I-Form

Advanced Manufacturing Research Centre

A World Leading SFI Research Centre

Science Foundation Ireland sfi For what's next

Introduction to Computer Vision

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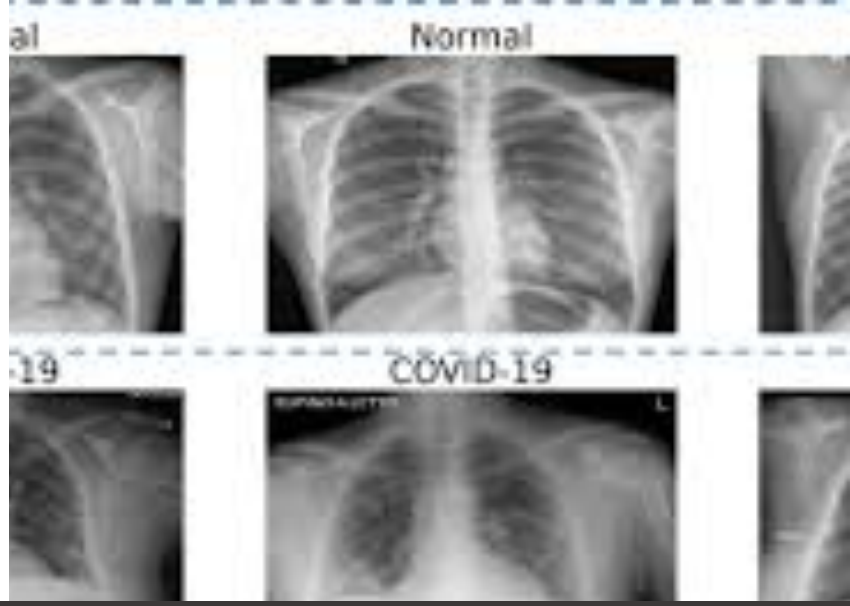
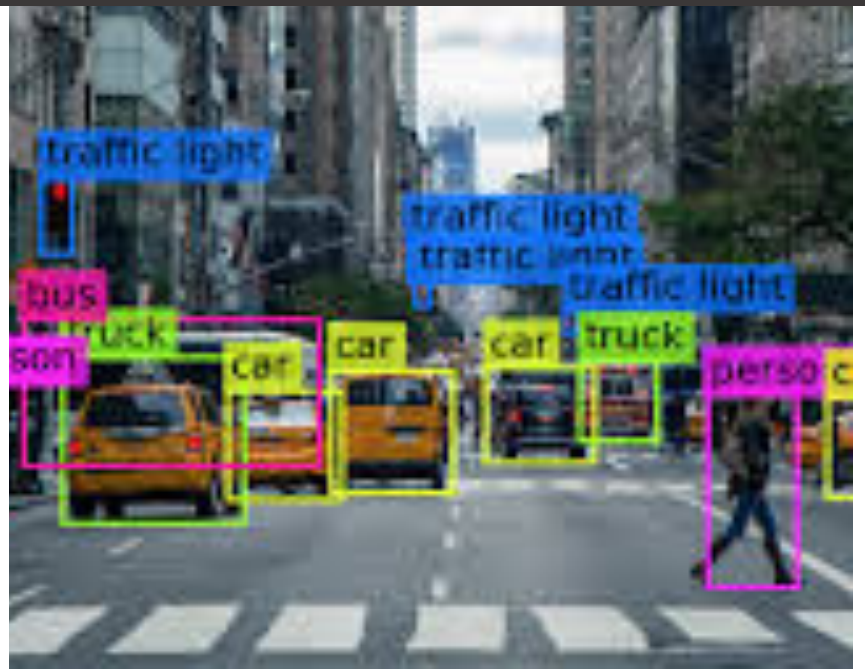
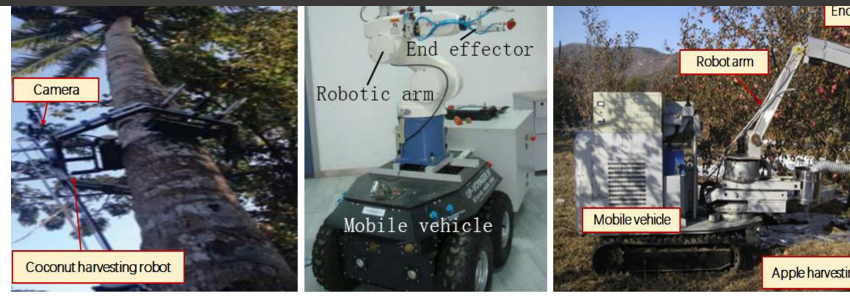


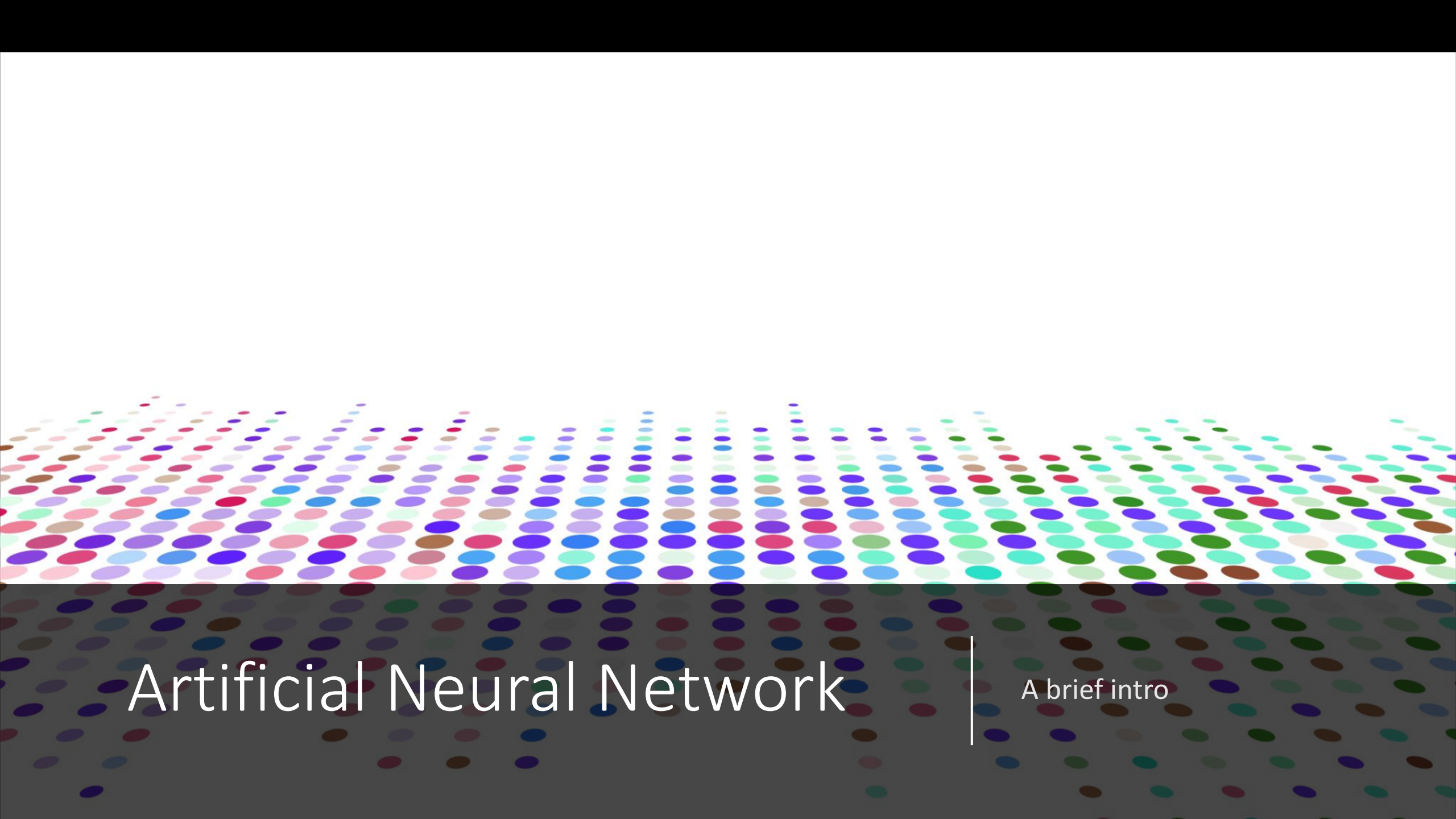
Why Computer Vision?

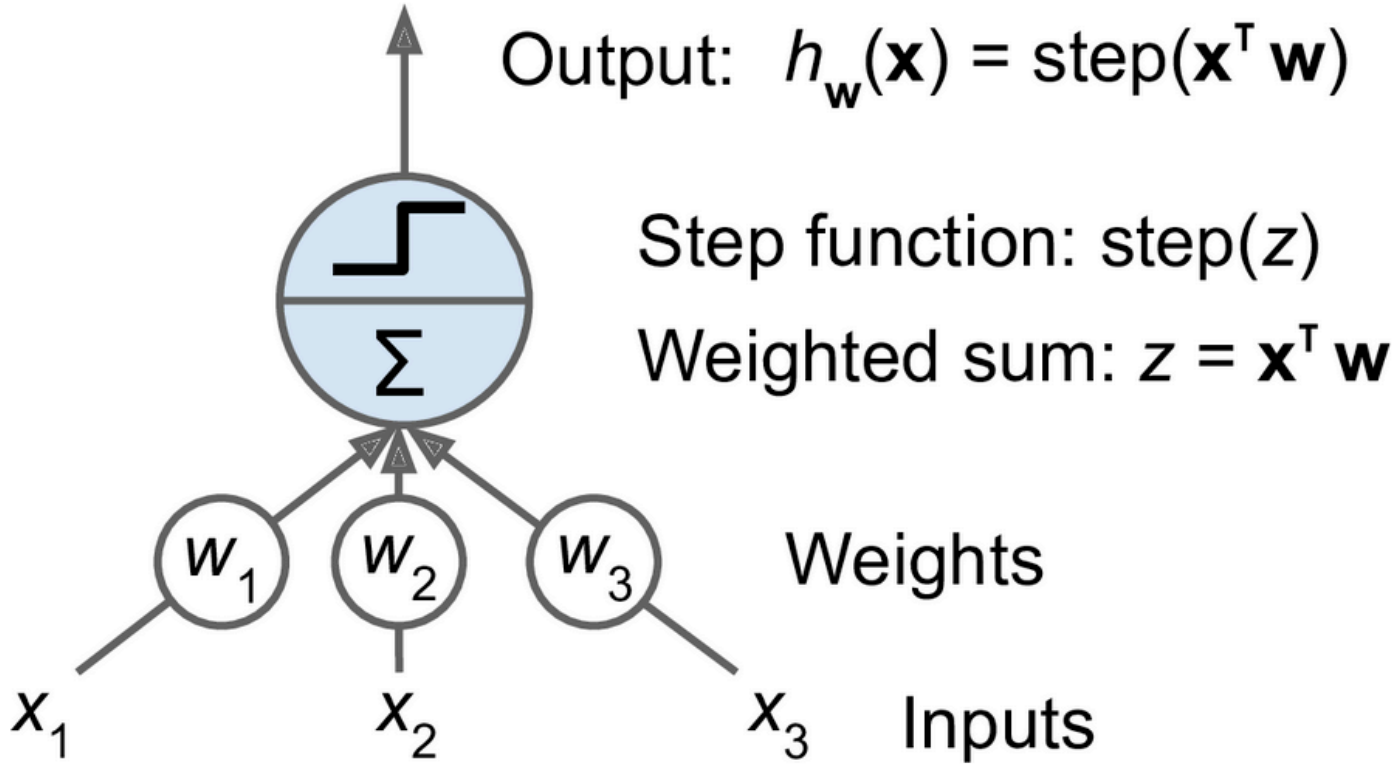




Outline

- Intro to Neural Network and Deep Learning
- Intro to TensorFlow/Keras
- Intro to Convolutional Neural Network
- Hands on TensorFlow


Artificial Neural Network
A brief intro



Basic Neural Network – Threshold Logic Unit

- Perceptron [Rosenblatt, 1957]
- Binary classifier that maps input to an output value
- Basic neural network building block
- Simplest feedforward neural network

Source: Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2nd Edition

Step functions

Heavside

$$heaviside(z) = \begin{cases} 0 & if\ z < 0 \\ 1 & if\ z \geq 0 \end{cases}$$

Sign

$$sng(z) = \begin{cases} -1 & if\ z < 0 \\ 0 & if\ z = 0 \\ +1 & if\ z > 0 \end{cases}$$

