# Lecture 5
# Neural Network and Deep Learning

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# Machine Learning ~ Looking for a Function

- Image recognition

$f($  $)$ → “Cat”

- Spam classification

$f($ “Tweets” $)$ → a spam message

- Weather prediction

$f($“*Observed Weather Conditions*”$)$ → Future weather condition

# Machine Learning ~ Training Framework







Training Data

A set of functions (models) $f_1, f_2, \ldots$

Goodness of function $f$

Pick the "best" function $f^*$

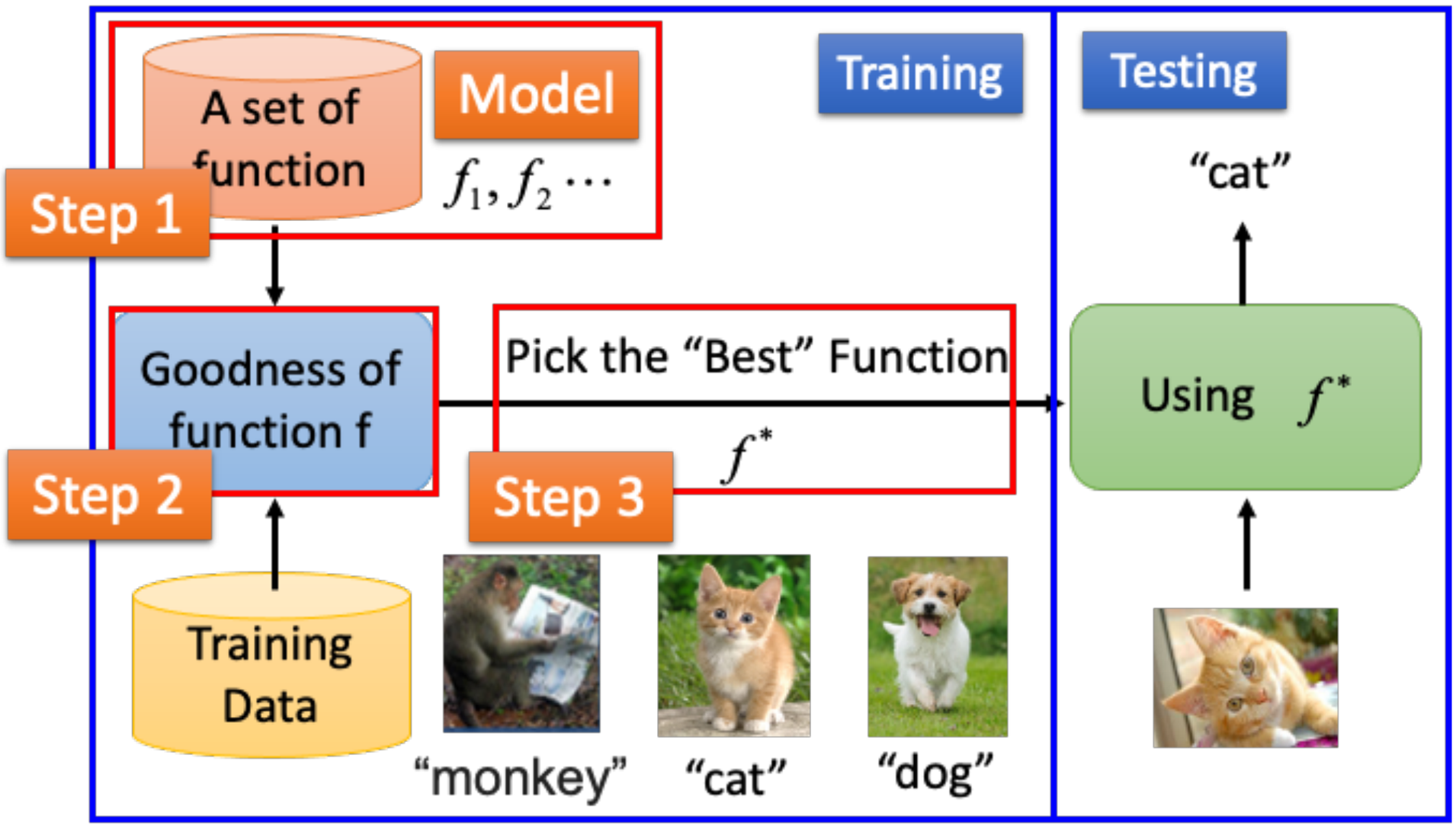
Trained Model

# Framework

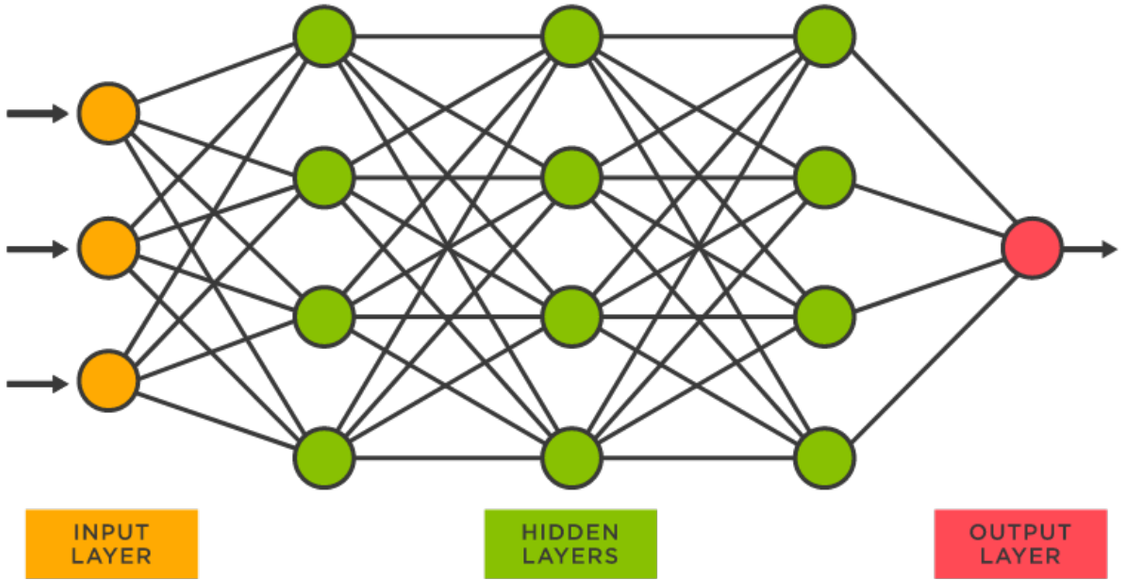
Image Recognition:

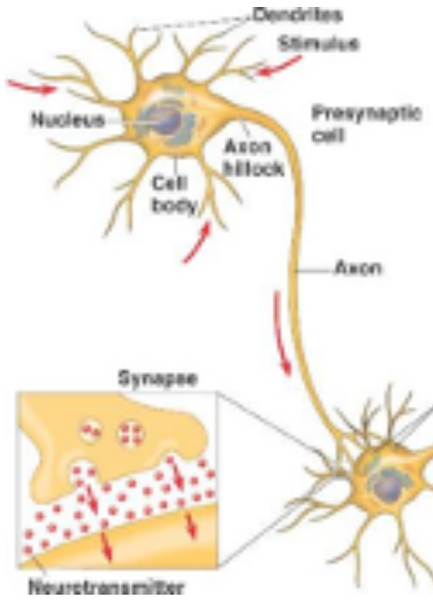
Framework

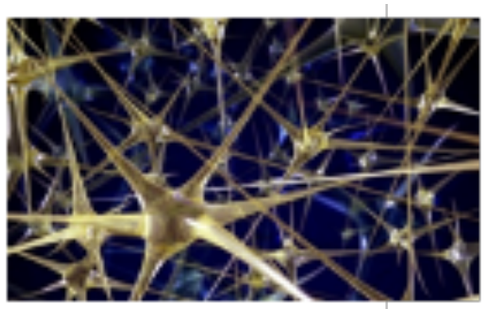
$f($  $)=$ "cat"



