Introduction to Deep Learning

Some slides were adated/taken from various sources, including Andrew Ng's Coursera Lectures, CS231n: Convolutional Neural Networks for Visual Recognition lectures, Stanford University CS Waterloo Canada lectures, Aykut Erdem, et.al. tutorial on Deep Learning in Computer Vision, Ismini Lourentzou's lecture slide on "Introduction to Deep Learning", Ramprasaath's lecture slides, 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

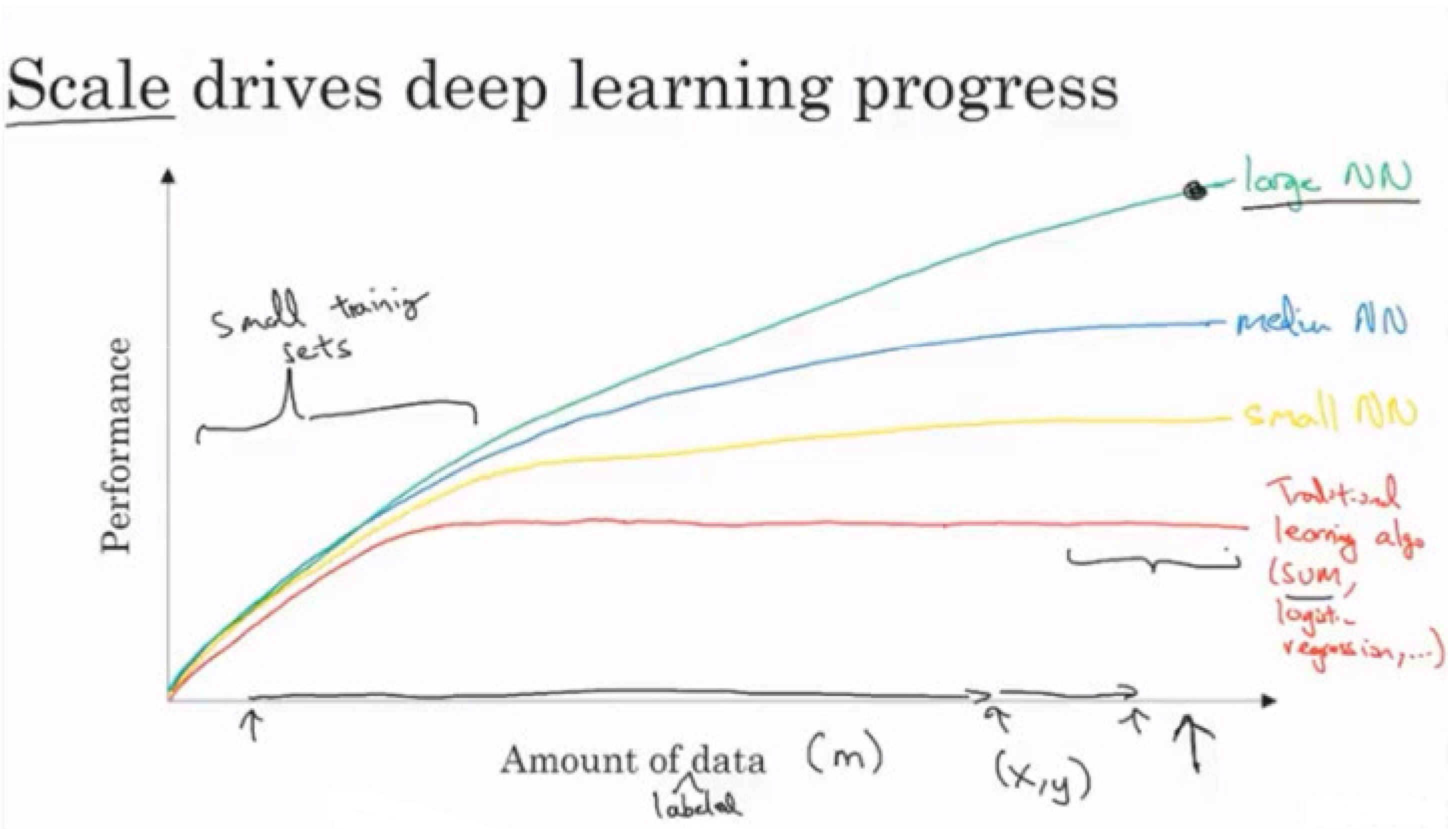
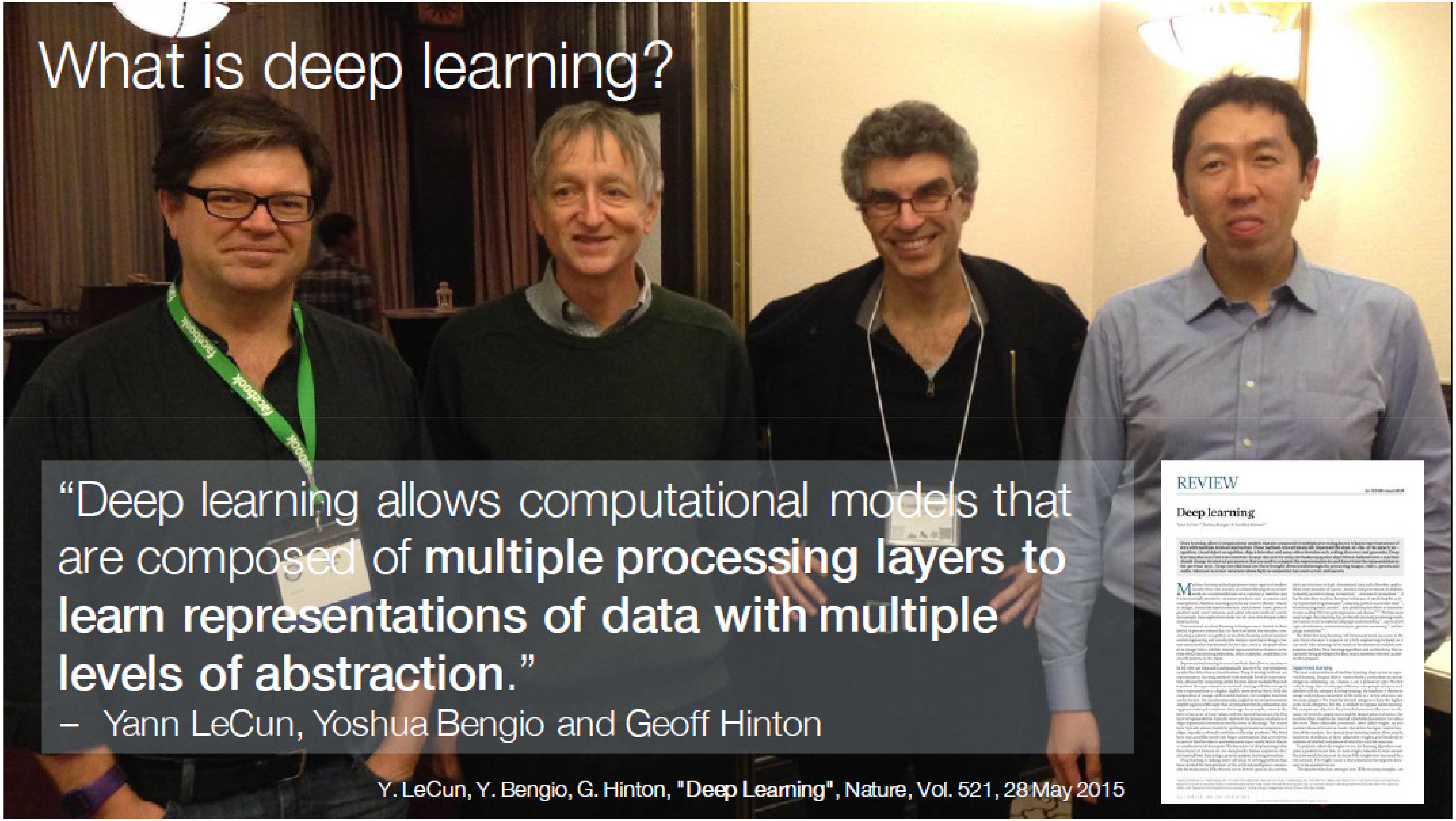


Image Source: Andrew Ng

- Data
- Computations
- Algorithm

What is deep learning?



"Deep learning allows computational models that are composed of **multiple processing layers to learn representations of data with multiple levels of abstraction.**"

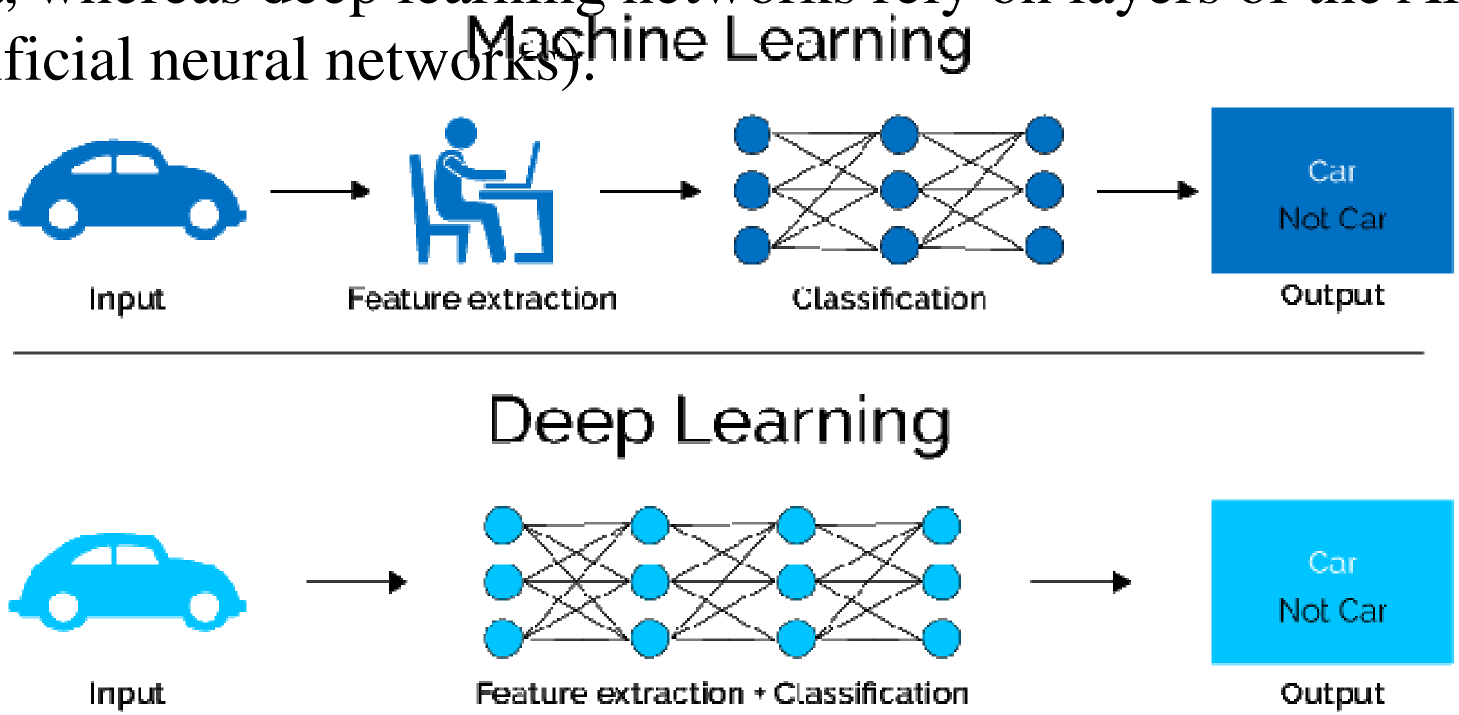
– Yann LeCun, Yoshua Bengio and Geoff Hinton

Y. LeCun, Y. Bengio, G. Hinton, "**Deep Learning**", Nature, Vol. 521, 28 May 2015

Machine Learning vs. Deep Learning

The key difference between deep learning and machine learning stems from the way data is presented to the system.

Machine learning algorithms almost always require structured data, whereas deep learning networks rely on layers of the ANN (artificial neural networks).

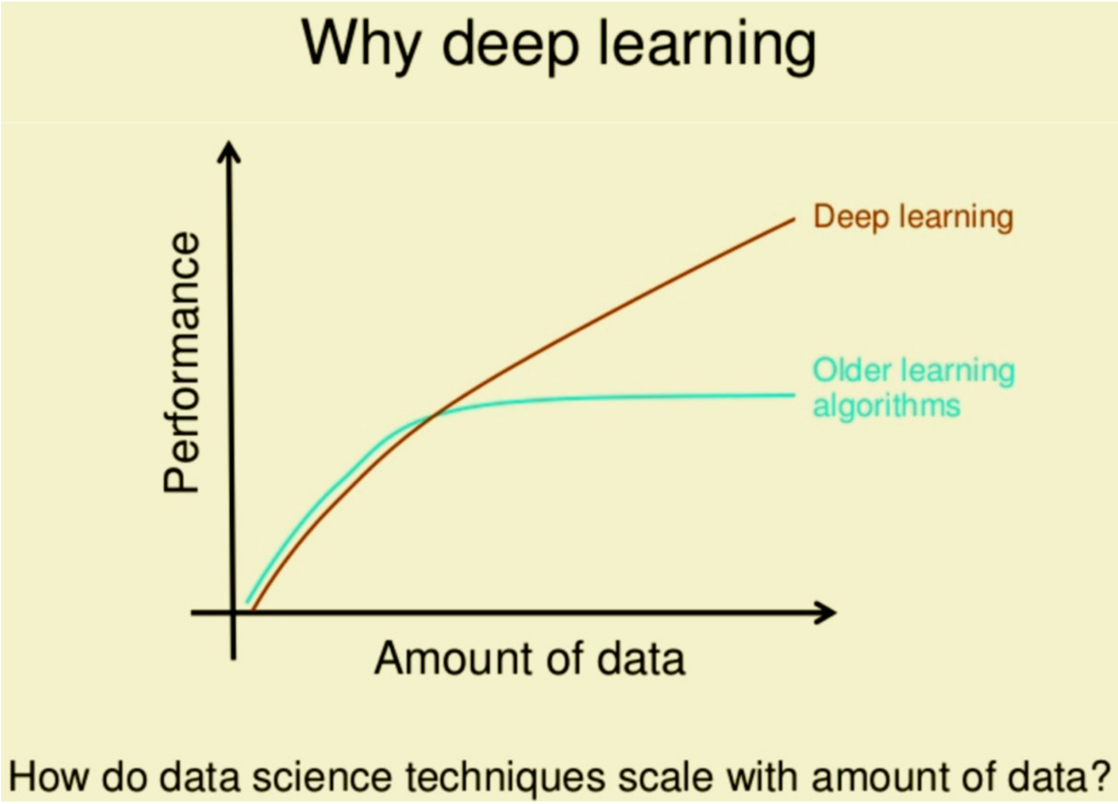


https://www.xenonstack.com/blog/static/public/uploads/media/machine-learning-vs-deep-learning.png

Problems with conventional machine learning

- Manually designed features are often **over-specified**, **incomplete** and take a **long time to design** and validate

- Less efficient to handle a large amount data with high order features



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?

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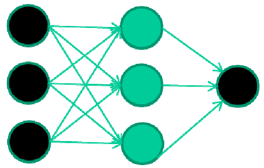
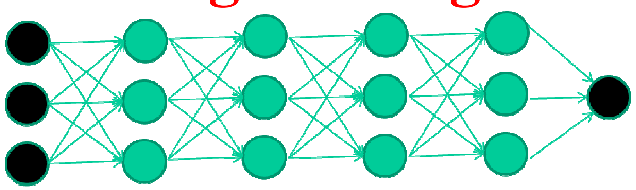
3. **multilayer neural networks have been around for 25 years. What's actually new?**

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



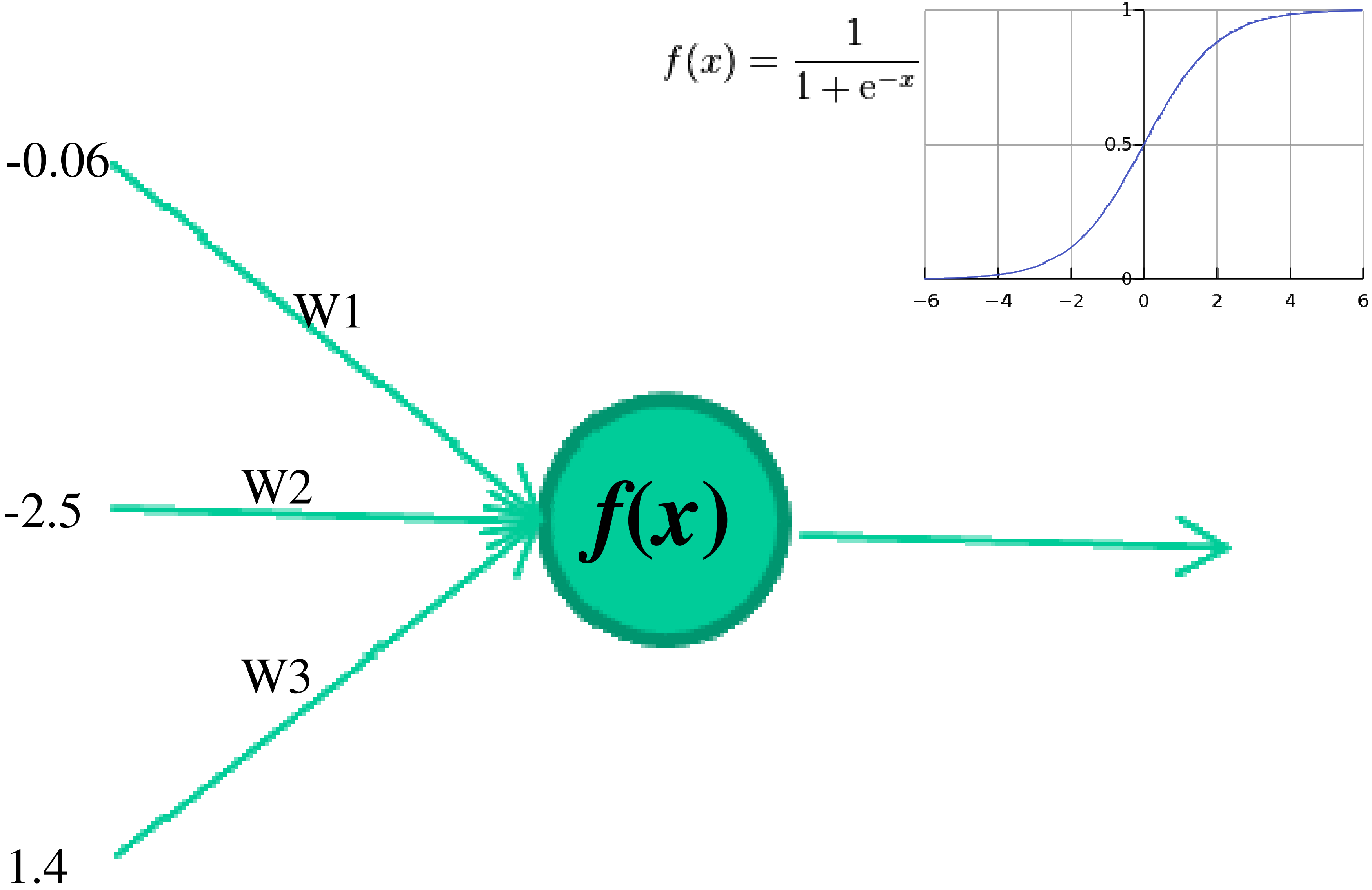
but these algorithms are not good at learning the weights for networks with more hidden layers



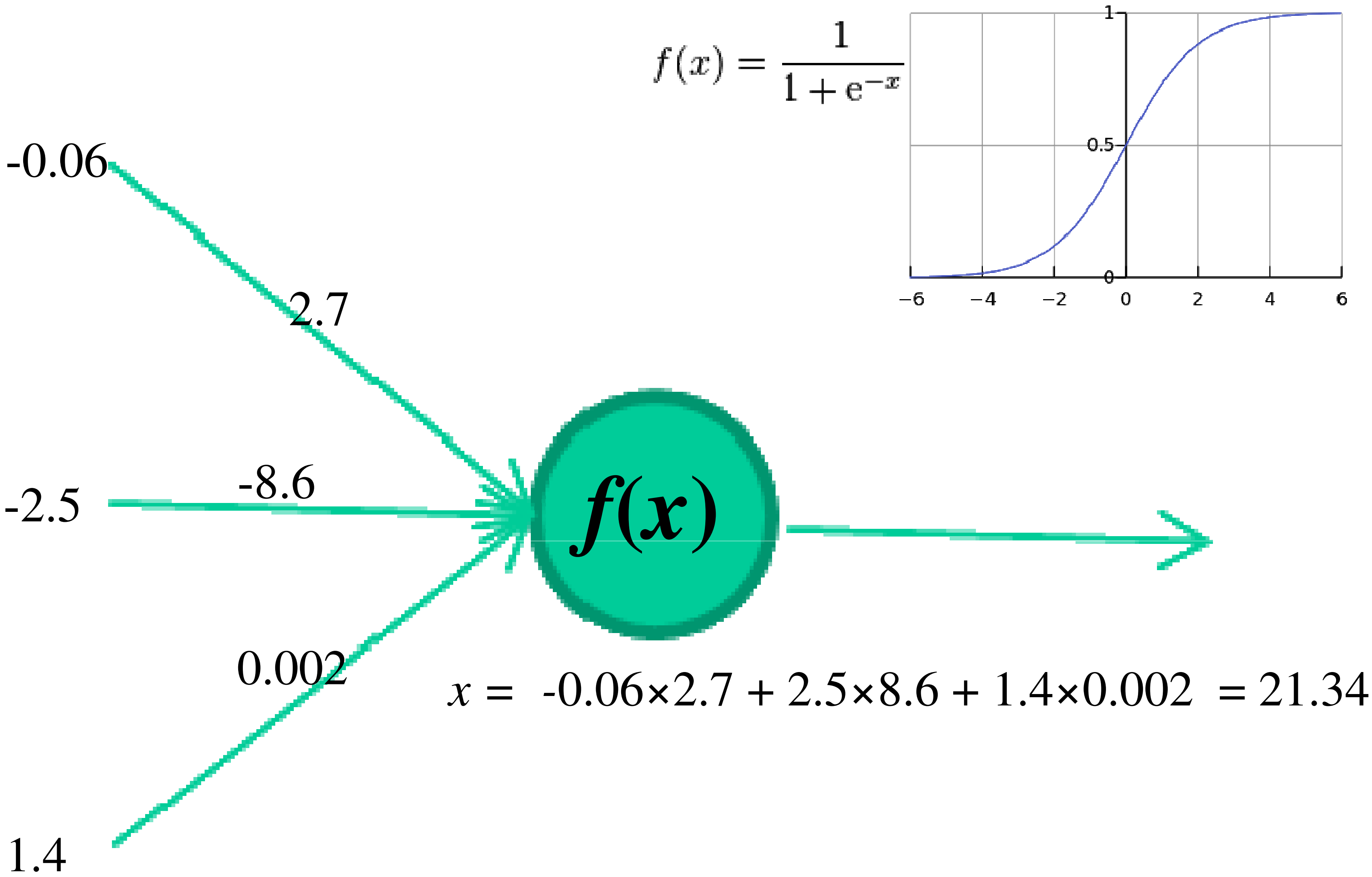
what's new is: **algorithms for training many-layer networks**

