Deep Learning & Convolutional neural networks (CNN)

Slide from:

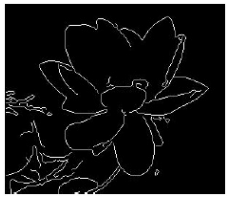
1. Y. Y. Lin

2. H. Y. Lee http://speech.ee.ntu.edu.tw/~tlkagk/courses.html

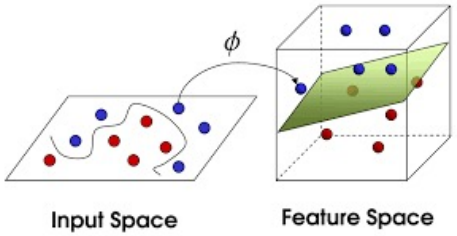
Conventional approach to object recognition

- Training phase

image collection → feature extraction → classifier training → trained classifier



histogram of oriented gradients (HoG)



support vector machines (SVMs)

dogs? ✗

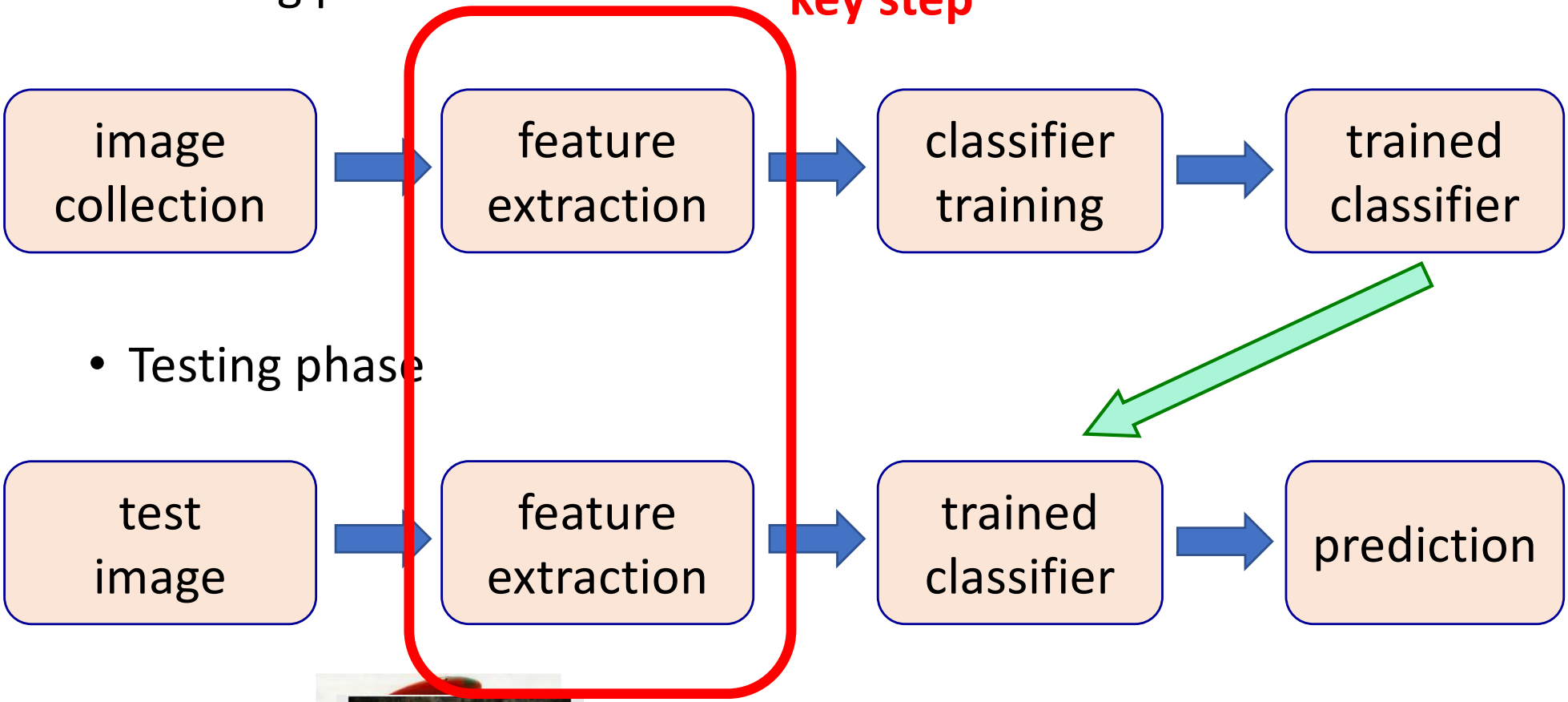
flowers? ○

trains? ✗

persons? ✗

Conventional approach to object recognition

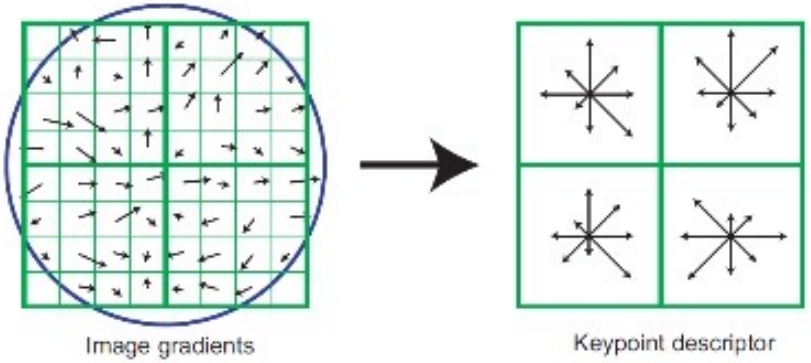
- Training phase



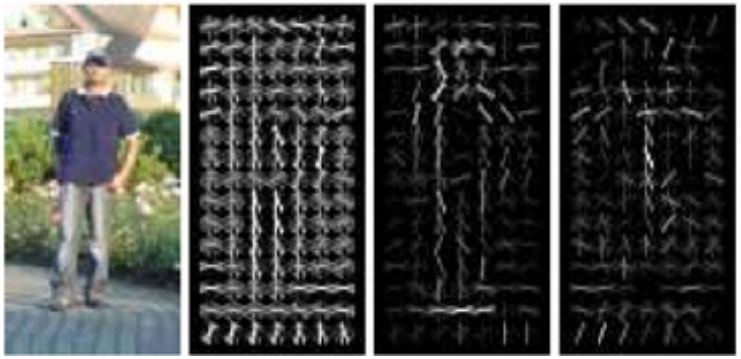
- Testing phase

Features are the keys

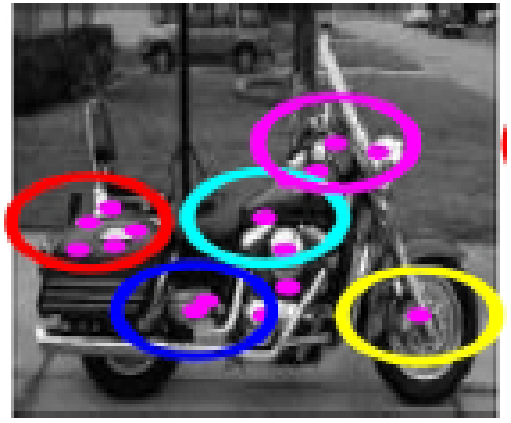
- Off-the-shelf visual features



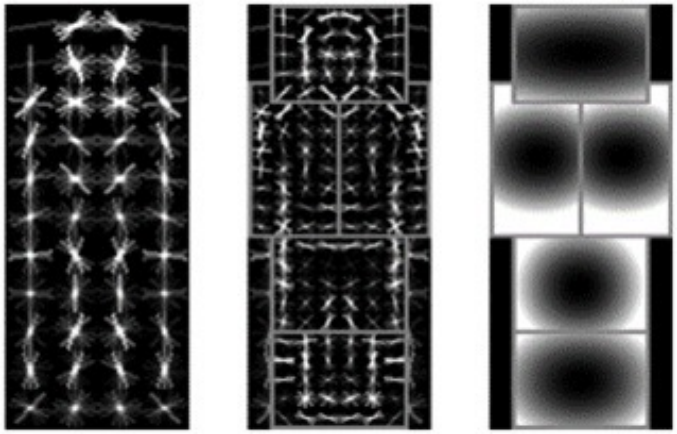
SIFT [Lowe, IJCV'04]



HoG [Dalal & Triggs, CVPR'05]



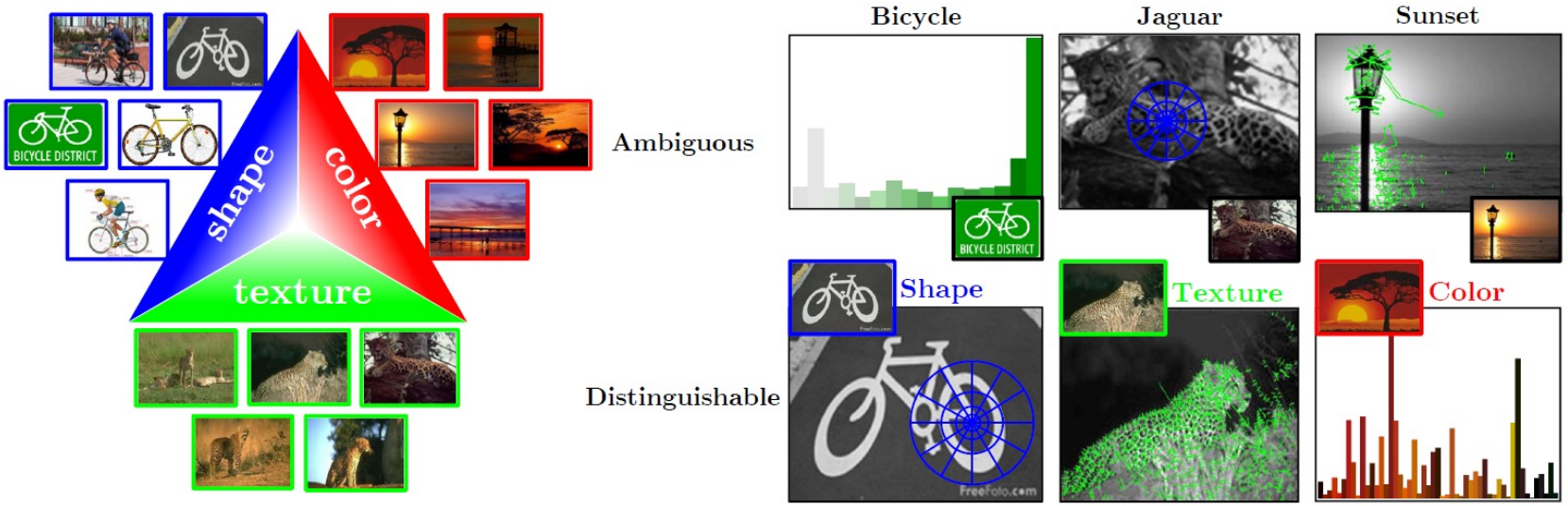
Constellation model [Fergus et al., CVPR'03]



DPM [Felzenszwalb et al., PAMI'10]

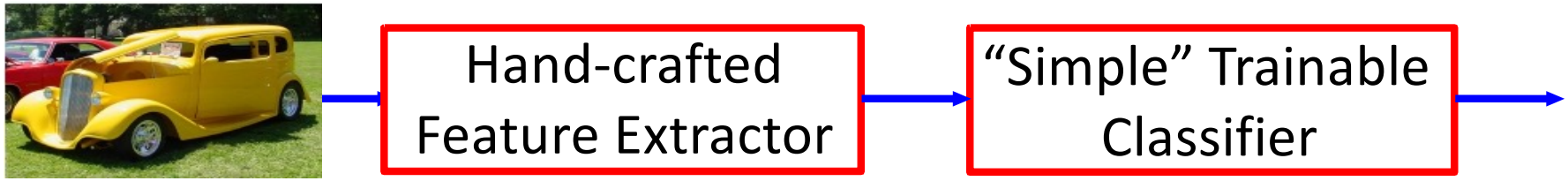
Features are the keys

- Features are the keys to recent progress in classification
- Are handcrafted features optimal?
- The optimal features for classification in general vary from task to task, even from category to category

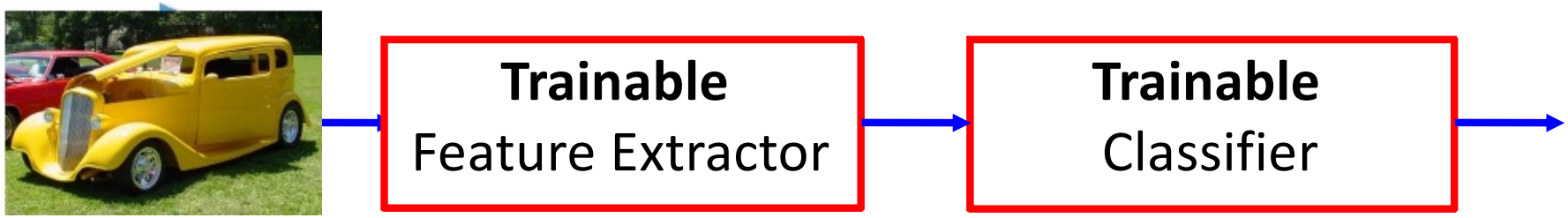


Conventional approaches vs. Deep learning

- Conventional approaches
  - Fixed/engineered features + trainable classifier



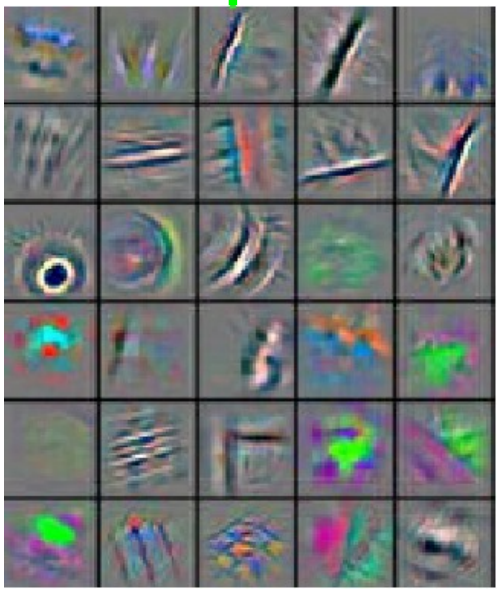
- Deep learning / End-to-end learning / Feature learning
  - Trainable features + trainable classifier

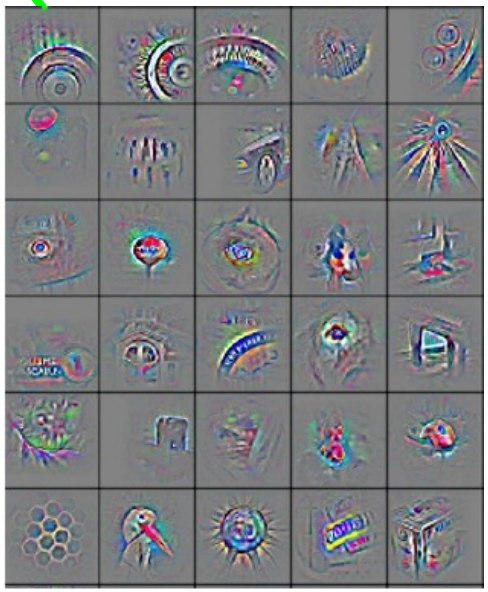


slide: Y LeCun & MA Ranzato

Deep learning = Learning hierarchical representations

Low-Level Feature → Mid-Level Feature → High-Level Feature → Trainable Classifier



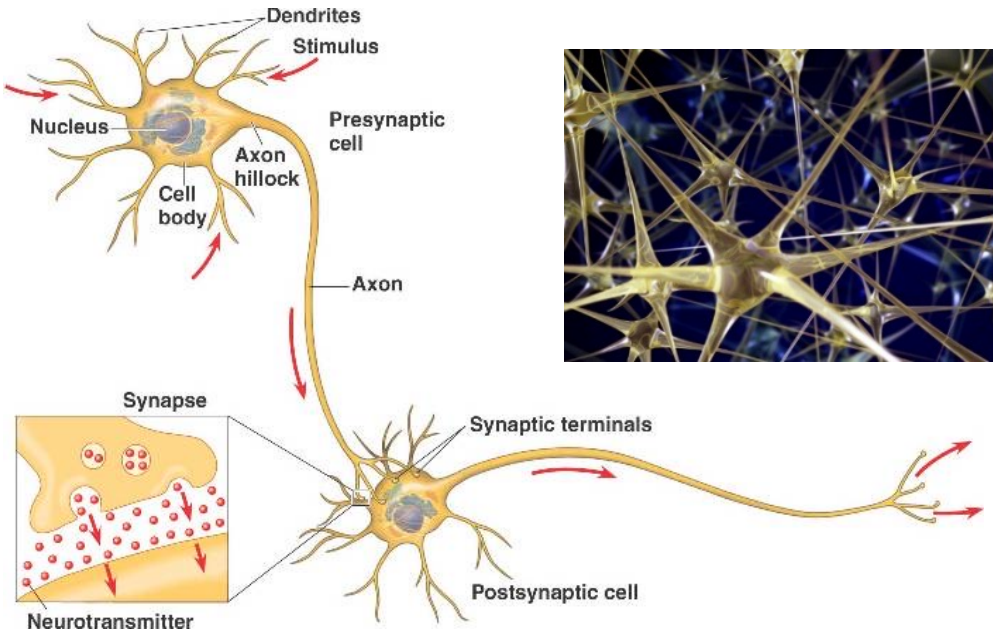


slide: Y LeCun & MA Ranzato

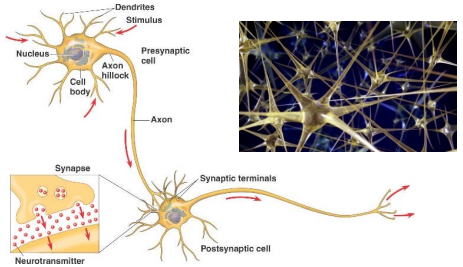
Deep Neural Networks (DNN)

