CS540 Introduction to Artificial Intelligence

Neural Networks: Review

University of Wisconsin-Madison

Spring 2023

Announcements

- **Homeworks:**
  - HW 7 due in one week
- Midterms are being graded; solutions on Canvas.
- Final exam is May 12, 5:05 - 7:05 pm.
- **Class roadmap**:
- Practice Questions on Canvas

Tuesday, April 4	Neural Network Review
Thursday, April 6	Uninformed Search
Tuesday, April 11	Informed Search
Thursday, April 13	Advanced Search

How to classify

Cats vs. dogs?

Neural networks can also be used for regression.

- Typically, no activation on outputs, mean squared error loss function.

How to classify

Cats vs. dogs?

Single-layer Perceptron

Multi-layer Perceptron

Training of neural networks

Convolutional neural networks

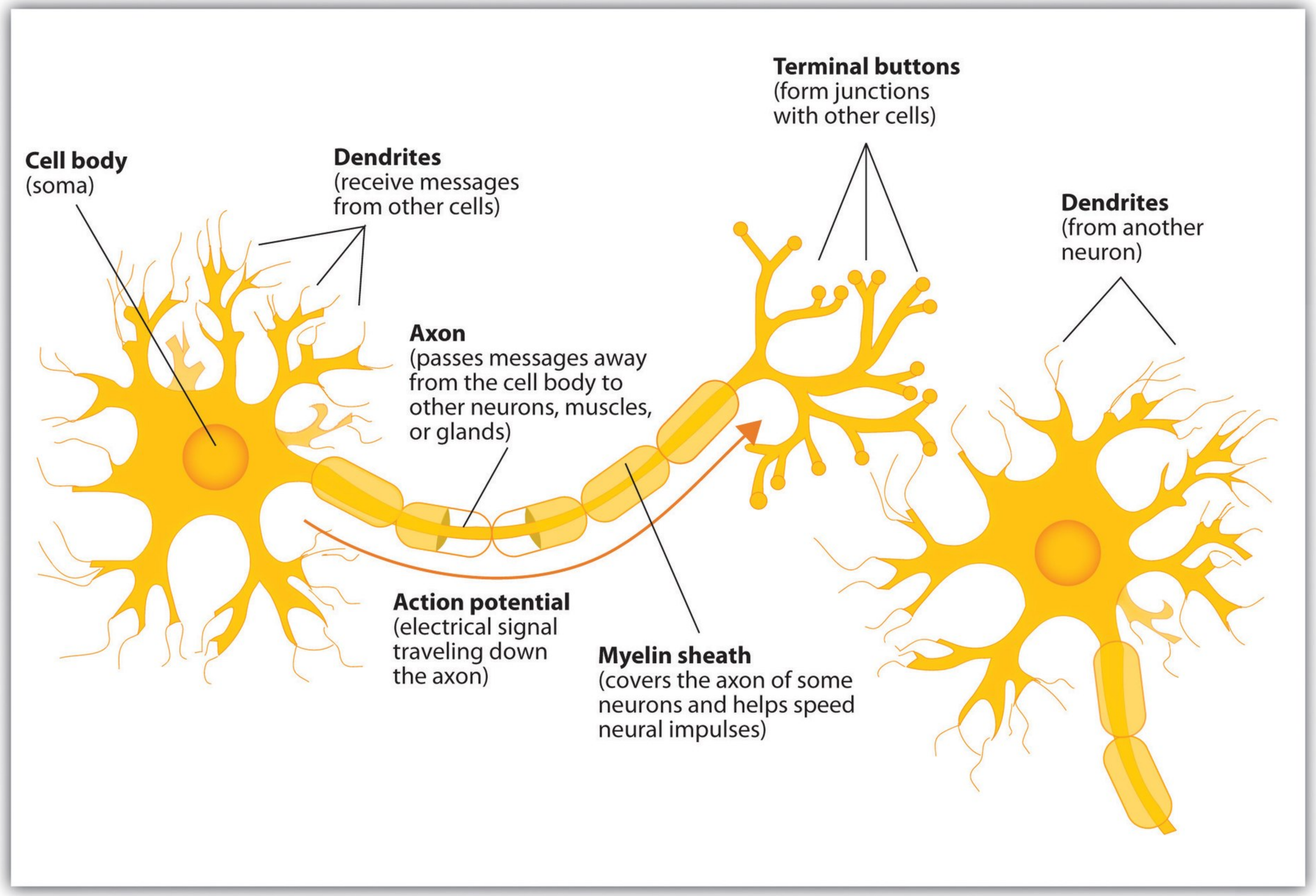
Neural networks can also be used for regression.

- Typically, no activation on outputs, mean squared error loss function.

Inspiration from neuroscience

- Inspirations from human brains
- Networks of simple and homogenous units (a.k.a **neuron**)

(wikipedia)

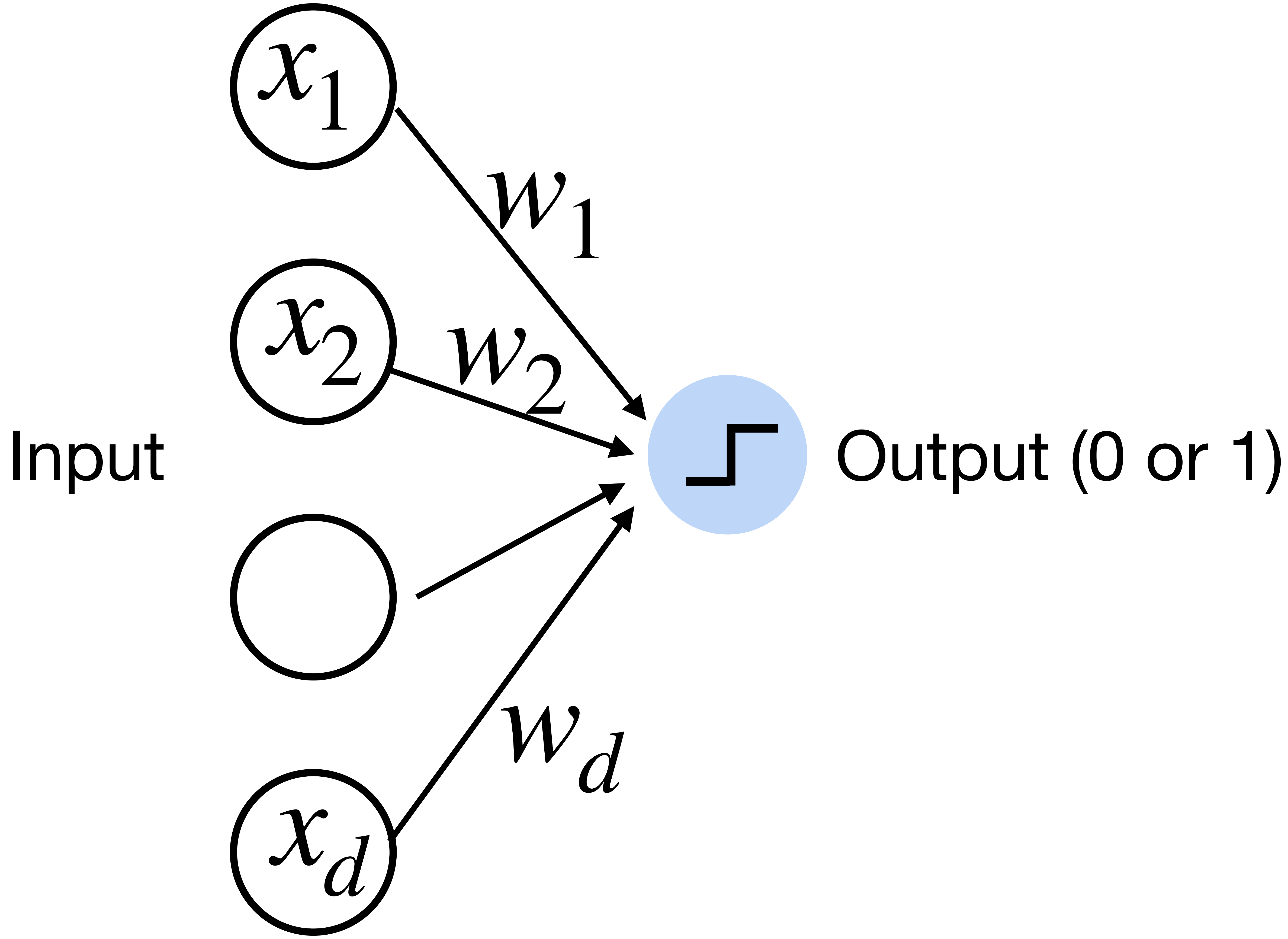


Perceptron

- Given input $\mathbf{x}$, weight $\mathbf{w}$ and bias b, perceptron outputs:

$$o = \sigma\left(\mathbf{w}^\top \mathbf{x} + b\right) \qquad \sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

Cats vs. dogs?



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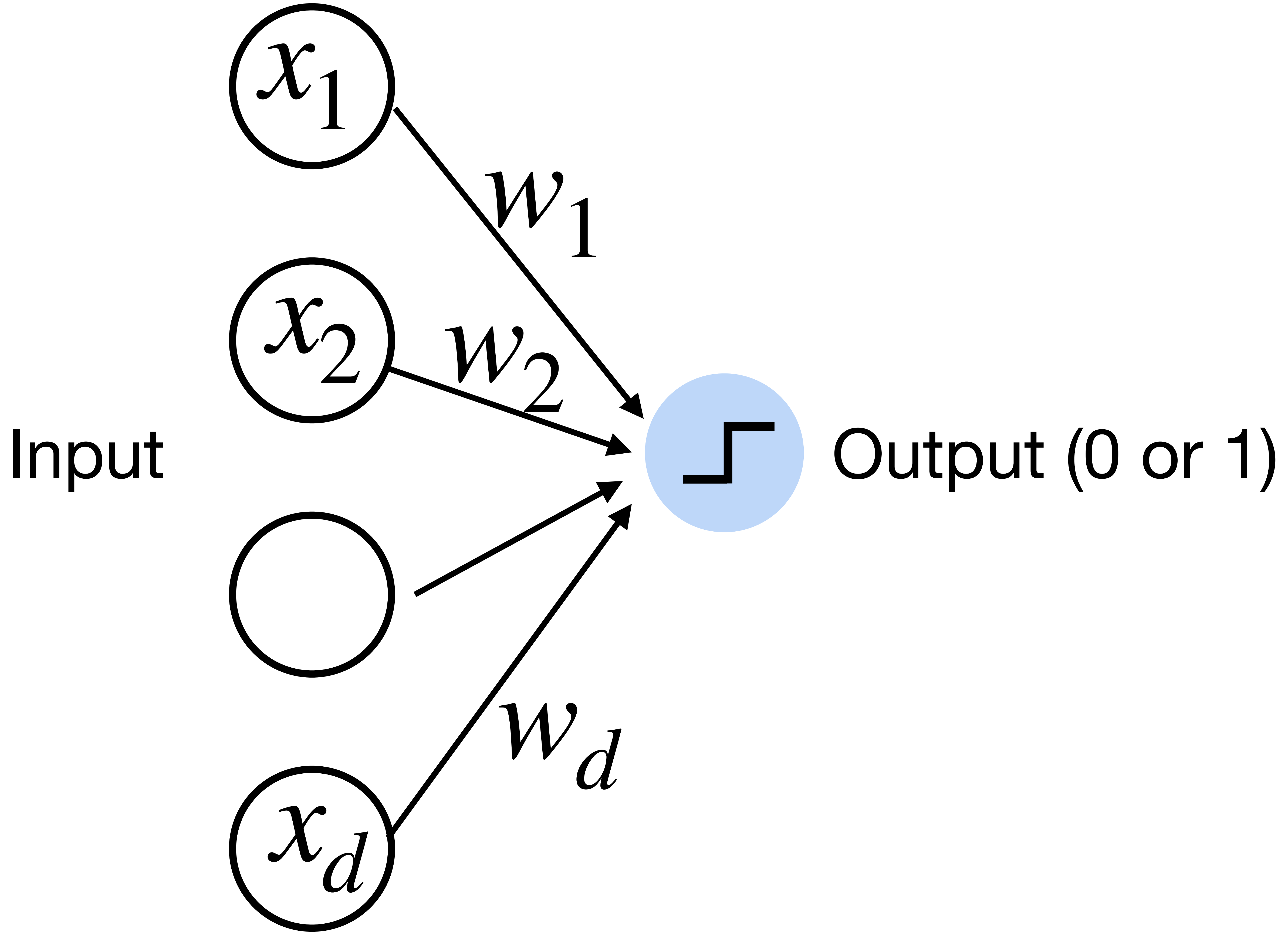
Activation function

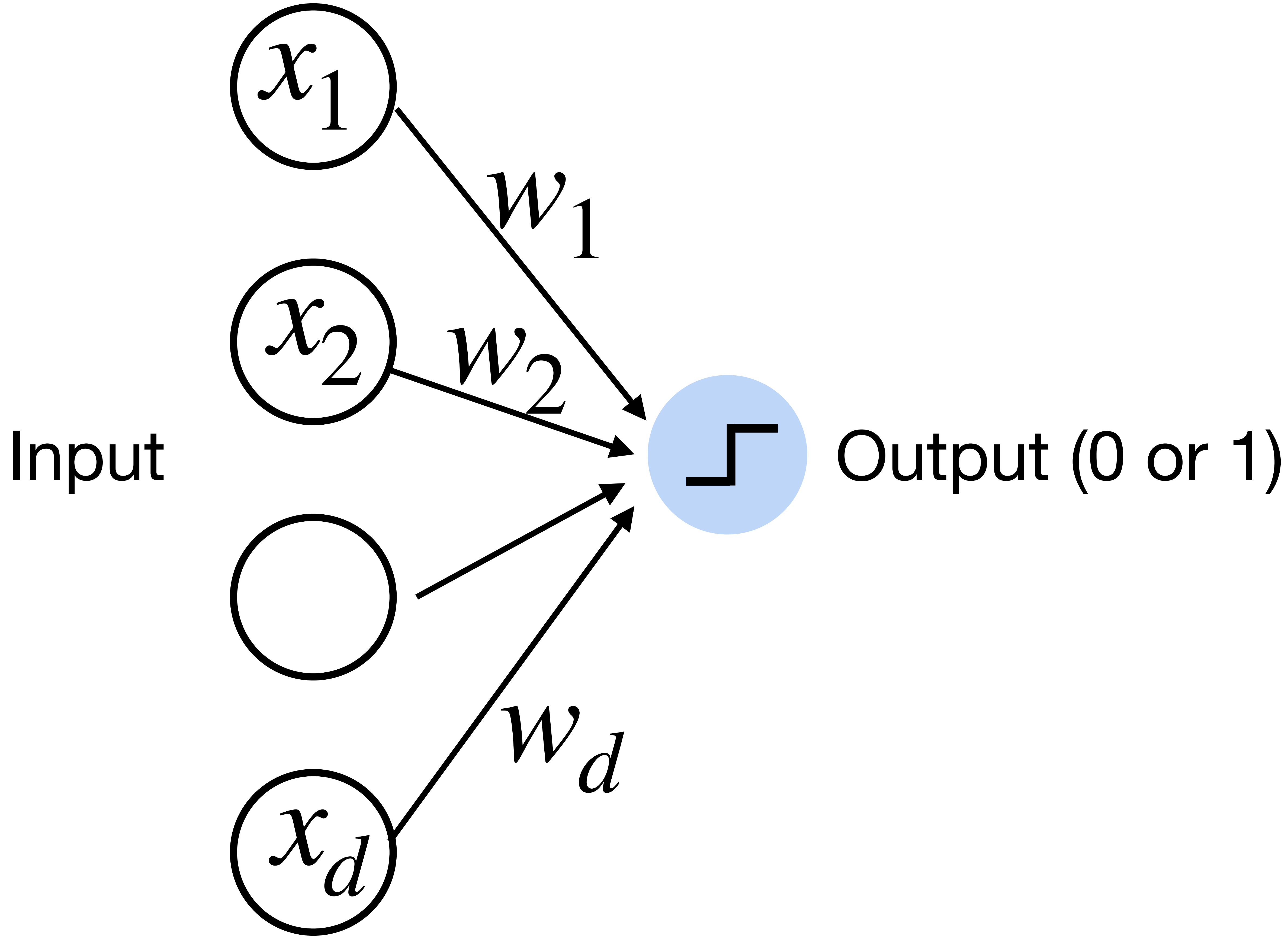
Cats vs. dogs?



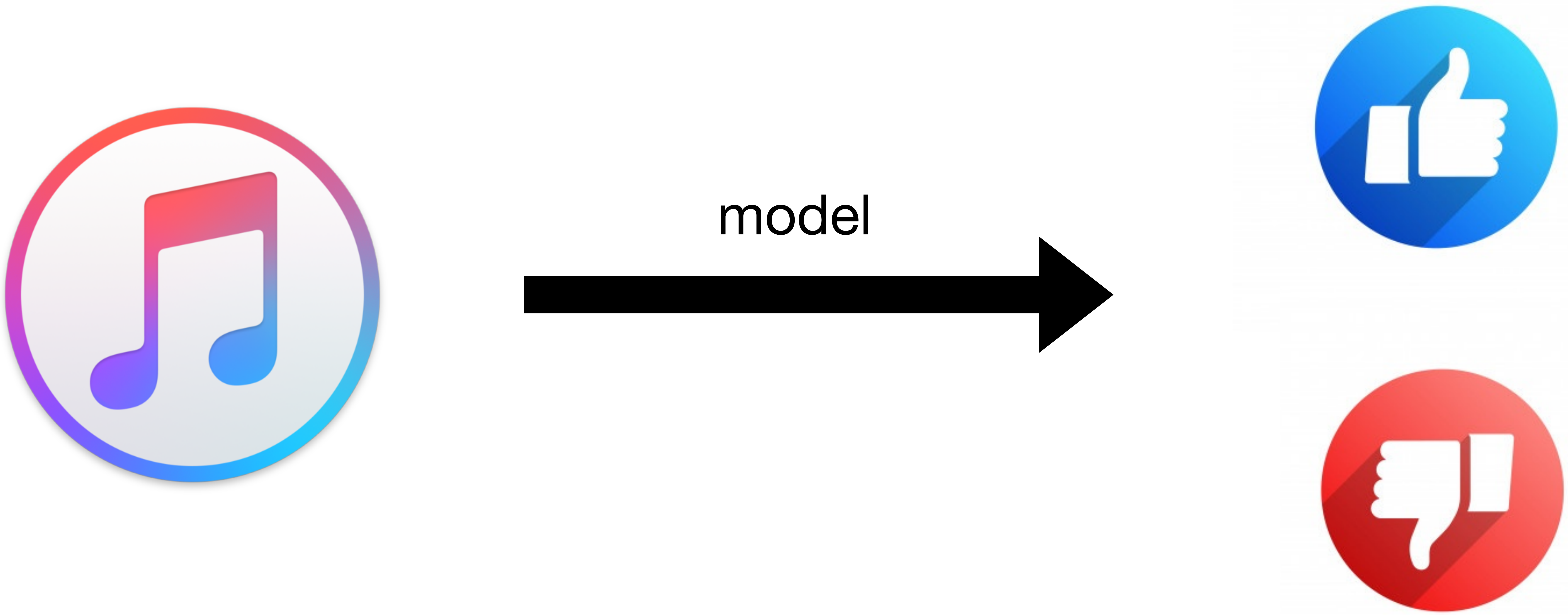
Perceptron

- Goal: learn parameters $\mathbf{w} = \{w_1, w_2, \ldots, w_d\}$ and b to minimize the classification error

Cats vs. dogs?



Example 2: Predict whether a user likes a song or not

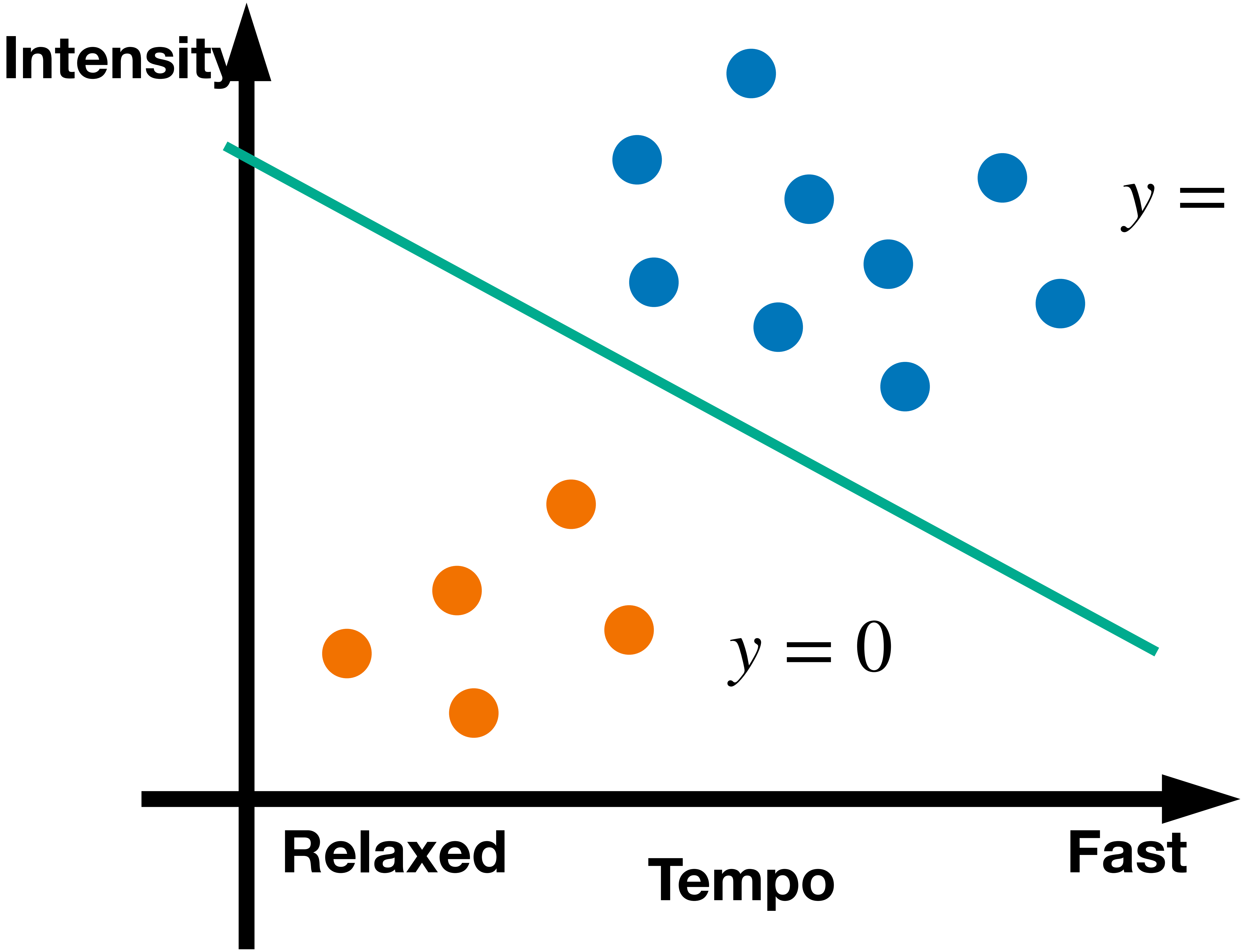


Example 2: Predict whether a user likes a song or not Using Perceptron

User Sharon

DisLike

Like



Learning logic functions using perceptron

The perceptron can learn an AND function

$x_1 = 1, x_2 = 1, y = 1$

$x_1 = 1, x_2 = 0, y = 0$

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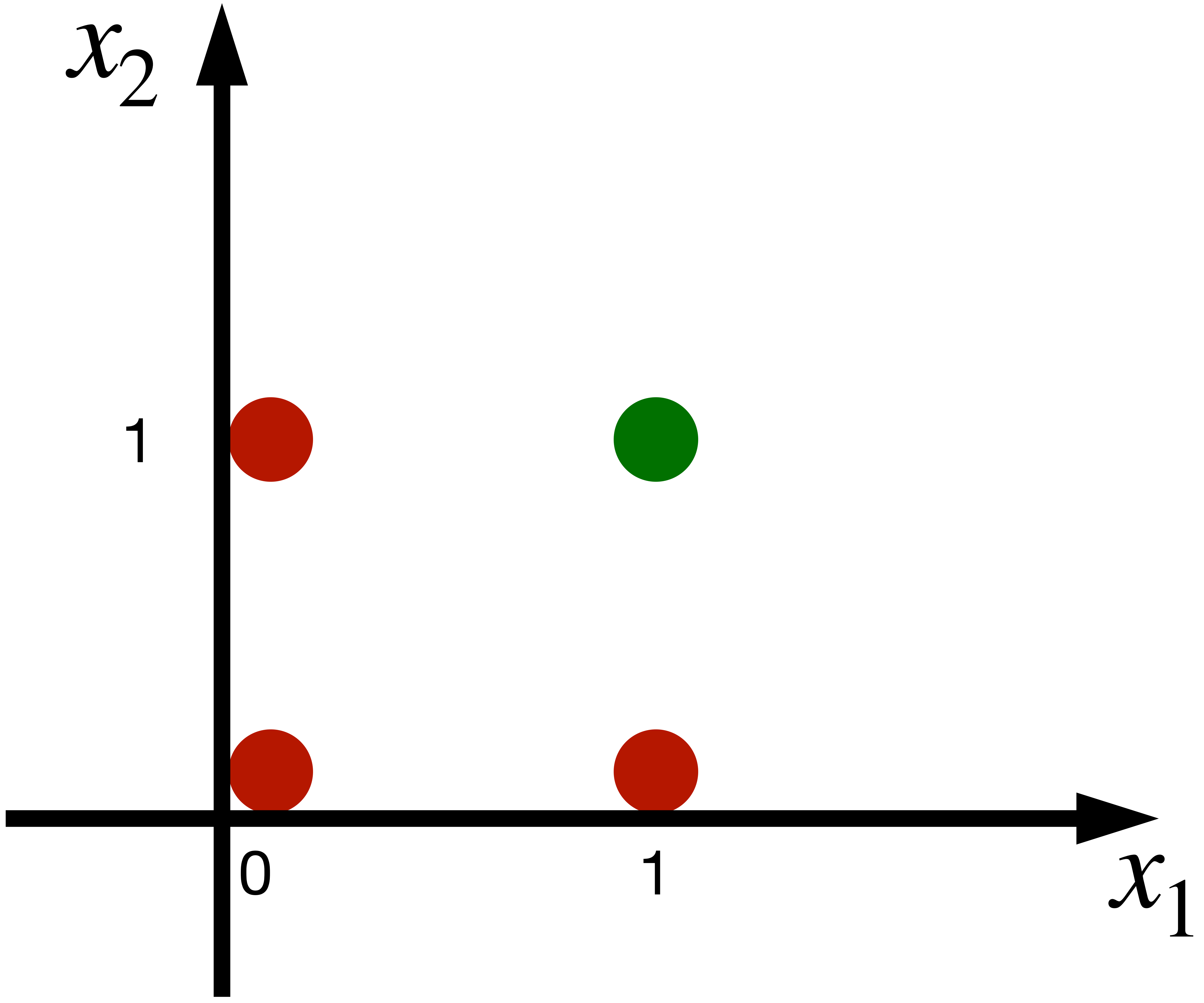

