn them)
3. The 'breakthrough' – the simple trick for training Deep neural networks

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





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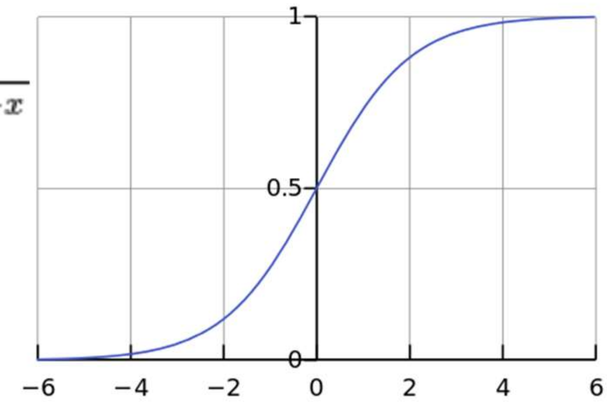
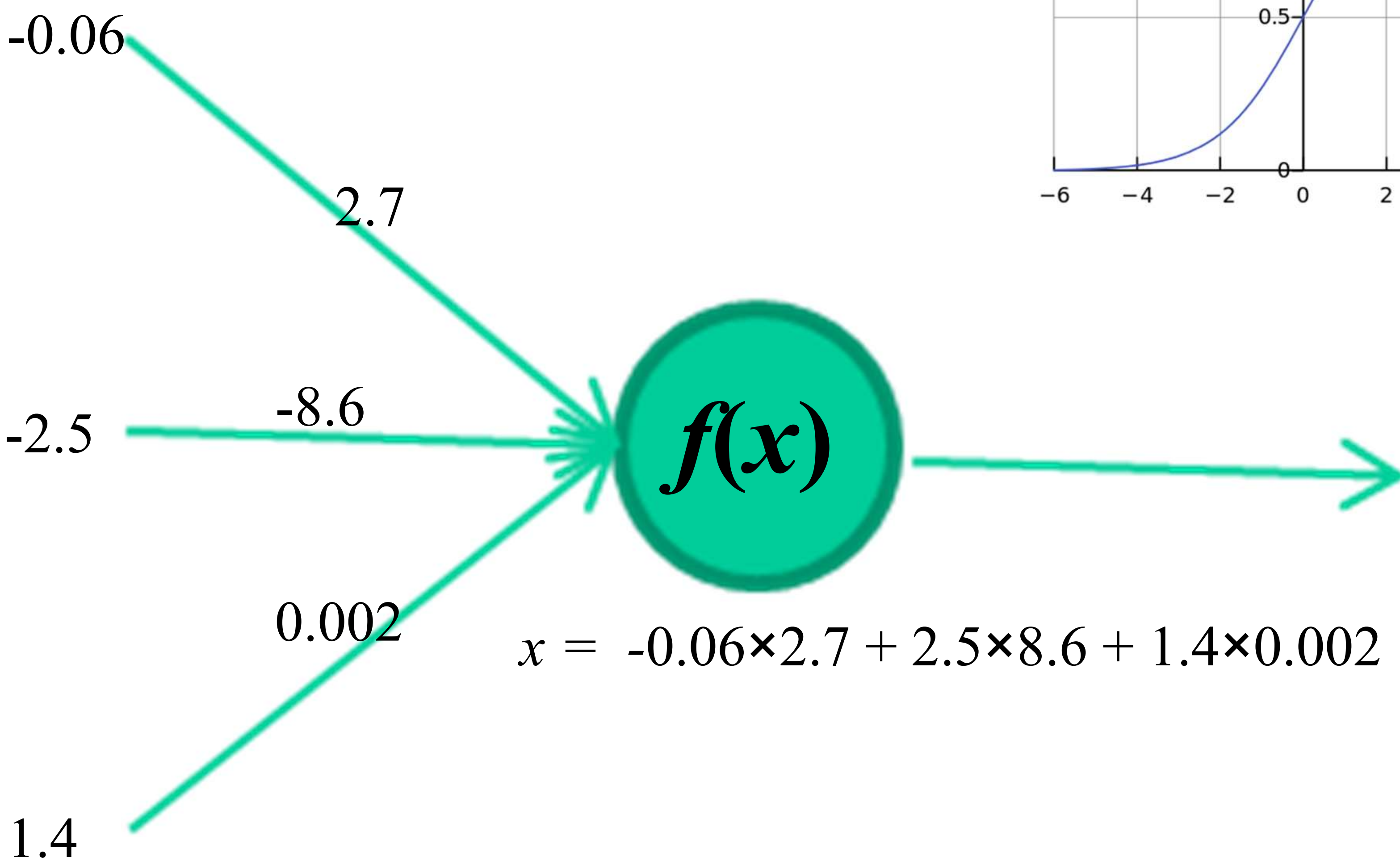
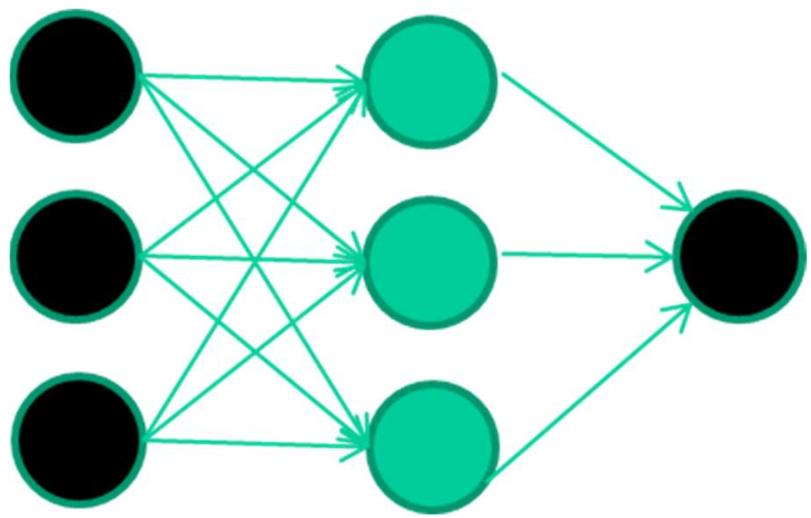




$$x = -0.06\times2.7 + 2.5\times8.6 + 1.4\times0.002 = 21.34$$

A dataset

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			



Training the neural network

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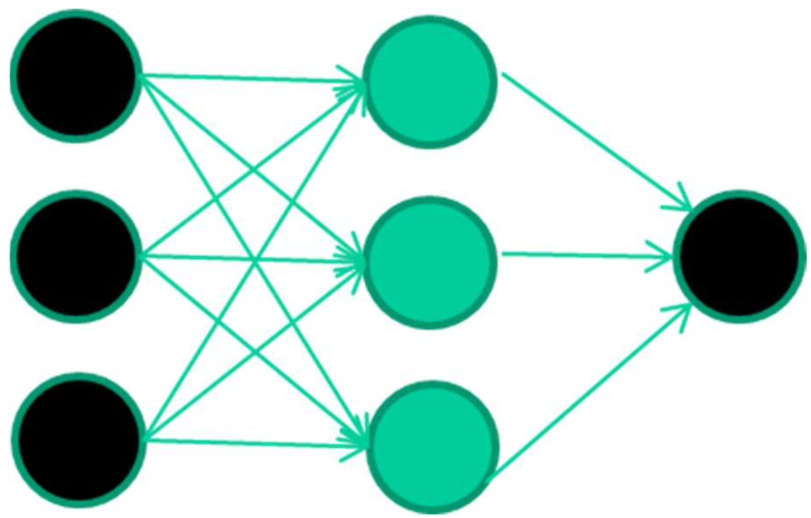

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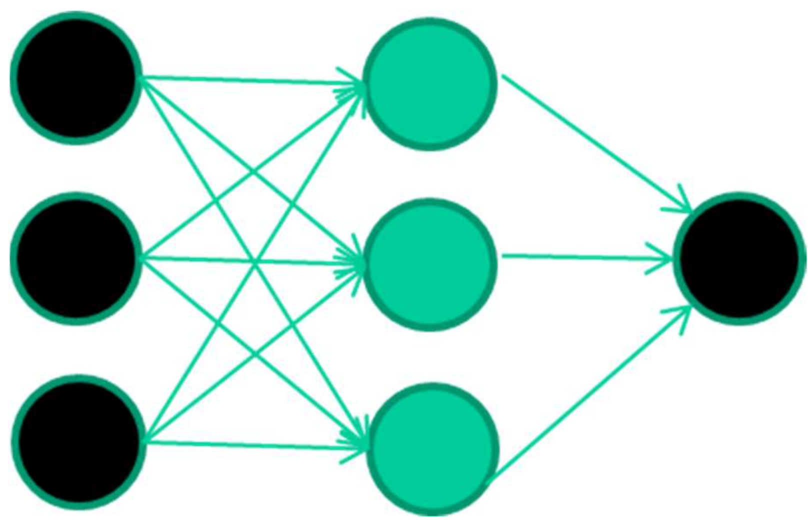
etc …			

Initialise with random weights



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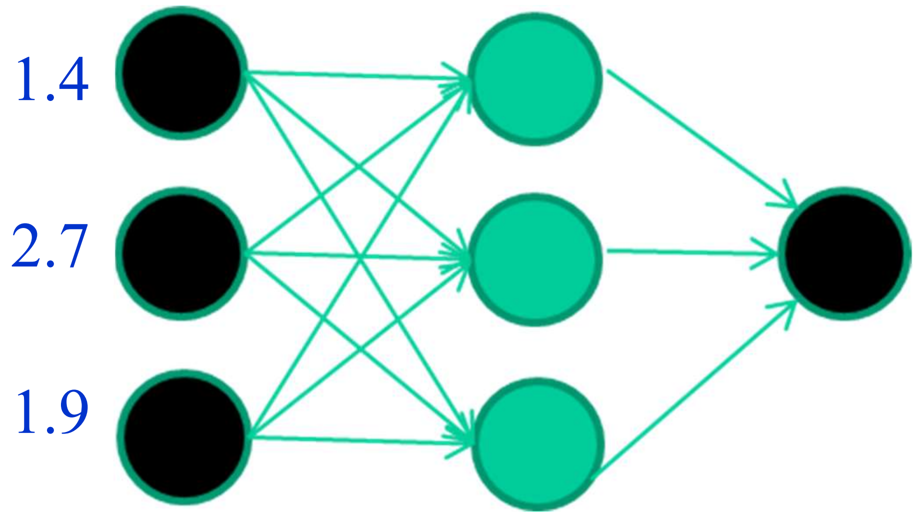
Present a training pattern



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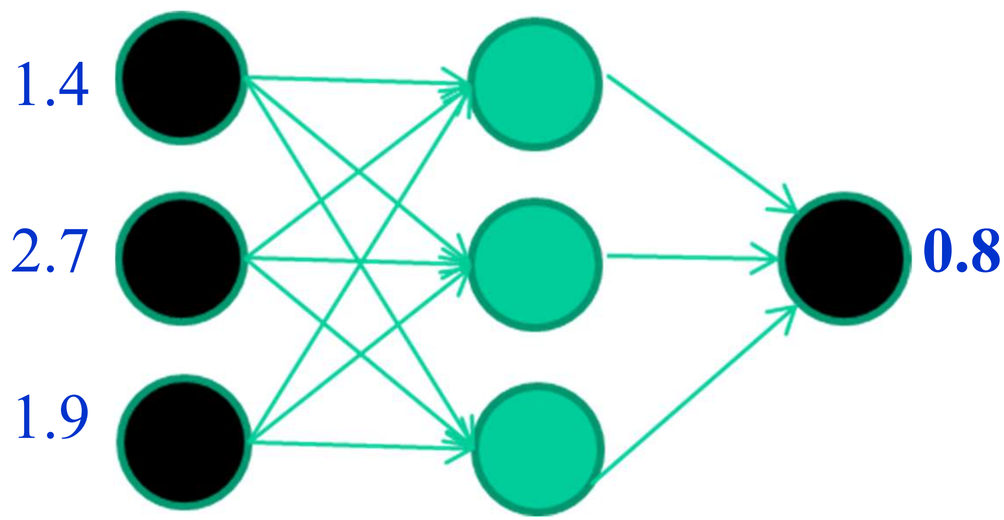
Feed it through to get output



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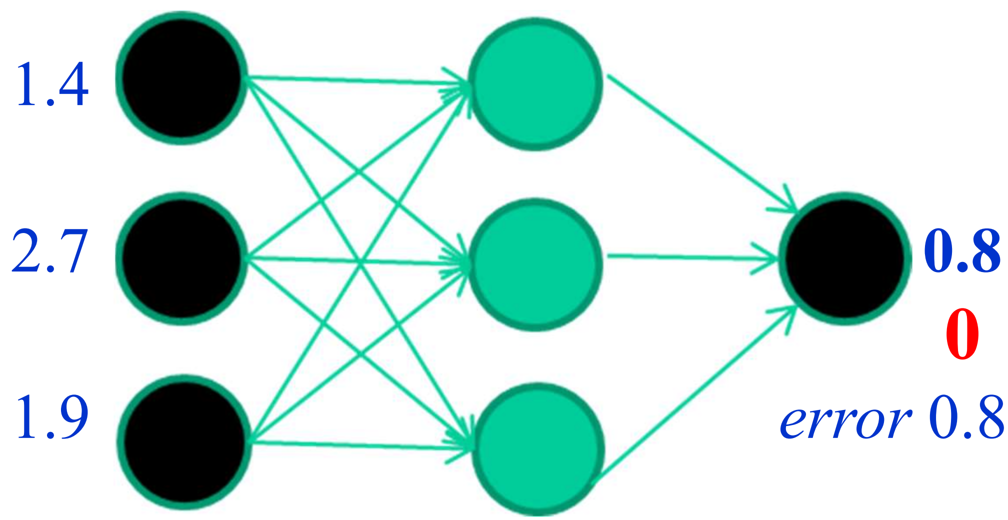
Compare with target output



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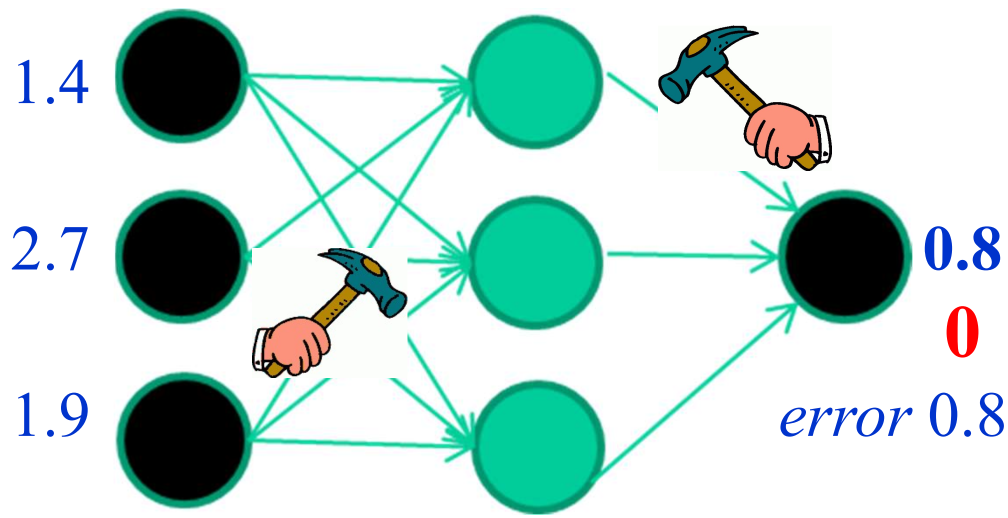
etc …			

Adjust weights based on error



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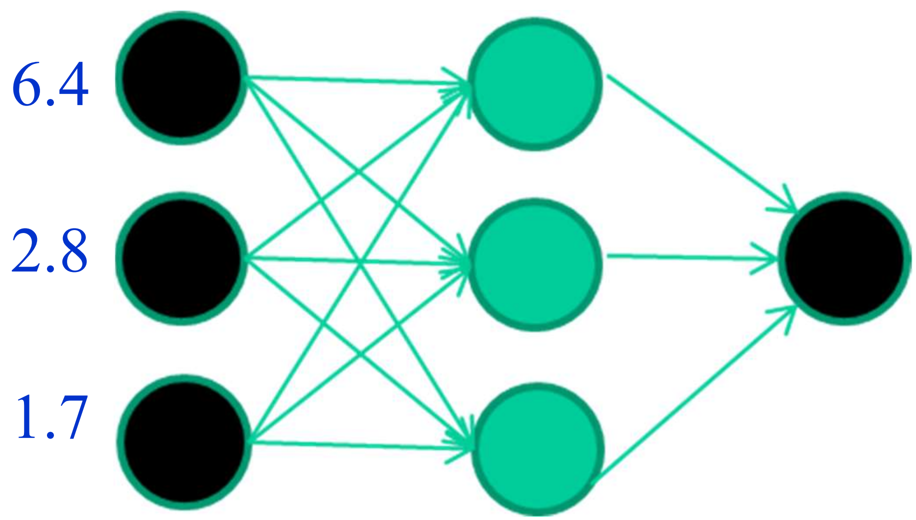