Perceptron

Output

$$h_{W,b}(X) = \phi(XW + b)$$

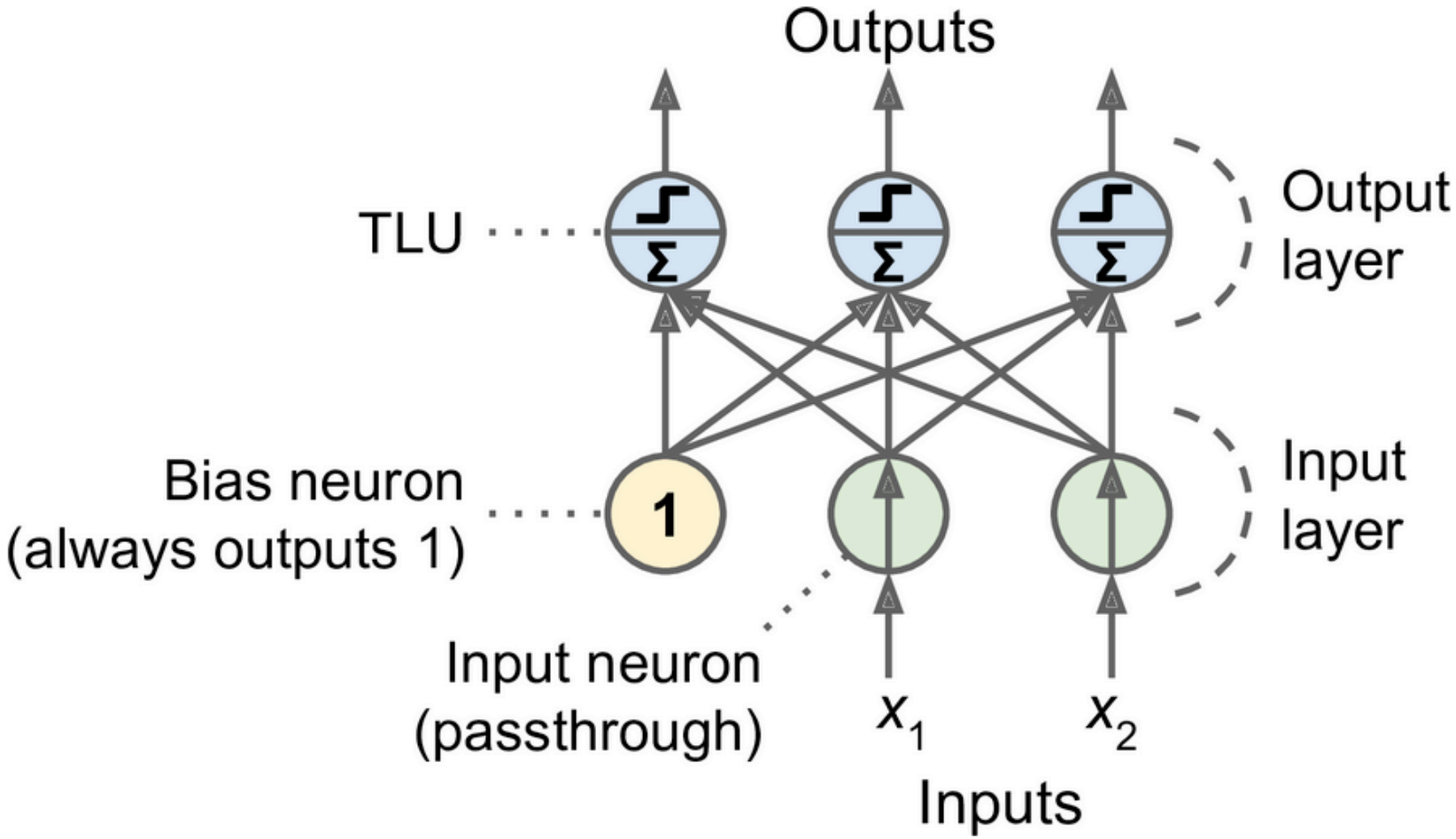
X Matrix input features

W Matrix connection weights

b Connection weights between bias and the neurons

ϕ *activation function*

(in TLU is a step function)



How does a perceptron learn?

- Hebb's rule

"Cells that fire together, wire together"

- Take into account error made during prediction
  - Make prediction for each instance at the time
  - Reinforce connections that help reduce the error

$$w_{i,j}^{t} = w_{i,j}^{t-1} + \eta\left(y_j - \hat{y}_j\right)x_i$$

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i^{th} input neuron

j^{th} output neuron

$$w_{i,j}^{t} = w_{i,j}^{t-1} + \eta\left(y_j - \hat{y}_j\right)x_i$$

How does a perceptron learn?

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$$w_{i,j}^{t} = w_{i,j}^{t-1} + \eta\left(y_j - \hat{y}_j\right)x_i$$

New weight for connection

How does a perceptron learn?

- Hebb's rule

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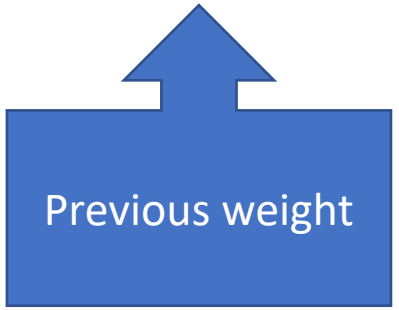
  - Make prediction for each instance at the time
  - Reinforce connections that help reduce the error

$$w_{i,j}^{t} = w_{i,j}^{t-1} + \eta\left(y_j - \hat{y}_j\right)x_i$$



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$$w_{i,j}^{t} = w_{i,j}^{t-1} + \eta\left(y_j - \hat{y}_j\right)x_i$$

Learning rate

How does a perceptron learn?

- Hebb's rule

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- Take into account error made during prediction
  - Make prediction for each instance at the time
  - Reinforce connections that help reduce the error

$$w_{i,j}^{t} = w_{i,j}^{t-1} + \eta\left(y_j - \hat{y}_j\right)x_i$$

Target output for the j^{th} output neuron

How does a perceptron learn?

- Hebb's rule

"Cells that fire together, wire together"

- Take into account error made during prediction
  - Make prediction for each instance at the time
  - Reinforce connections that help reduce the error

$$w_{i,j}^{t} = w_{i,j}^{t-1} + \eta\left(y_j - \hat{y}_j\right)x_i$$

output for the j^{th} output neuron

How does a perceptron learn?

- Hebb's rule

"Cells that fire together, wire together"

- Take into account error made during prediction
  - Make prediction for each instance at the time
  - Reinforce connections that help reduce the error

$$w_{i,j}^{t} = w_{i,j}^{t-1} + \eta\left(y_j - \hat{y}_j\right)x_i$$

i^{th} input value for the training instance

How does a perceptron learn?

- Hebb's rule

"Cells that fire together, wire together"

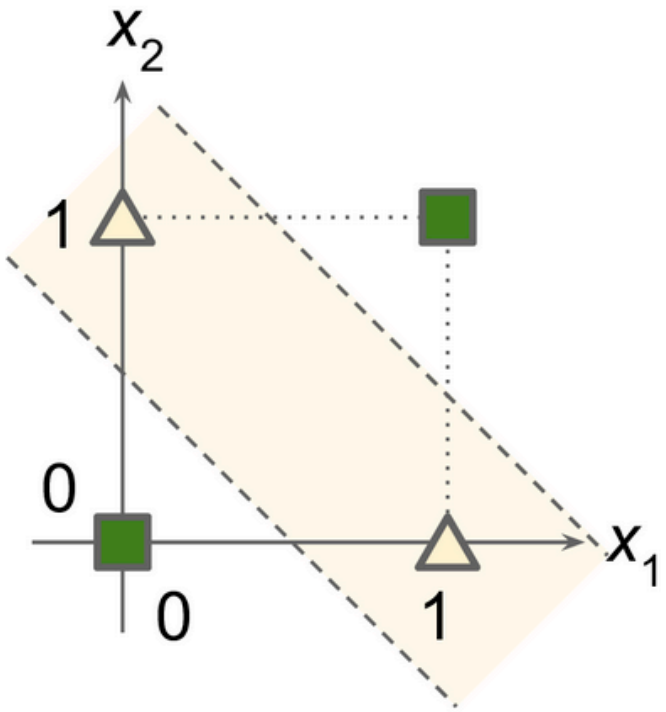
- Take into account error made during prediction
  - Make prediction for each instance at the time
  - Reinforce connections that help reduce the error

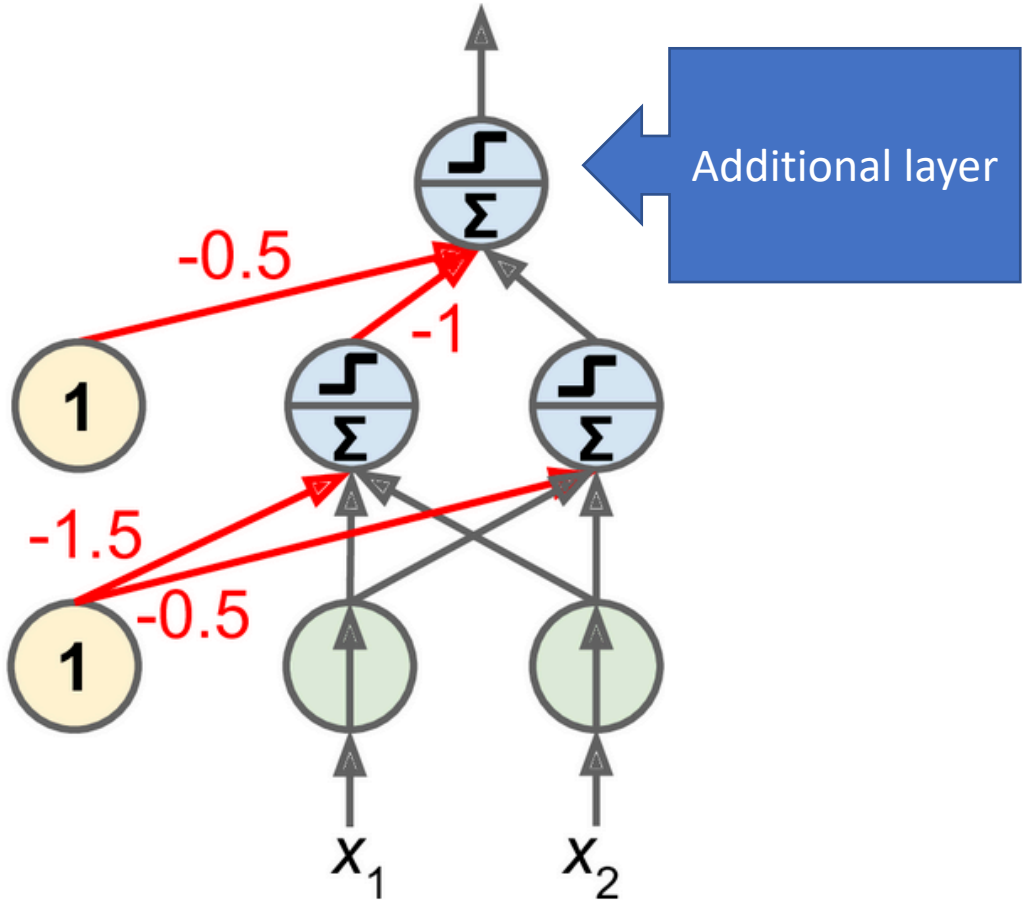
$$w_{i,j}^{t} = w_{i,j}^{t-1} + \eta\left(y_j - \hat{y}_j\right)x_i$$

  - Observation: linear decision boundaries ≡ logistic regression classifiers

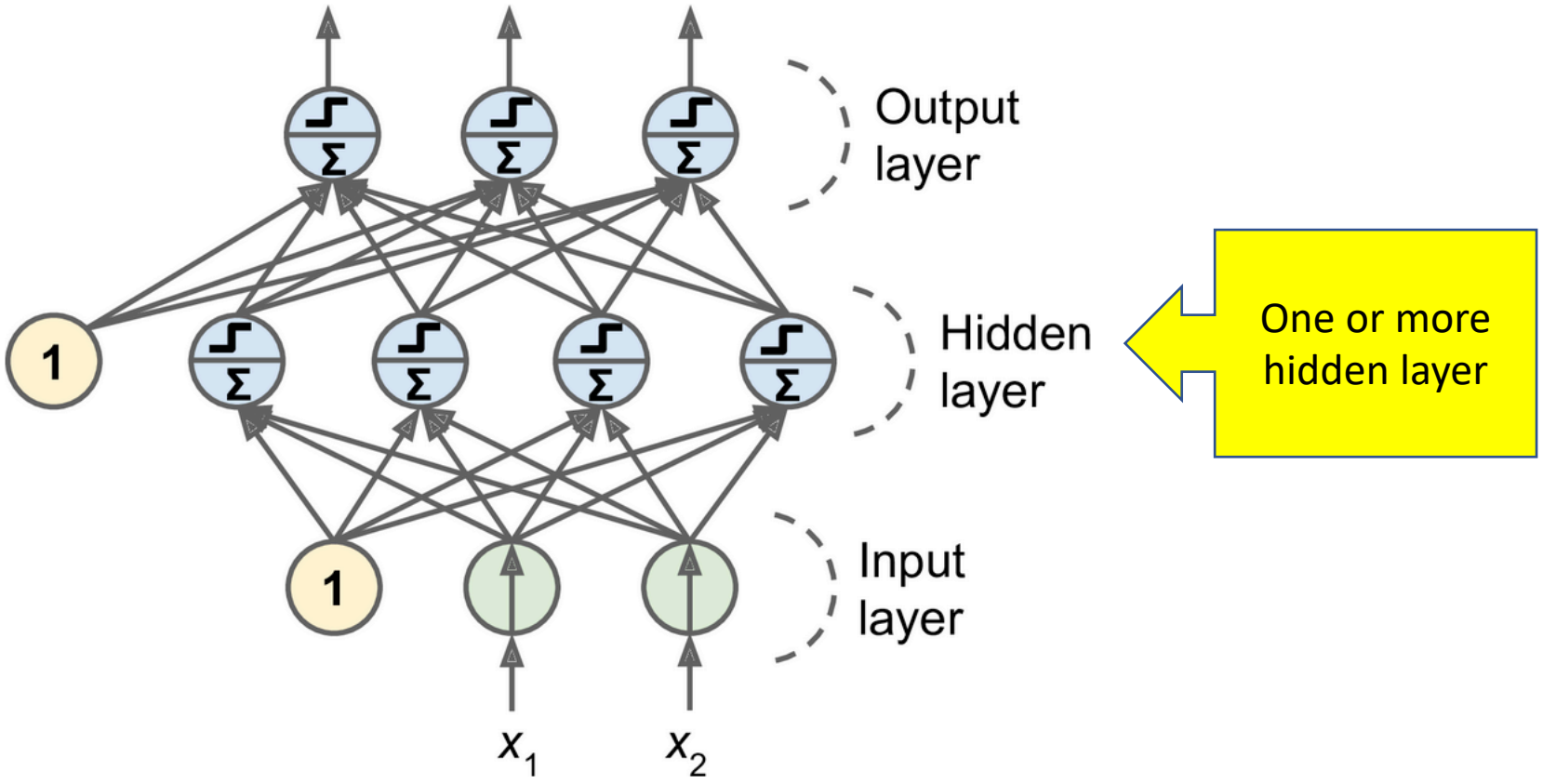
Multilayer Perceptron (MLP)

