an introduction to: Deep Learning

Based on Lecture Notes by David Corne

http://www.macs.hw.ac.uk/~dwcorne/

And others

http://www.cs.umd.edu/~djacobs/CMSC733/CNN.pdf

http://cs231n.stanford.edu

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.**

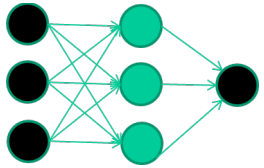
hmmm… OK, but:

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

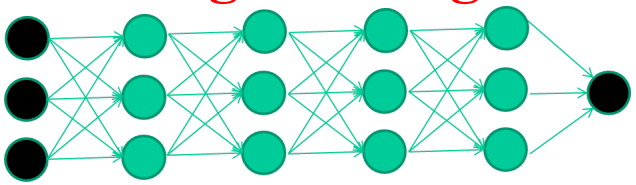
hmmm… OK, but:

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

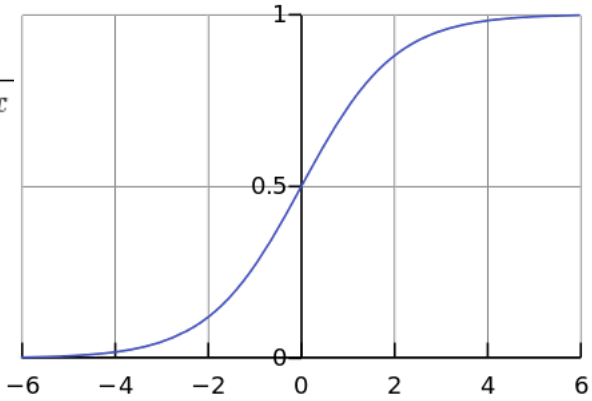


what's new is: **<u>algorithms for training many-later networks</u>**

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

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



-0.06

W1

-2.5

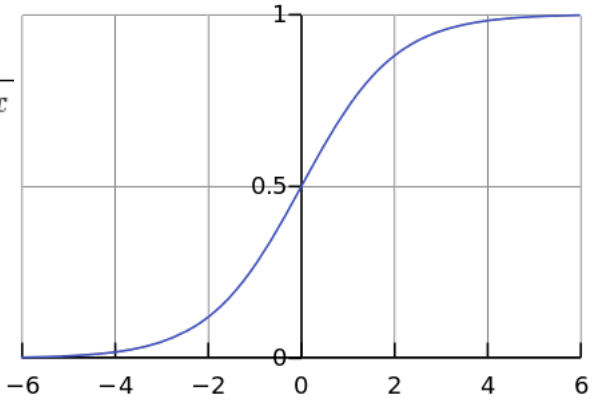
W2

W3

1.4

f(x)

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



-0.06

2.7

-2.5

-8.6

***f*(x)**

0.002

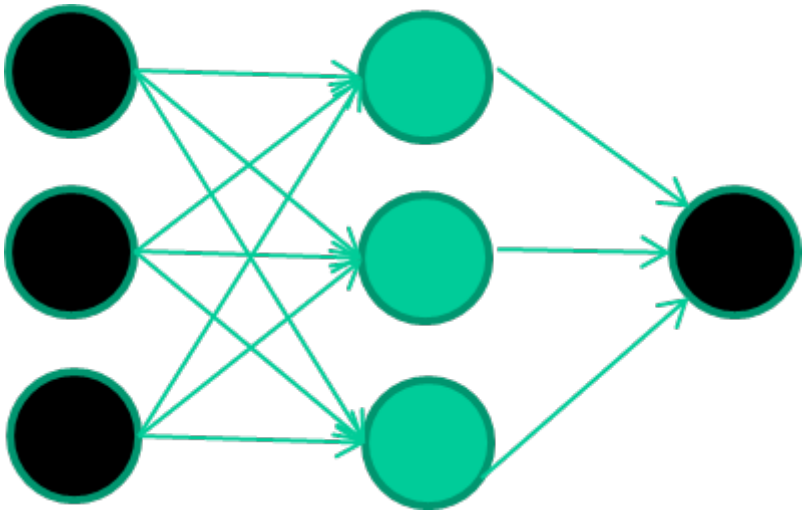
1.4

$x = -0.06 \times 2.7 + 2.5 \times 8.6 + 1.4 \times 0.002 = 21.34$

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

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
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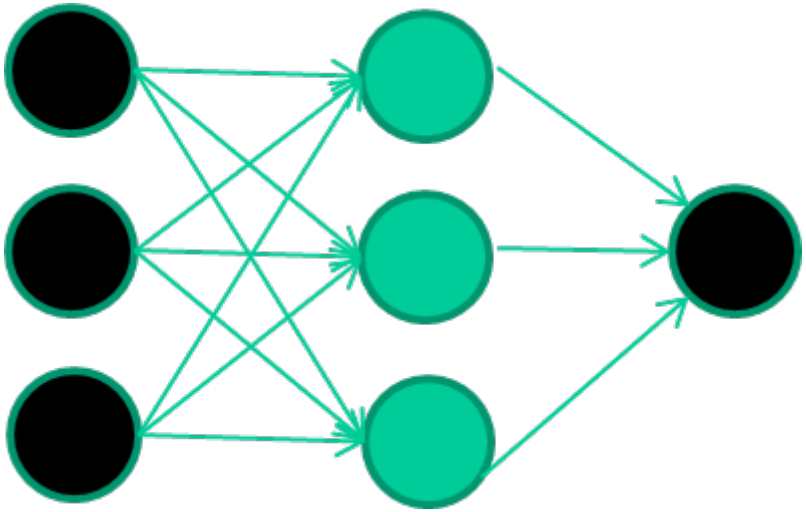
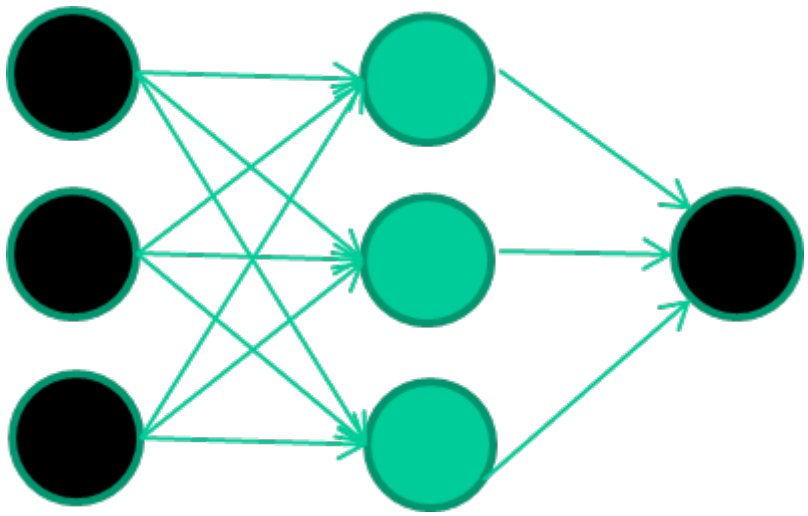
etc …



Training data

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 …			

Initialise with random weights



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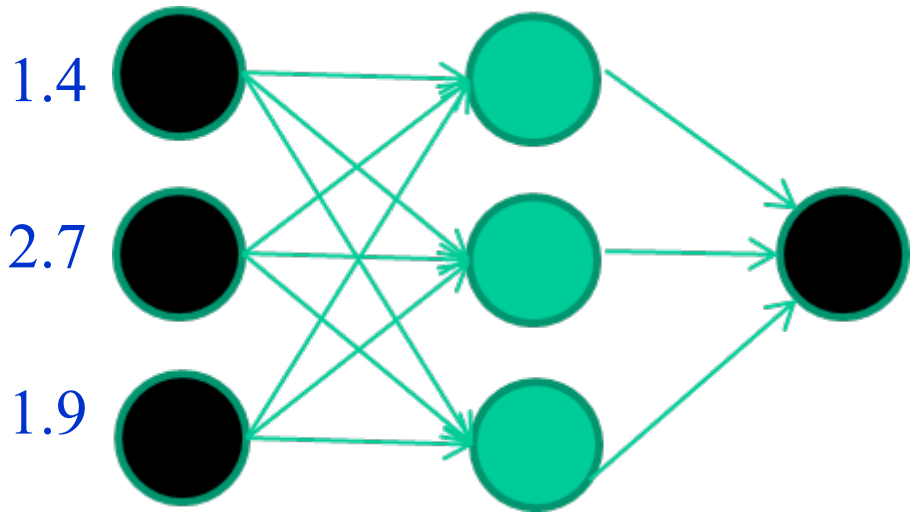
etc …			

Present a training pattern



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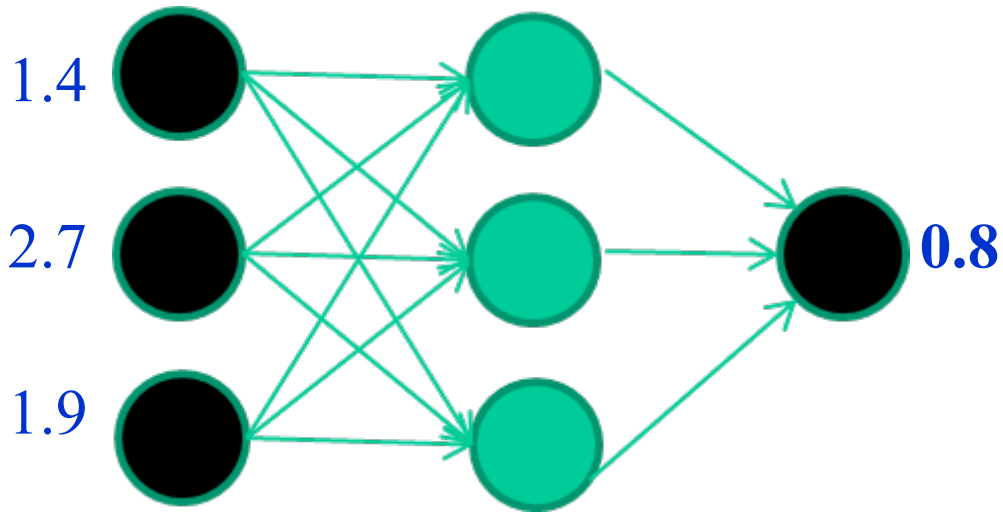
etc …			

Feed it through to get output



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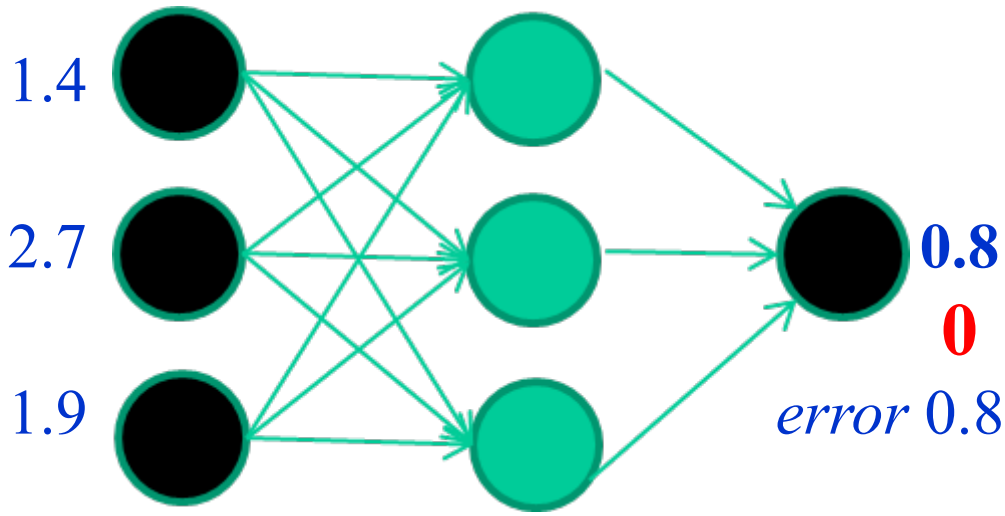
etc …			

Compare with target output



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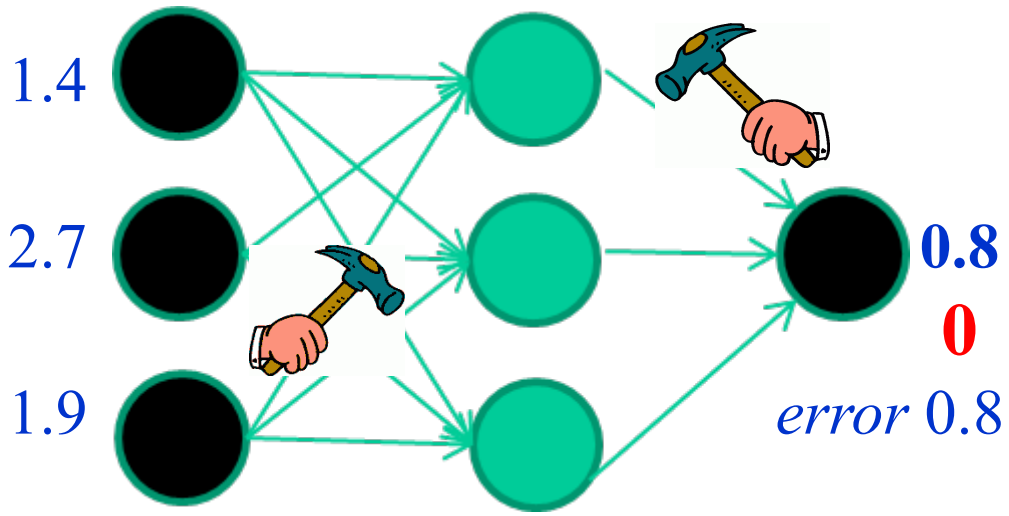
etc …			

Adjust weights based on error



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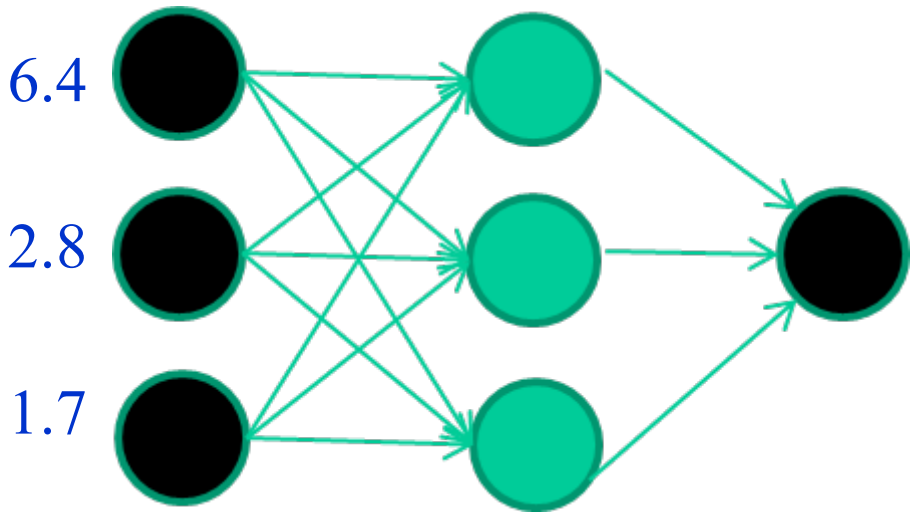

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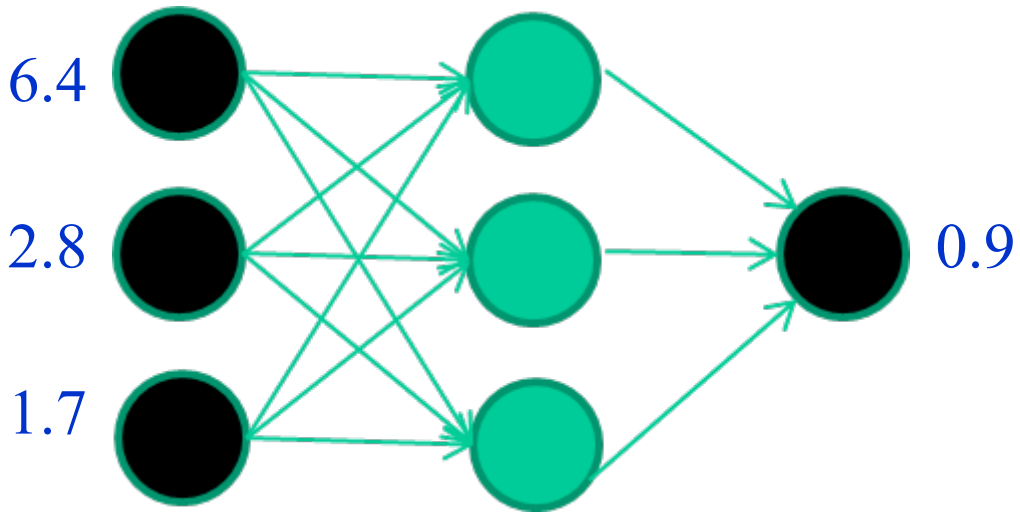

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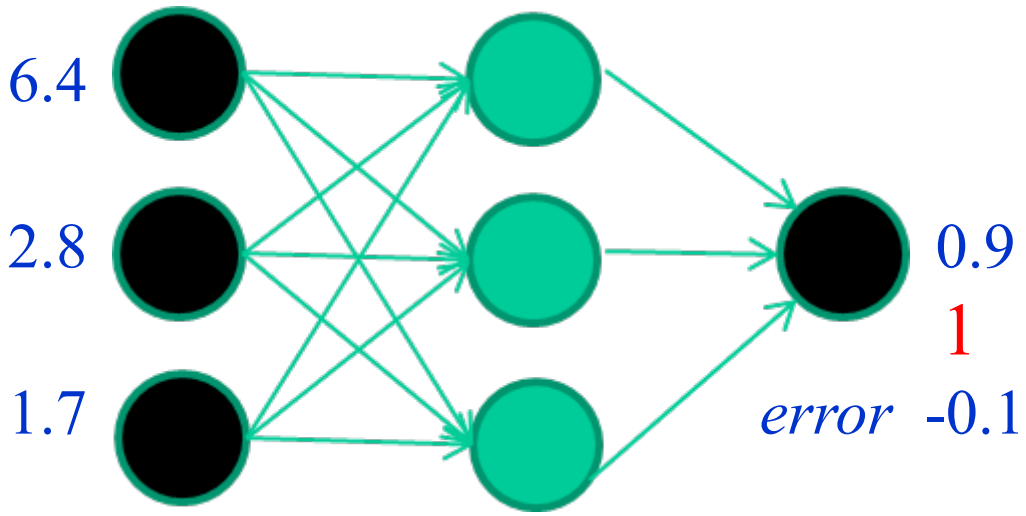

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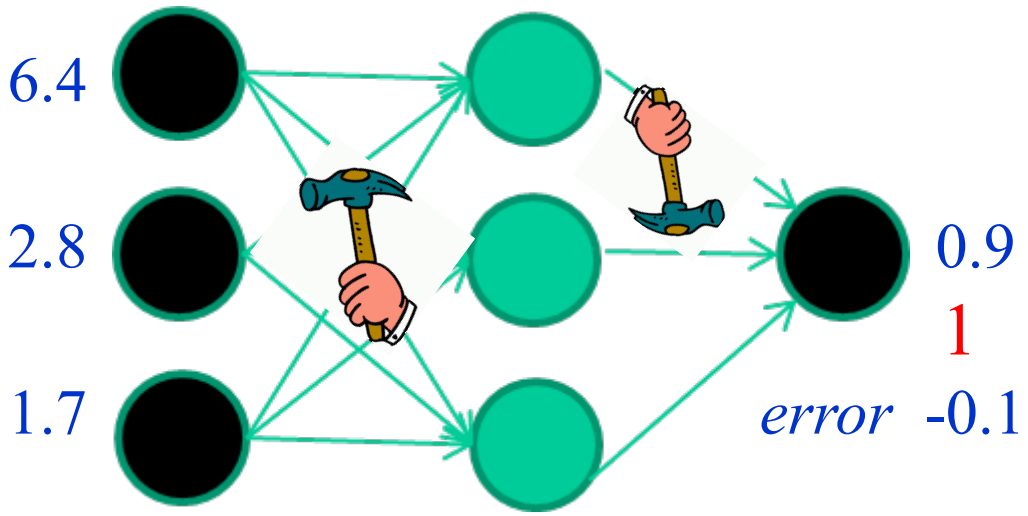

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6.4	2.8	1.7	1
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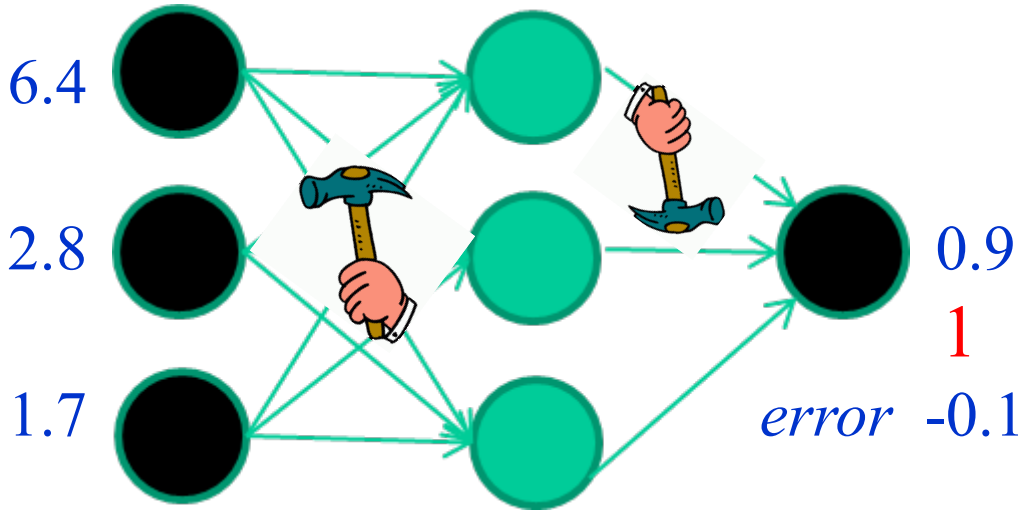
etc …

And so on ….

