مقرر التعلم التلقائي | السنة الخامسة – هندسة المعلوماتية / الذكاء الصنعي | Week 10

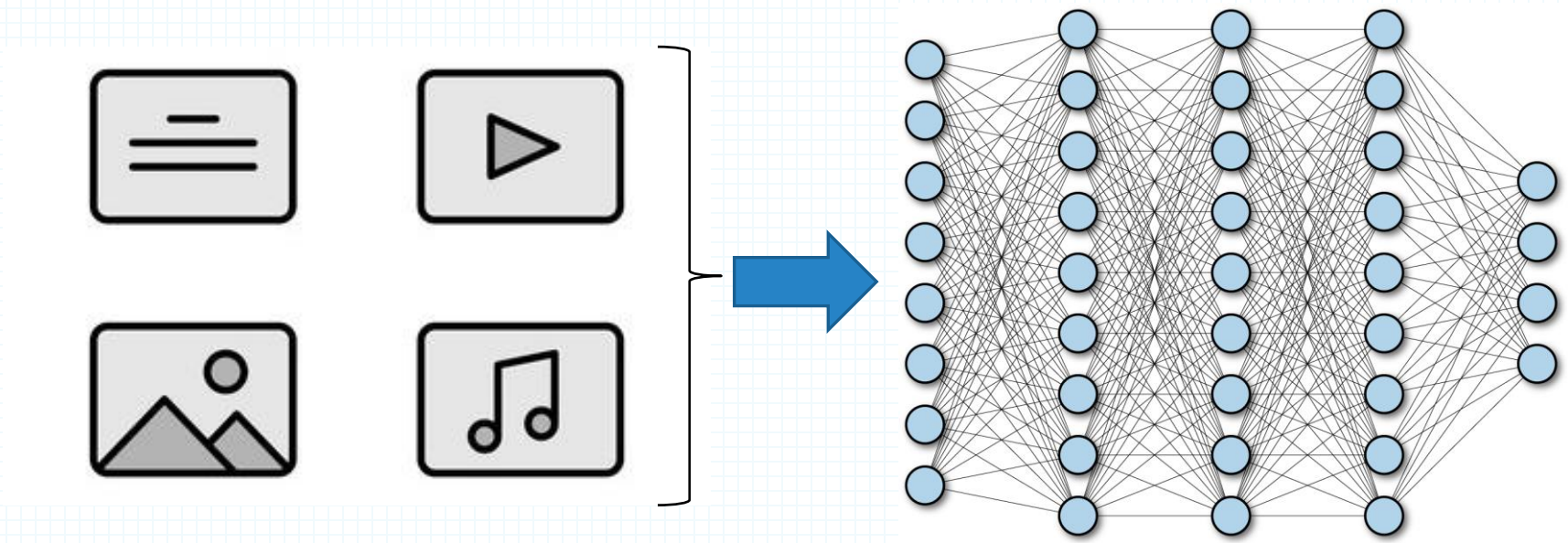
Well Known DL Architecture (till 2016)
CNN, RNN, LSTM

Dr. Riad Sonbol

Access Course Materials

Large networks

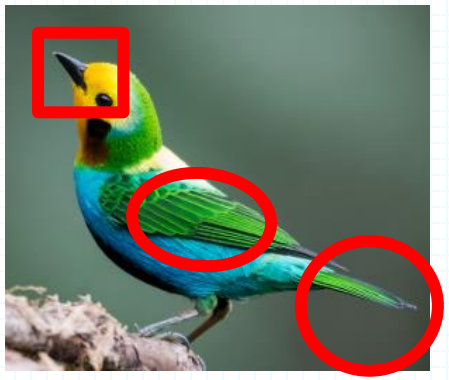
- What kind of neural networks can be used for large or variable length input vectors (e.g., time series)?
- Common networks:
  - CNN, RNN, etc



الشبكة العصبونية التلافيفية
Convolutional Neural Network (CNN)

Convolutions for feature extraction

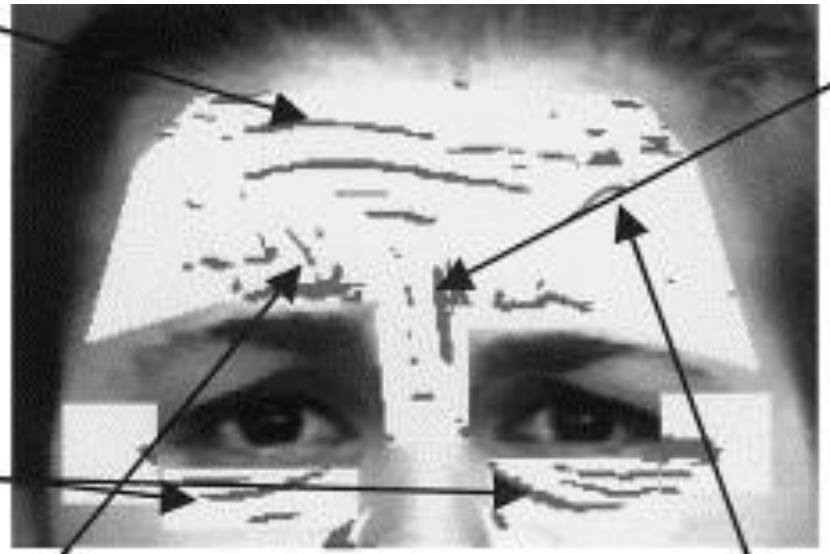
The same patterns appear in different regions.



Convolutions for feature extraction

Horizontal Line Detection

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



Vertical Line Detection

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

135^0 Diagonal Line Detection

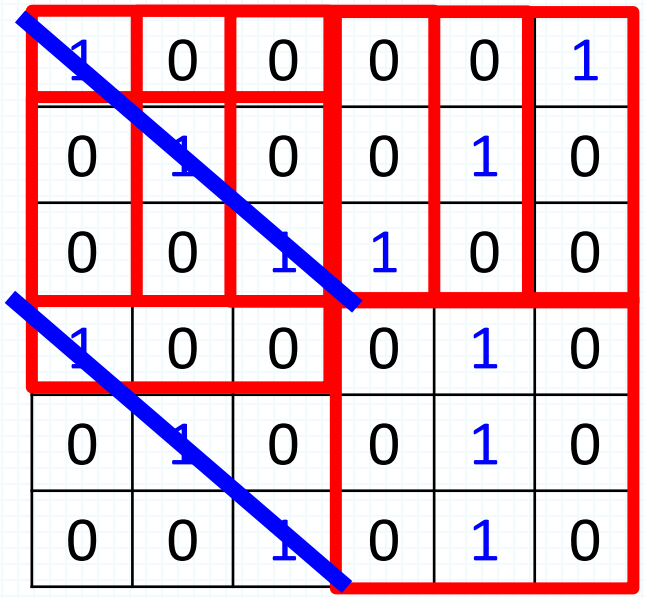
0	1	0	0	0
-1	0	1	0	0
0	-1	0	1	0
0	0	-1	0	1
0	0	0	-1	0

45^0 Diagonal Line Detection

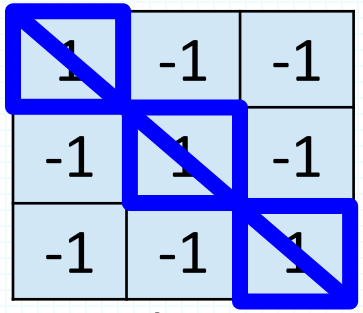
0	0	0	-1	0
0	0	-1	0	1
0	-1	0	1	0
-1	0	1	0	0
0	1	0	0	0

Convolutions for feature extraction

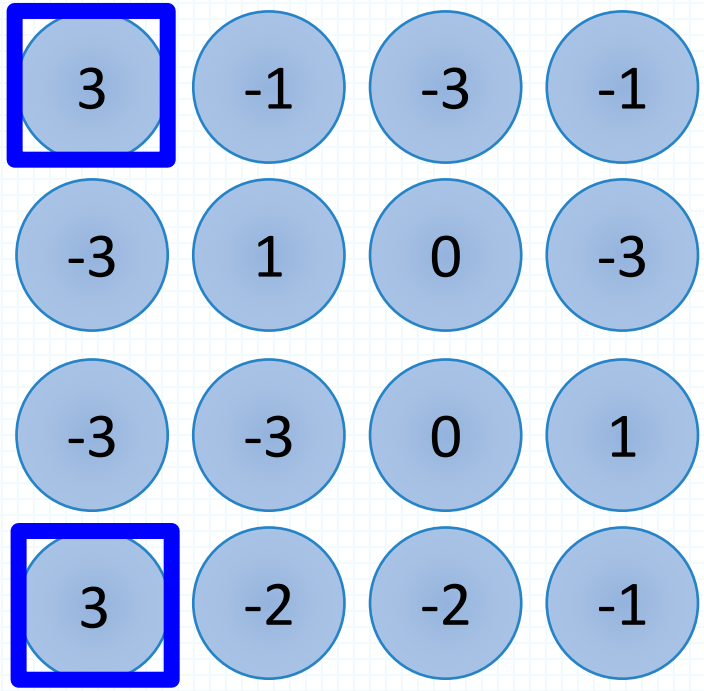
stride=1



6 x 6 image



Filter



Convolutions for feature extraction

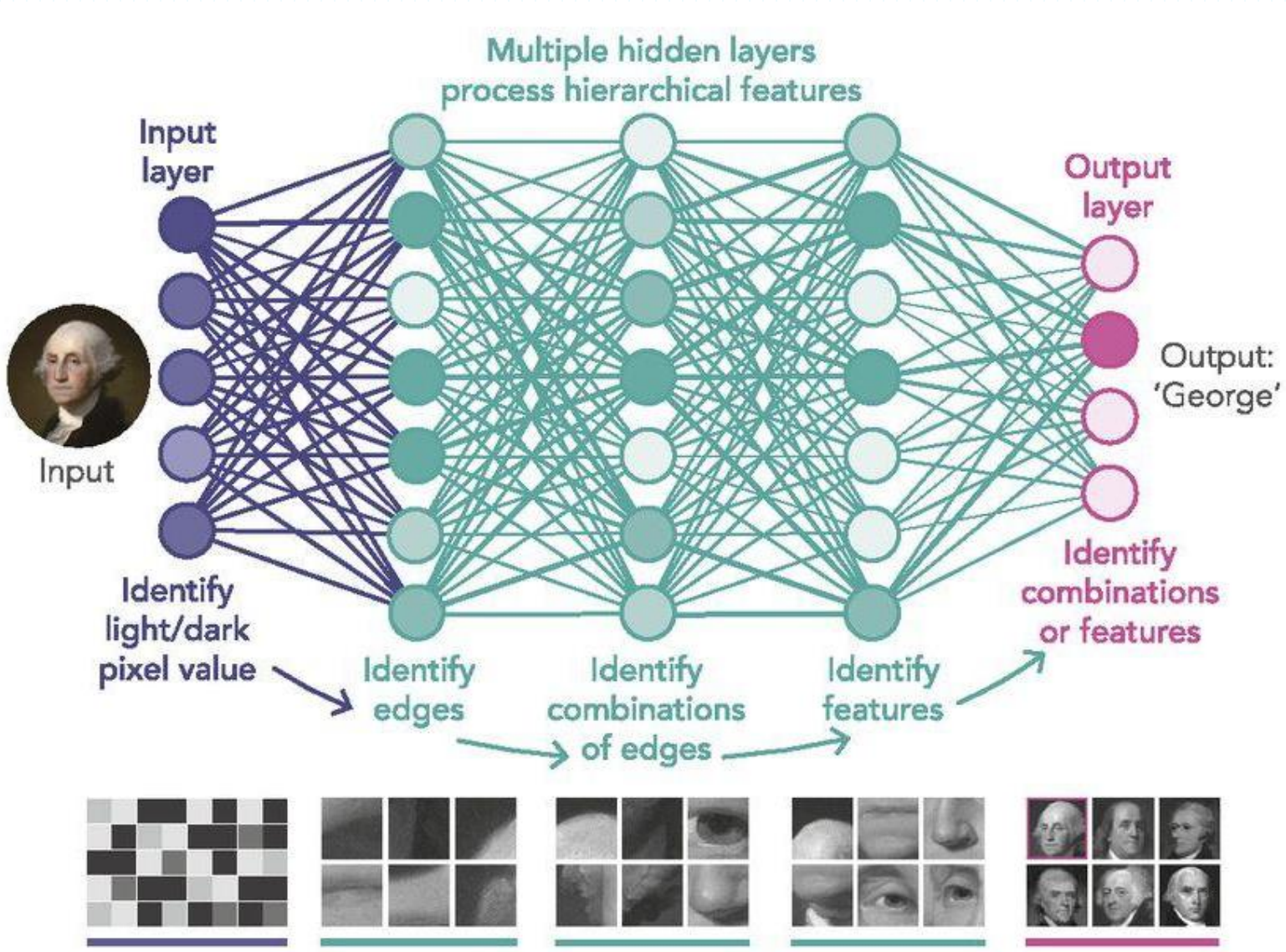
- In neural networks:
  - A **convolution** denotes the linear combination of a **subset of units** based on a **specific pattern of weights.**

$$a_j = \sum_i w_{ji} z_i$$

  - Convolutions are often combined with an activation function to produce a feature

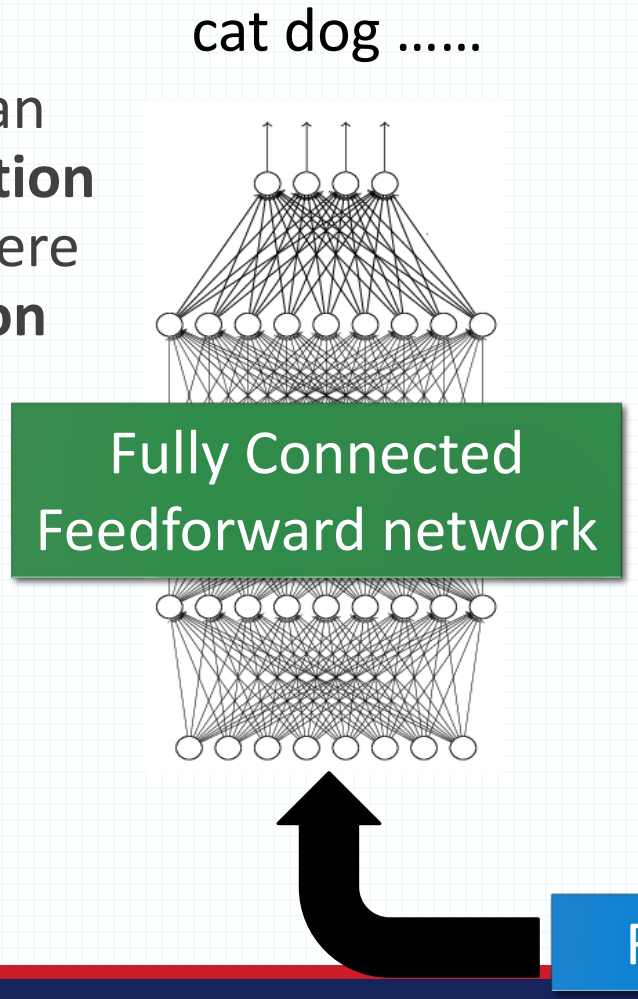
$$z_j = h(a_j) = h\left(\sum_i w_{ji} z_i\right)$$

Deeper Neural Networks!

