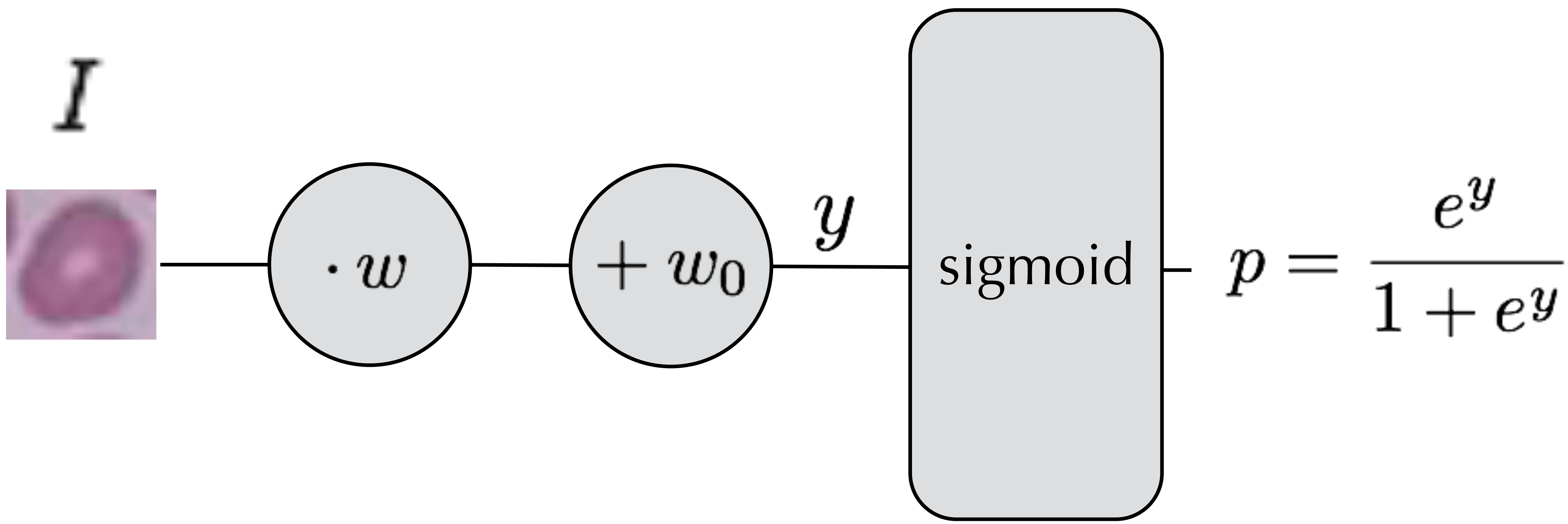
SSY097 - Image Analysis

Lecture 5 - (Convolutional) Neural Networks

Torsten Sattler
(slides adapted from Olof Enqvist)

Last Lecture



Learning linear classifiers

Last Lecture

$$p_k = \frac{e^{y_k}}{\sum_{m=0}^{n} e^{y_m}}$$

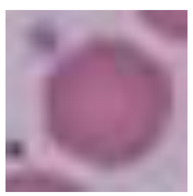
Softmax function for multi-class classification

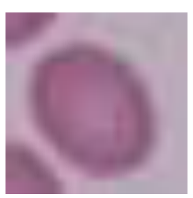
Last Lecture

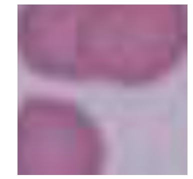
 p_1

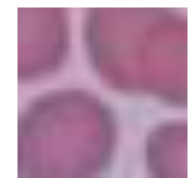
 $\rightarrow p_4$

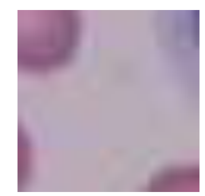
 $\rightarrow p_5$

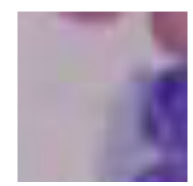
 $\rightarrow p_6$

 $\rightarrow p_8$

 $\rightarrow p_2$

 $\rightarrow p_3$

 $\rightarrow p_7$

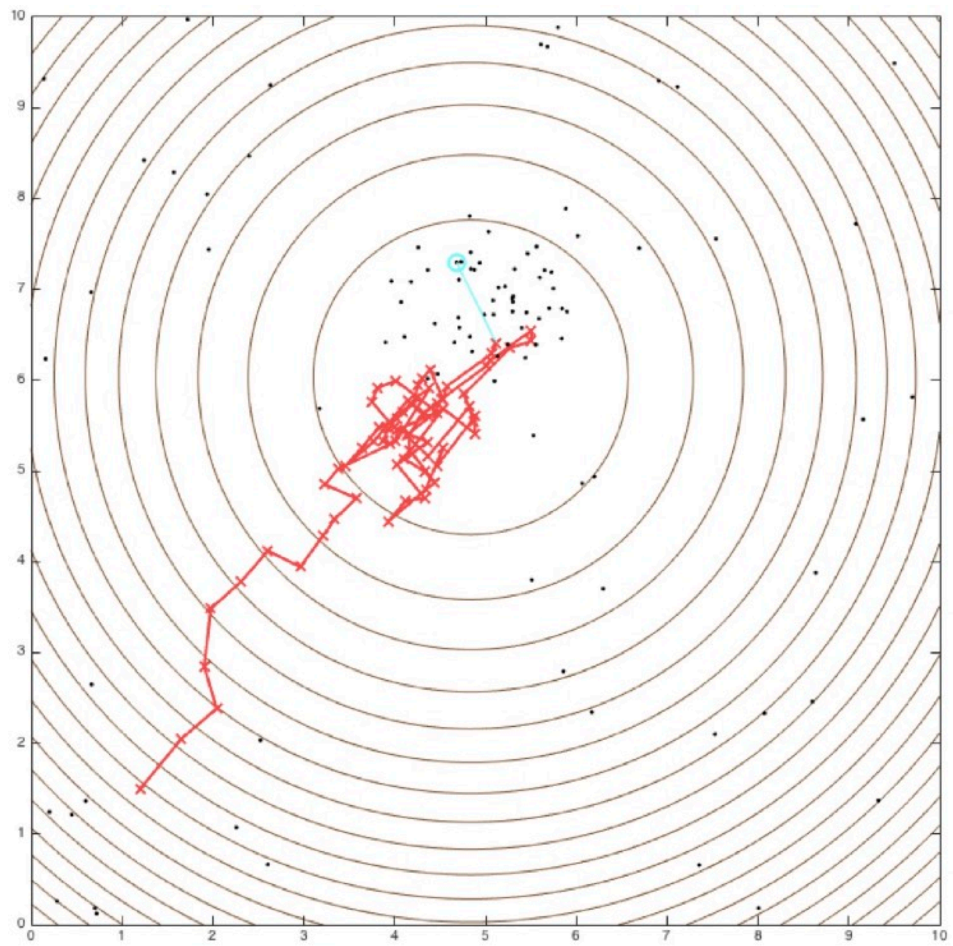
 $\rightarrow p_9$

$$-\Big(\sum_{\substack{\text{positive}\\\text{examples}}} \ln p_i \quad + \quad \sum_{\substack{\text{negative}\\\text{examples}}} \ln\left(1 - p_i\right) \Big)$$

Loss function: Negative Log-Likelihood

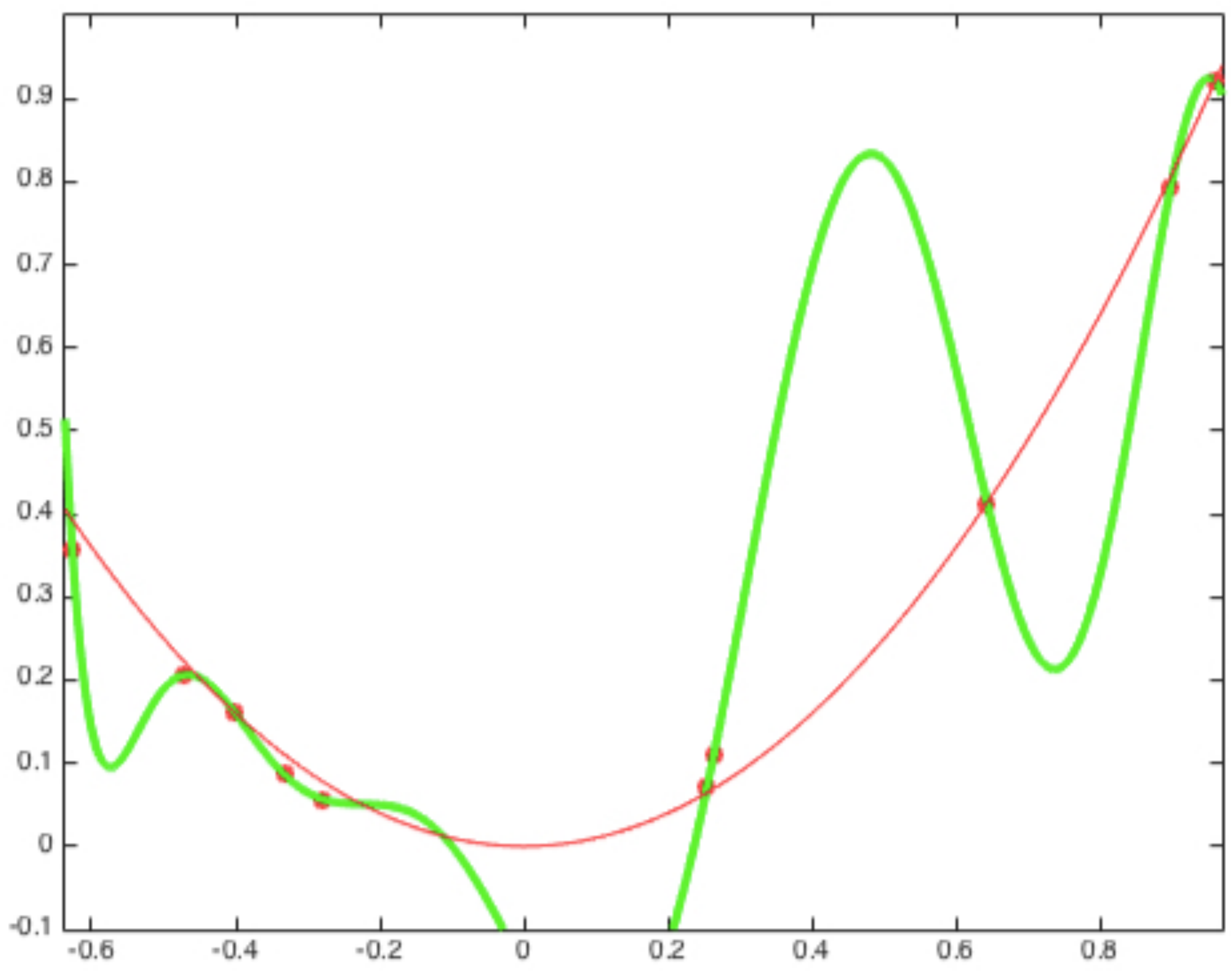
Last Lecture

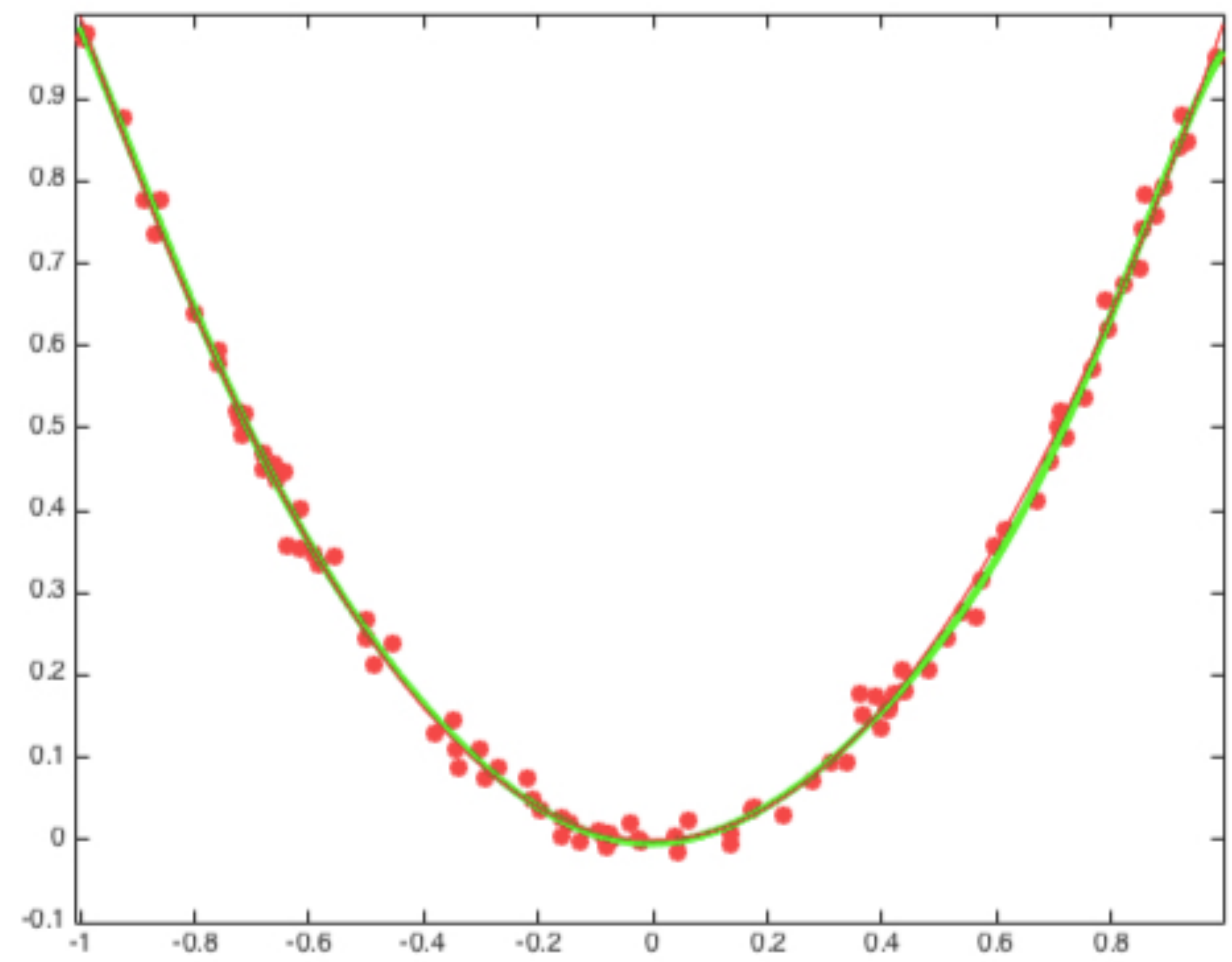
$$\theta^{(k+1)} = \theta^{(k)} - \mu \sum_i \nabla L_i(\theta) \approx \theta^{(k)} - \mu \nabla L_i(\theta)$$



Stochastic Gradient Descent (with Momentum)

Last Lecture

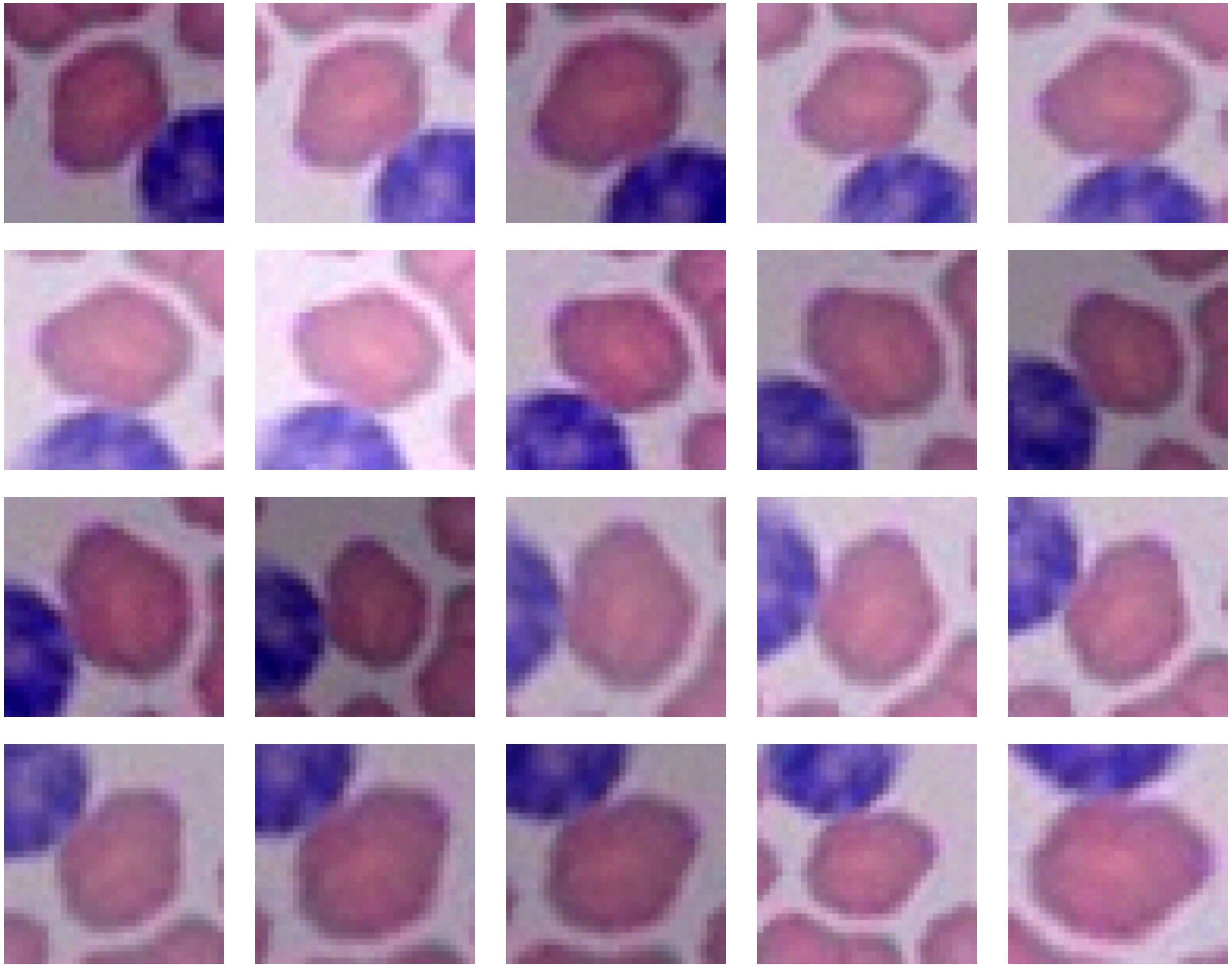




Overfitting

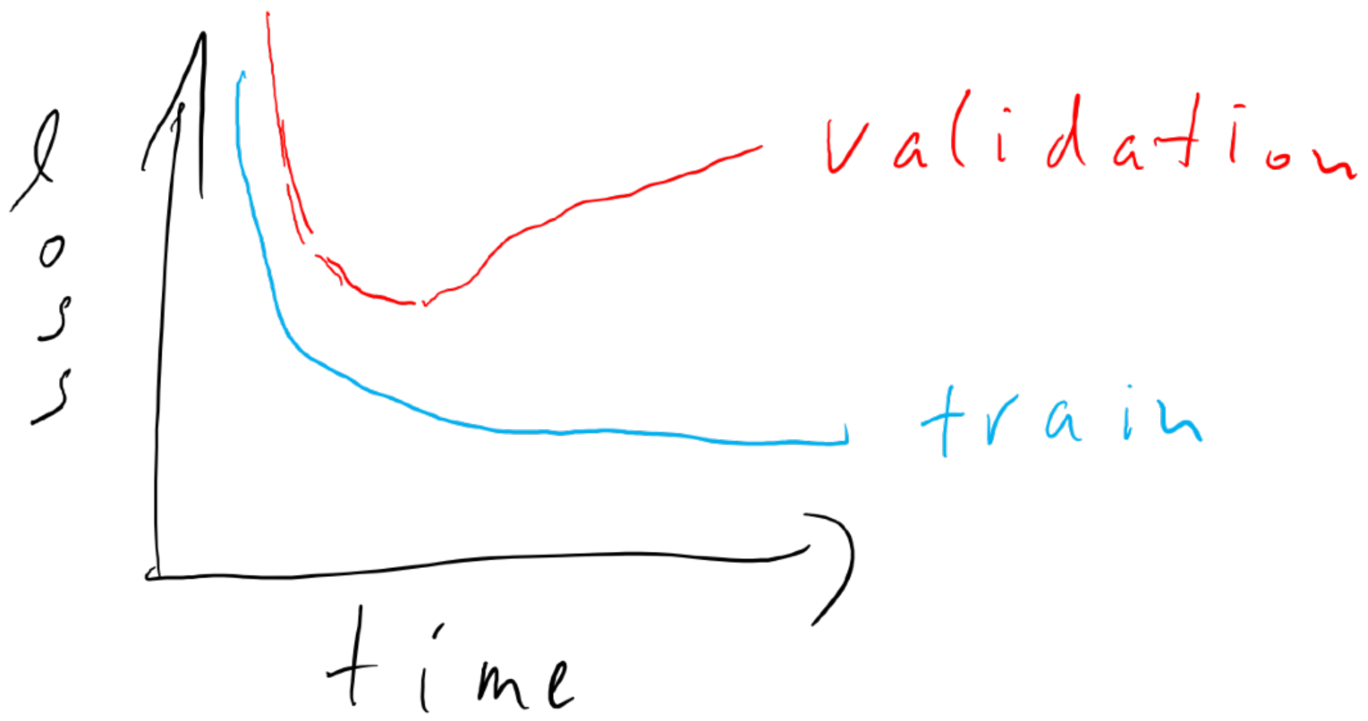
Last Lecture

- Rotate
- Scale
- Change brightness
- Add noise



Data augmentation

Last Lecture



Training, validation, test sets

Today

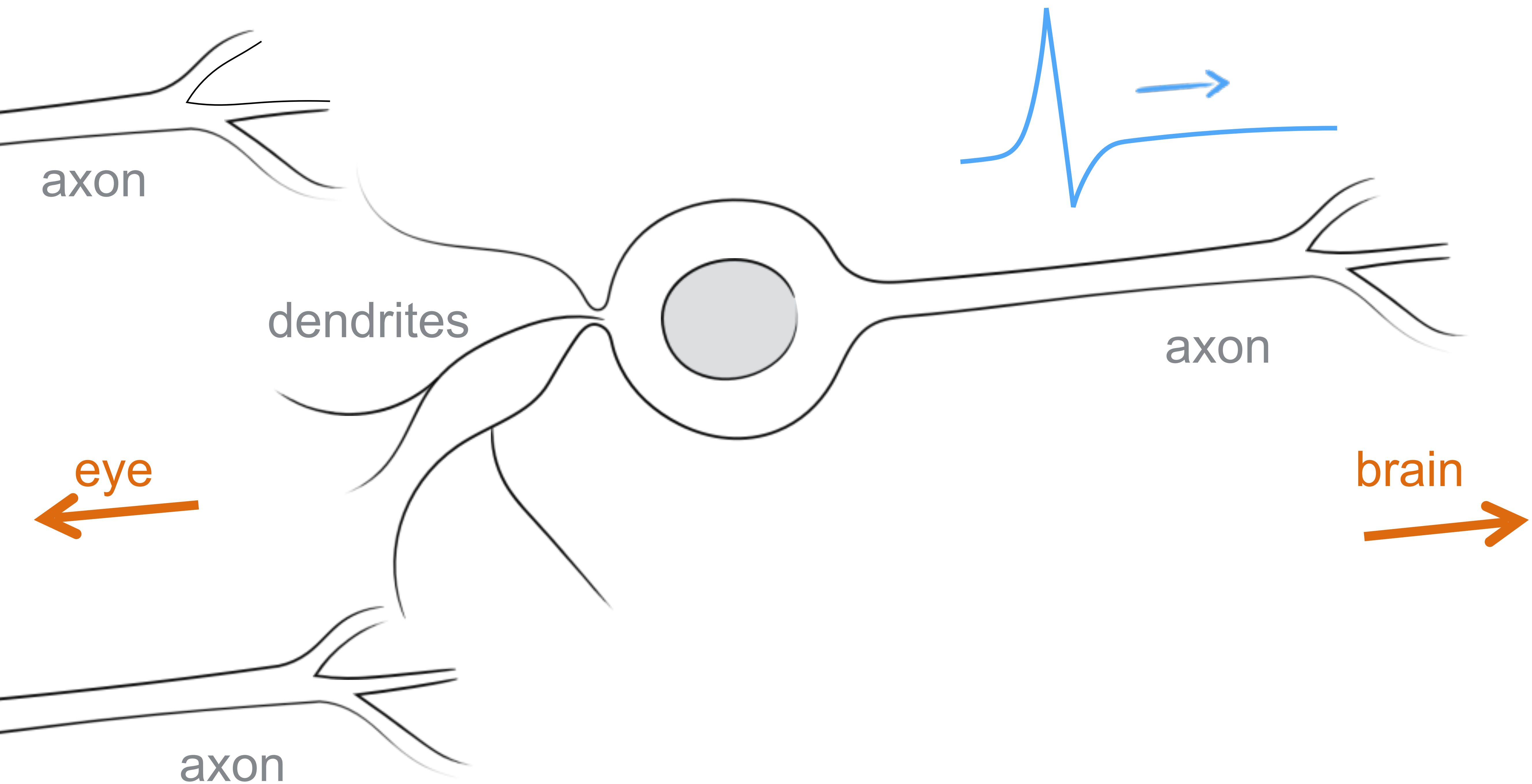
- Neural Networks
- Optimization: Backpropagation
- Convolutional Neural Networks
- Overfitting, Part II

