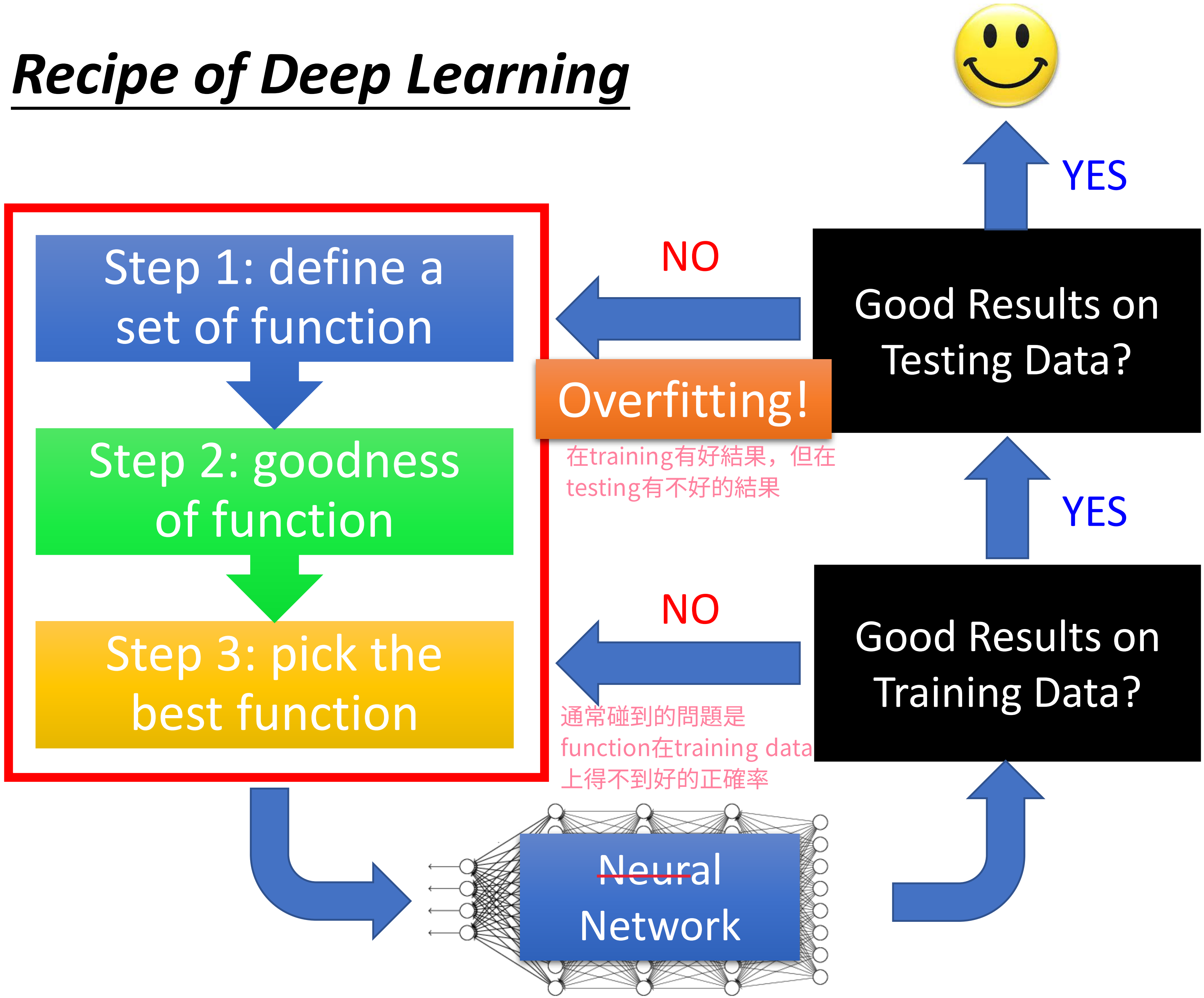
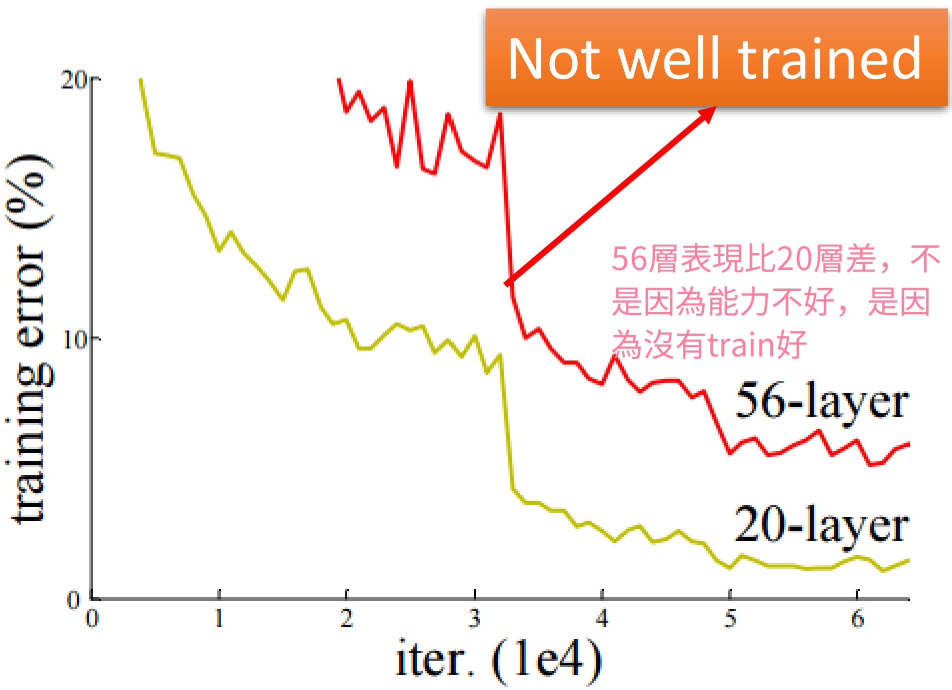
Tips for Deep Learning

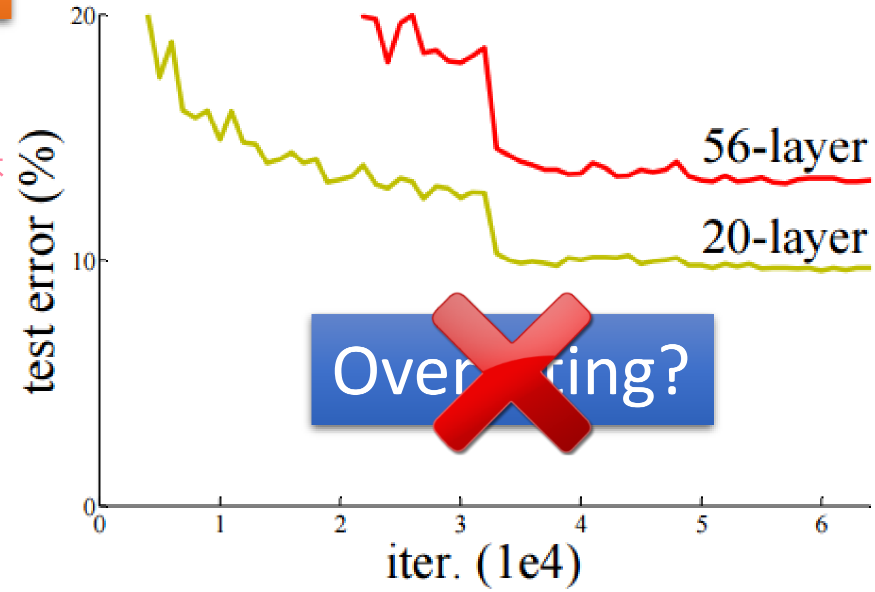
Recipe of Deep Learning



Do not always blame Overfitting



Training Data



Testing Data

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

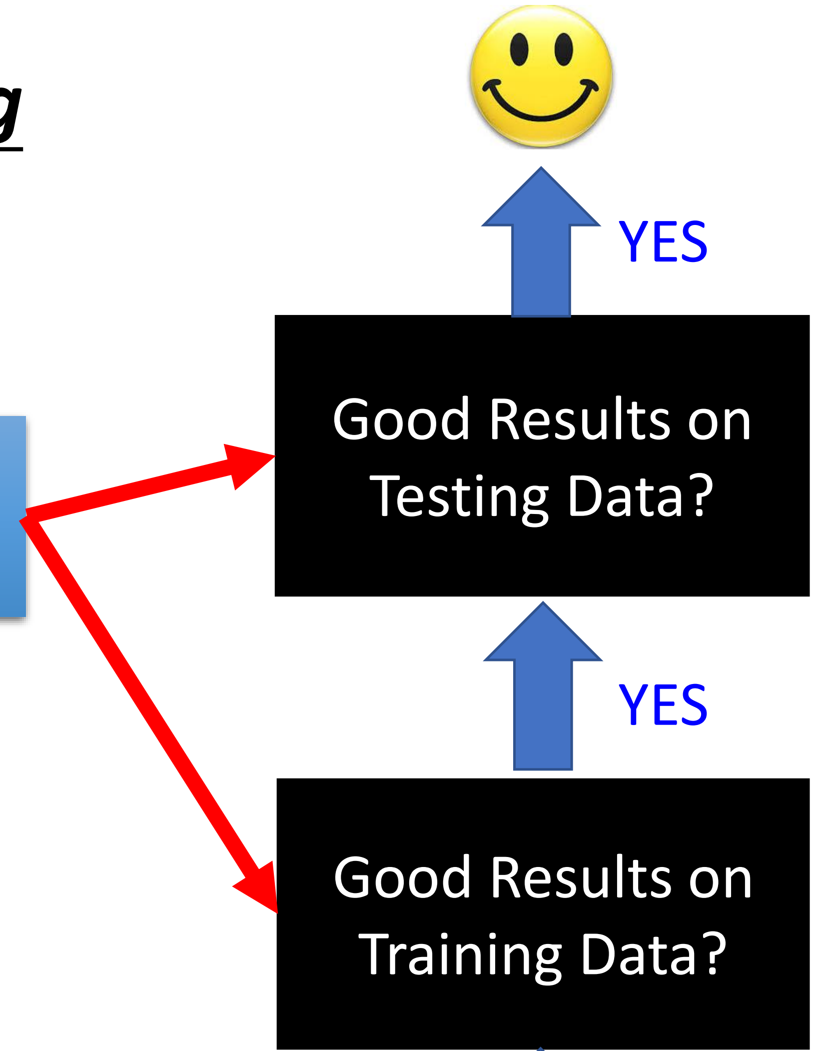
Recipe of Deep Learning

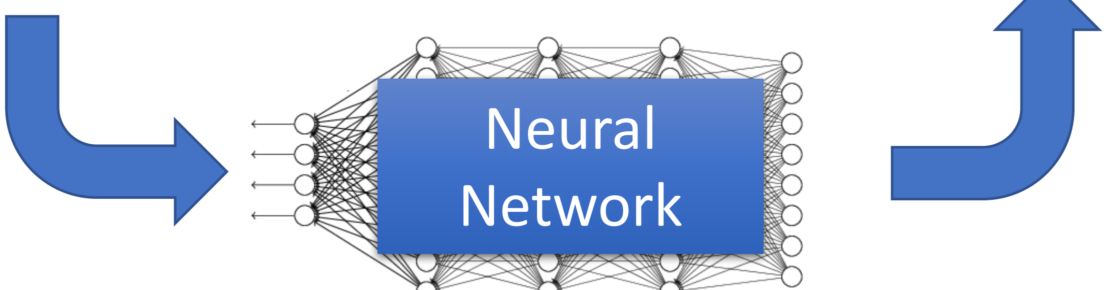
思考這個方法是要解什麼問題

Different approaches for different problems.

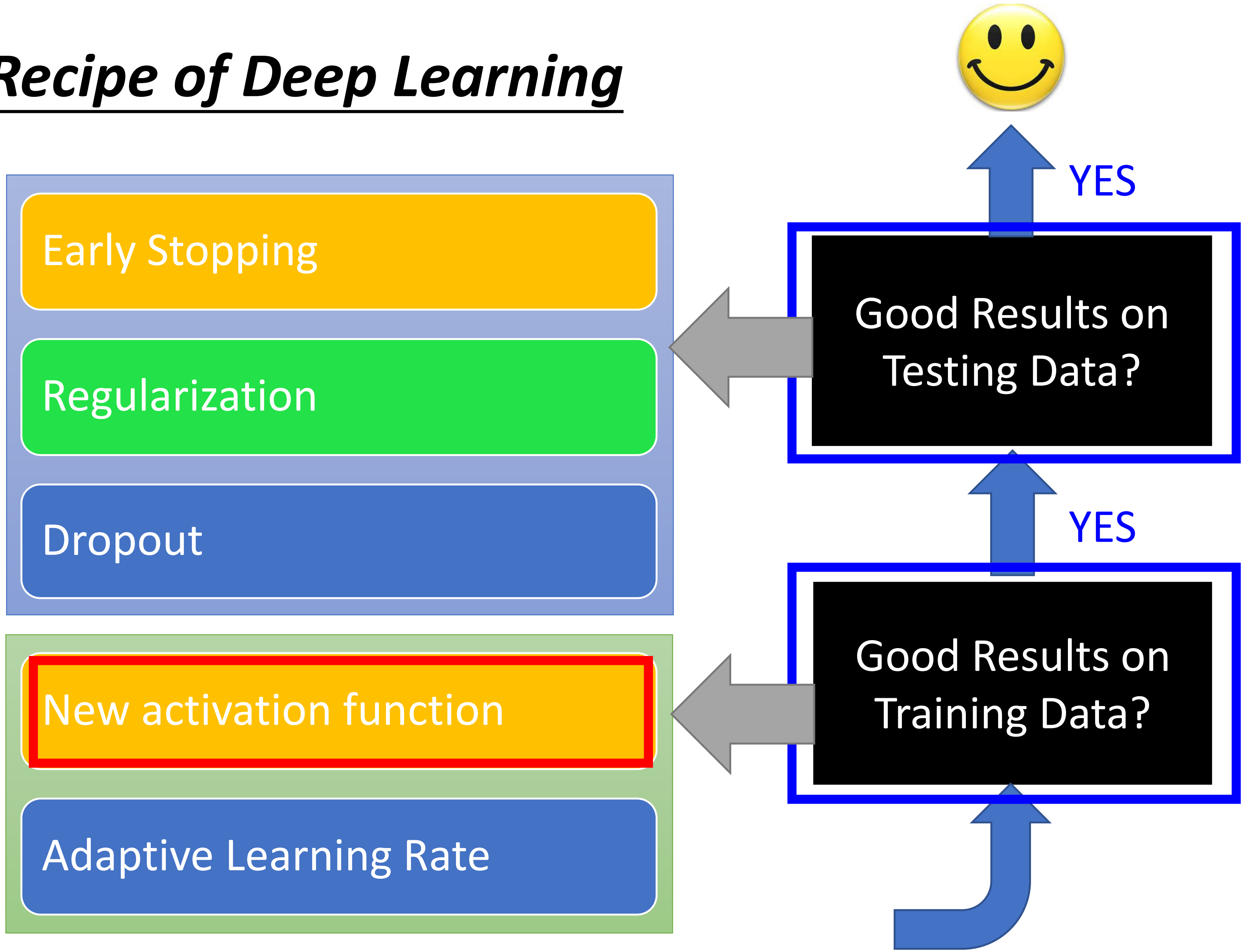
e.g. dropout for good results on testing data