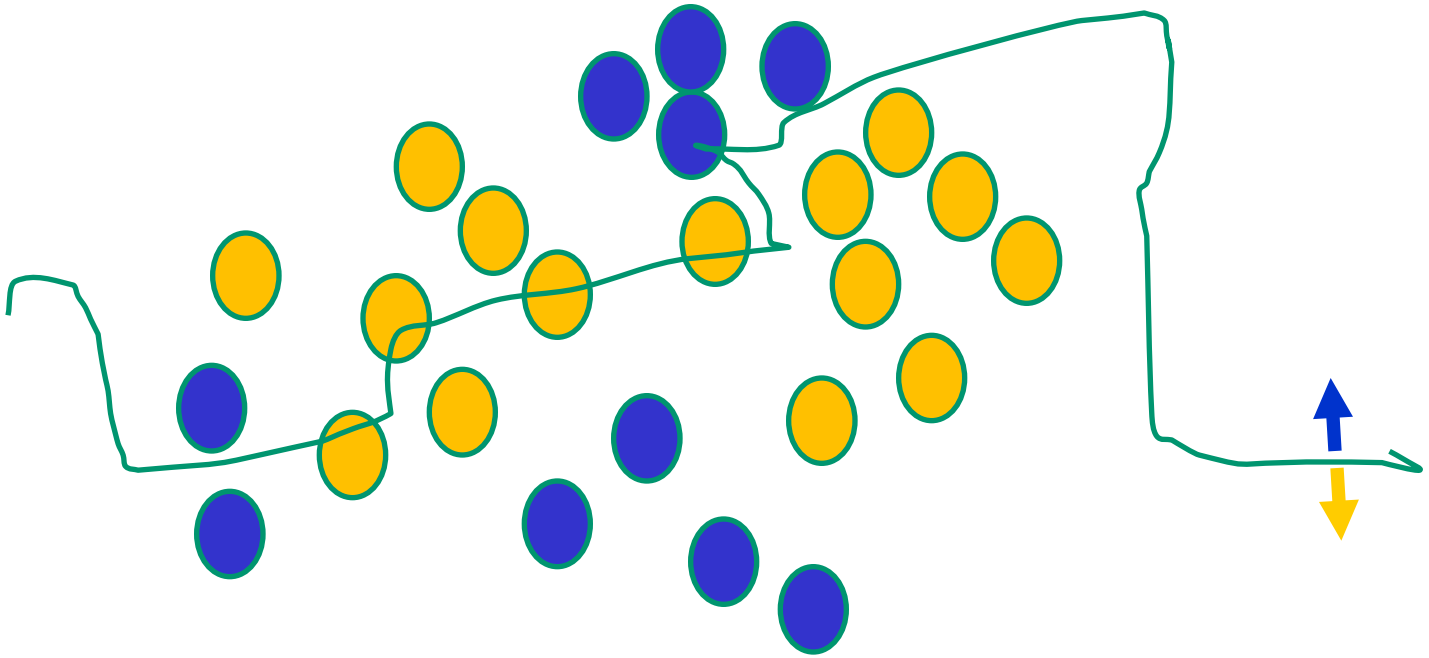


Repeat this thousands, maybe millions of times – each time taking a random training instance, and making slight weight adjustments

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

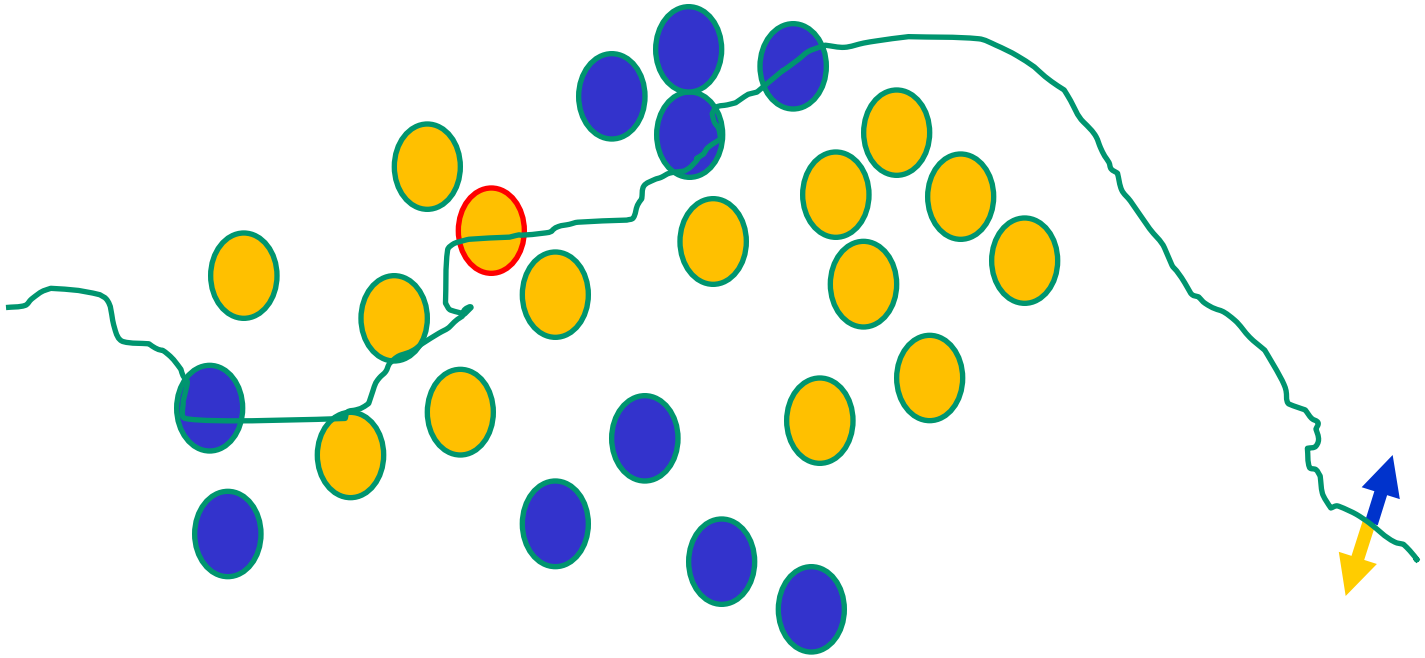
The decision boundary perspective…

Initial random weights



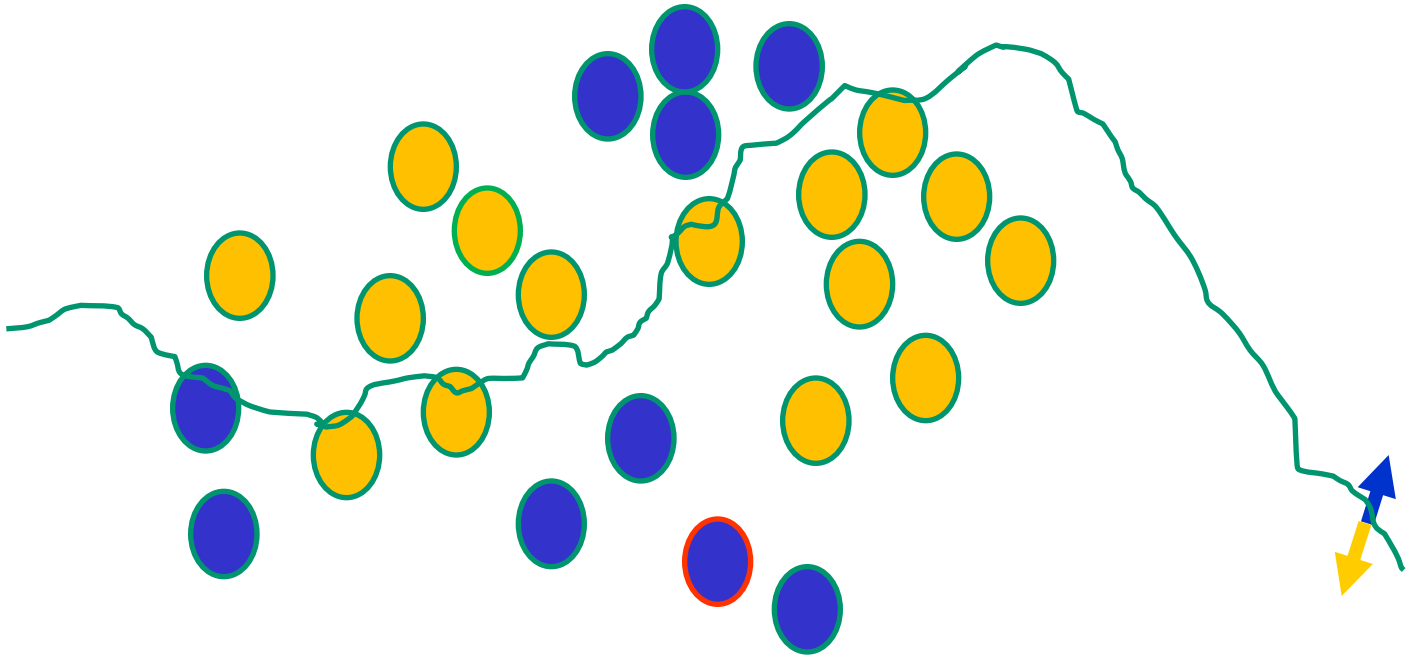
The decision boundary perspective…

Present a training instance / adjust the weights



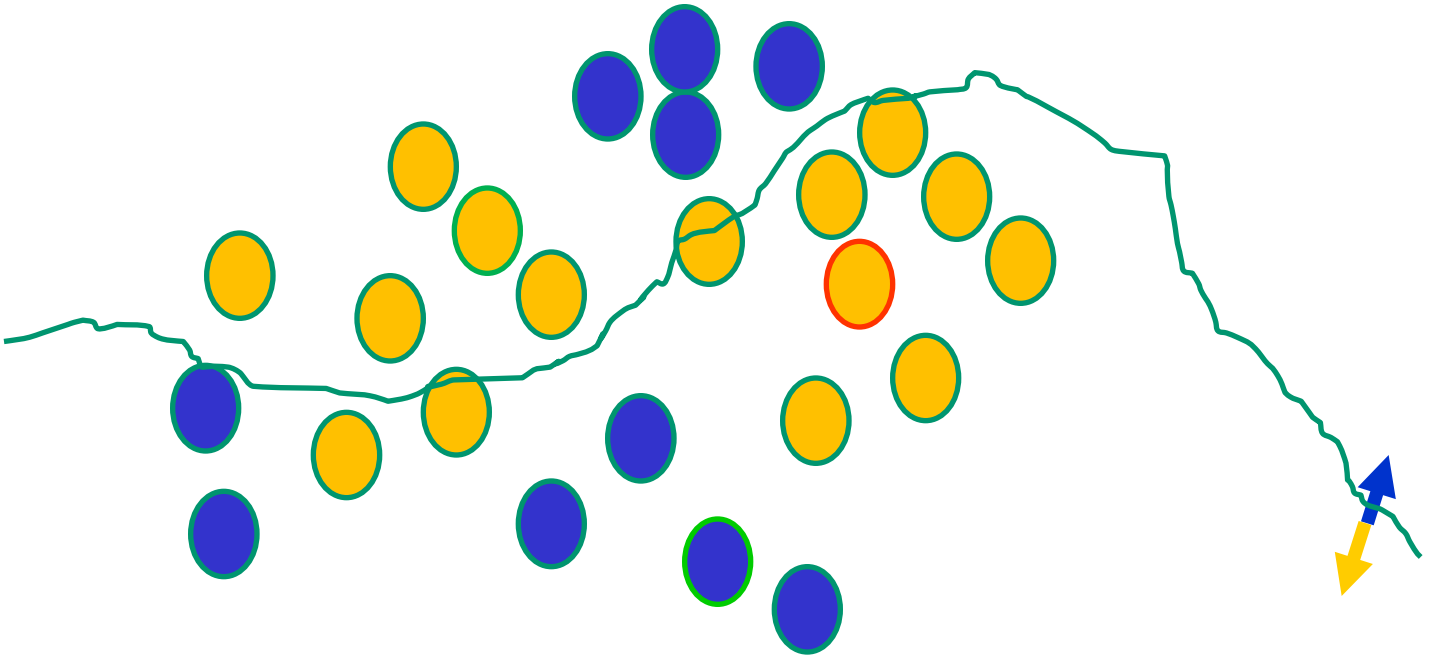
The decision boundary perspective…

Present a training instance / adjust the weights



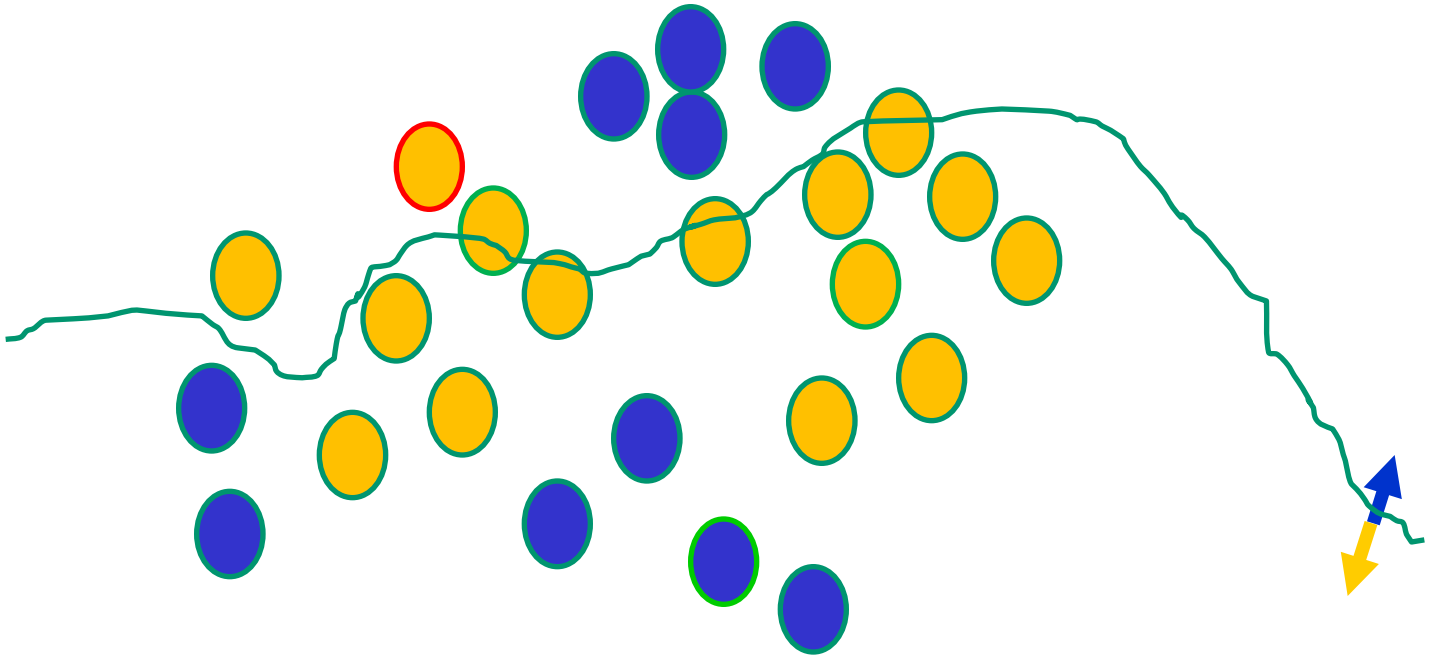
The decision boundary perspective…

Present a training instance / adjust the weights



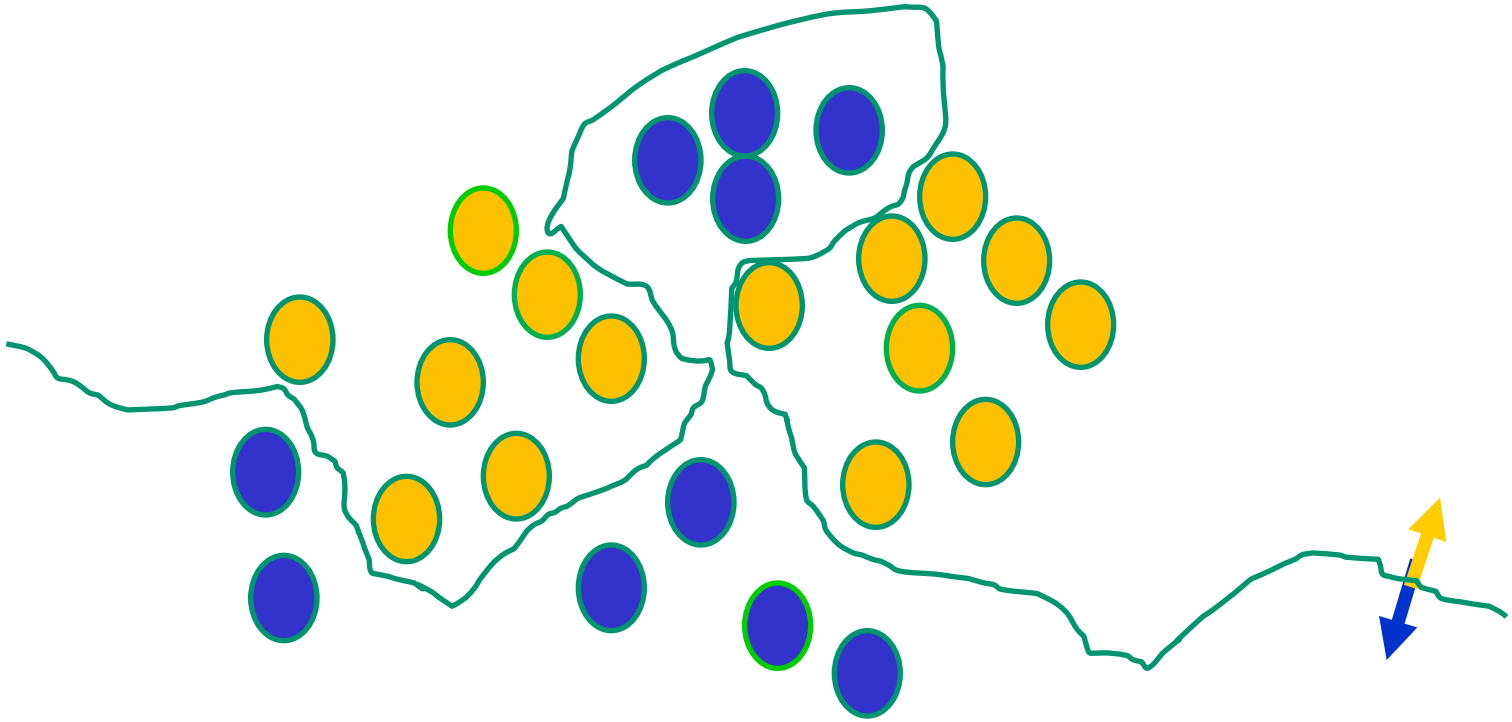
The decision boundary perspective…

Present a training instance / adjust the weights



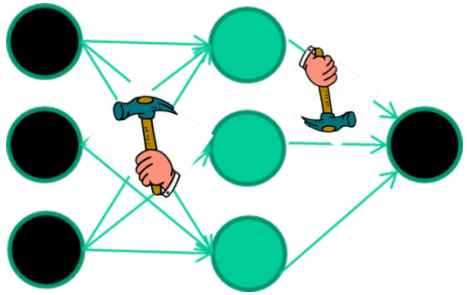
The decision boundary perspective…

Eventually ….