- Can solve XOR

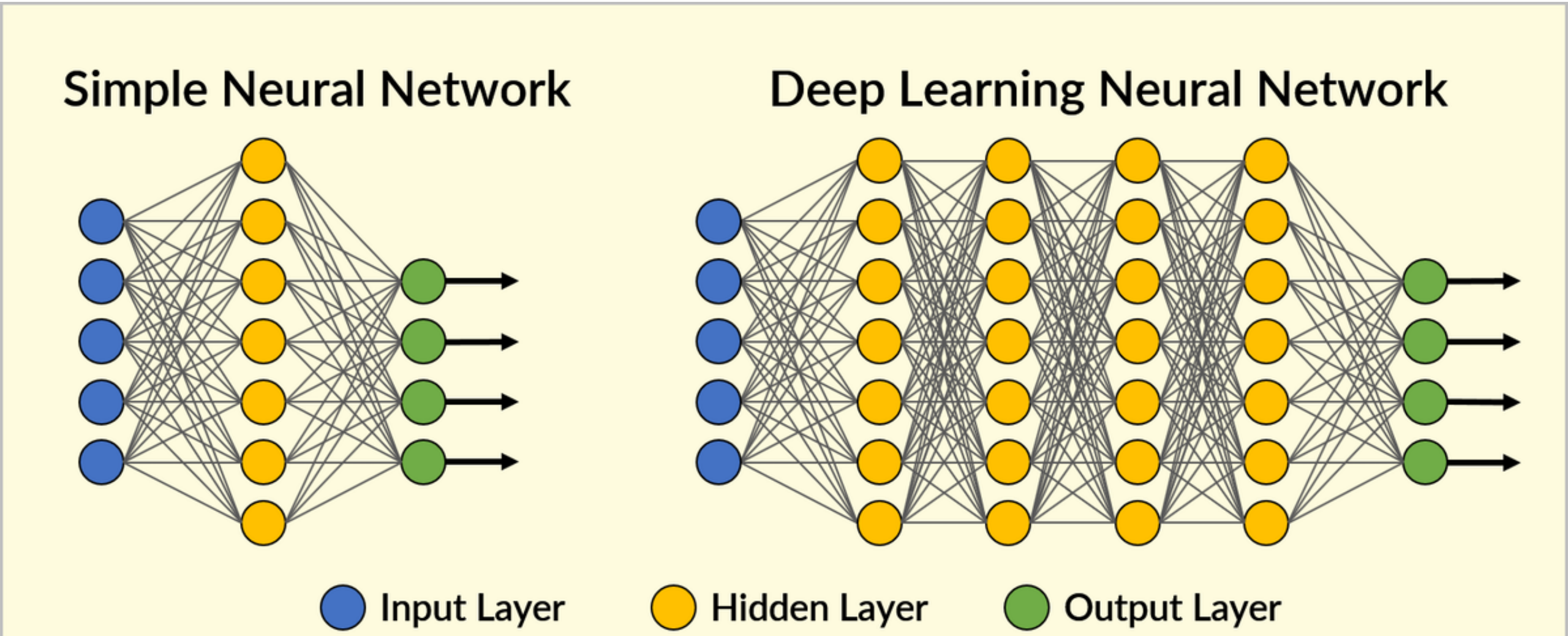




Multilayer Perceptron (MLP)

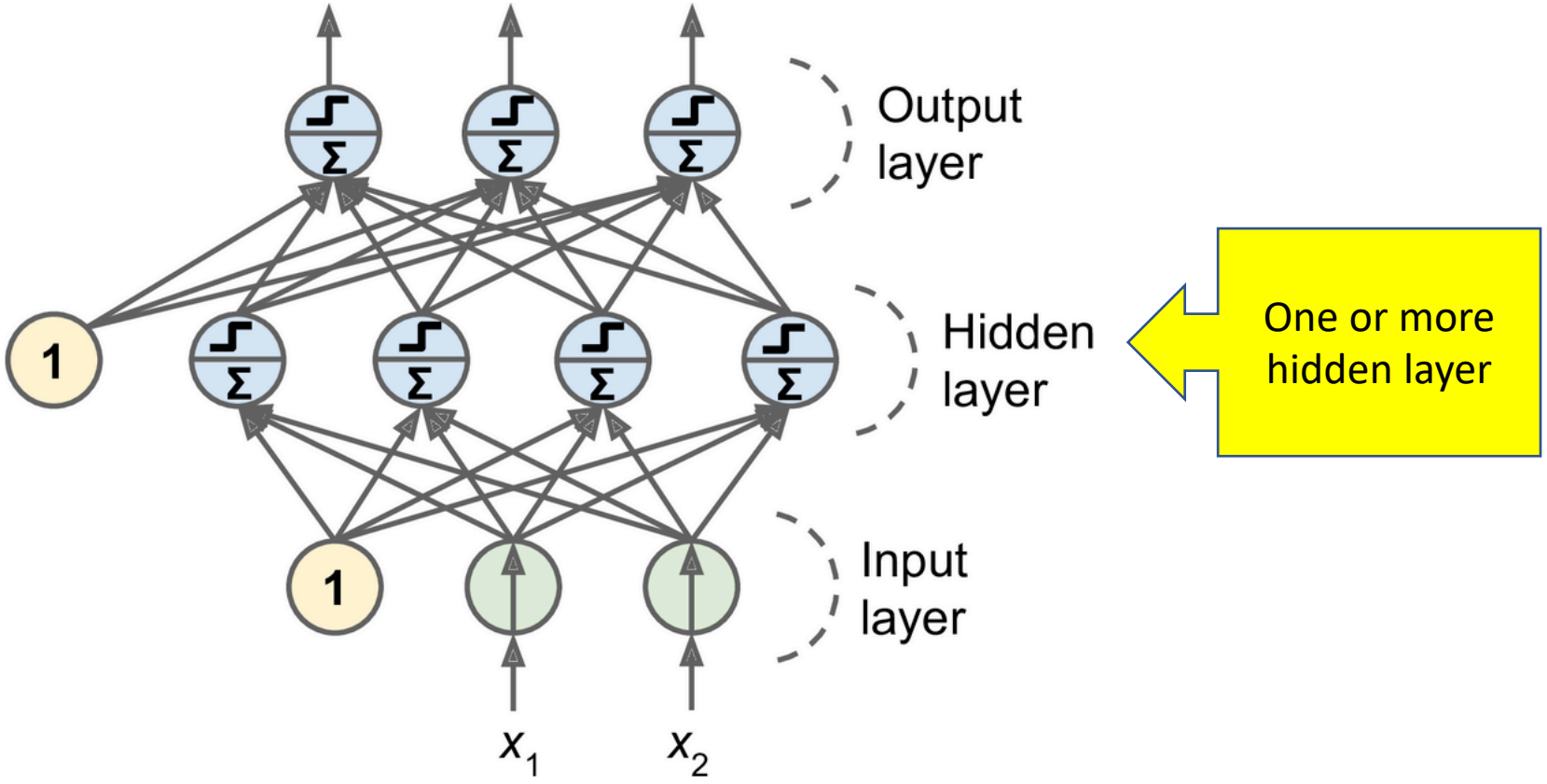


Deep Neural Network



https://www.securityinfowatch.com/video-surveillance/video-analytics/article/21069937/deep-learning-to-the-rescue

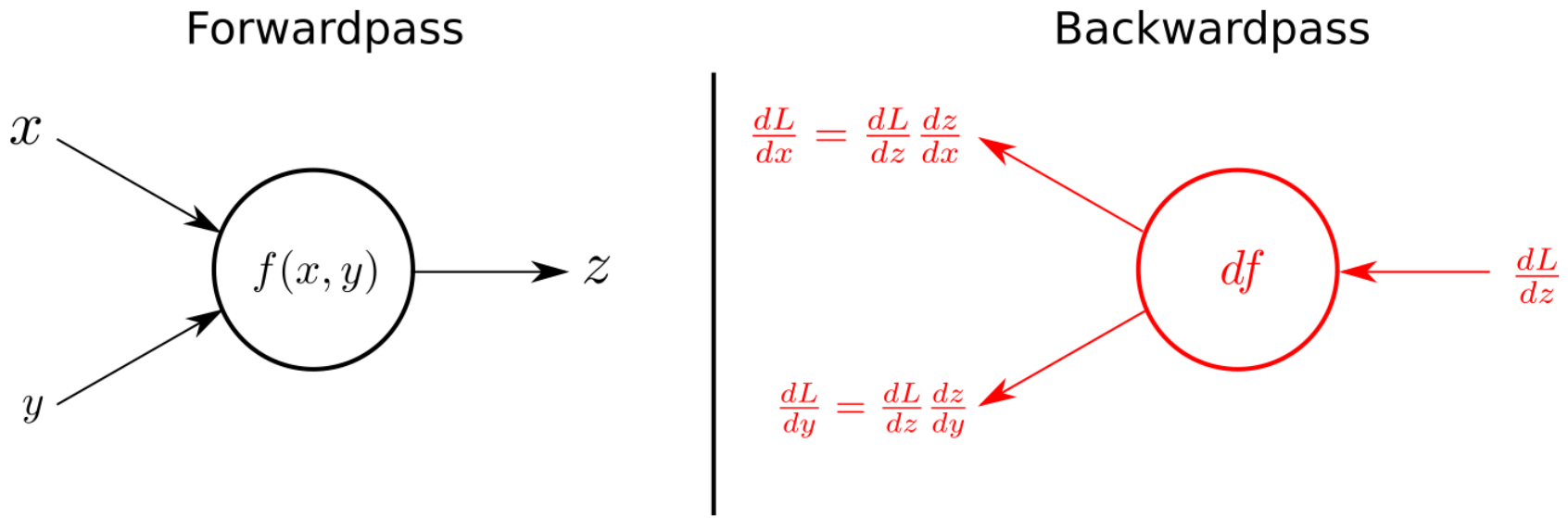
Multilayer Perceptron (MLP)



Feedforward Neural Network

Backpropagation

- Compute the gradient of the network's error wrt every model parameter
- Tweaks every single connection and bias weight to reduce error



https://github.com/Vercaca/NN-Backpropagation

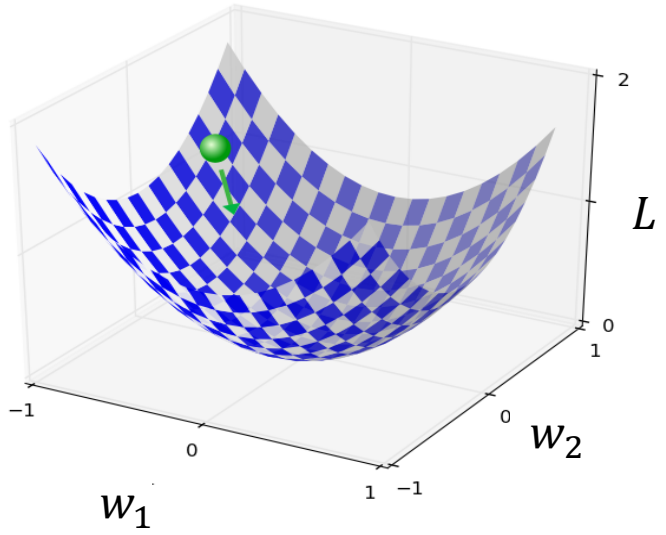
Backpropagation

- Handle mini-batch (small set of training instances)
- Go through training set multiple times (each is called *epoch*)

1. Forward pass: the mini-batch is passed from the input through all the hidden layers up to the output layer – weights for each layer are stored for back pass
2. Compute the error (loss function L)
3. Chain rule: compute how much each output connection contributed to the error
4. Reverse pass: computes how much of these error contributions came from connections in previous layer (apply again chain rule) up to the first input layer
5. Gradient Descent: tweak all the connection weights using the error gradients just computed

Gradient Descent

- L loss function (aka cost function)
- Minimise L -> find where L has a global minimum
- Analytically -> compute the derivatives
  - Don’t work with NN -> billions of weights



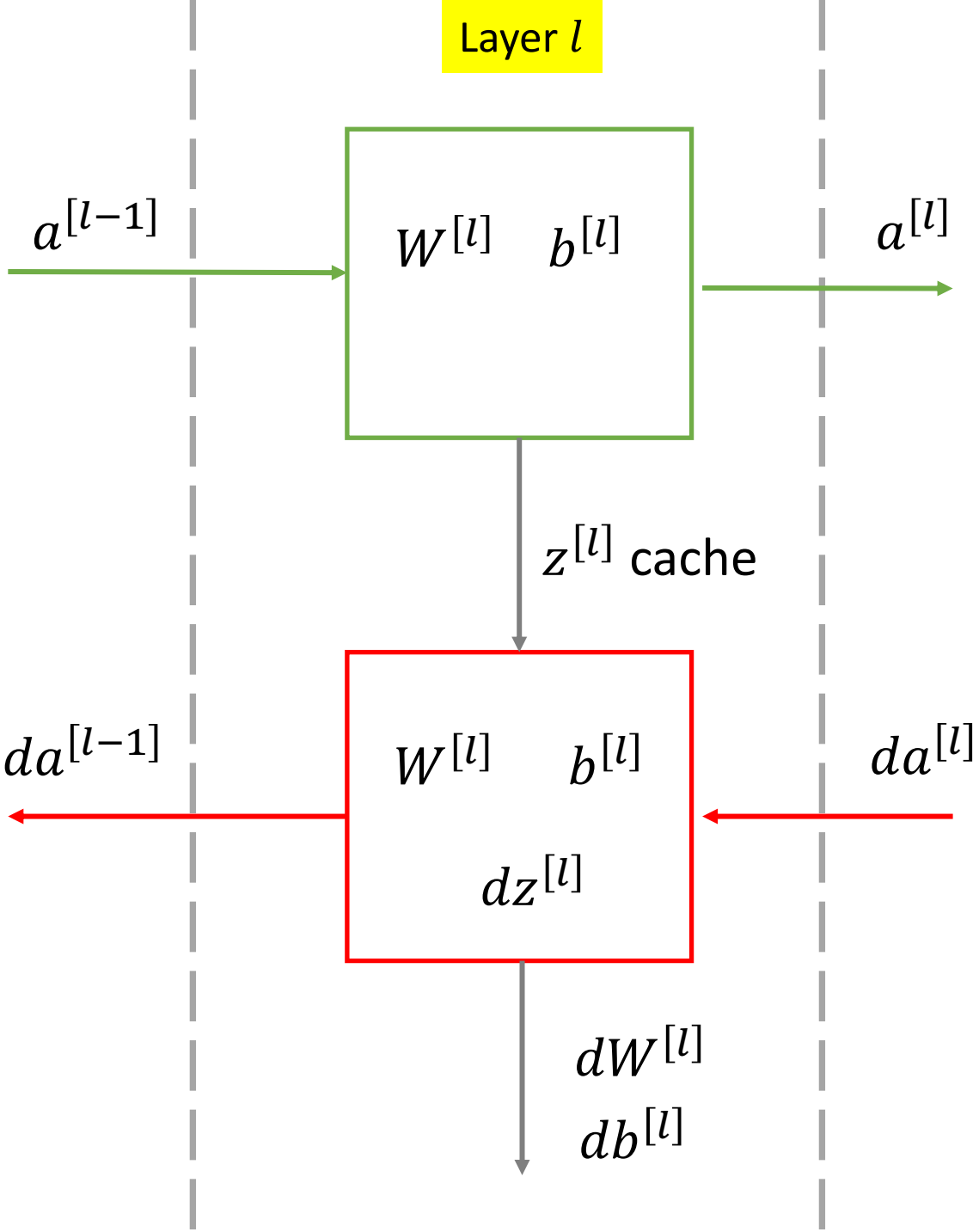
- Construct model using initial random weights
- Repeat until good performance
  - Apply model to the example
  - Compute the lost function

