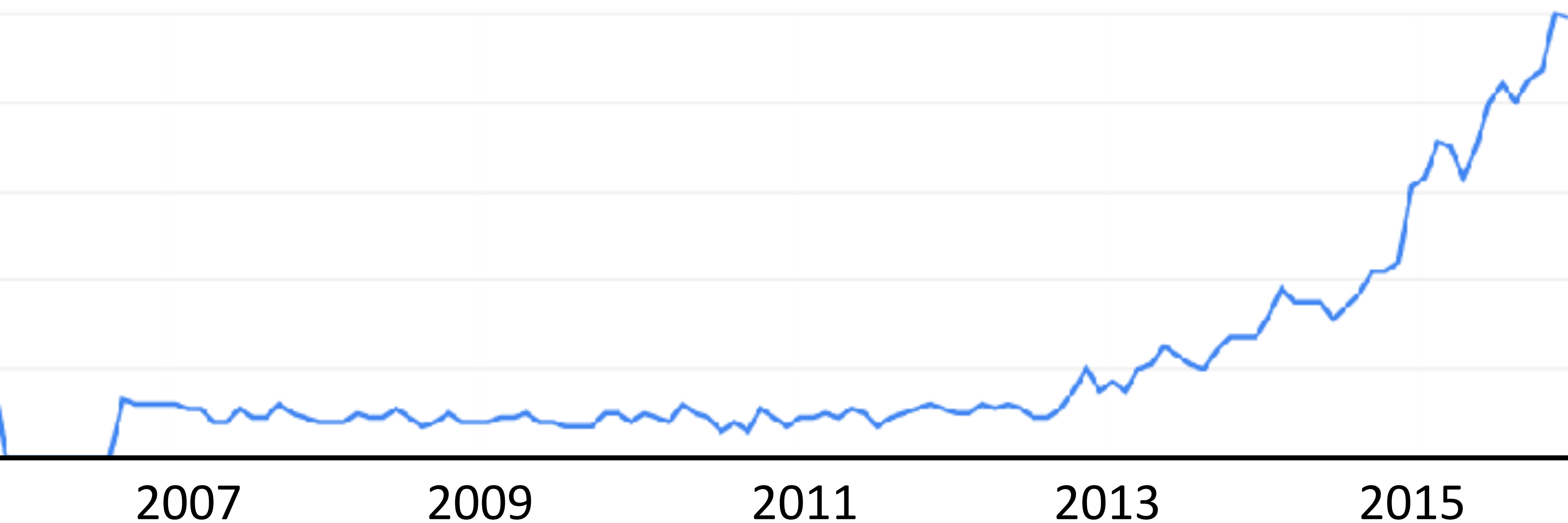
Deep Learning Tutorial

Courtesy of Hung-yi Lee

Deep learning attracts lots of attention.

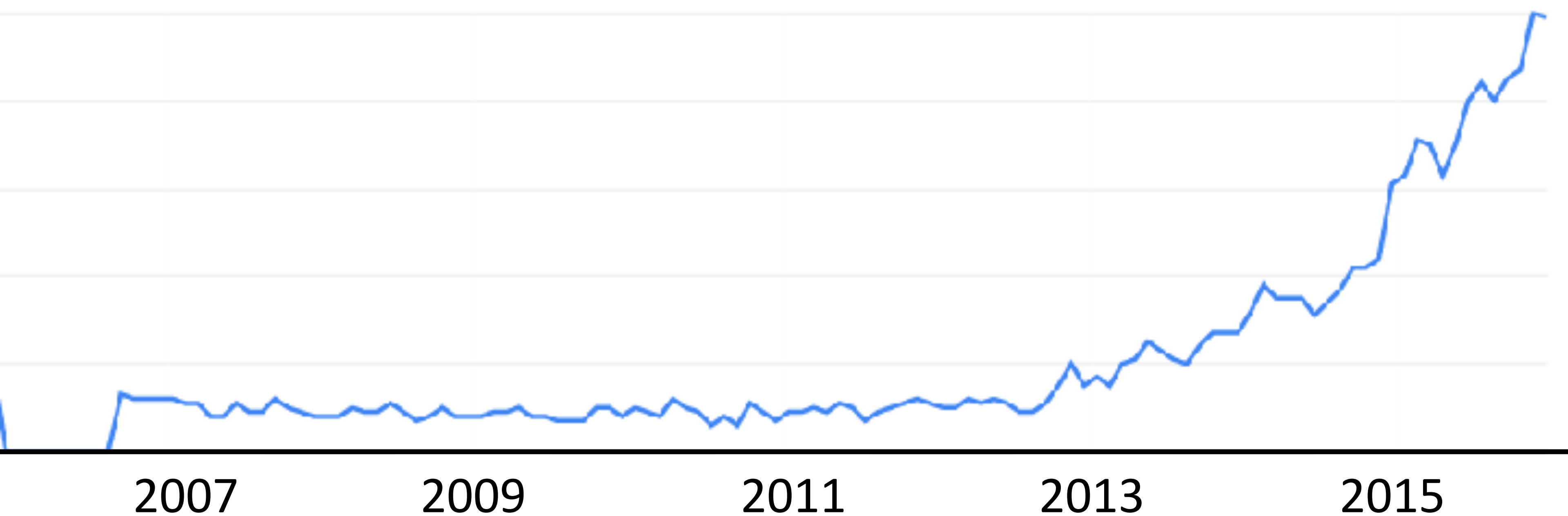
- Google Trends



Deep learning attracts lots of attention.

- Google Trends

Deep learning obtains many exciting results.



Outline

- Part I: Introduction of Deep Learning
- Part II: Why Deep?
- Part III: Tips for Training Deep Neural Network

Part I:
Introduction of Deep Learning

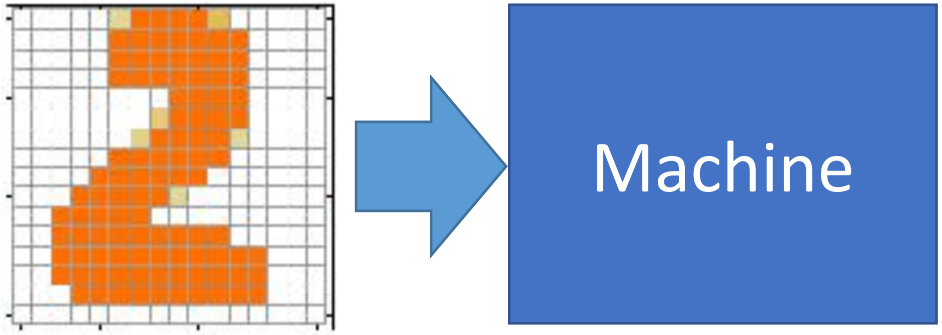
What people already knew in 1980s

Example Application

- Handwriting Digit Recognition

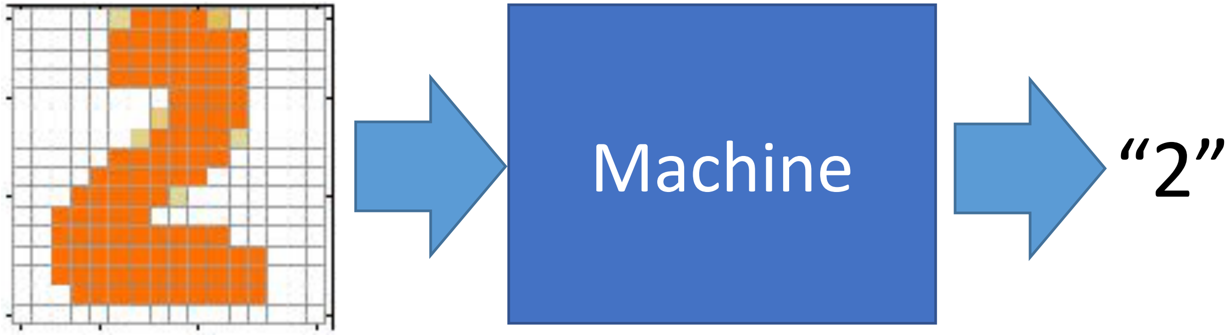
Example Application

- Handwriting Digit Recognition



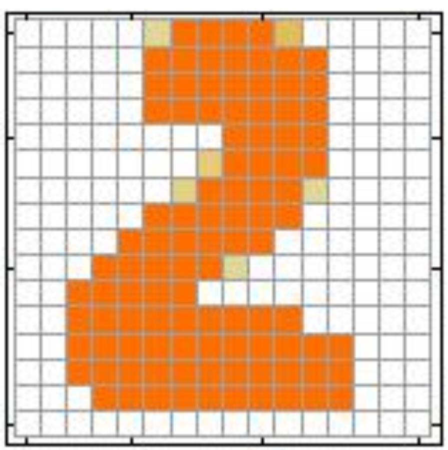
Example Application

- Handwriting Digit Recognition



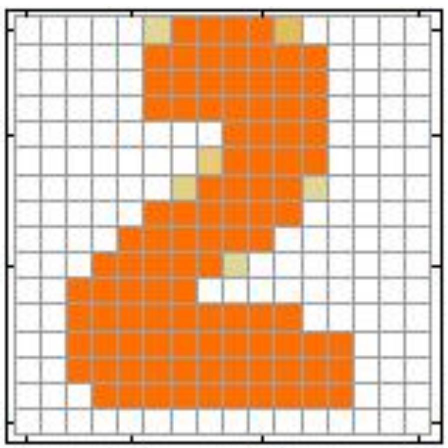
Handwriting Digit Recognition

Input **Output**



Handwriting Digit Recognition

Input



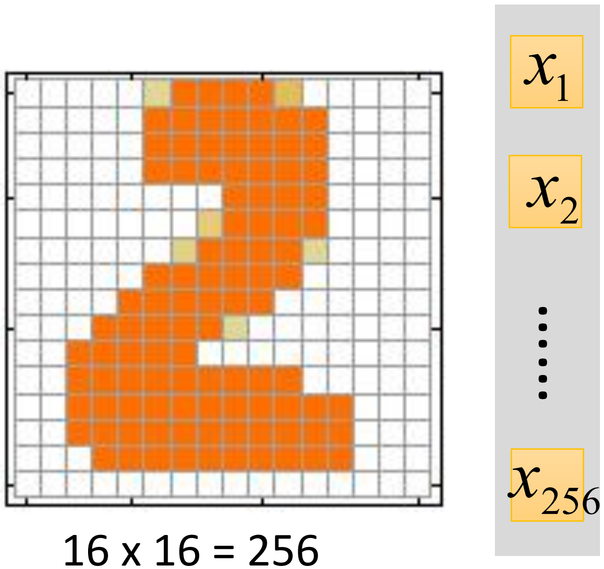
16 x 16 = 256

Output

Handwriting Digit Recognition

Input

Output



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Handwriting Digit Recognition

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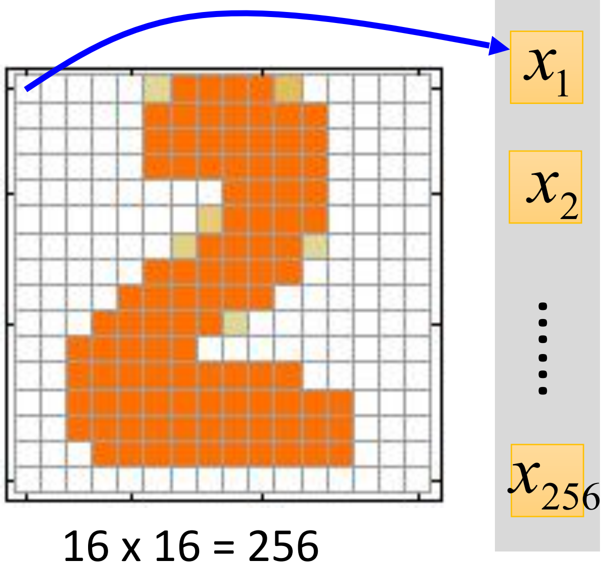

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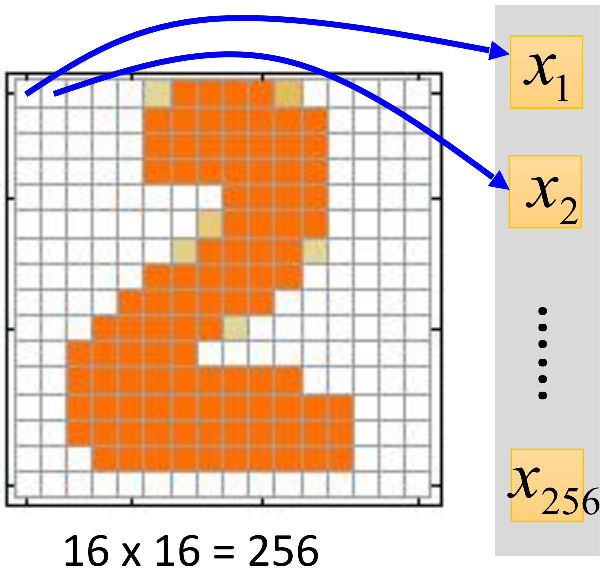

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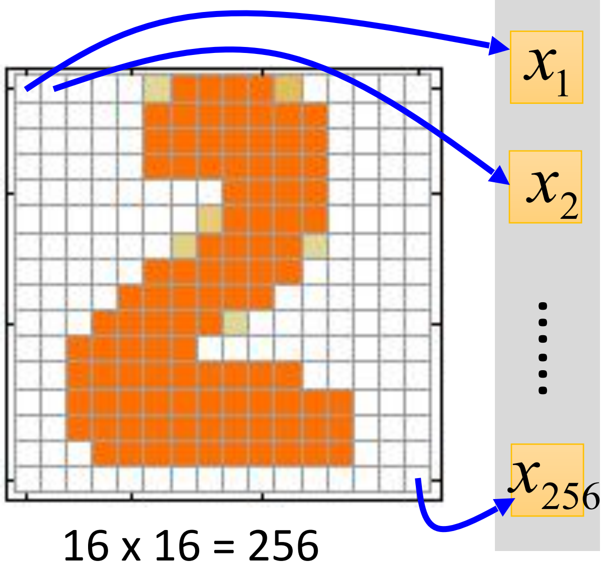

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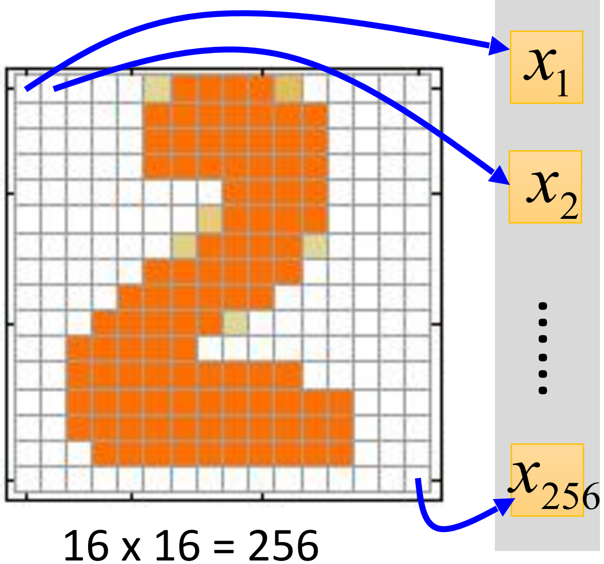


16 x 16 = 256

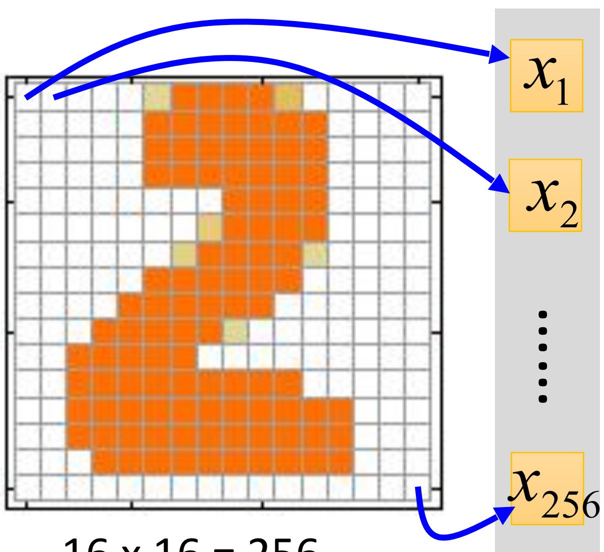
Ink → 1

No ink → 0

Output

Handwriting Digit Recognition

Input



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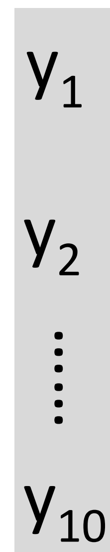

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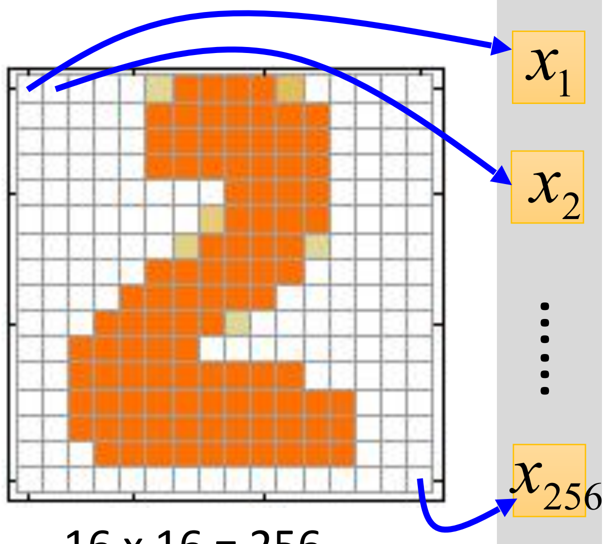

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Output

y_1

y_2

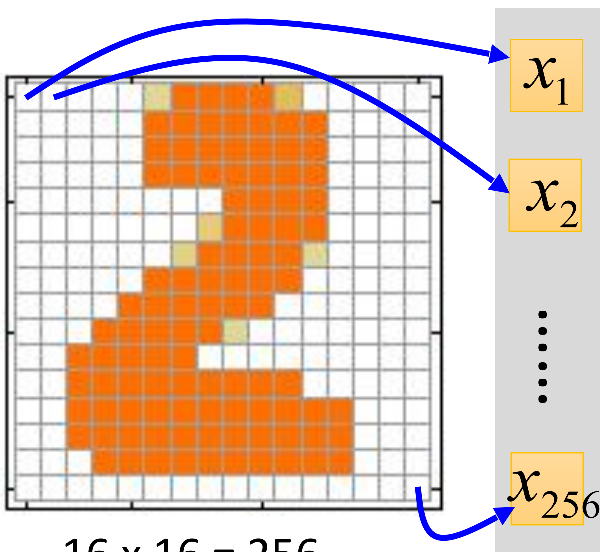
$\vdots$

y_{10}

Each dimension represents the confidence of a digit.

Handwriting Digit Recognition

Input



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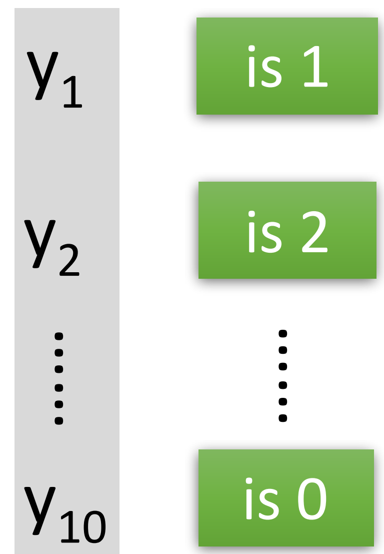

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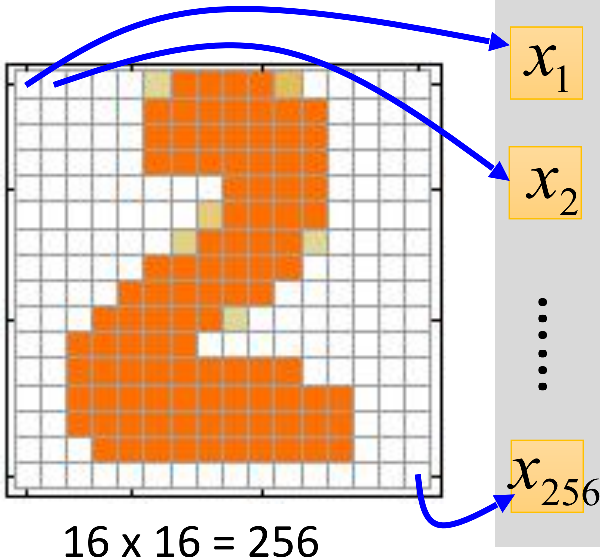

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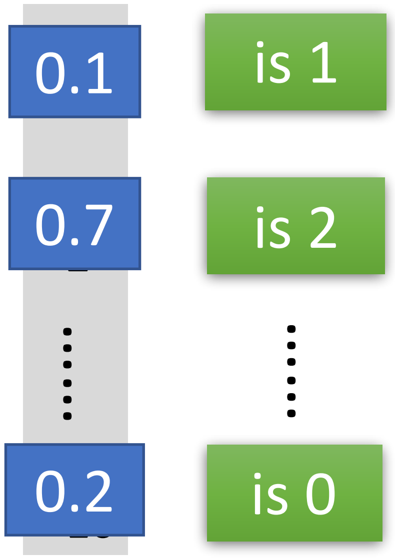

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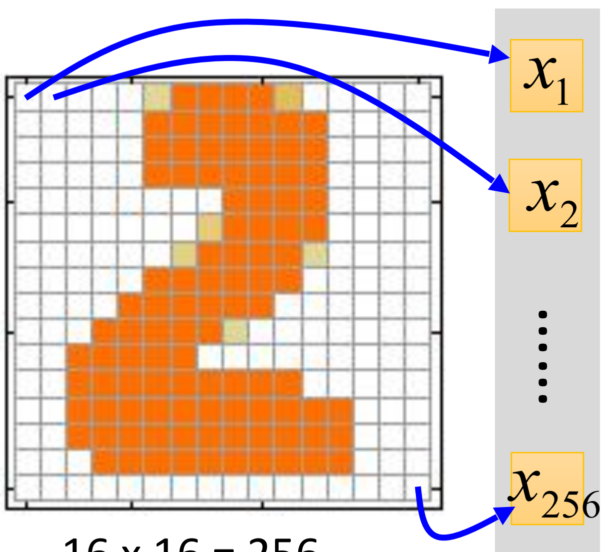

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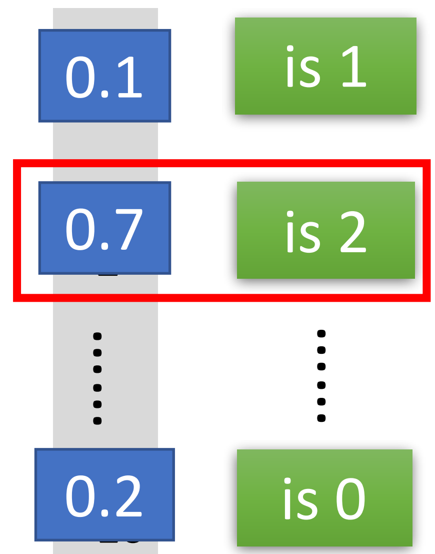

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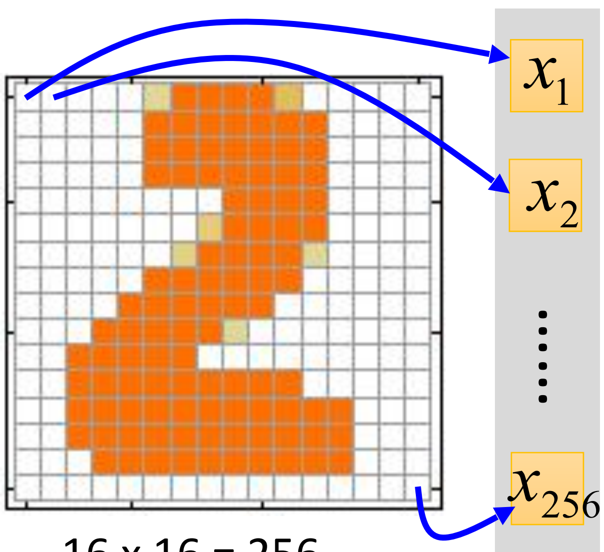

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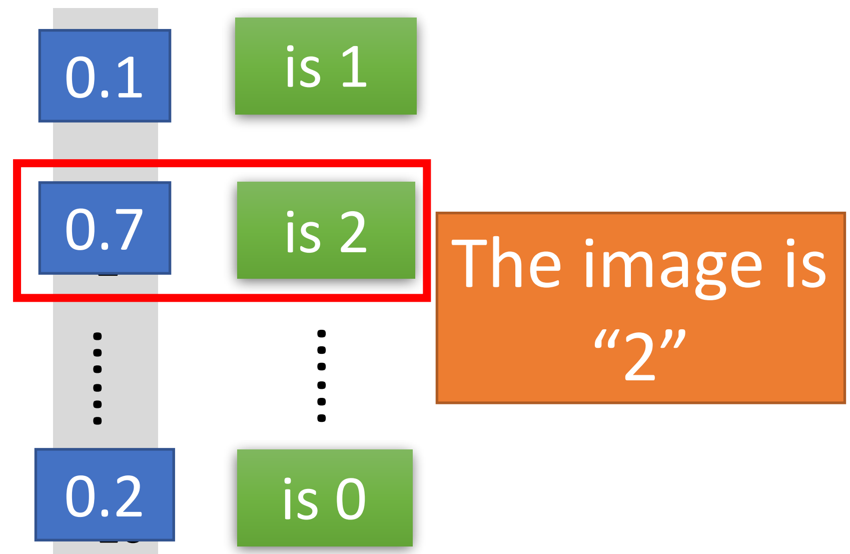

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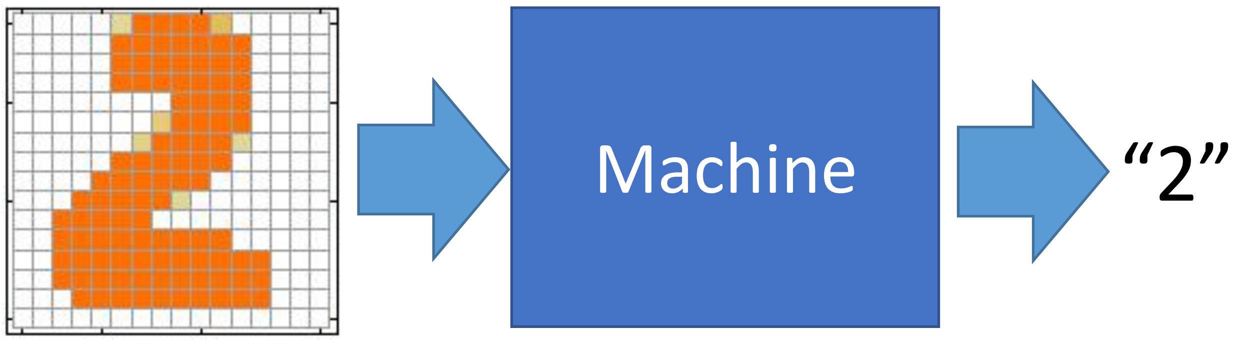
Example Application

- Handwriting Digit Recognition



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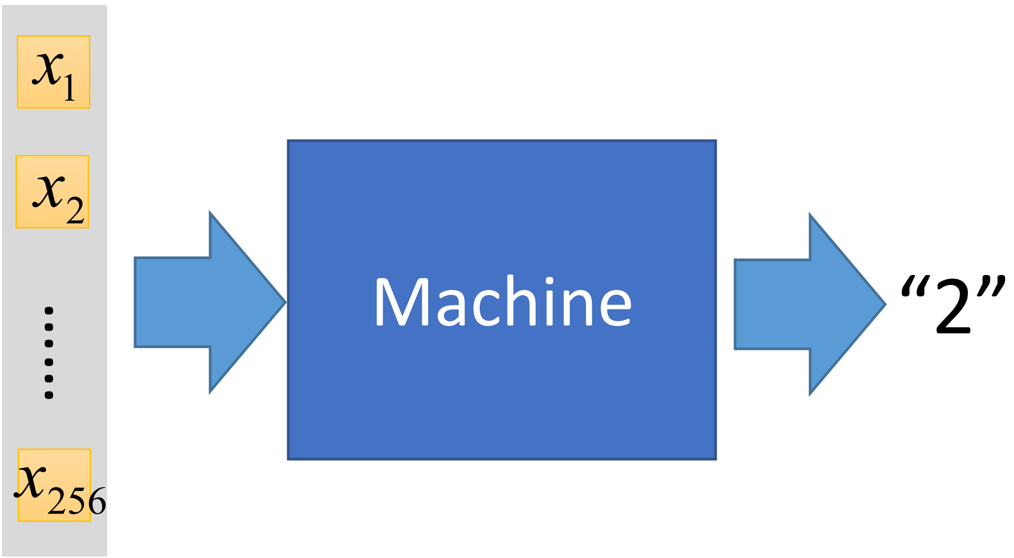

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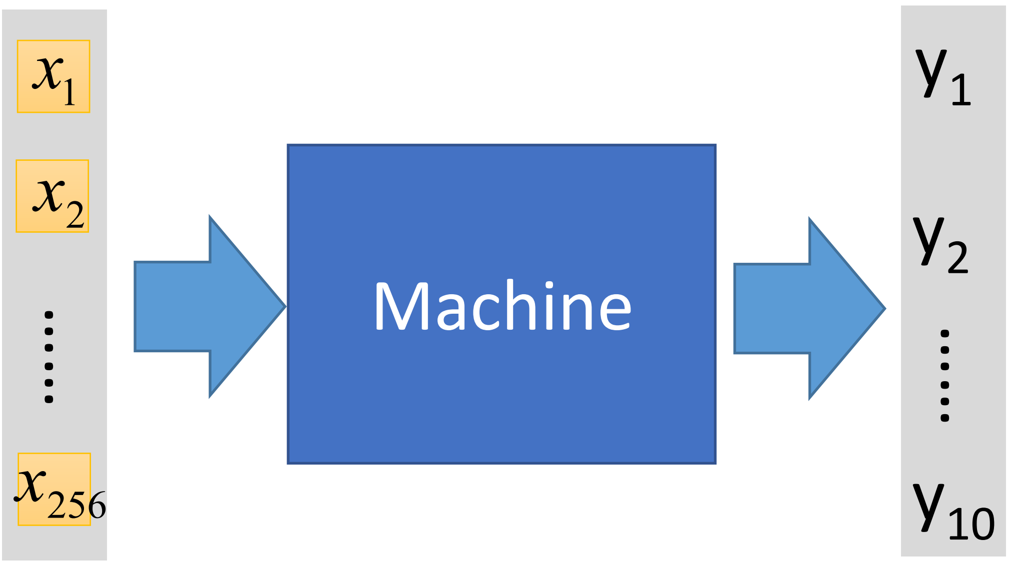

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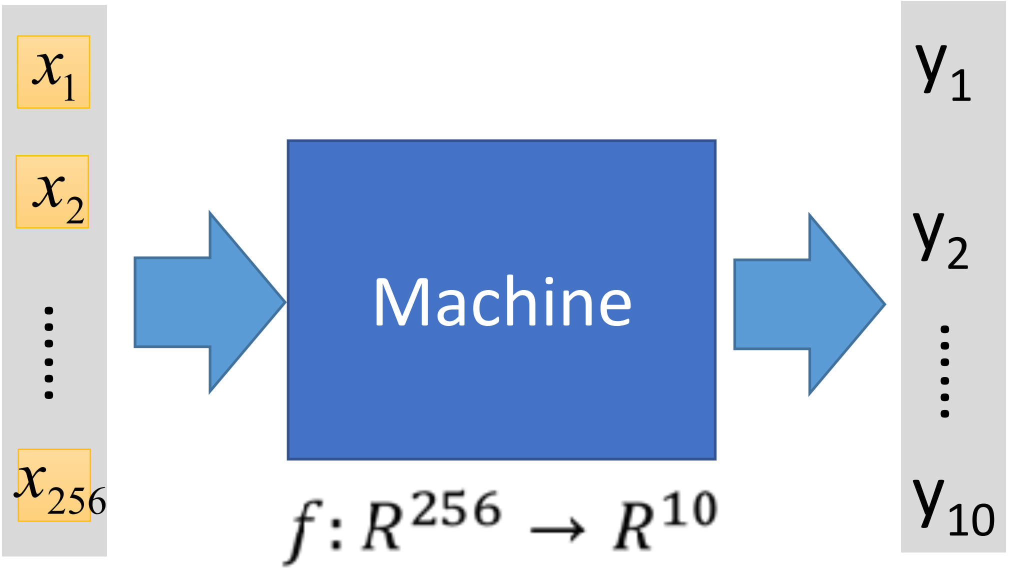

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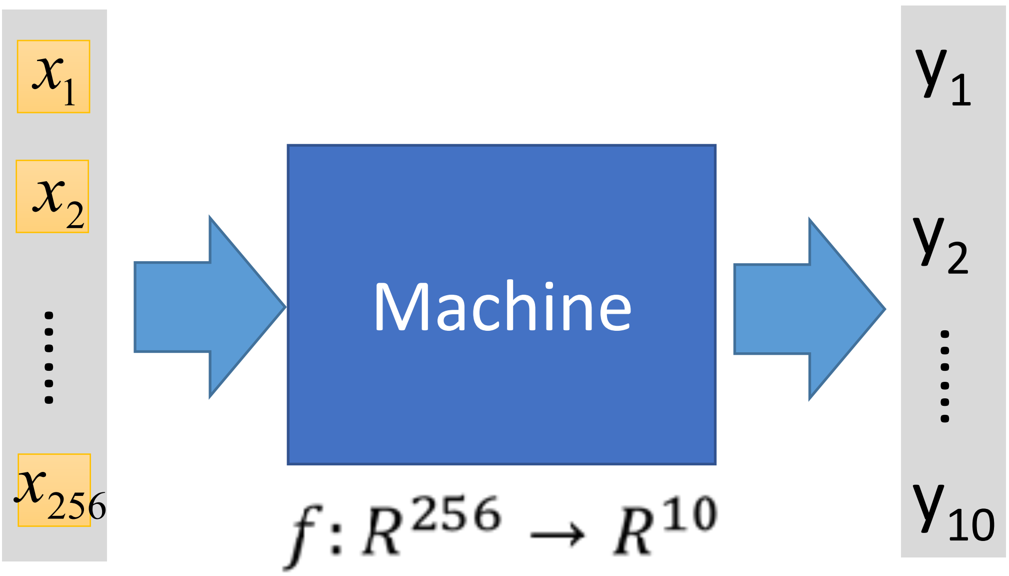


In deep learning, the function f is represented by neural network

Element of Neural Network

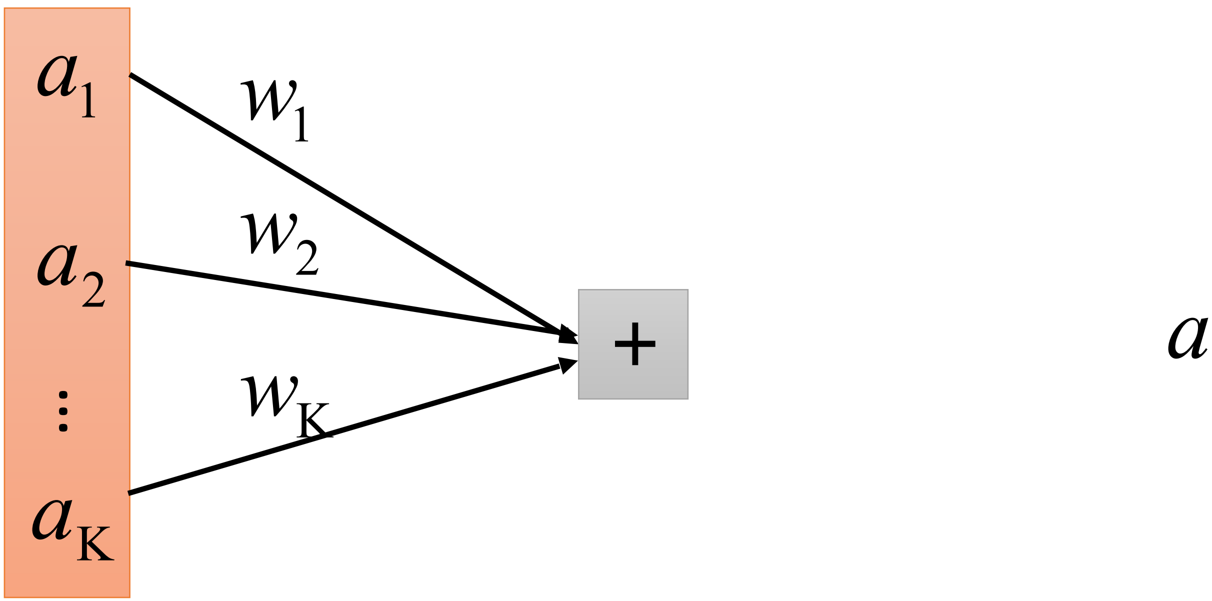
Neuron $f: R^K \rightarrow R$

$$\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_K \end{bmatrix}$$

a

Element of Neural Network

Neuron $f: R^K \rightarrow R$



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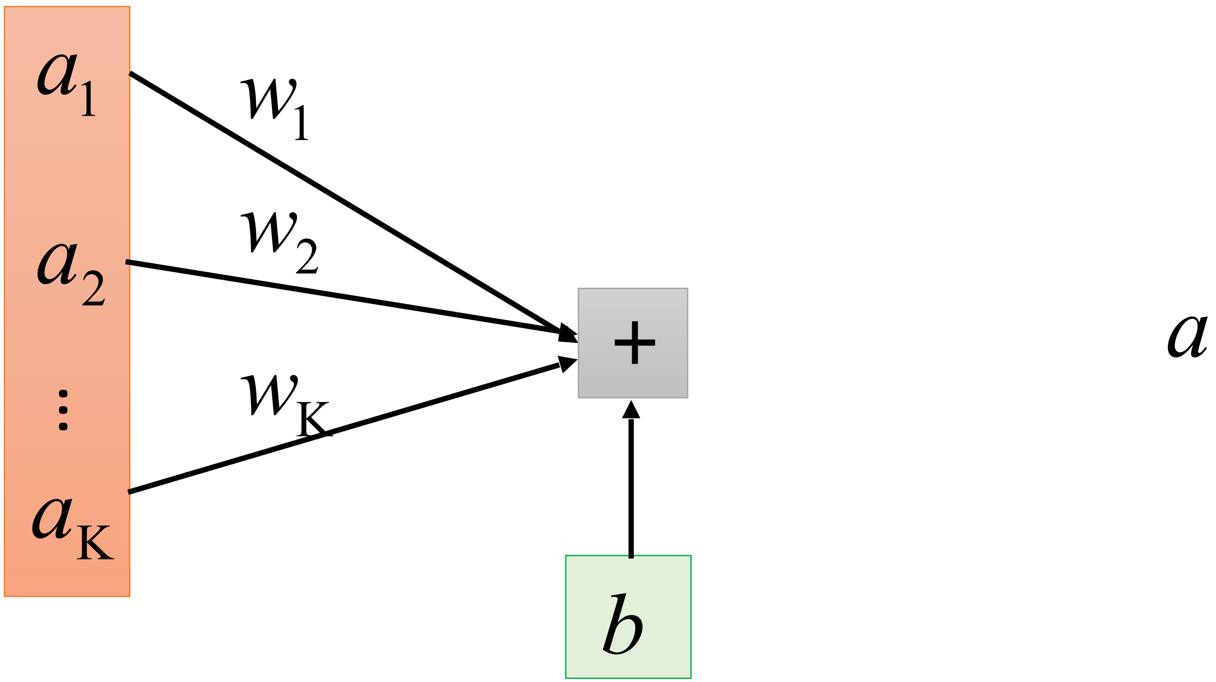

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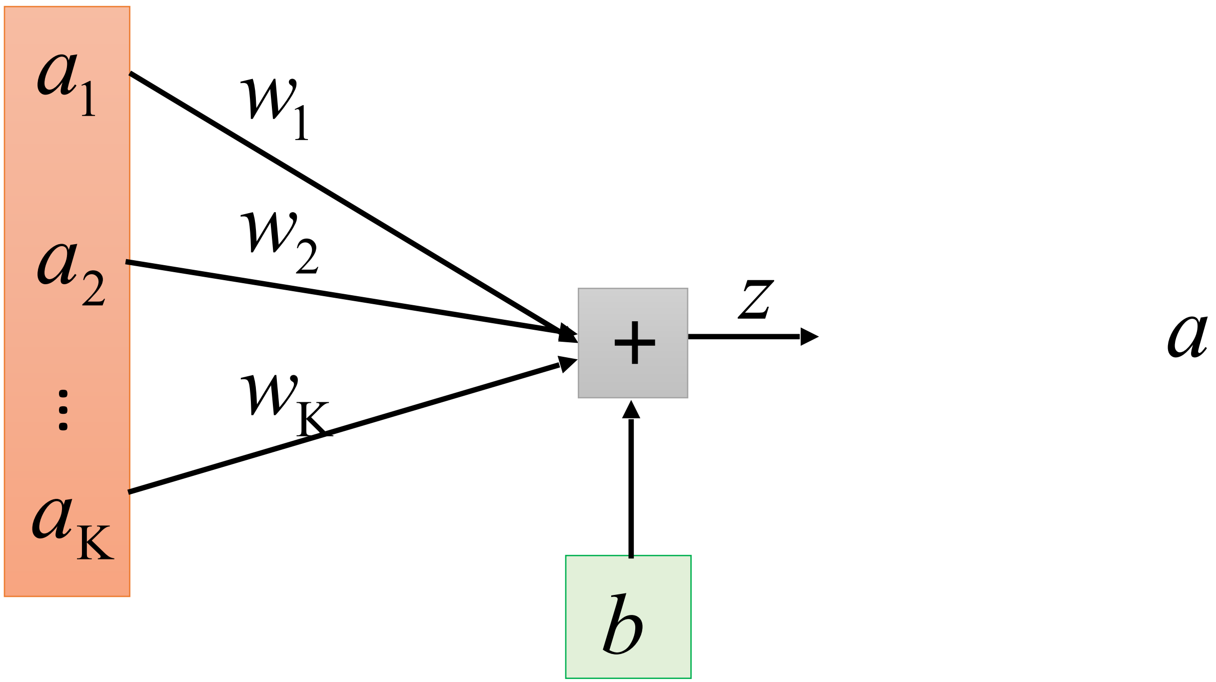
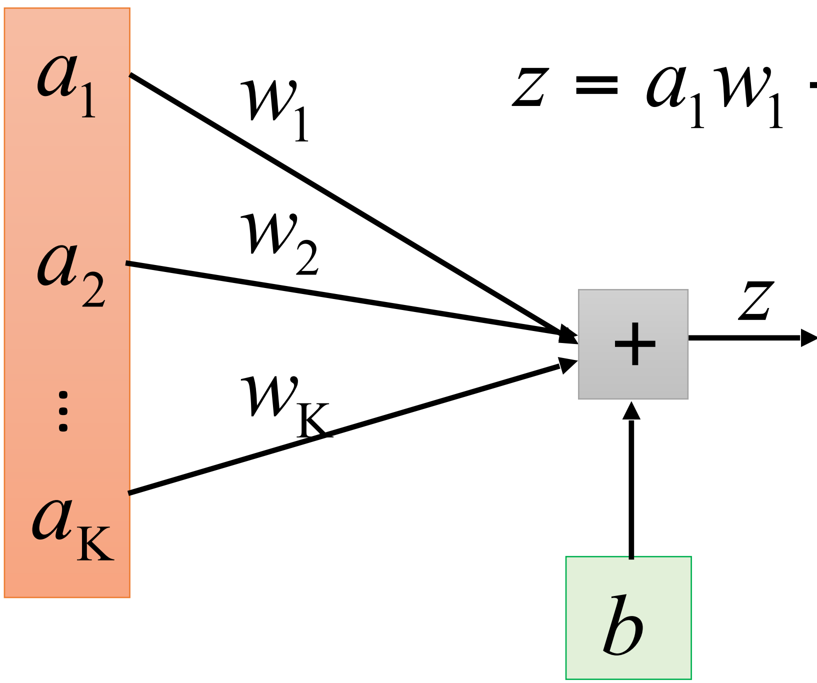


Element of Neural Network

Neuron $f: R^K \rightarrow R$

$$z = a_1 w_1 + a_2 w_2 + \cdots + a_K w_K + b$$



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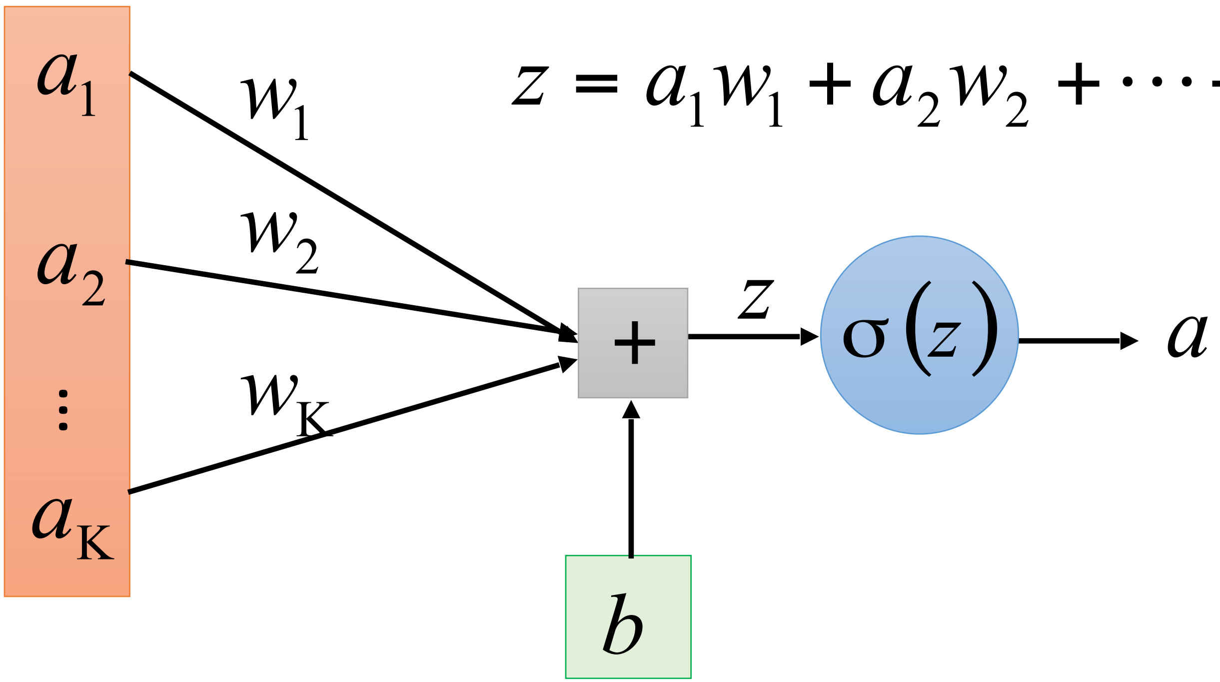

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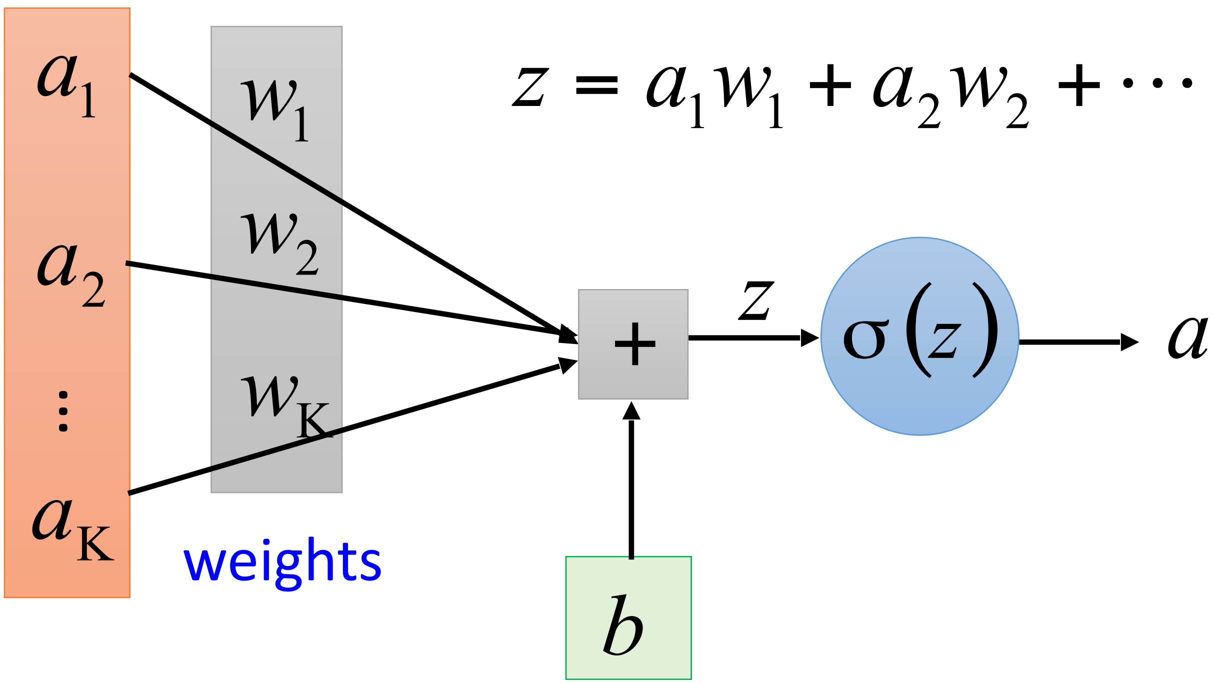

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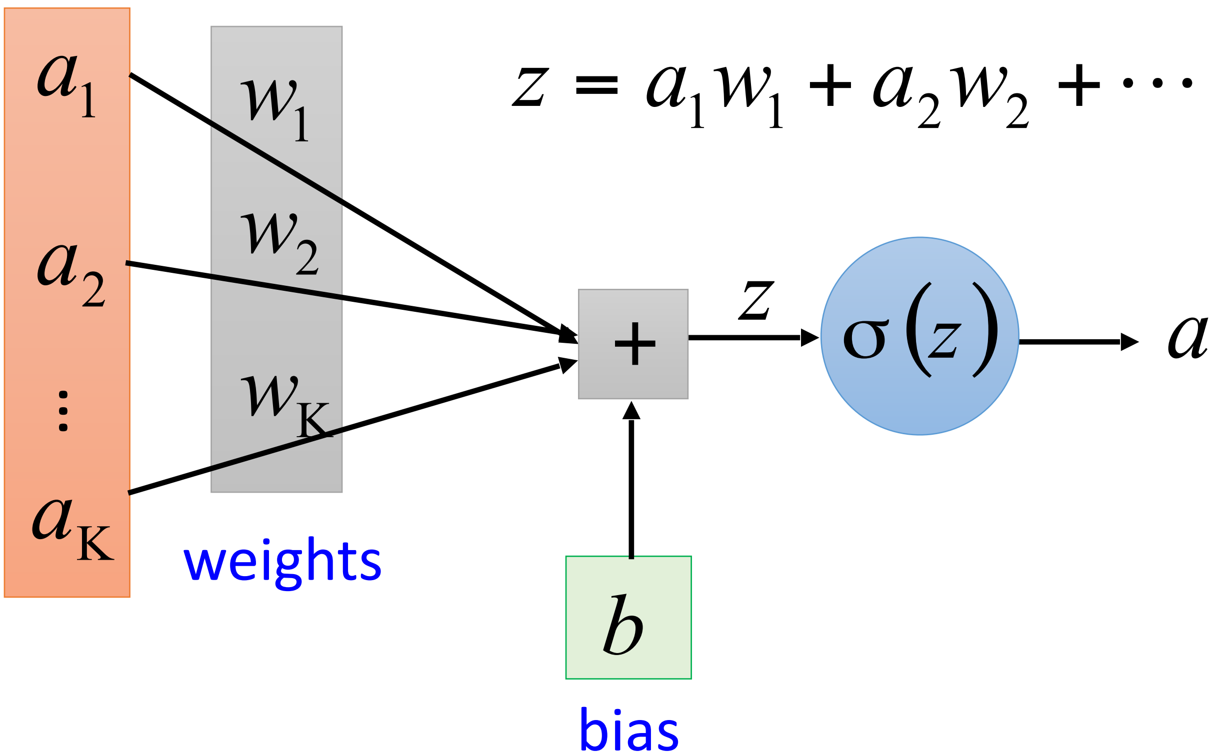

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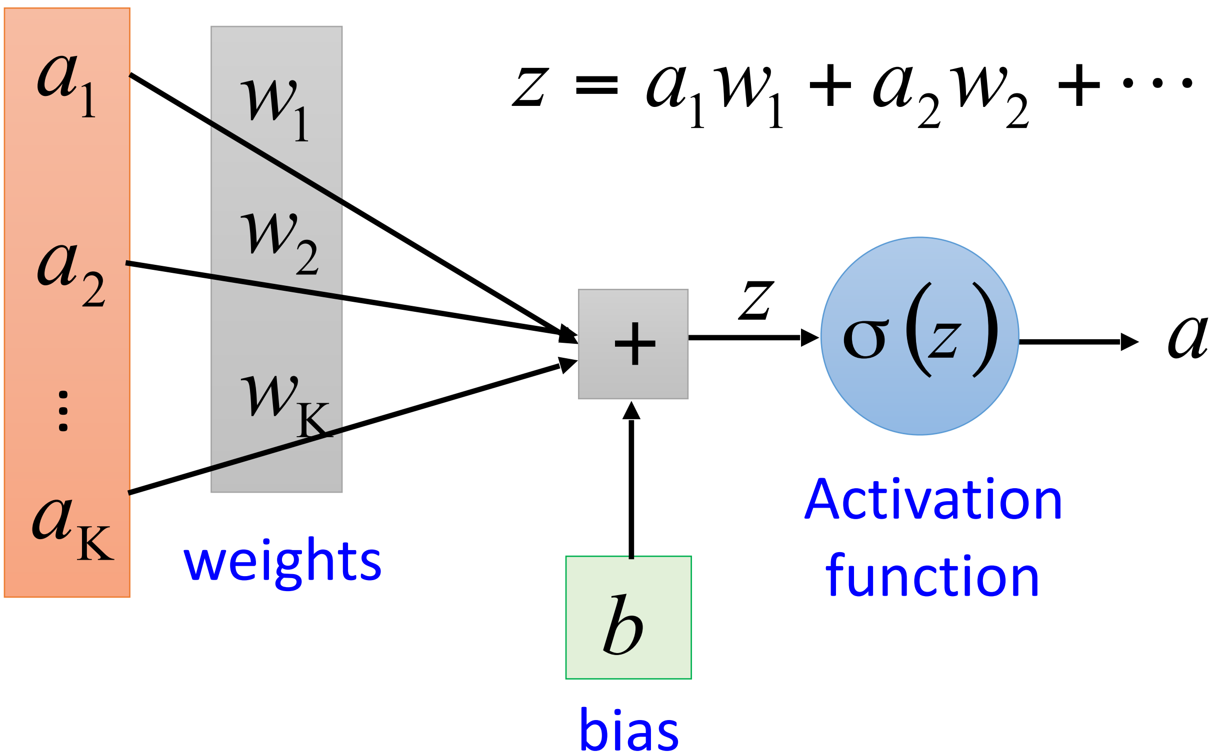
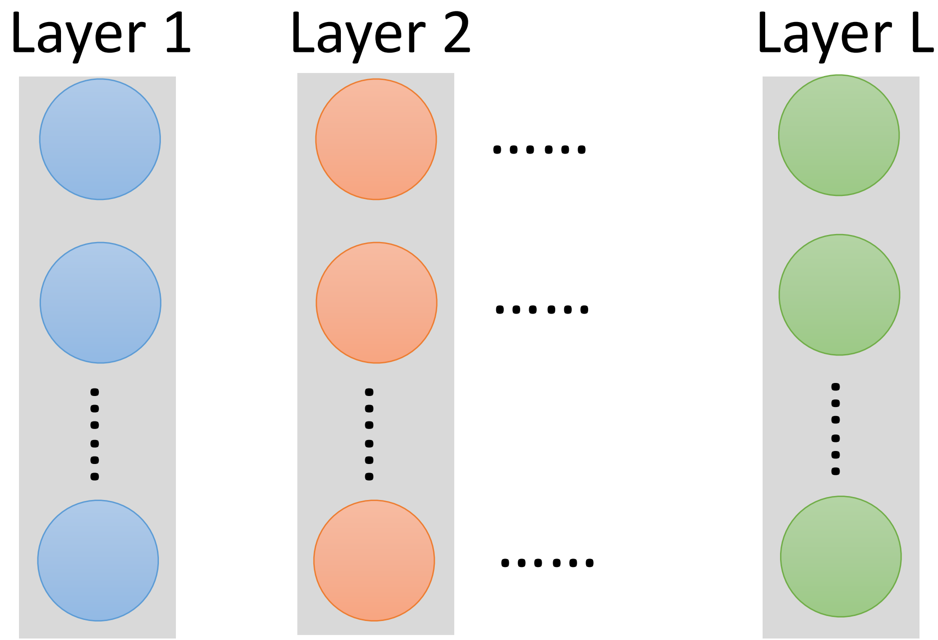


Neural Network

Neural Network



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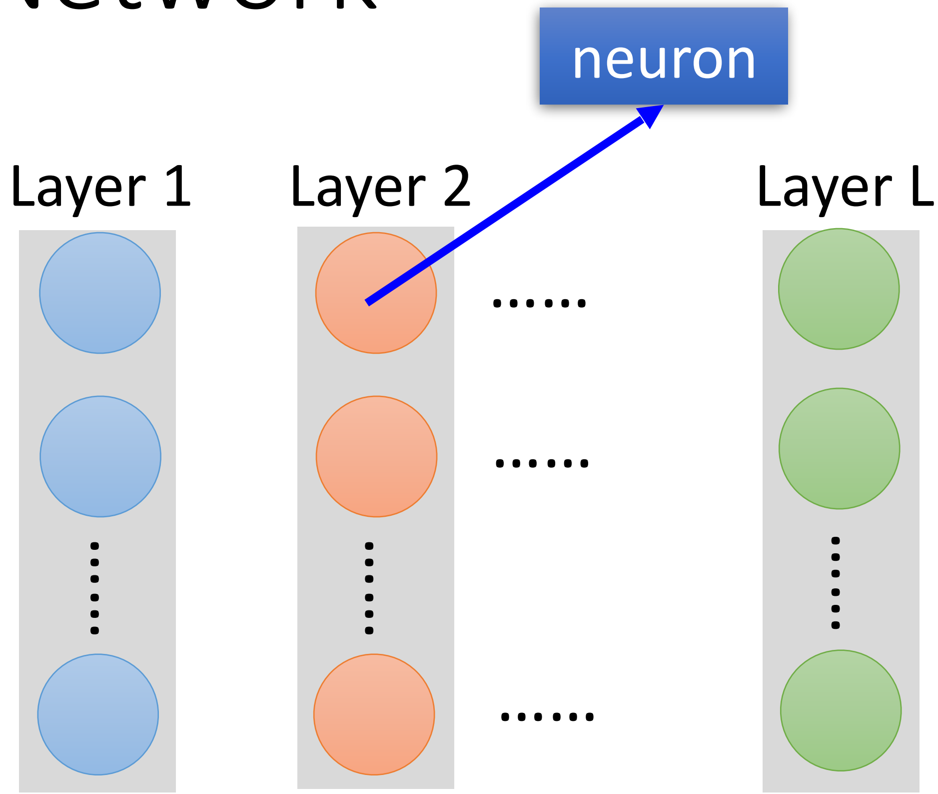

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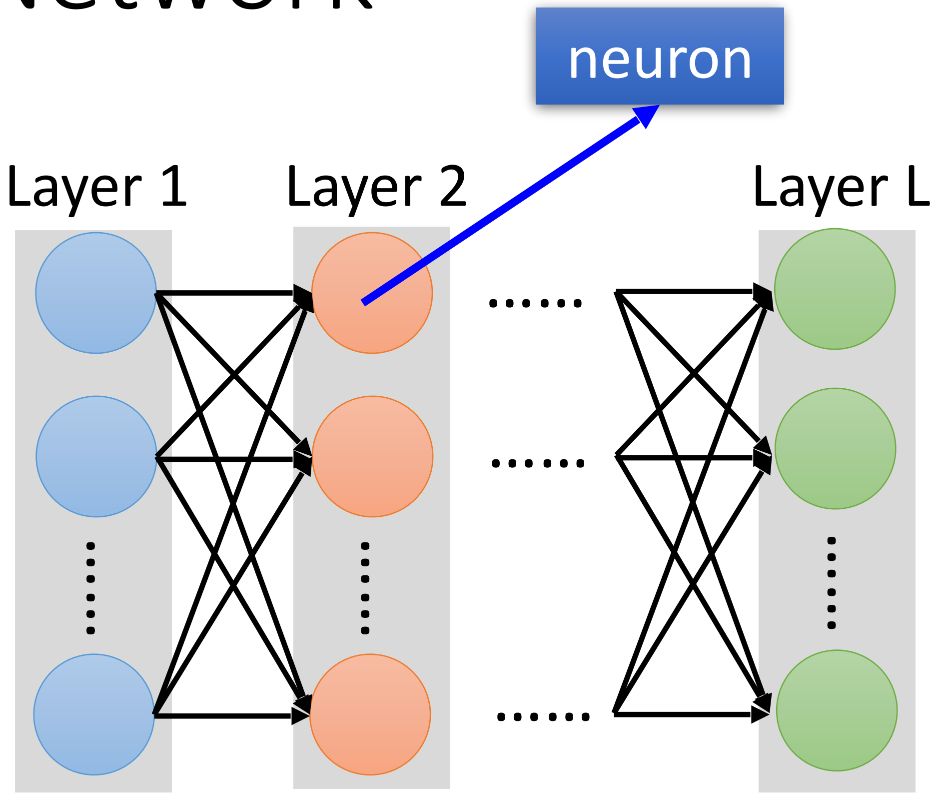

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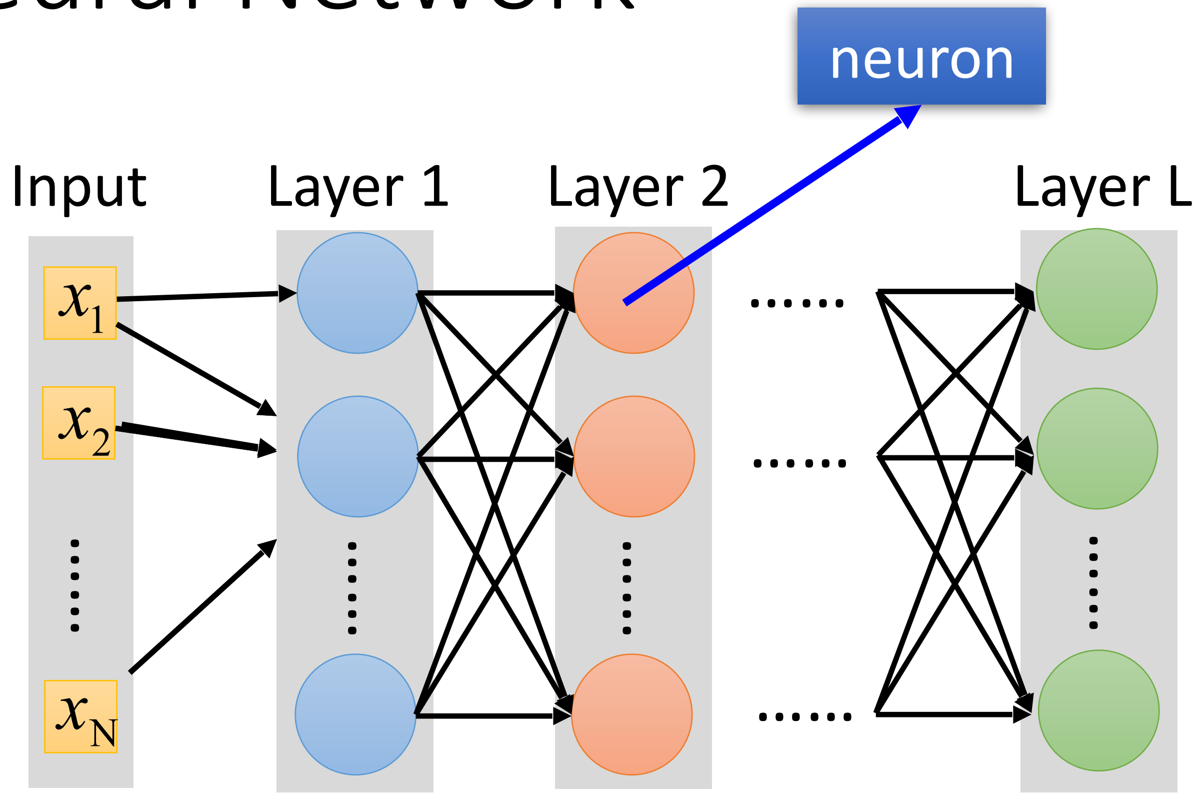

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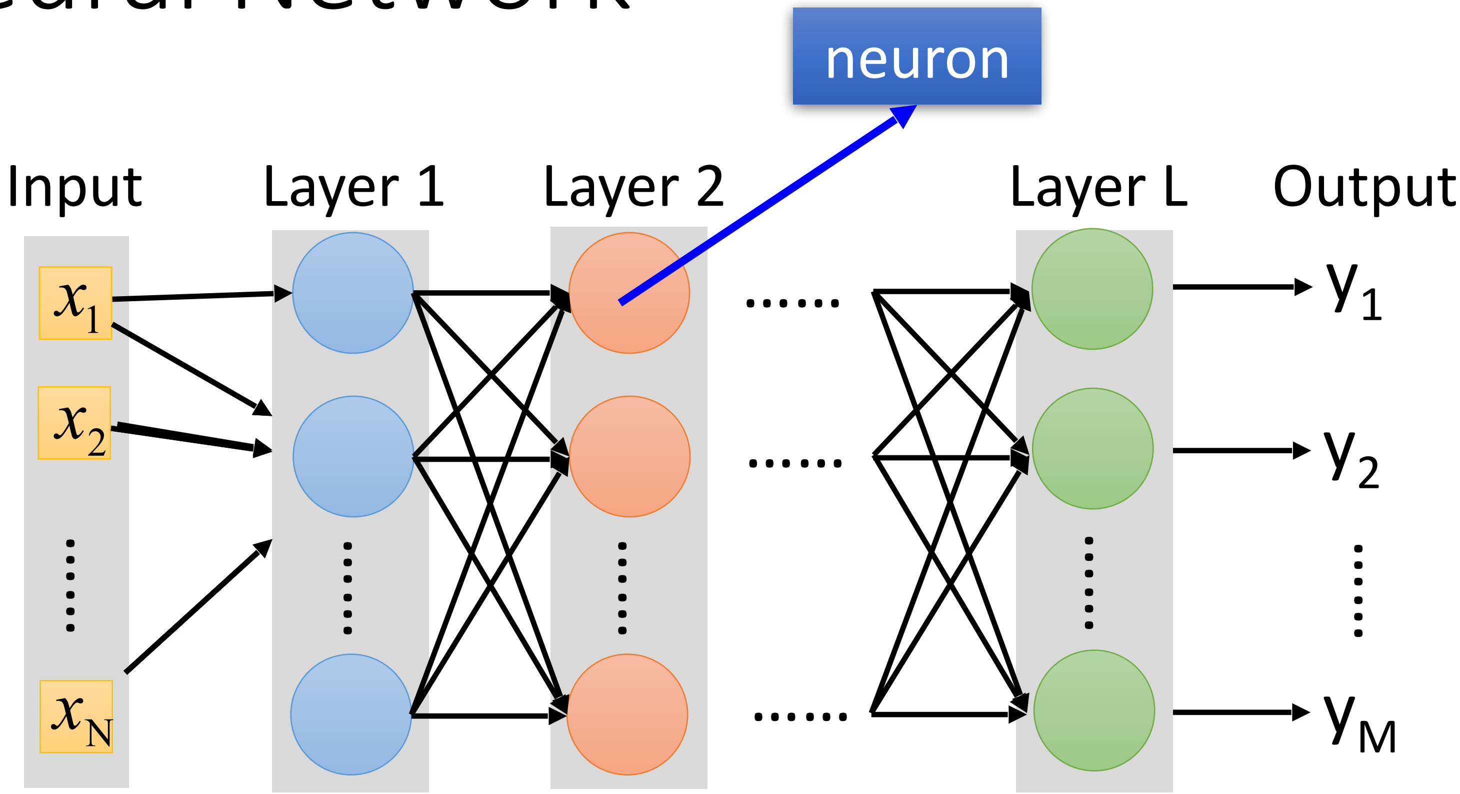

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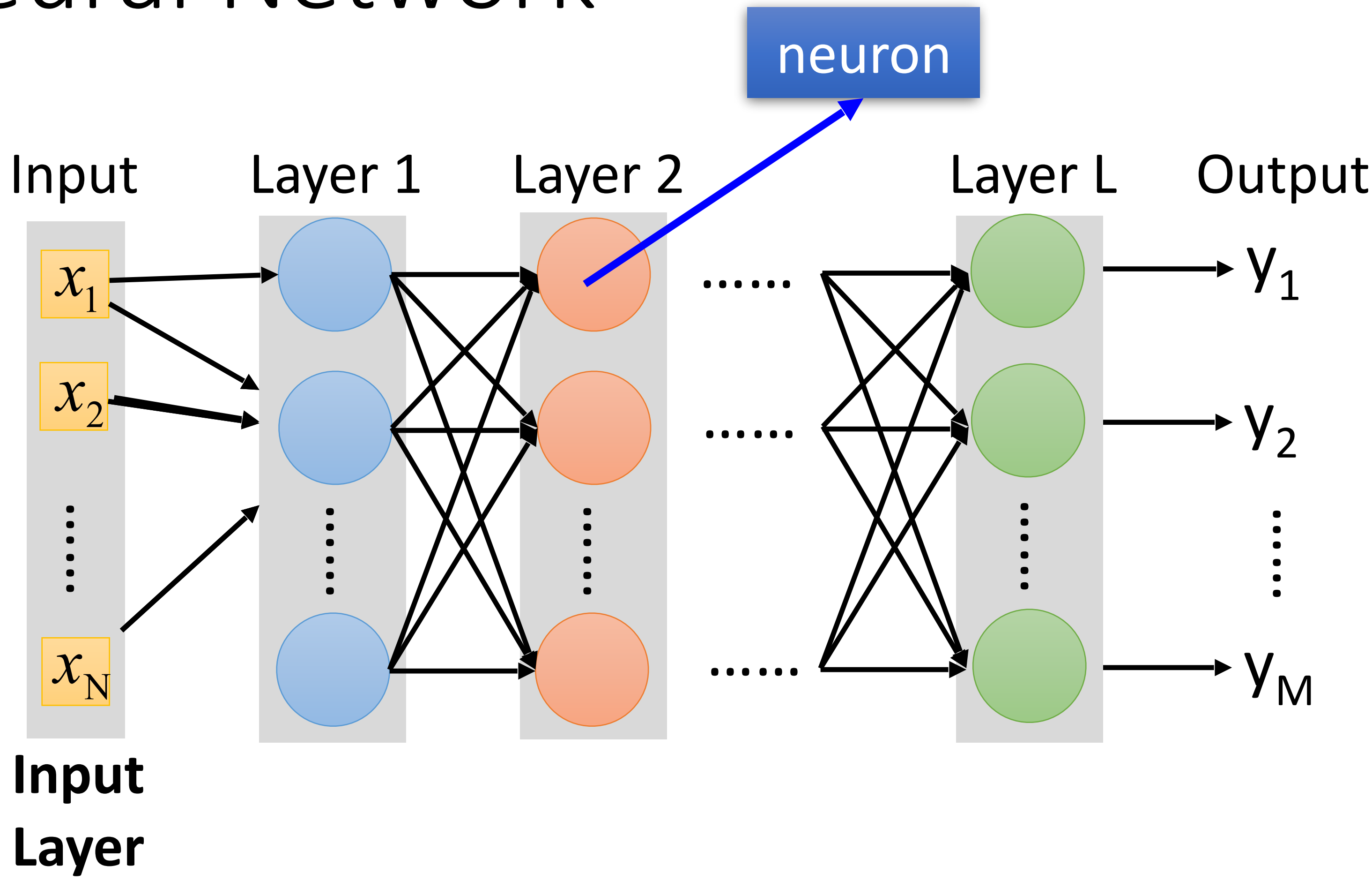

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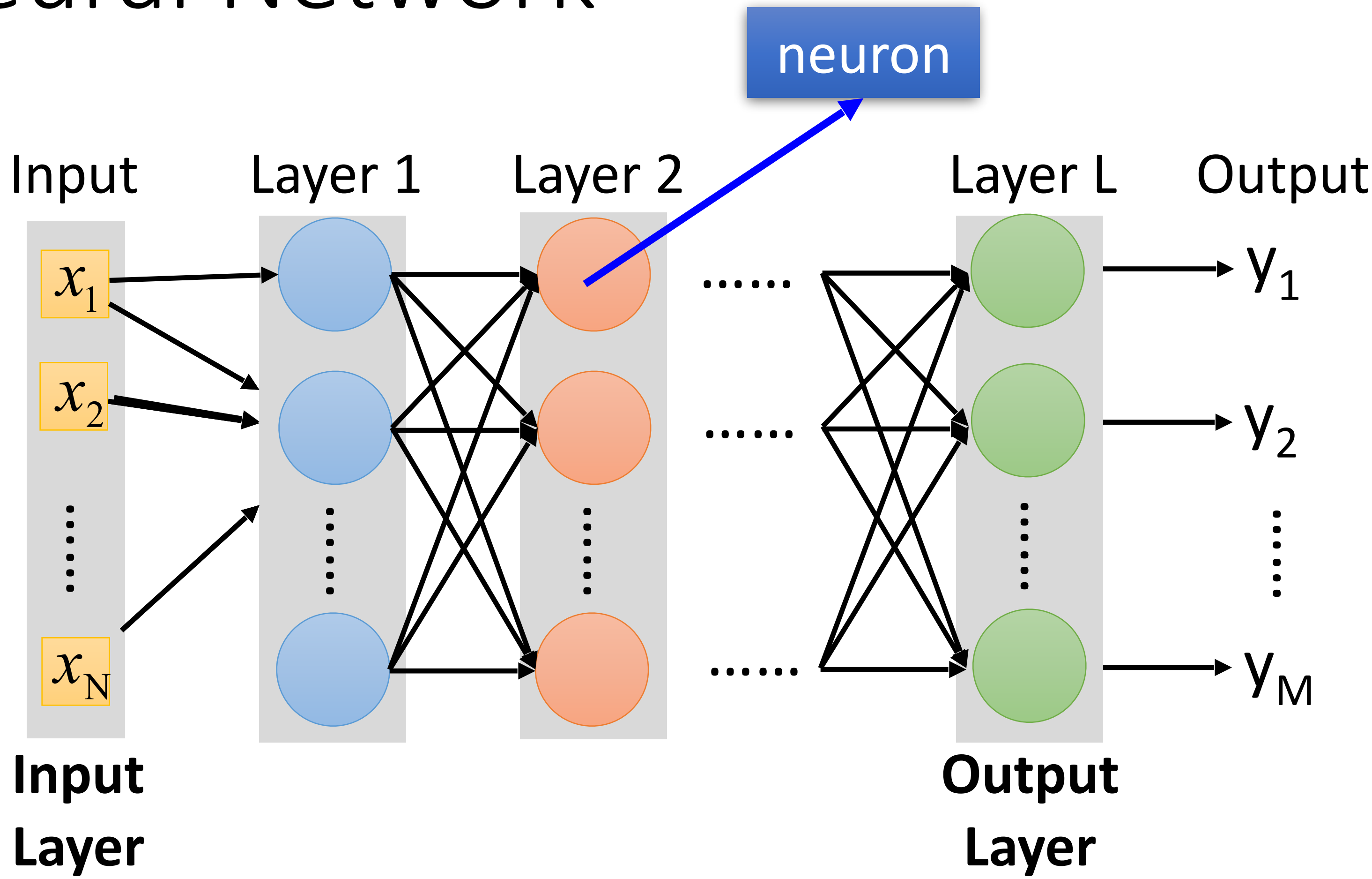

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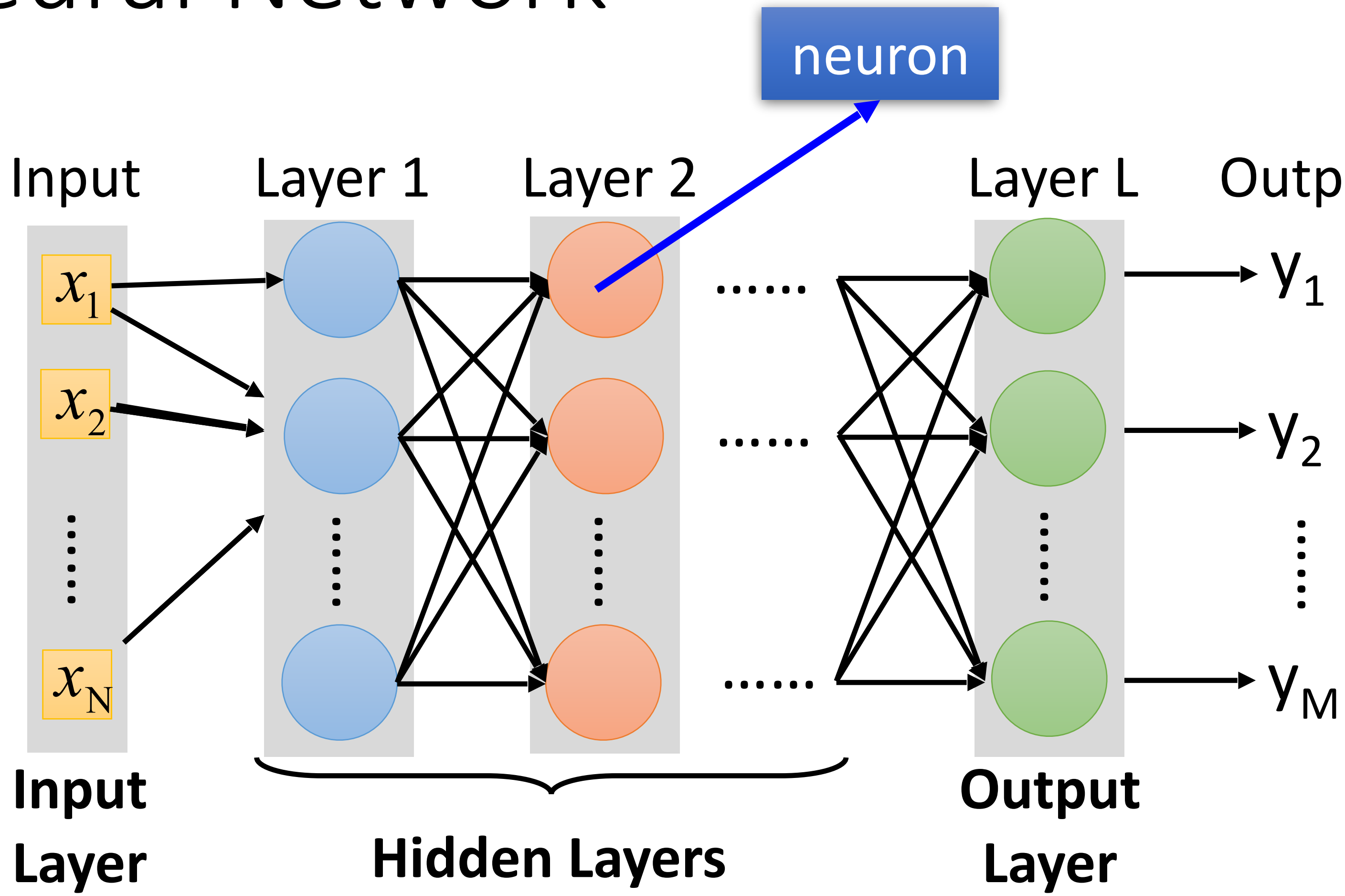

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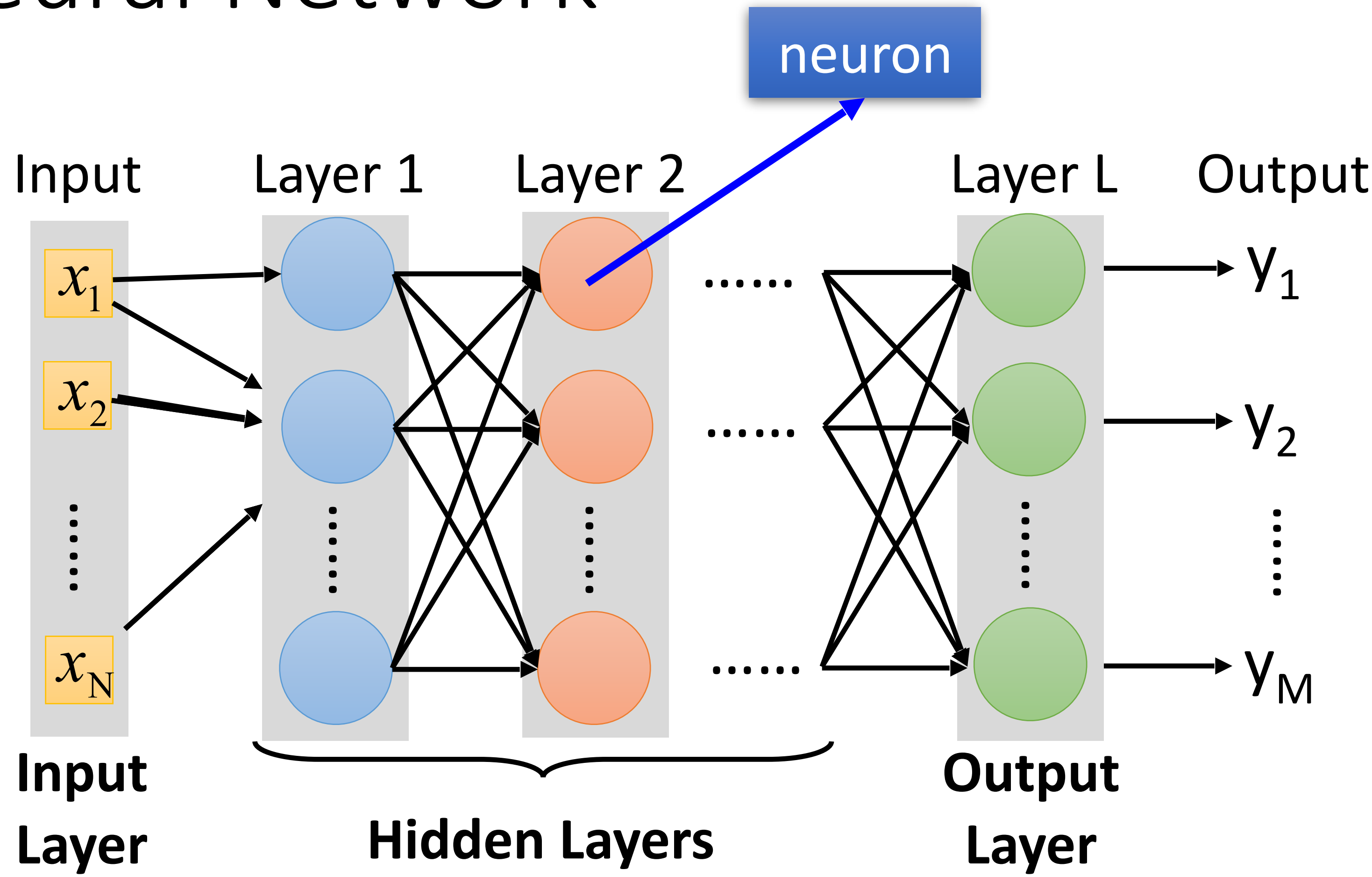
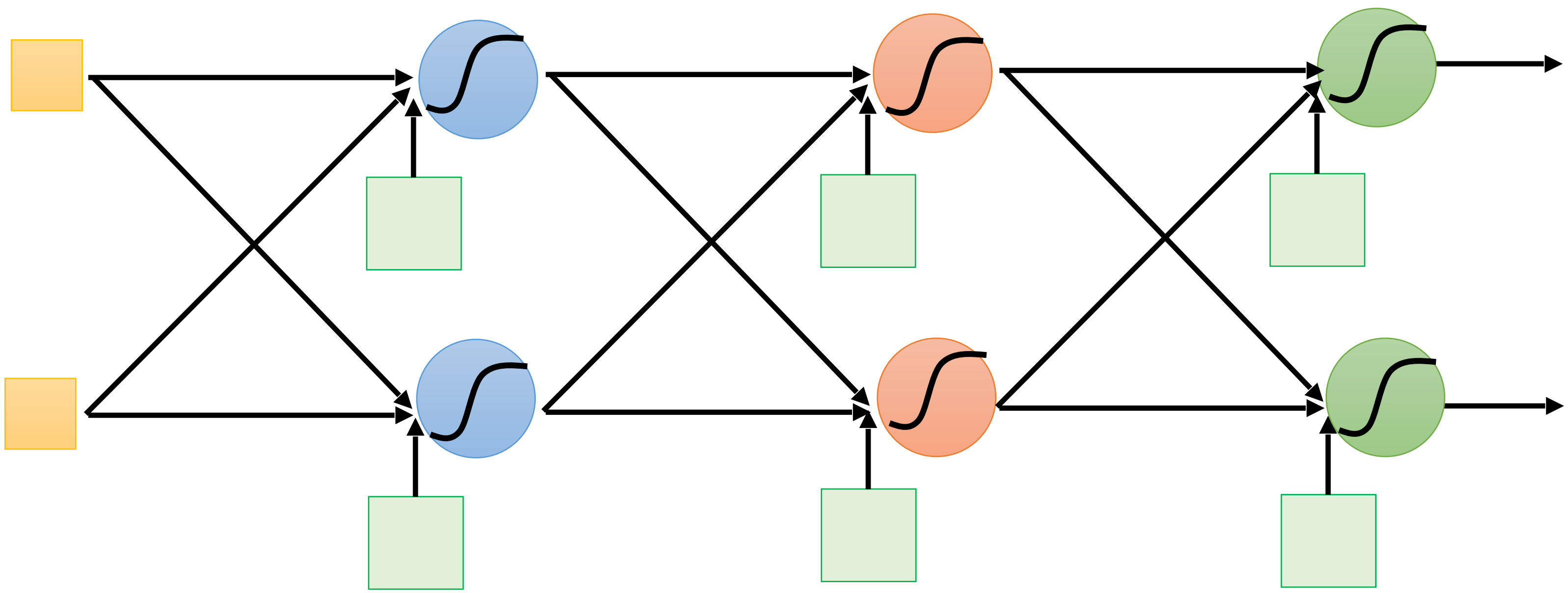


Deep means many hidden layers

Example of Neural Network



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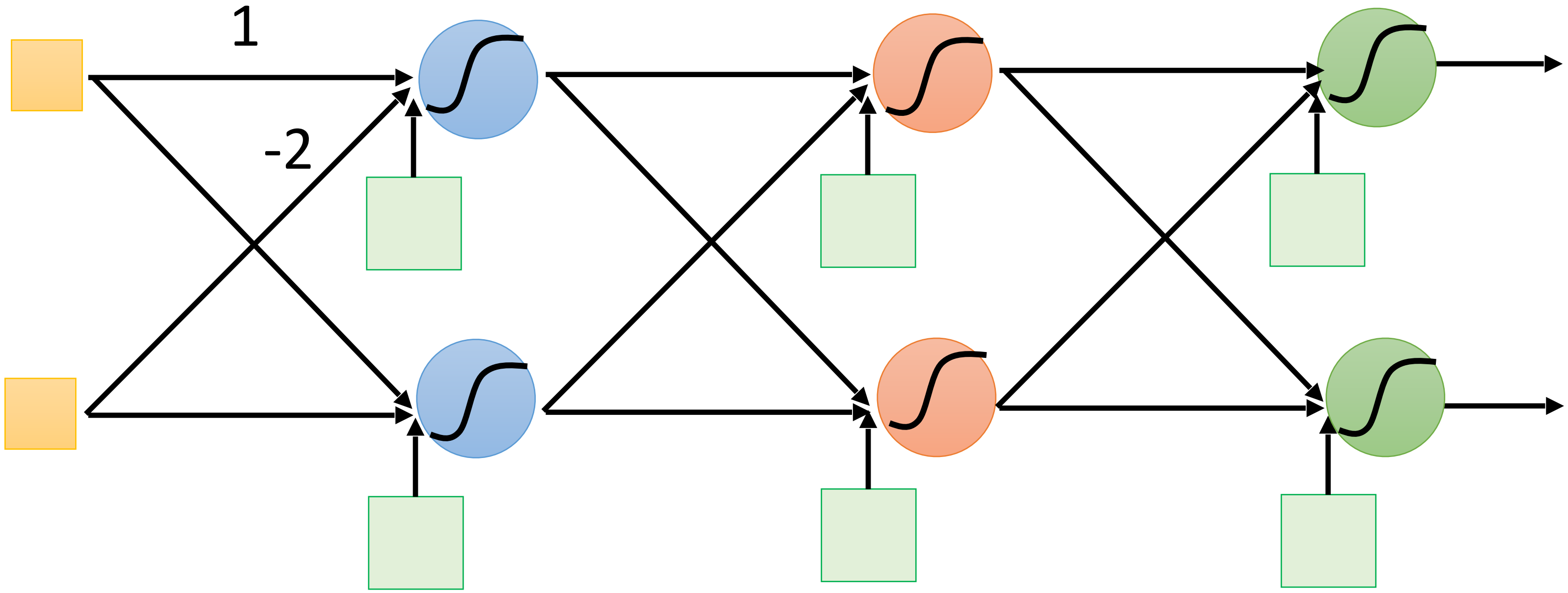

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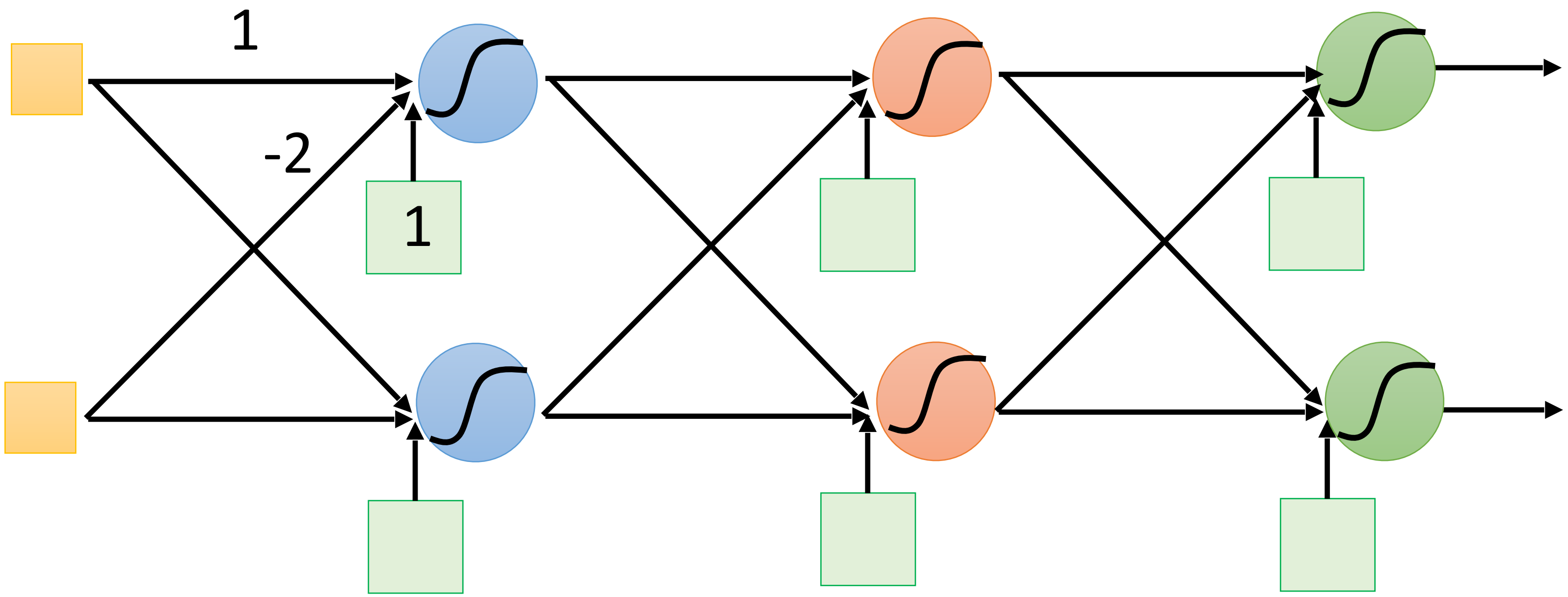

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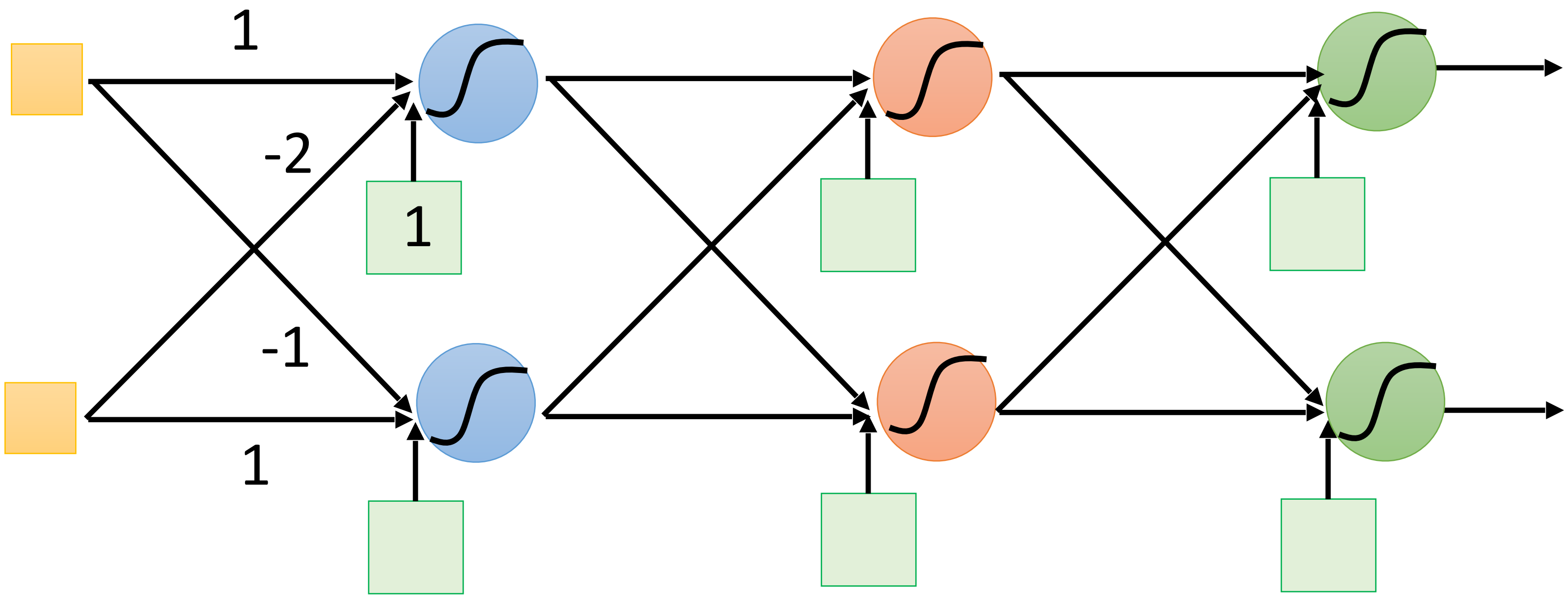

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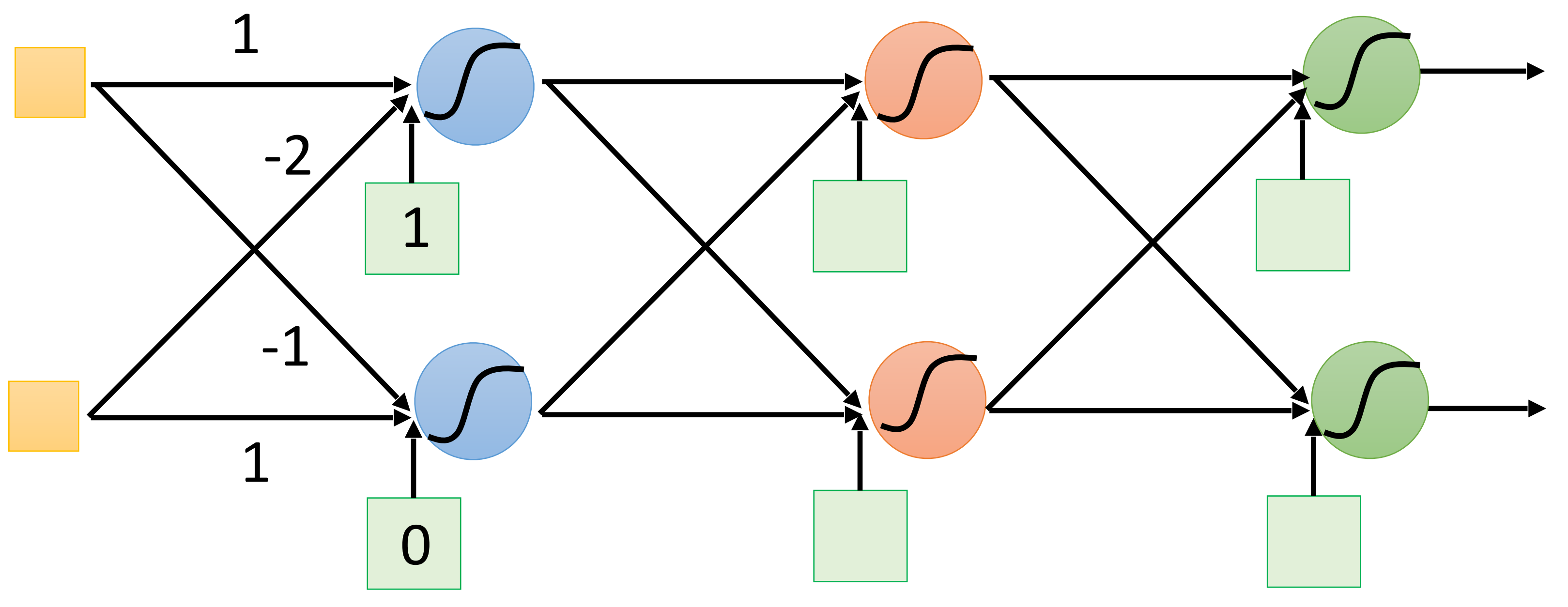

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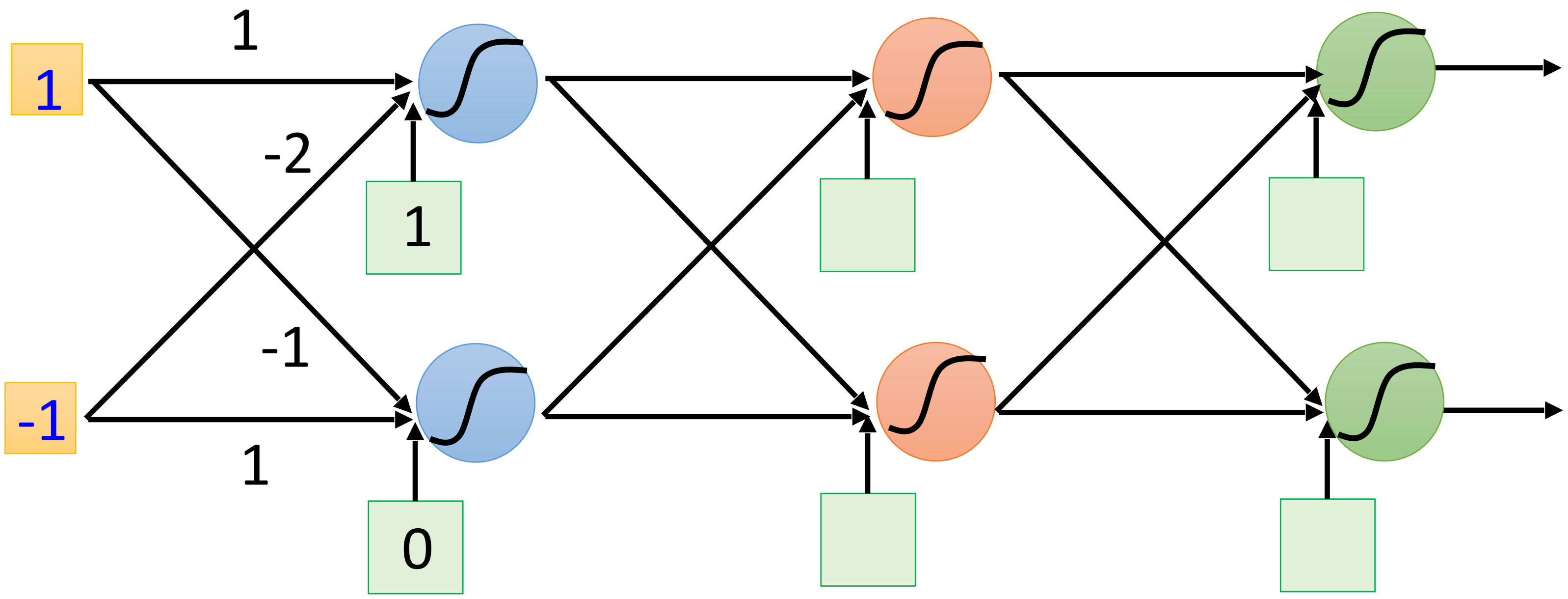

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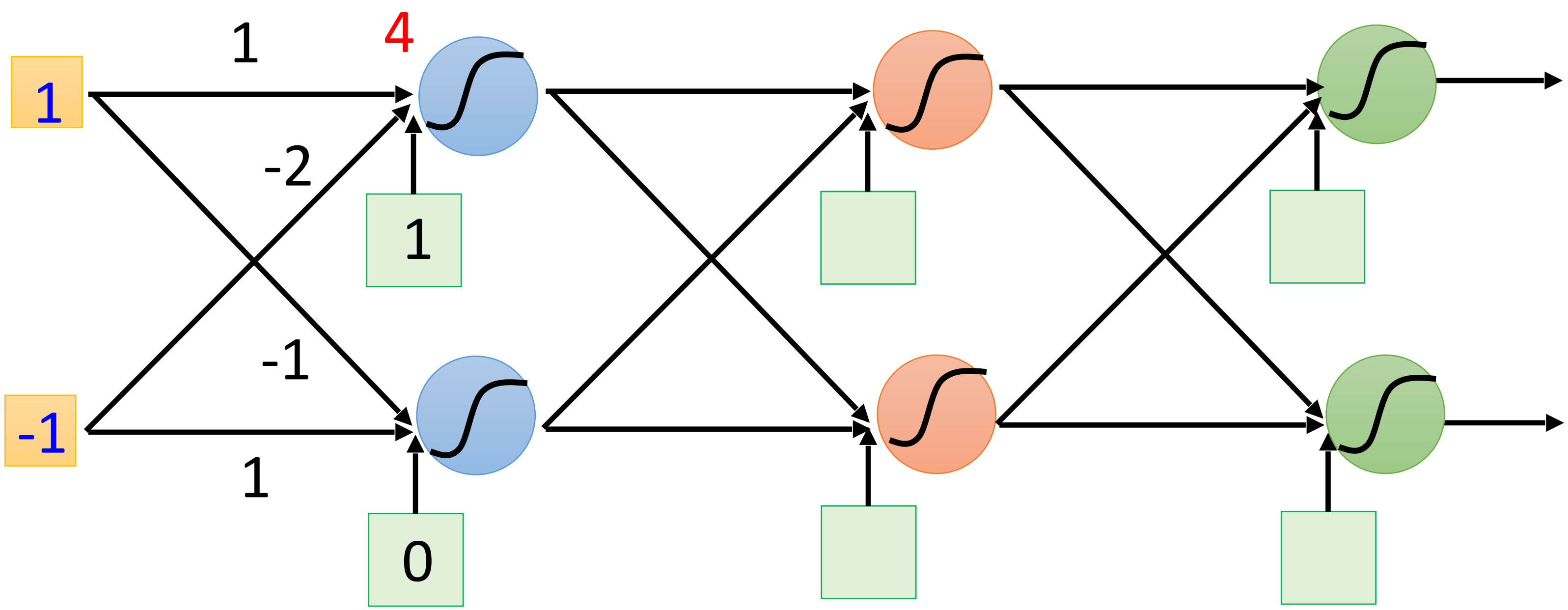

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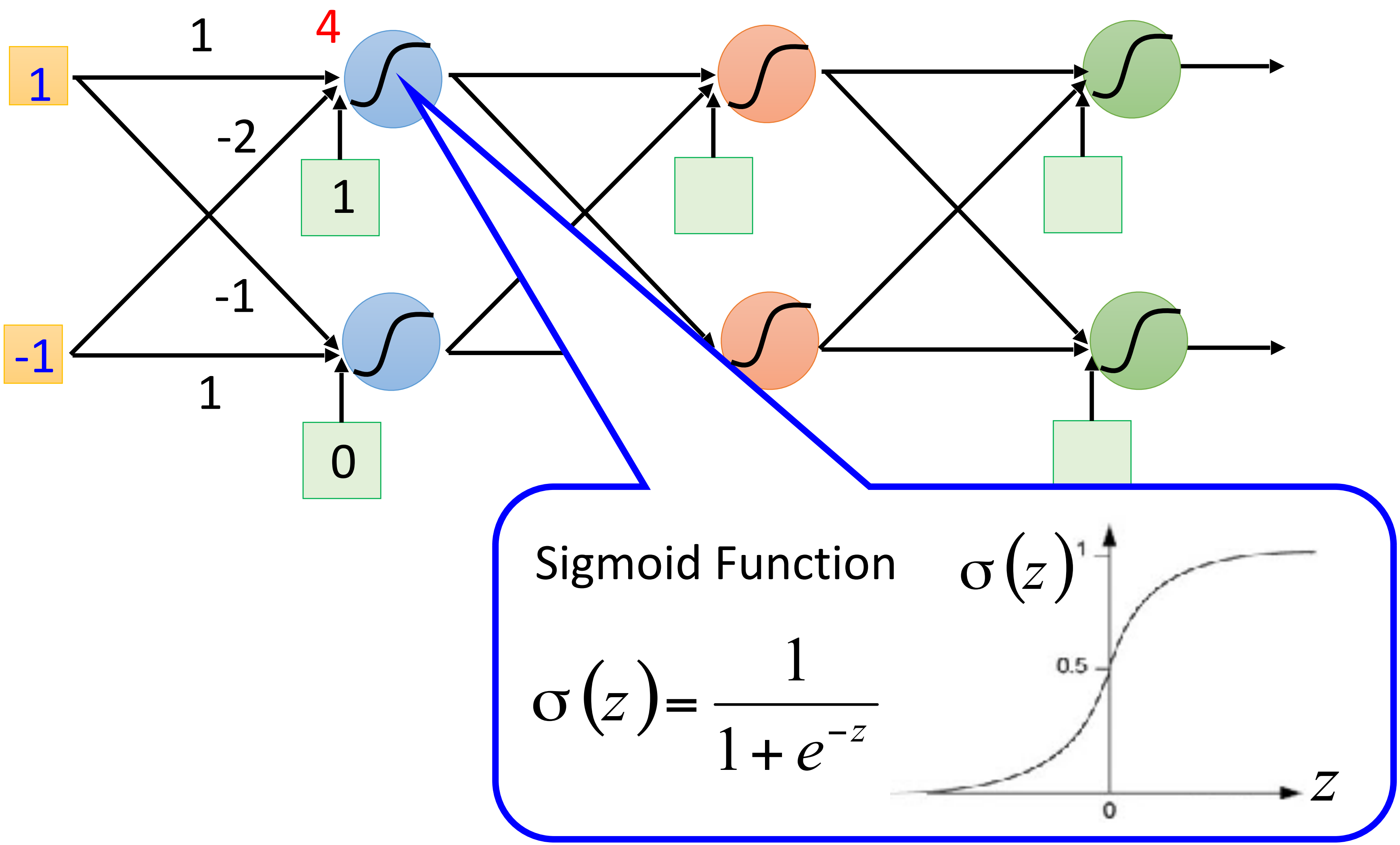
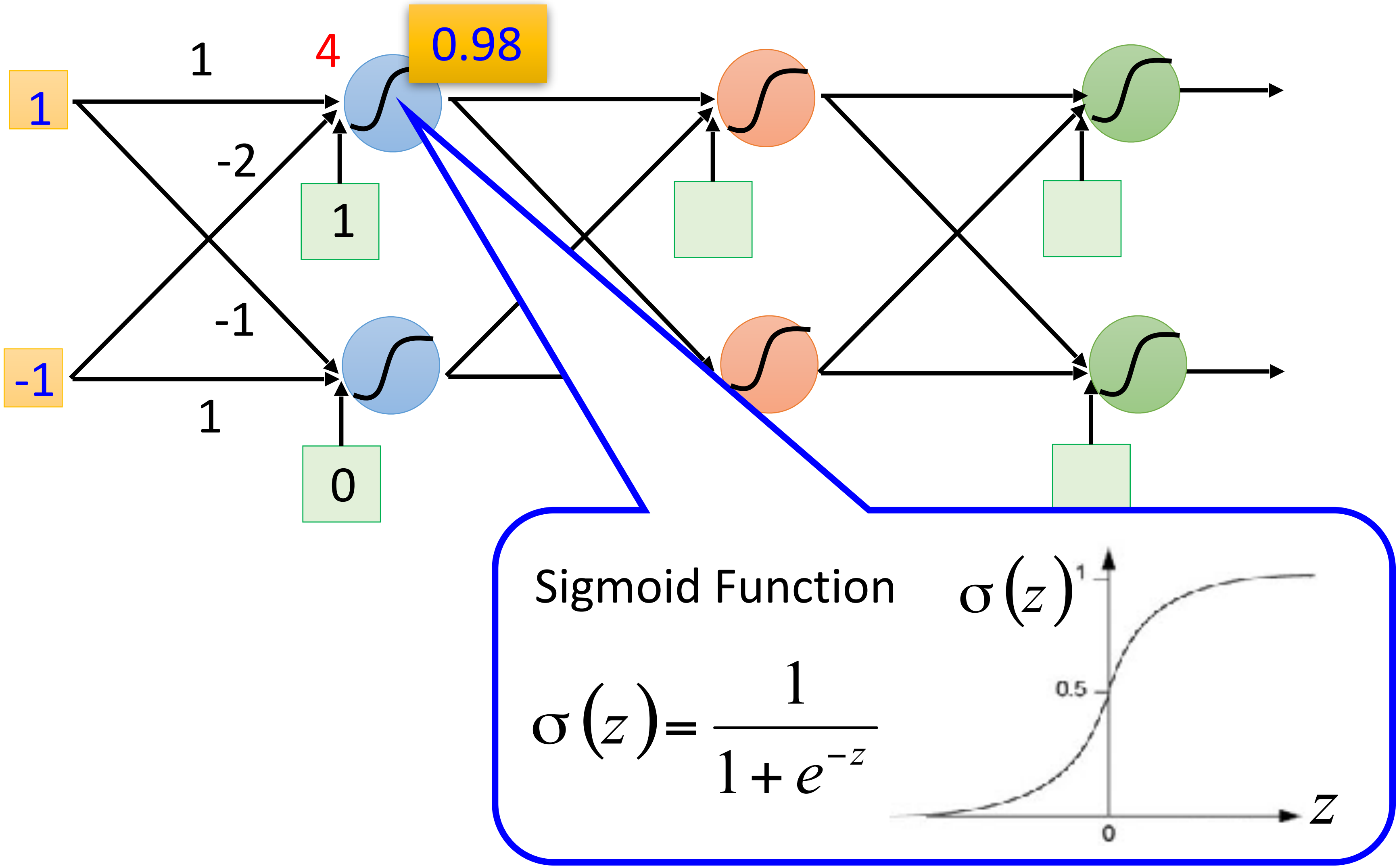


$$\sigma(z) = \frac{1}{1+e^{-z}}$$

Example of Neural Network



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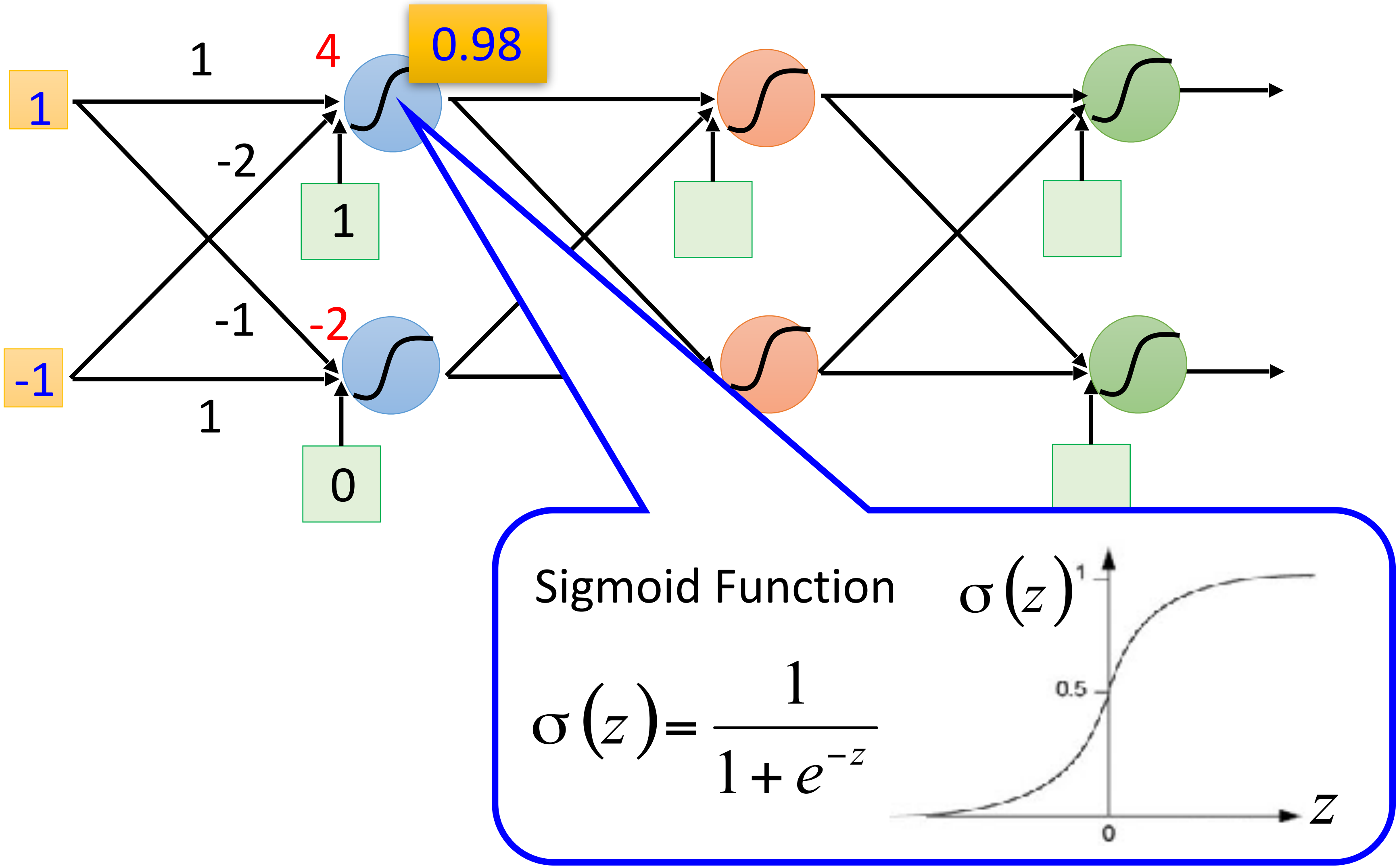

