Deep Learning Introduction

Md Modasshir

Topics

1. Introduction to Neural Network
2. Backpropagation and Gradient Descent
3. Edge Detection
4. Convolution as a layer
5. Convolutional Network

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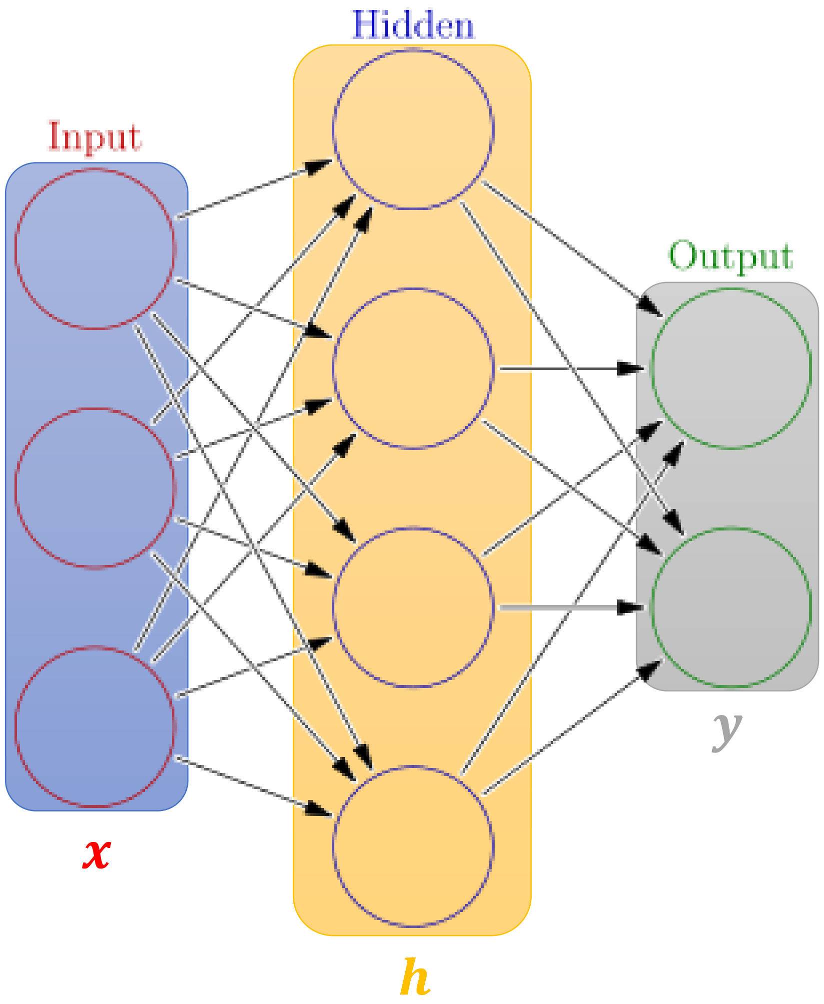

Weights

$$h = \sigma(\mathbf{W}_1 x + b_1)$$

$$y = \sigma(W_2 h + b_2)$$

Activation functions

4 + 2 = 6 neurons (not counting inputs)

[3 x 4] + [4 x 2] = 20 weights

4 + 2 = 6 biases

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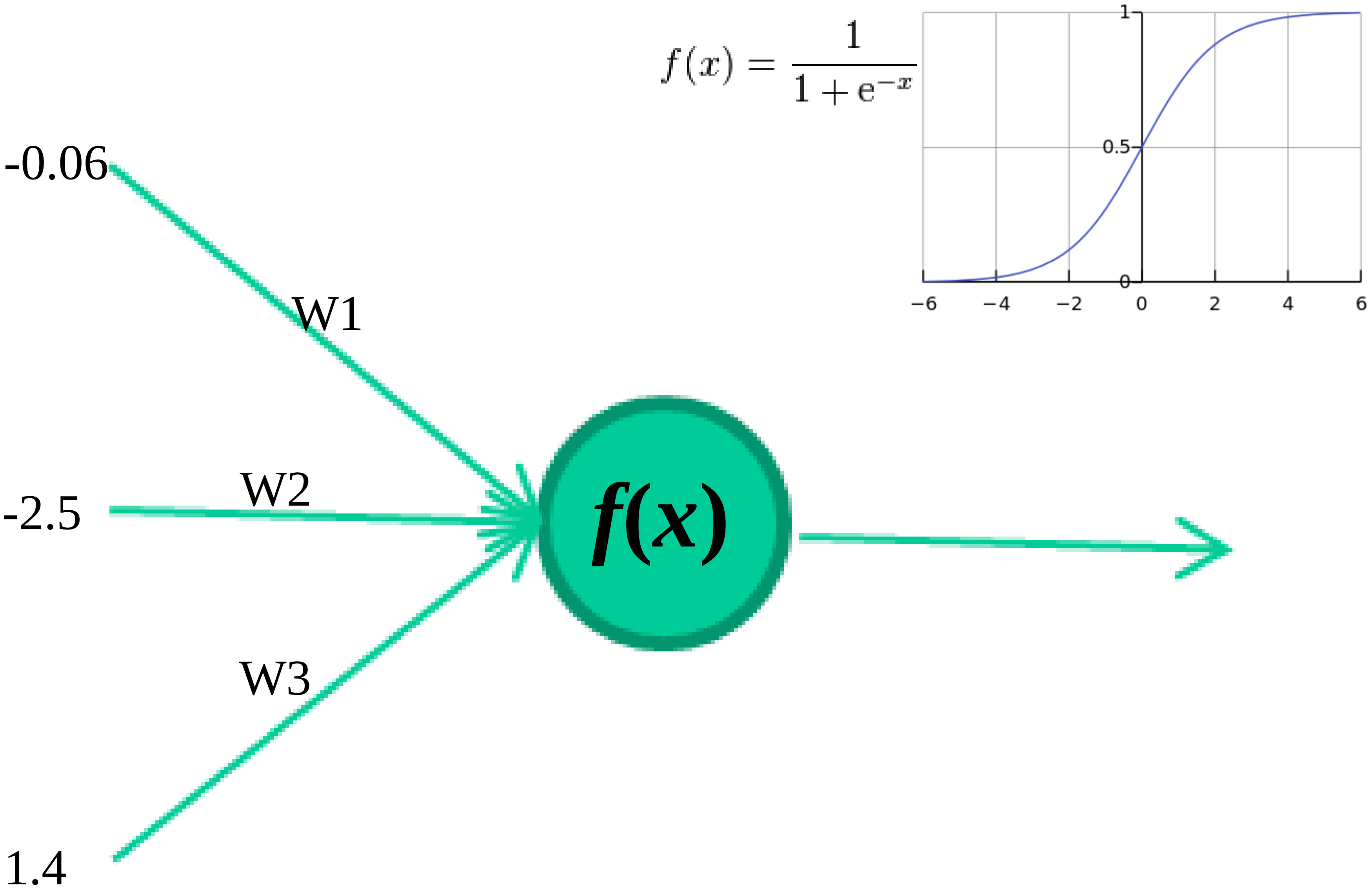
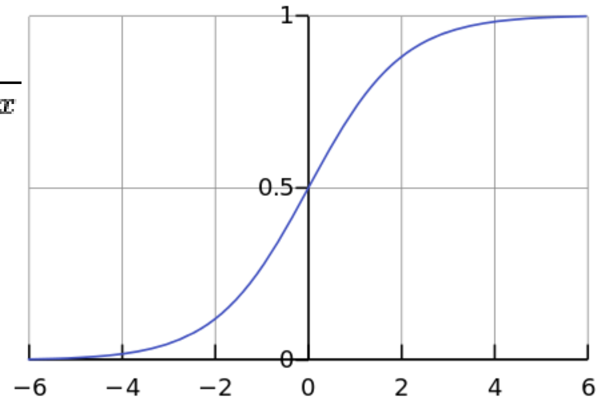
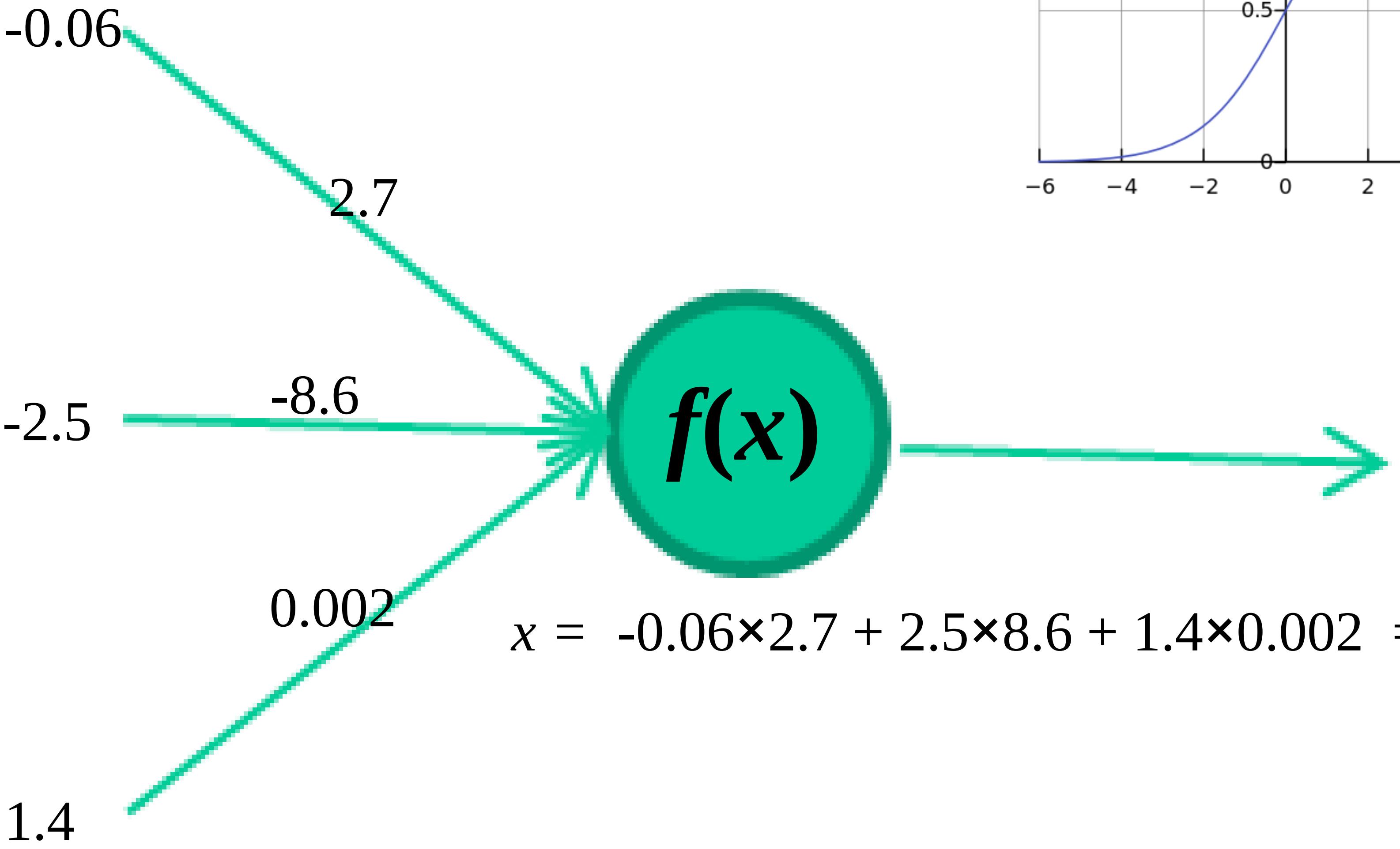
26 learnable **parameters**


