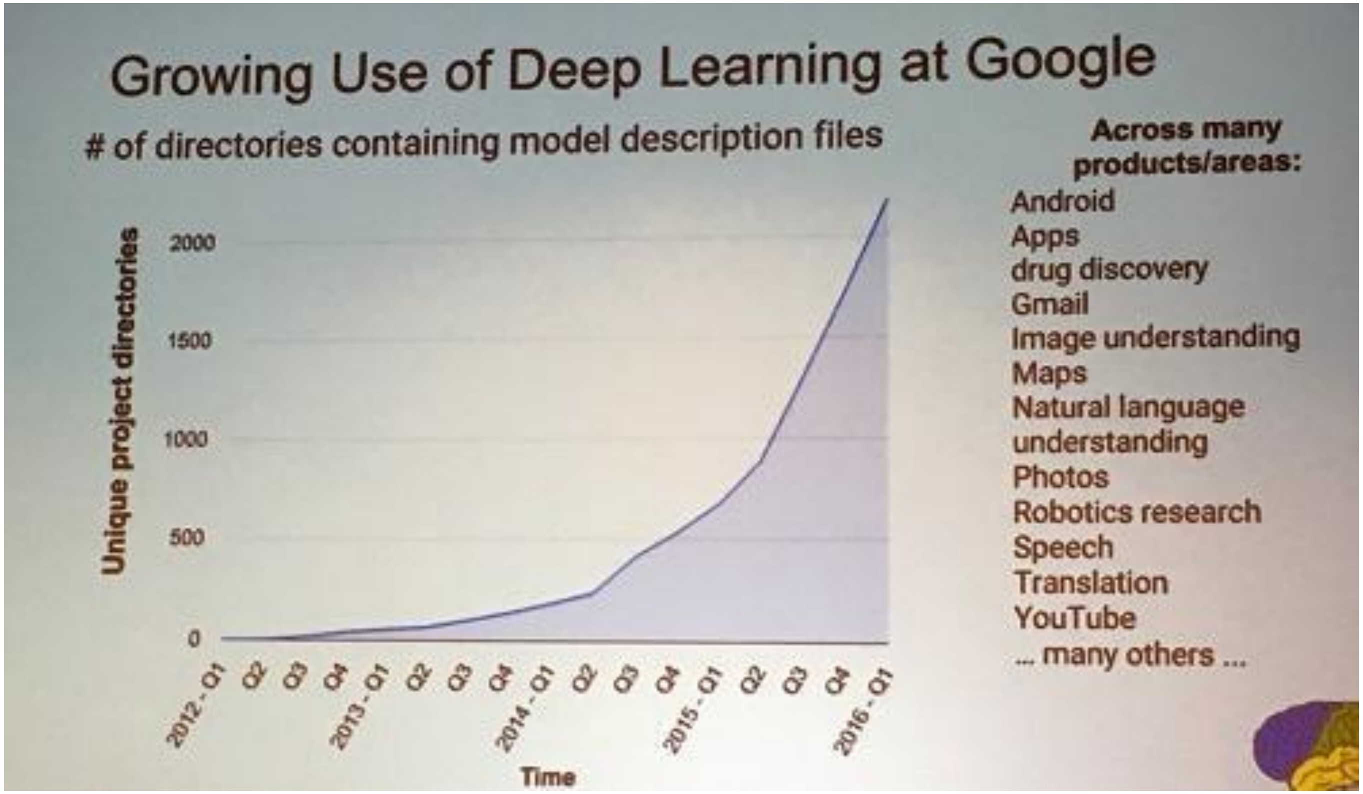
Deep Learning Tutorial

李宏毅

Hung-yi Lee

Deep learning attracts lots of attention.

- I believe you have seen lots of exciting results before.



Deep learning trends at Google. Source: SIGMOD/Jeff Dean

This talk focuses on the basic techniques.

Outline

Lecture I: Introduction of Deep Learning

Lecture II: Tips for Training Deep Neural Network

Lecture III: Variants of Neural Network

Lecture IV: Next Wave

Lecture I:
Introduction of Deep Learning

Outline of Lecture I

Introduction of Deep Learning

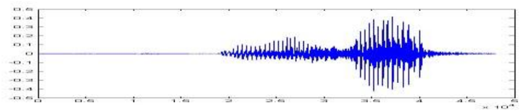
Let's start with general machine learning.

Why Deep?

"Hello World" for Deep Learning

Machine Learning
≈ Looking for a Function

- Speech Recognition

$f($  $) =$ "How are you"

- Image Recognition

$f($  $) =$ "Cat"

- Playing Go

$f($  $) =$ "5-5" (next move)

- Dialogue System

$f($ "Hi" $) =$ "Hello"

(what the user said) (system response)

Framework

Image Recognition:

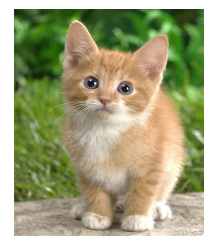
$f($  $)=$ "cat"

A set of function

Model

$f_1, f_2 \cdots$

$f_1($  $)=$ "cat"

$f_2($  $)=$ "money"

$f_1($  $)=$ "dog"

$f_2($  $)=$ "snake"

Framework

Image Recognition:

$f($  $)=$ "cat"

A set of function

Model

$f_1, f_2 \cdots$

$f_1($  $)=$ "cat"

$f_2($  $)=$ "money"

Better!

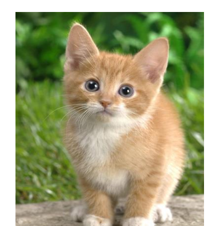
$f_1($  $)=$ "dog"

$f_2($  $)=$ "snake"

Goodness of function f

Training Data

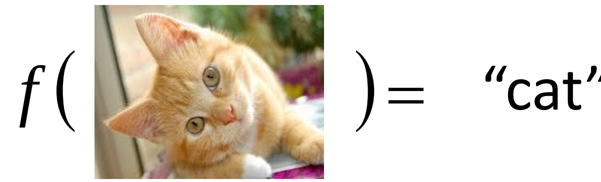
Supervised Learning

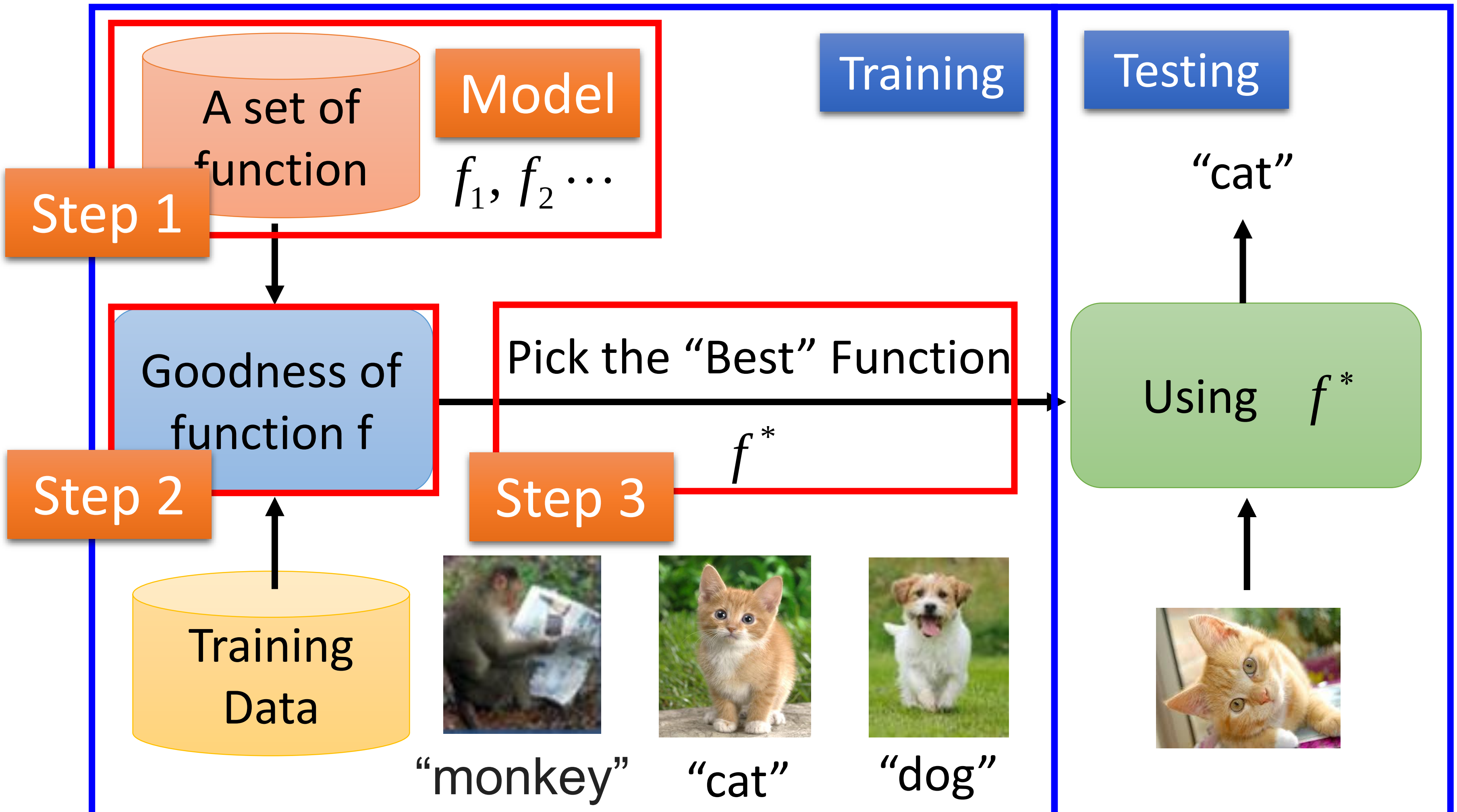
function input:   

function output: "monkey" "cat" "dog"

Framework

Image Recognition:

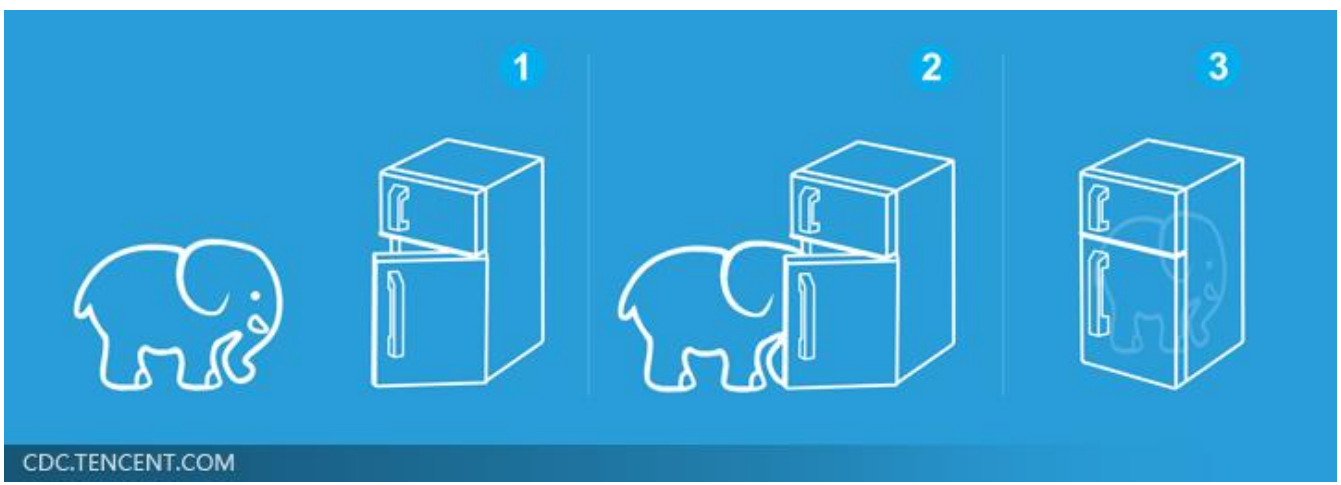




Three Steps for Deep Learning

Step 1: define a set of function → Step 2: goodness of function → Step 3: pick the best function

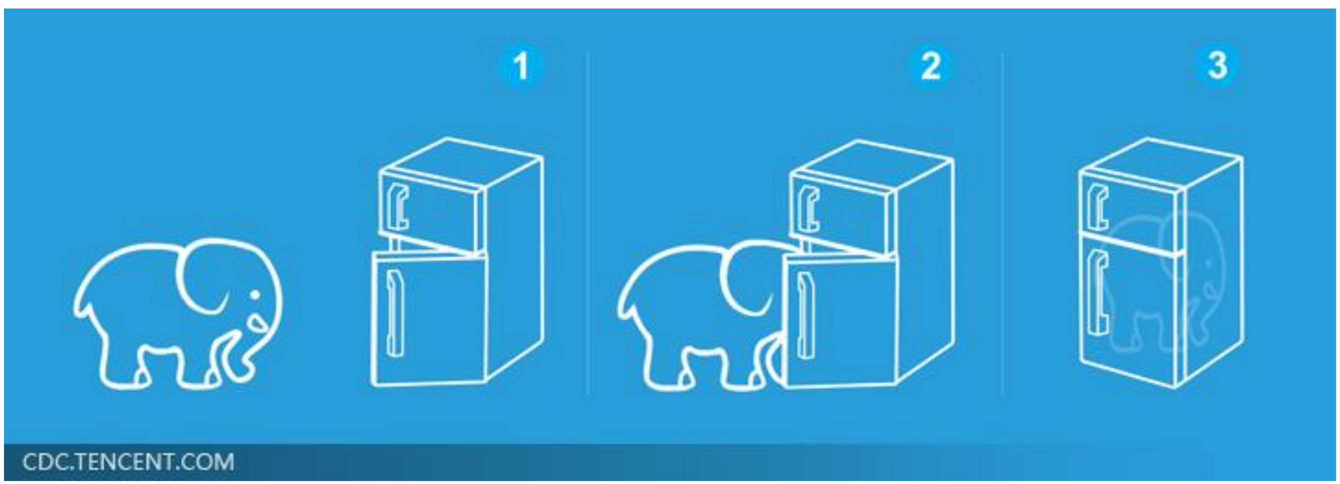
Deep Learning is so simple ……



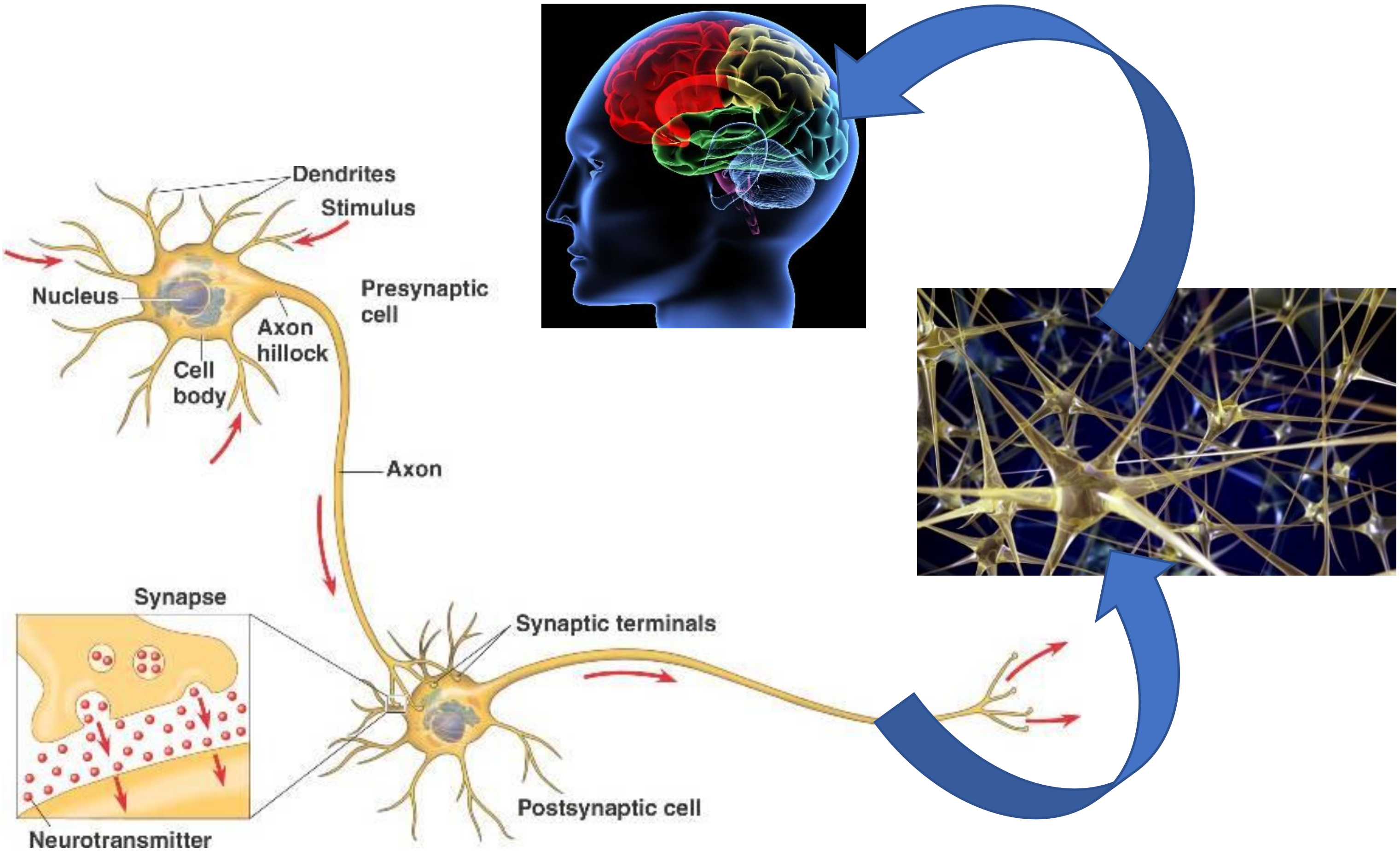
Three Steps for Deep Learning

Step 1: Neural Network → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



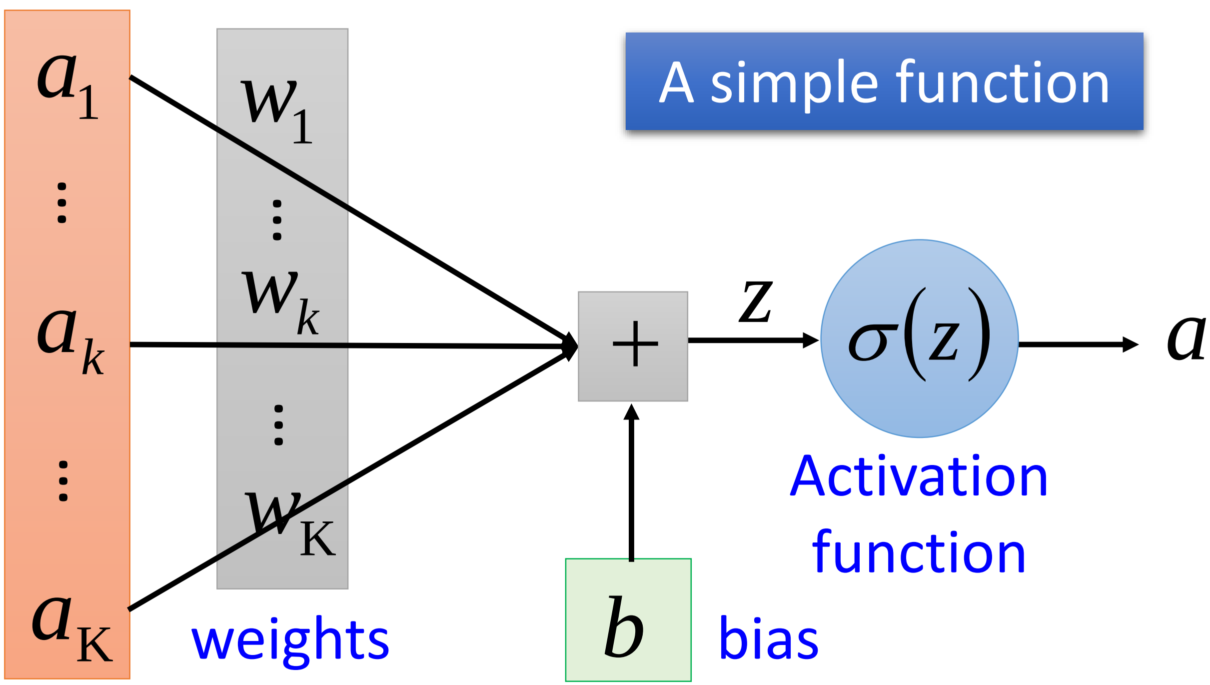
Human Brains



Neural Network

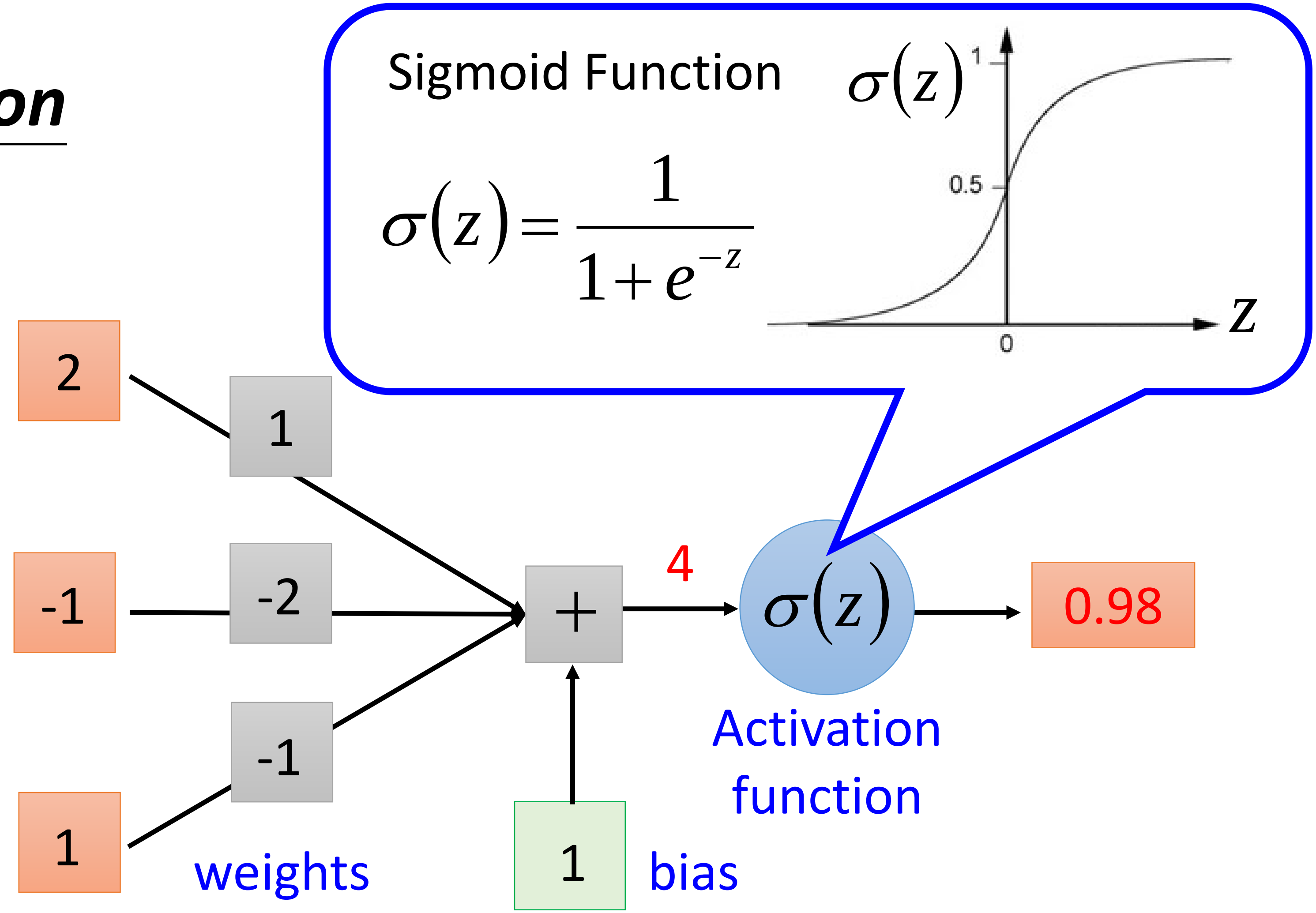
Neuron

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

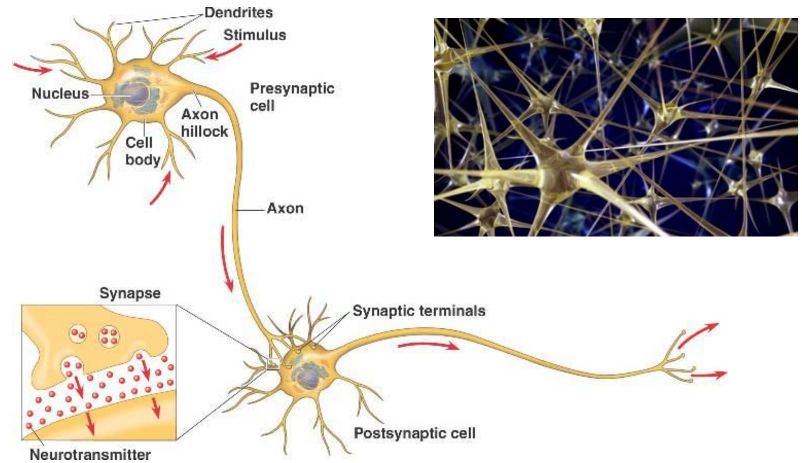


Neural Network

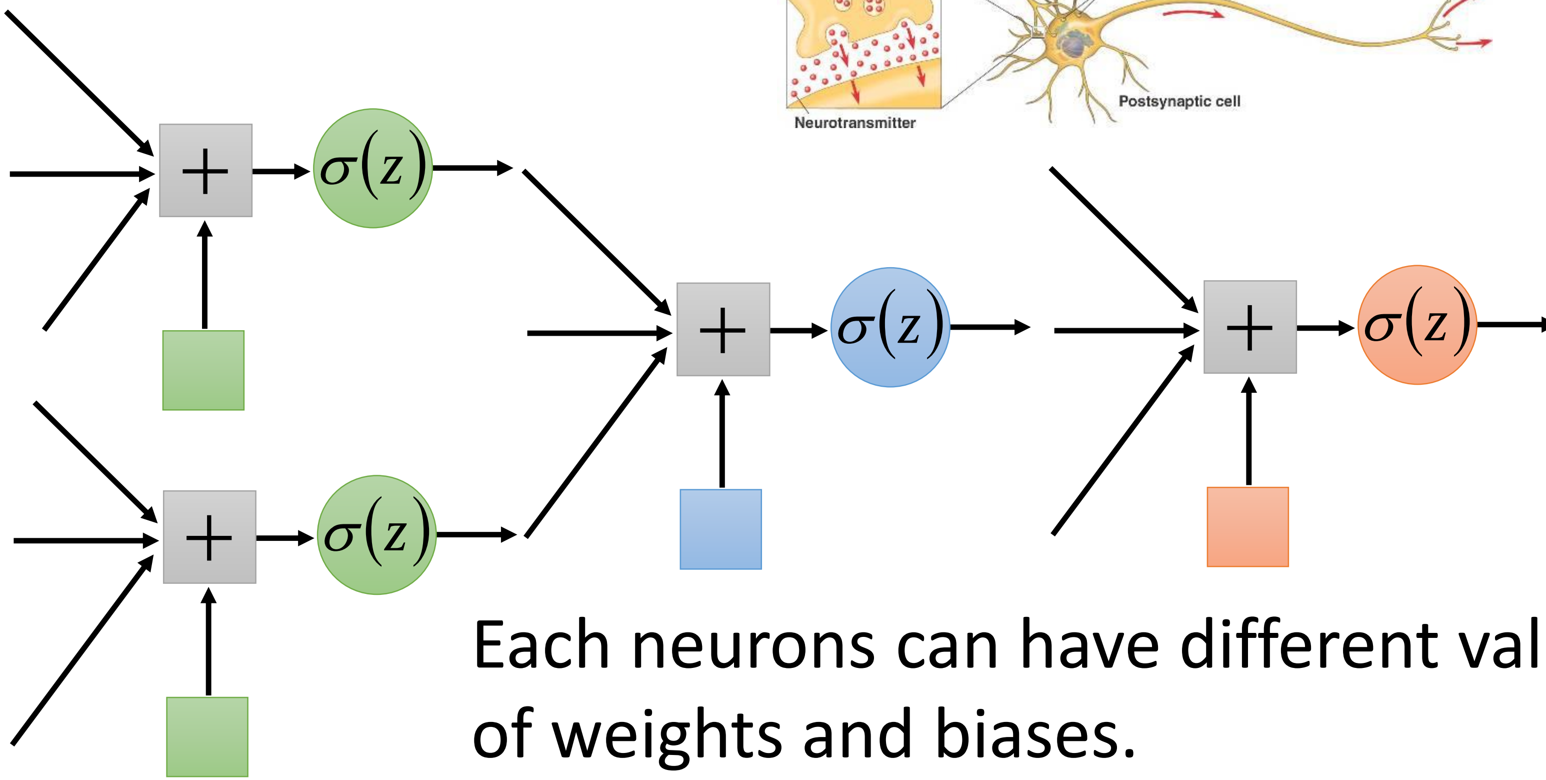
Neuron



Neural Network



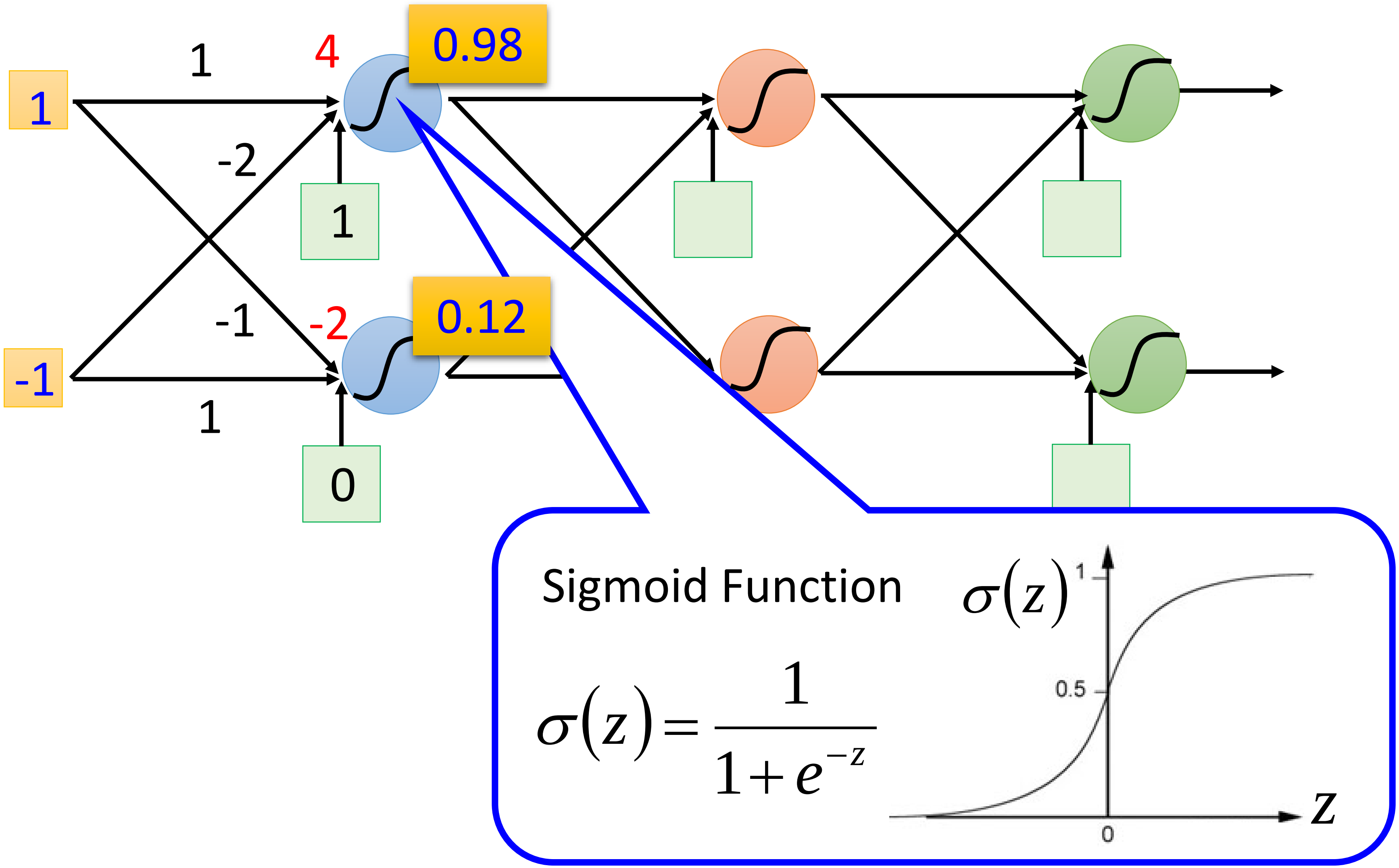
Different connections leads to different network structure



Each neurons can have different values of weights and biases.

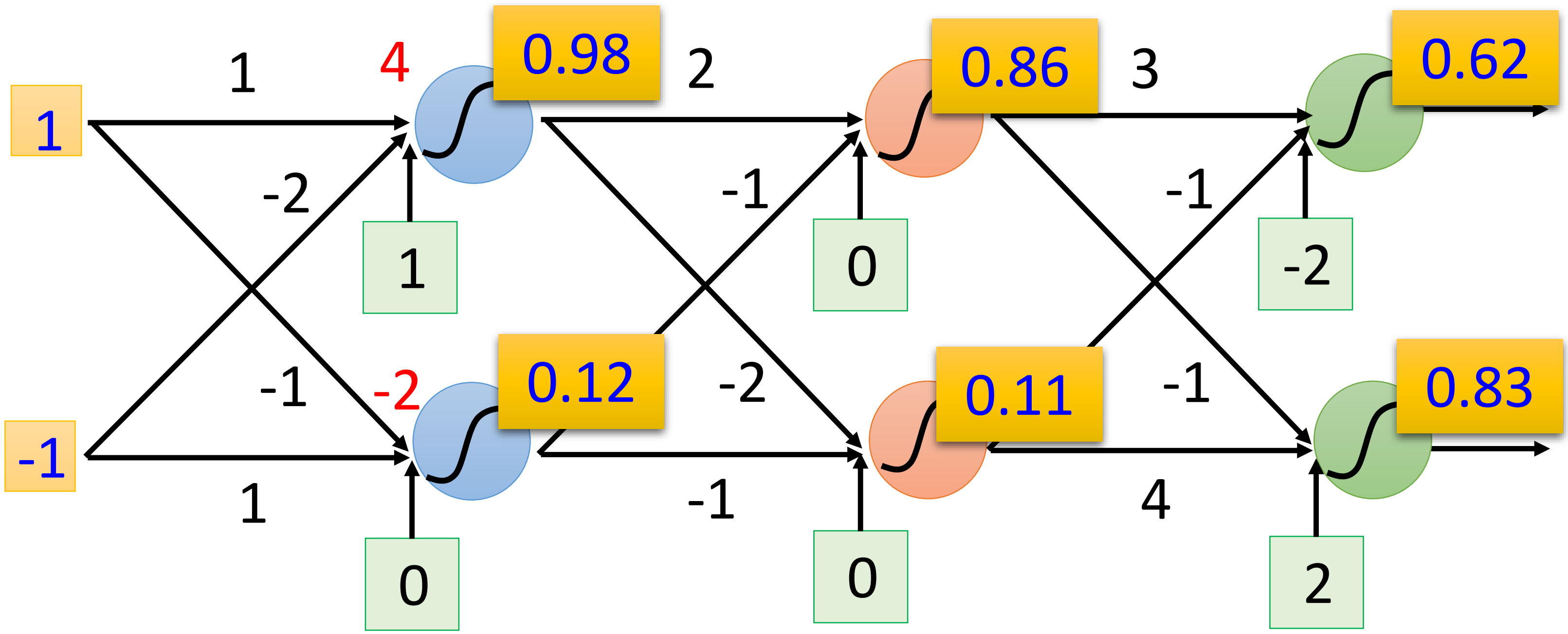
Weights and biases are network parameters θ

Fully Connect Feedforward Network

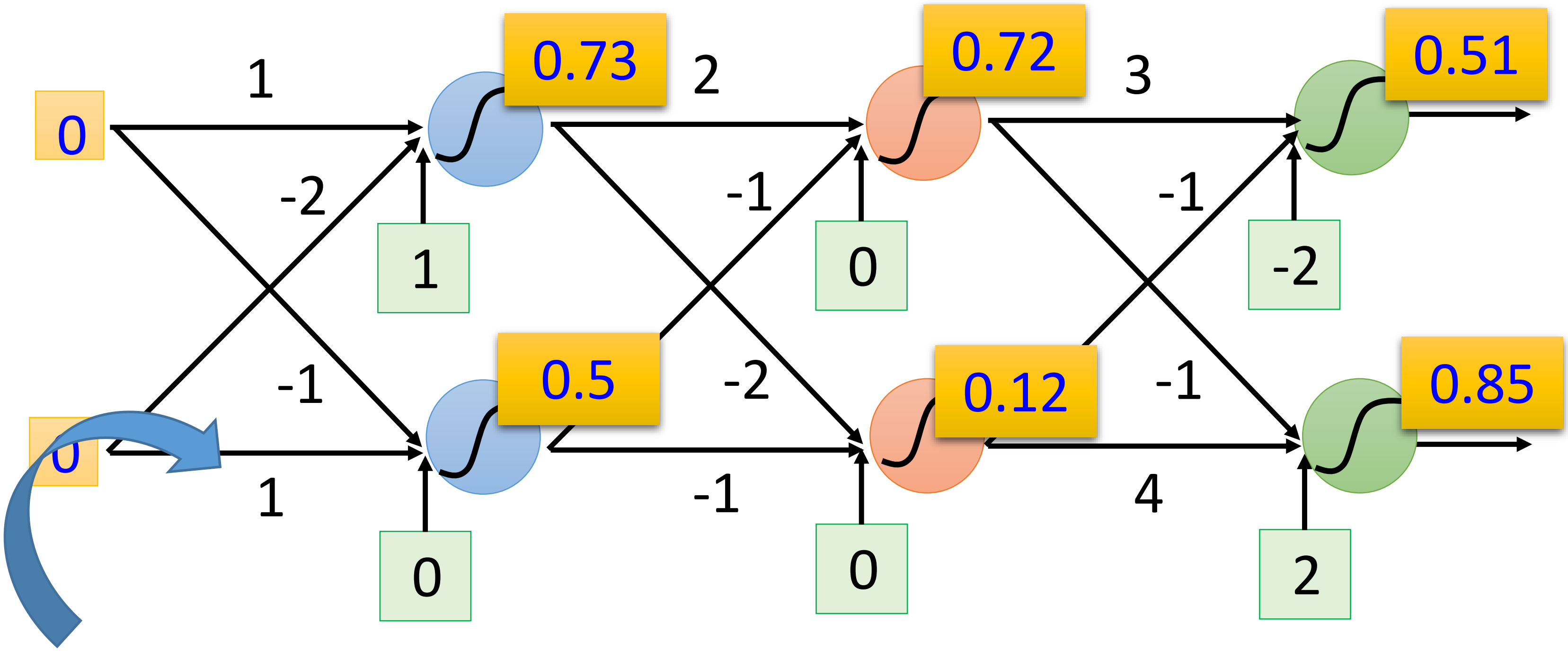


$$\sigma(z) = \frac{1}{1+e^{-z}}$$

Fully Connect Feedforward Network



Fully Connect Feedforward Network



This is a function.

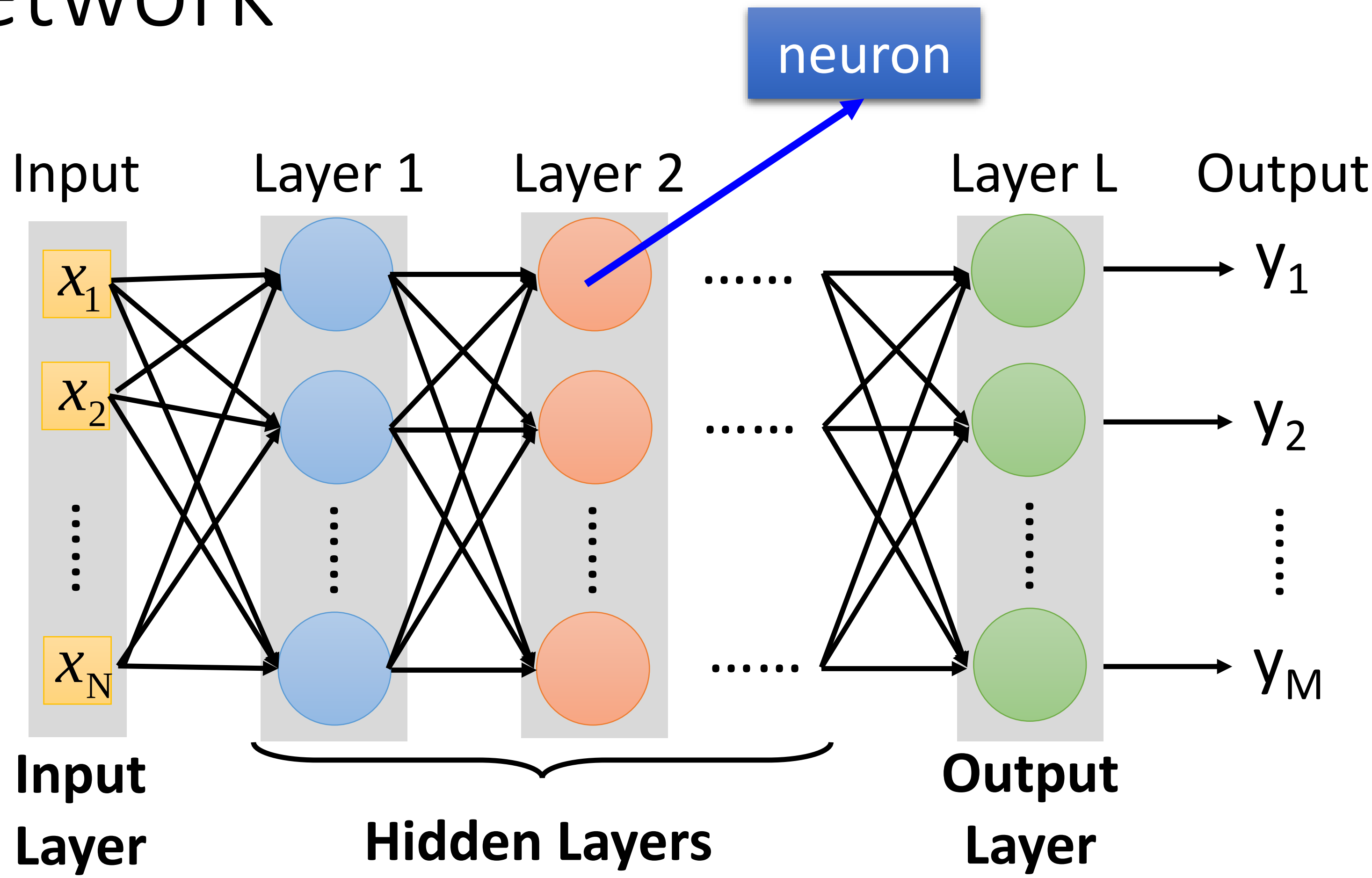
Input vector, output vector

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

Given parameters θ, define a function

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

Fully Connect Feedforward Network

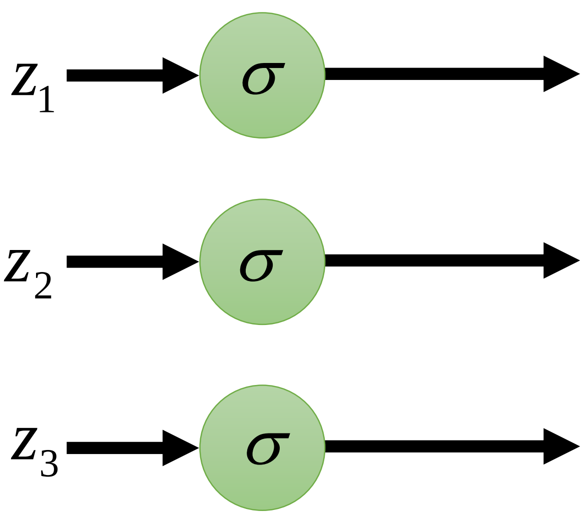


Deep means many hidden layers

Output Layer (Option)

- Softmax layer as the output layer

Ordinary Layer



$$y_1 = \sigma(z_1)$$

$$y_2 = \sigma(z_2)$$

$$y_3 = \sigma(z_3)$$

In general, the output of network can be any value.

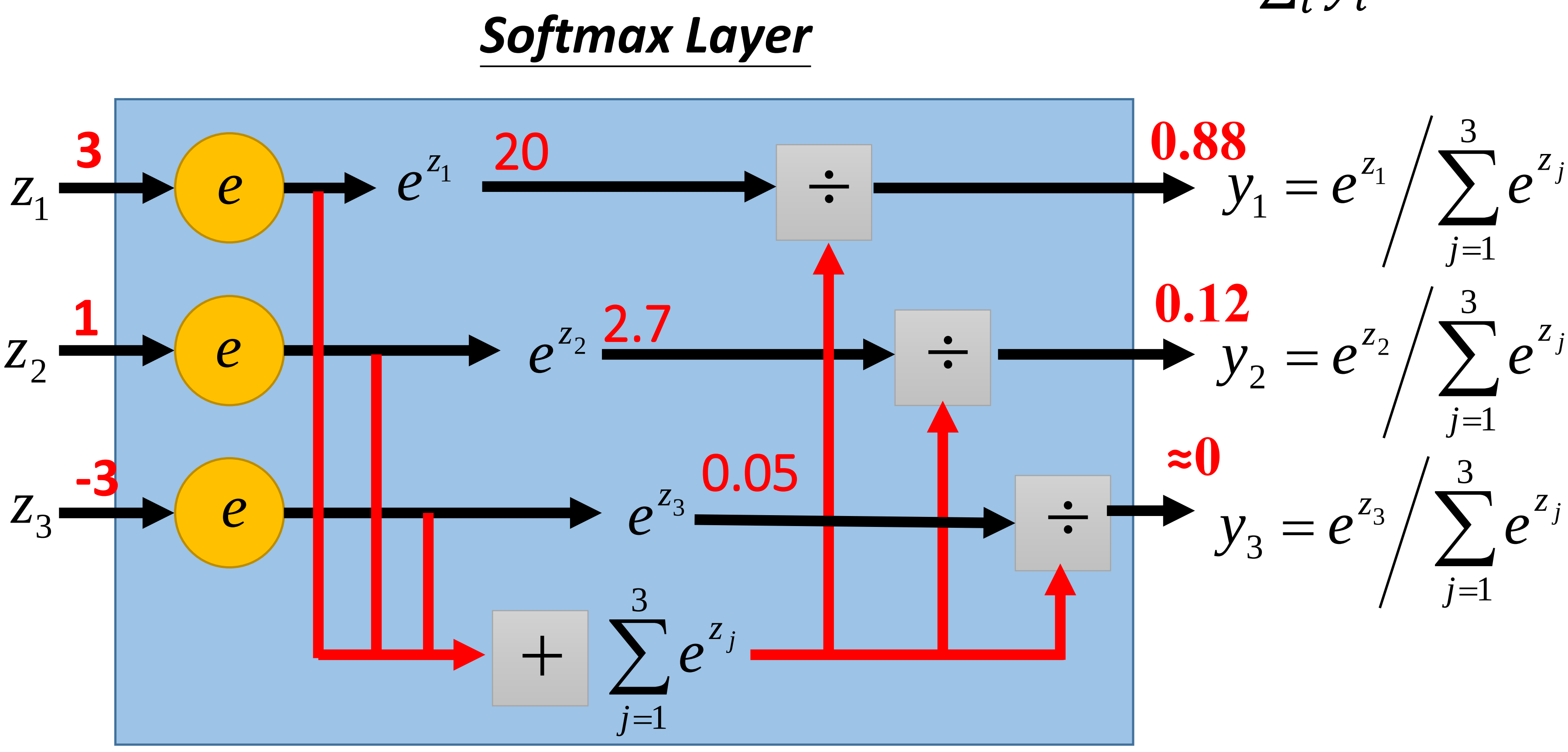
May not be easy to interpret

Output Layer (Option)

- Softmax layer as the output layer

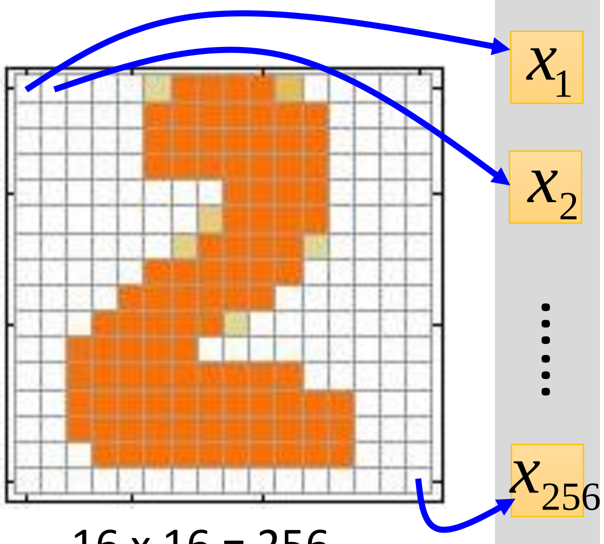
Probability:

- $1 > y_i > 0$
- $\sum_i y_i = 1$



Example Application

Input

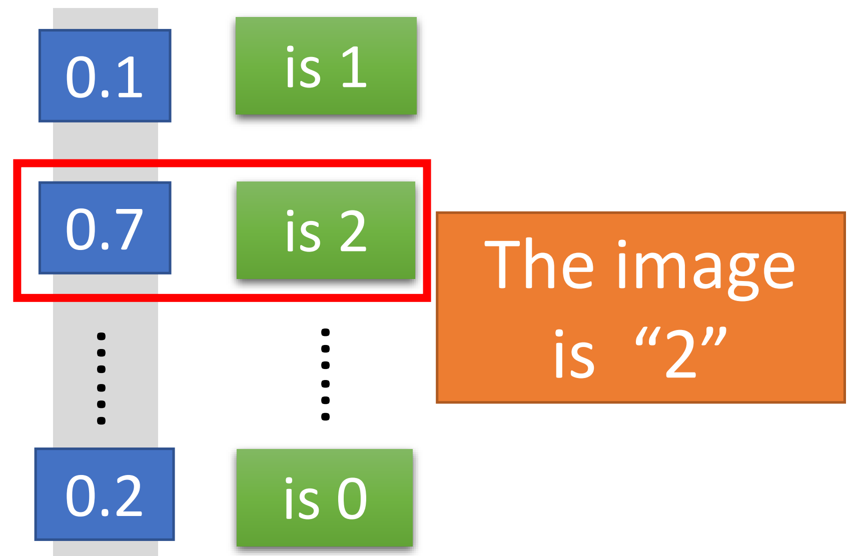


16 x 16 = 256

Ink → 1

No ink → 0

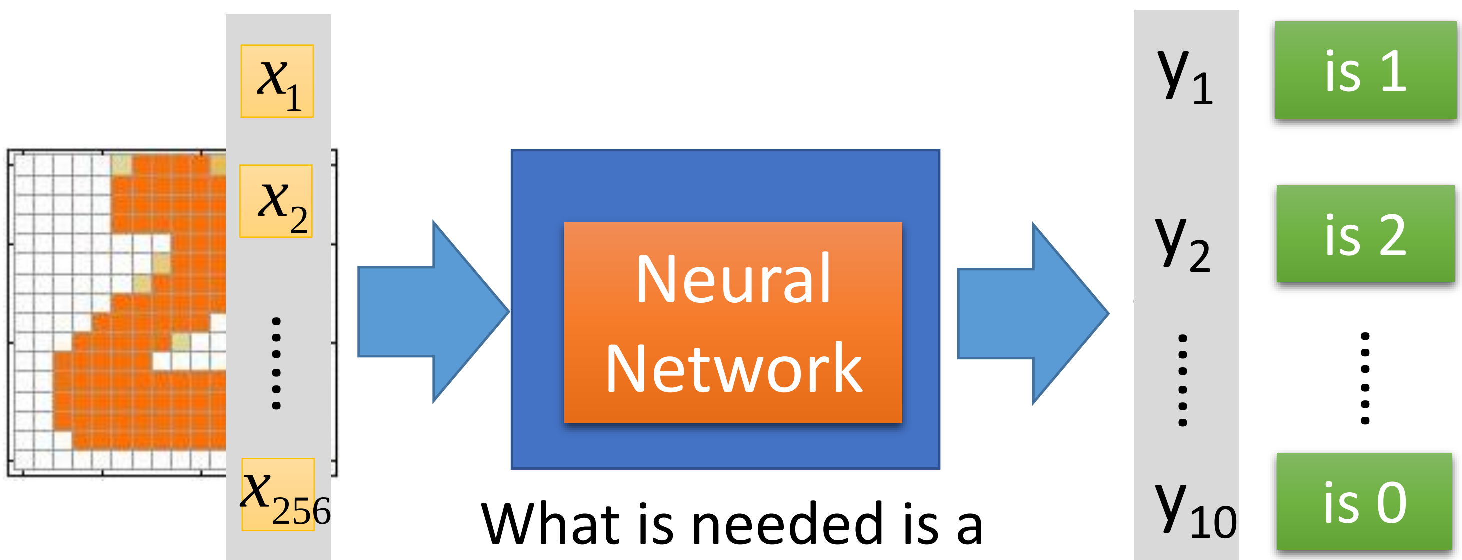
Output



Each dimension represents the confidence of a digit.

Example Application

- Handwriting Digit Recognition

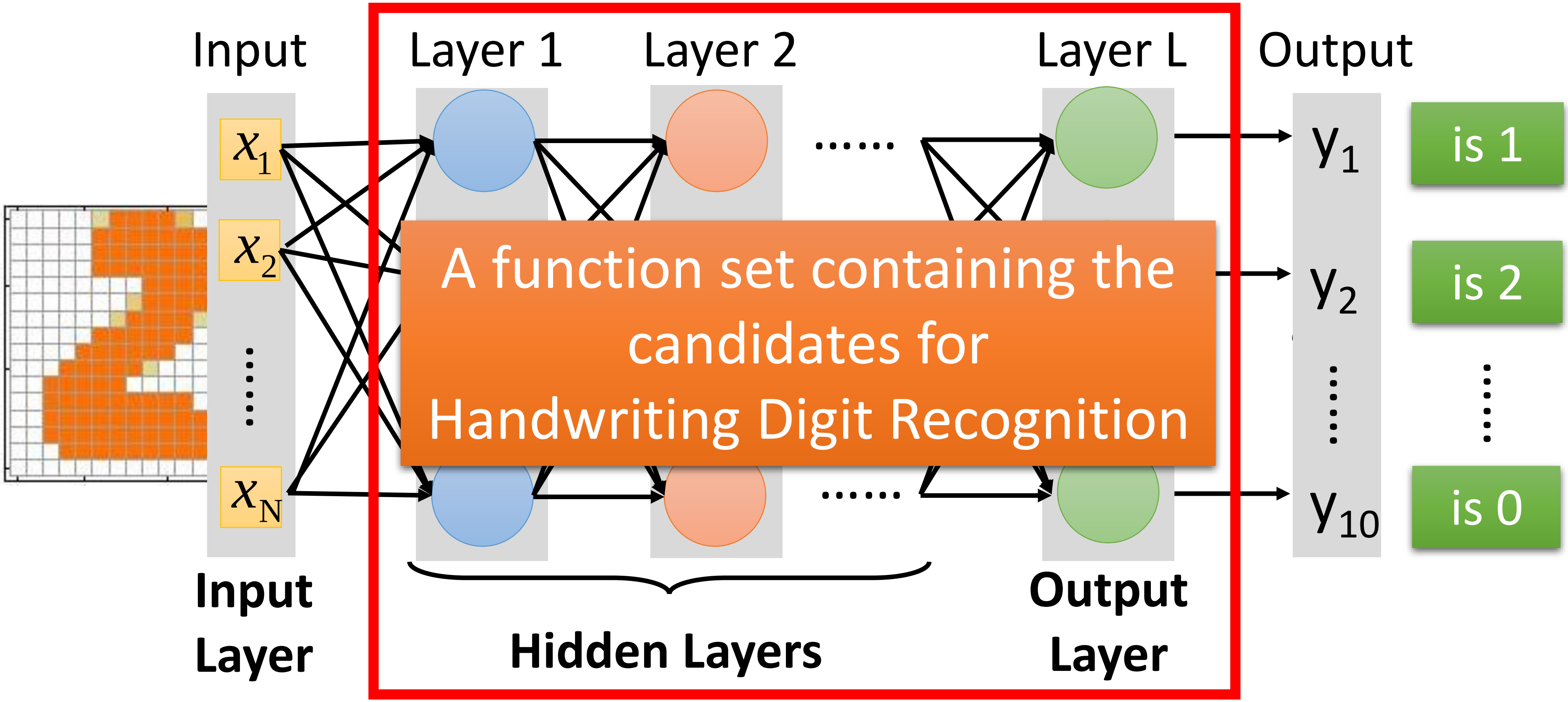


What is needed is a function ......

Input:
256-dim vector

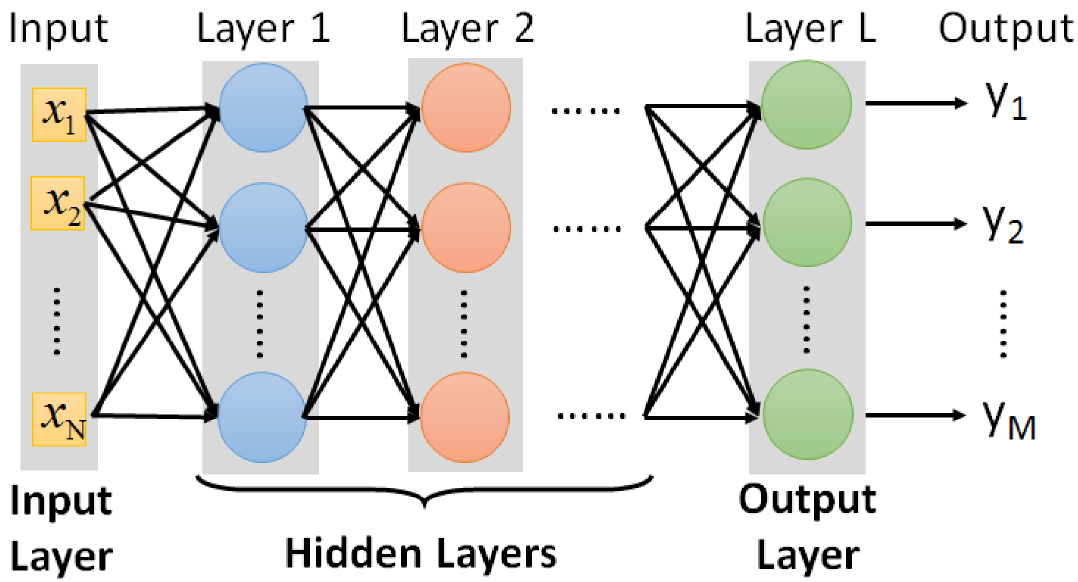
output:
10-dim vector

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?

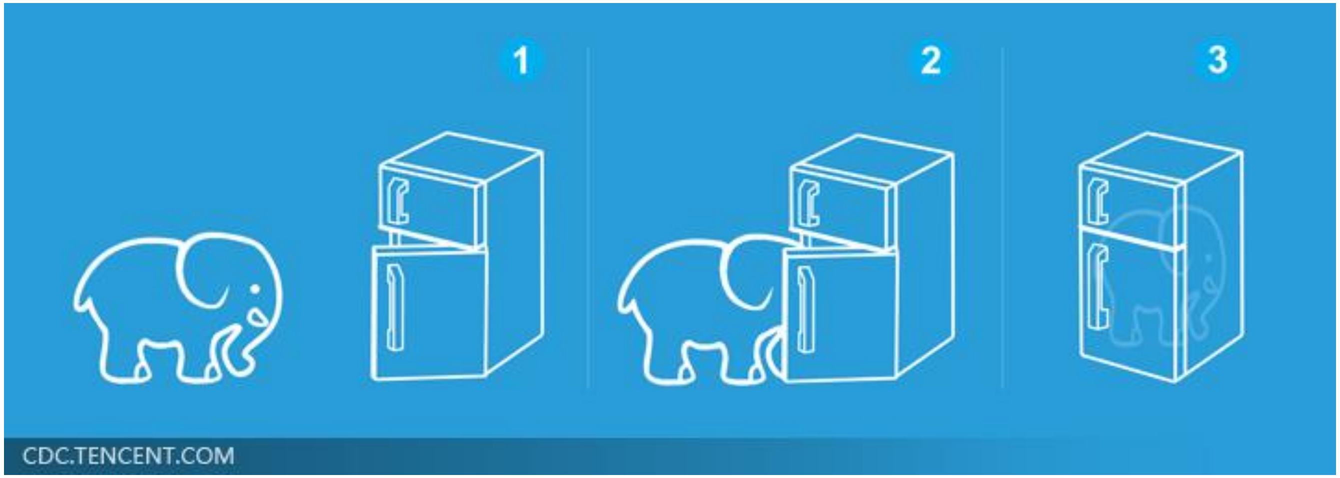
Trial and Error + **Intuition**

- Q: Can the structure be automatically determined?

Three Steps for Deep Learning

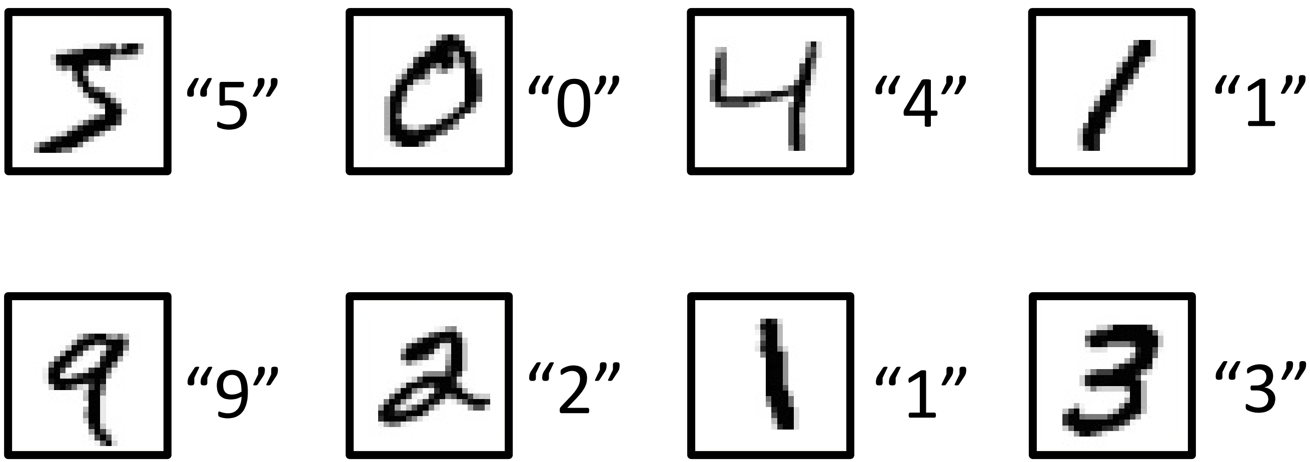
Step 1: Neural Network → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



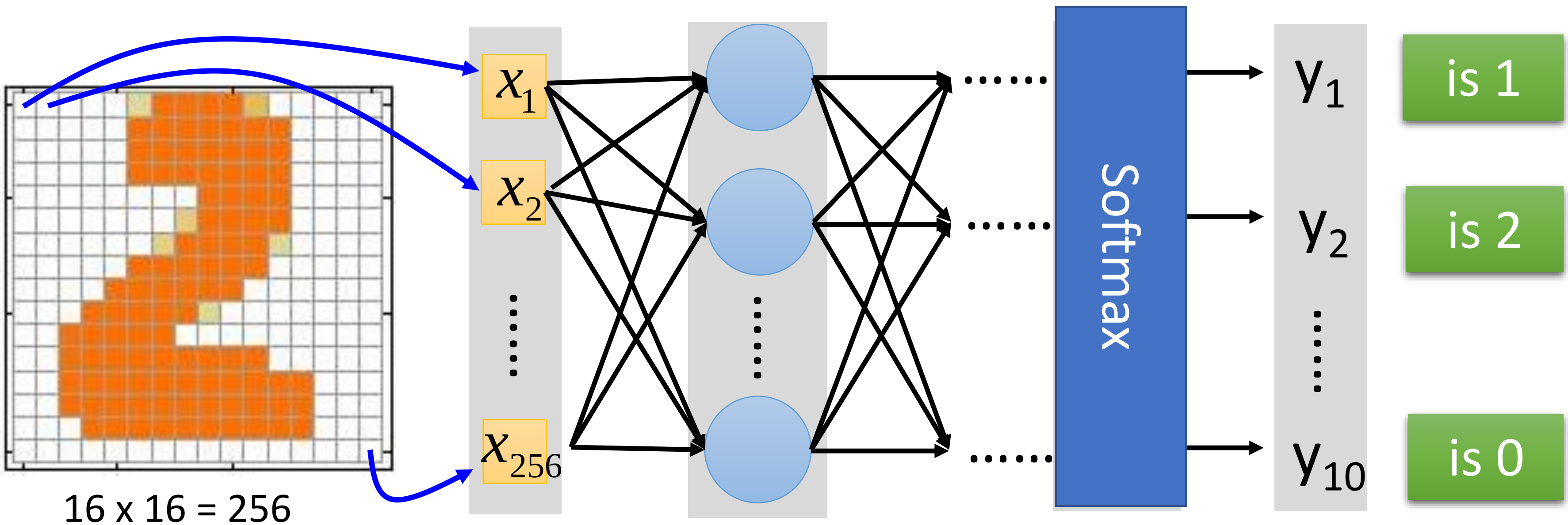
Training Data

- Preparing training data: images and their labels



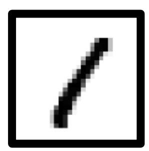
The learning target is defined on the training data.

Learning Target



Ink → 1
No ink → 0

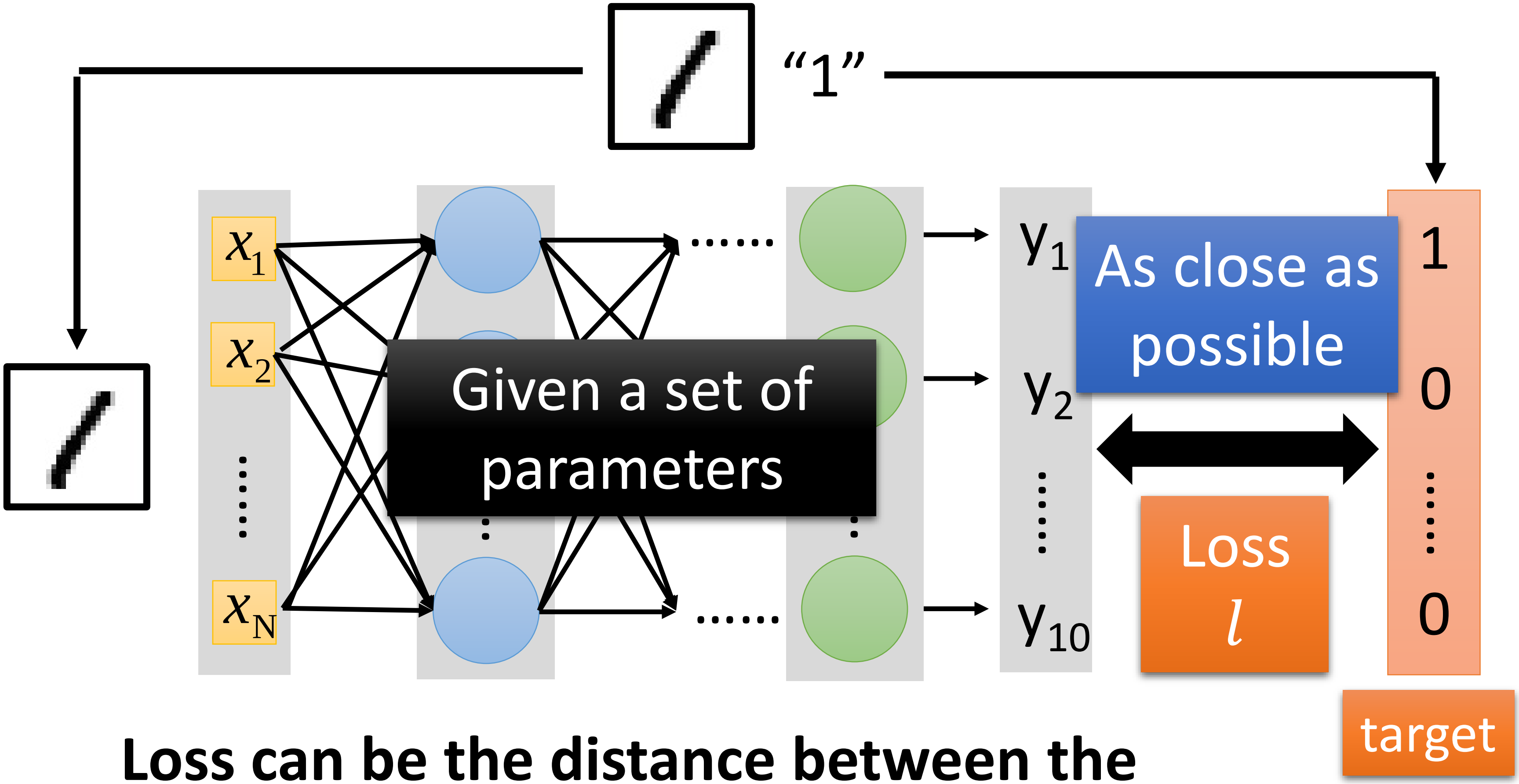
The learning target is ……

Input:  y_1 has the maximum value

Input:  y_2 has the maximum value

Loss

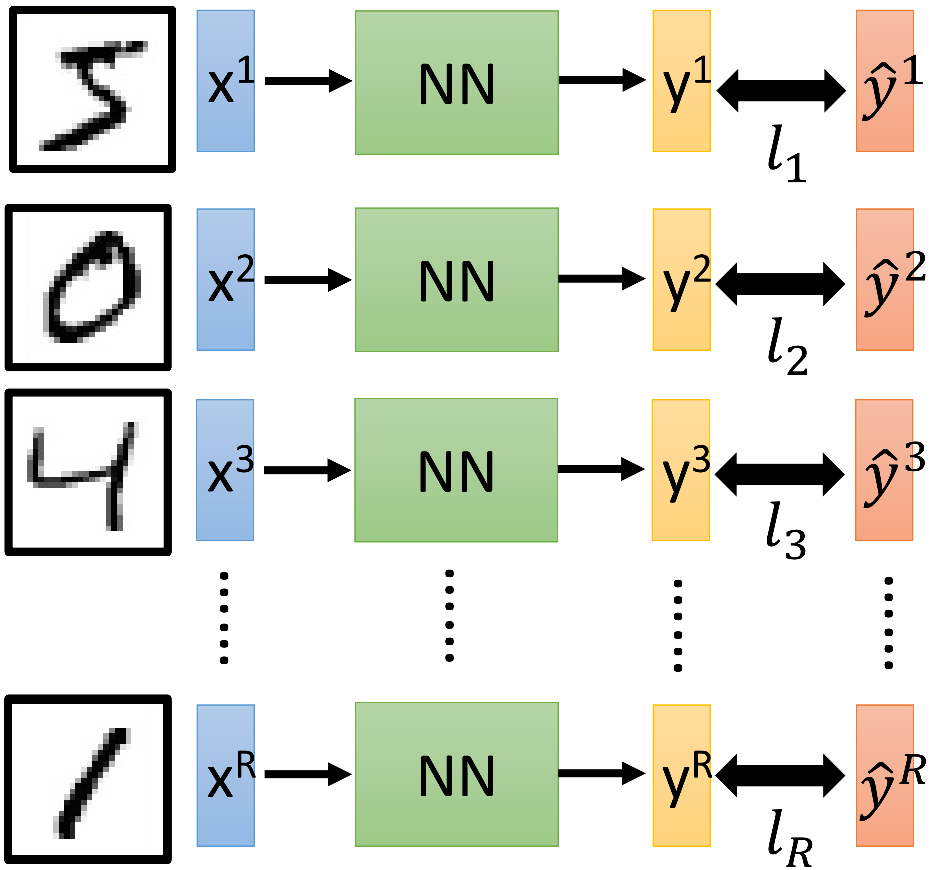
A good function should make the loss of all examples as small as possible.



Loss can be the distance between the network output and target

Total Loss

For all training data …



Total Loss:

$$\boxed{L = \sum_{r=1}^{R} l_r}$$

As small as possible

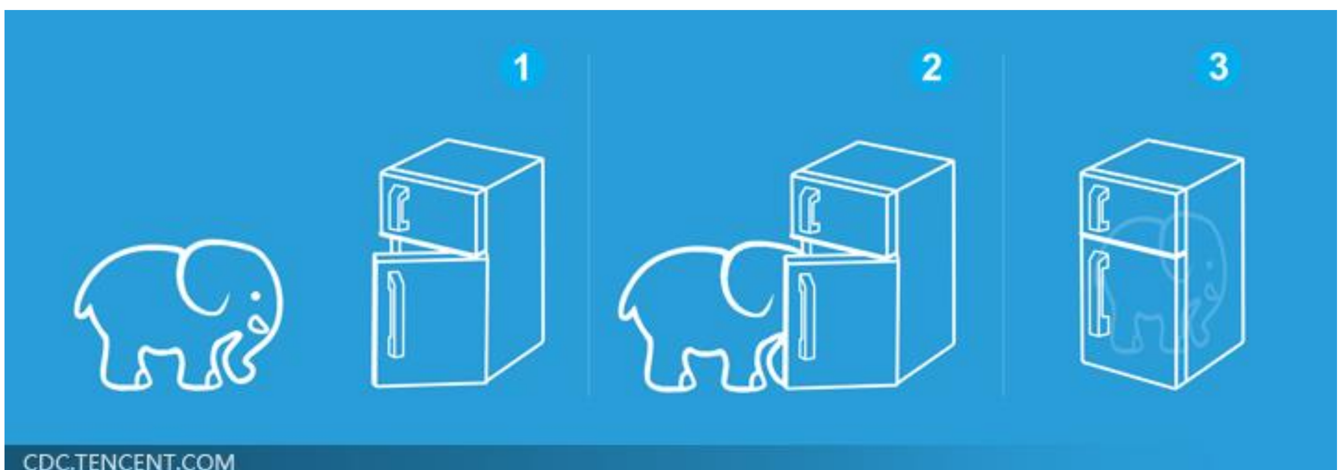
Find ***a function in function set*** that minimizes total loss L

Find ***the network parameters θ^**** that minimize total loss L

Three Steps for Deep Learning

Step 1: Neural Network → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



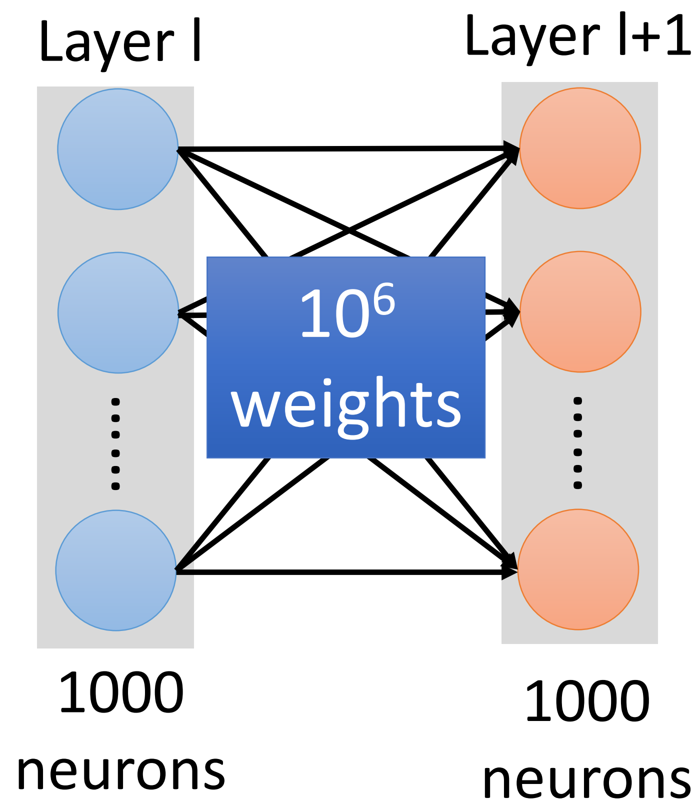
How to pick the best function

Find *network parameters θ^** that minimize total loss L

Enumerate all possible values

Network parameters $\theta = \underbrace{\{w_1, w_2, w_3, \cdots, b_1, b_2, b_3, \cdots\}}_{\text{Millions of parameters}}$

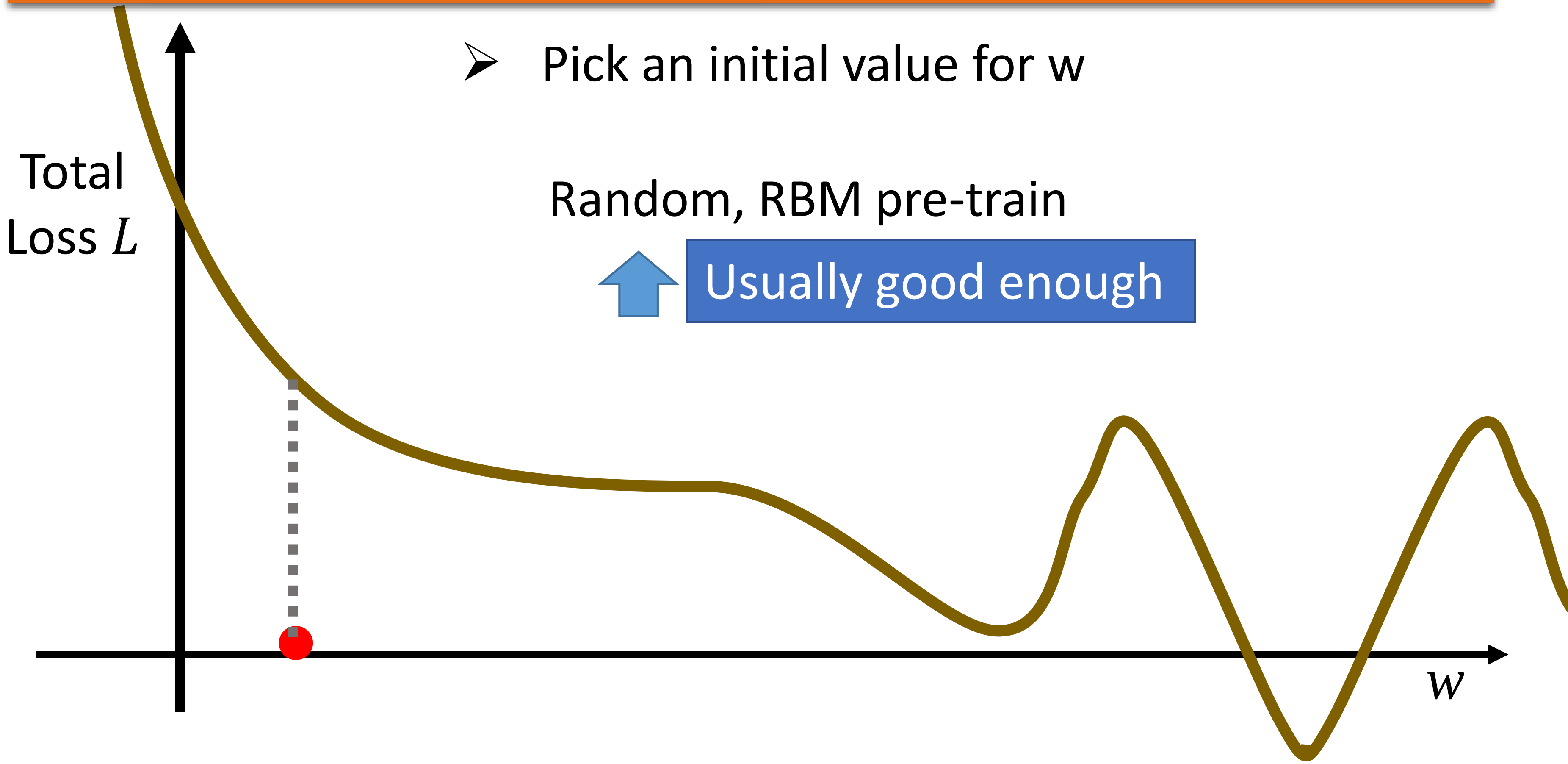
E.g. speech recognition: 8 layers and 1000 neurons each layer



Gradient Descent

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

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



- Pick an initial value for w

Random, RBM pre-train

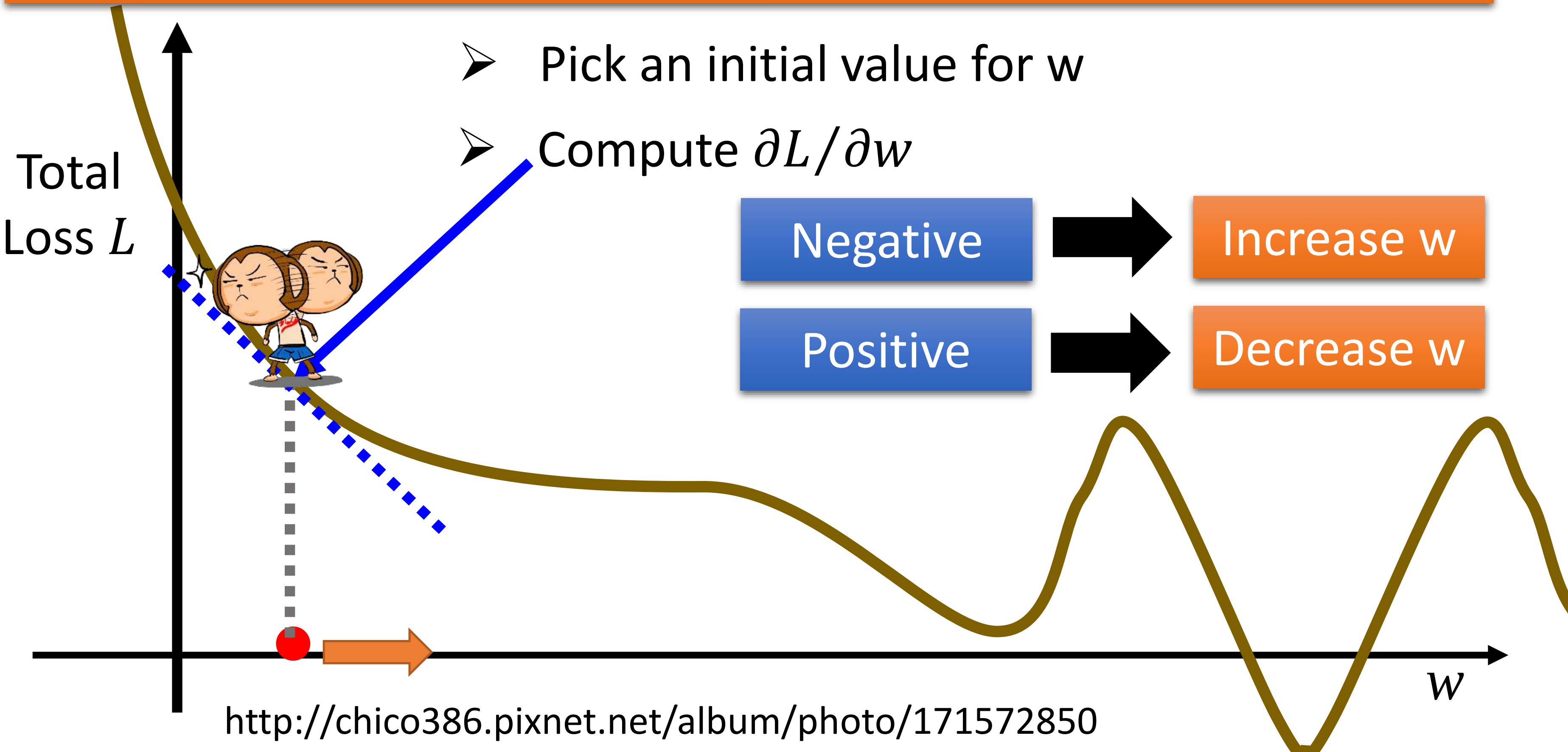
Usually good enough

Gradient Descent

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

Find *network parameters* θ^* that minimize total loss L

- Pick an initial value for w
- Compute $\partial L / \partial w$



http://chico386.pixnet.net/album/photo/171572850

Gradient Descent

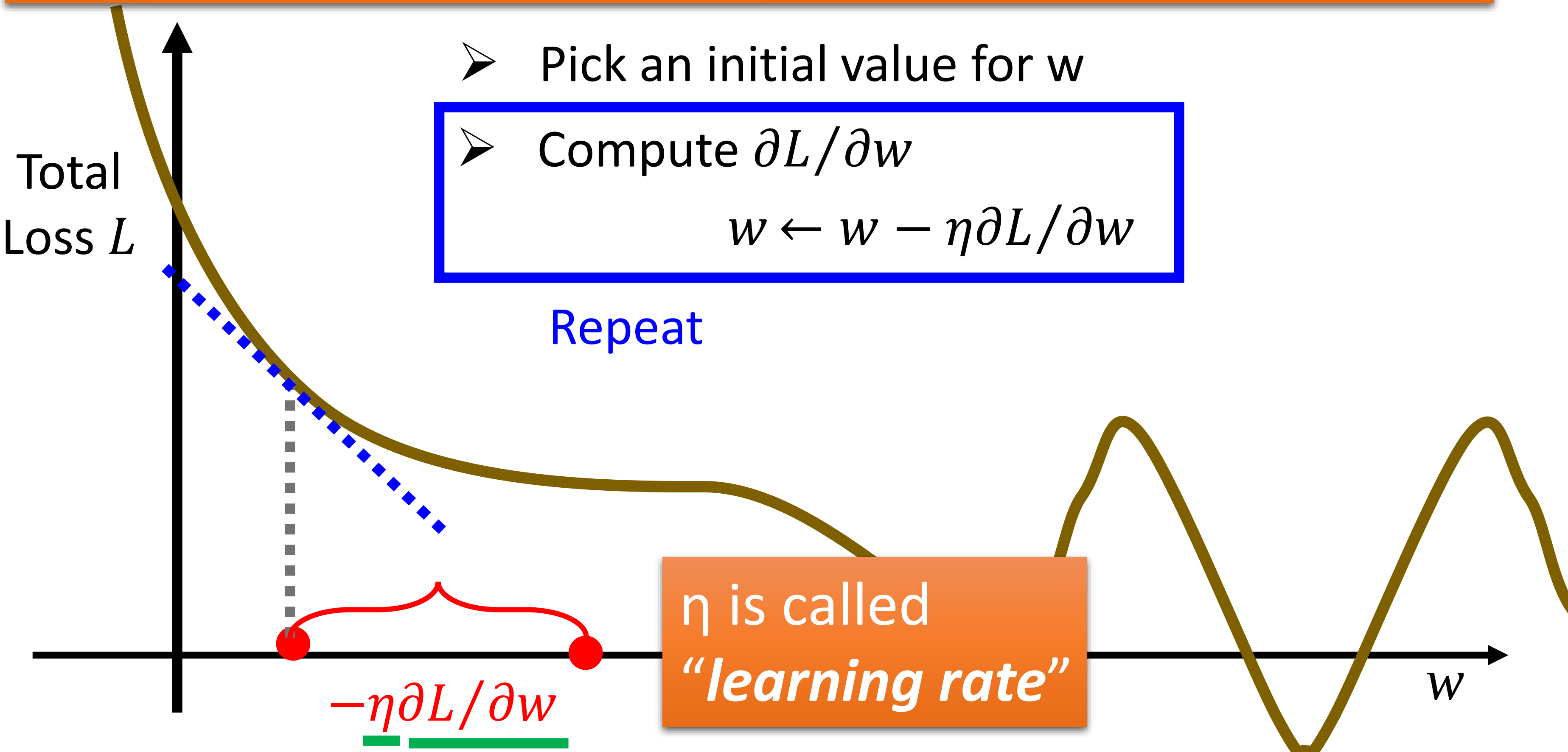
Network parameters $\theta = \{w_1, w_2, \cdots, b_1, b_2, \cdots\}$

Find ***network parameters*** θ^* that minimize total loss L

- Pick an initial value for w
- Compute $\partial L / \partial w$

  $w \leftarrow w - \eta \partial L / \partial w$

Repeat



η is called ***"learning rate"***

Gradient Descent

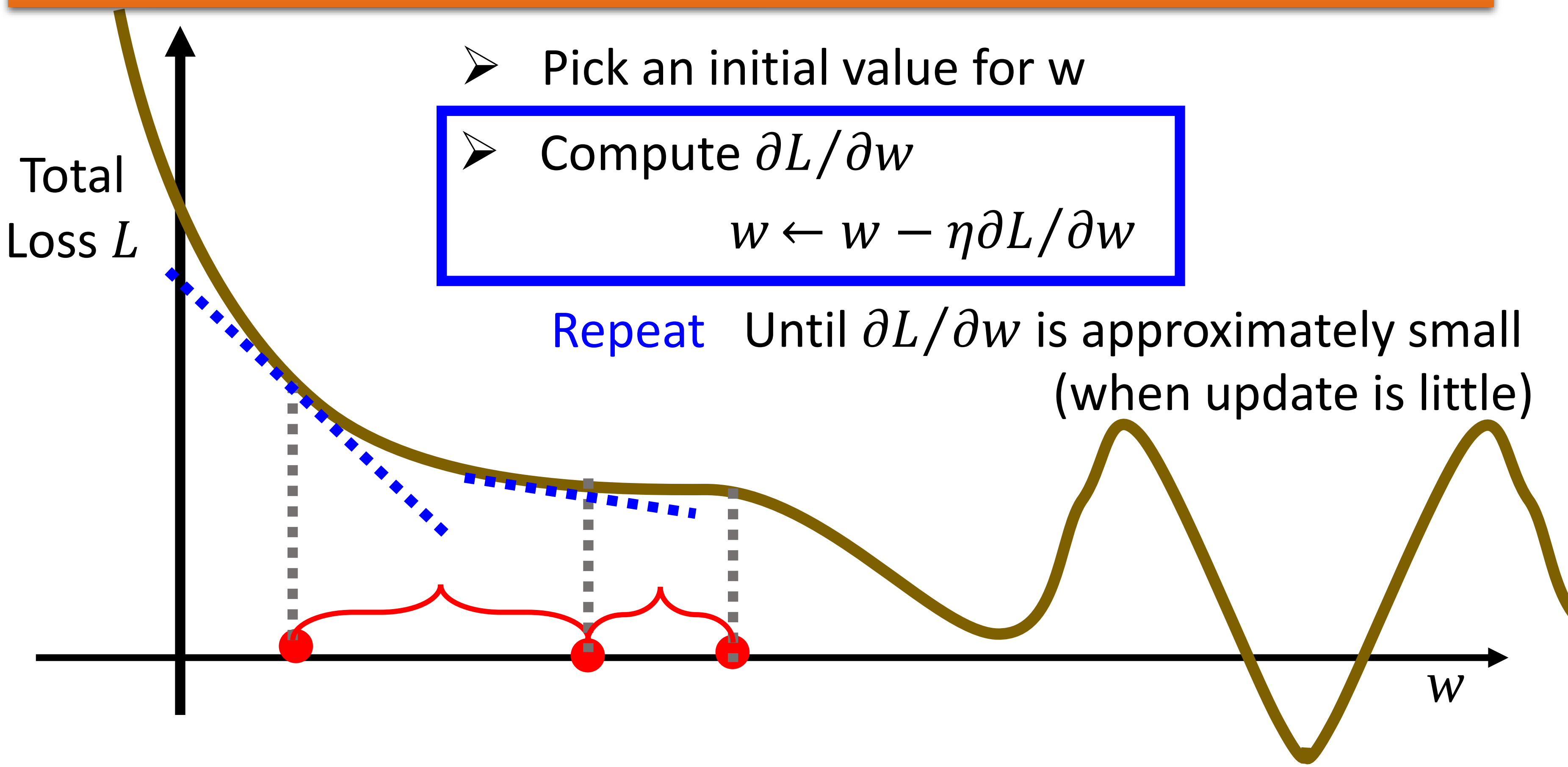
Network parameters $\theta = \{w_1, w_2, \cdots, b_1, b_2, \cdots\}$

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

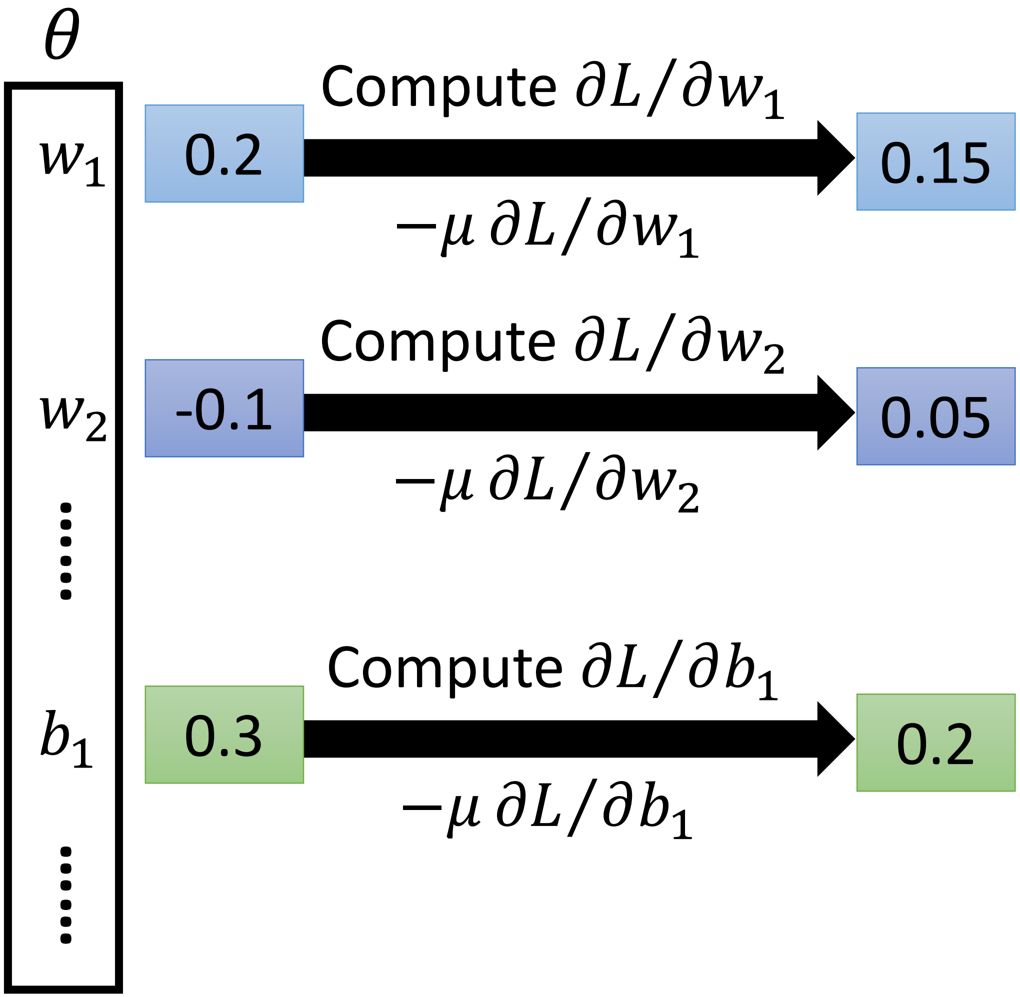
- Pick an initial value for w
- Compute $\partial L/\partial w$