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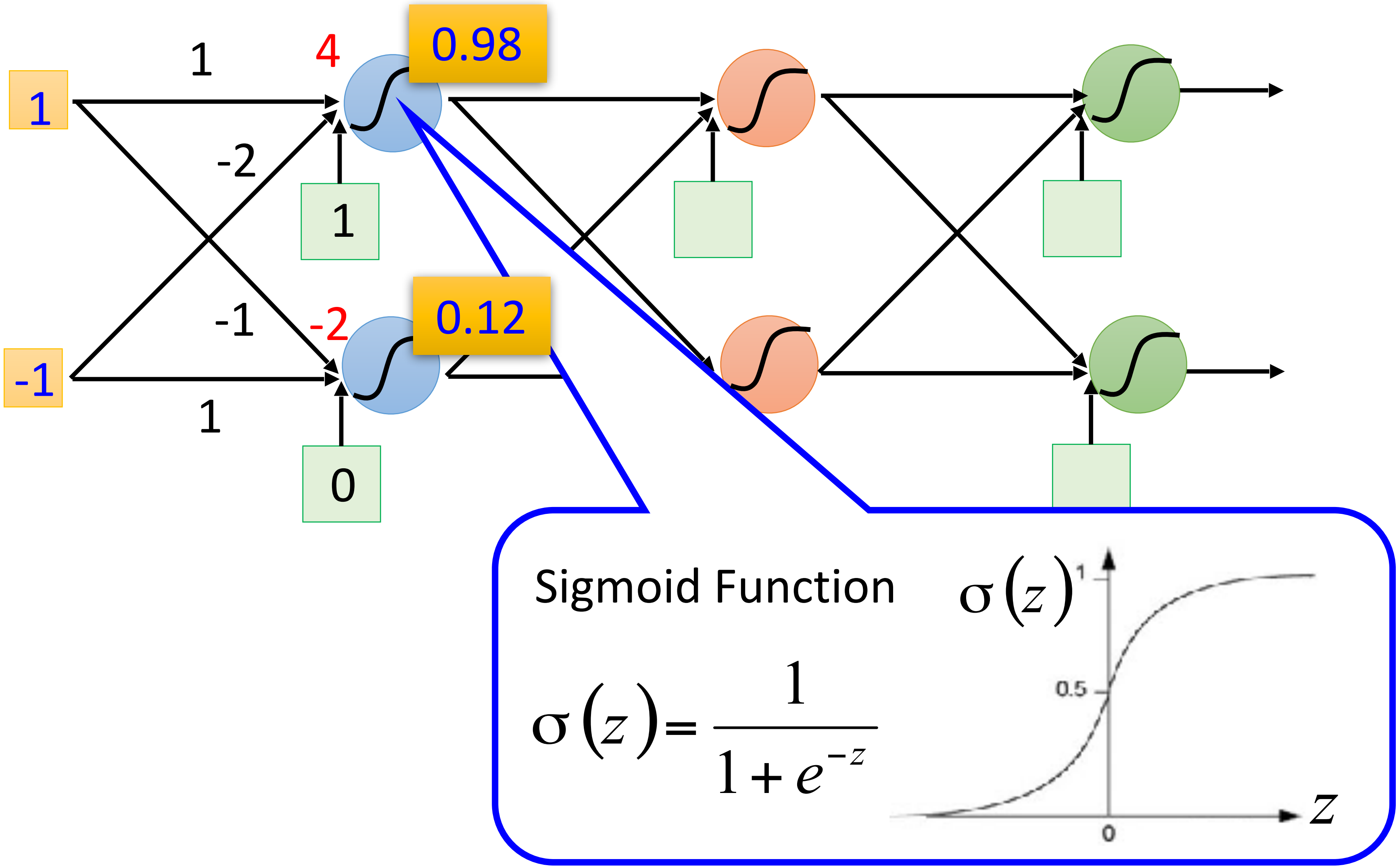

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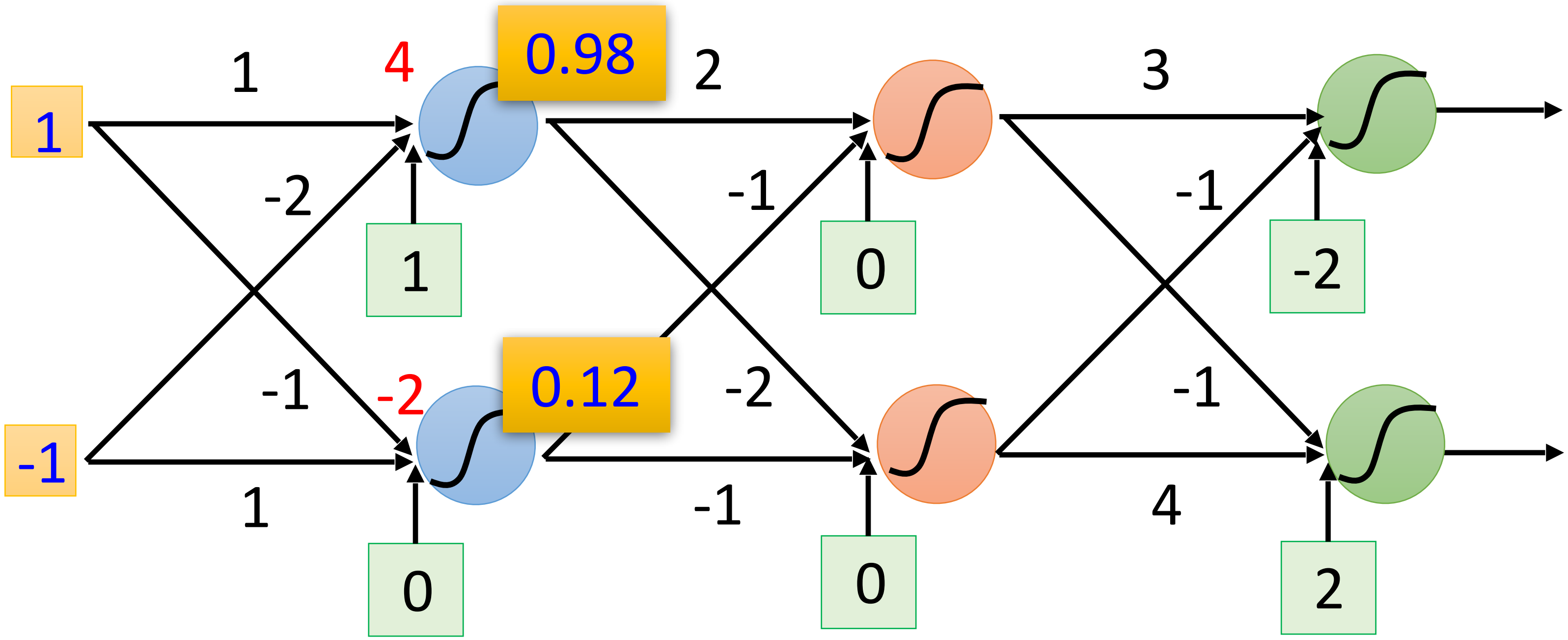

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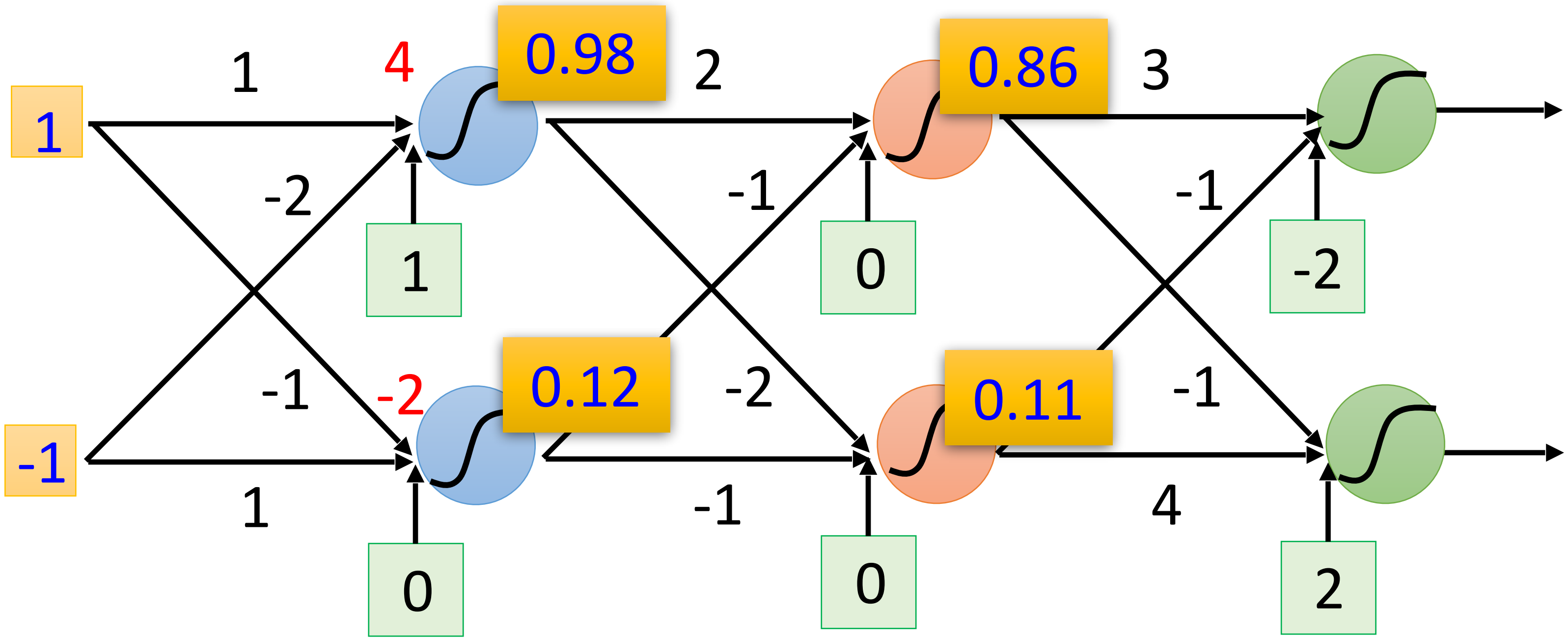

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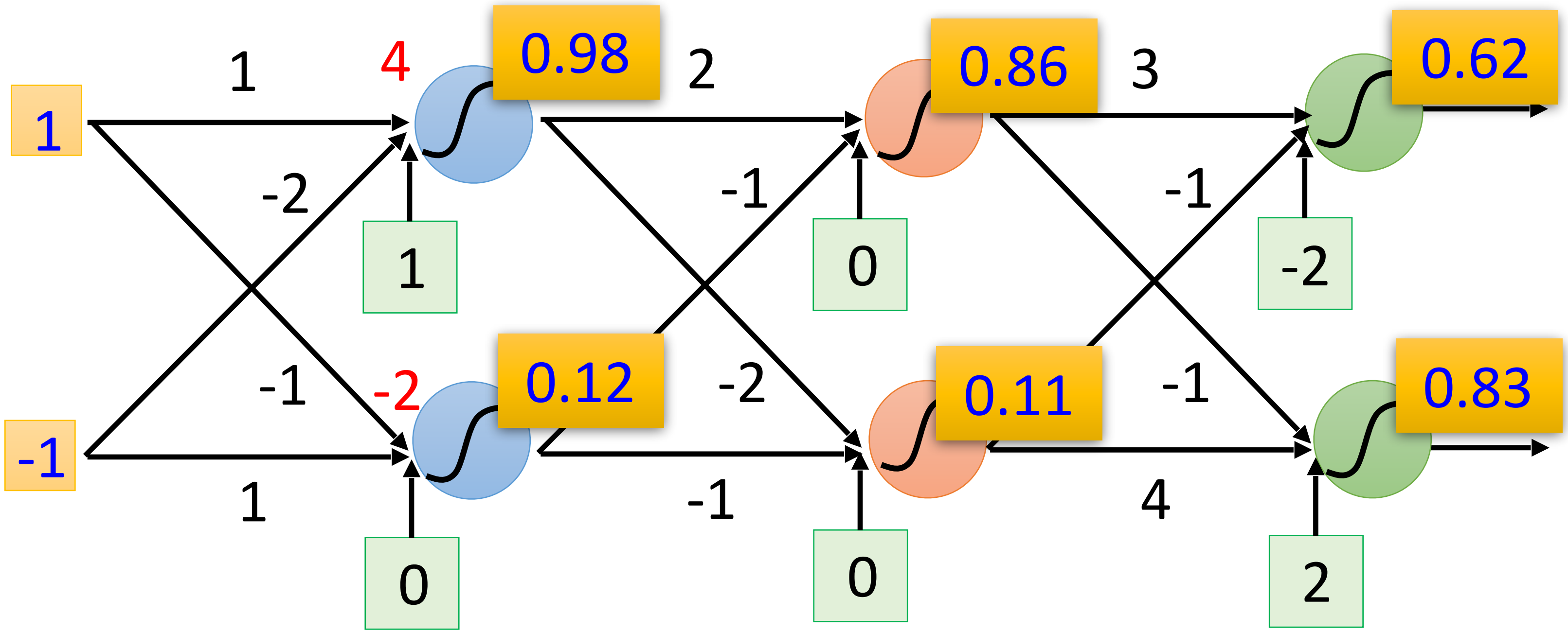

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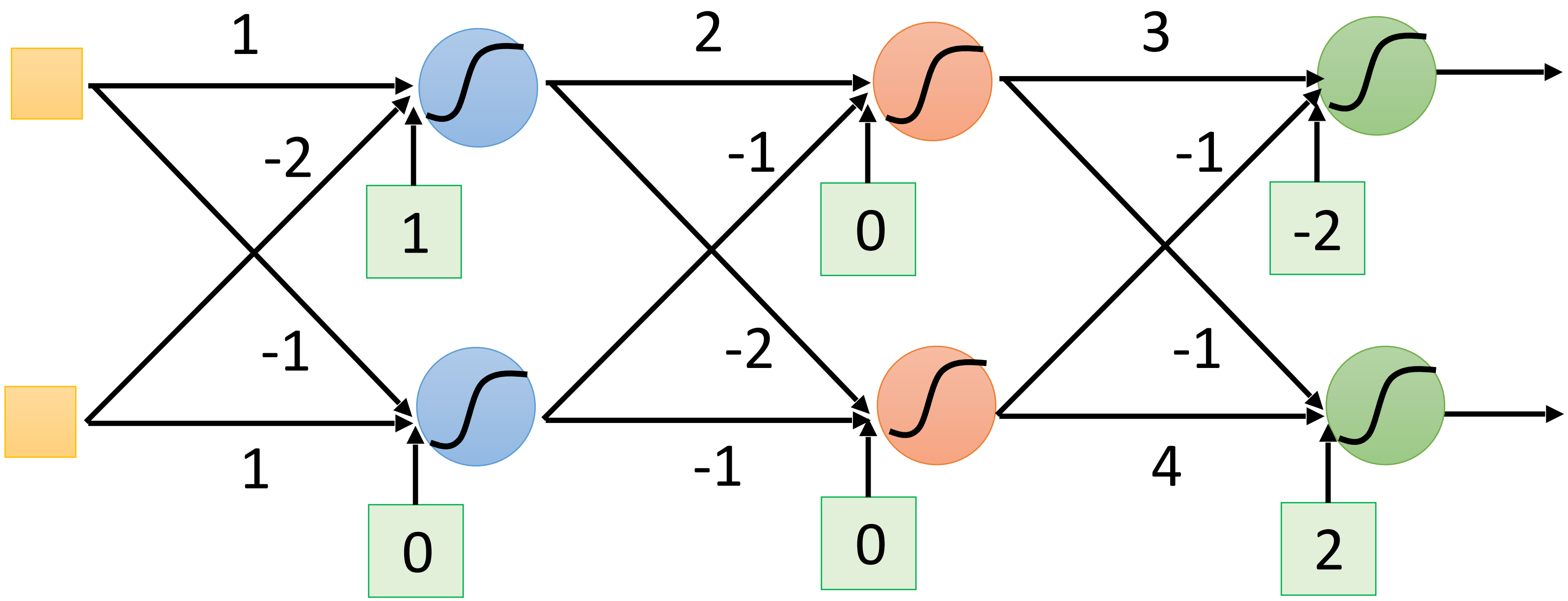

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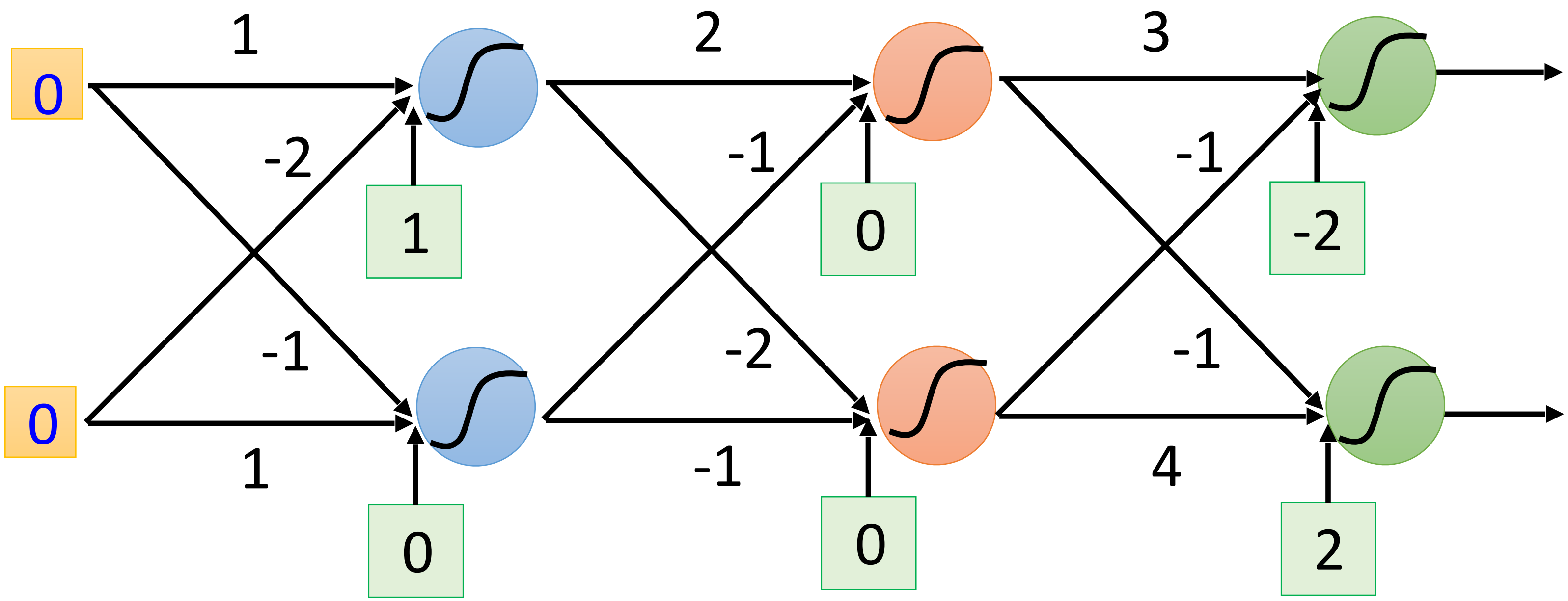

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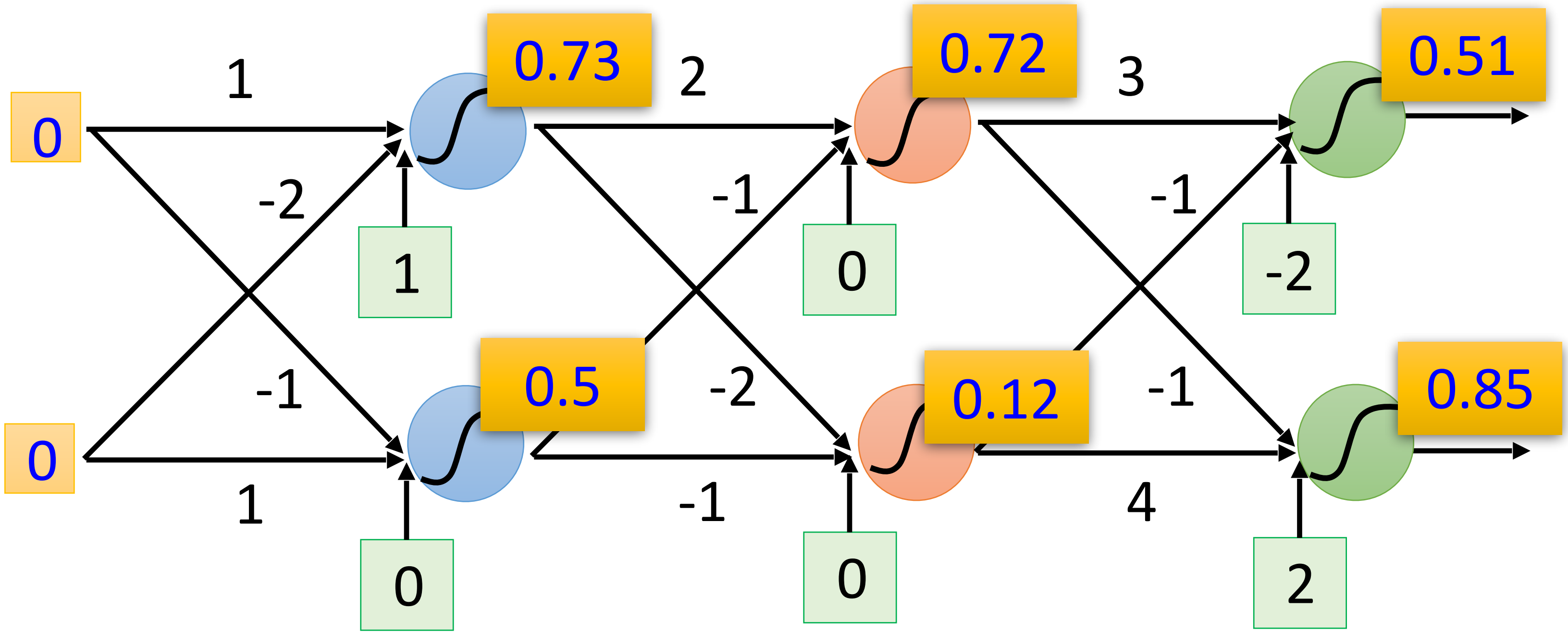

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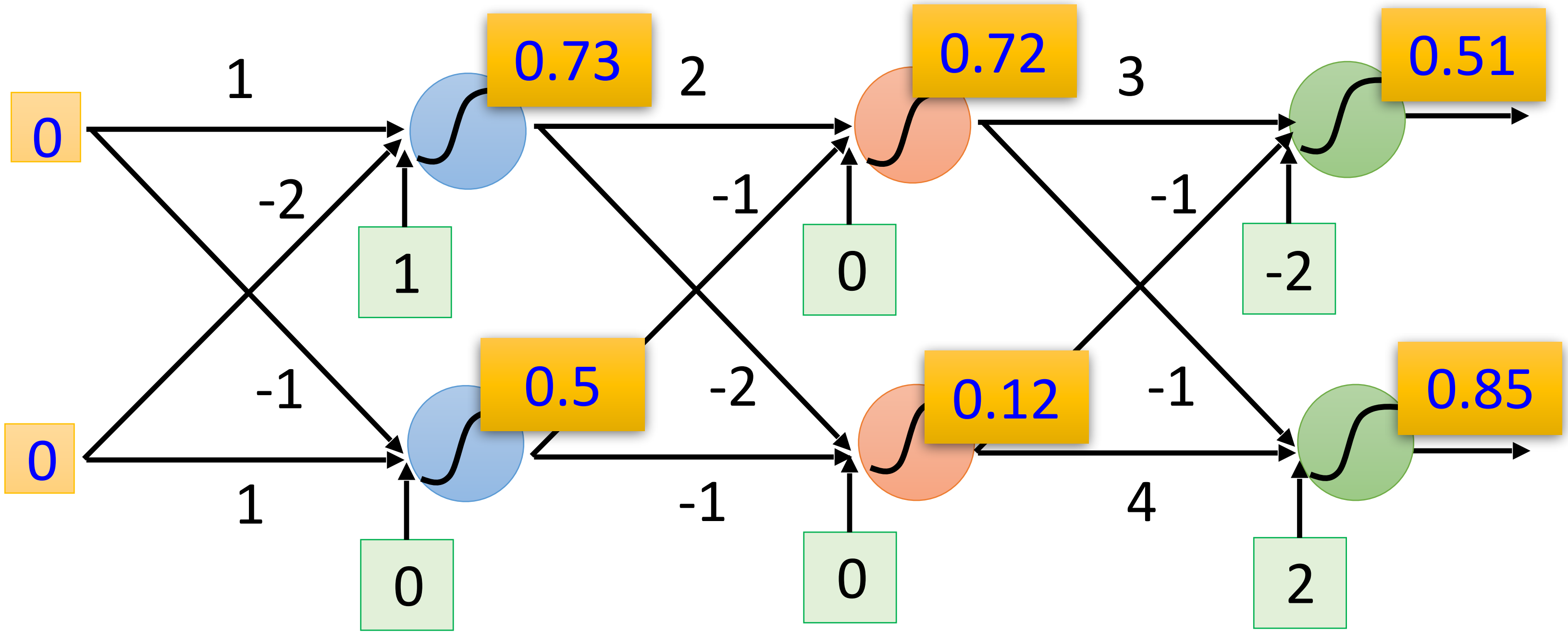
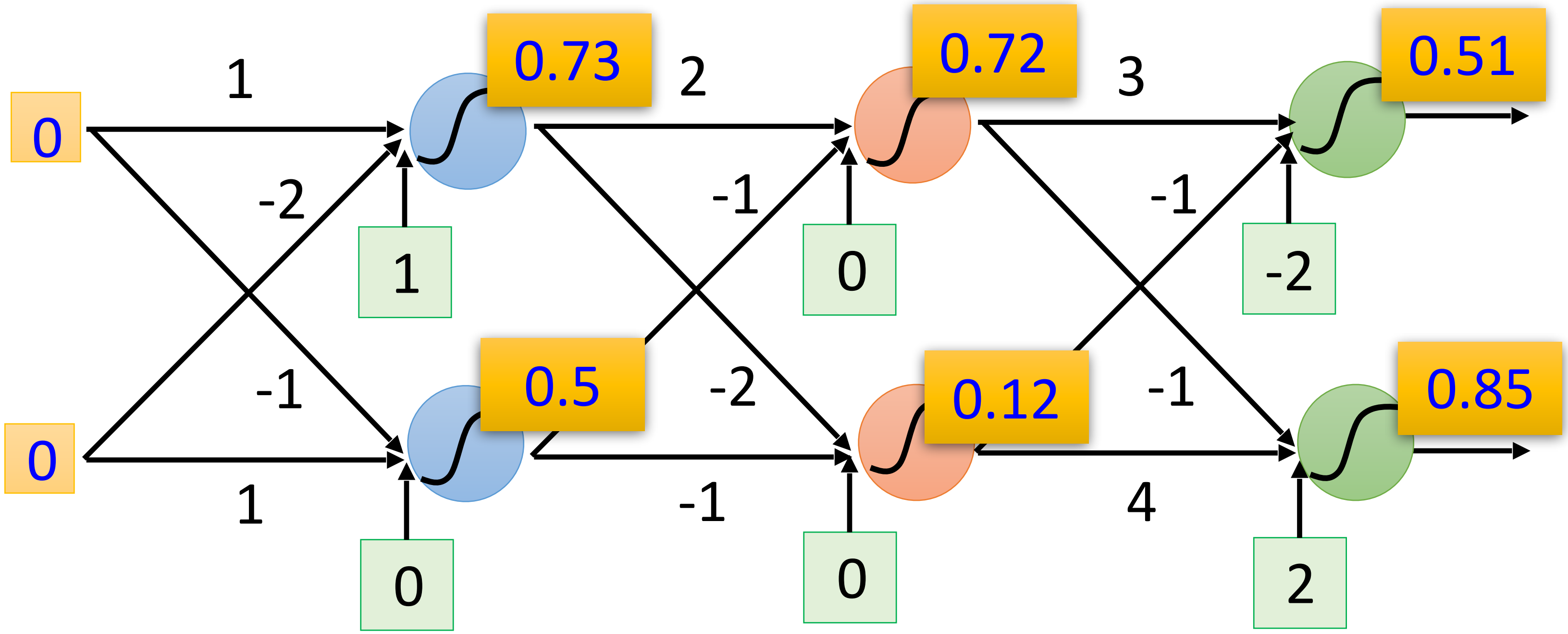


$f: R^2 \to R^2$

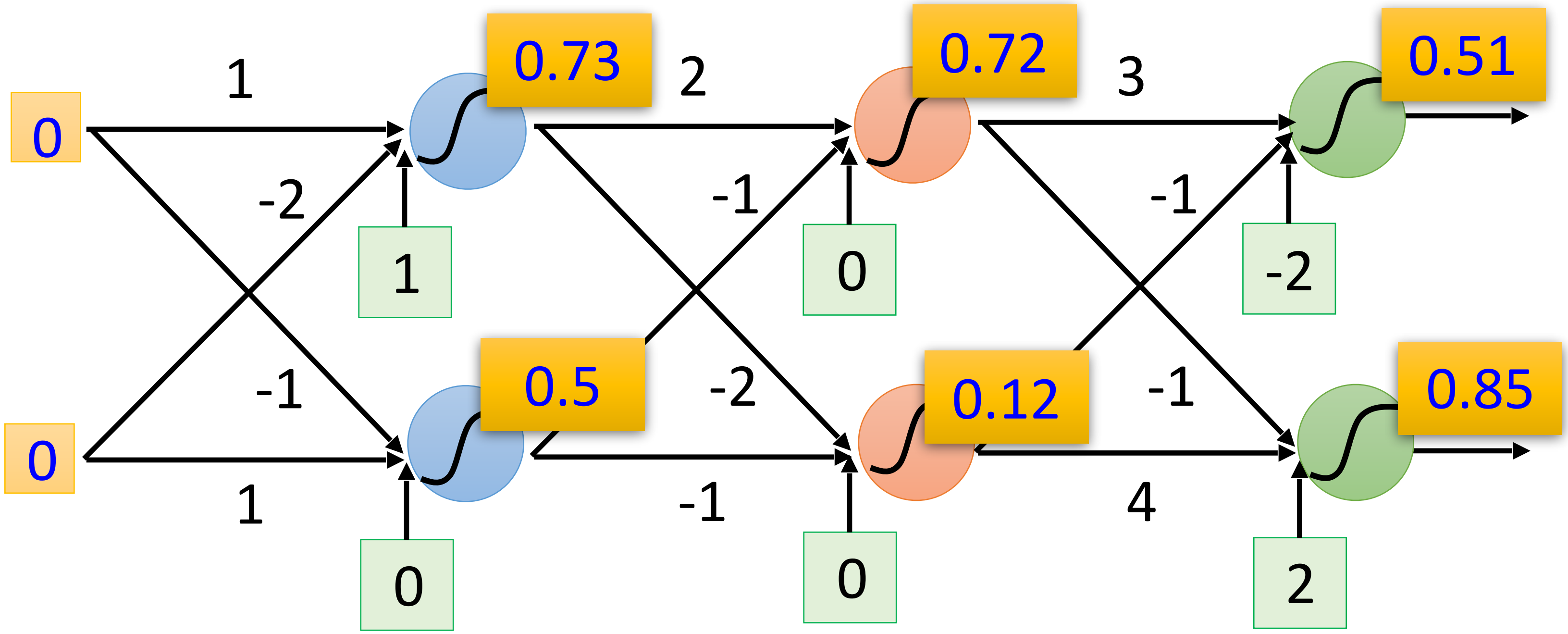
Example of Neural Network



$f: R^2 \to R^2$

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

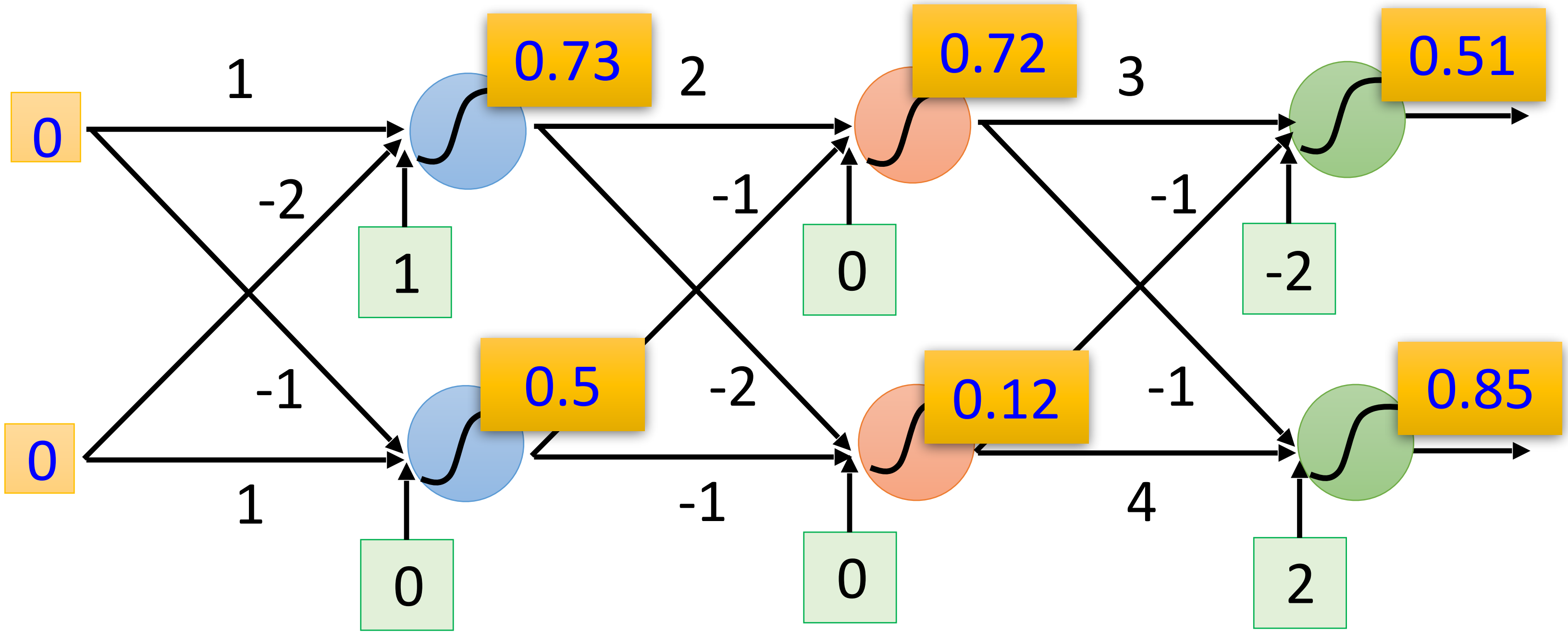
Example of Neural Network



$f: R^2 \rightarrow R^2$

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

Example of Neural Network

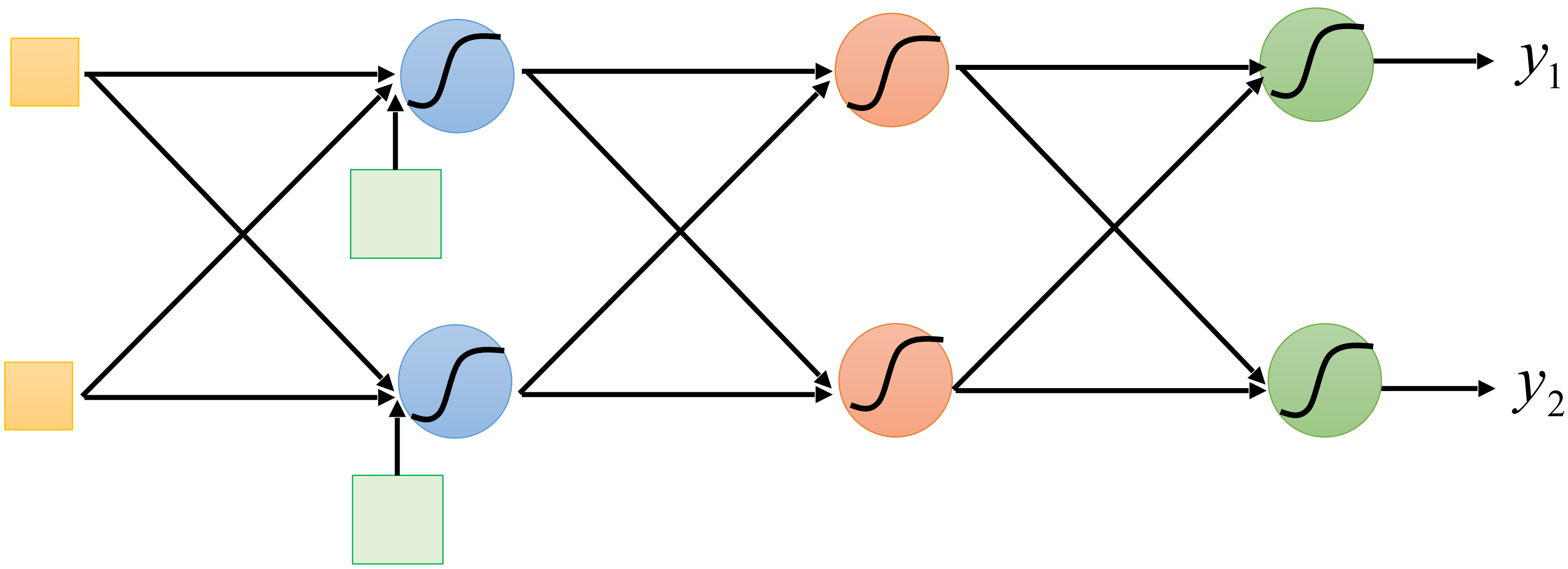


$f: R^2 \to R^2$

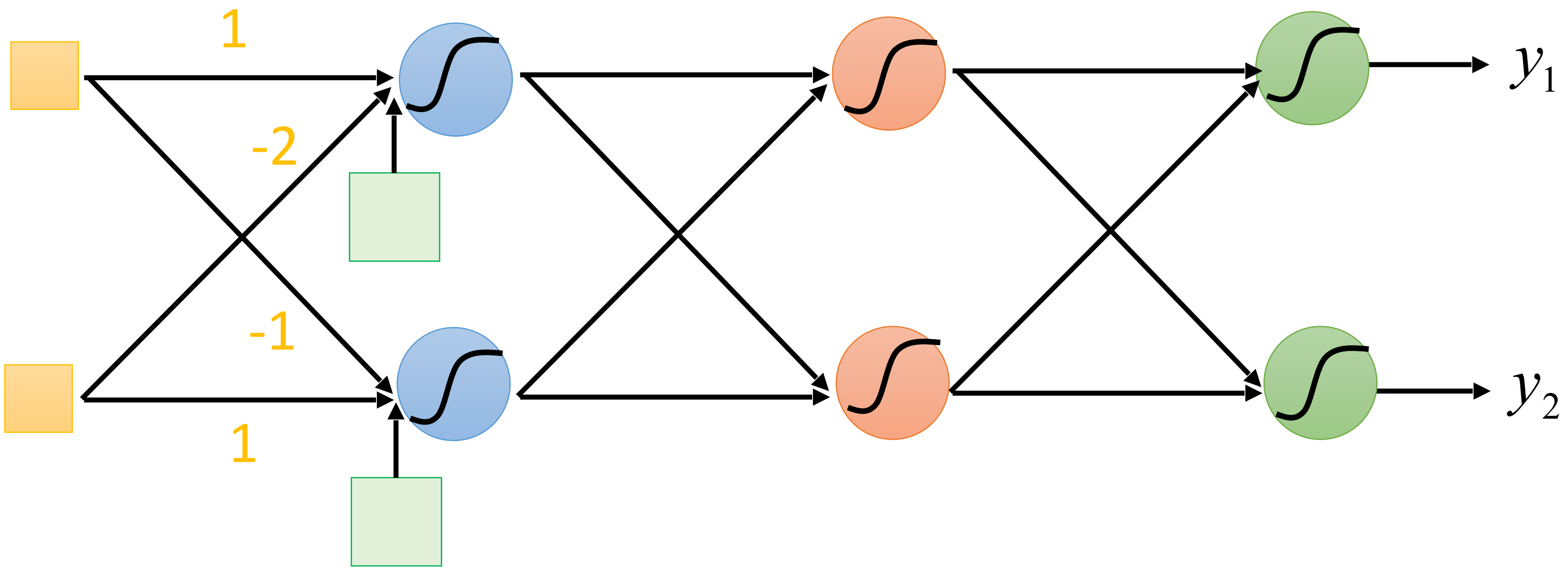
$$f\left(\begin{bmatrix} 1 \\ -1 \end{bmatrix}\right) = \begin{bmatrix} 0.62 \\ 0.83 \end{bmatrix} \quad f\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}\right) = \begin{bmatrix} 0.51 \\ 0.85 \end{bmatrix}$$

Different parameters define different function

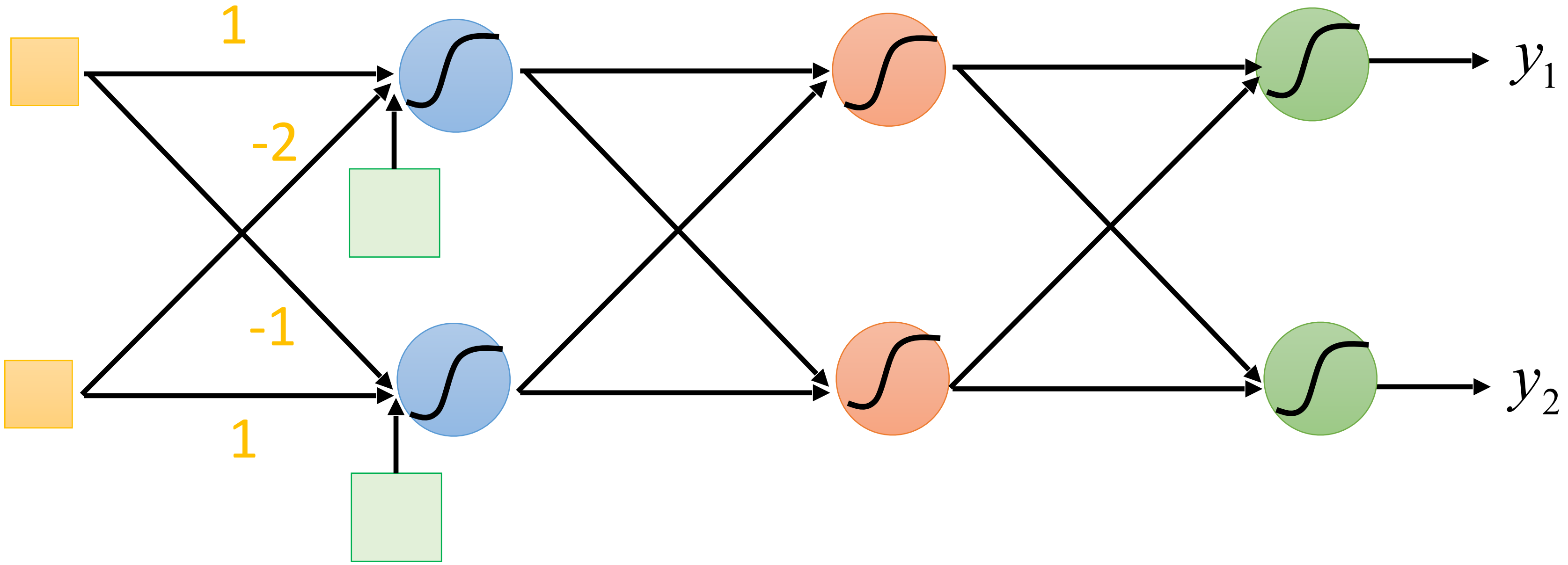
Matrix Operation



Matrix Operation

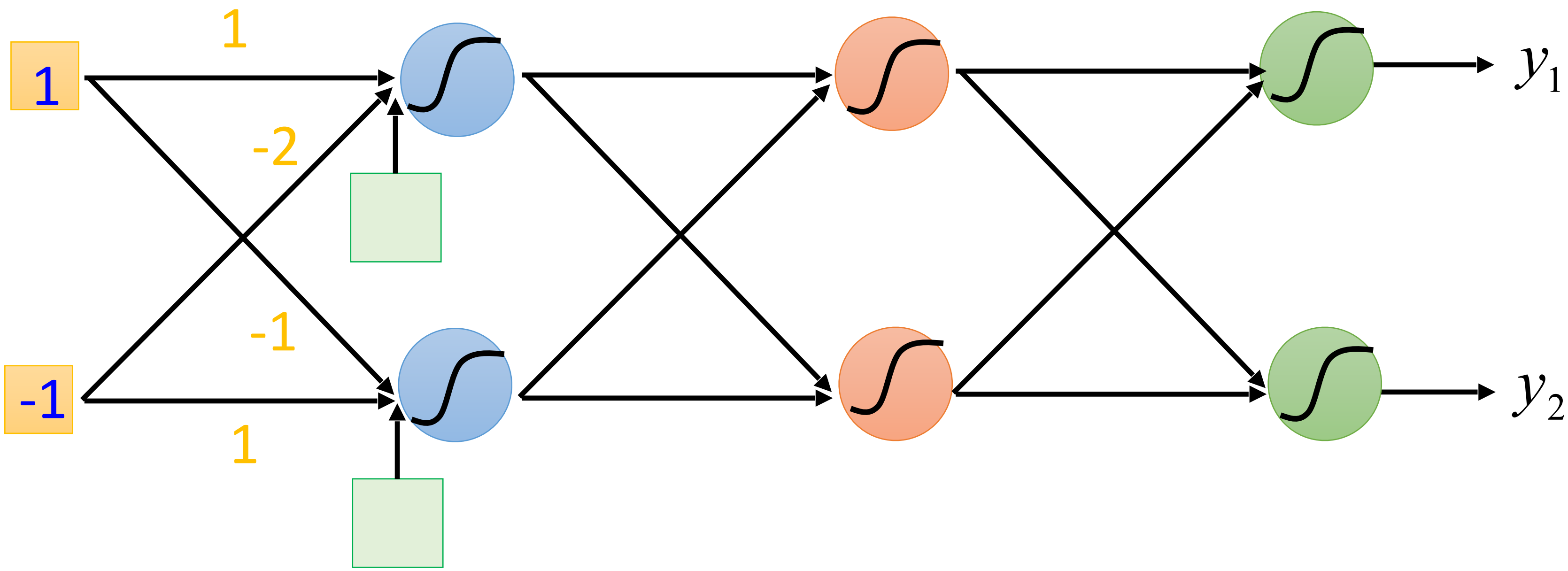


Matrix Operation



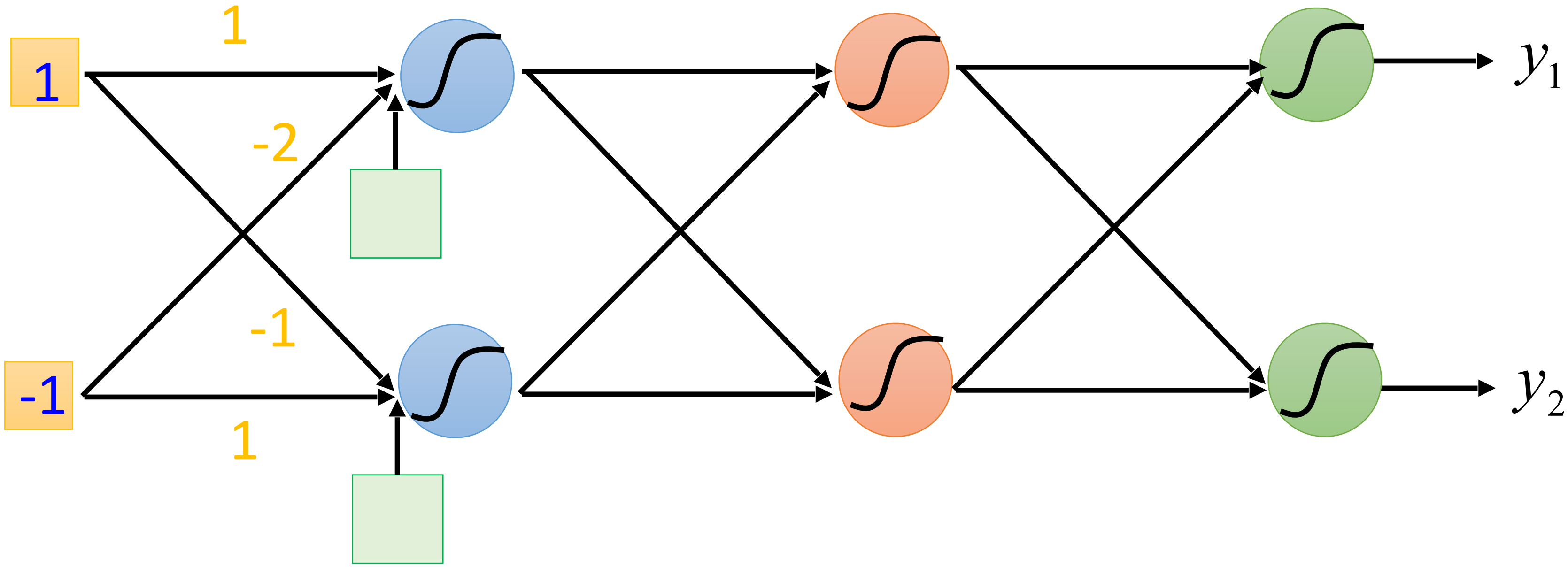
$$\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix}$$

Matrix Operation



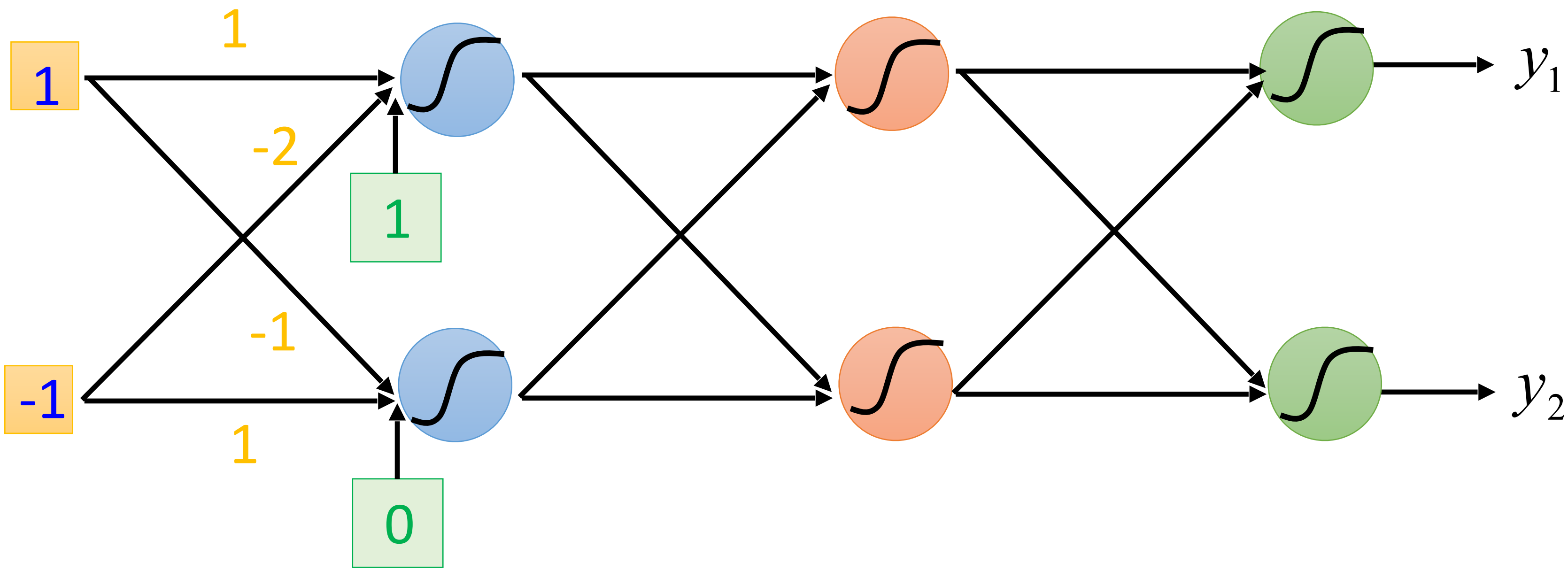
$$\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix}$$

Matrix Operation



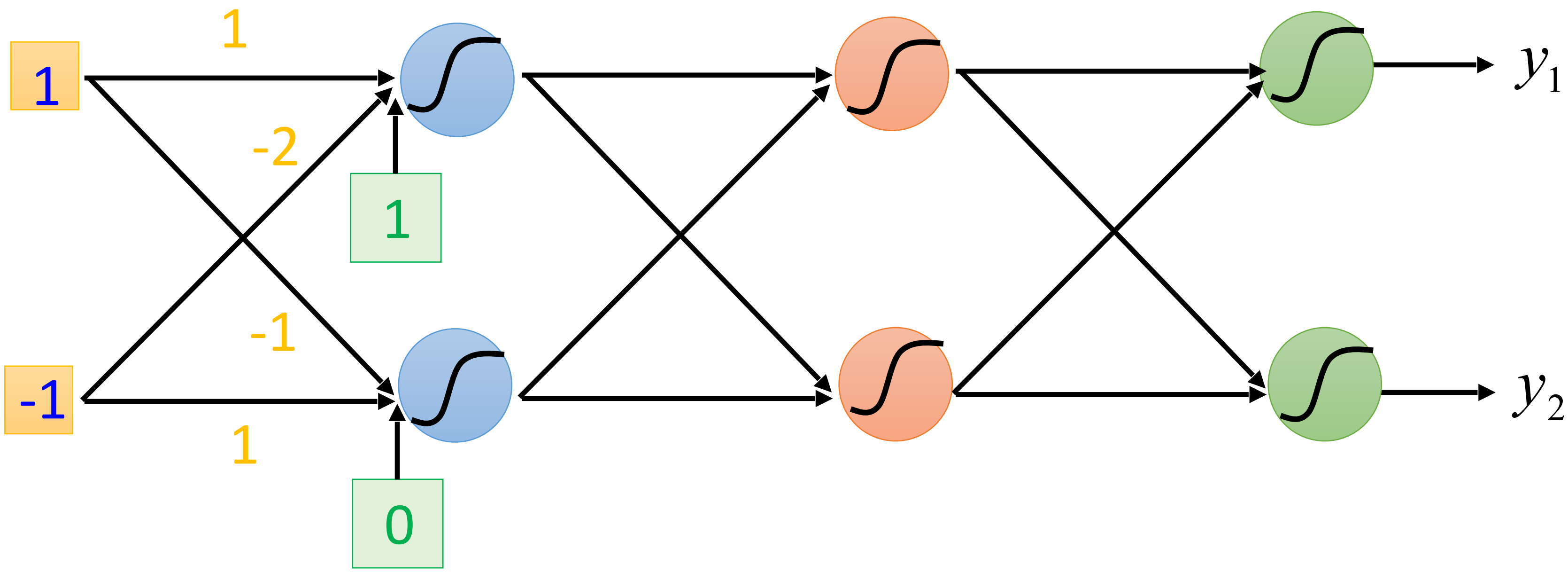
$$\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Matrix Operation



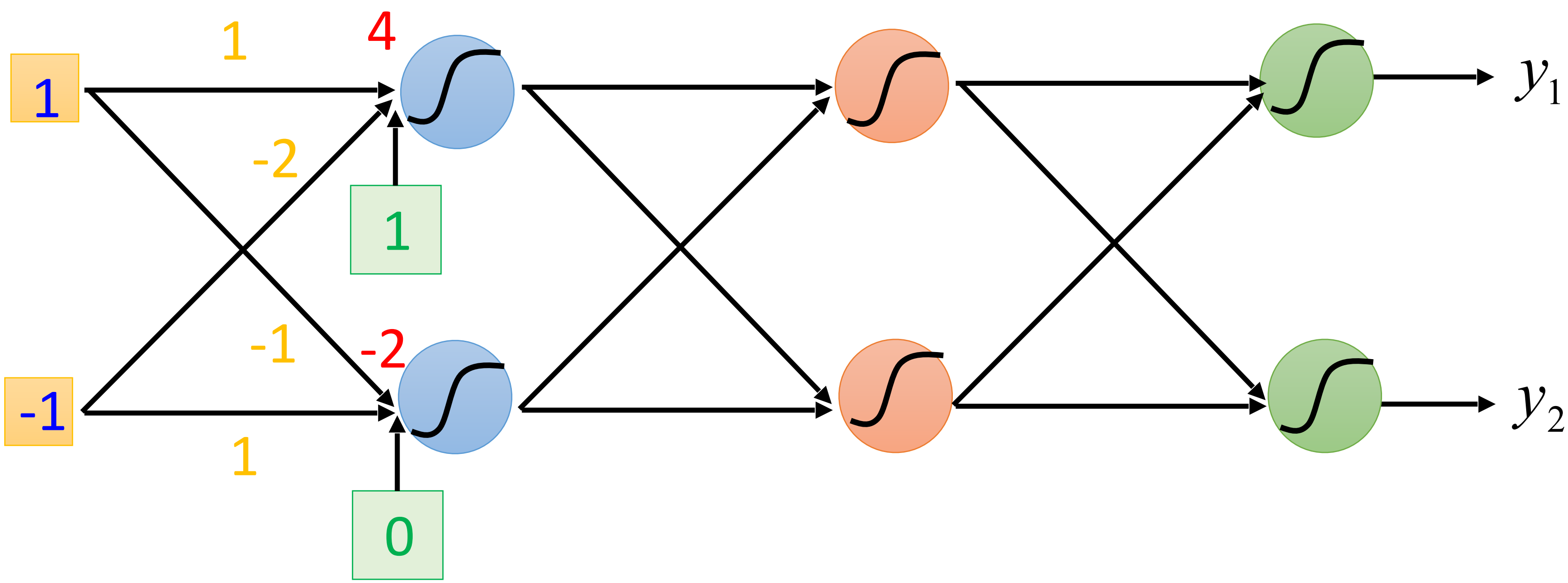
$$\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Matrix Operation



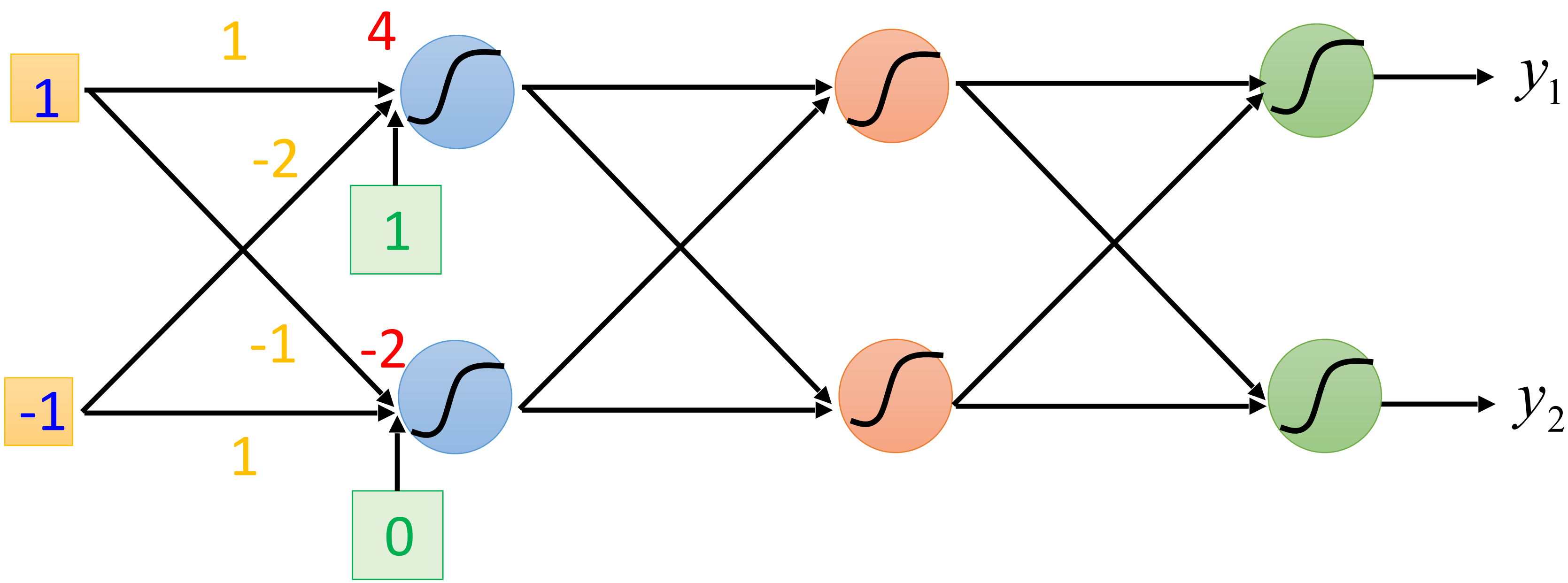
$$\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

Matrix Operation



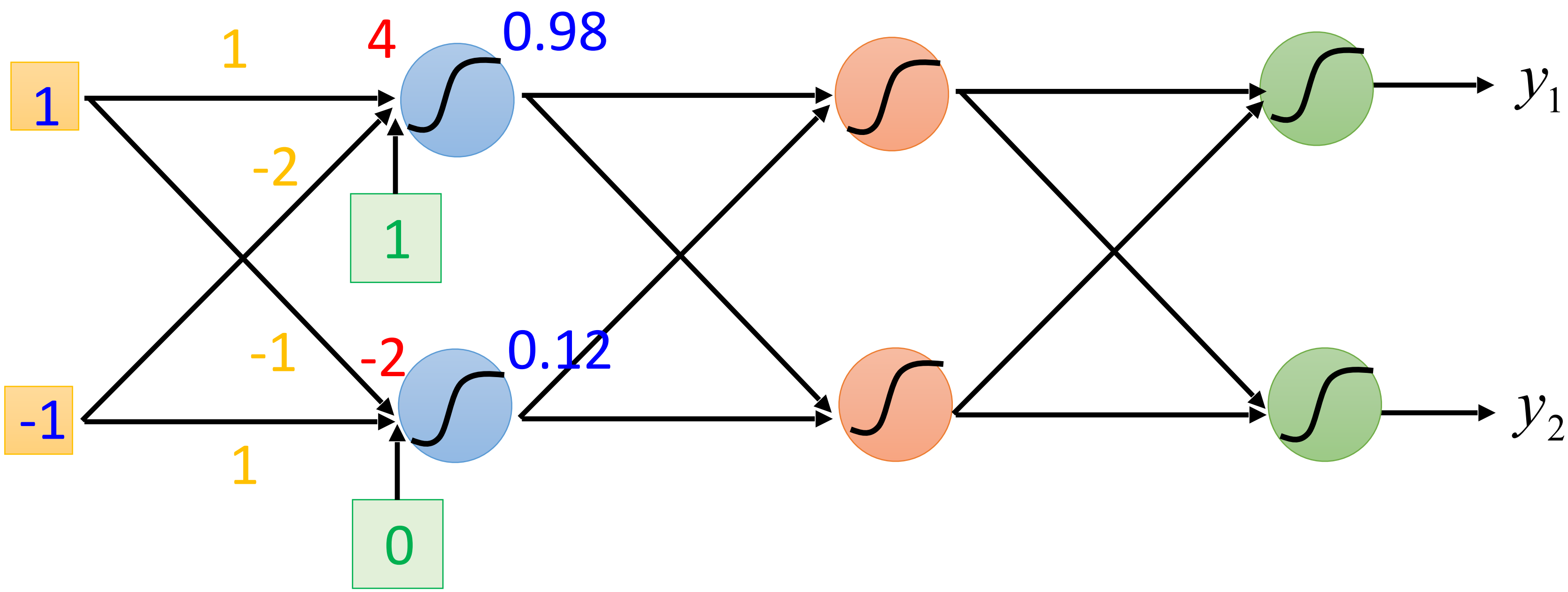
$$\underbrace{\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{\begin{bmatrix} 4 \\ -2 \end{bmatrix}}$$

Matrix Operation



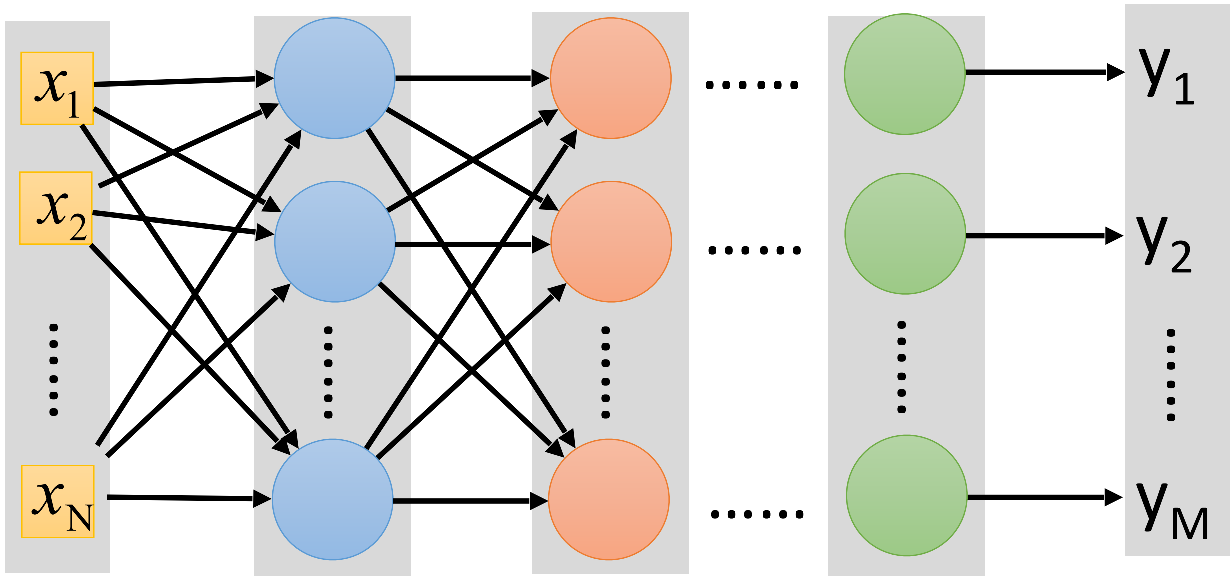
$$\underbrace{\sigma\left(\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right)}_{\begin{bmatrix} 4 \\ -2 \end{bmatrix}}$$

Matrix Operation

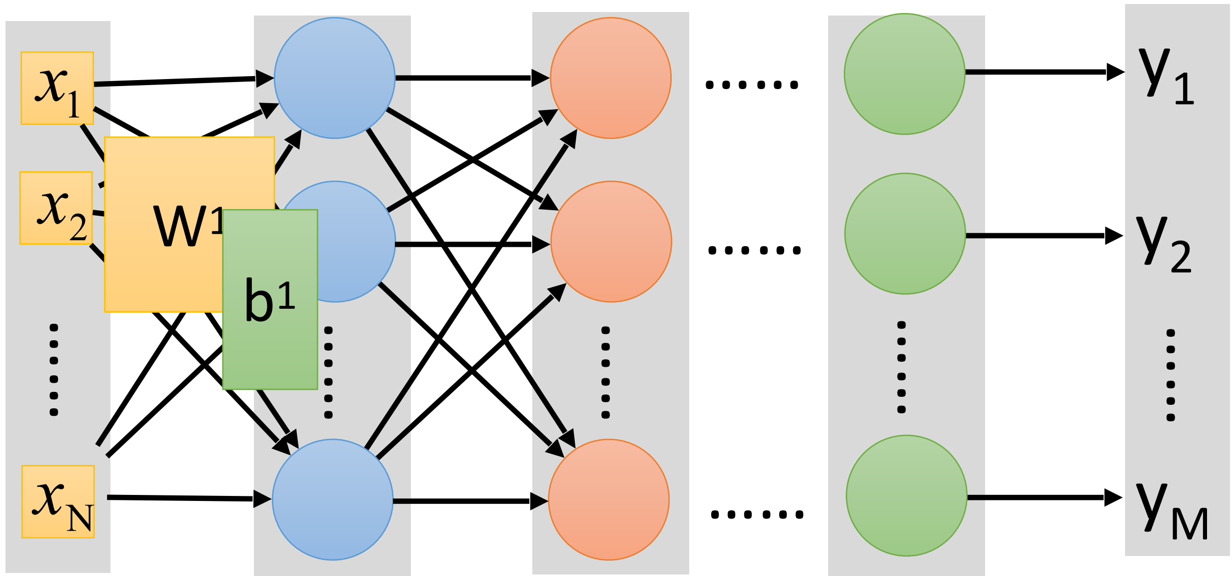


$$\sigma\left(\underbrace{\begin{bmatrix}1 & -2\\ -1 & 1\end{bmatrix}\begin{bmatrix}1\\ -1\end{bmatrix}+\begin{bmatrix}1\\ 0\end{bmatrix}}_{\begin{bmatrix}4\\ -2\end{bmatrix}}\right)=\begin{bmatrix}0.98\\ 0.12\end{bmatrix}$$

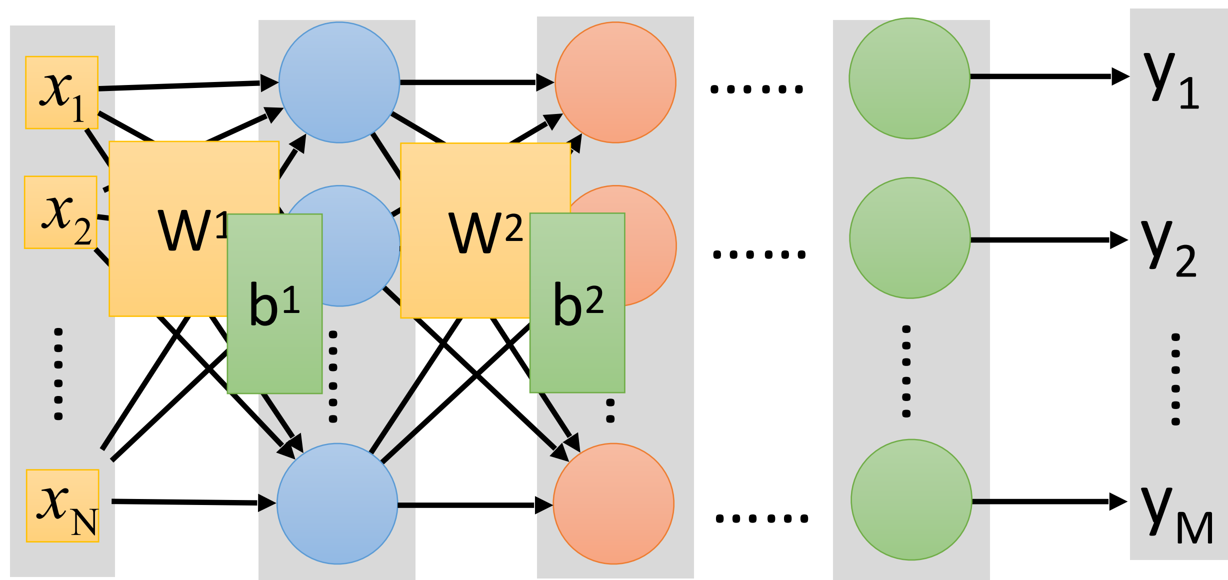
Neural Network



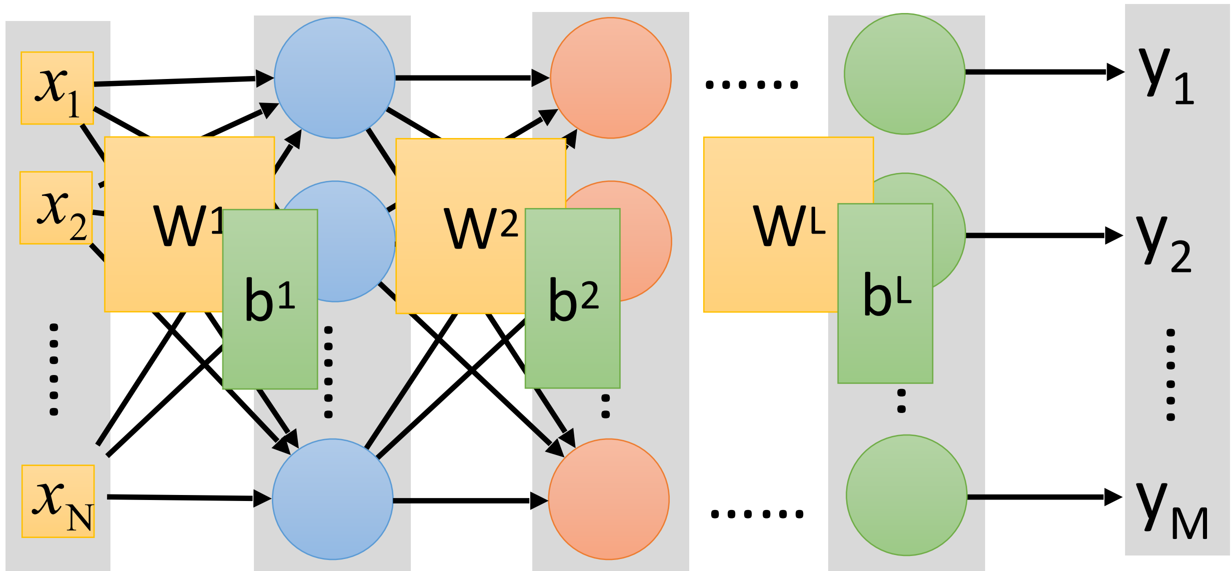
Neural Network



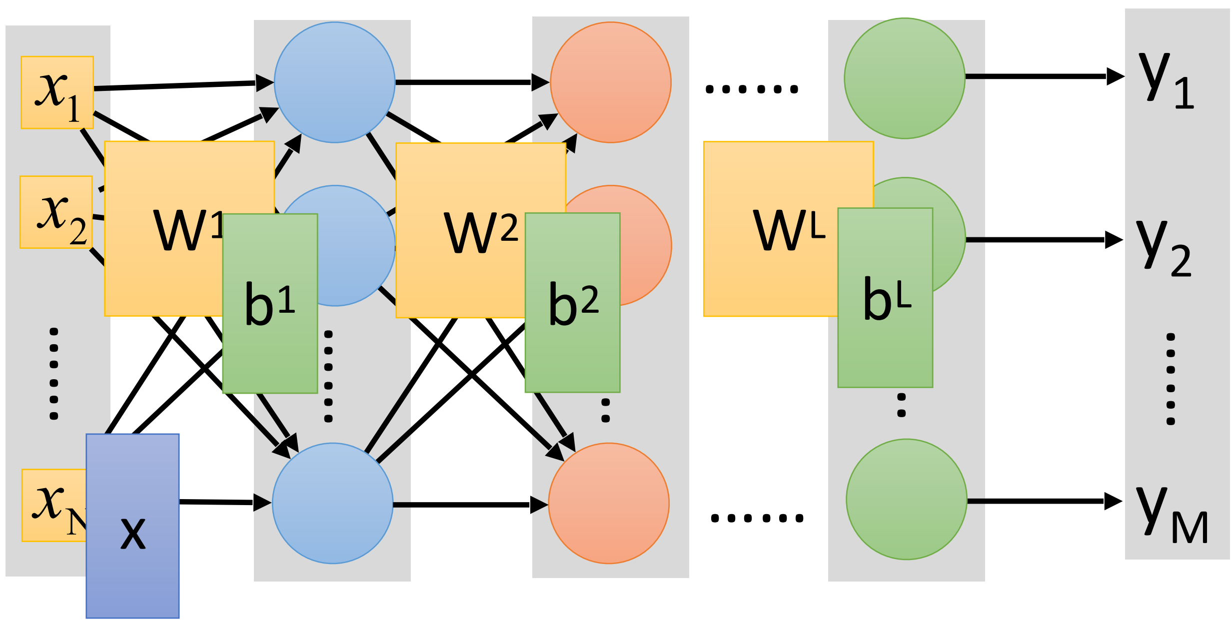
Neural Network



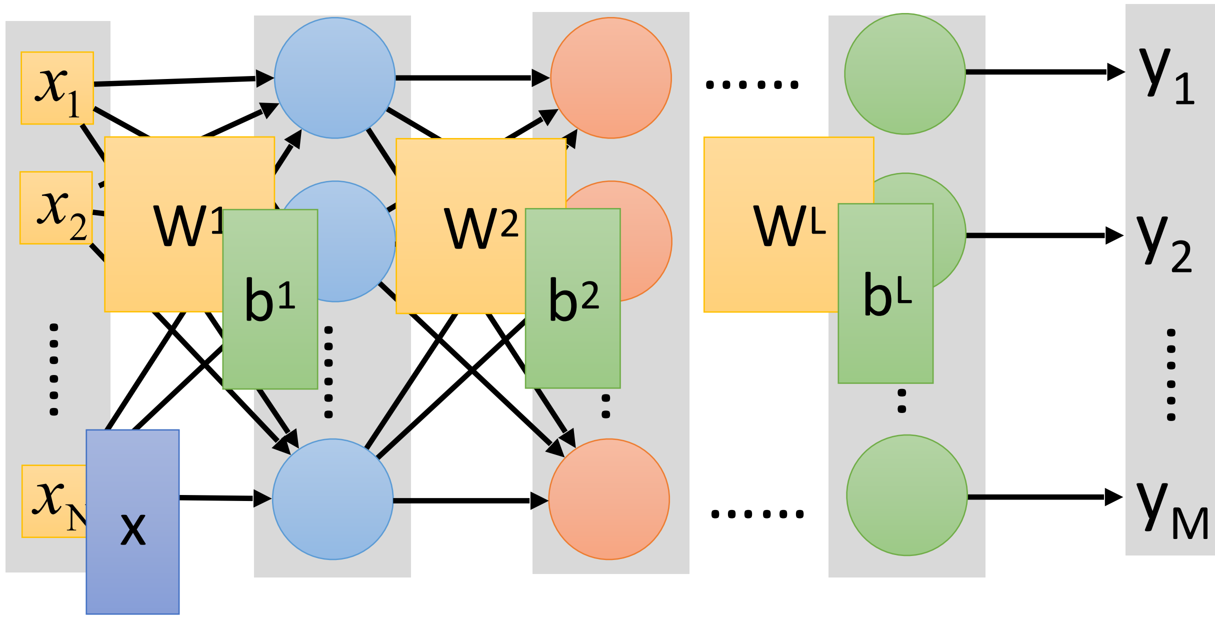
Neural Network



Neural Network

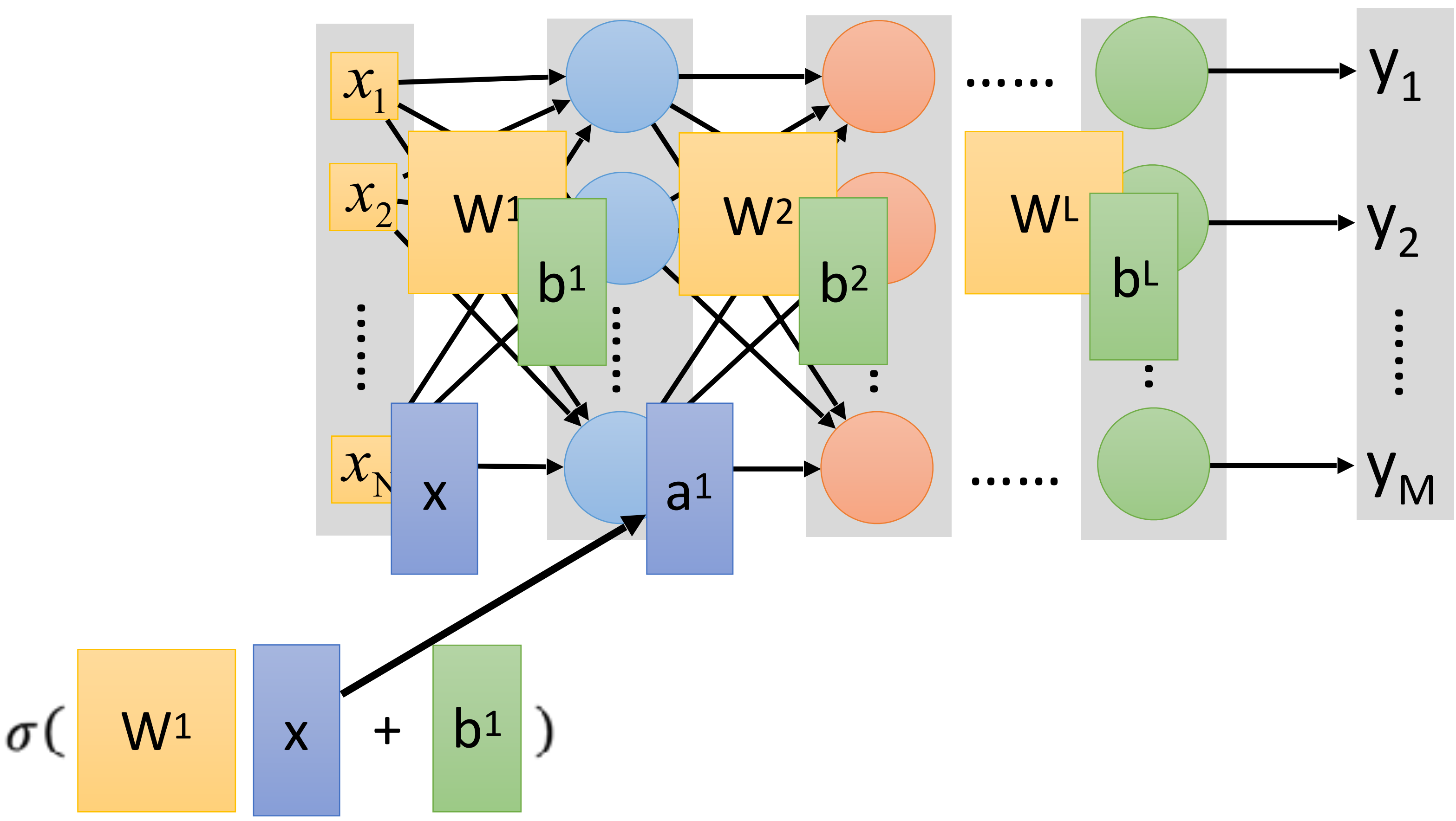


Neural Network

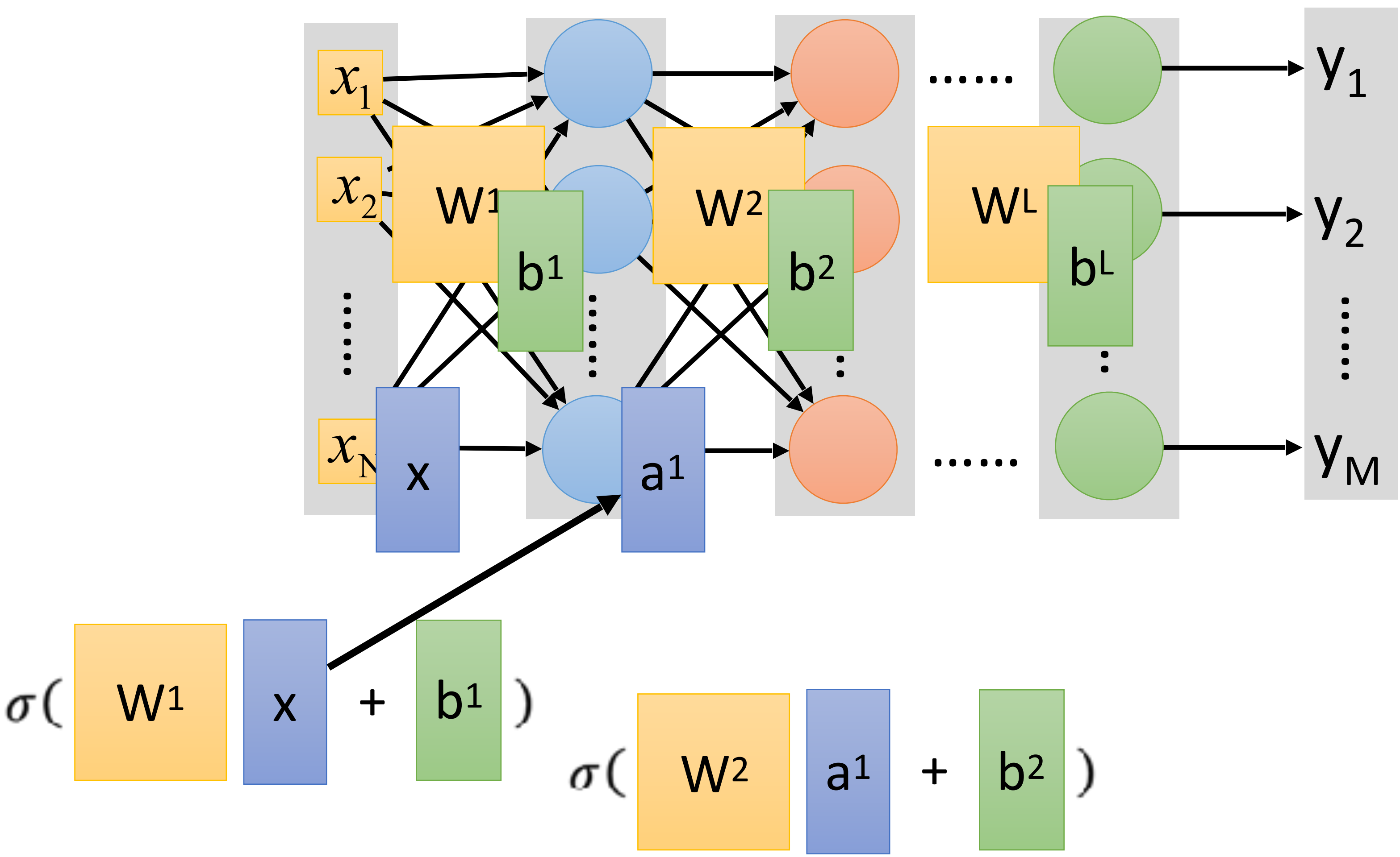


$$\sigma(W^1 \; x + b^1)$$

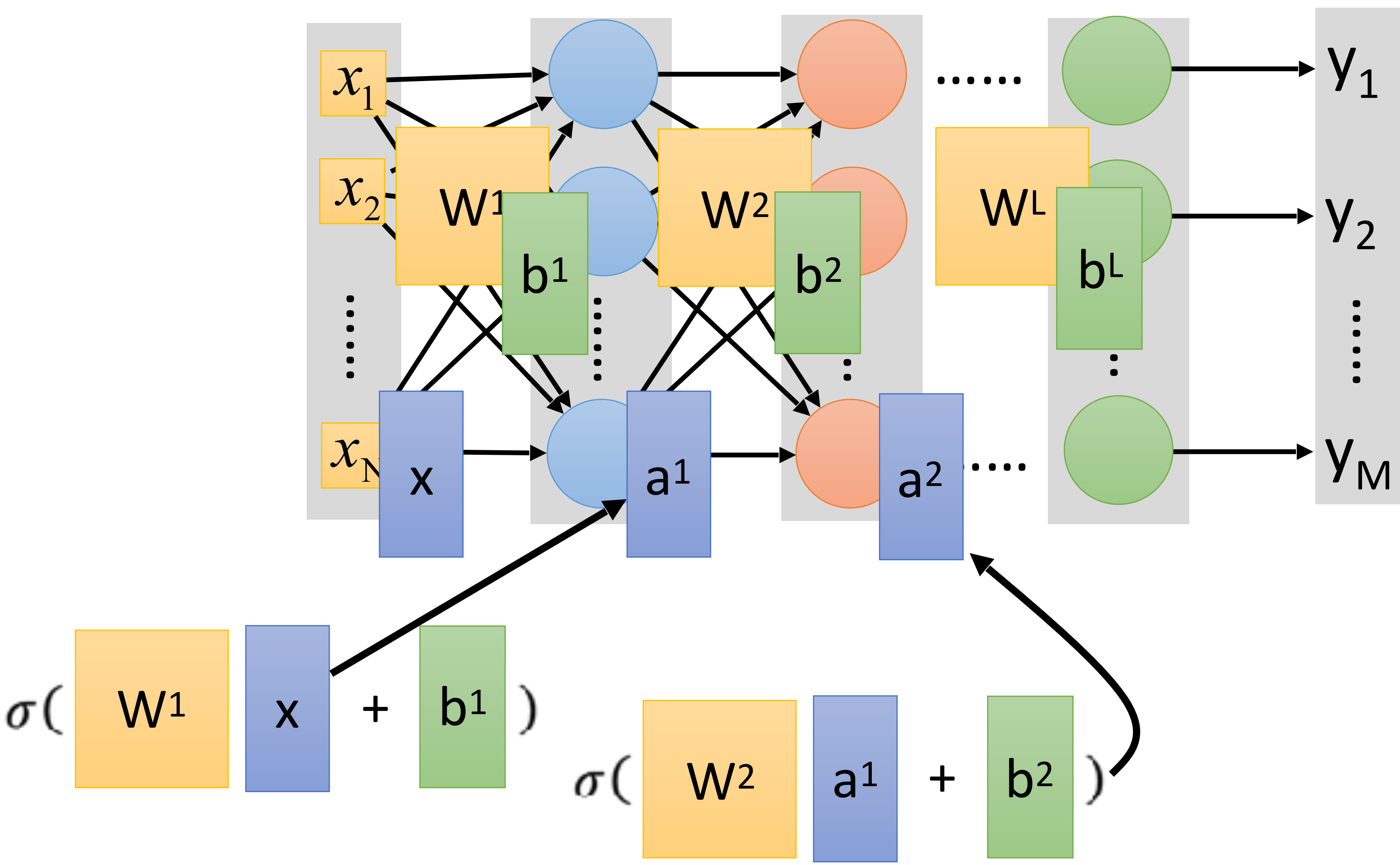
Neural Network



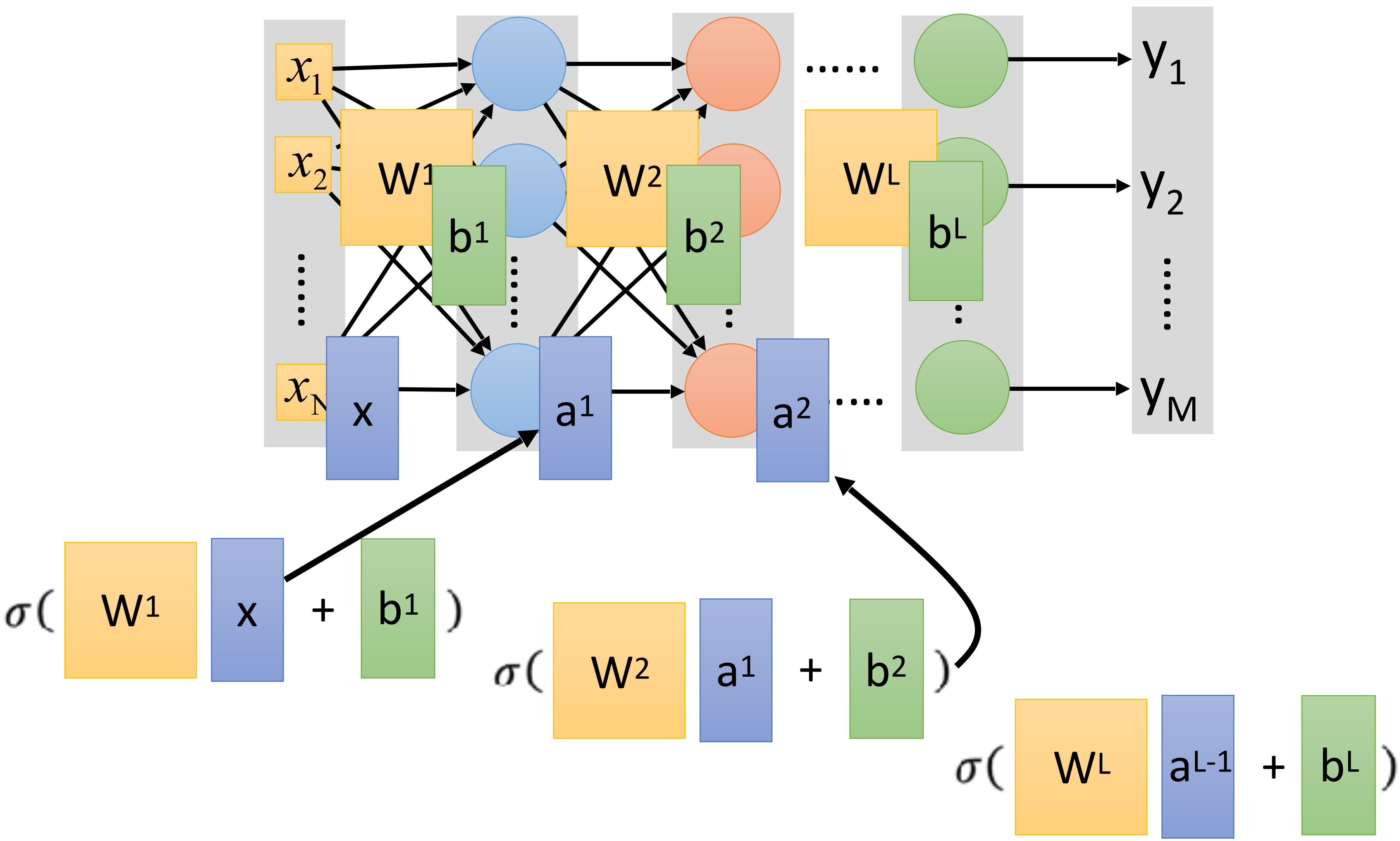
Neural Network



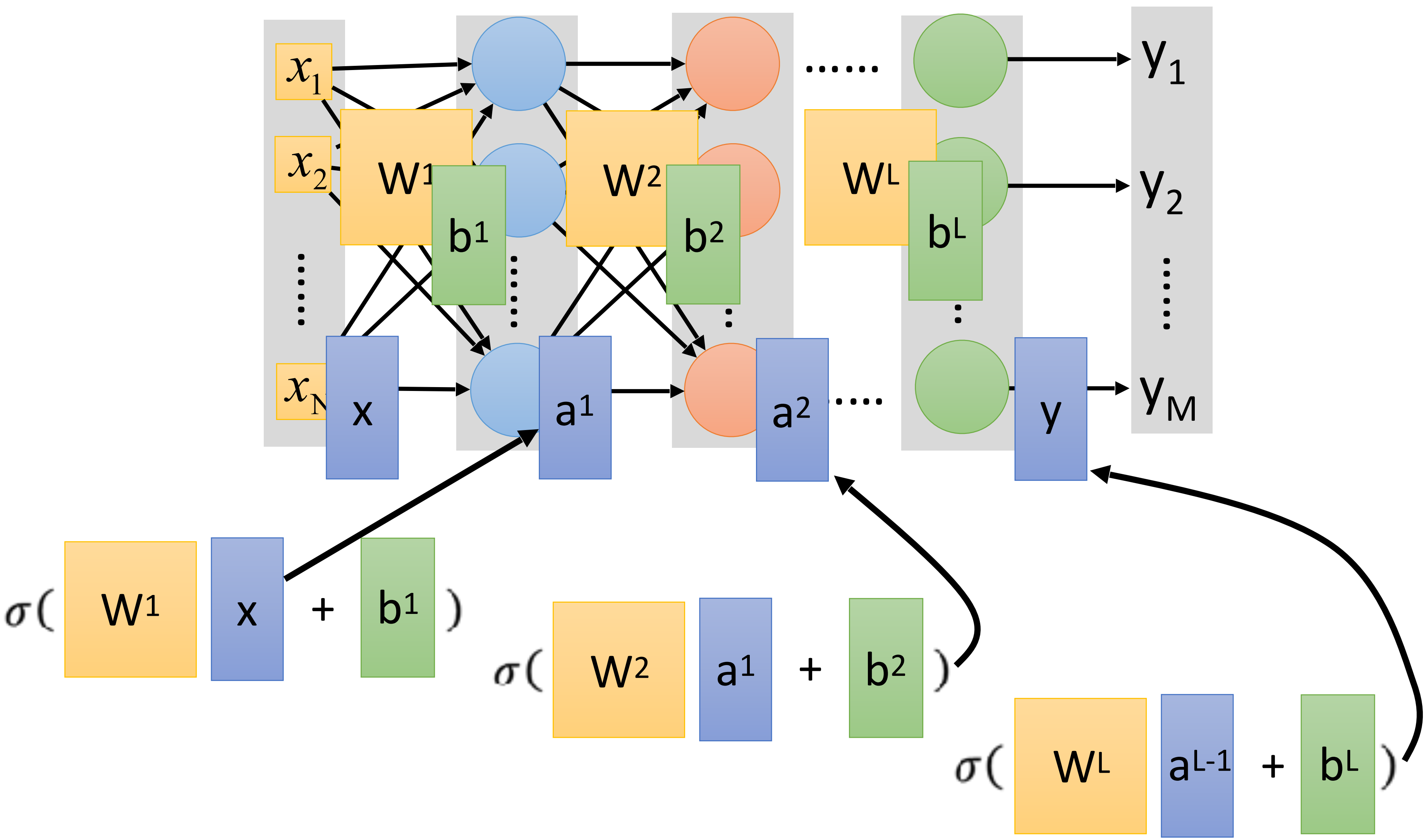
Neural Network



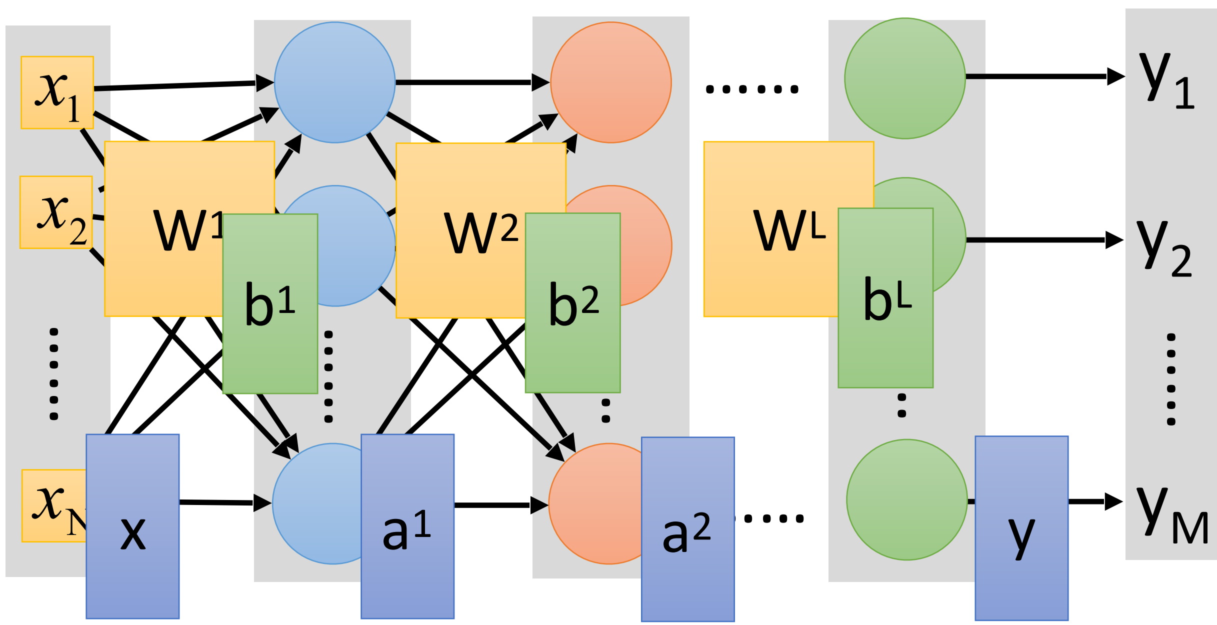
Neural Network



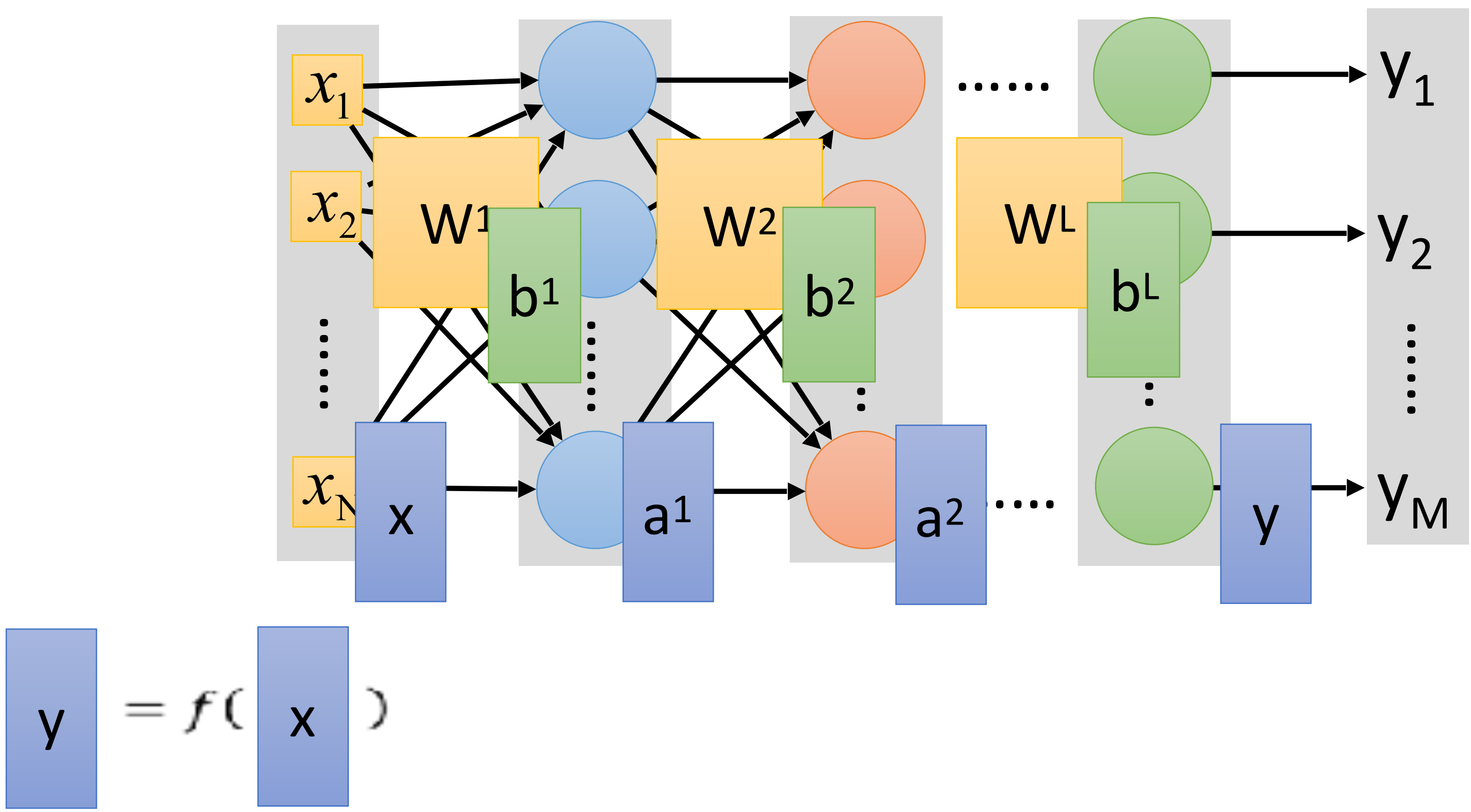
Neural Network



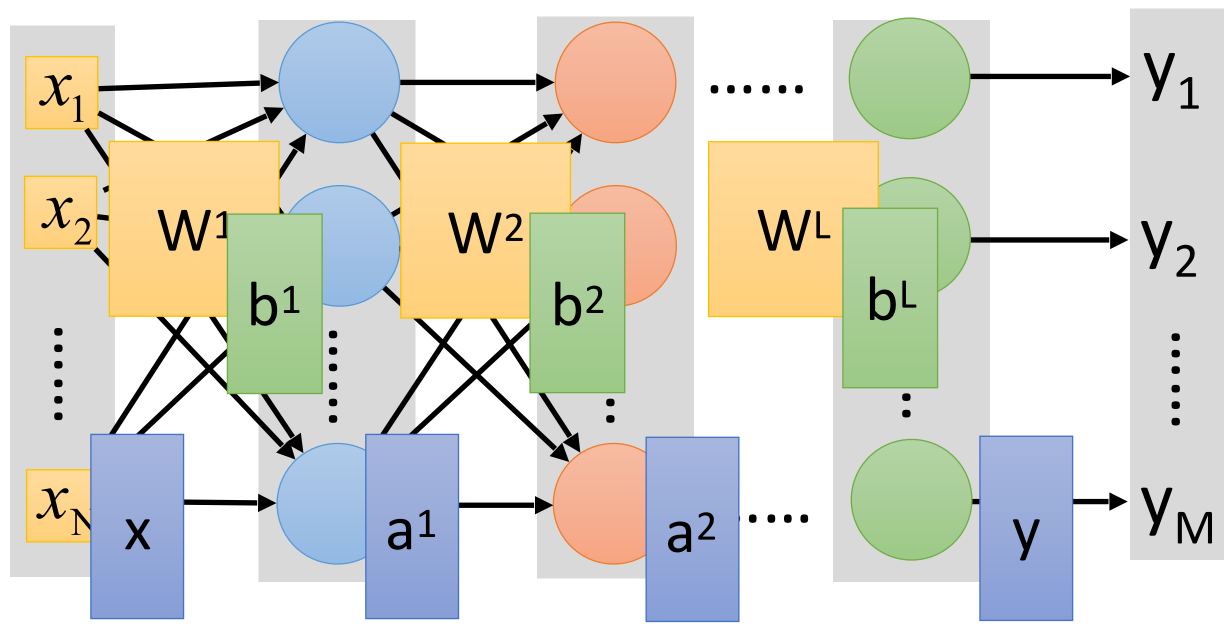
Neural Network



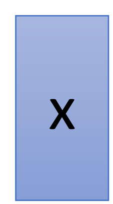
Neural Network



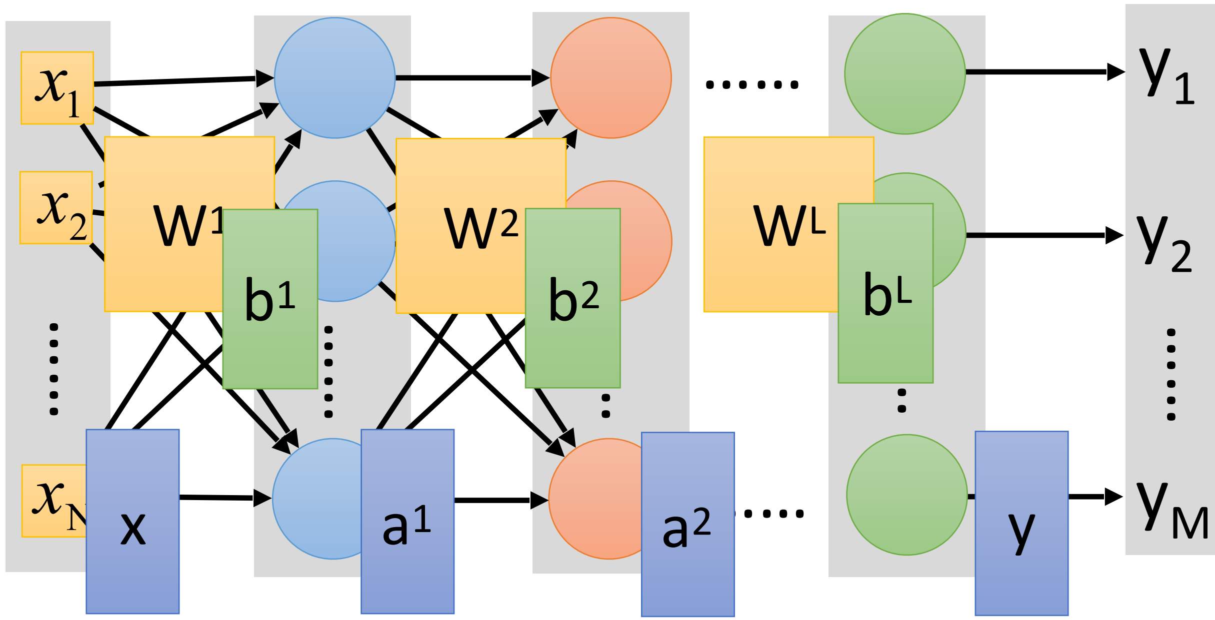
Neural Network



$$y = f(x)$$



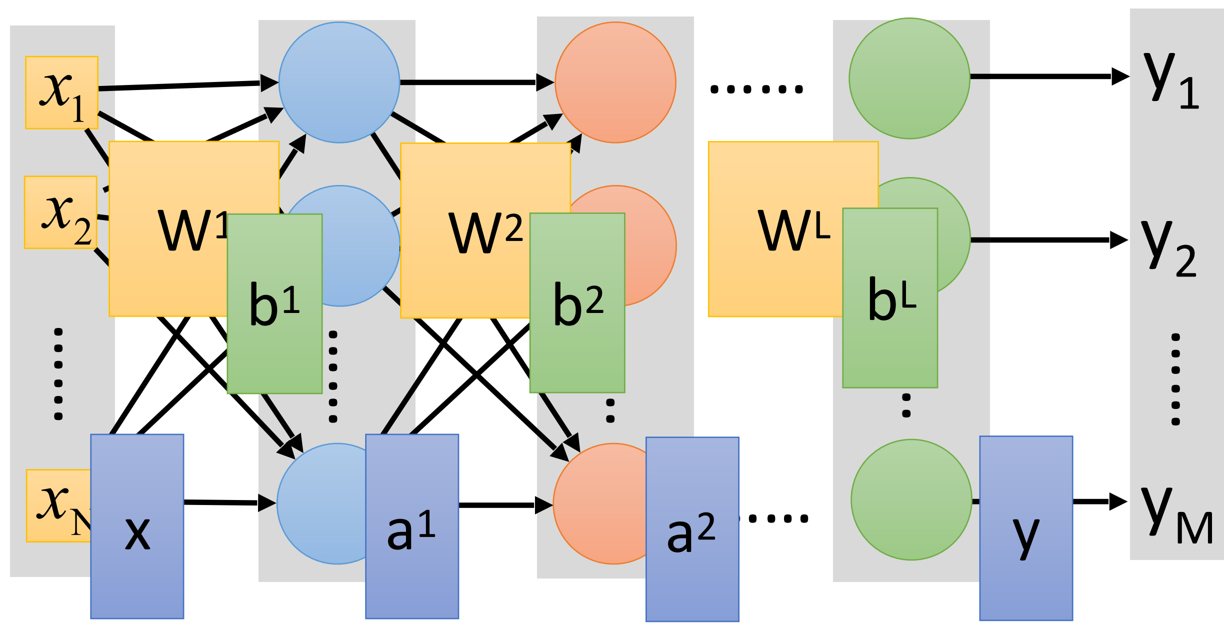
Neural Network



$$y = f(x)$$

$$\sigma(W^1 \; x + b^1)$$

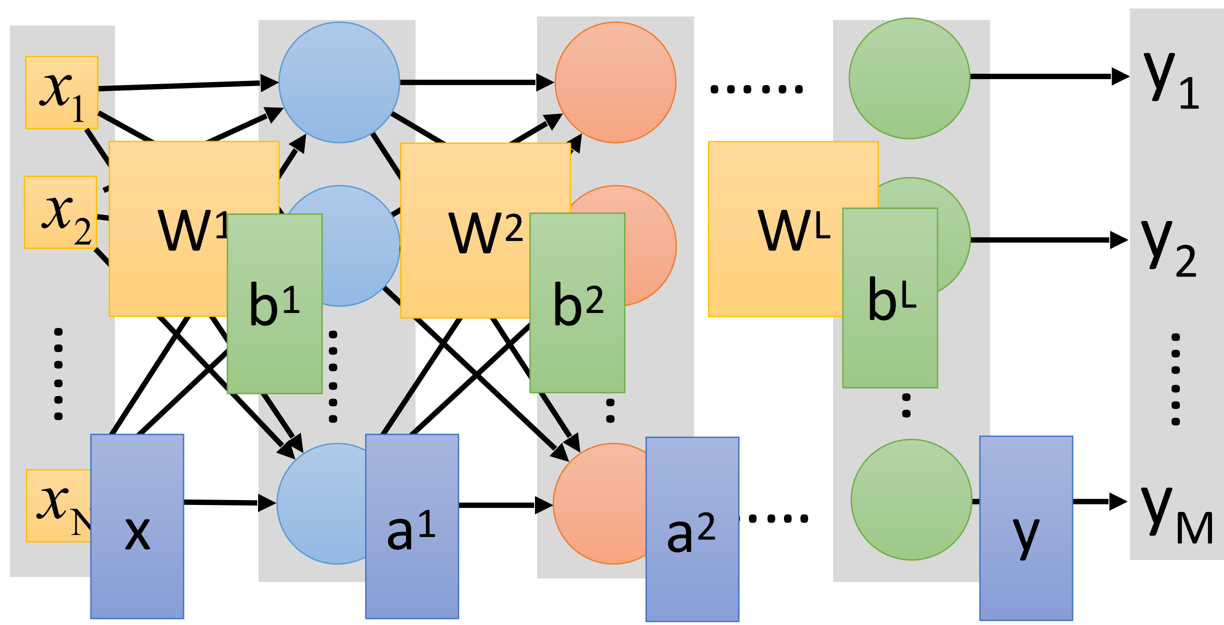
Neural Network



$$y = f(x)$$

$$\sigma(W^2 \; \sigma(W^1 \; x + b^1) + b^2)$$

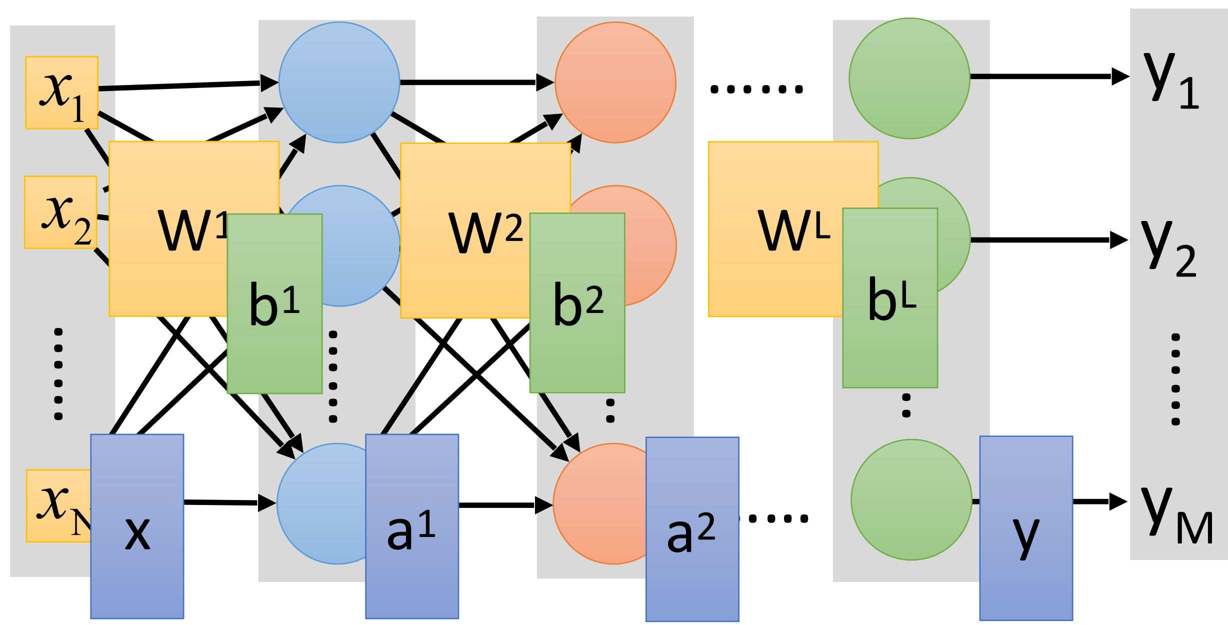
Neural Network



$$y = f(x)$$

$$= \sigma(W^L \ldots \sigma(W^2 \, \sigma(W^1 x + b^1) + b^2) \ldots + b^L)$$

Neural Network



$$y = f(x)$$

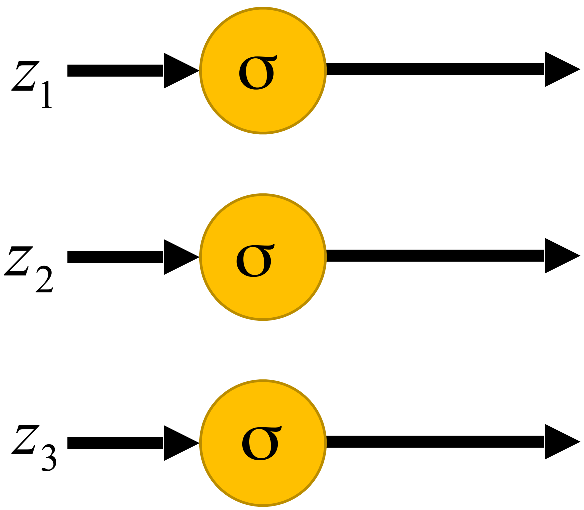
Using parallel computing techniques to speed up matrix operation

$$= \sigma(W^L \ldots \sigma(W^2 \, \sigma(W^1 x + b^1) + b^2) \ldots + b^L)$$

Softmax

- Softmax layer as the output layer

Ordinary Layer



$$y_1 = \sigma(z_1)$$

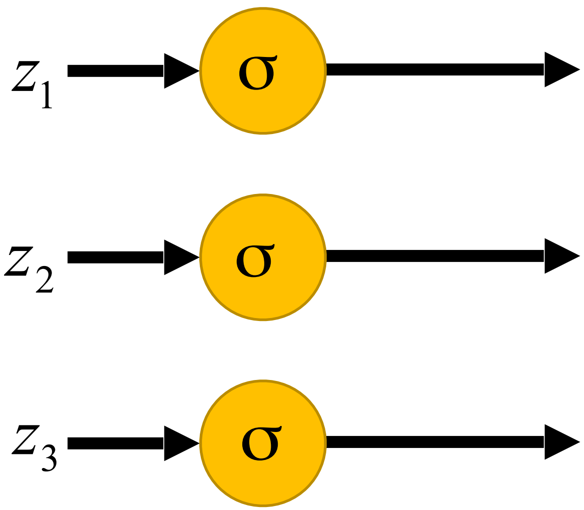
$$y_2 = \sigma(z_2)$$

$$y_3 = \sigma(z_3)$$

Softmax

- Softmax layer as the output layer

__Ordinary Layer__



$y_1 = \sigma(z_1)$

$y_2 = \sigma(z_2)$

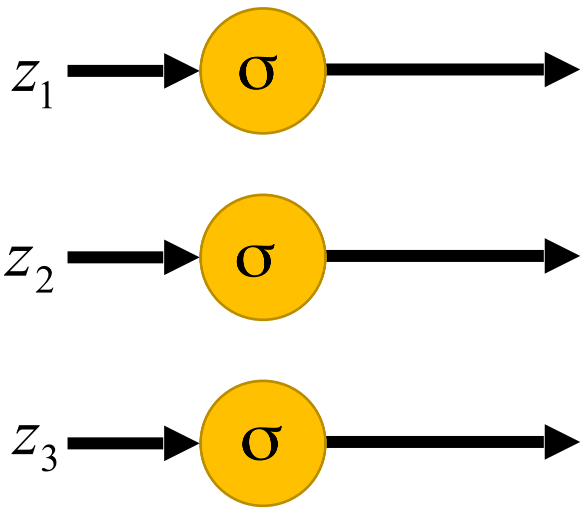
$y_3 = \sigma(z_3)$

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

Softmax

- Softmax layer as the output layer

<u>Ordinary Layer</u>



$$y_1 = \sigma(z_1)$$

$$y_2 = \sigma(z_2)$$

$$y_3 = \sigma(z_3)$$

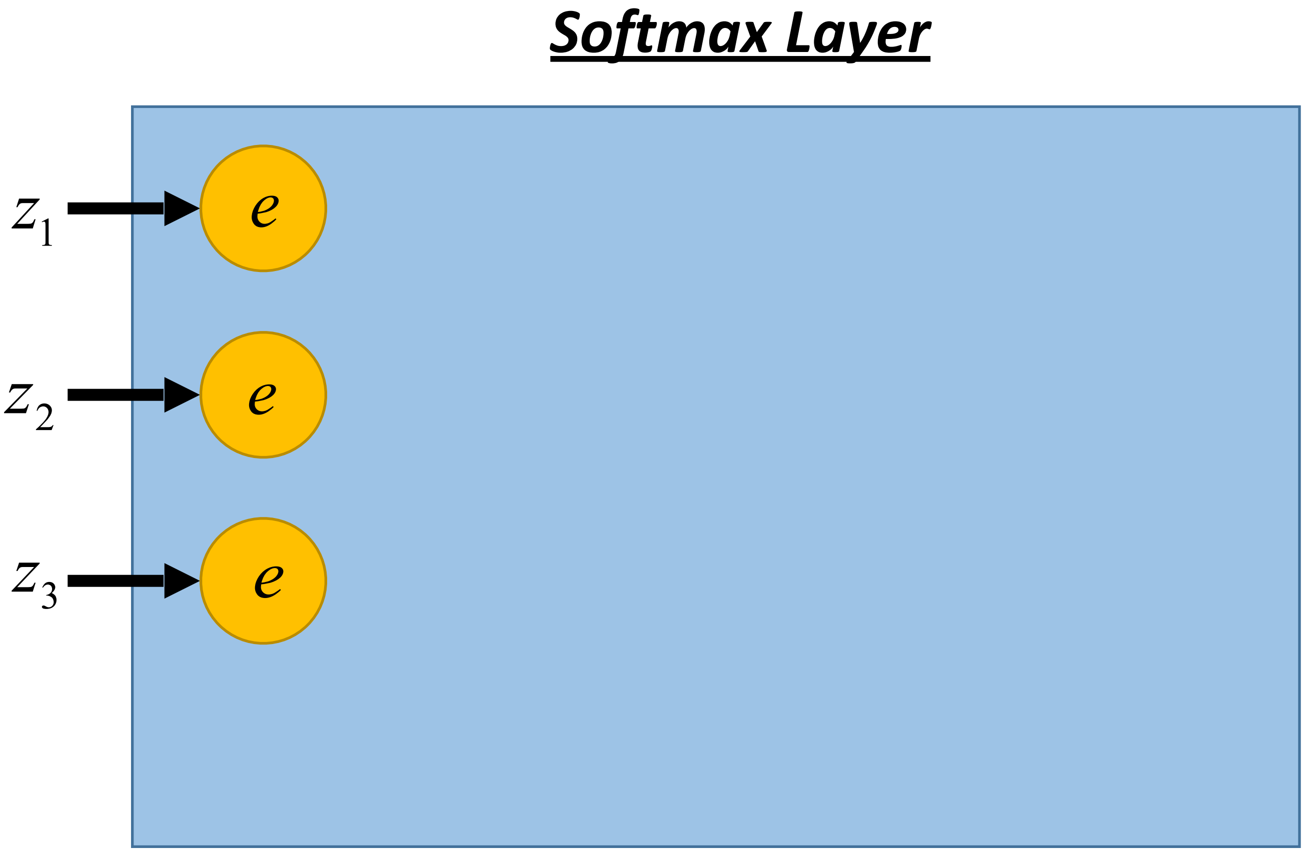
In general, the output of network can be any value.