testing結果不好時才應使用dropout



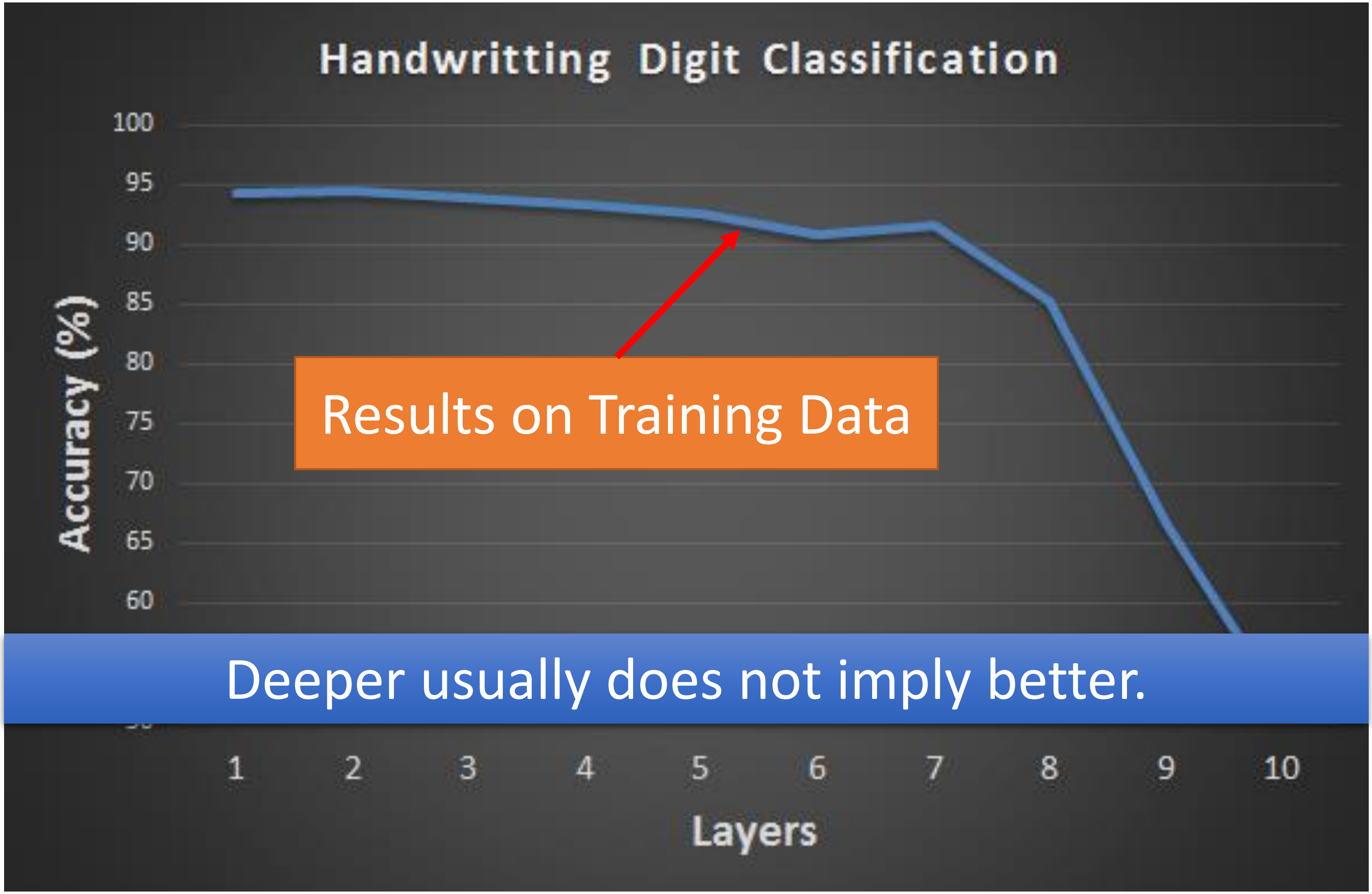


Recipe of Deep Learning

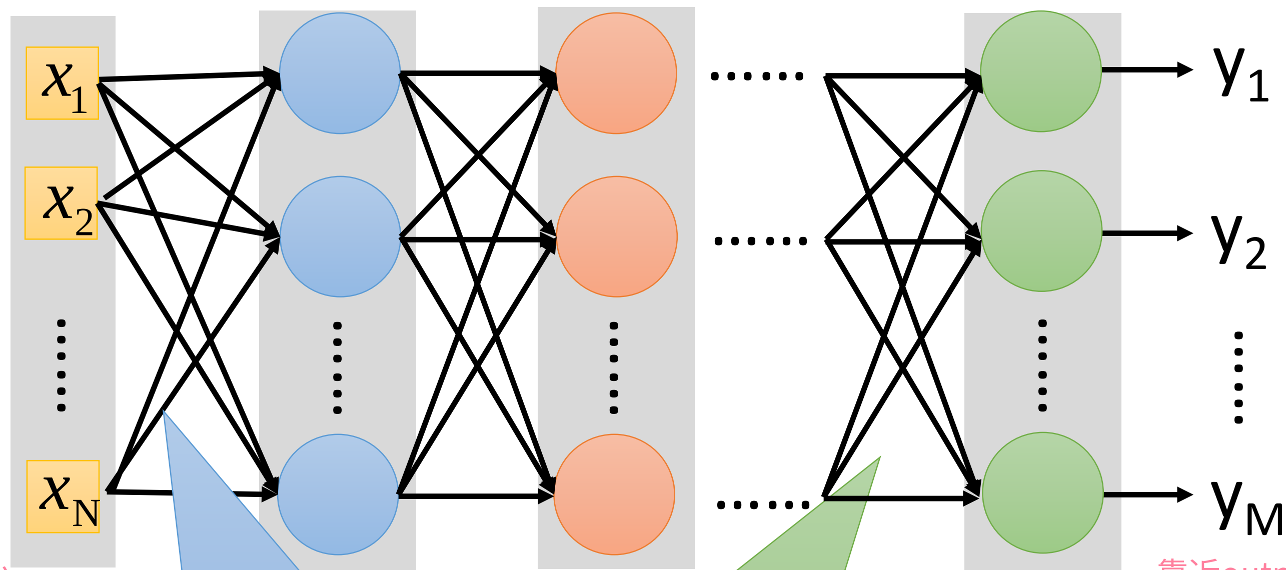


架構不好?

Hard to get the power of Deep …



Vanishing Gradient Problem



靠近input的微分值較小

靠近output的微分值較大

Smaller gradients

Larger gradients

Learn very slow

若設定相同的learning rate

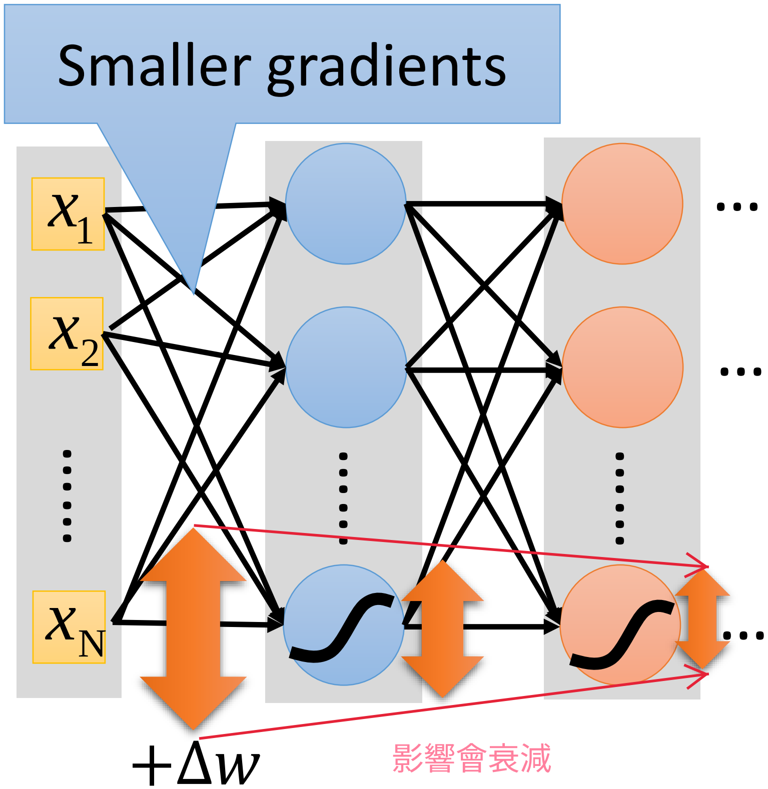
Learn very fast

Almost random

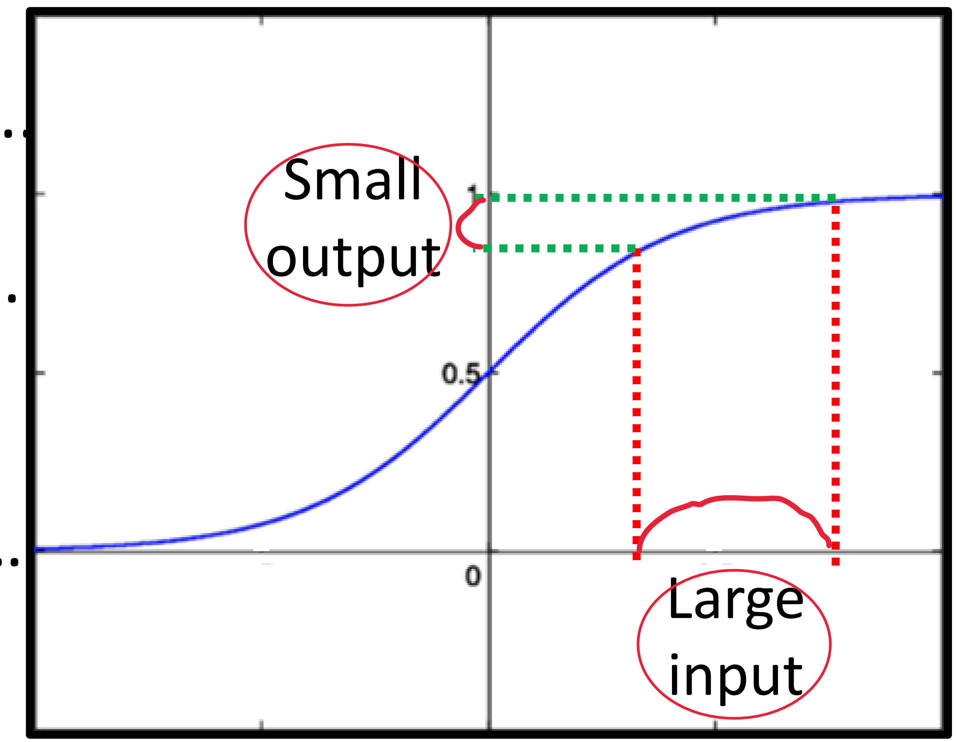
Already converge

based on random!?

Vanishing Gradient Problem



影響會衰減
所以通過越多層，最後對
output的影響越小



eg. sigmod function會把值硬壓在0跟1之間

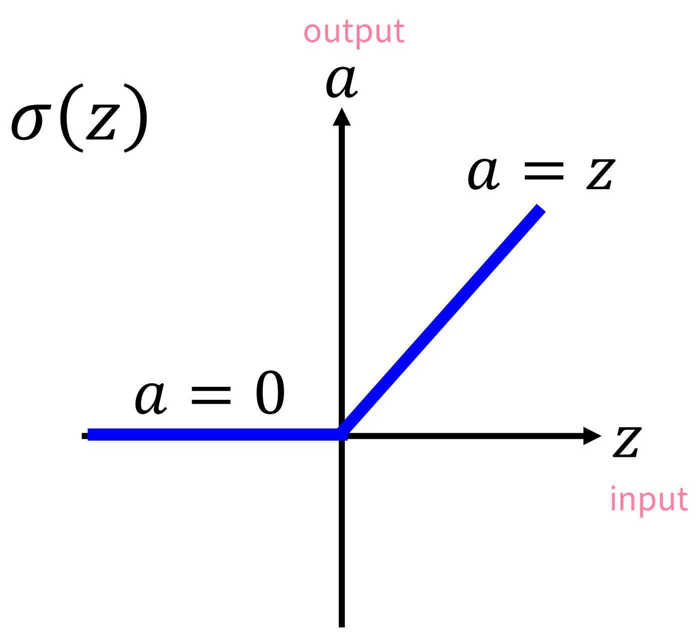
Intuitive way to compute the derivatives …

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

ReLU

改activation function，現在常用ReLU

- Rectified Linear Unit (ReLU)



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

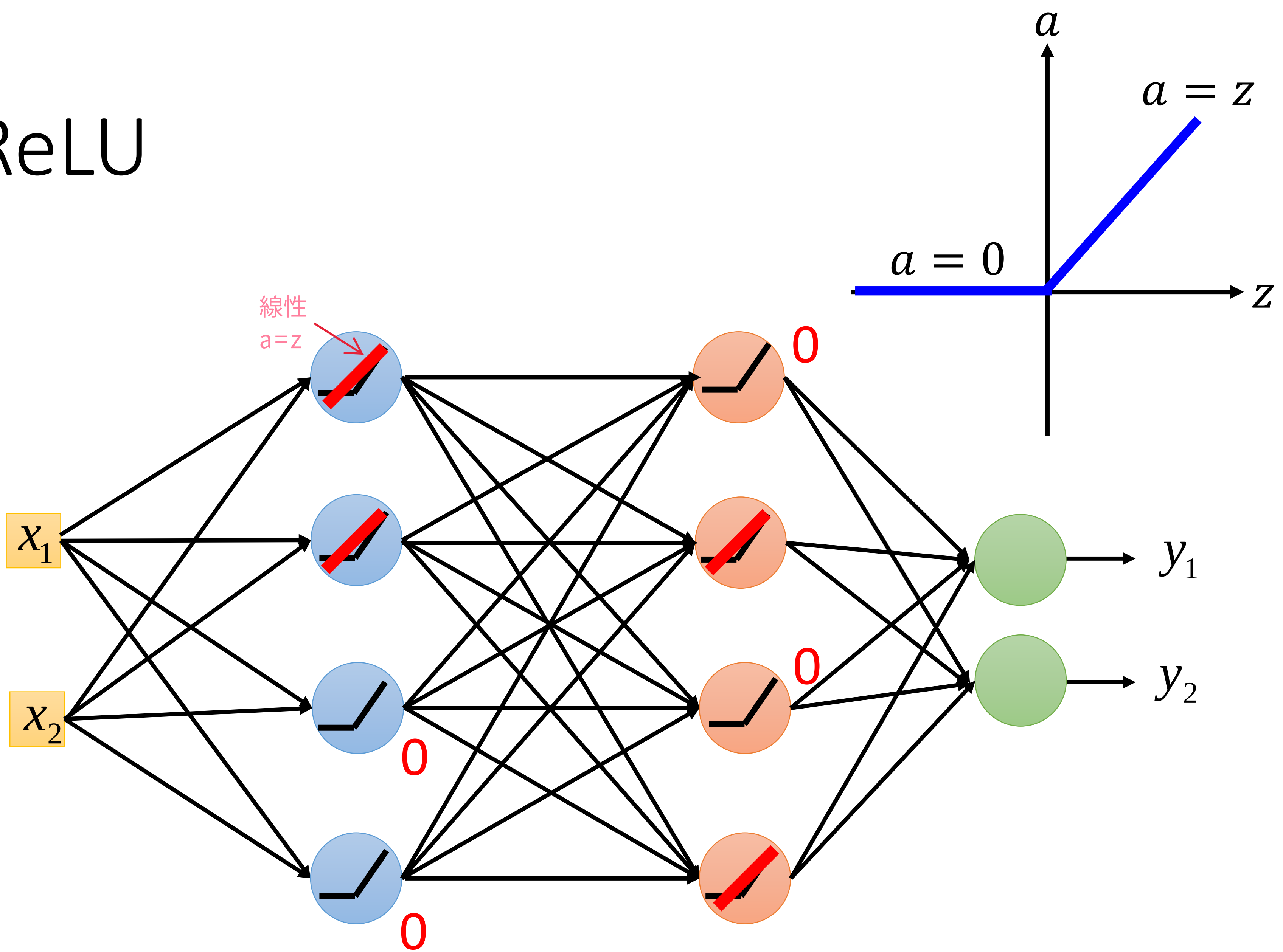
Reason:

1. Fast to compute
2. Biological reason
3. Infinite sigmoid with different biases

ReLU等於無窮多的sigmoid疊加的結果

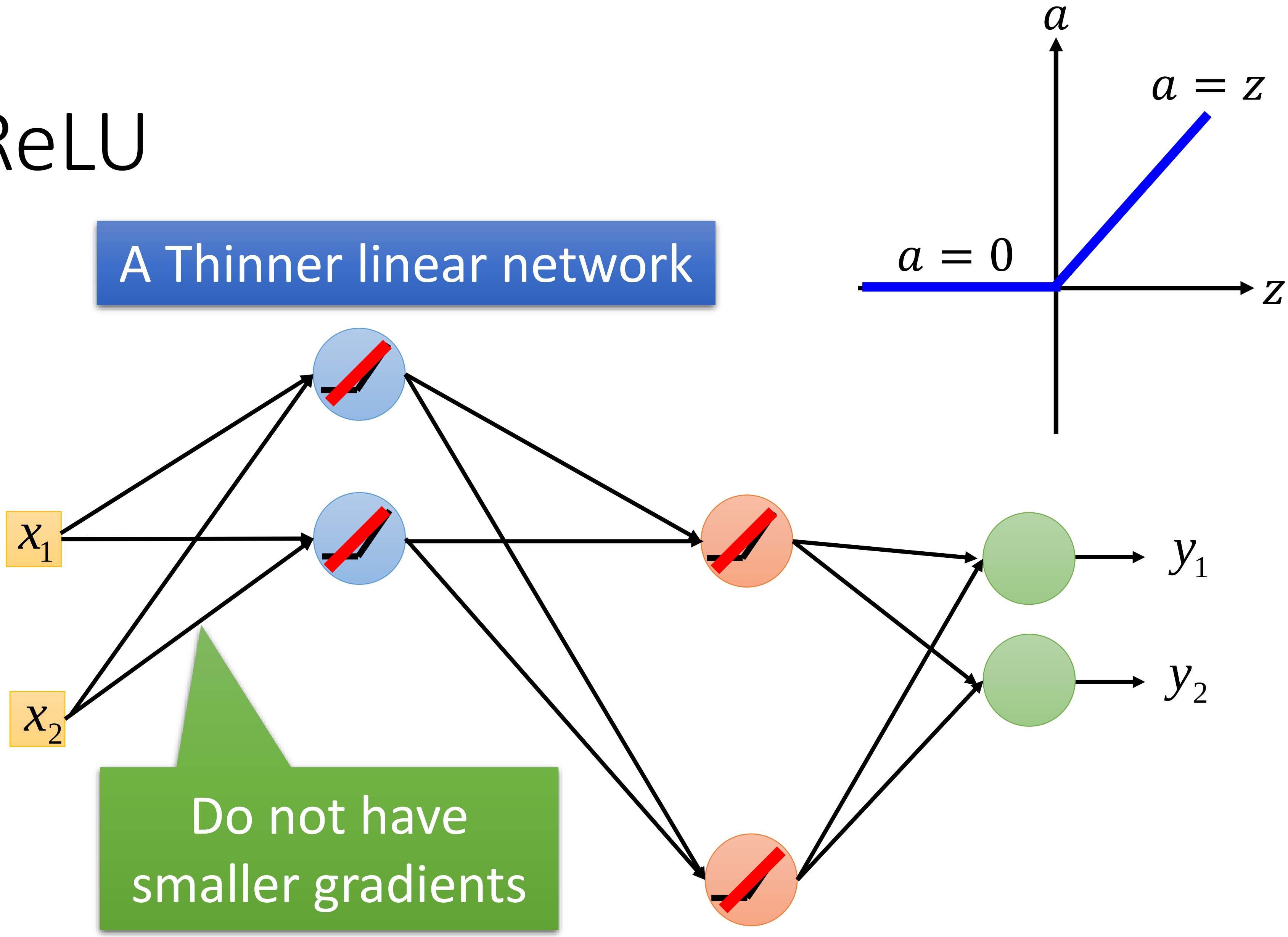
4. Vanishing gradient problem

ReLU



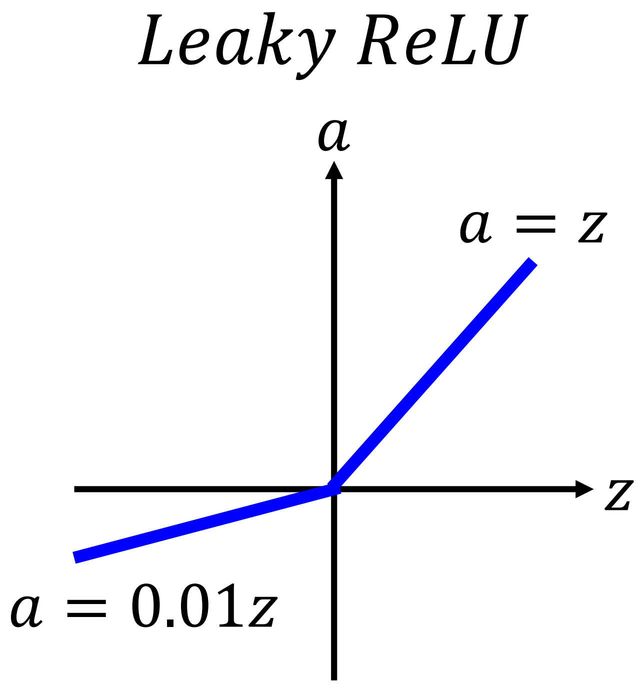
0的neuron沒影響，可拿掉

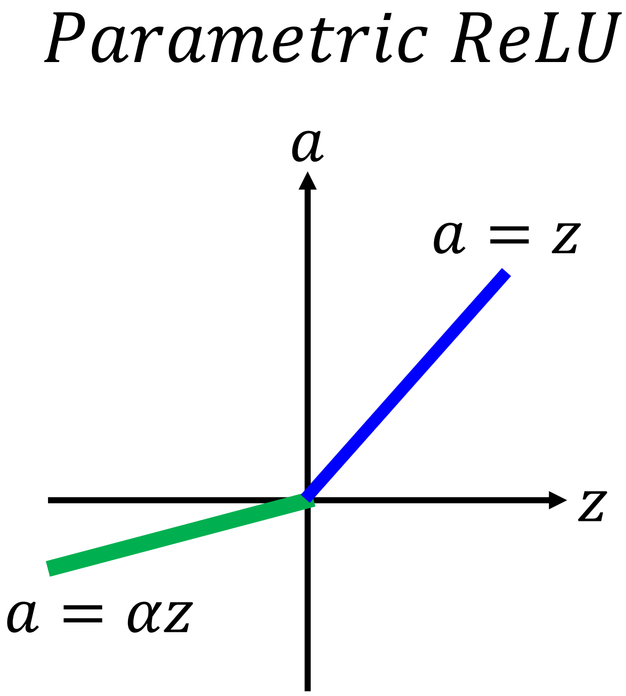
ReLU



因為ReLU的input=output，所以不會有前面提到影響遞減的問題

ReLU - variant





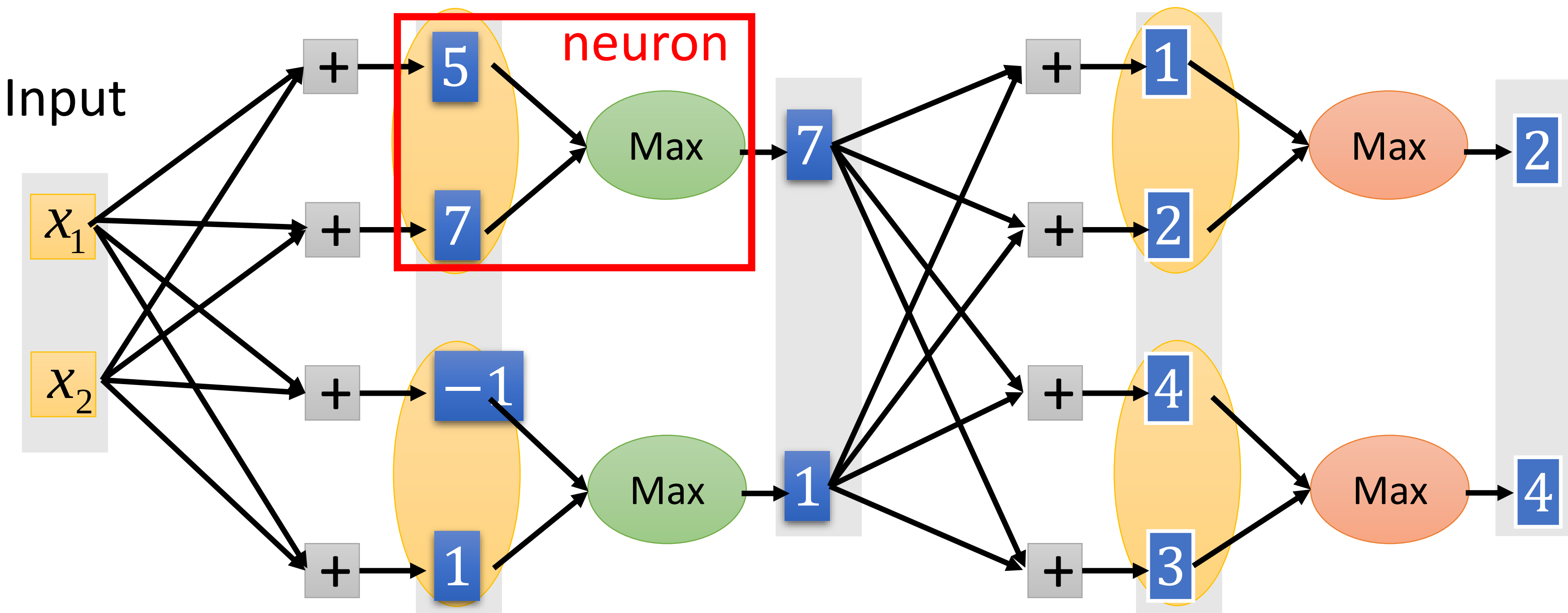
α also learned by gradient descent

Maxout

ReLU is a special cases of Maxout

機器自動學

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

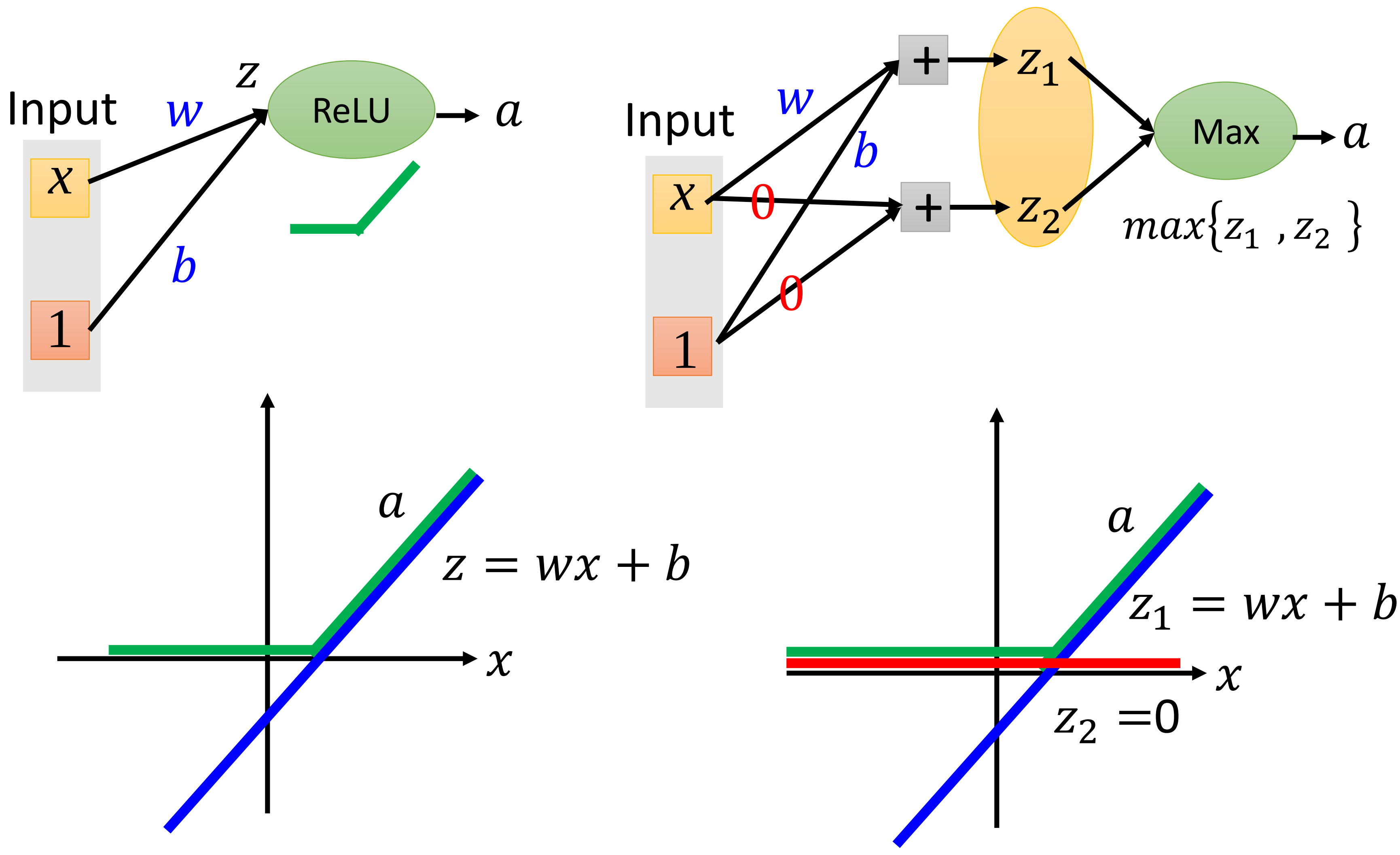


You can have more than 2 elements in a group.