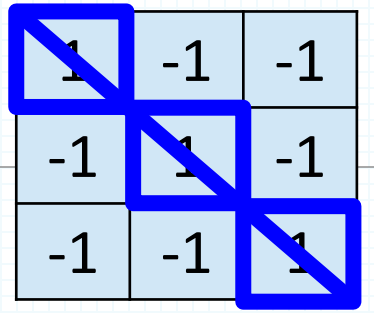


Convolution Neural Network

- A **convolutional neural network** refers to any network that includes an **alternation of convolution and pooling layers**, where **some of the convolution weights are shared.**
- Architecture:

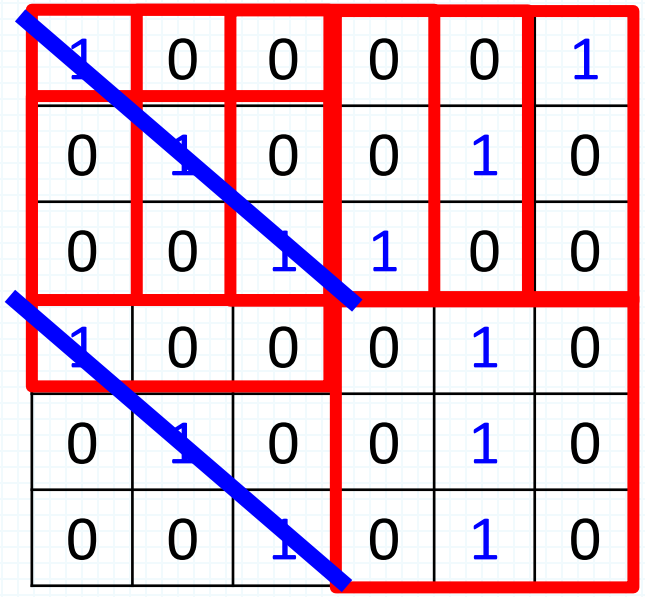


CNN – Convolution

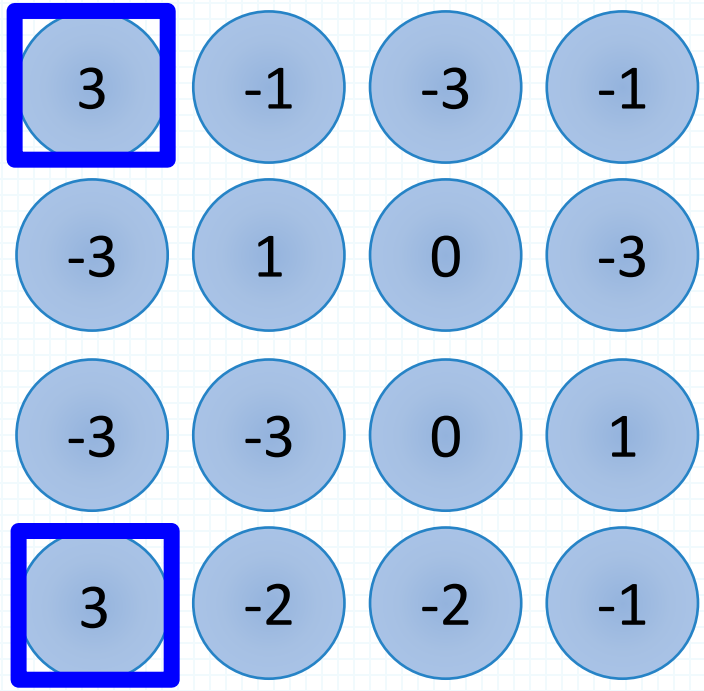


Filter 1

stride=1



6 x 6 image



CNN – Convolution

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

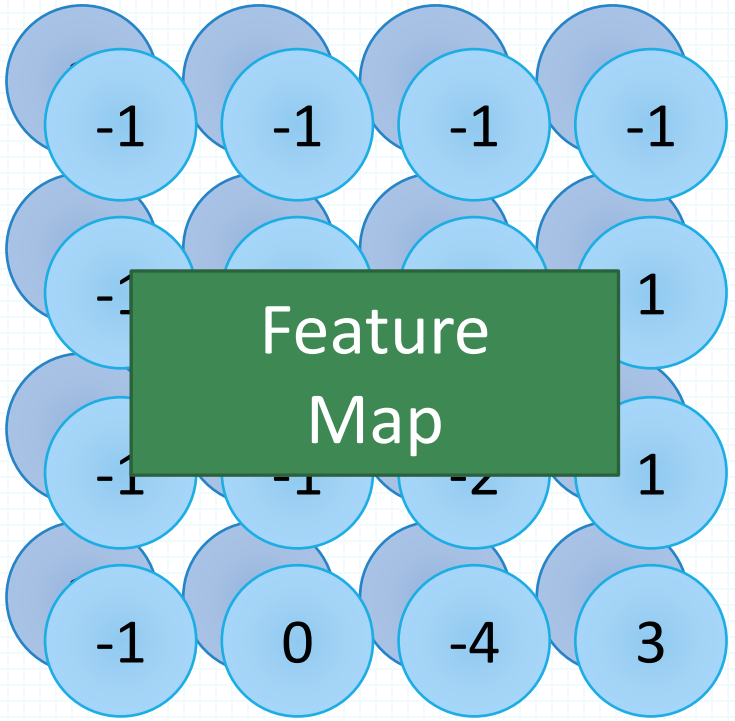
Filter 2

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 – 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

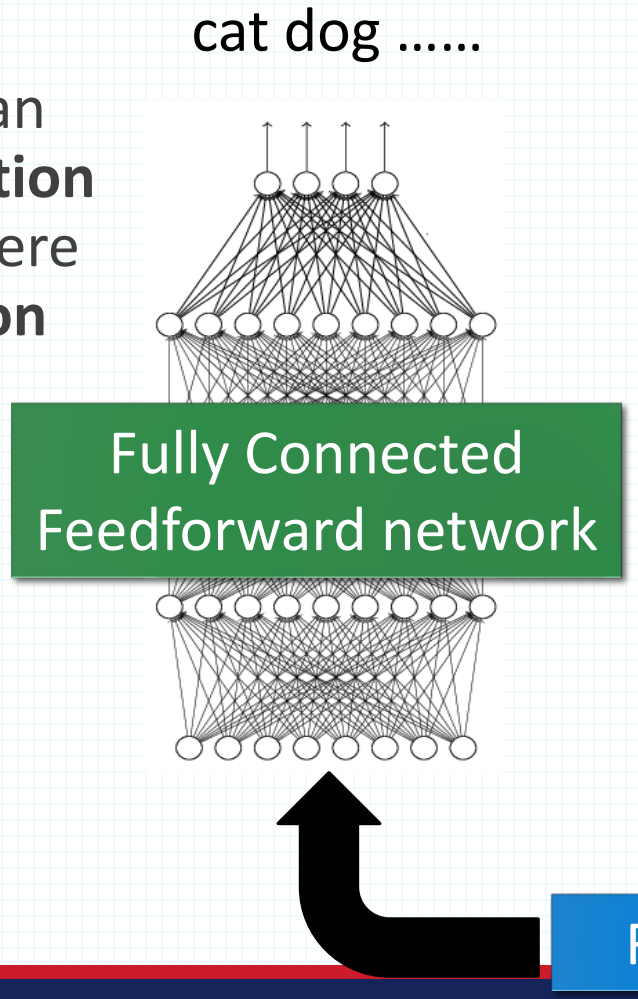
Matrix

⋮

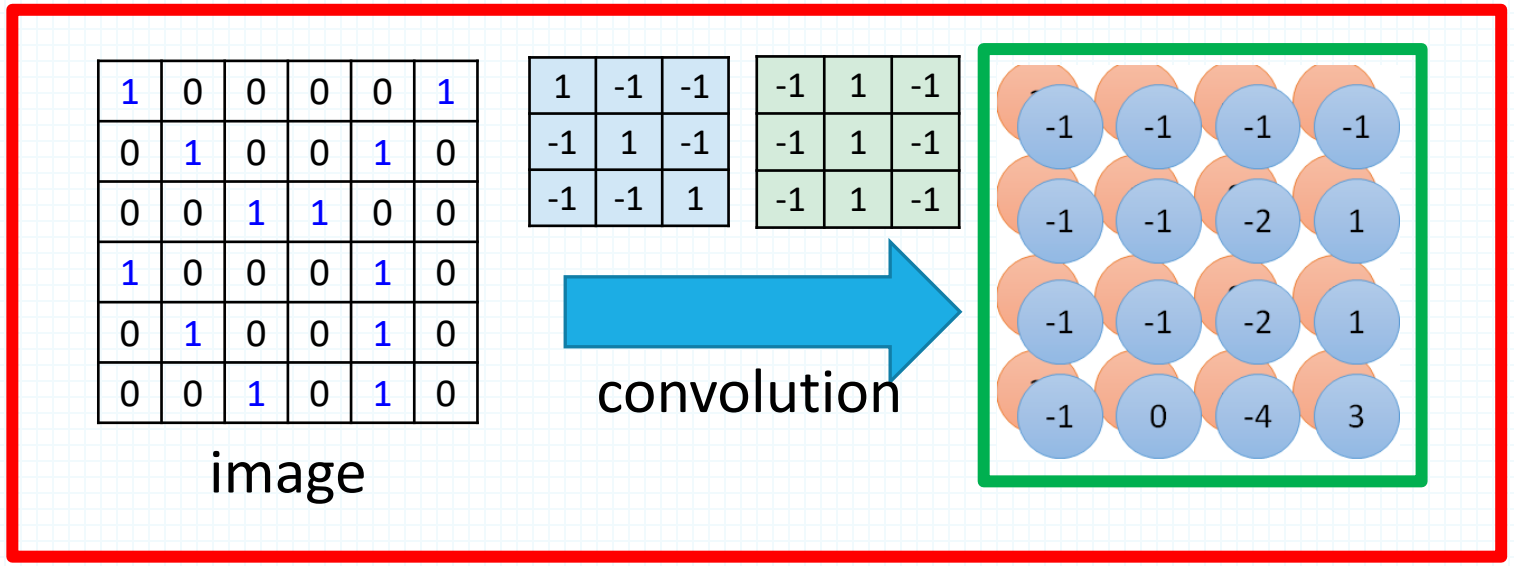
Each filter detects a small pattern (3 x 3).

Convolution Neural Network

- A **convolutional neural network** refers to any network that includes an **alternation of convolution and pooling layers**, where **some of the convolution weights are shared.**
- Architecture:

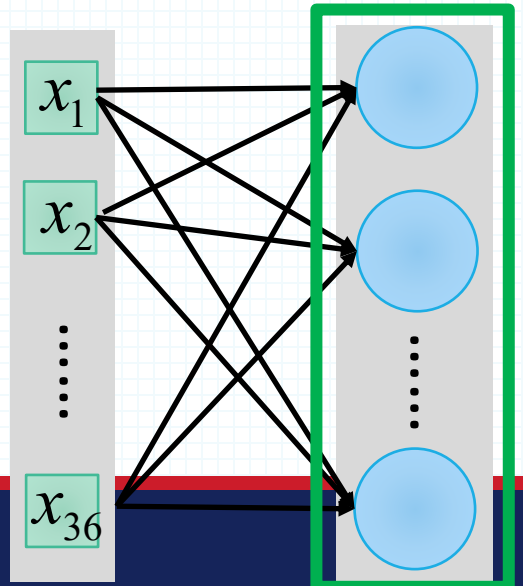


Convolution v.s. Fully Connected



Fully-connected

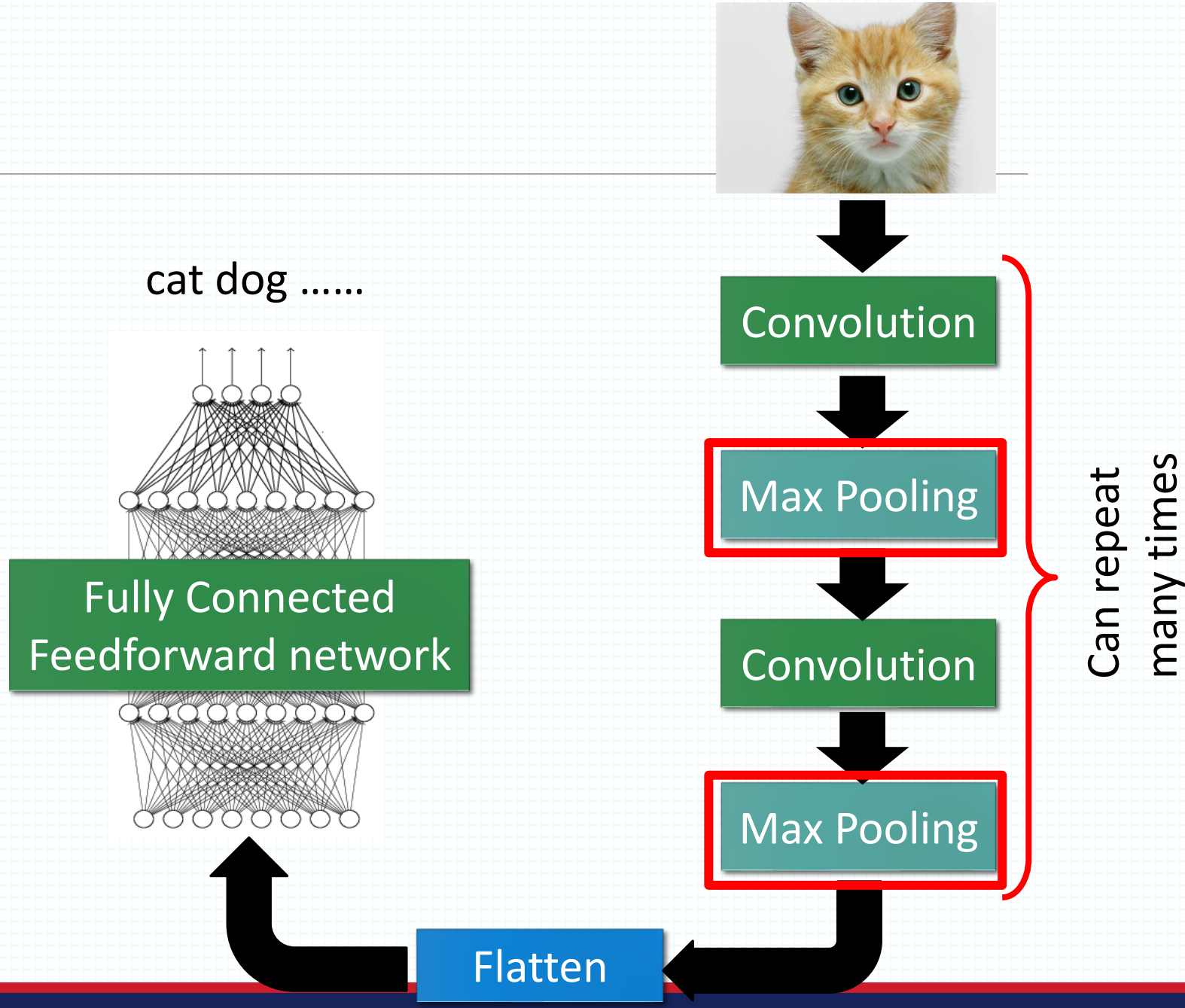
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0



- Sparse interactions: Fewer connections
- Parameter sharing: Fewer weights
- Handle inputs of varying length