  $w \leftarrow w - \eta \partial L/\partial w$

Repeat Until $\partial L/\partial w$ is approximately small (when update is little)



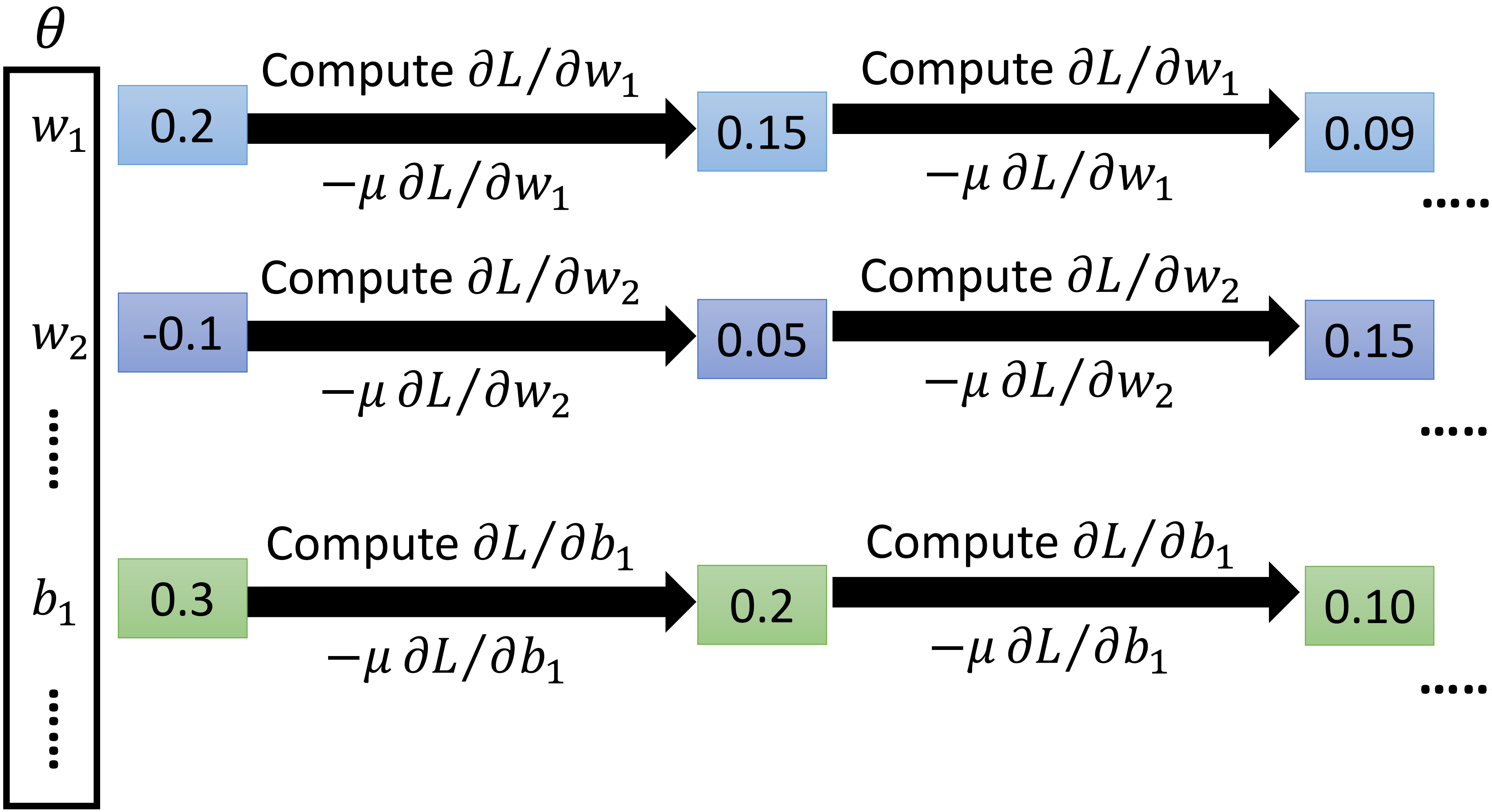
Gradient Descent



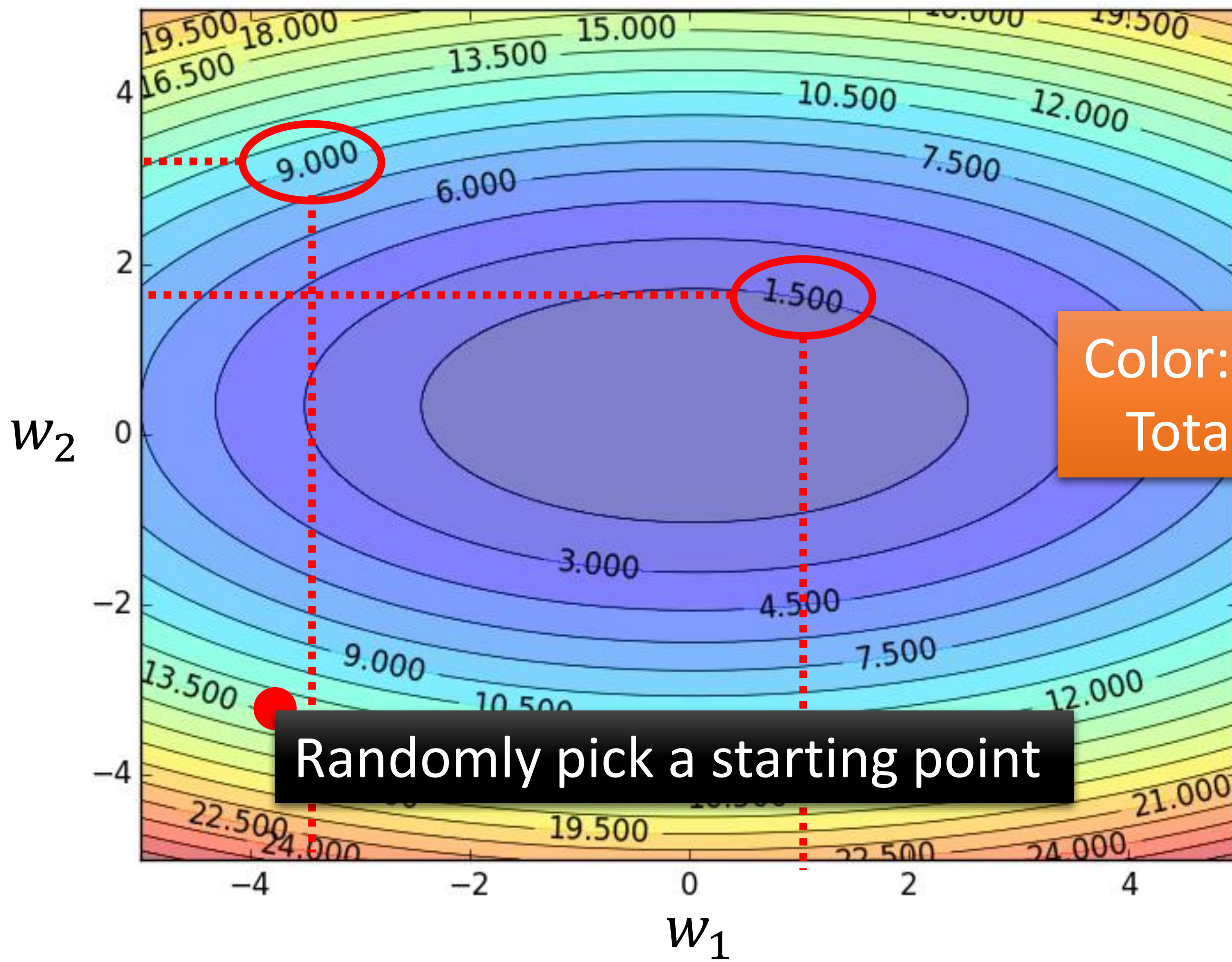
$$\nabla L = \begin{bmatrix} \frac{\partial L}{\partial w_1} \\ \frac{\partial L}{\partial w_2} \\ \vdots \\ \frac{\partial L}{\partial b_1} \\ \vdots \end{bmatrix}$$

gradient

Gradient Descent



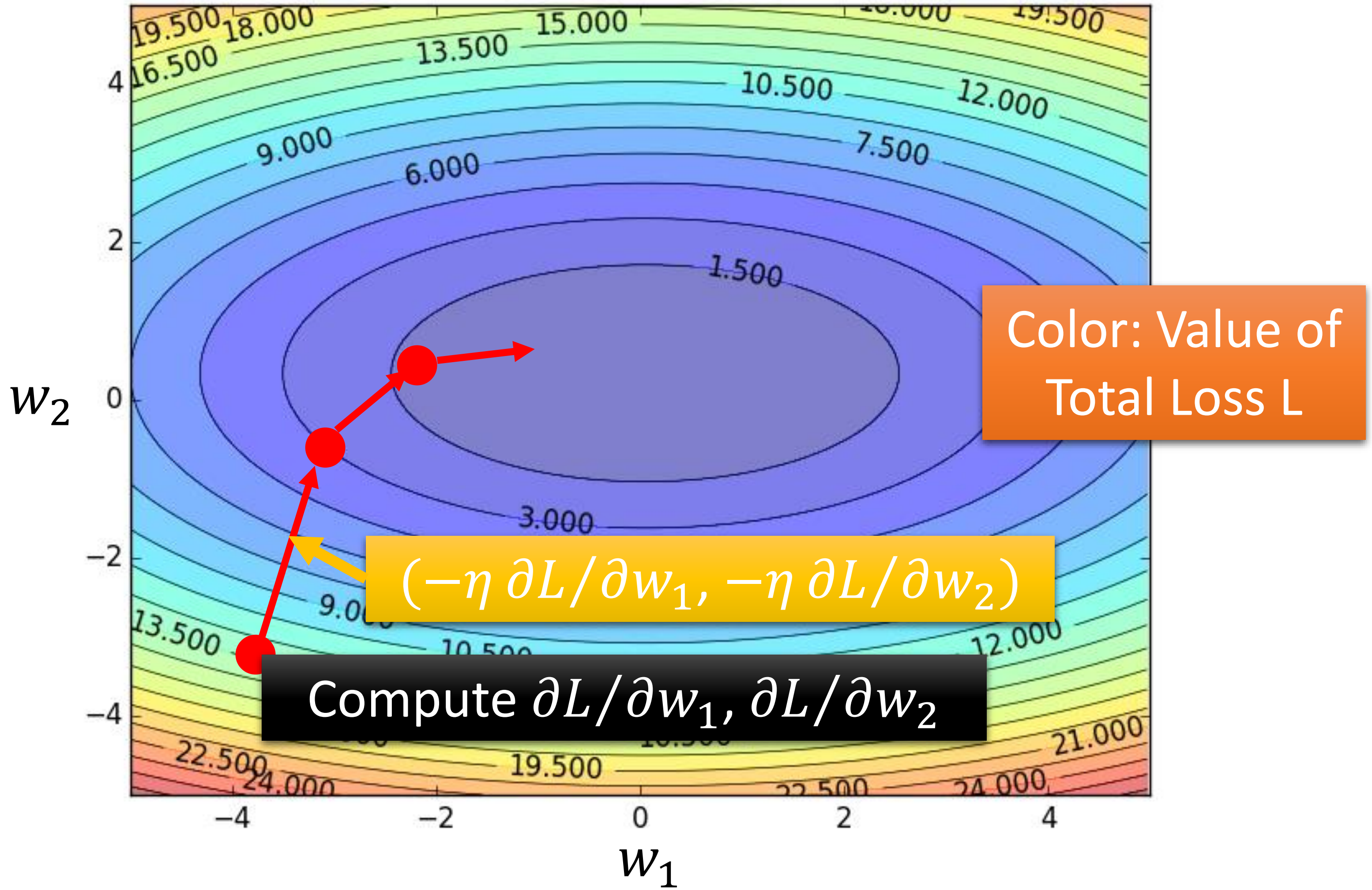
Gradient Descent



Color: Value of Total Loss L

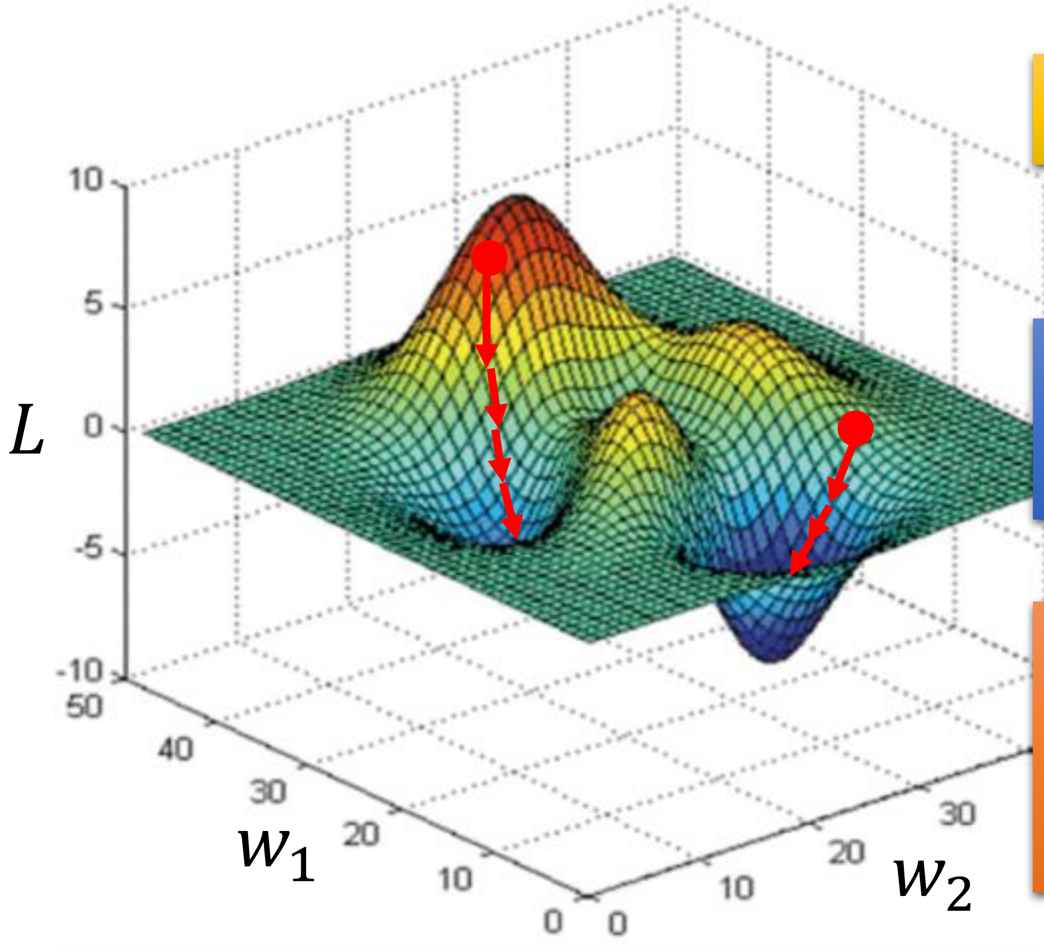
Gradient Descent

Hopfully, we would reach a minima .....



Gradient Descent - Difficulty

- Gradient descent never guarantee global minima



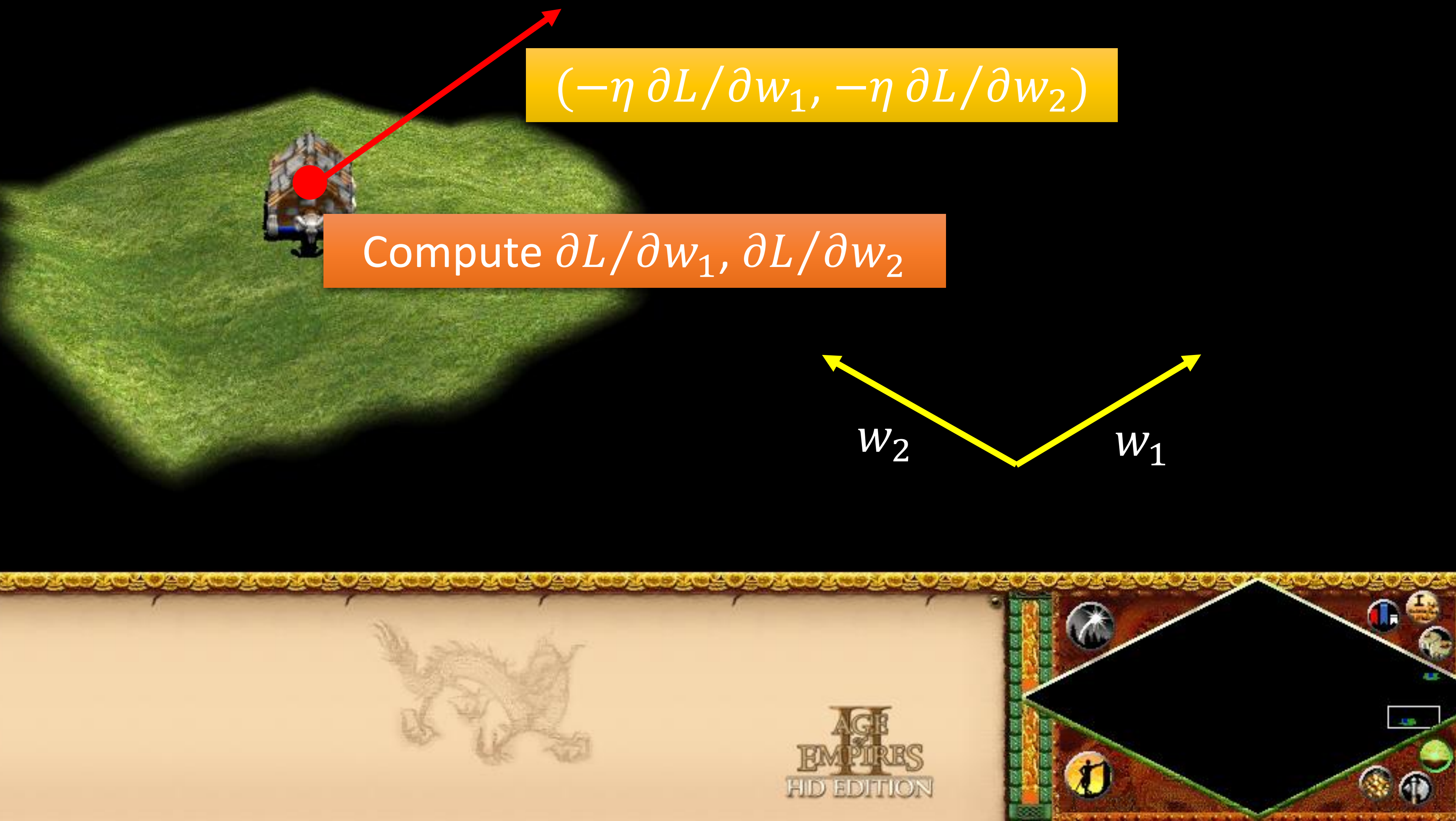
Different initial point

Reach different minima, so different results

There are some tips to help you avoid local minima, no guarantee.

You are playing Age of Empires …

You cannot see the whole map.

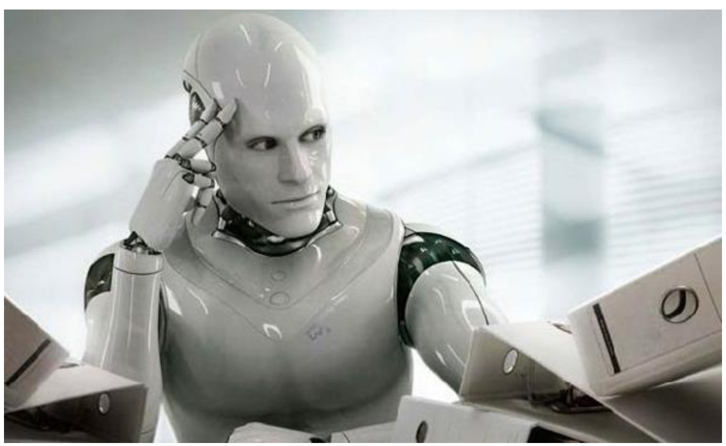


Gradient Descent

This is the “learning” of machines in deep learning ……

➡ Even alpha go using this approach.

People image ……



Actually …..

I hope you are not too disappointed :p

Backpropagation

- Backpropagation: an efficient way to compute $\partial L / \partial w$
  - Ref: http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/DNN%20backprop.ecm.mp4/index.html

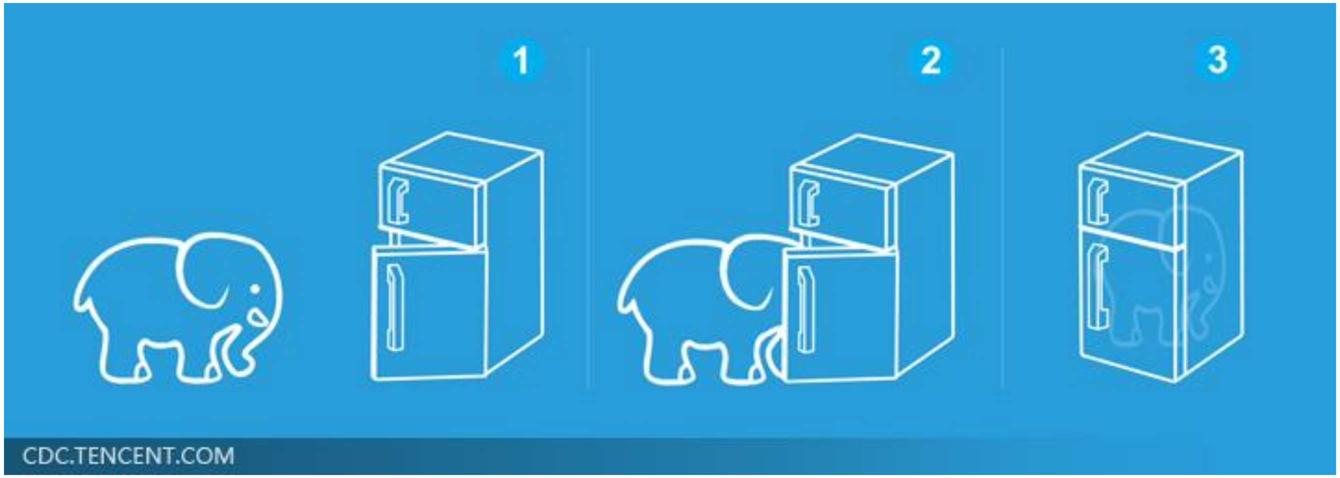
libdnn
台大周伯威
同學開發

Don’t worry about $\partial L / \partial w$, the toolkits will handle it.

Concluding Remarks

Step 1: define a set of function → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



Outline of Lecture I

Introduction of Deep Learning

Why Deep?

"Hello World" for Deep Learning

Deeper is Better?

Layer X Size	Word Error Rate (%)
1 X 2k	24.2
2 X 2k	20.4
3 X 2k	18.4
4 X 2k	17.8
5 X 2k	17.2
7 X 2k	17.1

Not surprised, more parameters, better performance

Seide, Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

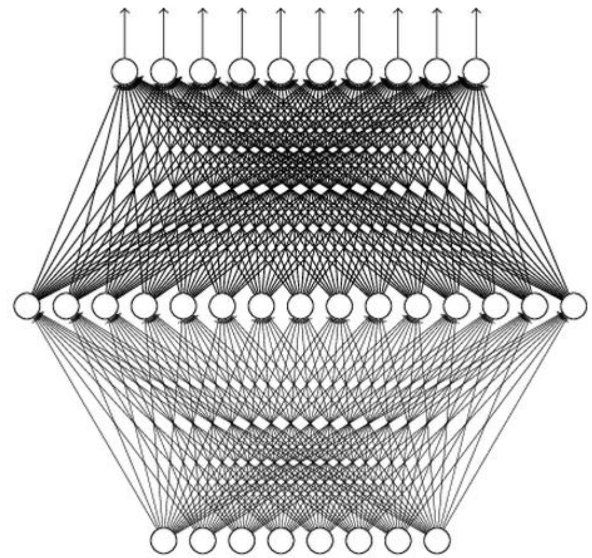
Universality Theorem

Any continuous function f

$$f : R^N \rightarrow R^M$$

Can be realized by a network with one hidden layer

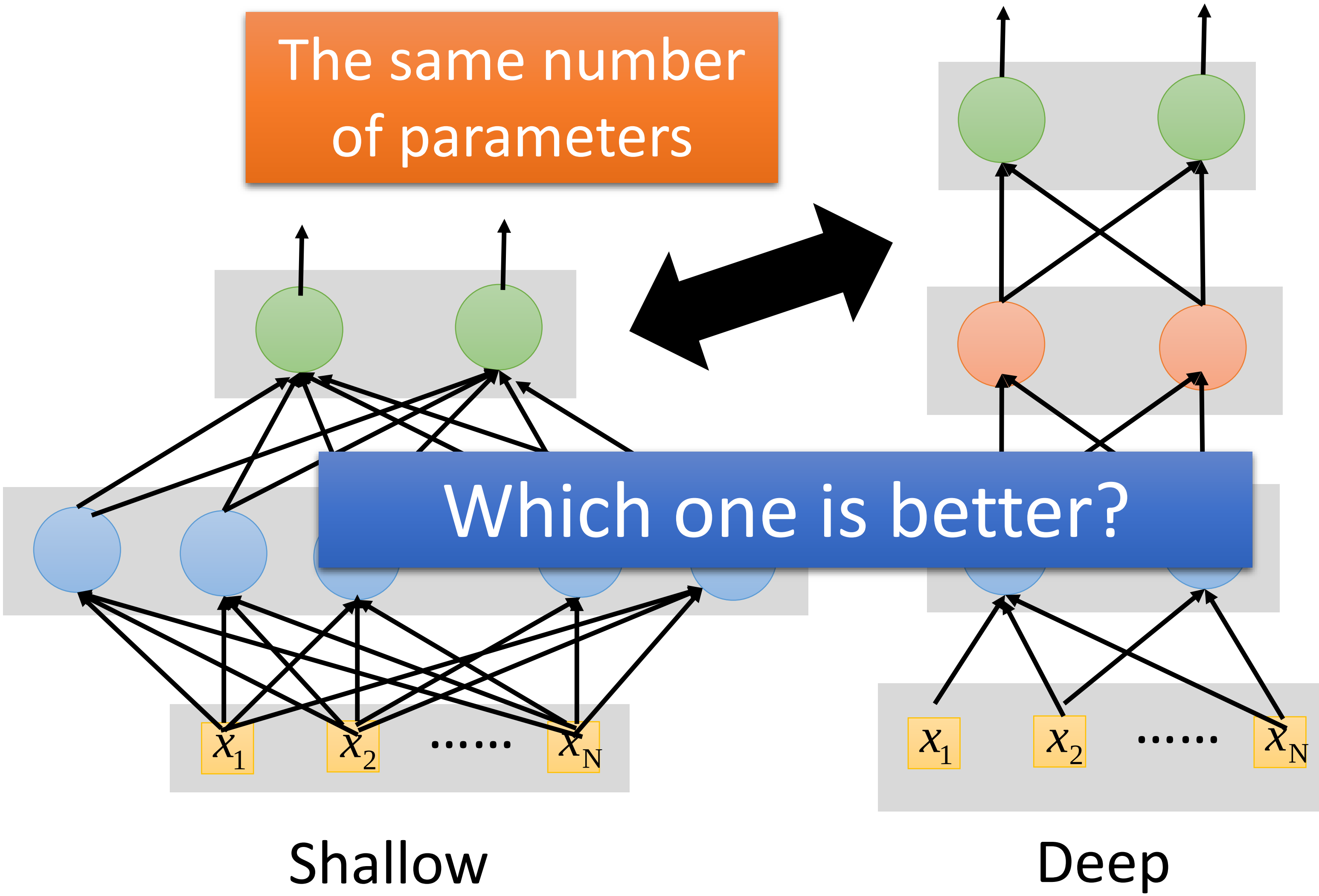
(given **enough** hidden neurons)



Reference for the reason: http://neuralnetworksanddeeplearning.com/chap4.html

Why "Deep" neural network not "Fat" neural network?

Fat + Short v.s. Thin + Tall



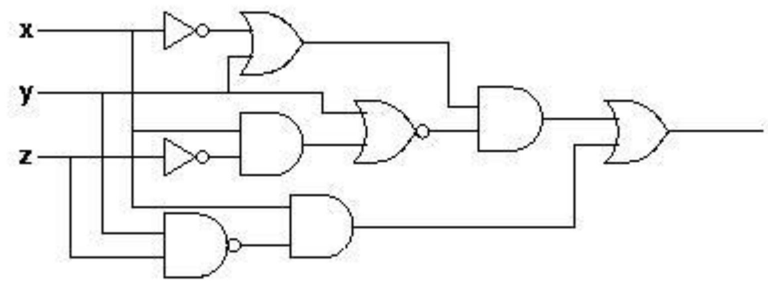
Fat + Short v.s. Thin + Tall

Layer X Size	Word Error Rate (%)	Layer X Size	Word Error Rate (%)
1 X 2k	24.2		
2 X 2k	20.4		
3 X 2k	18.4		
4 X 2k	17.8		
5 X 2k	17.2	1 X 3772	22.5
7 X 2k	17.1	1 X 4634	22.6
		1 X 16k	22.1

Why?

Seide, Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

Analogy



Logic circuits

- Logic circuits consists of **gates**
- **A two layers of logic gates** can represent **any Boolean function.**
- Using multiple layers of logic gates to build some functions are much simpler

→ less gates needed

Neural network

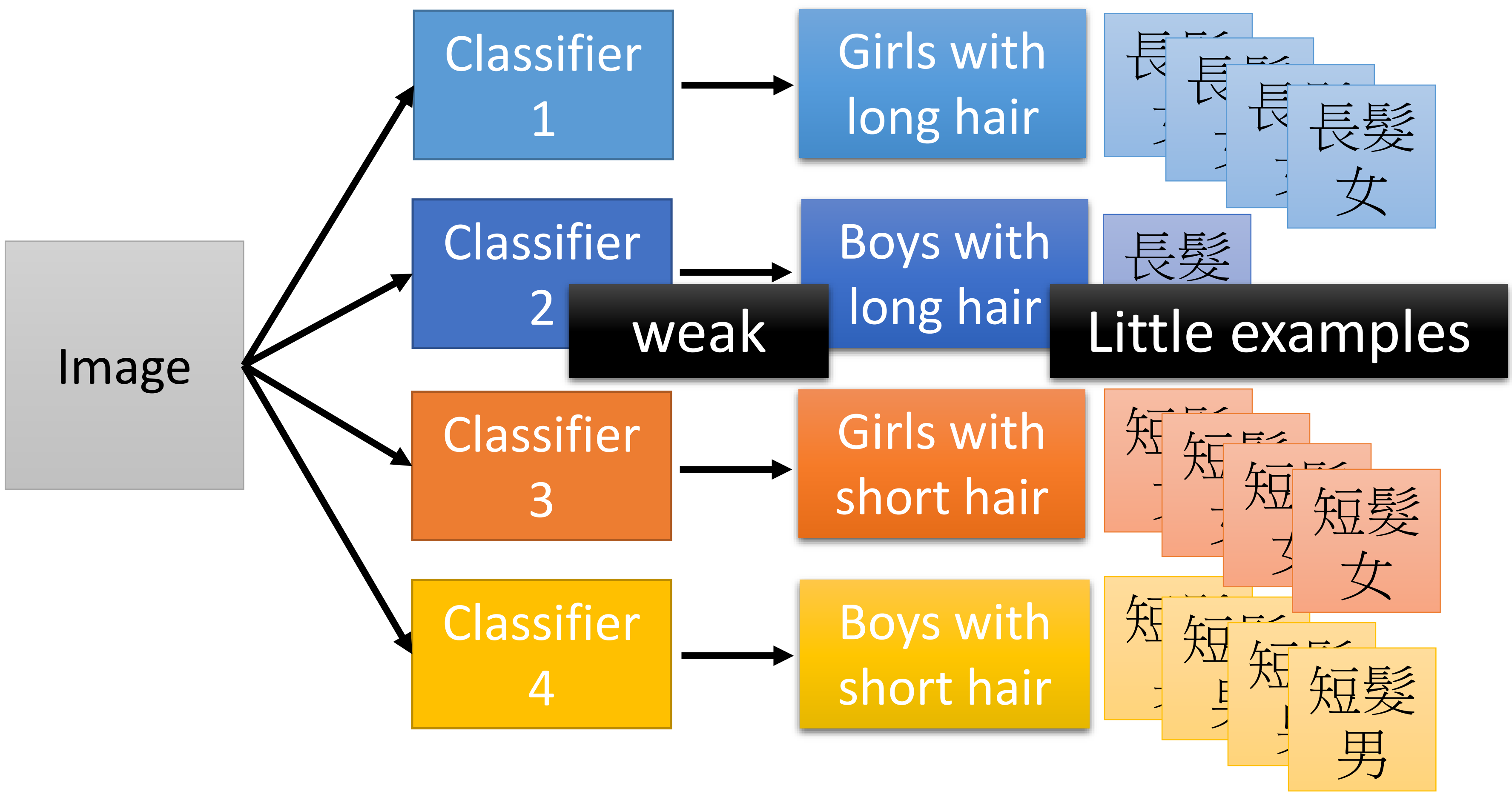
- Neural network consists of **neurons**
- **A hidden layer network** can represent **any continuous function.**
- Using multiple layers of neurons to represent some functions are much simpler

→ less parameters → less data?

This page is for EE background.

Modularization

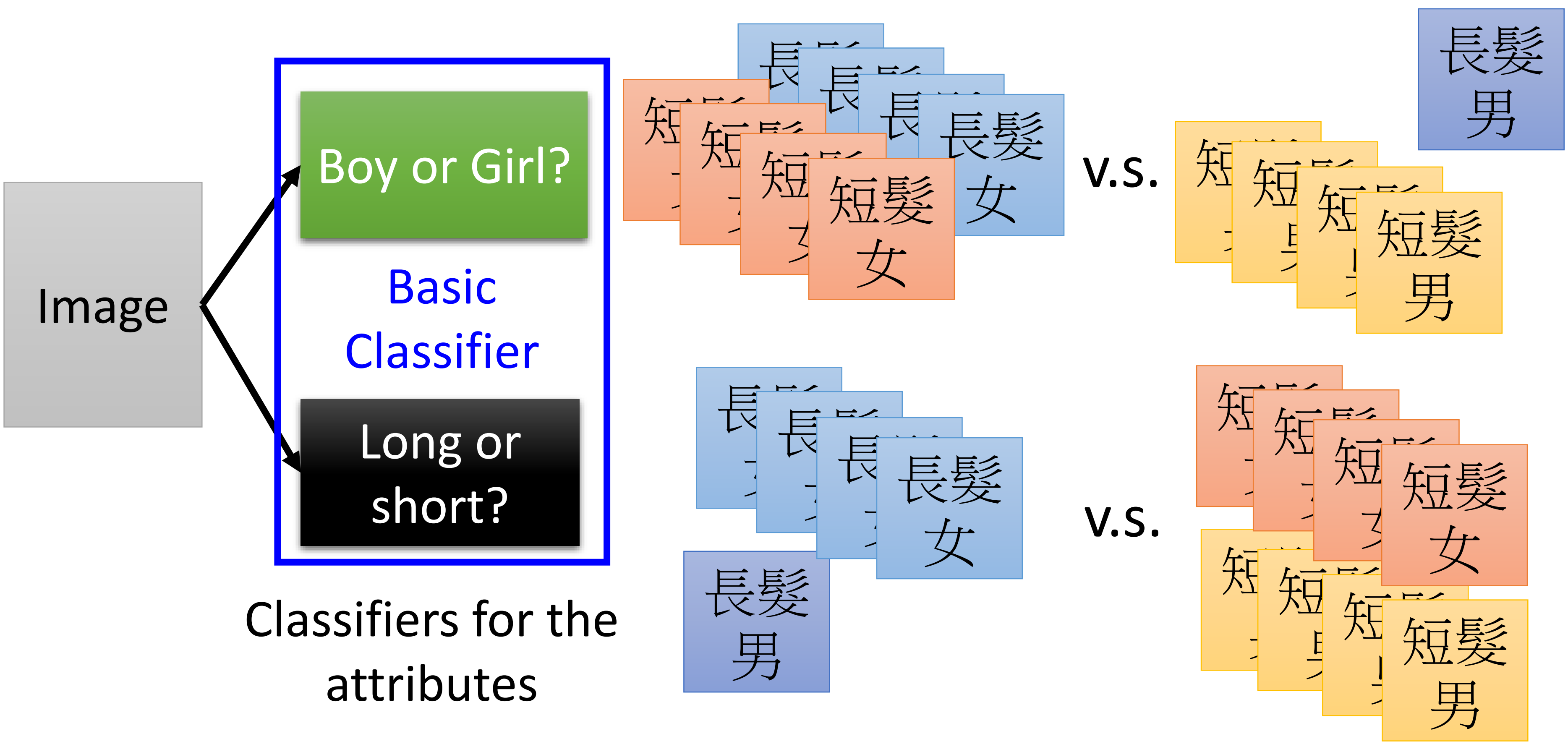
- Deep → Modularization



Modularization

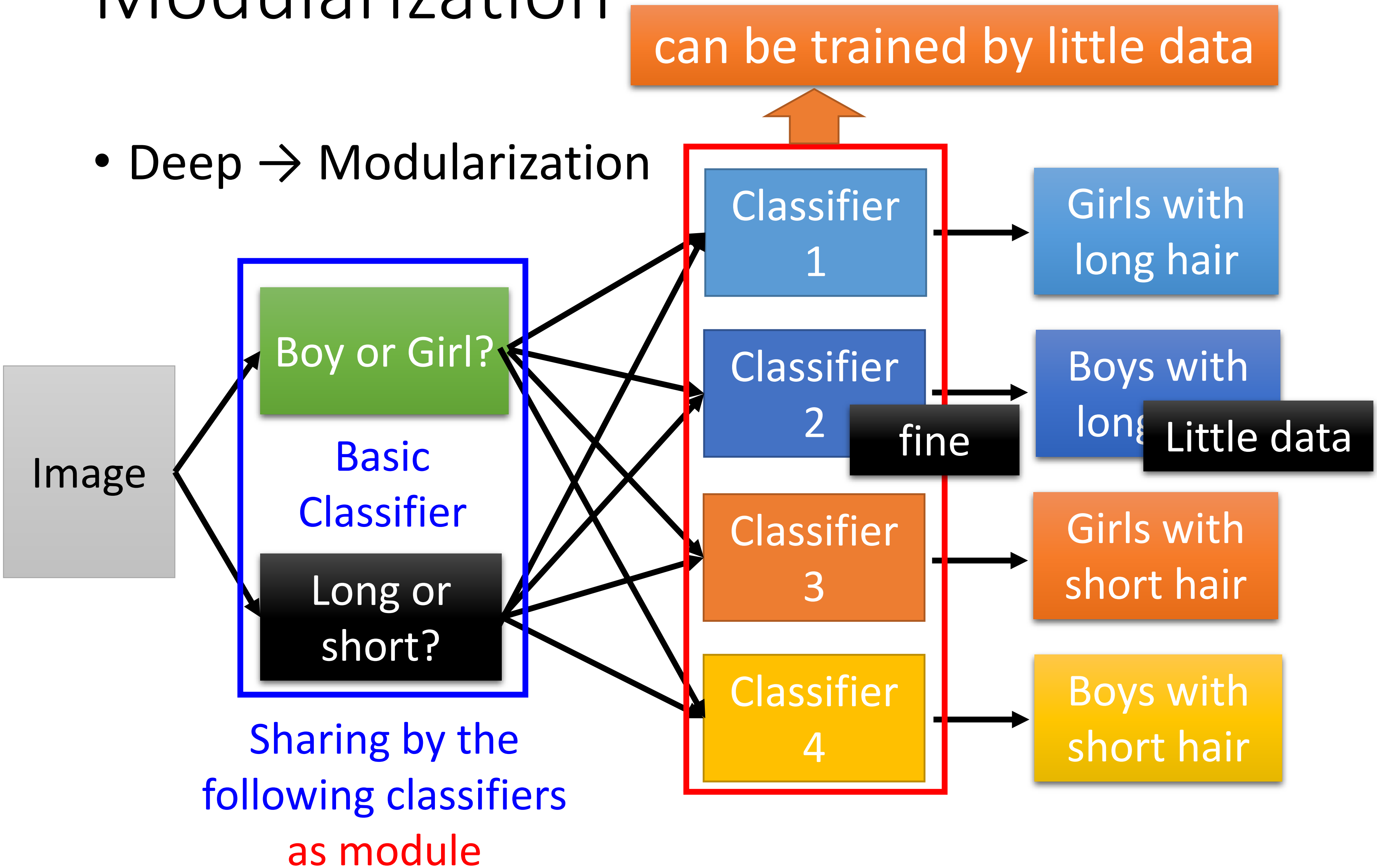
Each basic classifier can have sufficient training examples.

- Deep → Modularization



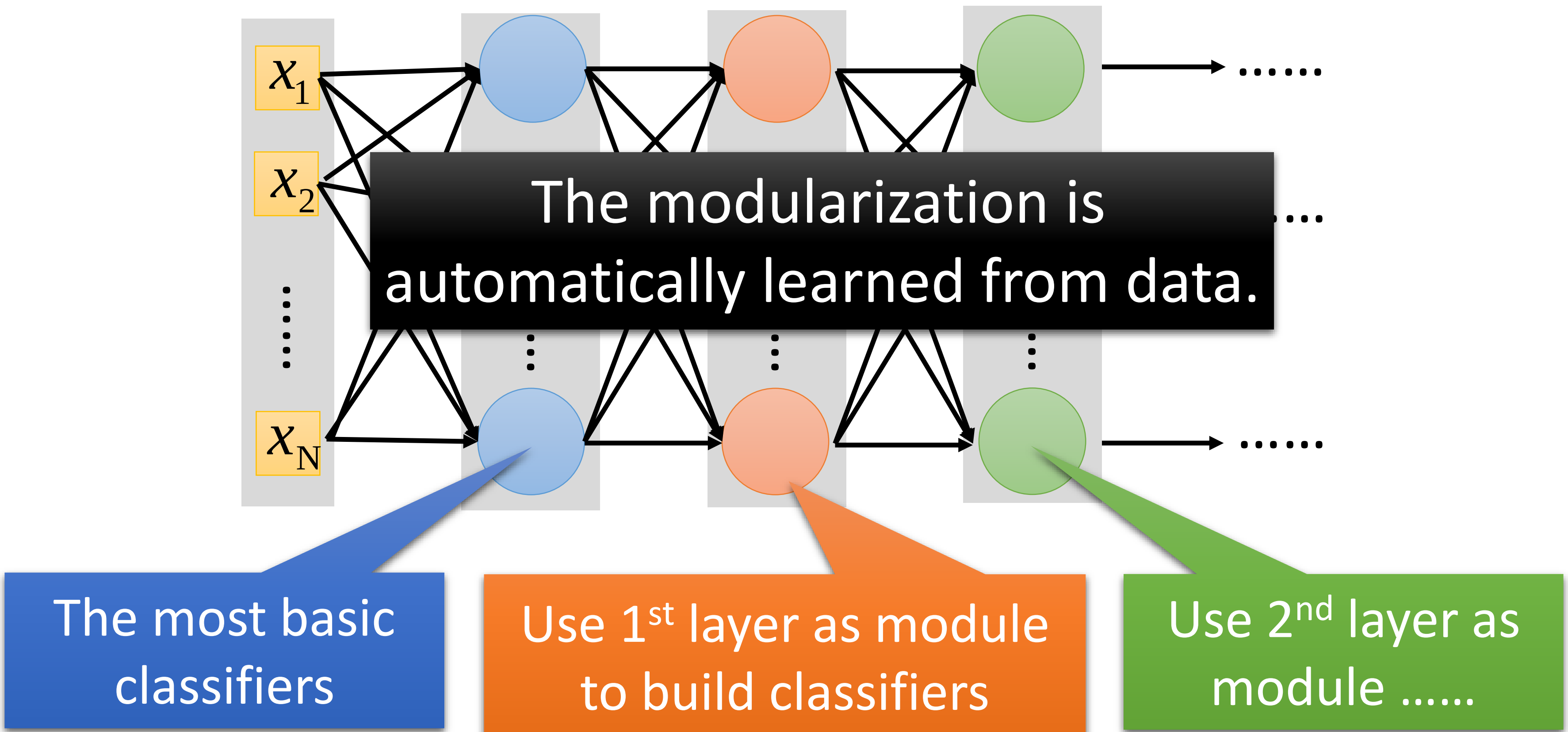
Modularization

- Deep → Modularization



Modularization

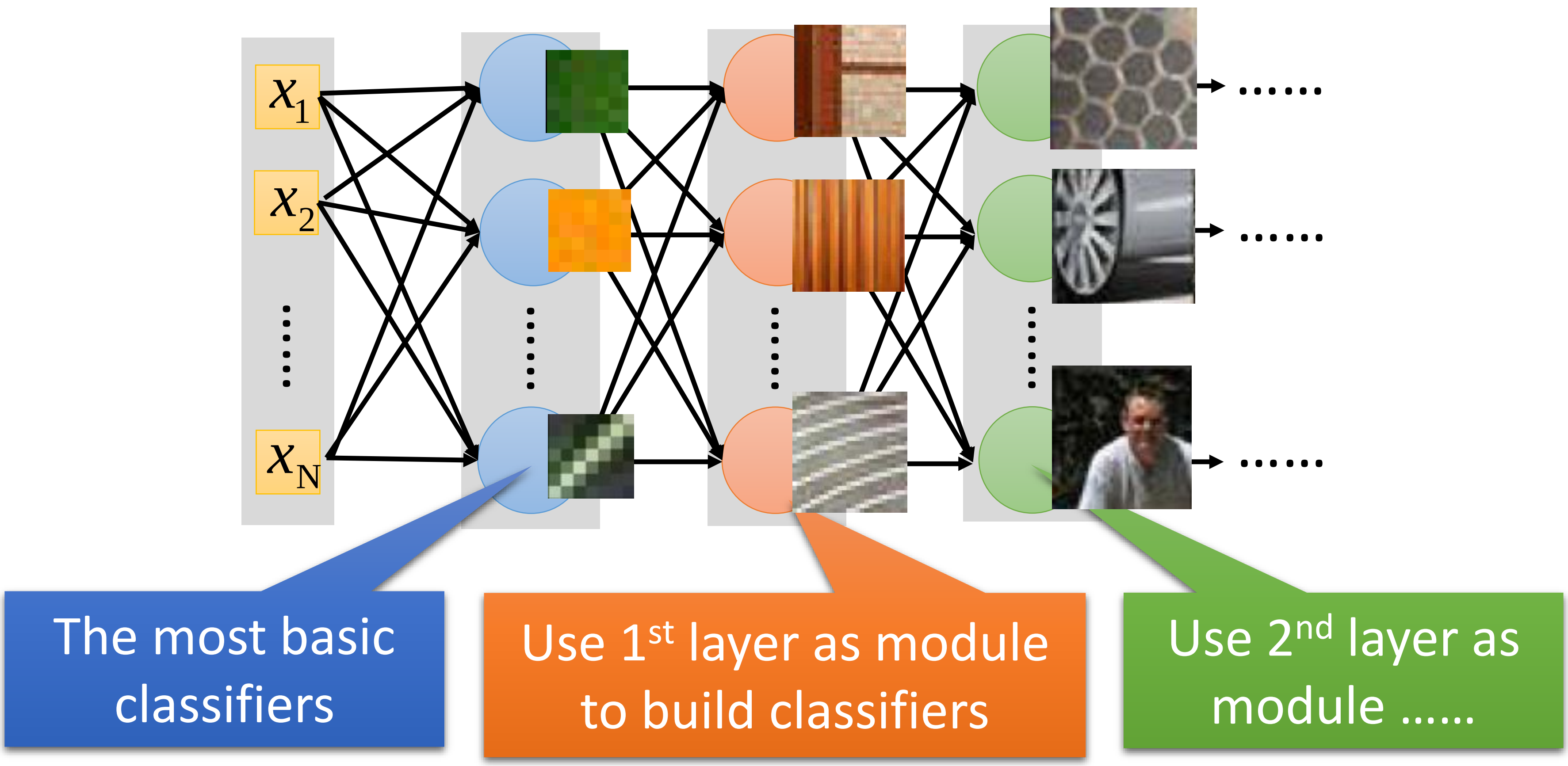
- Deep → Modularization → Less training data?



Modularization

Reference: Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision–ECCV 2014* (pp. 818-833)

- Deep → Modularization



Outline of Lecture I

Introduction of Deep Learning

Why Deep?

"Hello World" for Deep Learning

Keras

If you want to learn theano:

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

http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/RNN%20training%20(v6).ecm.mp4/index.html

TensorFlow or theano

Very flexible

Need some effort to learn

Interface of TensorFlow or Theano

keras

Easy to learn and use

(still have some flexibility)

You can modify it if you can write TensorFlow or Theano

Keras

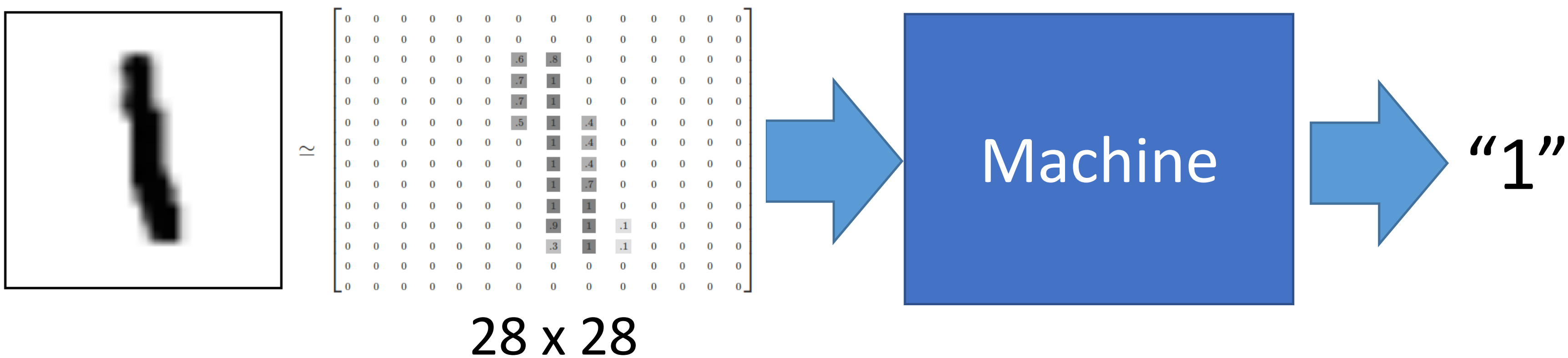
- François Chollet is the author of Keras.
  - He currently works for Google as a deep learning engineer and researcher.
- Keras means *horn* in Greek
- Documentation: http://keras.io/
- Example: https://github.com/fchollet/keras/tree/master/examples

感謝 沈昇勳 同學提供圖檔

使用 Keras 心得

Example Application

- Handwriting Digit Recognition



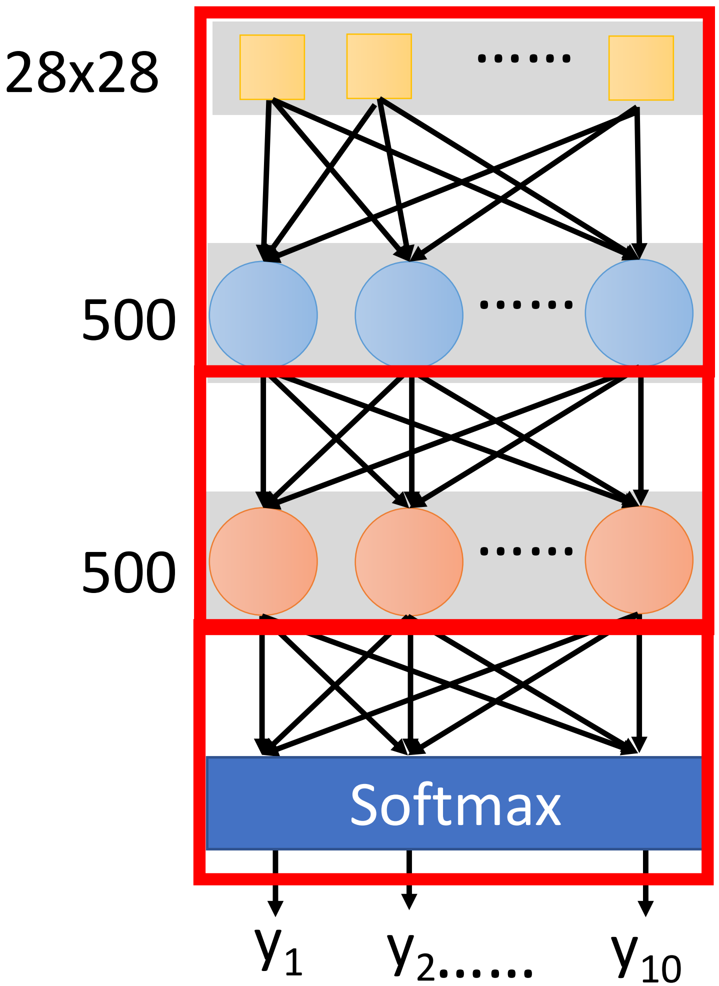
MNIST Data: http://yann.lecun.com/exdb/mnist/

“Hello world” for deep learning

Keras provides data sets loading function: http://keras.io/datasets/

Keras

Step 1: define a set of function → Step 2: goodness of function → Step 3: pick the best function




```
model = Sequential()
```

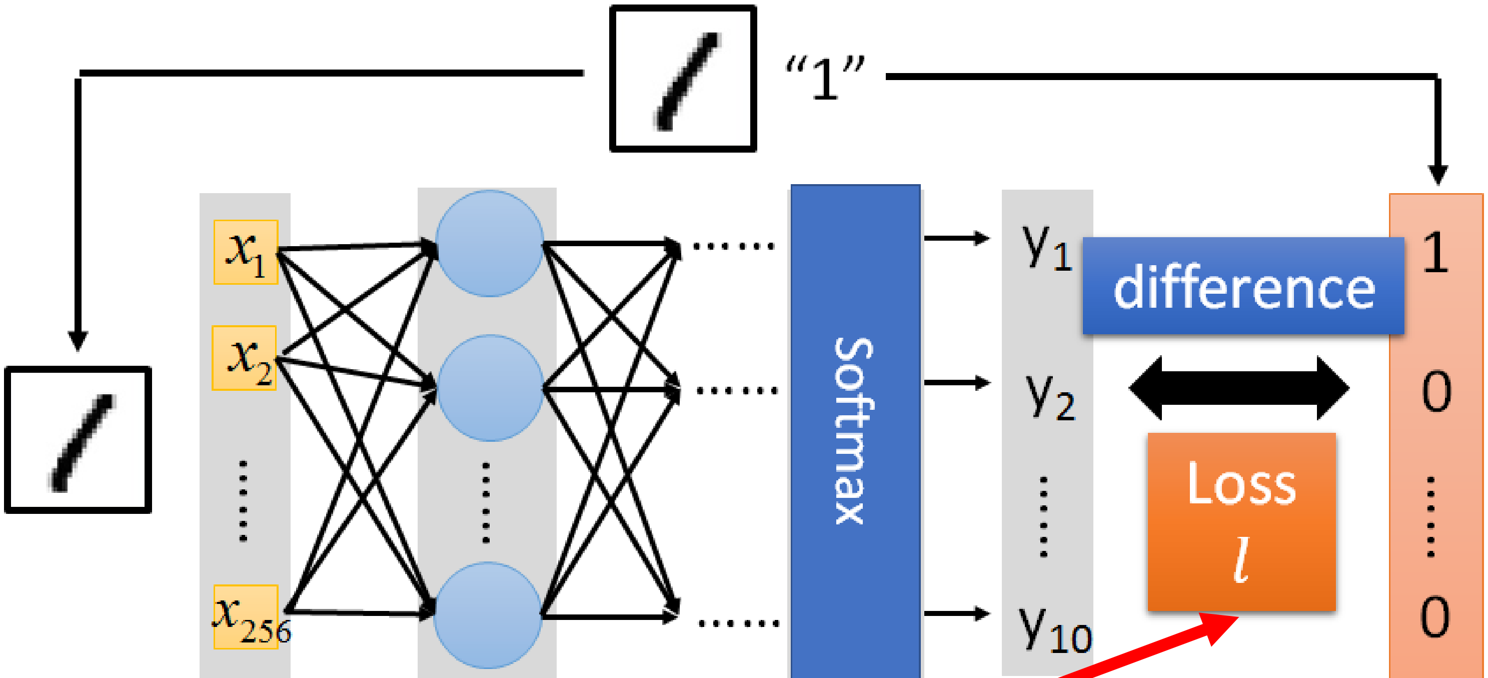
```
model.add( Dense( input_dim=28*28,
                  output_dim=500 ))
model.add( Activation('sigmoid') )
```

```
model.add( Dense( output_dim=500 ) )
model.add( Activation('sigmoid') )
```

```
model.add( Dense(output_dim=10 ) )
model.add( Activation('softmax') )
```

Keras

Step 1: define a set of function → **Step 2: goodness of function** → Step 3: pick the best function




```
model.compile(loss='mse',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

Keras

Step 1: define a set of function → Step 2: goodness of function → **Step 3: pick the best function**

Step 3.1: Configuration

```
model.compile(loss='mse',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

$$w \leftarrow w - \eta \partial L / \partial w$$

0.1

Step 3.2: Find the optimal network parameters

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```

Training data (Images)

Labels (digits)

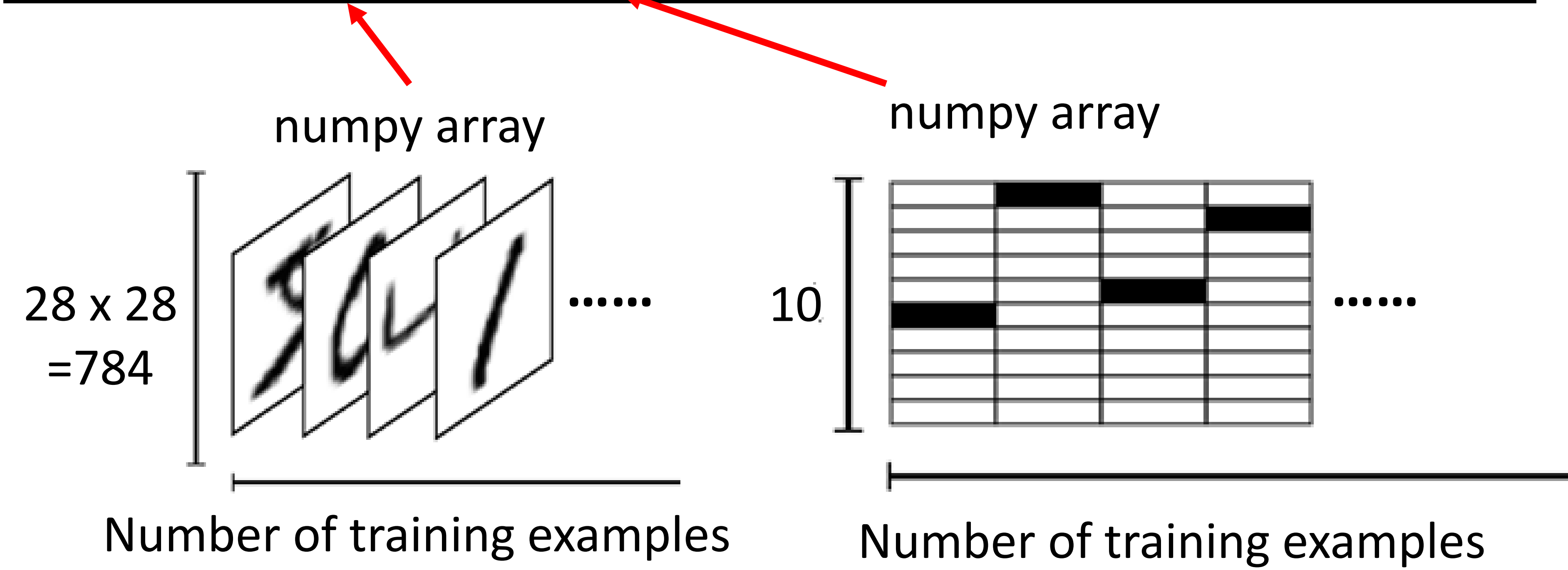
Next lecture

Keras

Step 1: define a set of function → Step 2: goodness of function → **Step 3: pick the best function**

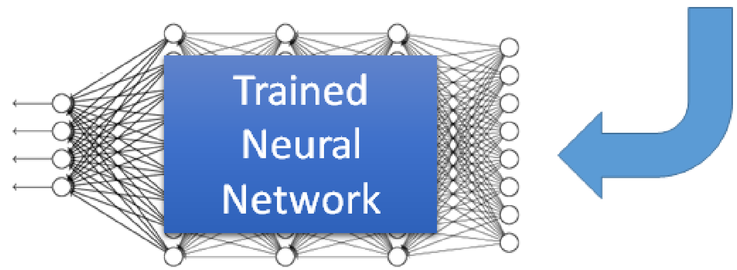
Step 3.2: Find the optimal network parameters

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```



https://www.tensorflow.org/versions/r0.8/tutorials/mnist/beginners/index.html

Keras



Save and load models

http://keras.io/getting-started/faq/#how-can-i-save-a-keras-model

How to use the neural network (testing):

case 1:

```
score = model.evaluate(x_test,y_test)
print('Total loss on Testing Set:', score[0])
print('Accuracy of Testing Set:', score[1])
```

case 2:

```
result = model.predict(x_test)
```

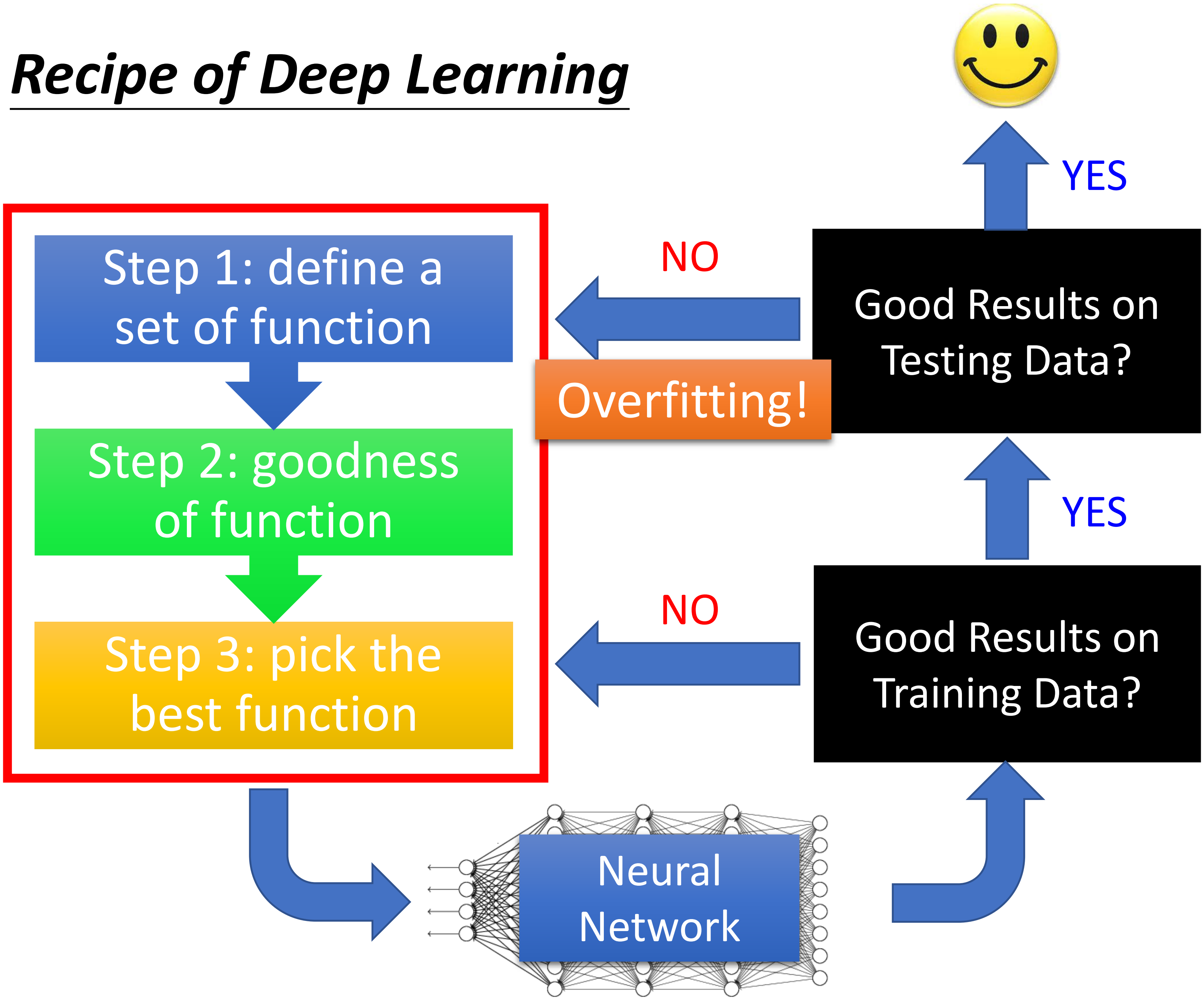
Keras

- Using GPU to speed training
  - Way 1
    - THEANO_FLAGS=device=gpu0 python YourCode.py
  - Way 2 (in your code)
    - import os
    - os.environ["THEANO_FLAGS"] = "device=gpu0"

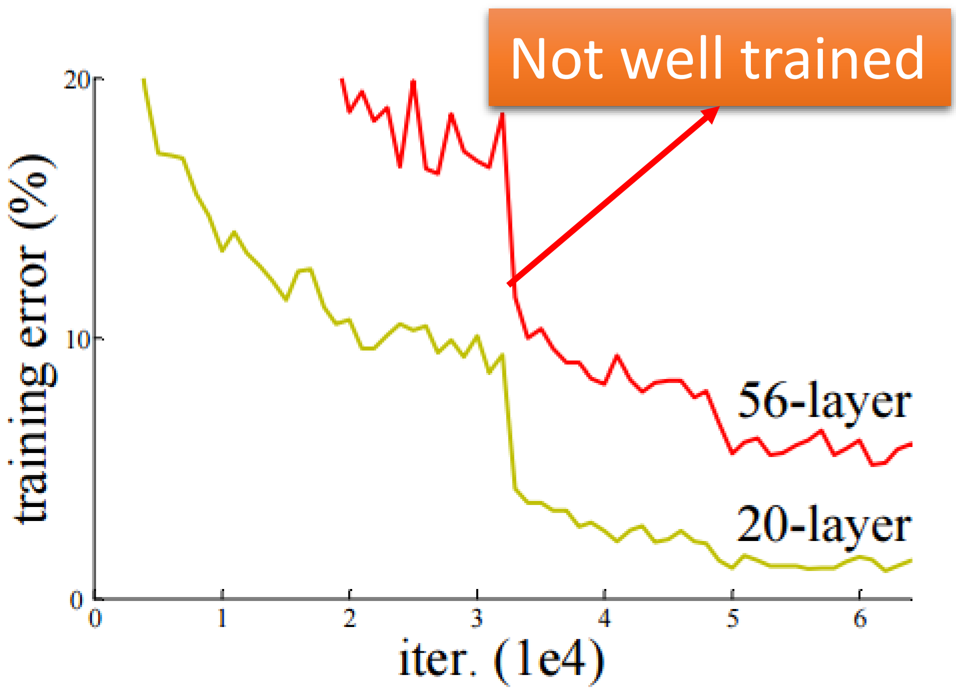
Live Demo

Lecture II:
Tips for Training DNN

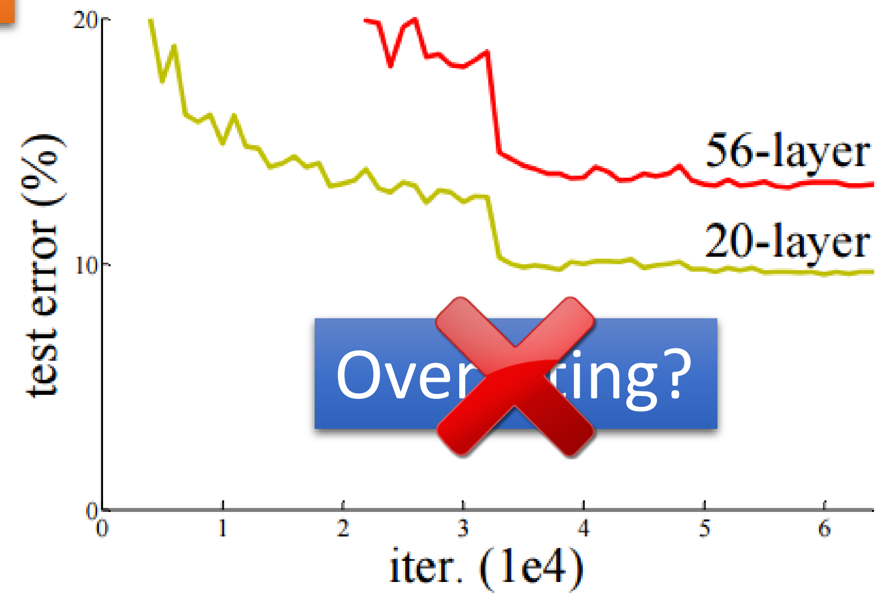
Recipe of Deep Learning



Do not always blame Overfitting



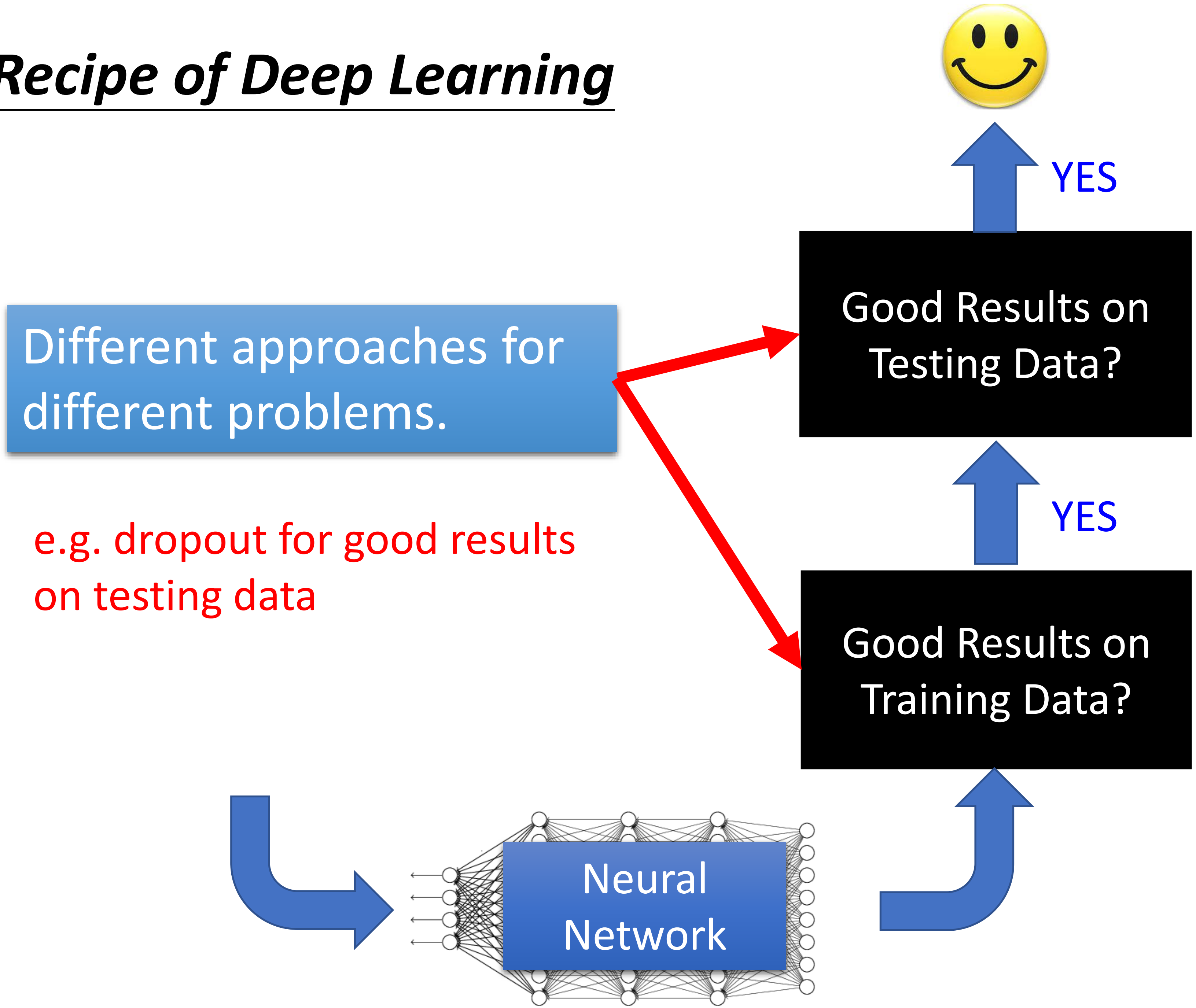
Training Data



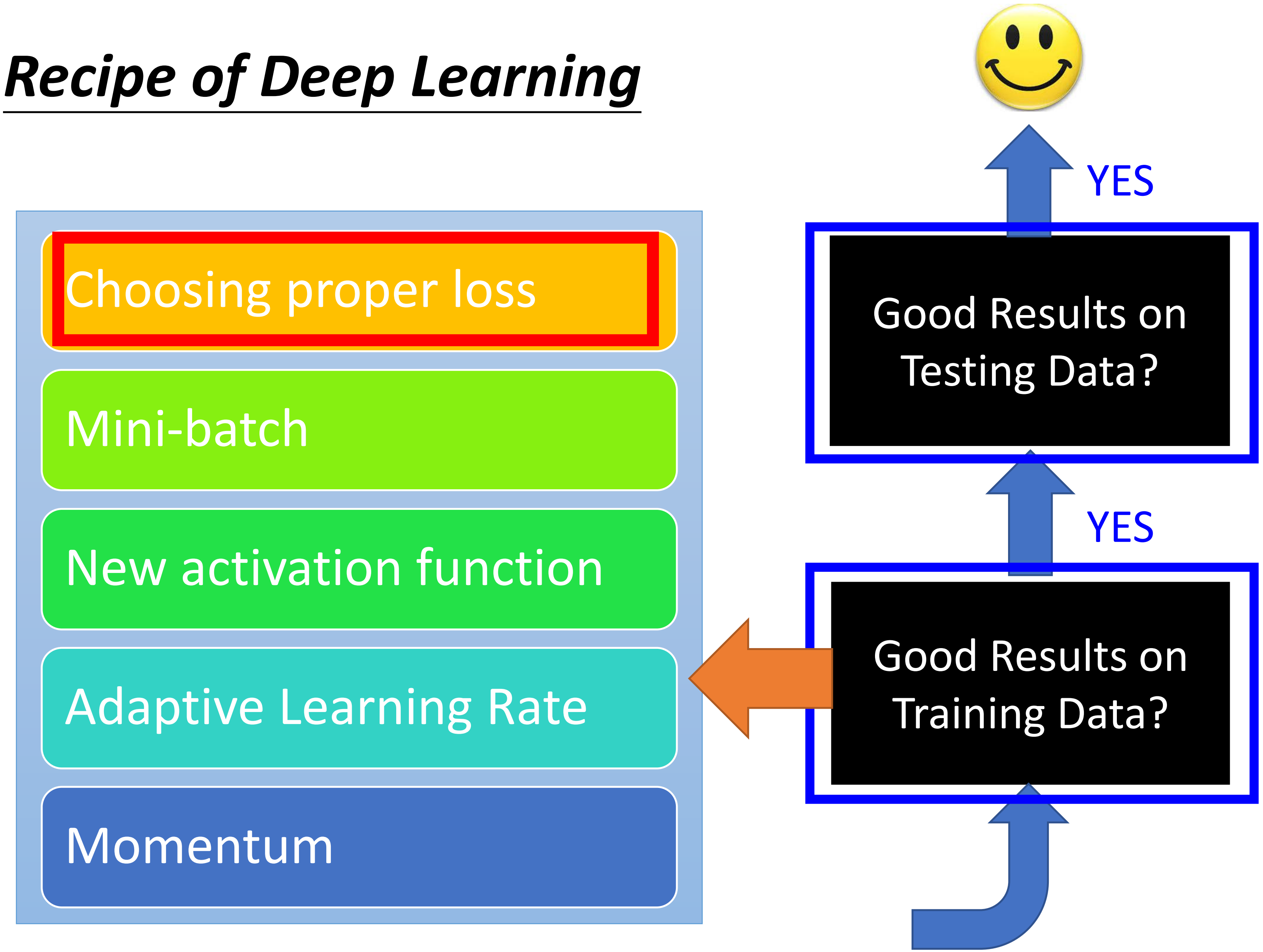
Testing Data

Deep Residual Learning for Image Recognition
http://arxiv.org/abs/1512.03385

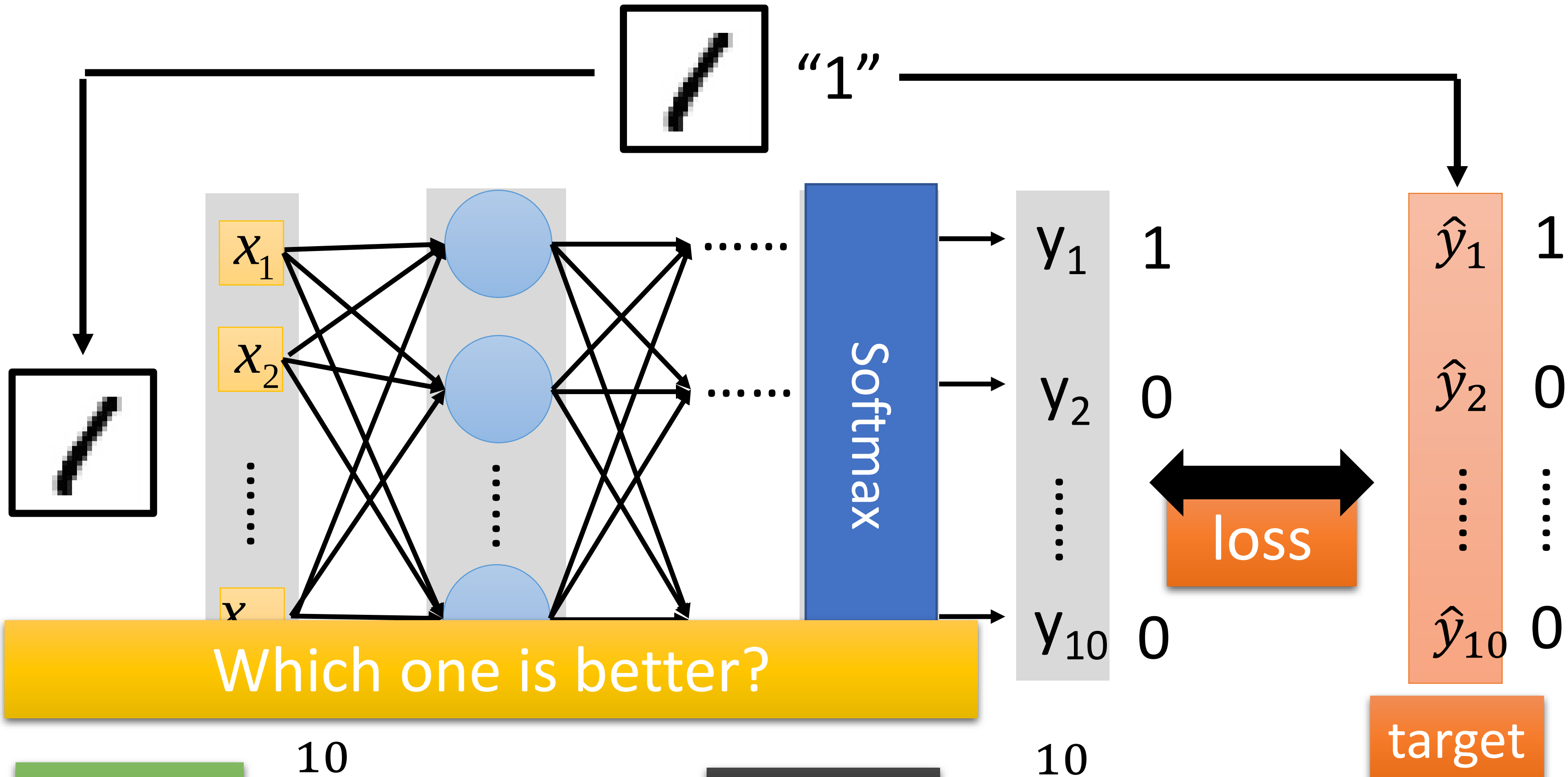
Recipe of Deep Learning



Recipe of Deep Learning



Choosing Proper Loss



Which one is better?