# Neural Network

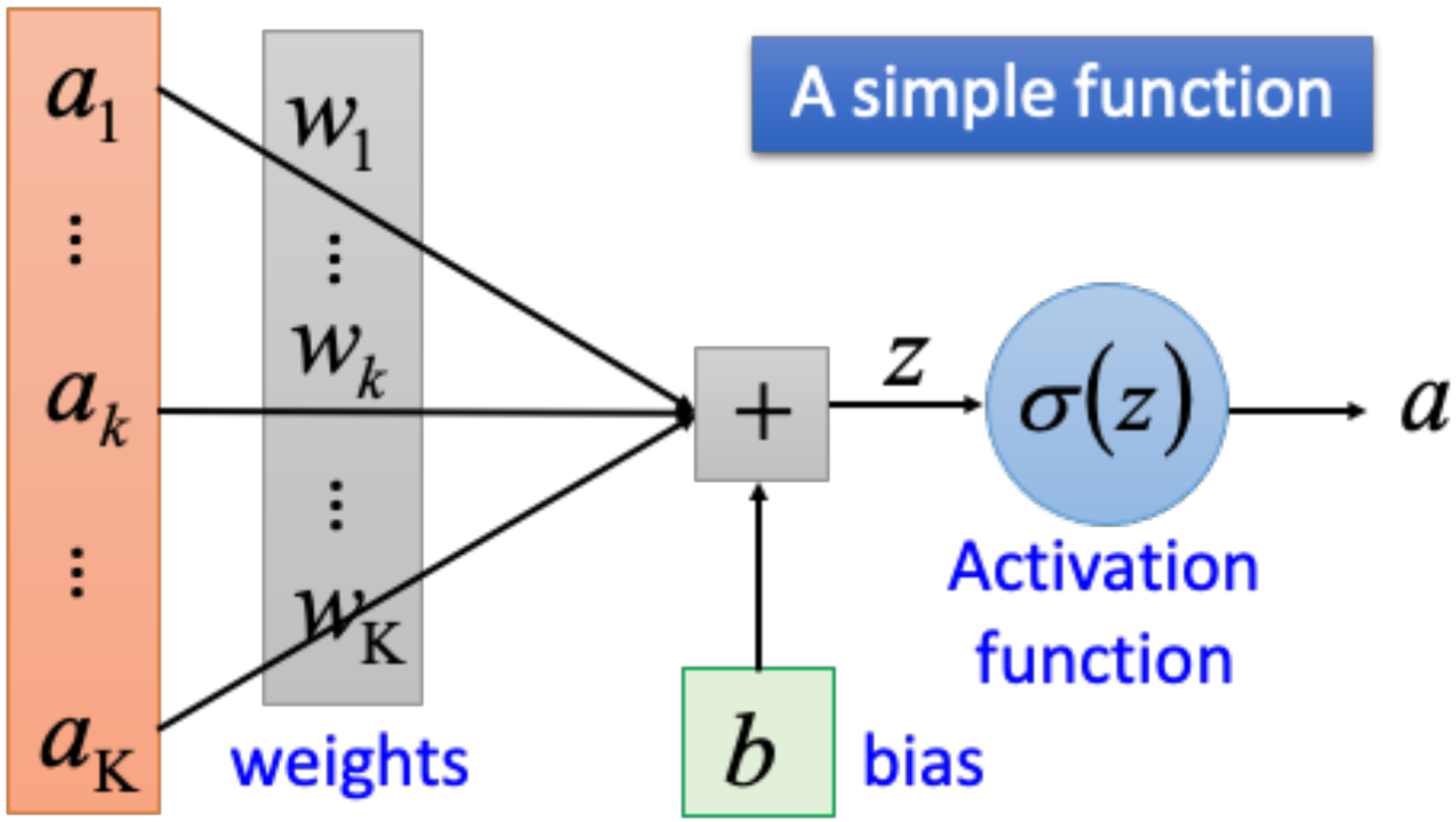


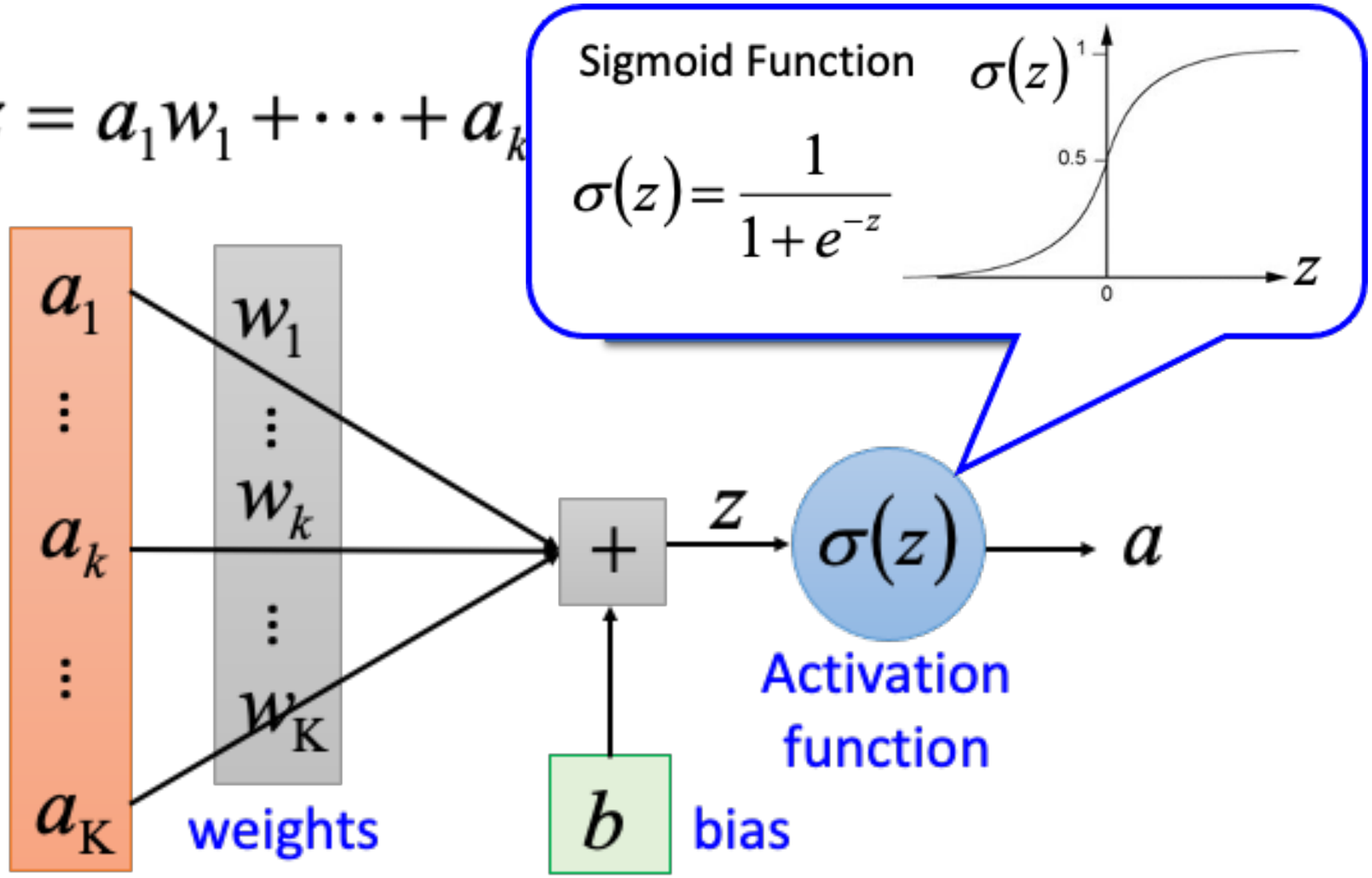
# At Each Neuron

$$z = a_1 w_1 + \cdots + a_k w_k + \cdots + a_K w_K + b$$

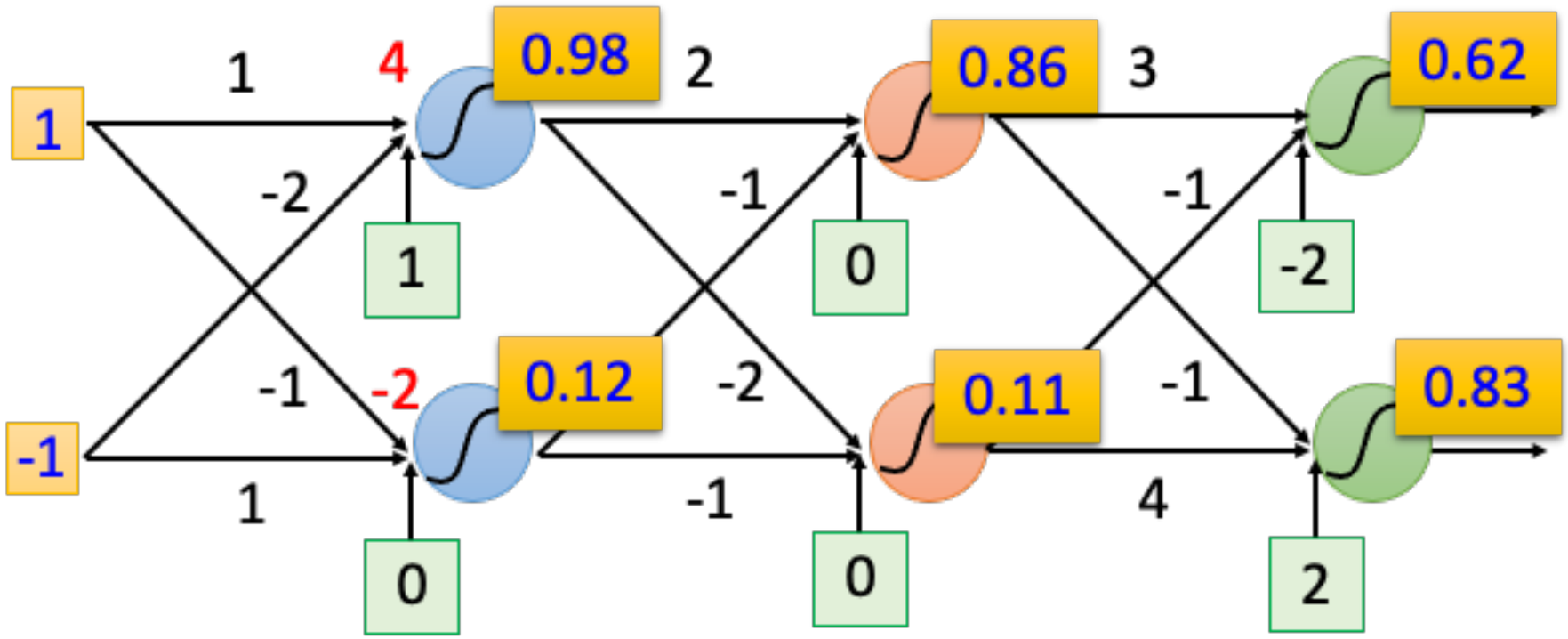


# At Each Neuron

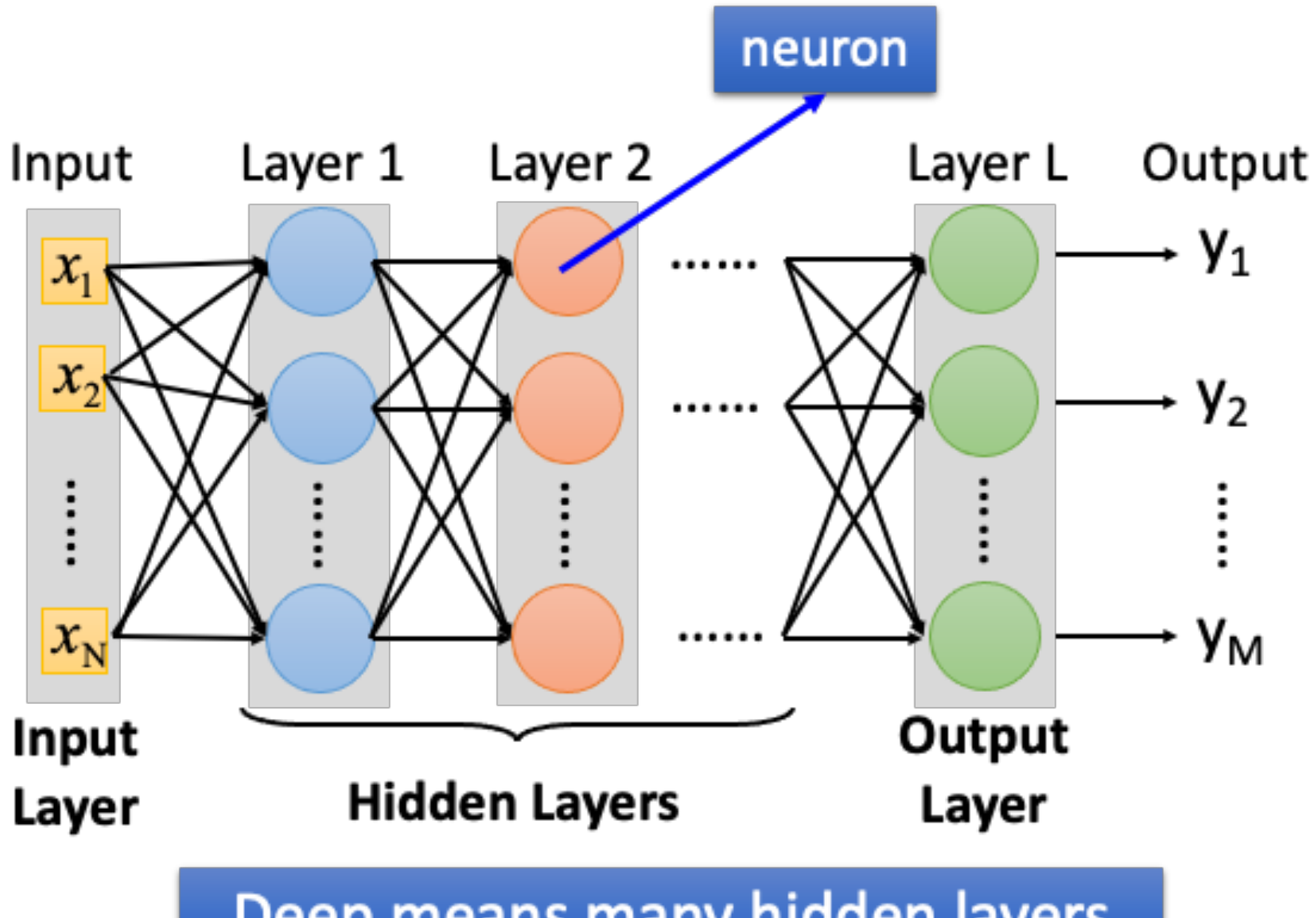
$$z = a_1 w_1 + \cdots + a_k$$



# Fully Connected Neural Network



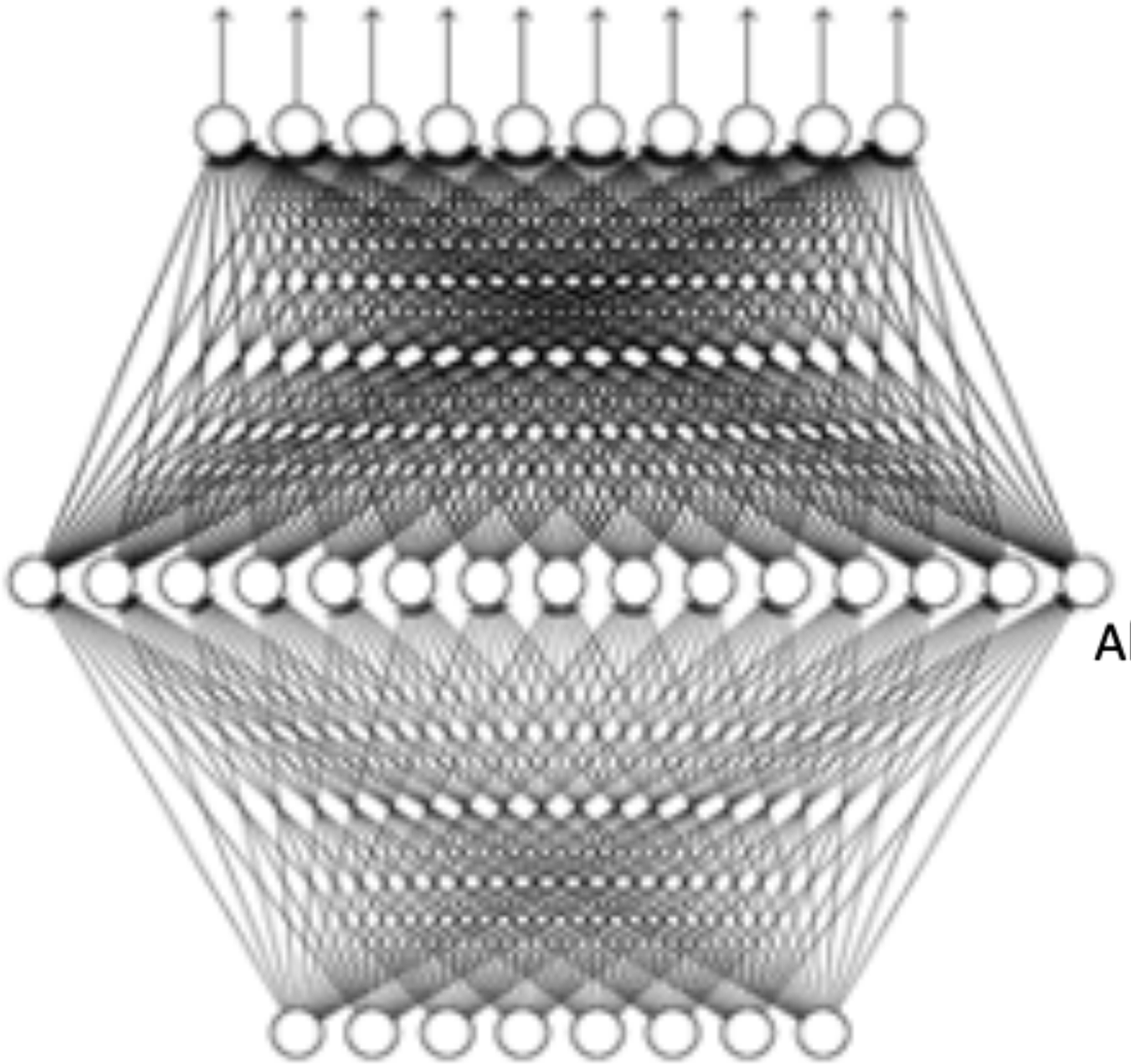
# Fully Connected Neural Network



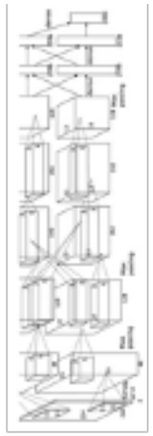

Deep means many hidden layers

# Deep Neural Network

Deep = Many hidden layers



8 layers



AlexNet (2012)

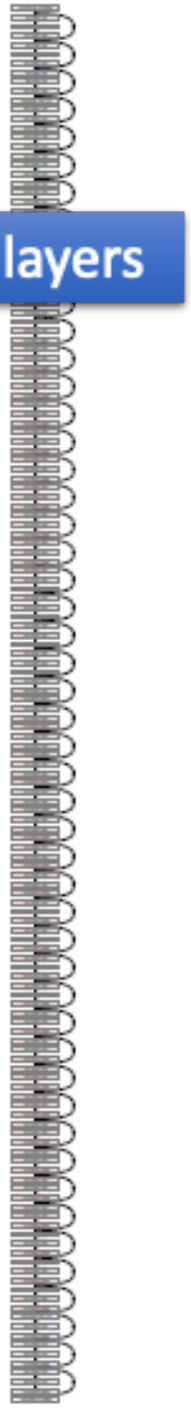
19 layers


VGG (2014)

22 layers

GoogleNet (2015)

152 layers

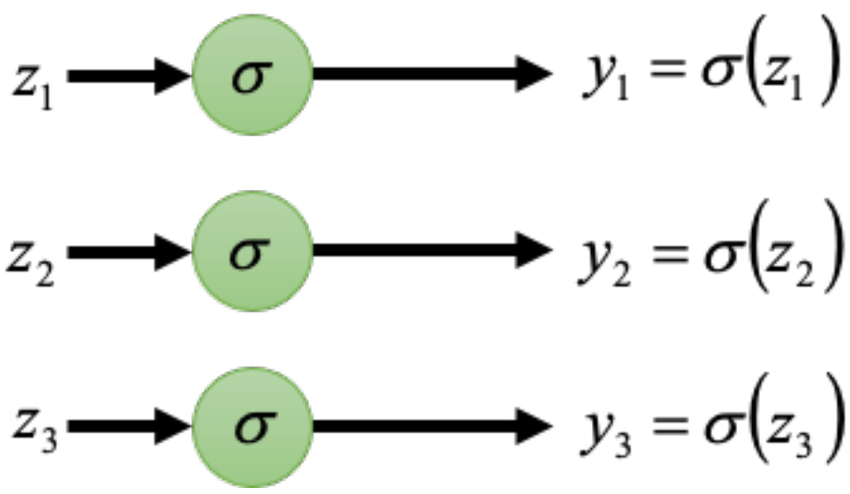


ResidualNet (2015)

