AI and Deep Learning

Deep Learning

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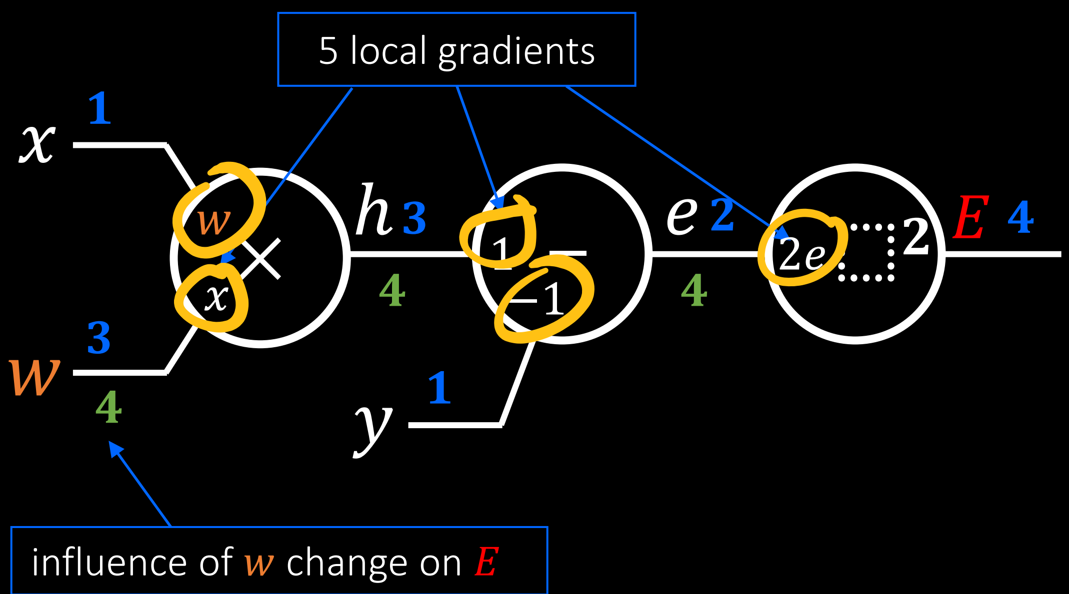
Agenda

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

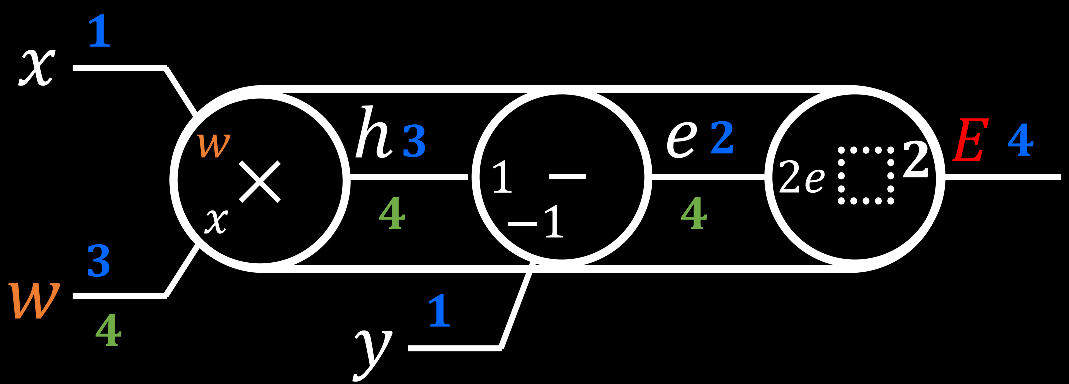
Influence of w change on E



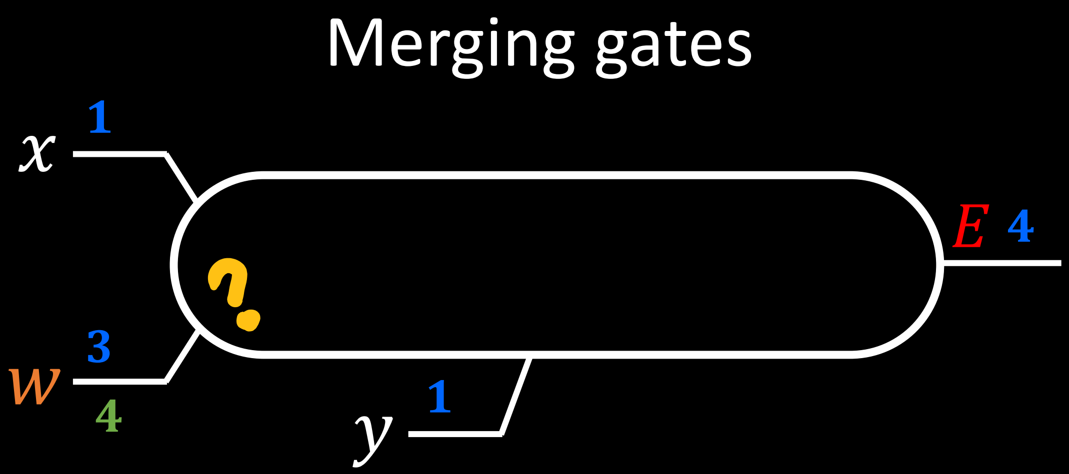
is multiplication of all the local gradients in the graph
(chain rule)

Influence of w change on E

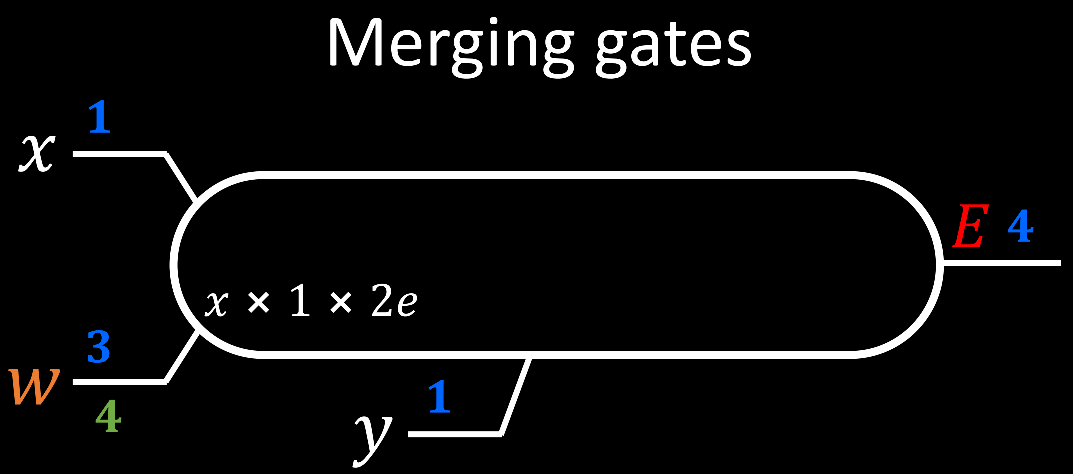
Merging gates



Influence of w change on E



Influence of w change on E



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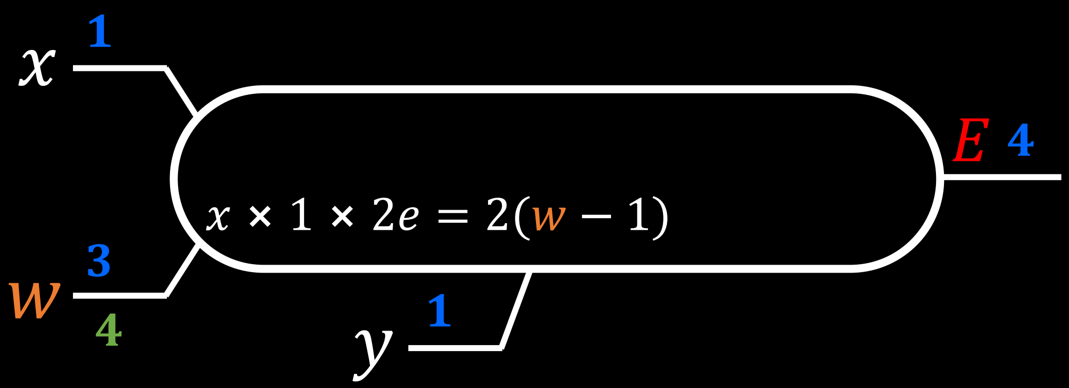
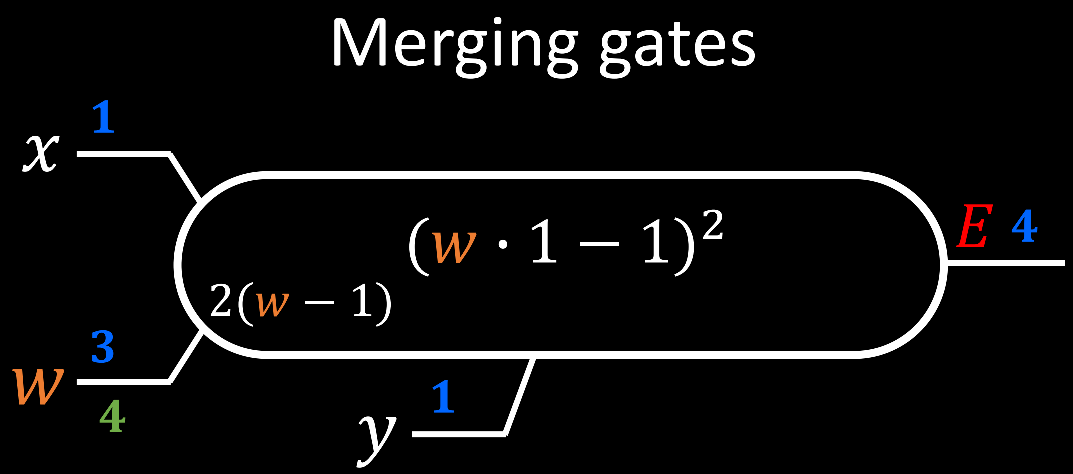
Influence of w change on E

