AI and Deep Learning

Deep Learning

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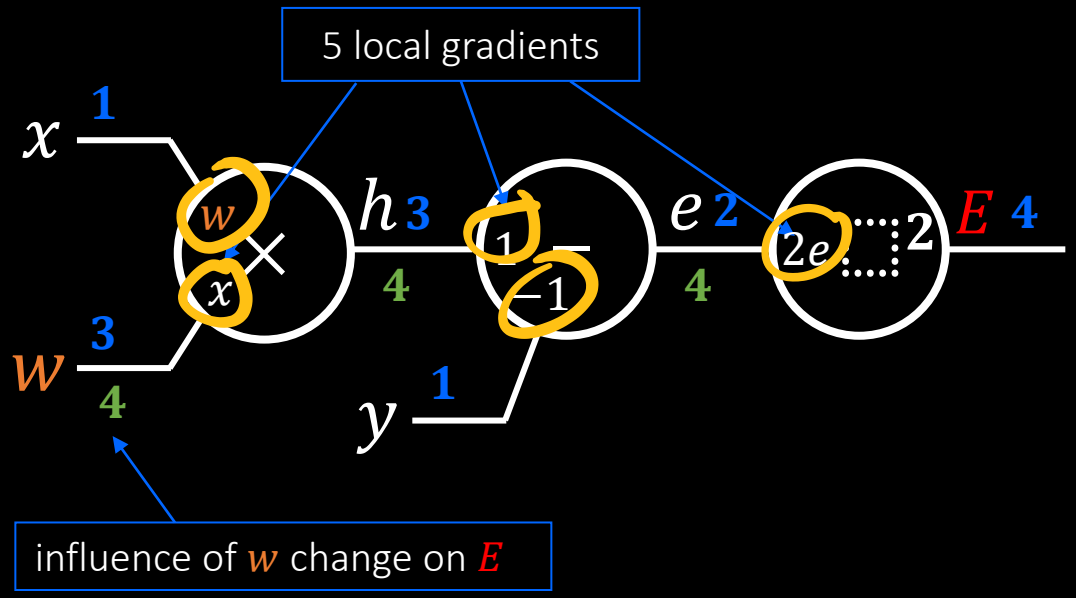
Yungcheol Byun

Agenda

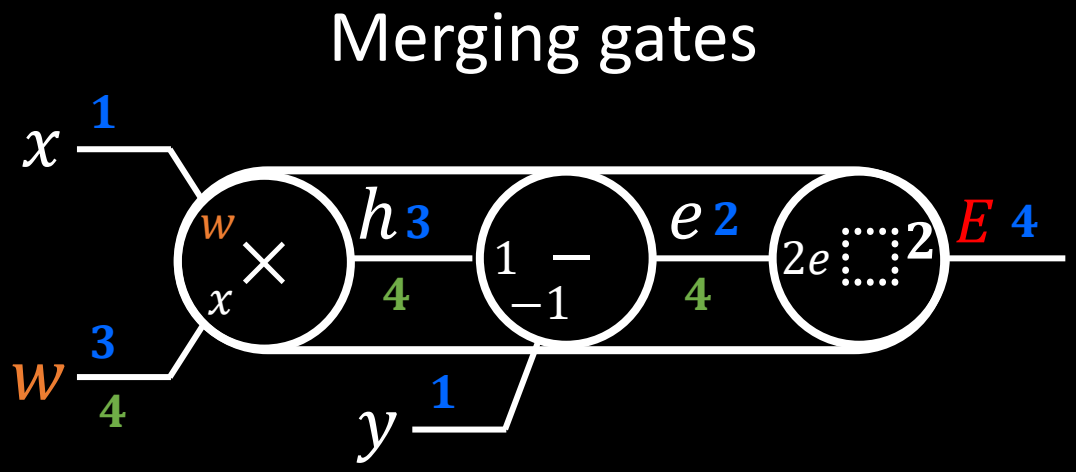
- Merging gates in a computation graph
- Vanishing gradient and ReLU
- MNIST application
- Overfitting and drop-out
- Deep Learning

Influence of w change on E



is multiplication of all the local gradients in the graph (chain rule)

Influence of w change on E



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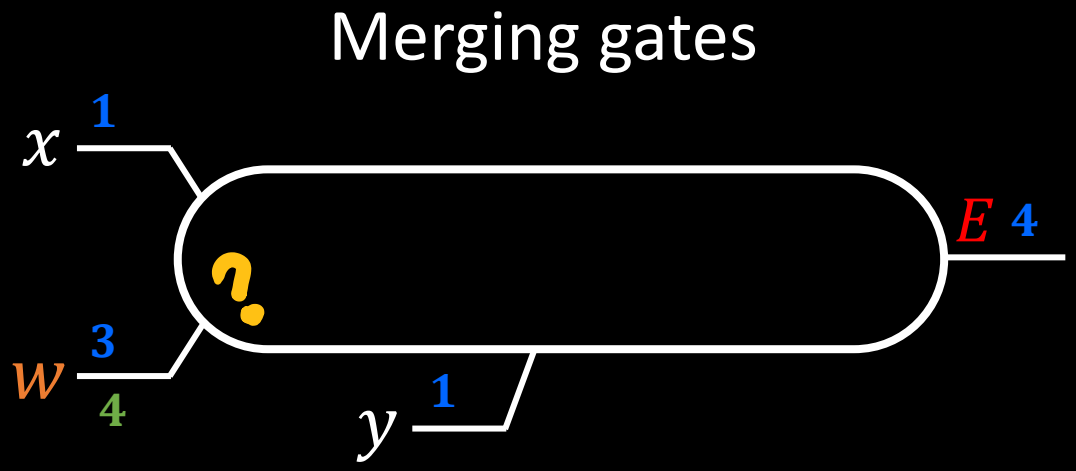
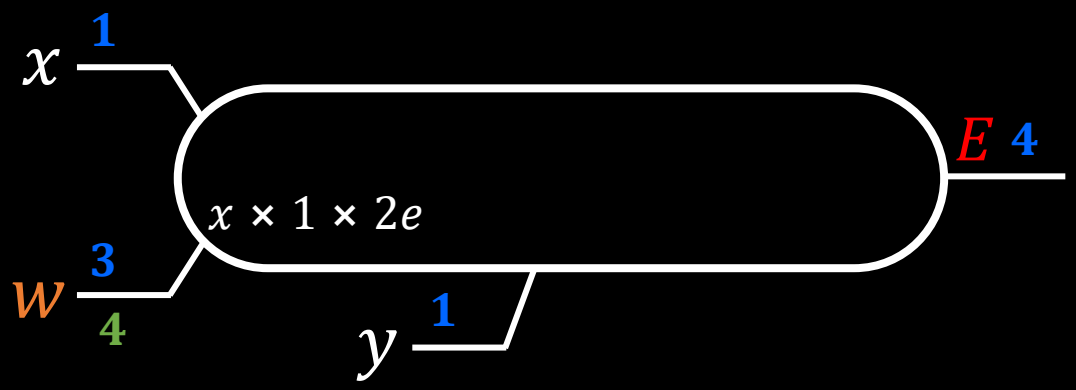


Influence of w change on E

Merging gates



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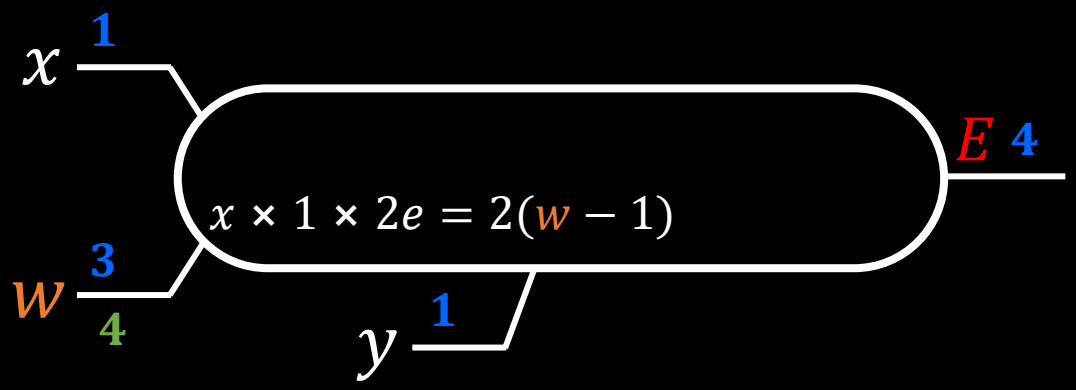
Influence of w change on E

Merging gates



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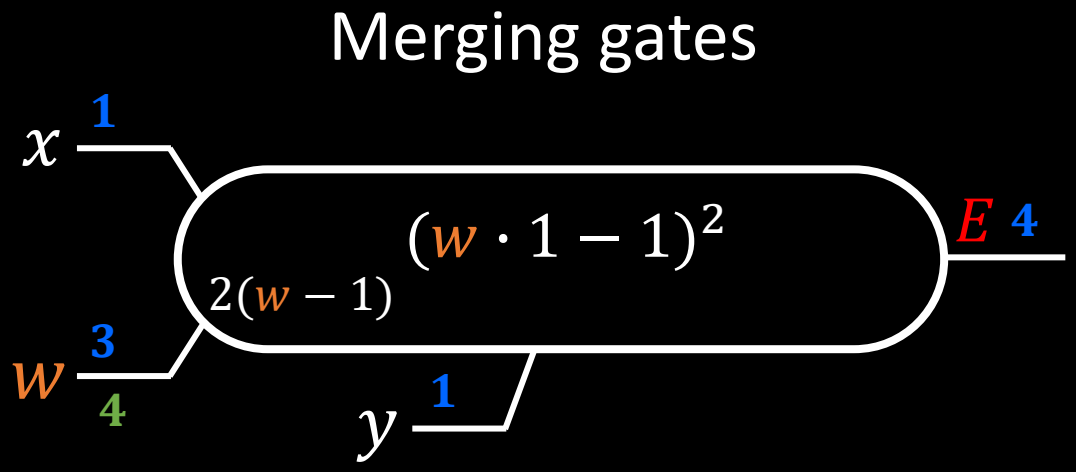
Influence of w change on E



Therefore, the local gradient is derivative of the function E.