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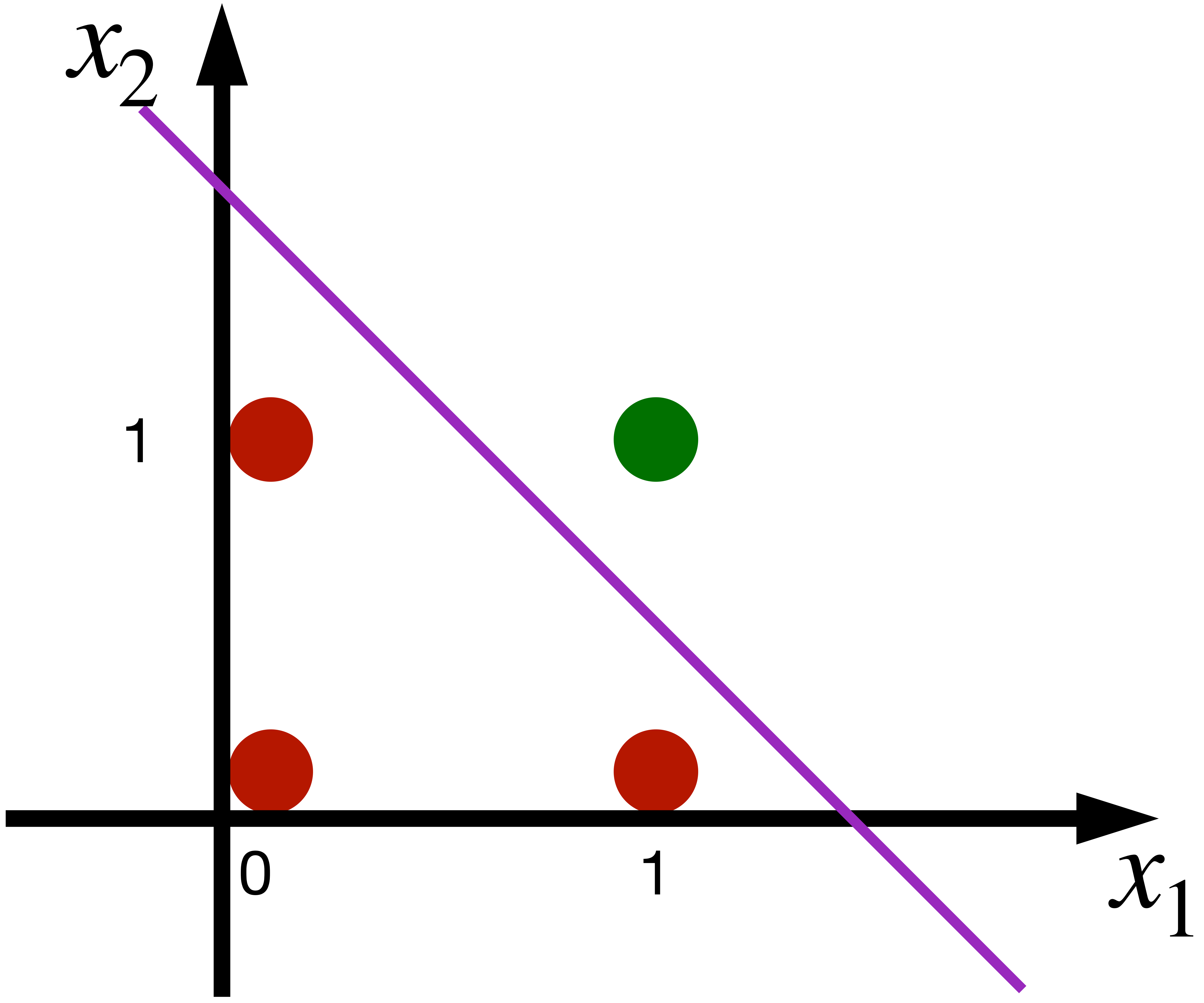
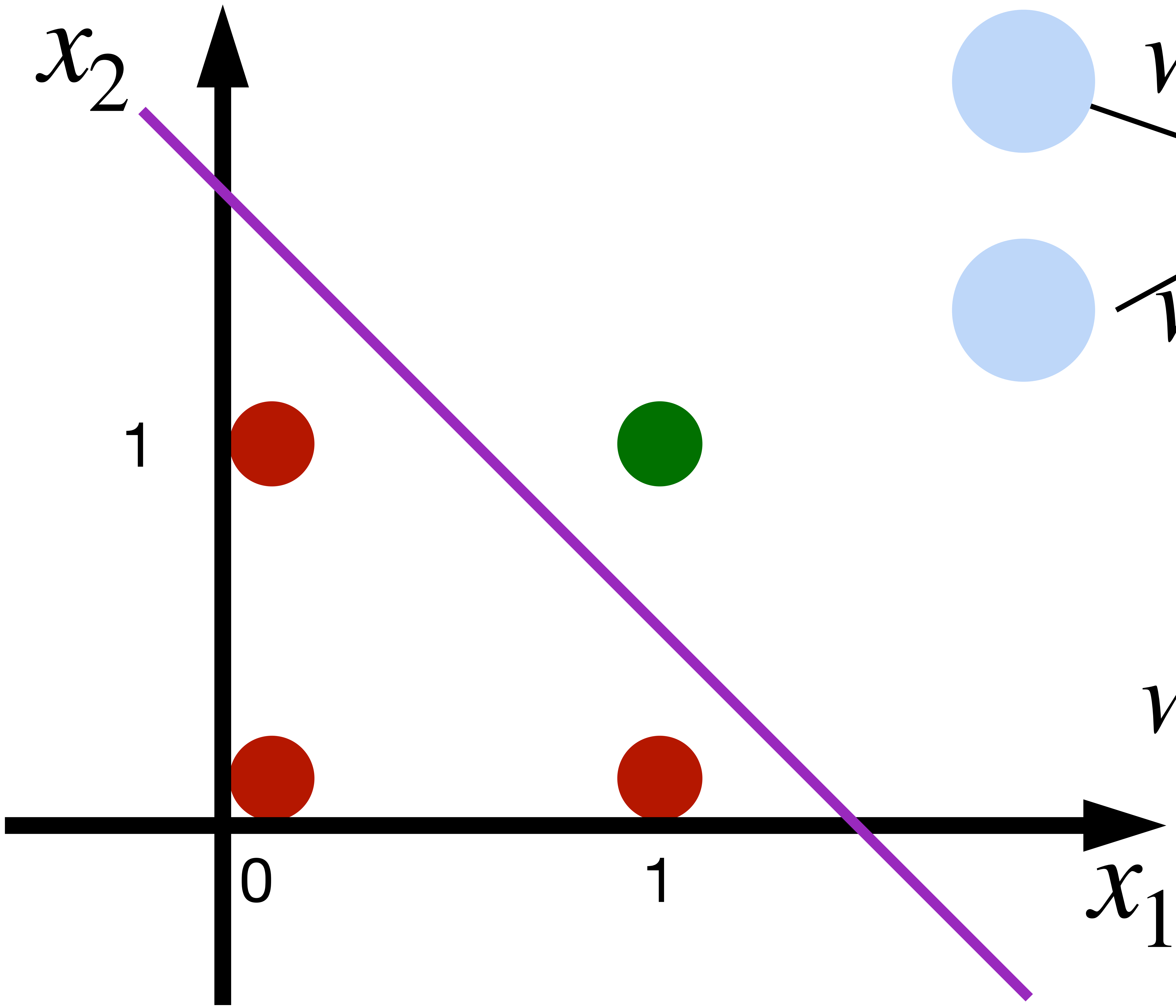
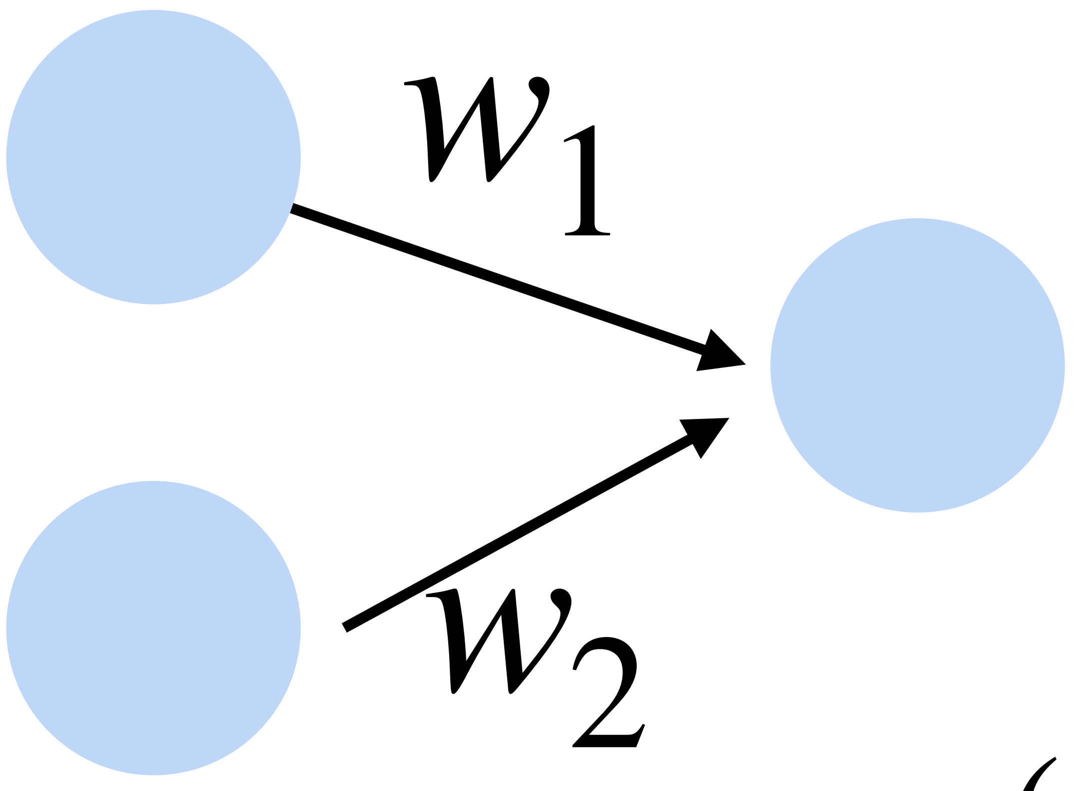


Learning logic functions using perceptron

The perceptron can learn an AND function





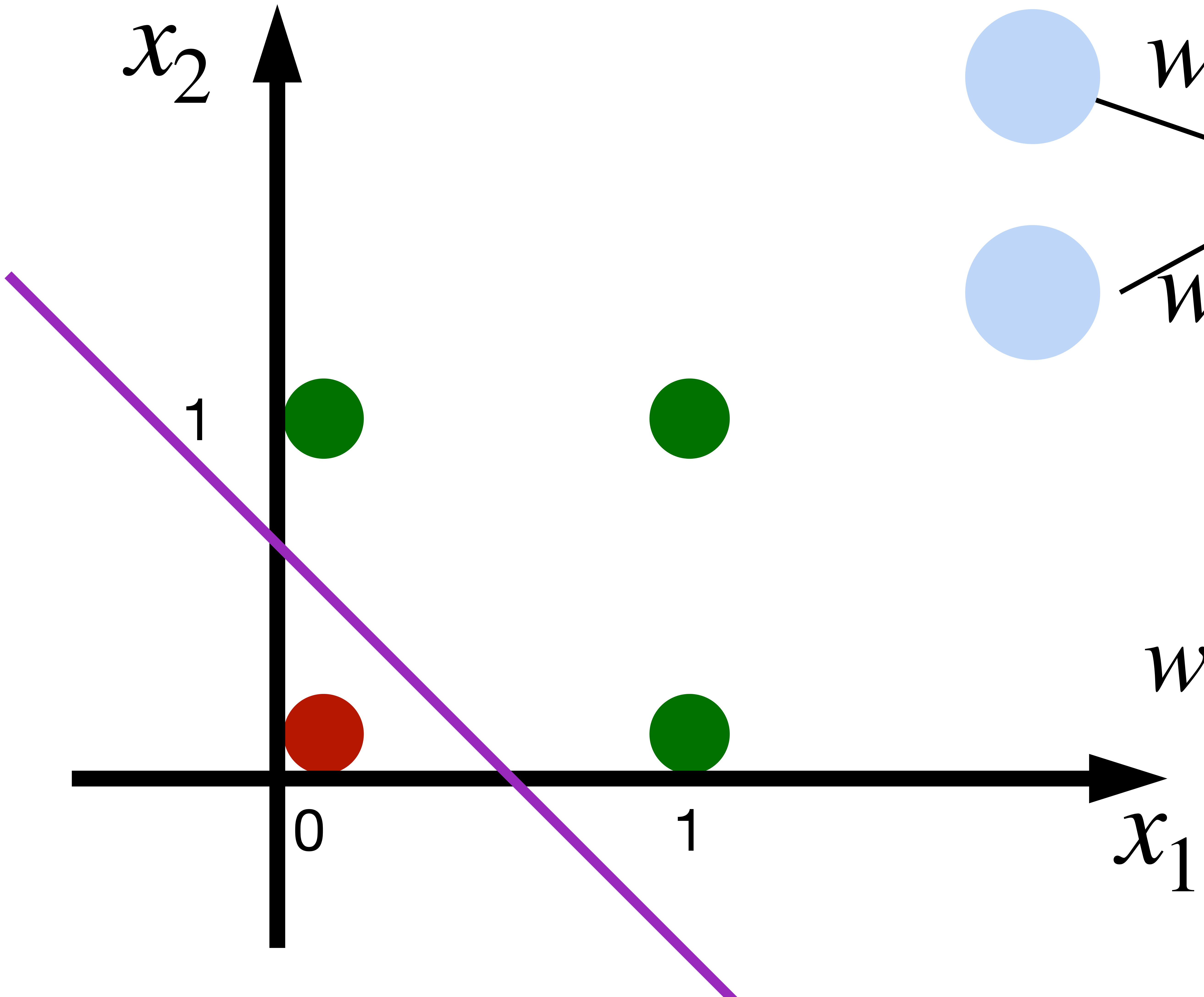
Output $\sigma(x_1 w_1 + x_2 w_2 + b)$

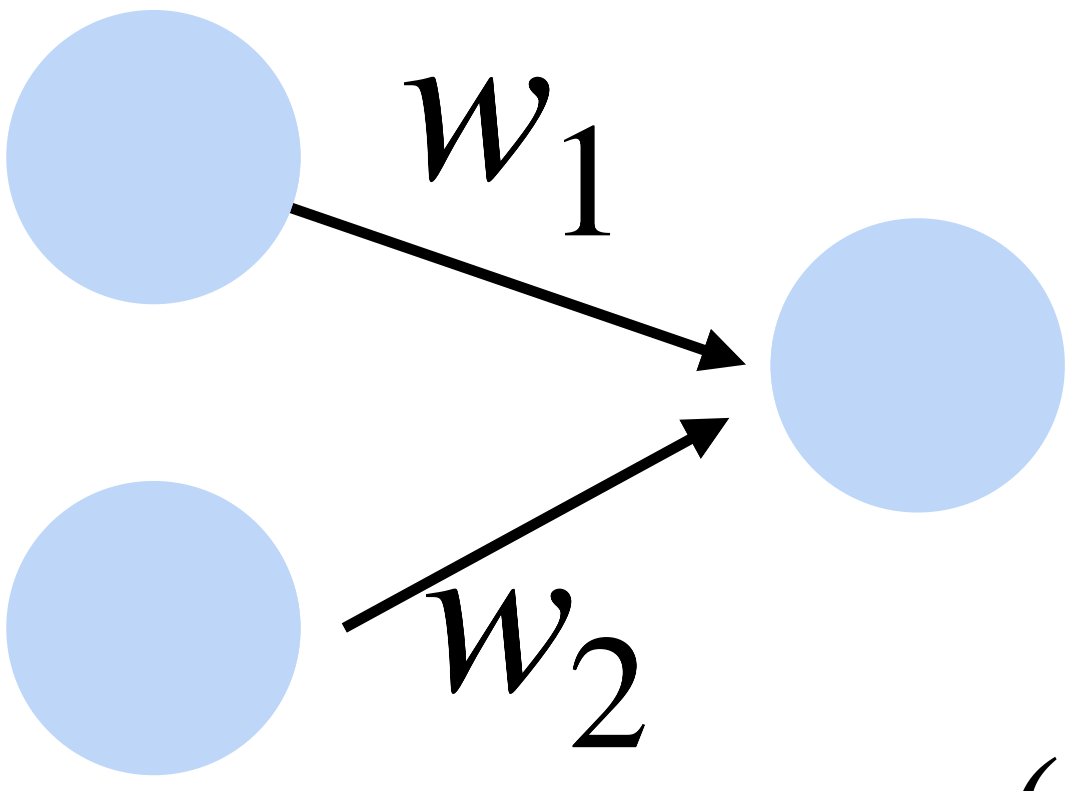
$$\sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$w_1 = 1, w_2 = 1, b = -1.5$$

Learning OR function using perceptron

The perceptron can learn an OR function





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XOR Problem (Minsky & Papert, 1969)

The perceptron cannot learn an XOR function
(neurons can only generate linear separators)

$$x_1 = 1, x_2 = 1, y = 0$$

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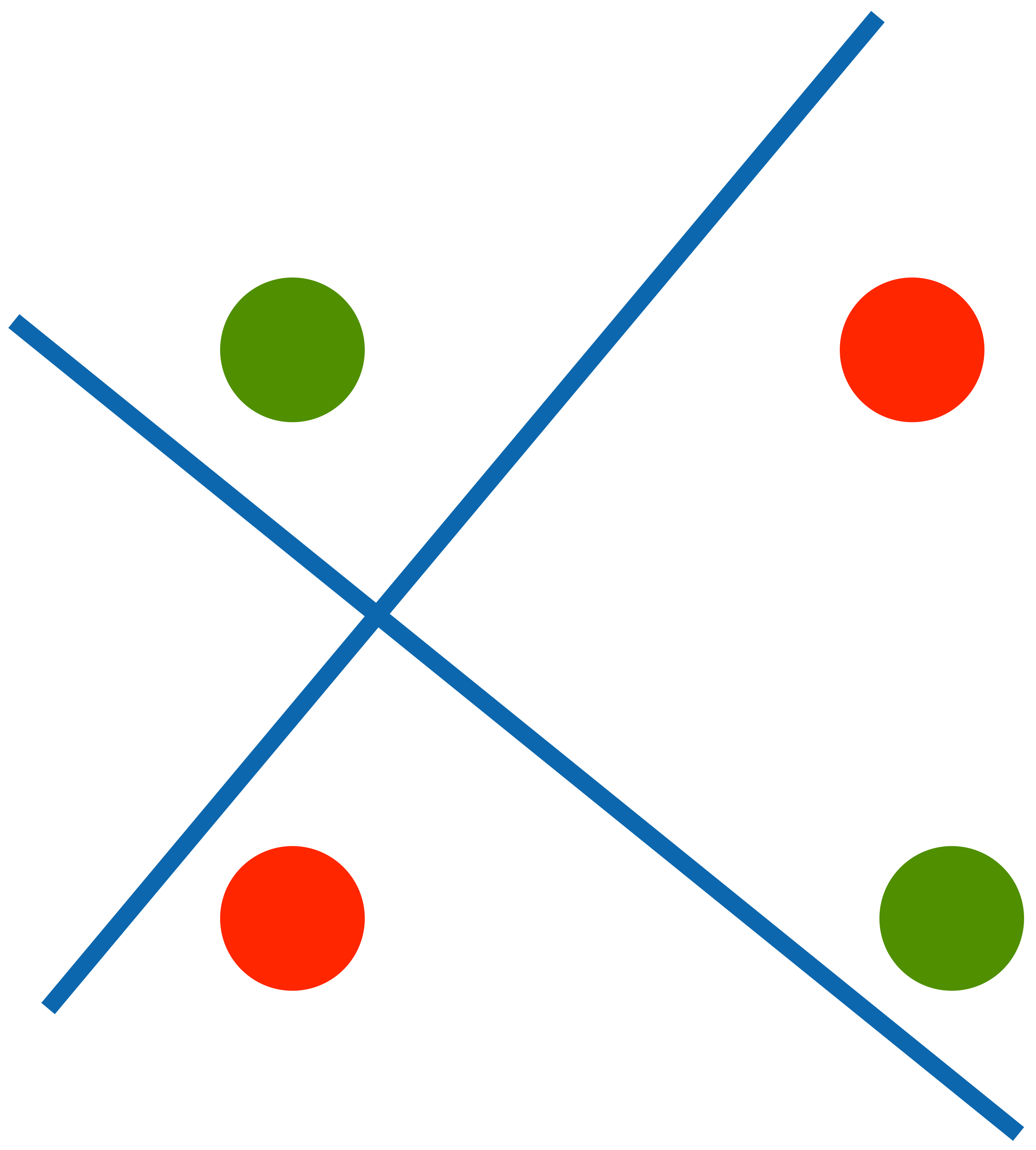

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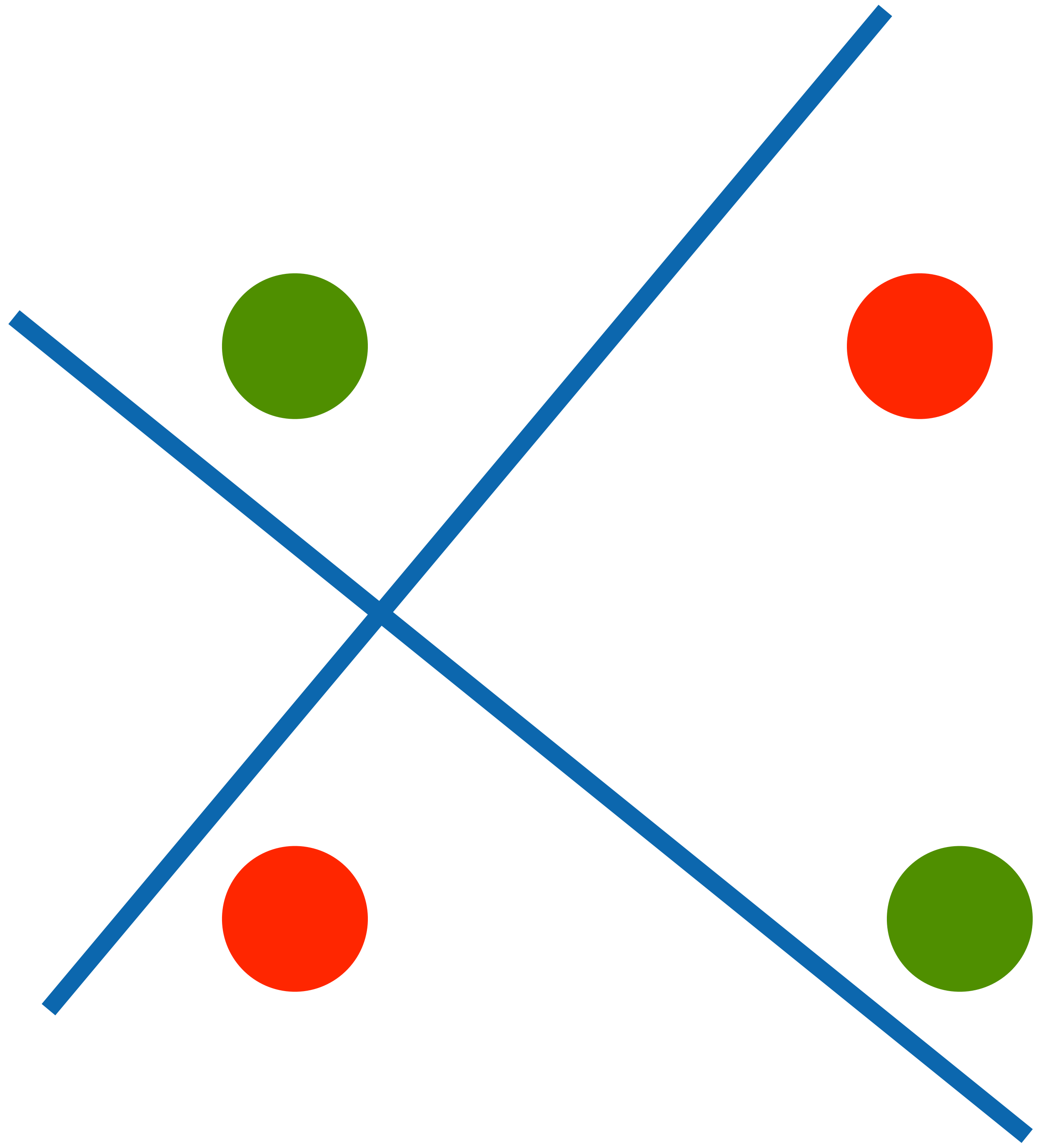


This contributed to the first AI winter

Quiz break

Which one of the following is NOT true about perceptron?

A. Perceptron only works if the data is linearly separable.

B. Perceptron can learn AND function

C. Perceptron can learn XOR function

D. Perceptron is a supervised learning algorithm

Quiz break

Which one of the following is NOT true about perceptron?

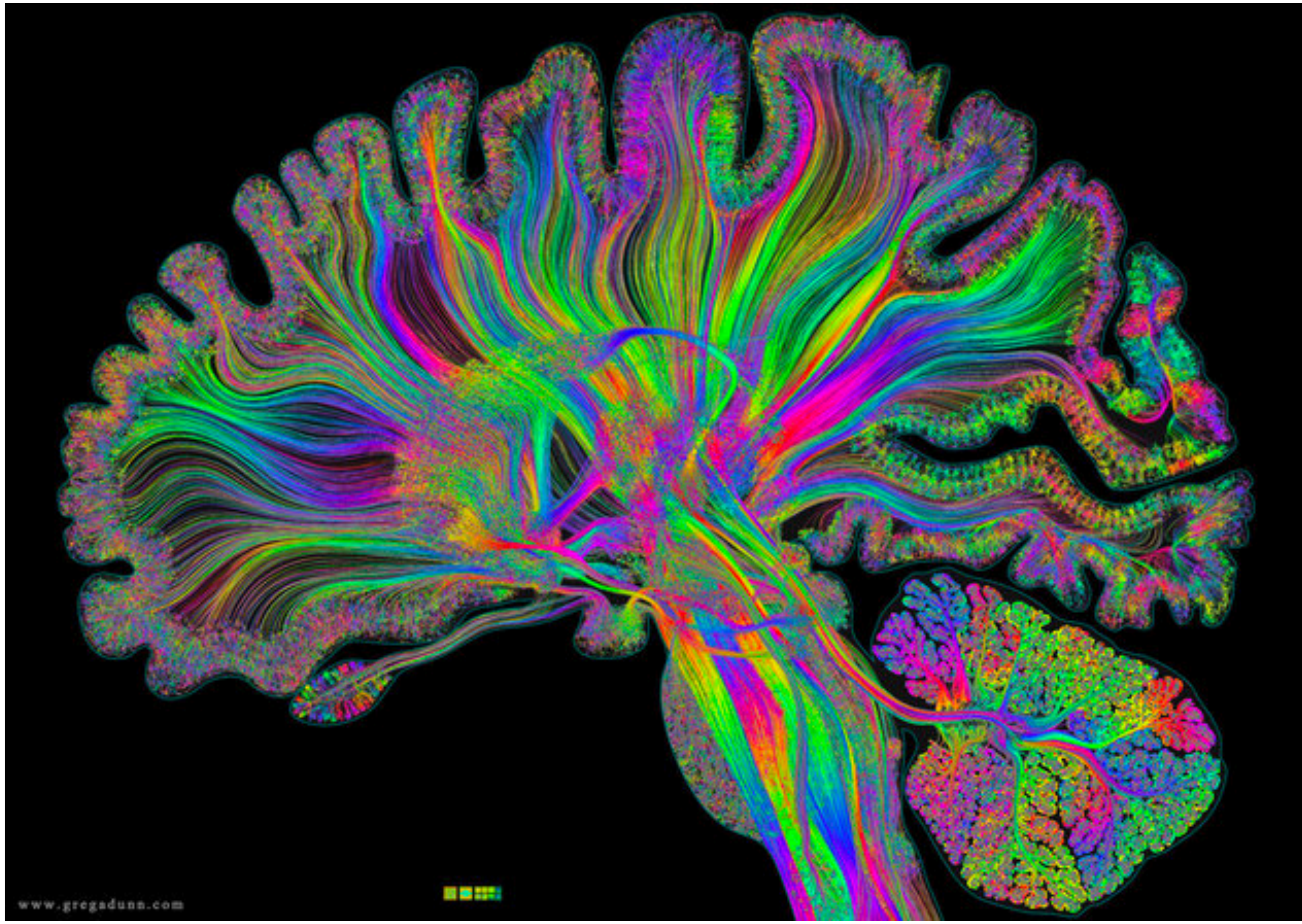
A. Perceptron only works if the data is linearly separable.

B. Perceptron can learn AND function

C. Perceptron can learn XOR function

D. Perceptron is a supervised learning algorithm

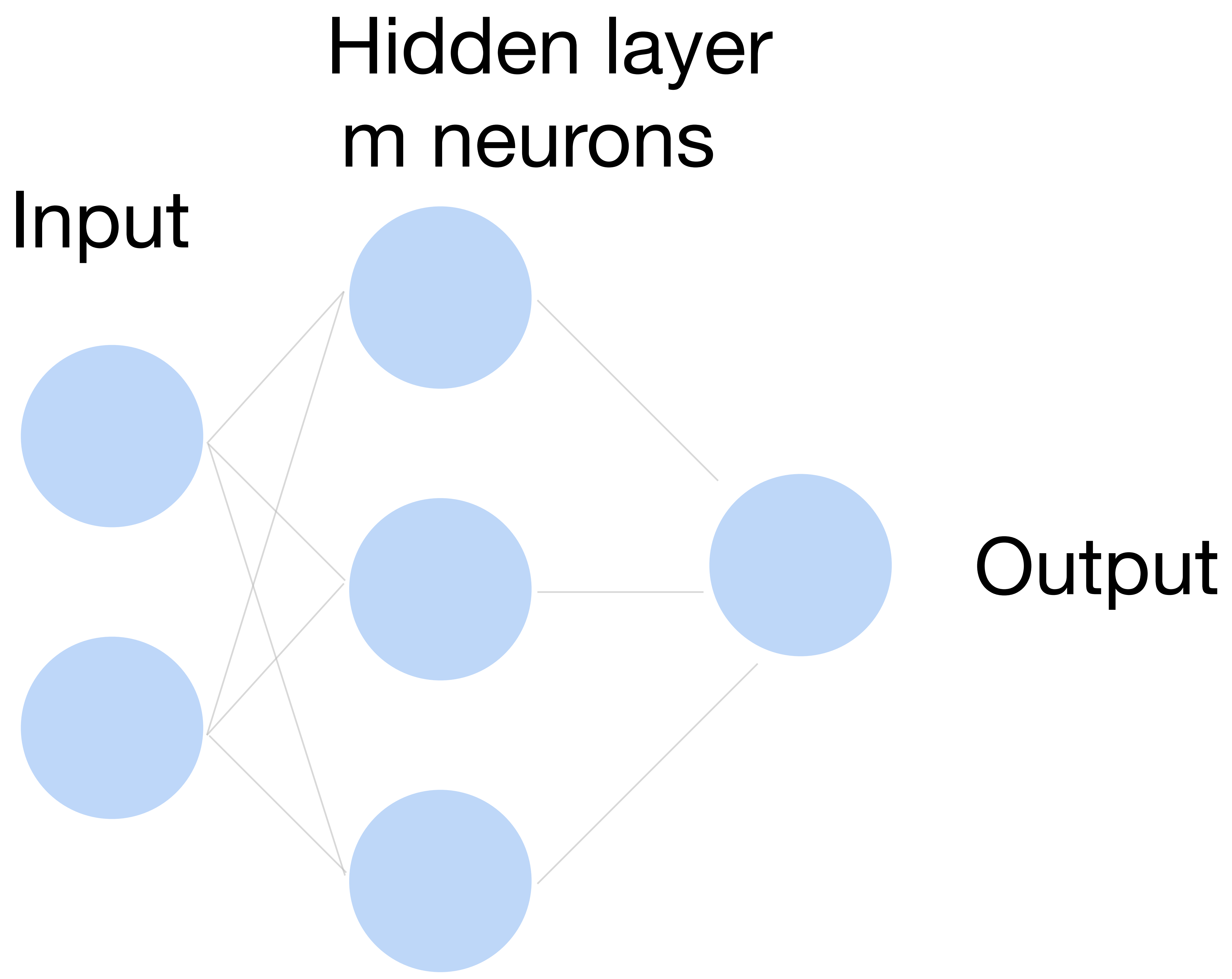
Multilayer Perceptron



Single Hidden Layer

How to classify

Cats vs. dogs?