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



$f(x) = \frac{1}{1+e^{-x}}$
1
0.5
0
−6
−4
−2
0
2
4
6
-0.06
-2.5
1.4
W1
W2
W3
$f(x)$

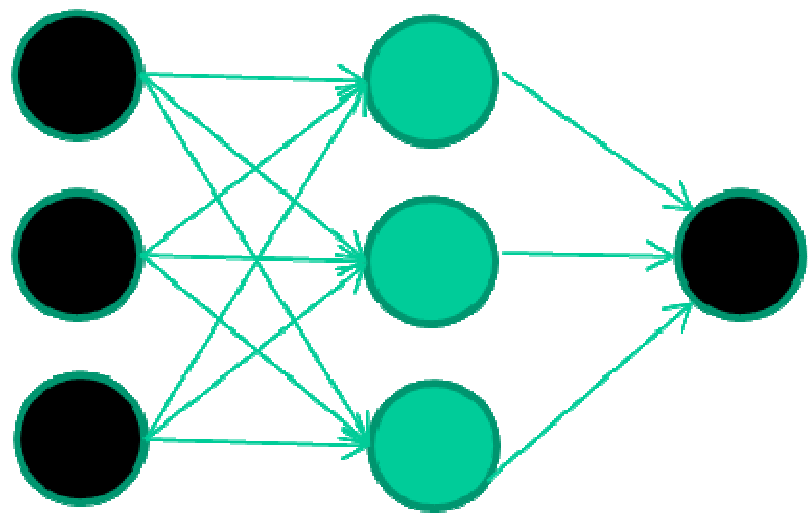


$$f(x) = \frac{1}{1 + e^{-x}}$$

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

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

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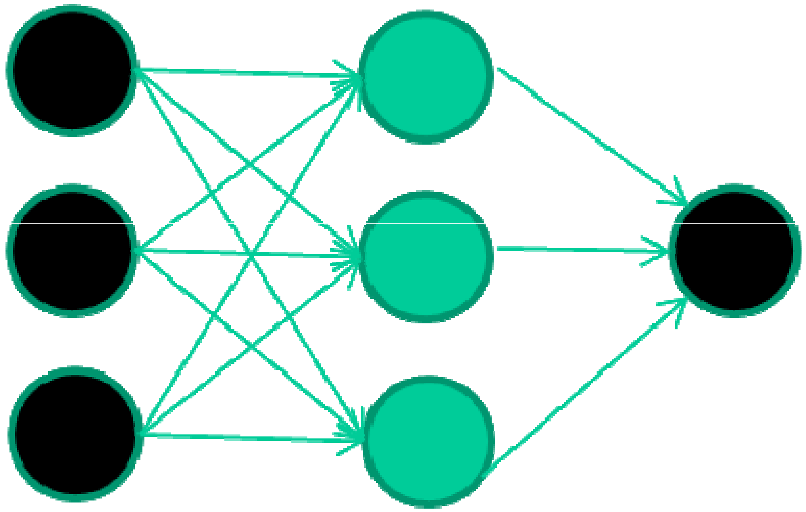

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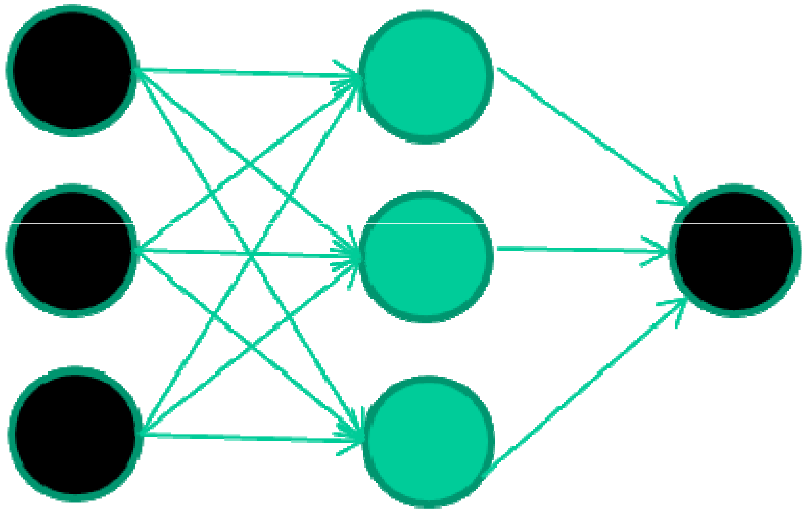
etc …			

Initialise with random weights



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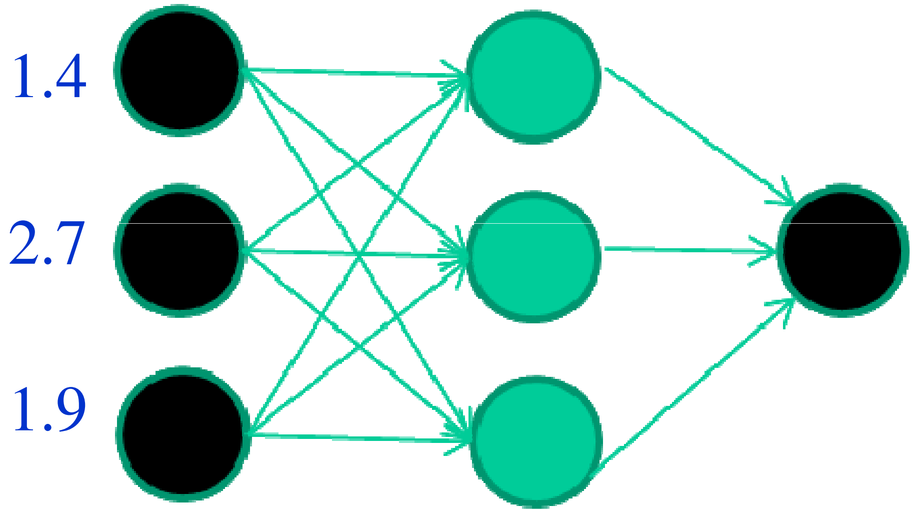
etc …			

Present a training pattern



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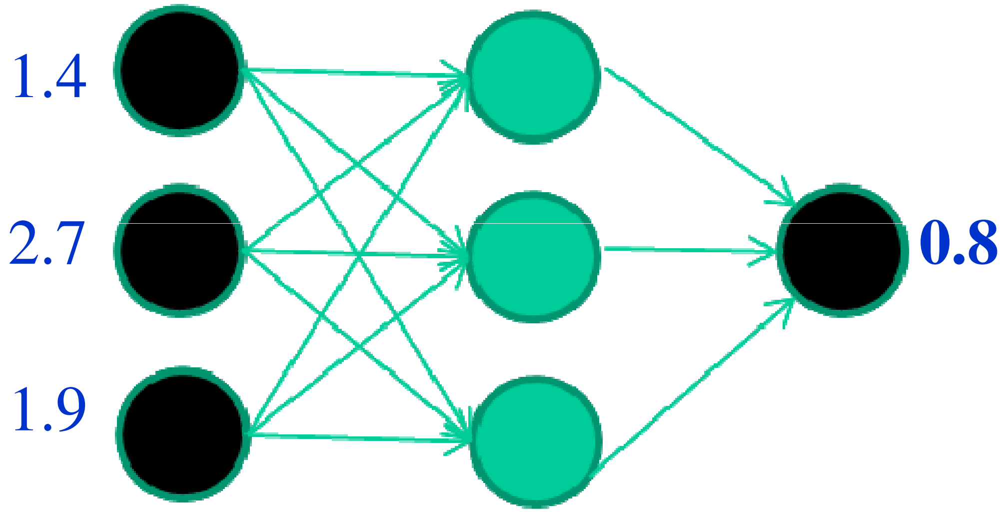
etc …			

Feed it through to get output



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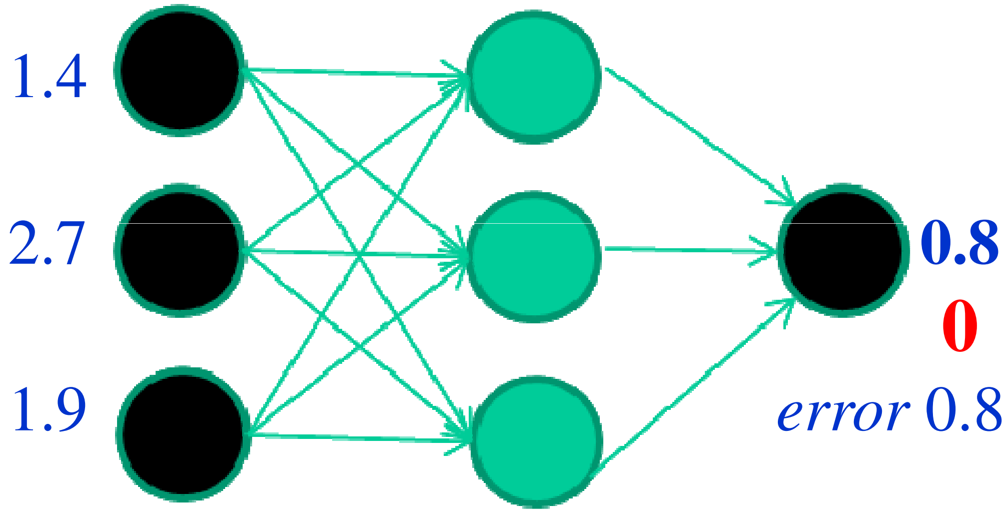
Compare with target output



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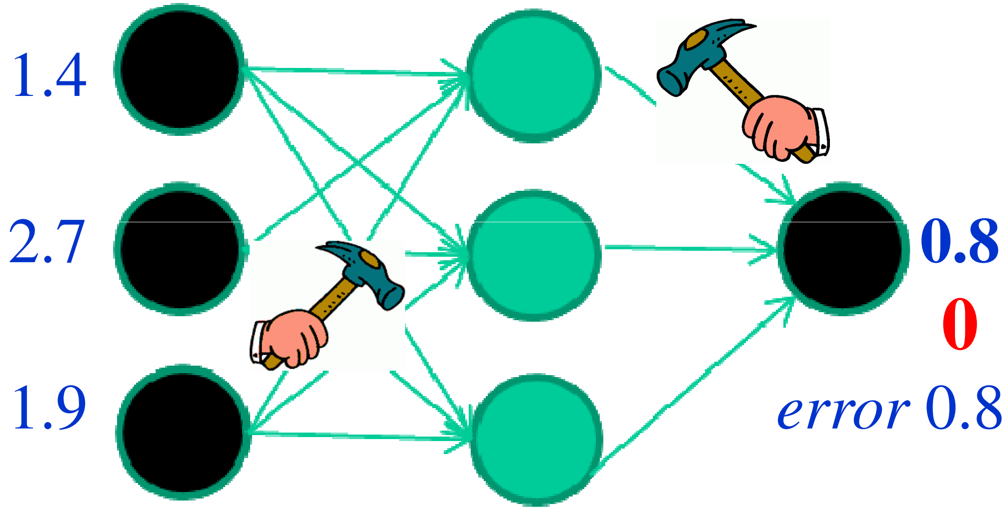
etc …			

Adjust weights based on error



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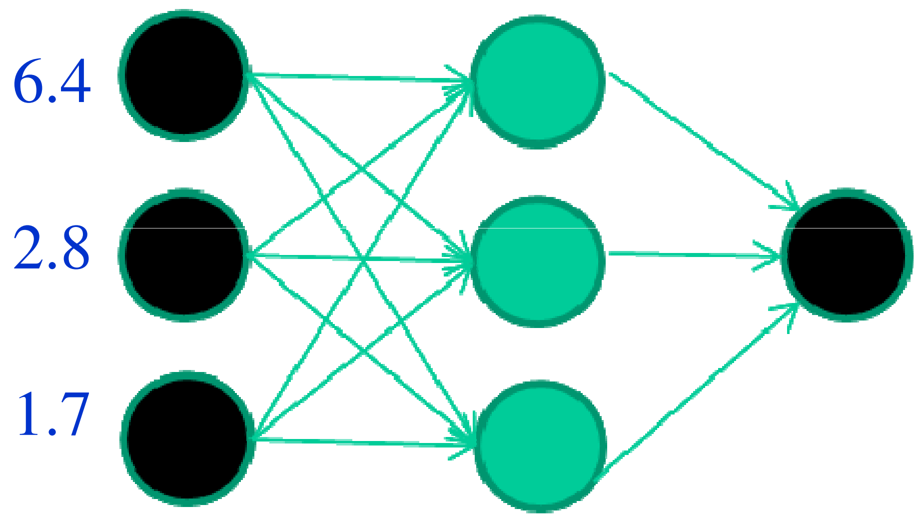

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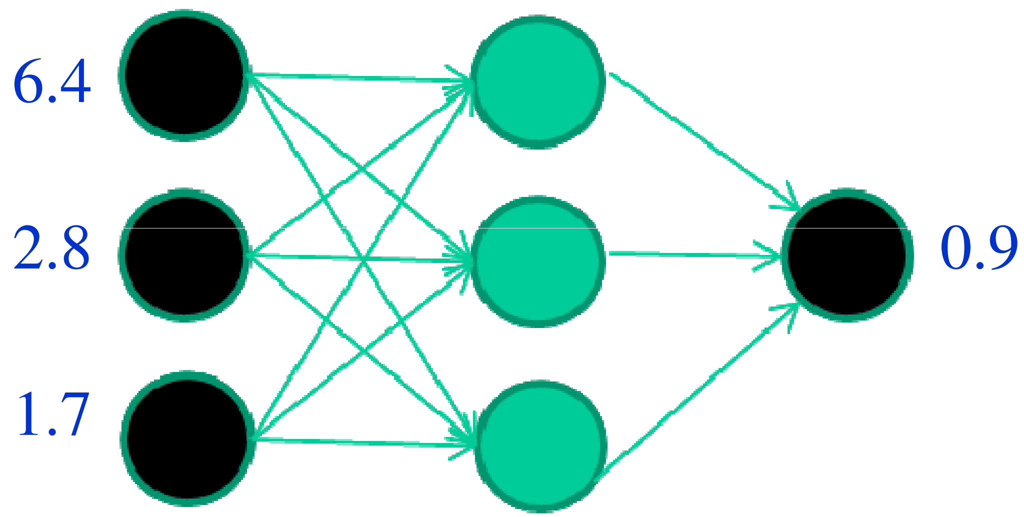

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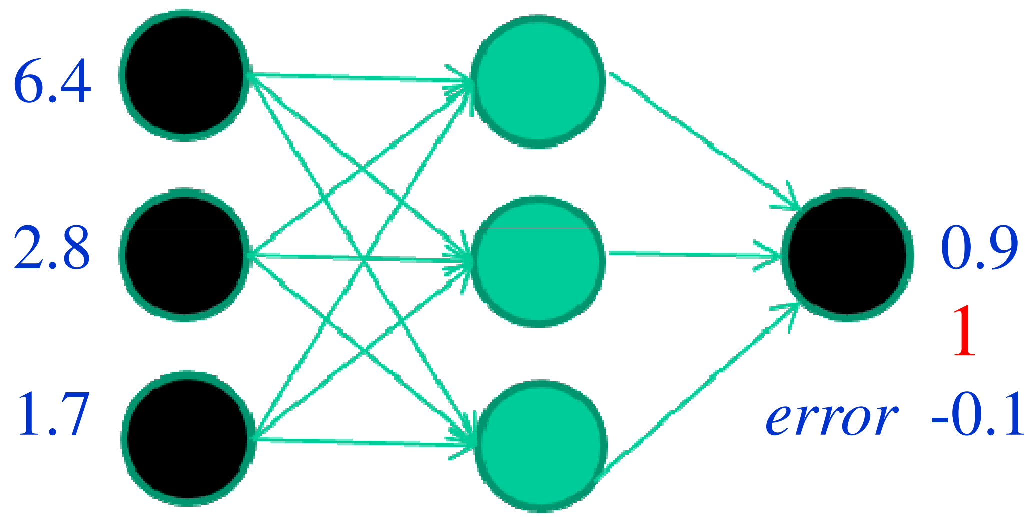

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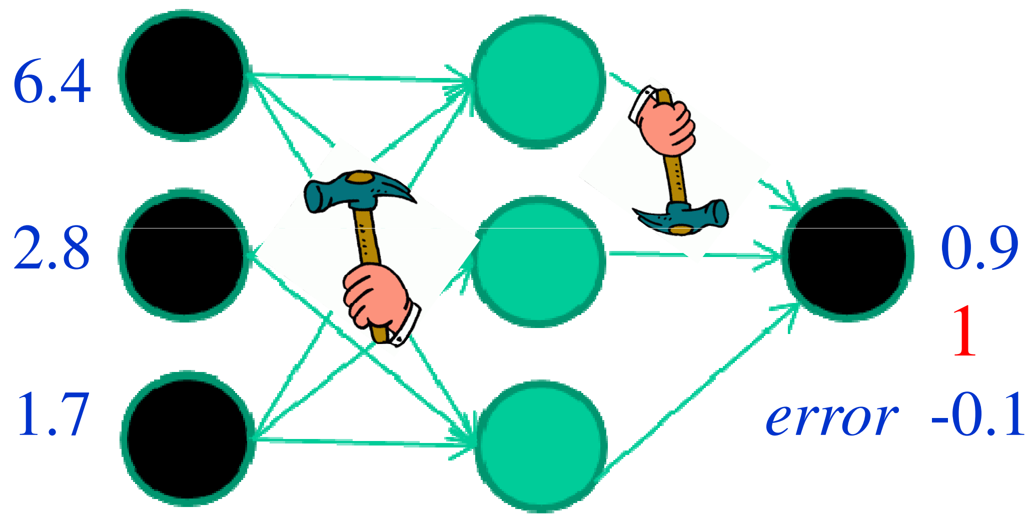

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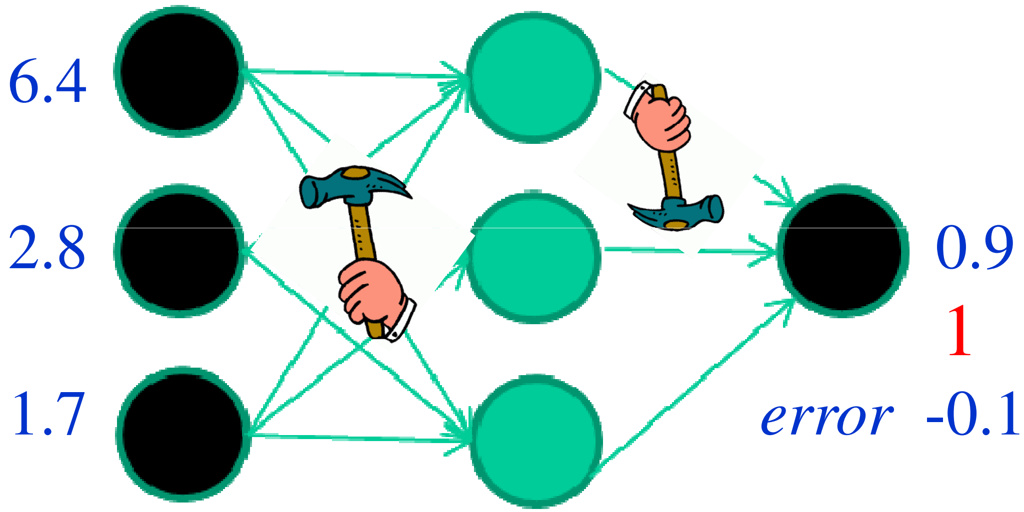
And so on ….