Pooling

- Pooling: commutative mathematical operation that combines several units
- Examples:
  - max, sum, product, average, Euclidean norm, etc.
- Commutative property (order does not matter):
  - max a, b = max(b, a)



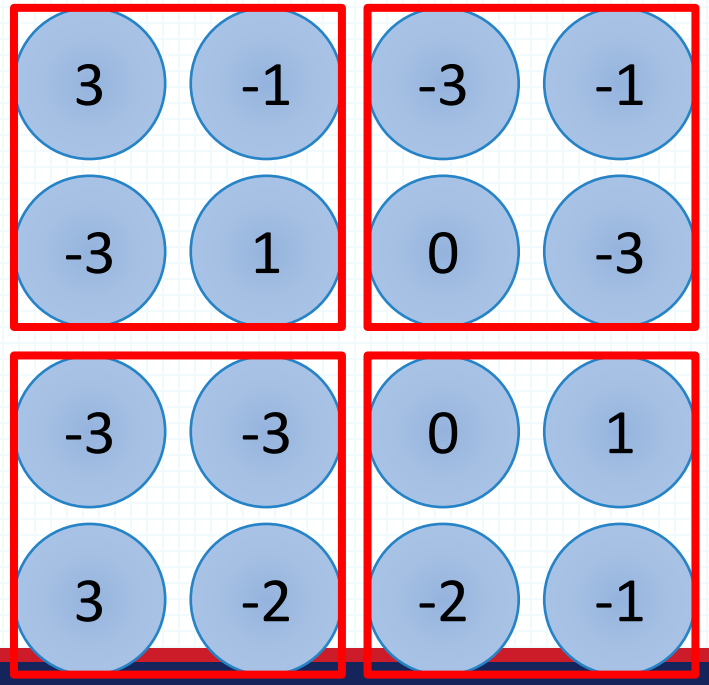
CNN – Max Pooling

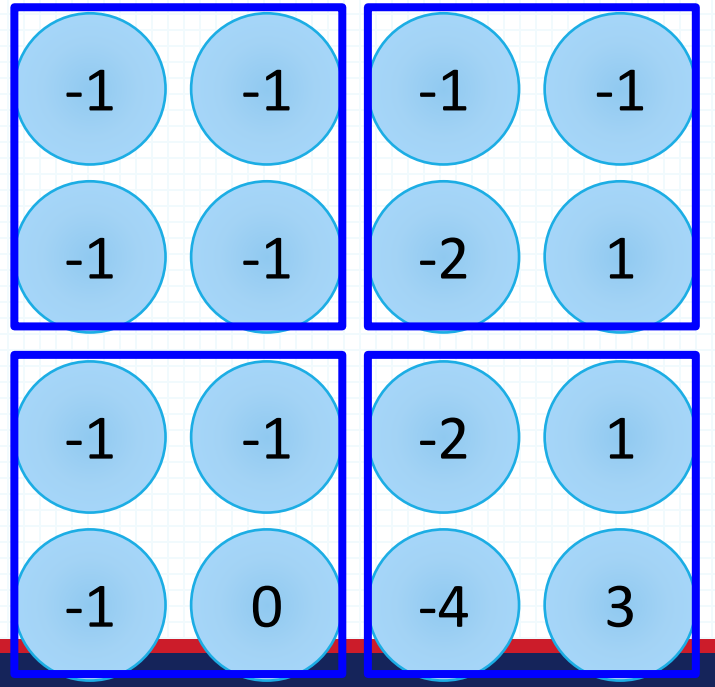
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

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

Filter 2

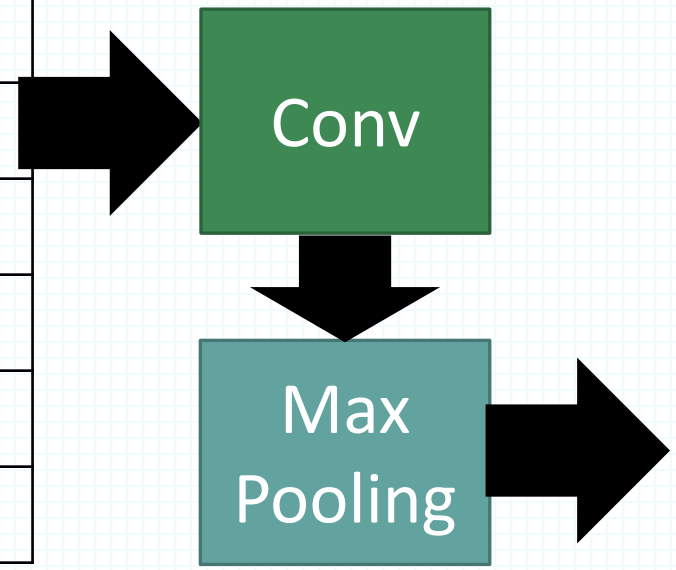




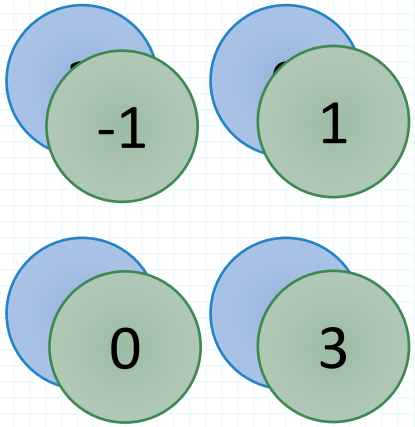
CNN – Max Pooling

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



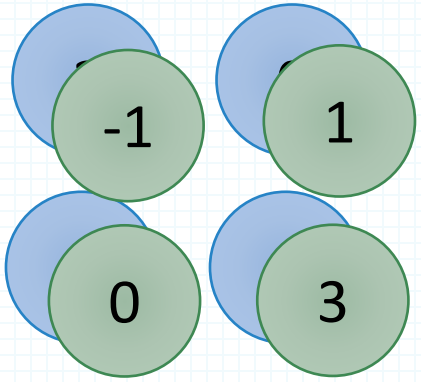
New image but smaller



2 x 2 image

Each filter is a channel

The whole CNN



A new image

Convolution

Max Pooling

Convolution

Max Pooling

Can repeat many times

Smaller than the original image

The number of the channel is the number of filters

The whole CNN

Convolution

Max Pooling

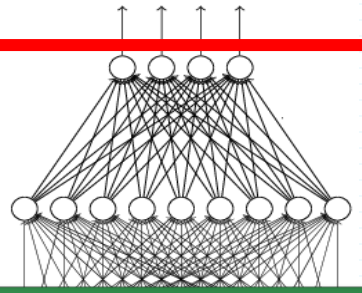
A new image

Convolution

Max Pooling

A new image

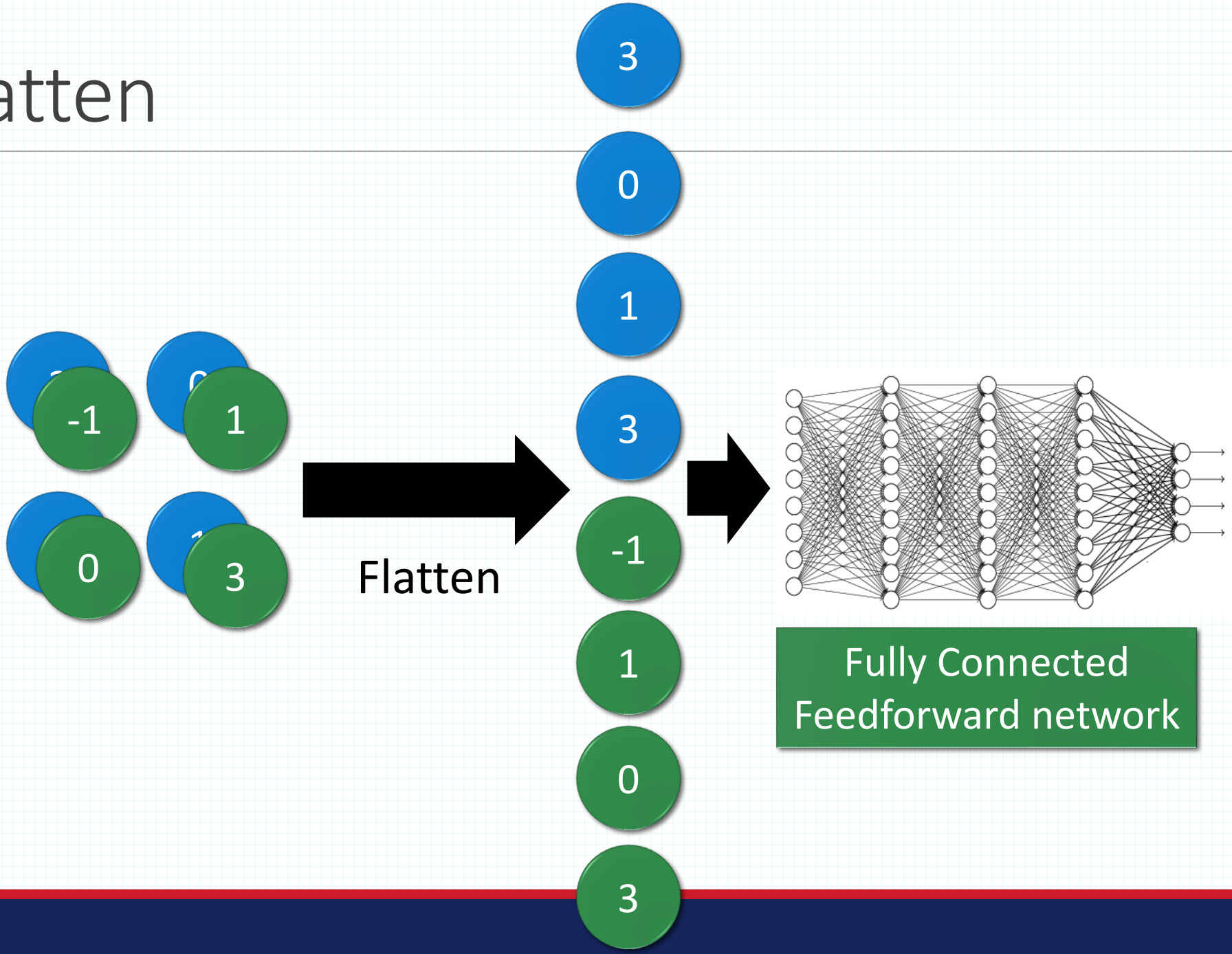
Flatten



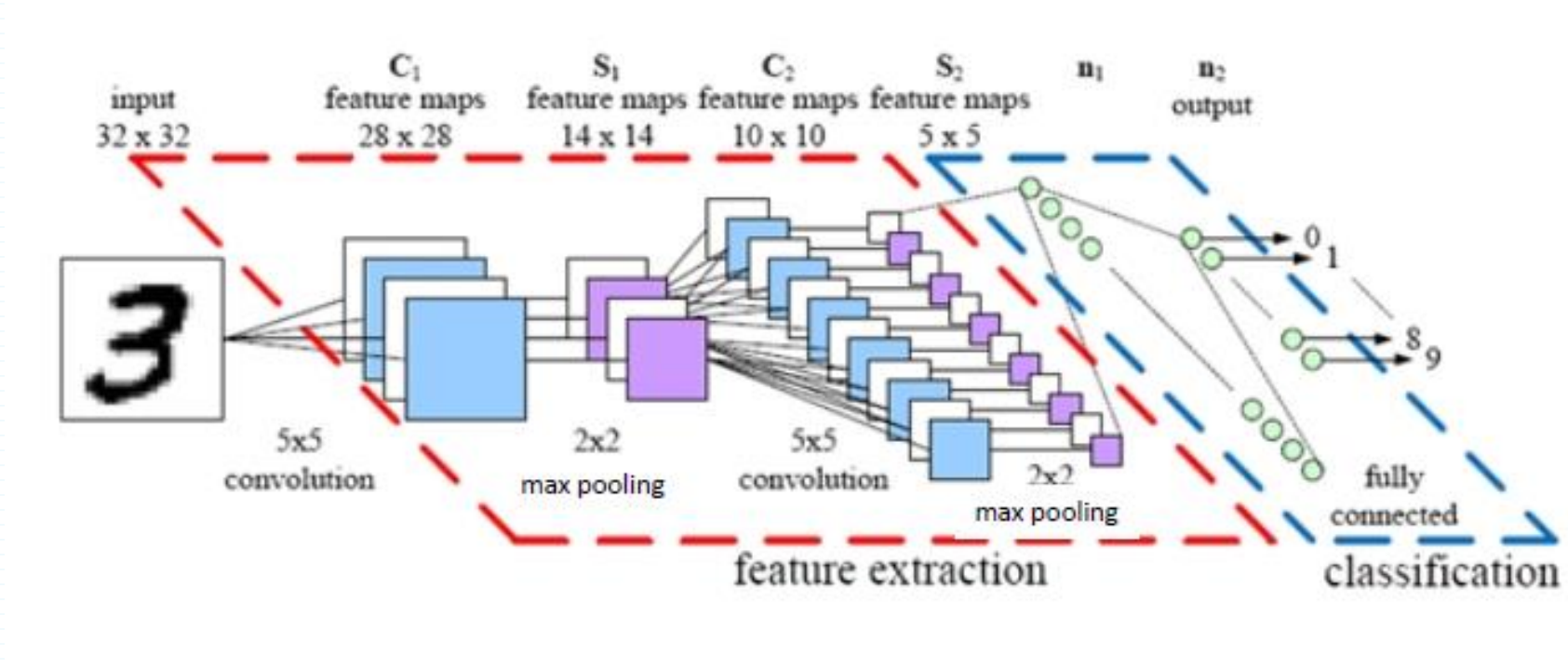
Fully Connected Feedforward network

cat dog ……

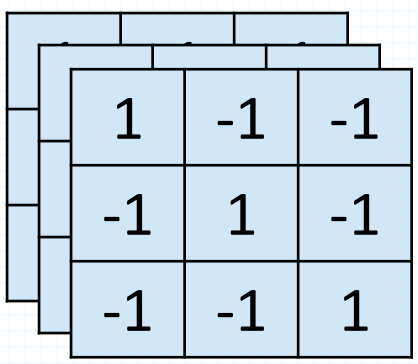
Flatten


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

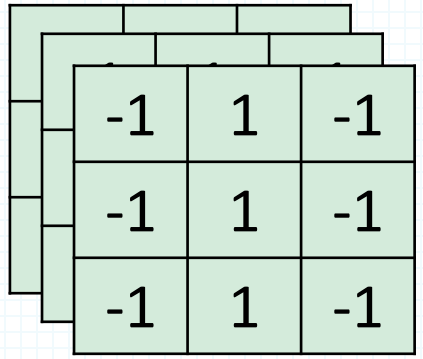
Example


input
32 x 32
C1
feature maps
28 x 28
S1
feature maps
14 x 14
C2
feature maps
10 x 10
S2
feature maps
5 x 5
n1
n2
output
0
1
8
9
5x5
convolution
2x2
max pooling
5x5
convolution
2x2
max pooling
fully
connected
feature extraction
classification