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

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

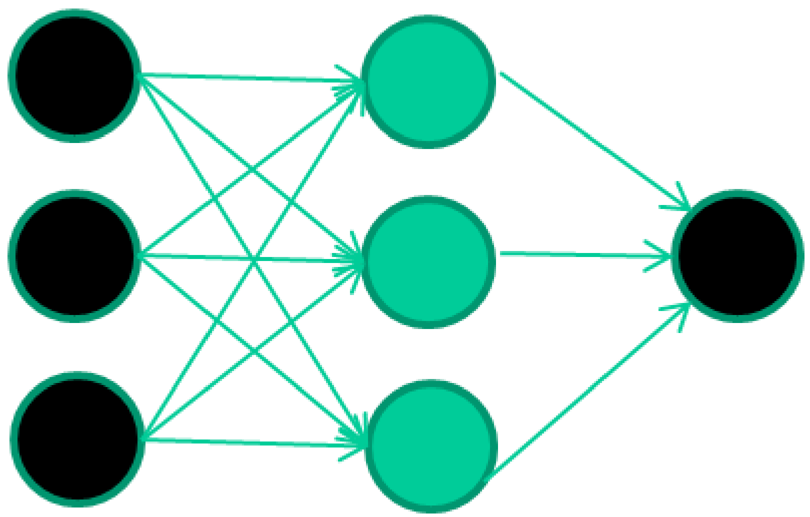




$$x = -0.06\times2.7 + 2.5\times8.6 + 1.4\times0.002 = 21.34$$

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

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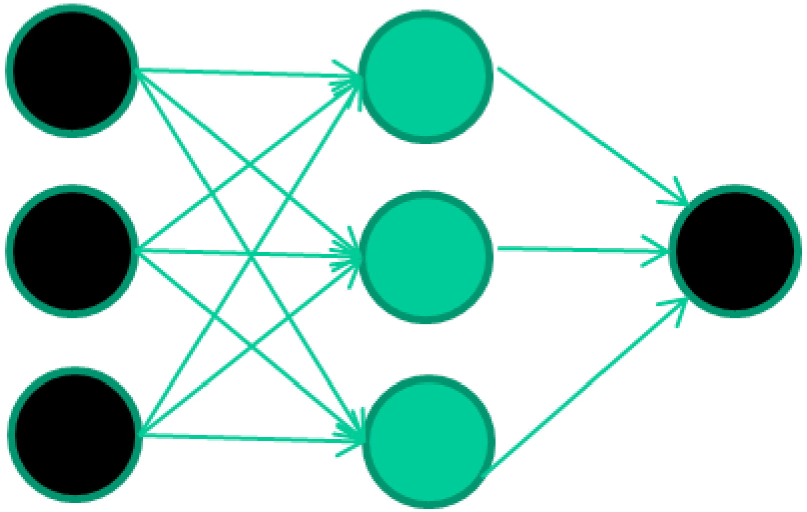
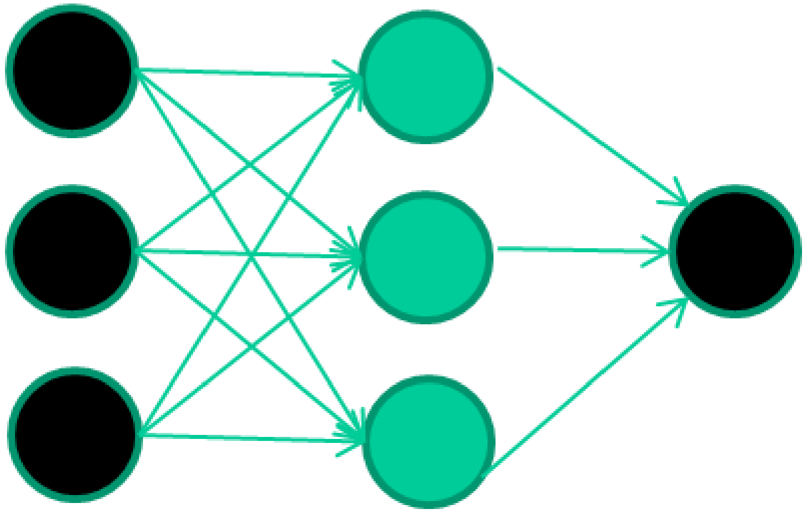
etc …



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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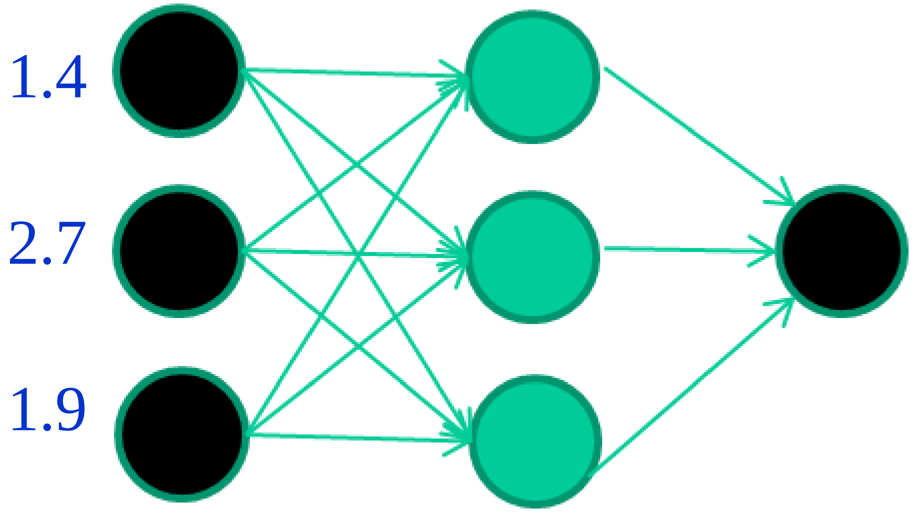
etc …			

Present a training pattern



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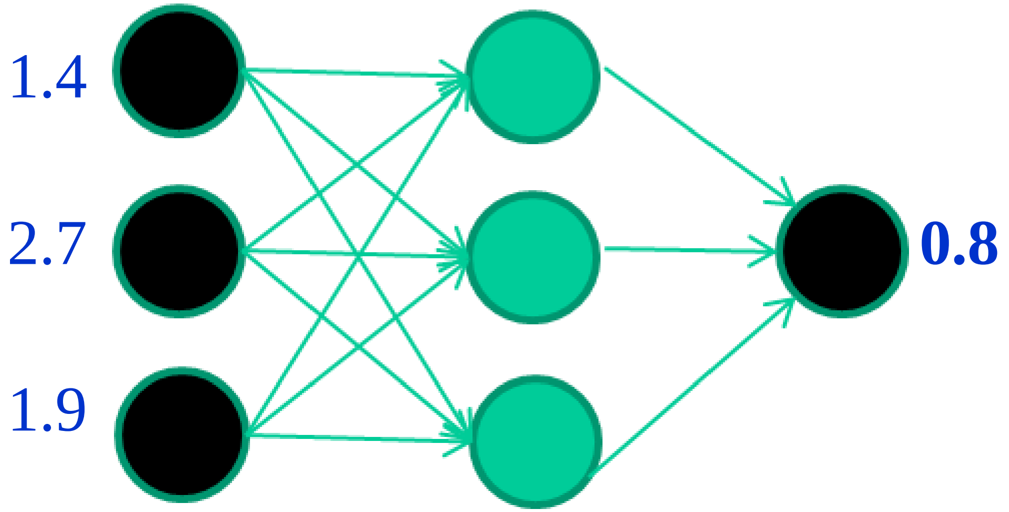
etc …			

Feed it through to get output



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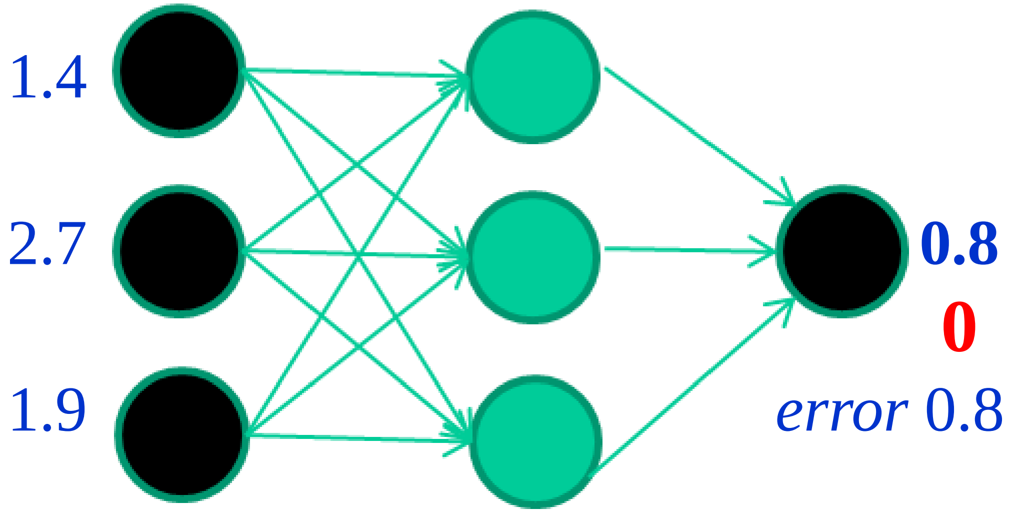
etc …

Compare with target output



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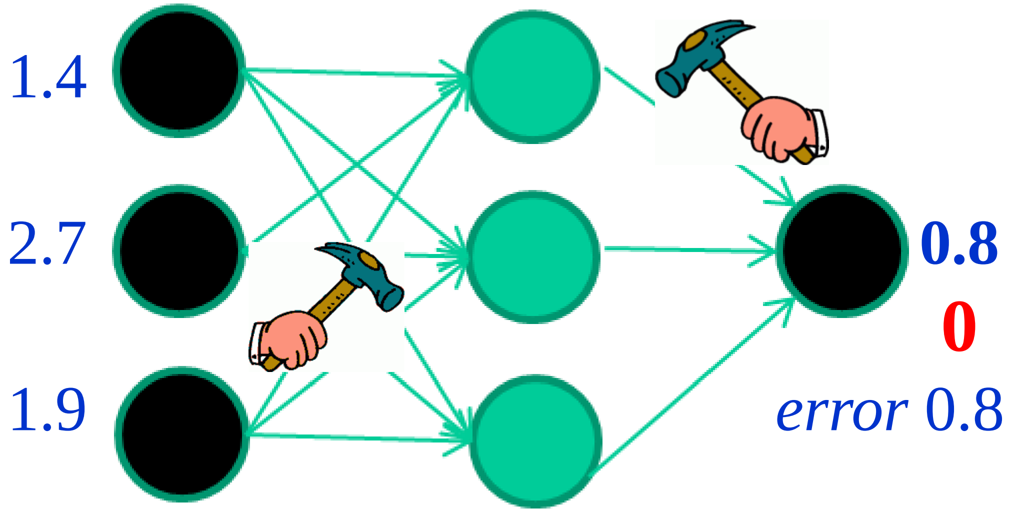
etc …			

Adjust weights based on error



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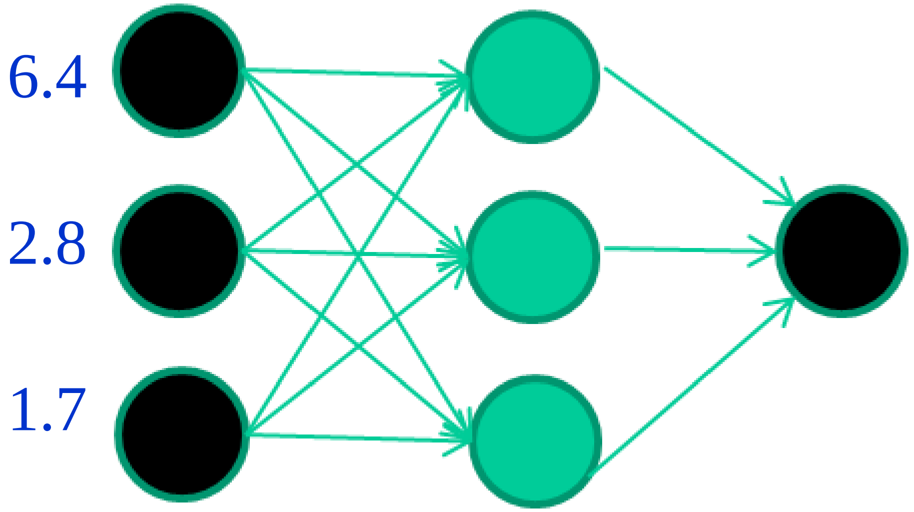