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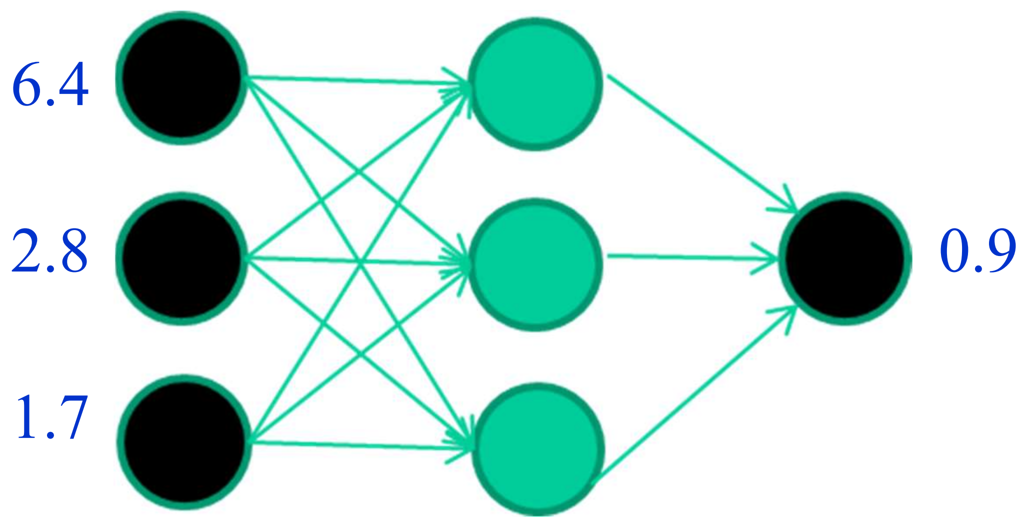

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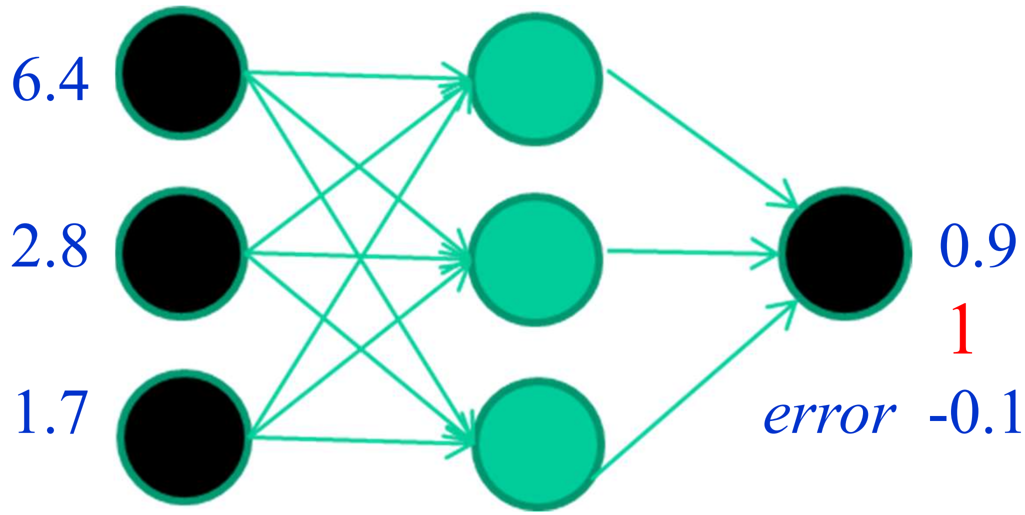

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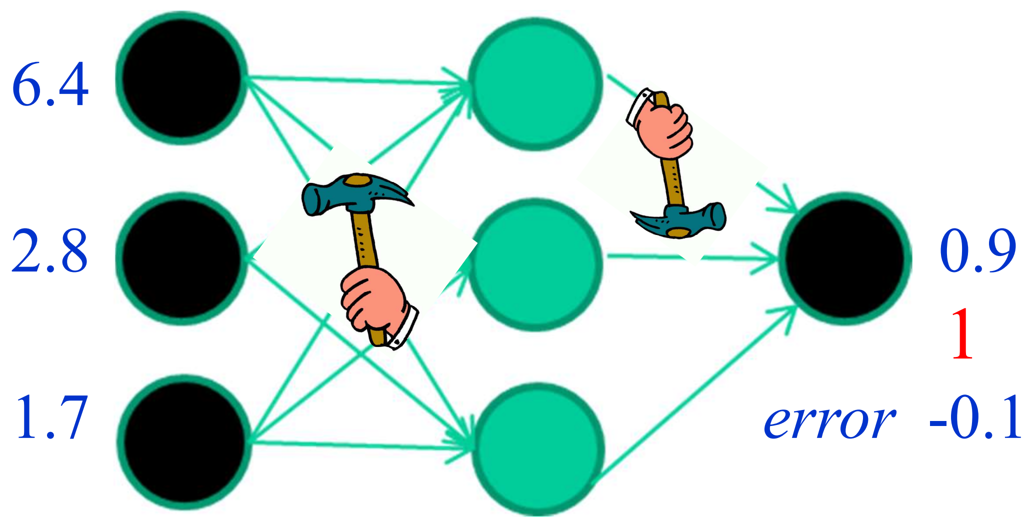

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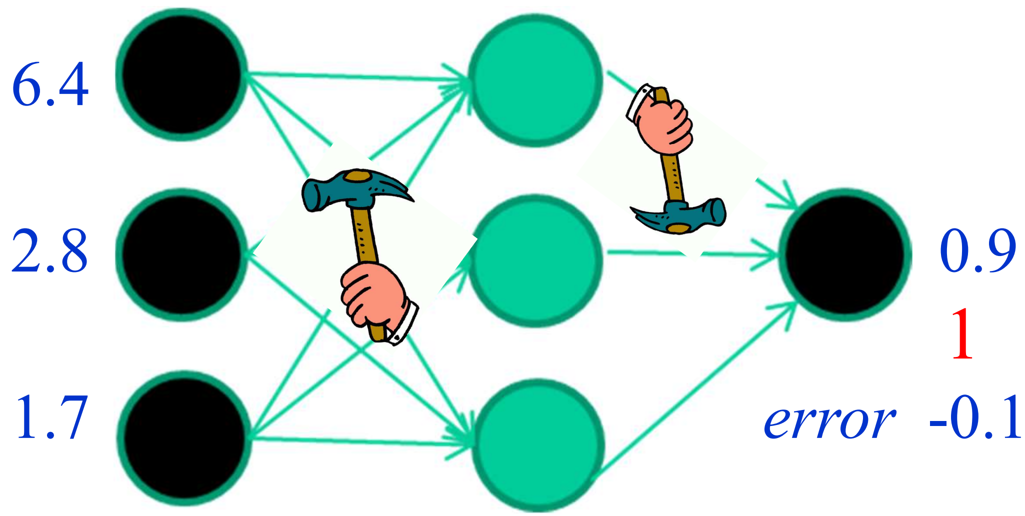
And so on ….

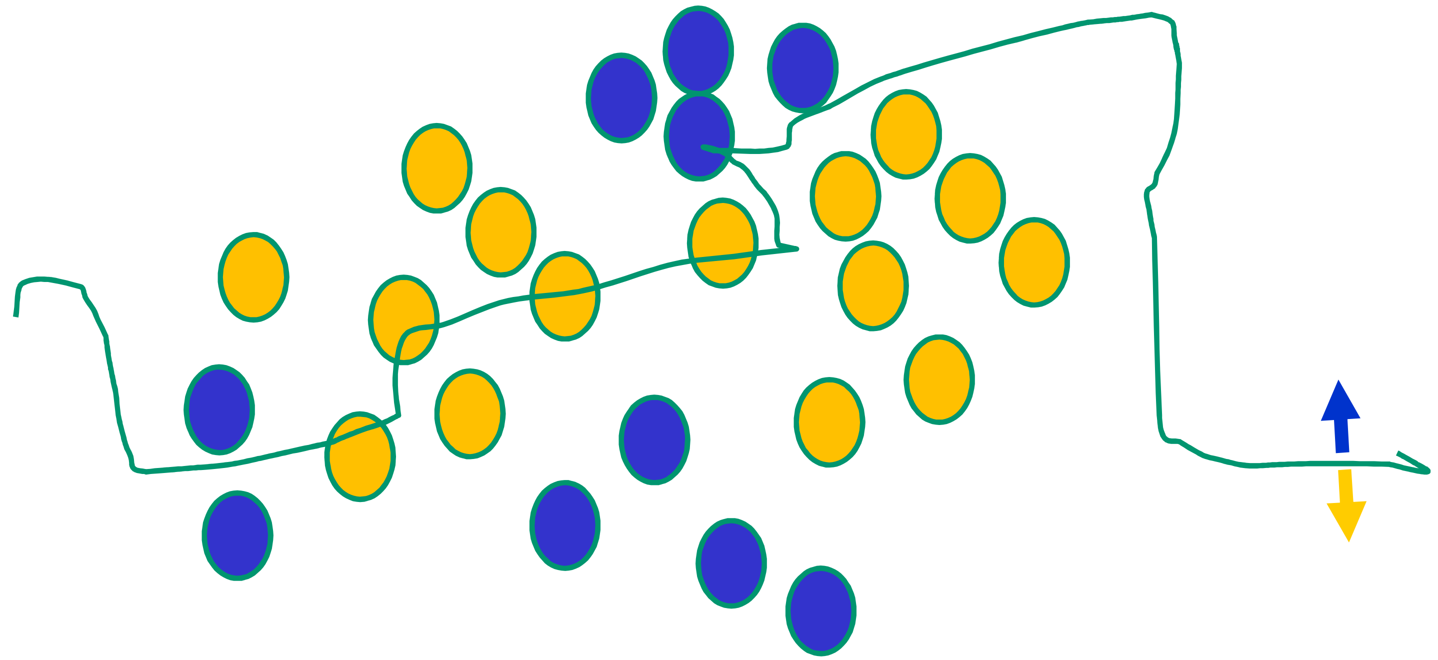


Repeat this thousands, maybe millions of times – each time taking a random training instance, and making slight weight adjustments

Algorithms for weight adjustment are designed to make changes that will reduce the error

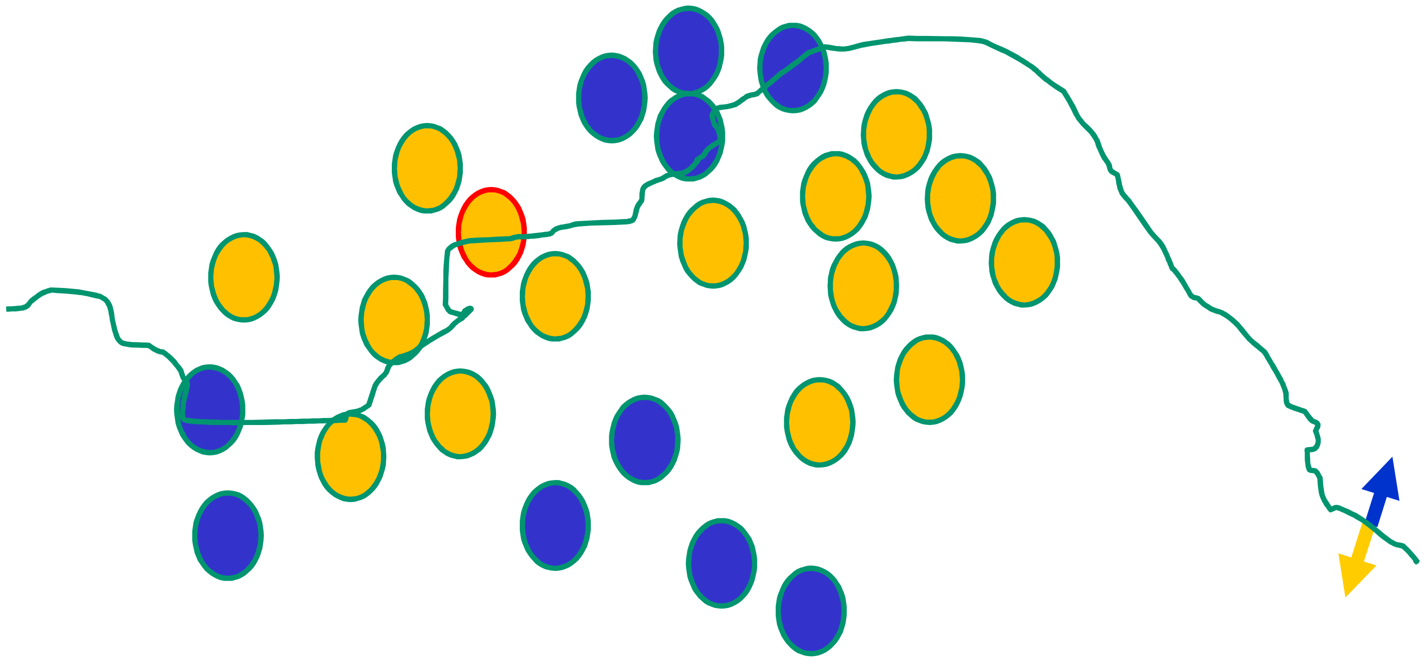
The decision boundary perspective…

Initial random weights



The decision boundary perspective…

Present a training instance / adjust the weights



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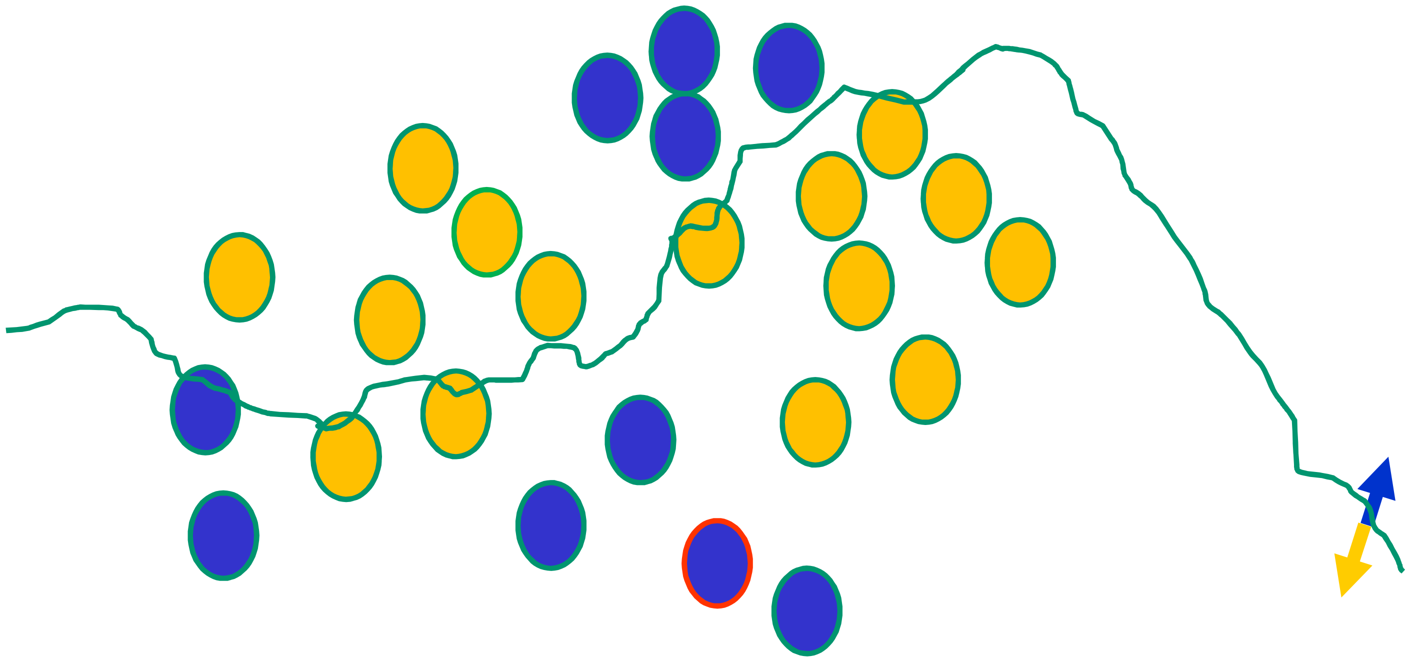

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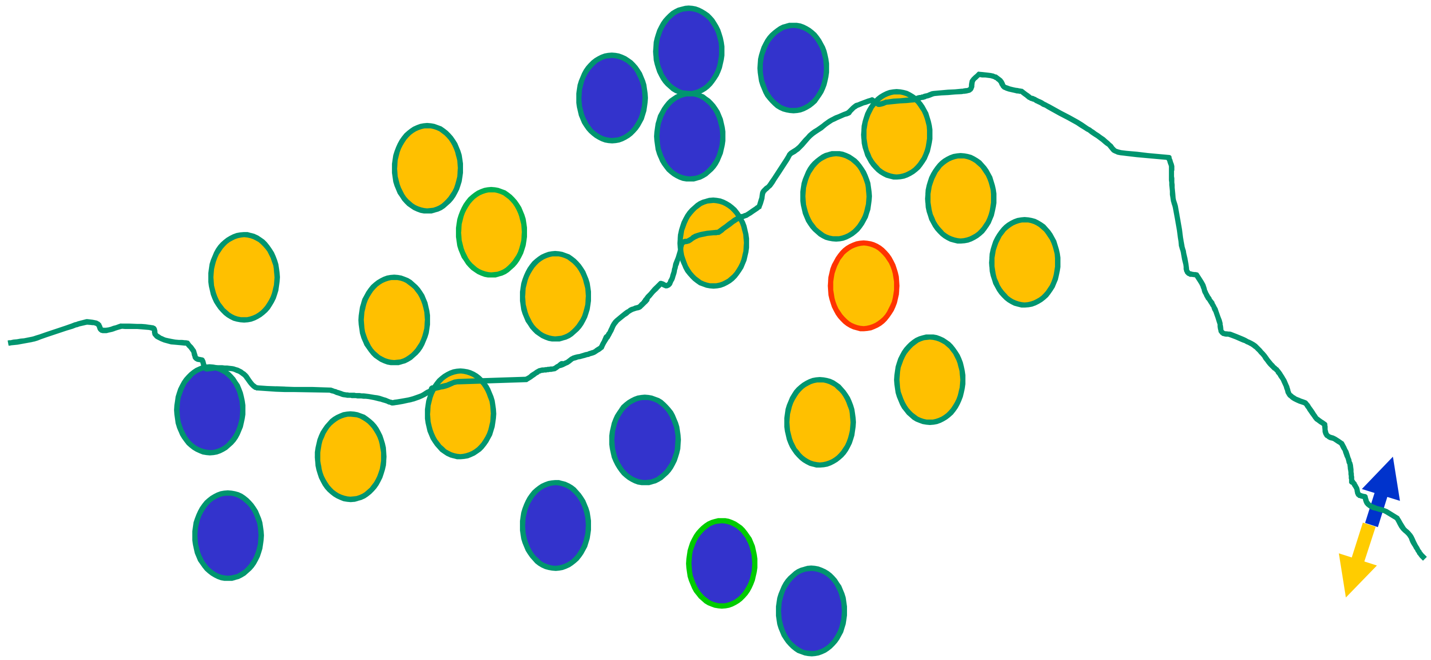