Observations:

- 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



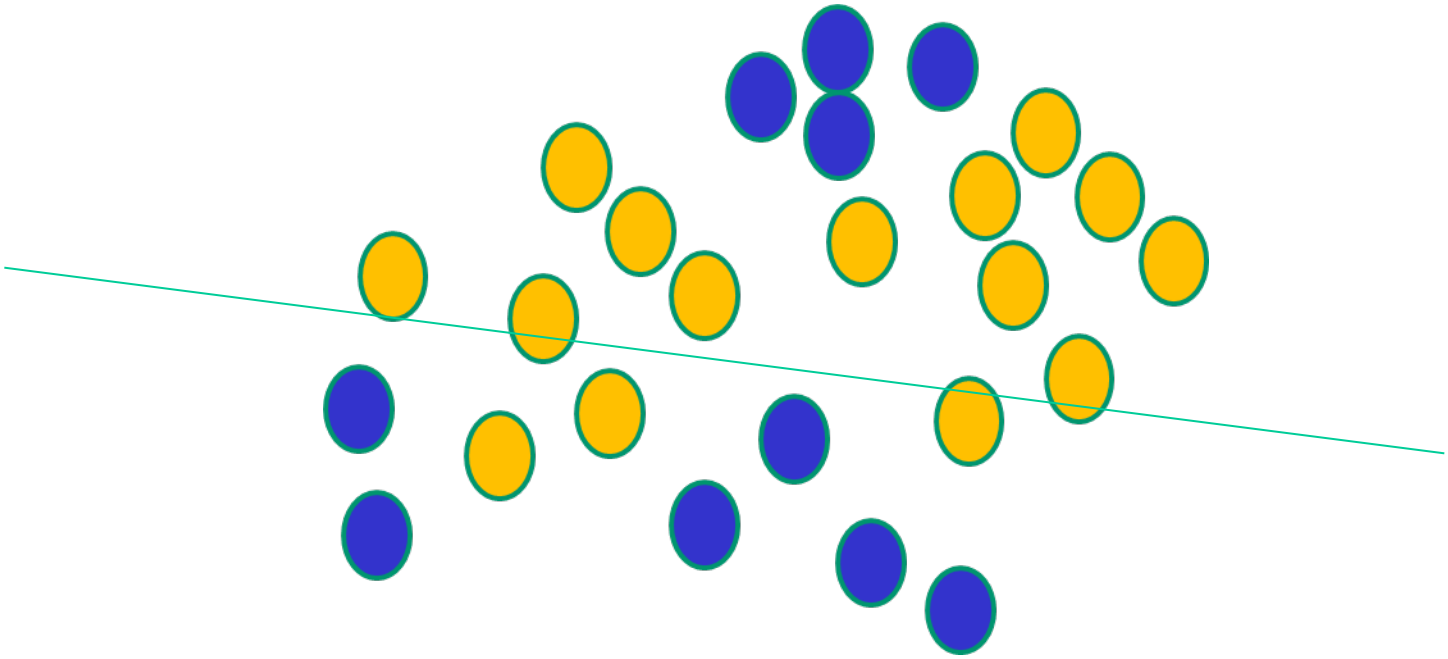
Some other points:

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.

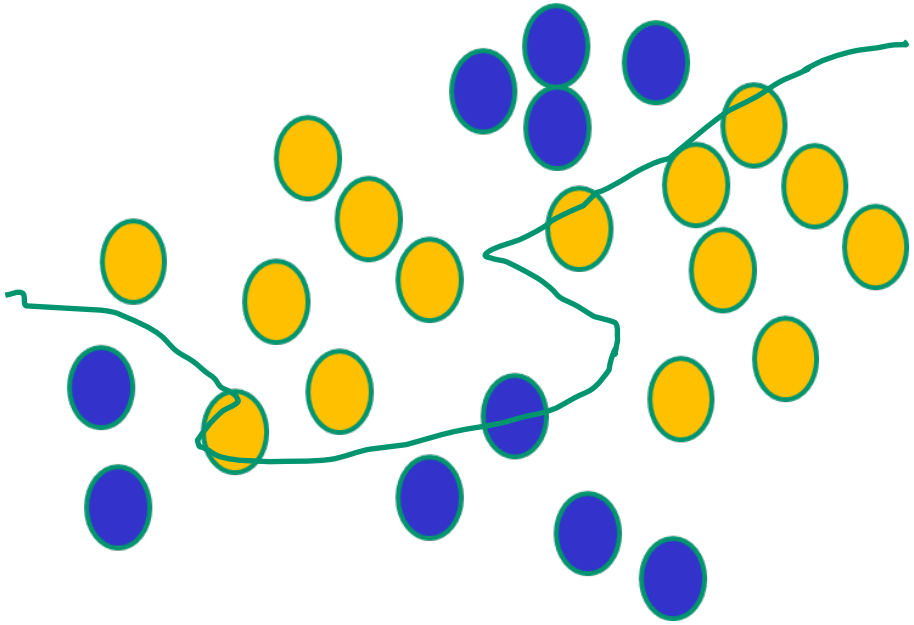
Some other ‘by the way’ points

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

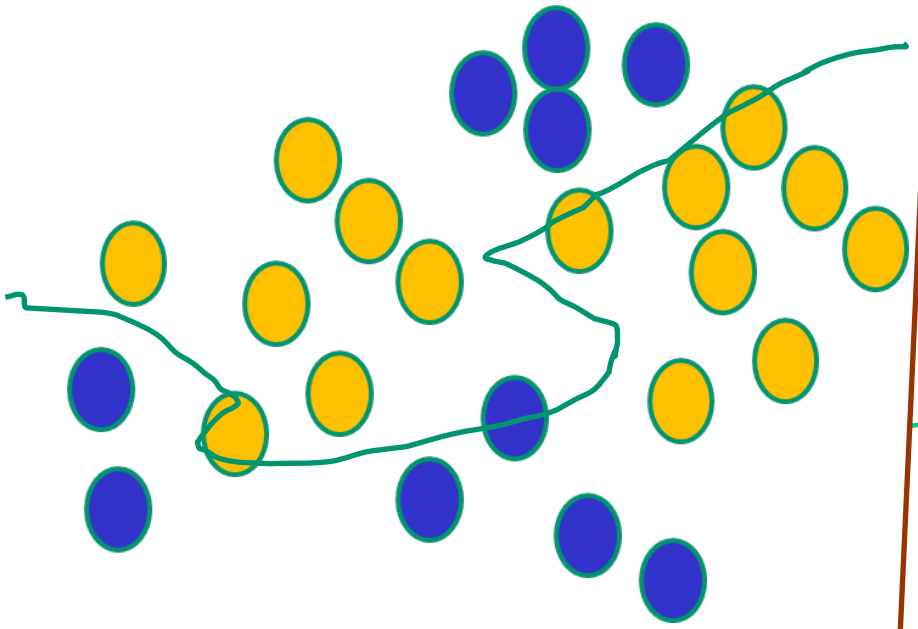
NNs use nonlinear $f(x)$ so they can draw complex boundaries, but keep the data unchanged

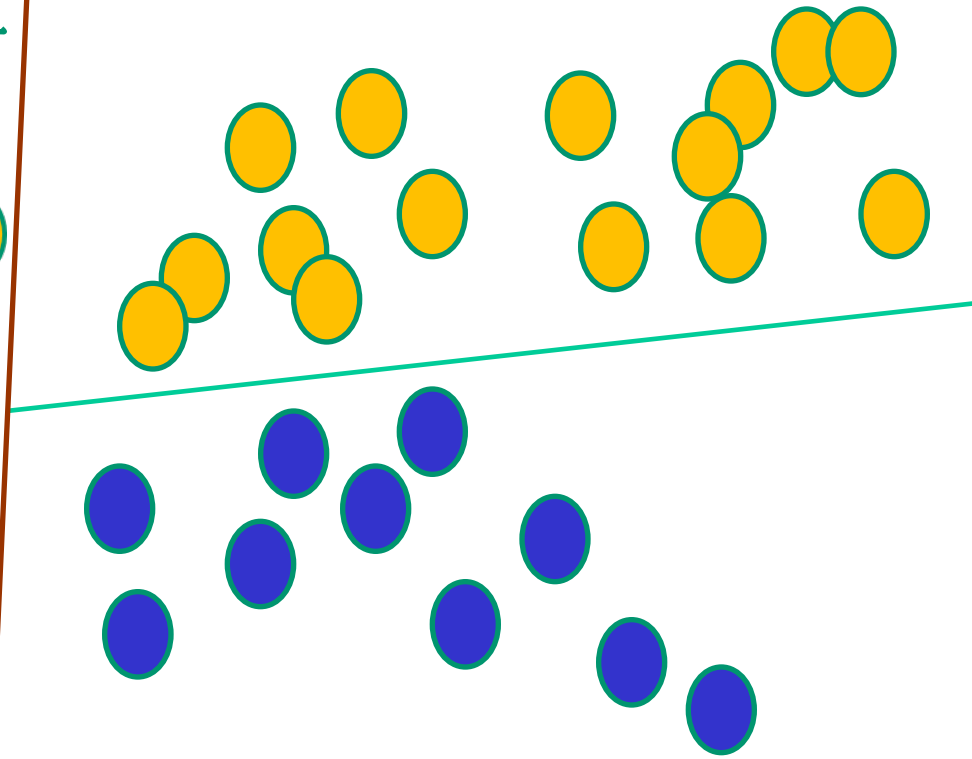


Some other 'by the way' points

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

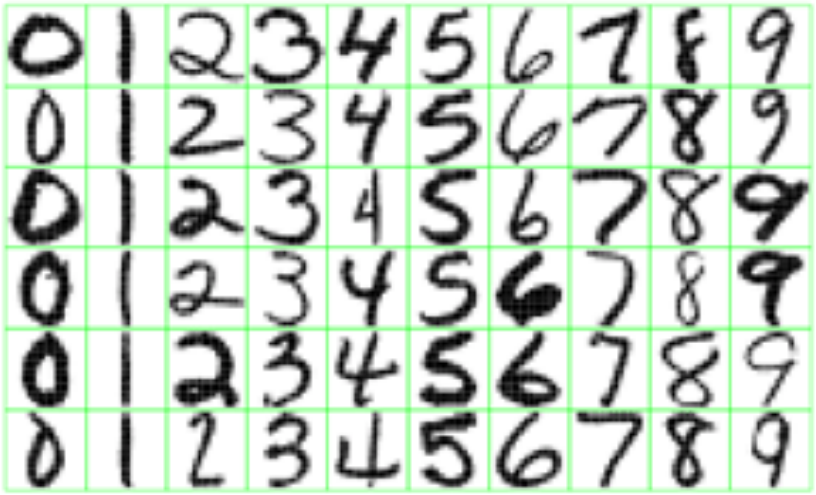
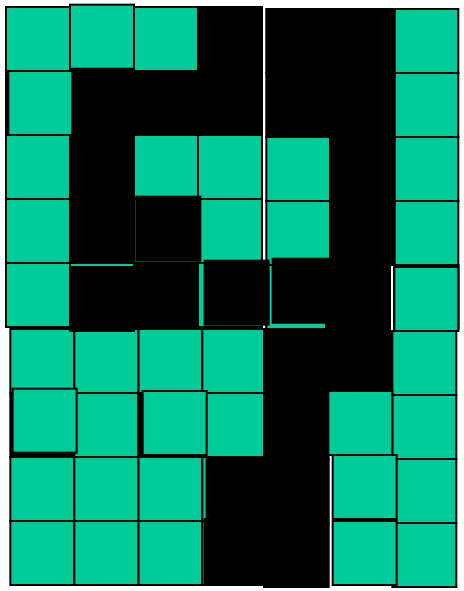
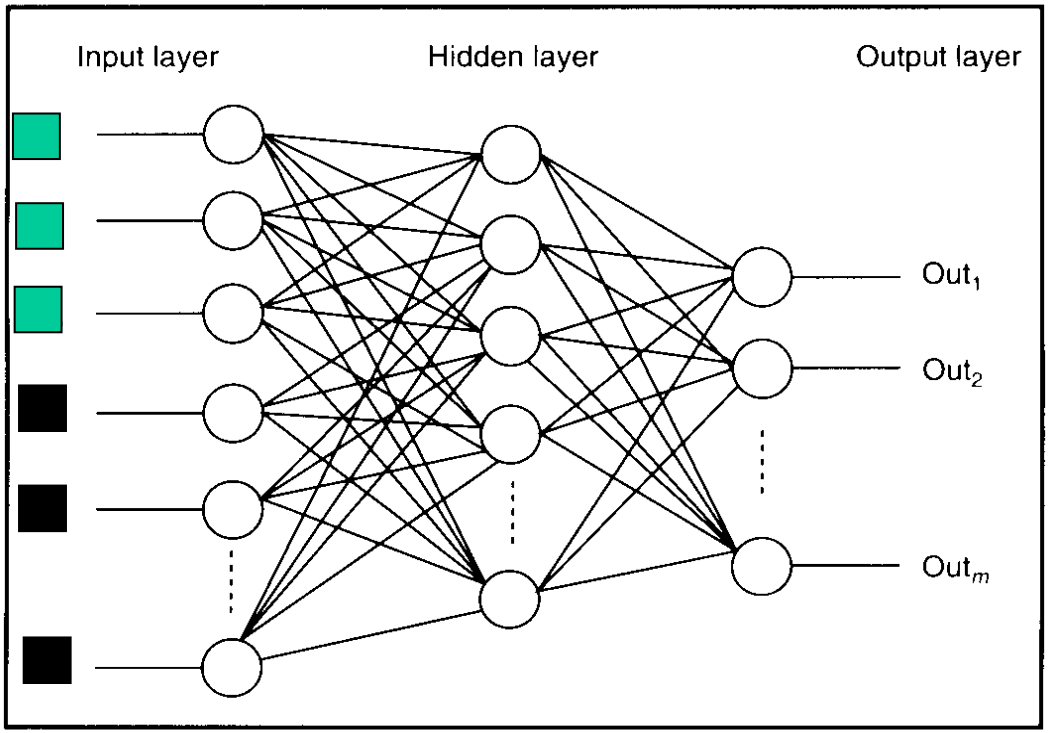
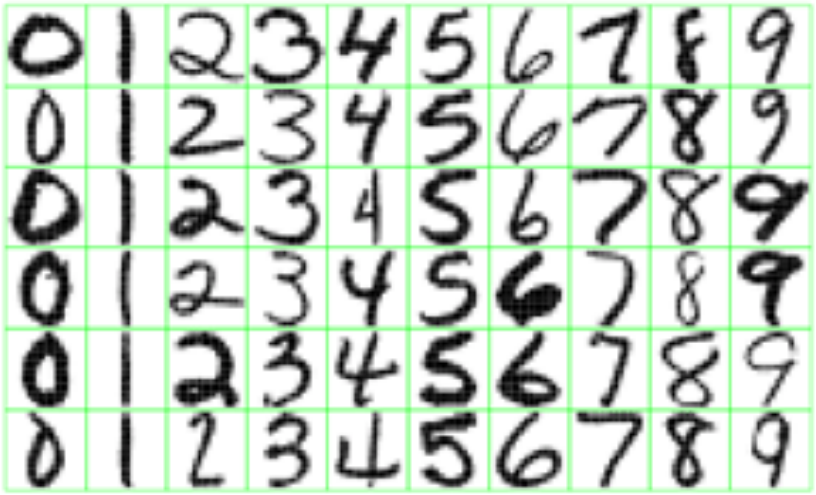


Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*







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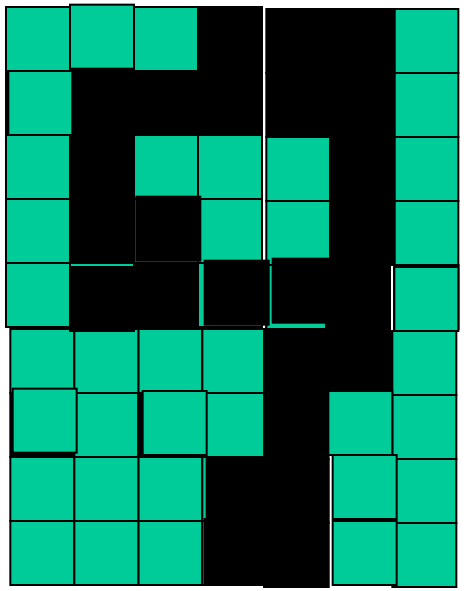
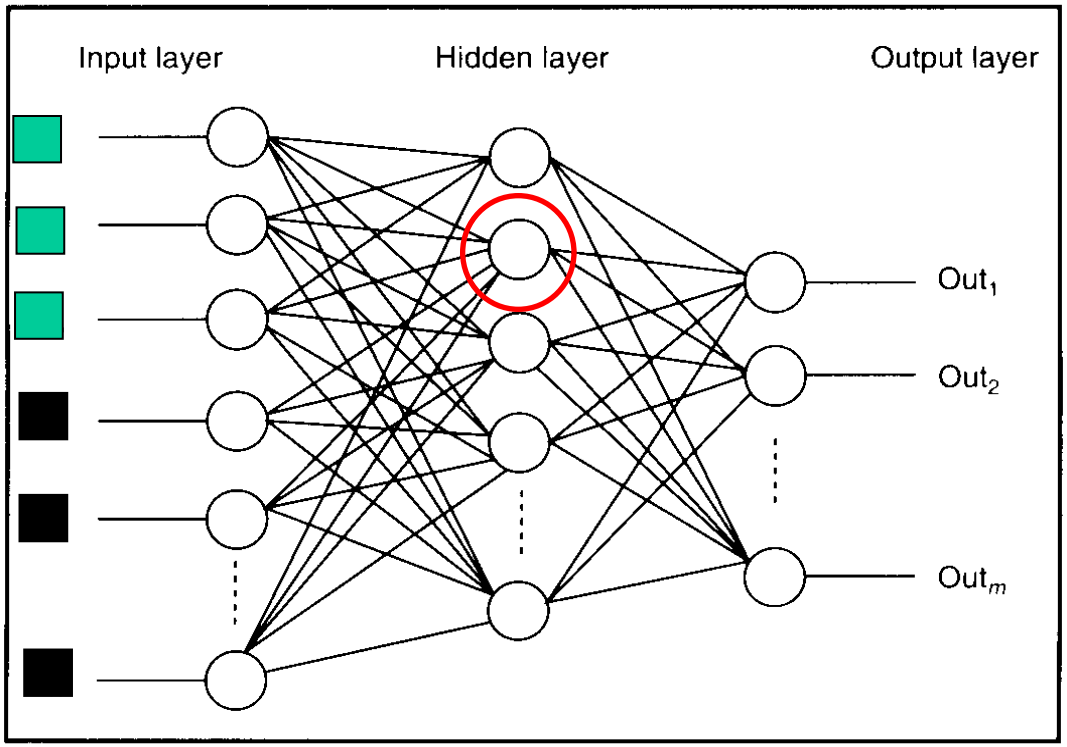
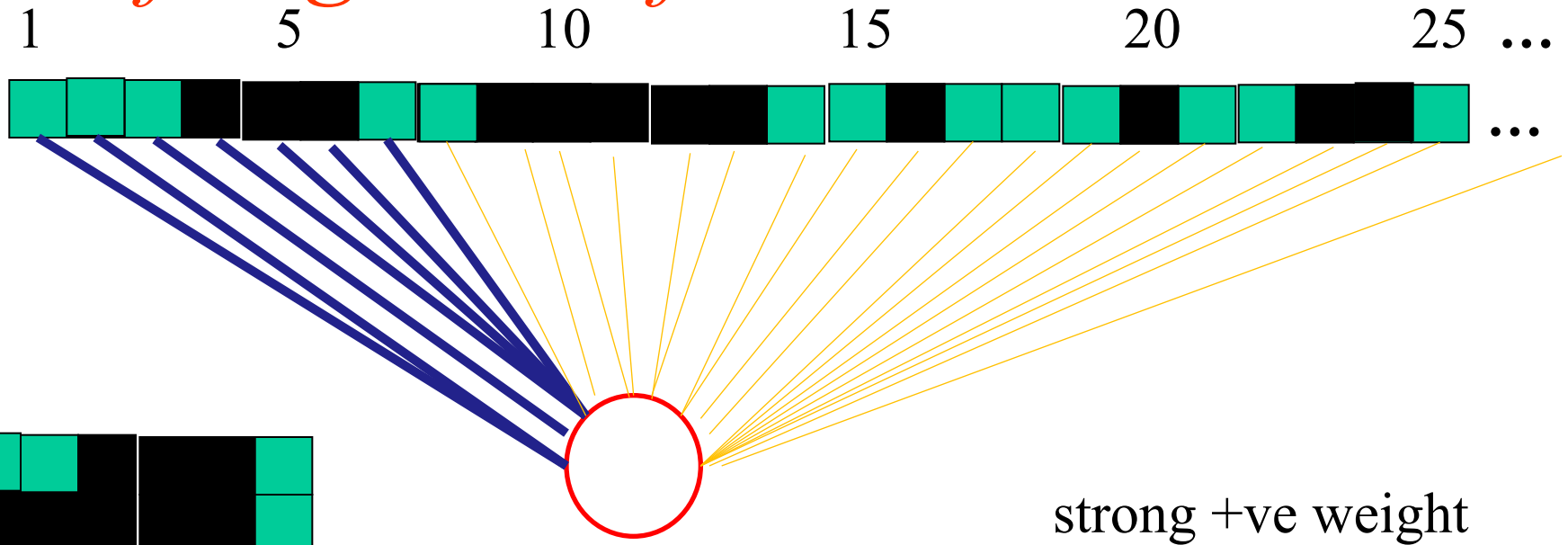
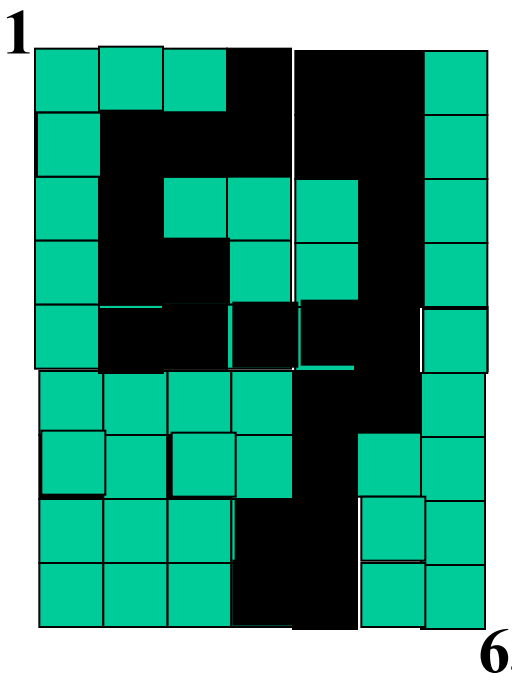


what is this unit doing?



Hidden layer units become *self-organised feature detectors*

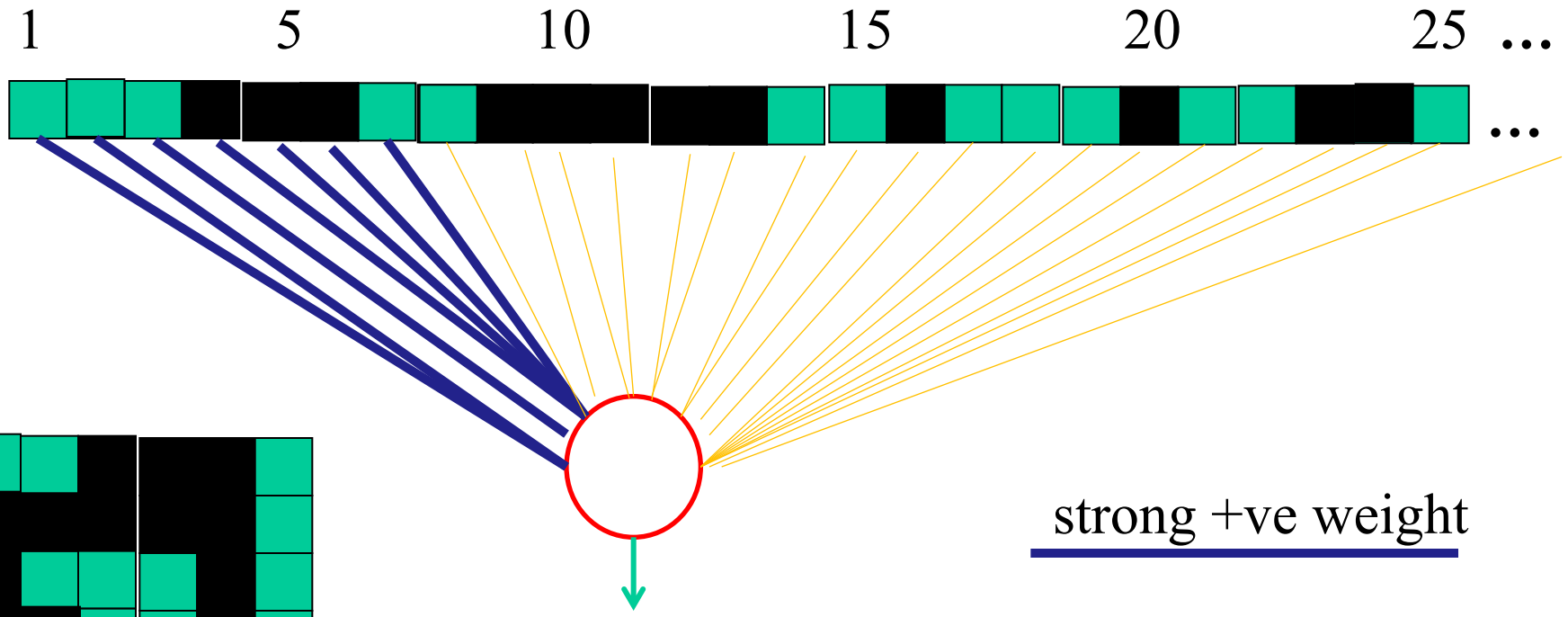


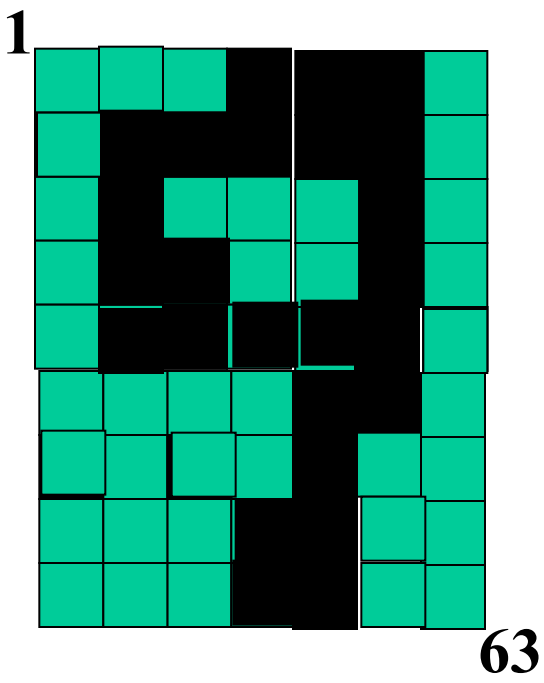


strong +ve weight

low/zero weight

What does this unit detect?





strong +ve weight

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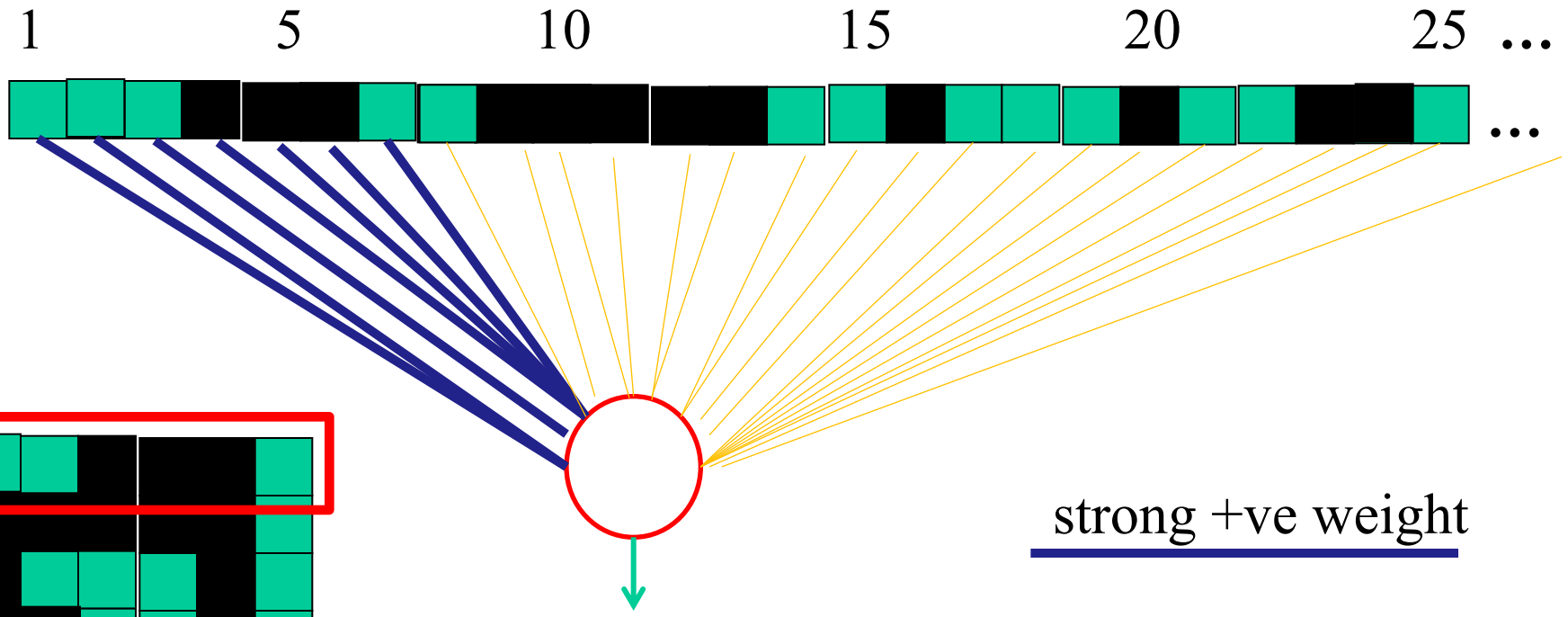
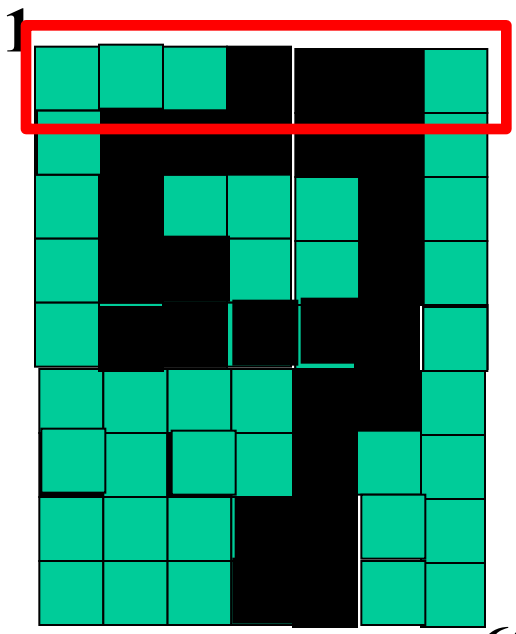


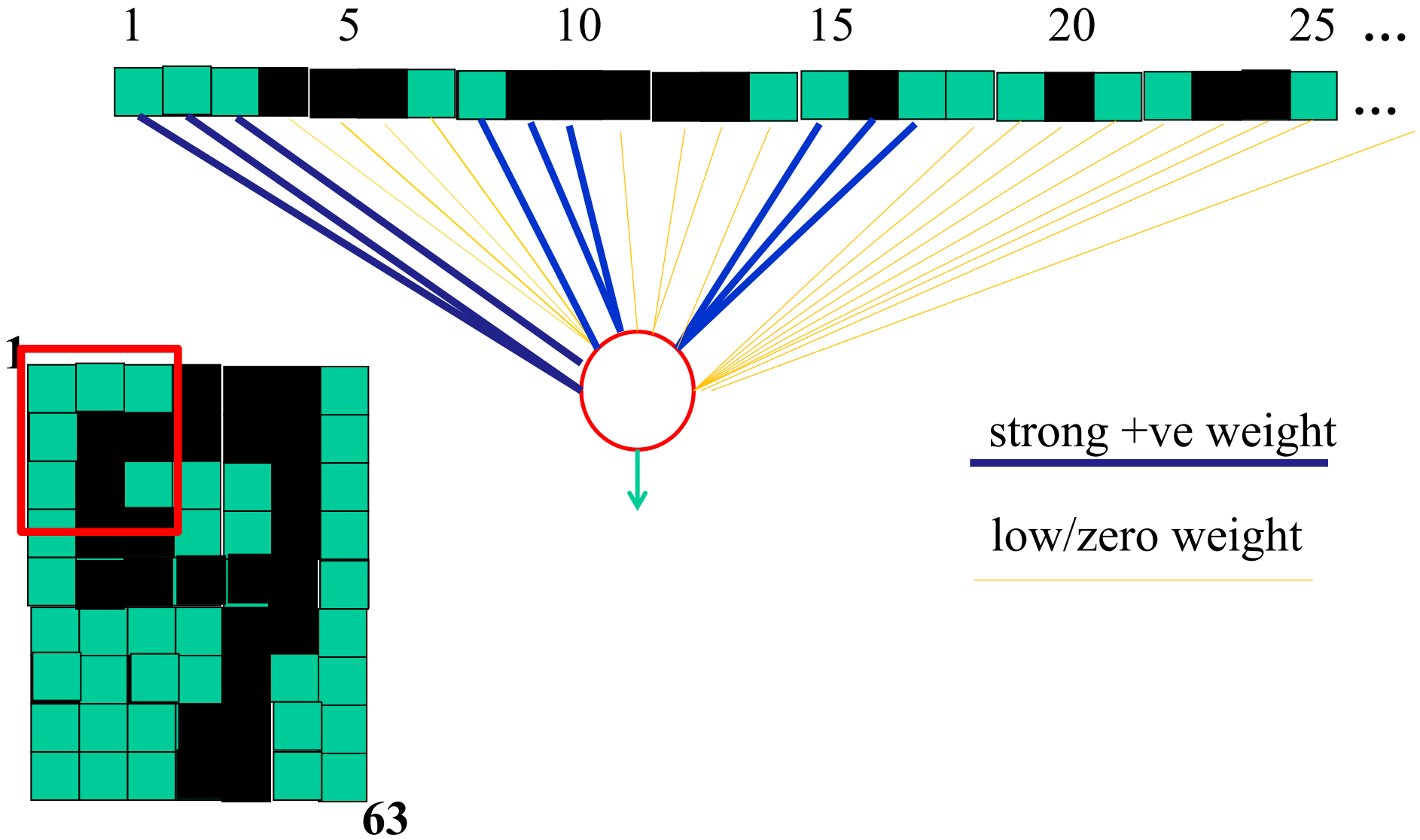


strong +ve weight

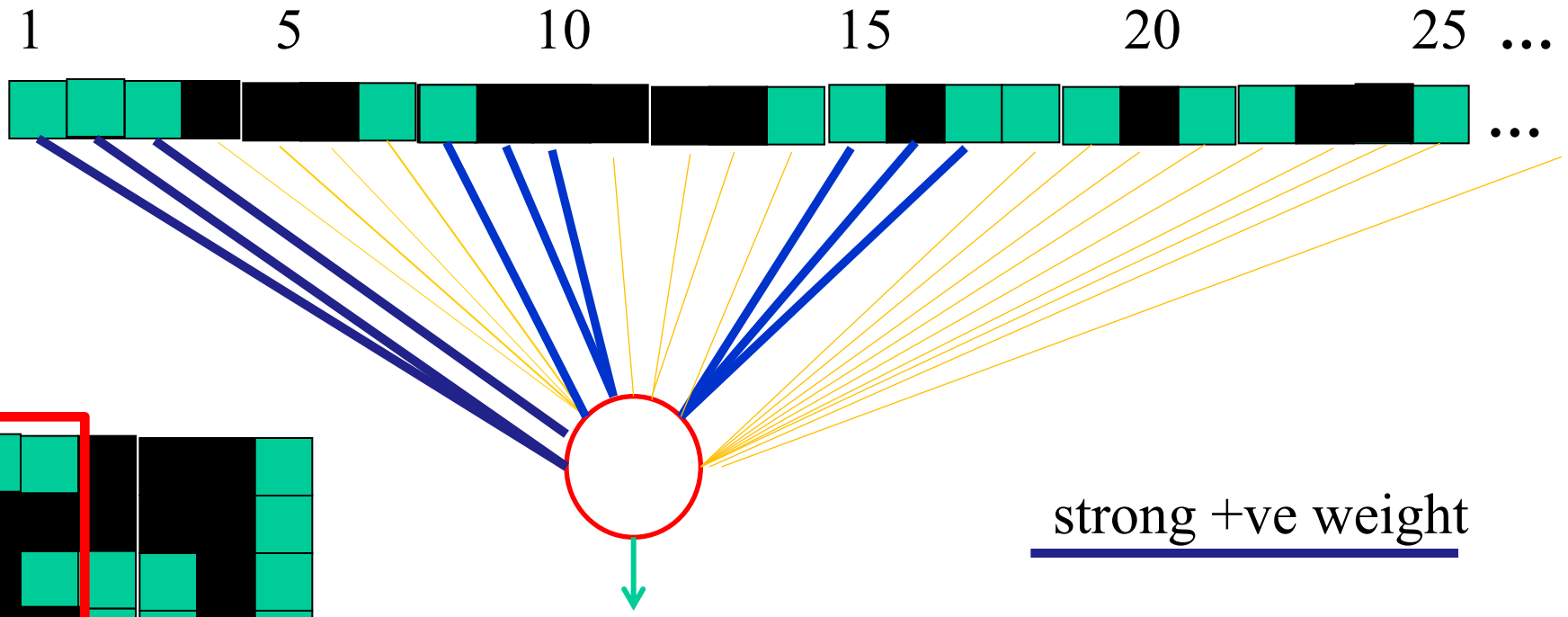
low/zero weight

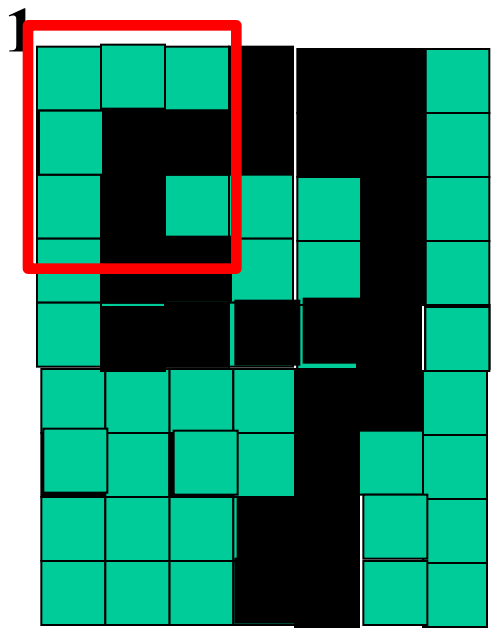
it will send strong signal for a horizontal line in the top row, ignoring everywhere else

What does this unit detect?