Square Error $\sum_{i=1}^{10}(y_i - \hat{y}_i)^2$ **=0**

Cross Entropy $-\sum_{i=1}^{10}\hat{y}_i \ln y_i$ **=0**

Let's try it

Square Error

```
model.compile(loss='mse',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

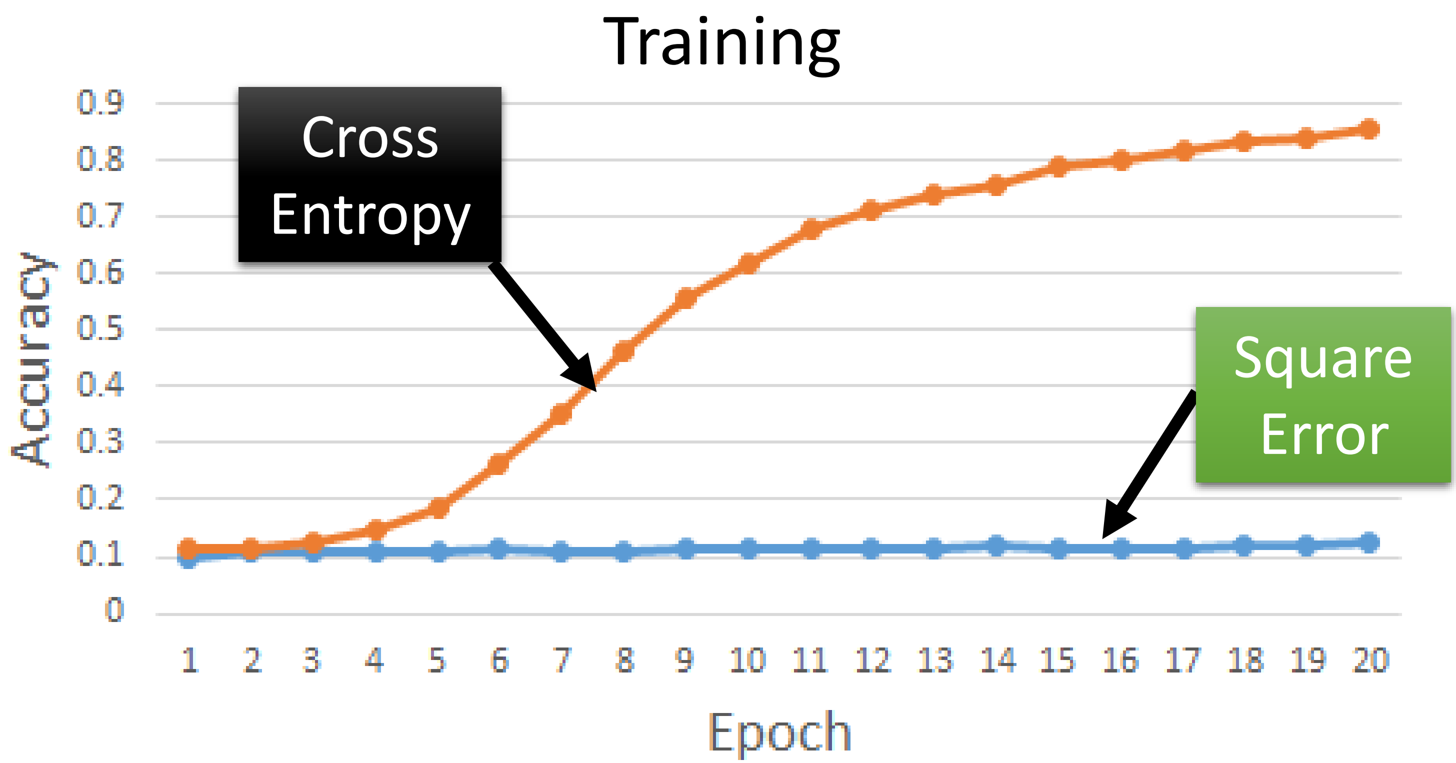
Cross Entropy

```
model.compile(loss='categorical_crossentropy',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

Let's try it

Testing:

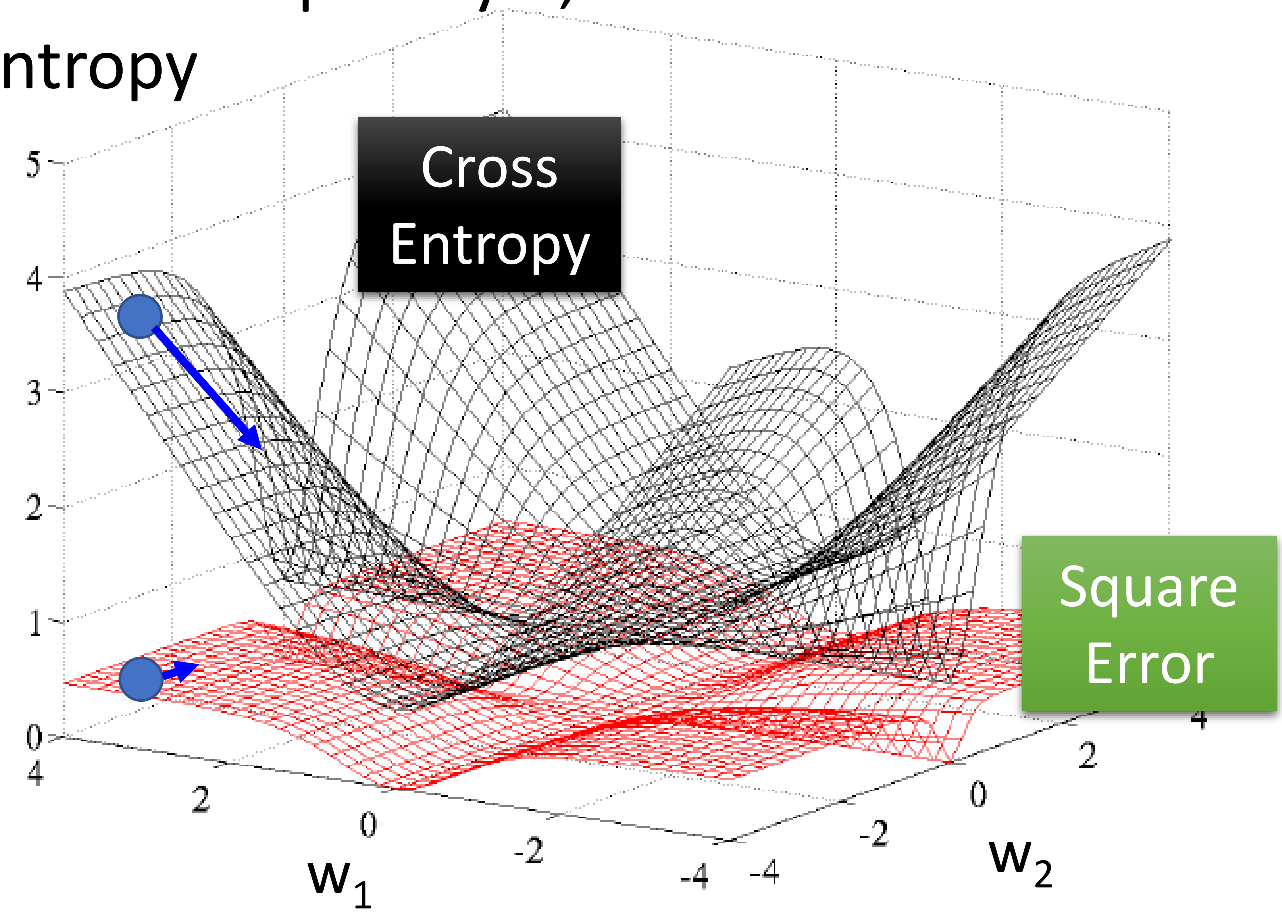
	Accuracy
Square Error	0.11
Cross Entropy	0.84



Choosing Proper Loss

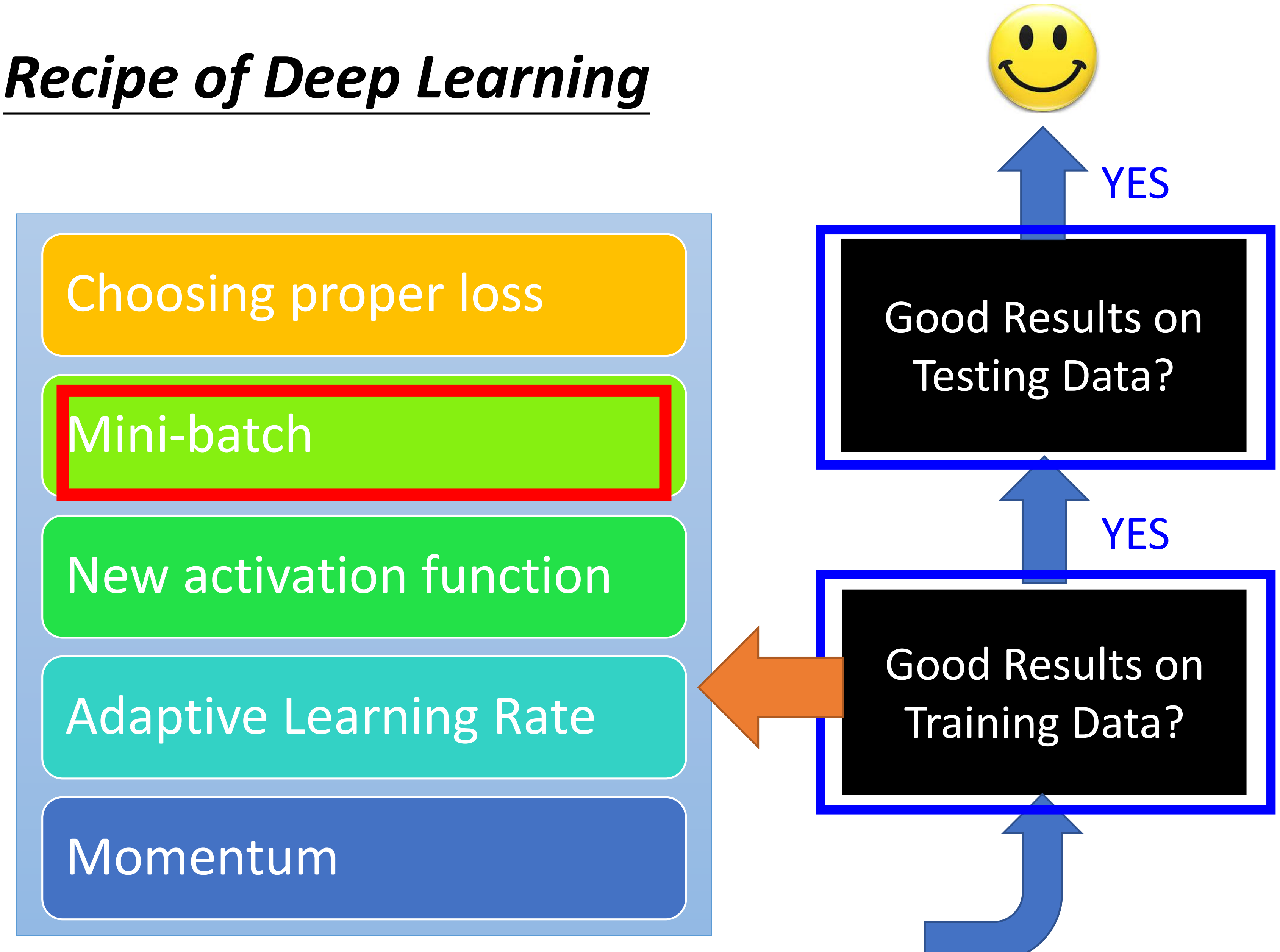
When using softmax output layer, choose cross entropy

Total Loss



http://jmlr.org/proceedings/papers/v9/glorot10a/glorot10a.pdf

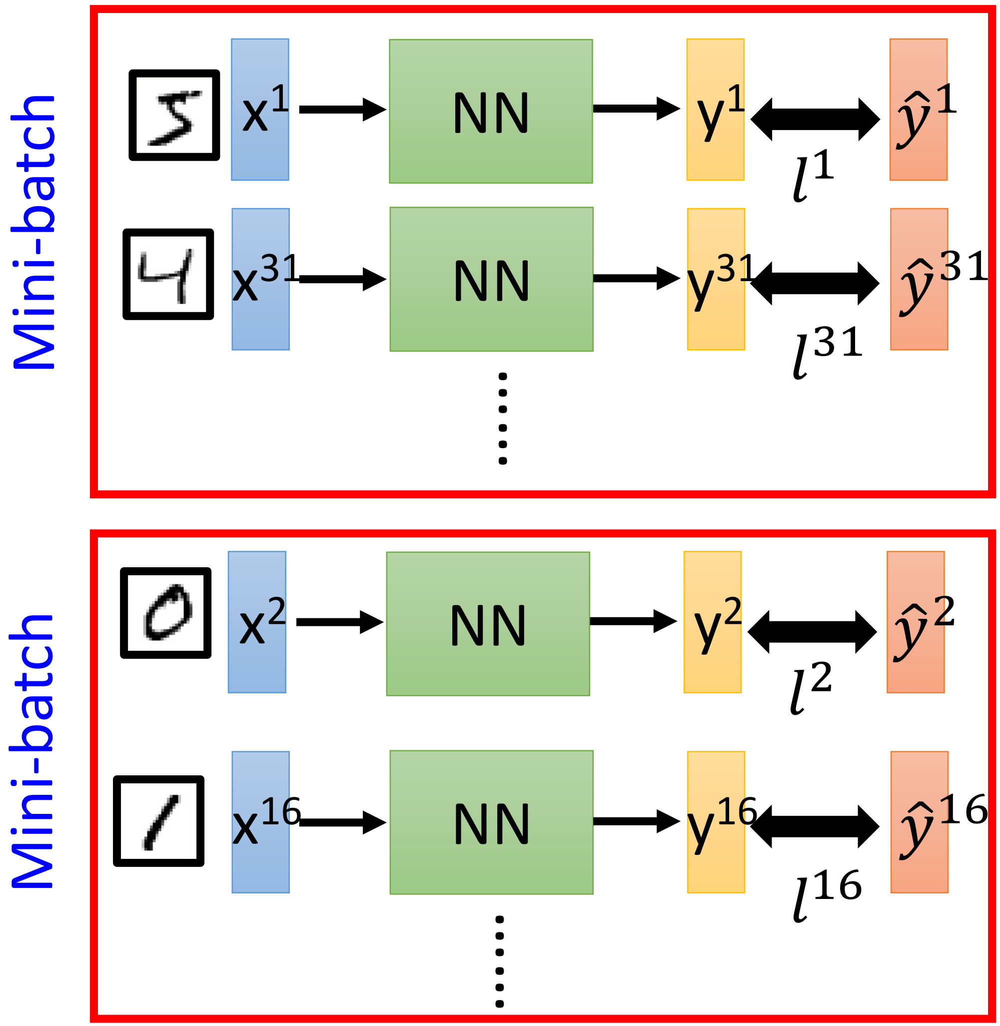
Recipe of Deep Learning




```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```

We do not really minimize total loss!

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

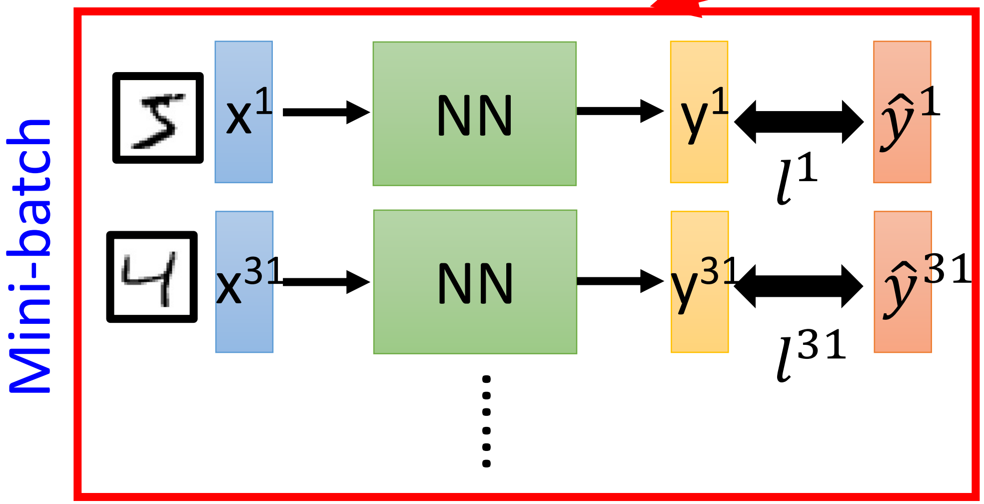
  ⋮
- Until all mini-batches have been picked

one epoch

Repeat the above process

Mini-batch

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```



100 examples in a mini-batch

Repeat 20 times

- 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

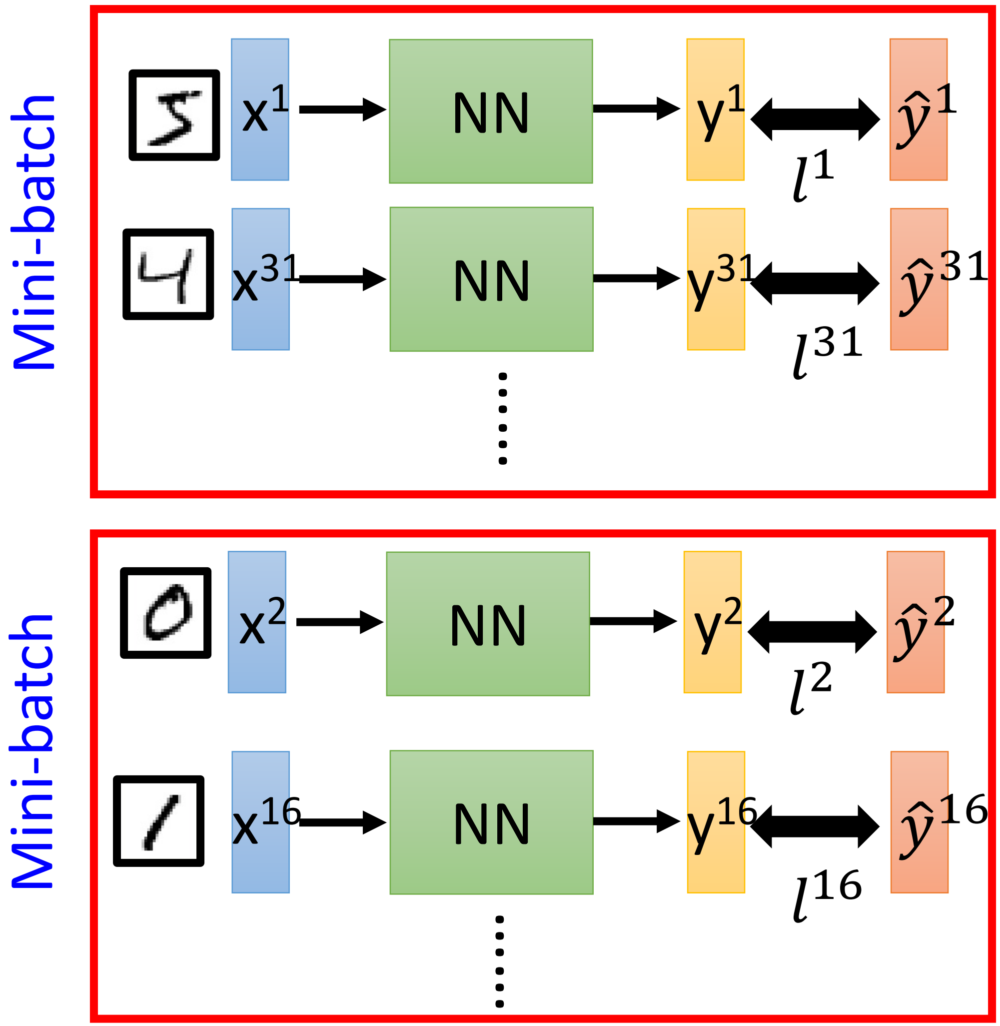
  ⋮

- Until all mini-batches have been picked

one epoch

We do not really minimize total loss!

Mini-batch



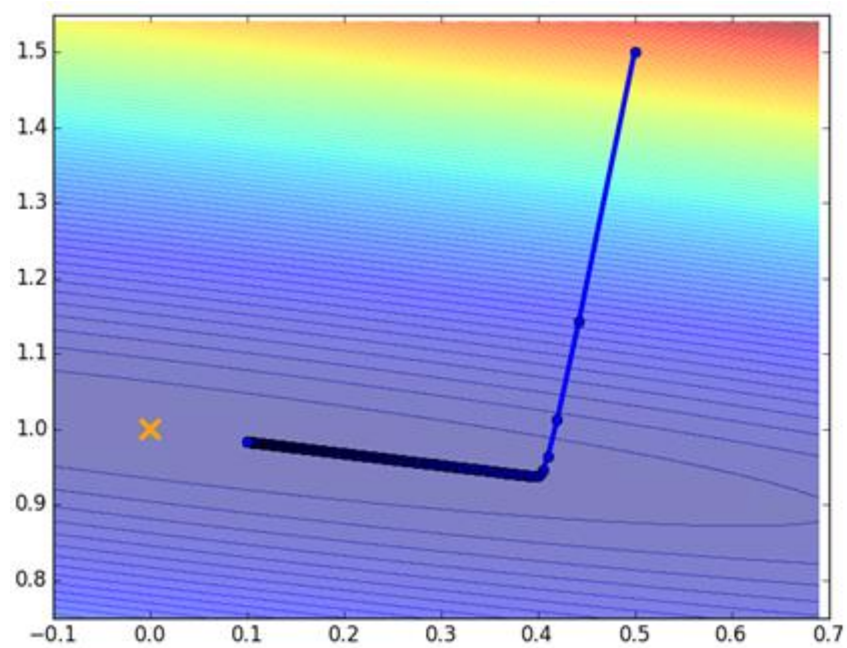
- Randomly initialize network parameters
- Pick the 1st batch
  $L' = l^1 + l^{31} + \cdots$
  Update parameters once
- Pick the 2nd batch
  $L'' = l^2 + l^{16} + \cdots$
  Update parameters once

⋮

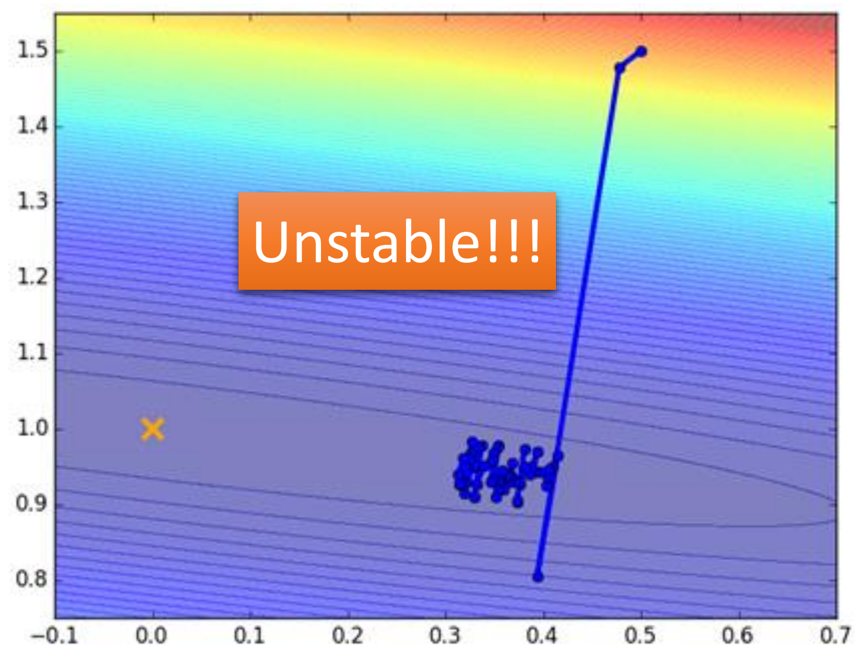
L is different each time when we update parameters!

Mini-batch

Original Gradient Descent



With Mini-batch



The colors represent the total loss.

Mini-batch is Faster

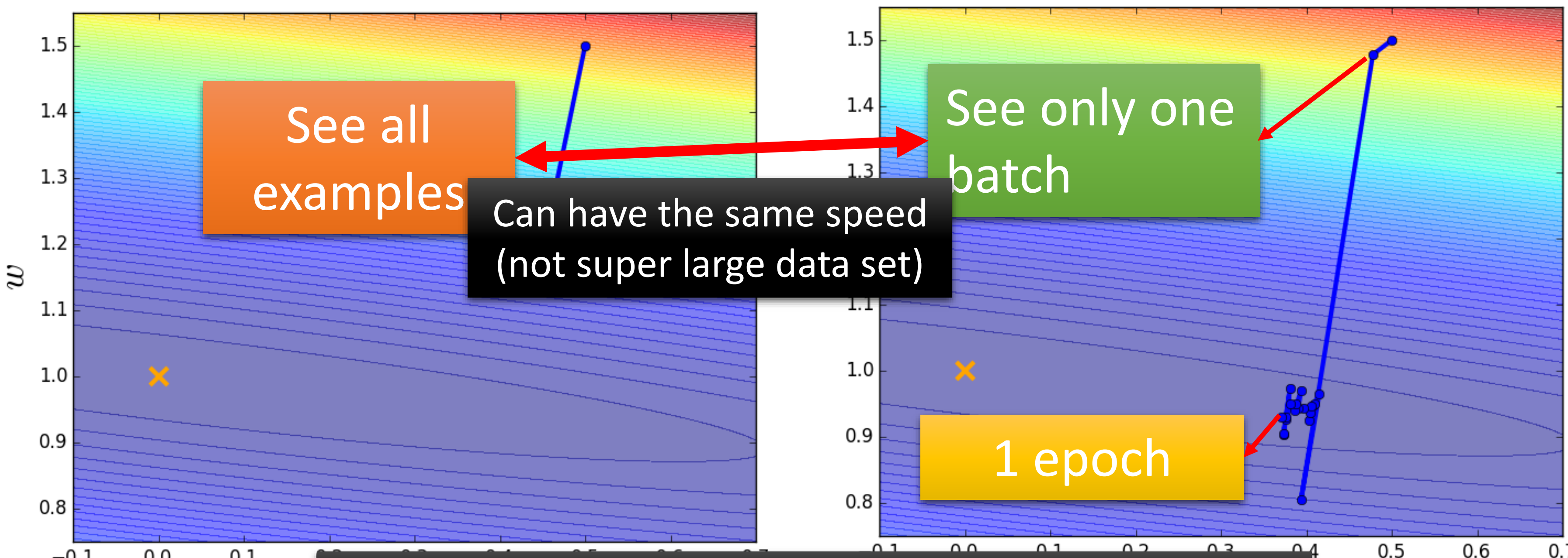
Not always true with parallel computing.

Original Gradient Descent

Update after seeing all examples

With Mini-batch

If there are 20 batches, update 20 times in one epoch.

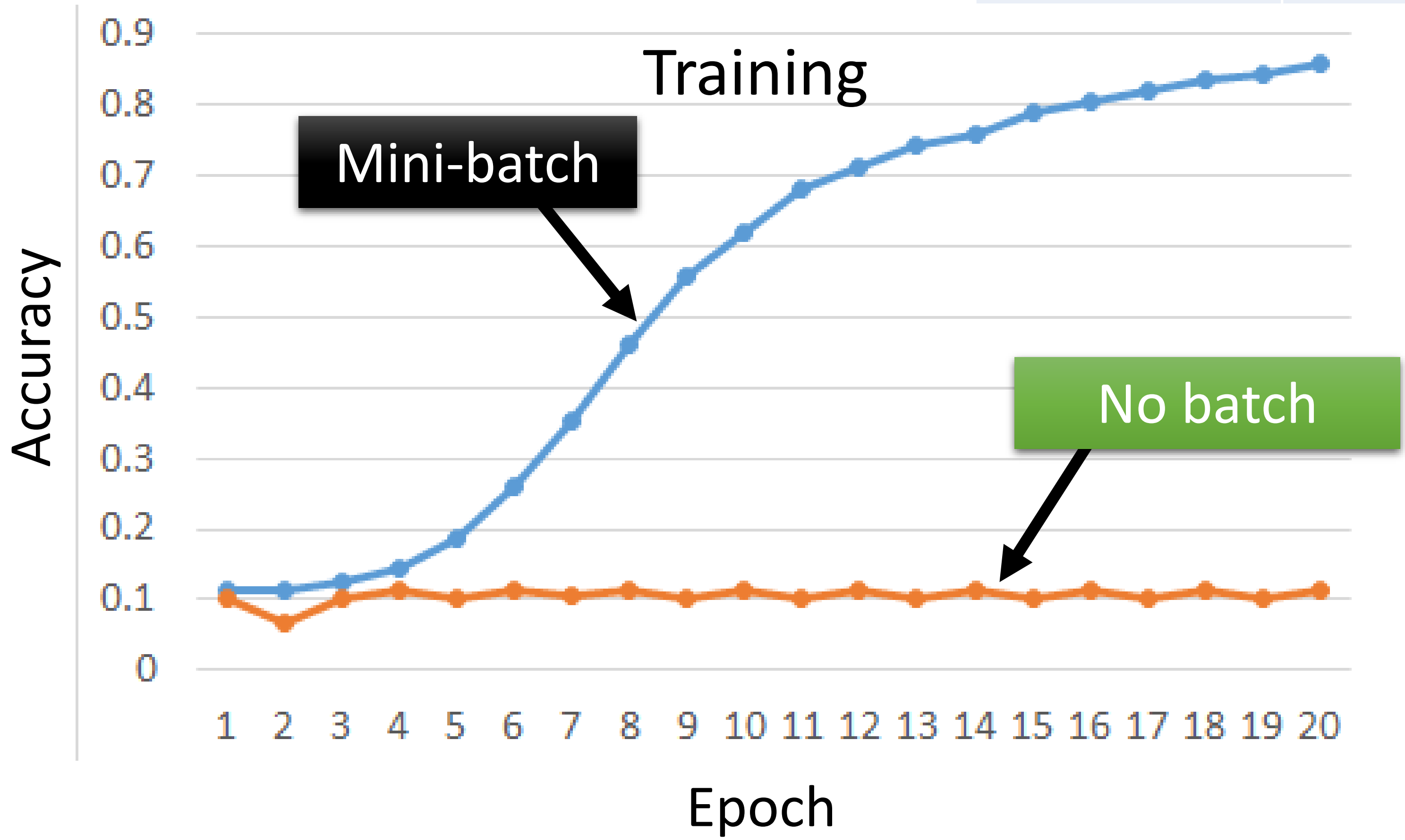


Mini-batch has better performance!

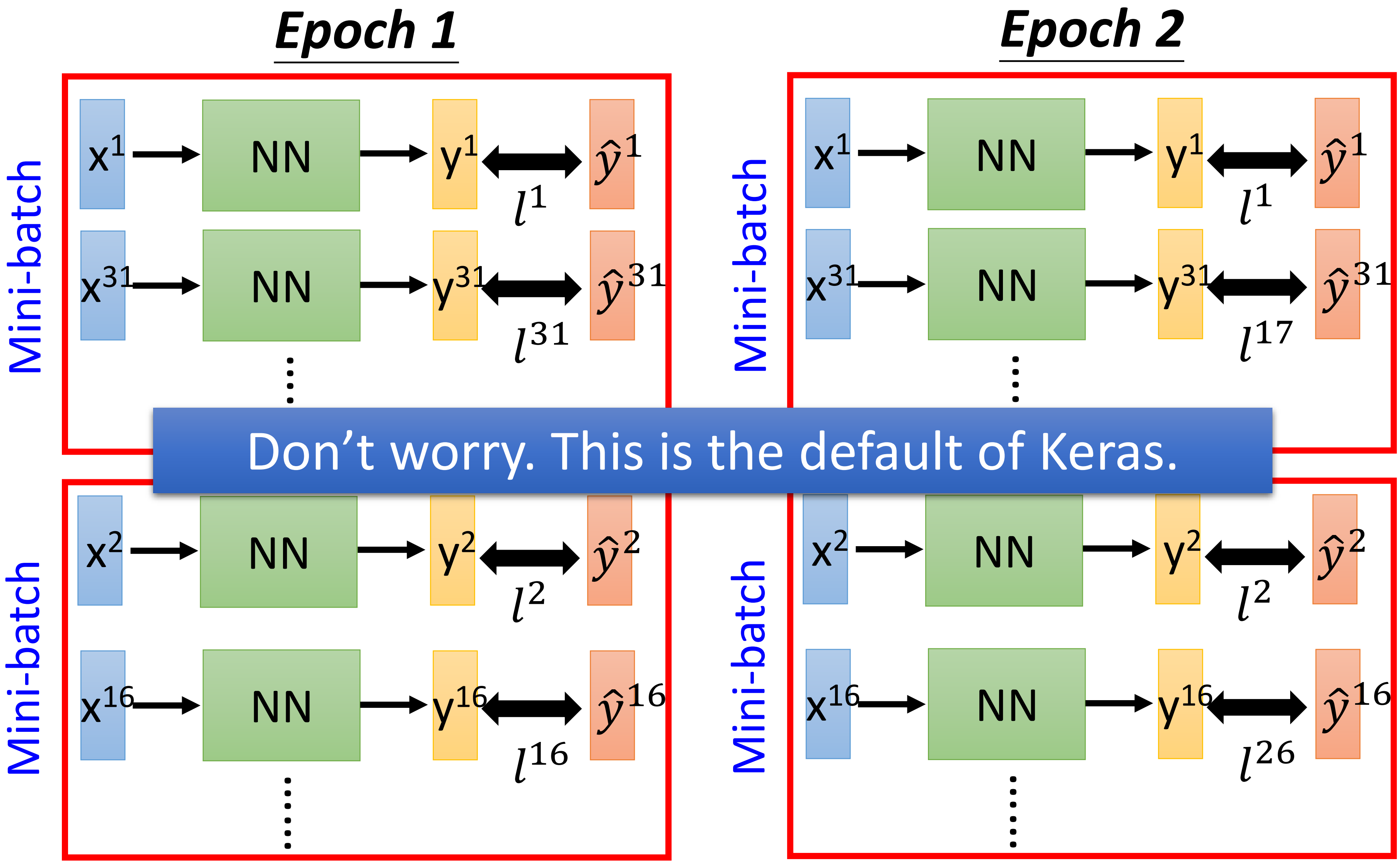
Mini-batch is Better!

Testing:

	Accuracy
Mini-batch	0.84
No batch	0.12

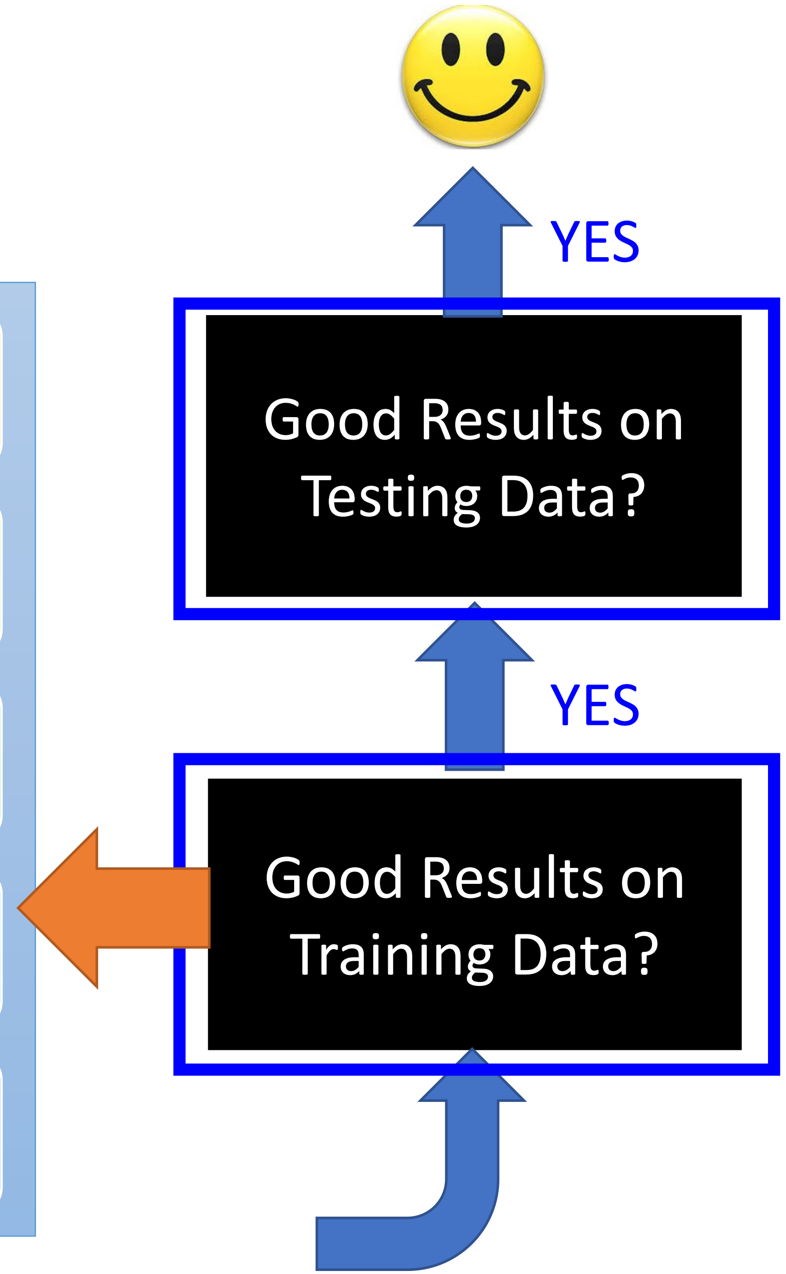


Shuffle the training examples for each epoch

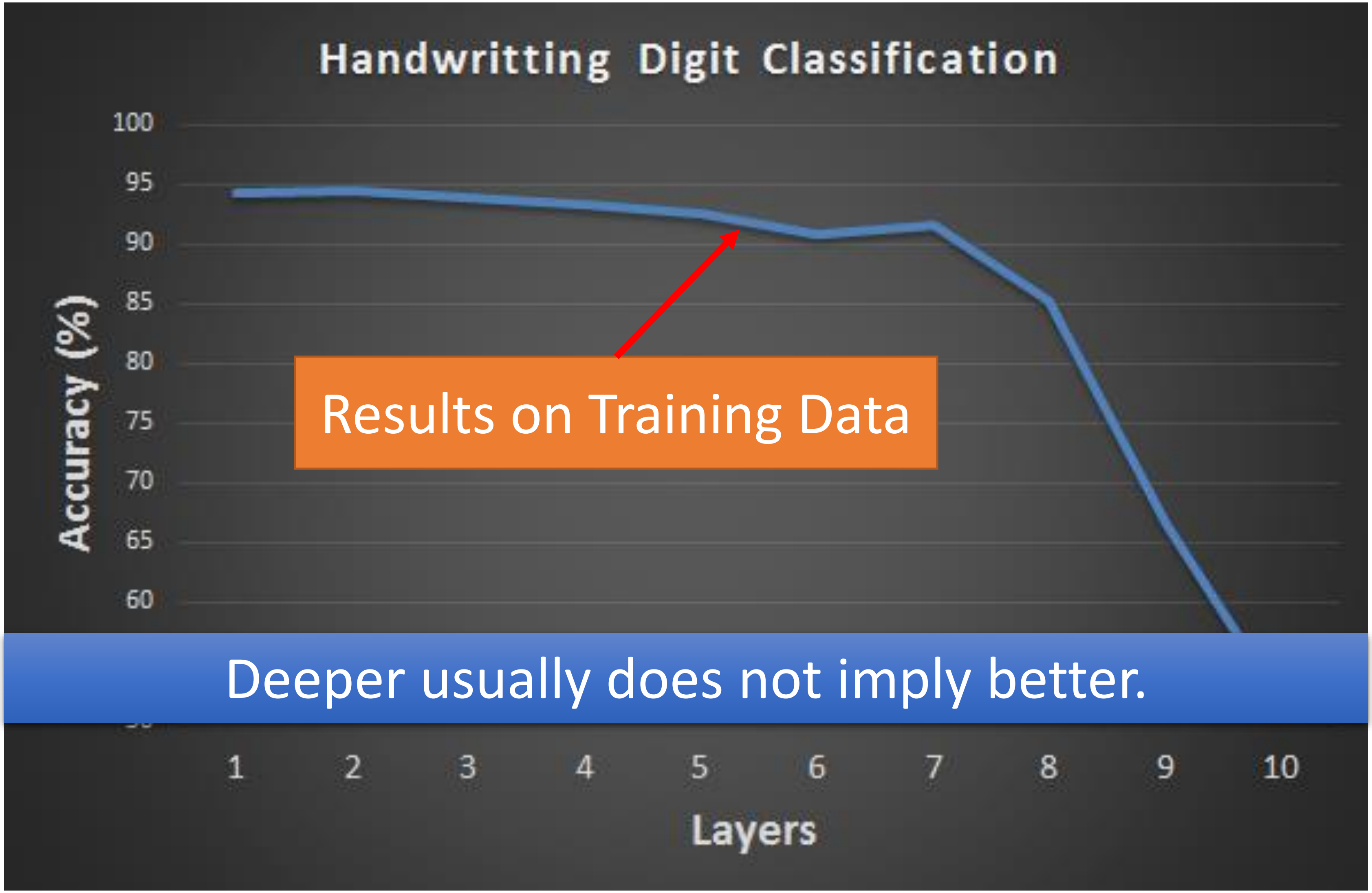


Recipe of Deep Learning

- Choosing proper loss
- Mini-batch
- New activation function
- Adaptive Learning Rate
- Momentum



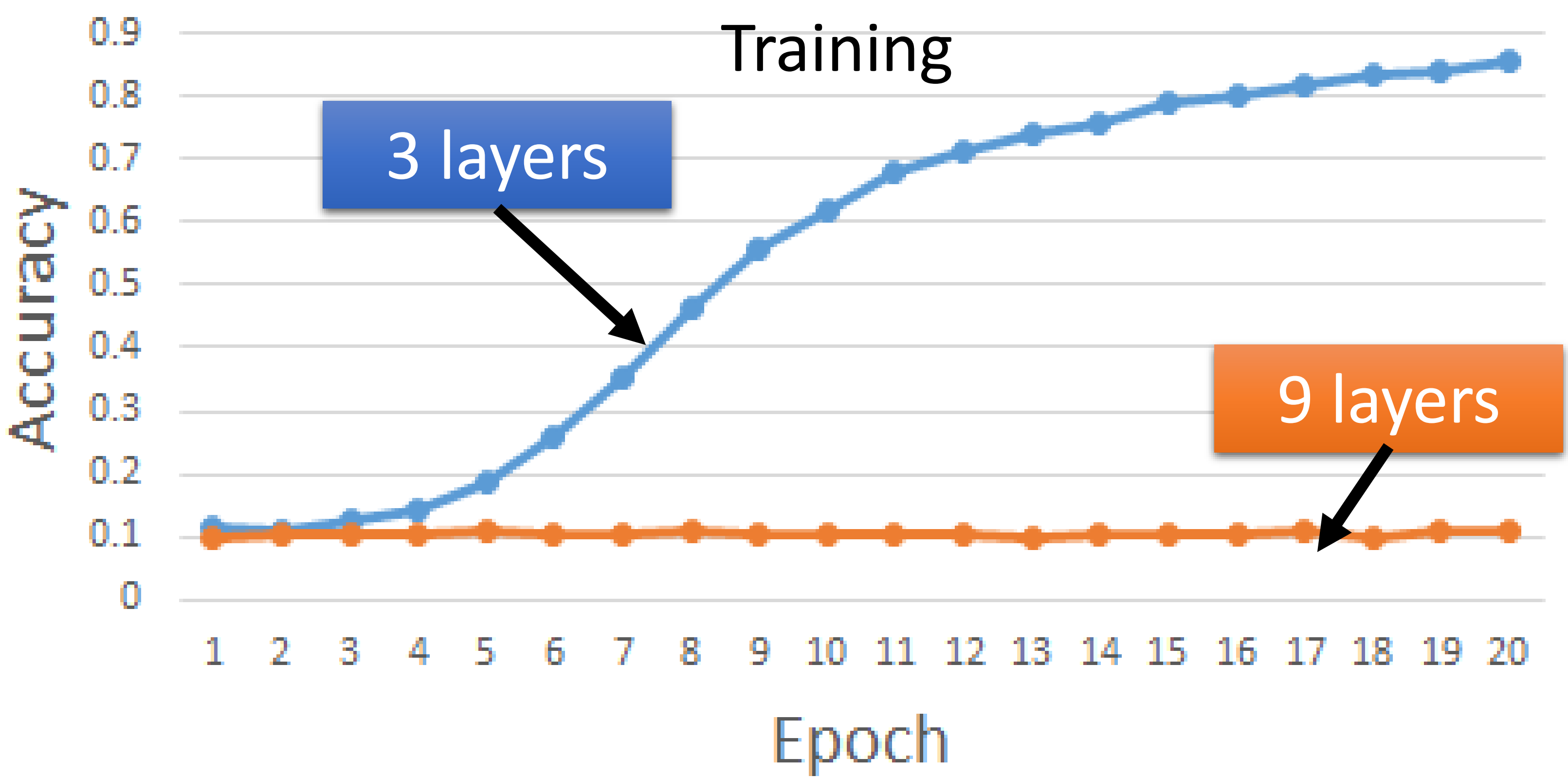
Hard to get the power of Deep …



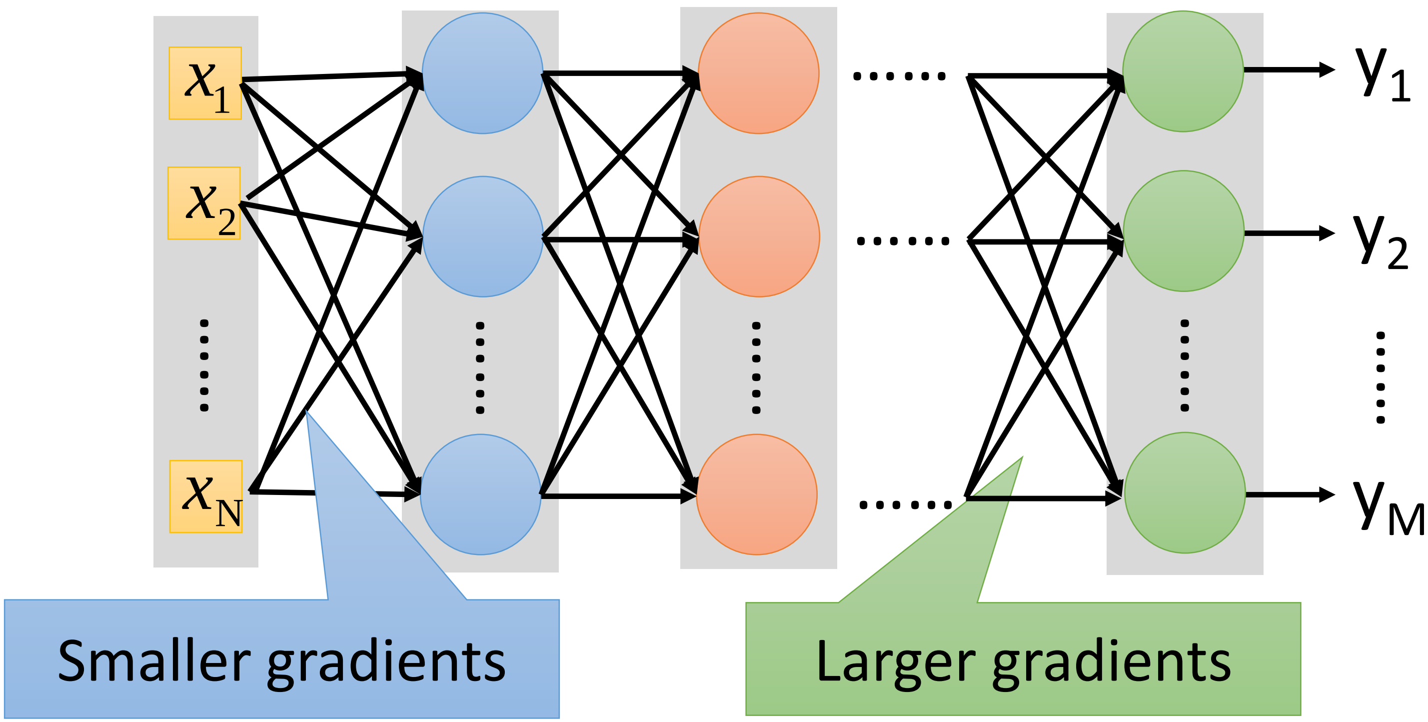
Let’s try it

Testing:

	Accuracy
3 layers	0.84
9 layers	0.11



Vanishing Gradient Problem



Learn very slow

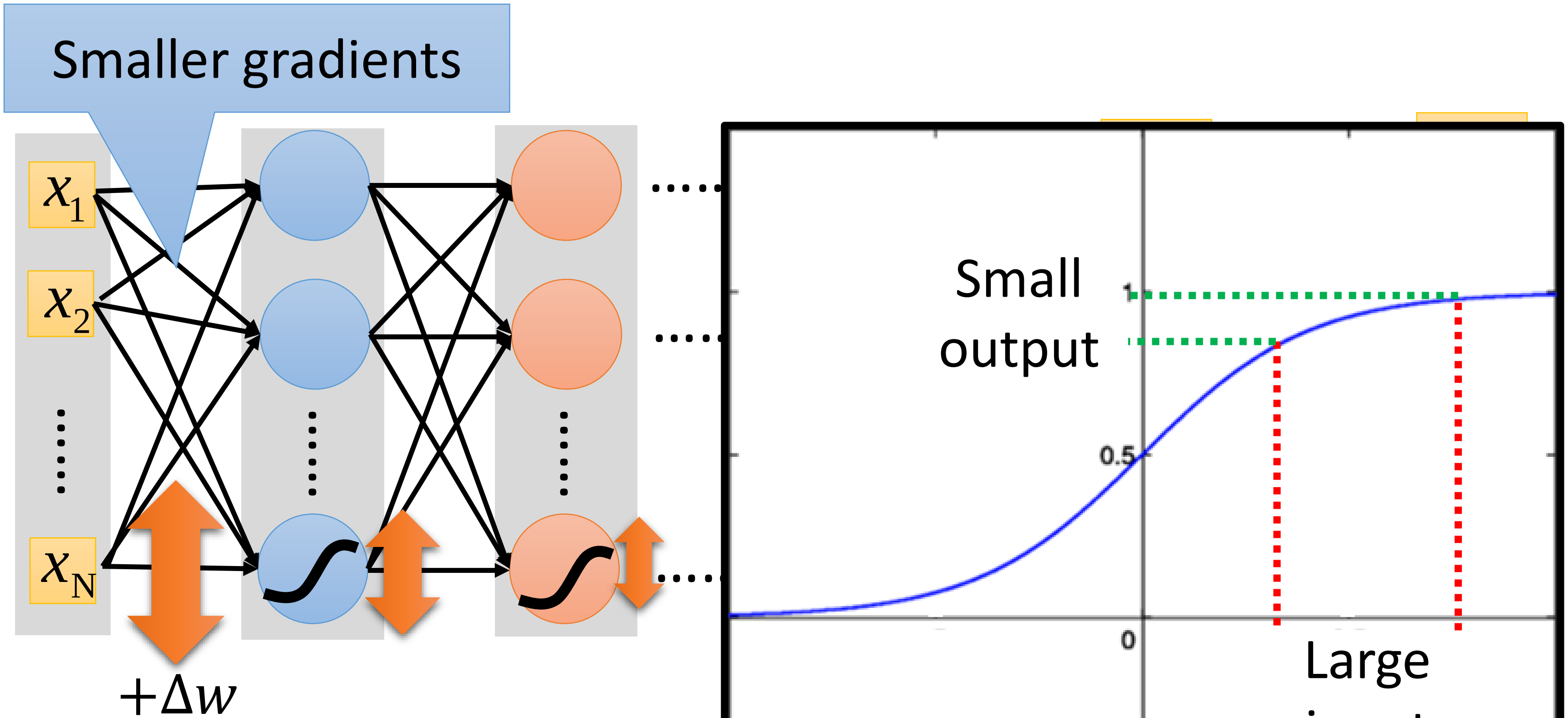
Almost random

Learn very fast

Already converge

based on random!?

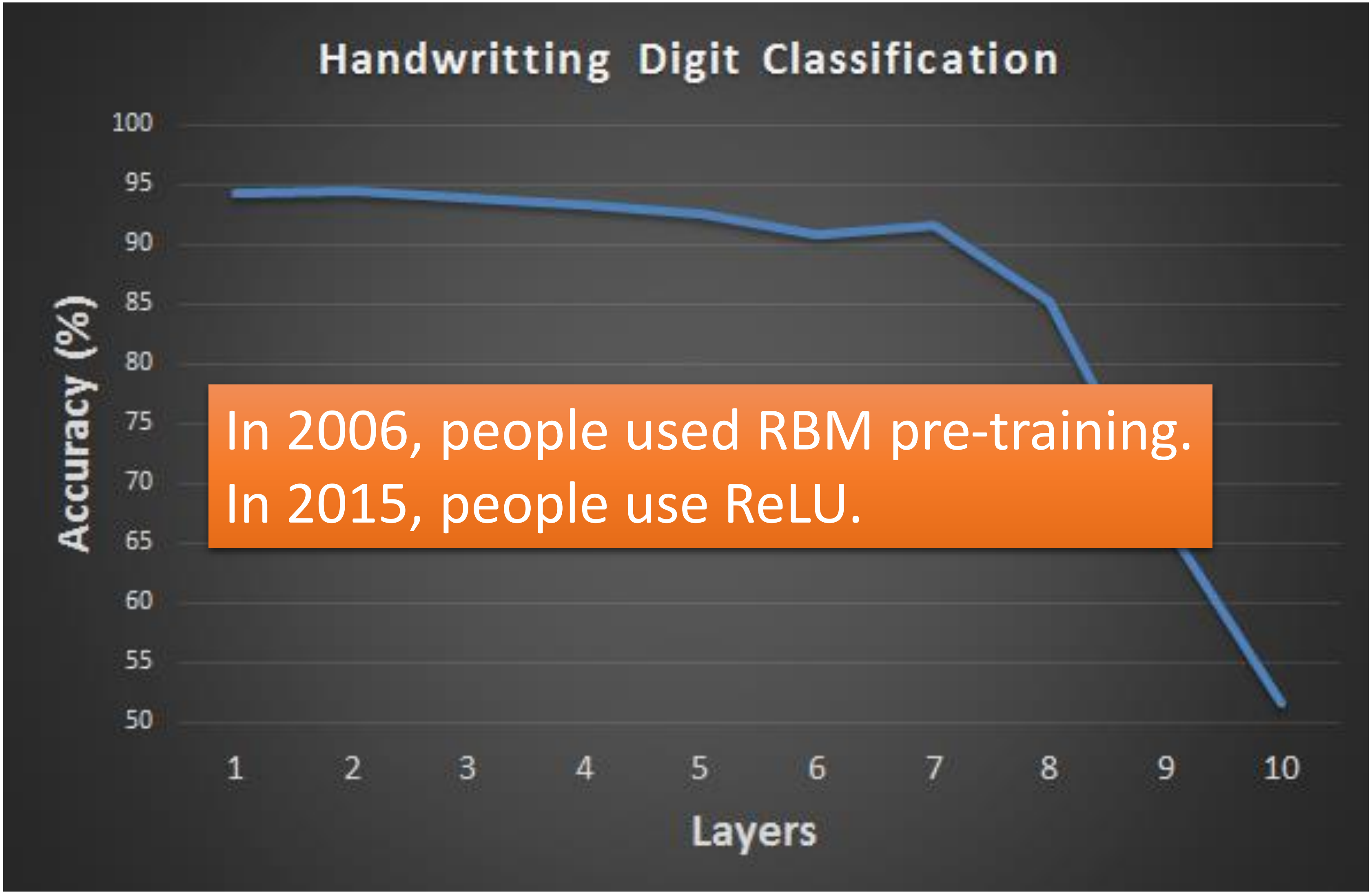
Vanishing Gradient Problem



Intuitive way to compute the derivatives …

$$\frac{\partial l}{\partial w} =? \ \frac{\Delta l}{\Delta w}$$

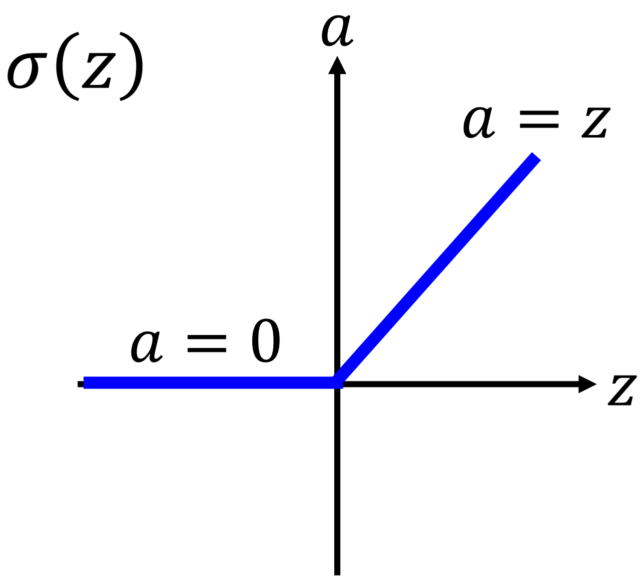
Hard to get the power of Deep …



In 2006, people used RBM pre-training.
In 2015, people use ReLU.

ReLU

- Rectified Linear Unit (ReLU)

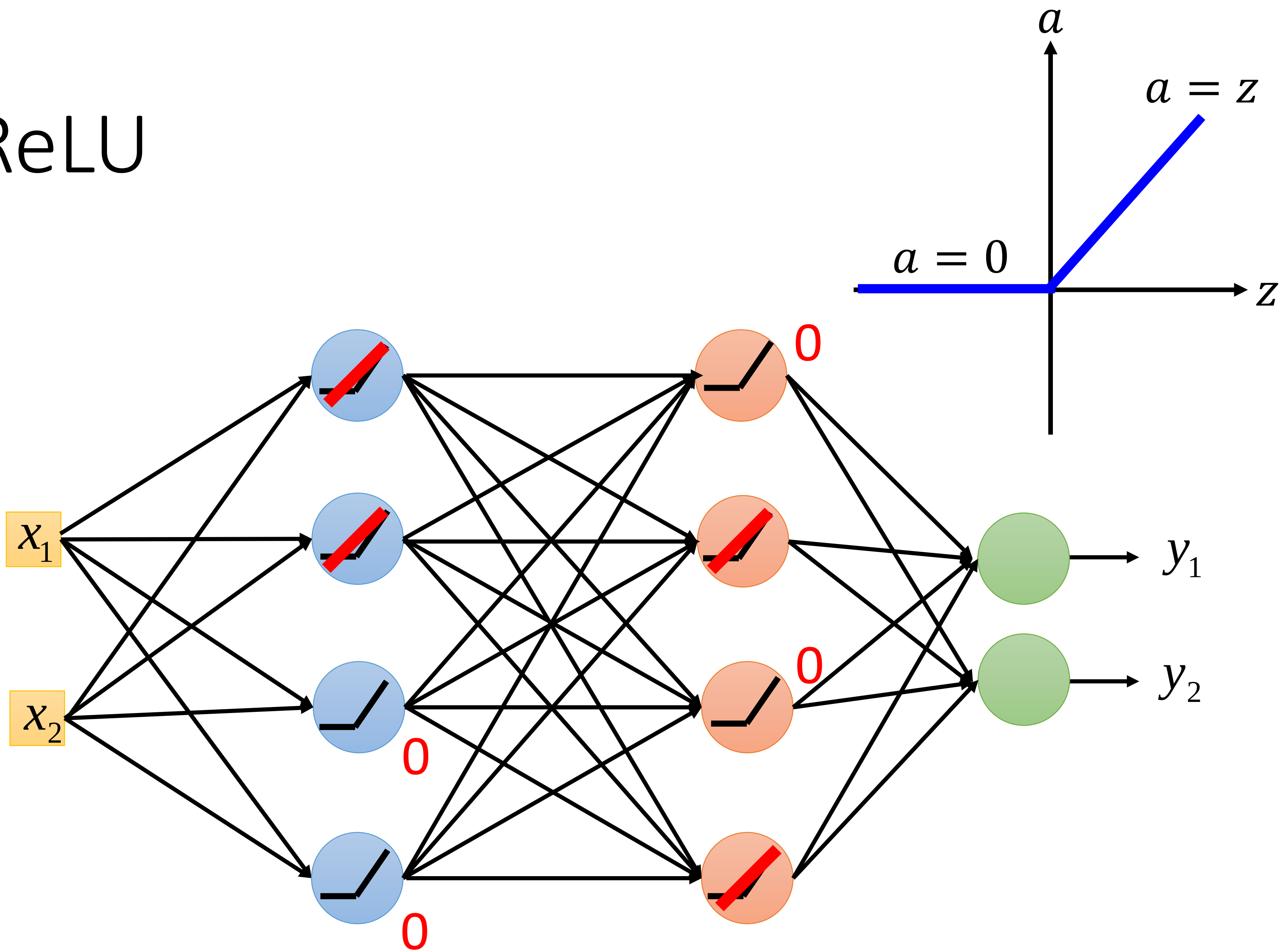


[Xavier Glorot, AISTATS'11]
[Andrew L. Maas, ICML'13]
[Kaiming He, arXiv'15]

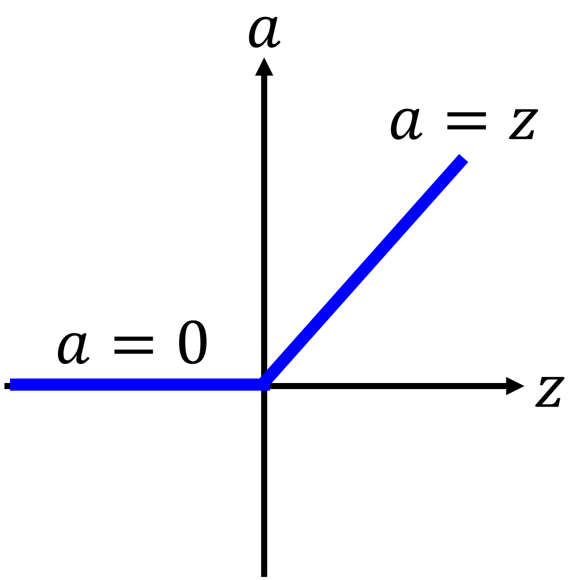
Reason:

1. Fast to compute
2. Biological reason
3. Infinite sigmoid with different biases
4. $\boxed{\text{Vanishing gradient problem}}$

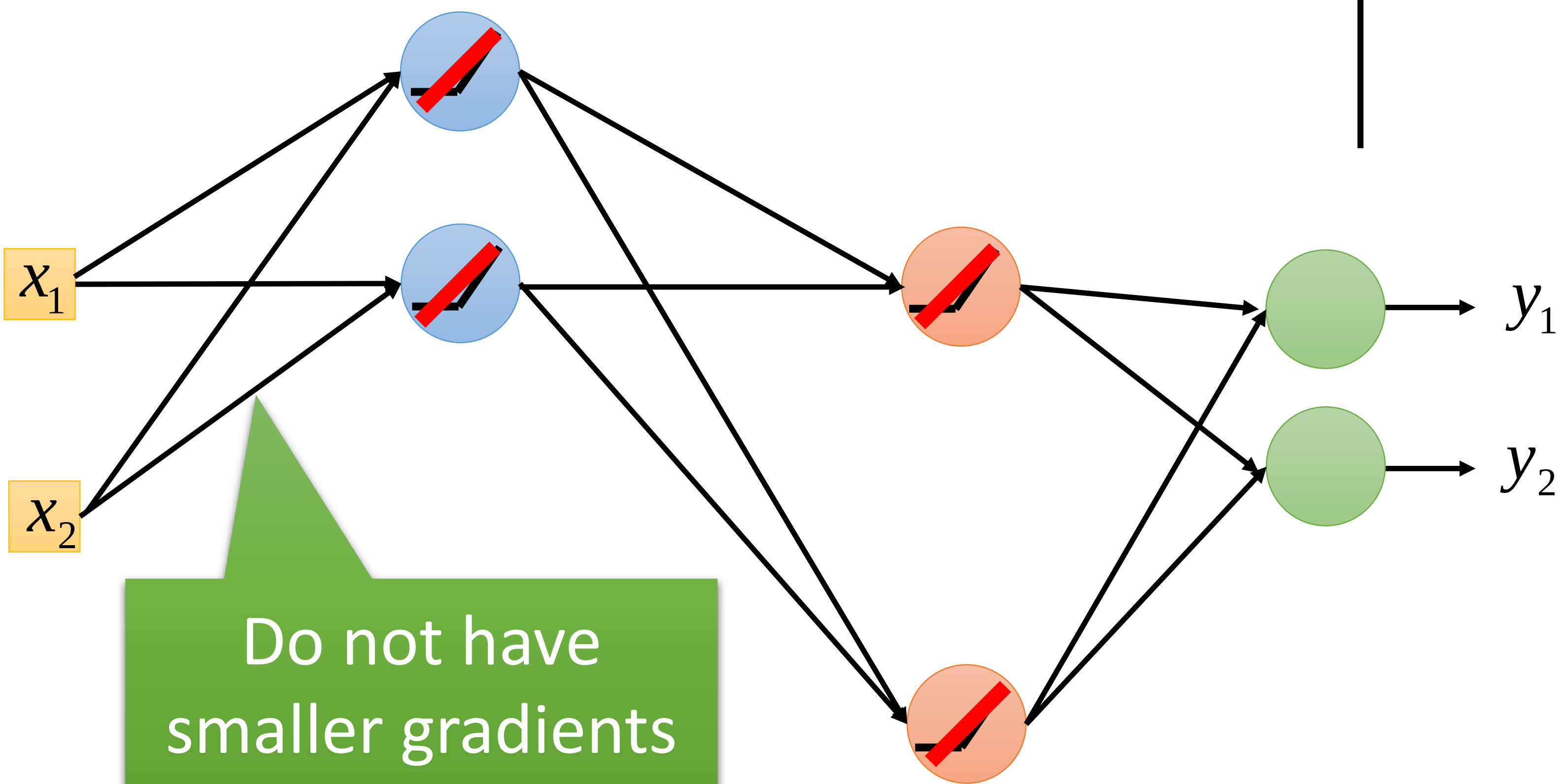
ReLU



ReLU



A Thinner linear network



Do not have smaller gradients

Let's try it

```
model.add( Activation('sigmoid') )
```

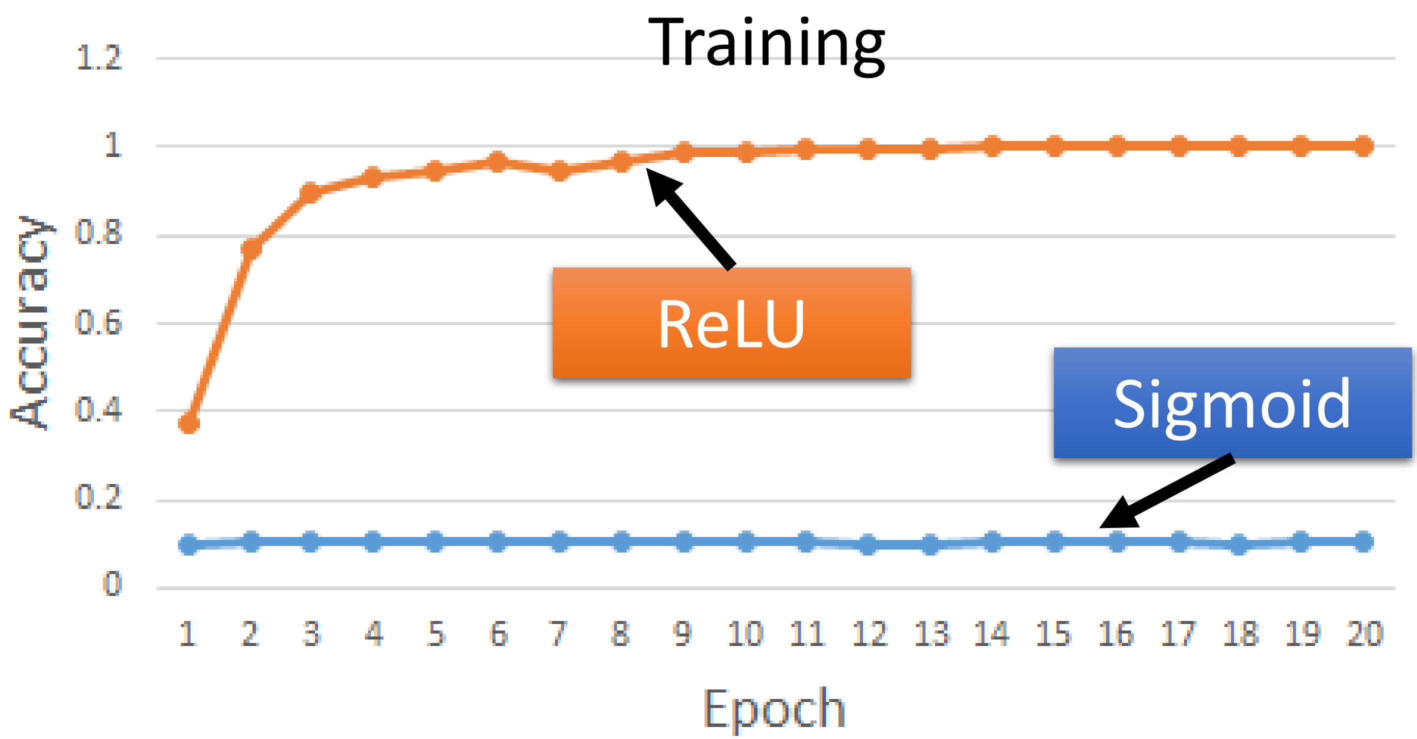
```
model.add( Activation('relu') )
```

Let’s try it

- 9 layers

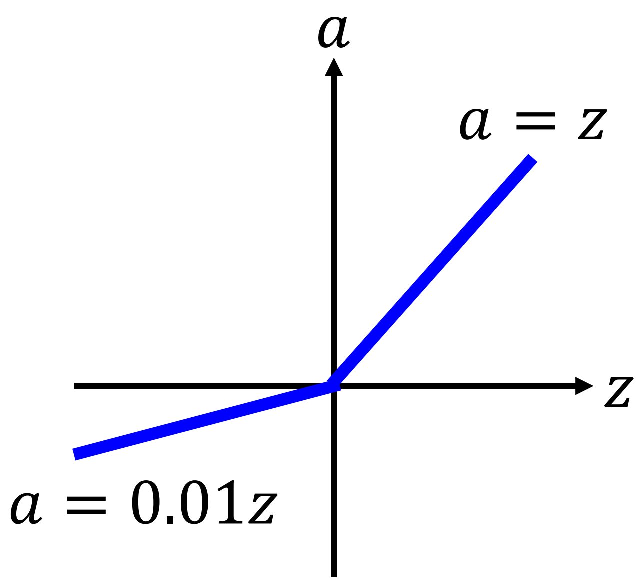
Testing:

9 layers	Accuracy
Sigmoid	0.11
ReLU	0.96

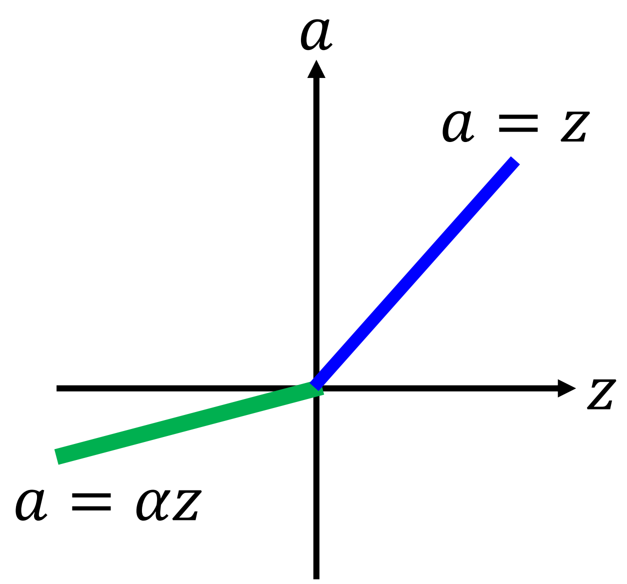


ReLU - variant

Leaky ReLU



Parametric ReLU

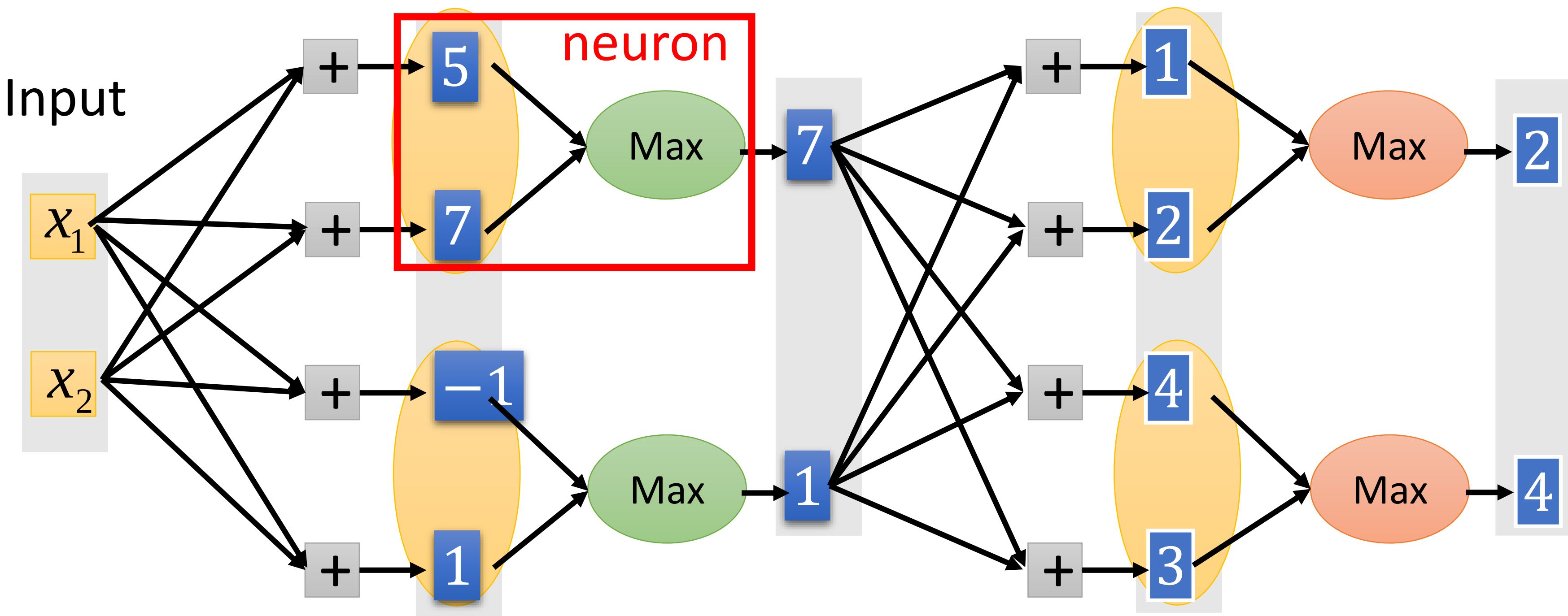


α also learned by gradient descent

Maxout

ReLU is a special cases of Maxout

- Learnable activation function [Ian J. Goodfellow, ICML'13]



You can have more than 2 elements in a group.

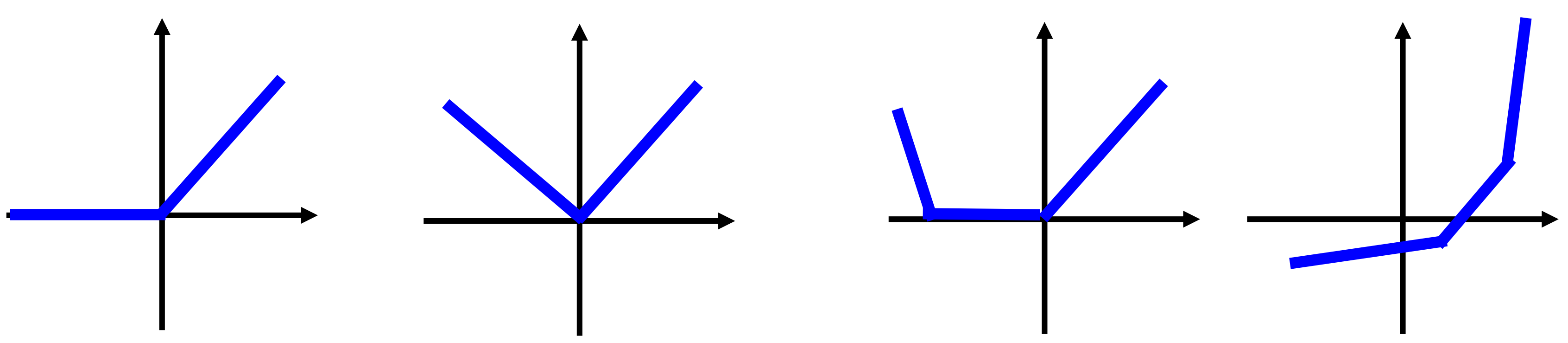
Maxout

ReLU is a special cases of Maxout

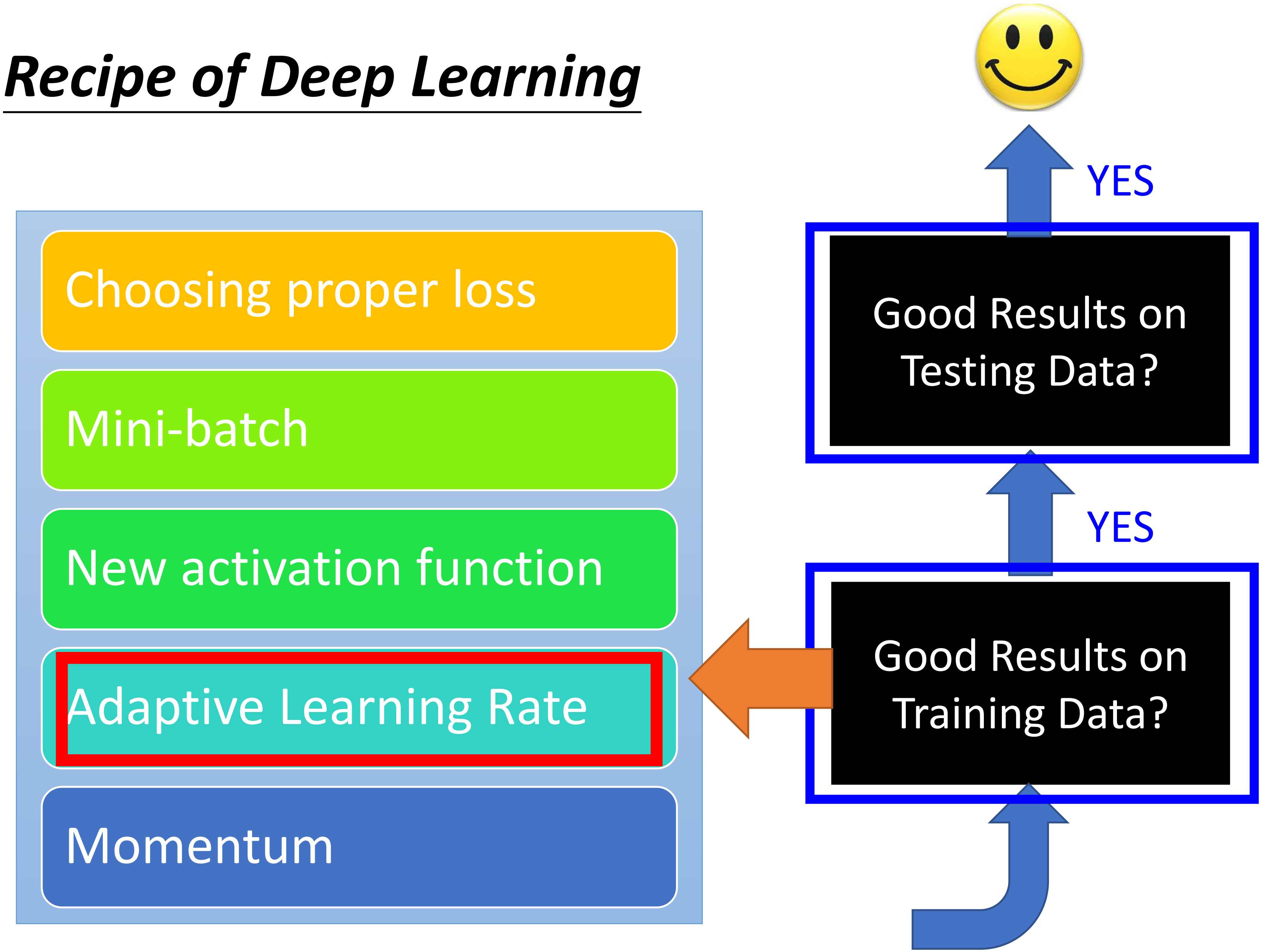
- Learnable activation function [Ian J. Goodfellow, ICML'13]
  - Activation function in maxout network can be any piecewise linear convex function
  - How many pieces depending on how many elements in a group

2 elements in a group

3 elements in a group

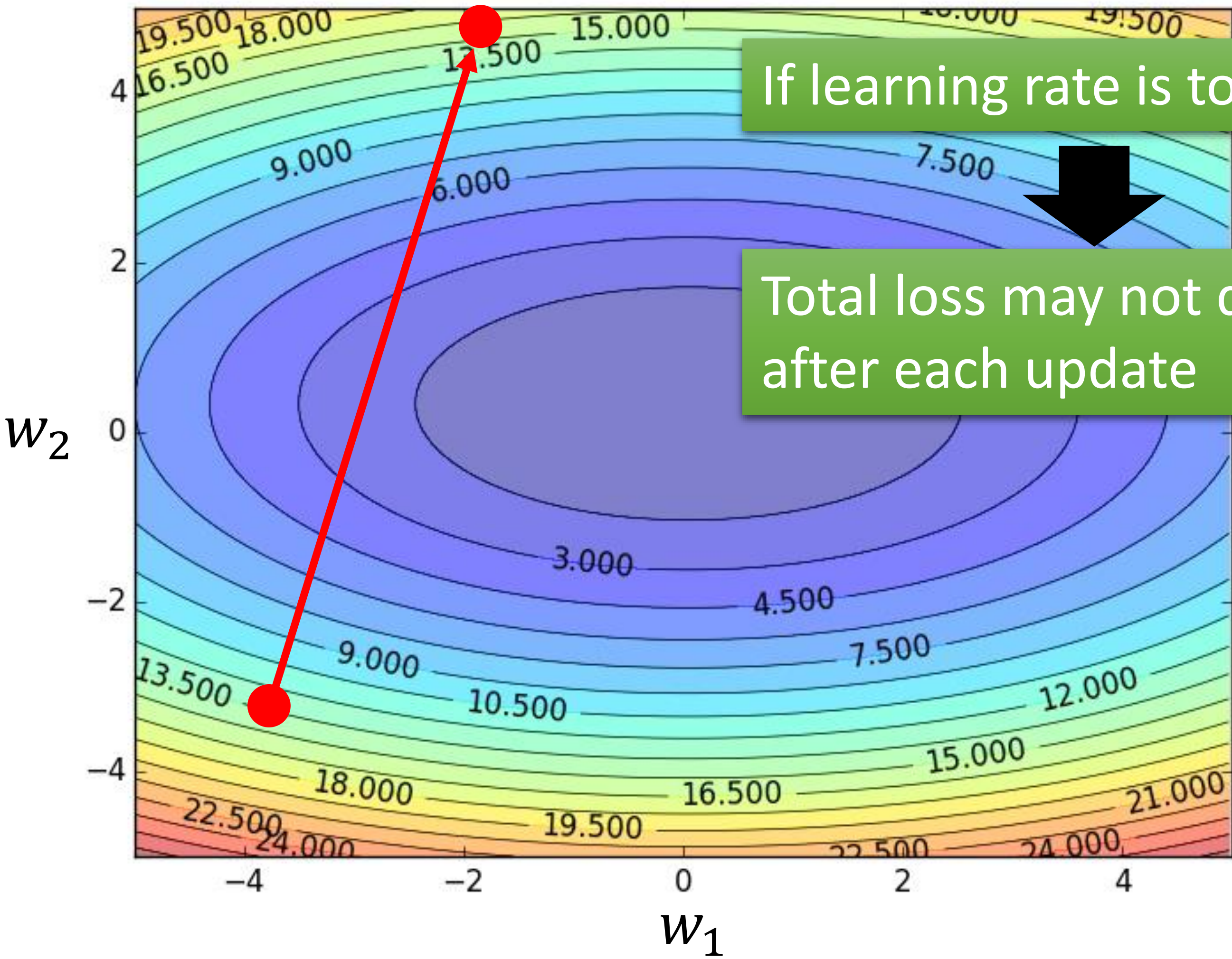


Recipe of Deep Learning



Learning Rates

Set the learning rate η carefully

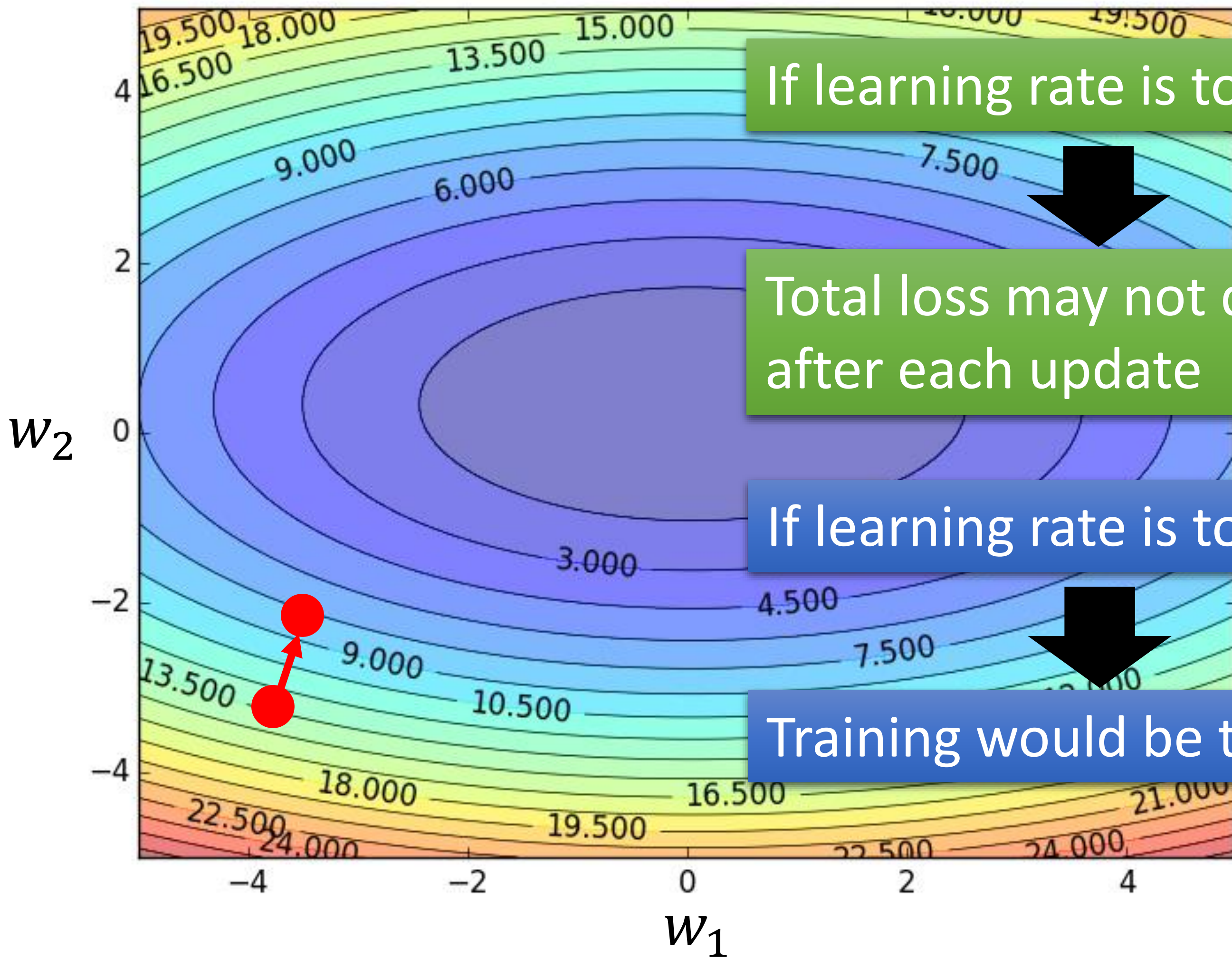


If learning rate is too large

Total loss may not decrease after each update

Learning Rates

Set the learning rate η carefully



If learning rate is too large

Total loss may not decrease after each update

If learning rate is too small

Training would be too slow

Learning Rates

- Popular & Simple Idea: Reduce the learning rate by some factor every few epochs.
  - At the beginning, we are far from the destination, so we use larger learning rate
  - After several epochs, we are close to the destination, so we reduce the learning rate
  - E.g. 1/t decay: $\eta^t = \eta / \sqrt{t + 1}$
- Learning rate cannot be one-size-fits-all
  - Giving different parameters different learning rates

Adagrad

Original: $w \leftarrow w - \eta \partial L \,/\, \partial w$

Adagrad: $\mathrm{w} \leftarrow w - \boxed{\eta_w} \partial L \,/\, \partial w$

Parameter dependent learning rate

$$\eta_w = \frac{\eta}{\sqrt{\boxed{\sum_{i=0}^{t} (g^i)^2}}}$$

constant

g^i is $\partial L \,/\, \partial w$ obtained at the i-th update

Summation of the square of the previous derivatives

Adagrad

$$\eta_w = \boxed{\frac{\eta}{\sqrt{\sum_{i=0}^{t}(g^i)^2}}}$$

w_1	g^0
	0.1

w_2	g^0
	20.0

Learning rate:

$$\frac{\eta}{\sqrt{0.1^2}} = \frac{\eta}{0.1}$$

$$\frac{\eta}{\sqrt{0.1^2 + 0.2^2}} = \frac{\eta}{0.22}$$

Learning rate:

$$\frac{\eta}{\sqrt{20^2}} = \frac{\eta}{20}$$

$$\frac{\eta}{\sqrt{20^2 + 10^2}} = \frac{\eta}{22}$$

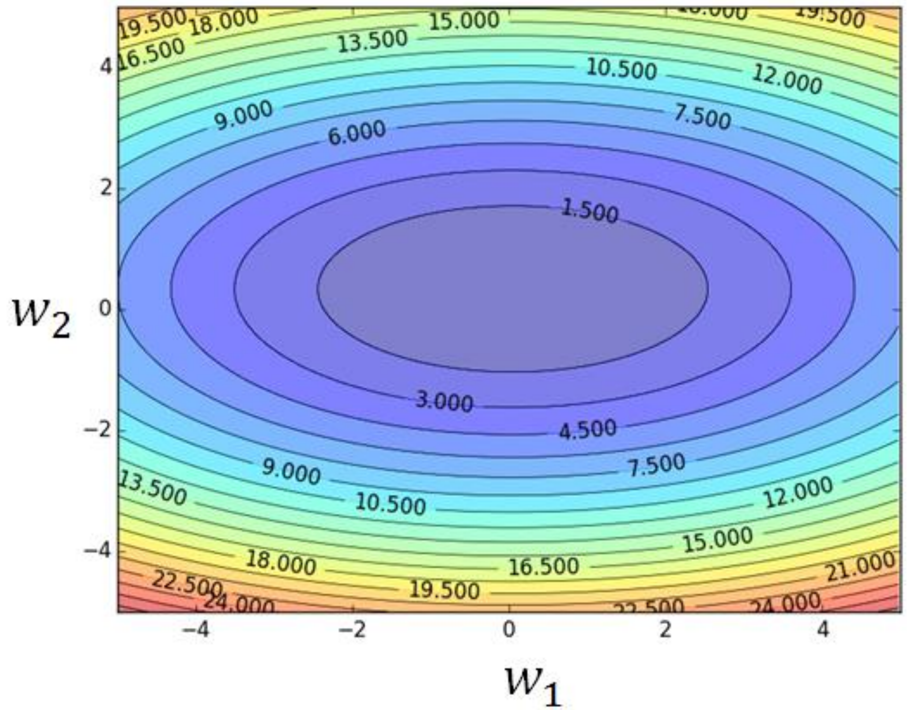
Observation: 1. Learning rate is smaller and smaller for all parameters

2. Smaller derivatives, larger learning rate, and vice versa

Why?

Larger derivatives

Smaller Learning Rate



Smaller Derivatives

Larger Learning Rate

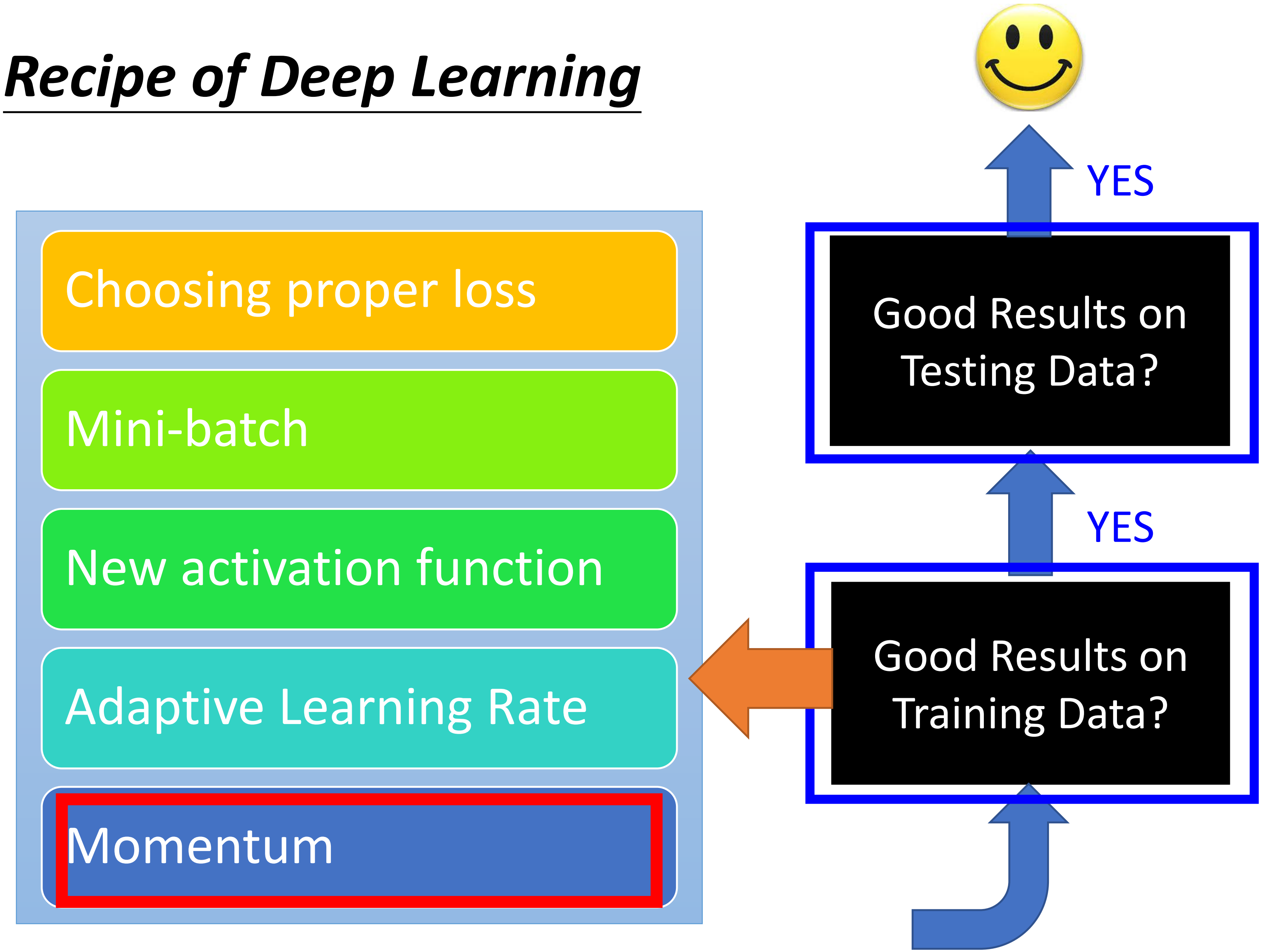
2. Smaller derivatives, larger learning rate, and vice versa

Why?

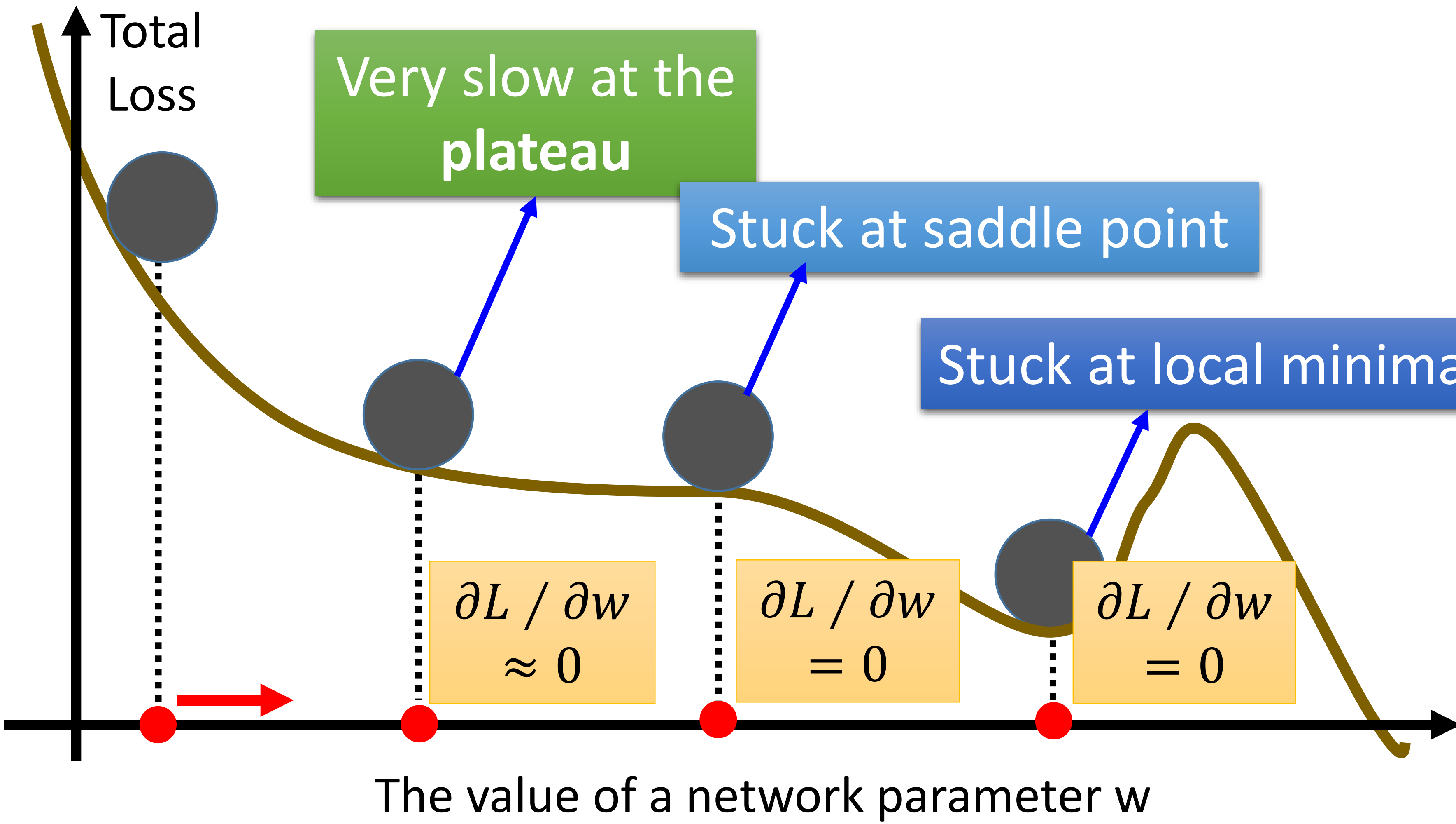
Not the whole story ……

- Adagrad [John Duchi, JMLR'11]
- RMSprop
  - https://www.youtube.com/watch?v=O3sxAc4hxZU
- Adadelta [Matthew D. Zeiler, arXiv'12]
- "No more pesky learning rates" [Tom Schaul, arXiv'12]
- AdaSecant [Caglar Gulcehre, arXiv'14]
- Adam [Diederik P. Kingma, ICLR'15]
- Nadam
  - http://cs229.stanford.edu/proj2015/054_report.pdf

Recipe of Deep Learning

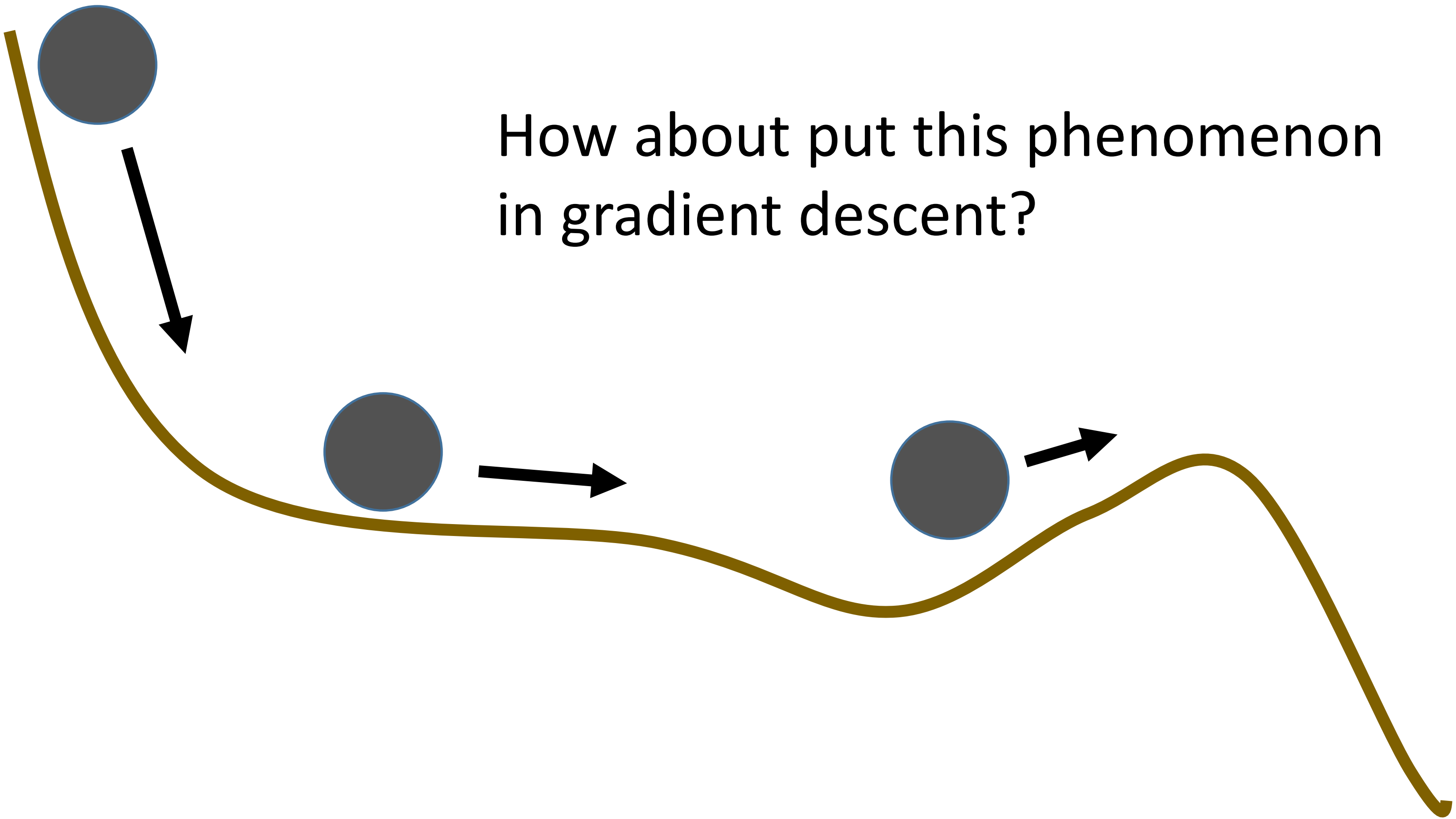


Hard to find optimal network parameters



In physical world ……

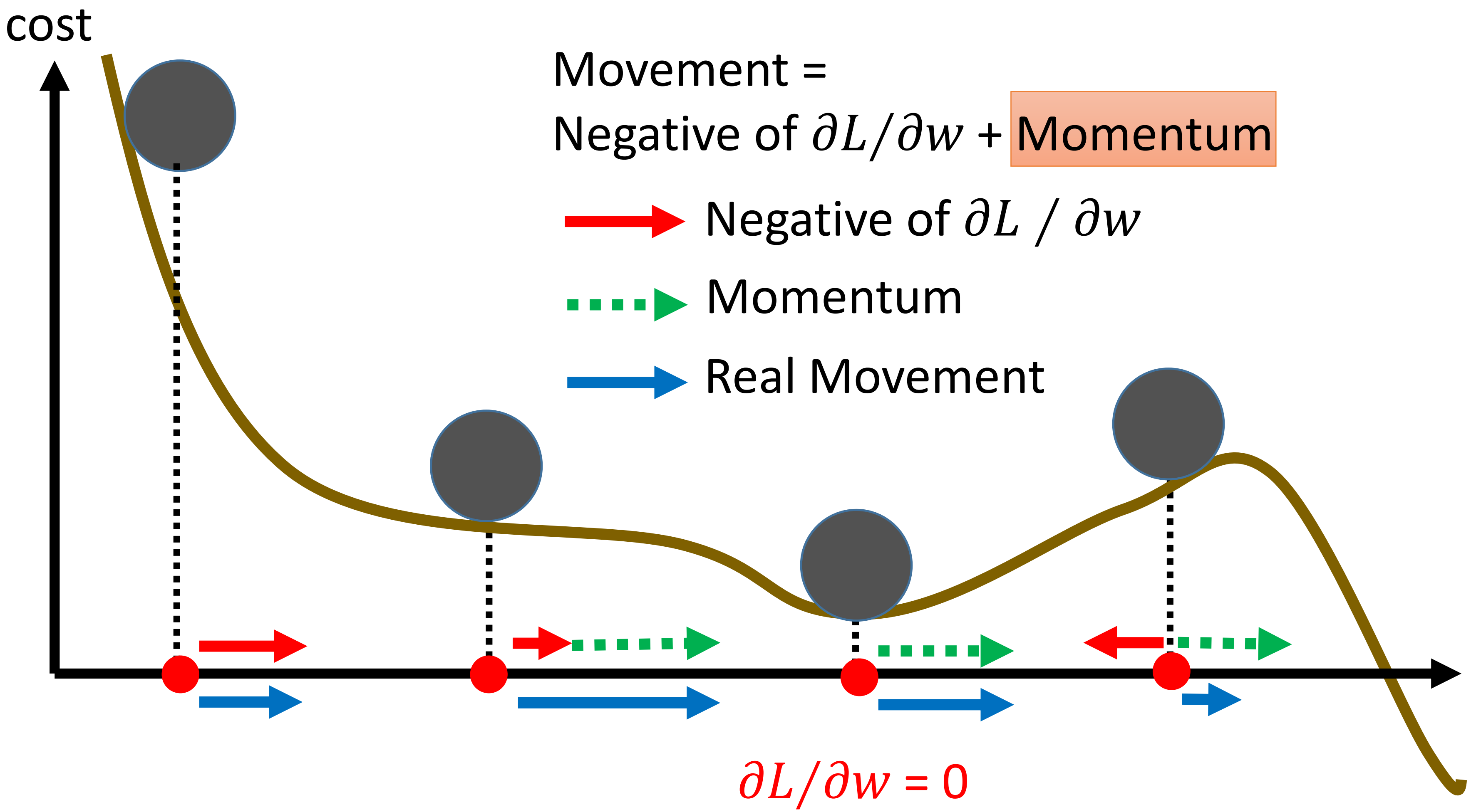
- Momentum



How about put this phenomenon in gradient descent?

Momentum

Still not guarantee reaching global minima, but give some hope ……



Adam

RMSProp (Advanced Adagrad) + Momentum