Neural networks and neurons

- Neural networks are presented as layers of interconnected neurons

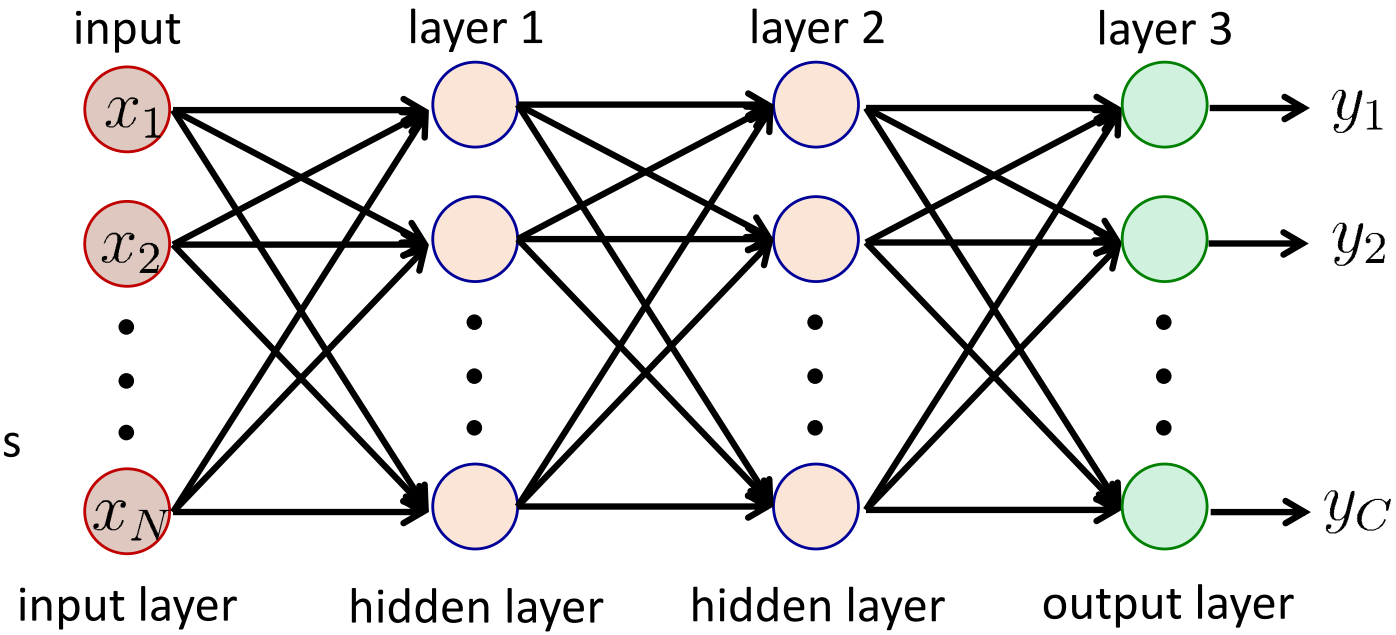


Neural networks and neurons



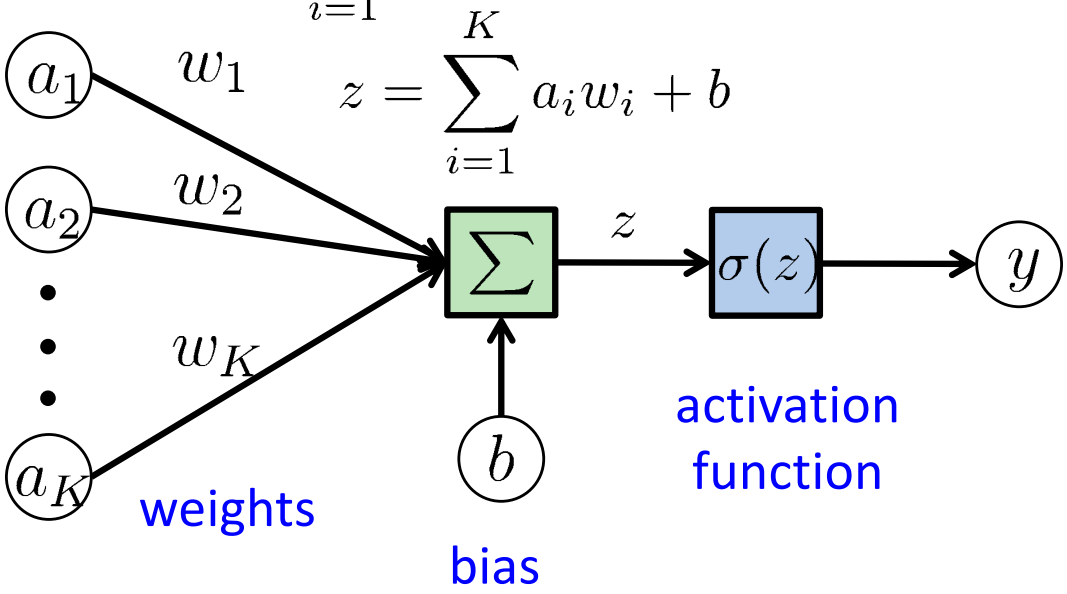
- Neural networks are presented as layers of interconnected neurons
  - Each layer of neurons takes messages from output of previous layer

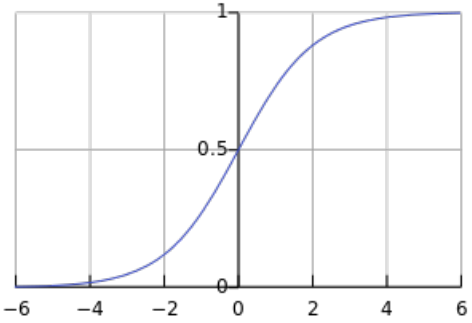
image of N pixels



A single neuron

- A function $f : R^K \mapsto R$
  - Map K inputs to 1 output
  - Compute the biased weighted sum
  - Apply a non-linear mapping function (activation function)
  - $$f((a)) = \sigma(\sum_{i=1}^{K} a_i w_i + b), \text{where } \sigma(z) = \frac{1}{1+\exp(-z)}$$

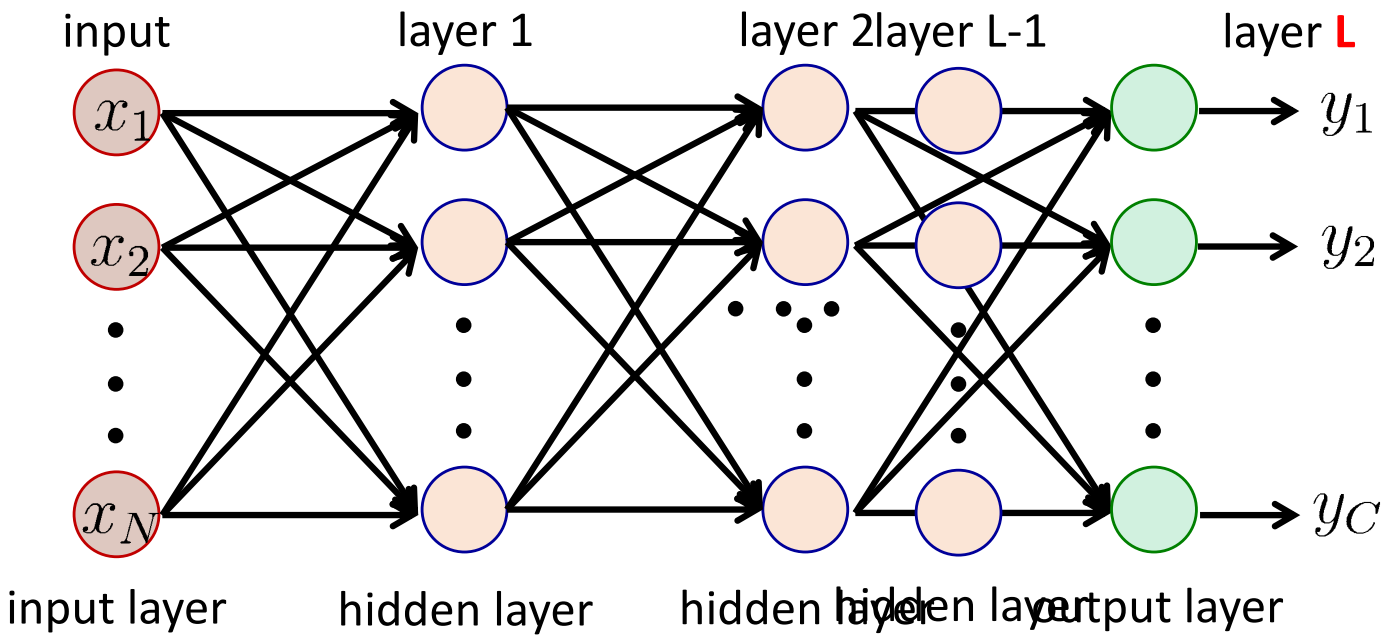




sigmoid function

What is deep neural networks (DNN)

- DNN is neural networks with many hidden layers



Ups and downs of Deep Learning

- 1958: Perceptron (linear model)
- 1969: Perceptron has limitation
- 1980s: Multi-layer perceptron
  - Do not have significant difference from DNN today
- 1986: Backpropagation
  - Usually more than 3 hidden layers is not helpful
- 1989: 1 hidden layer is "good enough", why deep?
- 2006: RBM (Restricted Boltzmann Machine) initialization
- 2009: GPU
- 2011: Start to be popular in speech recognition
- 2012: win ILSVRC image competition
- 2015.2: Image recognition surpassing human-level performance

Ups and downs of Deep Learning

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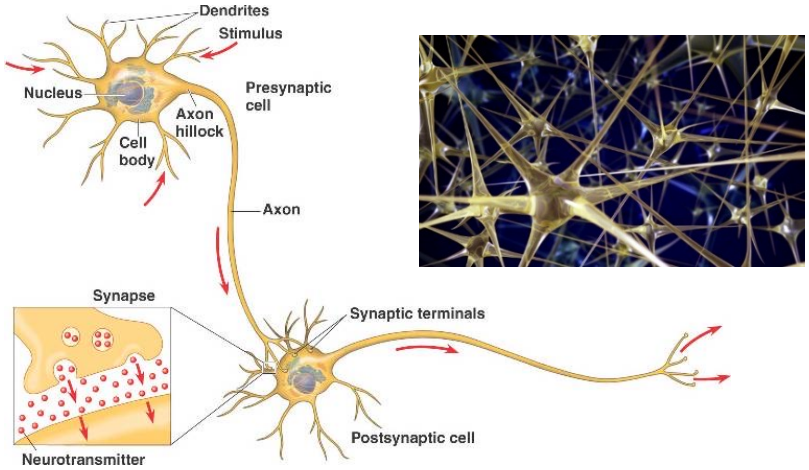
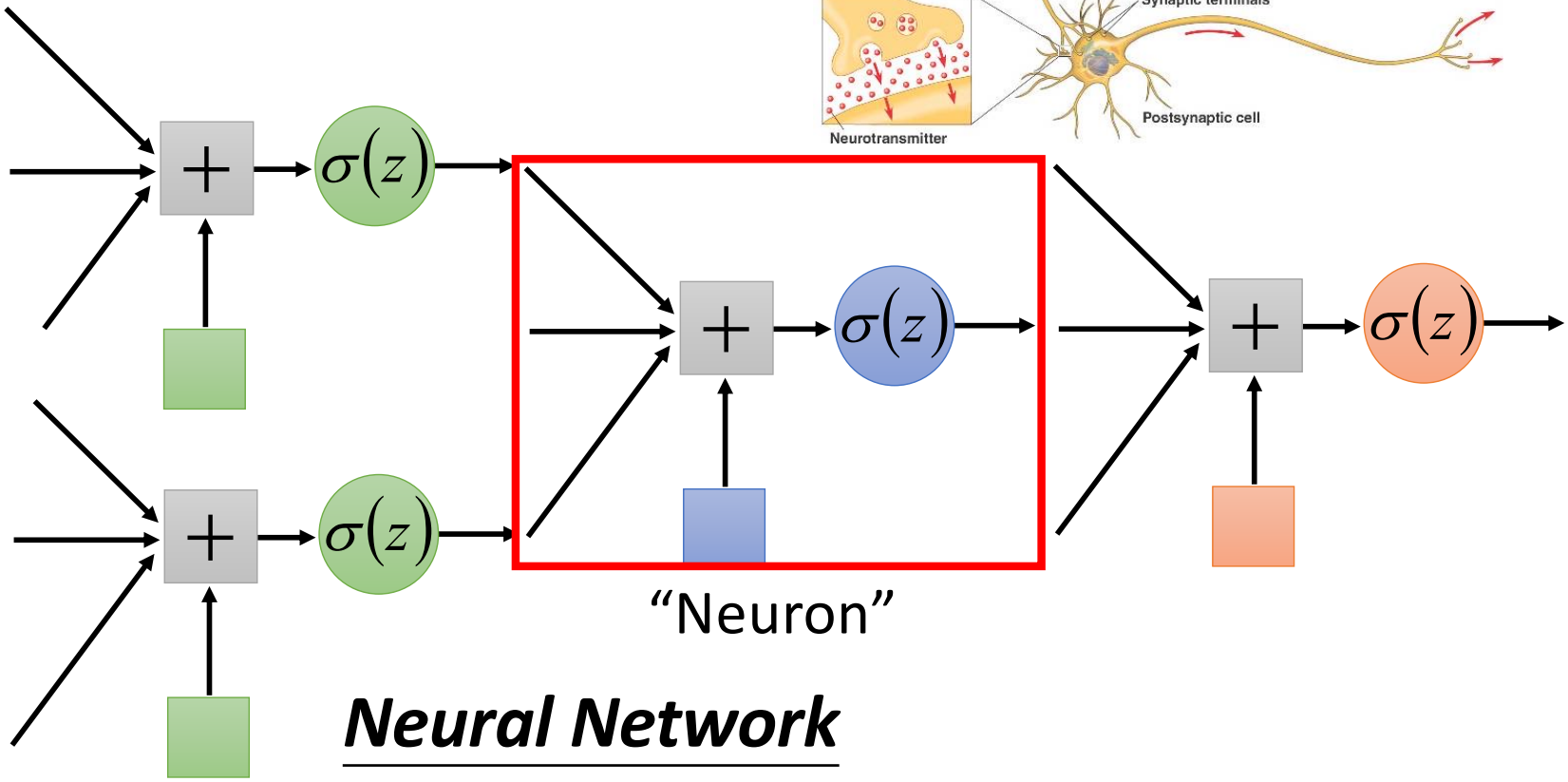
  - Do not have significant difference from DNN today

A classification problem

- 2011: Start to be popular in speech recognition
- 2012: win ILSVRC image competition
- 2015.2: Image recognition surpassing human-level performance
- 2016.3: Alpha GO beats Lee Sedol
- 2016.10: Speech recognition system as good as humans