手動設幾個element放一組

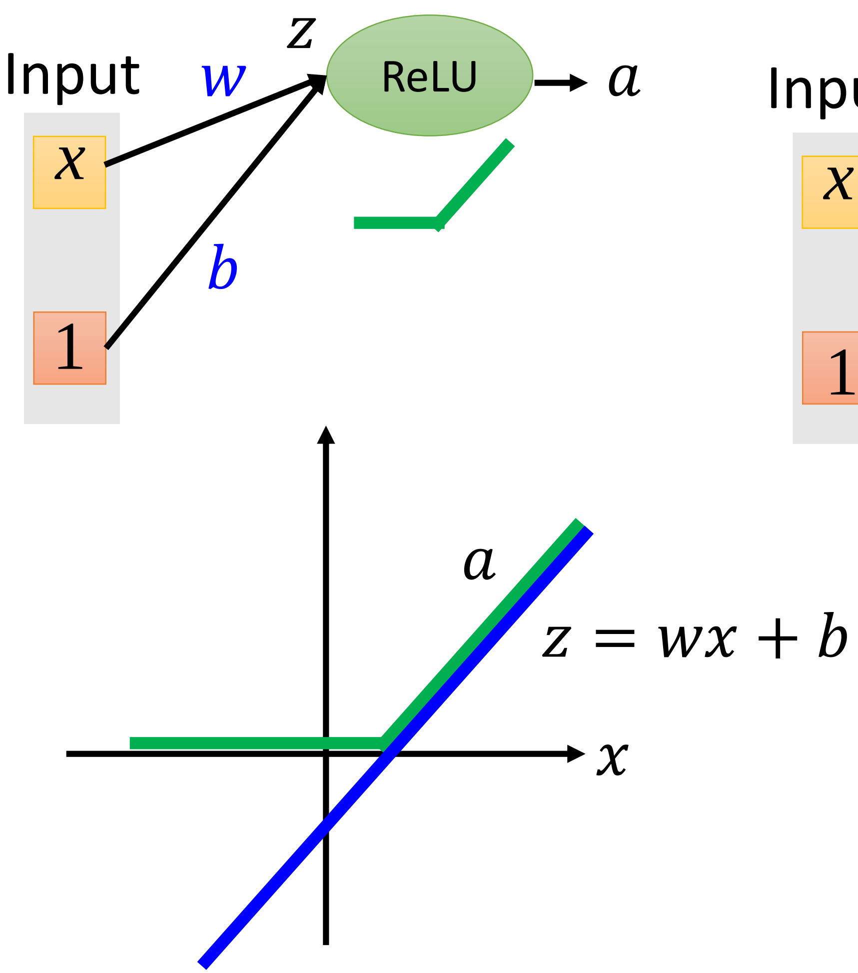
Maxout

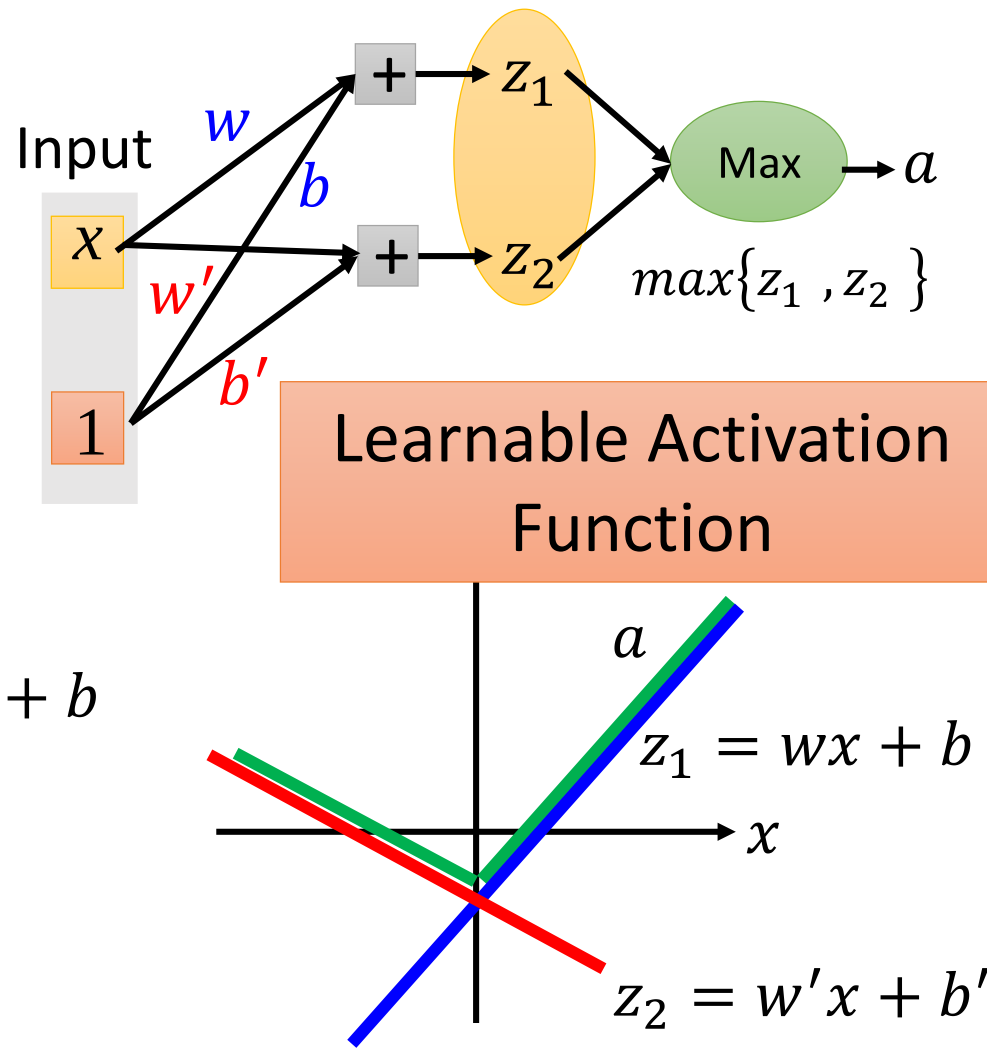
ReLU is a special cases of Maxout



Maxout

More than ReLU



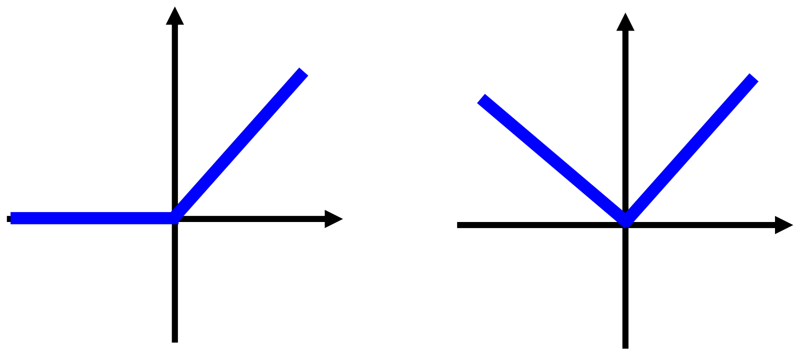


Learnable Activation Function

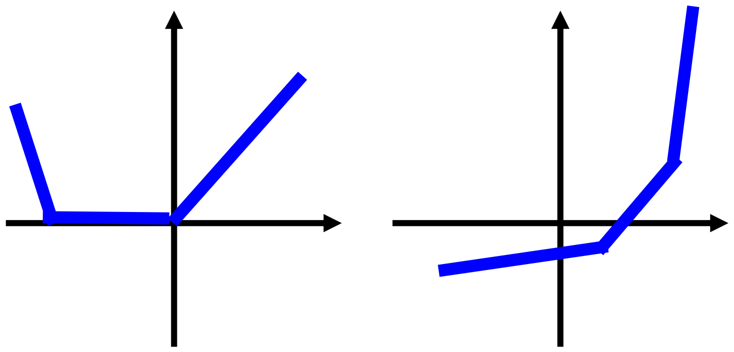
Maxout

- 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

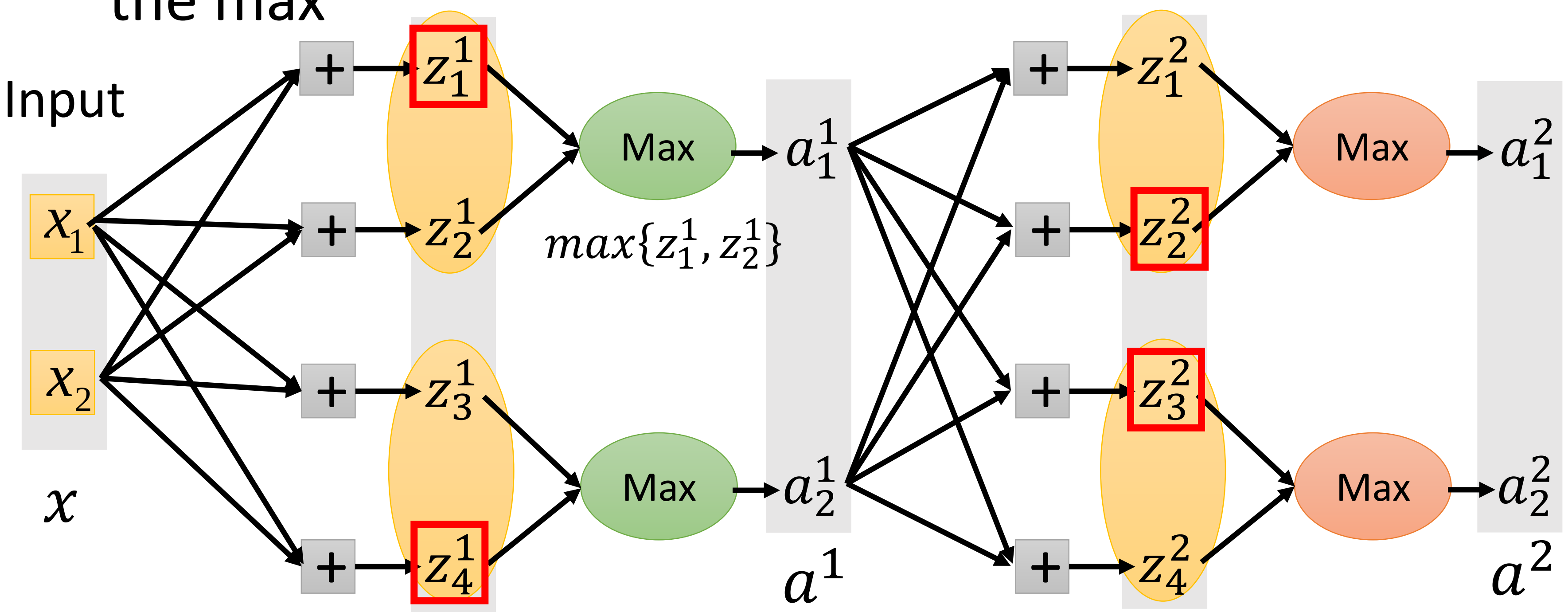


3 elements in a group



Maxout - Training

- Given a training data x, we know which z would be the max



Maxout - Training

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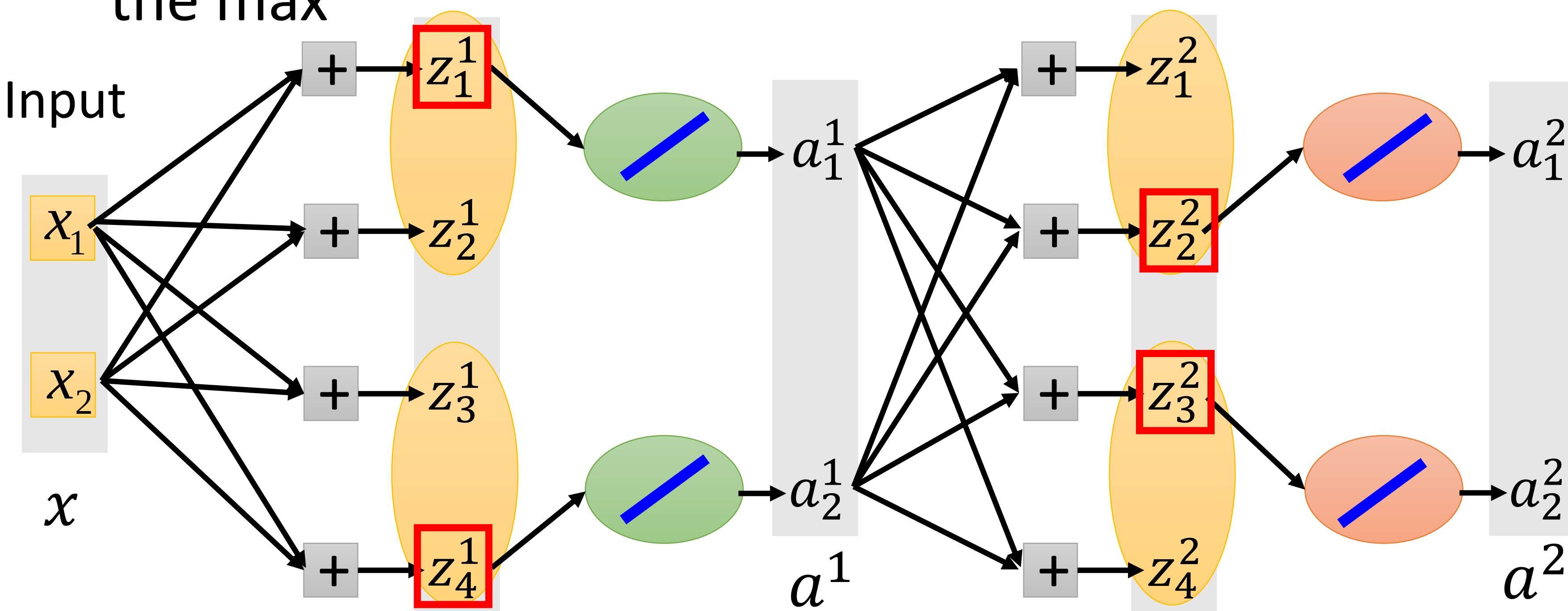
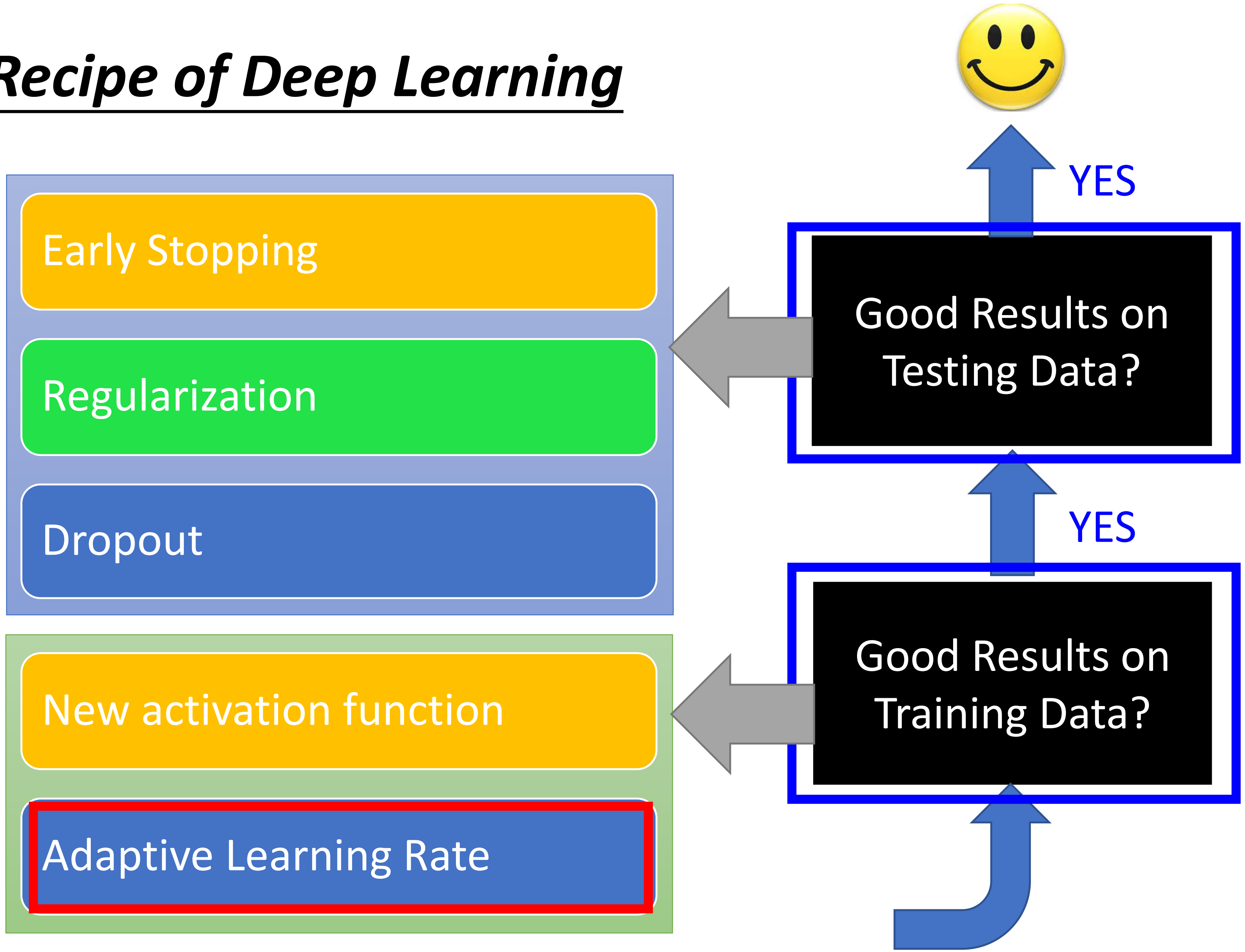


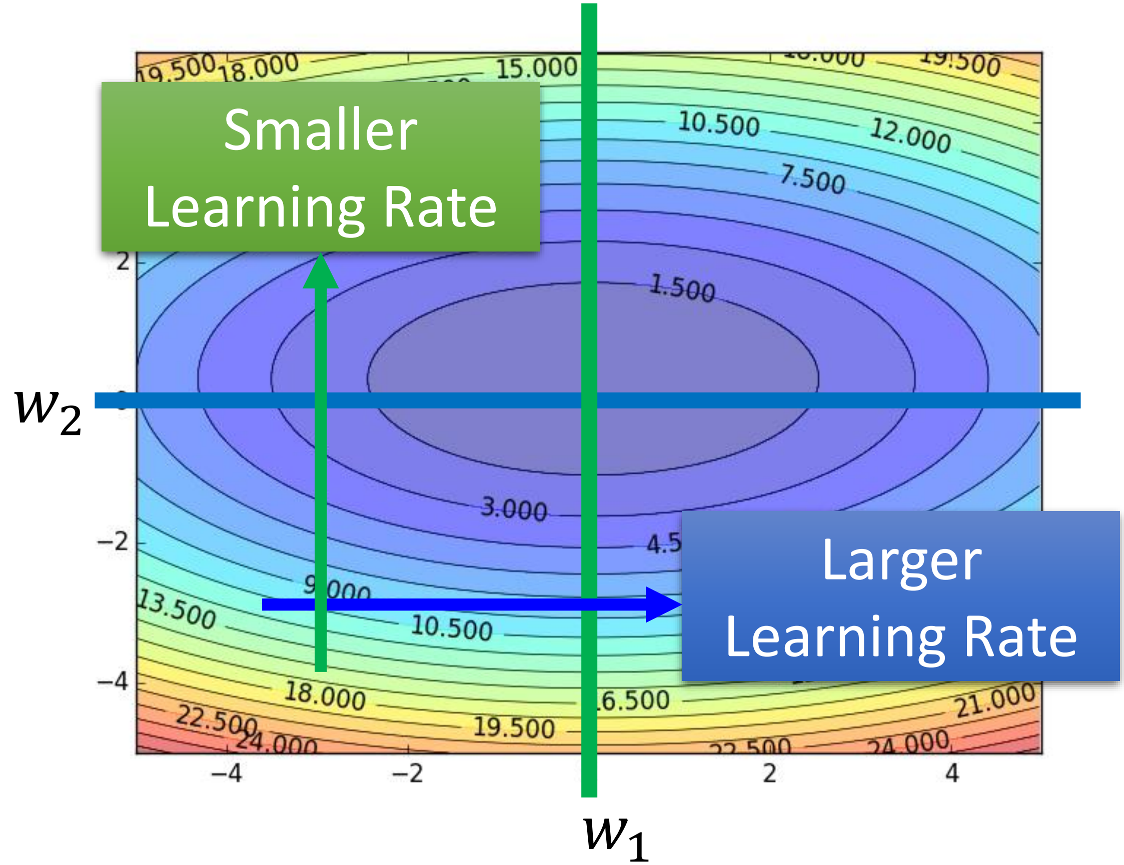
- Train this thin and linear network

Different thin and linear network for different examples

Recipe of Deep Learning



Review



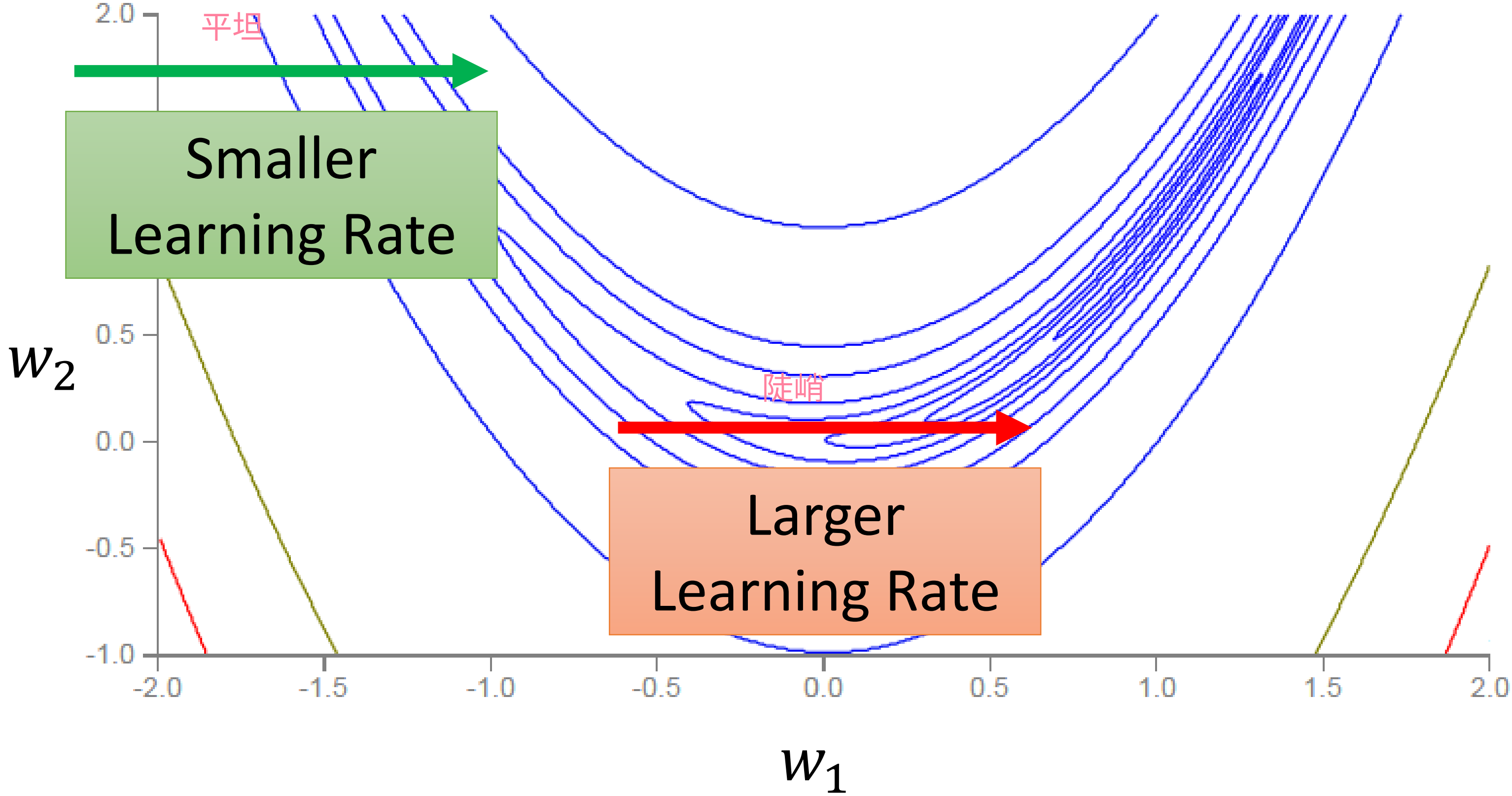
Adagrad

$$w^{t+1} \leftarrow w^t - \frac{\eta}{\sqrt{\sum_{i=0}^{t}(g^i)^2}} g^t$$

Use first derivative to estimate second derivative

RMSProp

Error Surface can be very complex when training NN.



RMSProp

$$w^1 \leftarrow w^0 - \frac{\eta}{\sigma^0} g^0 \qquad \sigma^0 = g^0$$

$$w^2 \leftarrow w^1 - \frac{\eta}{\sigma^1} g^1 \qquad \sigma^1 = \sqrt{\alpha(\sigma^0)^2 + (1-\alpha)(g^1)^2}$$

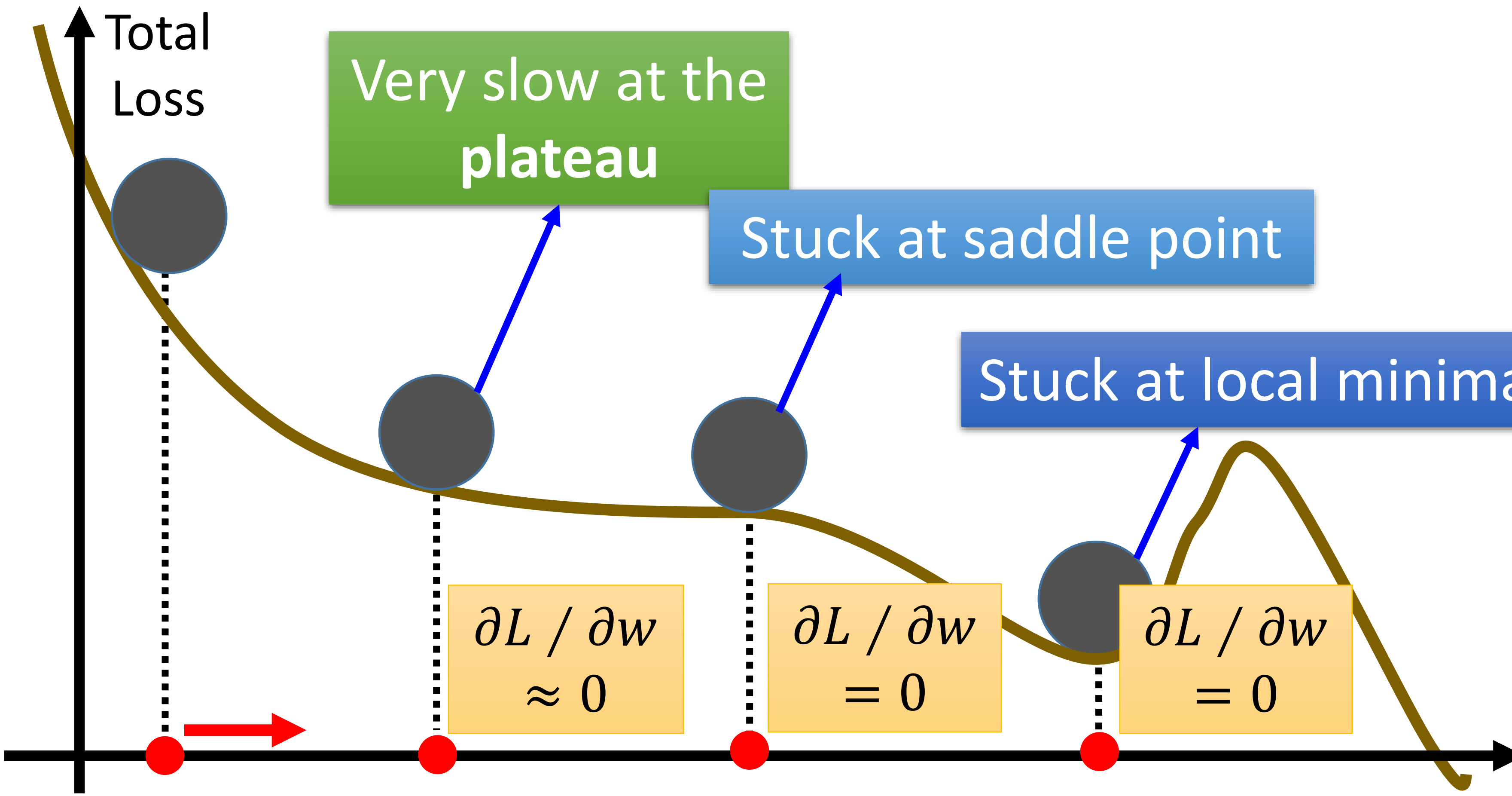
$$w^3 \leftarrow w^2 - \frac{\eta}{\sigma^2} g^2 \qquad \sigma^2 = \sqrt{\alpha(\sigma^1)^2 + (1-\alpha)(g^2)^2}$$

$$\vdots$$

$$w^{t+1} \leftarrow w^t - \frac{\eta}{\sigma^t} g^t \qquad \sigma^t = \sqrt{\alpha(\sigma^{t-1})^2 + (1-\alpha)(g^t)^2}$$