May not be easy to interpret

Softmax

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

- Softmax layer as the output layer

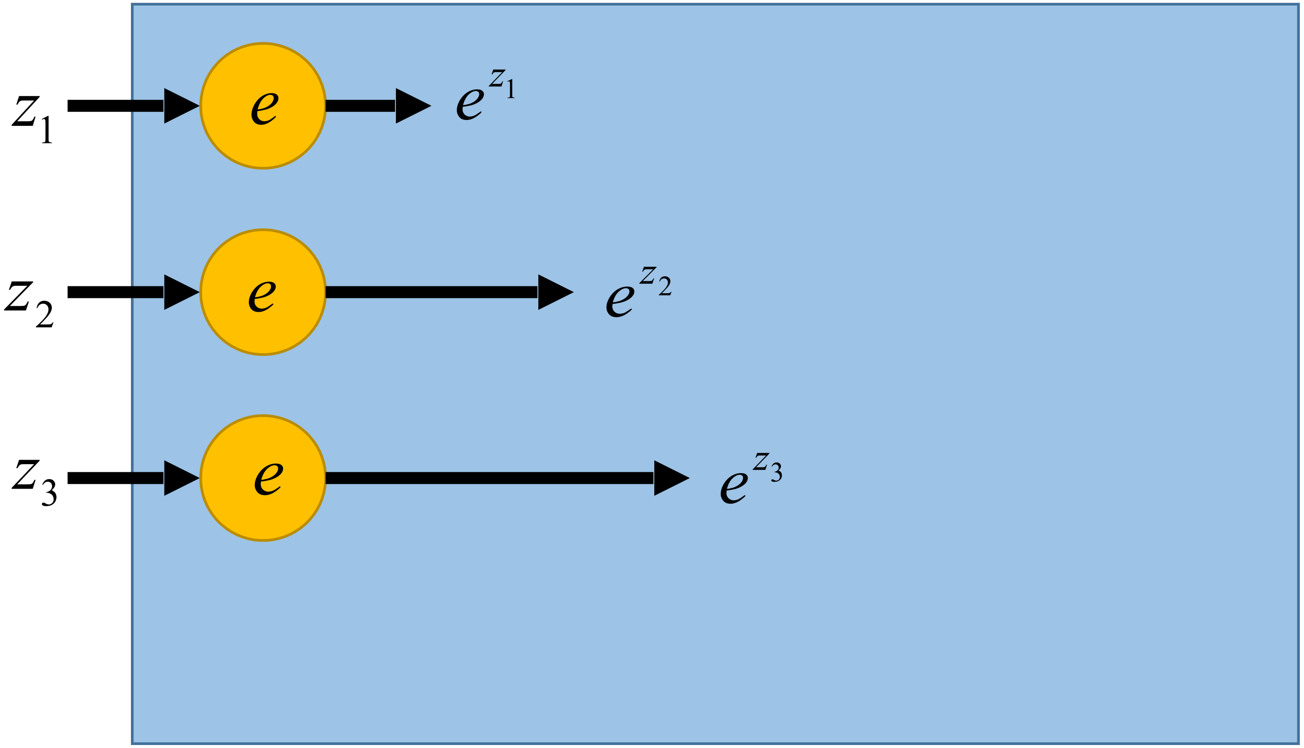


Softmax

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

- Softmax layer as the output layer

Softmax Layer

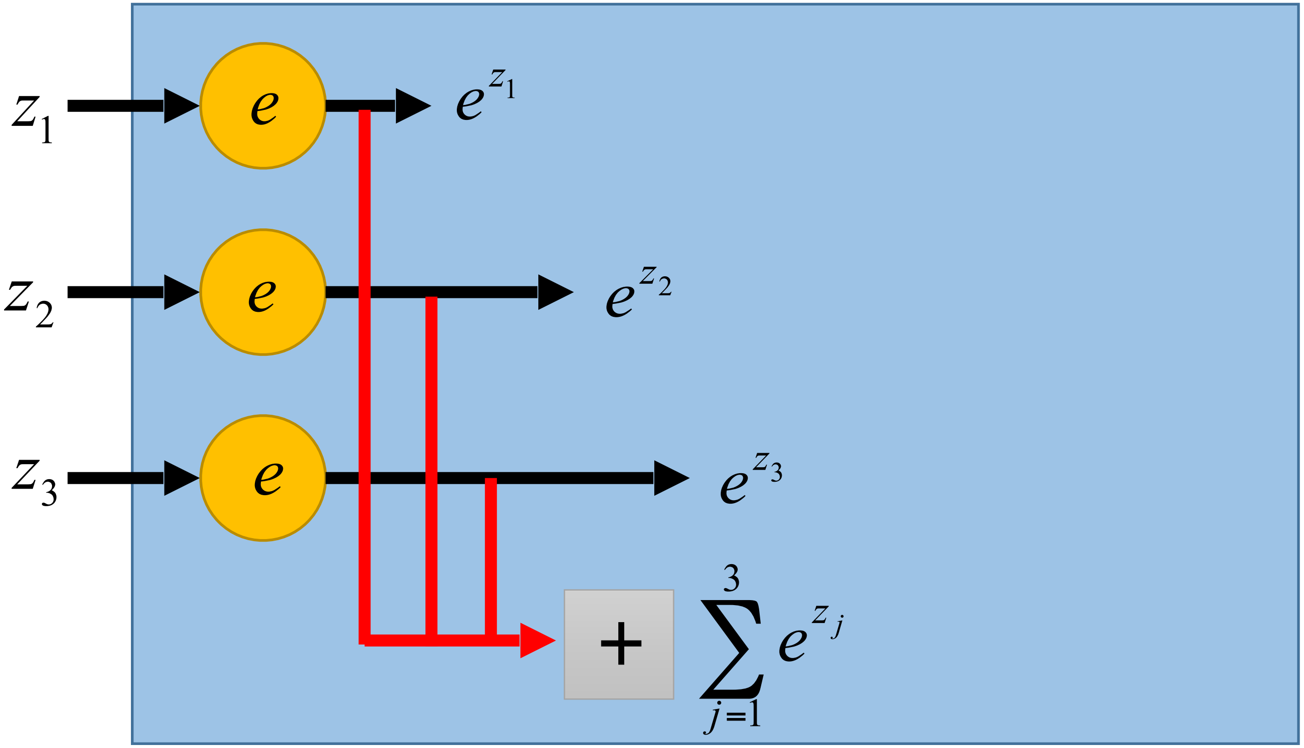


Softmax

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

- Softmax layer as the output layer

Softmax Layer

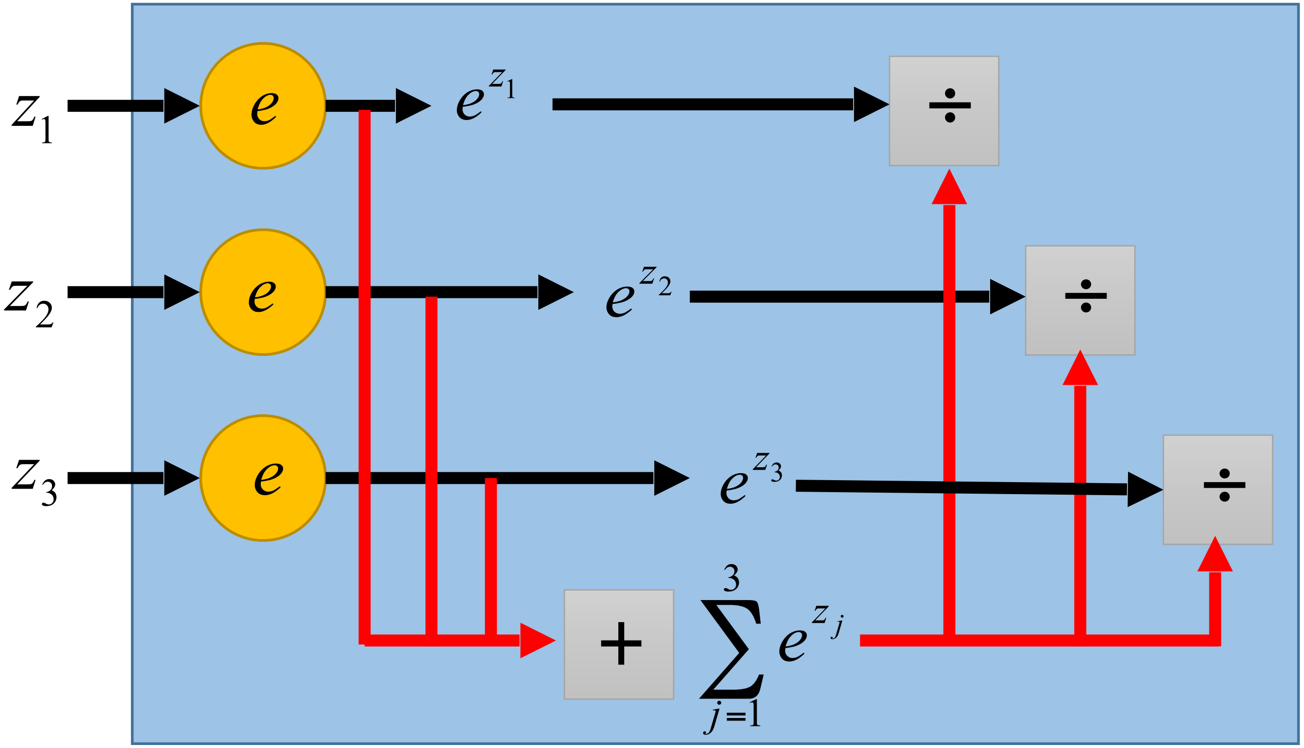


Softmax

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

- Softmax layer as the output layer

Softmax Layer

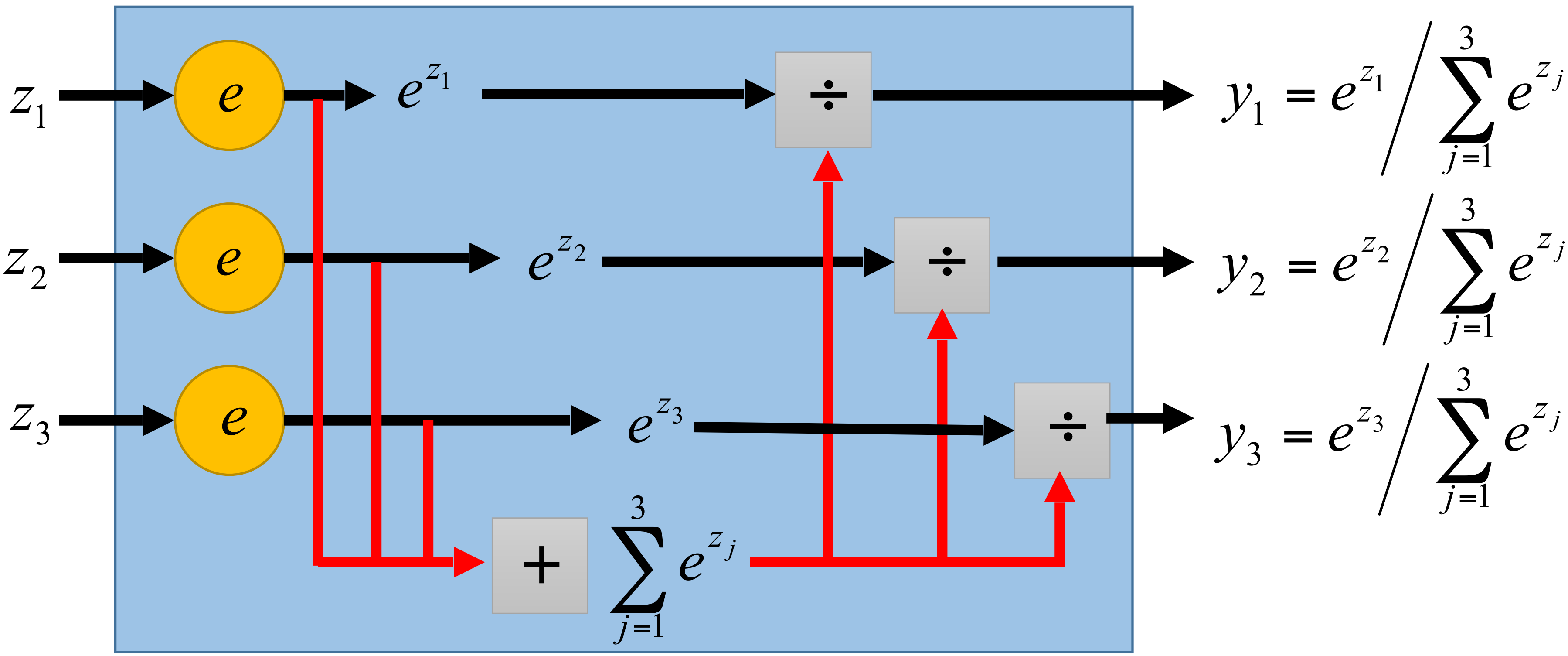


Softmax

***Probability*:**
- $1 > y_i > 0$
- $\sum_i y_i = 1$

- Softmax layer as the output layer

Softmax Layer

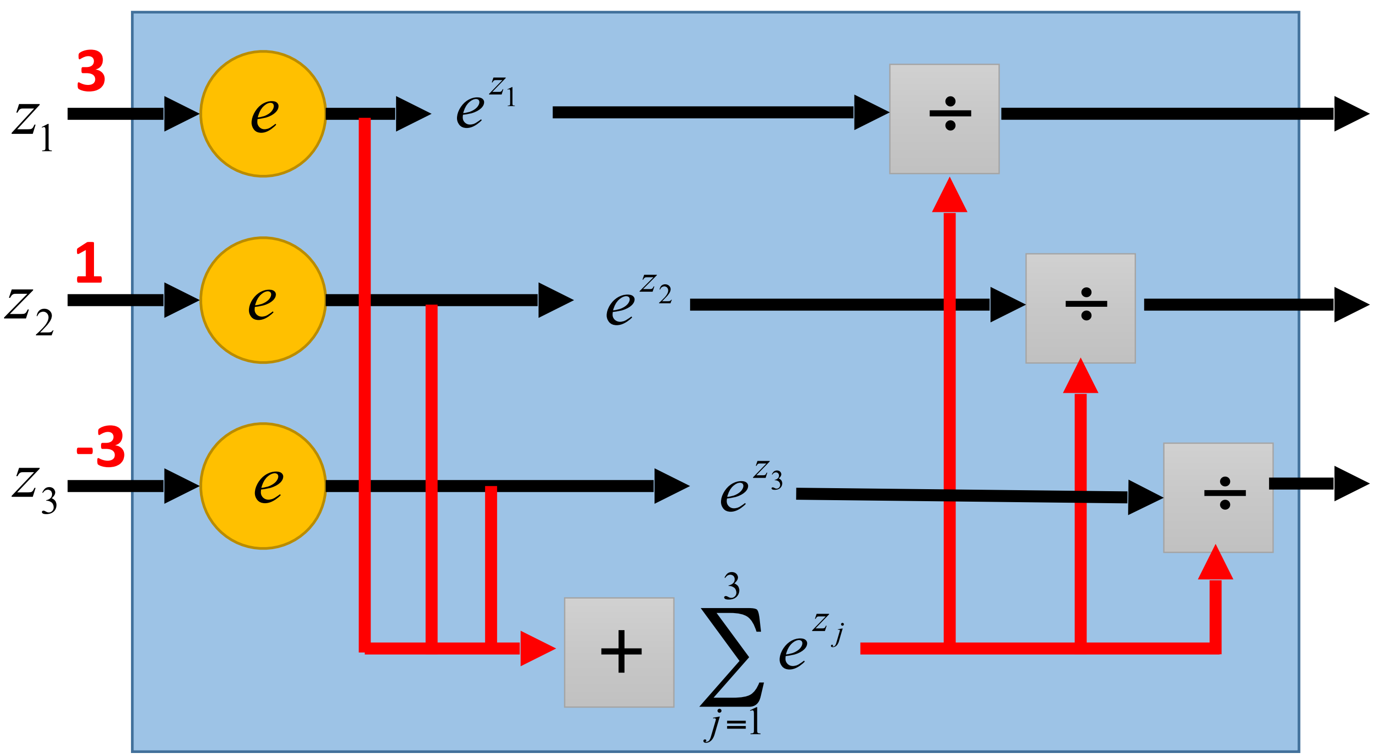


Softmax

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

- Softmax layer as the output layer

Softmax Layer



$$y_1 = e^{z_1} \Big/ \sum_{j=1}^{3} e^{z_j}$$

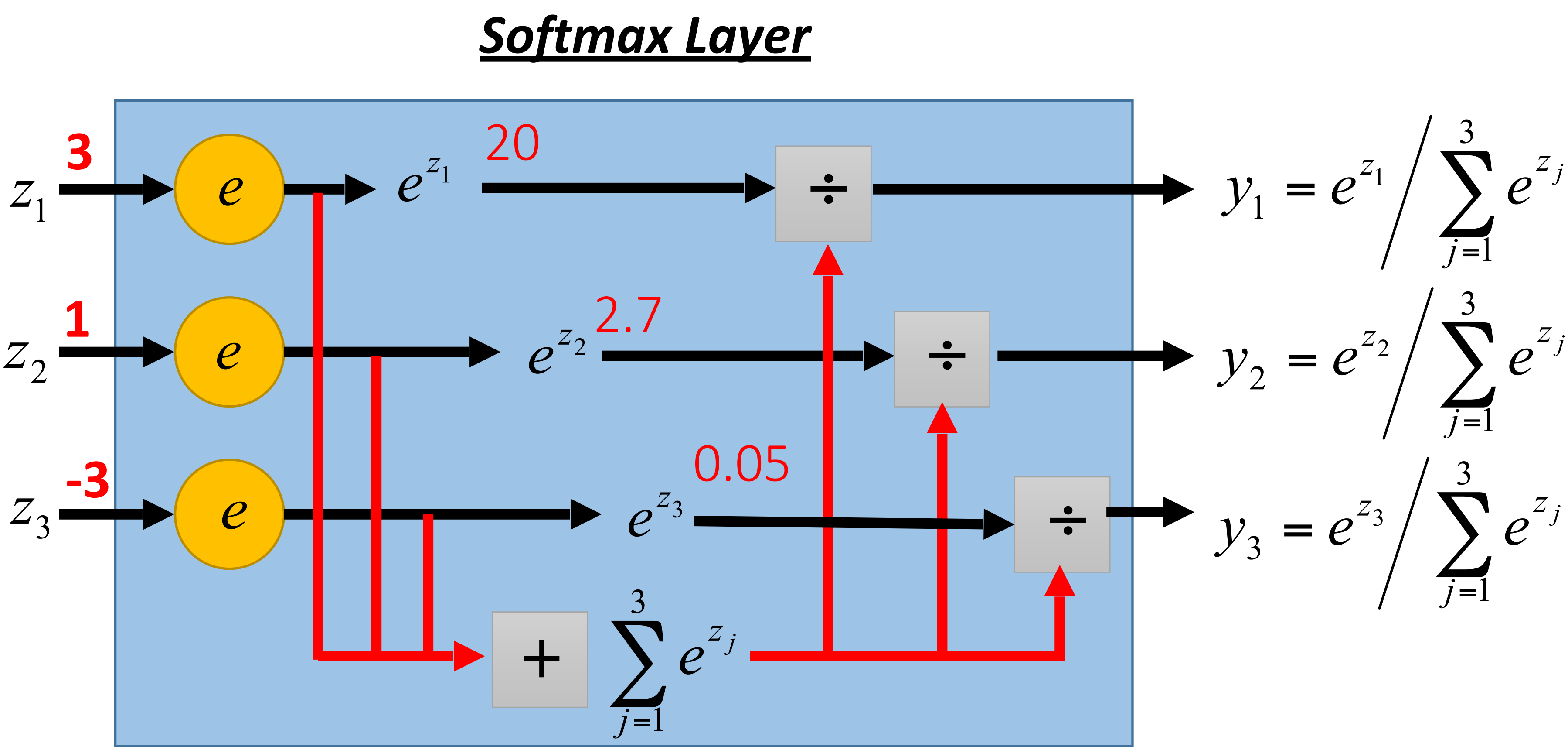
$$y_2 = e^{z_2} \Big/ \sum_{j=1}^{3} e^{z_j}$$

$$y_3 = e^{z_3} \Big/ \sum_{j=1}^{3} e^{z_j}$$

Softmax

• Softmax layer as the output layer

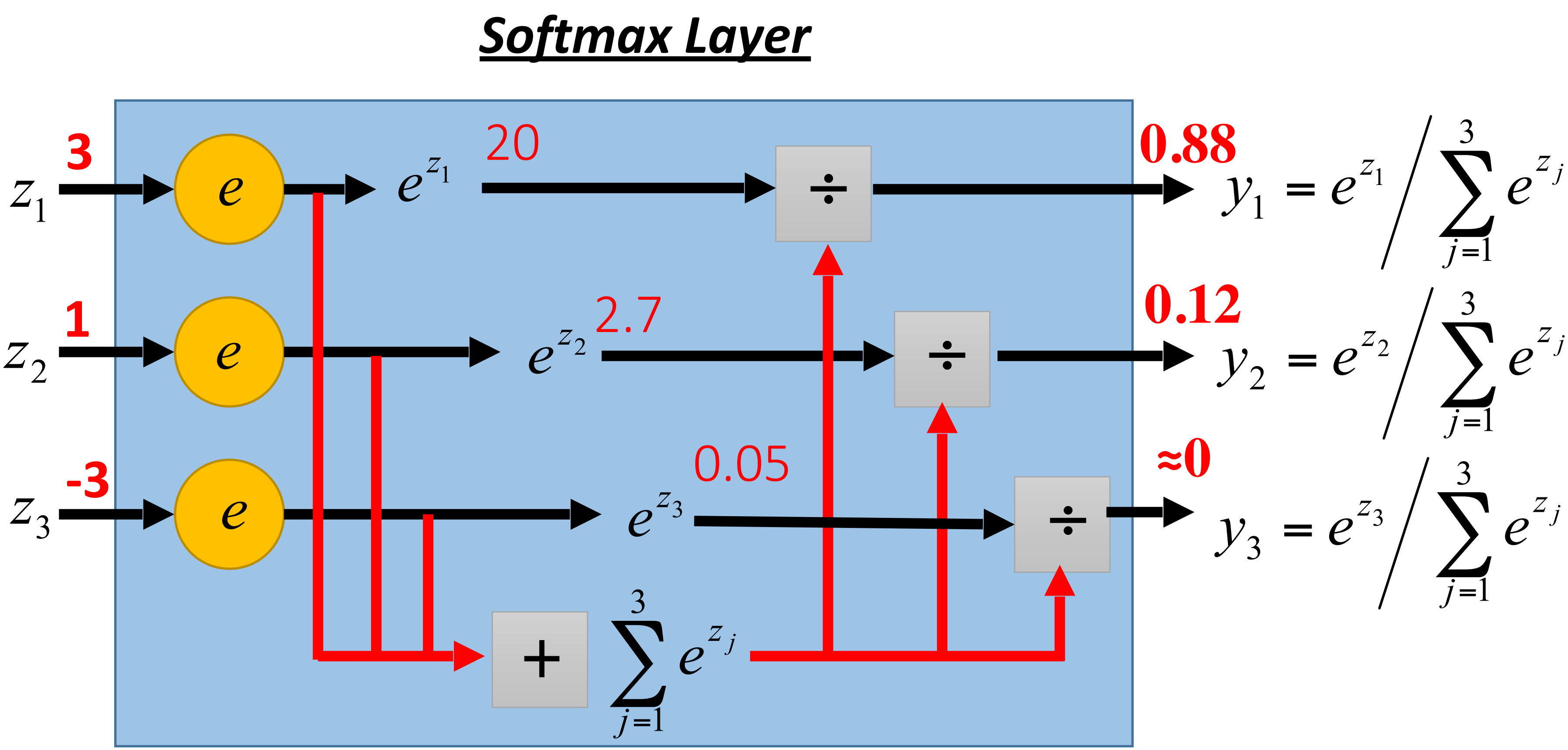
Probability:
- $1 > y_i > 0$
- $\sum_i y_i = 1$



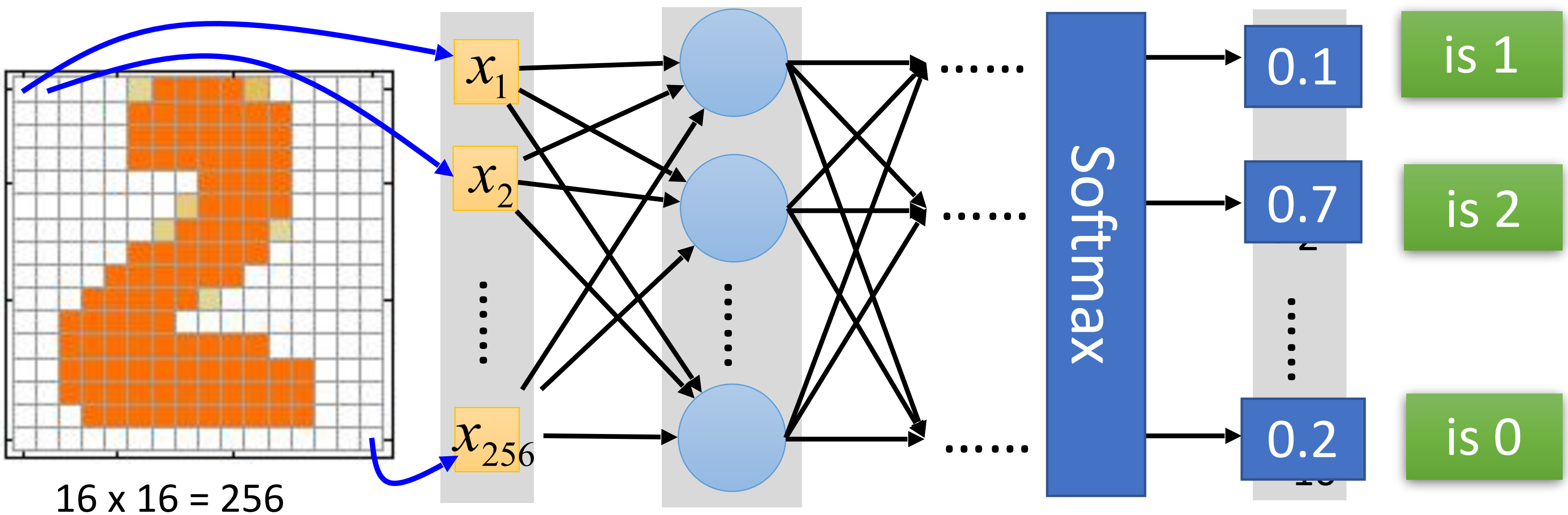
Softmax

- Softmax layer as the output layer

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



How to set network parameters

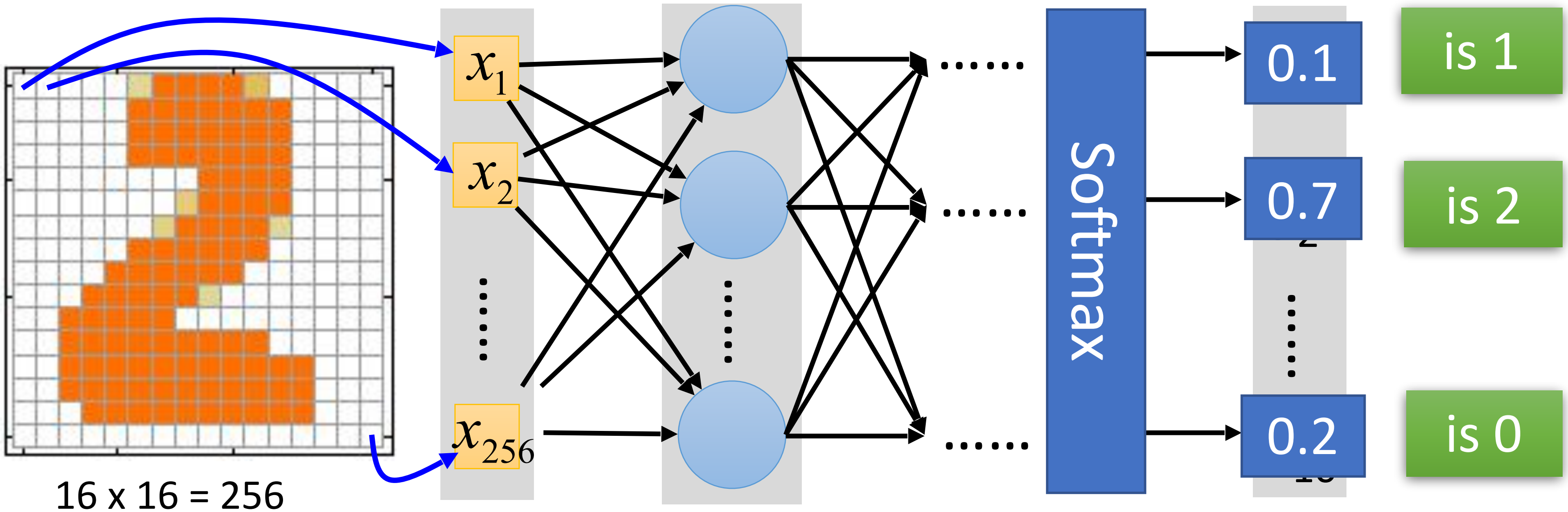


16 x 16 = 256

Ink → 1

No ink → 0

How to set network parameters



16 x 16 = 256

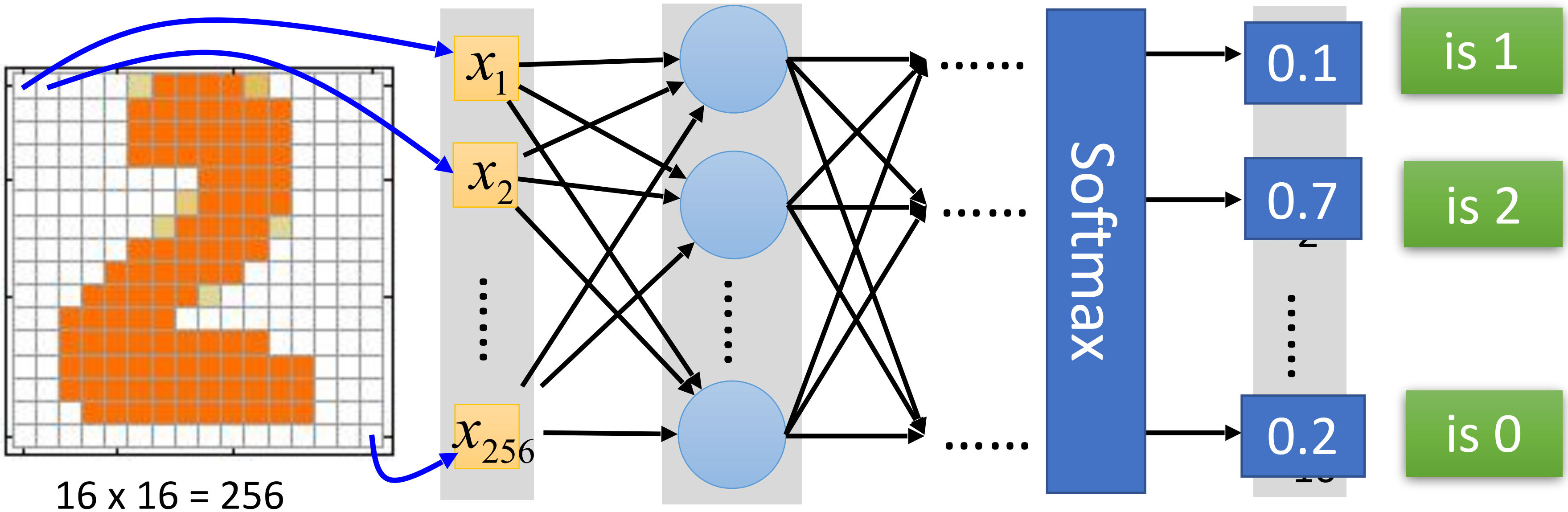
Ink → 1

No ink → 0

Set the network parameters θ such that ……

How to set network parameters

$$\theta = \{W^1, b^1, W^2, b^2, \cdots W^L, b^L\}$$



16 x 16 = 256

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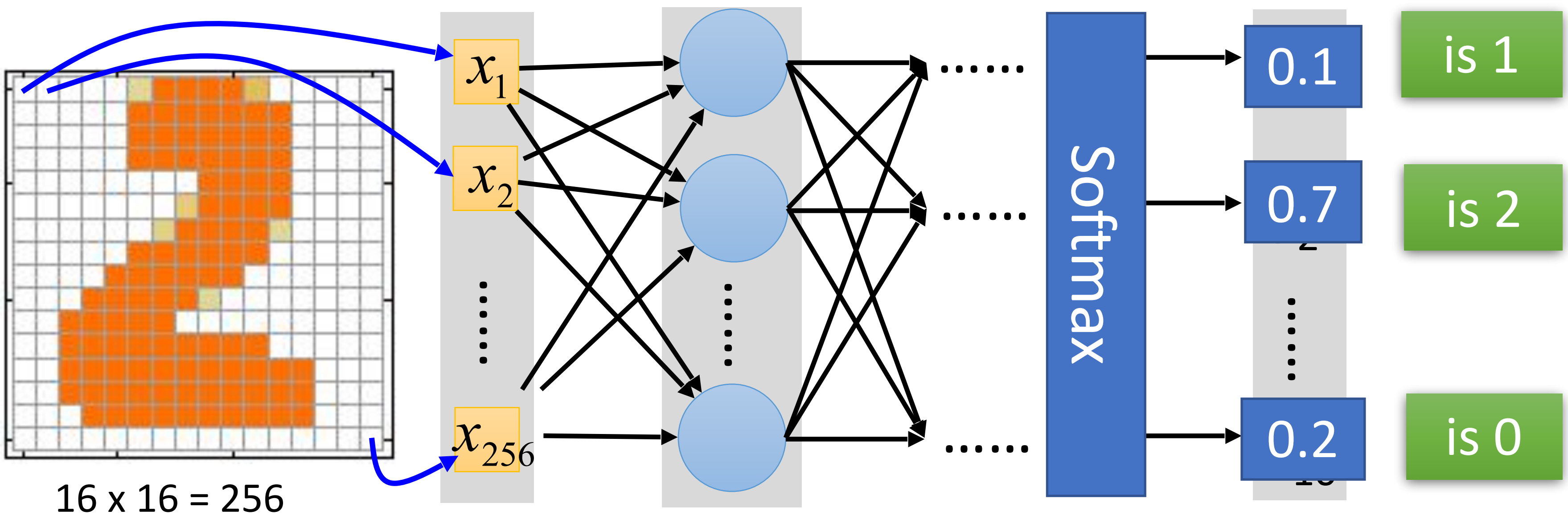
How to set network parameters

$$\theta = \{W^1, b^1, W^2, b^2, \cdots W^L, b^L\}$$

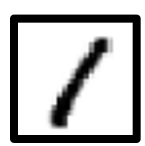


Ink → 1

No ink → 0

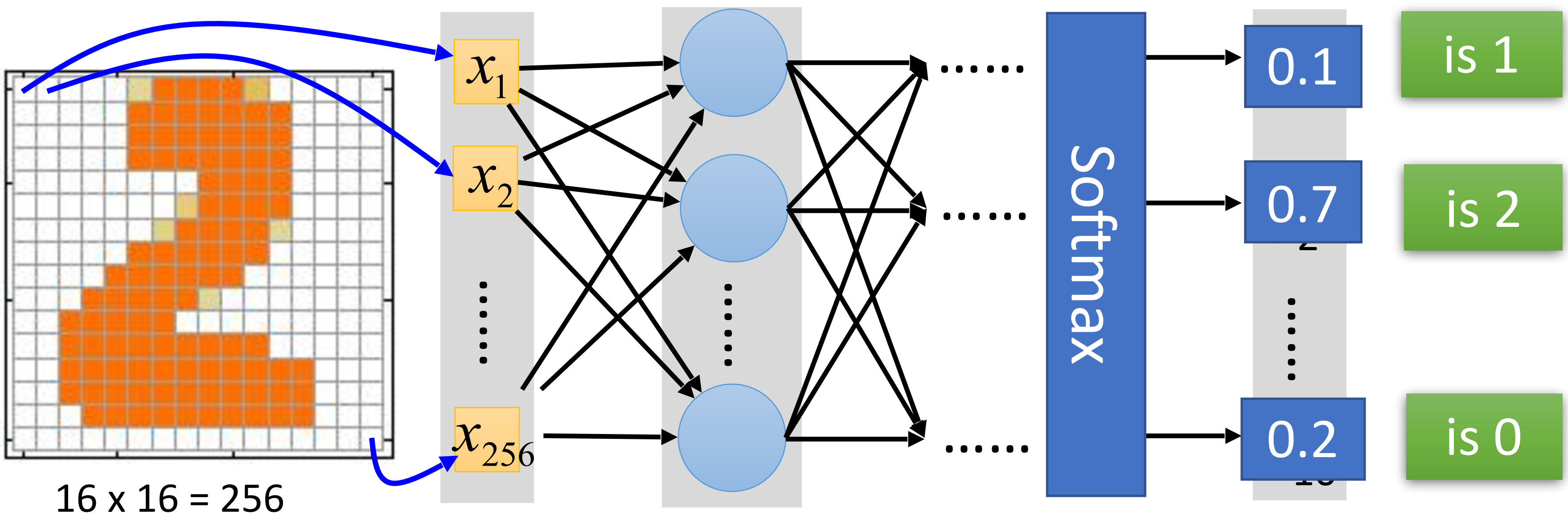
Set the network parameters θ such that ......

Input:



How to set network parameters

$$\theta = \{W^1, b^1, W^2, b^2, \cdots W^L, b^L\}$$

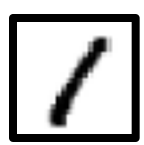


16 x 16 = 256

Ink → 1

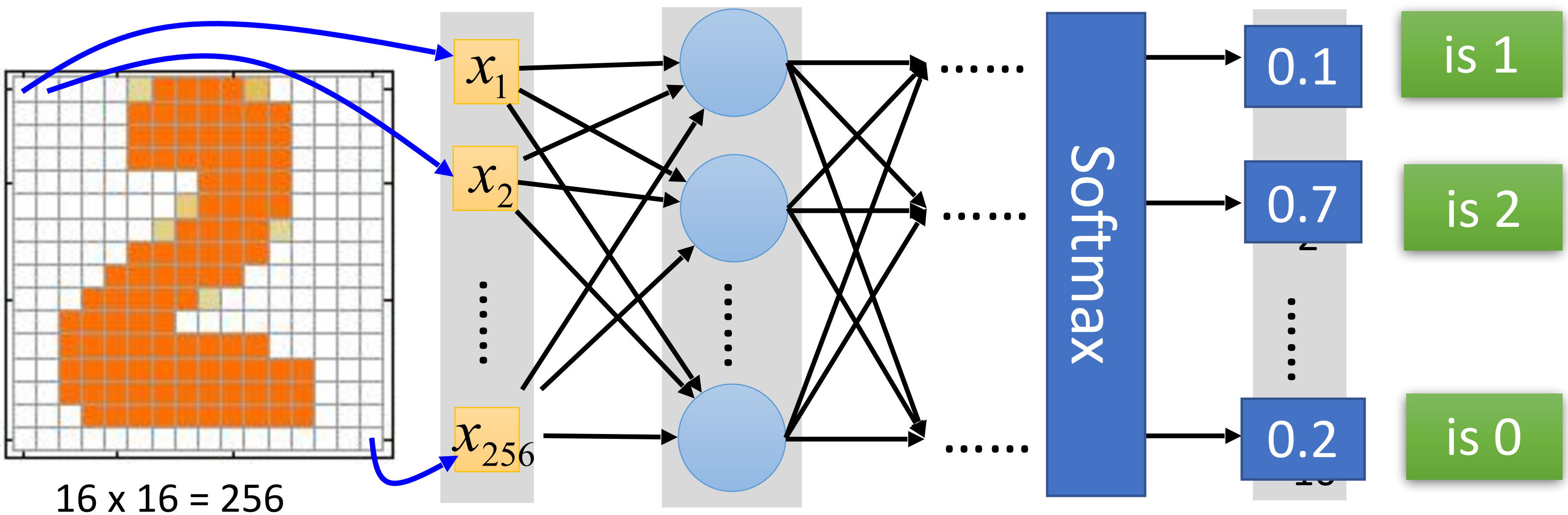
No ink → 0

Set the network parameters θ such that ......

Input:  y_1 has the maximum value

How to set network parameters

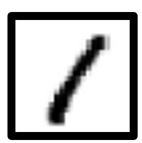
$$\theta = \{W^1, b^1, W^2, b^2, \cdots W^L, b^L\}$$



Ink → 1

No ink → 0

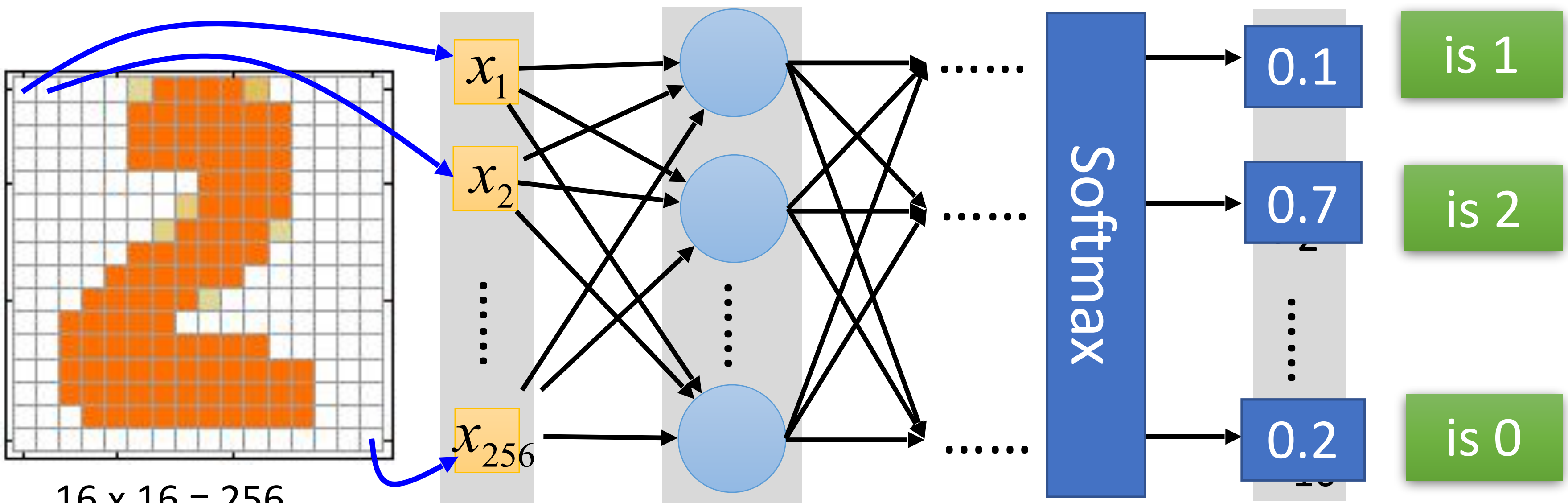
Set the network parameters θ such that ……

Input:  → y_1 has the maximum value

Input: 

How to set network parameters

$$\theta = \{W^1, b^1, W^2, b^2, \cdots W^L, b^L\}$$

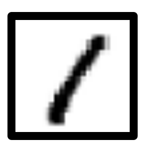


16 x 16 = 256

Ink → 1

No ink → 0

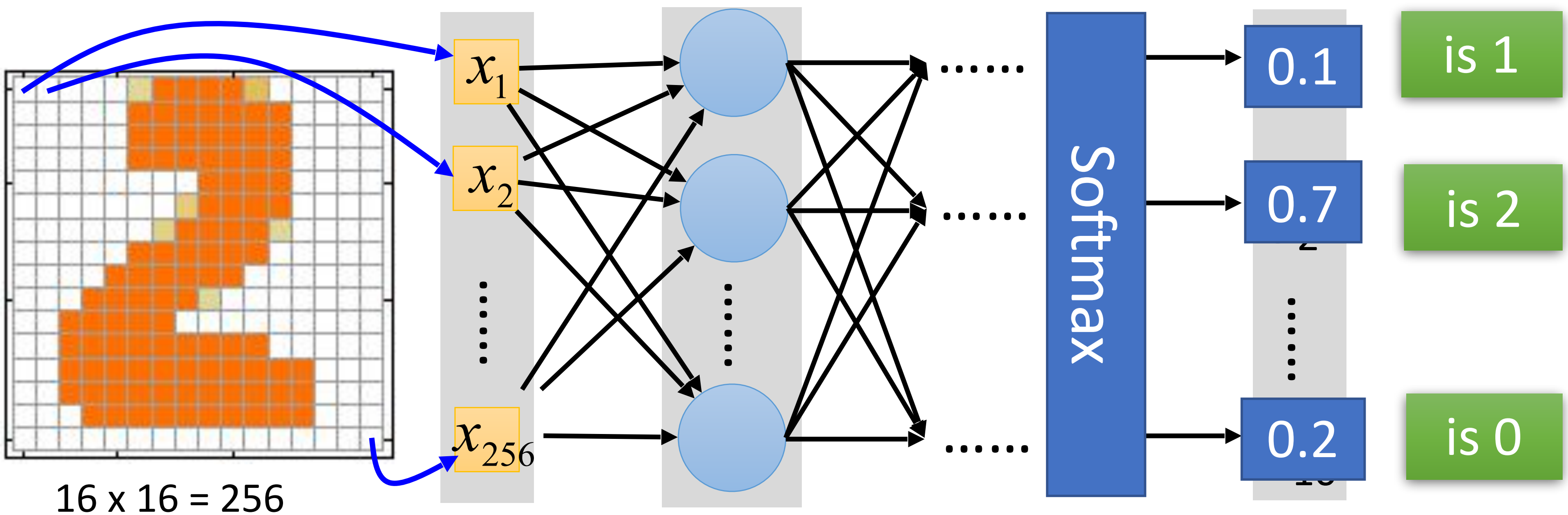
Set the network parameters θ such that ......

Input:  → y_1 has the maximum value

Input:  → y_2 has the maximum value

How to set network parameters

$$\theta = \{W^1, b^1, W^2, b^2, \cdots W^L, b^L\}$$



Ink → 1

No ink → 0

Set the network parameters θ such that ……

Input: … n value

How to let the neural network achieve this

Input:  y_2 has the maximum value

Training Data

- Preparing training data: images and their labels

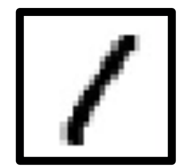
Training Data

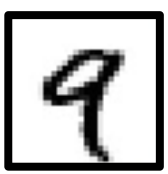
- Preparing training data: images and their labels


“5”

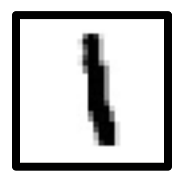

“0”

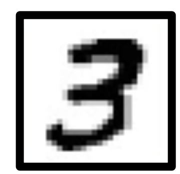

“4”


“1”


“9”

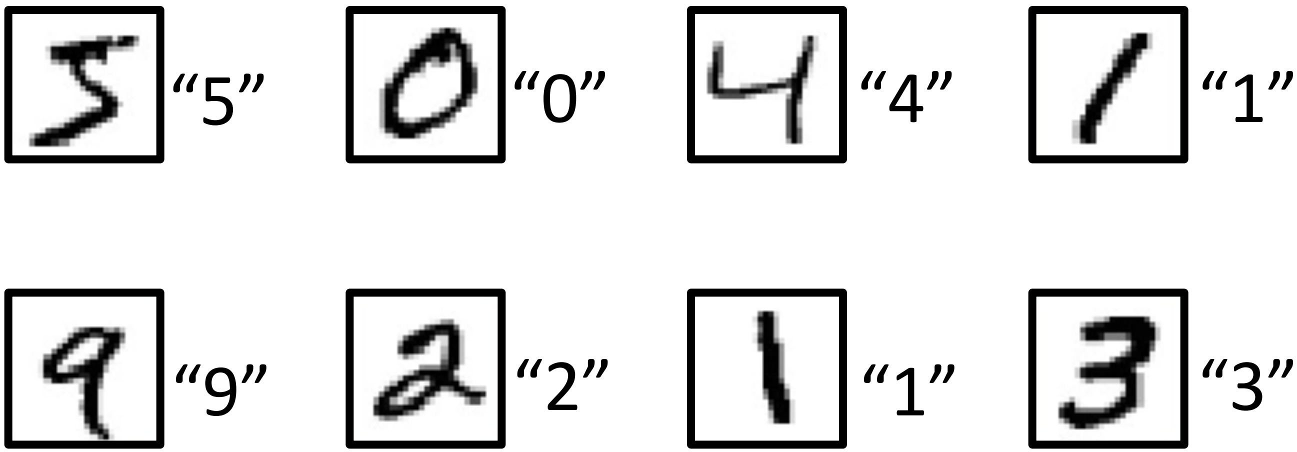

“2”


“1”


“3”

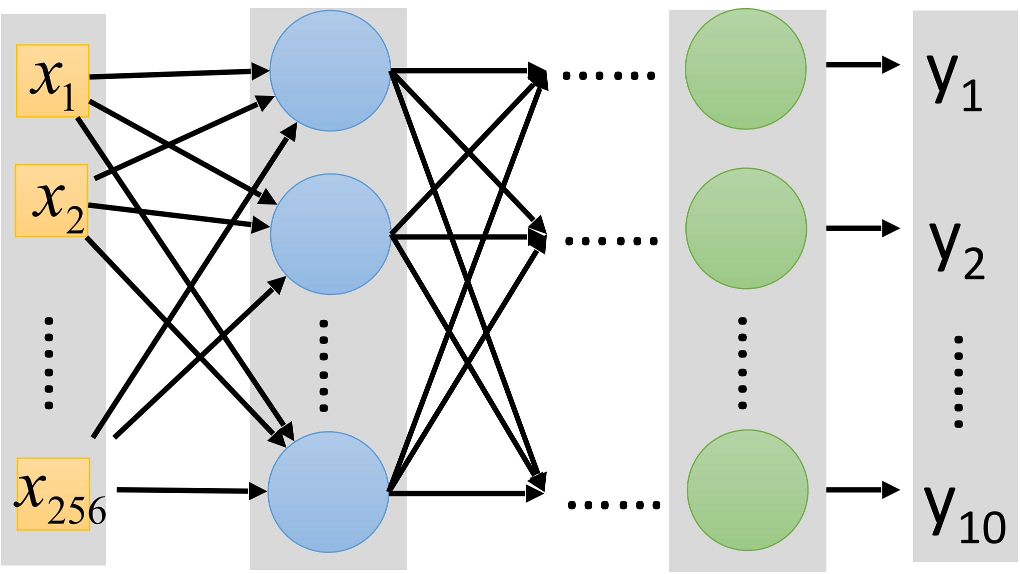
Training Data

- Preparing training data: images and their labels



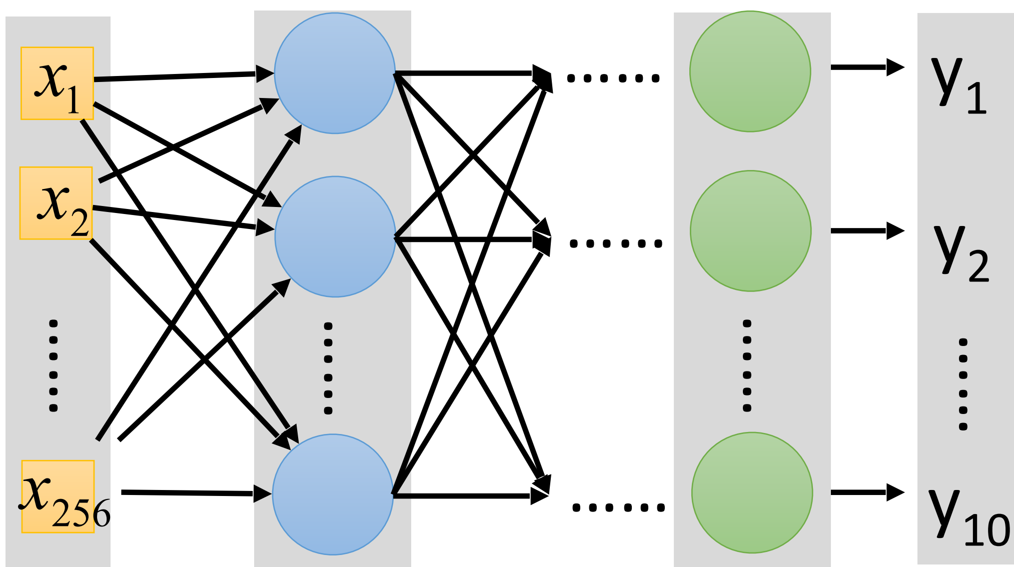
Using the training data to find the network parameters.

Cost



Cost

Given a set of network parameters θ, each example has a cost value.



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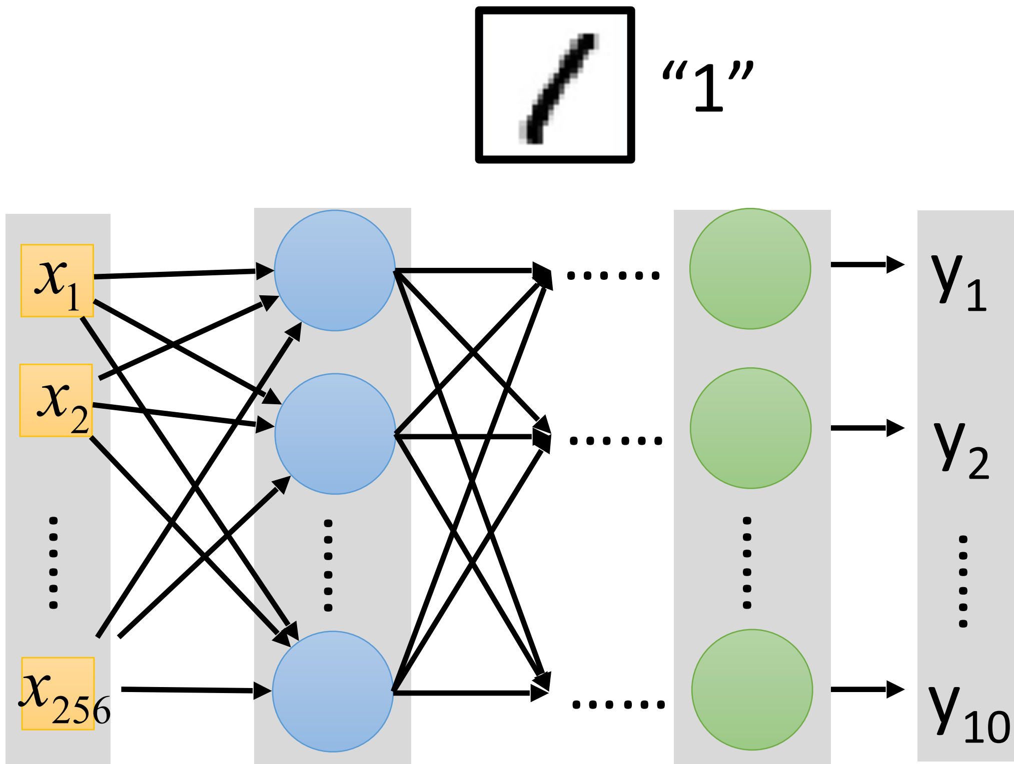

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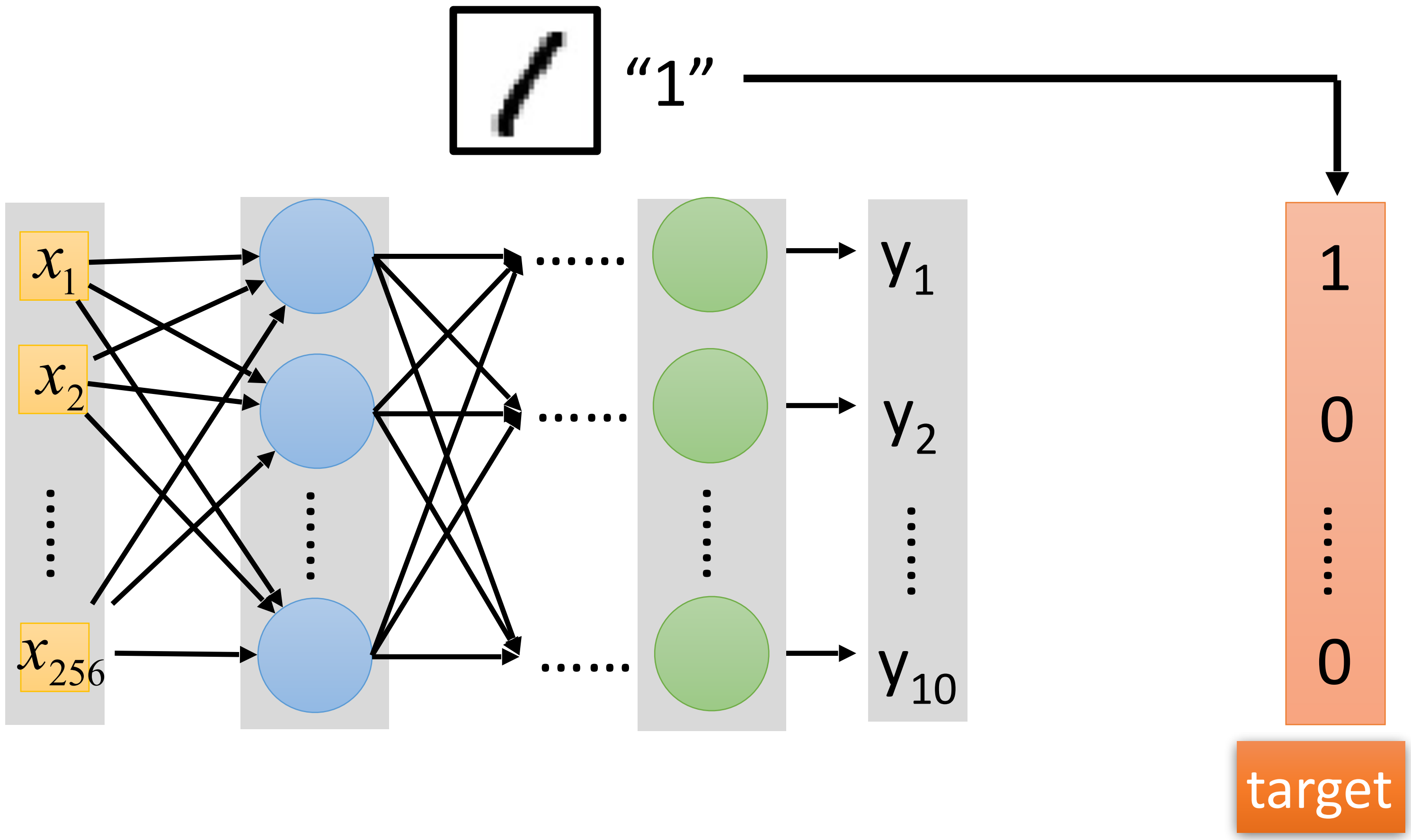

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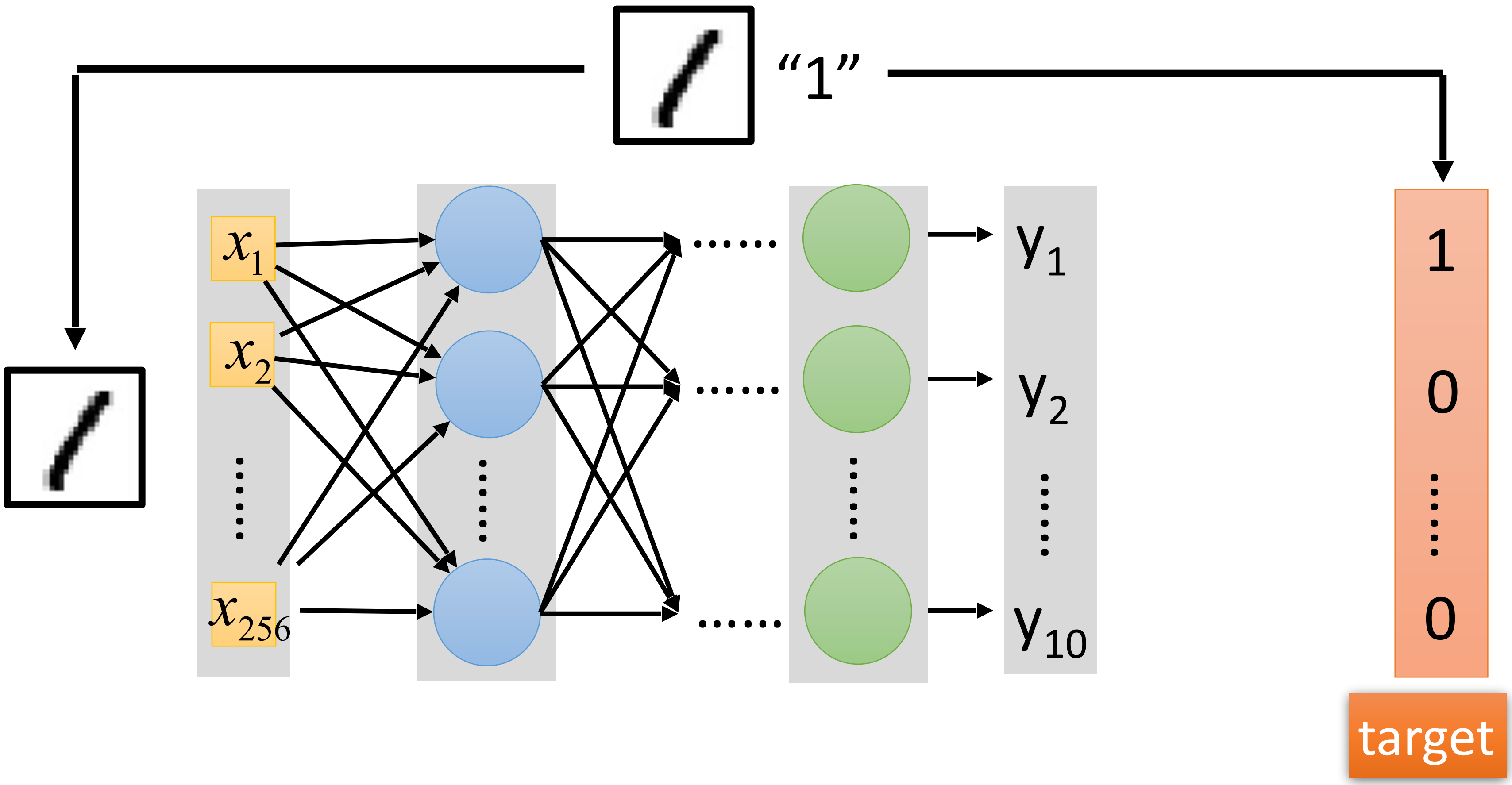

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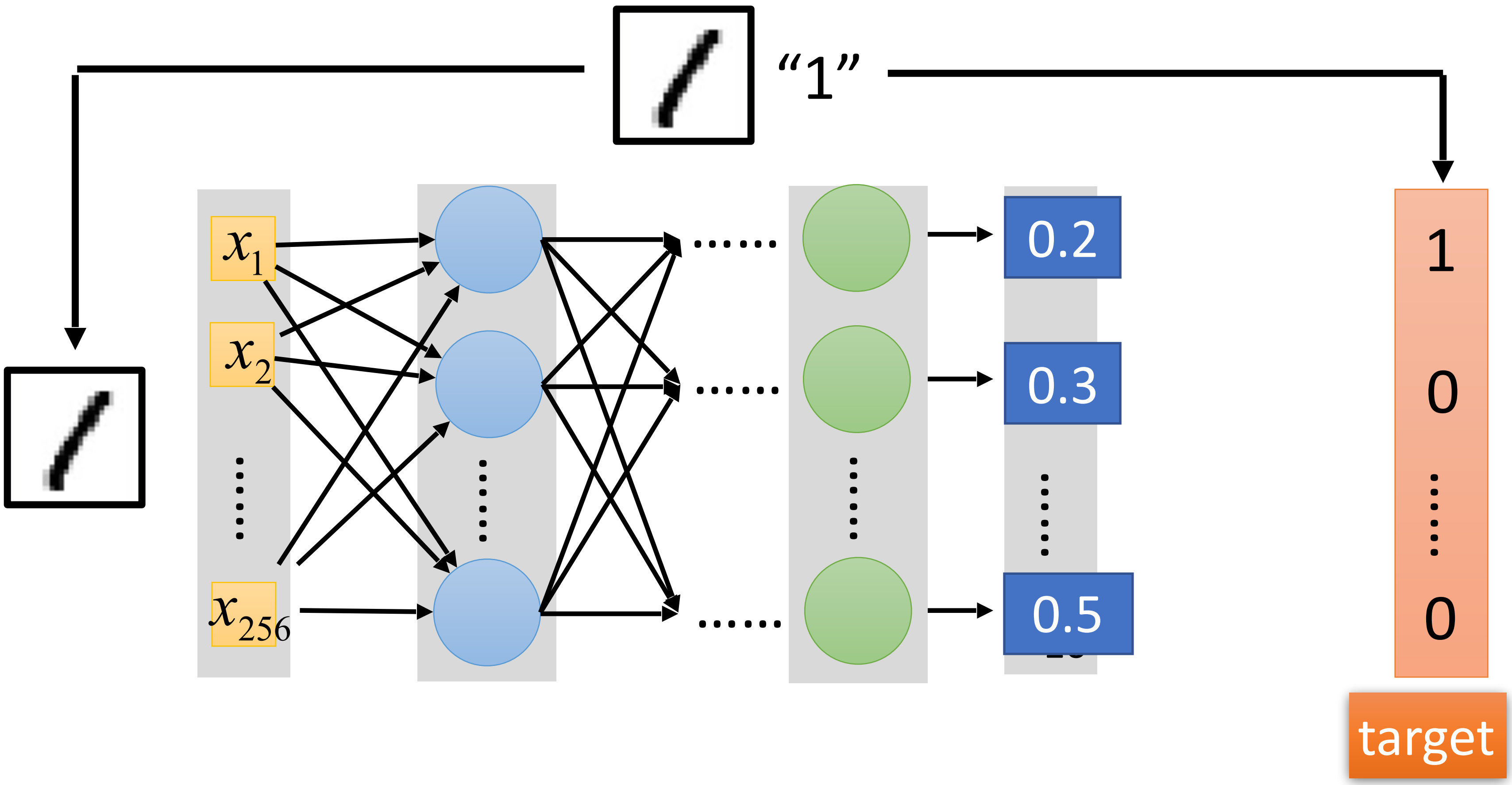

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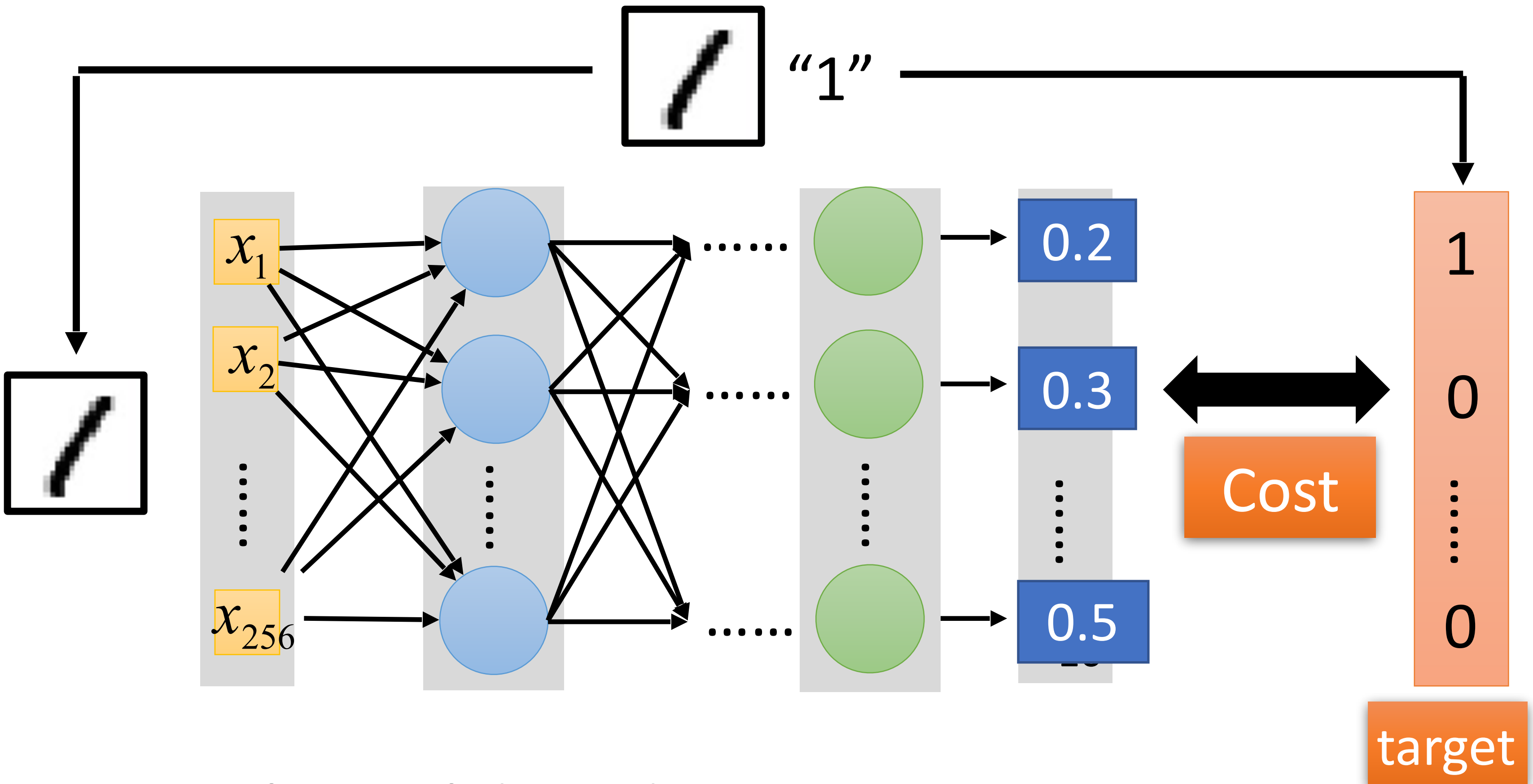

Cost can be Euclidean distance or cross entropy of the network output and target

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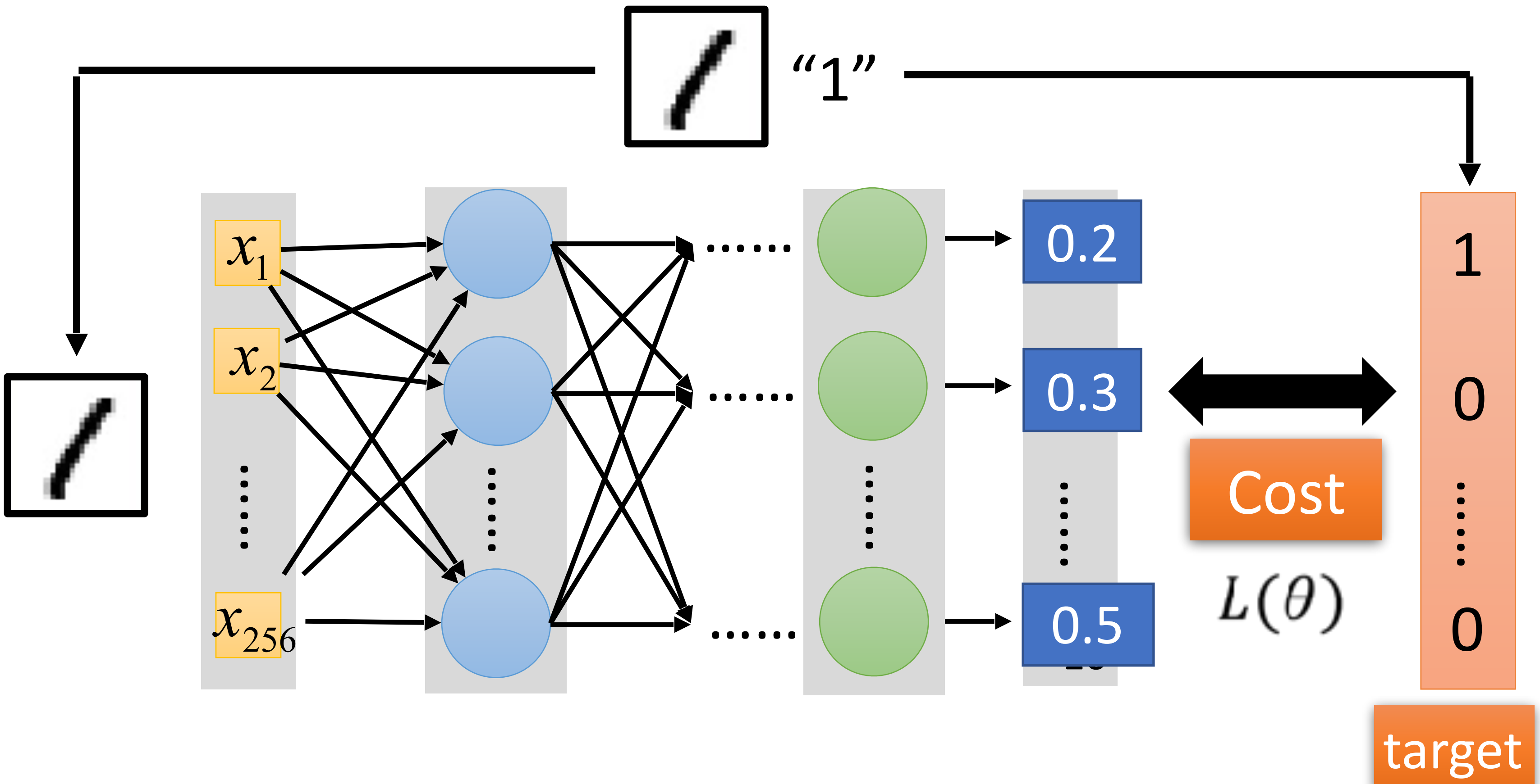
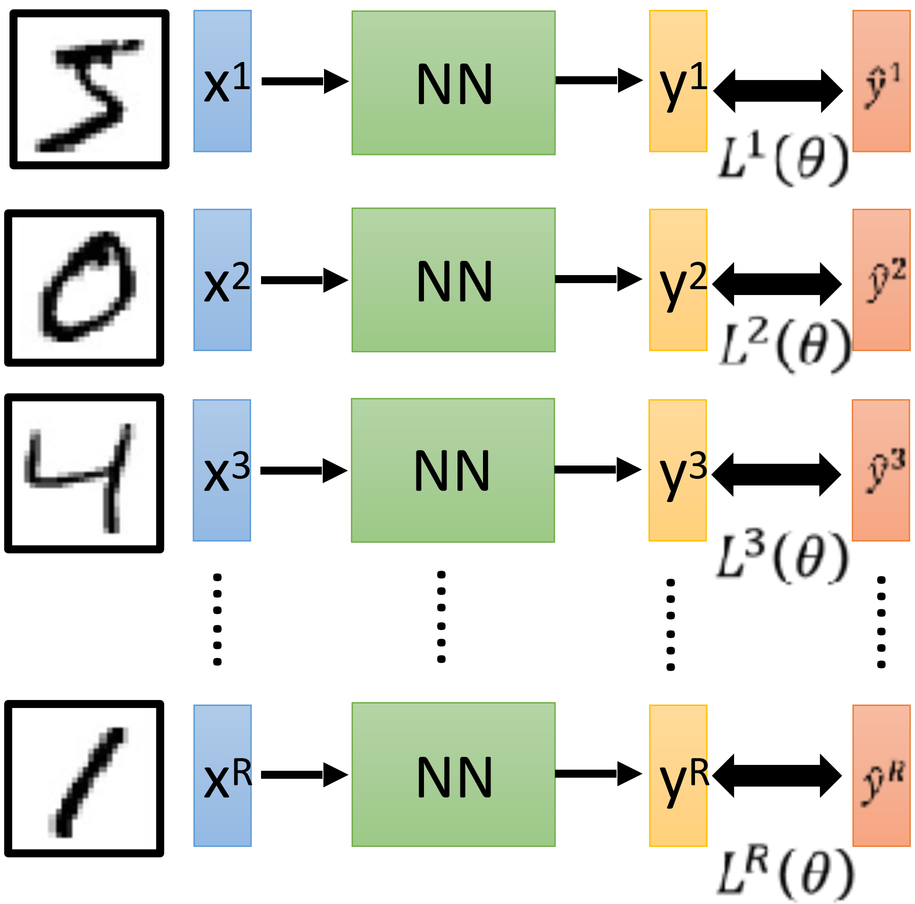


Cost can be Euclidean distance or cross entropy of the network output and target

Total Cost

For all training data …



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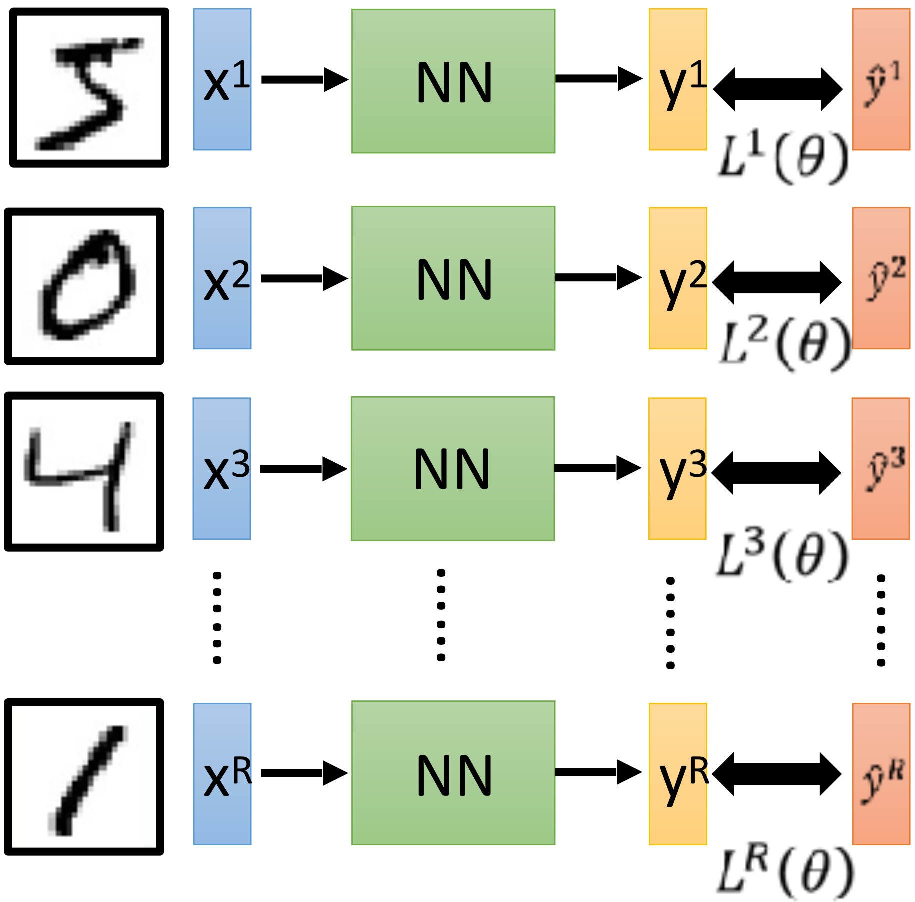
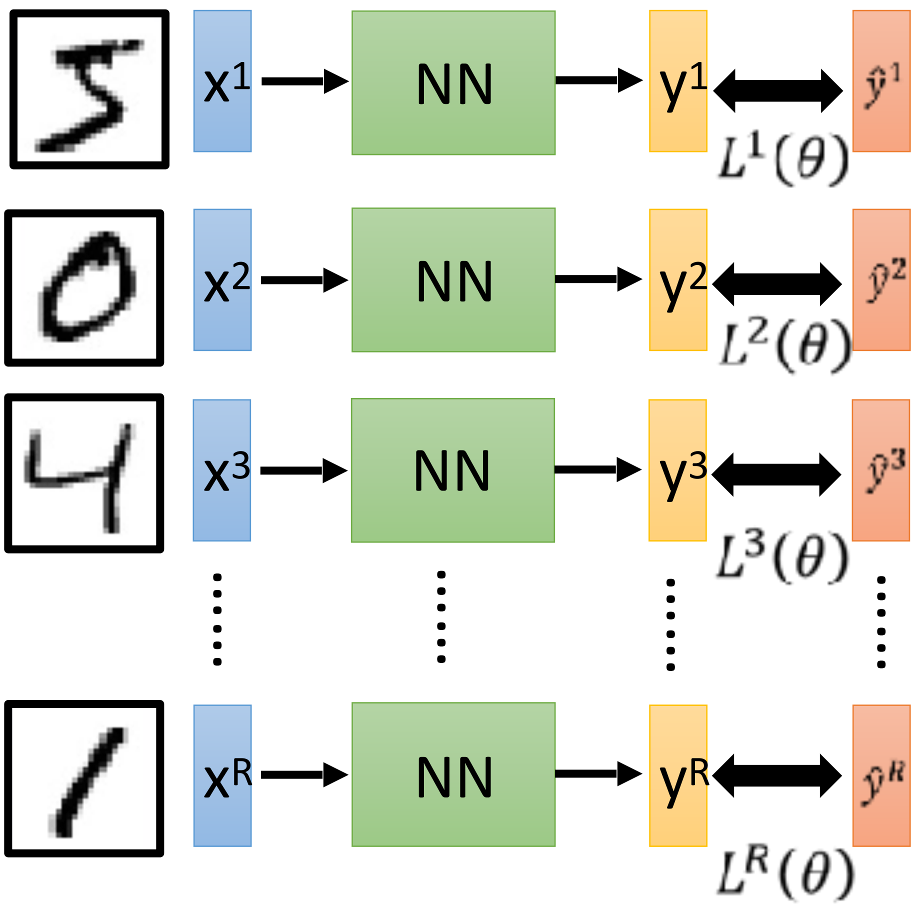


Total Cost:

$$C(\theta) = \sum_{r=1}^{R} L^r(\theta)$$

Total Cost

For all training data …



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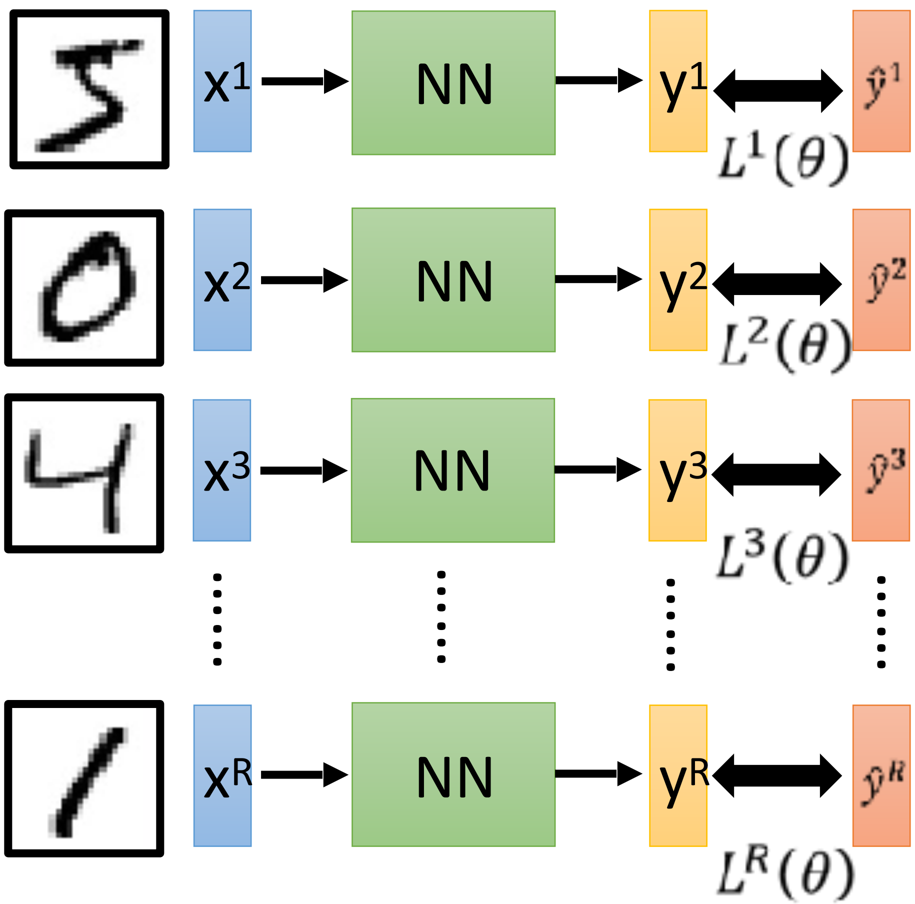
How bad the network parameters θ is on this task

Total Cost

For all training data …



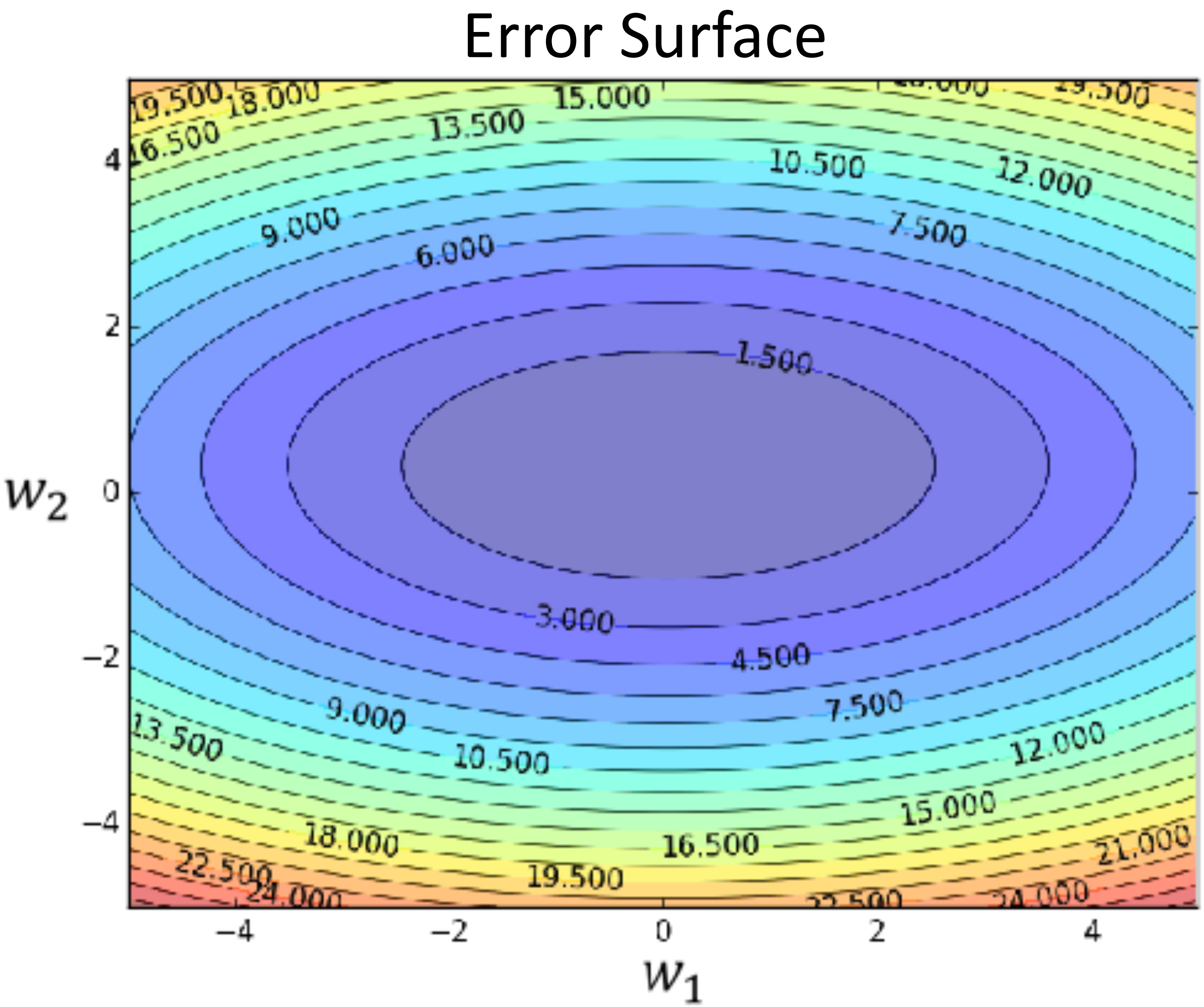
Total Cost:

$$C(\theta) = \sum_{r=1}^{R} L^r(\theta)$$

How bad the network parameters θ is on this task

Find the network parameters θ^* that minimize this value

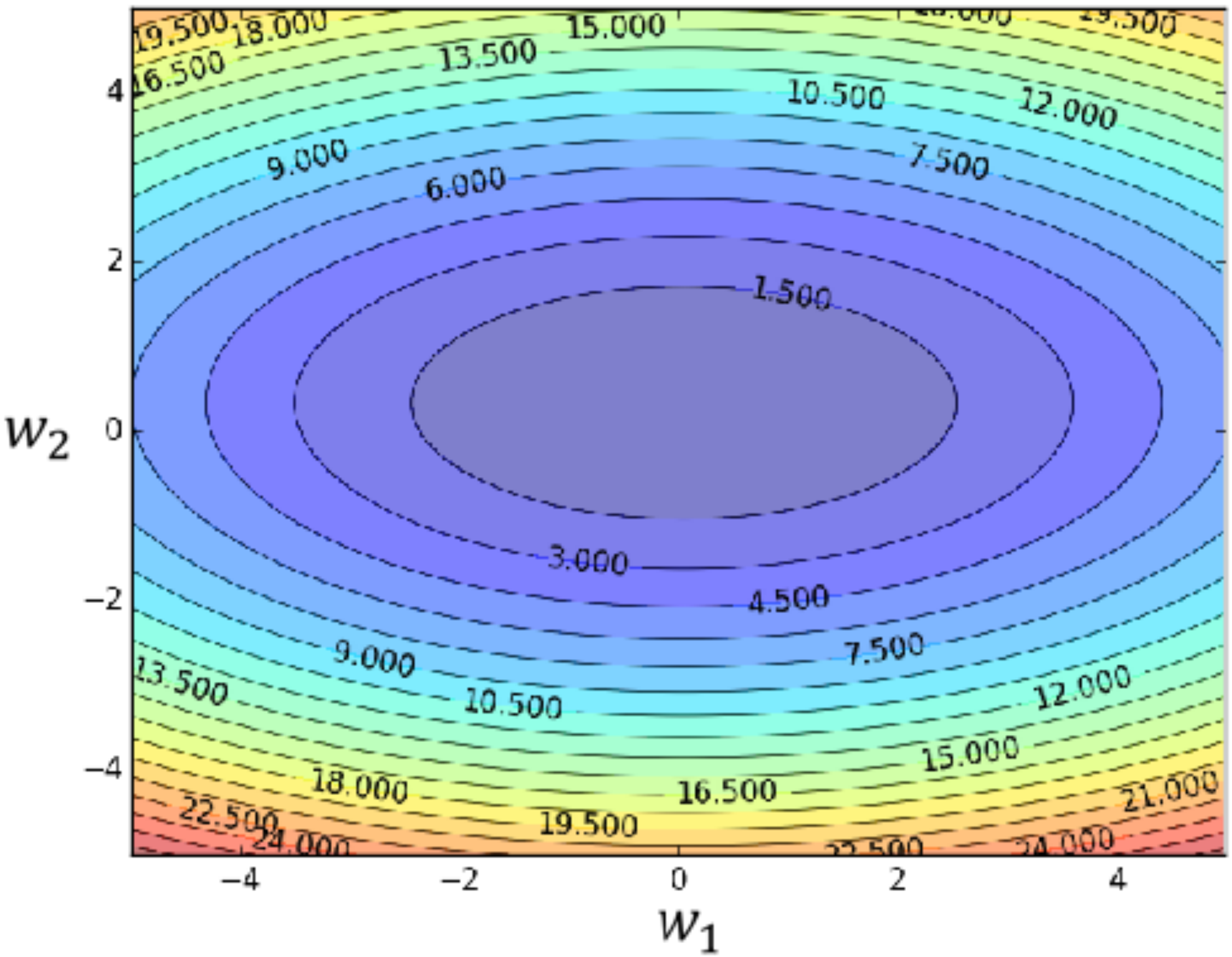
Gradient Descent



Gradient Descent

Assume there are only two parameters w_1 and w_2 in a network.