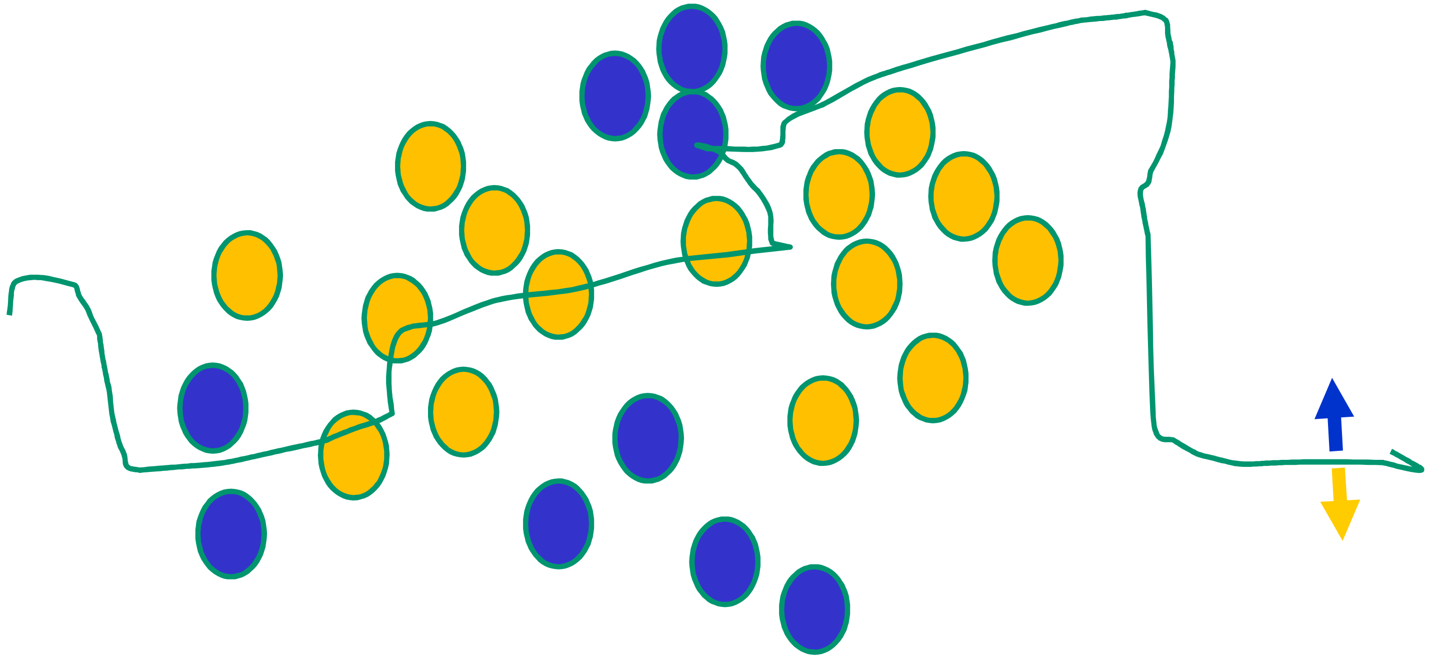


Repeat this thousands, maybe millions of times – each time taking a random training instance, and making slight weight adjustments

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

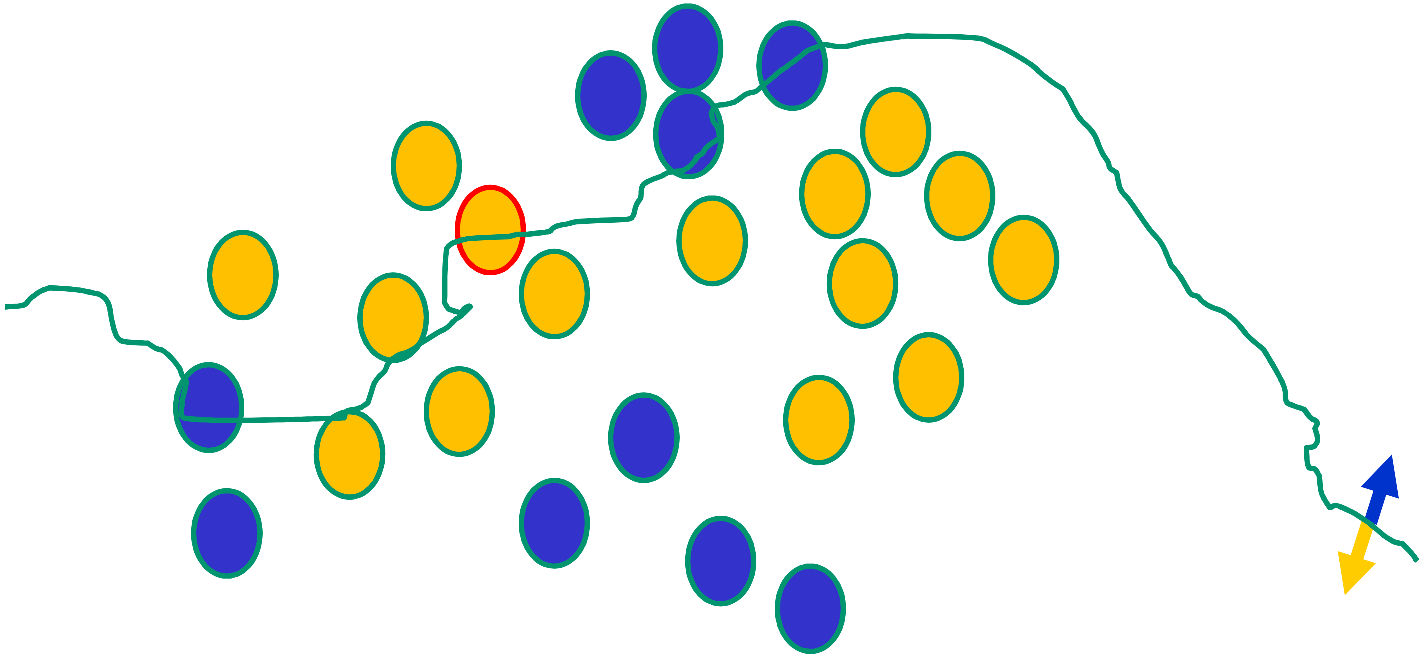
The decision boundary perspective…

Initial random weights



The decision boundary perspective…

Present a training instance / adjust the weights



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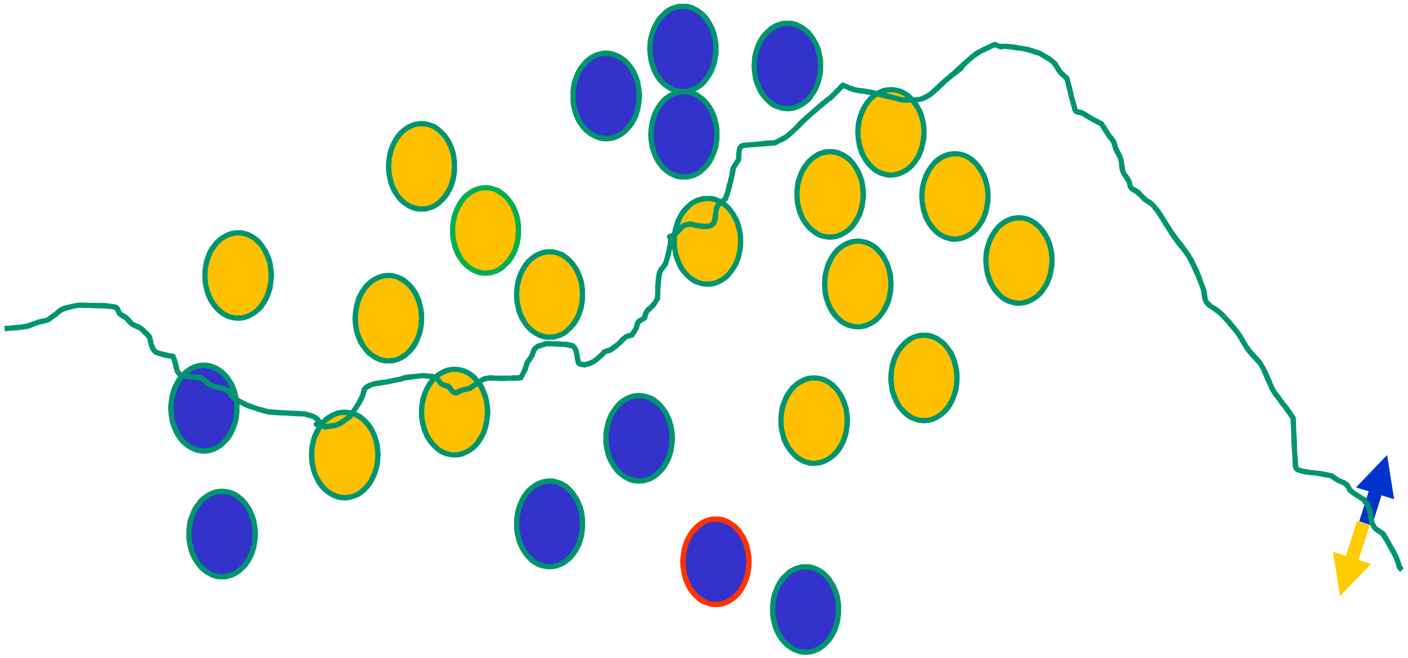

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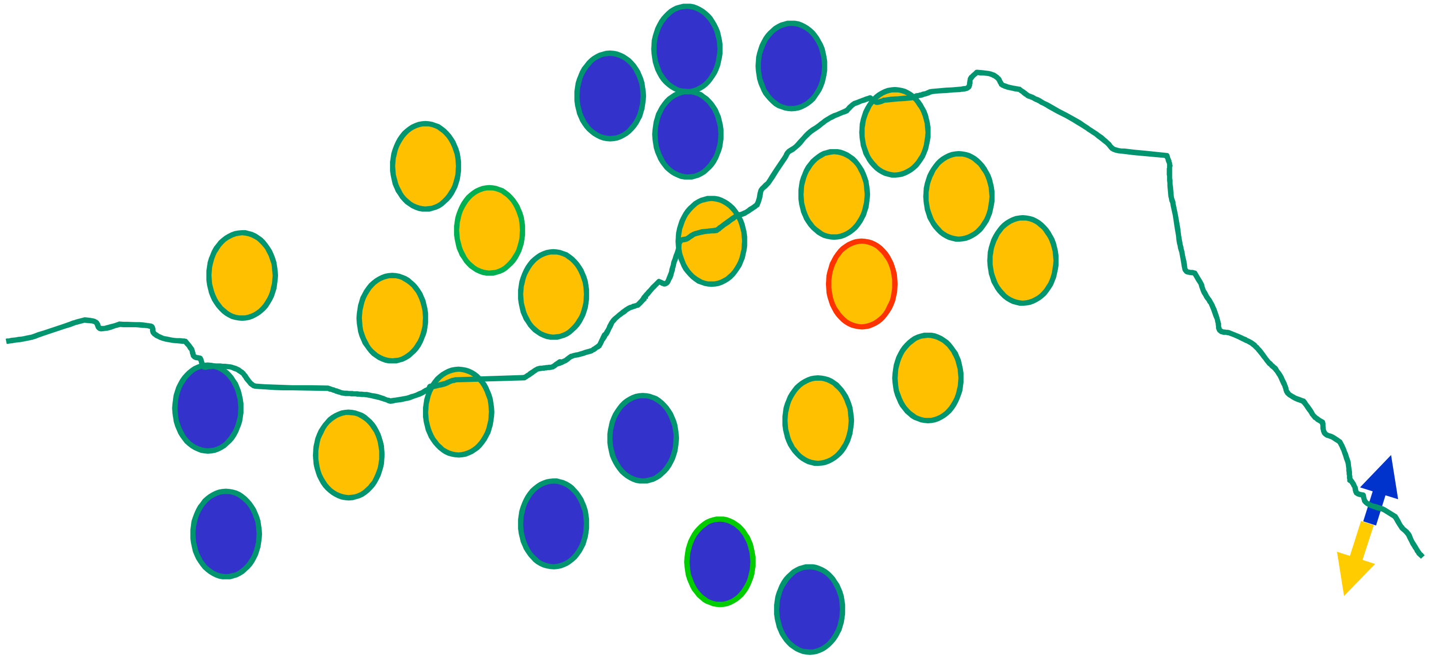

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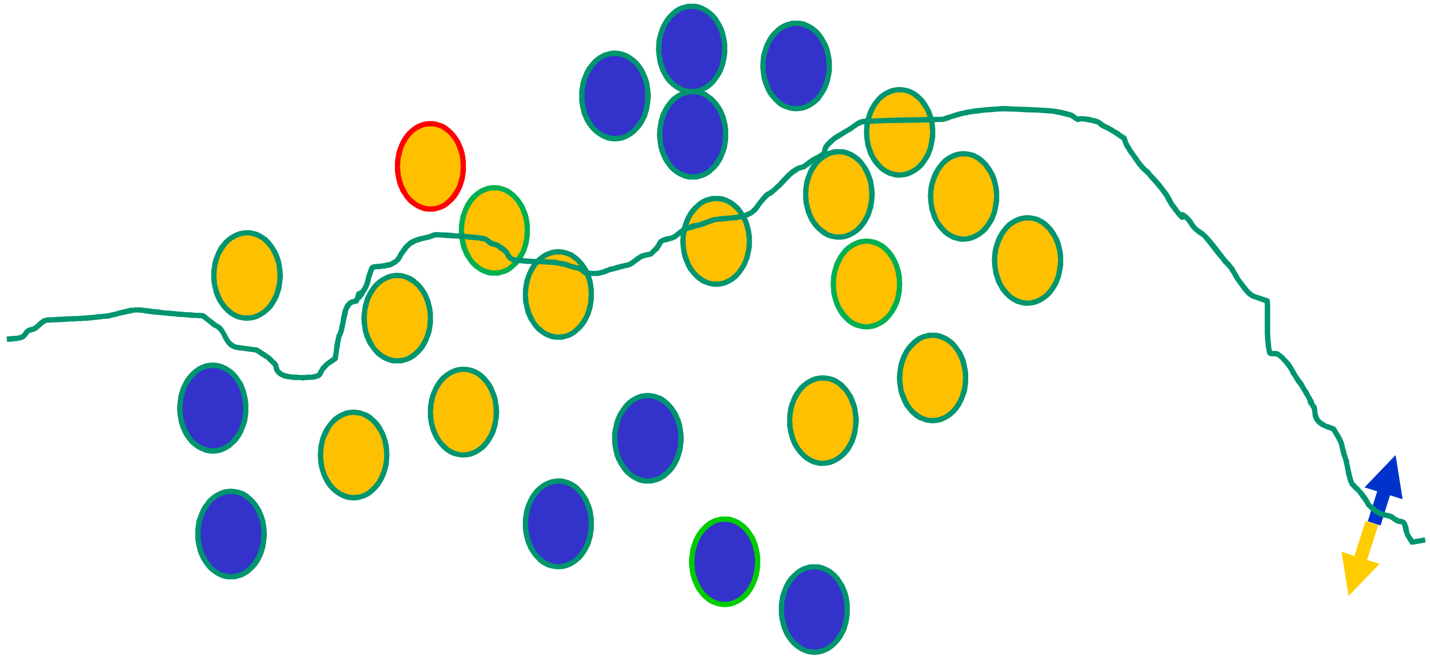
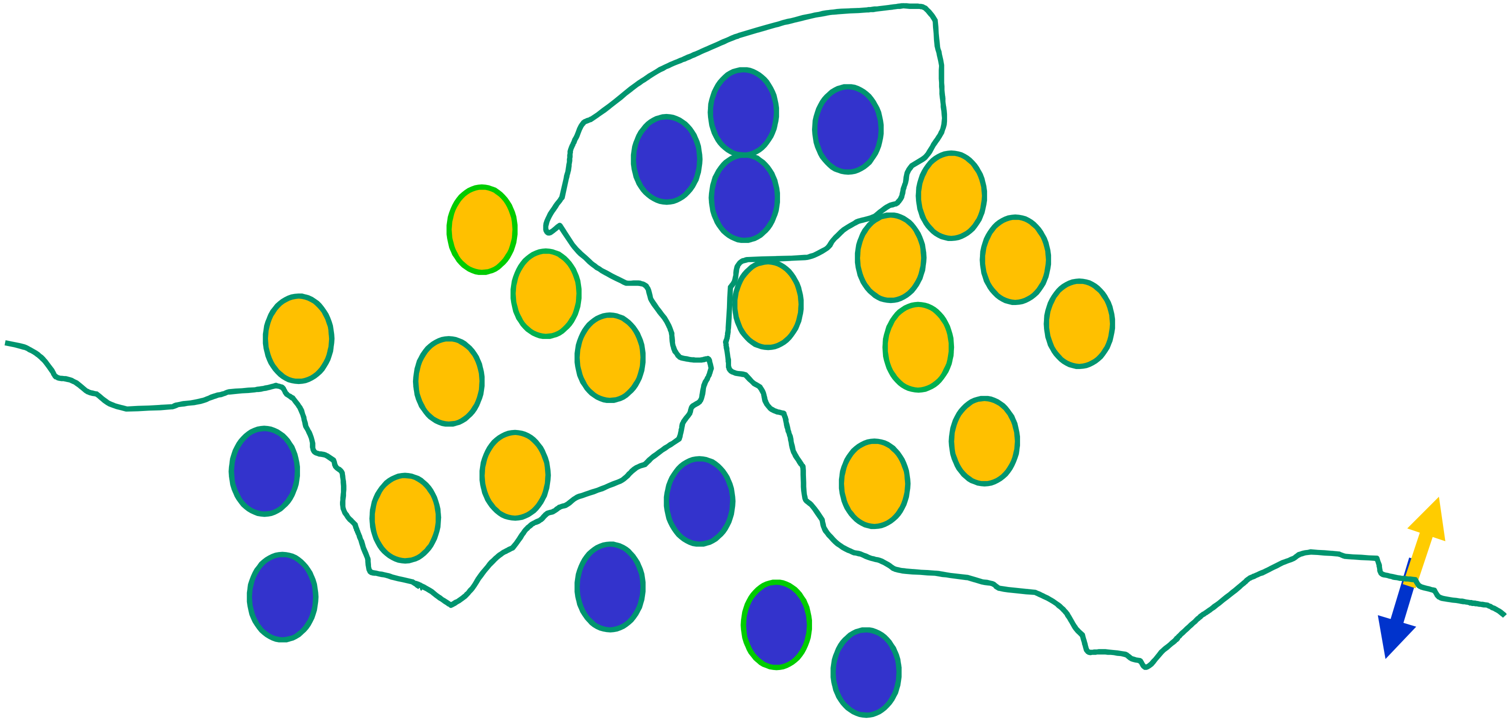


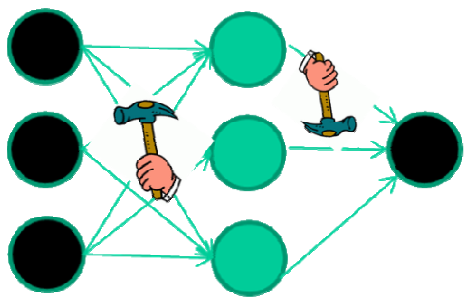
The decision boundary perspective…

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



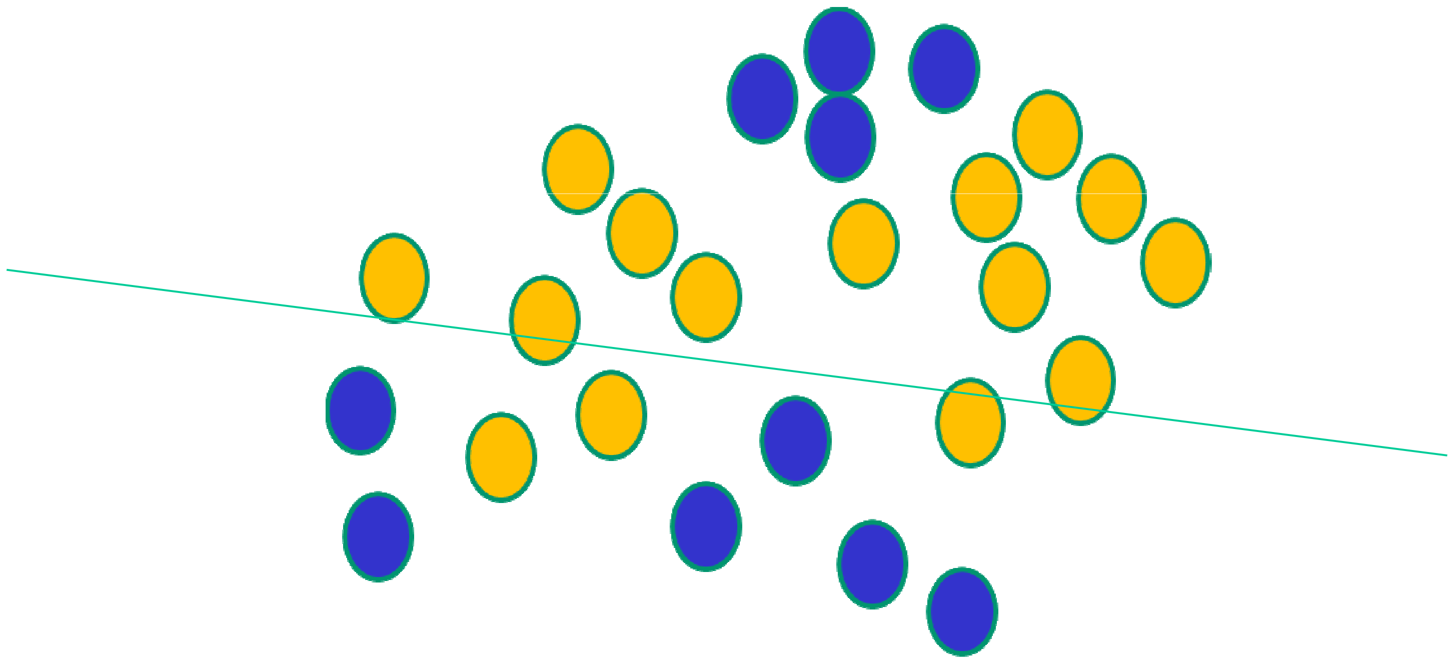
Some other points

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.