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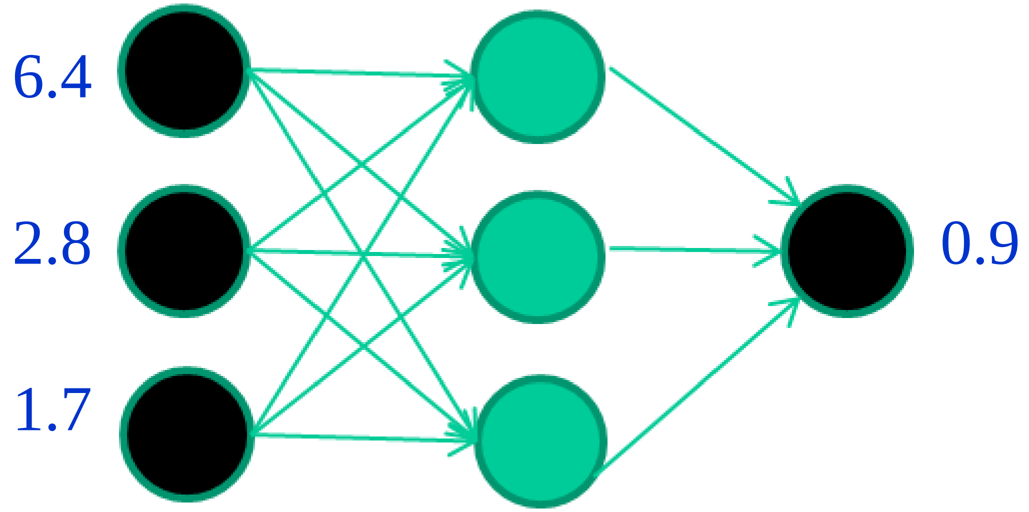

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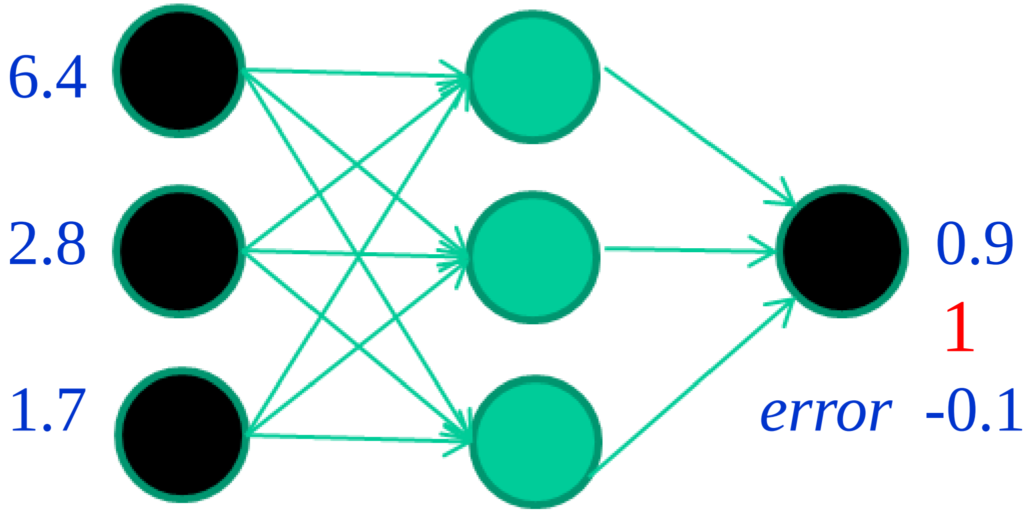

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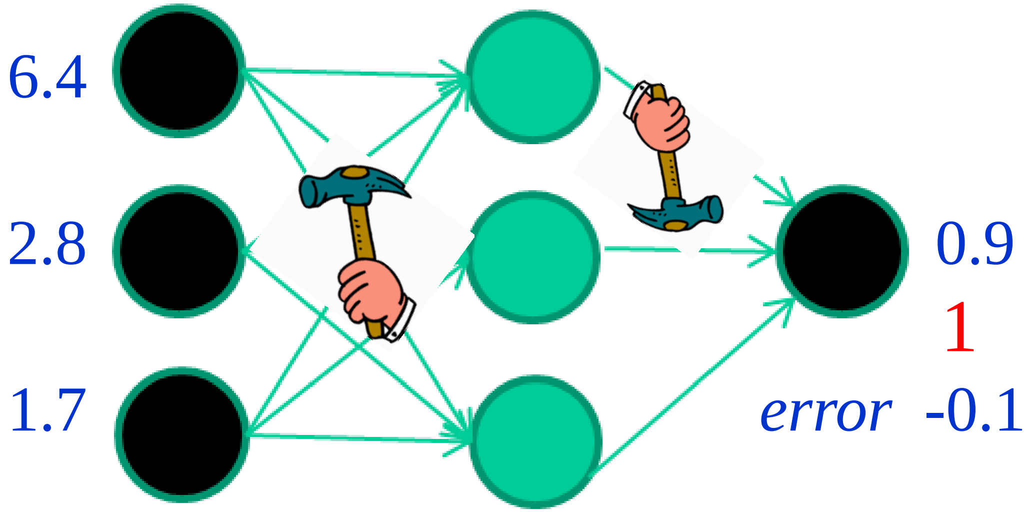

Training data

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1.4	2.7	1.9	0
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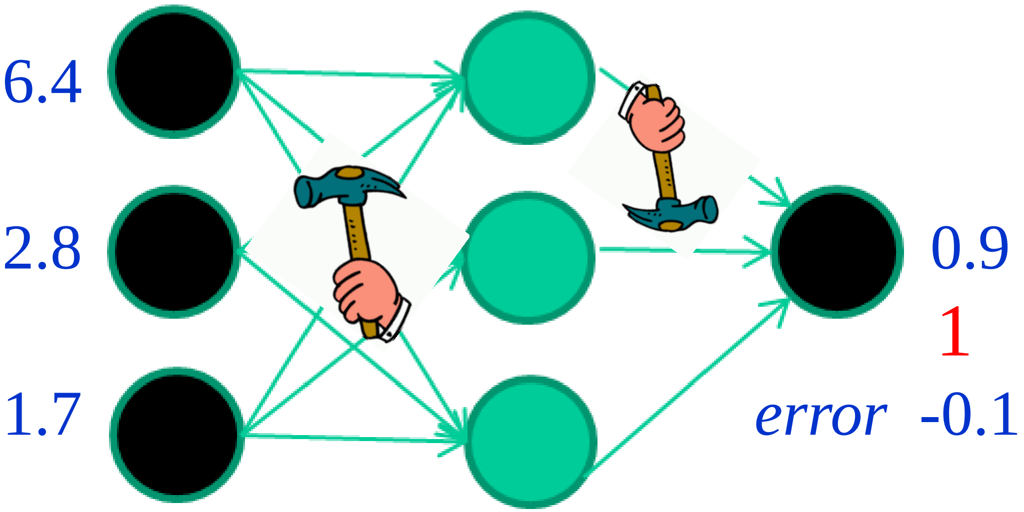
etc …			

And so on ….

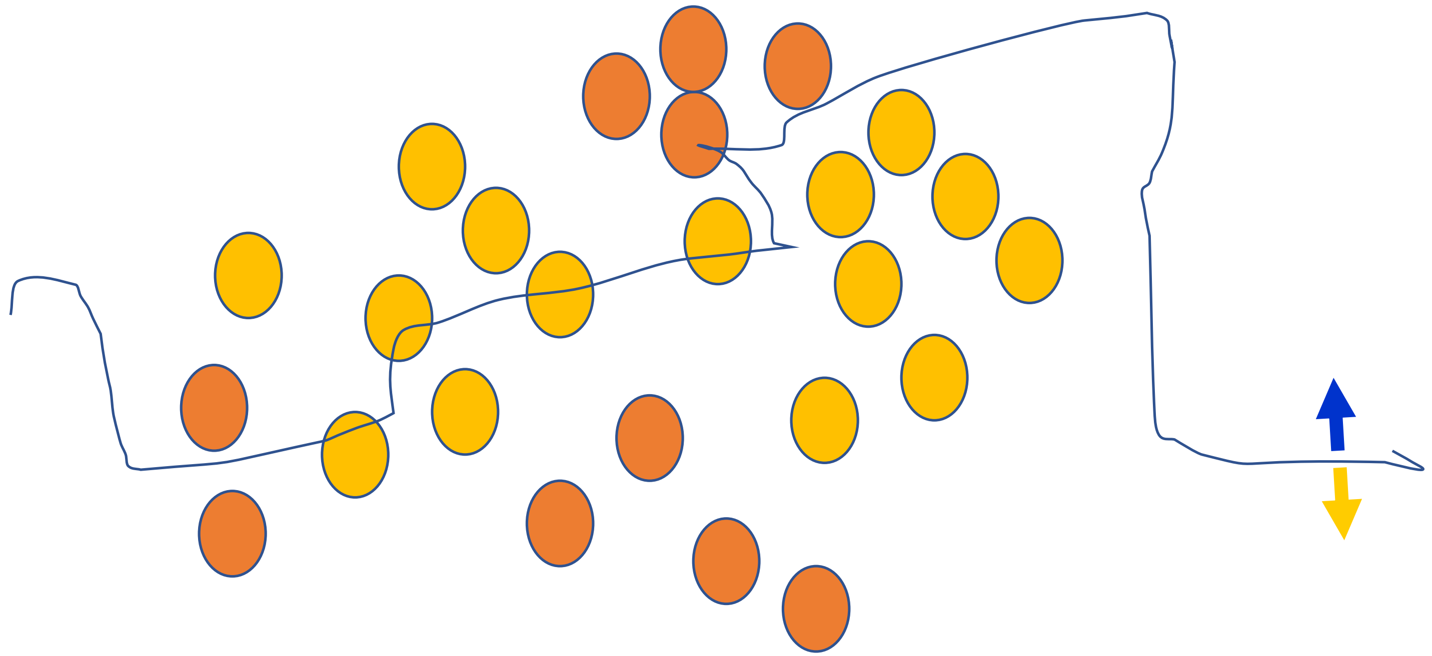


Repeat this thousands, maybe millions of times – each time taking a random training instance, and making slight weight adjustments