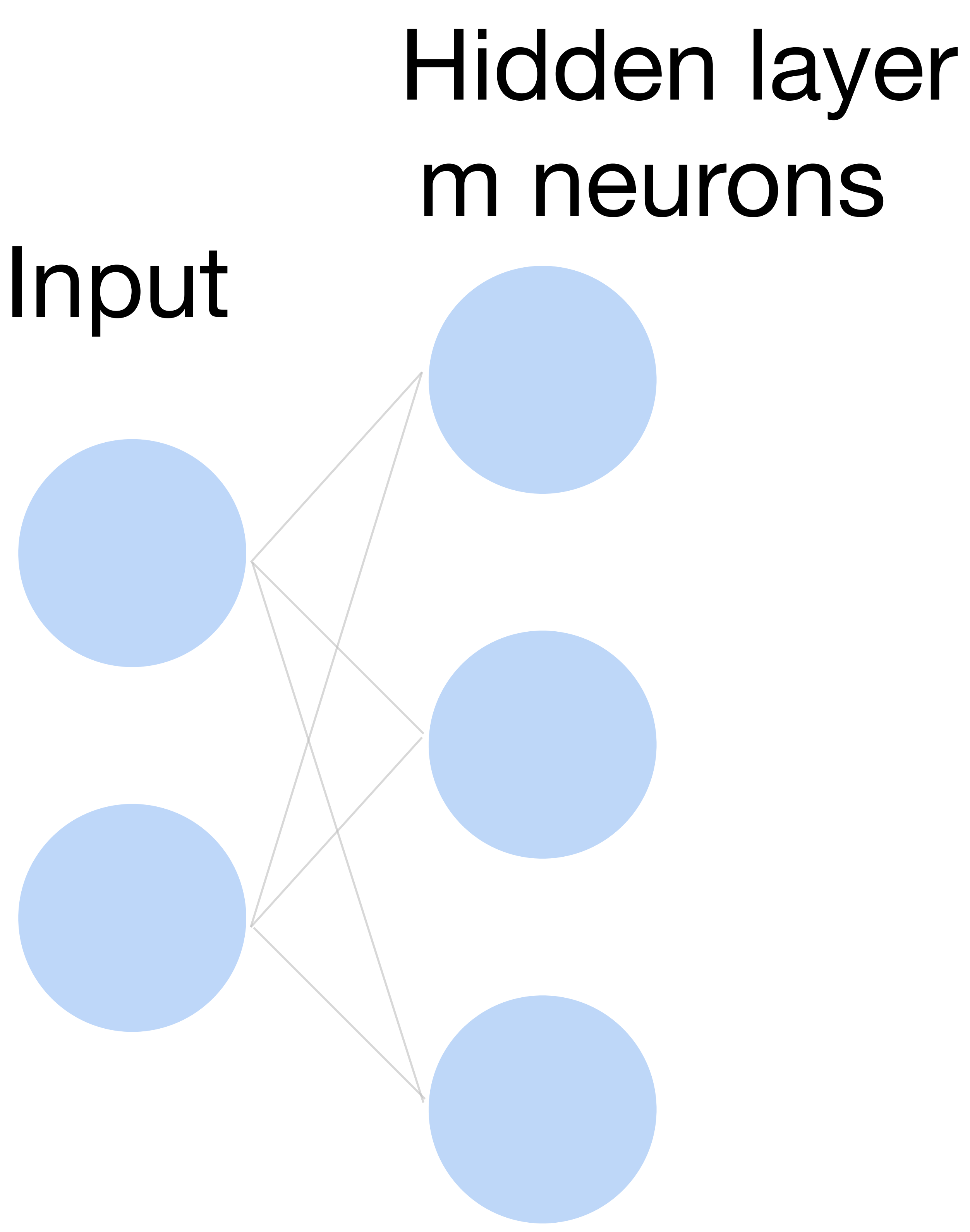


Single Hidden Layer

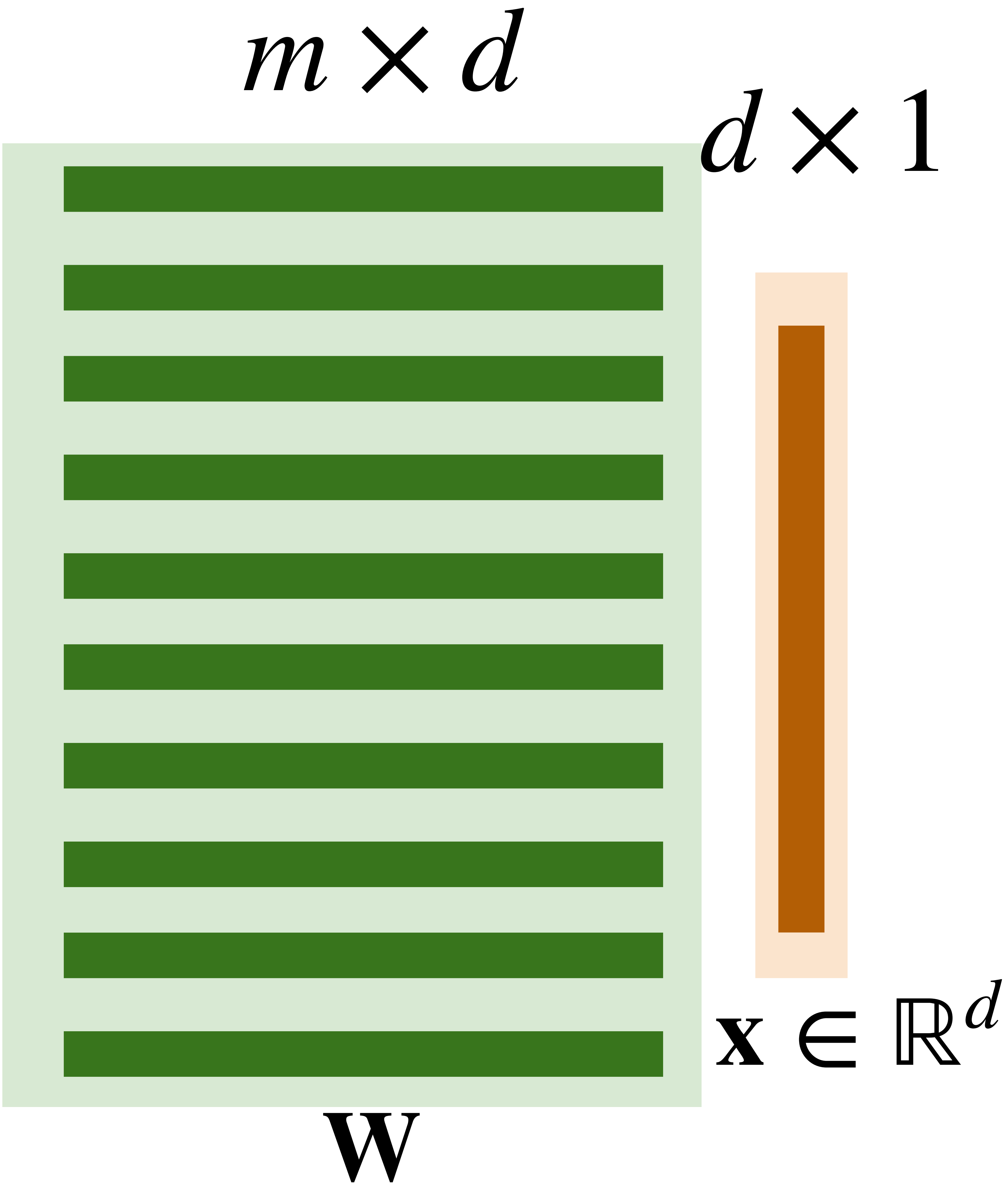
- Input $\mathbf{x} \in \mathbb{R}^d$
- Hidden $\mathbf{W} \in \mathbb{R}^{m \times d}, \mathbf{b} \in \mathbb{R}^m$
- Intermediate output

$$\mathbf{h} = \sigma(\mathbf{W}\mathbf{x} + \mathbf{b})$$

σ is an element-wise activation function



Neural networks with one hidden layer



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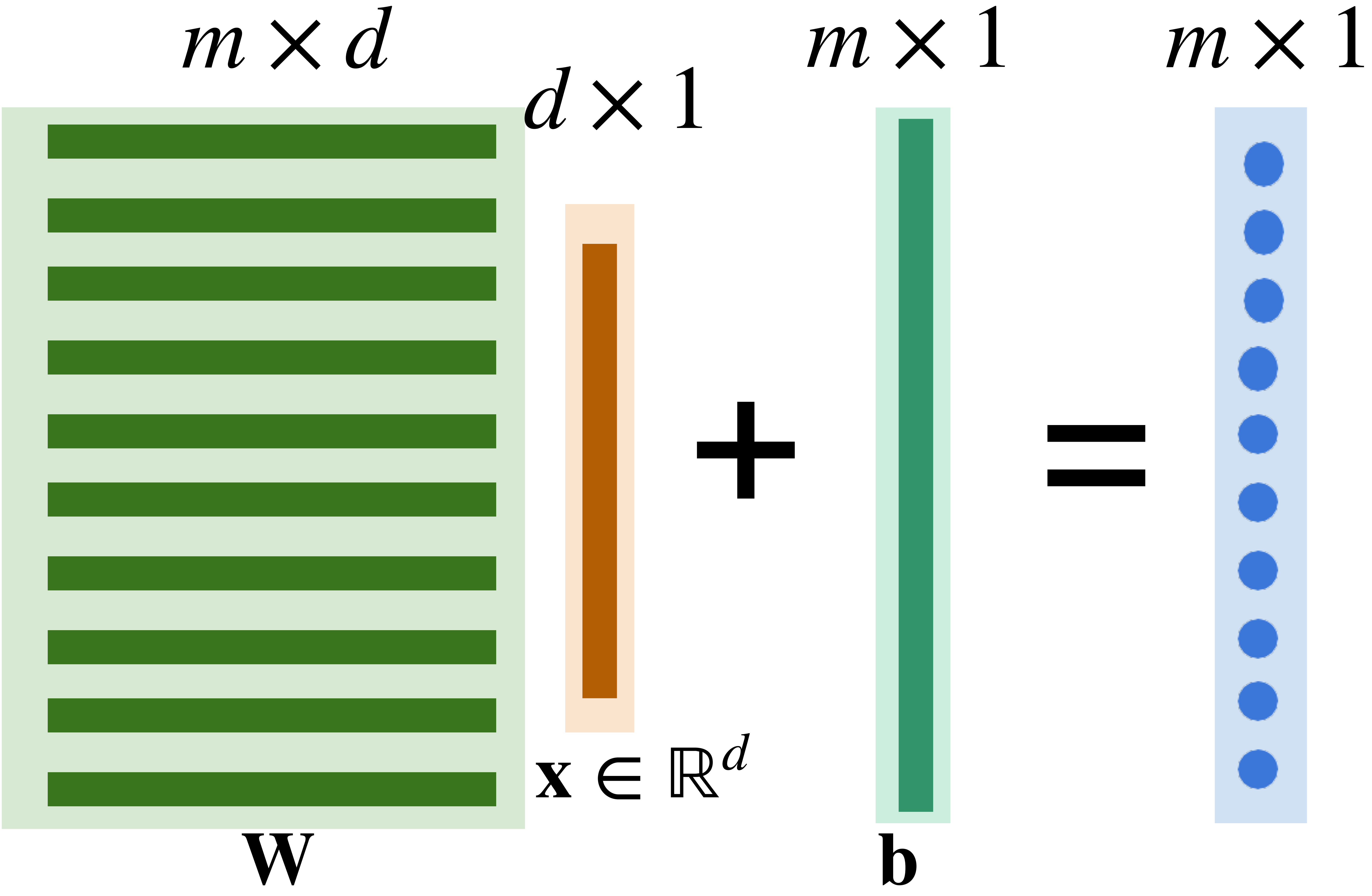

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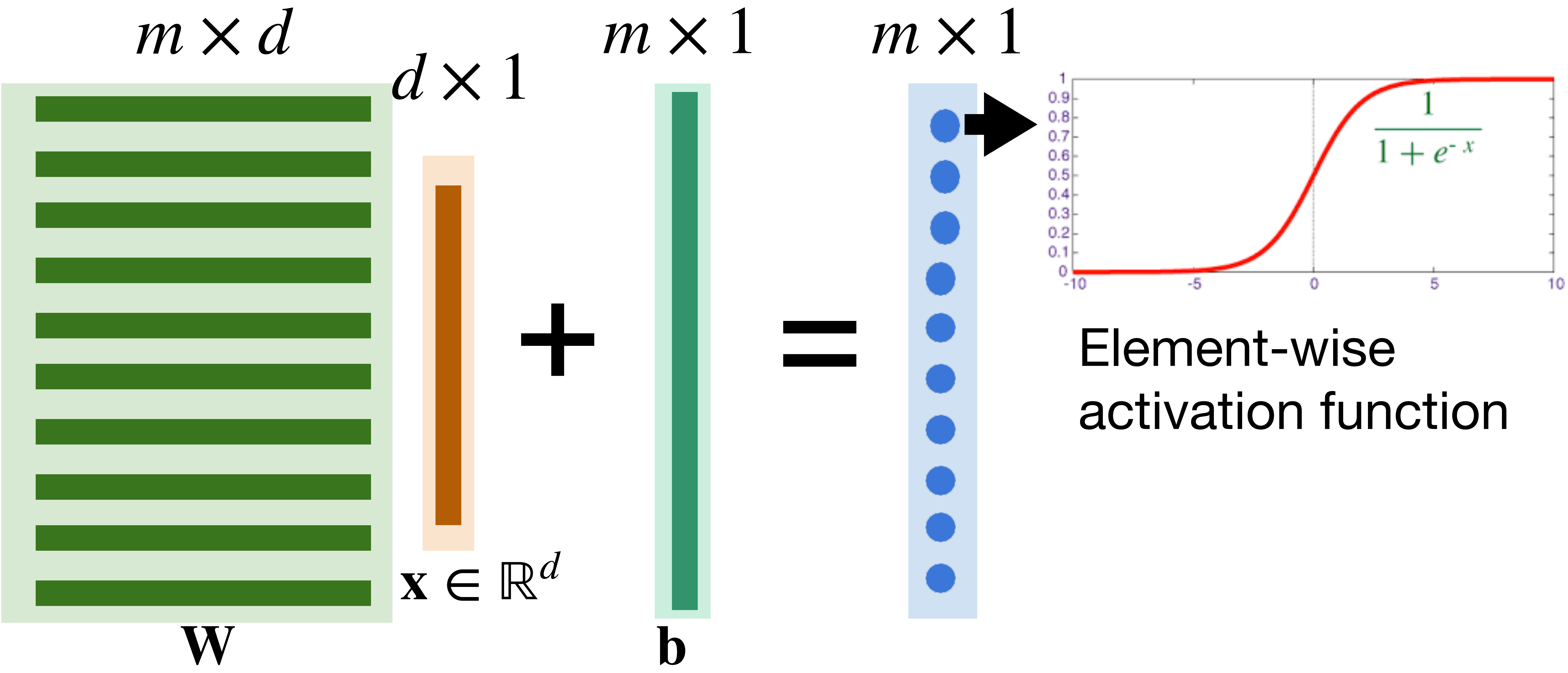
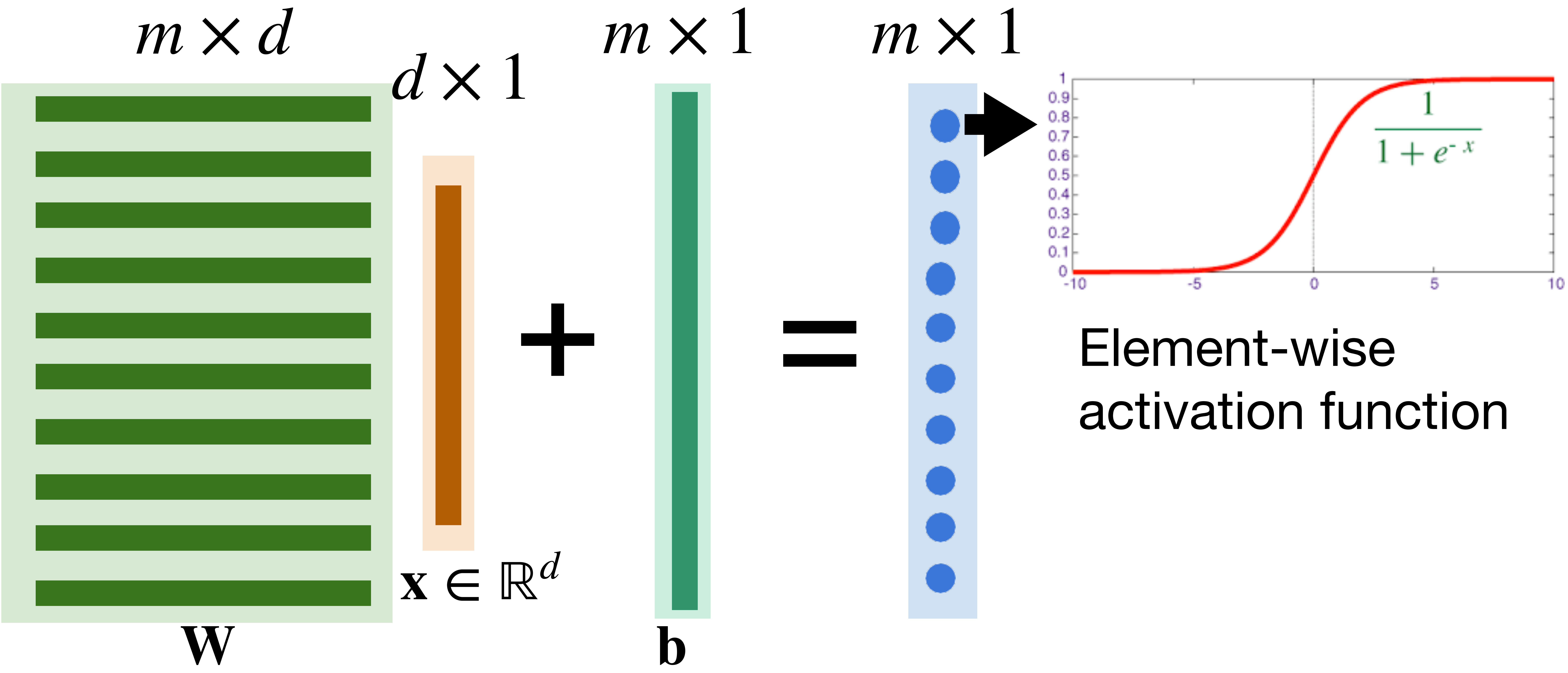


Neural networks with one hidden layer

Key elements: linear operations + Nonlinear activations



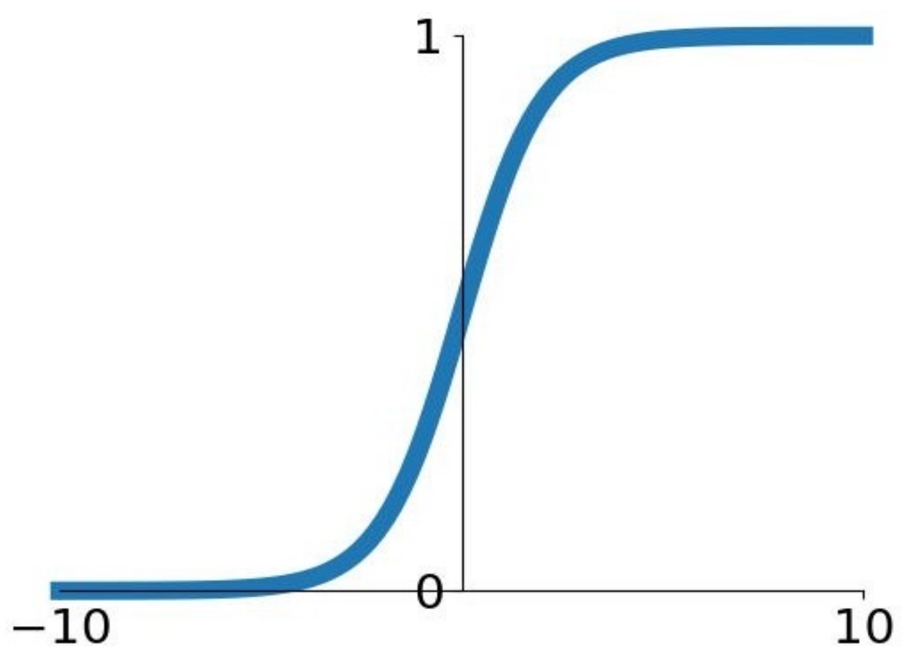
Element-wise activation function

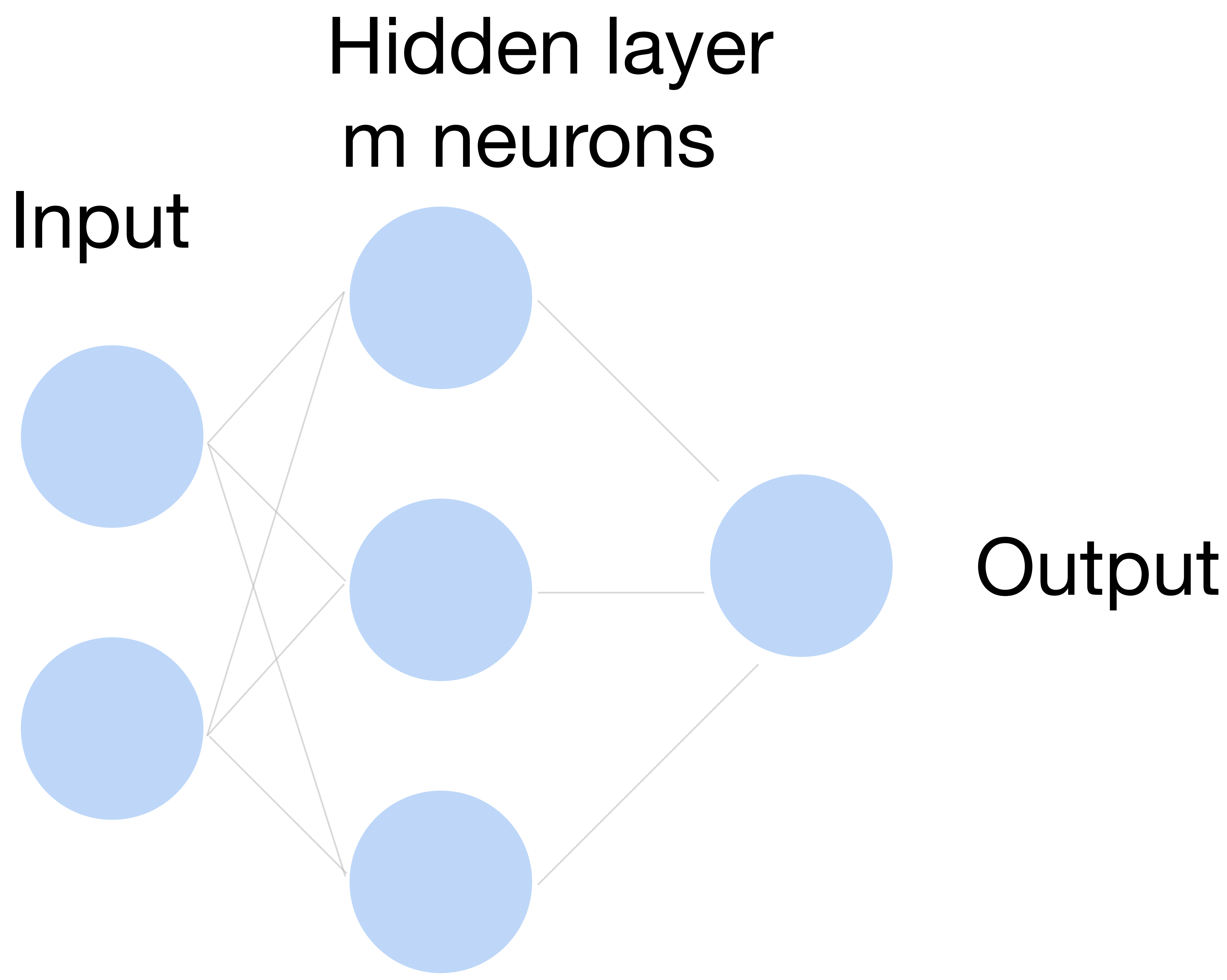
Single Hidden Layer

- Output $f = \mathbf{w}_2^\top \mathbf{h} + b_2$
- Normalize the output into probability using sigmoid

$$p(y = 1 \,|\, \mathbf{x}) = \frac{1}{1 + e^{-f}}$$

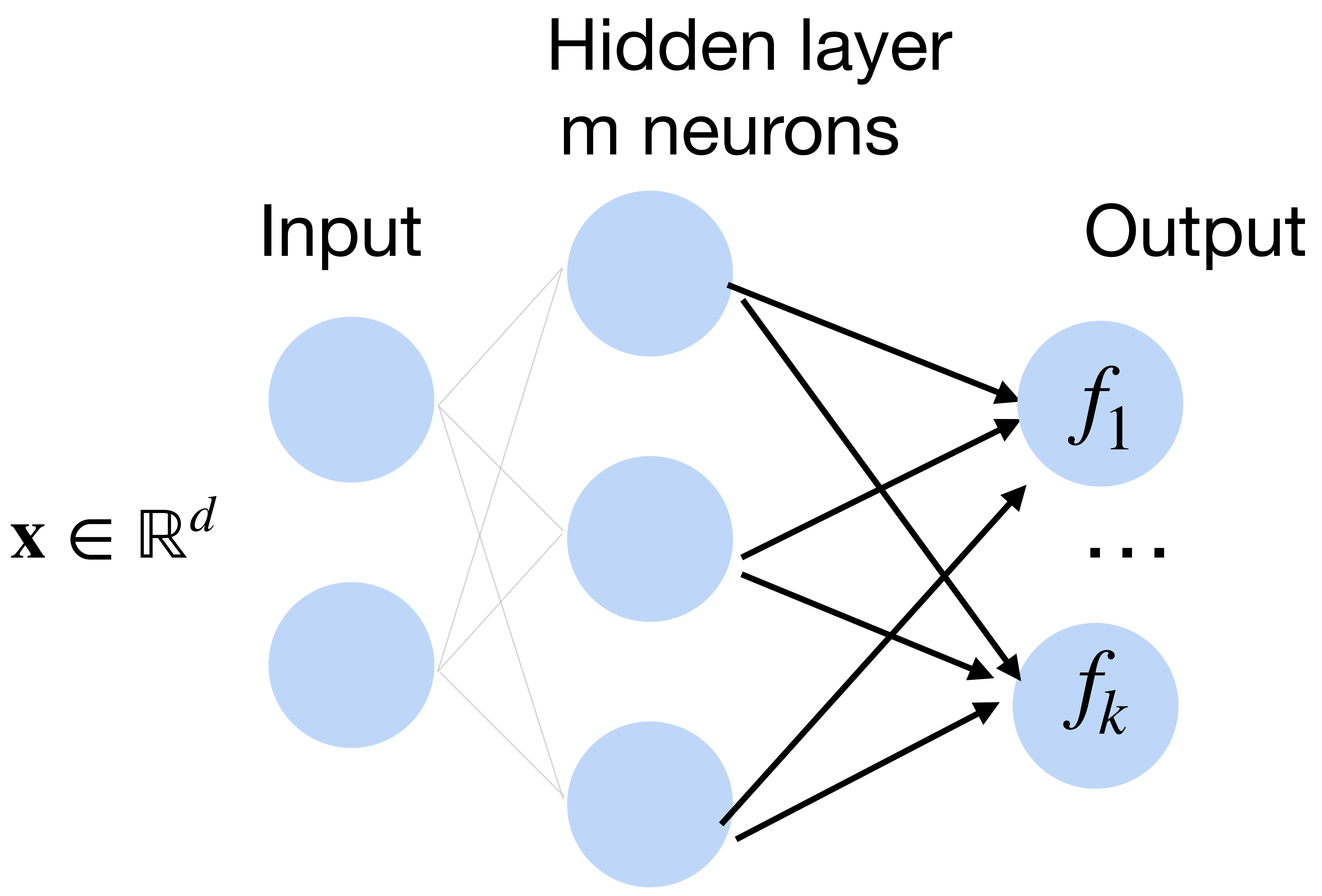
Sigmoid





Multi-class classification

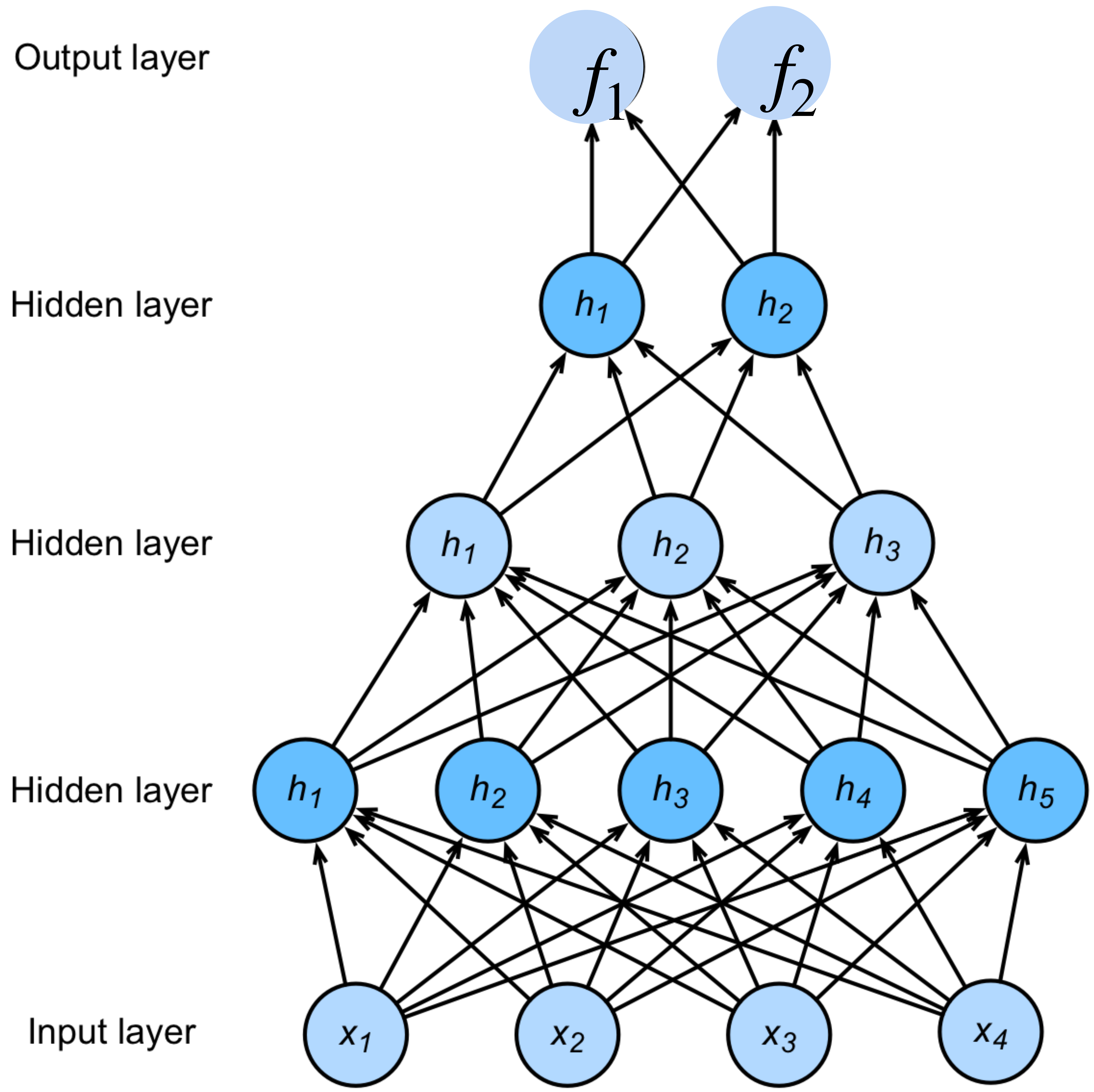
Turns outputs f into k probabilities (sum up to 1 across k classes)



$$p(y \mid \mathbf{x}) = \text{softmax}(\mathbf{f})$$

$$= \frac{\exp f_y(x)}{\sum_i^k \exp f_i(x)}$$

Deep neural networks (DNNs)



$$\mathbf{h}_1 = \sigma(\mathbf{W}_1\mathbf{x} + \mathbf{b}_1)$$
$$\mathbf{h}_2 = \sigma(\mathbf{W}_2\mathbf{h}_1 + \mathbf{b}_2)$$
$$\mathbf{h}_3 = \sigma(\mathbf{W}_3\mathbf{h}_2 + \mathbf{b}_3)$$
$$\mathbf{f} = \mathbf{W}_4\mathbf{h}_3 + \mathbf{b}_4$$
$$\mathbf{y} = \mathrm{softmax}(\mathbf{f})$$