Neural Network





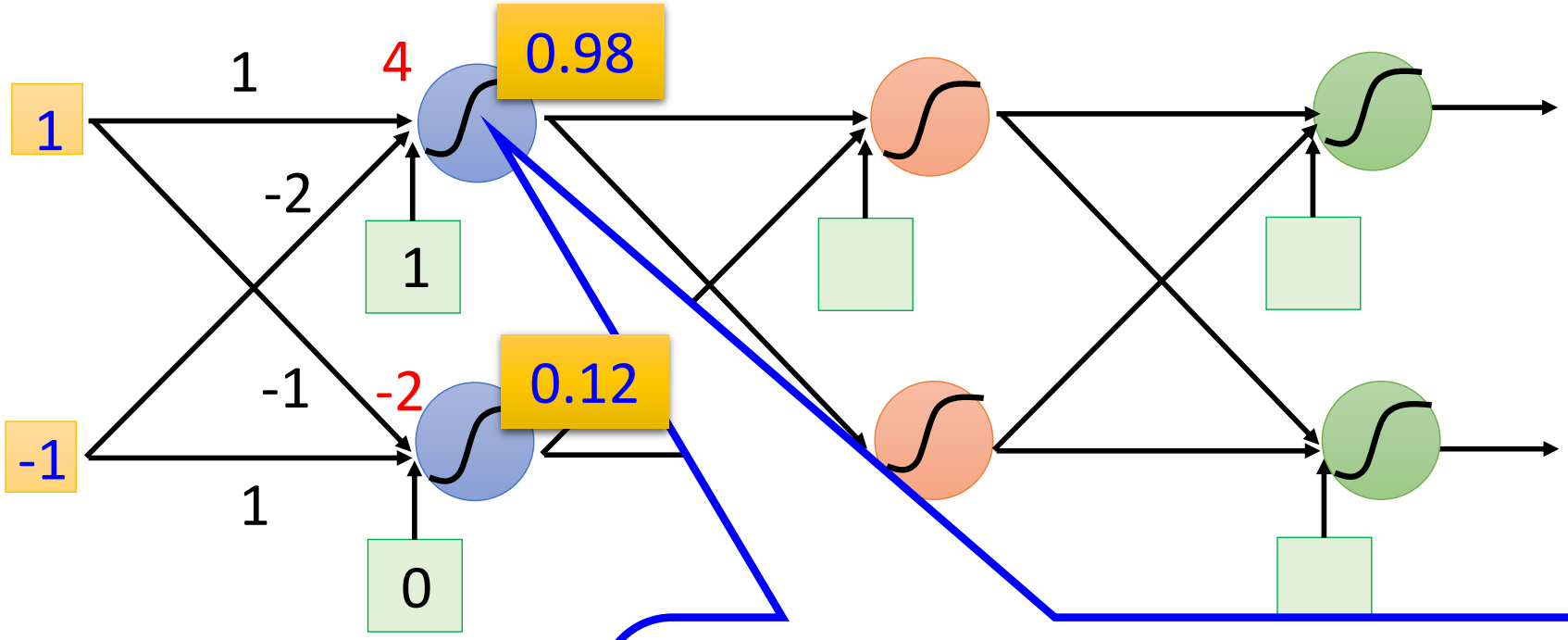
"Neuron"

Neural Network

Different connection leads to different network structures

Network parameter θ: all the weights and biases in the "neurons"

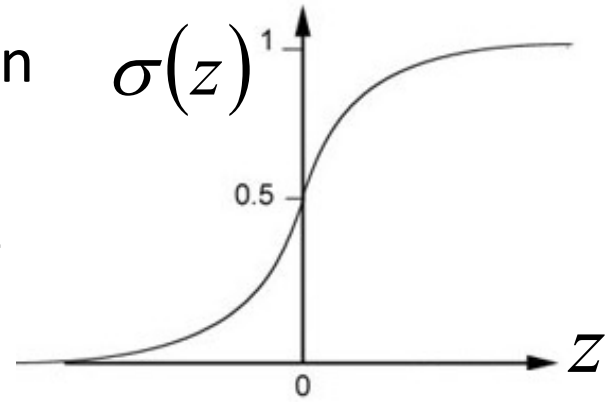
Fully Connect Feedforward Network



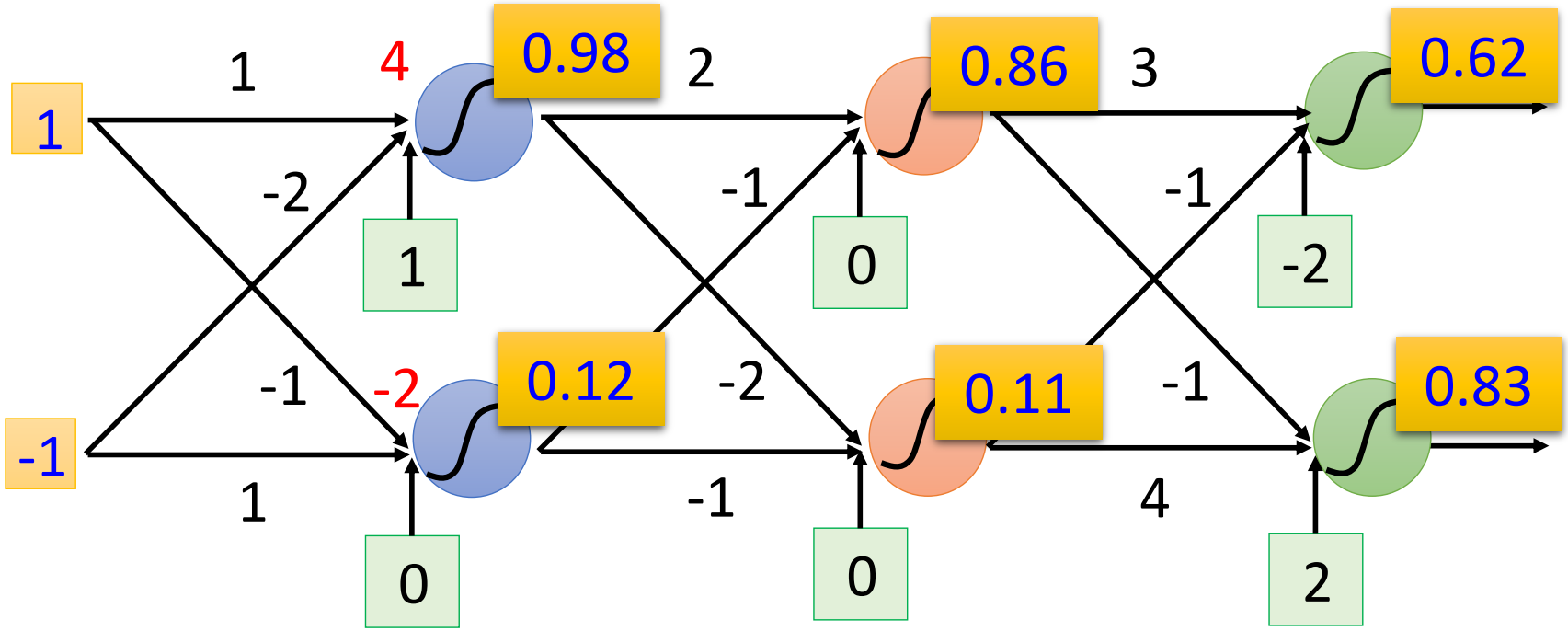
$$z = \sum_{i=1}^{K} a_i w_i + b$$

Sigmoid Function

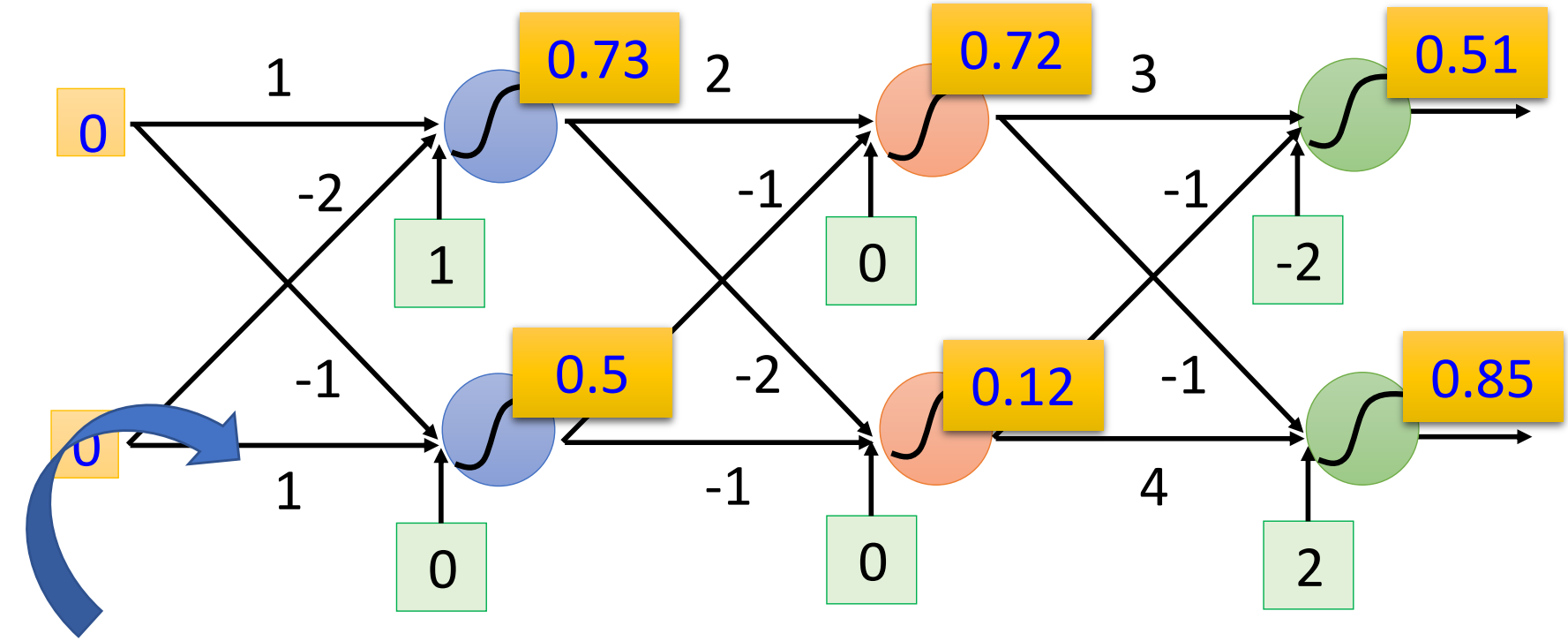
$$\sigma(z) = \frac{1}{1+e^{-z}}$$



Fully Connect Feedforward Network



Fully Connect Feedforward Network



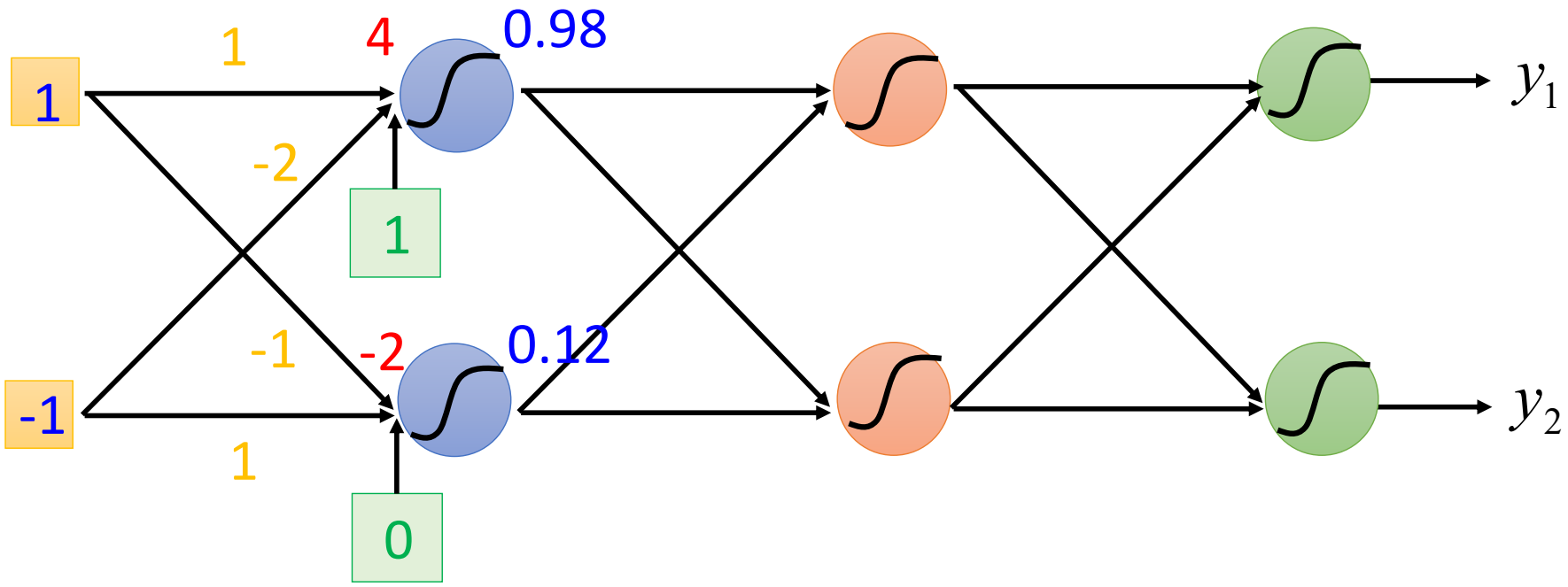
This is a function.

Input vector, output vector

$$f\left(\begin{bmatrix}1\\-1\end{bmatrix}\right)=\begin{bmatrix}0.62\\0.83\end{bmatrix} \quad f\left(\begin{bmatrix}0\\0\end{bmatrix}\right)=\begin{bmatrix}0.51\\0.85\end{bmatrix}$$

Given network structure, define ***a function set***

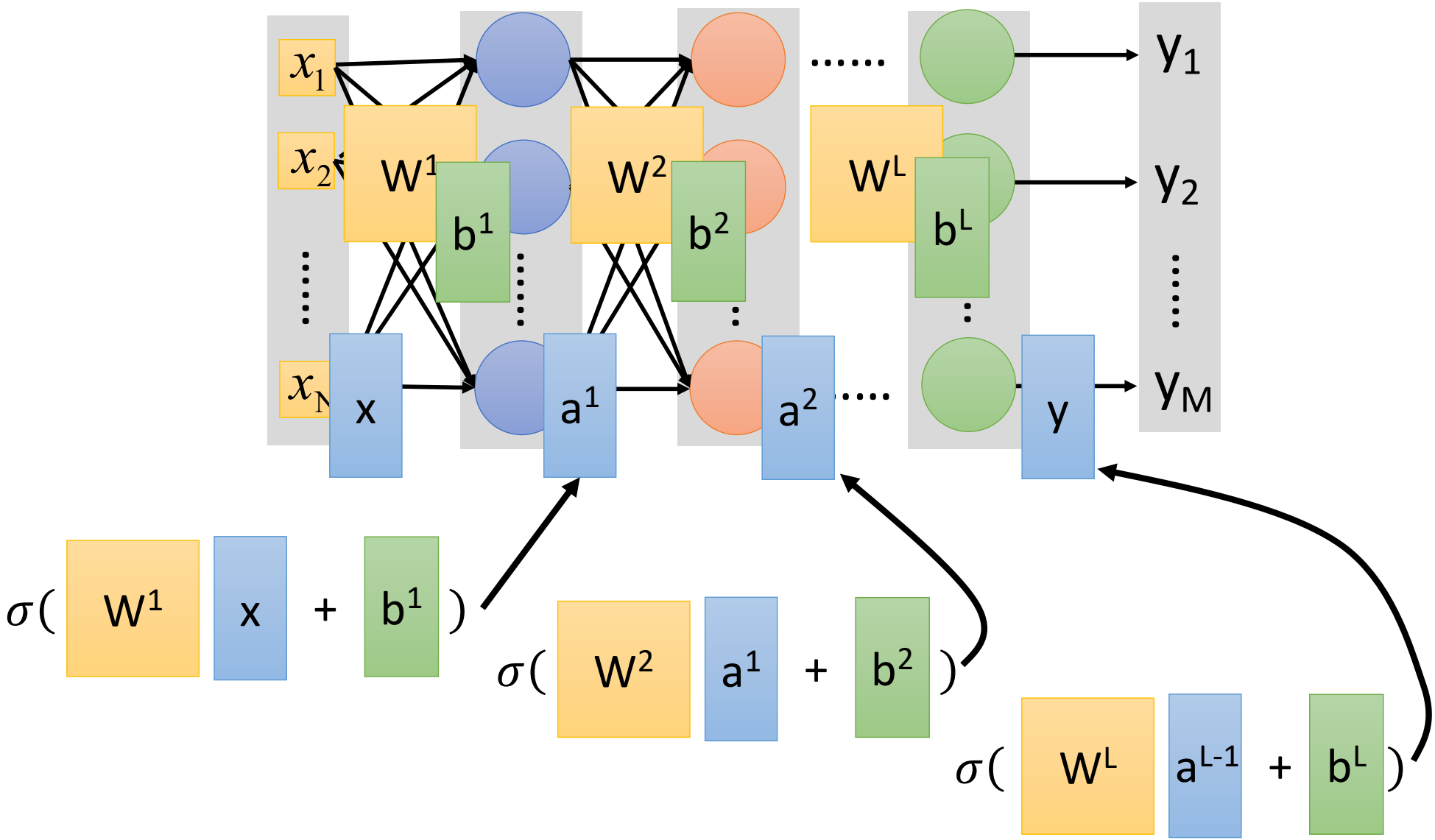
Matrix Operation



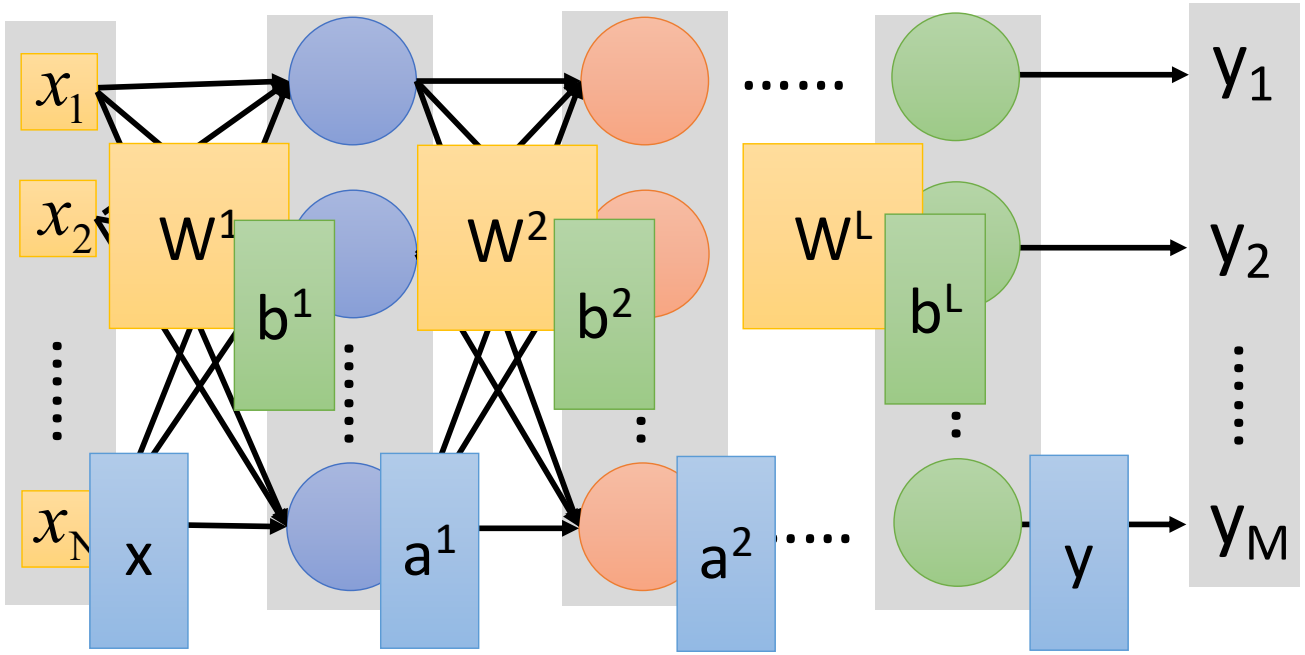
$$\sigma\left(\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