Root Mean Square of the gradients
with previous gradients being decayed

Hard to find optimal network parameters

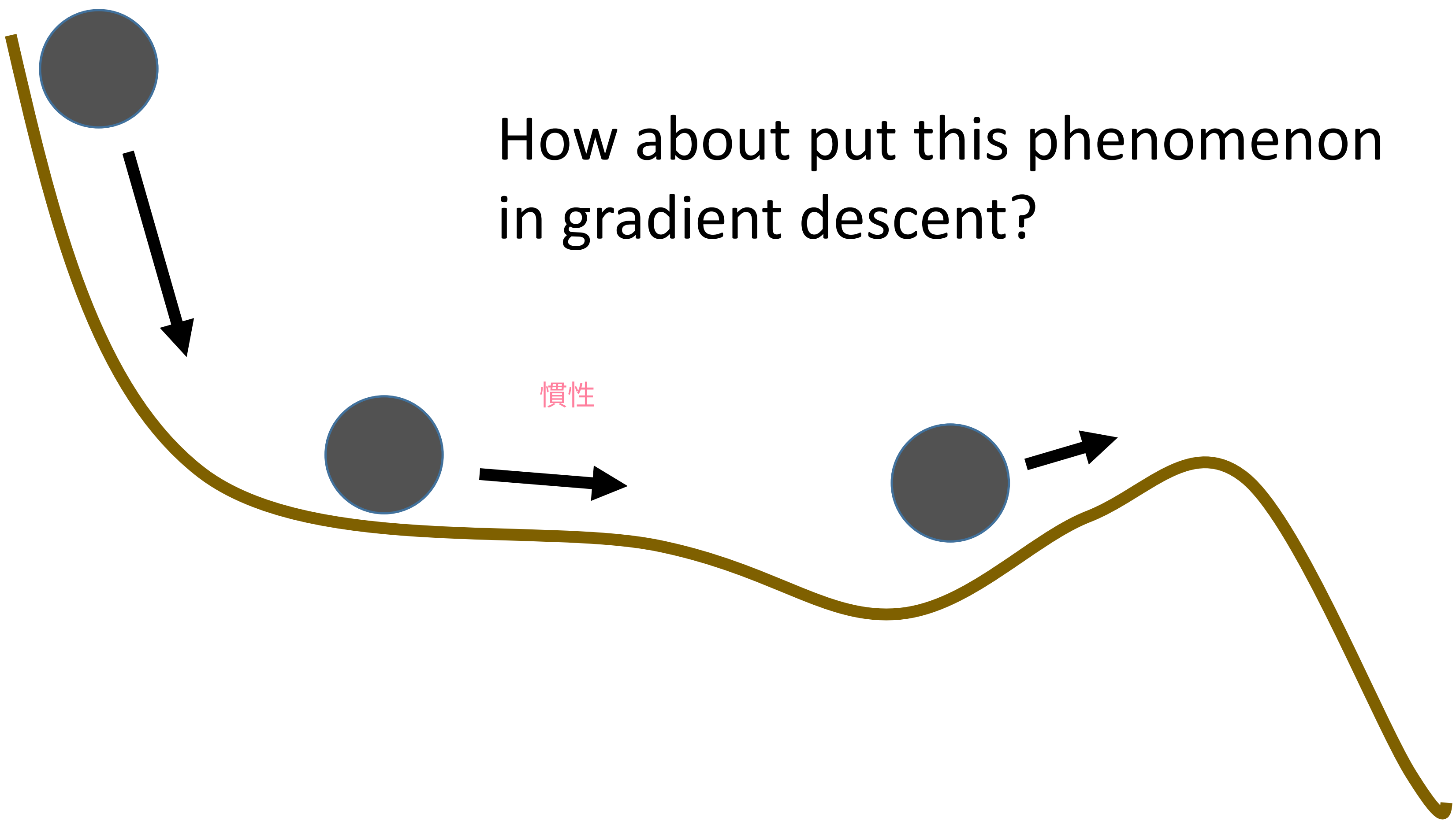


The value of a network parameter w

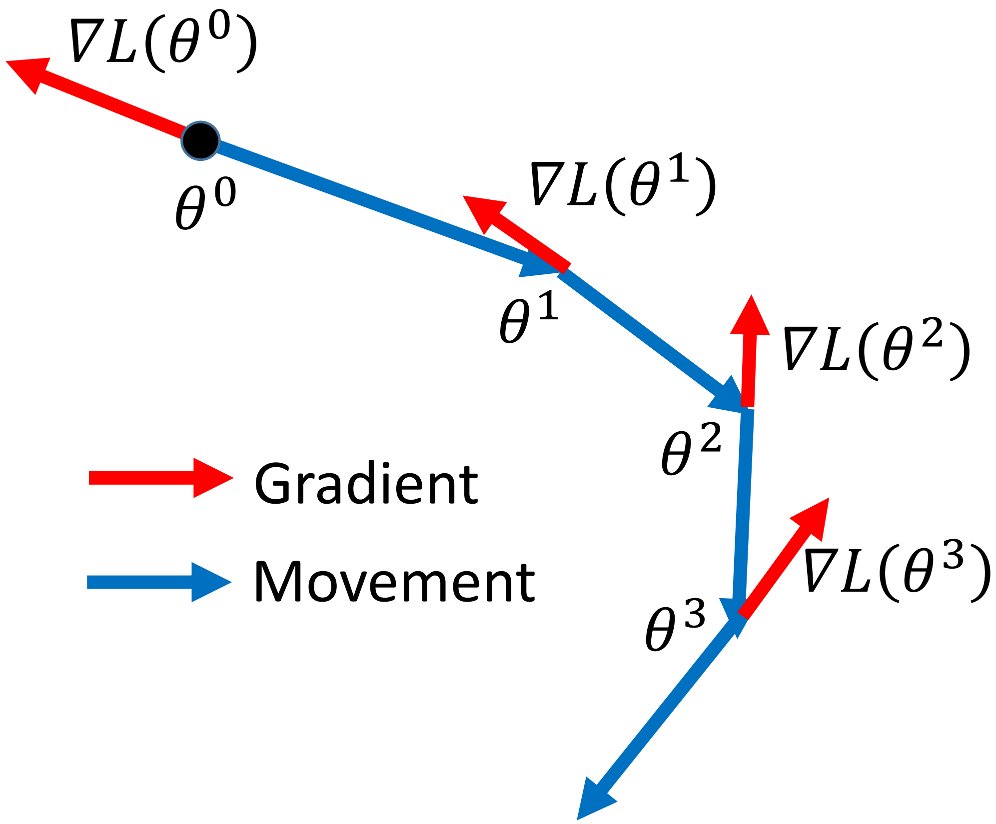
In physical world ……

- Momentum

How about put this phenomenon in gradient descent?



Review: Vanilla Gradient Descent



Start at position θ^0

Compute gradient at θ^0

Move to $\theta^1 = \theta^0 - \eta\nabla L(\theta^0)$

Compute gradient at θ^1

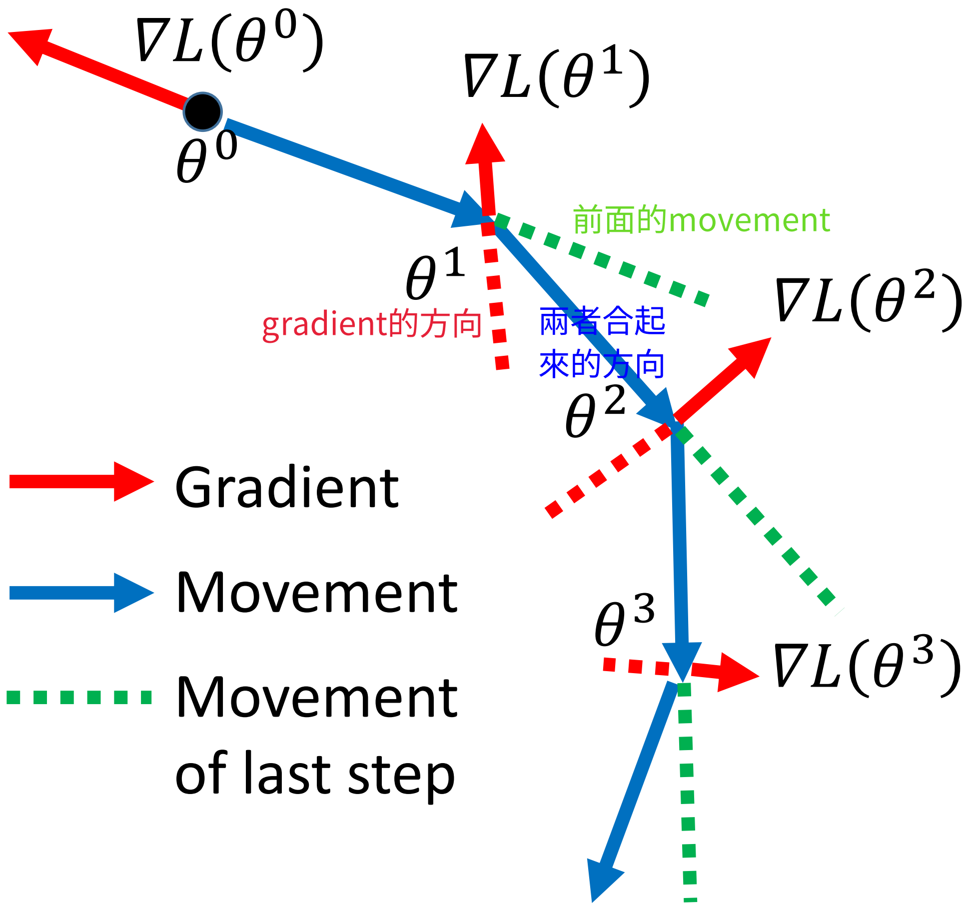
Move to $\theta^2 = \theta^1 - \eta\nabla L(\theta^1)$

⋮

Stop until $\nabla L(\theta^t) \approx 0$

Momentum

Movement: movement of last step minus gradient at present



Start at point θ^0

Movement $v^0=0$

Compute gradient at θ^0

Movement $v^1 = \lambda v^0 - \eta \nabla L(\theta^0)$

Move to $\theta^1 = \theta^0 + v^1$

Compute gradient at θ^1

Movement $v^2 = \lambda v^1 - \eta \nabla L(\theta^1)$

Move to $\theta^2 = \theta^1 + v^2$

Movement not just based on gradient, but previous movement.

Momentum

Movement: movement of last step minus gradient at present

v^i is actually the weighted sum of all the previous gradient: $\nabla L(\theta^0), \nabla L(\theta^1), \ldots \nabla L(\theta^{i-1})$

$v^0 = 0$

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

$v^2 = -\lambda\eta \nabla L(\theta^0) - \eta \nabla L(\theta^1)$

⋮

Start at point θ^0

Movement $v^0=0$

Compute gradient at θ^0

Movement $v^1 = \lambda v^0 - \eta \nabla L(\theta^0)$

Move to $\theta^1 = \theta^0 + v^1$

Compute gradient at θ^1

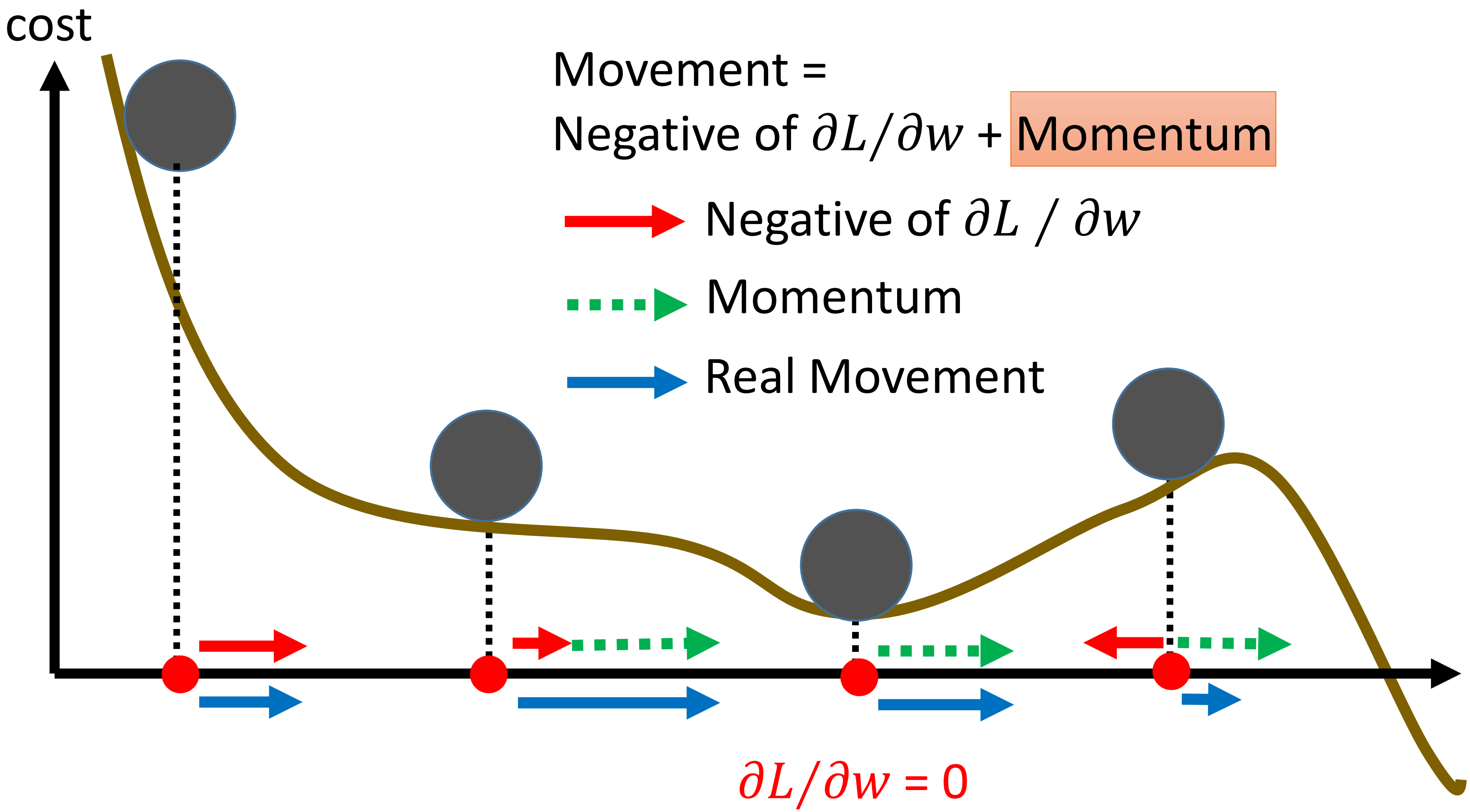
Movement $v^2 = \lambda v^1 - \eta \nabla L(\theta^1)$