The decision boundary perspective…

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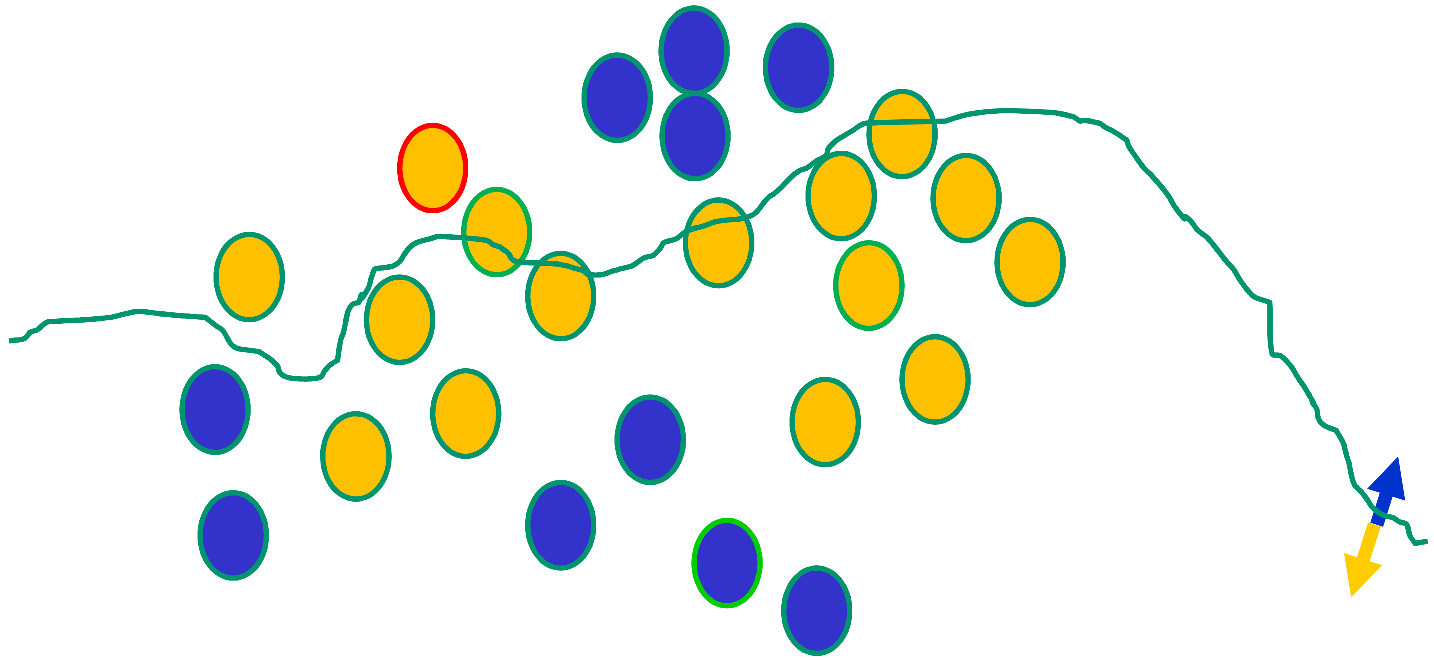
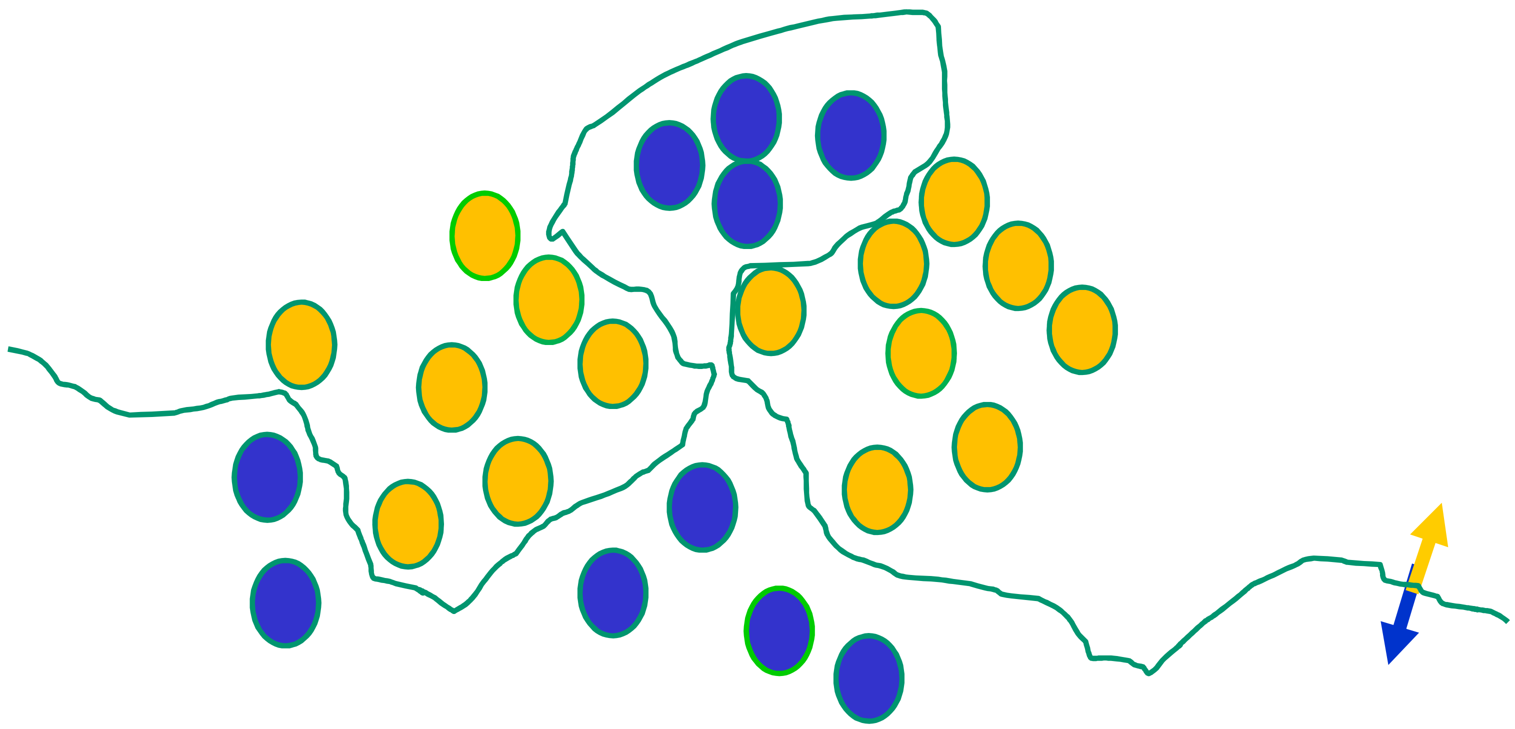


The decision boundary perspective…

Eventually ….

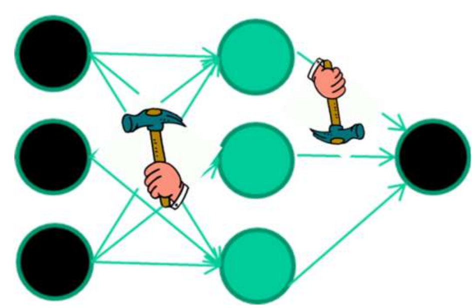


The point I am trying to make

- weight-learning algorithms for NNs are dumb

- they work by making thousands and thousands of tiny adjustments, each making the network do better at the most recent pattern, but perhaps a little worse on many others

- but, by dumb luck, eventually this tends to be good enough to learn effective classifiers for many real applications



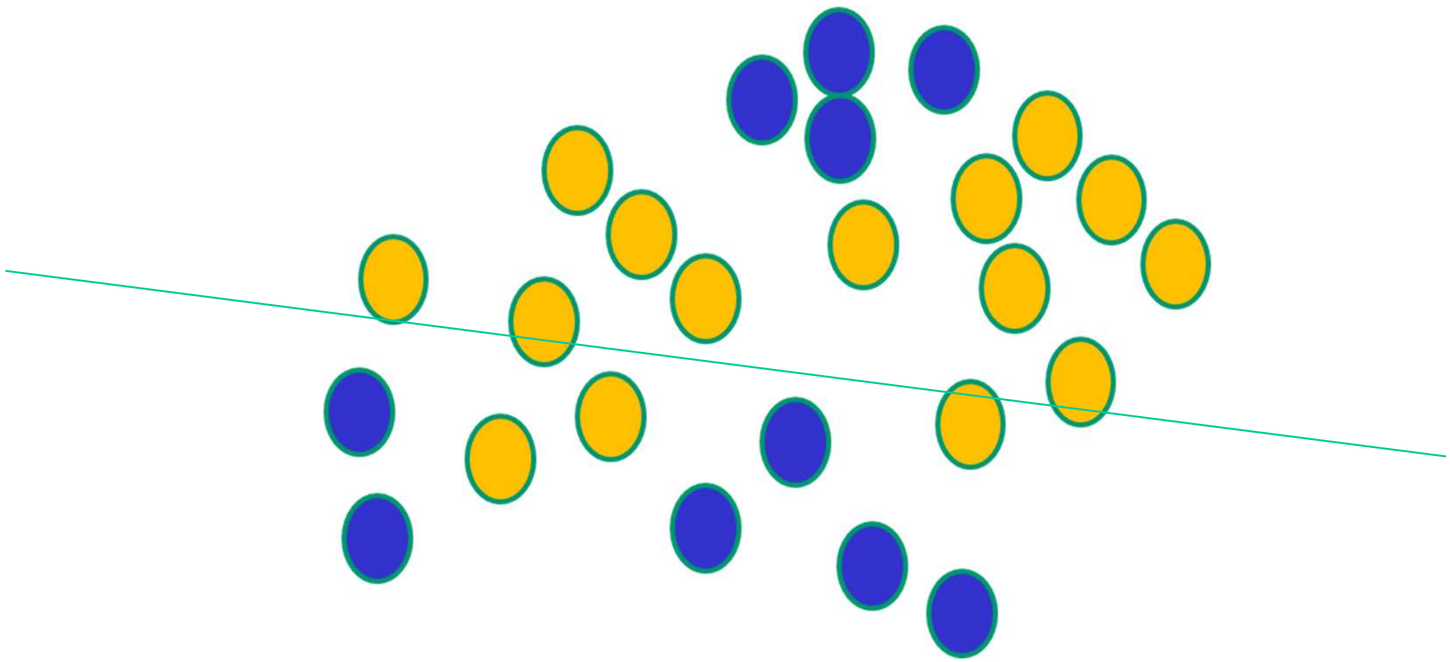
Some other points

Detail of a standard NN weight learning algorithm – **later**

If $f(x)$ is non-linear, a network with 1 hidden layer can, in theory, learn perfectly any classification problem. A set of weights exists that can produce the targets from the inputs. The problem is finding them.

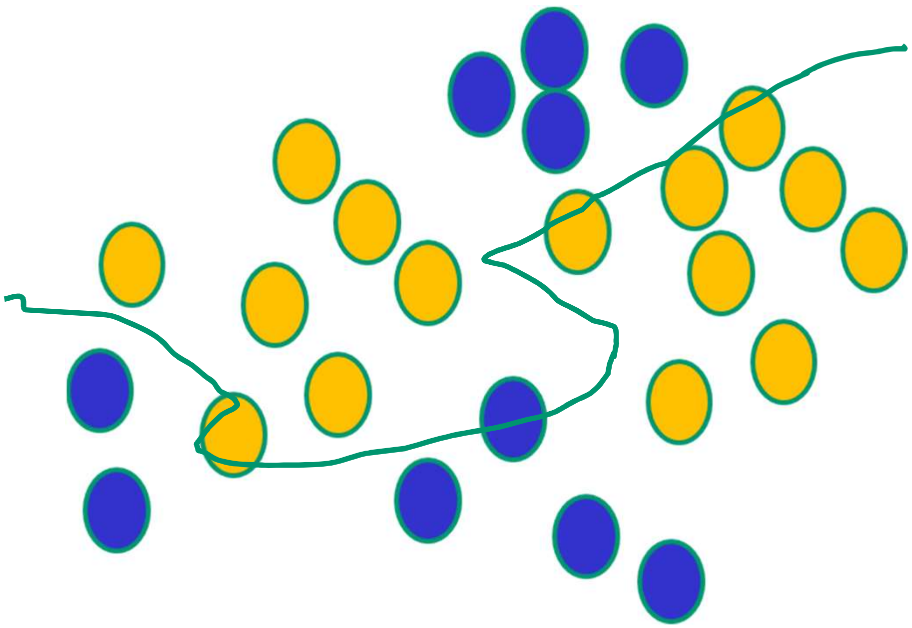
Some other ‘by the way’ points

If $f(x)$ is linear, the NN can **only** draw straight decision boundaries (even if there are many layers of units)



Some other 'by the way' points

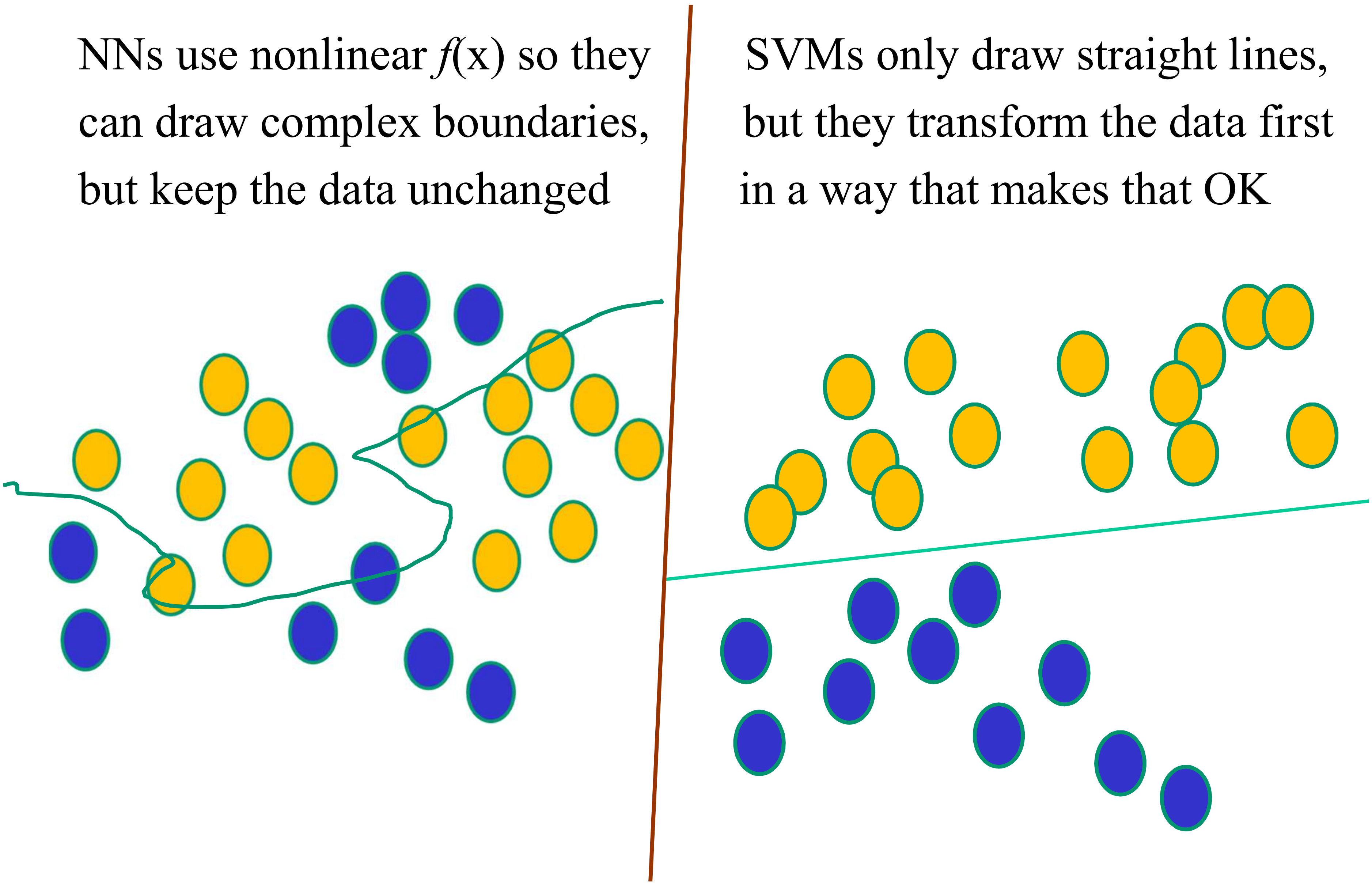
NNs use nonlinear *f*(x) so they can draw complex boundaries, but keep the data unchanged