Error Surface



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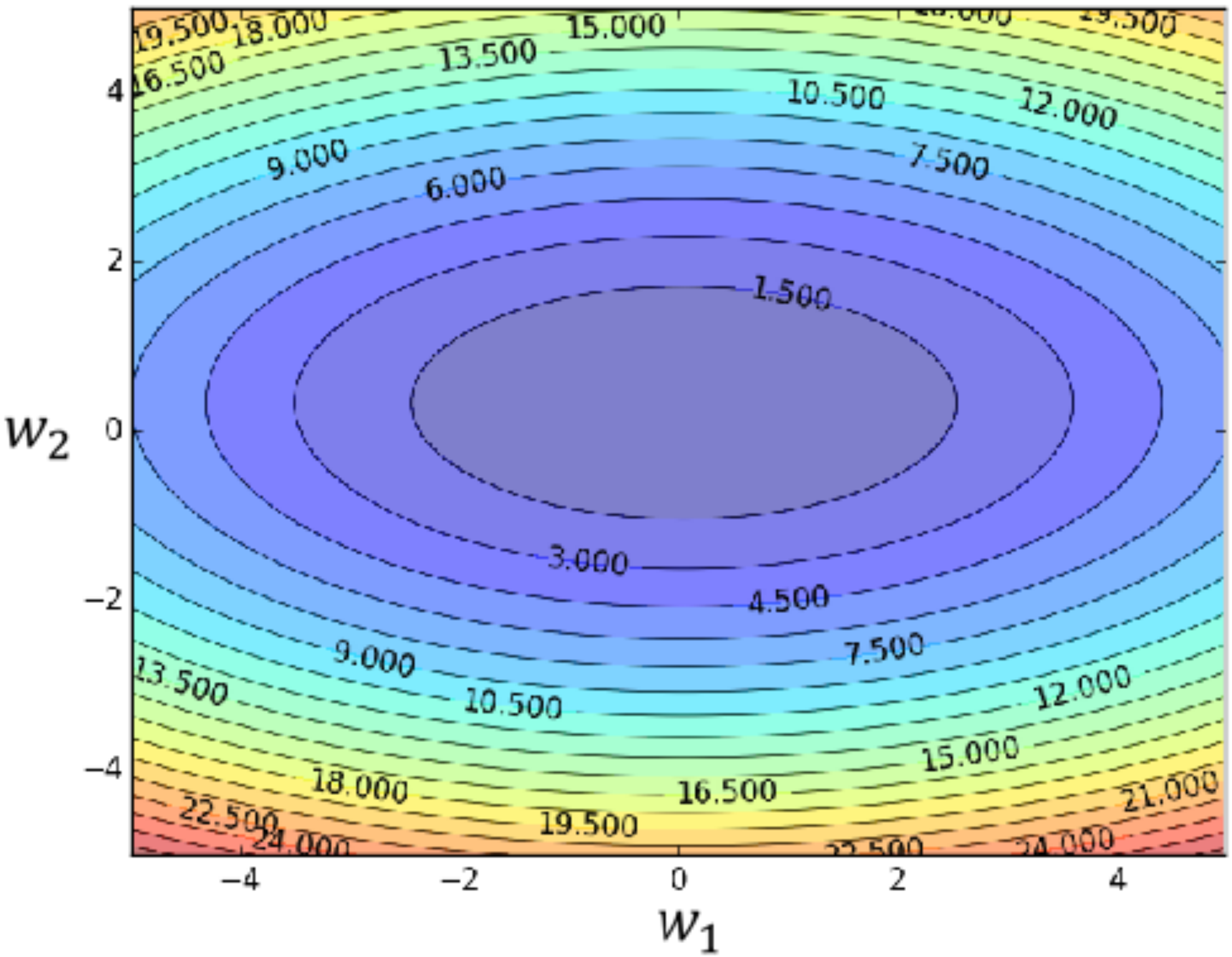

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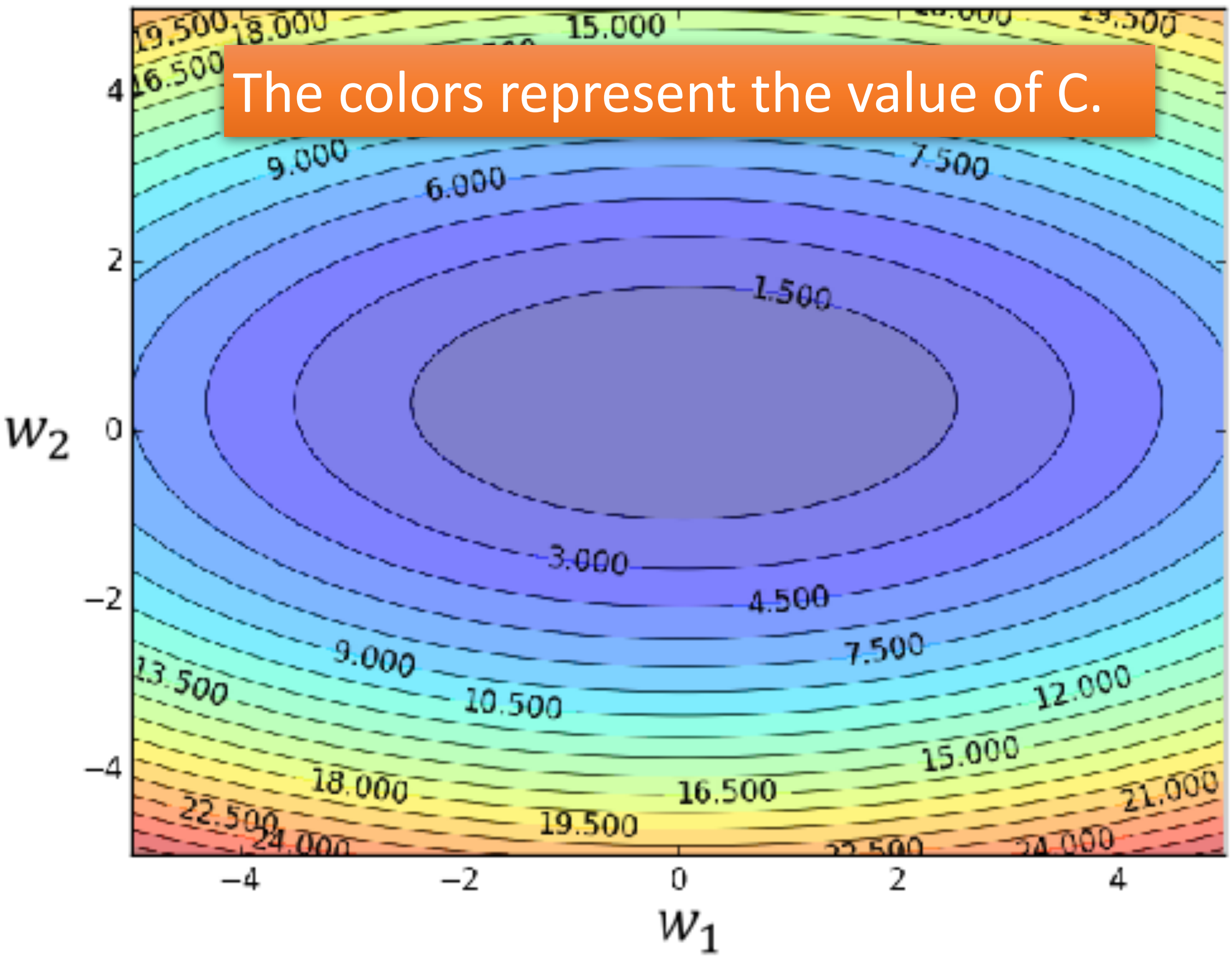

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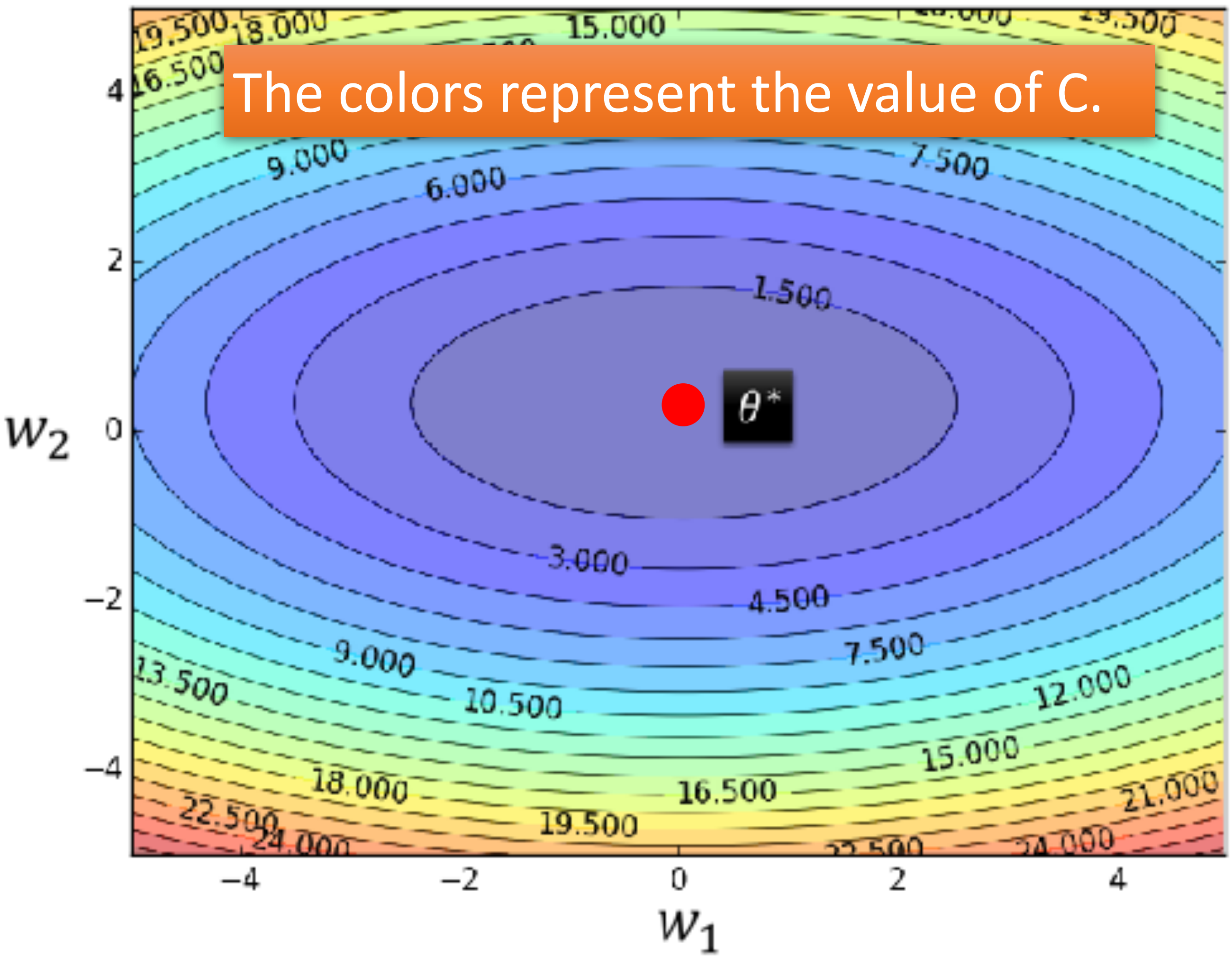

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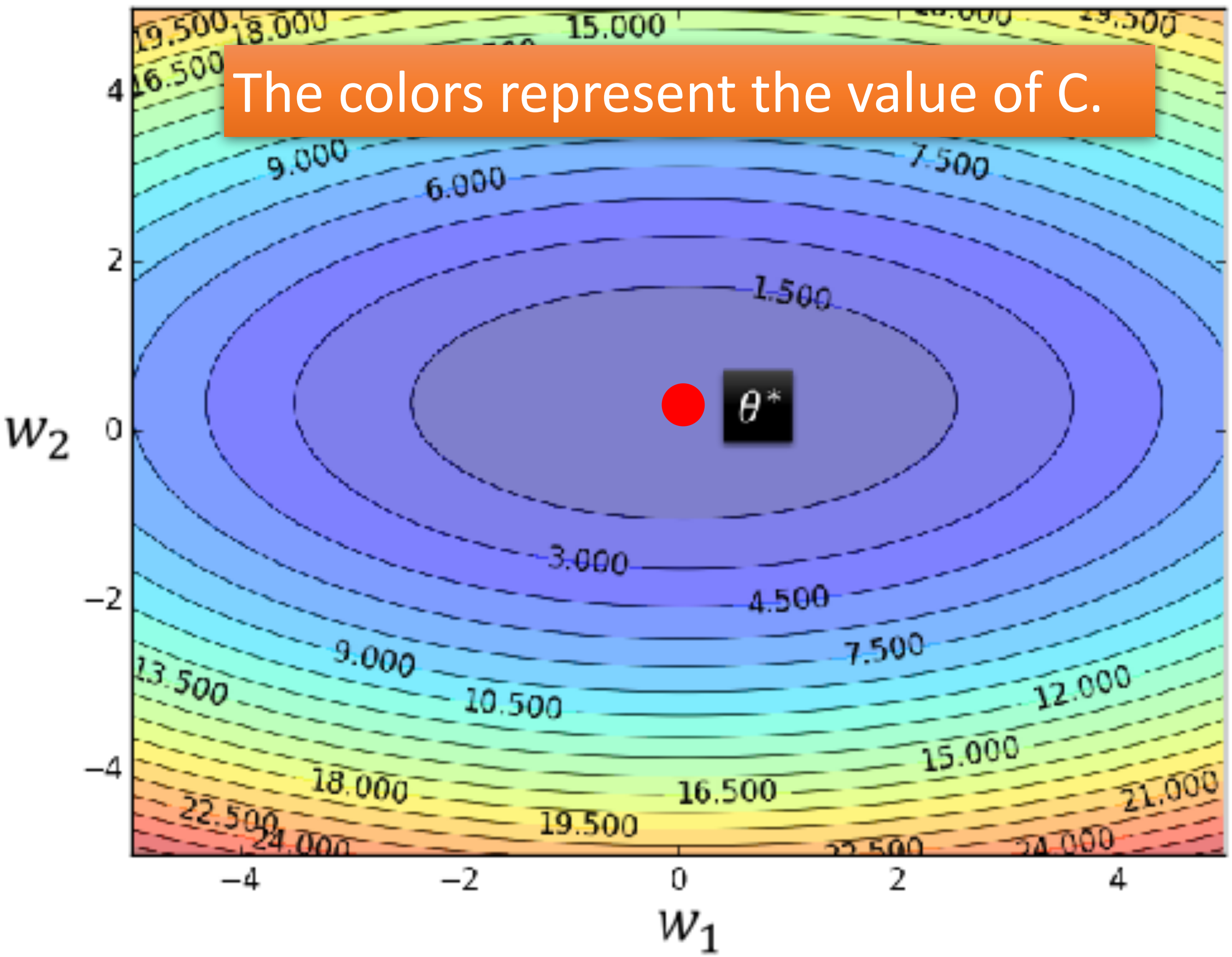

Randomly pick a starting point θ^0

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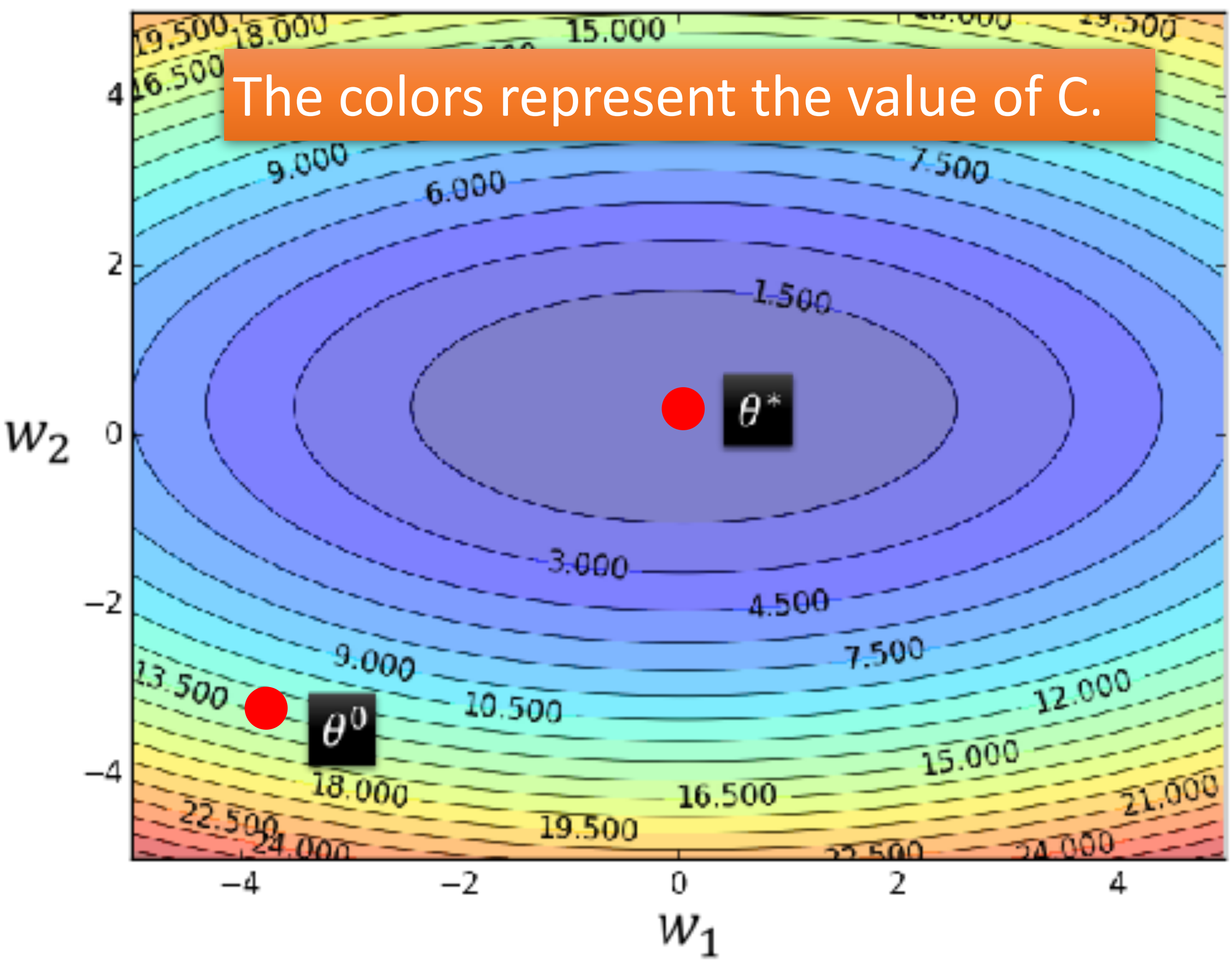

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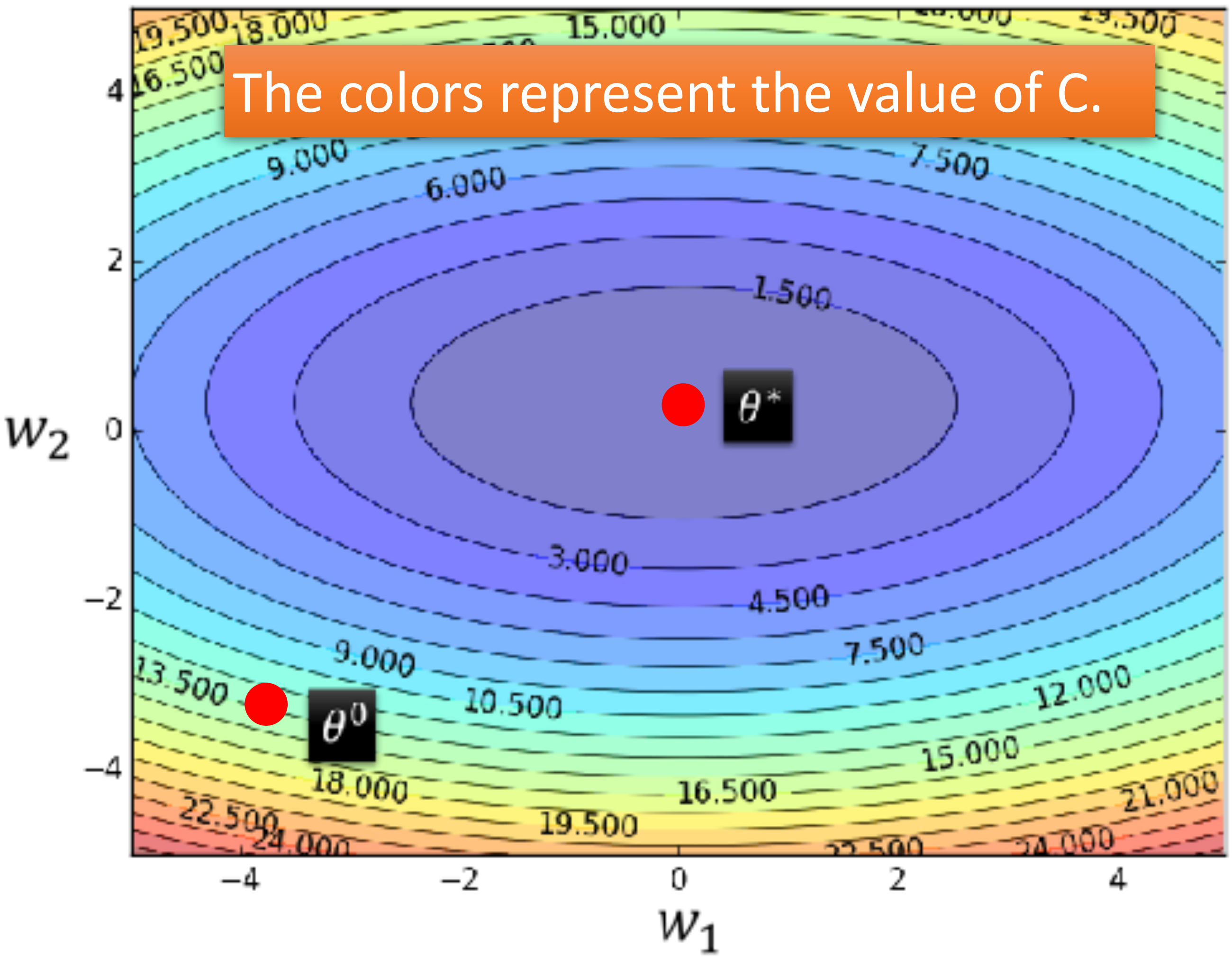

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Compute the negative gradient at θ^0

Gradient Descent

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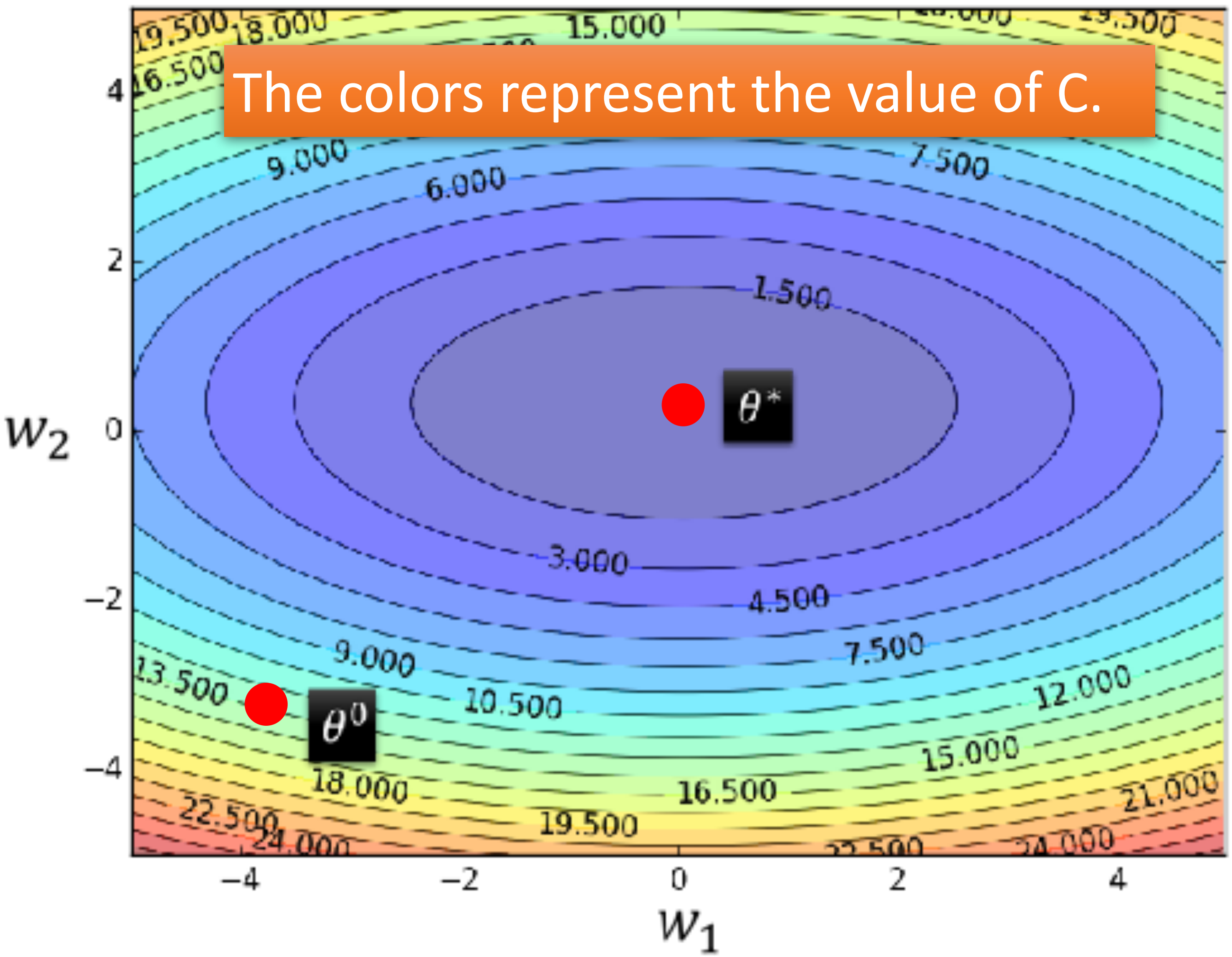

Randomly pick a starting point θ^0

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$$\rightarrow -\nabla C(\theta^0)$$

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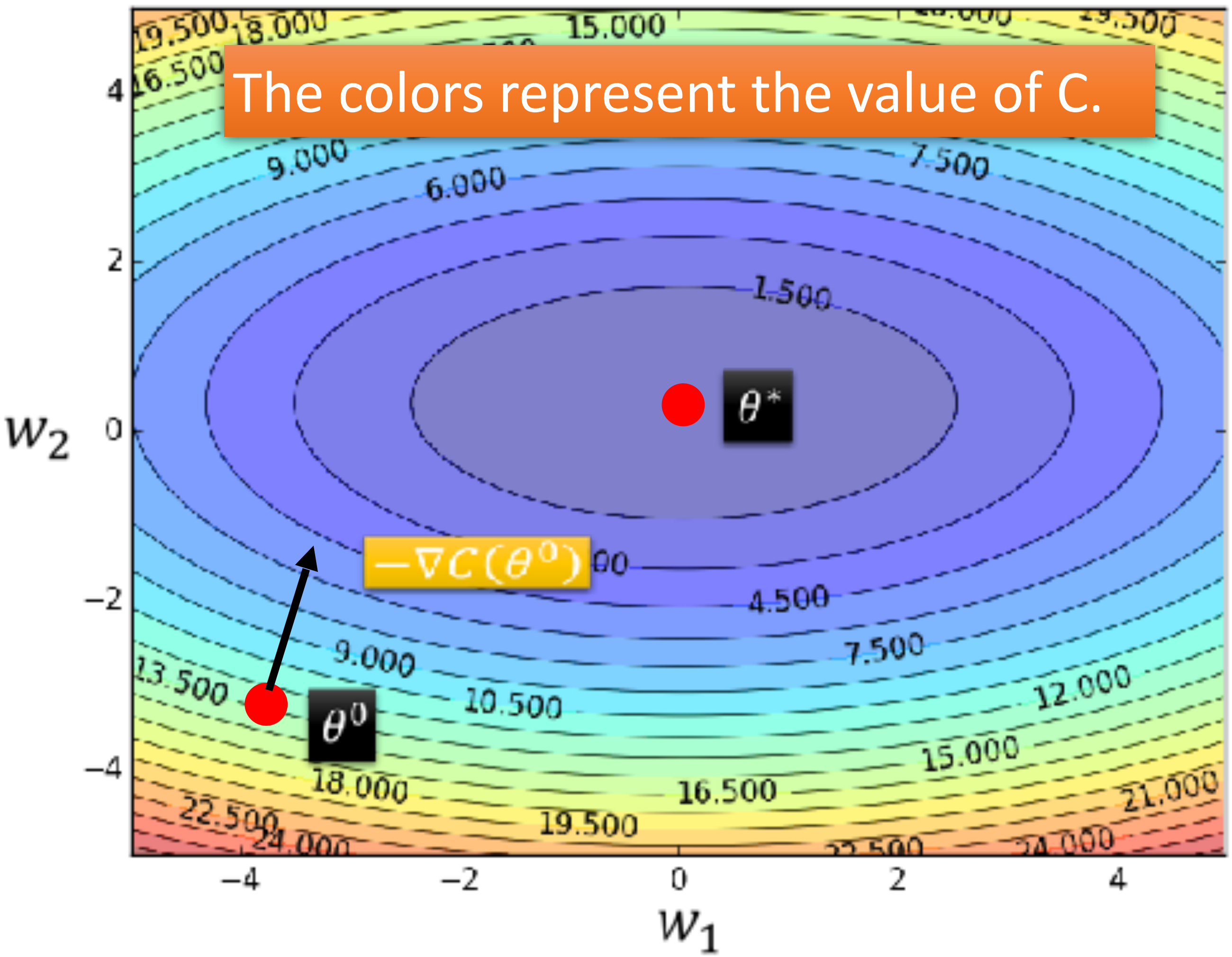

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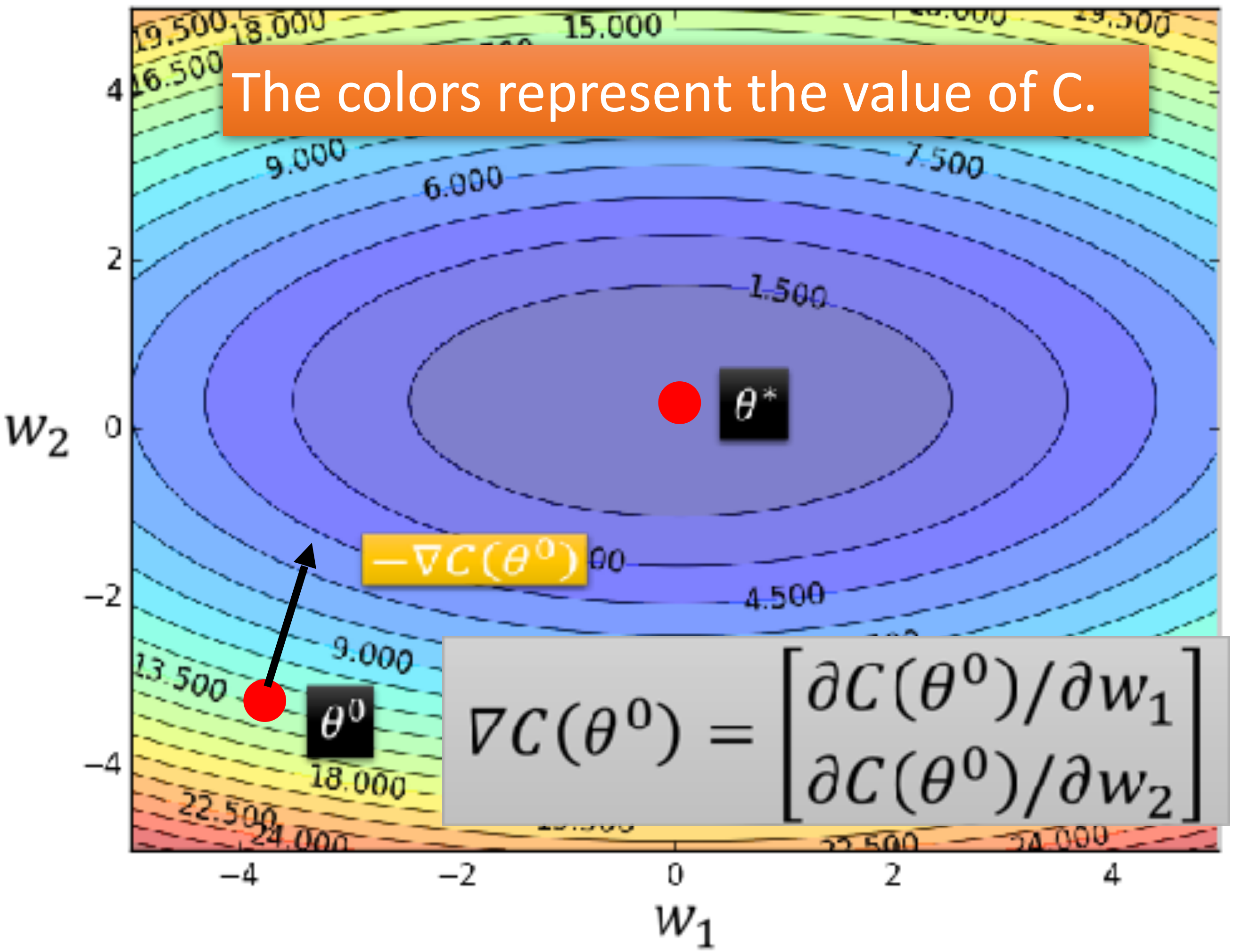

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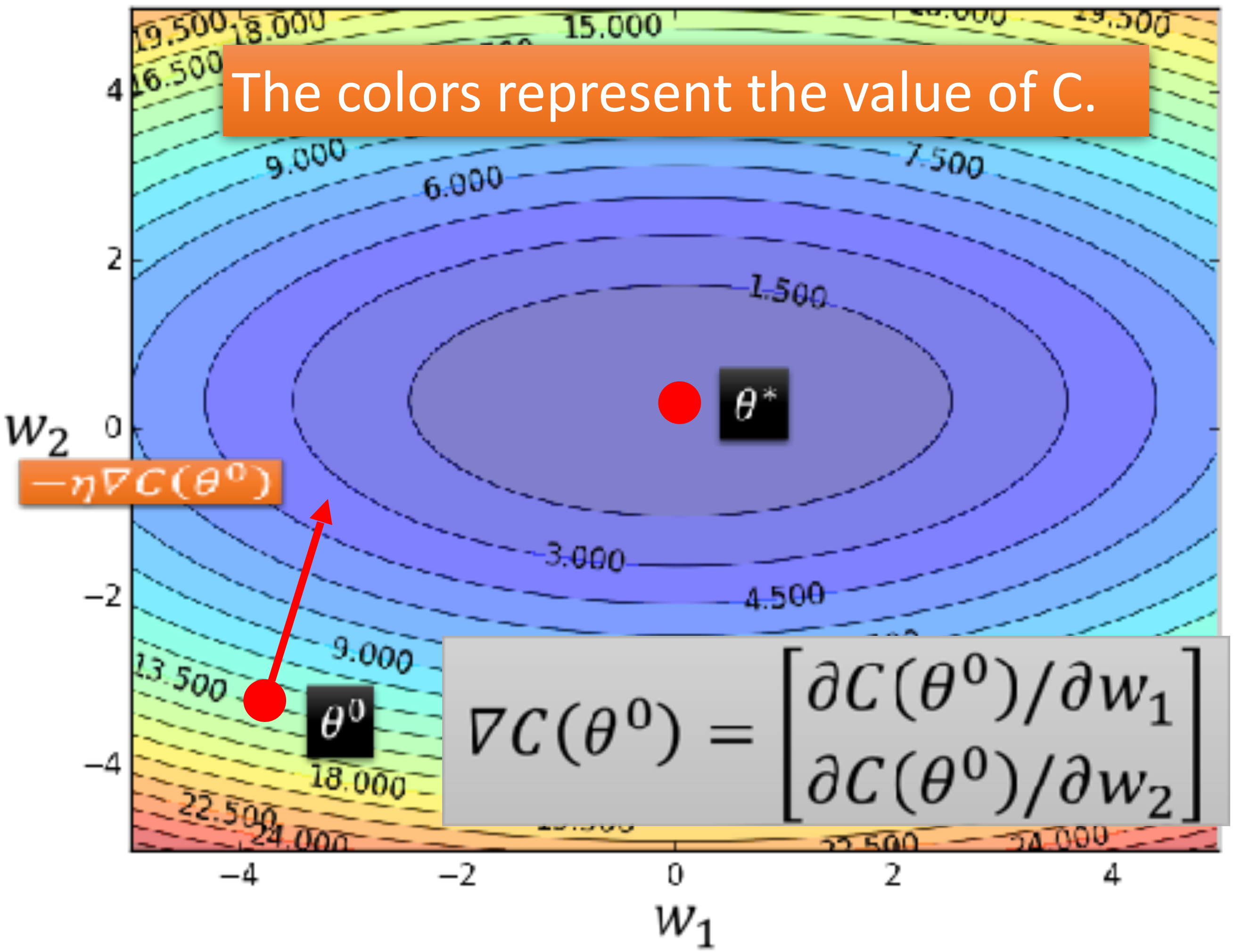

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Compute the negative gradient at θ^0

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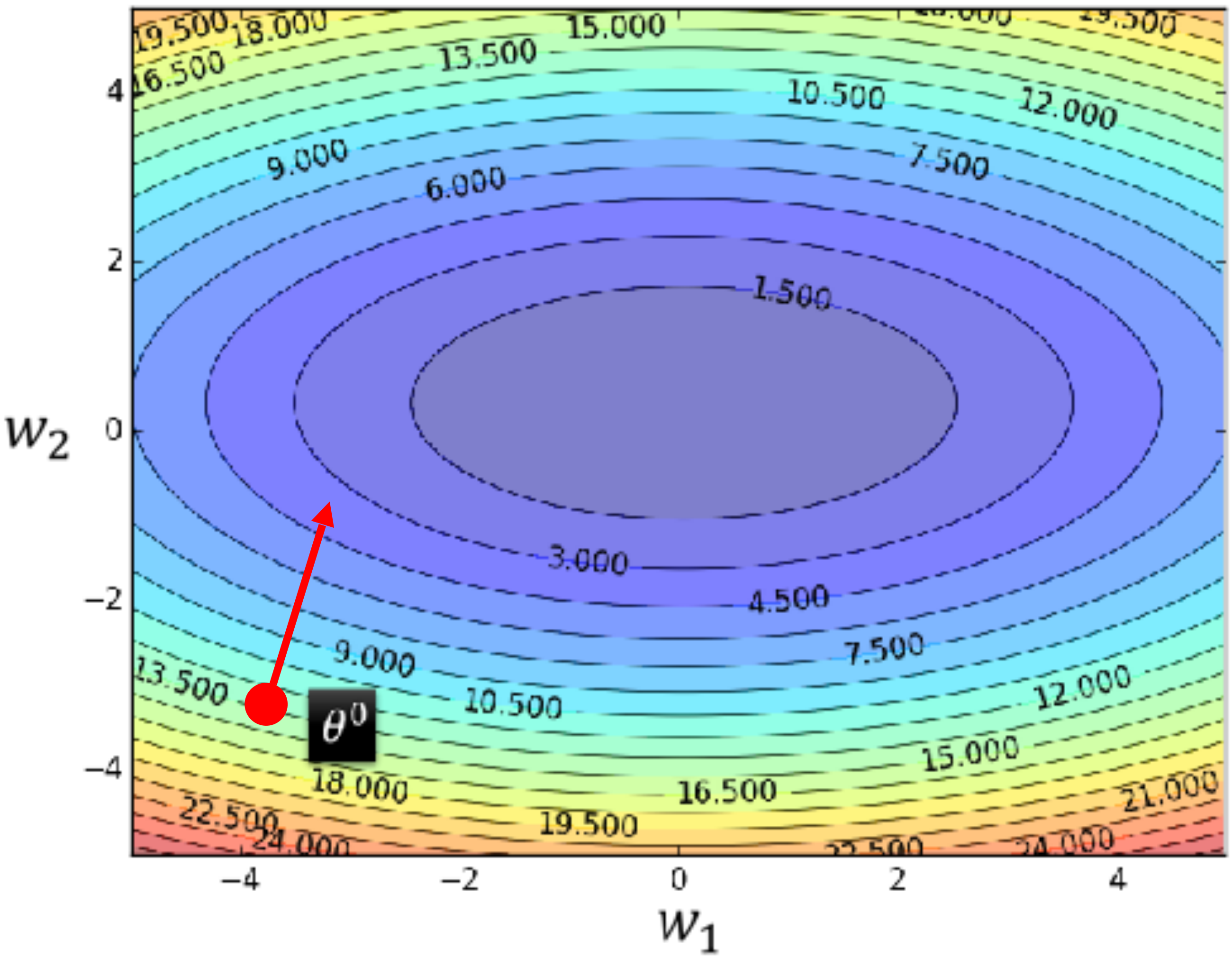
Times the learning rate η

$\Rightarrow -\eta \nabla C(\theta^0)$

Gradient Descent



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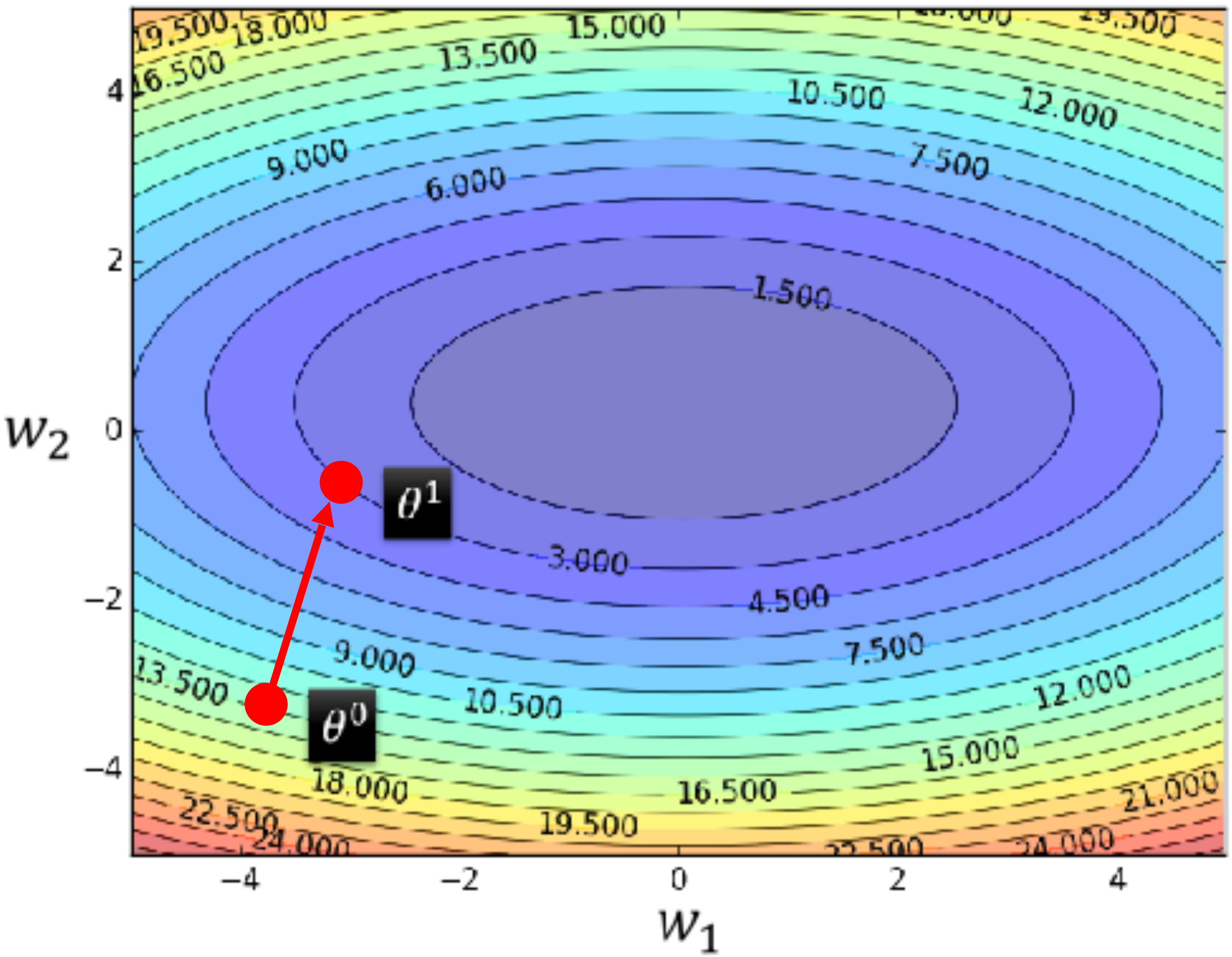

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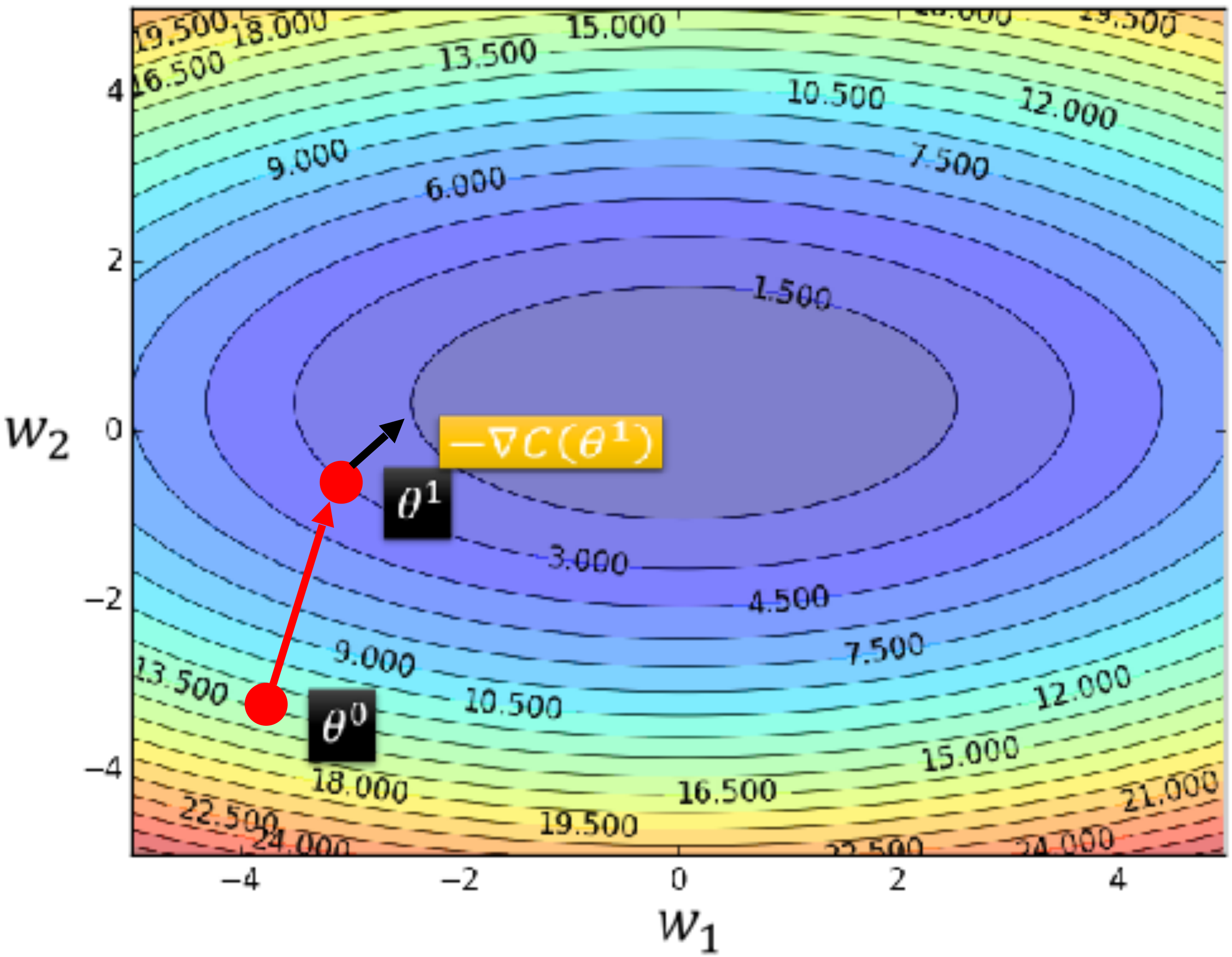

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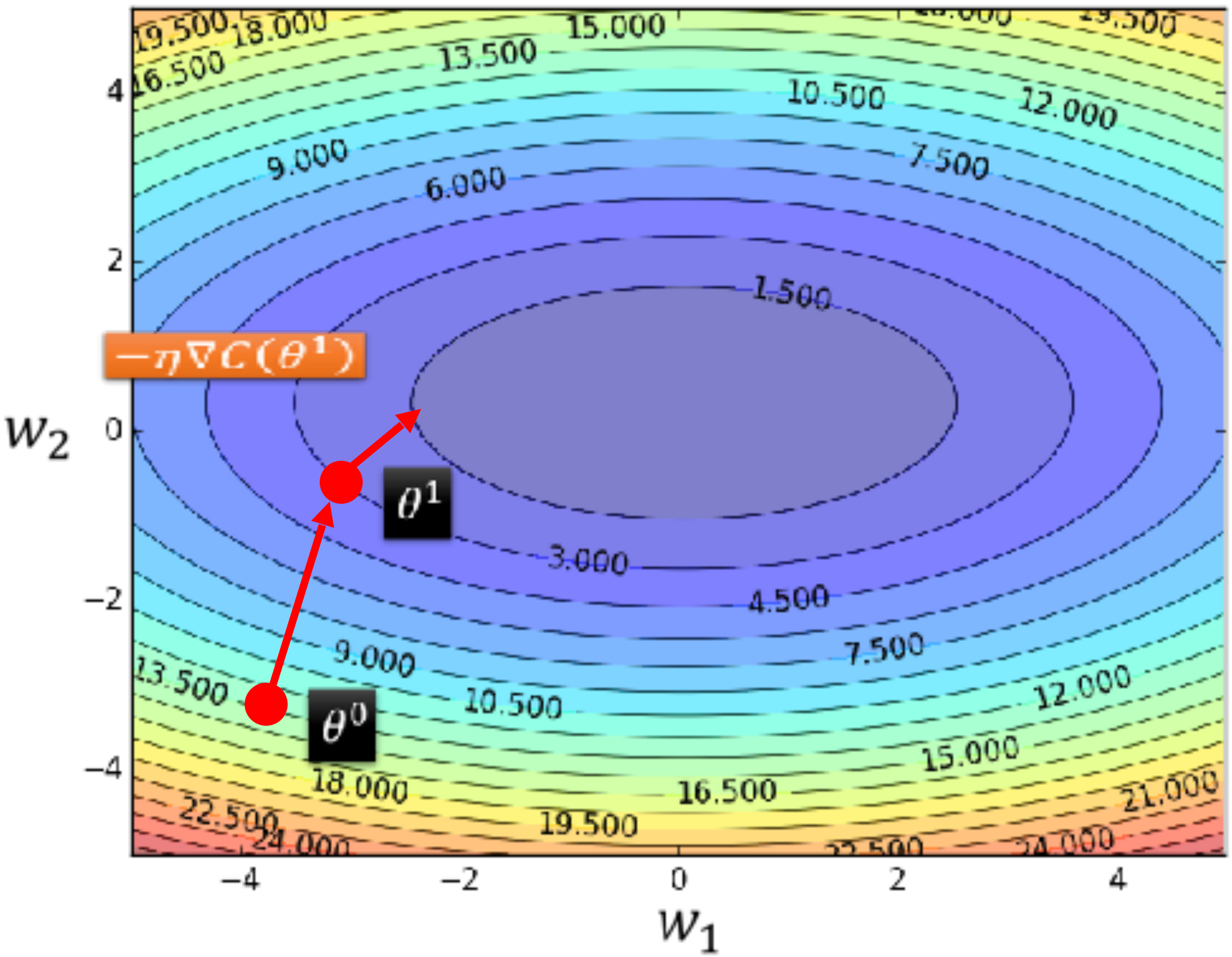
Gradient Descent



Randomly pick a starting point θ^0

Compute the negative gradient at θ^0

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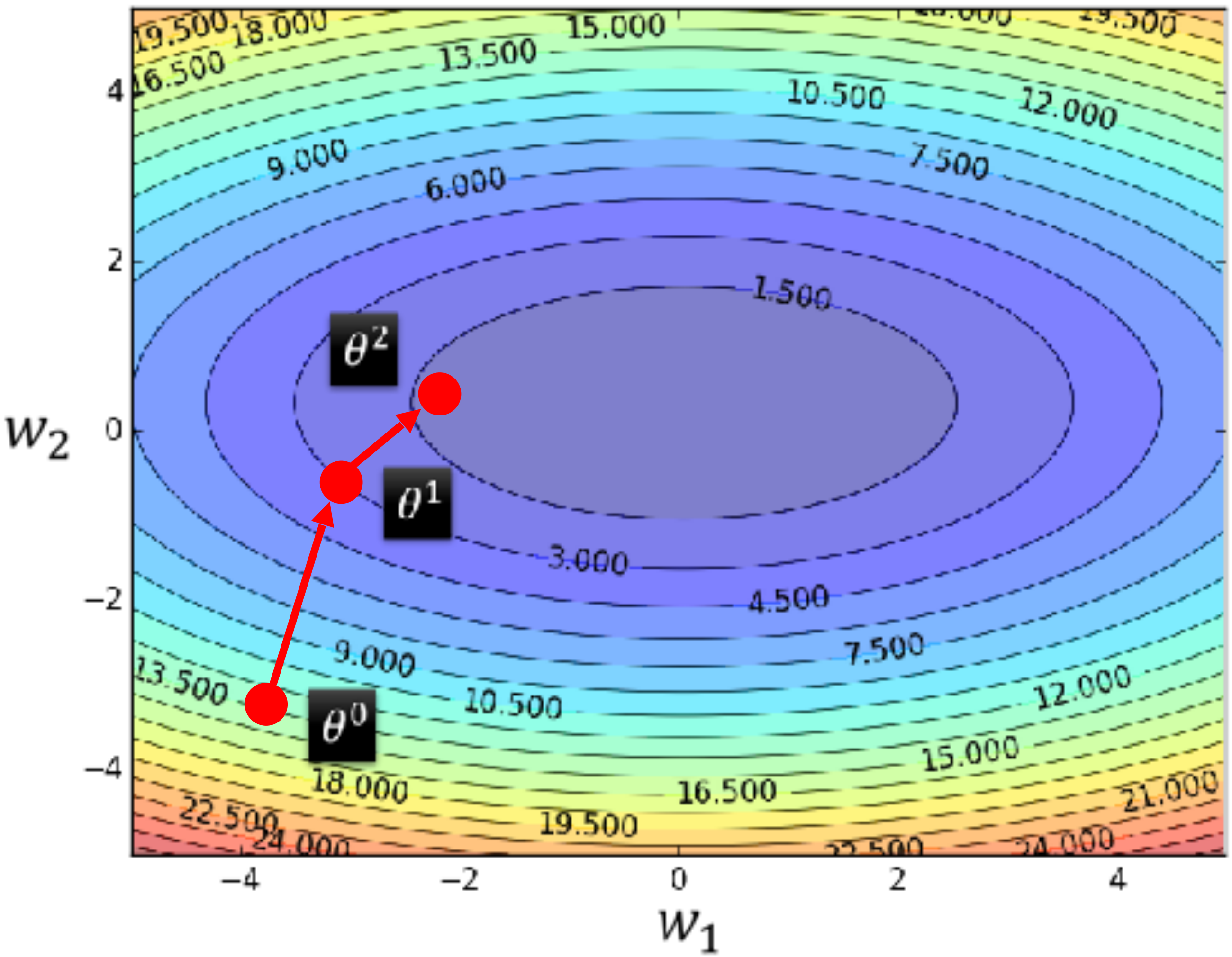
Times the learning rate η

$\Rightarrow -\eta\nabla C(\theta^0)$

Gradient Descent



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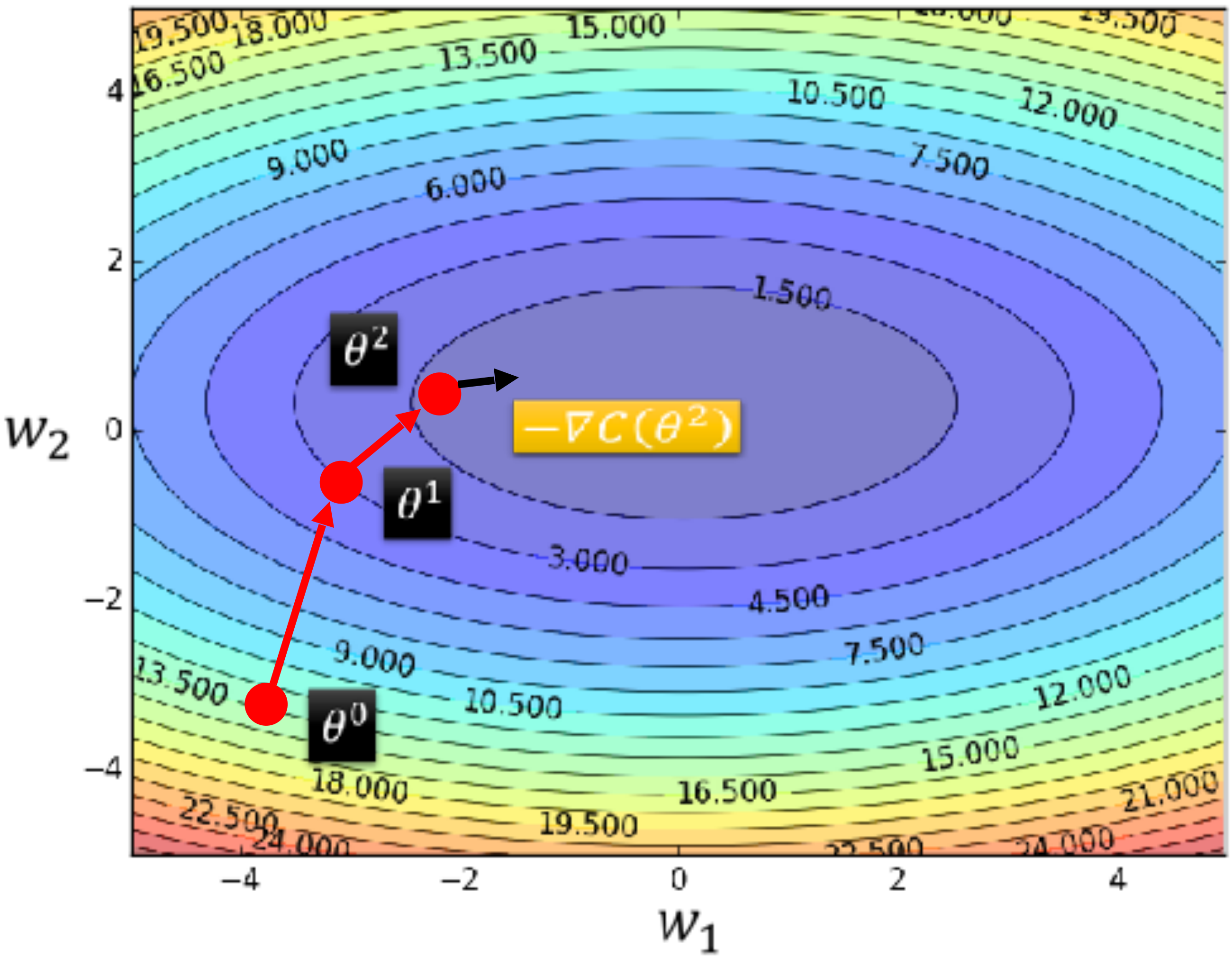

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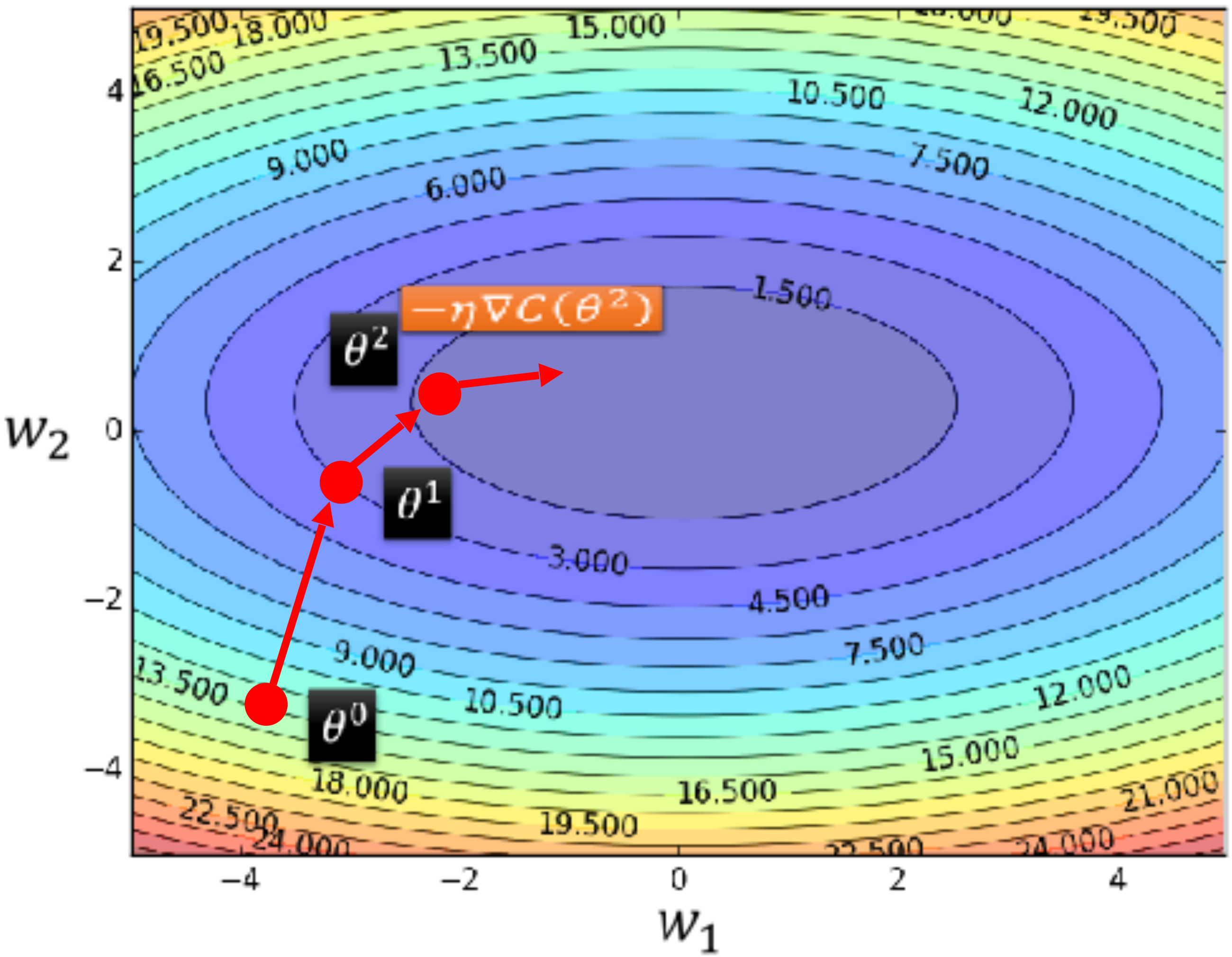

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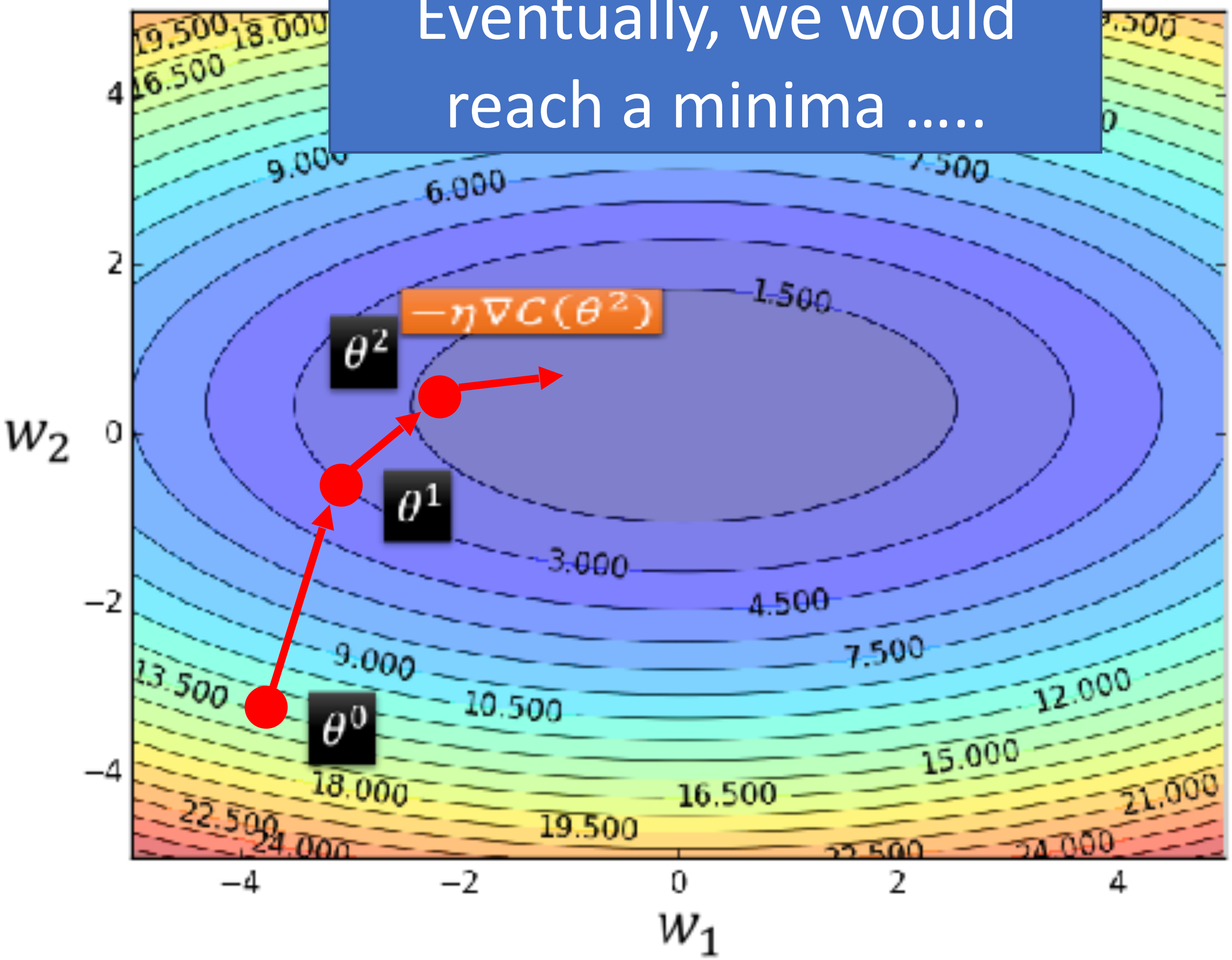
Gradient Descent

Eventually, we would reach a minima .....



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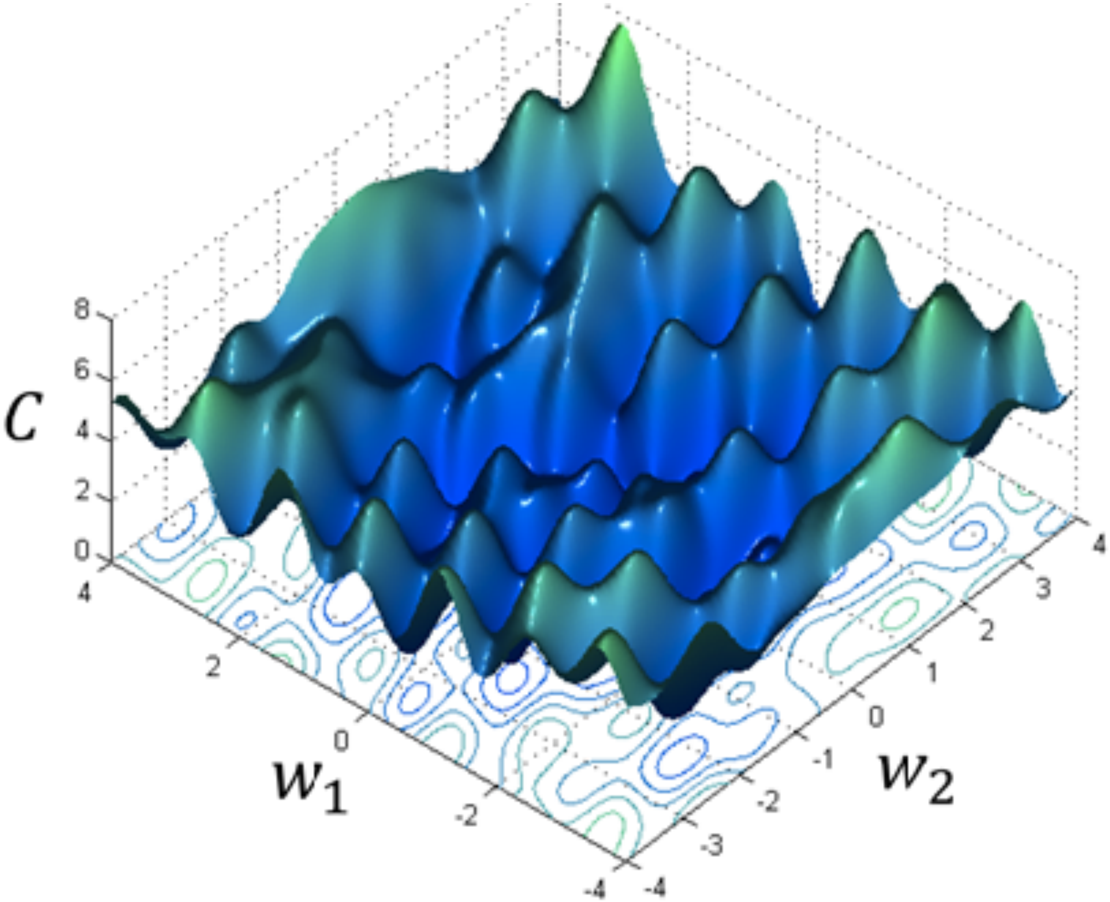
Local Minima

- Gradient descent never guarantee global minima



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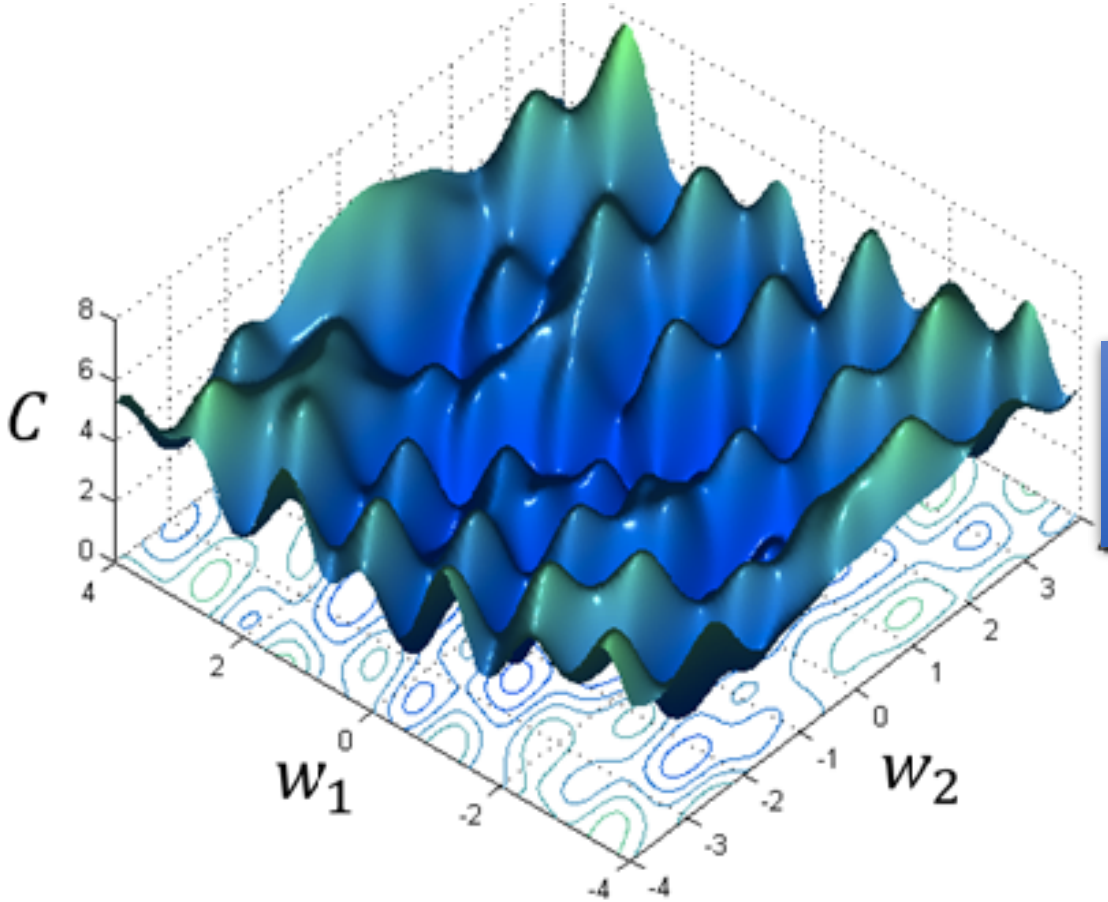

Different initial point θ^0

Reach different minima, so different results

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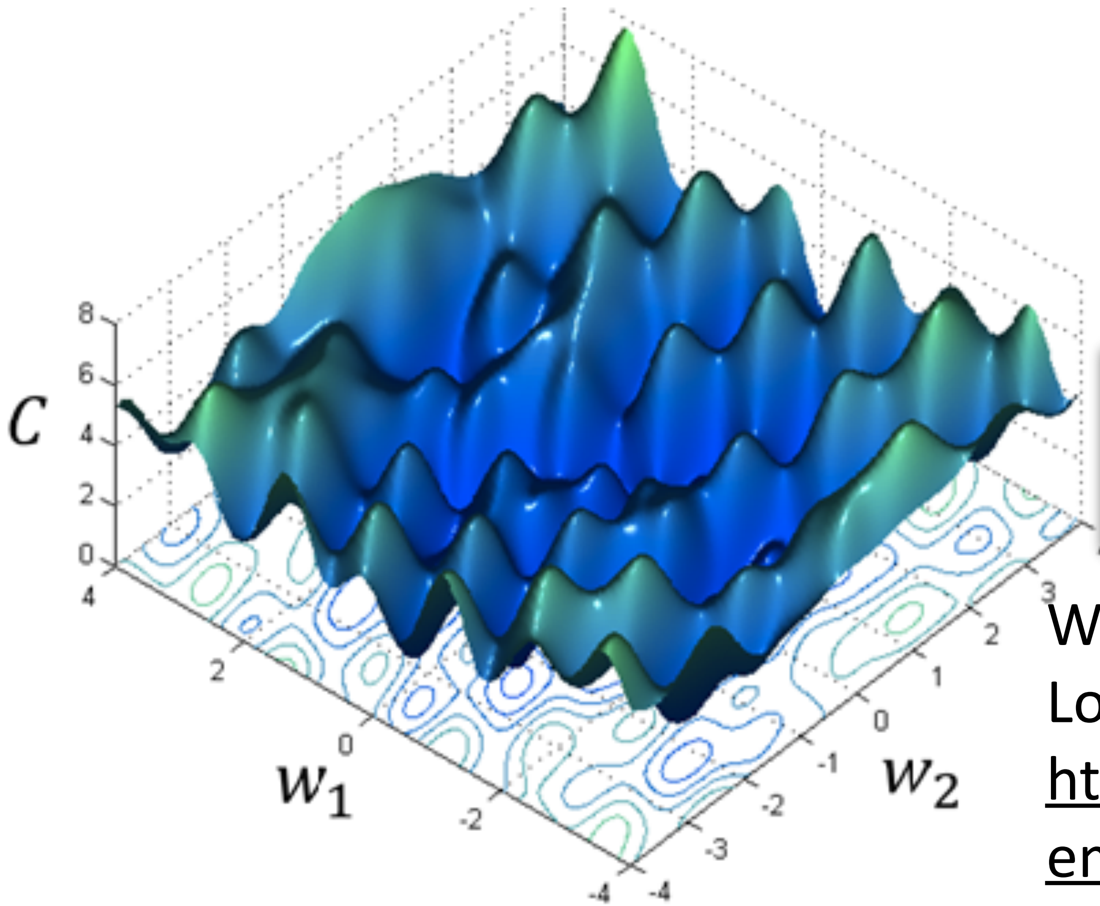

Different initial point θ^0

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Who is Afraid of Non-Convex Loss Functions?
http://videolectures.net/eml07_lecun_wia/

Part II:
Why Deep?

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

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Not surprised, more parameters, better performance

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Universality Theorem

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Any continuous function f

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$$f : R^N \rightarrow R^{\mathrm{M}}$$

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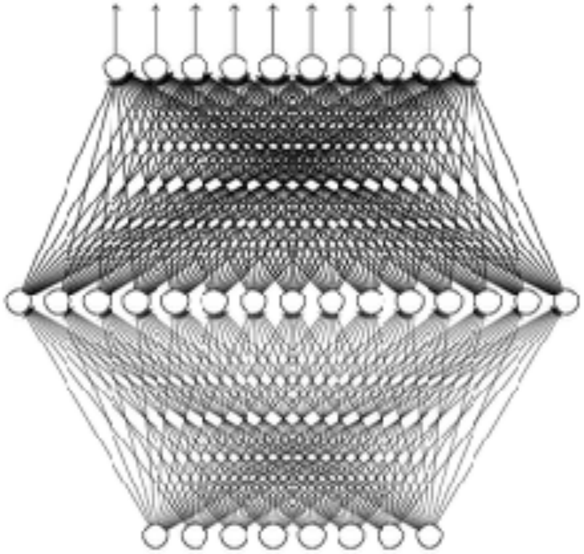

Reference for the reason: http://neuralnetworksanddeeplearning.com/chap4.html

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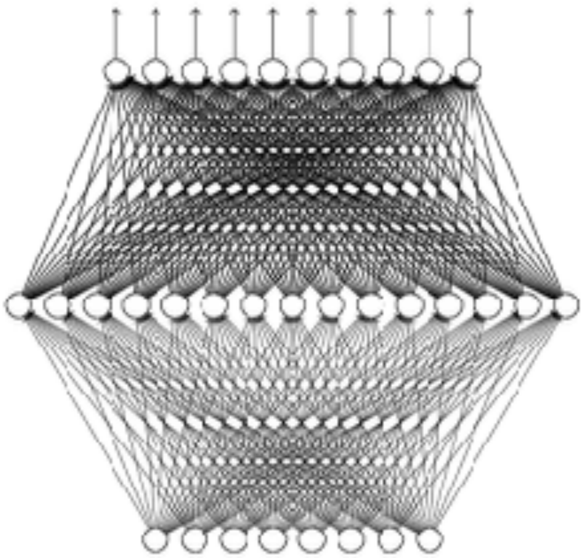
(given **enough** hidden neurons)



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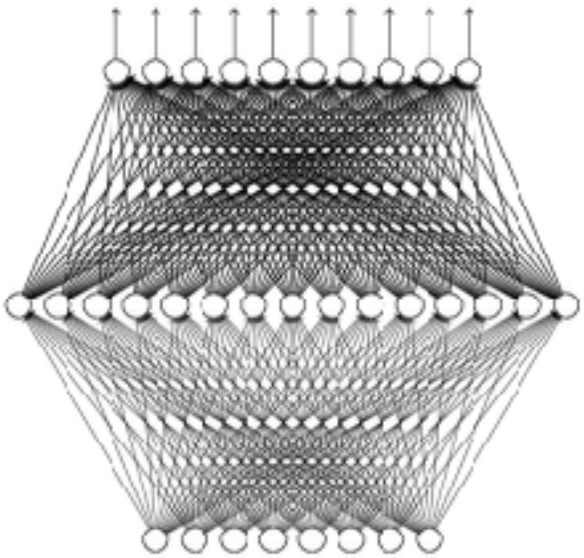

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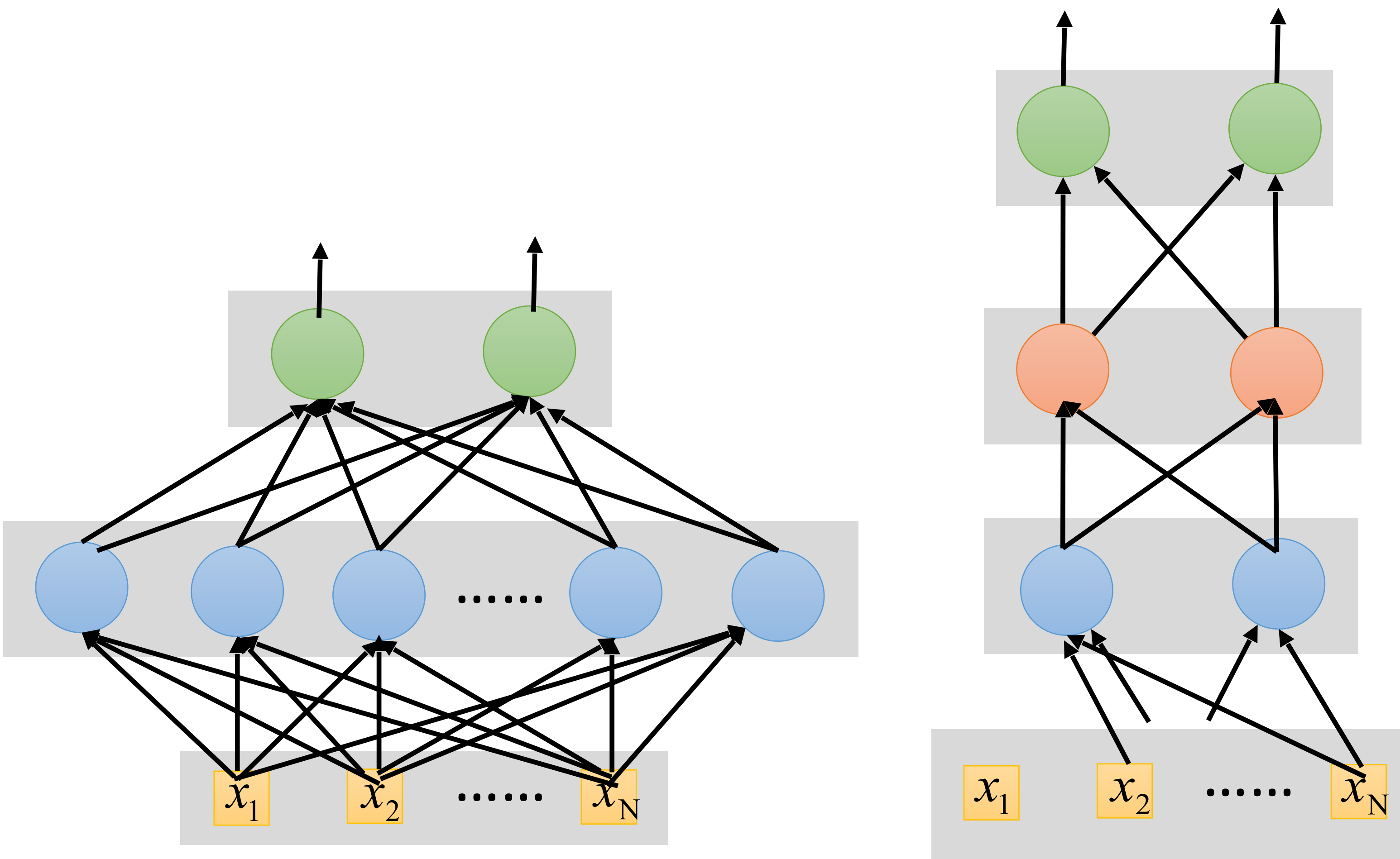
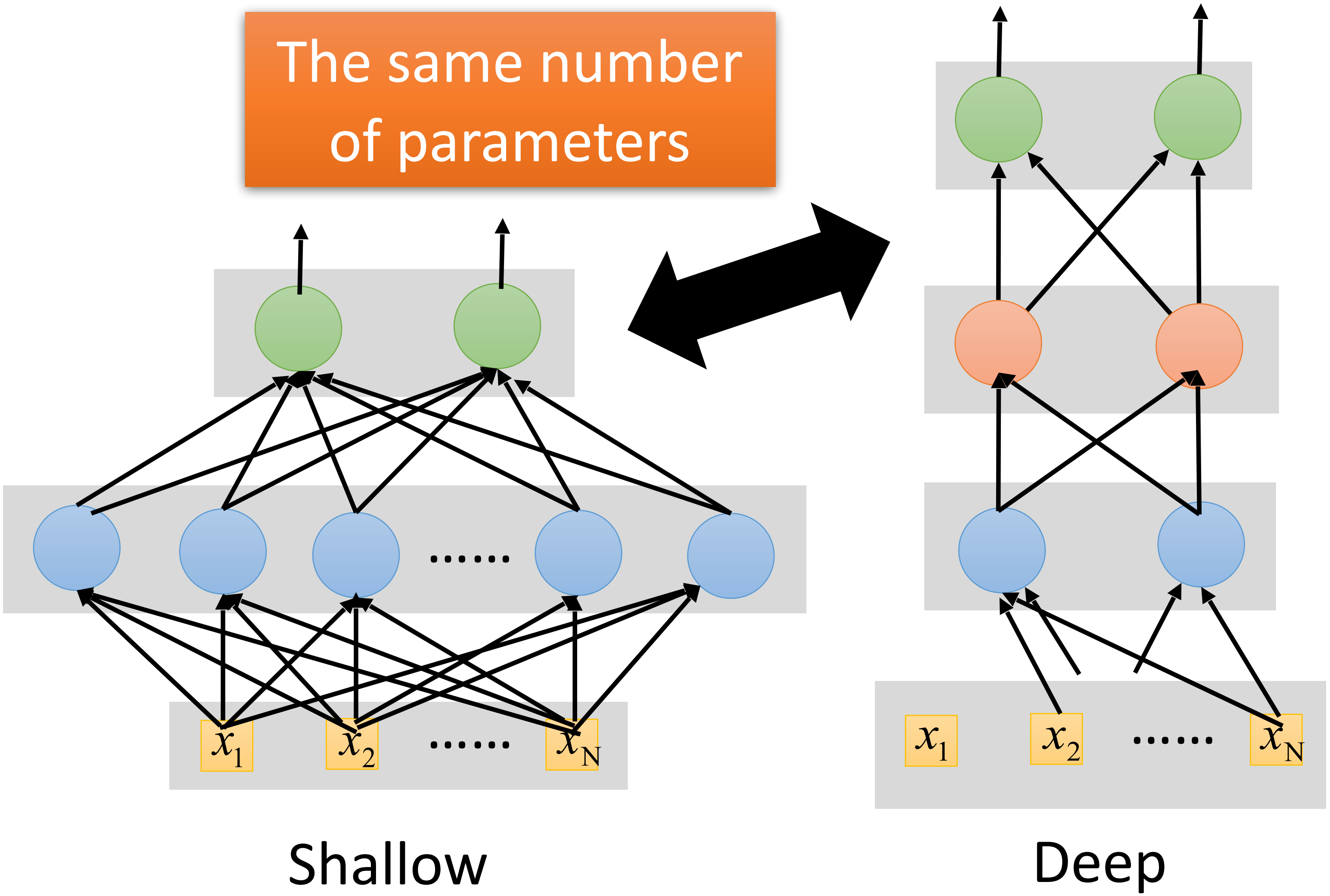
Why "Deep" neural network not "Fat" neural network?

Fat + Short v.s. Thin + Tall



Shallow   Deep

Fat + Short v.s. Thin + Tall



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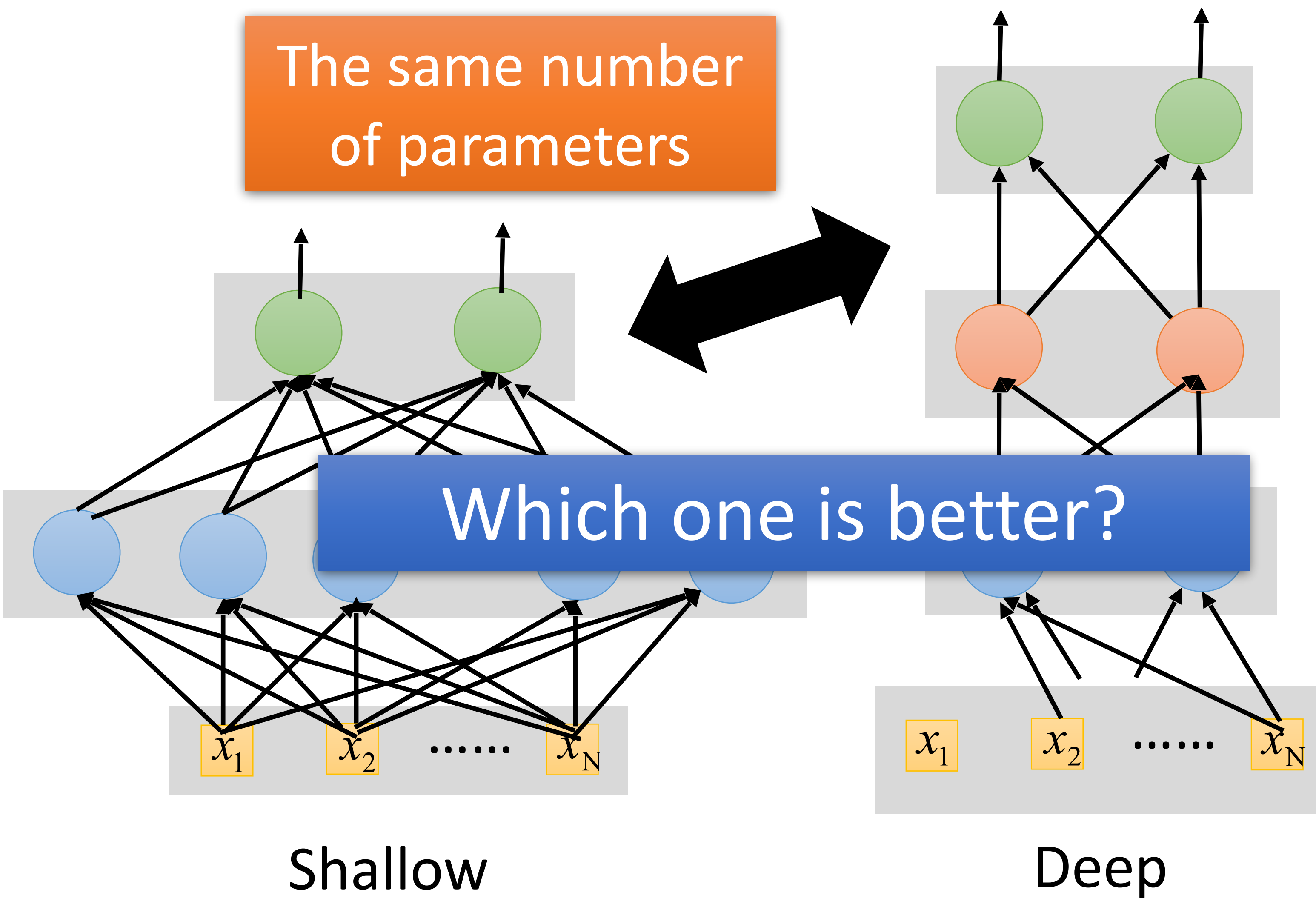

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Why Deep?

- Deep → Modularization

Image

Girls with long hair

Boys with long hair

Girls with short hair

Boys with short hair

Why Deep?

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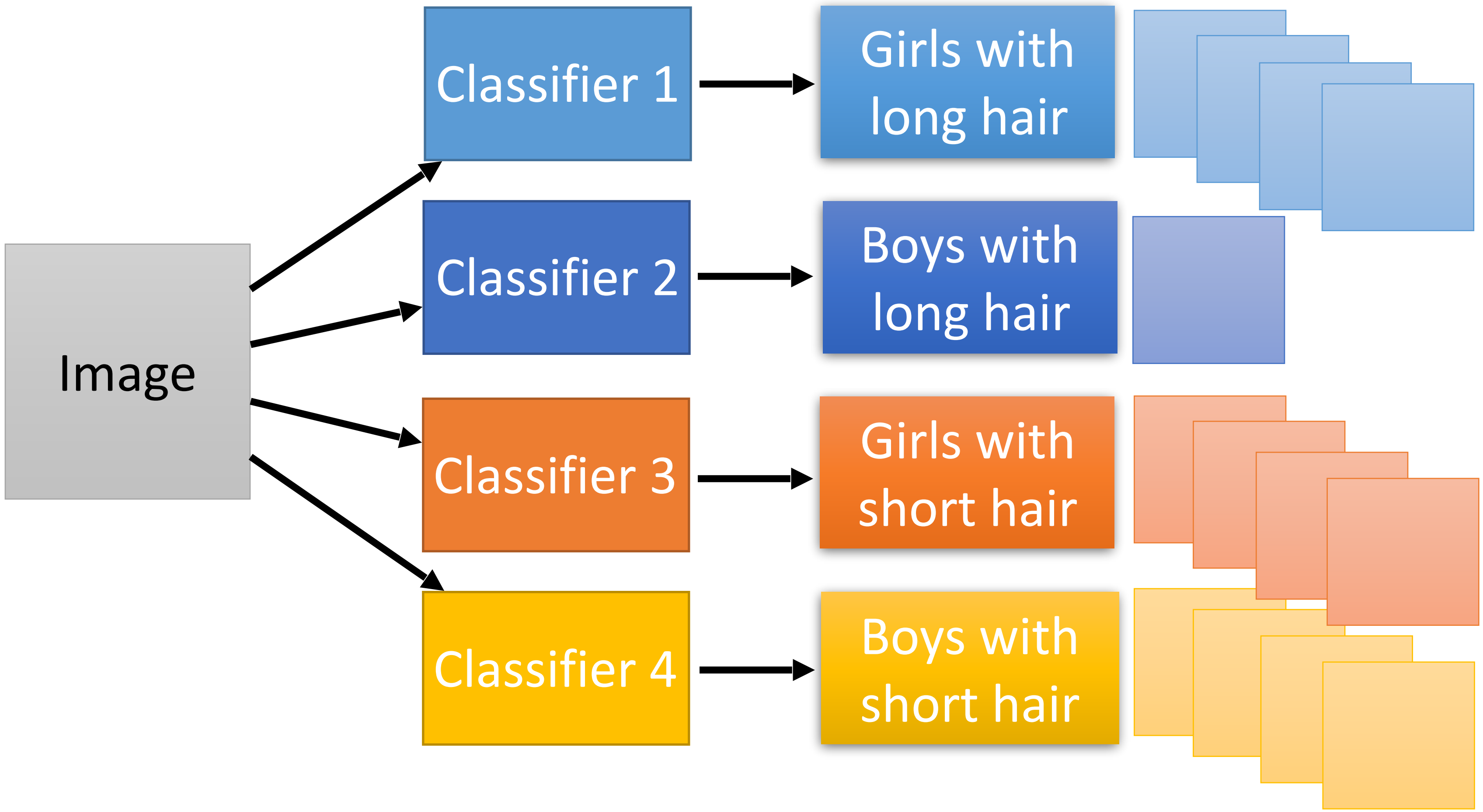

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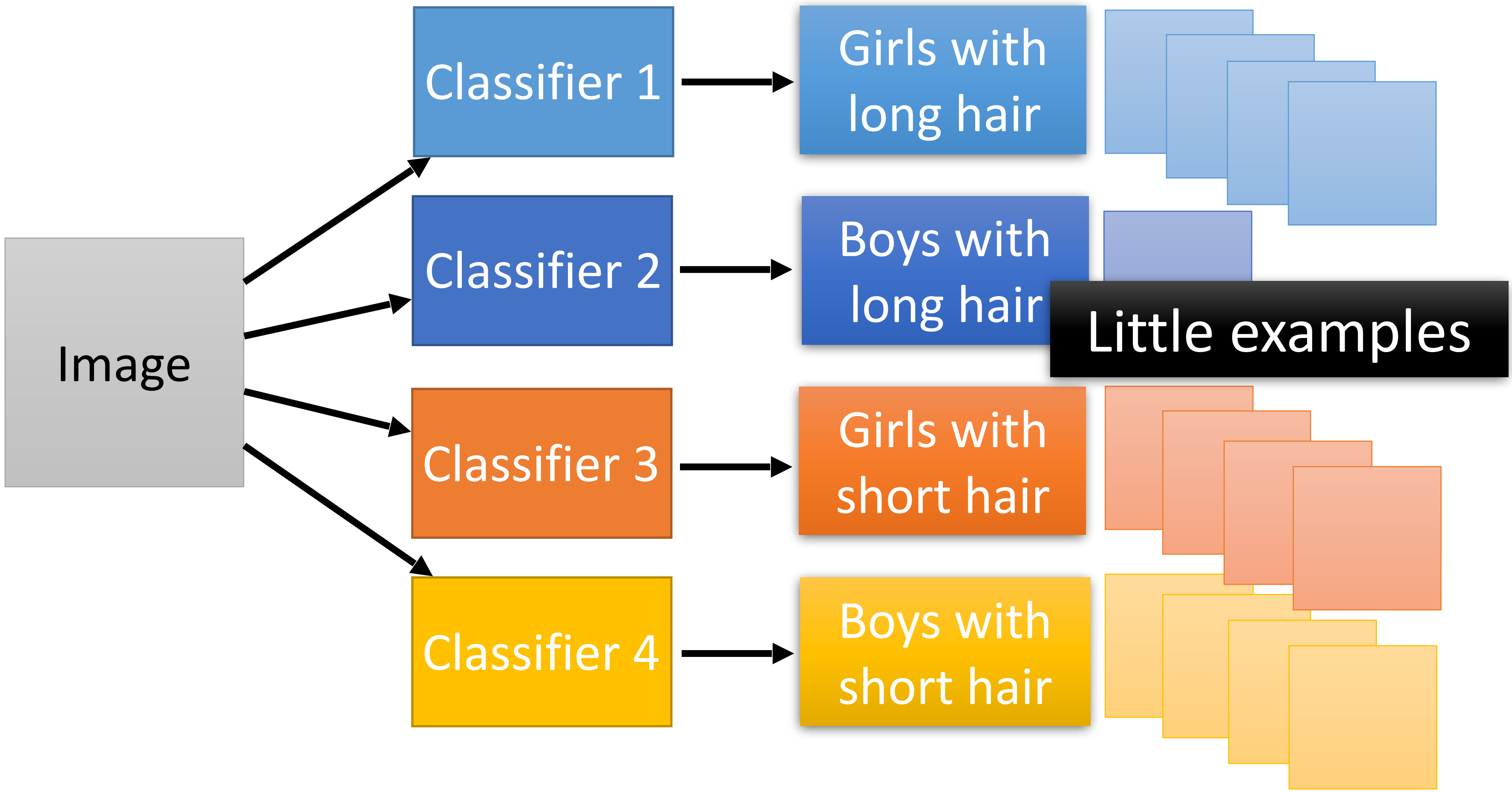

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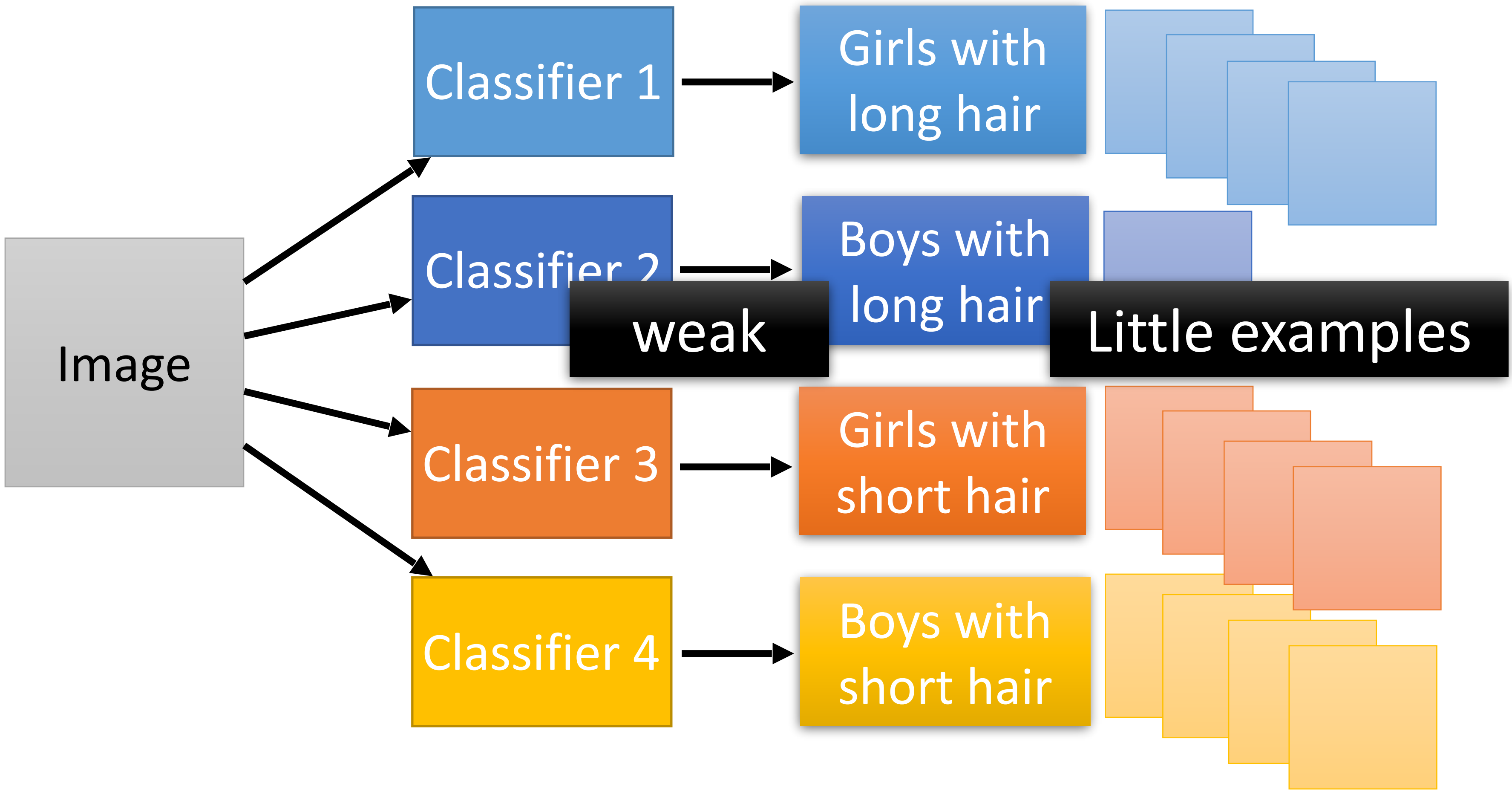

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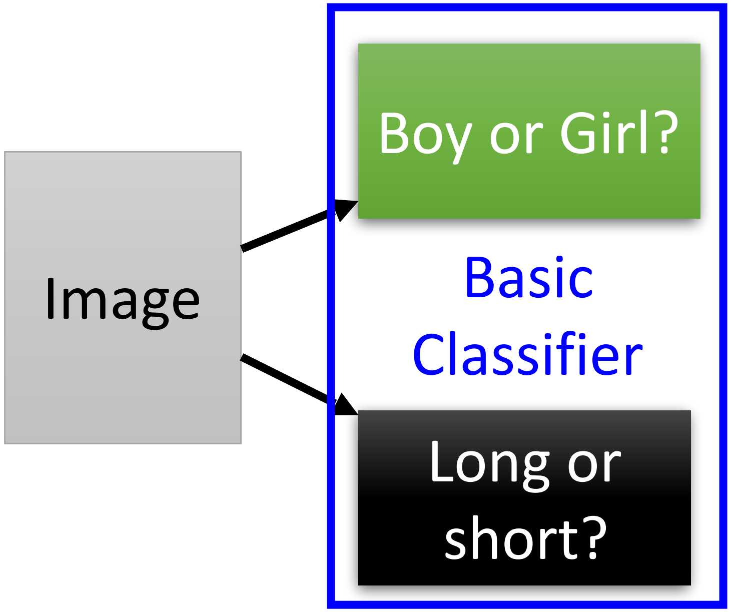

Classifiers for the attributes

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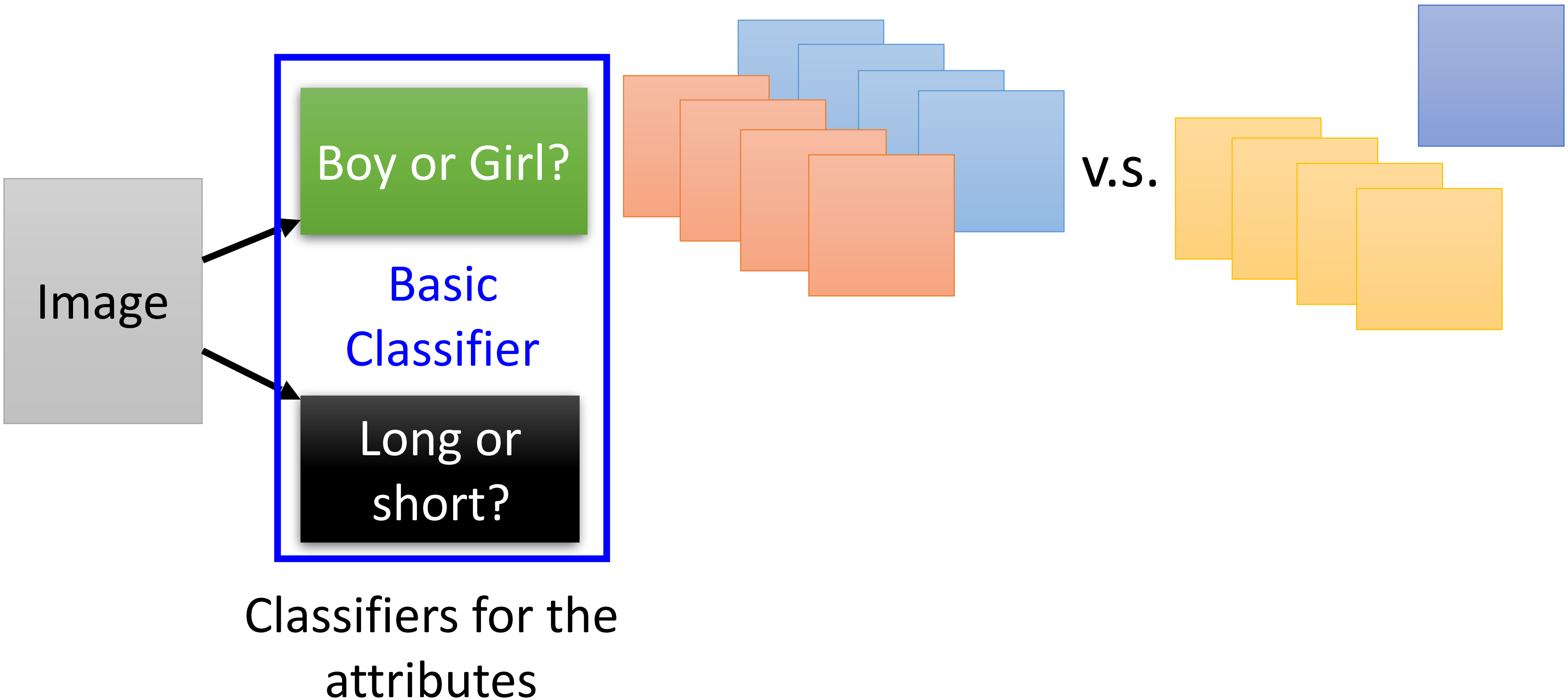

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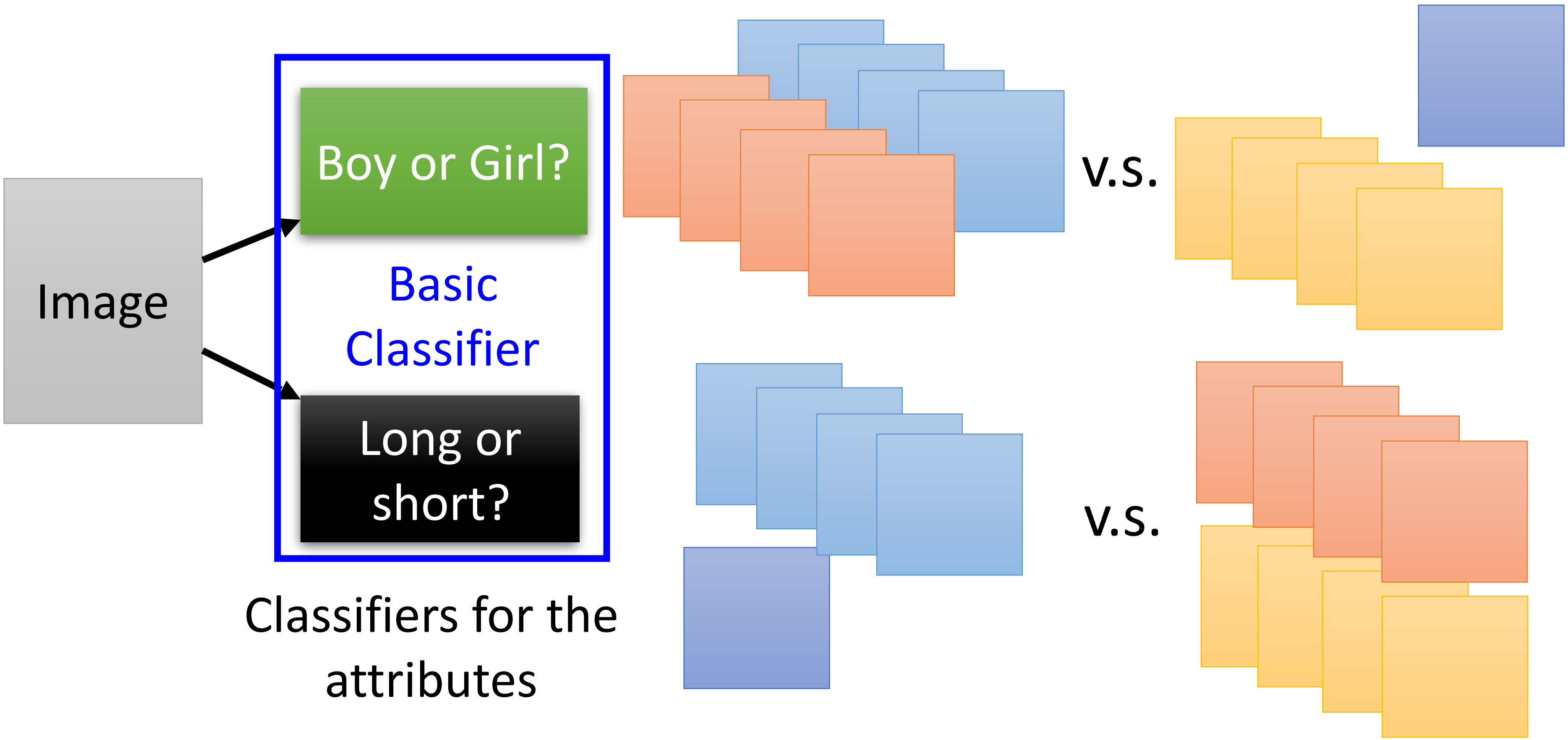
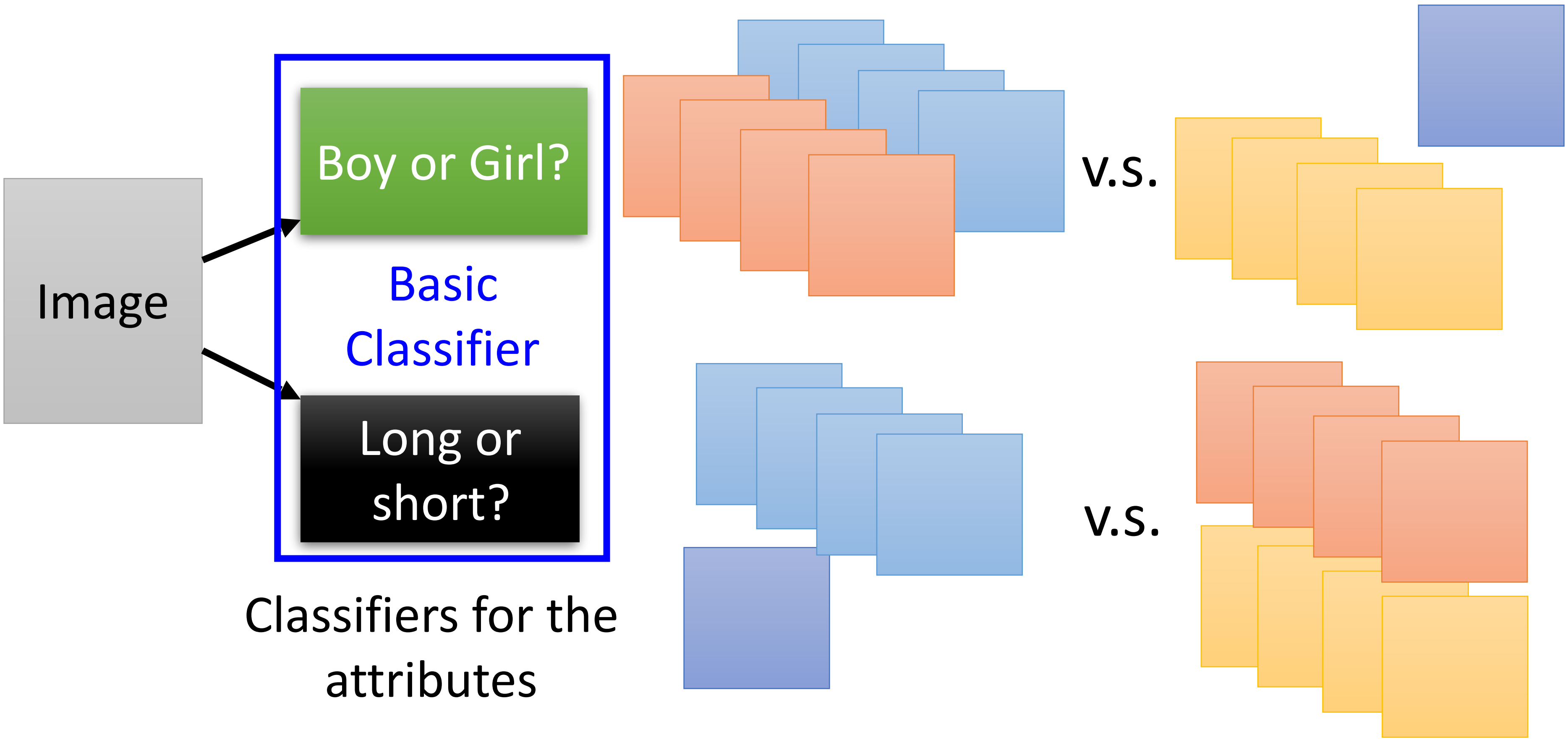


Classifiers for the attributes

Why Deep?

Each basic classifier can have sufficient training examples.

