Tips for Training Deep Learning

Recap: Stochastic Gradient Descent

$$l^{(i)} = -\log\left(\exp\left(z_k^{(i)}\right) / \sum_j \exp(z_j^{(i)})\right)$$

$$L = \frac{1}{N}\boxed{\sum_{i=1}^{N}} l^{(i)}$$

Loss is the summation over all training examples

- ***Gradient Descent***

$$\theta^{(i+1)} \leftarrow \theta^{(i)} - \eta \nabla L(\theta^{(i)})$$

- ***Stochastic Gradient Descent (SGD)***

Faster!

Randomly pick one example $\boldsymbol{x}^{(i)}$ to update parameters

$$\boxed{l^{(i)}} = -\log\left(\exp\left(z_k^{(i)}\right) / \sum_j \exp(z_j^{(i)})\right)$$

$$\theta^{(i+1)} \leftarrow \theta^{(i)} - \eta \nabla l(\theta^{(i)})$$

Loss for only one example, *i.e.* i^{th} sample

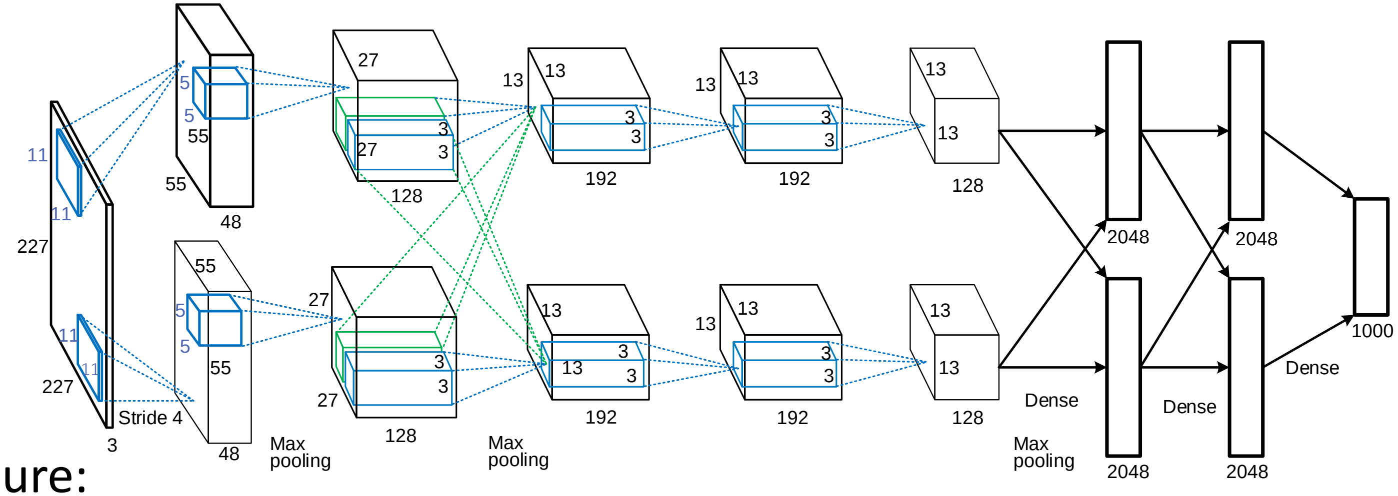
Minibatch SGD

Loop:

1. **Sample** a batch of data
2. **Forward** prop it through the graph (network), get loss
3. **Backprop** to calculate the gradients
4. **Update** the parameters using the gradient

Case Study: AlexNet

[Krizhevsky *et al.* 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details:

- heavy data augmentation
- first use of ReLU
- used Norm layers (not common anymore)
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 0.01, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 0.0005

7 CNN ensemble: 18.2%→ 15.4%

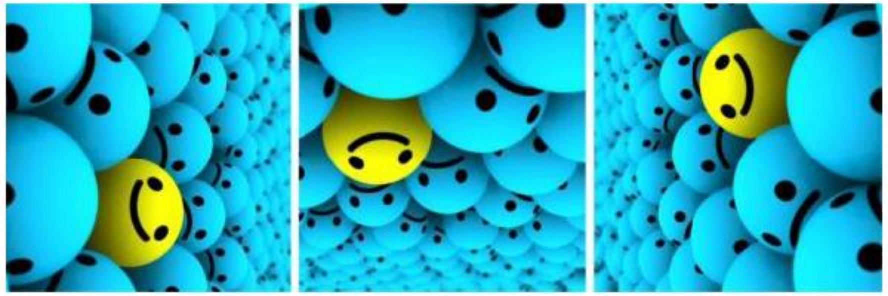
Data Augmentation

Crop:

Flip:

Scale:

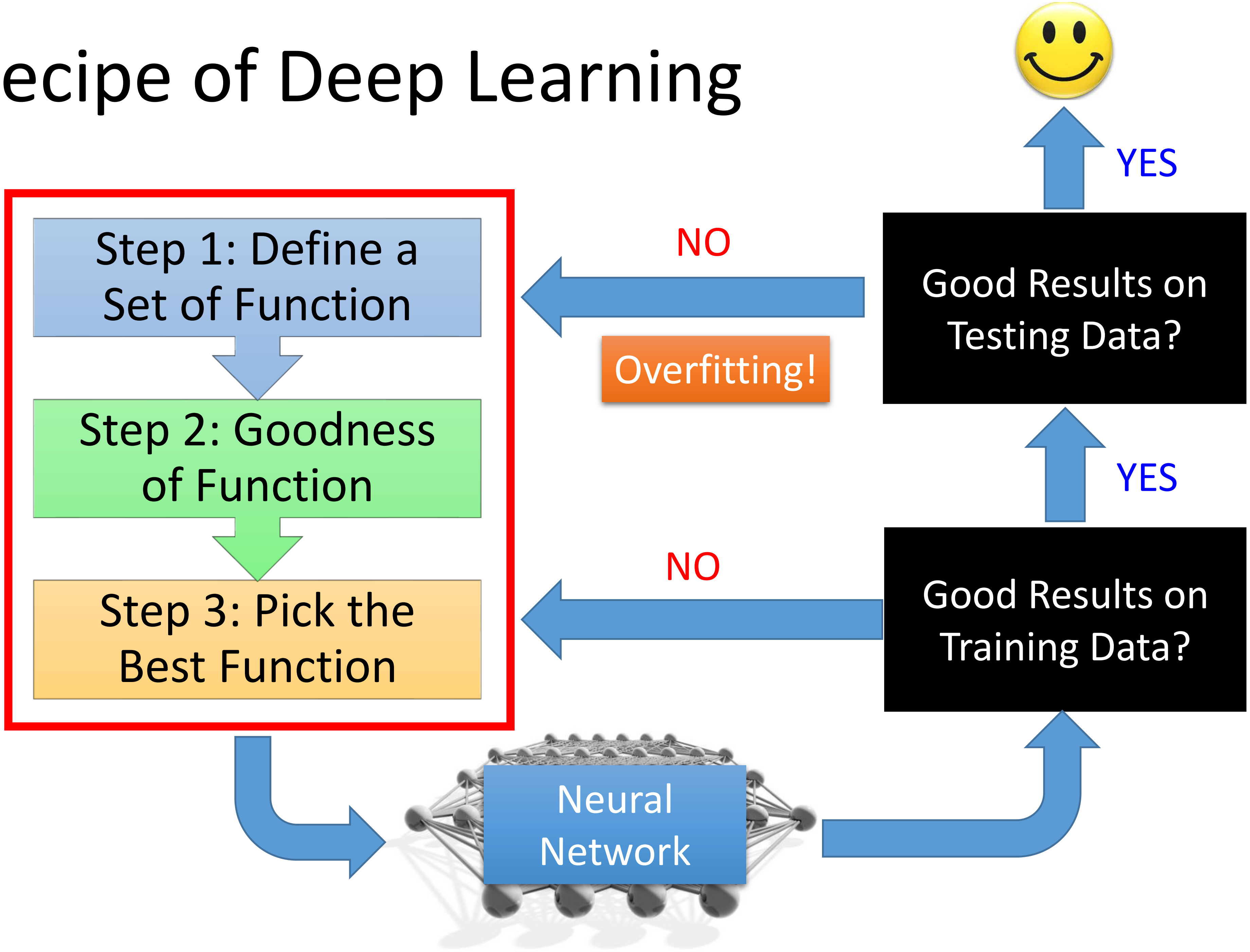
Rotate:



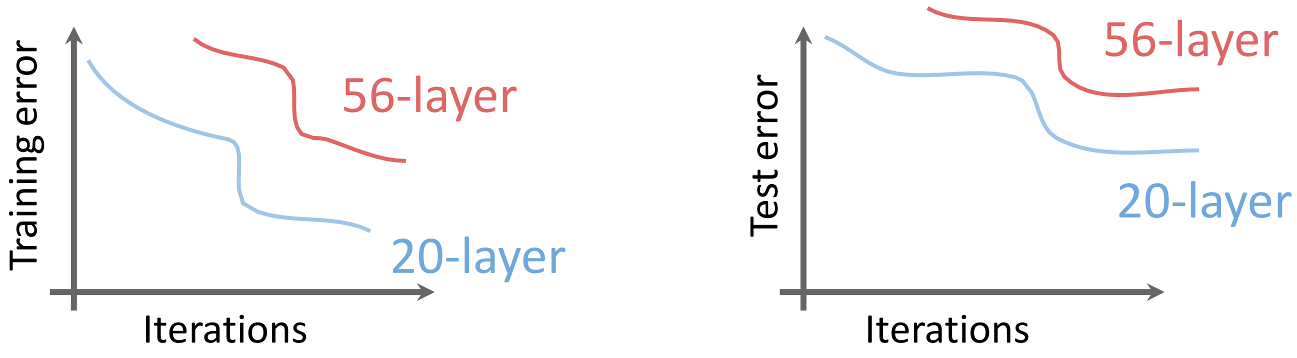
Translation:

Noise:

Recipe of Deep Learning



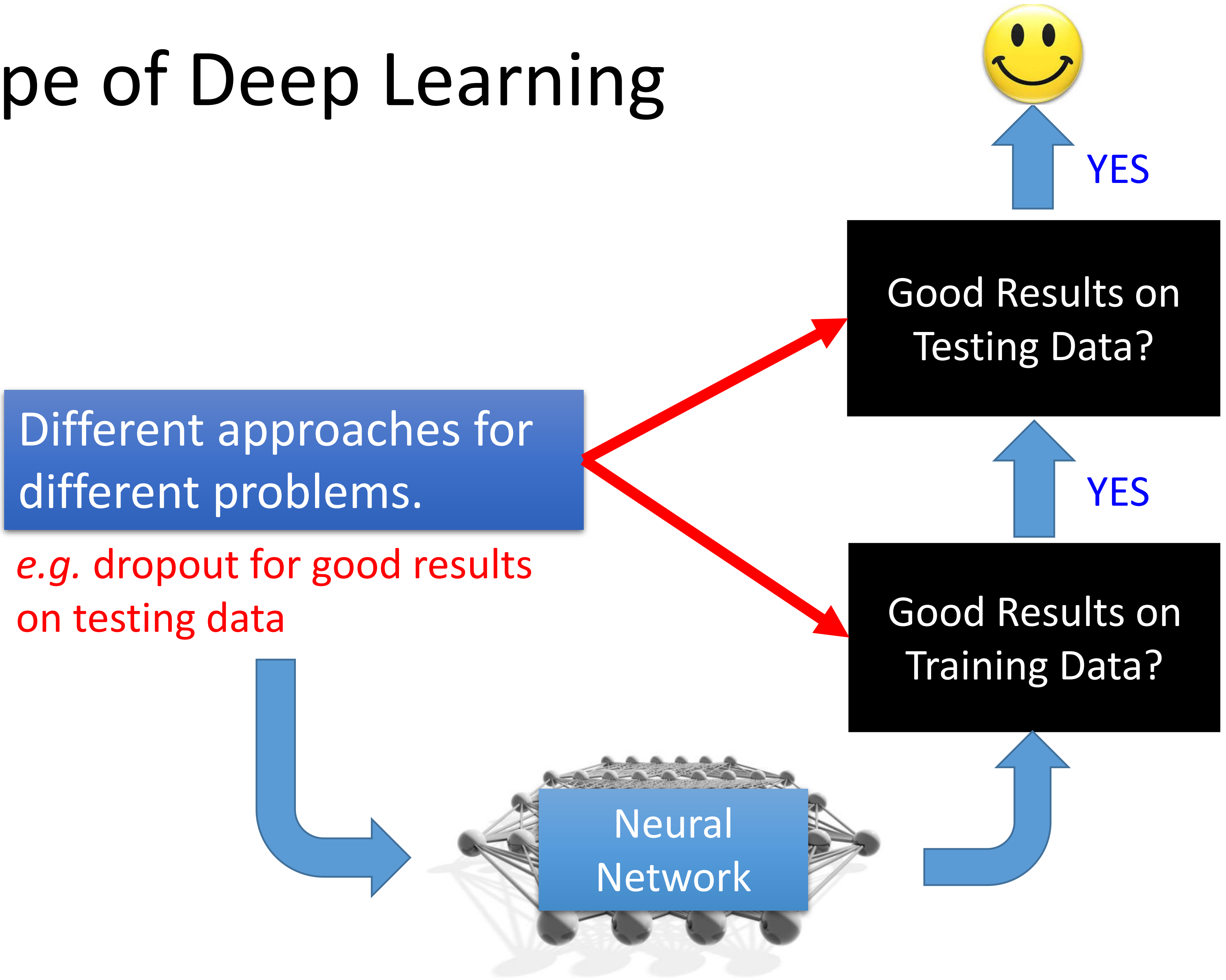
Do not always blame Overfitting



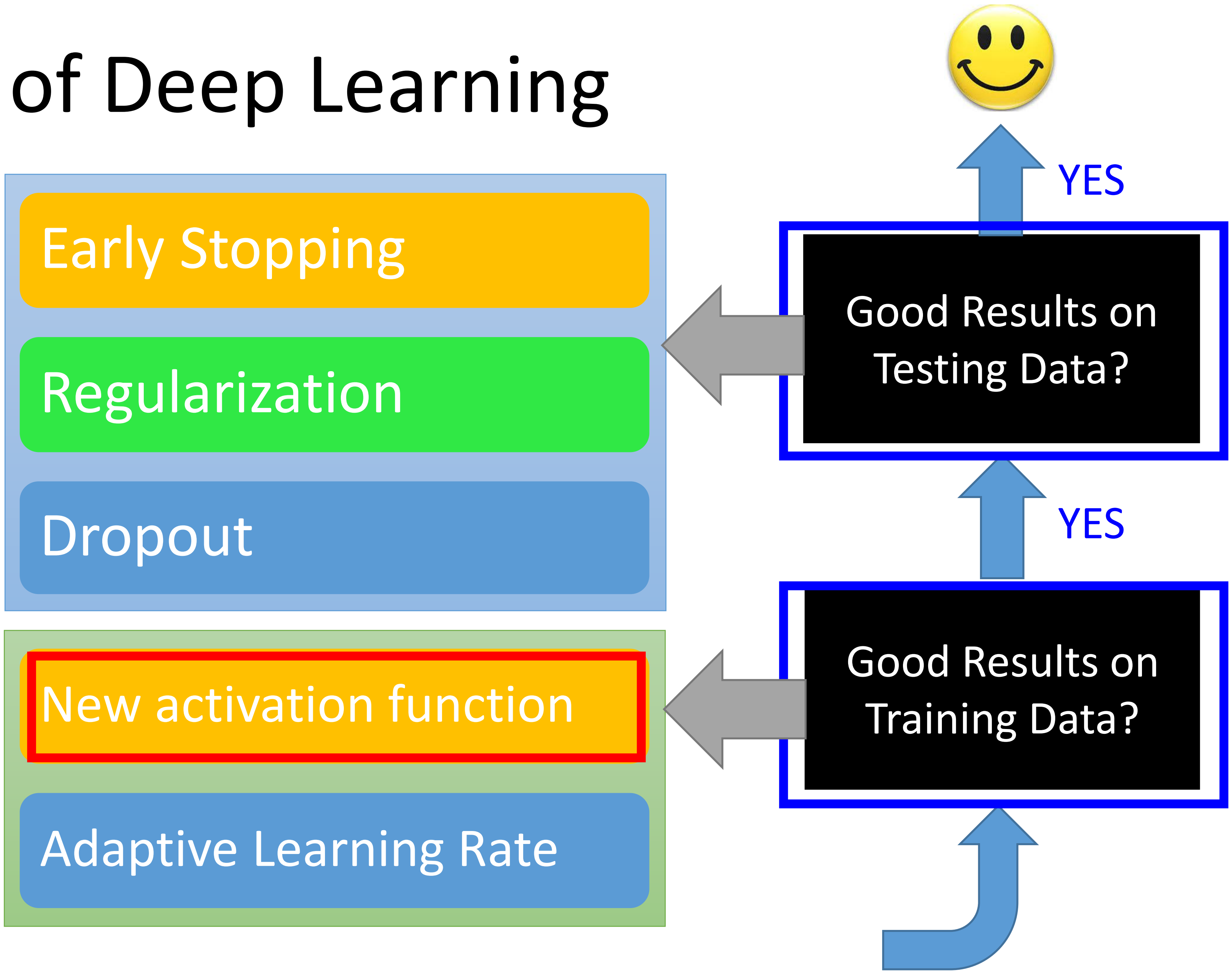
Please refer to:

Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, Deep Residual Learning for Image Recognition, CVPR, 2016.

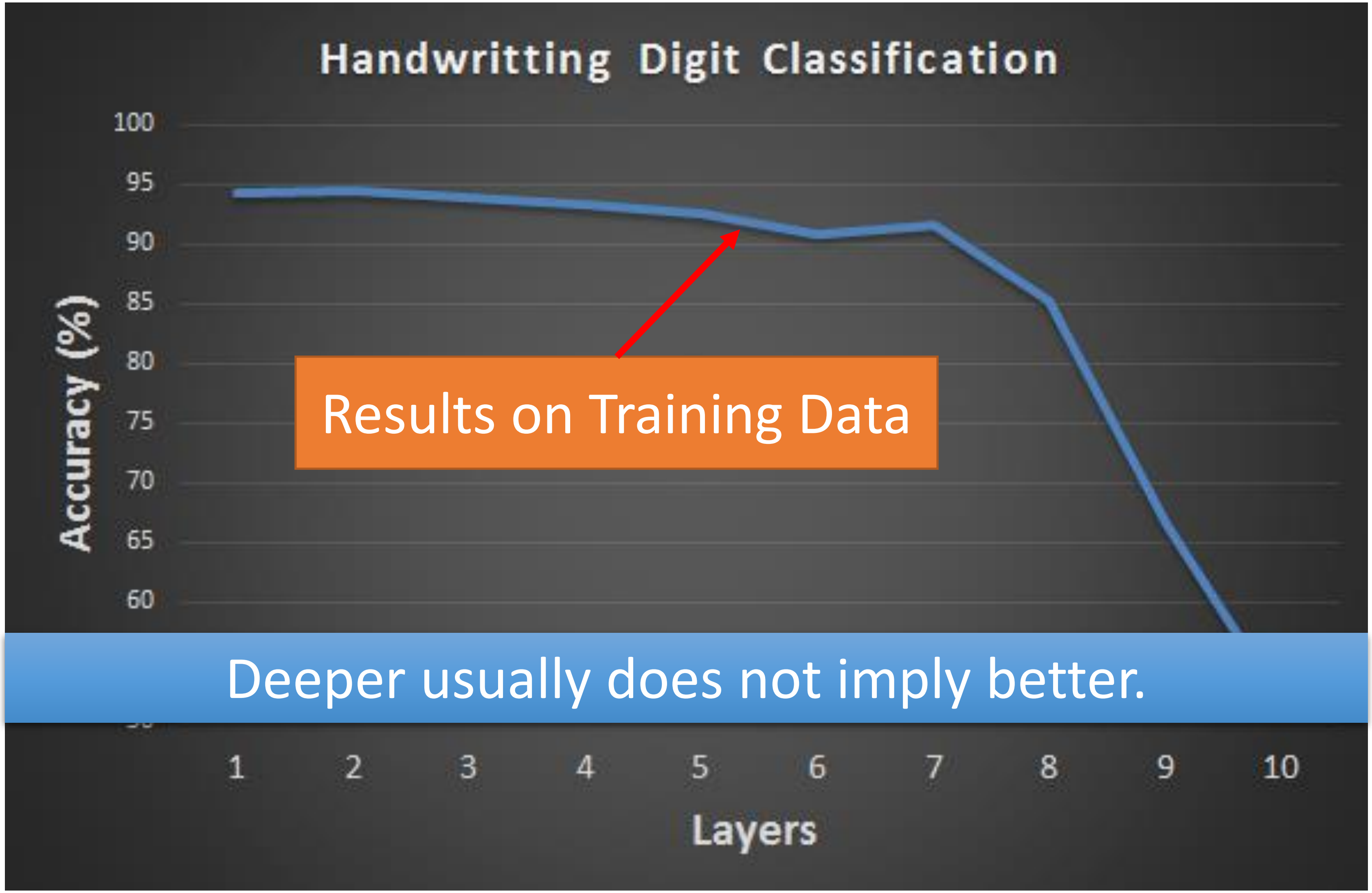
Recipe of Deep Learning



Recipe of Deep Learning

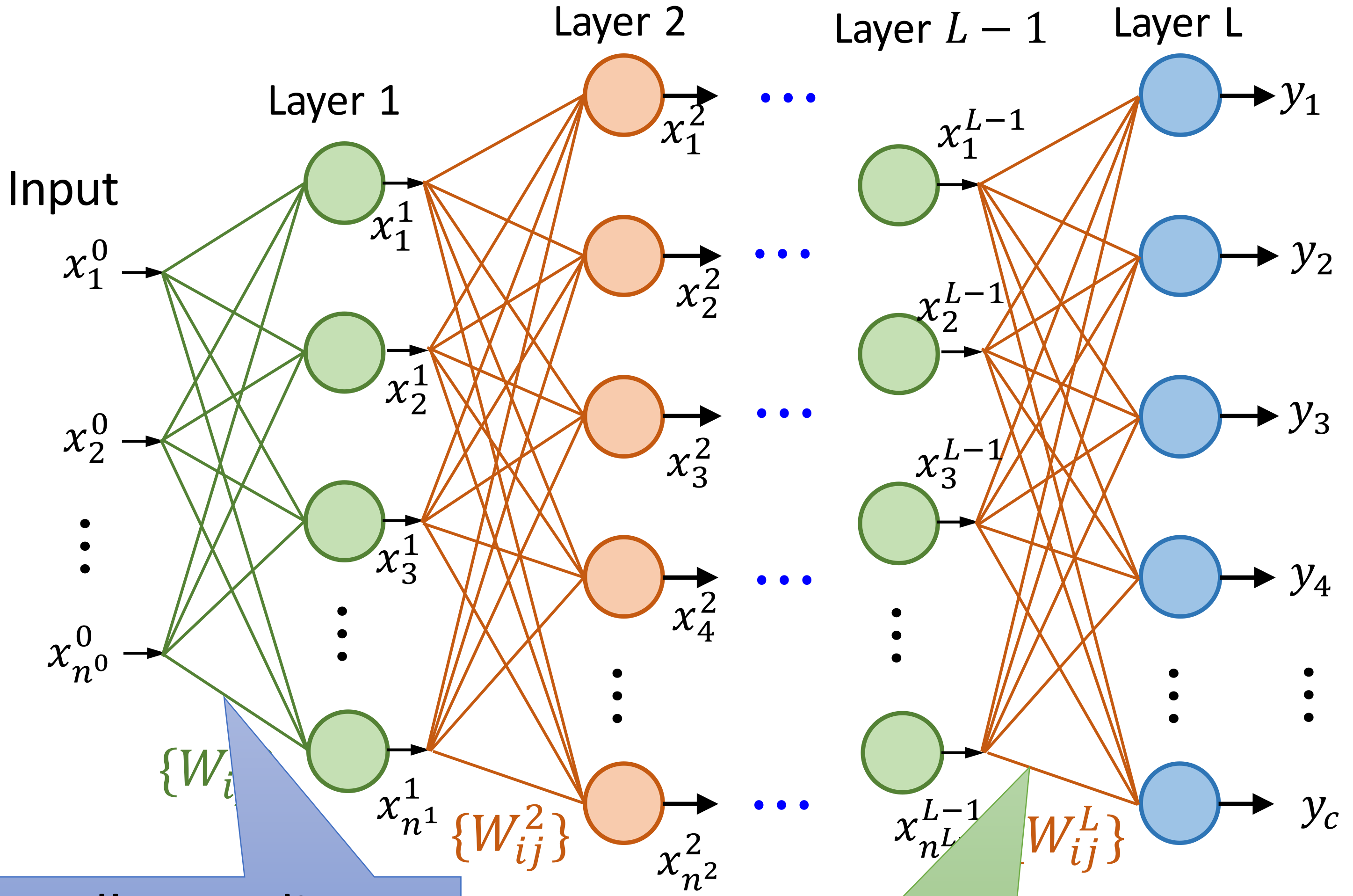


Hard to get the power of Deep …



Vanishing Gradient Problem

See Gradient flow in recurrent nets: the difficulty of learning long term dependencies, by Sepp Hochreiter, Yoshua Bengio, Paolo Frasconi, and Jürgen Schmidhuber (2001).



Smaller gradients

Learn very slow

Almost random

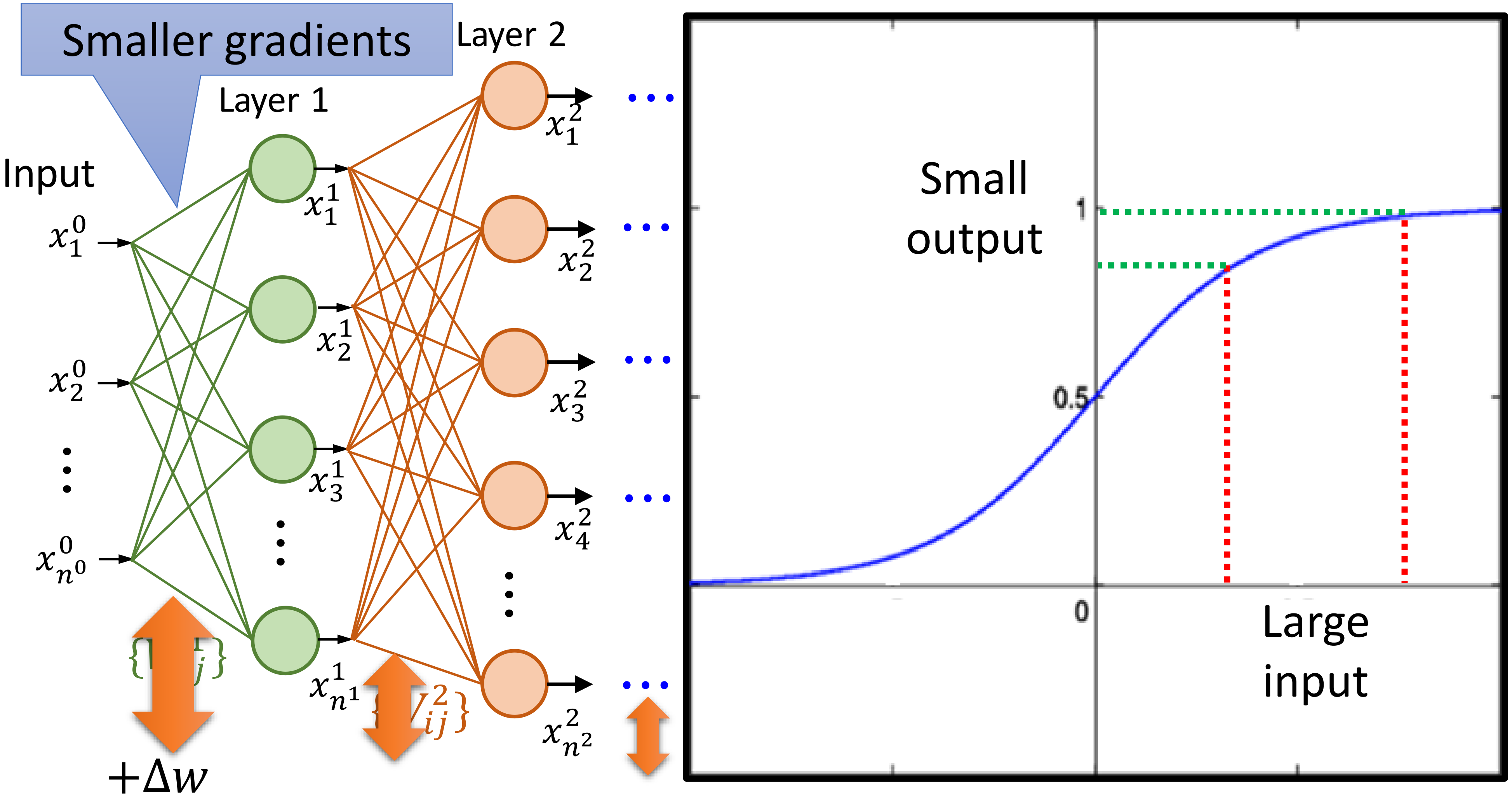
Larger gradients

Learn very fast

Already converge

converge based on random!?