CNN – Colorful image

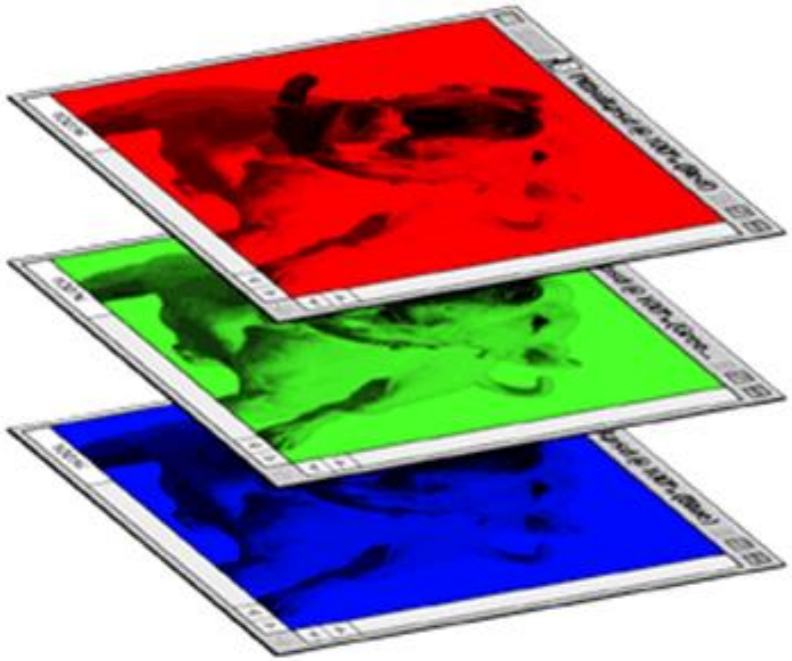


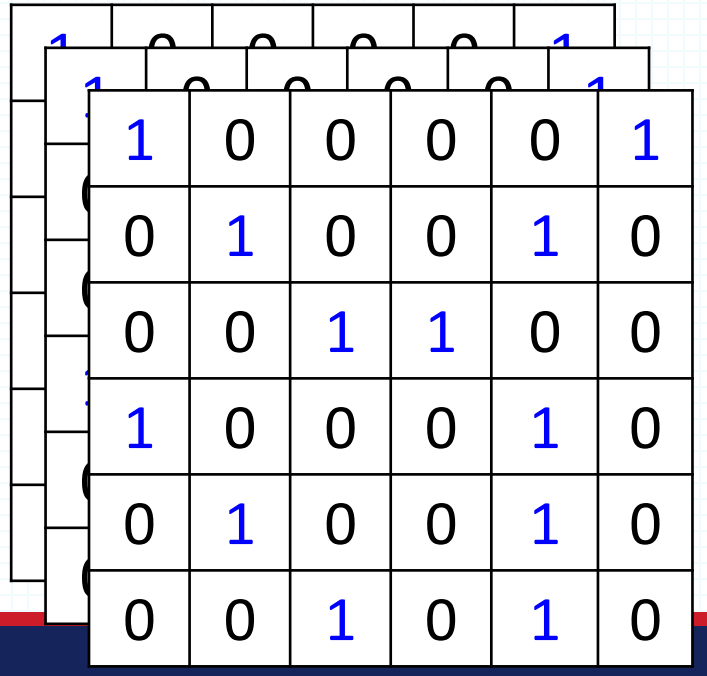
Filter 1



Filter 2

Colorful image

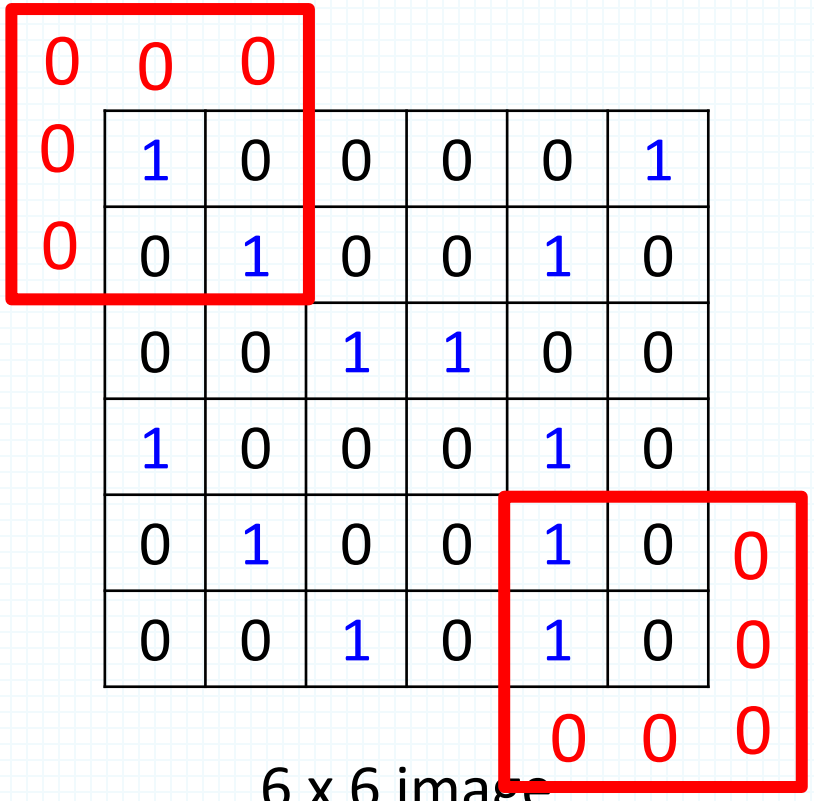




CNN – Zero Padding

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

Filter 1



You will get another 6 x 6 images in this way

Zero padding

More Application: Playing Go

19 x 19 matrix (image)

Network

Next move (19 x 19 positions)

19 x 19 vector

Black: 1

white: -1

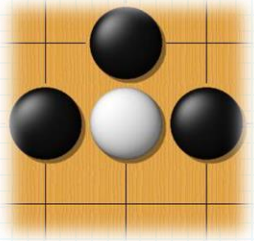
none: 0

Fully-connected feedforward network can be used

But CNN performs much better.

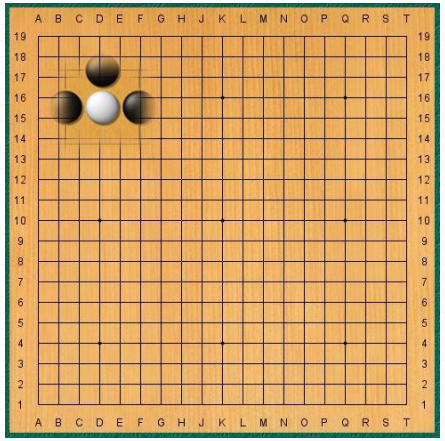
Why CNN for playing Go?

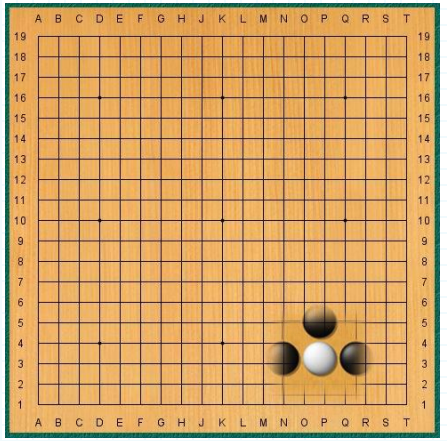
- Some patterns are much smaller than the whole image



- The same patterns appear in different regions.

Alpha Go uses 5 x 5 for first layer



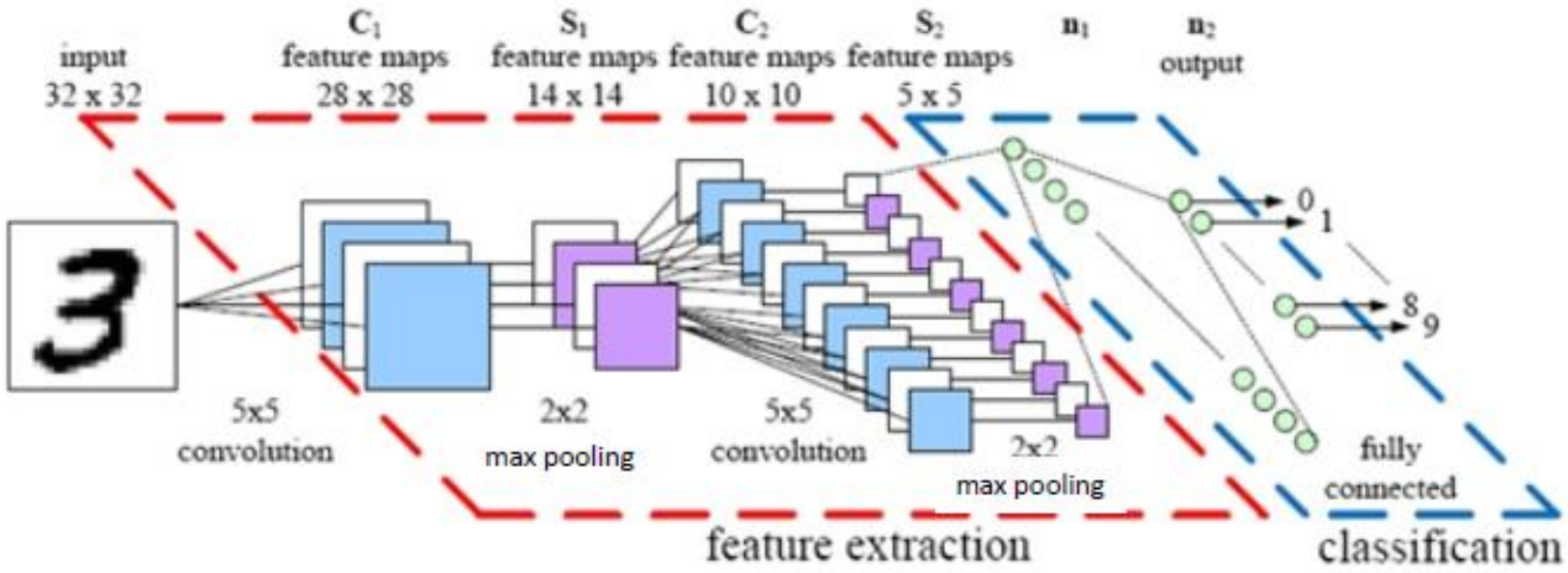


Parameters

- **# of filters**: integer indicating the # of filters applied to each window.
- **kernel size:** tuple (width, height) indicating the size of the window.
- **Stride:** tuple (horizontal, vertical) indicating the horizontal and vertical shift between each window.
- **Padding:** “valid” or ”same”. Valid indicates no input padding. Same indicates that the input is padded with a border of zeros to ensure that the output has the same size as the input.

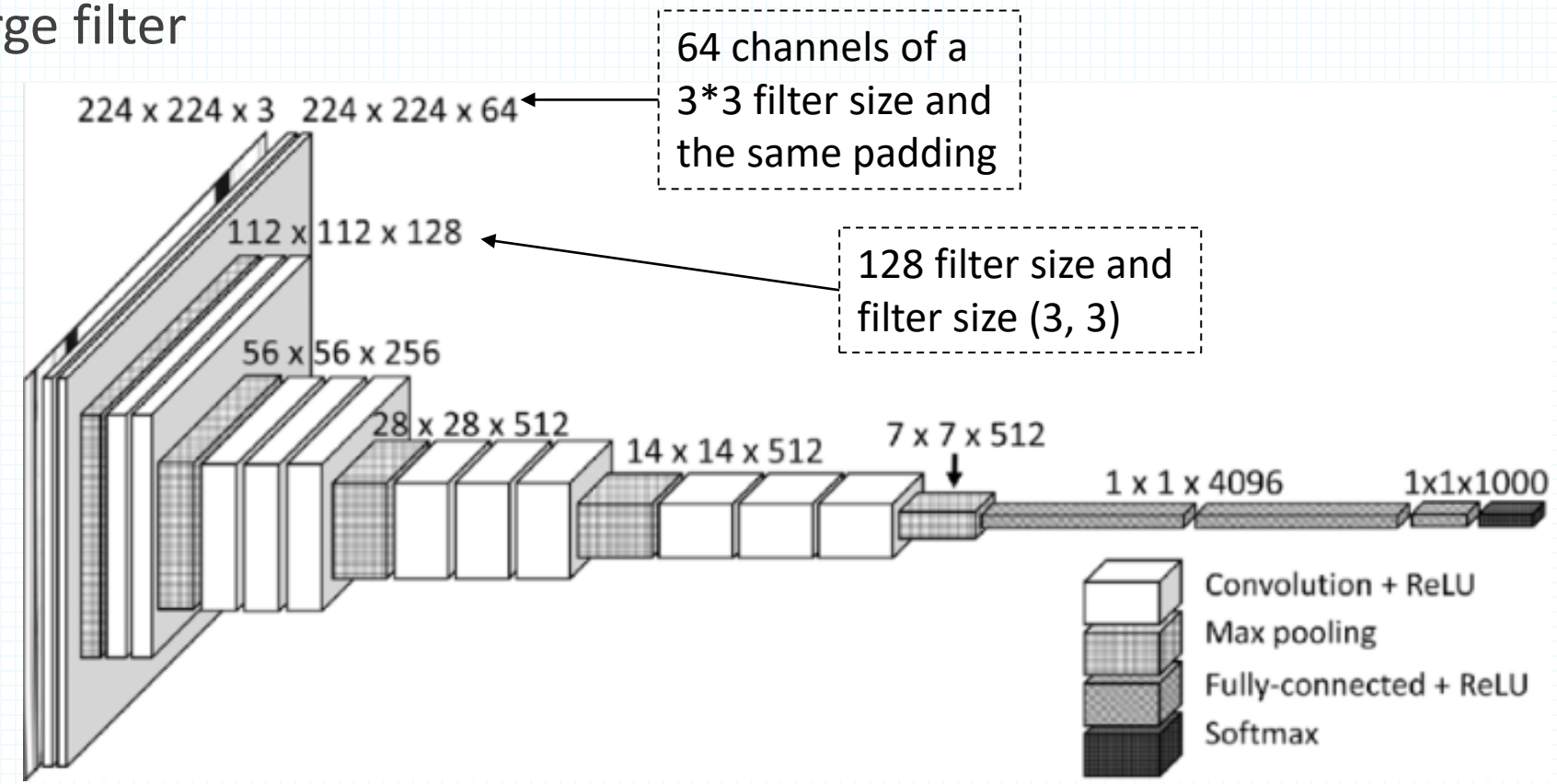
Training

- Convolutional neural networks are trained in the same way as other neural networks
  - backpropagation
- Weight sharing:
  - Combine gradients of shared weights into a single gradient