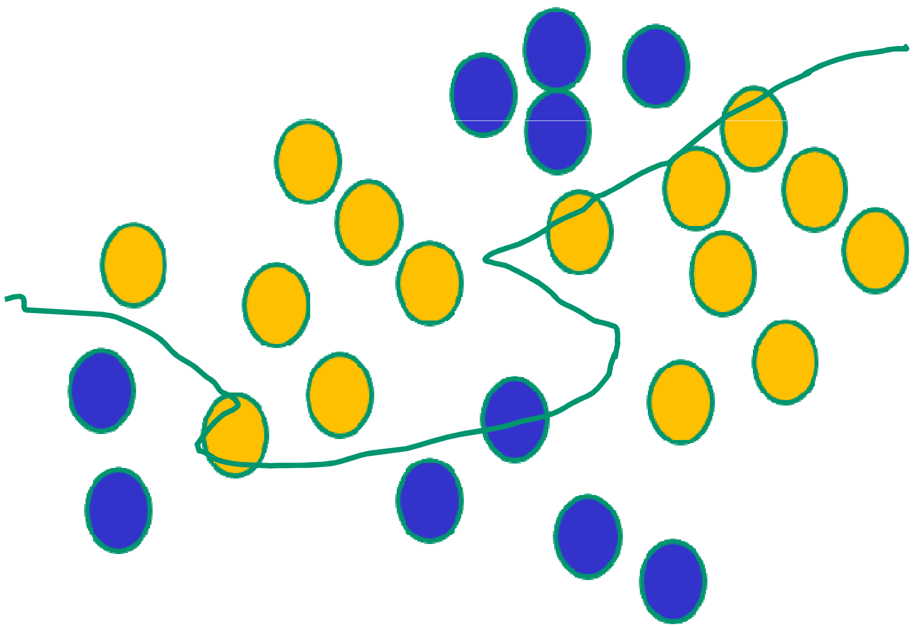
Some other ‘by the way’ points

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



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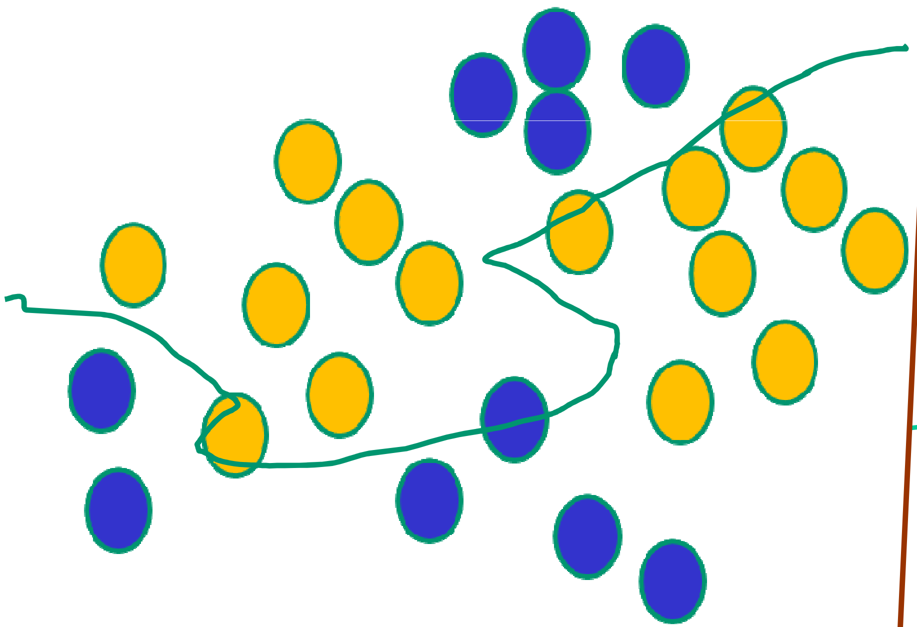
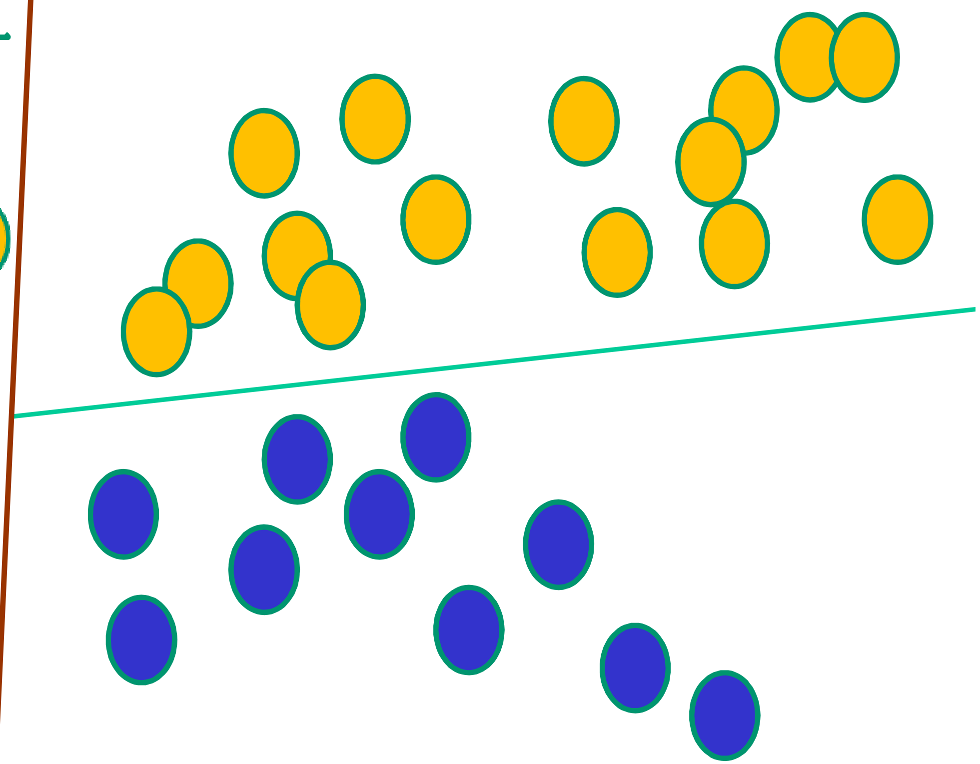


SVMs only draw straight lines, but they transform the data first in a way that makes that OK



Deep Neural Network

Multiple Hidden Layers

Why Multiple Hidden Layers?

Feature detectors

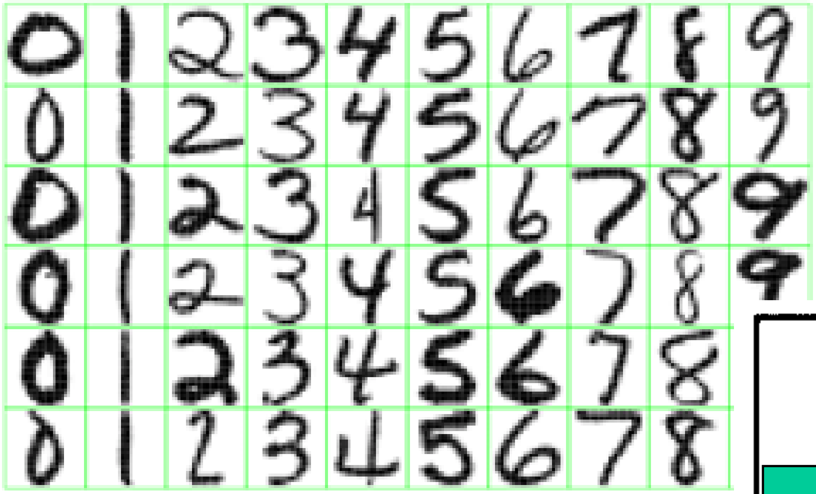
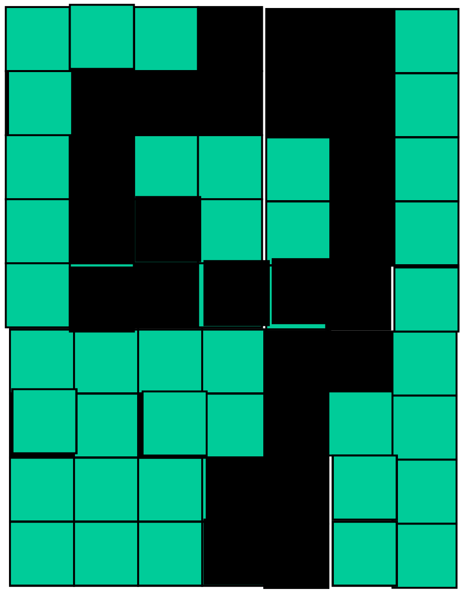
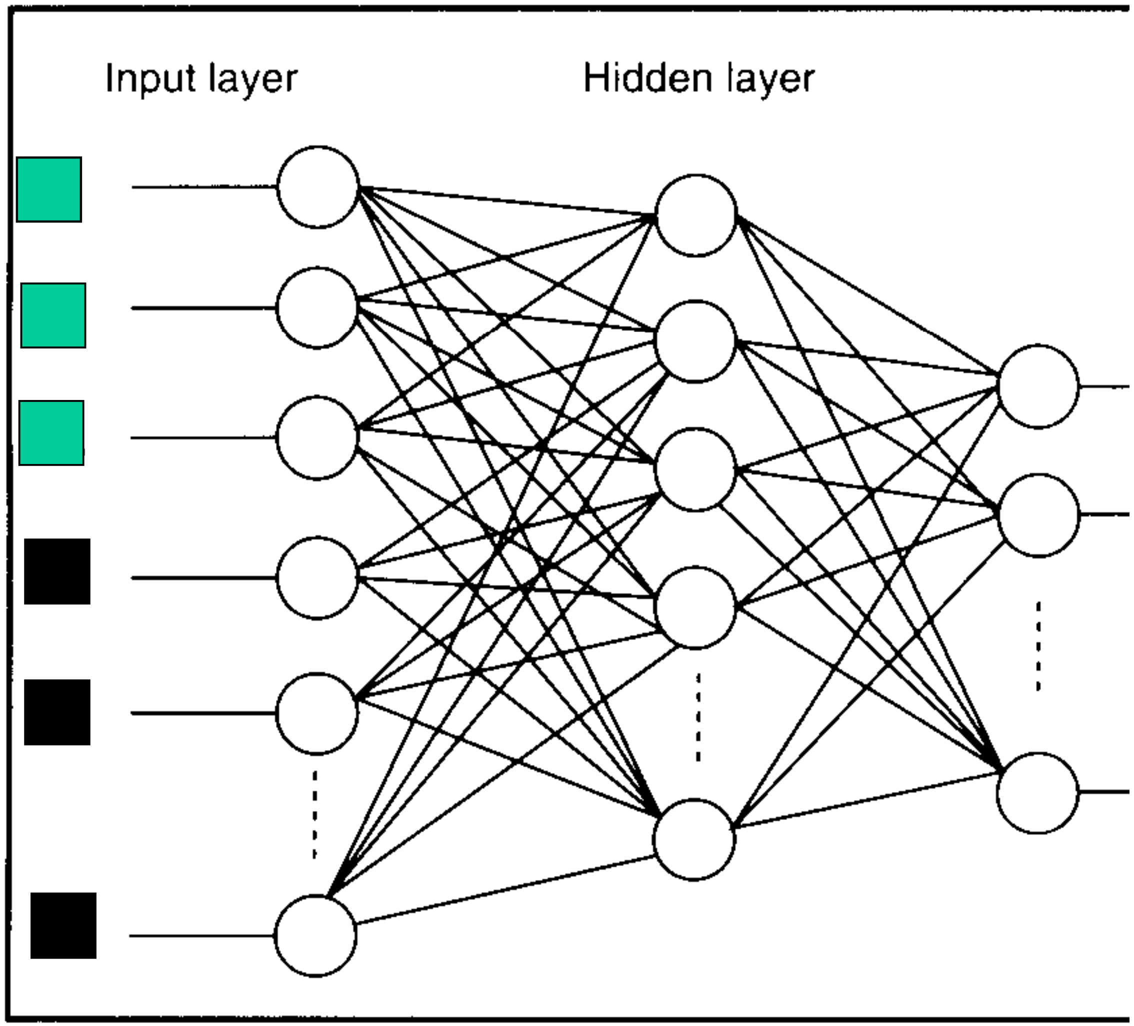
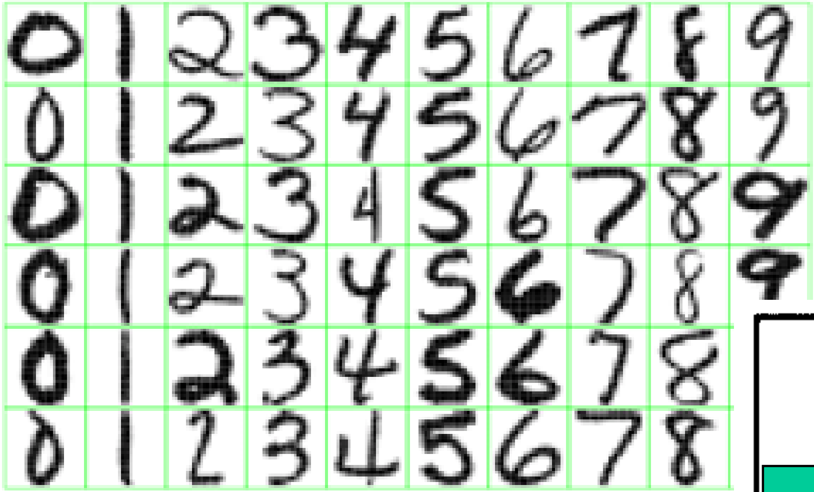


Figure 1.2: *Examples of handwritten digits from postal envelopes.*





what is this unit doing?



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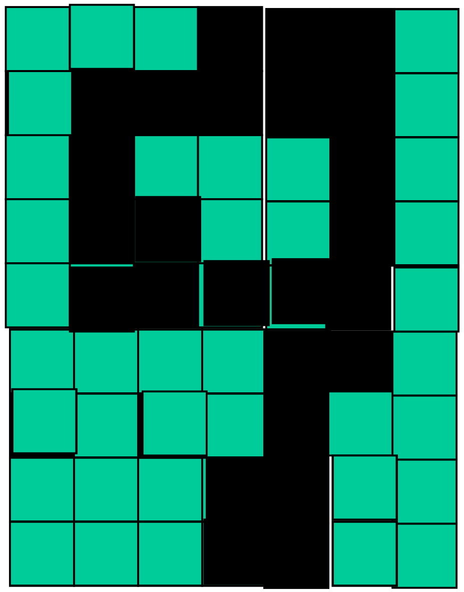
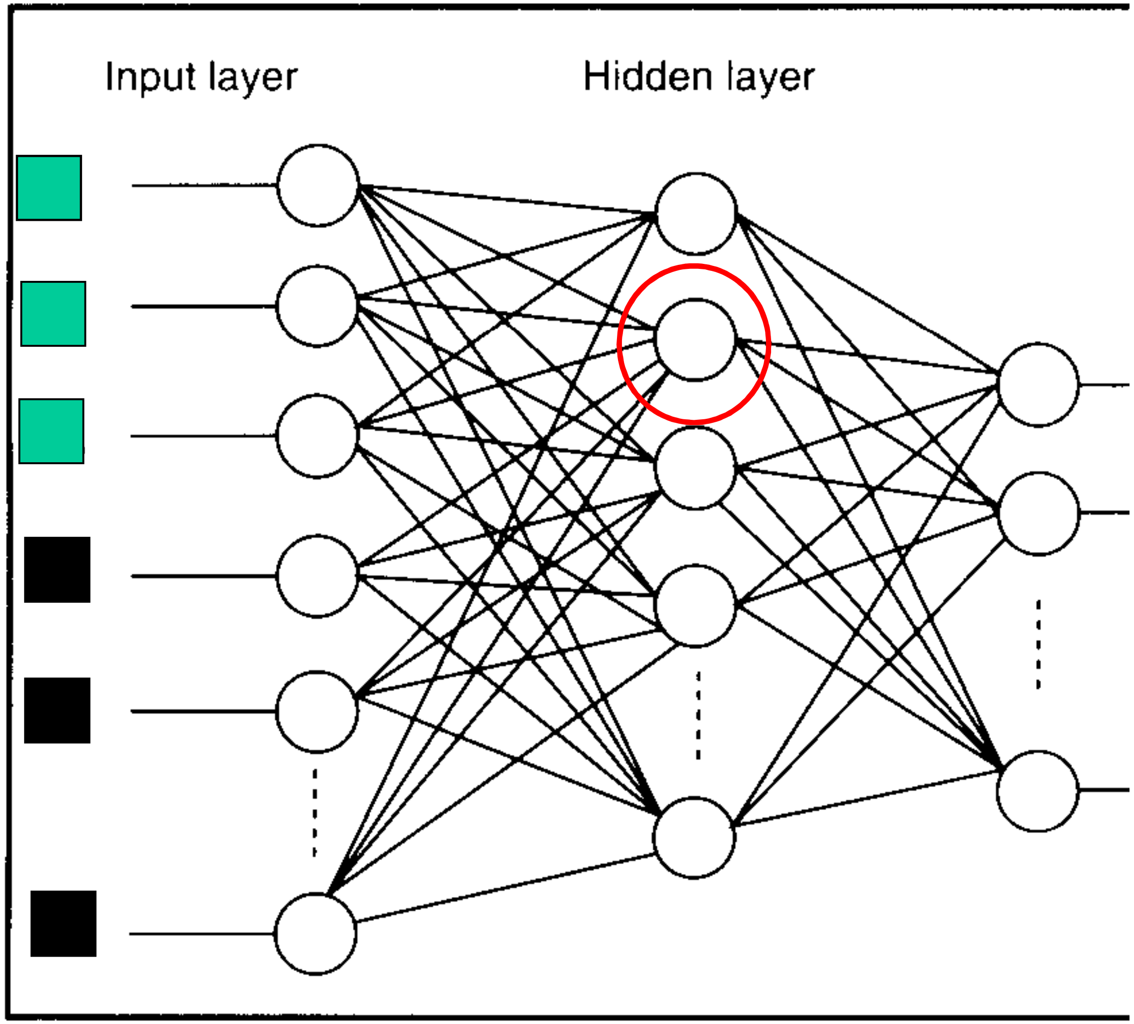
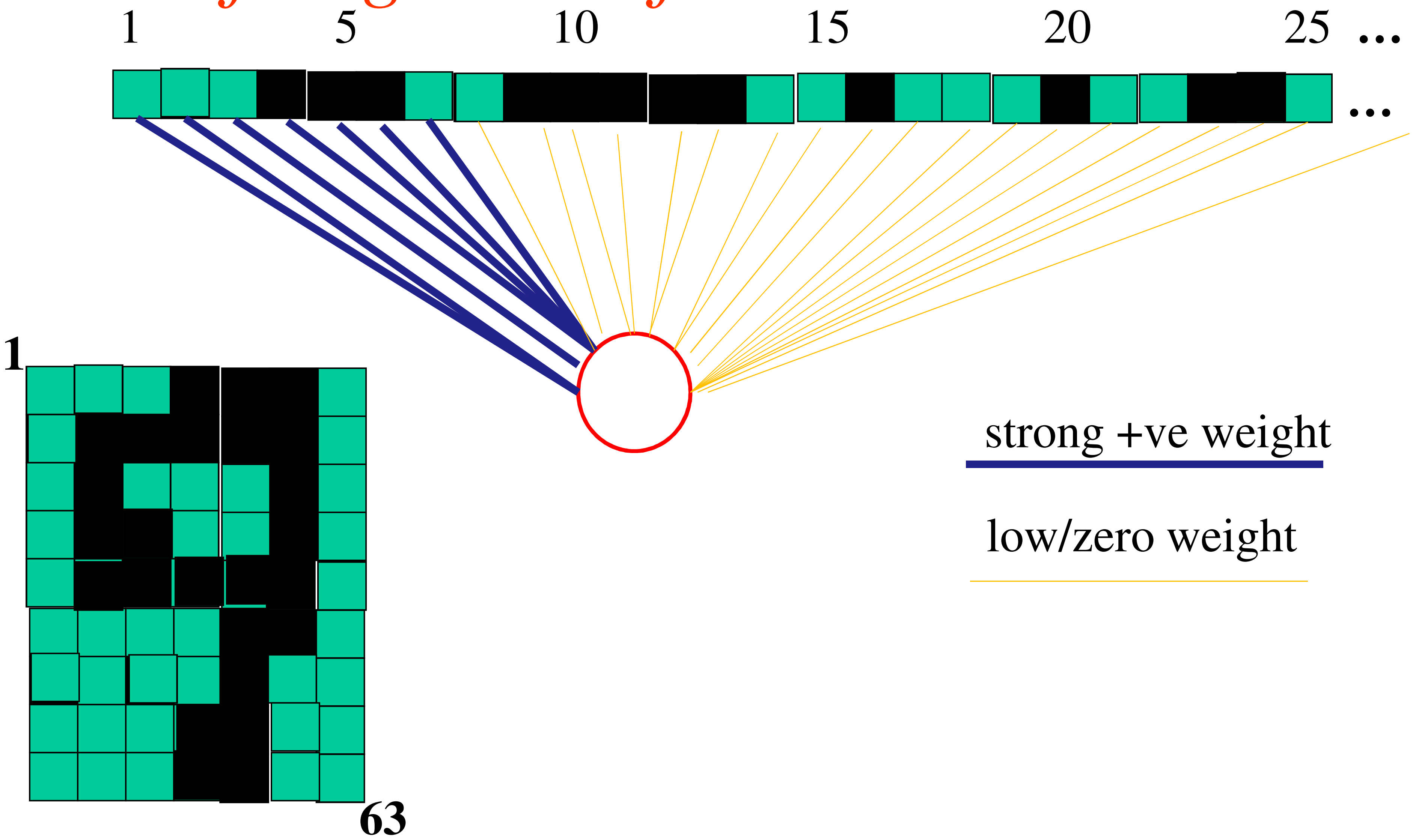
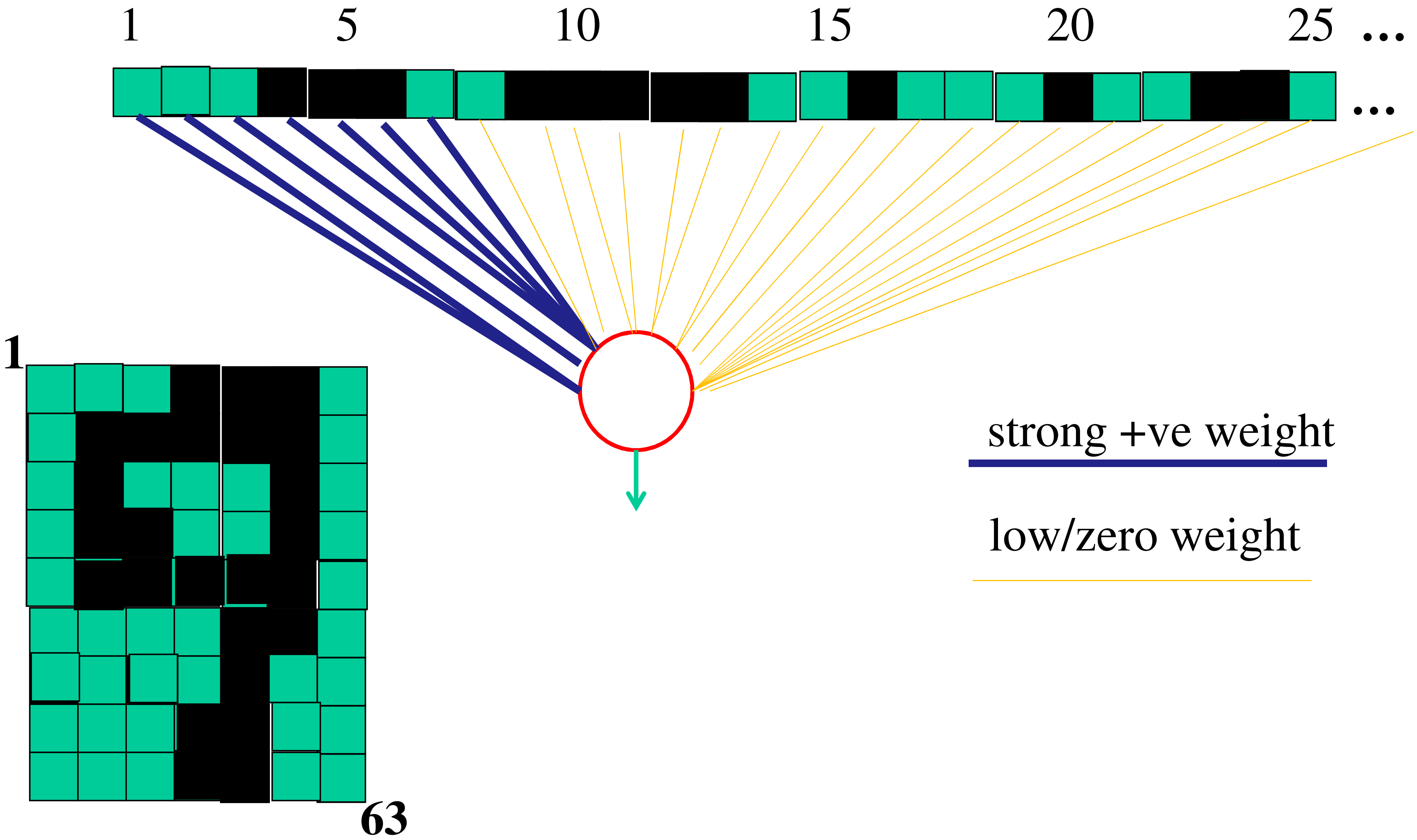