$$L = \frac{1}{m}\sum_{i} L_i$$

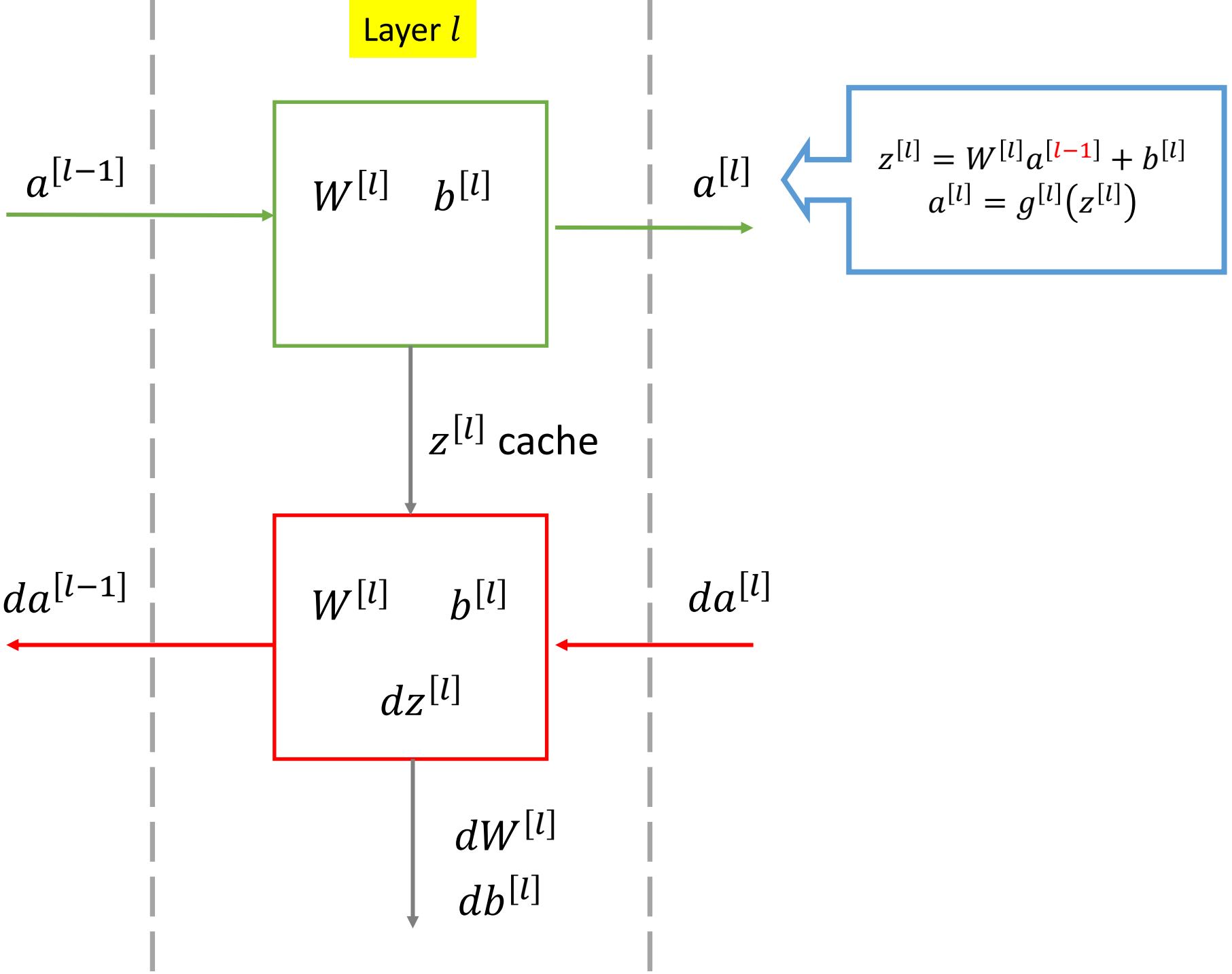
  - Compute derivatives

$$\partial L$$

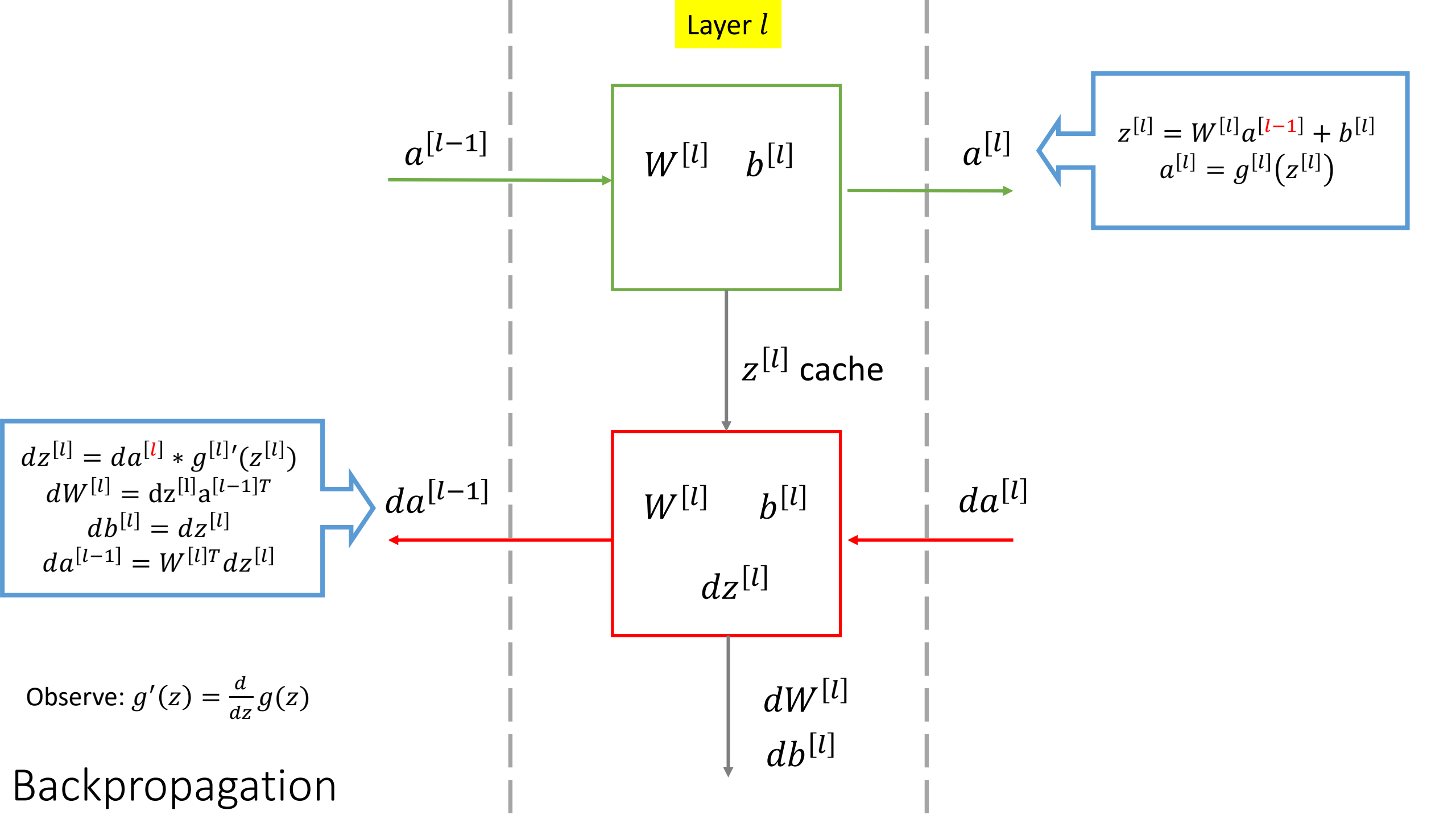
  - Adjust weights using the weights update



Backpropagation

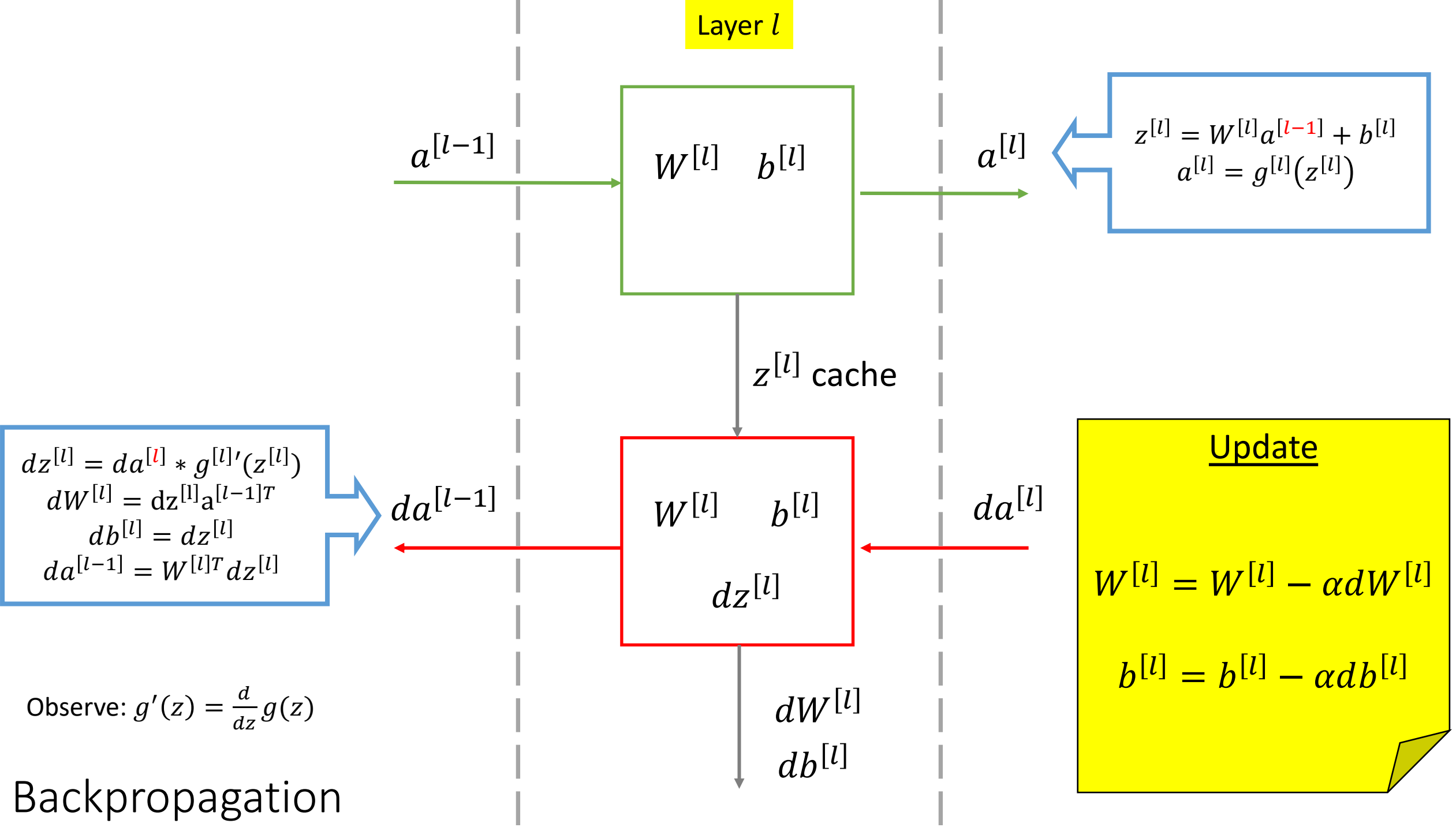


Backpropagation



Observe: $g'(z) = \frac{d}{dz}g(z)$

Backpropagation



Backpropagation

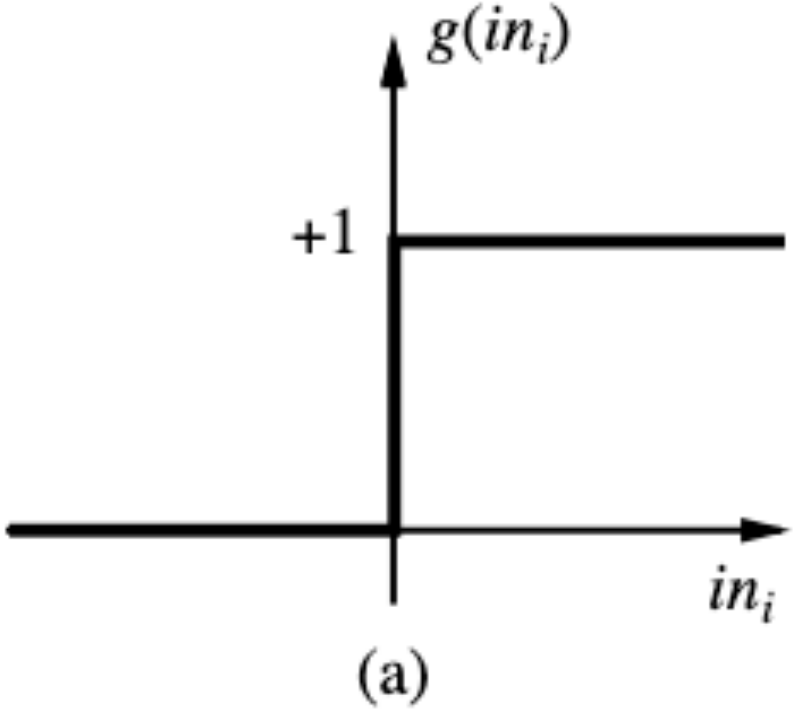
Activation Functions

- In each layer a function g is applied to the product

$$z^{[l]} = W^{[l]}A^{[l-1]} + b^{[1]}$$

$$g^{[l]}\left(z^{[l]}\right)$$

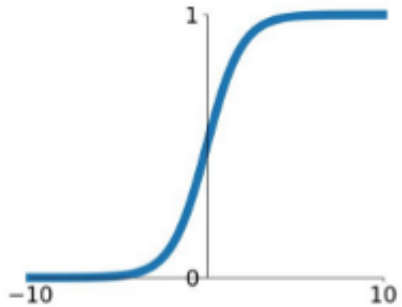
- In MLP g is the step function
- The step function contains only flat segment => no gradient