Merging gates



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

Influence of w change on E



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

Influence of w change on E

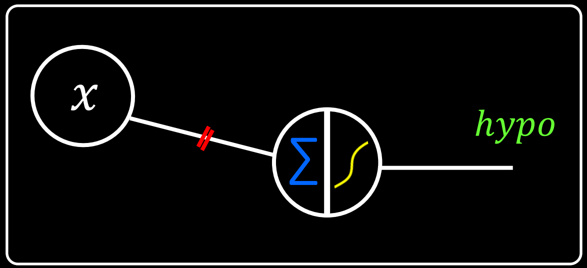
$$E = (w \cdot 1 - 1)^2$$

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

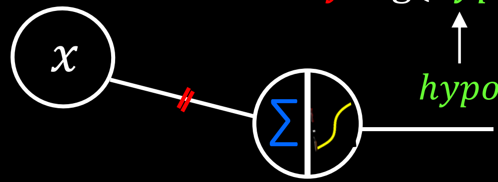


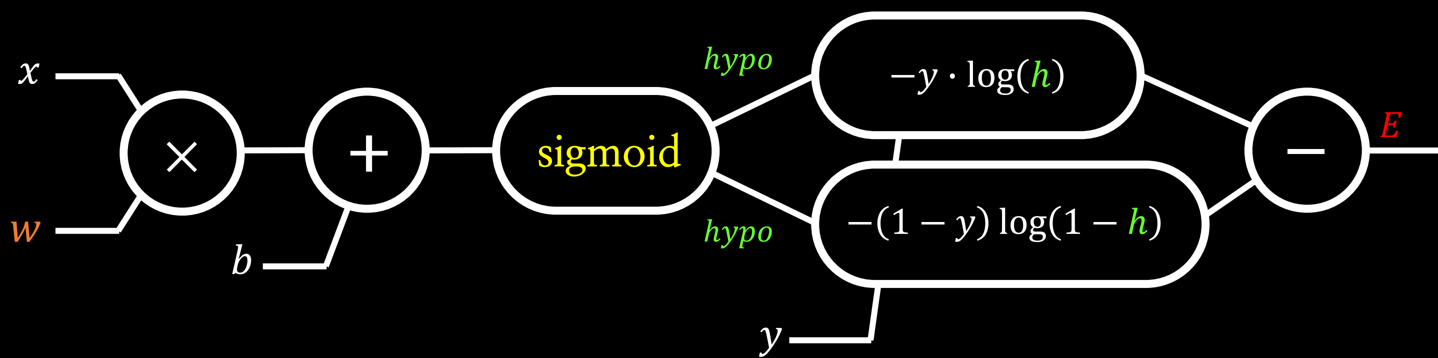
$$hypo = \frac{1}{1 + e^{-wx}}$$

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

Computational Graph

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



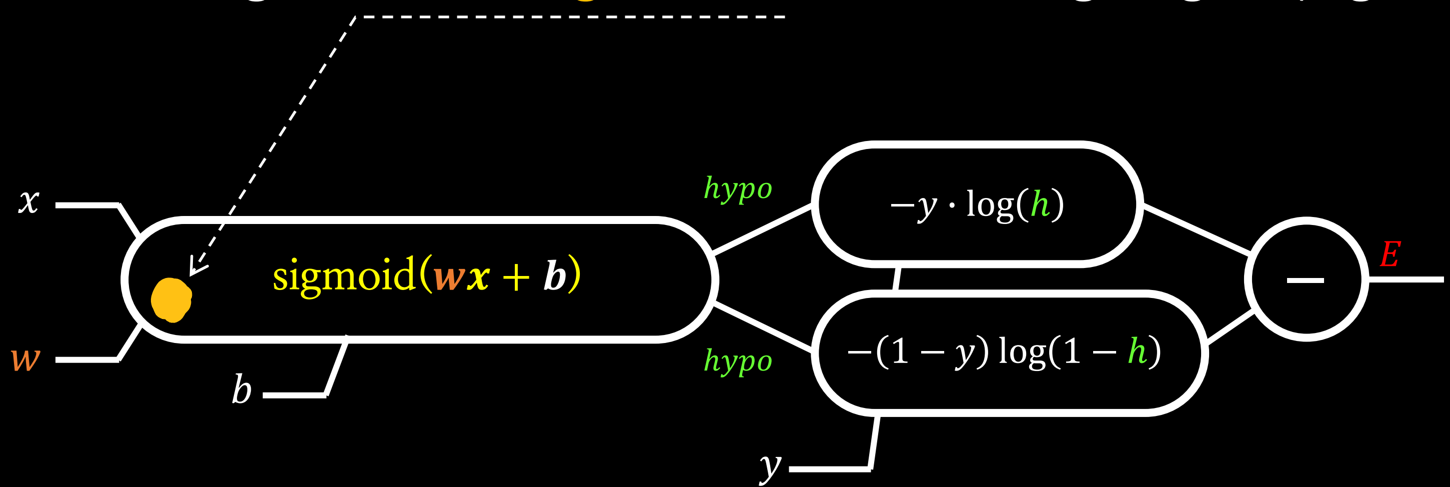


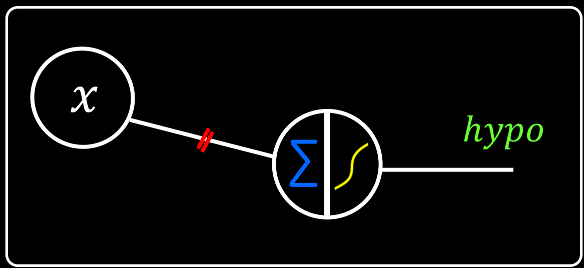
$$\frac{\partial E}{\partial w} =$$

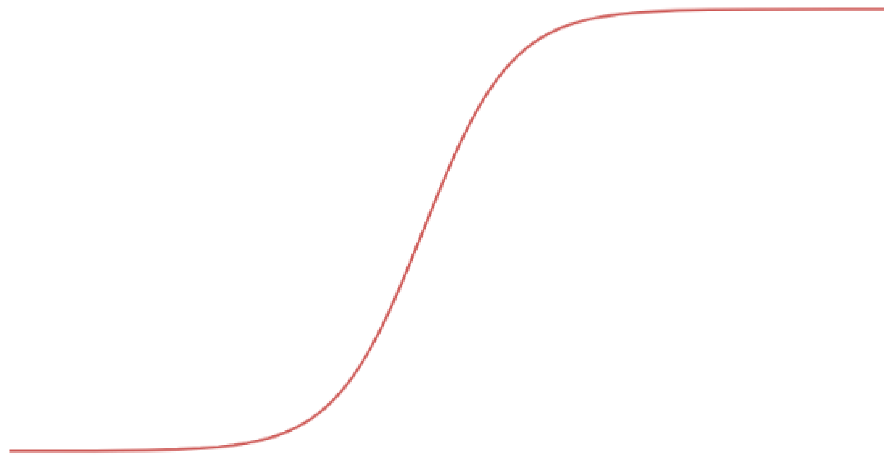