Influence of w change on E

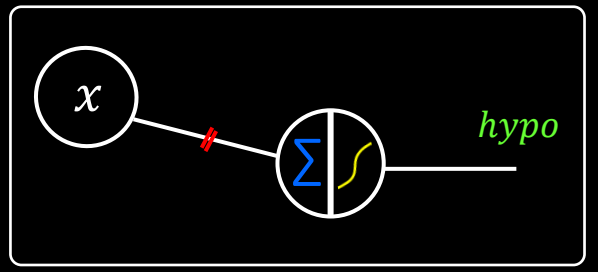
$$E = (w \cdot 1 - 1)^2$$

Derivative of E with respect to w

$$\frac{\partial E}{\partial w} = \frac{\partial}{\partial w}(w \cdot 1 - 1)^2 = 2(w - 1)$$

Cost/Error function

for logistic regression



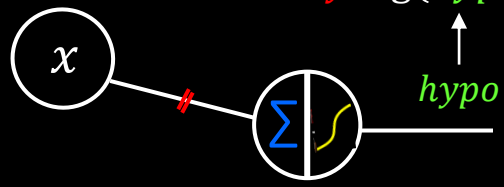
$$hypo = \frac{1}{1 + e^{-wx}}$$

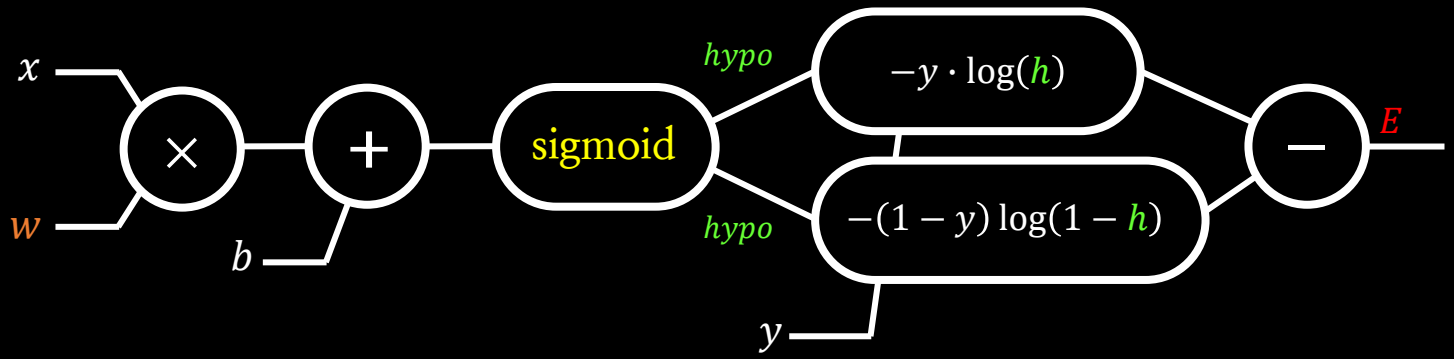
$$E = -y \log(hypo) - (1 - y)\log(1 - hypo)$$

Computational Graph

Binary Cross Entropy 오류함수(loss function)

$$E = -y\log(hypo) - (1-y)\log(1-hypo)$$



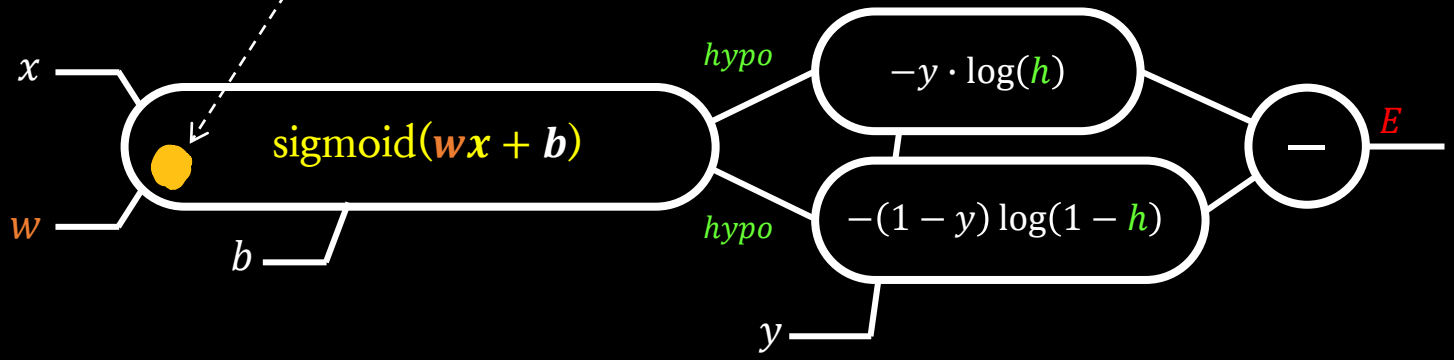


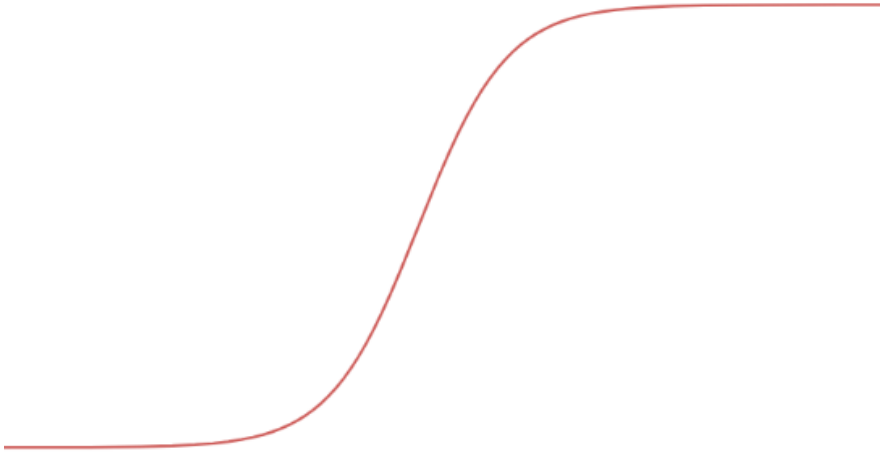
$$\frac{\partial E}{\partial w} =$$

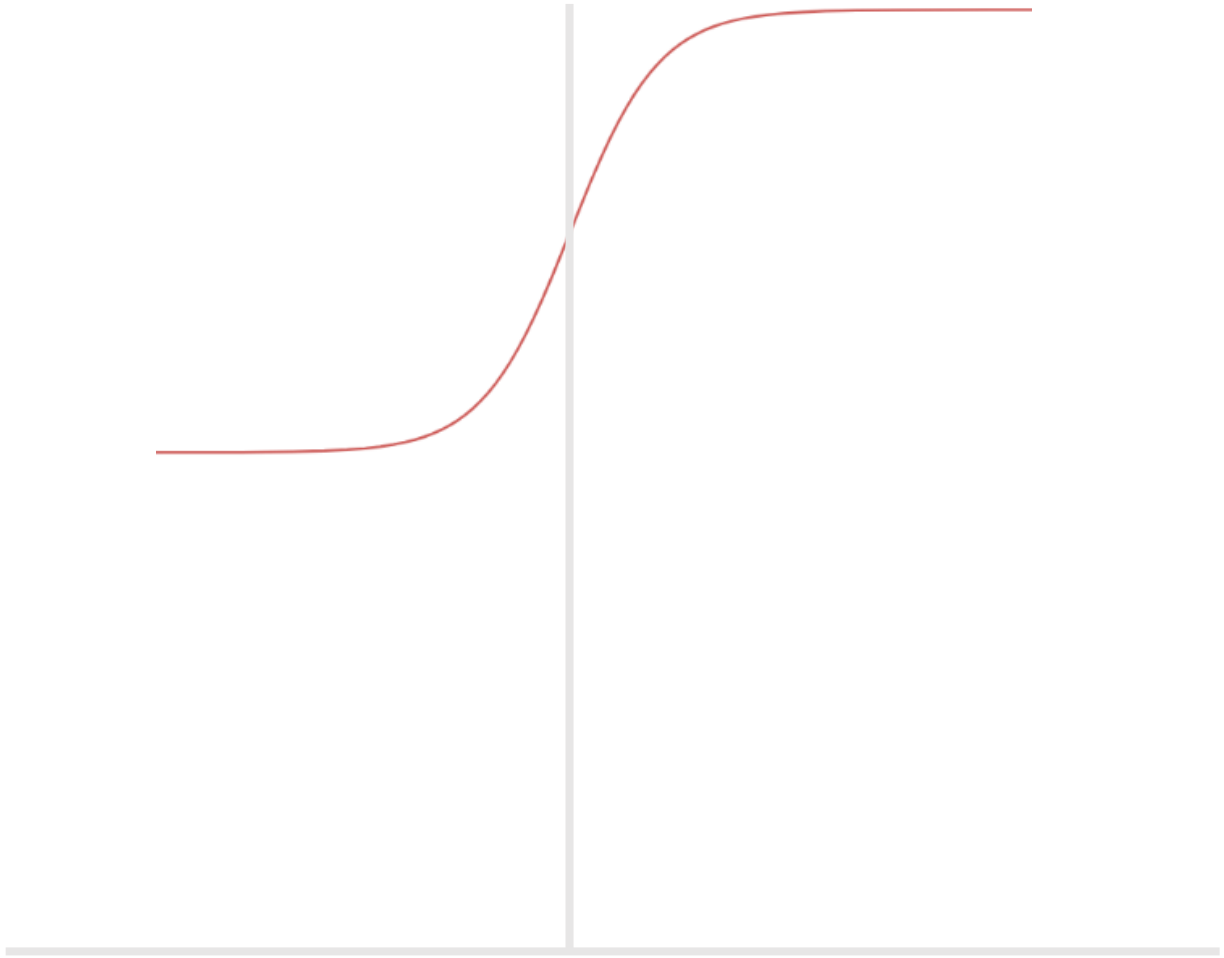
Computational Graph

Merging gates

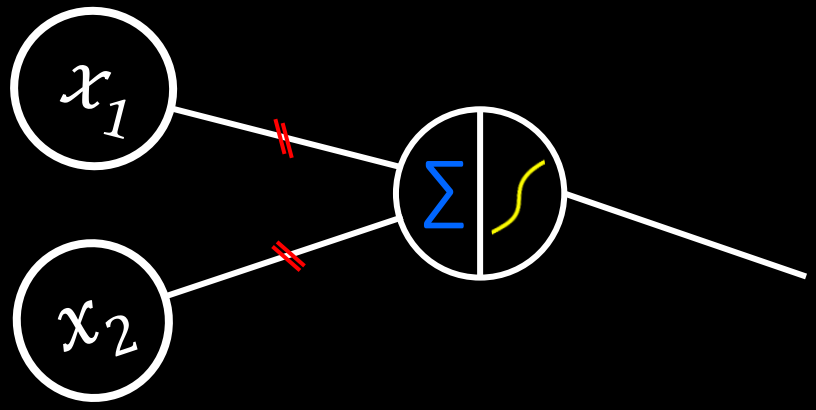
How we get the local gradient of the merged gate(sigmoid)?