```
model.compile(loss='categorical_crossentropy',
              optimizer=SGD(lr=0.1),
              metrics=['accuracy'])
```

```
model.compile(loss='categorical_crossentropy',
              optimizer=Adam(),
              metrics=['accuracy'])
```

Algorithm 1: *Adam*, our proposed algorithm for stochastic optimization. See section 2 for details, and for a slightly more efficient (but less clear) order of computation. g_t^2 indicates the elementwise square $g_t \odot g_t$. Good default settings for the tested machine learning problems are $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$. All operations on vectors are element-wise. With β_1^t and β_2^t we denote β_1 and β_2 to the power t.

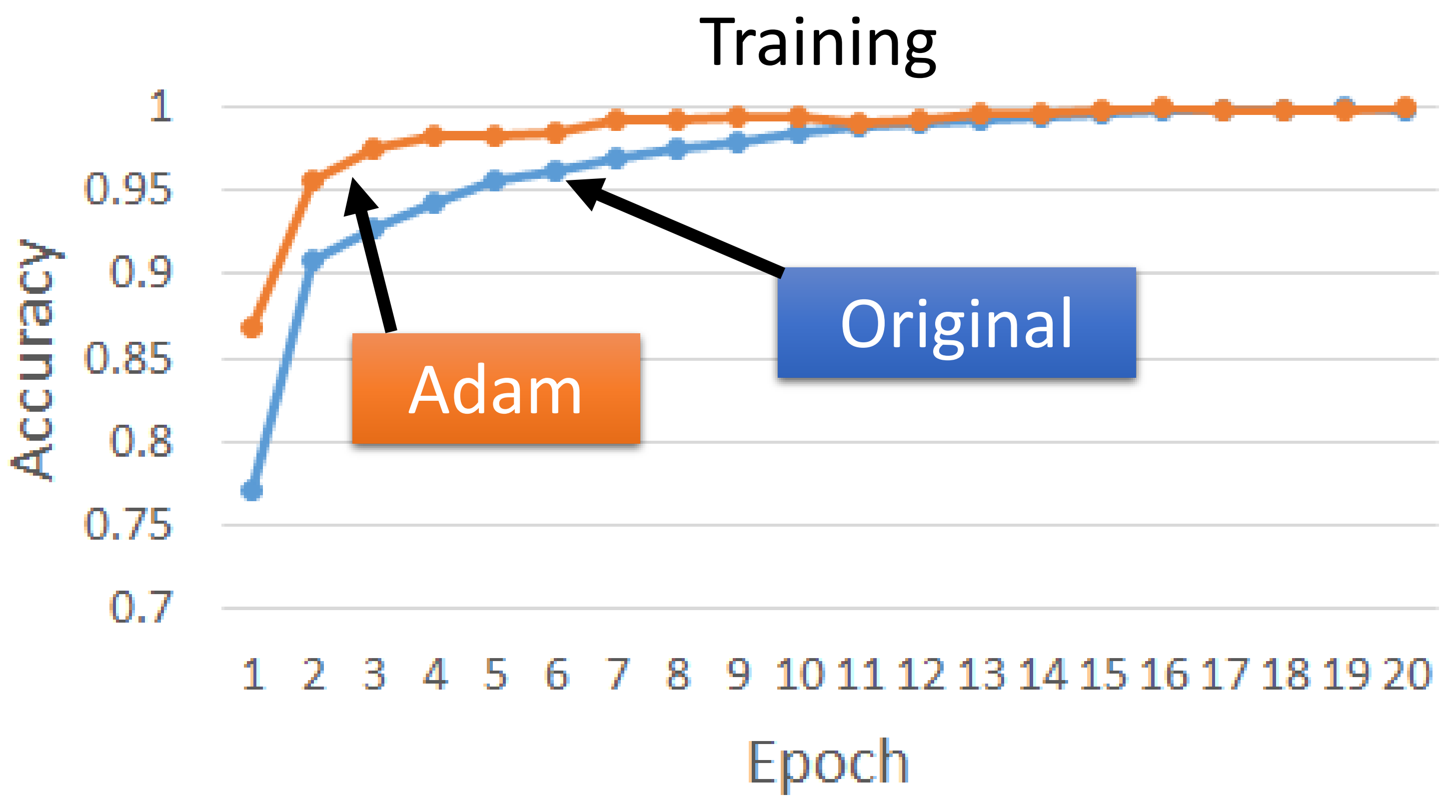
Require: α: Stepsize
Require: $\beta_1, \beta_2 \in [0, 1)$: Exponential decay rates for the moment estimates
Require: $f(\theta)$: Stochastic objective function with parameters θ
Require: θ_0: Initial parameter vector
  $m_0 \leftarrow 0$ (Initialize 1st moment vector)
  $v_0 \leftarrow 0$ (Initialize 2nd moment vector)
  $t \leftarrow 0$ (Initialize timestep)
  while θ_t not converged **do**
    $t \leftarrow t + 1$
    $g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ (Get gradients w.r.t. stochastic objective at timestep t)
    $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$ (Update biased first moment estimate)
    $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$ (Update biased second raw moment estimate)
    $\widehat{m}_t \leftarrow m_t / (1 - \beta_1^t)$ (Compute bias-corrected first moment estimate)
    $\widehat{v}_t \leftarrow v_t / (1 - \beta_2^t)$ (Compute bias-corrected second raw moment estimate)
    $\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t / (\sqrt{\widehat{v}_t} + \epsilon)$ (Update parameters)
  end while
  return θ_t (Resulting parameters)

Let's try it

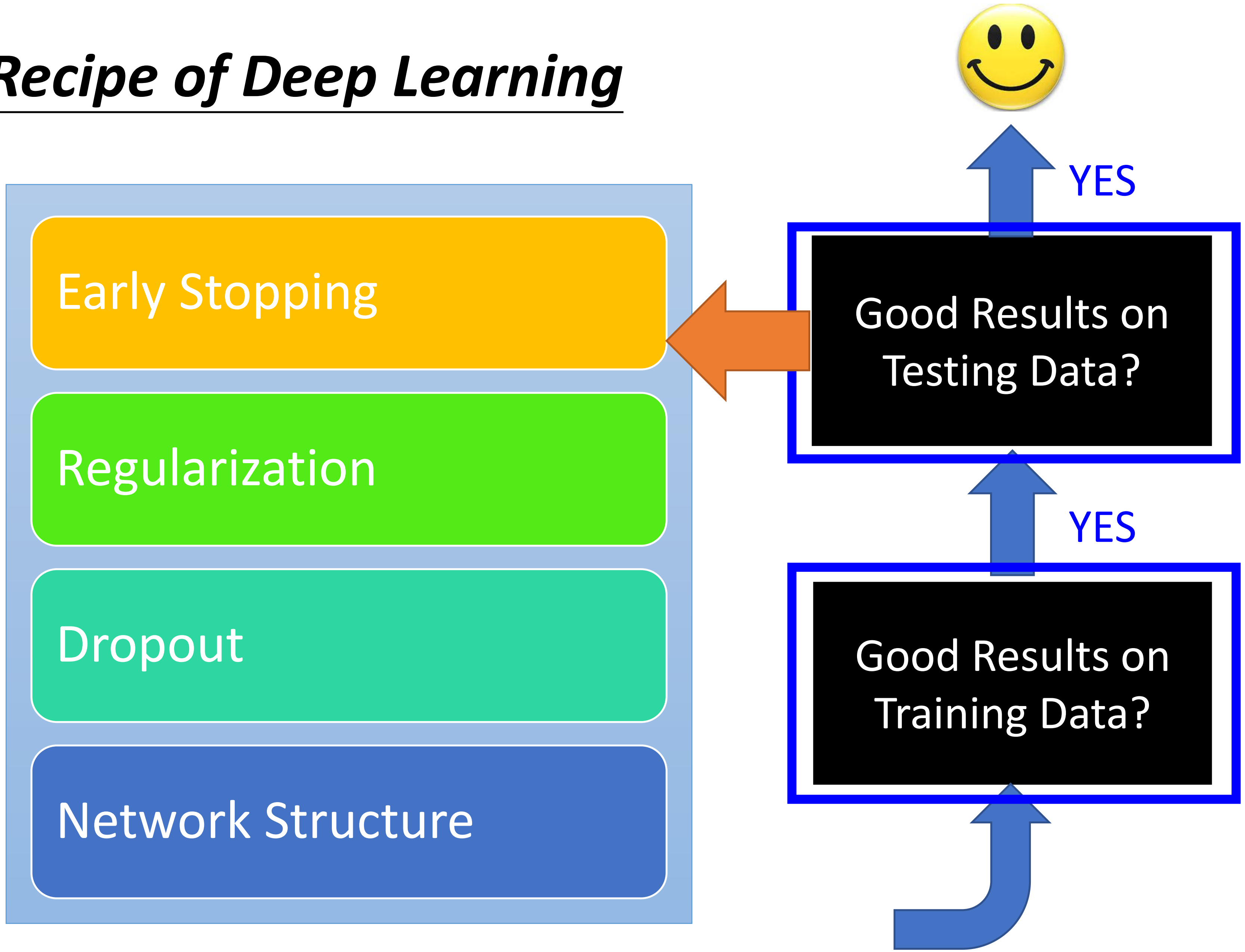
Testing:

	Accuracy
Original	0.96
Adam	0.97

- ReLU, 3 layer



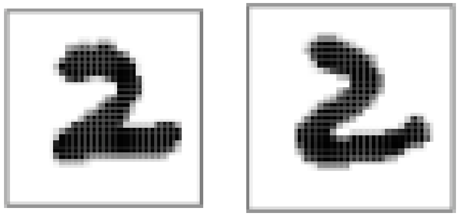
Recipe of Deep Learning



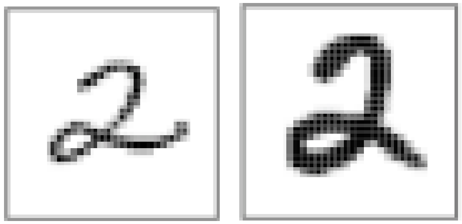
Why Overfitting?

- Training data and testing data can be different.

Training Data:



Testing Data:



Learning target is defined by the training data.

The parameters achieving the learning target do not necessary have good results on the testing data.

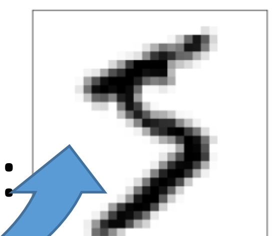
Panacea for Overfitting

- Have more training data
- ***Create*** more training data (?)

Handwriting recognition:

Original Training Data:

Created Training Data:



Shift 15 °

Why Overfitting?

- For experiments, we added some noises to the testing data

```
       -1.36230370e-01,   1.03749340e-01,   1.15432226e-01,
        2.58670464e-01,   1.48774333e+00,   1.92885328e+00,
        1.70038673e+00,   2.46242981e+00,   1.21244572e+00,
       -9.28660713e-01,   3.63209761e-01,  -1.81327713e+00,
       -1.97910760e-01,   4.32874592e-01,  -5.40565788e-01,
        2.95630655e-01,   2.07984424e+00,  -1.84243292e+00,
       -5.11166017e-01,  -5.80935128e-01,   1.06273647e+00,
        1.80551097e-02,   2.27983997e-02,  -1.67979148e+00,
        8.12423001e-01,  -6.25888706e-01,  -1.25027082e+00,
        6.15135458e-01,  -1.21394611e-01,  -1.28089527e+00,
        3.24609806e-01,   6.70569391e-01,   1.49161323e-01,
        8.01573609e-01,   6.43116741e-01,  -9.37629233e-02,
        1.74677366e+00,   6.80996008e-01,  -7.03717611e-01,
        1.02079749e-01,   1.19505614e+00,  -2.77959386e-01,
       -5.21652916e-02,   3.53683601e-01,  -4.08310762e-01,
       -1.81042967e+00,  -9.03308062e-01,   1.05404509e+00,
       -9.80876877e-01,   3.52078891e-01,   6.65981840e-01,
        1.06550150e+00,  -2.28433613e-01,   3.64483904e-01,
       -1.51484666e+00,  -7.52612872e-02,  -2.97058082e-01,
       -7.27414382e-01,  -2.45875340e-01,  -1.27948942e-01,
       -3.69310620e-01,  -2.62300428e+00,   2.11585073e+00,
        6.85561585e-01,  -1.57443985e-01,   1.38128777e+00,
        6.84265587e-02,   3.12536292e-01,   4.54253185e-01,
       -7.88471875e-01,  -6.58403343e-02,  -1.41847985e+00,
       -1.39753340e-01,  -5.55354856e-01,  -5.01917779e-01,
        6.93118522e-01,  -2.45360497e-01,  -1.26943186e+00,
       -2.62323855e-01])

n [3]: x test[0]
```

Why Overfitting?

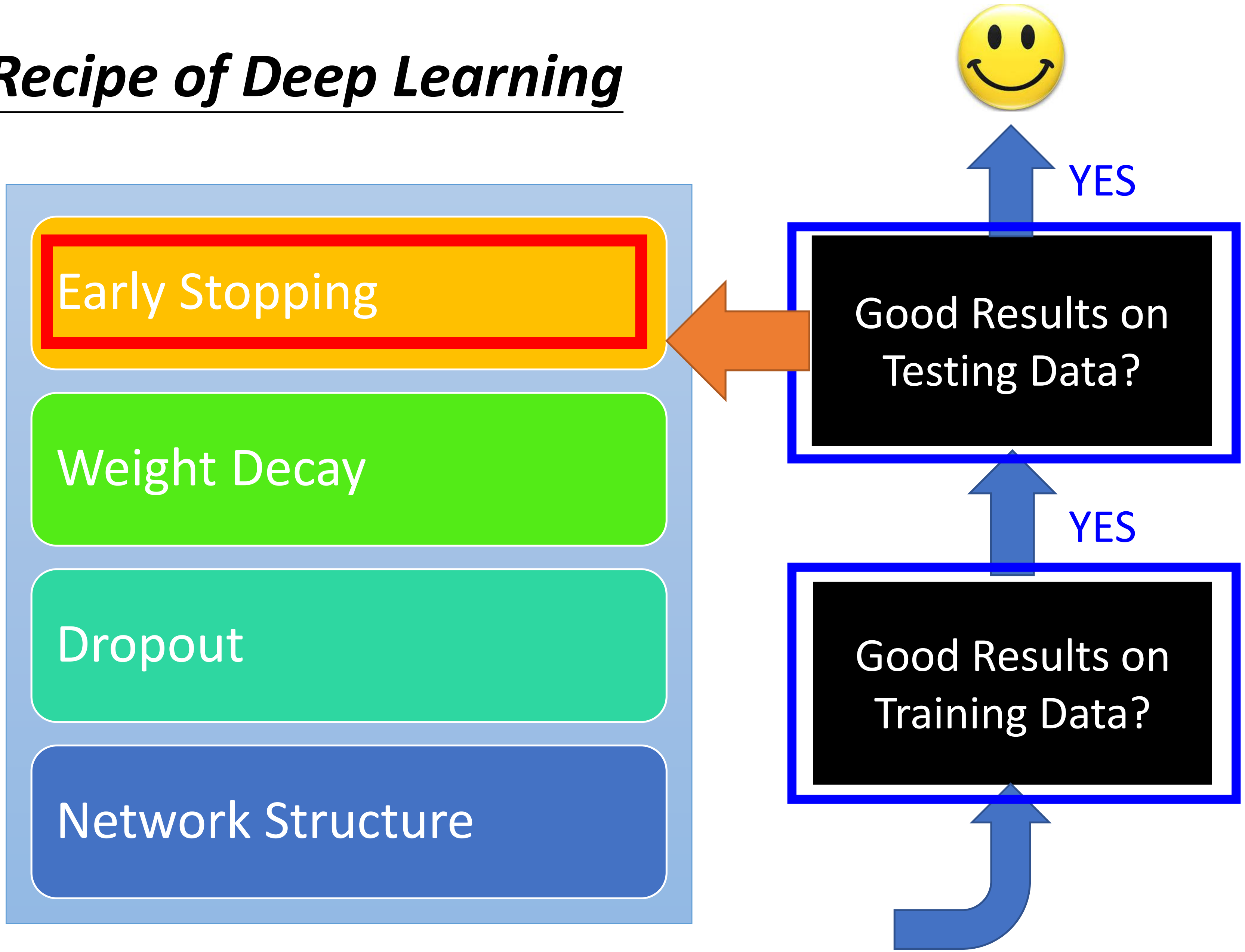
- For experiments, we added some noises to the testing data

Testing:

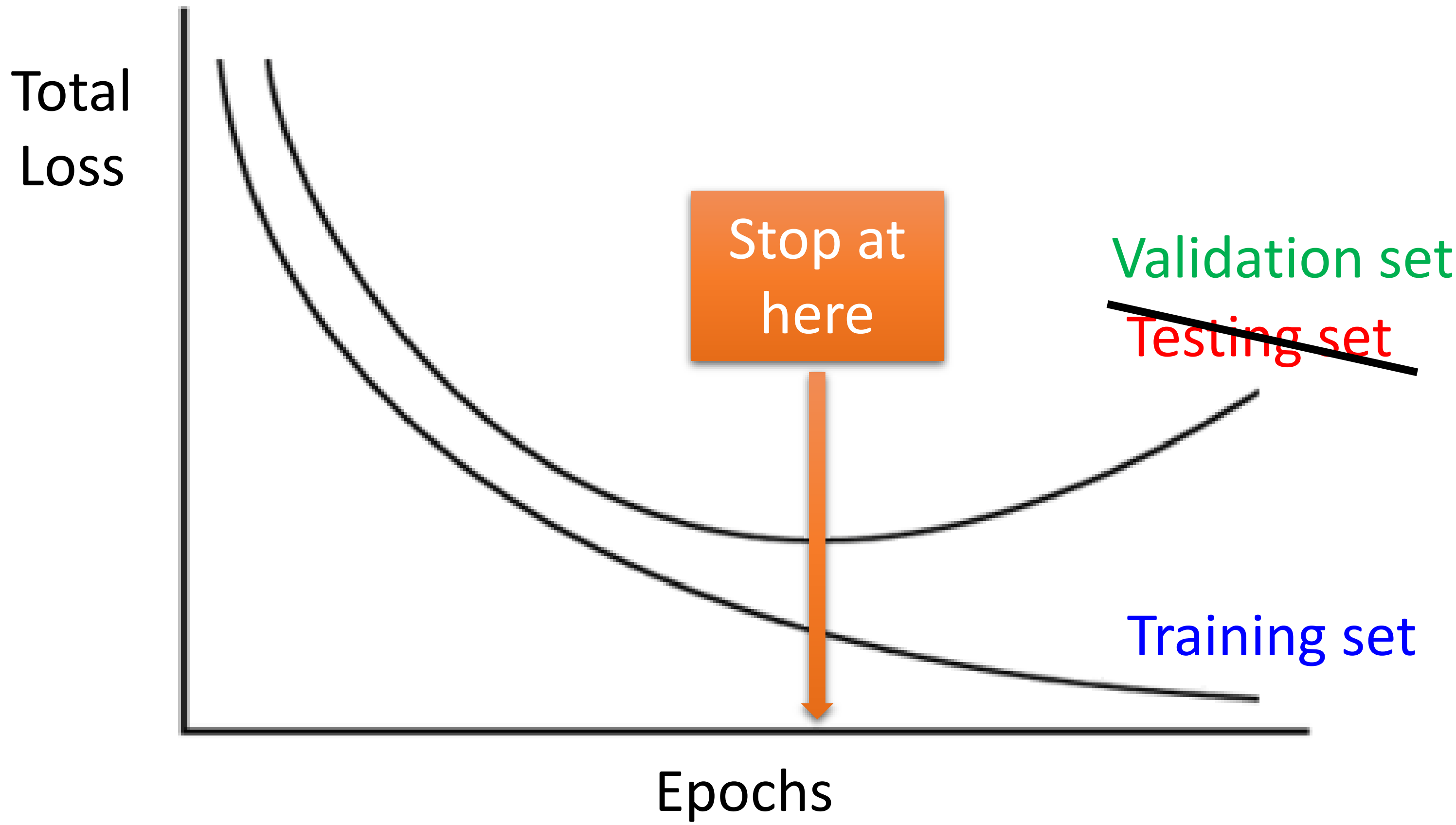
	Accuracy
Clean	0.97
Noisy	0.50

Training is not influenced.

Recipe of Deep Learning

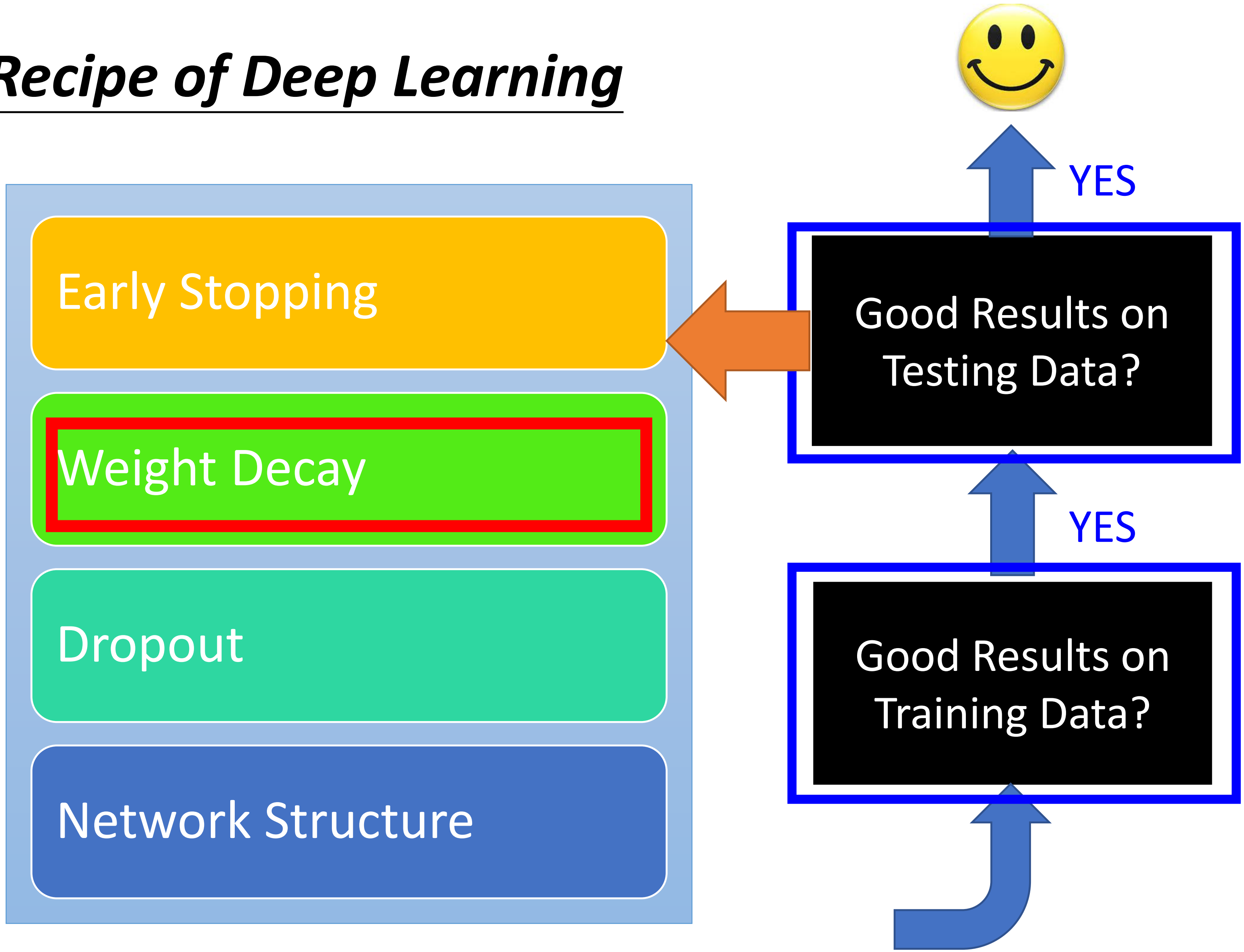


Early Stopping



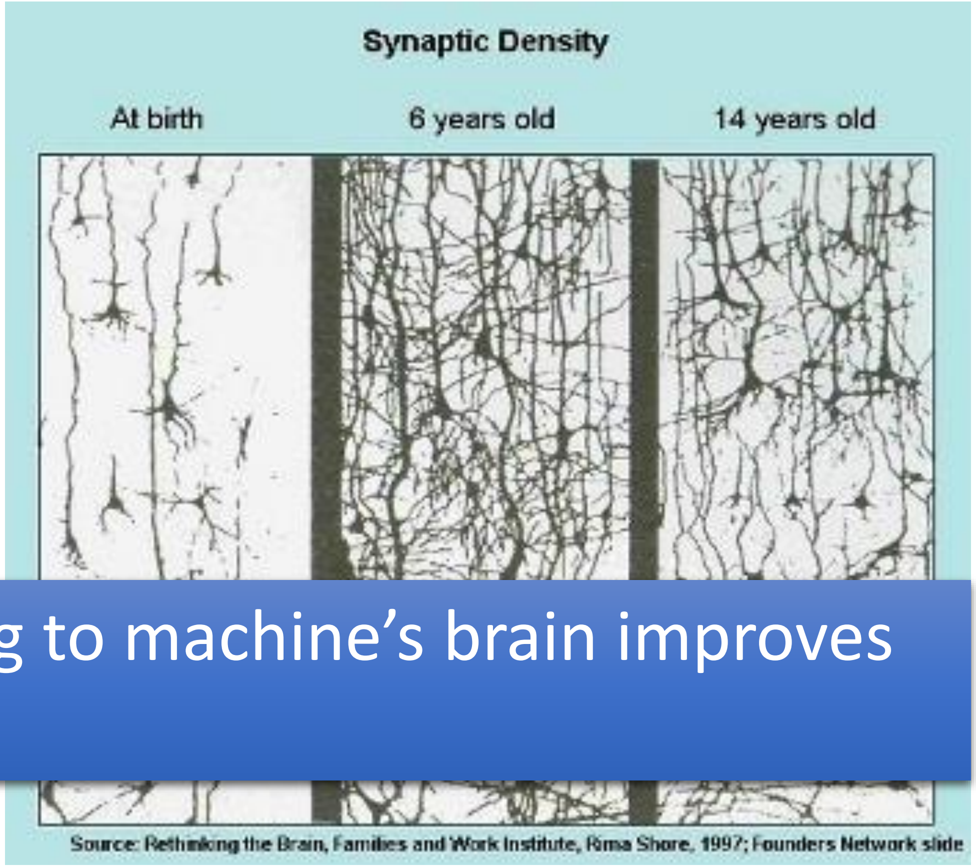
Keras: http://keras.io/getting-started/faq/#how-can-i-interrupt-training-when-the-validation-loss-isnt-decreasing-anymore

Recipe of Deep Learning



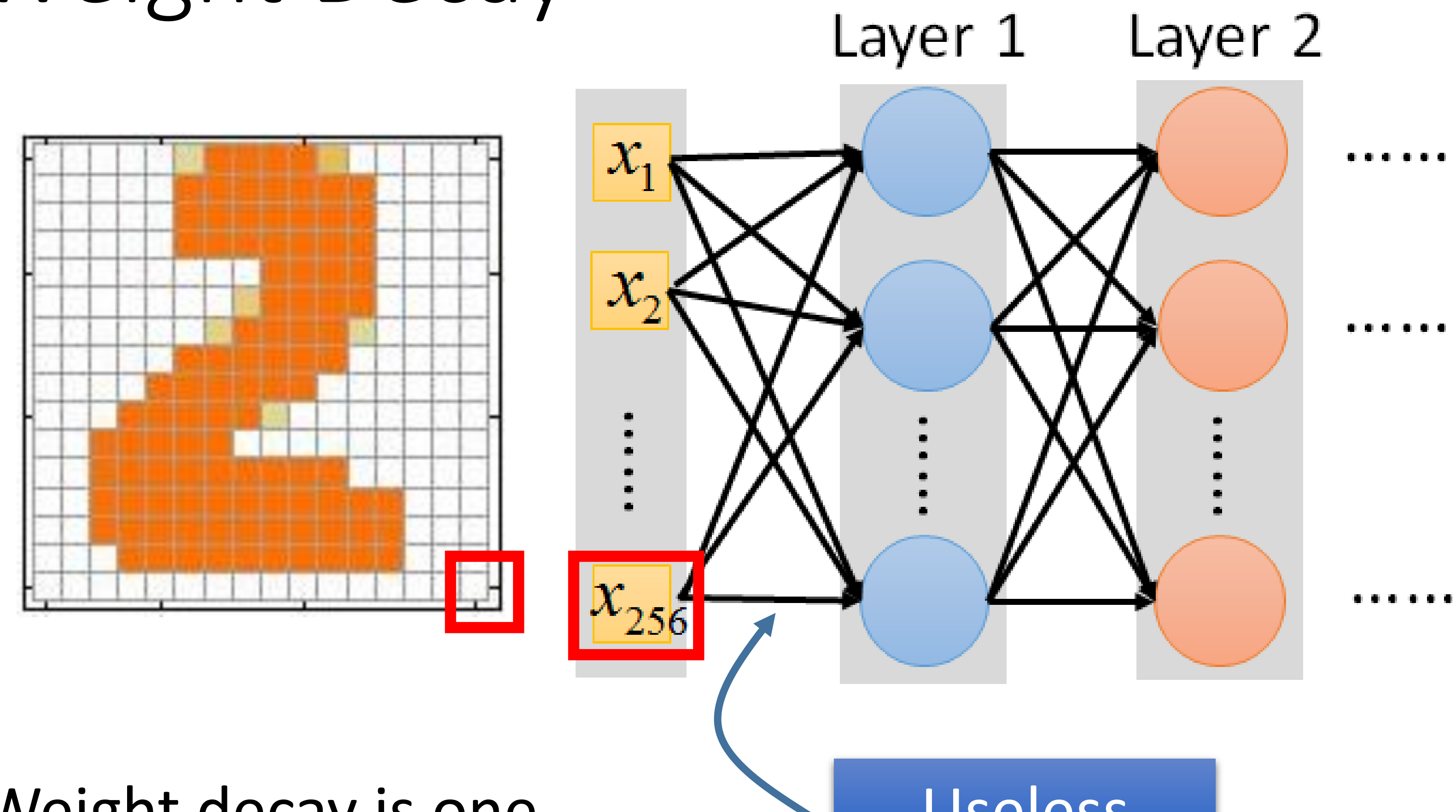
Weight Decay

- Our brain prunes out the useless link between neurons.



Doing the same thing to machine's brain improves the performance.

Weight Decay



Weight decay is one kind of regularization

Close to zero (萎縮了)

Weight Decay

- Implementation

Original: $w \leftarrow w - \eta \dfrac{\partial L}{\partial w}$

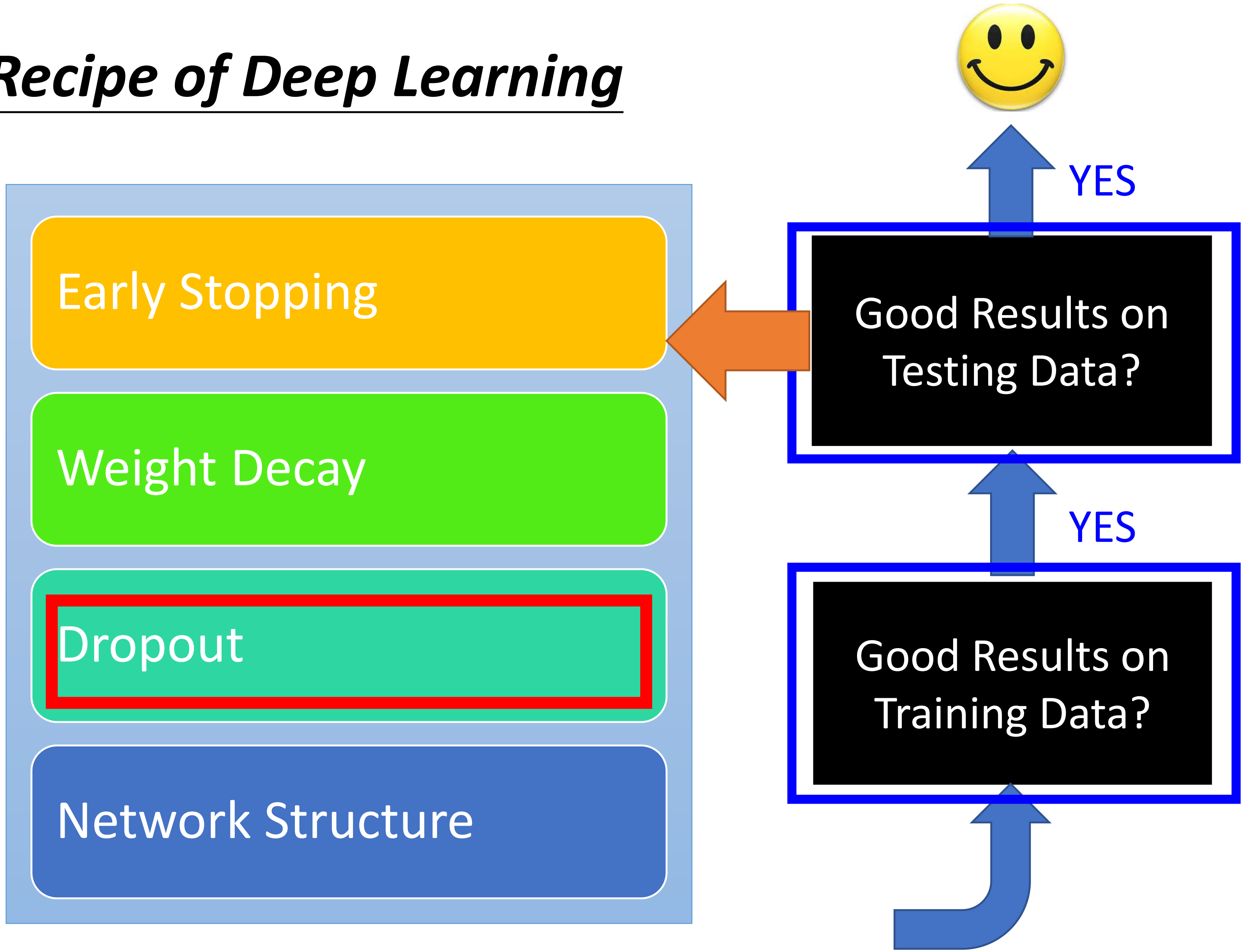
$$\lambda = 0.01$$

Weight Decay: $w \leftarrow \underline{\boxed{0.99}}\, w - \eta \dfrac{\partial L}{\partial w}$

Smaller and smaller

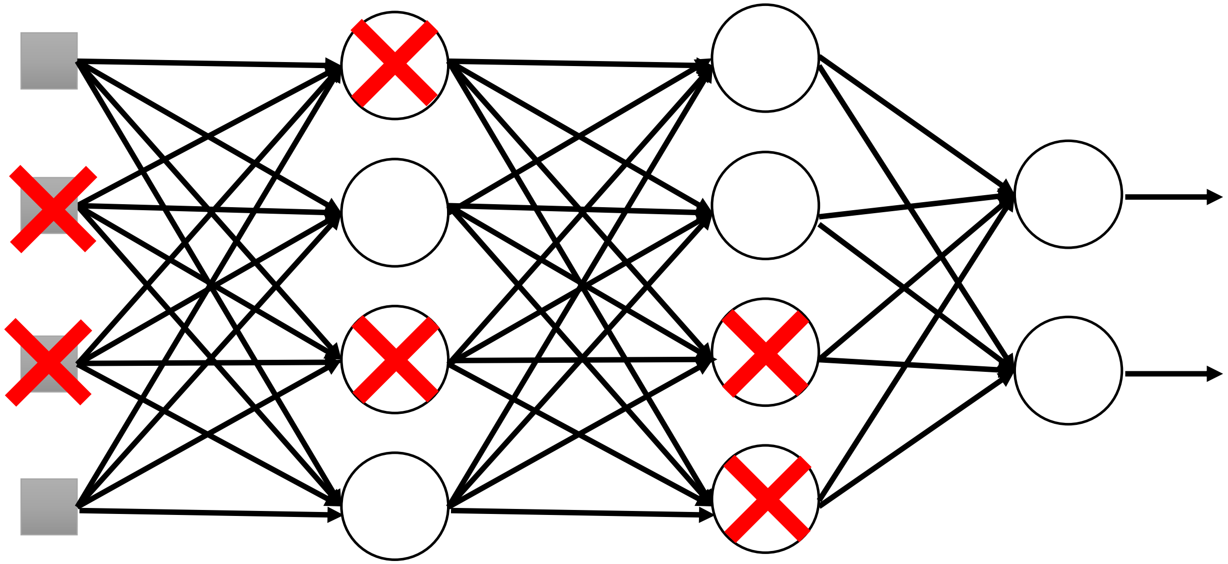
Keras: http://keras.io/regularizers/

Recipe of Deep Learning



Dropout

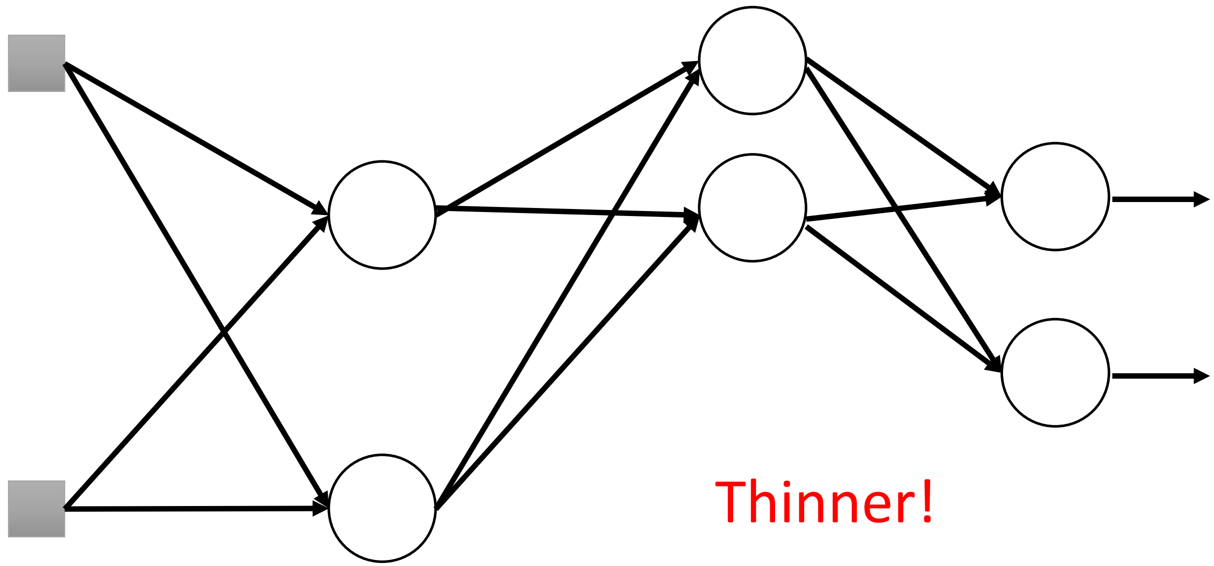
Training:



- **Each time before updating the parameters**
  - Each neuron has p% to dropout

Dropout

Training:



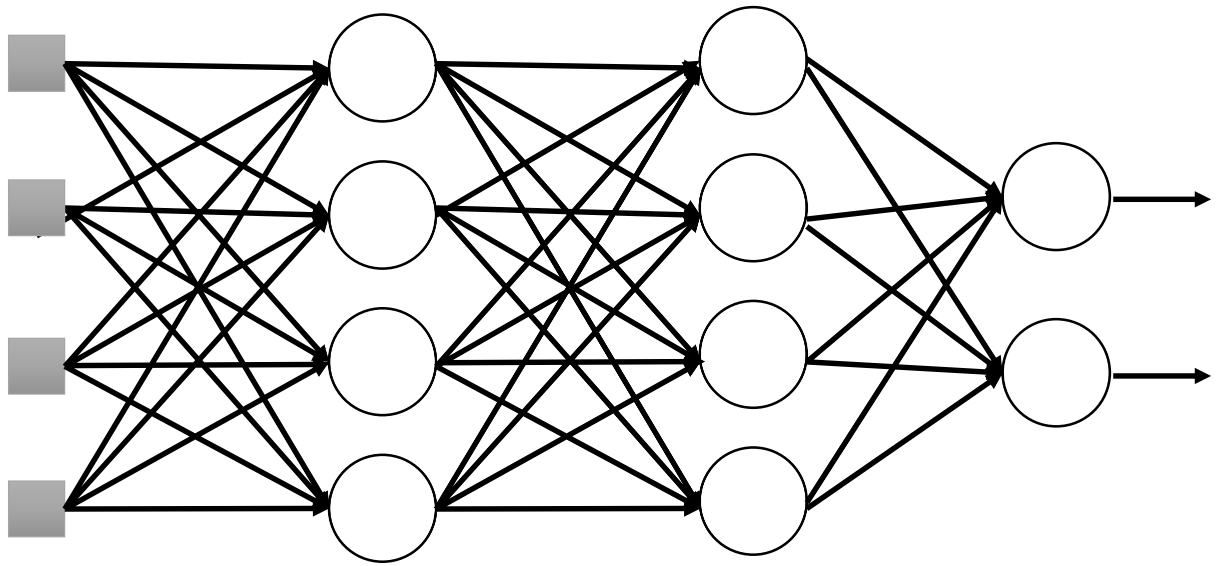
- **Each time before updating the parameters**
  - Each neuron has p% to dropout

    The structure of the network is changed.
  - Using the new network for training

For each mini-batch, we resample the dropout neurons

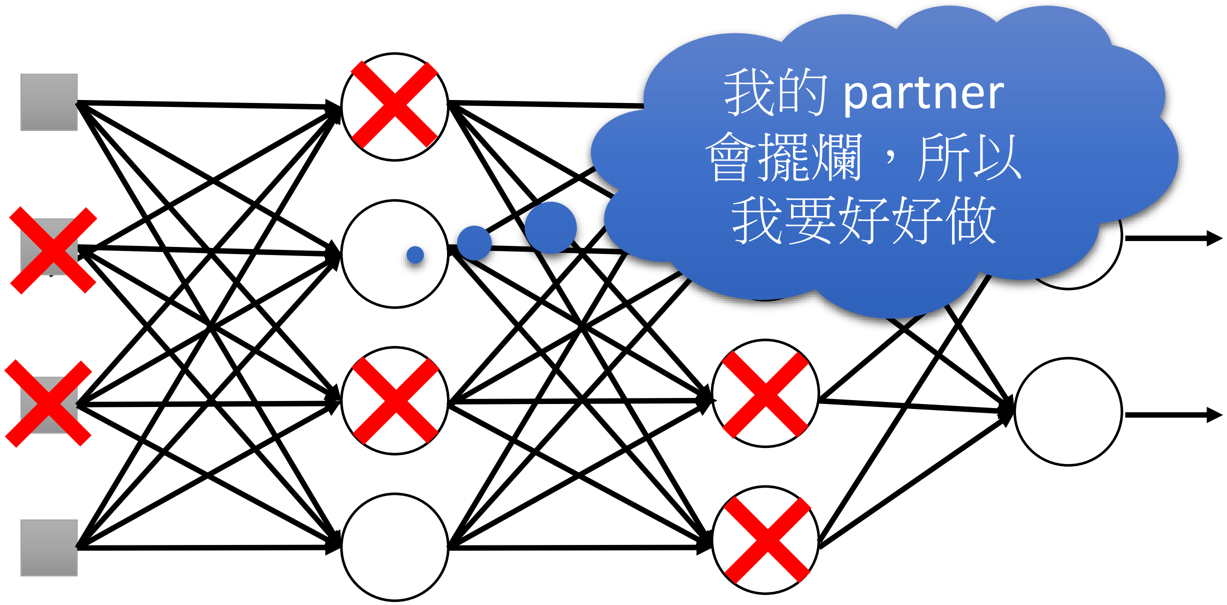
Dropout

Testing:



- **No dropout**
  - If the dropout rate at training is p%, all the weights times (1-p)%
  - Assume that the dropout rate is 50%. If a weight $w = 1$ by training, set $w = 0.5$ for testing.

Dropout - Intuitive Reason



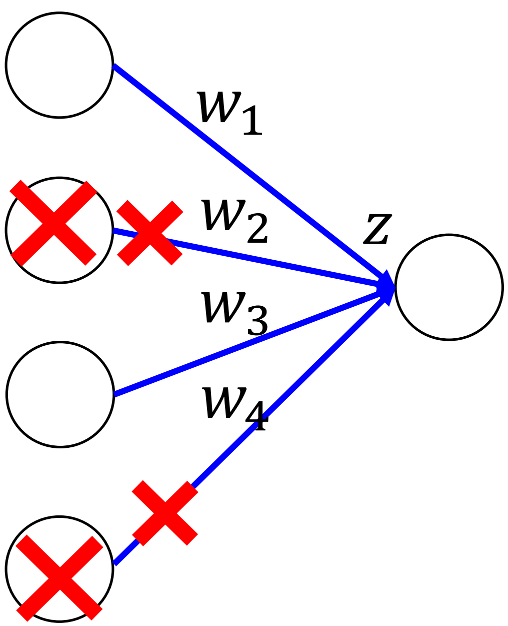
- When teams up, if everyone expect the partner will do the work, nothing will be done finally.
- However, if you know your partner will dropout, you will do better.
- When testing, no one dropout actually, so obtaining good results eventually.

Dropout - Intuitive Reason

- Why the weights should multiply (1-p)% (dropout rate) when testing?

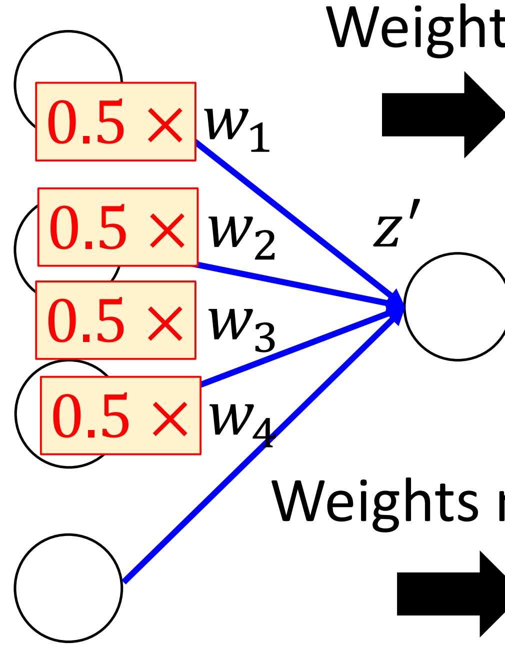
Training of Dropout

Assume dropout rate is 50%



Testing of Dropout

No dropout



Weights from training

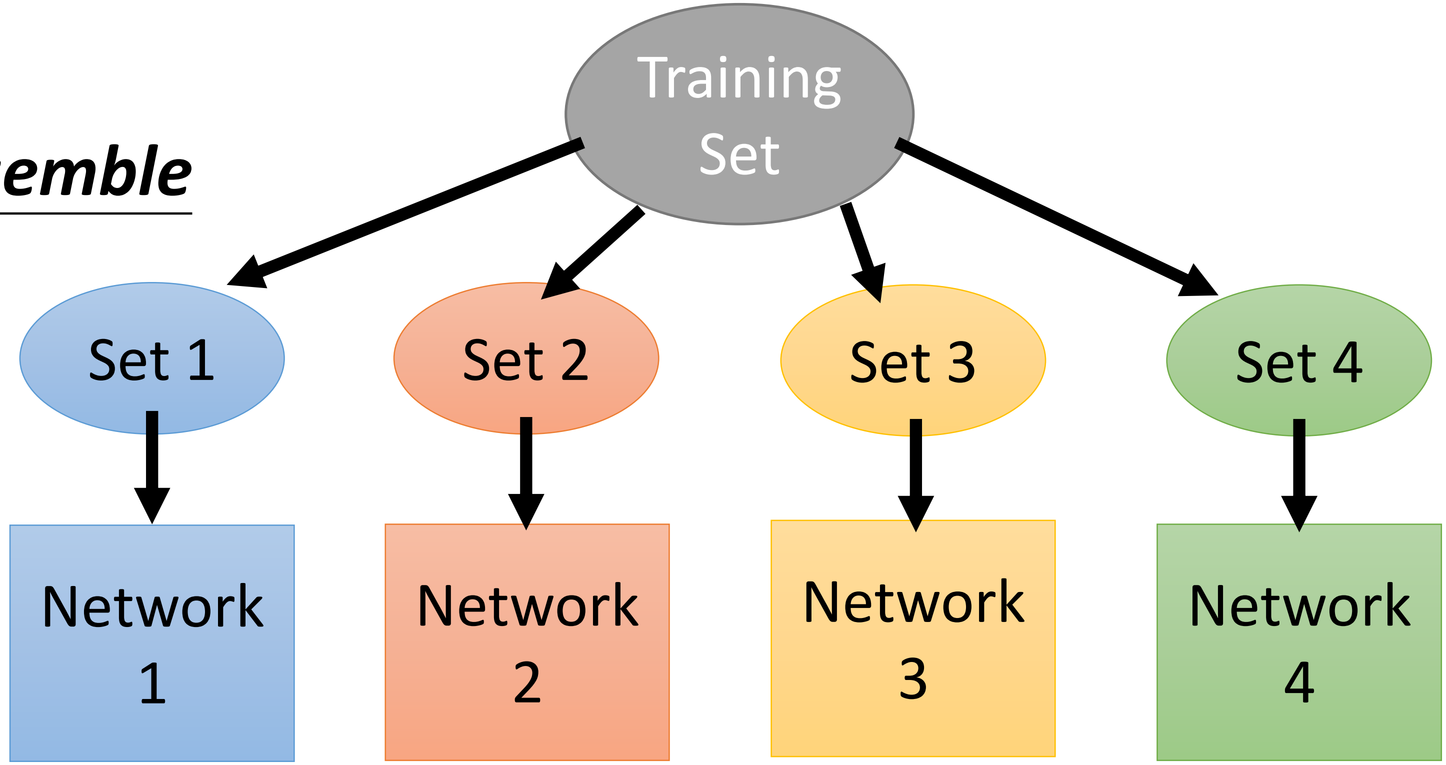
$\Rightarrow z' \approx 2z$

Weights multiply (1-p)%

$\Rightarrow z' \approx z$

Dropout is a kind of ensemble.

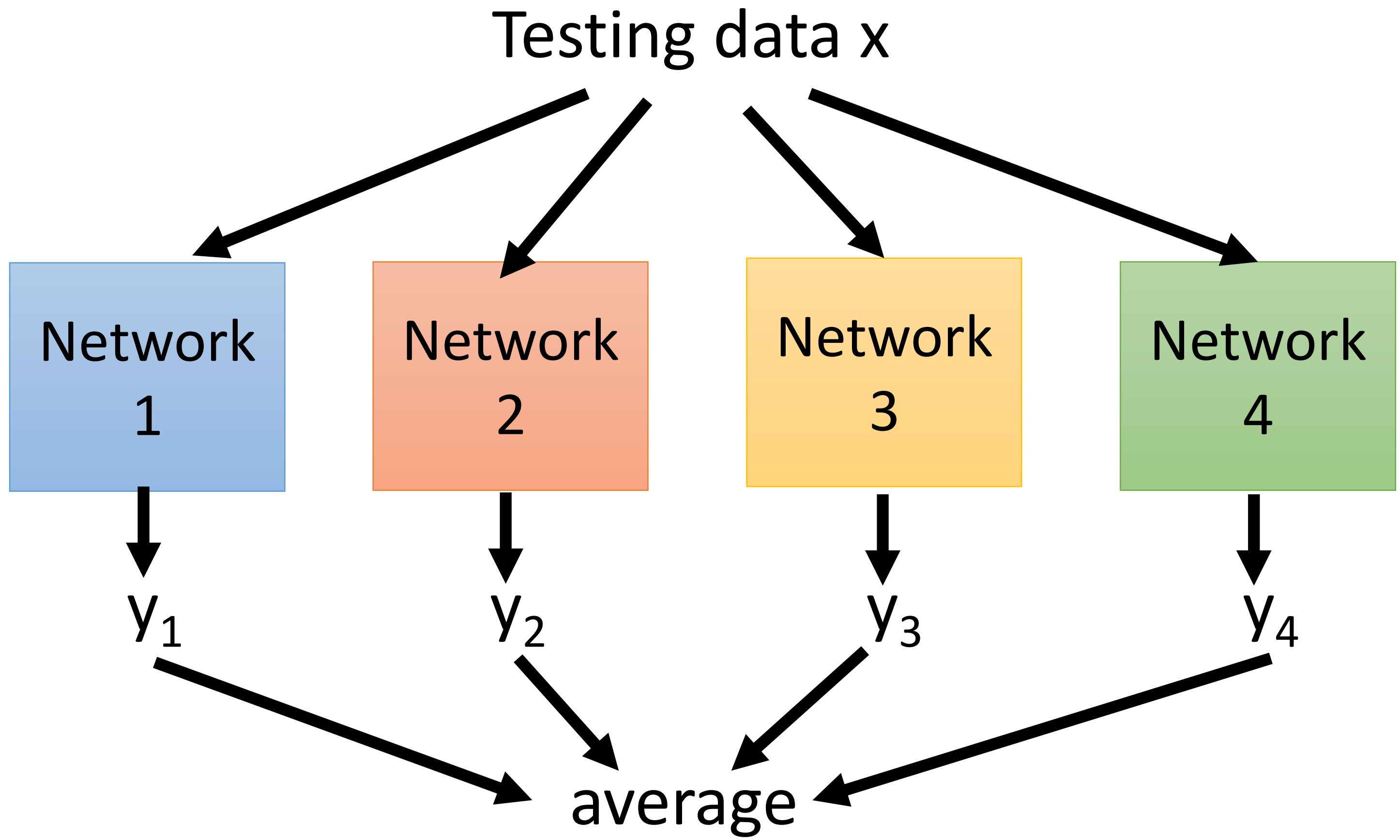
Ensemble



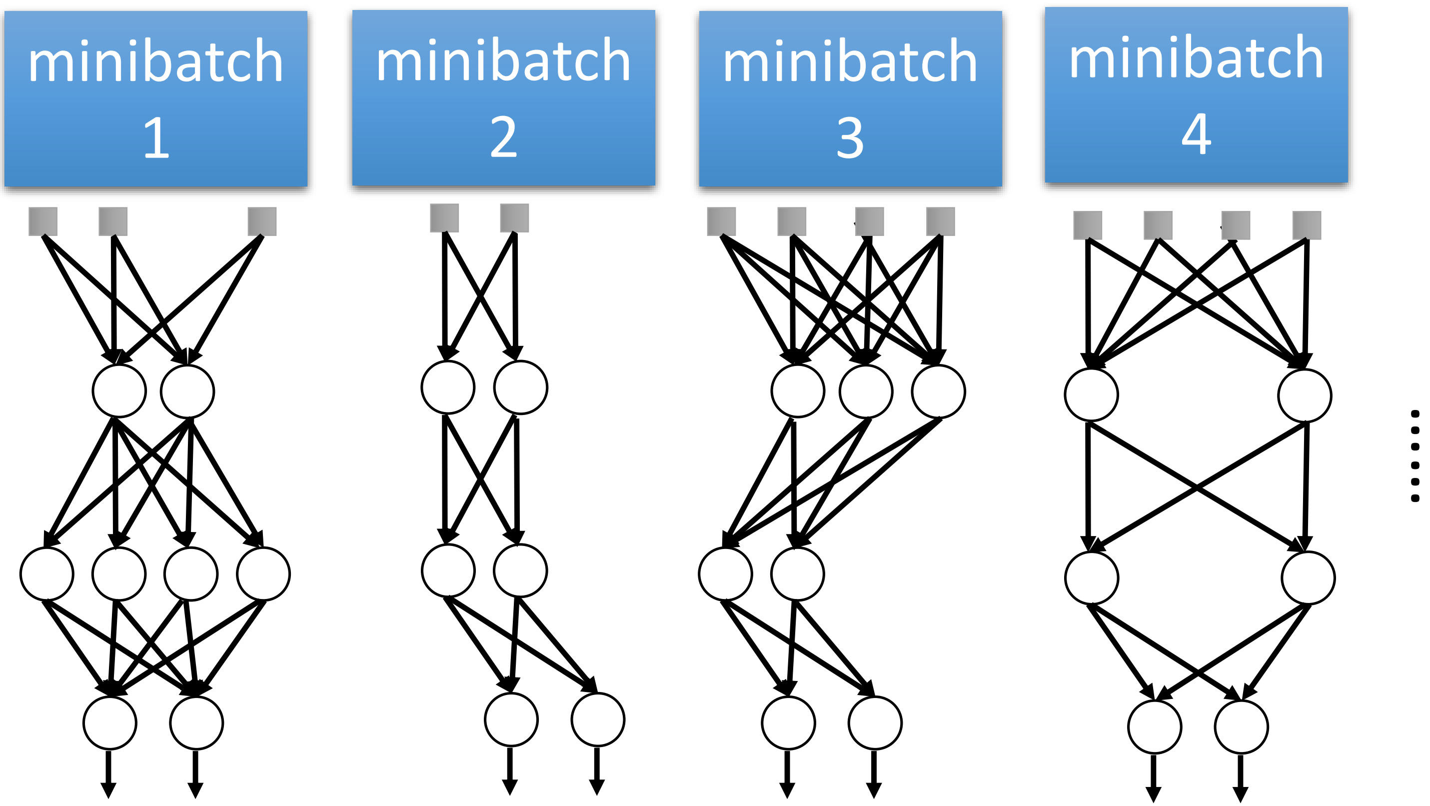
Train a bunch of networks with different structures

Dropout is a kind of ensemble.

Ensemble



Dropout is a kind of ensemble.



Training of Dropout

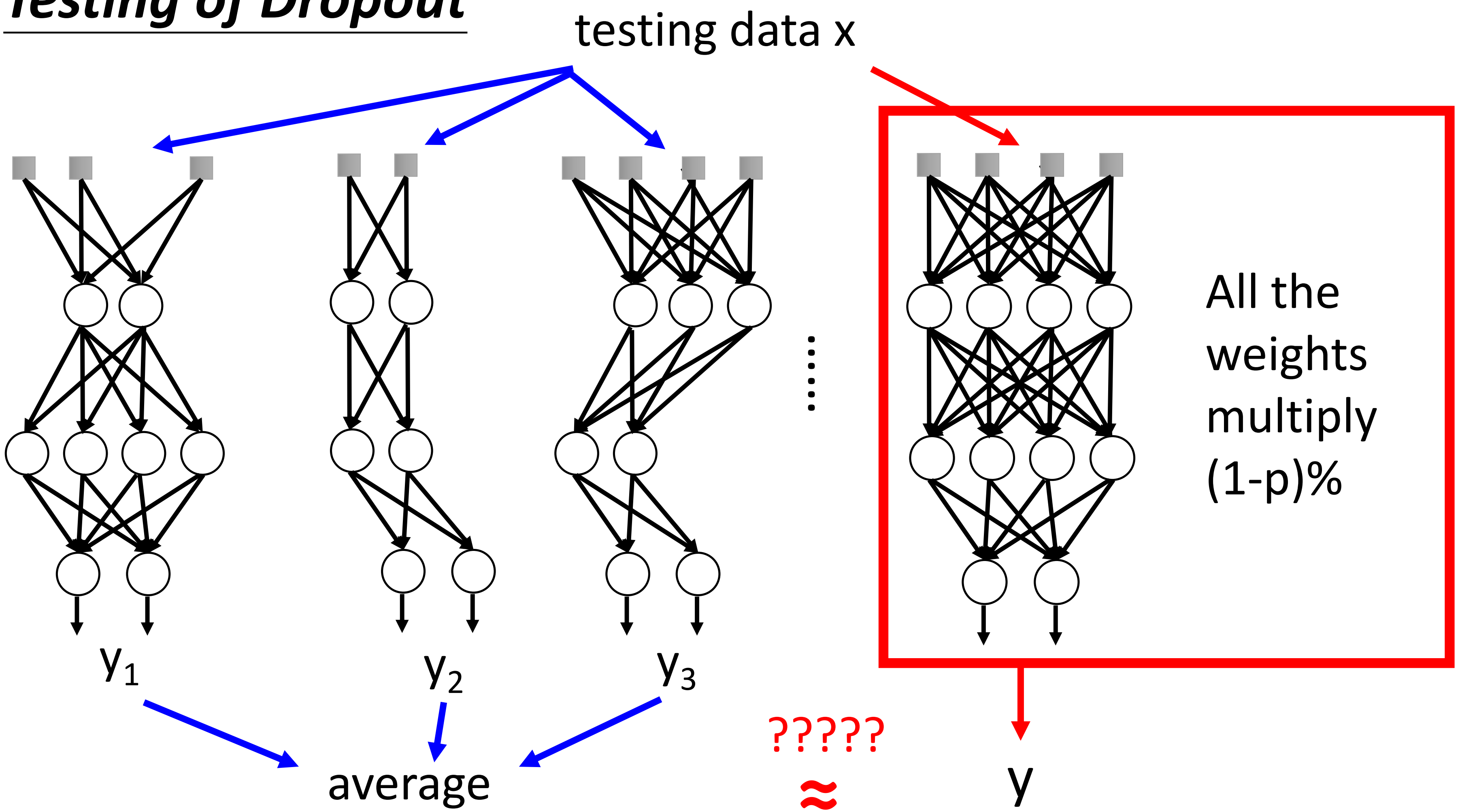
M neurons

2^M possible networks

- Using one mini-batch to train one network
- Some parameters in the network are shared

Dropout is a kind of ensemble.

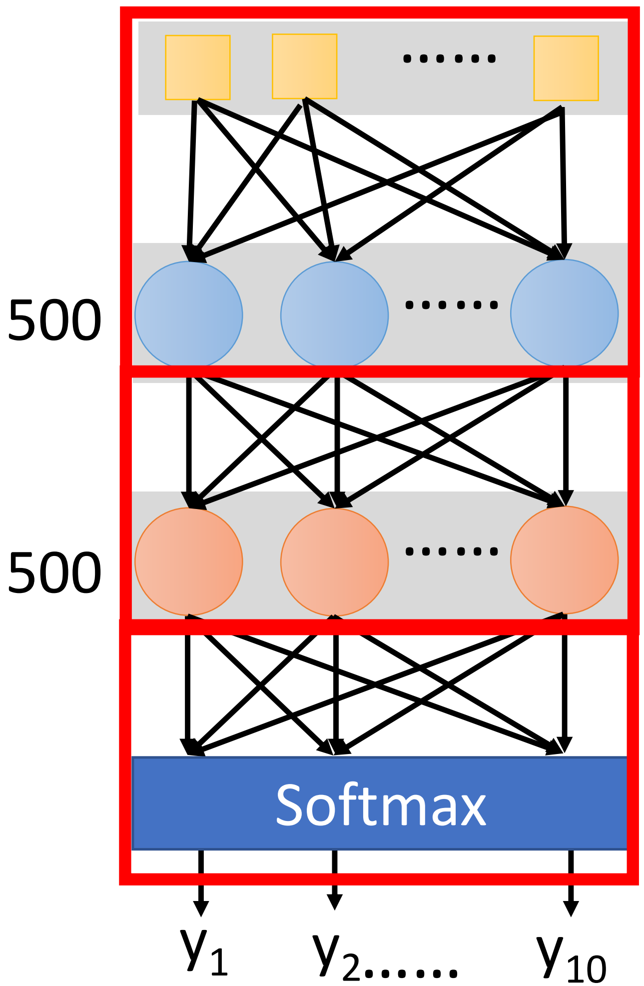
Testing of Dropout



More about dropout

- More reference for dropout [Nitish Srivastava, JMLR'14] [Pierre Baldi, NIPS'13][Geoffrey E. Hinton, arXiv'12]
- Dropout works better with Maxout [Ian J. Goodfellow, ICML'13]
- Dropconnect [Li Wan, *ICML'13*]
  - Dropout delete neurons
  - Dropconnect deletes the connection between neurons
- Annealed dropout [S.J. Rennie, SLT'14]
  - Dropout rate decreases by epochs
- Standout [J. Ba, NISP'13]
  - Each neural has different dropout rate

Let's try it




```
model = Sequential()
```

```
model.add( Dense( input_dim=28*28,
                  output_dim=500 ))
model.add( Activation('sigmoid') )
```

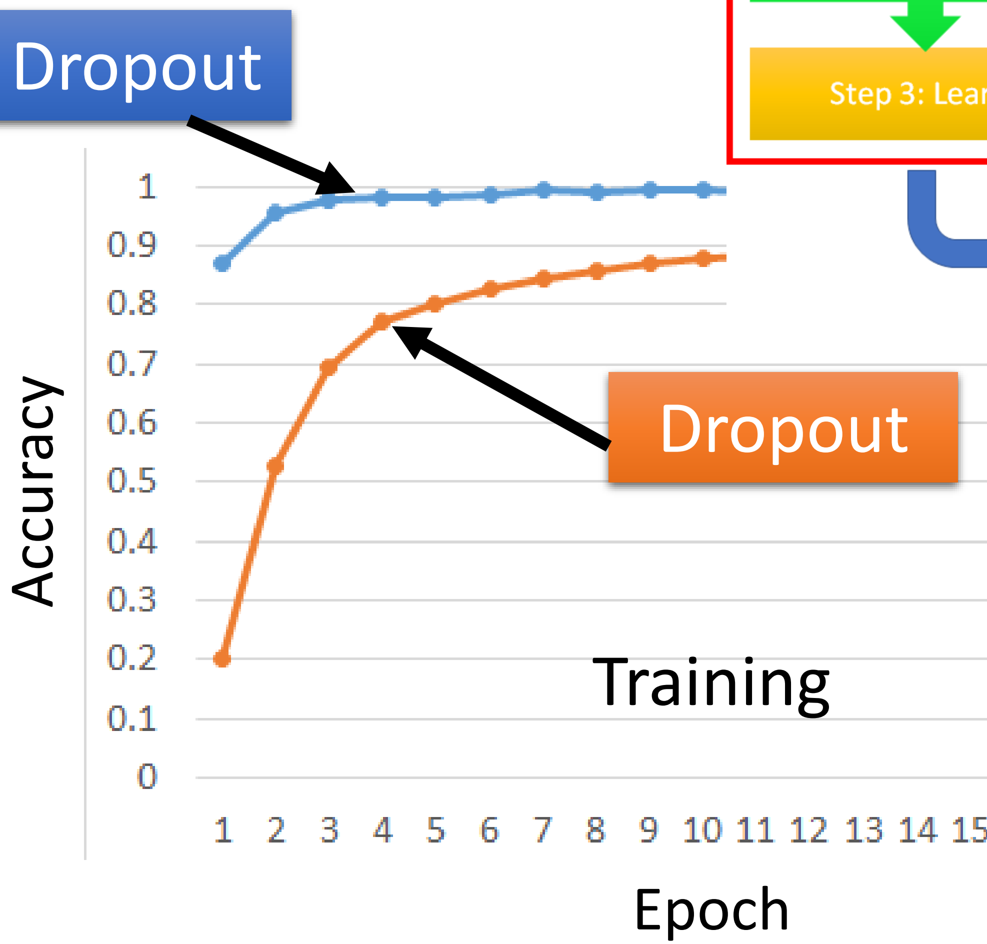
model.add(dropout(0.8))

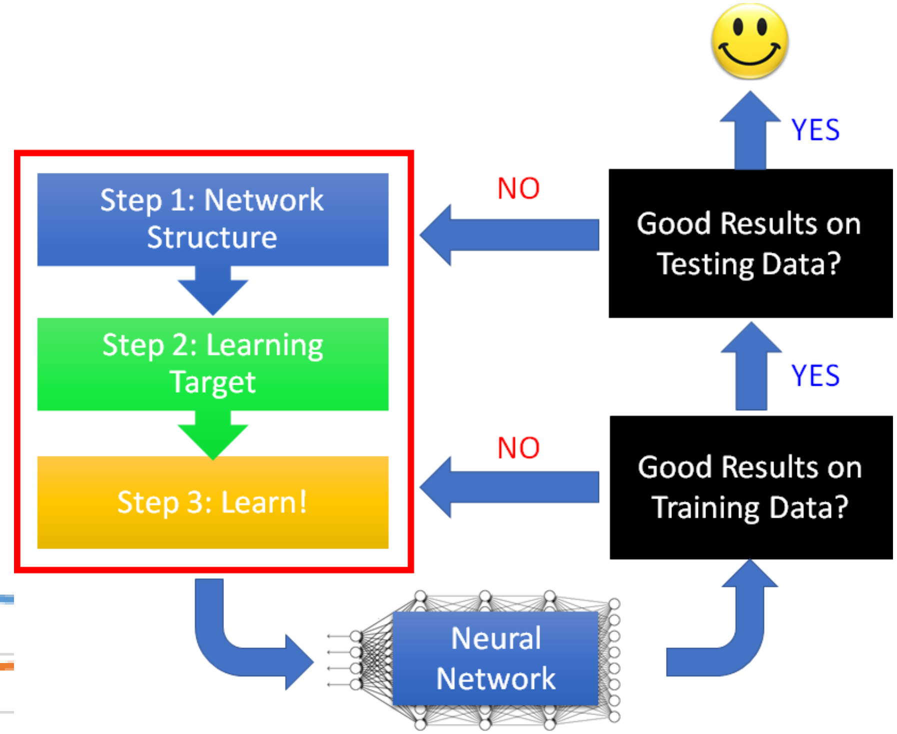
```
model.add( Dense( output_dim=500 ) )
model.add( Activation('sigmoid') )
```

model.add(dropout(0.8))

```
model.add( Dense(output_dim=10 ) )
model.add( Activation('softmax') )
```

Let's try it

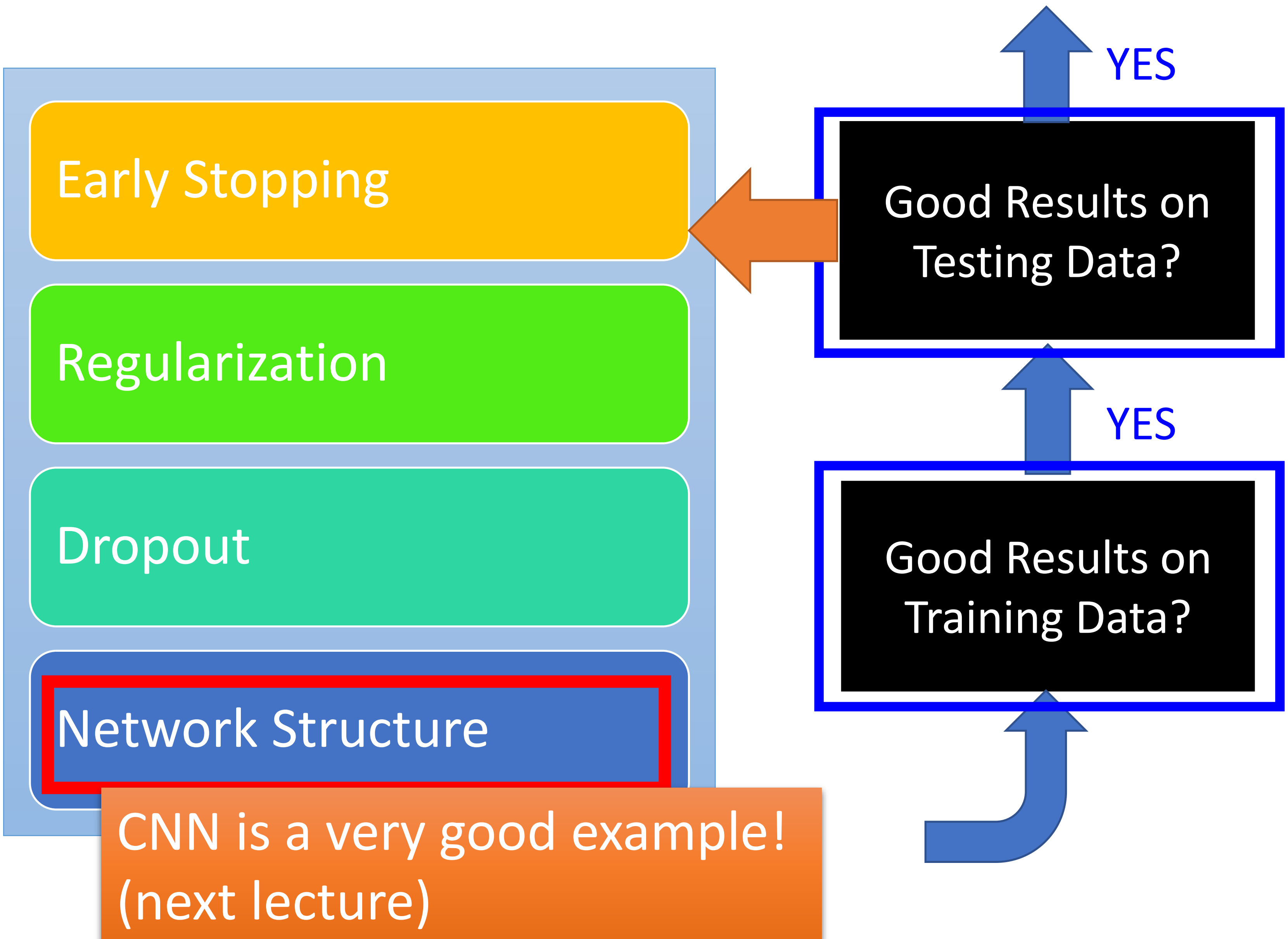




Testing:

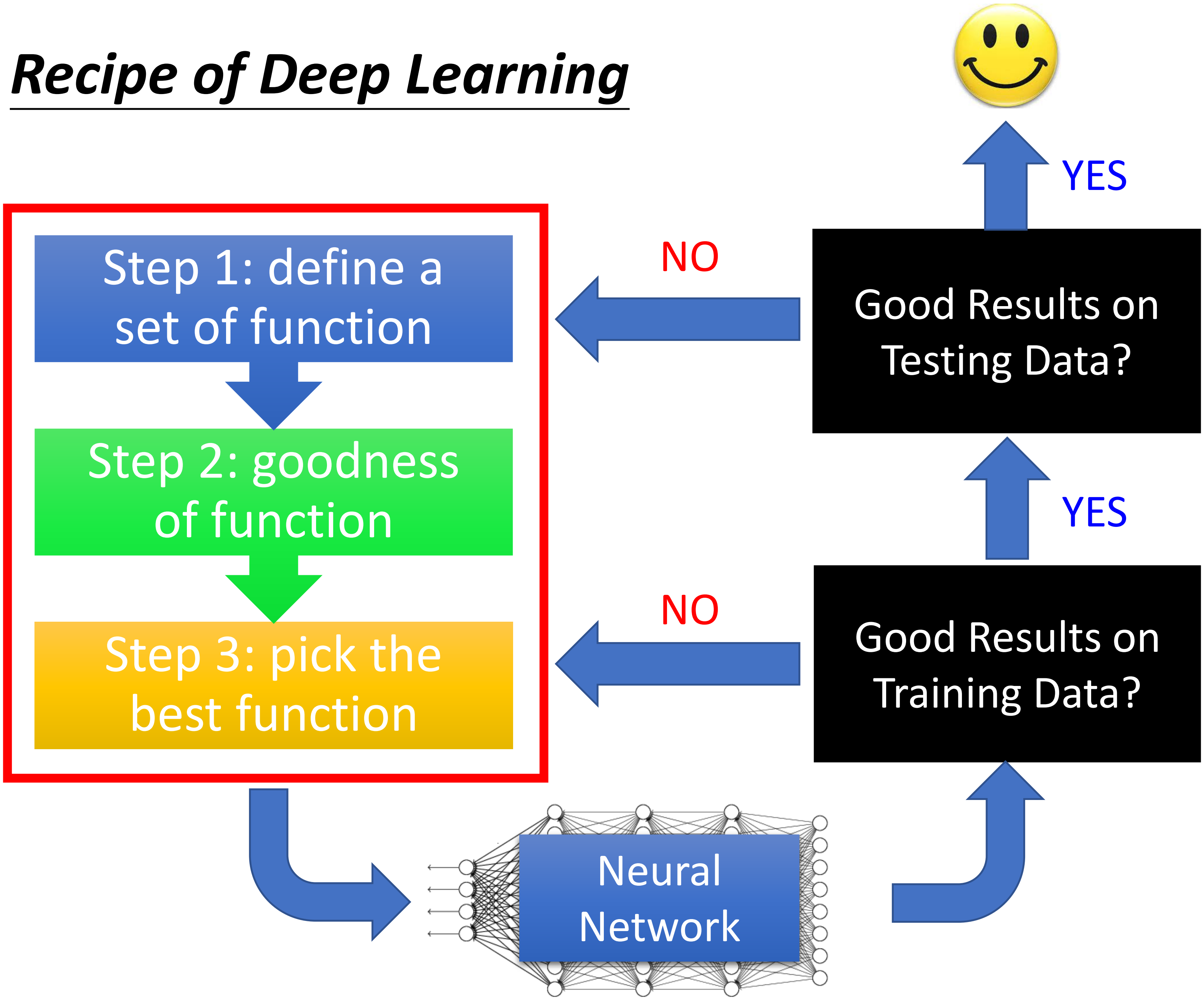
	Accuracy
Noisy	0.50
+ dropout	0.63

Recipe of Deep Learning



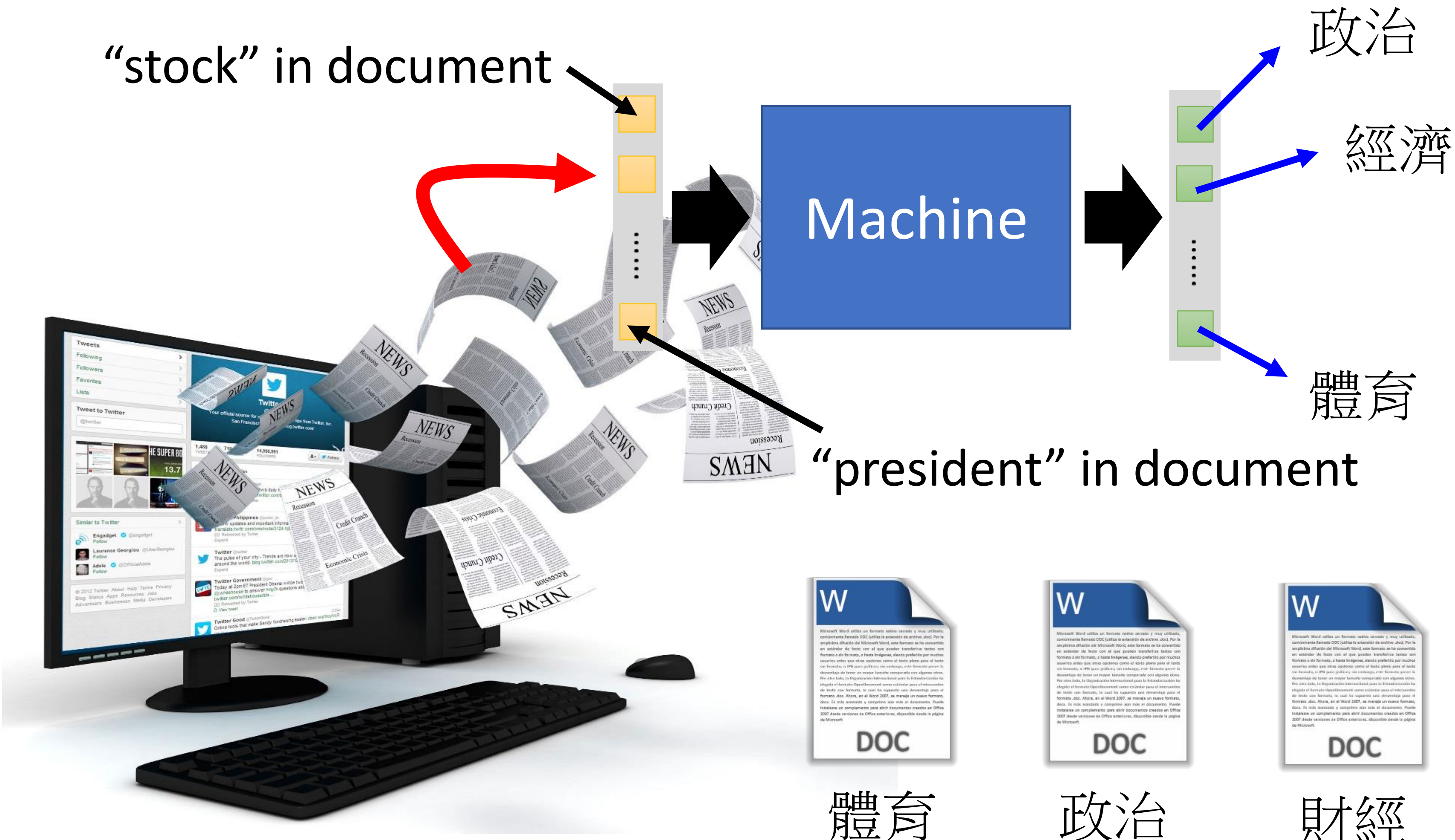
Concluding Remarks of Lecture II

Recipe of Deep Learning



Let’s try another task

Document Classification



http://top-breaking-news.com/

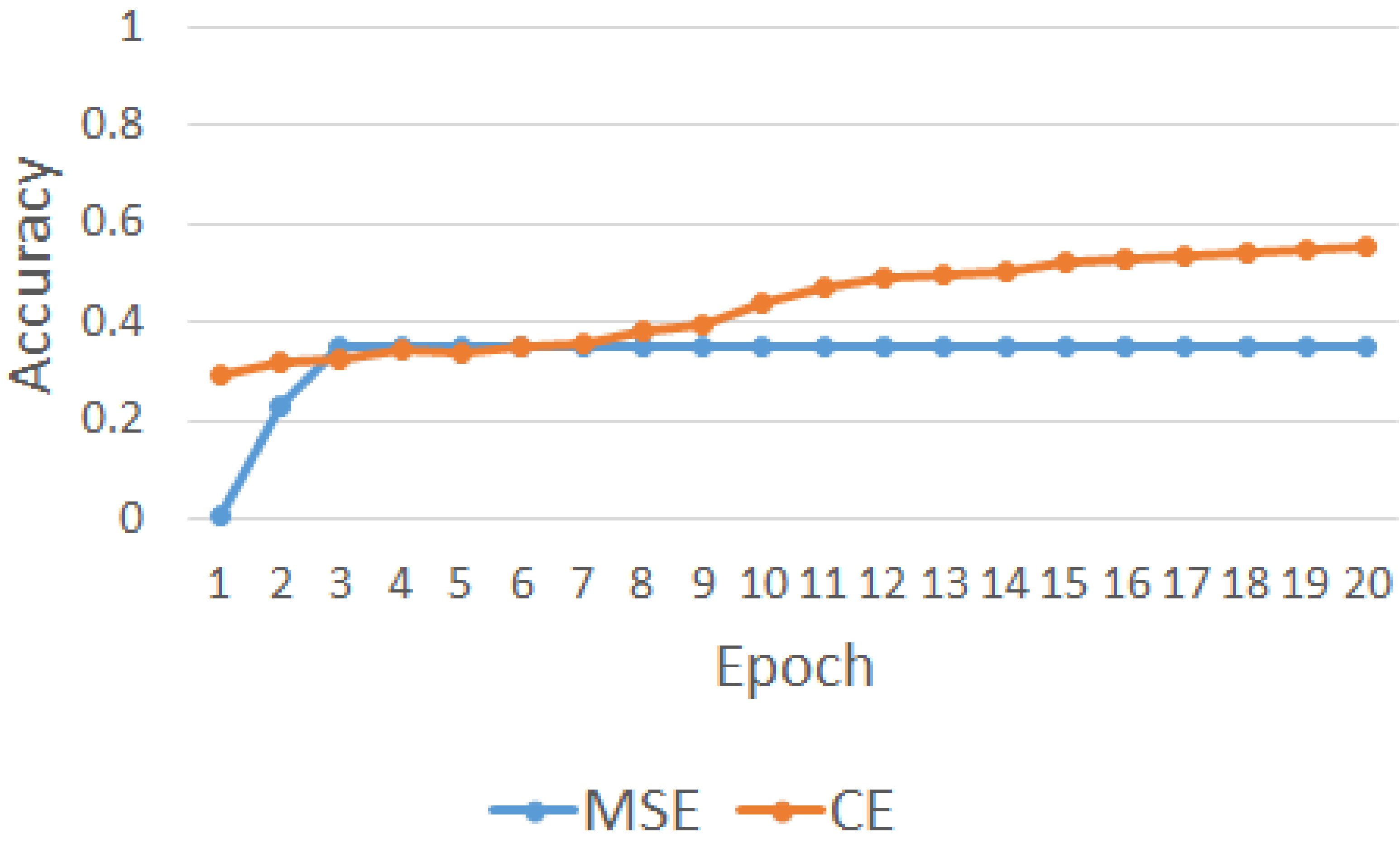
Data

```
In [8]: x_train.shape
Out[8]: (8982, 1000)

In [9]: y_train.shape
Out[9]: (8982, 46)

In [10]: x_test.shape
Out[10]: (2246, 1000)