$$\begin{bmatrix} 4 \\ -2 \end{bmatrix}$$

Neural Network



Neural Network

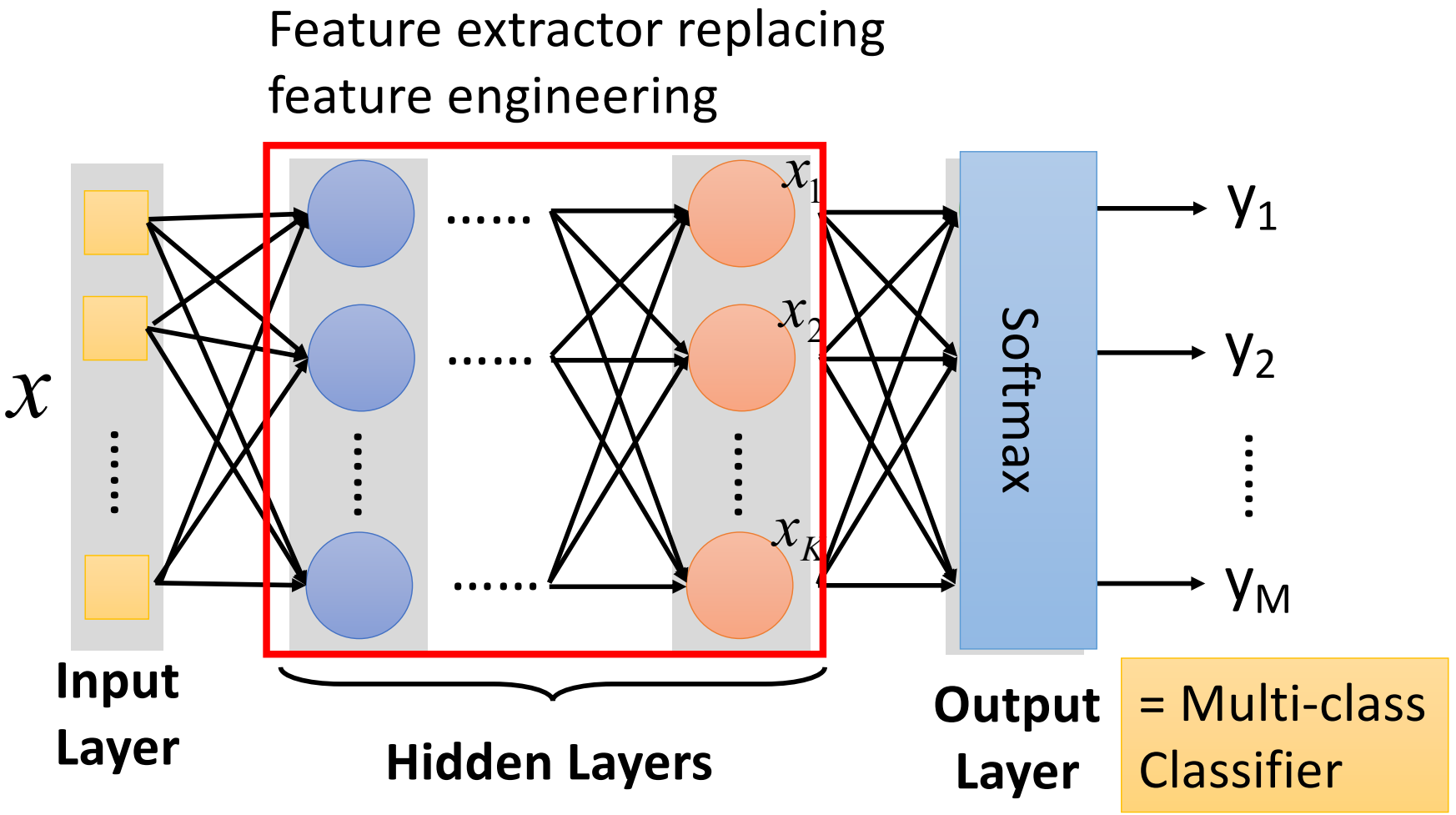


$$y = f(x)$$

Using parallel computing techniques to speed up matrix operation

$$= \sigma(W^L \cdots \sigma(W^2 \sigma(W^1 x + b^1) + b^2) \cdots + b^L)$$

Output Layer as Multi-Class Classifier

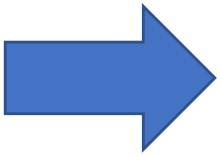


Softmax

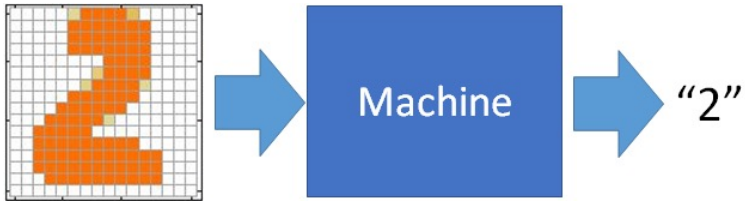
$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$

EX.

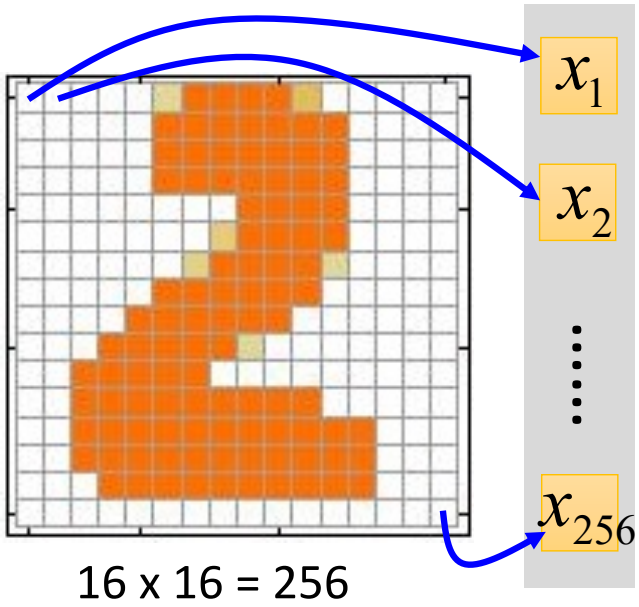
1.0	0.0236405
2.0	0.0642617
3.0	0.174681
4.0	0.474833
1.0	0.0236405
2.0	0.0642617
3.0	0.174681



Example Application



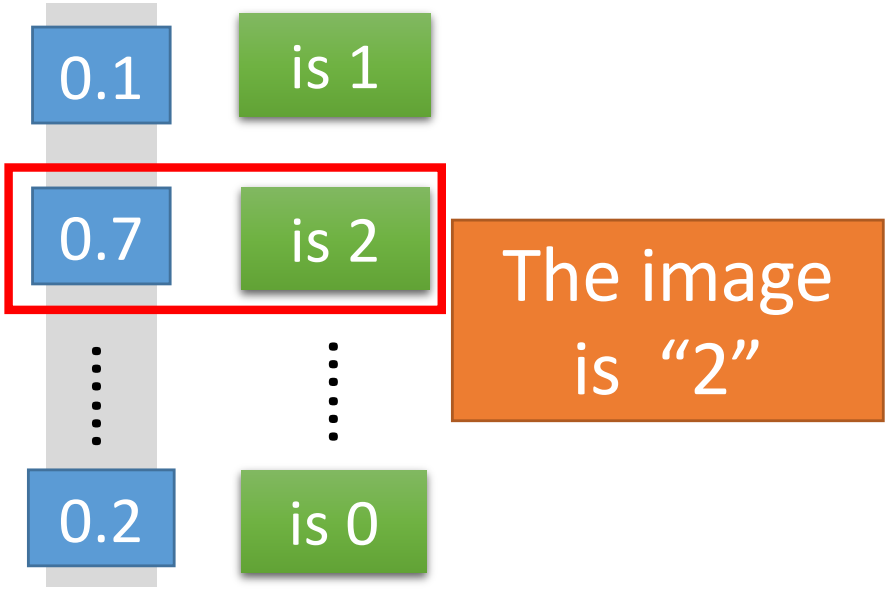
Input



Ink → 1

No ink → 0

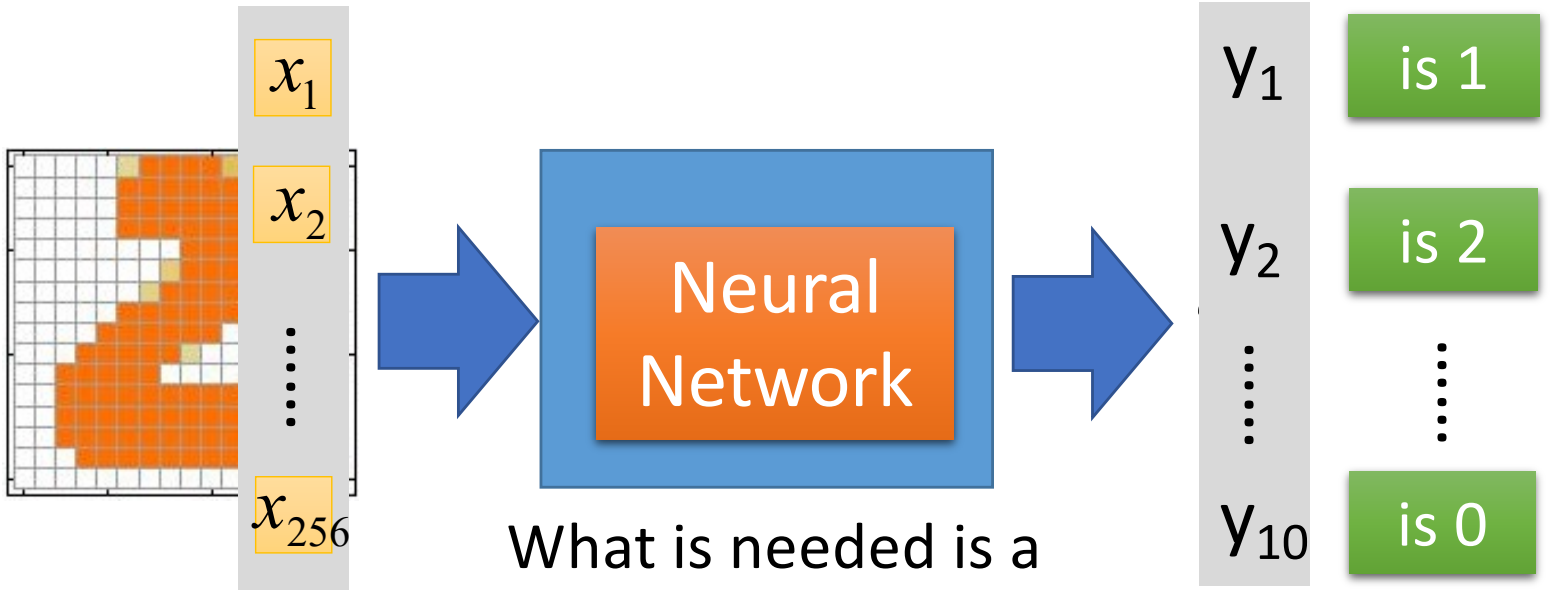
Output



Each dimension represents the confidence of a digit.

Example Application

- Handwriting Digit Recognition

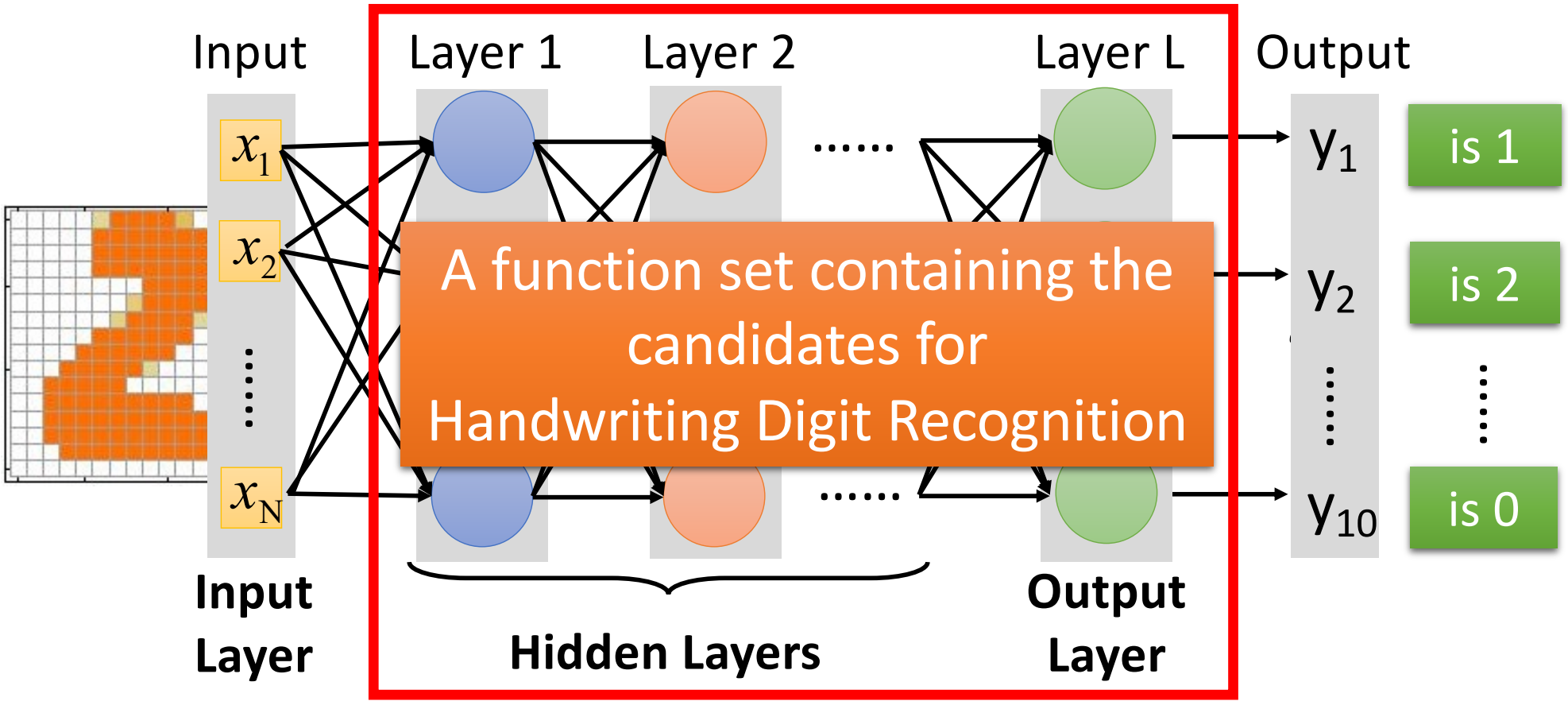


What is needed is a function ……

Input:
256-dim vector

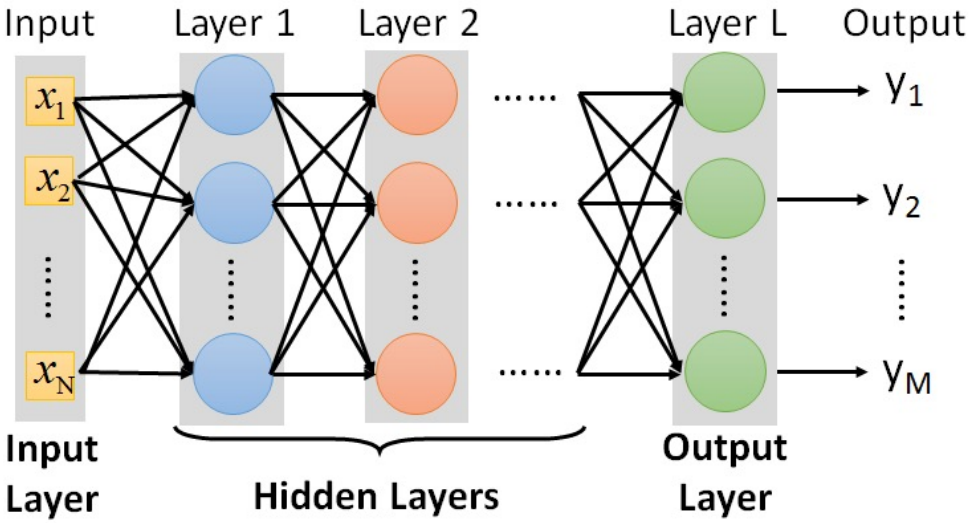
output:
10-dim vector

Example Application



You need to decide the network structure to let a good function in your function set.