Computational Graph

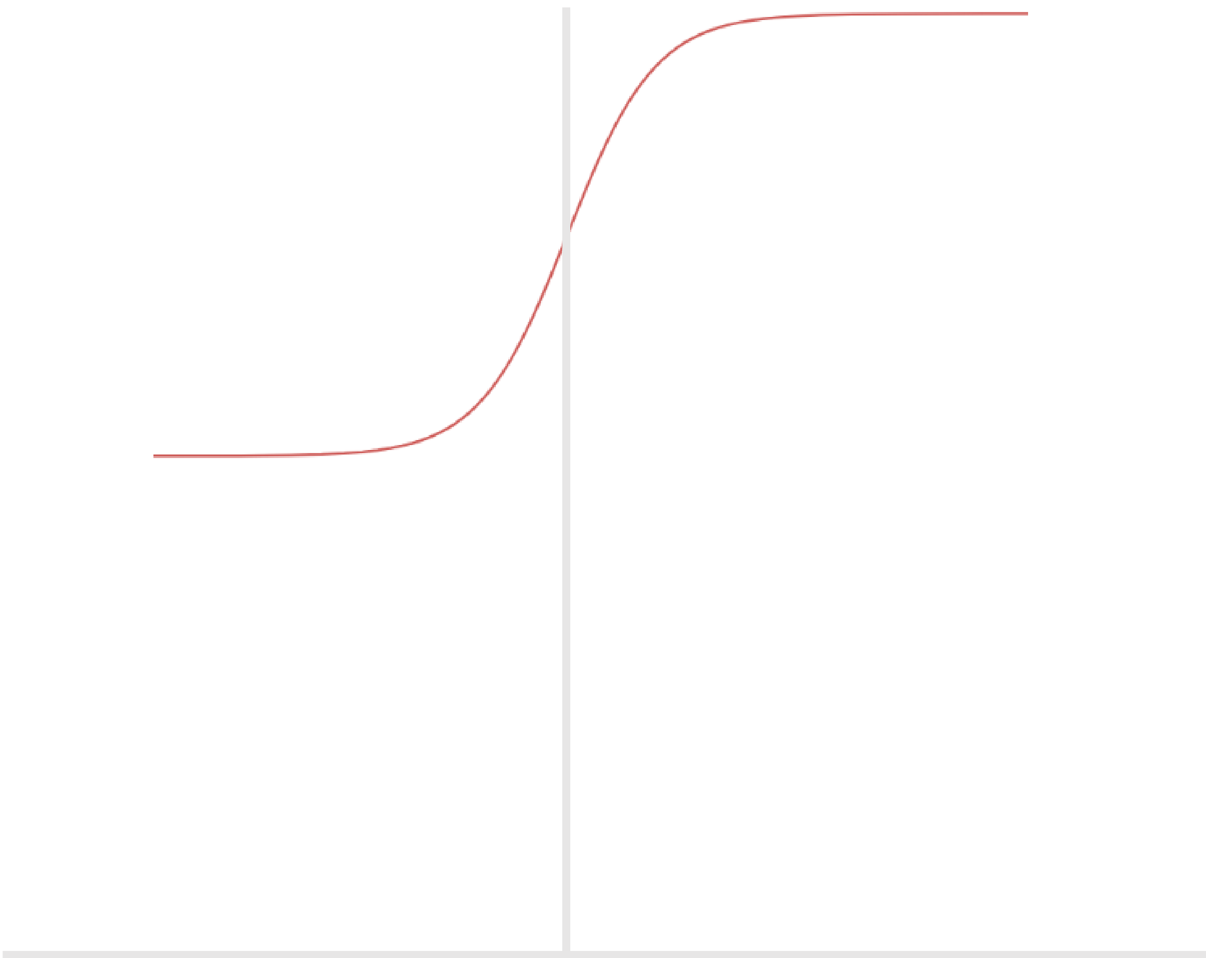
Merging gates

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

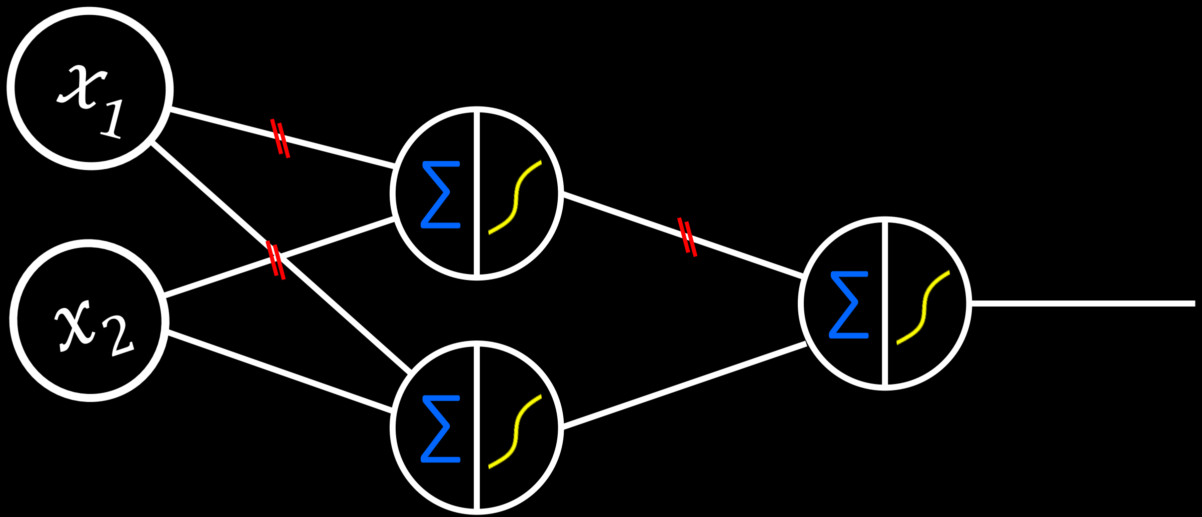




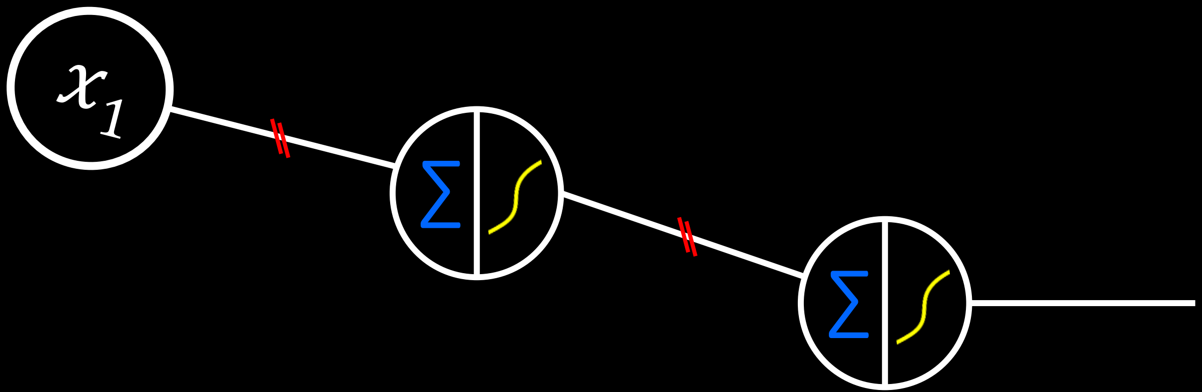




3-layer NN



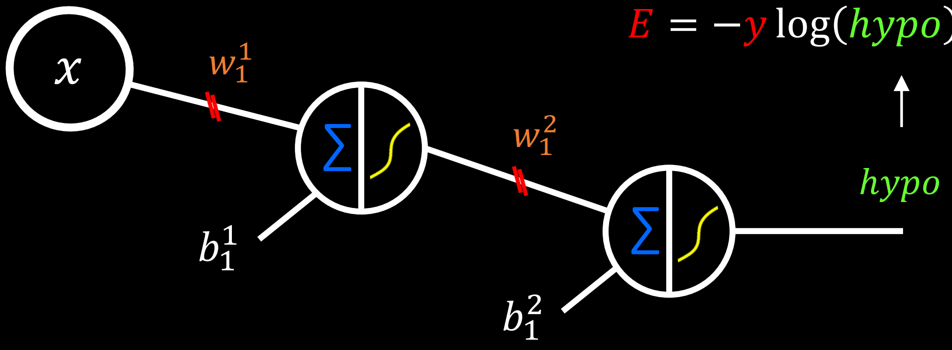
3-layer NN (simplified)

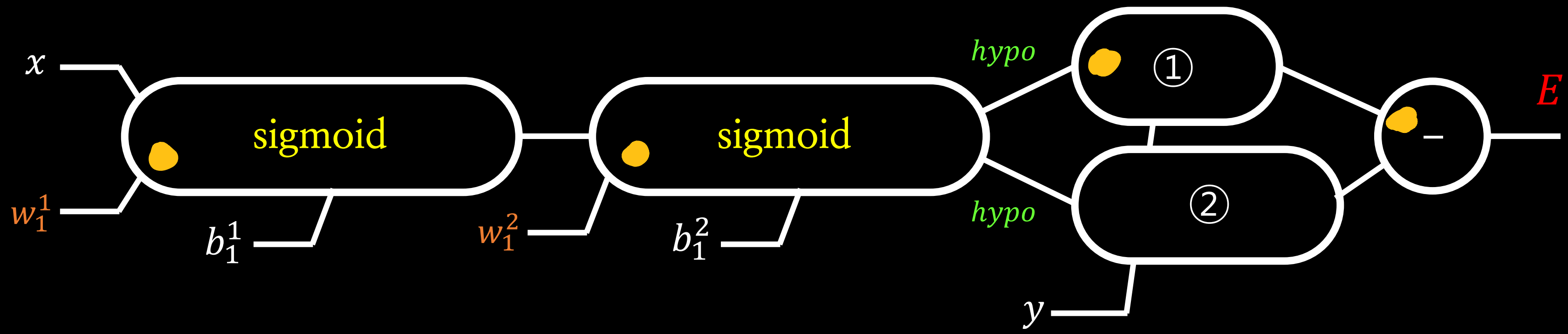


Influence of w change on E

$$\overset{①}{}\qquad\qquad\qquad\overset{②}{}$$

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

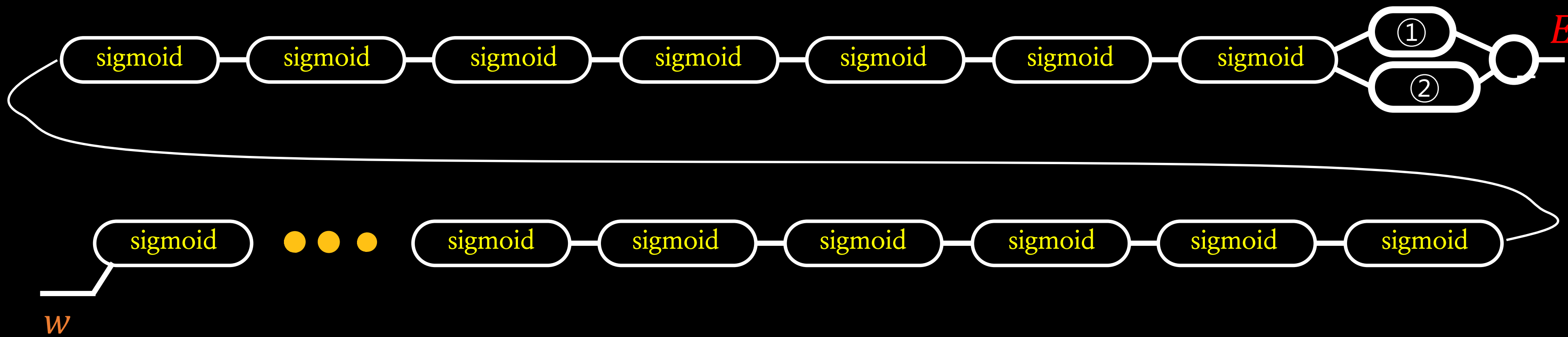




10-layer Neural Network

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, 20 multiplications for 10 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