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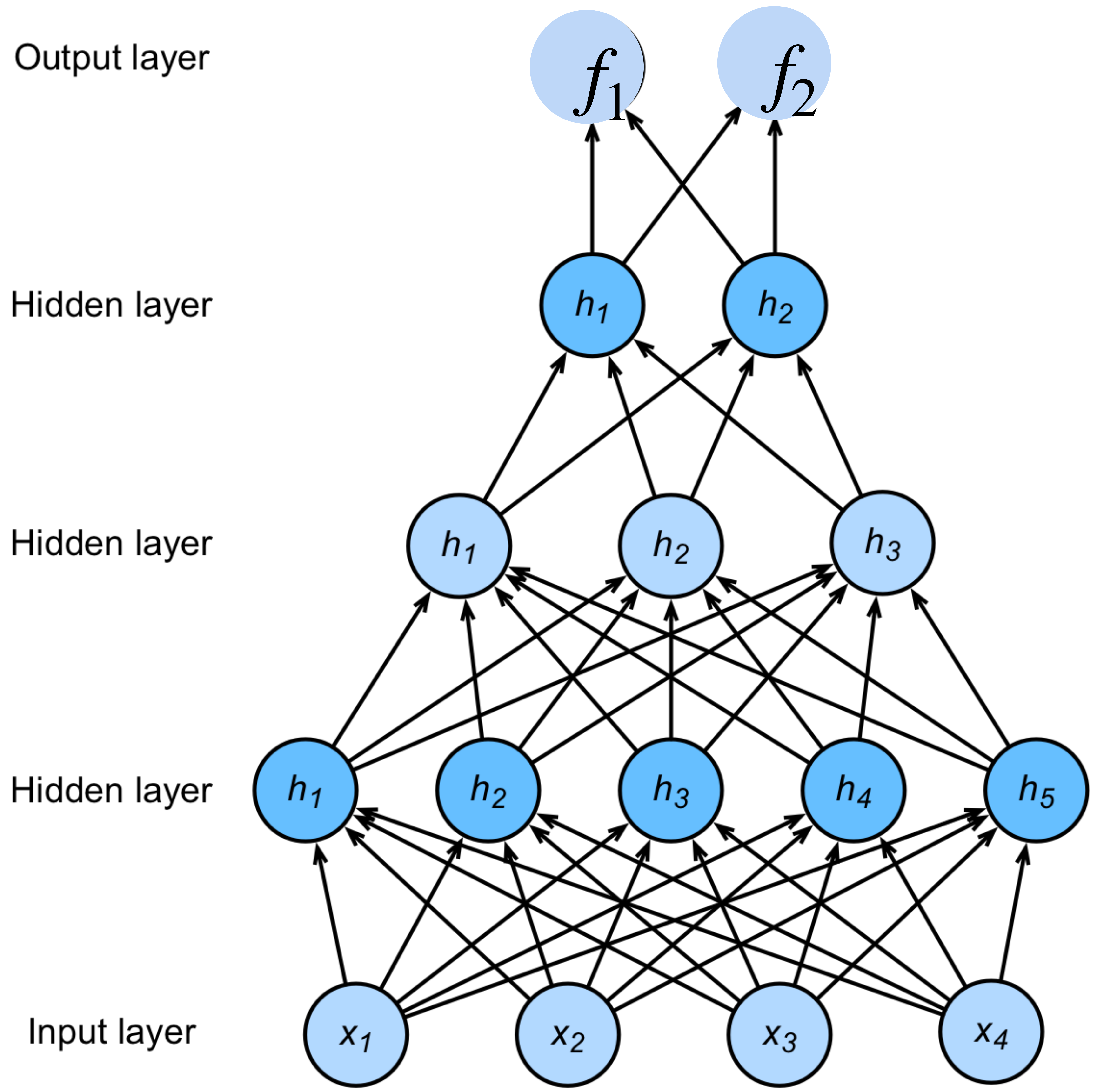

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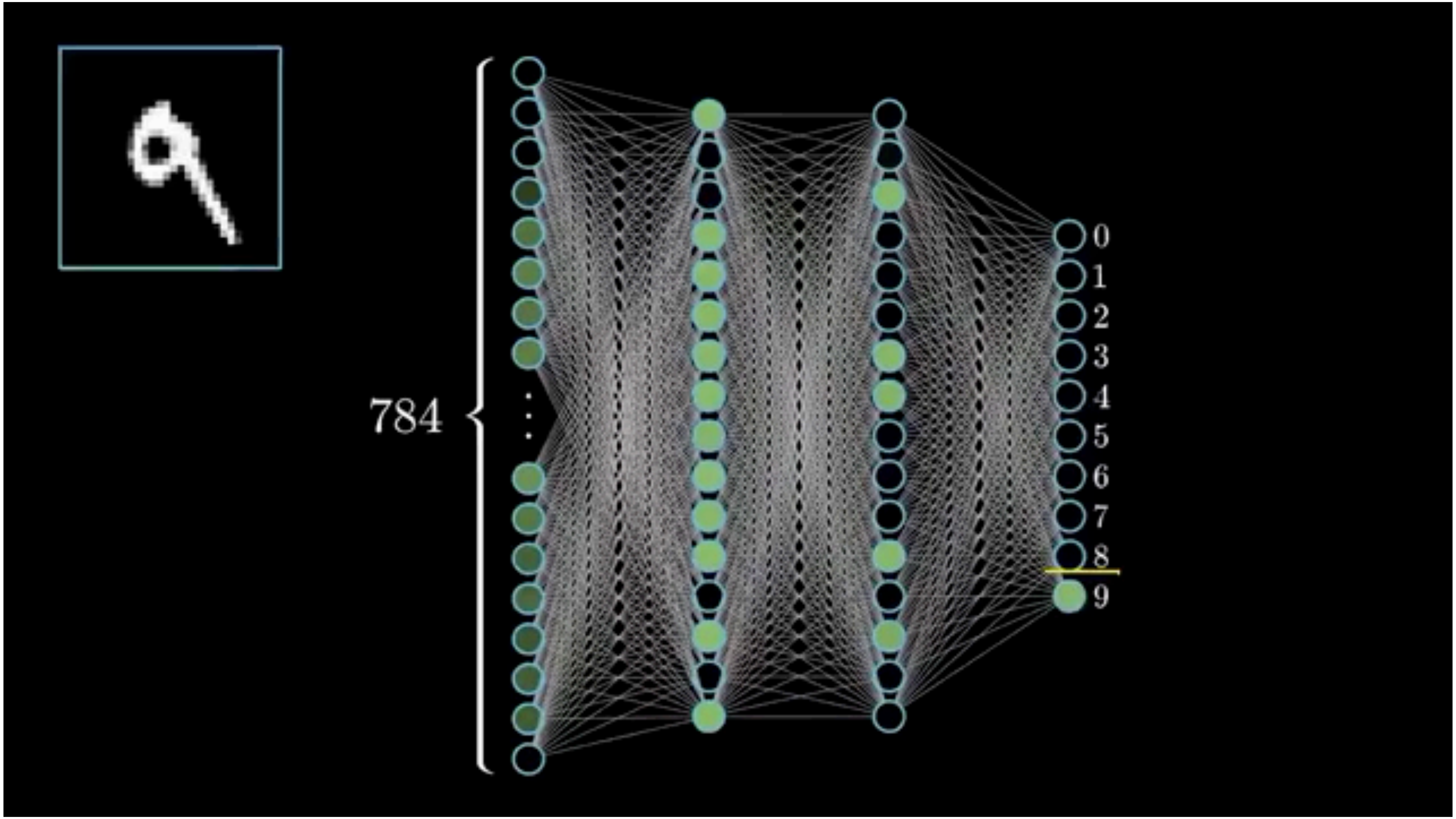
NNs are composition of nonlinear functions

Classify MNIST handwritten digits



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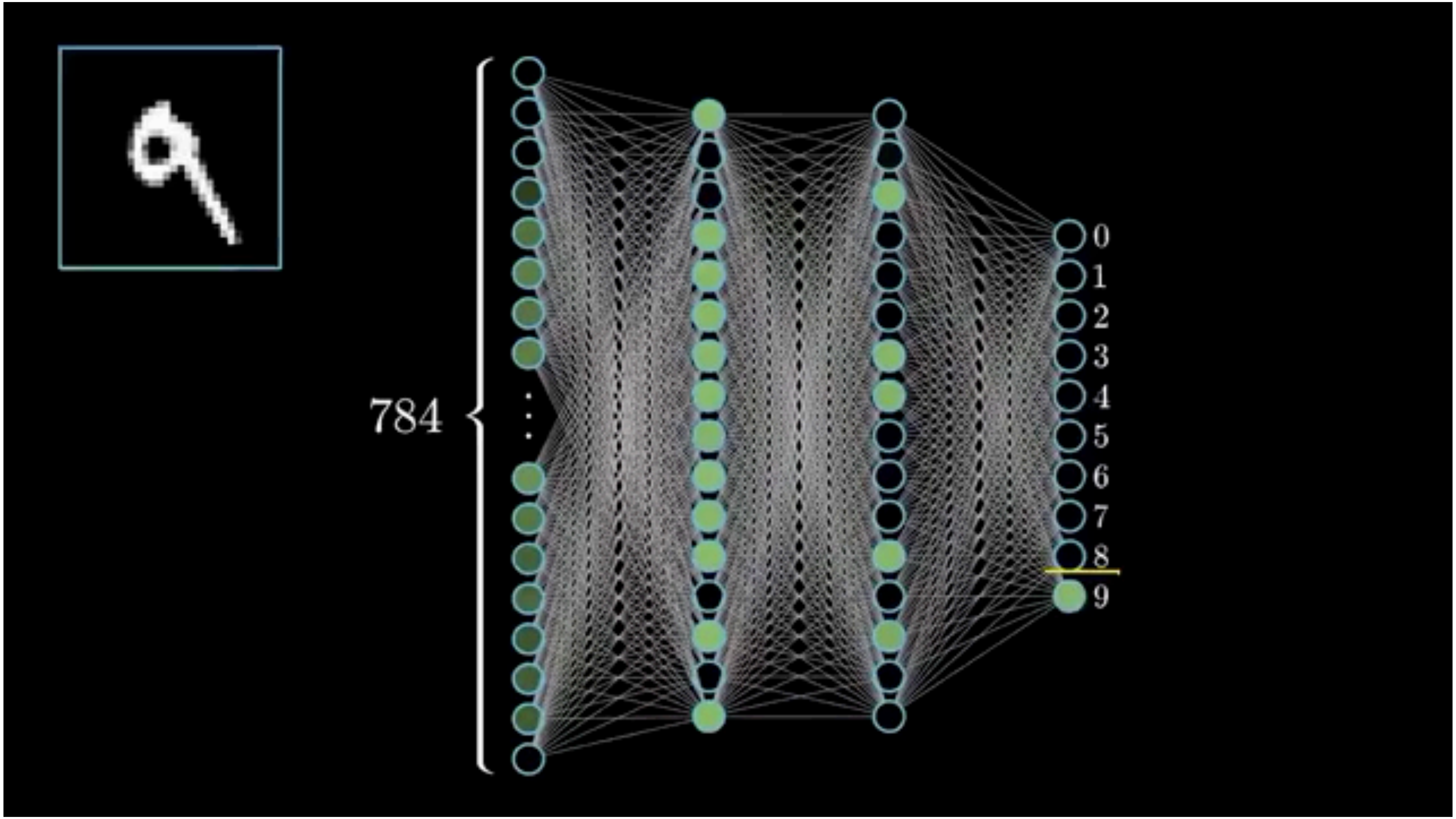
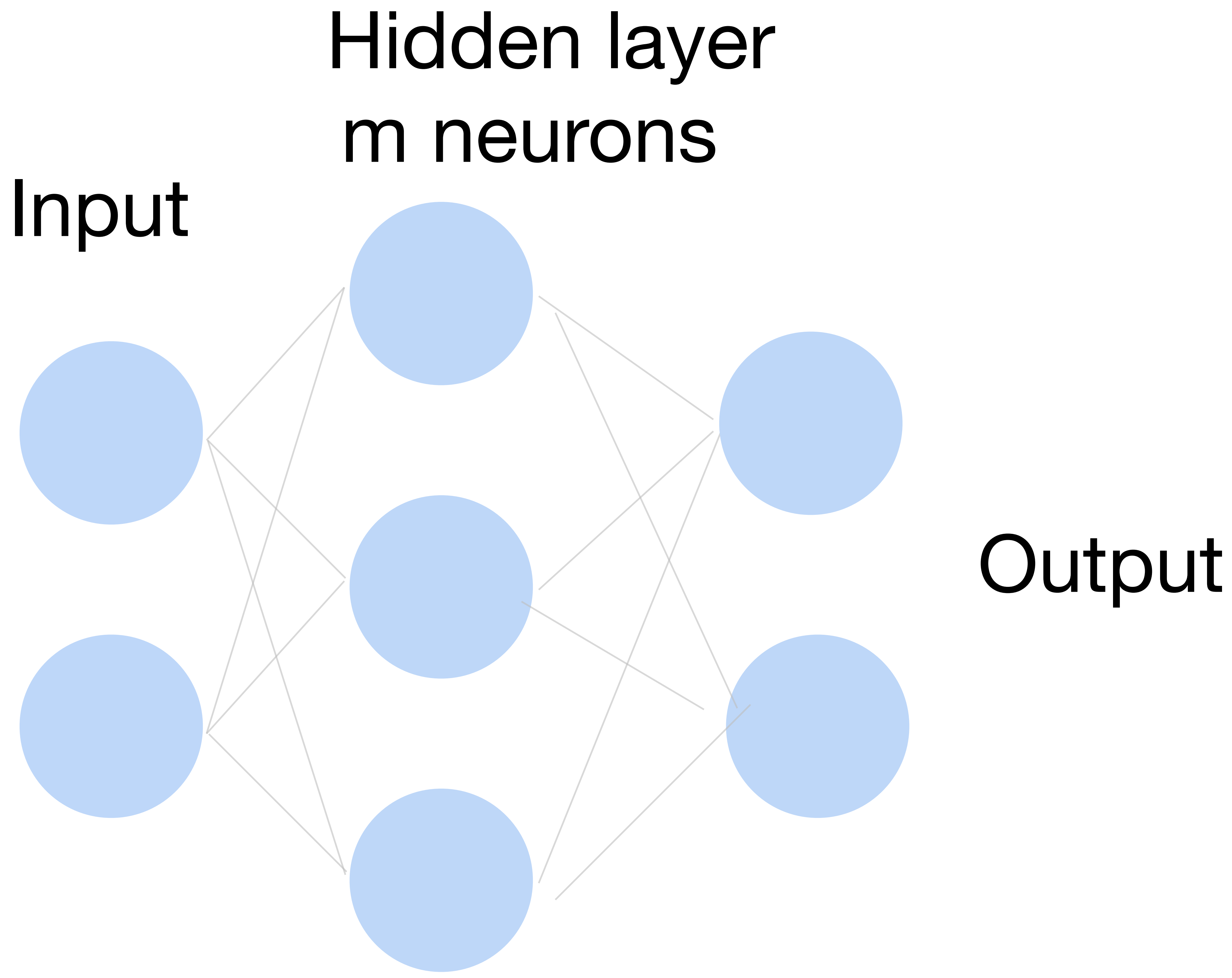


How to train a neural network?

Loss function: $$\frac{1}{|D|}\sum_i \ell(\mathbf{x}_i, y_i)$$



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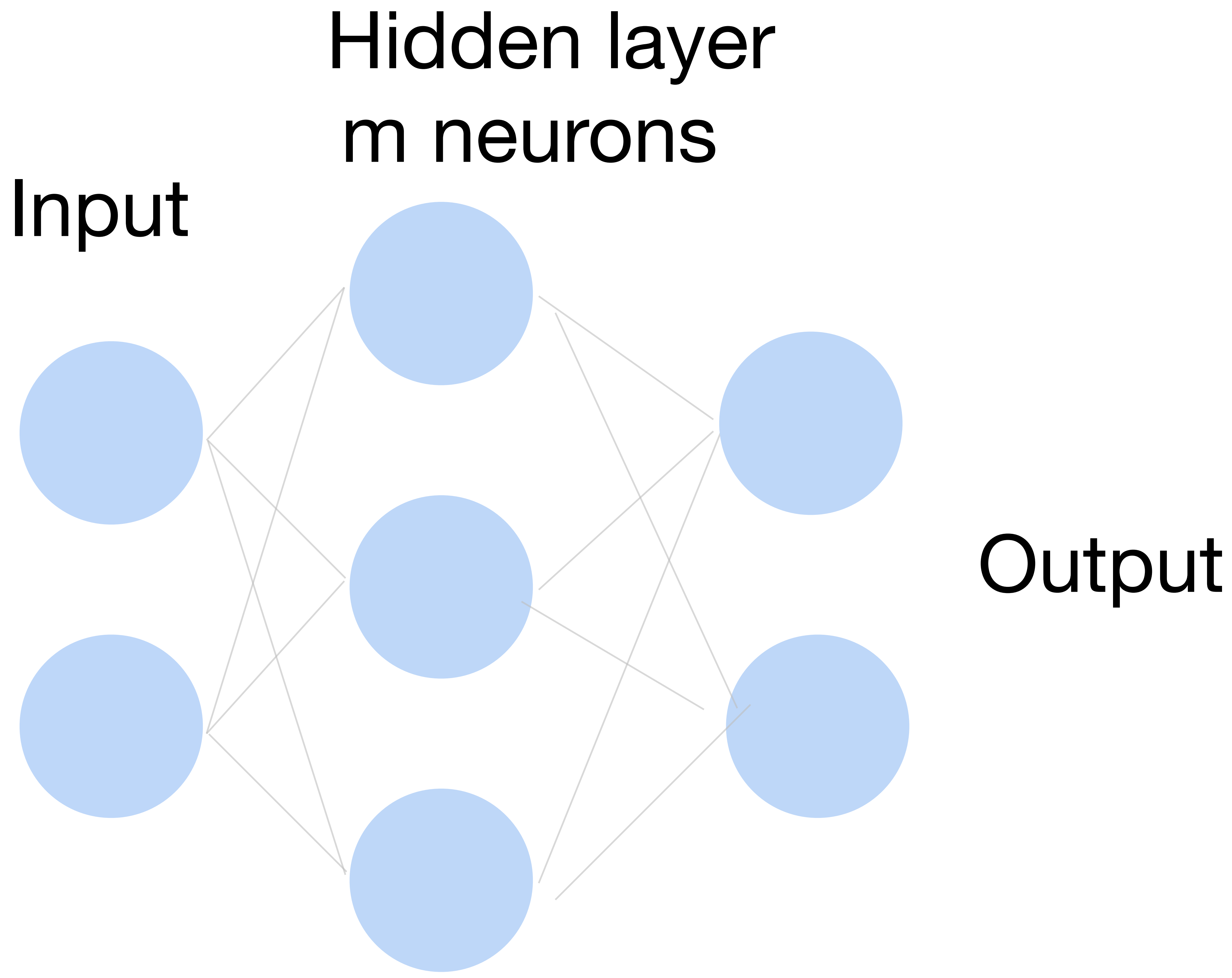
Per-sample loss:

$$\ell(\mathbf{x}, y) = \sum_{j=1}^{K} -y_j \log p_j$$



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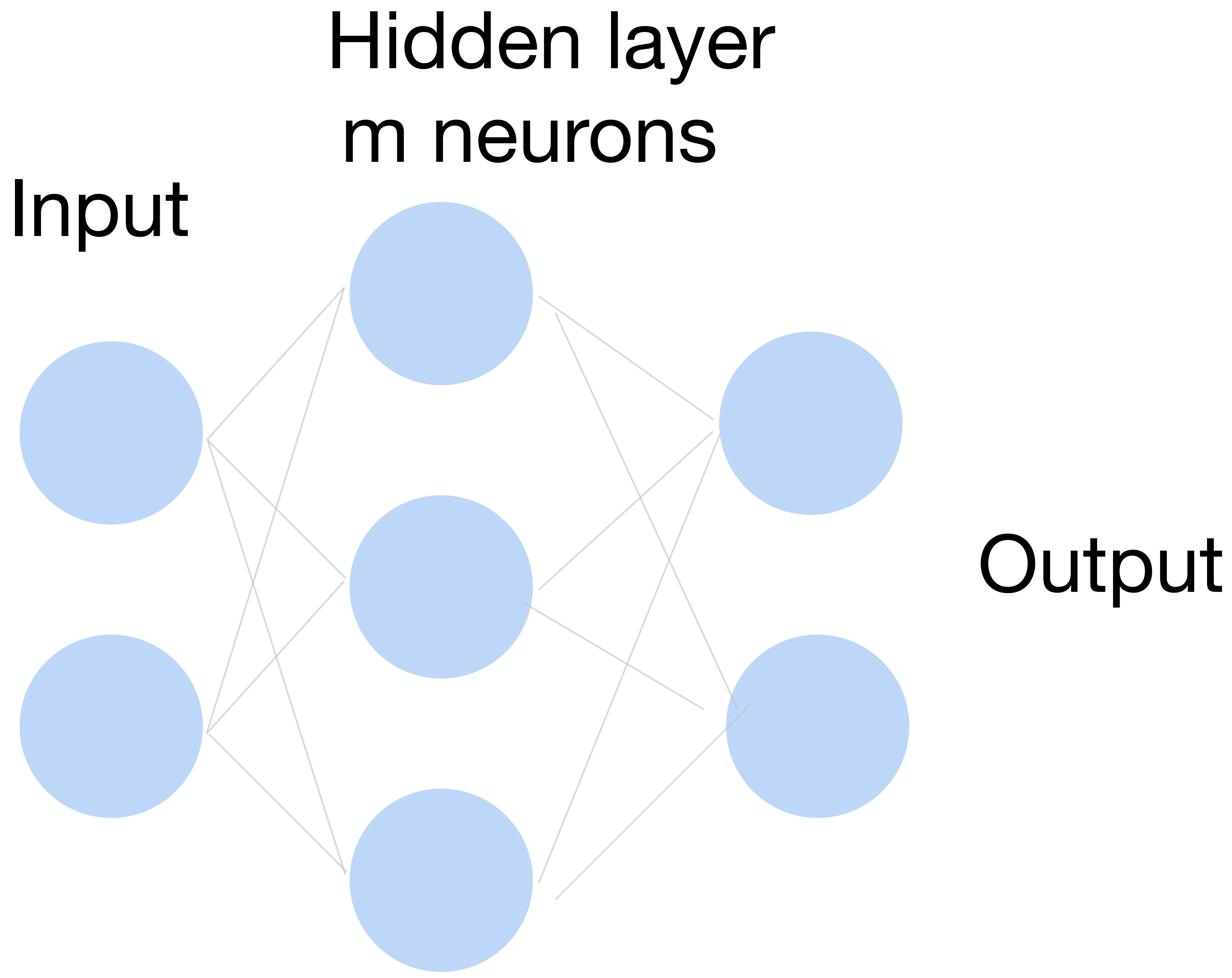
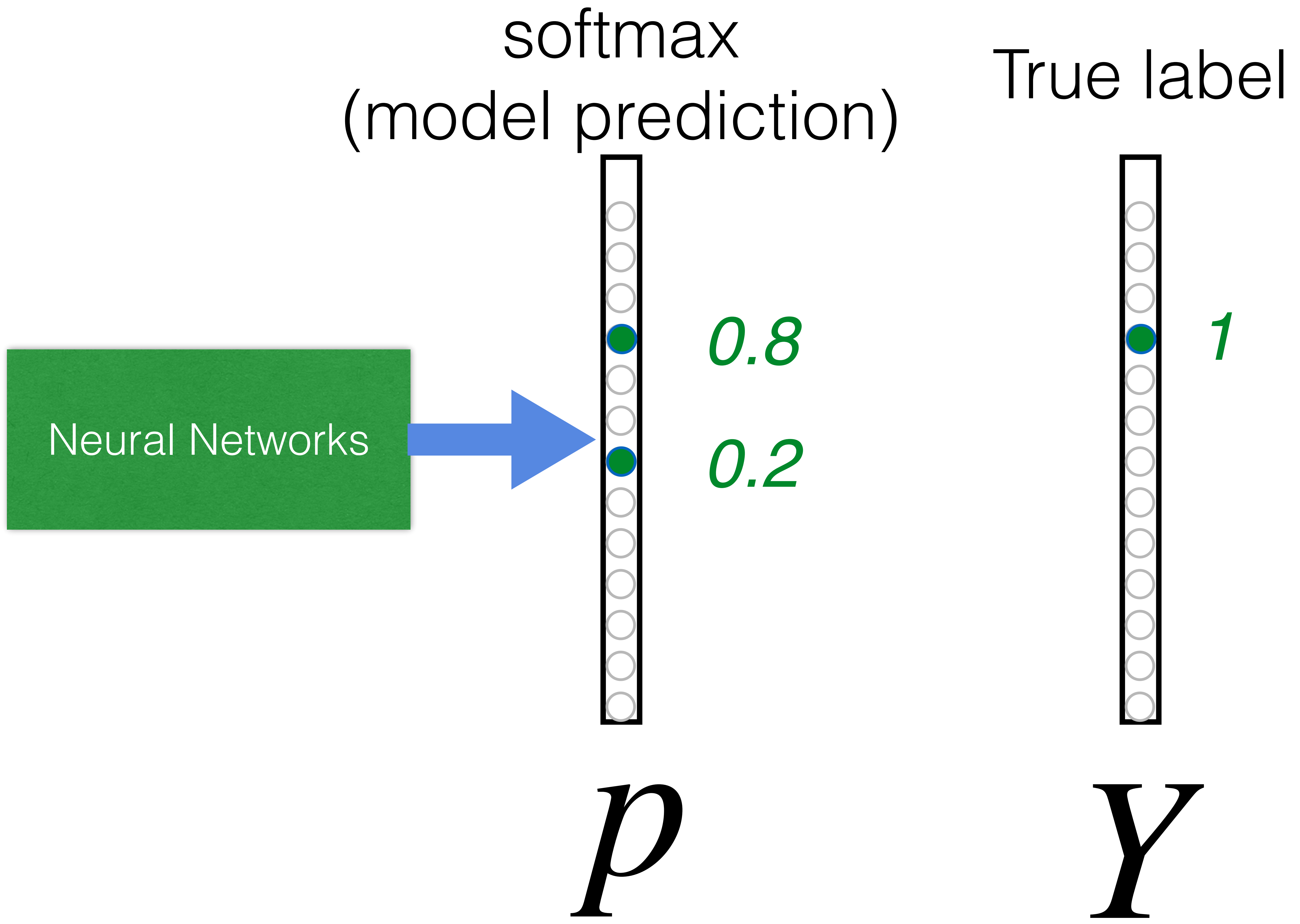
Also known as cross-entropy loss or softmax loss



Cross-Entropy Loss



$$L_{CE} = \sum_j - y_j \log(p_j)$$

$$= -\log(0.8)$$

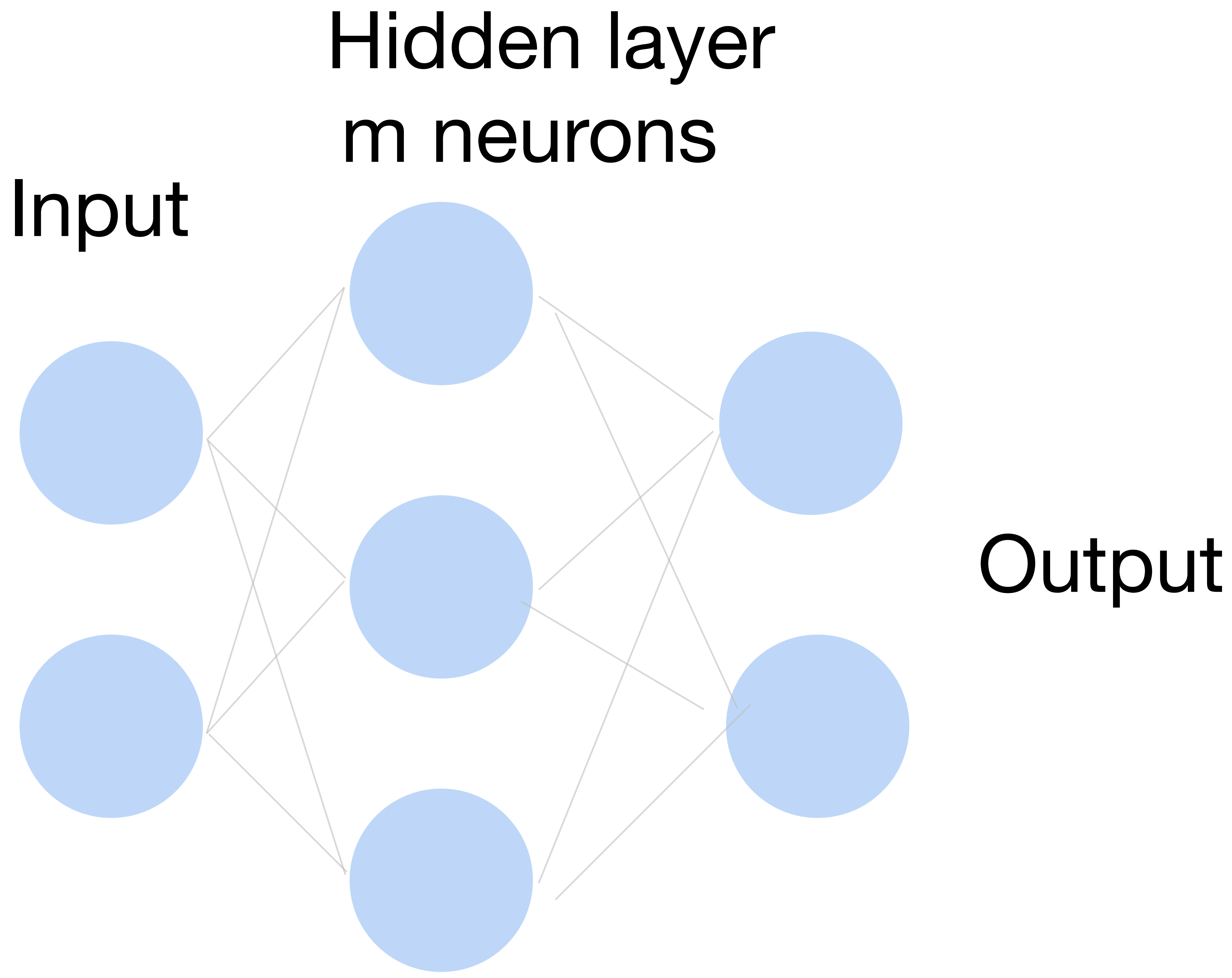
Goal: push **p** and **Y** to be identical

How to train a neural network?