Hidden layer units become *self-organised feature detectors*



What does this unit detect?



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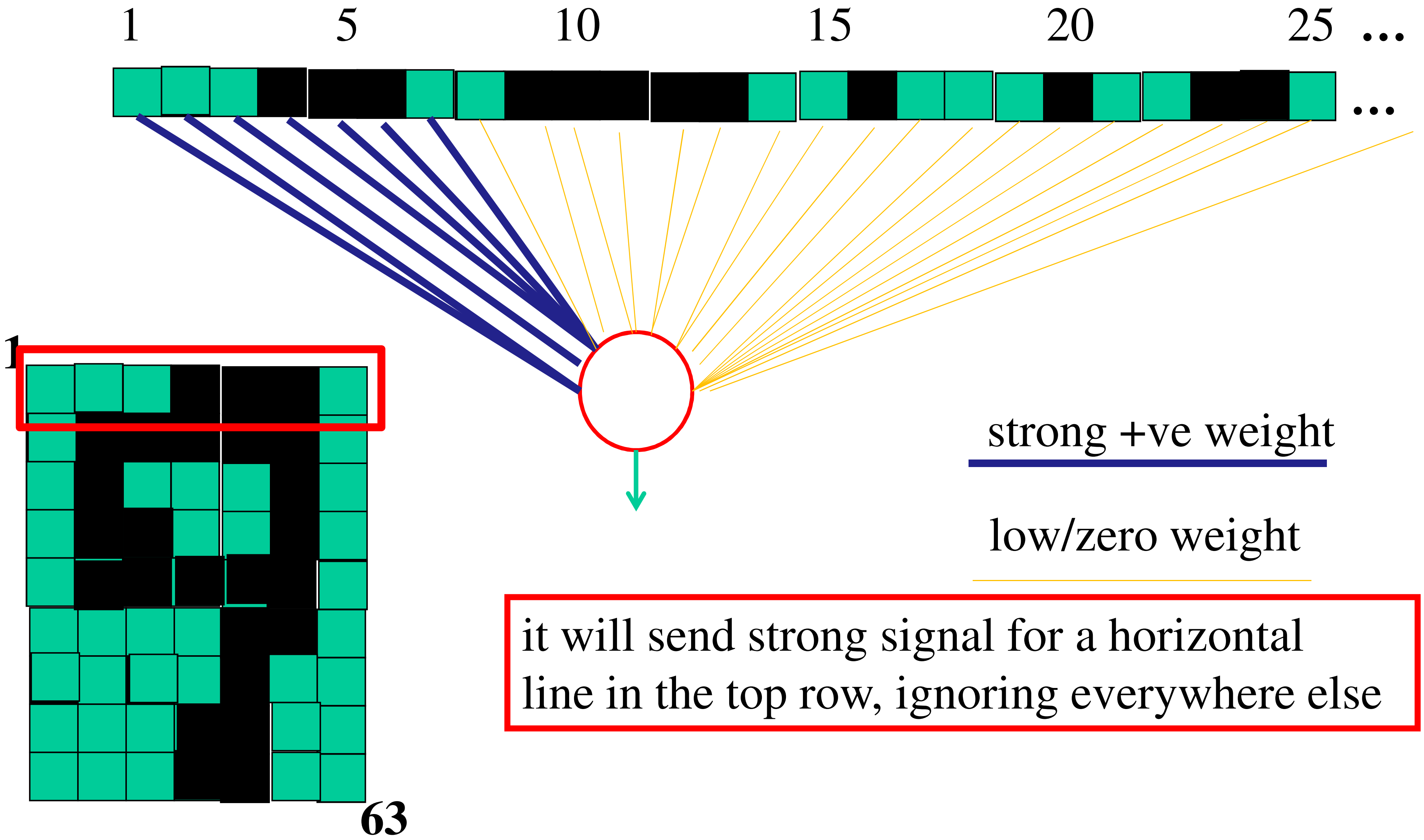
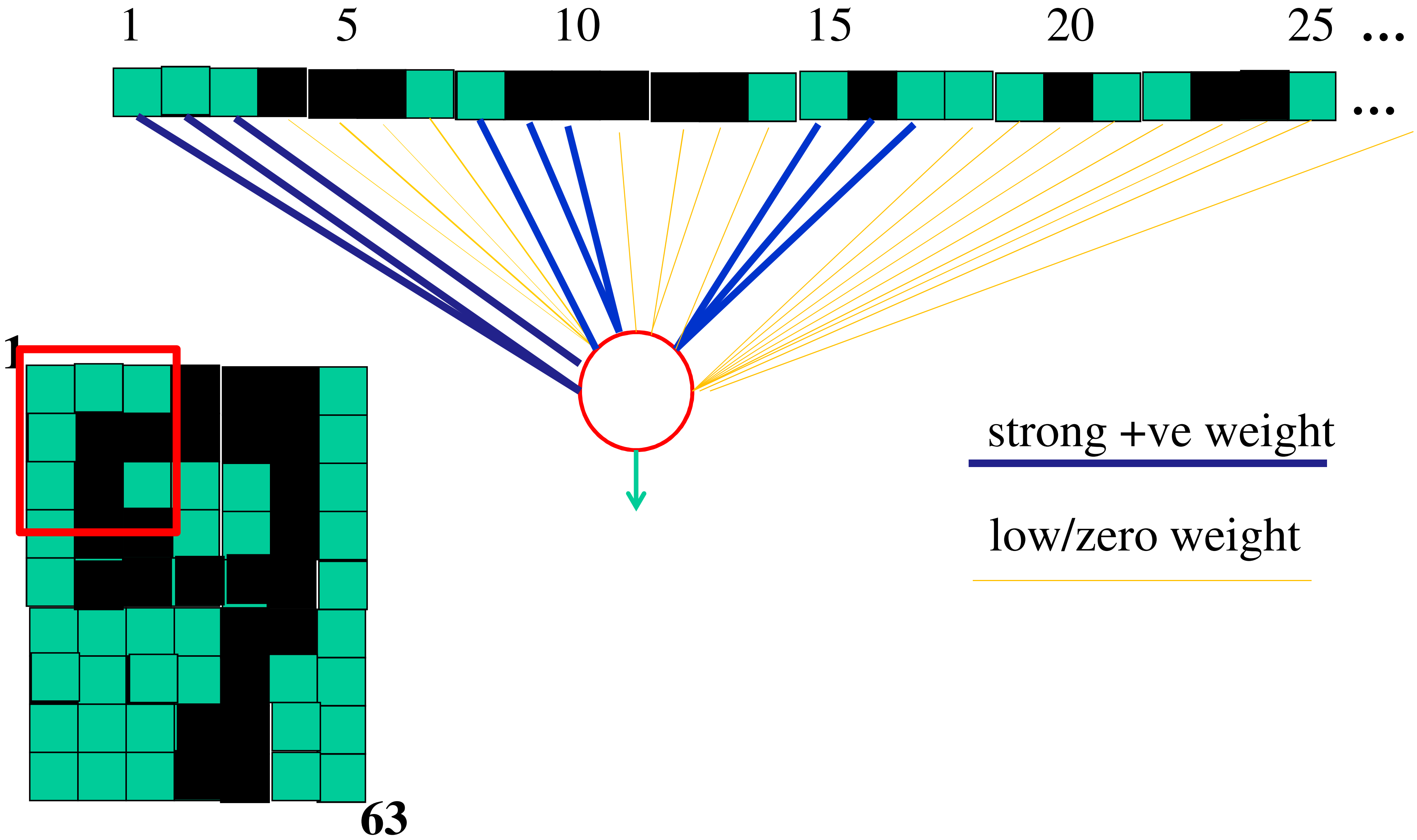


it will send strong signal for a horizontal line in the top row, ignoring everywhere else

What does this unit detect?



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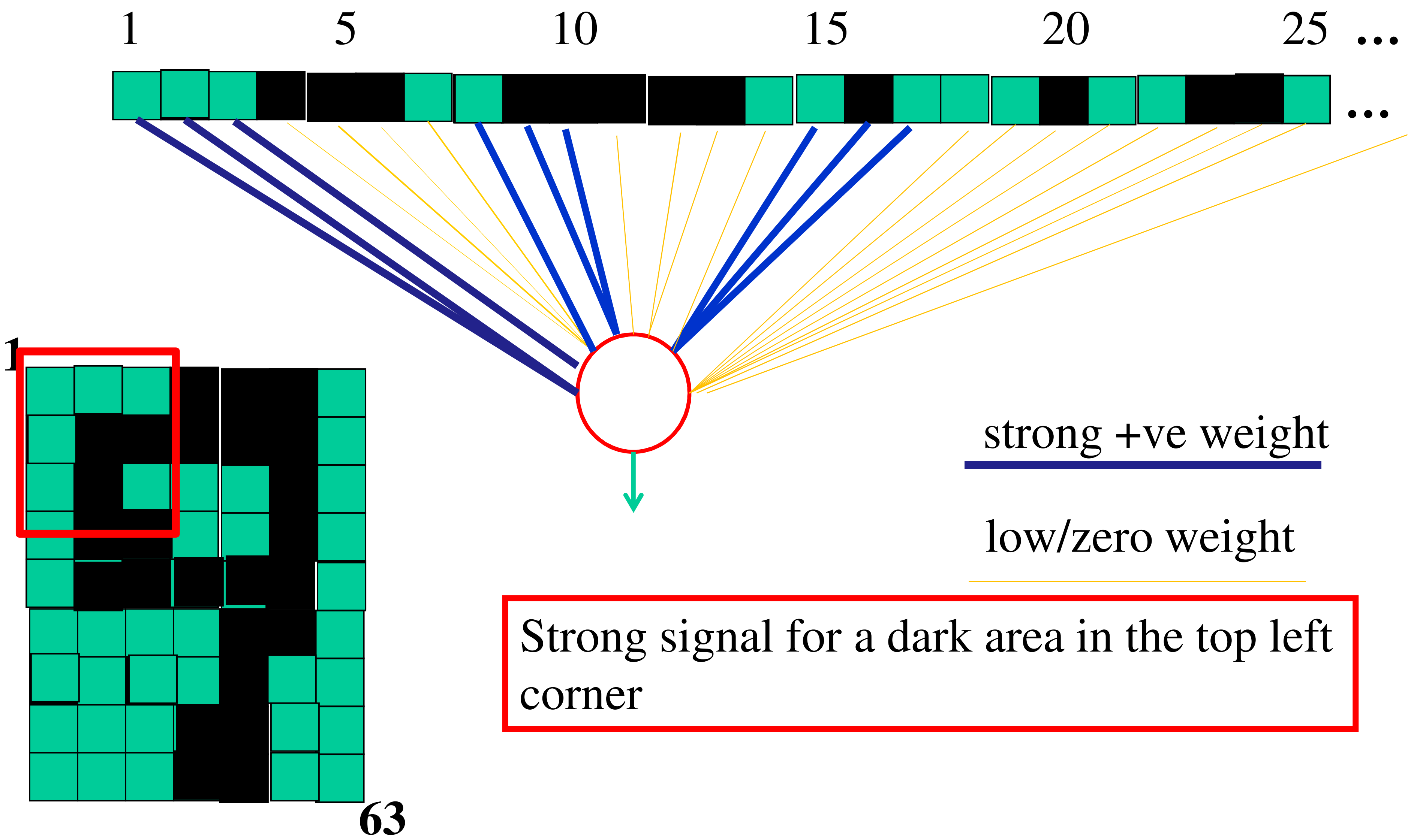


Strong signal for a dark area in the top left corner

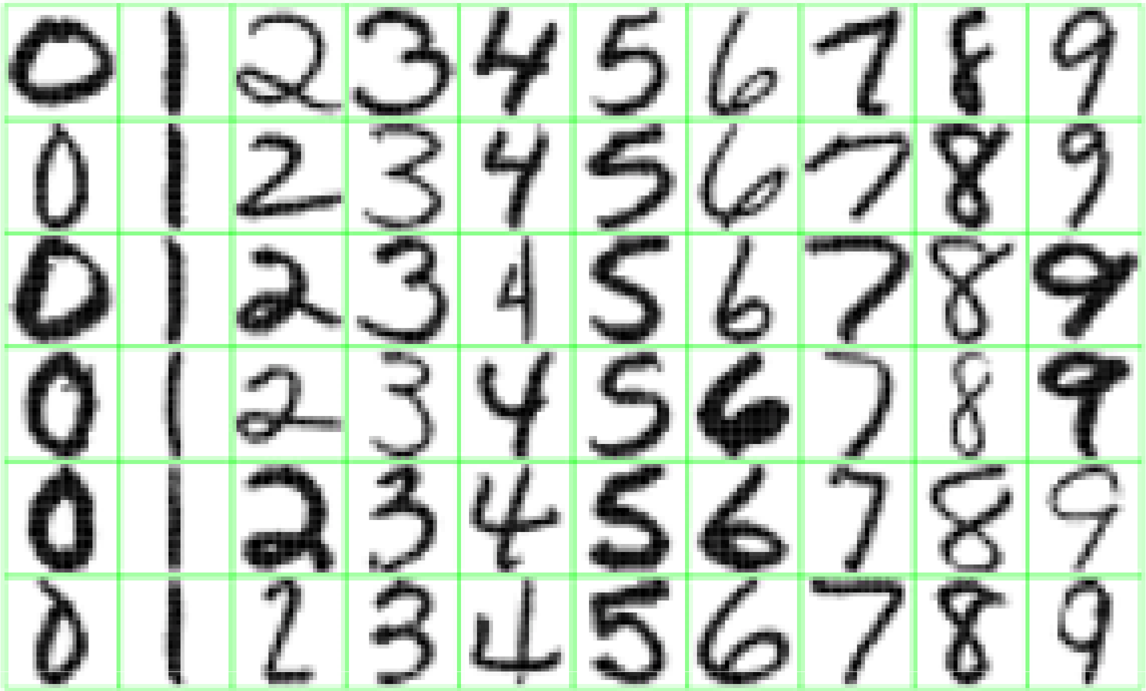
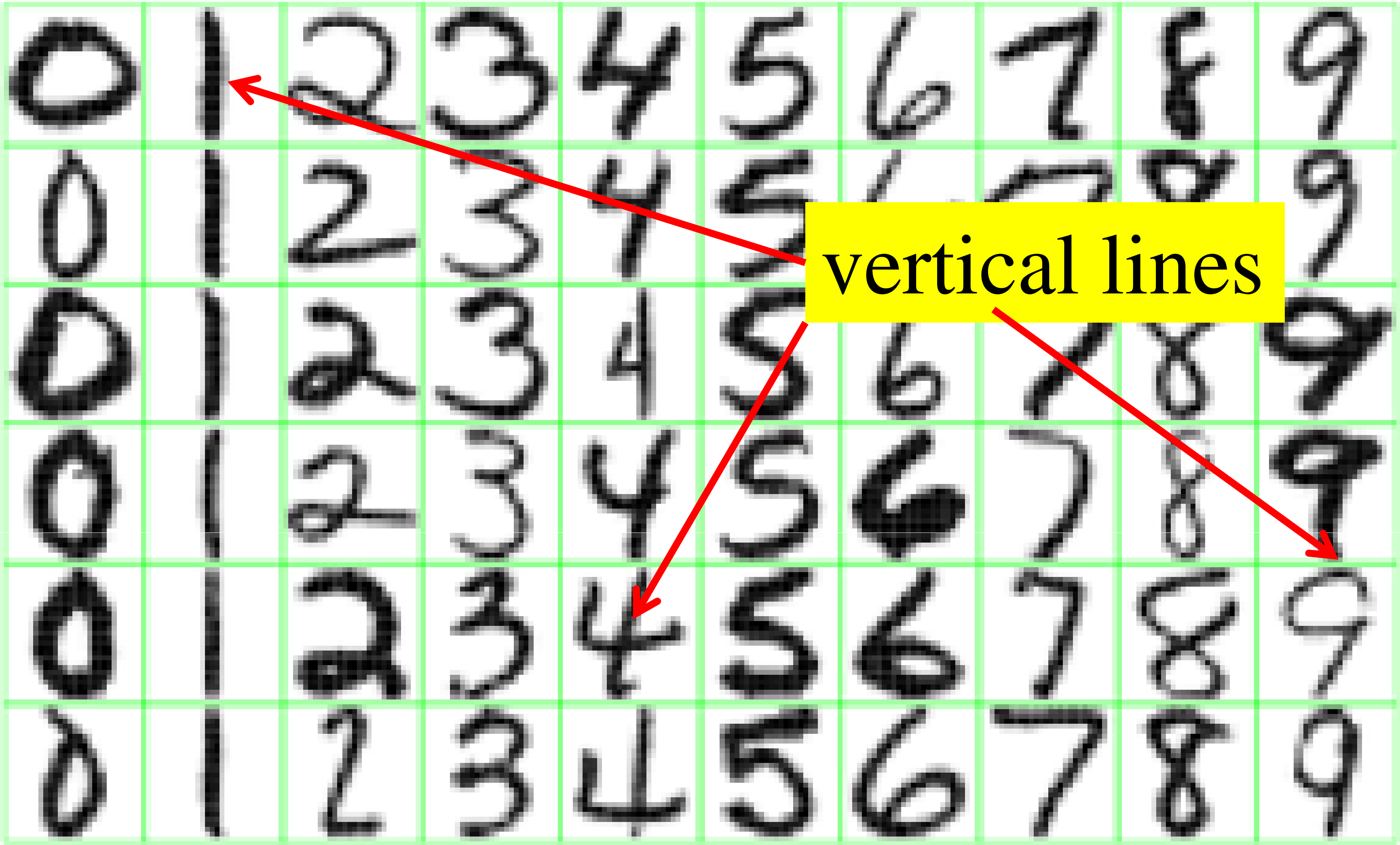


Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*

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

1



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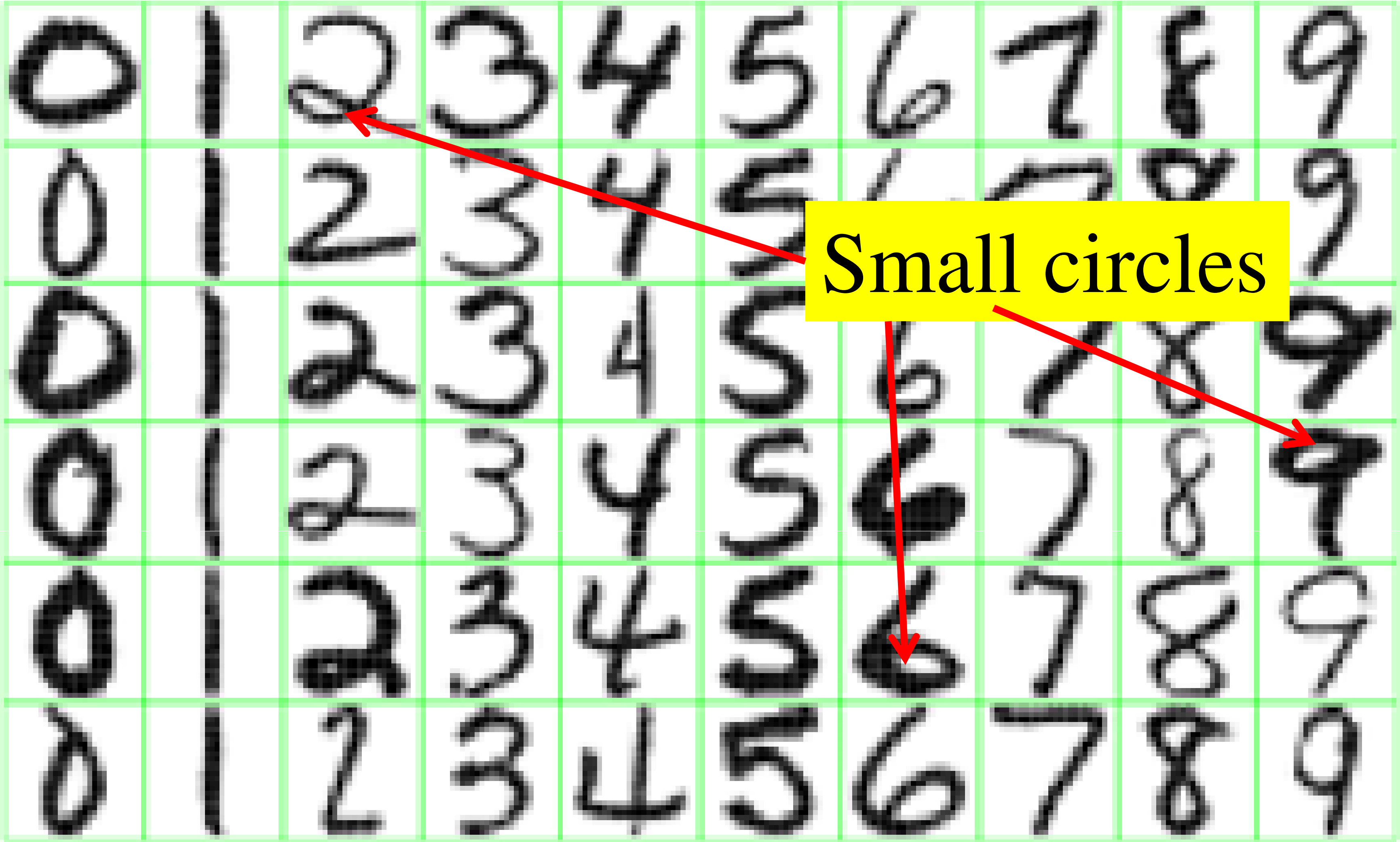

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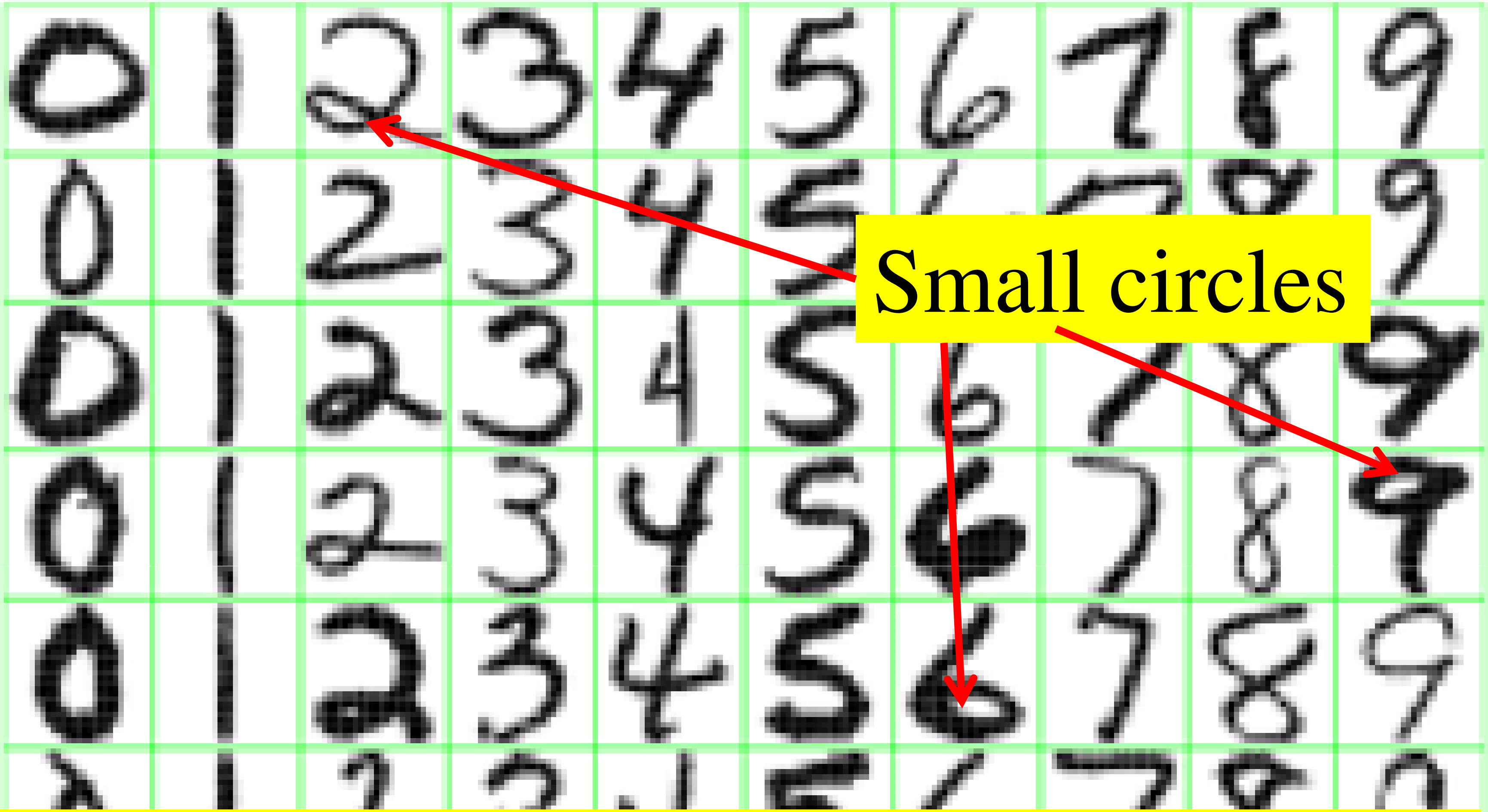
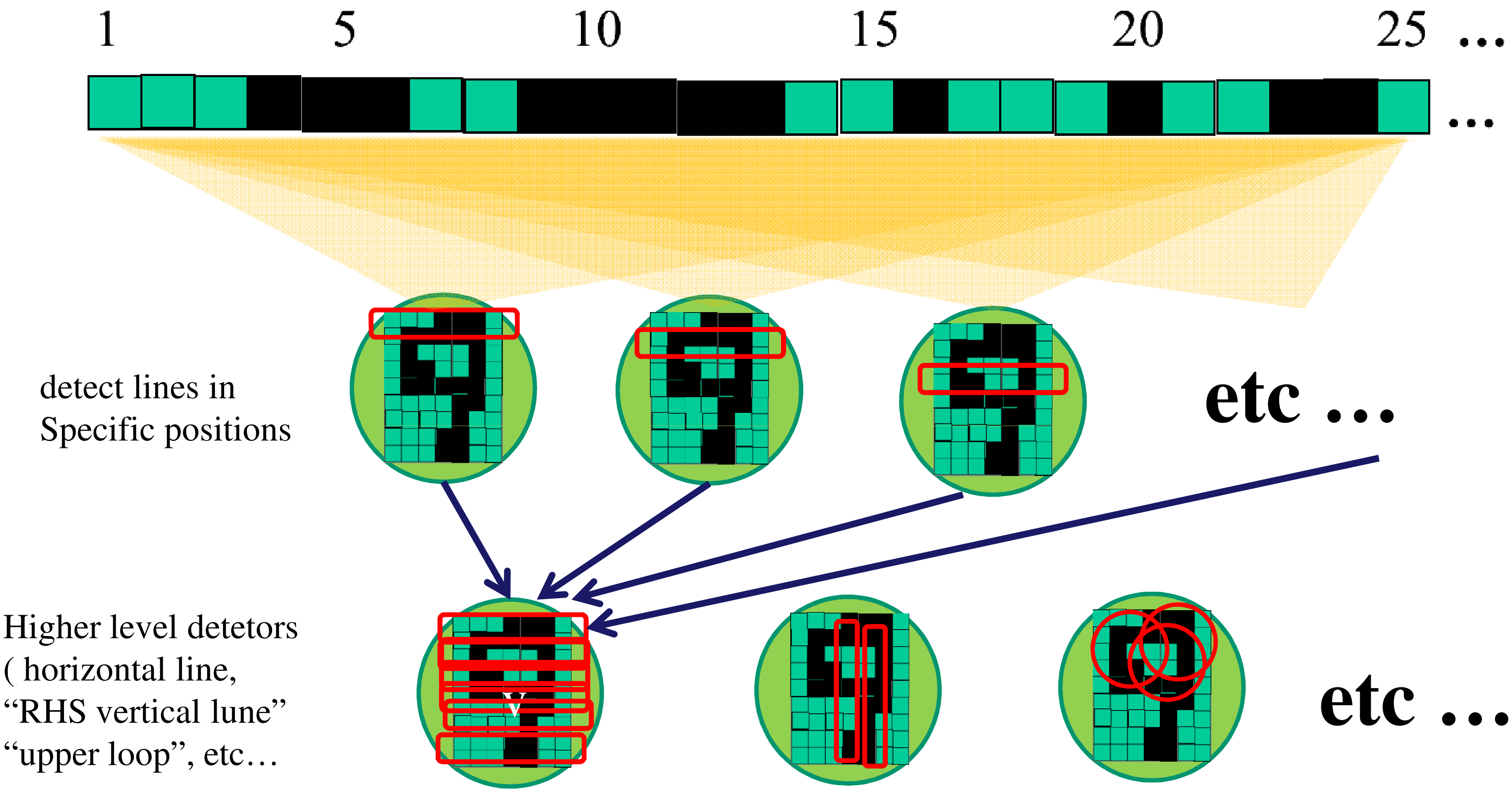


1

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

successive layers can learn higher-level features …



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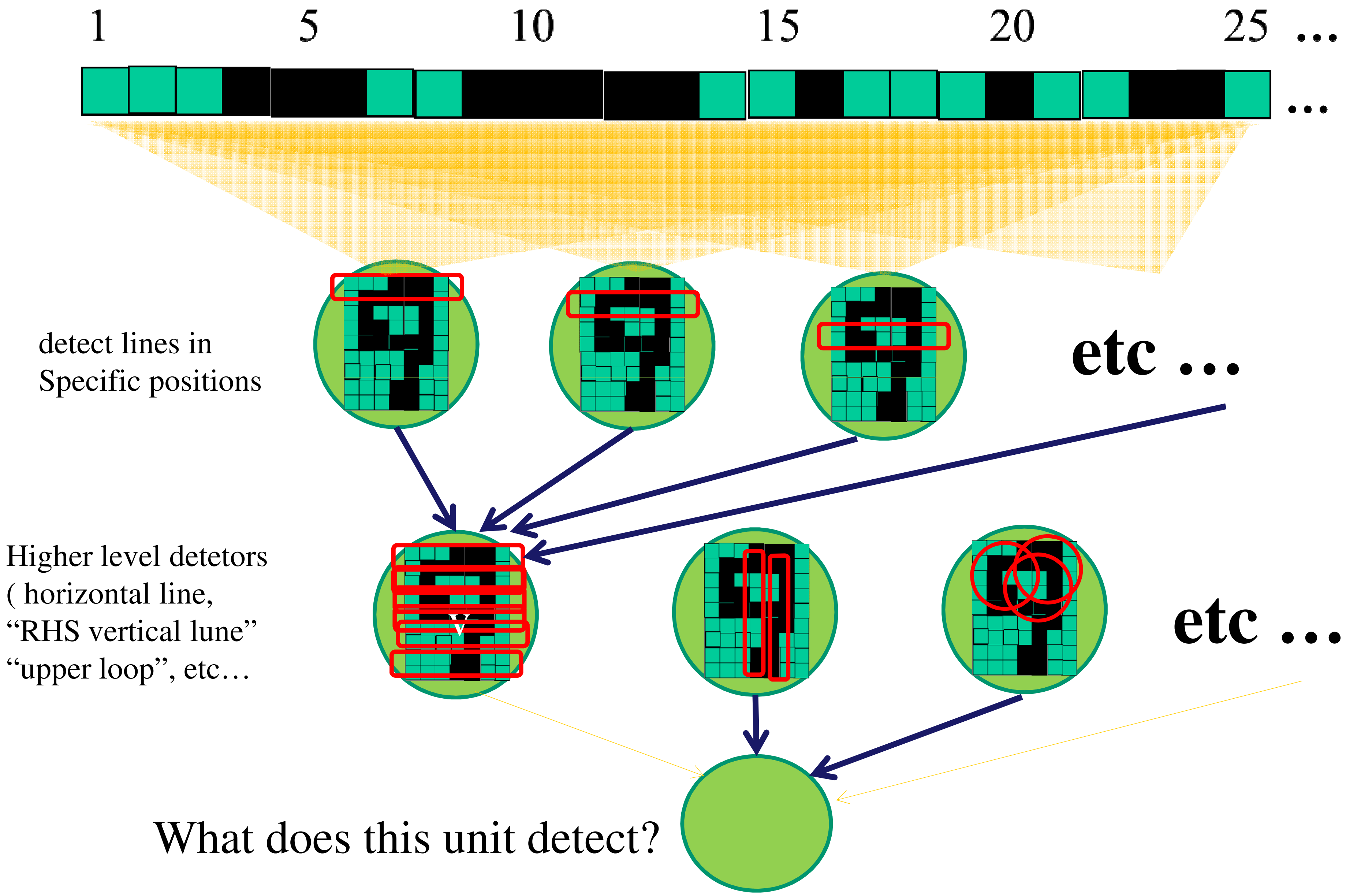
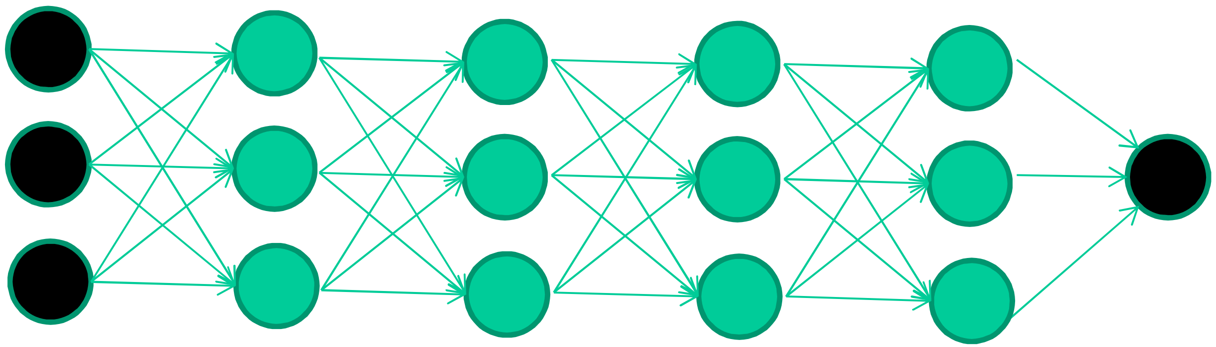
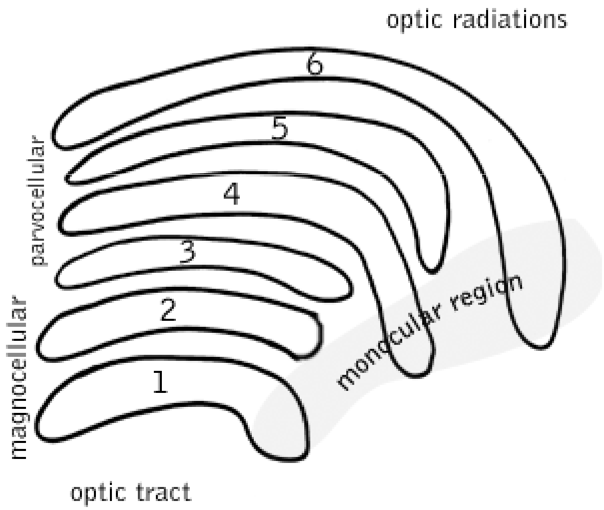


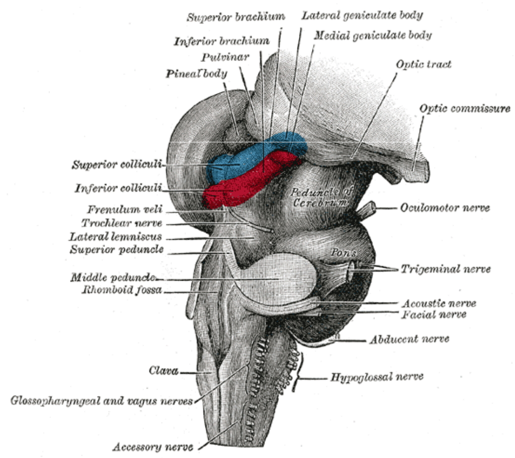
So: *multiple layers make sense*



So: *multiple layers make sense*

Your brain works that way





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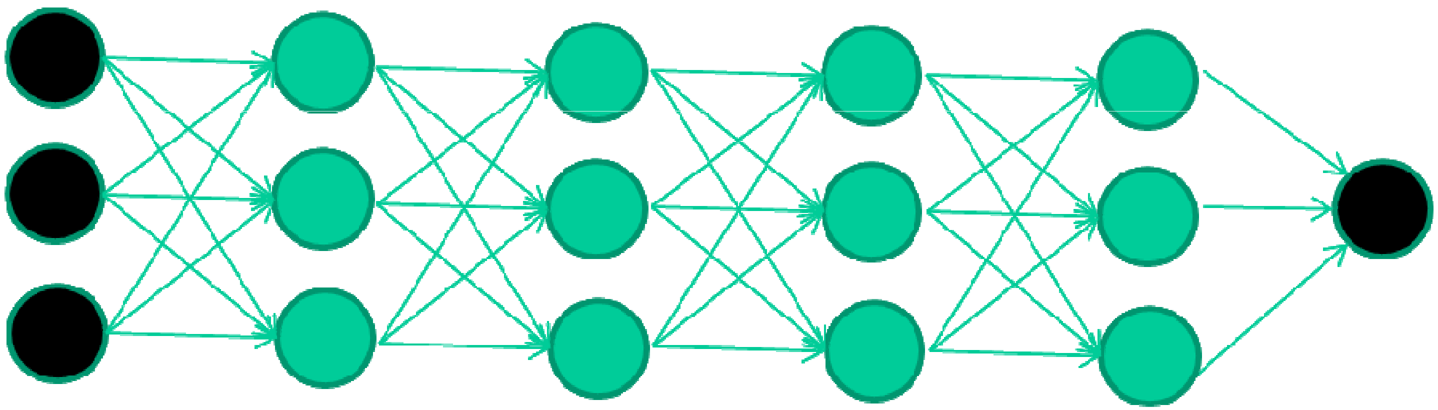
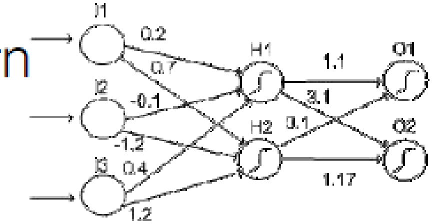
Many-layer neural network architectures should be capable of learning the true underlying features and 'feature logic', and therefore generalise very well …



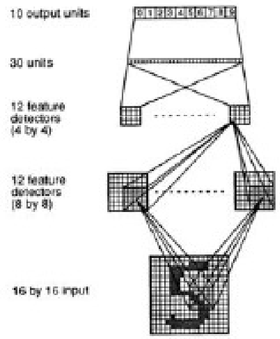
History of Neural Network

1990s

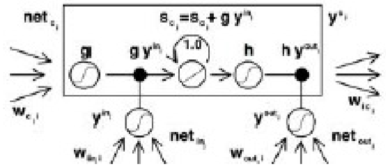
- **Multi-layer perceptrons** can theoretically learn any function (Cybenko, 1989; Hornik, 1991)