FAQ



- Q: How many layers? How many neurons for each layer?

Trial and Error + Intuition

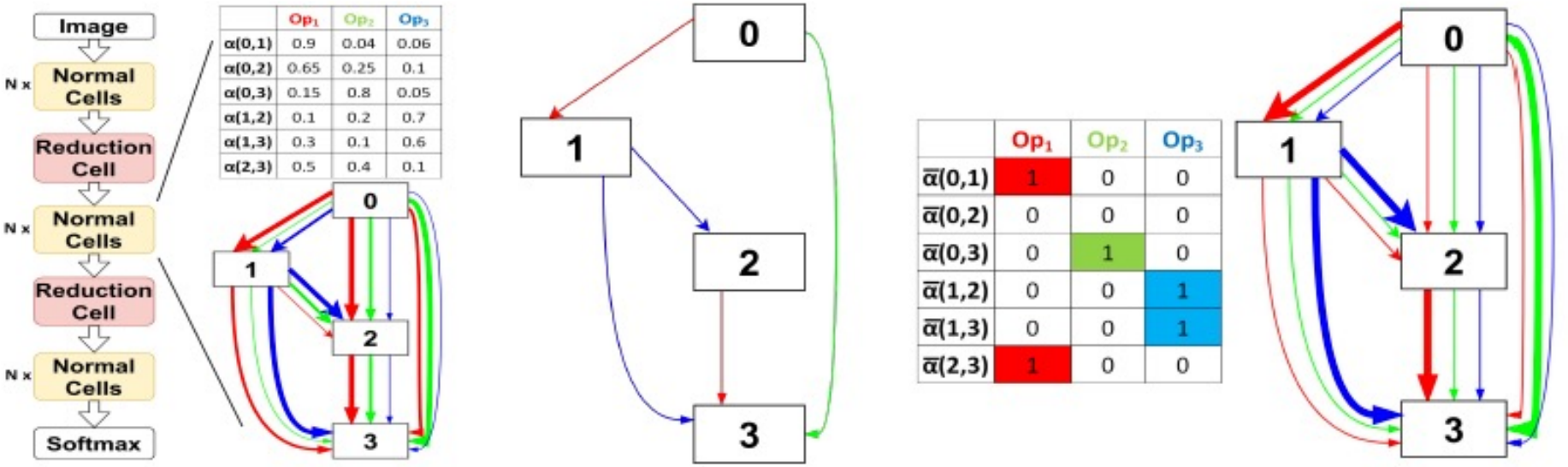
- Q: Can the structure be automatically determined?
  - E.g. Evolutionary Artificial Neural Networks
- Q: Can we design the network structure?

Convolutional Neural Network (CNN)

FAQ

- Q: Can the structure be automatically determined?
  - E.g. Evolutionary Artificial Neural Networks

N. Sinha and K.W. Chen, “Evolving Neural Architecture Using One Shot Model,” GECCO 2021.



FAQ

- Q: Can the structure be automatically determined?
  - E.g. Evolutionary Artificial Neural Networks

N. Sinha and K.W. Chen, “Evolving Neural Architecture Using One Shot Model,” GECCO 2021.

Architecture	Test Error (%) C10	C100	Params (M)	Search Time (GPU Days)	Search Method
DenseNet-BC [14]	3.46	17.18	25.6	-	manual
PNAS [18]	3.41	-	3.2	225	SMBO
NASNet-A [37]	2.65	-	3.3	1800	RL
ENAS [26]	2.86	-	4.6	0.45	RL
DARTS [21]	2.76 ± 0.09	17.54	3.3	4	gradient-based
GDAS [8]	2.93	18.38	3.4	0.83	gradient-based
SNAS [33]	2.85 ± 0.02	-	2.8	1.5	gradient-based
SETN [7]	2.69	17.25	4.6	1.8	gradient-based
PDARTS [2]	2.50	16.55	3.4	0.3	gradient-based
AmoebaNet-A [27]	3.34 ± 0.06	18.93	3.2	3150	evolution
Large-scale Evolution† [28]	5.4	-	5.4	2750	evolution
Hierarchical Evolution† [19]	3.75	-	15.7	300	evolution
NSGANetV1-A2 [24]	2.65	17.42	0.9	27	evolution
NSGA-NET [23]	2.75	-	3.3	4	evolution
RSPS[17]	2.86 ± 0.08	-	4.3	2.7	random
EvNAS-A (Ours)	**2.47±0.06**	**16.37**	**3.6**	**3.83**	**evolution**
EvNAS-B (Ours)	2.62 ± 0.06	16.51	3.8	3.83	evolution
EvNAS-C (Ours)	2.63 ± 0.05	16.86	3.4	3.83	evolution
EvNAS-Rand (Ours)	2.84 ± 0.08	-	2.7	0.62	random
EvNAS-ND (Ours)	2.78 ± 0.1	-	3.8	3.83	evolution
EvNAS-NDF (Ours)	2.75 ± 0.09	-	3.1	3.83	evolution
EvNAS-NDT (Ours)	2.67 ± 0.06	-	3.5	3.83	evolution
EvNAS-Mut (Ours)	2.79 ± 0.06	-	3.4	3.83	evolution
EvNAS-Cross (Ours)	2.81 ± 0.08	-	3.2	3.83	evolution

Training neural networks

- Collect a set of labeled training data $D = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{N}$
- Training neural networks: Finding network parameters $\theta = \{\mathbf{w}, \mathbf{b}\}$ to minimize the loss between true training label $\mathbf{y}_i$ and the estimated label, e.g.,

$$L(\theta) = \sum_{i=1}^{N} \|\mathbf{y}_i - g_{\mathbf{w}}(\mathbf{x}_i)\|^2$$

- Minimization can be done by gradient descent if $L(\cdot)$ is differentiable with respect to θ
- Back-propagation: a widely used method for optimizing multi-layer neural networks

Gradient Descent

Network parameters $\theta = \{w_1, w_2, \cdots, b_1, b_2, \cdots\}$

Starting Parameters $\theta^0 \longrightarrow \theta^1 \longrightarrow \theta^2 \longrightarrow \cdots\cdots$

$$\nabla L(\theta) = \begin{bmatrix} \partial L(\theta)/\partial w_1 \\ \partial L(\theta)/\partial w_2 \\ \vdots \\ \partial L(\theta)/\partial b_1 \\ \partial L(\theta)/\partial b_2 \\ \vdots \end{bmatrix}$$

$Compute\ \nabla L(\theta^0)$ $\quad \theta^1 = \theta^0 - \eta \nabla L(\theta^0)$

$Compute\ \nabla L(\theta^1)$ $\quad \theta^2 = \theta^1 - \eta \nabla L(\theta^1)$

Millions of parameters ……

To compute the gradients efficiently, we use ***backpropagation***.

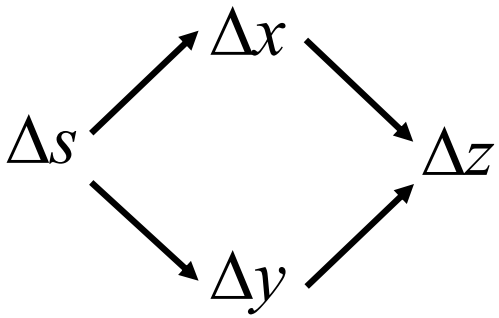
Chain Rule

Case 1 $y = g(x) \quad z = h(y)$

$$\Delta x \to \Delta y \to \Delta z \qquad \frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx}$$

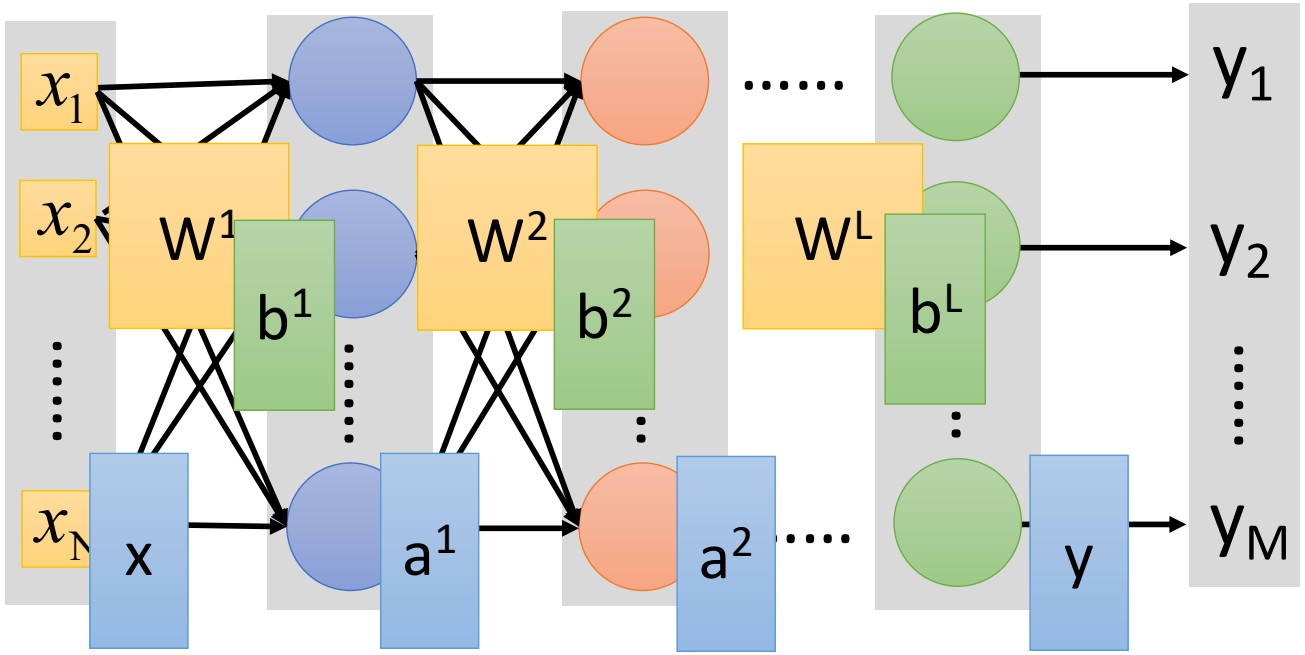
Case 2

$$x = g(s) \qquad y = h(s) \qquad z = k(x, y)$$



$$\frac{dz}{ds} = \frac{\partial z}{\partial x}\frac{dx}{ds} + \frac{\partial z}{\partial y}\frac{dy}{ds}$$

Neural Network



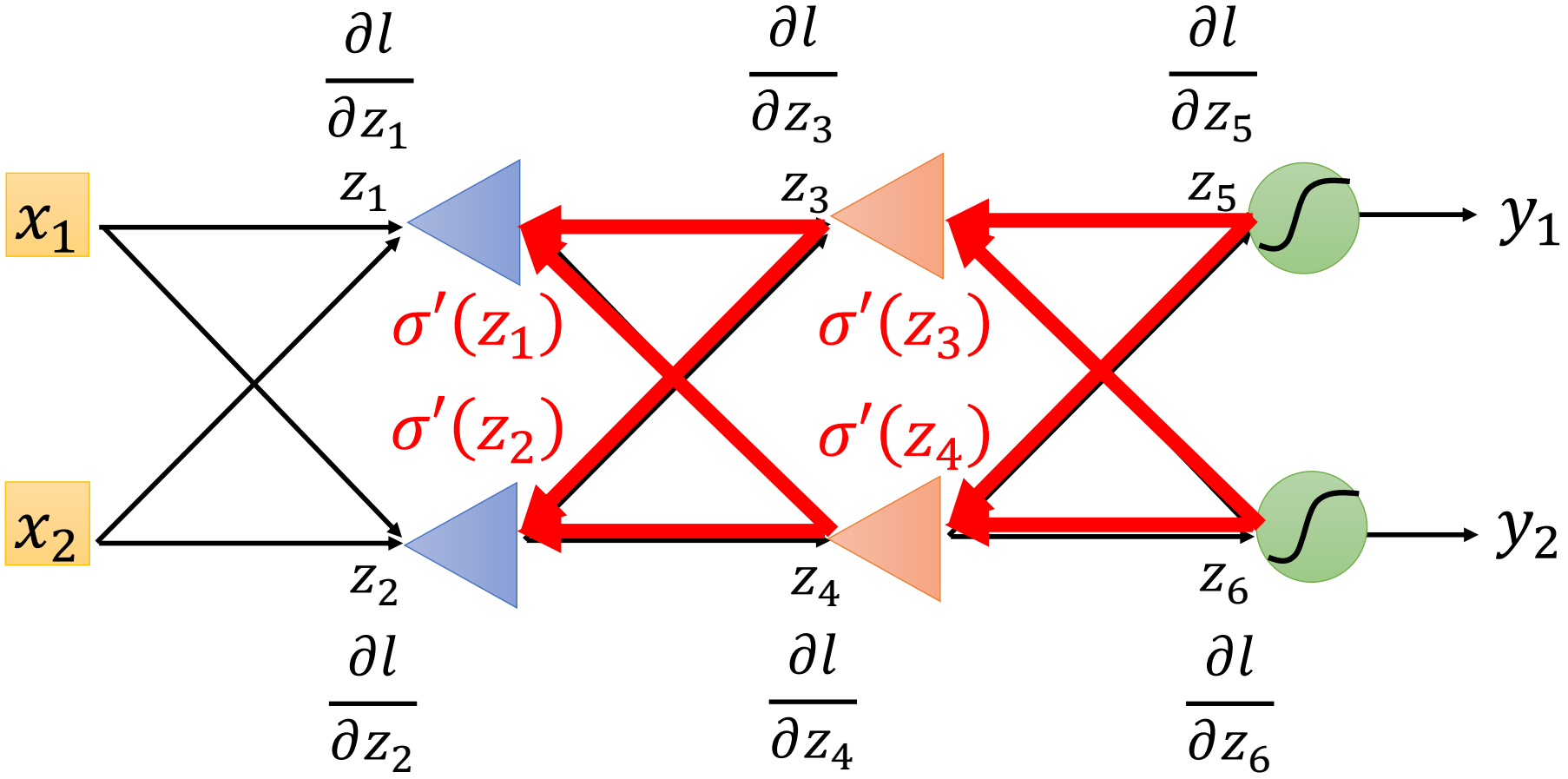
$$y = f(x)$$

$$= \sigma(W^L \cdots \sigma(W^2 \sigma(W^1 x + b^1) + b^2) \cdots + b^L)$$

Backpropagation – Backward Pass

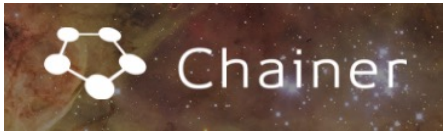
Compute $\partial l/\partial z$ for all activation function inputs z

Compute $\partial l/\partial z$ from the output layer



Backpropagation

- Backpropagation: an efficient way to compute $\partial L/\partial w$ in neural network