Neural Networks

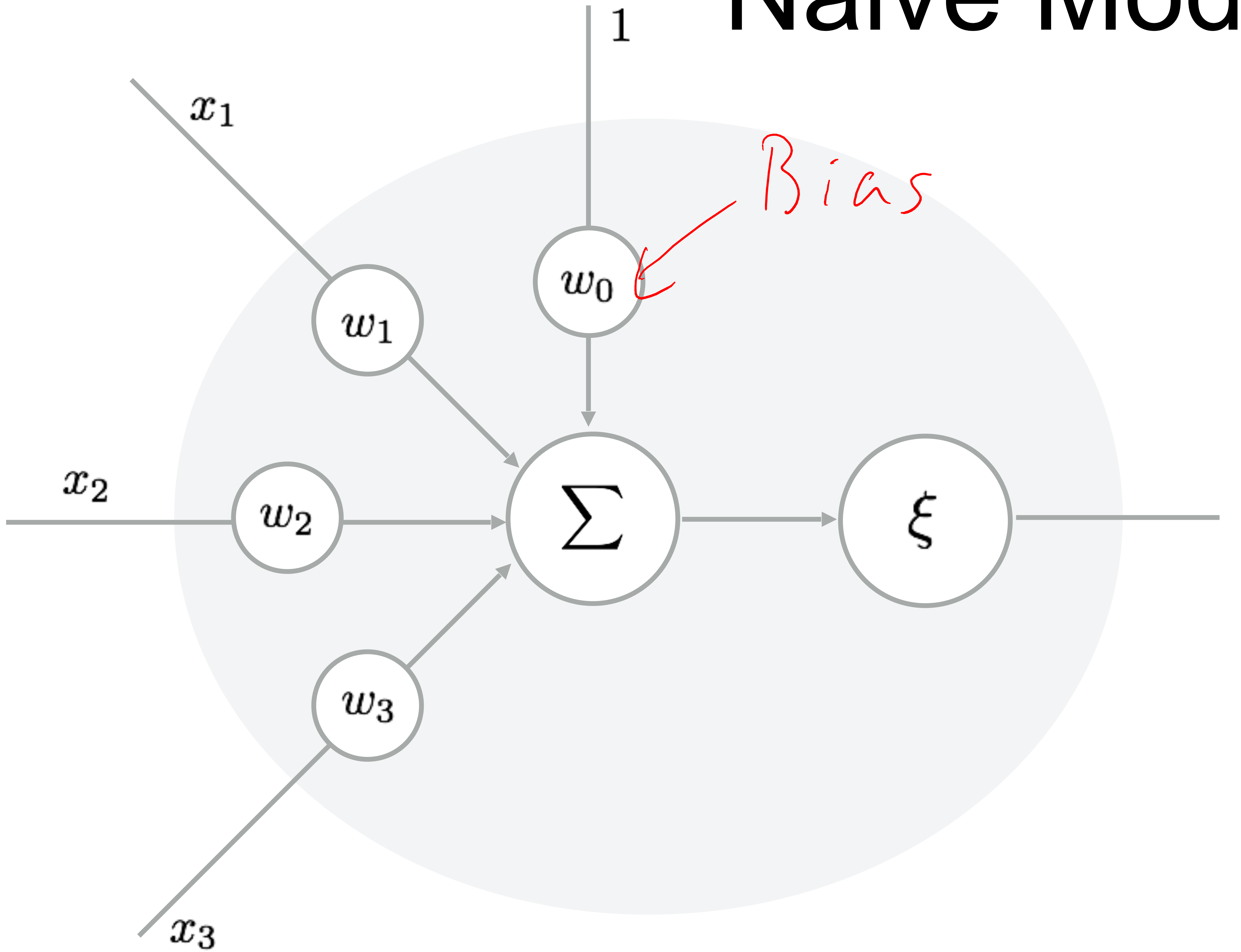
Recognition Revisited

Is there a robin in this image?

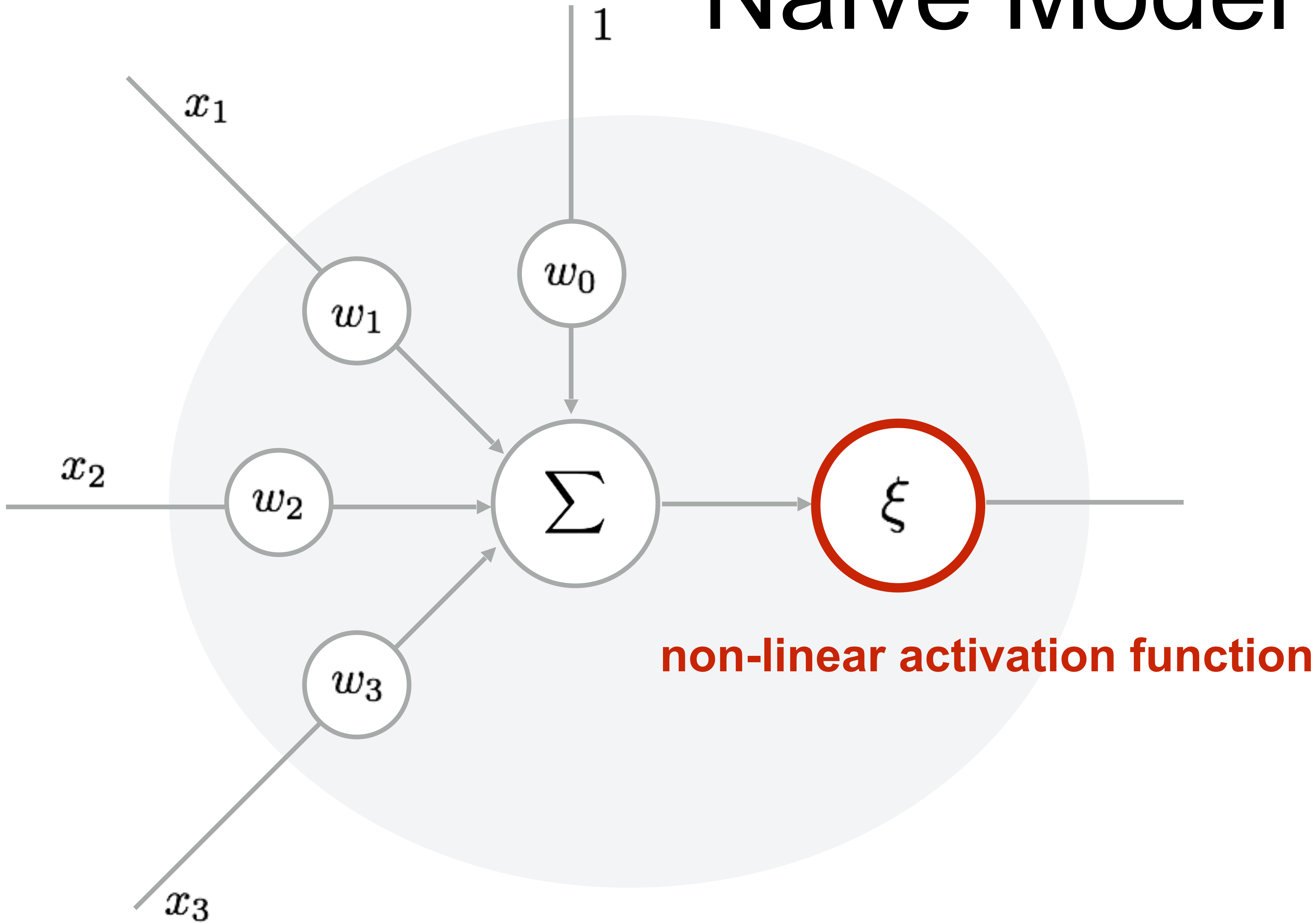
A Neuron



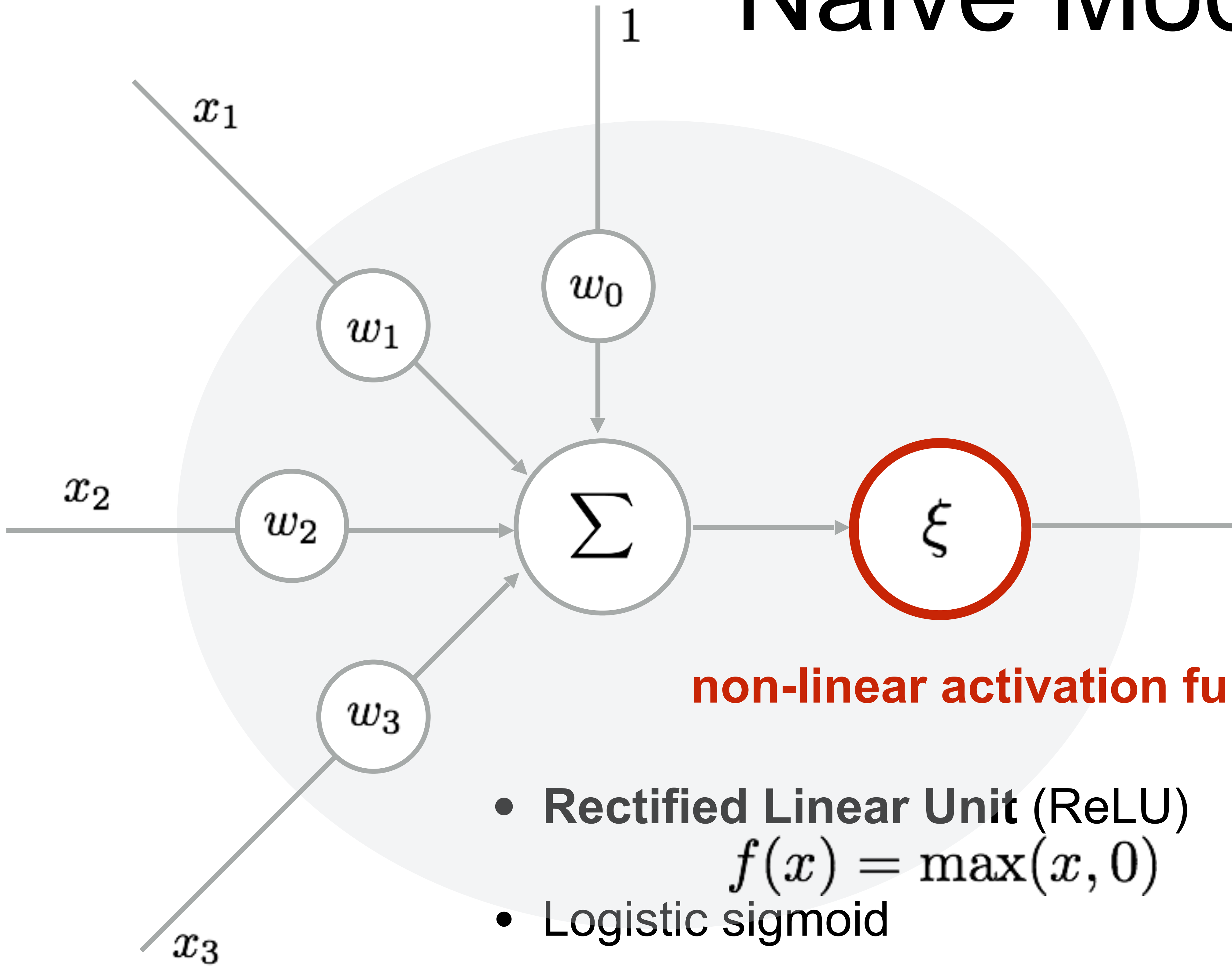
Naive Model



Naive Model



Naive Model

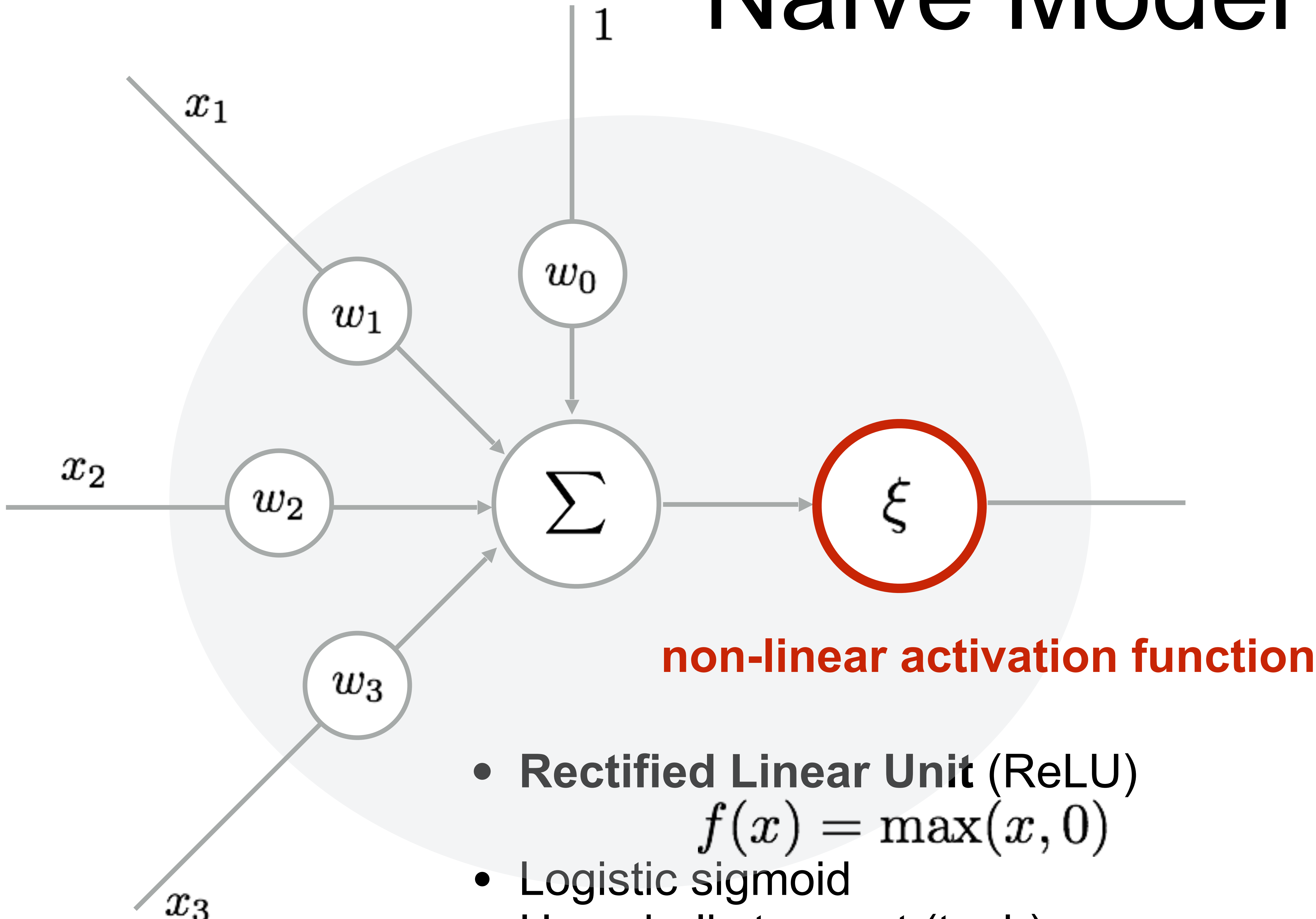


- **Rectified Linear Unit** (ReLU)

$$f(x) = \max(x, 0)$$

- Logistic sigmoid

Naive Model

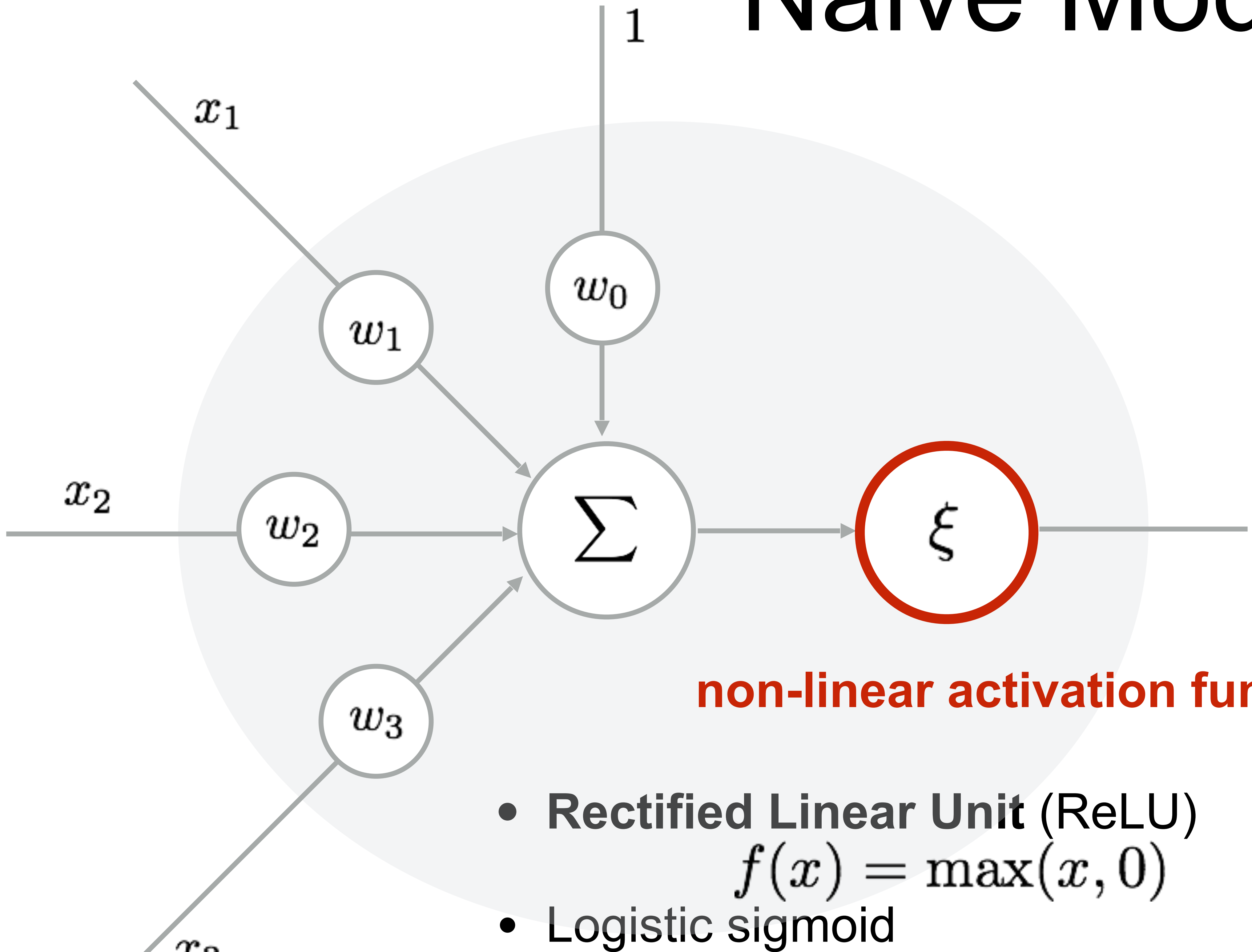


- **Rectified Linear Unit** (ReLU)

$$f(x) = \max(x, 0)$$

- Logistic sigmoid
- Hyperbolic tangent (tanh)

Naive Model



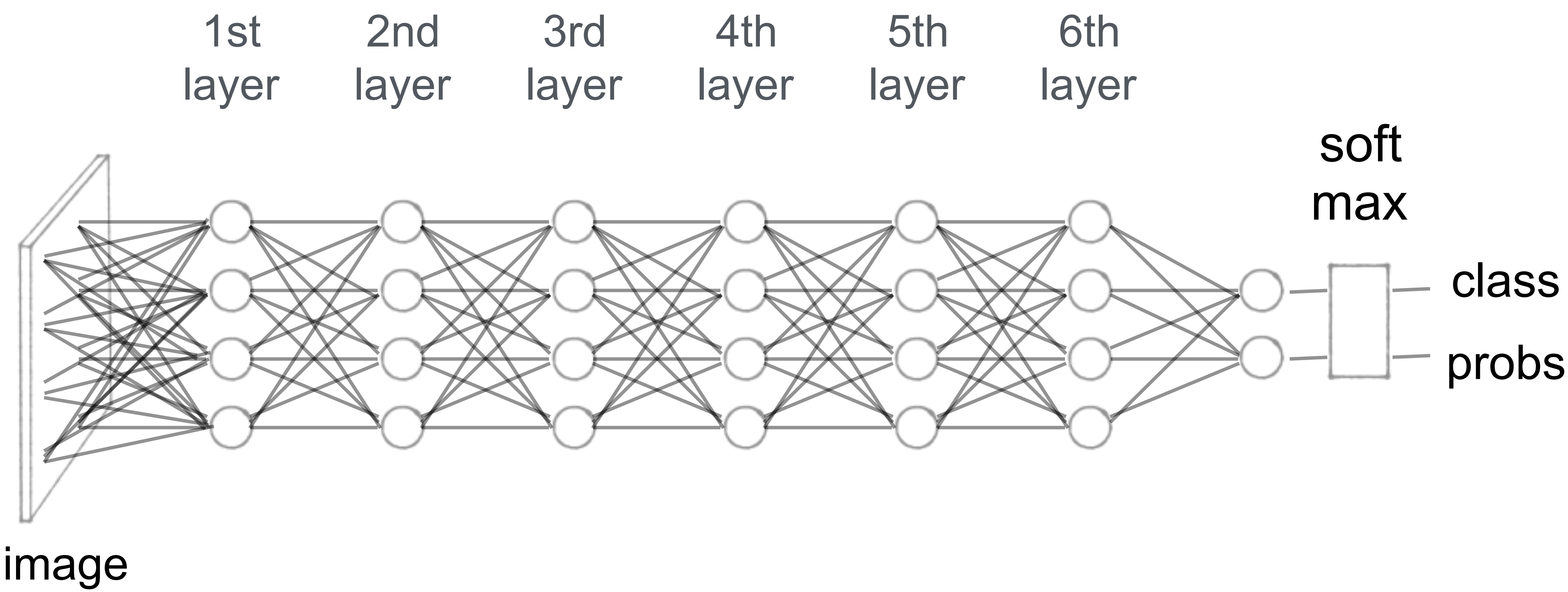
non-linear activation function

- **Rectified Linear Unit** (ReLU)