- Deep → Modularization



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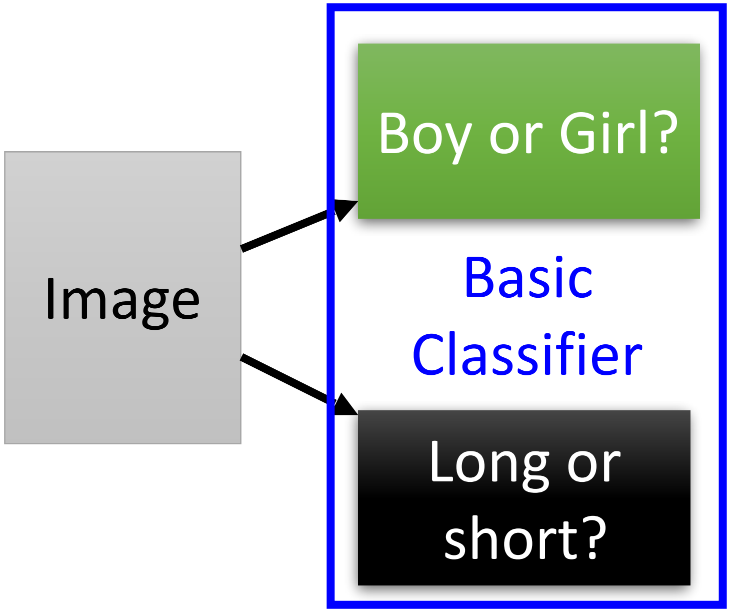

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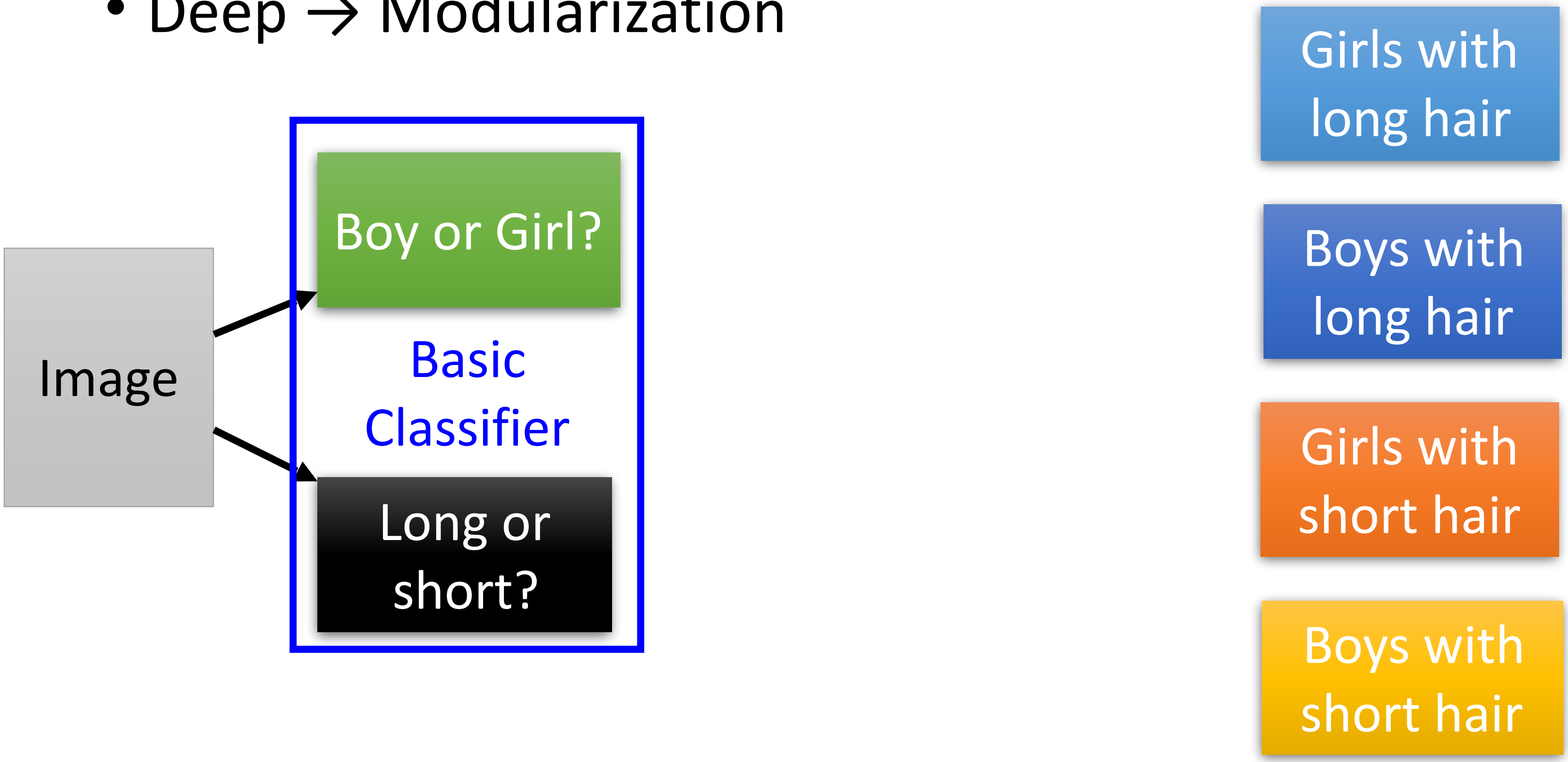

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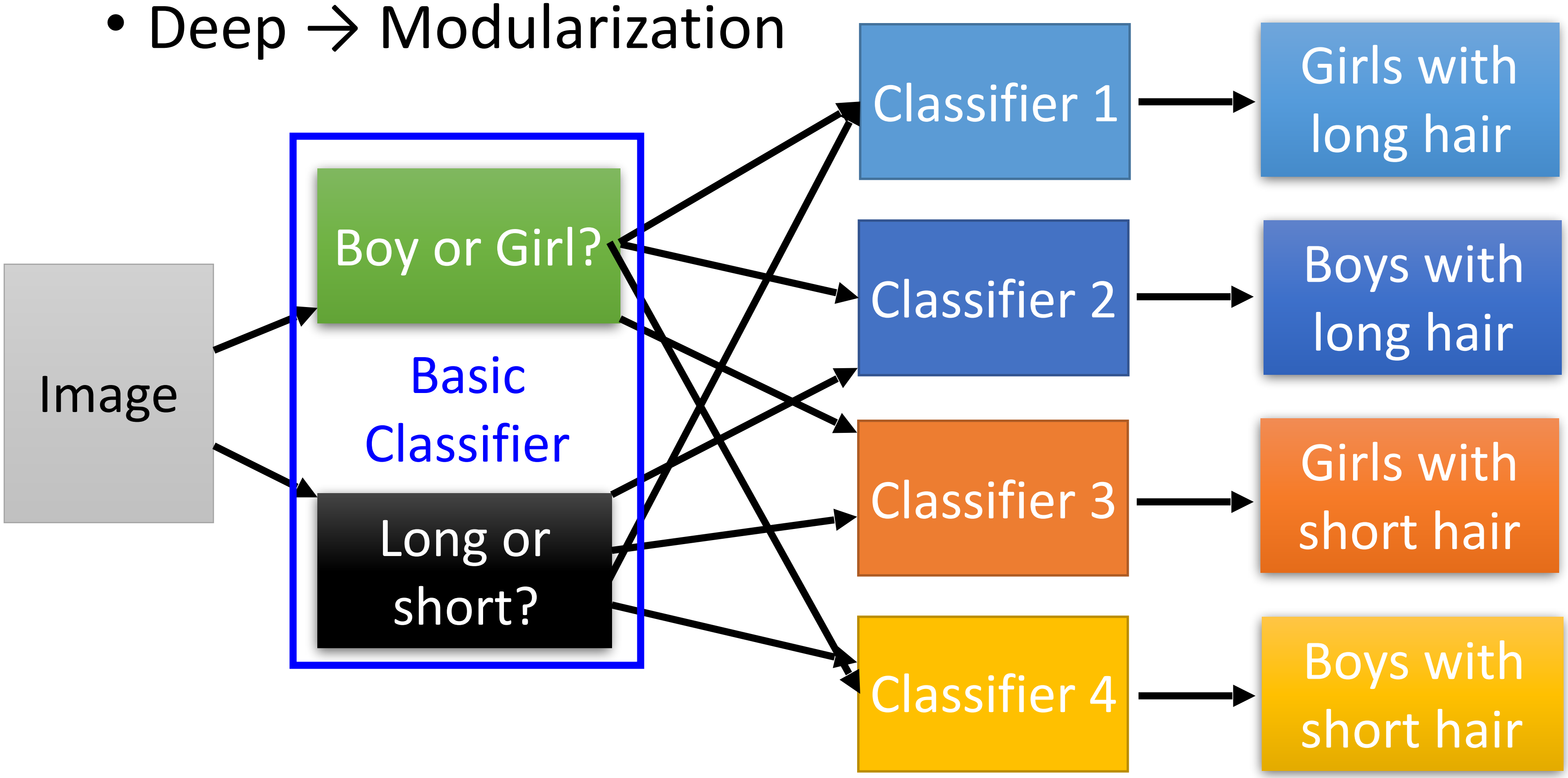

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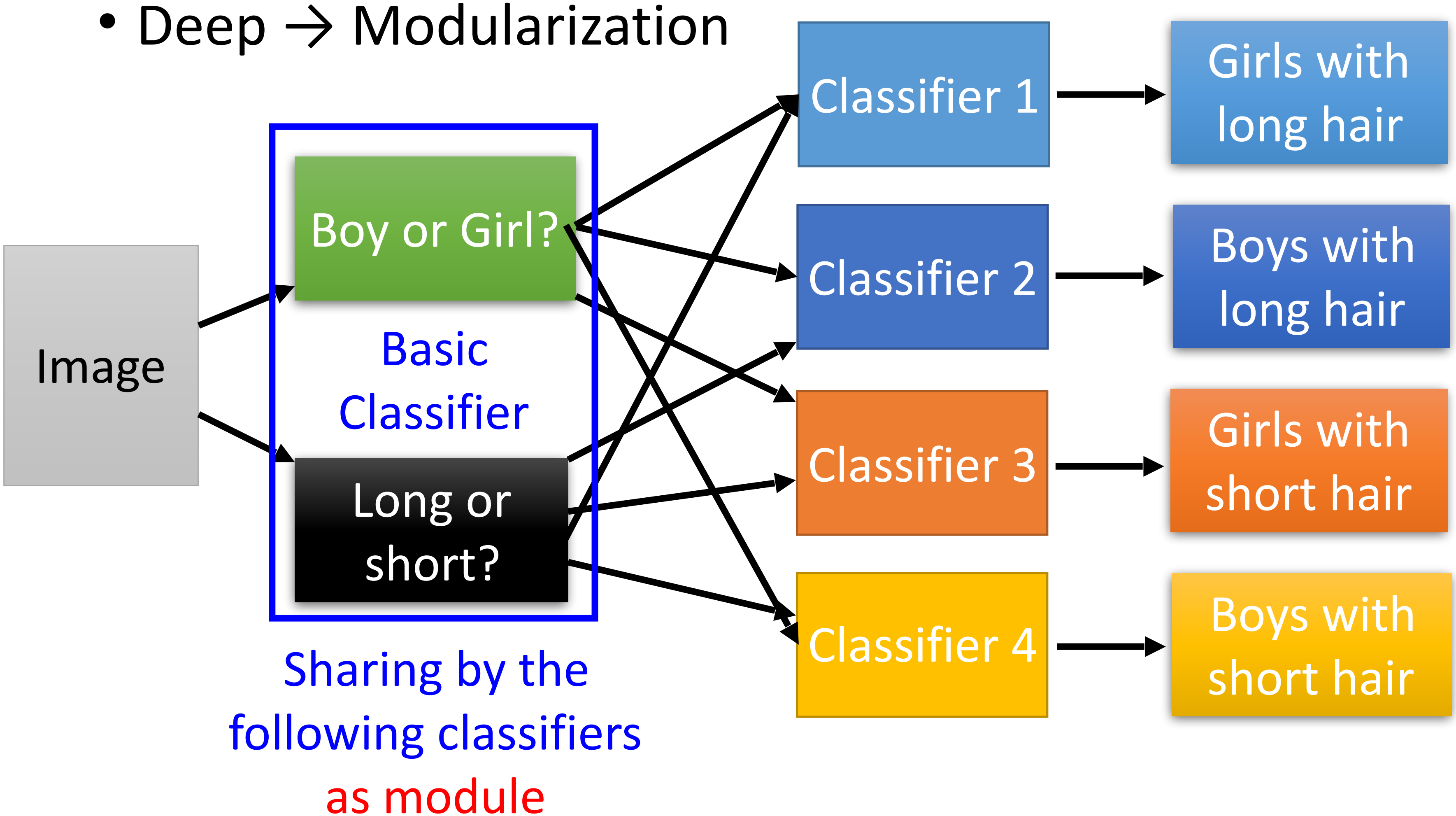

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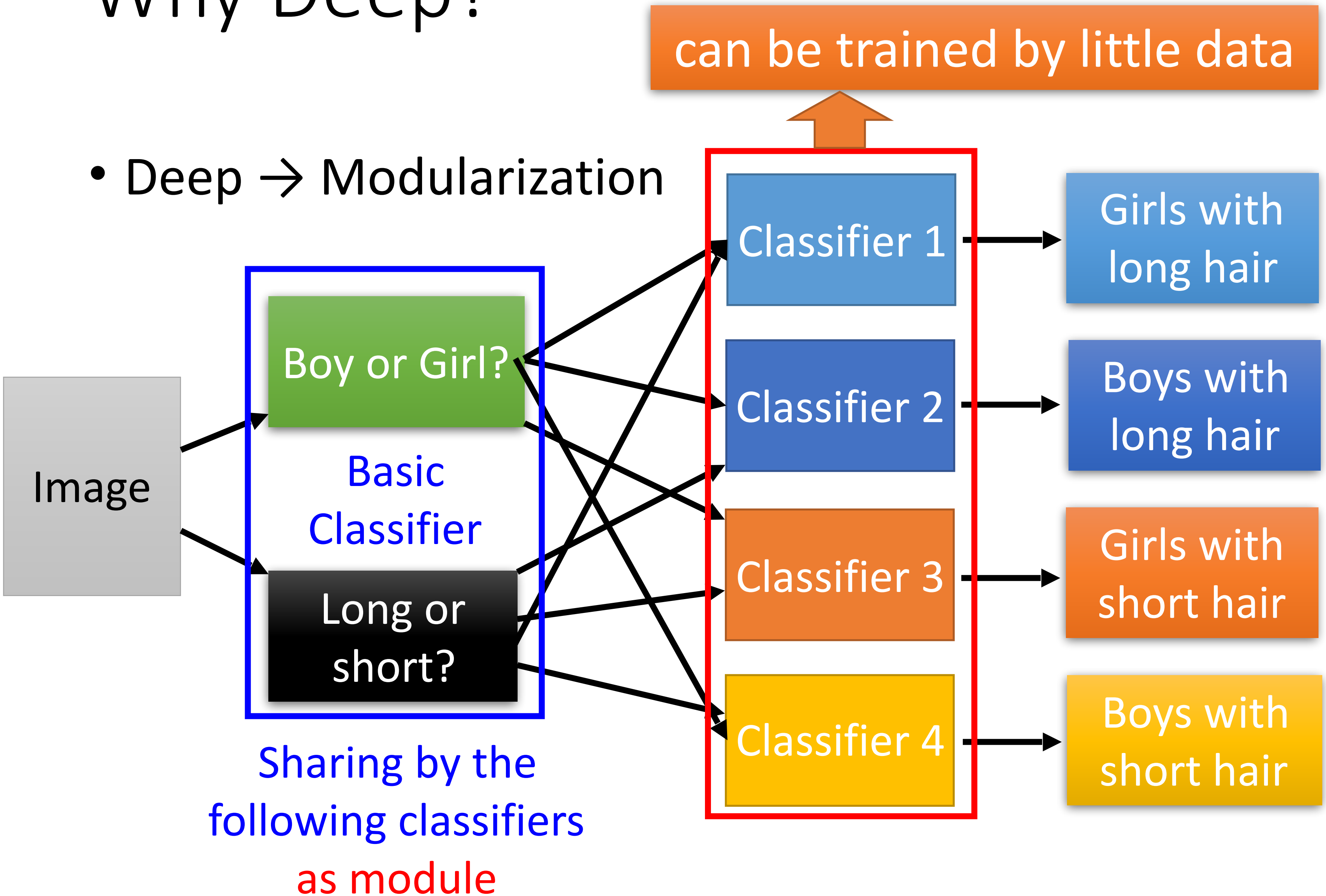

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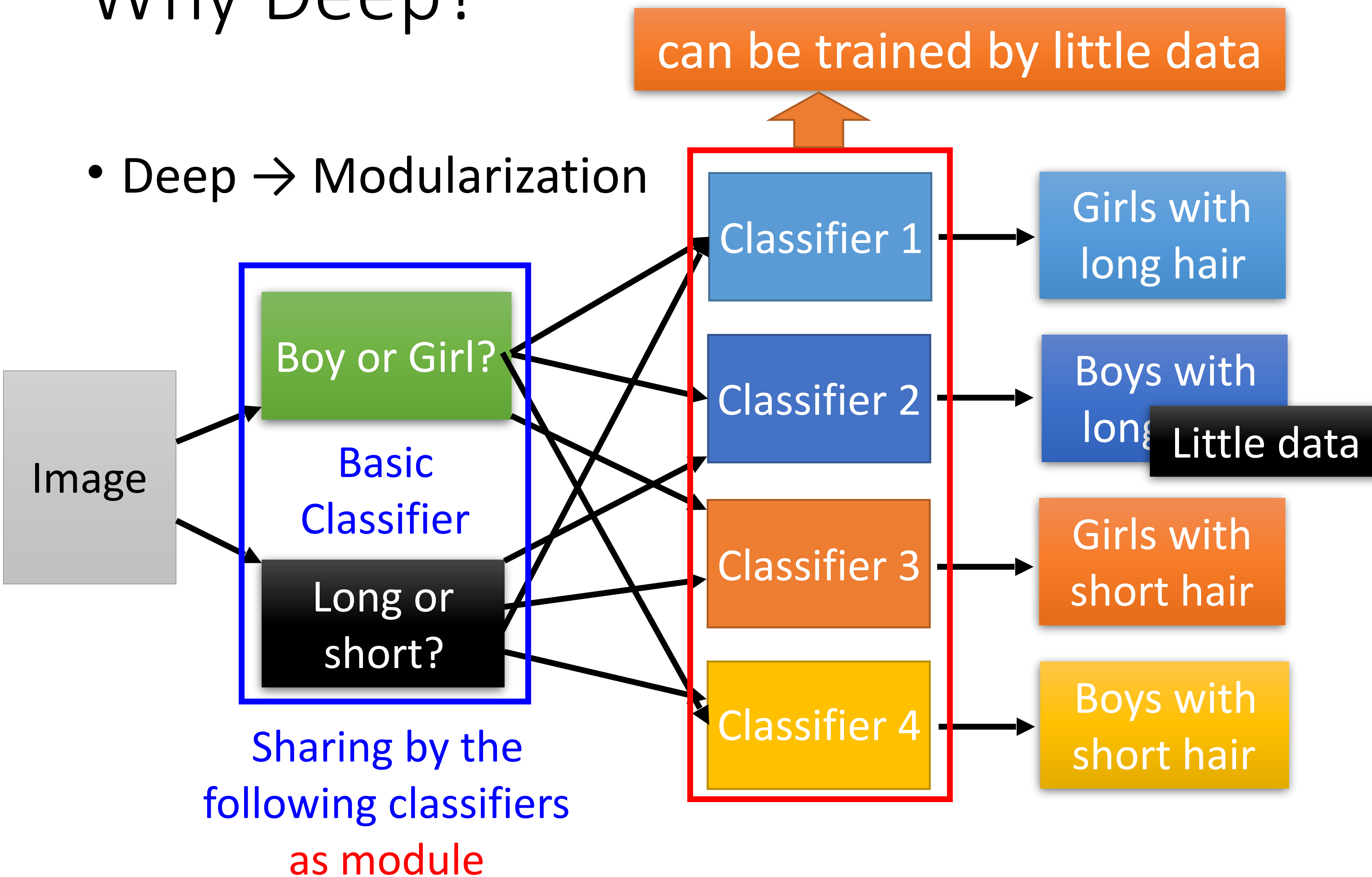

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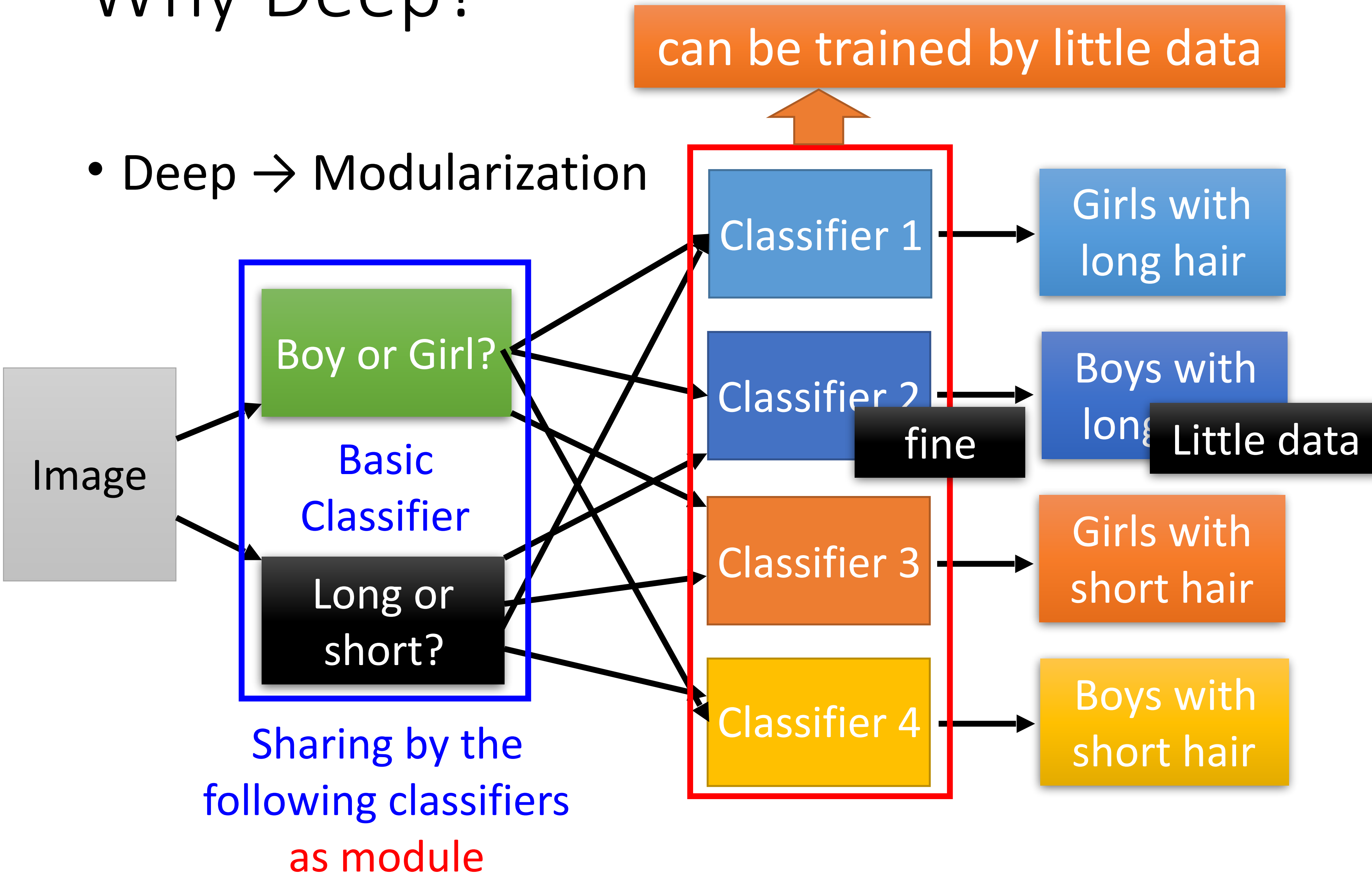

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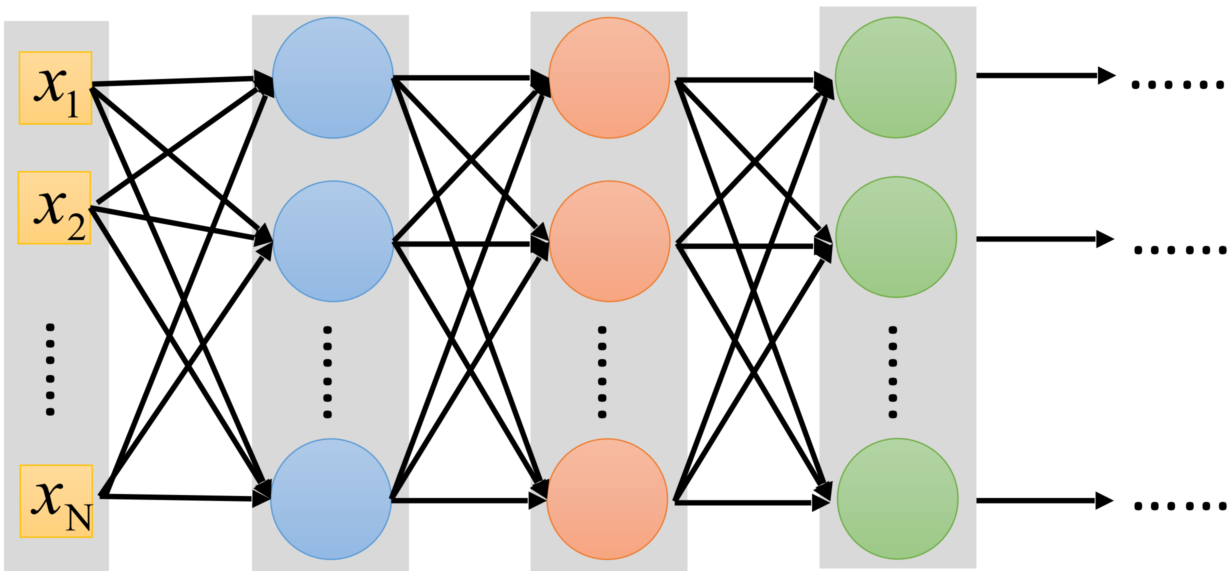

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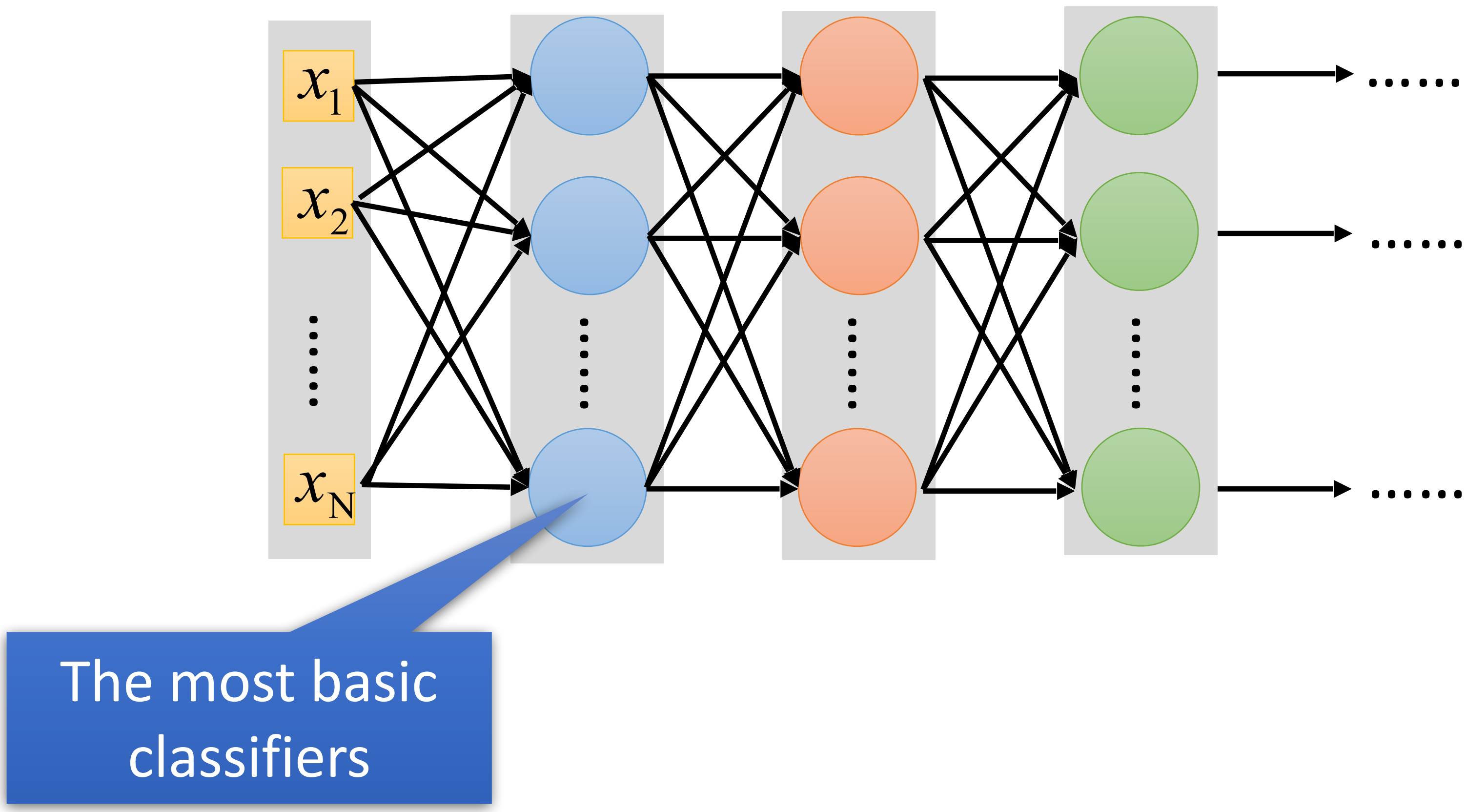

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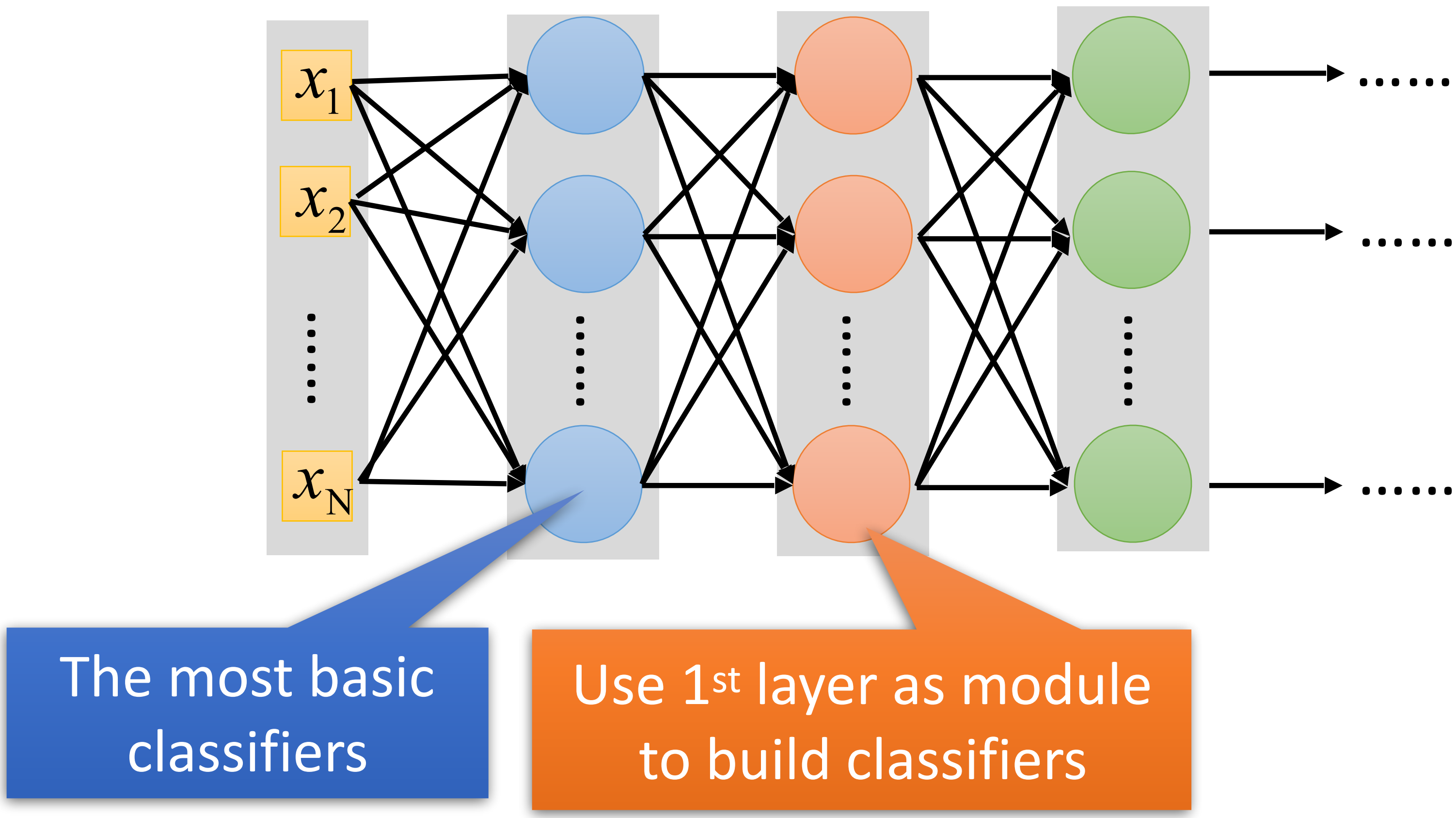

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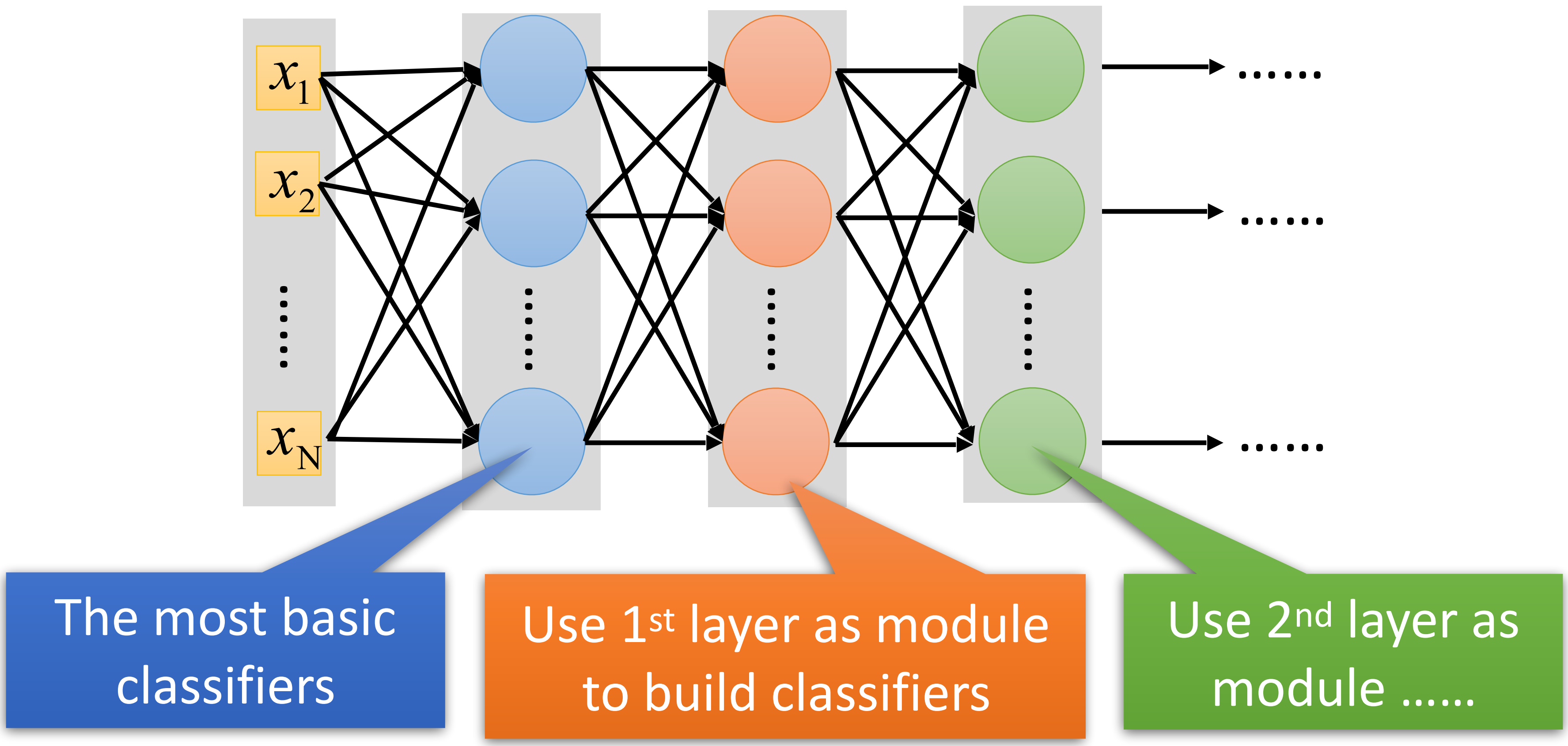

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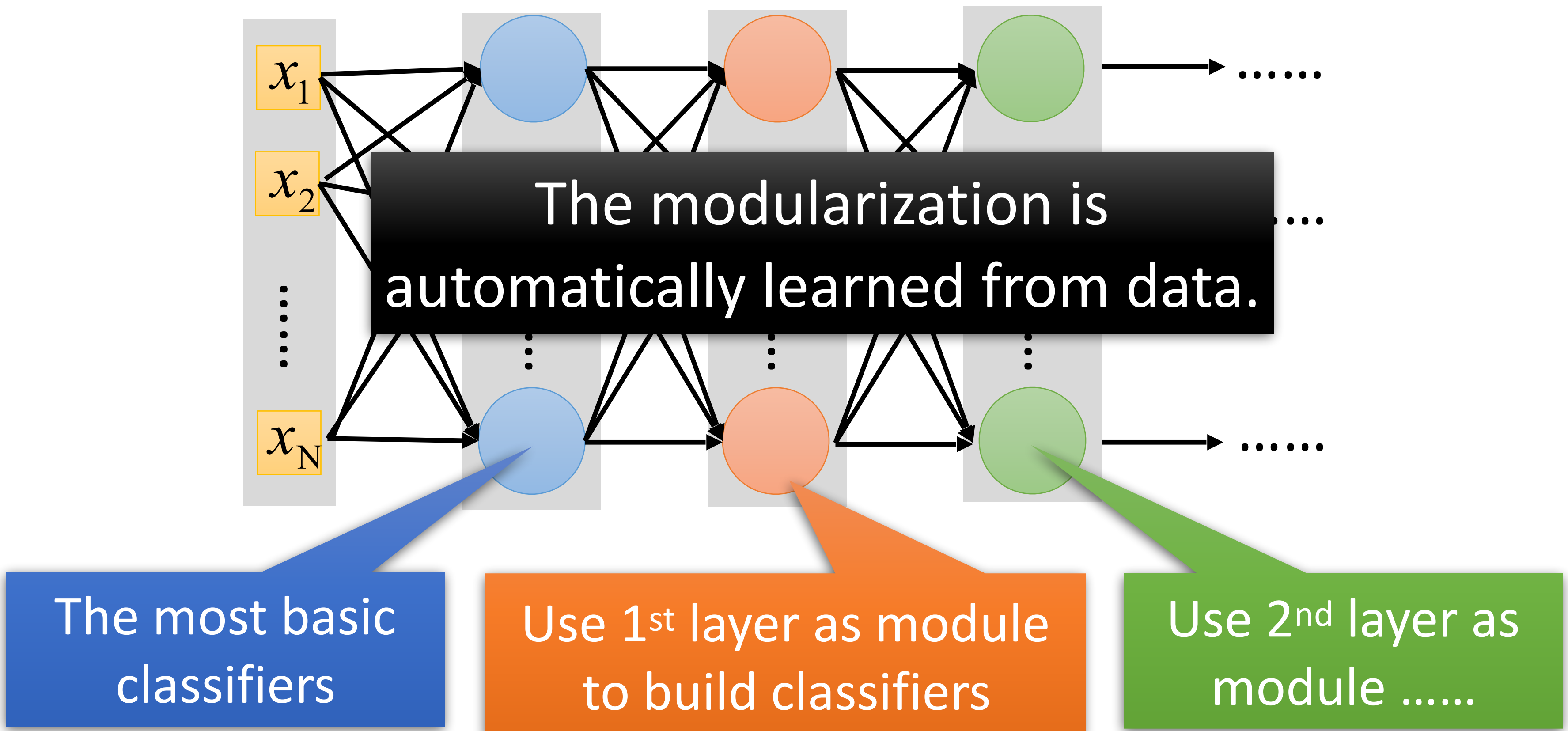
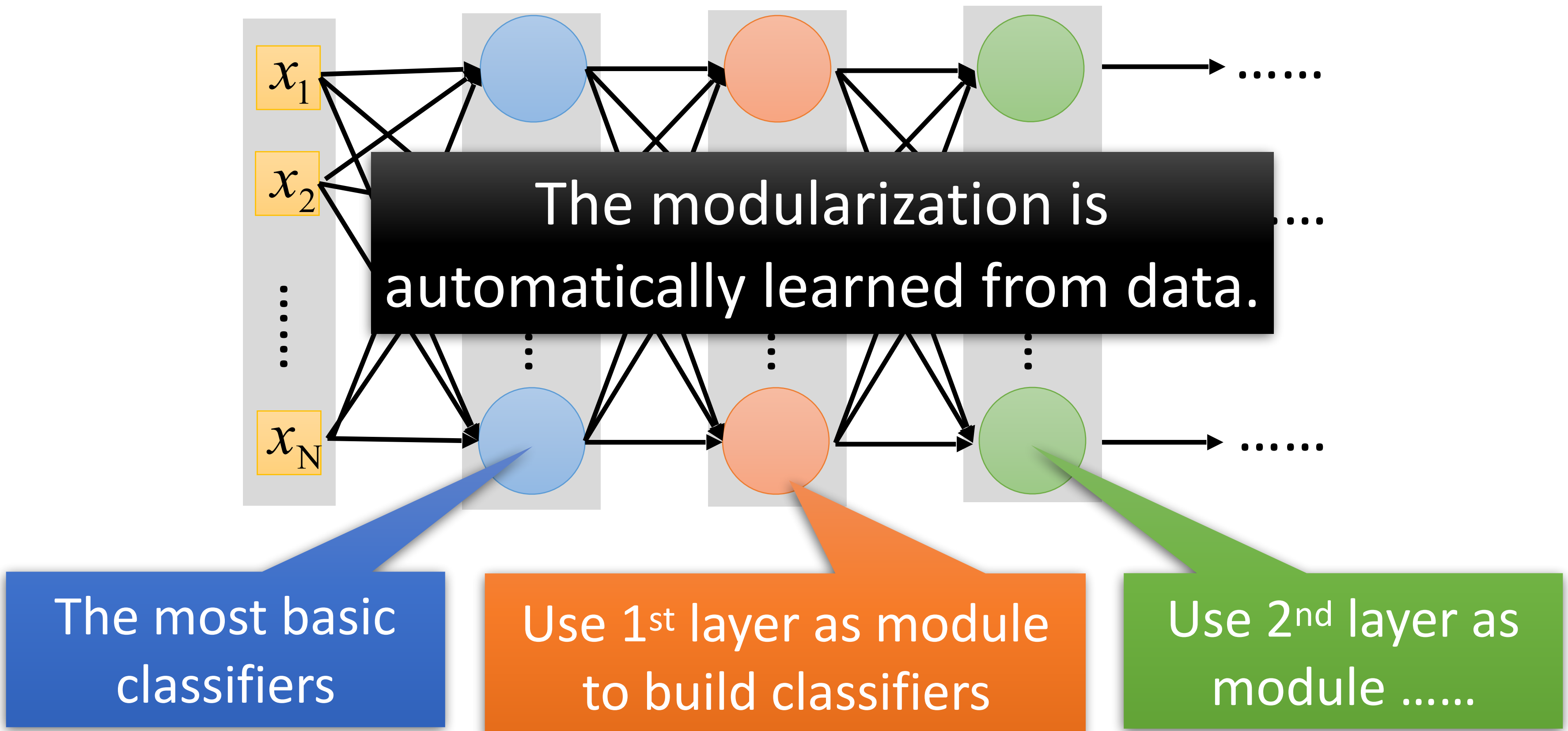


Why Deep?

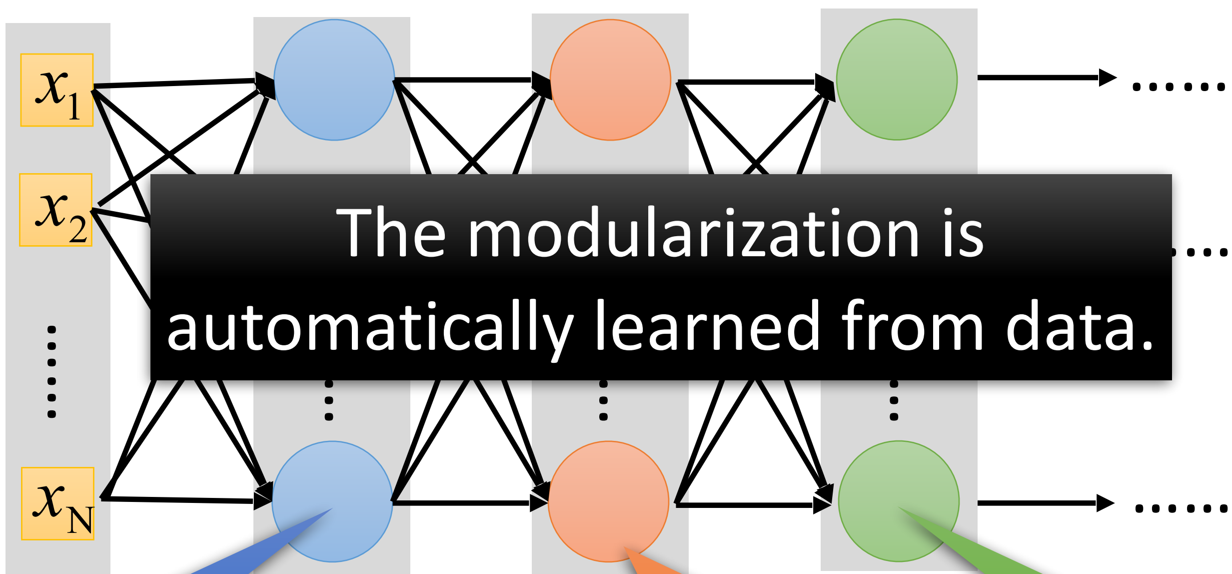
- Deep → Modularization → Less training data?



Why Deep?

Deep Learning also works on small data set like TIMIT.

- Deep → Modularization → Less training data?



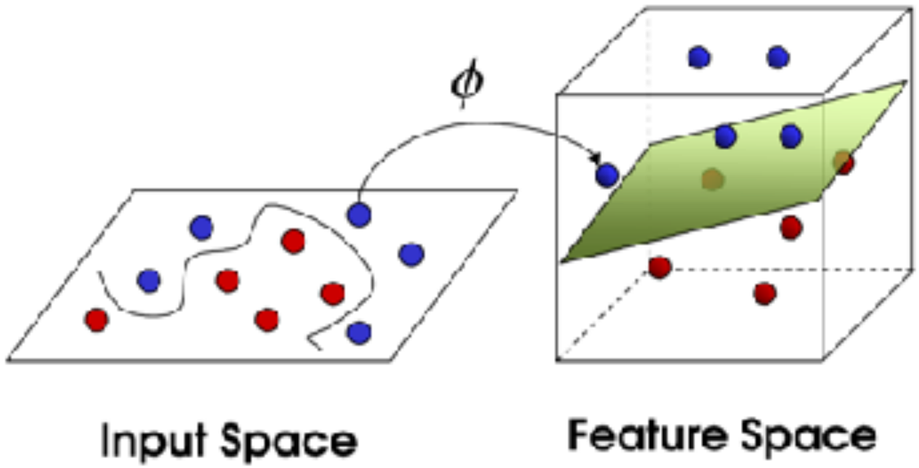
The modularization is automatically learned from data.

The most basic classifiers

Use 1st layer as module to build classifiers

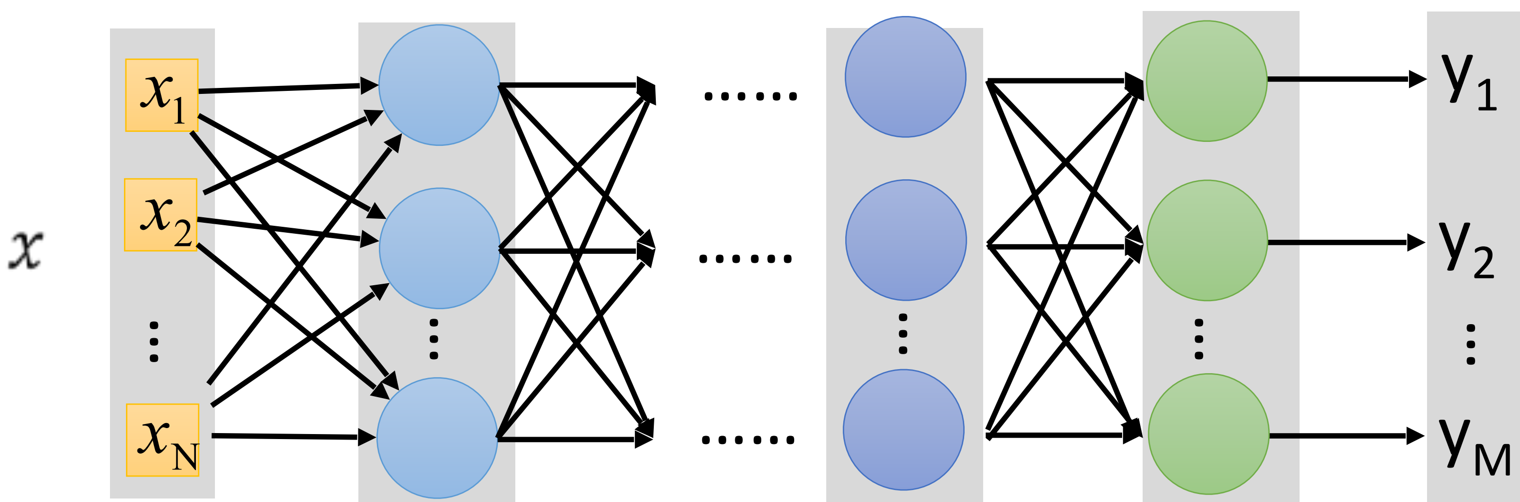
Use 2nd layer as module ……

[SVM](#)



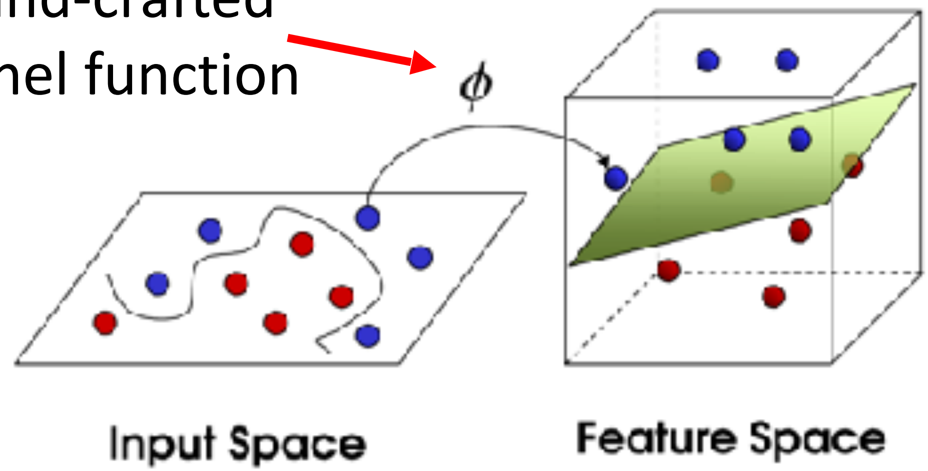
Source of image: http://www.gipsa-lab.grenoble-inp.fr/transfert/seminaire/455_Kadri2013Gipsa-lab.pdf

[Deep Learning](#)



SVM

Hand-crafted kernel function



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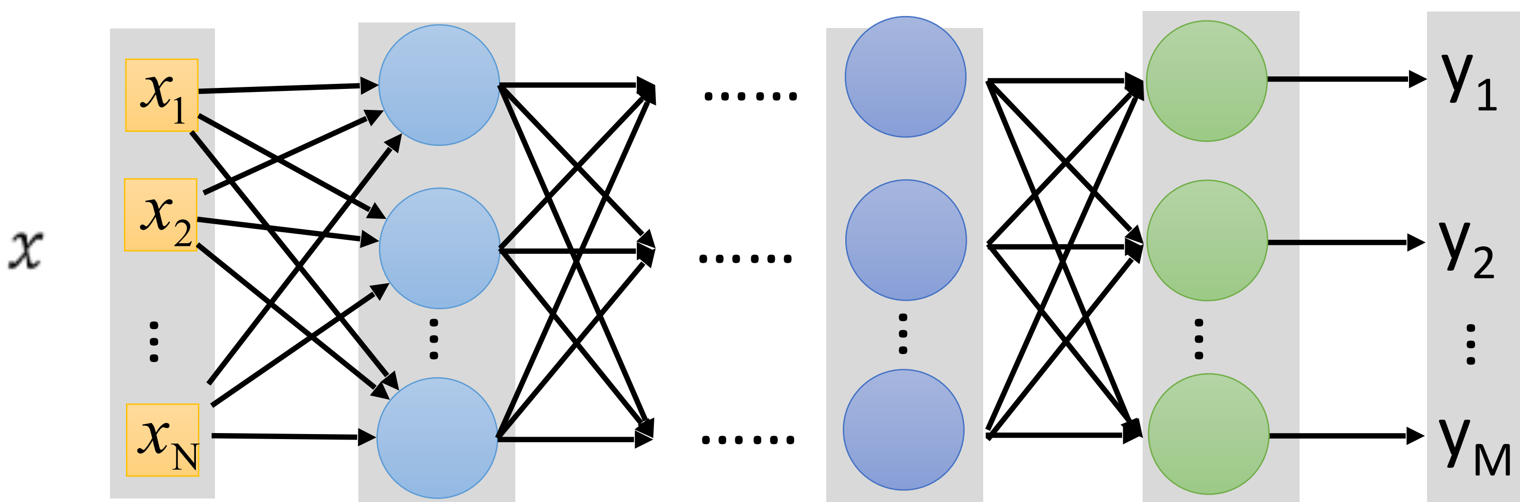
Deep Learning



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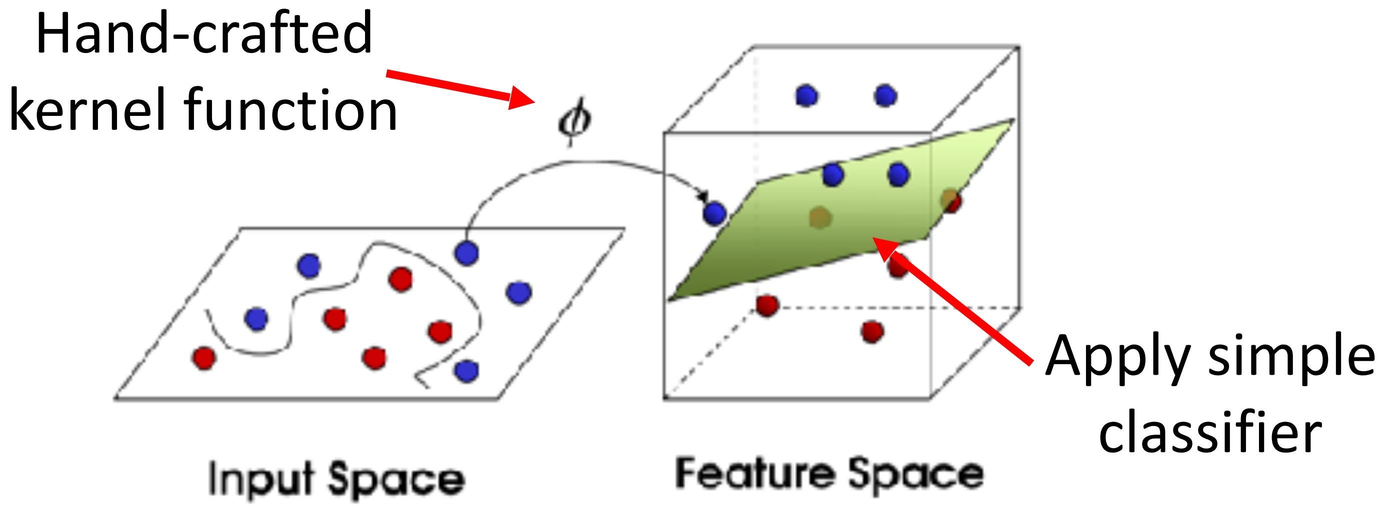

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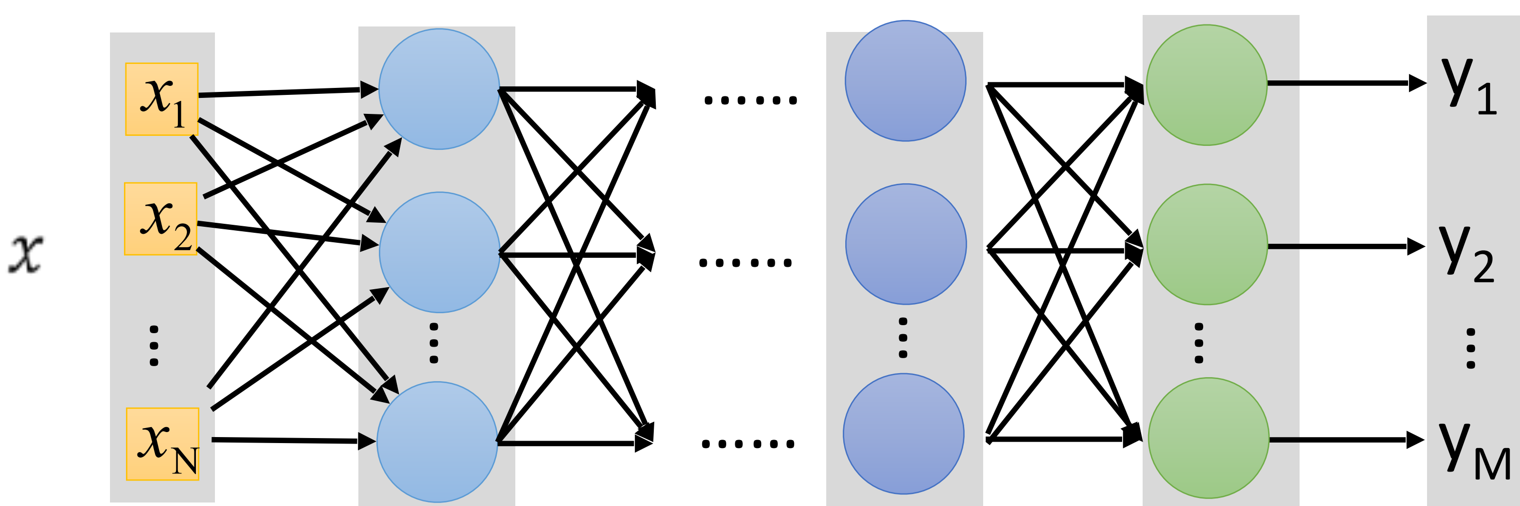

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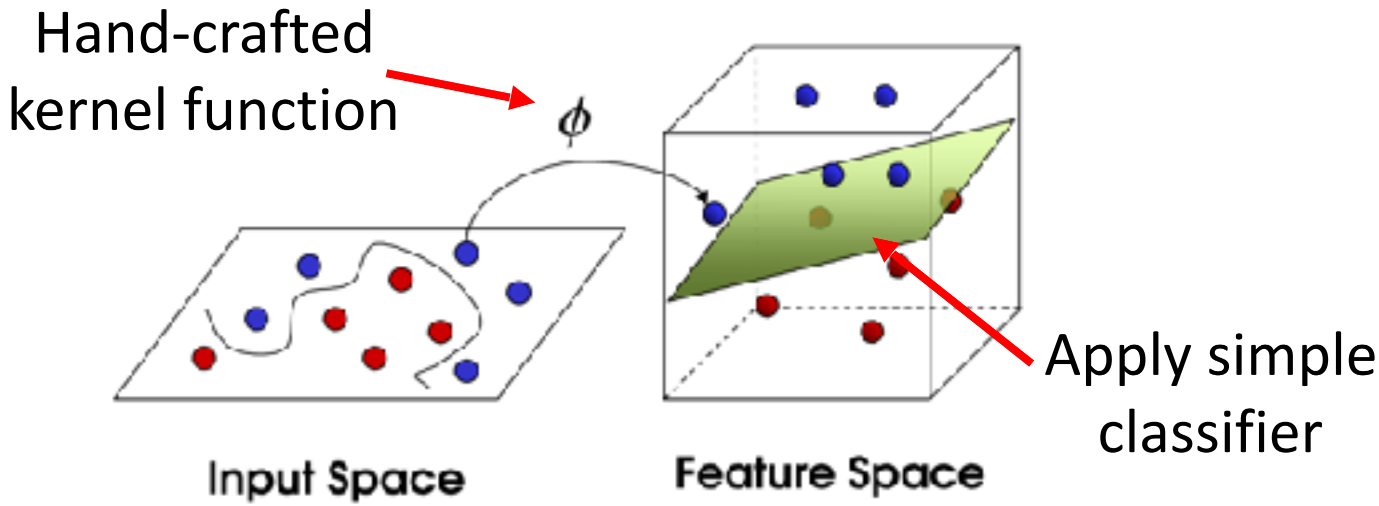

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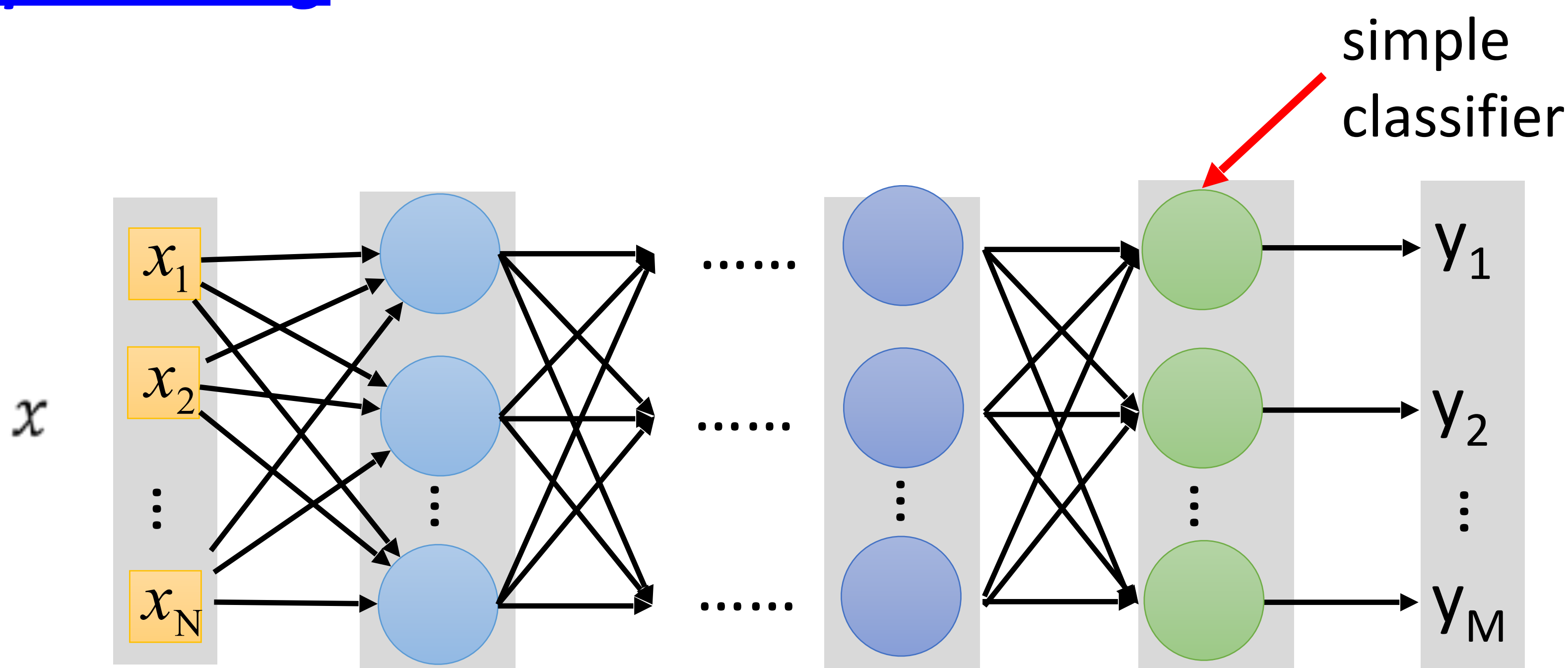
Deep Learning



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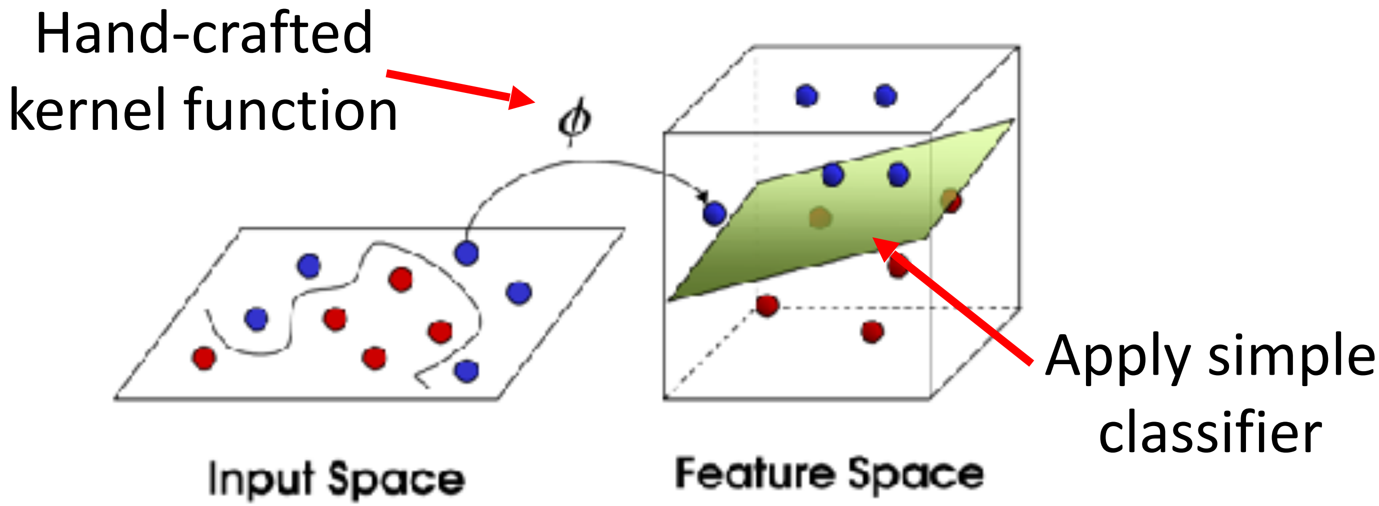

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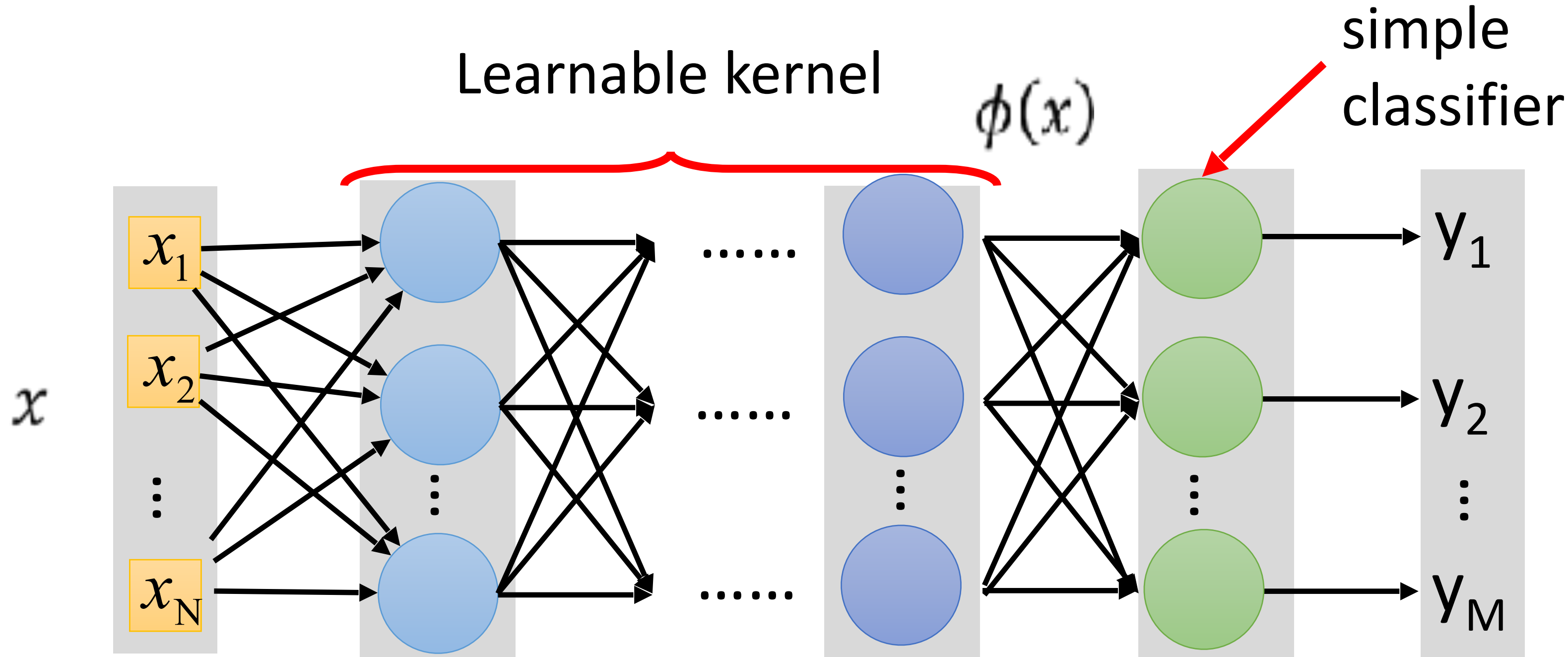
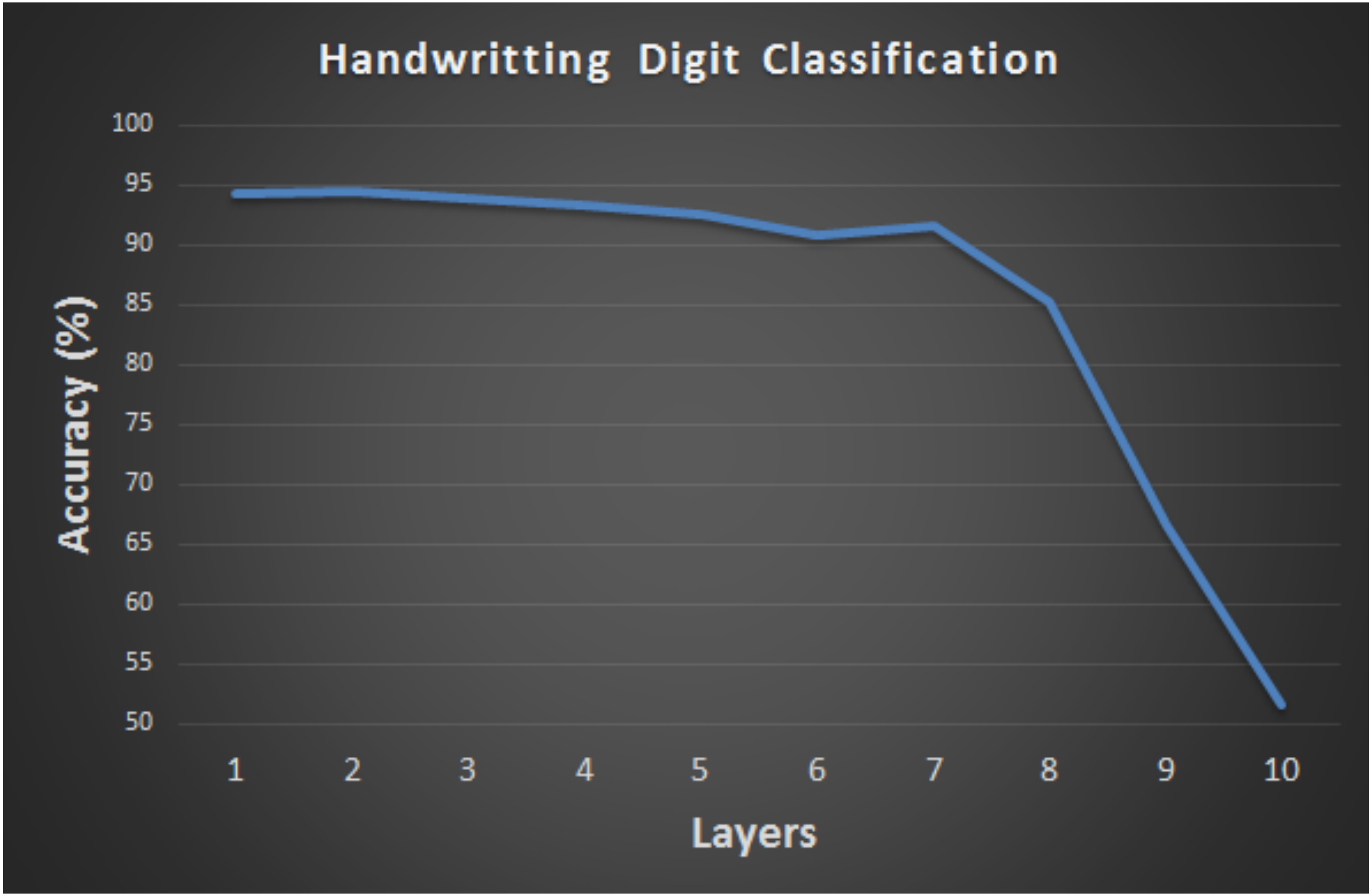


Hard to get the power of Deep …



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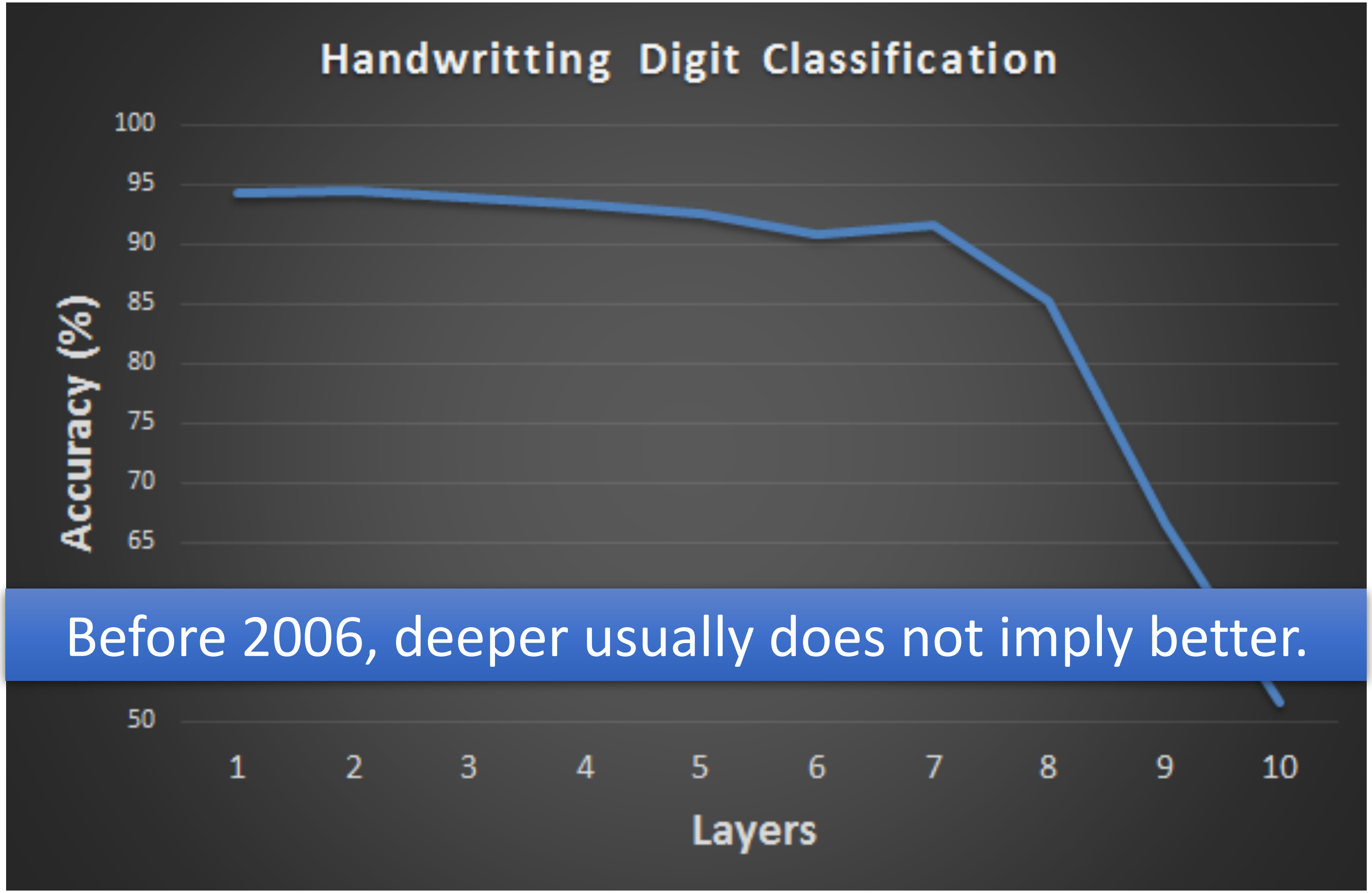
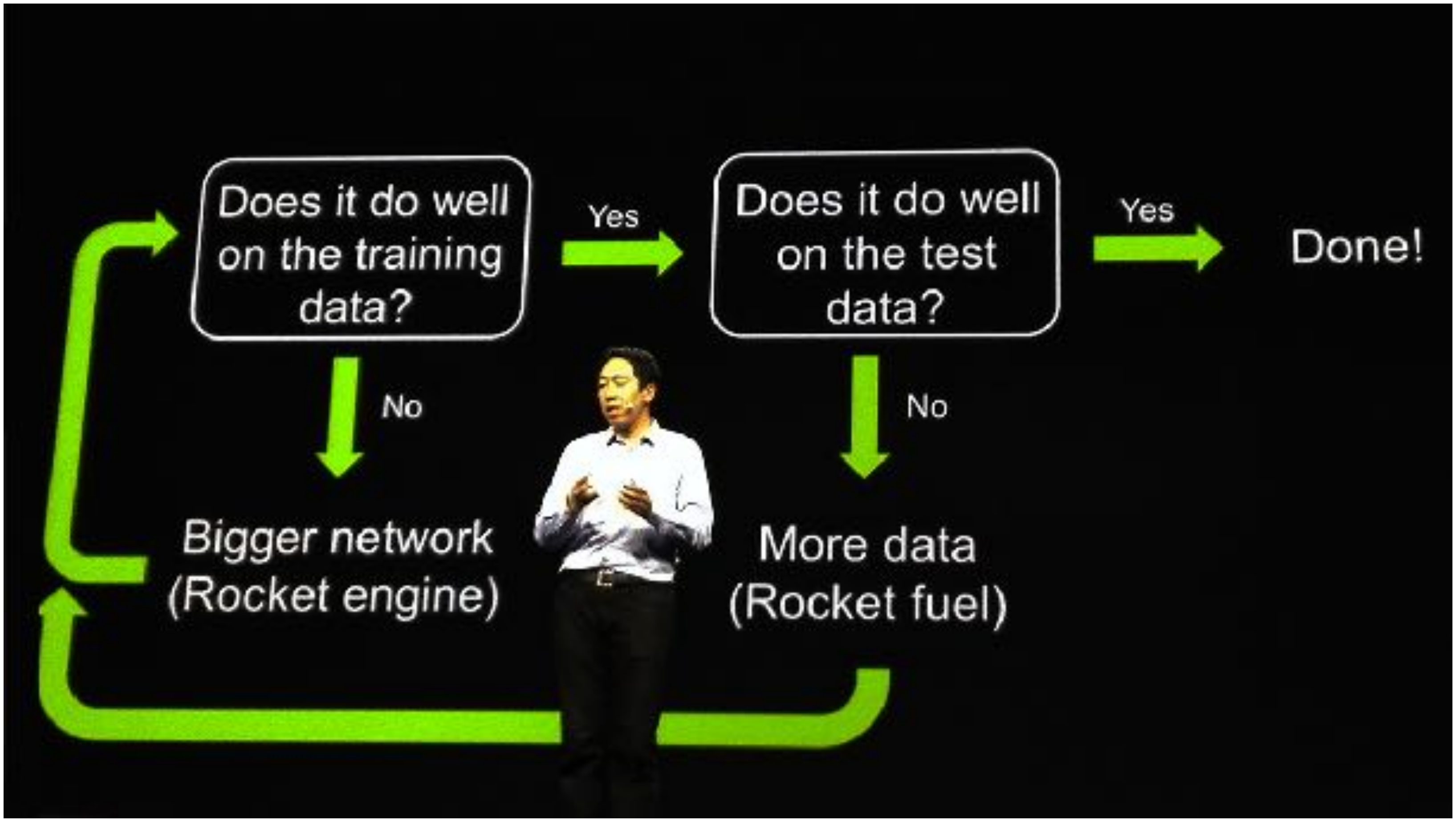


Before 2006, deeper usually does not imply better.

Part III:
Tips for Training DNN

Recipe for Learning



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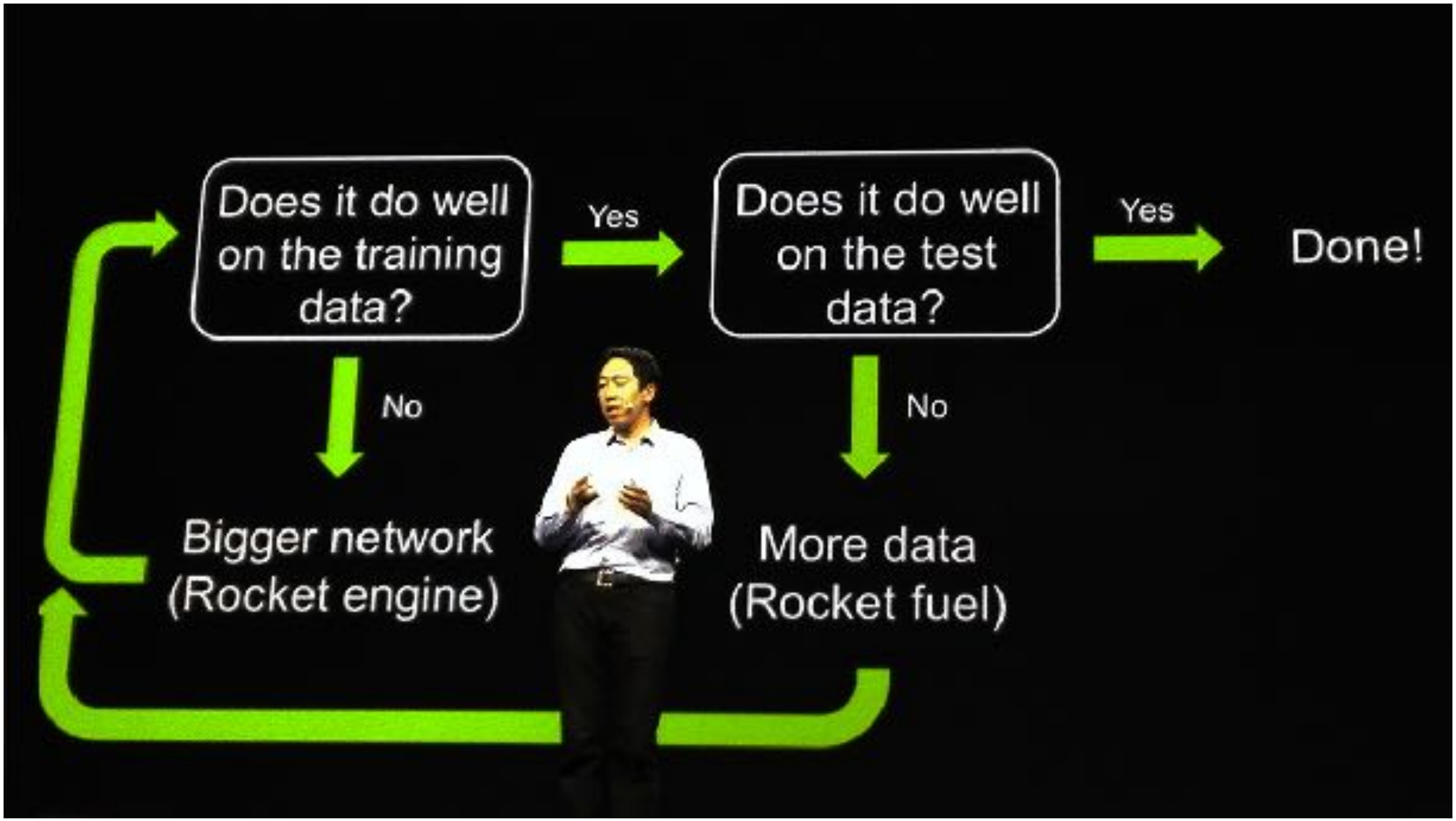

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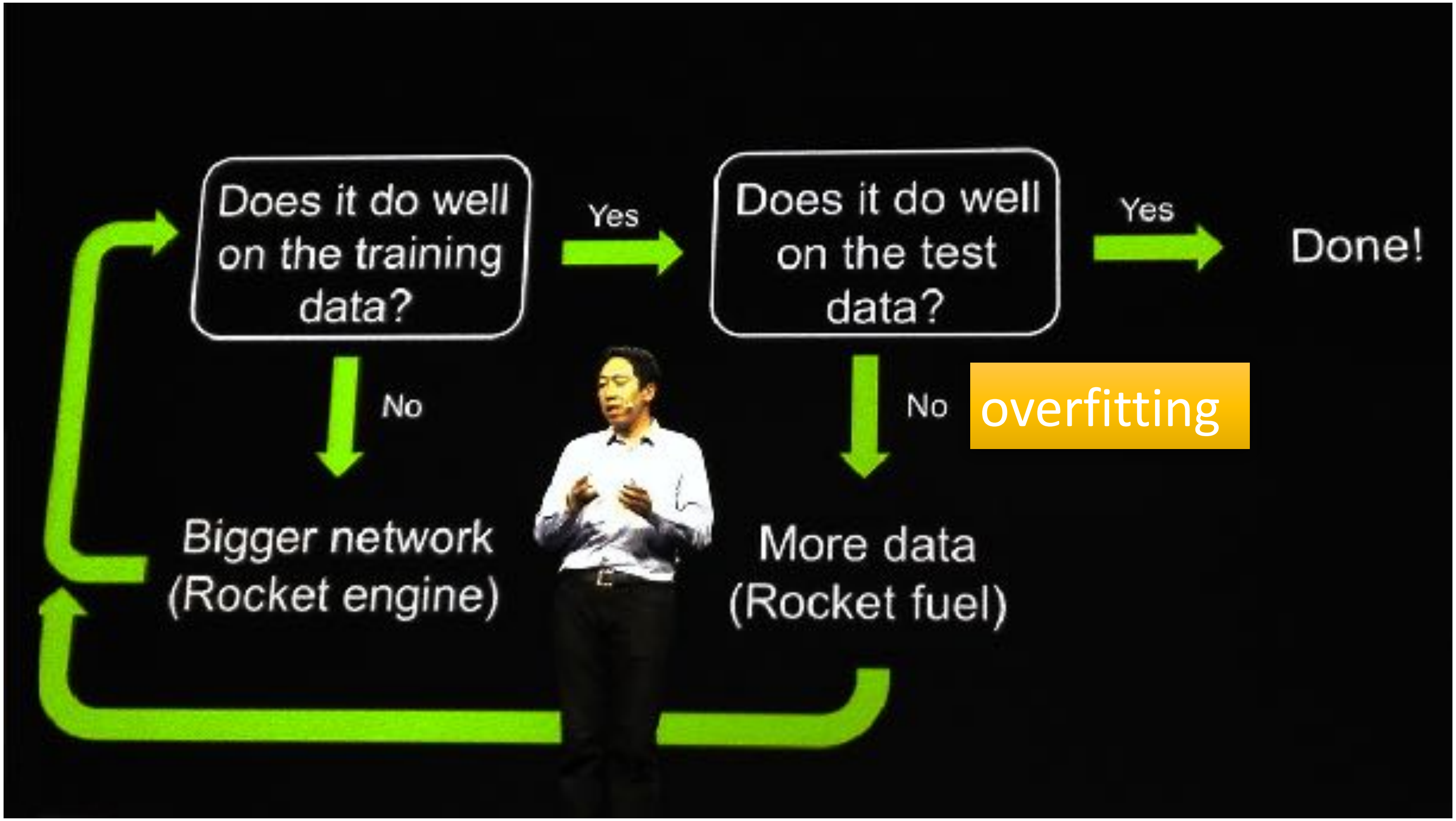

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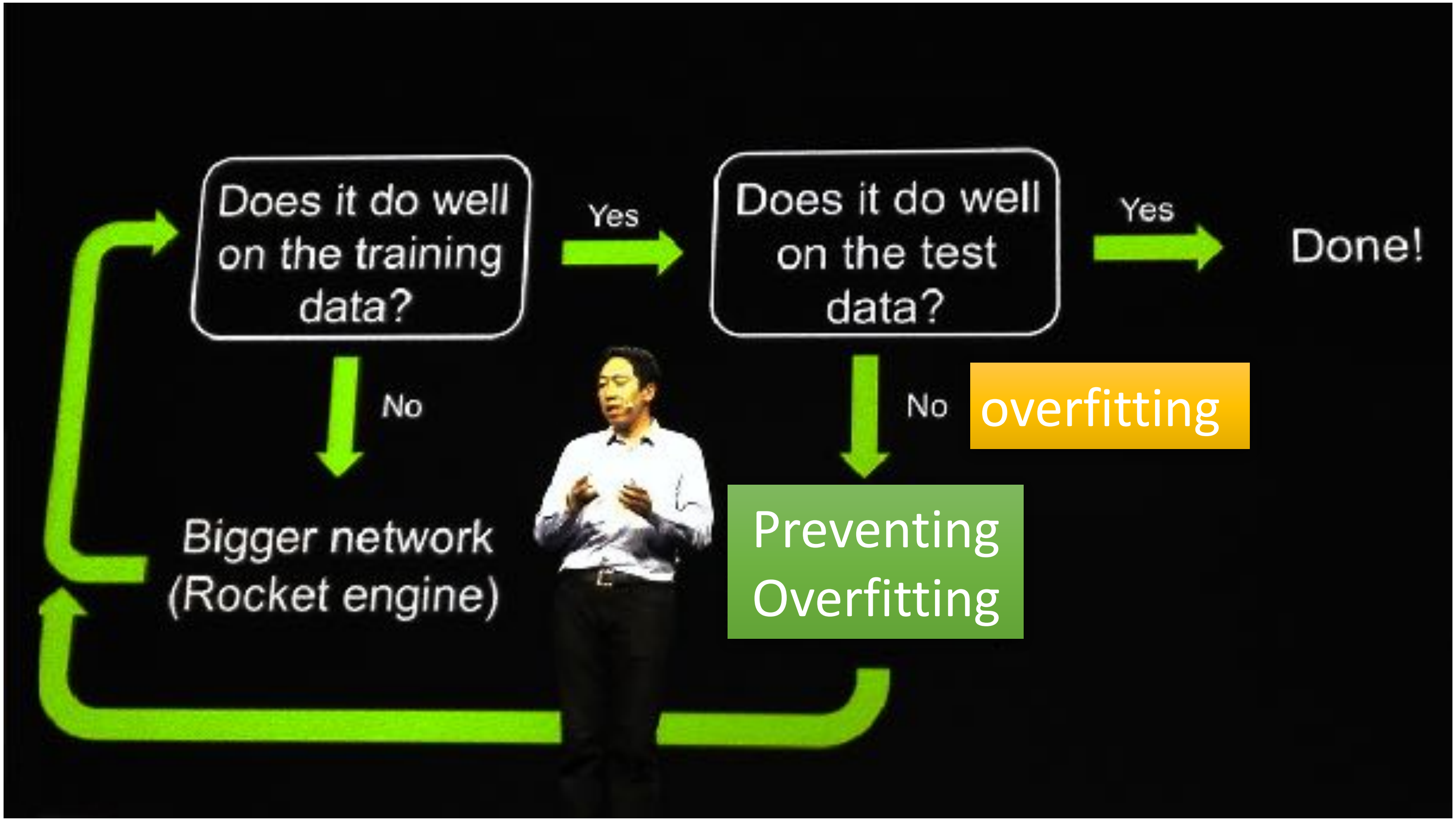

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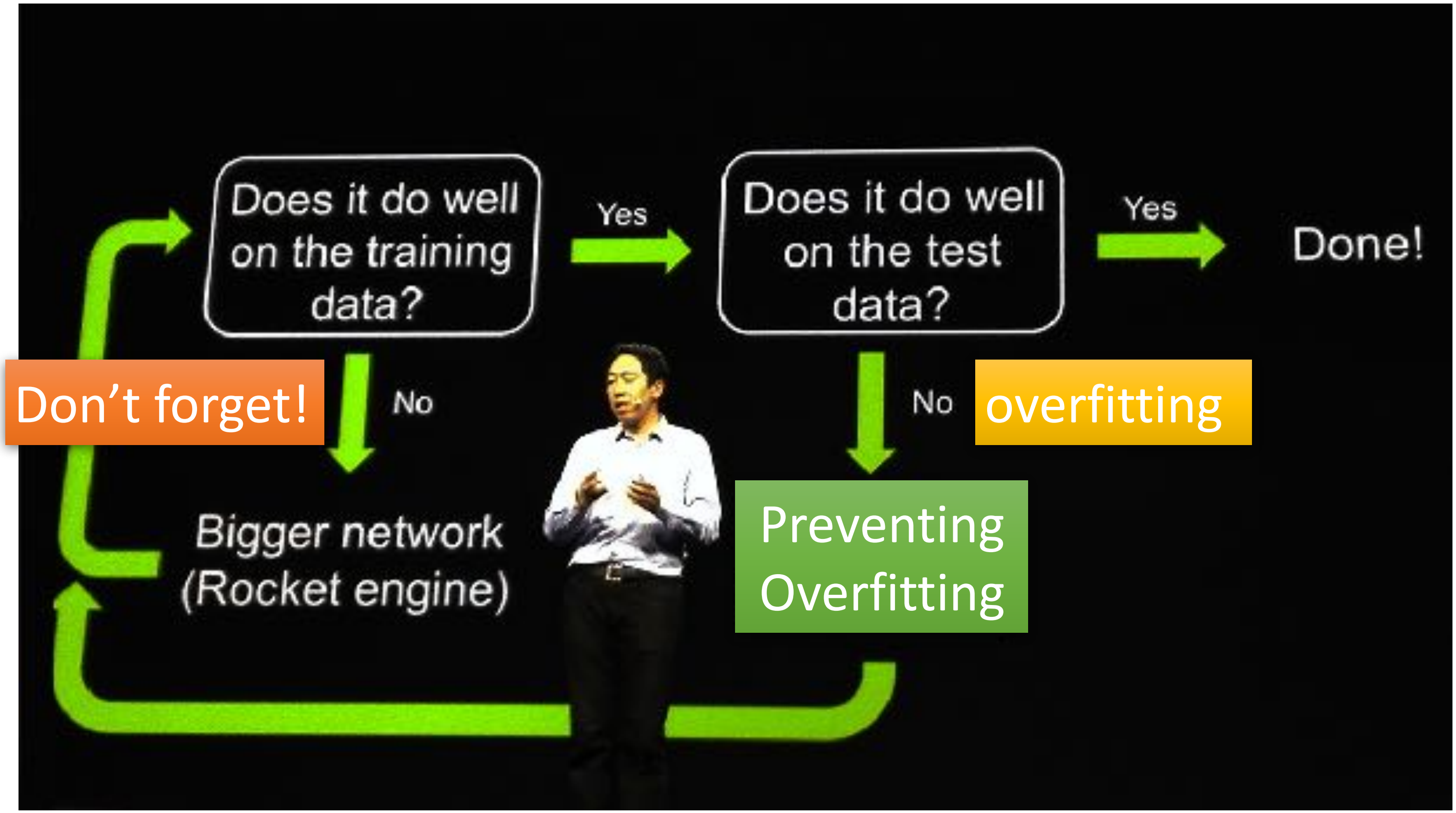

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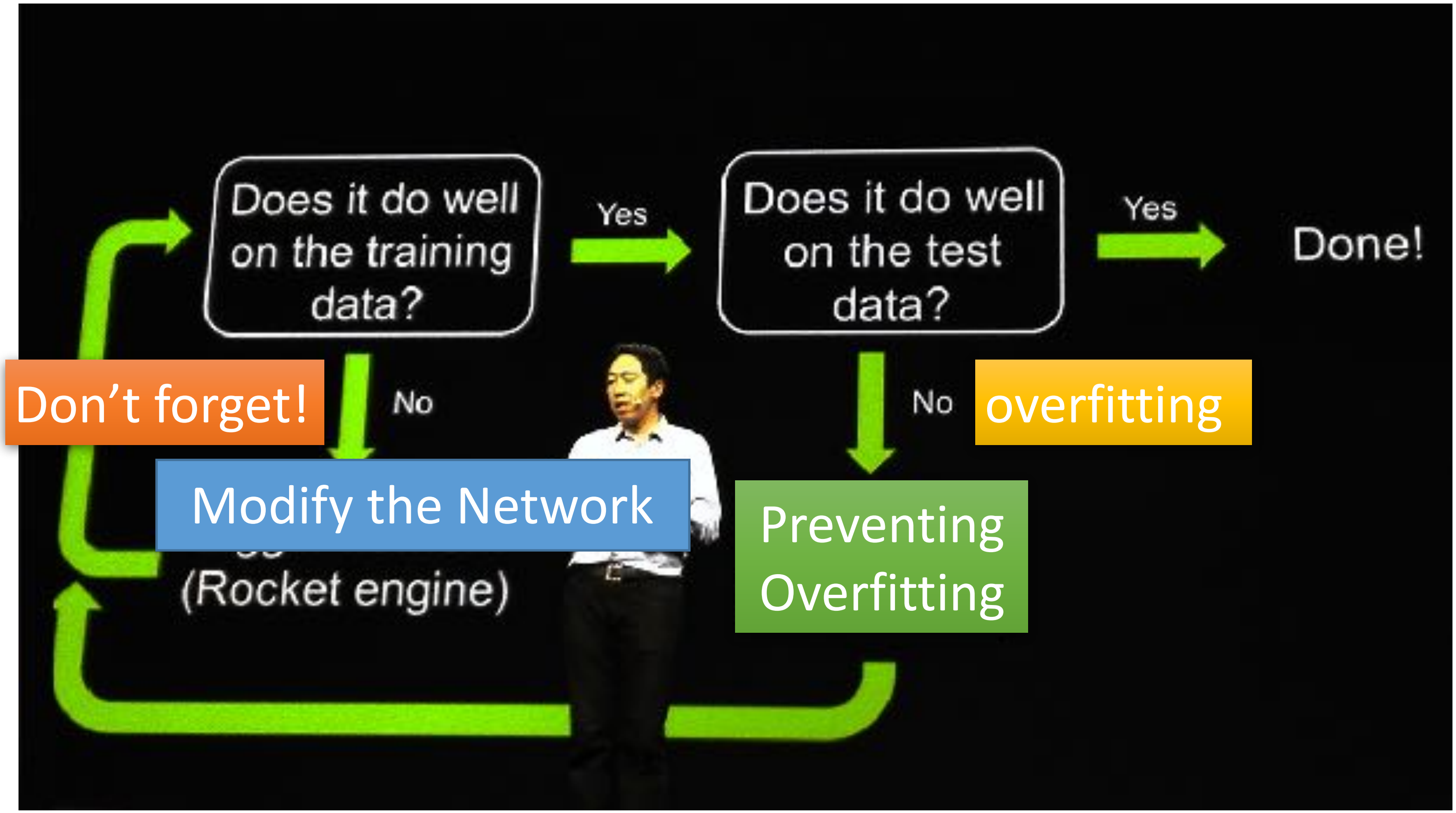

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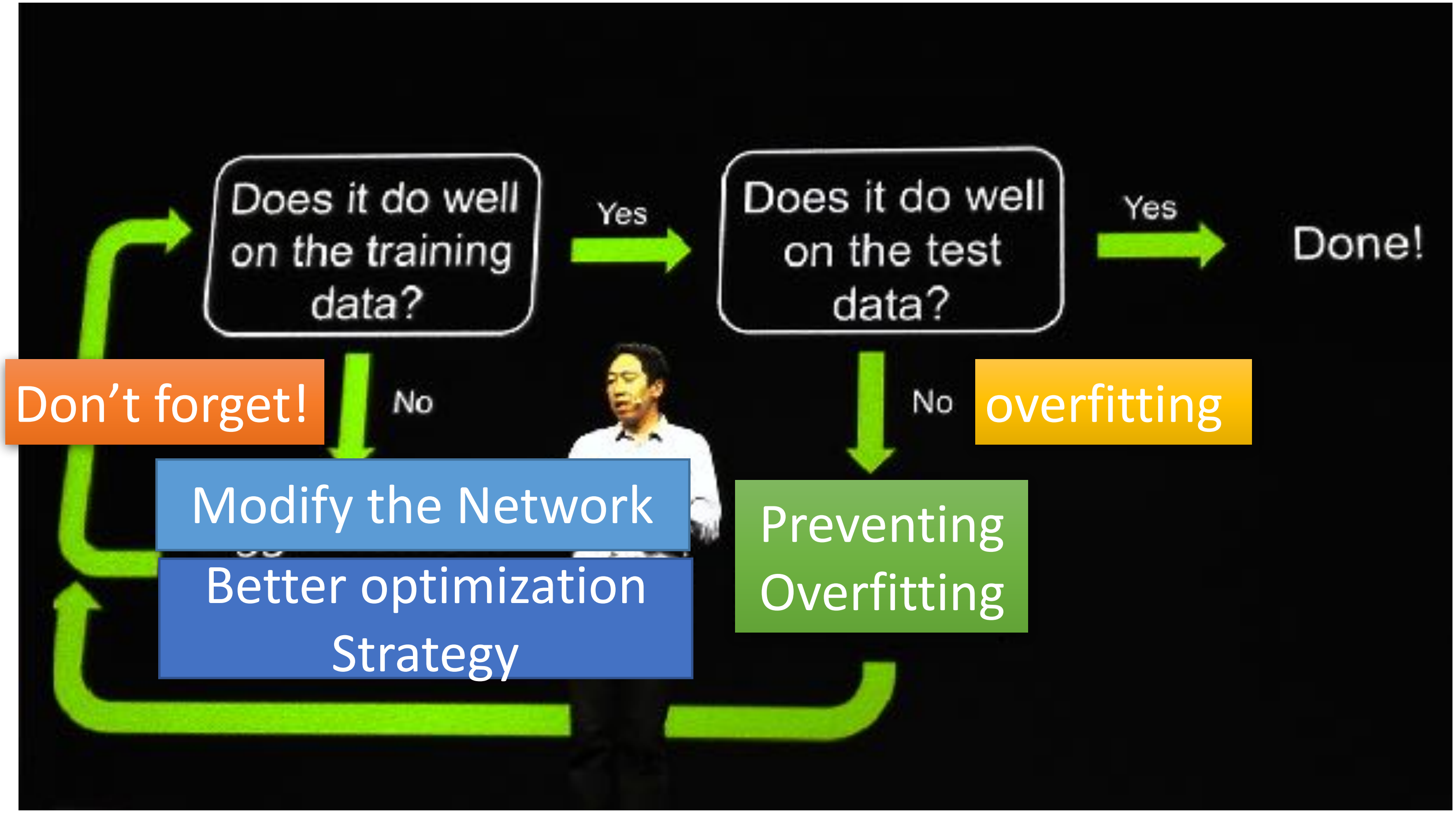

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Recipe for Learning

- Modify the Network
  - New activation functions, for example, ReLU or Maxout
- Better optimization Strategy
  - Adaptive learning rates
- Prevent Overfitting
  - Dropout

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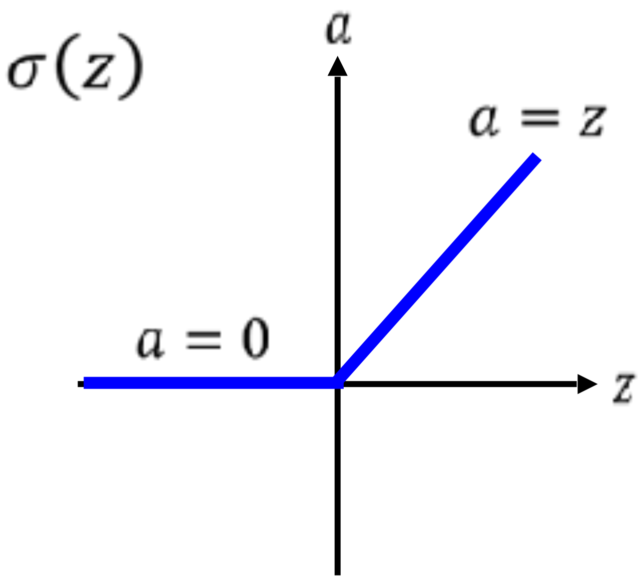
Only use this approach when you already obtained good results on the training data.

Part III:
Tips for Training DNN
New Activation Function

ReLU

- Rectified Linear Unit (ReLU)

Reason:



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

ReLU

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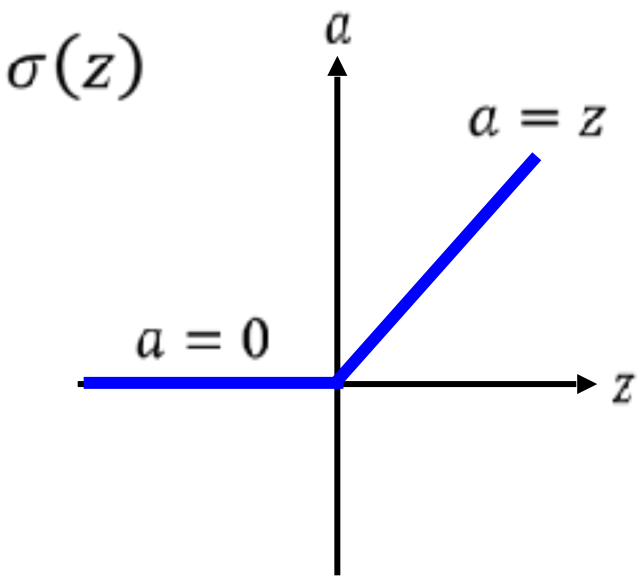

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Reason:

1. Fast to compute

ReLU

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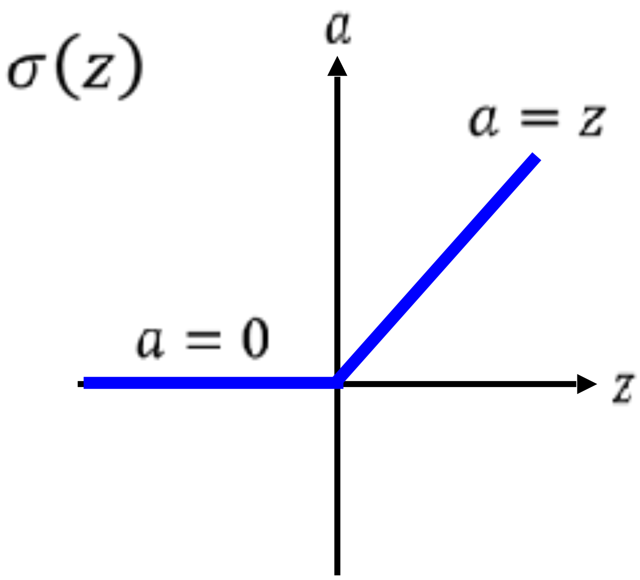

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Reason:

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2. Biological reason

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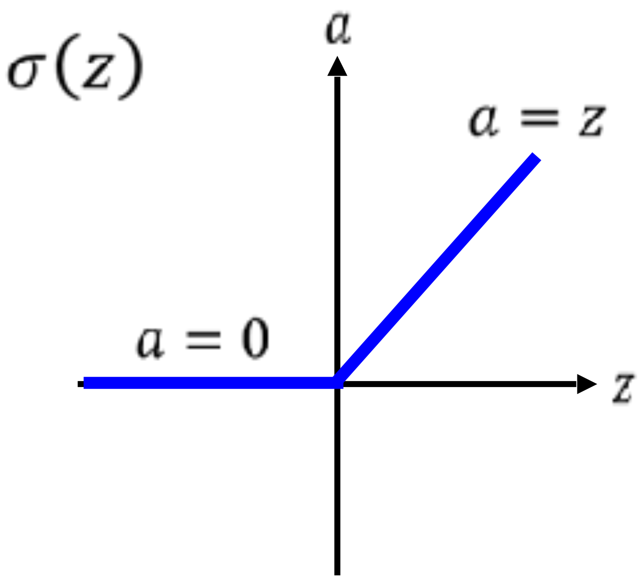

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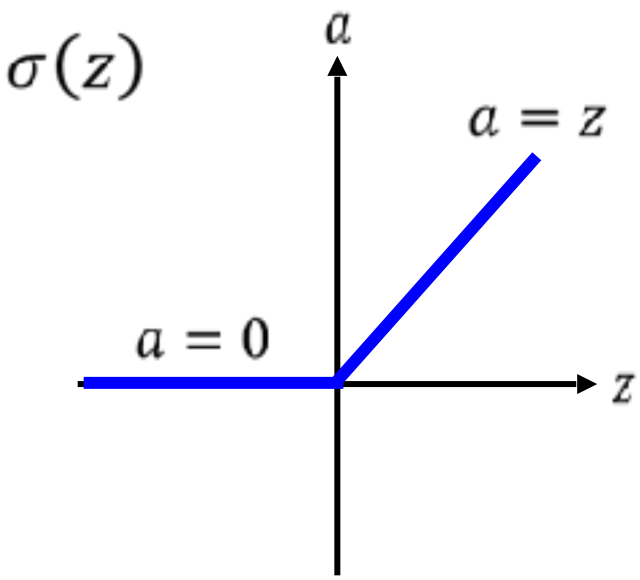

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Reason:

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3. Infinite sigmoid with different biases
4. Vanishing gradient problem

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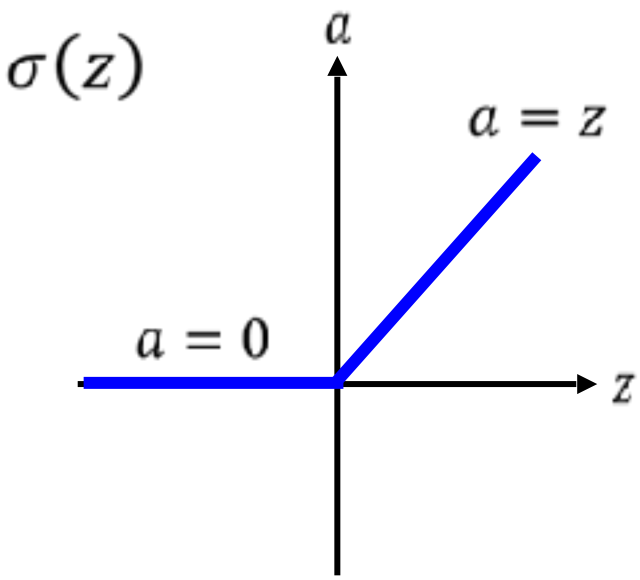

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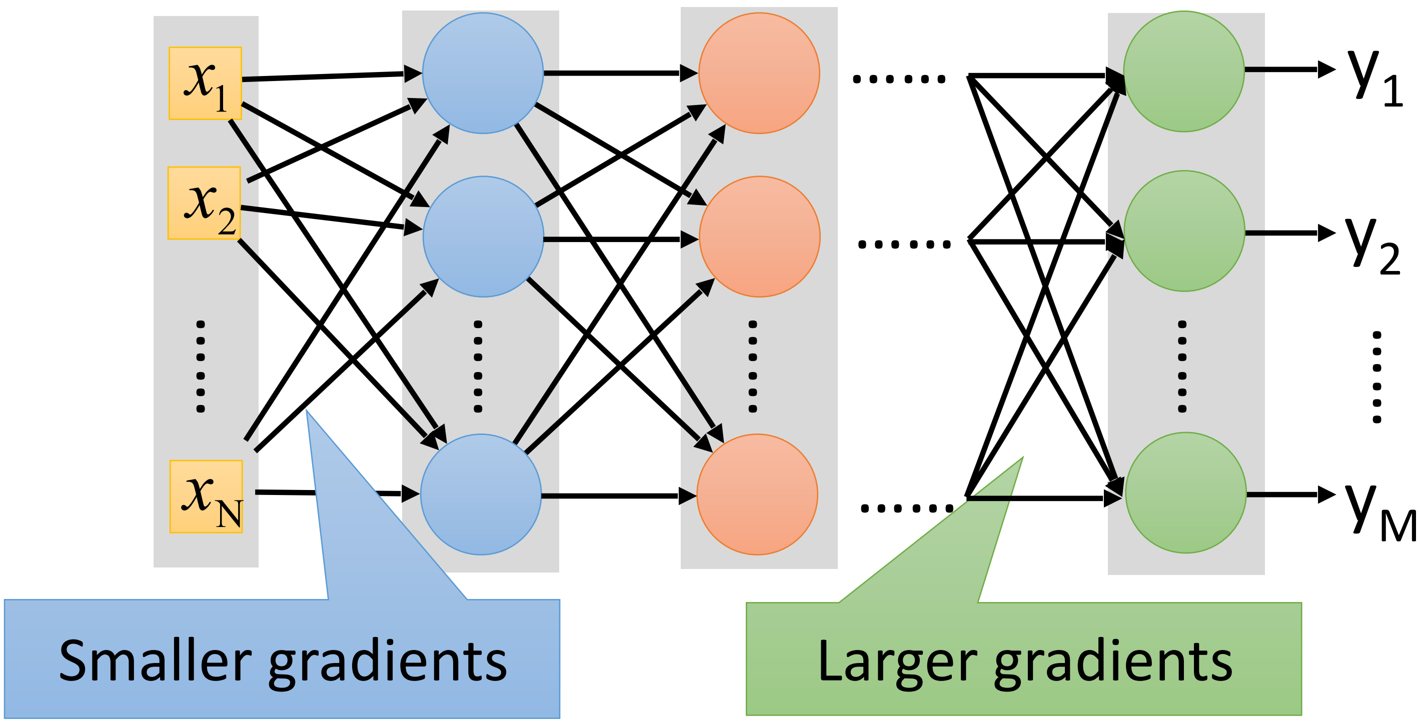

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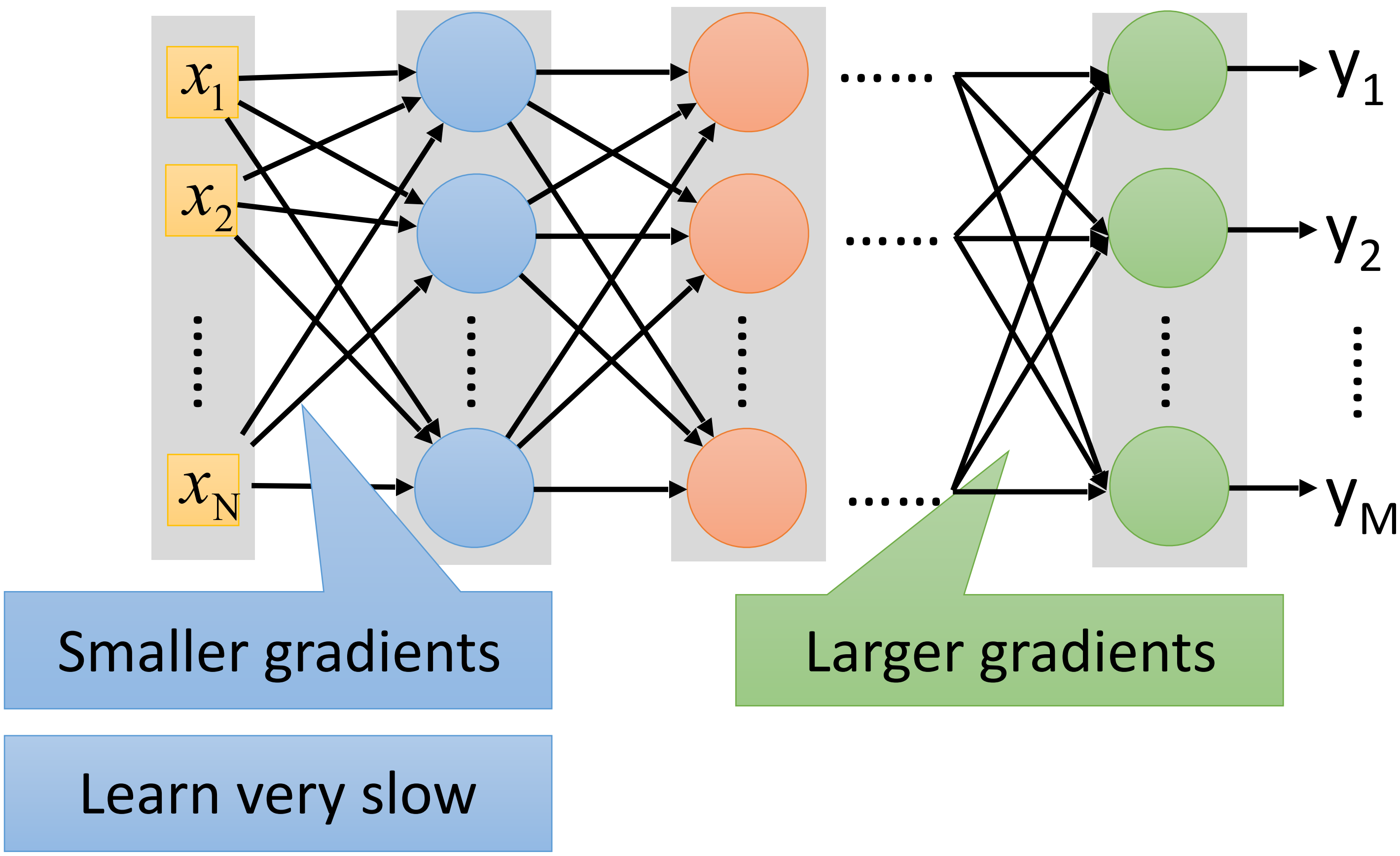

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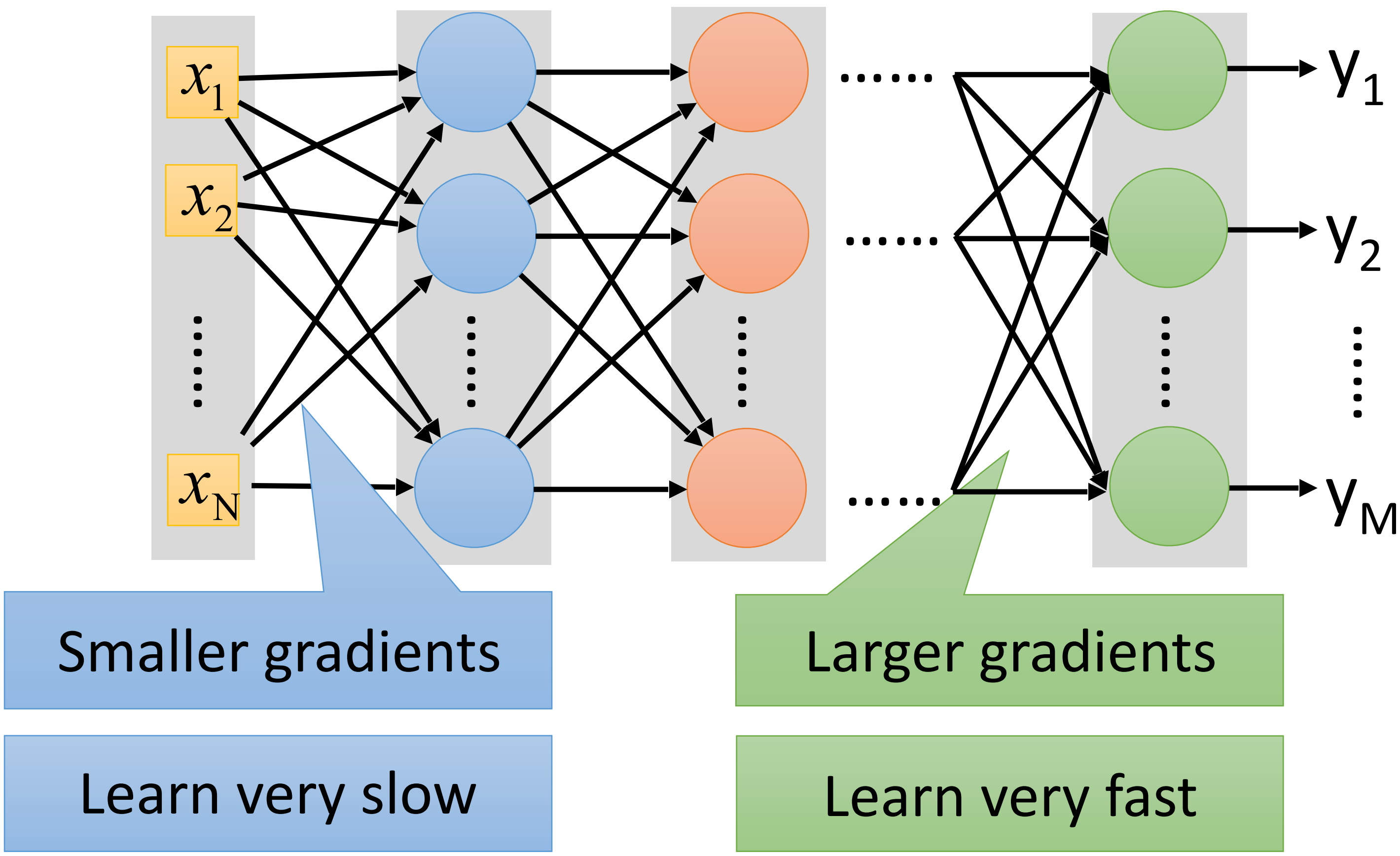

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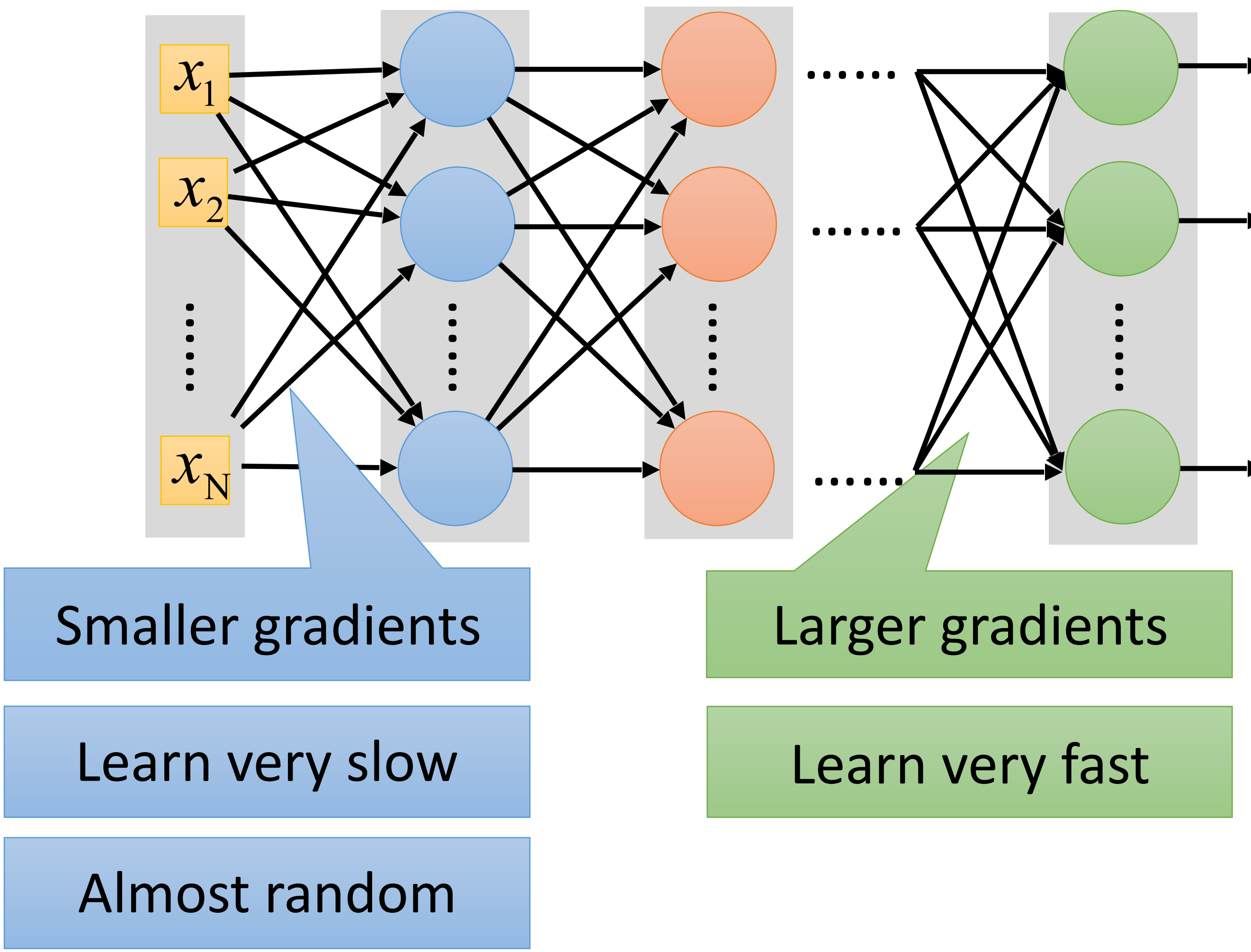

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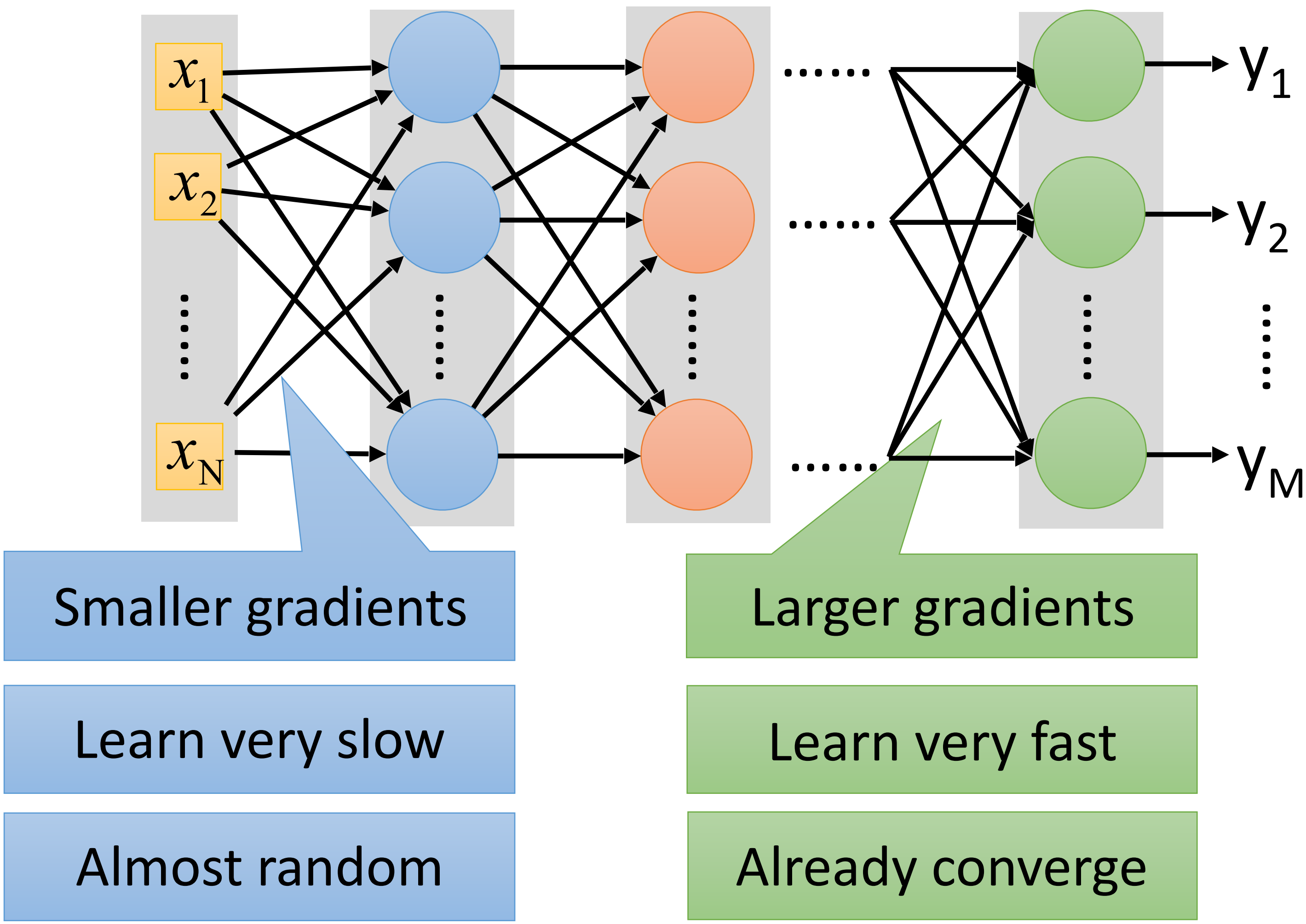

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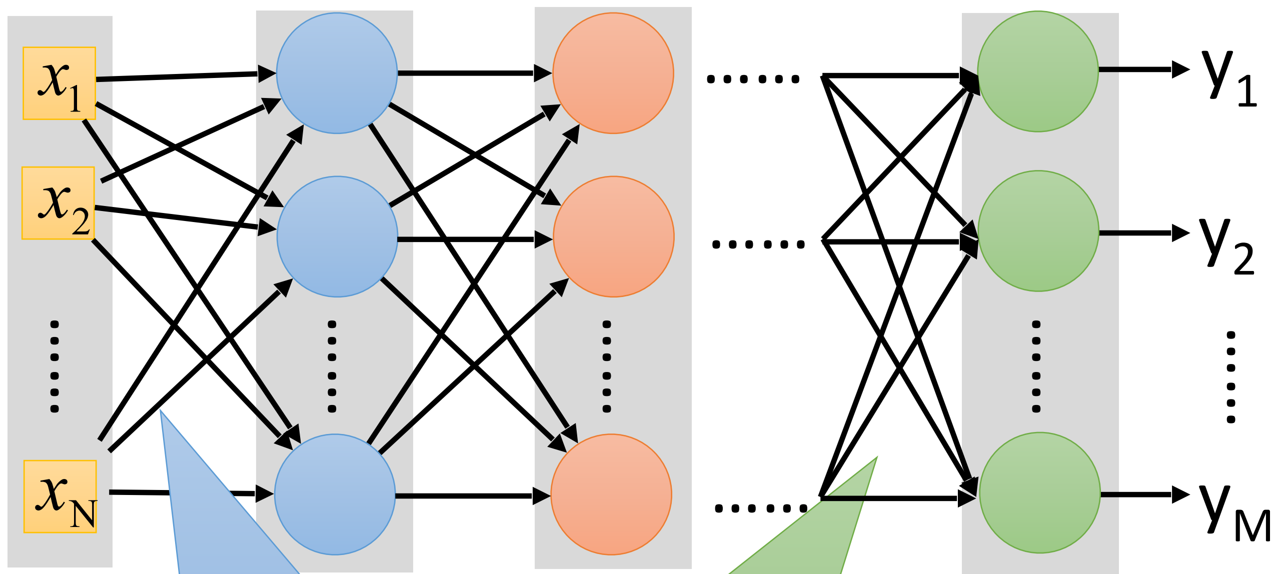


Smaller gradients

Learn very slow

Almost random

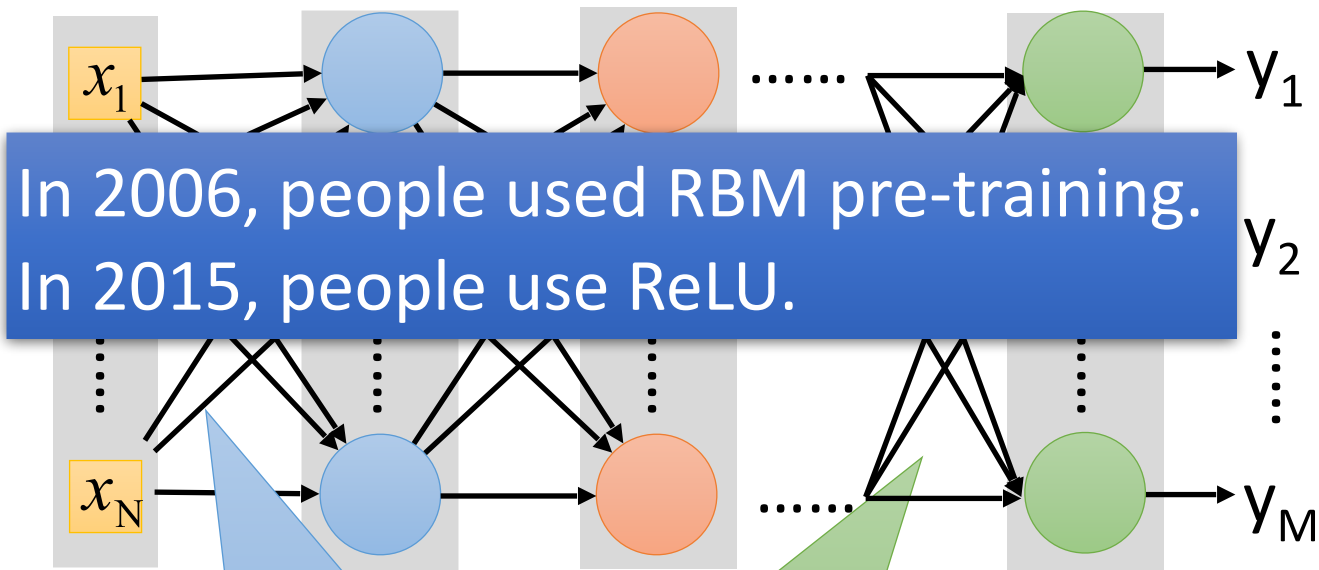
Larger gradients

Learn very fast

Already converge

based on random!?