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

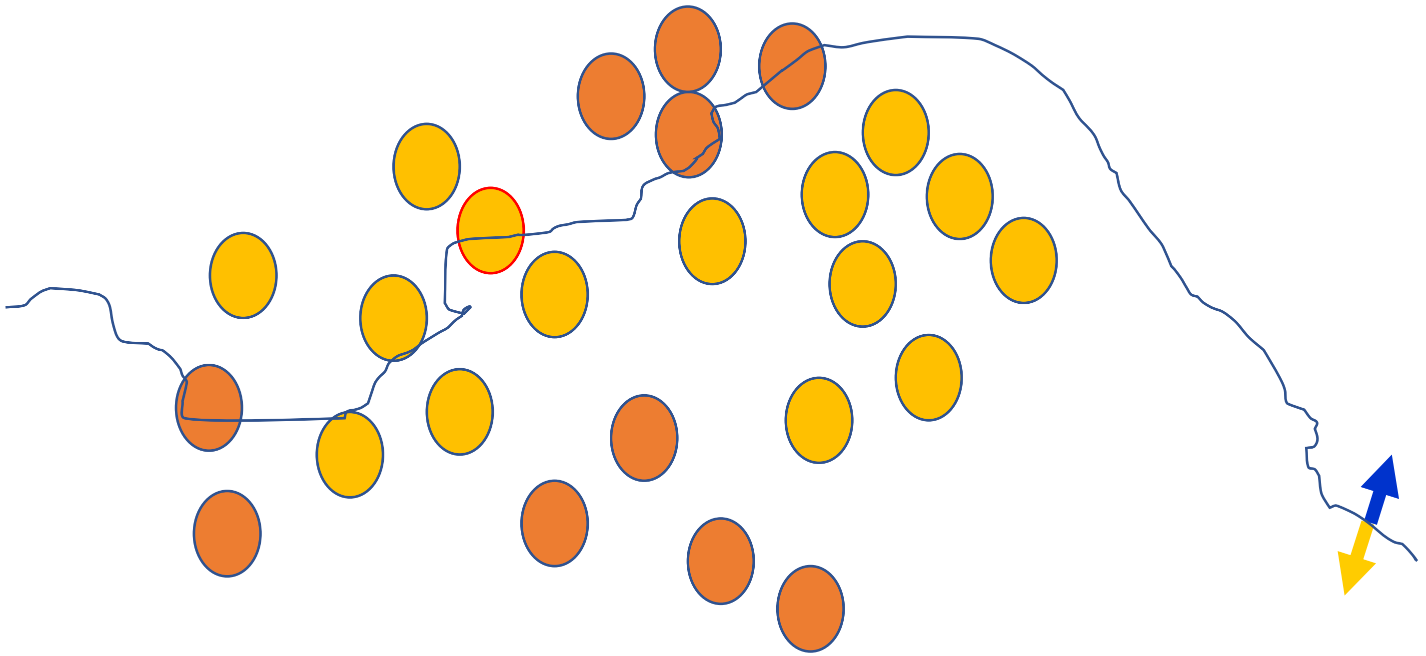
The decision boundary perspective…

Initial random weights



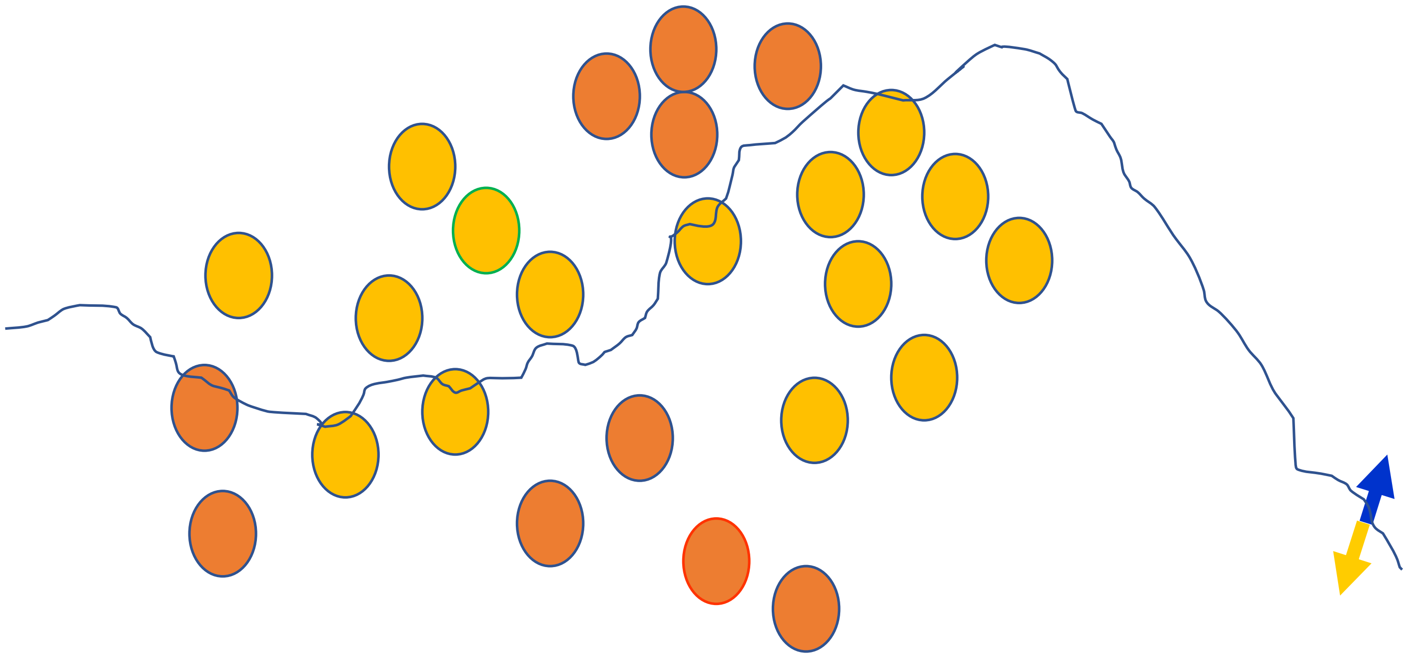
The decision boundary perspective…

Present a training instance / adjust the weights



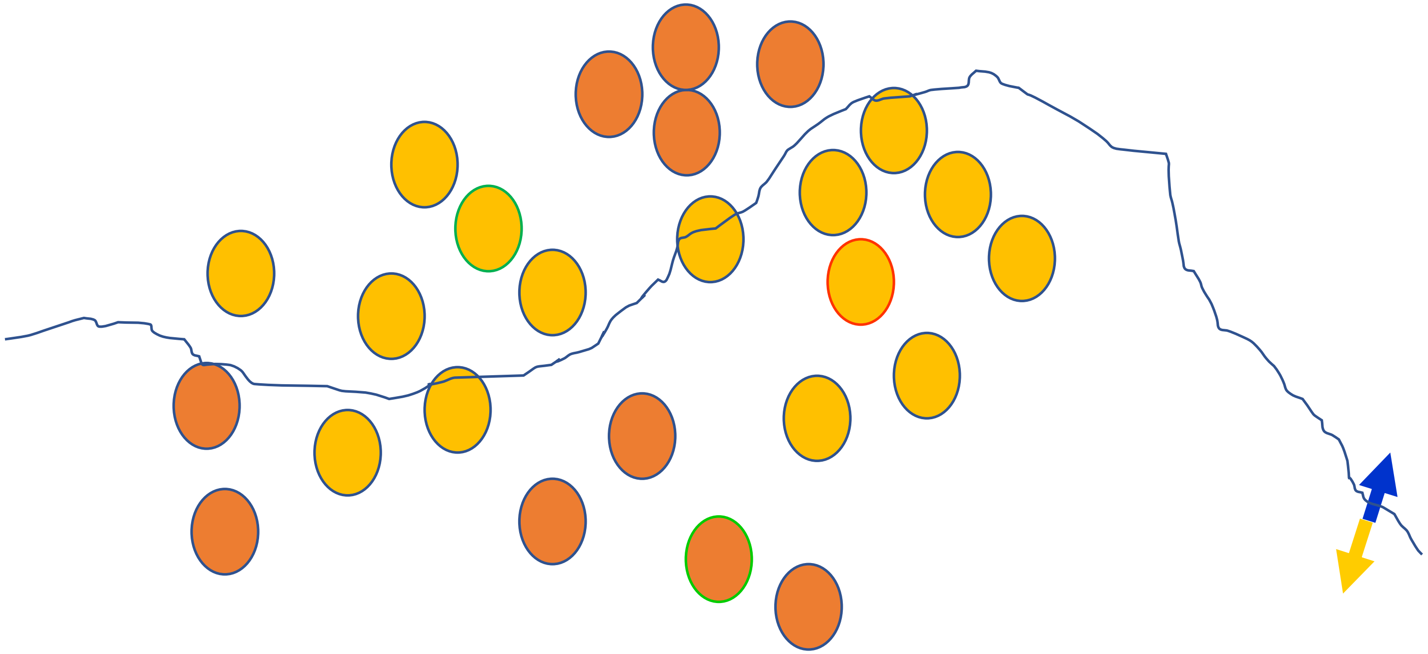
The decision boundary perspective…

Present a training instance / adjust the weights



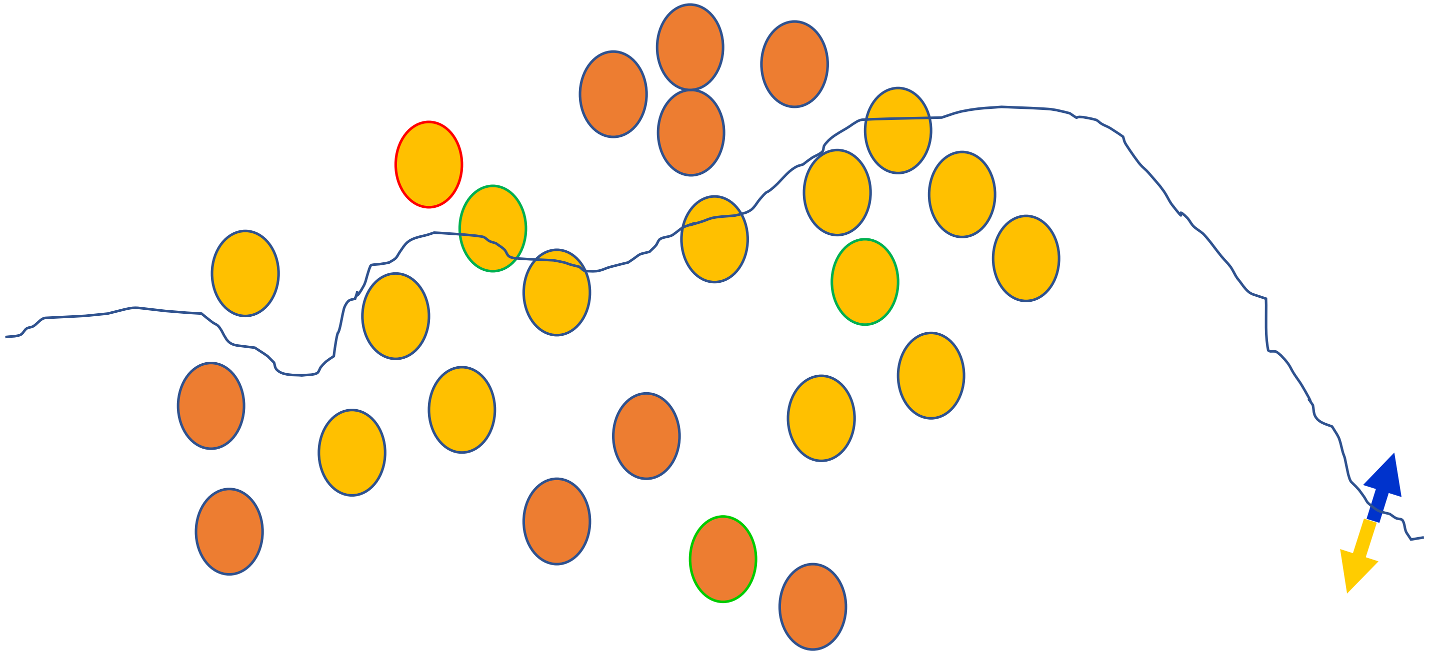
The decision boundary perspective…

Present a training instance / adjust the weights



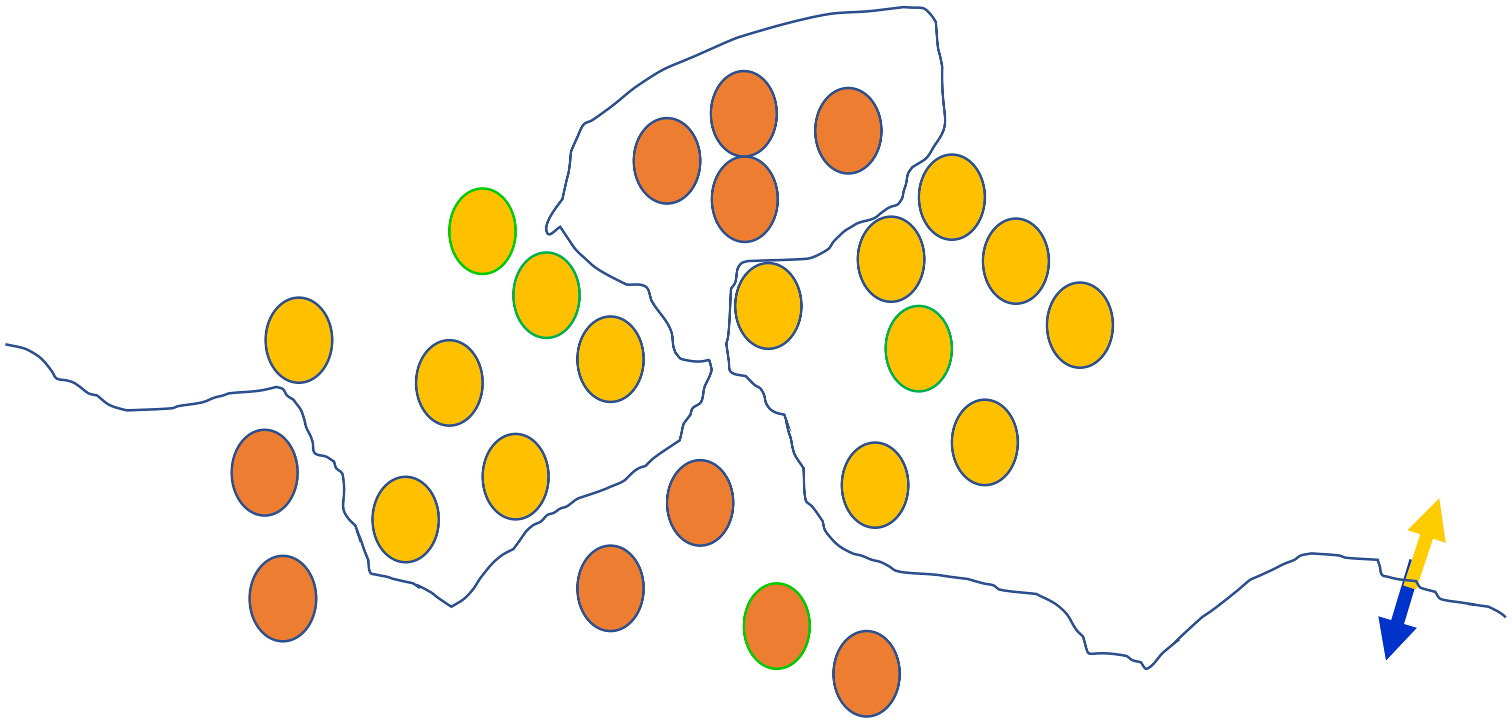
The decision boundary perspective…

Present a training instance / adjust the weights



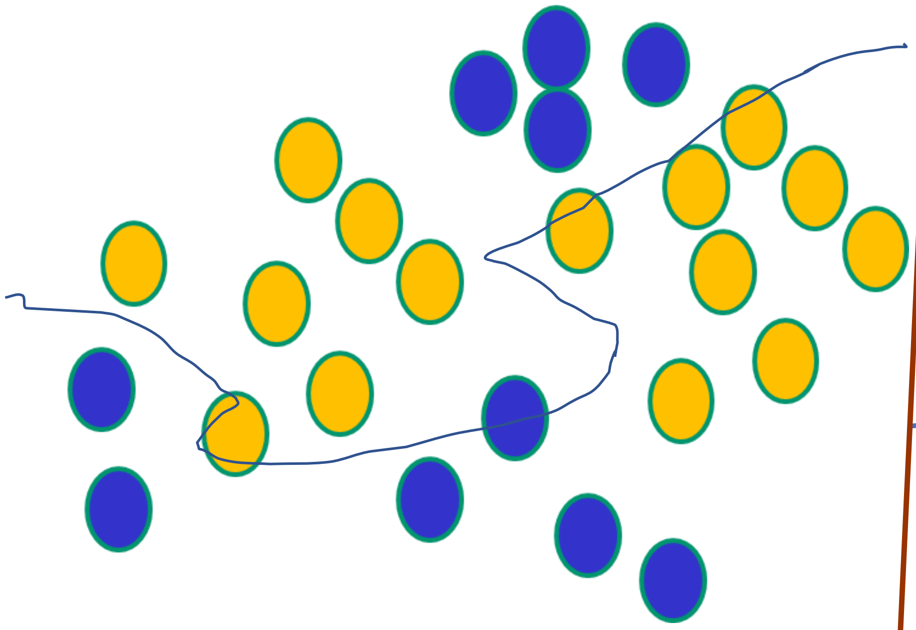
The decision boundary perspective…

Eventually ….