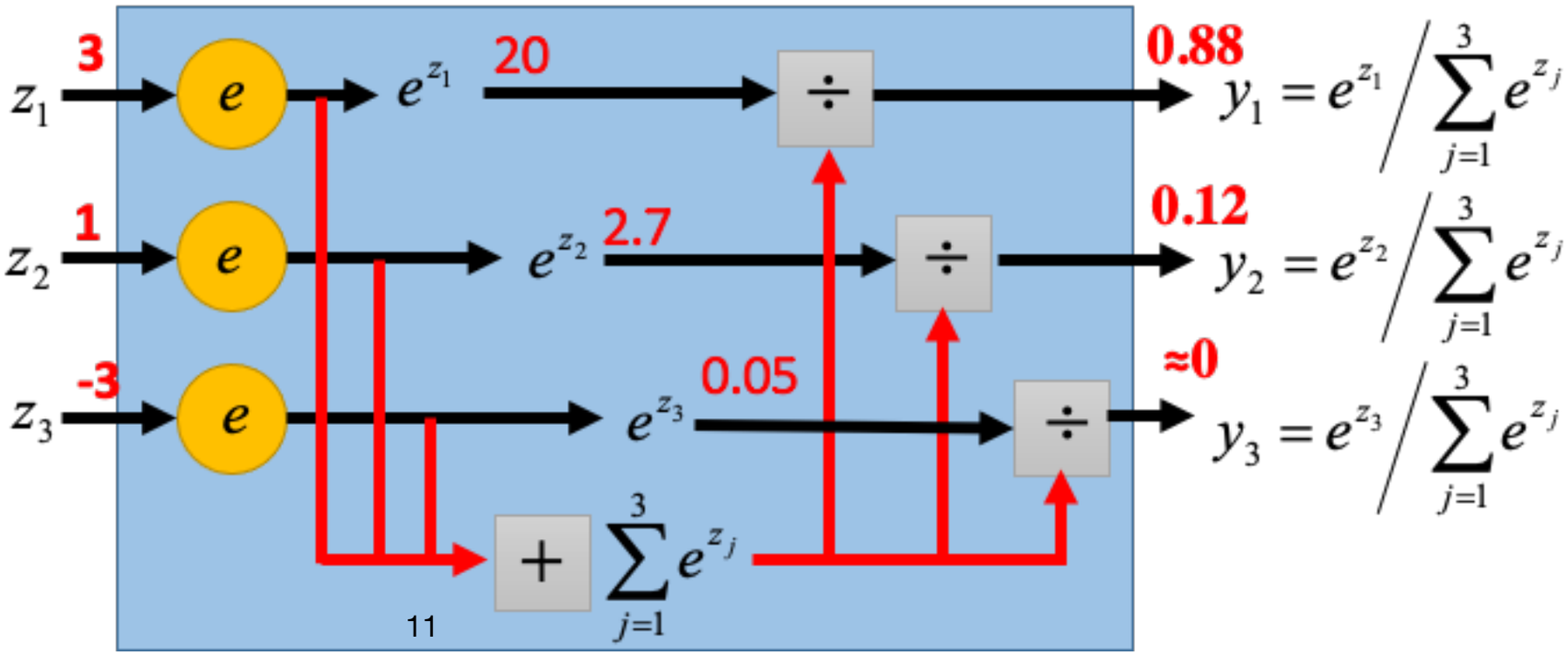
Using multiple layers of neurons to represent some functions

# Output Layer

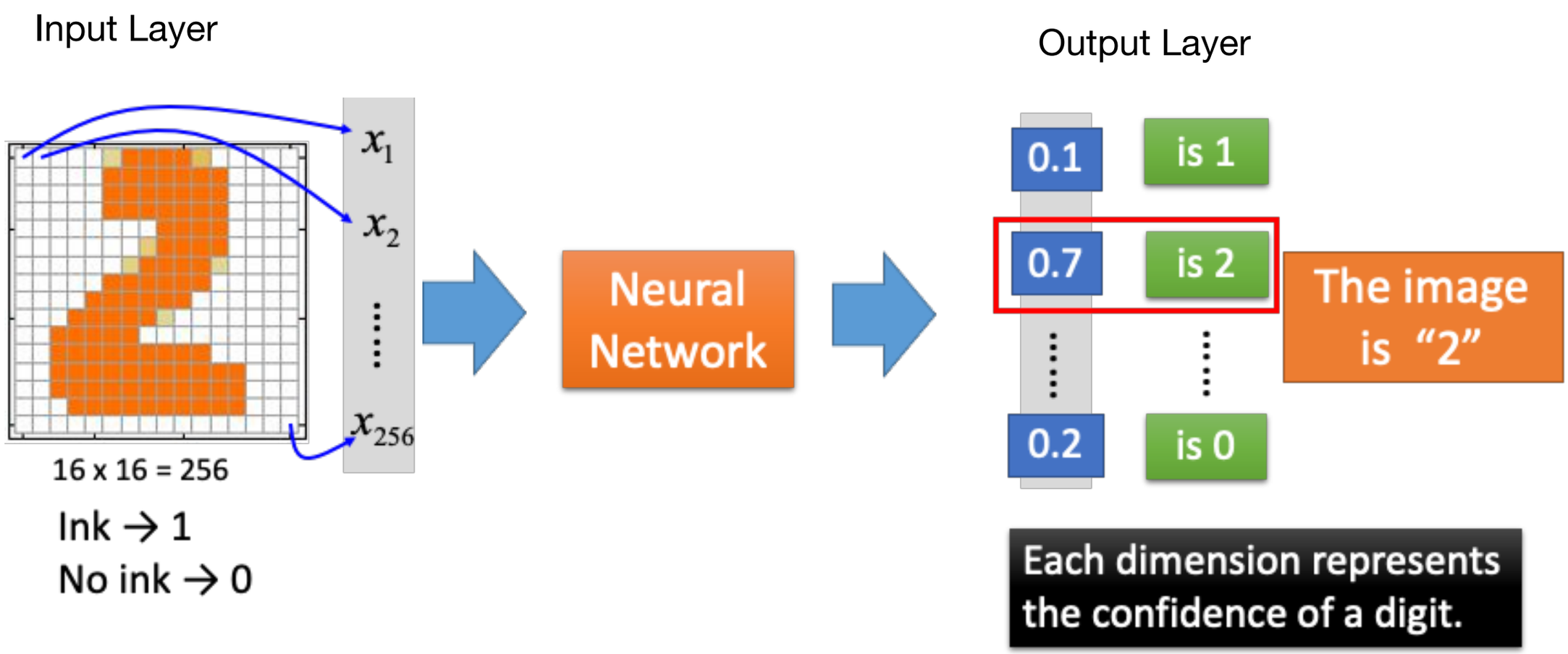
***Ordinary Layer***



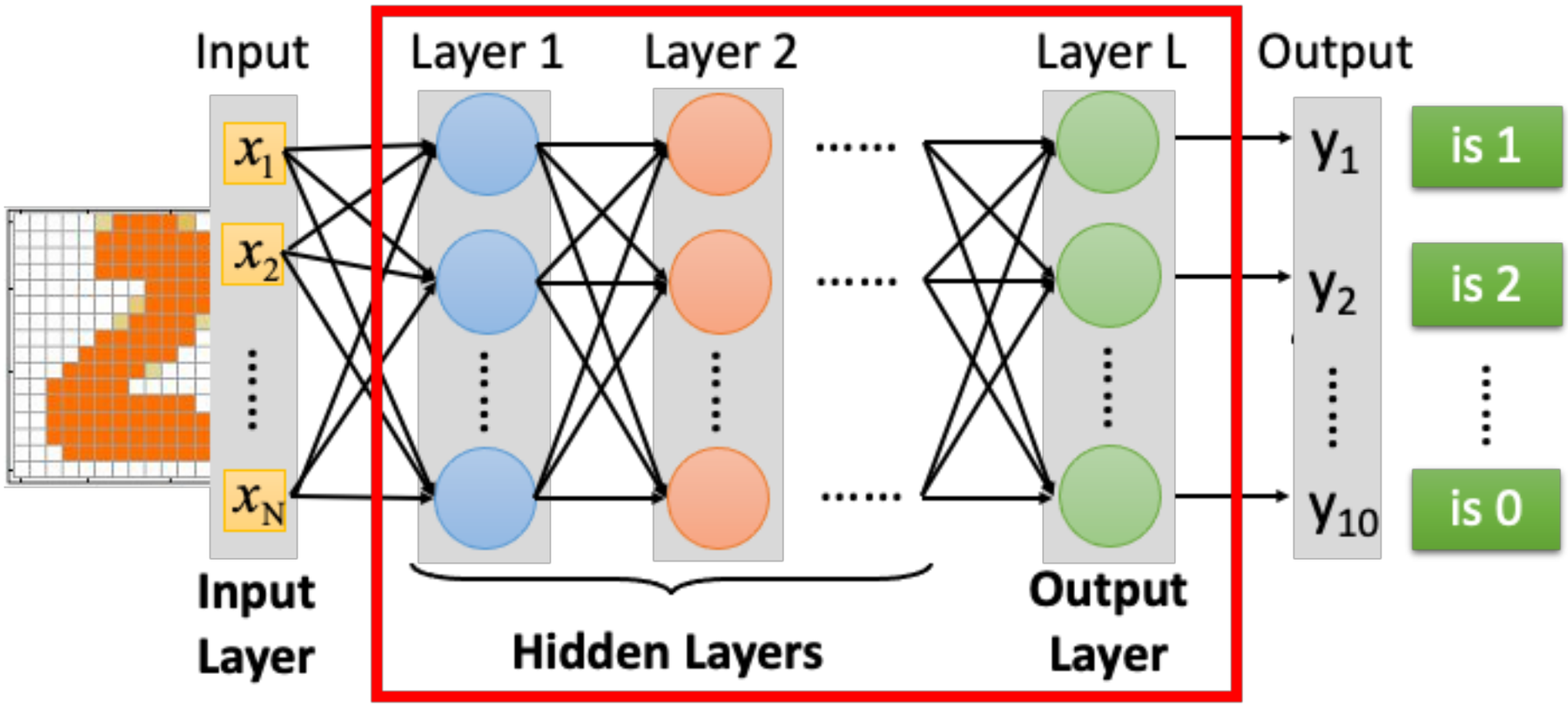

***Softmax Layer***



# An Example


Input Layer
$x_1$
$x_2$
$x_{256}$
16 x 16 = 256
Ink → 1
No ink → 0
Neural Network
Output Layer
0.1
is 1
0.7
is 2
0.2
is 0
The image is "2"
Each dimension represents the confidence of a digit.

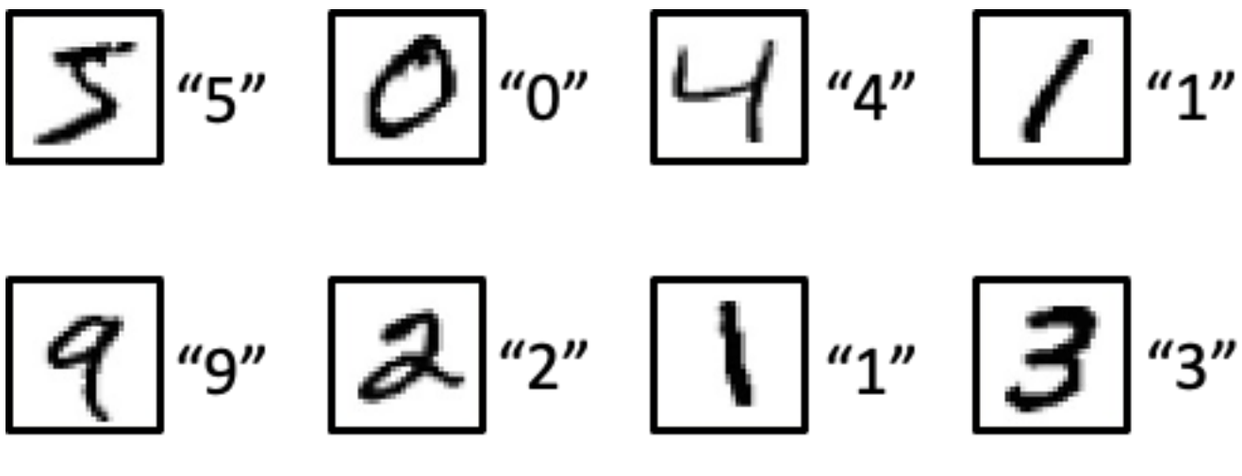
# An Example




Needs to determine the network structure

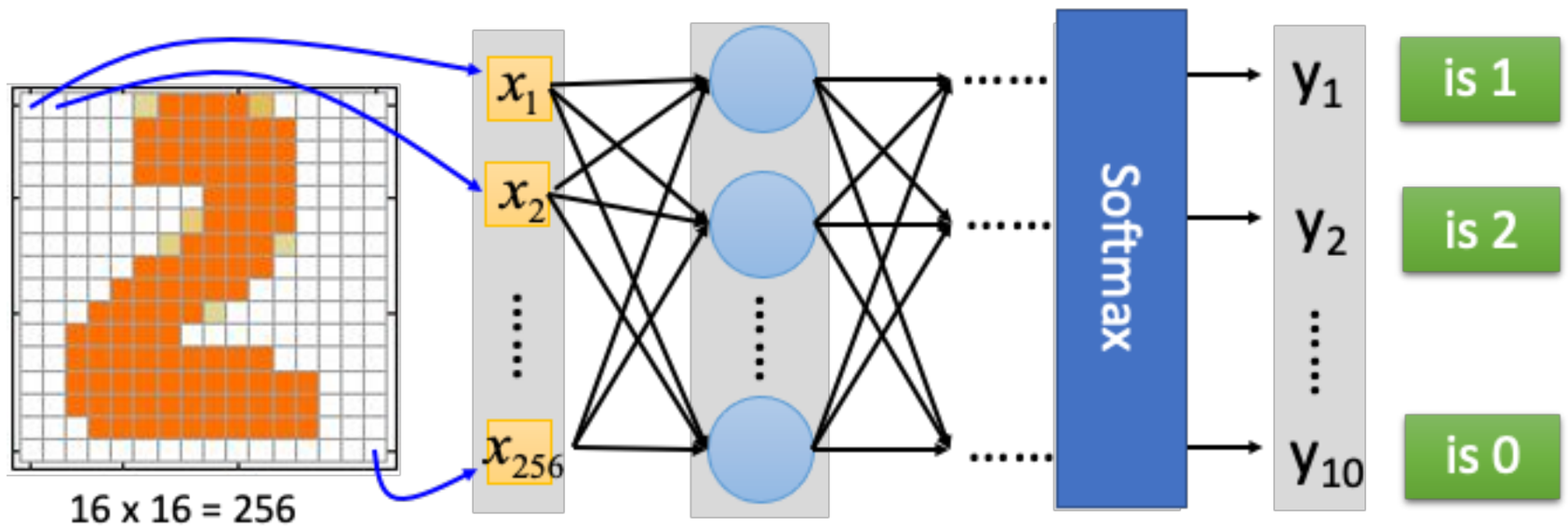
How many layers?
How many neurons for each layer?

# Learning Target




The learning target is defined on the training data.