Activation Functions

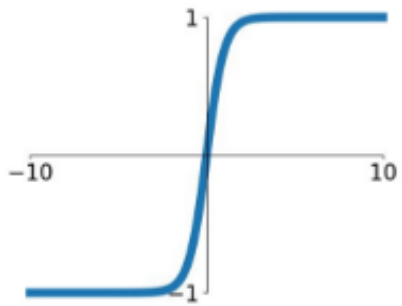
Sigmoid

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



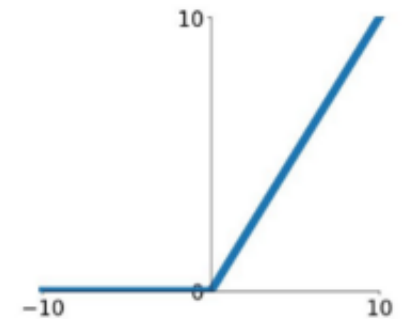
tanh

$$\tanh(x)$$



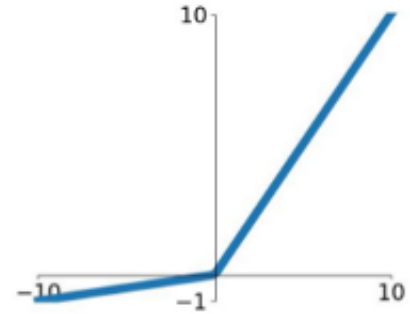
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

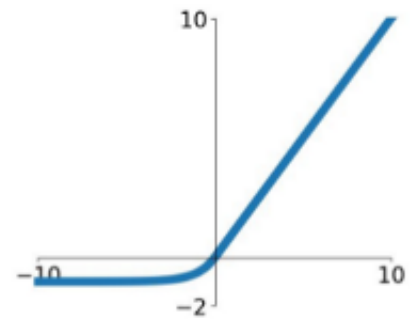


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



https://medium.com/@shrutijadon10104776/survey-on-activation-functions-for-deep-learning-9689331ba092

Introduction to TensorFlow/Keras

TensorFlow

- www.tensorflow.org
- Released under open source license on 9th Nov 2015
- Version 2.4.0
- Open source library for numerical computation using data flow graph
- Originally developed by Google Brain Team
- Provides an extensive suite of functions to build various model from scratch

TensorFlow Main Concepts

N-dimensional vector

Used to represent n-dimensional dataset

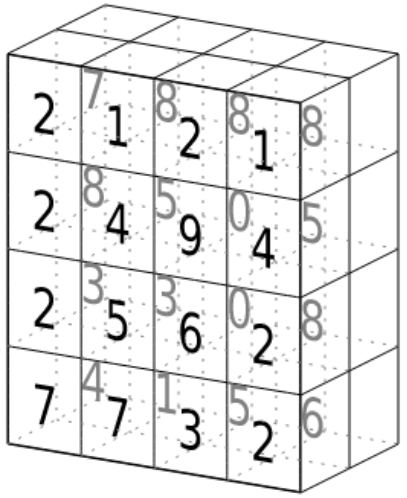
tensor

't'
'e'
'n'
's'
'o'
'r'

tensor of dimensions [6]
(vector of dimension 6)

3	1	4	1
5	9	2	6
5	3	5	8
9	7	9	3
2	3	8	4
6	2	6	4

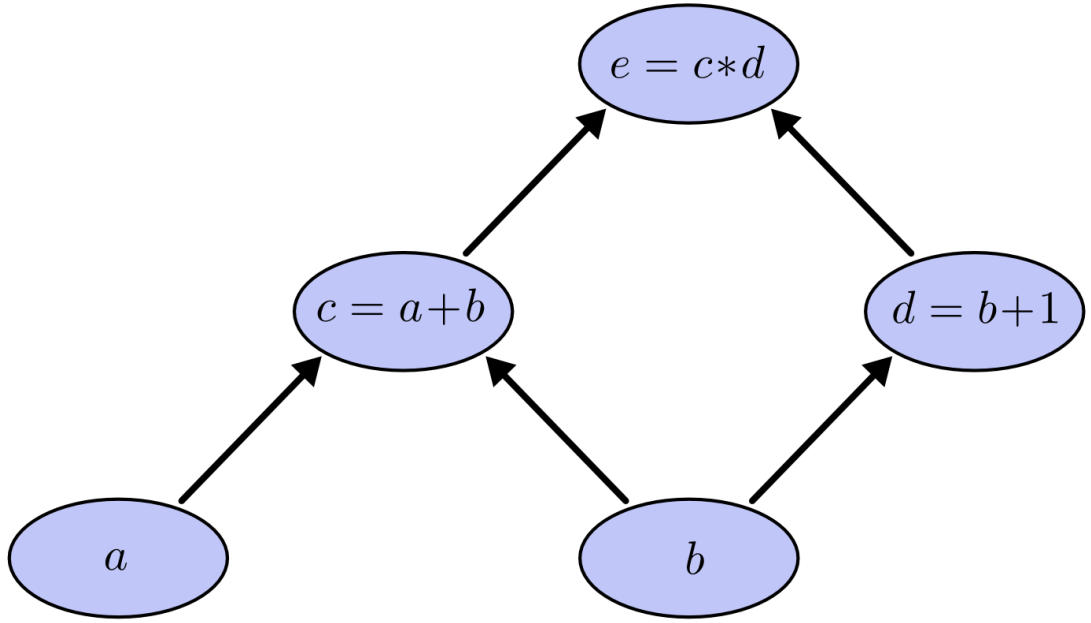
tensor of dimensions [6,4]
(matrix 6 by 4)



tensor of dimensions [4,4,2]

TensorFlow Main Concepts: Computational Graphs flow

- TensorFlow separates the definition of the computations from the execution
- The computation is based on the computational data flow graph
- Leaf and start vertices are always tensors
- Complex operations are represented in hierarchical order
- Traversing the graph in reverse order results in sub-expressions
- Operations at the same level are independent

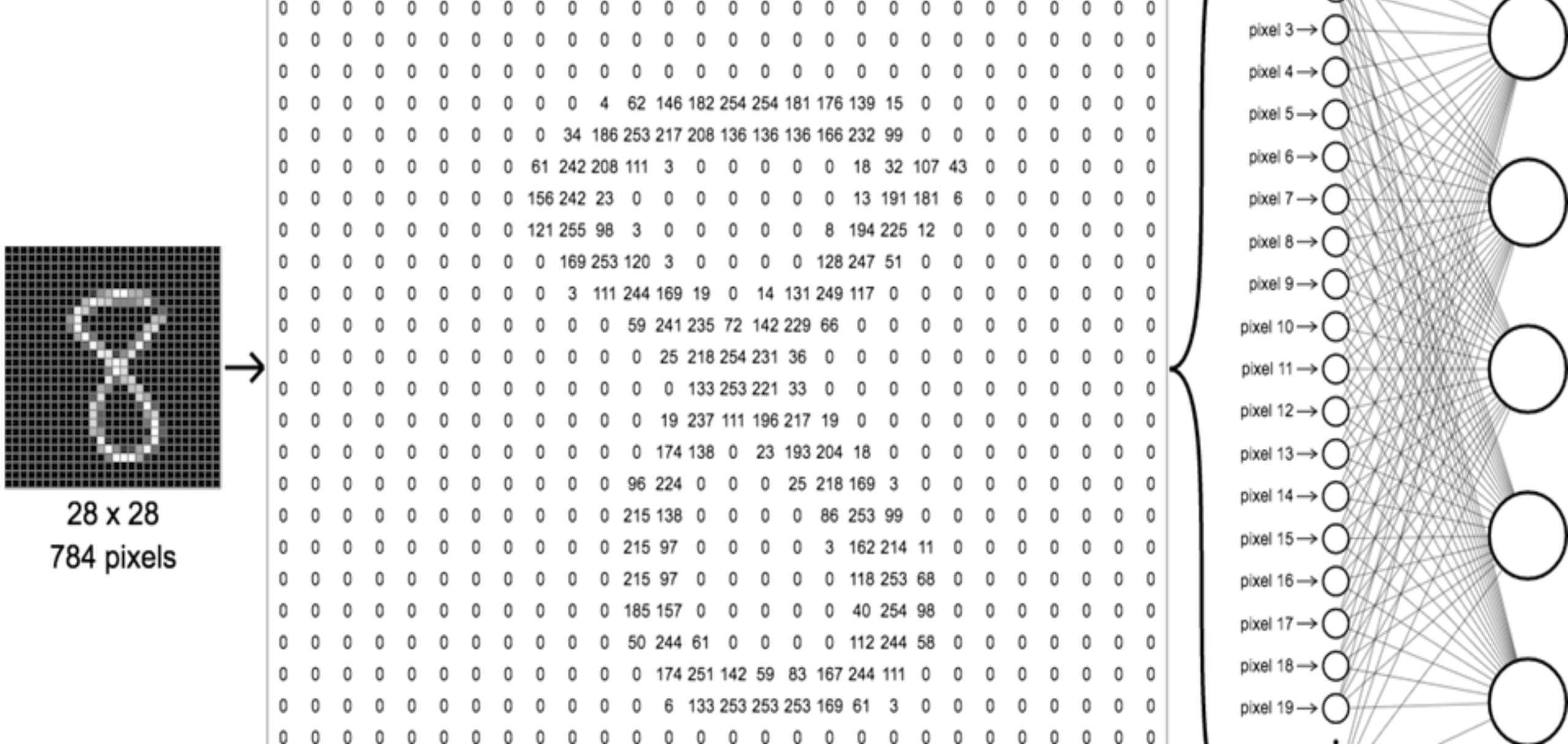


Keras

- www.keras.io
- Minimalist, highly modular, neural network library
- Written in Python
- Run on the top of TensorFlow/Theano and CNTK
- Focus on running fast experiments
- Fast prototyping
- Support convolutional and recurrent networks, and their combination
- Support arbitrary connectivity schema (multi-input, multi-output)
- Run seamlessly on GPU/CPU

Image classification in Keras

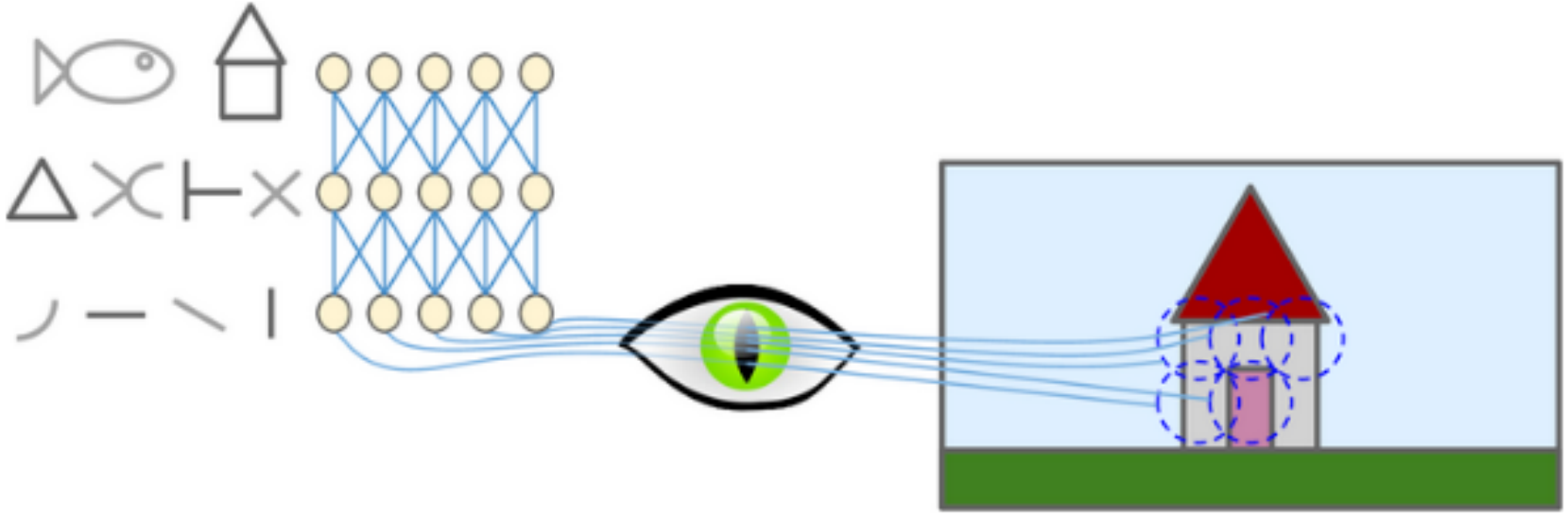
- Fashion MNIST dataset
- 60000 instances
- 28 x 28 images
- 10 categories



Convolutional Neural Network

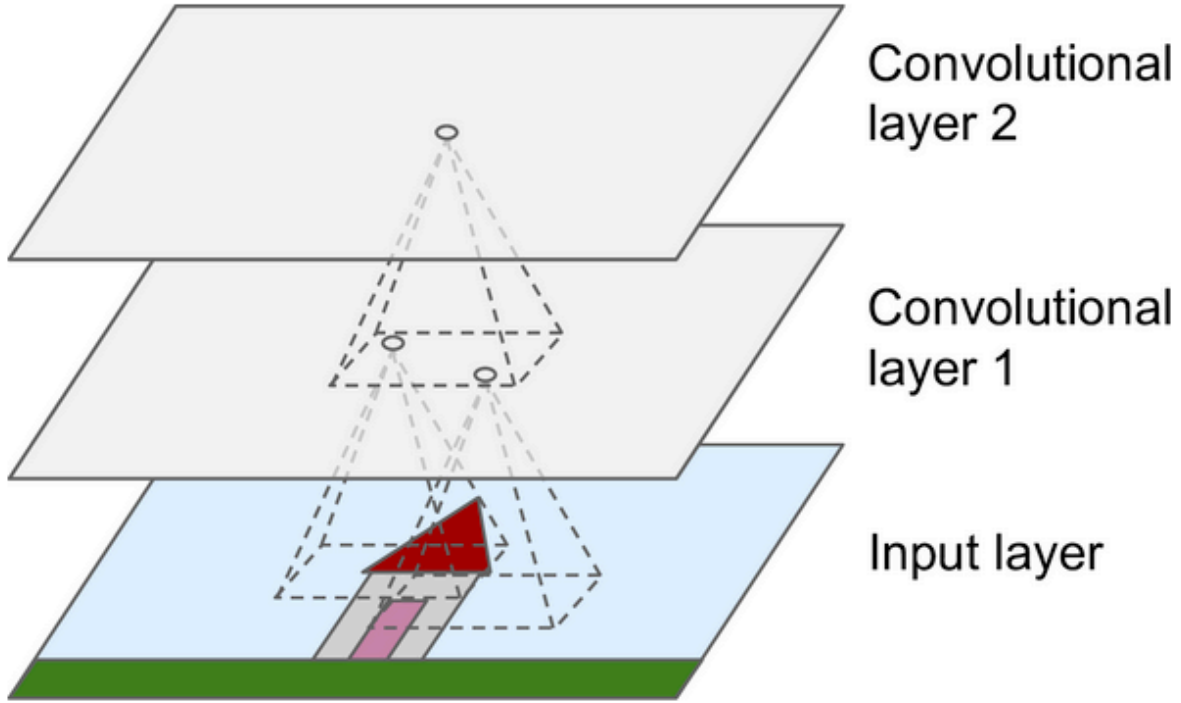
Visual Cortex

- In 1958-1959 Hubel & Wiesel showed some neurons in the visual cortex have *local receptive field*
- Some neurons react only to vertical horizontal lines
- … other to lines with different orientation
- … some react to complex patterns



Convolutional layer

- Idea
  - Neurons in the early layer of the network extract *local* visual features
  - Neurons in the later layers combine these features to extract higher-order features
- Sparse connectivity
- Parameter sharing



Less parameters than fully connected layer!