Vanishing Gradient Problem

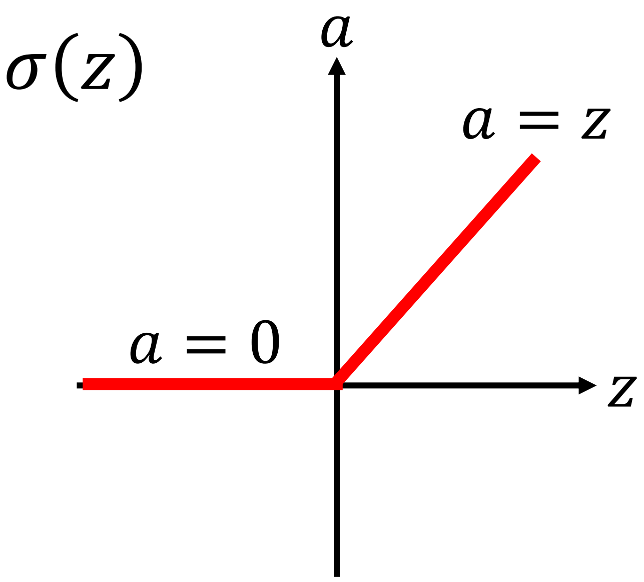


Intuitive way to compute the derivatives …

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

ReLU

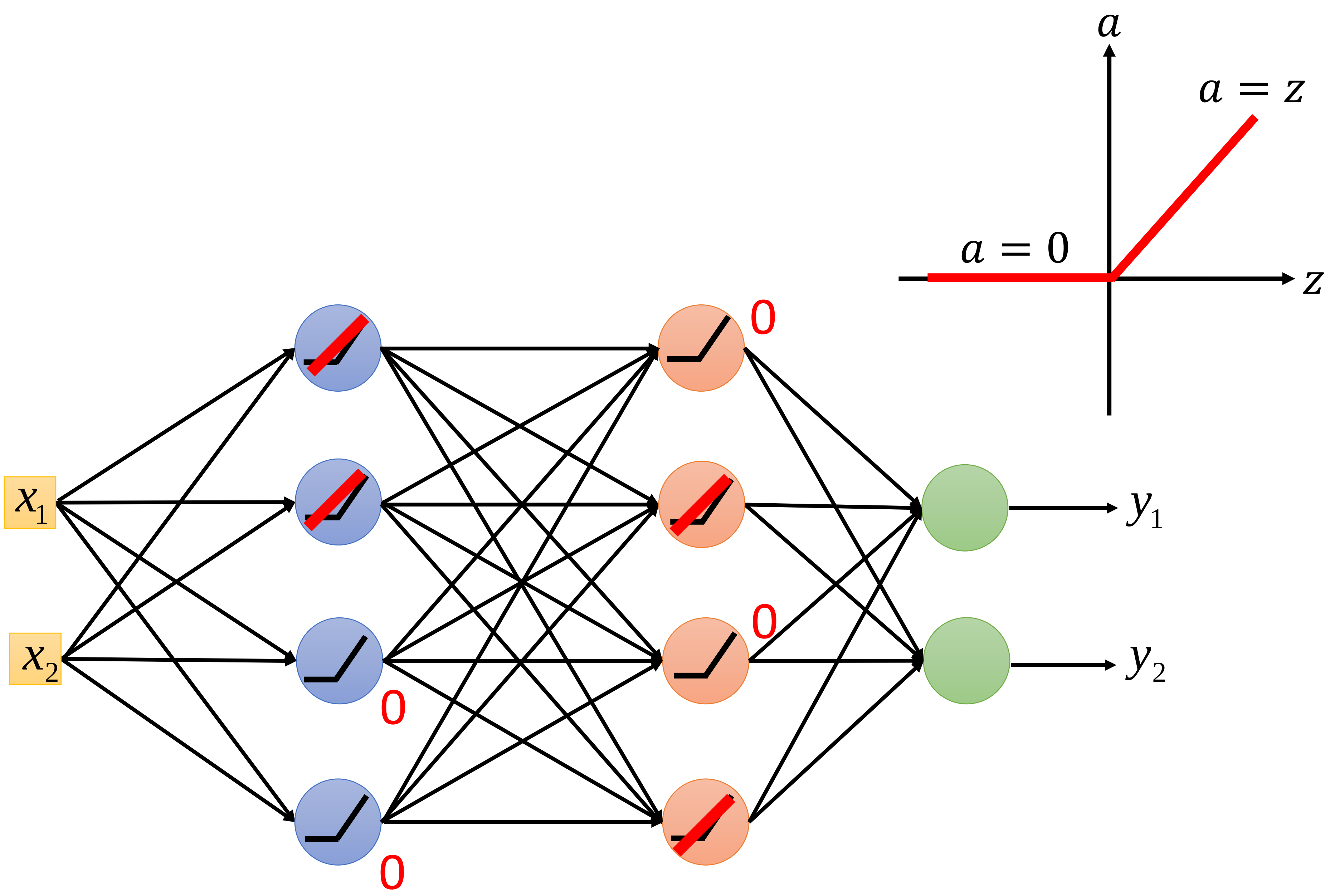
- Rectified Linear Unit (ReLU)



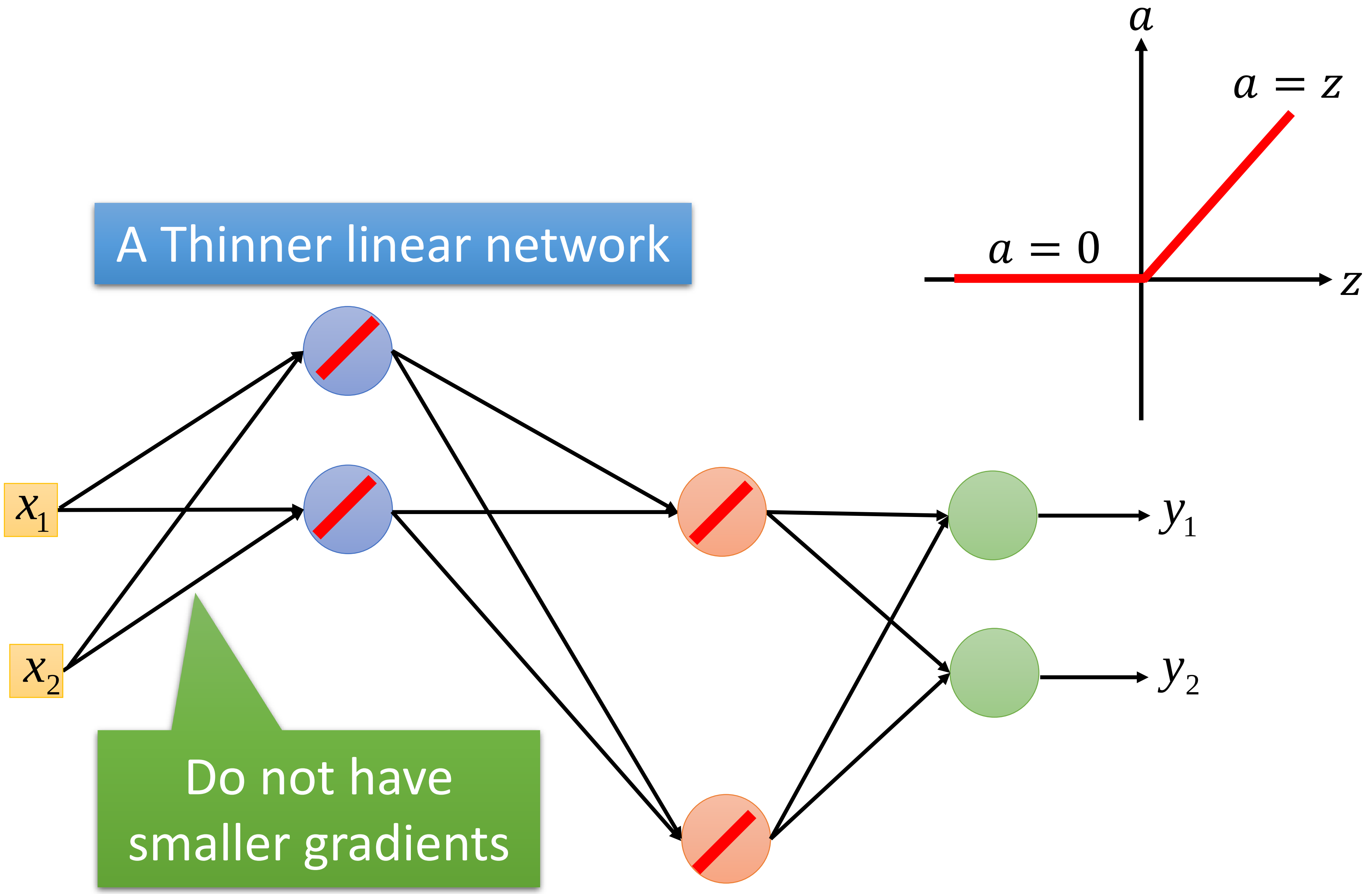
Reason:

1. Fast to compute
2. Biological reason
3. Infinite sigmoid with different biases
4. Vanishing gradient problem

ReLU

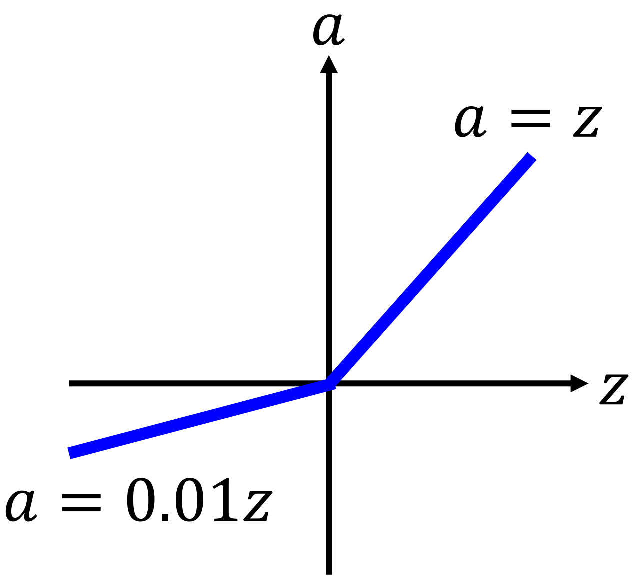


ReLU

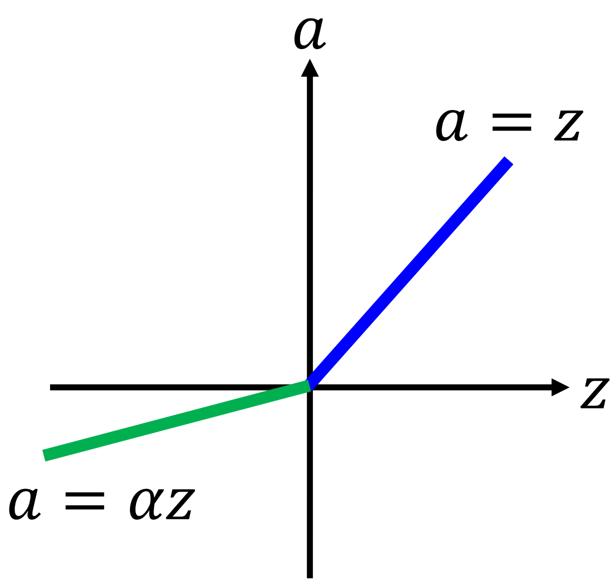

A Thinner linear network
Do not have
smaller gradients
x_1
x_2
y_1
y_2
a
$a = z$
$a = 0$
z