Architecture design: VGG

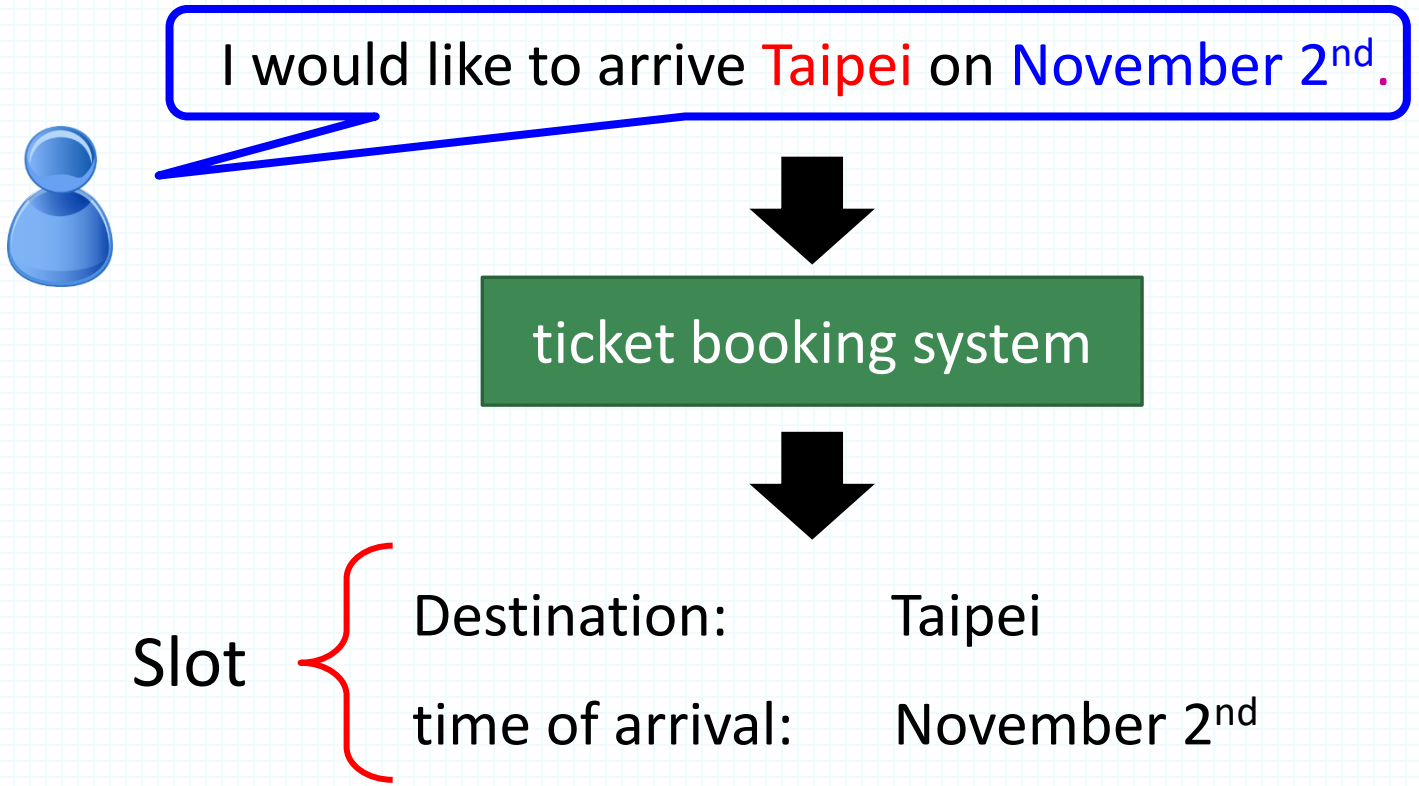
- What is the preferred filter size?
- VGG (Visual Geometry Group at Oxford, 2014): stack of small filters is often preferred to single large filter
  - Fewer parameters
  - Deeper network



الشبكات العصبونية التكراريّة
Recurrent Neural Networks

Example Application

- Slot Filling

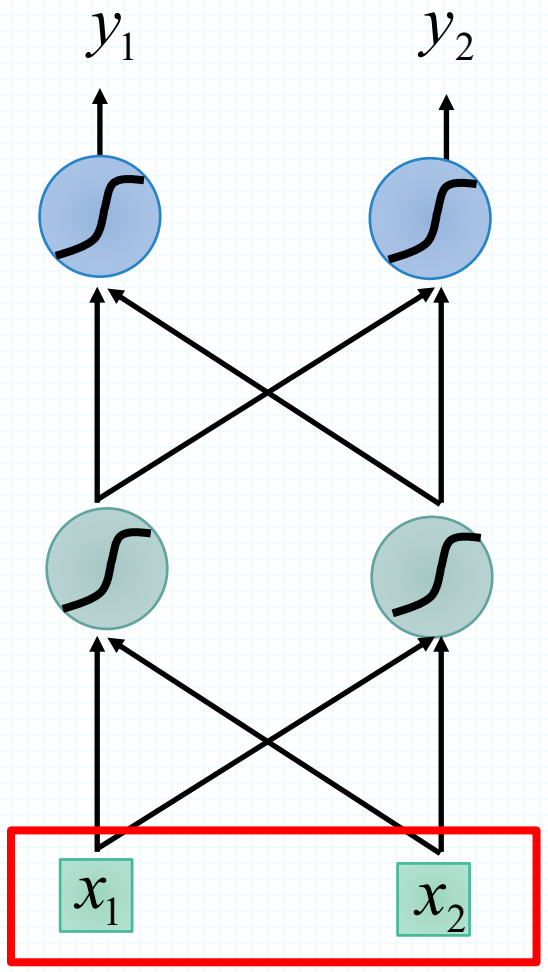


Example Application

Solving slot filling by Feedforward network?

Input: a word

(Each word is represented as a vector)



Taipei

How can we represent each word?

1-of-N encoding

How to represent each word as a vector?

1-of-N Encoding lexicon = {apple, bag, cat, dog, elephant}

The vector is lexicon size.

Each dimension corresponds to a word in the lexicon

The dimension for the word is 1, and others are 0

apple = [1 0 0 0 0]

bag = [0 1 0 0 0]

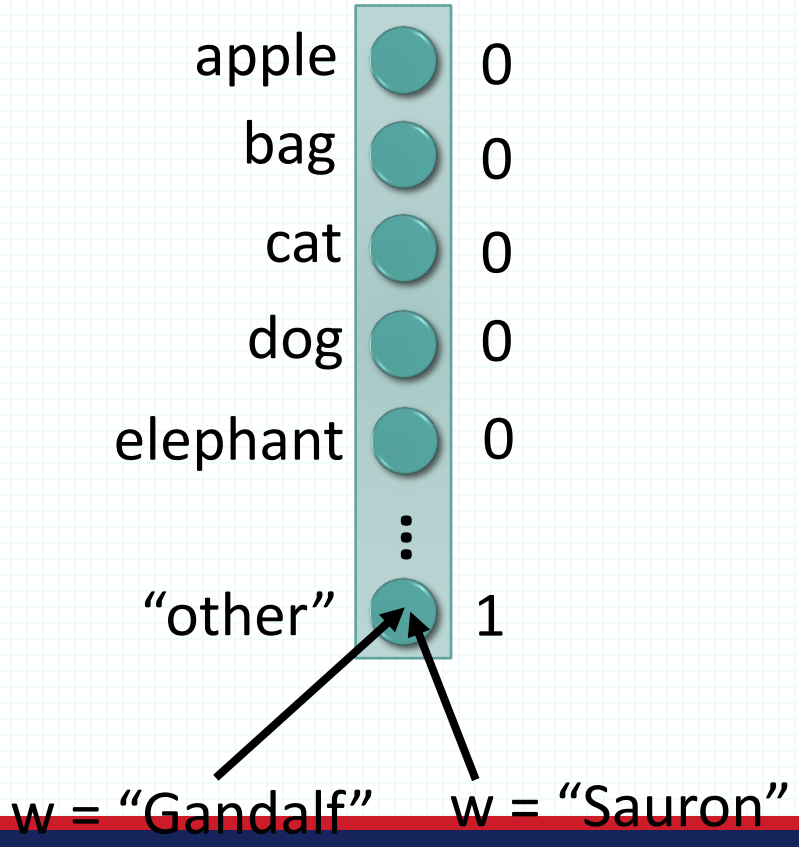
cat = [0 0 1 0 0]

dog = [0 0 0 1 0]

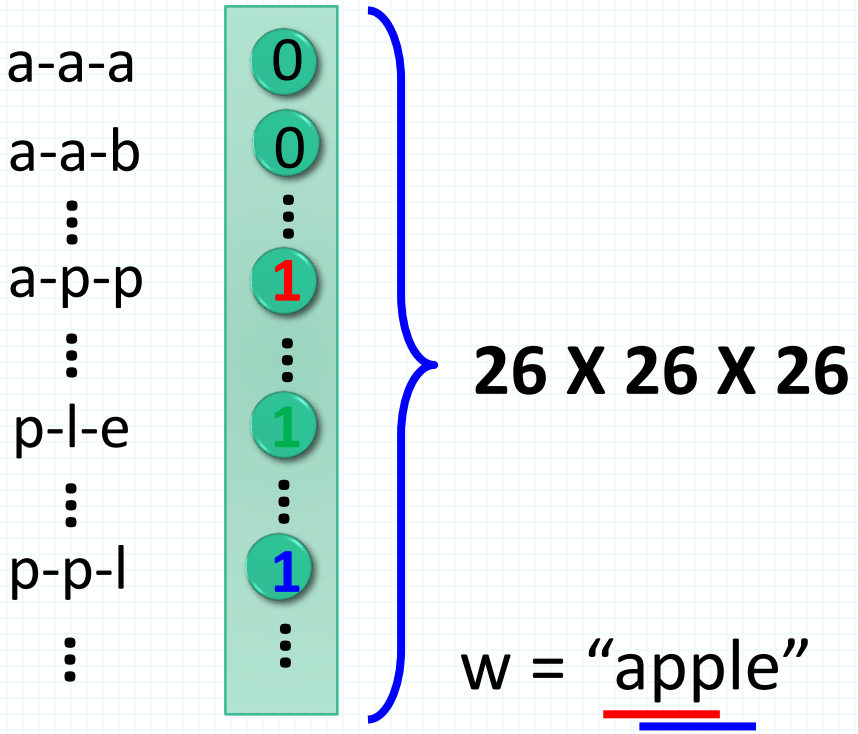
elephant = [0 0 0 0 1]

Beyond 1-of-N encoding

Dimension for "Other"



Word hashing



Example Application

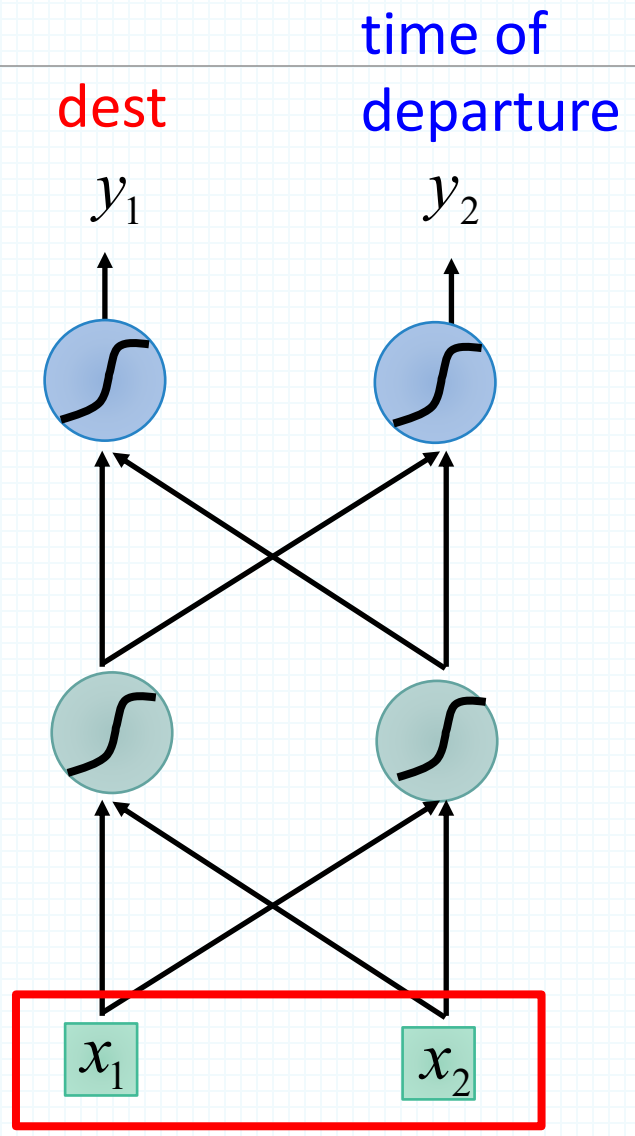
Solving slot filling by Feedforward network?

Input: a word

(Each word is represented as a vector)

Output:

Probability distribution that the input word belonging to the slots



Example Application

arrive Taipei on November 2nd

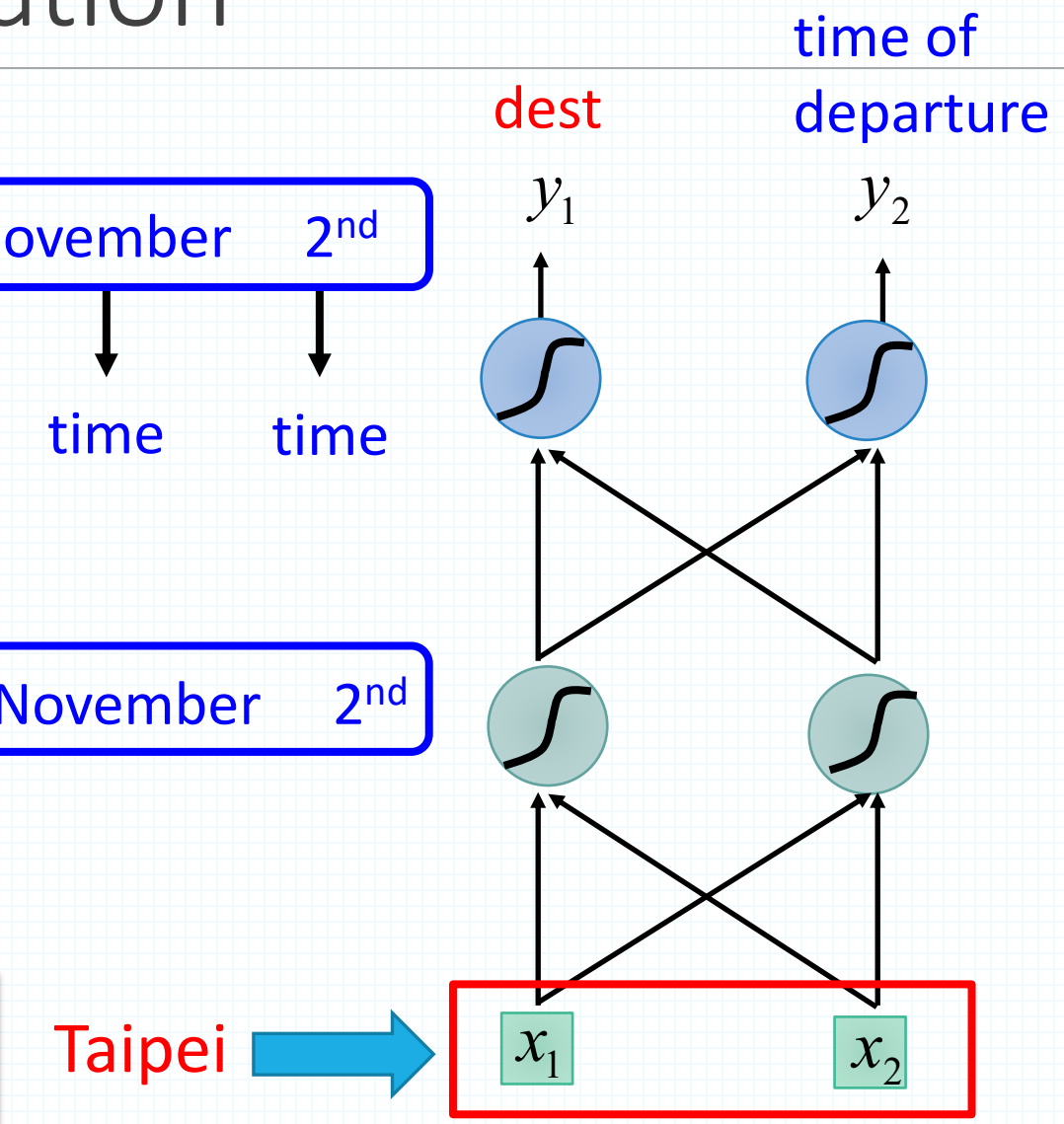
other dest other time time

Problem?