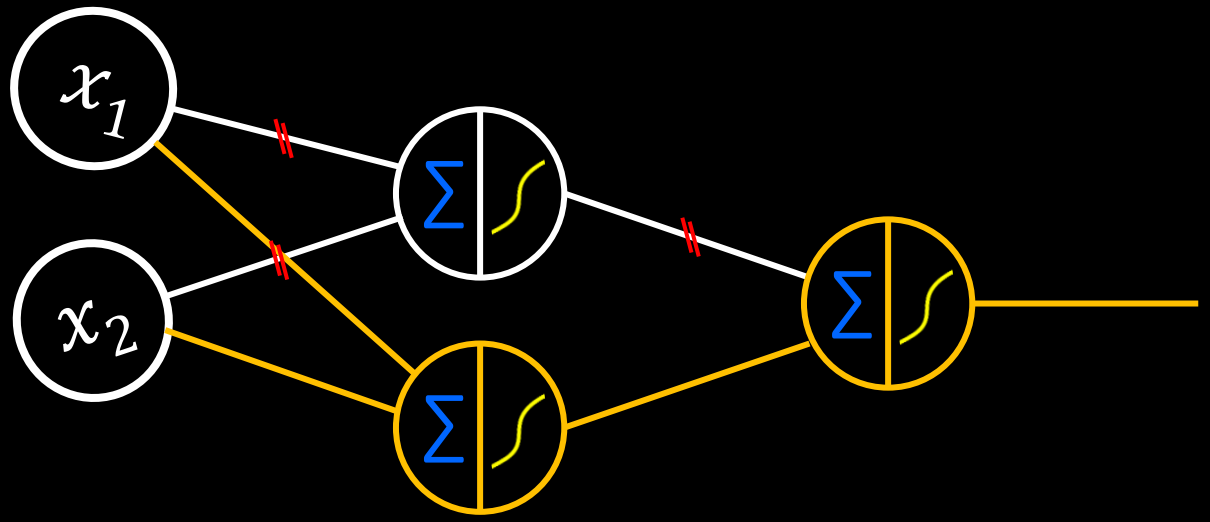




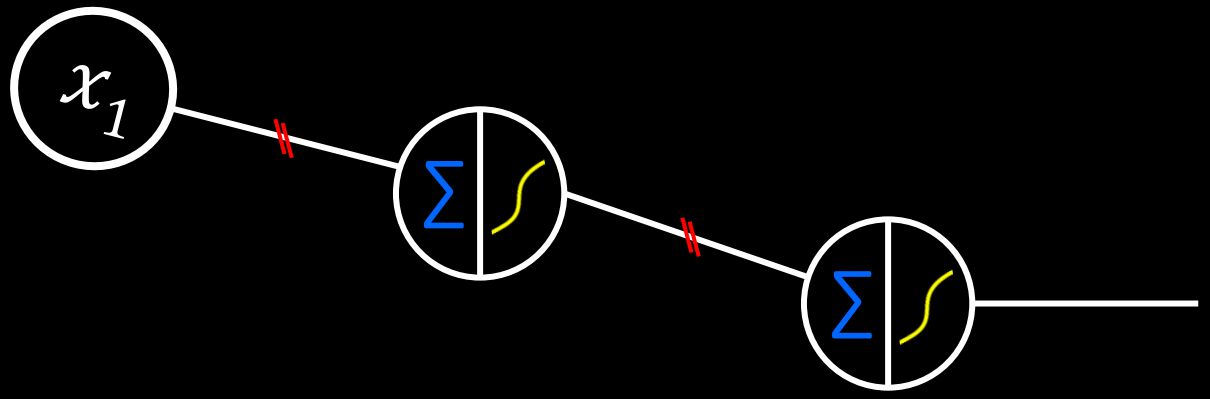
1 Neuron (2-layer)



3-layer NN



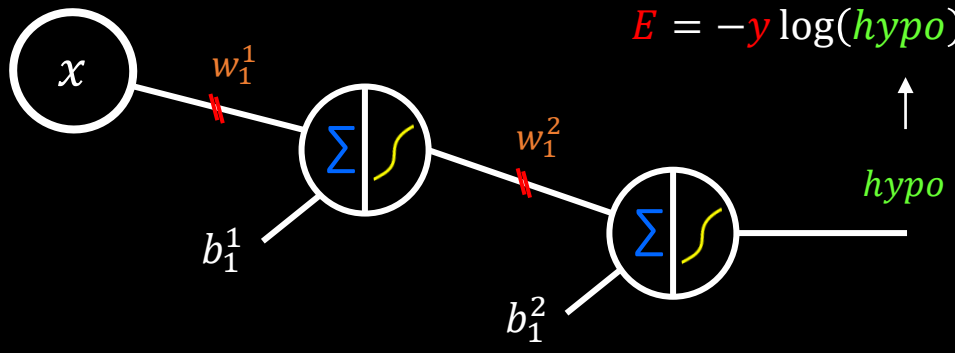
3-layer NN (simplified)

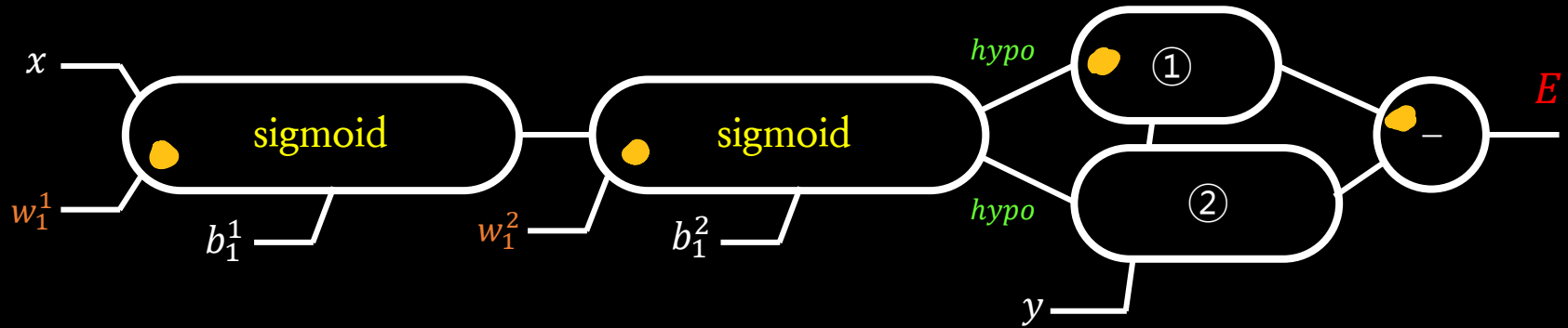


Influence of w change on E

$$E = -y\log(hypo) - (1-y)\log(1-hypo)$$

① ②

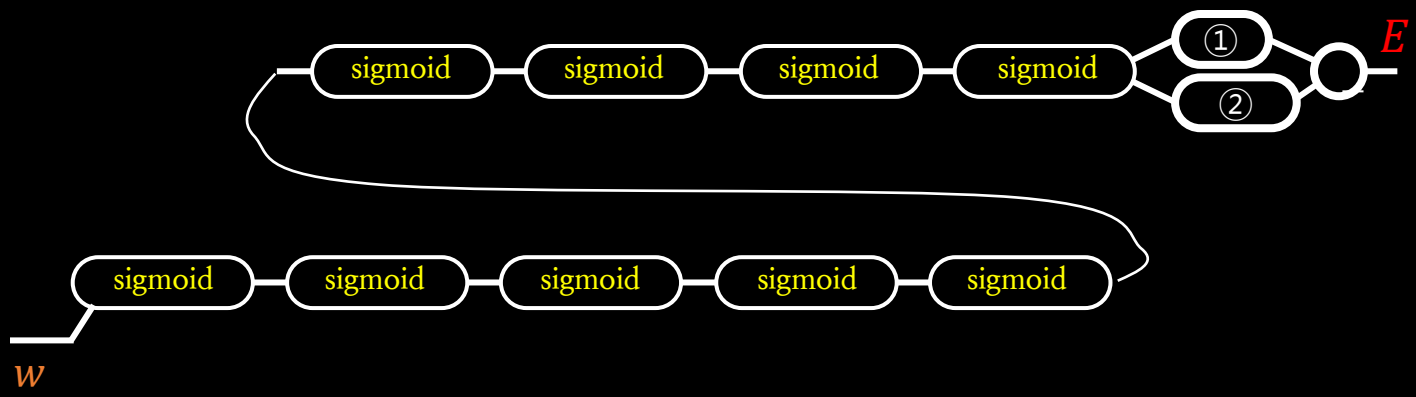




10-layer Neural Network

The giant monster, computational graph!

Influence of w change on E



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

Hint: chain rule!

Vanishing Gradient

- The derivative of sigmoid function is sigmoid x (1-sigmoid)
- Two multiplication of sigmoid for a single neuron, 18 multiplications for 9 connected neurons
- Each sigmoid gives us the value between 0 and 1.