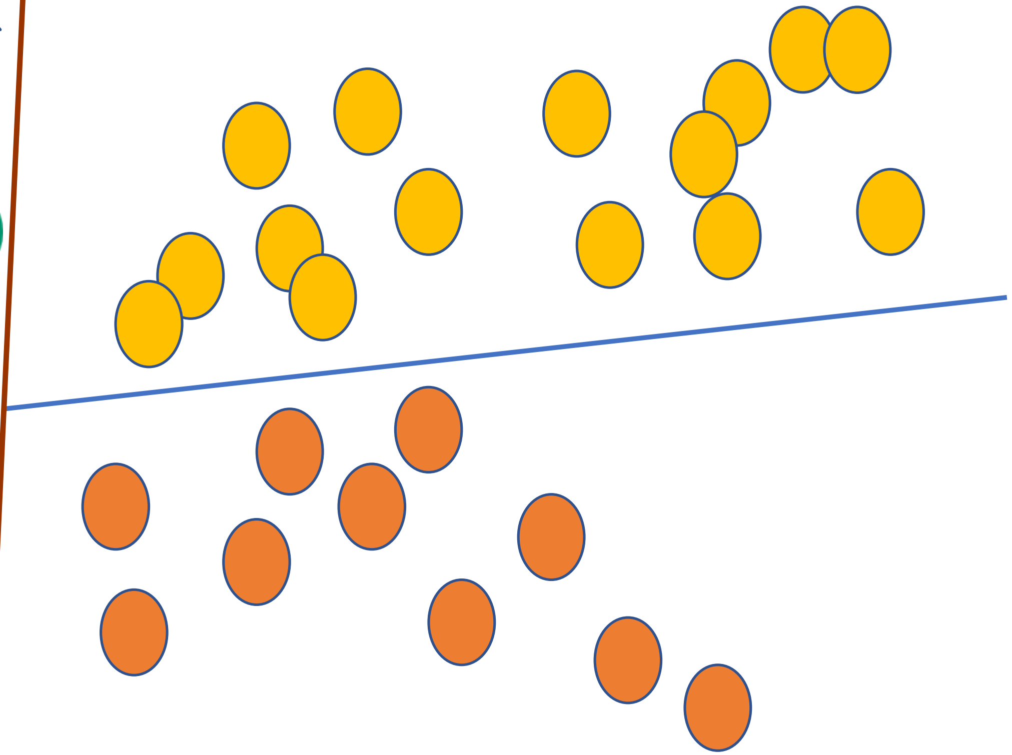


Some other ‘by the way’ points

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



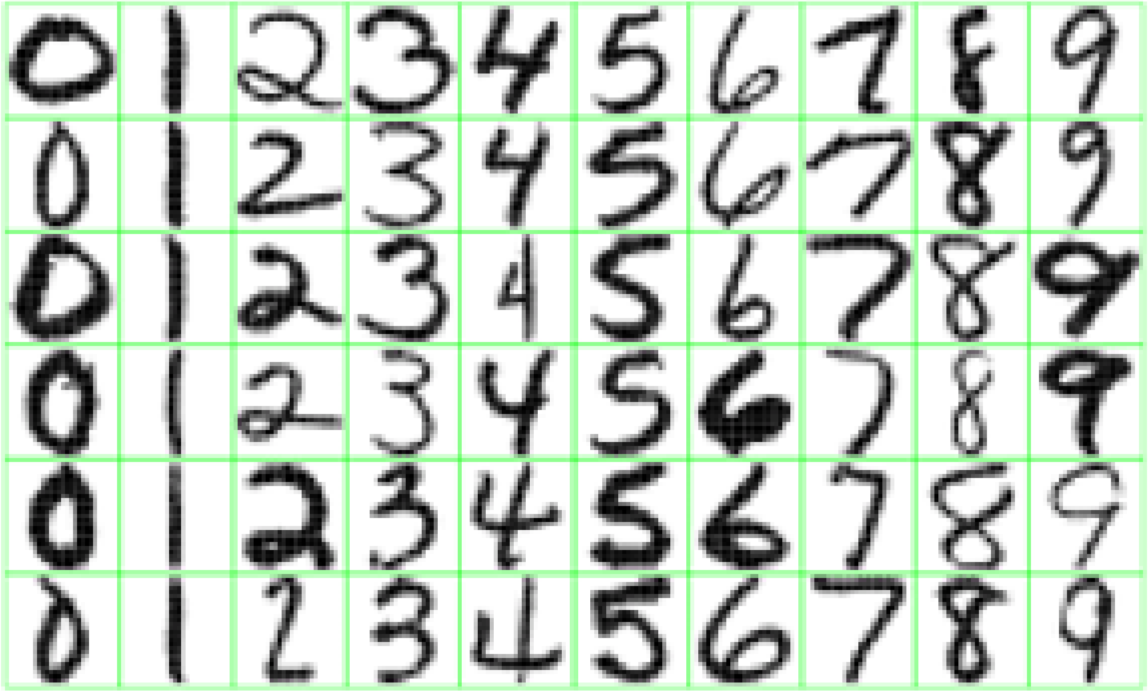


Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*

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

1

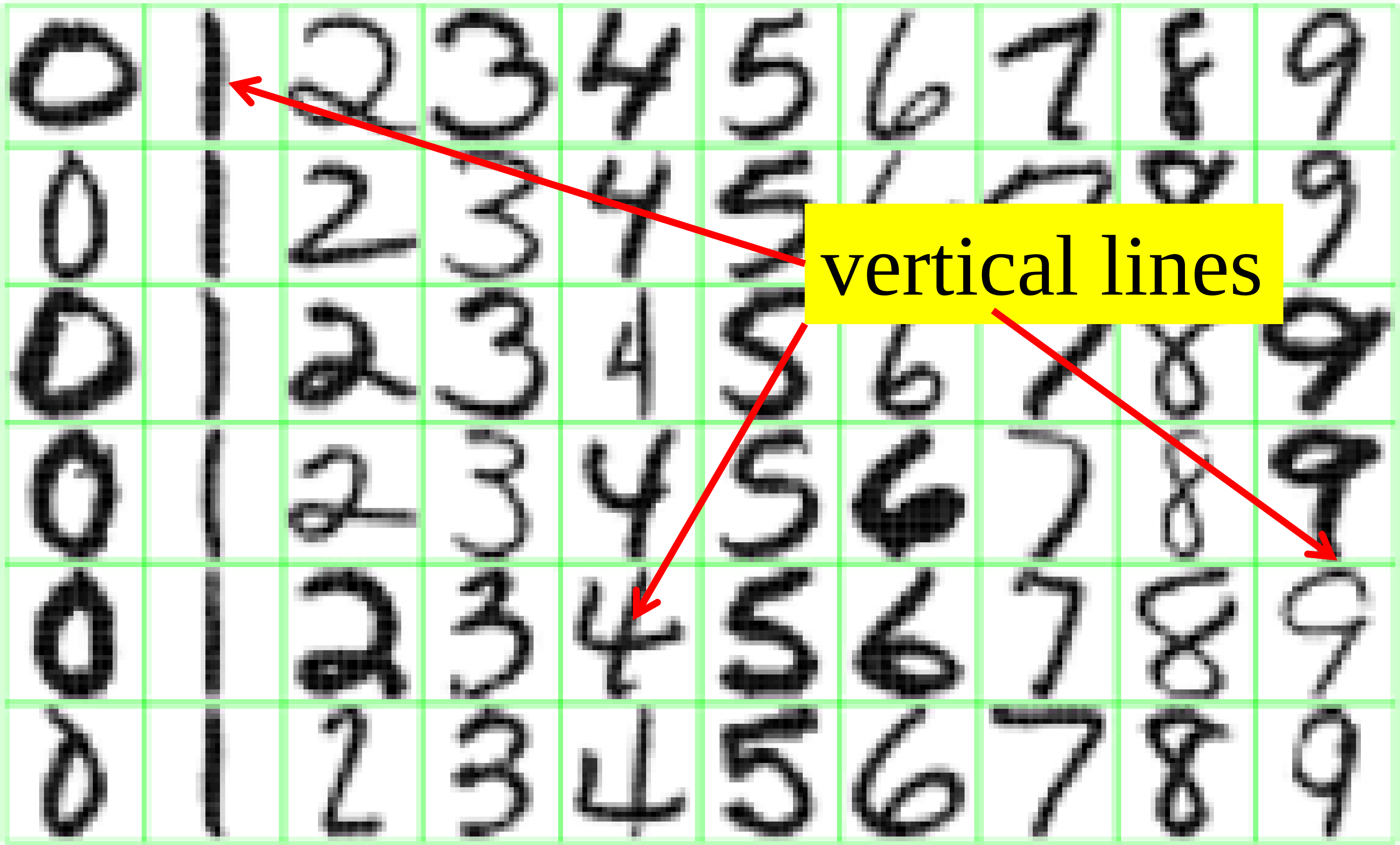


Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*

1

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1

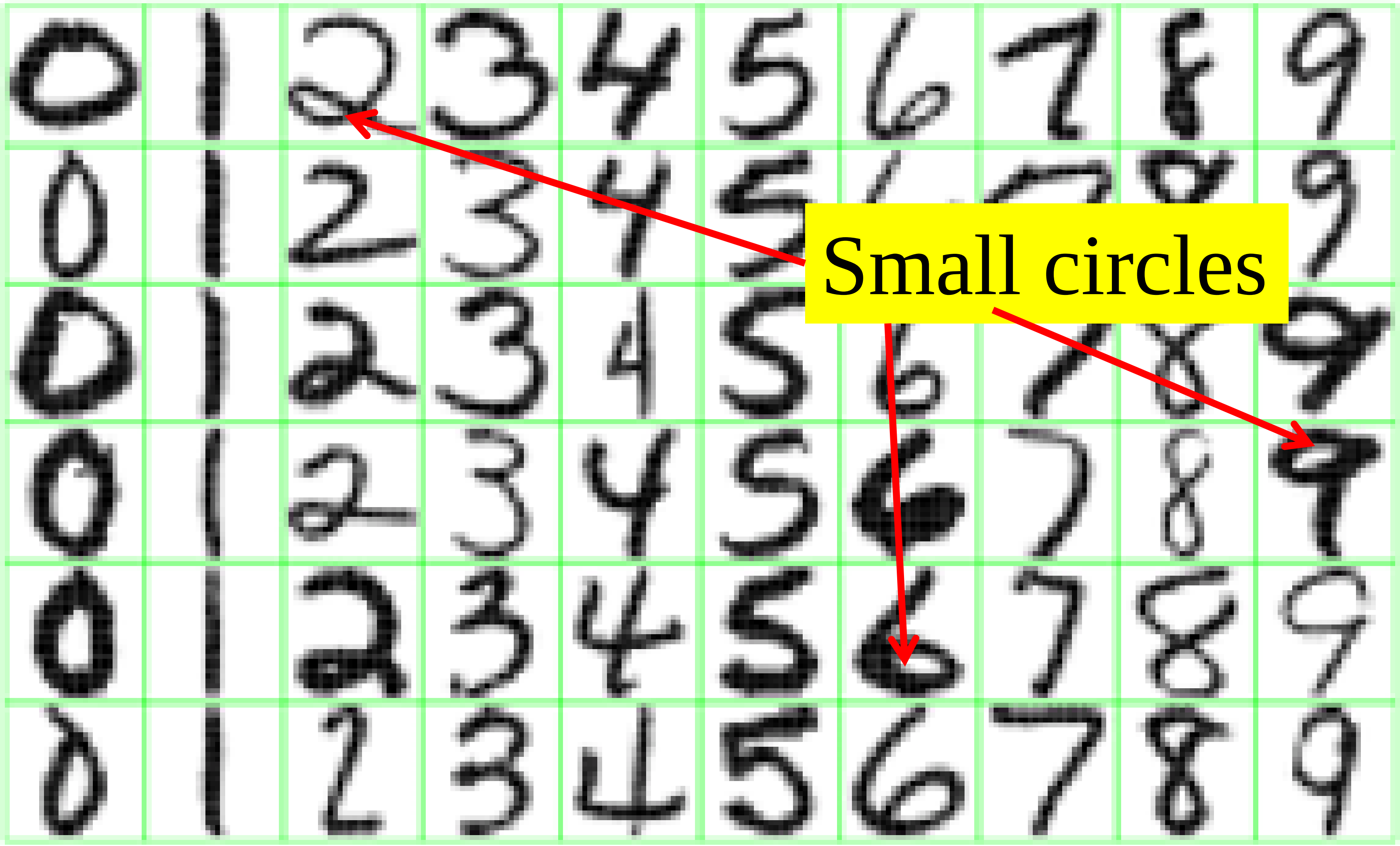


Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*

1

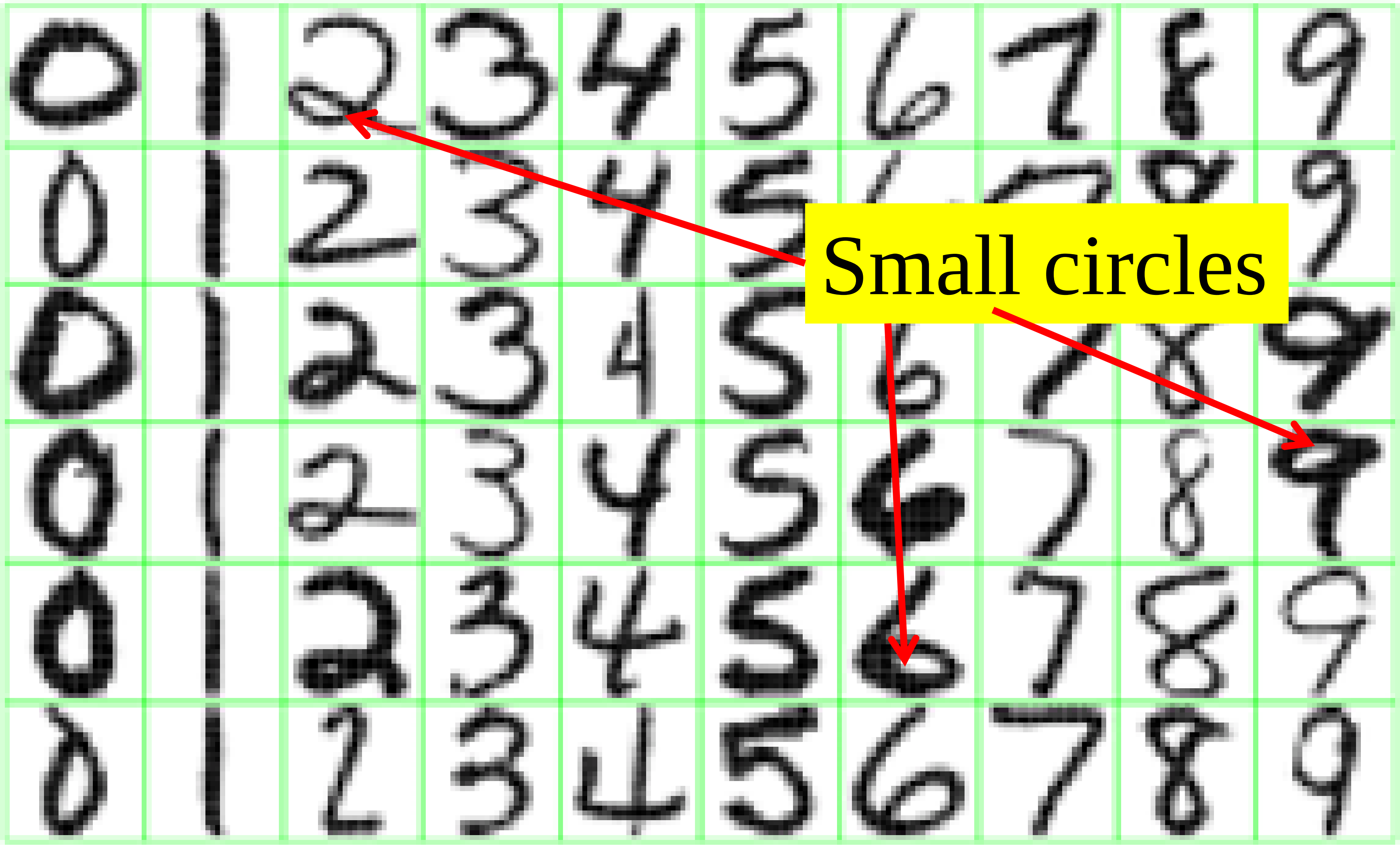
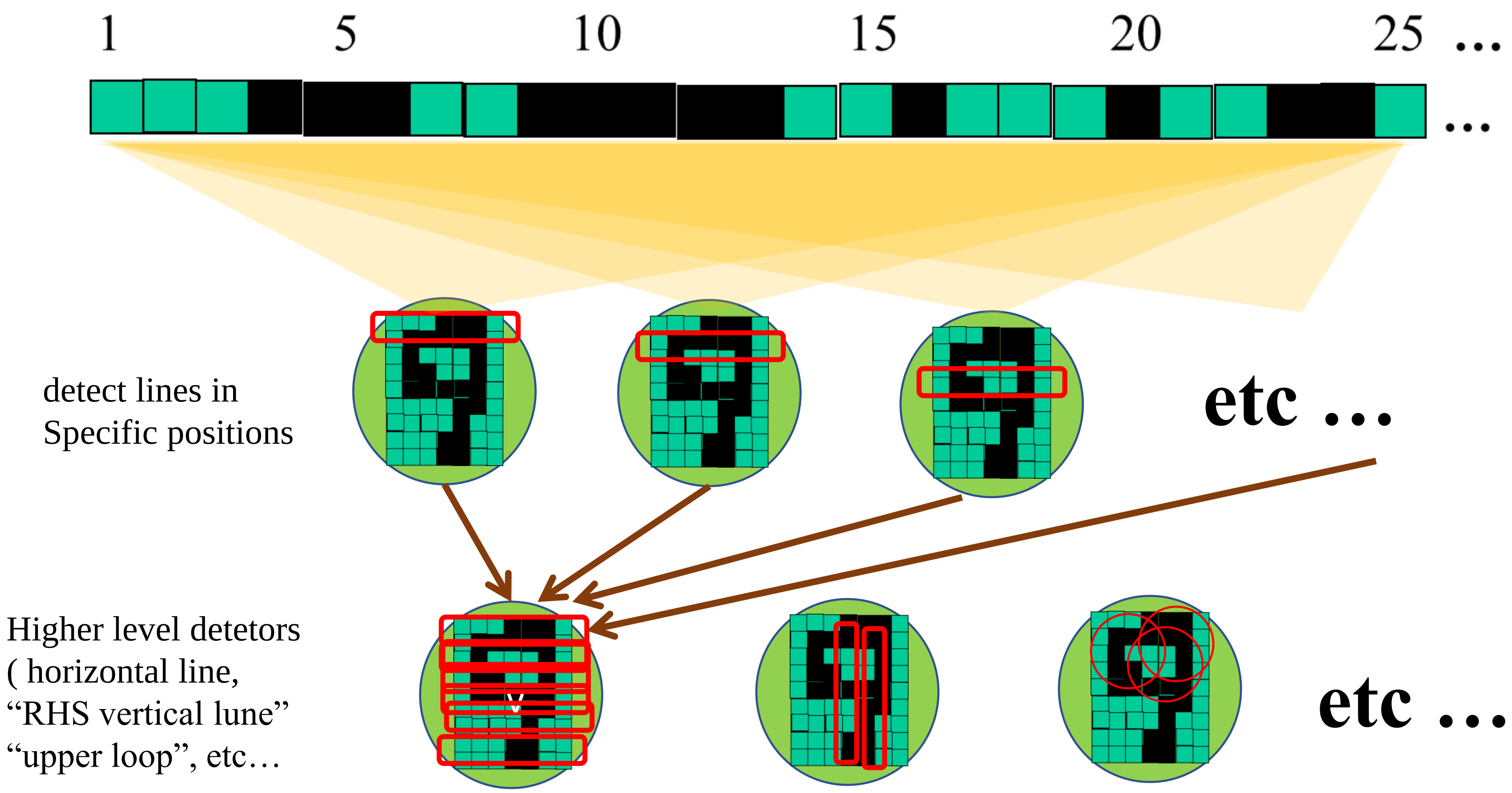