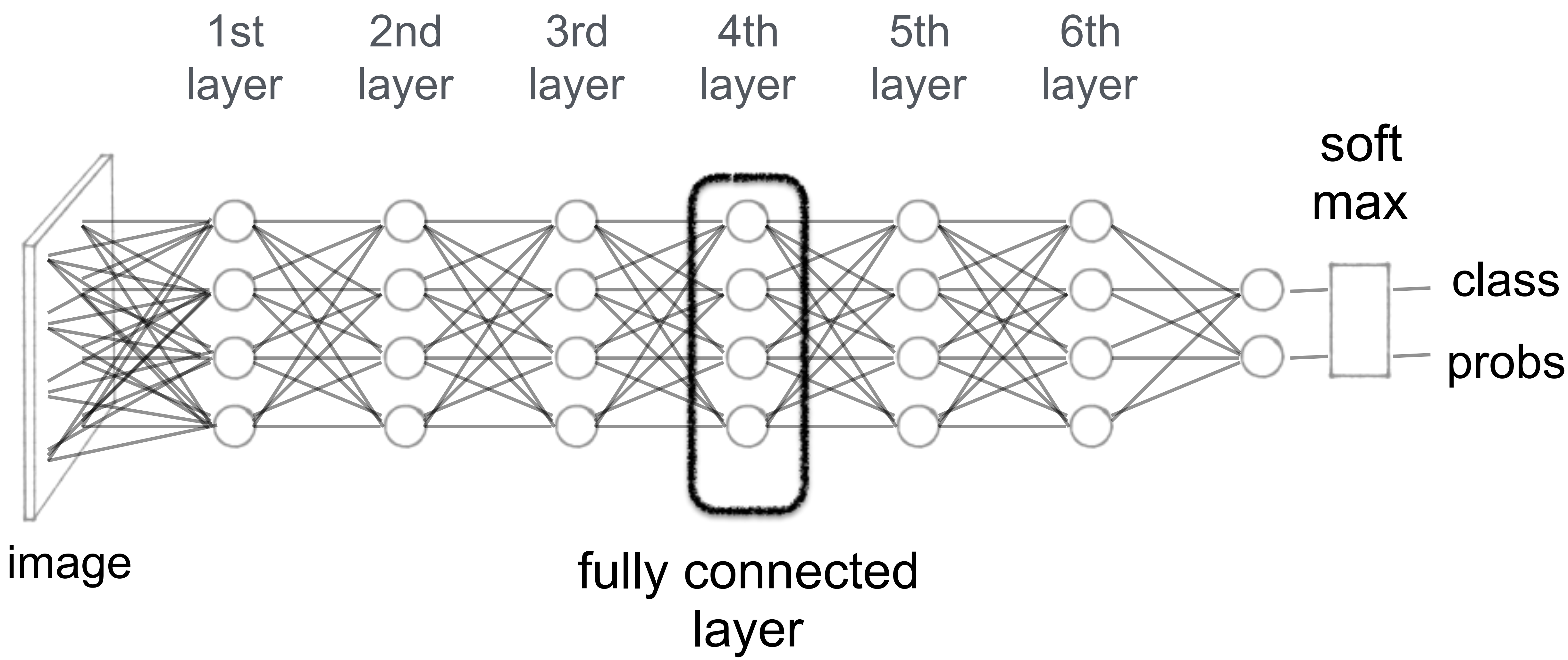
$$f(x) = \max(x, 0)$$

- Logistic sigmoid
- Hyperbolic tangent (tanh)
- …

A Neural Network

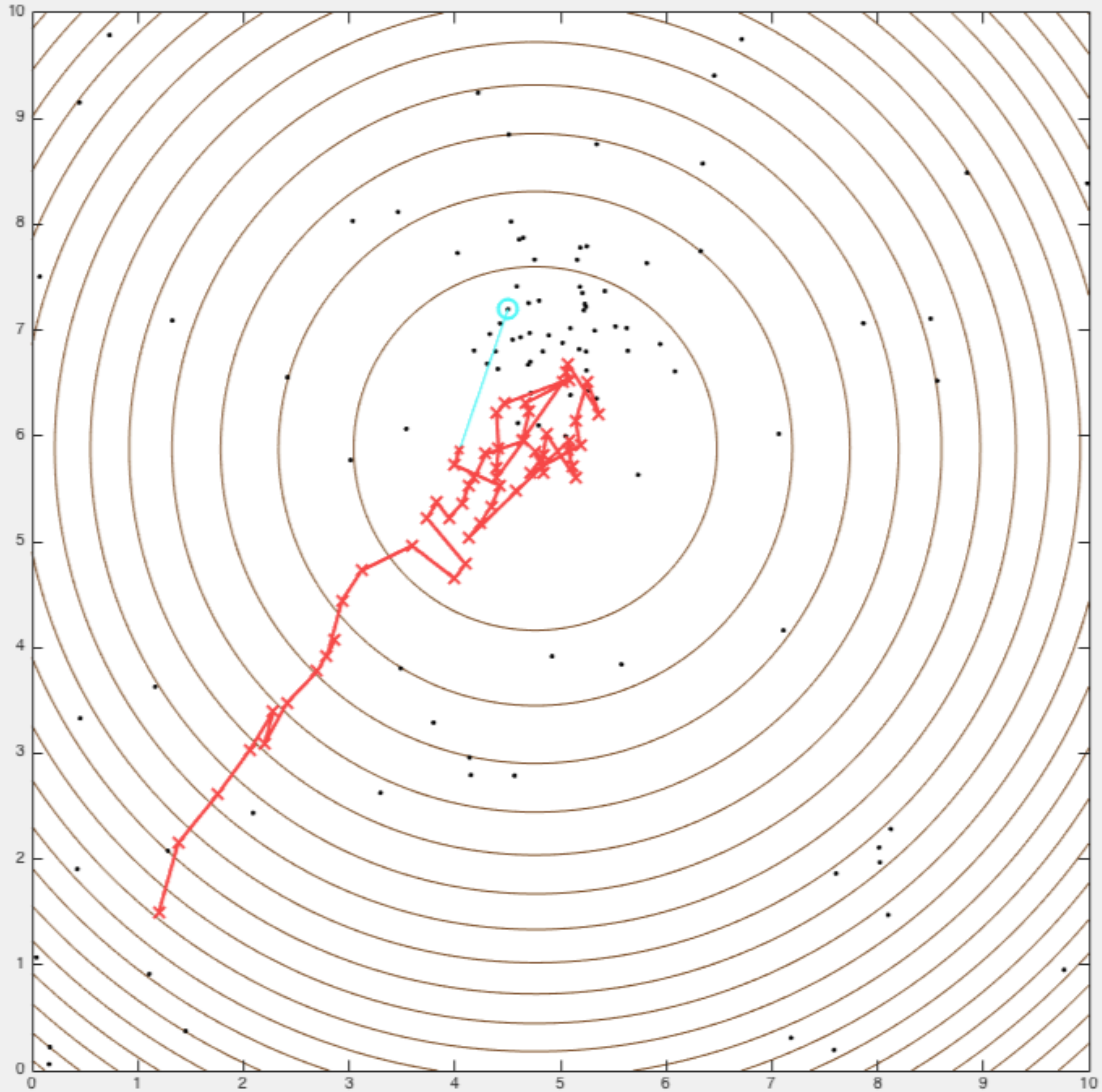


A Neural Network



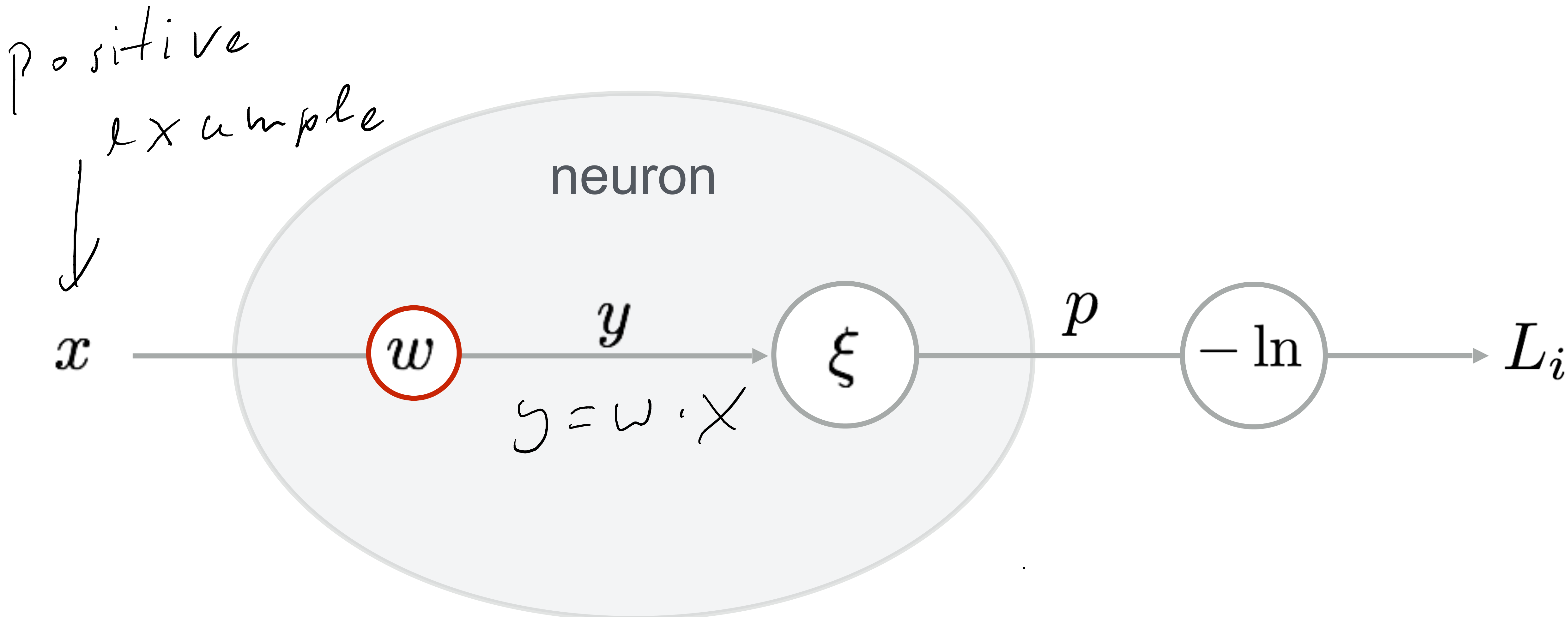
Optimization: Backpropagation
(backprop)

Stochastic Gradient Descent

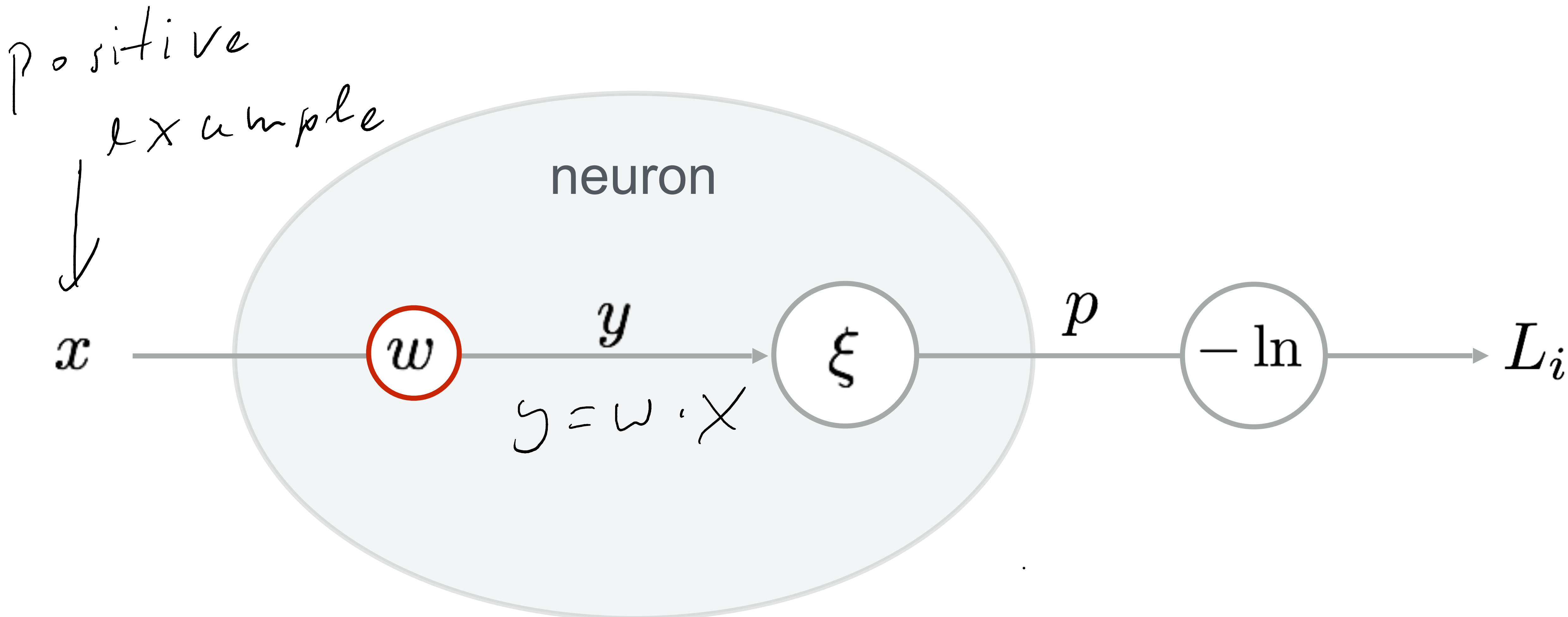


How do we differentiate?

The Chain Rule

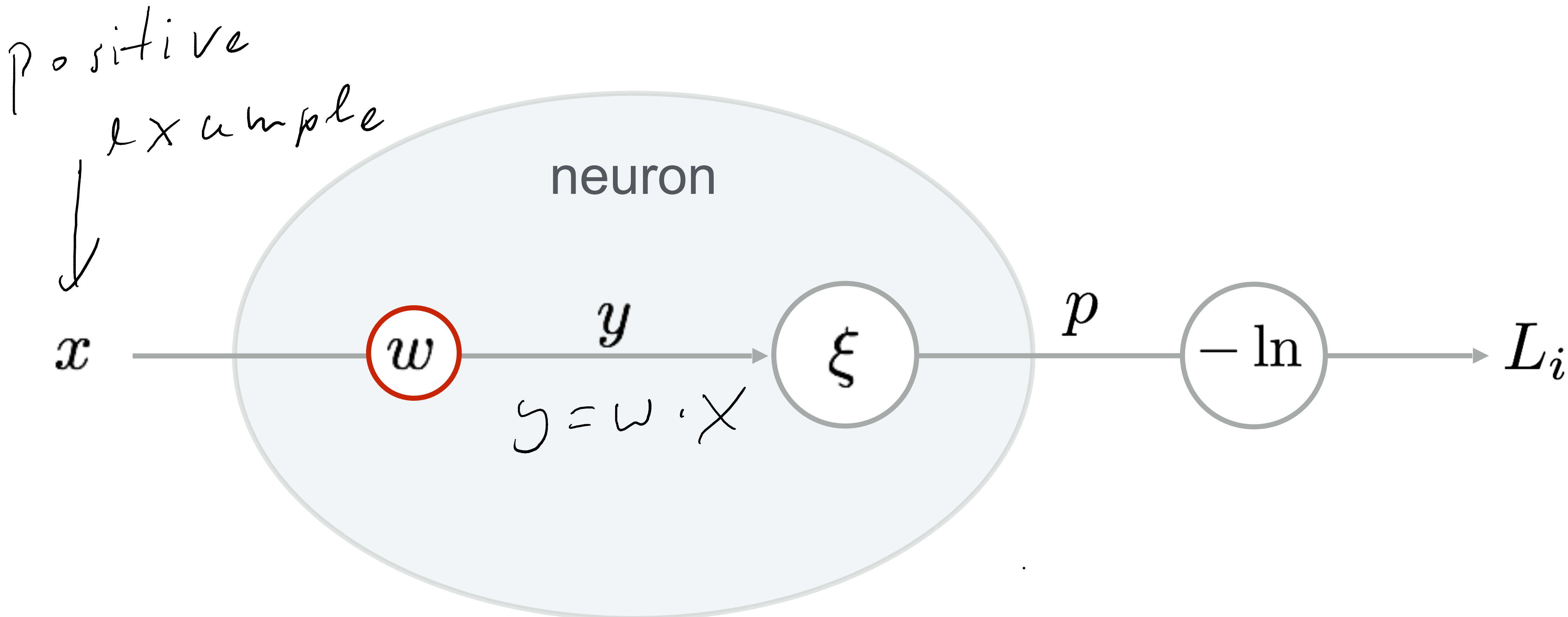


The Chain Rule



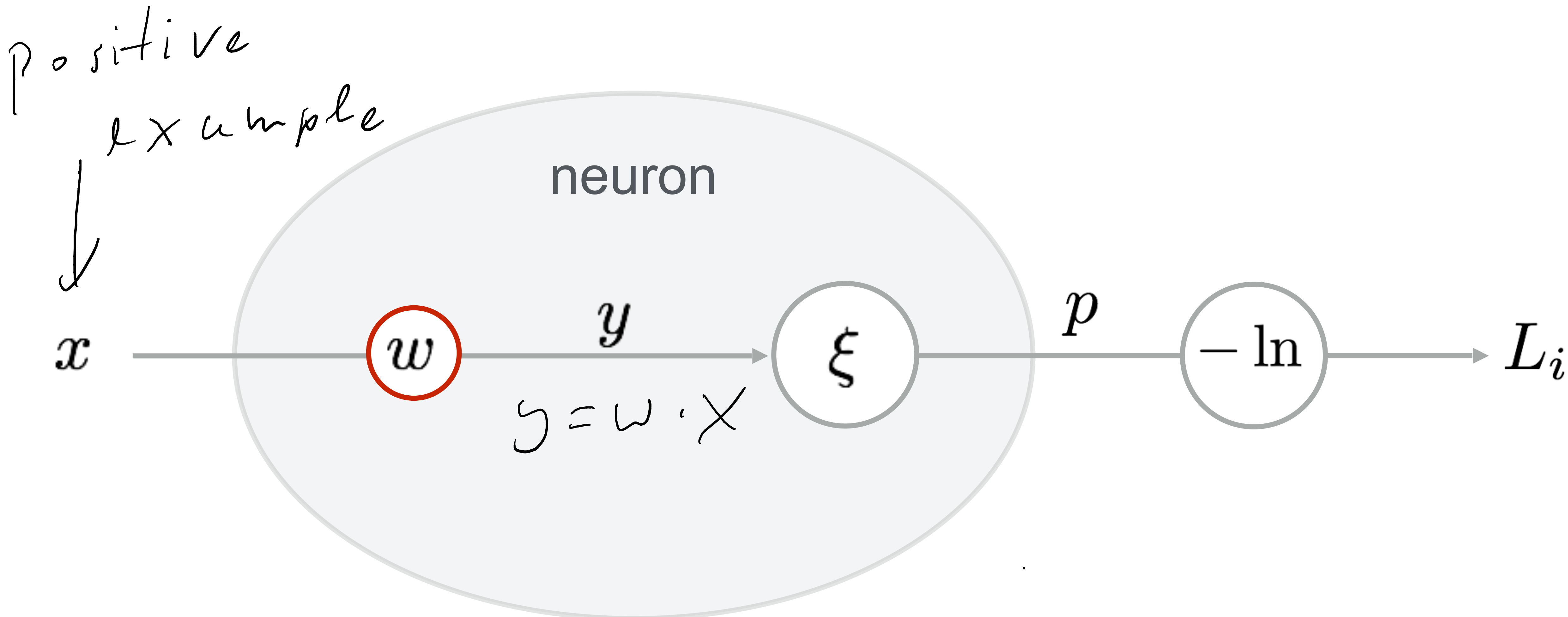
Gradient $\dfrac{\partial L_i}{\partial w}$

The Chain Rule



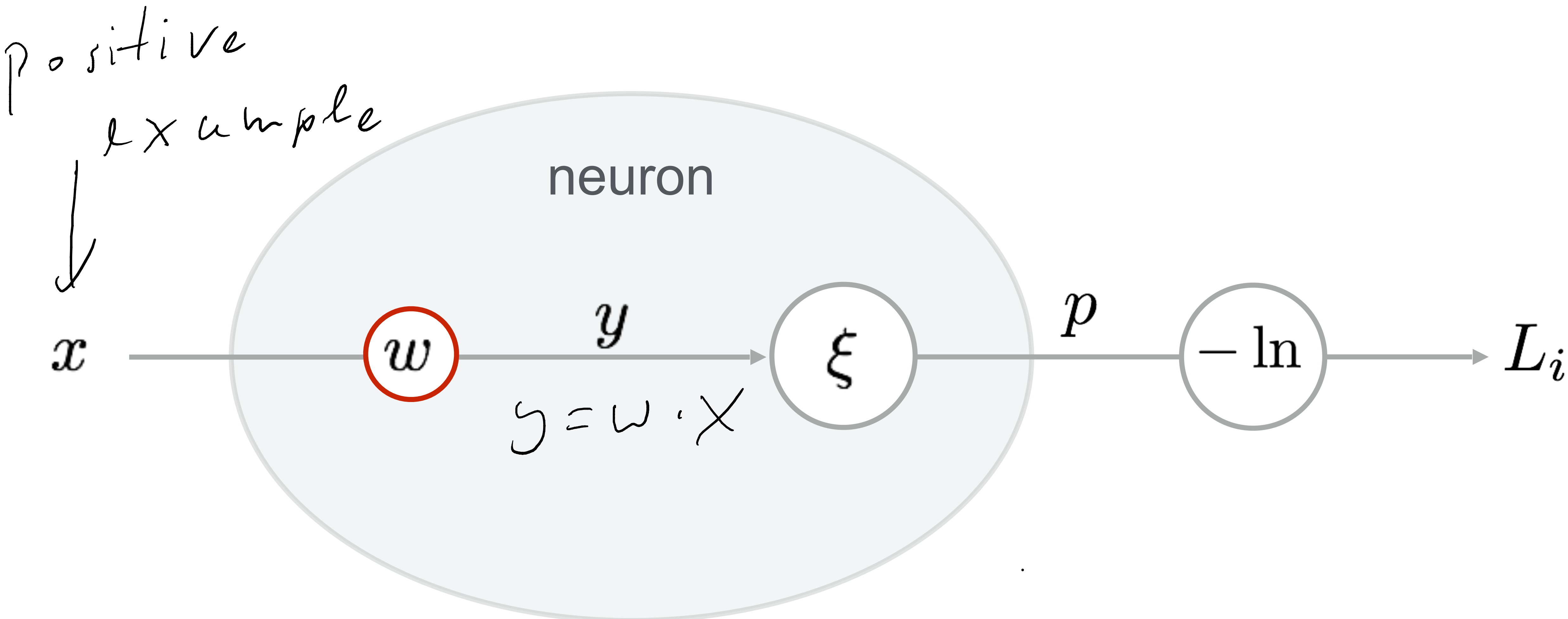
Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p}$

The Chain Rule



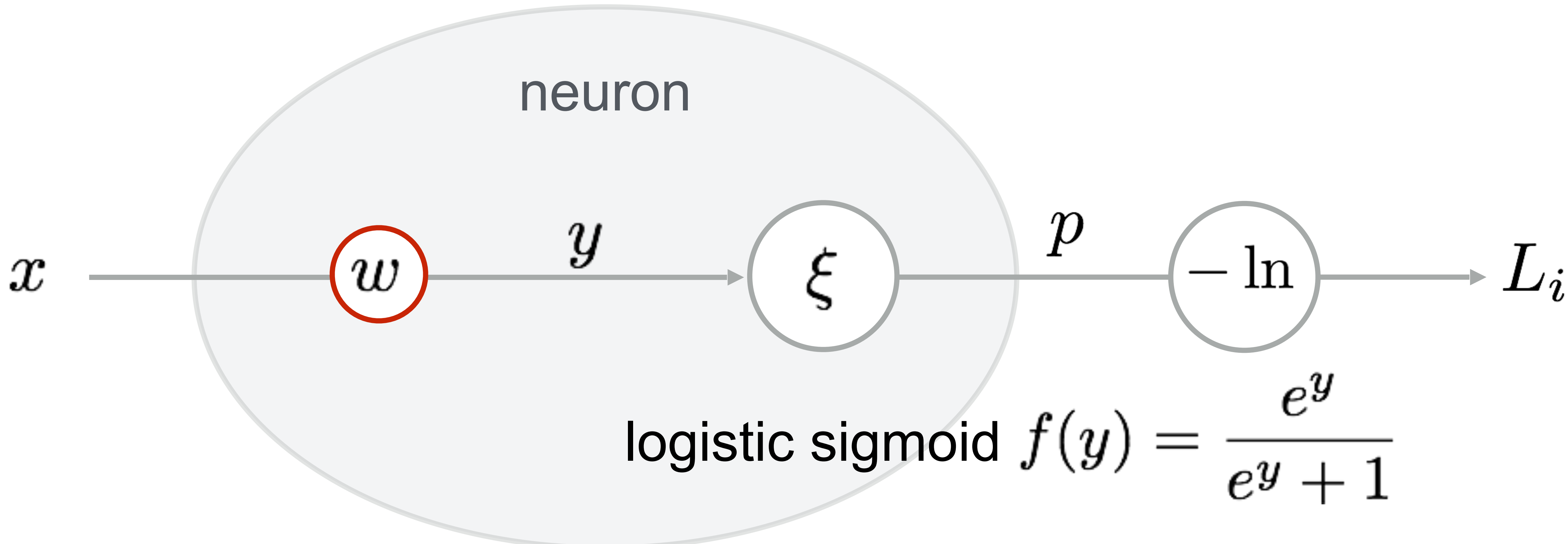
Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p}\dfrac{\partial p}{\partial y}$

The Chain Rule



Gradient $$\frac{\partial L_i}{\partial w} = \frac{\partial L_i}{\partial p} \frac{\partial p}{\partial y} \frac{\partial y}{\partial w}$$

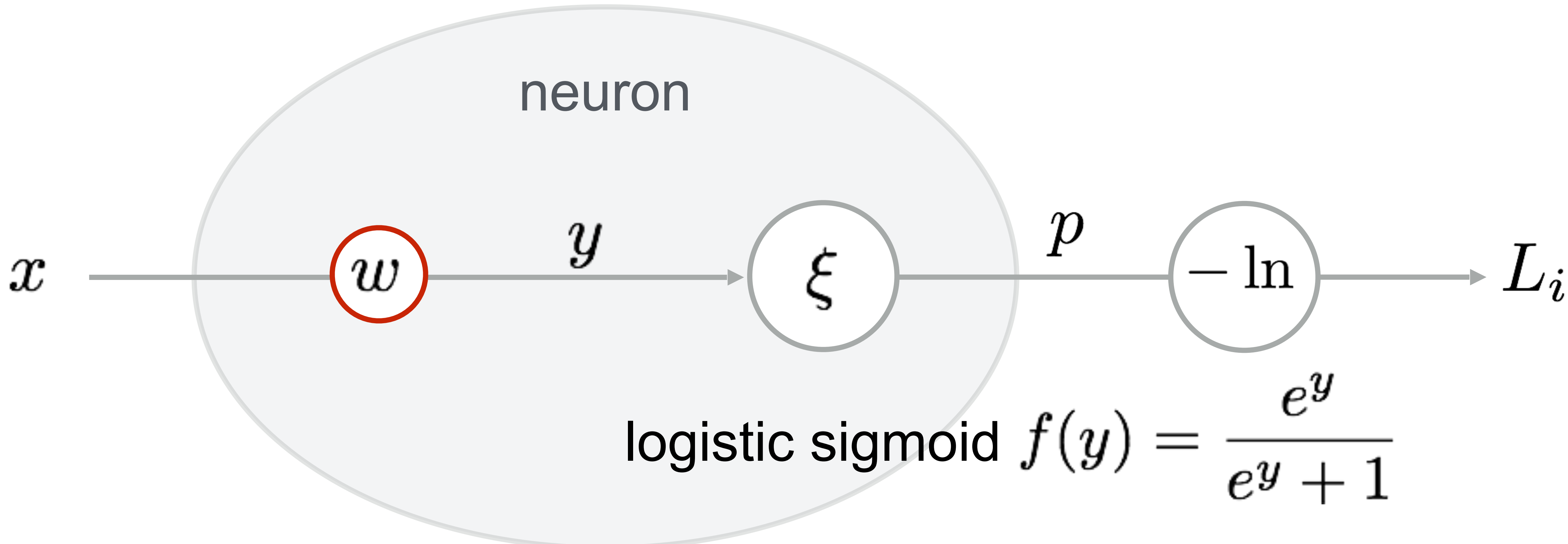
The Chain Rule



logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$

Gradient $$\frac{\partial L_i}{\partial w} = \frac{\partial L_i}{\partial p}\frac{\partial p}{\partial y}\frac{\partial y}{\partial w}$$