What does this unit detect?





strong +ve weight

low/zero weight

Strong signal for a dark area in the top left corner

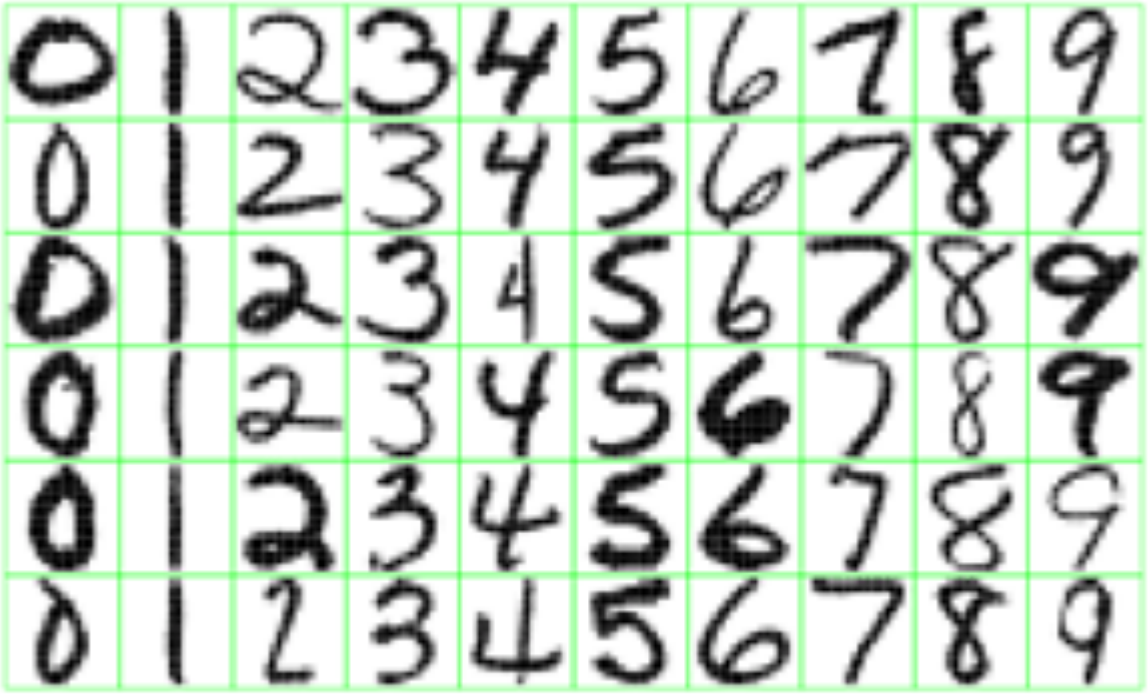


Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*

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

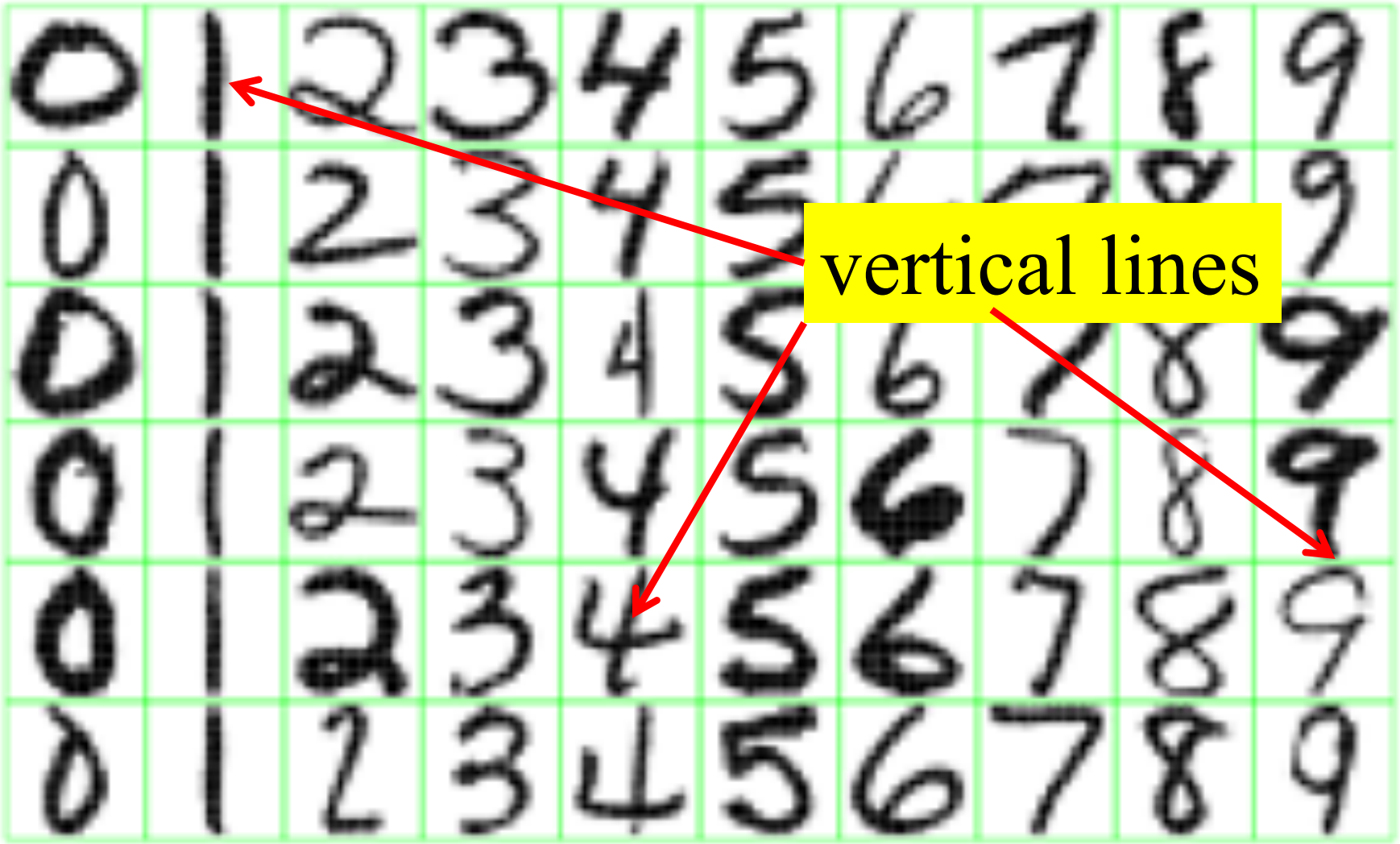


Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*

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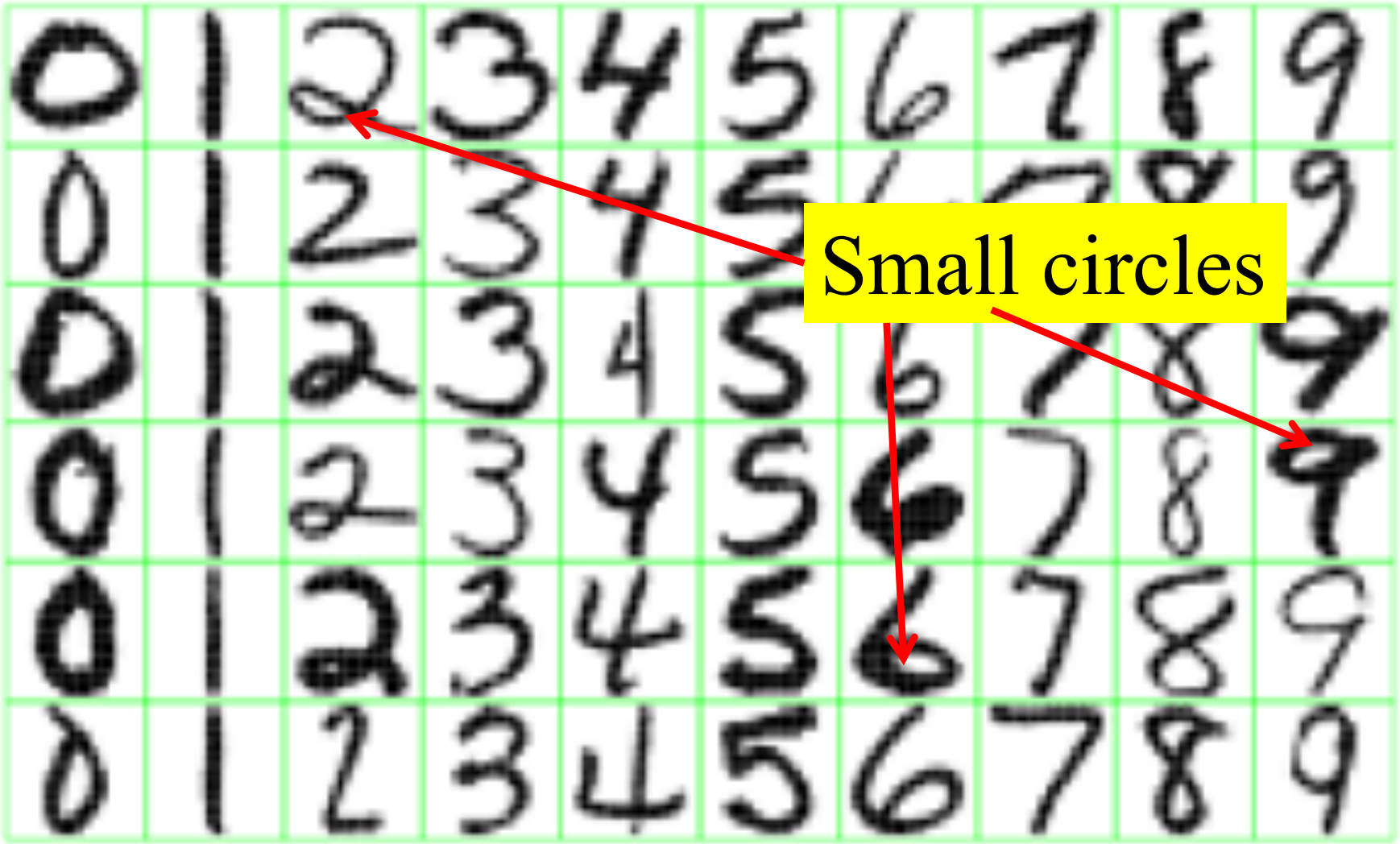
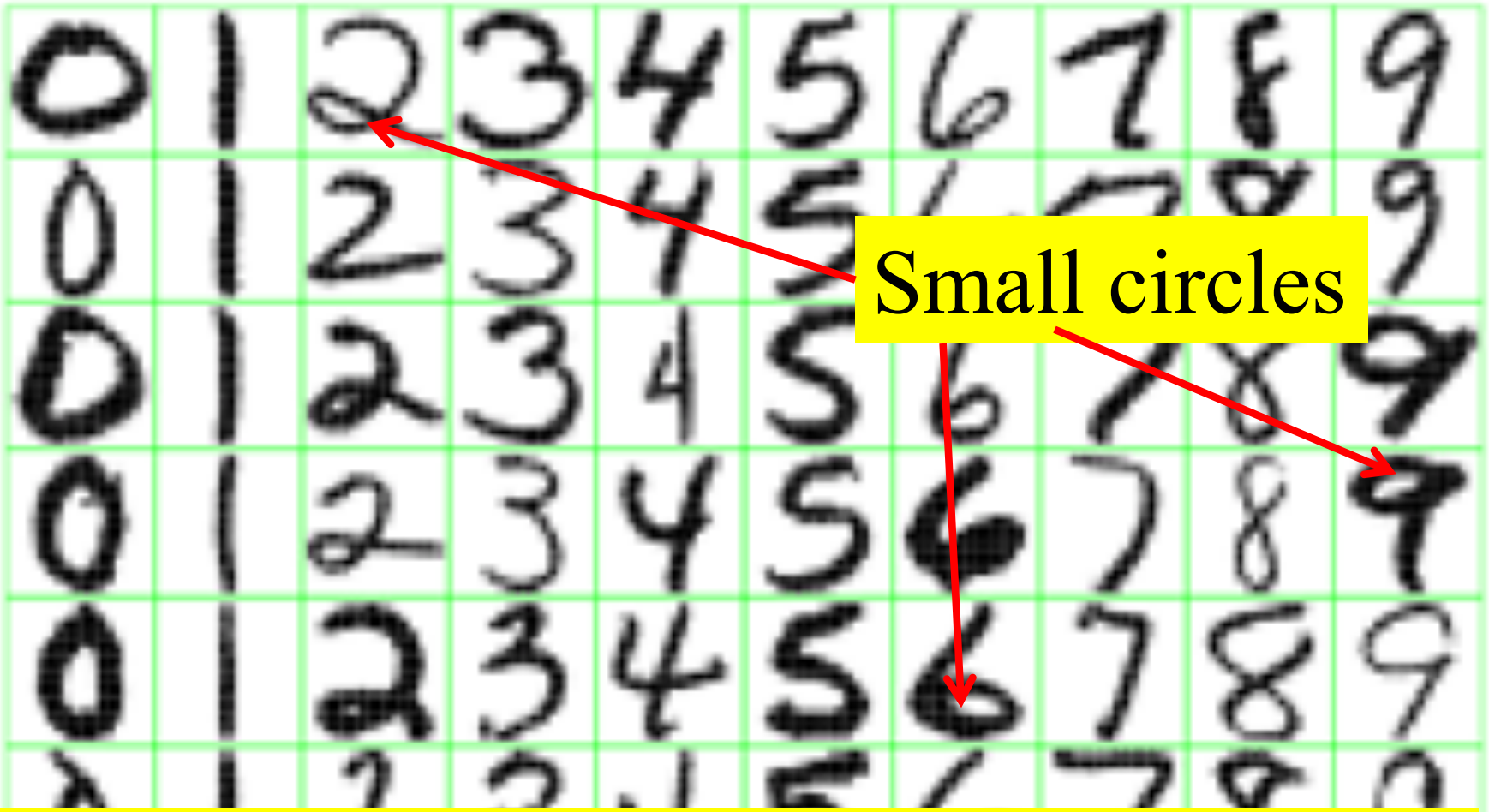


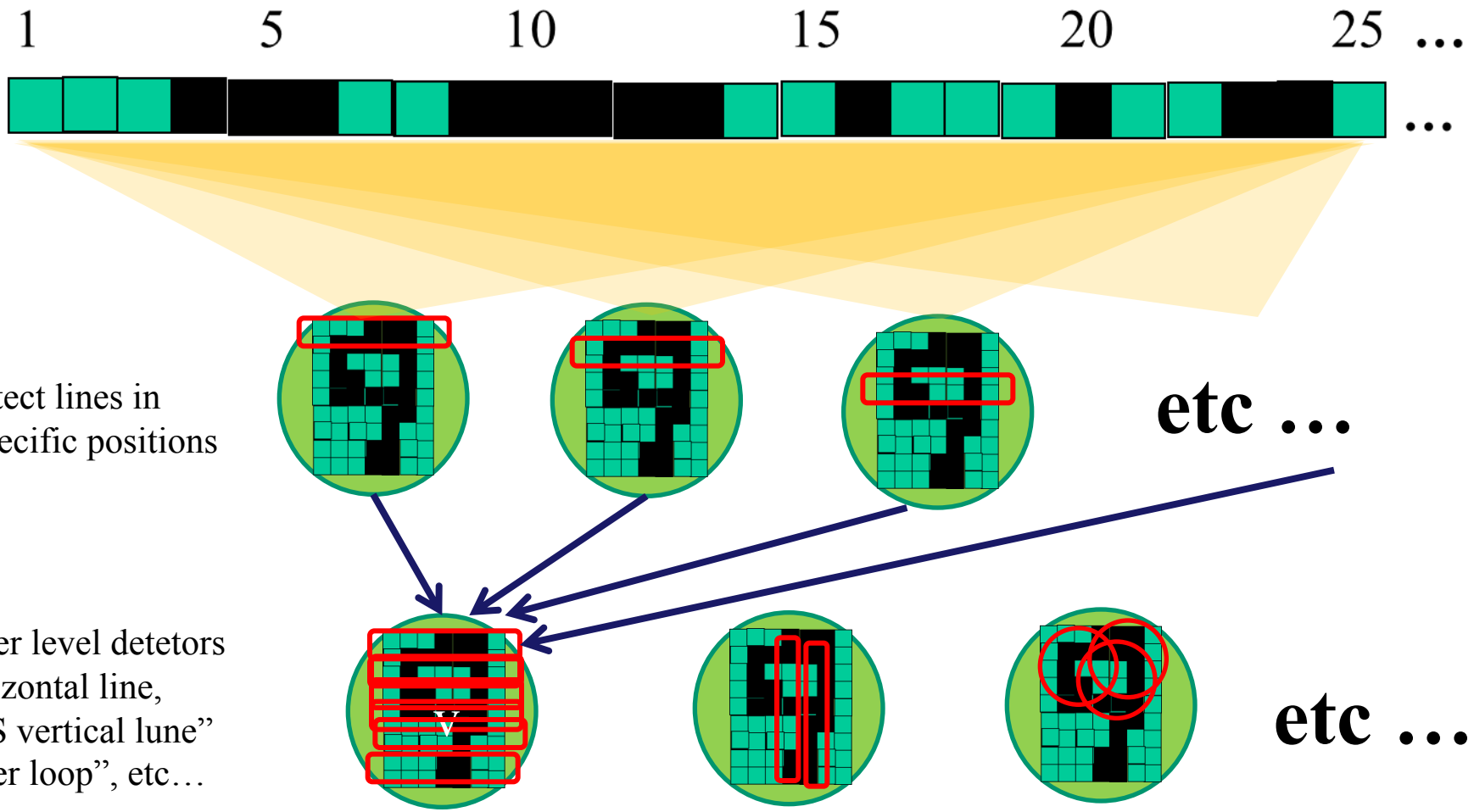
Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*