Vanishing Gradient Problem



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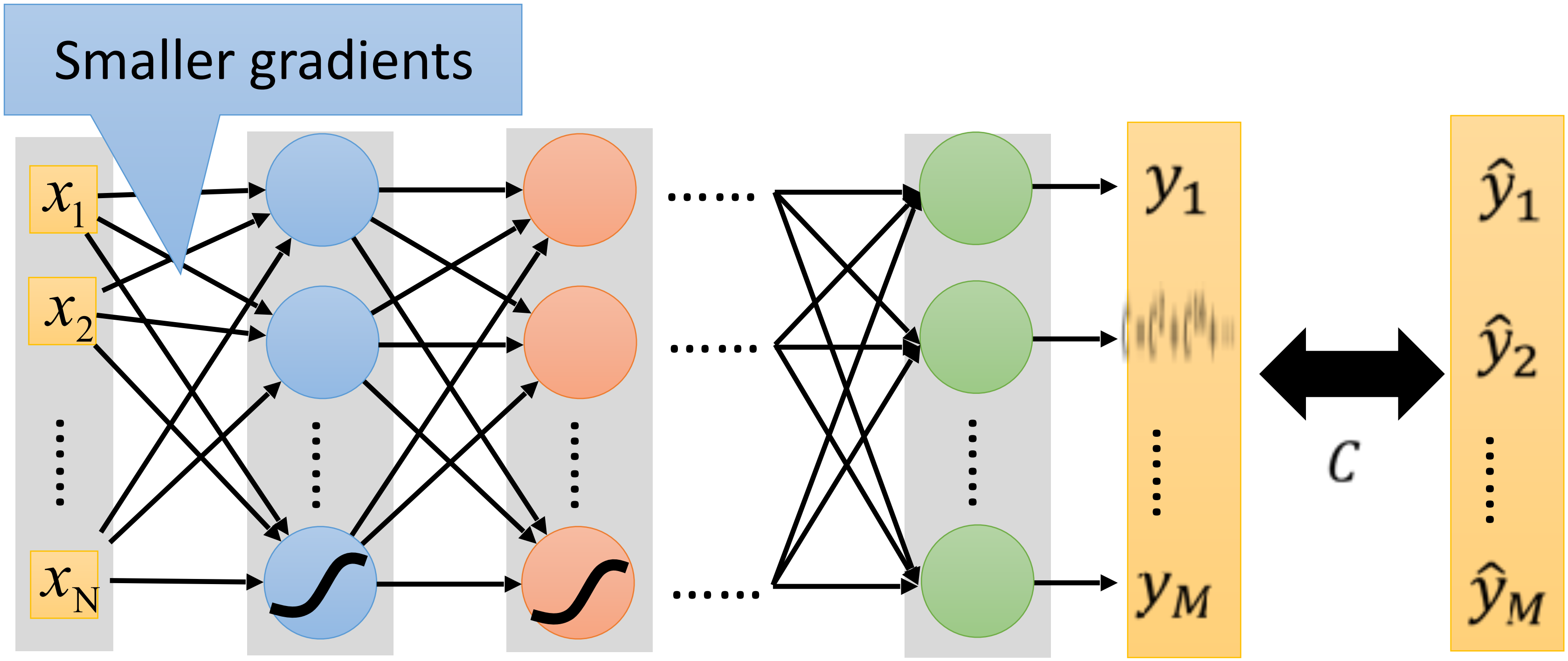

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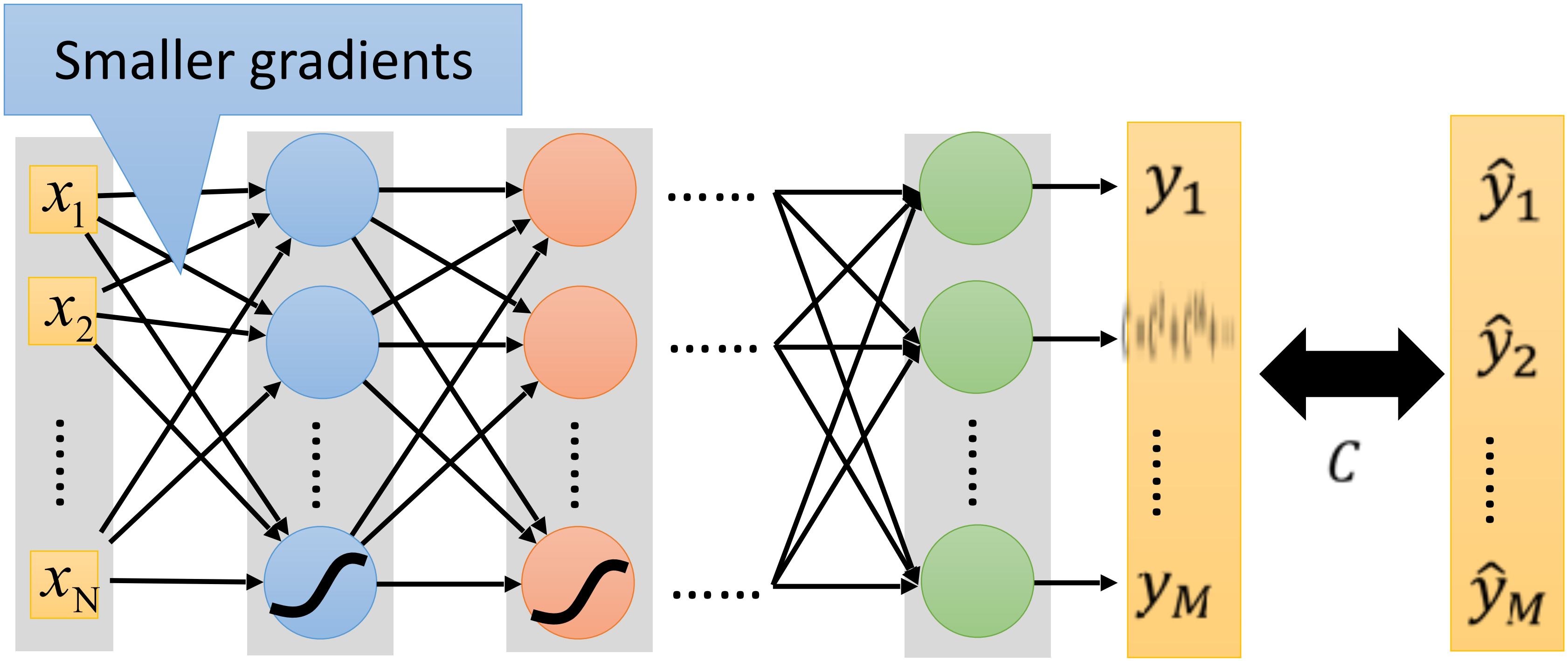
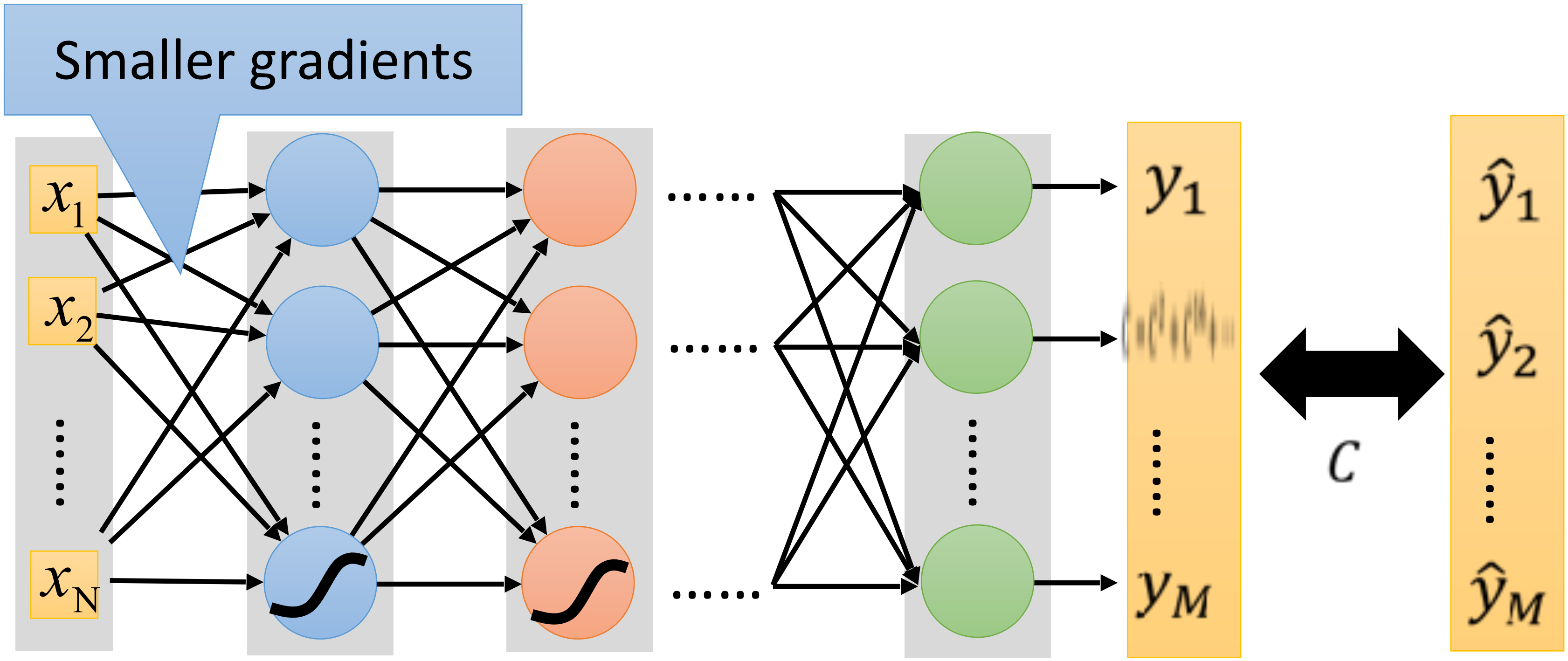


$$\frac{\partial C}{\partial w} = ?$$

Vanishing Gradient Problem



Intuitive way to compute the gradient …

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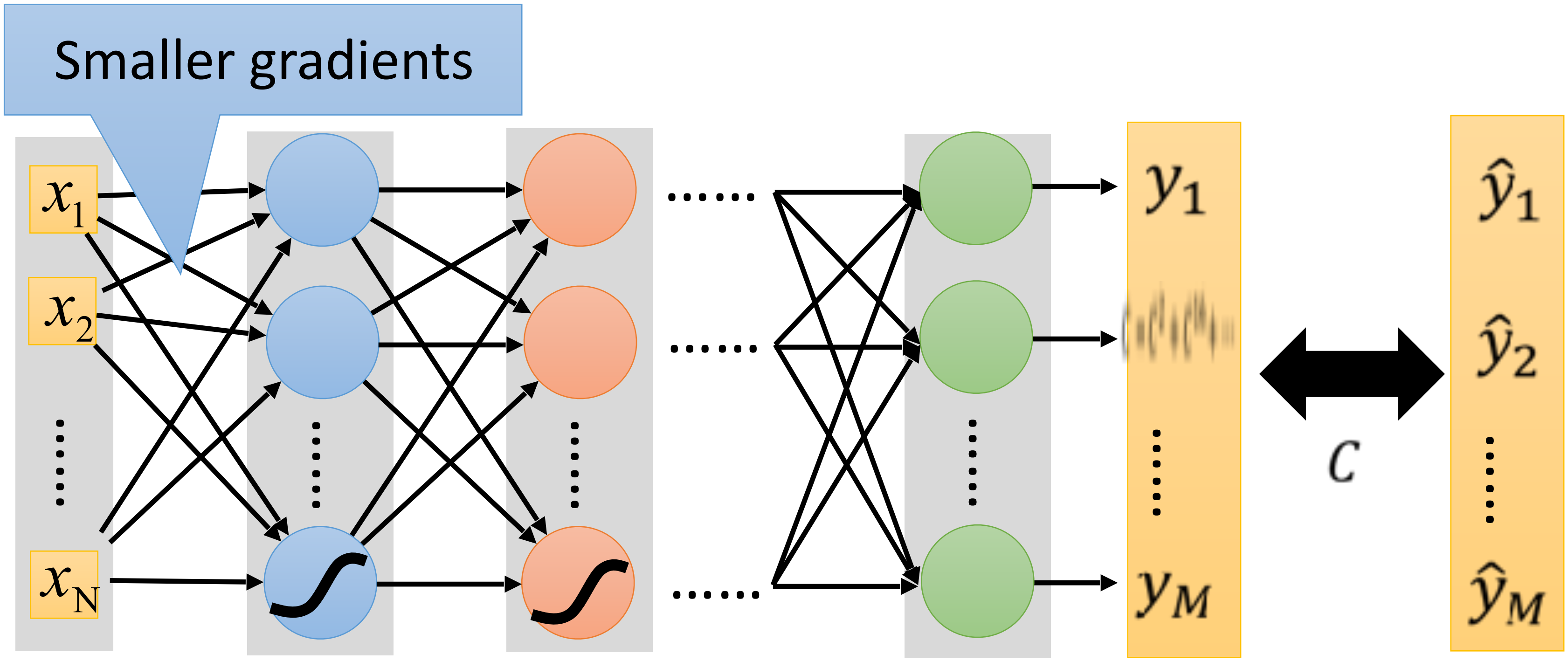

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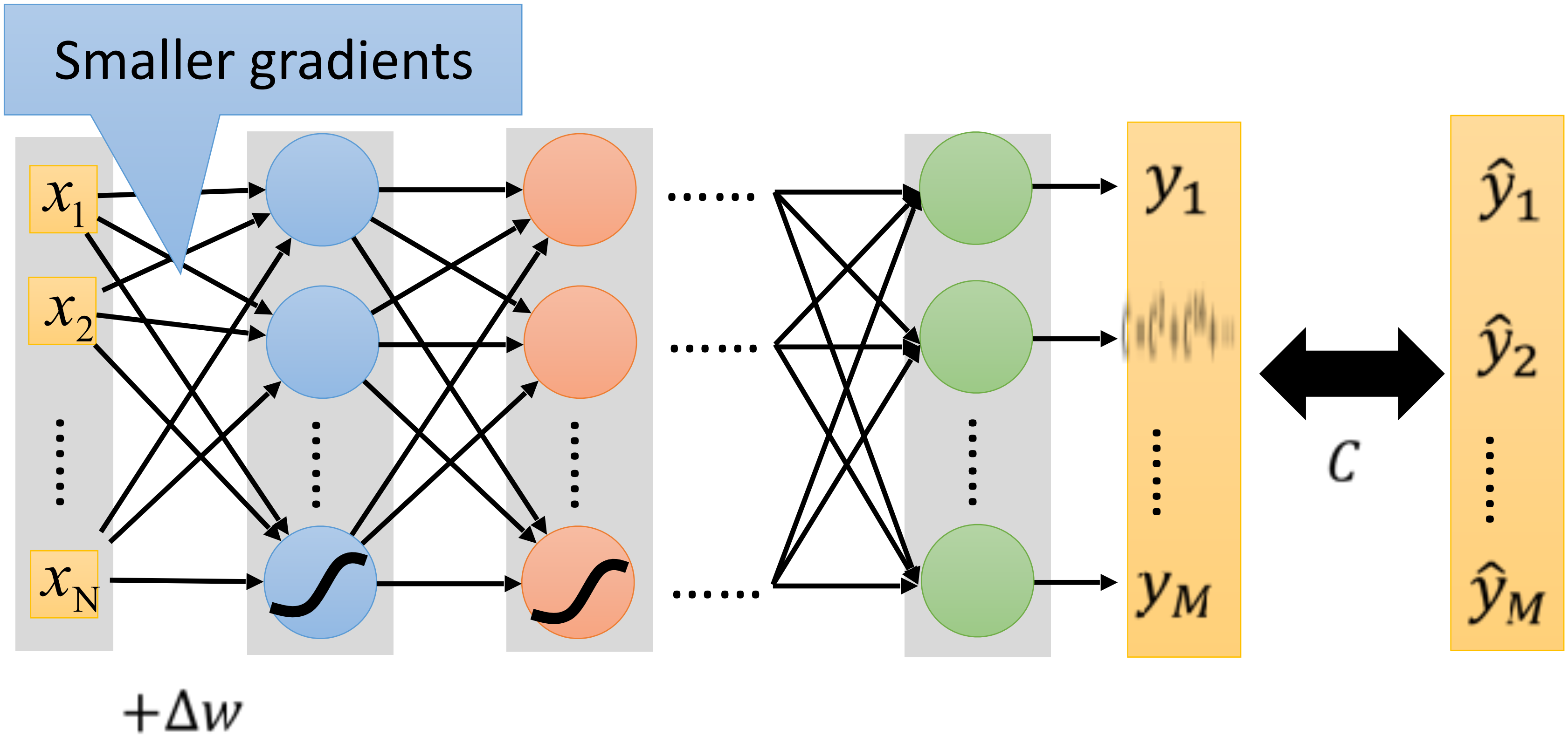

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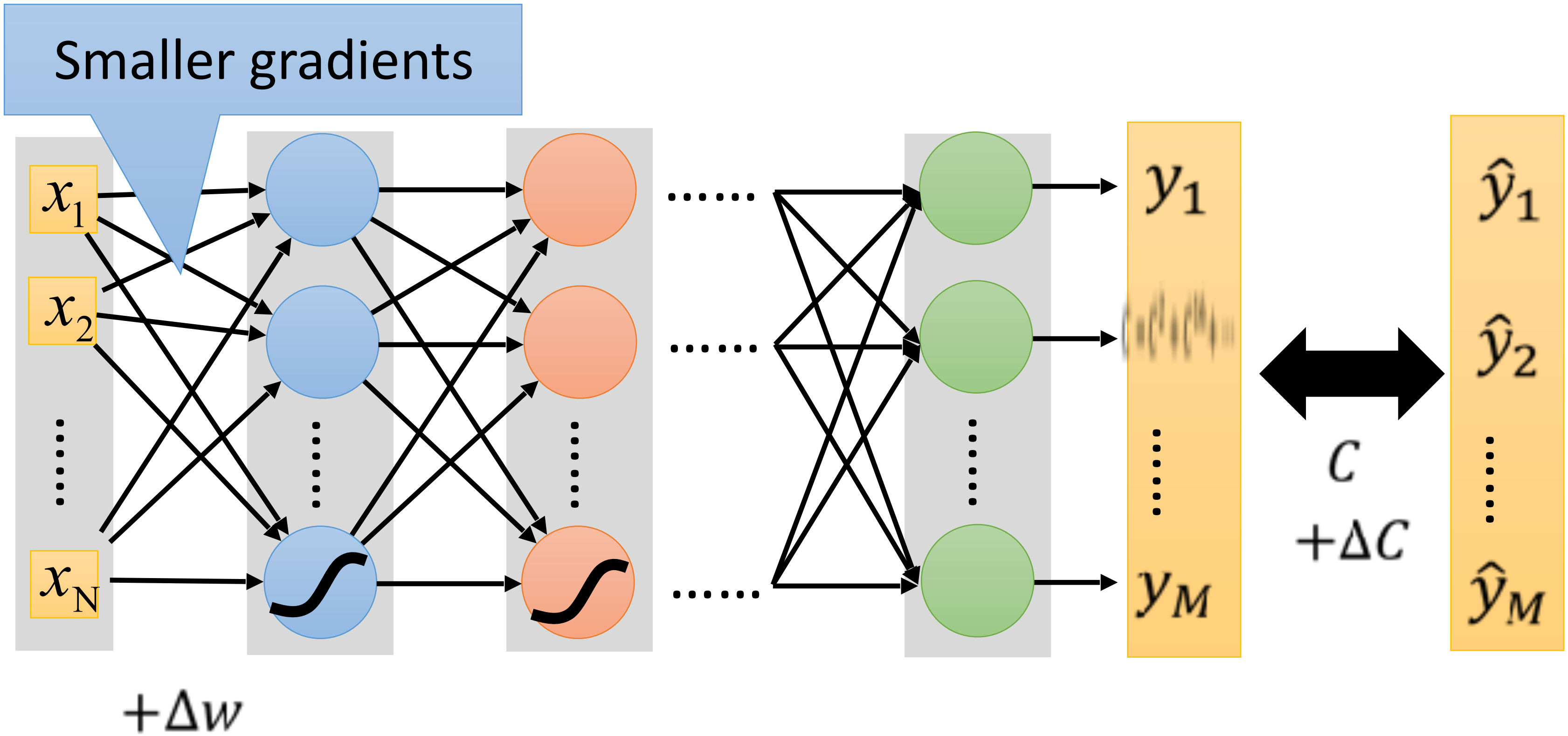

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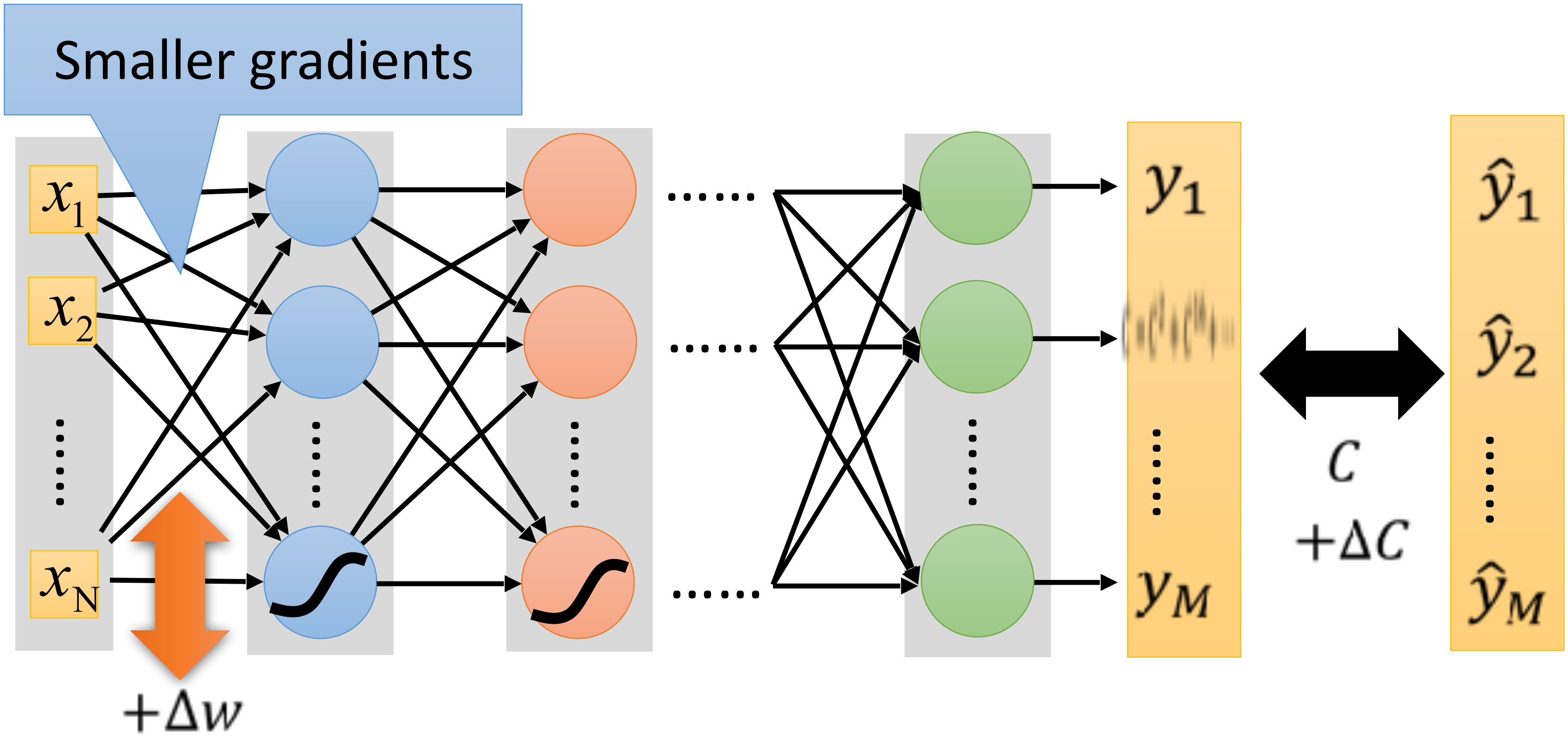

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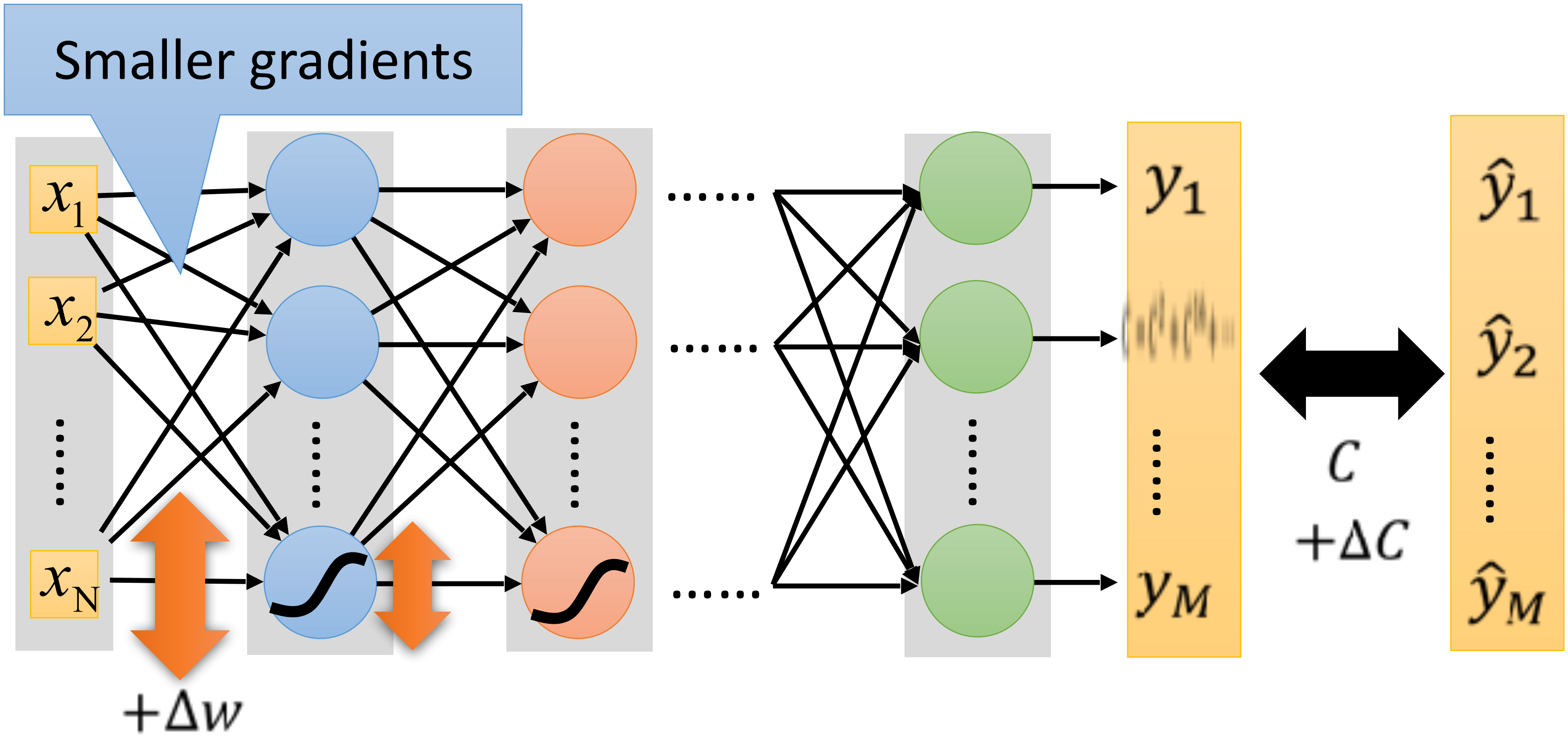

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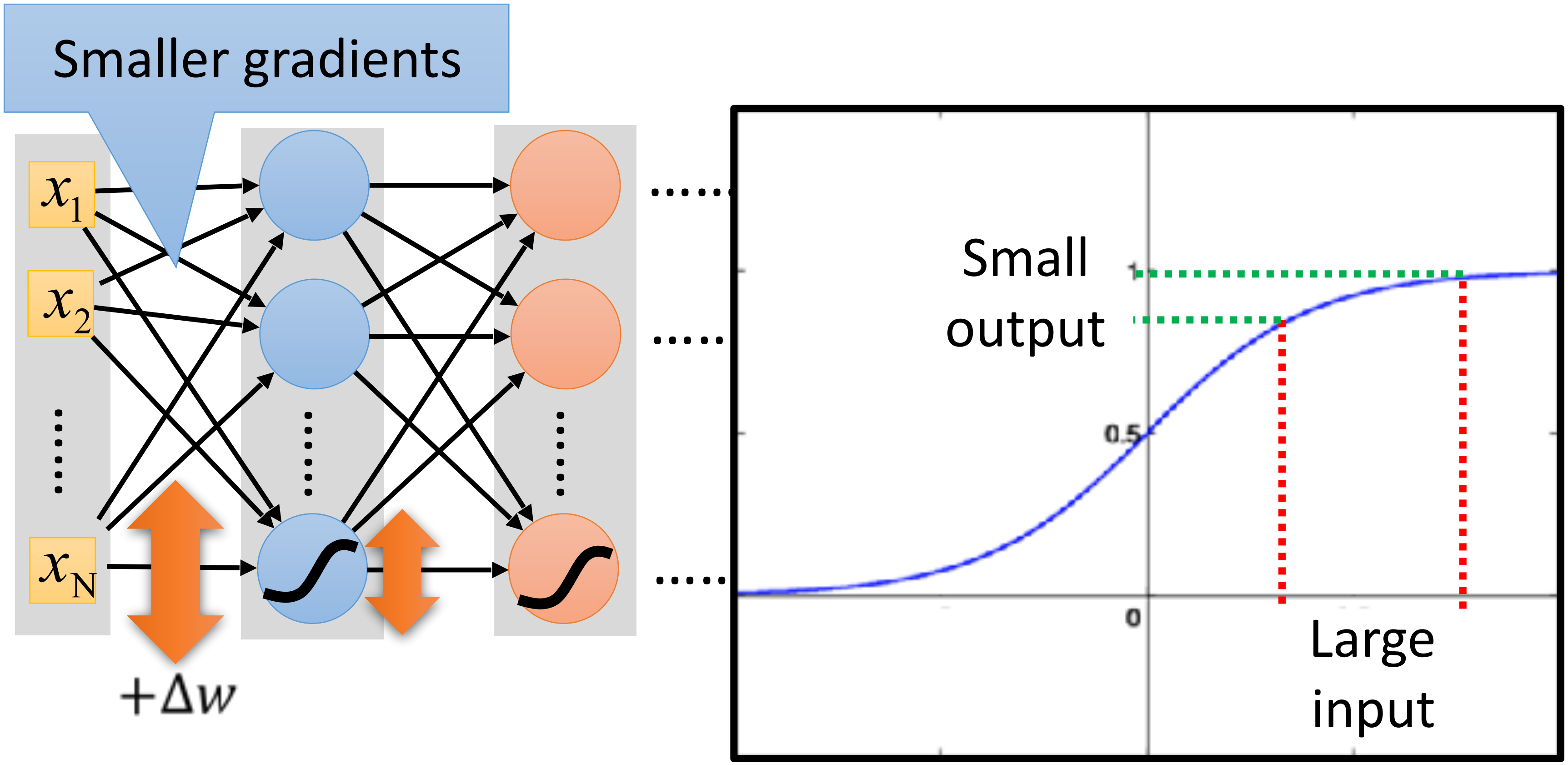
$$\frac{\partial C}{\partial w} =? \ \frac{\Delta C}{\Delta w}$$

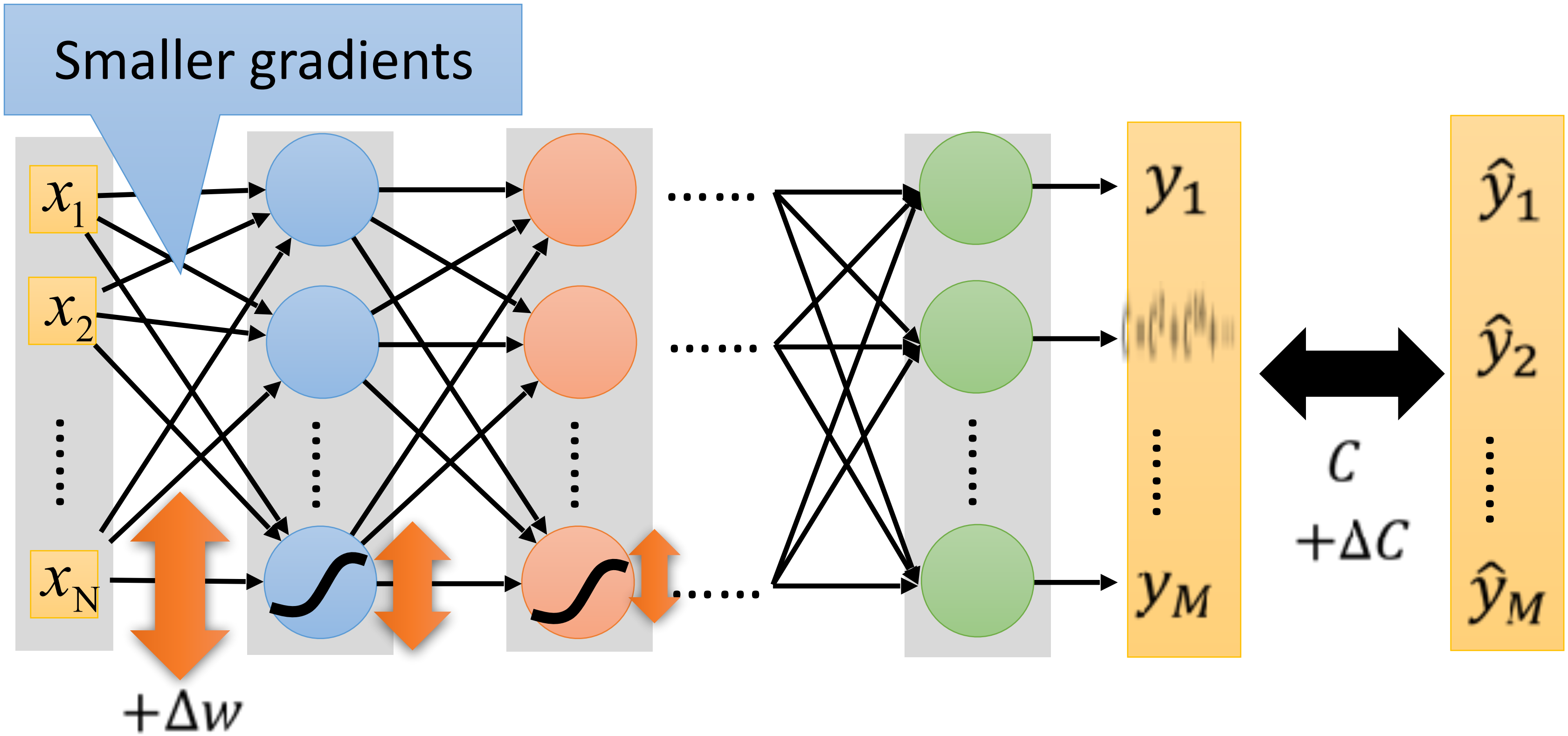
Vanishing Gradient Problem



Intuitive way to compute the gradient …

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

Vanishing Gradient Problem



Intuitive way to compute the gradient …

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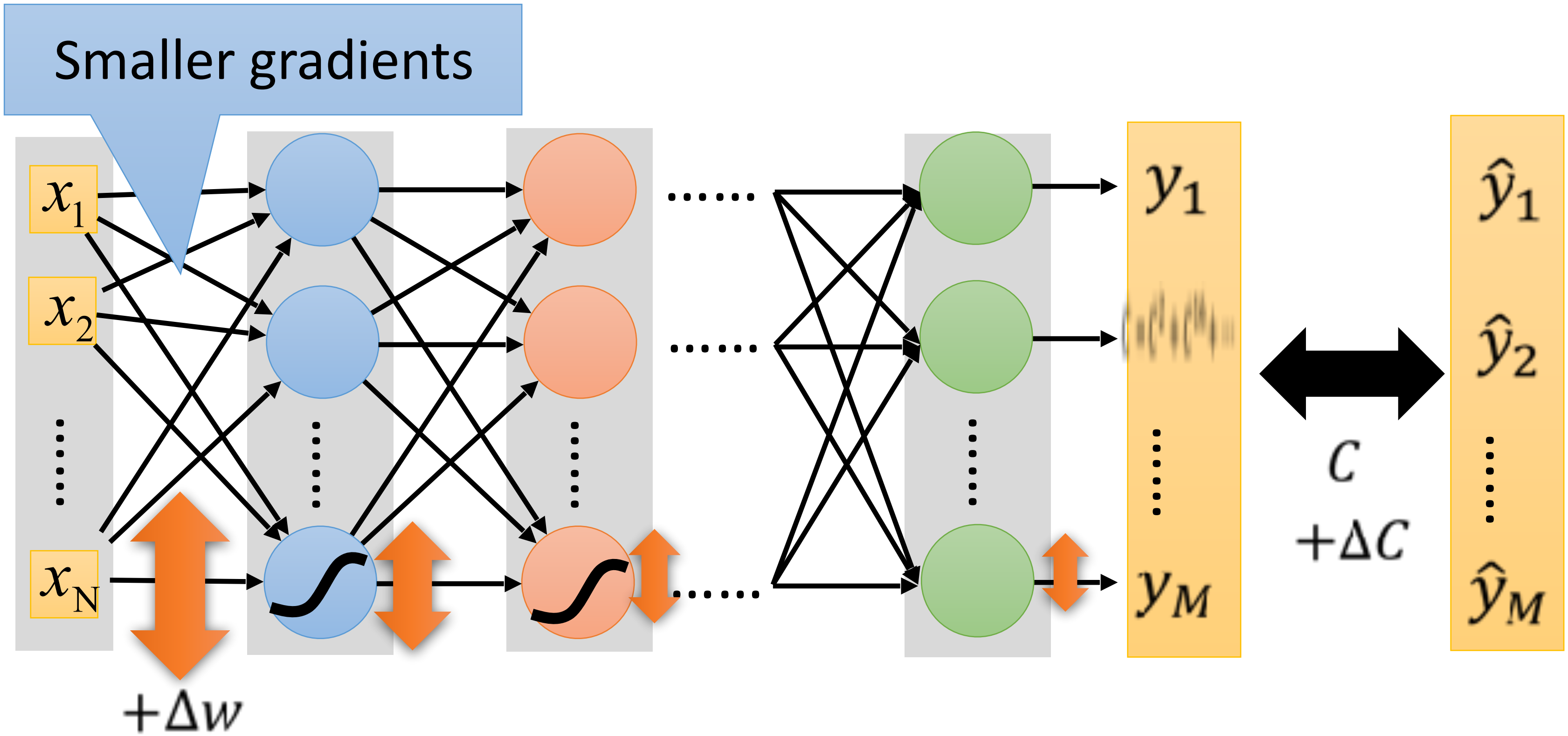
Vanishing Gradient Problem



Intuitive way to compute the gradient …

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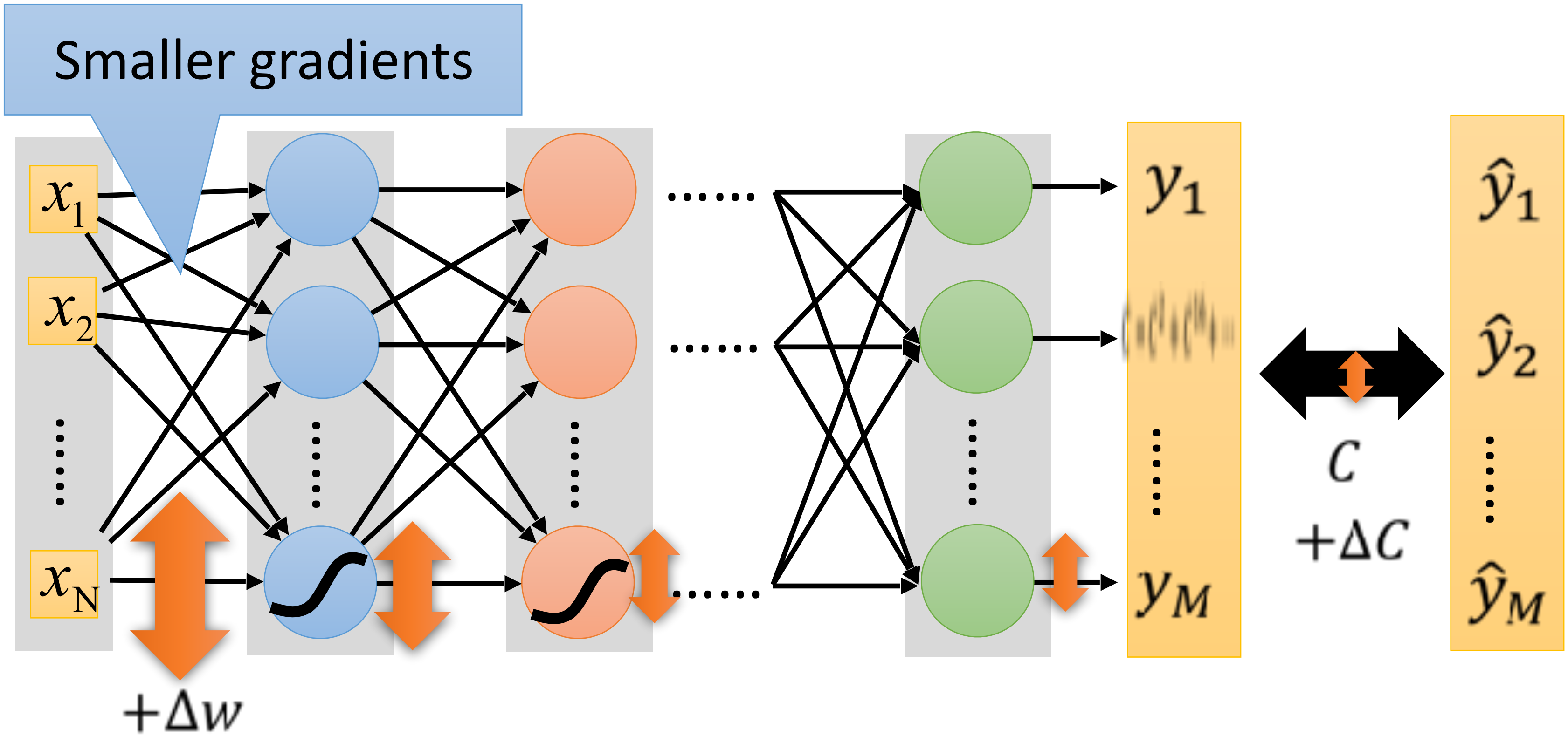
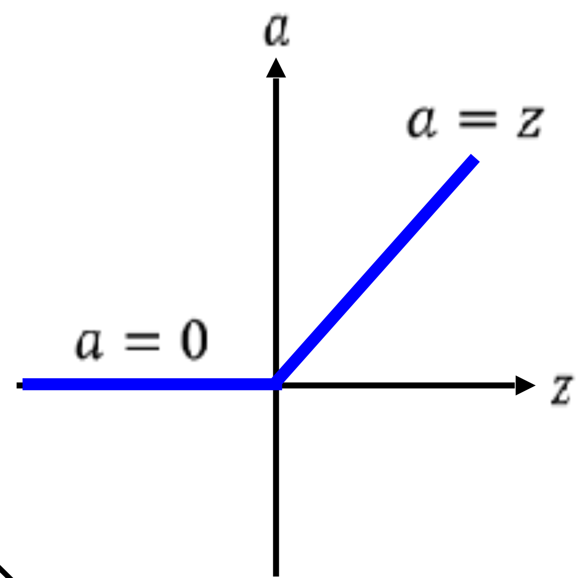
Vanishing Gradient Problem

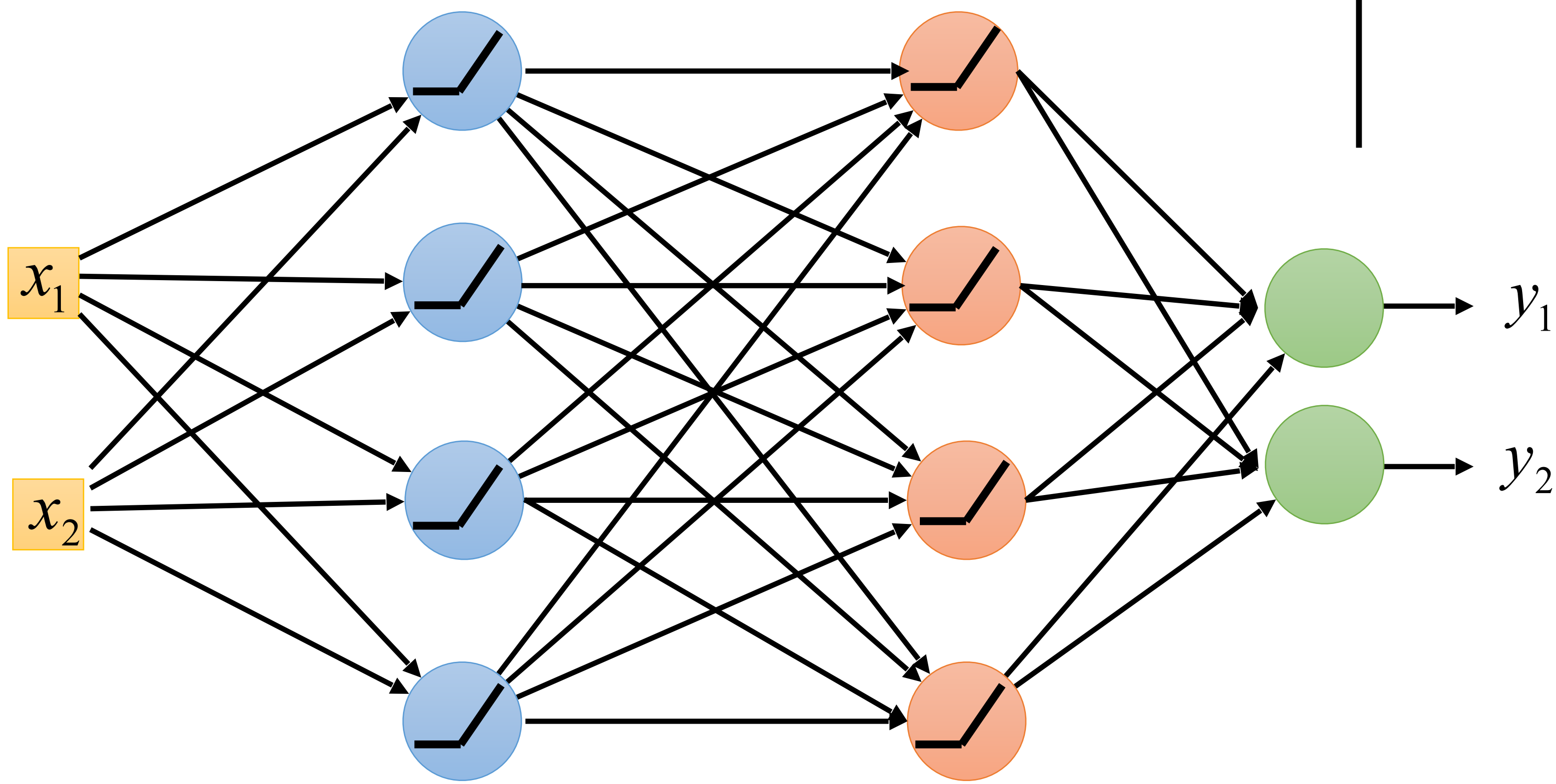


Intuitive way to compute the gradient …

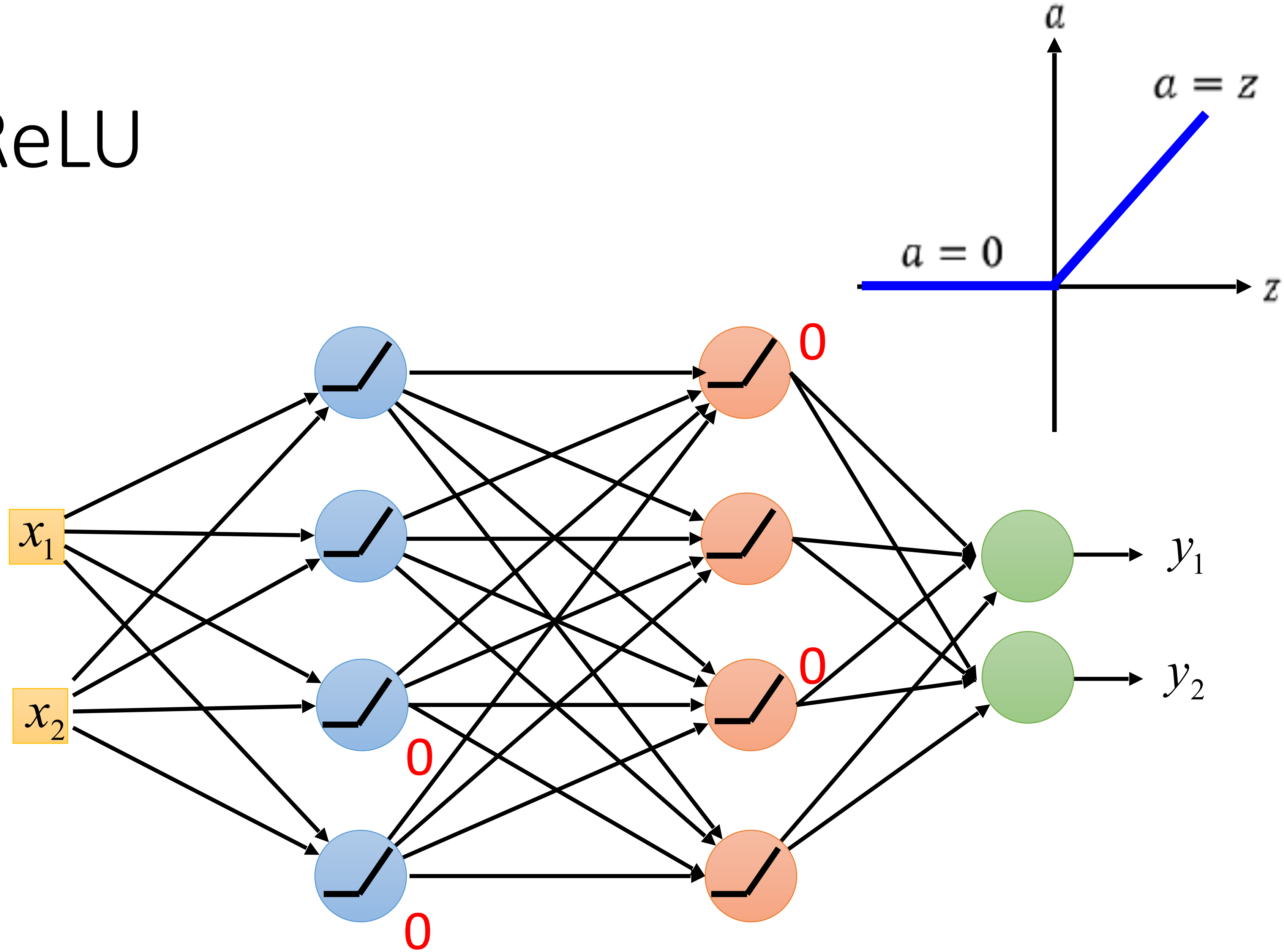
$$\frac{\partial C}{\partial w} =? \ \frac{\Delta C}{\Delta w}$$

ReLU

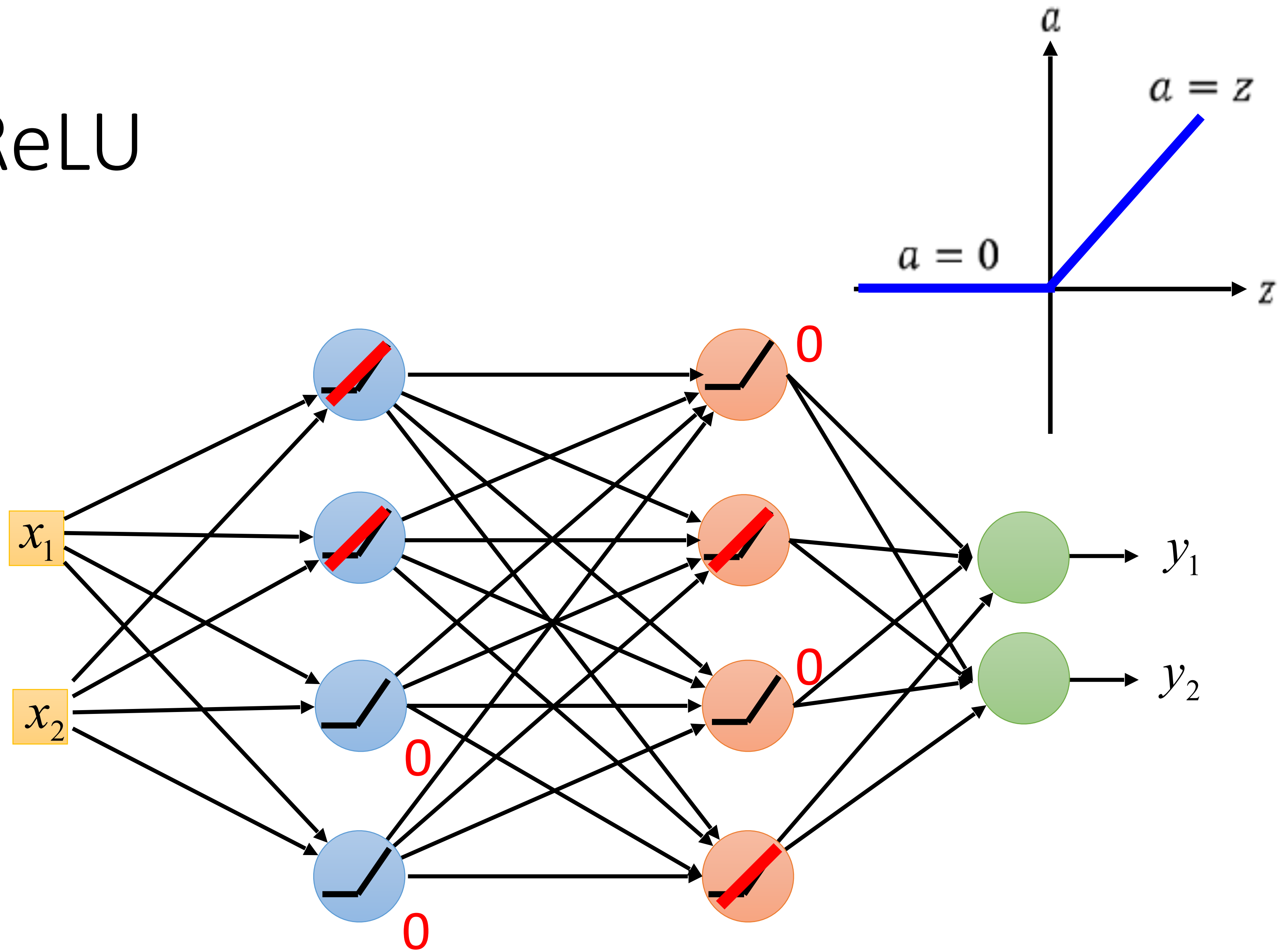




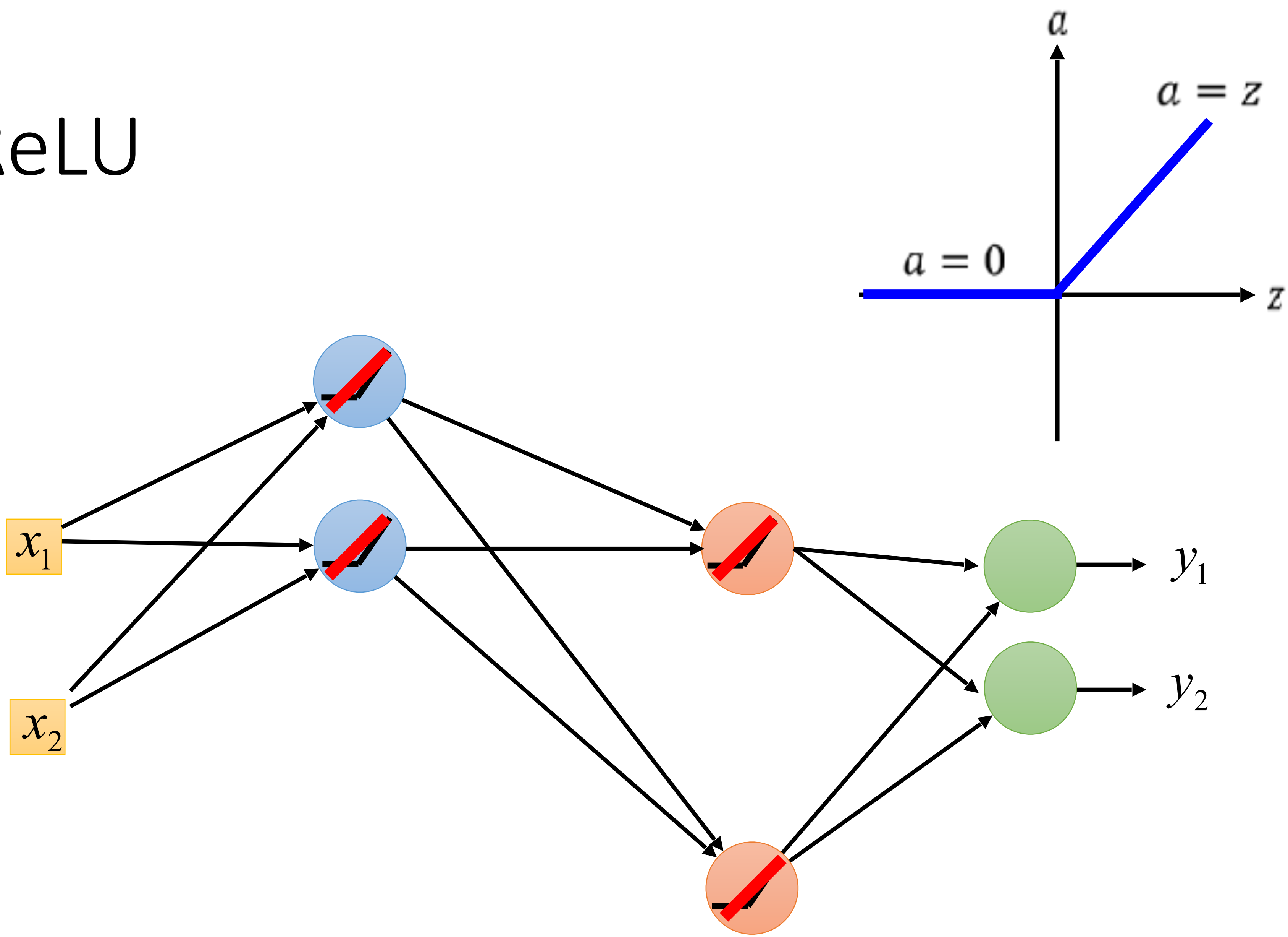
ReLU



ReLU

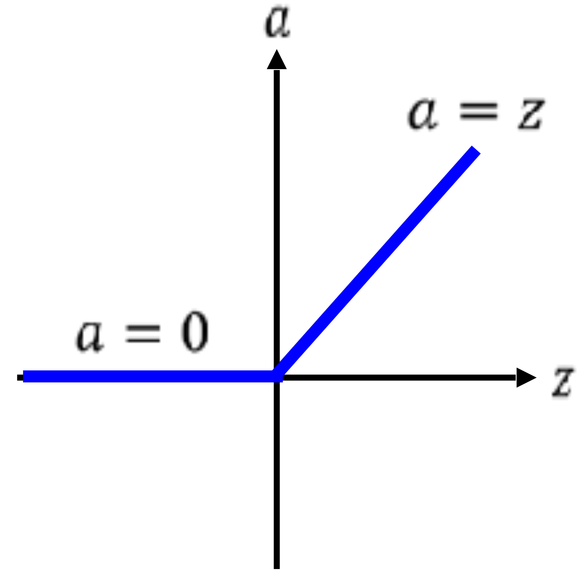


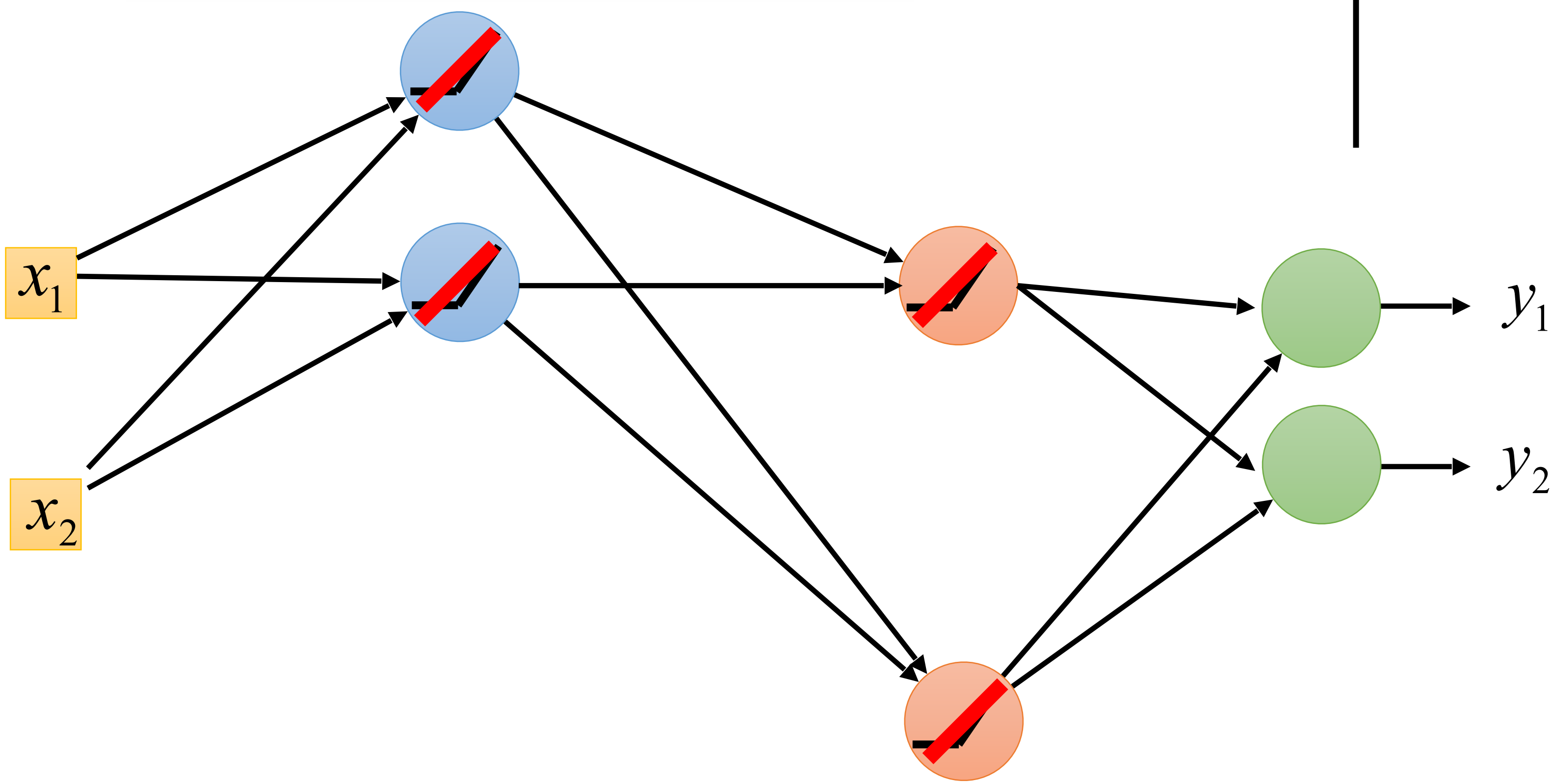
ReLU



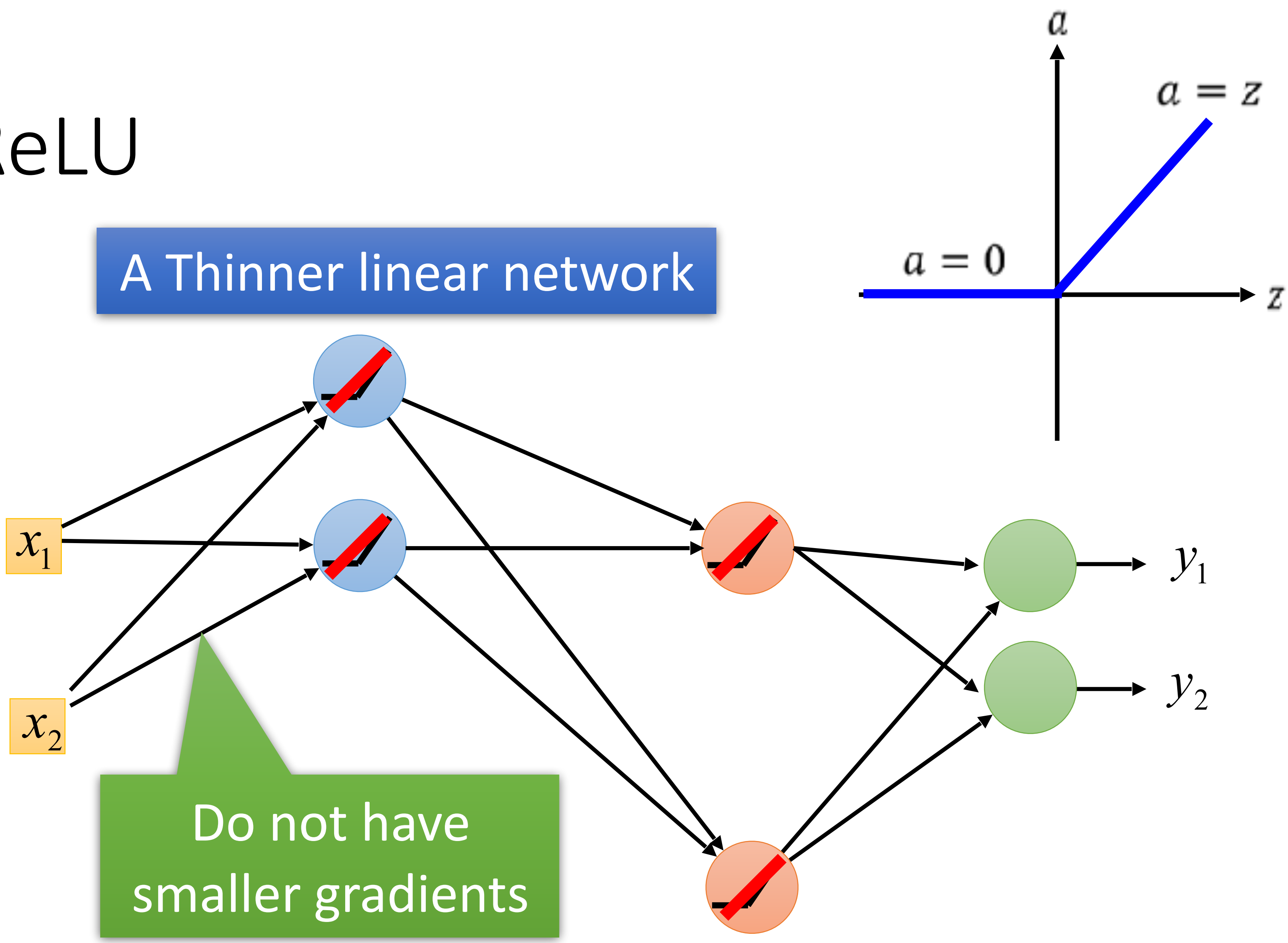
ReLU

A Thinner linear network





ReLU


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

Maxout

ReLU is a special cases of Maxout

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

Maxout

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Input

x_1

x_2

Maxout

ReLU is a special cases of Maxout

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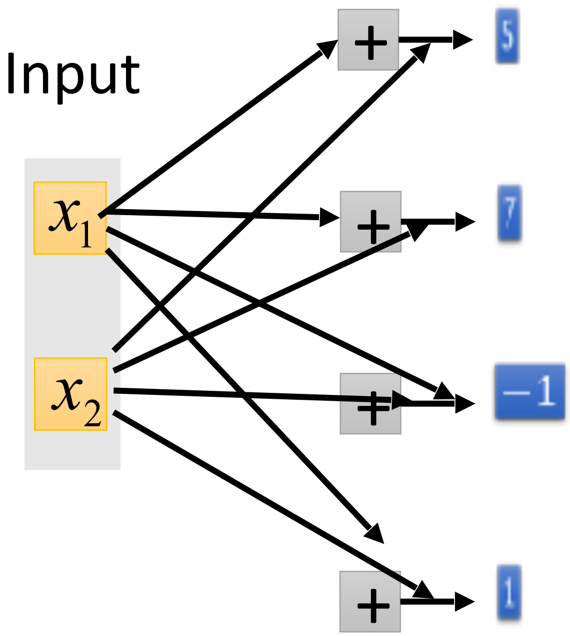

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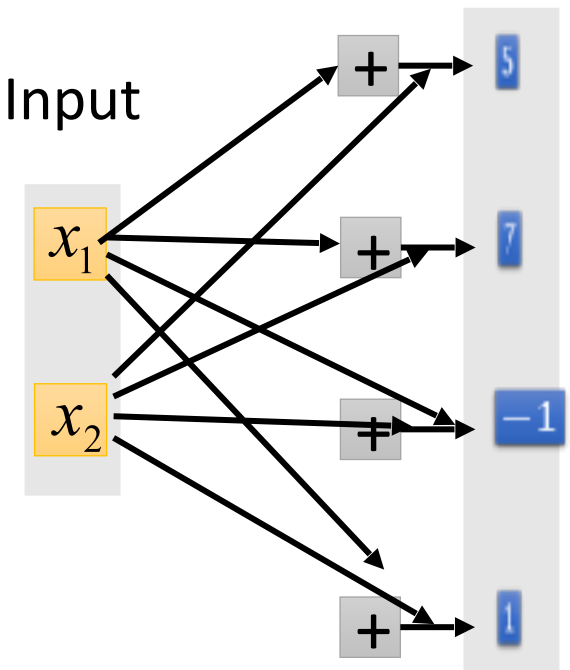

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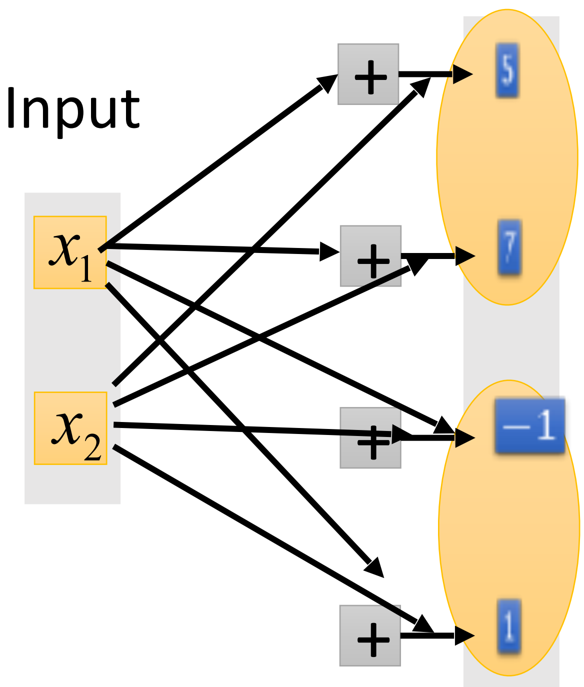

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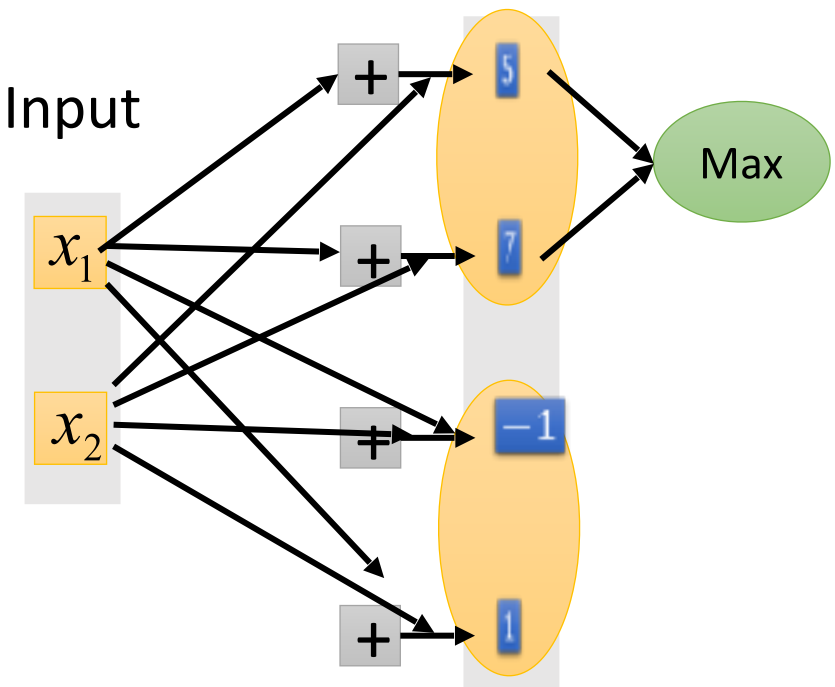

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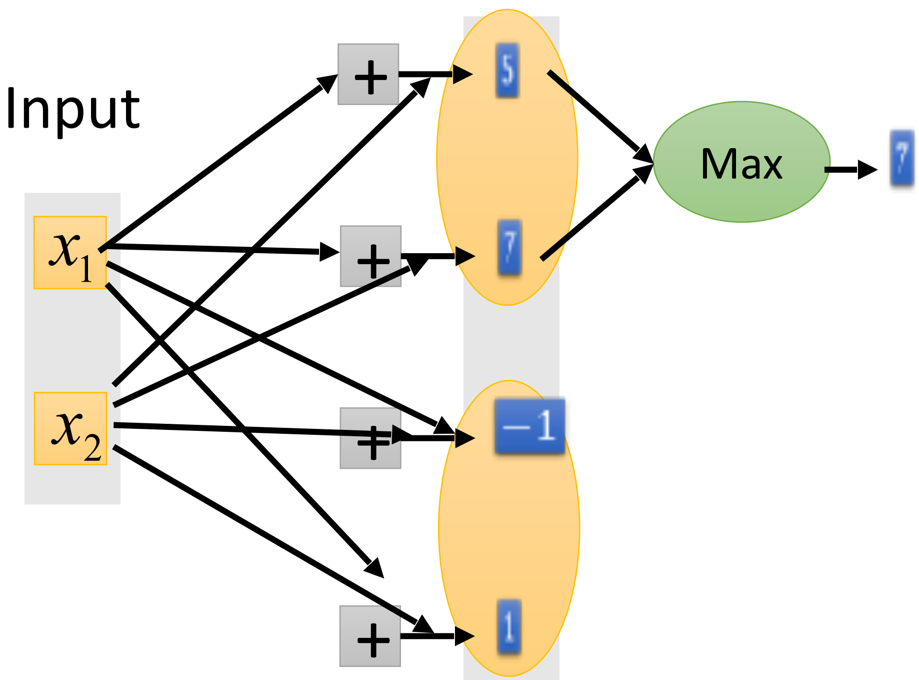

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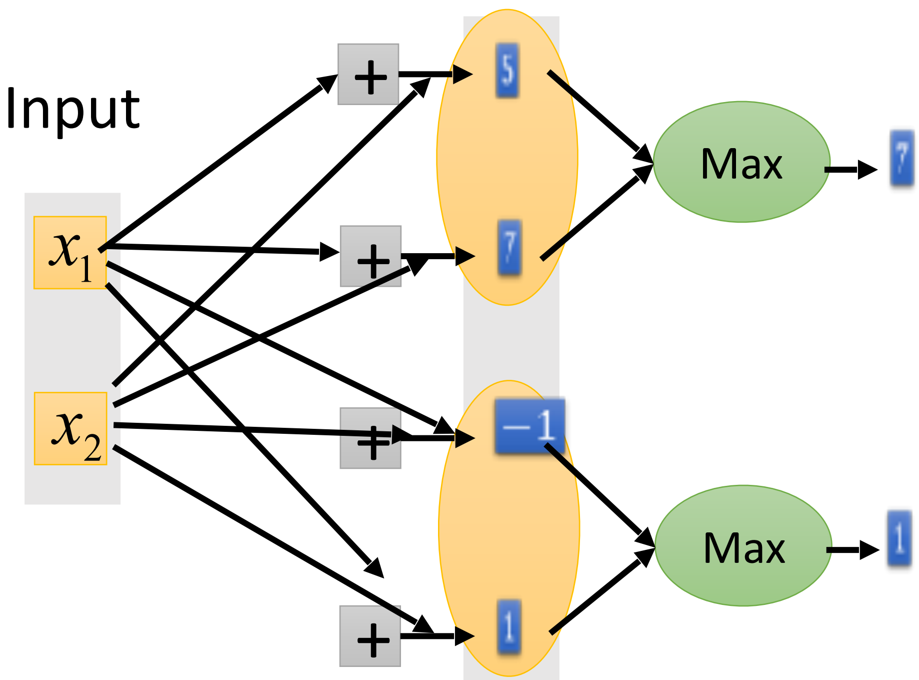

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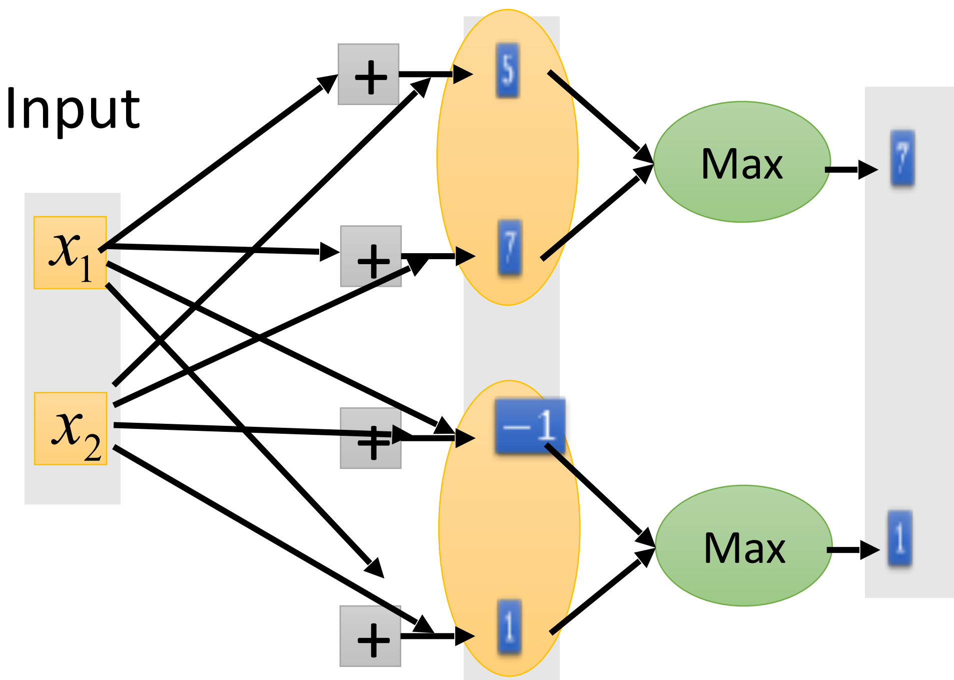

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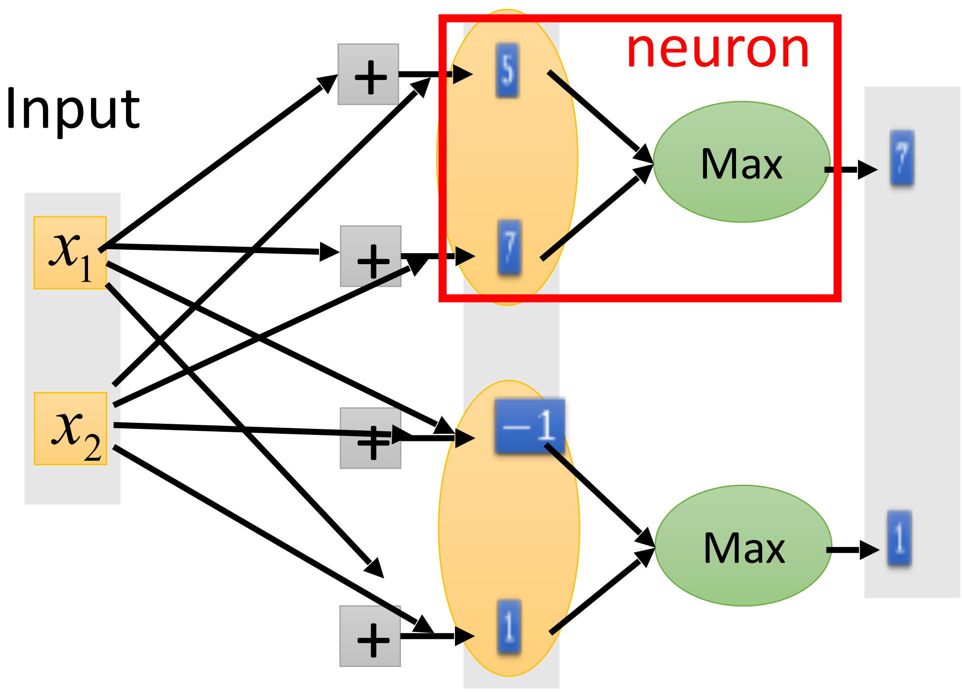

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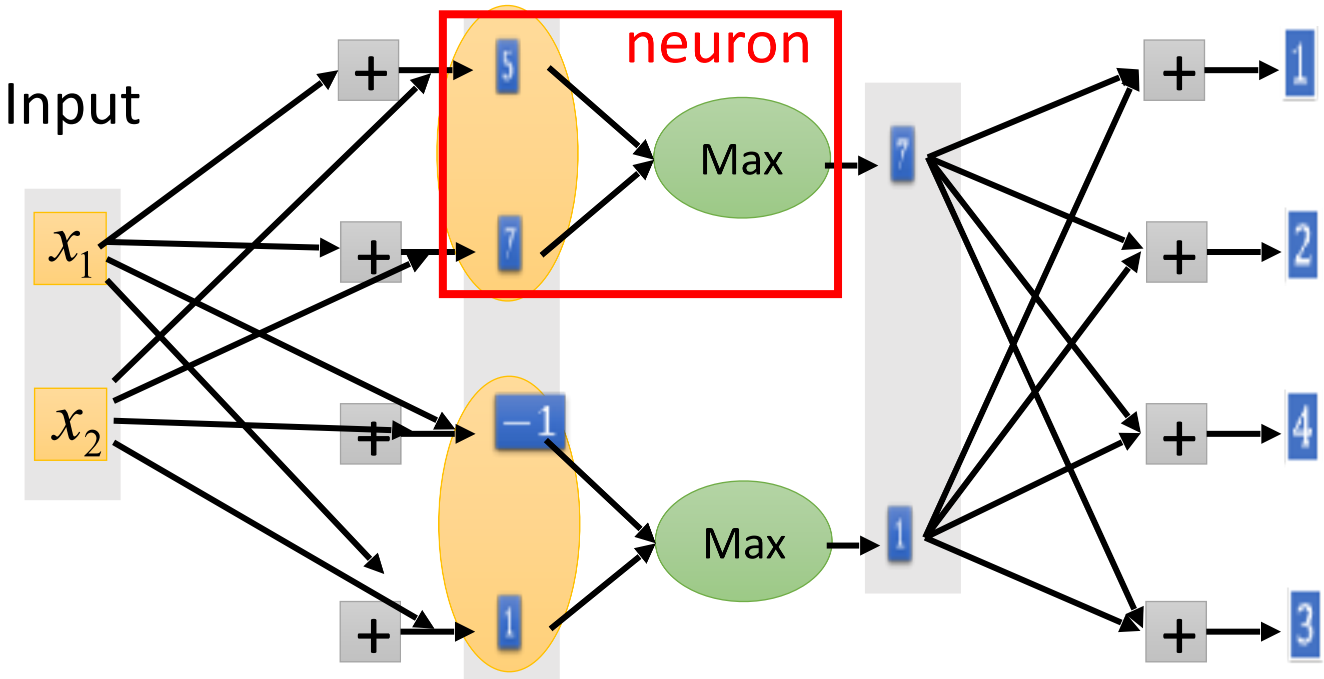

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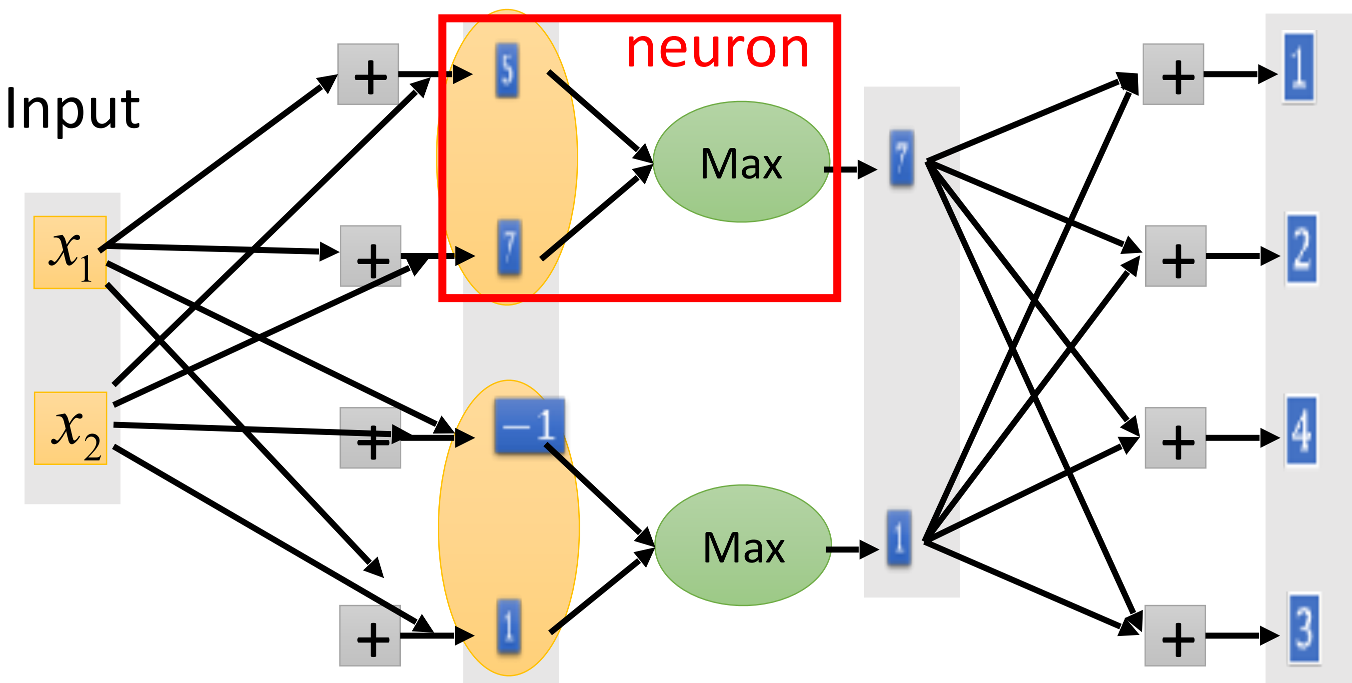

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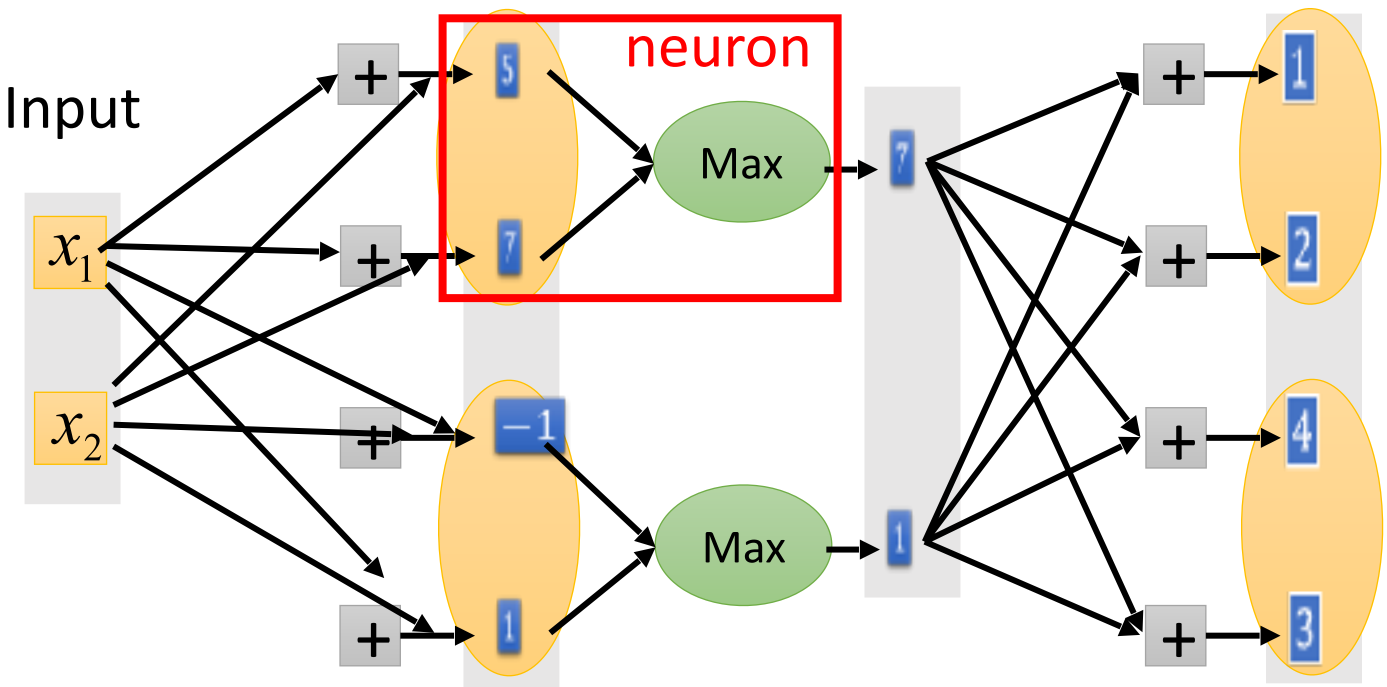

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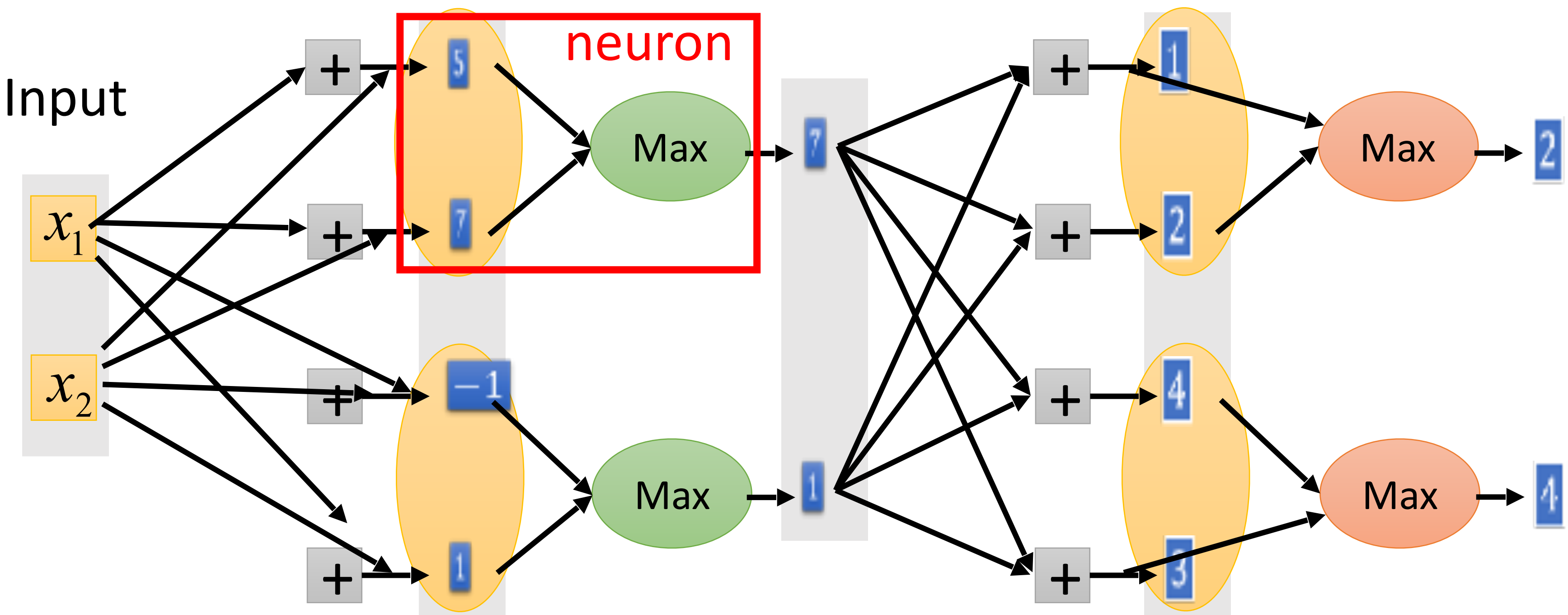

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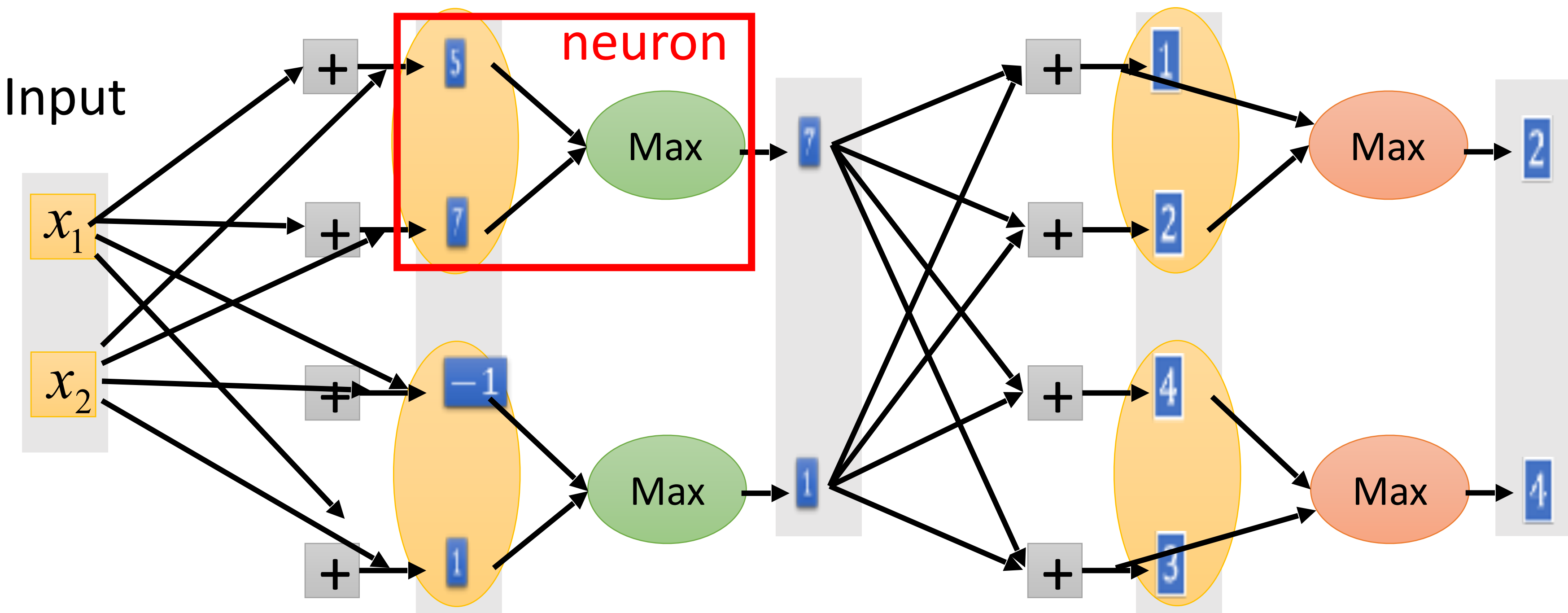

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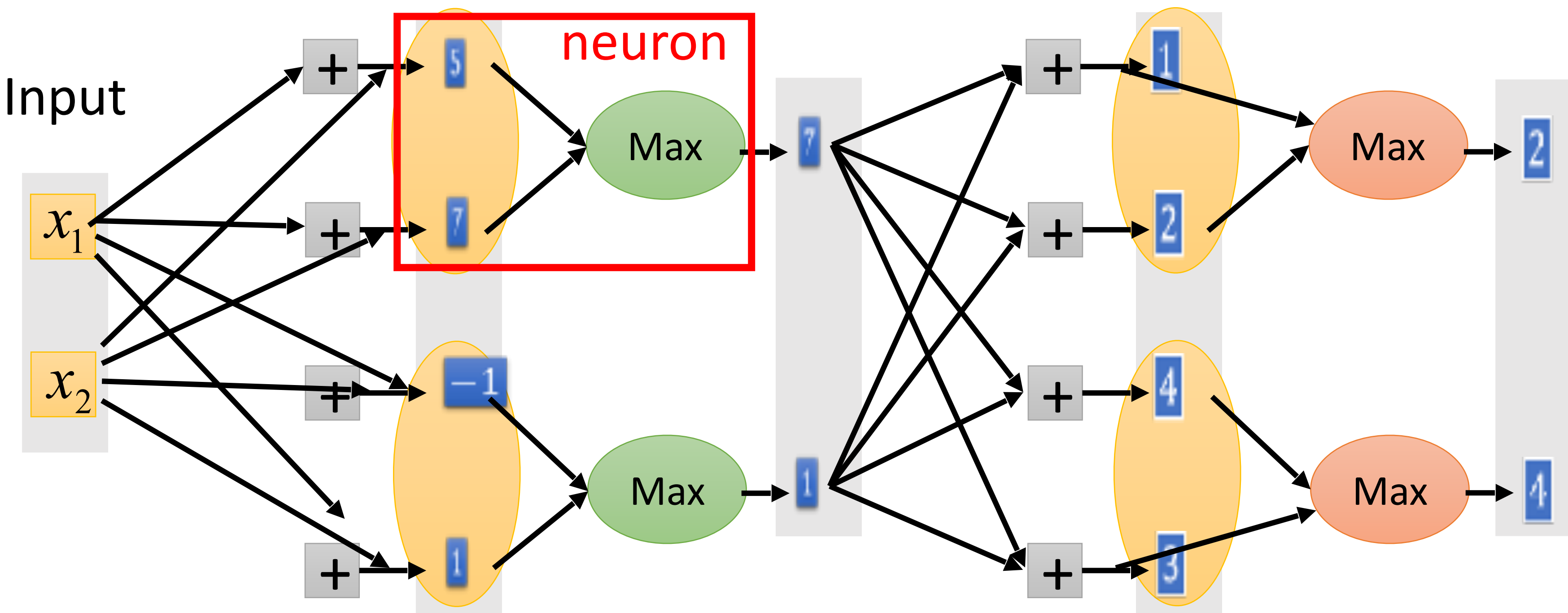

You can have more than 2 elements in a group.