0.5x0.5 x 0.1x0.9 x 0.8x0.2 x 0.5x0.5 x 0.3x0.7 x 0.4x0.6 x 0.5x0.5 x 0.2x0.8 x 0.5x0.5 x 0.6x0.4
= 0.00000010886 x ①

Vanishing Gradient

- The influence of w change on E is calculated through *many* multiplications of the values between 0 and 1, which gives us almost 0.
- Vanishing Gradient
- $w = w - \alpha \cdot$ (almost 0)
- $b = b - \alpha \cdot$ (almost 0)
- Therefore, no updates in w and b

(Lab) 18.py

- XOR problem using 4-layer neural networks
- Failed owing to vanishing gradient

https://github.com/yungbyun/neuralnetworks

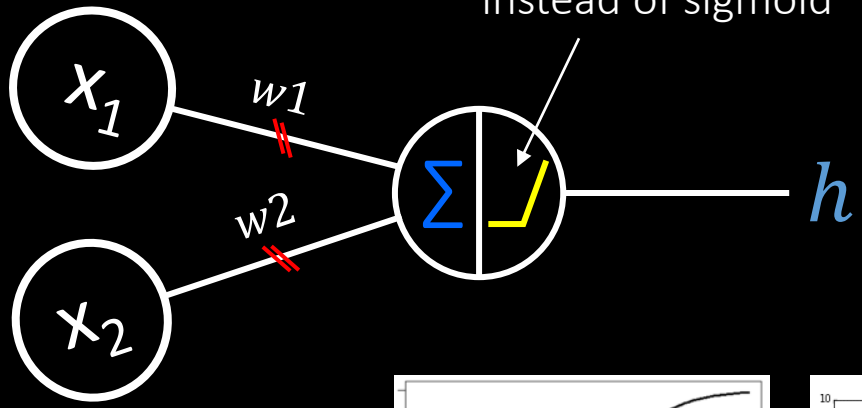
The Dark Age in Artificial Intelligence and Neural Networks (~2006)

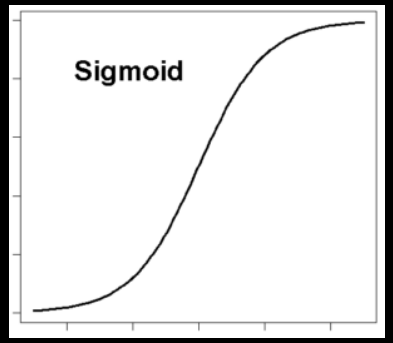
since back-propagation by Hinton in 1986

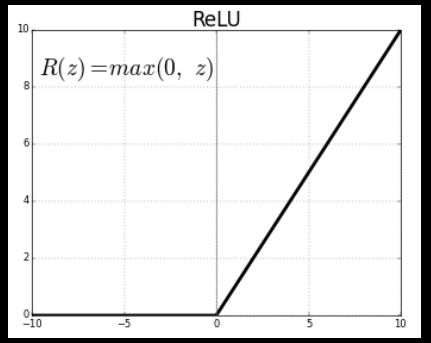
ReLU

proposed by Hahnloser in 2000 and demonstrated for deep networks in 2011

using ReLU (Rectified Linear Unit) instead of sigmoid







(Lab) 19.py

- Solving vanishing gradient problem using ReLU activation function
- Back-propagation is working by using ReLU.

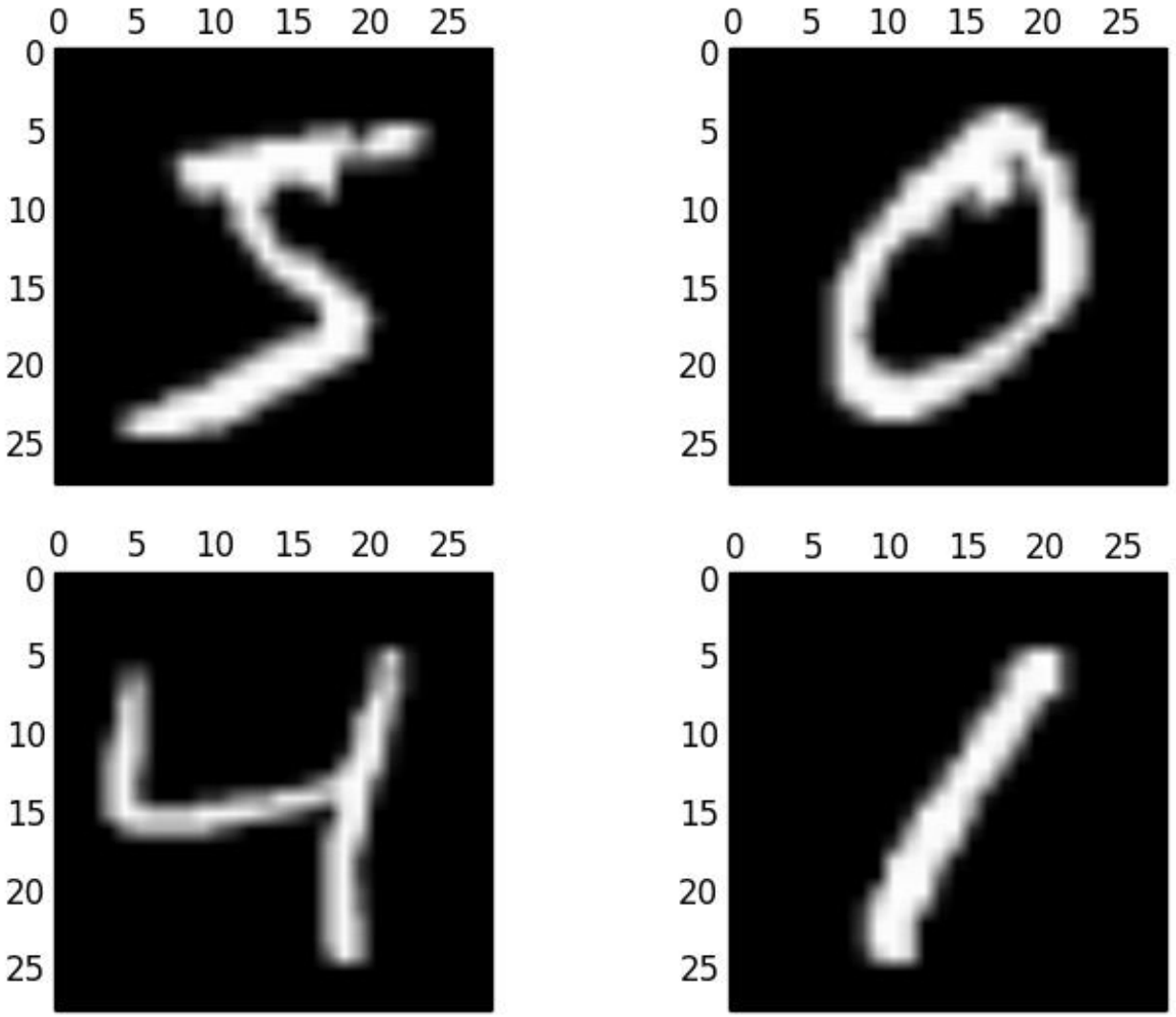
https://github.com/yungbyun/neuralnetworks

So, now can go deeper.

MNIST

Modified National Institute of Standards and Technology (USA)