Variants of ReLU

Leaky ReLU



Parametric ReLU



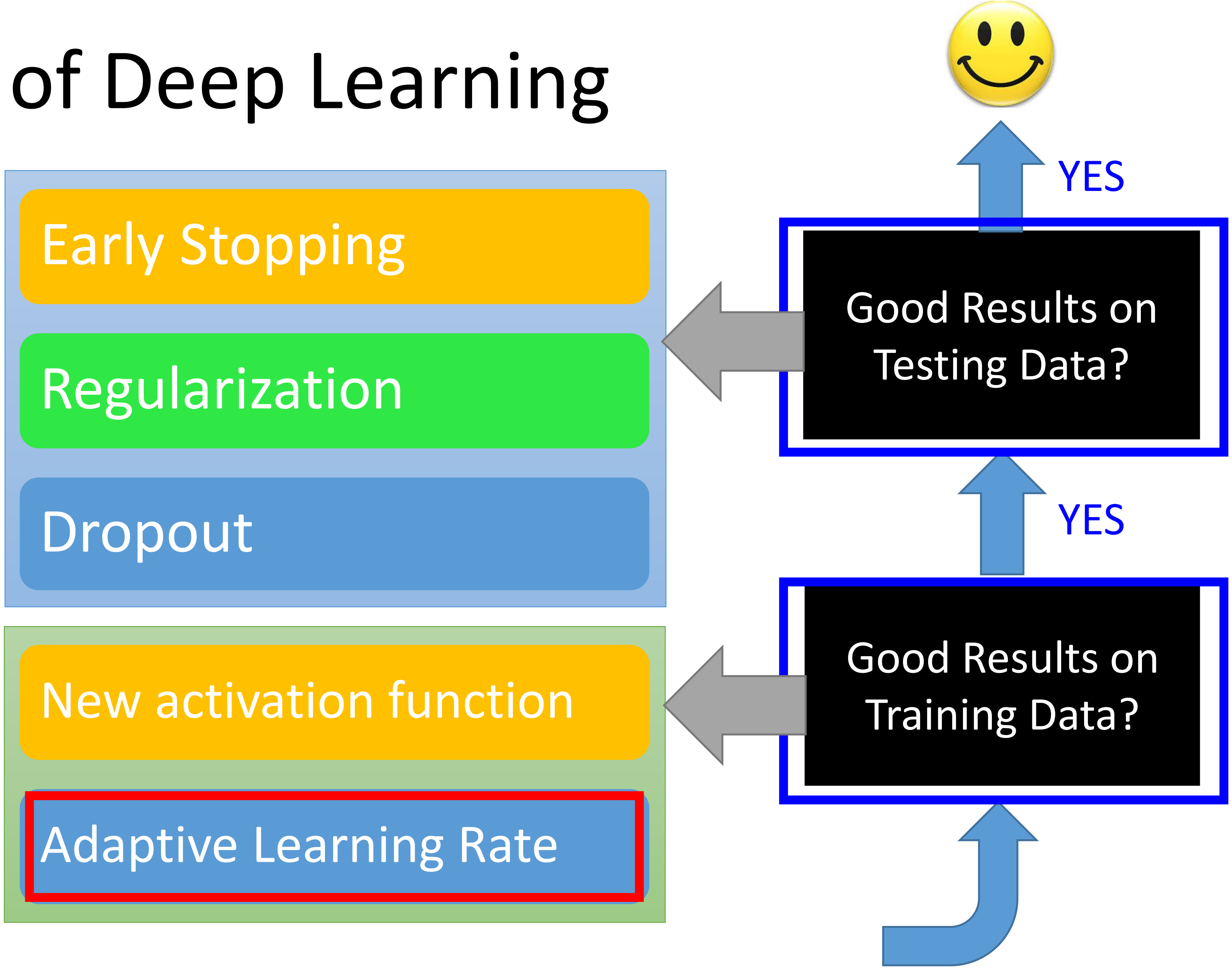
α also learned by gradient descent

Maxout

ReLU is a special case of Maxout

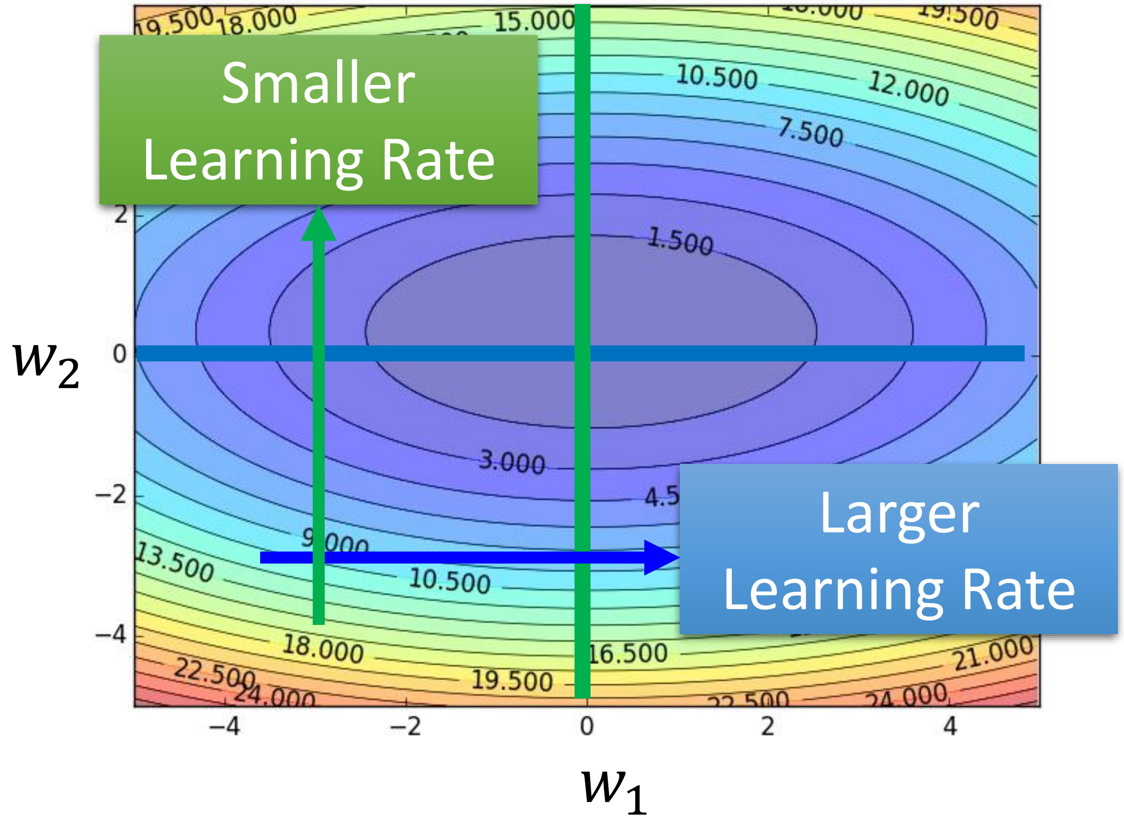
- Learnable activation function [Ian J. Goodfellow, ICML'13]

Recipe of Deep Learning



Review

AdaGrad

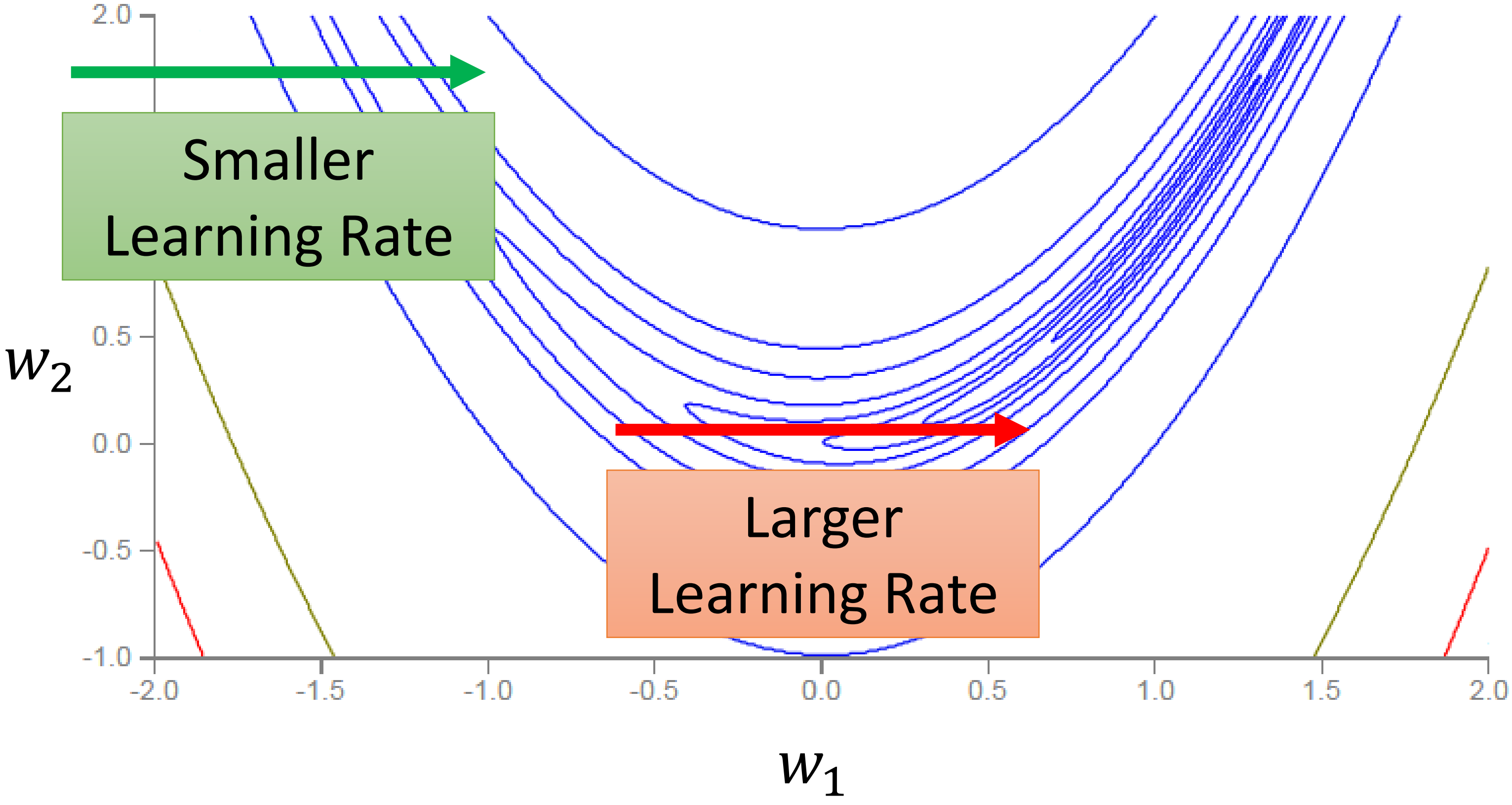


$$w^{(t+1)} \leftarrow w^{(t)} - \frac{\eta}{\sqrt{\sum_{i=0}^{t}\left(g^{(i)}\right)^2}} g^{(t)}$$

Use first derivative to estimate second derivative

RMSProp

Error Surface can be very complex when training NN.



RMSProp

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

AdaGrad

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

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

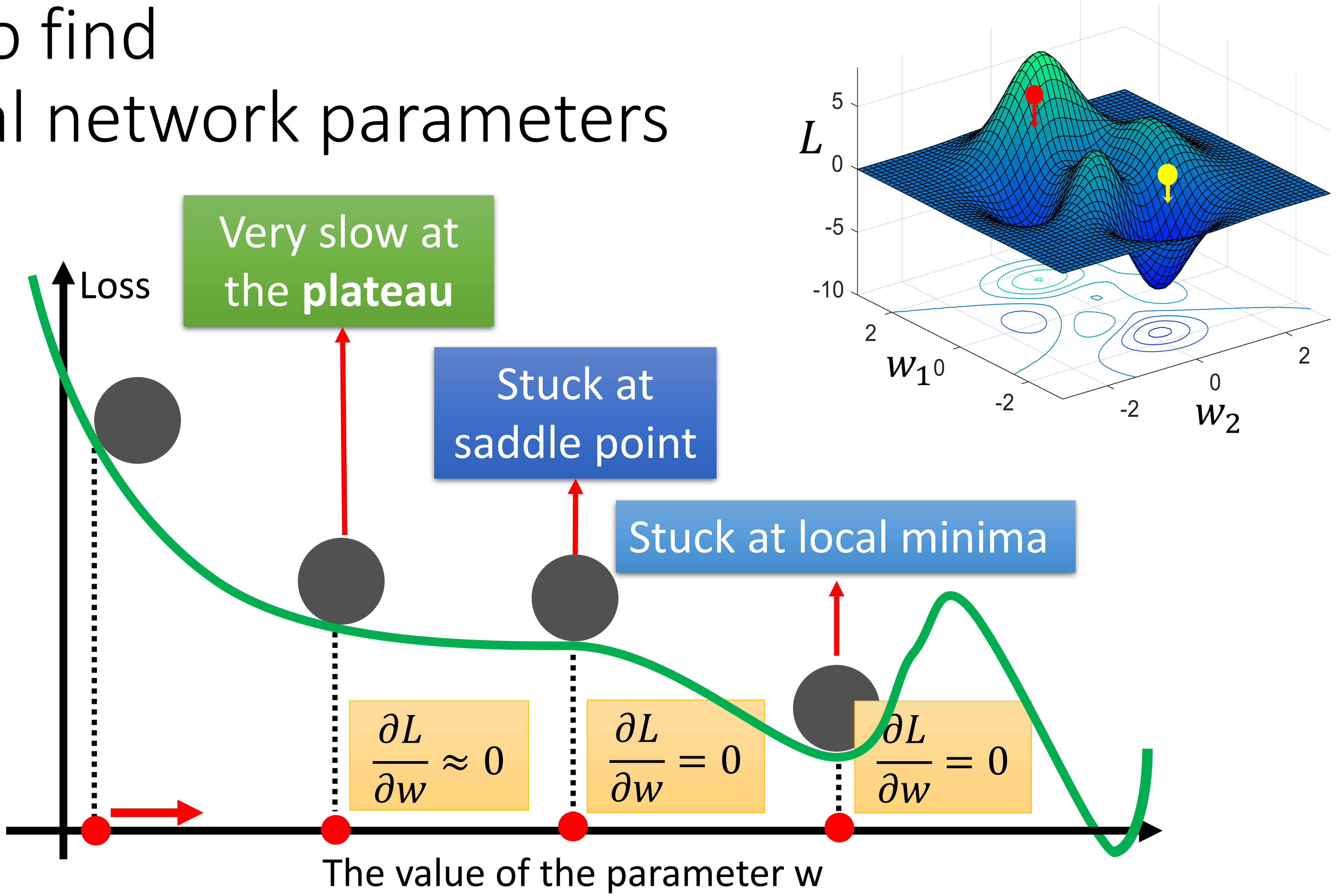
$$w^{(3)} \leftarrow w^{(2)} - \frac{\eta}{\sigma^{(2)}} g^{(2)} \qquad \sigma^{(2)} = \sqrt{\alpha(\sigma^{(1)})^2 + (1-\alpha)(g^{(2)})^2}$$