leave Taipei on November 2nd

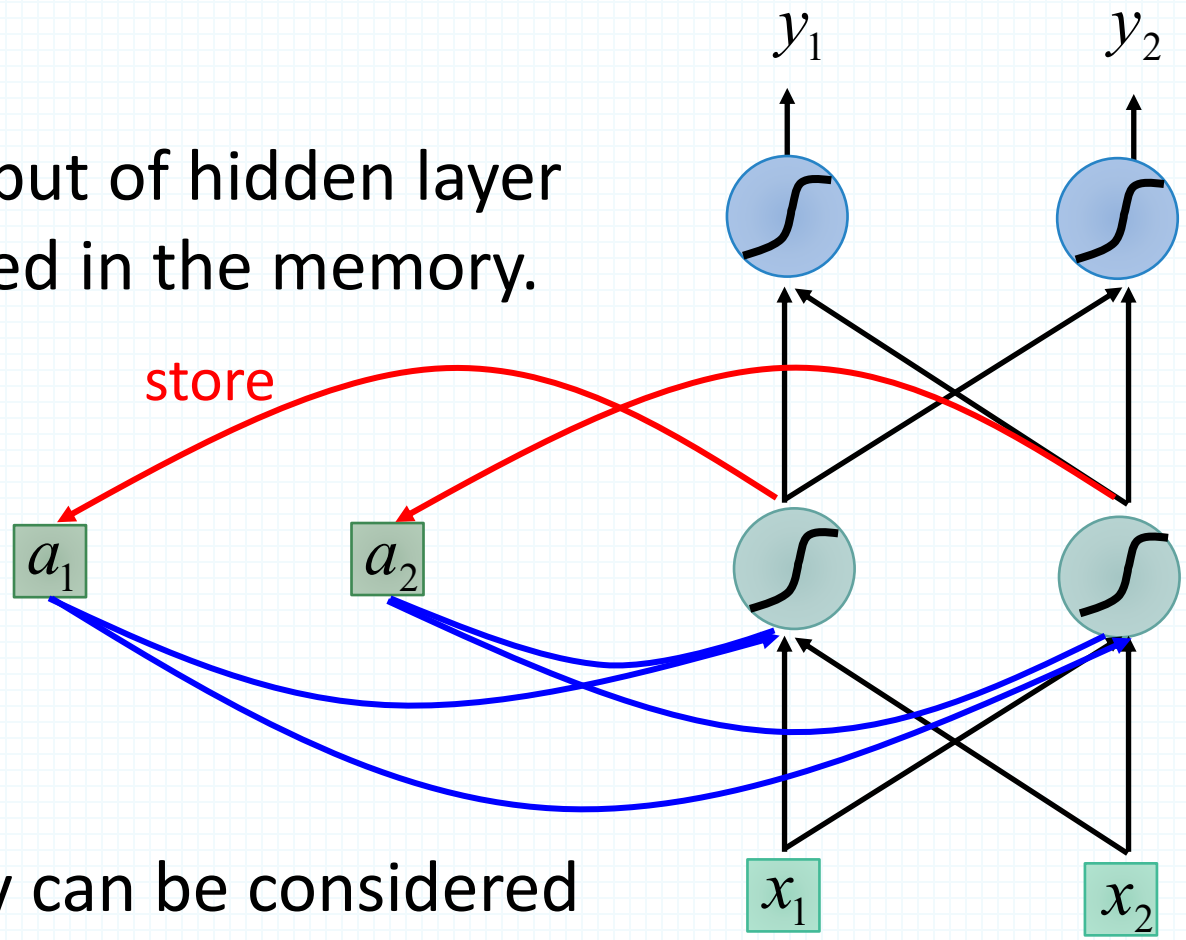
place of departure

Neural network needs memory!



Recurrent Neural Network (RNN)

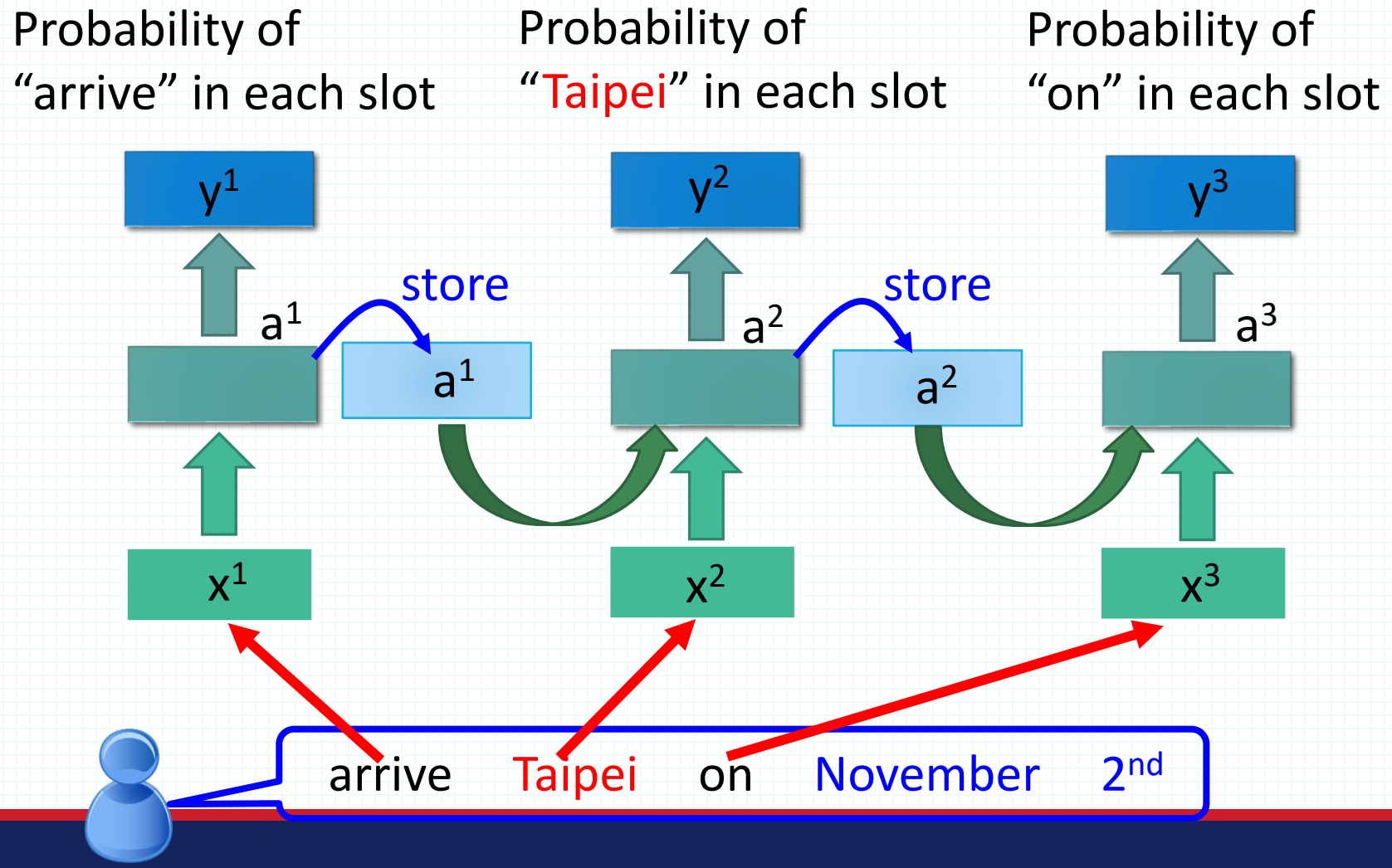
The output of hidden layer are stored in the memory.



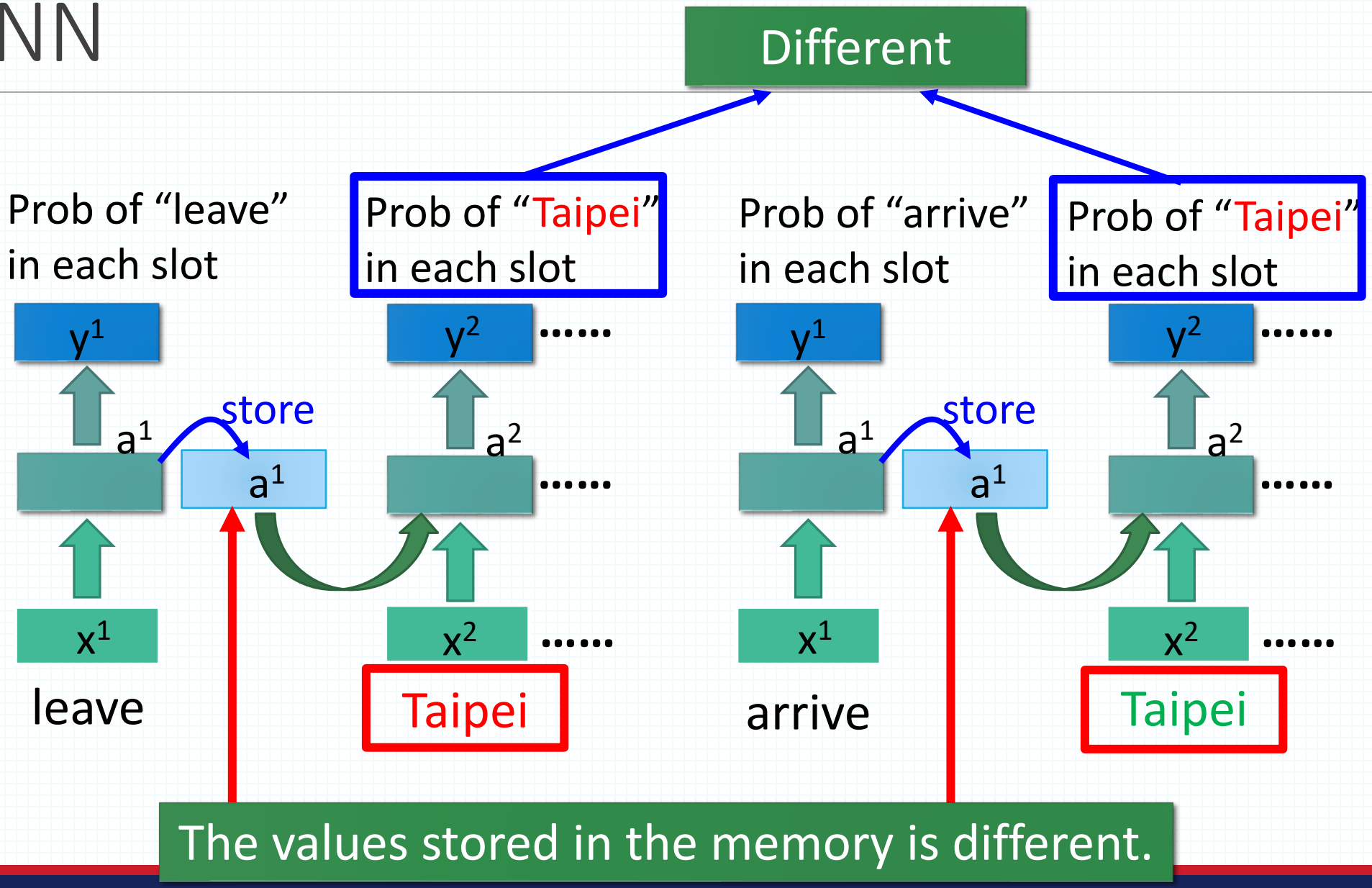
Memory can be considered as another input.

RNN

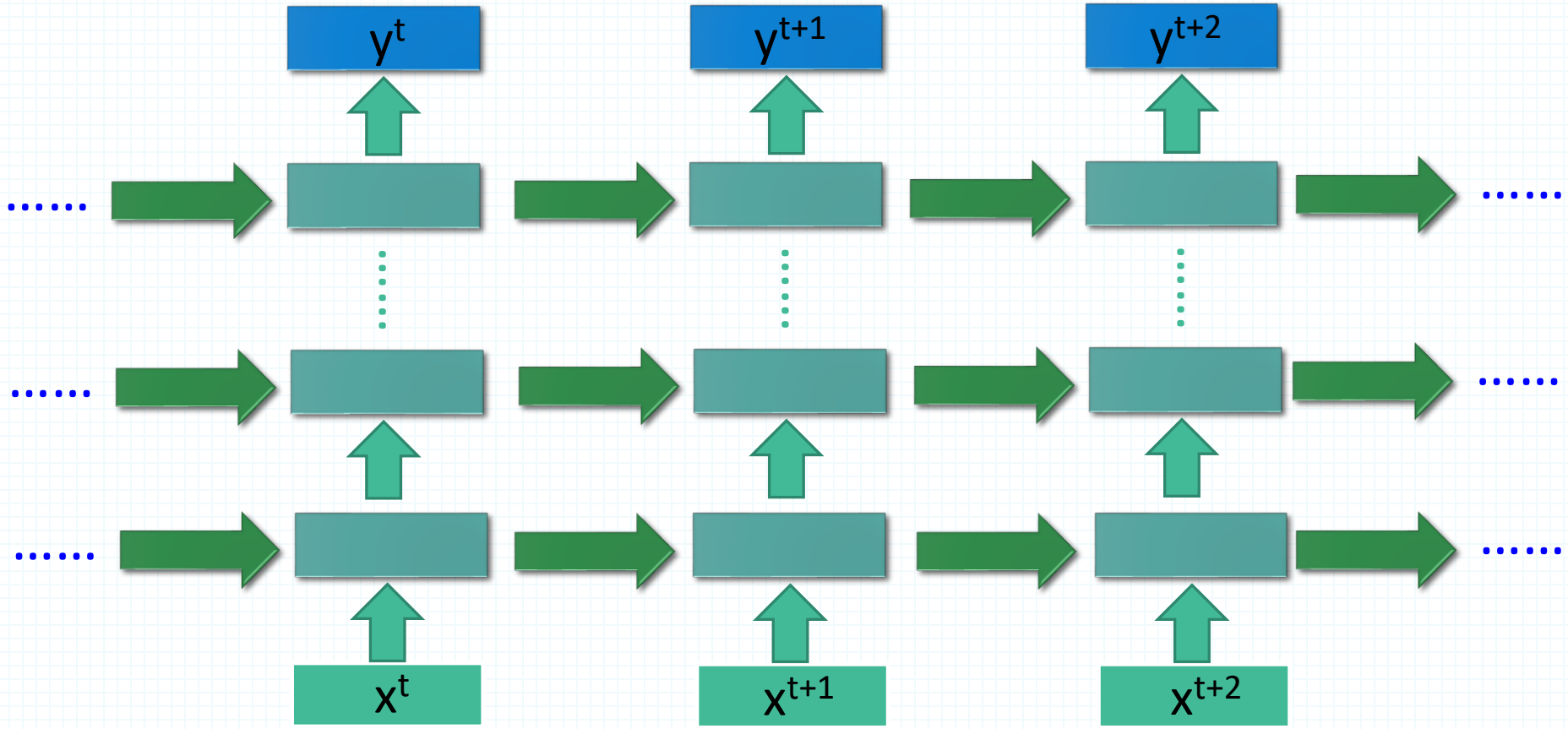
The same network is used again and again.