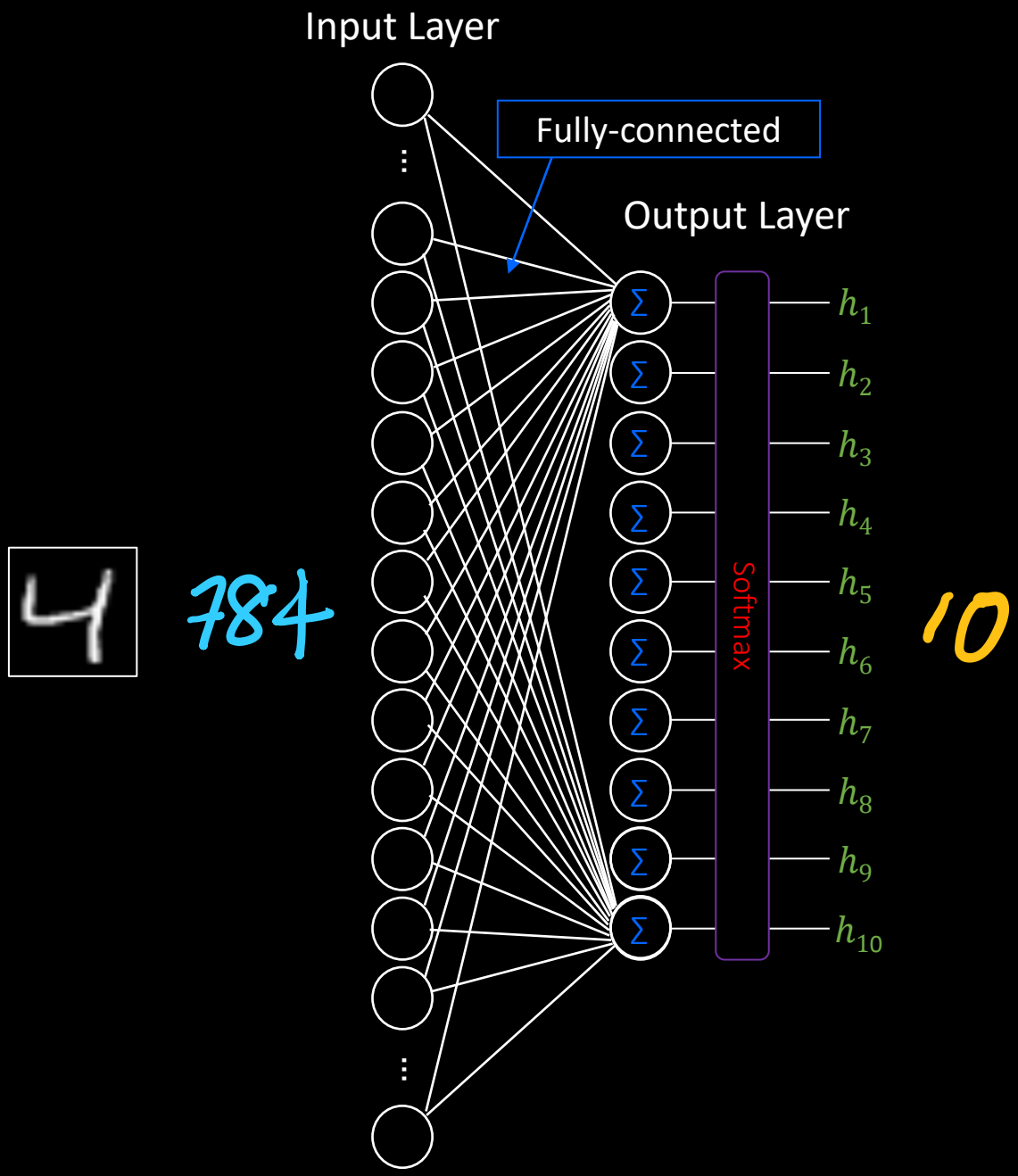
MNIST

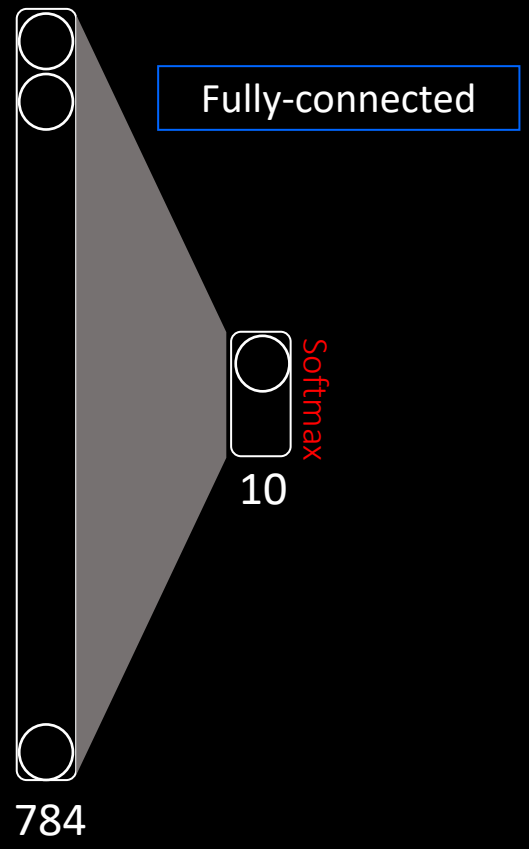

0 5 10 15 20 25
0
5
10
15
20
25

(Lab) 20.py

- 60,000 training images + 10,000 testing images
- Input image : 28 * 28 pixels → 784 pixels
- 784 dimension
- 10 classes (output: 0 ~ 9)
- Softmax
- 90.23% of recognition rate

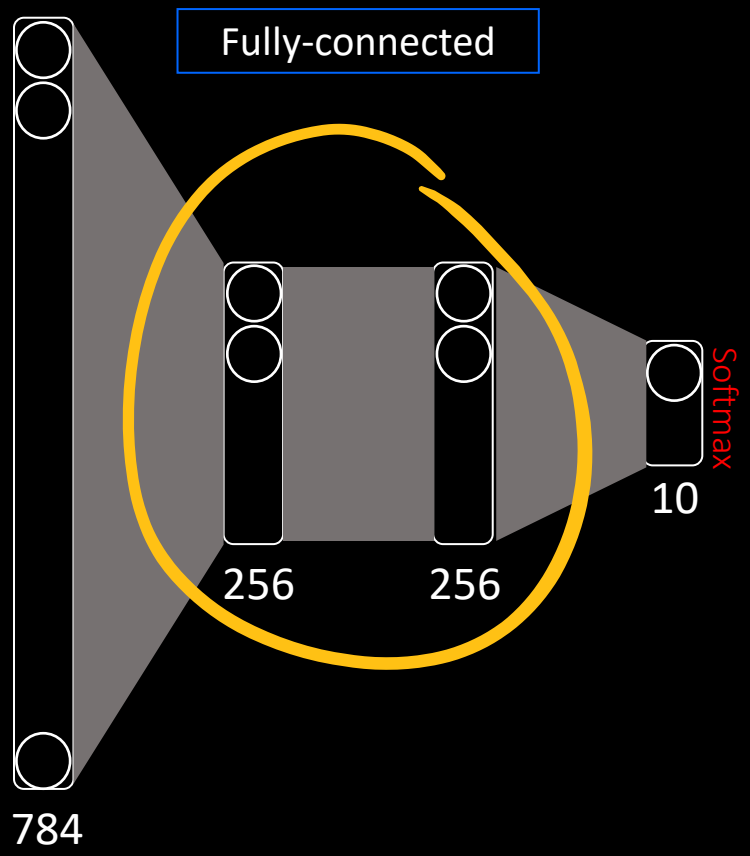
https://github.com/yungbyun/neuralnetworks


Input Layer
Fully-connected
Output Layer
Softmax
784
10
h_1
h_2
h_3
h_4
h_5
h_6
h_7
h_8
h_9
h_{10}


Fully-connected
Softmax
10
784

(Lab) 21.py

- Deep Neural Network (4-layer)
- ReLU
- 94.55% accuracy



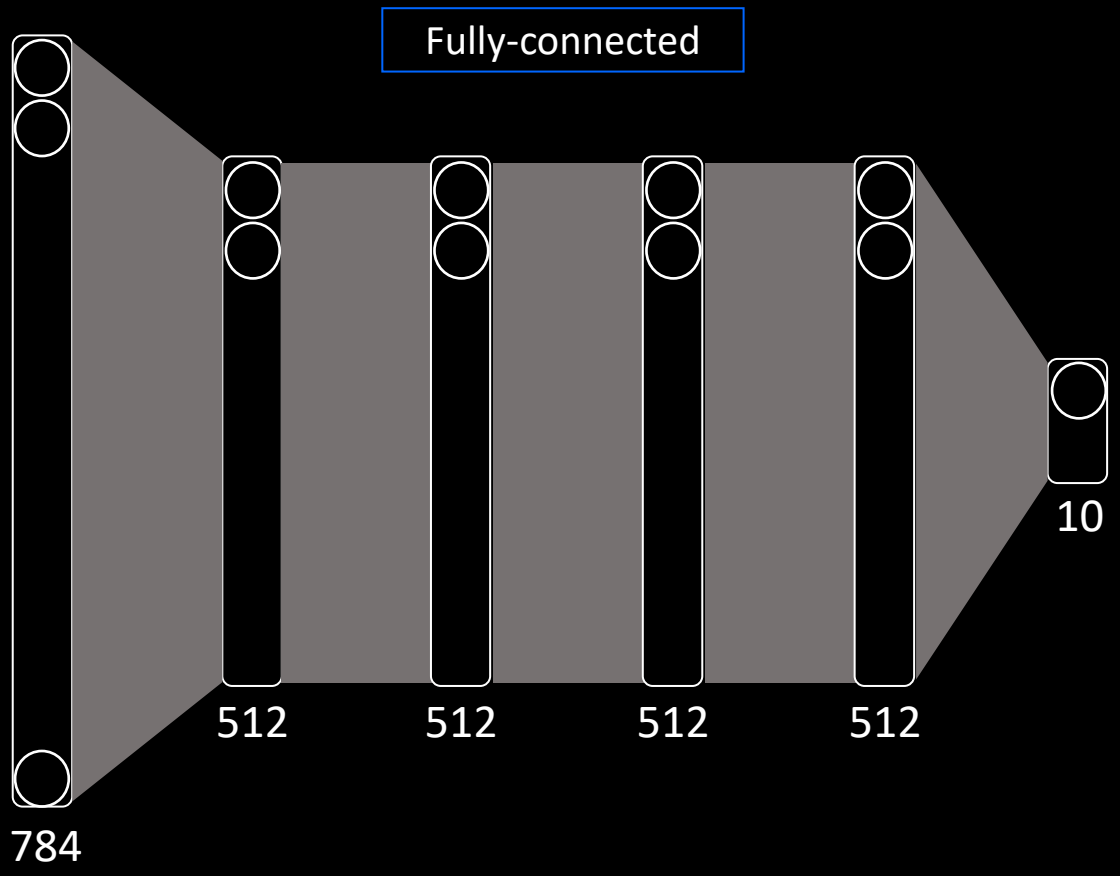
https://github.com/yungbyun/neuralnetworks

(Lab) 22.py

- Applying initialization method for w and b, not randomly
- 97.23% of accuracy

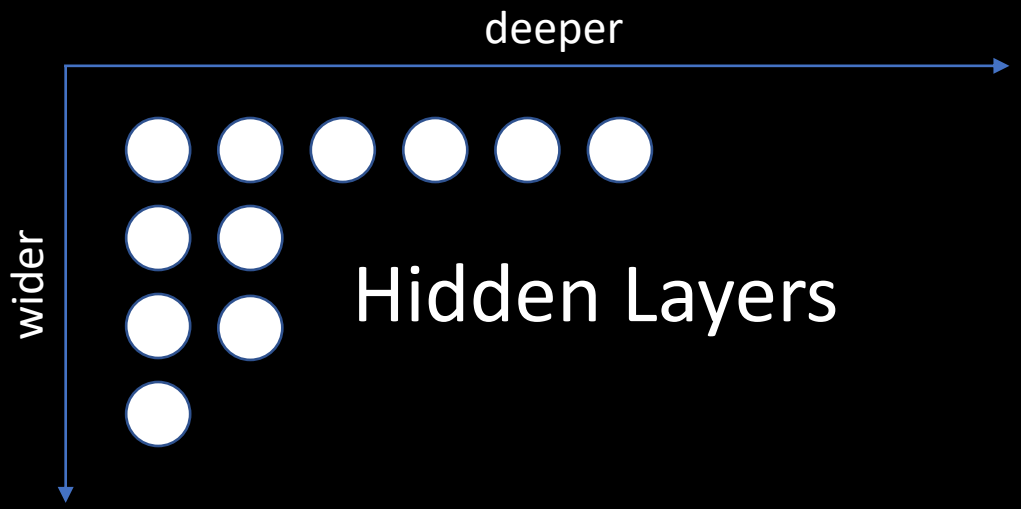
https://github.com/yungbyun/neuralnetworks

(Lab) 23.py



- Applying initialization method for w and b, not randomly
- 6-layer deep neural networks
- 97.83% of accuracy