Some other 'by the way' points

NNs use nonlinear *f*(x) so they can draw complex boundaries, but keep the data unchanged

SVMs only draw straight lines, but they transform the data first in a way that makes that OK



Feature detectors

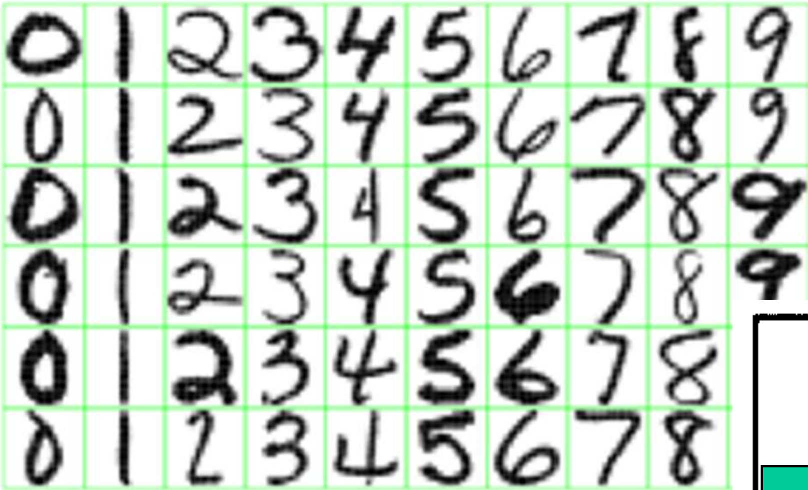
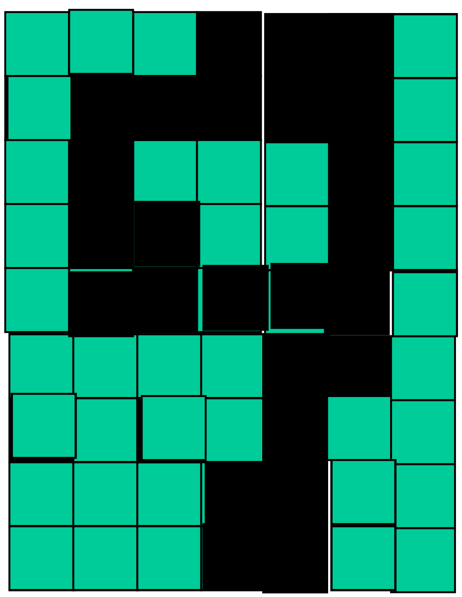
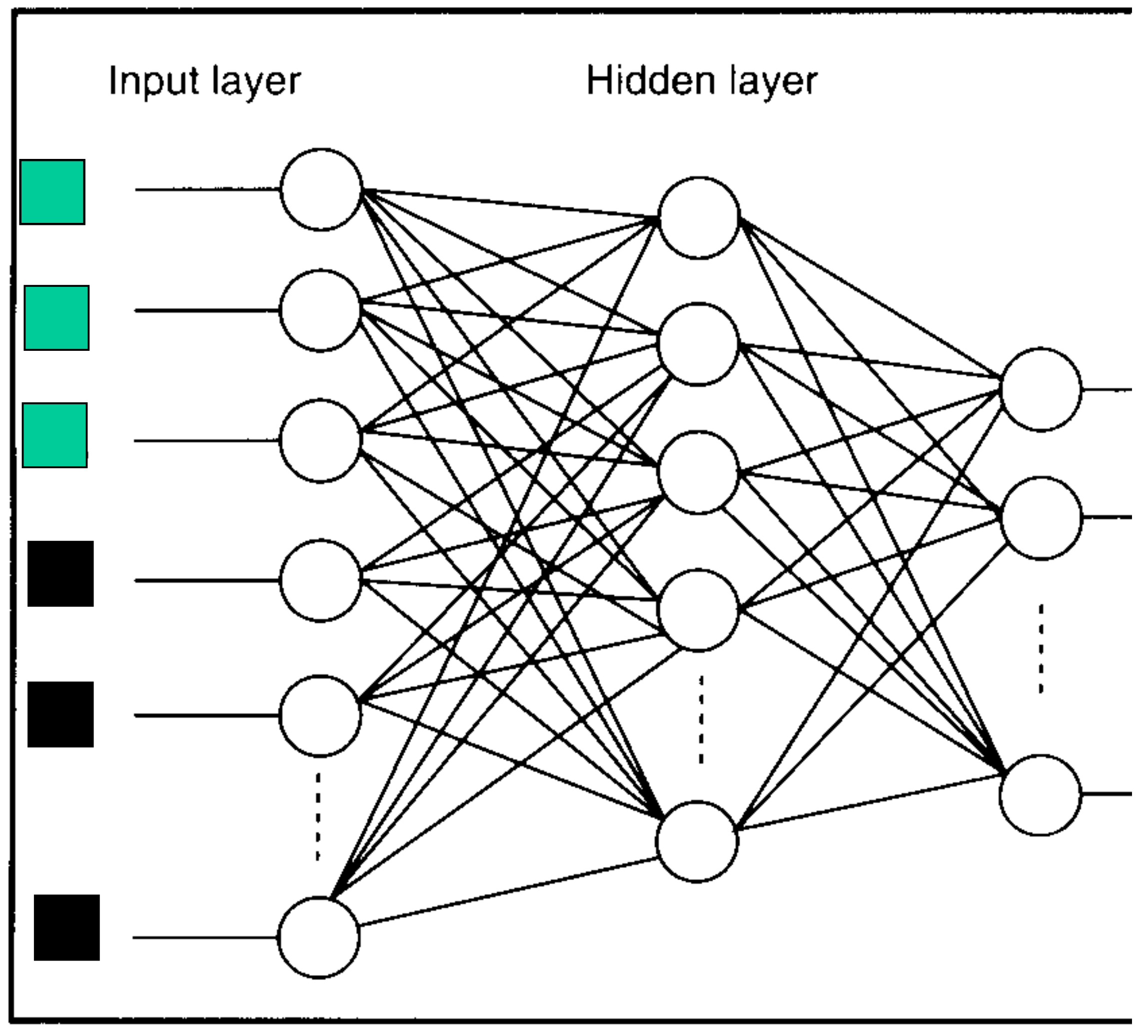
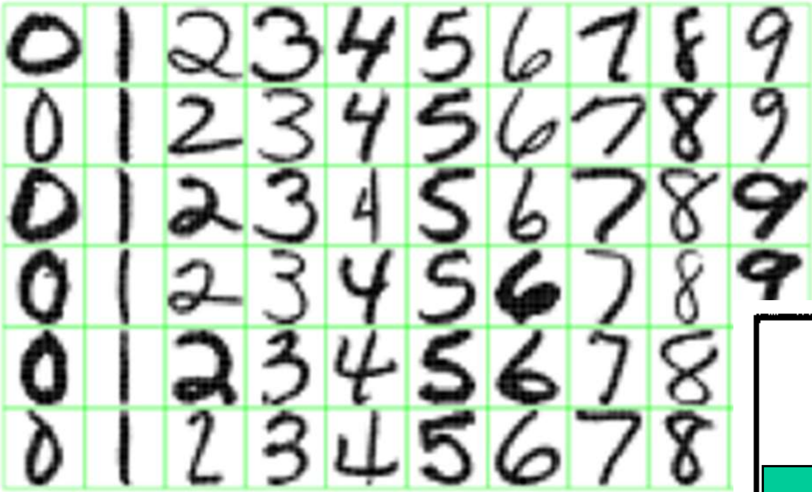


Figure 1.2: *Examples of handwritten digits from postal envelopes.*





what is this unit doing?



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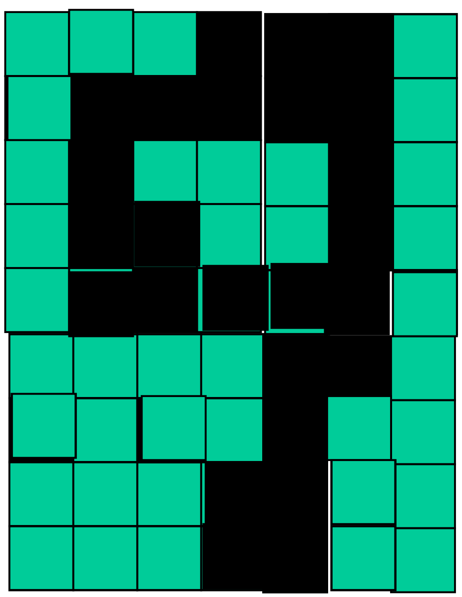
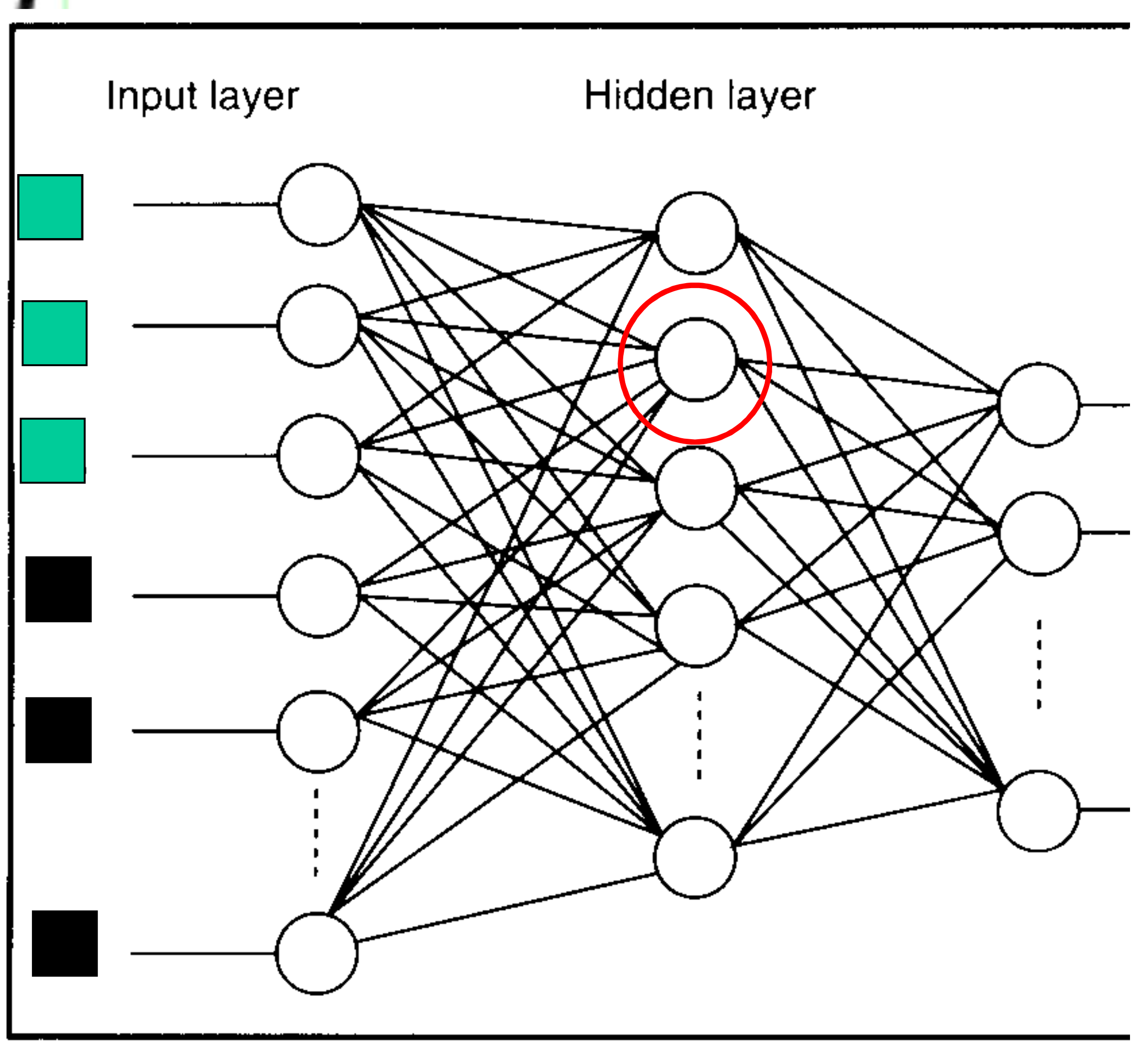
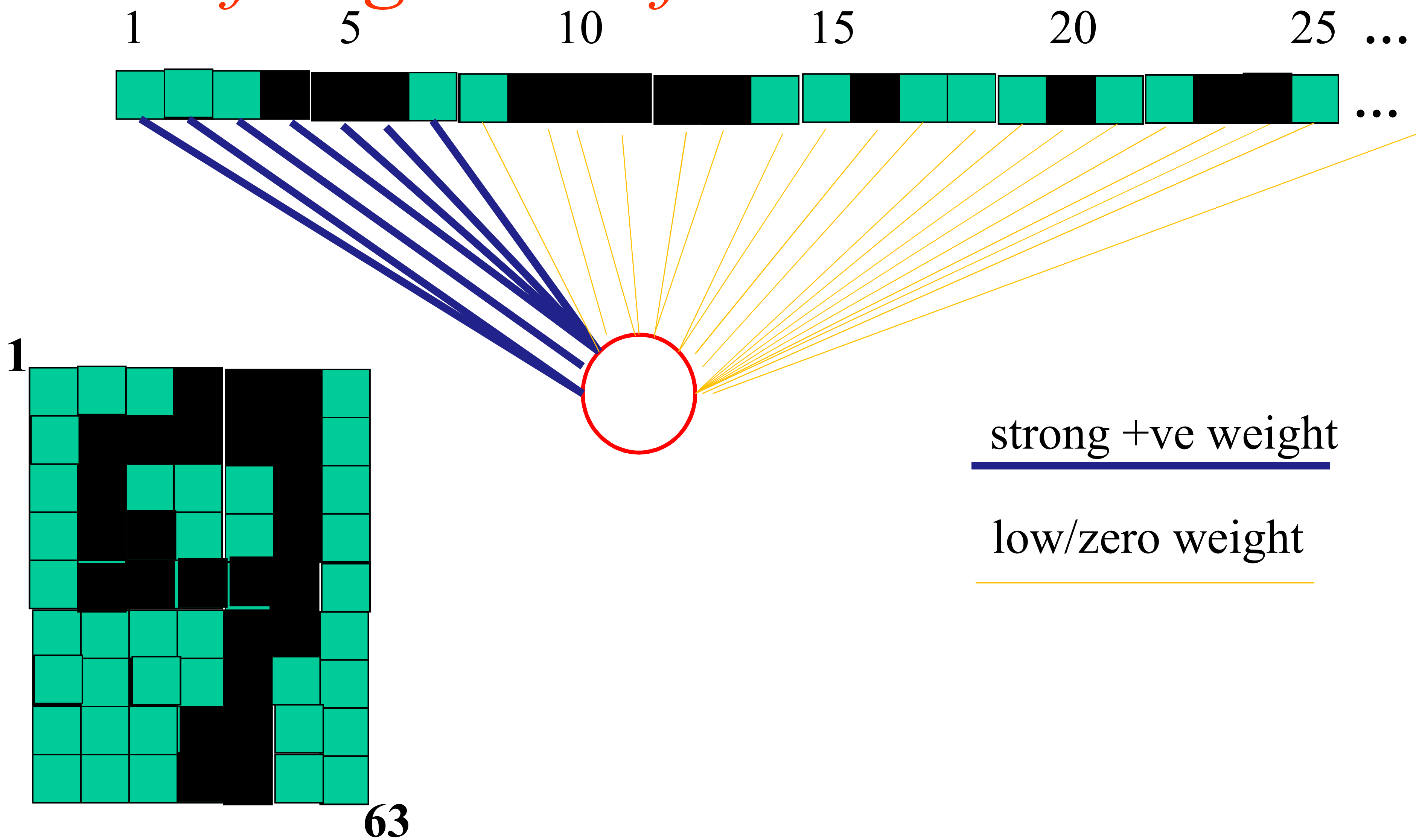
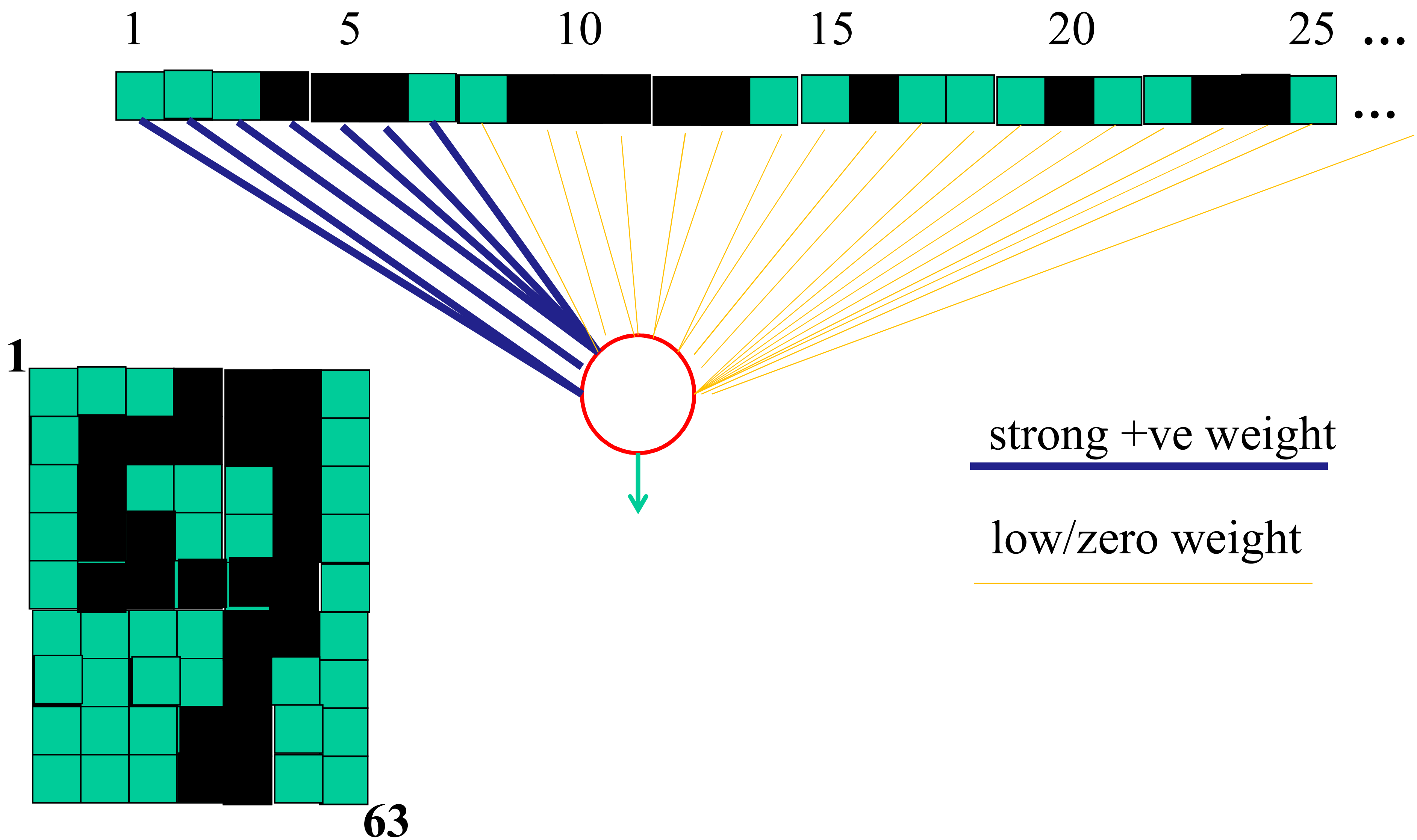