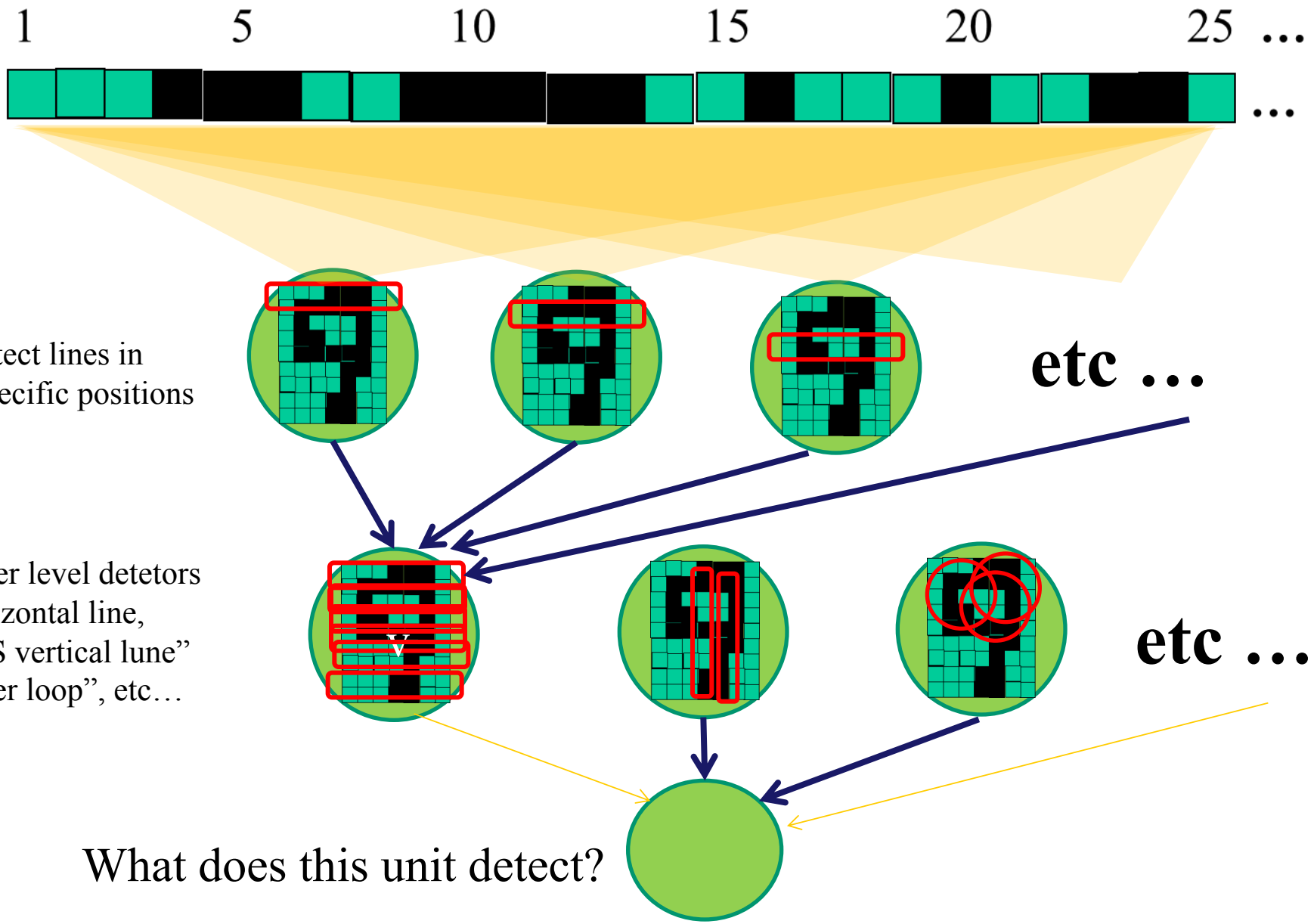
1

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

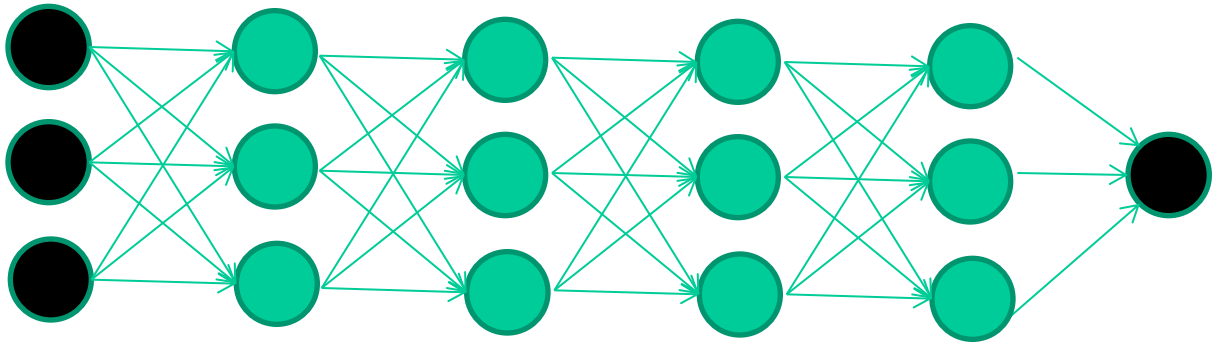
successive layers can learn higher-level features …



successive layers can learn higher-level features …

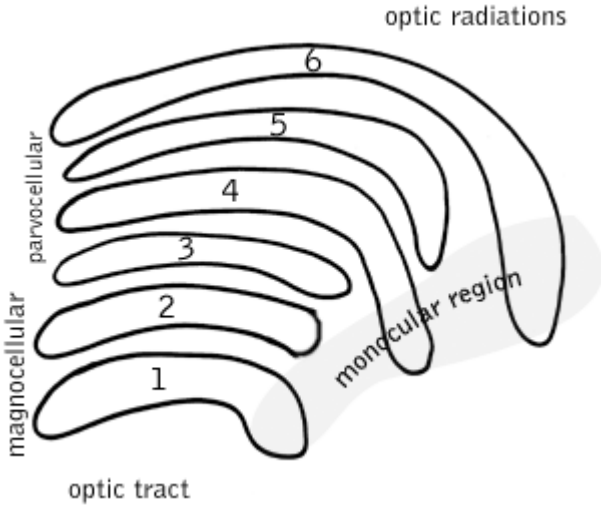


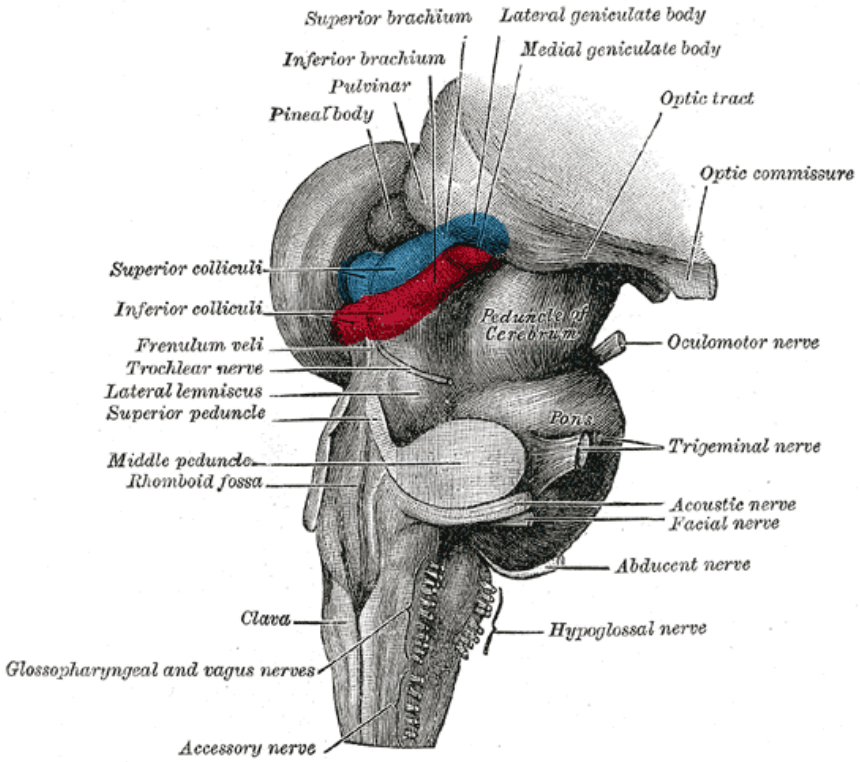
So: *multiple layers make sense*



So: *multiple layers make sense*

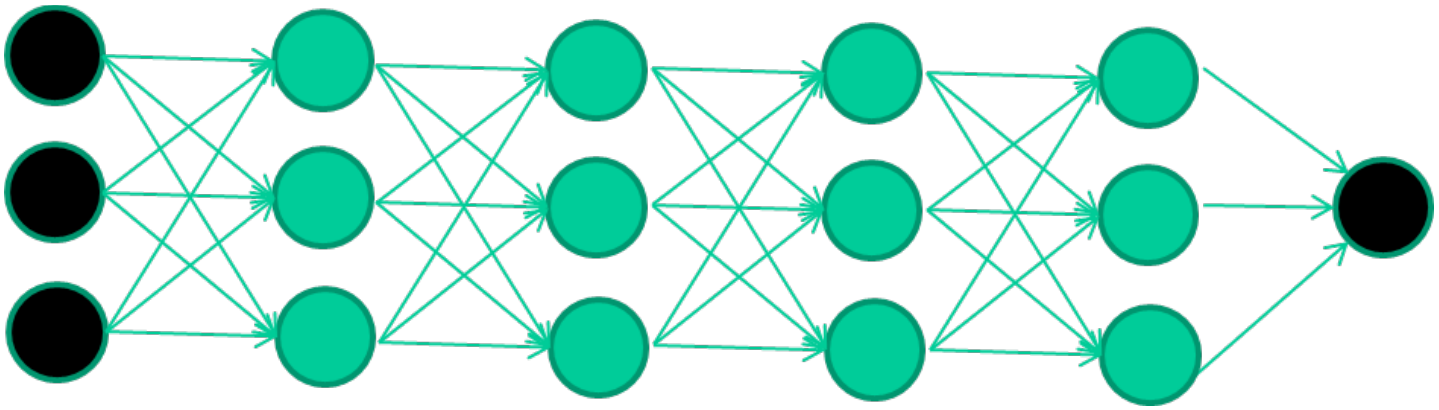
Your brain works that way



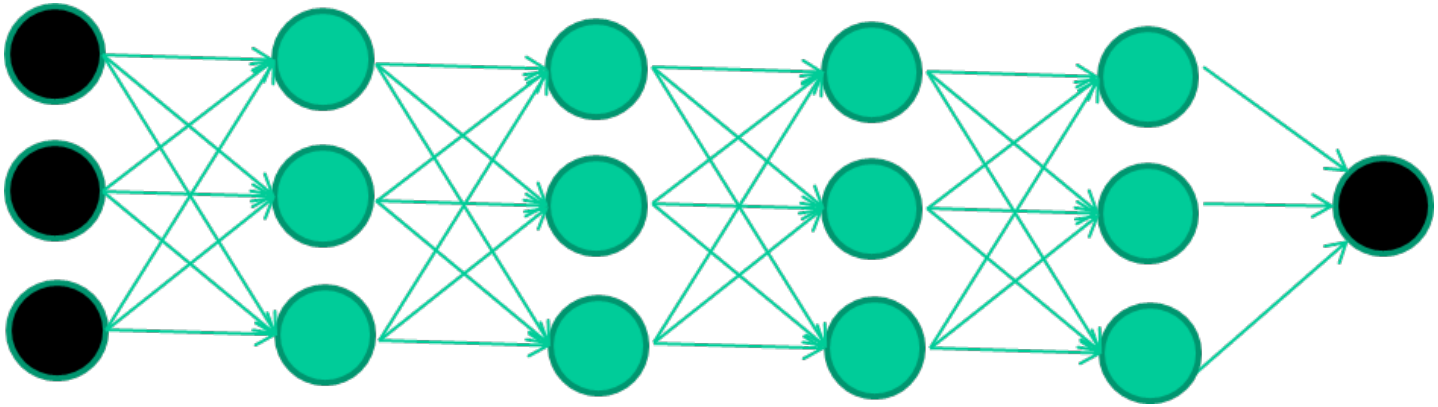


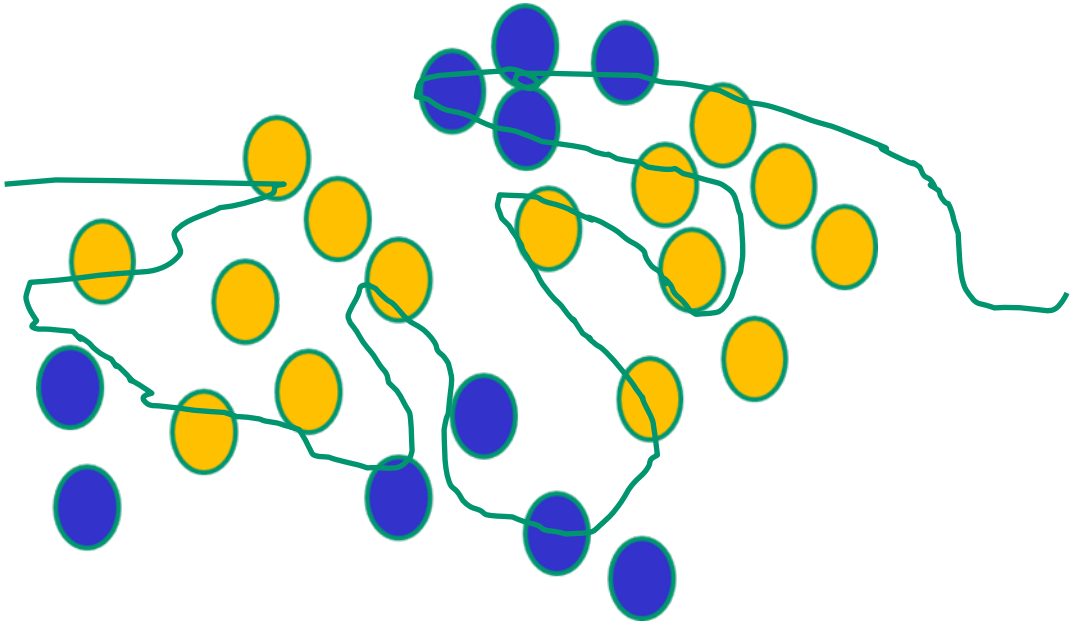
So: *multiple layers make sense*

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



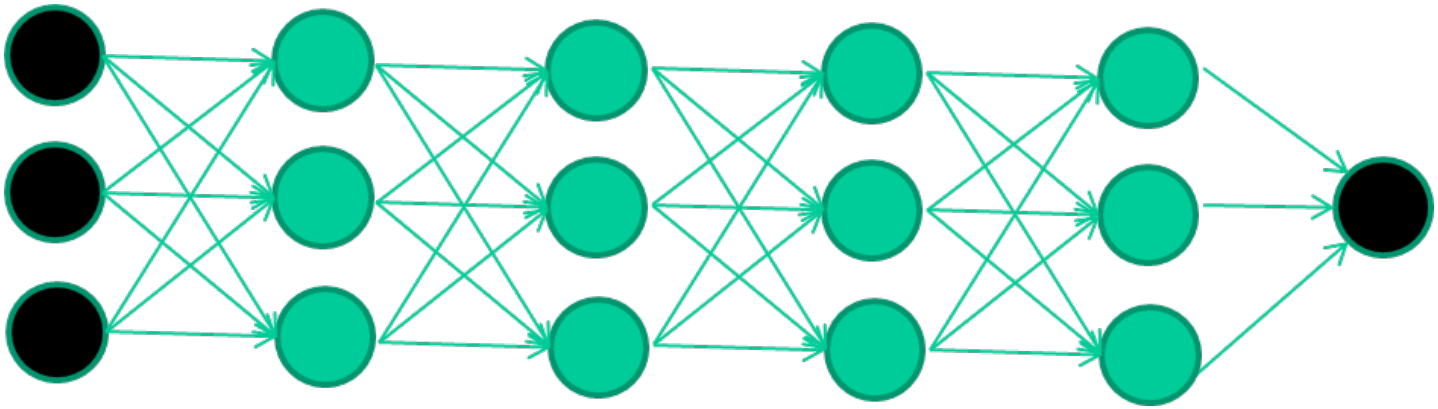
But, until very recently, our weight-learning algorithms simply did not work on multi-layer architectures