The Chain Rule



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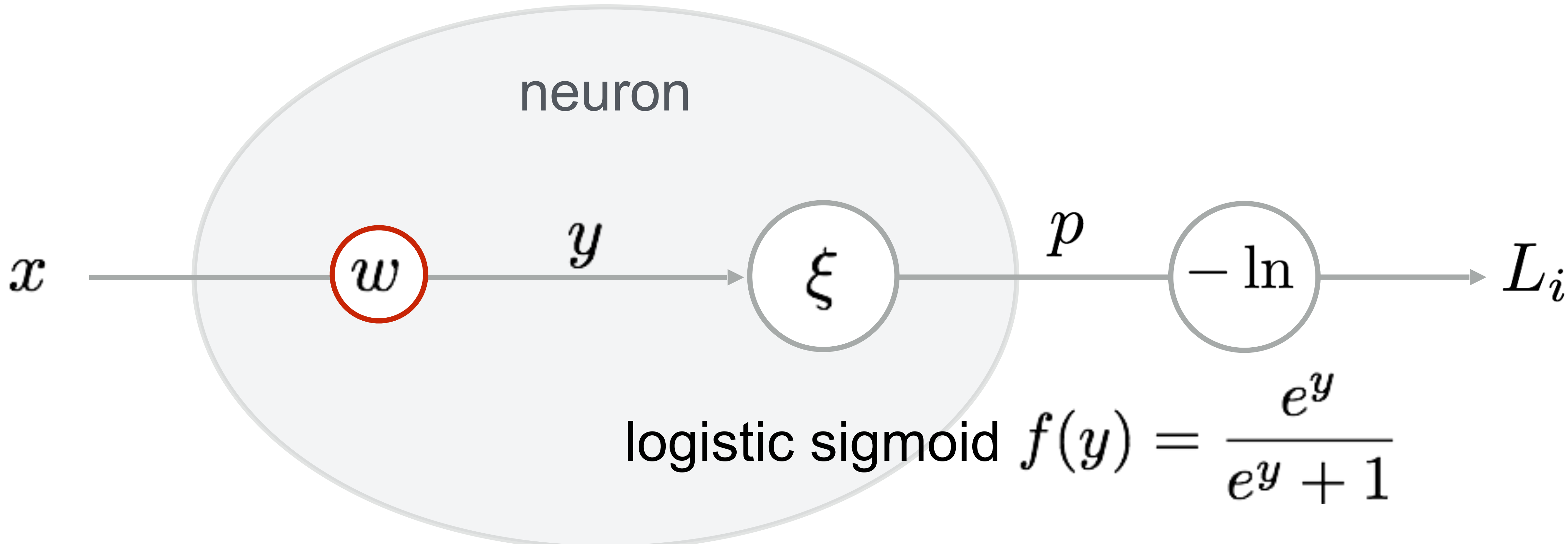
Gradient $$\frac{\partial L_i}{\partial w} = \underbrace{\frac{\partial L_i}{\partial p}} \frac{\partial p}{\partial y} \frac{\partial y}{\partial w}$$

The Chain Rule

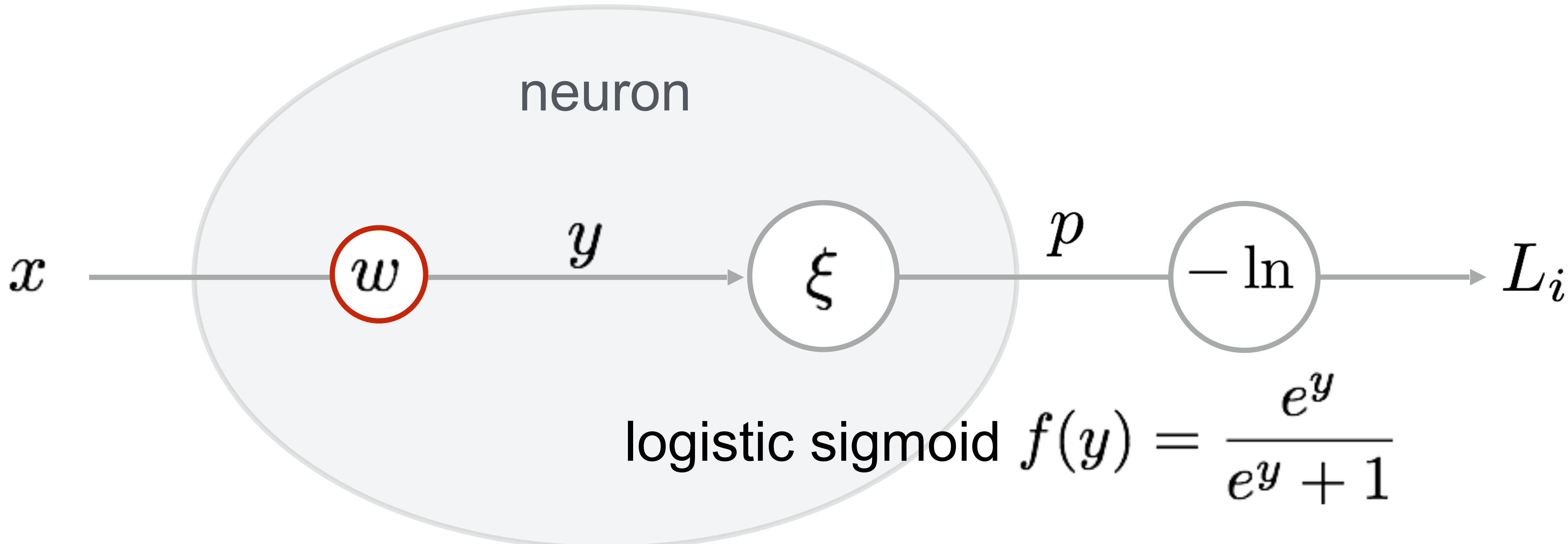


logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$

Gradient $\dfrac{\partial L_i}{\partial w} = \underbrace{\dfrac{\partial L_i}{\partial p}} \dfrac{\partial p}{\partial y} \dfrac{\partial y}{\partial w}$

$$\frac{\partial L_i}{\partial p} = \frac{\partial}{\partial p}(-\ln p)$$

The Chain Rule



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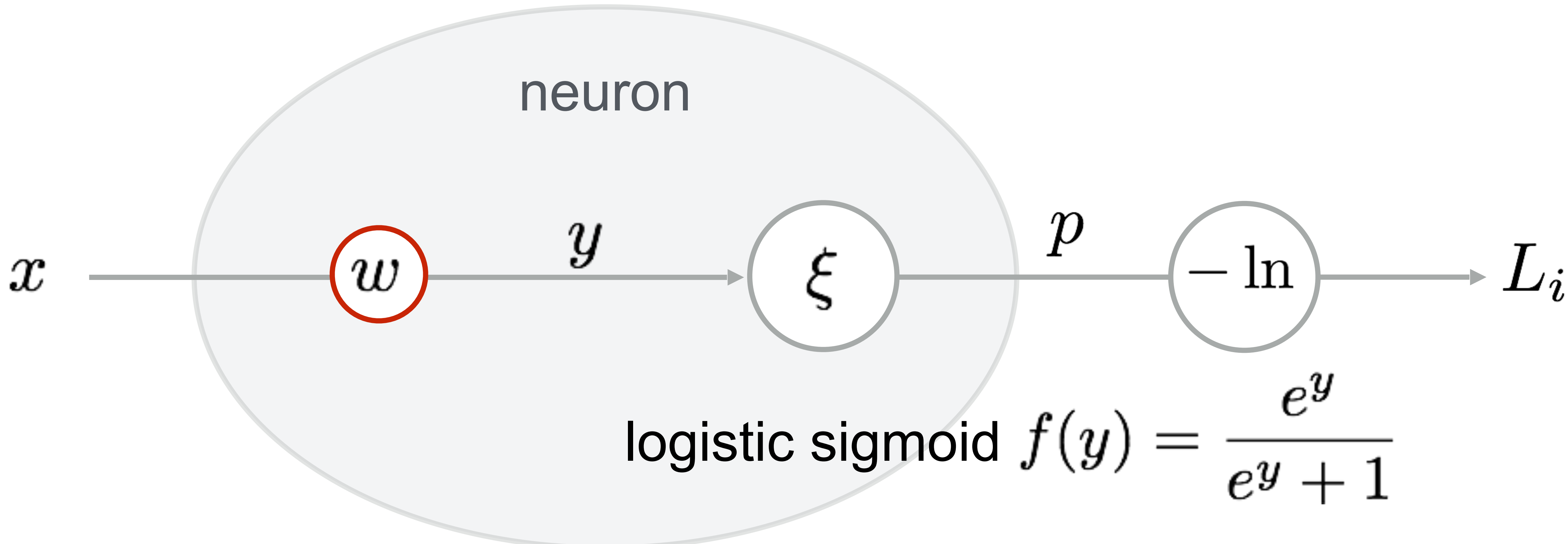
Gradient $\frac{\partial L_i}{\partial w} = \underbrace{\frac{\partial L_i}{\partial p}}\frac{\partial p}{\partial y}\frac{\partial y}{\partial w}$

$$\frac{\partial L_i}{\partial p} = \frac{\partial}{\partial p}(-\ln p) = -\frac{1}{p}$$

The Chain Rule

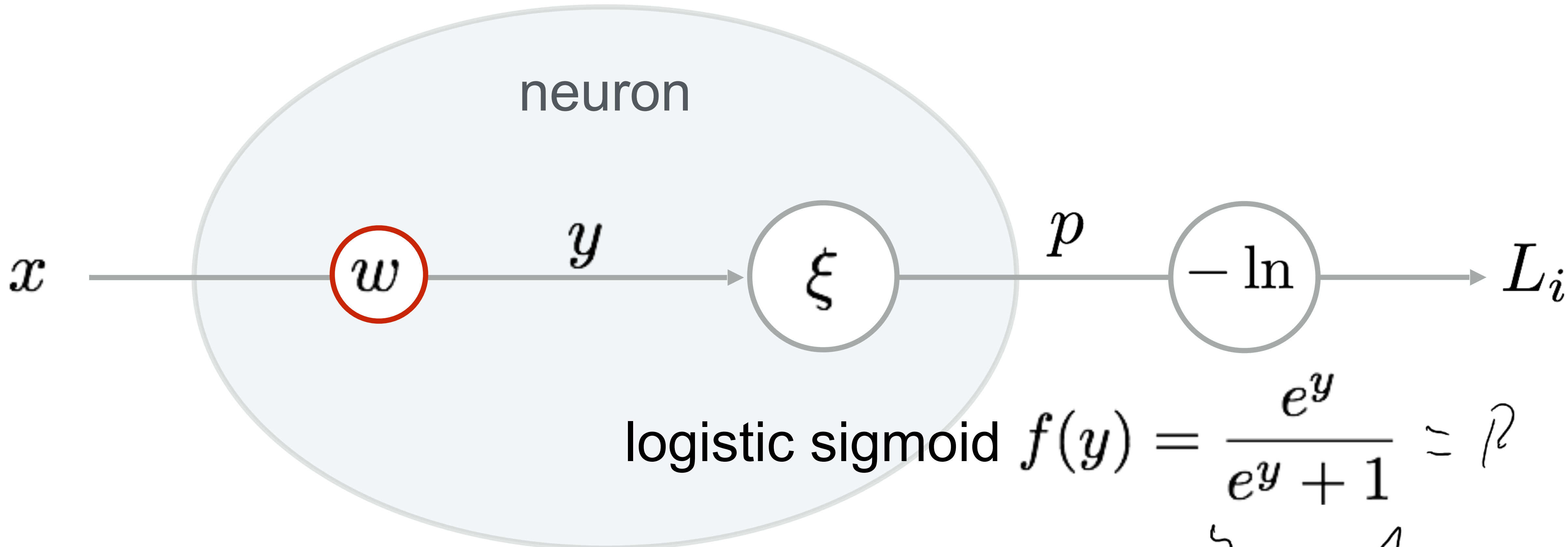


logistic sigmoid $f(y) = \frac{e^y}{e^y + 1}$

Gradient $$\frac{\partial L_i}{\partial w} = \underbrace{\frac{\partial L_i}{\partial p}} \frac{\partial p}{\partial y} \frac{\partial y}{\partial w} = -\frac{1}{p} \frac{\partial p}{\partial y} \frac{\partial y}{\partial w}$$

$$\frac{\partial L_i}{\partial p} = \frac{\partial}{\partial p}(-\ln p) = -\frac{1}{p}$$

The Chain Rule



logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1} = p$

$$\frac{e^y}{e^y+1} \cdot \frac{1}{e^y+1}$$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p}\dfrac{\partial p}{\partial y}\dfrac{\partial y}{\partial w} = -\dfrac{1}{p}\dfrac{\partial p}{\partial y}\dfrac{\partial y}{\partial w}$

$$e^y\left(1 + e^y - e^y\right)$$

The Chain Rule

logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1} = p$

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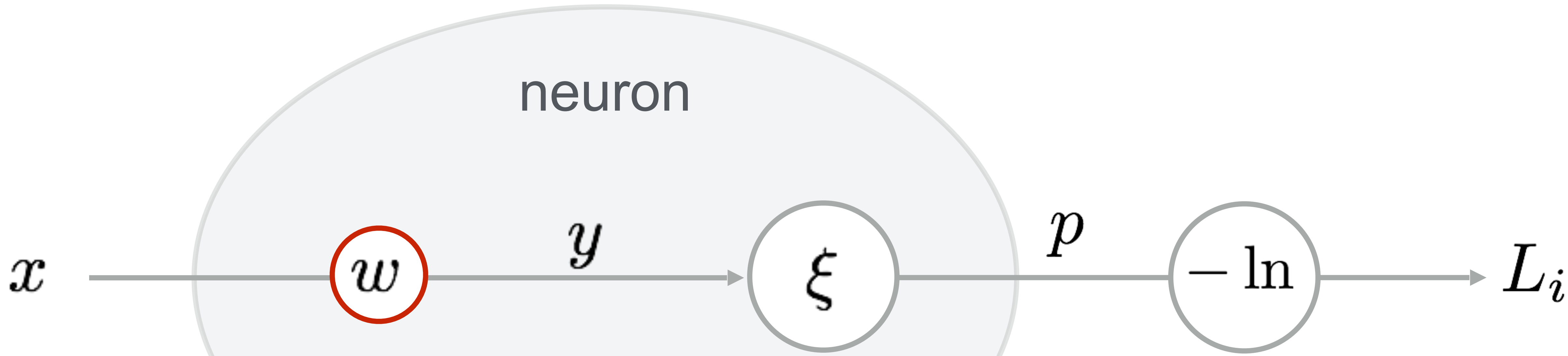


logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$ $= p$

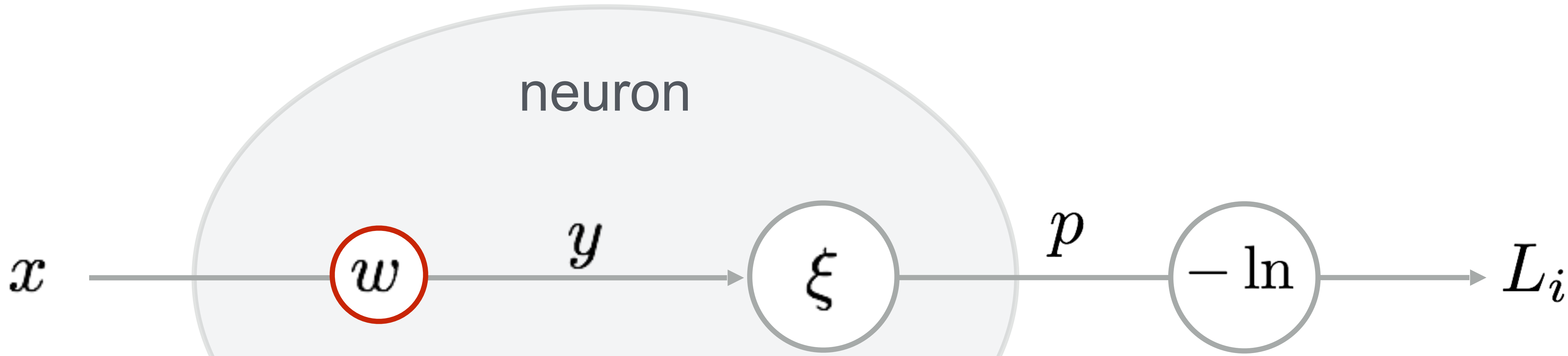
$\dfrac{e^y}{e^y+1} \cdot \dfrac{1}{e^y+1}$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p} \underbrace{\dfrac{\partial p}{\partial y}}_{} \dfrac{\partial y}{\partial w} = -\dfrac{1}{p} \dfrac{\partial p}{\partial y} \dfrac{\partial y}{\partial w}$

$e^y(1 + e^y - e^y)$

$$\frac{\partial p}{\partial y} = \frac{\partial}{\partial y} \frac{e^y}{e^y + 1}$$

The Chain Rule



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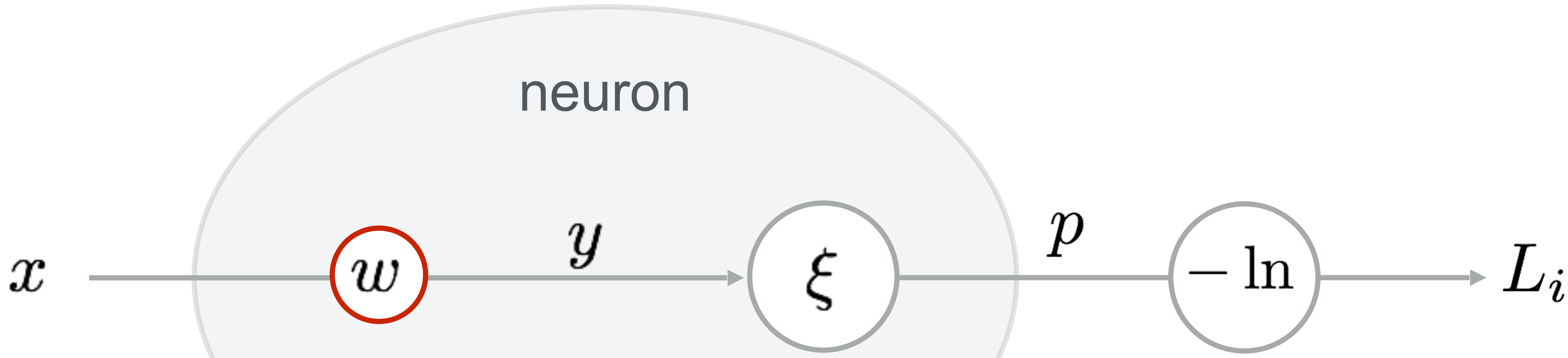
$$\frac{e^y}{e^y+1} \cdot \frac{1}{e^y+1}$$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p}\underbrace{\dfrac{\partial p}{\partial y}}\dfrac{\partial y}{\partial w} = -\dfrac{1}{p}\dfrac{\partial p}{\partial y}\dfrac{\partial y}{\partial w}$

$$e^y(1+e^y-e^y)$$

$$\frac{\partial p}{\partial y} = \frac{\partial}{\partial y}\frac{e^y}{e^y+1} = \frac{e^y(1+e^y)-(e^y)^2}{(e^y+1)^2}$$

The Chain Rule



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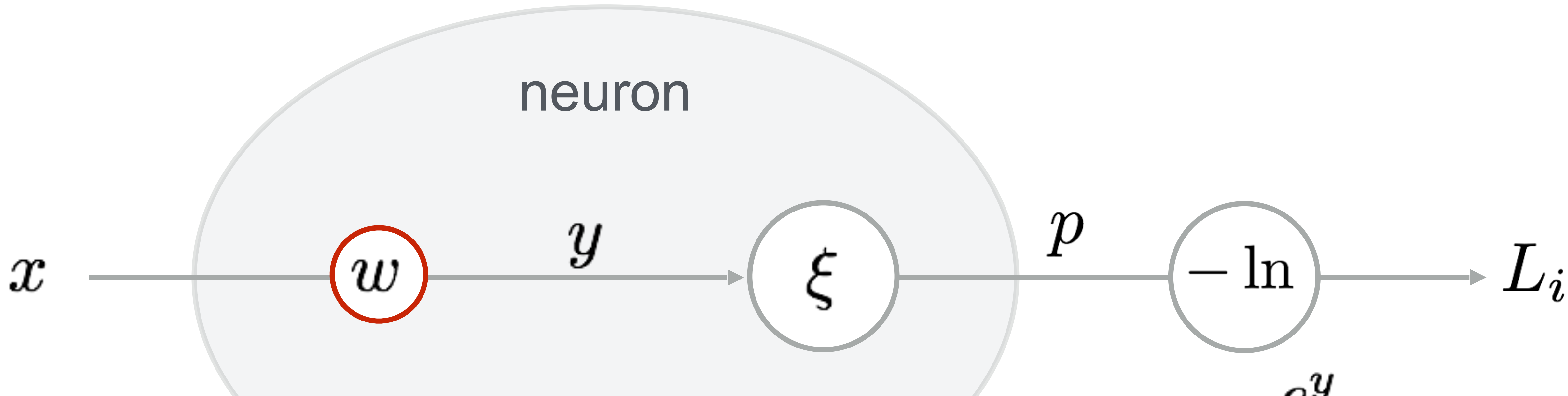
$$\frac{e^y}{e^y+1} \cdot \frac{1}{e^y+1}$$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p} \underbrace{\dfrac{\partial p}{\partial y}} \dfrac{\partial y}{\partial w} = -\dfrac{1}{p} \dfrac{\partial p}{\partial y} \dfrac{\partial y}{\partial w}$

$$e^y(1+e^y-e^y)$$

$$\frac{\partial p}{\partial y} = \frac{\partial}{\partial y} \frac{e^y}{e^y+1} = \frac{e^y(1+e^y) - (e^y)^2}{(e^y+1)^2} = \frac{e^y}{(e^y+1)^2}$$

The Chain Rule



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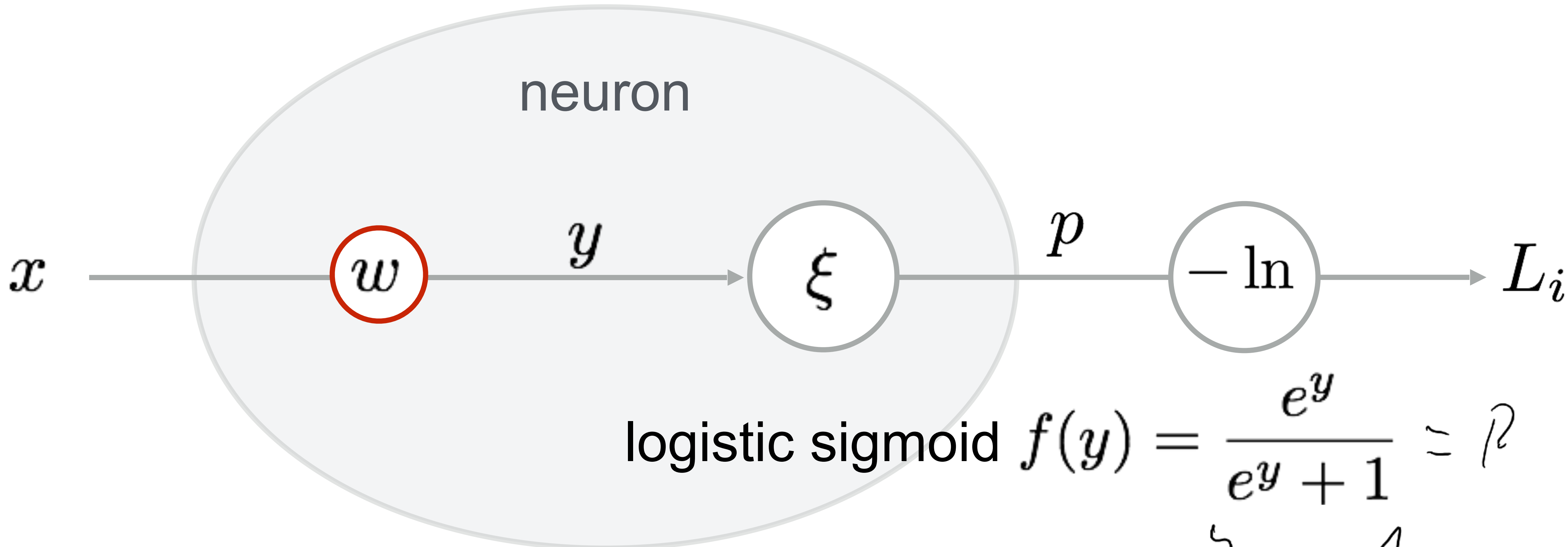
$$\frac{e^y}{e^y+1} \cdot \frac{1}{e^y+1}$$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p} \underbrace{\dfrac{\partial p}{\partial y}} \dfrac{\partial y}{\partial w} = -\dfrac{1}{p} \dfrac{\partial p}{\partial y} \dfrac{\partial y}{\partial w}$

$$e^y(1 + e^y - e^y)$$

$$\frac{\partial p}{\partial y} = \frac{\partial}{\partial y} \frac{e^y}{e^y + 1} = \frac{e^y(1 + e^y) - (e^y)^2}{(e^y + 1)^2} = \frac{e^y}{(e^y + 1)^2} = p(1 - p)$$