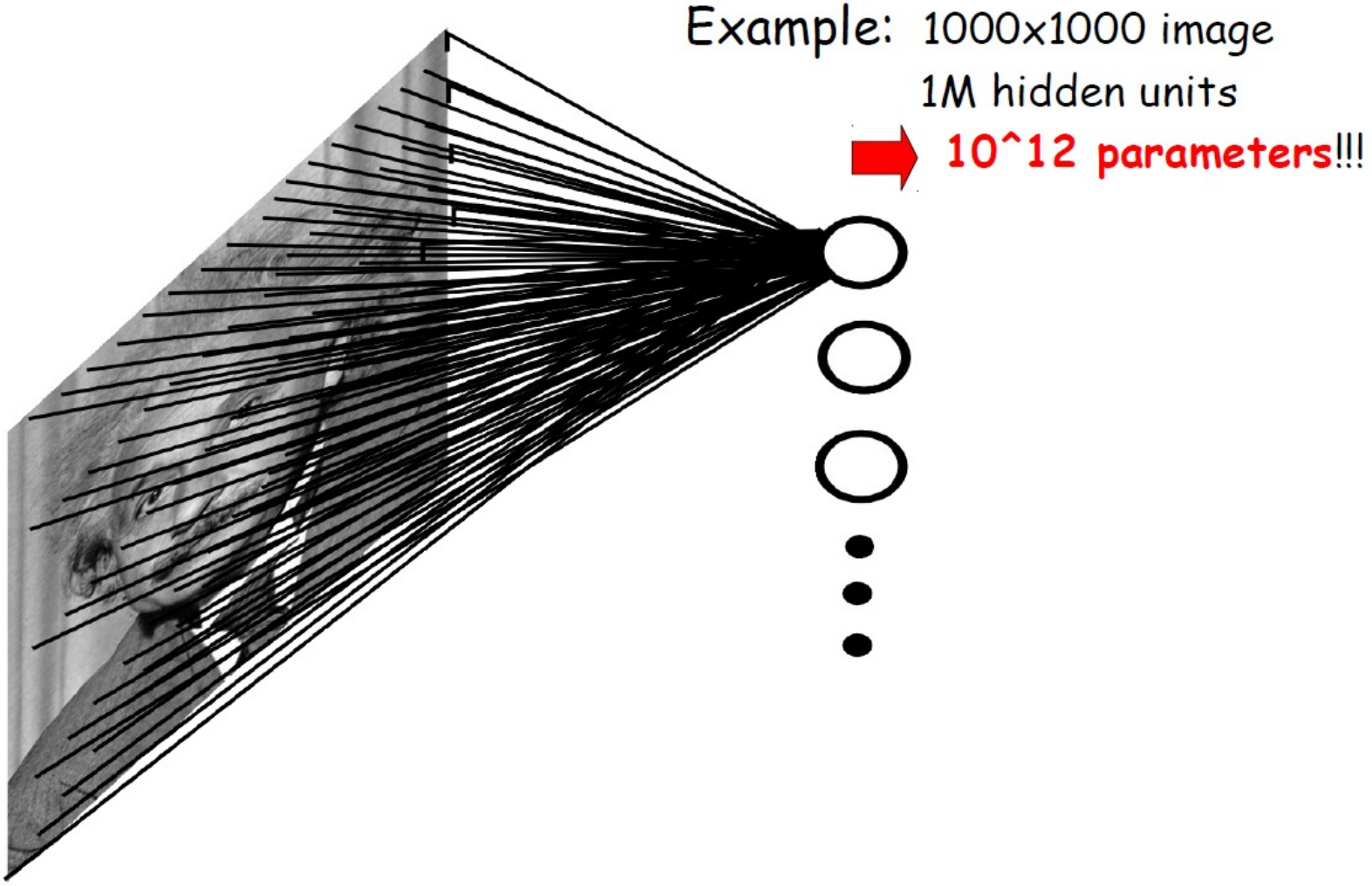


libdnn
台大周伯威
同學開發

Ref:
http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20backprop.ecm.mp4/index.html

Convolutional Neural Networks (CNN)

of parameters in fully connected NN



slide: MA Ranzato

What makes deep learning successful in computer vision?

Li Fei-Fei

IMAGENET

Geoffrey Hinton

Data collection

One million images with labels

Evaluation task

Predict 1,000 image categories

Deep learning

CNN is not new

Design network structure

New training strategies

A. Krizhevsky, L. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," NIPS, 2012.

Convolutional neural networks (CNN)

- CNN: a multi-layer neural network with
  1. Local connectivity
  2. Weight sharing
- Why local connectivity?
  - Spatial correlation is local (locality of spatial dependencies)
  - Reduce # of parameters
- Why weight sharing?
- Statistics is at different locations (stationarity of statistics)
  - Reduce # of parameters

Why Local Connectivity

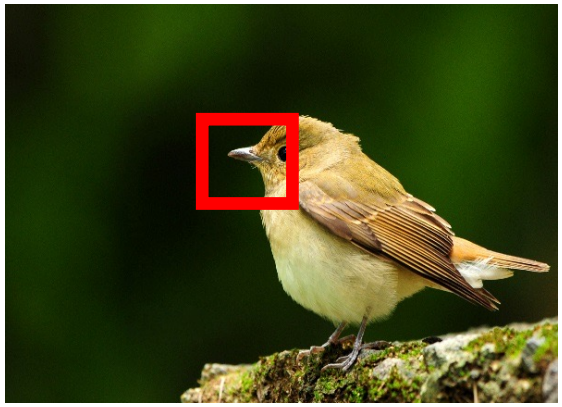
- Some patterns are much smaller than the whole image

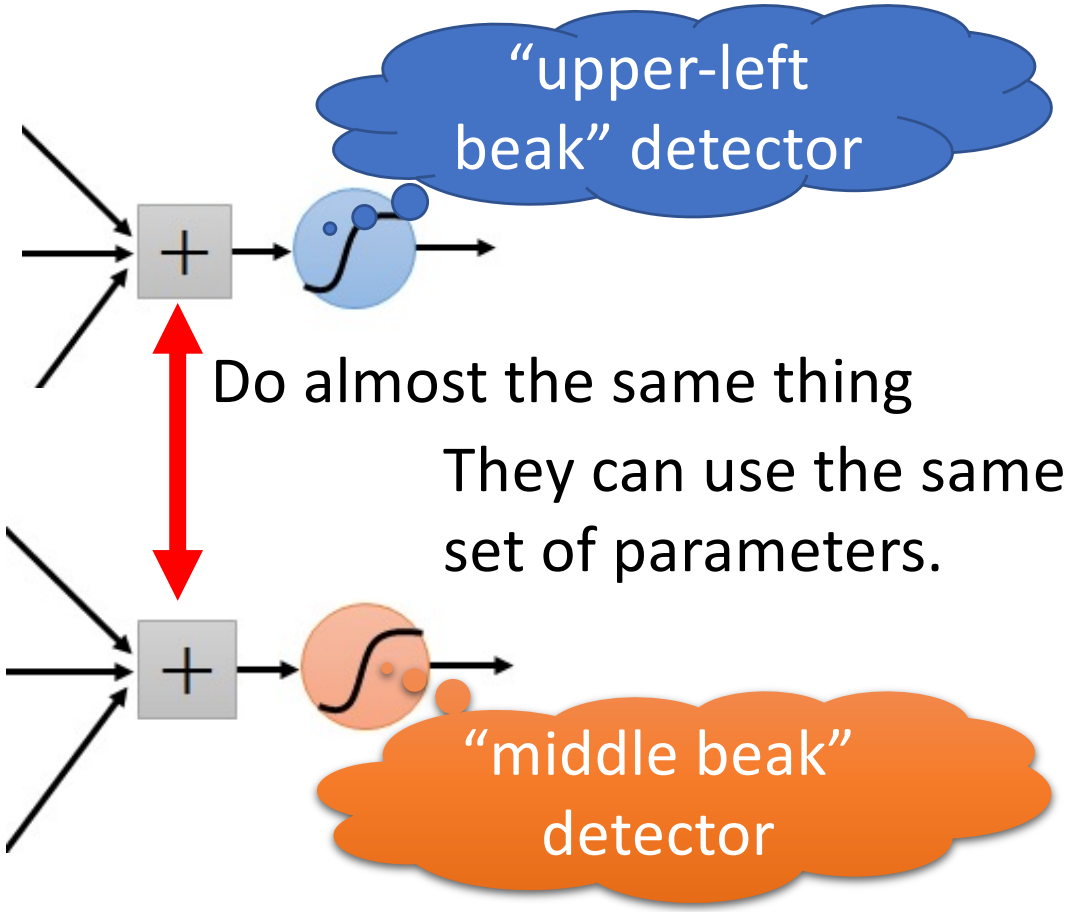
A neuron does not have to see the whole image to discover the pattern.

Connecting to small region with less parameters

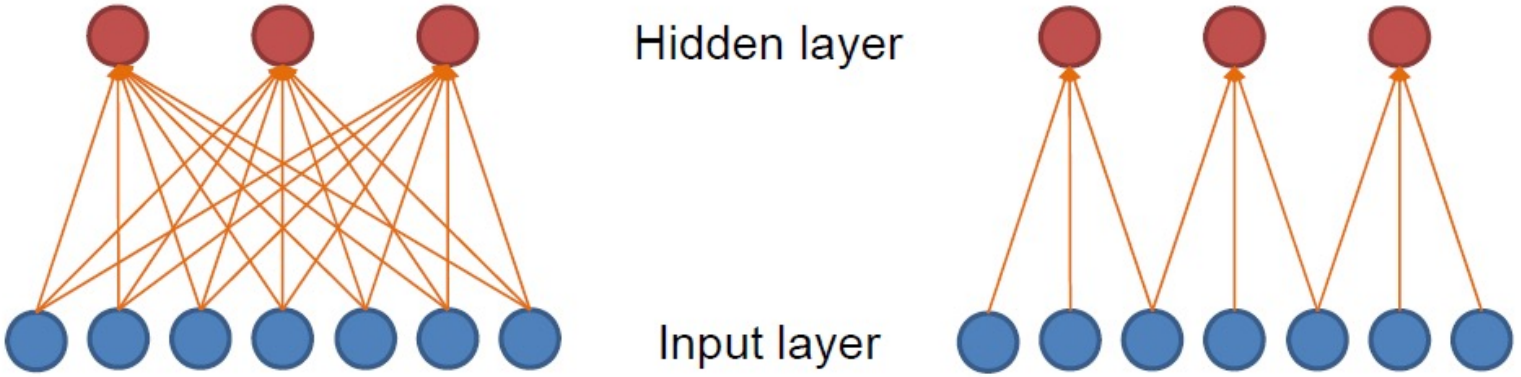
Why Weight Sharing

- The same patterns appear in different regions.





CNN: Local connectivity



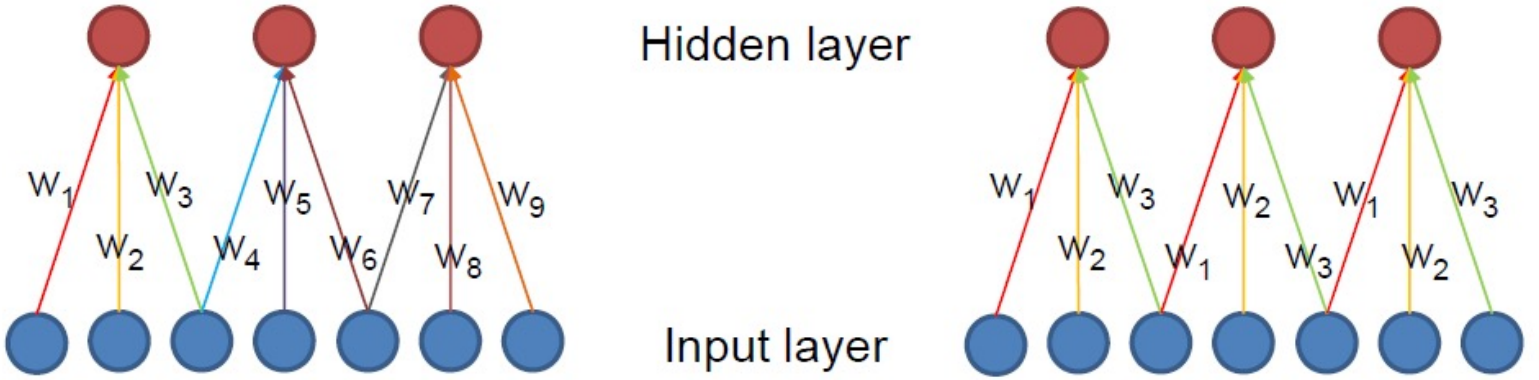
Global connectivity

Local connectivity

- # input units (neurons): 7
- # hidden units: 3
- Number of parameters
  - Global connectivity: 3 x 7 = 21
  - Local connectivity: 3 x 3 = 9

slide: J.-B. Huang

CNN: Weight sharing



Without weight sharing

With weight sharing

- # input units (neurons): 7
- # hidden units: 3
- Number of parameters
  - Without weight sharing: 3 x 3 = 9
  - With weight sharing : 3 x 1 = 3