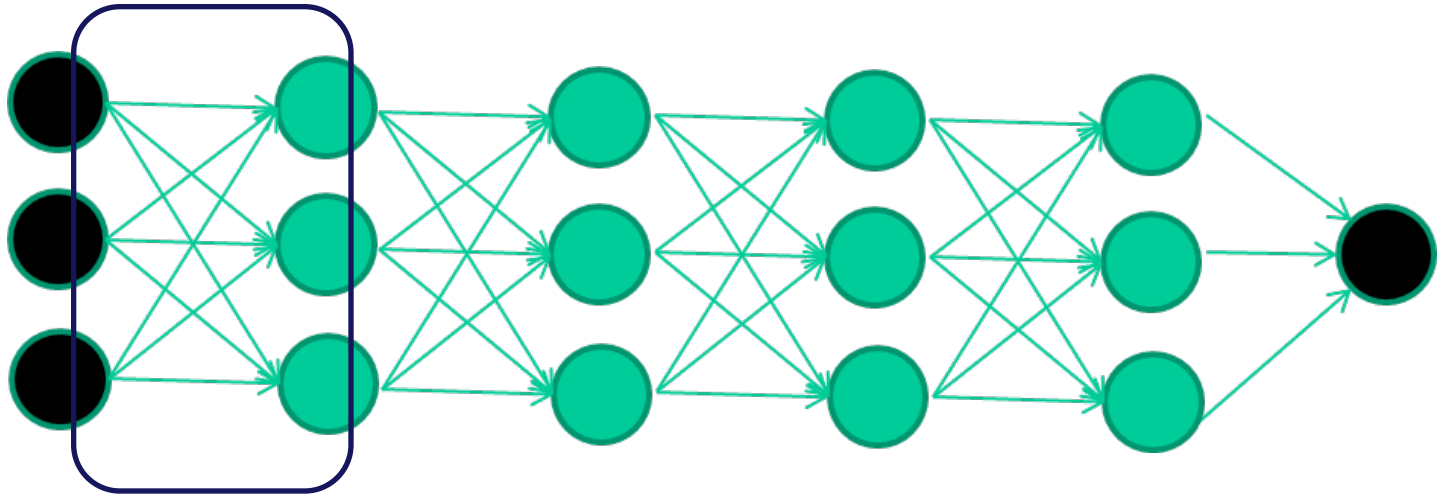


Along came deep learning …

The new way to train multi-layer NNs…

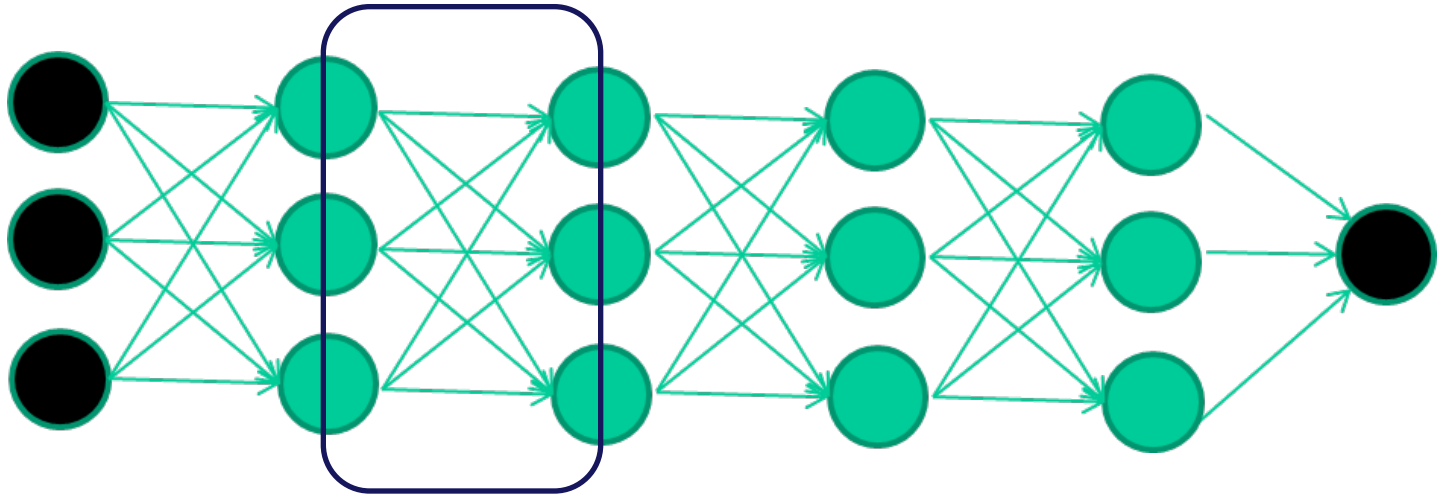


The new way to train multi-layer NNs…



Train **this** layer first

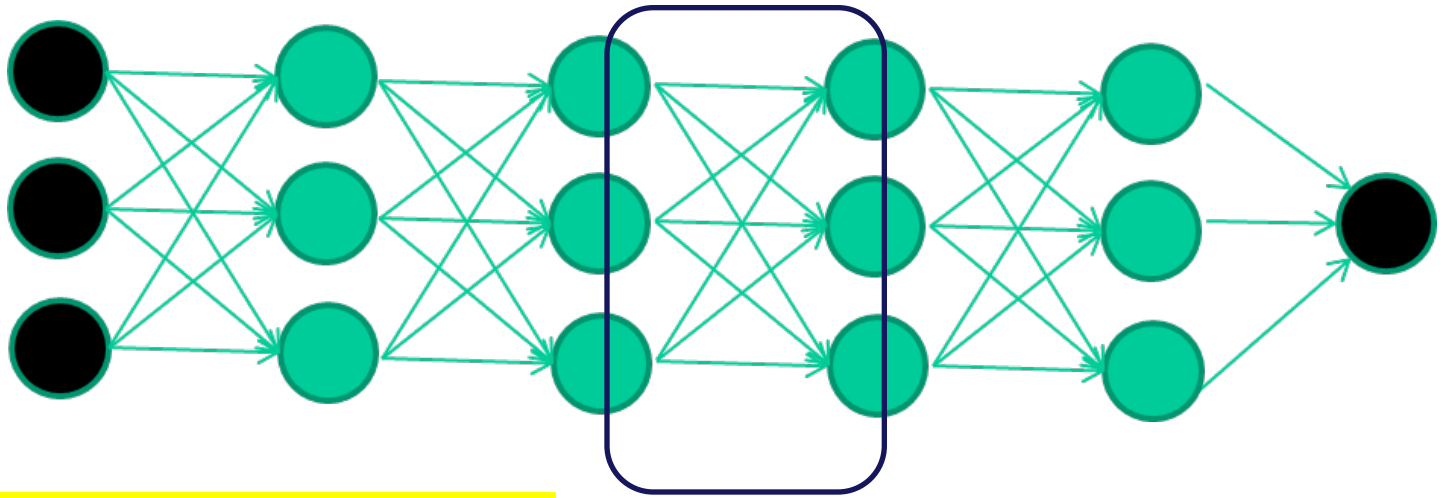
The new way to train multi-layer NNs…



Train **this** layer first

then **this** layer

The new way to train multi-layer NNs…

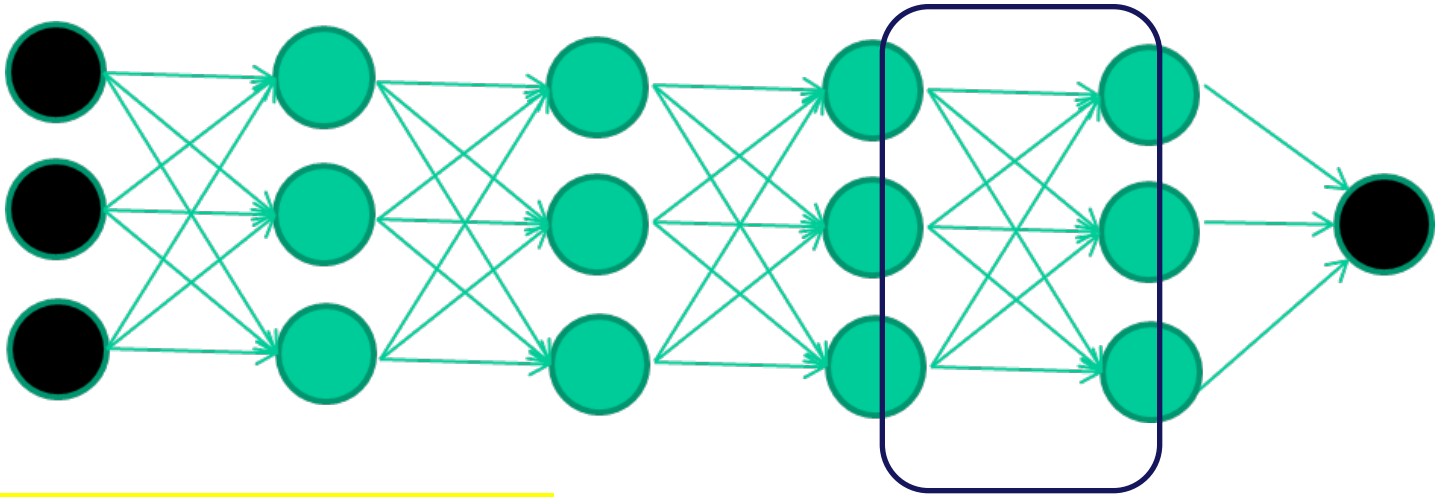


Train **this** layer first

then **this** layer

then **this** layer

The new way to train multi-layer NNs…



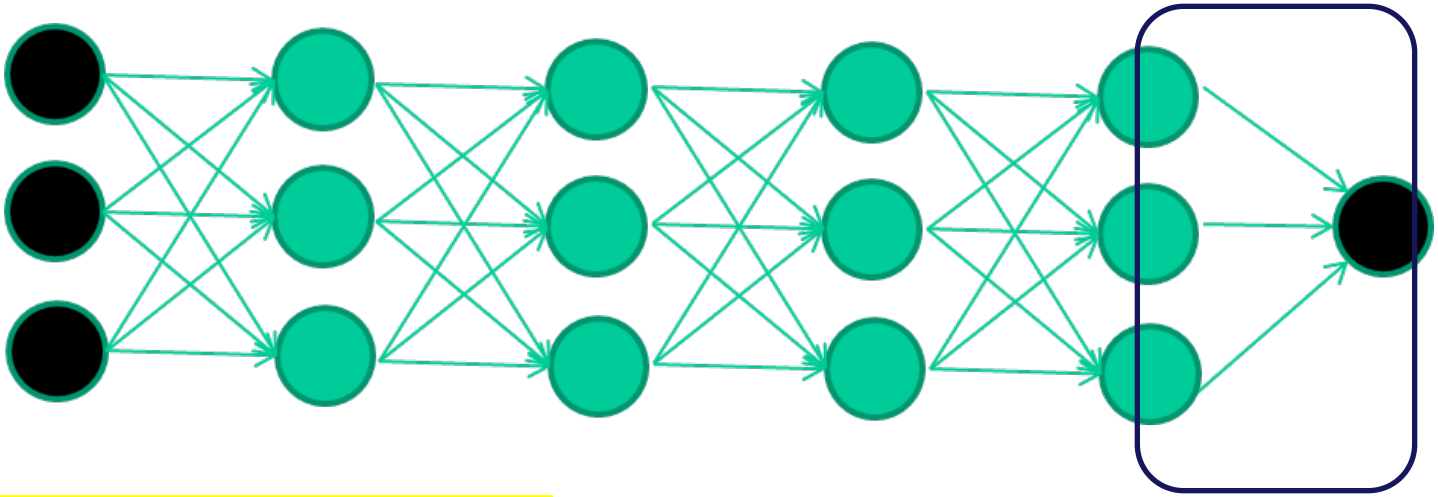
Train **this** layer first

then **this** layer

then **this** layer

then **this** layer

The new way to train multi-layer NNs…



Train **this** layer first

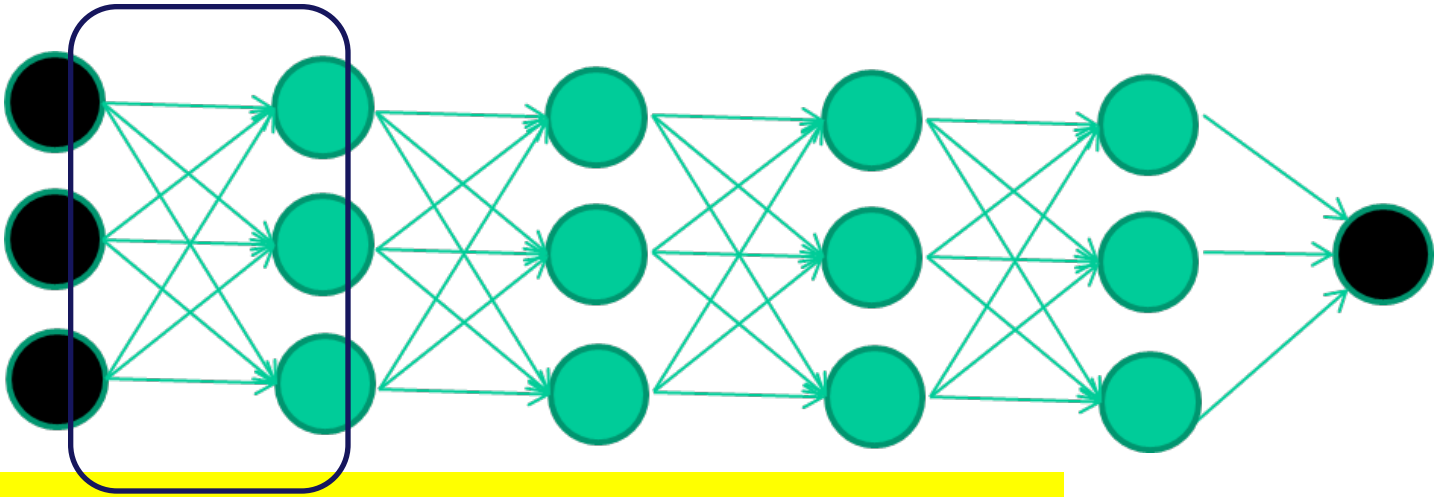
then **this** layer

then **this** layer

then **this** layer

finally **this** layer

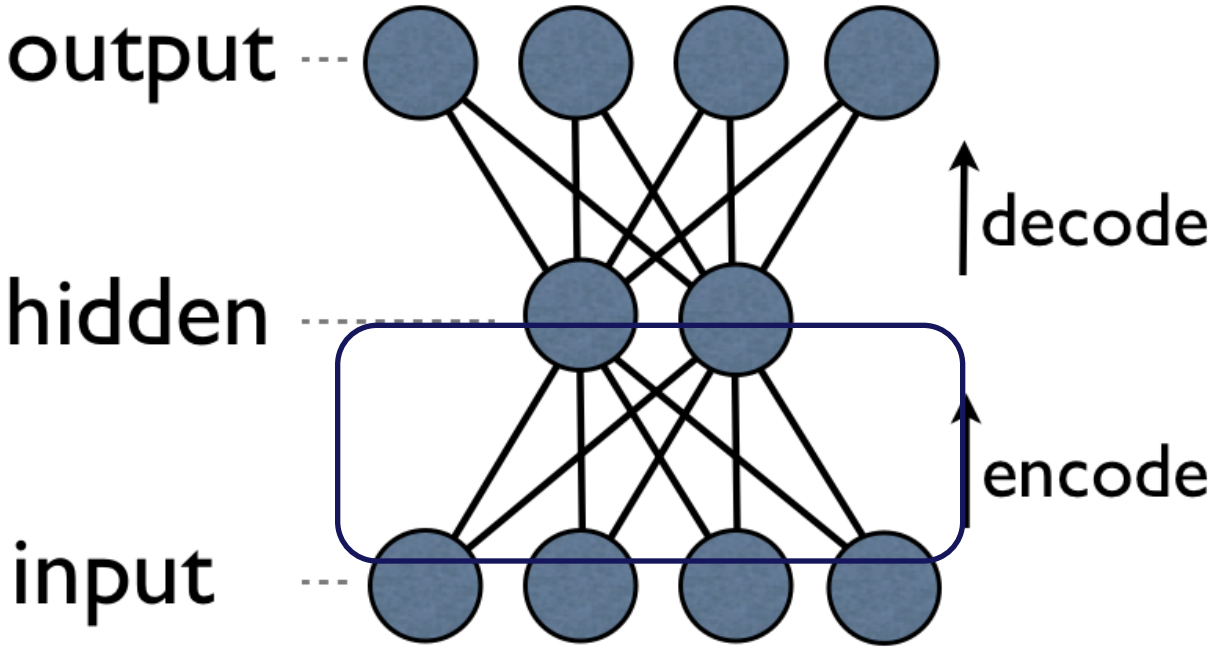
The new way to train multi-layer NNs…



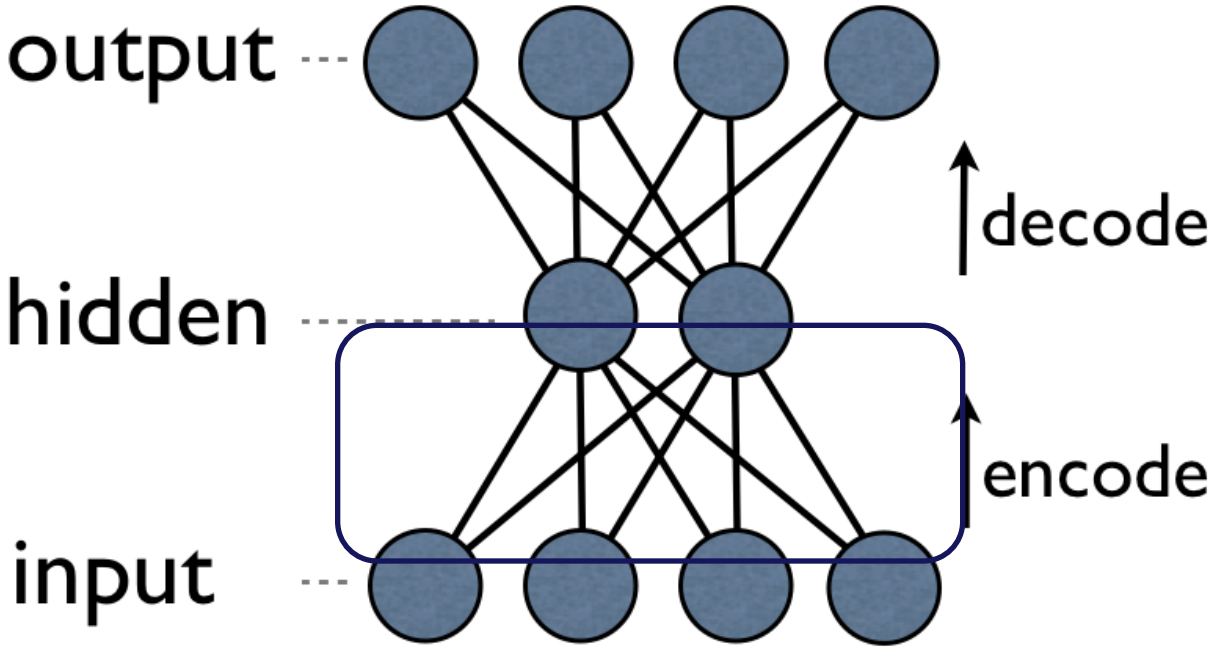
EACH of the (non-output) layers is trained to be an ***auto-encoder***

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 reproduce the input

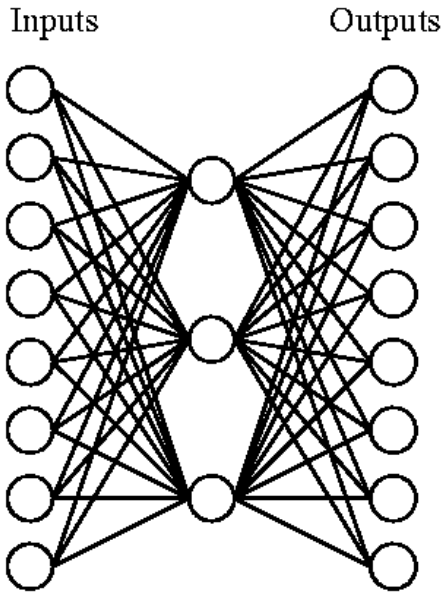


an auto-encoder is trained, with an absolutely standard weight-adjustment algorithm to reproduce the input



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

Hidden Layer Representations

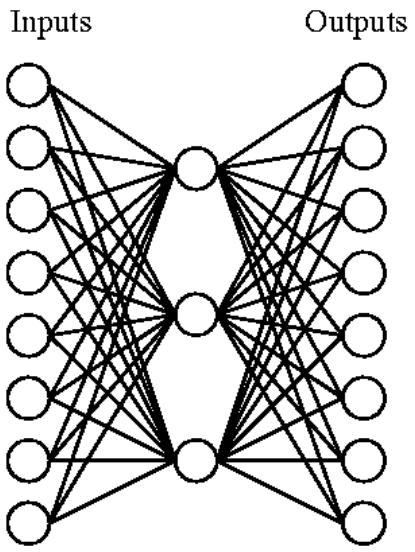


Target Function:

Input		Output
10000000	→	10000000
01000000	→	01000000
00100000	→	00100000
00010000	→	00010000
00001000	→	00001000
00000100	→	00000100
00000010	→	00000010
00000001	→	00000001

Can this be learned?

Hidden Layer Representations

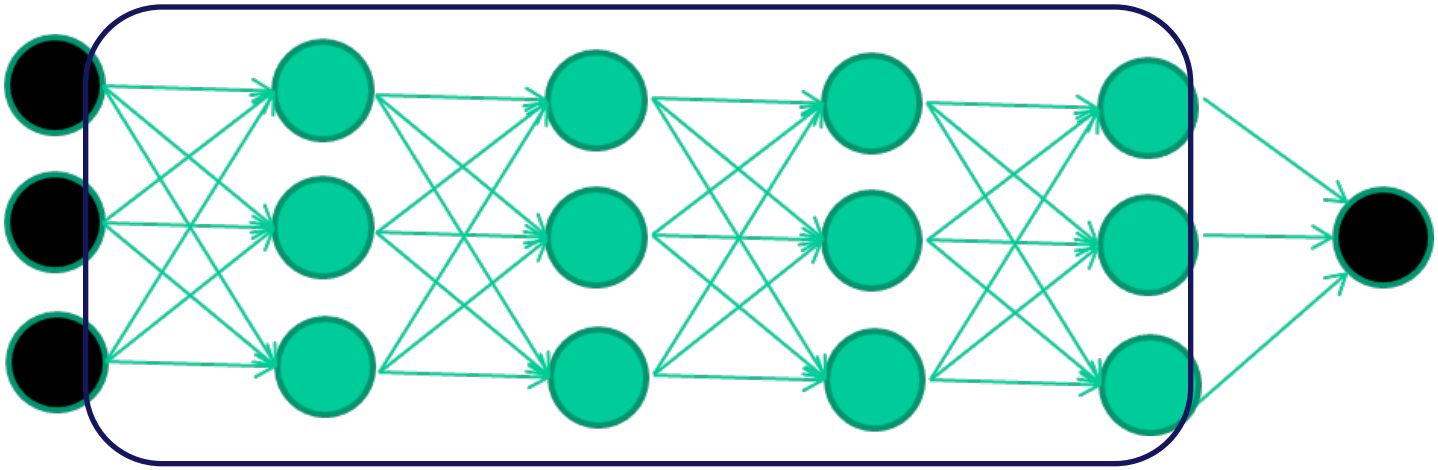


Input		Hidden Values				Output
10000000	→	.89	.04	.08	→	10000000
01000000	→	.01	.11	.88	→	01000000
00100000	→	.01	.97	.27	→	00100000
00010000	→	.99	.97	.71	→	00010000
00001000	→	.03	.05	.02	→	00001000
00000100	→	.22	.99	.99	→	00000100
00000010	→	.80	.01	.98	→	00000010
00000001	→	.60	.94	.01	→	00000001

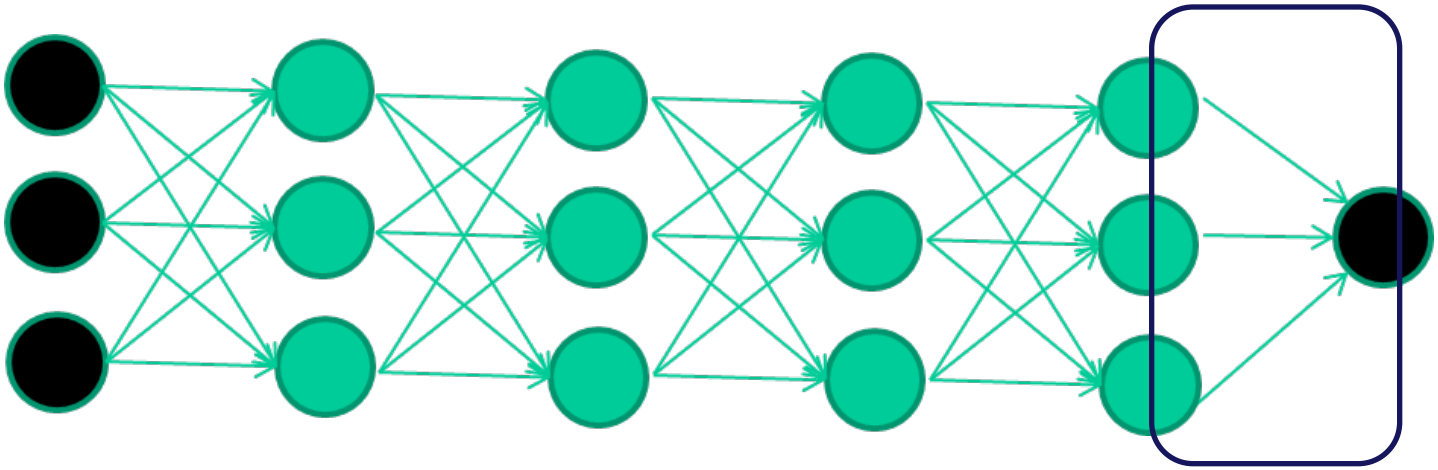
1 0 0
0 0 1
0 1 0
1 1 1
0 0 0
0 1 1
1 0 1
1 1 0

Hidden layers allow a network to invent appropriate internal representations.