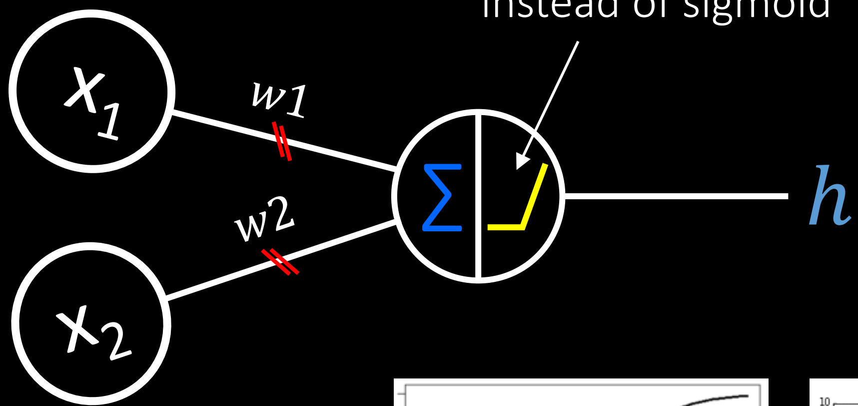
- XOR problem using 4-layer neural networks
- Failed owing to vanishing gradient

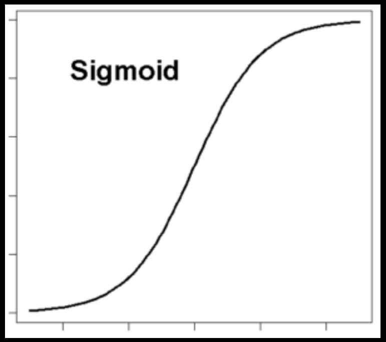
The Dark Age in Artificial Intelligence and Neural Networks (~ 2006)

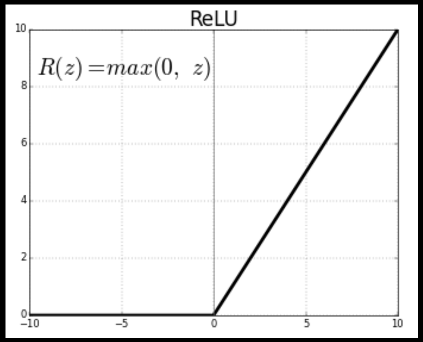
since back-propagation by Hinton in 1986 proposed by Hahnloser in 2000 and demonstrated for deep networks in 2011

ReLU

using ReLU (Rectified Linear Unit) instead of sigmoid







(Lab) 19.py

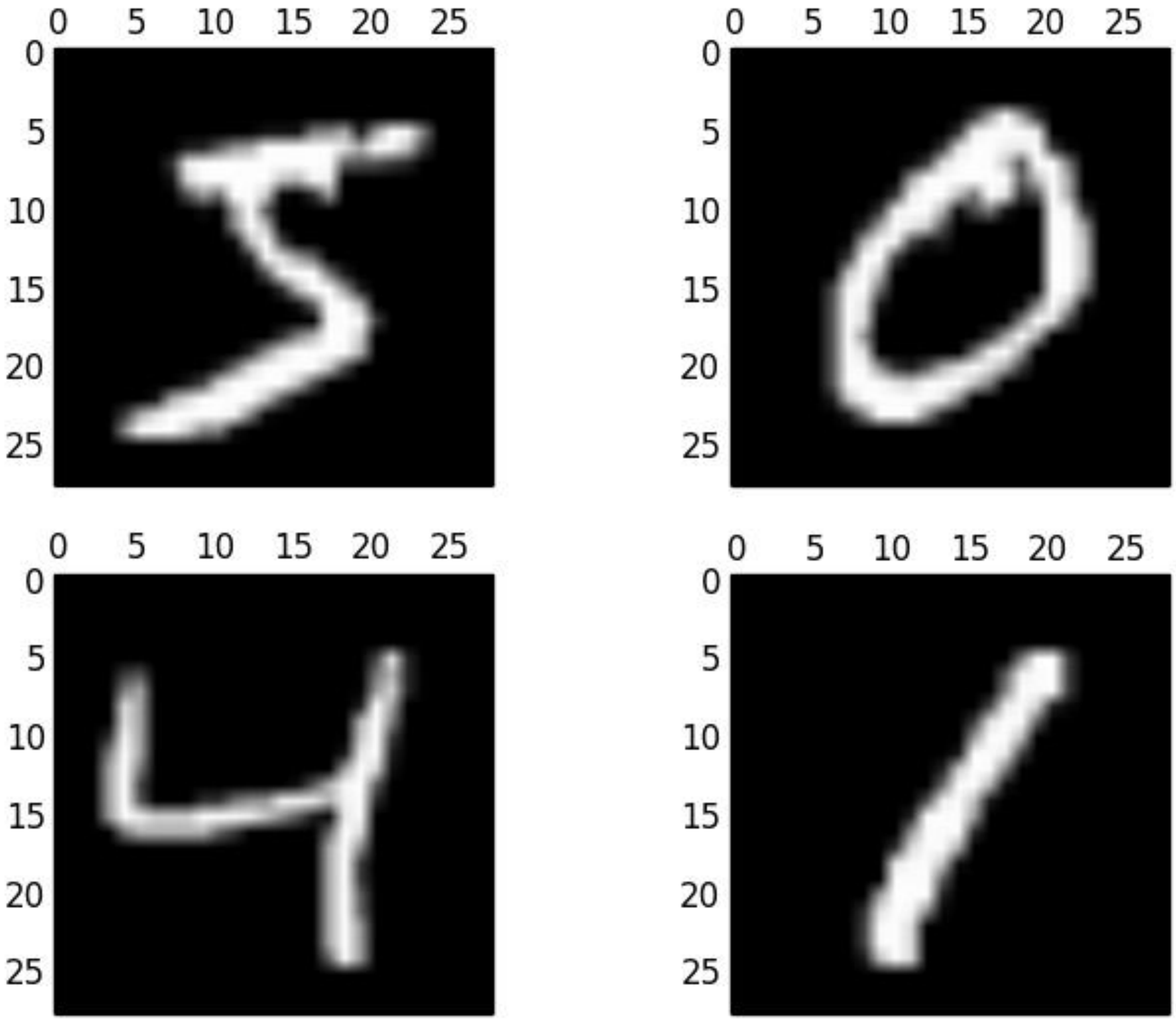
- Solving vanishing gradient problem using ReLU activation function
- Back-propagation is working by using ReLU.

So, now can go deeper.

MNIST

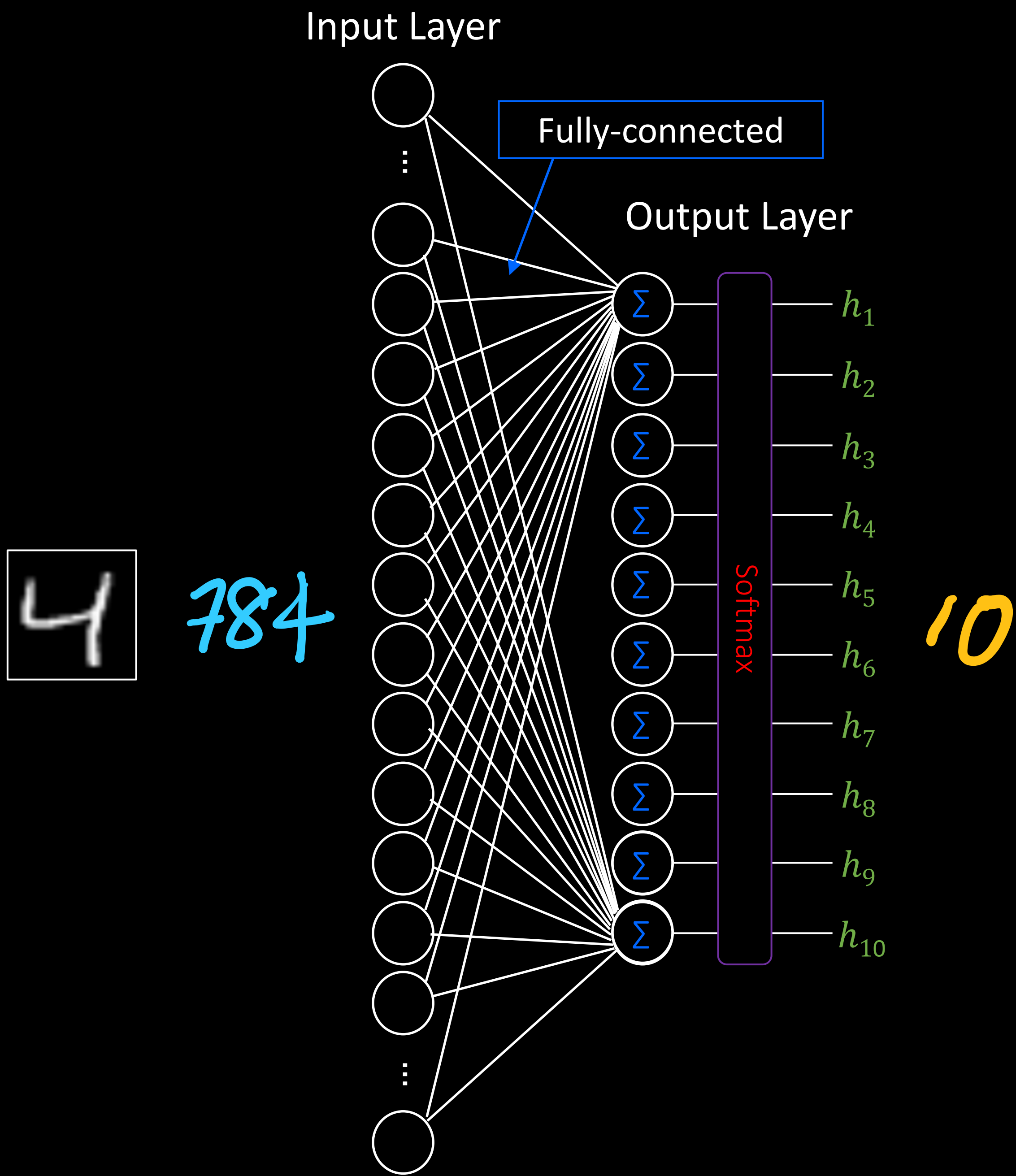
Modified National Institute of Standards and Technology (USA)