RNN

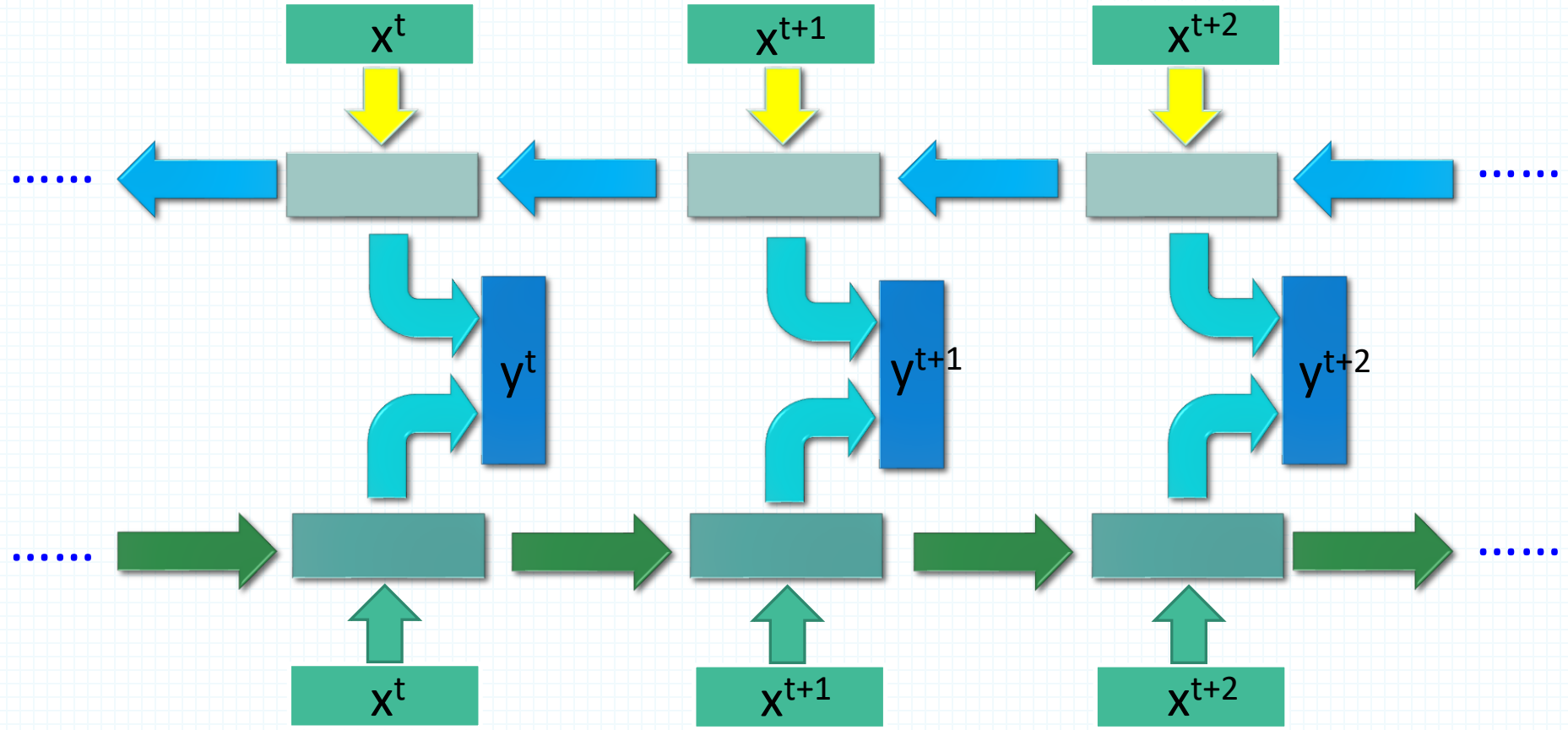

Different
Prob of "leave" in each slot
Prob of "Taipei" in each slot
Prob of "arrive" in each slot
Prob of "Taipei" in each slot
y^1
y^2
.....
a^1
a^2
store
x^1
x^2
leave
Taipei
arrive
Taipei
The values stored in the memory is different.

Of course it can be deep …



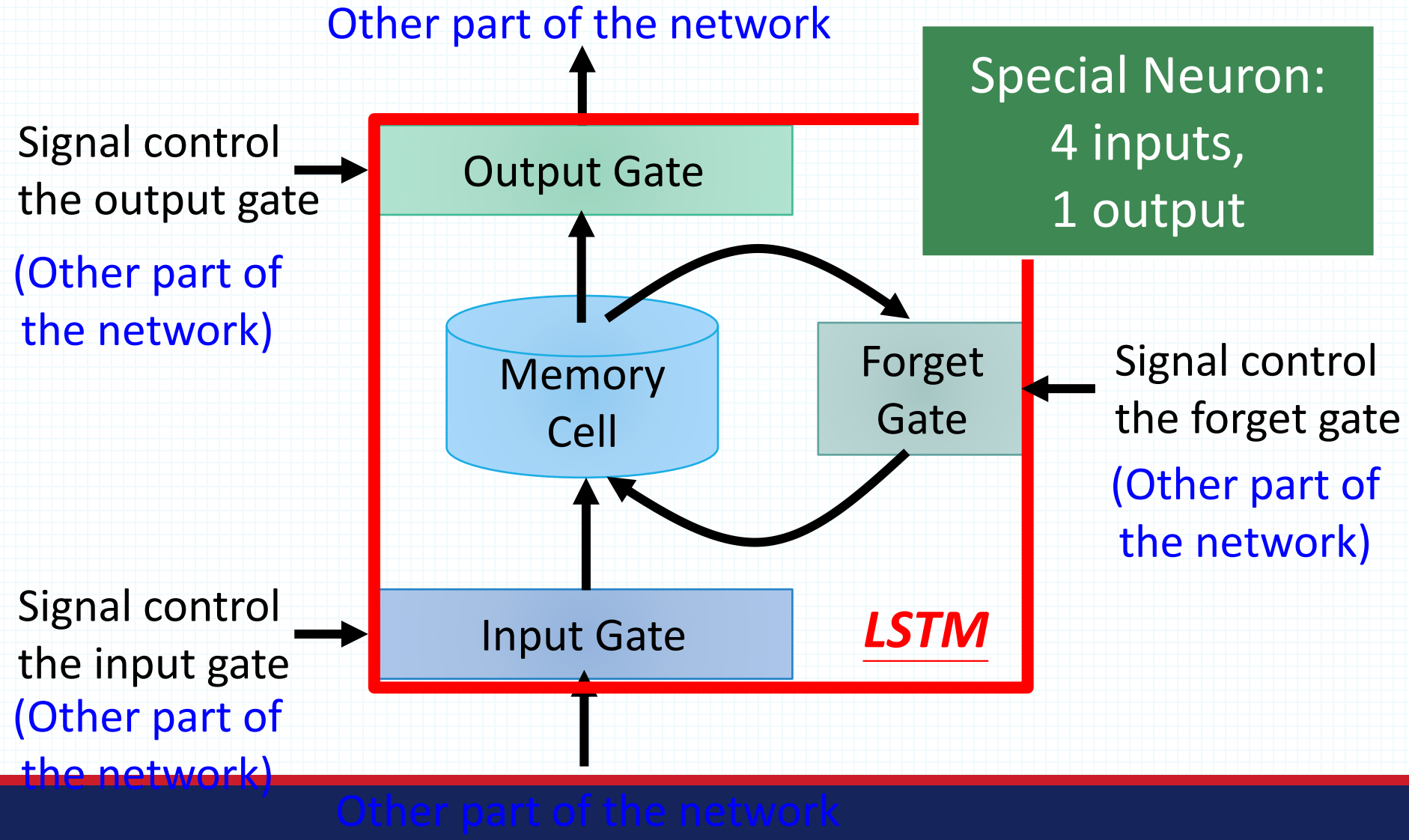
Bidirectional RNN

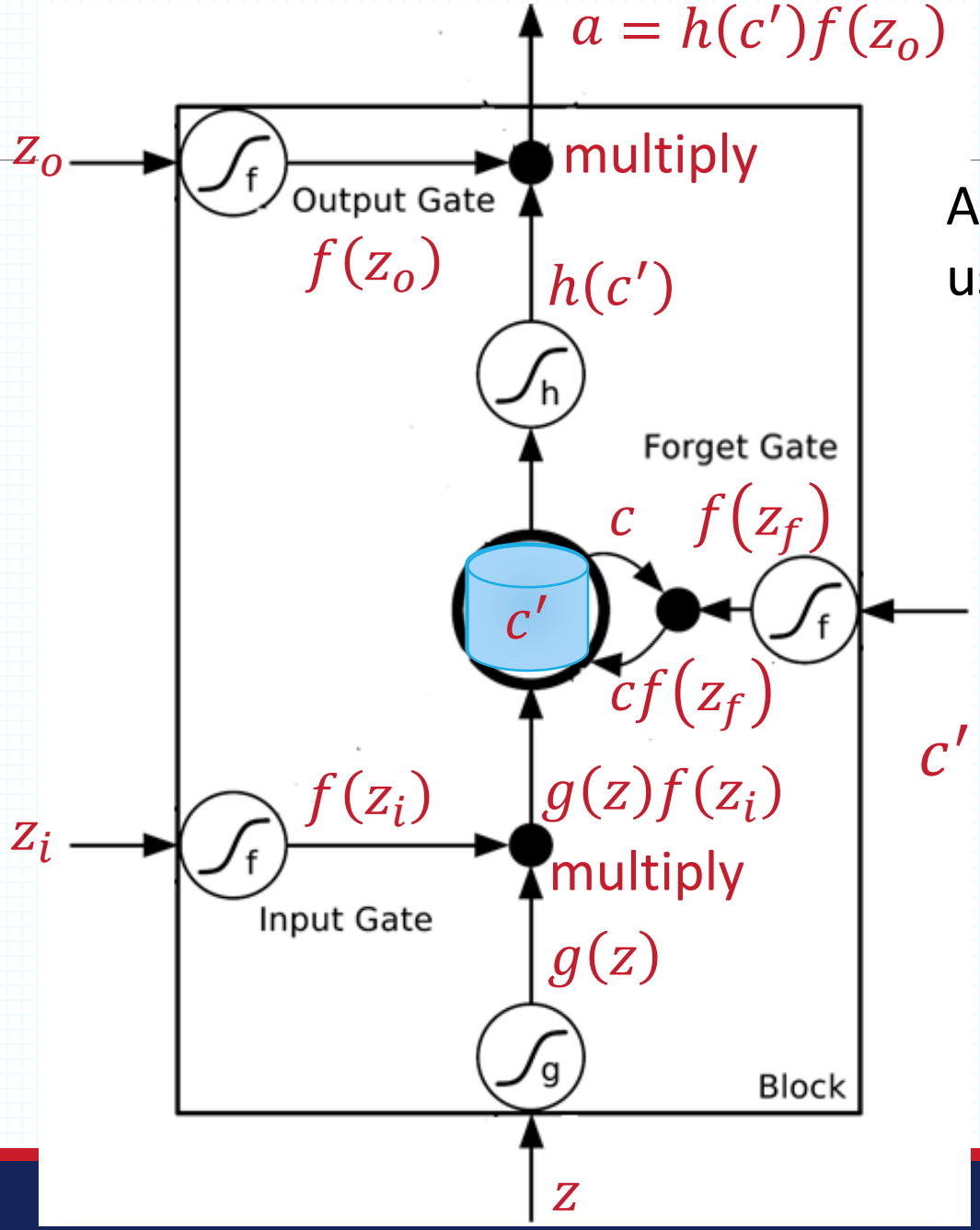
We can combine past and future evidence in separate chains



Long Short-term Memory (LSTM)

Long Short-term Memory (LSTM)





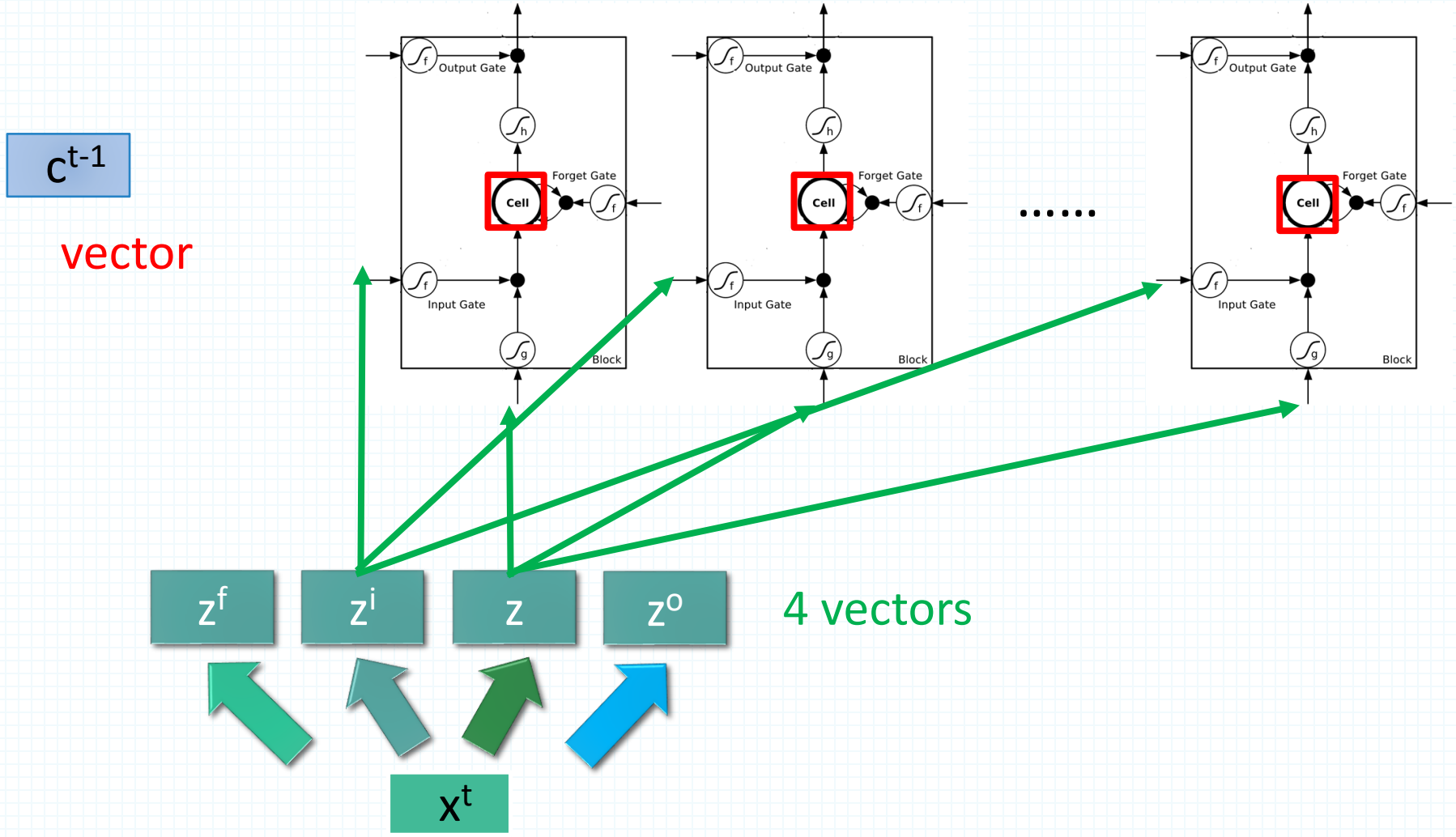
Activation function f is usually a sigmoid function