# Learning Target




Ink → 1

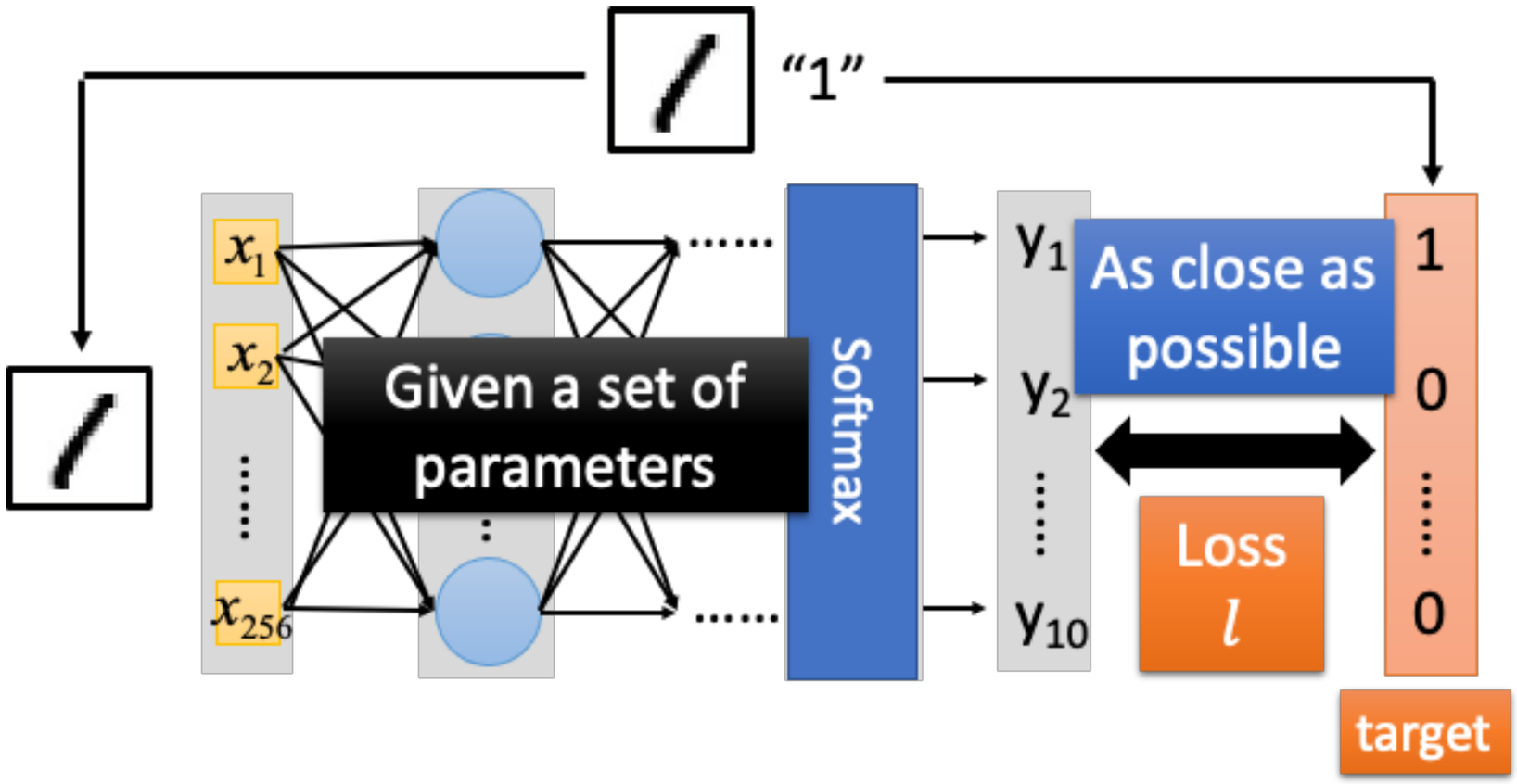
No ink → 0

The learning target is ……

Input:  → $y_1$ has the maximum value

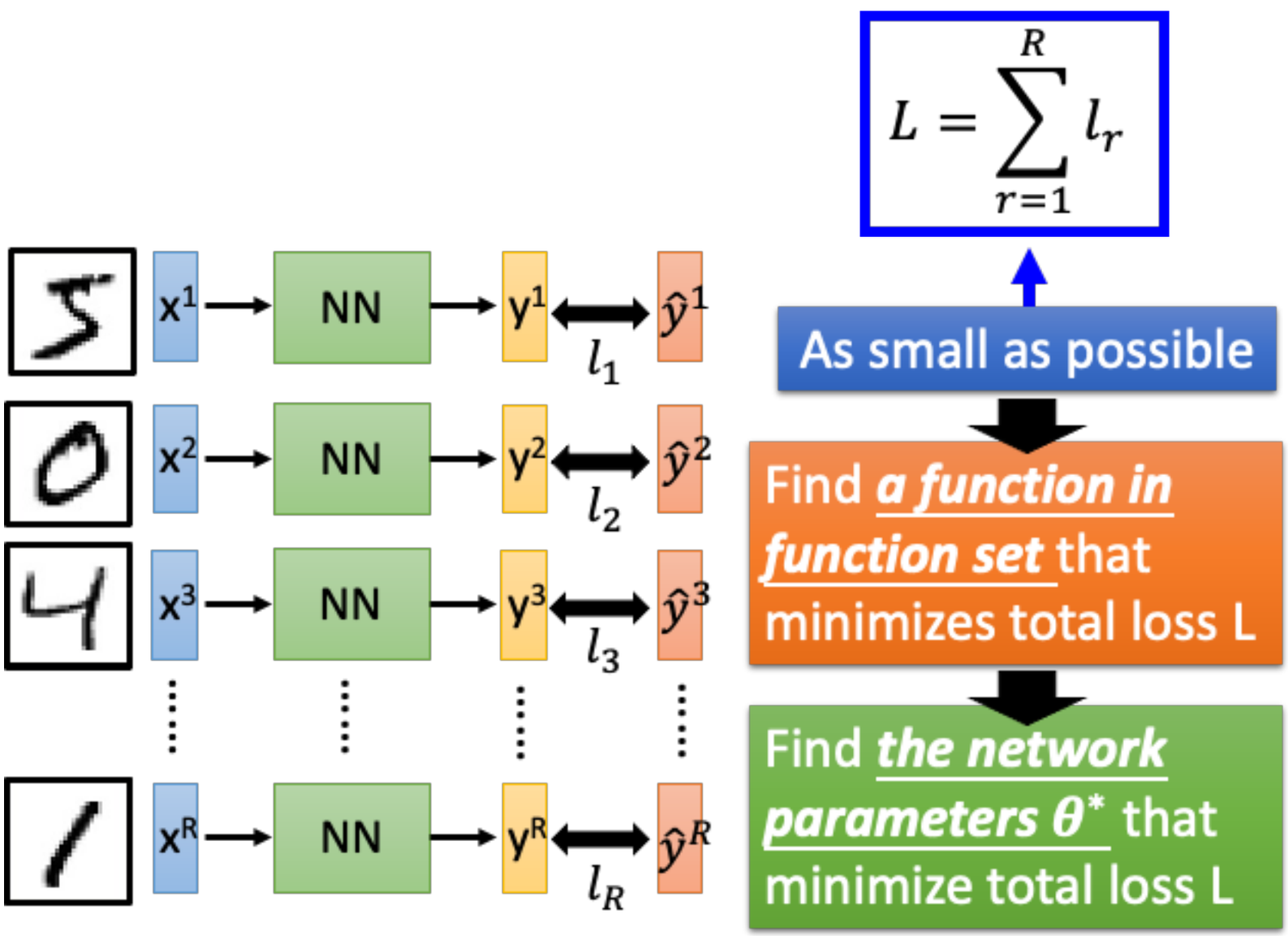
Input:  → $y_2$ has the maximum value

# Good Function = Loss as Small as Possible




Loss can be square error or cross entropy between the output and the target

# Total Loss


$x^1$
NN
$y^1$
$\hat{y}^1$
$l_1$
$x^2$
NN
$y^2$
$\hat{y}^2$
$l_2$
$x^3$
NN
$y^3$
$\hat{y}^3$
$l_3$
$x^R$
NN
$y^R$
$\hat{y}^R$
$l_R$
$L = \sum_{r=1}^{R} l_r$
As small as possible
Find *a function in function set* that minimizes total loss L
Find *the network parameters* $\theta^*$ that minimize total loss L