The Chain Rule



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$$\frac{e^y}{e^y+1} \cdot \frac{1}{e^y+1}$$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p} \underbrace{\dfrac{\partial p}{\partial y}} \dfrac{\partial y}{\partial w} = -\dfrac{1}{p} p(1-p) \dfrac{\partial y}{\partial w}$

$$e^y(1 + e^y - e^y)$$

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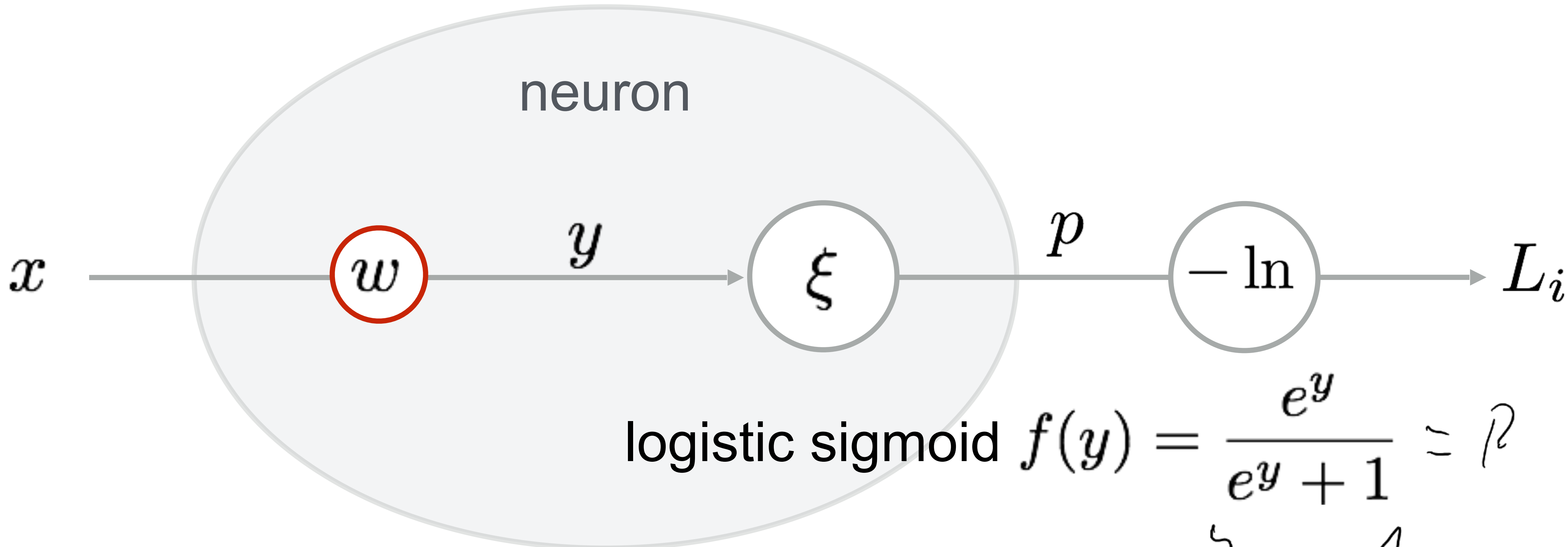
The Chain Rule



logistic sigmoid $f(y) = \dfrac{e^y}{e^y+1}$ $= p$

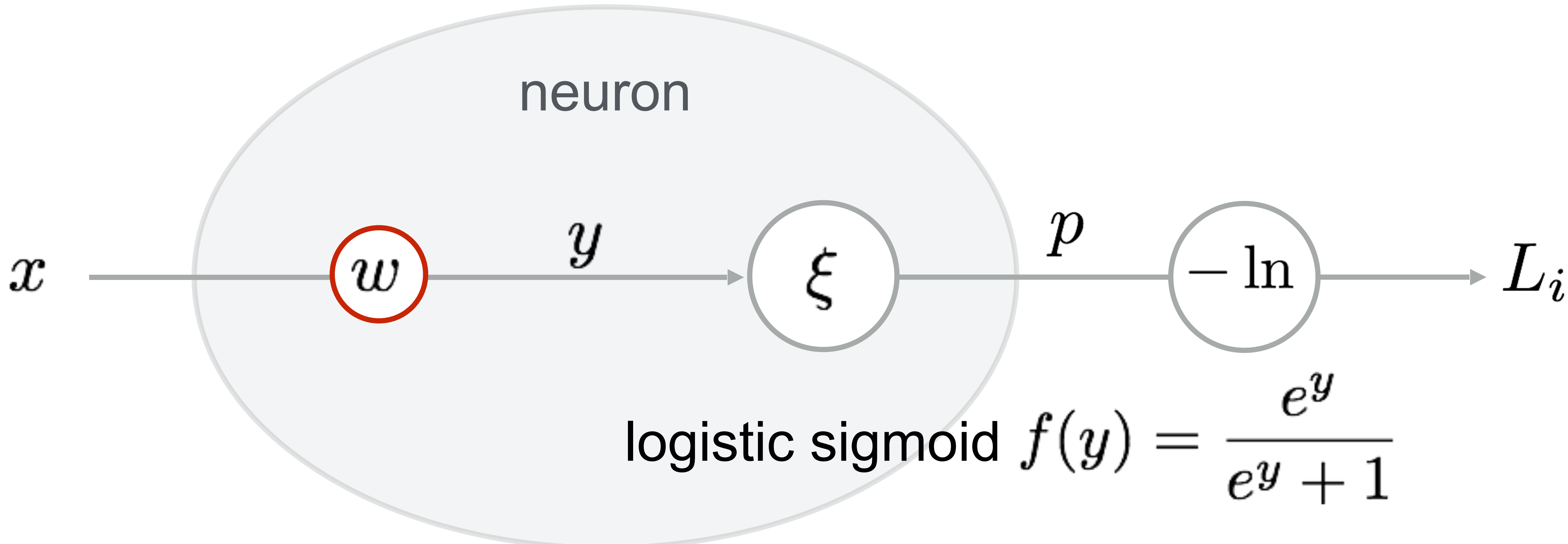
$\frac{e^y}{e^y+1} \cdot \frac{1}{e^y+1}$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p}\underbrace{\dfrac{\partial p}{\partial y}}\dfrac{\partial y}{\partial w} = -\dfrac{1}{p}p(1-p)\dfrac{\partial y}{\partial w} = (p-1)\dfrac{\partial y}{\partial w}$

$e^y(1+e^y-e^y)$

$$\frac{\partial p}{\partial y} = \frac{\partial}{\partial y}\frac{e^y}{e^y+1} = \frac{e^y(1+e^y)-(e^y)^2}{(e^y+1)^2} = \frac{e^y}{(e^y+1)^2} = p(1-p)$$

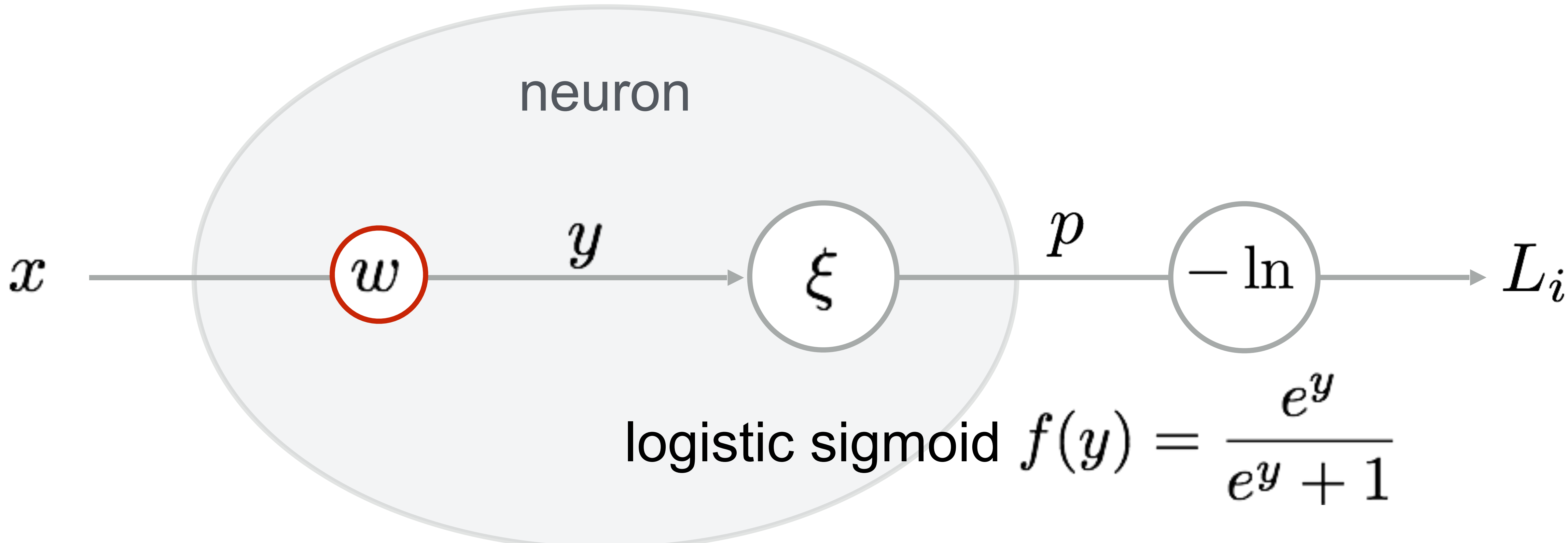
The Chain Rule



logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p}\dfrac{\partial p}{\partial y}\dfrac{\partial y}{\partial w} = (p-1)\dfrac{\partial y}{\partial w}$

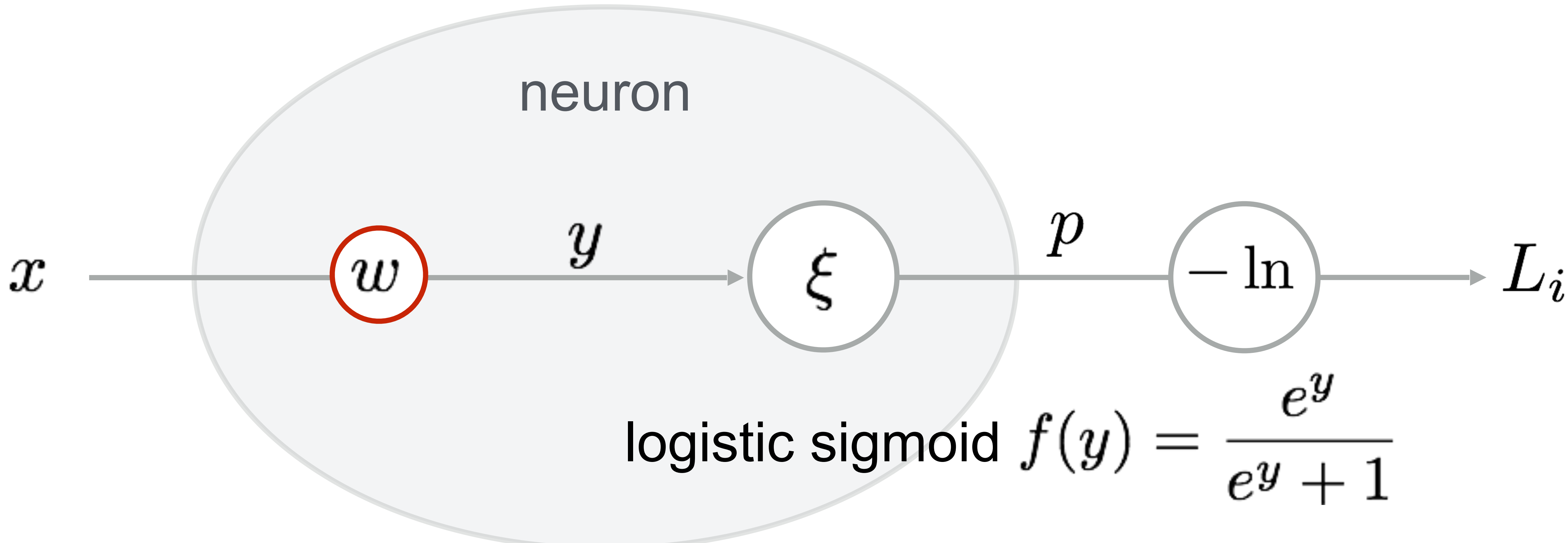
The Chain Rule



logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p}\dfrac{\partial p}{\partial y}\underbrace{\dfrac{\partial y}{\partial w}} = (p-1)\dfrac{\partial y}{\partial w}$

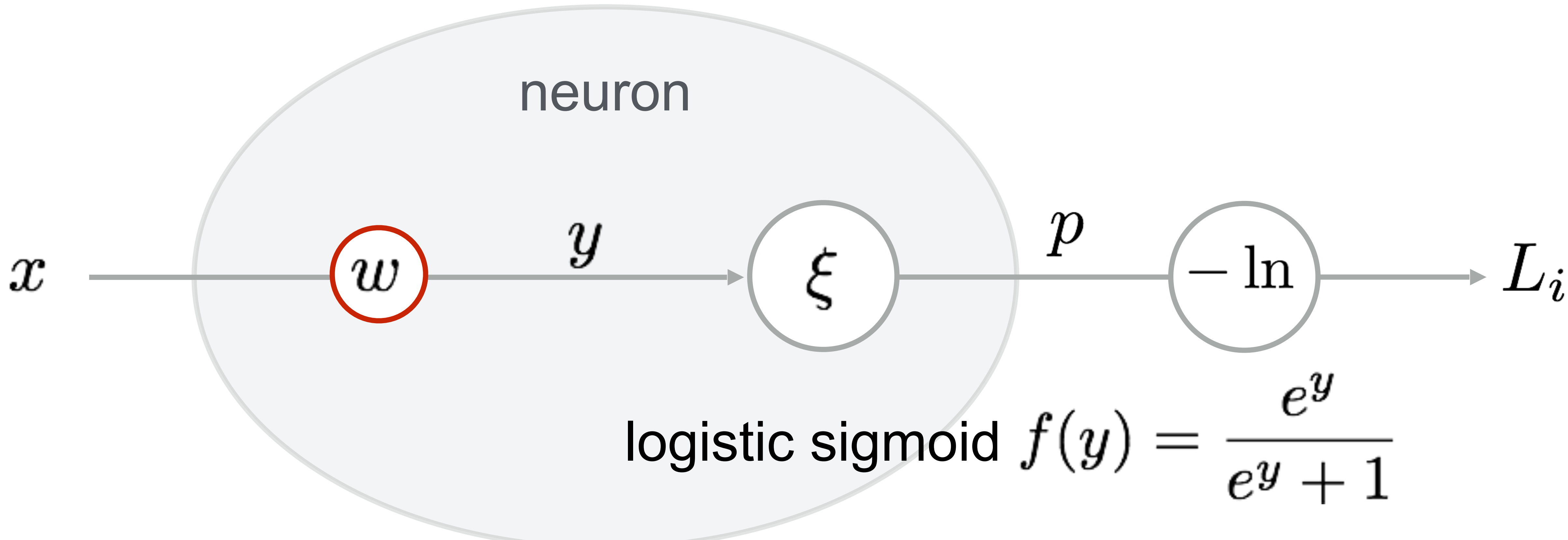
The Chain Rule



logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$

Gradient $$\frac{\partial L_i}{\partial w} = \frac{\partial L_i}{\partial p}\frac{\partial p}{\partial y}\underbrace{\frac{\partial y}{\partial w}}_{\frac{\partial y}{\partial w} = \frac{\partial}{\partial w} wx} = (p-1)\frac{\partial y}{\partial w}$$

The Chain Rule

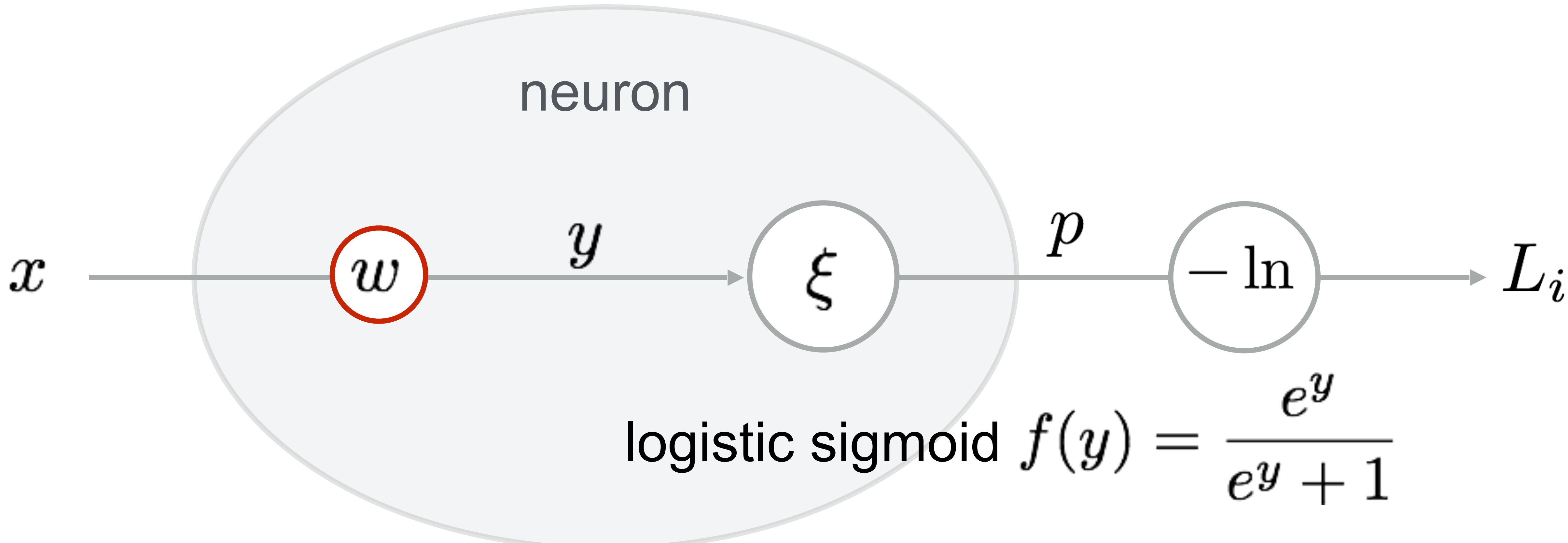


logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$

Gradient $$\frac{\partial L_i}{\partial w} = \frac{\partial L_i}{\partial p}\frac{\partial p}{\partial y}\underbrace{\frac{\partial y}{\partial w}} = (p-1)\frac{\partial y}{\partial w}$$

$$\frac{\partial y}{\partial w} = \frac{\partial}{\partial w} wx = x$$

The Chain Rule

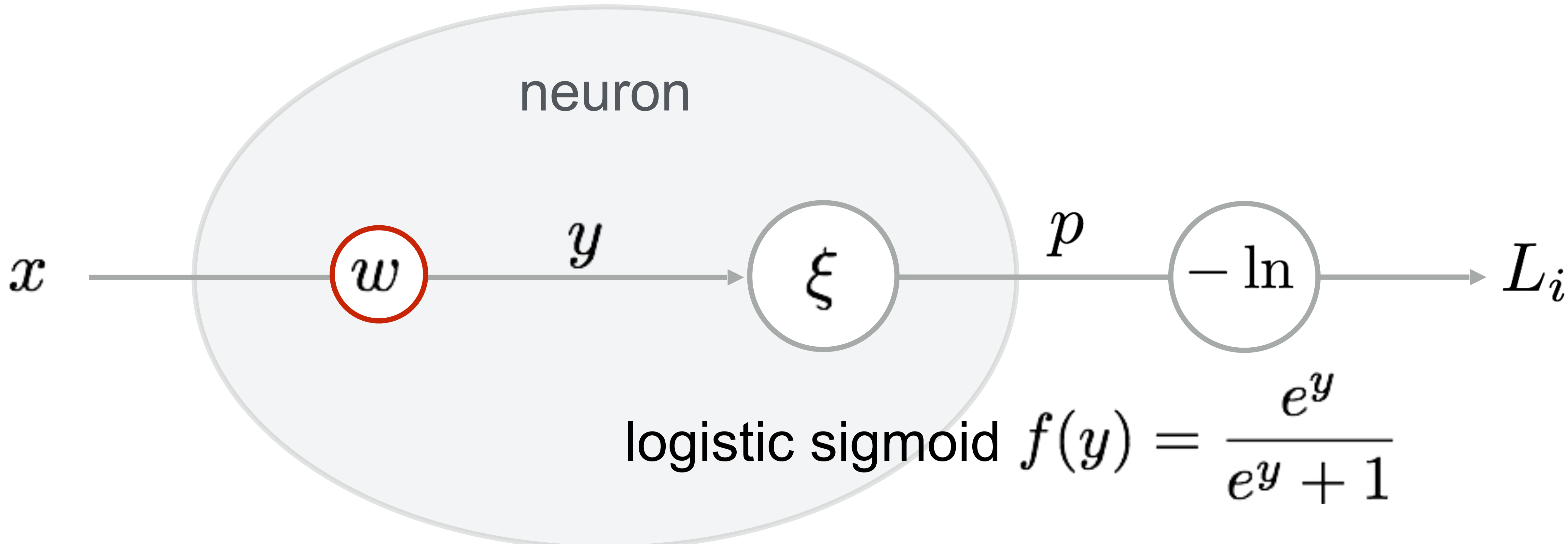


logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$

Gradient $\dfrac{\partial L_i}{\partial w} = \dfrac{\partial L_i}{\partial p}\dfrac{\partial p}{\partial y}\dfrac{\partial y}{\partial w} = (p-1)\dfrac{\partial y}{\partial w} = (p-1)x$

$$\frac{\partial y}{\partial w} = \frac{\partial}{\partial w} wx = x$$

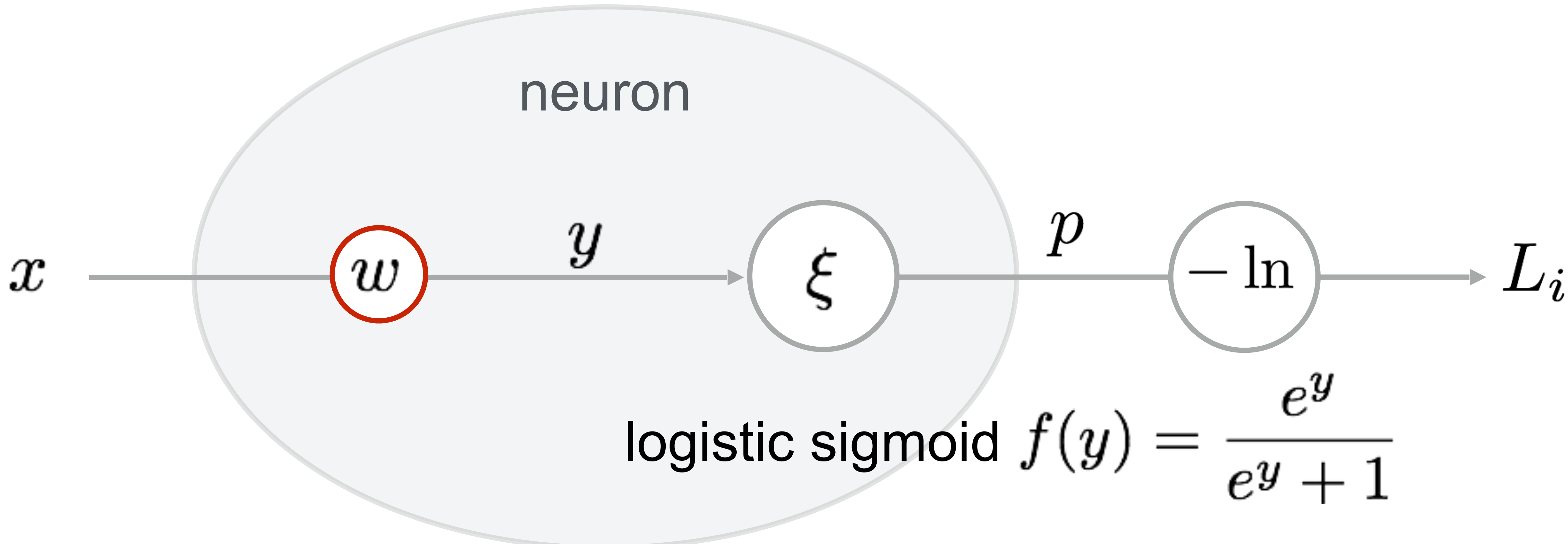
The Chain Rule



logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$

Gradient for positive example: $\dfrac{\partial L_i}{\partial w} = (p-1)x$

The Chain Rule



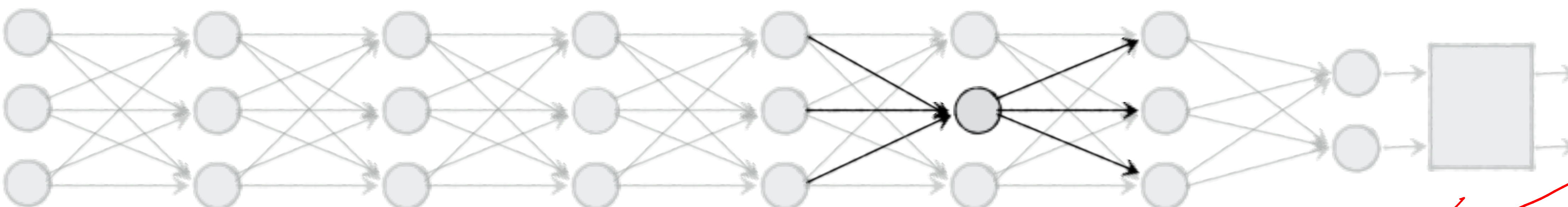
logistic sigmoid $f(y) = \dfrac{e^y}{e^y + 1}$