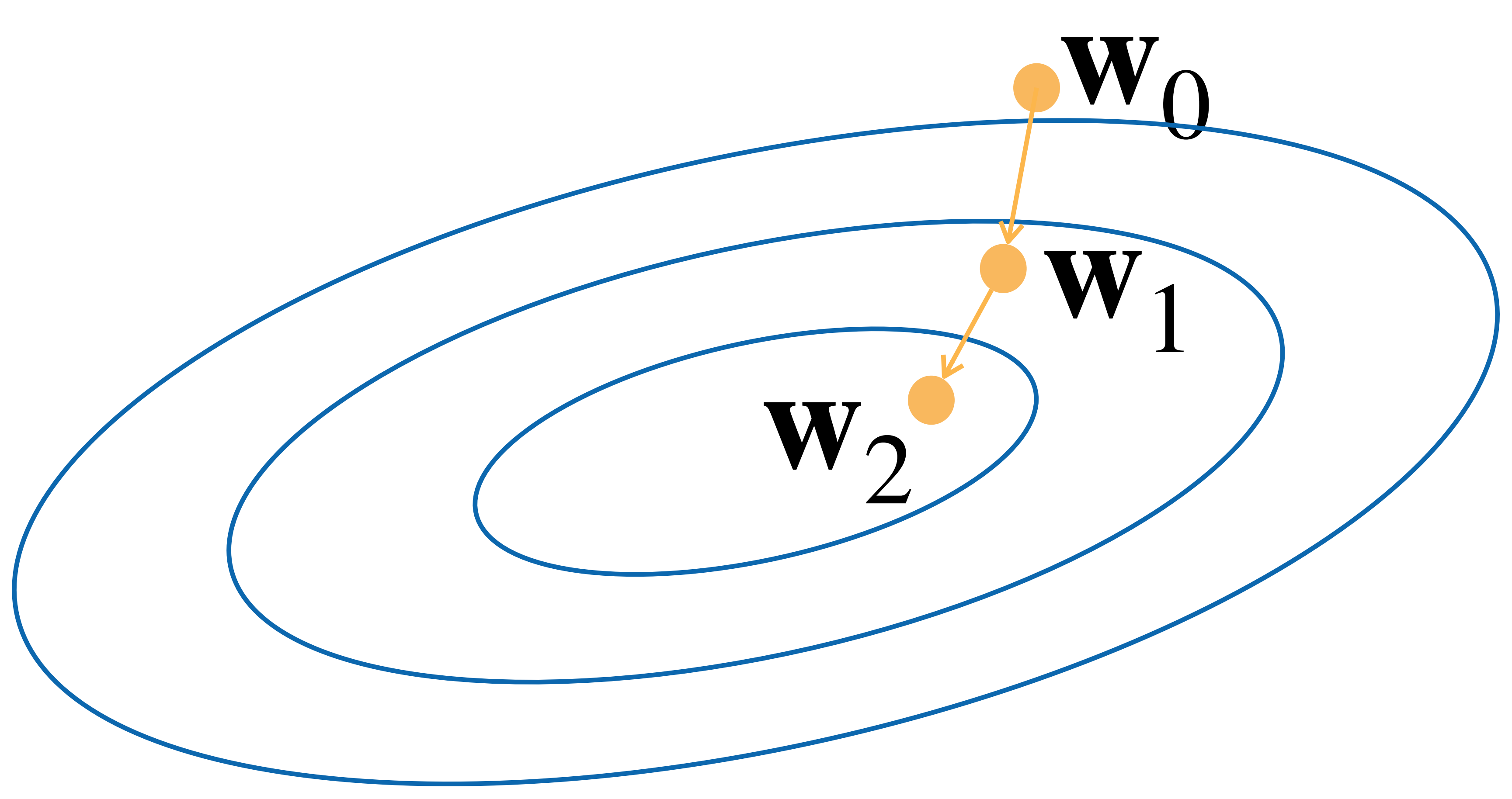
Update the weights W to minimize the loss function

$$L = \frac{1}{|D|} \sum_i \ell(\mathbf{x}_i, y_i)$$

Use gradient descent!



Gradient Descent



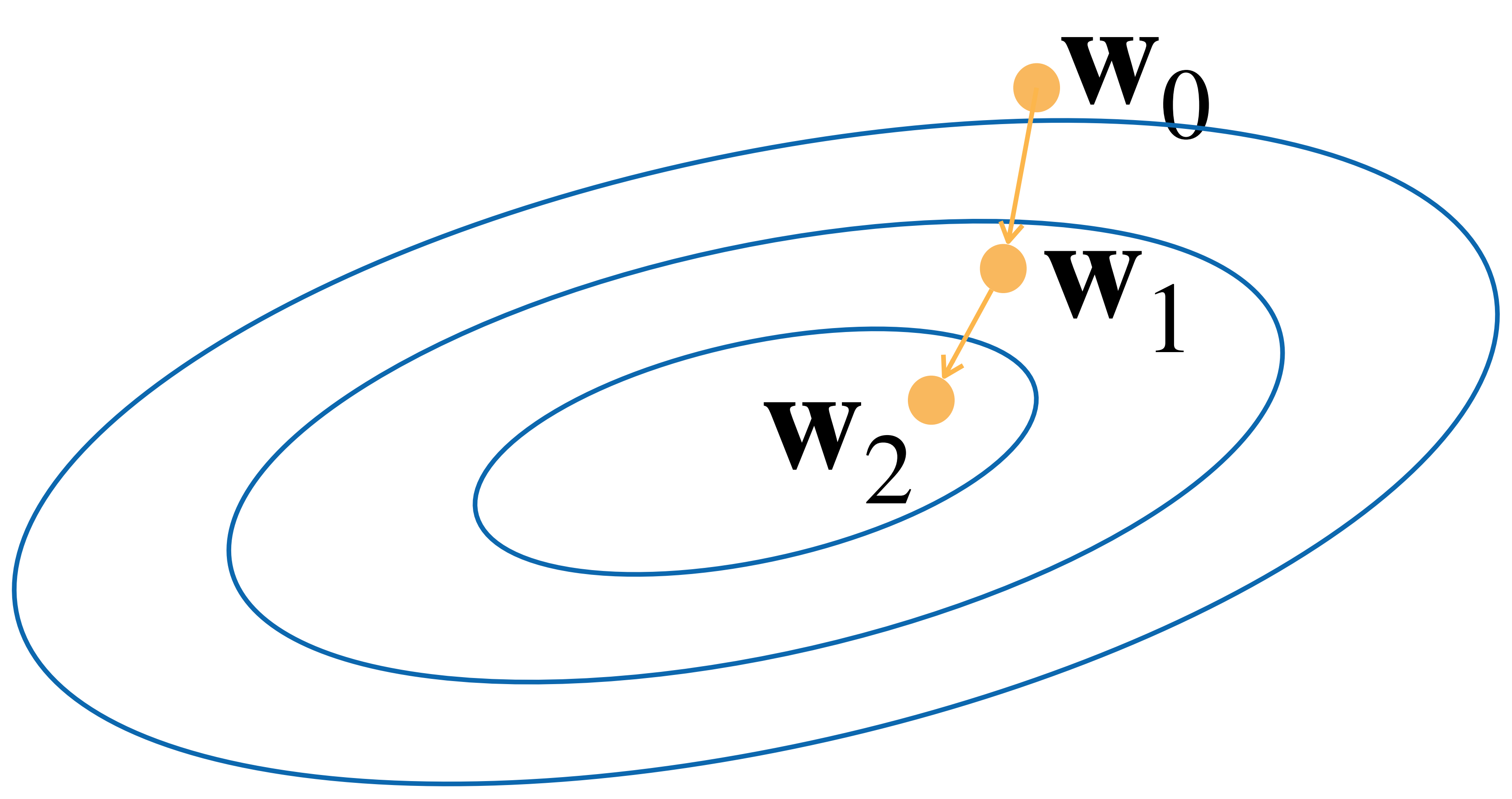
- Choose a learning rate $\alpha > 0$
- Initialize the model parameters w_0
- For t =1,2,…
  - Update parameters:

$$\mathbf{w}_t = \mathbf{w}_{t-1} - \alpha \frac{\partial L}{\partial \mathbf{w}_{t-1}}$$

$$= \mathbf{w}_{t-1} - \alpha \frac{1}{|D|} \sum_{\mathbf{x} \in D} \frac{\partial \ell(\mathbf{x}_i, y_i)}{\partial \mathbf{w}_{t-1}}$$

- Repeat until converges

Gradient Descent



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D can
be very large.
Expensive

- Repeat until converges

Minibatch Stochastic Gradient Descent

- Choose a learning rate $\alpha > 0$
- Initialize the model parameters w_0
- For t =1,2,…
  - **Randomly sample a subset (mini-batch)** $B \subset D$
    Update parameters:

$$\mathbf{w}_t = \mathbf{w}_{t-1} - \alpha \frac{1}{|B|} \sum_{\mathbf{x} \in B} \frac{\partial \ell(\mathbf{x}_i, y_i)}{\partial \mathbf{w}_{t-1}}$$

- Repeat

Calculate gradient: backpropagation with chain rule

- Define a loss function L, must compute $\frac{\partial L}{\partial \mathbf{W}}, \frac{\partial L}{\partial b}$ for all weights and biases.

Calculate gradient: backpropagation with chain rule

- Define a loss function L, must compute $\dfrac{\partial L}{\partial \mathbf{W}}, \dfrac{\partial L}{\partial b}$ for all weights and biases.
- Gradient to a variable =
  gradient on the top x gradient from the current operation

$$\frac{\partial L}{\partial \boldsymbol{W}} = \frac{\partial L}{\partial \boldsymbol{z_1}} \frac{\partial \boldsymbol{z_1}}{\partial \boldsymbol{W}}$$

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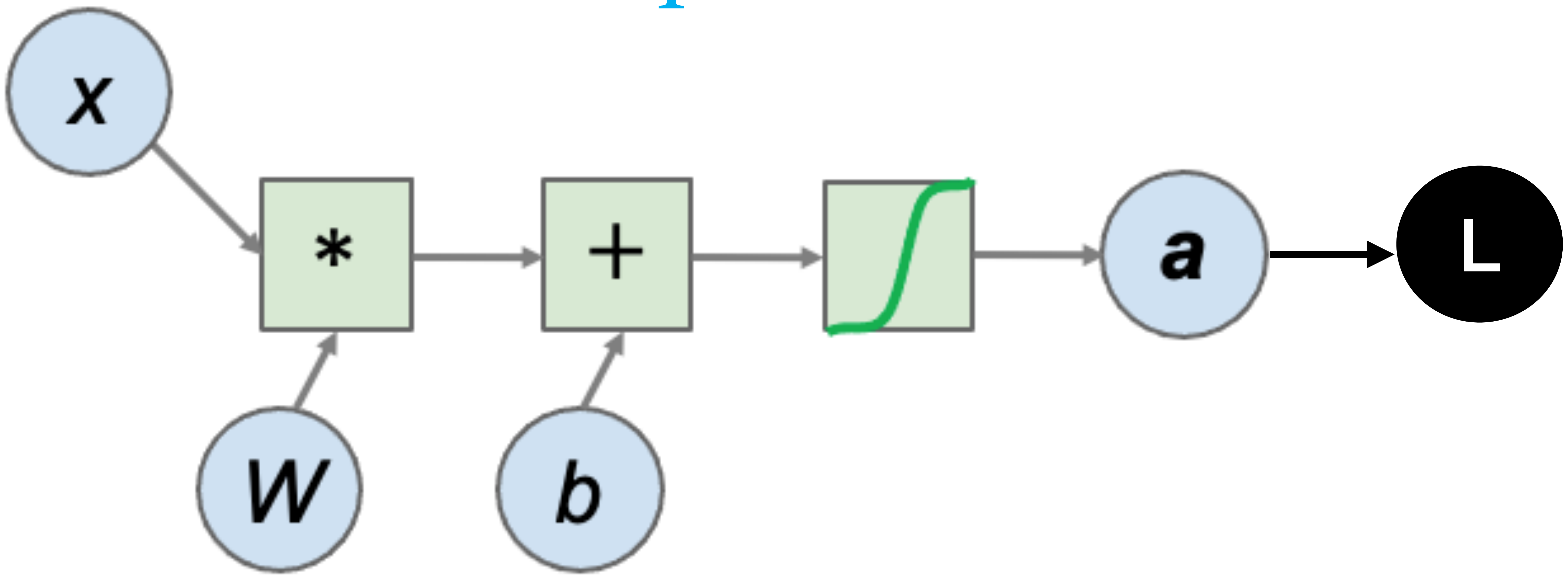

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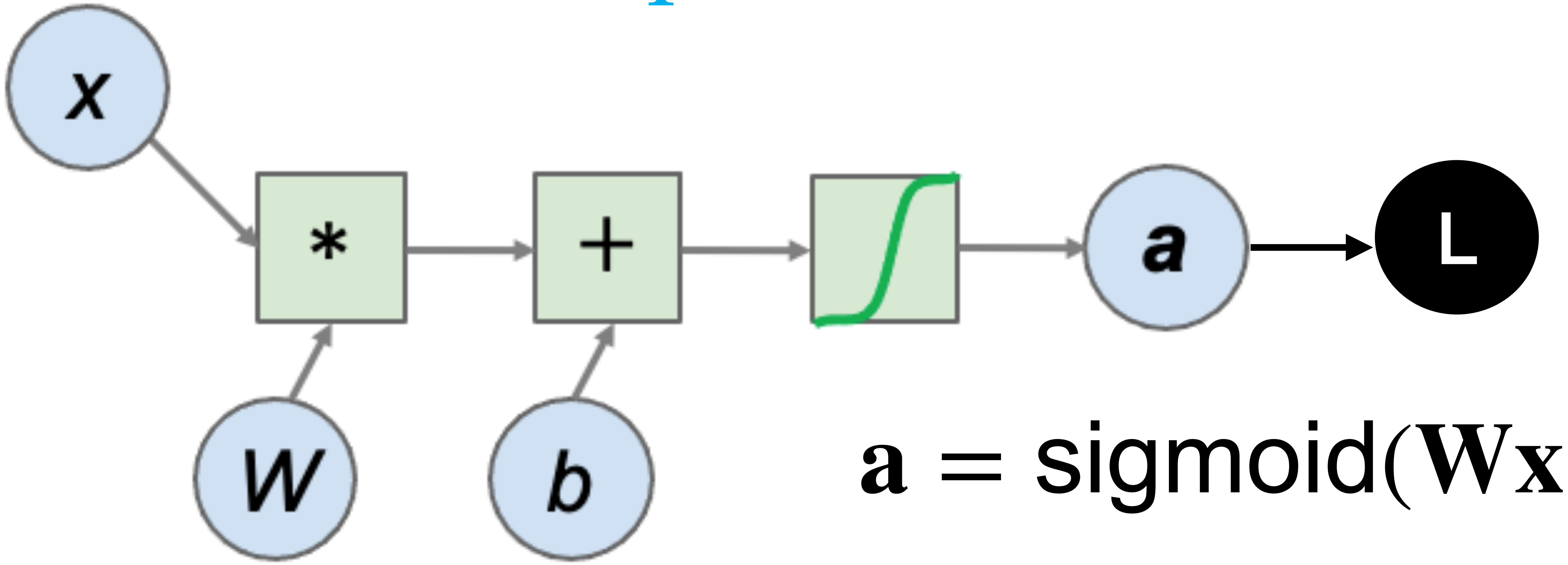

$$\mathbf{a} = \text{sigmoid}(\mathbf{W}\mathbf{x} + \mathbf{b})$$

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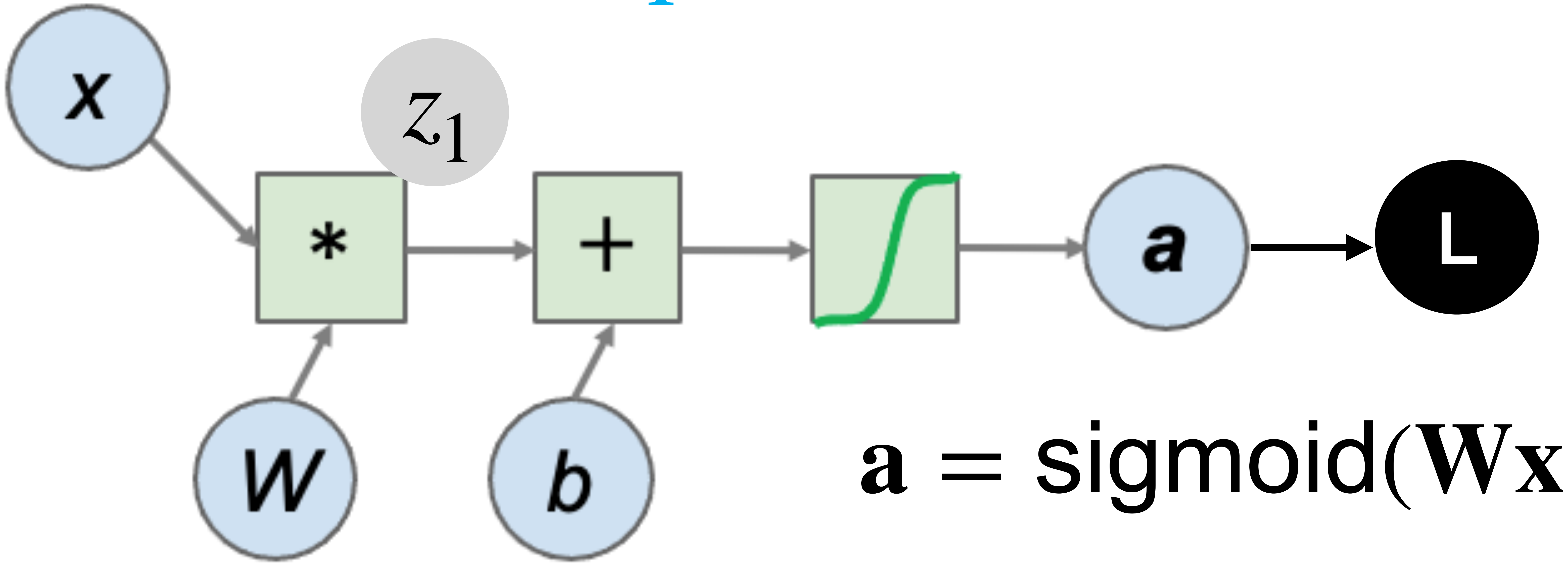

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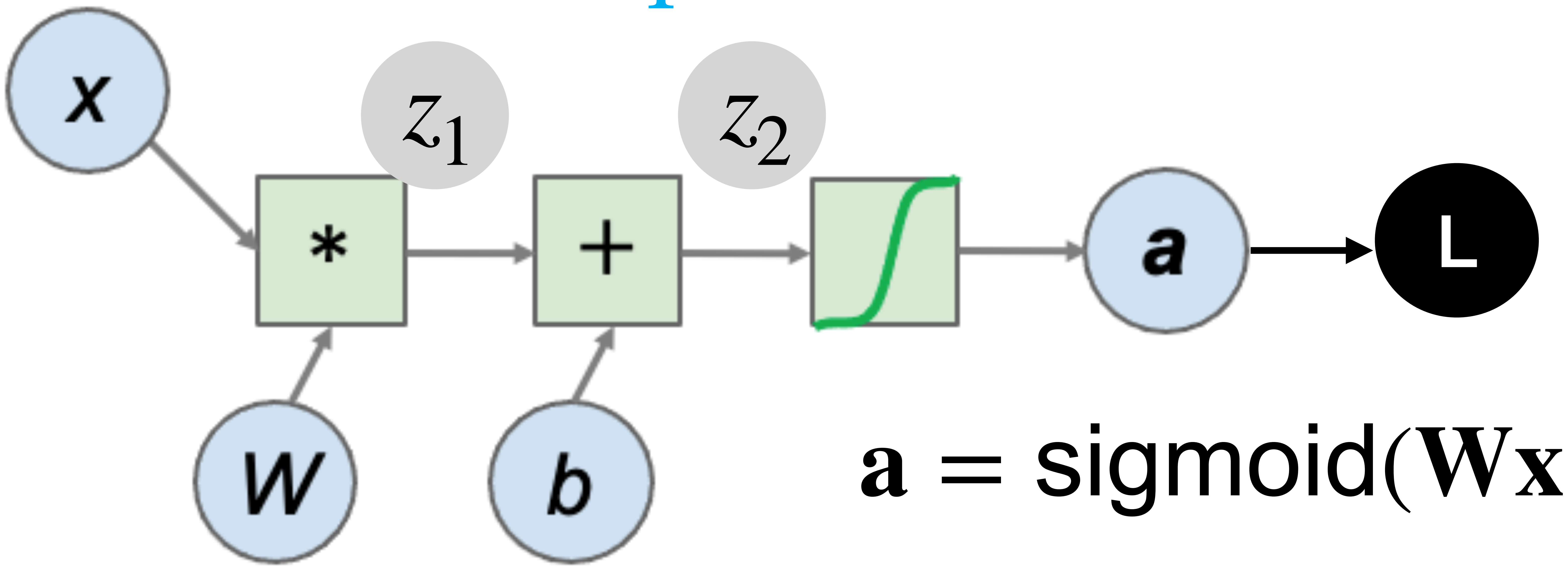

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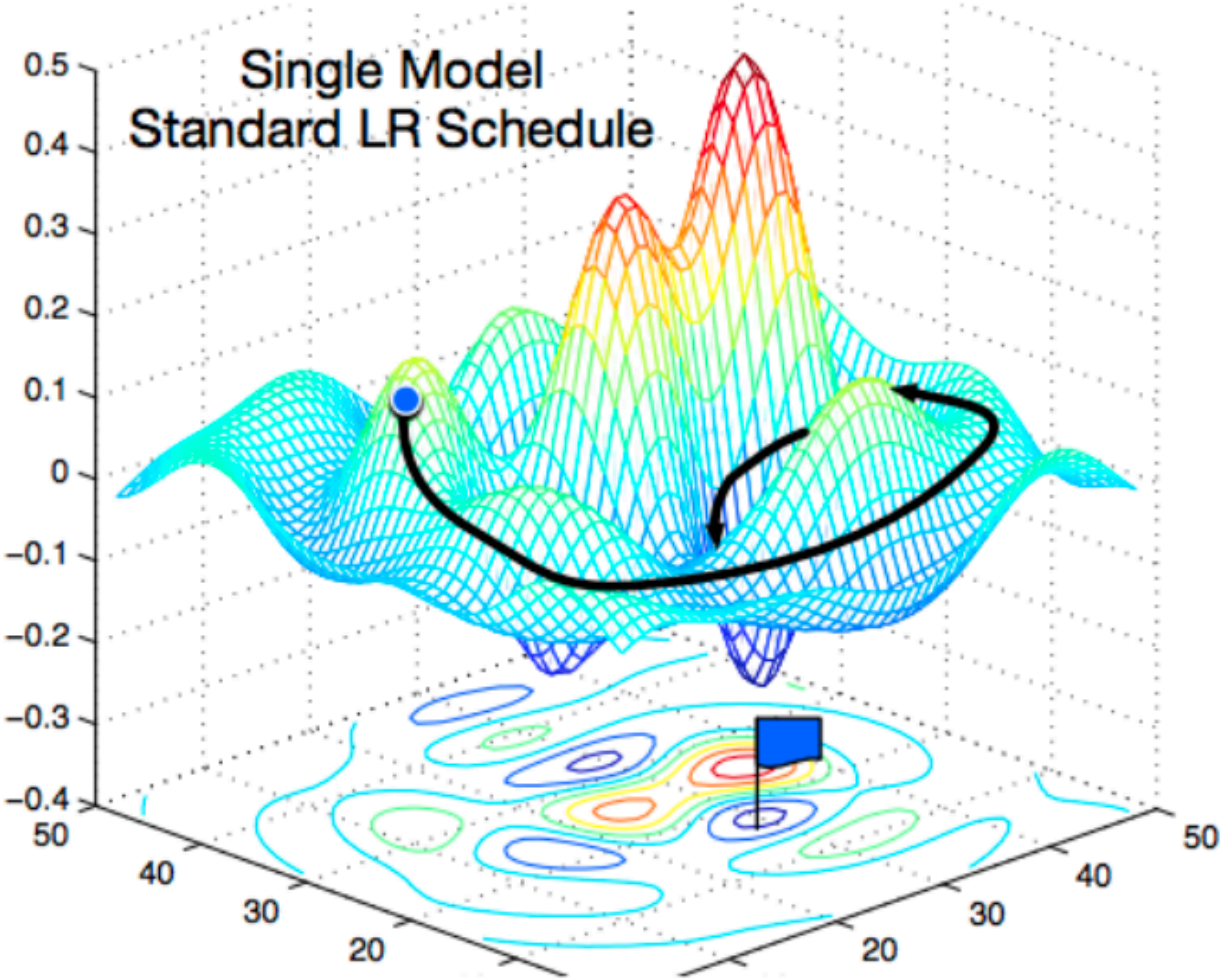
Non-convex Optimization



[Gao and Li et al., 2018]

How to classify

Cats vs. dogs?