In [11]: y_test.shape
Out[11]: (2246, 46)
```

```
In [12]: x_train[0]
Out[12]:
array([ 0.,  1.,  1.,  0.,  1.,  1.,  1.,  1.,  1
        0.,  0.,  1.,  1.,  1.,  0.,  1.,  0.,  0
        1.,  0.,  0.,  1.,  1.,  0.,  1.,  0.,  0
        1.,  0.,  0.,  0.,  1.,  1.,  0.,  0.,  0
        1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0
        0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  1.,  1.,  0.,  0.,  0.,  0.,  1.,  1.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,
        0.,  0.,  0.,  0.,  0.,  1.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  1.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  1.,  1.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,
        0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
```

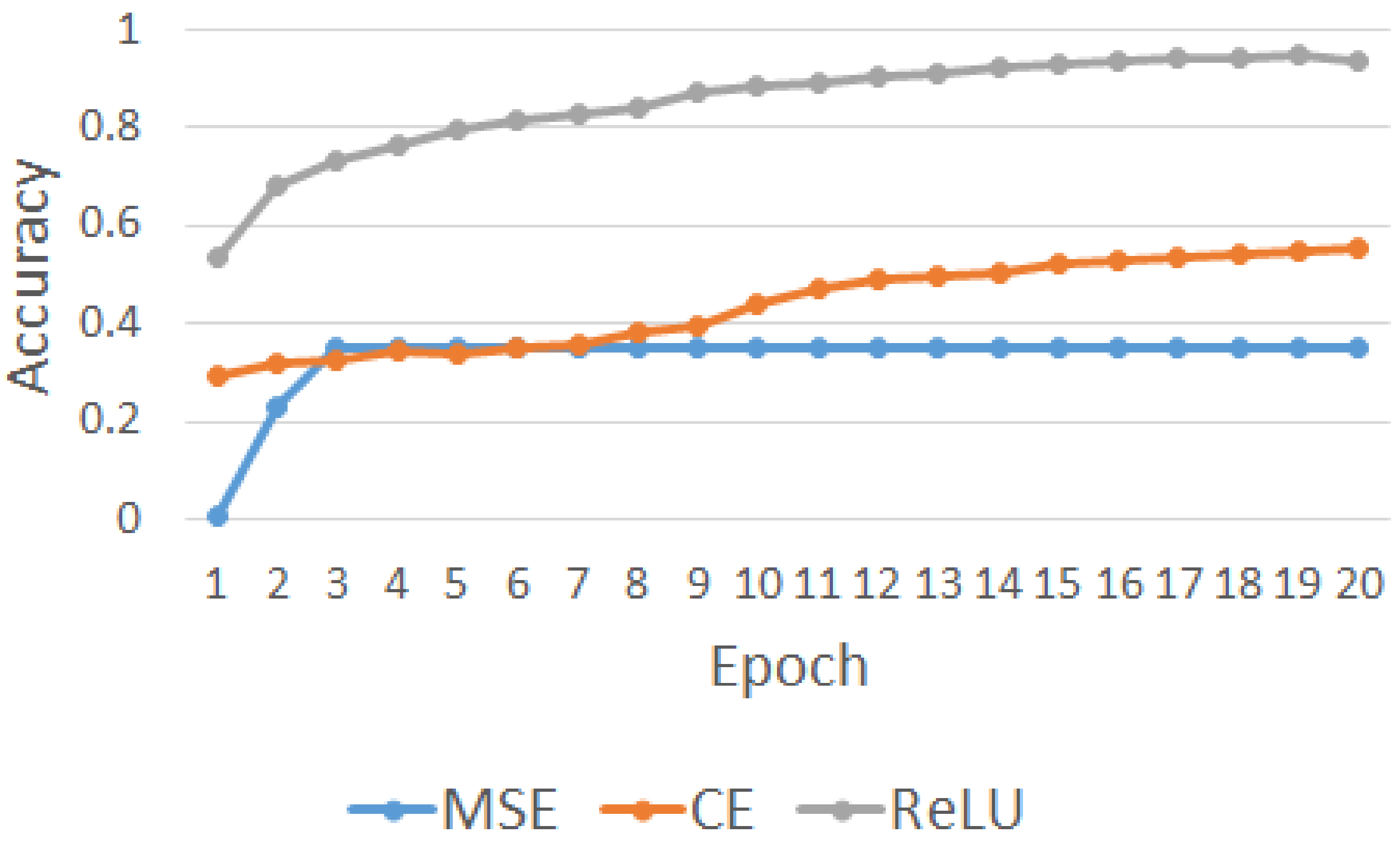
```
In [13]: y_train[0]
Out[13]:
array([ 0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  0.,  0.])
```

MSE



1
0.8
0.6
0.4
0.2
0
Accuracy
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Epoch
MSE
CE

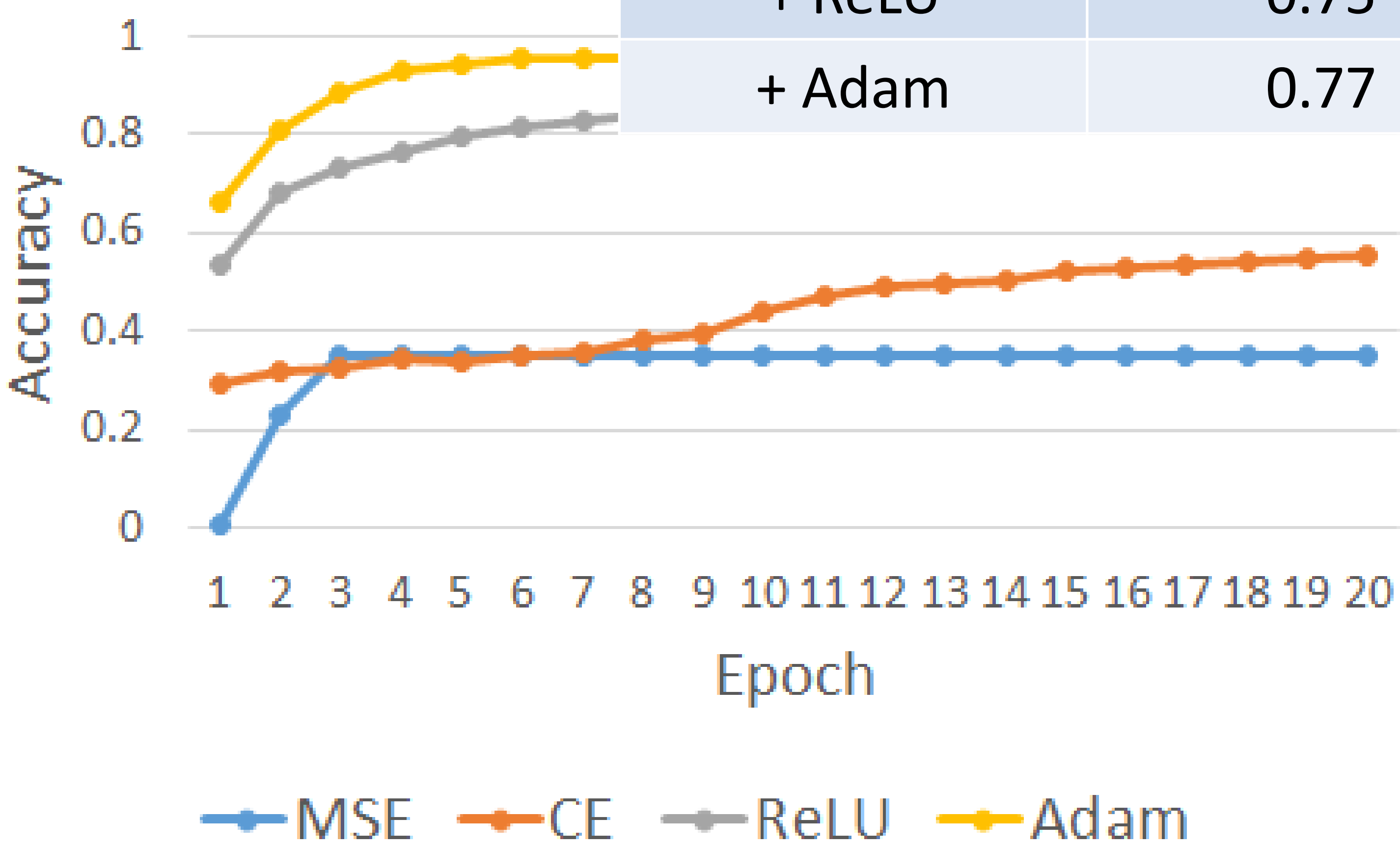
ReLU



1
0.8
0.6
0.4
0.2
0
Accuracy
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Epoch
MSE
CE
ReLU

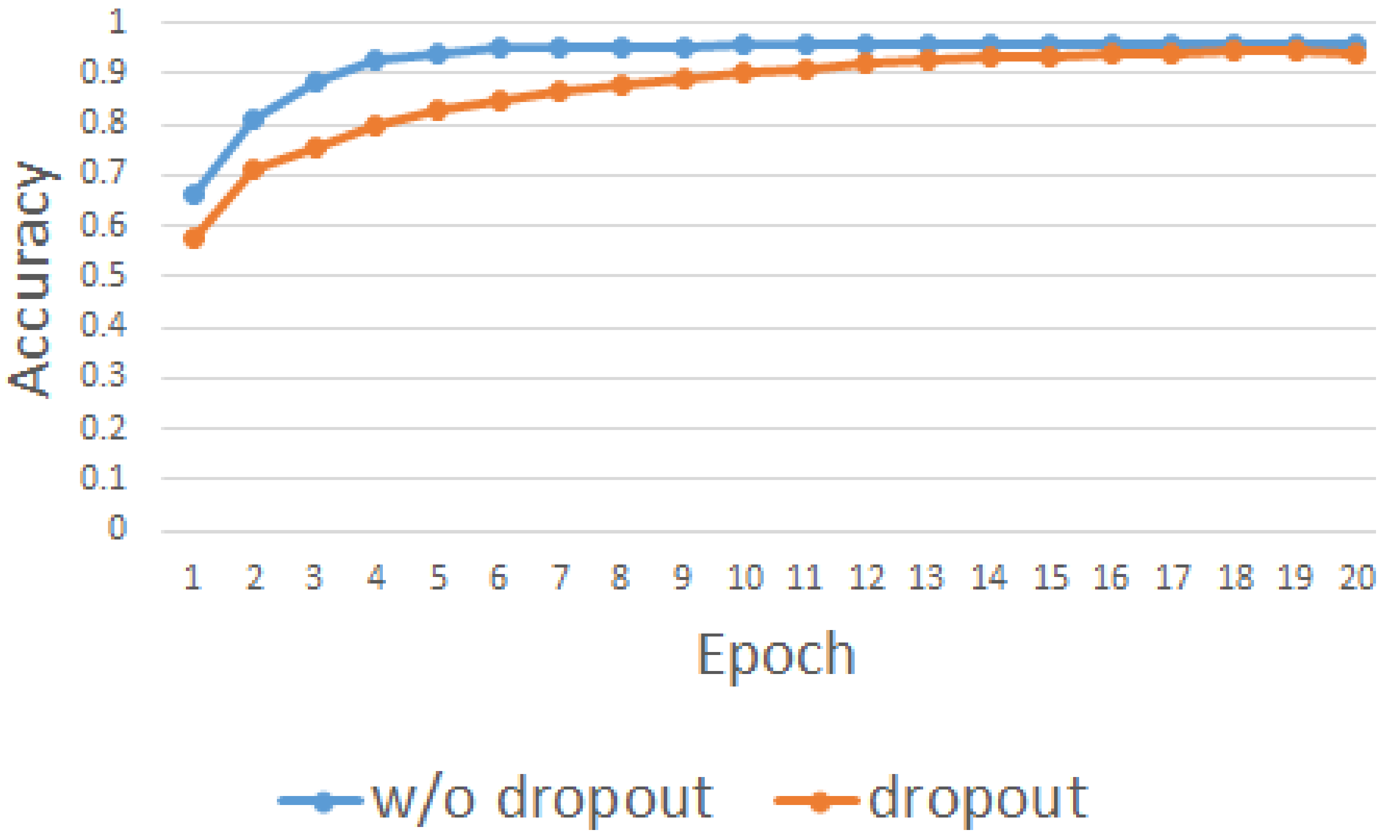
Adaptive Learn

	Accuracy
MSE	0.36
CE	0.55
+ ReLU	0.75
+ Adam	0.77



Dropout

	Accuracy
Adam	0.77
+ dropout	0.79



Lecture III:
Variants of Neural Networks

Variants of Neural Networks

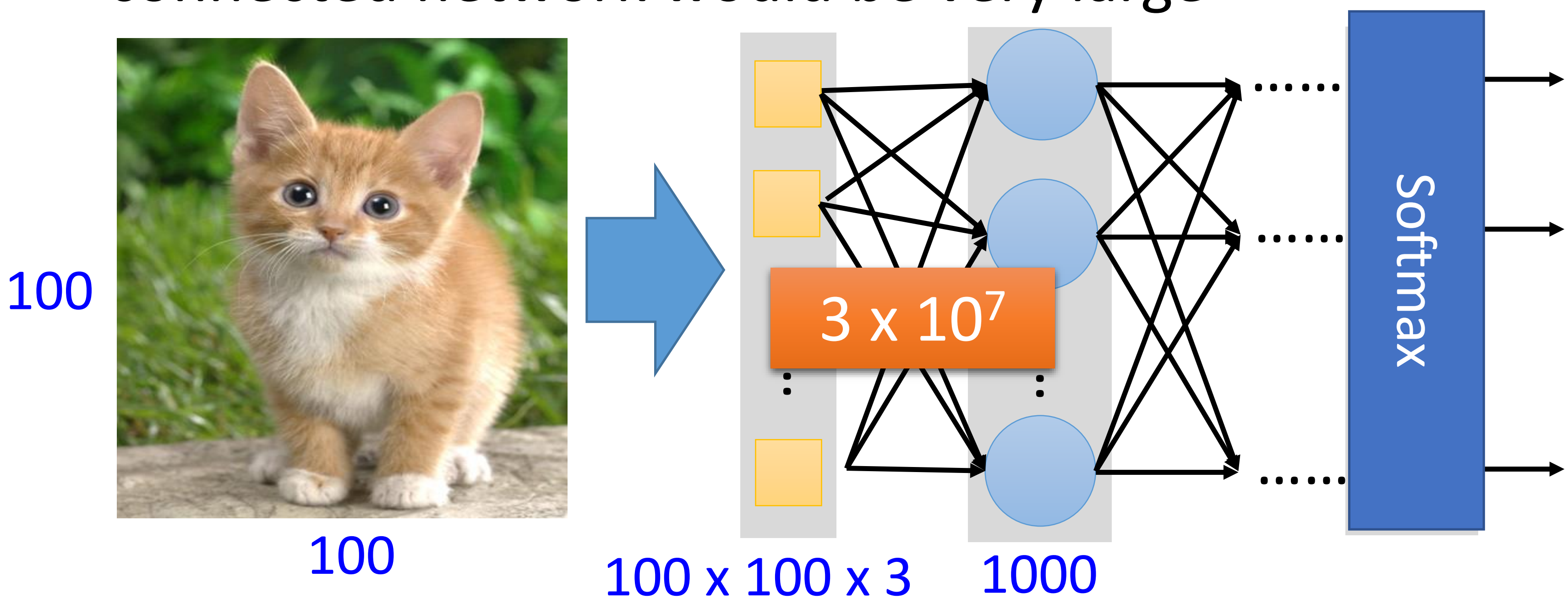
Convolutional Neural Network (CNN)

Widely used in image processing

Recurrent Neural Network (RNN)

Why CNN for Image?

- When processing image, the first layer of fully connected network would be very large



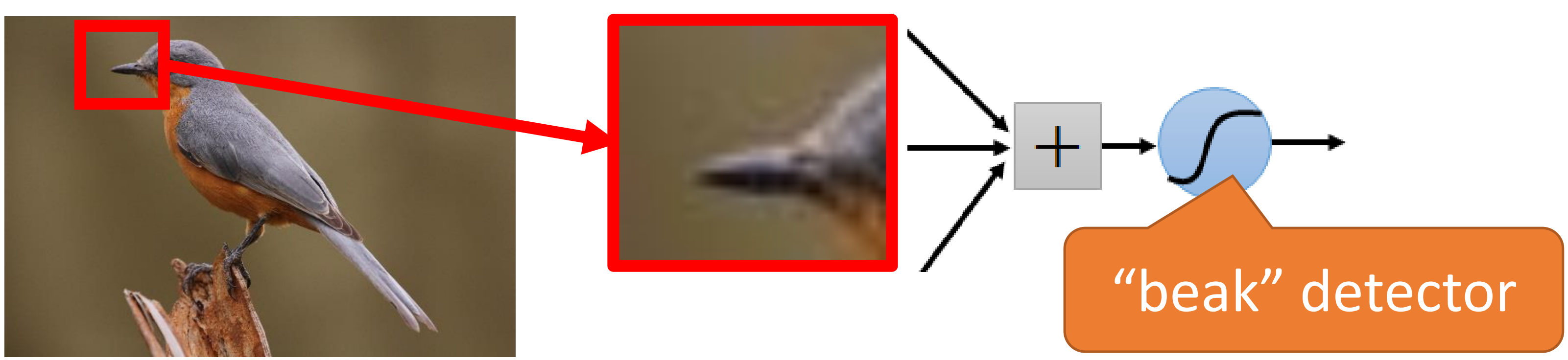
Can the fully connected network be simplified by considering the properties of image recognition?

Why CNN for Image

- Some patterns are much smaller than the whole image

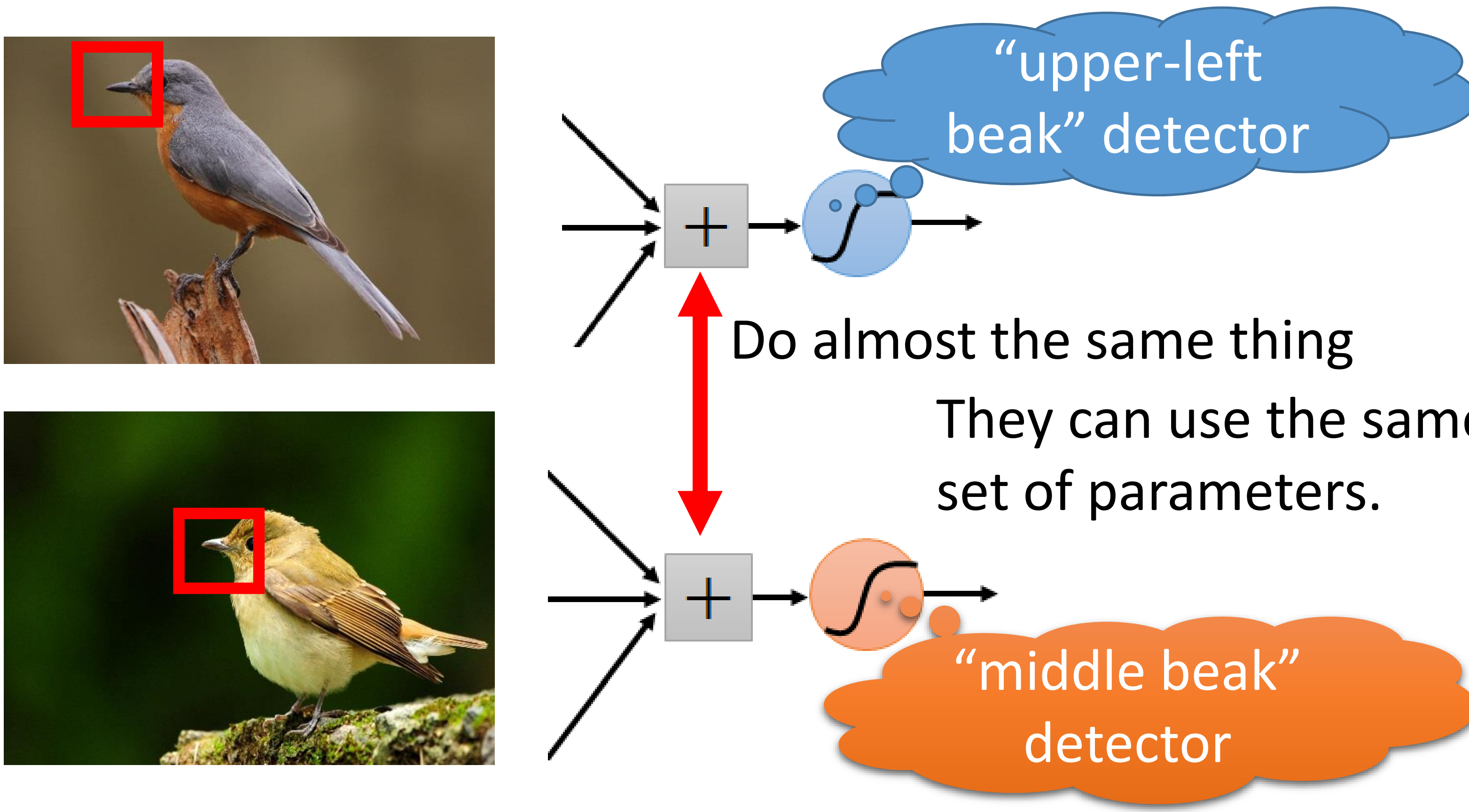
A neuron does not have to see the whole image to discover the pattern.

Connecting to small region with less parameters



Why CNN for Image

- The same patterns appear in different regions.



Why CNN for Image

- Subsampling the pixels will not change the object

bird

subsampling

bird

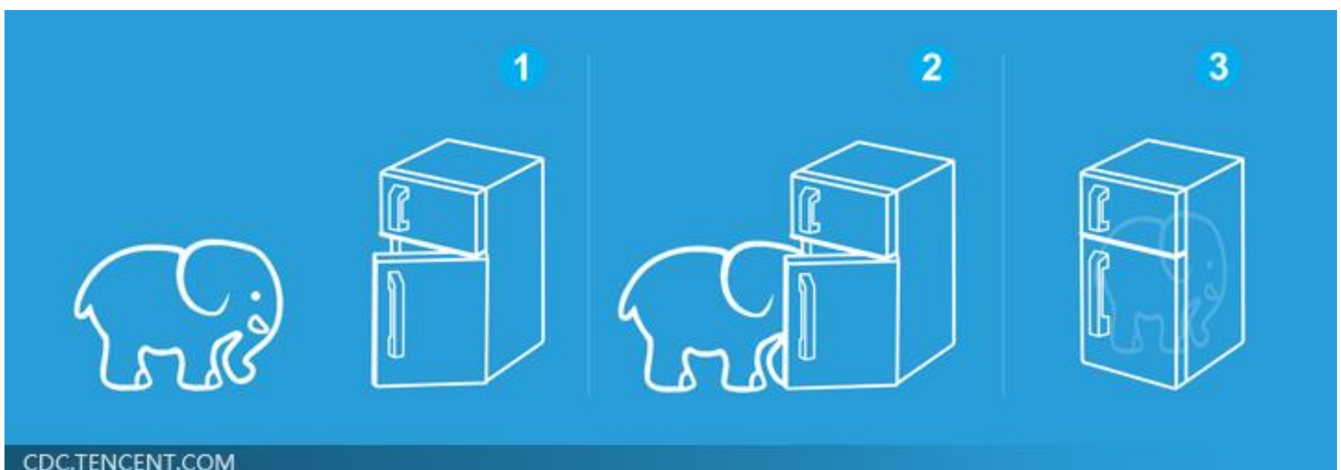
We can subsample the pixels to make image smaller

Less parameters for the network to process the image

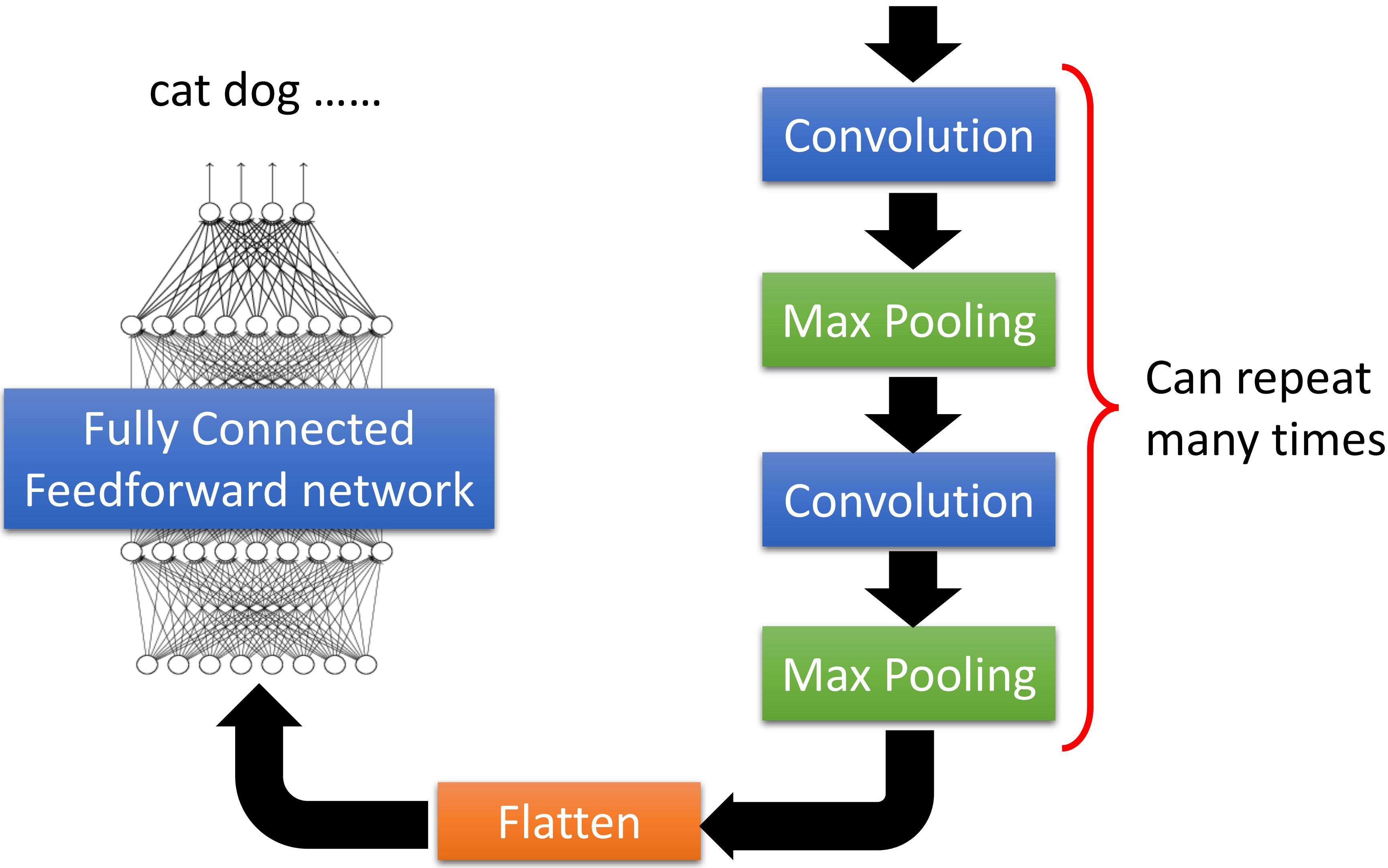
Three Steps for Deep Learning

Step 1: Convolutional Neural Network → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



The whole CNN



The whole CNN

Property 1

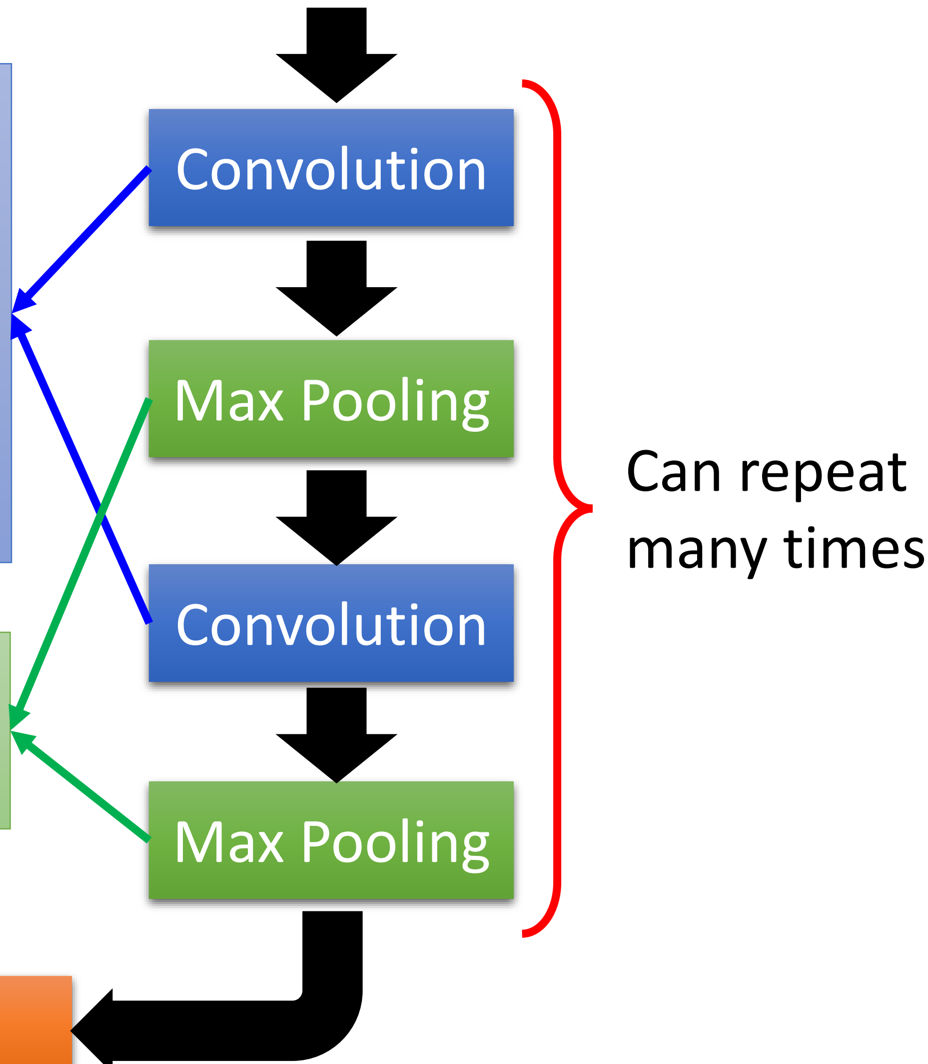
- Some patterns are much smaller than the whole image

Property 2

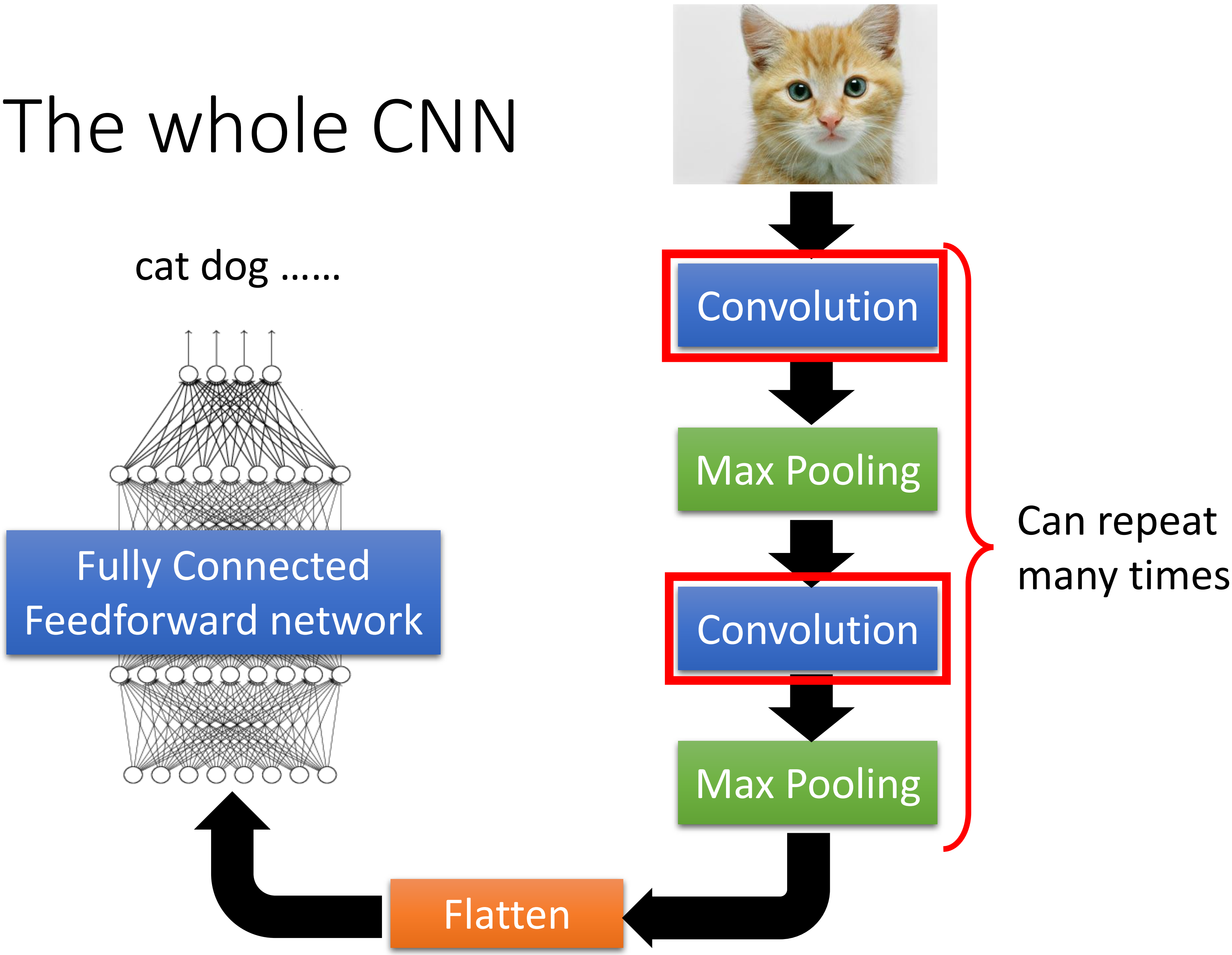
- The same patterns appear in different regions.

Property 3

- Subsampling the pixels will not change the object



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

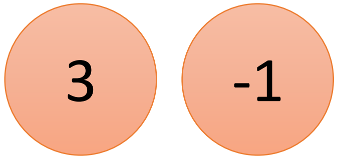
1	-1	-1
-1	1	-1
-1	-1	1

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

3 -3

We set stride=1 below

CNN – Convolution

Filter 1

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

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

Property 2

CNN – Convolution

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

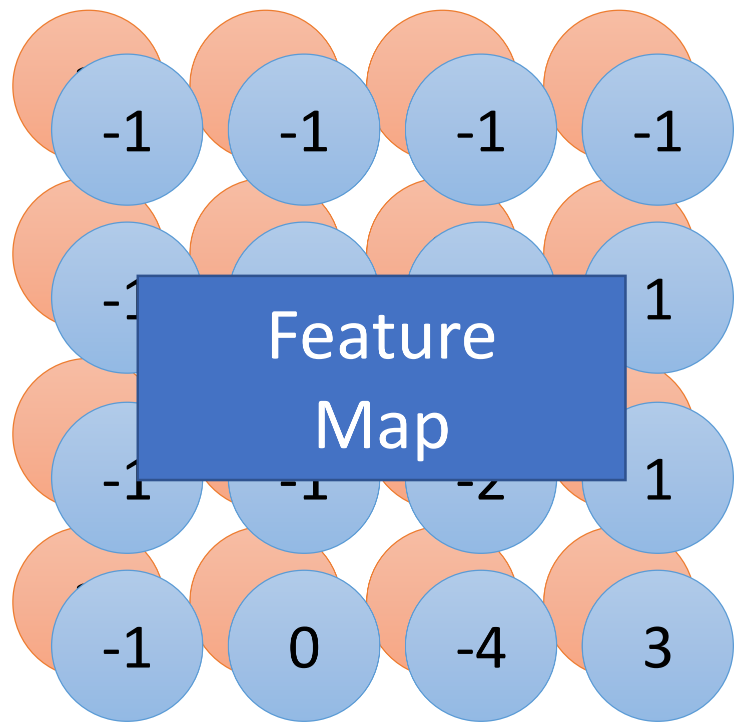
Filter 2

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 – Zero Padding

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

Filter 1

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

6 x 6 image

You will get another 6 x 6 images in this way

→ Zero padding

CNN – Colorful image

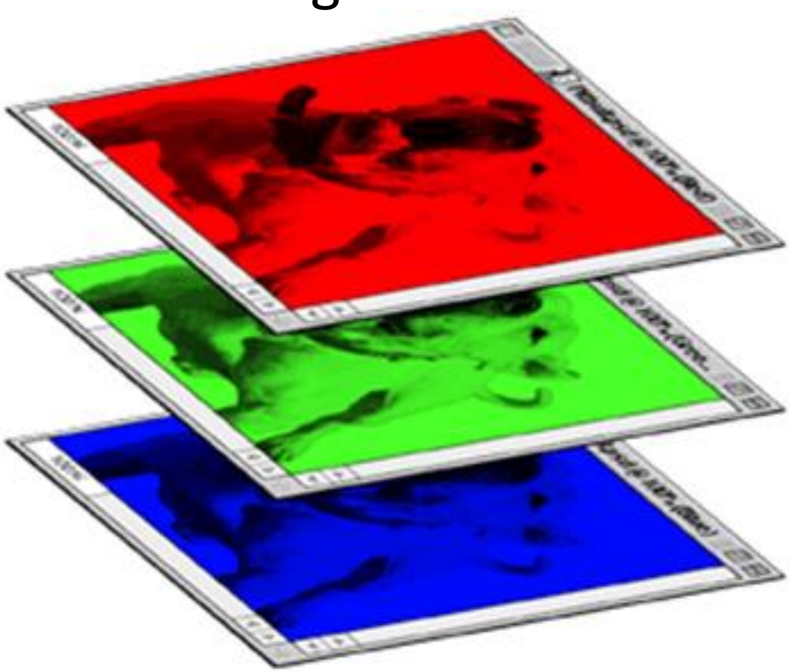
Filter 1

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

Filter 2

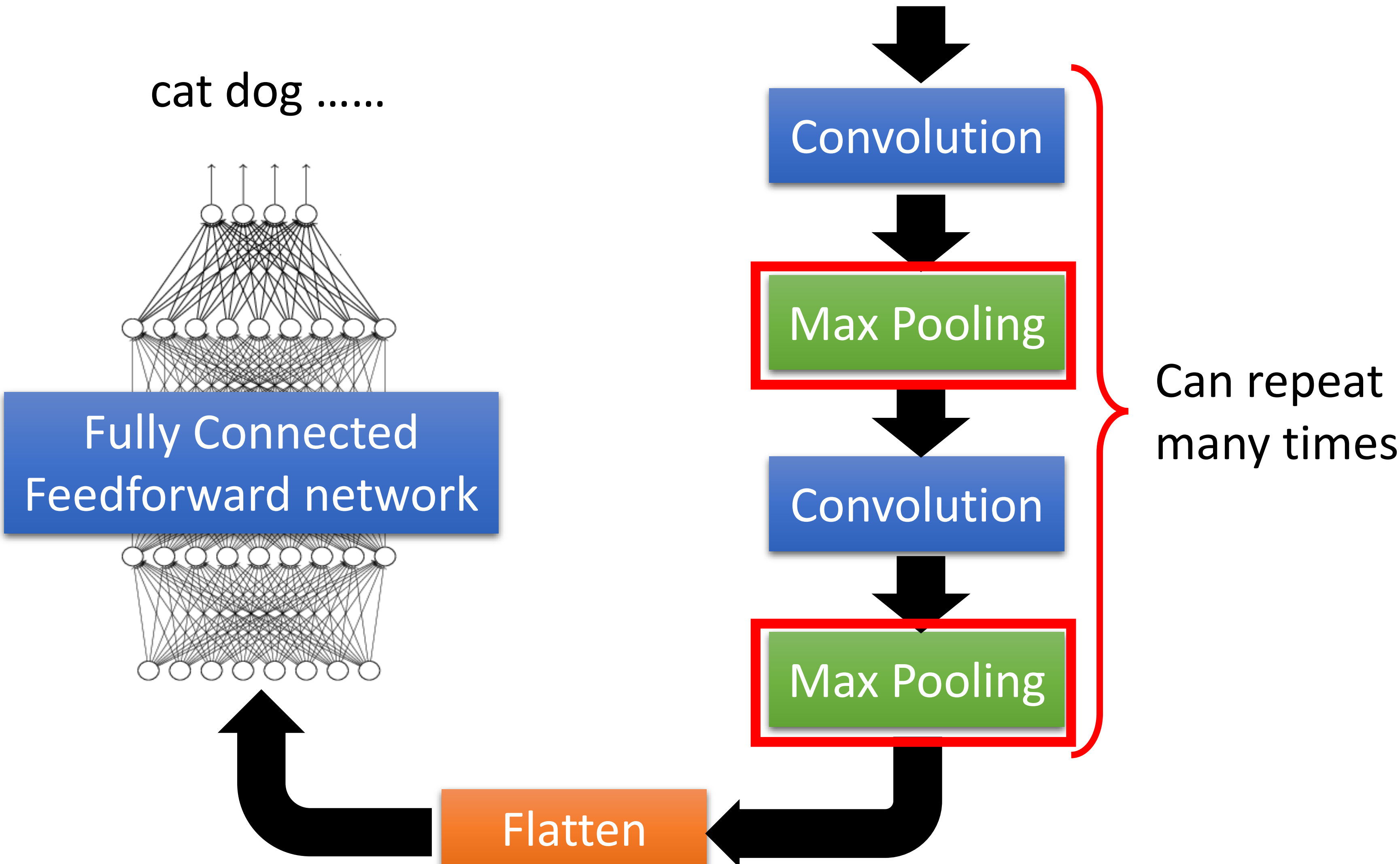
-1	1	-1
-1	1	-1
-1	1	-1

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



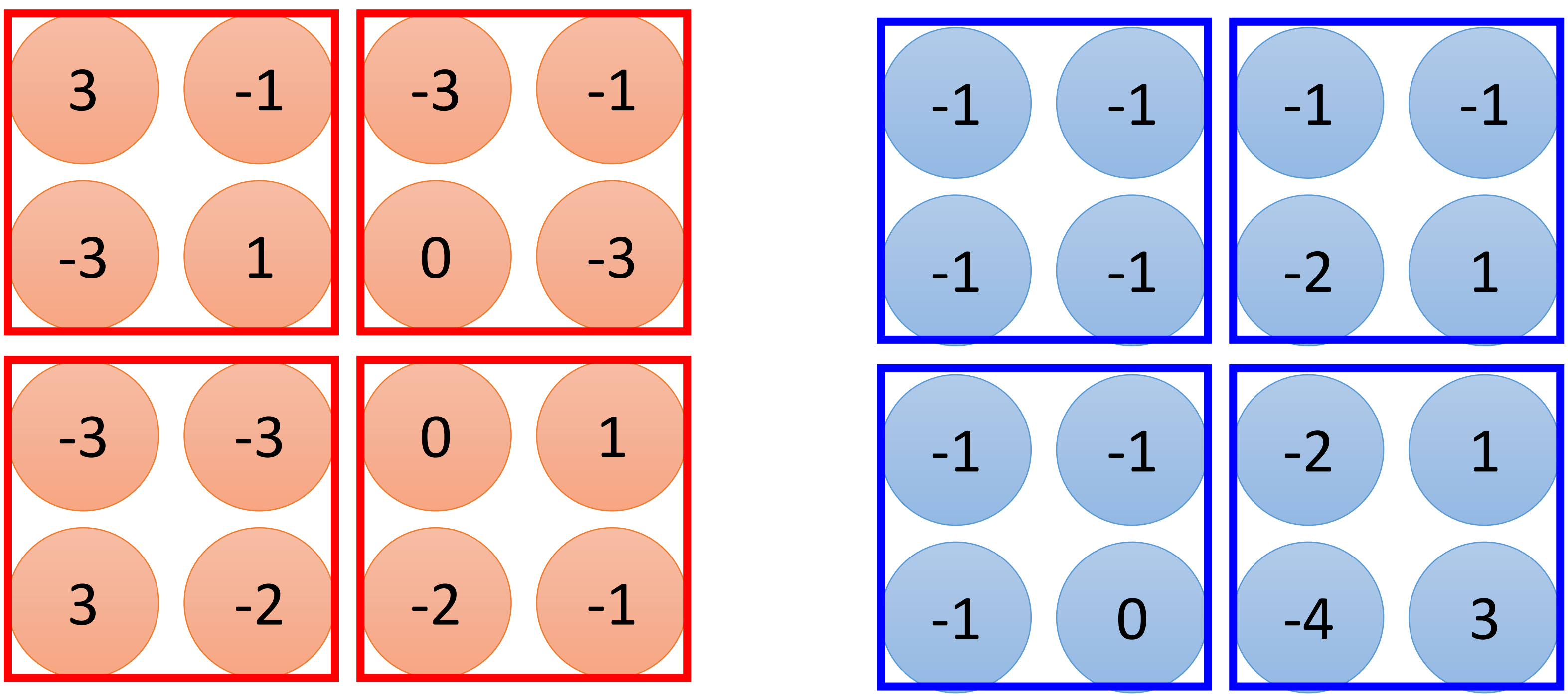
CNN – Max Pooling

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

Filter 1

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

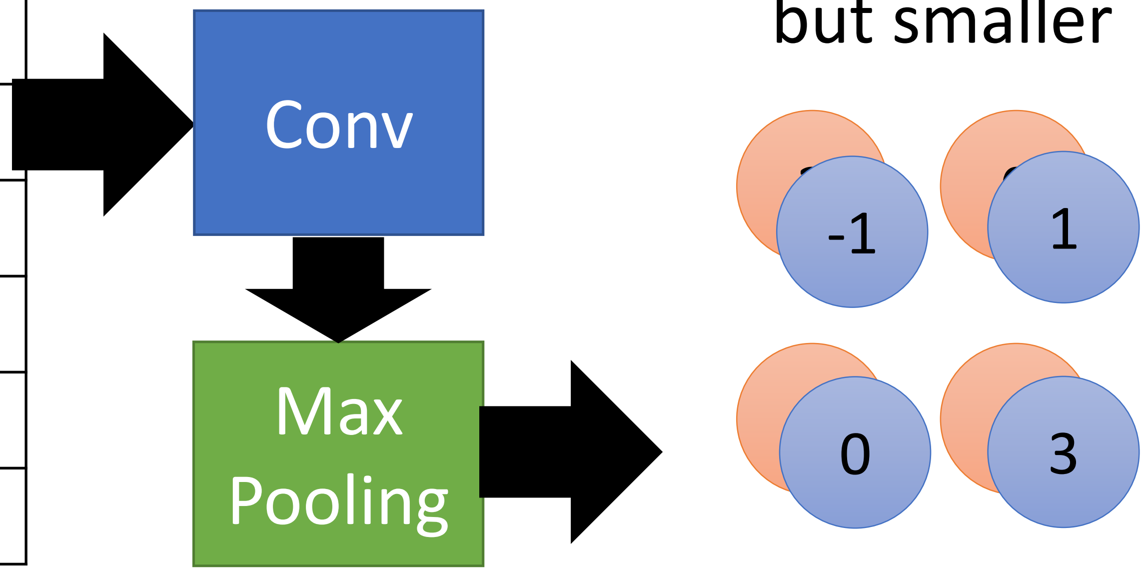
Filter 2



CNN – Max Pooling

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

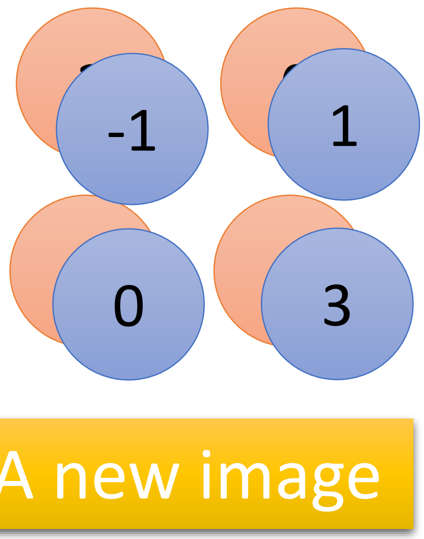


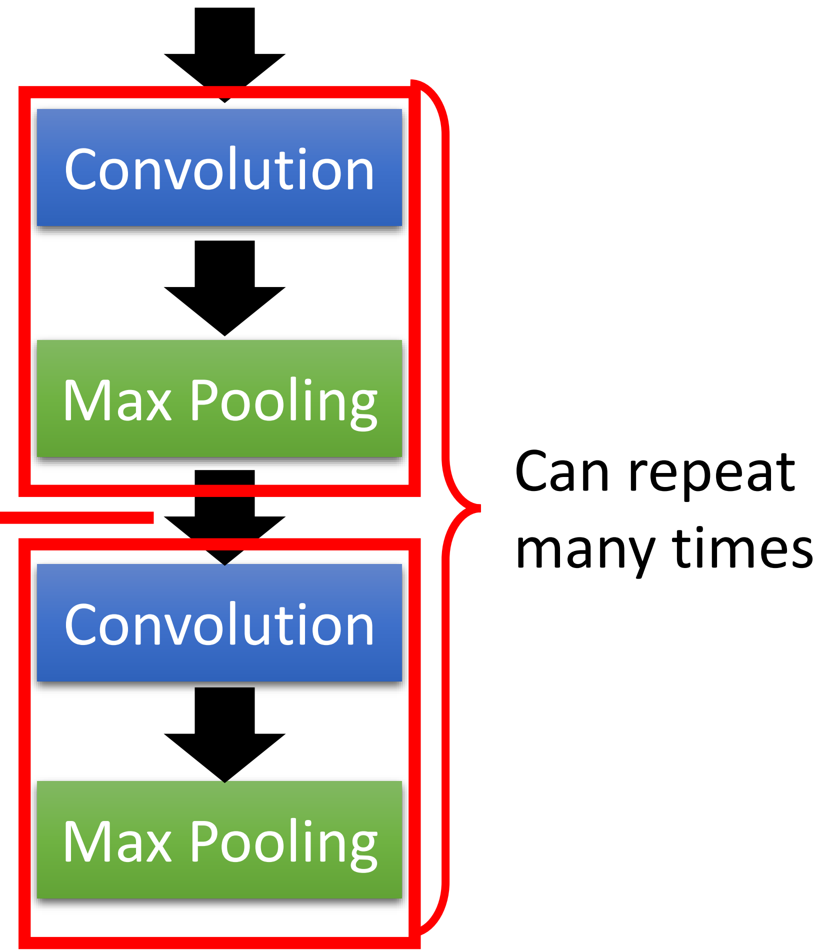
New image but smaller

2 x 2 image

Each filter is a channel

The whole CNN

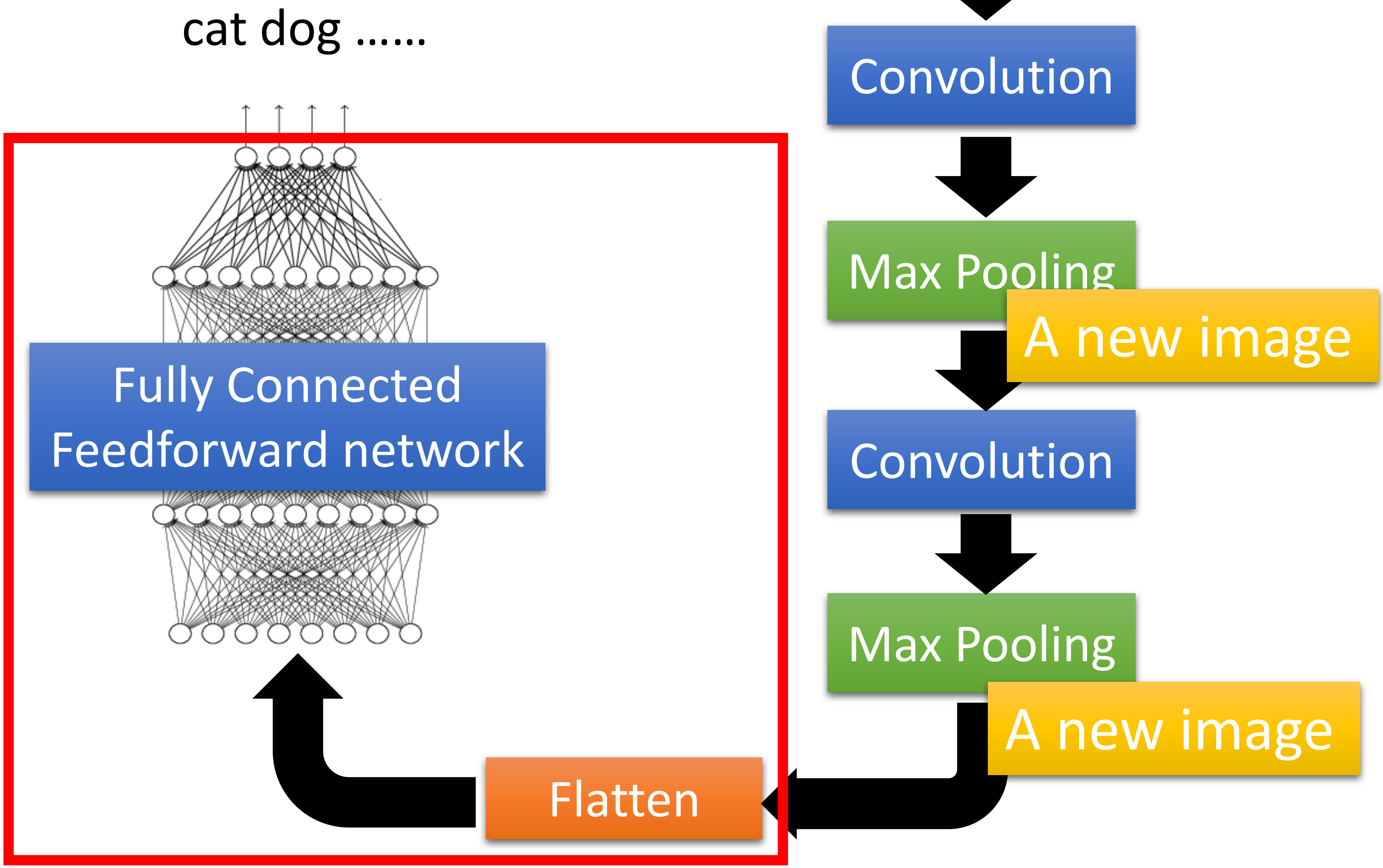




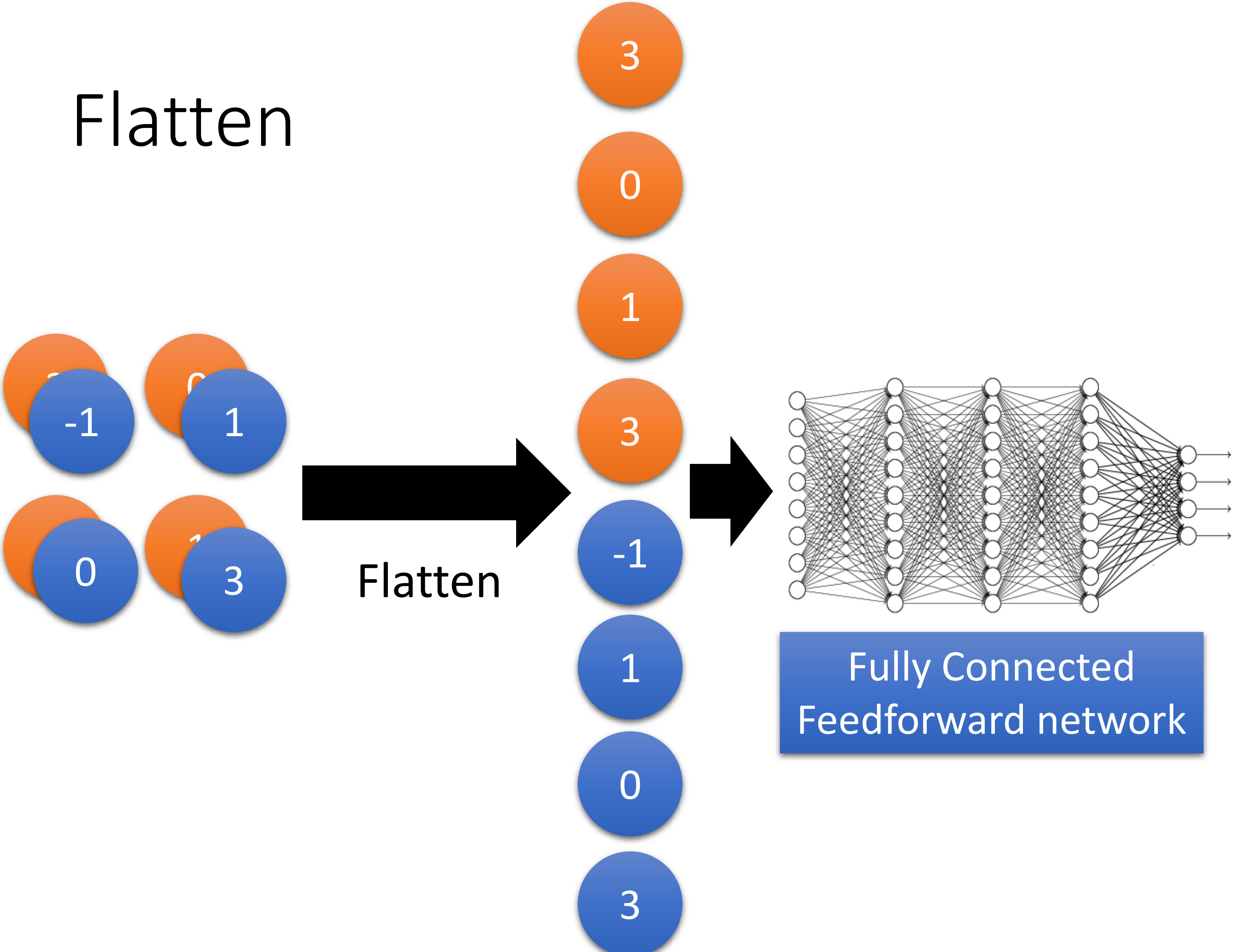
Smaller than the original image

The number of the channel is the number of filters

The whole CNN

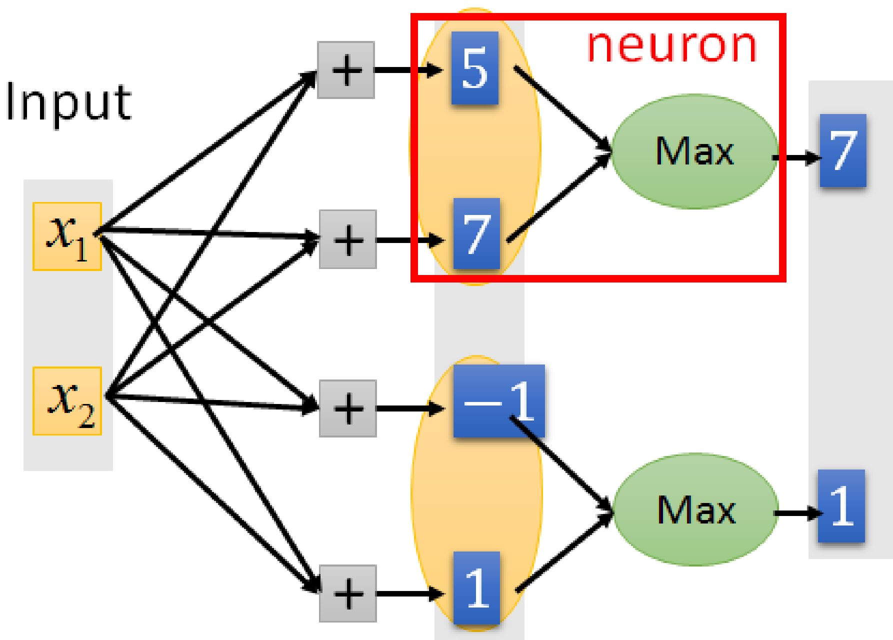


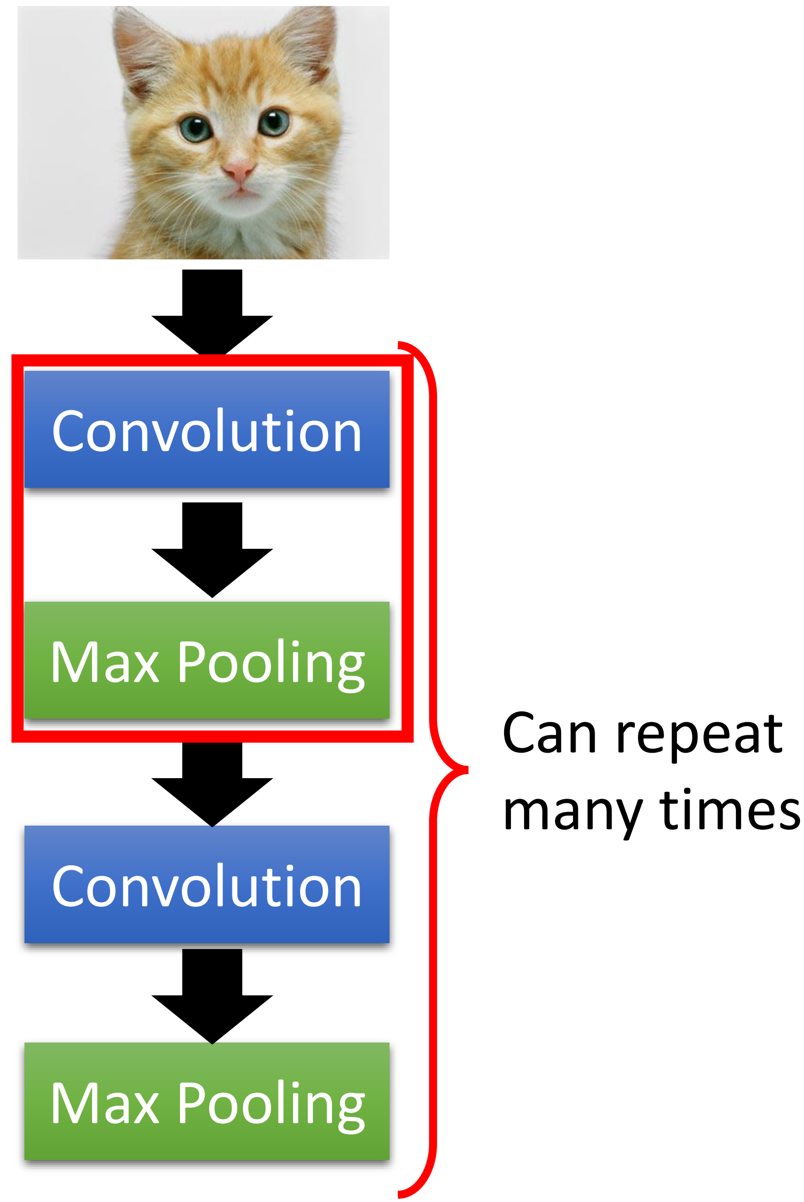
Flatten

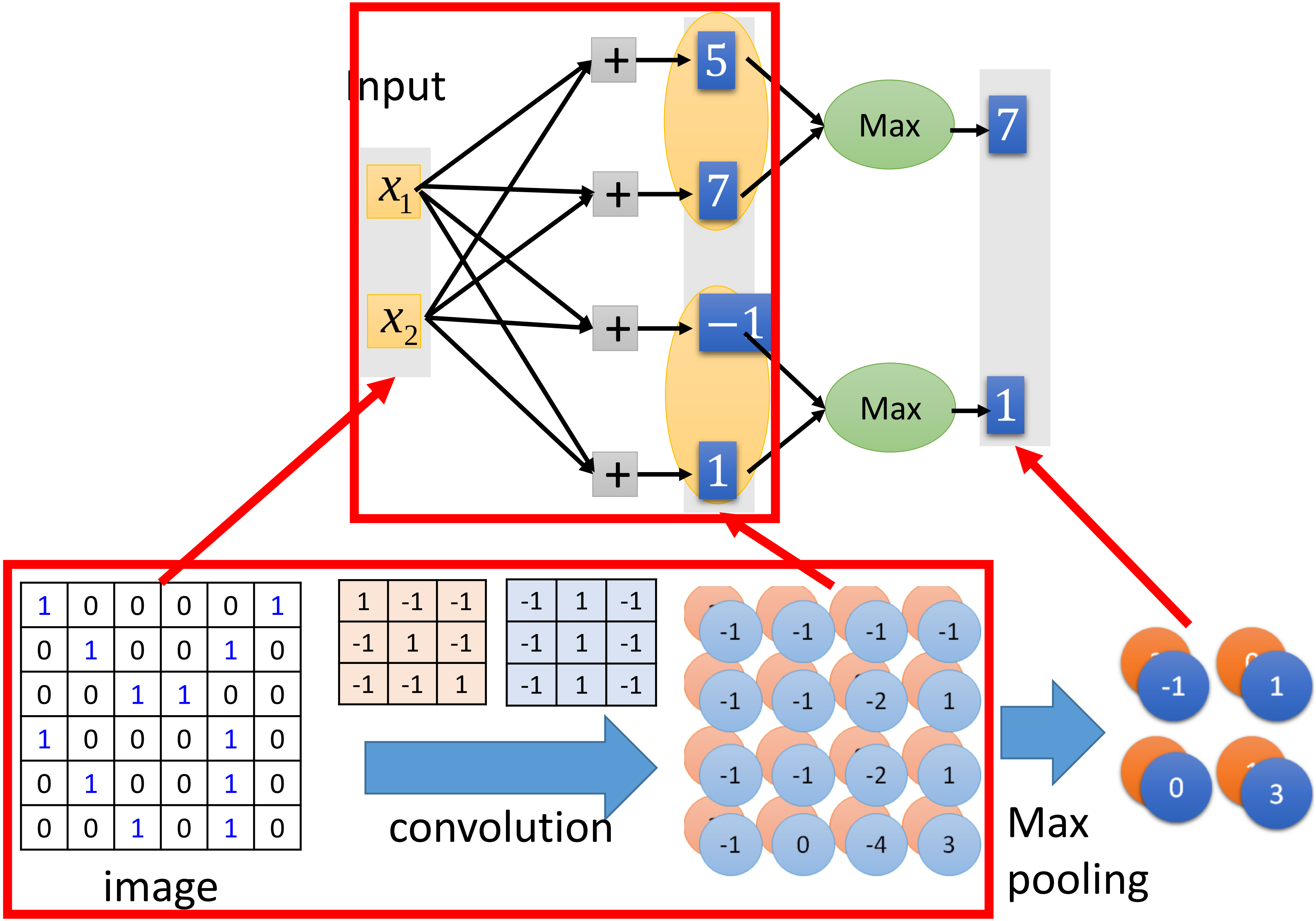


-1
1
0
3
Flatten
3
0
1
3
-1
1
0
3
Fully Connected
Feedforward network

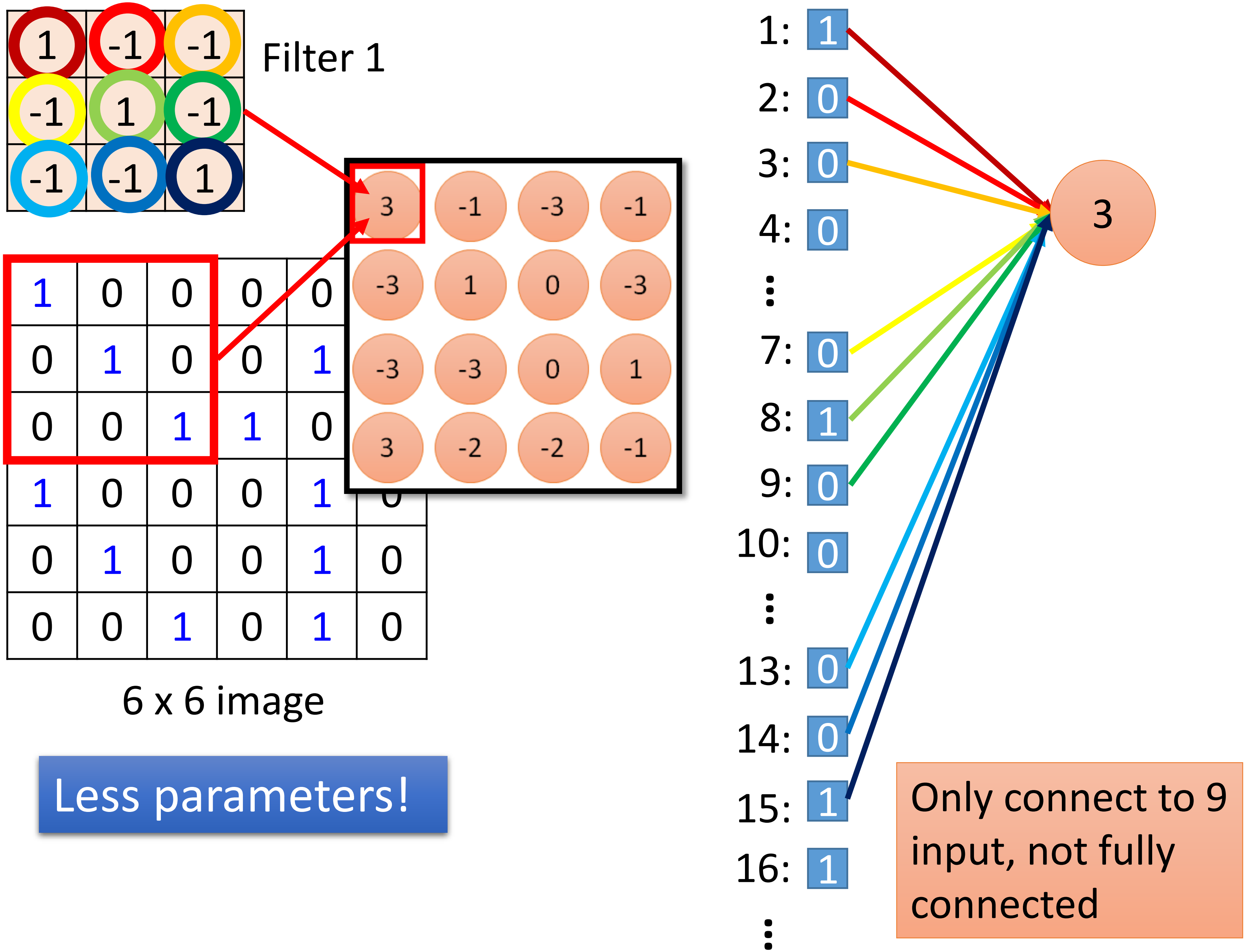
The whole CNN

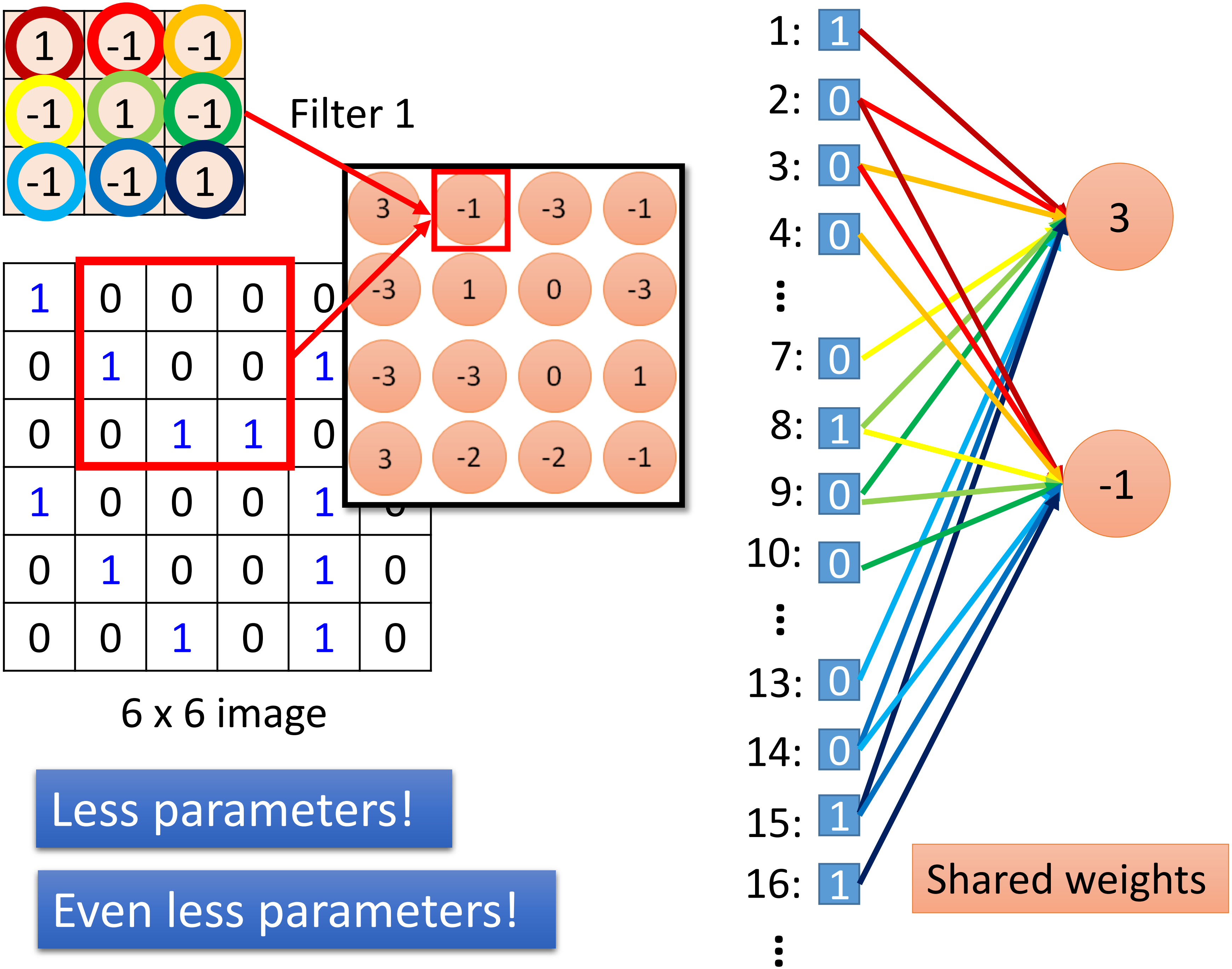




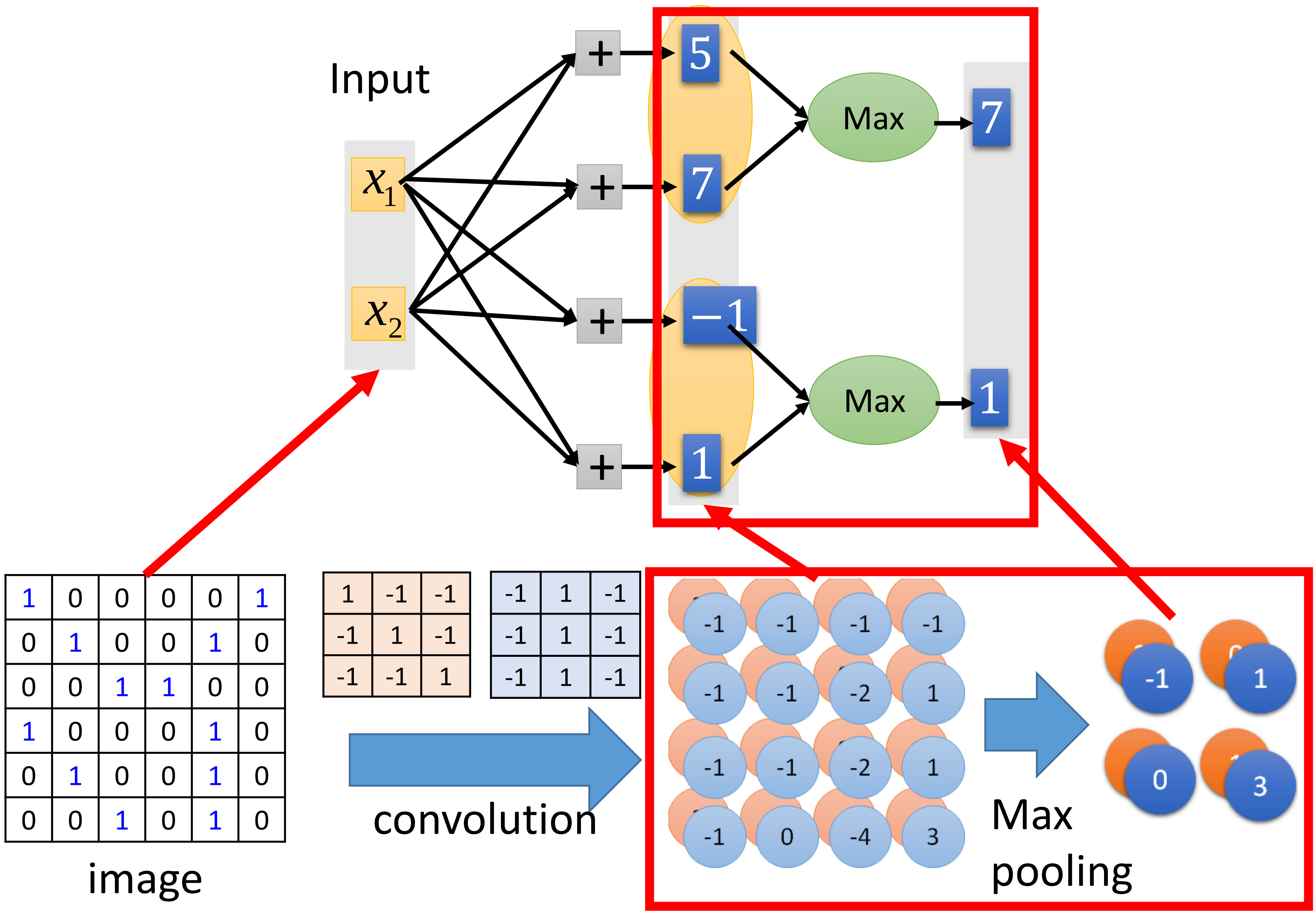


(Ignoring the non-linear activation function after the convolution.)

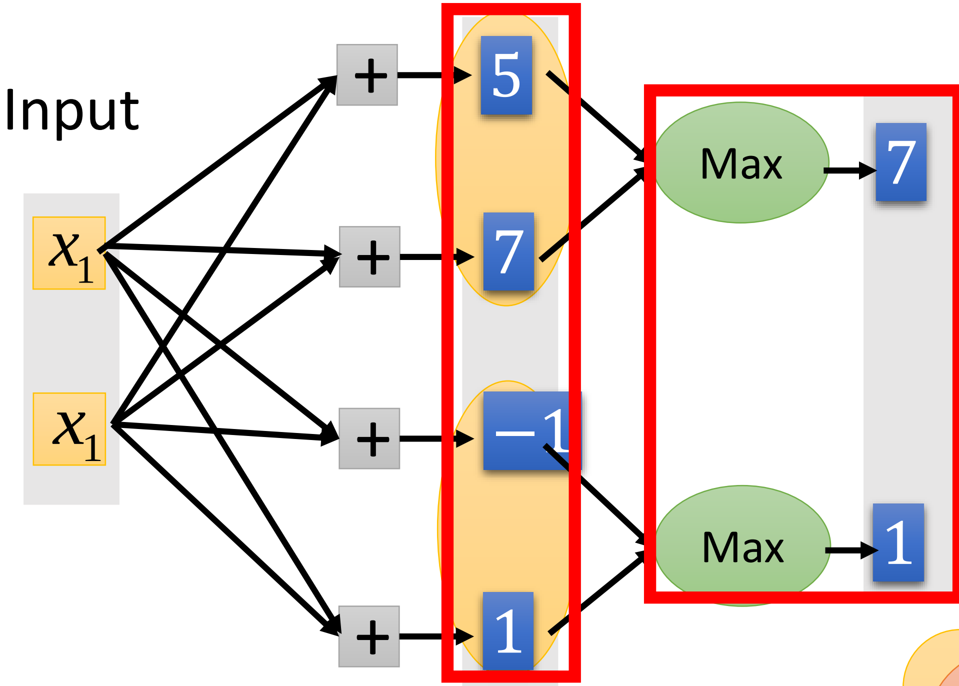

Filter 1
6 x 6 image
Less parameters!
Only connect to 9 input, not fully connected

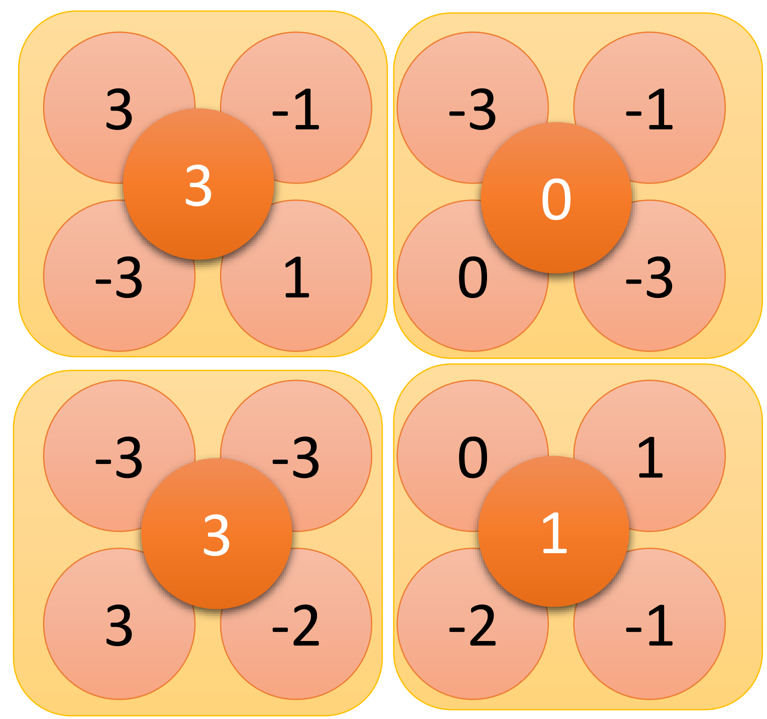


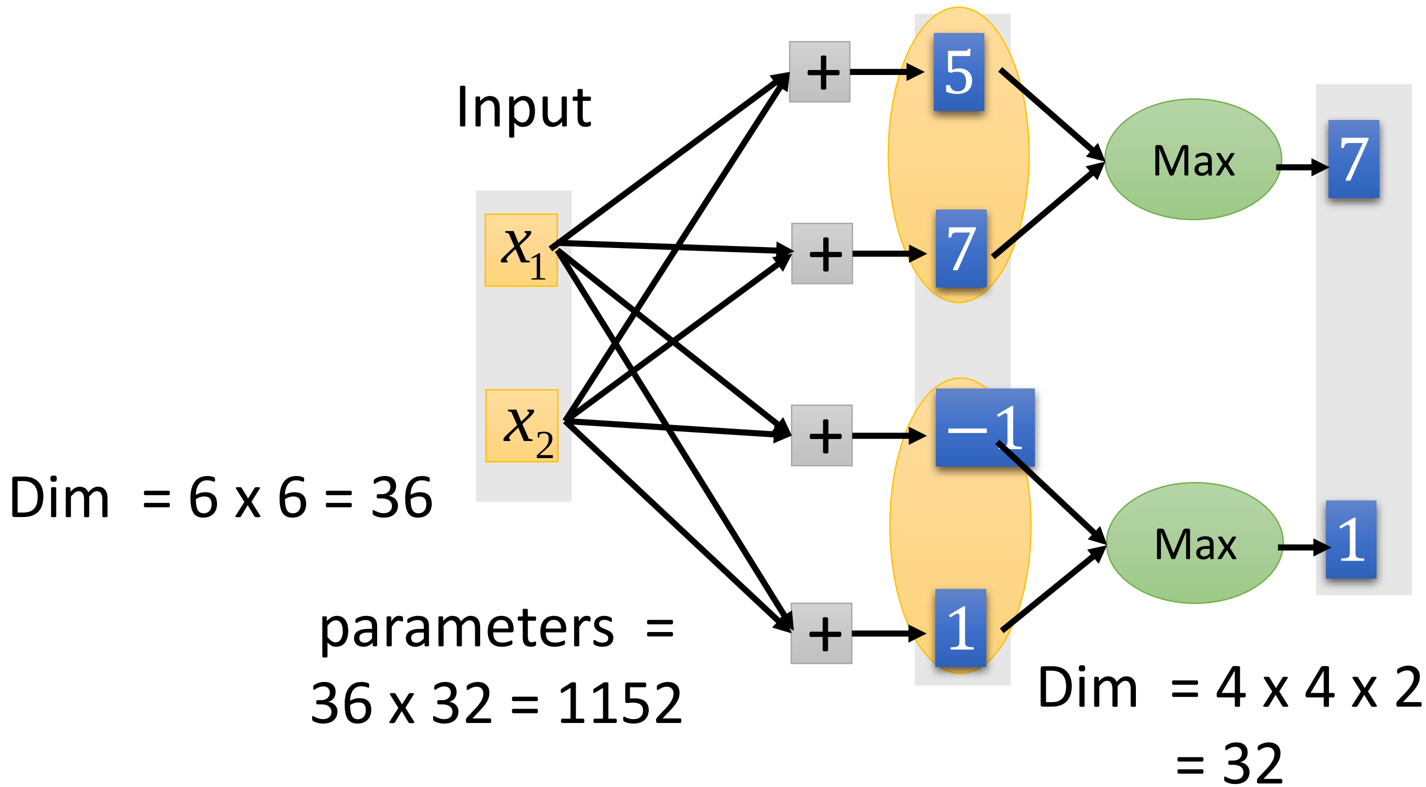
1 -1 -1
-1 1 -1
-1 -1 1
Filter 1
1 0 0 0 0
0 1 0 0 1
0 0 1 1 0
1 0 0 0 1
0 1 0 0 1 0
0 0 1 0 1 0
3 -1 -3 -1
-3 1 0 -3
-3 -3 0 1
3 -2 -2 -1
6 x 6 image
Less parameters!
Even less parameters!
1: 1
2: 0
3: 0
4: 0
7: 0
8: 1
9: 0
10: 0
13: 0
14: 0
15: 1
16: 1
3
-1
Shared weights



(Ignoring the non-linear activation function after the convolution.)


Input
x_1
x_1
+
+
+
+
5
7
−1
1
Max
Max
7
1


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

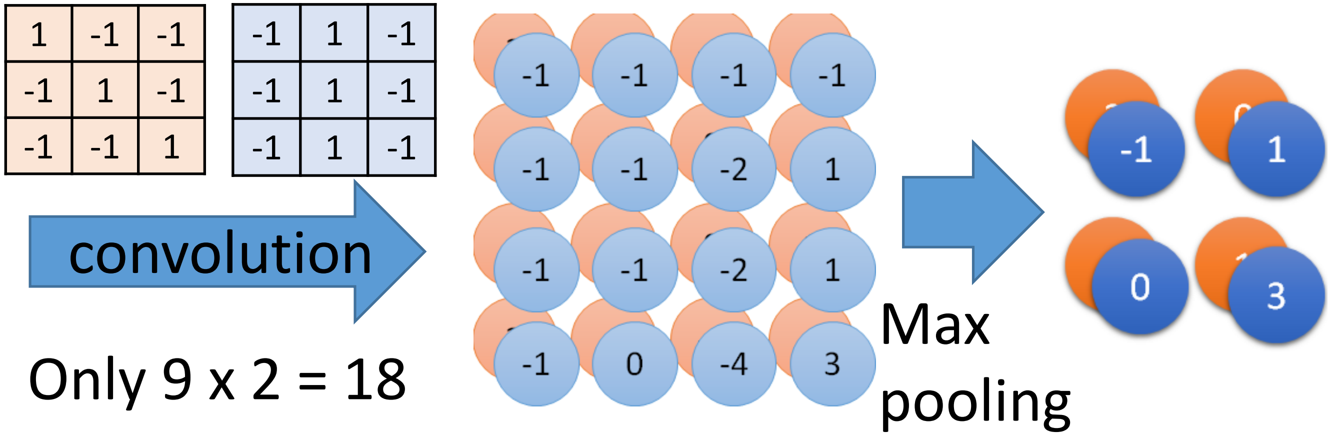


1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

image

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

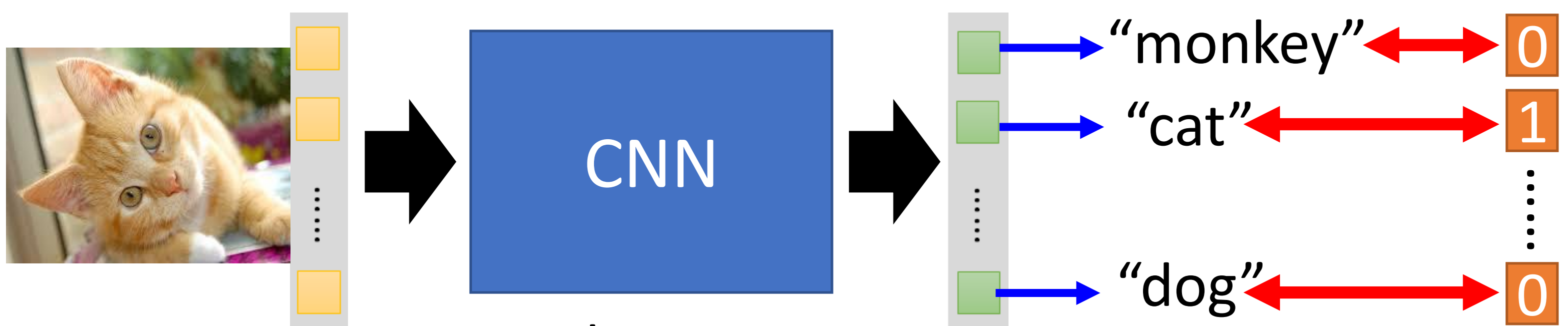
-1	1	-1
-1	1	-1
-1	1	-1



Only 9 x 2 = 18
parameters

Convolutional Neural Network

Step 1: Convolutional Neural Network → Step 2: goodness of function → Step 3: pick the best function



Convolution, Max Pooling, fully connected

Learning: Nothing special, just gradient descent ……

Playing Go

19 x 19 matrix (image)

Black: 1

white: -1

none: 0

Network

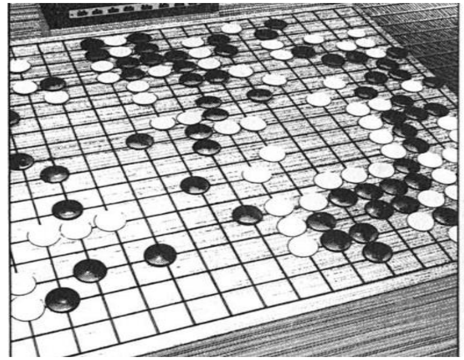
Next move (19 x 19 positions)

19 x 19 vector

Fully-connected feedword network can be used

But CNN performs much better.

Playing Go



record of previous plays

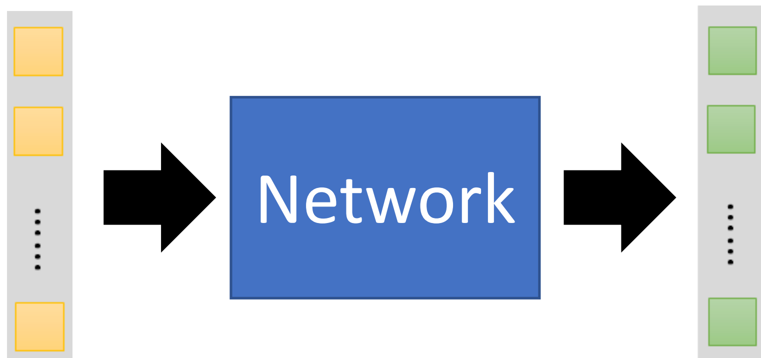
進藤光 v.s. 社清春

黑: 5之五

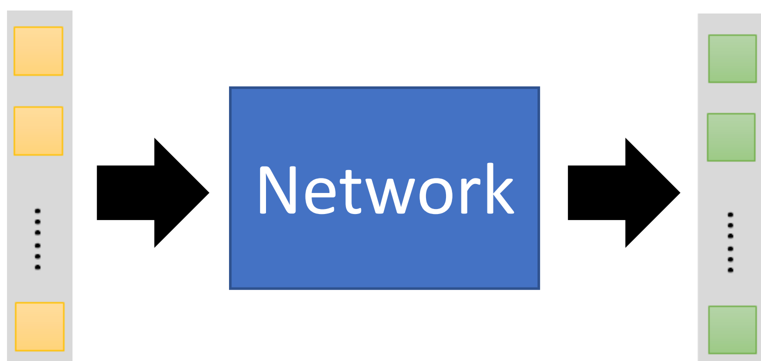
→ 白: 天元

→ 黑: 五之5

Training:



Target:
"天元" = 1
else = 0

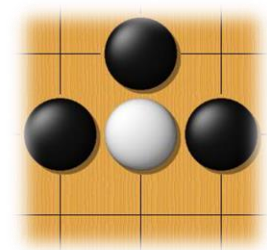


Target:
"五之 5" = 1
else = 0

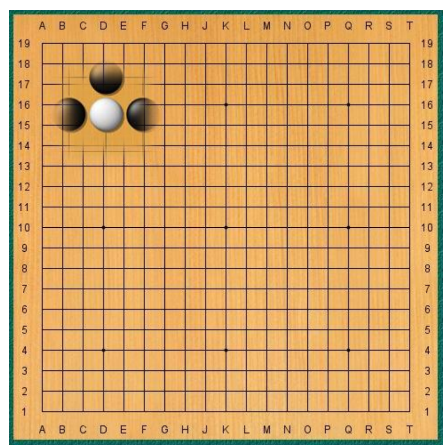
Why CNN for playing Go?

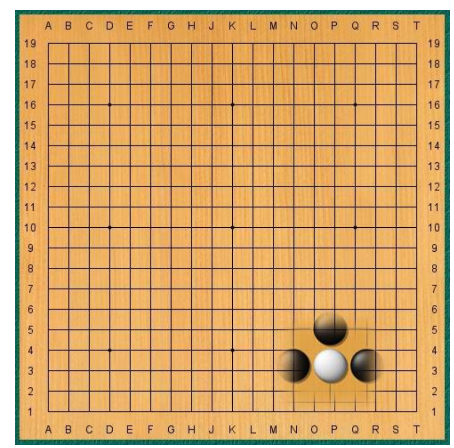
- Some patterns are much smaller than the whole image

Alpha Go uses 5 x 5 for first layer



- The same patterns appear in different regions.





Why CNN for playing Go?

- Subsampling the pixels will not change the object

Max Pooling

How to explain this???