CNN

cat dog ……

Convolution

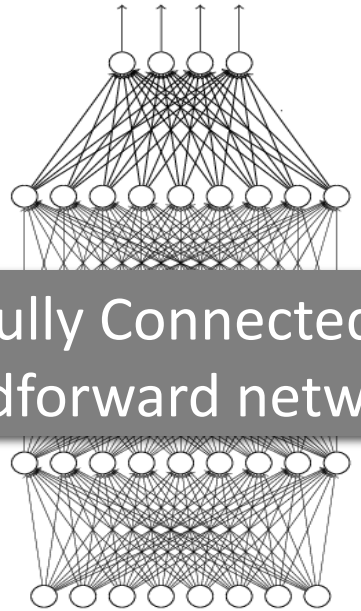
Max Pooling

Convolution

Max Pooling

Can repeat many times

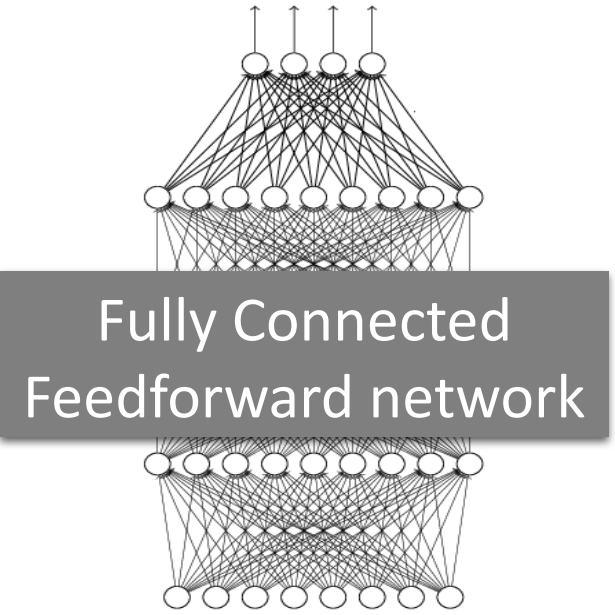
Flatten



Fully Connected Feedforward network

http://speech.ee.ntu.edu.tw/~tlkagk/courses/ML_2017/Lecture/CNN.pptx

CNN



1. Some pattern are much smaller than the whole image

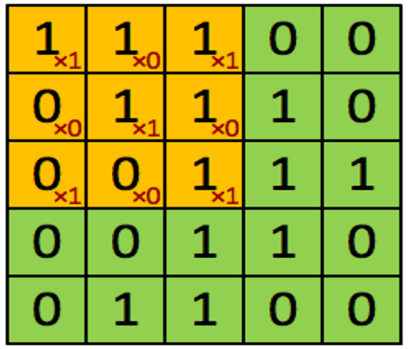
2. Same patterns appear in different regions

3. Subsampling the pixel will not change the object

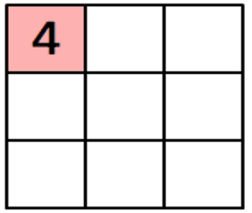
http://speech.ee.ntu.edu.tw/~tlkagk/courses/ML_2017/Lecture/CNN.pptx

Filters

- Neuron weights represented as a small image the size of receptive field
- If neurons at the same layer use all the same filter they will output a *feature map*
- No need to define filters, the convolutional layer learns them!

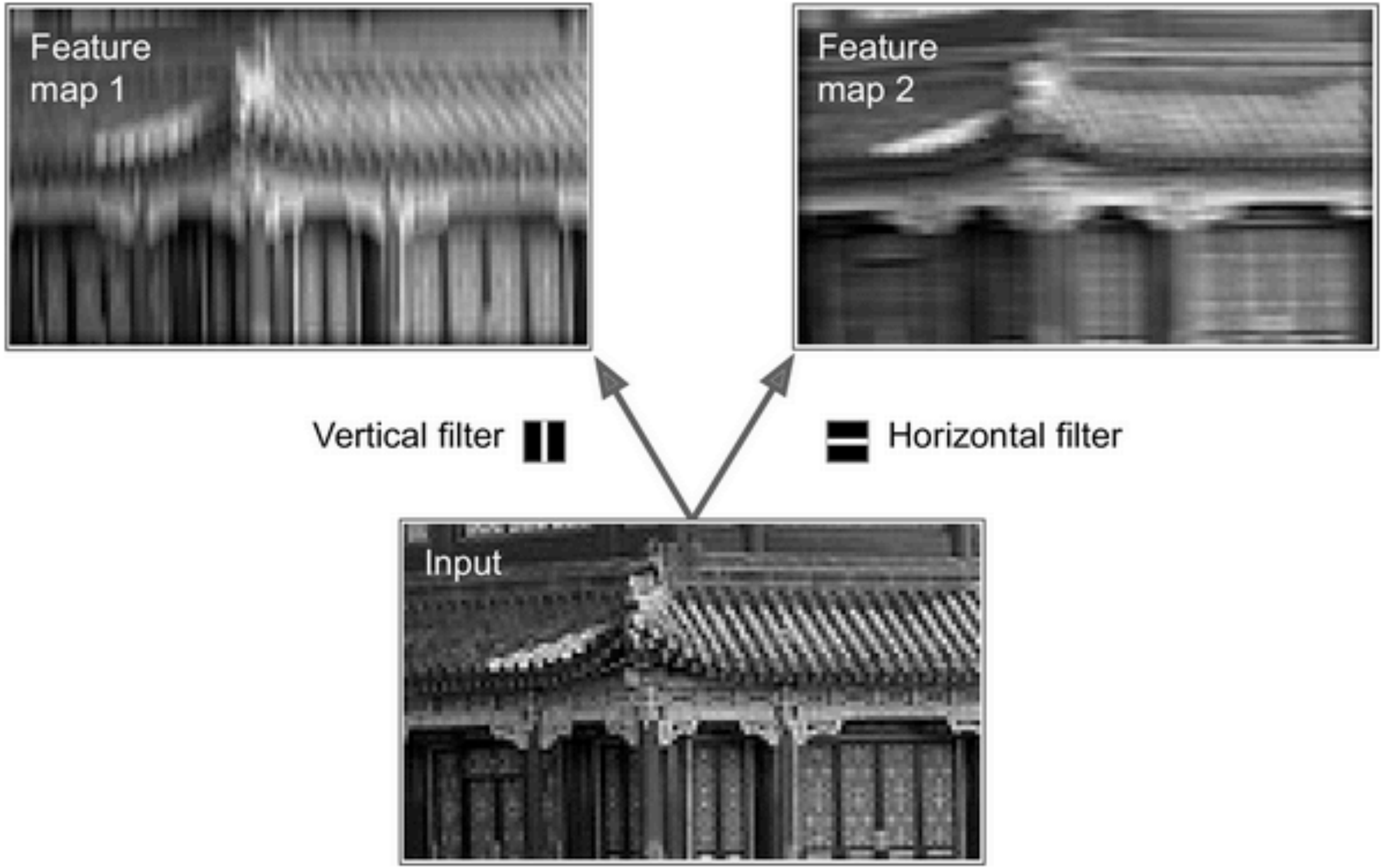


Image



Convolved Feature

http://cs229.stanford.edu/section/cs229_deep_learning_friday.pptx


Feature
map 1
Feature
map 2
Vertical filter
Horizontal filter
Input

Filters

Stride = 1

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

6 x 6 image

*

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

=

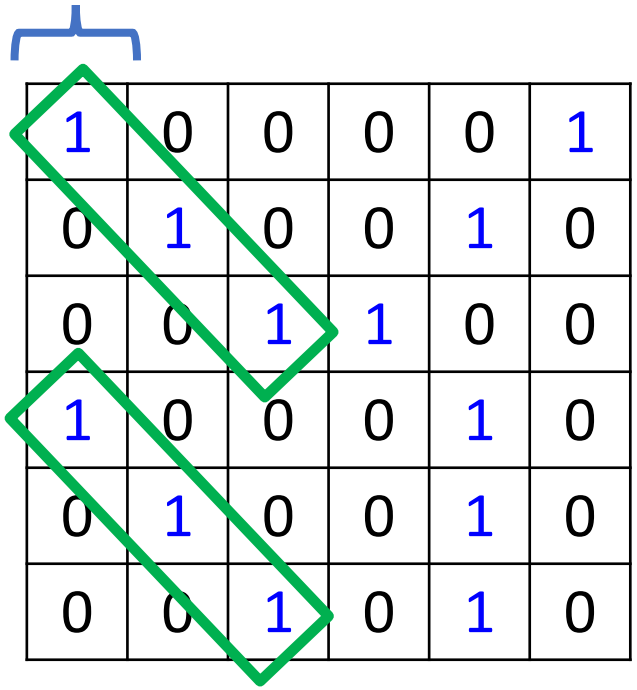
3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