$$\vdots$$

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

Root Mean Square of the gradients with previous gradients being decayed

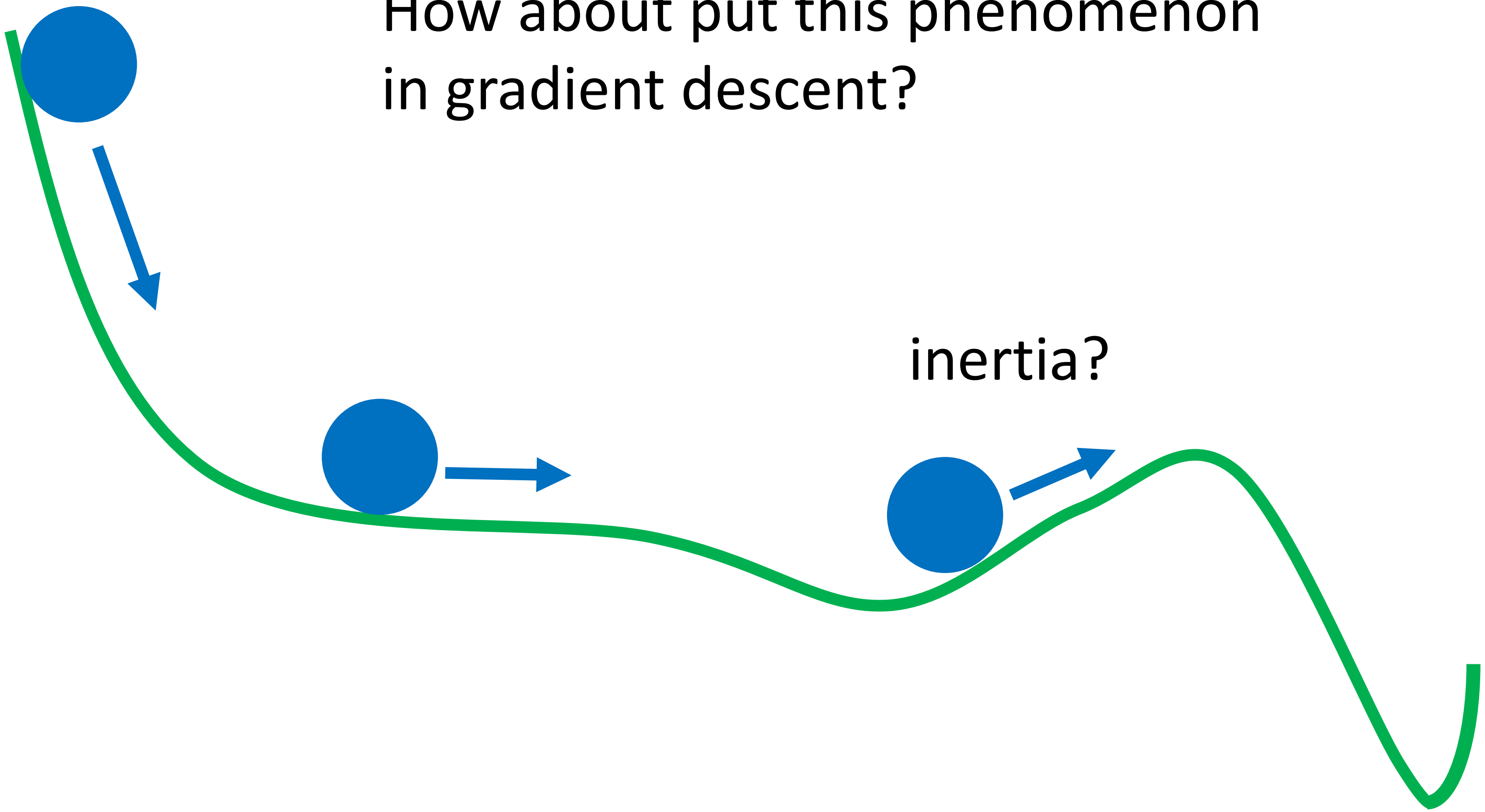
Hard to find optimal network parameters



In physical world ……

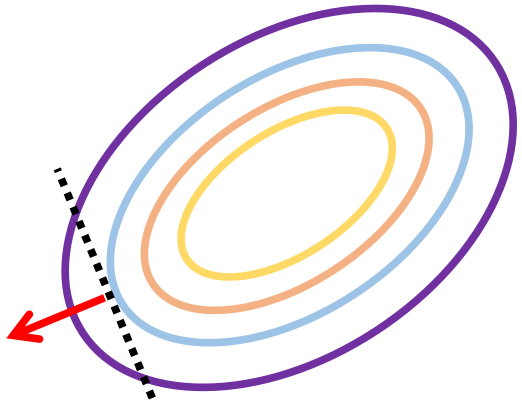
- Momentum

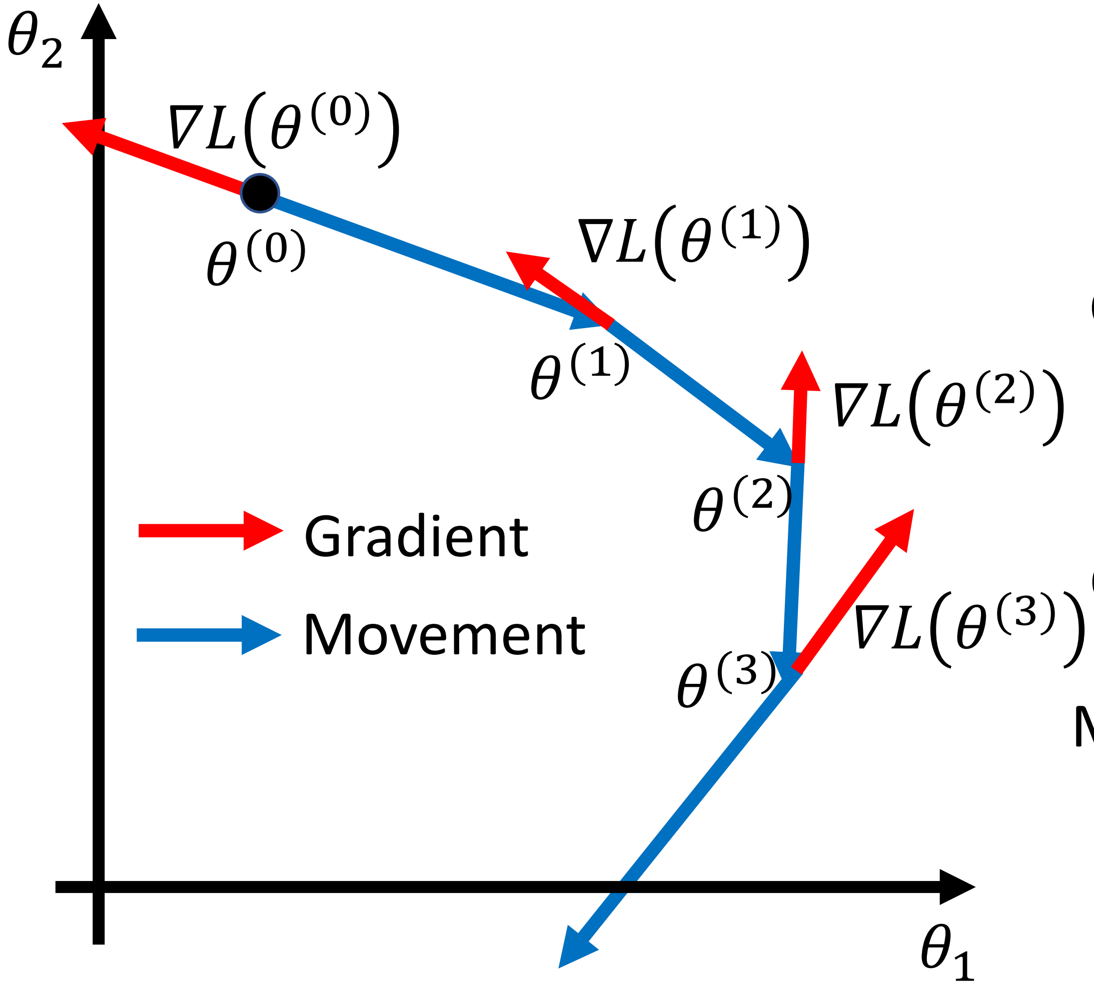
How about put this phenomenon
in gradient descent?



Review: Vanilla Gradient Descent

Gradient: the normal direction of the contour of loss function





Start at position $\theta^{(0)}$

Compute gradient at $\theta^{(0)}$

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

Compute gradient at $\theta^{(1)}$

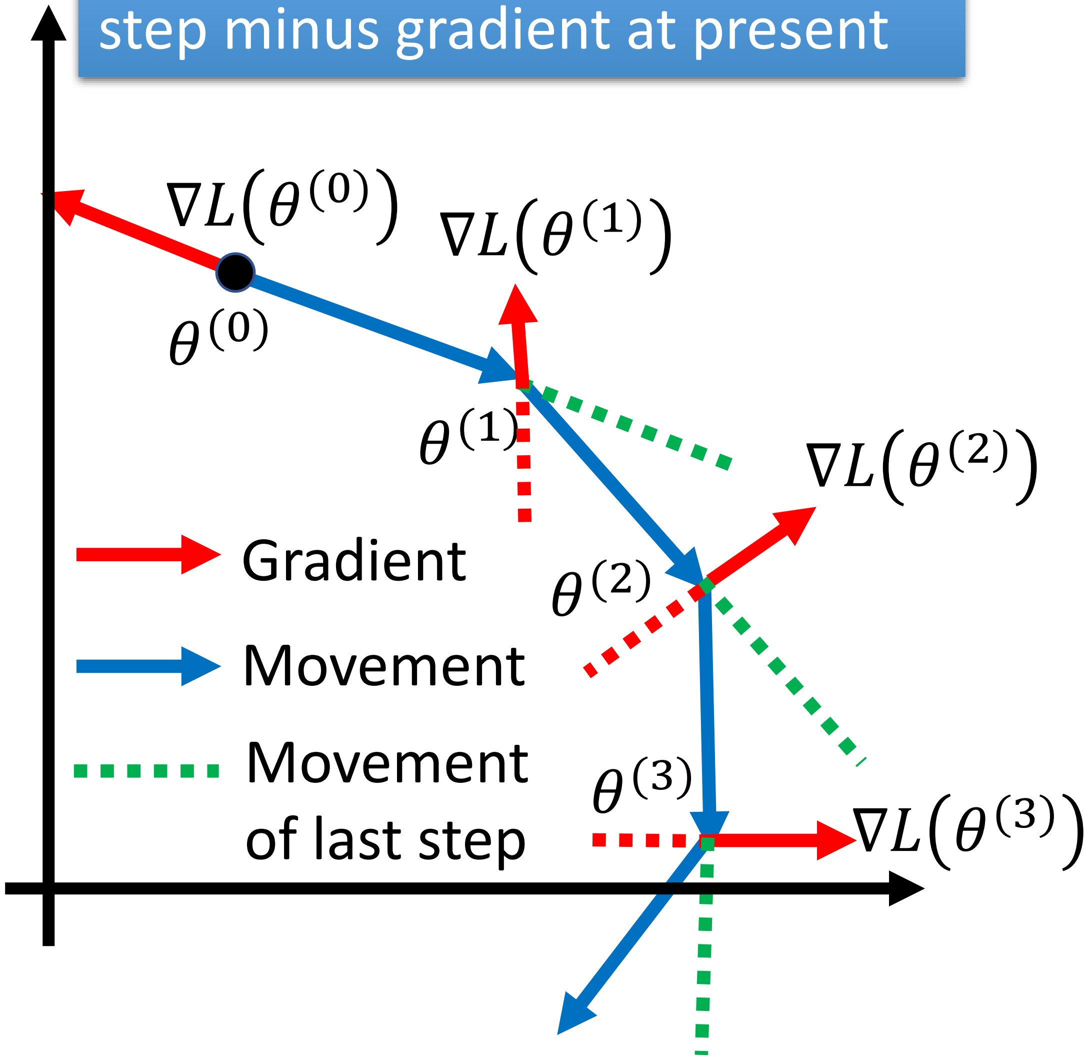
Move to $\theta^{(2)} = \theta^{(1)} - \eta\nabla L(\theta^{(1)})$

⋮

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

Momentum

Movement: movement of last step minus gradient at present



Start at point $\theta^{(0)}$

Movement $v^{(0)} = 0$

Compute gradient at $\theta^{(0)}$

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

Move to $\theta^{(1)} = \theta^{(0)} + v^{(1)}$

Compute gradient at $\theta^{(1)}$

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

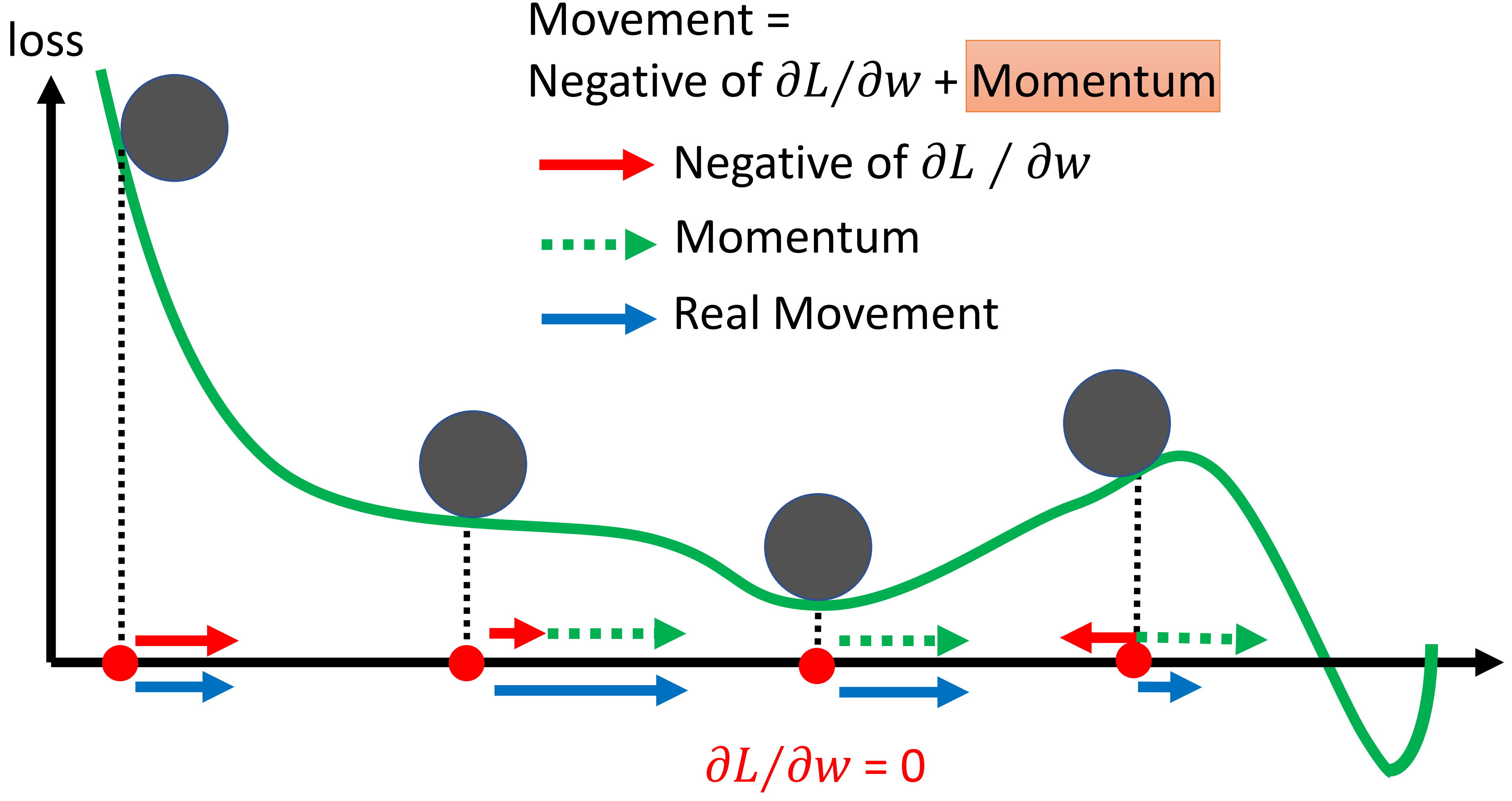
Move to $\theta^{(2)} = \theta^{(1)} + v^{(2)}$

Movement not just based on gradient, but previous movement.

Momentum

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

Movement = Negative of $\partial L/\partial w$ + Momentum



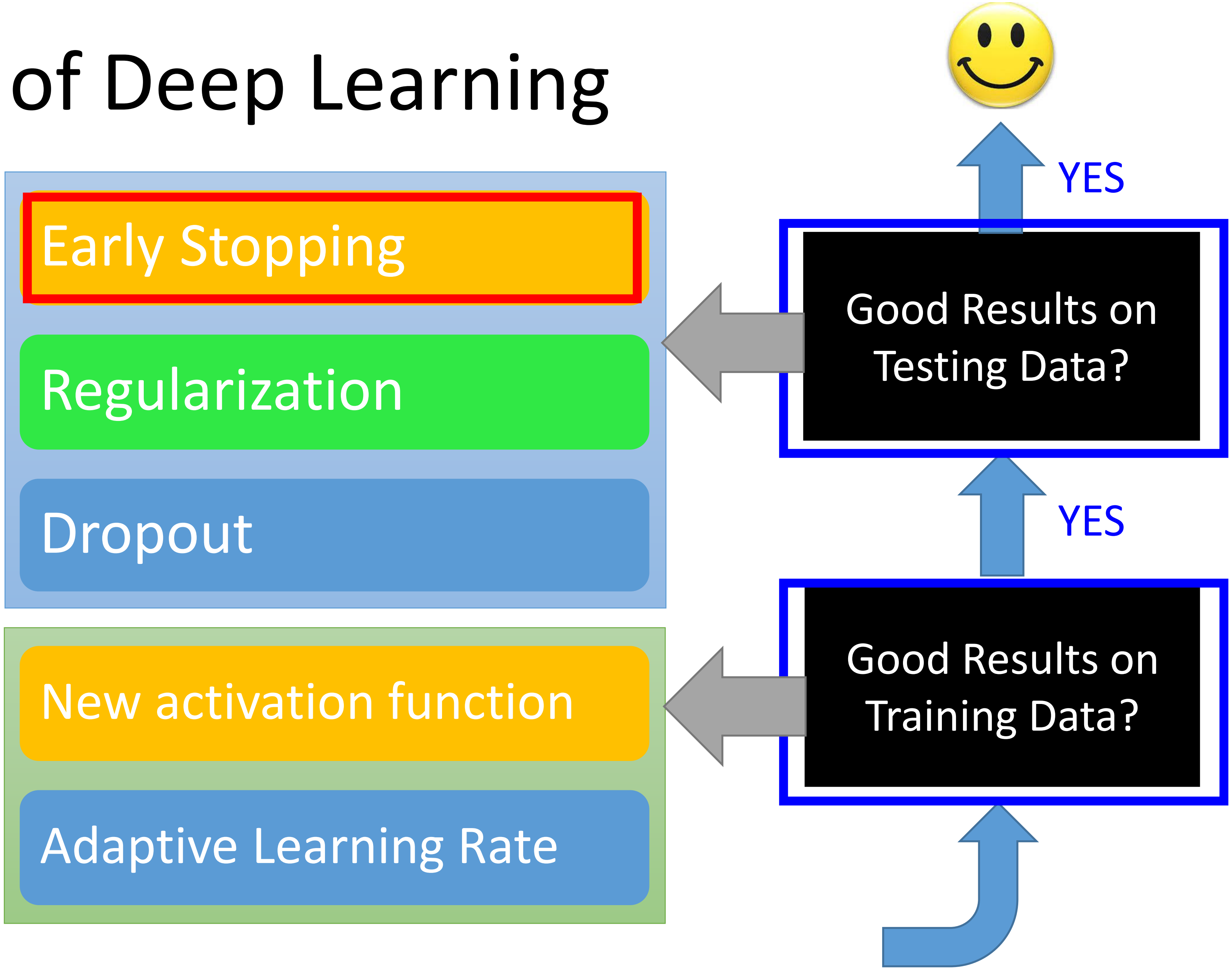
Adam

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.