Neural network architecture. The input to the policy network is a $19 \times 19 \times 48$ image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a 23×23 image, then convolves k filters of kernel size 5×5 with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a 21×21 image, then convolves k filters of kernel size 3×3 with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size 1×1 with strid … max func-
tion. The … Extended
Data Table 3 additionally show the results of training with $k = 128$, 256 and 384 filters.

Alpha Go does not use Max Pooling ……

Variants of Neural Networks

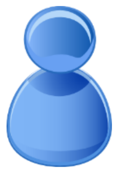
Convolutional Neural Network (CNN)

Recurrent Neural Network (RNN)

Neural Network with Memory

Example Application

- Slot Filling



I would like to arrive Taipei on November 2nd.

ticket booking system

Slot

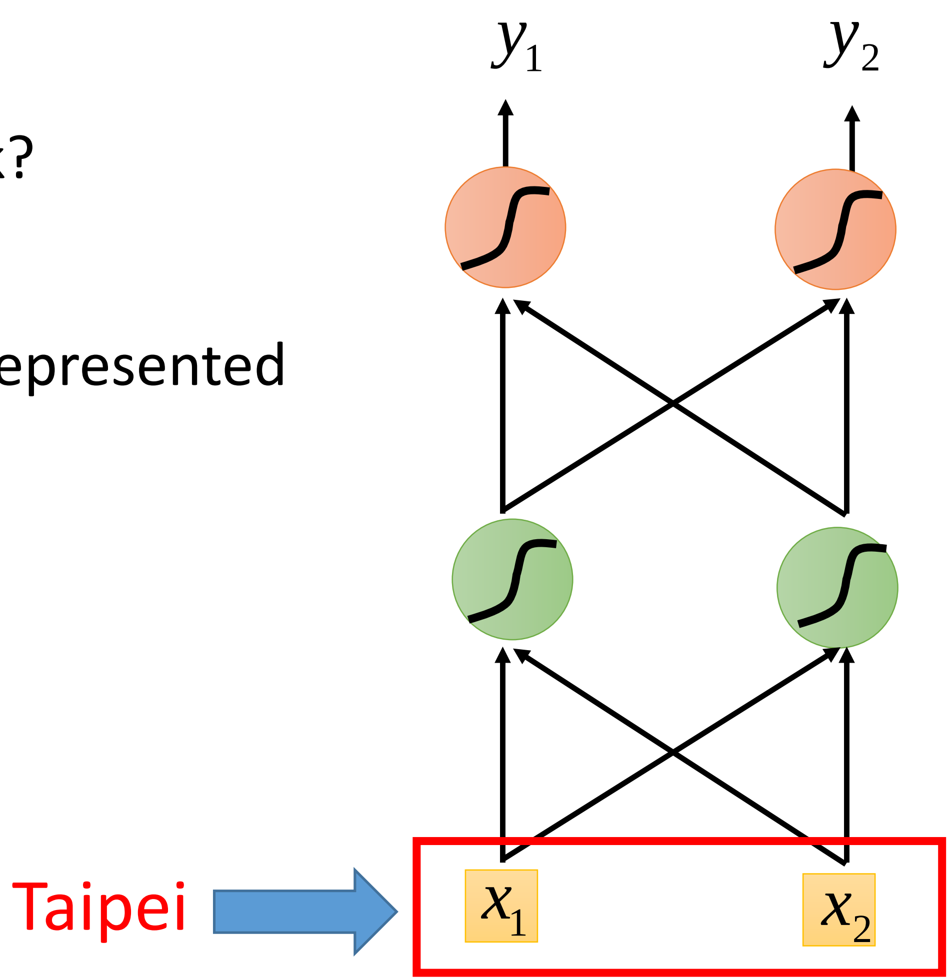
Destination:	Taipei
time of arrival:	November 2nd

Example Application

Solving slot filling by Feedforward network?

Input: a word

(Each word is represented as a vector)



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]

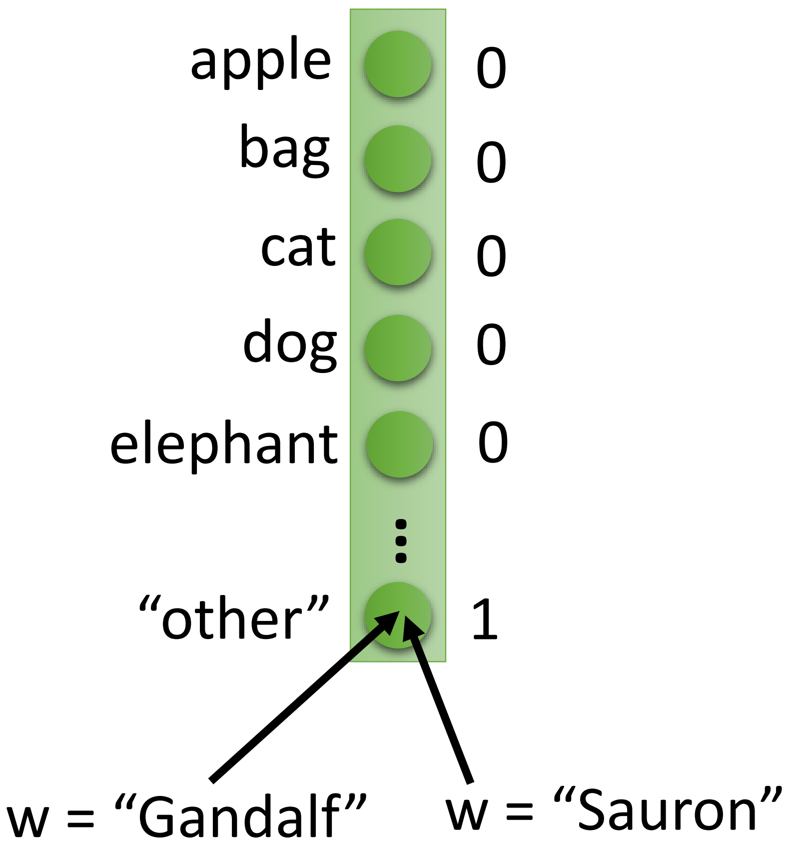
cat = [0 0 1 0 0]

dog = [0 0 0 1 0]

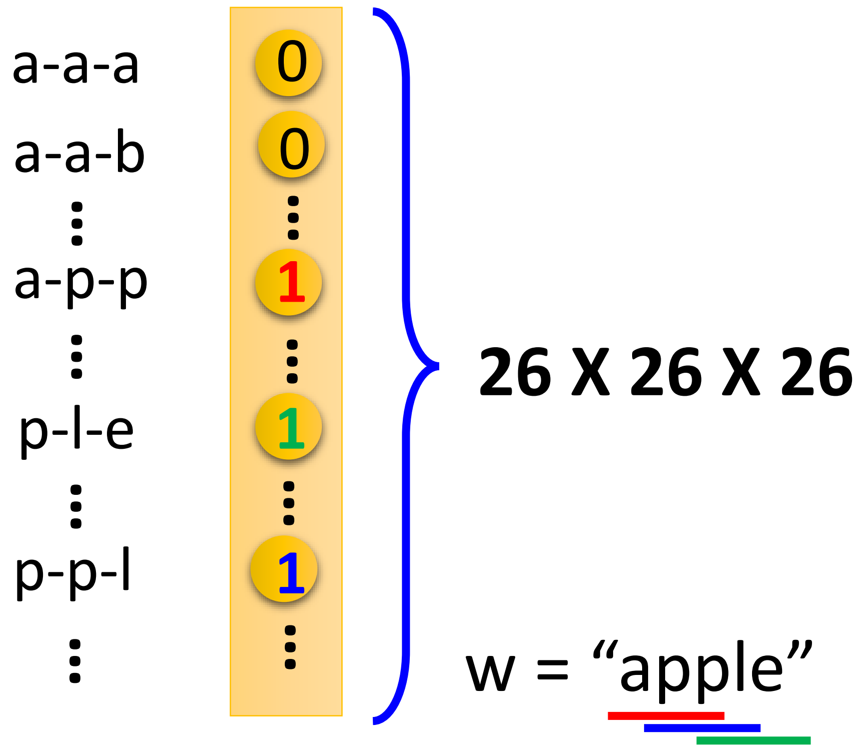
elephant = [0 0 0 0 1]

Beyond 1-of-N encoding

Dimension for "Other"



Word hashing



Example Application

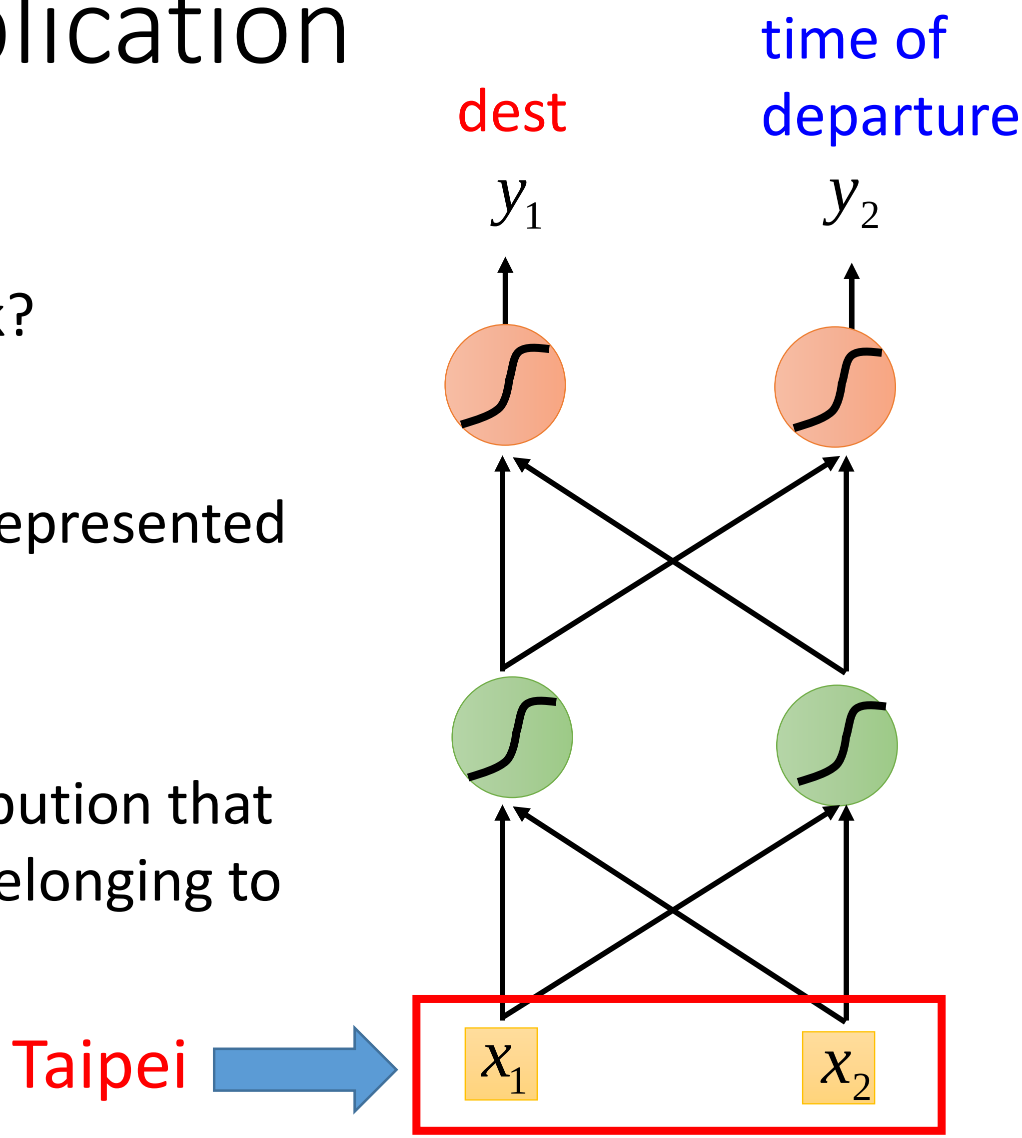
Solving slot filling by Feedforward network?

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 2^{nd}

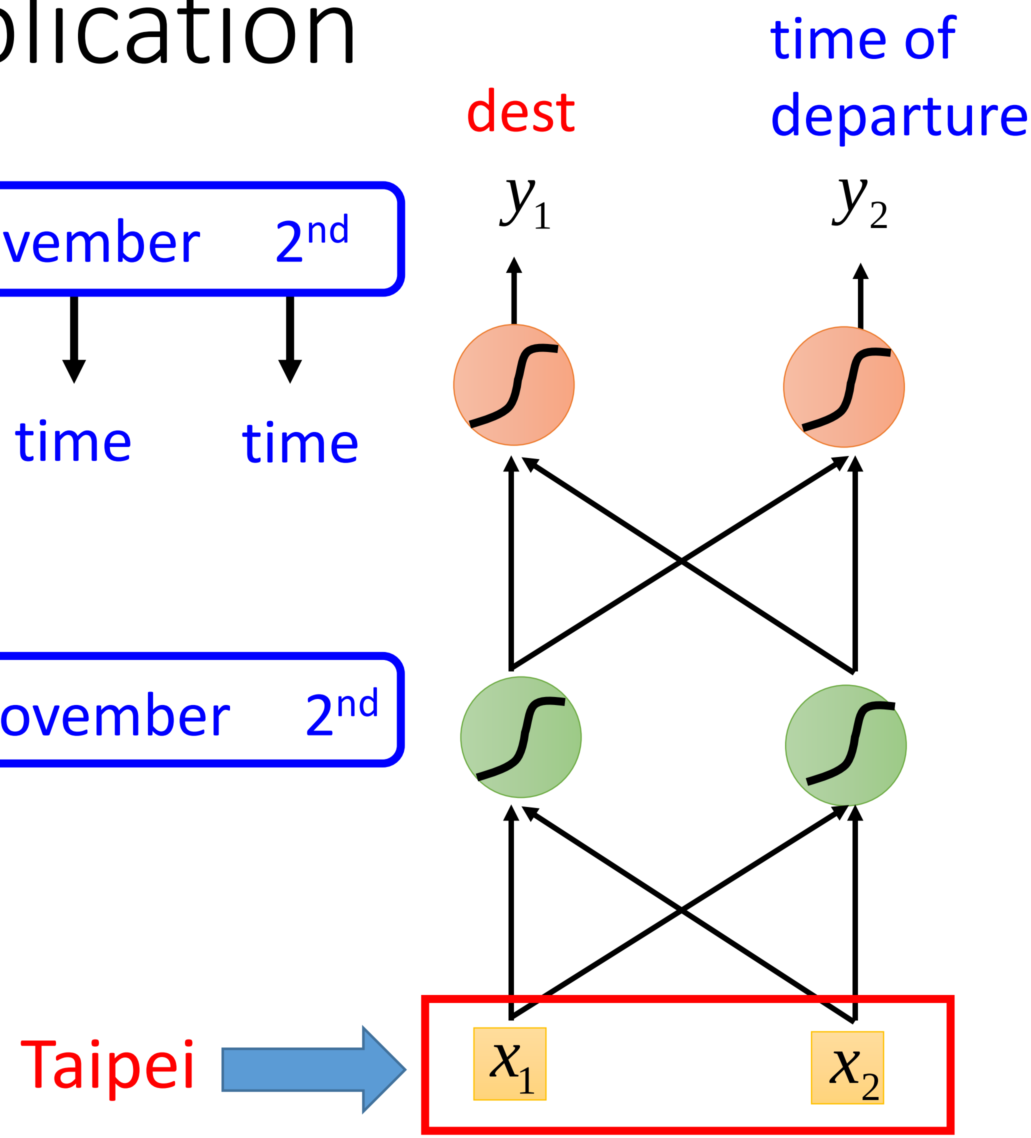
other dest other time time

Problem?

leave Taipei on November 2^{nd}

place of departure

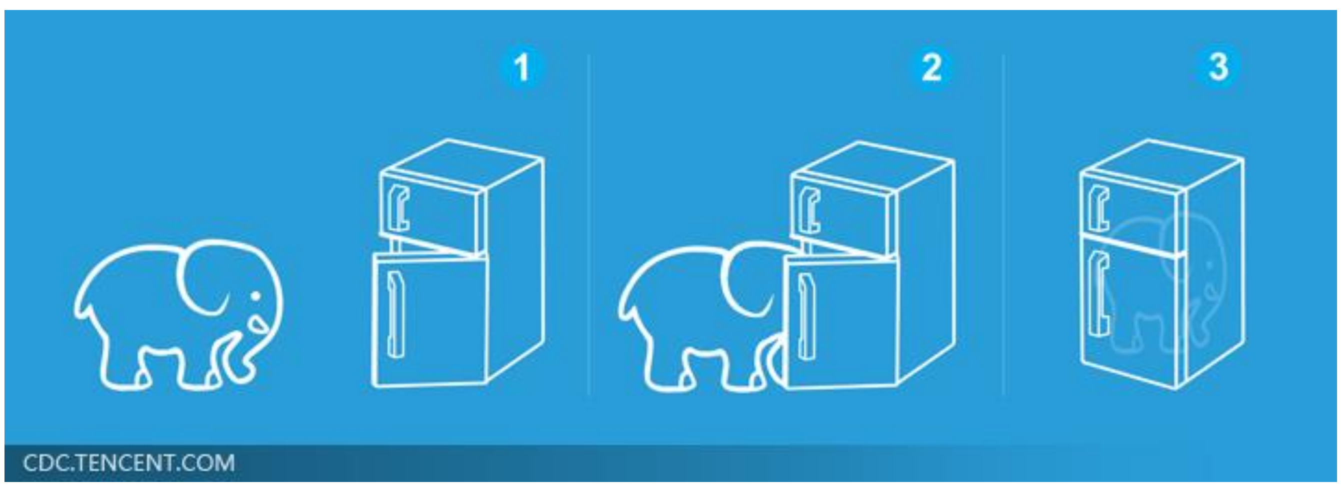
Neural network needs memory!



Three Steps for Deep Learning

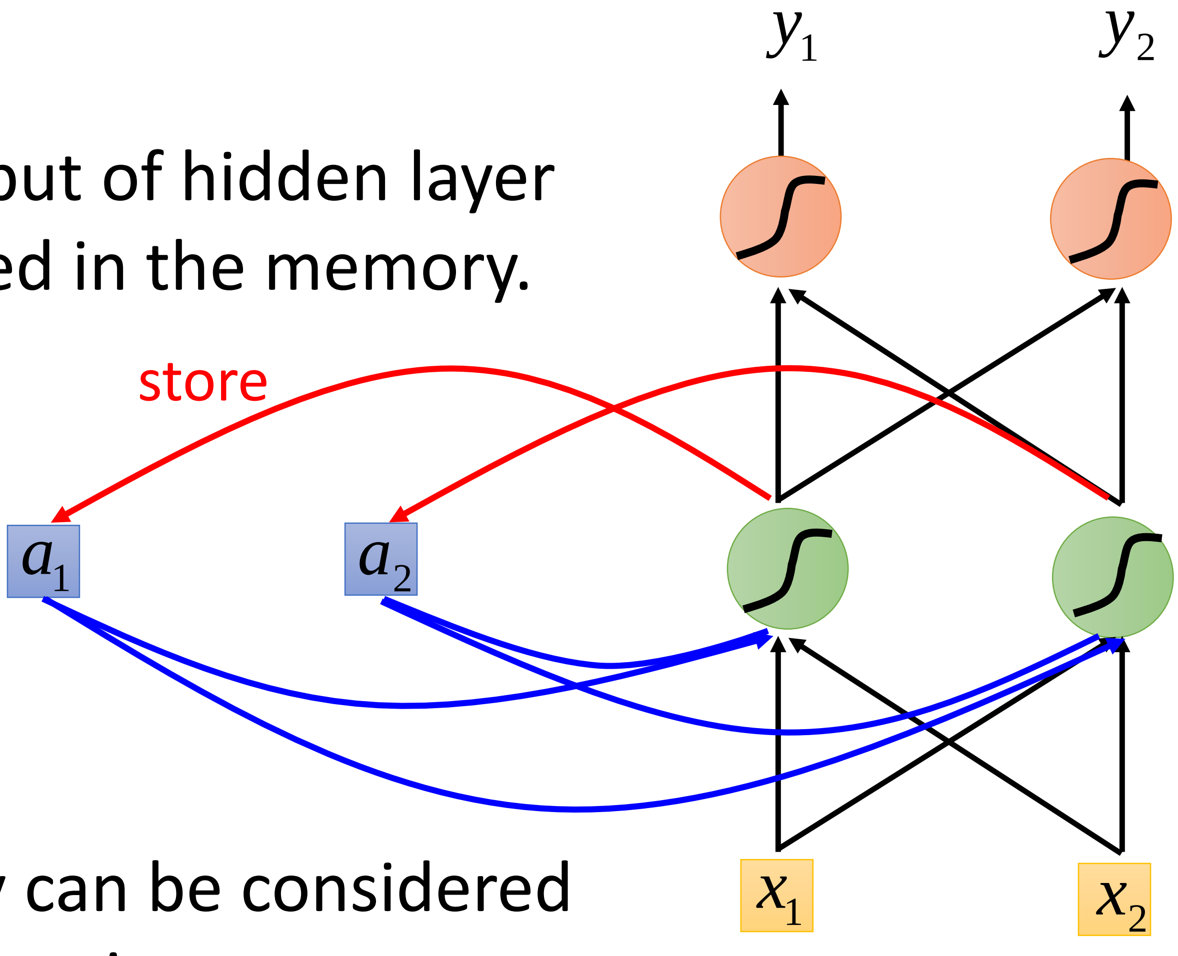
Step 1: Recurrent Neural Network → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



Recurrent Neural Network (RNN)

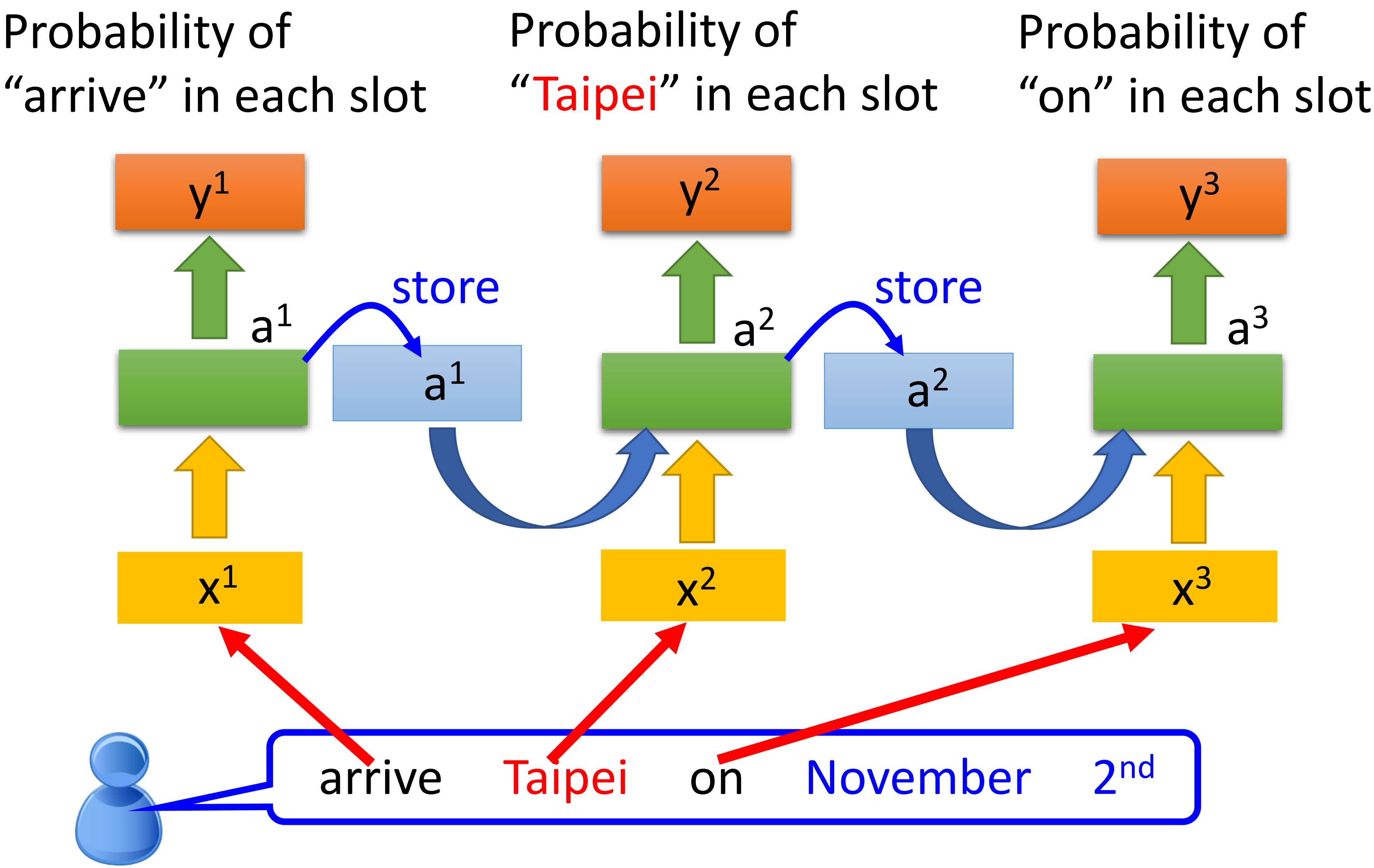
The output of hidden layer are stored in the memory.



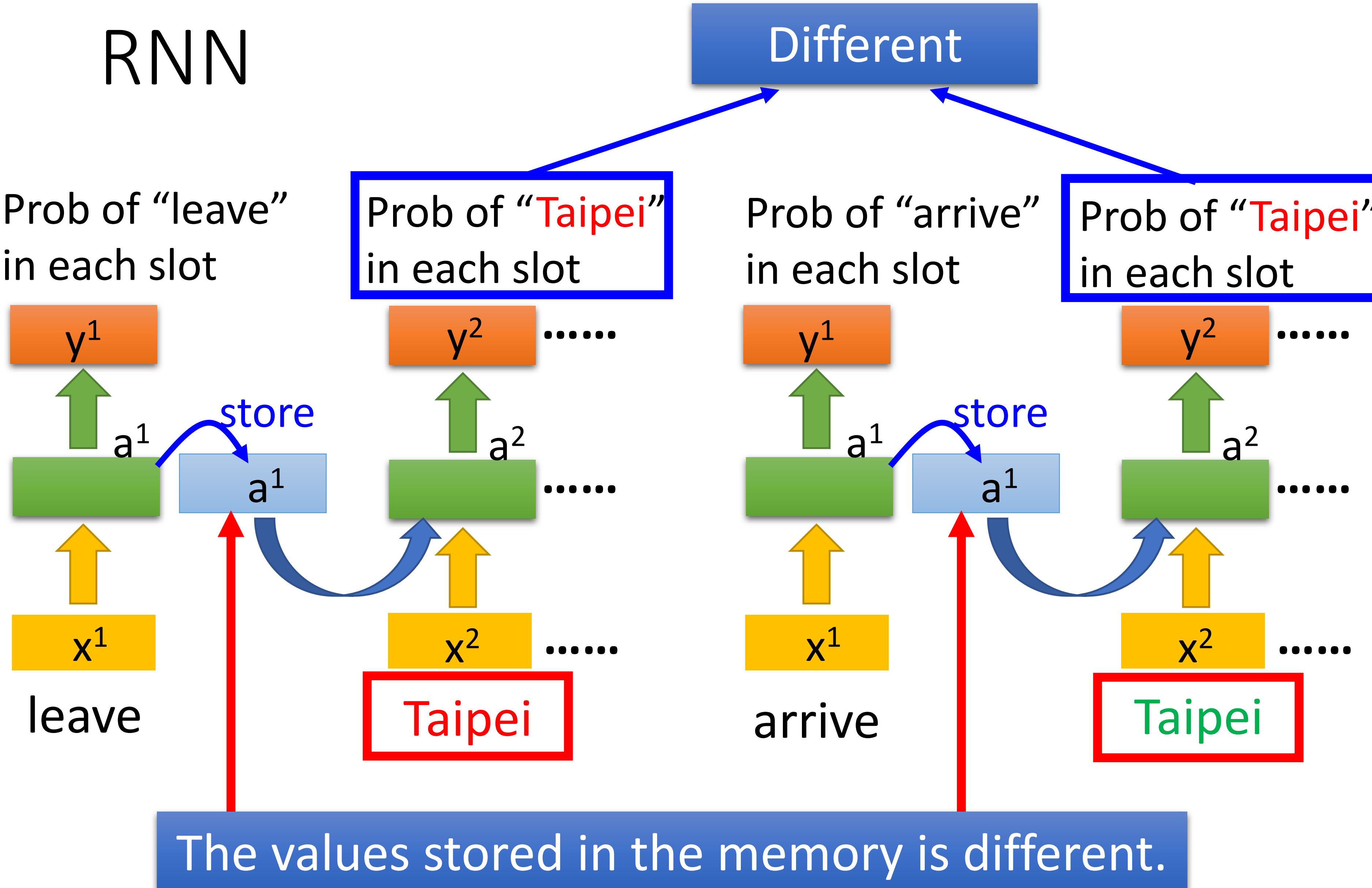
Memory can be considered as another input.

RNN

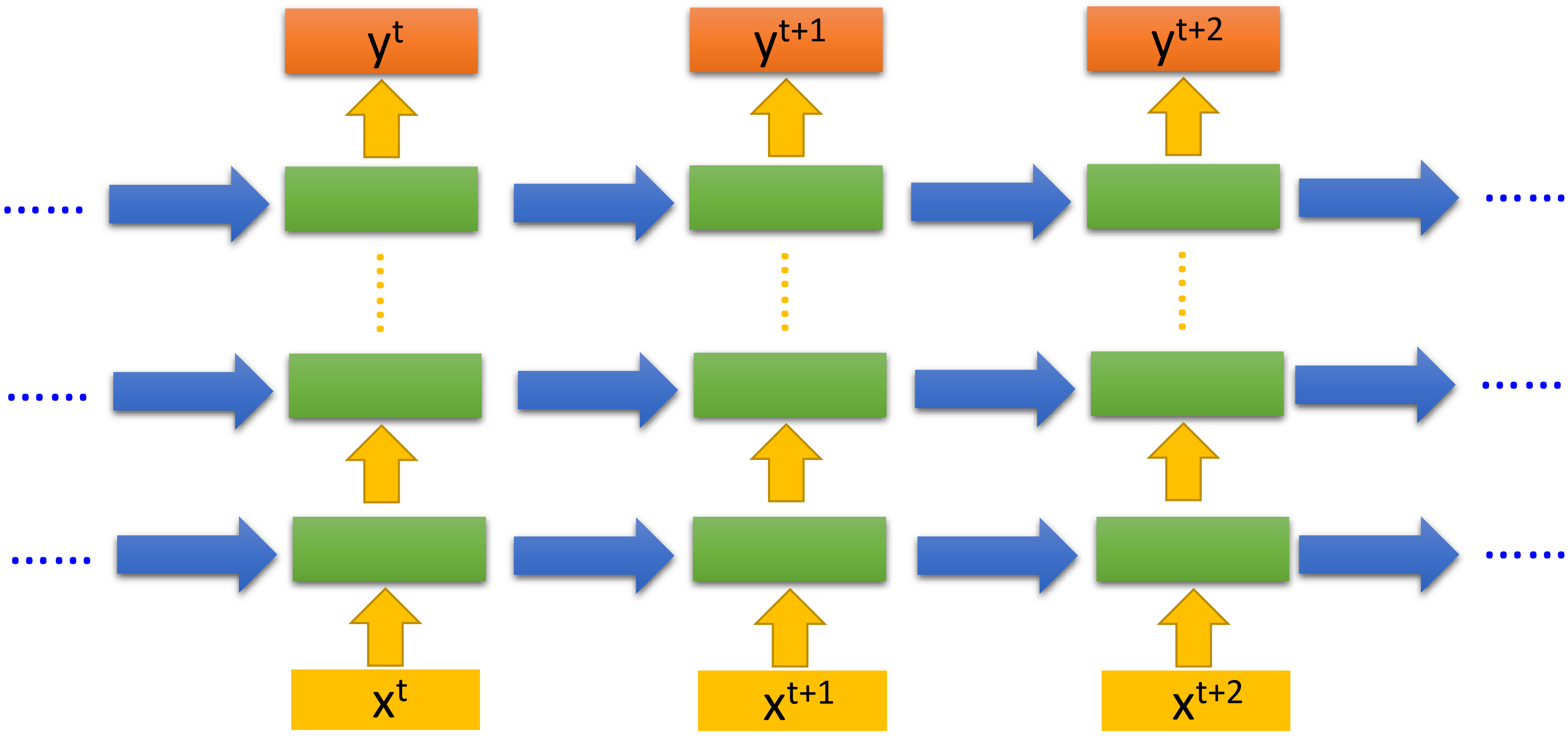
The same network is used again and again.



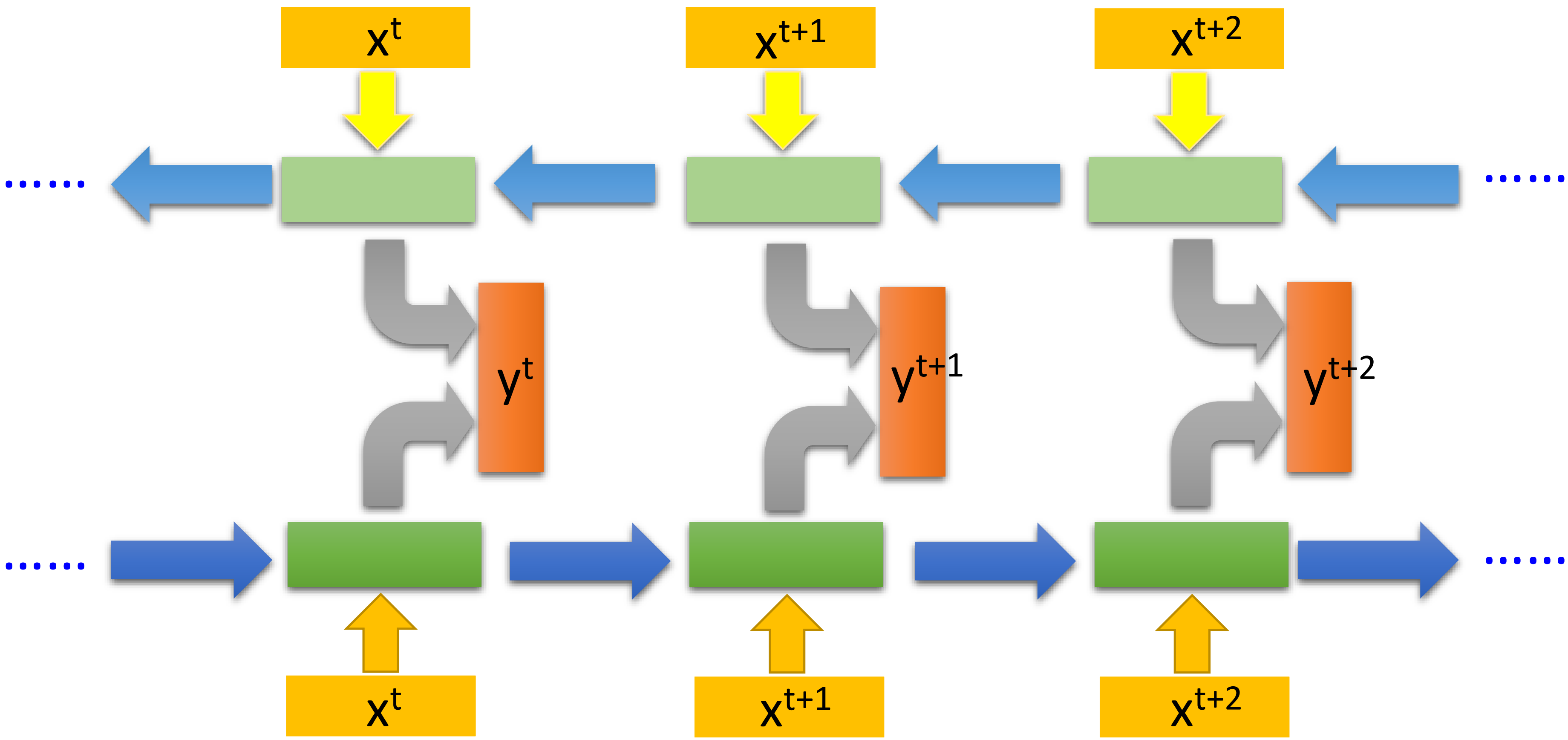
RNN


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
......
y^1
y^2
......
store
a^1
a^1
a^2
......
store
a^1
a^1
a^2
......
x^1
x^2
......
x^1
x^2
......
leave
Taipei
arrive
Taipei
The values stored in the memory is different.

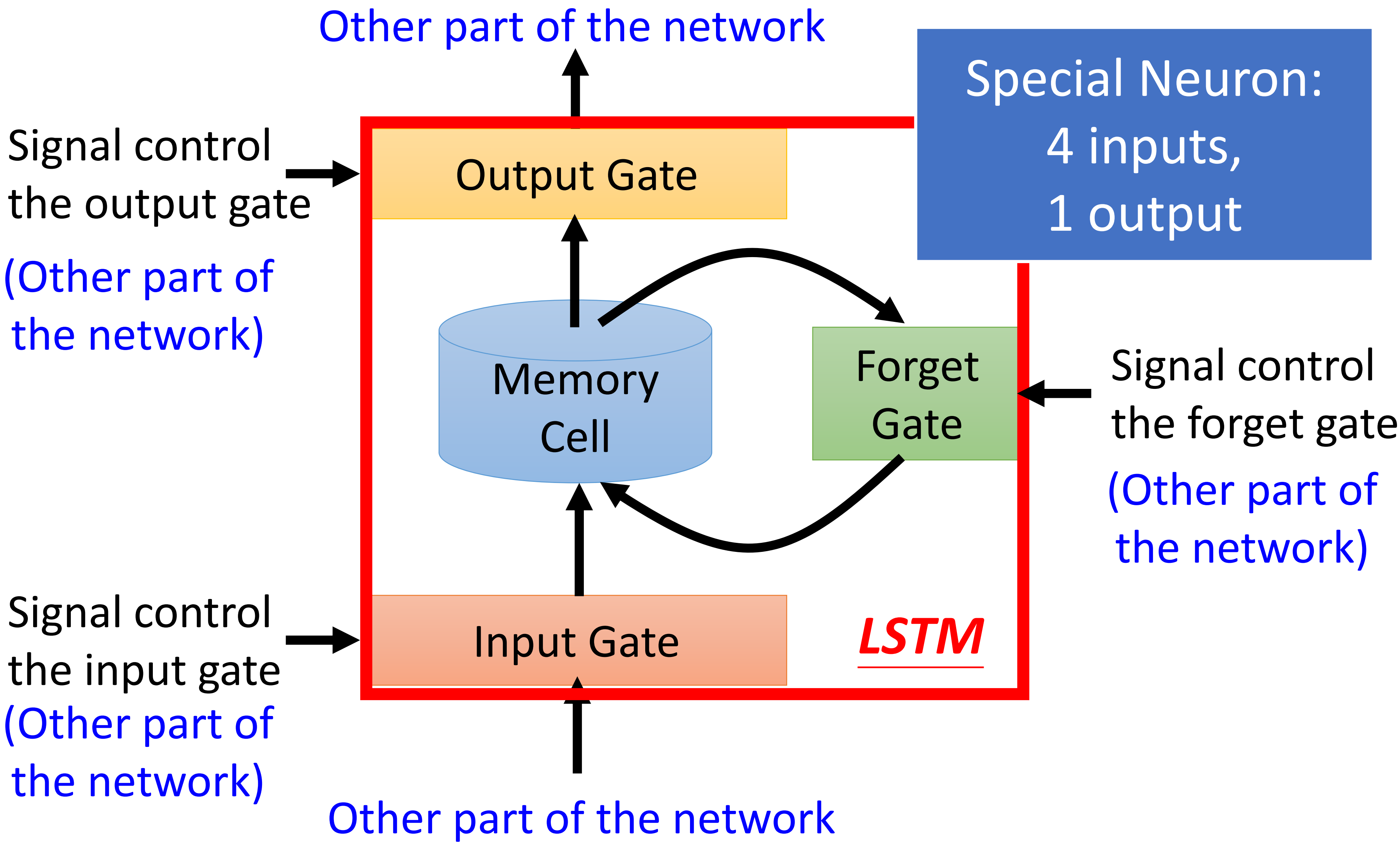
Of course it can be deep …

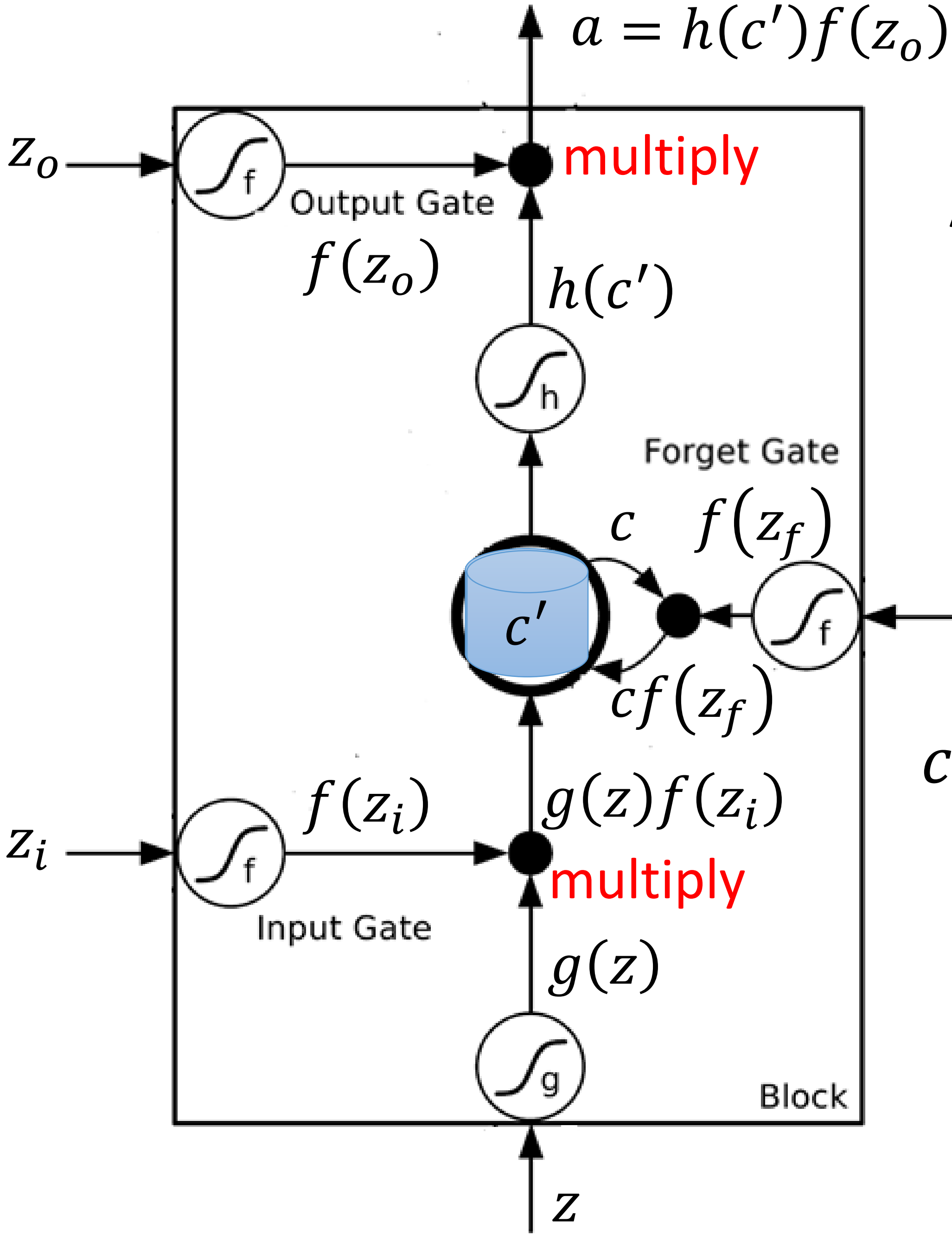


Bidirectional RNN



Long Short-term Memory (LSTM)



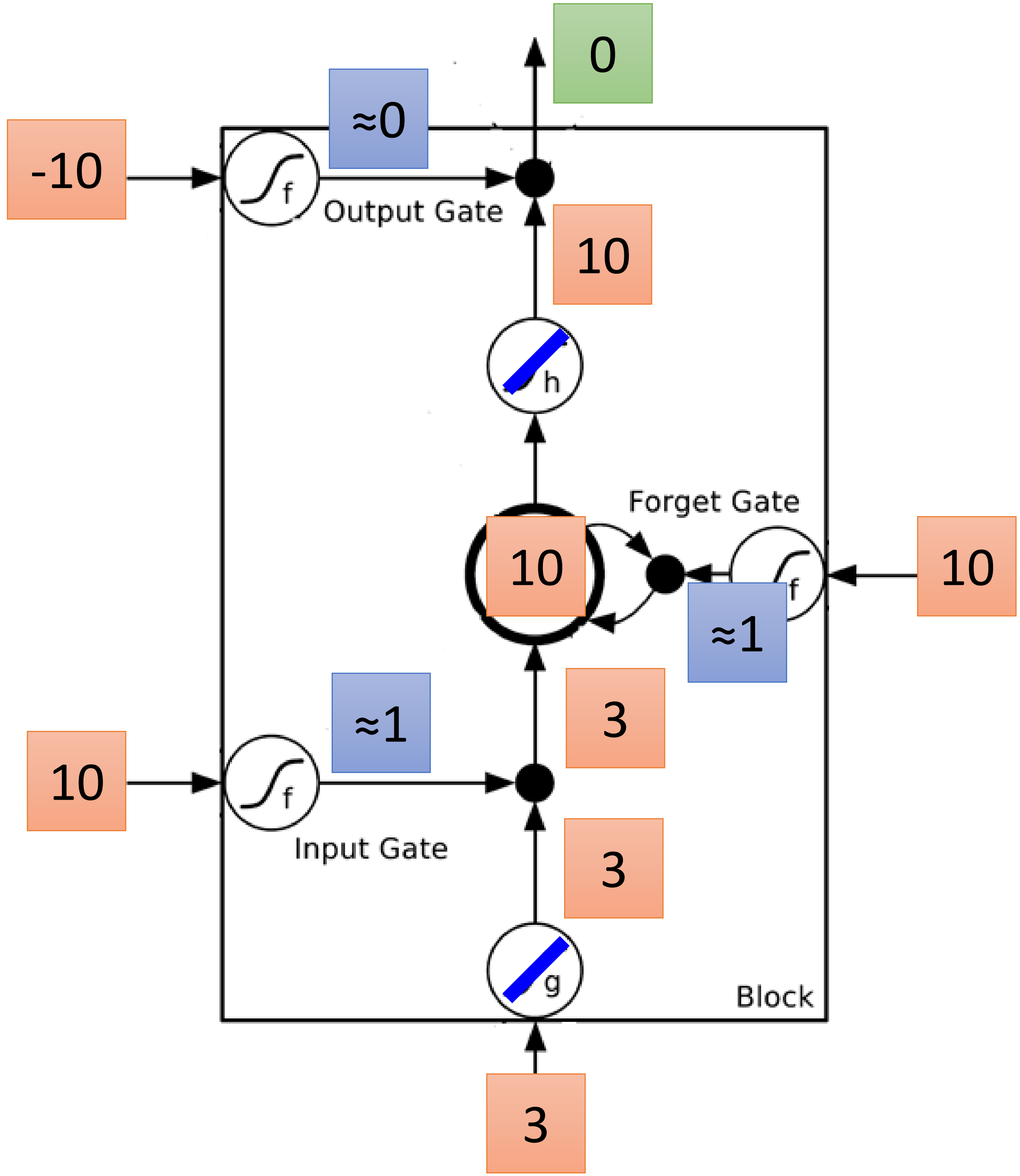


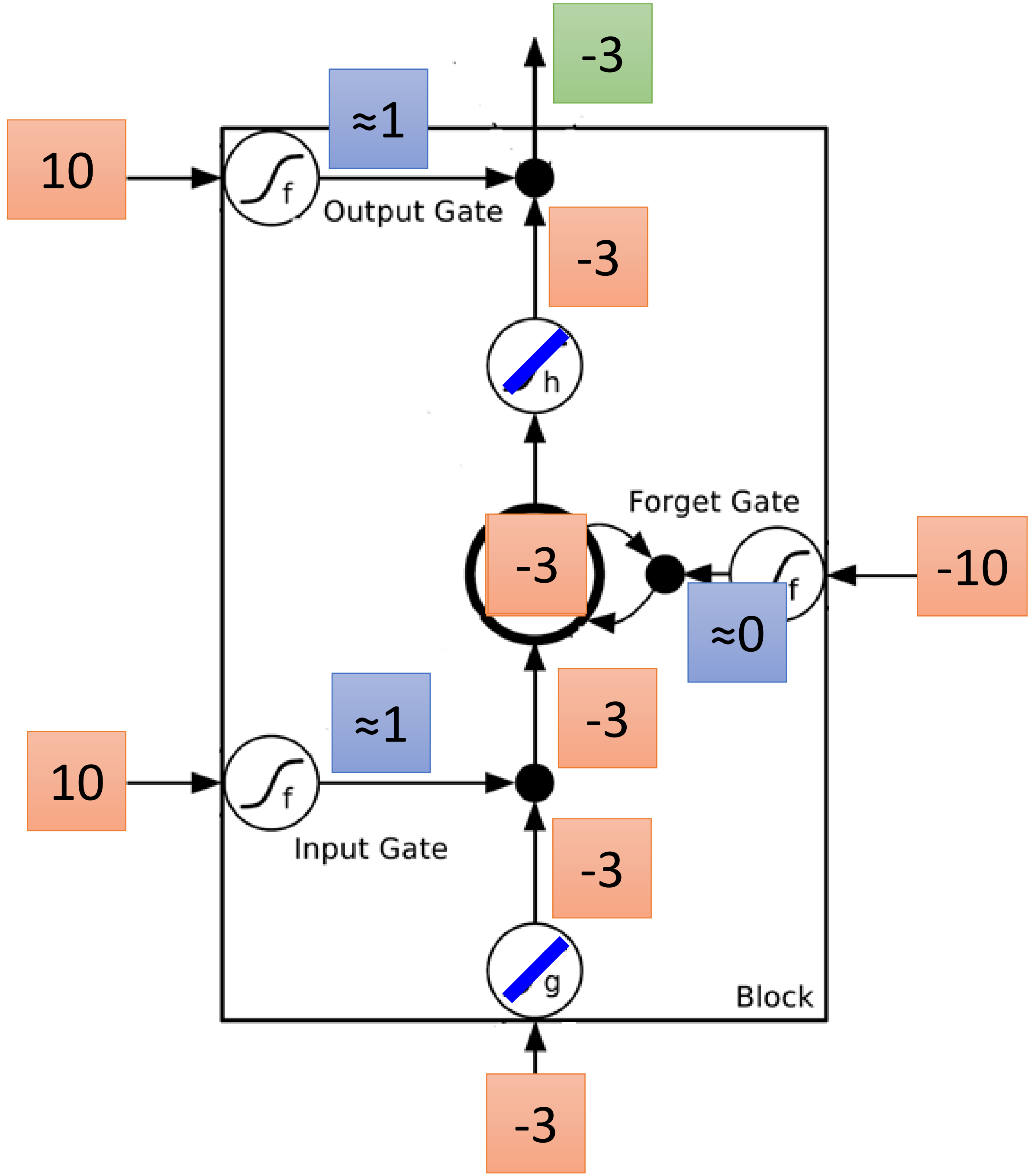
Activation function f is usually a sigmoid function

Between 0 and 1

Mimic open and close gate

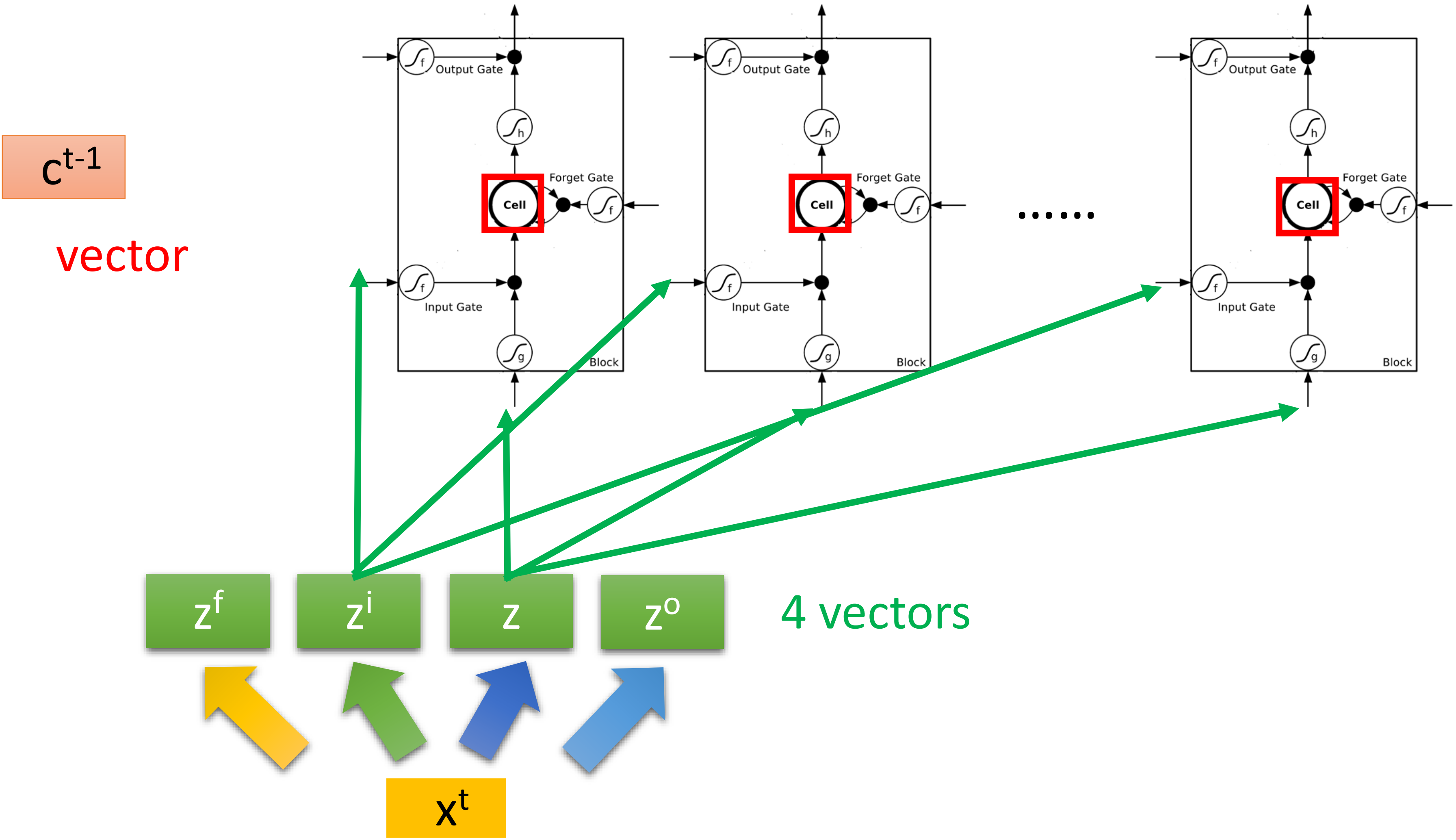
$$c' = g(z)f(z_i) + cf(z_f)$$


0
≈0
-10
Output Gate
10
h
Forget Gate
10
10
≈1
≈1
10
Input Gate
3
3
g
Block
3

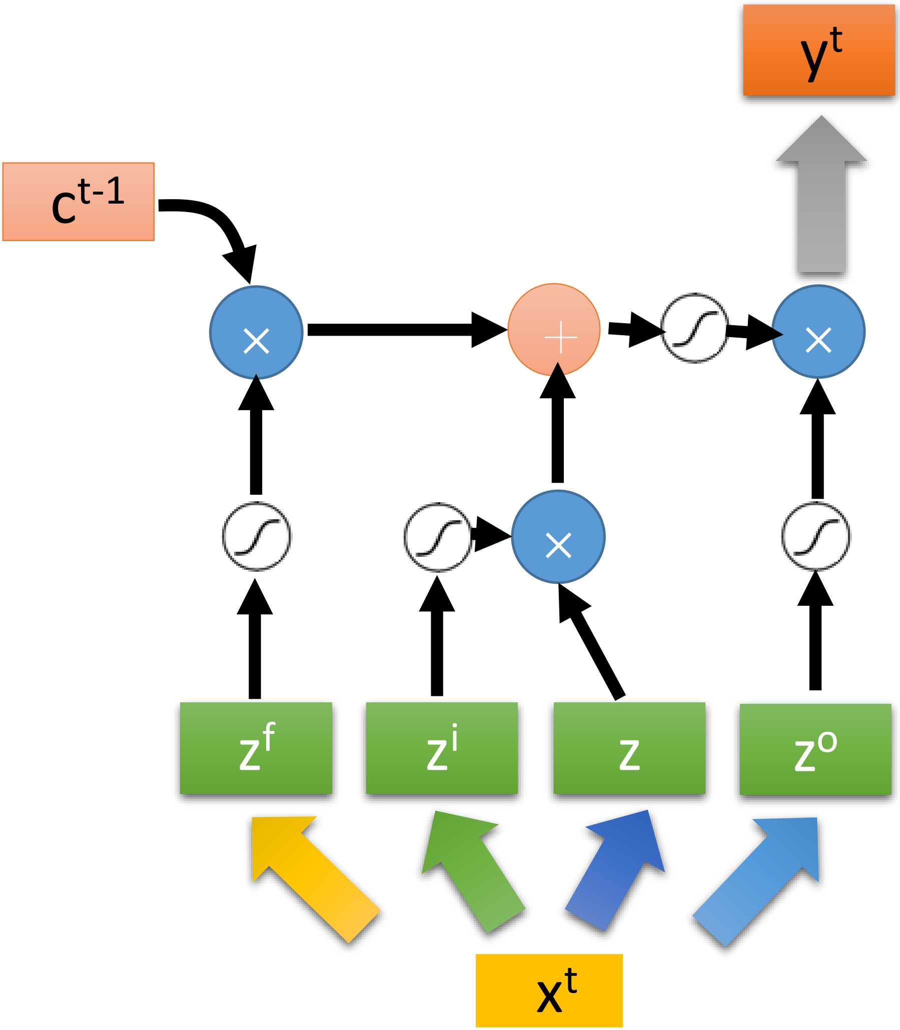


10
≈1
-3
Output Gate
-3
Forget Gate
-3
-10
≈0
≈1
-3
10
Input Gate
-3
Block
-3

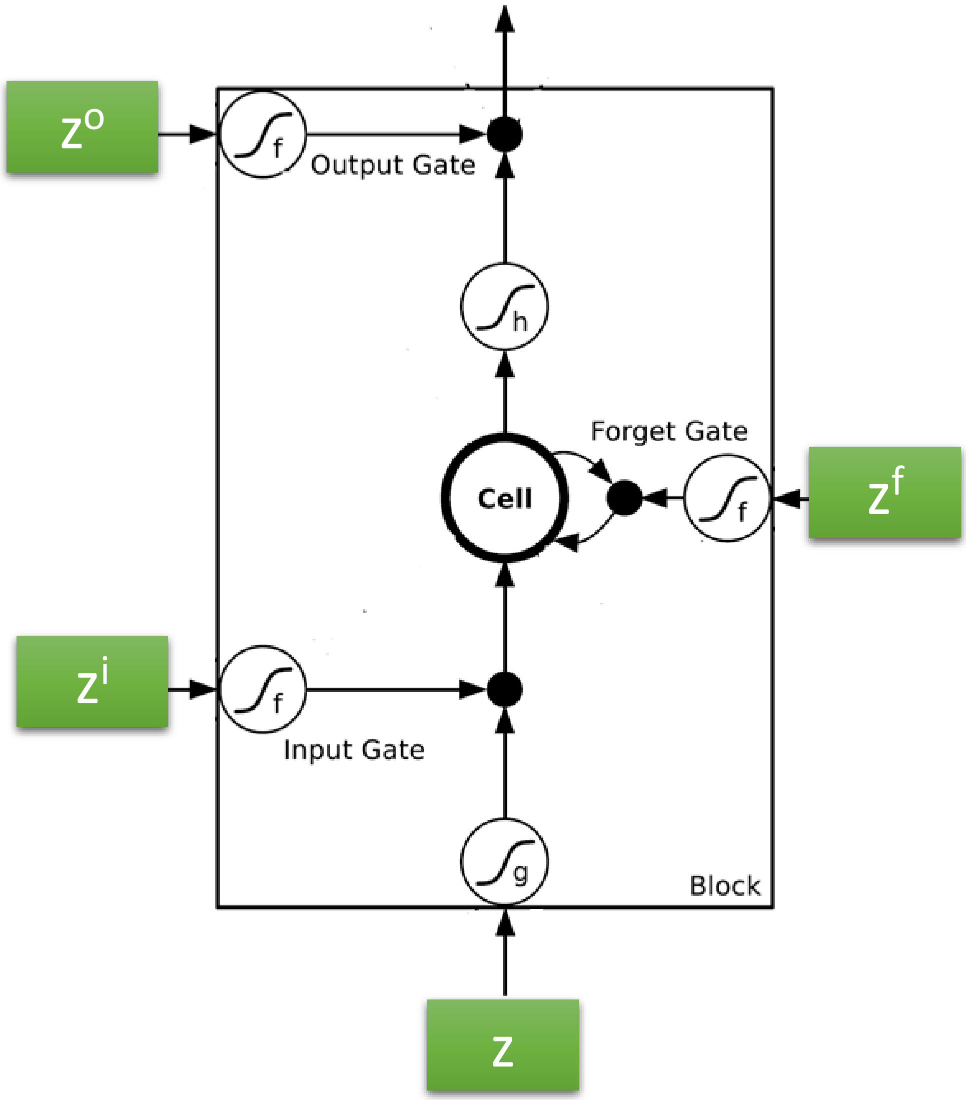
LSTM


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

LSTM



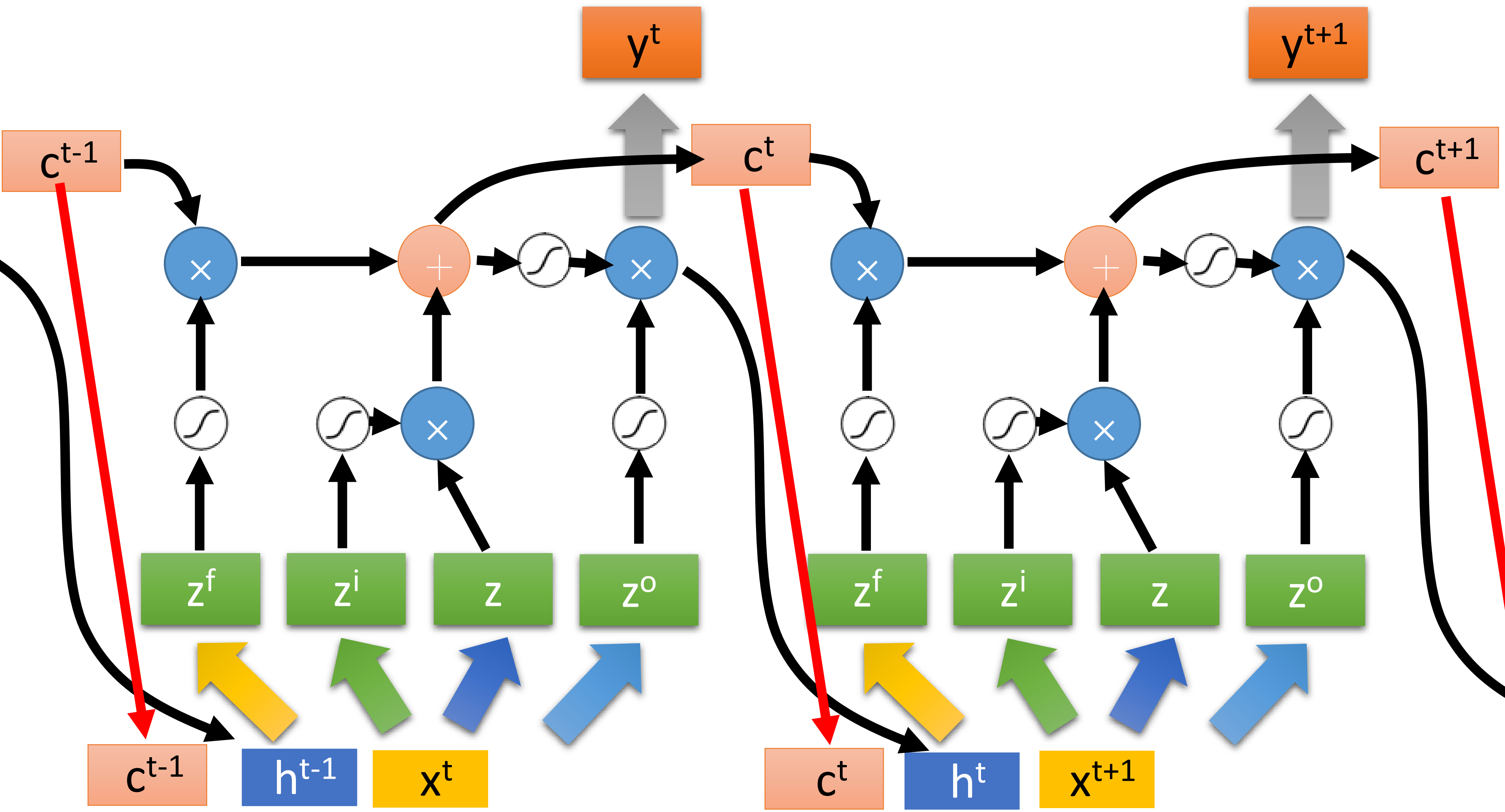
y^t
c^{t-1}
z^f
z^i
z
z^o
x^t



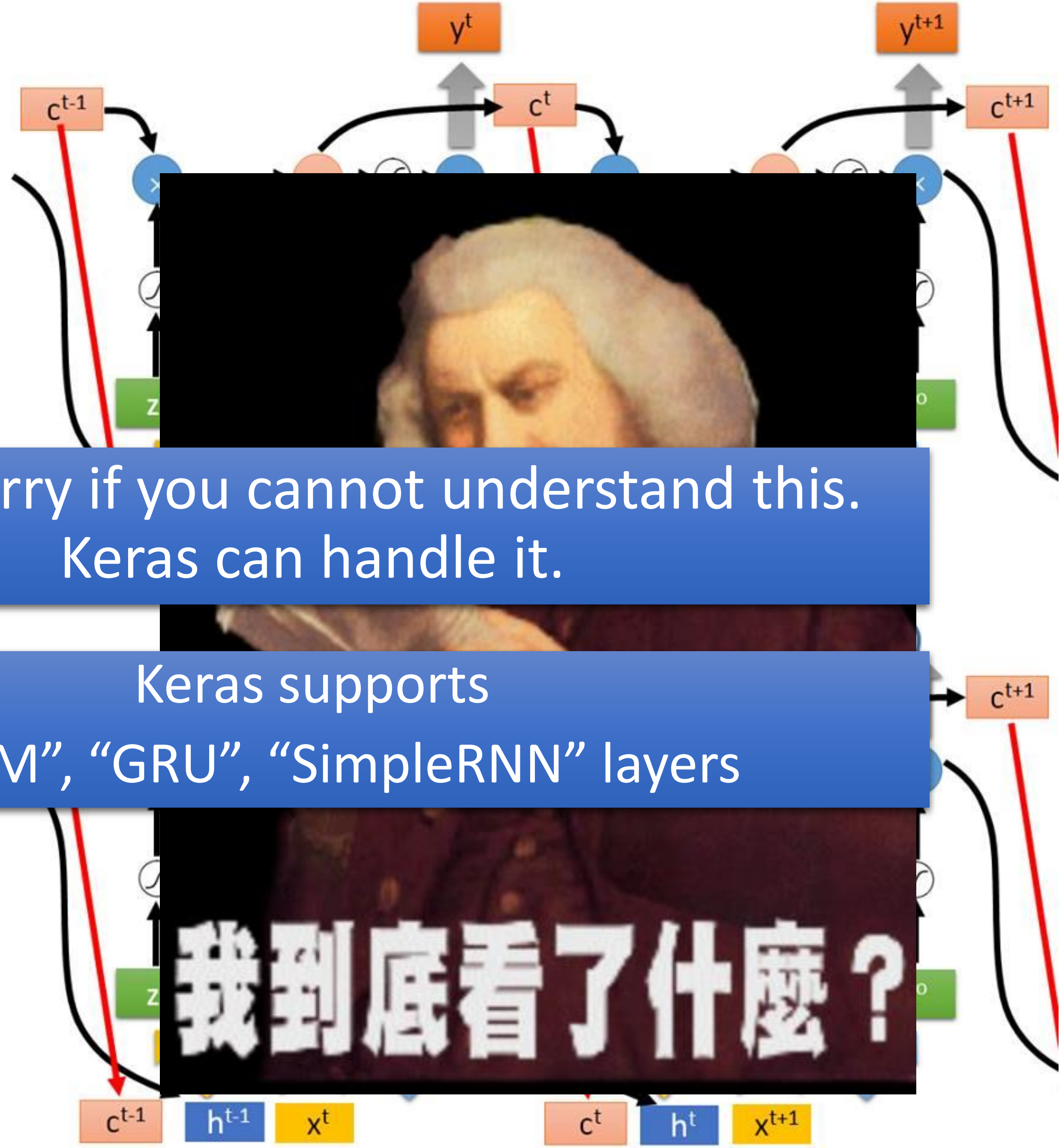
z^o
Output Gate
h
Forget Gate
Cell
z^f
z^i
Input Gate
g
Block
z

LSTM

Extension: “peephole”



Multiple-layer LSTM



Don’t worry if you cannot understand this.
Keras can handle it.

Keras supports
“LSTM”, “GRU”, “SimpleRNN” layers

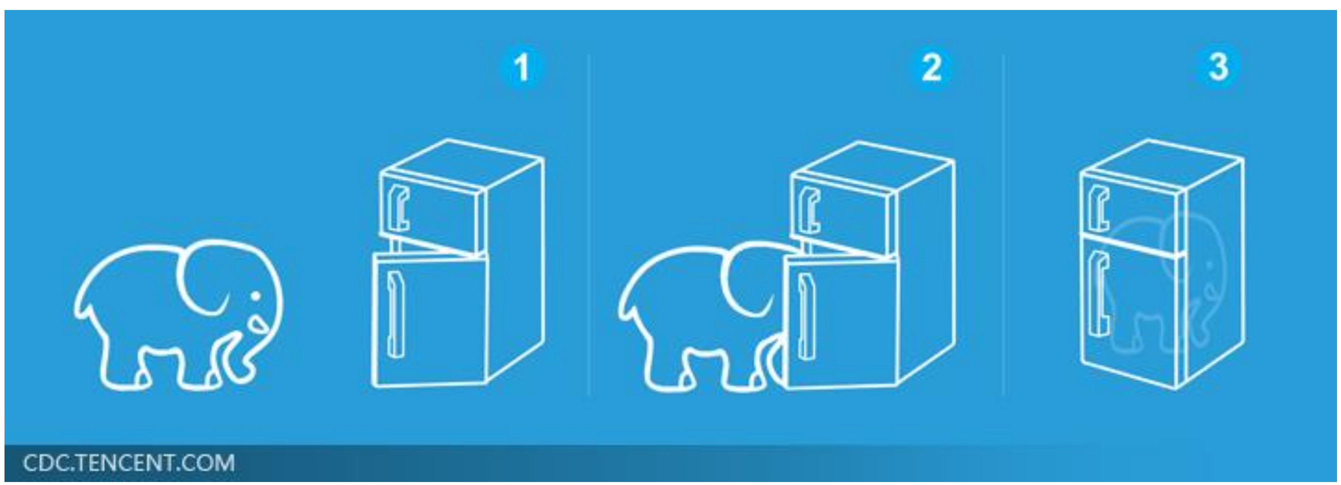
This is quite standard now.

https://img.komicolle.org/2015-09-20/src/14426967627131.gif

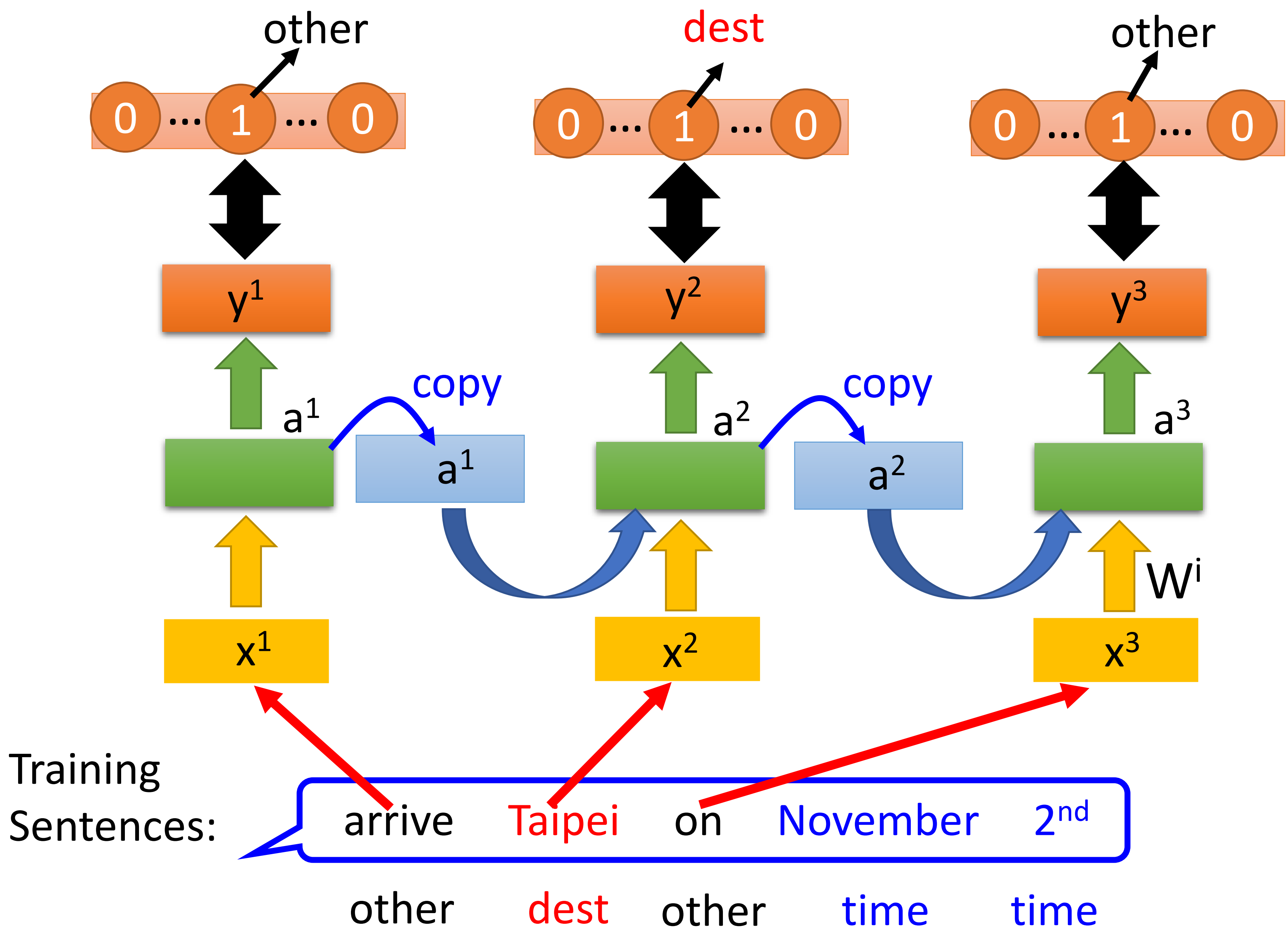
Three Steps for Deep Learning

Step 1: define a set of function → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



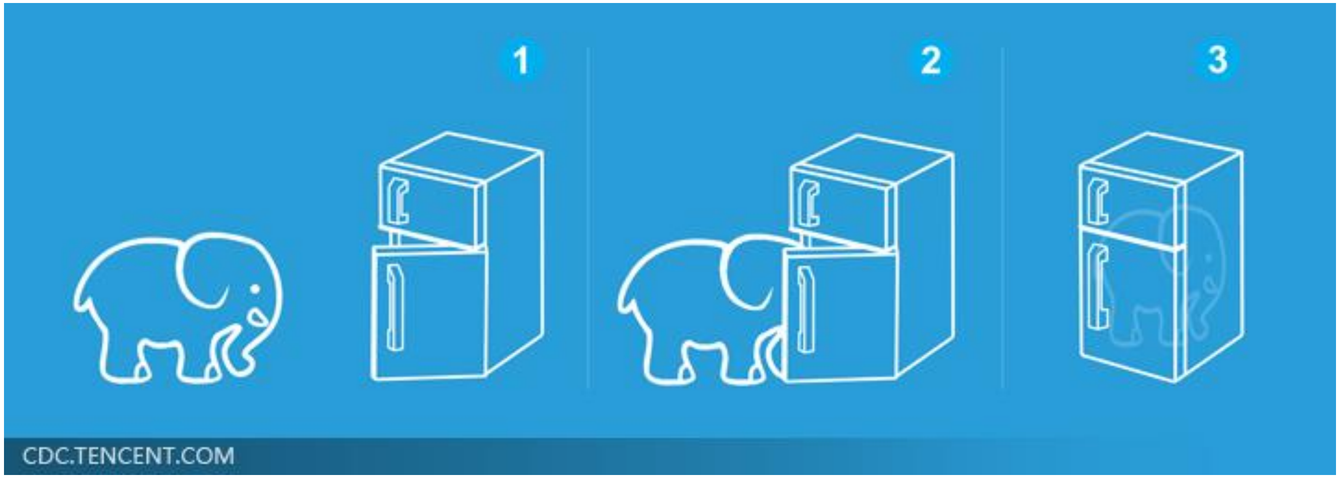
Learning Target



Three Steps for Deep Learning

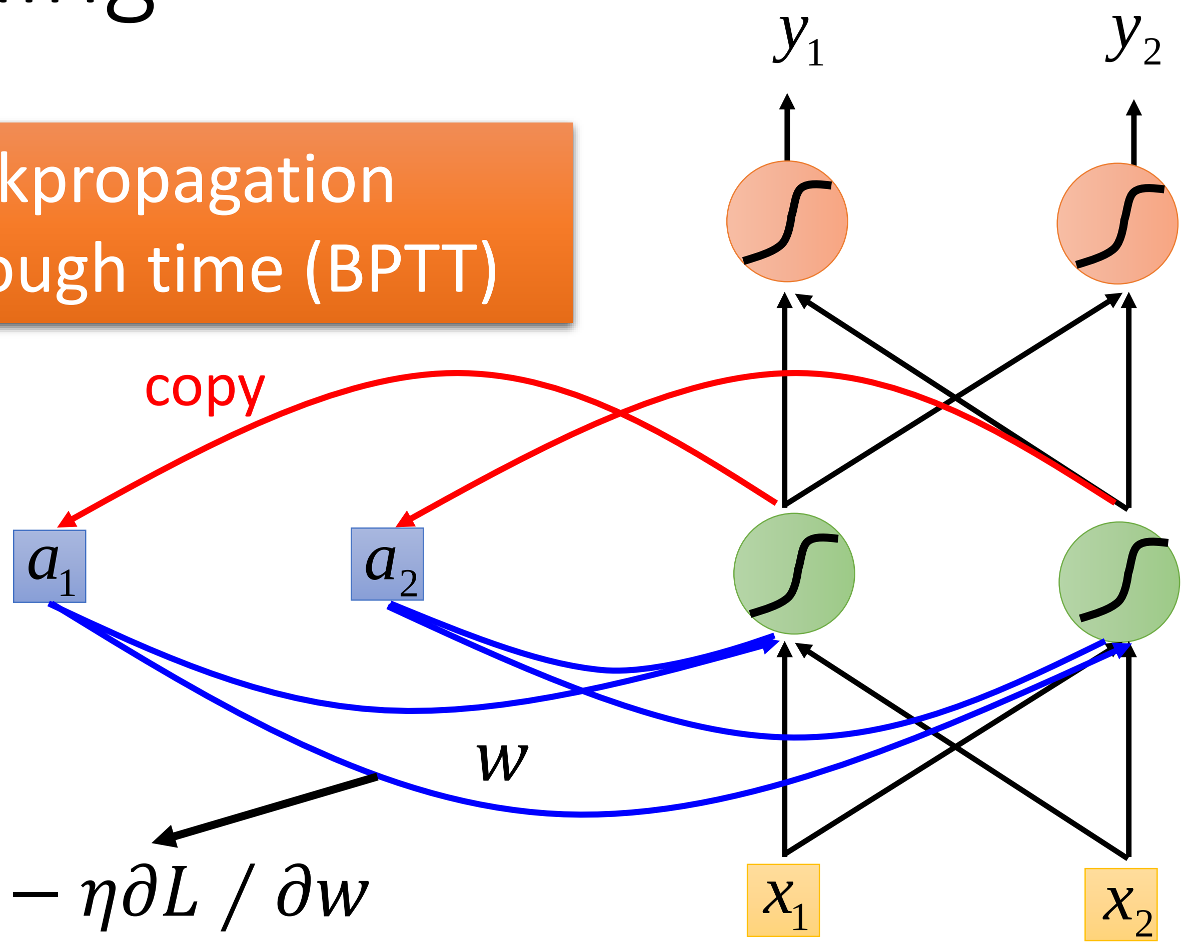
Step 1: define a set of function → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



Learning

Backpropagation through time (BPTT)



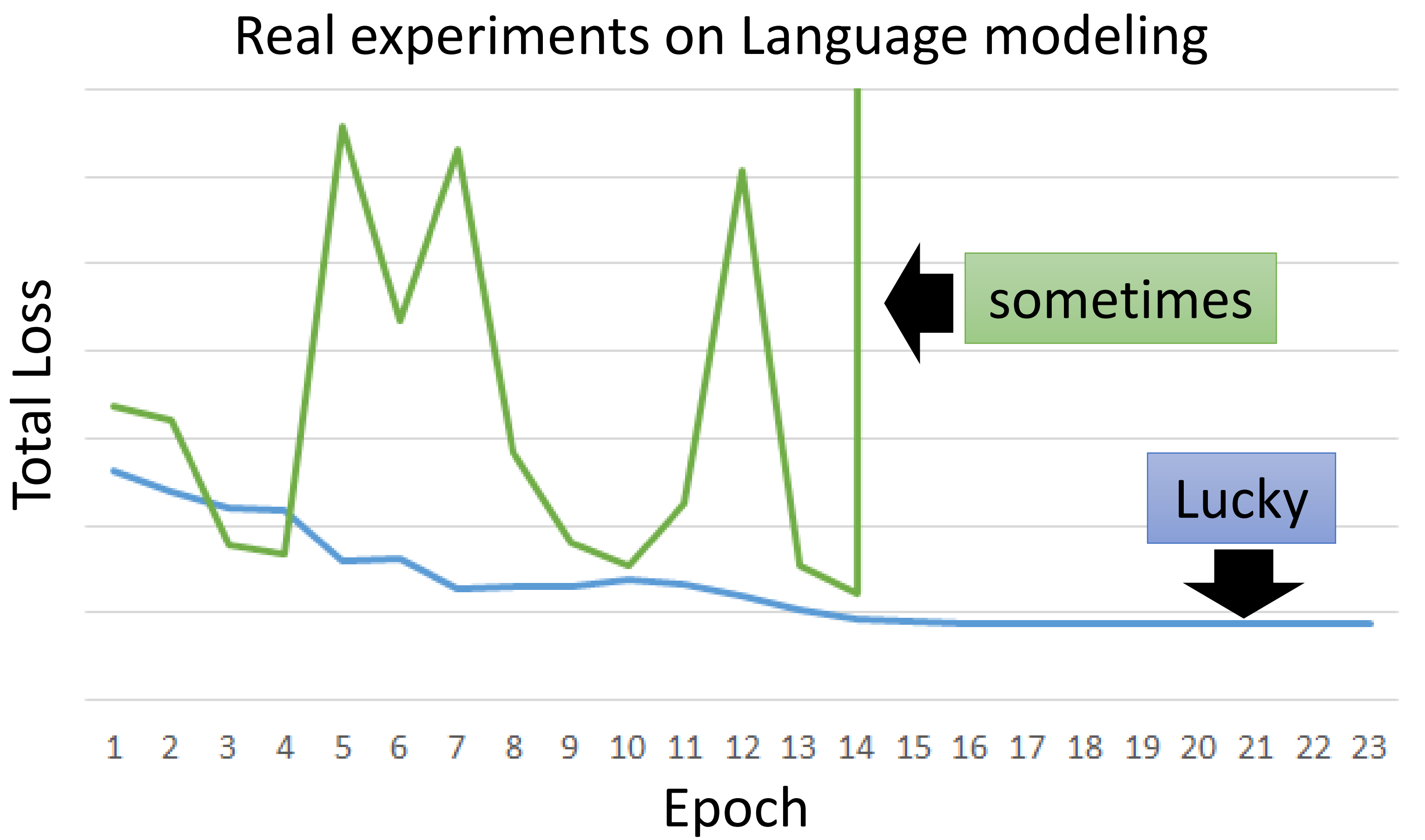
$$w \leftarrow w - \eta \partial L / \partial w$$

RNN Learning is very difficult in practice.

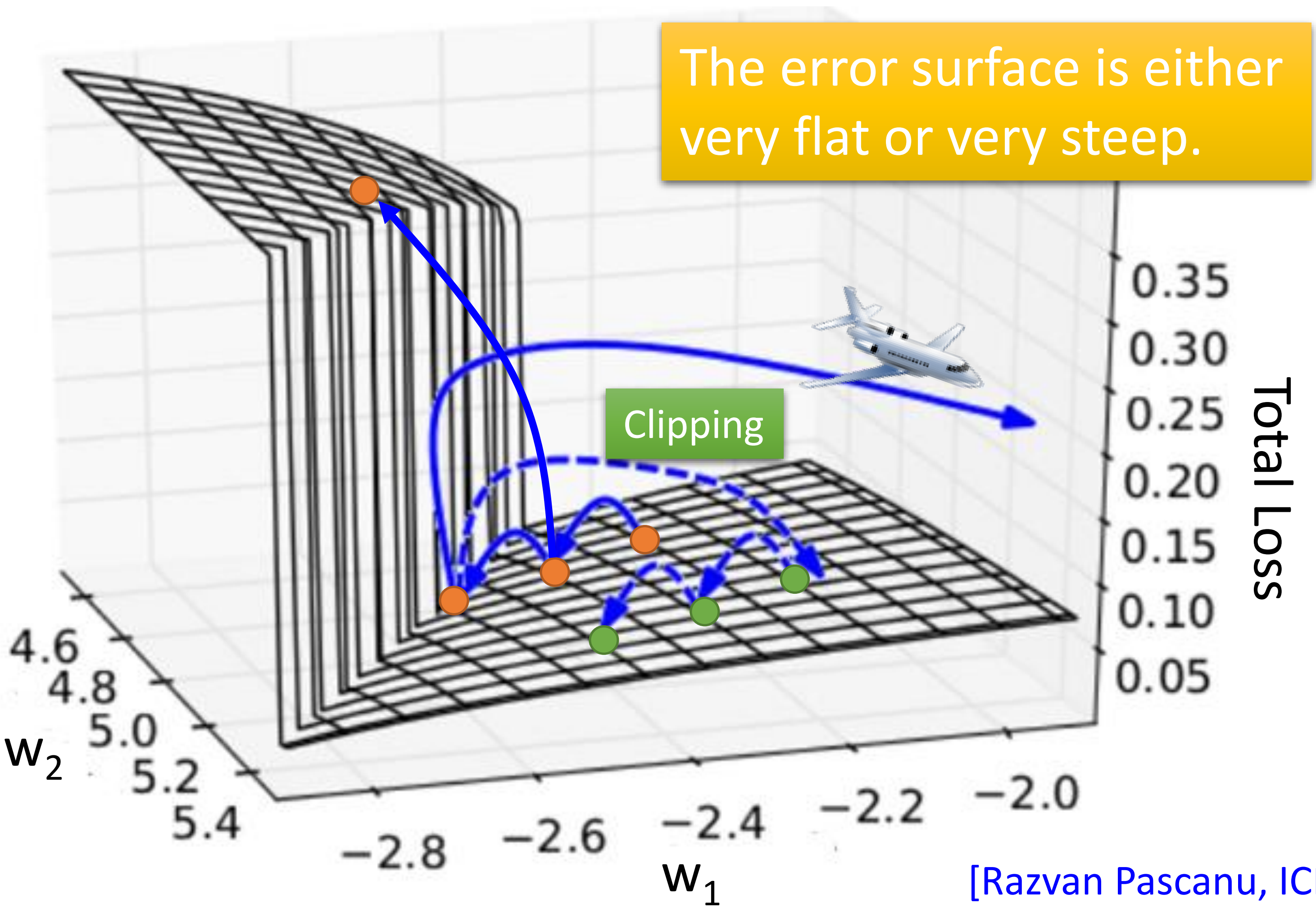
感謝 曾柏翔 同學
提供實驗結果

Unfortunately ……

- RNN-based network is not always easy to learn



The error surface is rough.



[Razvan Pascanu, ICML’13]

Why?

$w = 1 \Rightarrow y^{1000} = 1$

$w = 1.01 \Rightarrow y^{1000} \approx 20000$

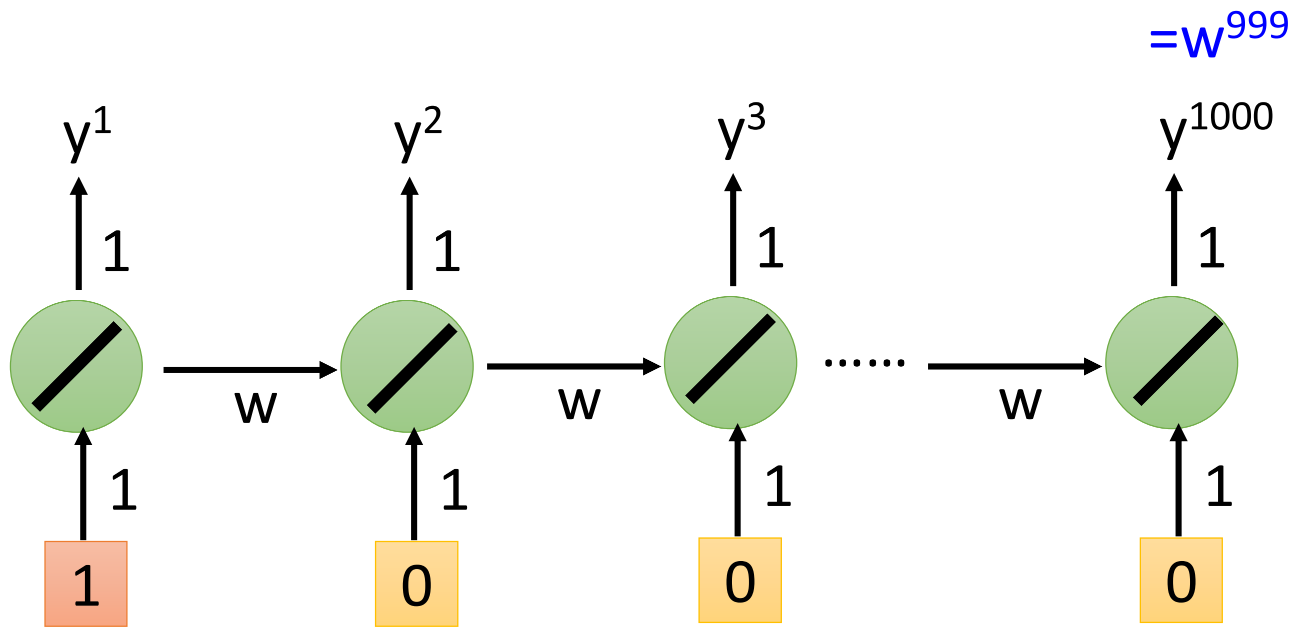
Large $\partial L / \partial w$ → Small Learning rate?

$w = 0.99 \Rightarrow y^{1000} \approx 0$

$w = 0.01 \Rightarrow y^{1000} \approx 0$

small $\partial L / \partial w$ → Large Learning rate?

Toy Example



Helpful Techniques

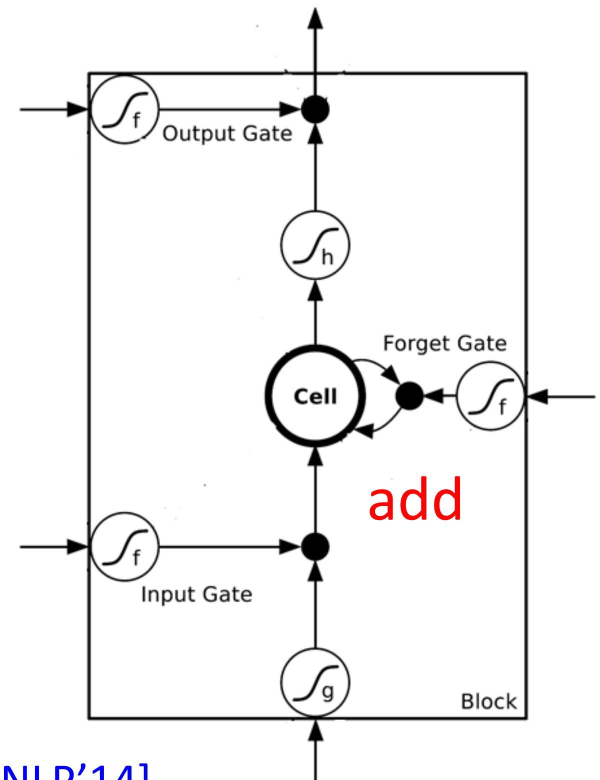
- Long Short-term Memory (LSTM)
  - Can deal with gradient vanishing (not gradient explode)

➢ Memory and input are ***added***

➢ The influence never disappears unless forget gate is closed

➡ No Gradient vanishing
(If forget gate is opened.)

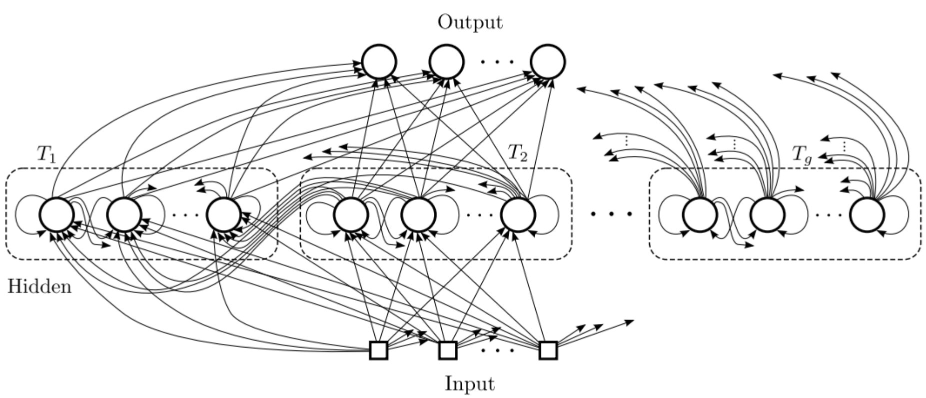
Gated Recurrent Unit (GRU): simpler than LSTM



[Cho, EMNLP'14]

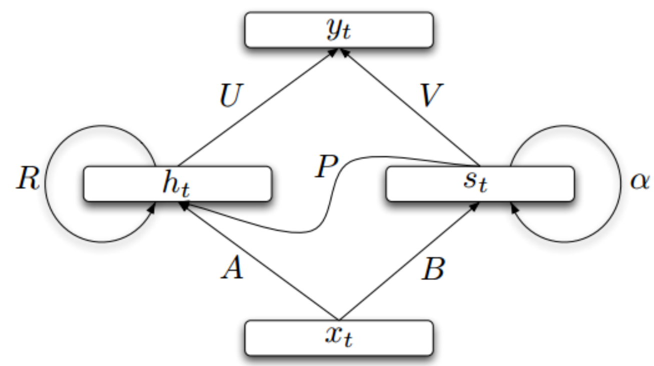
Helpful Techniques

Clockwise RNN



[Jan Koutnik, JMLR’14]

Structurally Constrained Recurrent Network (SCRN)



[Tomas Mikolov, ICLR’15]

Vanilla RNN Initialized with Identity matrix + ReLU activation function [Quoc V. Le, arXiv’15]

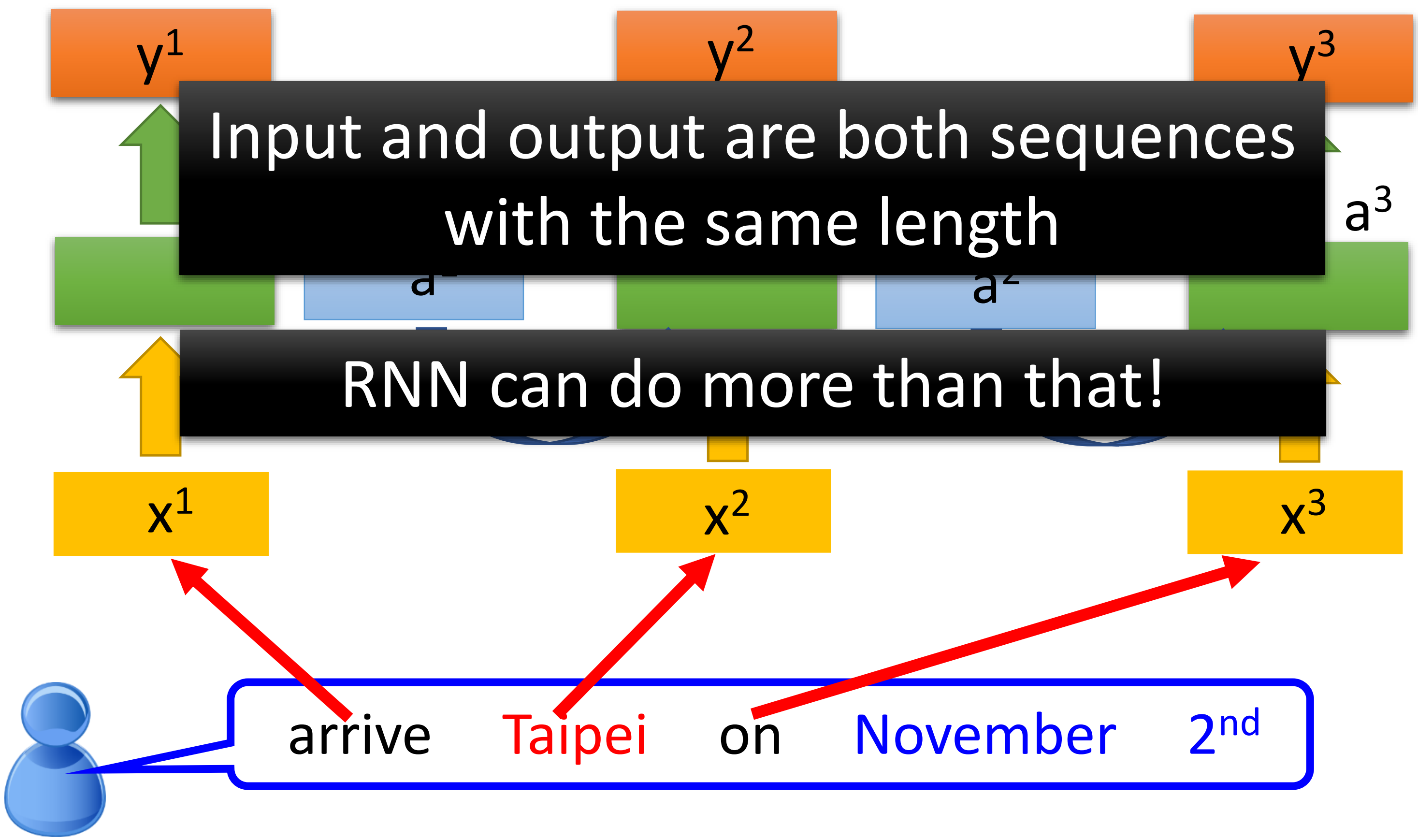
- ➢ Outperform or be comparable with LSTM in 4 different tasks

More Applications ……

Probability of “arrive” in each slot

Probability of “Taipei” in each slot

Probability of “on” in each slot

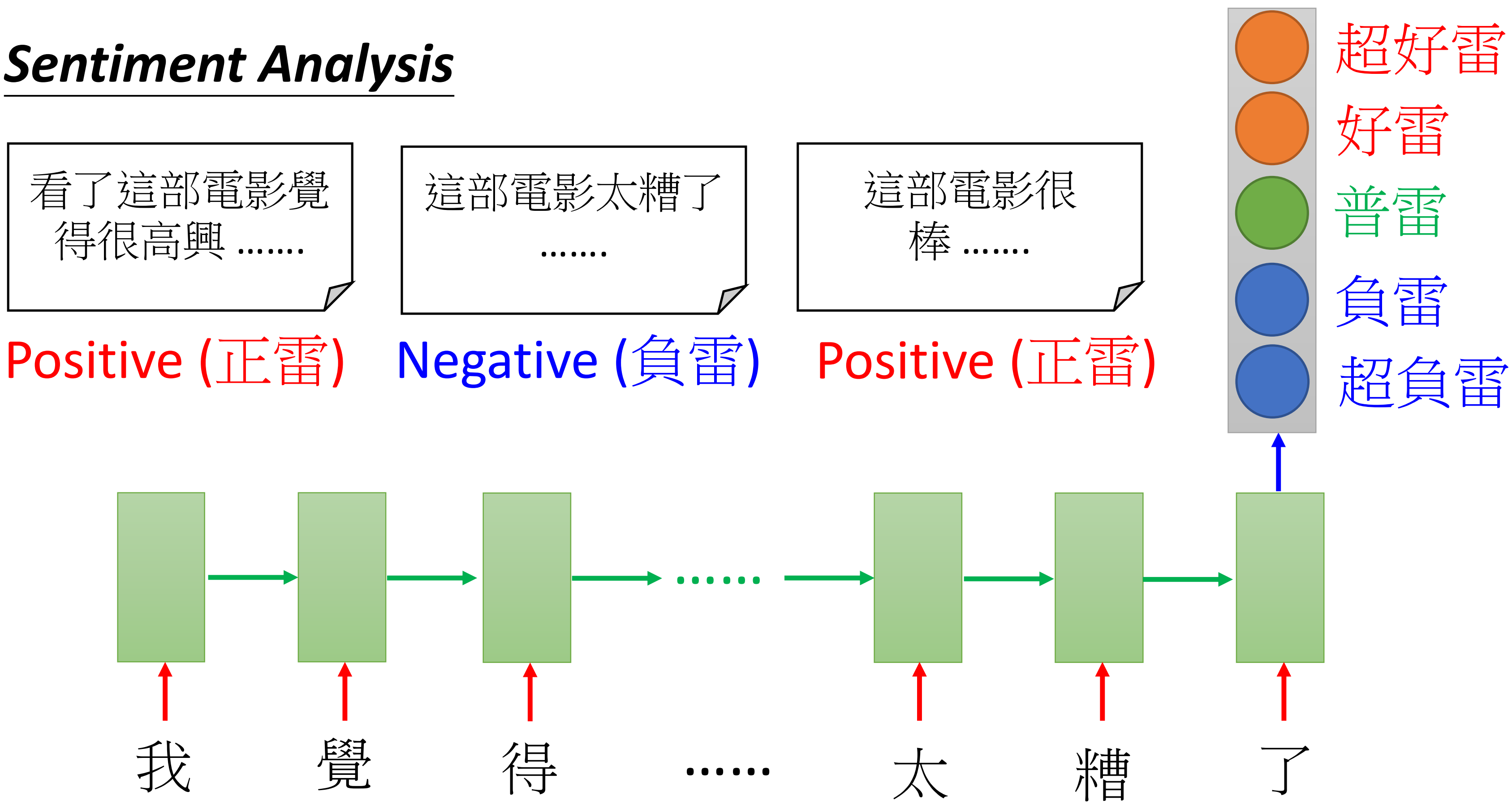


Many to one

Keras Example:
https://github.com/fchollet/keras/blob/master/examples/imdb_lstm.py

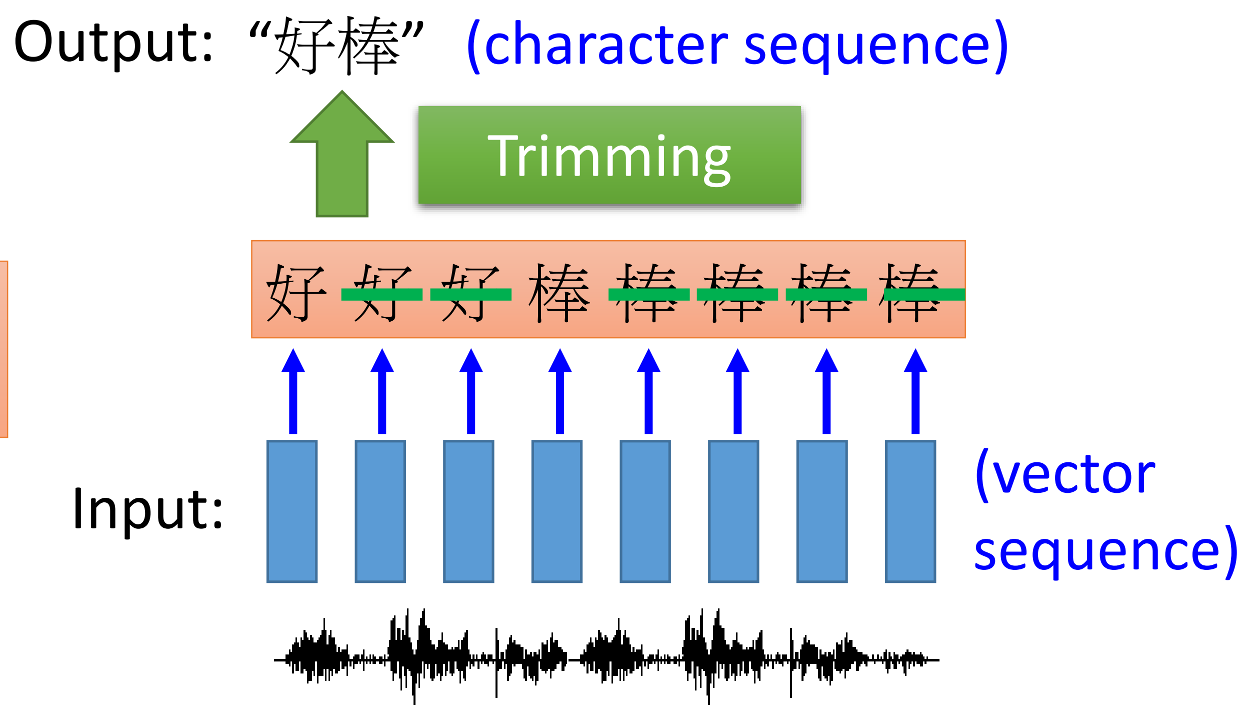
- Input is a vector sequence, but output is only one vector

Sentiment Analysis



Many to Many (Output is shorter)

- Both input and output are both sequences, ***but the output is shorter.***
  - E.g. ***Speech Recognition***

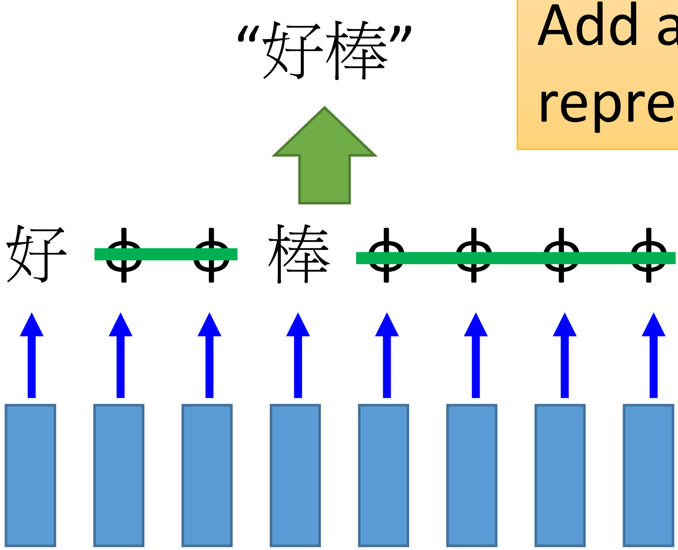


Problem?

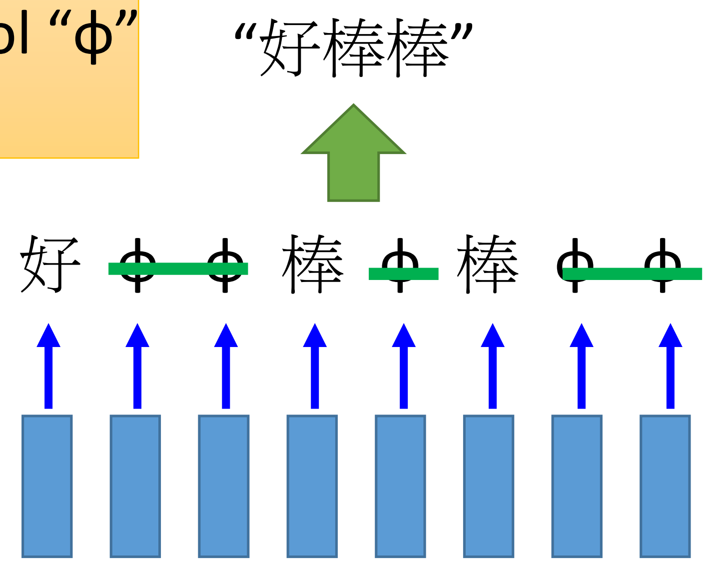
Why can’t it be “好棒棒”

Many to Many (Output is shorter)

- Both input and output are both sequences, ***but the output is shorter.***
- Connectionist Temporal Classification (CTC) [Alex Graves, ICML’06][Alex Graves, ICML’14][Haşim Sak, Interspeech’15][Jie Li, Interspeech’15][Andrew Senior, ASRU’15]

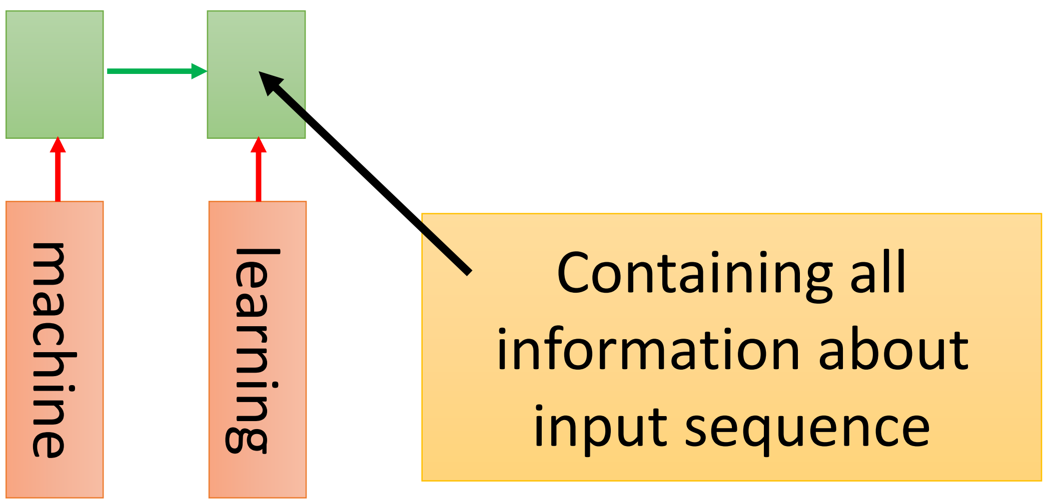


Add an extra symbol “ϕ” representing “null”



Many to Many (No Limitation)

- Both input and output are both sequences ***with different lengths***. → ***Sequence to sequence learning***
  - E.g. ***Machine Translation*** (machine learning→機器學習)



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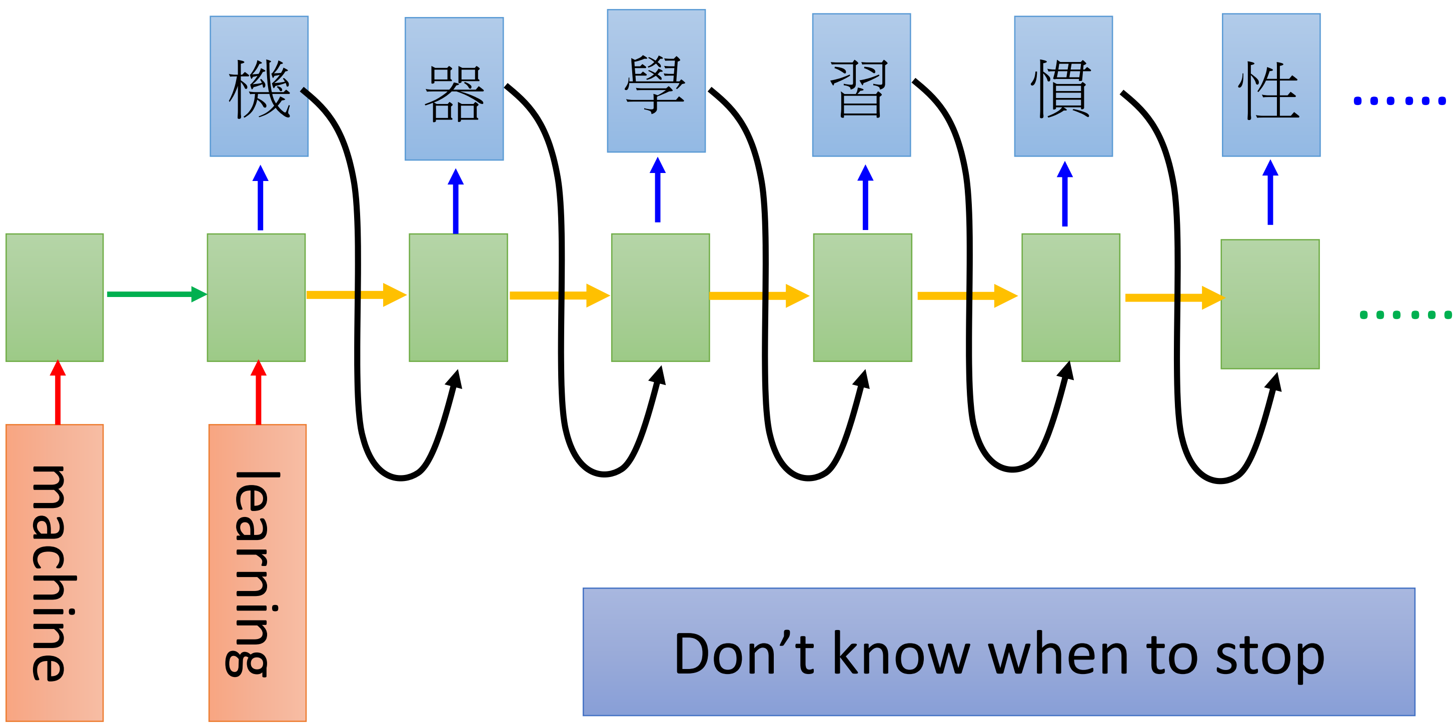
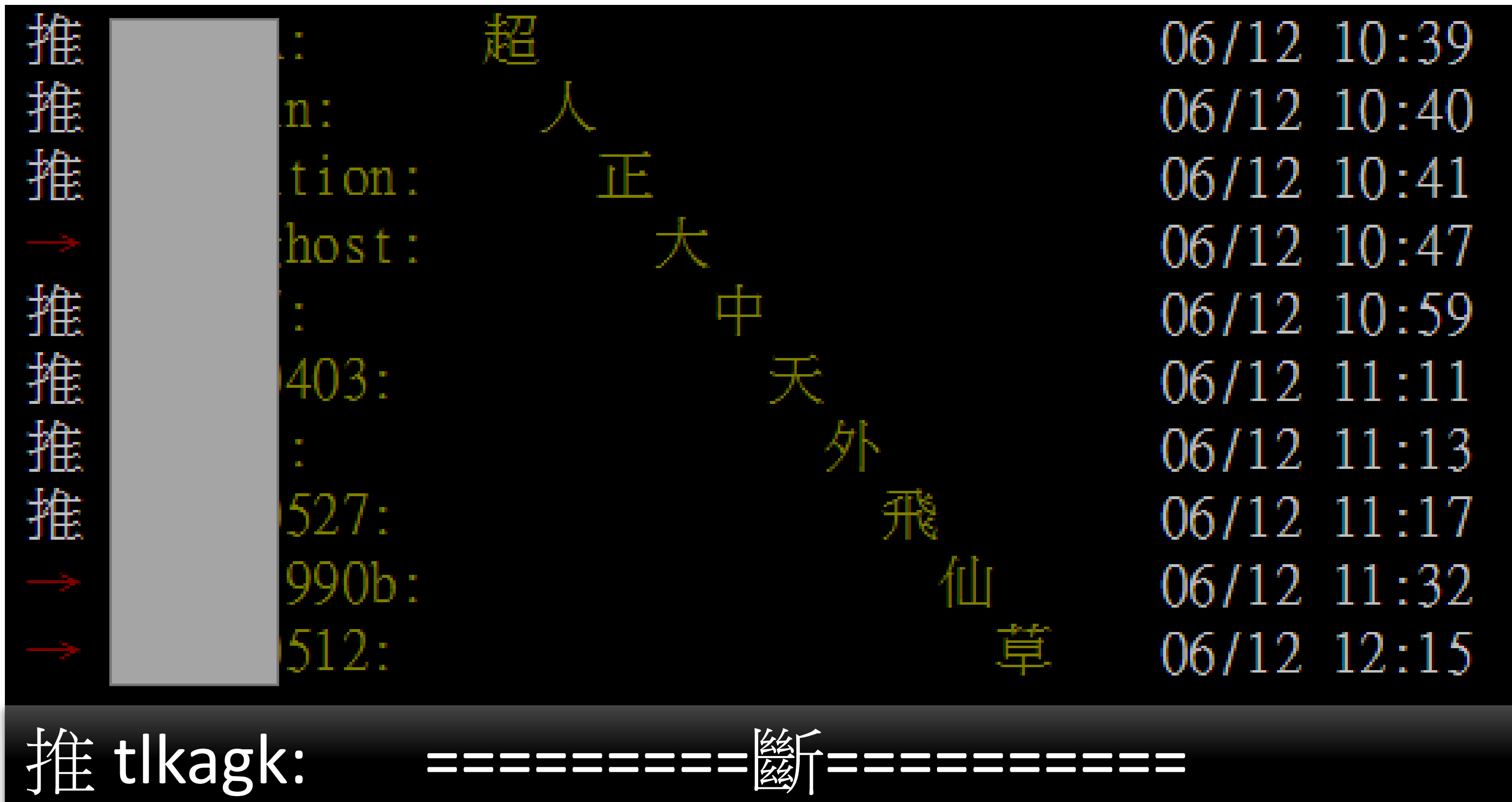


Many to Many (No Limitation)



Ref:http://zh.pttpedia.wikia.com/wiki/%E6%8E%A5%E9%BE%8D%E6%8E%A8%E6%96%87 (鄉民百科)