Move to $\theta^2 = \theta^1 + v^2$

Movement not just based on gradient, but previous movement

Momentum

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



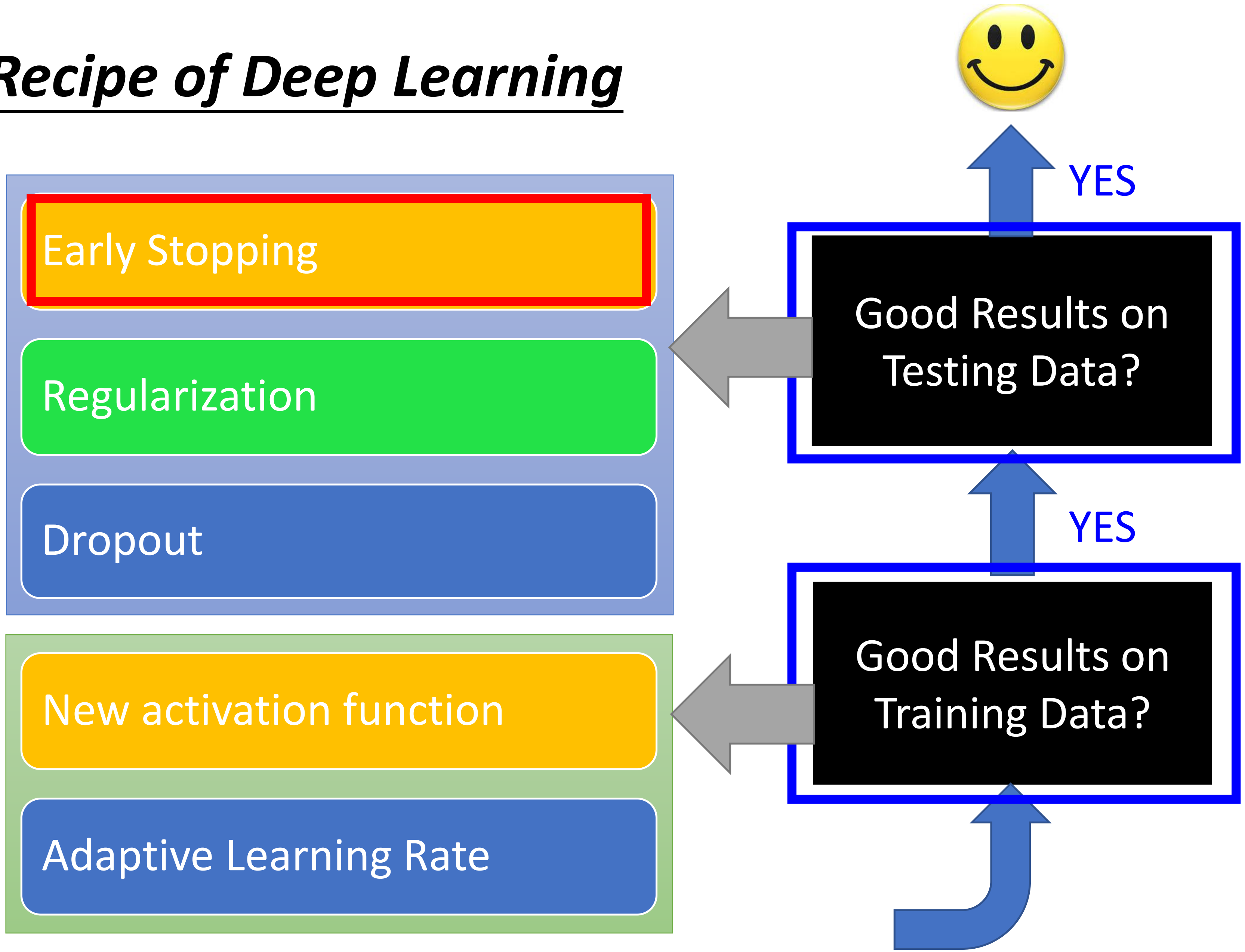
Adam

RMSProp + Momentum

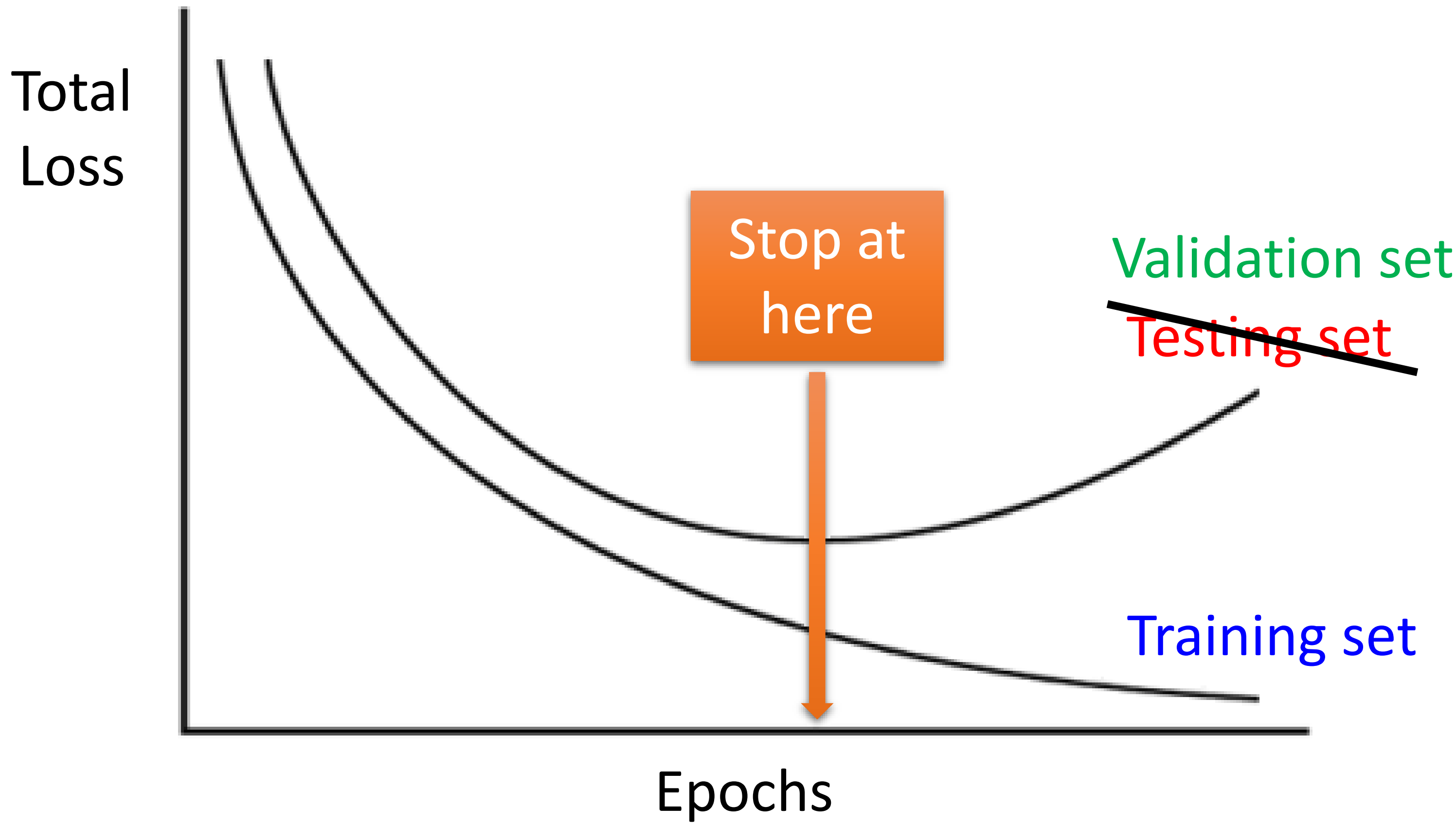
Algorithm 1: *Adam*, our proposed algorithm for stochastic optimization. See section 2 for details, and for a slightly more efficient (but less clear) order of computation. g_t^2 indicates the elementwise square $g_t \odot g_t$. Good default settings for the tested machine learning problems are $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ 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) → for momentum
  $v_0 \leftarrow 0$ (Initialize 2nd moment vector) → for RMSprop
  $t \leftarrow 0$ (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)

Recipe of Deep Learning

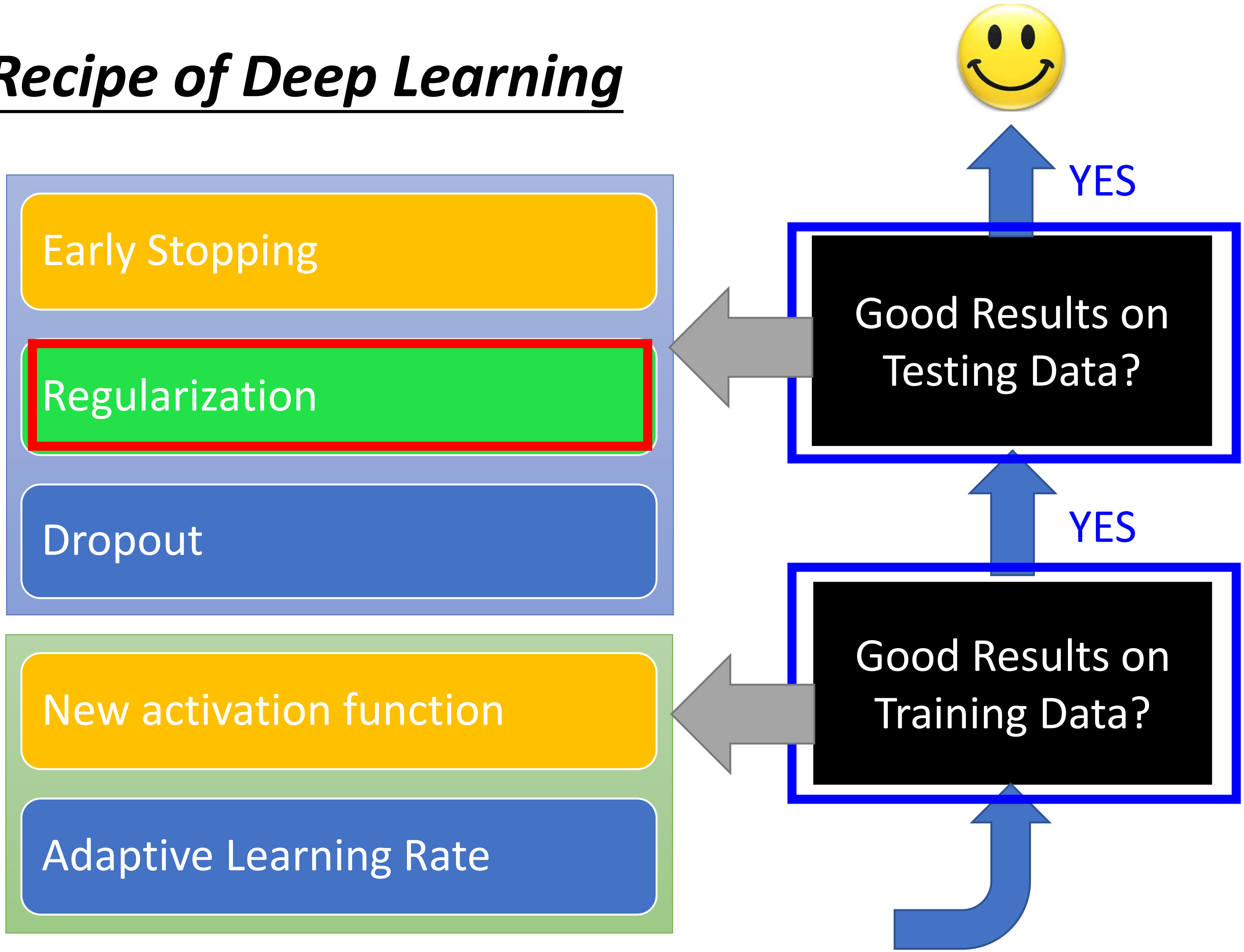


Early Stopping



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

Recipe of Deep Learning



Regularization

- New loss function to be minimized
  - Find a set of weight not only minimizing original cost but also close to zero

$$L'(\theta) = \underbrace{L(\theta)}_{} + \lambda \frac{1}{2} \underline{\|\theta\|_2}$$

→ Regularization term

Original loss
(e.g. minimize square error, cross entropy …)

$$\theta = \{w_1, w_2, \ldots\}$$

L2 regularization:

$$\|\theta\|_2 = (w_1)^2 + (w_2)^2 + \ldots$$

(usually not consider biases)

Regularization

L2 regularization:

$$\|\theta\|_2 = (w_1)^2 + (w_2)^2 + \ldots$$

- New loss function to be minimized

$$\mathrm{L}'(\theta) = L(\theta) + \lambda \frac{1}{2}\|\theta\|_2$$

Gradient: $$\frac{\partial \mathrm{L}'}{\partial w} = \frac{\partial \mathrm{L}}{\partial w} + \lambda w$$

Update: $$w^{t+1} \rightarrow w^t - \eta \frac{\partial \mathrm{L}'}{\partial w} = w^t - \eta\left(\frac{\partial \mathrm{L}}{\partial w} + \lambda w^t\right)$$

$$= \underbrace{(1-\eta\lambda)w^t}_{\text{Closer to zero}} - \eta \underline{\frac{\partial \mathrm{L}}{\partial w}}$$

Weight Decay

Regularization

L1 regularization:

$$\|\theta\|_1 = |w_1| + |w_2| + \ldots$$

- New loss function to be minimized

$$\mathrm{L}'(\theta) = L(\theta) + \lambda \frac{1}{2}\|\theta\|_1 \qquad \frac{\partial \mathrm{L}'}{\partial w} = \frac{\partial \mathrm{L}}{\partial w} + \lambda \operatorname{sgn}(w)$$

Update:

$$w^{t+1} \rightarrow w^t - \eta \frac{\partial \mathrm{L}'}{\partial w} = w^t - \eta \left(\frac{\partial \mathrm{L}}{\partial w} + \lambda \operatorname{sgn}(w^t) \right)$$

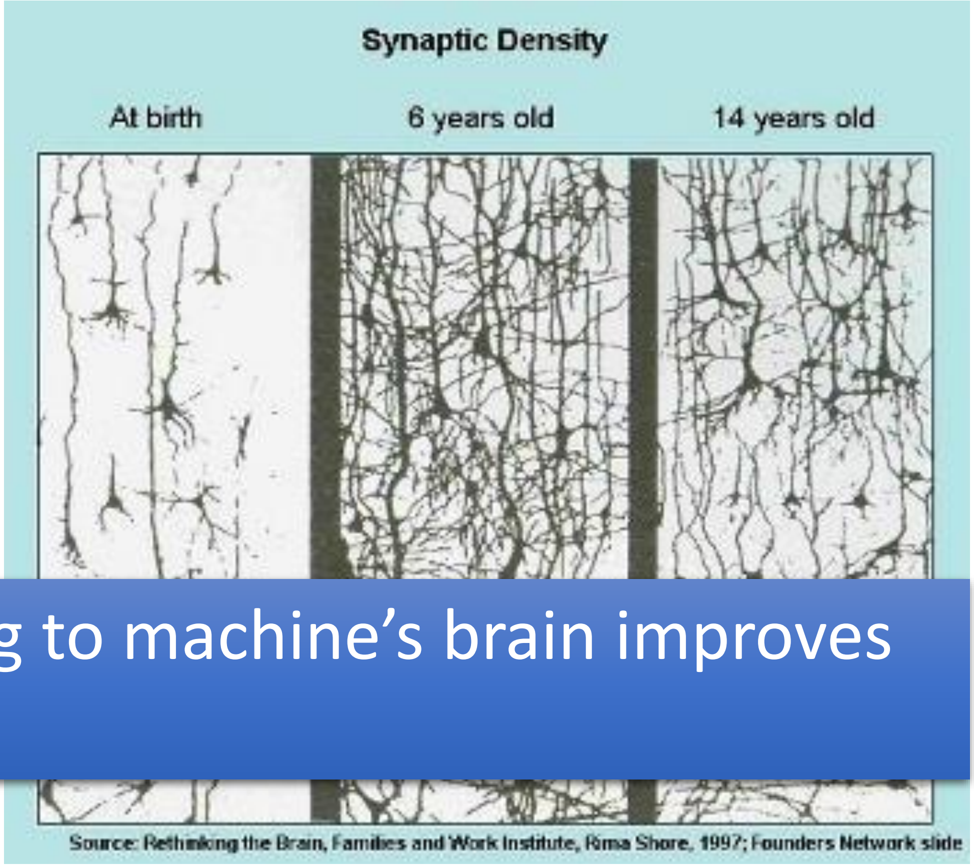
$$= w^t - \eta \frac{\partial \mathrm{L}}{\partial w} - \underline{\eta \lambda \operatorname{sgn}(w^t)}$$ Always delete

$$= (1 - \eta\lambda) w^t - \eta \frac{\partial \mathrm{L}}{\partial w}$$ …… L2

Regularization - Weight Decay

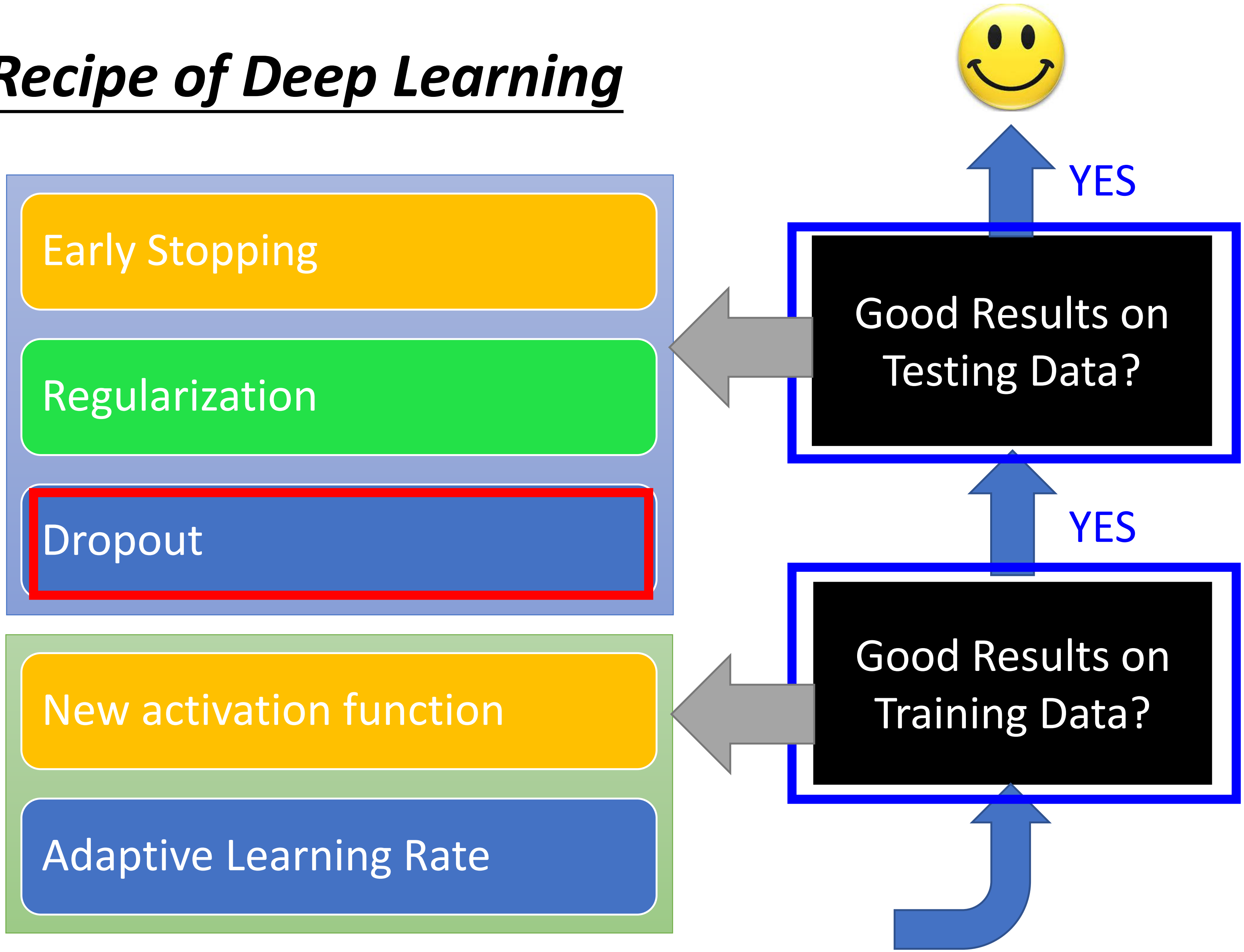
- Our brain prunes out the useless link between neurons.

沒有更新(使用)的參數會刪除



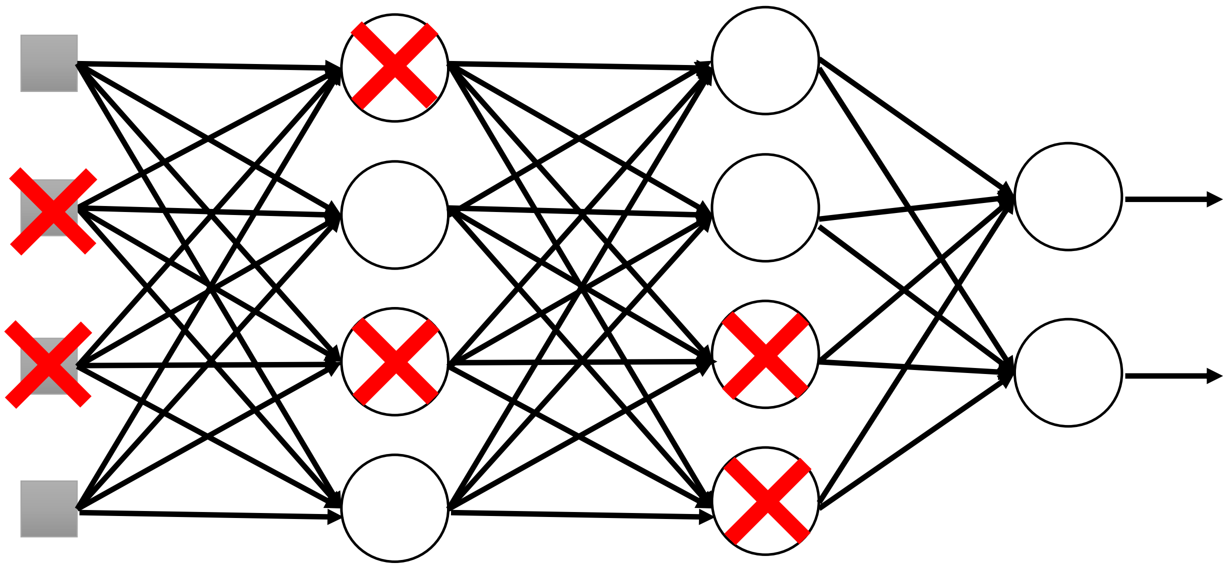
Doing the same thing to machine's brain improves the performance.