Figure 1.2: *Examples of handwritten digits from U.S. postal envelopes.*

successive layers can learn higher-level features …



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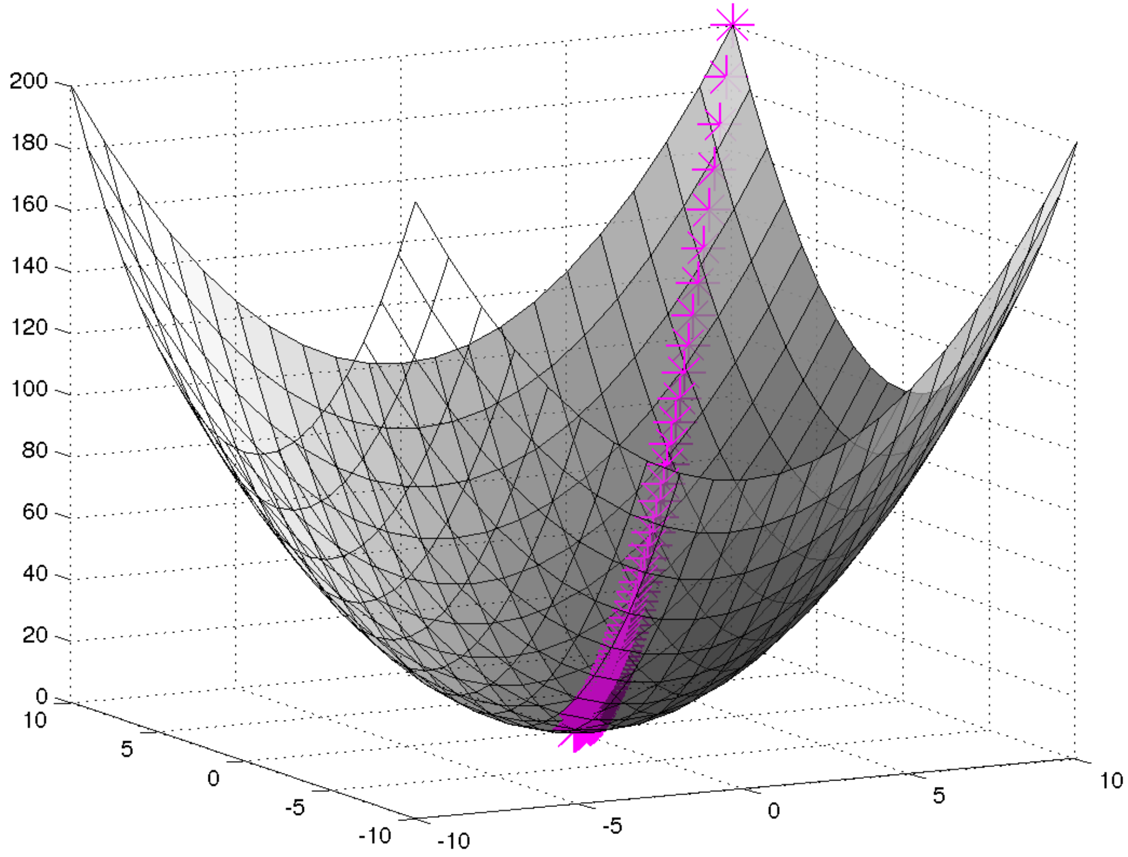
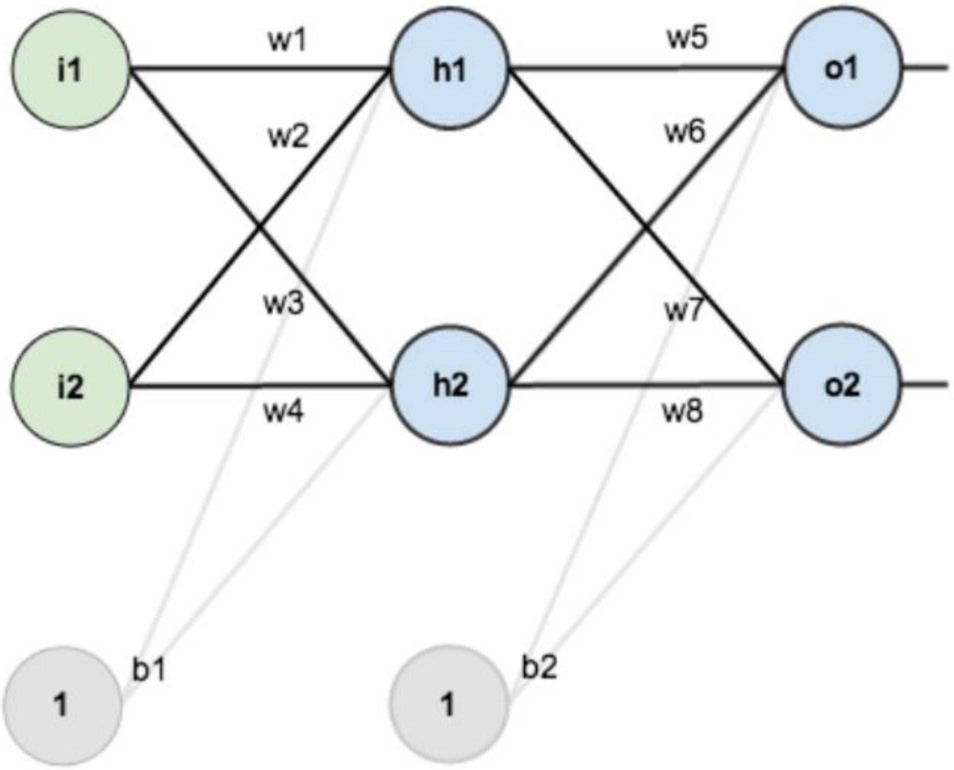
Gradient descent

Likelihood: ascent

Loss: descent

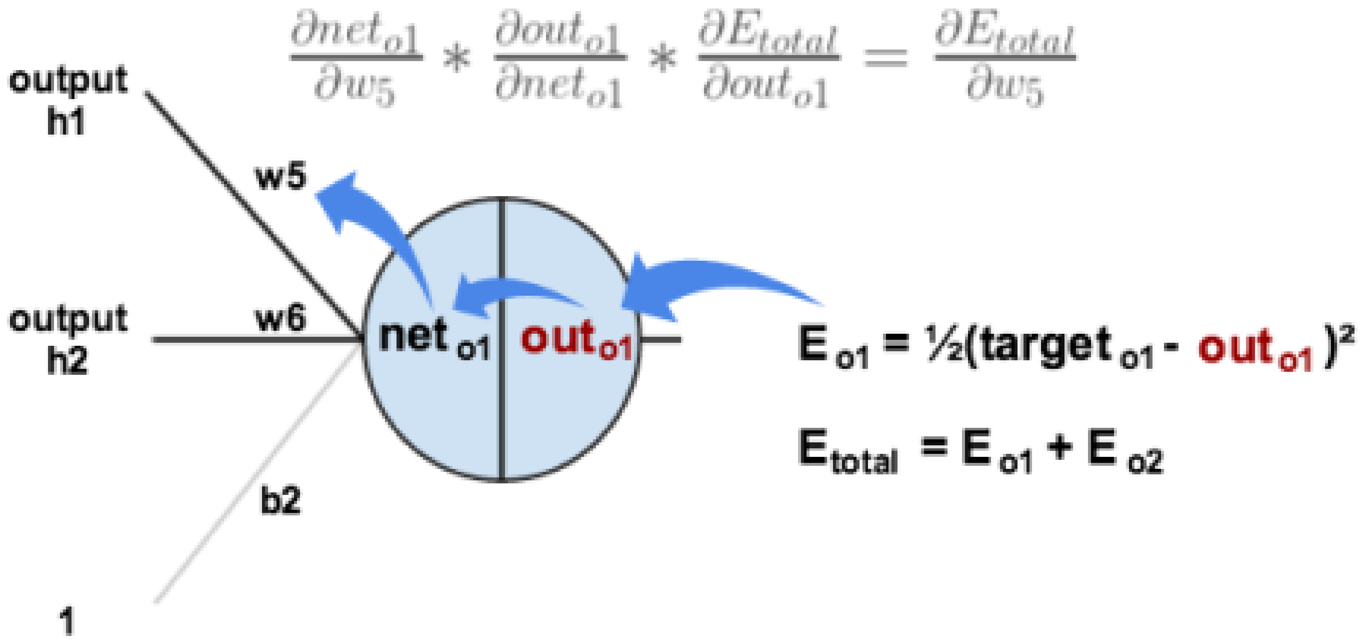


Backpropagation



https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/

Backpropagation and Gradient Descent



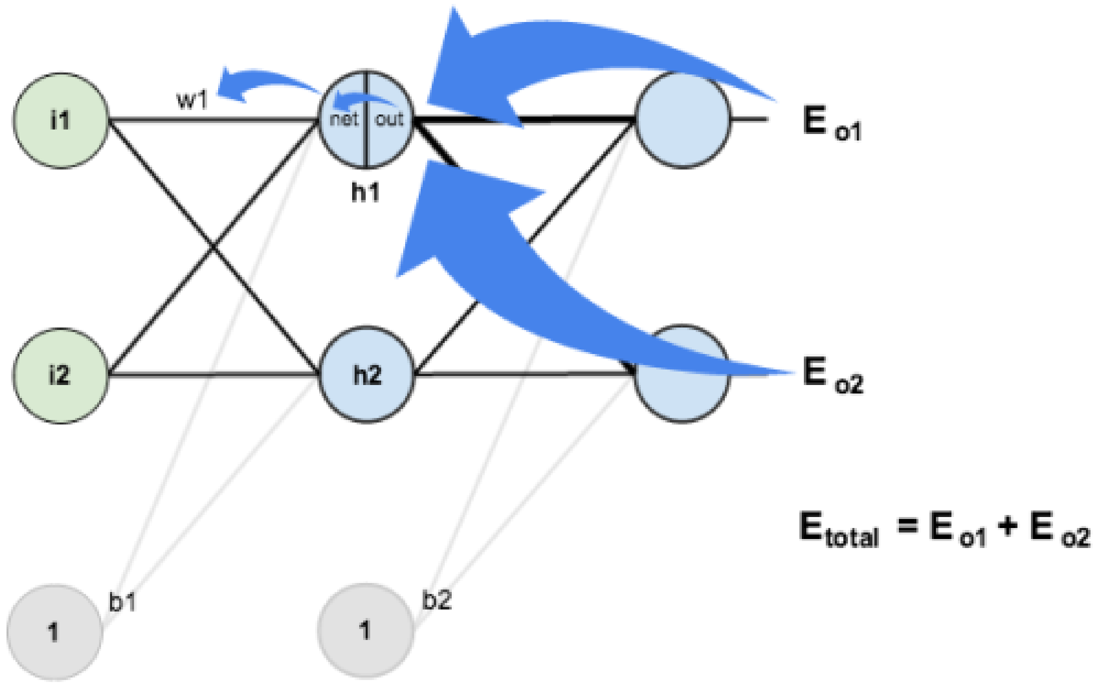
https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/

Backpropagation and Gradient Descent

$$\frac{\partial E_{total}}{\partial w_1} = \frac{\partial E_{total}}{\partial out_{h1}} * \frac{\partial out_{h1}}{\partial net_{h1}} * \frac{\partial net_{h1}}{\partial w_1}$$

$$\downarrow$$

$$\frac{\partial E_{total}}{\partial out_{h1}} = \frac{\partial E_{o1}}{\partial out_{h1}} + \frac{\partial E_{o2}}{\partial out_{h1}}$$



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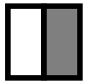
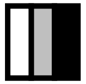
Vertical edge detection example

$$
\begin{bmatrix} 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \end{bmatrix} * \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \end{bmatrix}
$$


$$
\begin{bmatrix} 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \end{bmatrix} * \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 0 & -30 & -30 & 0 \\ 0 & -30 & -30 & 0 \\ 0 & -30 & -30 & 0 \\ 0 & -30 & -30 & 0 \end{bmatrix}
$$



Vertical and Horizontal Edge Detection

1	0	-1
1	0	-1
1	0	-1

Vertical

1	1	1
0	0	0
-1	-1	-1

Horizontal

$$\begin{bmatrix} 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \end{bmatrix} * \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 30 & 10 & -10 & -30 \\ 30 & 10 & -10 & -30 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Edge Detection

[Interactive Edge Detection]