Decision Boundry



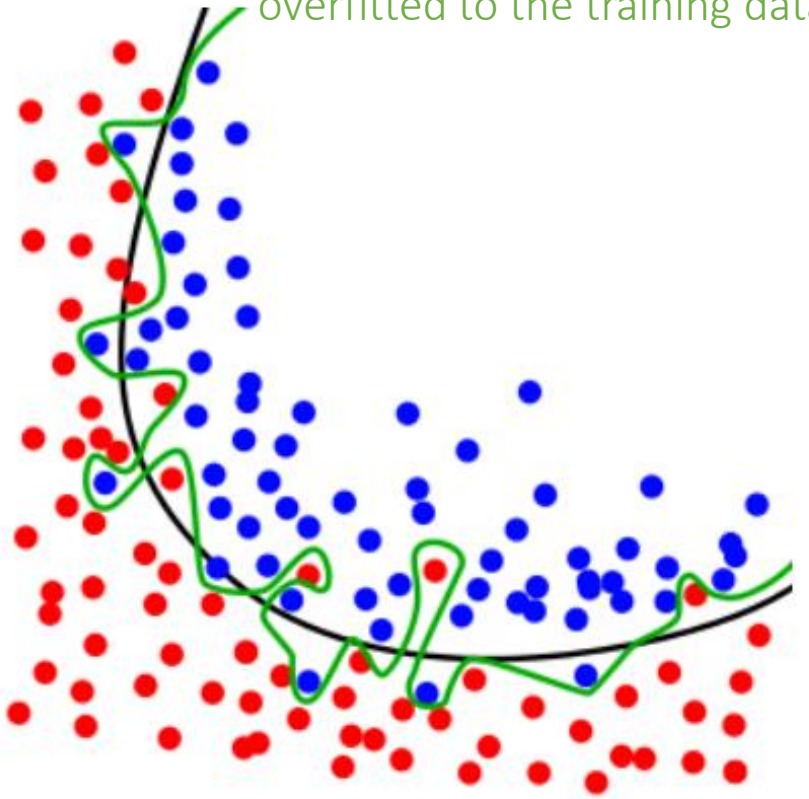
“

Lots of neurons (connections, synapses) give us so complicated decision boundry

Which do you think is desirable decision boundary?

overfitted to the training data

View from above



While the black line fits the data well, the green line is overfit.

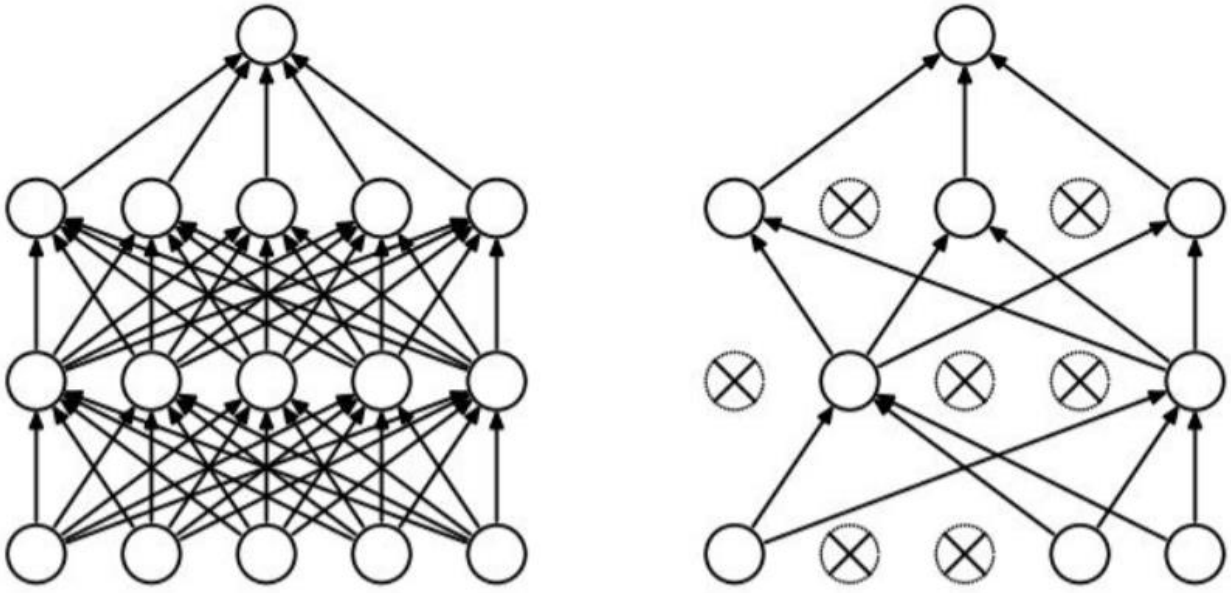
https://elitedatascience.com

Overfitting and drop-out

- The deeper the network is, the more the decision boundary is complex.
- Good at training data but errors for testing data → overfitted to the training data
- Making it less complex by drop-out some neurons while learning.

Regularization: **Dropout**

"randomly set some neurons to zero in the forward pass"



(a) Standard Neural Net

(b) After applying dropout.

[Srivastava et al., 2014]

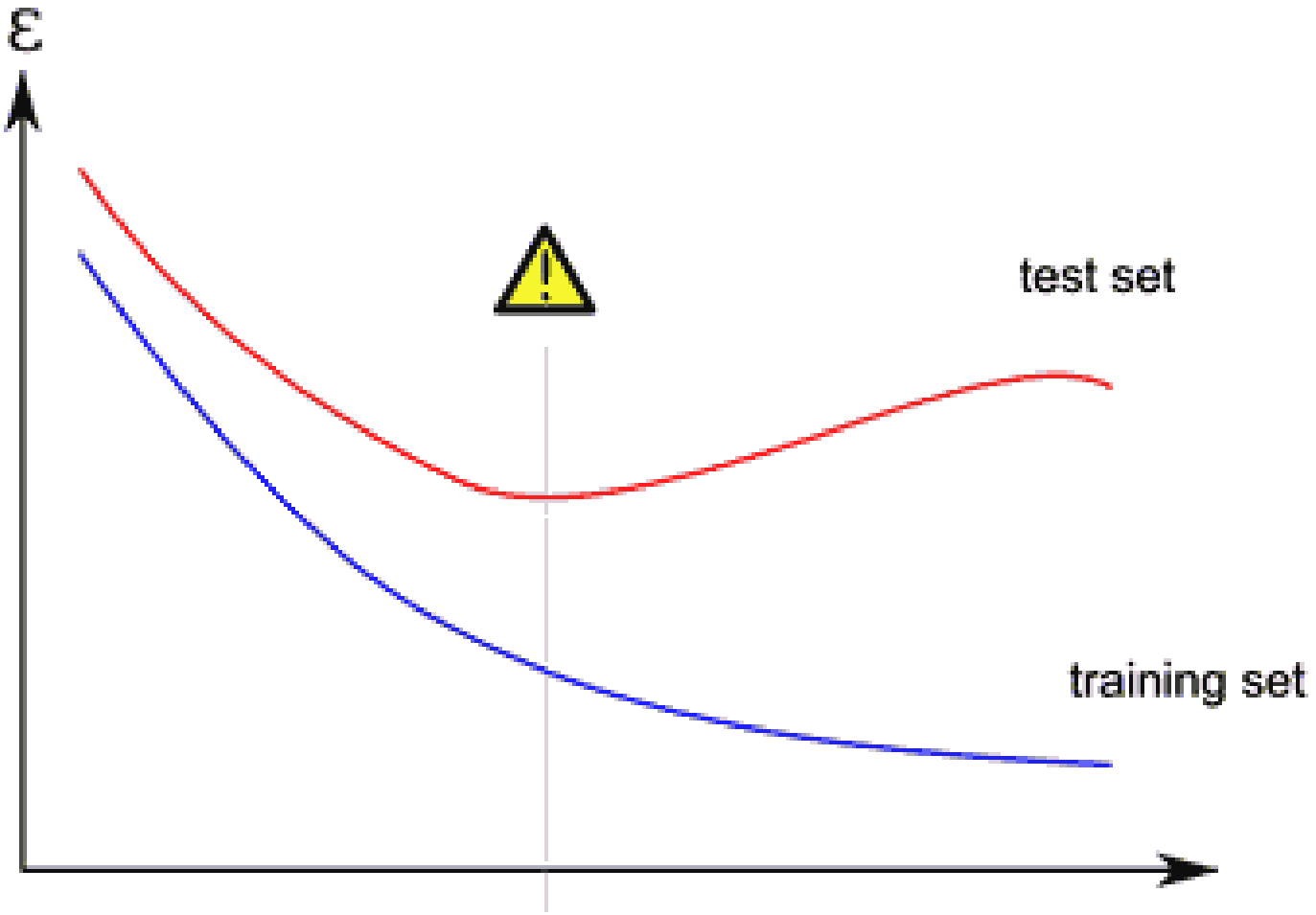
(Lab) 24.py

- Applying dropout
- 98.13% (←97.83%) of recognition accuracy

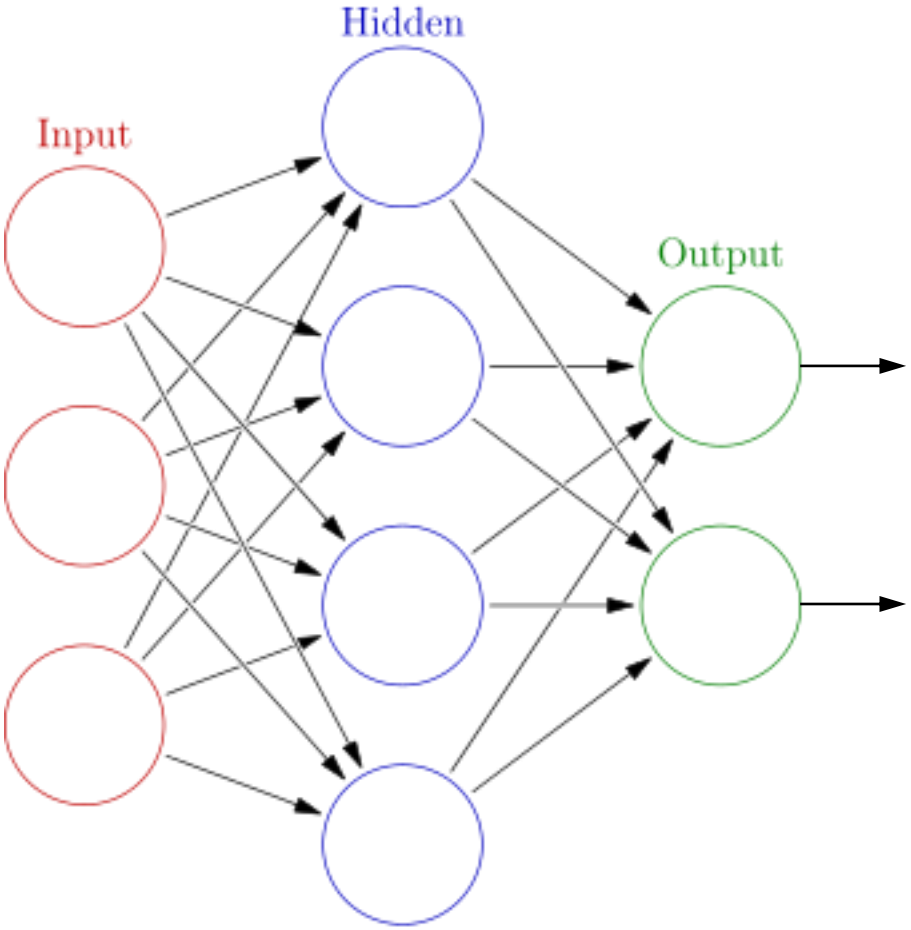
How to Prevent Overfitting

- Train with more data
- Reduce features
- Early stopping
- Ensemble
- Regularization