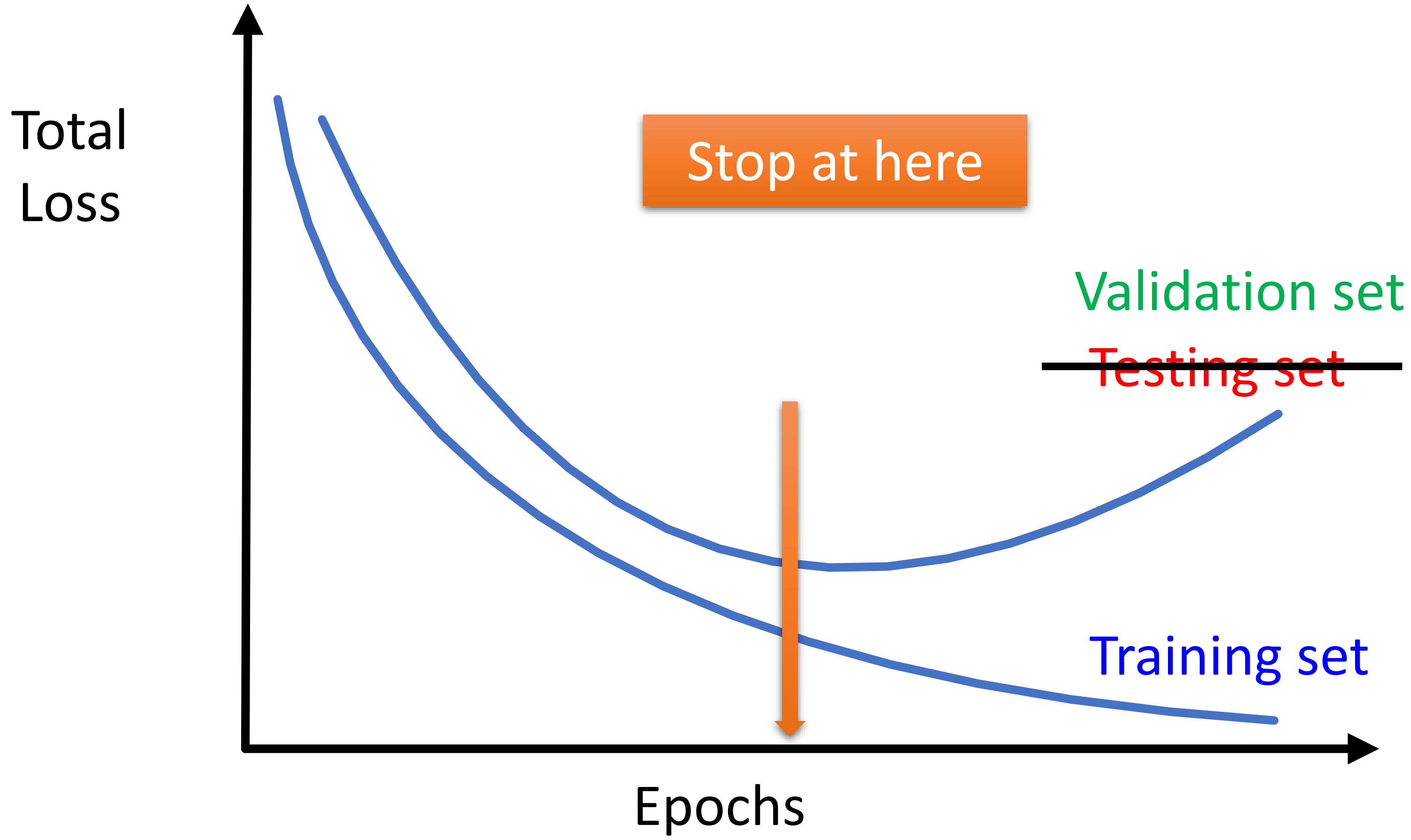
Require: α: Stepsize
Require: $\beta_1, \beta_2 \in [0, 1)$: Exponential decay rates for the moment estimates
Require: $f(\theta)$: Stochastic objective function with parameters θ
Require: θ_0: Initial parameter vector
  $m_0 \leftarrow 0$ (Initialize 1st moment vector) → for momentum
  $v_0 \leftarrow 0$ (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)

RMSProp + Momentum

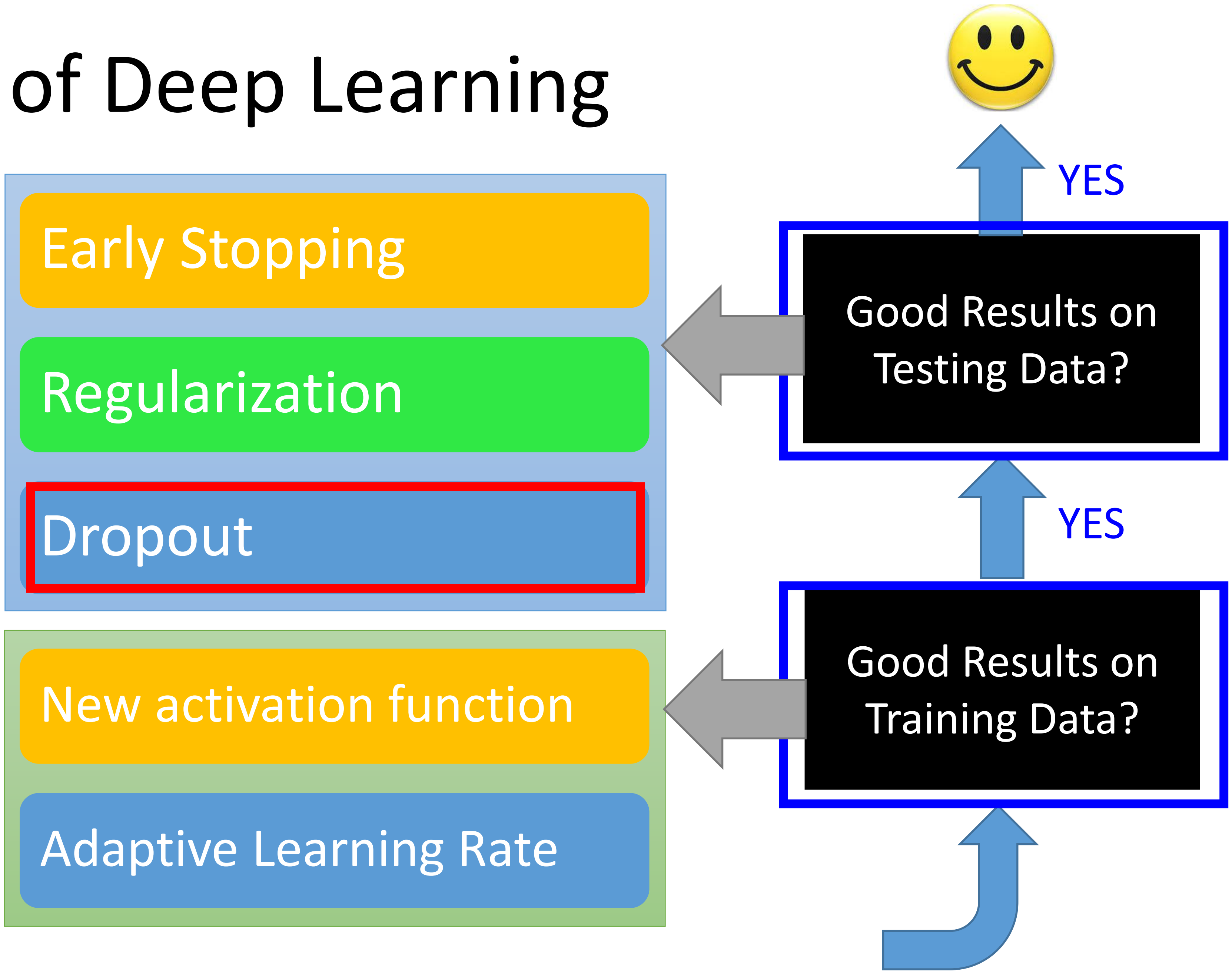
Recipe of Deep Learning



Early Stopping

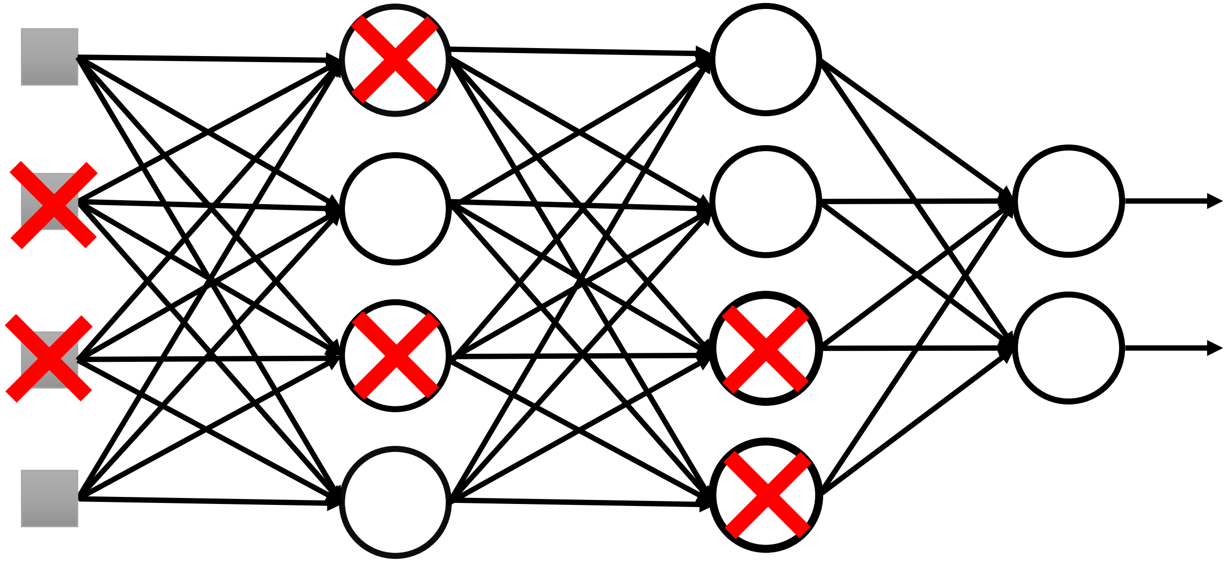


Recipe of Deep Learning



Dropout

Training:

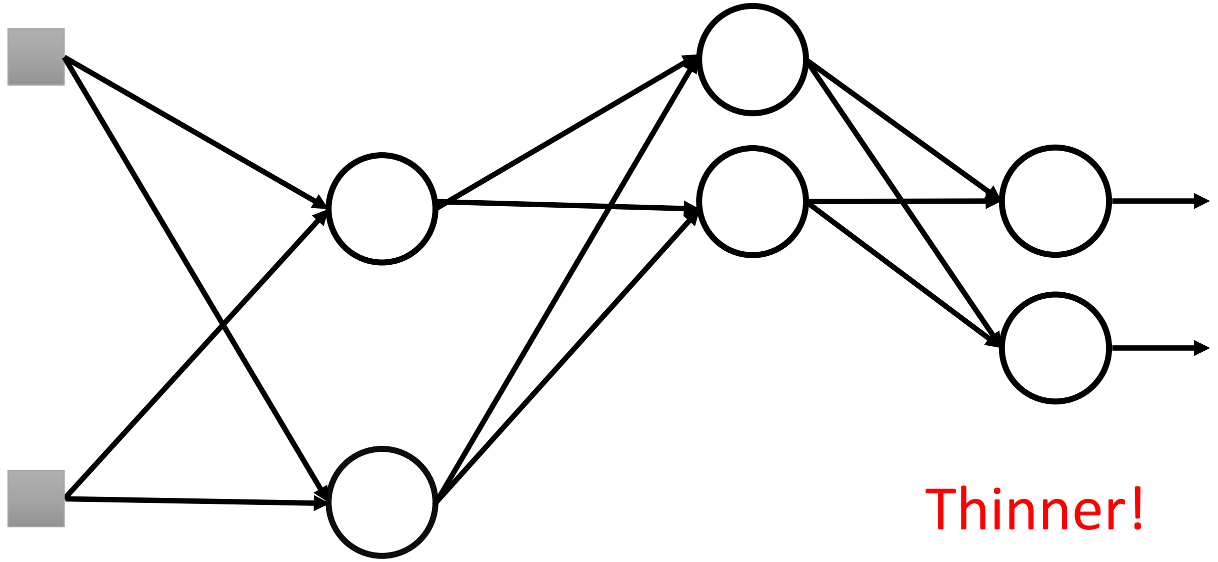


▫ **Each time before updating the parameters**

- Each neuron has $p\%$ to be preserved, *i.e.* $1 - p\%$ to dropout

Dropout

Training:



- **Each time before updating the parameters**
  - Each neuron has $p\%$ to be preserved

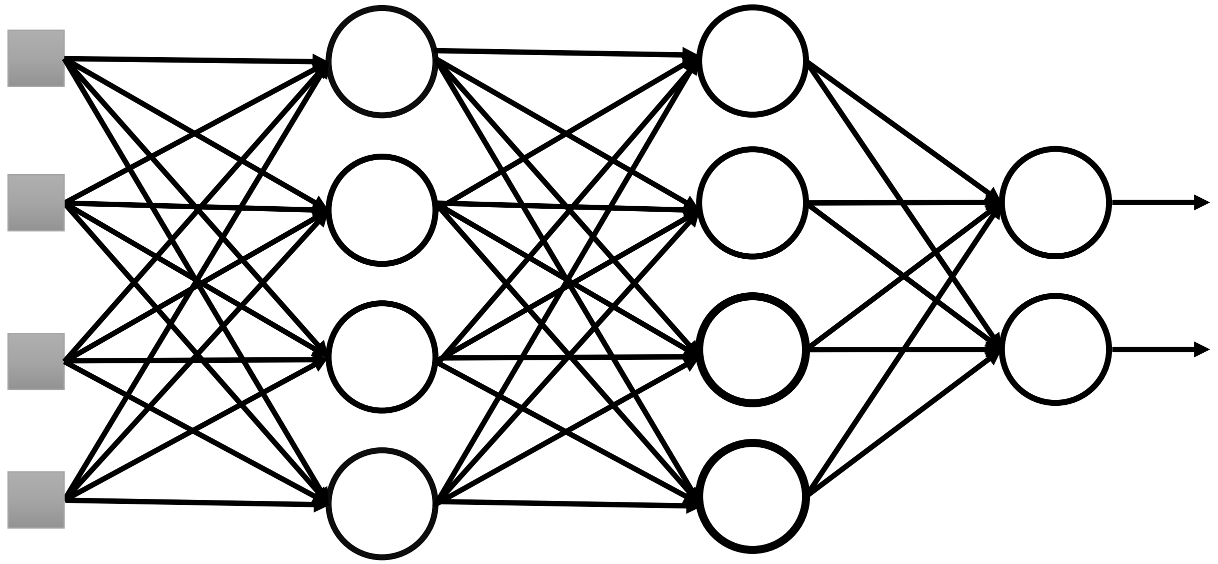
  The structure of the network is changed.