Between 0 and 1

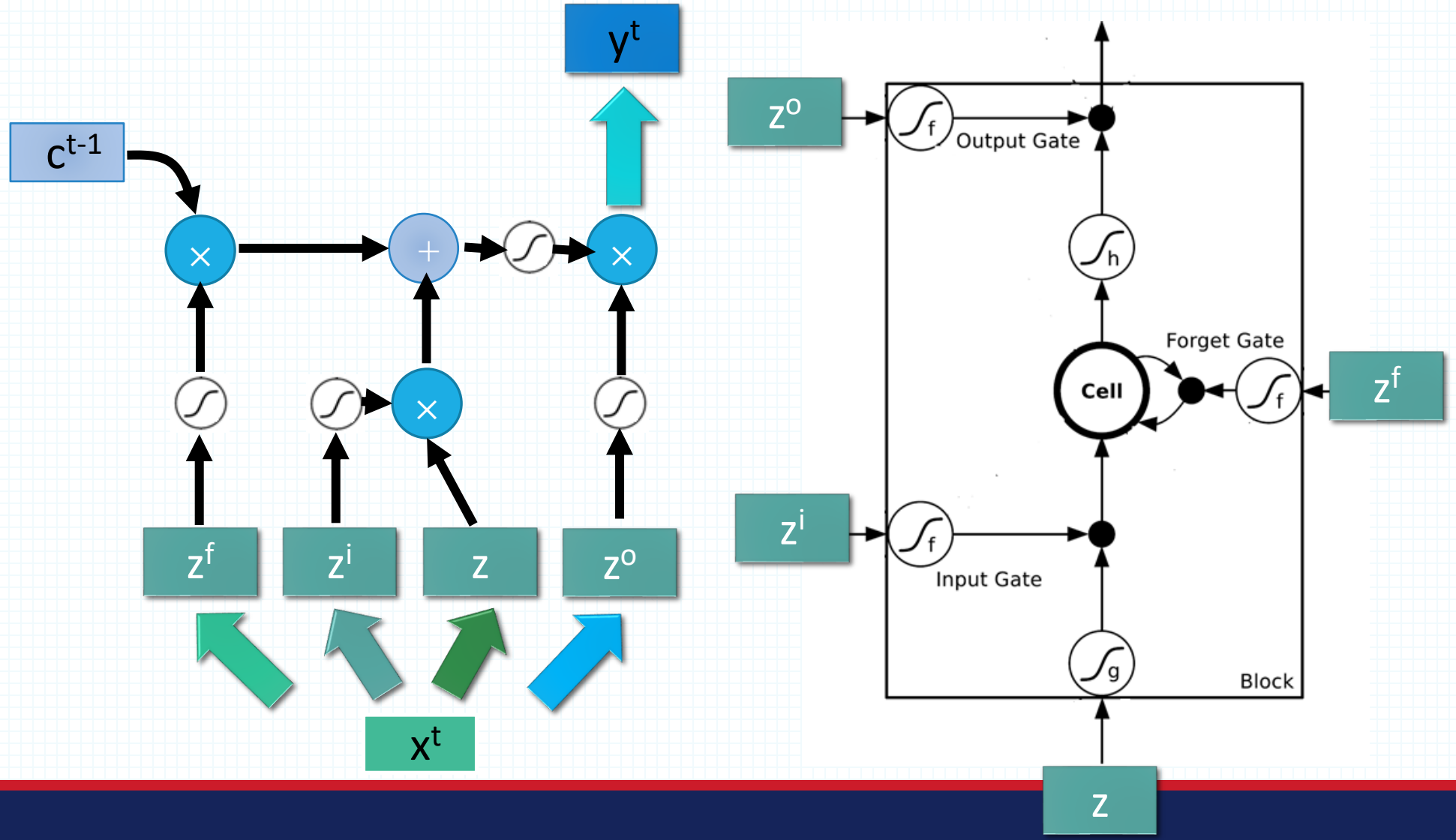
Mimic open and close gate

$$c' = g(z)f(z_i) + cf(z_f)$$

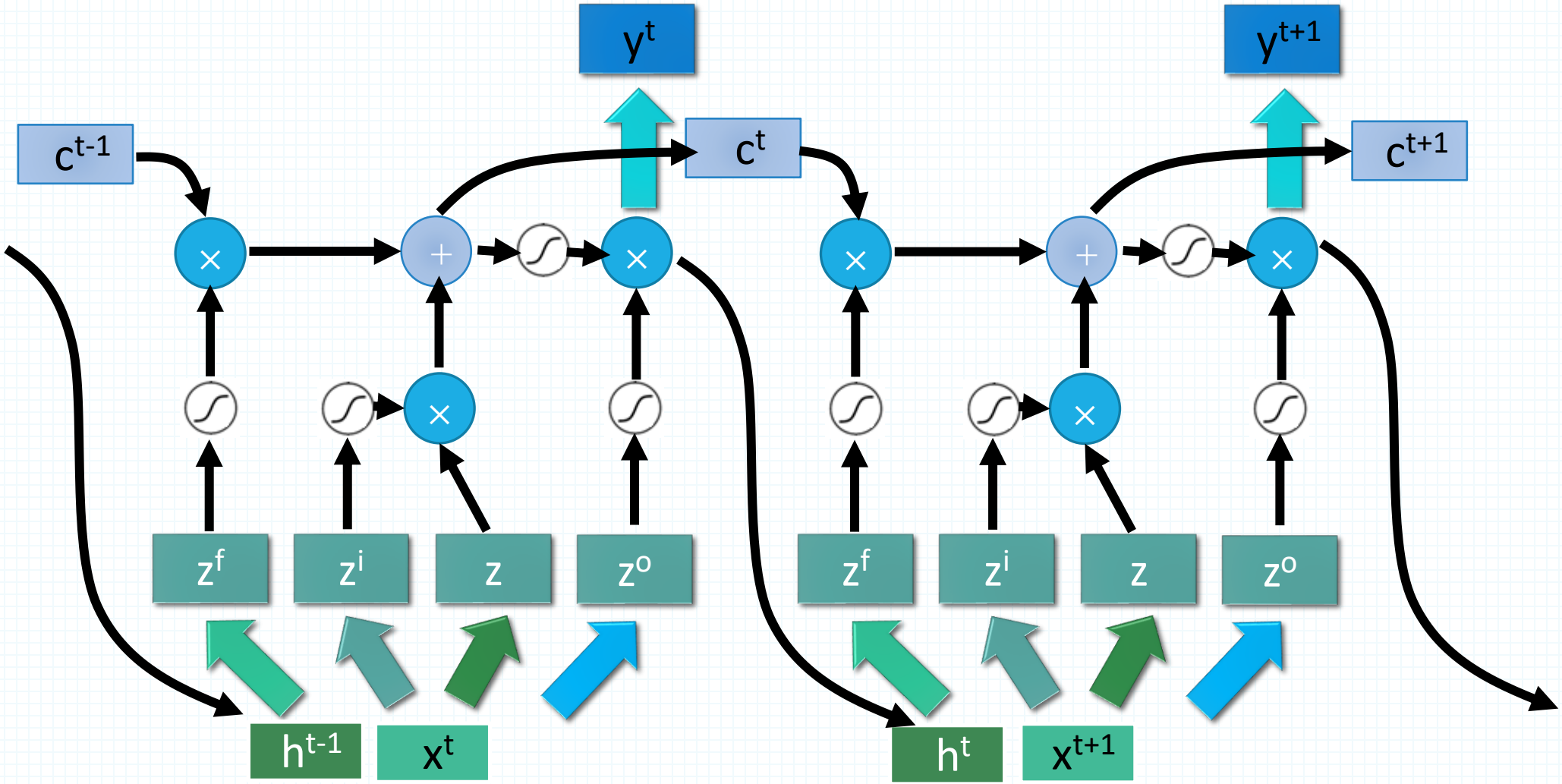
LSTM


c^{t-1}
vector
Output Gate
Forget Gate
Cell
Input Gate
Block
.....
z^f
z^i
z
z^o
4 vectors
x^t

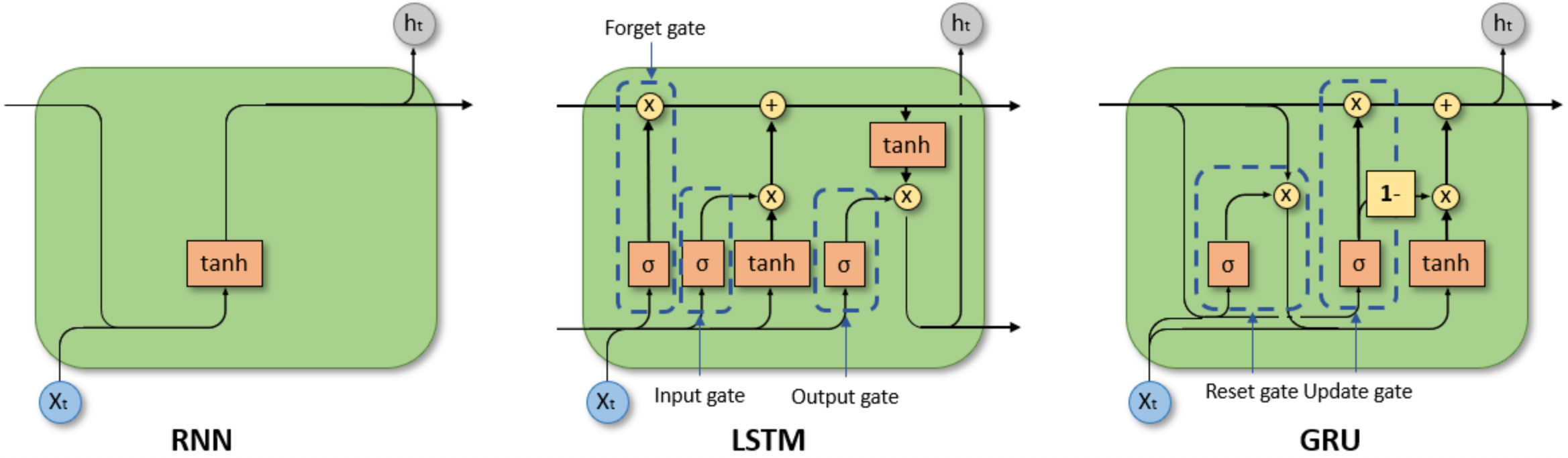
LSTM


y^t
c^{t-1}
z^f
z^i
z
z^o
x^t
z^o
Output Gate
Forget Gate
Cell
z^f
z^i
Input Gate
Block
z

LSTM



LSTM vs GRU


ht
tanh
Xt
RNN
Forget gate
ht
tanh
σ
σ
tanh
σ
Xt
Input gate
Output gate
LSTM
ht
1-
σ
σ
tanh
Xt
Reset gate Update gate
GRU

Limitations of RNN/LSTM

- Sequential computation
- Slow training
- Difficult long-range dependencies
- Hard to parallelize

These limitations motivated the development of Attention and Transformers.

Encoder-Decoder Model (Seq2Seq Model)

Encoder-Decoder Model

- $X^{(i)}$: i^{th} input
- $Y^{(i)}$: i^{th} output
- C: context (embedding)

Usage:

- Machine translation
- Question answering
- Dialog

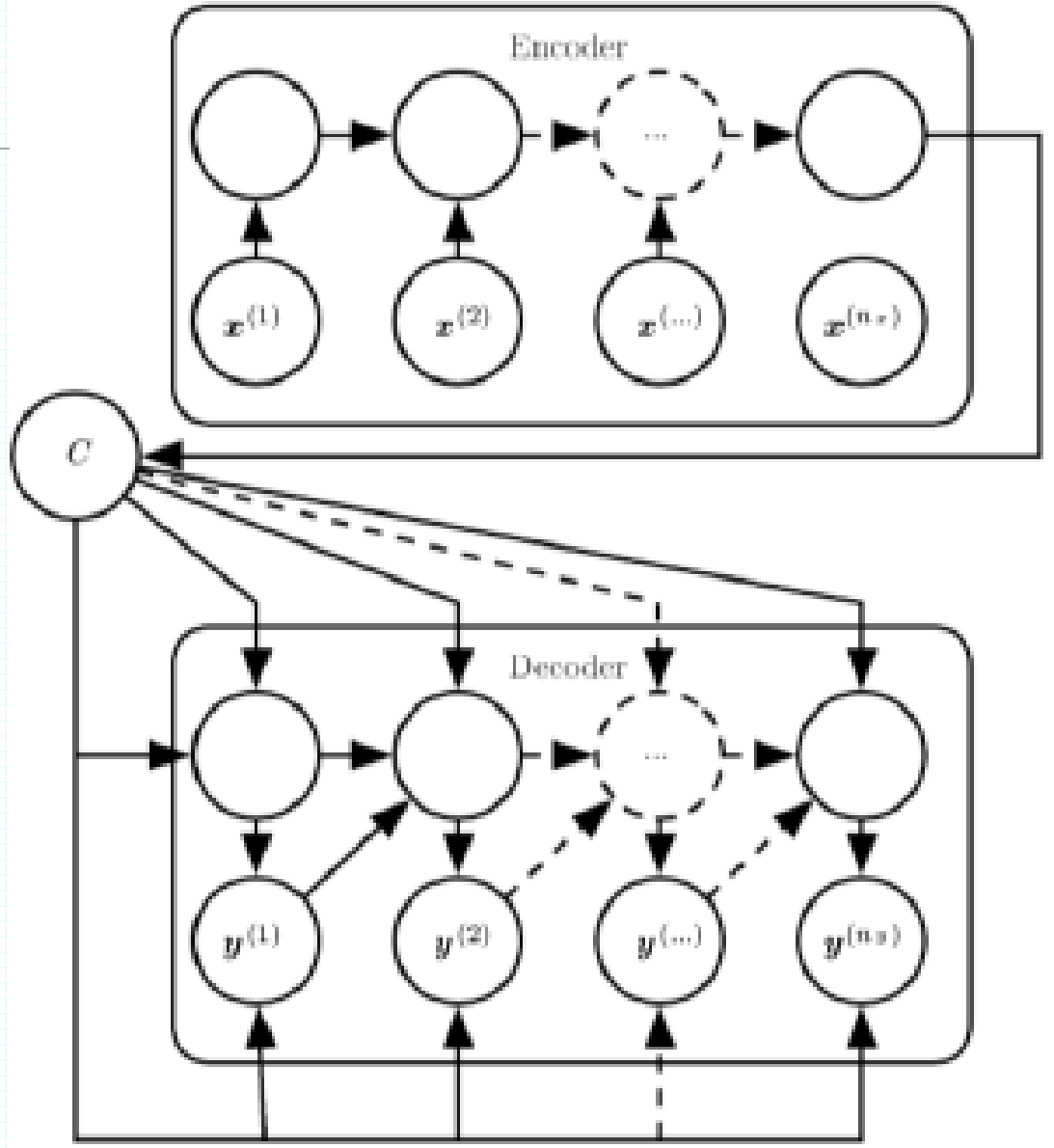


Image Caption Generation

- Input an image, but output a sequence of words

[Kelvin Xu, arXiv'15][Li Yao, ICCV'15]