Repeat for every filter

1. Some pattern are much smaller than the whole image
=>
Each filter detects a small pattern (3x3)

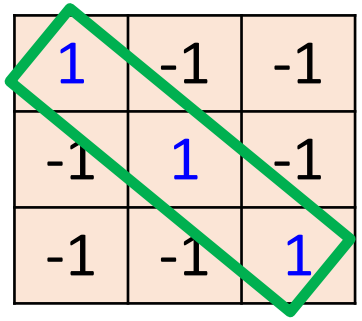
Filters

Stride = 1



6 x 6 image

*



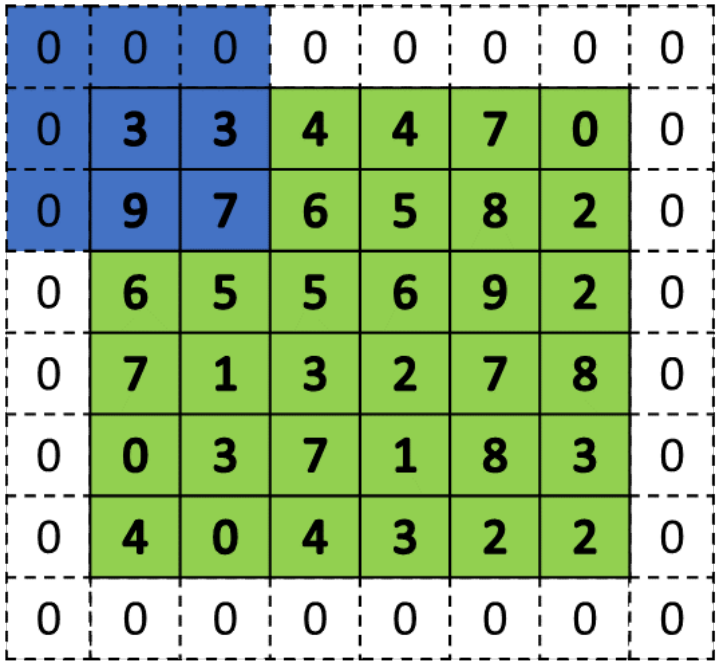
Filter 1

=

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

2. Same patterns appear in different regions

Padding



$6 \times 6 \rightarrow 8 \times 8$

$*$

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

3×3

$=$

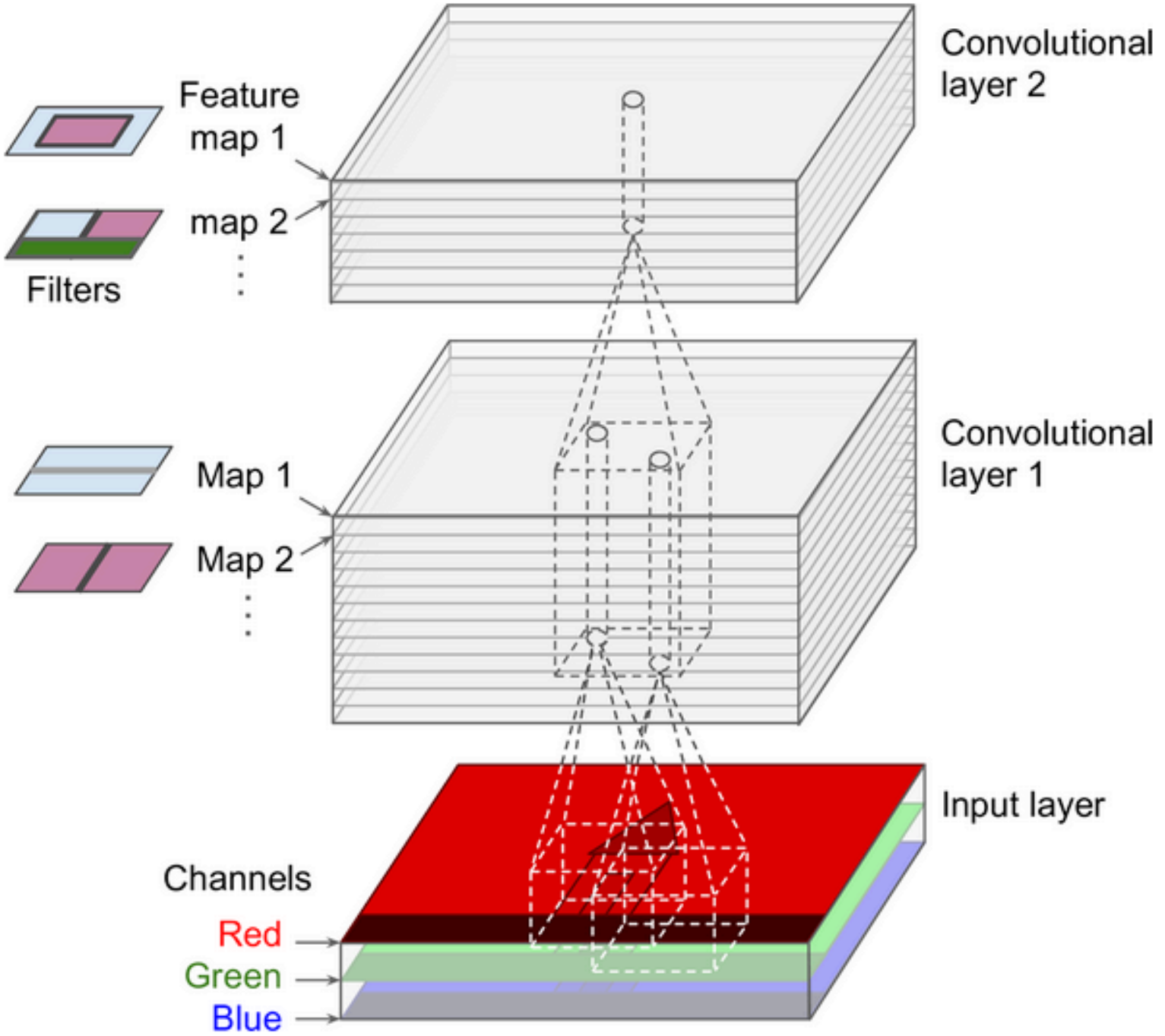
-10	-13	1			
-9	3	0			

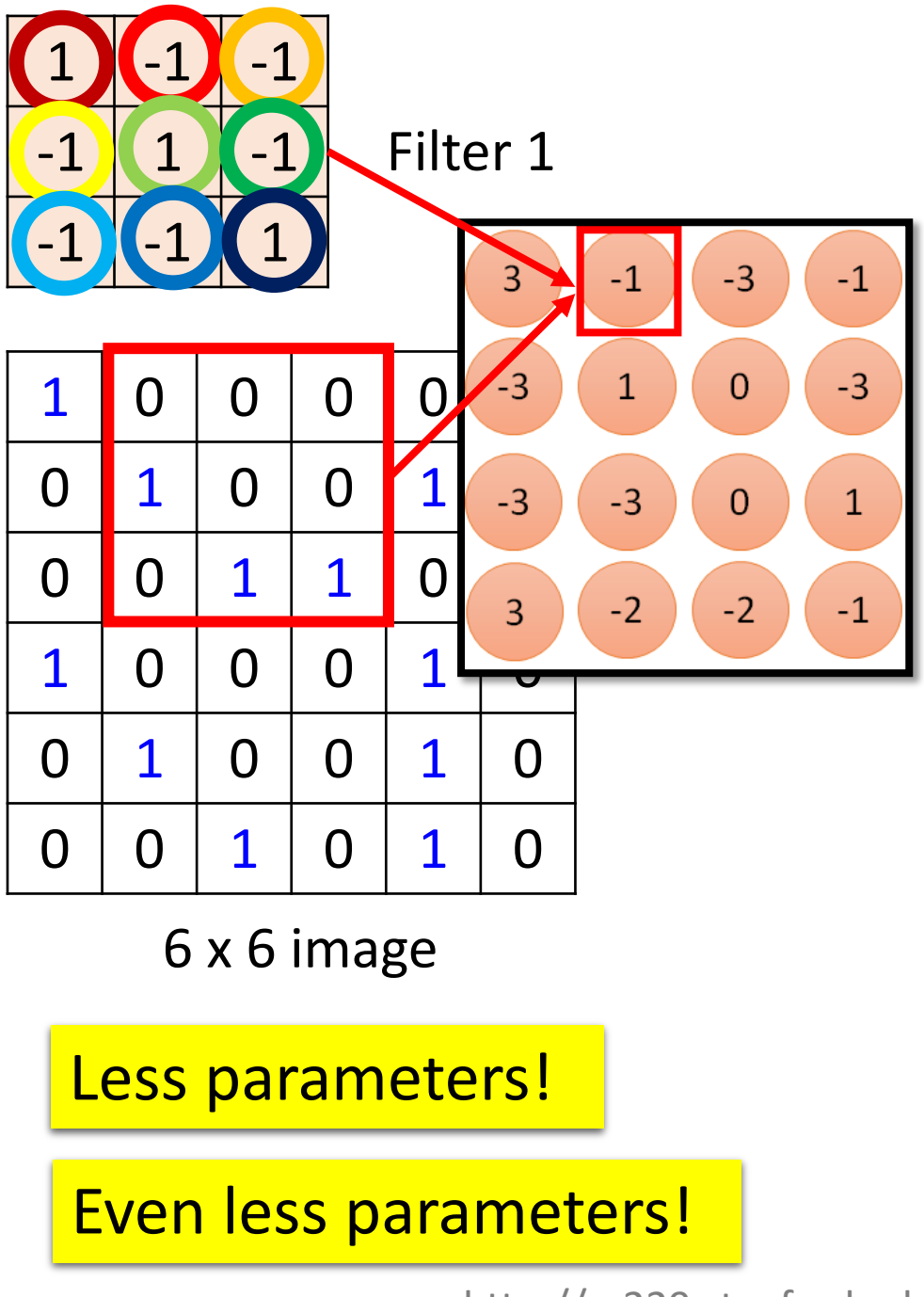
6×6

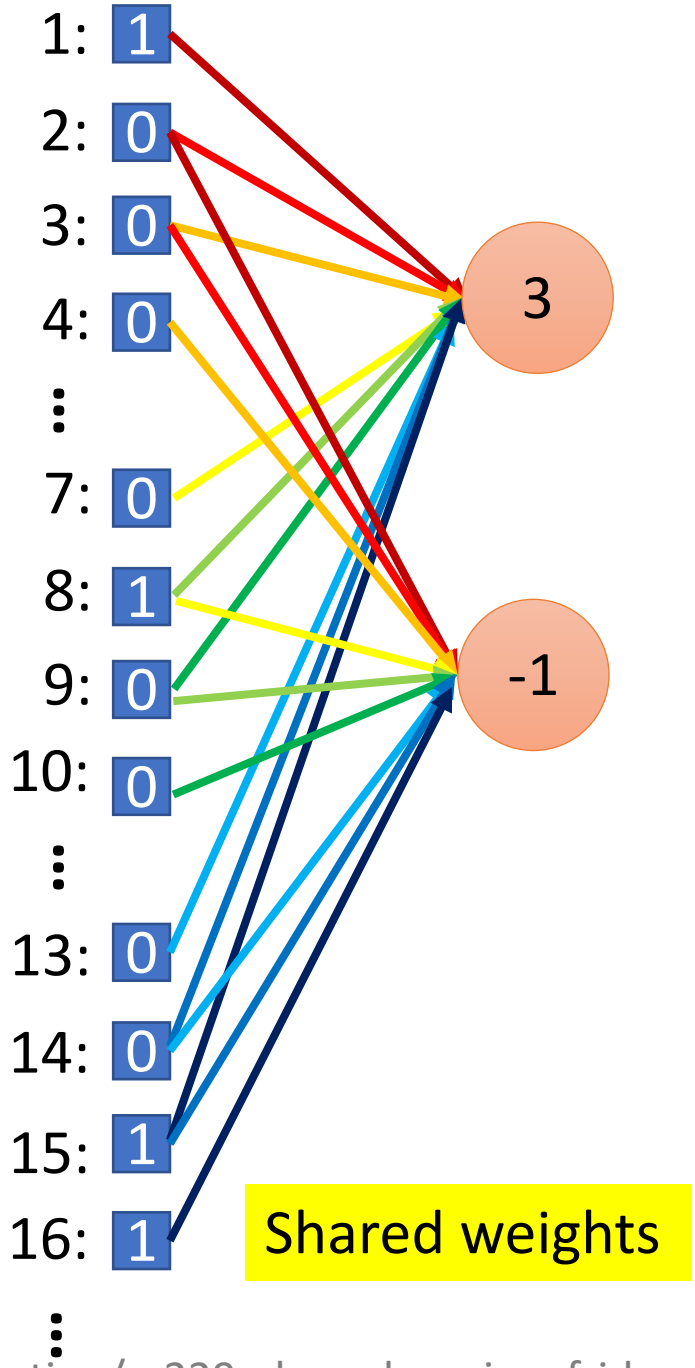
http://datahacker.rs/what-is-padding-cnn/

- Input images are usually in three channels: RGB
- Convolutional layer has multiple filters
- 1 feature map x filter

  => 3D
- Neurons in different feature maps use different parameter
- A neuron receptive field extends across all the previous layer of the feature maps
  => applies multiple trainable filters to its input
- Translational invariance







Less parameters!

Even less parameters!