Maxout

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Maxout

ReLU is a special cases of Maxout

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  - Activation function in maxout network can be any piecewise linear convex function

Maxout

ReLU is a special cases of Maxout

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  - How many pieces depending on how many elements in a group

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2 elements in a group

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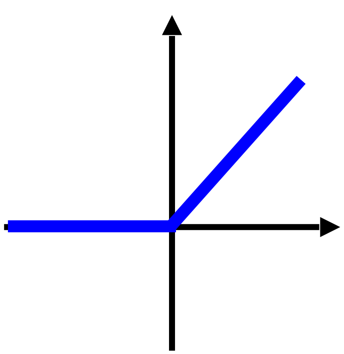

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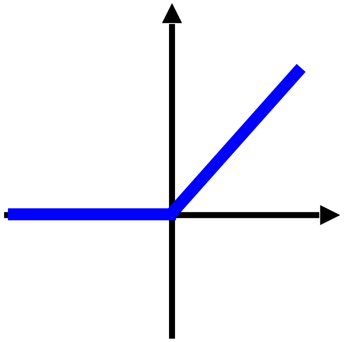

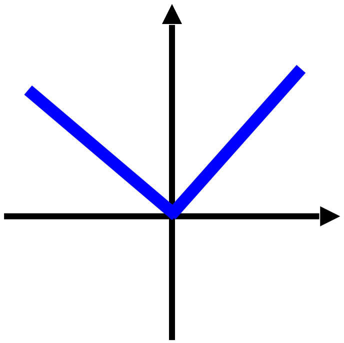

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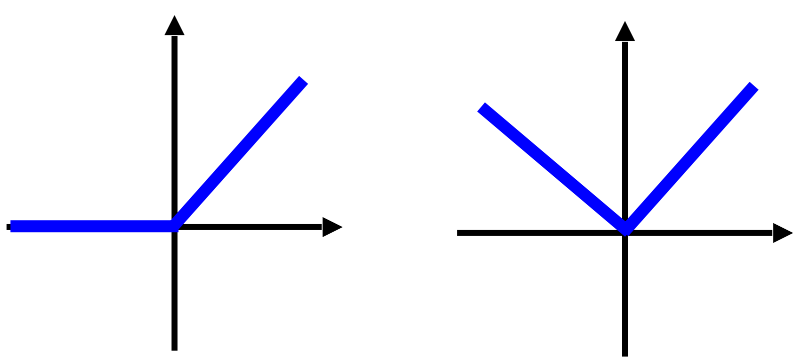
2 elements in a group

3 elements in a group



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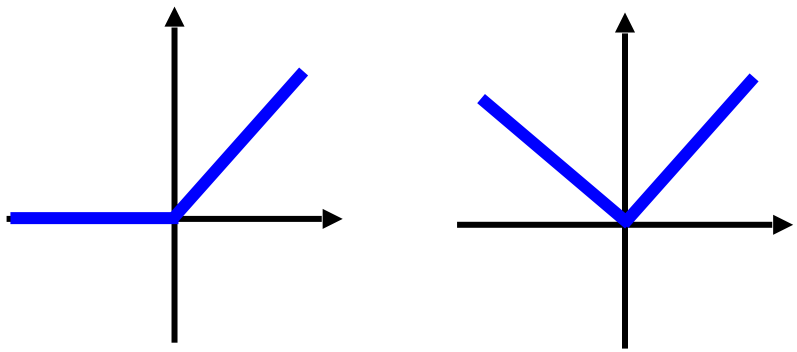
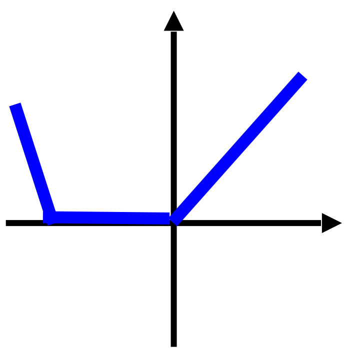


3 elements in a group



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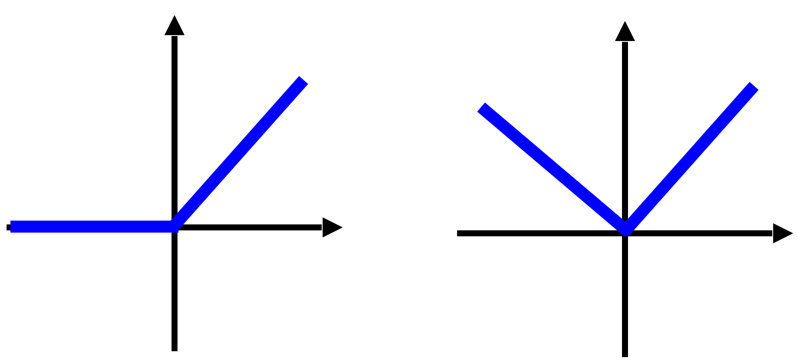
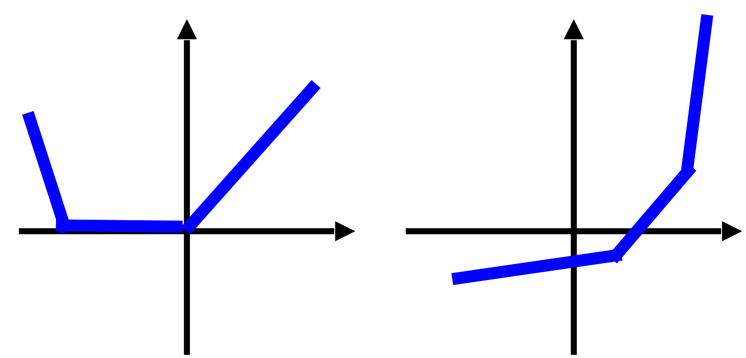


3 elements in a group

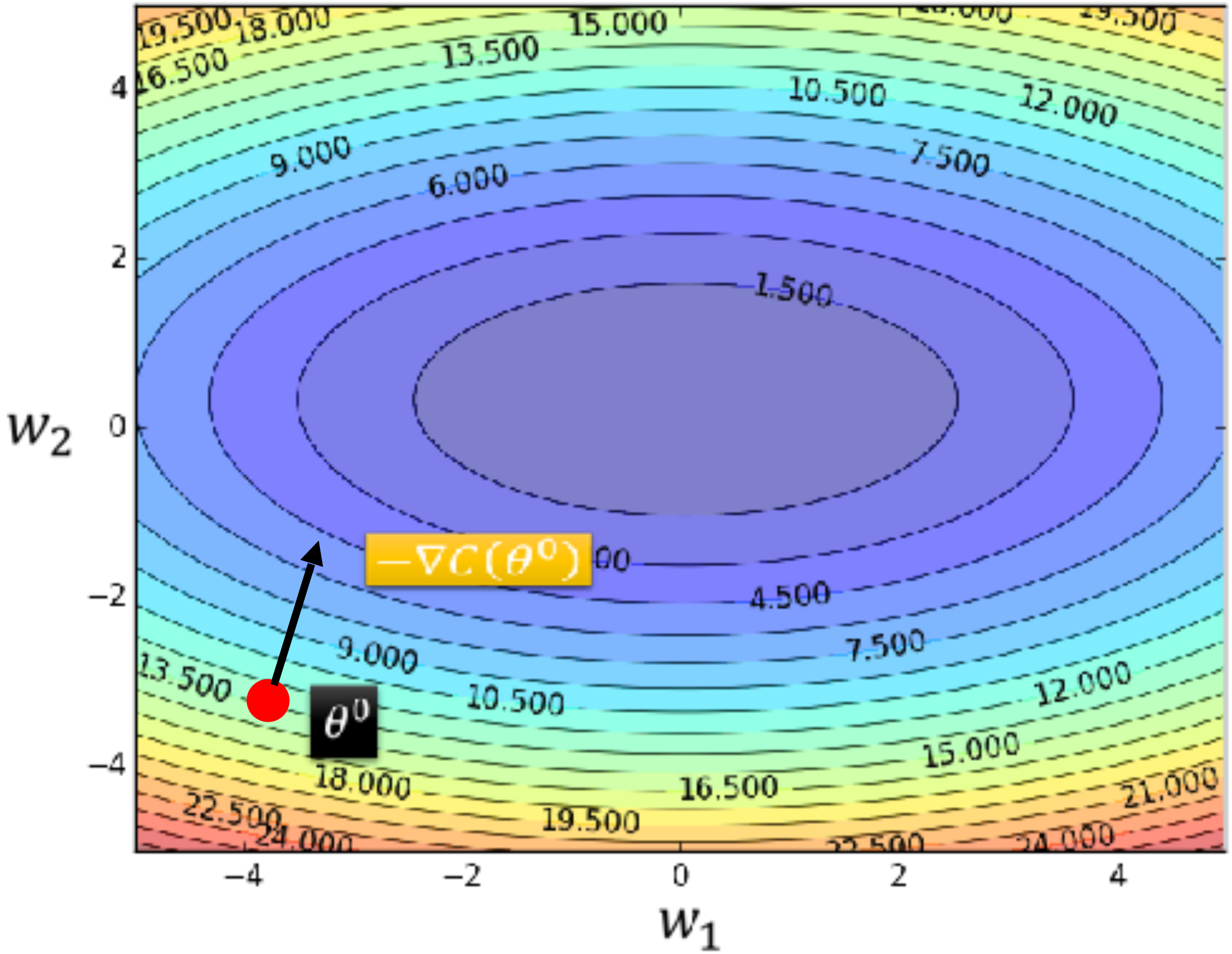


Part III:

Tips for Training DNN

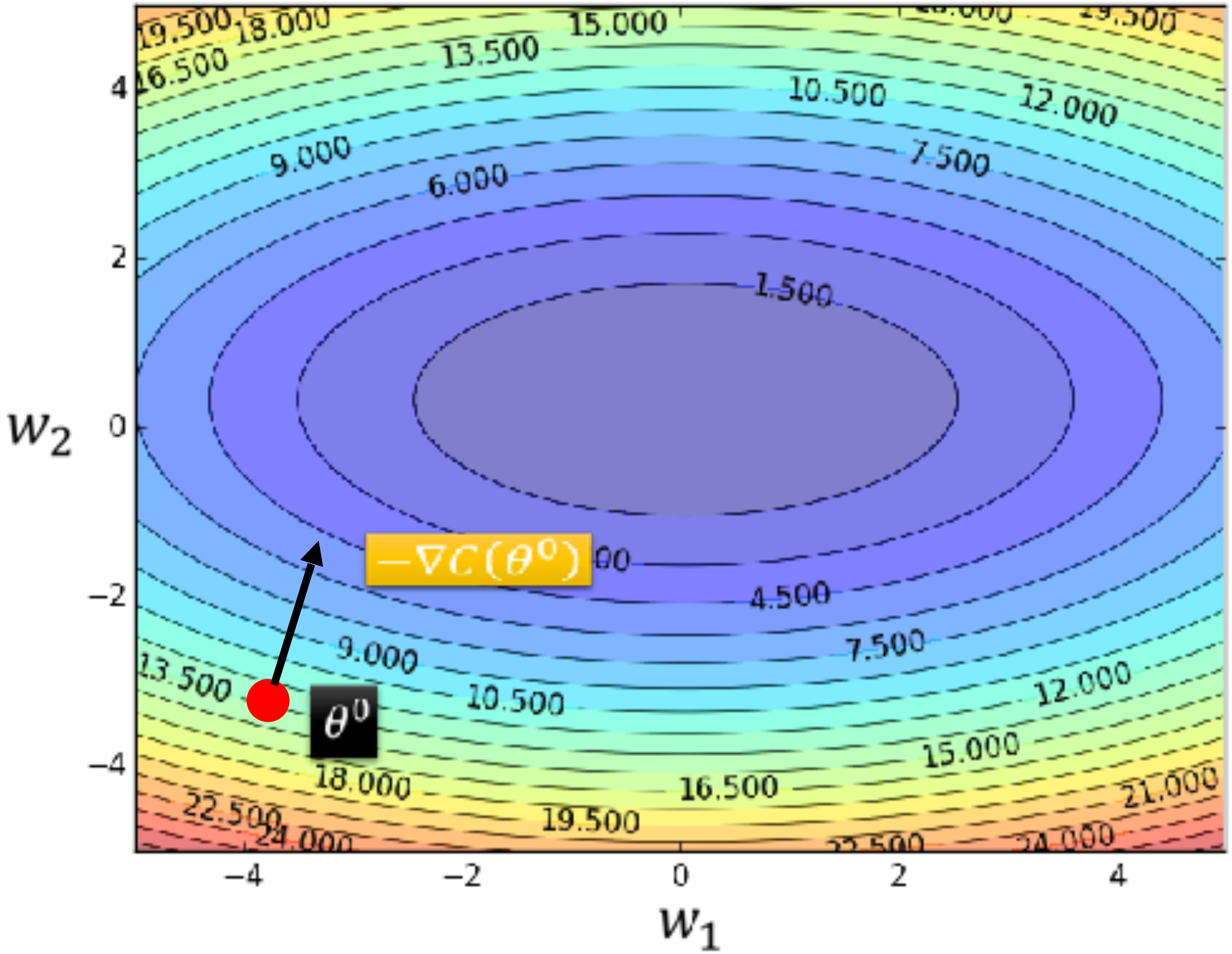
Adaptive Learning Rate

Learning Rate



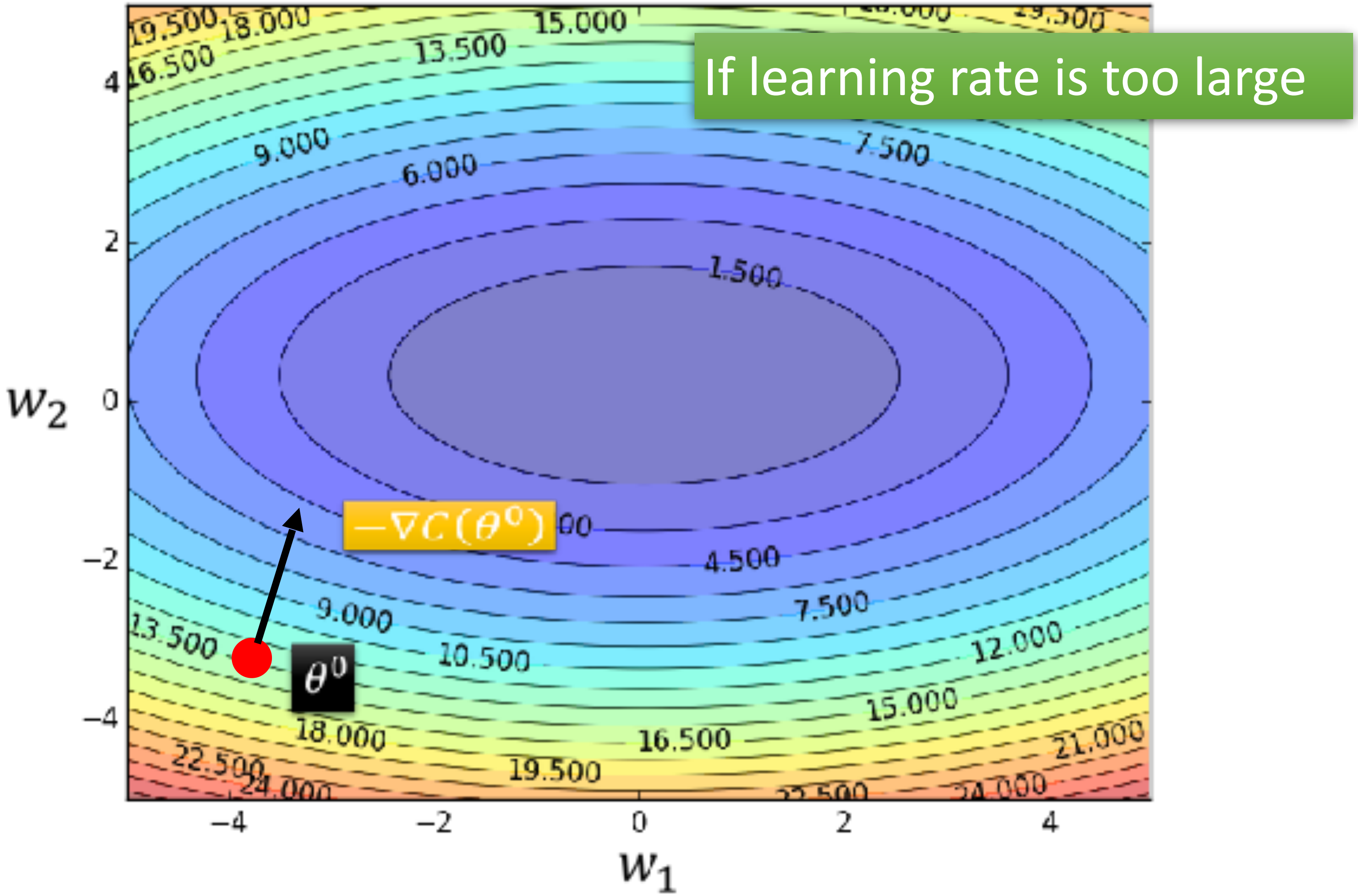
Learning Rate

Set the learning rate η carefully



Learning Rate

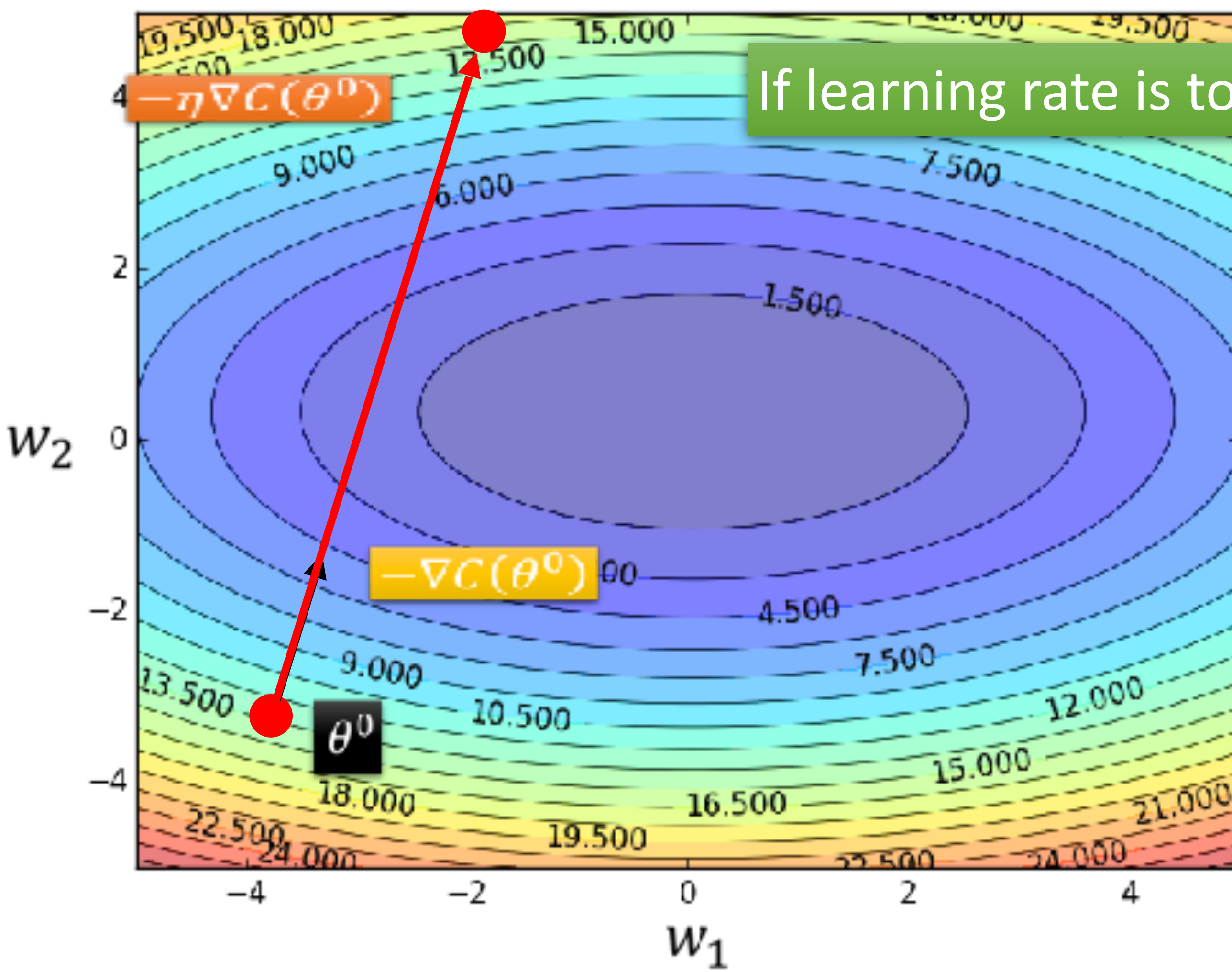
Set the learning rate η carefully



Learning Rate

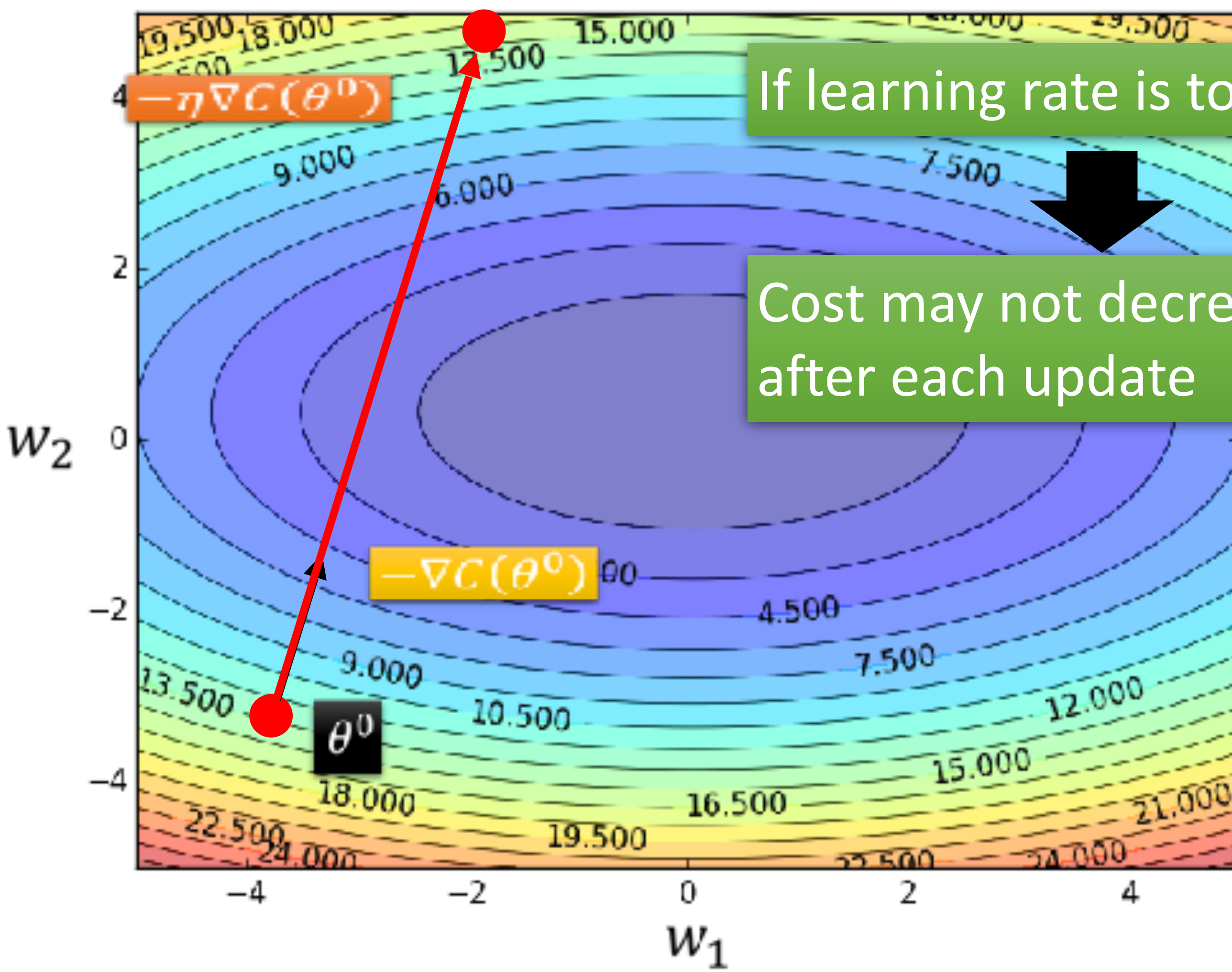
Set the learning rate η carefully

If learning rate is too large



Learning Rate

Set the learning rate η carefully

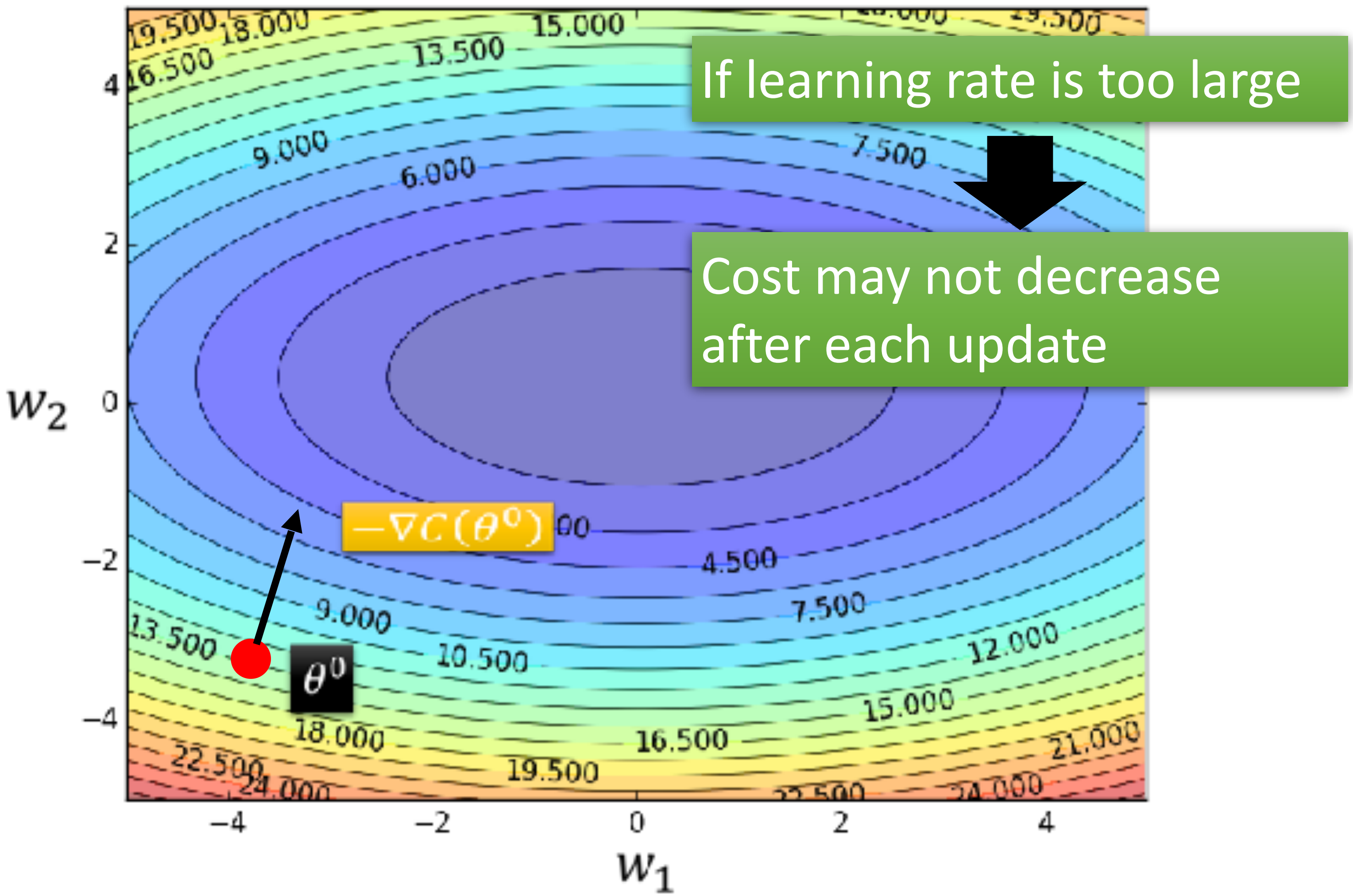


If learning rate is too large

Cost may not decrease after each update

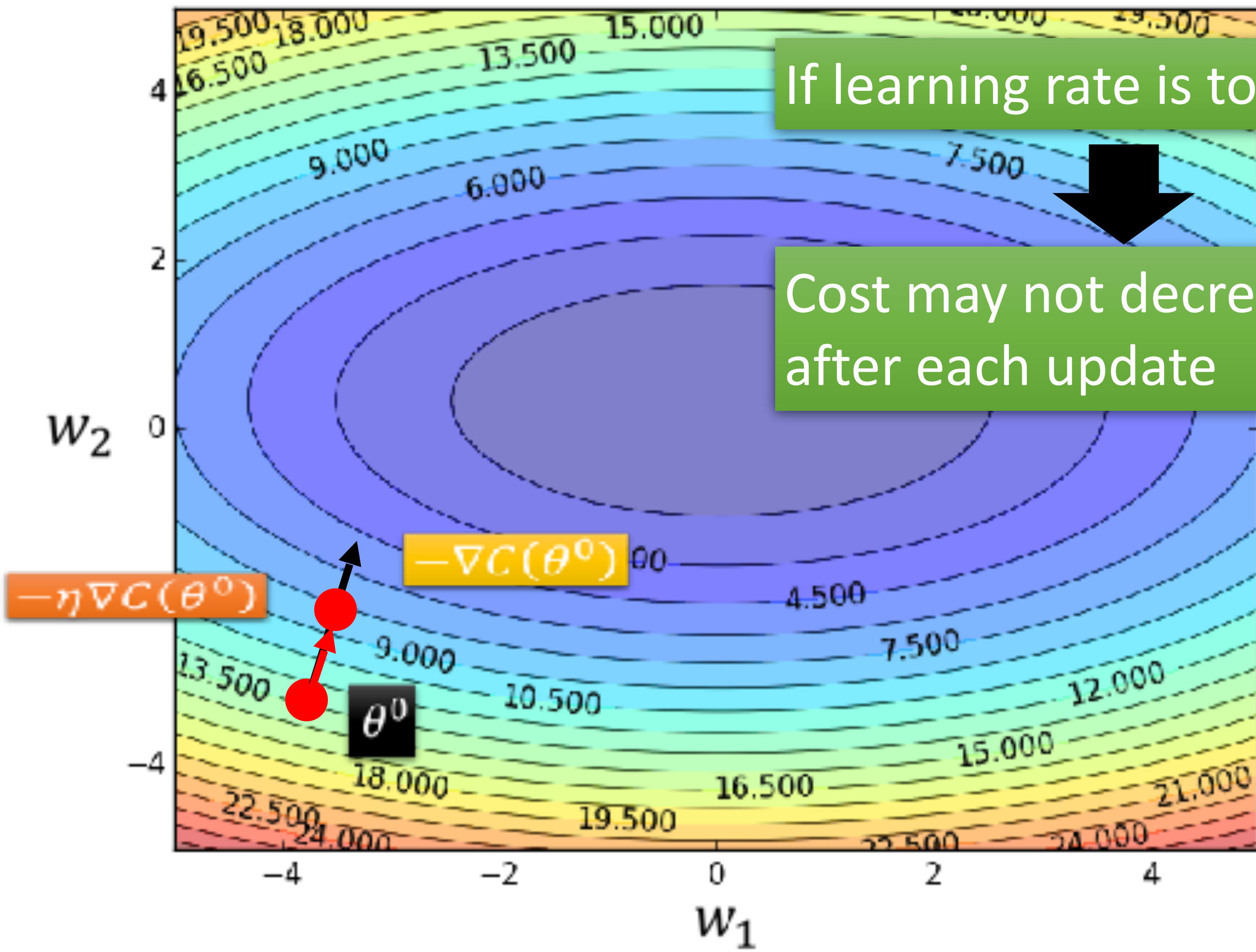
Learning Rate

Set the learning rate η carefully



Learning Rate

Set the learning rate η carefully

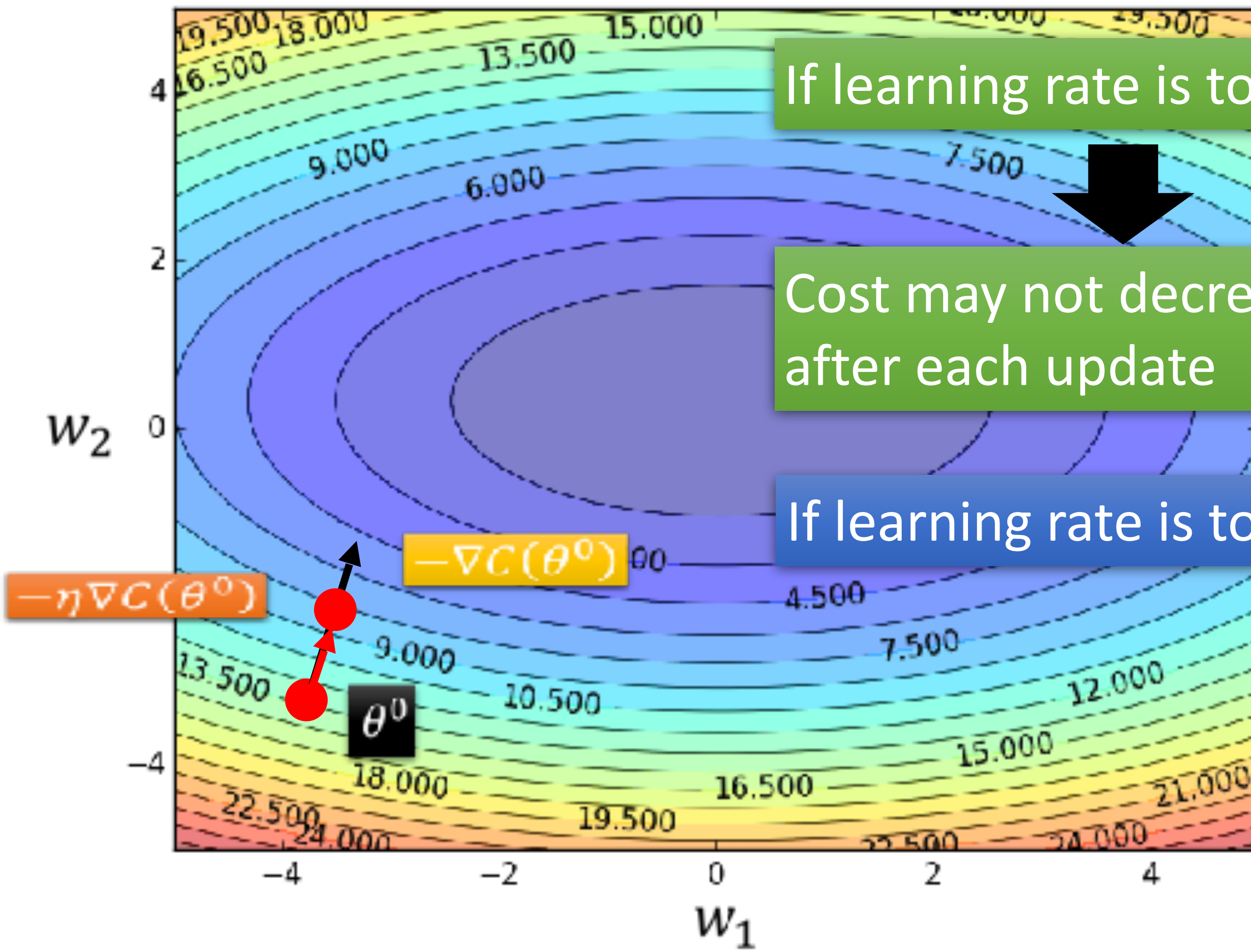


If learning rate is too large

Cost may not decrease after each update

Learning Rate

Set the learning rate η carefully



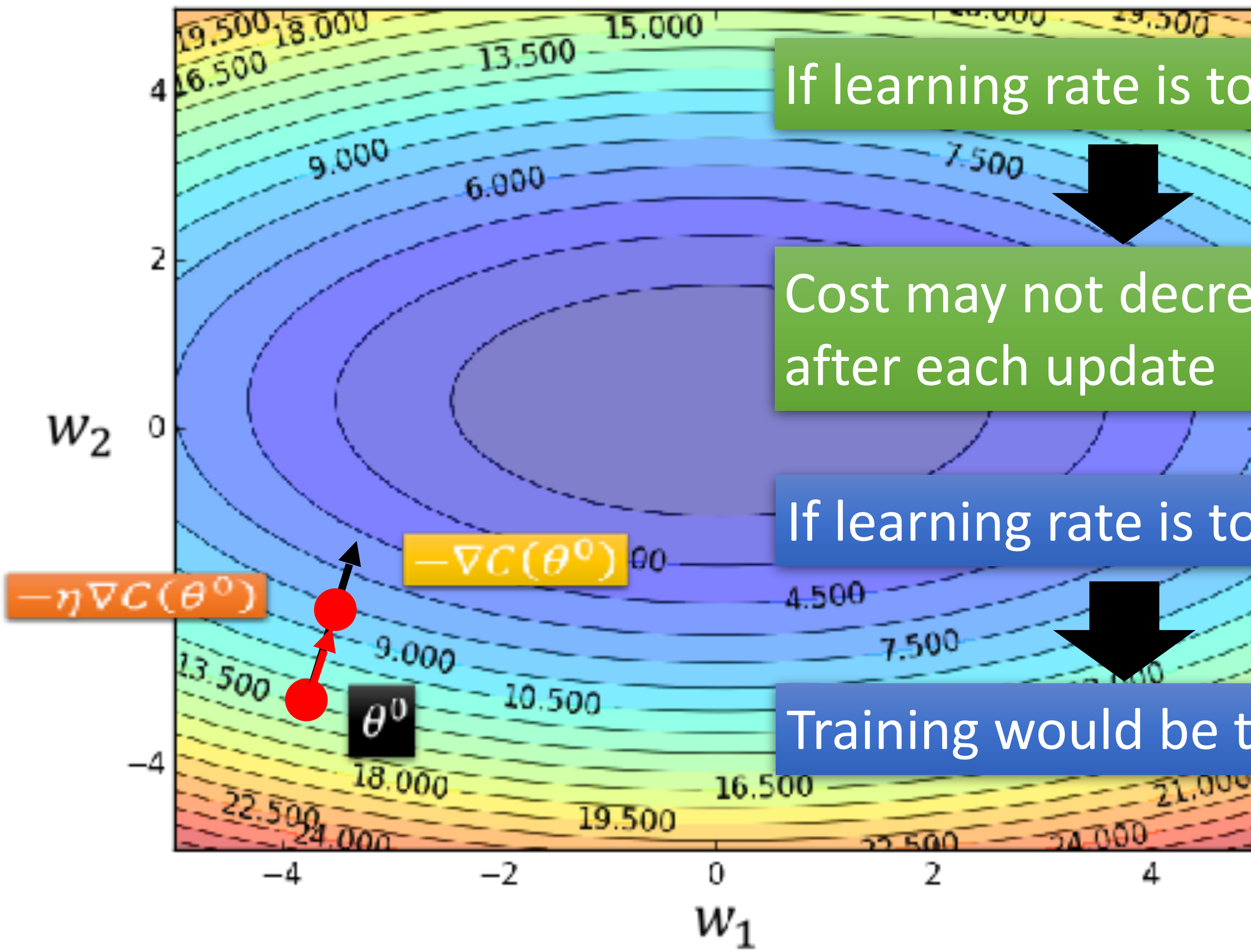
If learning rate is too large

Cost may not decrease after each update

If learning rate is too small

Learning Rate

Set the learning rate η carefully



If learning rate is too large

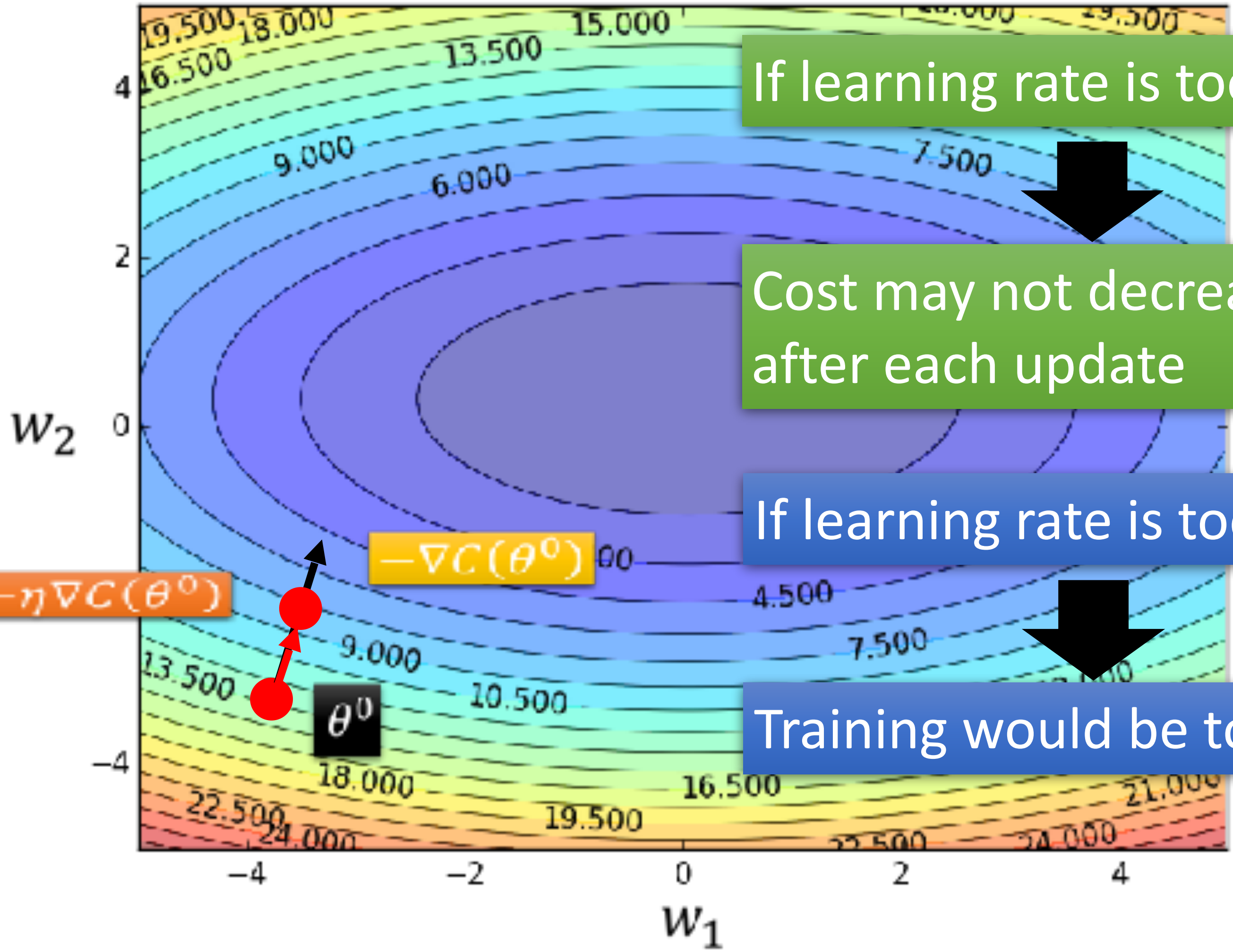
Cost may not decrease after each update

If learning rate is too small

Training would be too slow

Learning Rate

Can we give different parameters different learning rates?



If learning rate is too large

Cost may not decrease after each update

If learning rate is too small

Training would be too slow

Adagrad

Original Gradient Descent

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Adagrad

Original Gradient Descent

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Each parameter w are considered separately

$$w^{t+1} \leftarrow w^t - \eta_w g^t$$

Adagrad

Original Gradient Descent

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Each parameter w are considered separately

$$w^{t+1} \leftarrow w^t - \eta_w \underline{g^t}$$

Adagrad

Original Gradient Descent

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Each parameter w are considered separately

$$w^{t+1} \leftarrow w^t - \eta_w g^t \qquad g^t = \frac{\partial C(\theta^t)}{\partial w}$$

Adagrad

Original Gradient Descent

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Each parameter w are considered separately

$$w^{t+1} \leftarrow w^t - \boxed{\eta_w} \underline{g^t} \qquad \underline{g^t} = \frac{\partial C(\theta^t)}{\partial w}$$

Parameter dependent learning rate

Adagrad

Original Gradient Descent

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Each parameter w are considered separately

$$w^{t+1} \leftarrow w^t - \boxed{\eta_w} \underline{g^t} \qquad \underline{g^t} = \frac{\partial C(\theta^t)}{\partial w}$$

Parameter dependent learning rate

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

Adagrad

Original Gradient Descent

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Each parameter w are considered separately

$$w^{t+1} \leftarrow w^t - \boxed{\eta_w} \underline{g^t} \qquad \underline{g^t} = \frac{\partial C(\theta^t)}{\partial w}$$

Parameter dependent learning rate

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

constant

Adagrad

Original Gradient Descent

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Each parameter w are considered separately

$$w^{t+1} \leftarrow w^t - \boxed{\eta_w} \underline{g^t} \qquad \underline{g^t} = \frac{\partial C(\theta^t)}{\partial w}$$

Parameter dependent learning rate

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

constant

Summation of the square of the previous derivatives

Adagrad

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

Adagrad

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

	g^0		
w_1	0.1		

Adagrad

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

	g^0		
w_1	0.1		

Learning rate:

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

Adagrad

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

	g^0
w_1	0.1

Learning rate:

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

Adagrad

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

	g^0	g^1	……
w_1	0.1	0.2	……

Learning rate:

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

Adagrad

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

w_1	g^0	g^1	……
	0.1	0.2	……

Learning rate:

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

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

Adagrad

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

	g^0	g^1	……
w_1	0.1	0.2	……

Learning rate:

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

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

Adagrad

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

w_1

g^0	g^1	……
0.1	0.2	……

w_2

g^0
20.0

Learning rate:

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

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

Adagrad

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

w_1

g^0	g^1	……
0.1	0.2	……

Learning rate:

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

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

w_2

g^0
20.0

Learning rate:

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

Adagrad

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

w_1

g^0	g^1	……
0.1	0.2	……

Learning rate:

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

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

w_2

g^0
20.0

Learning rate:

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

Adagrad

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

w_1

g^0	g^1	……
0.1	0.2	……

Learning rate:

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

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

w_2

g^0	g^1	……
20.0	10.0	……

Learning rate:

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

Adagrad

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

w_1

g^0	g^1	……
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w_2

g^0	g^1	……
20.0	10.0	……

Learning rate:

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

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

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

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

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<u>Observation:</u>

Adagrad

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

w_1

g^0	g^1	……
0.1	0.2	……

Learning rate:

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

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w_2

g^0	g^1	……
20.0	10.0	……

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

Adagrad

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

w_1

g^0	g^1	……
0.1	0.2	……

w_2

g^0	g^1	……
20.0	10.0	……

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:

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

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

<u>Observation:</u> 1. Learning rate is smaller and smaller for all parameters

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

Adagrad

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

w_1

g^0	g^1	……
0.1	0.2	……

w_2

g^0	g^1	……
20.0	10.0	……

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:

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

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

<u>Observation:</u> 1. Learning rate is smaller and smaller for all parameters

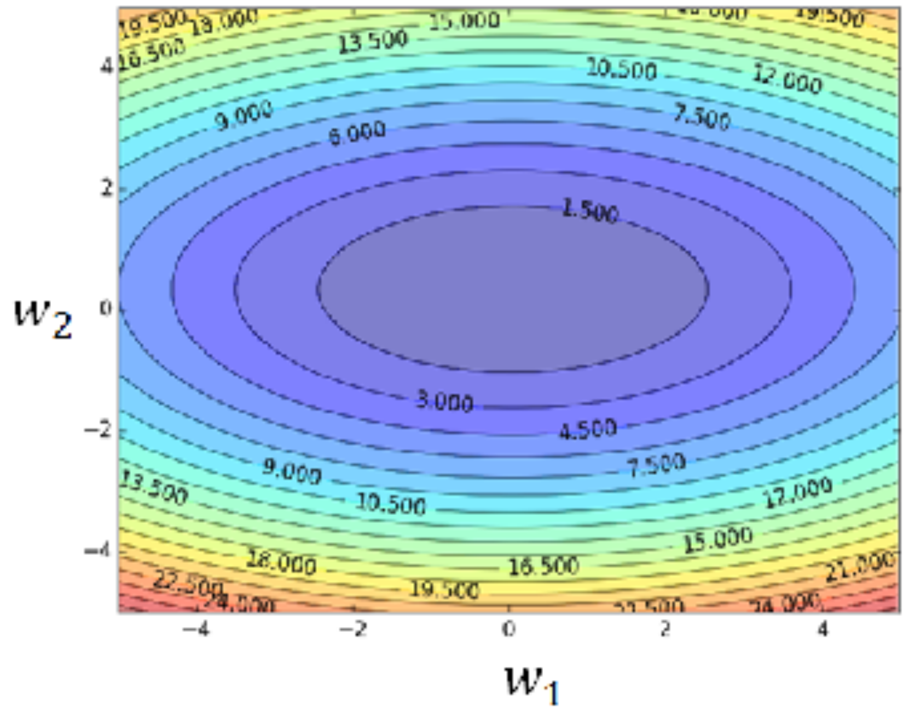
2. Smaller derivatives, larger le

Why?

rate, and vice versa

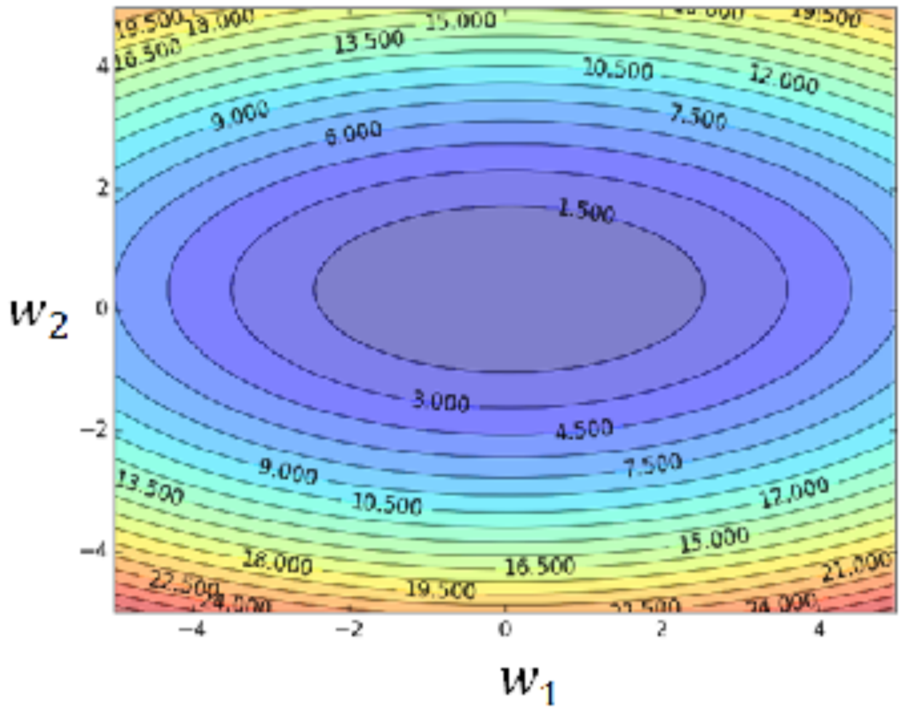
2. Smaller derivatives, larger le
rate, and vice versa

Why?



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

Why?



2. Smaller derivatives, larger le
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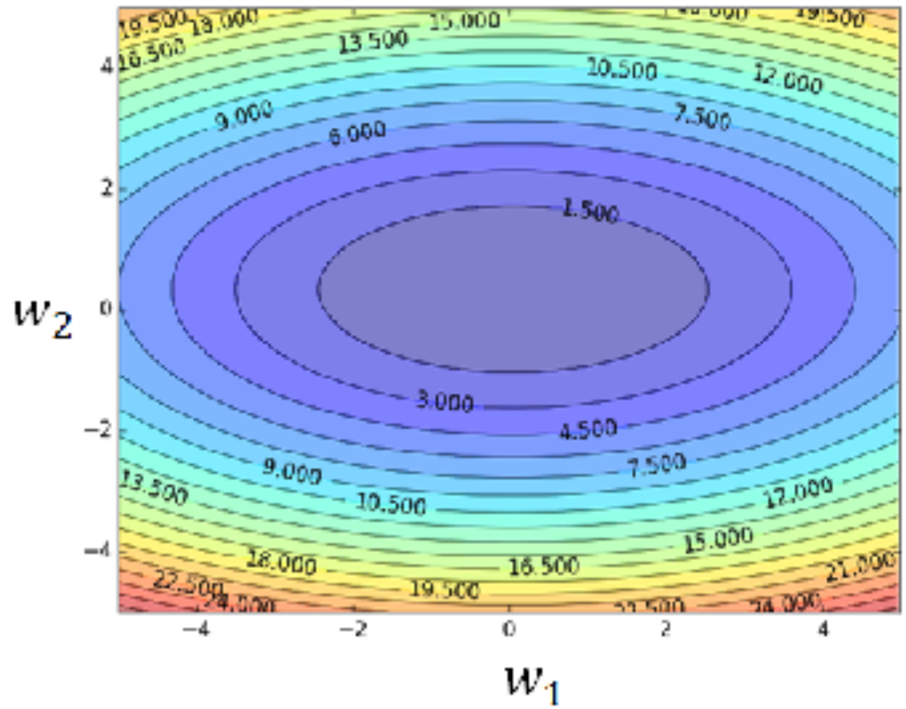
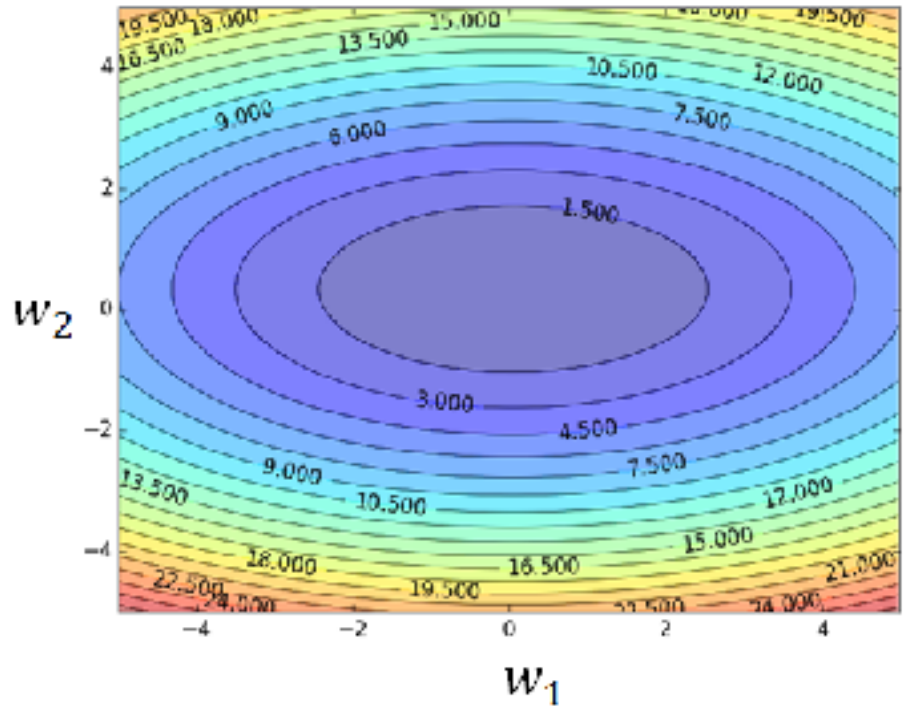
Why?



Smaller Derivatives

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

Why?



Smaller Derivatives

Larger Learning Rate

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Why?

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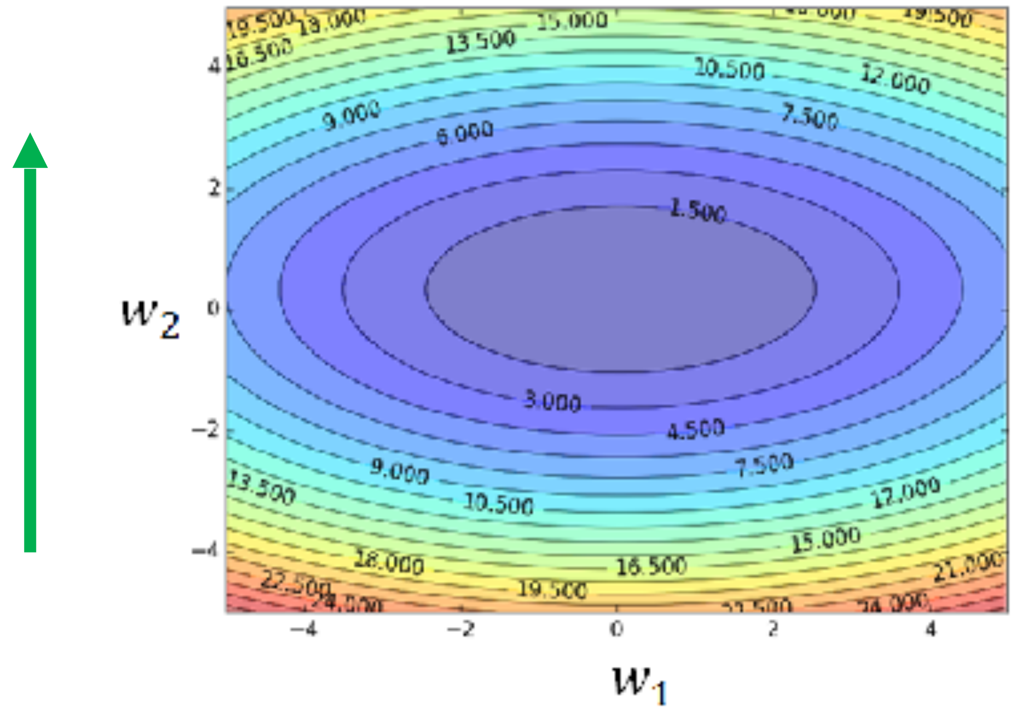

Smaller Derivatives

Larger Learning Rate

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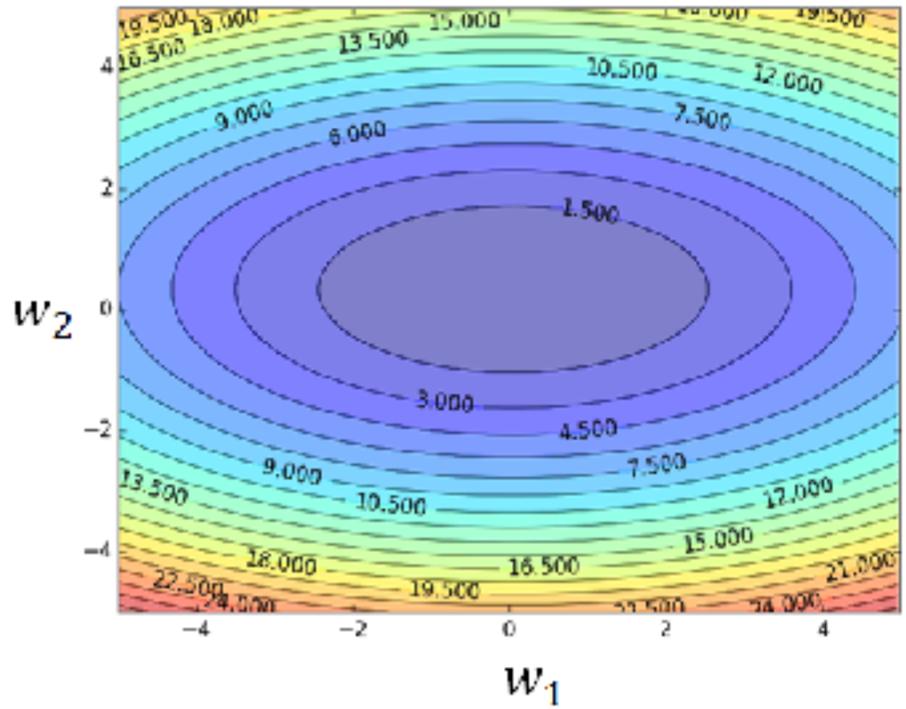
Why?

rate, and vice versa

Larger derivatives



Smaller Derivatives

Larger Learning Rate

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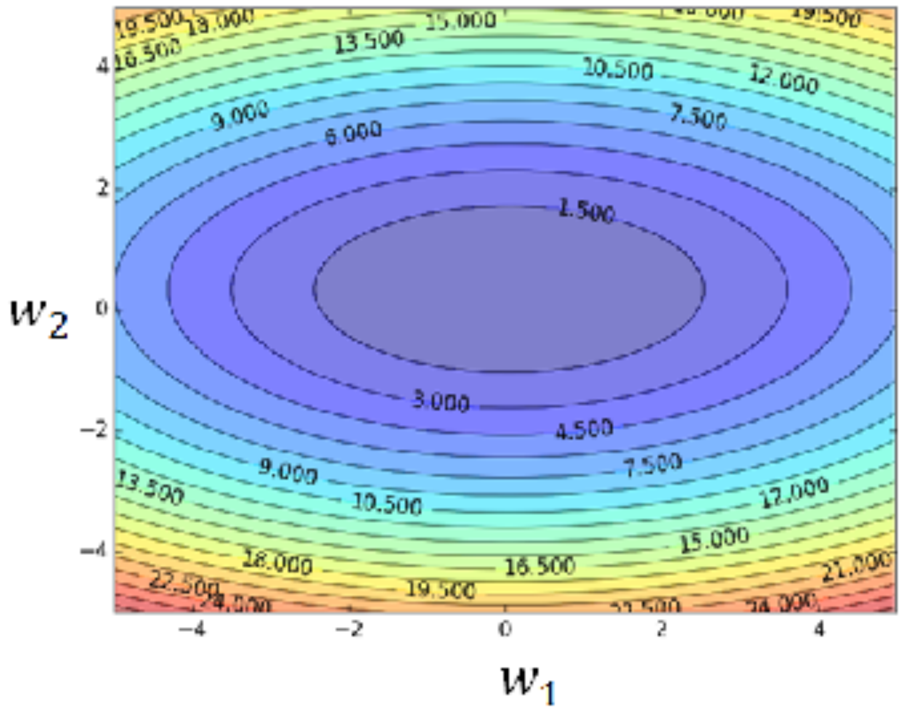
Larger derivatives

Smaller Learning Rate



Smaller Derivatives

Larger Learning Rate

2. Smaller derivatives, larger le
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]
- Adam [Diederik P. Kingma, ICLR'15]
- AdaSecant [Caglar Gulcehre, arXiv'14]
- "No more pesky learning rates" [Tom Schaul, arXiv'12]

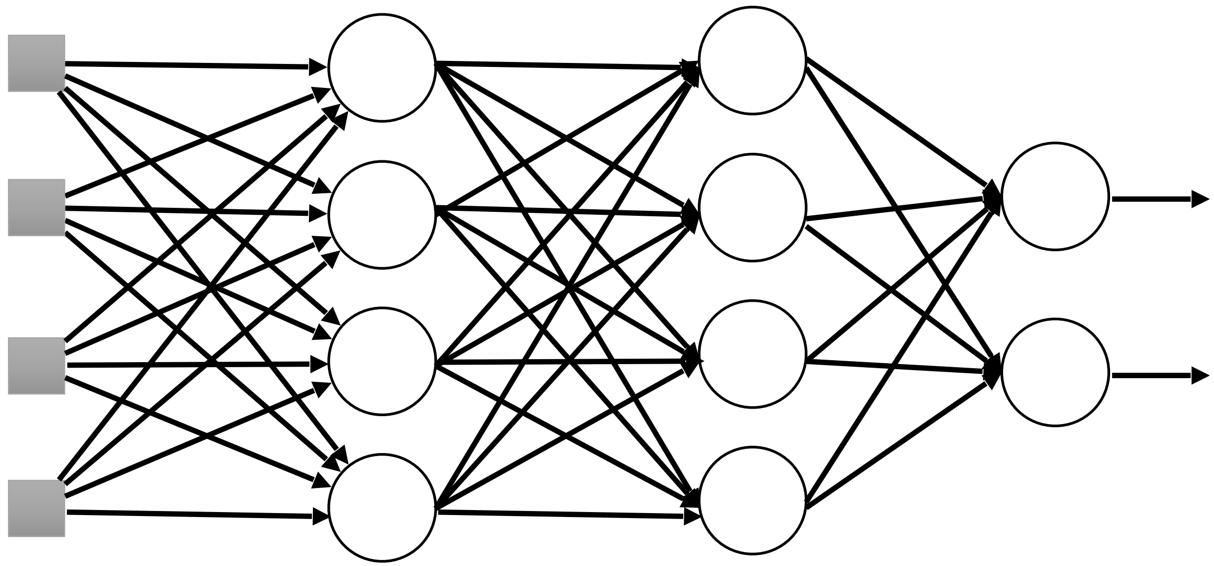
Part III:
Tips for Training DNN

Dropout

Dropout

Pick a mini-batch

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$



Dropout

Pick a mini-batch

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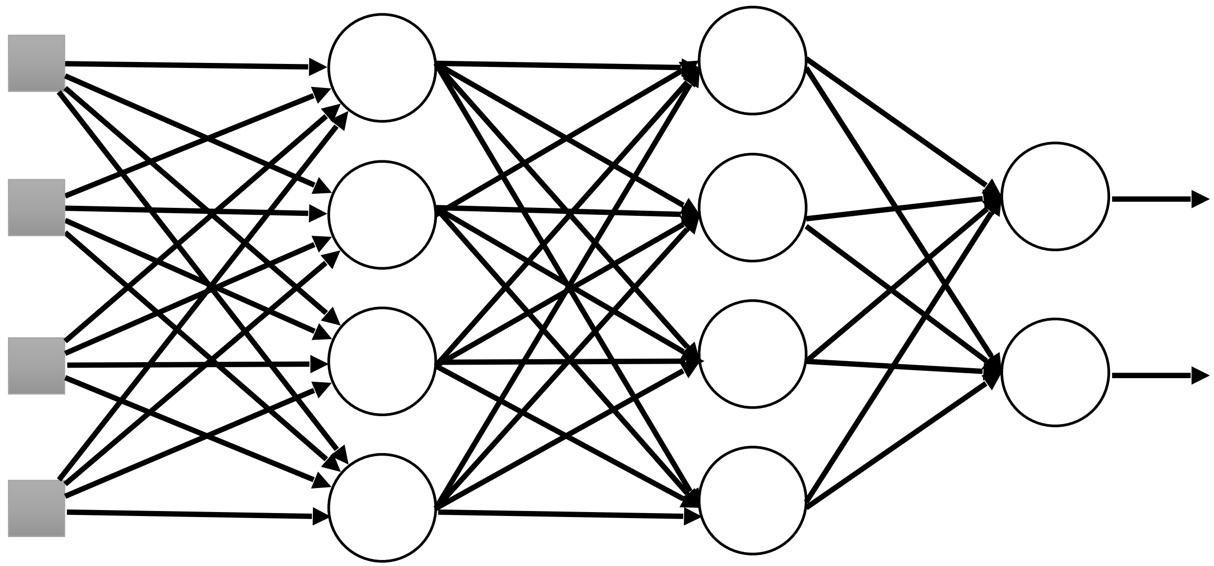
Training:



Dropout

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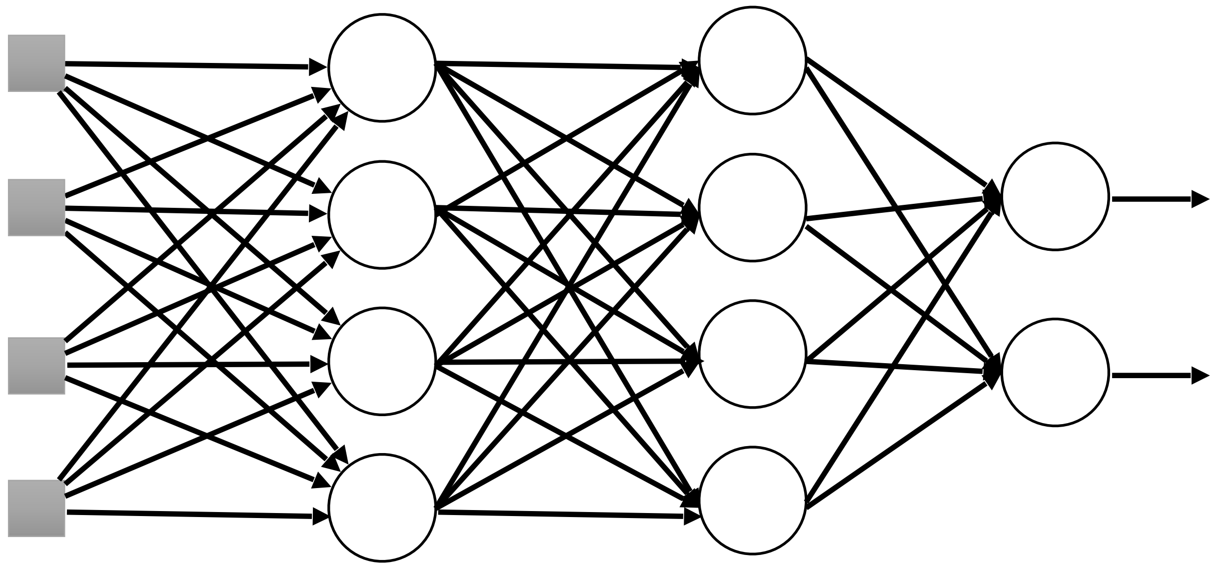
Training:



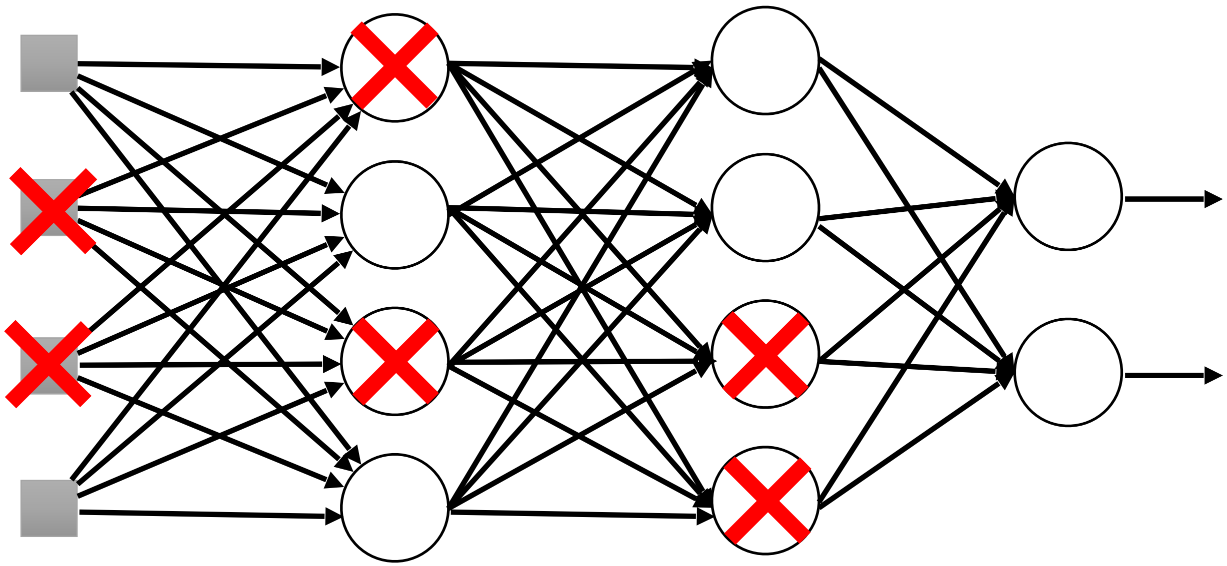
➢ **Each time before computing the gradients**

Dropout

Pick a mini-batch

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Training:



➢ **Each time before computing the gradients**

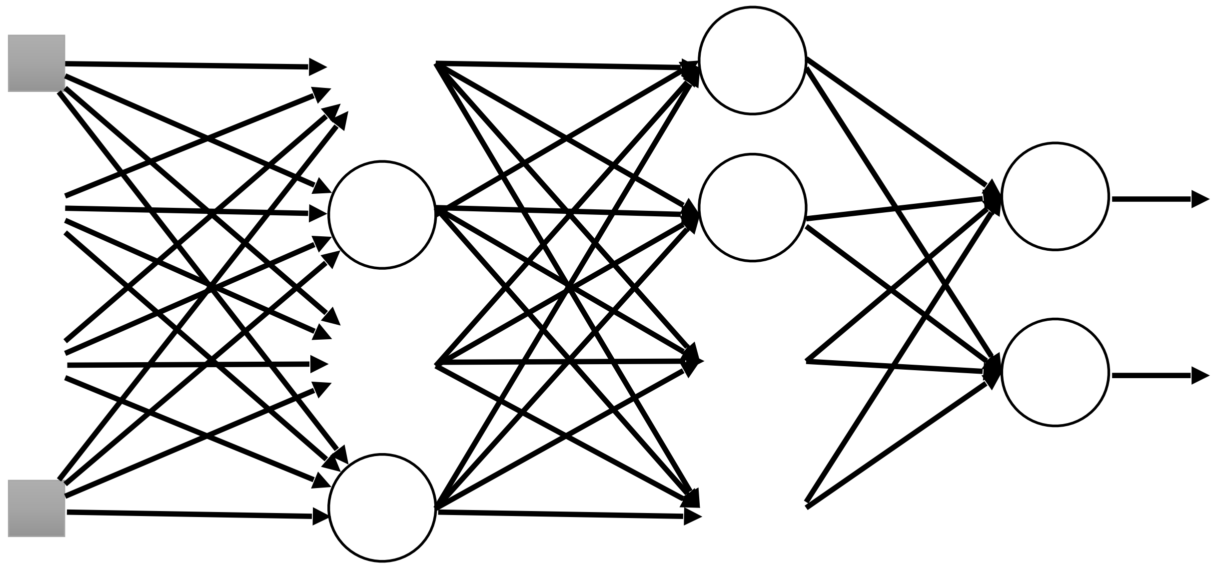
- Each neuron has p% to dropout

Dropout

Pick a mini-batch

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Training:



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Dropout

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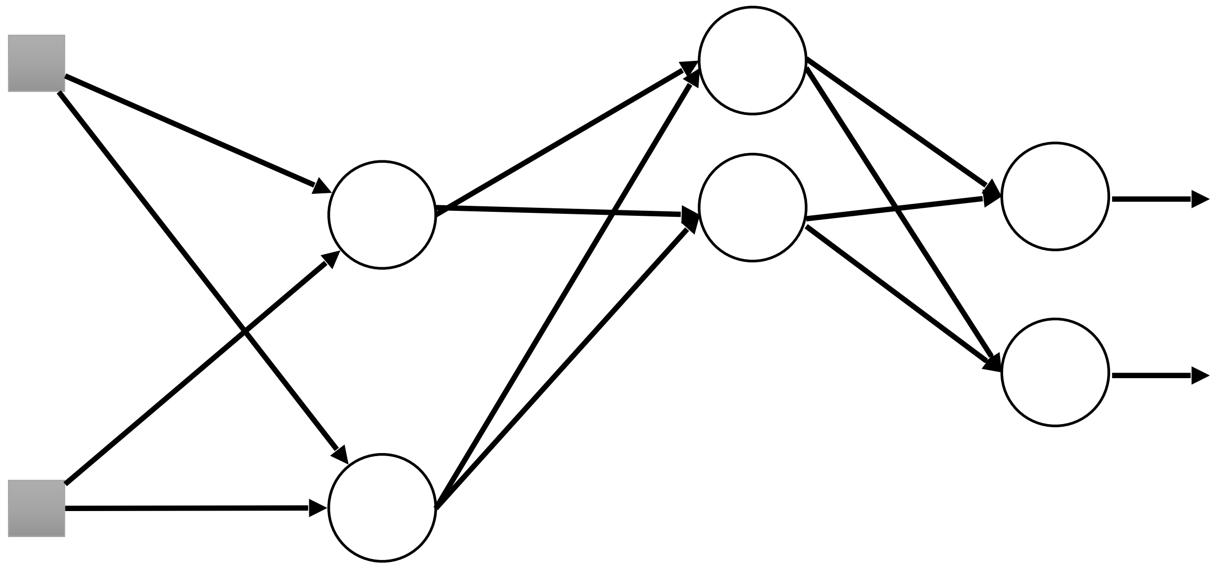
$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Training:



➢ **Each time before computing the gradients**

- Each neuron has p% to dropout

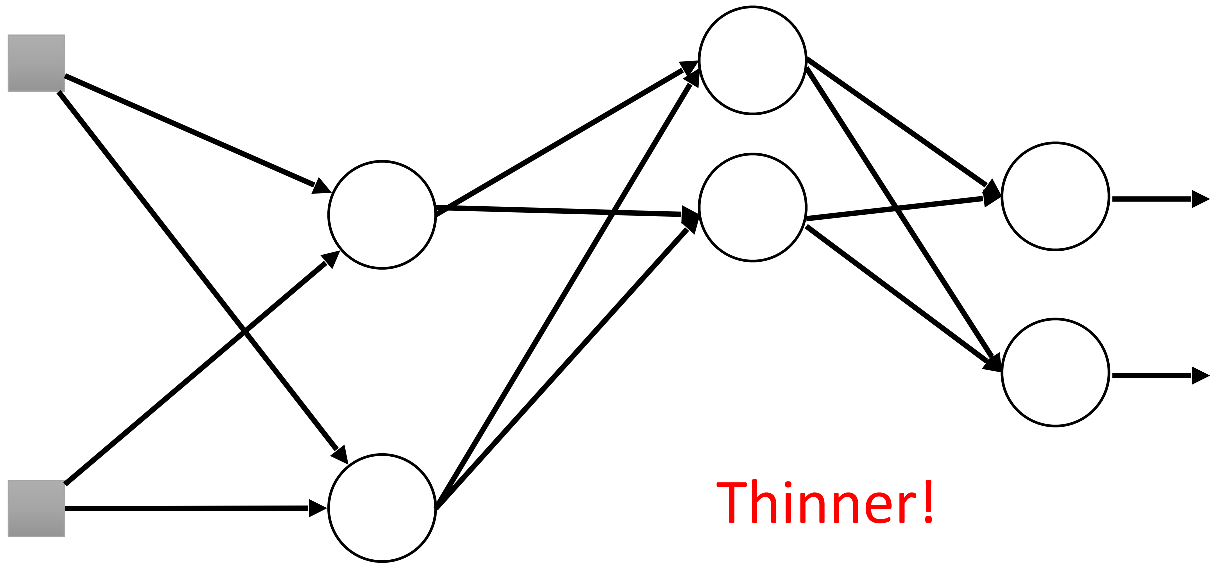
The structure of the network is changed.

Dropout

Pick a mini-batch

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Training:



- ➢ **Each time before computing the gradients**
  - Each neuron has p% to dropout

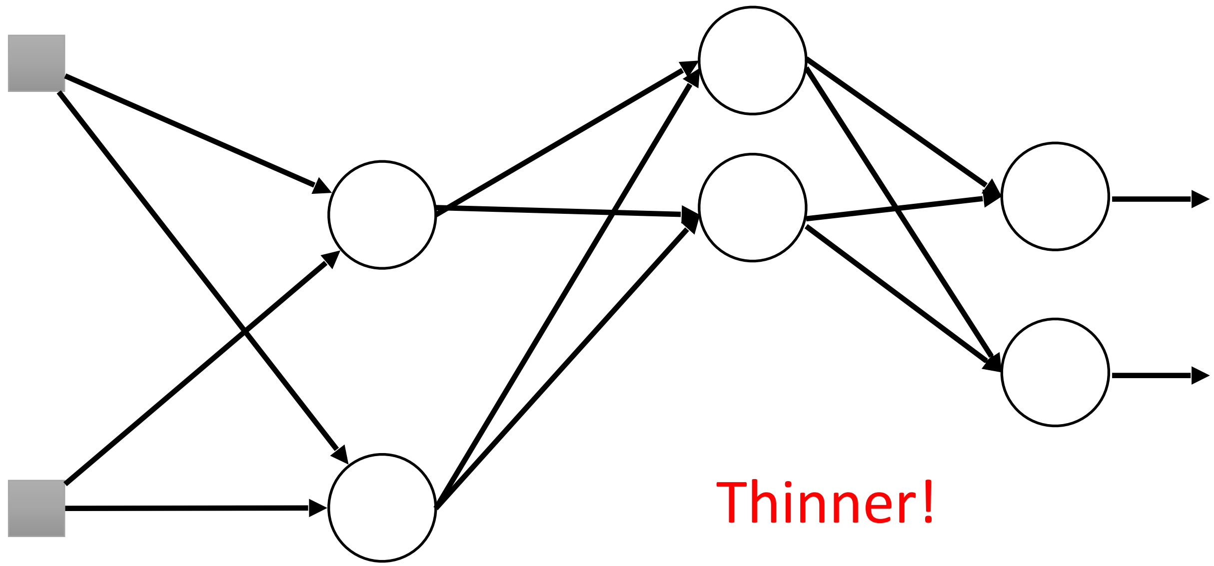
The structure of the network is changed.

Dropout

Pick a mini-batch

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Training:



➢ **Each time before computing the gradients**

- Each neuron has p% to dropout

  ➡ **The structure of the network is changed.**

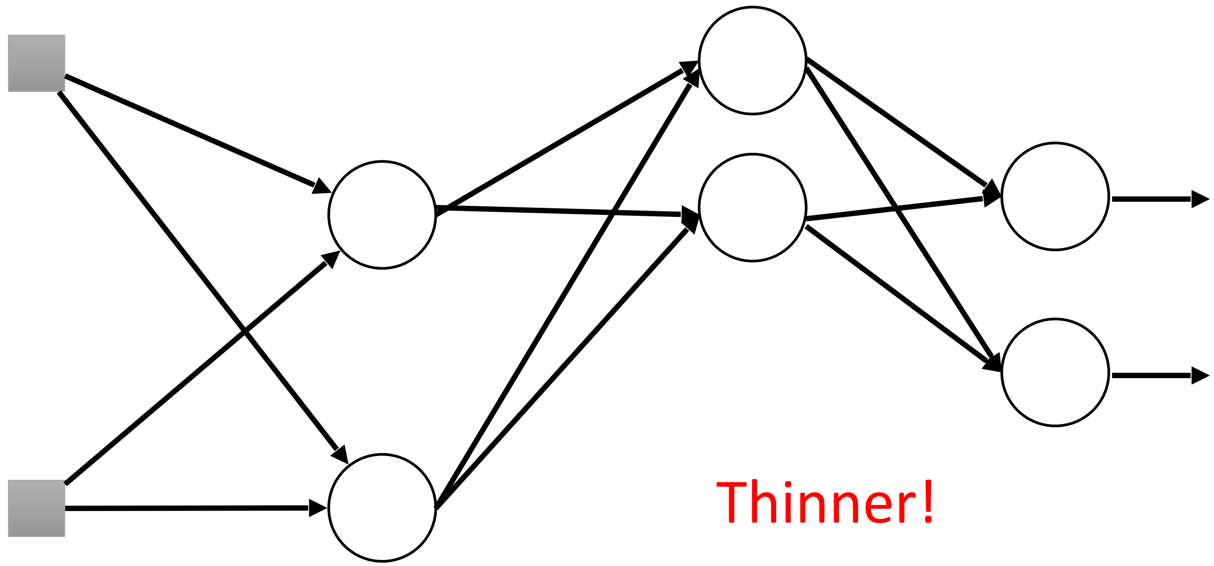
- Using the new network for training

Dropout

Pick a mini-batch

$$\theta^t \leftarrow \theta^{t-1} - \eta \nabla C(\theta^{t-1})$$

Training:



Thinner!

➢ **Each time before computing the gradients**

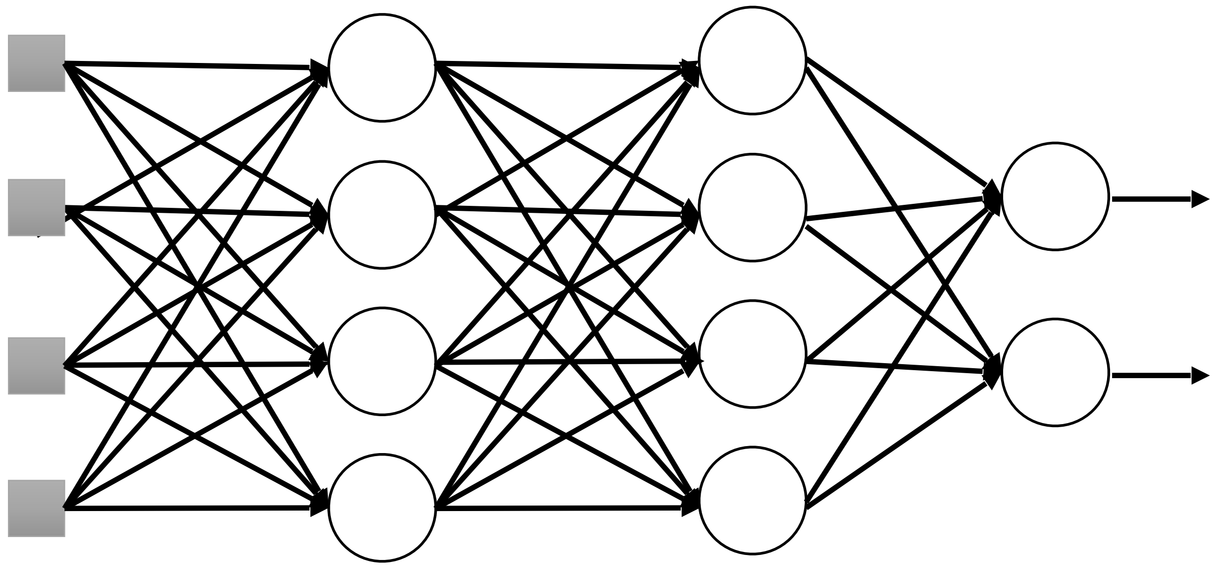
- Each neuron has p% to dropout

  The structure of the network is changed.

- Using the new network for training

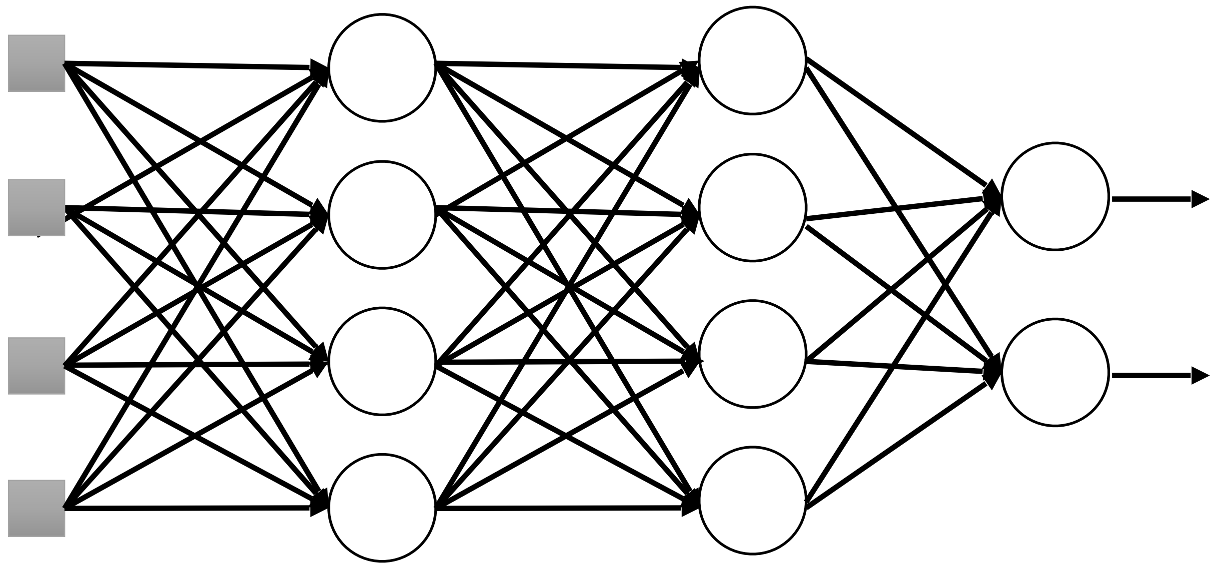
For each mini-batch, we resample the dropout neurons

Dropout



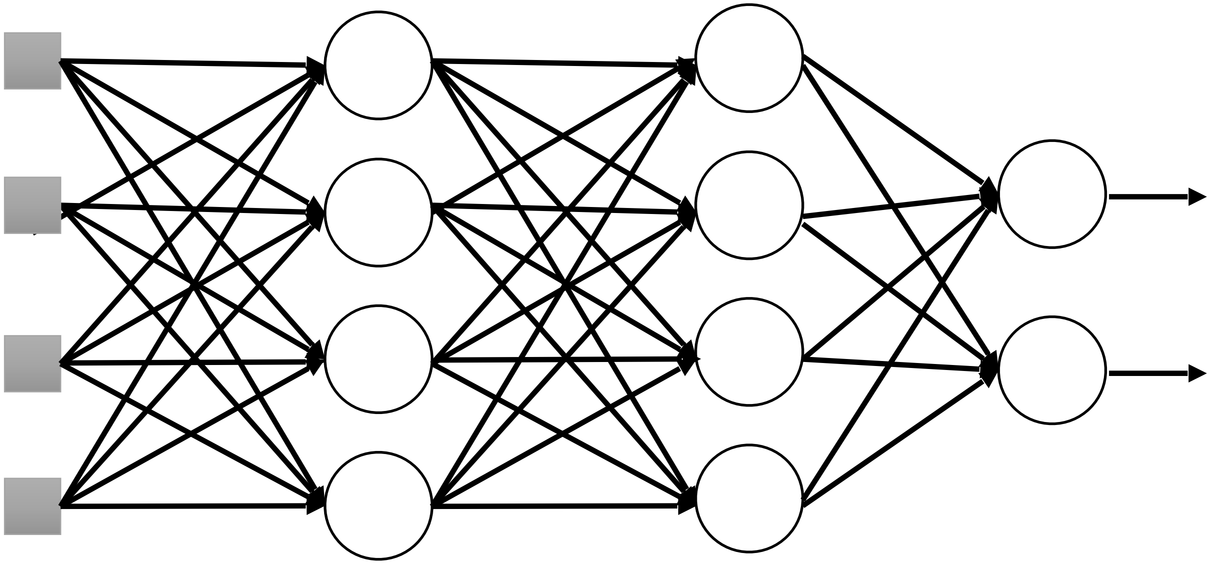
Dropout

Testing:



Dropout

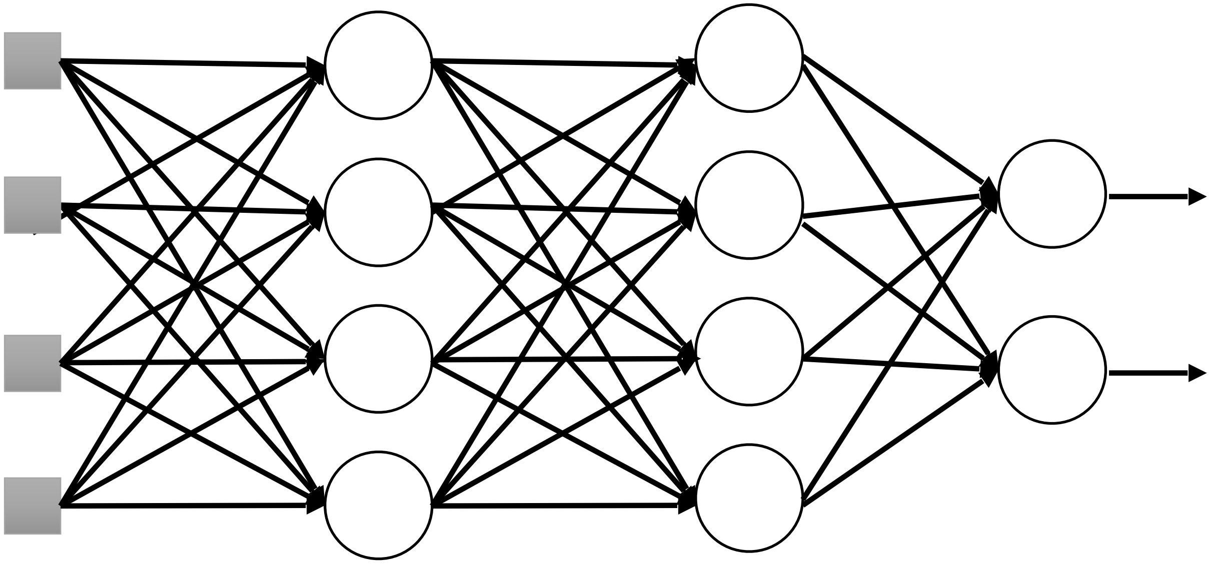
Testing:



➢ **No dropout**

Dropout

Testing:

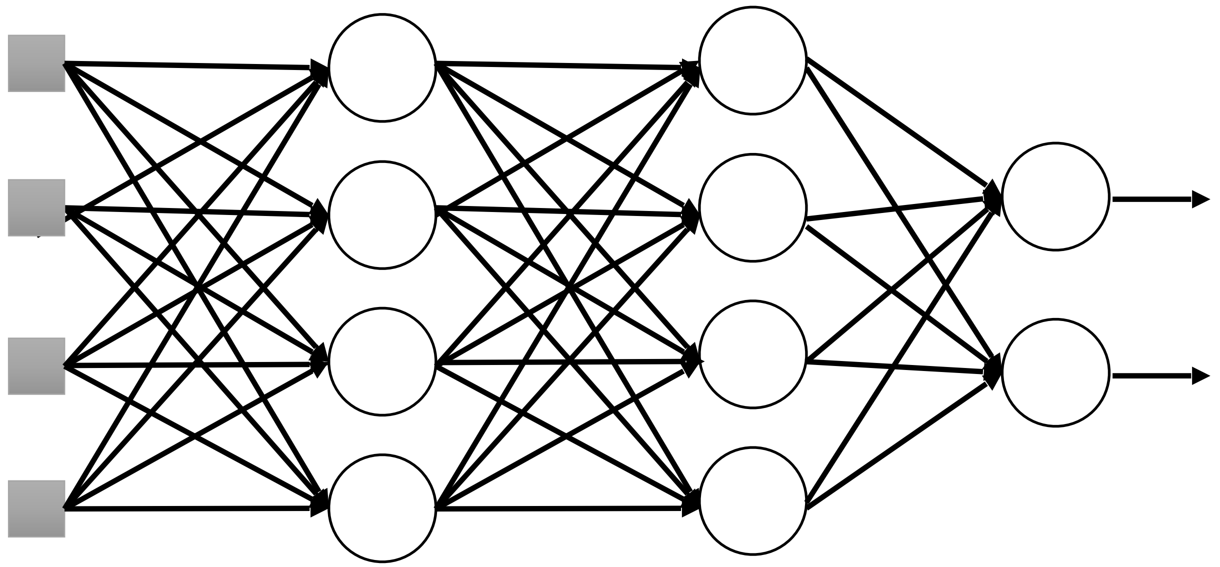


➢ **No dropout**

- If the dropout rate at training is p%, all the weights times (1-p)%

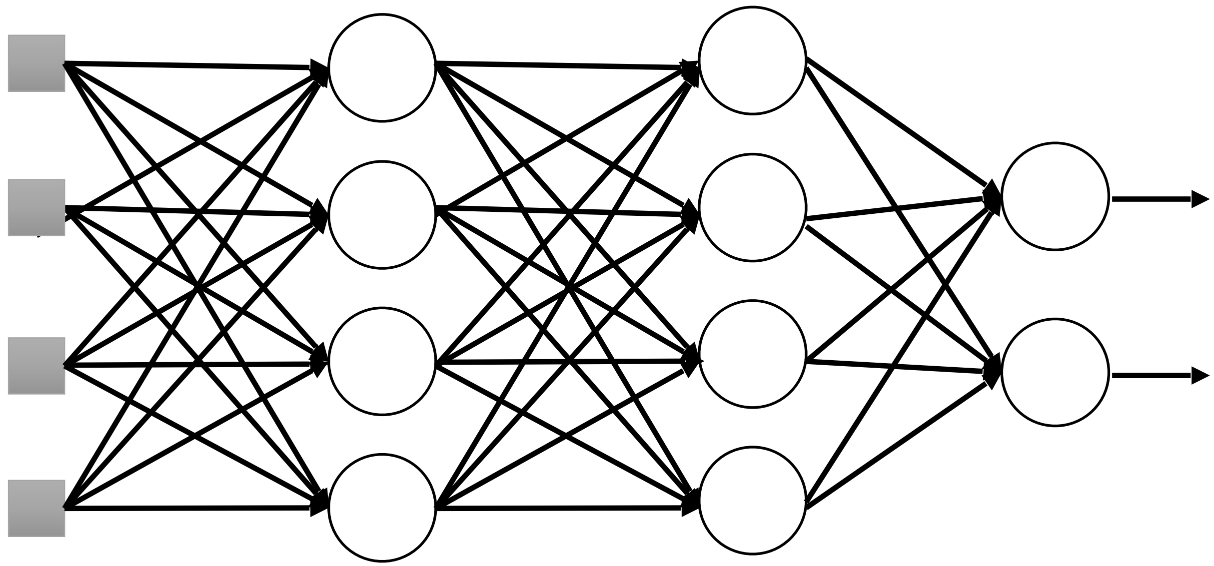
Dropout

Testing:

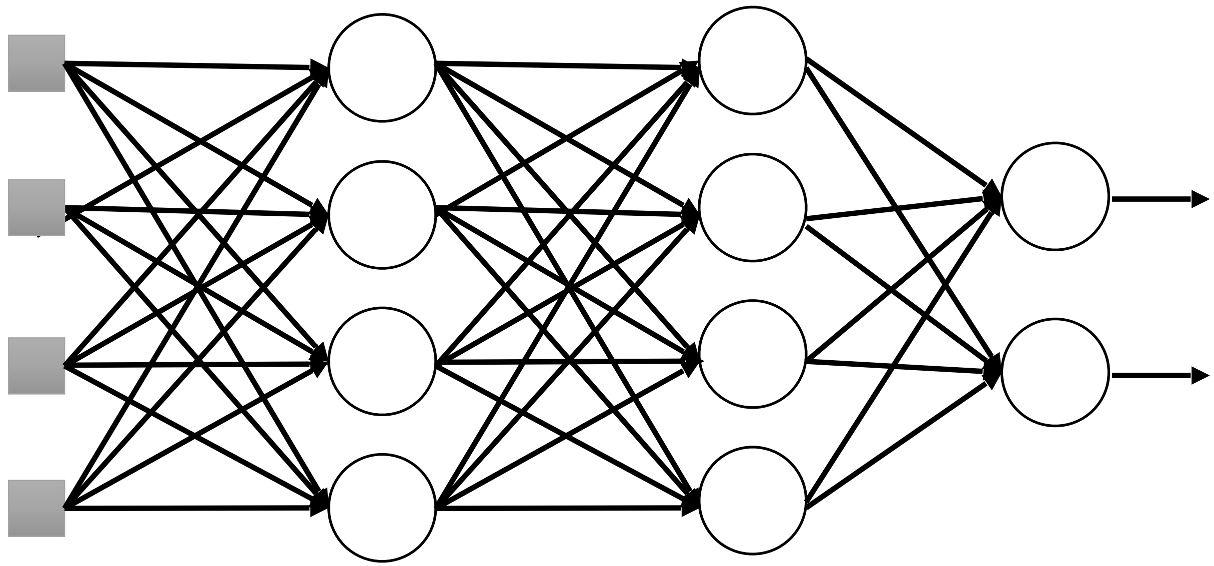


- ➢ **No dropout**
  - If the dropout rate at training is p%, all the weights times (1-p)%
  - Assume that the dropout rate is 50%. If a weight $w = 1$ by training, set $w = 0.5$ for testing.

Dropout - Intuitive Reason

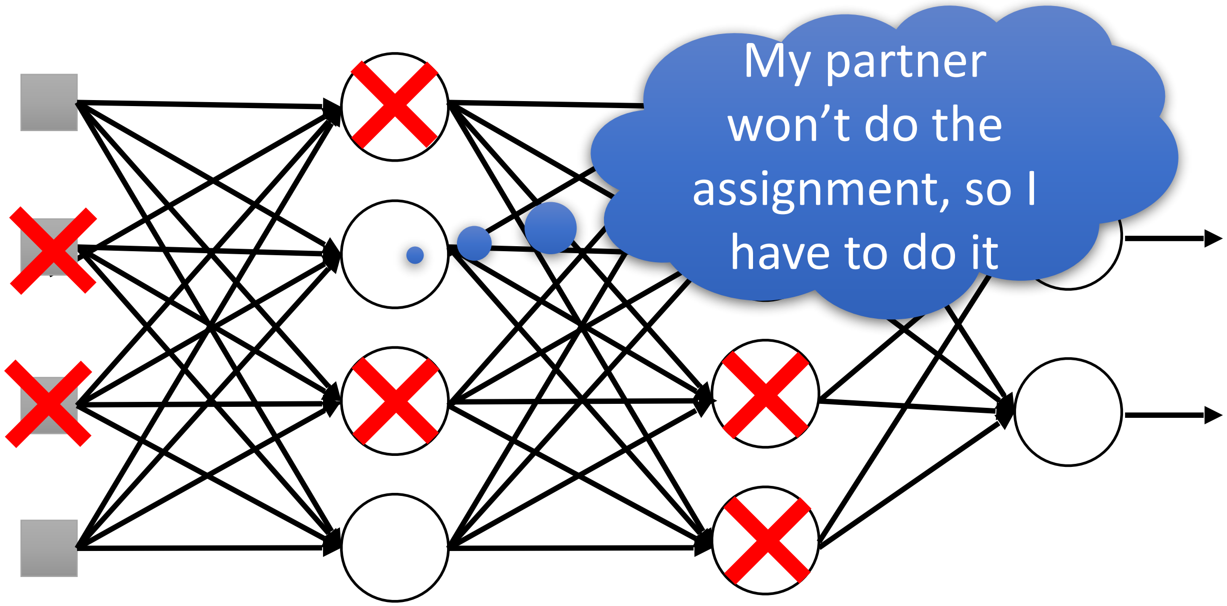


Dropout - Intuitive Reason



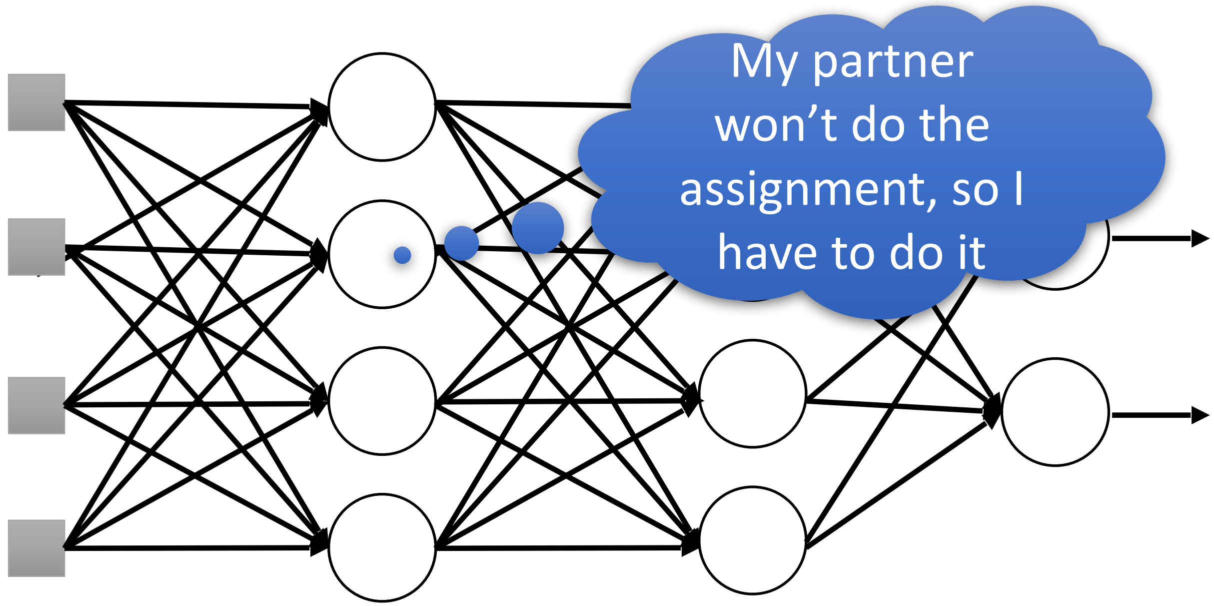
➢ When teams up, if everyone expect the partner will do the work, nothing will be done finally.

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.

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

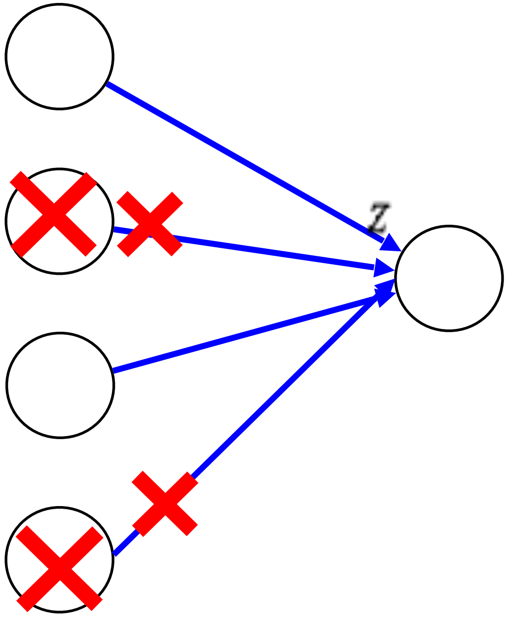
- Why the weights should multiply (1-p)% (dropout rate) when testing?

Dropout - Intuitive Reason

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

<u>Training of Dropout</u>

Assume dropout rate is 50%



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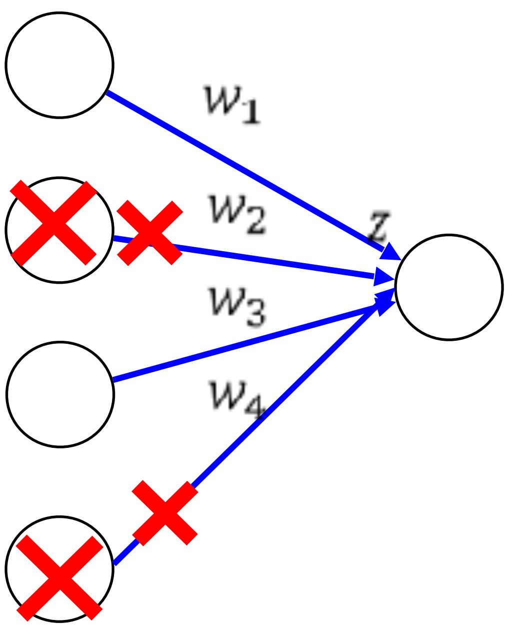

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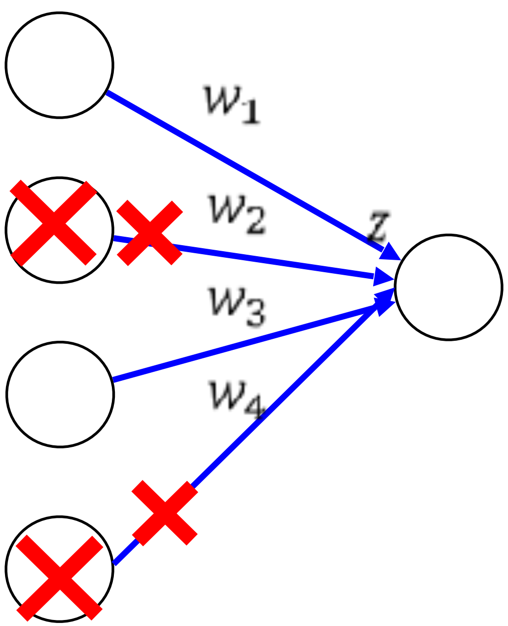

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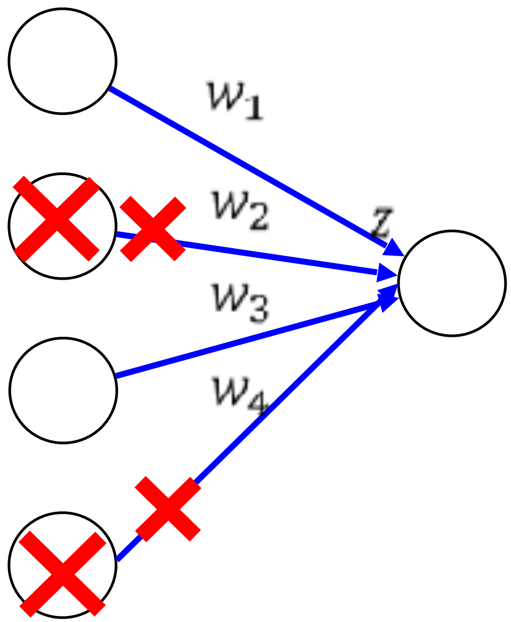

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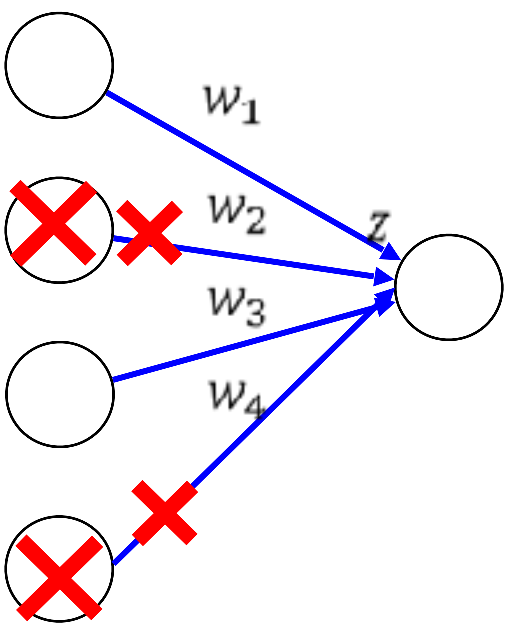
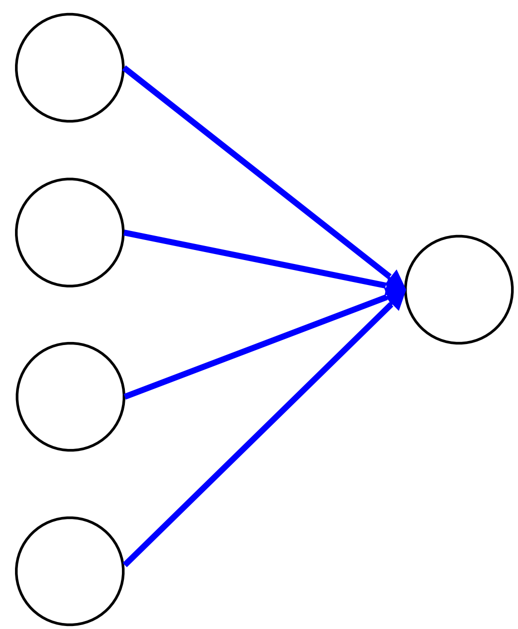


Testing of Dropout

No dropout



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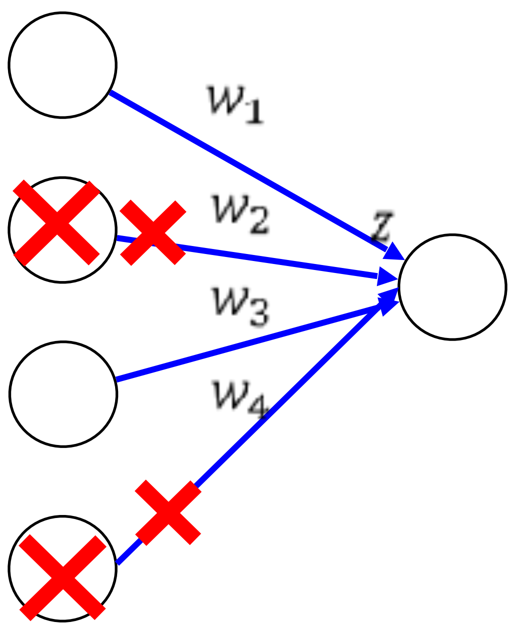
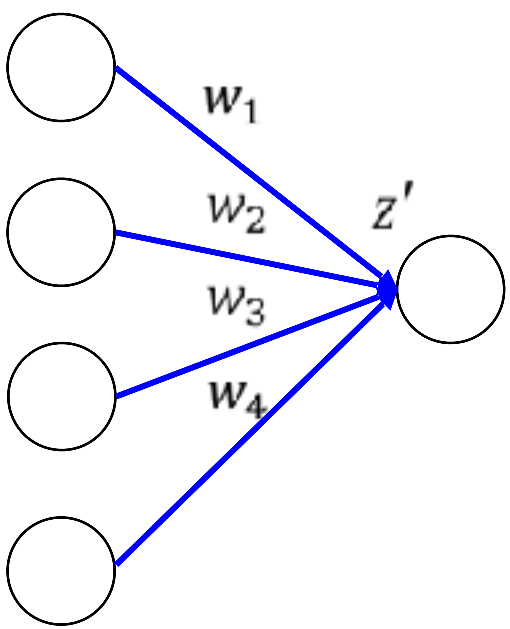


<u>Testing of Dropout</u>

No dropout



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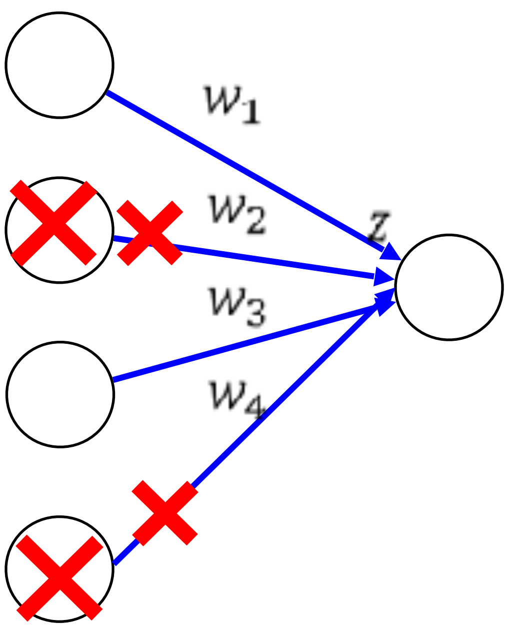
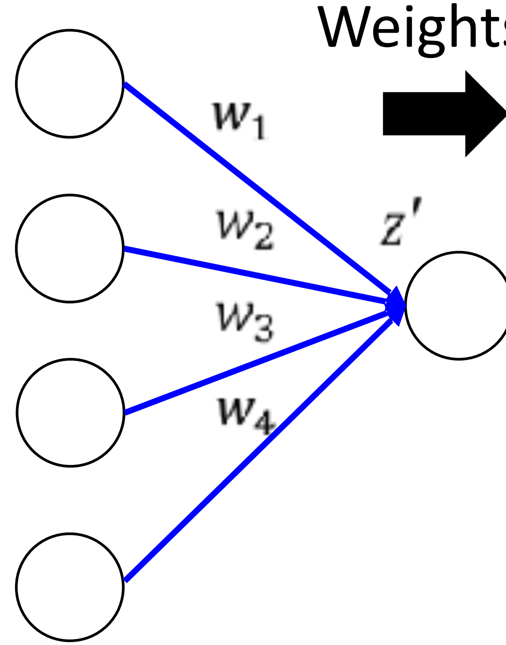


Testing of Dropout

No dropout

Weights from training

$\Rightarrow z' \approx 2z$



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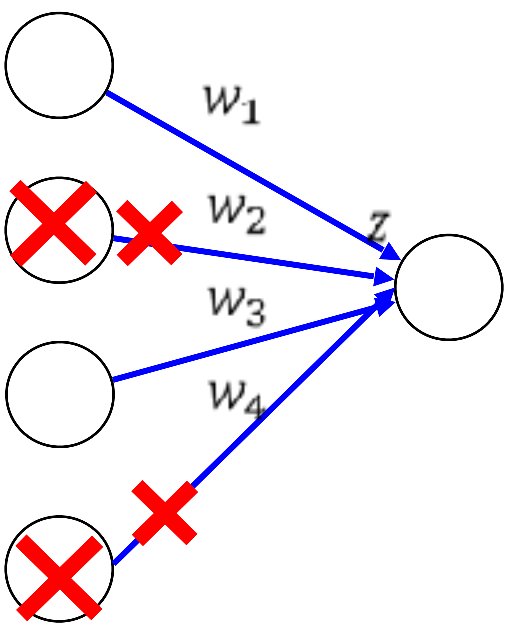
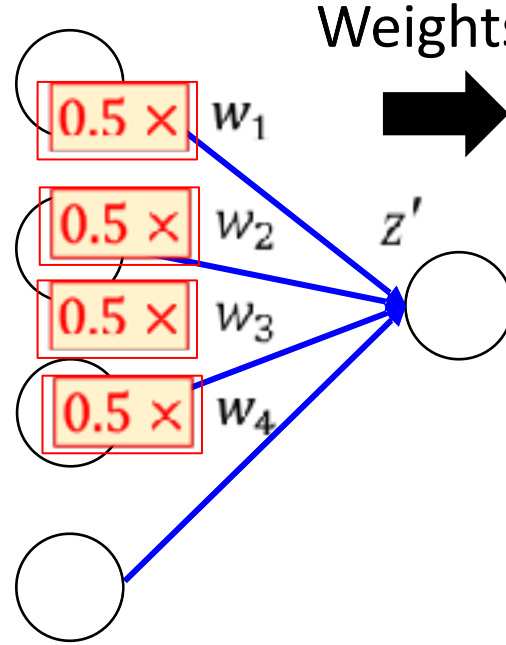


Testing of Dropout

No dropout



Weights from training

$z' \approx 2z$

Dropout - Intuitive Reason

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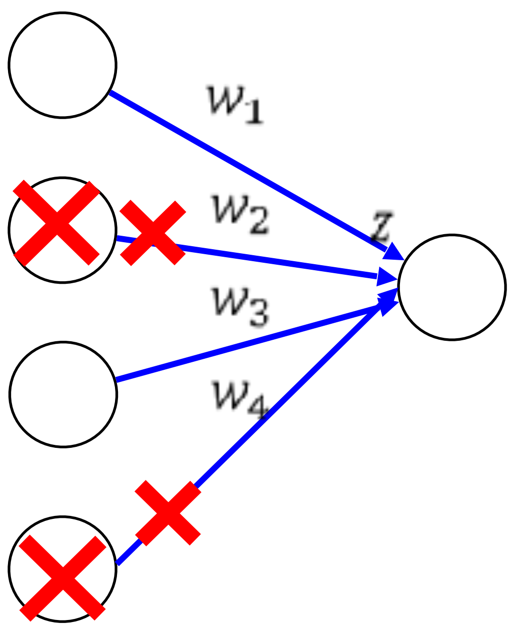
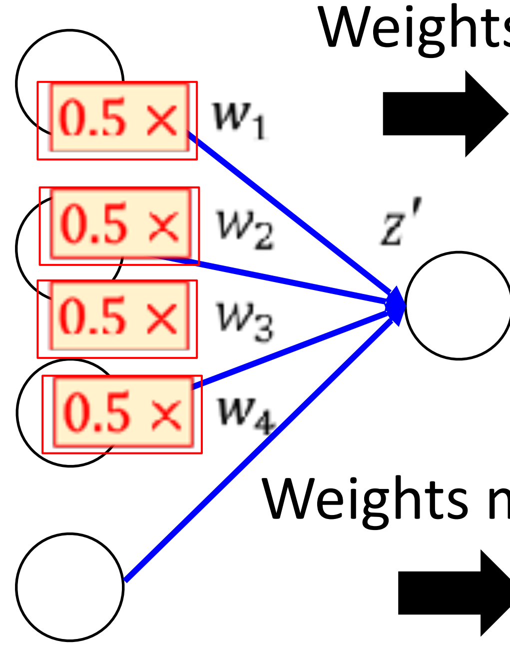


Testing of Dropout

No dropout



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

Weights multiply (1-p)% ➡ $z' \approx z$

Concluding Remarks

Concluding Remarks

- Introduction of deep learning
- Discussing some reasons using deep learning
- New techniques for deep learning
    - ReLU, Maxout
    - Giving all the parameters different learning rates
    - Dropout

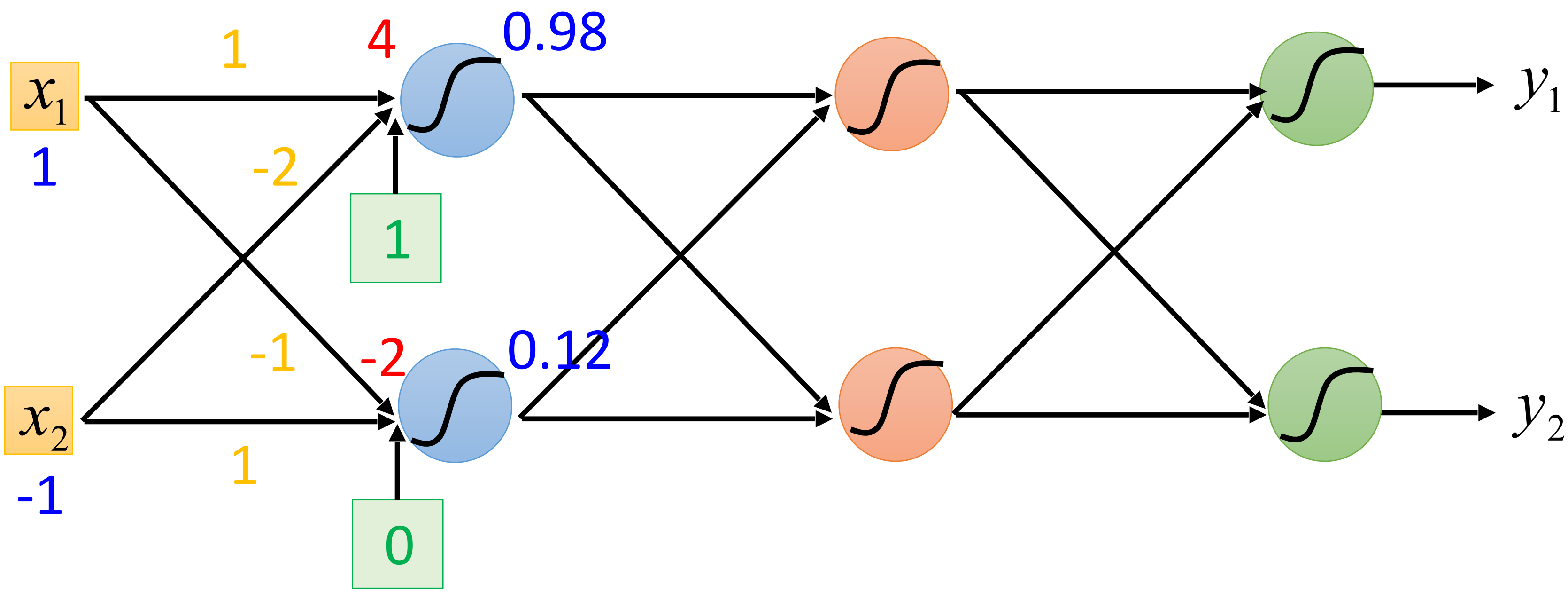
Reading Materials

- “Neural Networks and Deep Learning”
  - written by Michael Nielsen
  - http://neuralnetworksanddeeplearning.com/
- “Deep Learning” (not finished yet)
  - Written by Yoshua Bengio, Ian J. Goodfellow and Aaron Courville
  - http://www.iro.umontreal.ca/~bengioy/dlbook/

Thank you
for your attention!