slide: J.-B. Huang

Why CNN for Image

- Subsampling the pixels will not change the object

bird

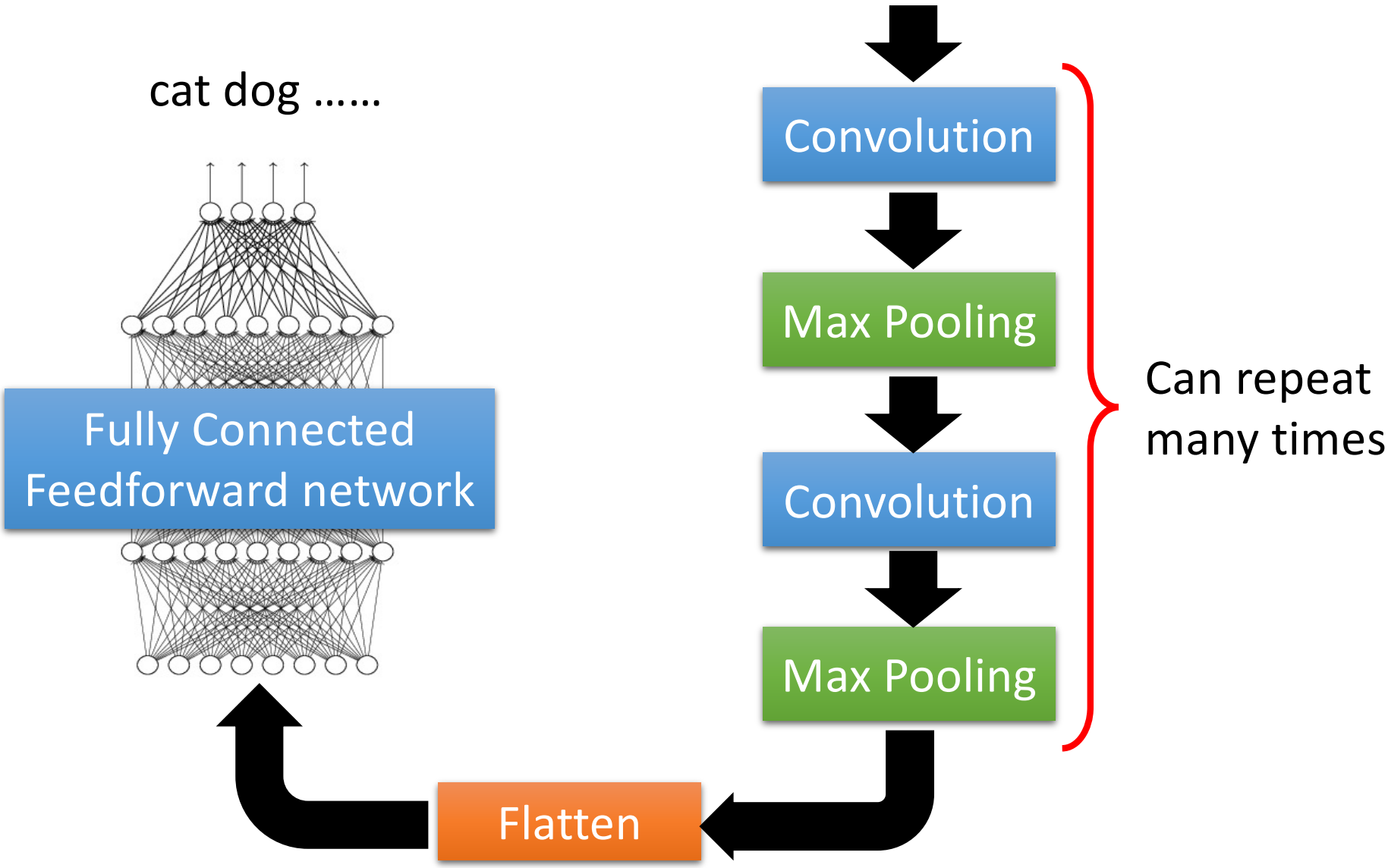
subsampling

bird

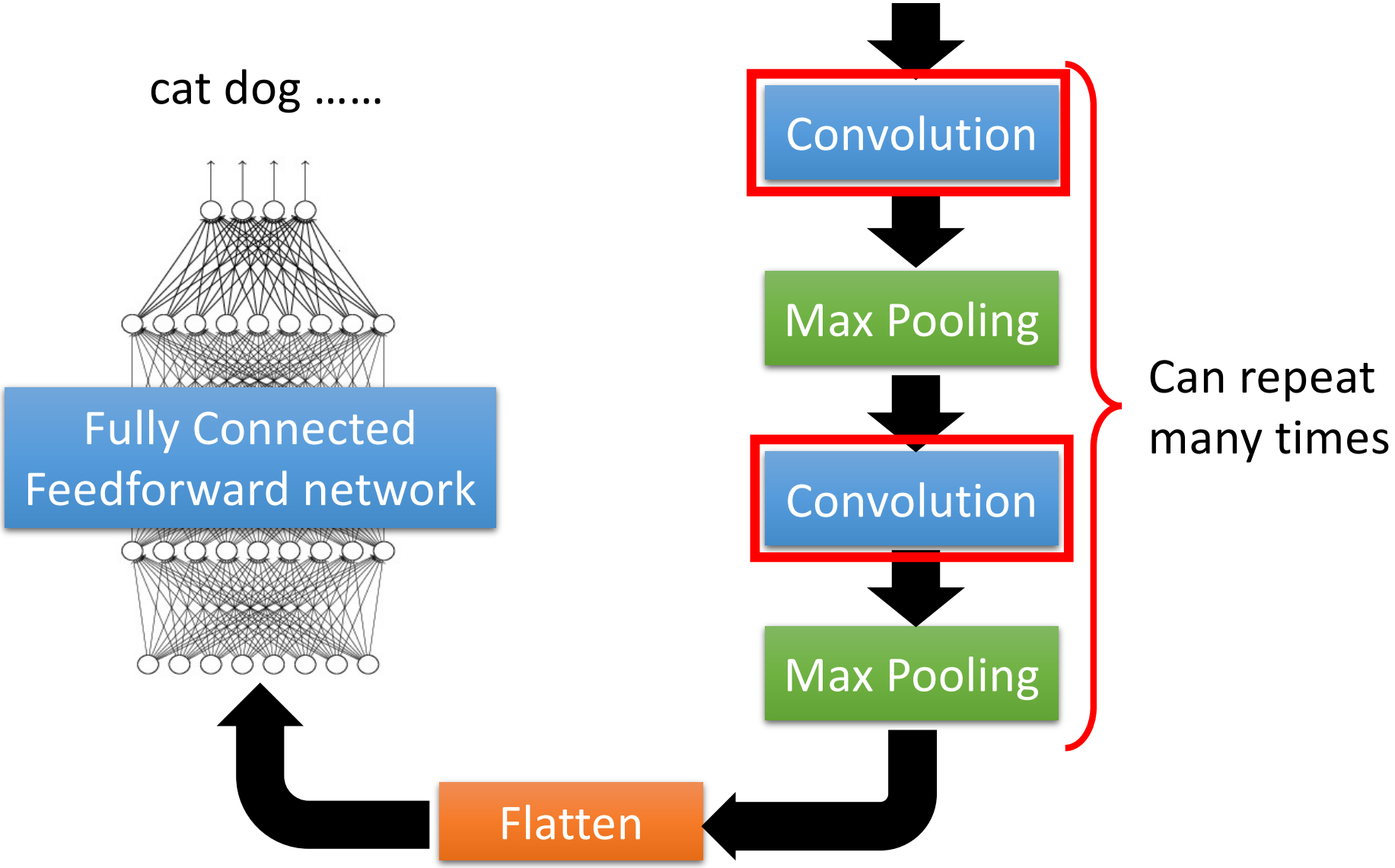
We can subsample the pixels to make image smaller

→ Less parameters for the network to process the image

The whole CNN



The whole CNN



CNN – Convolution

Those are the network parameters to be learned.

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

Matrix

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

Filter 2

Matrix

⋮

Property 1

Each filter detects a small pattern (3 x 3).

CNN – Convolution

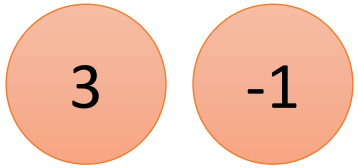
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

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



CNN – Convolution

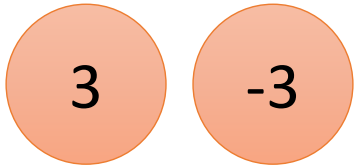
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

If stride=2

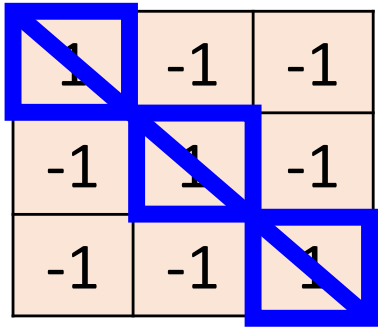
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image



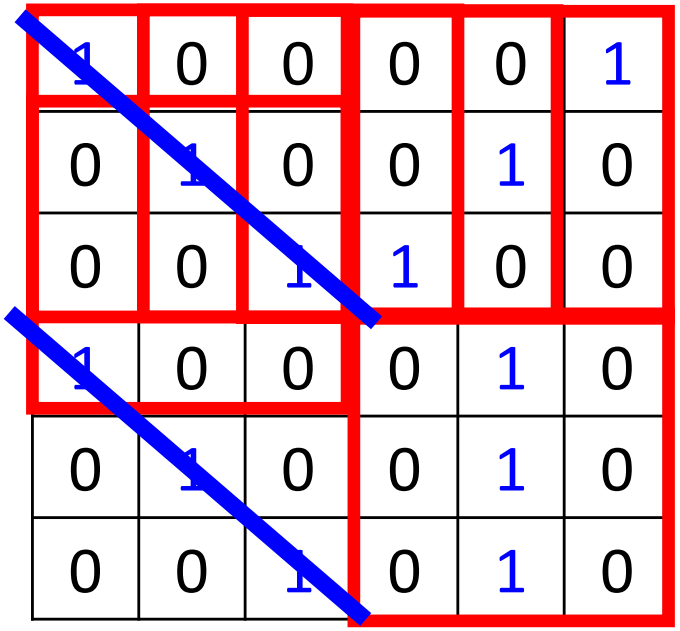
We set stride=1 below

CNN – Convolution

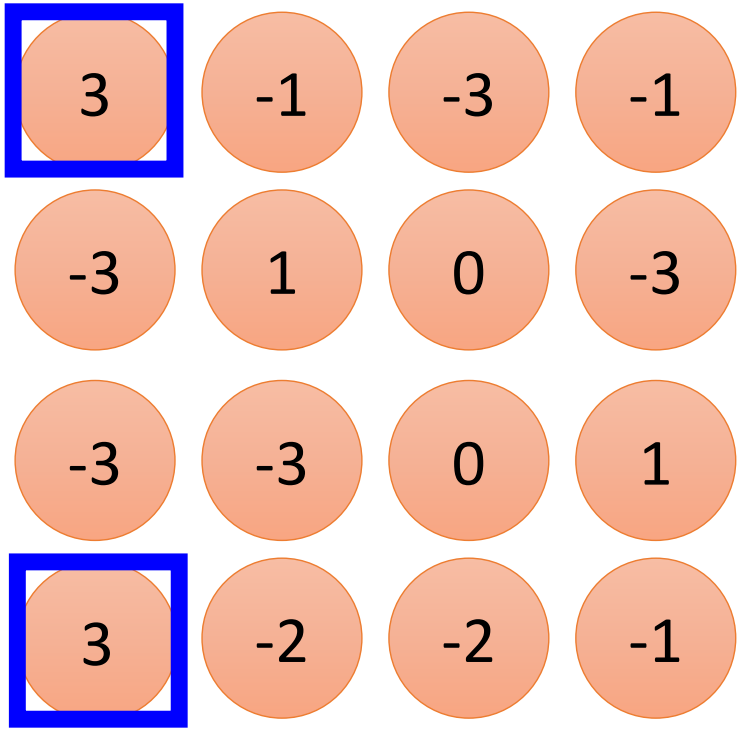


Filter 1

stride=1



6 x 6 image



Property 2

CNN – Convolution

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

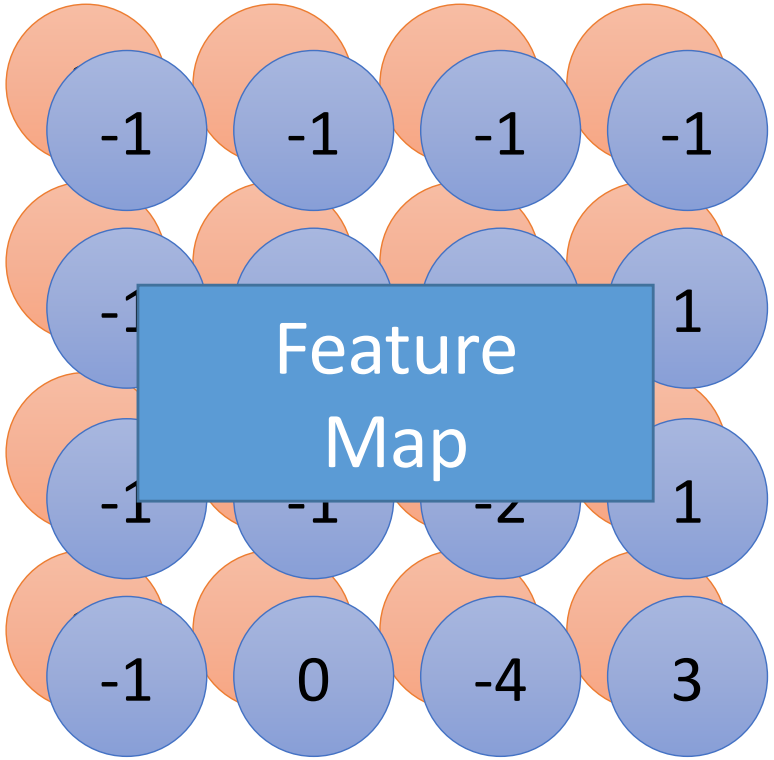
Filter 2

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

Do the same process for every filter



4 x 4 image

CNN – Colorful image

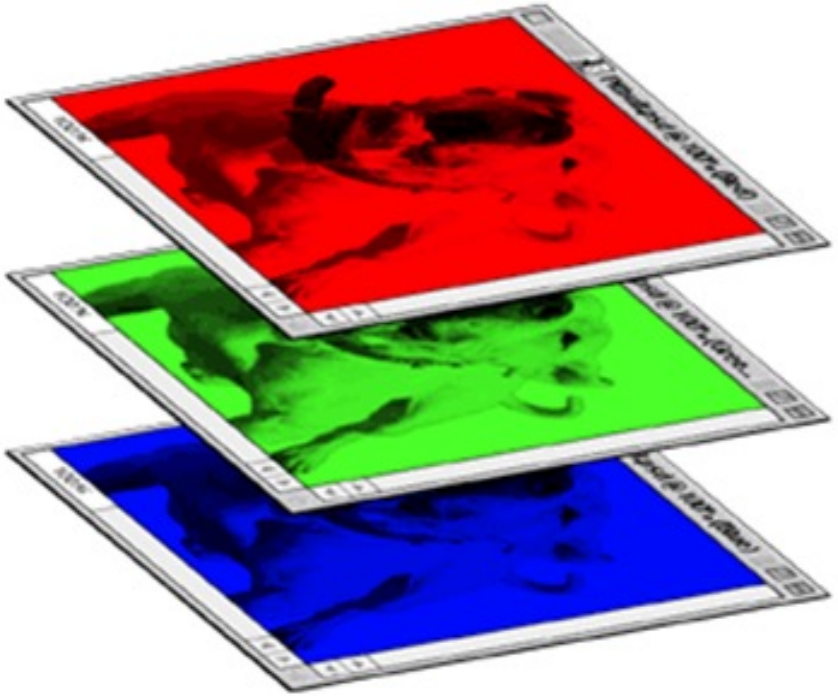
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

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

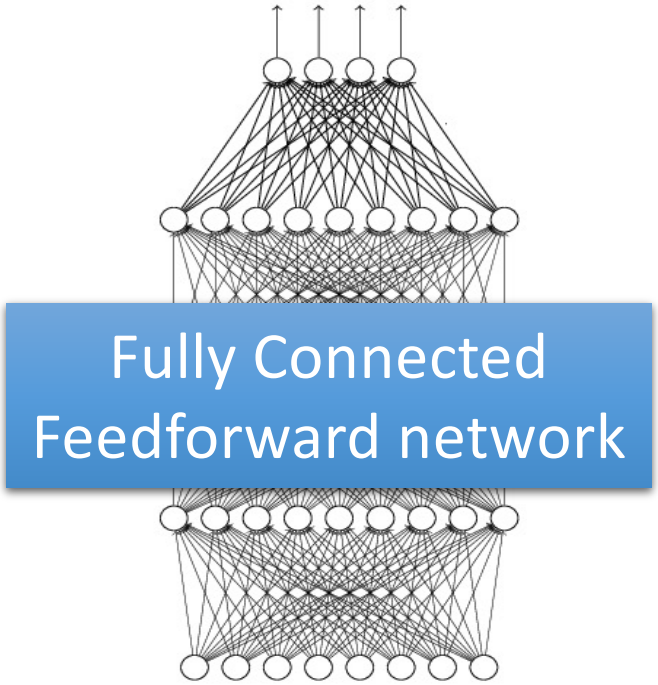
Filter 2

Colorful image



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

The whole CNN



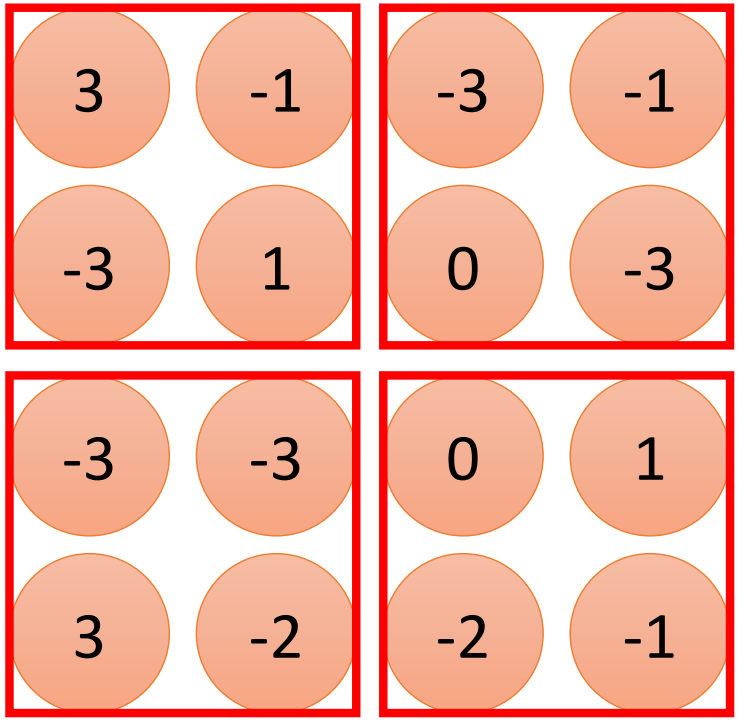
CNN – Max Pooling

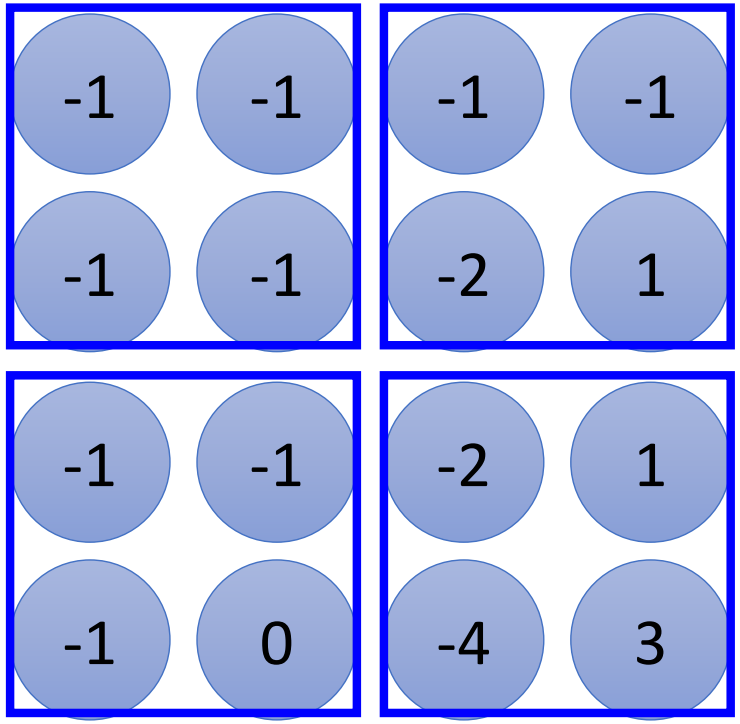
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