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Dual

12MP

wide-angle and
telephoto cameras

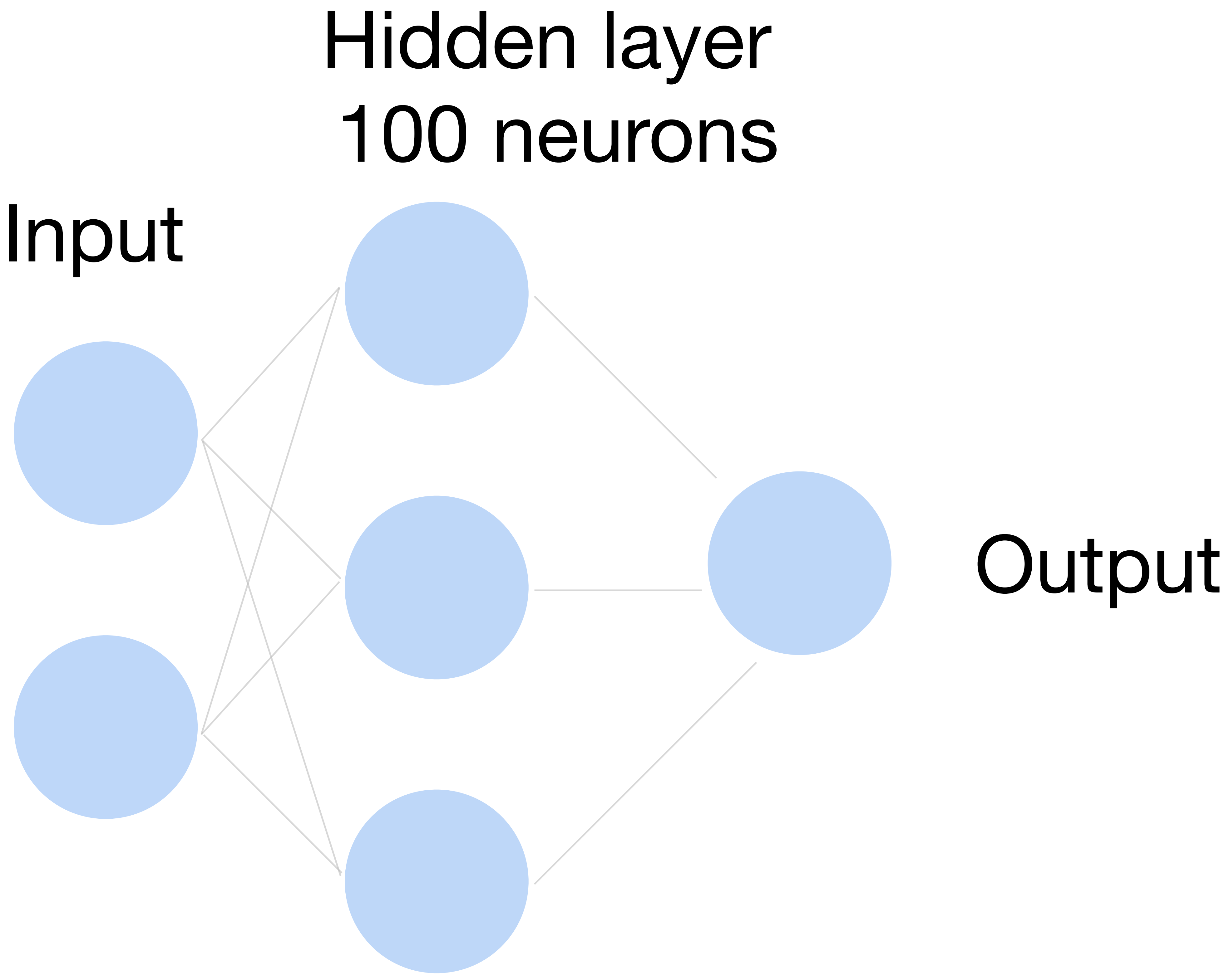
36M floats in a RGB image!

Fully Connected Networks

Cats vs. dogs?

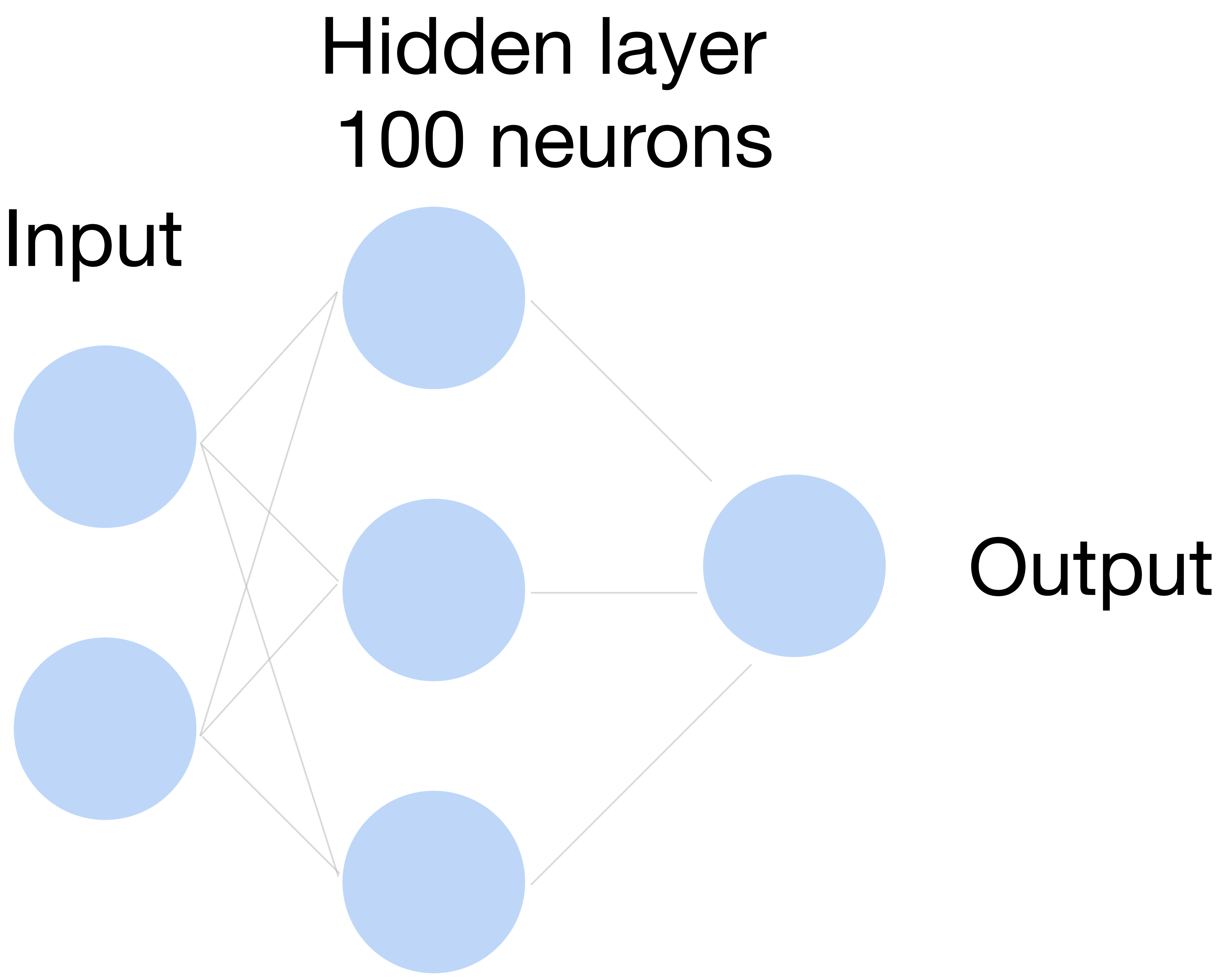
Fully Connected Networks

Cats vs. dogs?



Fully Connected Networks

Cats vs. dogs?



~ 36M elements x 100 = ~**3.6B** parameters!

Convolutions come to rescue!

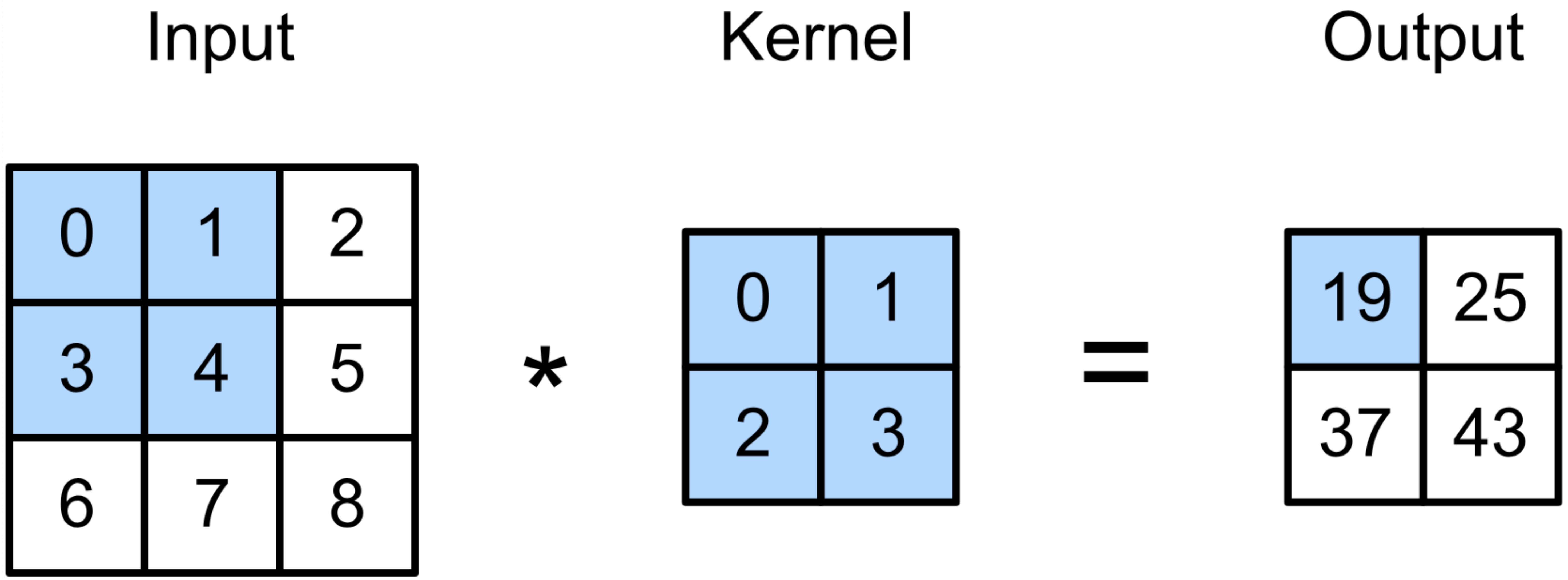
Where is Waldo?

Why Convolution?

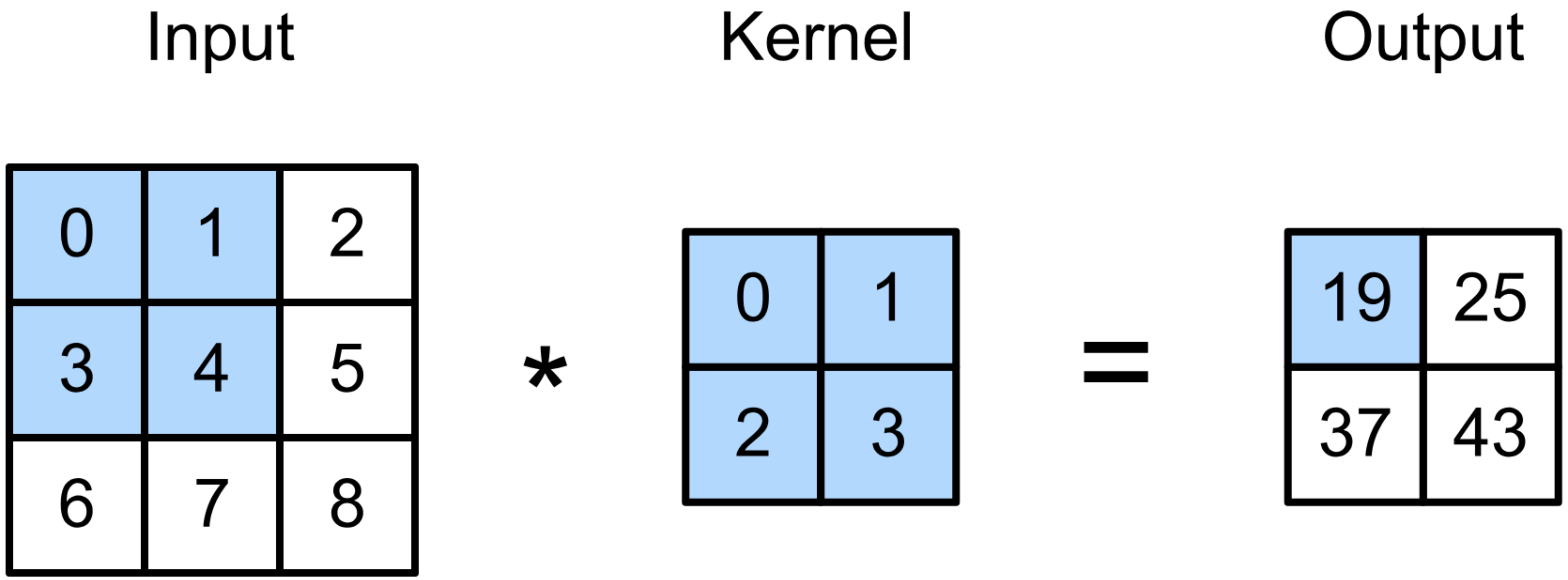
- Translation Invariance
- Locality

2-D Convolution

2-D Convolution



2-D Convolution



$$
\begin{aligned}
0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 &= 19, \\
1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 &= 25, \\
3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 &= 37, \\
4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 &= 43.
\end{aligned}
$$

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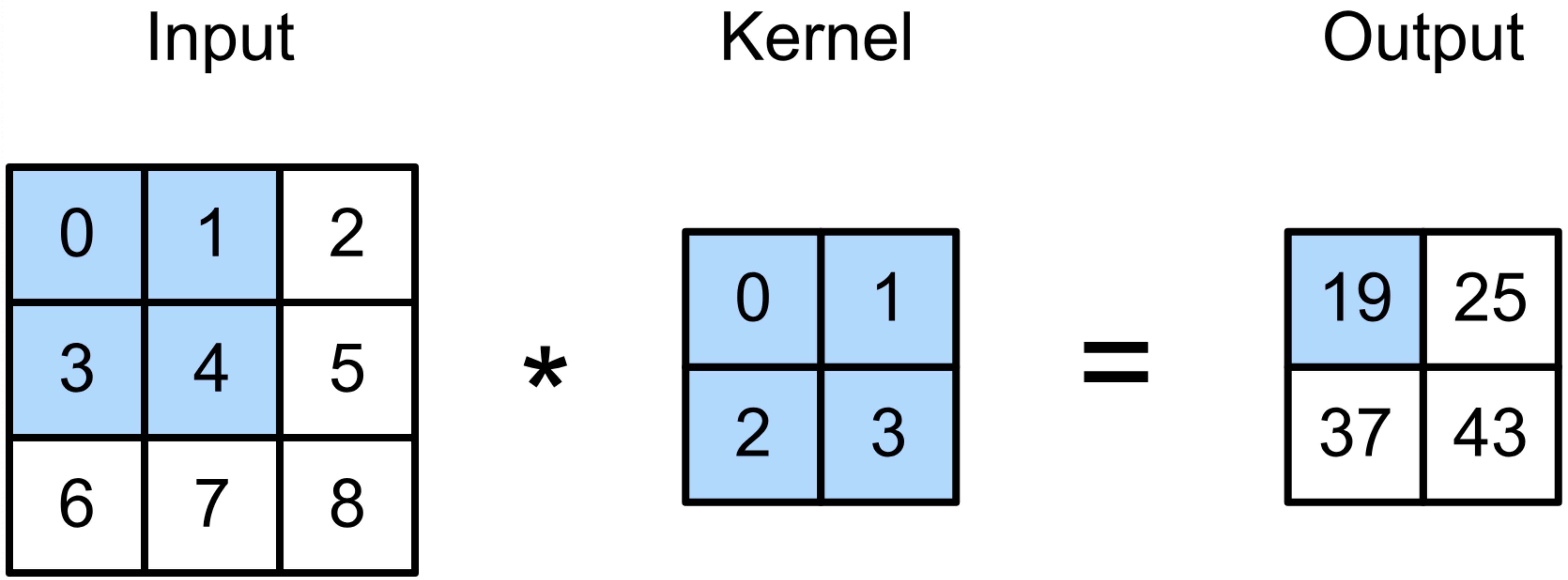

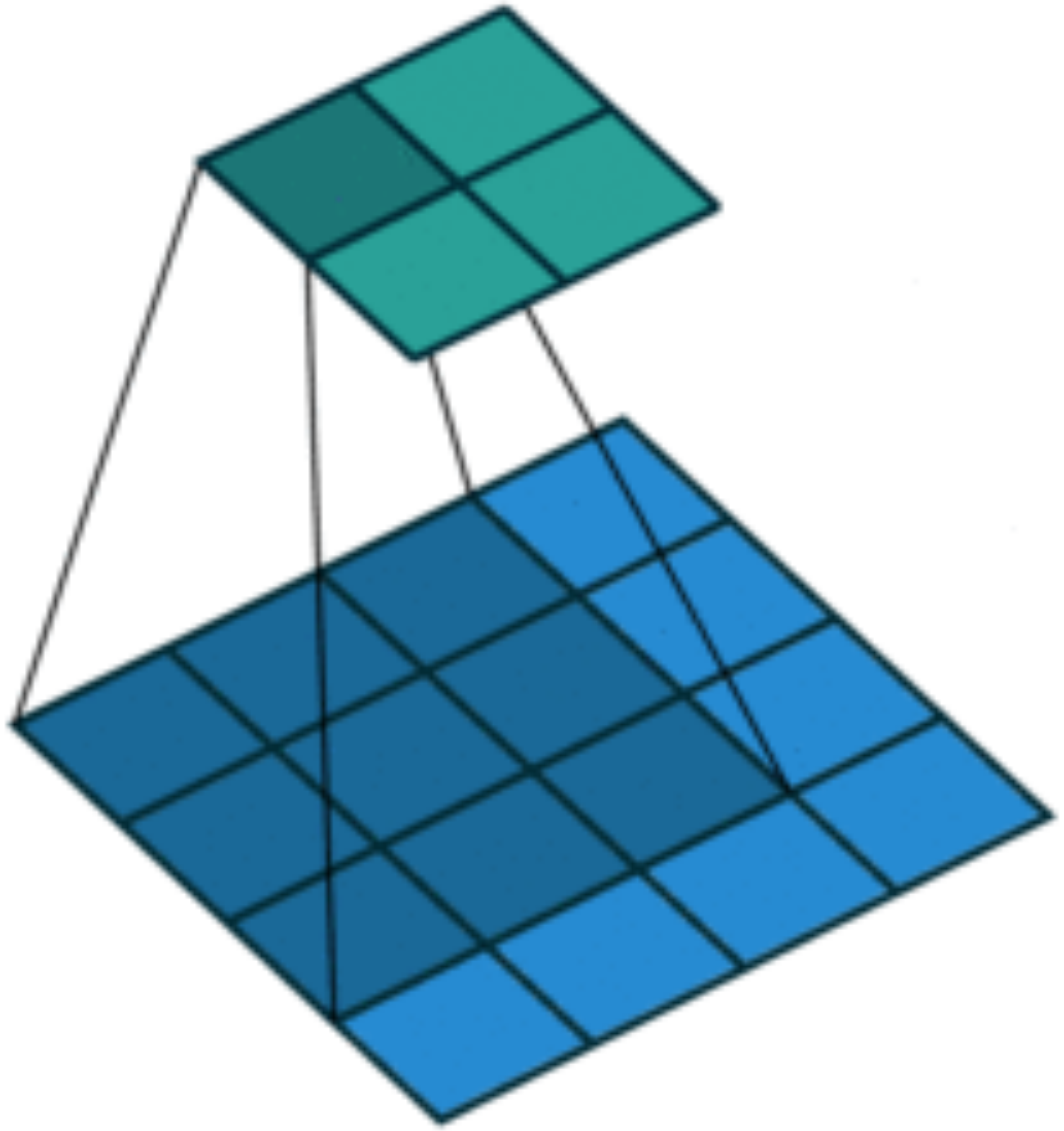

(vdumoulin@ Github)

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\begin{aligned}
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4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 &= 43.
\end{aligned}
$$

2-D Convolution Layer

$$\begin{bmatrix} 0 & 1 & 2 \\ 3 & 4 & 5 \\ 6 & 7 & 8 \end{bmatrix} * \begin{bmatrix} 0 & 1 \\ 2 & 3 \end{bmatrix} = \begin{bmatrix} 19 & 25 \\ 37 & 43 \end{bmatrix}$$

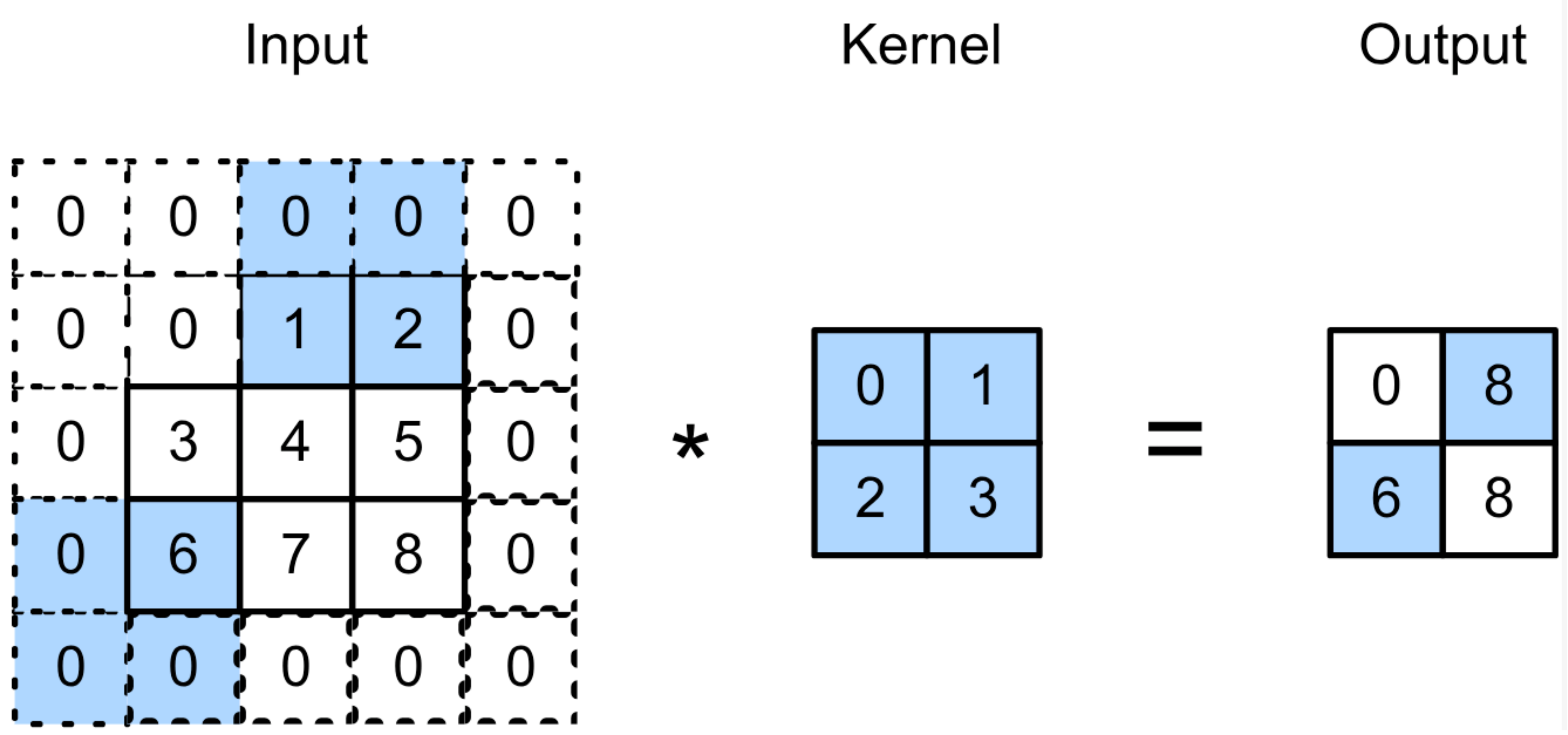
- $\mathbf{X} : n_h \times n_w$ input matrix
- $\mathbf{W} : k_h \times k_w$ kernel matrix
- b: scalar bias
- $\mathbf{Y} : (n_h - k_h + 1) \times (n_w - k_w + 1)$ output matrix

$$\mathbf{Y} = \mathbf{X} \star \mathbf{W} + b$$

- **W** and *b* are learnable parameters

2-D Convolution Layer with Stride and Padding

- Stride is the #rows/#columns per slide
- Padding adds rows/columns around input
- Output shape



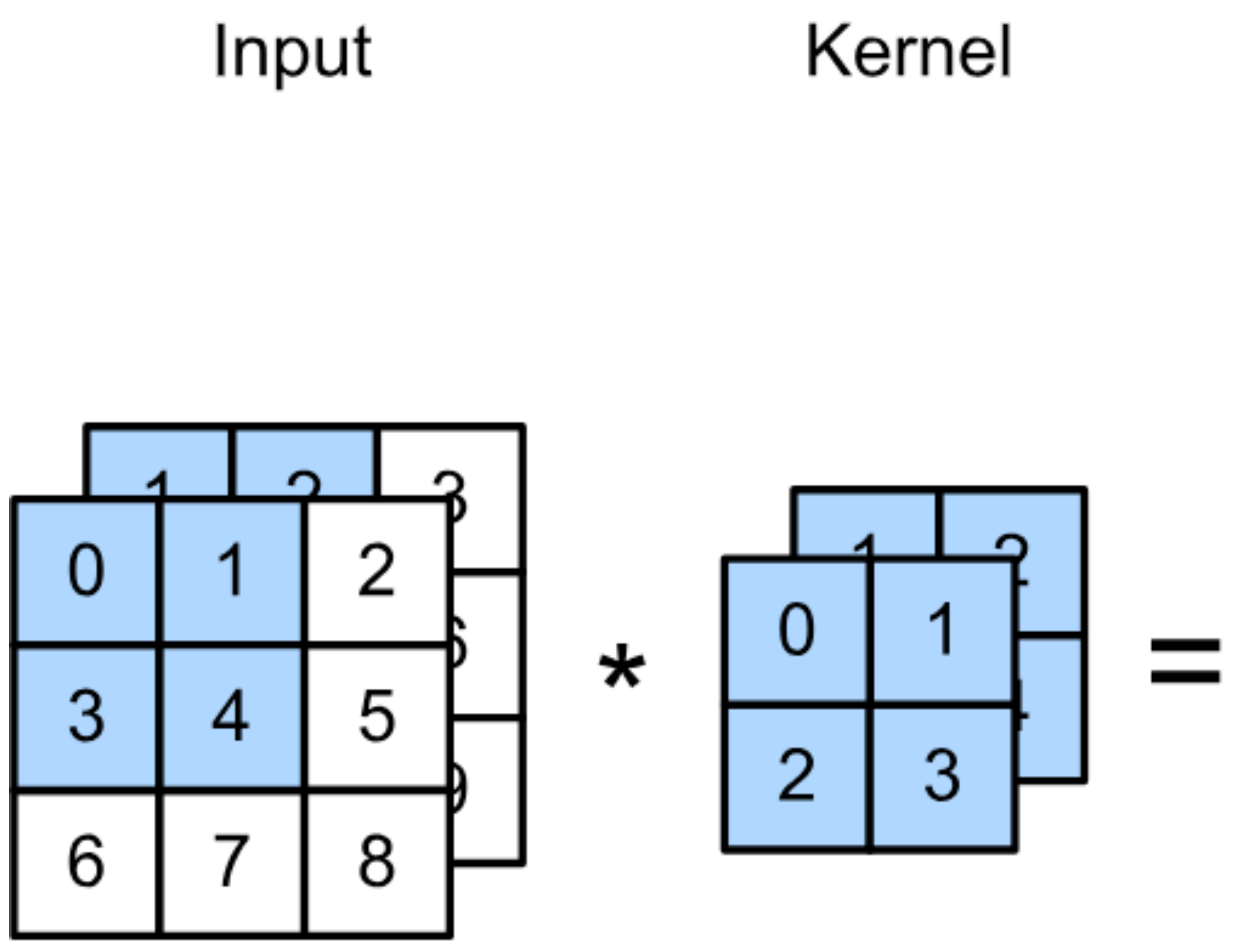
Kernel/filter size

$$\lfloor (n_h - k_h + p_h + s_h)/s_h \rfloor \times \lfloor (n_w - k_w + p_w + s_w)/s_w \rfloor$$

Input size **Pad** **Stride**

Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a kernel for each channel, and then sum results over channels



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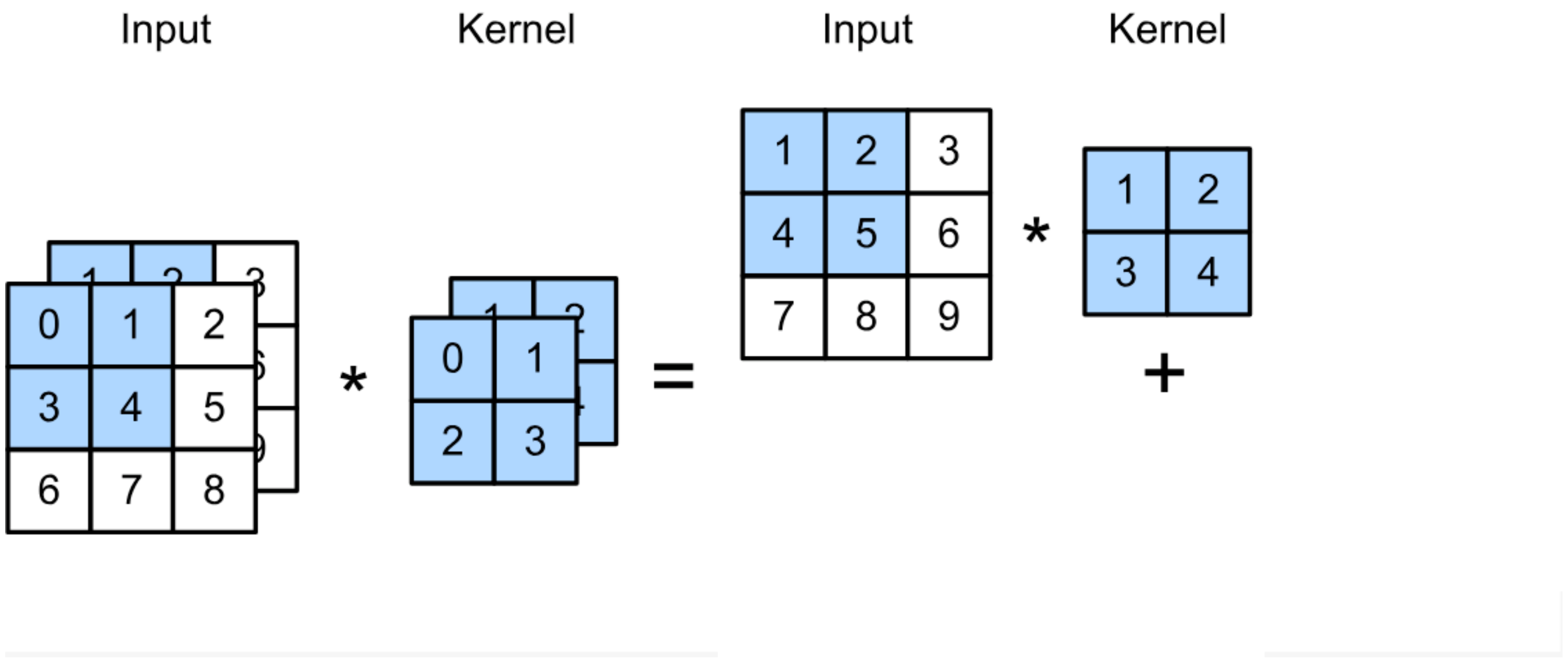