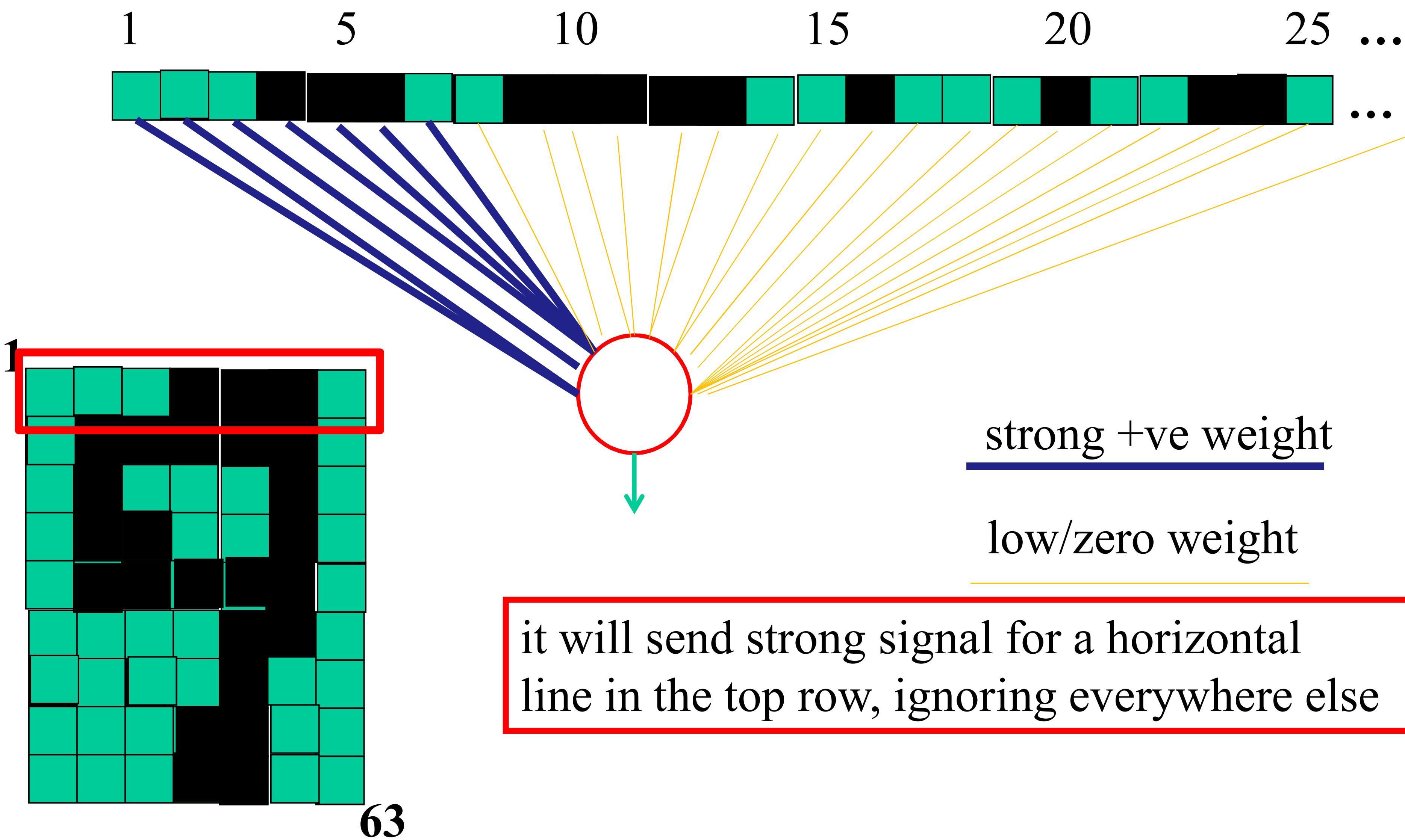
Hidden layer units become *self-organised feature detectors*



What does this unit detect?

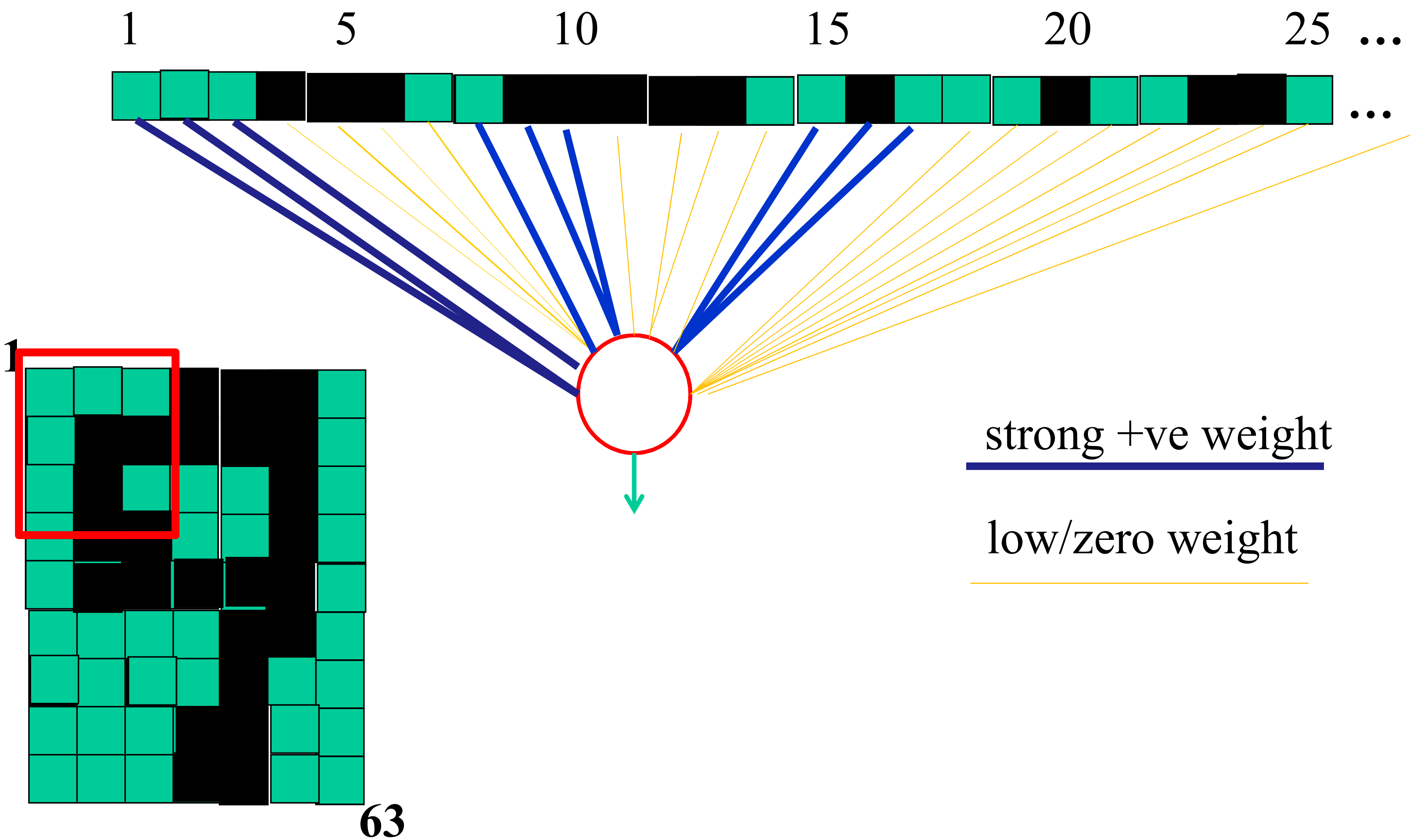


What does this unit detect?



it will send strong signal for a horizontal line in the top row, ignoring everywhere else

What does this unit detect?



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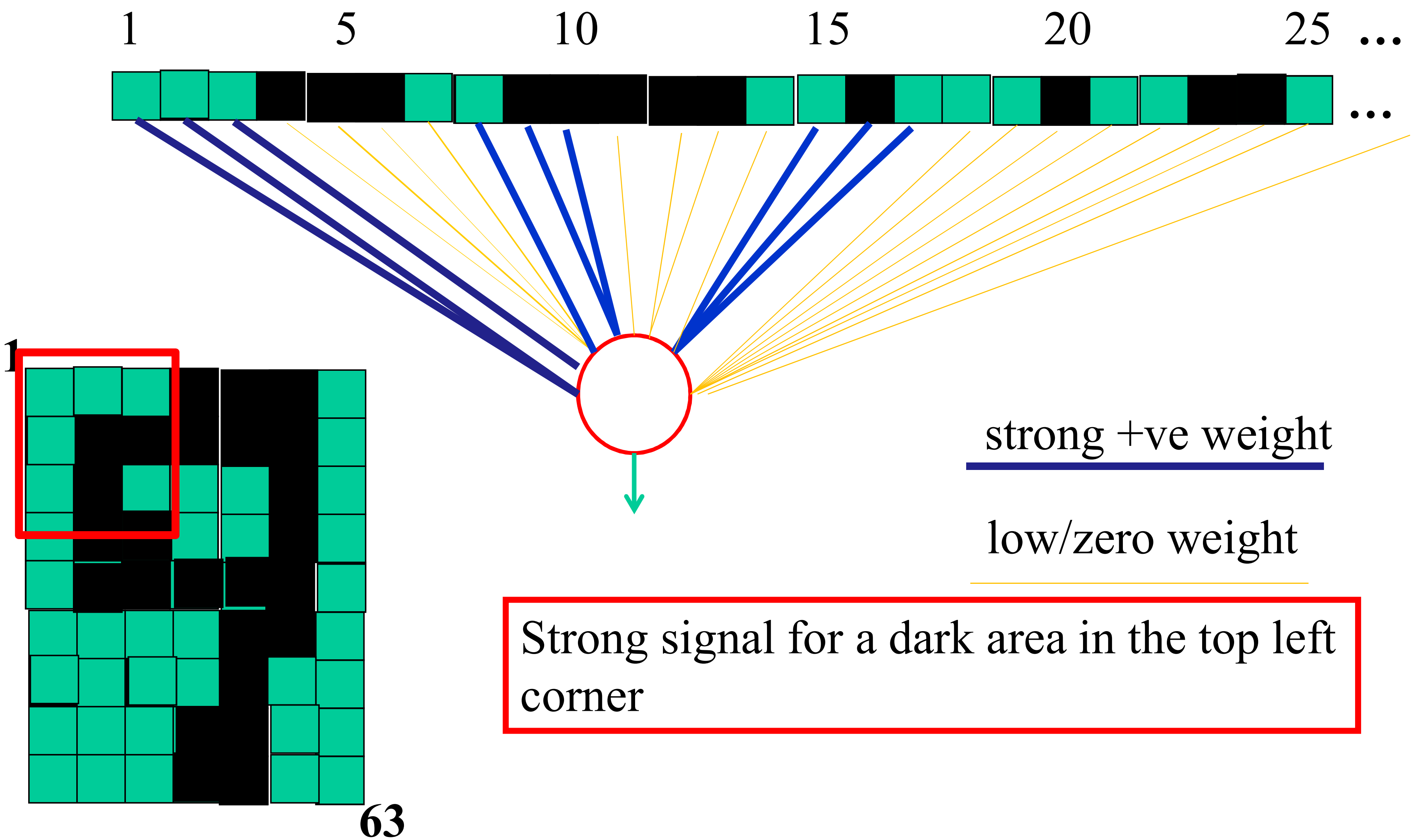


Strong signal for a dark area in the top left corner

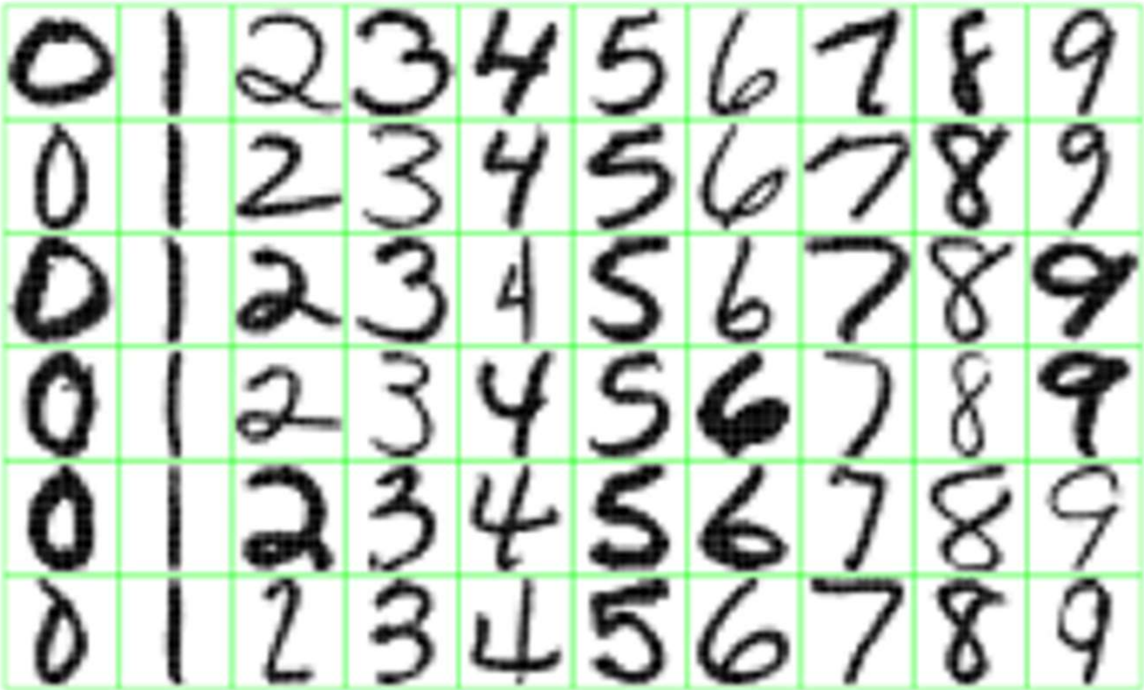
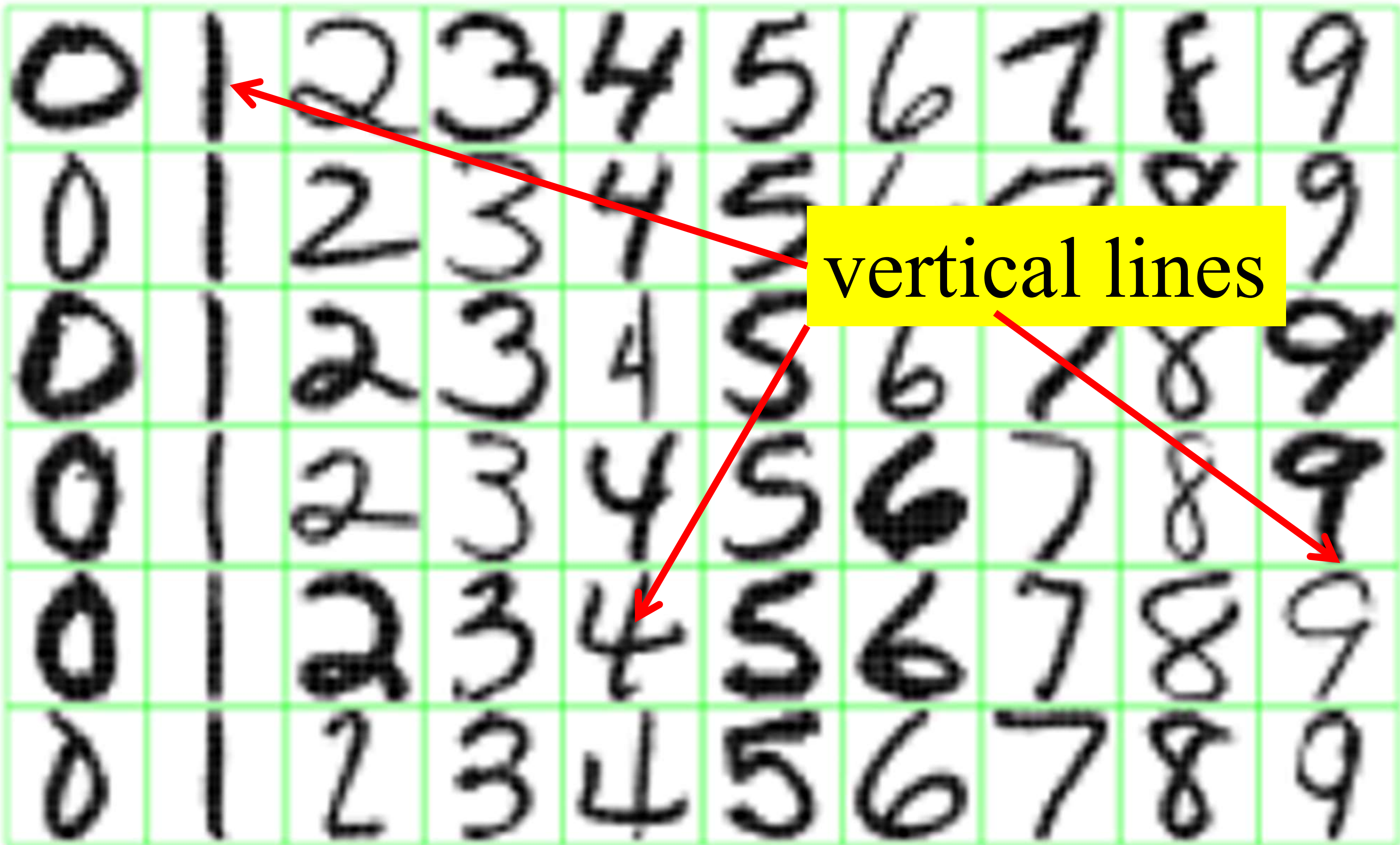


Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*

What features might you expect a good NN to learn, when trained with data like this?