Many to Many (No Limitation)

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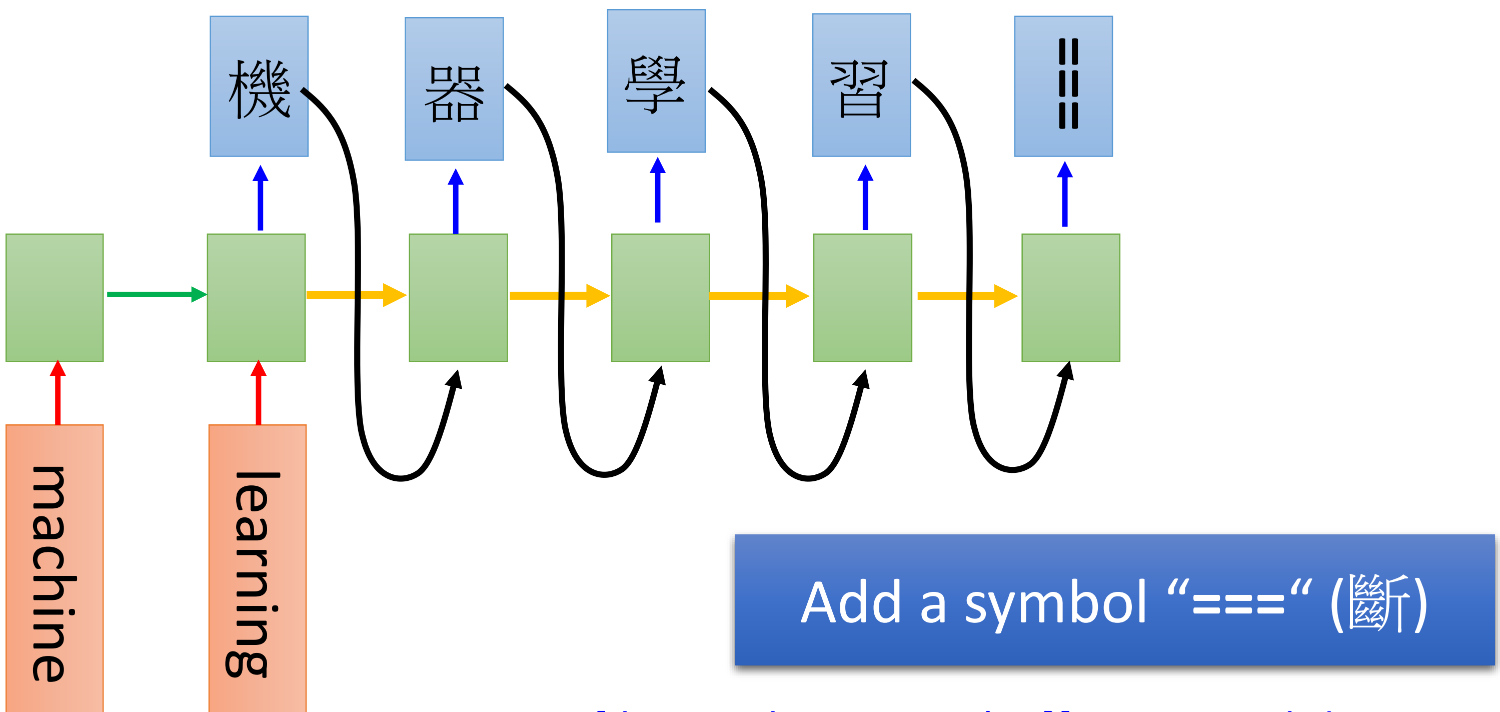
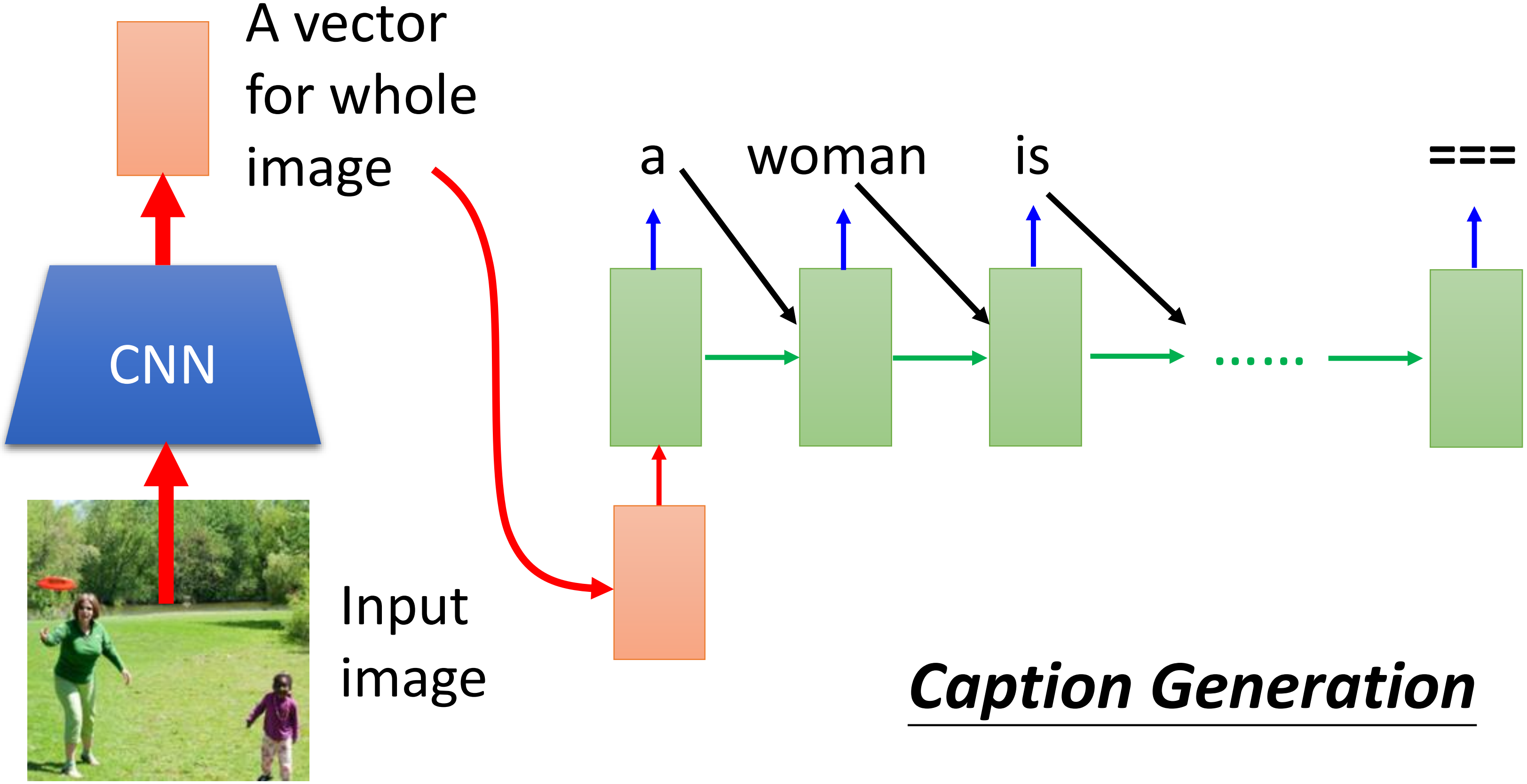


[Ilya Sutskever, NIPS'14][Dzmitry Bahdanau, arXiv'15]

One to Many

- Input an image, but output a sequence of words

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

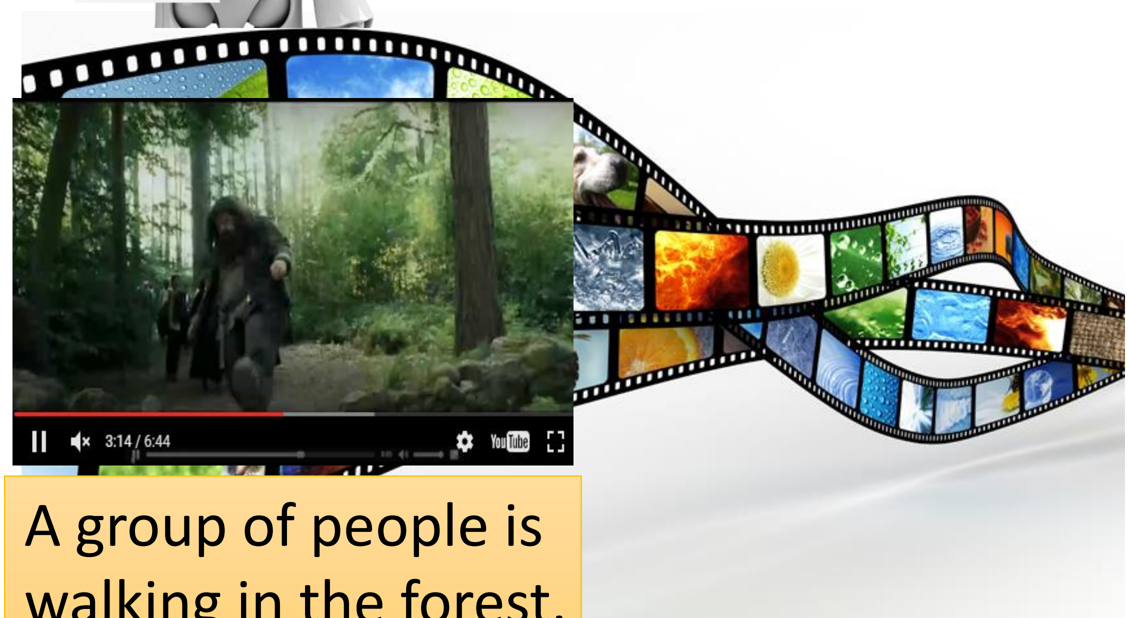


Application: Video Caption Generation

Video

A girl is running.

A group of people is knocked by a tree.



A group of people is walking in the forest.

Video Caption Generation

- Can machine describe what it see from video?
- Demo: 曾柏翔、吳柏瑜、盧宏宗

Concluding Remarks

Convolutional Neural Network (CNN)

Recurrent Neural Network (RNN)

Lecture IV:
Next Wave

Outline

Supervised Learning

- $\boxed{\text{Ultra Deep Network}}$
- Attention Model

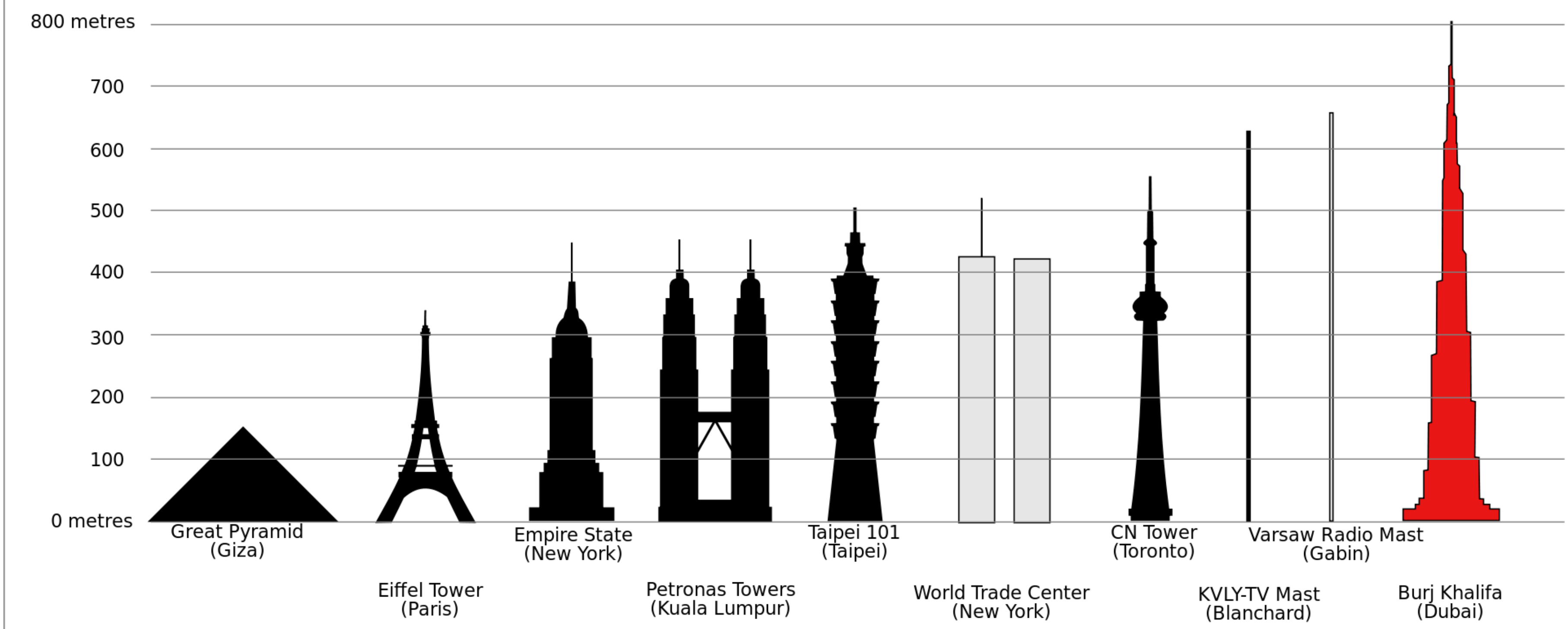
New network structure

Reinforcement Learning

Unsupervised Learning

- Image: Realizing what the World Looks Like
- Text: Understanding the Meaning of Words
- Audio: Learning human language without supervision

Skyscraper



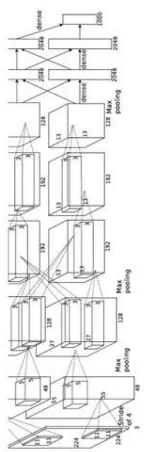
https://zh.wikipedia.org/wiki/%E9%9B%99%E5%B3%B0%E5%A1%94#/media/File:BurjDubaiHeight.svg

Ultra Deep Network

http://cs231n.stanford.edu/slides/winter1516_lecture8.pdf

8 layers

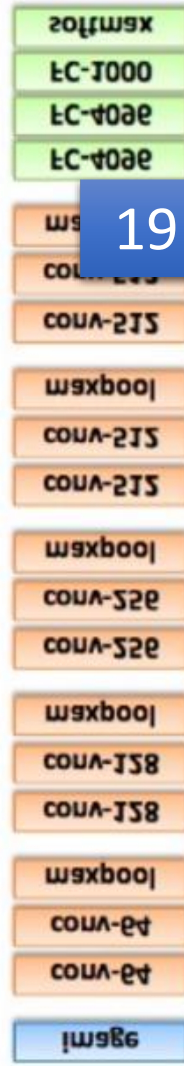
16.4%



AlexNet (2012)

19 layers

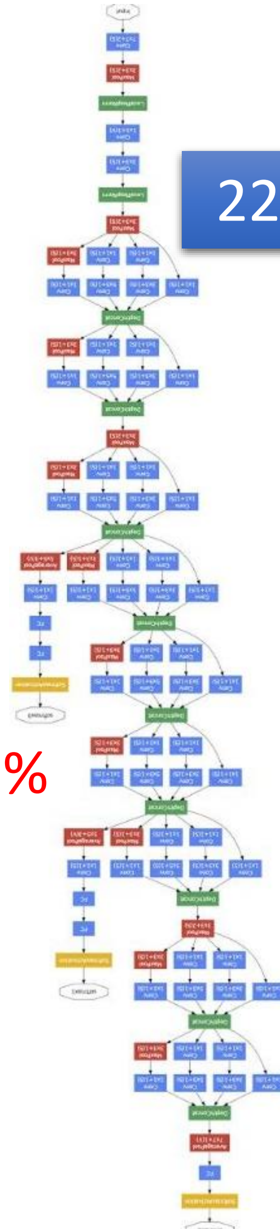
7.3%



VGG (2014)

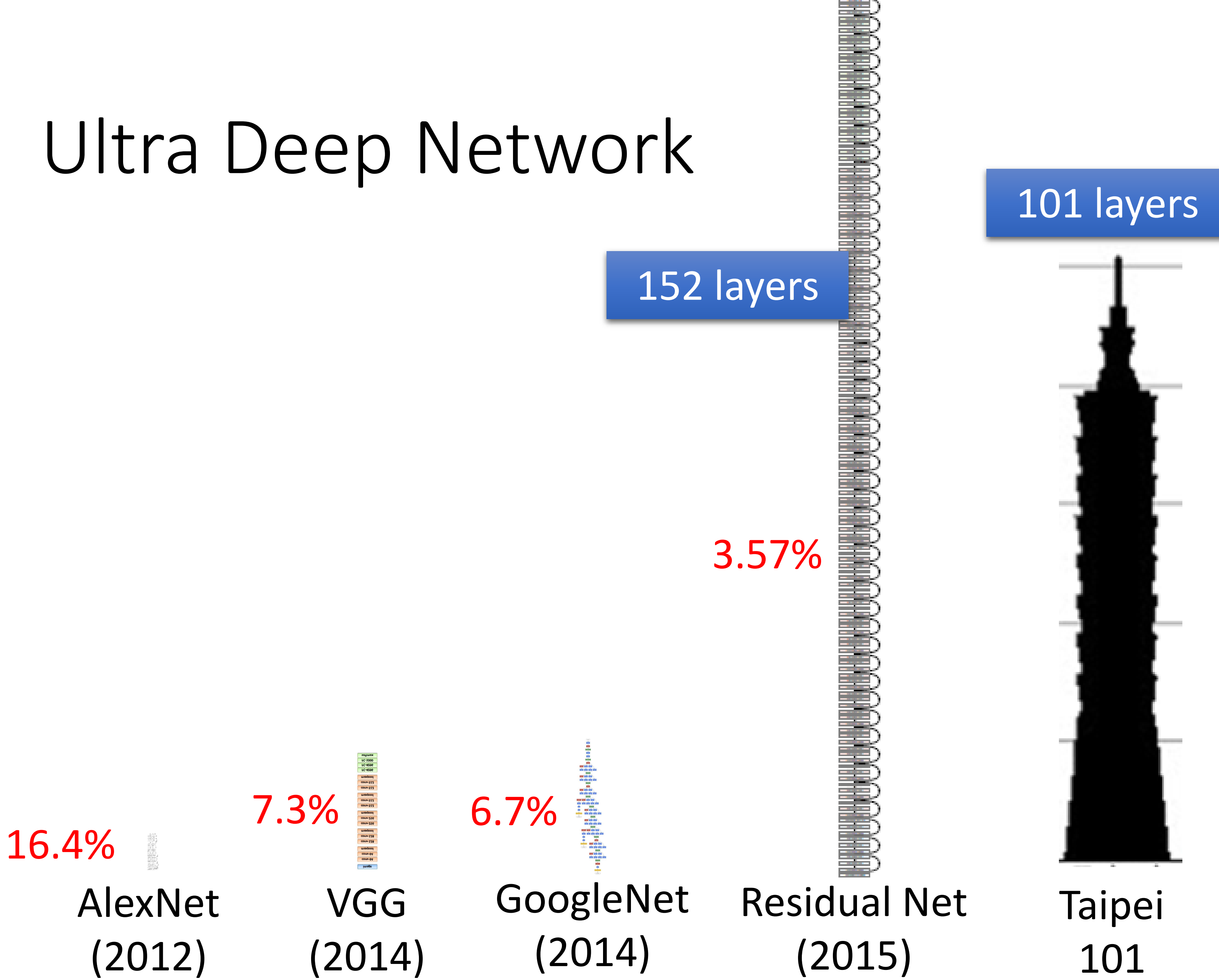
22 layers

6.7%



GoogleNet (2014)

Ultra Deep Network

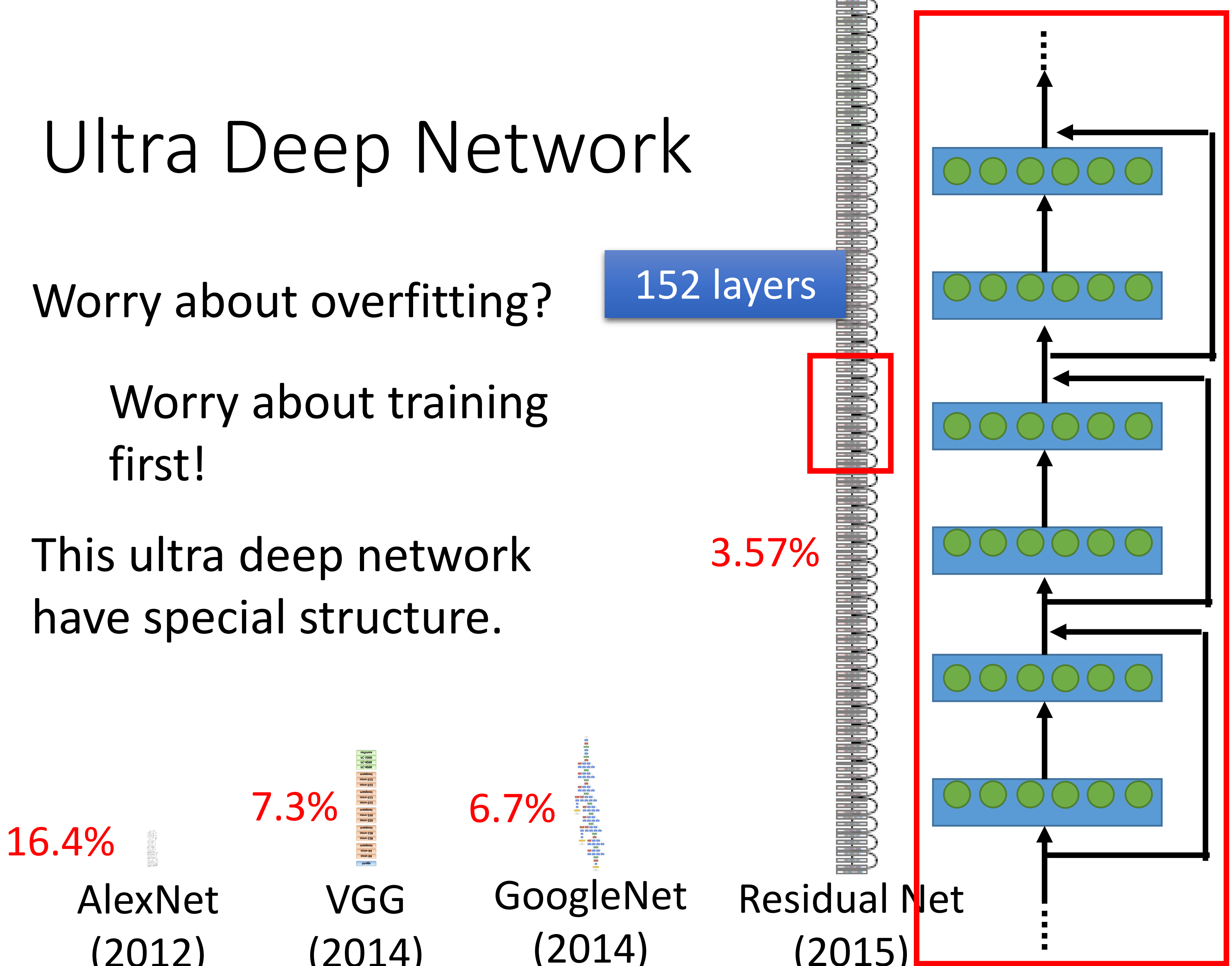


Ultra Deep Network

Worry about overfitting?

Worry about training first!

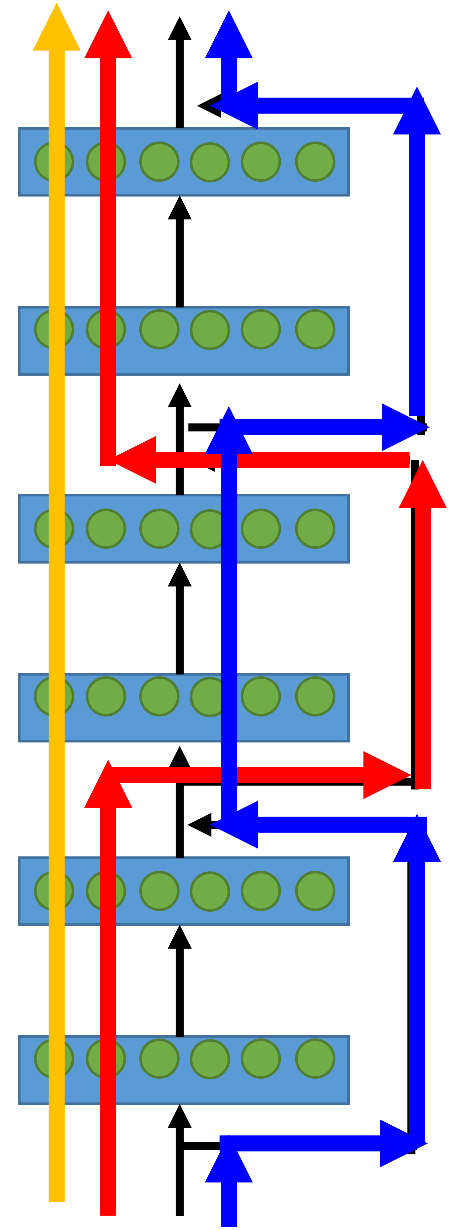
This ultra deep network have special structure.



Ultra Deep Network

- Ultra deep network is the ensemble of many networks with different depth.

Ensemble
- **6 layers**
- **4 layers**
- **2 layers**



Residual Networks are Exponential Ensembles of Relatively Shallow Networks
https://arxiv.org/abs/1605.06431

Ultra Deep Network

- FractalNet

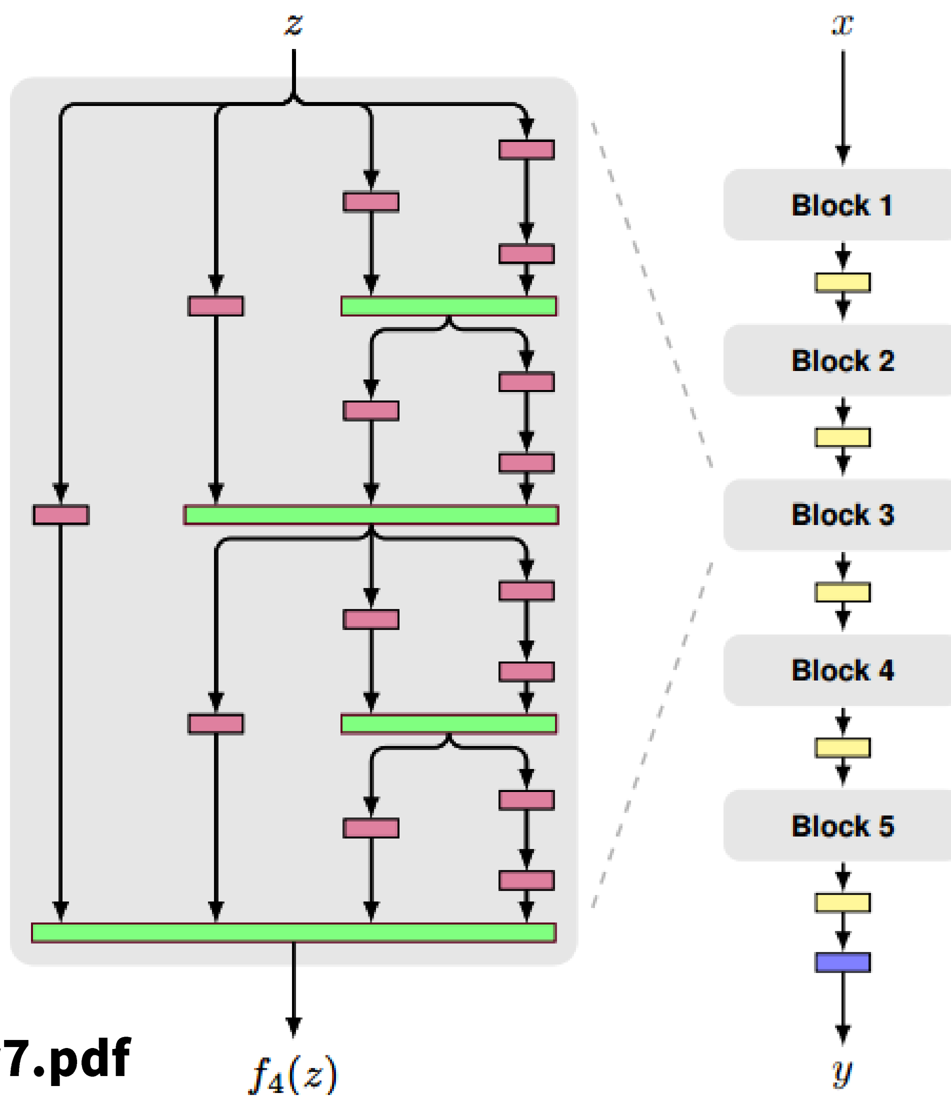
FractalNet: Ultra-Deep Neural Networks without Residuals https://arxiv.org/abs/1605.07648

Resnet in Resnet

Resnet in Resnet: Generalizing Residual Architectures https://arxiv.org/abs/1603.08029

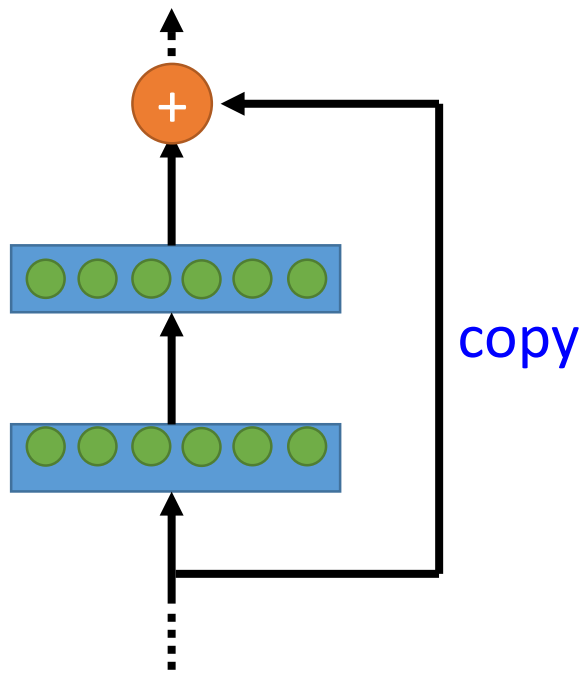
Good Initialization?

All you need is a good init http://arxiv.org/pdf/1511.06422v7.pdf



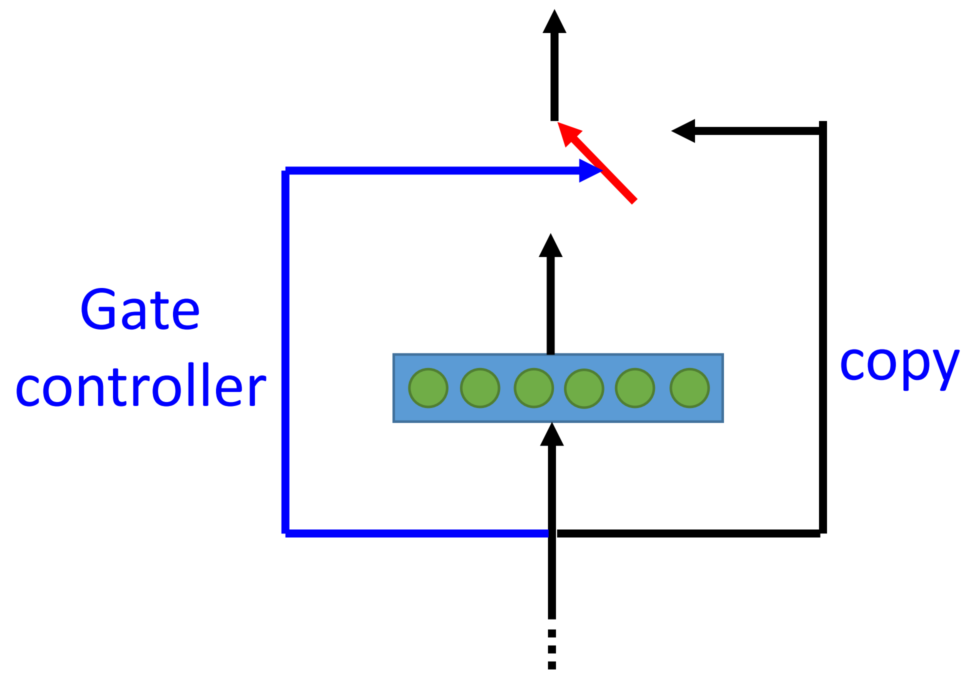
Ultra Deep Network

- **Residual Network**

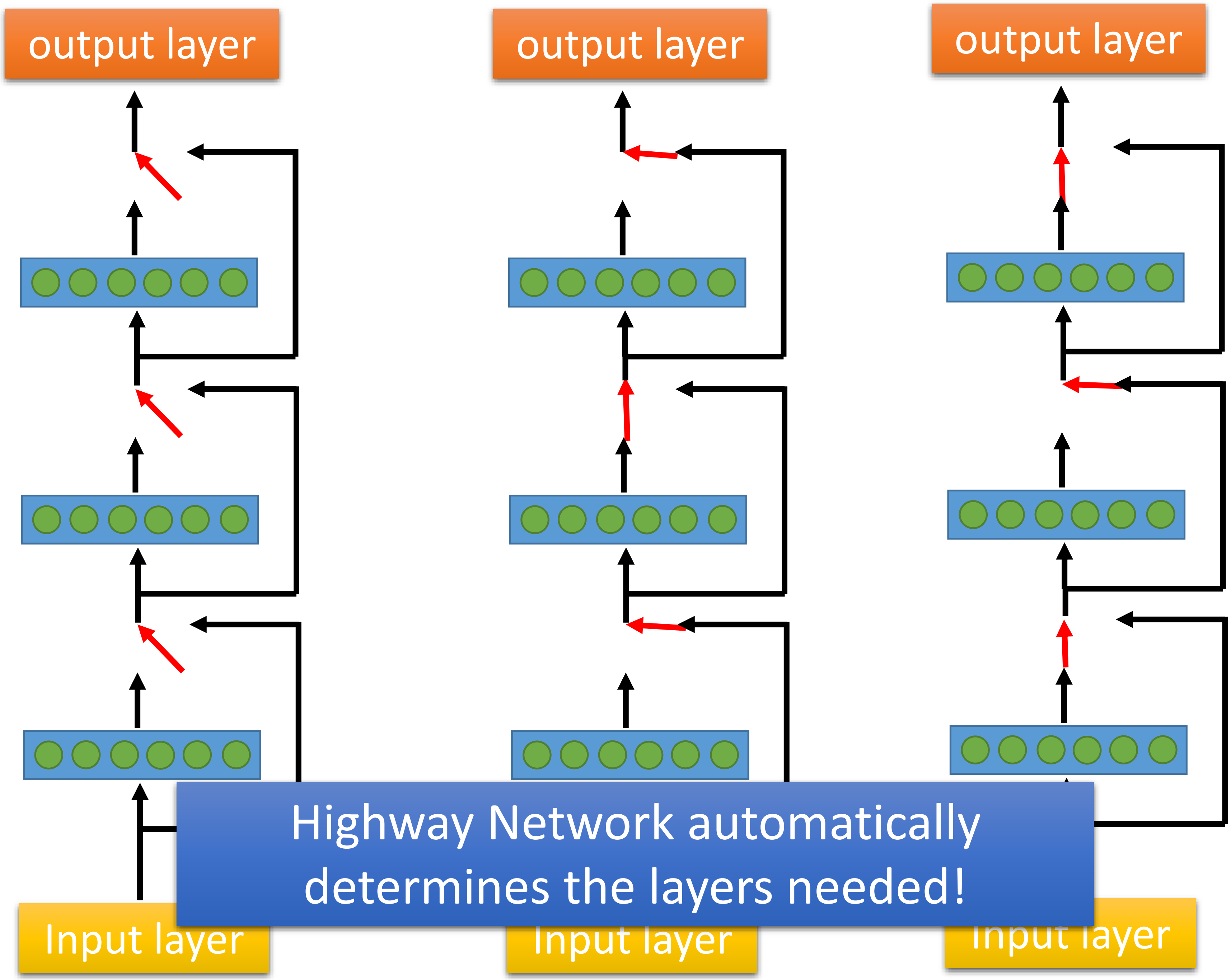


Deep Residual Learning for Image Recognition
http://arxiv.org/abs/1512.03385

- **Highway Network**



Training Very Deep Networks
https://arxiv.org/pdf/1507.06228v2.pdf


output layer
output layer
output layer
Input layer
Input layer
Input layer
Highway Network automatically determines the layers needed!

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- Image: Realizing what the World Looks Like
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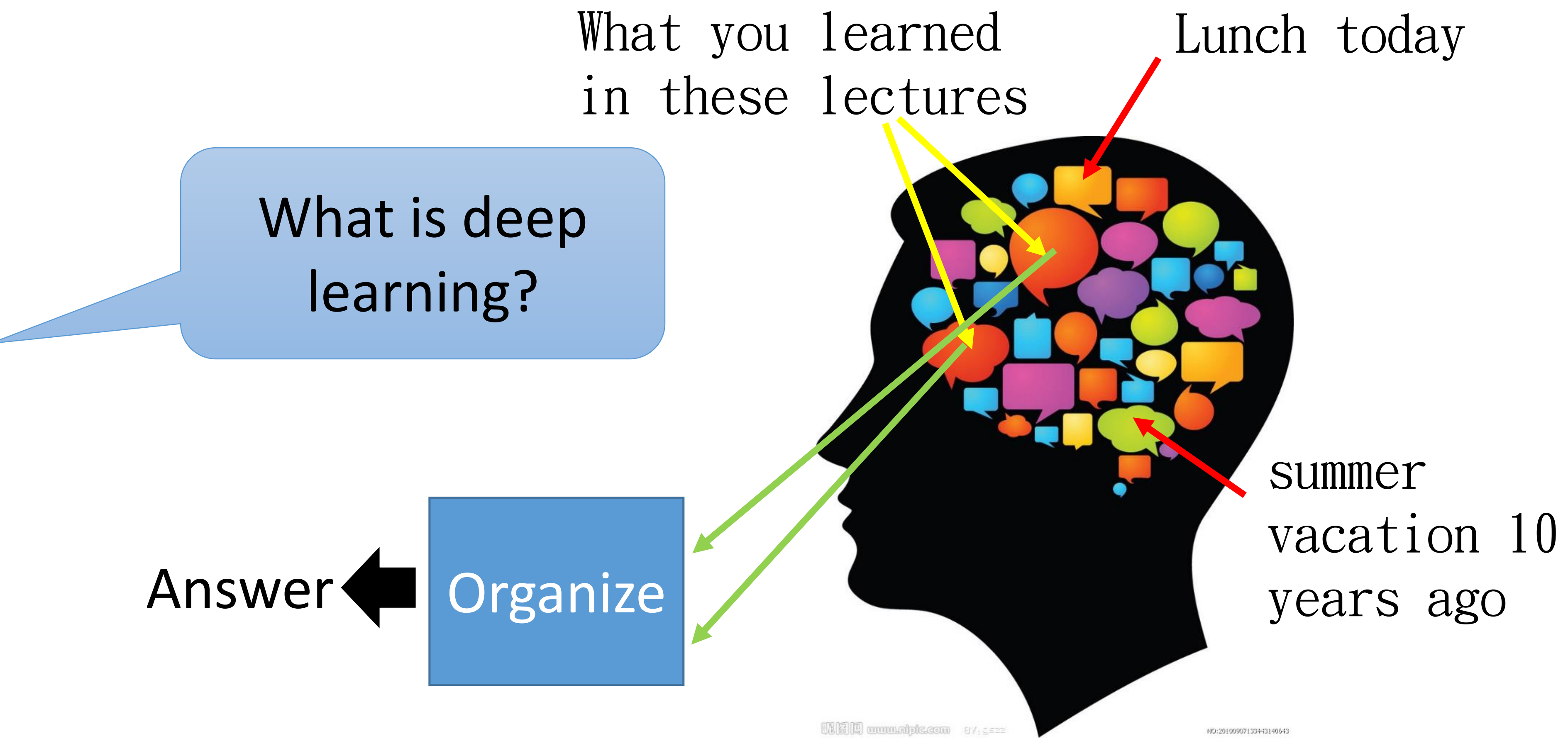
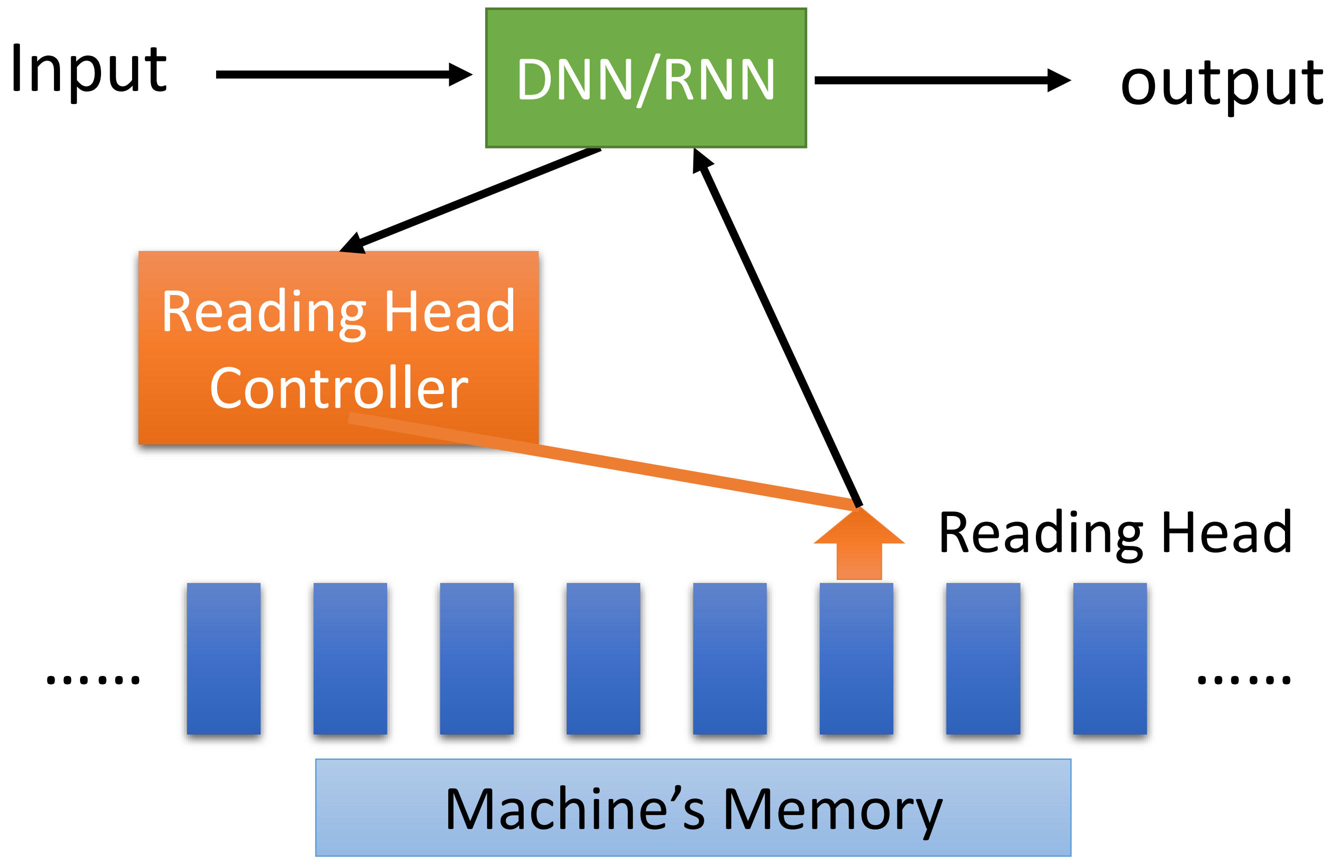
Attention-based Model



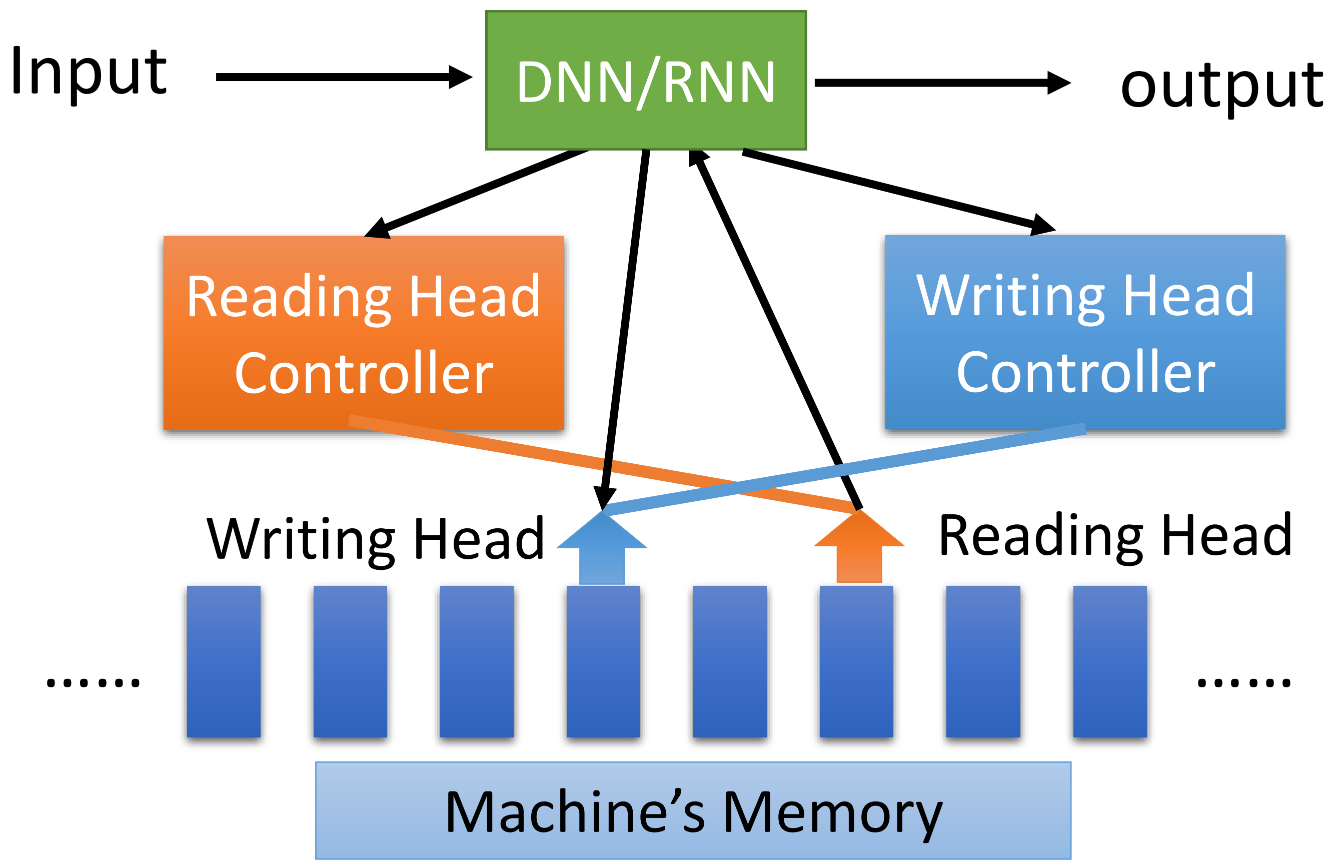
http://henrylo1605.blogspot.tw/2015/05/blog-post_56.html

Attention-based Model



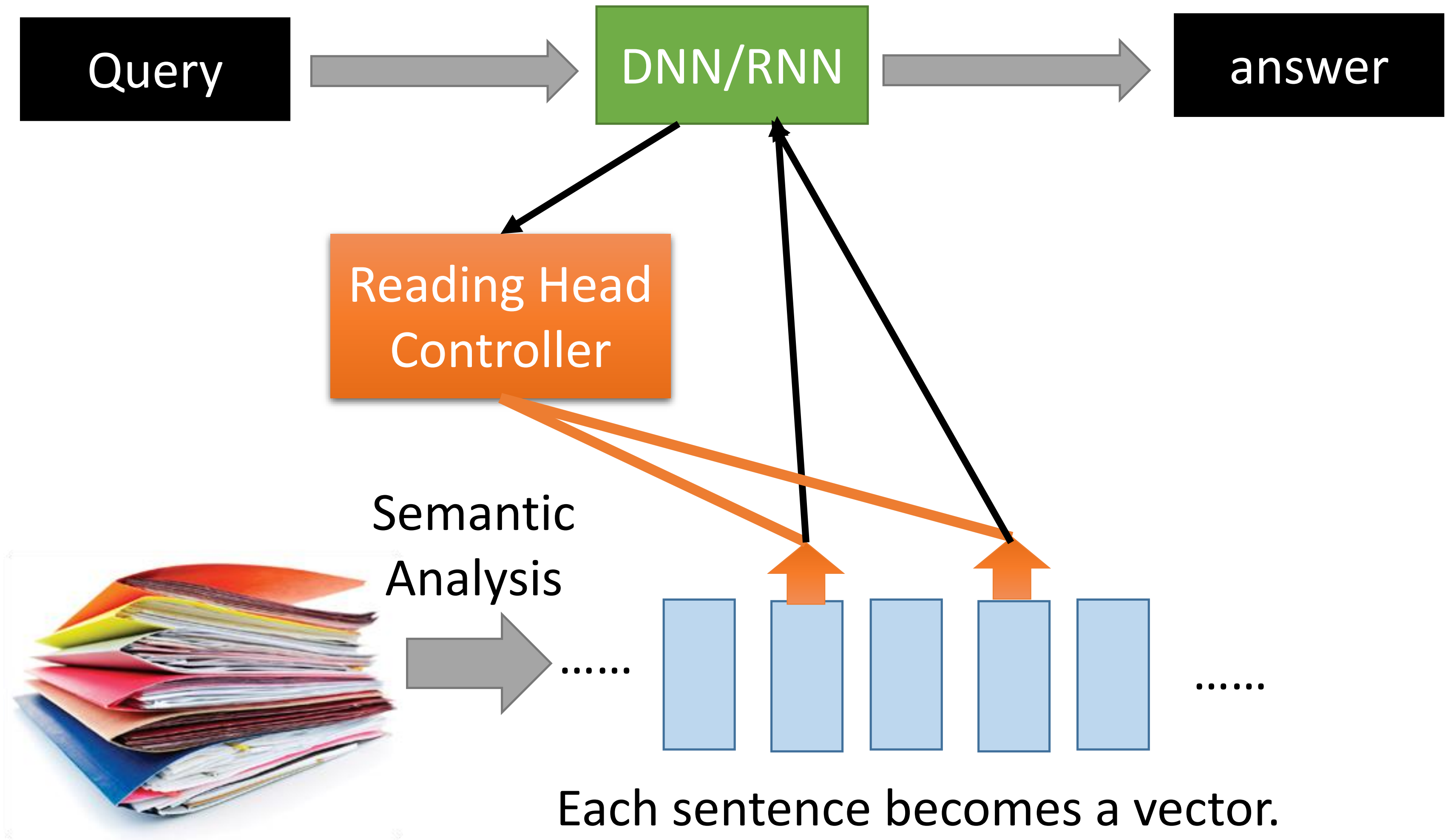
Ref:
http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/Attain%20(v3).ecm.mp4/index.html

Attention-based Model v2



Neural Turing Machine

Reading Comprehension



Reading Comprehension

- End-To-End Memory Networks. S. Sukhbaatar, A. Szlam, J. Weston, R. Fergus. NIPS, 2015.

The position of reading head:

Story (16: basic induction)	Support	Hop 1	Hop 2	Hop 3
Brian is a frog.	yes	0.00	0.98	0.00
Lily is gray.		0.07	0.00	0.00
Brian is yellow.	yes	0.07	0.00	1.00
Julius is green.		0.06	0.00	0.00
Greg is a frog.	yes	0.76	0.02	0.00
What color is Greg? Answer: yellow Prediction: yellow				

Keras has example:
https://github.com/fchollet/keras/blob/master/examples/babi_memnn.py

Visual Question Answering

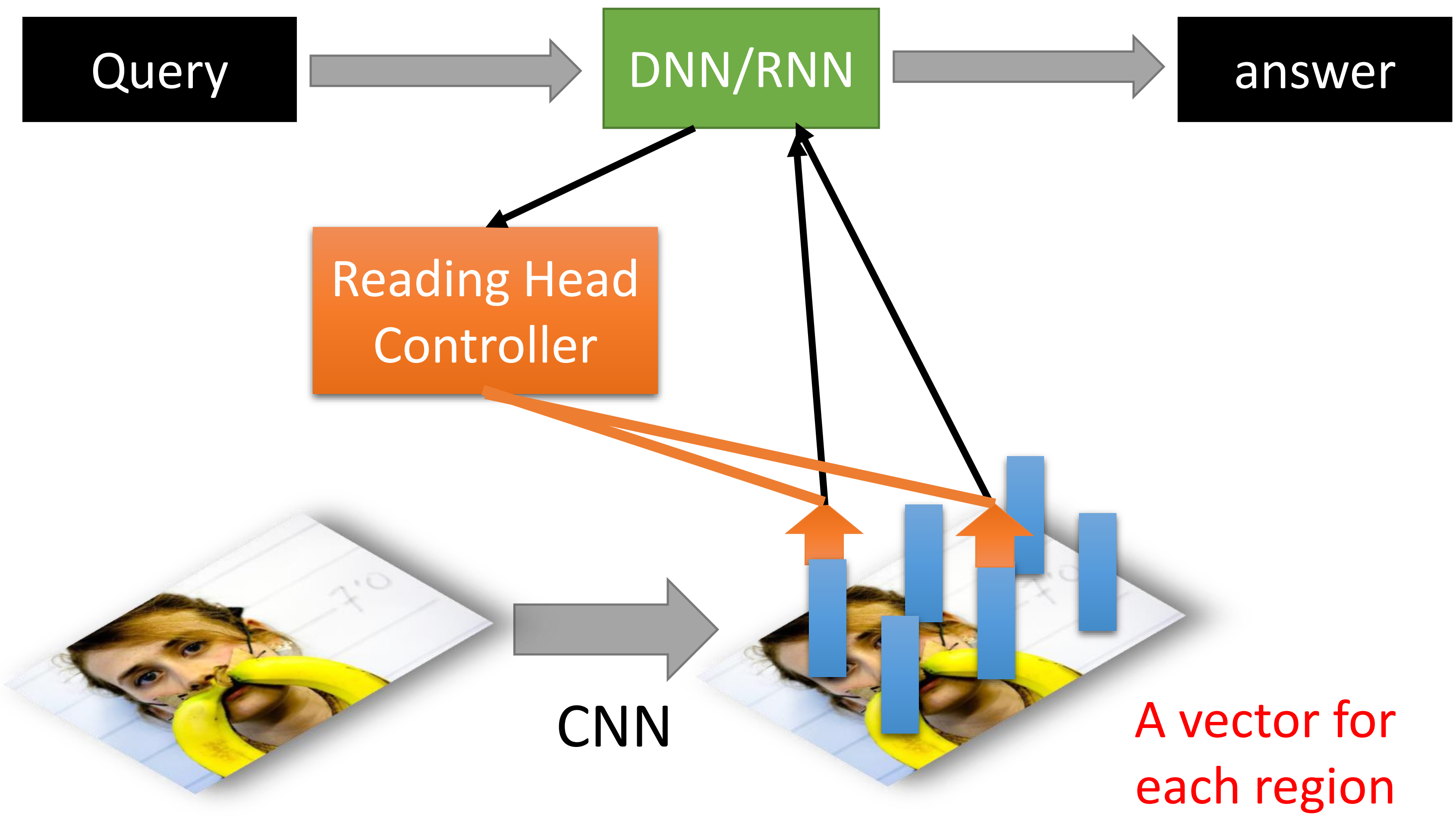
What is the mustache made of?

AI System

bananas

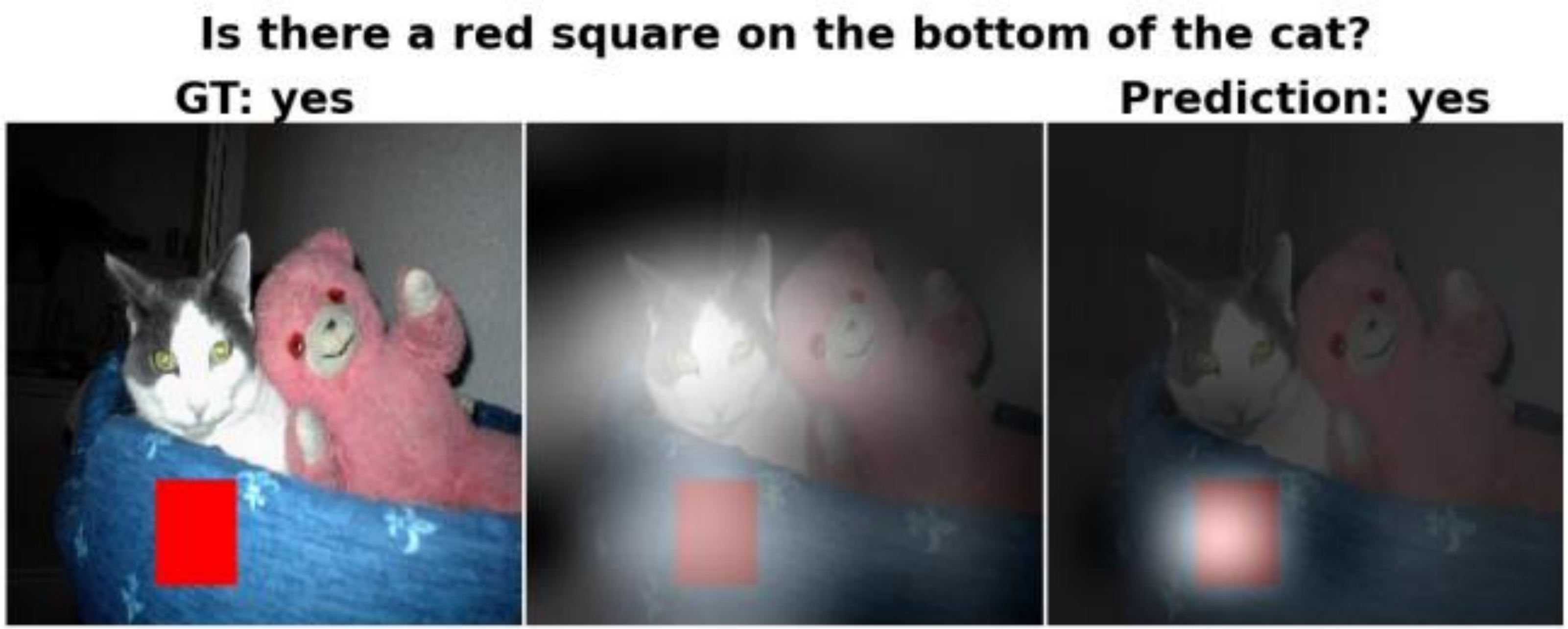
source: http://visualqa.org/

Visual Question Answering



Visual Question Answering

- Huijuan Xu, Kate Saenko. Ask, Attend and Answer: Exploring Question-Guided Spatial Attention for Visual Question Answering. arXiv Pre-Print, 2015



Speech Question Answering

- **TOEFL Listening Comprehension Test by Machine**
- Example:

Audio Story: (The original story is 5 min long.)

Question: “ What is a possible origin of Venus’ clouds? ”

Choices:

(A) gases released as a result of volcanic activity

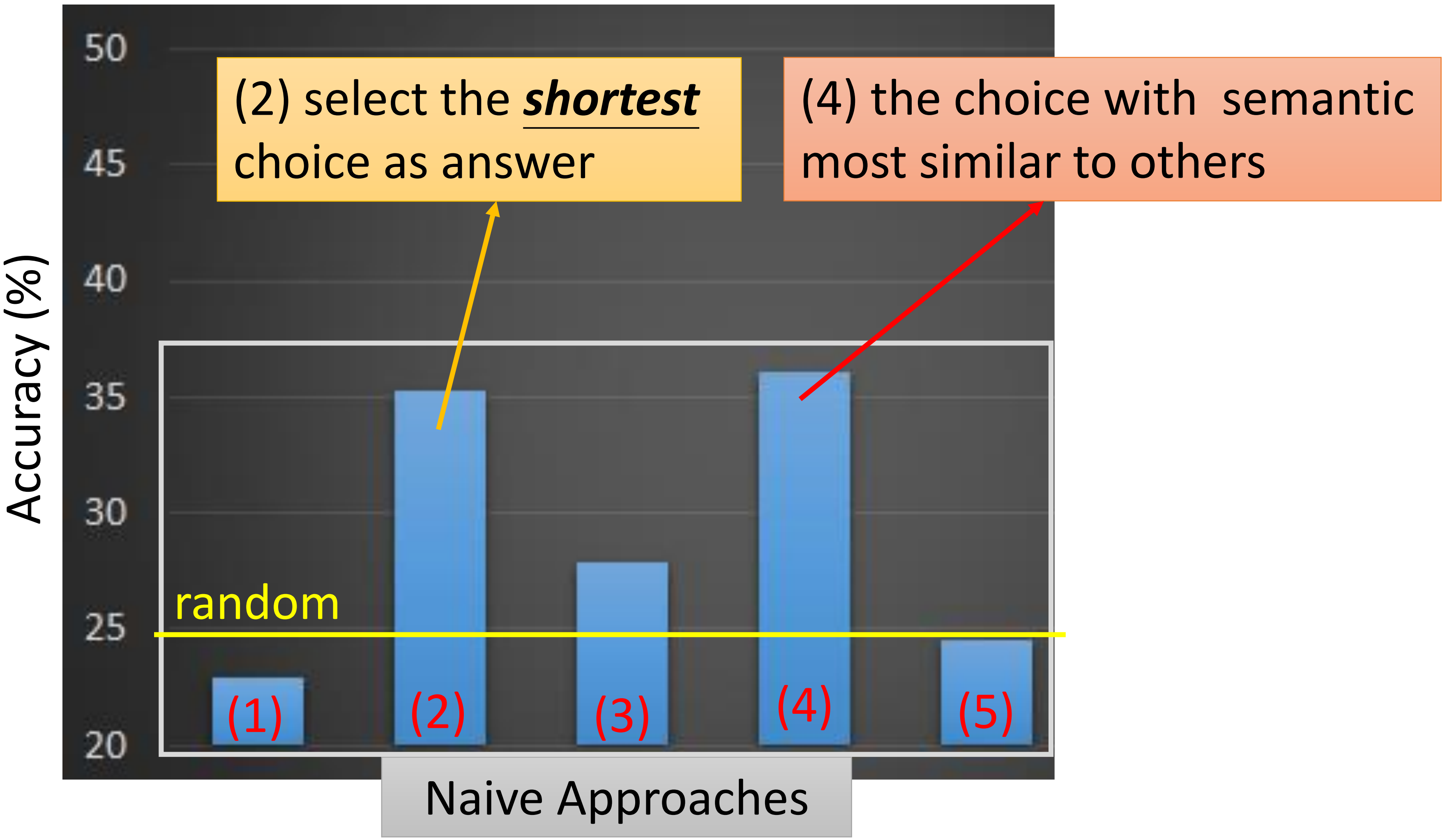
(B) chemical reactions caused by high surface temperatures

(C) bursts of radio energy from the plane's surface

(D) strong winds that blow dust into the atmosphere

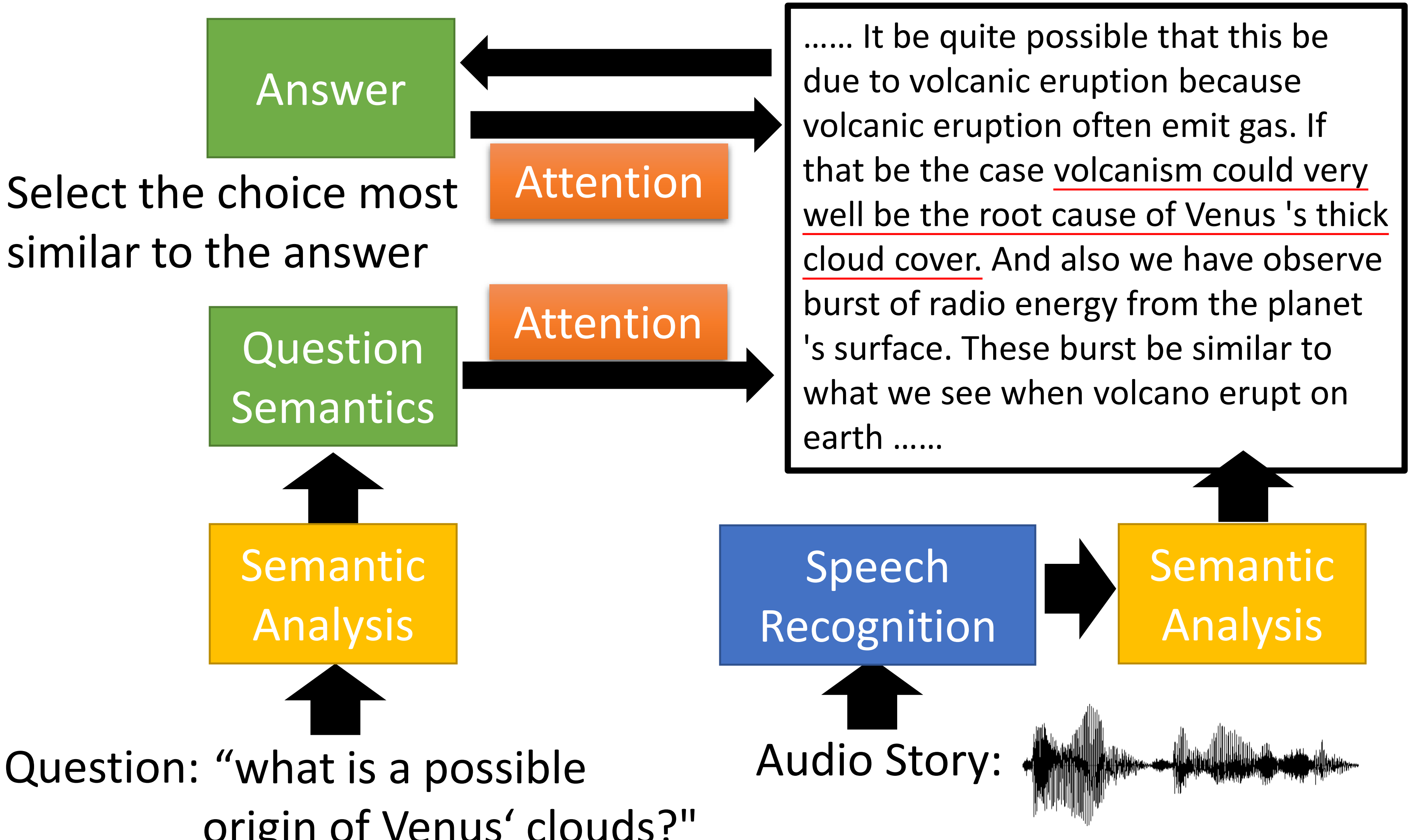
Simple Baselines

Experimental setup:
717 for training,
124 for validation, 122 for testing



Model Architecture

Everything is learned from training examples

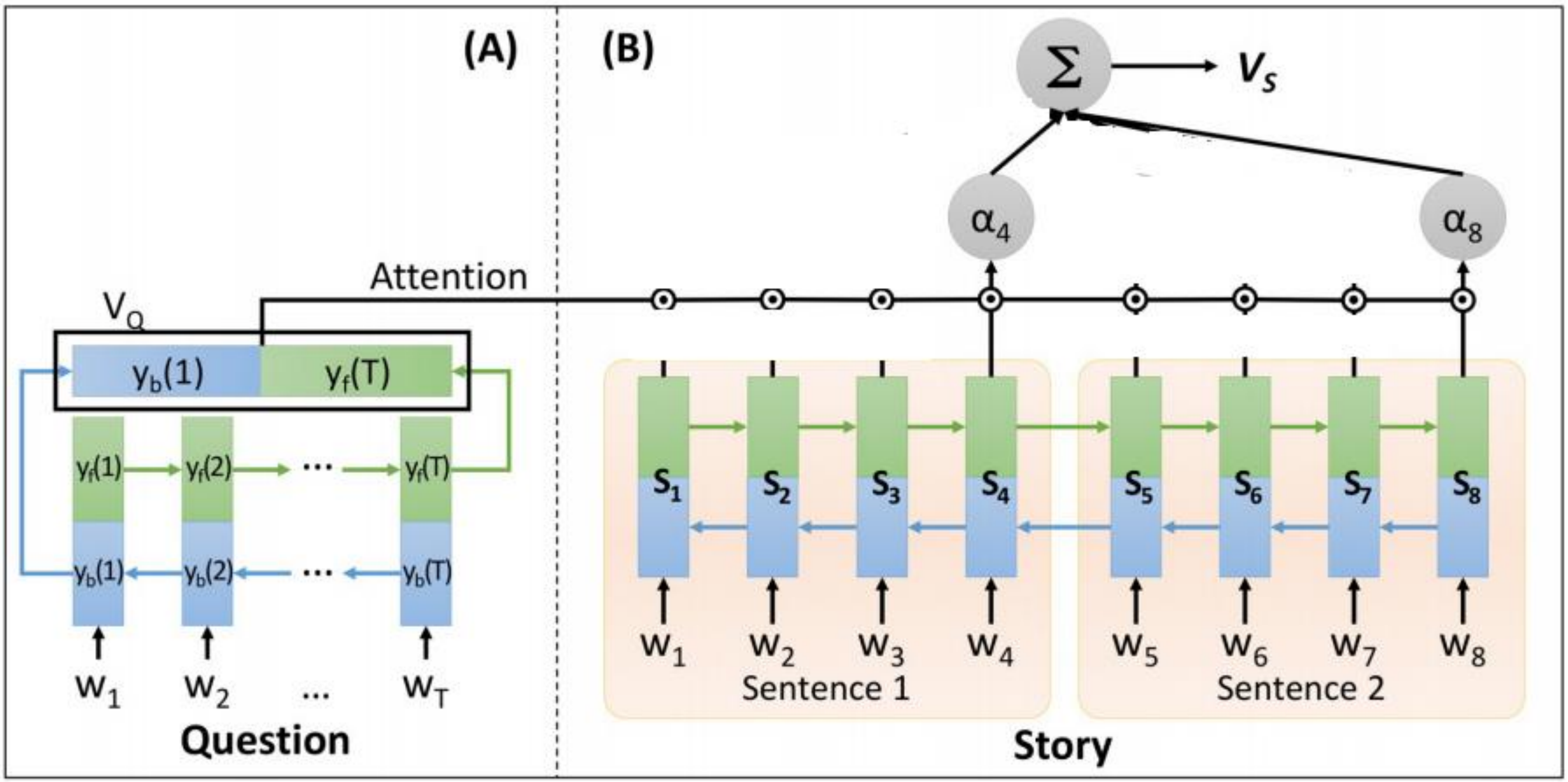


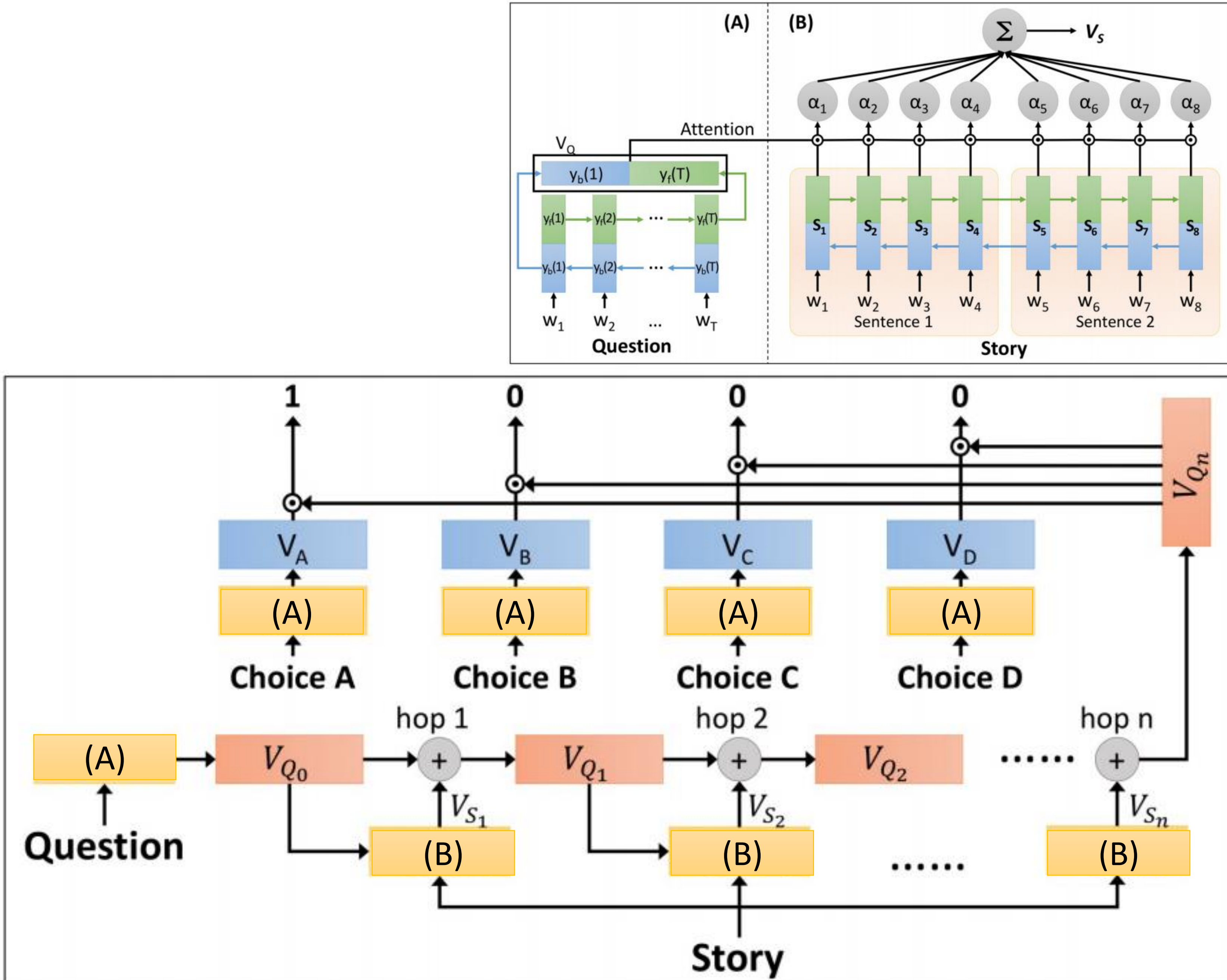
Model Architecture

Word-based Attention

Model Architecture

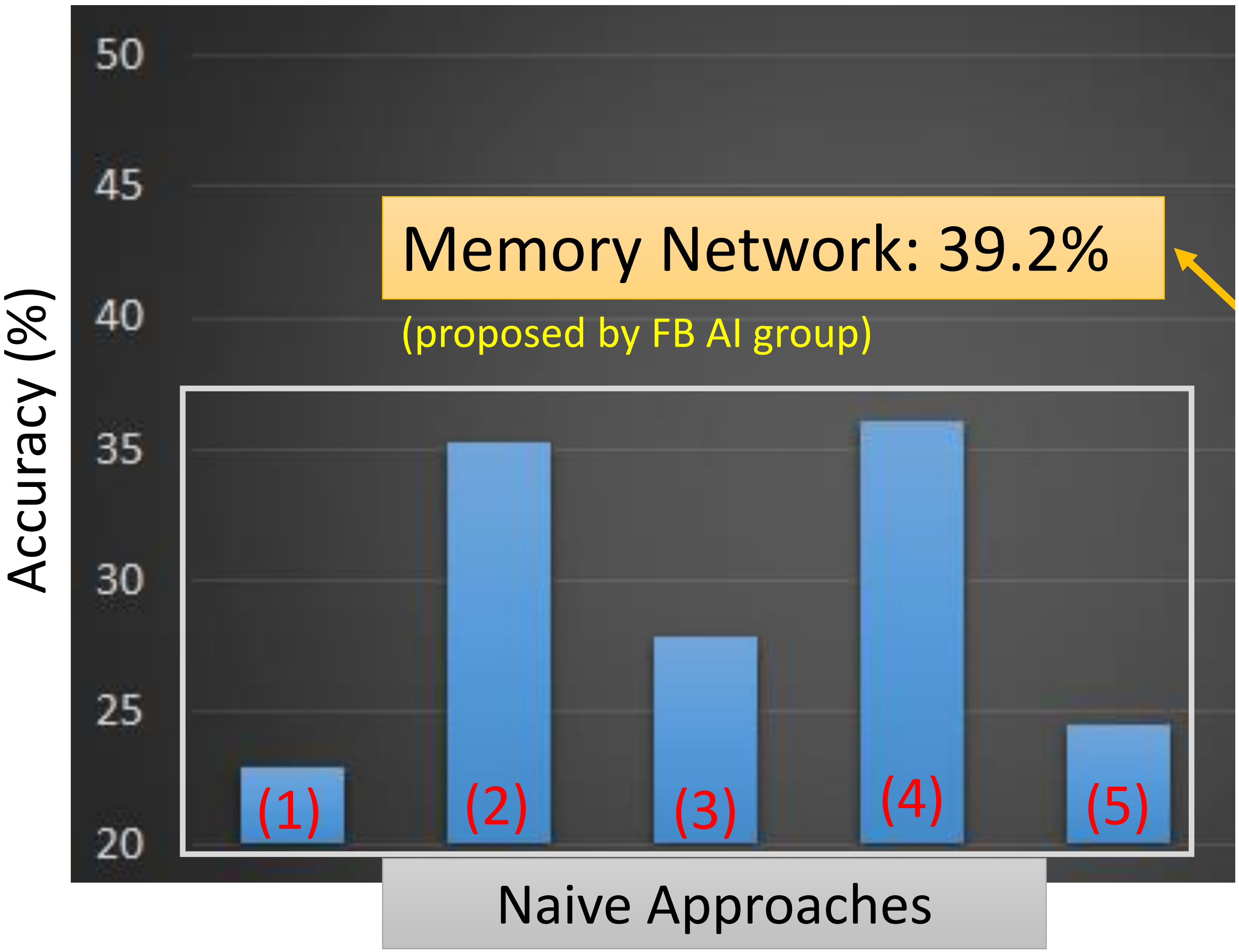
Sentence-based Attention





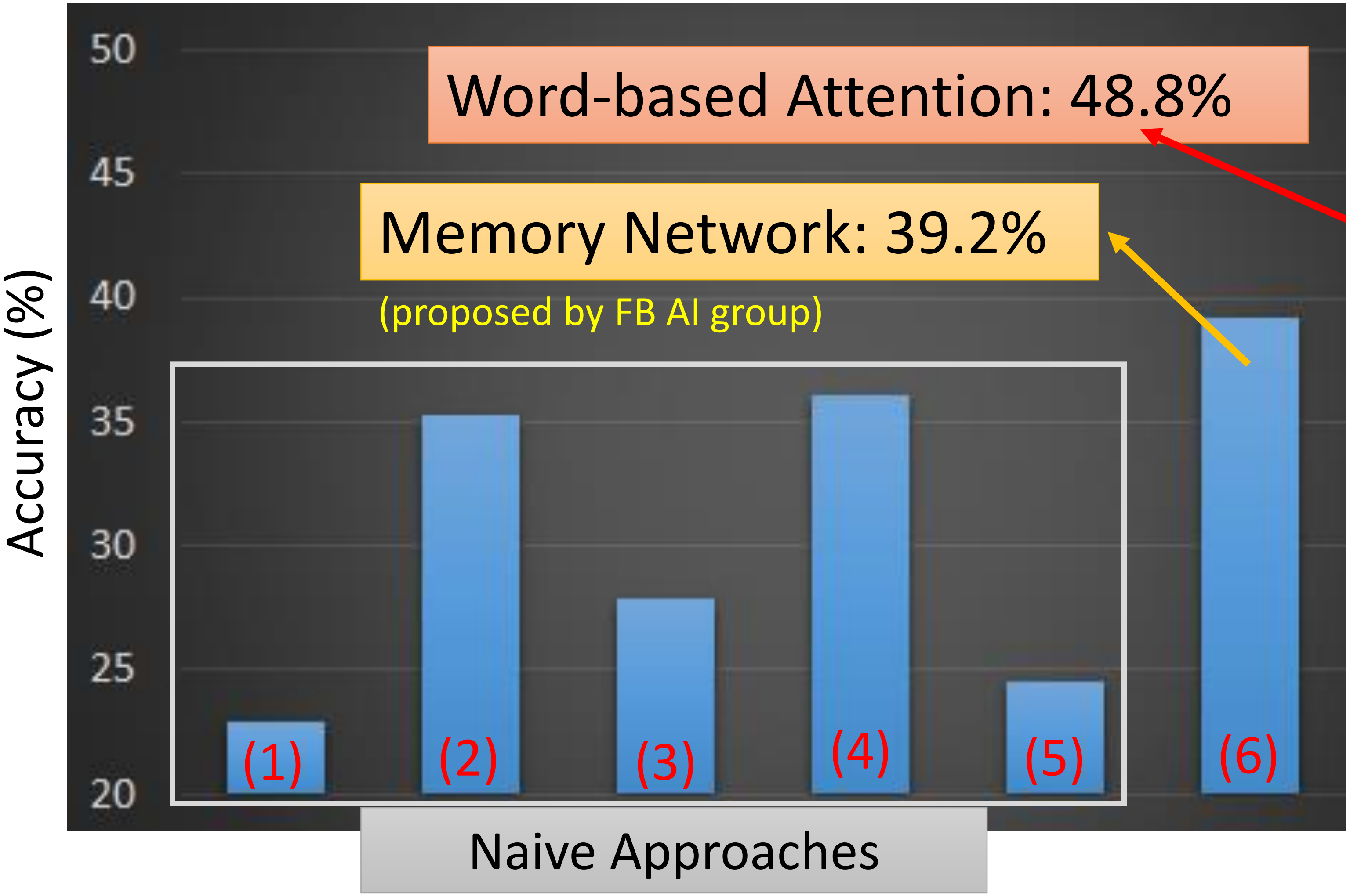
(A)
(B)
Σ
V_S
$α_1$ $α_2$ $α_3$ $α_4$ $α_5$ $α_6$ $α_7$ $α_8$
Attention
V_Q
$y_b(1)$ $y_f(T)$
$y_f(1)$ $y_f(2)$ ... $y_f(T)$
$y_b(1)$ $y_b(2)$ ... $y_b(T)$
w_1 w_2 ... w_T
Question
S_1 S_2 S_3 S_4 S_5 S_6 S_7 S_8
w_1 w_2 w_3 w_4 w_5 w_6 w_7 w_8
Sentence 1
Sentence 2
Story
1 0 0 0
V_{Q_n}
V_A V_B V_C V_D
(A) (A) (A) (A)
Choice A
Choice B
Choice C
Choice D
hop 1
hop 2
hop n
(A)
V_{Q_0}
V_{Q_1}
V_{Q_2}
......
Question
V_{S_1}
V_{S_2}
V_{S_n}
(B) (B) ...... (B)
Story

Supervised Learning



Supervised Learning

[Tseng & Lee, Interspeech 16]
[Fang & Hsu & Lee, SLT 16]



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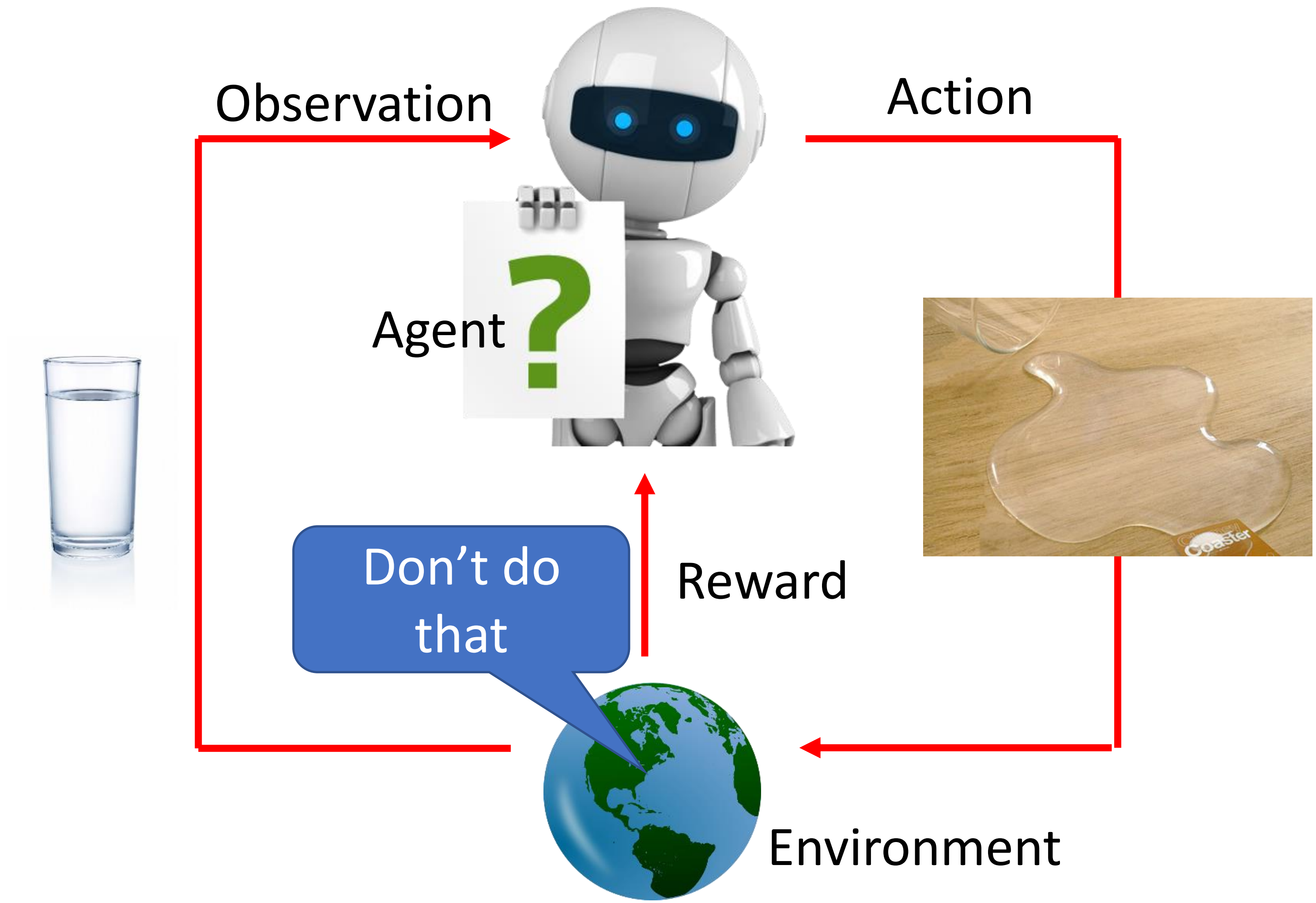
Scenario of Reinforcement Learning



Scenario of Reinforcement Learning

http://www.sznews.com/news/content/2013-11/26/content_8800180.htm

Supervised v.s. Reinforcement

- Supervised

Learning from teacher

"Hello" Say "Hi"

"Bye bye" Say "Good bye"

- Reinforcement

……. ……. ……

Hello ☺ ……

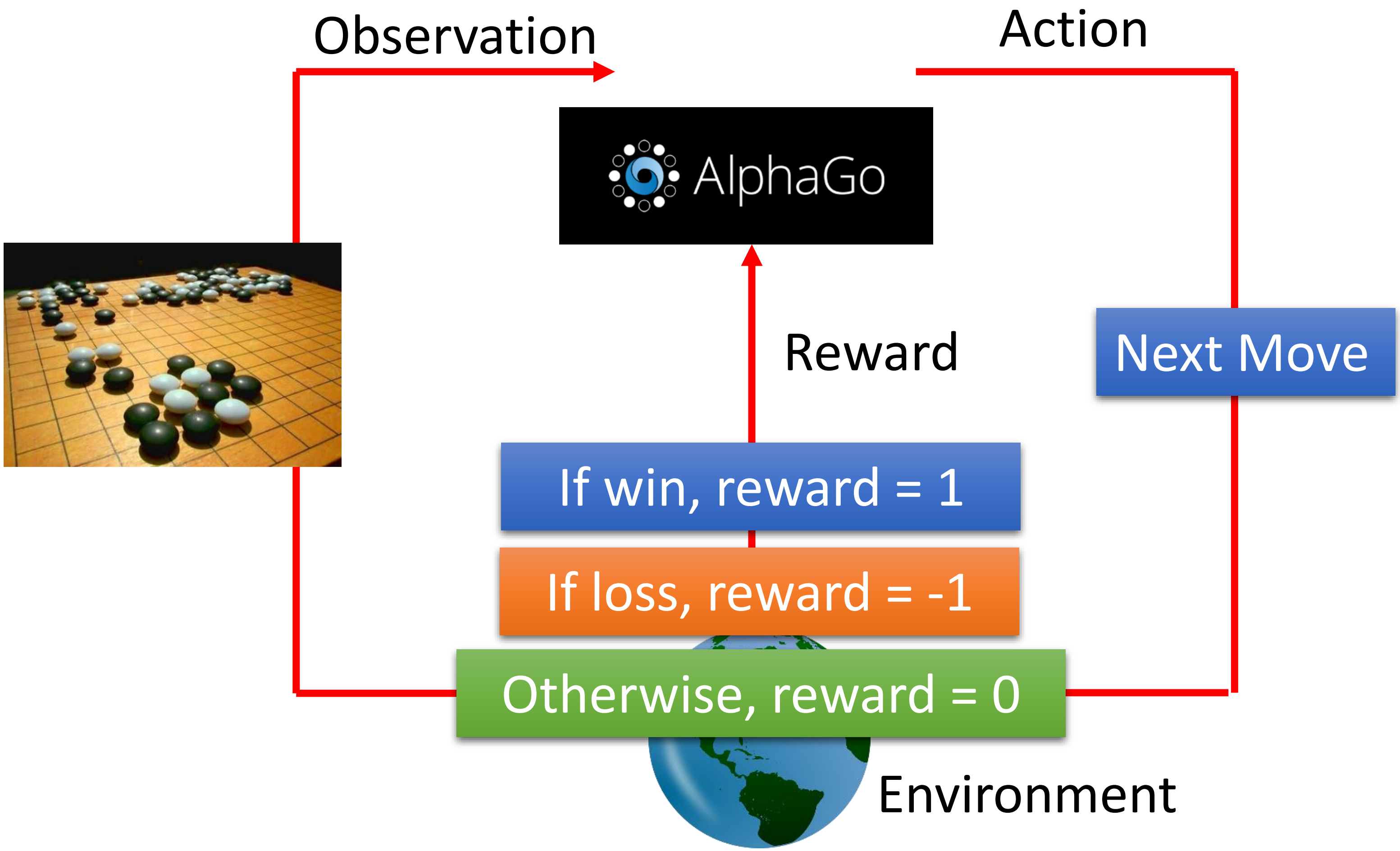
Bad

Learning from critics

Agent Agent

Scenario of Reinforcement Learning

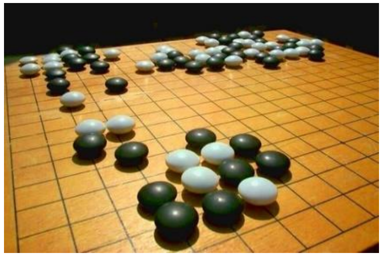
Agent learns to take actions to maximize expected reward.



Supervised v.s. Reinforcement

- Supervised:

Next move: "5-5"



Next move: "3-3"

- Reinforcement Learning

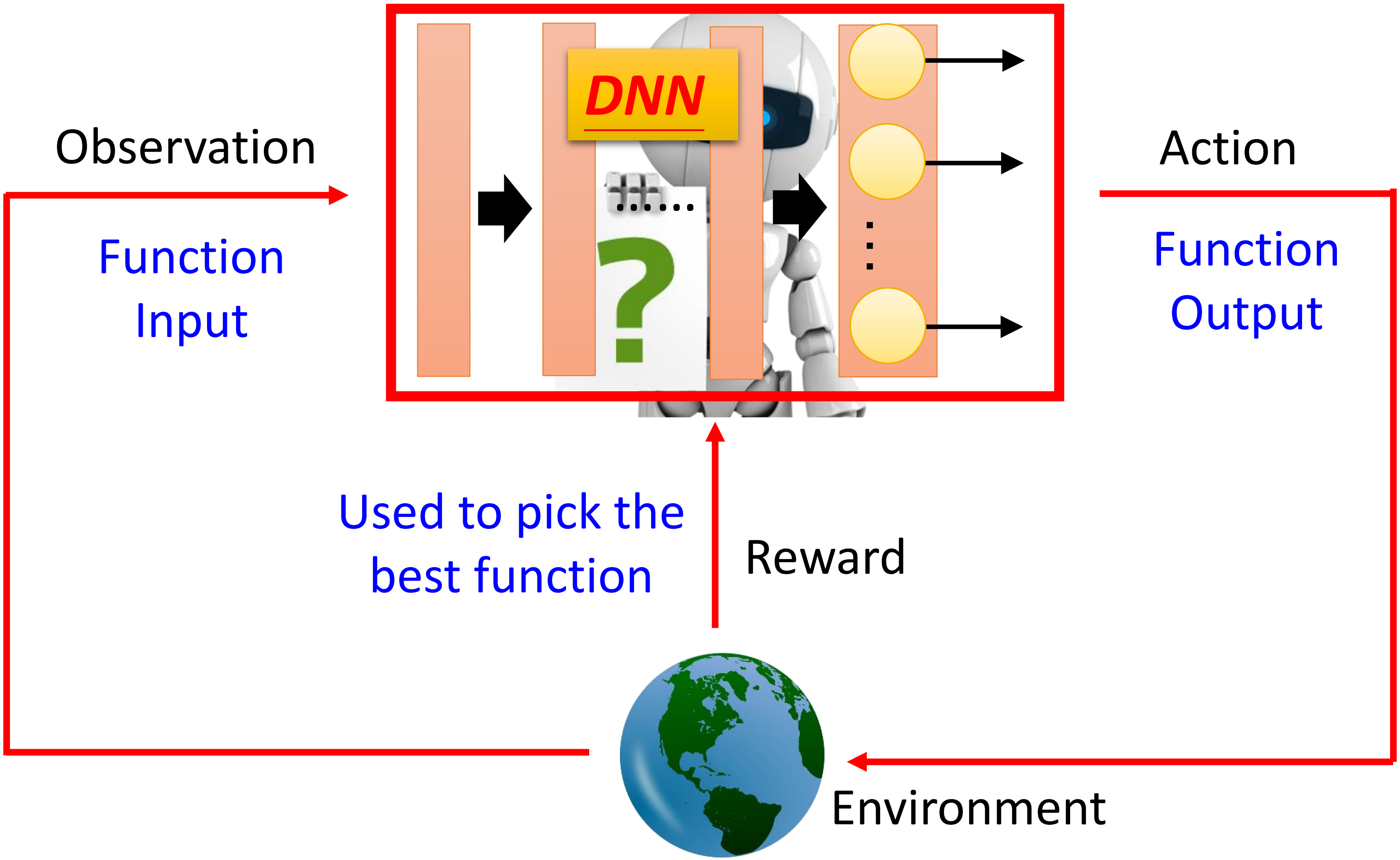
First move → …… many moves …… → Win!

Alpha Go is supervised learning + reinforcement learning.

Difficulties of Reinforcement Learning

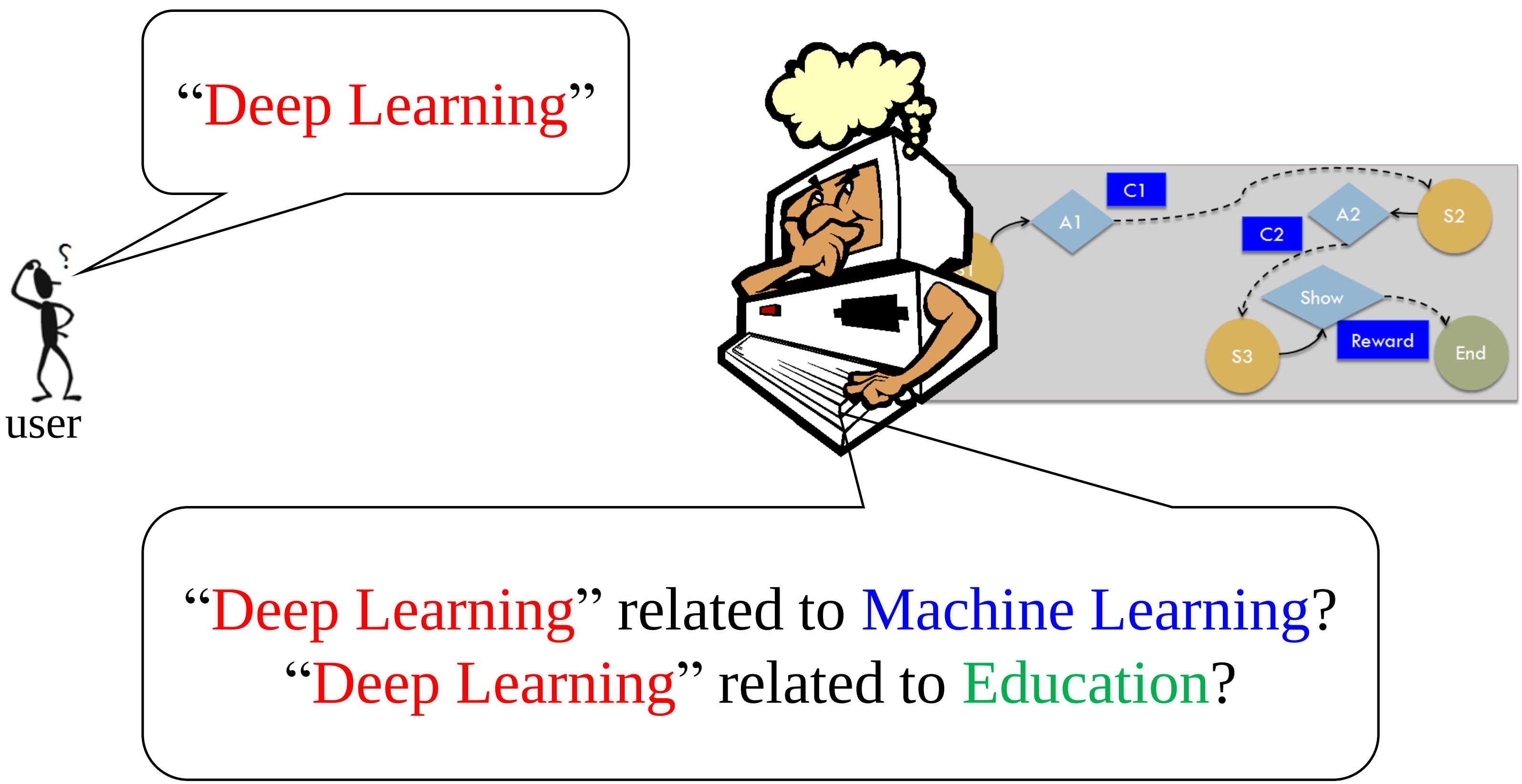
- It may be better to sacrifice immediate reward to gain more long-term reward
    - E.g. Playing Go
- Agent's actions affect the subsequent data it receives