Gradient for positive example: $\dfrac{\partial L_i}{\partial w} = (p-1)x$

Gradient for negative example: $\dfrac{\partial L_i}{\partial w} = px$

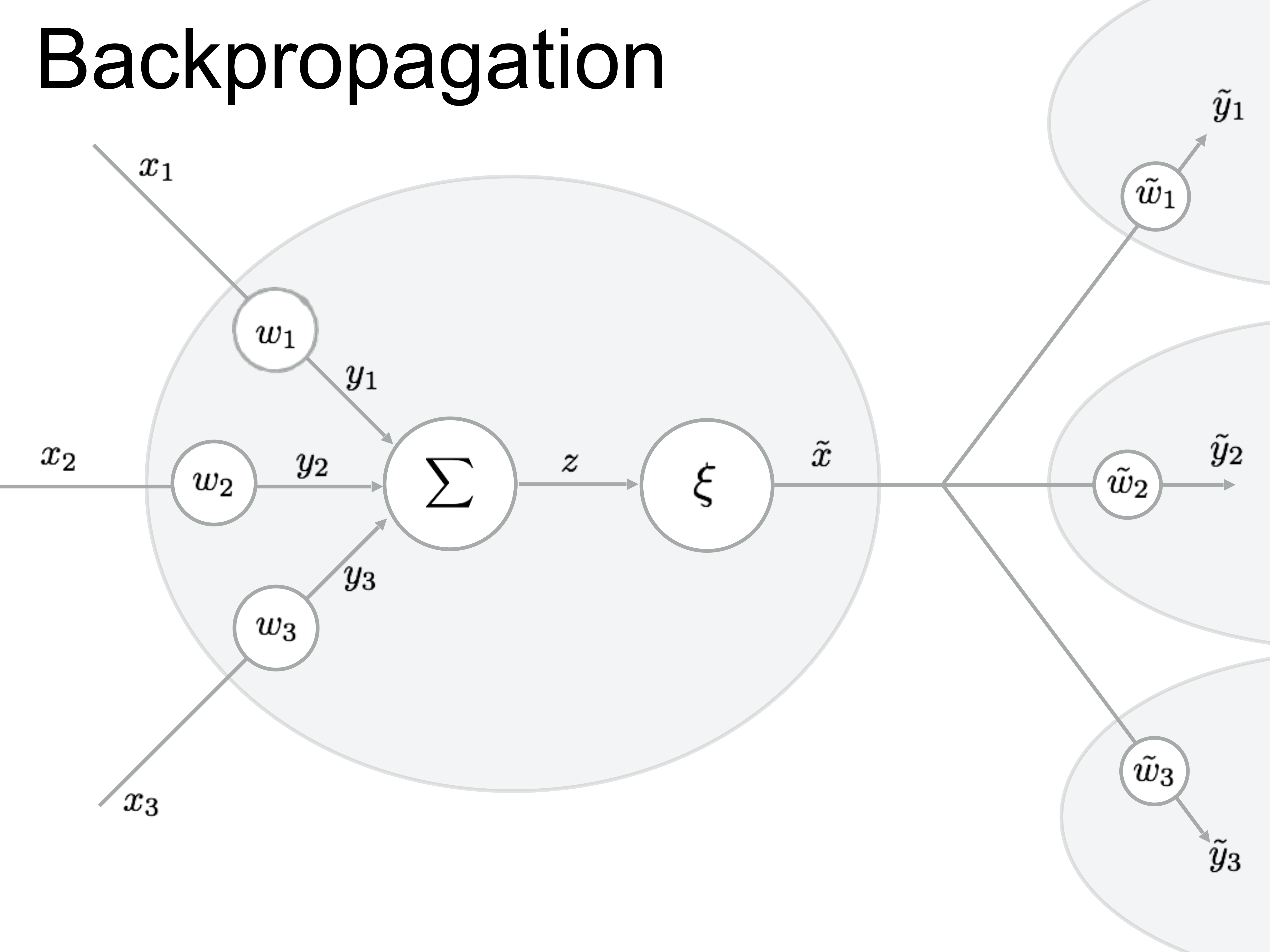
Network Structure

Image I_i



loss L_i

Backpropagation



Stochastic Gradient Descent

$$\theta^{(k+1)} = \theta^{(k)} - \mu \sum_i \nabla L_i(\theta) \approx \theta^{(k)} - \mu \nabla L_i(\theta)$$

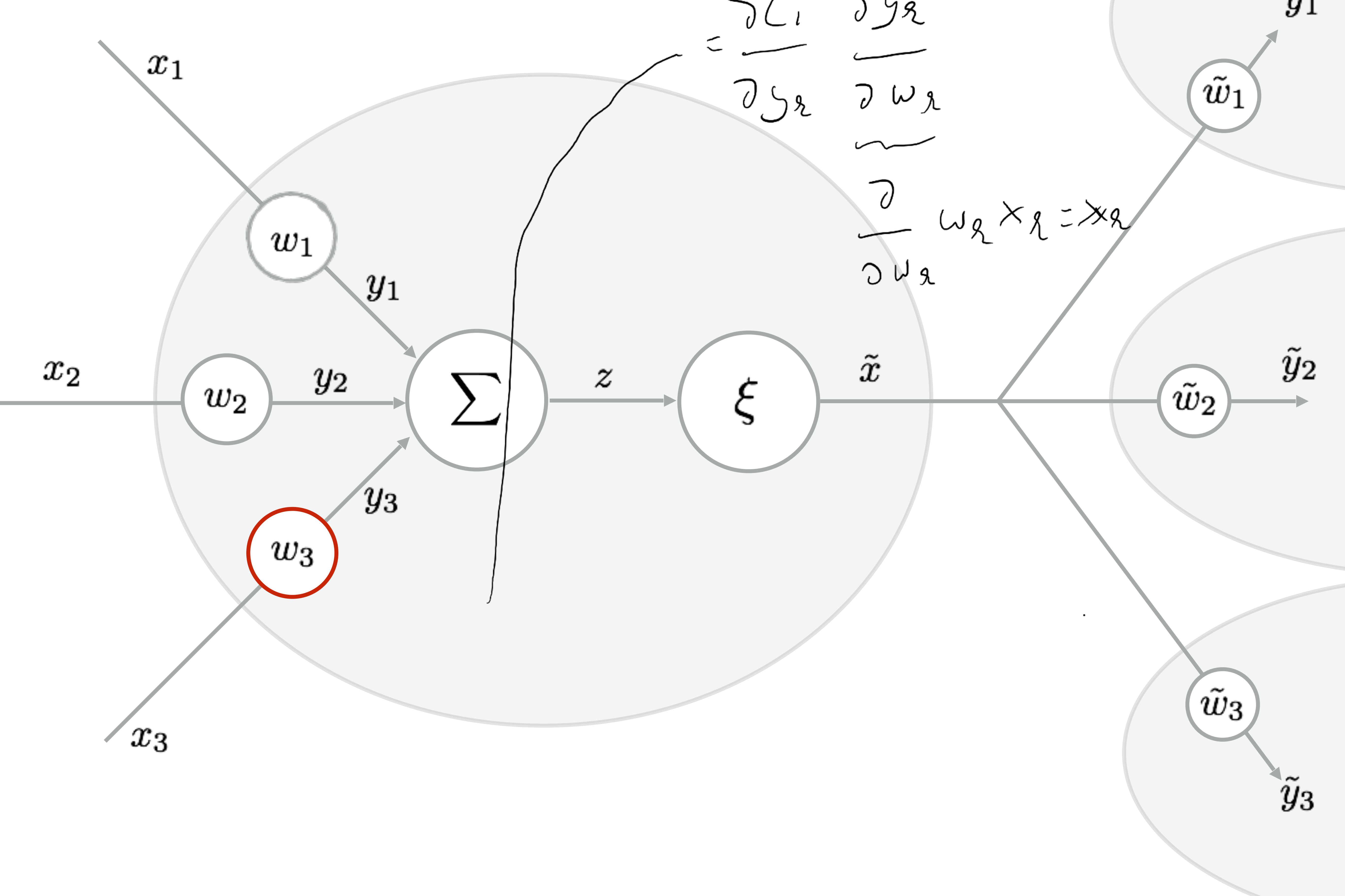
parameters

gradient

$w_k \rightarrow \begin{pmatrix} \vdots \\ \cdot \\ \vdots \end{pmatrix}$

$\frac{\partial L_i}{\partial w_k} \rightarrow \begin{pmatrix} \vdots \\ \cdot \\ \vdots \end{pmatrix}$

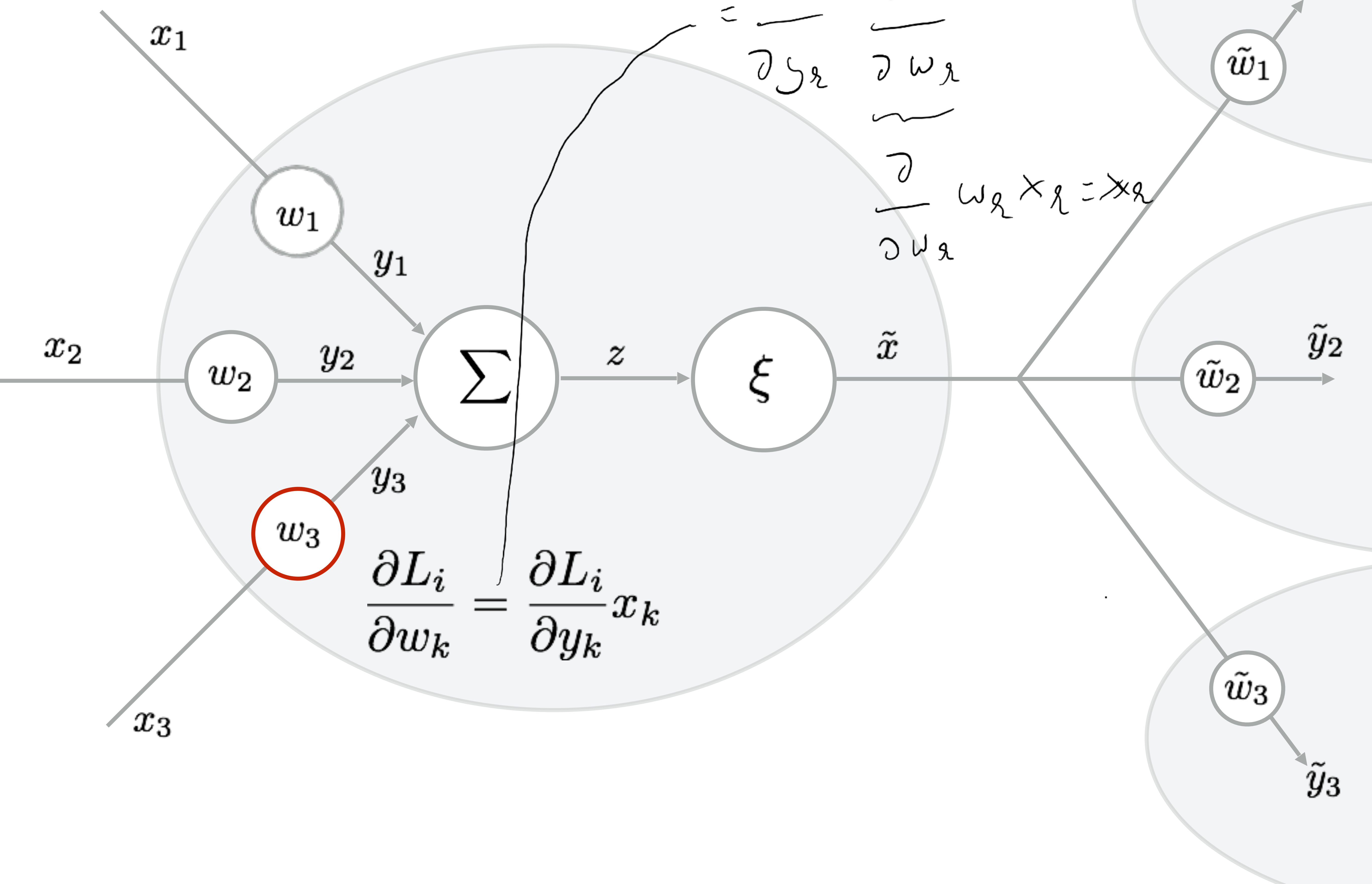
Backpropagation



$$= \frac{\partial L_i}{\partial y_k} \underbrace{\frac{\partial y_k}{\partial w_k}}$$

$$\frac{\partial}{\partial w_k} w_k x_k = x_k$$

Backpropagation

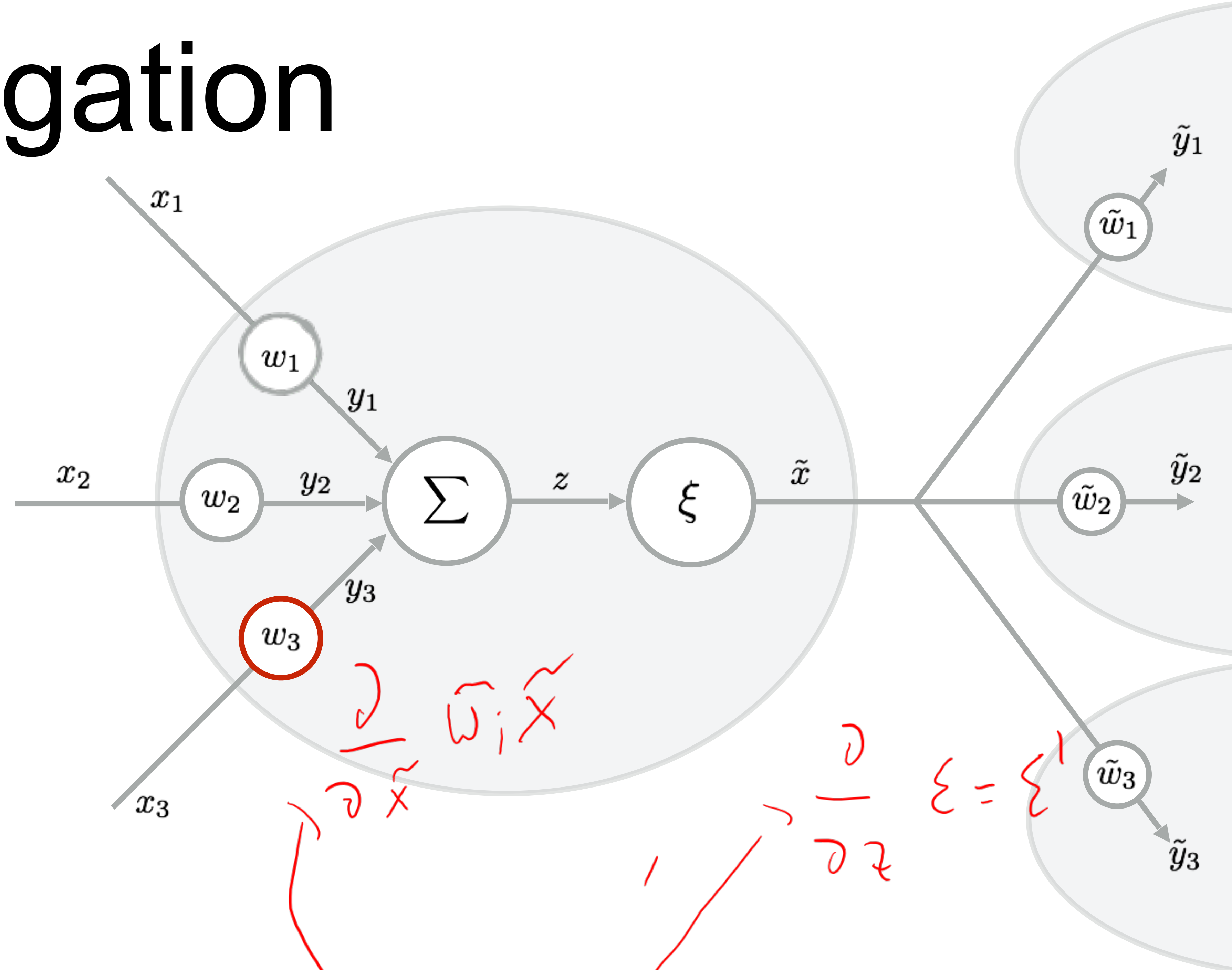


$$\frac{\partial L_i}{\partial w_k} = \frac{\partial L_i}{\partial y_k} x_k$$

$$= \frac{\partial L_i}{\partial y_k} \frac{\partial y_k}{\partial w_k}$$

$$\frac{\partial}{\partial w_k} w_k x_k = x_k$$

Backpropagation



$$\frac{\partial}{\partial \tilde{x}} \tilde{w}_i \tilde{x}$$

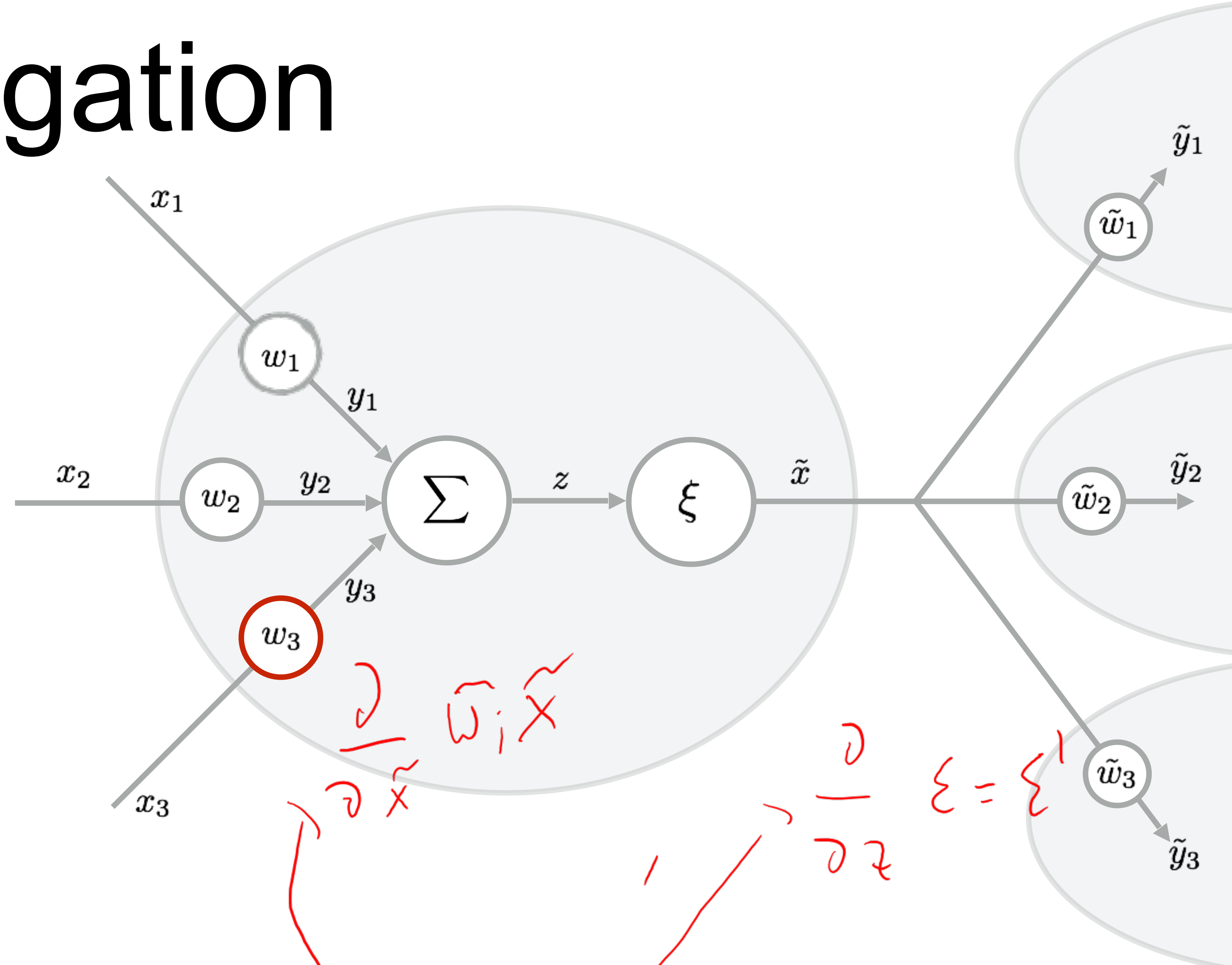
$$\frac{\partial}{\partial z} \xi = \xi'$$

$$\frac{\partial L_i}{\partial w_k} = \frac{\partial L_i}{\partial y_k} x_k$$

$$\frac{\partial}{\partial y_k} \left(\sum_i y_i \right) = 1$$

$\cdot 1$

Backpropagation



$$\frac{\partial L_i}{\partial w_k} = \underbrace{\frac{\partial L_i}{\partial y_k}} x_k$$

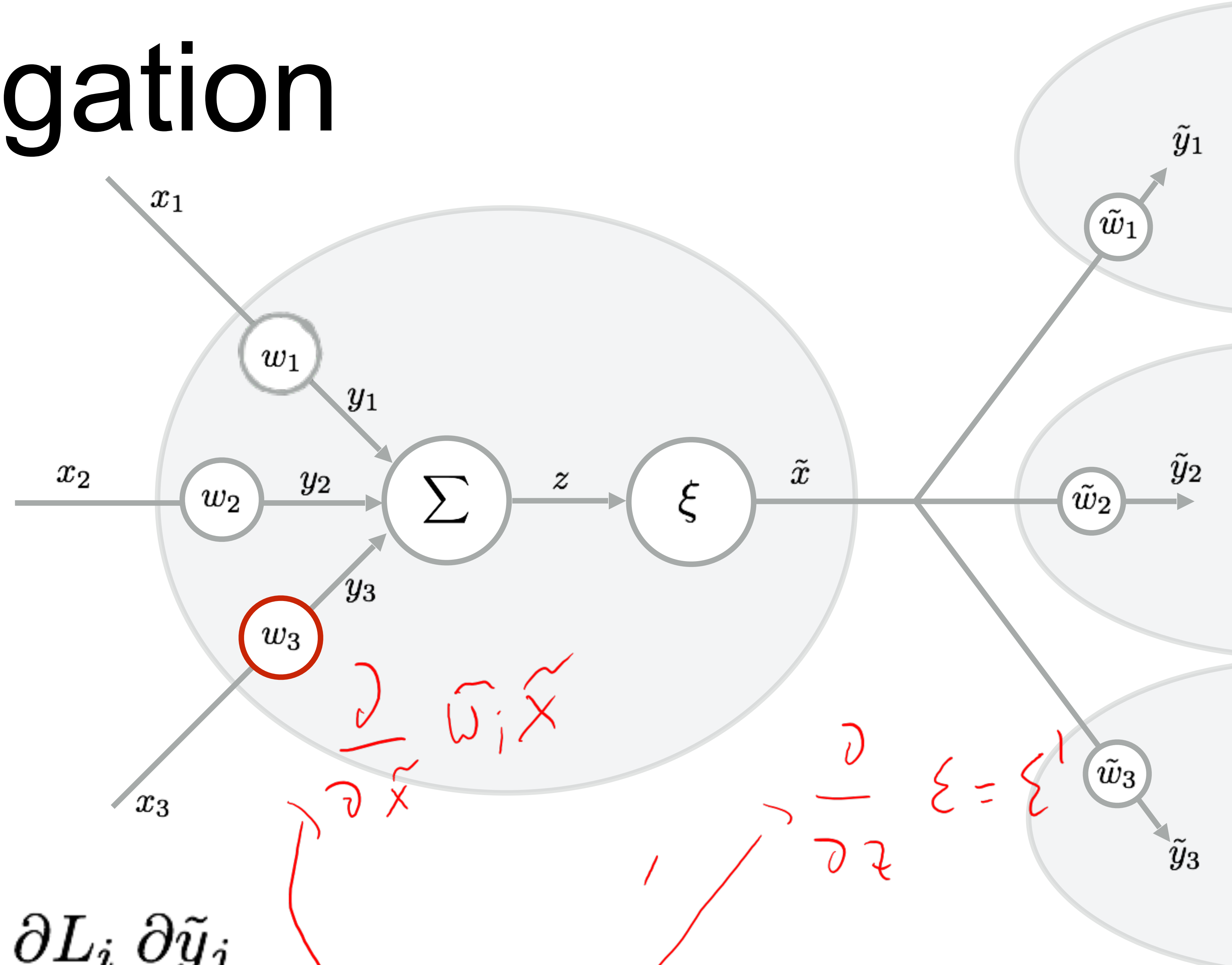
$\frac{\partial}{\partial \tilde{x}} \tilde{w}_i \tilde{x}$