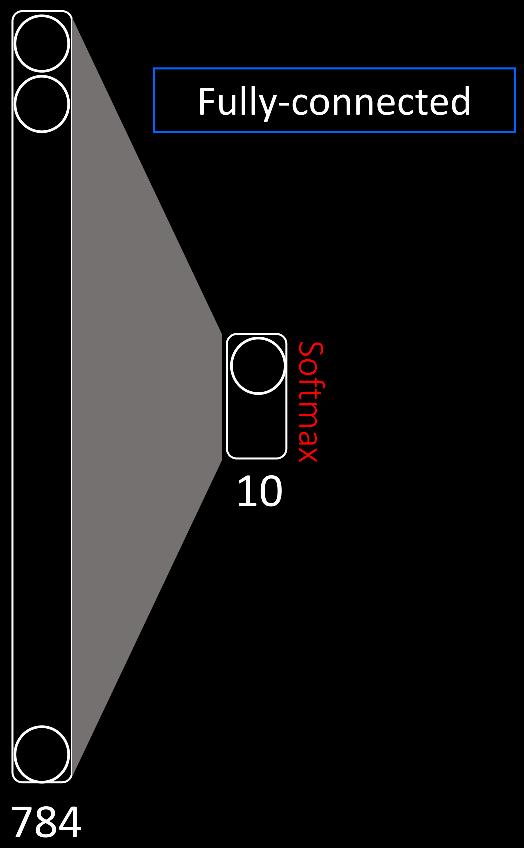
MNIST


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

(Lab) 20.py

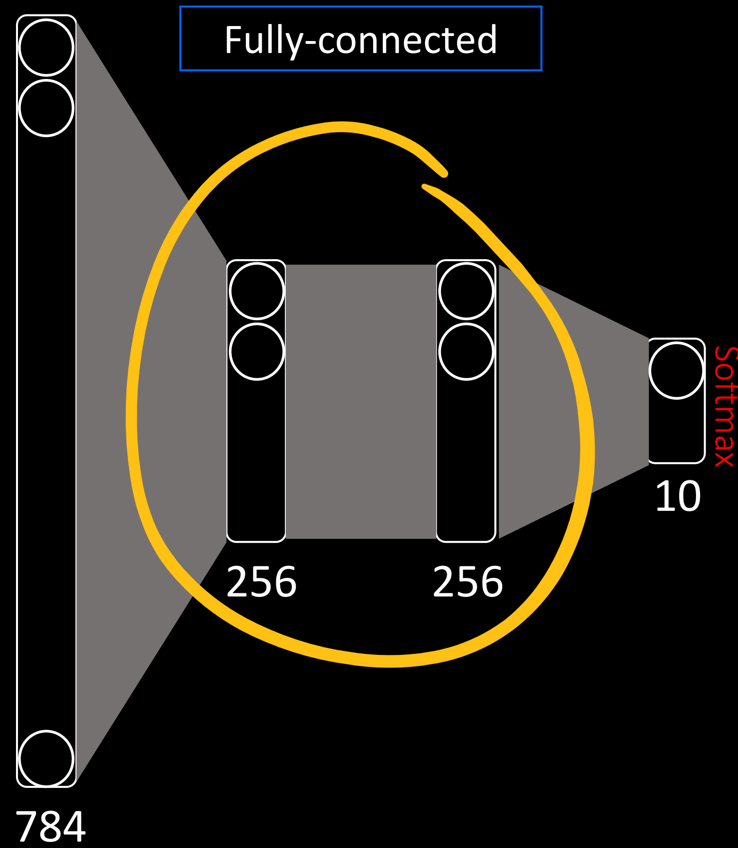
- 60,000 training images + 10,000 testing images
- Input image : 28 * 28 pixels → 784 pixels
- 784 dimension
- 10 classes (output: 0 ~ 9)
- Softmax
- 90.23% of recognition rate


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


Fully-connected
Softmax
10
784

(Lab) 21.py

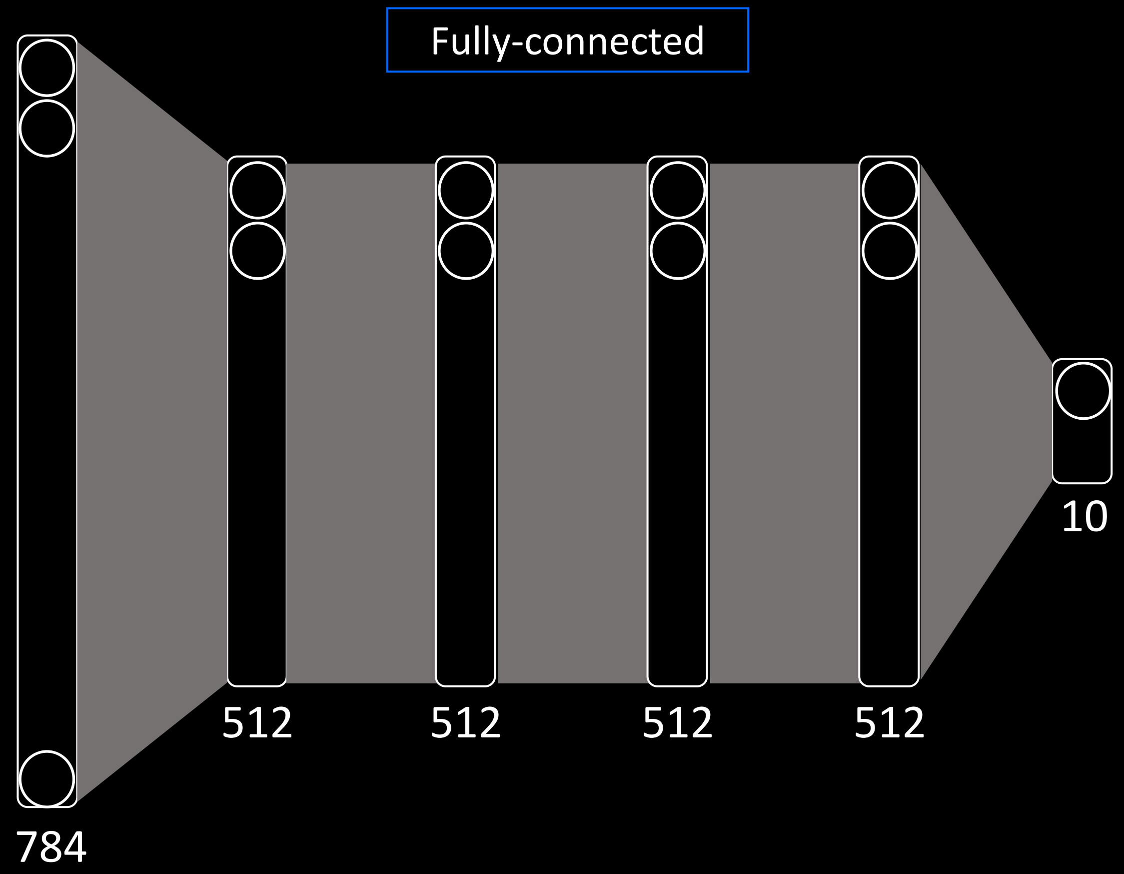
- Deep Neural Network (4-layer)
- ReLU
- 94.55% accuracy



(Lab) 22.py

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

(Lab) 23.py

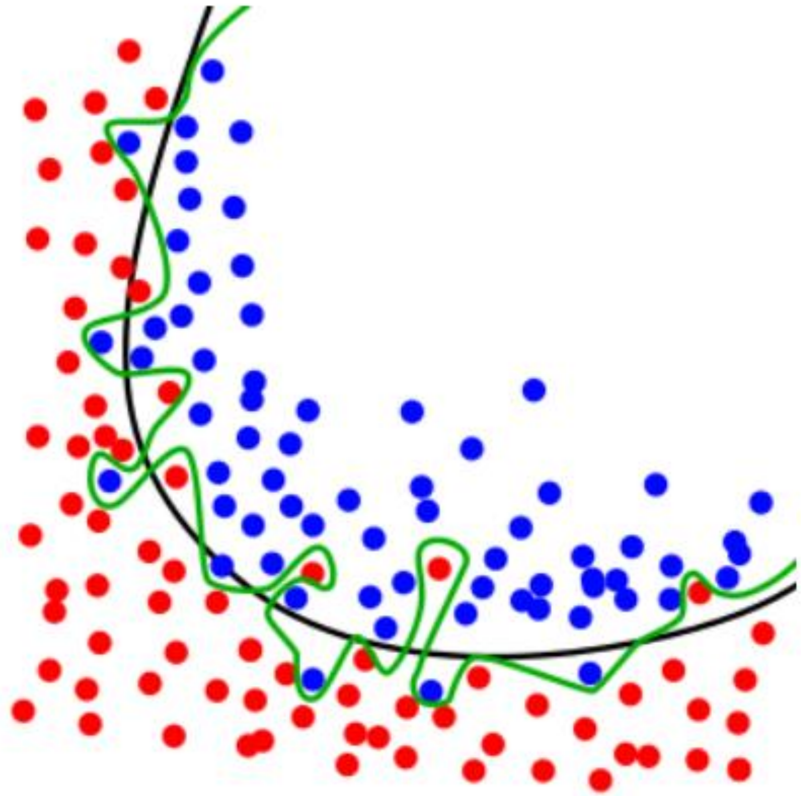


- Applying initialization method for w and b, not randomly
- 6-layer deep neural networks
- 97.83% of accuracy

Decision Boundry

Which do you think is desirable decision boundary?