Recipe of Deep Learning



Dropout

Training:

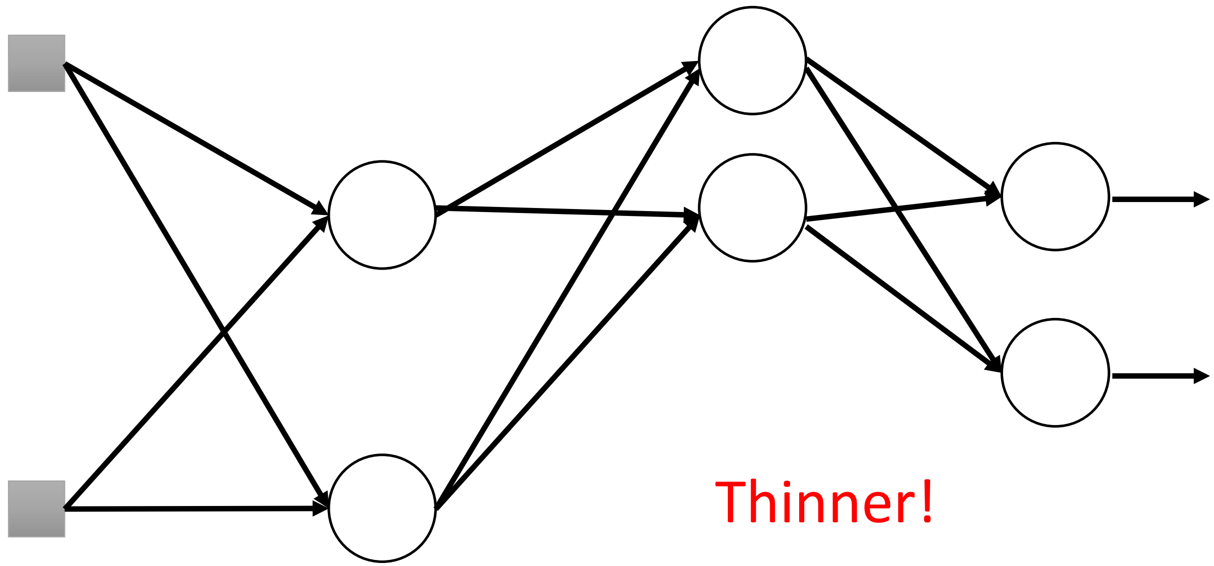


- **Each time before updating the parameters**
  - Each neuron has p% to dropout

丢掉X的neuron

Dropout

Training:



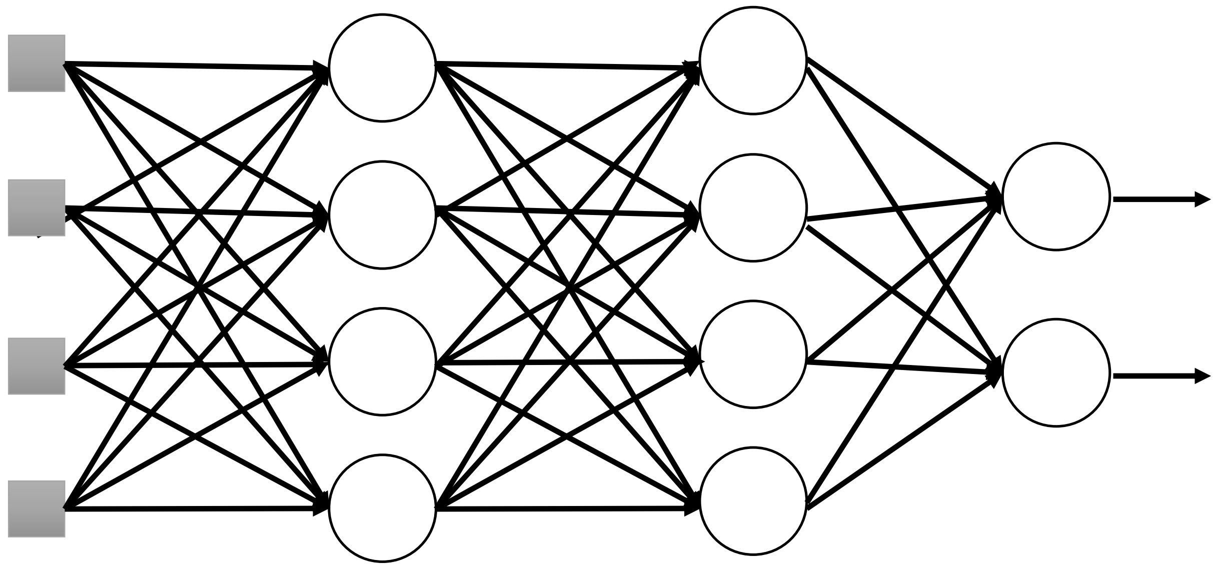
- **Each time before updating the parameters**
  - Each neuron has p% to dropout

    The structure of the network is changed.
  - Using the new network for training 每次皆須重新sampling，故每次的structure都不同

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

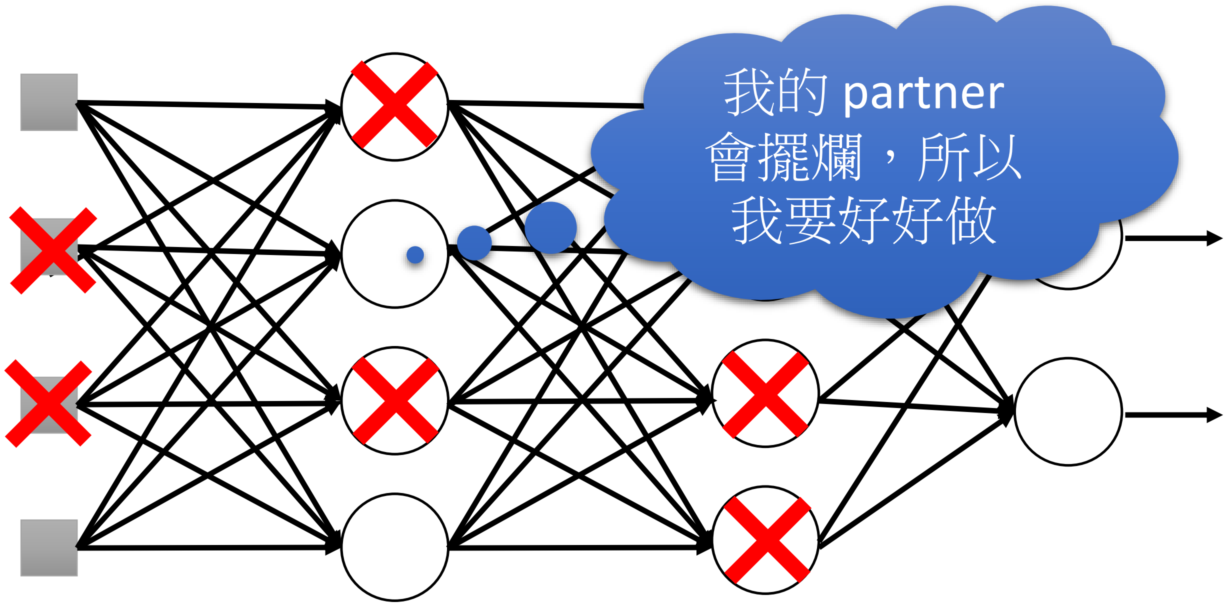
Testing

No dropout
(拿下重物後就變很強)

Training

Dropout (腳上綁重物)

Dropout - Intuitive Reason



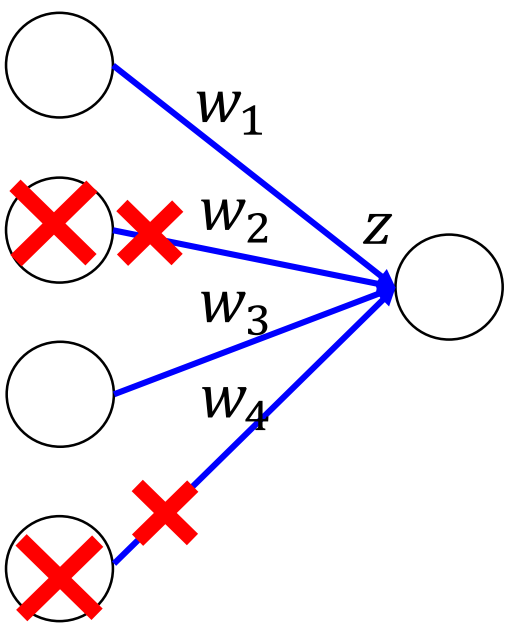
- When teams up, if everyone expect the partner will do the work, nothing will be done finally.
- However, if you know your partner will dropout, you will do better.
- When testing, no one dropout actually, so obtaining good results eventually.

Dropout - Intuitive Reason

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

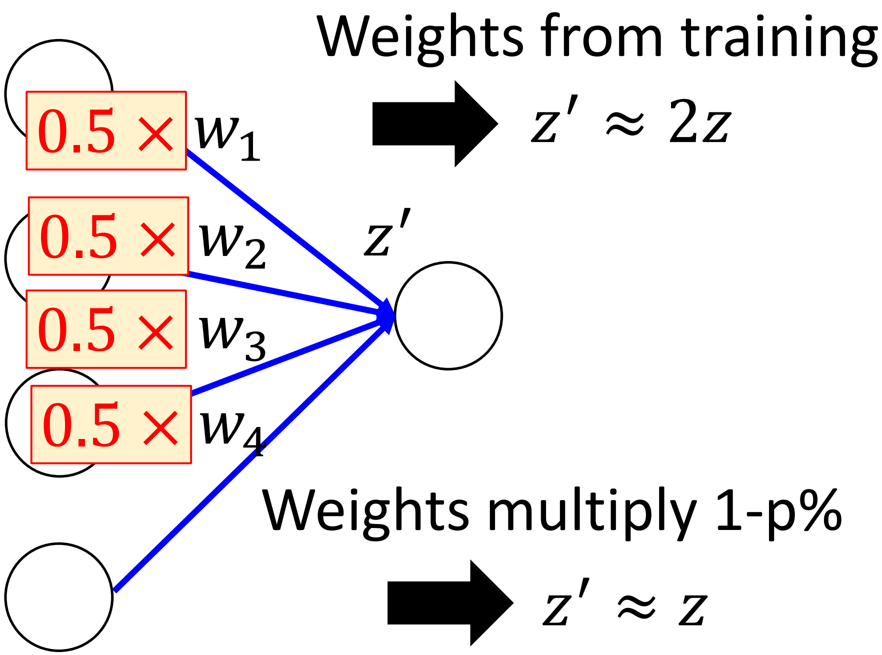
Training of Dropout

Assume dropout rate is 50%

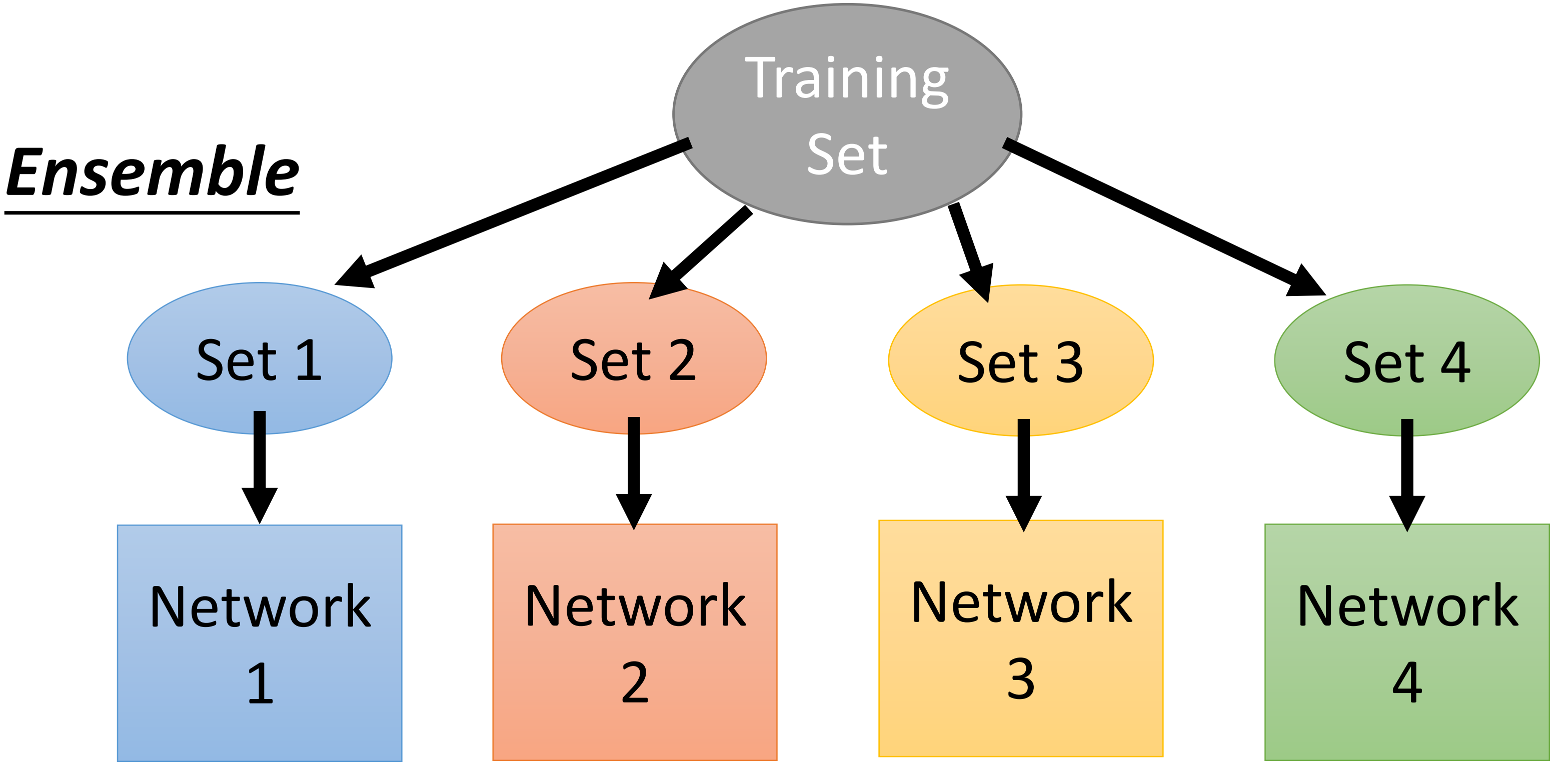


Testing of Dropout

No dropout



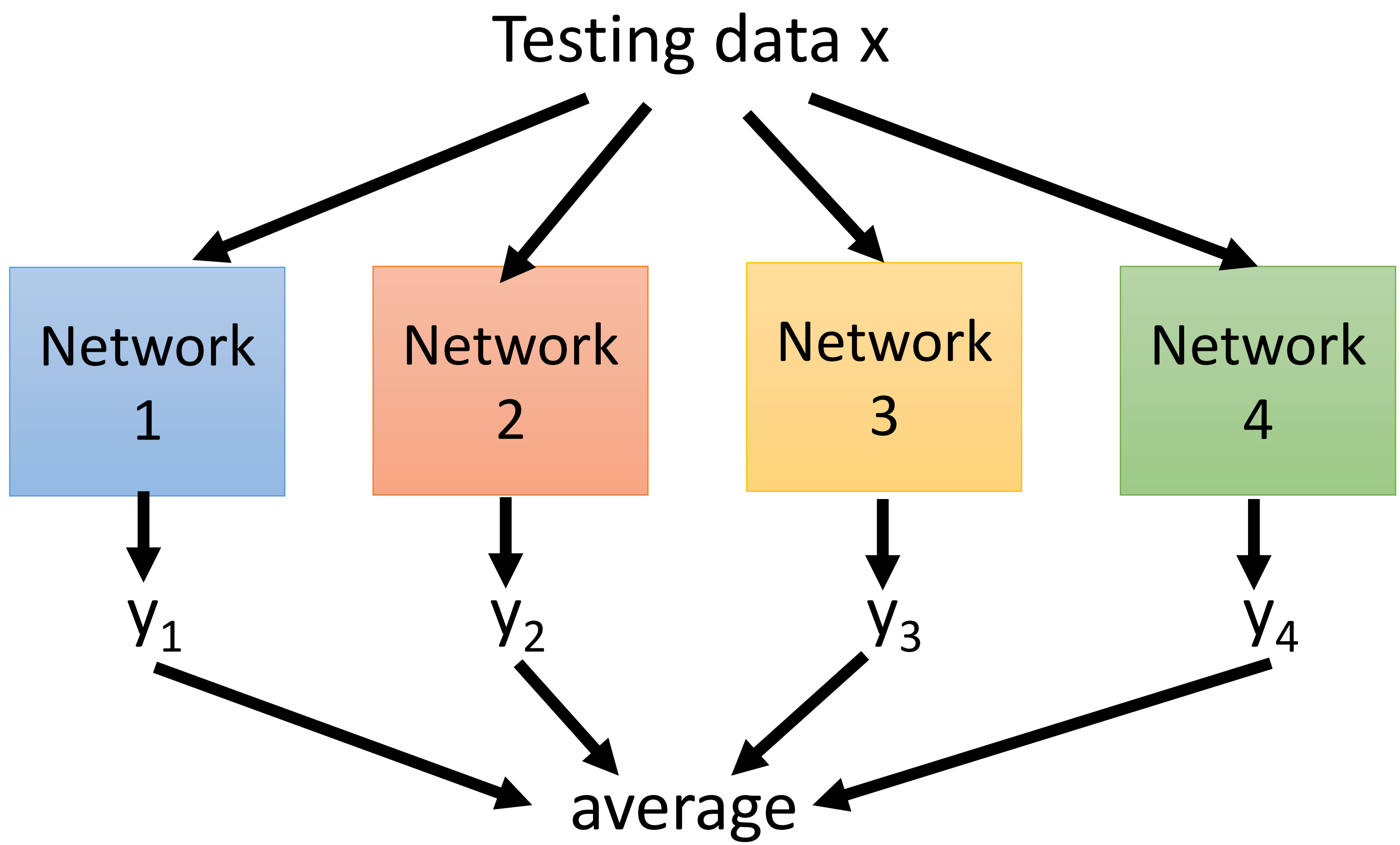
Dropout is a kind of ensemble.