Early stopping



Fully-connected



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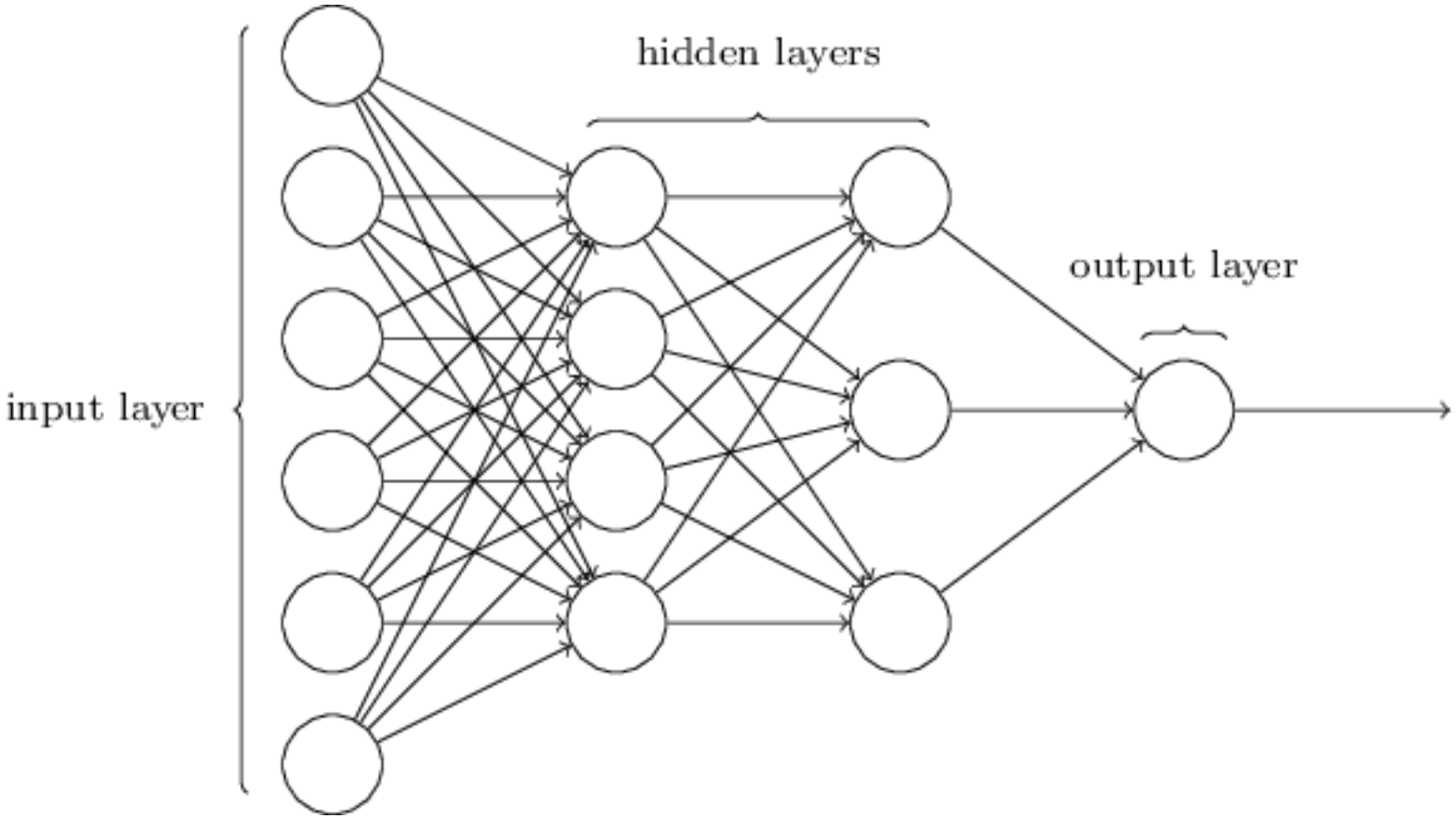
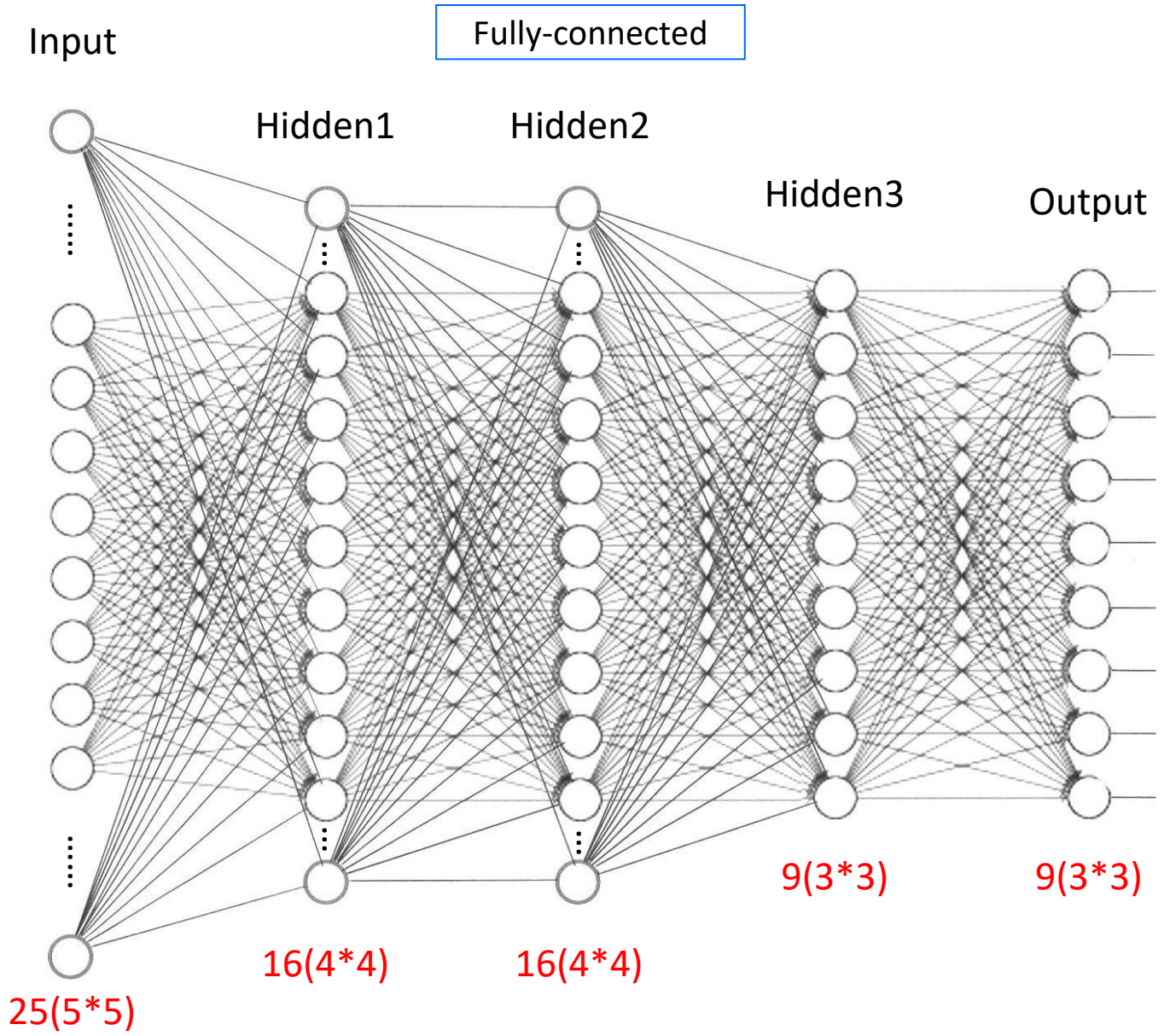
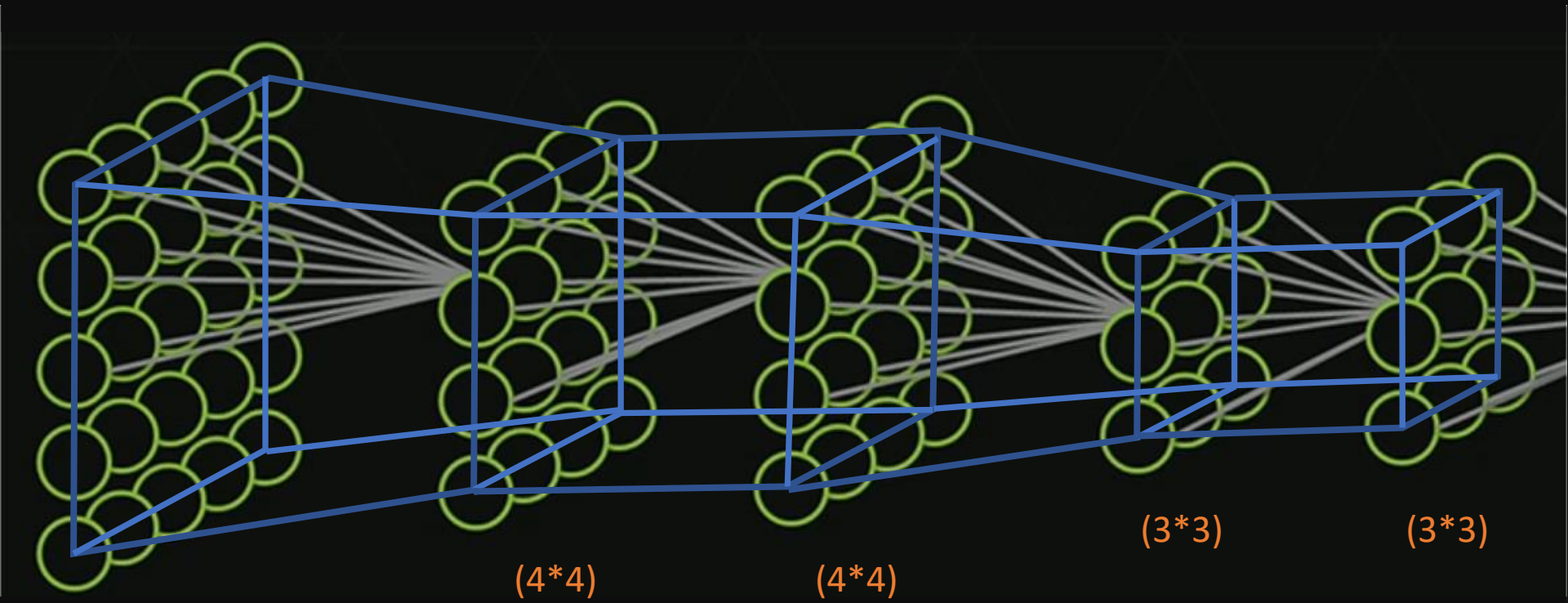