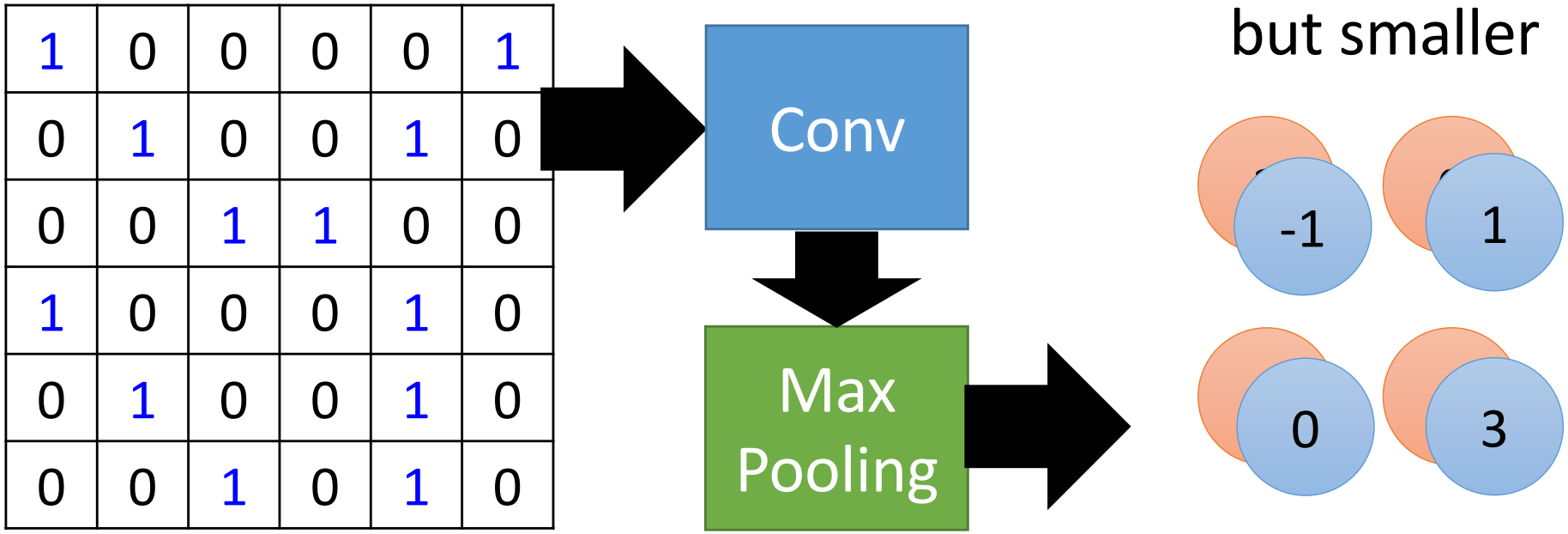
-1	1	-1
-1	1	-1
-1	1	-1

Filter 2





CNN – Max Pooling

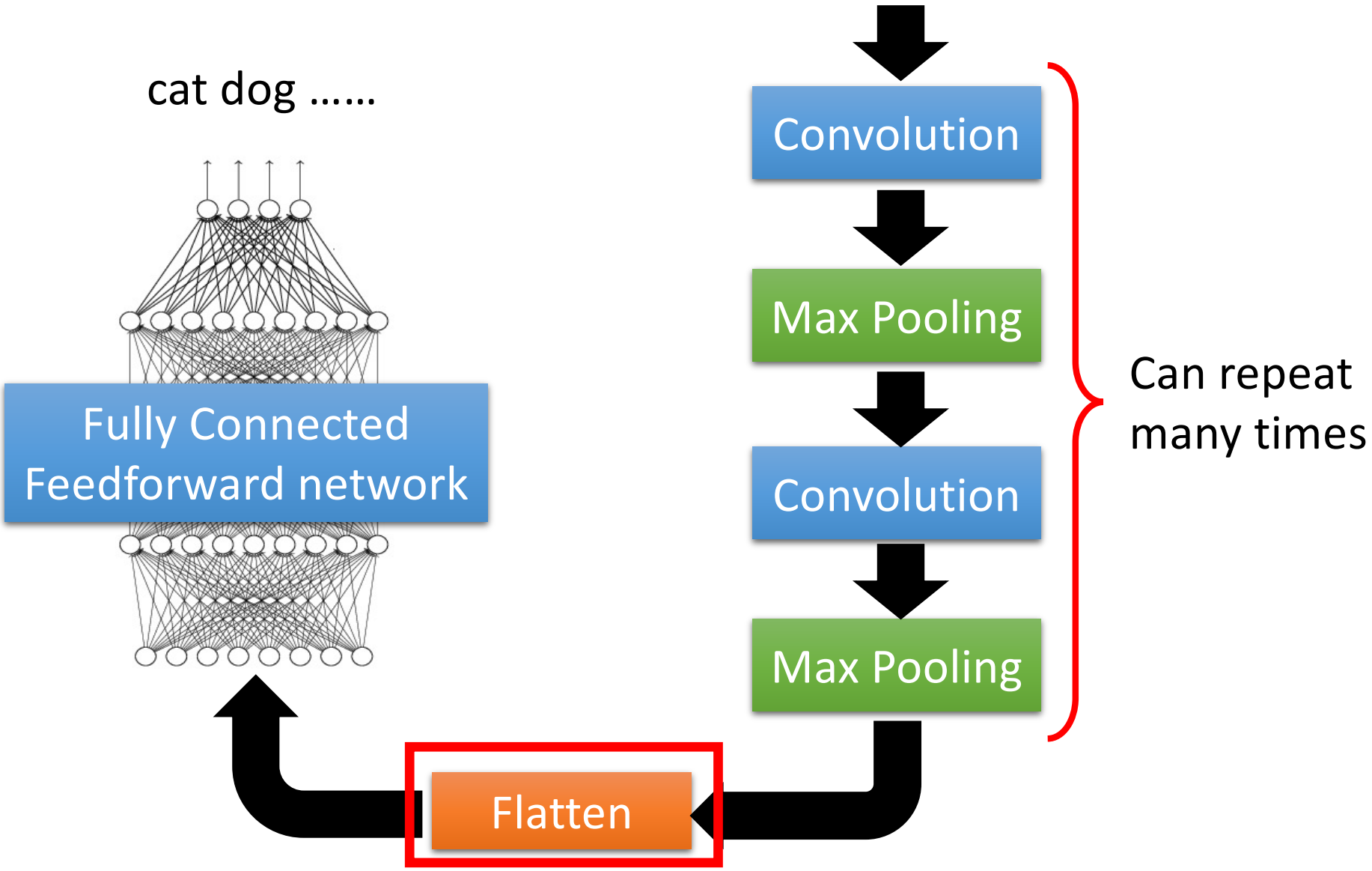


6 x 6 image

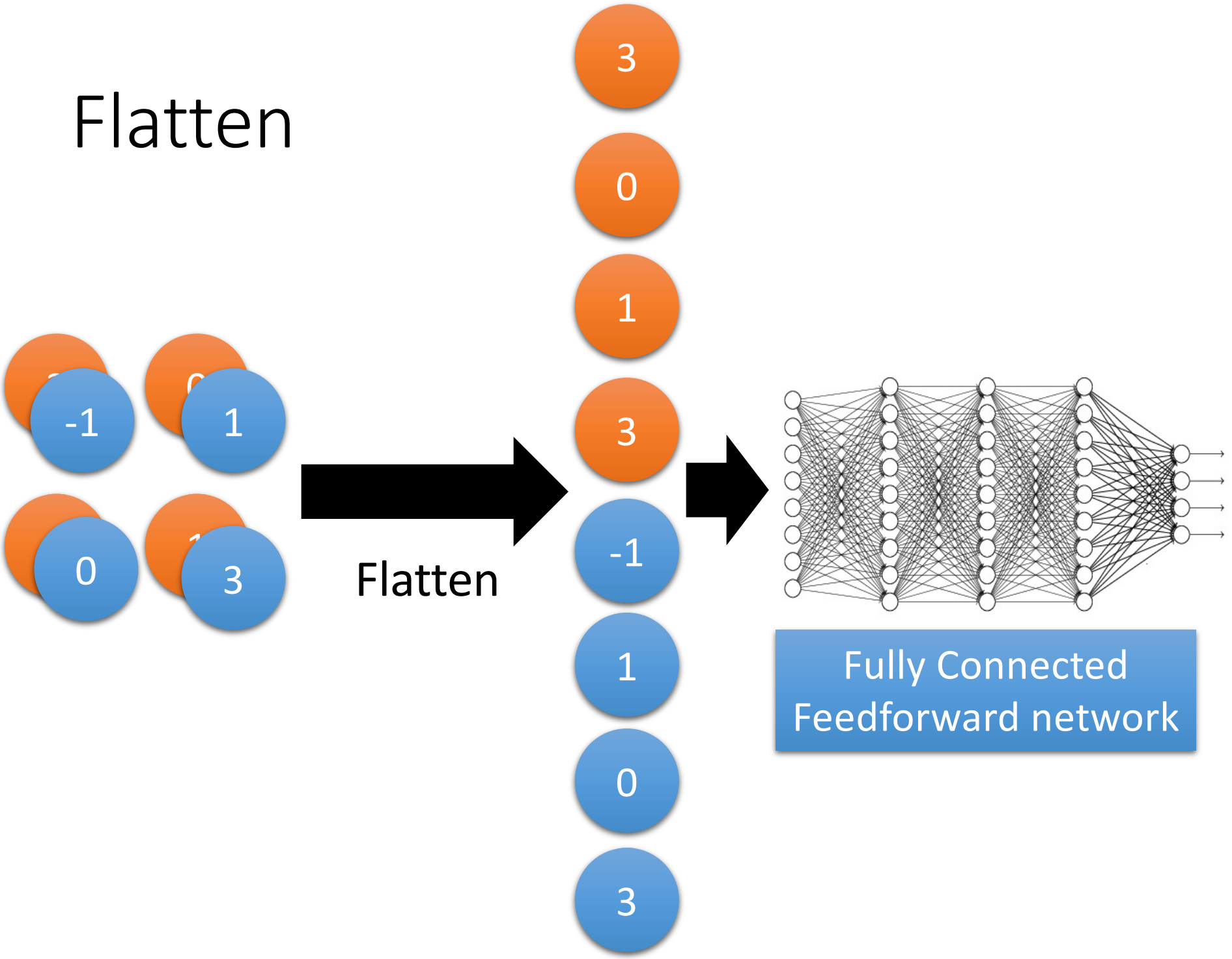
2 x 2 image

Each filter is a channel

The whole CNN



Flatten


-1
1
0
3
Flatten
3
0
1
3
-1
1
0
3
Fully Connected
Feedforward network

What makes deep learning successful in computer vision?

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IMAGENET

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Data collection

One million images with labels

Evaluation task

Predict 1,000 image categories

Deep learning

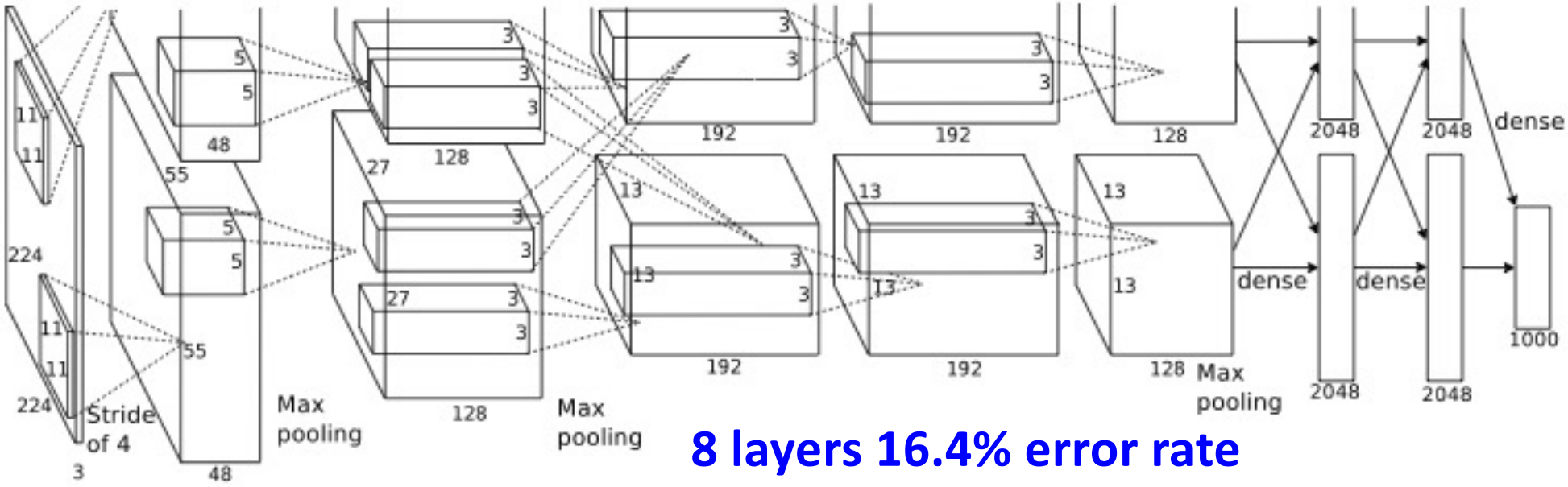
CNN is not new

Design network structure

New training strategies

A. Krizhevsky, L. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," NIPS, 2012.

Modern CNN: AlexNet



8 layers 16.4% error rate

Input: 224*224*3=**150K**

Neurons: 290400+186624+64896+64896+43264+4096+4096+1000=**650K**

Weights: 11*11*3*48*2(35K)+5*5*48*128*2(307K)+128*3*3*192*4(884K)+ 192*3*3*192*2(663K)+192*3*3*128*2(442K)+6*6*128*2048*4(38M)+4096*4096(17M)+4096*1000(4M)=**60M**

- **More data (1.2M)**
- **Trained on two GPUs for a week**
- **Dropout**

slide: M. Sun

ImageNet ISLVRC 2012-2014

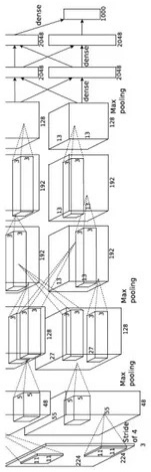
Best non-convnet in 2012: 26.2%

Team	Year	Place	Error (top-5)	External data
SuperVision – Toronto (7 layers)	2012	-	16.4%	no
SuperVision	2012	1st	15.3%	ImageNet 22k
Clarifai – NYU (7 layers)	2013	-	11.7%	no
Clarifai	2013	1st	11.2%	ImageNet 22k
VGG – Oxford (16 layers)	2014	2nd	7.32%	no
GoogLeNet (19 layers)	2014	1st	6.67%	no
Human expert*			5.1%	

slide: J.-B. Huang

Deep = Many hidden layers

8 layers



16.4%

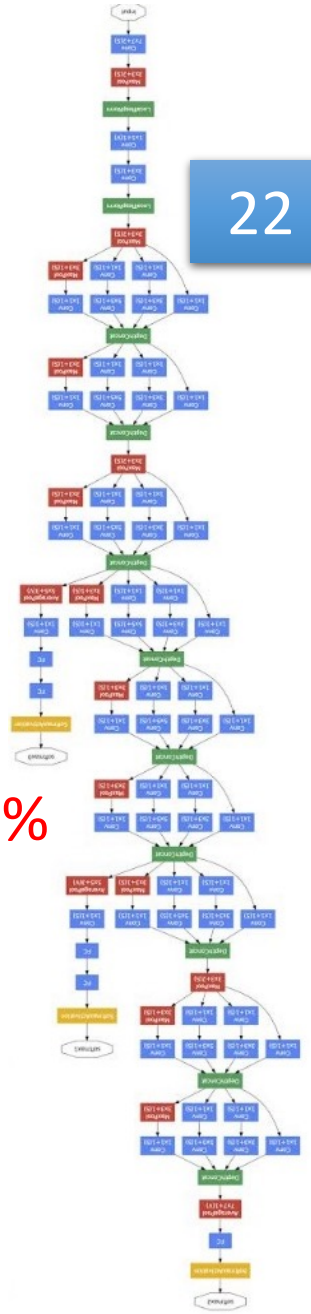
AlexNet (2012)

19 layers

7.3%

VGG (2014)

22 layers



6.7%

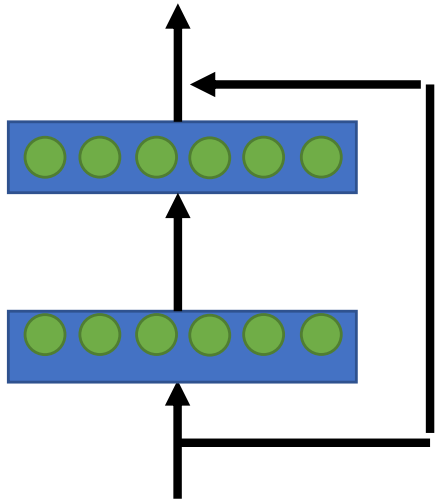
GoogleNet (2014)

Deep = Many hidden layers

152 layers

101 layers

Special structure



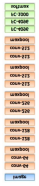
Ref:
https://www.youtube.com/watch?v=dxB6299gpvI

16.4%

7.3%

6.7%

3.57%



AlexNet (2012)

VGG (2014)

GoogleNet (2014)

Residual Net (2015)

Taipei 101

http://www.image-net.org/

IMAGENET

14,197,122 images, 21841 synsets indexed

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ImageNet is an image database organized according to the WordNet hierarchy (currently only the nouns), in which each node of the hierarchy is depicted by hundreds and thousands of images. Currently we have an average of over five hundred images per node. We hope ImageNet will become a useful resource for researchers, educators, students and all of you who share our passion for pictures.

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What do these images have in common? *Find out!*

Research updates on improving ImageNet data

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How we teach computers to understand pictures – Fei Fei Li