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

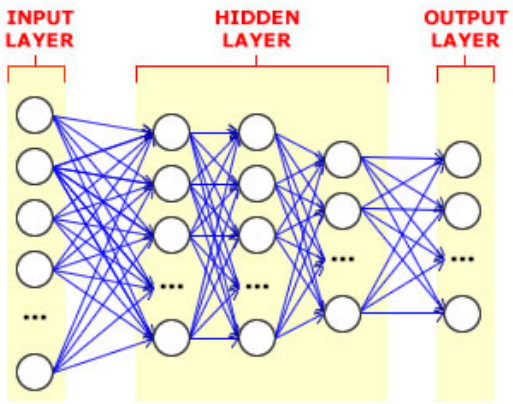


Final layer trained to predict class based on outputs from previous layers



And that's that

- That's the basic idea
- There are many many types of deep learning,
- different kinds of autoencoder, variations on architectures and training algorithms, etc…
- Very fast growing area …

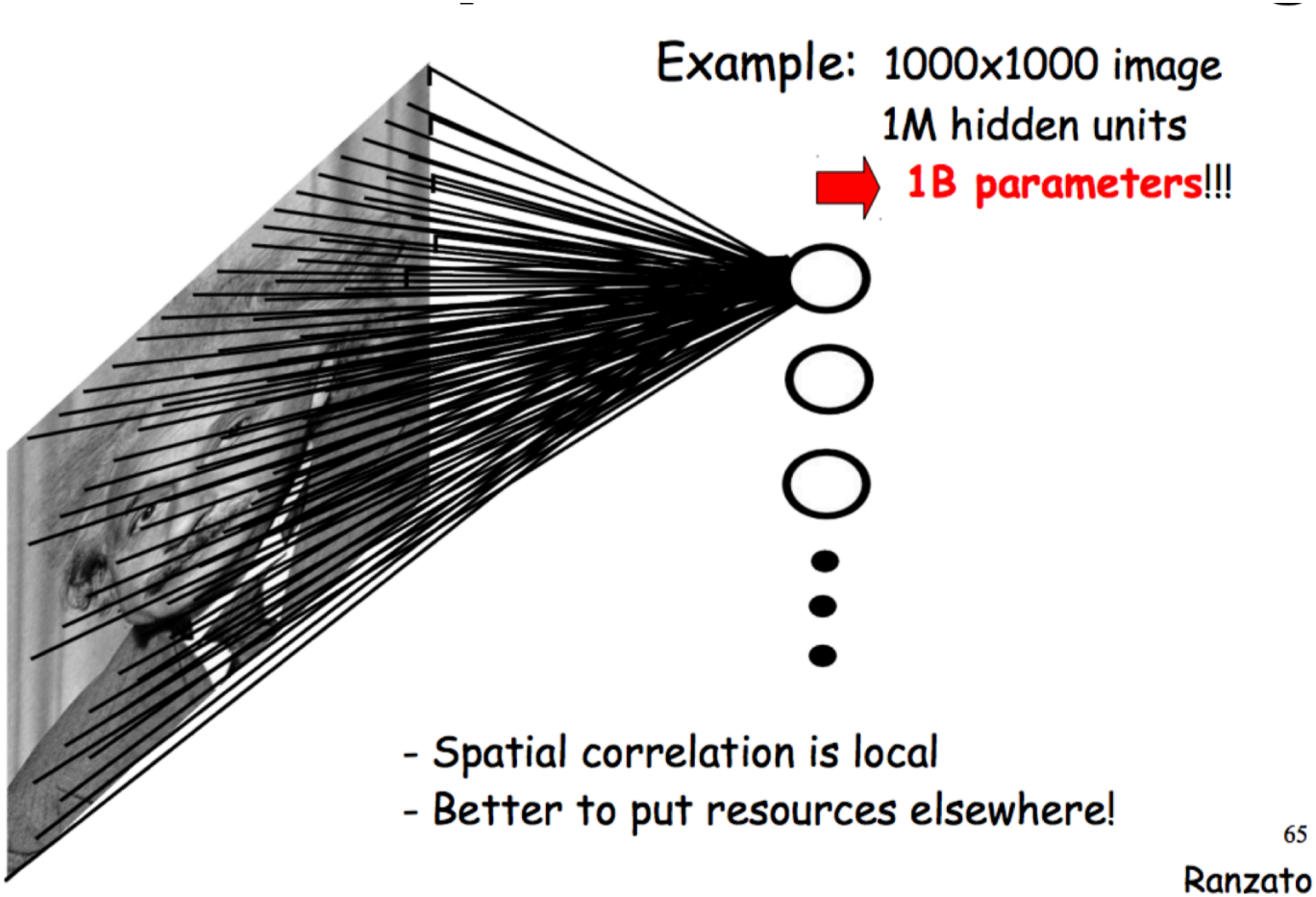


Convolutional Neural Network

- Popular deep learning network for image classification
- One of the earliest DL Algorithms (1998)
- Basic idea:
  - multiple layers of auto-encoders in the form of convolutional layers to detect features
  - Convolutional layers cut down on weights needed to be learned

LeCun et al. "Gradient-based learning applied to document recognition" IEEE 1998

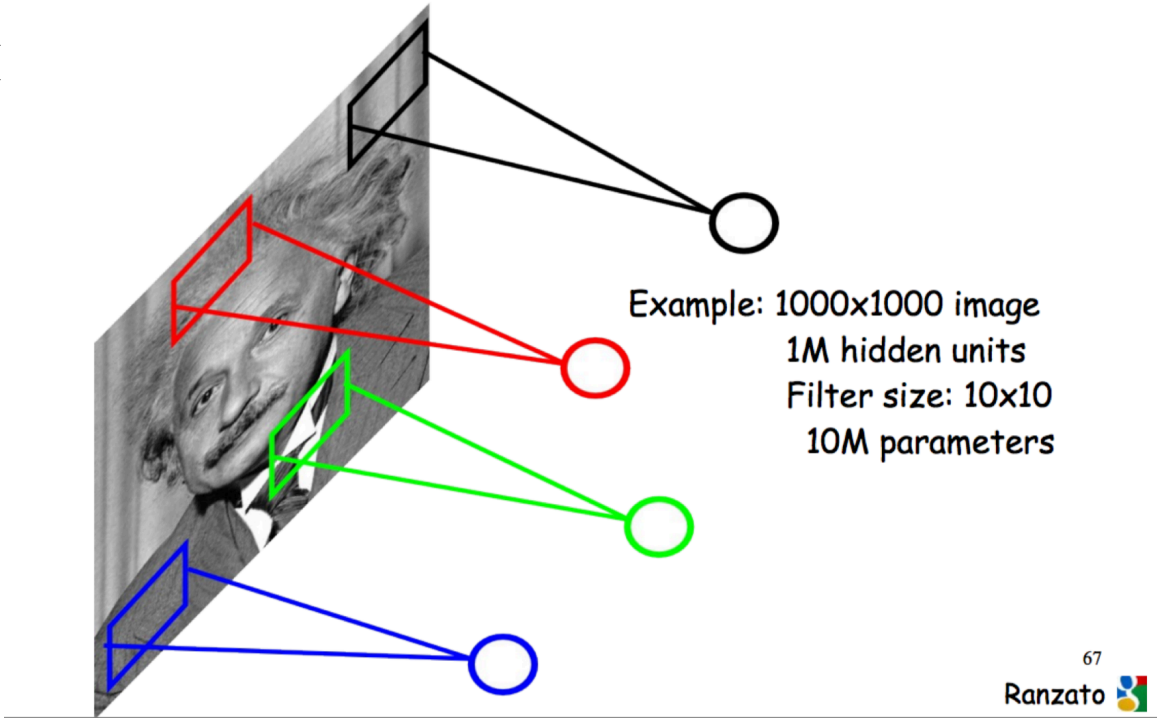
Convolutional Neural Network



http://www.cs.umd.edu/~djacobs/CMSC733/CNN.pdf

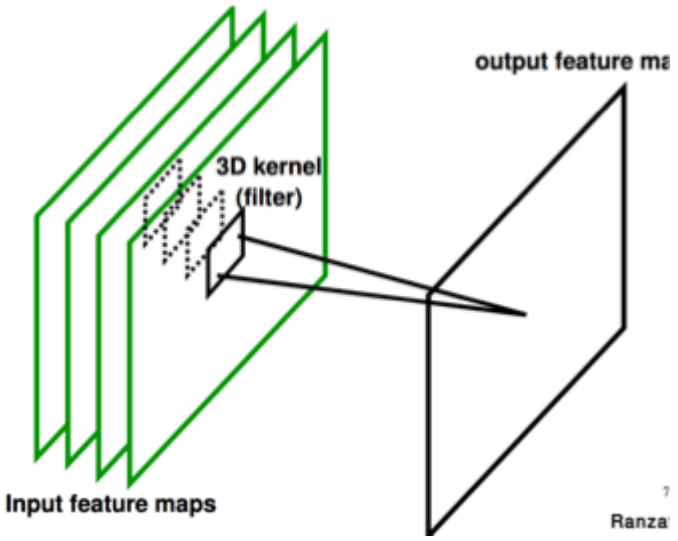
Convolutional Neural Network

- Kernels (no not SVM kernels) but small regions of image.
- Kernels + Neurons = Convolution Layer



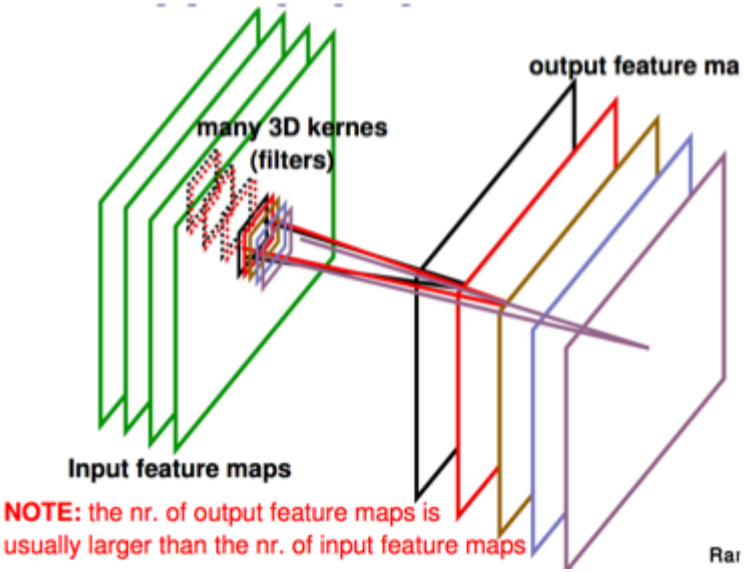
Convolutional Neural Network

- If the input has 3 channels (R,G,B), 3 separate k by k filter is applied to each channel.
- Output of convolving 1 feature is called a *feature map*.

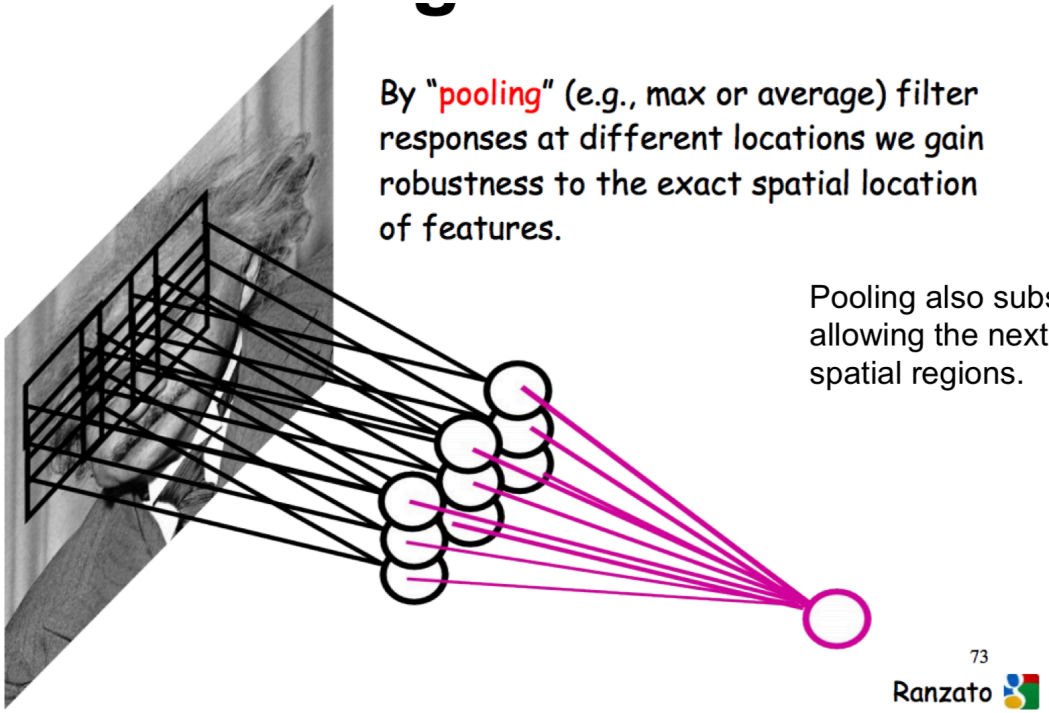


Convolutional Neural Network

- Each filter detects features in the output of previous layer.
- So to capture different features, learn multiple filters
- This is an example of a “convolution layer”

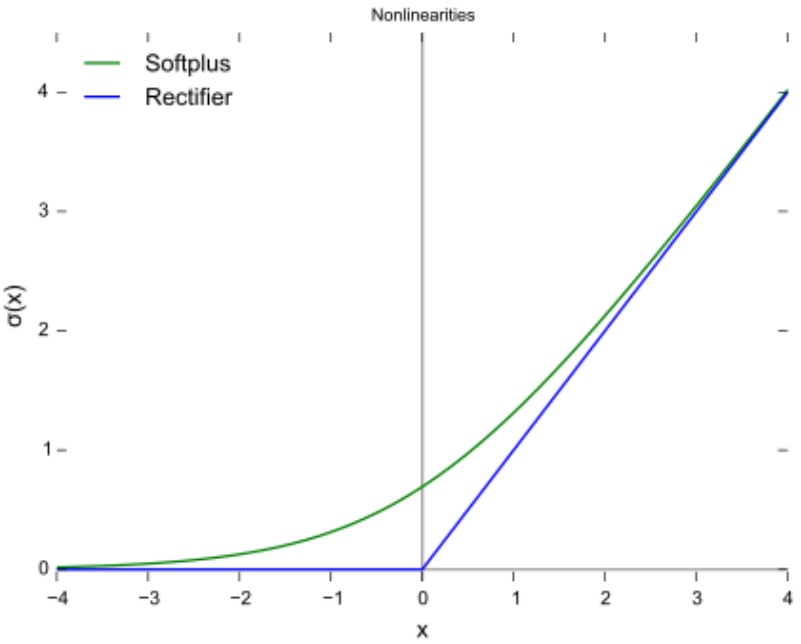


Convolutional Neural Network



Pooling Layer

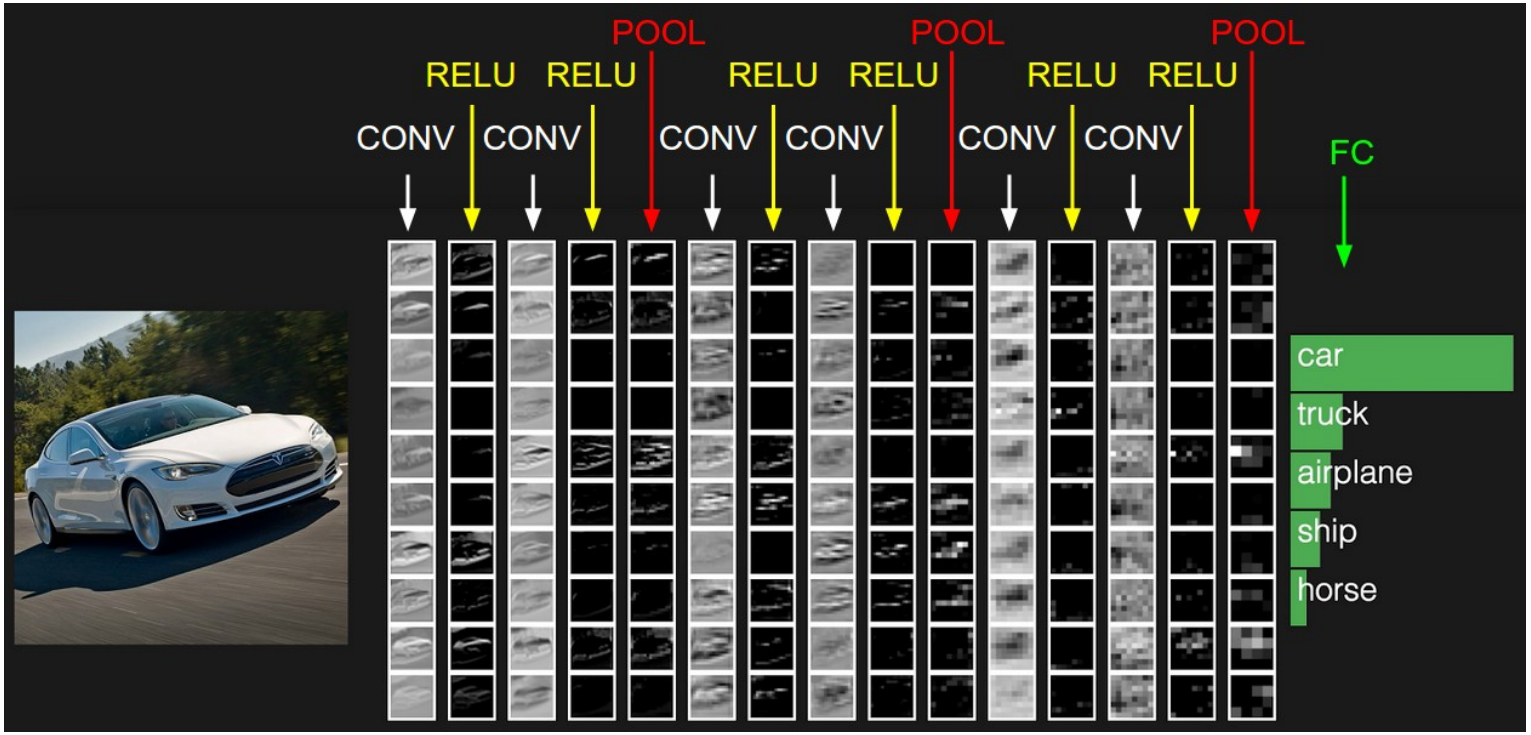
Convolutional Neural Network



ReLu Layer (rectified linear unit) – non-linear unit

Nair, Vinod, and Geoffrey E. Hinton. "Rectified linear units improve restricted boltzmann machines." *Proceedings of the 27th international conference on machine learning (ICML-10)*. 2010.

Convolutional Neural Network



Example of a Convolutional Neural Network

Demo: http://cs231n.stanford.edu/

Convolutional Neural Network

- Nice tutorial on CNN implementation using Tensorflow and Python:
  - https://www.tensorflow.org/tutorials/deep_cnn
- No implementation of CNNs in R 😕