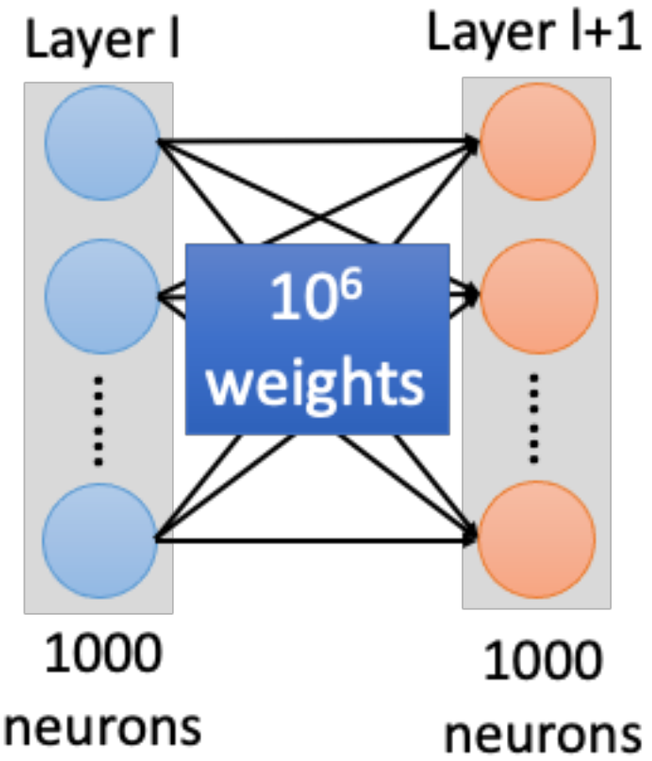
# Total Loss

Find ***network parameters $\theta^*$*** that minimize total loss L

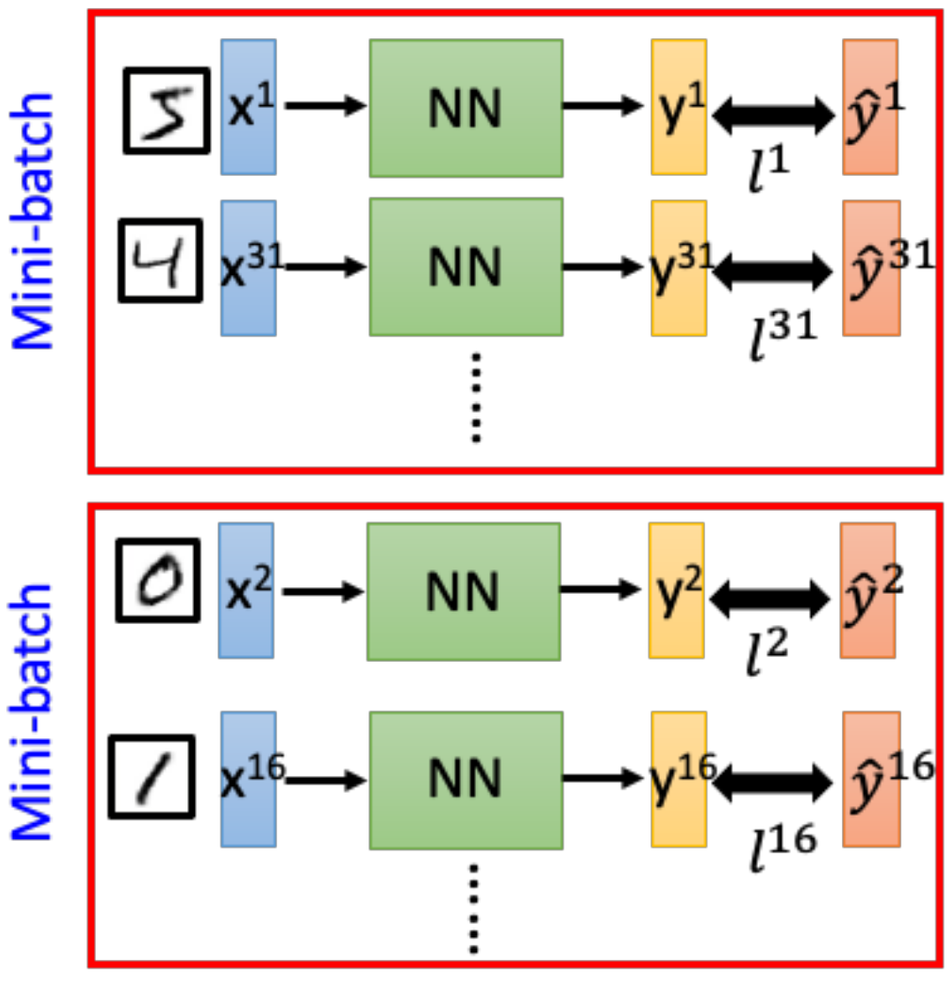
Enumerate all possible values

Network parameters $\theta = \{w_1, w_2, w_3, \cdots, b_1, b_2, b_3, \cdots\}$

Millions of parameters



# Mini-batch




- Randomly initialize network parameters

- Pick the 1st batch

  $L' = l^1 + l^{31} + \cdots$

  Update parameters once

- Pick the 2nd batch

  $L'' = l^2 + l^{16} + \cdots$

  Update parameters once

  ⋮

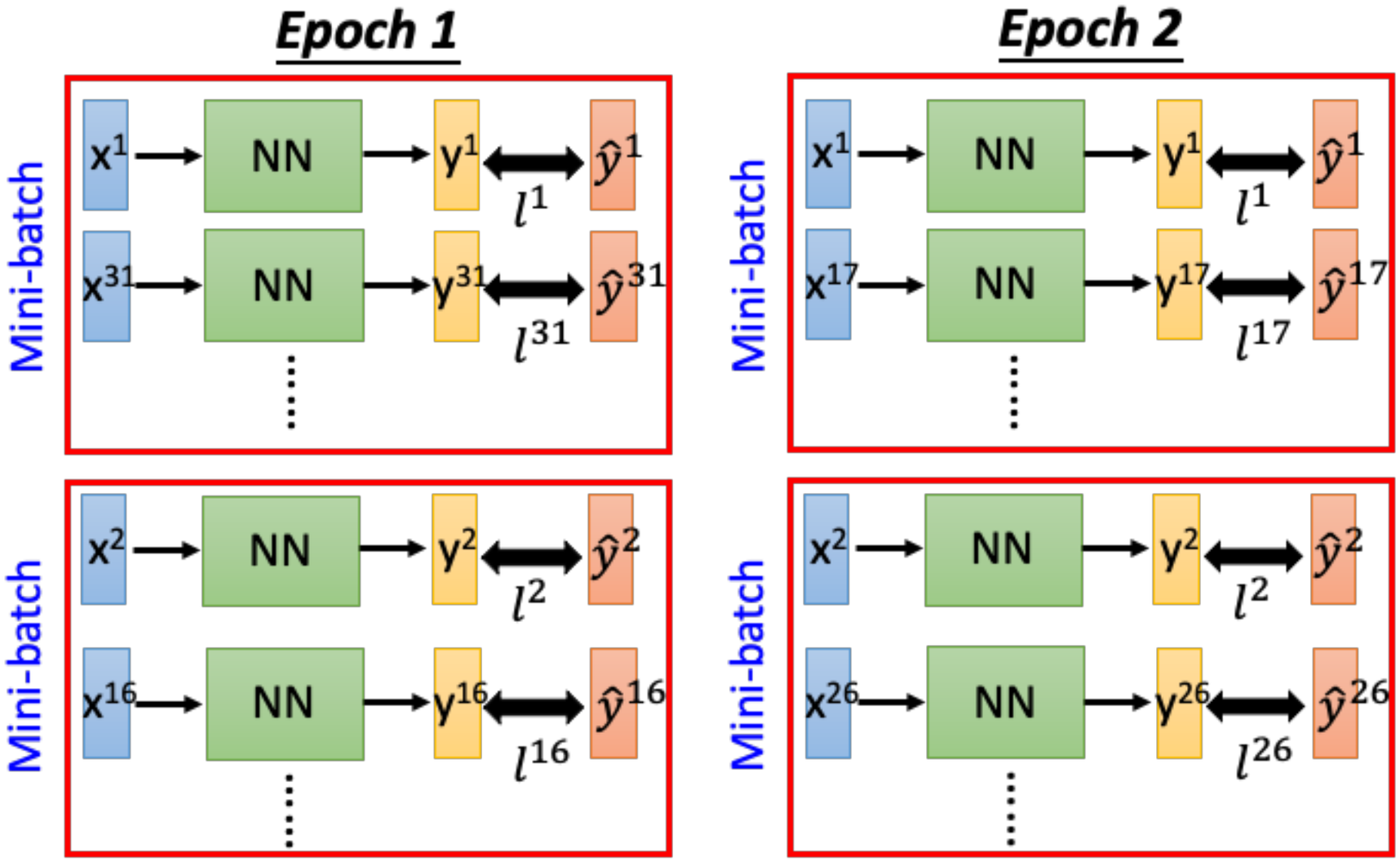
- Until all mini-batches have been picked

one epoch

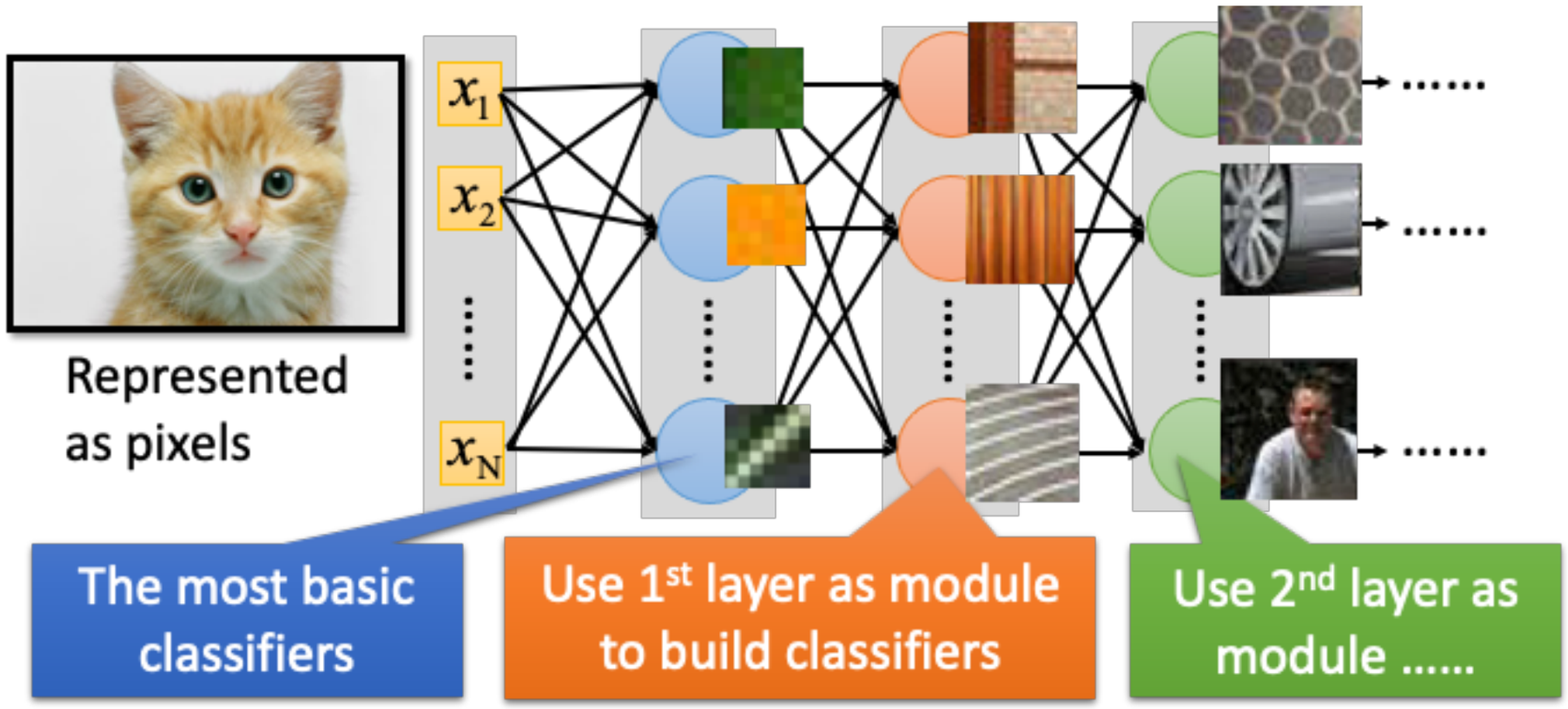
Repeat the above process

We do not really minimize total loss!

# Mini-batch


Epoch 1
Epoch 2
Mini-batch
Mini-batch
Mini-batch
Mini-batch
NN
NN
NN
NN
NN
NN
NN
NN
$x^1$
$x^{31}$
$x^2$
$x^{16}$
$x^1$
$x^{17}$
$x^2$
$x^{26}$
$y^1$
$y^{31}$
$y^2$
$y^{16}$
$y^1$
$y^{17}$
$y^2$
$y^{26}$
$\hat{y}^1$
$\hat{y}^{31}$
$\hat{y}^2$
$\hat{y}^{16}$
$\hat{y}^1$
$\hat{y}^{17}$
$\hat{y}^2$
$\hat{y}^{26}$
$l^1$
$l^{31}$
$l^2$
$l^{16}$
$l^1$
$l^{17}$
$l^2$
$l^{26}$

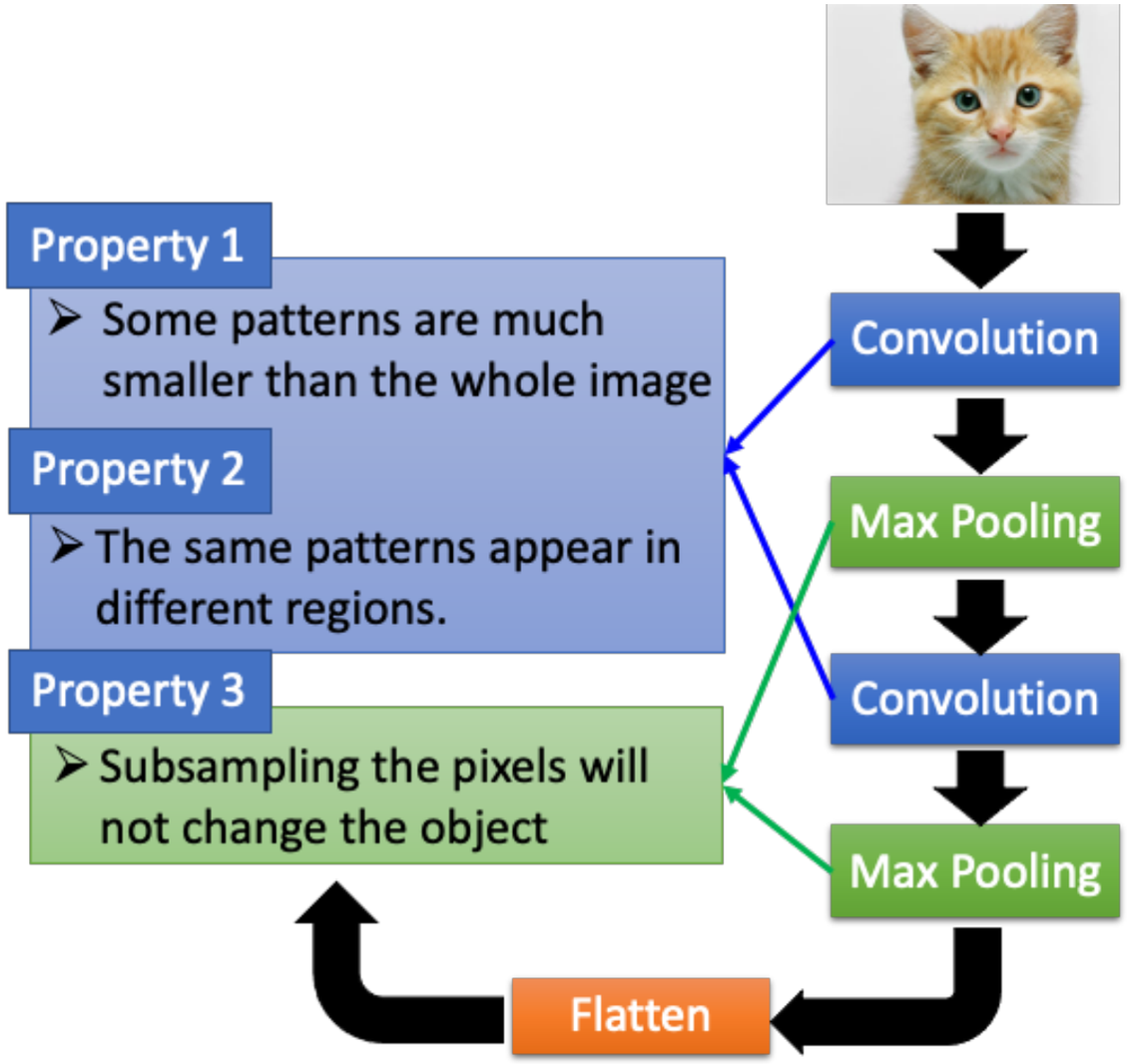
# Convolutional Neural Network (CNN)




Each pixel as one input

Can we simplify the network by considering the properties of Images?

# Convolutional Neural Network (CNN)




**We can subsample the pixels to make image smaller**

**Less parameters for the network to process the image**

# CNN -Convolution

| | | | | | |
|---|---|---|---|---|---|
| 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 |

Filter1
Matrix

| | | |
|---|---|---|
| -1 | 1 | -1 |
| -1 | 1 | -1 |
| -1 | 1 | -1 |

Filter 2
Matrix

…
…
…
…

Each filter detects a small region (3x3) Property 1

# CNN -Convolution

| | | | | | |
|---|---|---|---|---|---|
| 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 |

| | | |
|---|---|---|
| 1 | -1 | -1 |
| -1 | 1 | -1 |
| -1 | -1 | 1 |

Filter 1

3

# CNN -Convolution

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 |

| | | | | | |
|---|---|---|---|---|---|
| 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 |

| | | |
|---|---|---|
| 1 | -1 | -1 |
| -1 | 1 | -1 |
| -1 | -1 | 1 |

Filter 1

3

-1

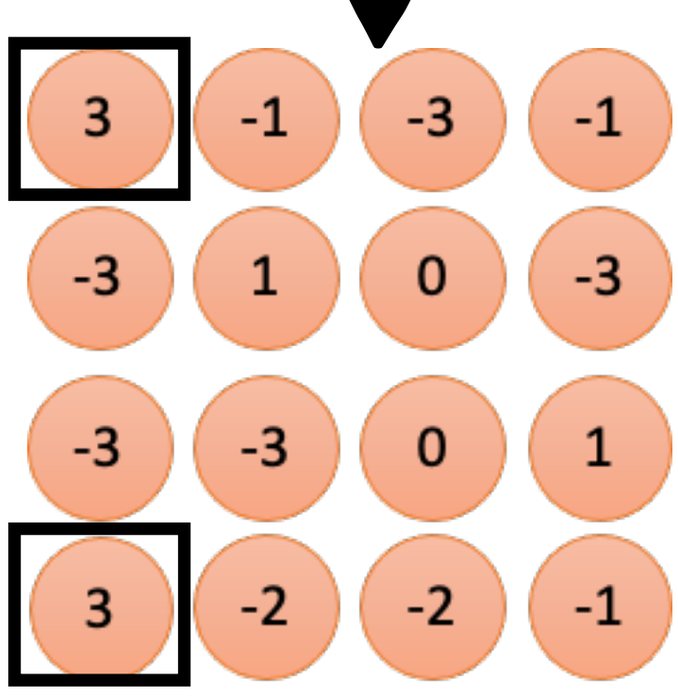
-3

# CNN -Convolution

| | | | | | |
|---|---|---|---|---|---|
| 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 |

| | | |
|---|---|---|
| 1 | -1 | -1 |
| -1 | 1 | -1 |
| -1 | -1 | 1 |

Filter 1



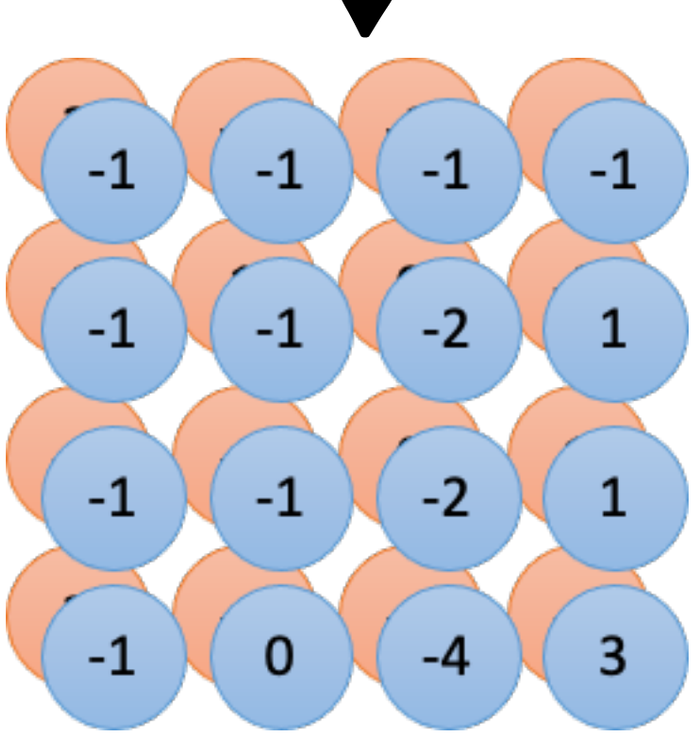

Property 2: Same patterns appears at different region!