1



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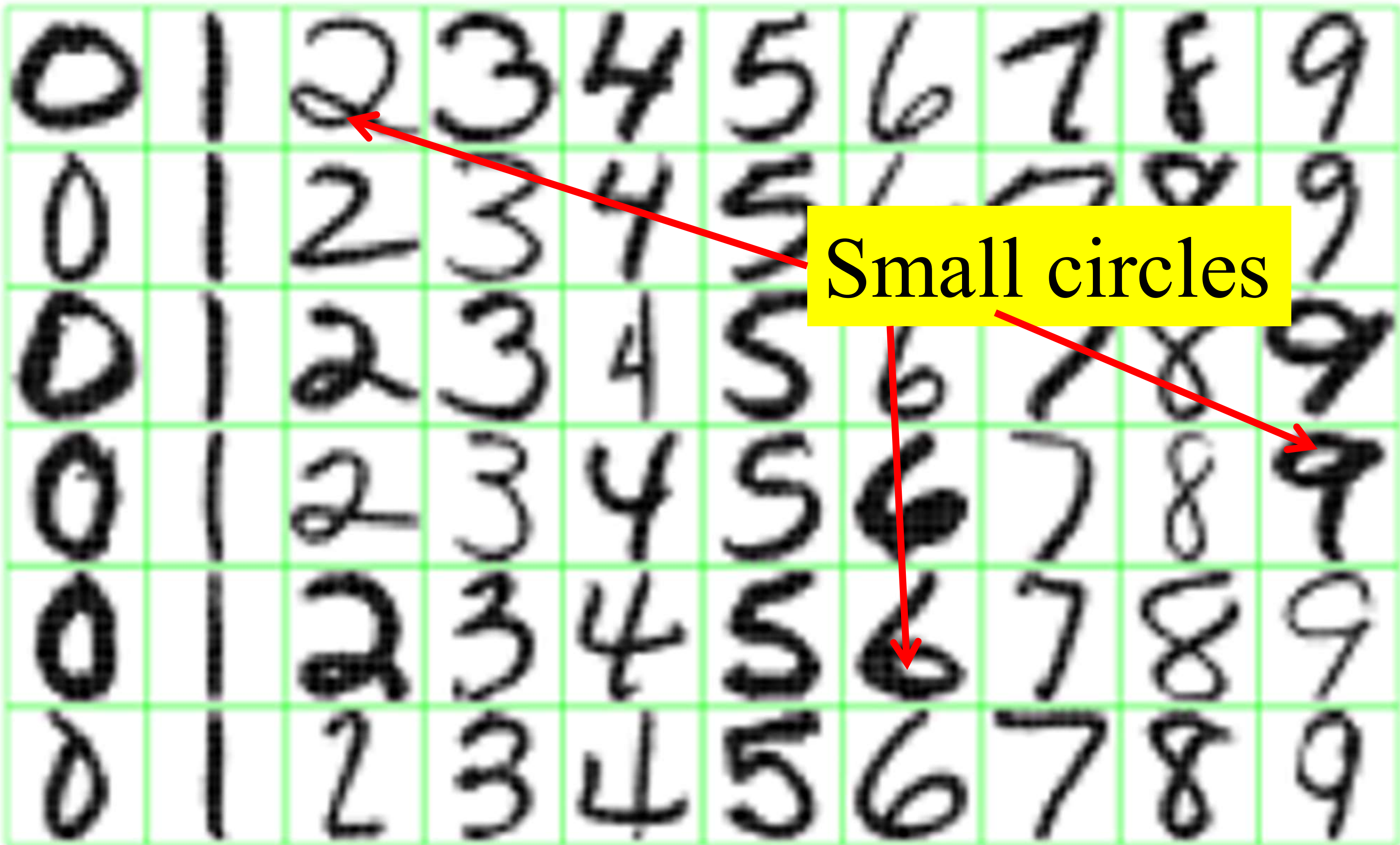

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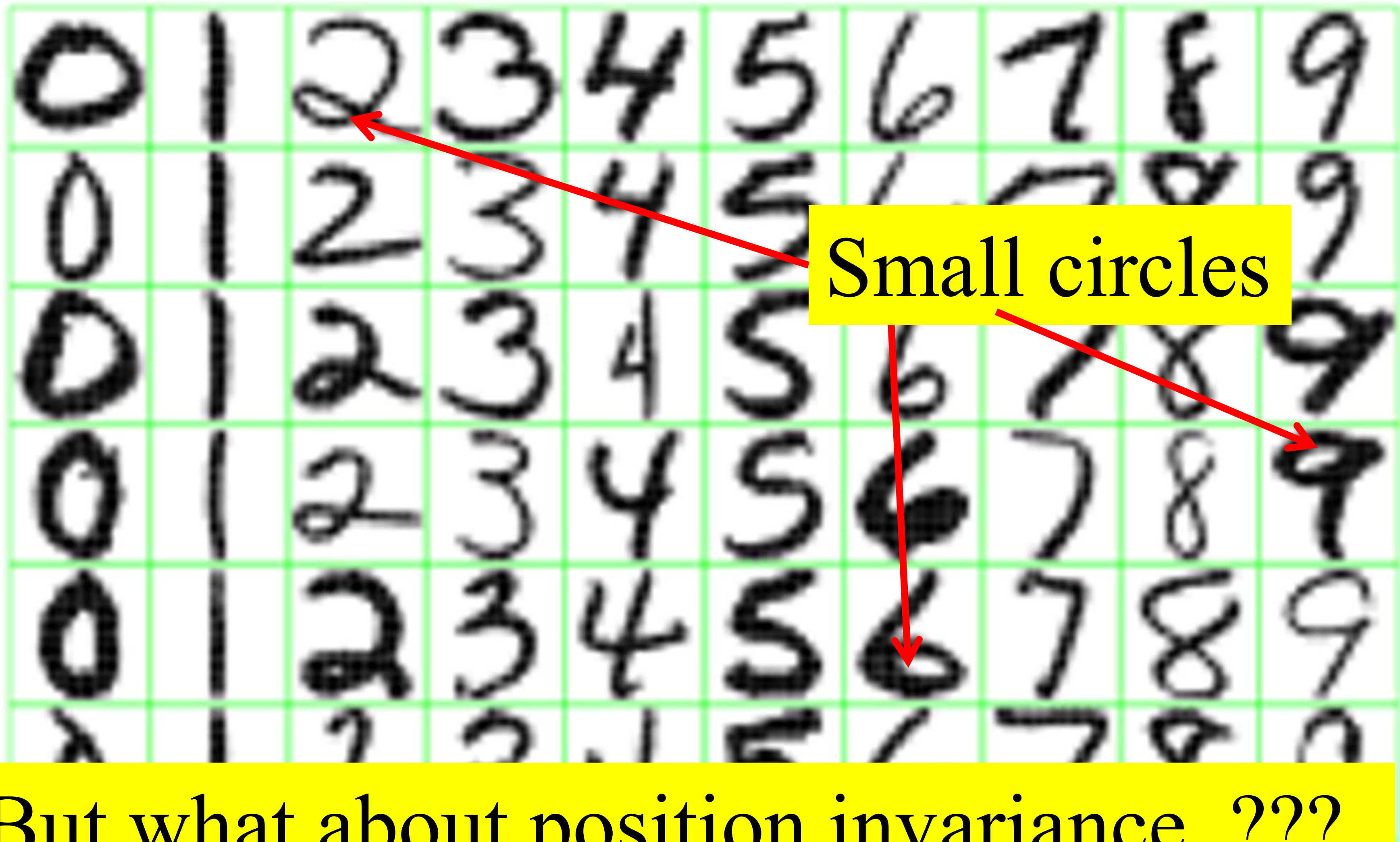
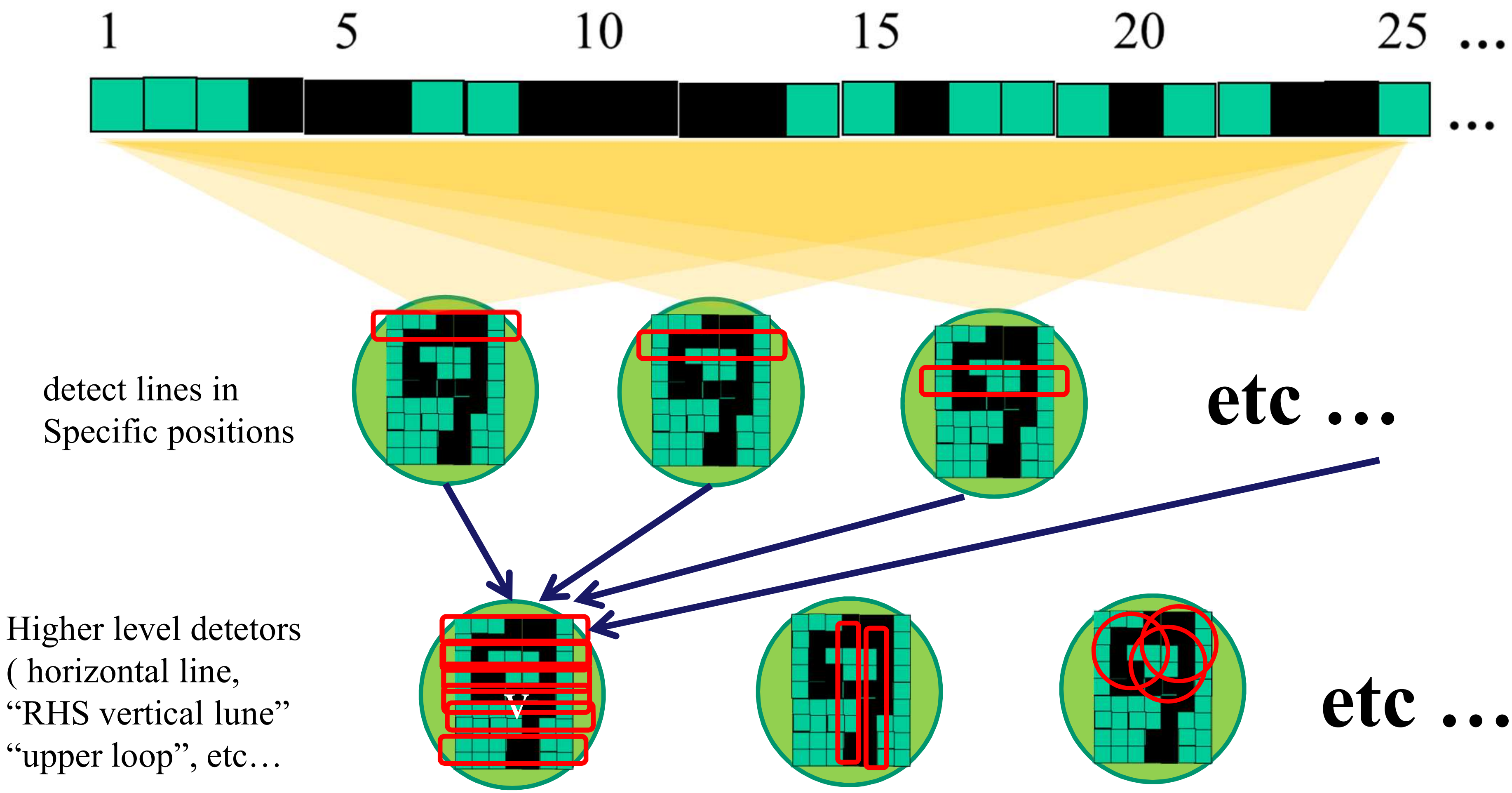


But what about position invariance ???
our example unit detectors were tied to specific parts of the image

successive layers can learn higher-level features …



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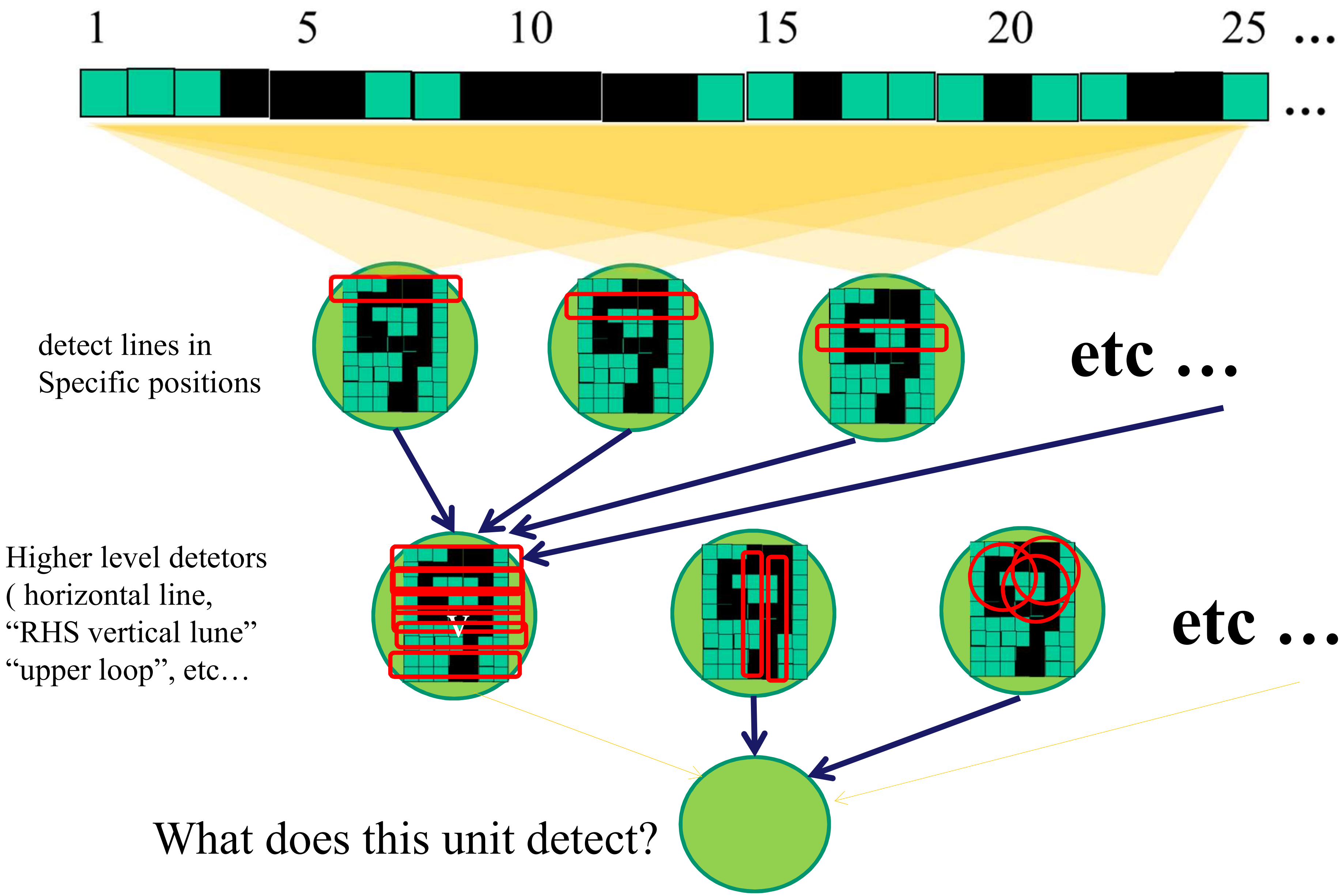
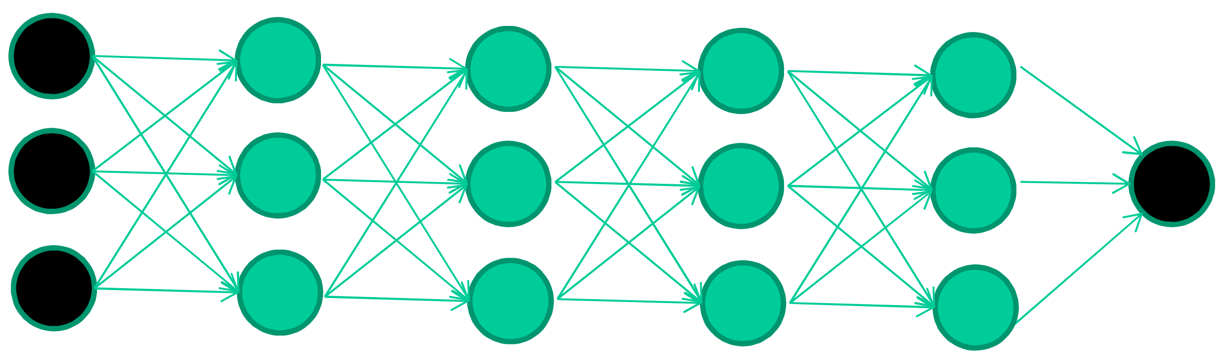
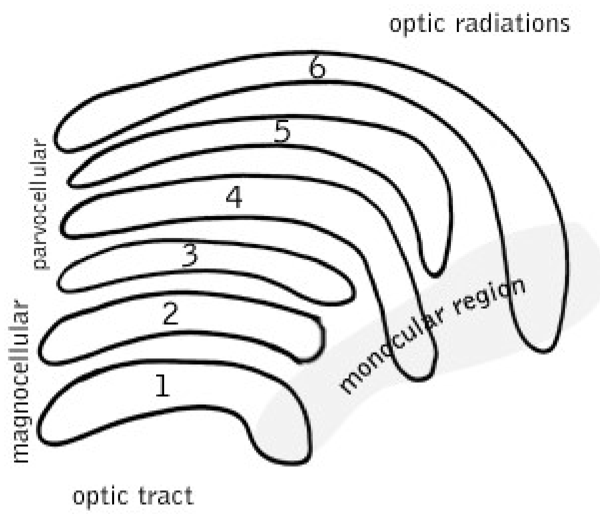