View from above



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

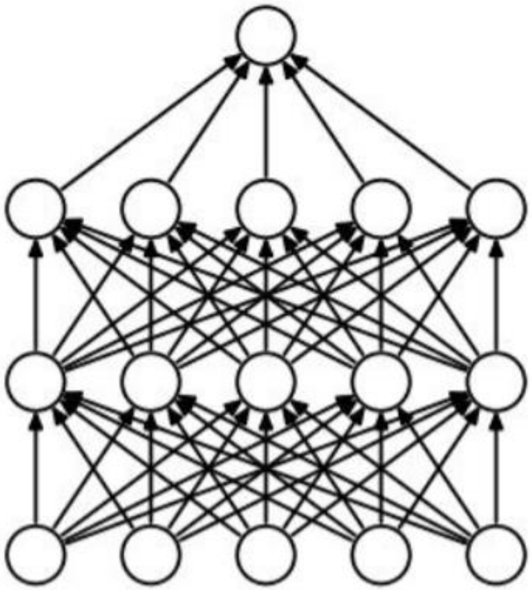
https://elitedatascience.com

Overfitting and drop-out

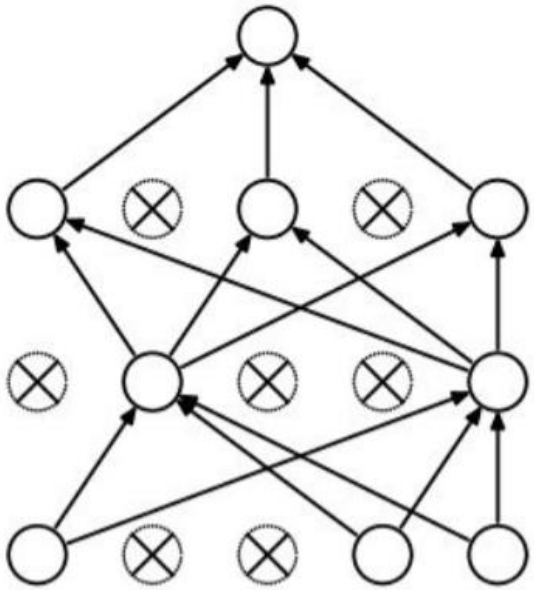
- The deeper the network is, the more the decision boundary is complex.
- Good at learning data but errors for testing data → overfitted to the training data
- Making it less complex by drop-out some neurons while learning.

Regularization: **Dropout**

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



(a) Standard Neural Net



(b) After applying dropout.

[Srivastava et al., 2014]