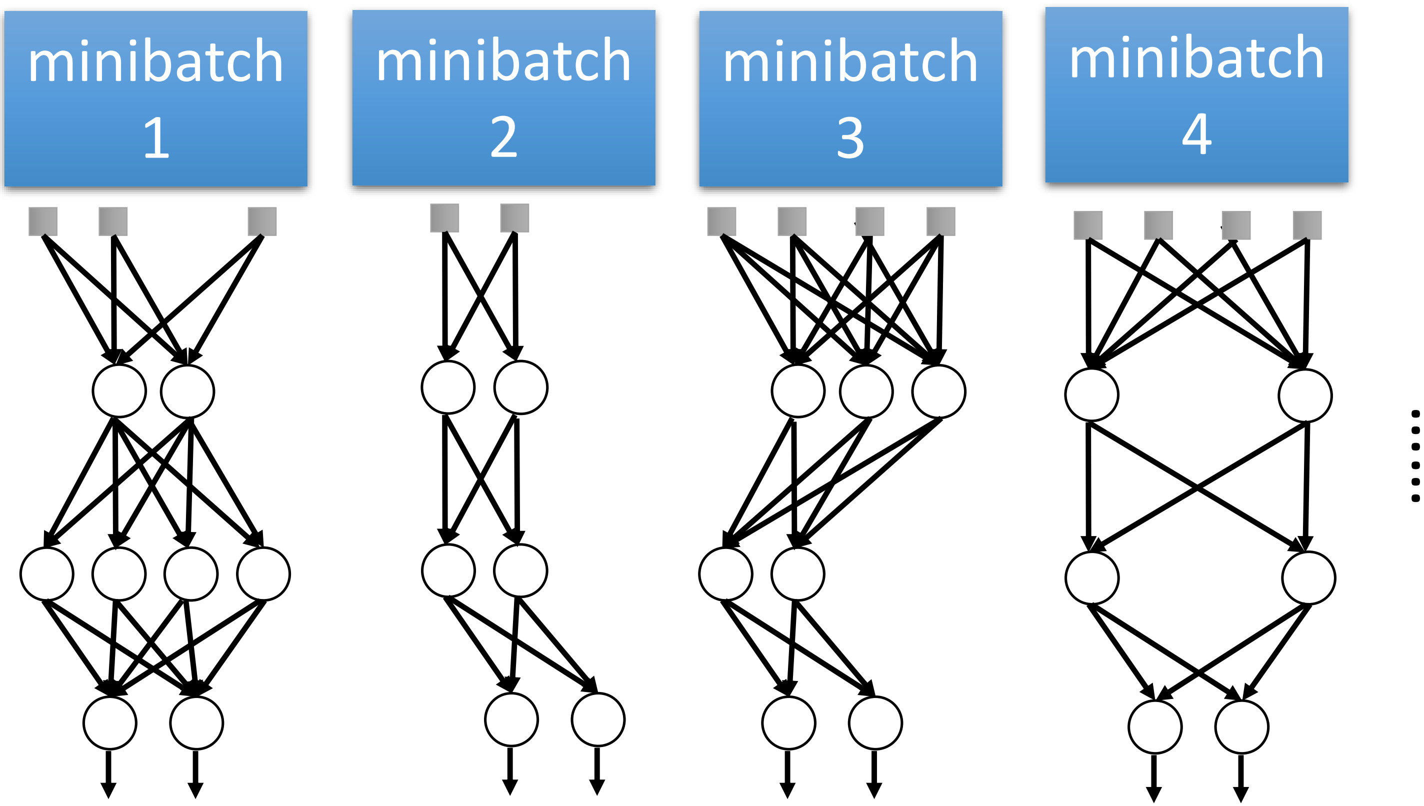
Train a bunch of networks with different structures

Dropout is a kind of ensemble.

Ensemble



Dropout is a kind of ensemble.



Training of Dropout

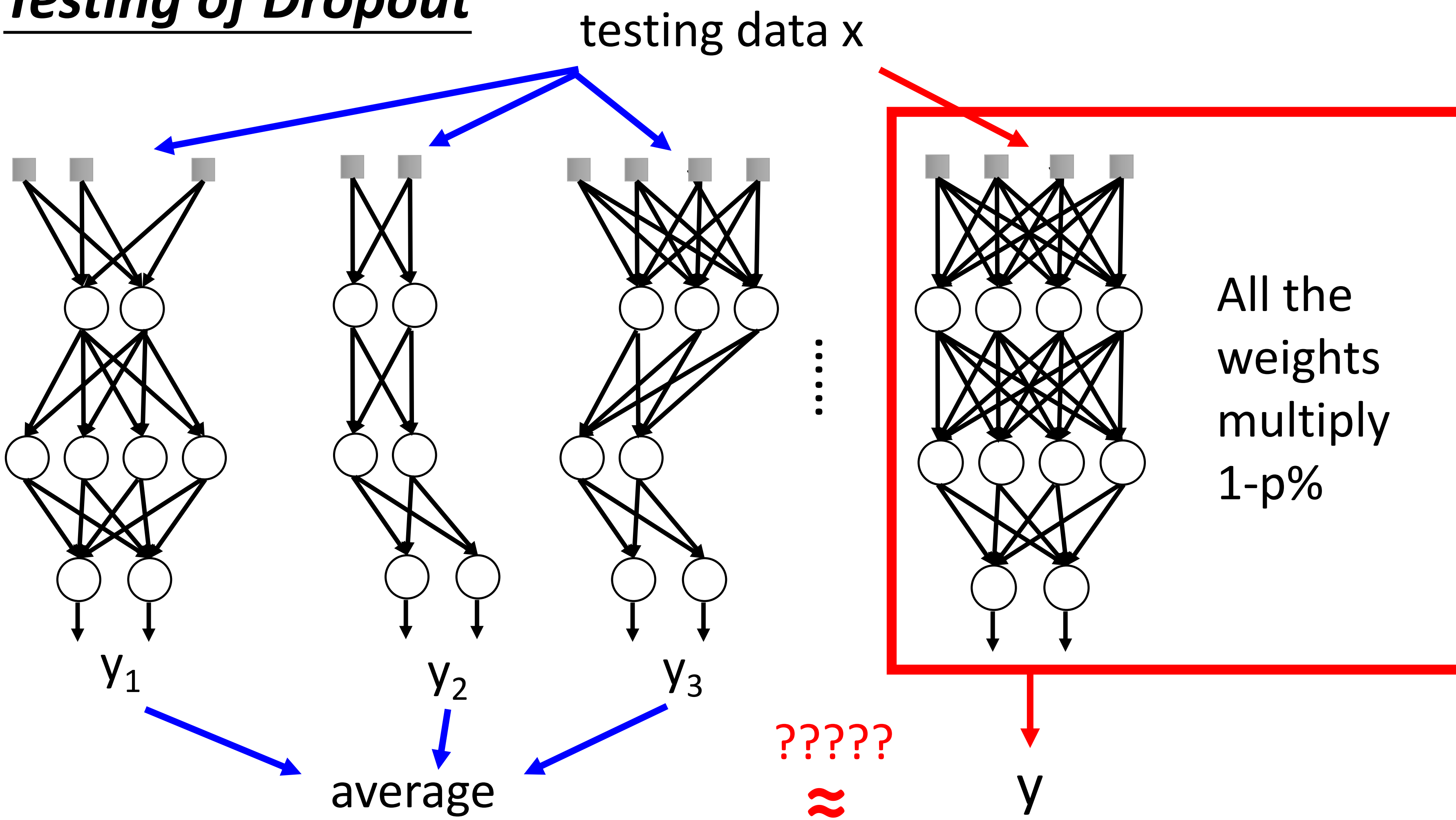
M neurons

2^M possible networks

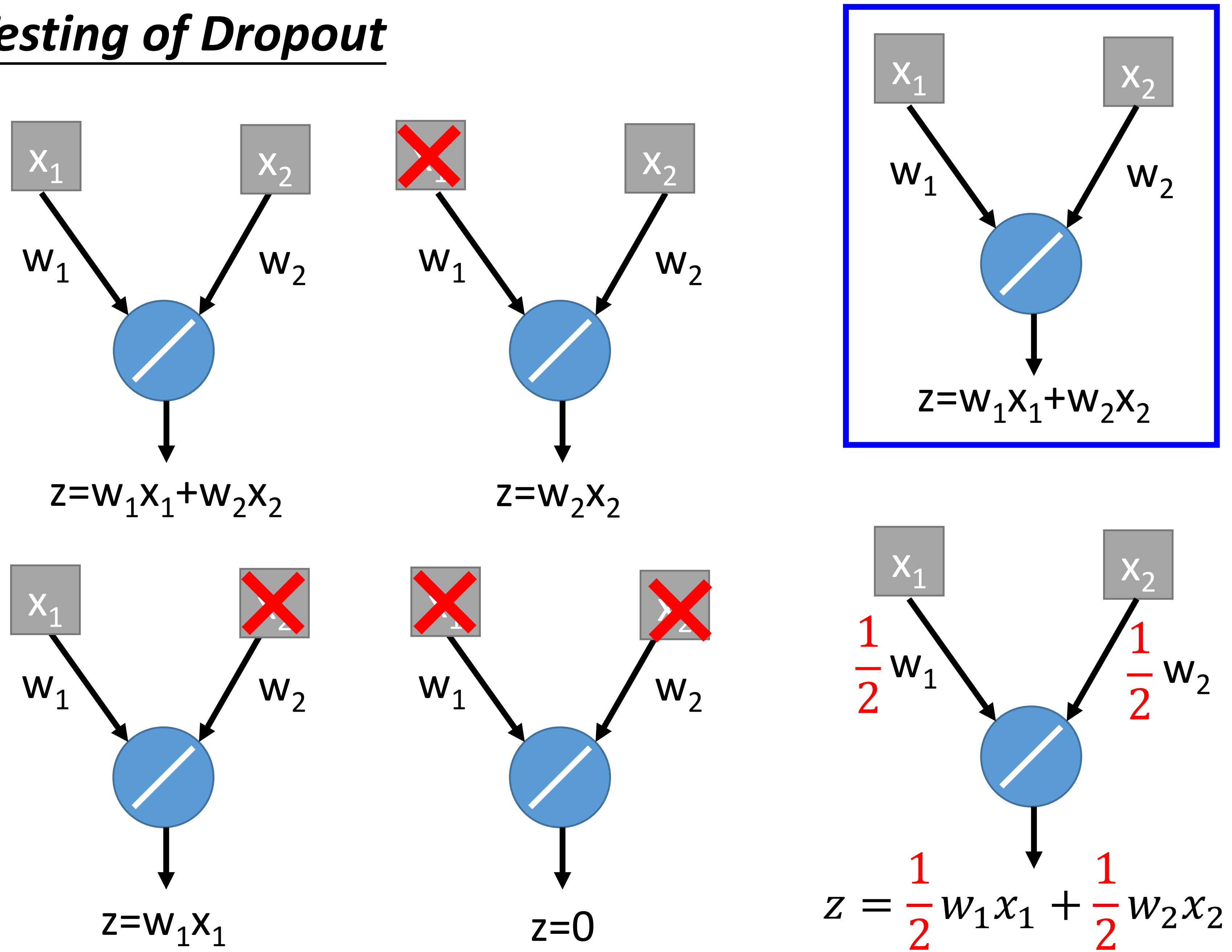
- ➢Using one mini-batch to train one network
- ➢Some parameters in the network are shared

Dropout is a kind of ensemble.

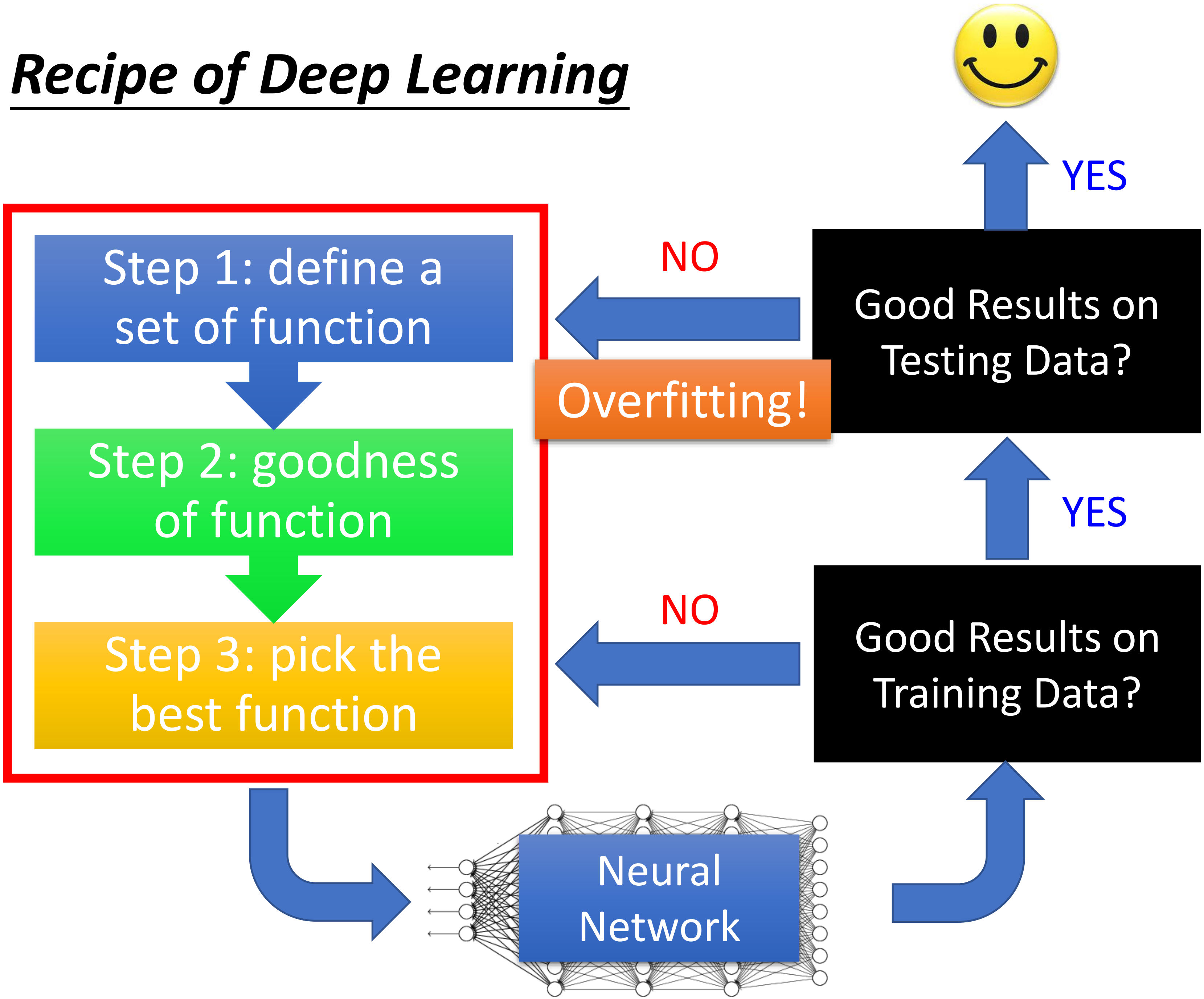
Testing of Dropout



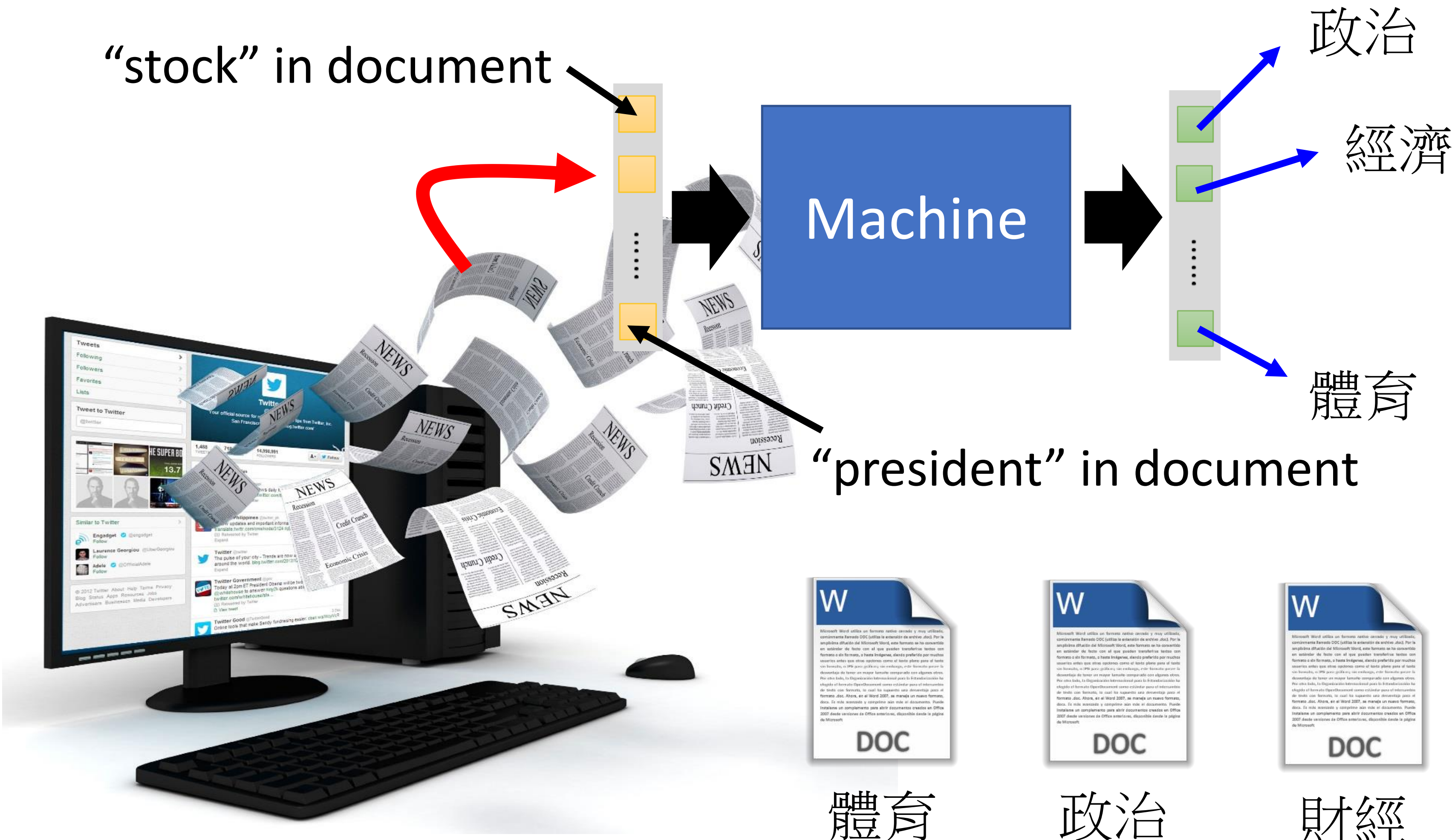
Testing of Dropout



Recipe of Deep Learning



Try another task



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

Try another task

```
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.])
```

Live Demo