# CNN -Convolution

| | | | | | |
|---|---|---|---|---|---|
| 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 |

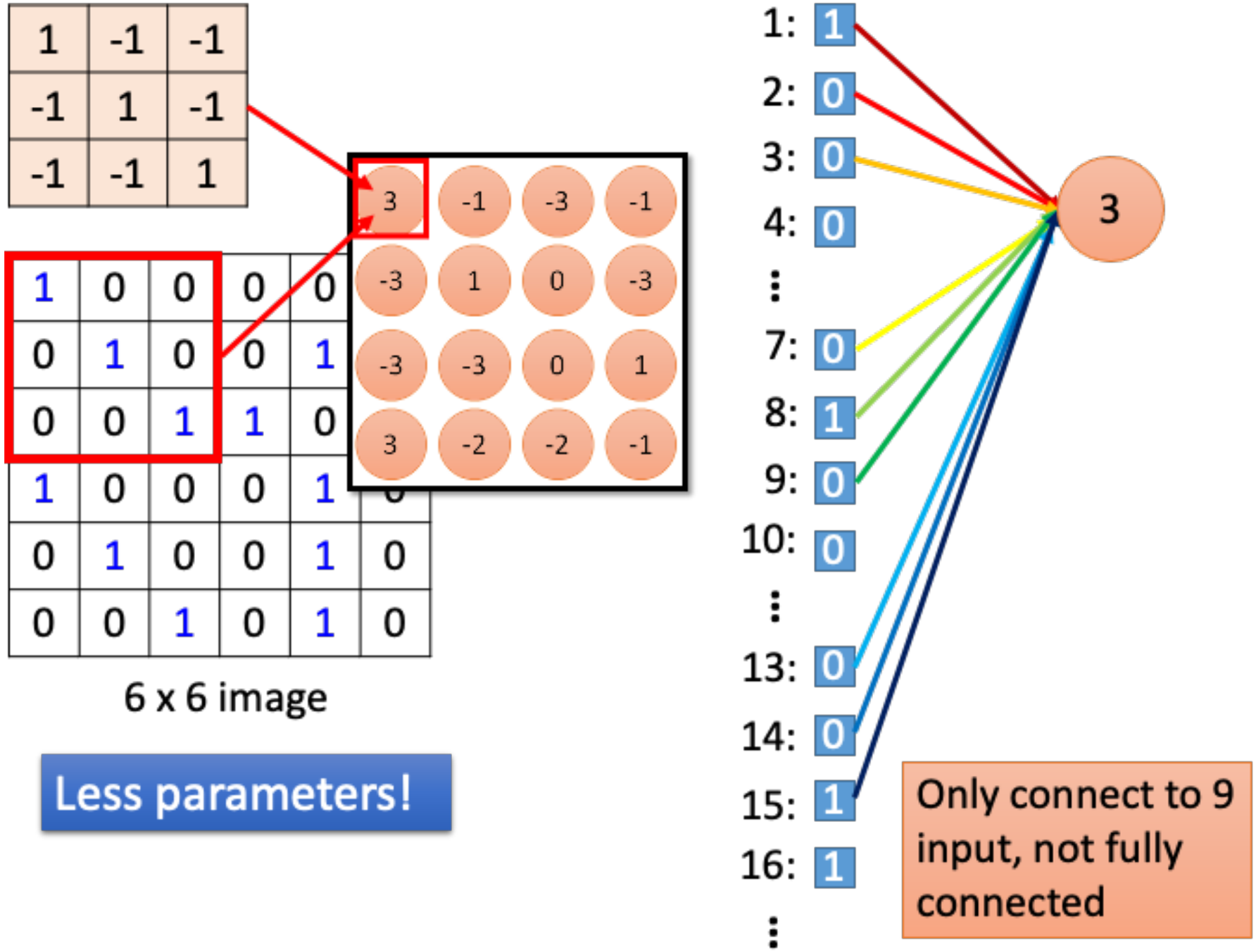
| | | |
|---|---|---|
| -1 | 1 | -1 |
| -1 | 1 | -1 |
| -1 | 1 | -1 |

Filter2

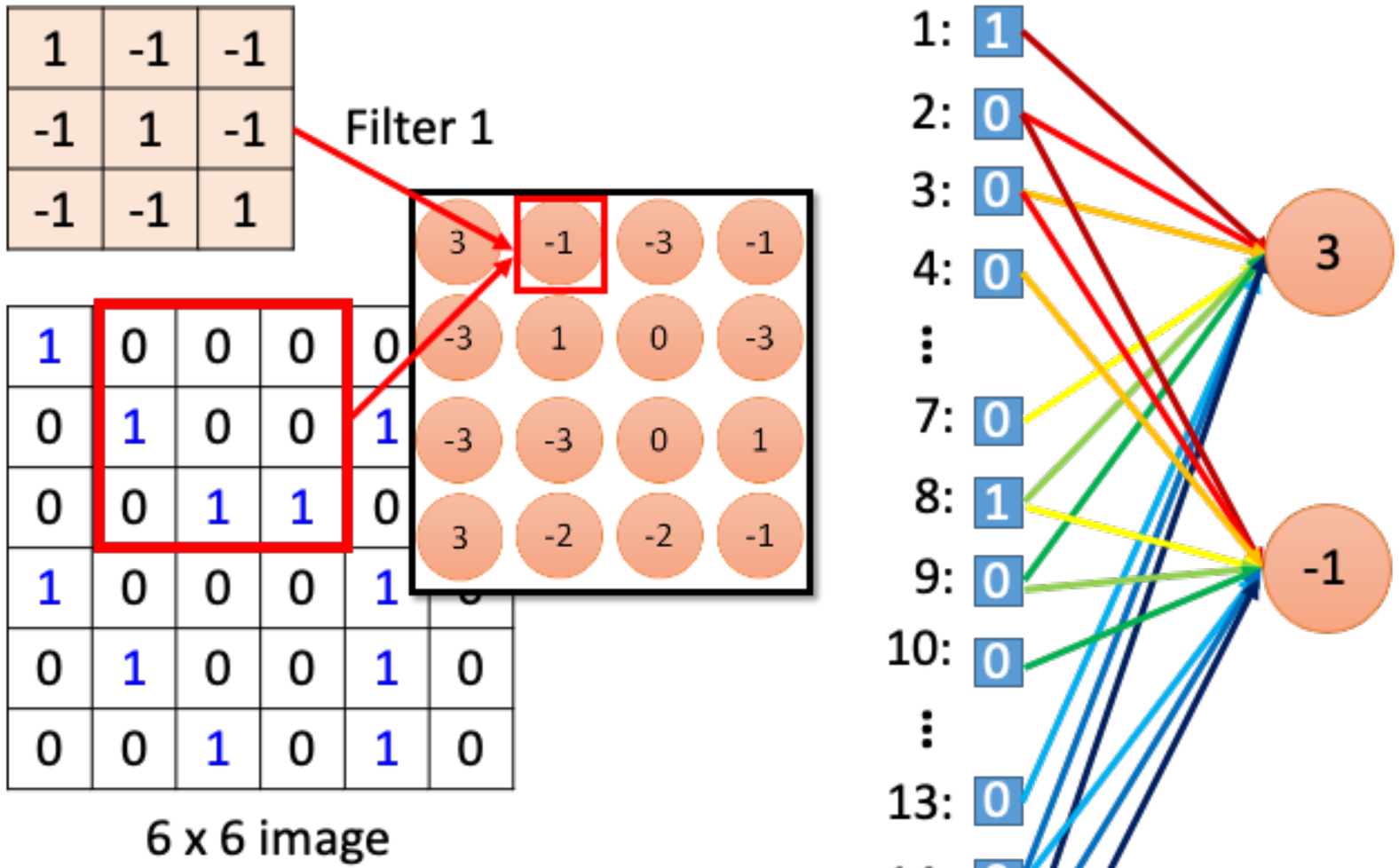



Property 2: Same patterns appears at different region!