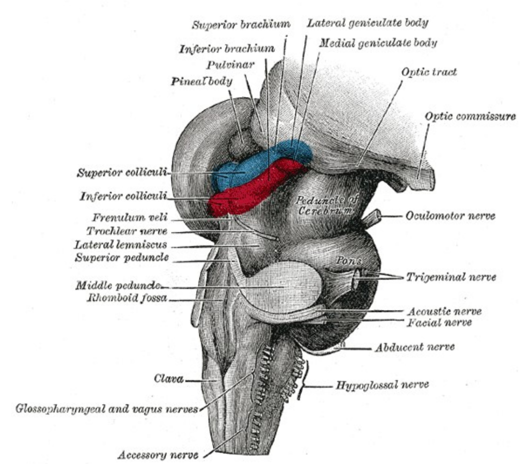
So: *multiple layers make sense*



So: *multiple layers make sense*

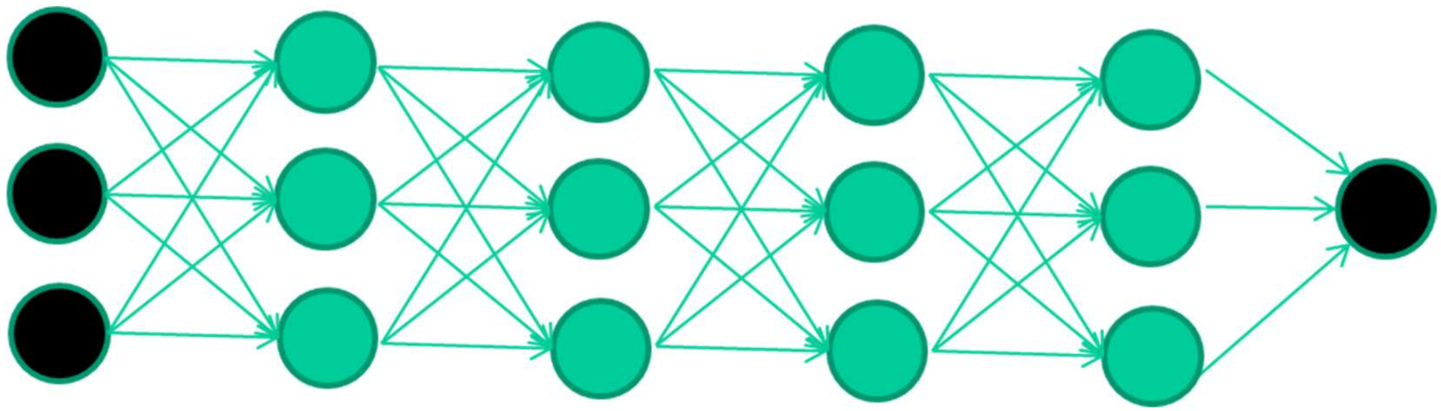
Your brain works that way



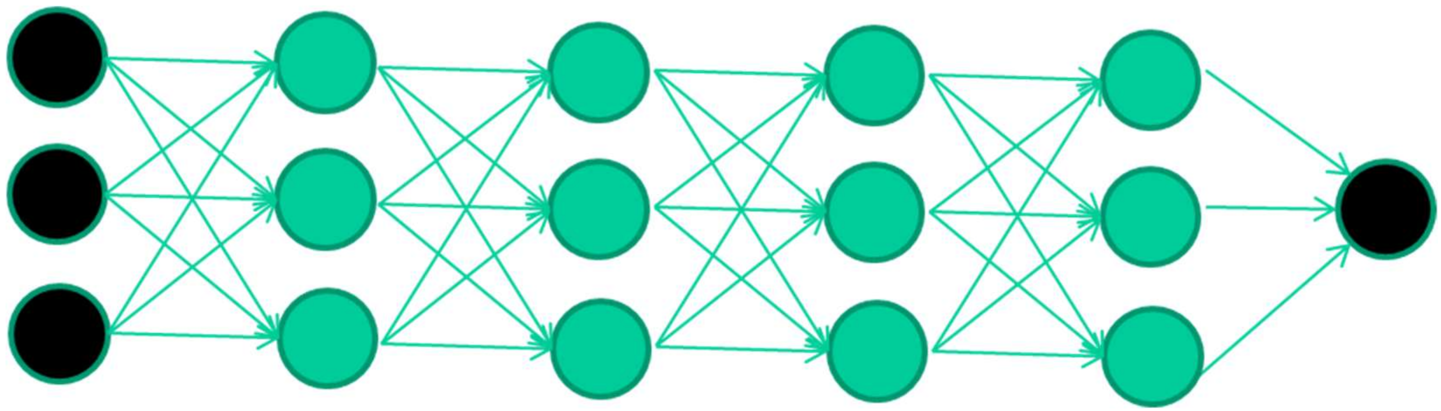


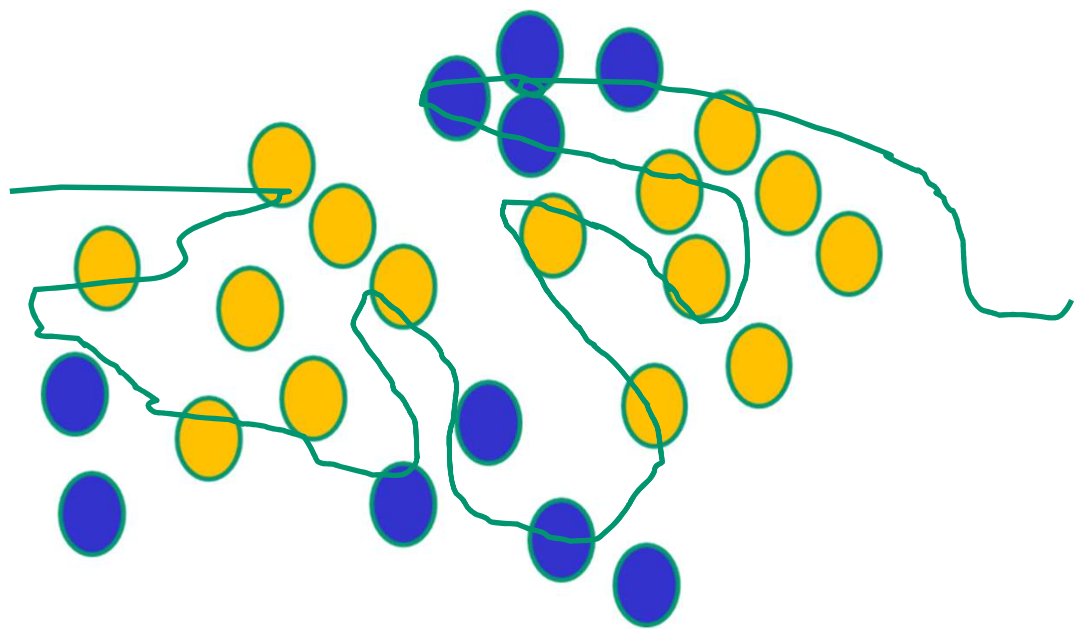
So: *multiple layers make sense*

Many-layer neural network architectures should be capable of learning the true underlying features and 'feature logic', and therefore generalise very well …



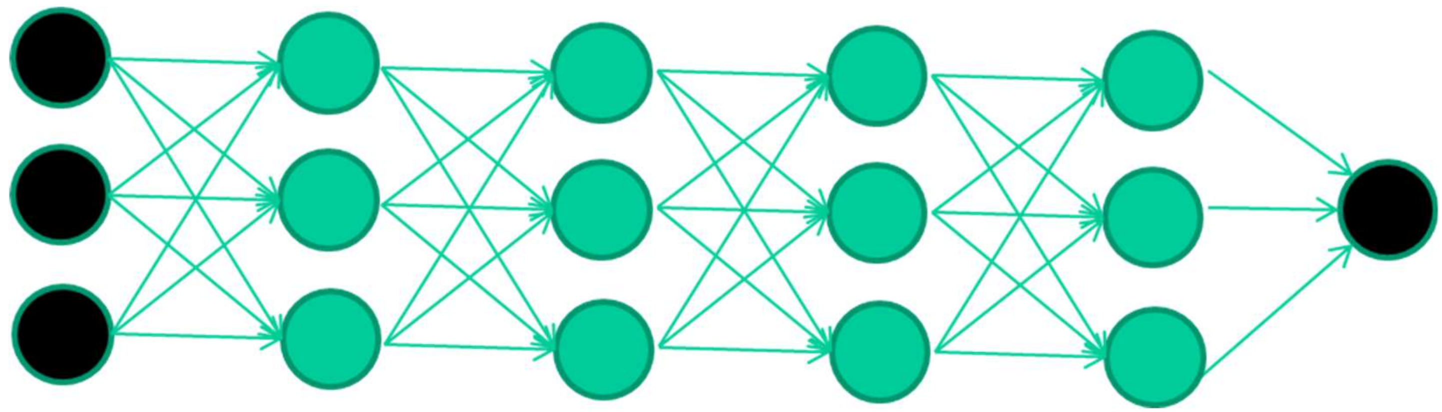
But, until very recently, our weight-learning algorithms simply did not work on multi-layer architectures





Along came deep learning …

The new way to train multi-layer NNs…



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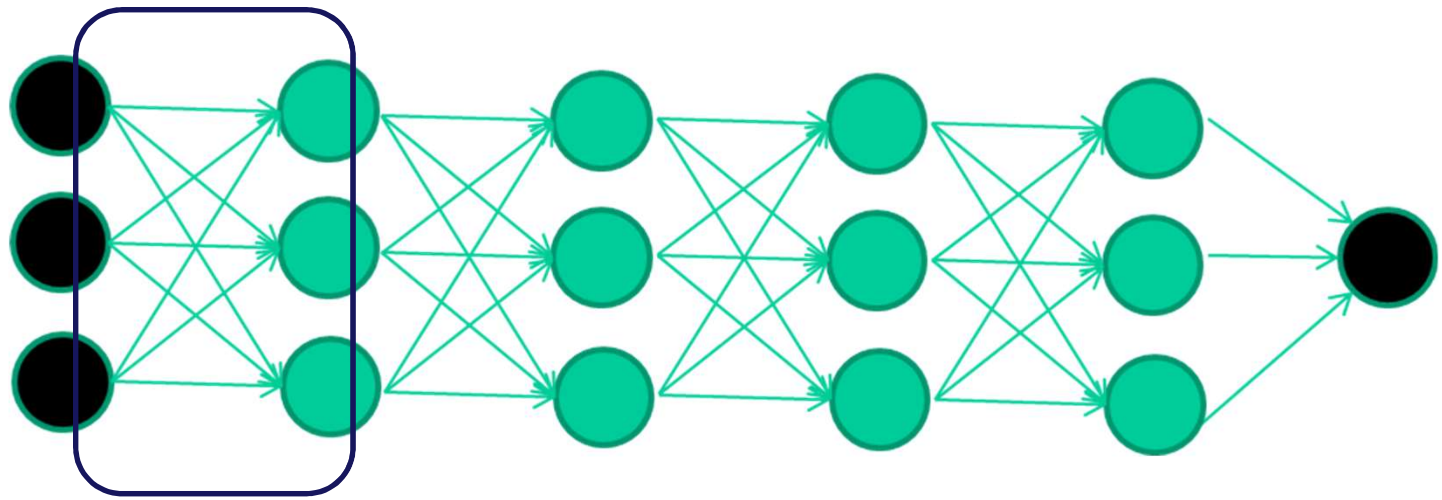
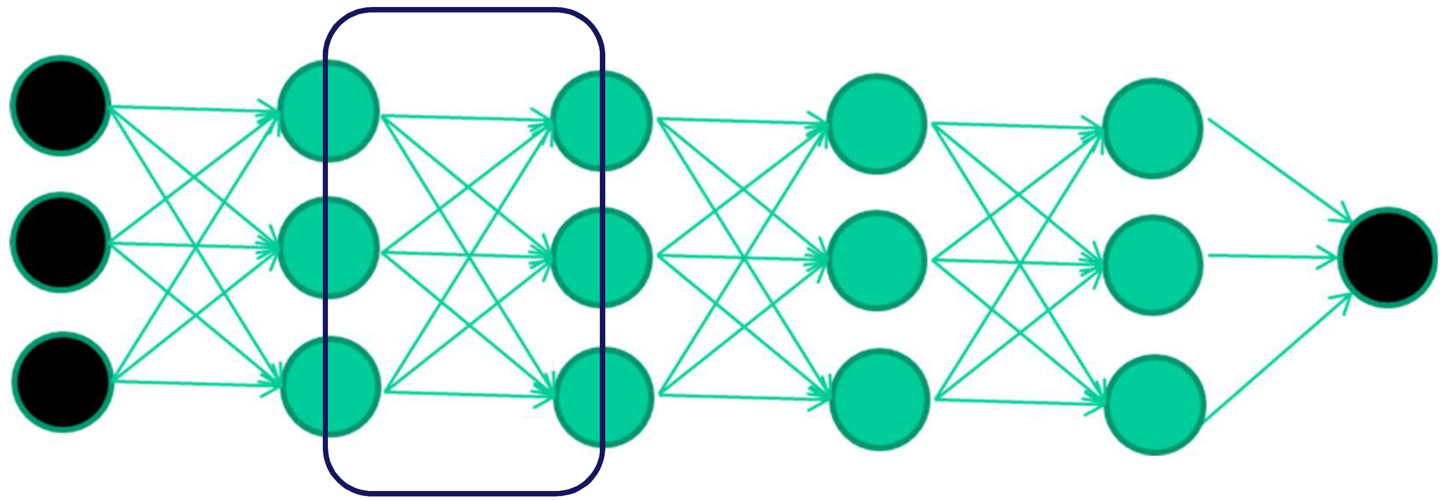