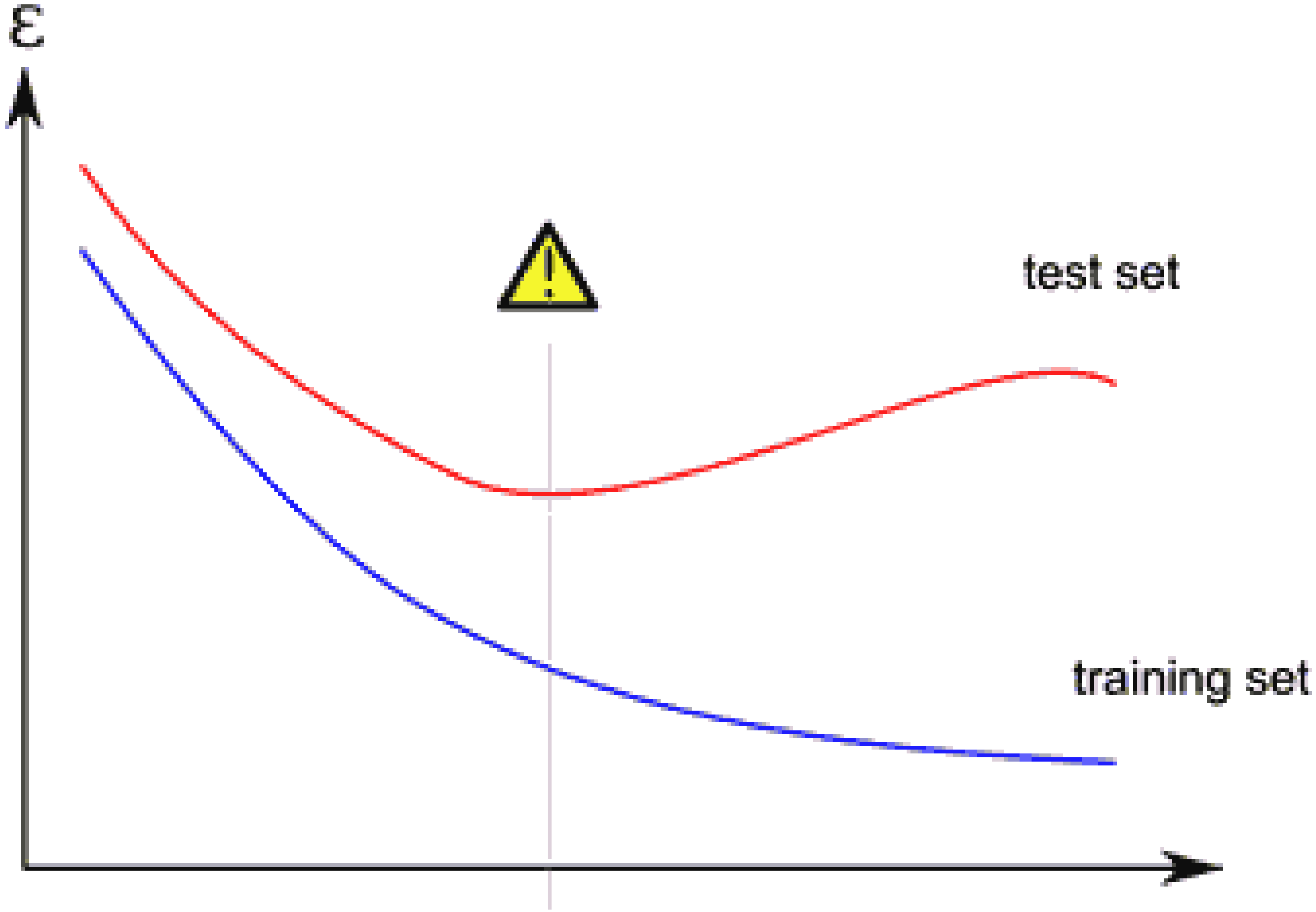
(Lab) 24.py

- Applying dropout
- 98.13% of recognition accuracy

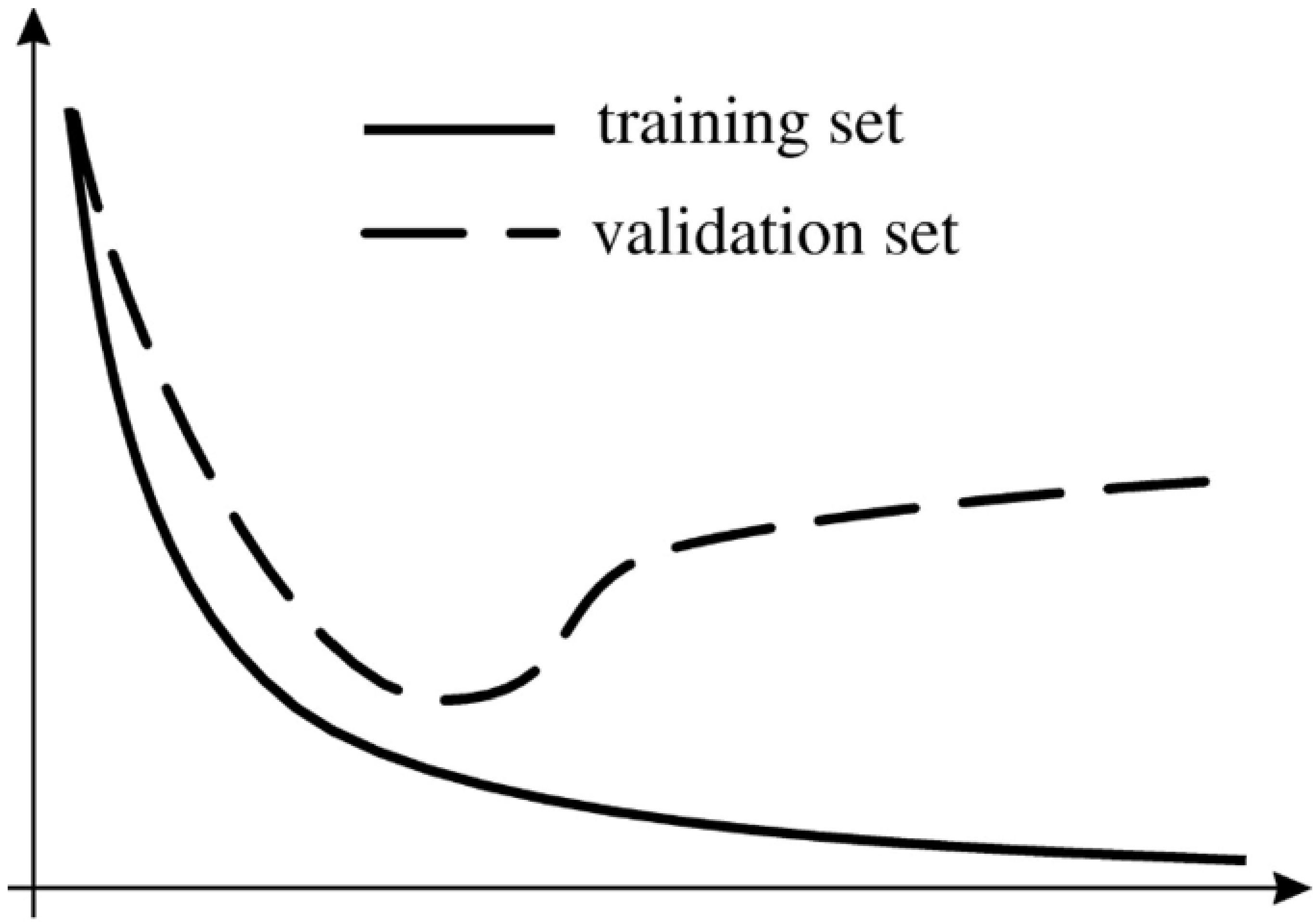
How to Prevent Overfitting

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

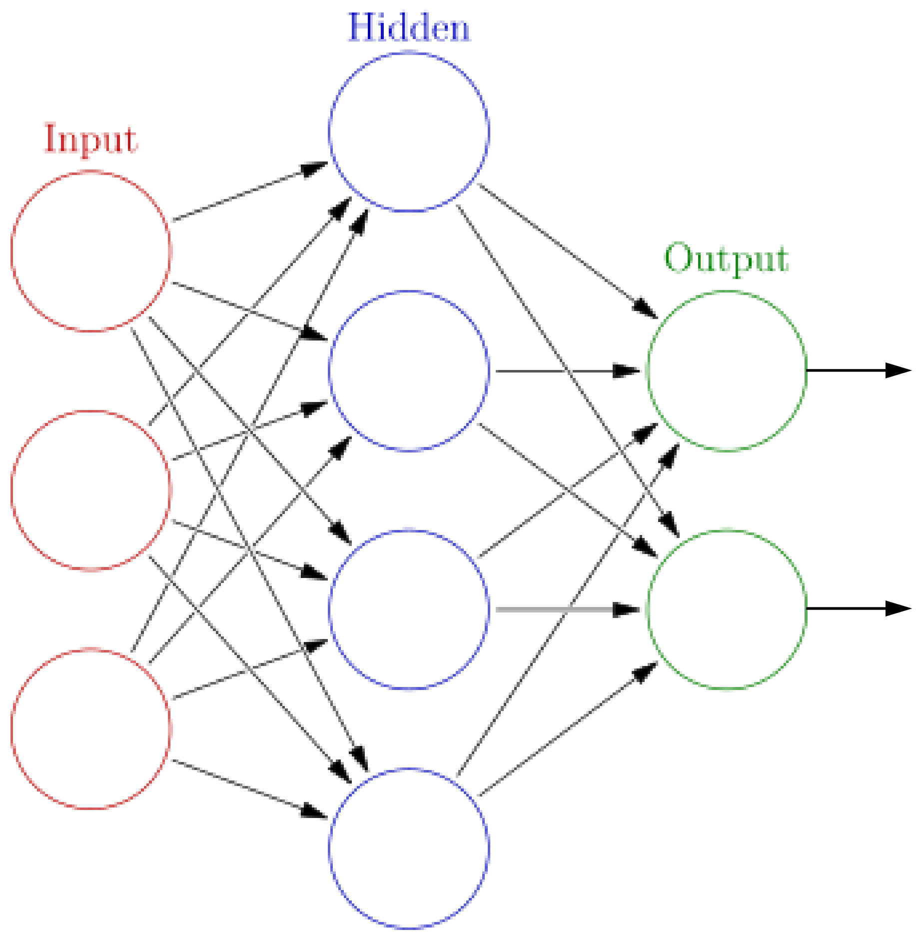
Early stopping



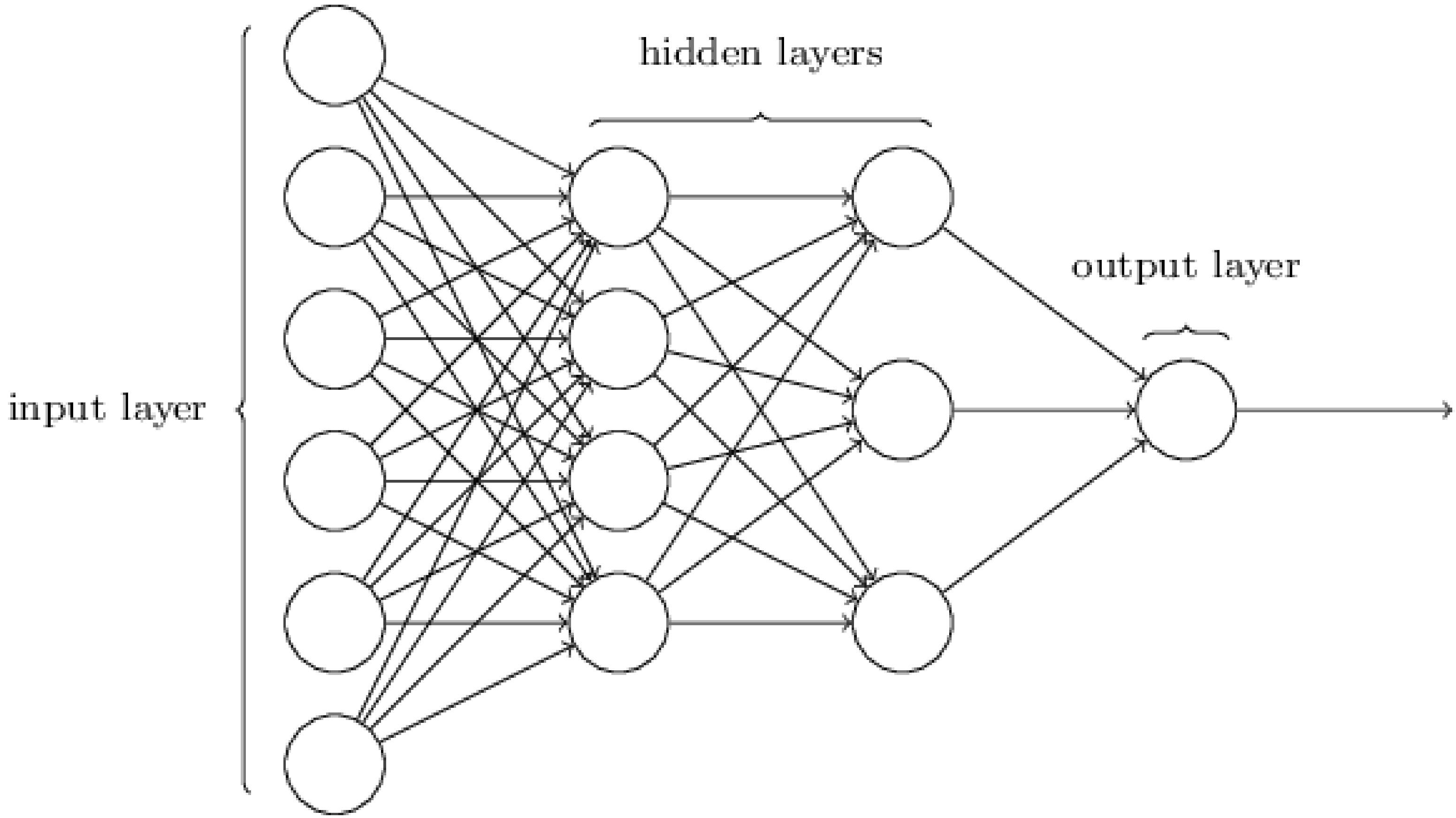
Early stopping

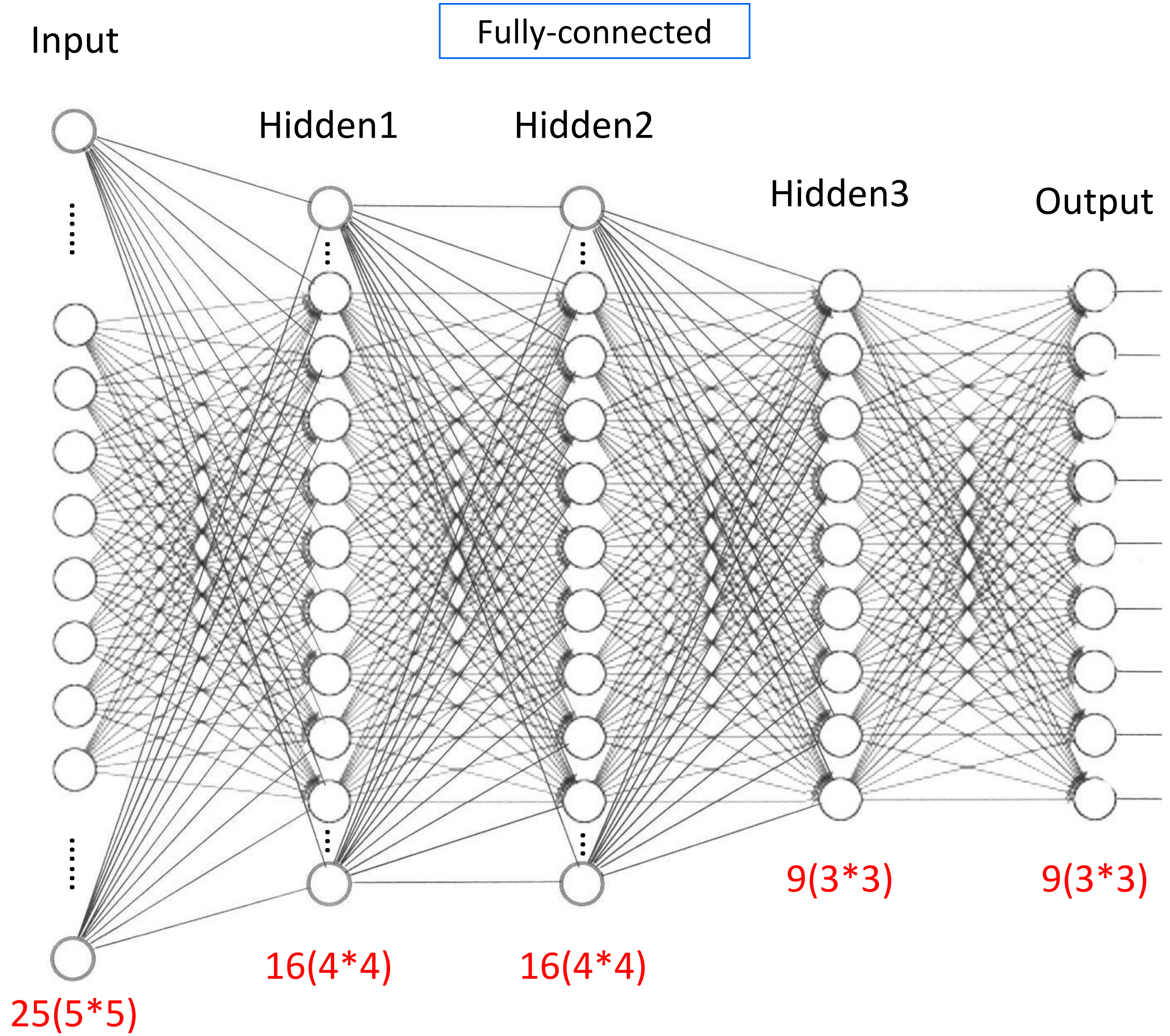


Fully-connected