    - E.g. Exploration

Deep Reinforcement Learning



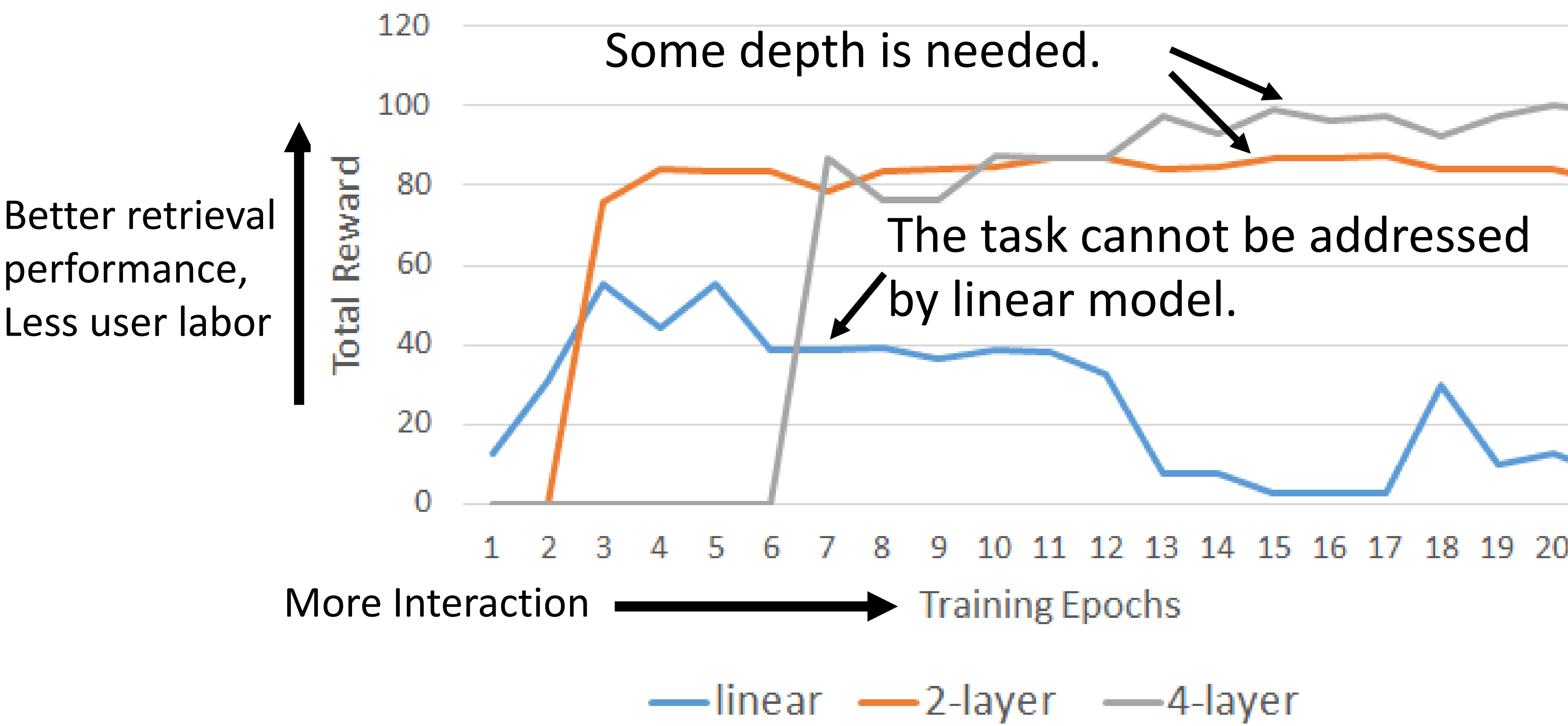
Application: Interactive Retrieval

- Interactive retrieval is helpful. [Wu & Lee, INTERSPEECH 16]



Deep Reinforcement Learning

- Different network depth



More applications

- Alpha Go, Playing Video Games, Dialogue
- Flying Helicopter
  - https://www.youtube.com/watch?v=0JL04JJjocc
- Driving
  - https://www.youtube.com/watch?v=0xo1Ldx3L5Q
- Google Cuts Its Giant Electricity Bill With DeepMind-Powered AI
  - http://www.bloomberg.com/news/articles/2016-07-19/google-cuts-its-giant-electricity-bill-with-deepmind-powered-ai

To learn deep reinforcement learning ……

- Lectures of David Silver
  - http://www0.cs.ucl.ac.uk/staff/D.Silver/web/Teaching.html
  - 10 lectures (1:30 each)
- Deep Reinforcement Learning
  - http://videolectures.net/rldm2015_silver_reinforcement_learning/

Outline

Supervised Learning

- Ultra Deep Network
- Attention Model

New network structure

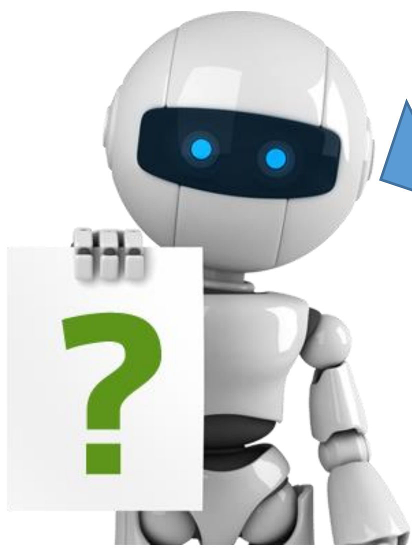
Reinforcement Learning

Unsupervised Learning

- Image: Realizing what the World Looks Like
- Text: Understanding the Meaning of Words
- Audio: Learning human language without supervision

Does machine know what the world look like?

Ref: https://openai.com/blog/generative-models/



Draw something!

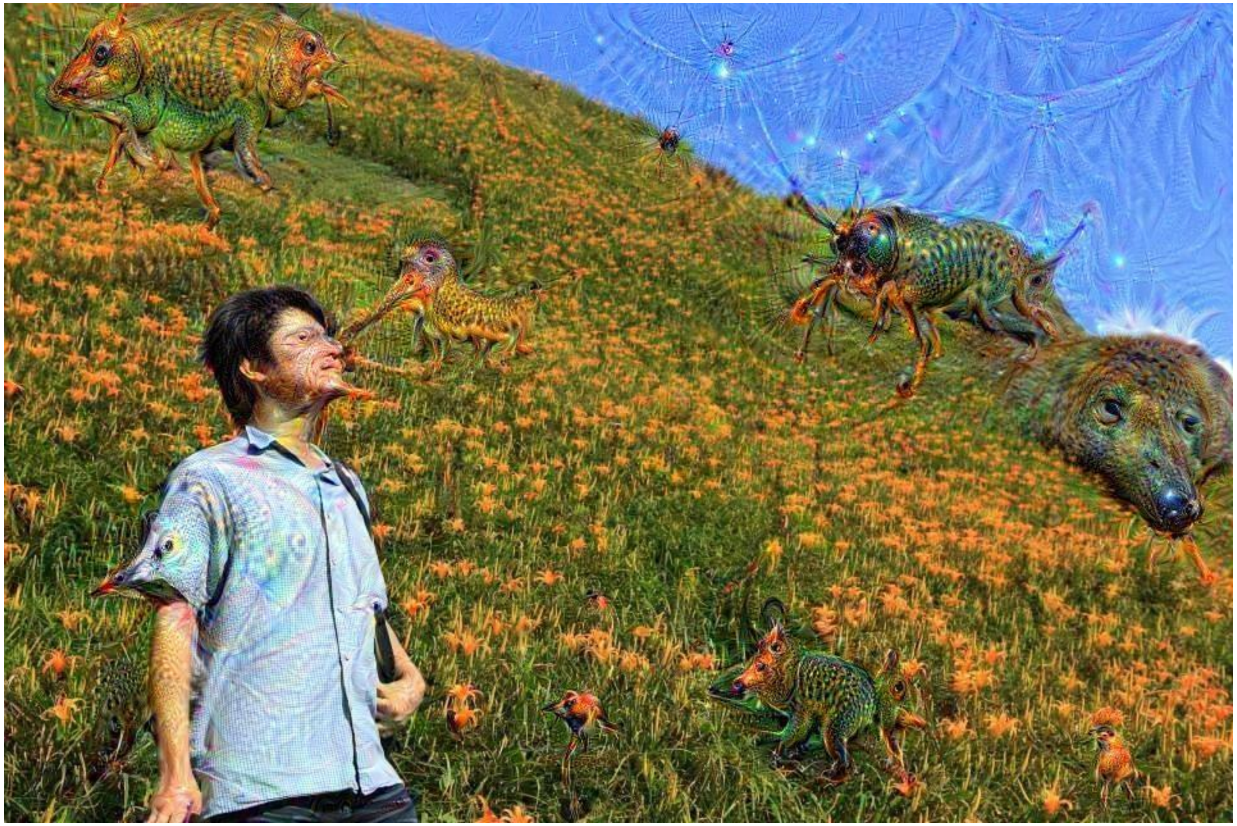
Deep Dream

- Given a photo, machine adds what it sees ……

http://deepdreamgenerator.com/

Deep Dream

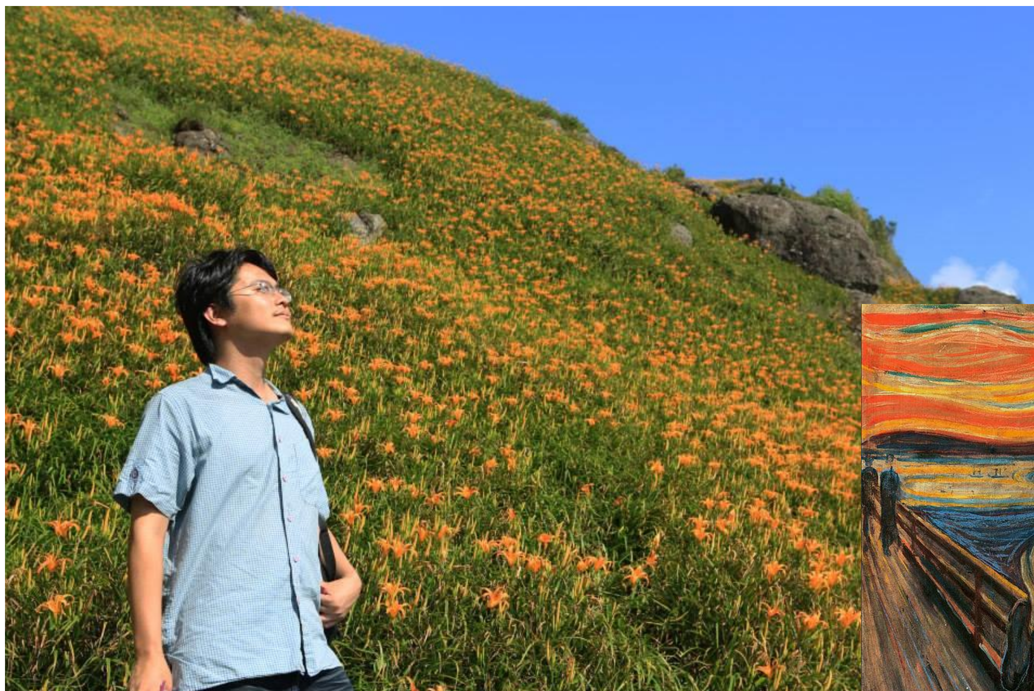
- Given a photo, machine adds what it sees ……

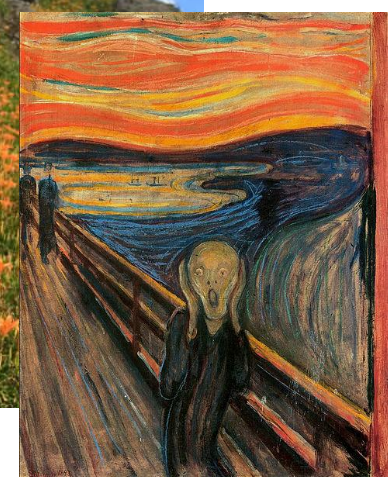


http://deepdreamgenerator.com/

Deep Style

- Given a photo, make its style like famous paintings





https://dreamscopeapp.com/

Deep Style

- Given a photo, make its style like famous paintings

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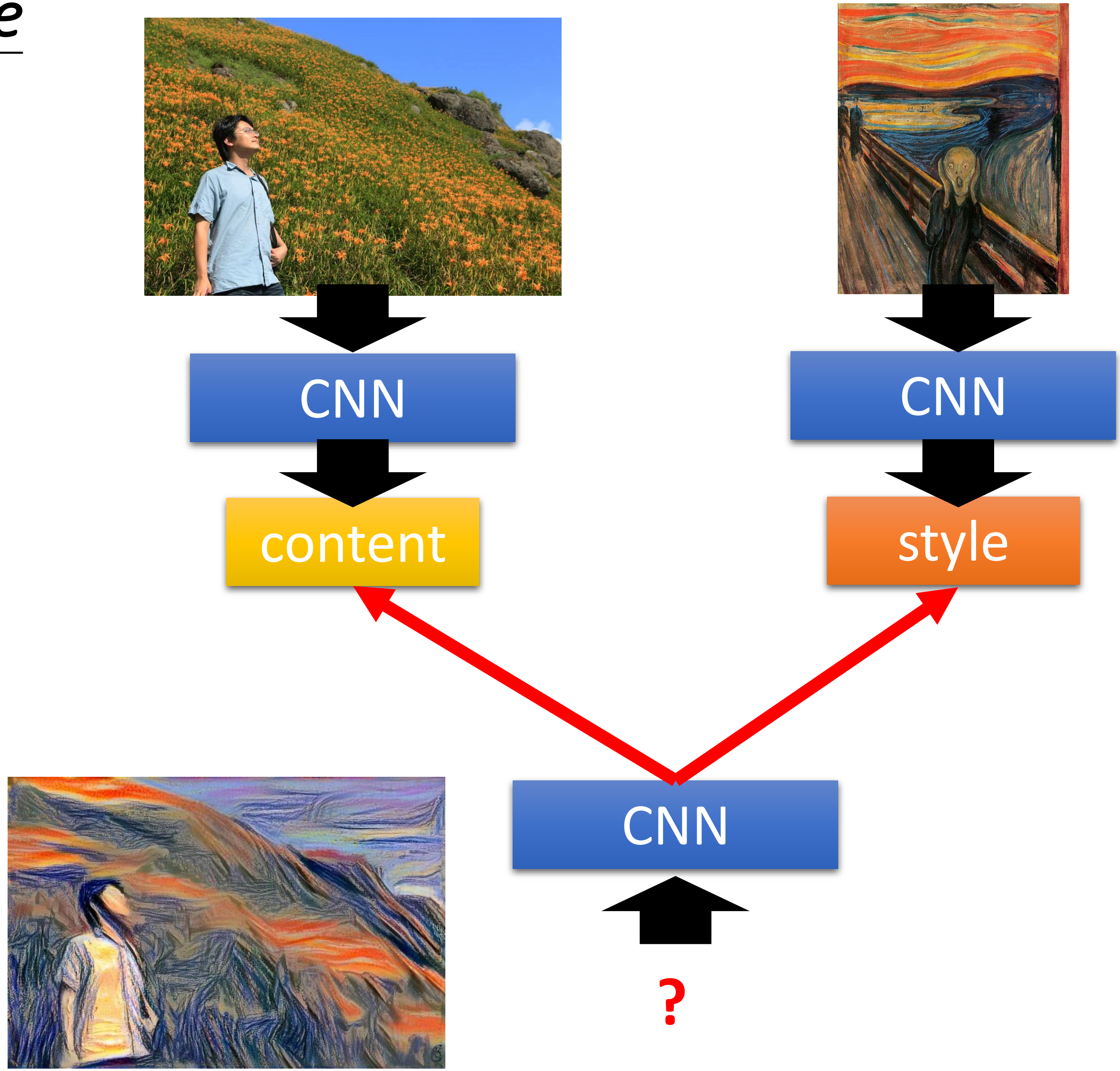
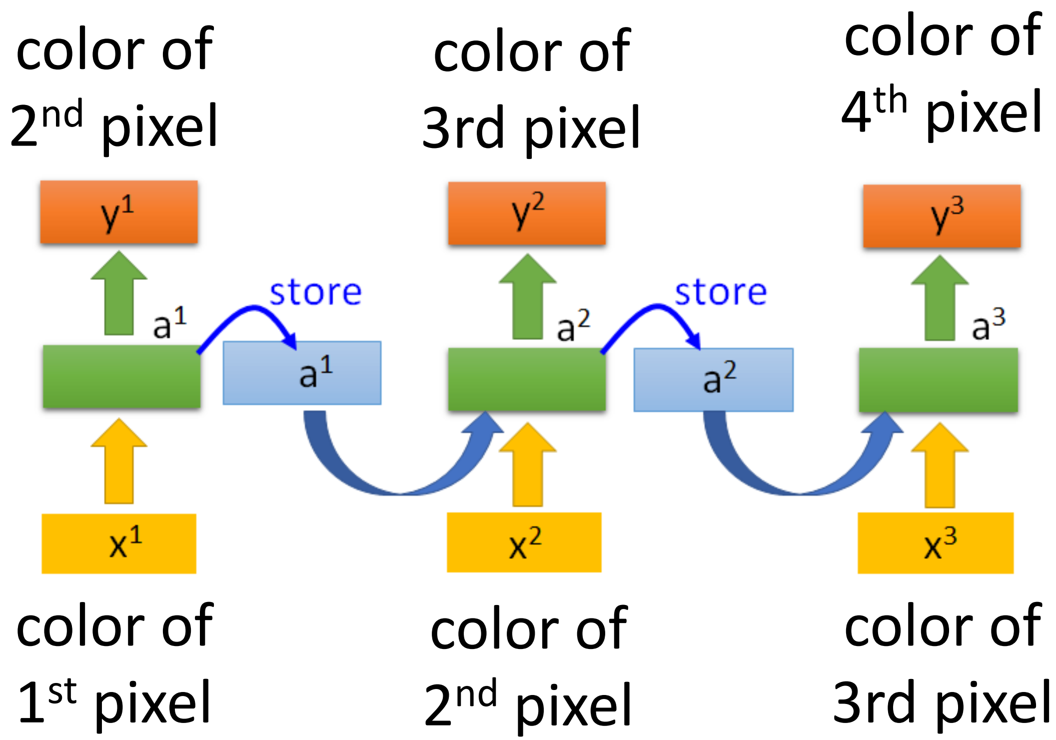
Deep Style

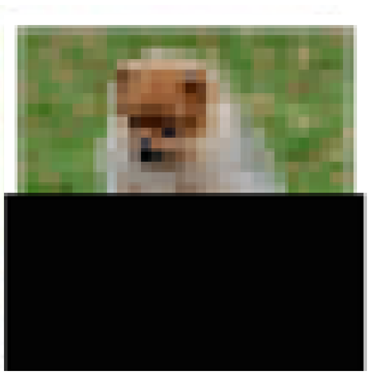


Generating Images by RNN



Generating Images by RNN

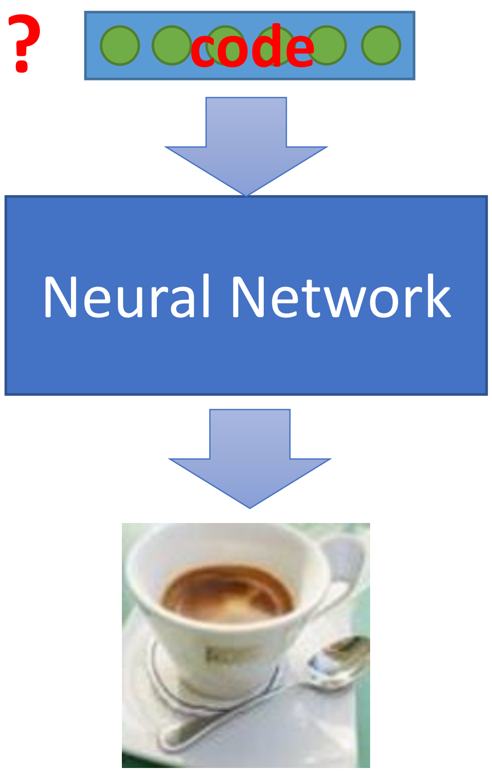
- **Pixel Recurrent Neural Networks**
  - https://arxiv.org/abs/1601.06759



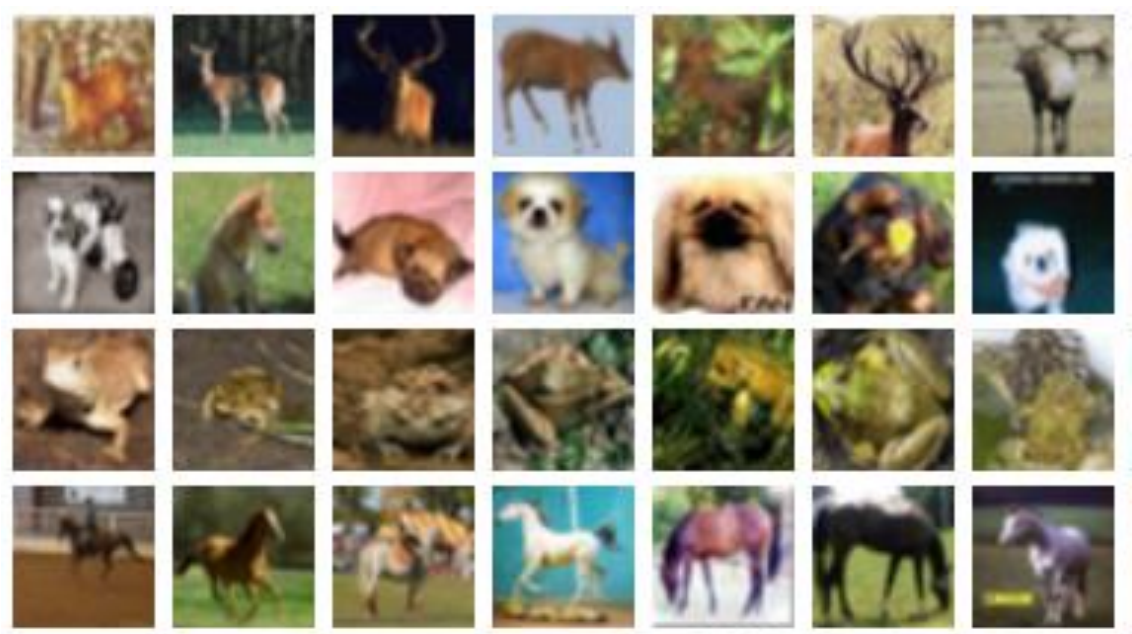
Real World

Generating Images

- Training a decoder to generate images is unsupervised

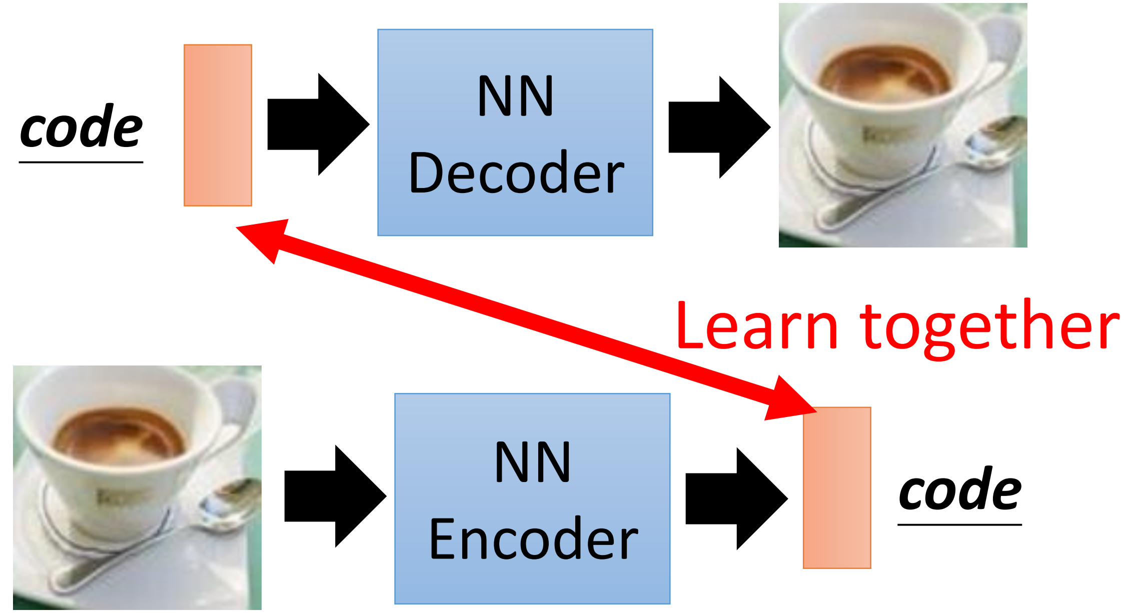


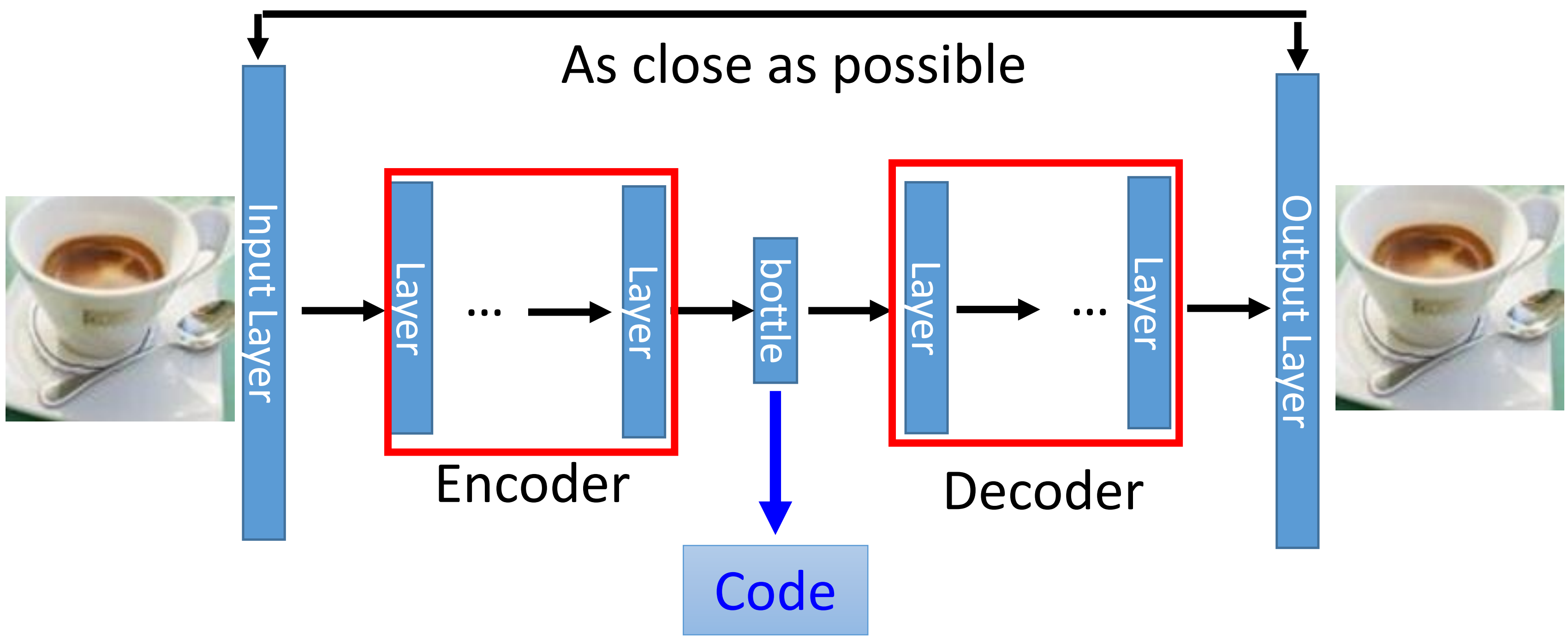
Training data is a lot of images



Auto-encoder

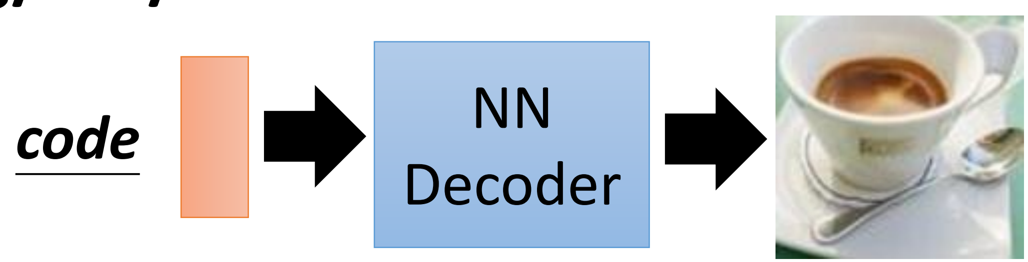
Not state-of-the-art approach



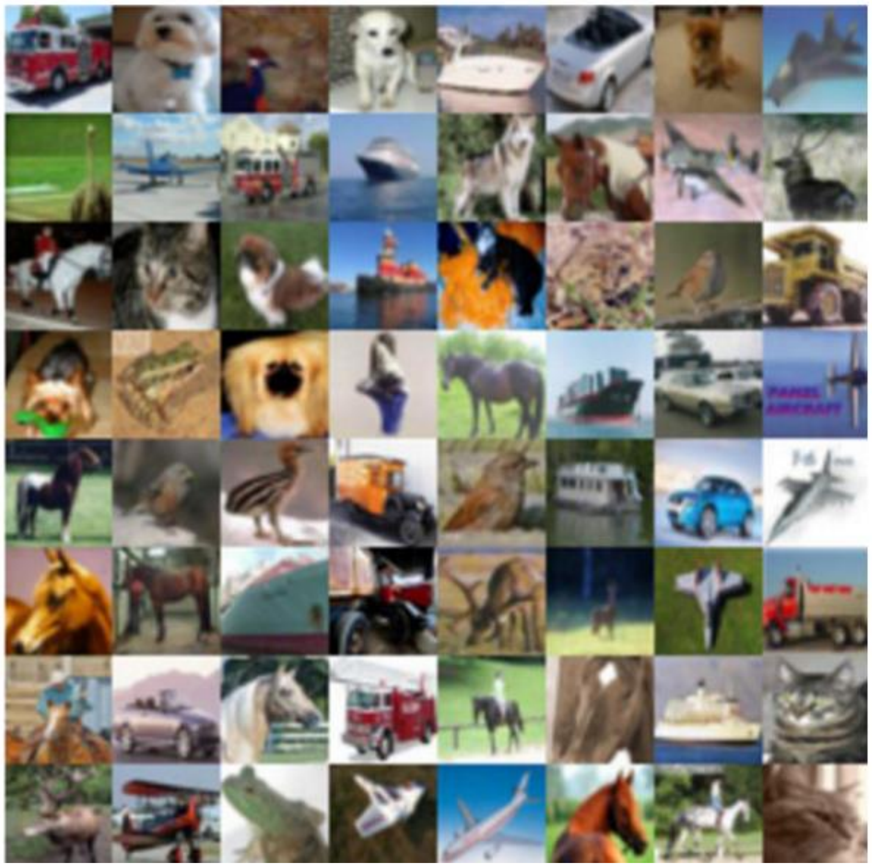


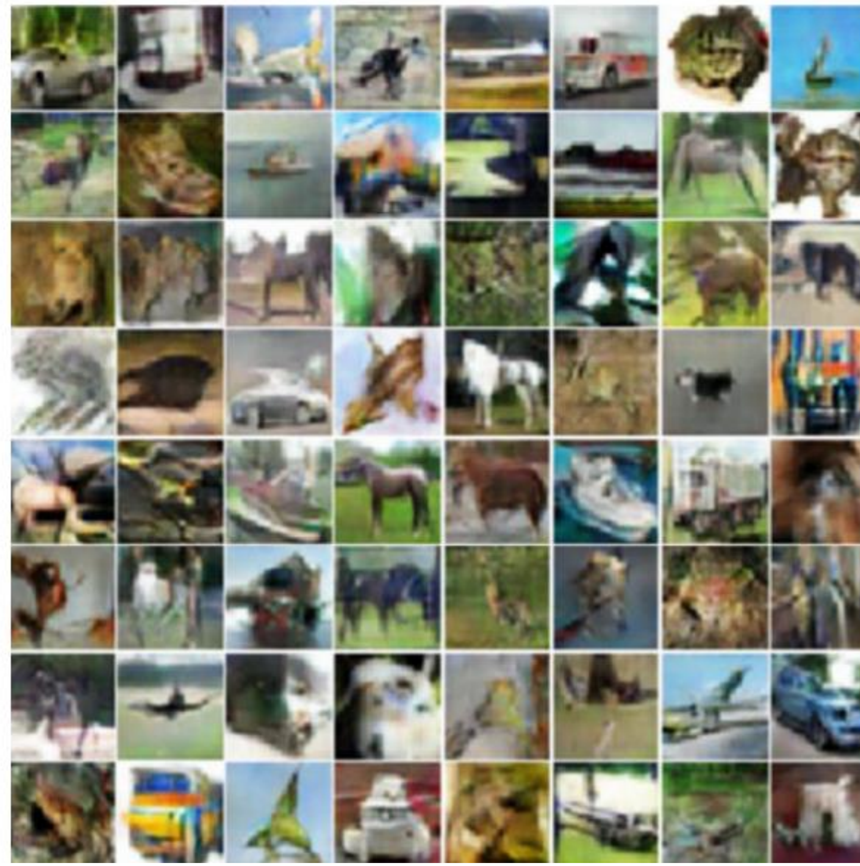
Generating Images

- Training a decoder to generate images is unsupervised
- Variation Auto-encoder (VAE)
  - Ref: **Auto-Encoding Variational Bayes, https://arxiv.org/abs/1312.6114**
- Generative Adversarial Network (GAN)
  - Ref: **Generative Adversarial Networks, http://arxiv.org/abs/1406.2661**



Which one is machine-generated?





Ref: https://openai.com/blog/generative-models/

畫漫畫!!!

https://github.com/mattya/chainer-DCGAN

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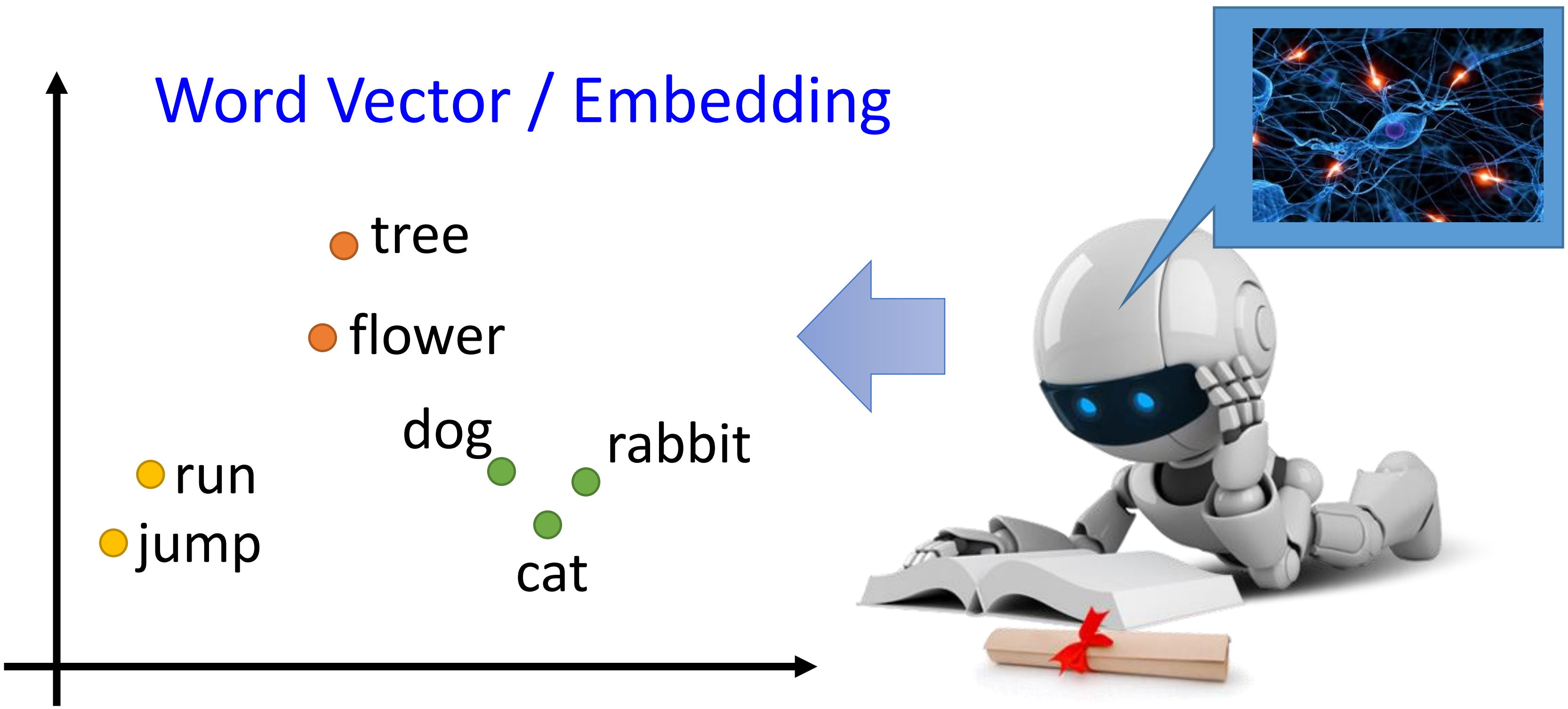
Machine Reading

- Machine learn the meaning of words from reading a lot of documents without supervision

http://top-breaking-news.com/

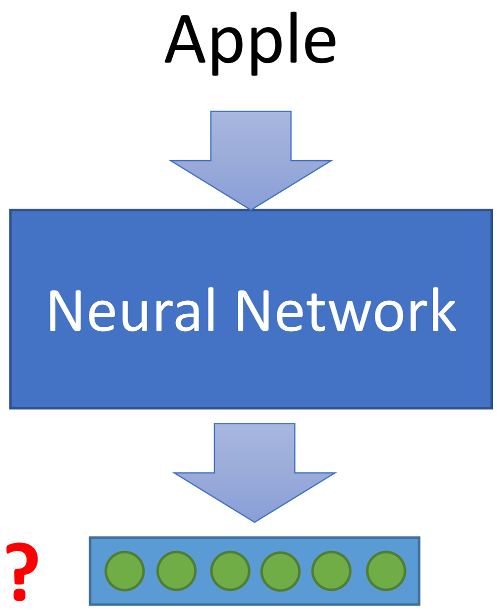
Machine Reading

- Machine learn the meaning of words from reading a lot of documents without supervision



Machine Reading

- Generating Word Vector/Embedding is unsupervised



Training data is a lot of text

https://garavato.files.wordpress.com/2011/11/stacksdocuments.jpg?w=490

Machine Reading

- Machine learn the meaning of words from reading a lot of documents without supervision
- A word can be understood by its context

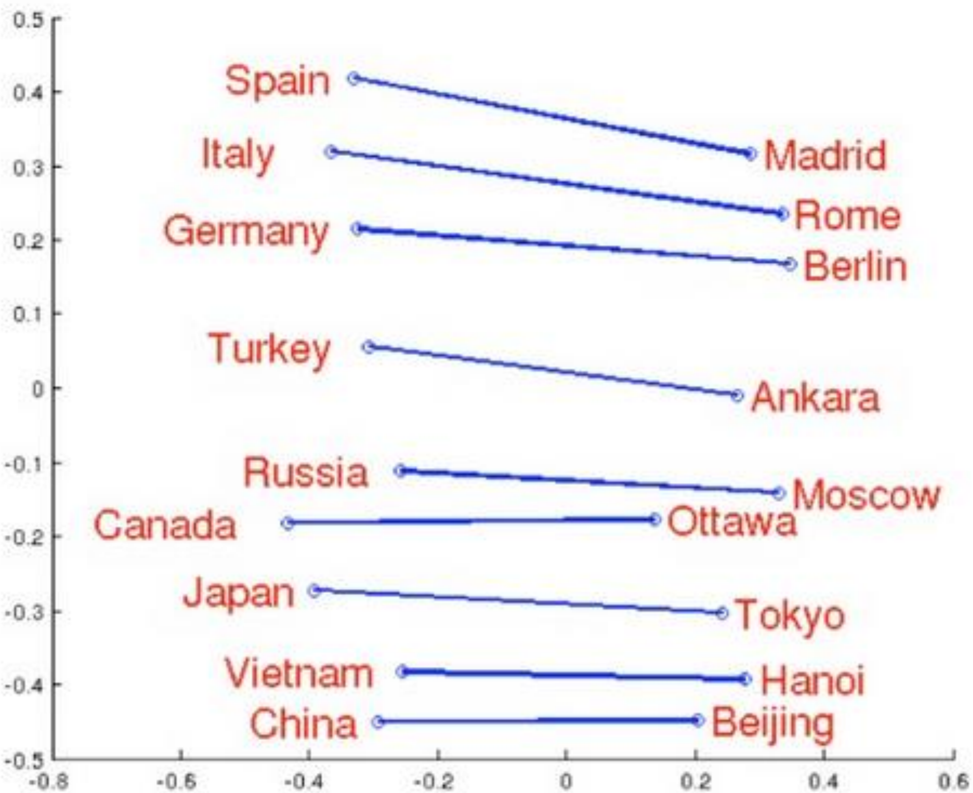
蔡英文、馬英九 are something very similar

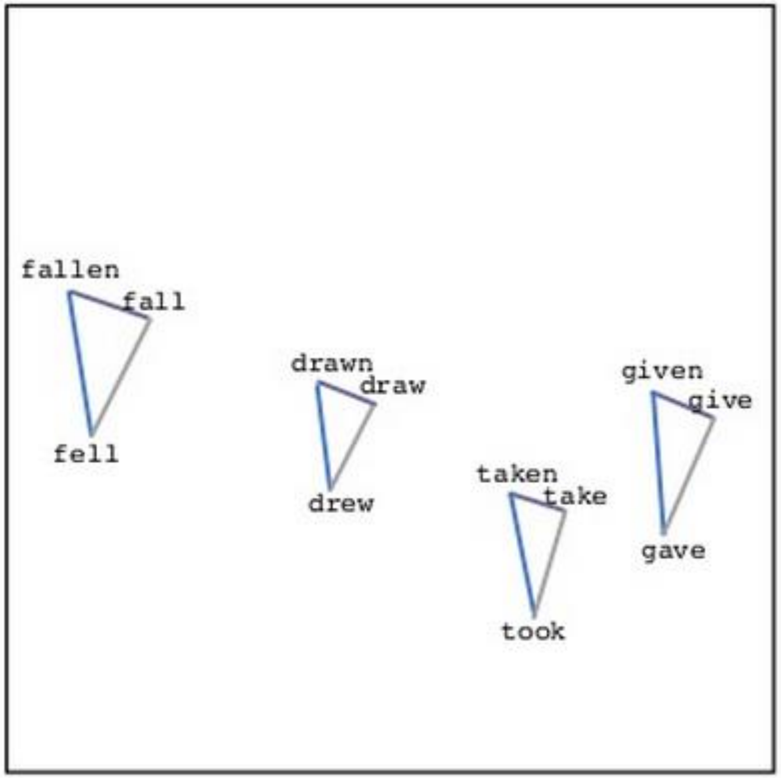
You shall know a word by the company it keeps

馬英九 520宣誓就職

蔡英文 520宣誓就職

Word Vector





Source: http://www.slideshare.net/hustwj/cikm-keynotenov2014

Word Vector

$$V(Germany) \approx V(Berlin) - V(Rome) + V(Italy)$$

- Characteristics

$$V(hotter) - V(hot) \approx V(bigger) - V(big)$$
$$V(Rome) - V(Italy) \approx V(Berlin) - V(Germany)$$
$$V(king) - V(queen) \approx V(uncle) - V(aunt)$$

- Solving analogies

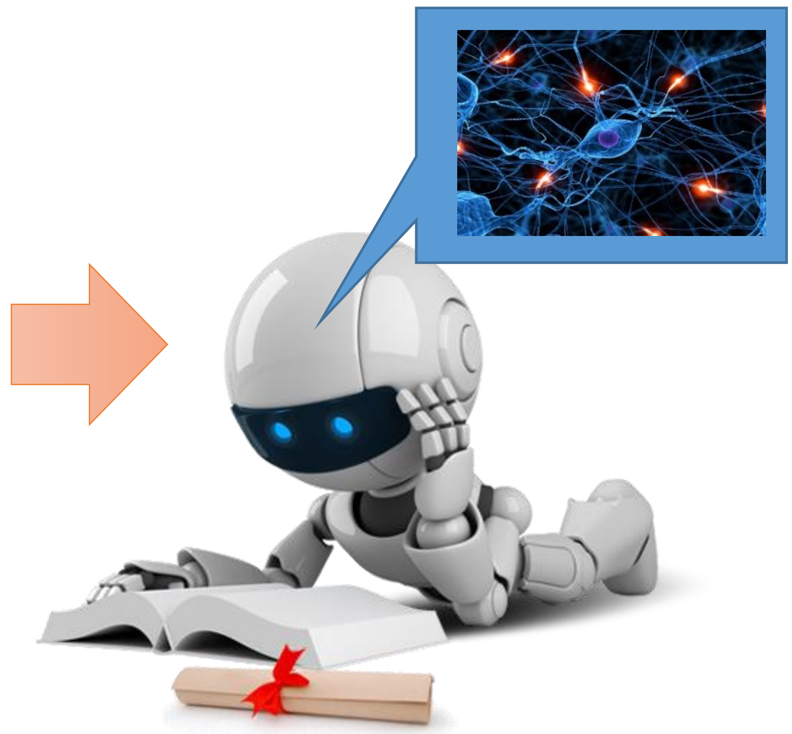
Rome : Italy = Berlin : ?

Compute $\underline{V(Berlin) - V(Rome) + V(Italy)}$

Find the word w with the closest V(w)

Machine Reading

- Machine learn the meaning of words from reading a lot of documents without supervision



Demo

- Model used in demo is provided by 陳仰德
- Part of the project done by 陳仰德、林資偉
- TA: 劉元銘
- Training data is from PTT (collected by 葉青峰)

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Learning from Audio Book

Machine does not have any prior knowledge

Machine listens to lots of audio book

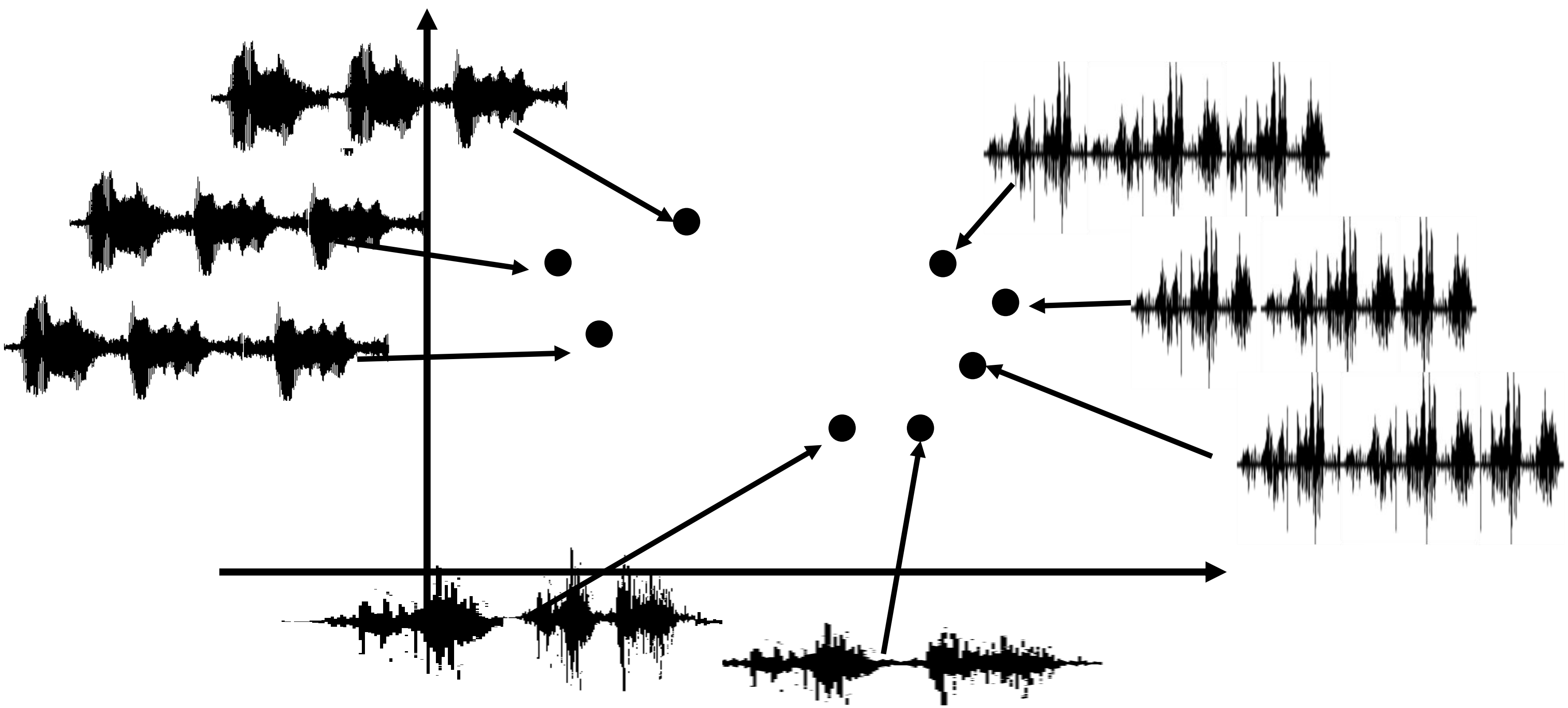
Like an infant

[Chung, Interspeech 16)

Audio Word to Vector

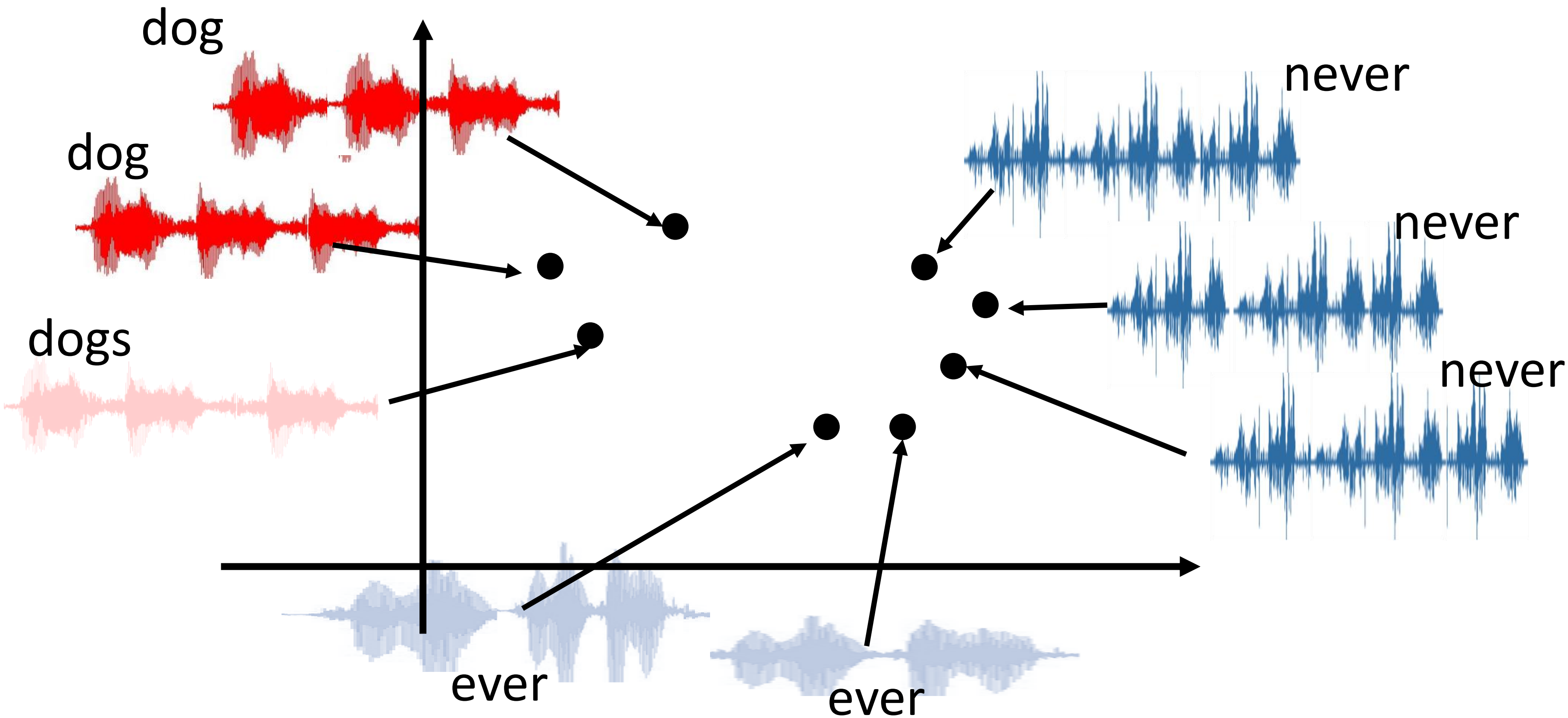
- Audio segment corresponding to an unknown word

Fixed-length vector



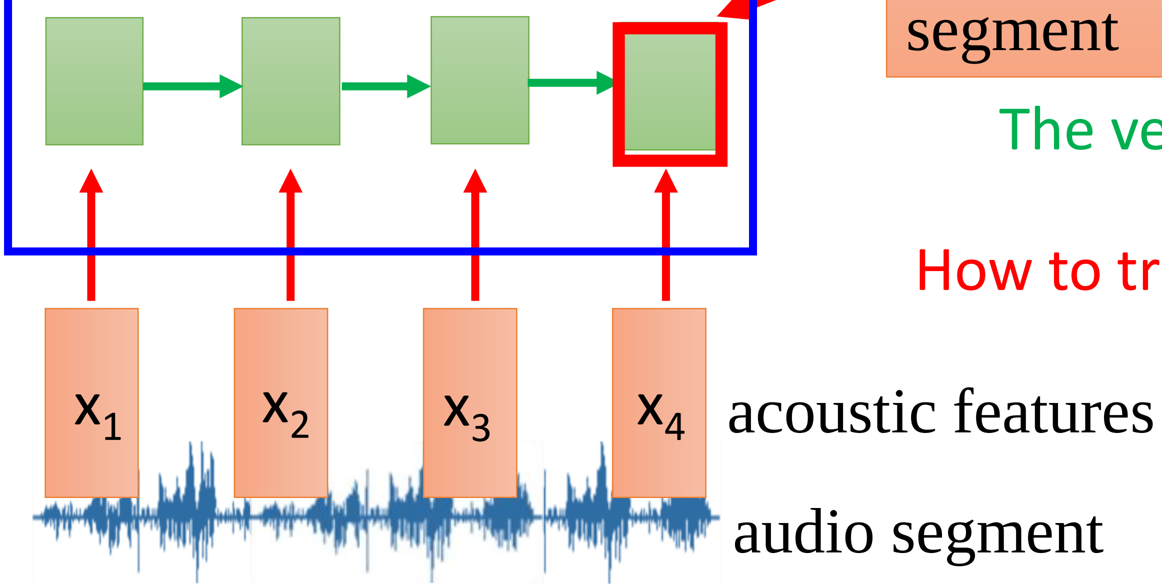
Audio Word to Vector

- The audio segments corresponding to words with similar pronunciations are close to each other.



Sequence-to-sequence Auto-encoder

RNN Encoder



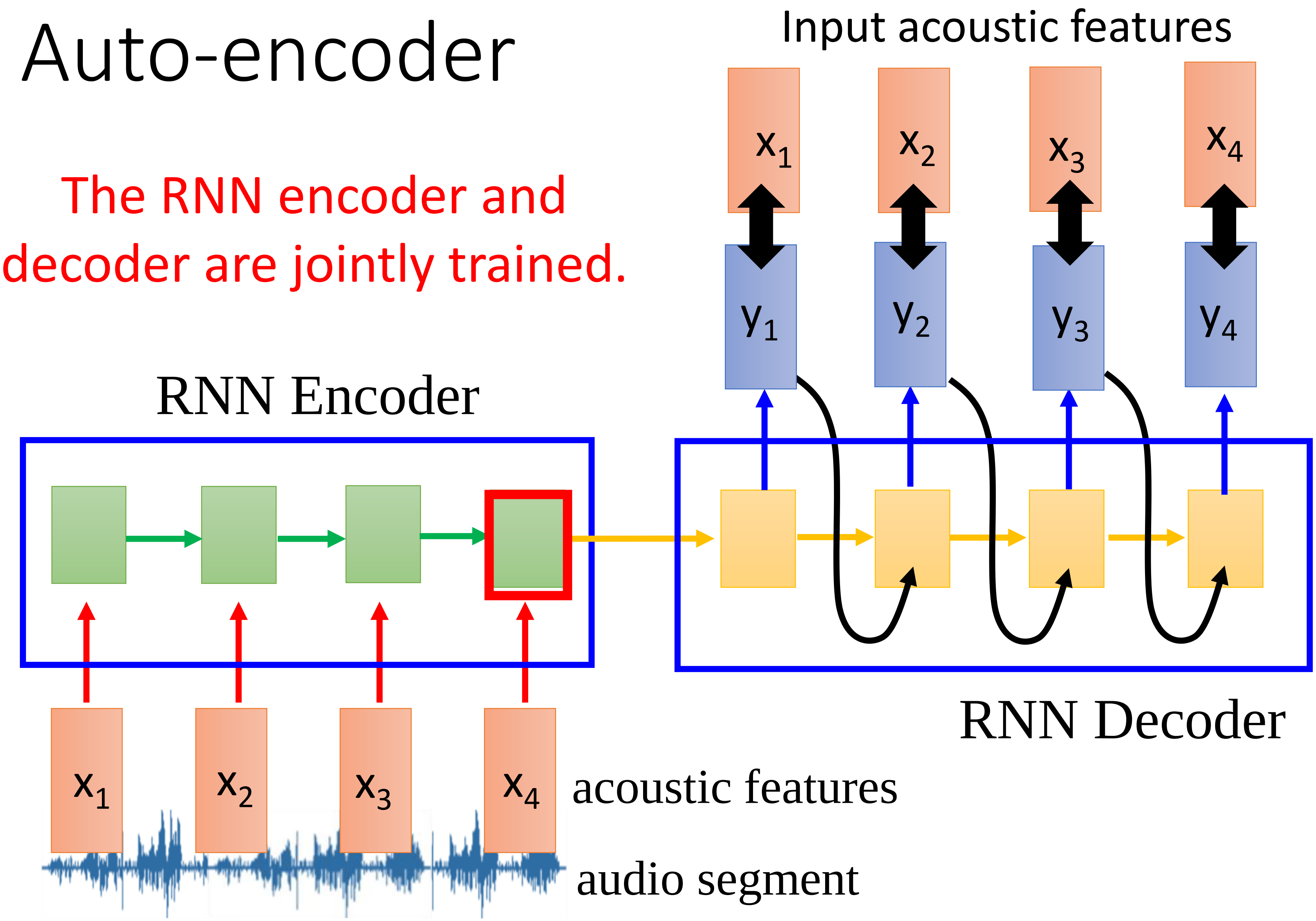
The values in the memory represent the whole audio segment

The vector we want

How to train RNN Encoder?

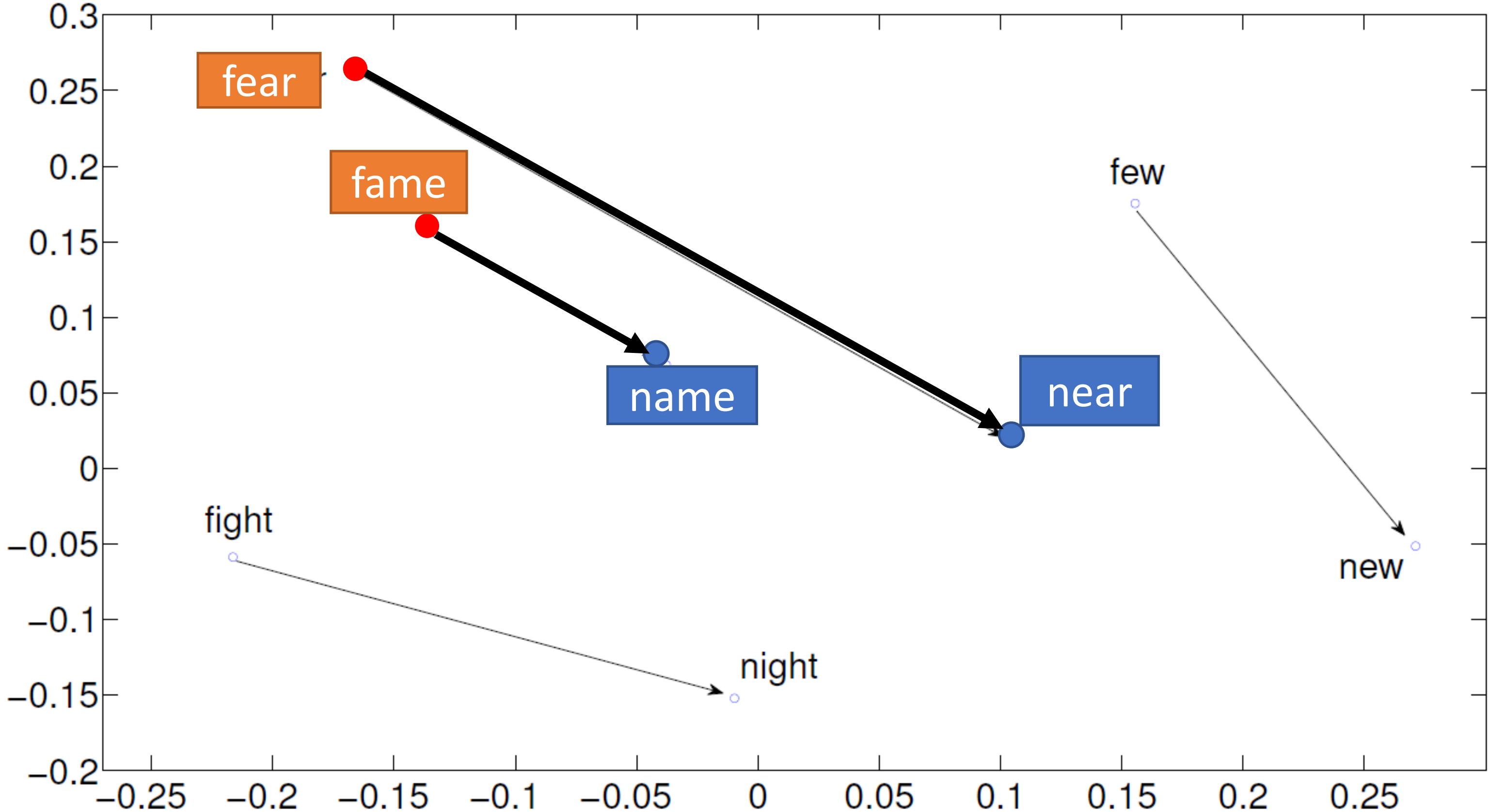
Sequence-to-sequence Auto-encoder

The RNN encoder and decoder are jointly trained.

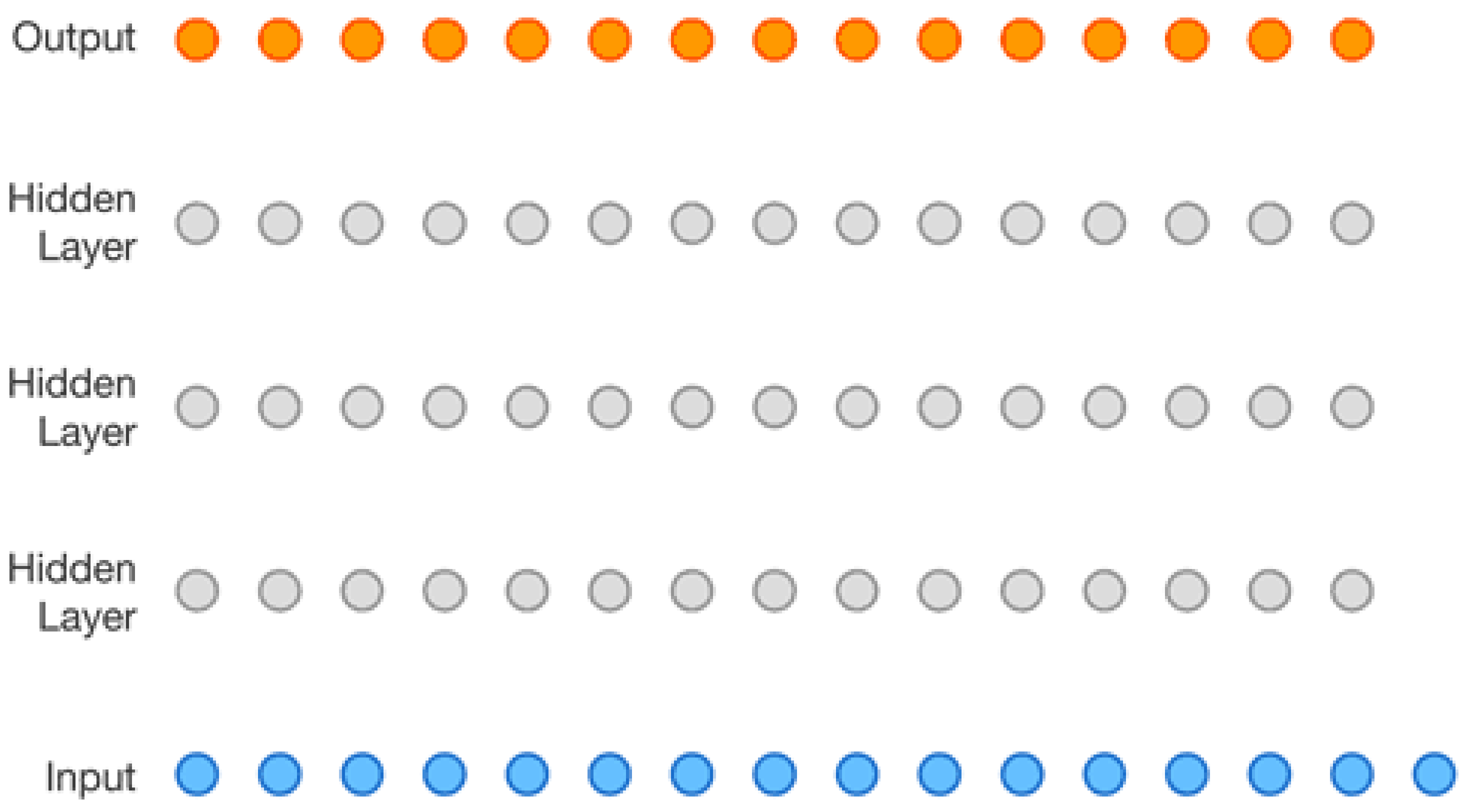


Audio Word to Vector - Results

- Visualizing embedding vectors of the words



WaveNet (DeepMind)



https://deepmind.com/blog/wavenet-generative-model-raw-audio/

Concluding Remarks

Concluding Remarks

Lecture I: Introduction of Deep Learning

Lecture II: Tips for Training Deep Neural Network

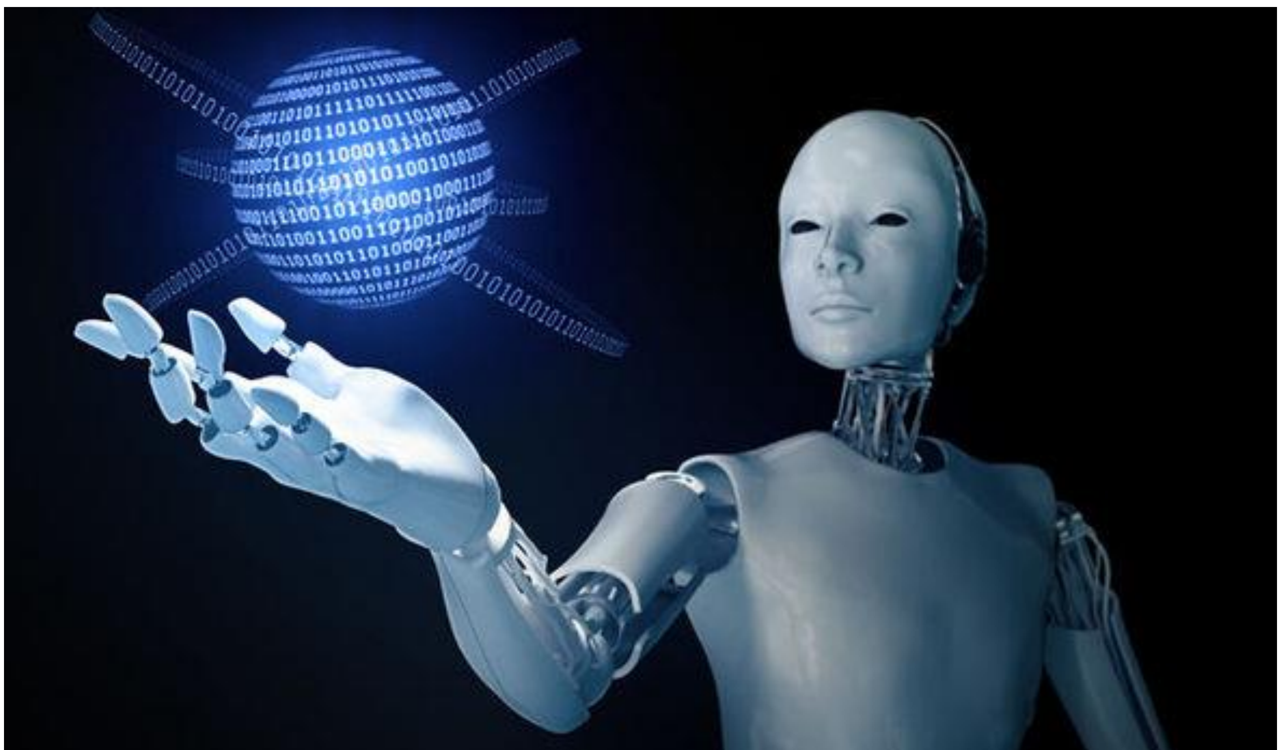
Lecture III: Variants of Neural Network

Lecture IV: Next Wave

AI 即將取代多數的工作?

- New Job in AI Age → AI 訓練師

(機器學習專家、資料科學家)



http://www.express.co.uk/news/science/651202/First-step-towards-The-Terminator-becoming-reality-AI-beats-champ-of-world-s-oldest-game

AI 訓練師

機器不是自己會學嗎？
為什麼需要 AI 訓練師

戰鬥是寶可夢在打，
為什麼需要寶可夢訓練師？

AI 訓練師

Step 1: define a set of function → Step 2: goodness of function → Step 3: pick the best function

寶可夢訓練師

- 寶可夢訓練師要挑選適合的寶可夢來戰鬥
  - 寶可夢有不同的屬性
- 召喚出來的寶可夢不一定能操控
  - E.g. 小智的噴火龍
  - 需要足夠的經驗

AI 訓練師

- 在 step 1，AI訓練師要挑選合適的模型
  - 不同模型適合處理不同的問題
- 不一定能在 step 3 找出 best function
  - E.g. Deep Learning
  - 需要足夠的經驗

AI 訓練師

- 厲害的 AI ， AI 訓練師功不可沒
- 讓我們一起朝 AI 訓練師之路邁進

http://www.gvm.com.tw/webonly_content_10787.html

- 台大電機系 資料科學與智慧網路組 首屆招生：

  碩士生甄試20名，考試入學10名

  博士生甄試2名，考試入學1名

- 招生公告：105.09.20
- 報名期間：105.10.04 ~ 10.12
- 招生網址：

  https://comm.ntu.edu.tw/new/Master.php

- 招生說明會：
  - 時間：105.09.28 12:20
  - 地點：台大博理館 112 R

國立臺灣大學 National Taiwan University 電信工程學研究所丙組

資料科學與智慧網路組

NTU GICE Data Science and Smart Networking