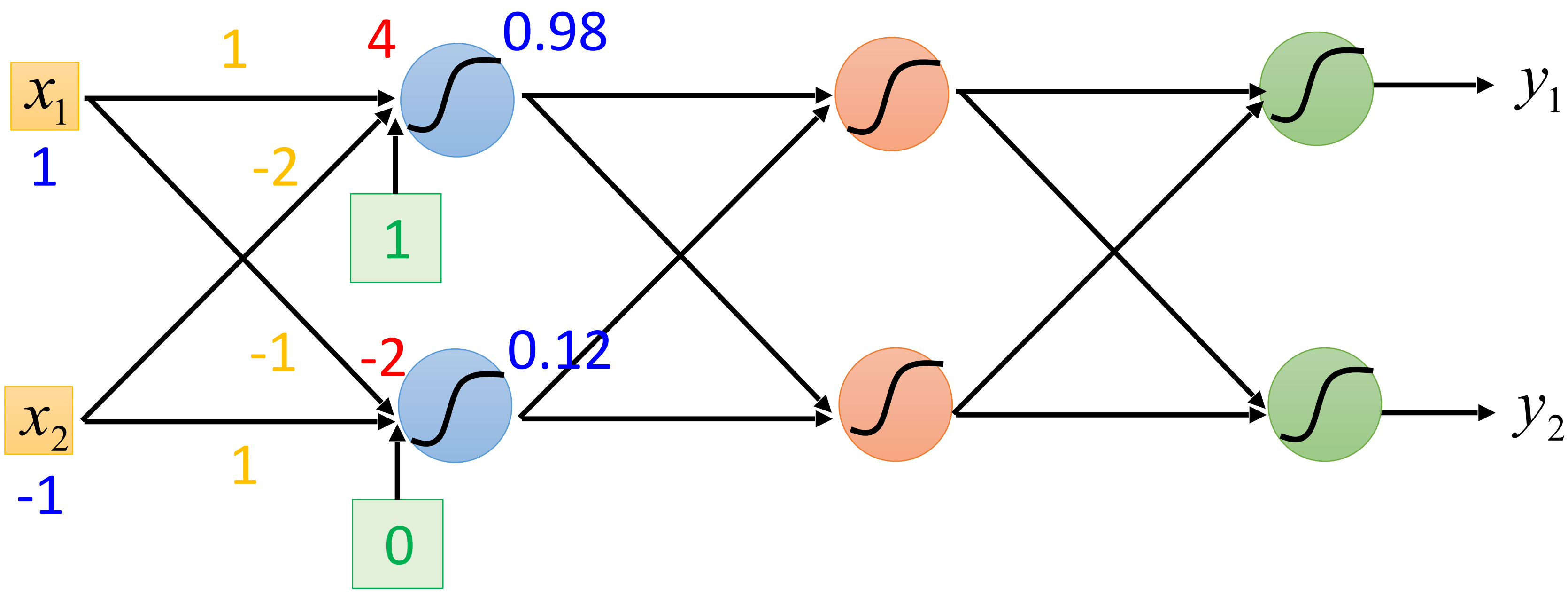
Appendix

Matrix Operation



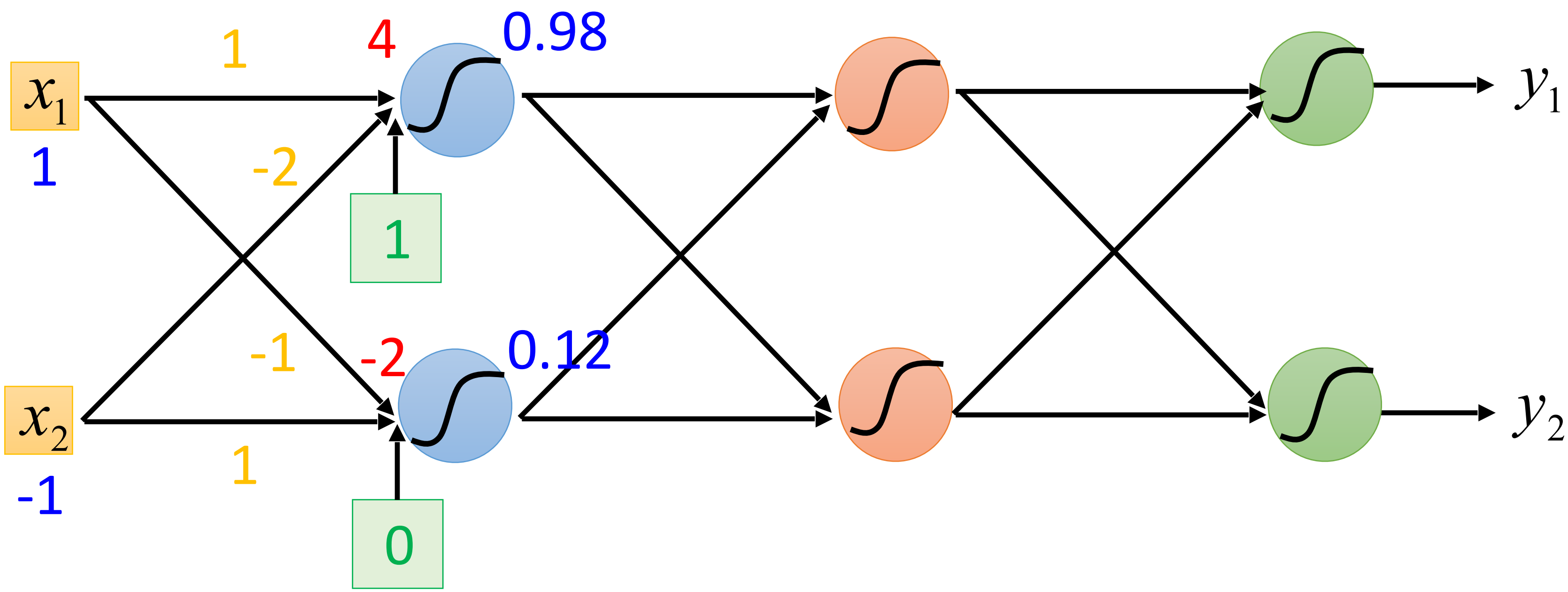
$$\sigma\left(\begin{bmatrix}1 & -2\\ -1 & 1\end{bmatrix}\begin{bmatrix}1\\ -1\end{bmatrix}+\begin{bmatrix}1\\ 0\end{bmatrix}\right)=\begin{bmatrix}0.98\\ 0.12\end{bmatrix}$$

Matrix Operation



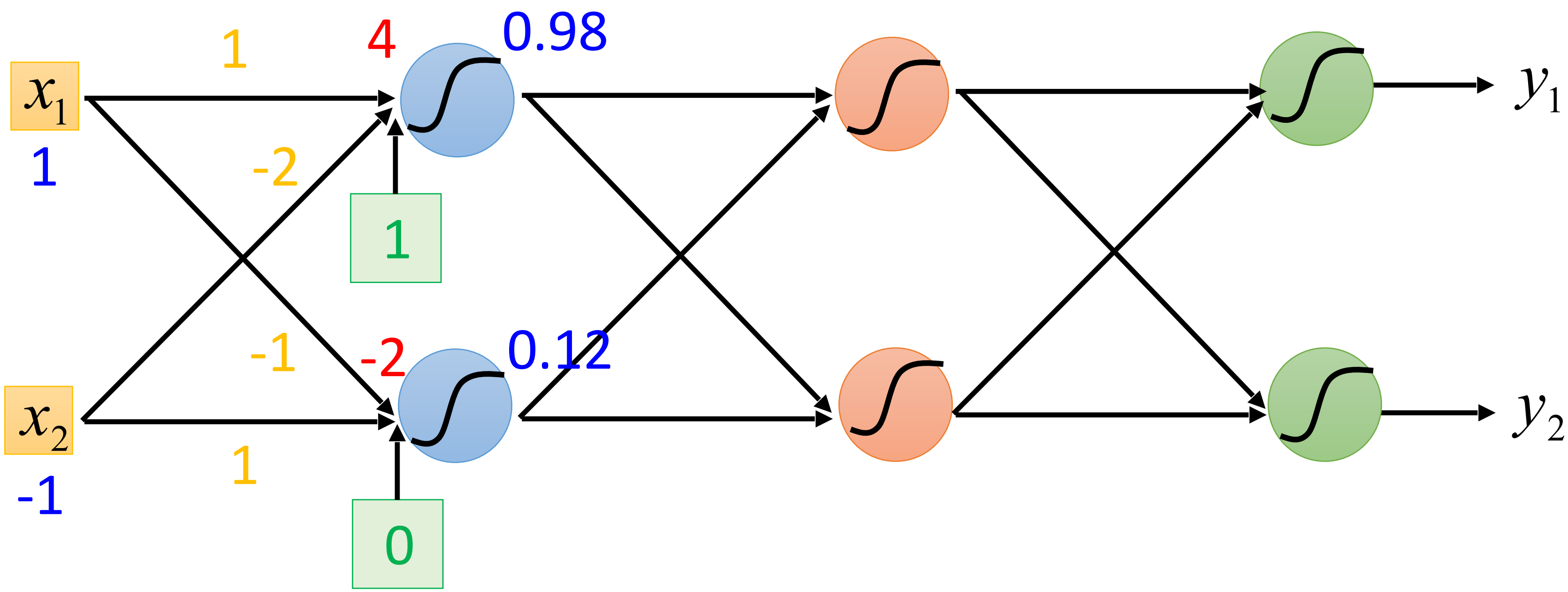
$$\sigma\left(\boxed{\quad W \quad} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

Matrix Operation



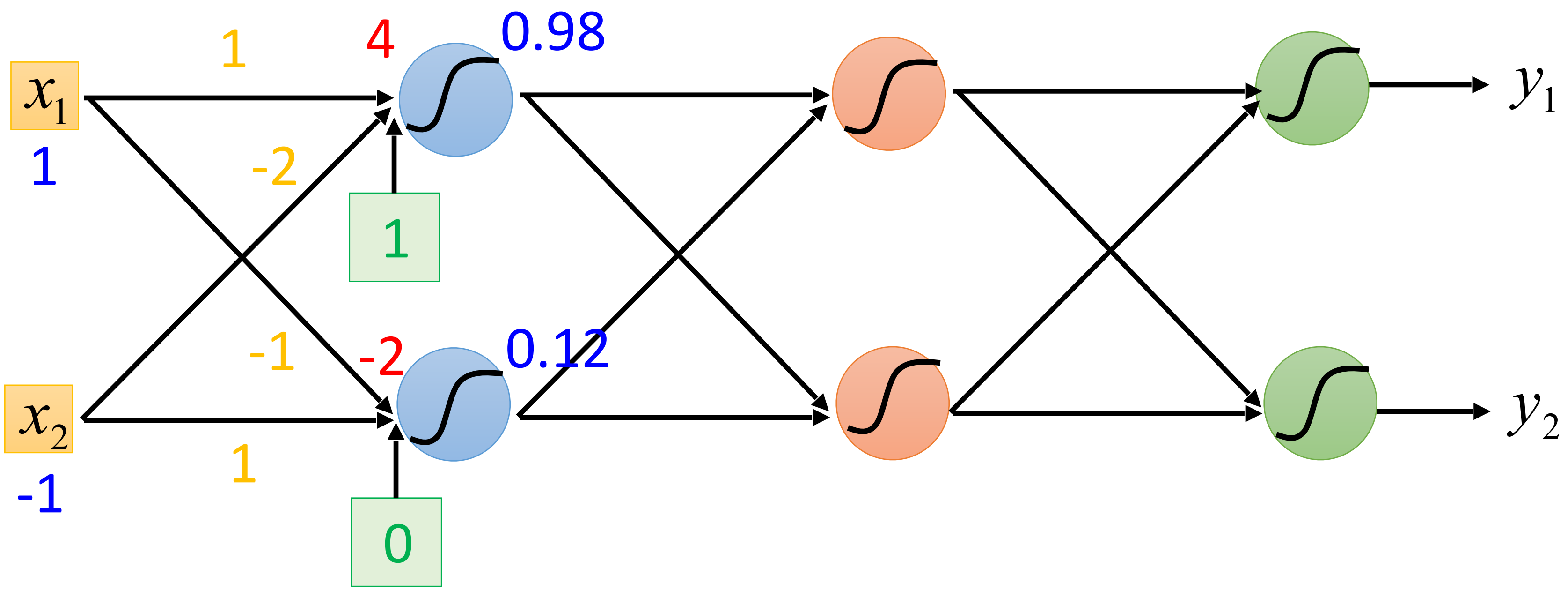
$$\sigma\left(W \; x + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

Matrix Operation



$$\sigma\left(W \; x + b \right) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

Matrix Operation



$$\sigma(\ W\ x + b\ ) = a$$

Why Deep? – Logic Circuits

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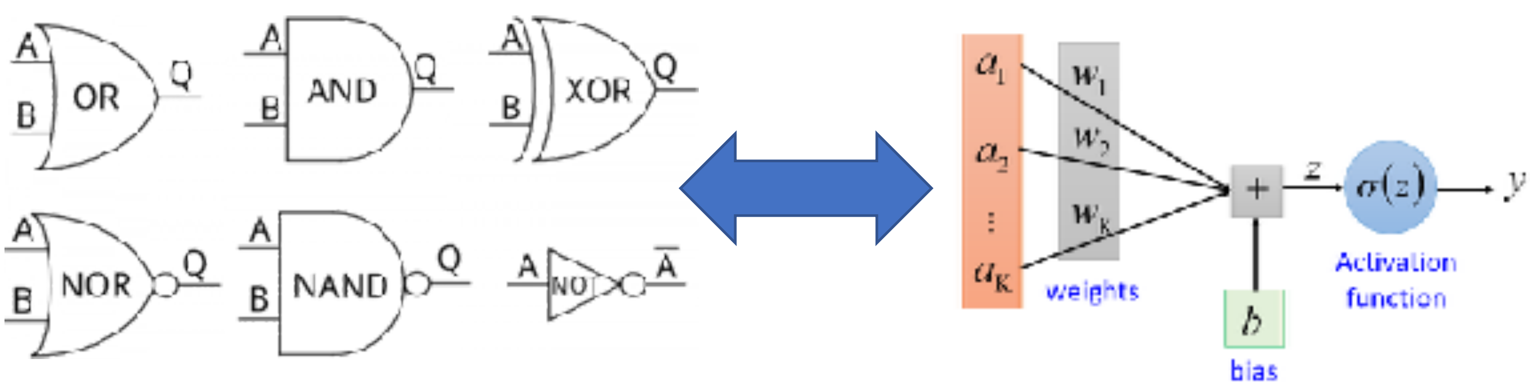

Boosting

Deep Learning

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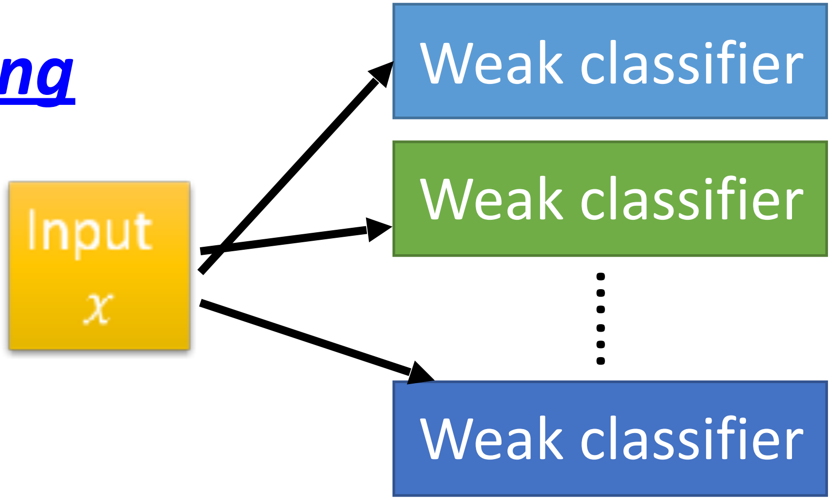

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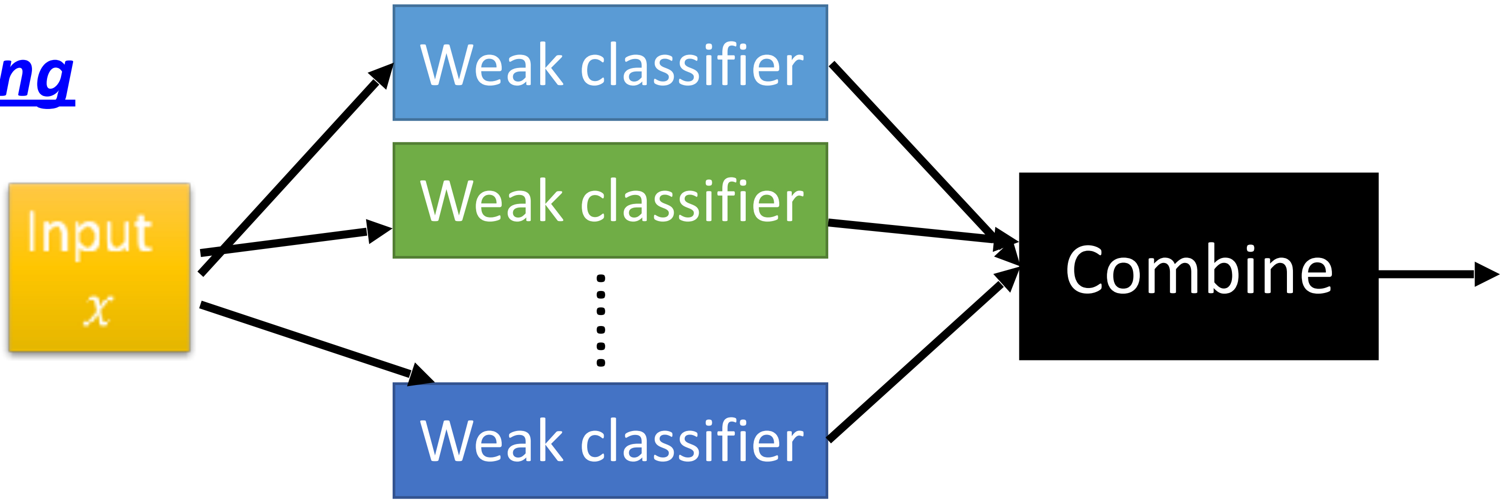

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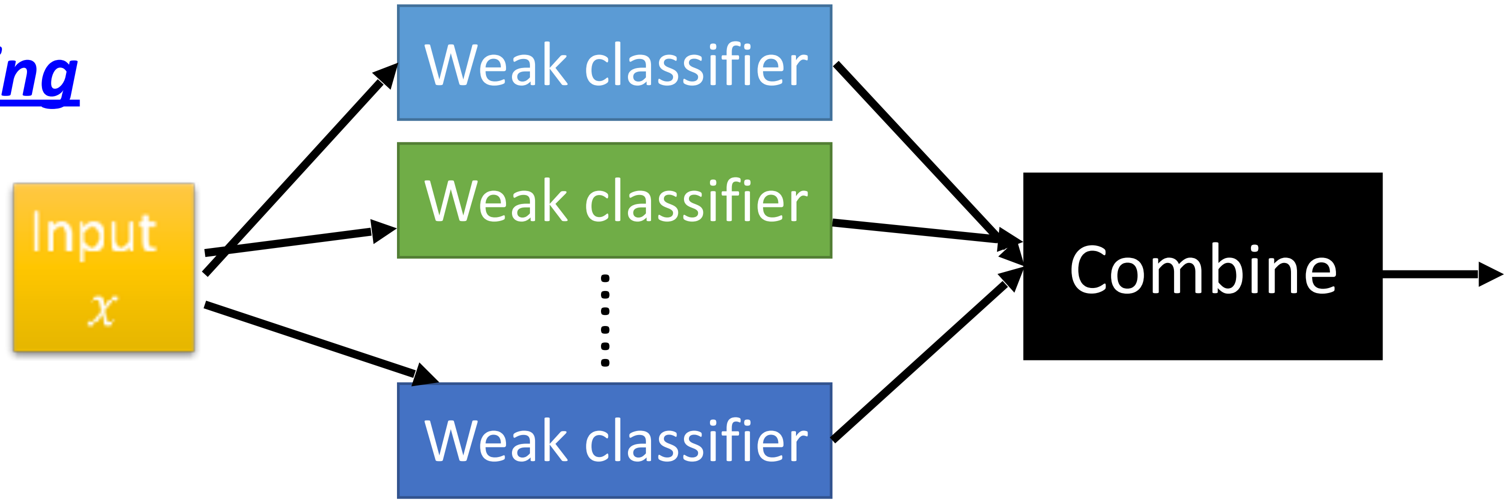

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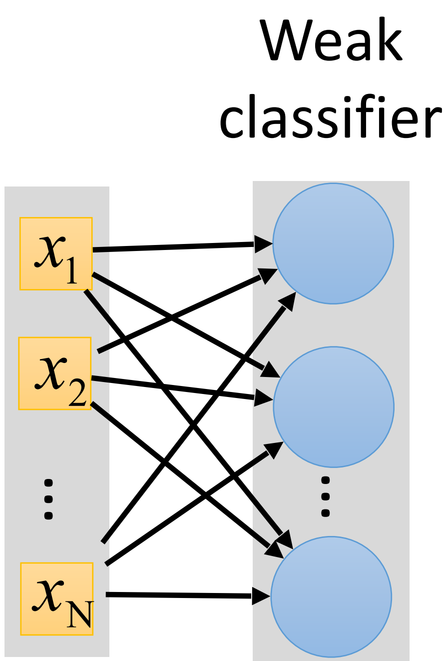

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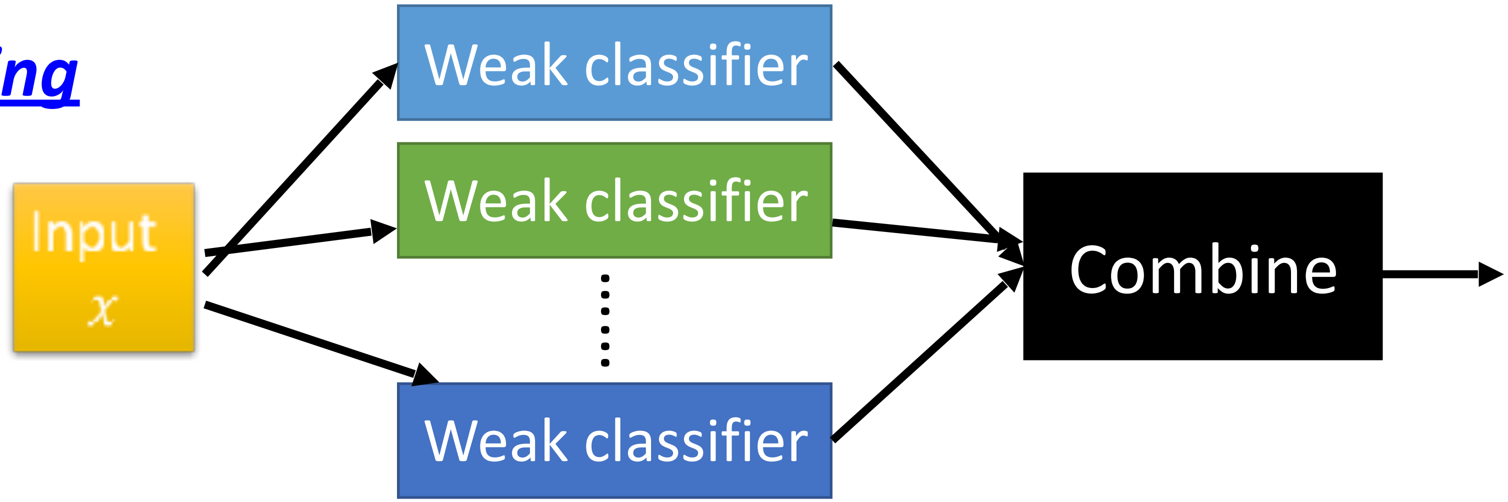

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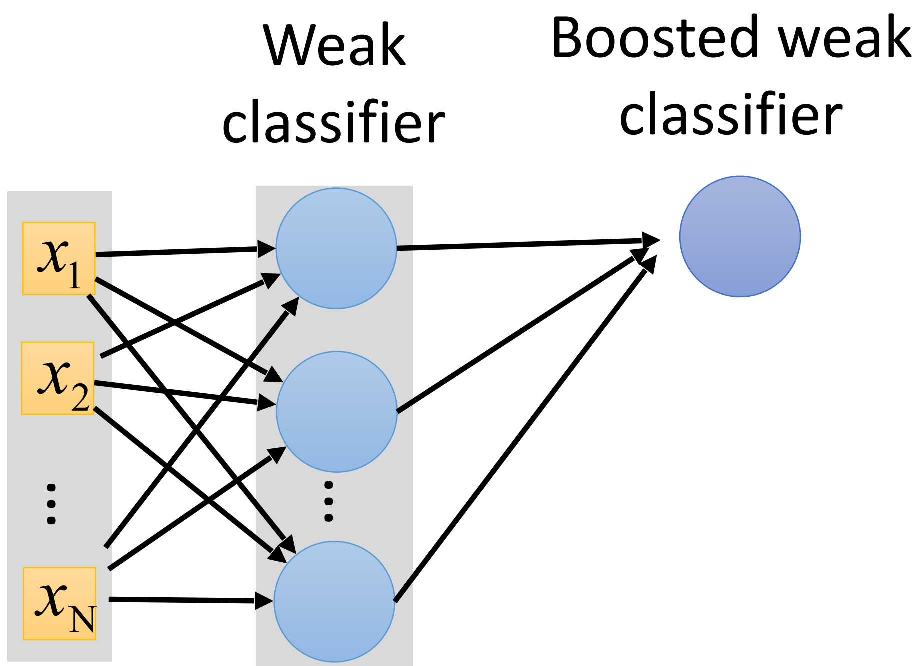

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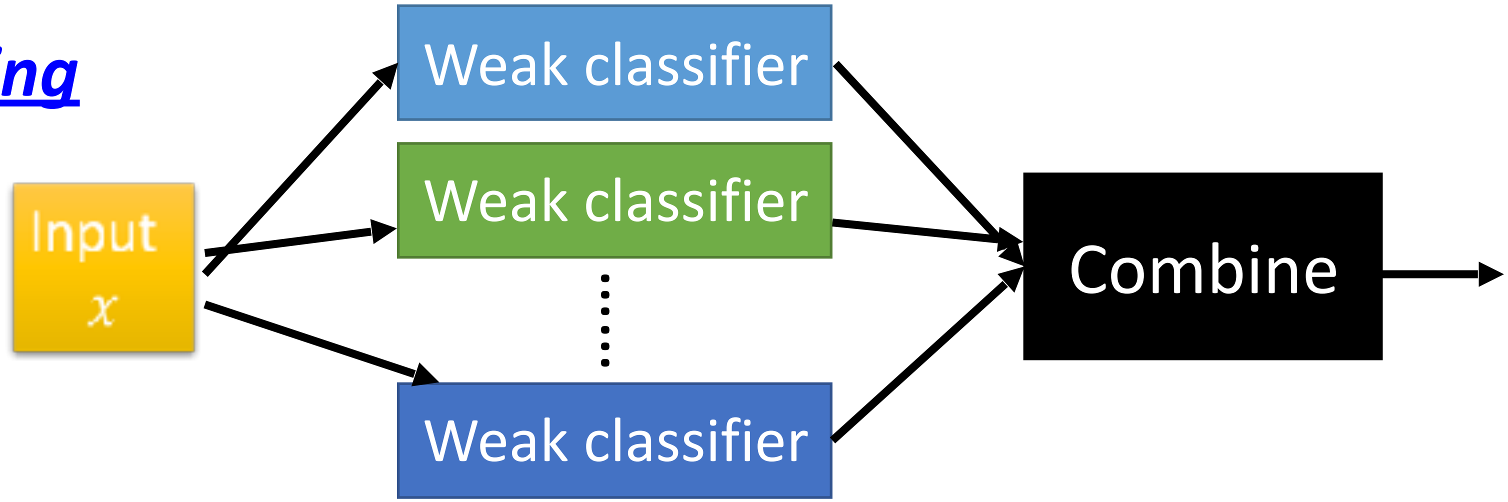

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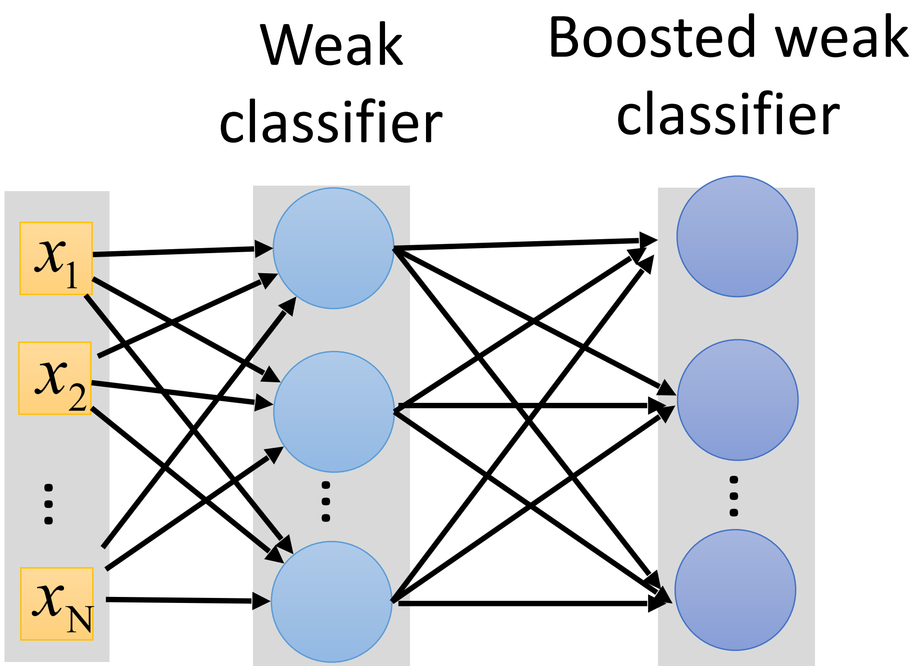

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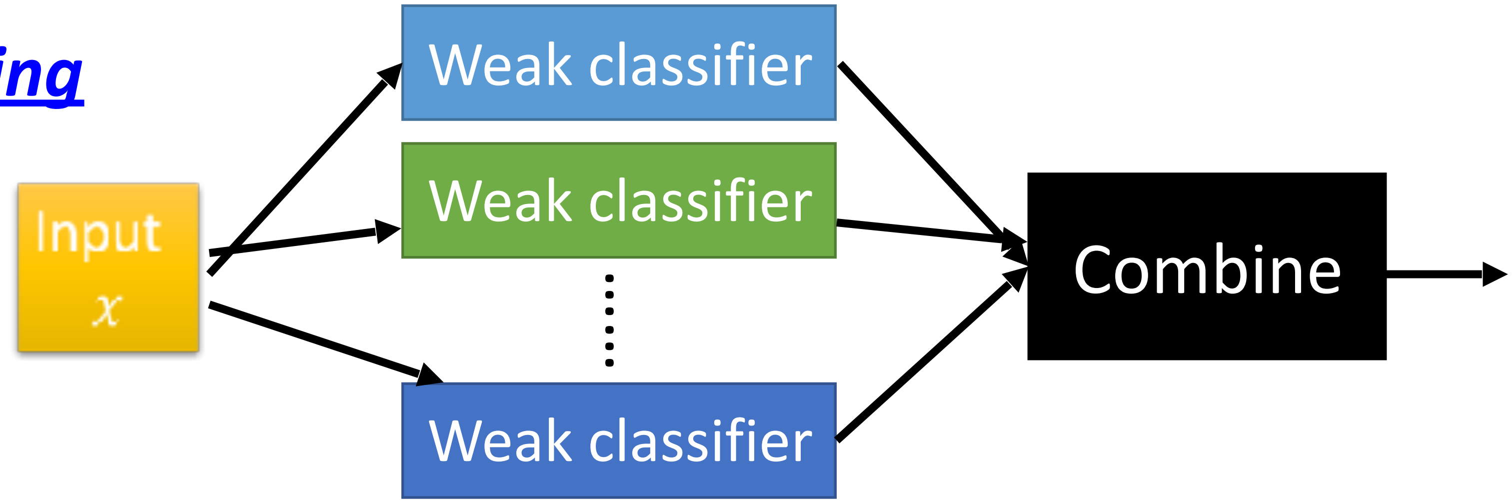

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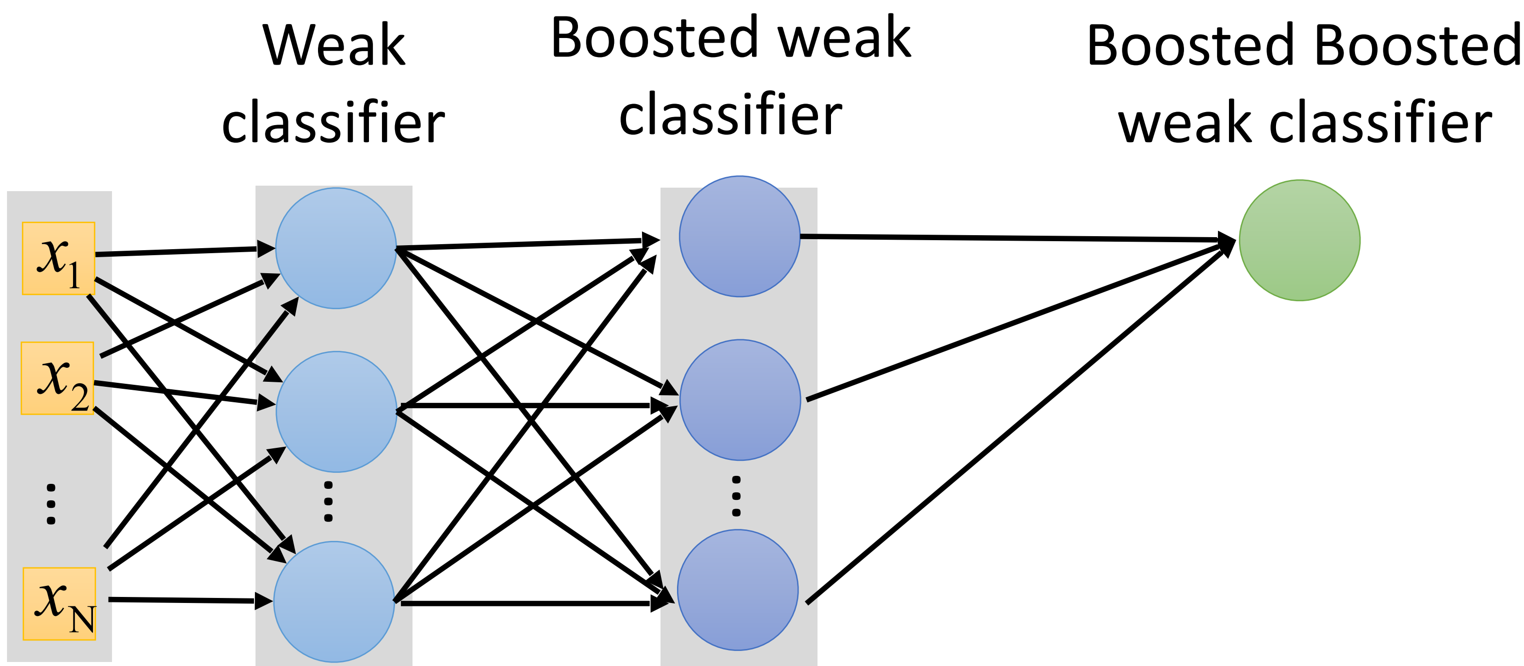

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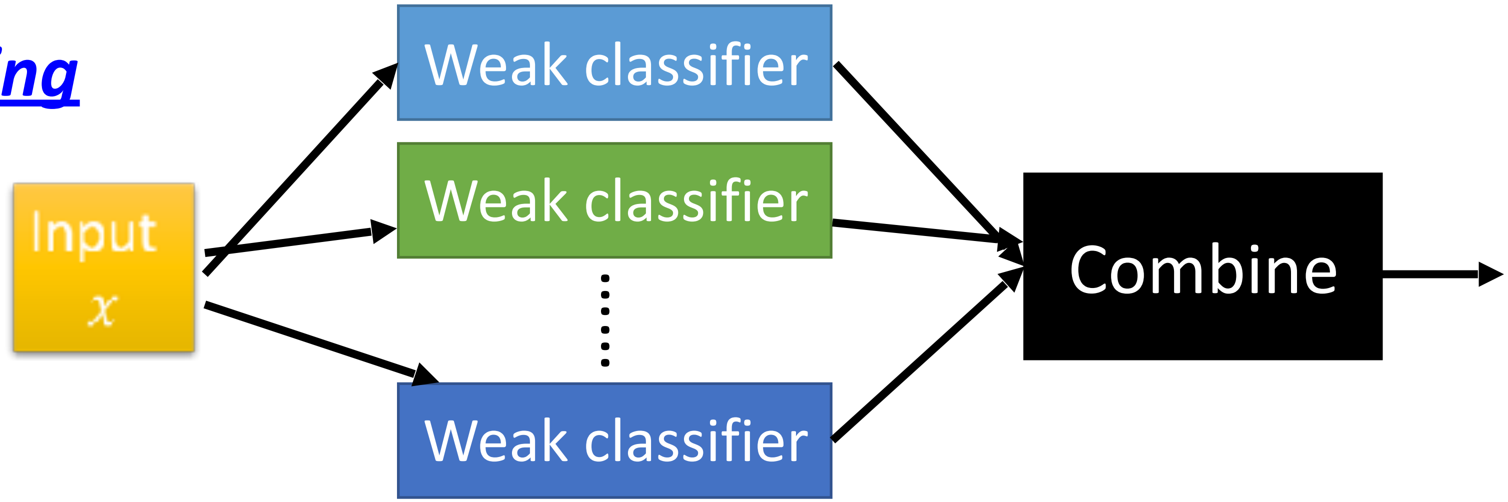

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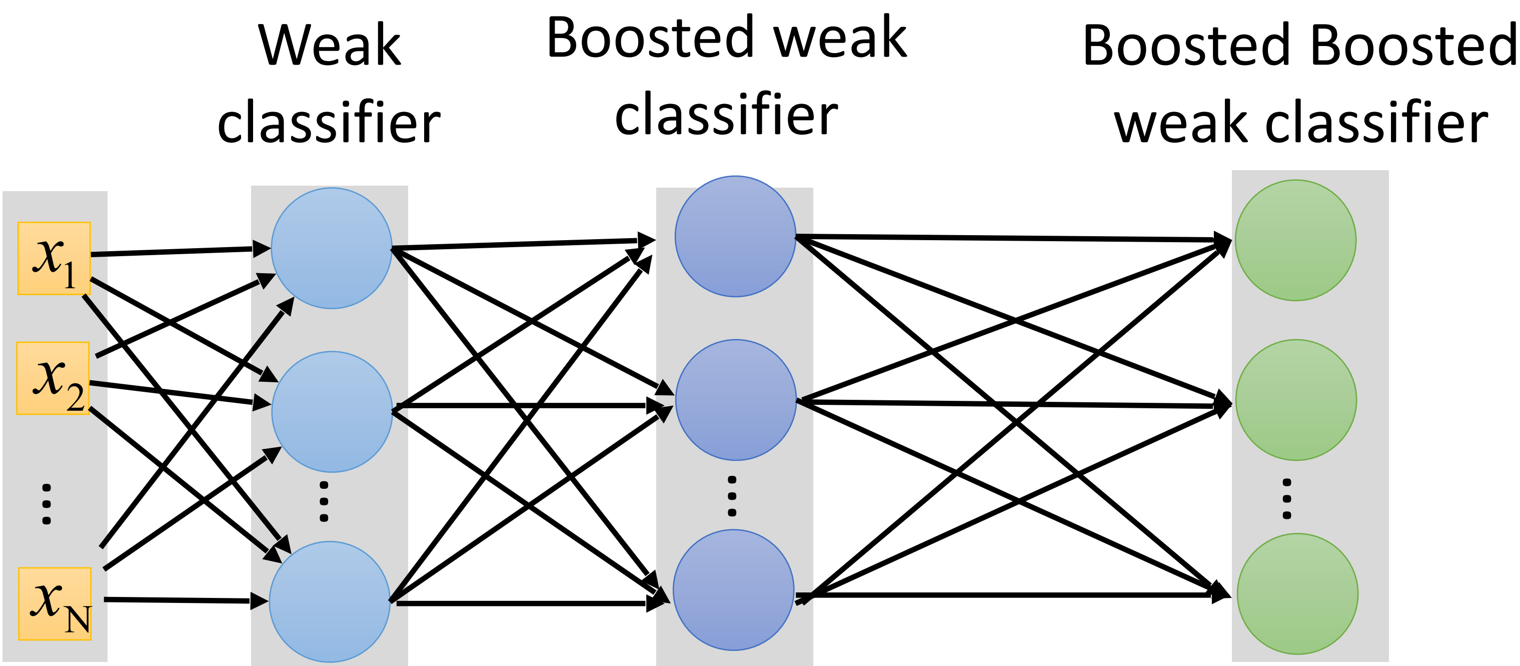

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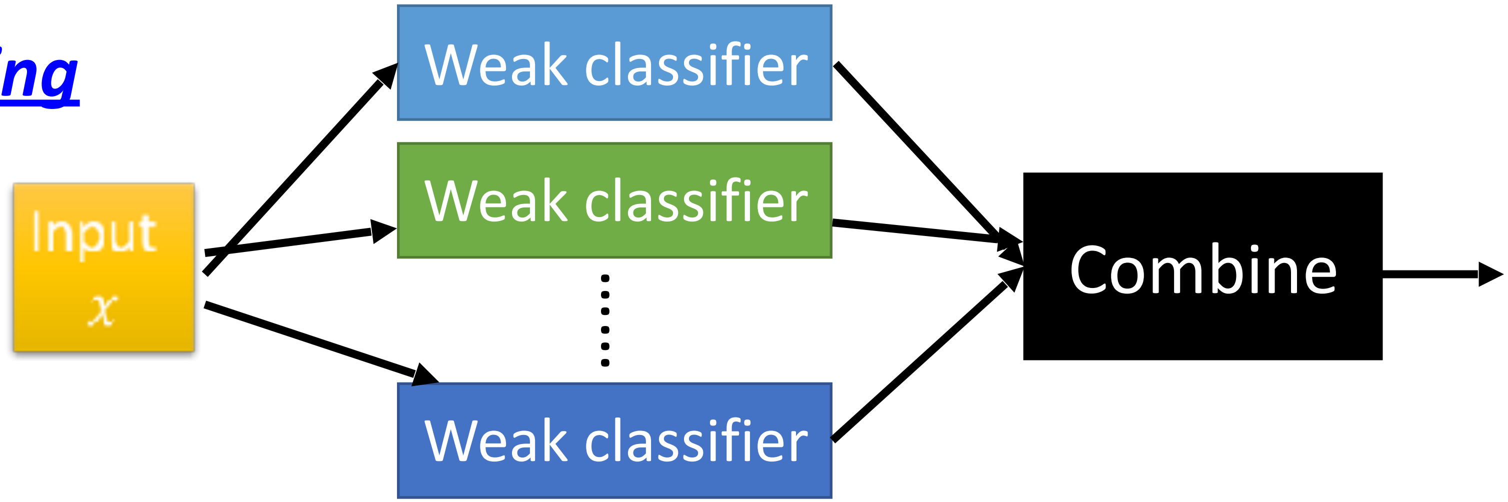

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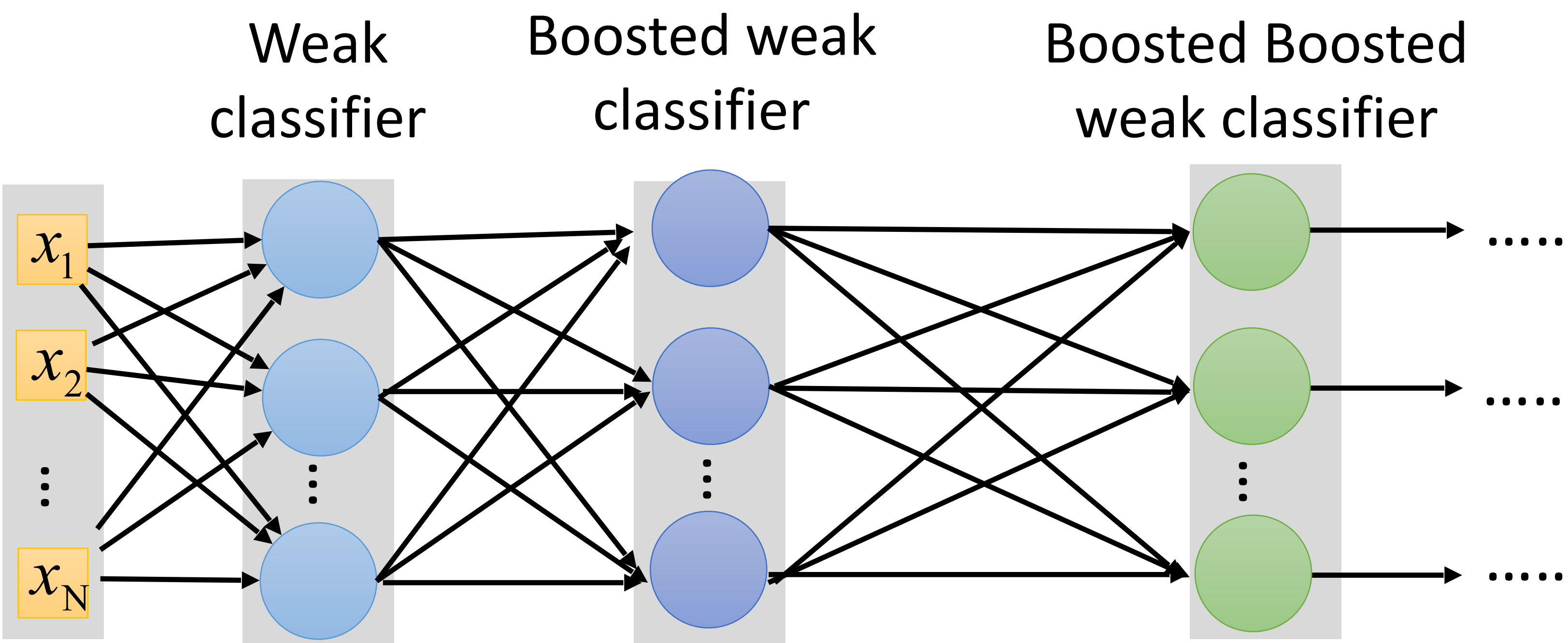

Maxout

ReLU is a special cases of Maxout

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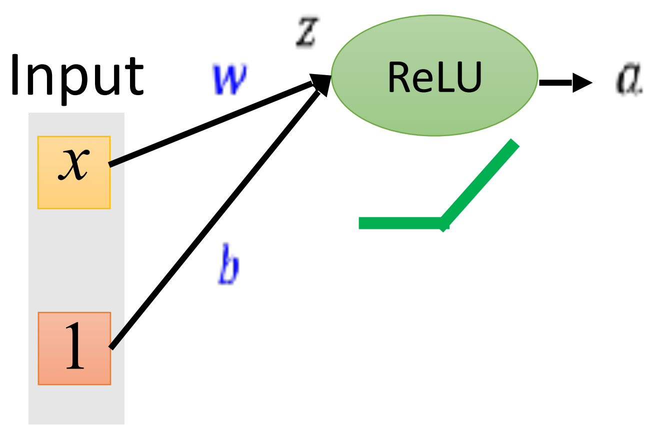

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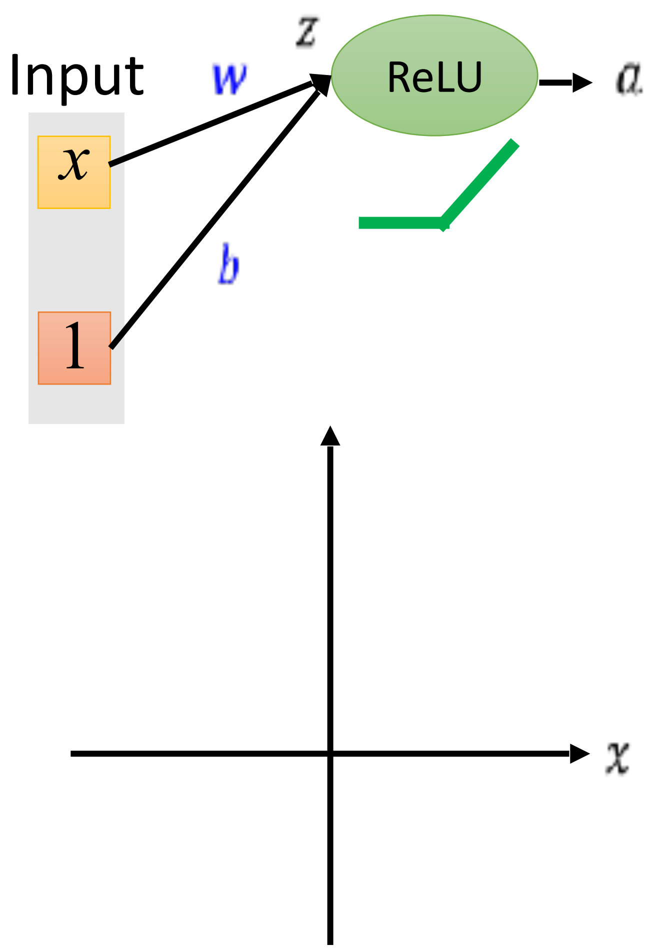

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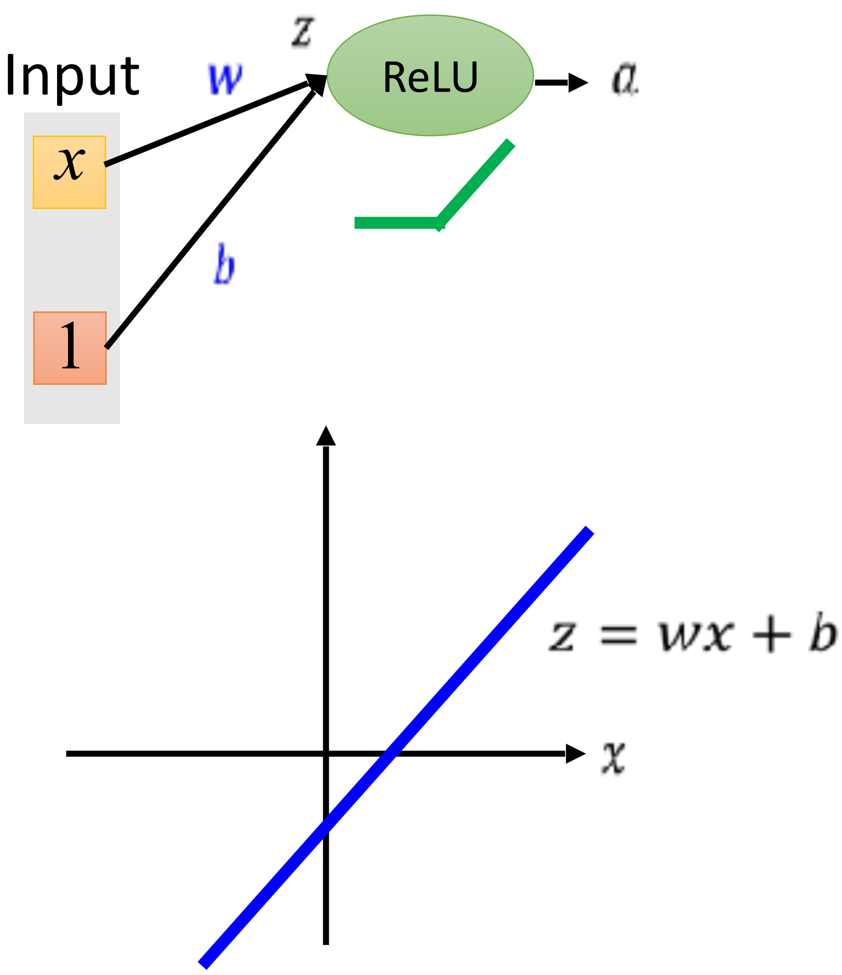

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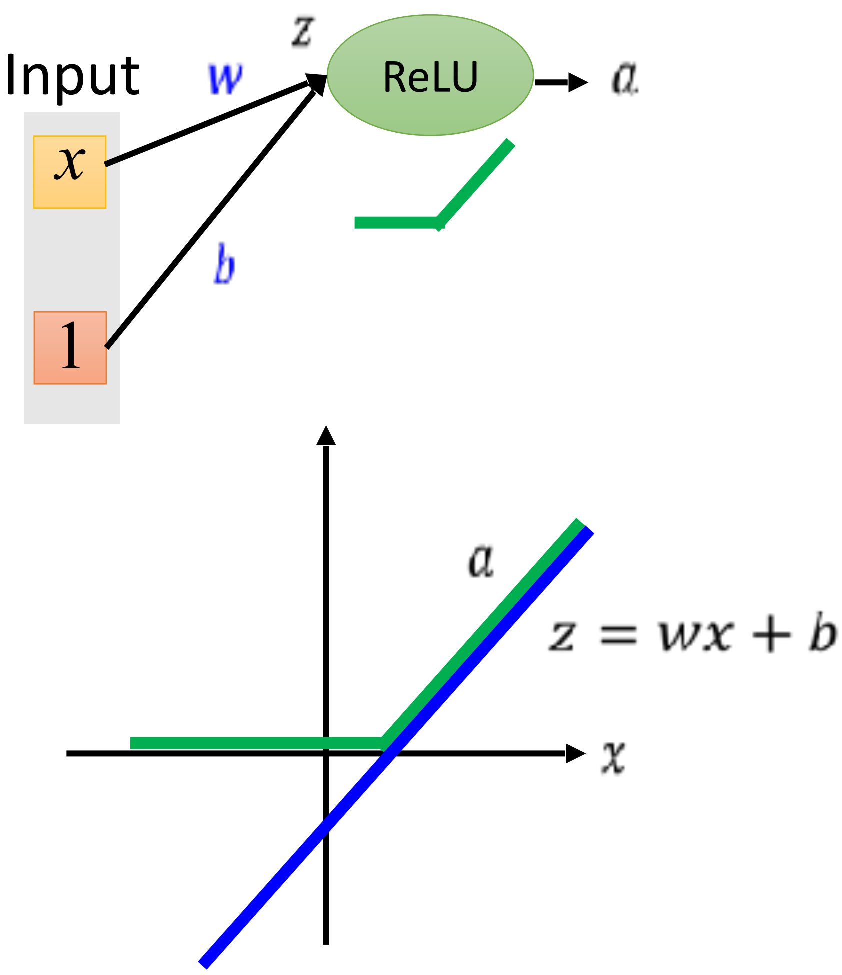

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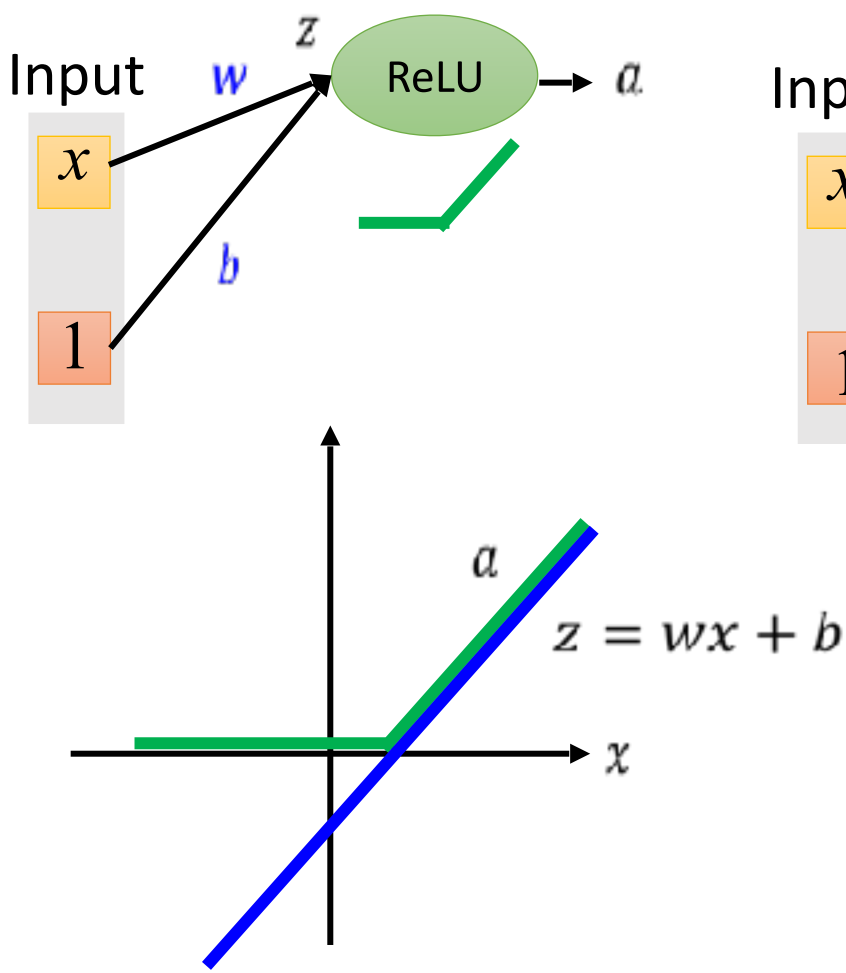

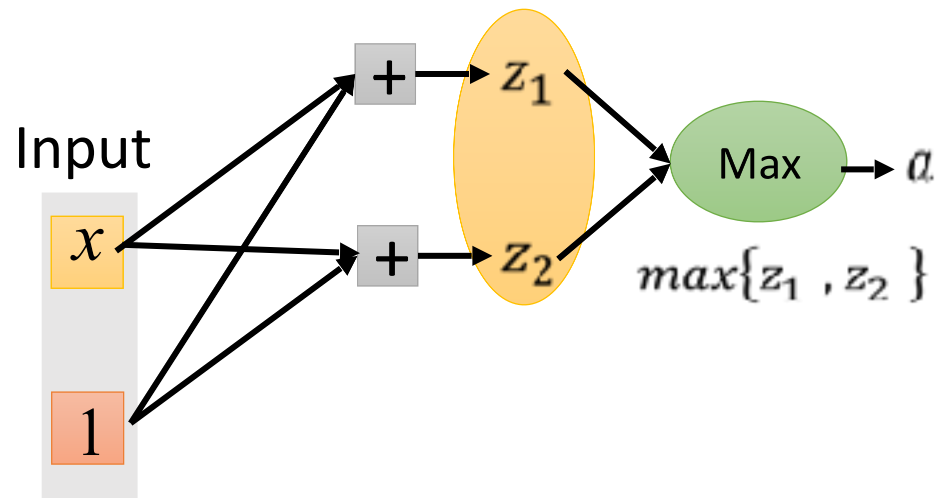

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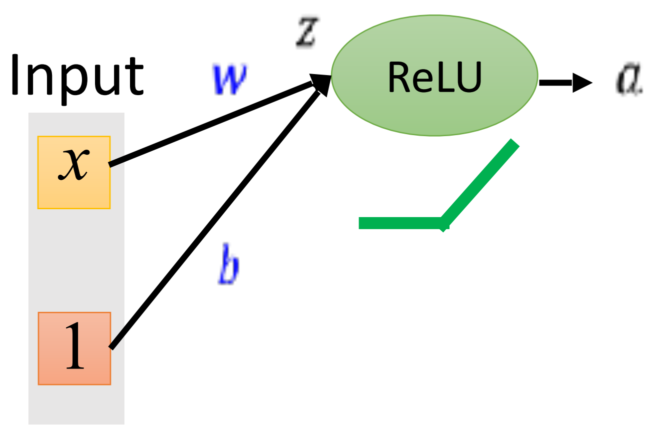

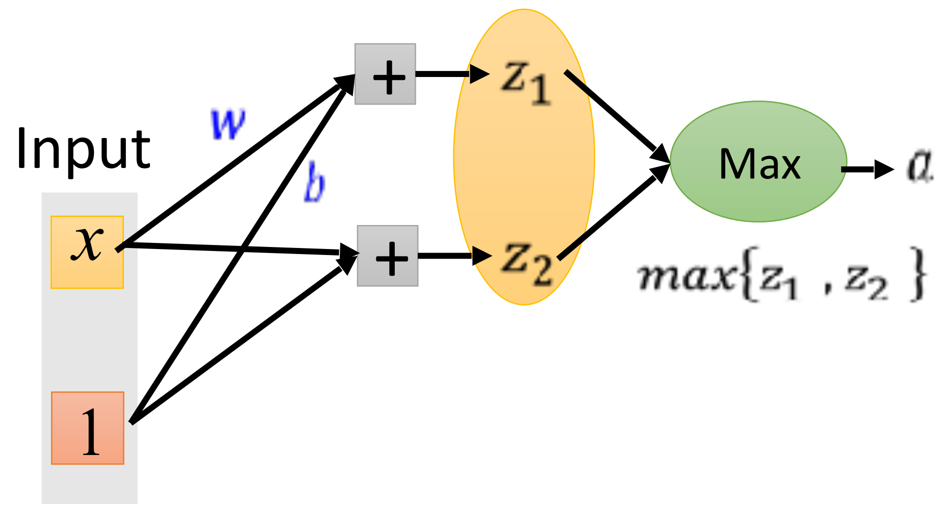

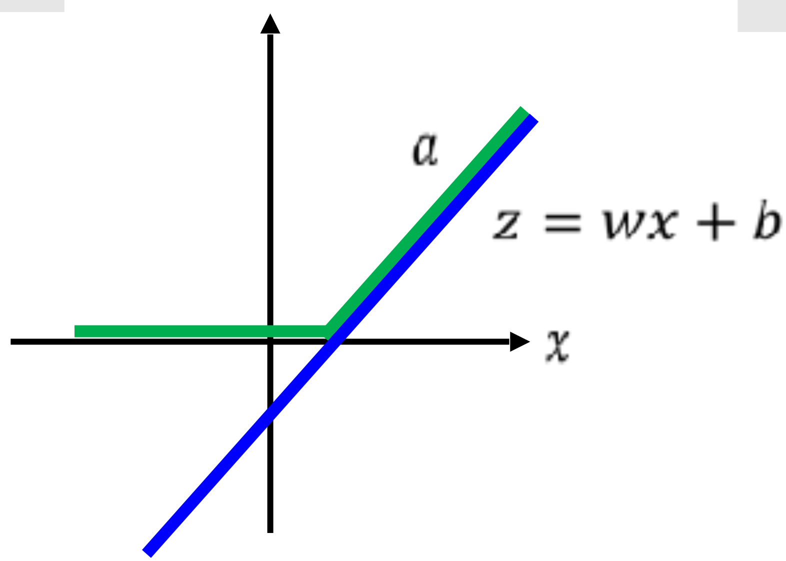

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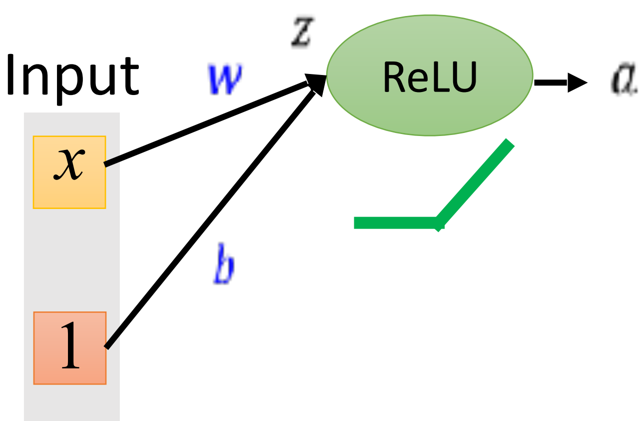

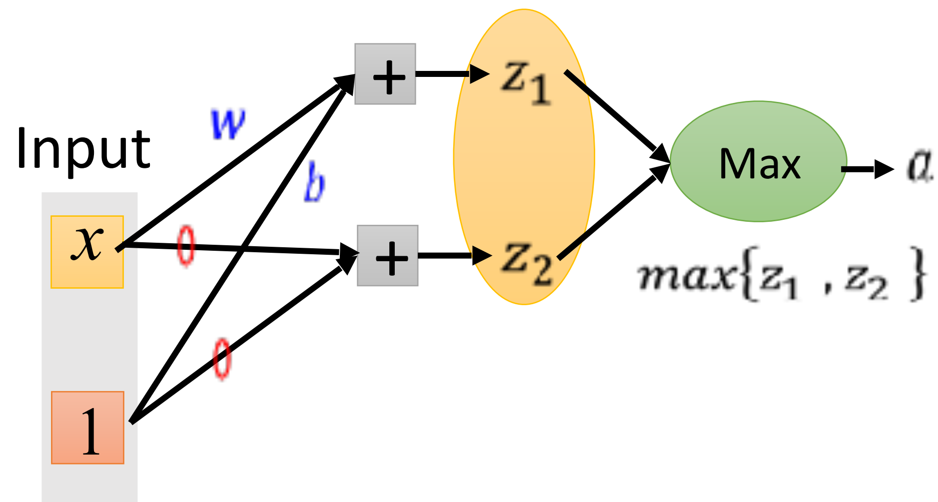

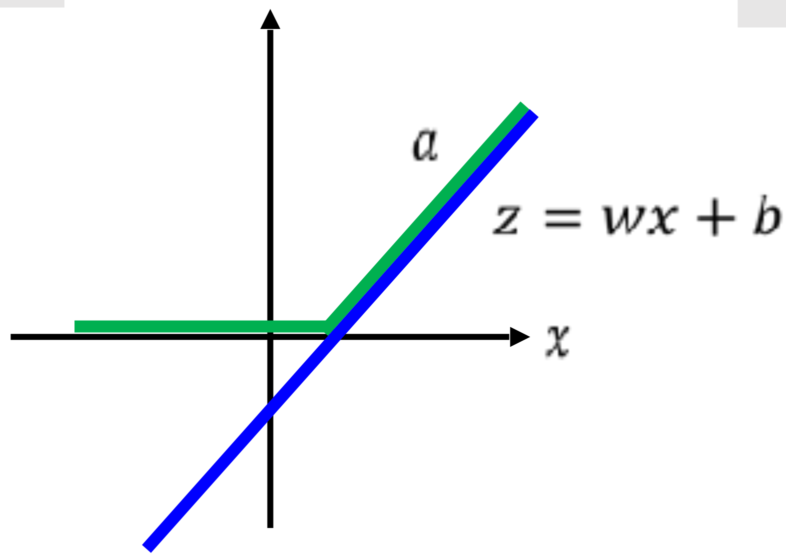

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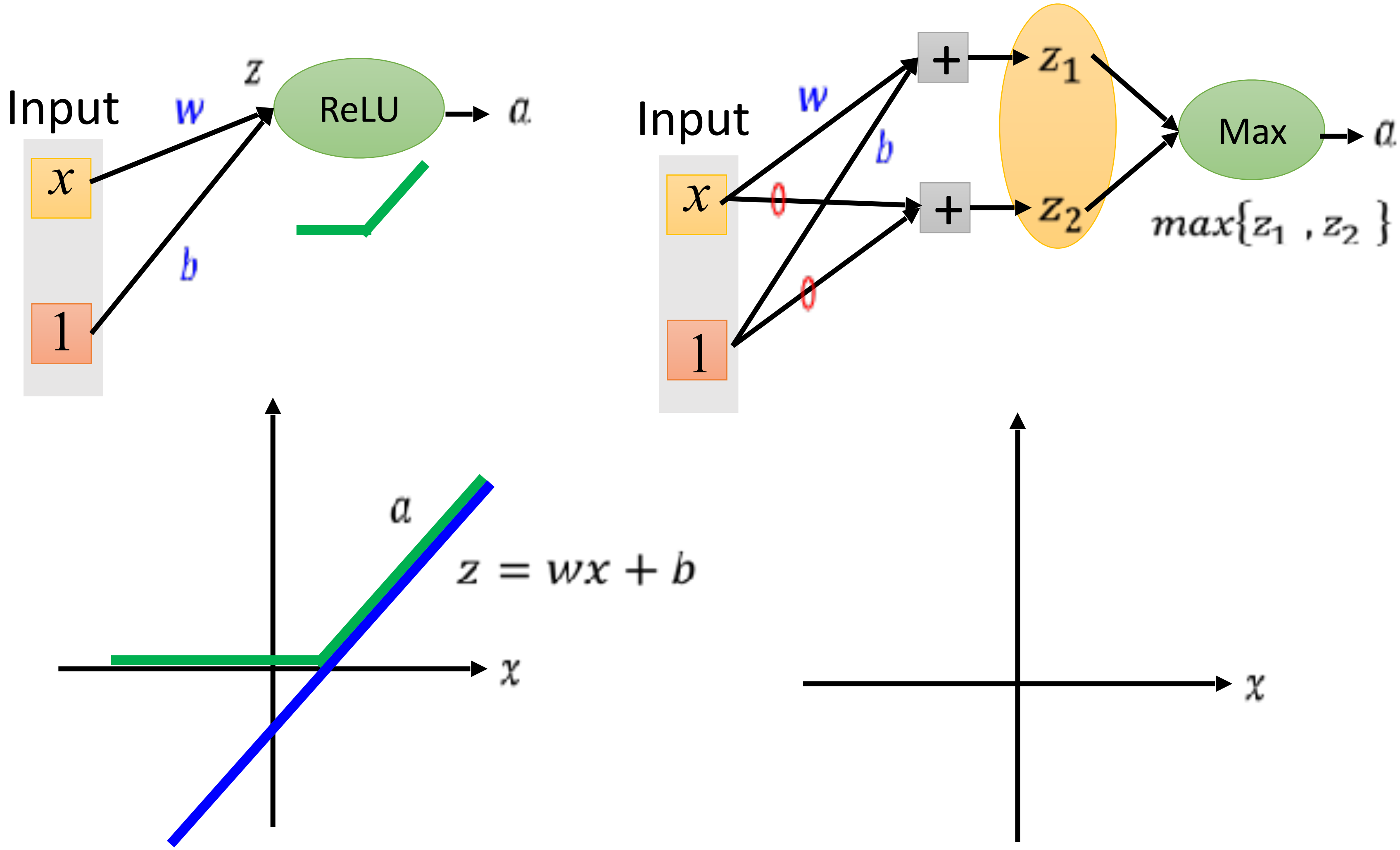

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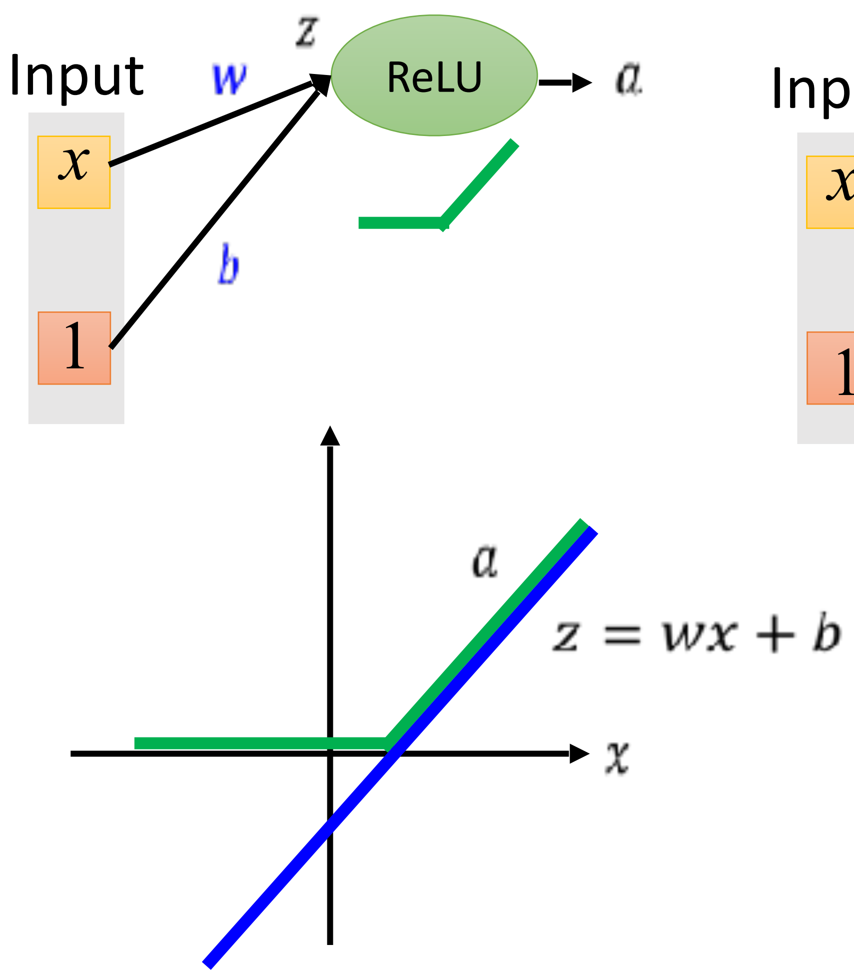

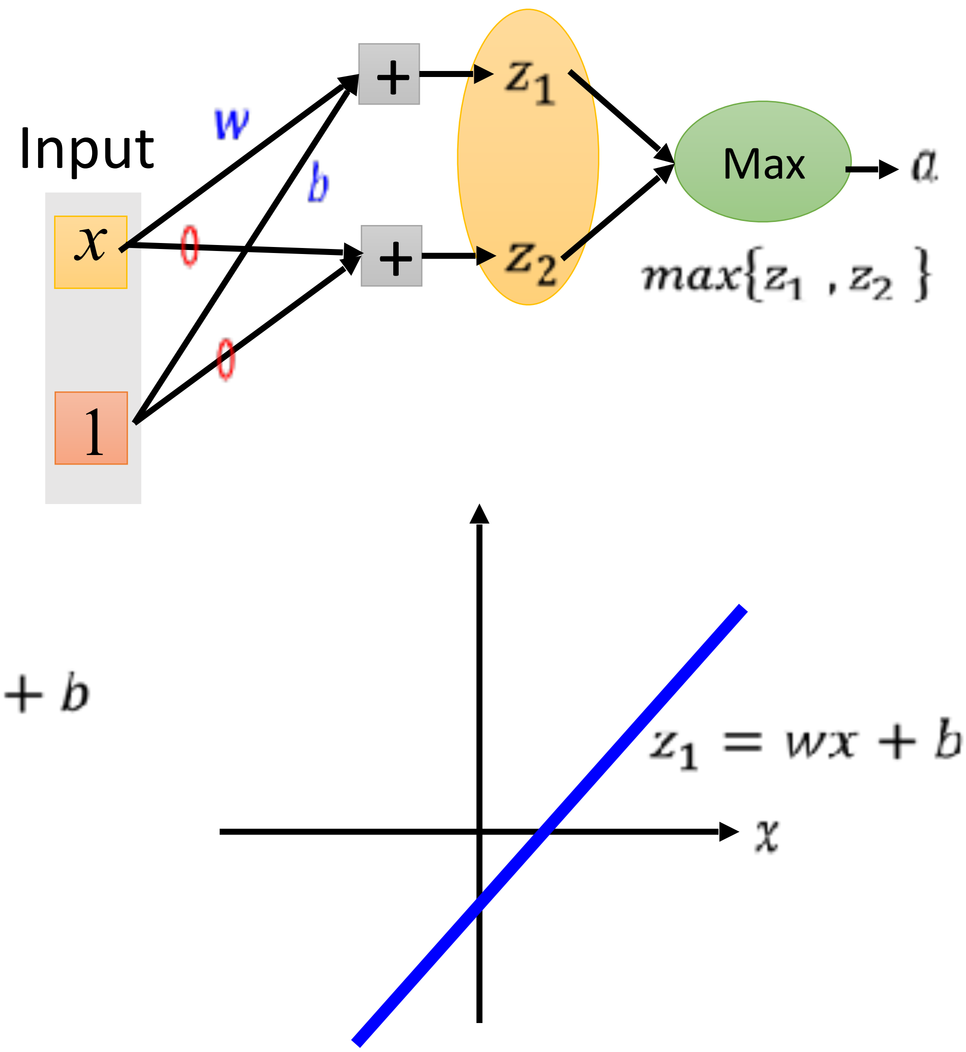

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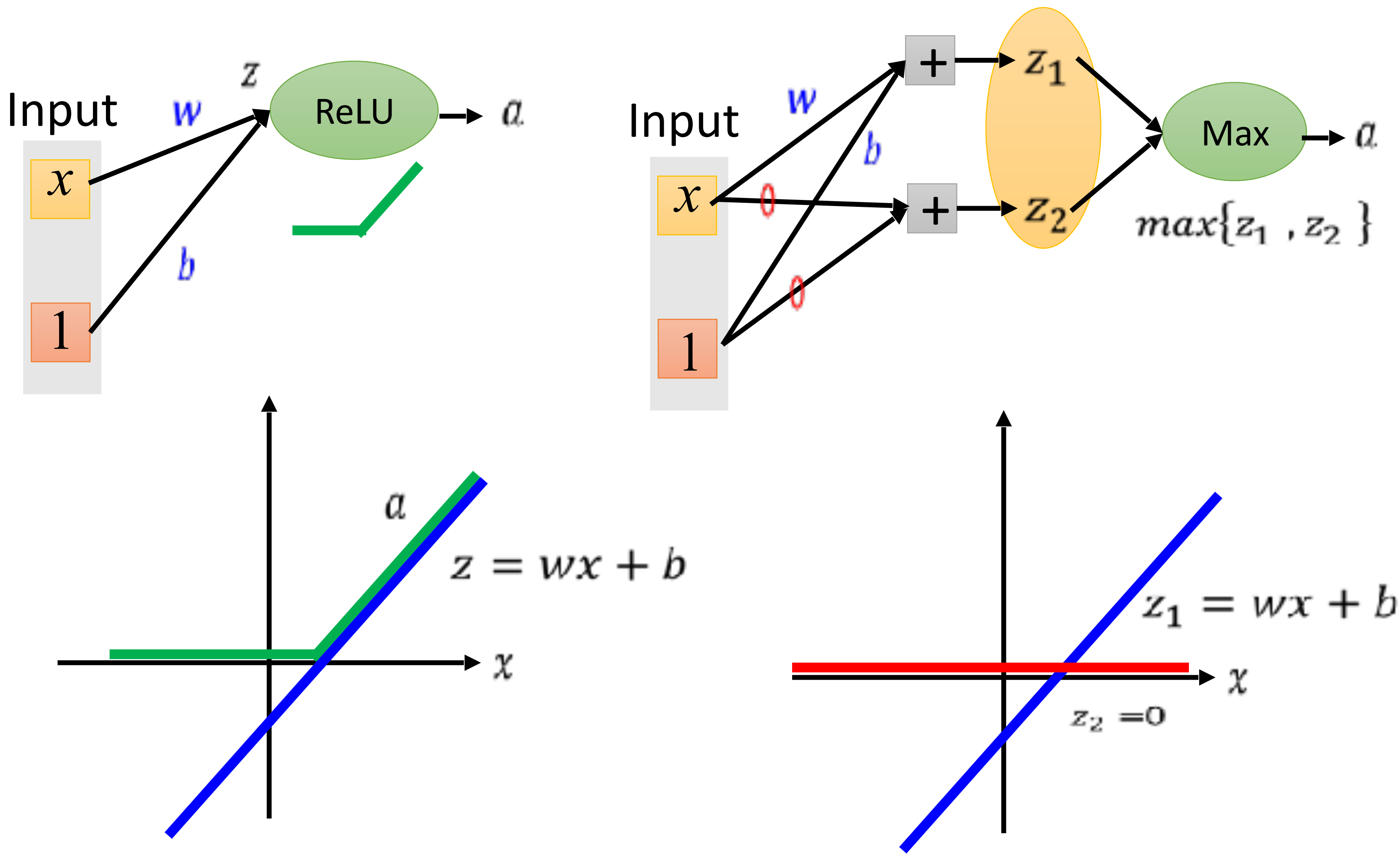

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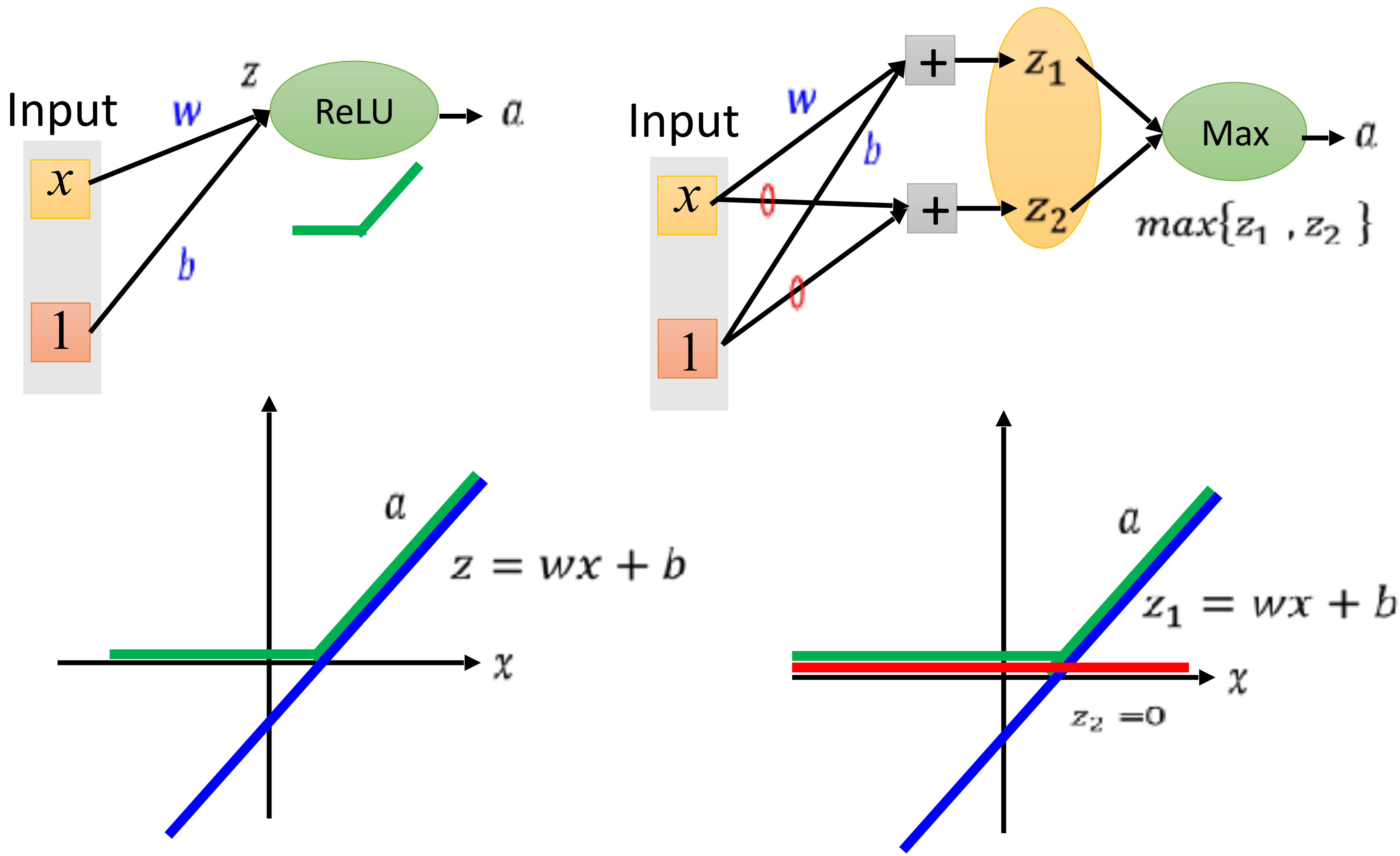

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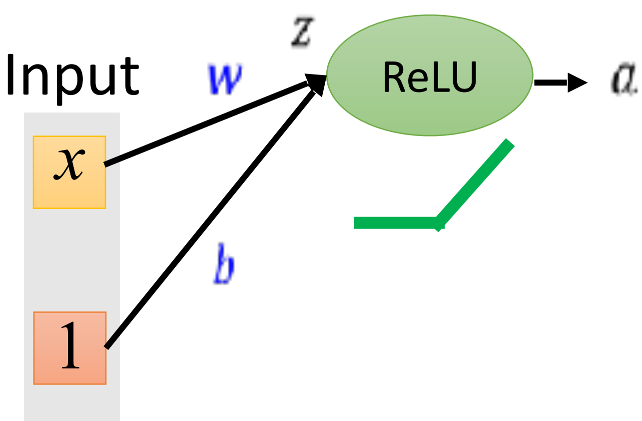

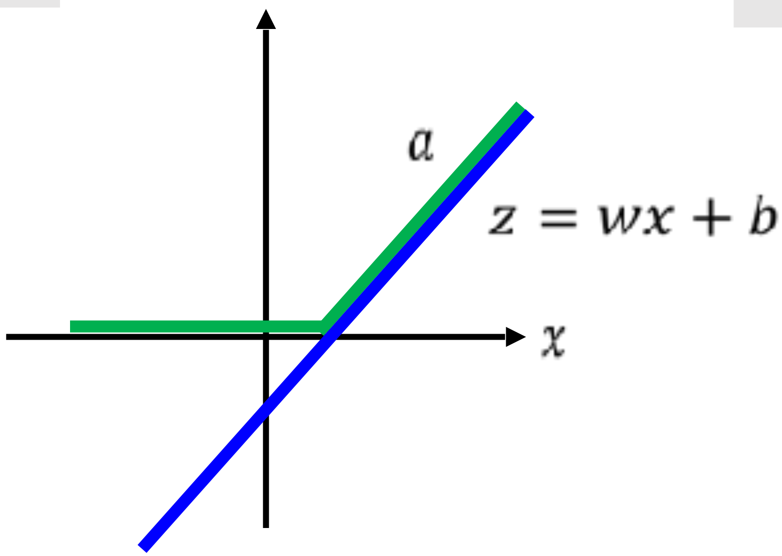

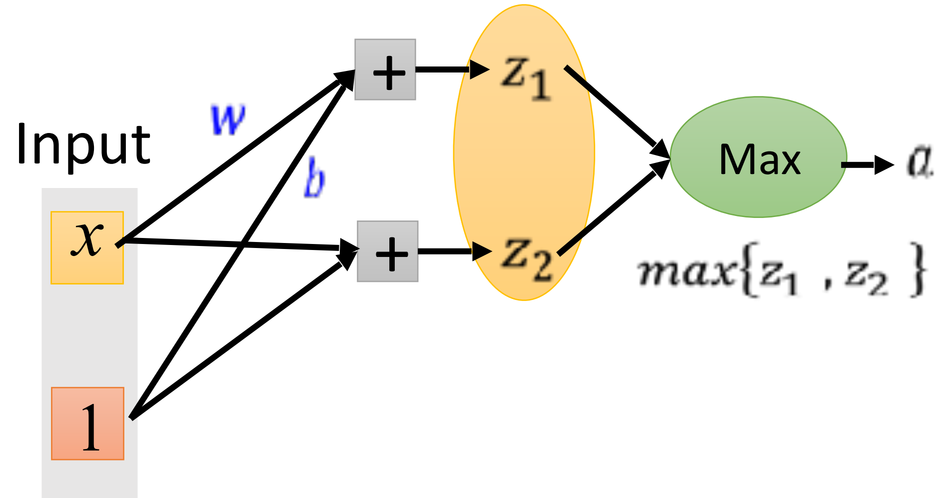

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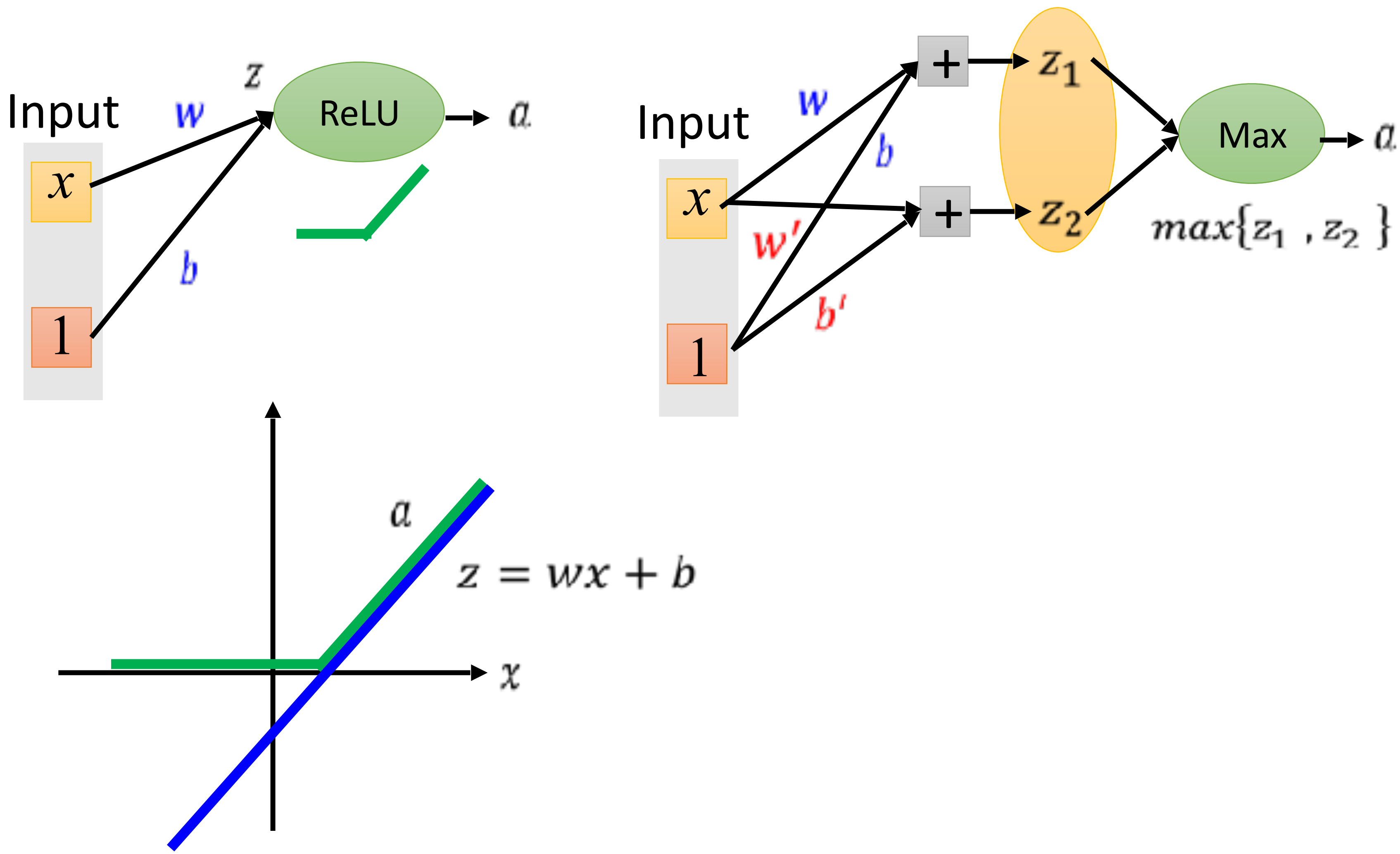

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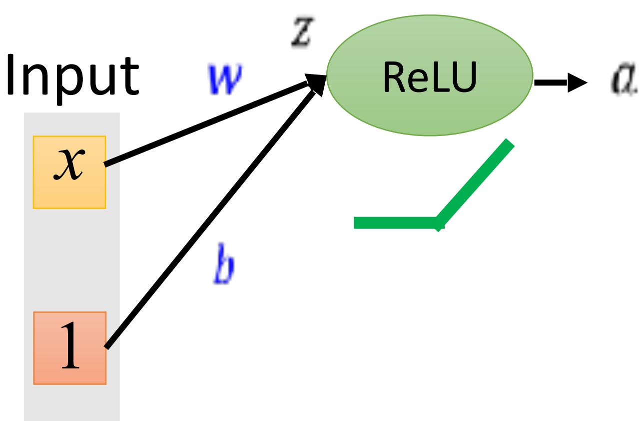

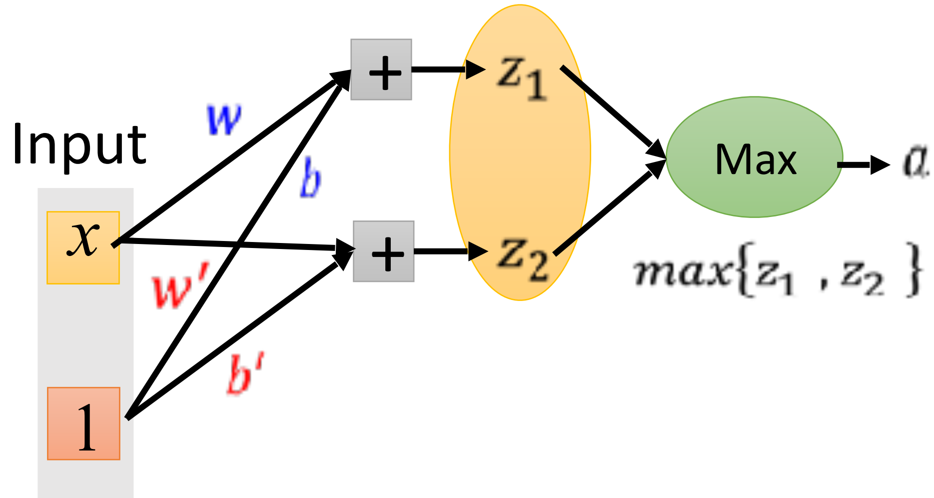

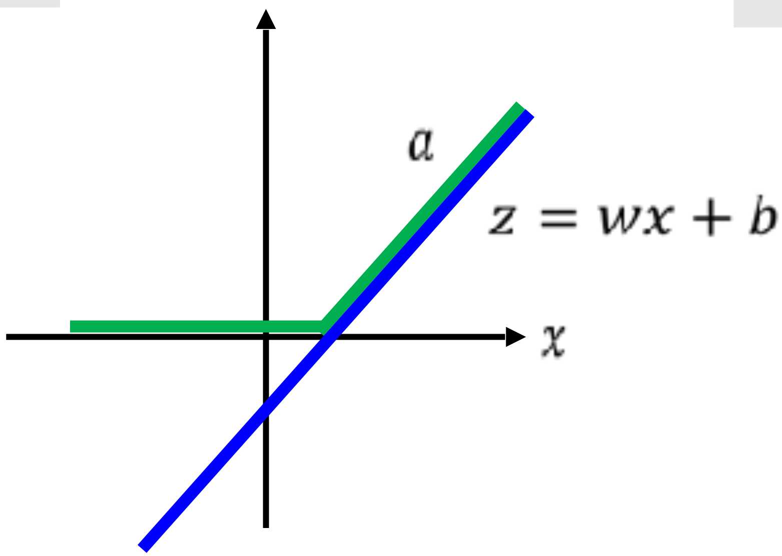

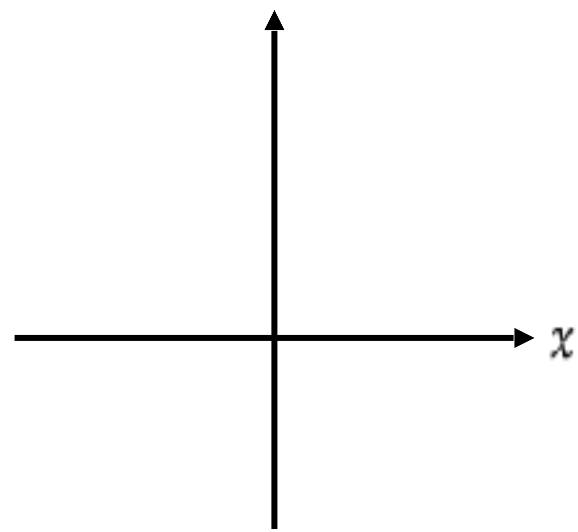

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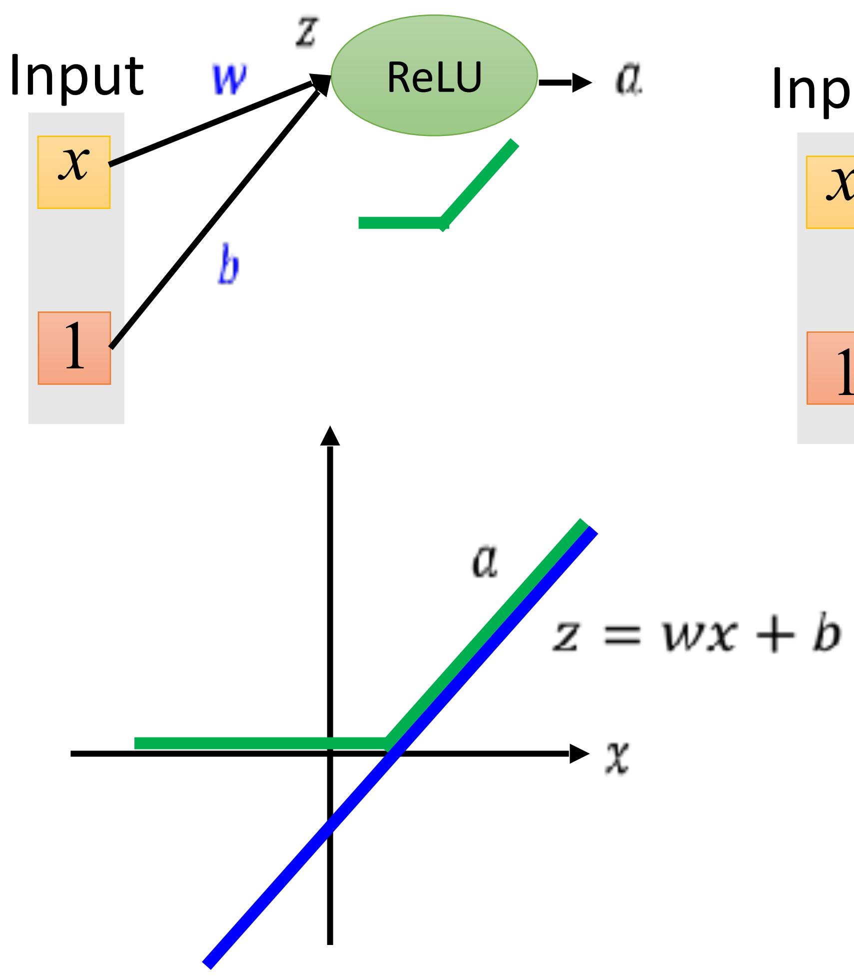

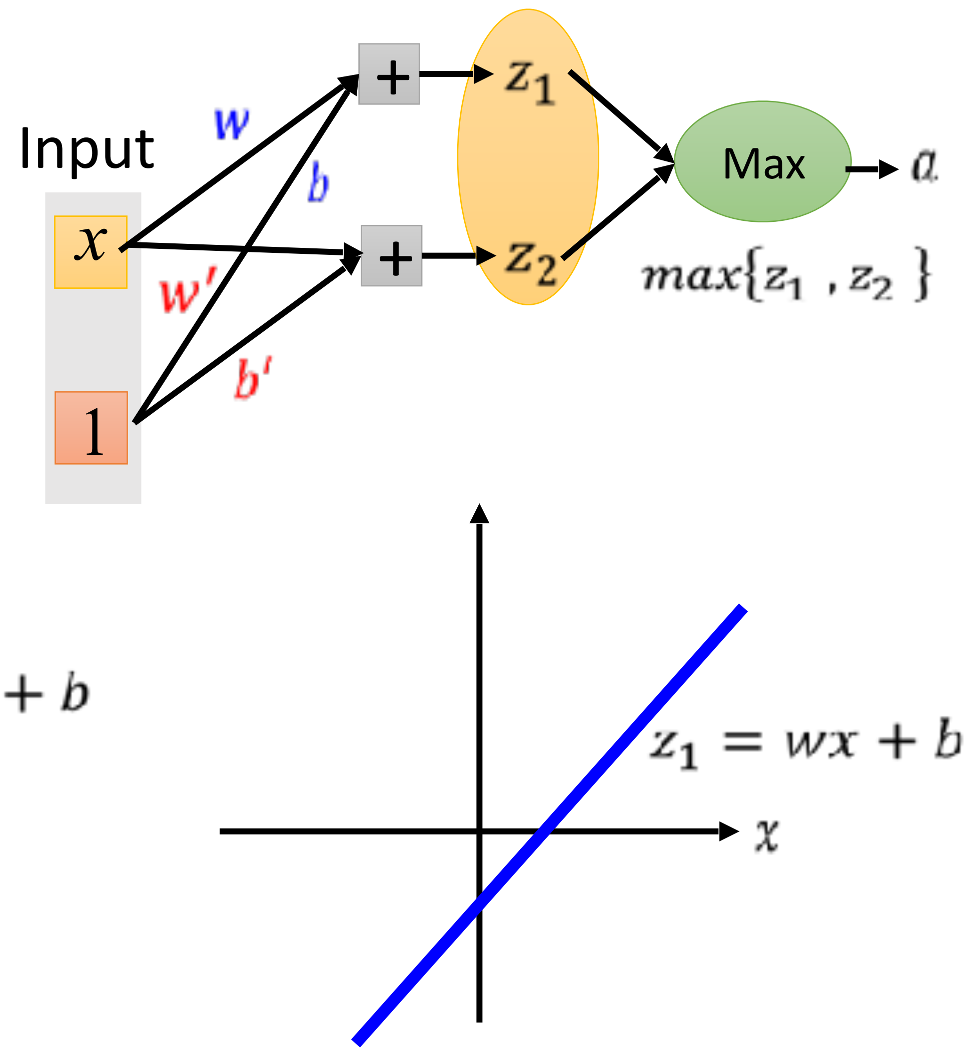

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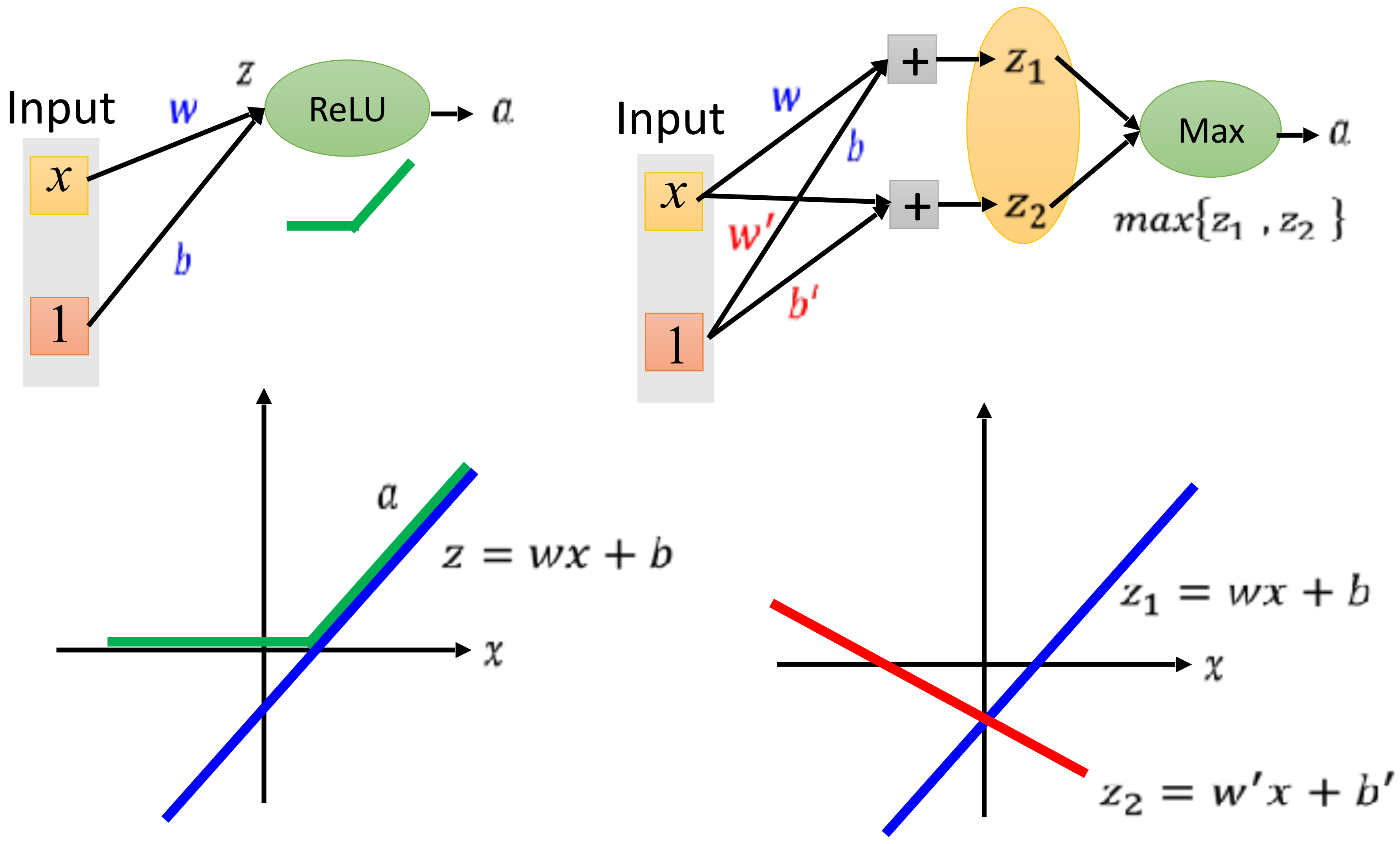

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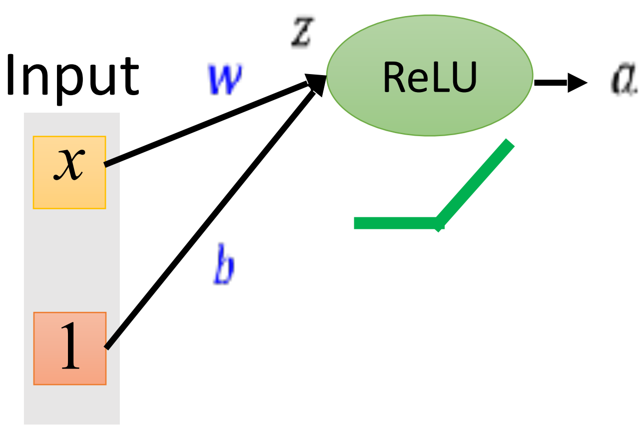

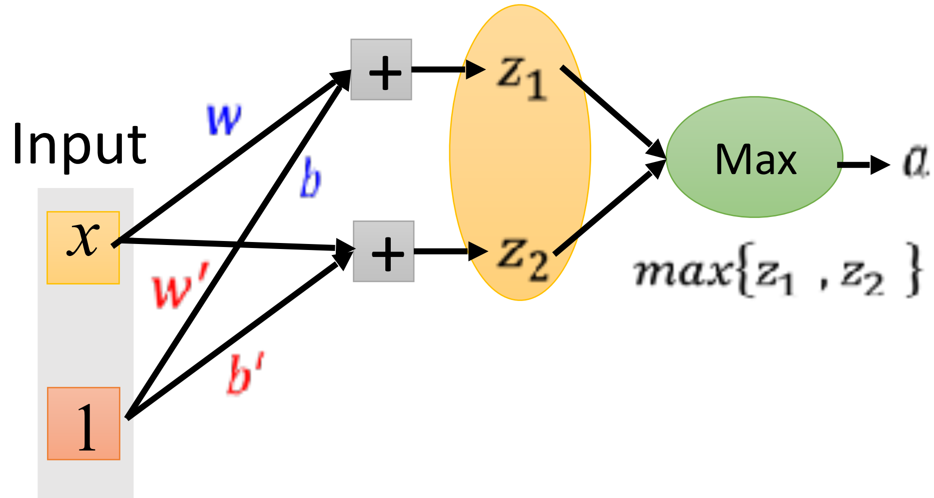

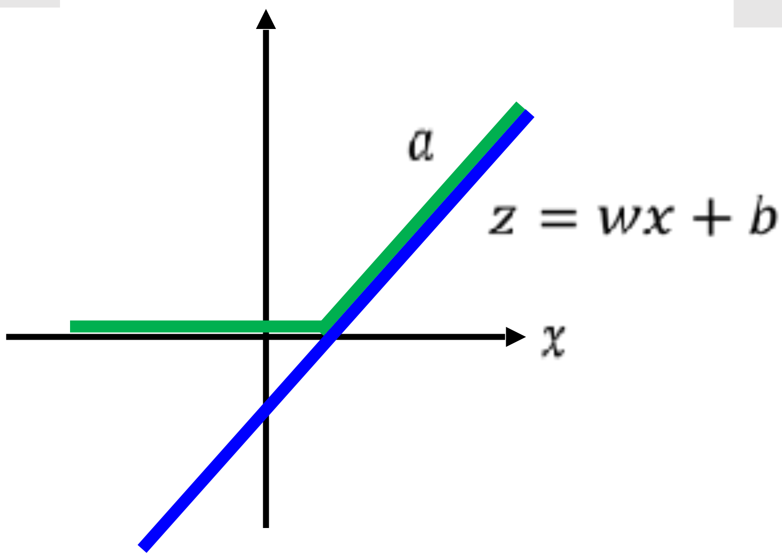

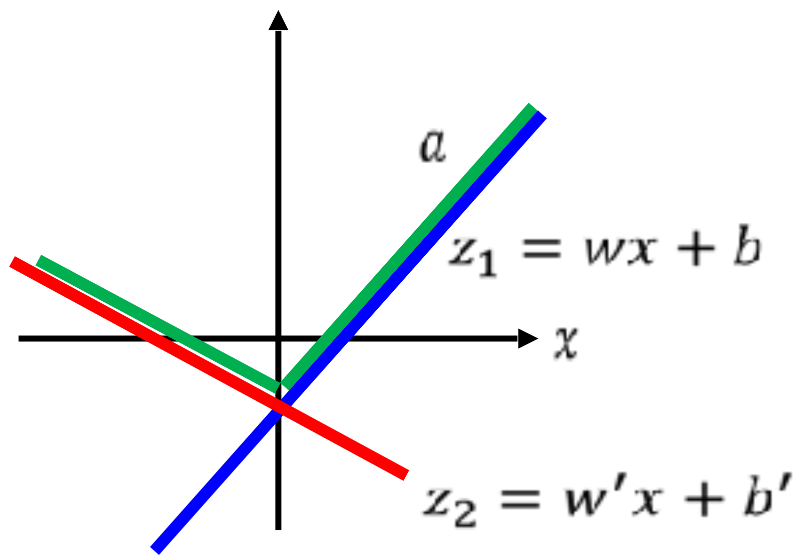

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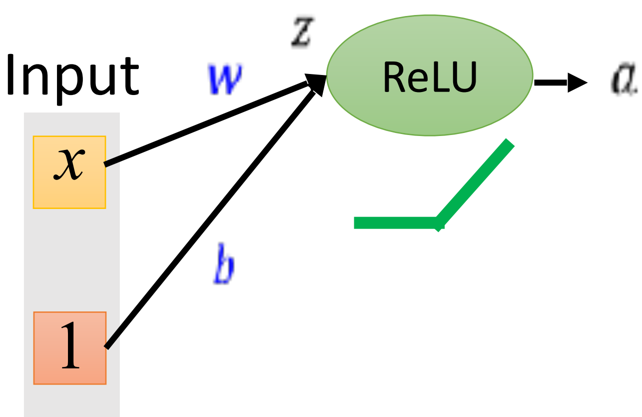

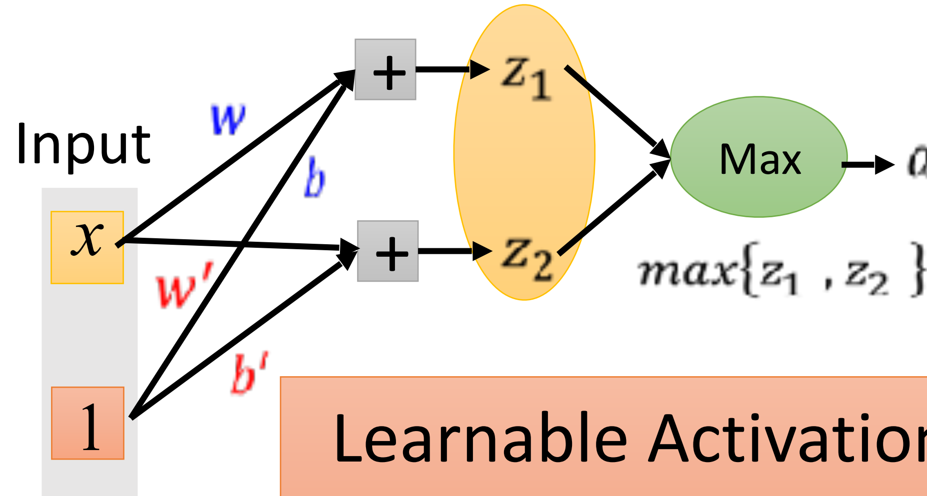

Learnable Activation Function