Shared weights

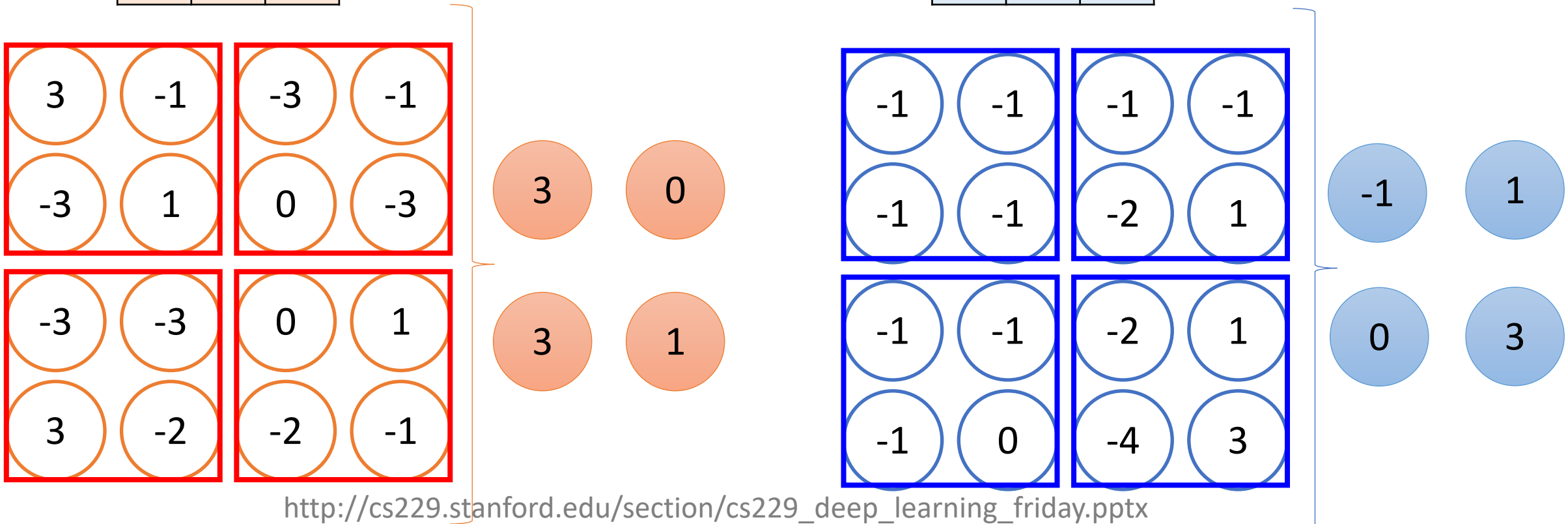
Max Pooling

1	-1	-1
-1	1	-1
-1	-1	1

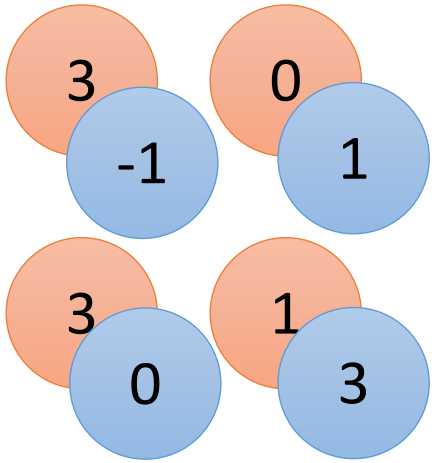
Filter 1

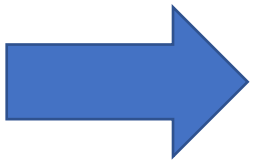
-1	1	-1
-1	1	-1
-1	1	-1

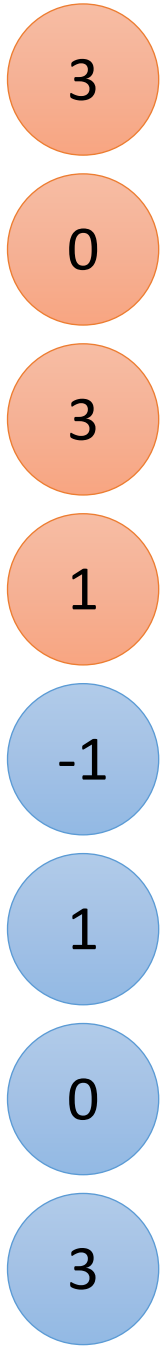
Filter 2

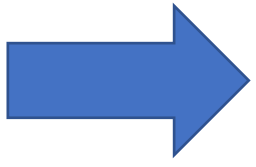


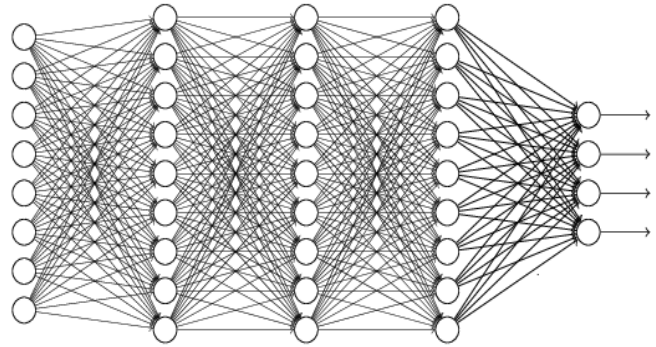
Flatten







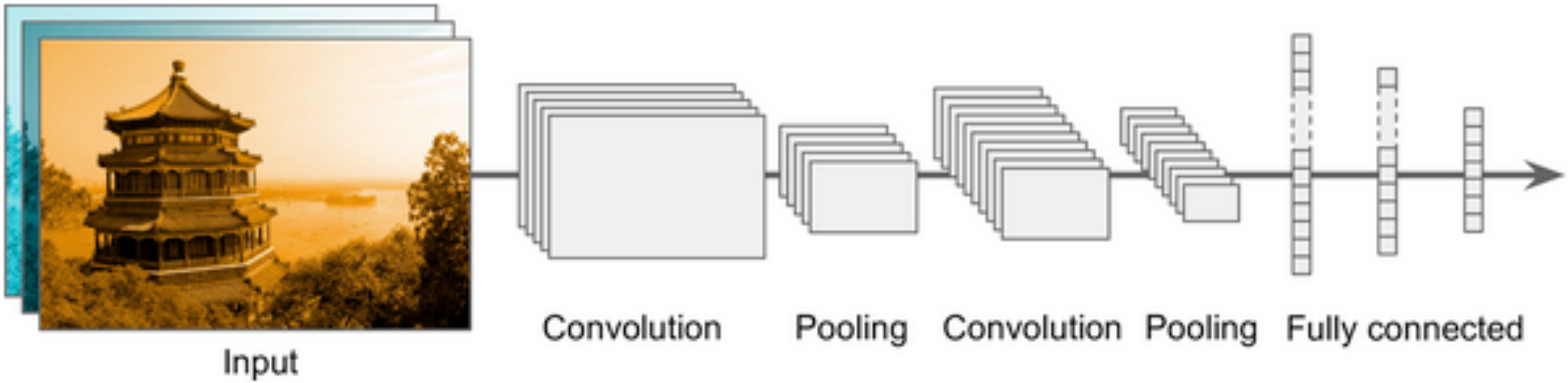




Fully Connected Feedforward network

http://cs229.stanford.edu/section/cs229_deep_learning_friday.pptx

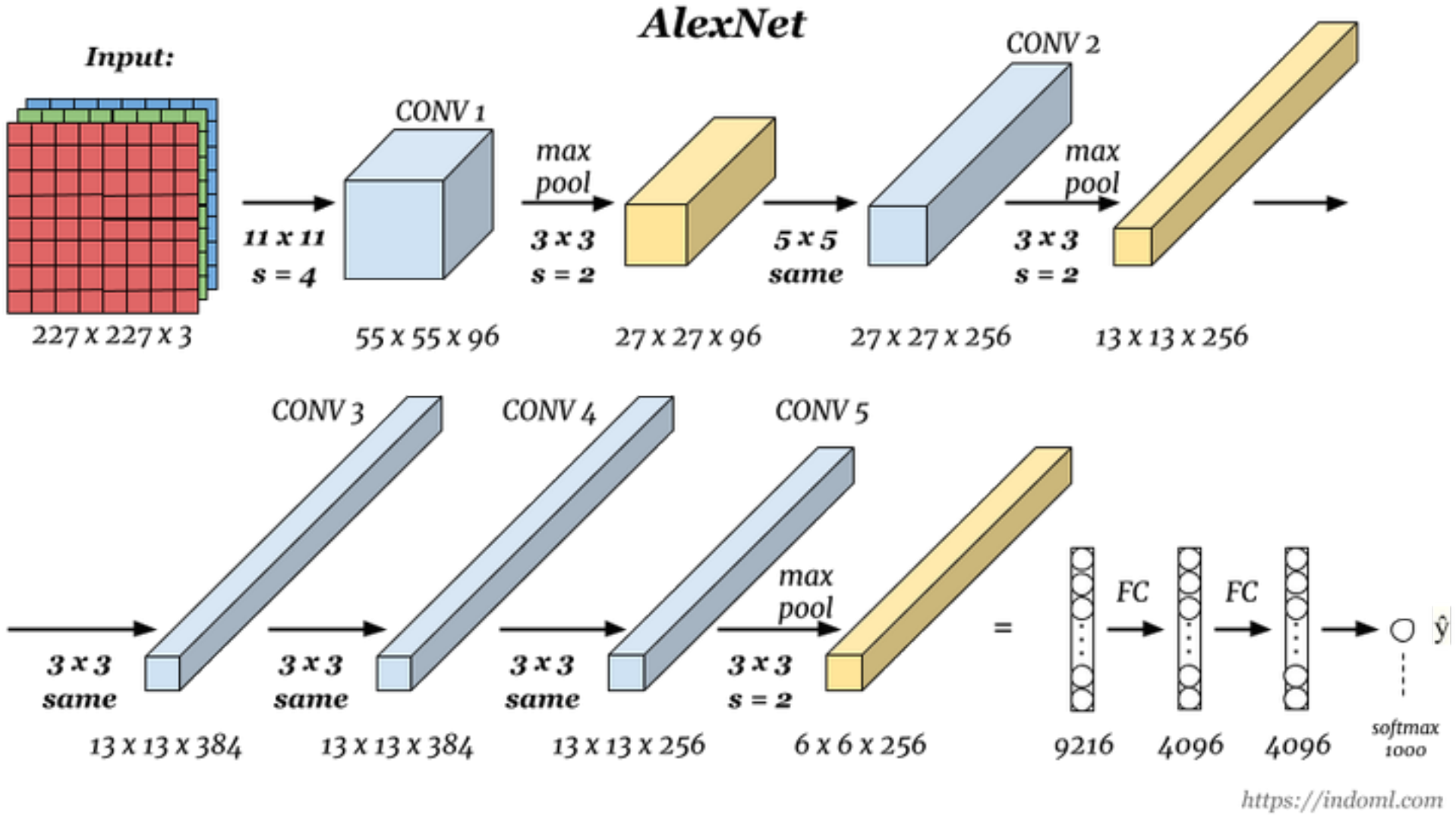
Recap


Input
Convolution
Pooling
Convolution
Pooling
Fully connected

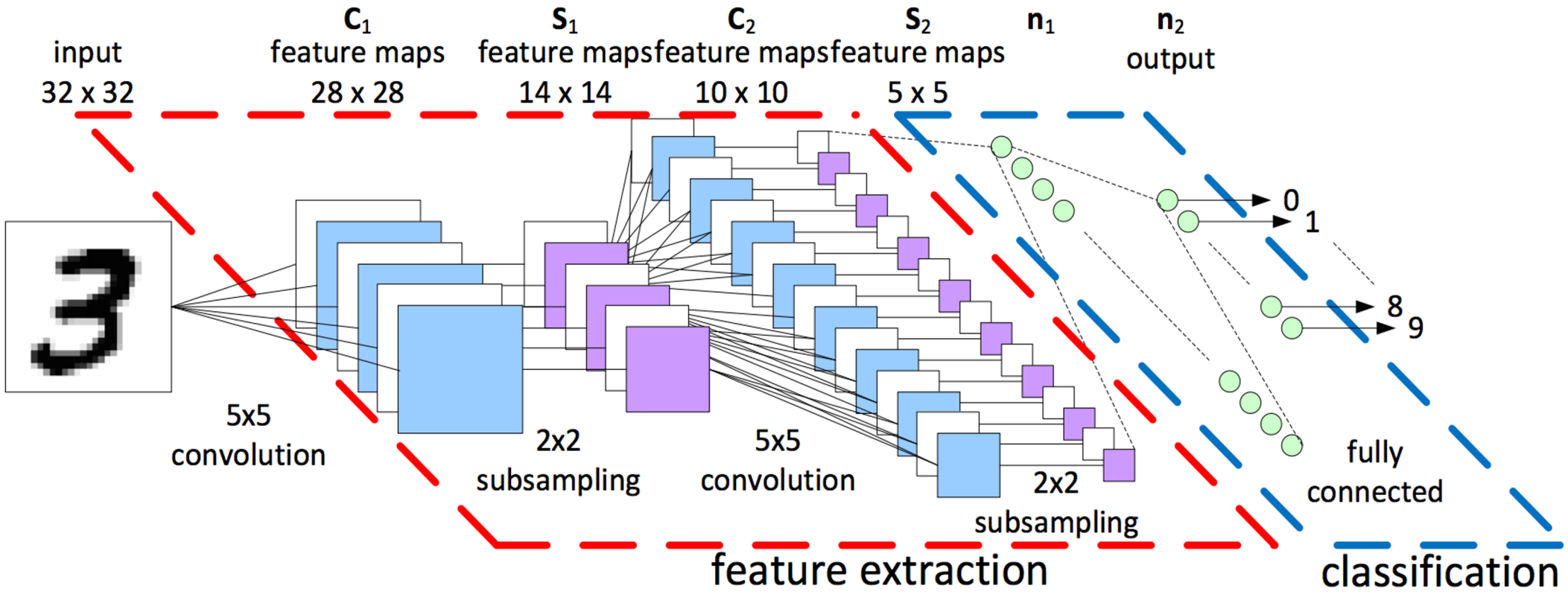
Recap

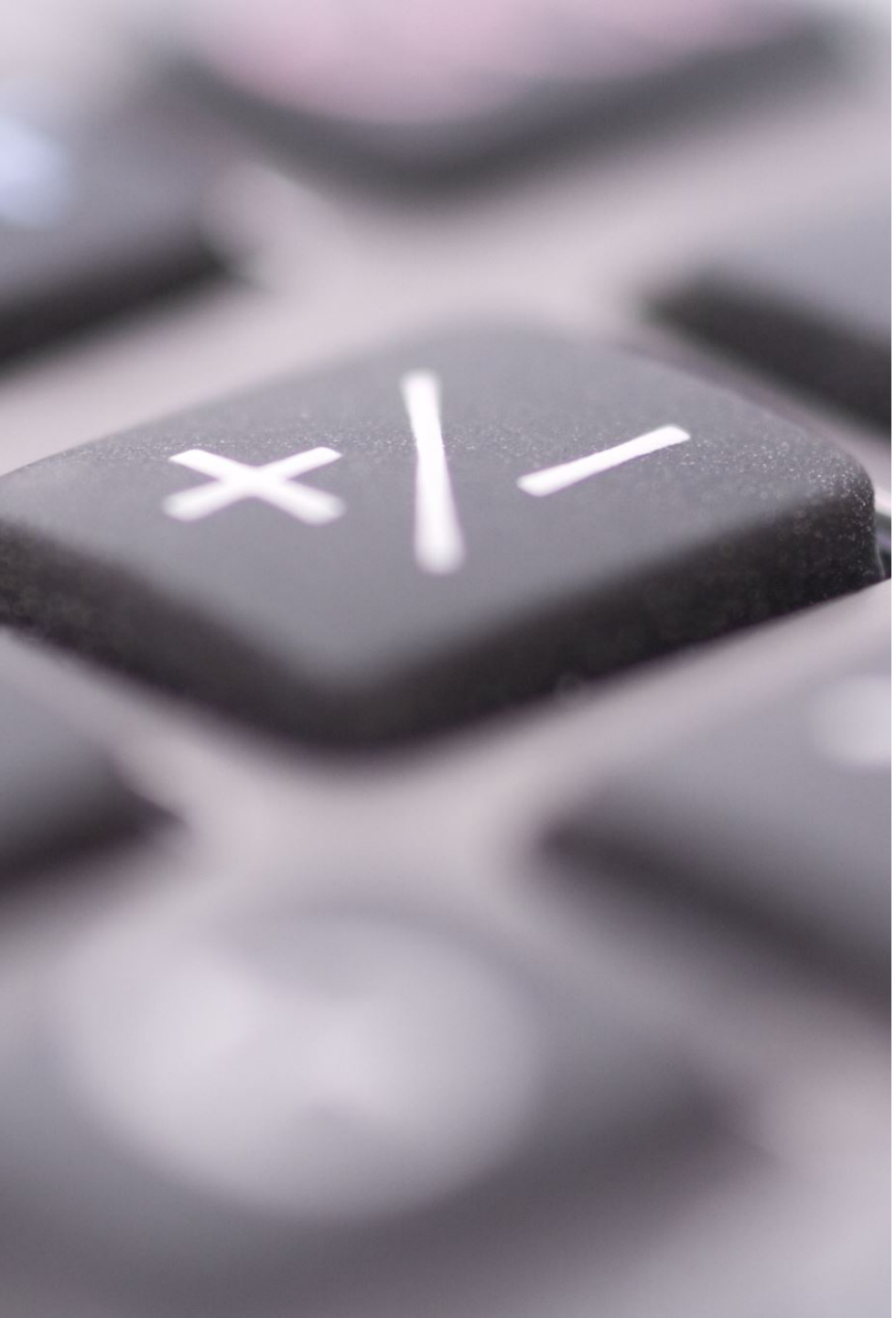
- Number of channel (e.g. RGB) in input must match the filter
- Multiple filters can be used in a convolutional layer to detect multiple features
- The output of the layer will have the same number of channel as the number of filter
- Finally to make up a convolutional layer we add the bias and the activation function (ReLU or tanh)
- Notation
  - f filter
  - s stride
  - p padding

AlexNet


AlexNet
Input:
227 x 227 x 3
11 x 11
s = 4
CONV 1
55 x 55 x 96
max
pool
3 x 3
s = 2
27 x 27 x 96
5 x 5
same
CONV 2
27 x 27 x 256
max
pool
3 x 3
s = 2
13 x 13 x 256
3 x 3
same
CONV 3
13 x 13 x 384
3 x 3
same
CONV 4
13 x 13 x 384
3 x 3
same
13 x 13 x 256
3 x 3
s = 2
CONV 5
max
pool
6 x 6 x 256
=
9216
FC
4096
FC
4096
softmax
1000
ŷ
https://indoml.com

CNN in action





Resources

- http://neuralnetworksanddeeplearning.com/chap1.html
- Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow
- https://github.com/ageron/handson-ml2/
- http://cs229.stanford.edu/syllabus-spring2020.html
- https://colab.research.google.com/drive/1-6s9KHSa-vzrRqfq8yQ_urBeJu_G6zma?usp=sharing
- https://colab.research.google.com/drive/12IzTI1uHmzEG9ACQwfdl0lVo6W9NPfN1?usp=sharing