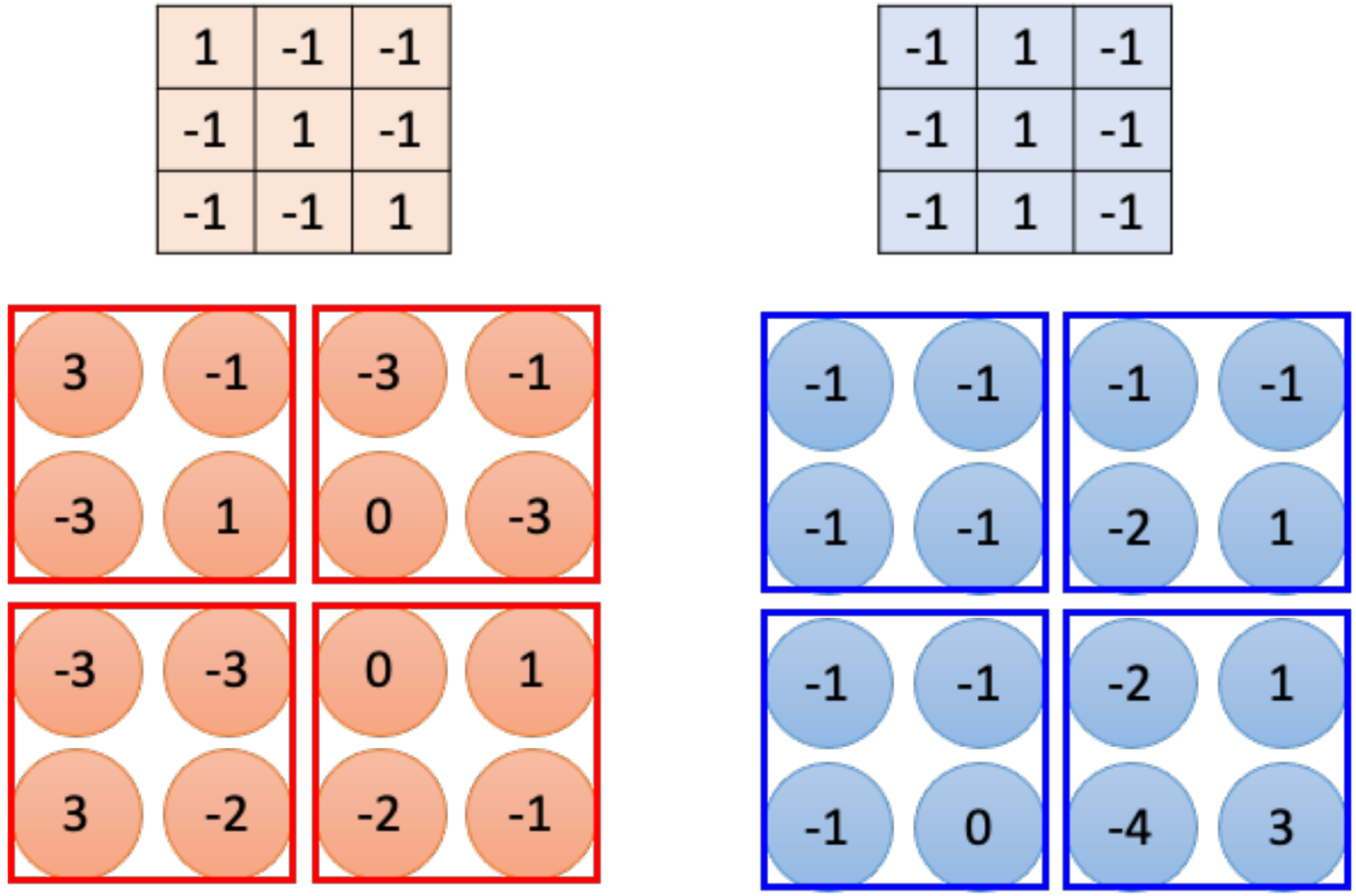
# CNN -Convolution



# CNN -Convolution



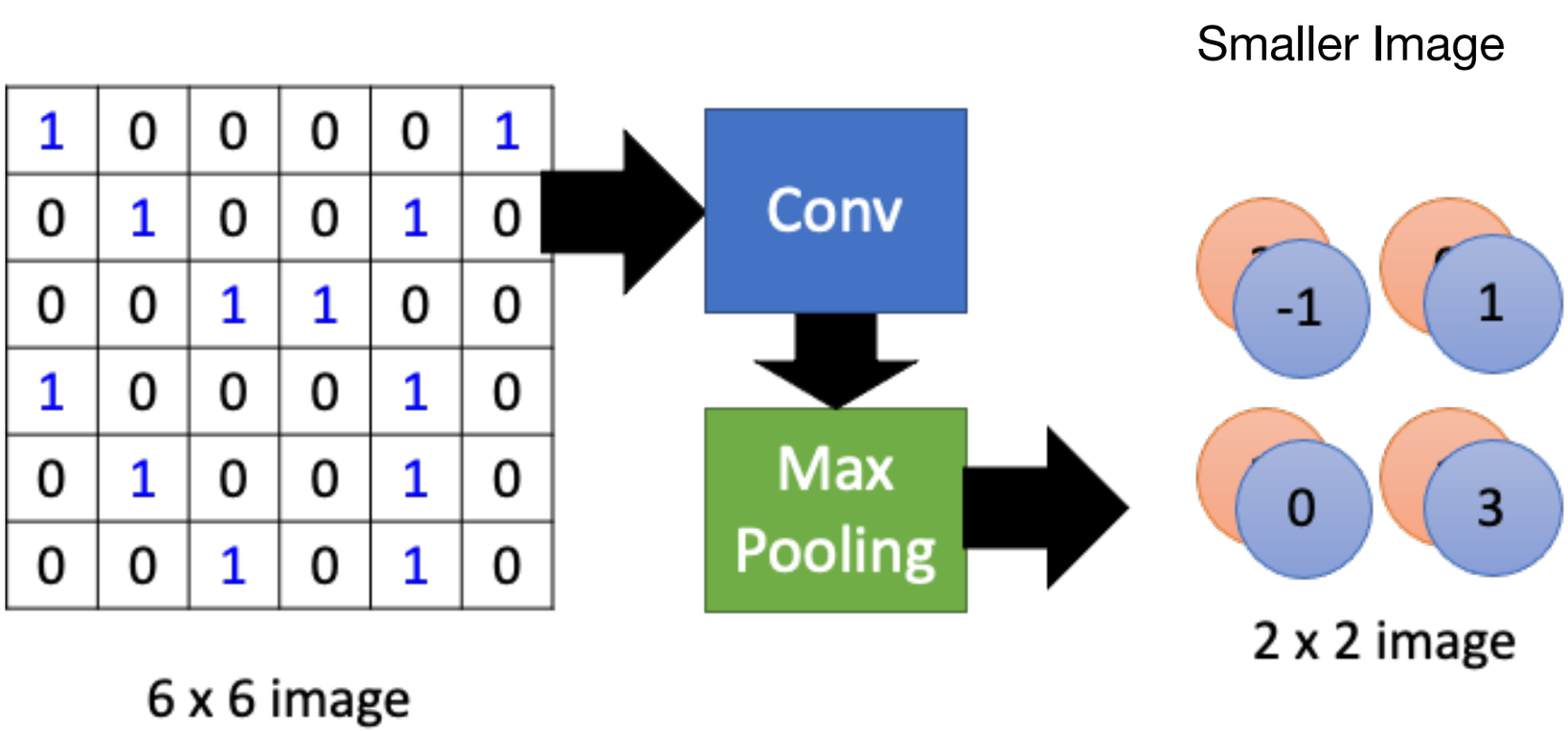
# CNN -Max Pooling



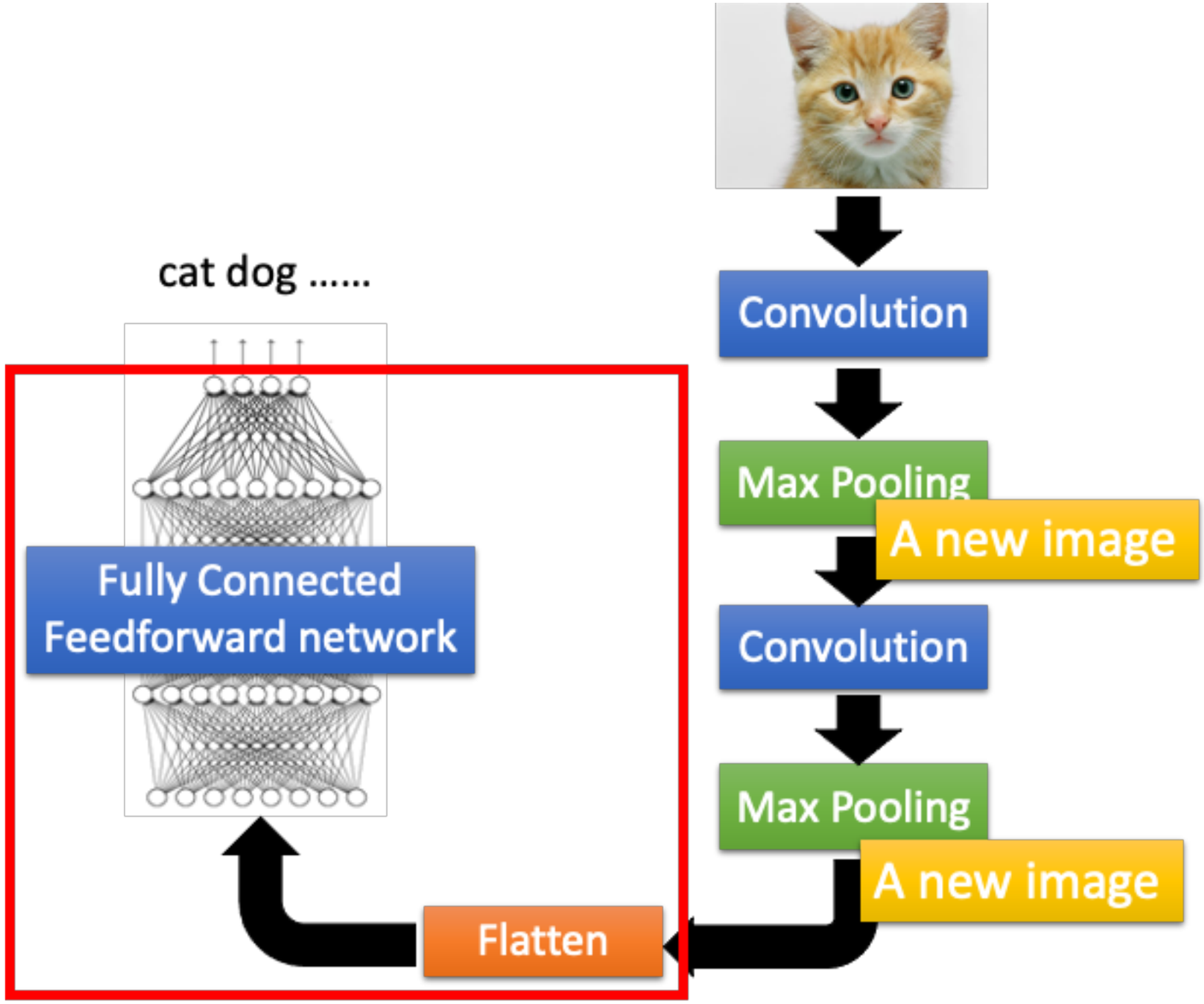


Take the dominant Features
Feature Dimensionality Reductio

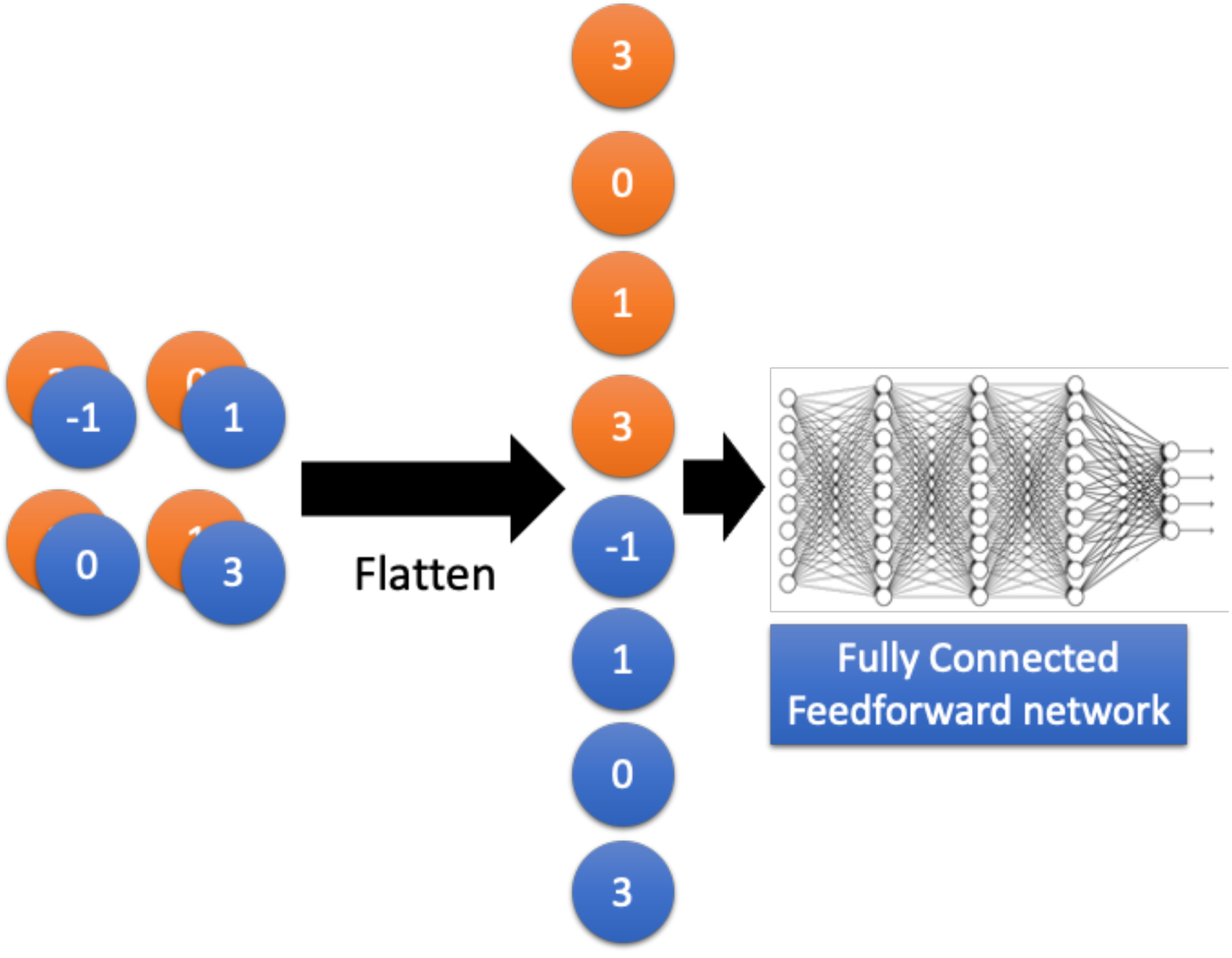
# CNN -Convolution



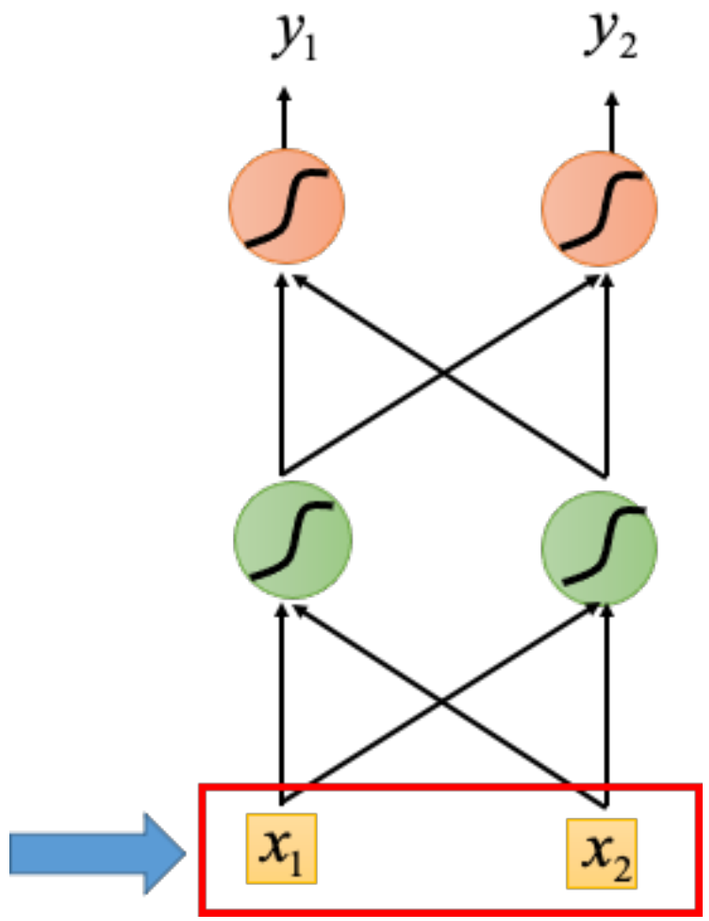
# The Whole CNN



# Flatten


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

# Recurrent Neural Network




Input: Vector

# Word to Vector

1to N encoding → Embedding to high dimensional space

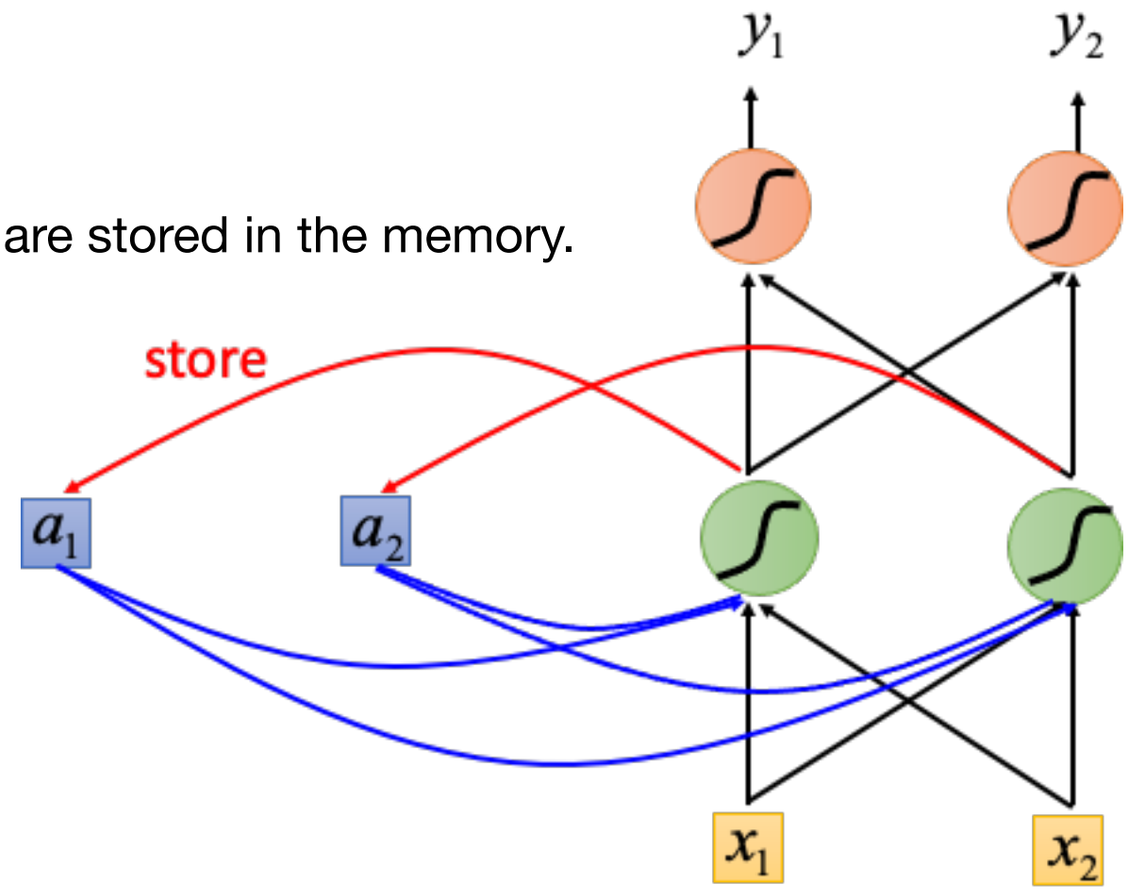
lexicon = {apple, bag, cat, dog, elephant}

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]