Train **this** layer first

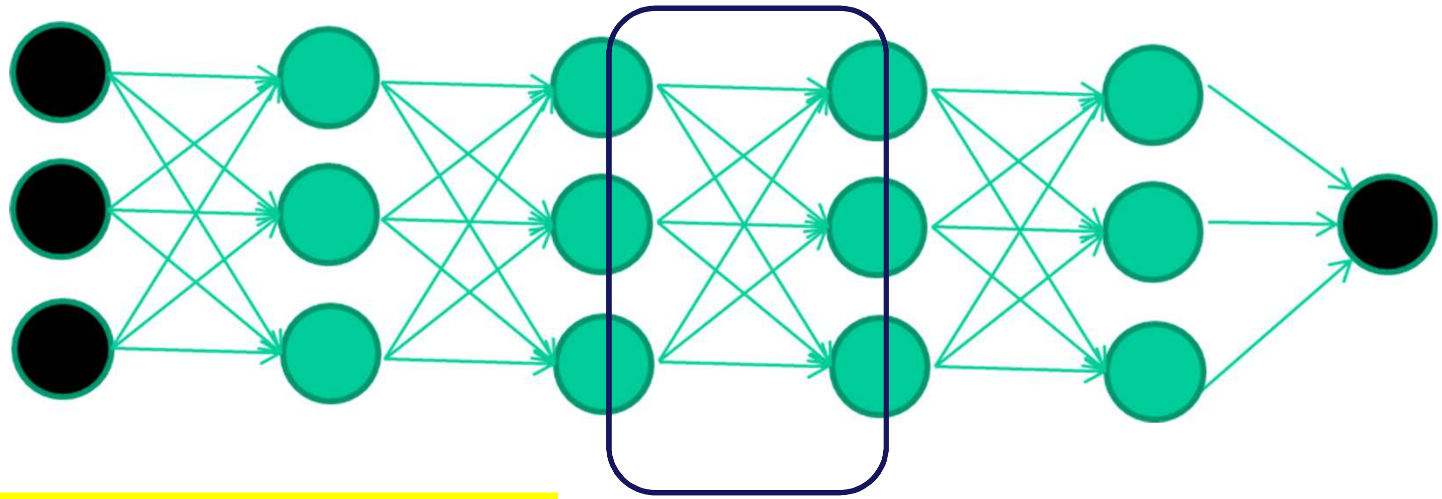
The new way to train multi-layer NNs…



Train **this** layer first

then **this** layer

The new way to train multi-layer NNs…

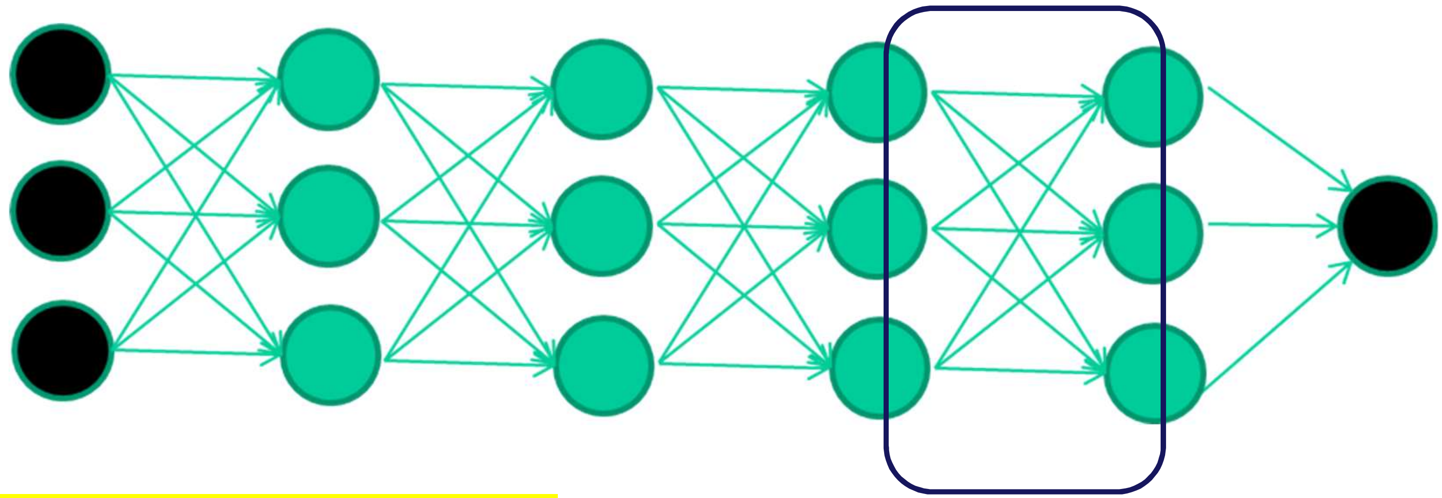


Train **this** layer first

then **this** layer

then **this** layer

The new way to train multi-layer NNs…



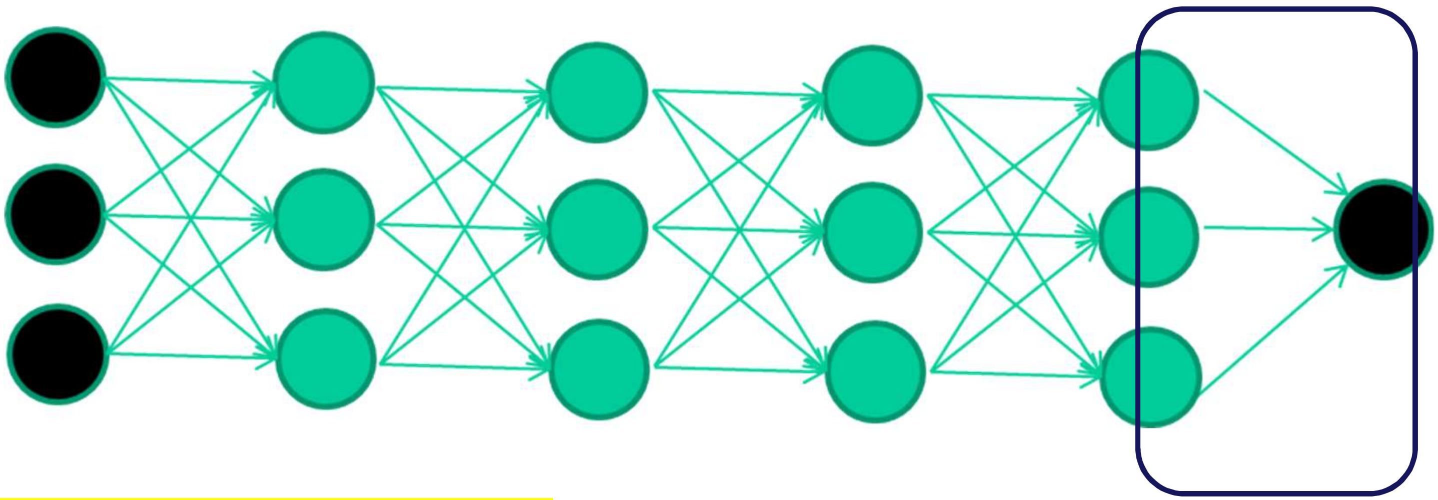
Train **this** layer first

then **this** layer

then **this** layer

then **this** layer

The new way to train multi-layer NNs…



Train **this** layer first

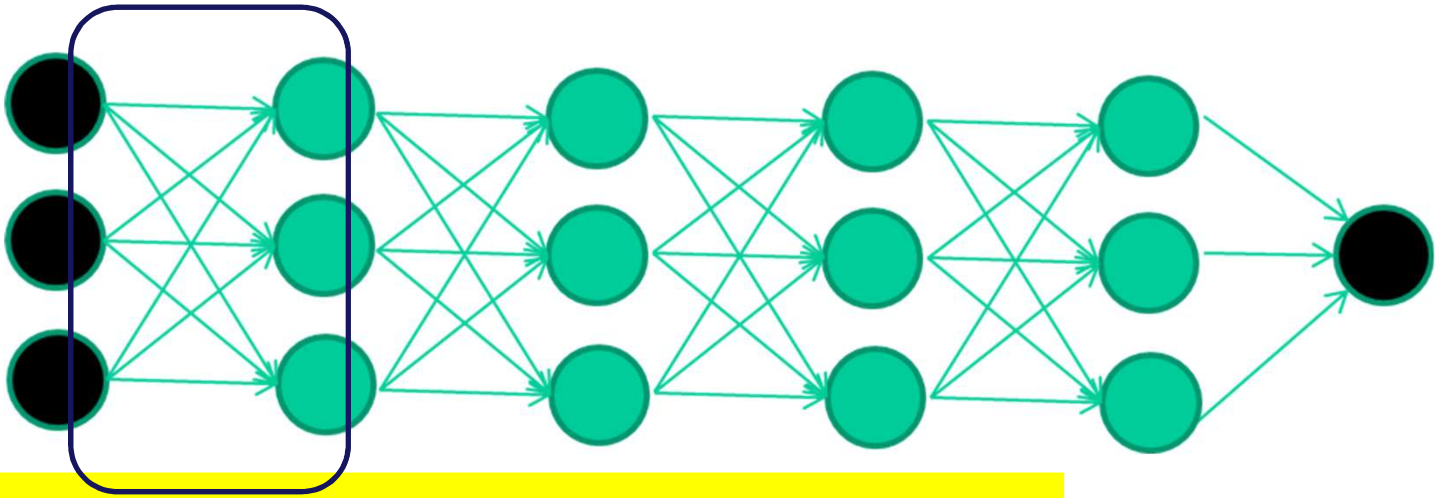
then **this** layer

then **this** layer

then **this** layer

finally **this** layer

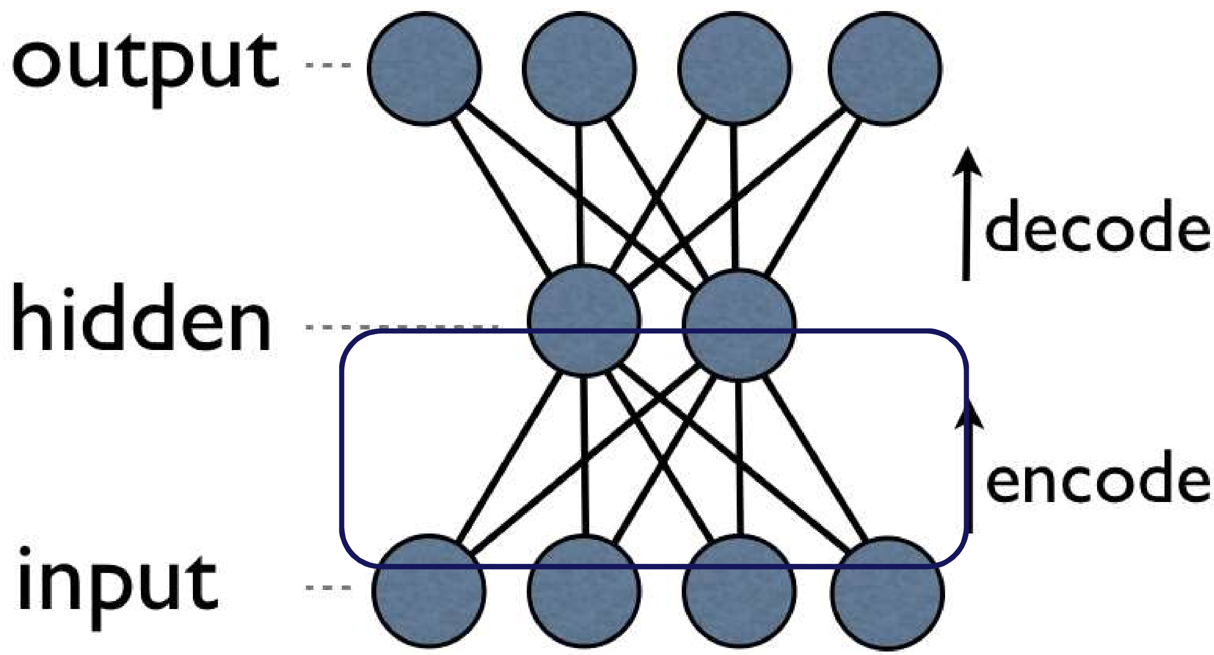
The new way to train multi-layer NNs…



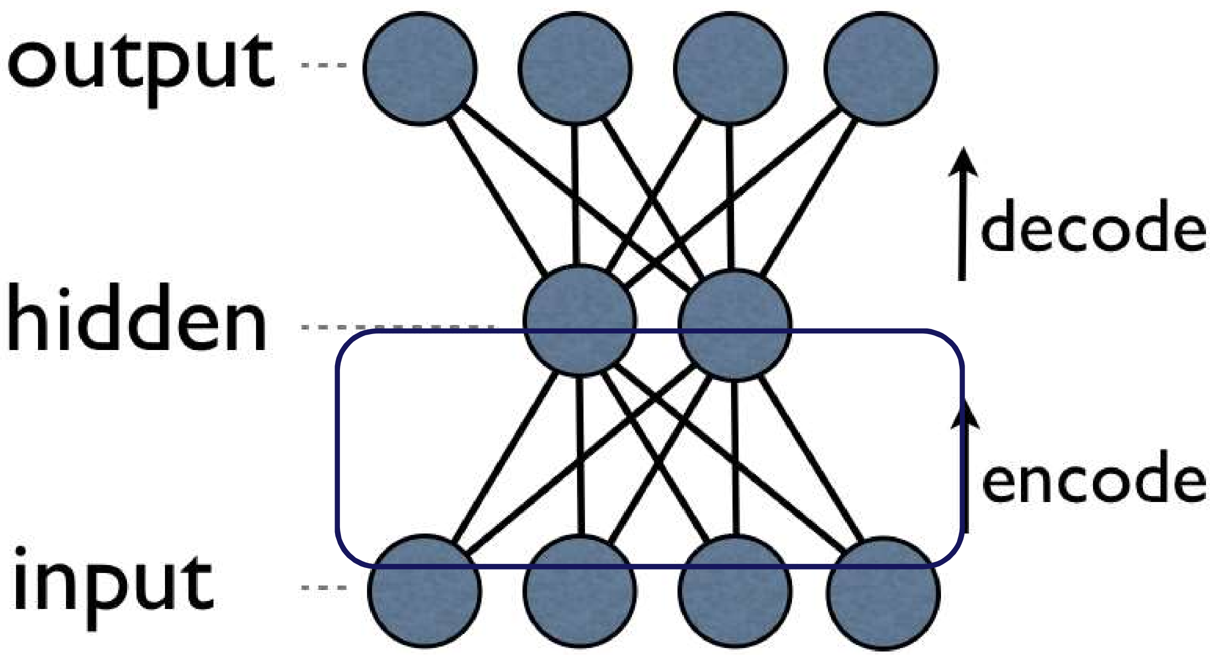
EACH of the (non-output) layers is trained to be an ***auto-encoder***

Basically, it is forced to learn good features that describe what comes from the previous layer

an auto-encoder is trained, with an absolutely standard weight-adjustment algorithm to <u>reproduce the input</u>

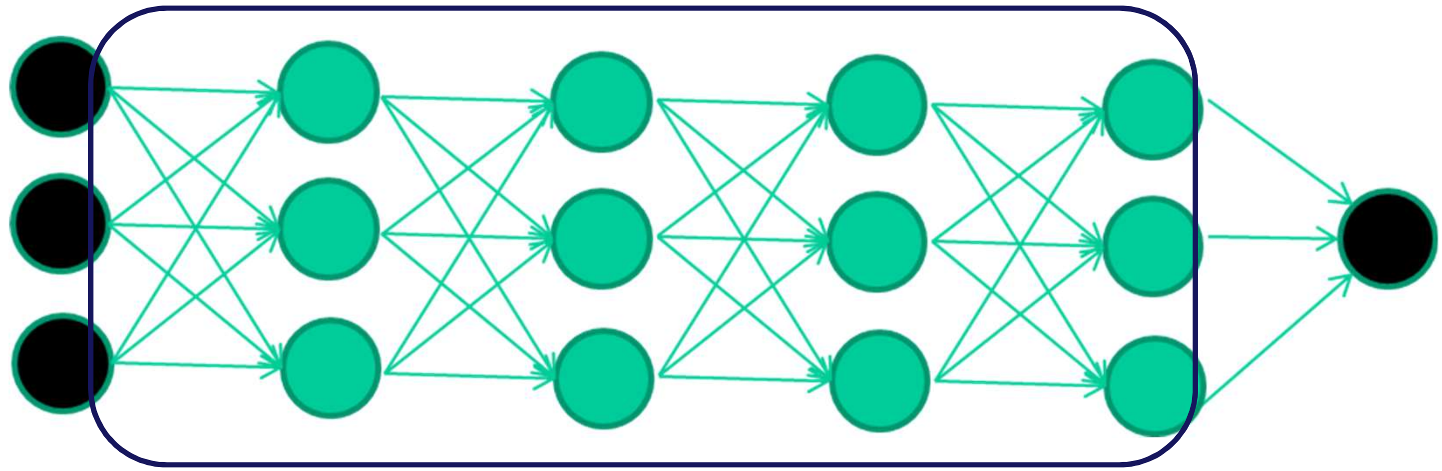


an auto-encoder is trained, with an absolutely standard weight-adjustment algorithm to <u>reproduce the input</u>

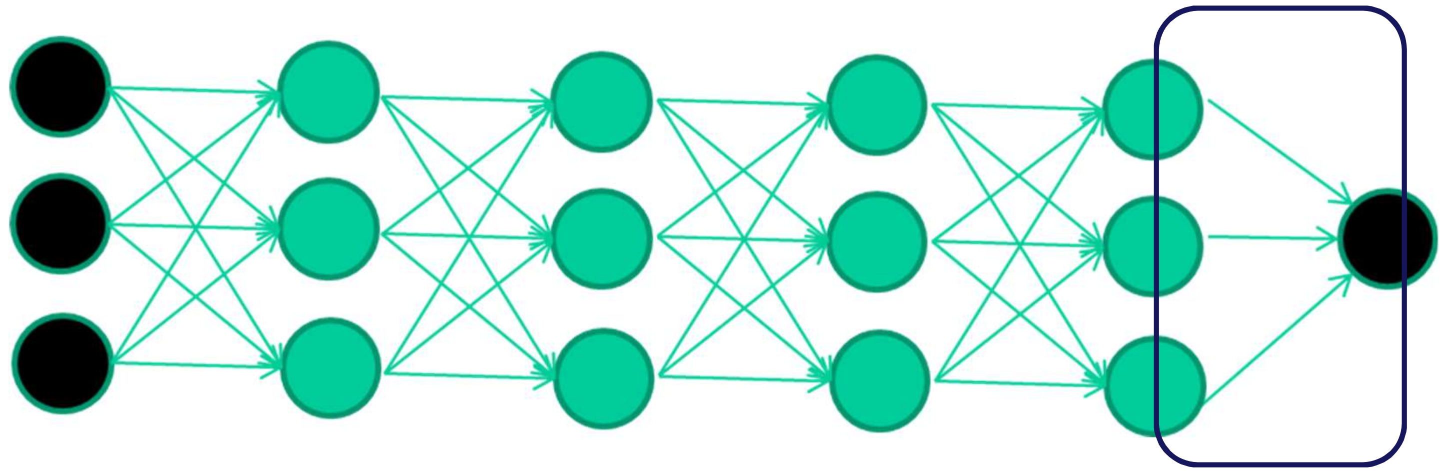


By making this happen with (many) fewer units than the inputs, this forces the 'hidden layer' units to become good feature detectors

intermediate layers are each trained to be auto encoders (or similar)



Final layer trained to predict class based on outputs from previous layers



To continue…