  - Using the new network for training

For each minibatch, we resample the dropout neurons

Dropout

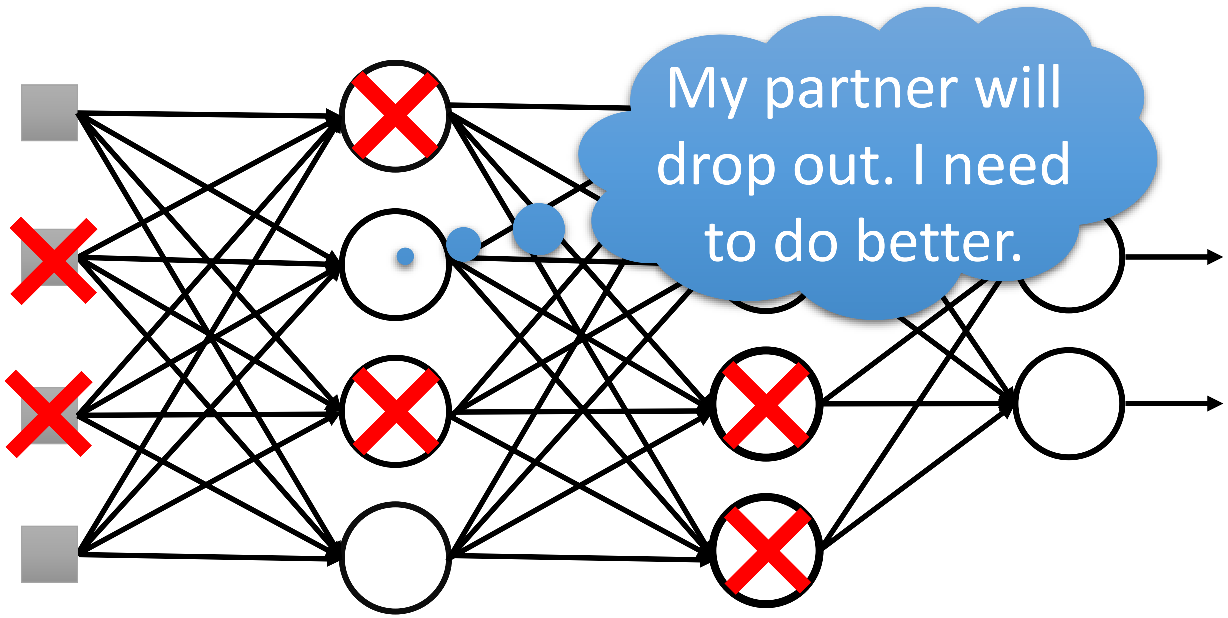
Testing:



No dropout

- If the keep rate at training is $p\%$, all the weights at testing times $p\%$
- Assume that the keep rate is 50%.
- If a weight $w = 1$ by training, set $w = 0.5$ for testing.

Dropout: Intuitive Reason



Dropout: A Simple Way to Prevent Neural Networks from Overfitting

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Toronto, Ontario, M5S 3G4, Canada.

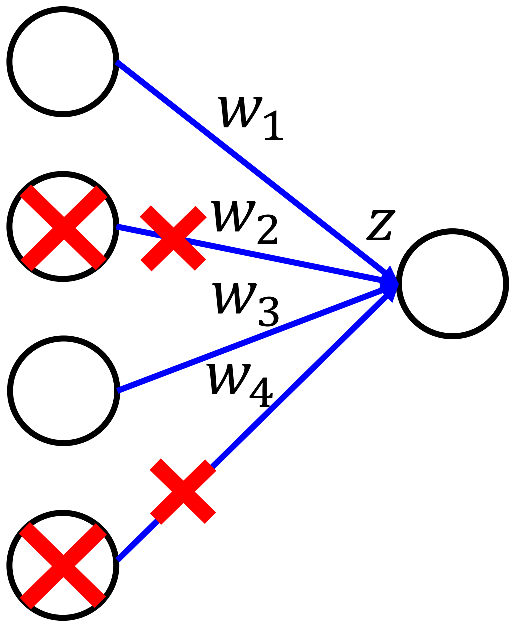
- When teams up, if everyone expect the partner will do the work, nothing will be done finally.
- However, if you know your partner will dropout, you will do better.
- When testing, no one dropout actually, so obtaining good results eventually.

Dropout: Intuitive Reason

- Why the weights should multiply $p\%$ ($p\%$ is the keep rate) when testing?

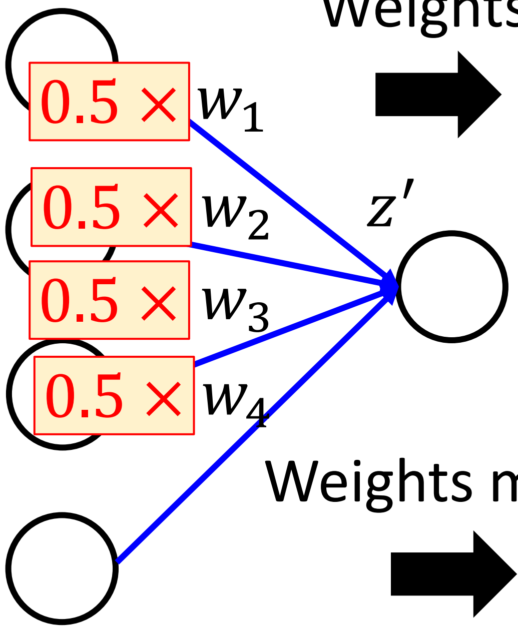
Training of Dropout

Assume keep rate is 50%



Testing of Dropout

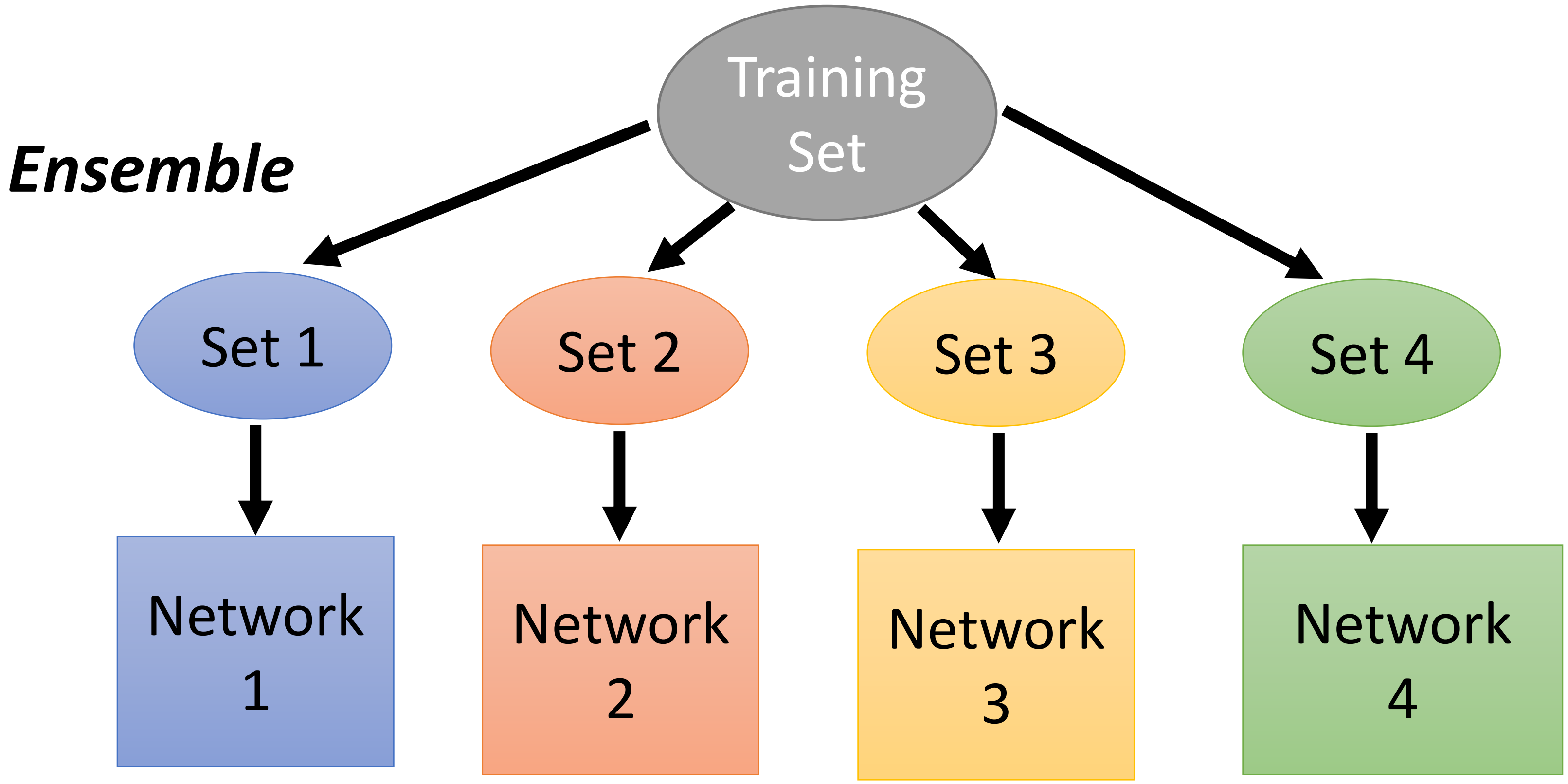
No dropout



Weights from training $\Rightarrow$ $z' \approx 2z$

Weights multiply $p\%$ $\Rightarrow$ $z' \approx z$

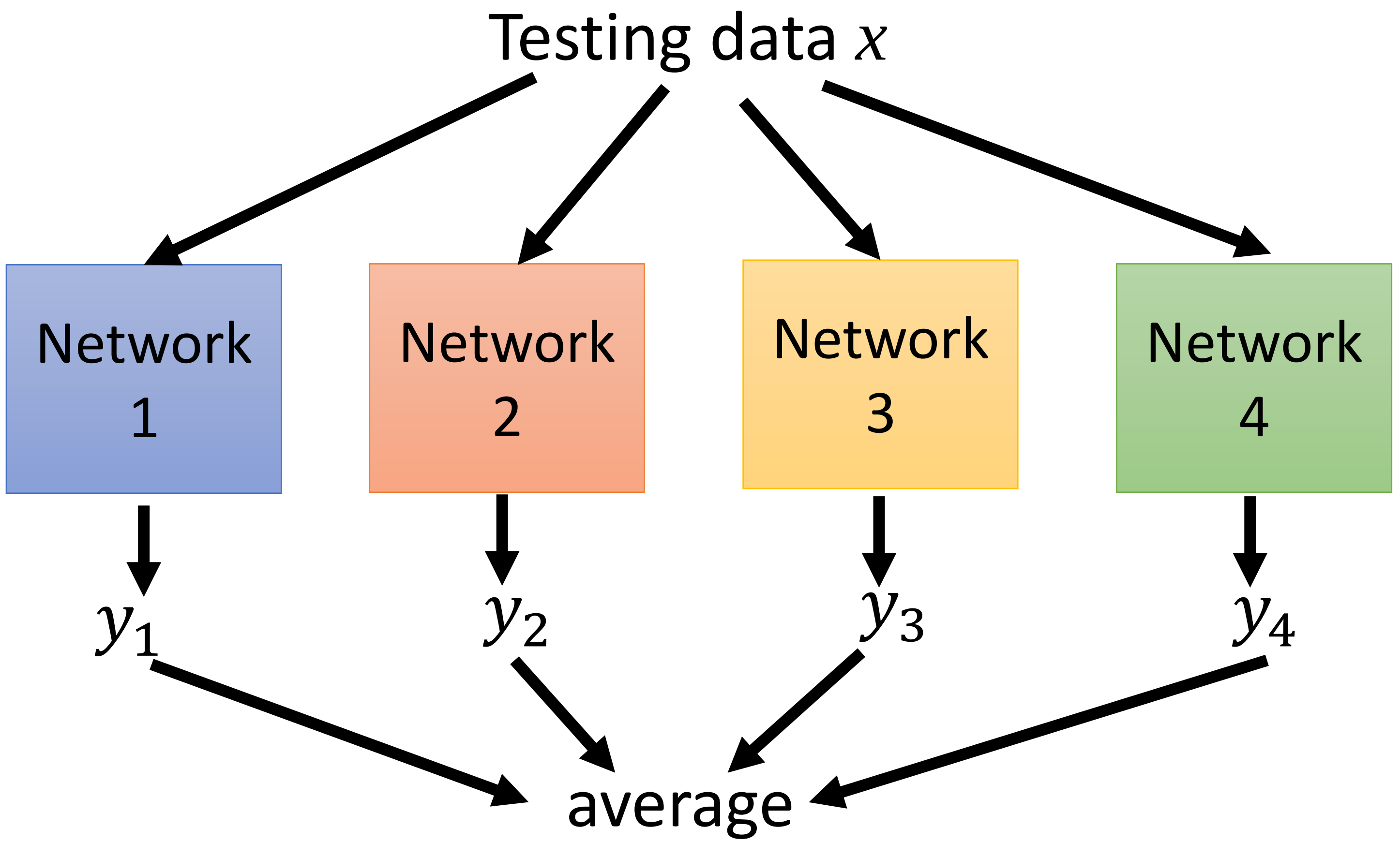
Dropout is a kind of ensemble.