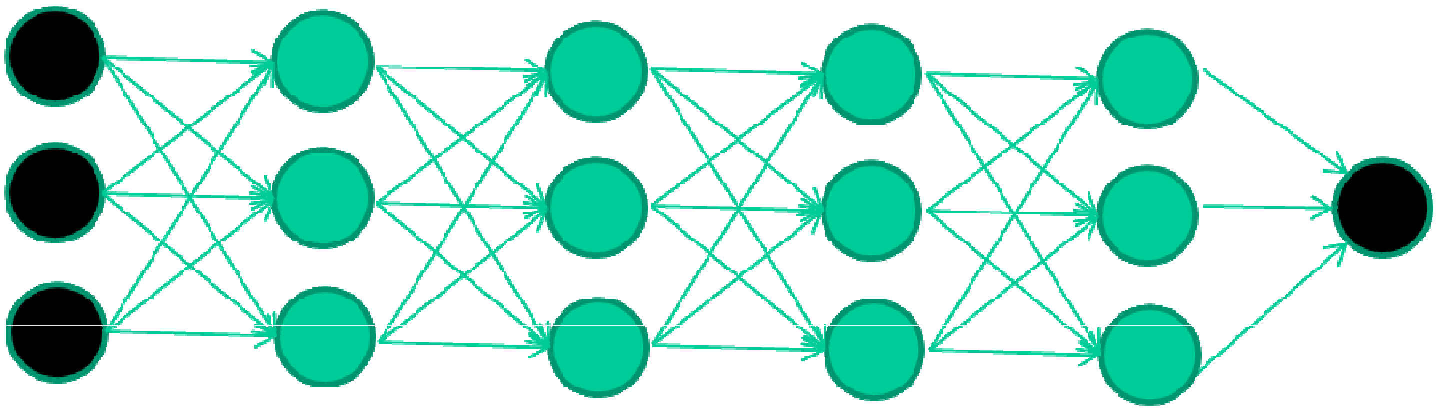
- Training multi-layer perceptrons
  - **Back propagation** (Rumelhart, Hinton, Williams, 1986)
  - **Backpropagation through time** (BPTT) (Werbos, 1988)

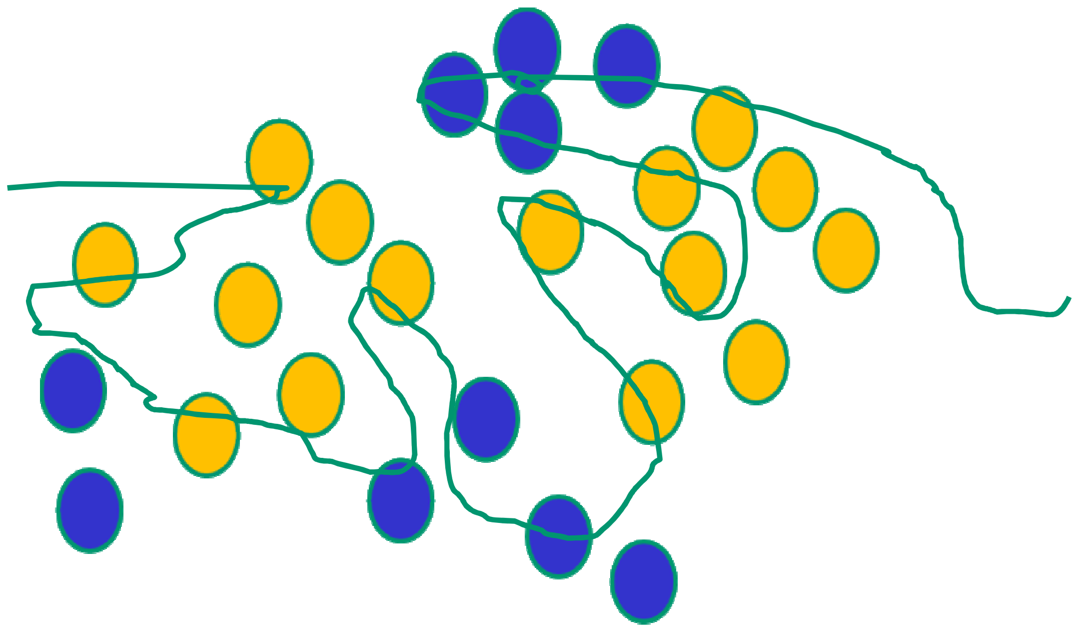


- New neural architectures
  - **Convolutional neural nets** (LeCun et al., 1989)
  - **Long-short term memory networks** (LSTM) (Schmidhuber, 1997)



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





Why it failed then

- Too many parameters to learn from few labeled examples.
- “I know my features are better for this task”.
- Non-convex optimization? No, thanks.
- Black-box model, no interpretability.

- Very slow and inefficient
- Overshadowed by the success of SVMs (Cortes and Vapnik, 1995)
- Vanishing Gradient Problem

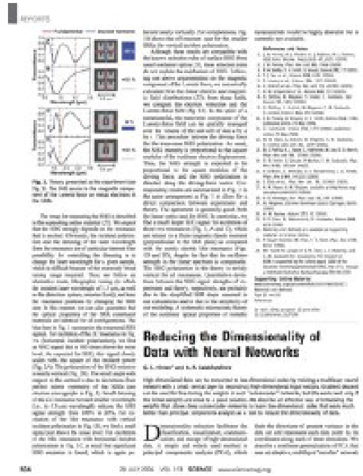
A major breakthrough in 2006

2006 Breakthrough: Hinton and Salakhutdinov

Reducing the Dimensionality of Data with Neural Networks

G. E. Hinton* and R. R. Salakhutdinov

High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. Gradient descent can be used for fine-tuning the weights in such "autoencoder" networks, but this works well only if the initial weights are close to a good solution. We describe an effective way of initializing the weights that allows deep autoencoder networks to learn low-dimensional codes that work much better than principal components analysis as a tool to reduce the dimensionality of data.

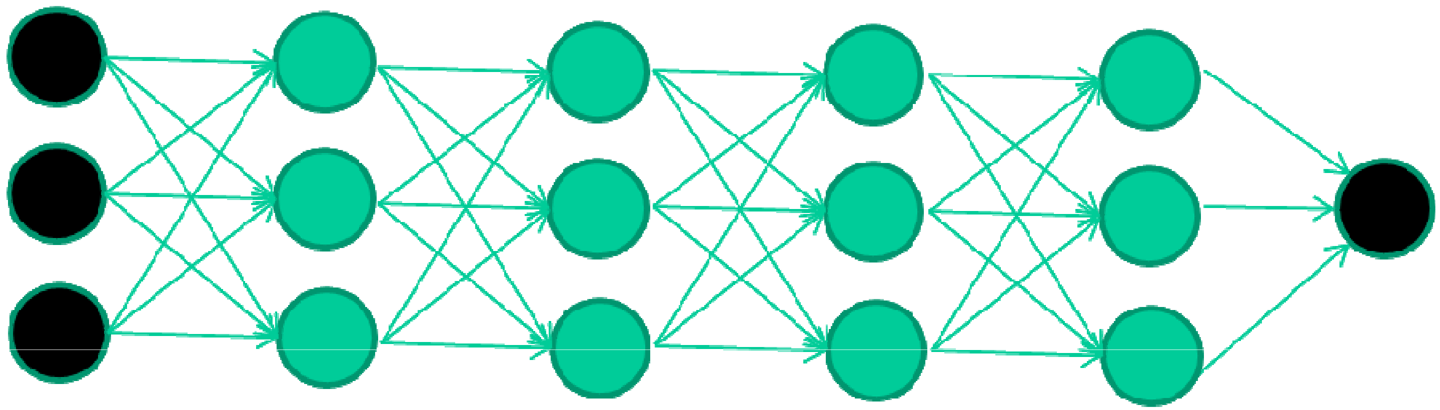

Reducing the Dimensionality of Data with Neural Networks

- The first solution to the **vanishing gradient problem**.
- Build the model in a layer-by-layer fashion using unsupervised learning
  - The features in early layers are already initialized or "pretrained" with some suitable features (weights).
  - Pretrained features in early layers only need to be adjusted slightly during supervised learning to achieve good results.

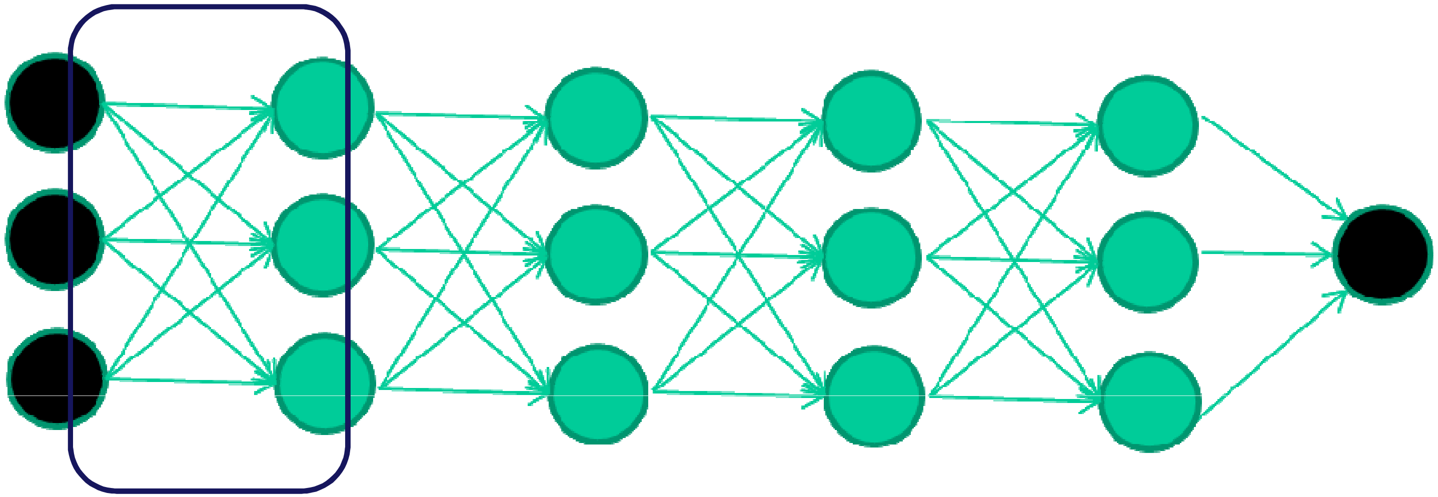
G. E. Hinton and R. R. Salakhutdinov, **"Reducing the dimensionality of data with neural networks"**, Science, Vol. 313, 28 July 2006.