Fully-connected

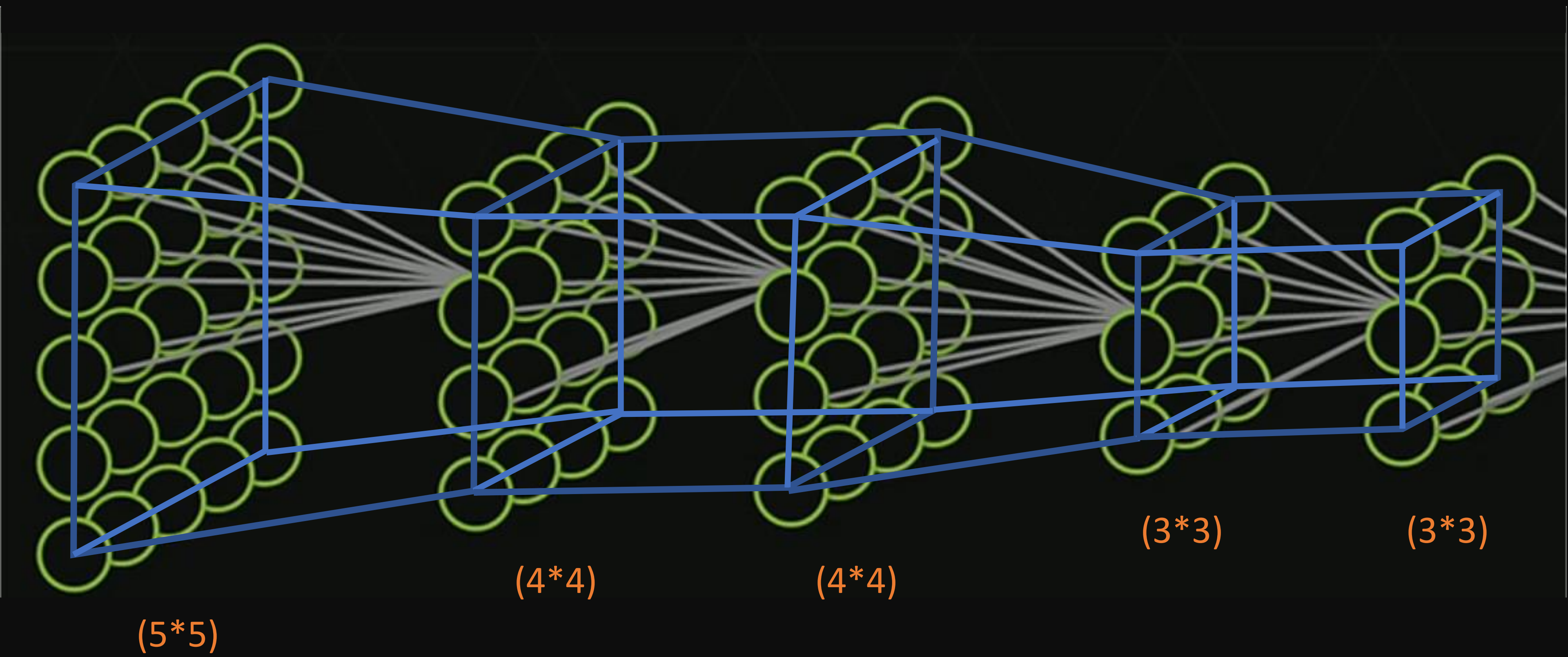




Fully connected, then how many synapses(parameters) are there?

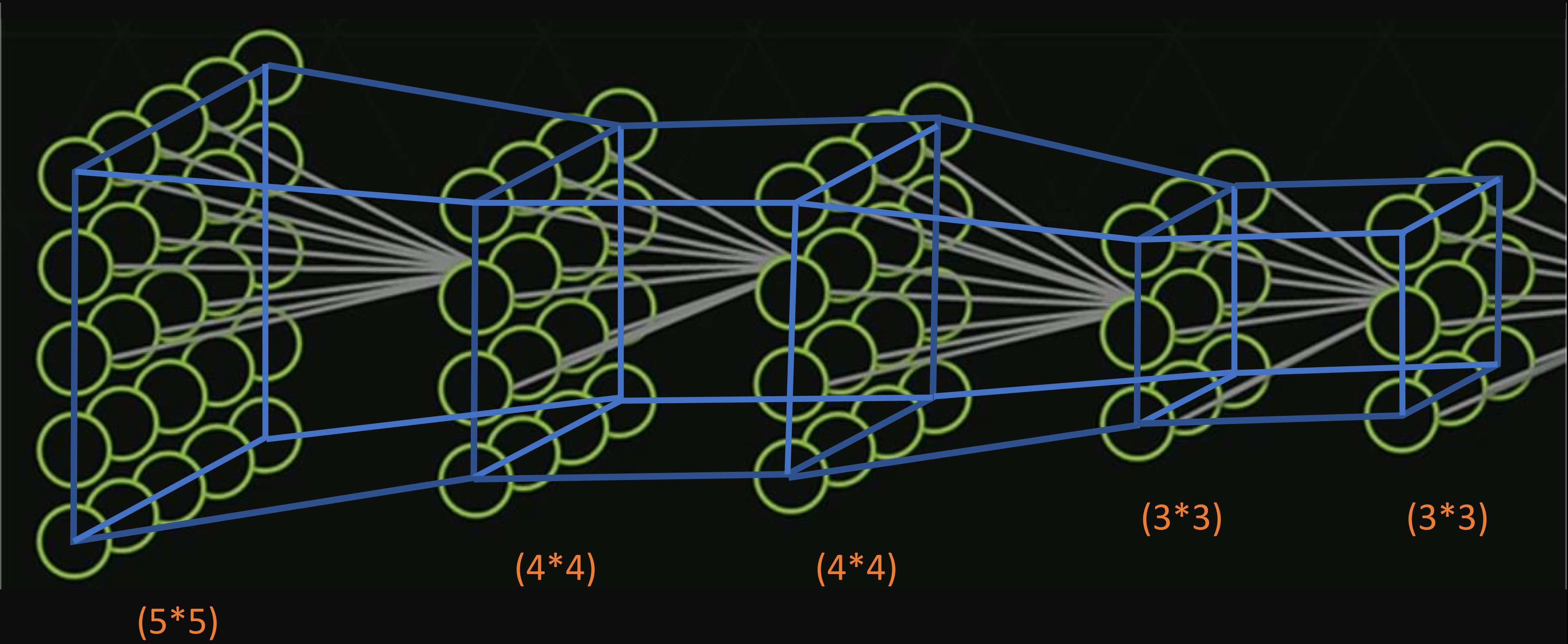
$$25 * 16 + 16 * 16 + 16 * 9 + 9 * 9 = 881$$

Fully-connected



Fully connected, so how many connections are there?

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






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?