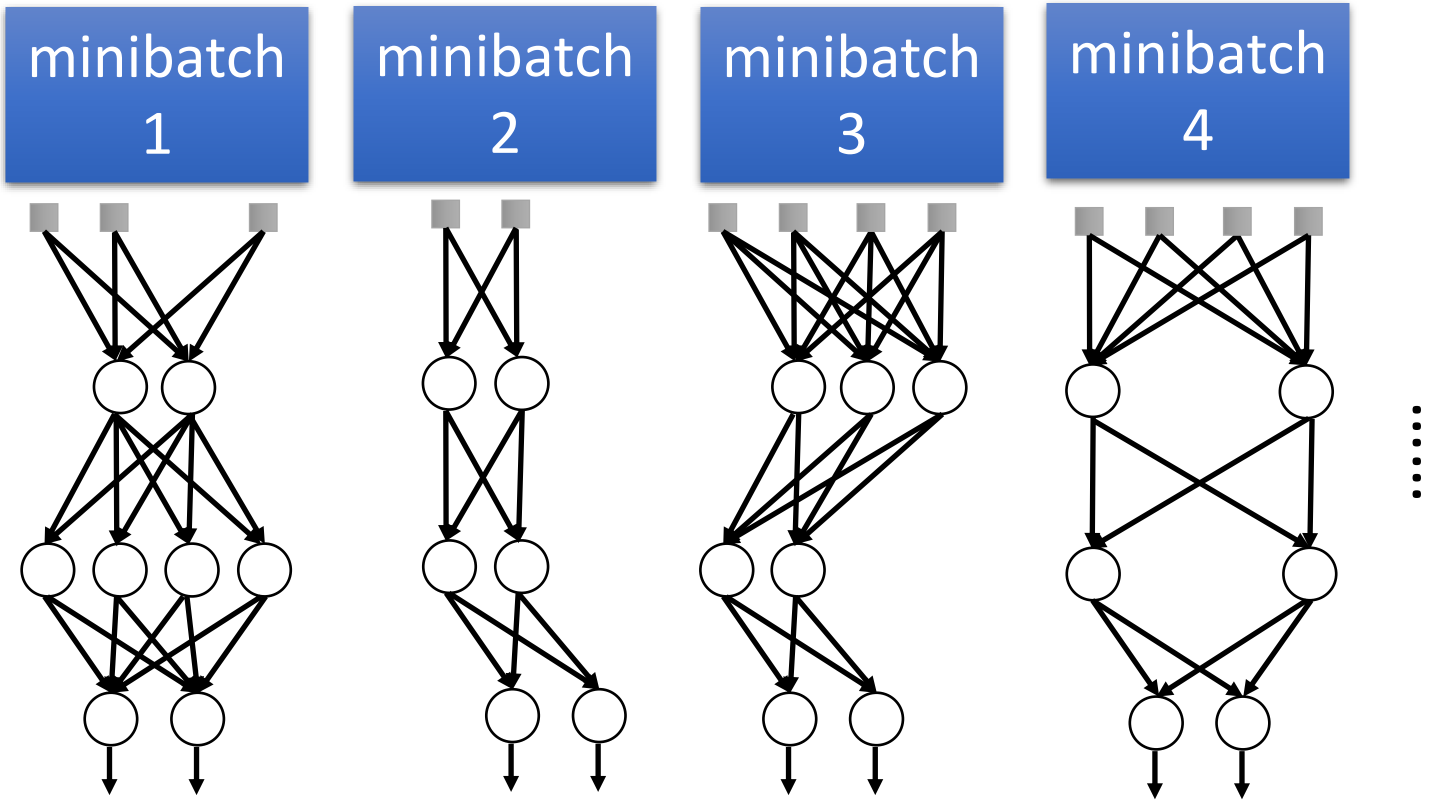
Train a bunch of networks with different structures

Dropout is a kind of ensemble.

Ensemble



Dropout is a kind of ensemble.



Training of Dropout

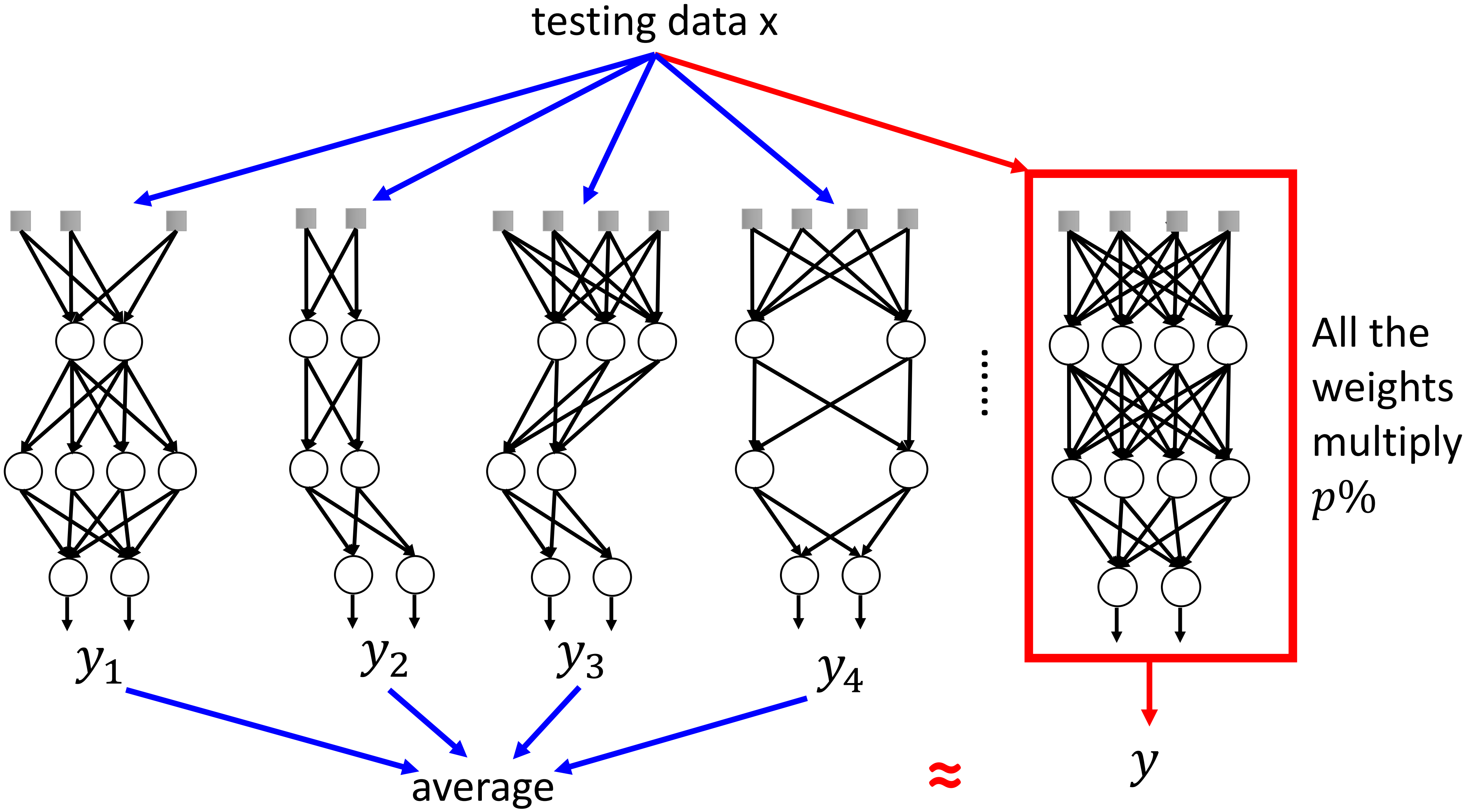
M neurons

2^M possible networks

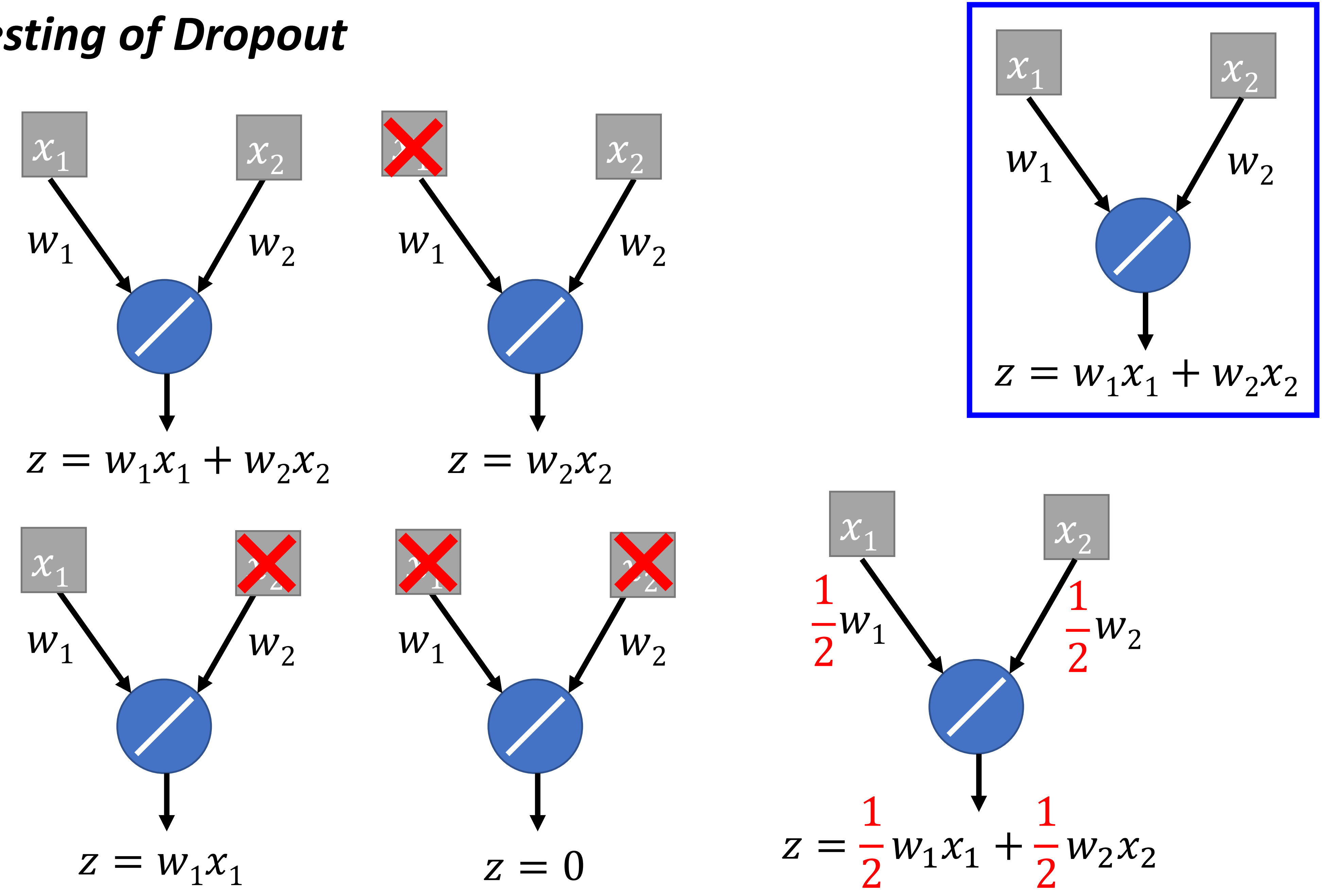
- Using one minibatch to train one network
- Some parameters in the network are shared

Dropout is a kind of ensemble.

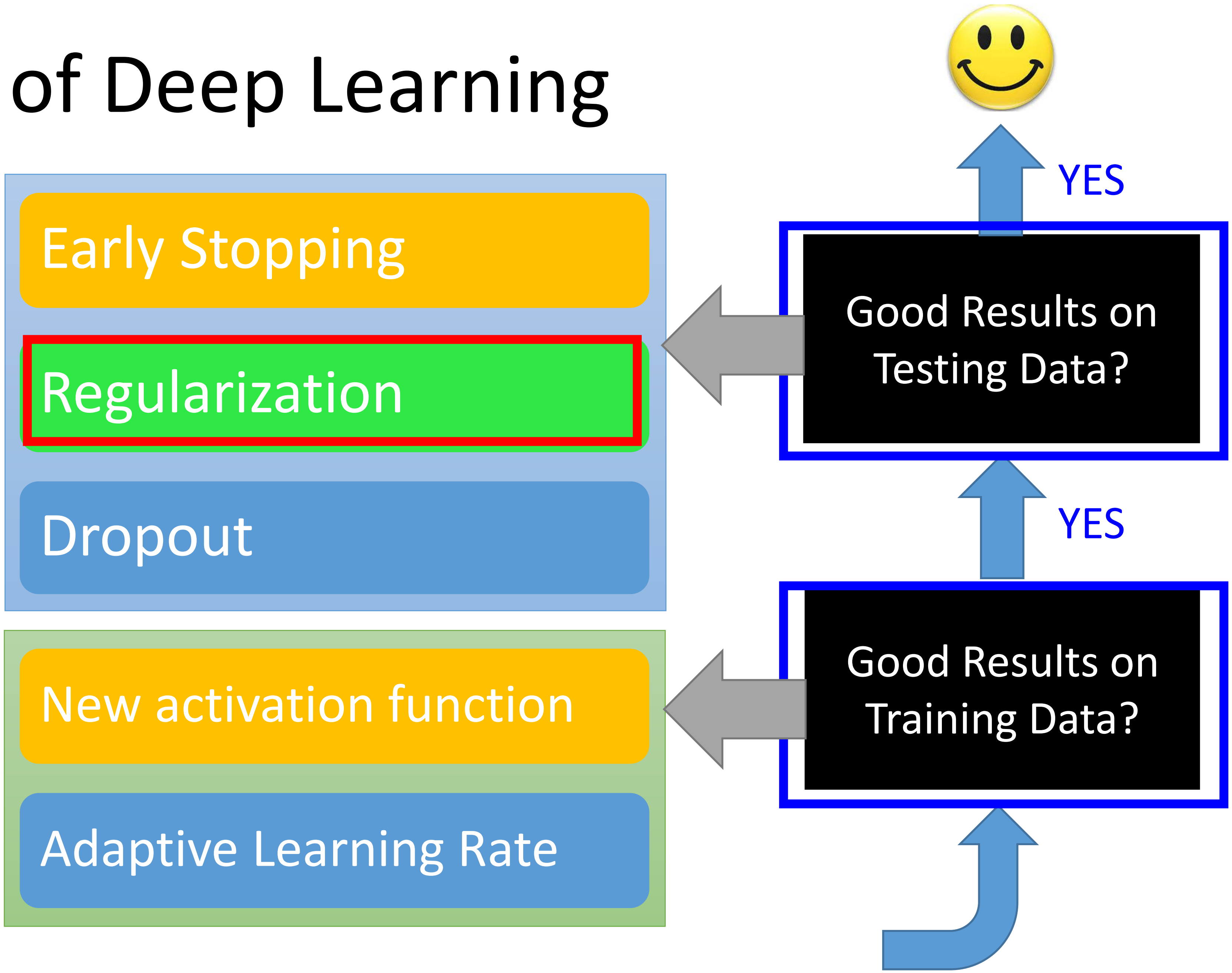
Testing of Dropout



Testing of Dropout



Recipe of Deep Learning



Regularization

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

$$L'(\theta) = \underbrace{L(\theta)}_{\text{Original loss}} + \lambda \frac{1}{2} \|\theta\|_2 \rightarrow \text{Regularization term}$$

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

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

L2 regularization:

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

(usually not consider biases)

Regularization

L2 regularization:

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

- New loss function to be minimized

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

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

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

$$= \boxed{(1 - \eta\lambda) w^{(t)}} - \eta \underline{\frac{\partial L}{\partial w}}$$

Weight Decay

Closer to zero

Regularization

L1 regularization:

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

- New loss function to be minimized

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

Update:

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

$$= w^{(t)} - \eta \frac{\partial \text{L}}{\partial w} - \underline{\eta \lambda \, \text{sgn}\left(w^{(t)}\right)}$$ Always delete

---

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

Regularization: L1 vs. L2

L1 regularization: $\|\theta\|_1 = |w_1| + |w_2| + \cdots$

$$w^{(t+1)} = w^{(t)} - \eta \frac{\partial \mathrm{L}}{\partial w} - \eta\lambda\,\mathrm{sgn}\left(w^{(t)}\right)$$

L2 regularization: $\|\theta\|_2 = (w_1)^2 + (w_2)^2 + \cdots$

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


THANK
YOU