$\frac{\partial}{\partial z} \xi = \xi'$

$\frac{\partial}{\partial y_k} \left(\sum_i y_i \right) = 1$

1

Backpropagation



$$\frac{\partial L_i}{\partial w_k} = \underbrace{\frac{\partial L_i}{\partial y_k}} x_k$$

$$\frac{\partial L_i}{\partial y_k} = \sum_j \frac{\partial L_i}{\partial \tilde{y}_j} \frac{\partial \tilde{y}_j}{\partial y_k}$$

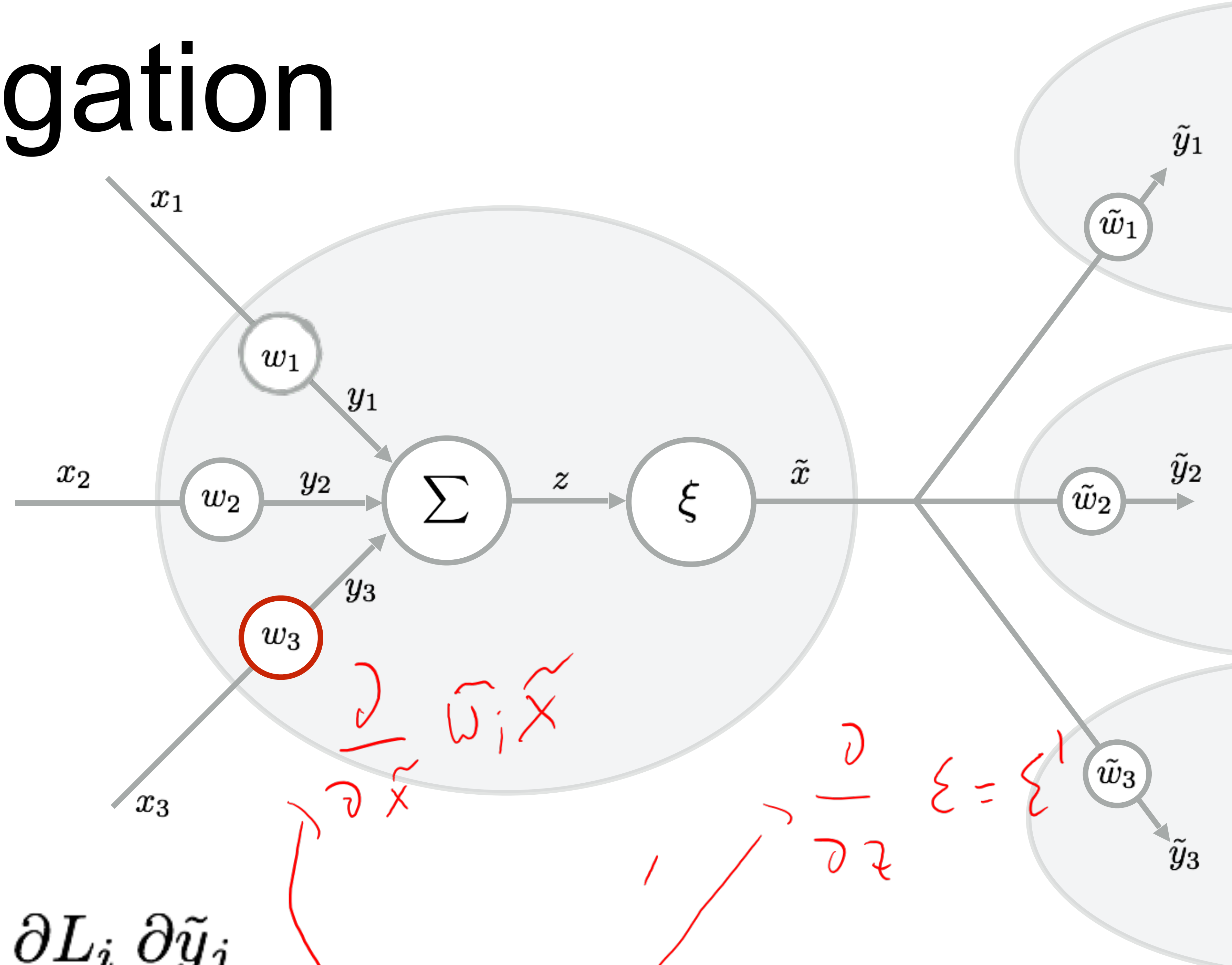
$\frac{\partial}{\partial \tilde{x}} \tilde{w}_i \tilde{x}$

$\frac{\partial}{\partial z} \xi = \xi'$

$\frac{\partial}{\partial y_k} \left(\sum_i y_i \right) = 1$

$\cdot 1$

Backpropagation



$\frac{\partial}{\partial \tilde{x}} \tilde{w}_i \tilde{x}$

$\frac{\partial}{\partial z} \xi = \xi'$

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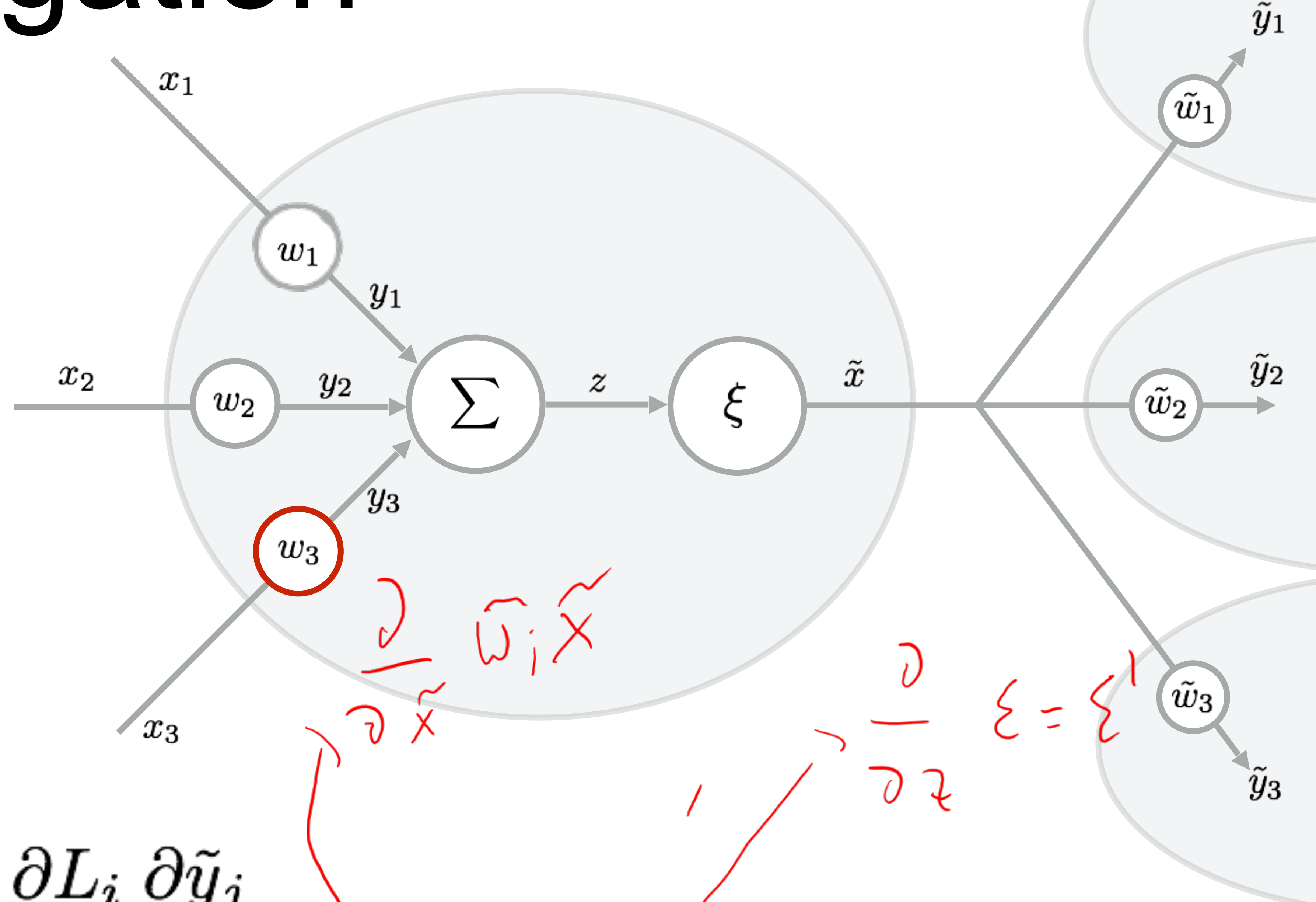
$\frac{\partial}{\partial y_k} \left(\sum_i y_i \right) = 1$

1

Backpropagation



$\frac{\partial}{\partial \tilde{x}} \tilde{w}_i \tilde{x}$

$\frac{\partial}{\partial z} \xi = \xi'$

$$\frac{\partial L_i}{\partial w_k} = \underbrace{\frac{\partial L_i}{\partial y_k}} x_k$$

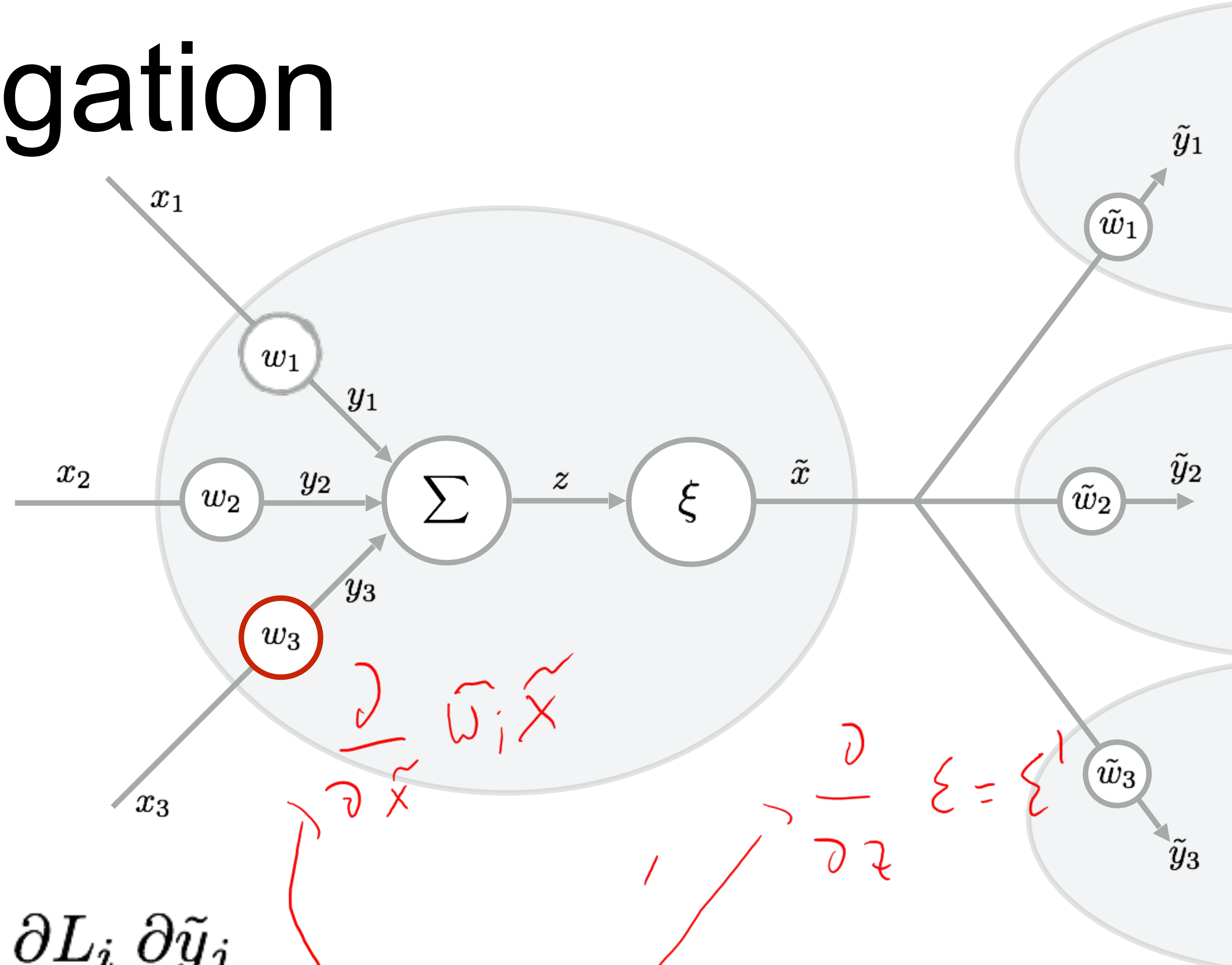
$$\frac{\partial L_i}{\partial y_k} = \sum_j \frac{\partial L_i}{\partial \tilde{y}_j} \underbrace{\frac{\partial \tilde{y}_j}{\partial y_k}}$$

$\frac{\partial}{\partial y_k} \left(\sum y_i \right) = 1$

$$\frac{\partial \tilde{y}_j}{\partial y_k} = \frac{\partial \tilde{y}_j}{\partial \tilde{x}} \frac{\partial \tilde{x}}{\partial z} \frac{\partial z}{\partial y_k}$$

$\cdot 1$

Backpropagation



$\frac{\partial}{\partial \tilde{x}} \tilde{w}_i \tilde{x}$

$\frac{\partial}{\partial z} \xi = \xi'$

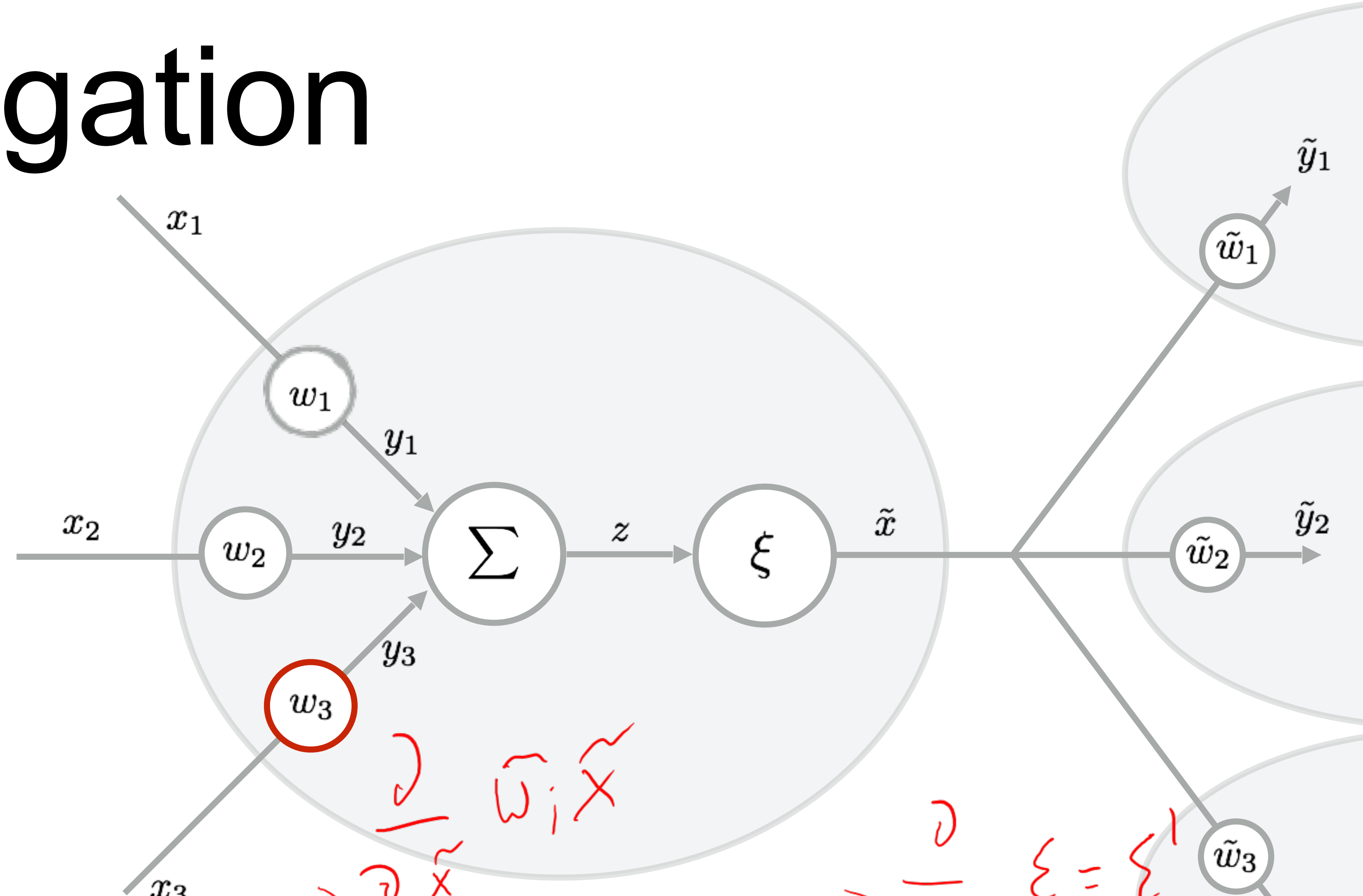
$$\frac{\partial L_i}{\partial w_k} = \underbrace{\frac{\partial L_i}{\partial y_k}} x_k$$

$$\frac{\partial L_i}{\partial y_k} = \sum_j \frac{\partial L_i}{\partial \tilde{y}_j} \underbrace{\frac{\partial \tilde{y}_j}{\partial y_k}}$$

$\frac{\partial}{\partial y_k} \left(\sum_i y_i \right) = 1$

$$\frac{\partial \tilde{y}_j}{\partial y_k} = \frac{\partial \tilde{y}_j}{\partial \tilde{x}} \frac{\partial \tilde{x}}{\partial z} \frac{\partial z}{\partial y_k} = \tilde{w}_j \xi' \cdot 1$$

Backpropagation



$\frac{\partial}{\partial \tilde{x}} \tilde{w}_j \tilde{x}$

$\frac{\partial}{\partial z} \xi = \xi'$

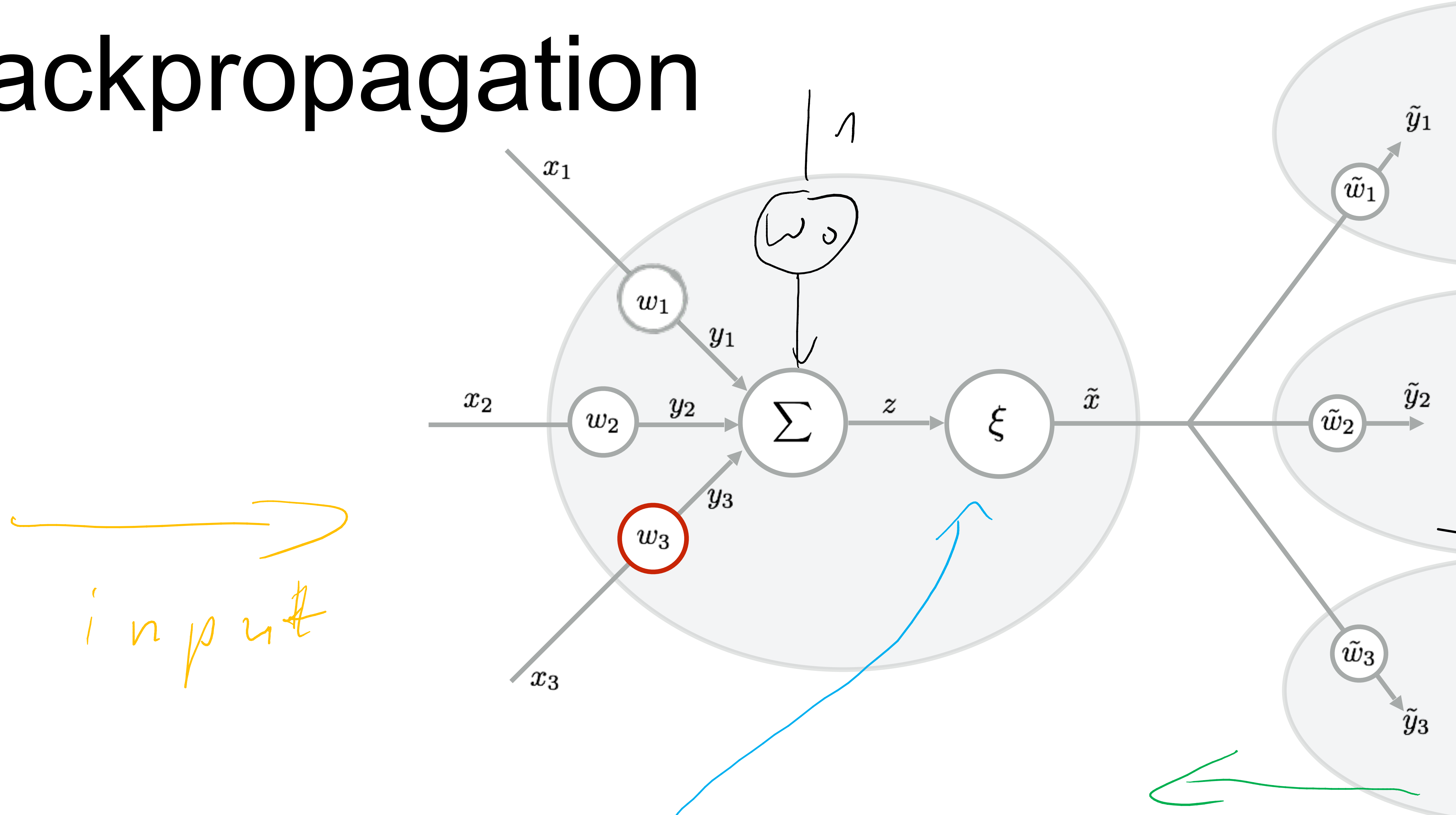
$$\frac{\partial L_i}{\partial w_k} = \underbrace{\frac{\partial L_i}{\partial y_k}} x_k$$

$$\frac{\partial L_i}{\partial y_k} = \sum_j \frac{\partial L_i}{\partial \tilde{y}_j} \underbrace{\frac{\partial \tilde{y}_j}{\partial y_k}} = \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

$\frac{\partial}{\partial y_k} \left(\sum_i y_i \right) = 1$

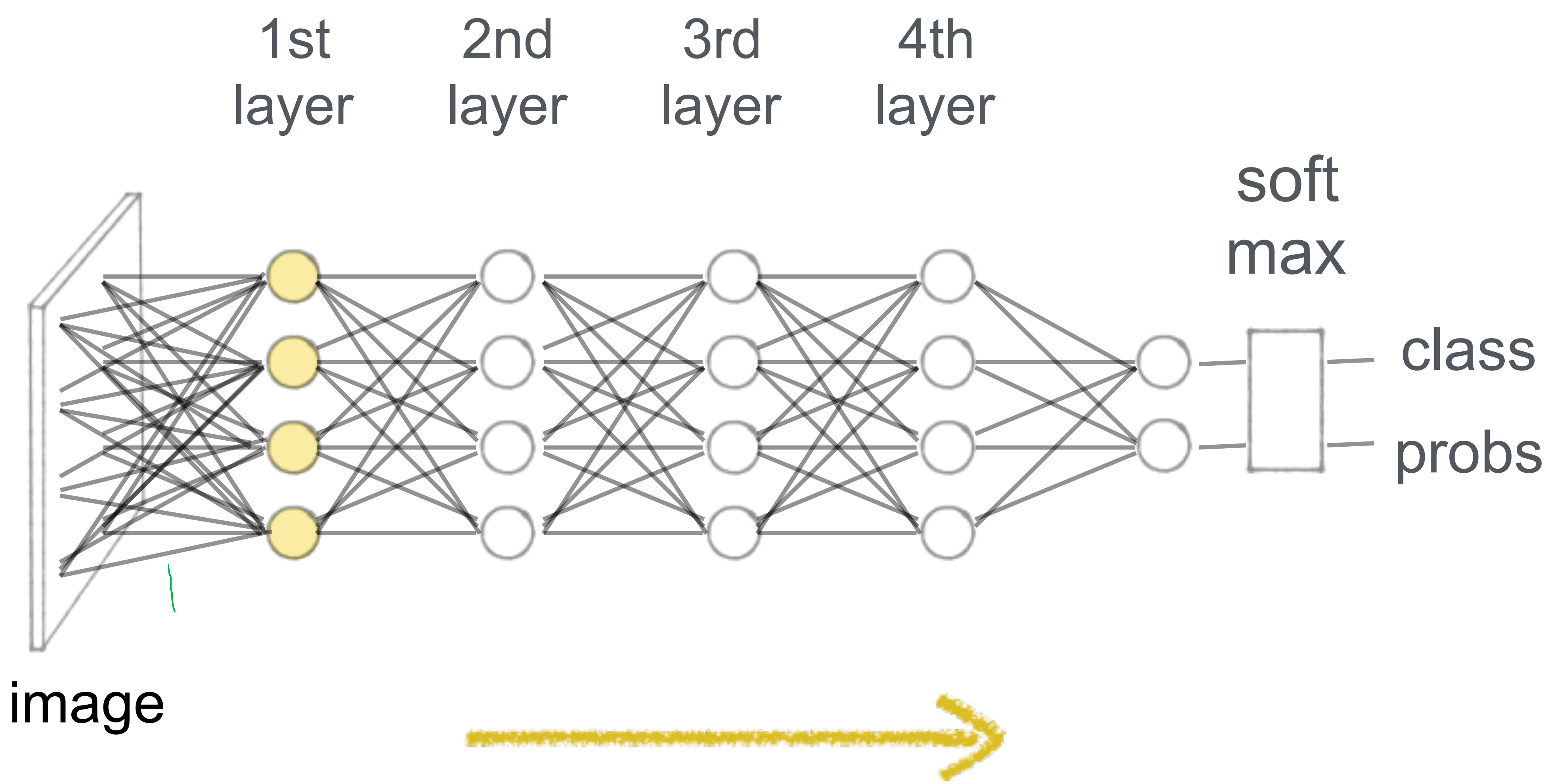
$$\frac{\partial \tilde{y}_j}{\partial y_k} = \frac{\partial \tilde{y}_j}{\partial \tilde{x}} \frac{\partial \tilde{x}}{\partial z} \frac{\partial z}{\partial y_k} = \tilde{w}_j \xi' \cdot 1$$