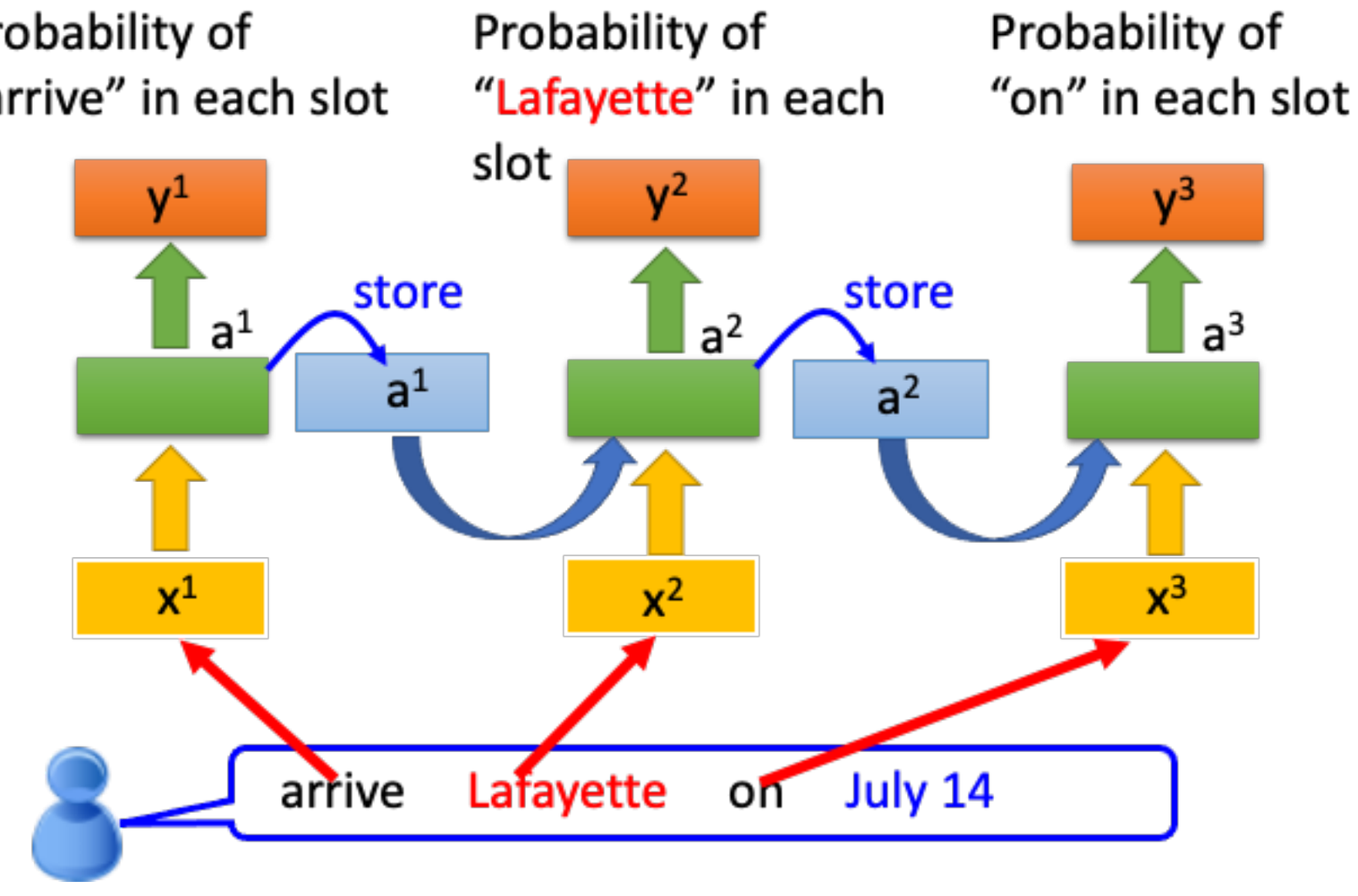
Popular techniques: Word2Vector, Node2Vector

# RNN

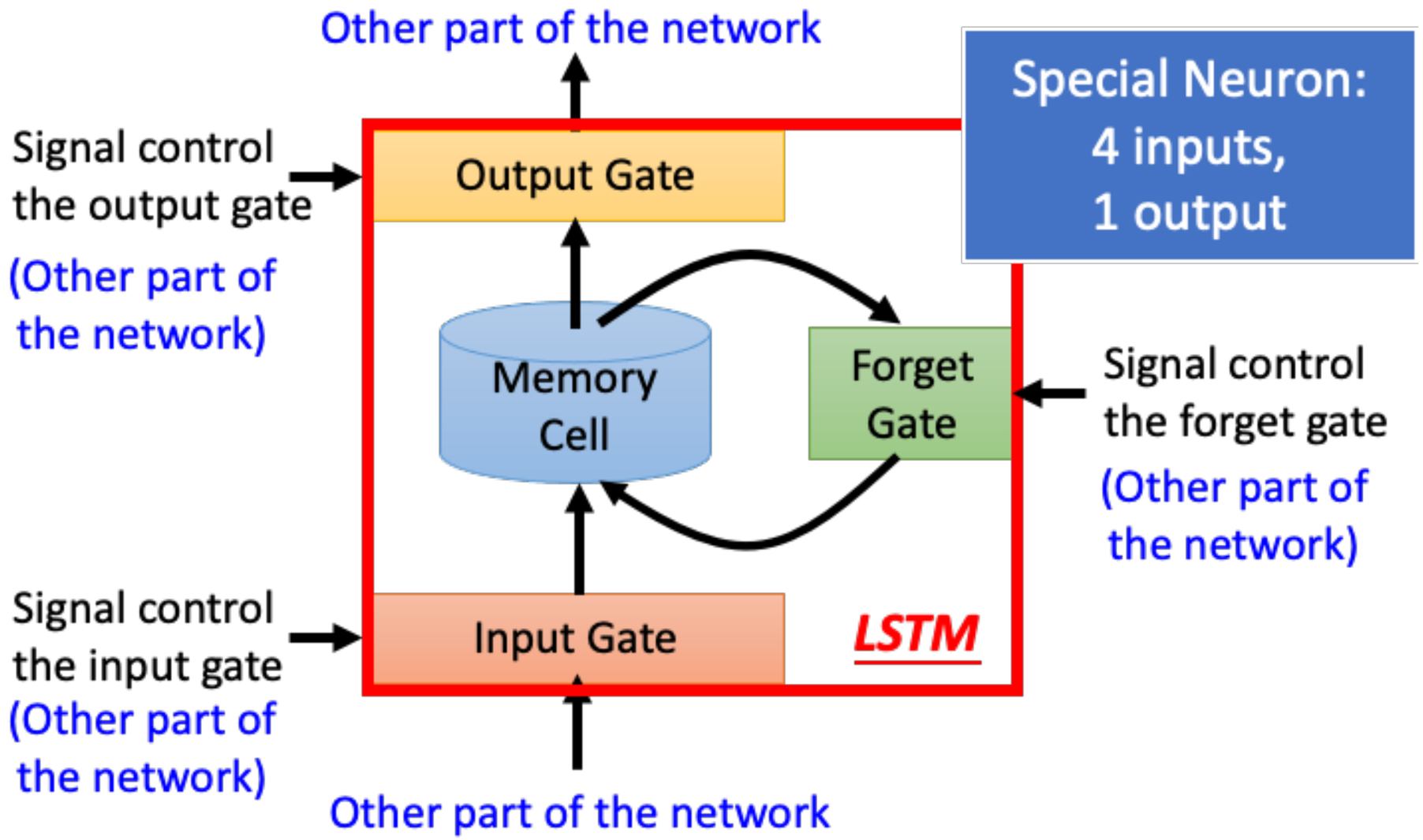
The output of hidden layer are stored in the memory.



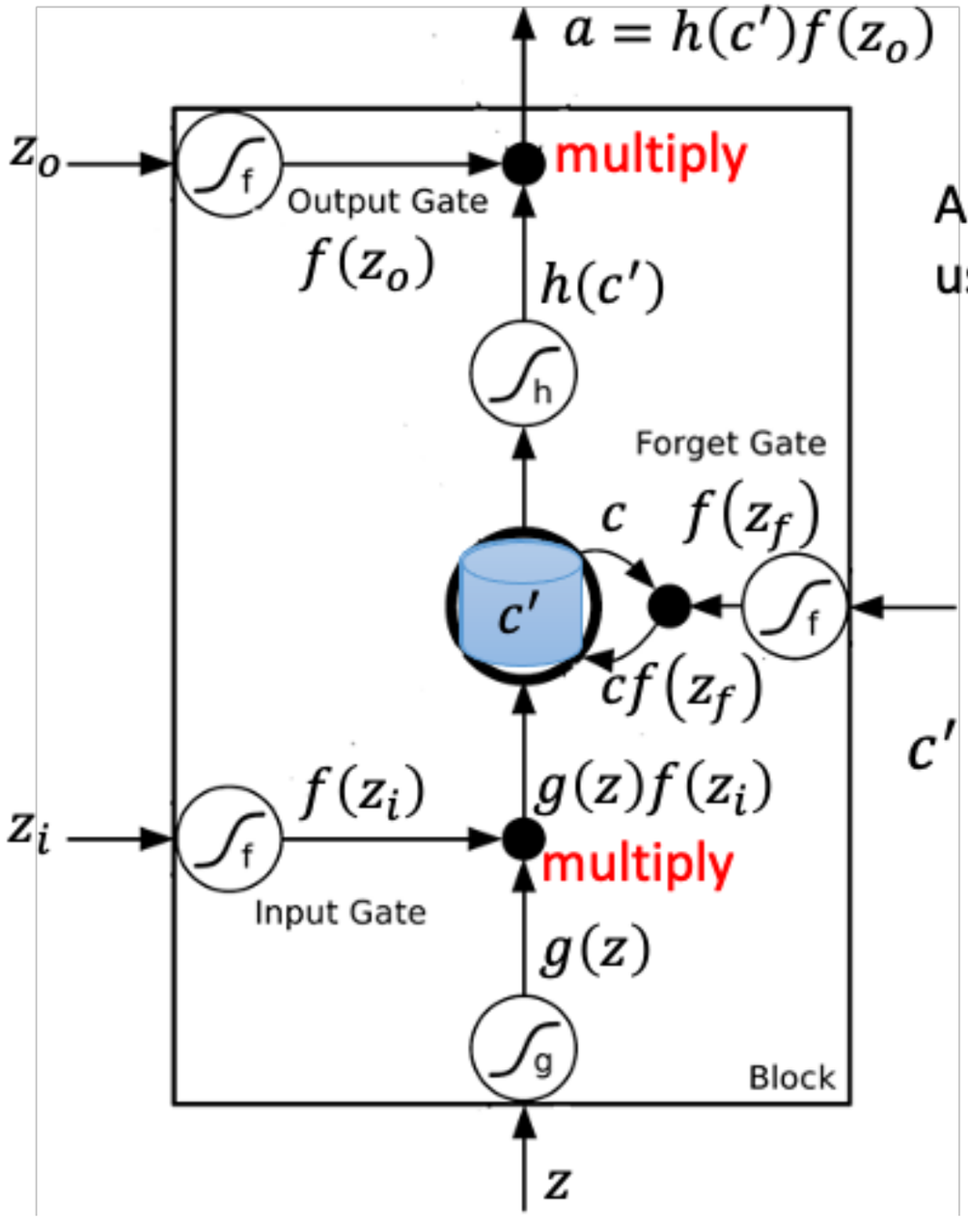
# RNN


Probability of "arrive" in each slot
Probability of "Lafayette" in each slot
Probability of "on" in each slot
y1
y2
y3
a1
a2
a3
store
store
a1
a2
x1
x2
x3
arrive
Lafayette
on
July 14

# Long Short-term Memory (LSTM)



# Long Short-term Memory (LSTM)



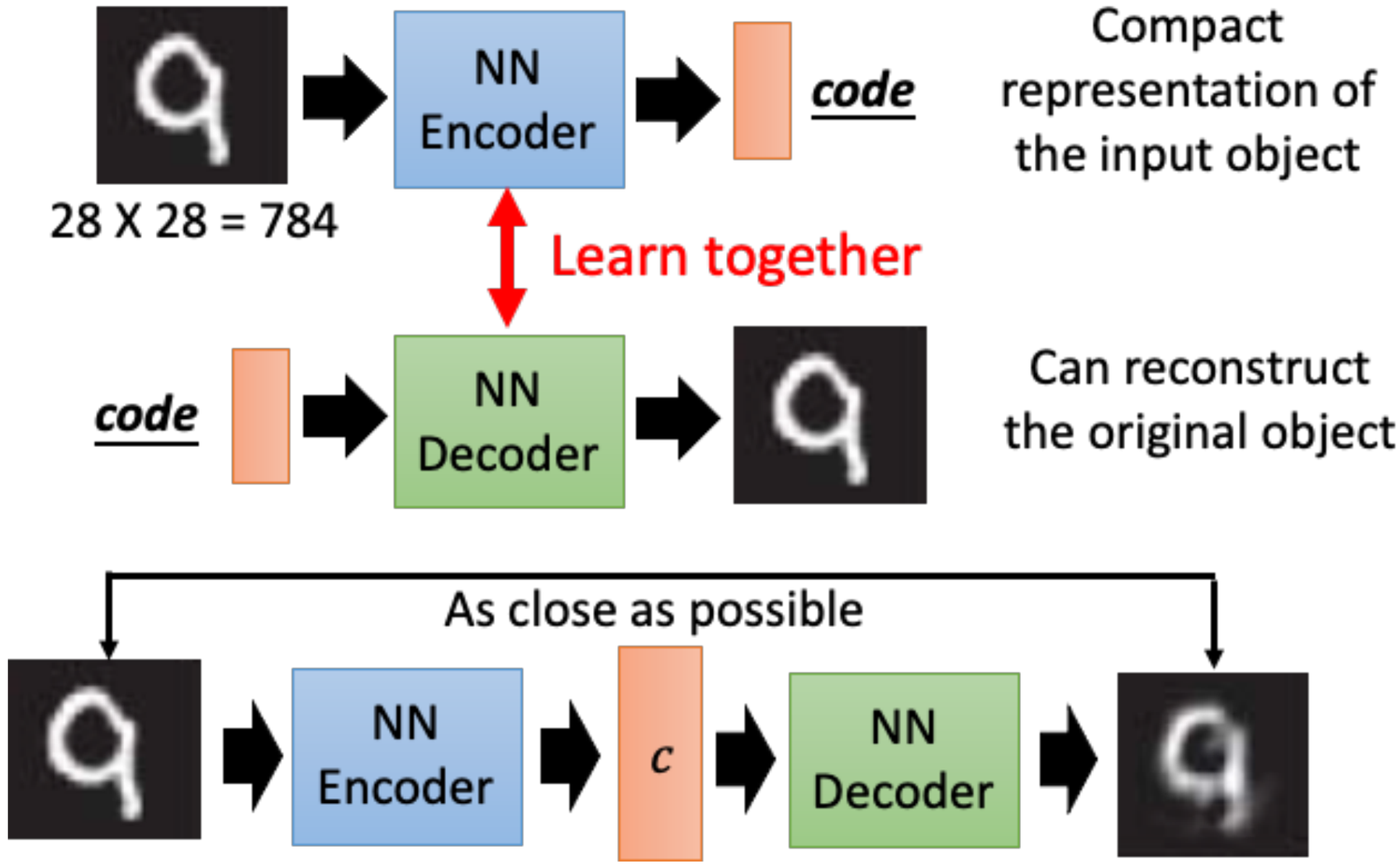

Activation function f is usually a sigmoid function

Between 0 and 1

Mimic open and close gate

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

# Auto-Encoder



# Deep Auto-Encoder