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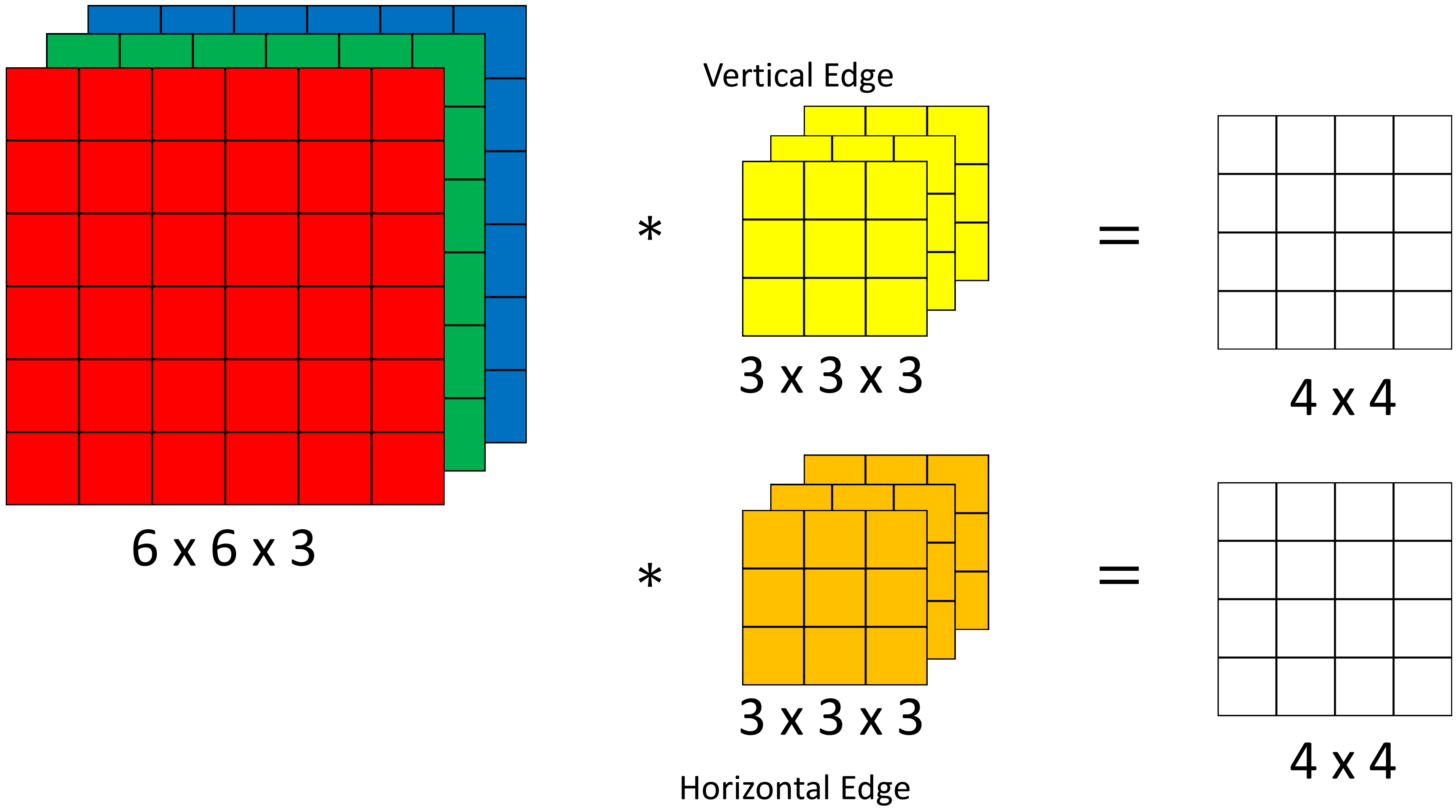
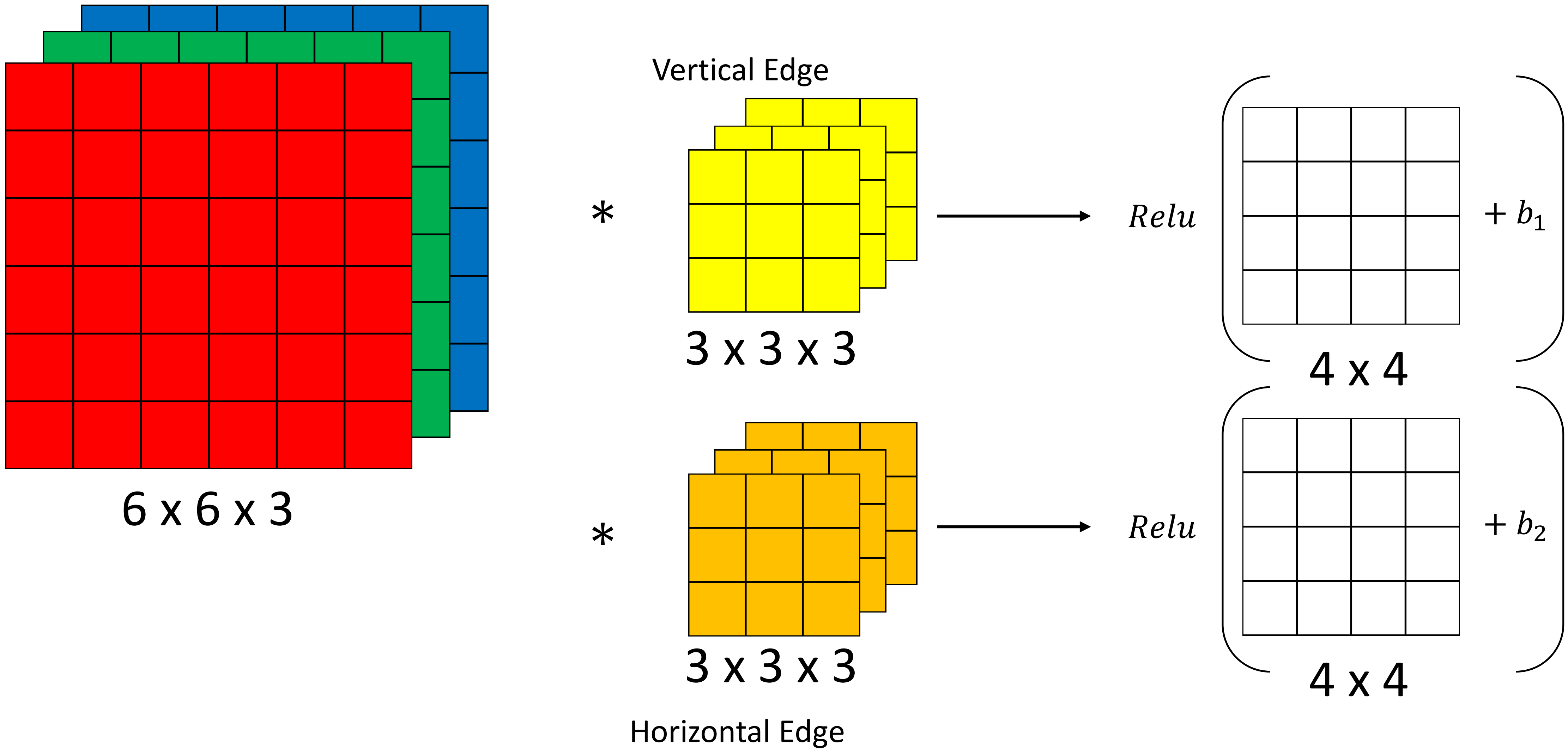
Convolution as a layer



Convolution as a layer



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Convolutional Layer: Padding

- **Same:** Pad so that output size is the same as the input size.

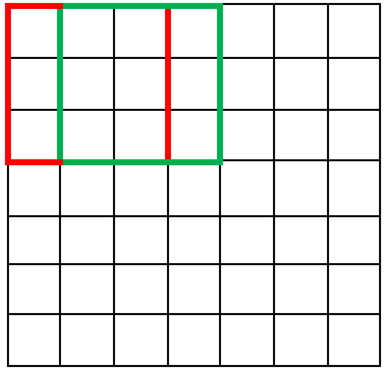
- **Valid:** for $n * n$ image and $k * k$ kernel,

  the output is $(n - k + 1) \; * \; (n - k + 1)$

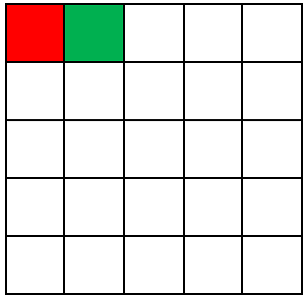
Convolutional Layer: Stride

Stride 1

7 x 7 Input Volume

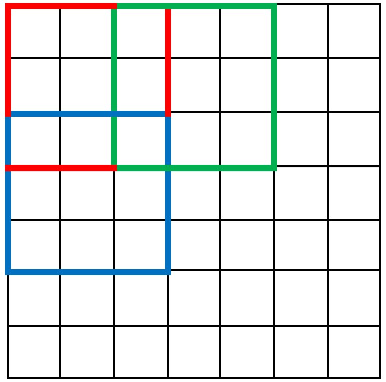


5 x 5 Output Volume

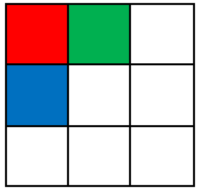


Stride 2

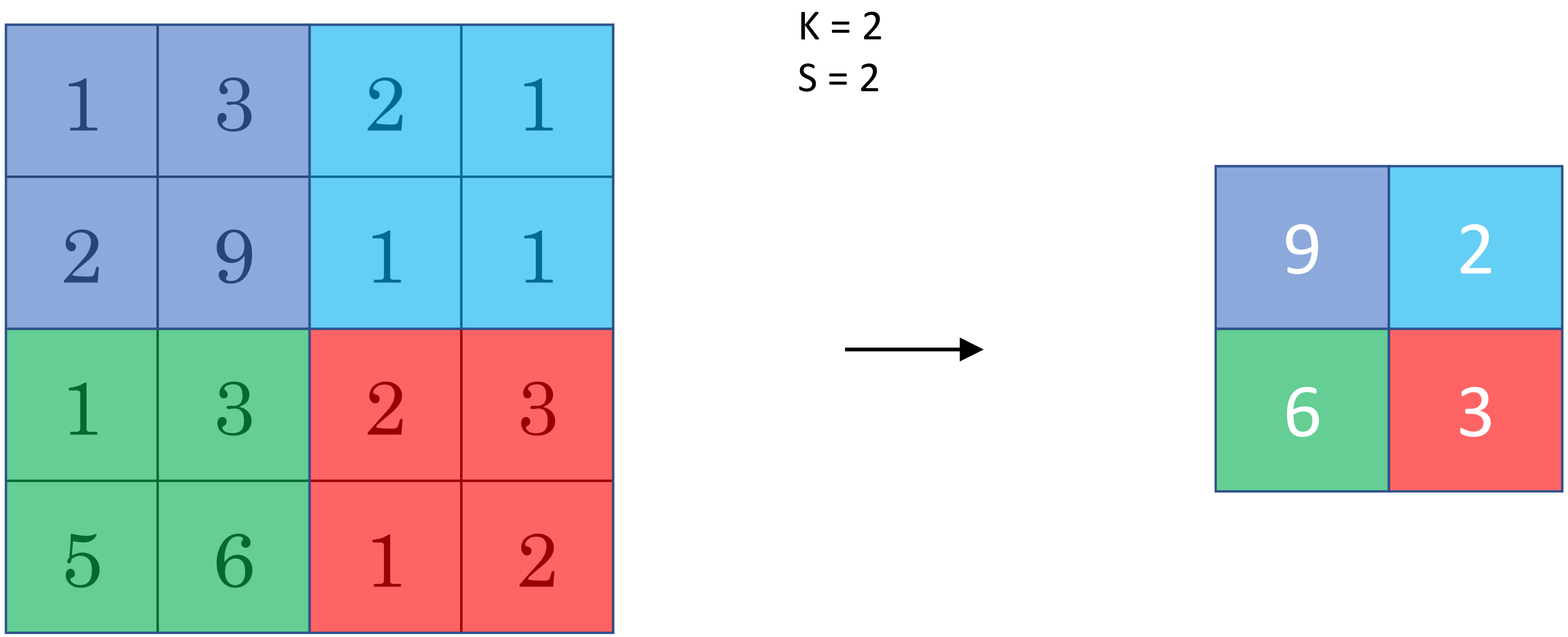
7 x 7 Input Volume



3 x 3 Output Volume



Pooling layer: Max pooling



Pooling layer: Average pooling

1	3	2	1
2	9	1	1
1	4	2	3
5	6	1	2

K = 2
S = 2

→

3.75	1.25
4	2