Along came deep learning …

The new way to train multi-layer NNs…

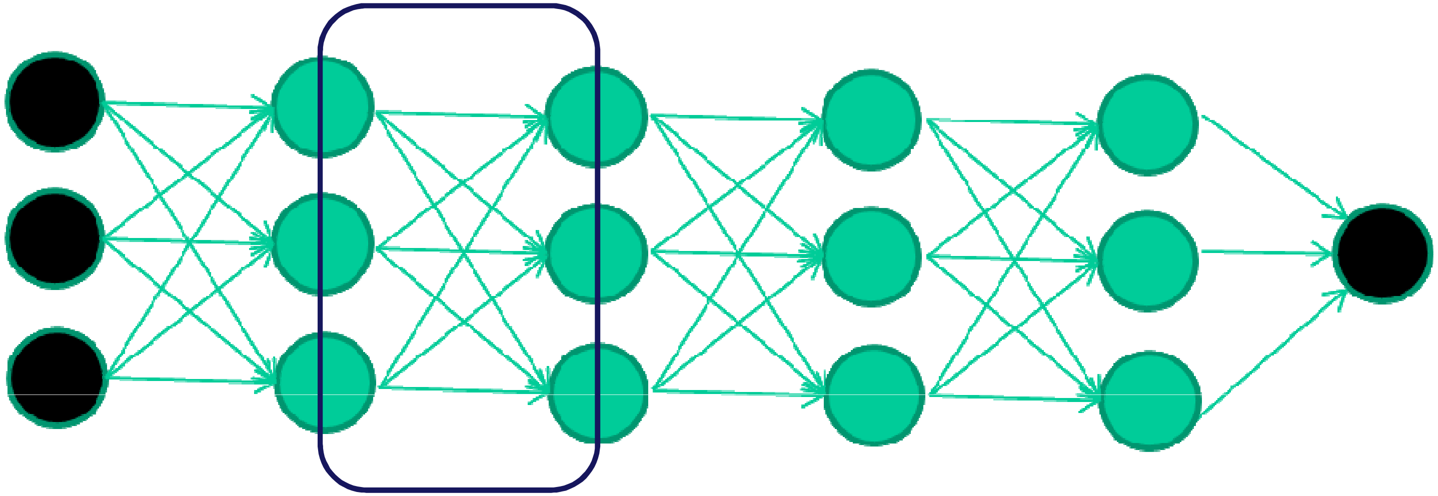


The new way to train multi-layer NNs…



Train **this** layer first

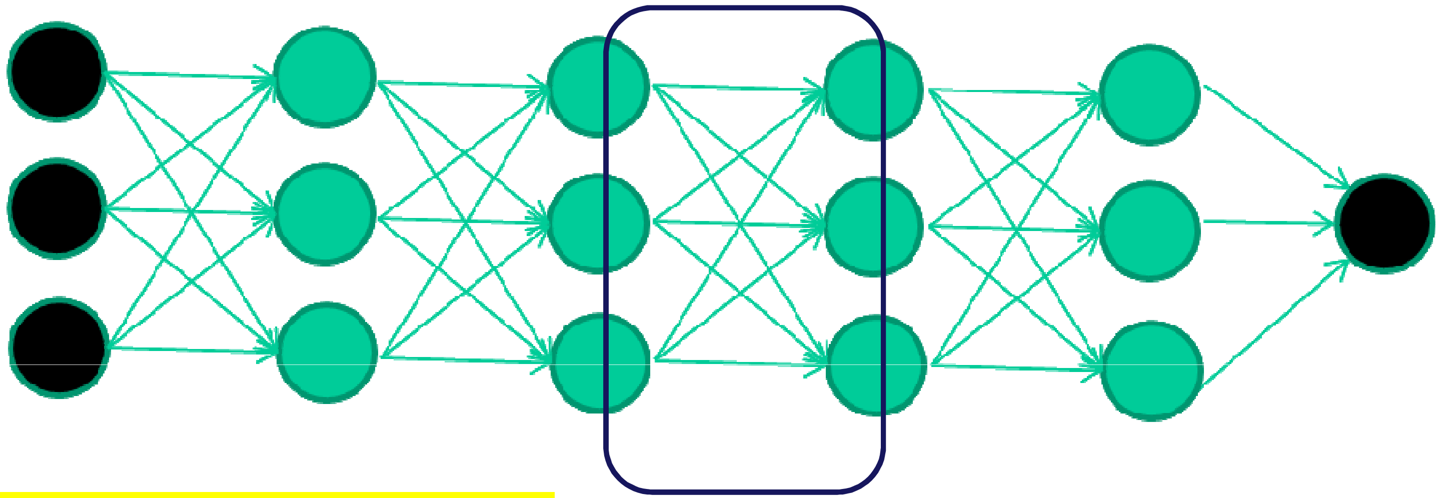
The new way to train multi-layer NNs…



Train **this** layer first

then **this** layer

The new way to train multi-layer NNs…

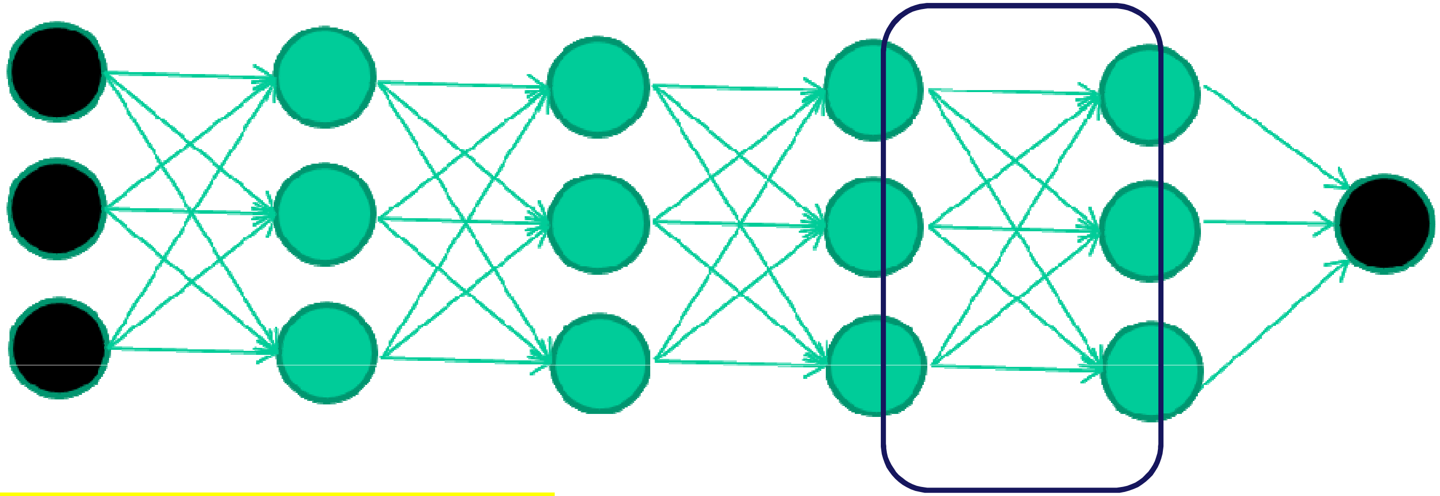


Train **this** layer first

then **this** layer

then **this** layer

The new way to train multi-layer NNs…



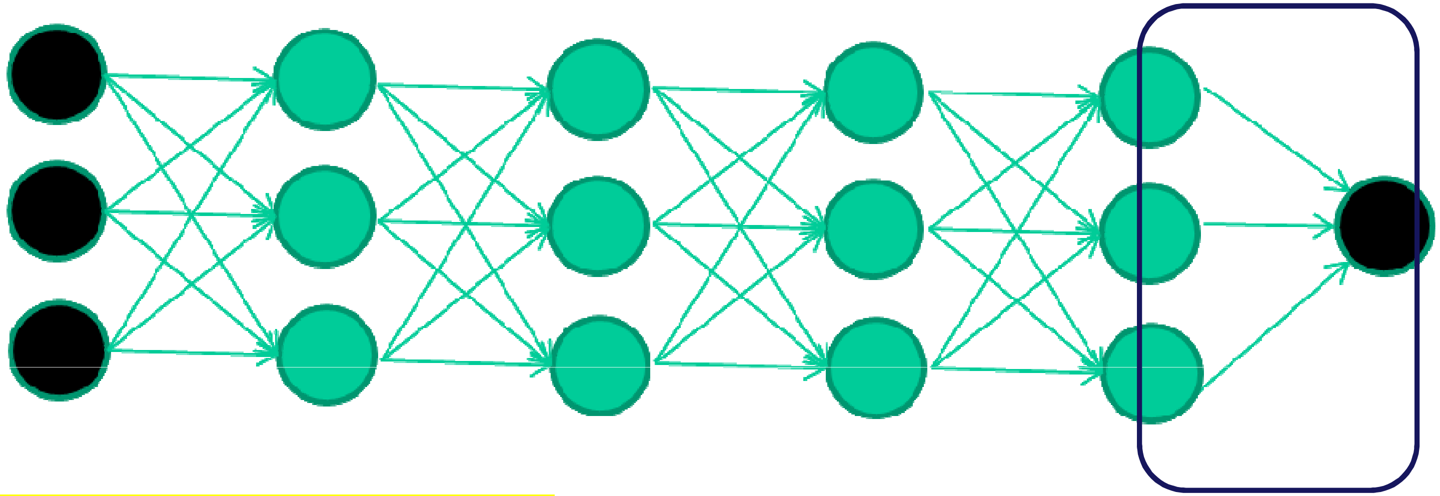
Train **this** layer first

then **this** layer

then **this** layer

then **this** layer

The new way to train multi-layer NNs…



Train **this** layer first

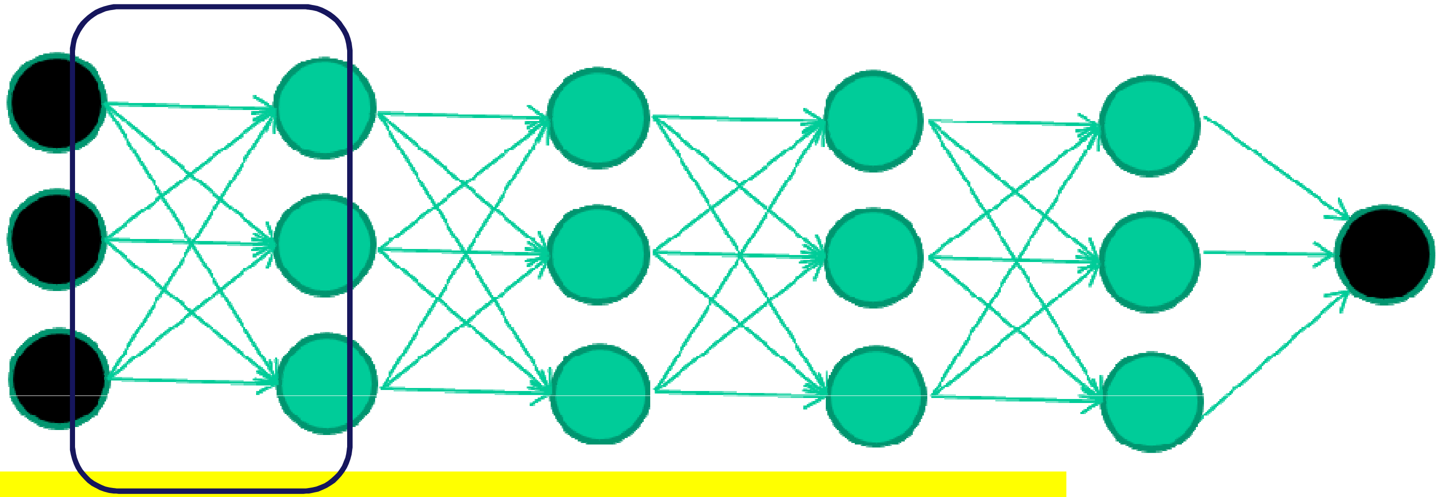
then **this** layer

then **this** layer

then **this** layer

finally **this** layer

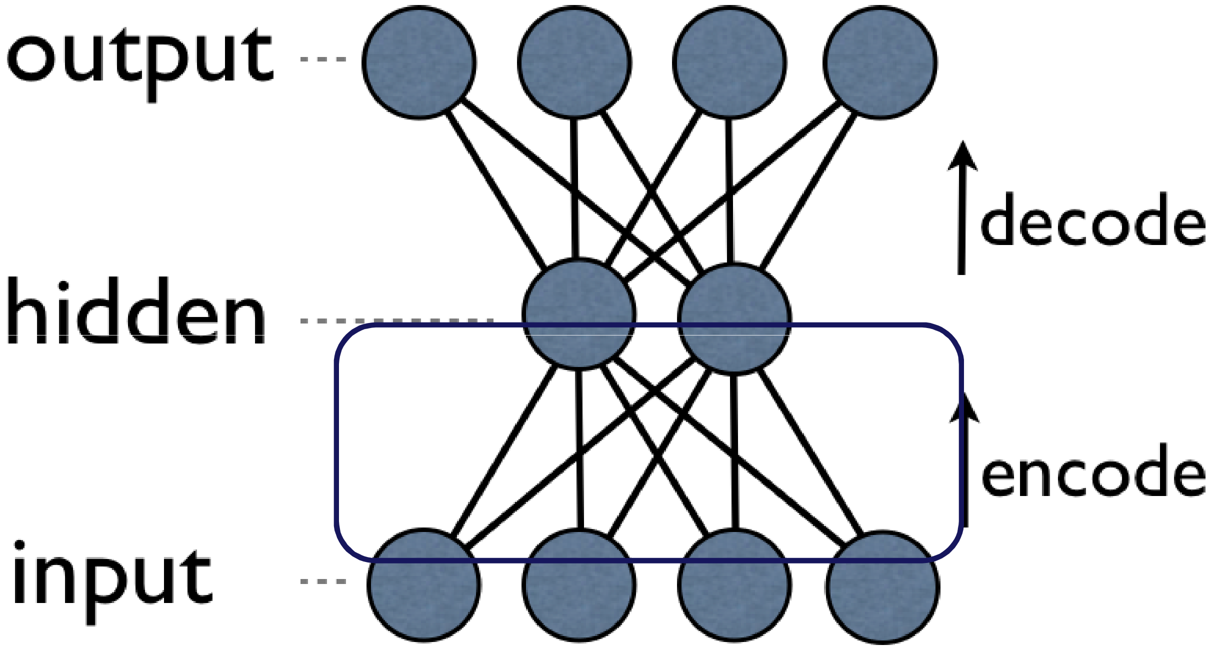
The new way to train multi-layer NNs…



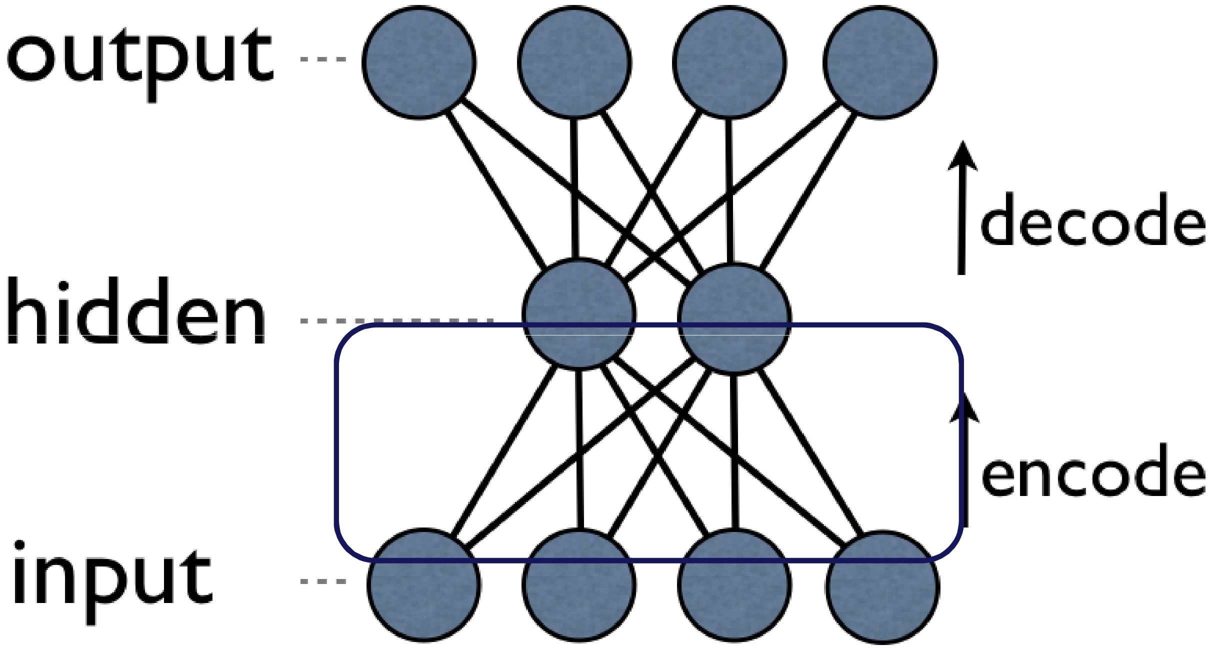
EACH of the (non-output) layers is trained to be an ***auto-encoder***

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 <u>reproduce the input</u>

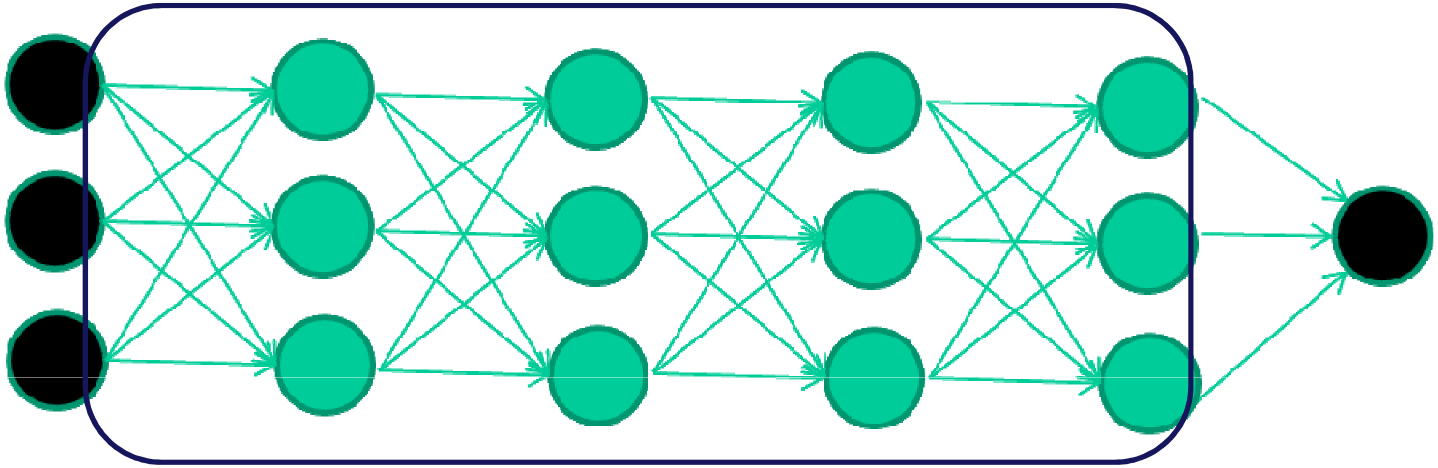


an auto-encoder is trained, with an absolutely standard weight-adjustment algorithm to <u>reproduce the input</u>

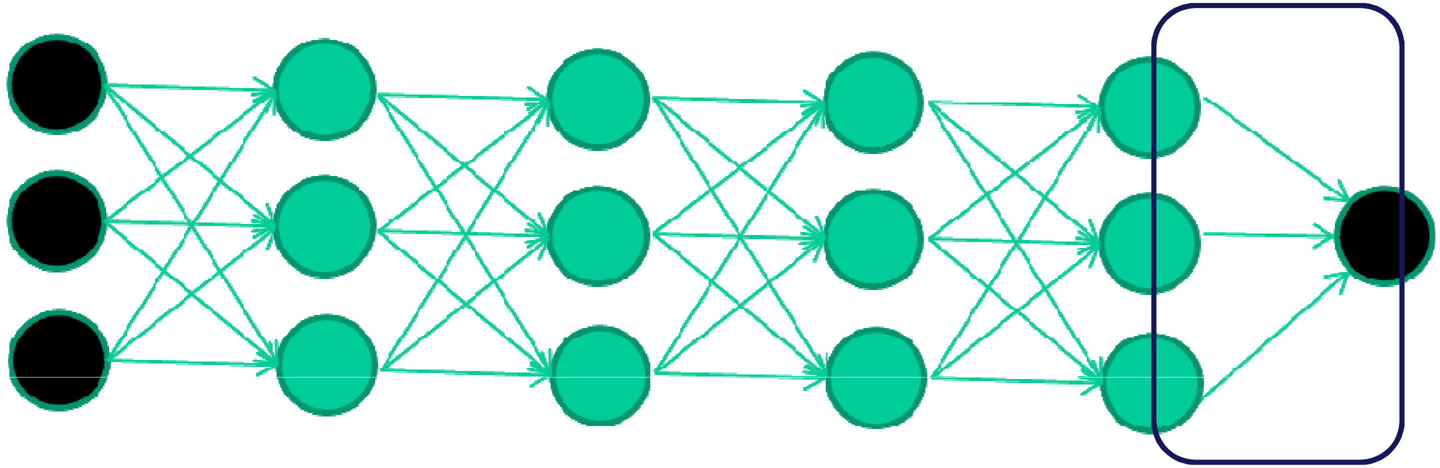


By making this happen with (many) fewer units than the inputs, this forces the 'hidden layer' units to become good feature detectors

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



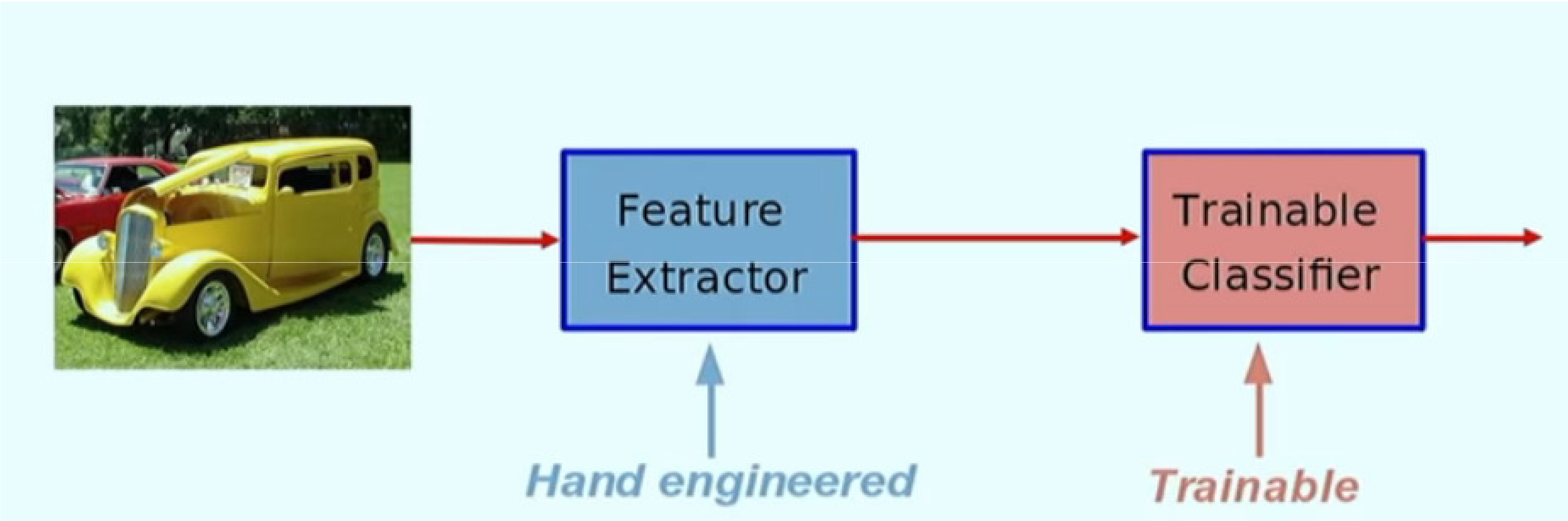
Final layer trained to predict class based on outputs from previous layers



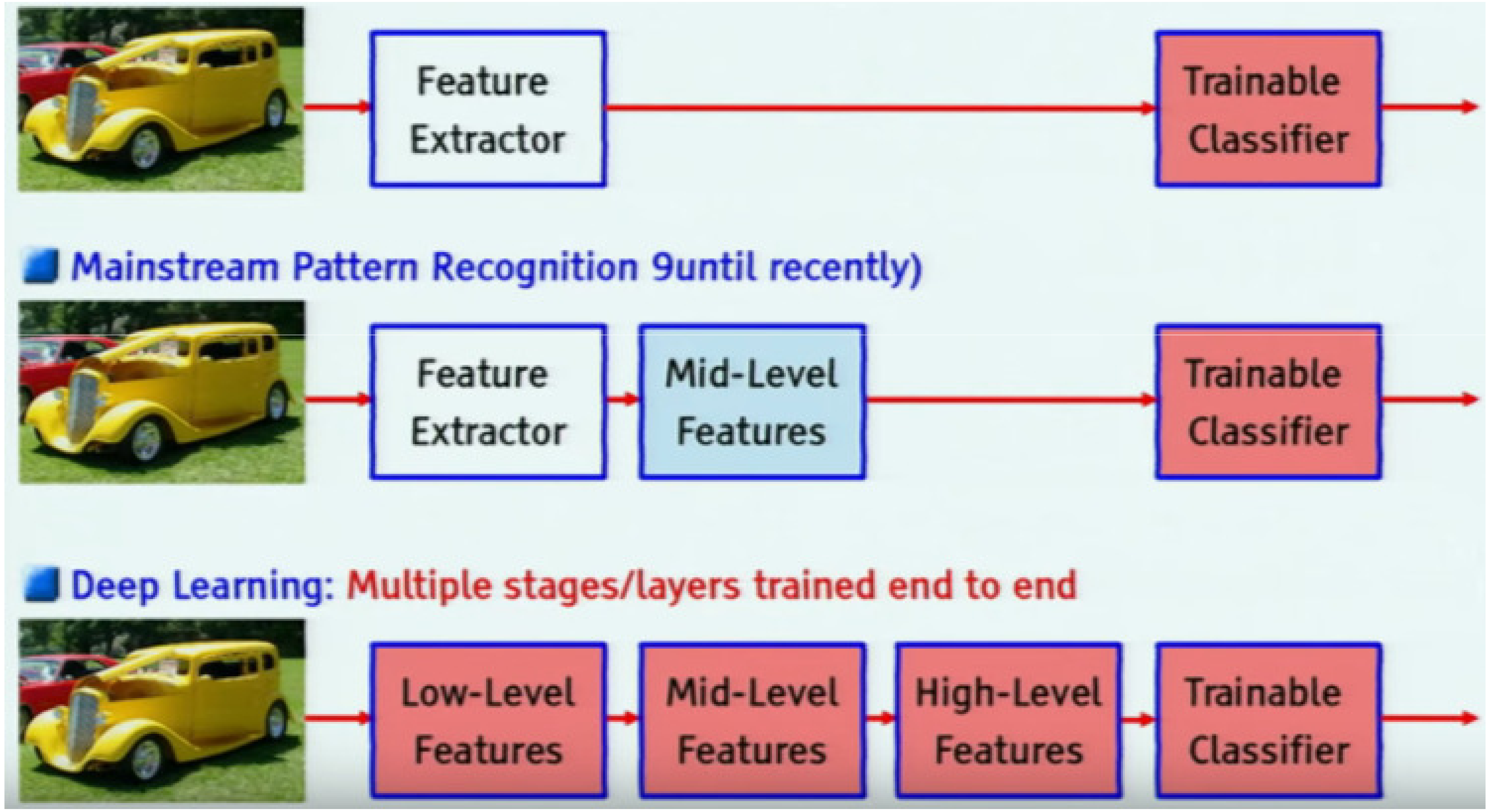
So what is deep learning?

Take a vision example : CNN for Object Recognition

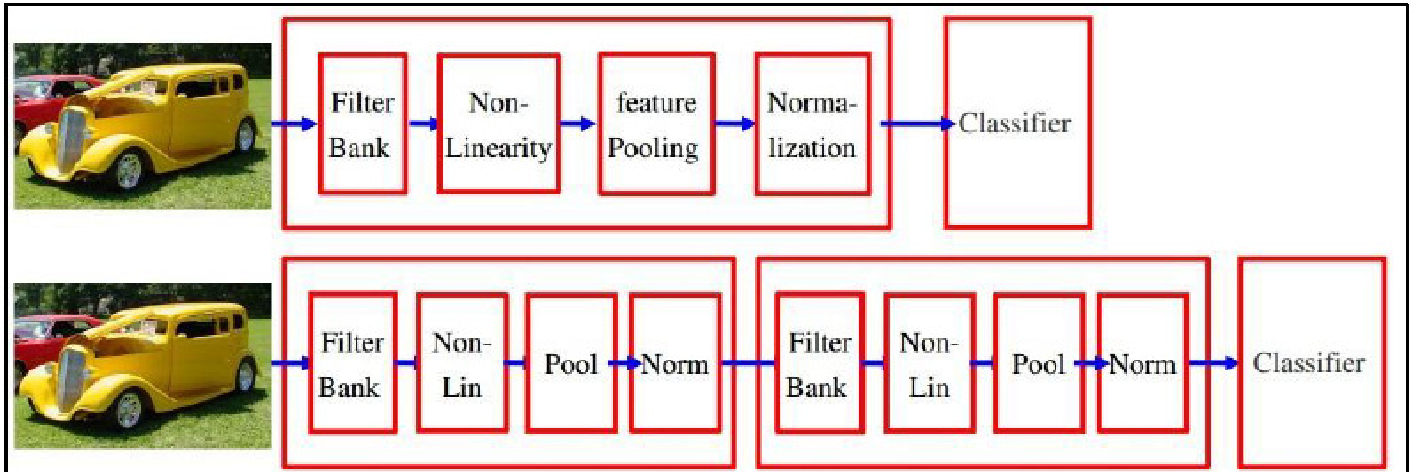
Conventional Object Recognition



CNN based Object Recognition



CNN based Object Recognition



- First stage: dense SIFT, HOG, GIST, sparse coding, RBM, auto-encoders.....
- Second stage: K-means, sparse coding, LCC....
- Pooling: average, L2, max, max with bias (elastic templates).....
- Convolutional Nets: same architecture, but everything is trained.

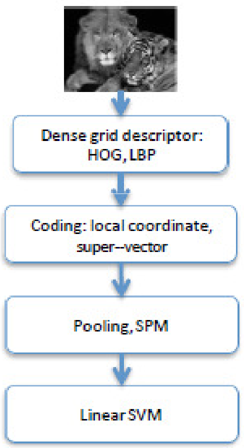
CNNs: end-to-end models

(slide from Yann LeCun)

IMAGENET Large Scale Visual Recognition Challenge

Year 2010

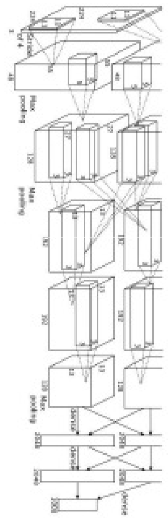
NEC-UIUC



[Lin CVPR 2011]

Year 2012

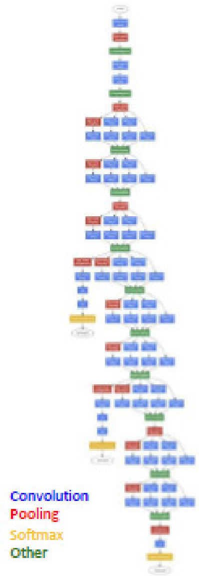
SuperVision



[Krizhevsky NIPS 2012]

Year 2014

GoogLeNet

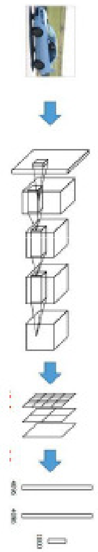


[Szegedy arxiv 2014]

VGG

[Simonyan arxiv 2014]

MSRA



[He arxiv 2014]

Year 2015

Deep Residual Learning for Image Recognition

Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun

[He arxiv 2015]

To continue...