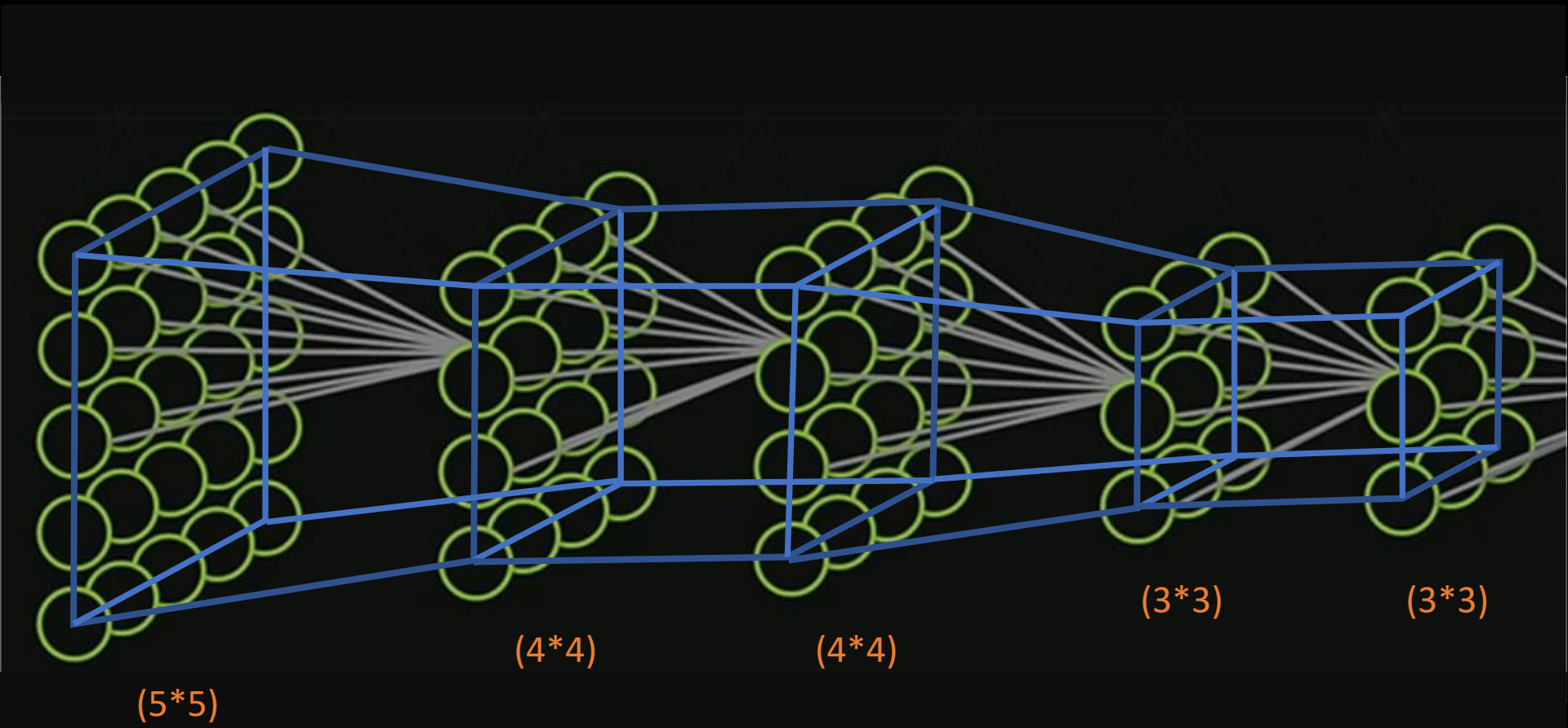
Fully connected, then how many connections(synapses, parameters) are there?

25 * 16 + 16 * 16 + 16 * 9 + 9 * 9 = 881

Fully-connected



Fully-connected



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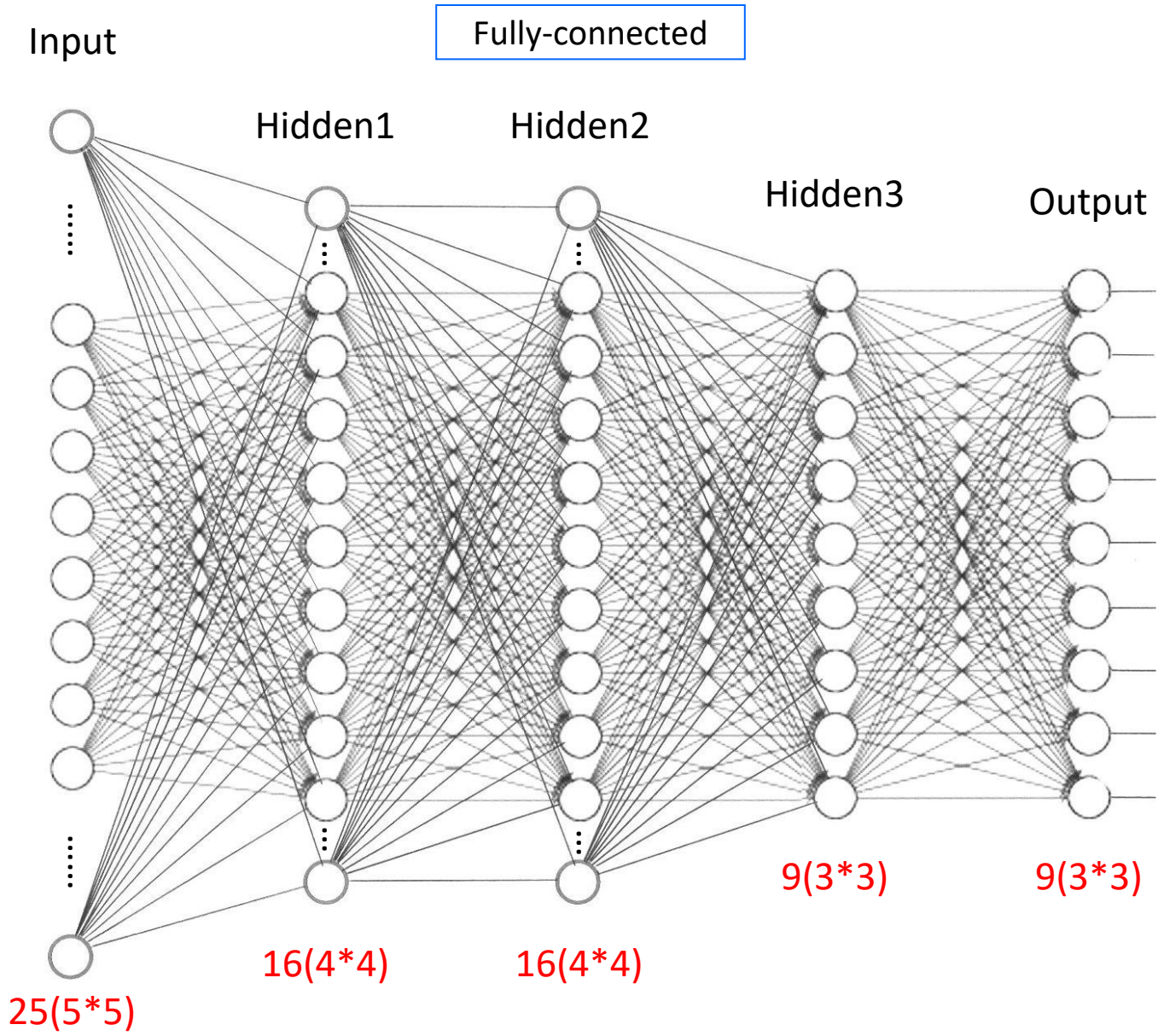

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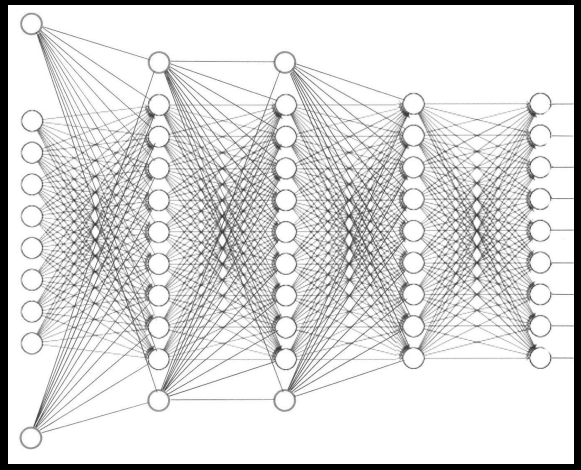
Geoffrey Hinton, Yann LeCun, Yoshua Bengio, Andrew Ng

Google Baidu 百度 facebook IBM

Deep Learning

- in early 2000s (2006, 2010, 2012)
- Deep Neural Networks
- Activation functions (ReLU)
- Weight initialization methods
- Dropout (2014)
- Big data
- GPU

Fully-connected



FCNN

Any problem? Yes, so CNN!