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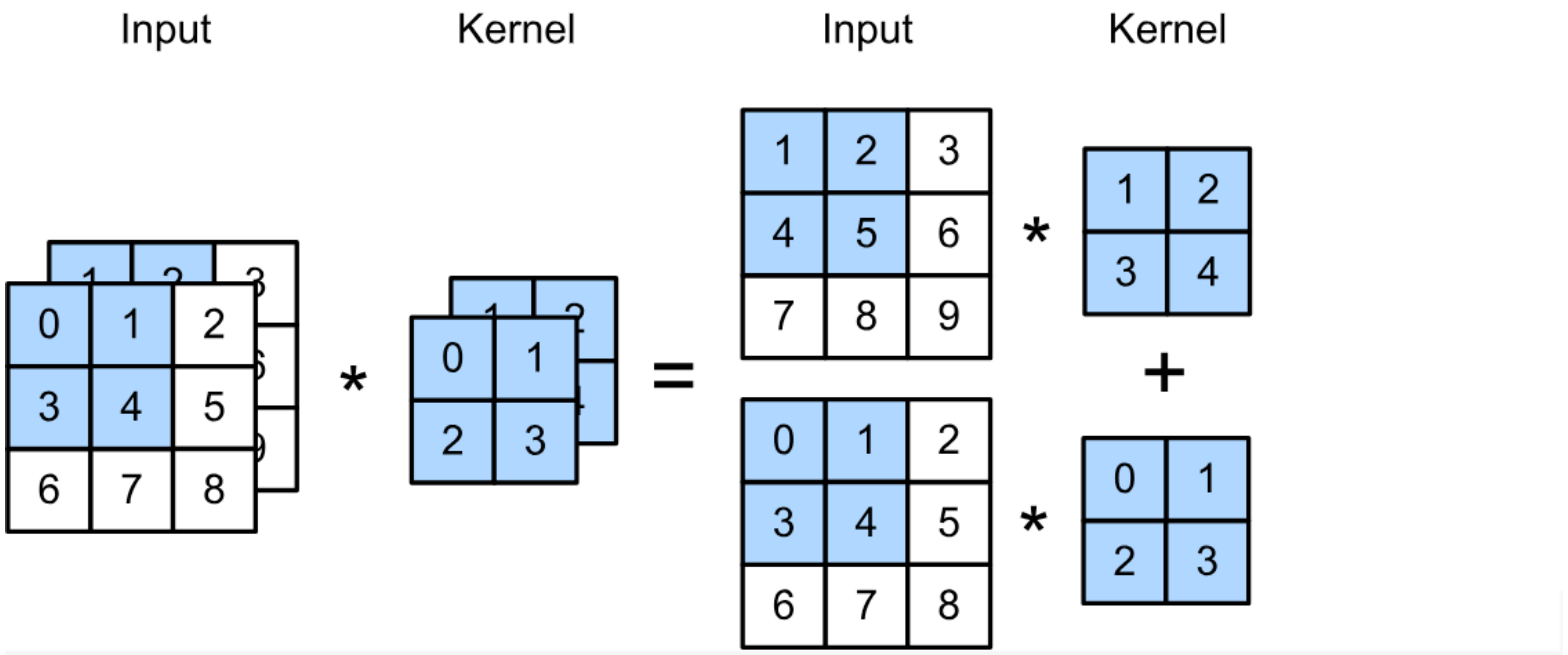

)

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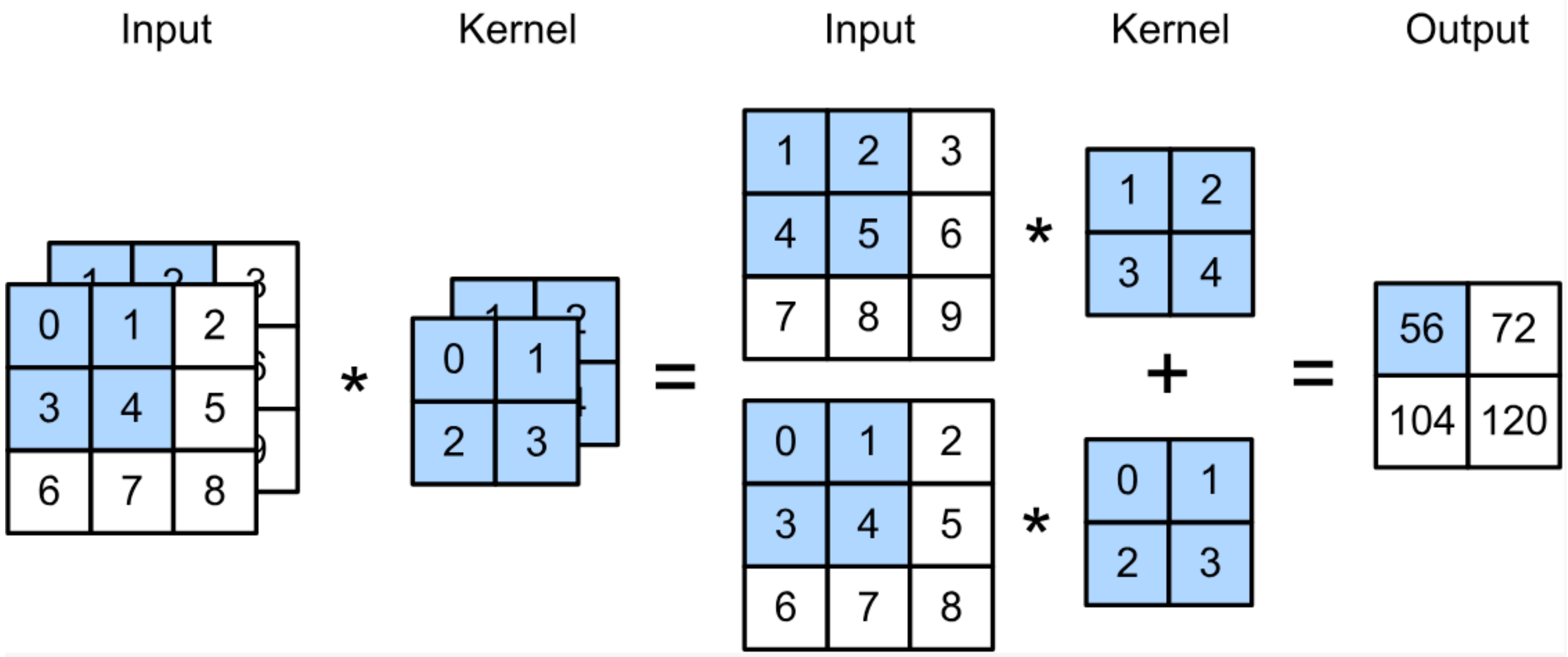

)

Multiple Input Channels

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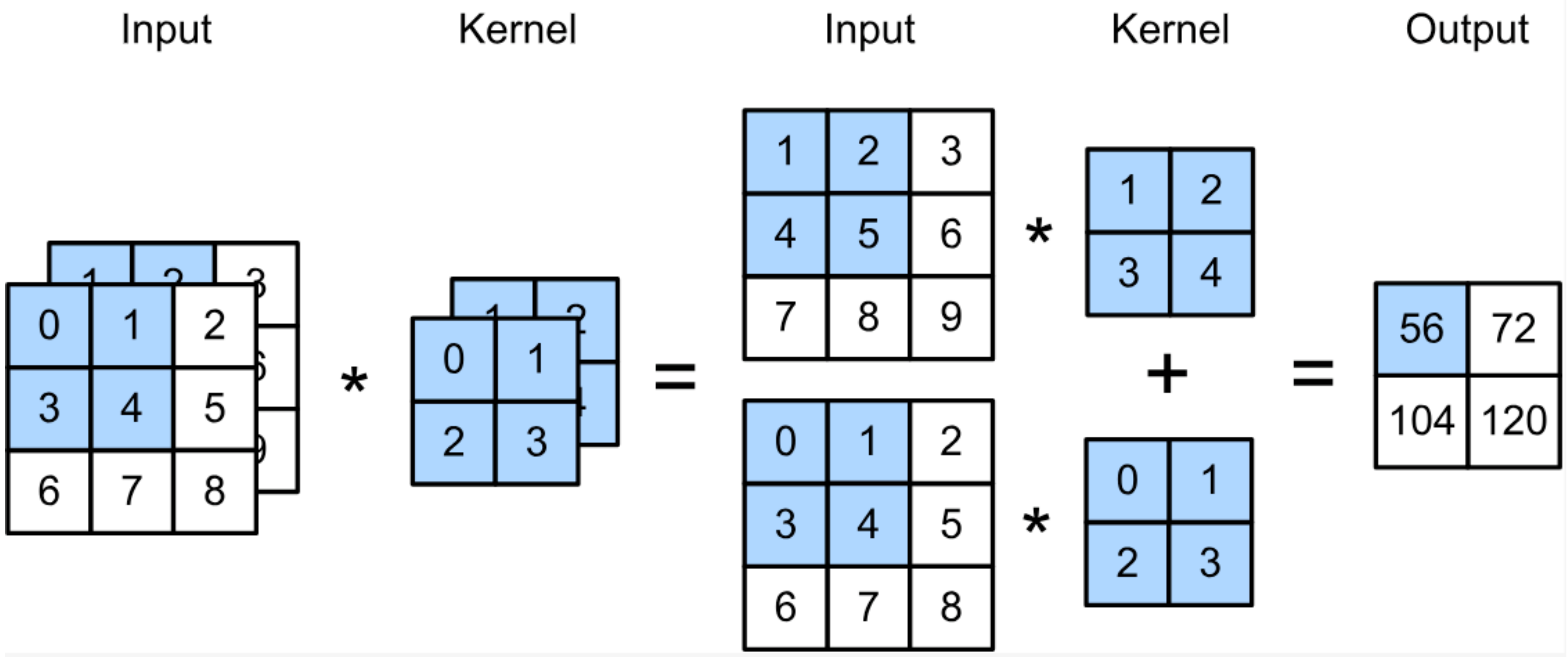
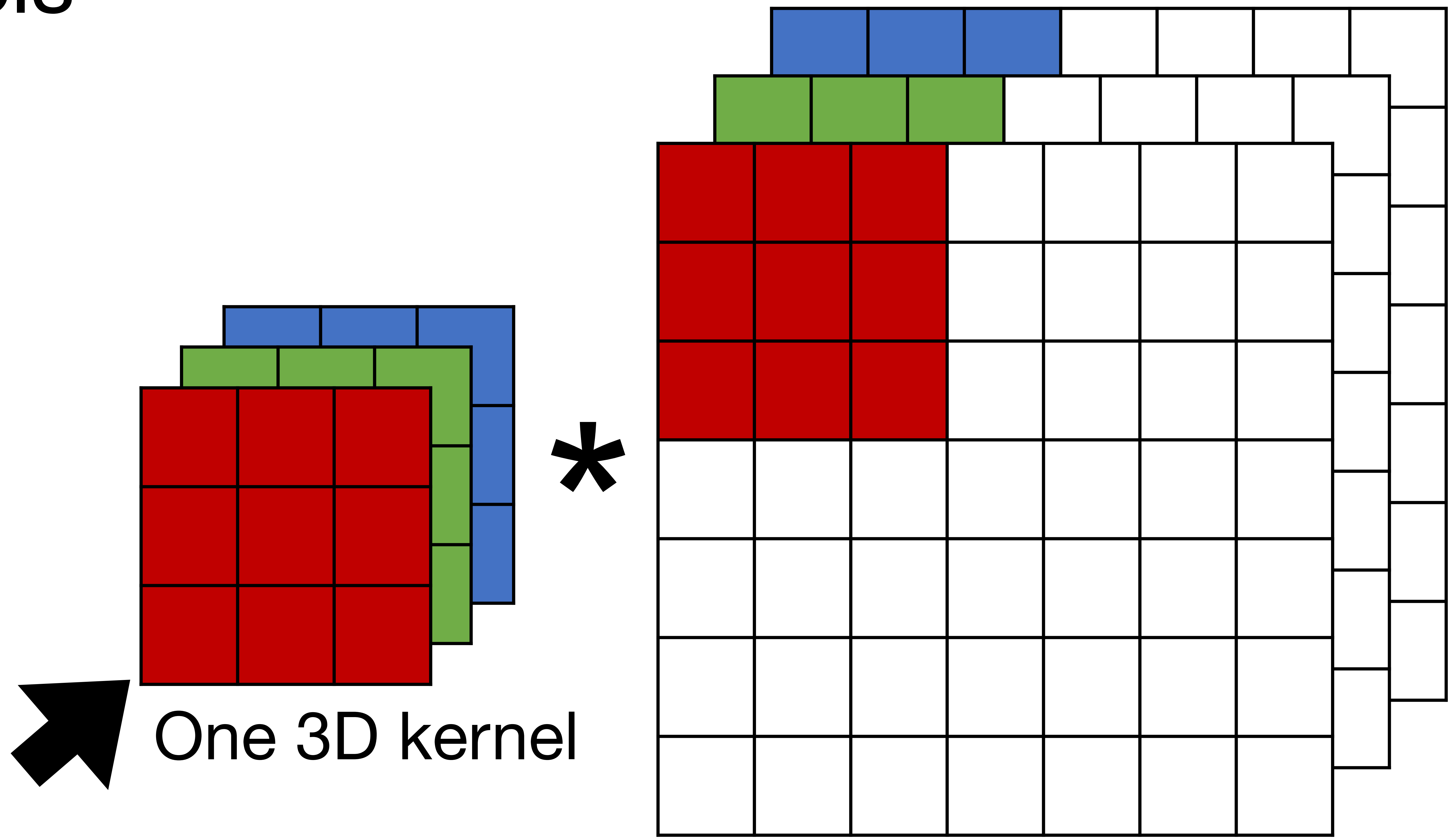


$$(1 \times 1 + 2 \times 2 + 4 \times 3 + 5 \times 4)$$
$$+(0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3)$$
$$= 56$$

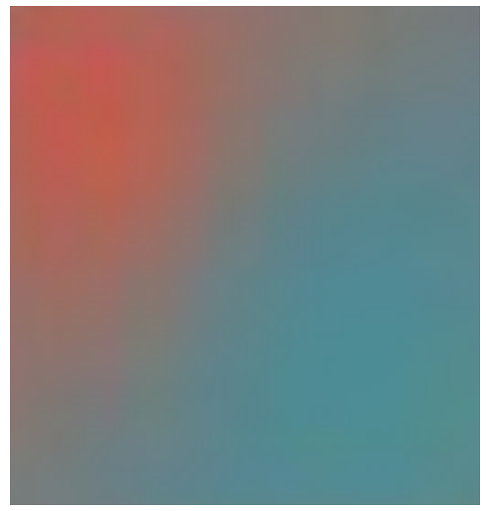
Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a 2D kernel for each channel, and then sum results over channels



Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Also call each 3D kernel a "**filter**", which produce only **one** output channel (due to summation over channels)



One filter
(3 channels)

*

RGB (3 input channels)

Multiple filters (in one layer)

- Apply multiple filters on the input
- Each filter may learn different features about the input
- Each filter (3D kernel) produces one output channel

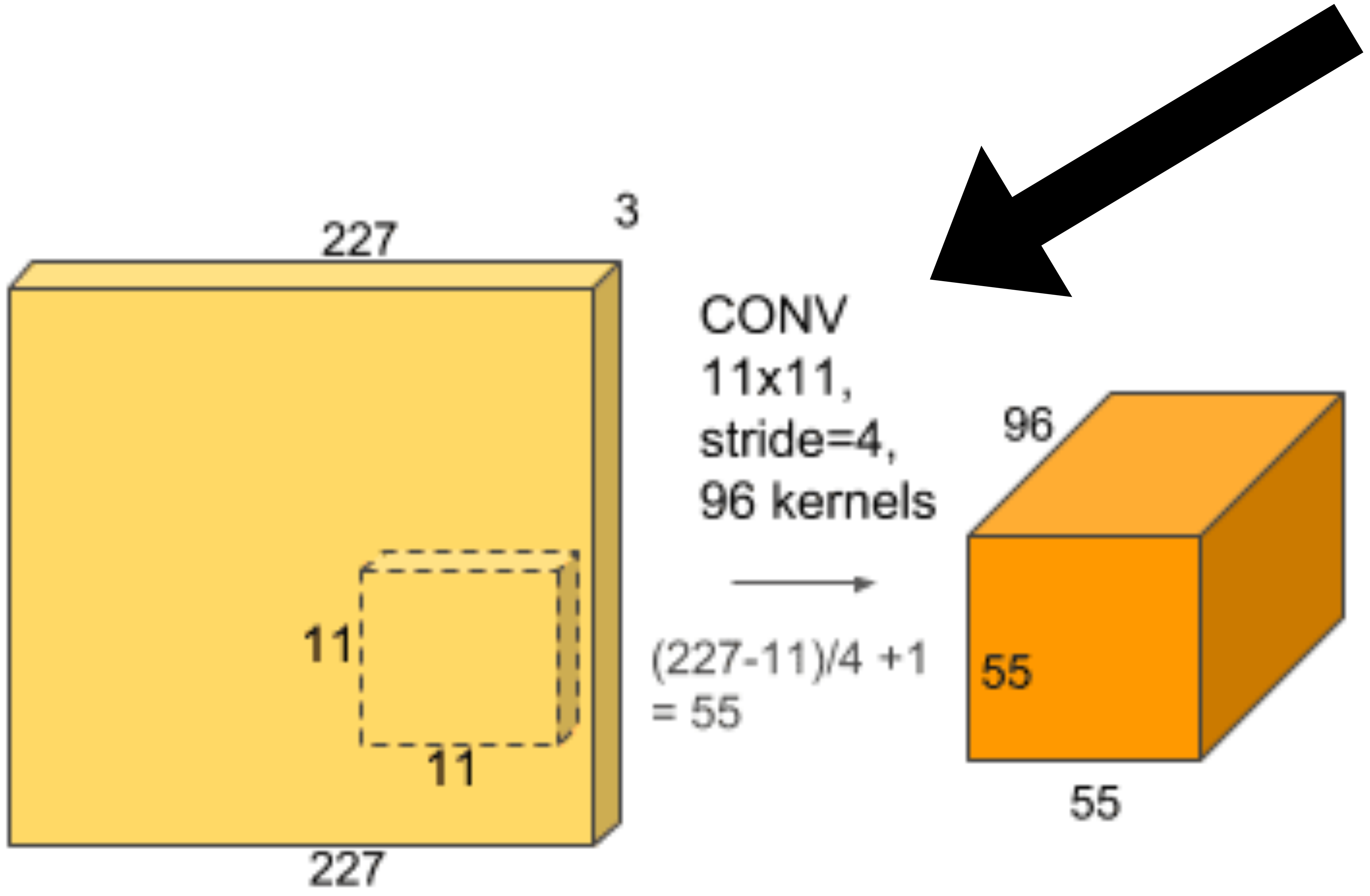
*

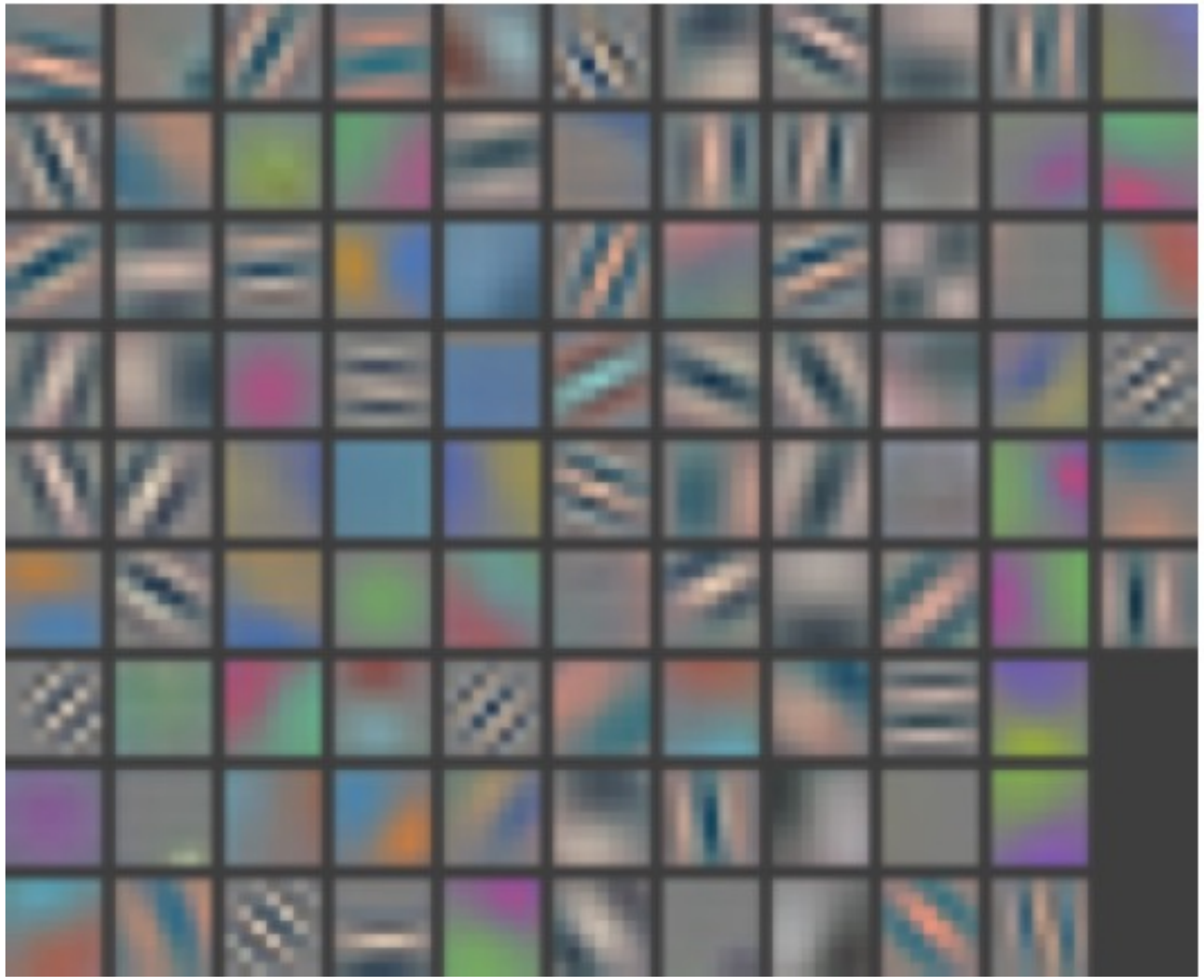
A different filter

RGB (3 input channels)

Conv1 Filters in AlexNet

- 96 filters (each of size 11x11x3)
- Gabor filters





Figures from Visualizing and Understanding Convolutional Networks by *M. Zeiler and R. Fergus*

Multiple Output Channels

- The # of output channels = # of filters
- Input $\mathbf{X} : c_i \times n_h \times n_w$
- Kernel $\mathbf{W} : c_o \times c_i \times k_h \times k_w$
- Output $\mathbf{Y} : c_o \times m_h \times m_w$

$$\mathbf{Y}_{i,:,:} = \mathbf{X} \star \mathbf{W}_{i,:,:,:}$$

$$\text{for } i = 1, \ldots, c_o$$

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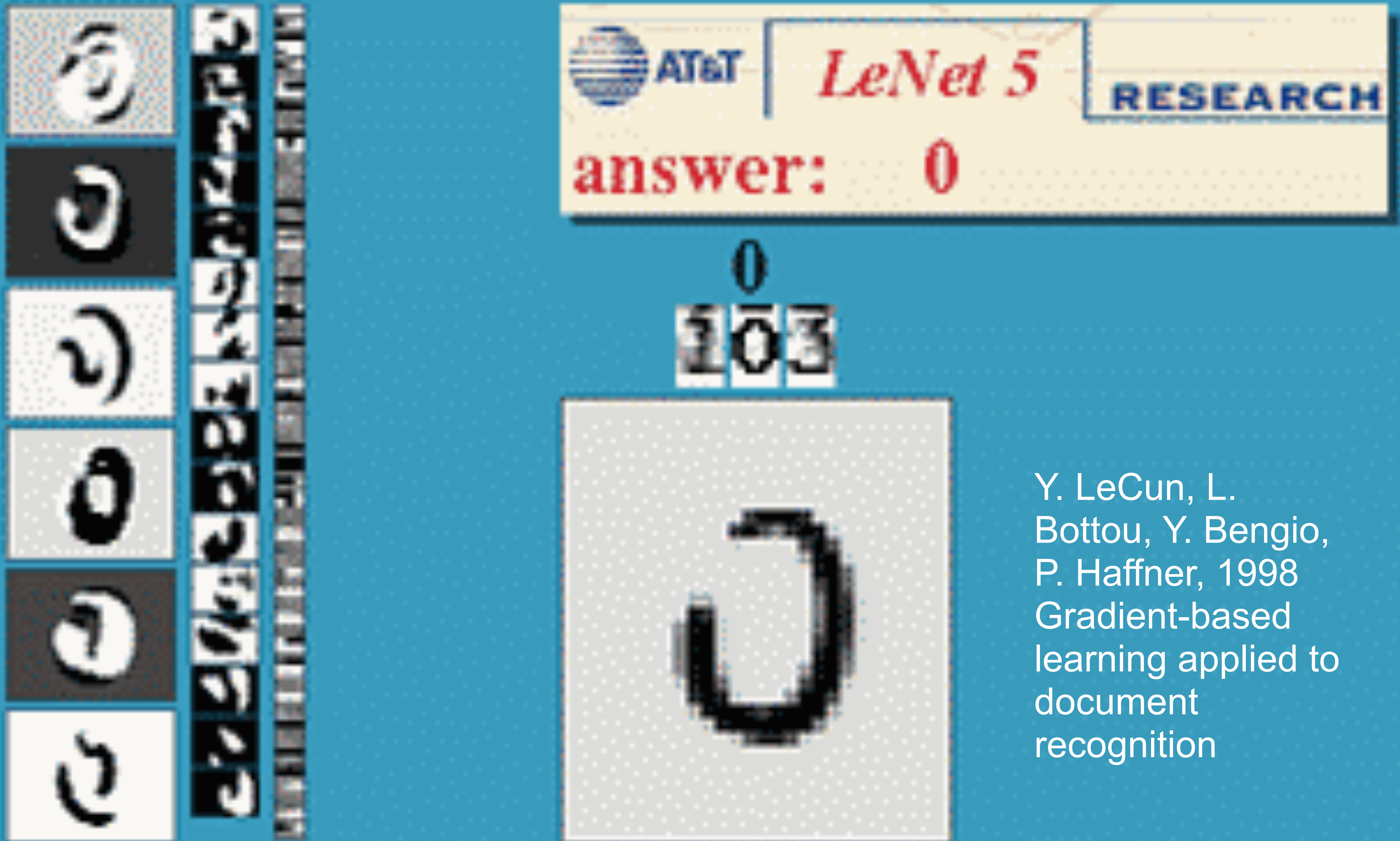
Convolutional Neural Networks

LeNet Architecture

gluon-cv.mxnet.io

Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, 1998 Gradient-based learning applied to document recognition



Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, 1998 Gradient-based learning applied to document recognition

Quiz break

Which one of the following is NOT true?

A. LeNet has two convolutional layers

B. The first convolutional layer in LeNet has 5x5x6x3 parameters, in case of RGB input

C. Pooling is performed right after convolution

D. Pooling layer does not have learnable parameters

Quiz break

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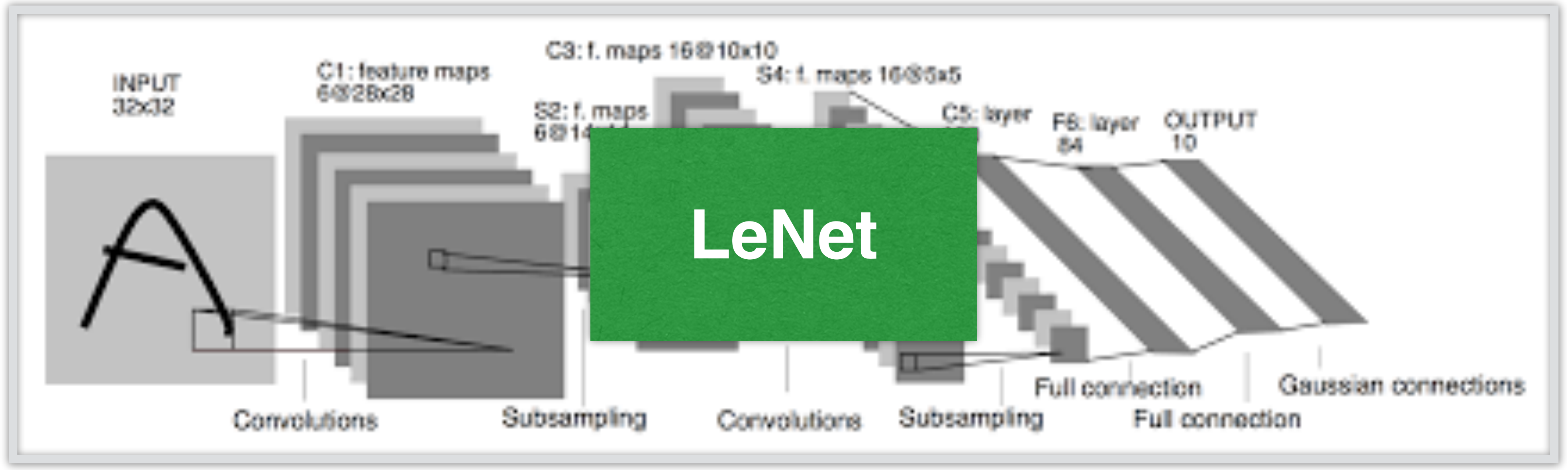
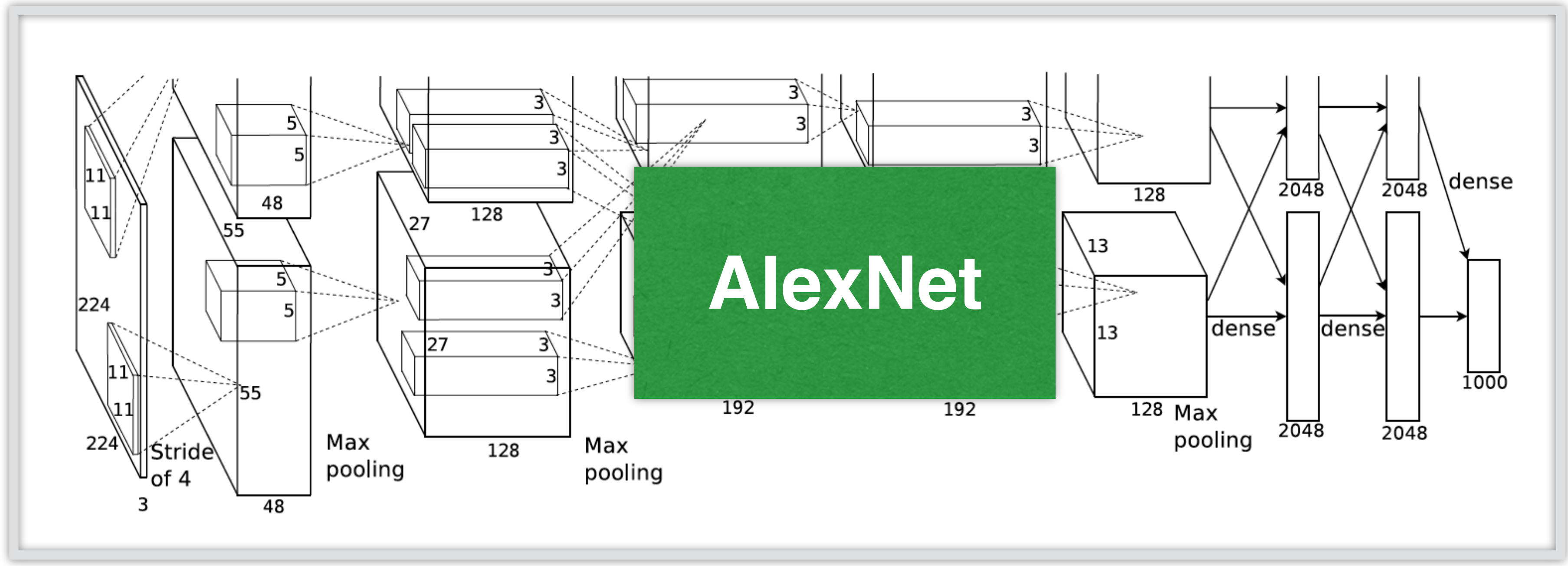
D. Pooling layer does not have learnable parameters

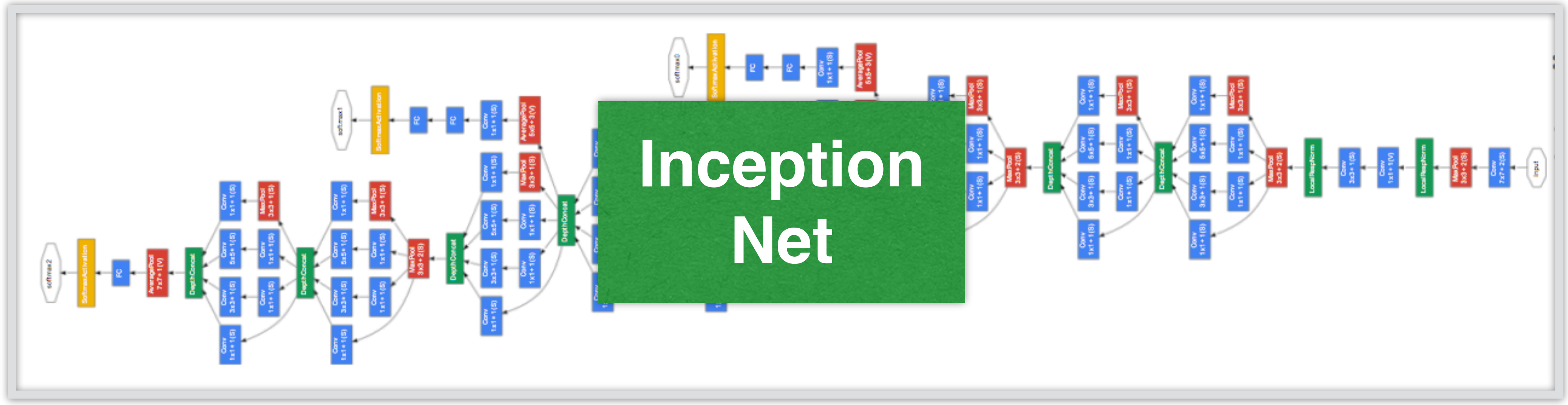
Pooling is performed after ReLU: conv->relu->pooling

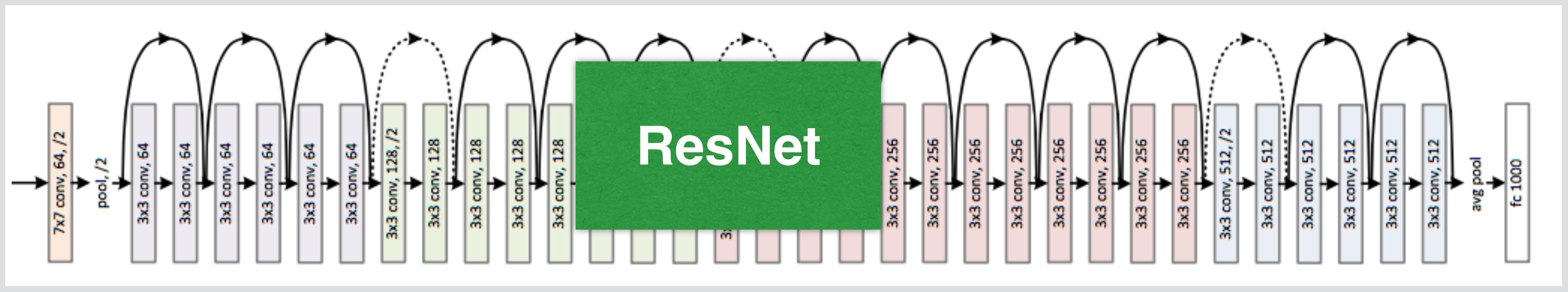
Evolution of neural net architectures

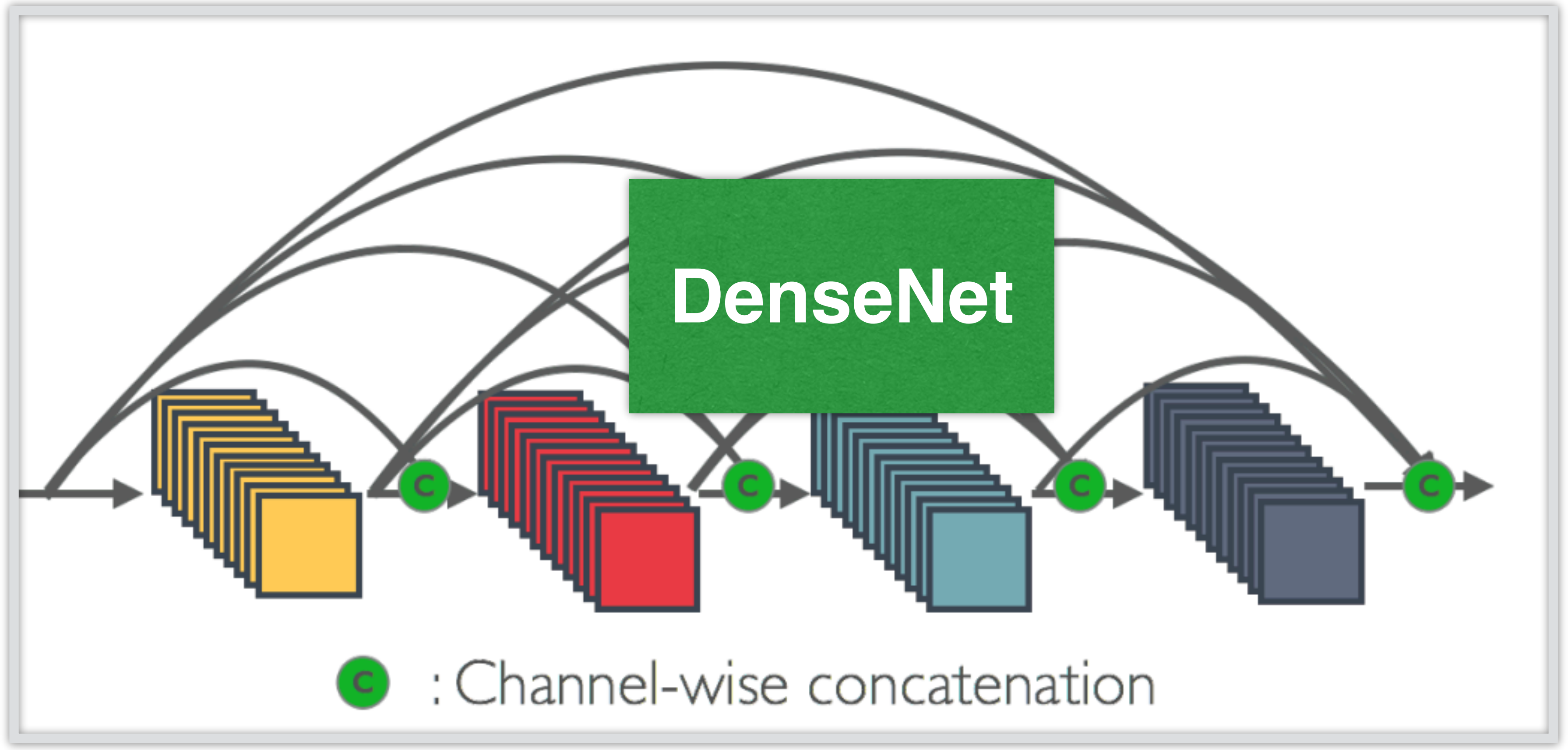
Evolution of neural net architectures





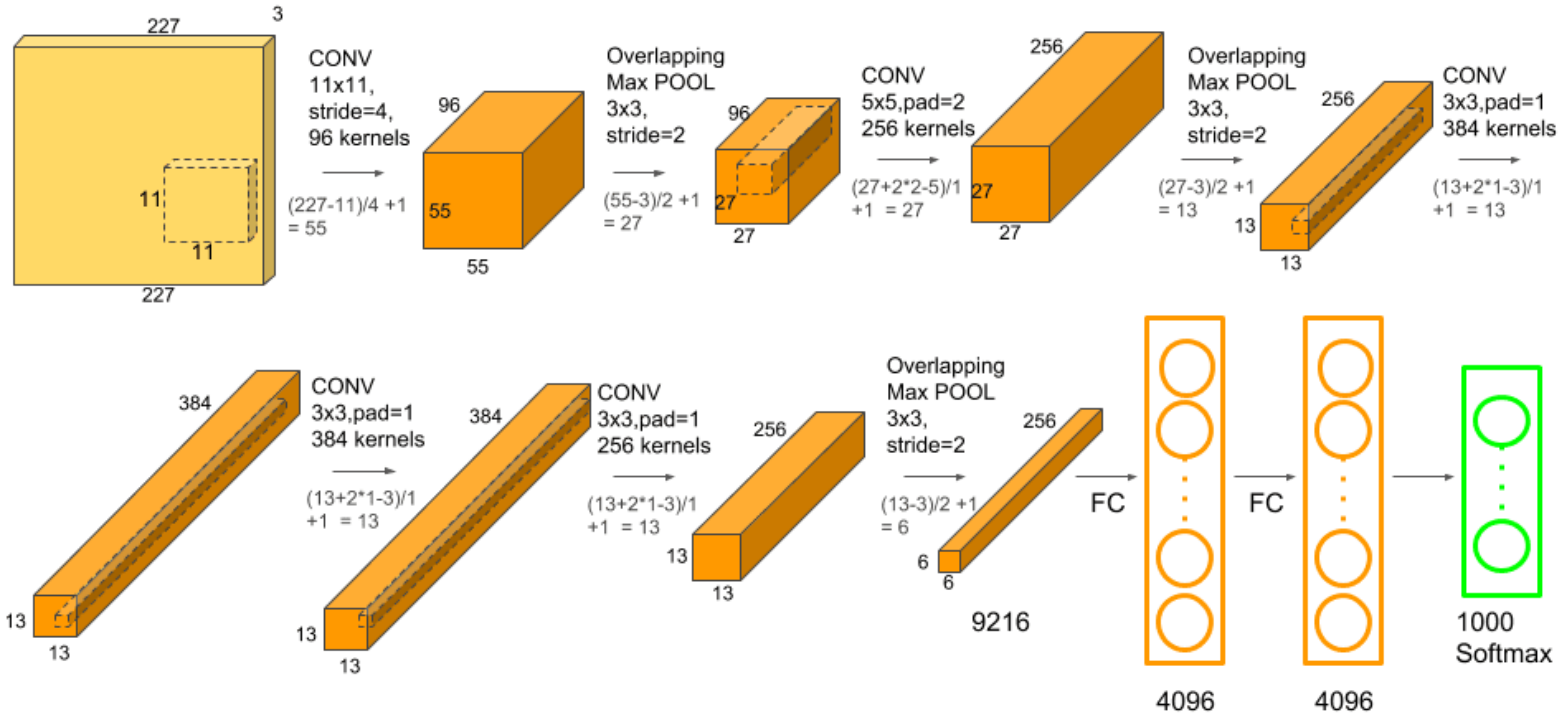






Deng et al. 2009

AlexNet

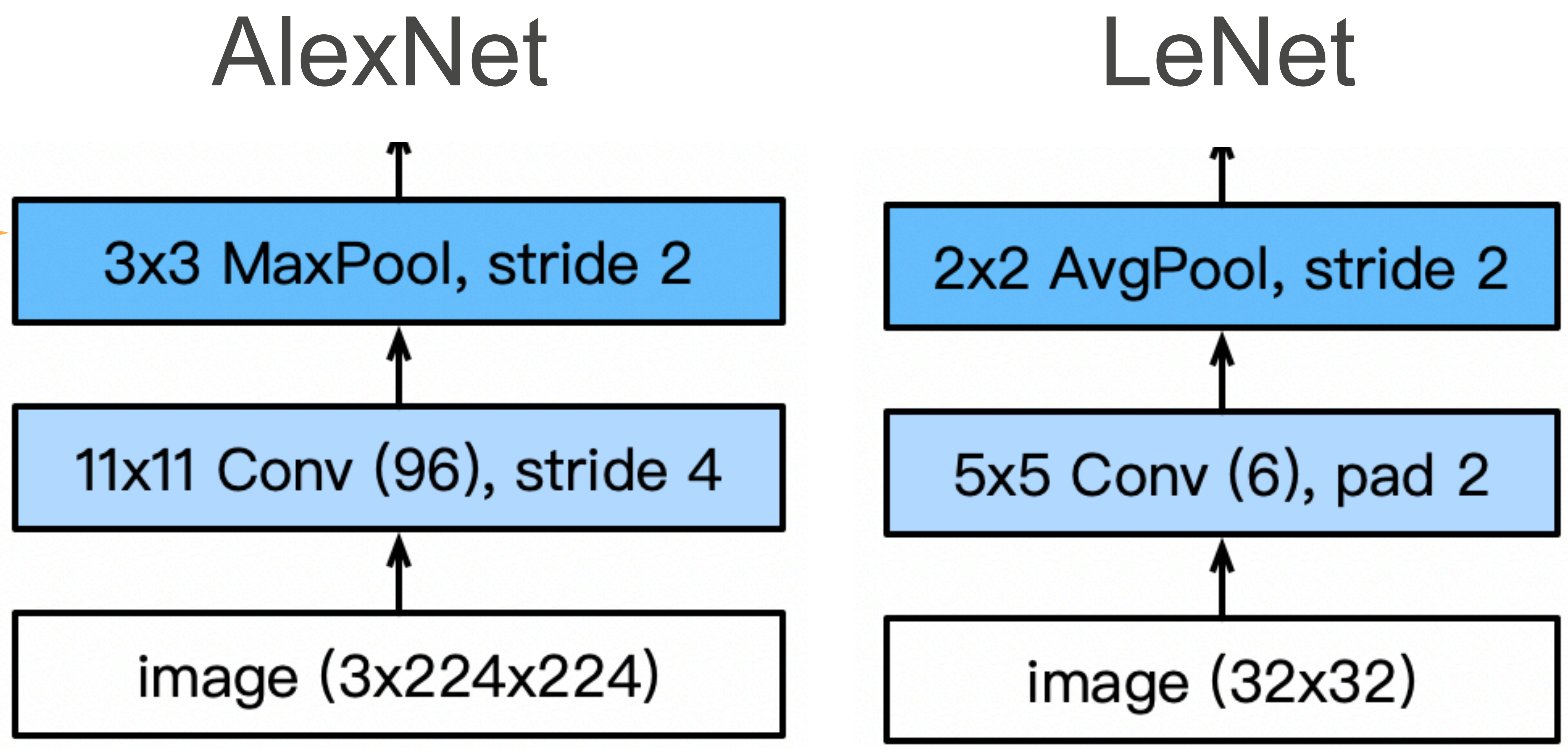


[Krizhevsky et al. 2012]

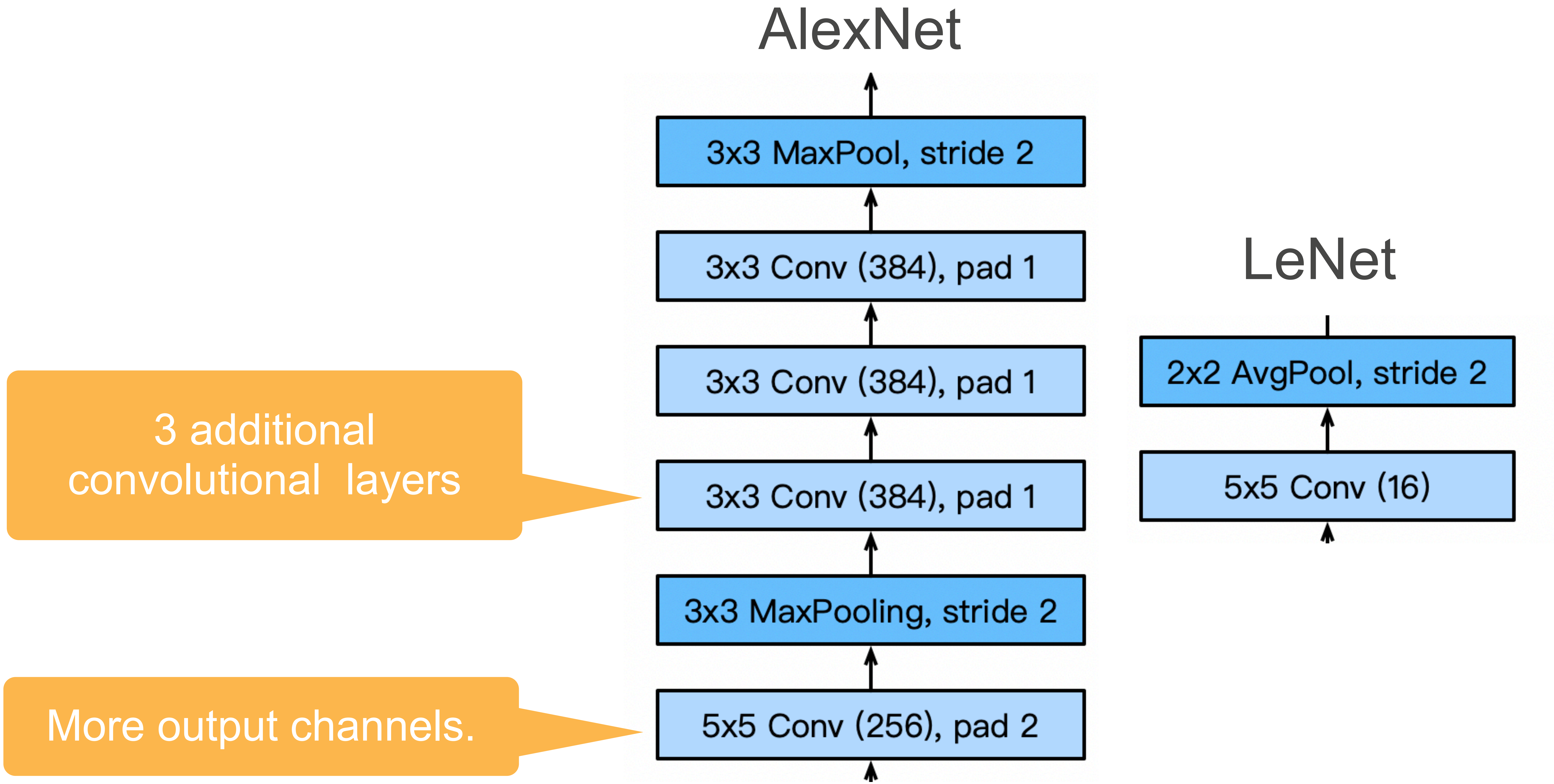
AlexNet vs LeNet Architecture

Larger pool size, change to max pooling

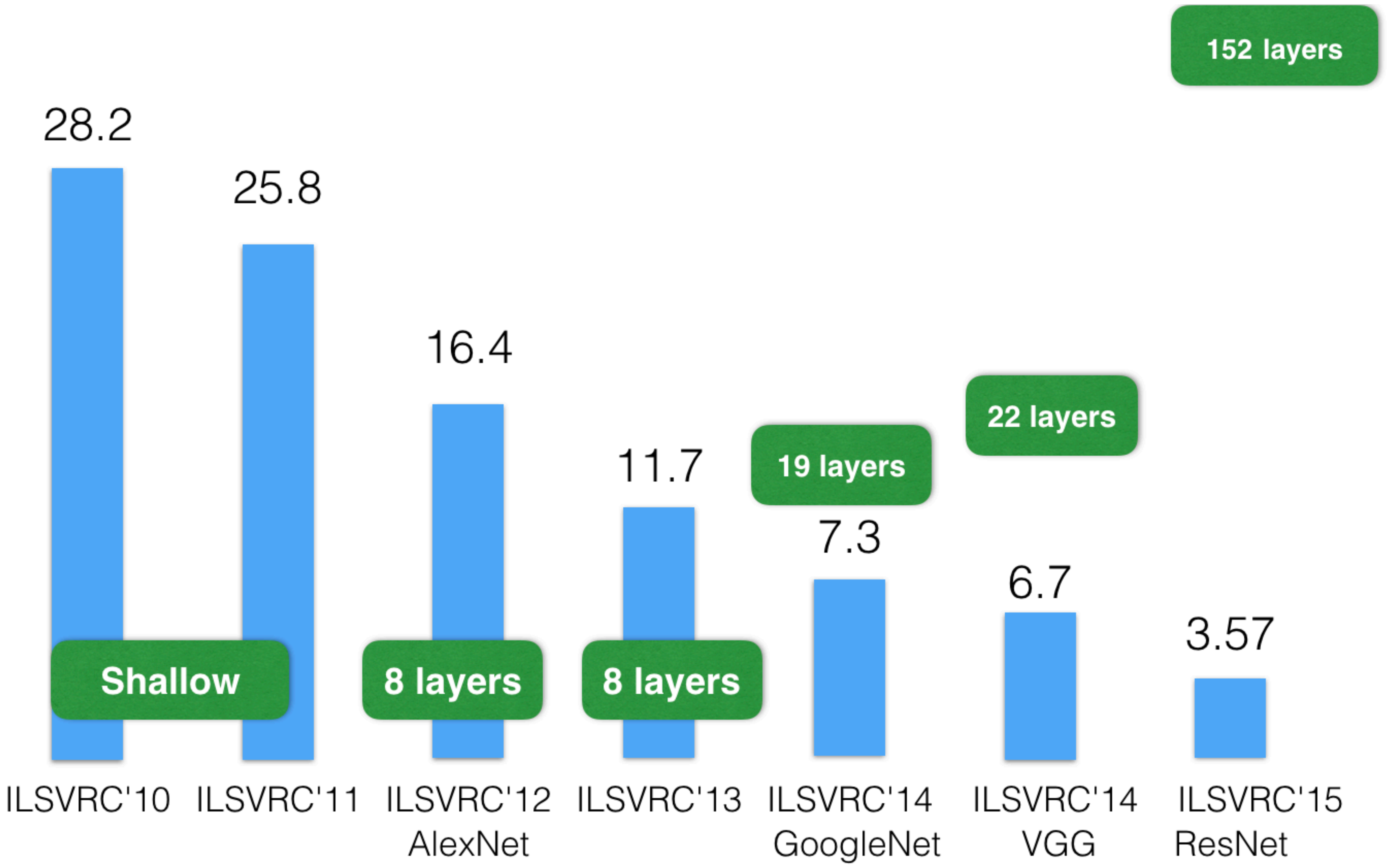
Larger kernel size, stride because of the increased image size, and more output channels.



AlexNet Architecture



ResNet: Going deeper in depth



ImageNet Top-5 error%

[He et al. 2015]

Going deeper in deep learning

Going deeper in deep learning

- Convolutional neural networks are one of many special types of layers.

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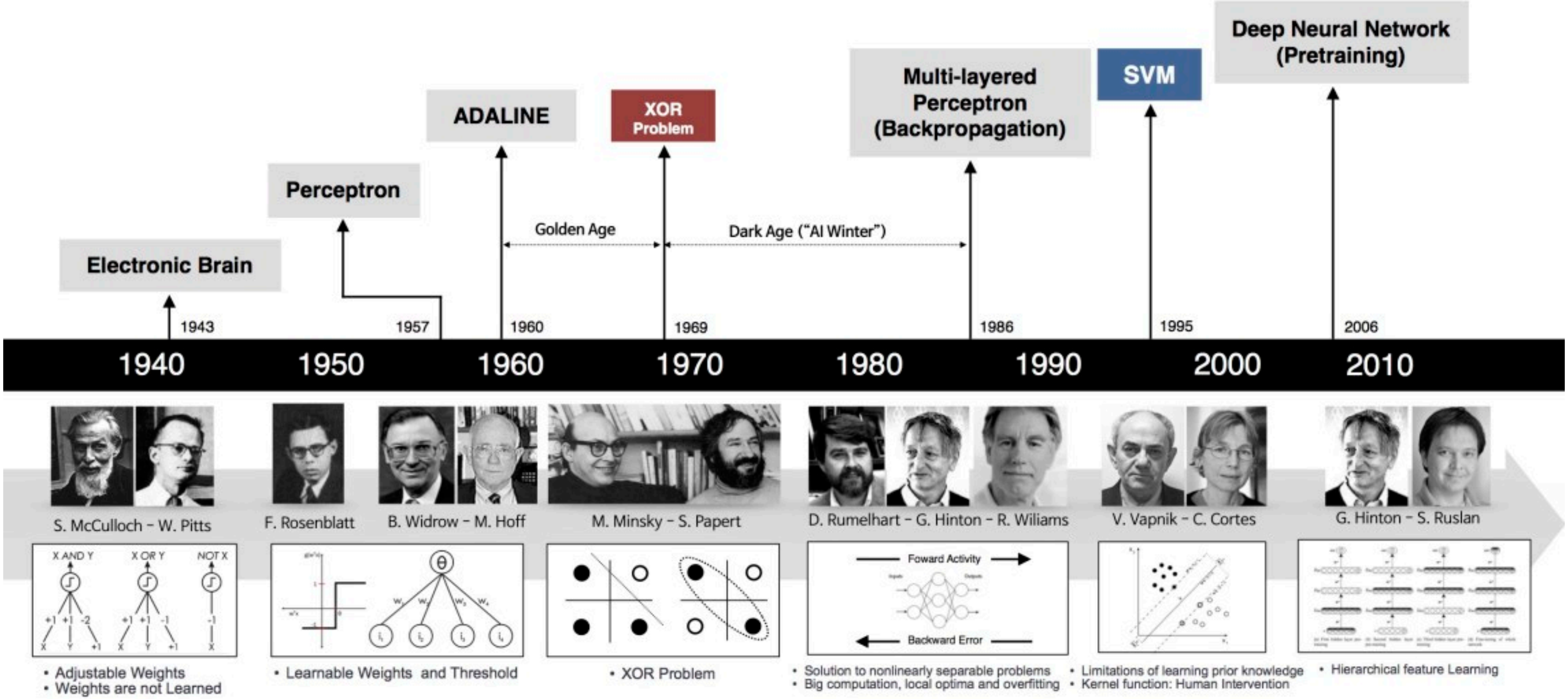
  - Graph neural networks: take graph data as input.
  - Transformers: take sequences as input and learn what parts of input to pay attention to.

Brief history of neural networks



What we’ve learned today…

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- Modeling a single neuron

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- Modeling a single neuron
    - Linear perceptron

What we've learned today…

- Modeling a single neuron
    - Linear perceptron
    - Limited power of a single neuron

What we’ve learned today…

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    - Linear perceptron
    - Limited power of a single neuron
- Multi-layer perceptron

What we’ve learned today…

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- Training of neural networks

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    - Loss function (cross entropy)

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    - Convolution, pooling, stride, padding

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    - Loss function (cross entropy)
    - Backpropagation and SGD
- Convolutional neural networks
    - Convolution, pooling, stride, padding
    - Basic architectures (LeNet etc.)
    - More advanced architectures (AlexNet, ResNet etc)

Thank you!

Some of the slides in these lectures have been adapted from materials developed by Alex Smola and Mu Li:
https://courses.d2l.ai/berkeley-stat-157/index.html