Backpropagation



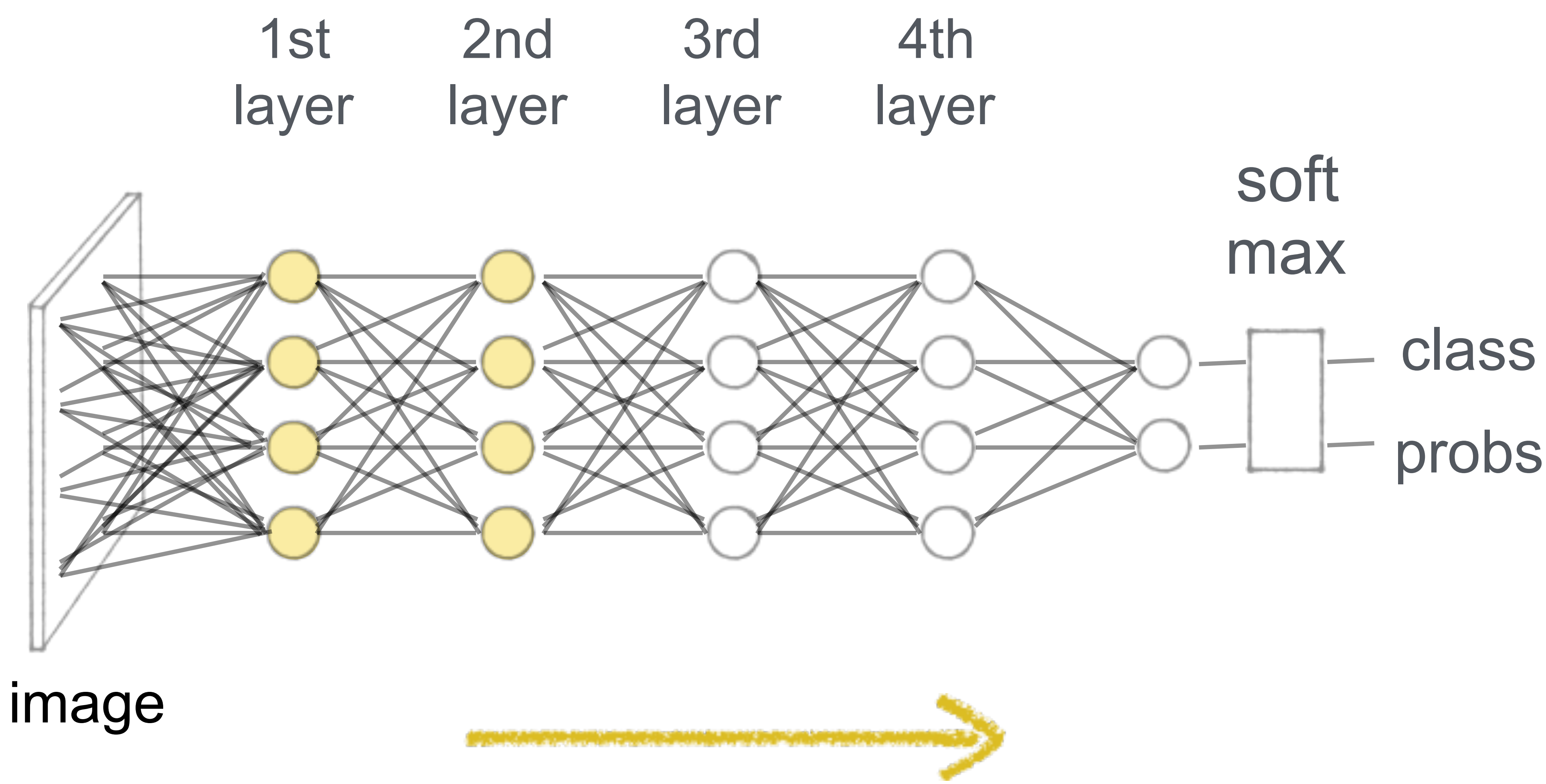
$$\frac{\partial L_i}{\partial w_k} = x_k \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backprop: Forward Pass



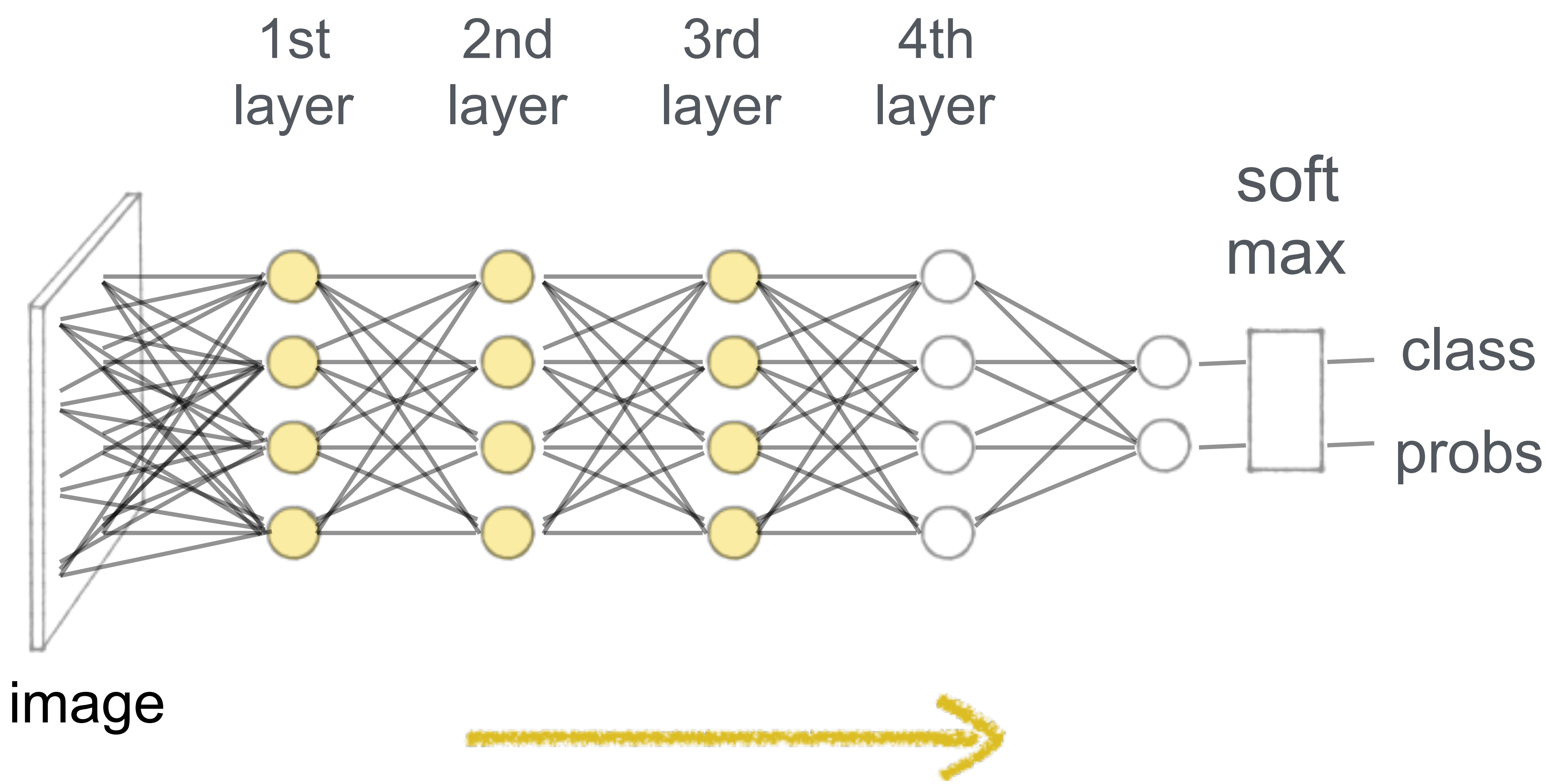
$$\frac{\partial L_i}{\partial w_k} = \underline{x_k}\xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backprop: Forward Pass



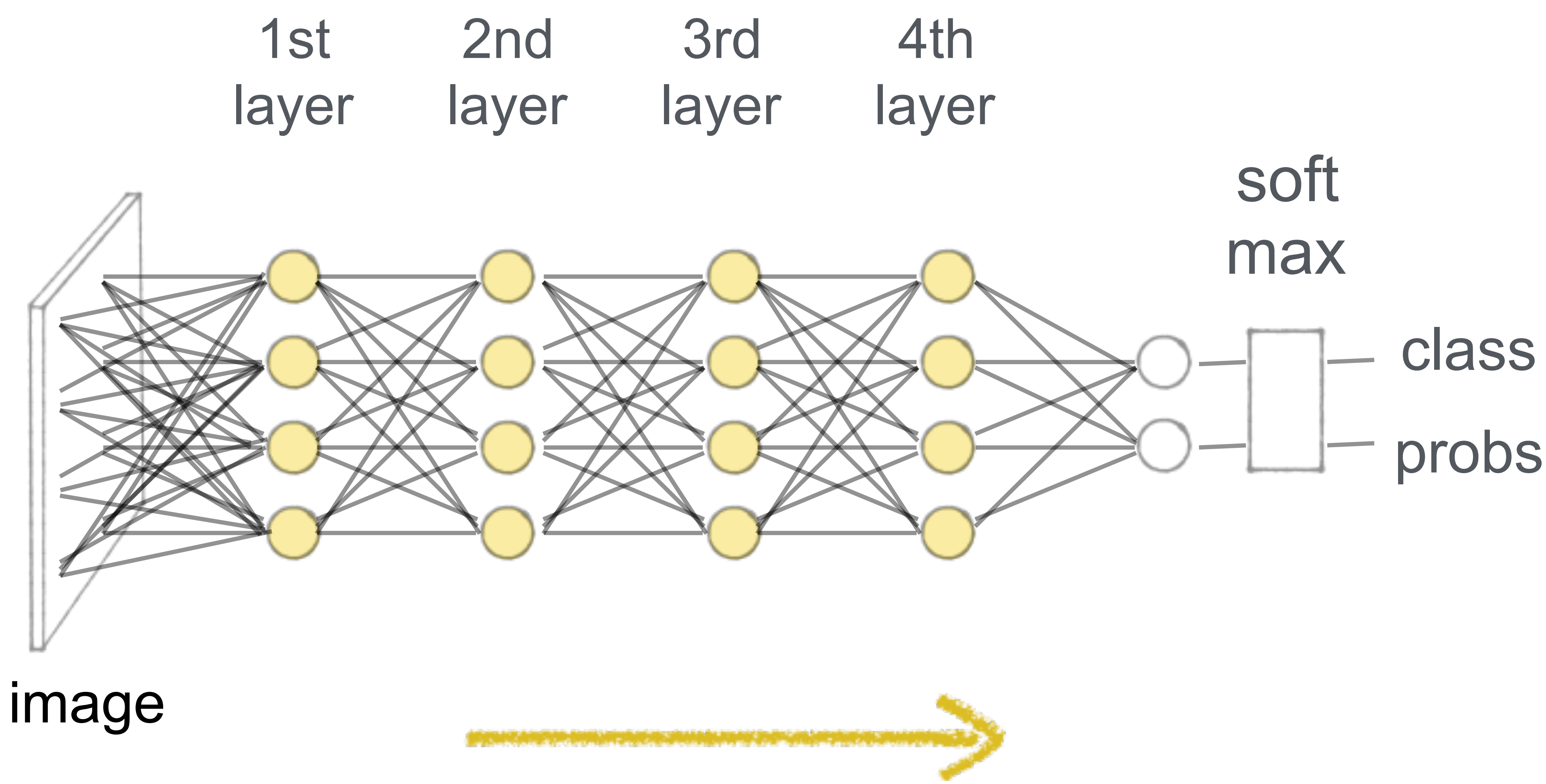
$$\frac{\partial L_i}{\partial w_k} = \underline{x_k} \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backprop: Forward Pass



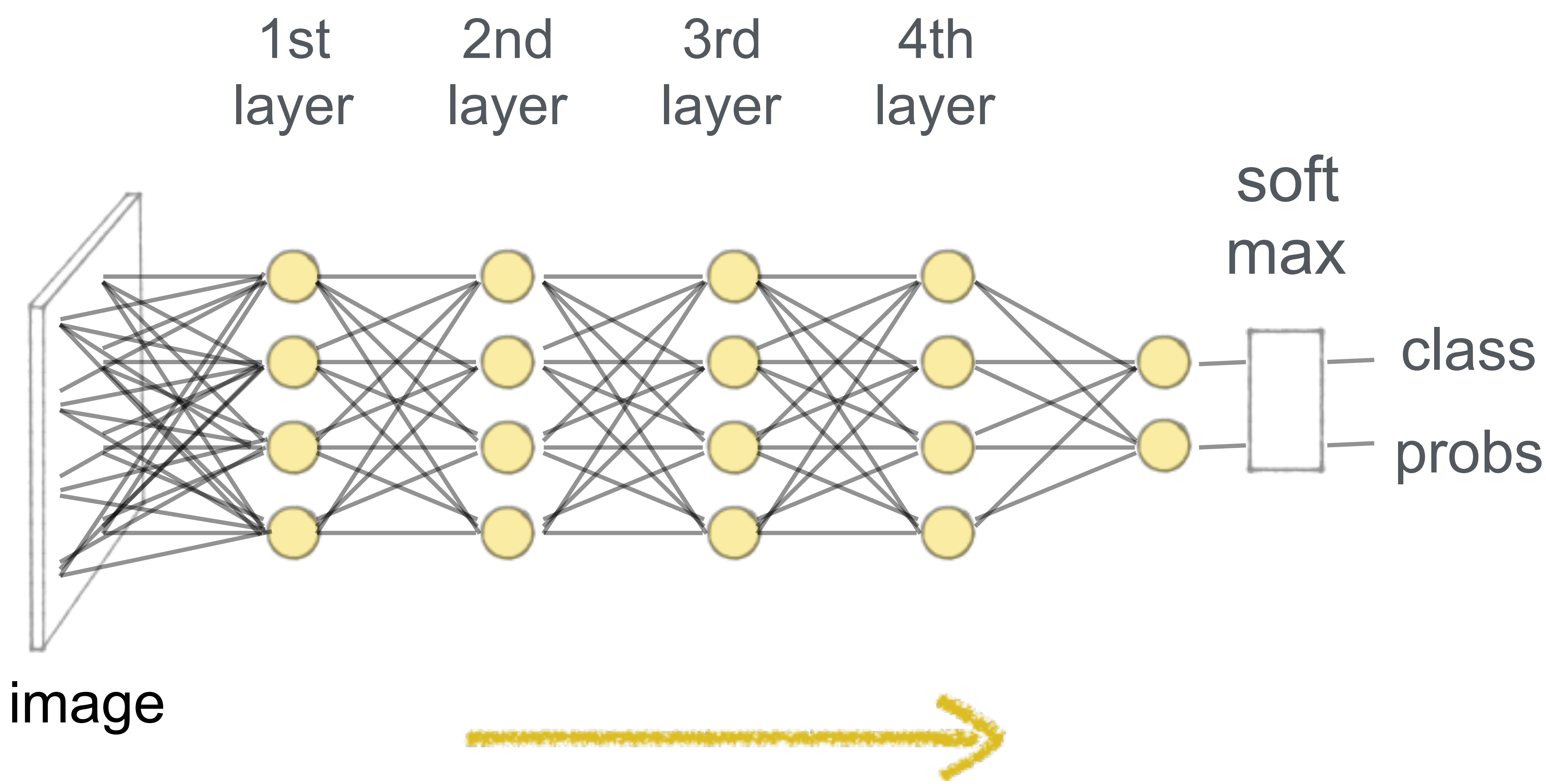
$$\frac{\partial L_i}{\partial w_k} = x_k \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backprop: Forward Pass



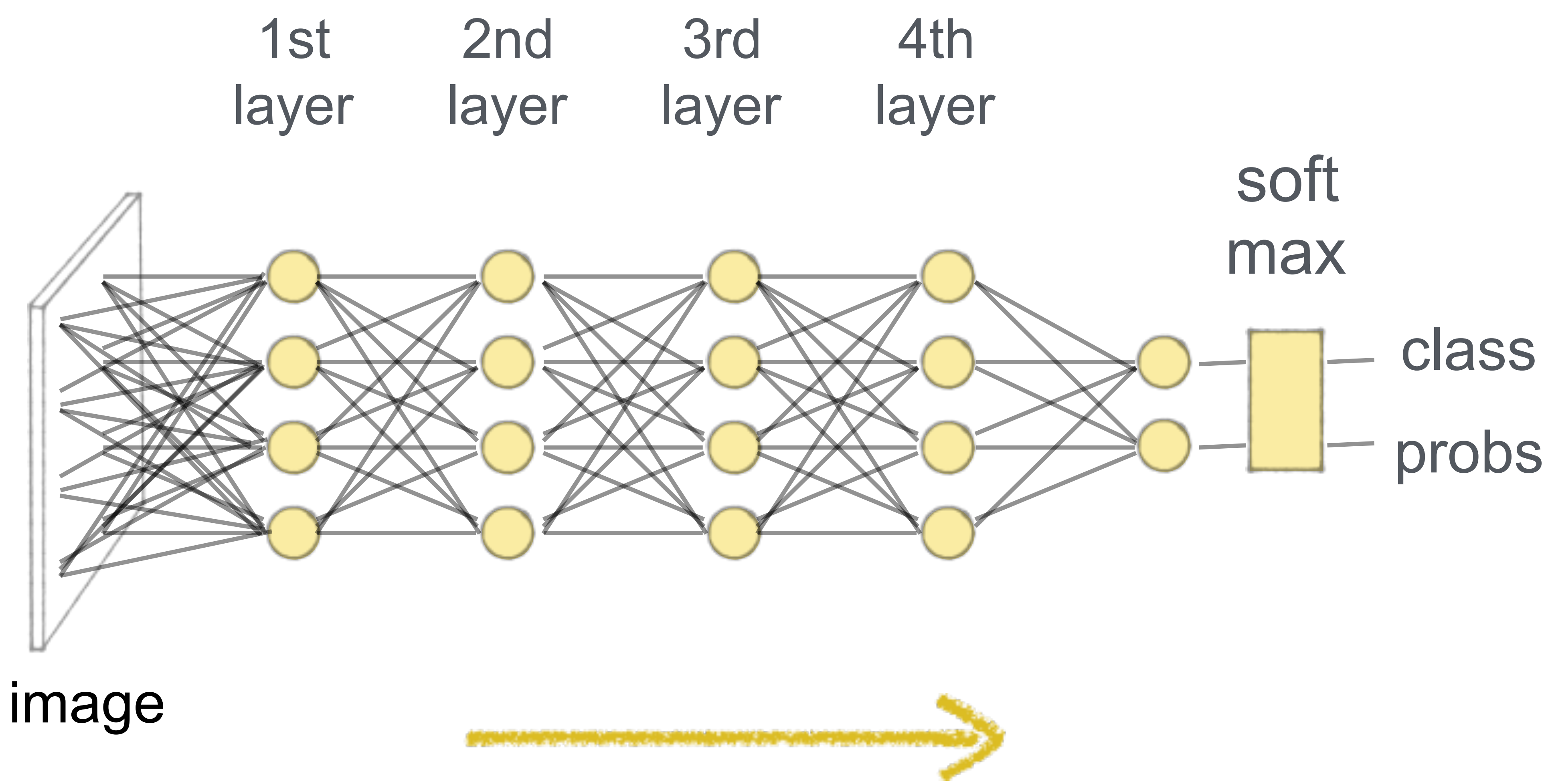
$$\frac{\partial L_i}{\partial w_k} = \underline{x_k \xi'} \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backprop: Forward Pass



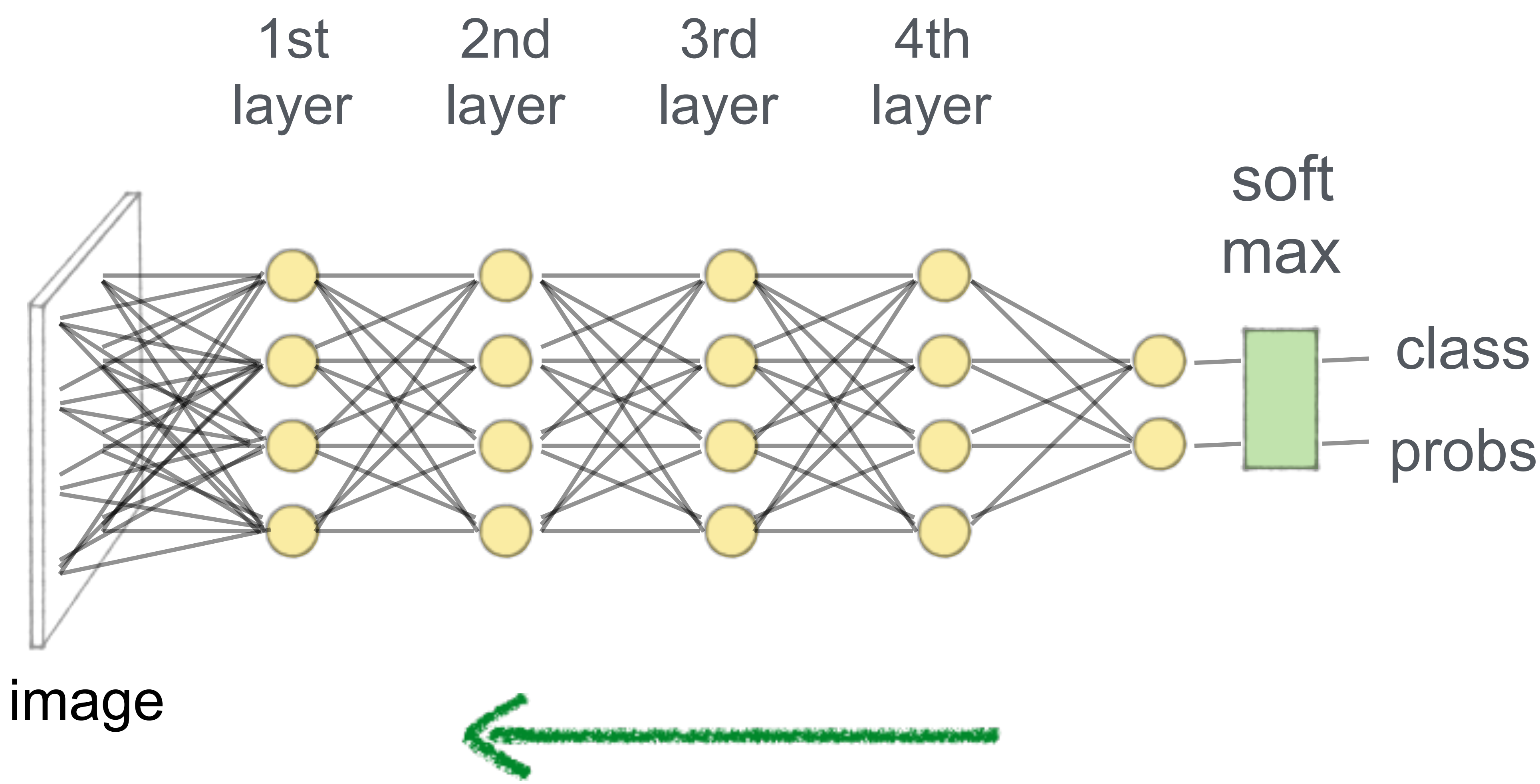
$$\frac{\partial L_i}{\partial w_k} = x_k \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backprop: Forward Pass



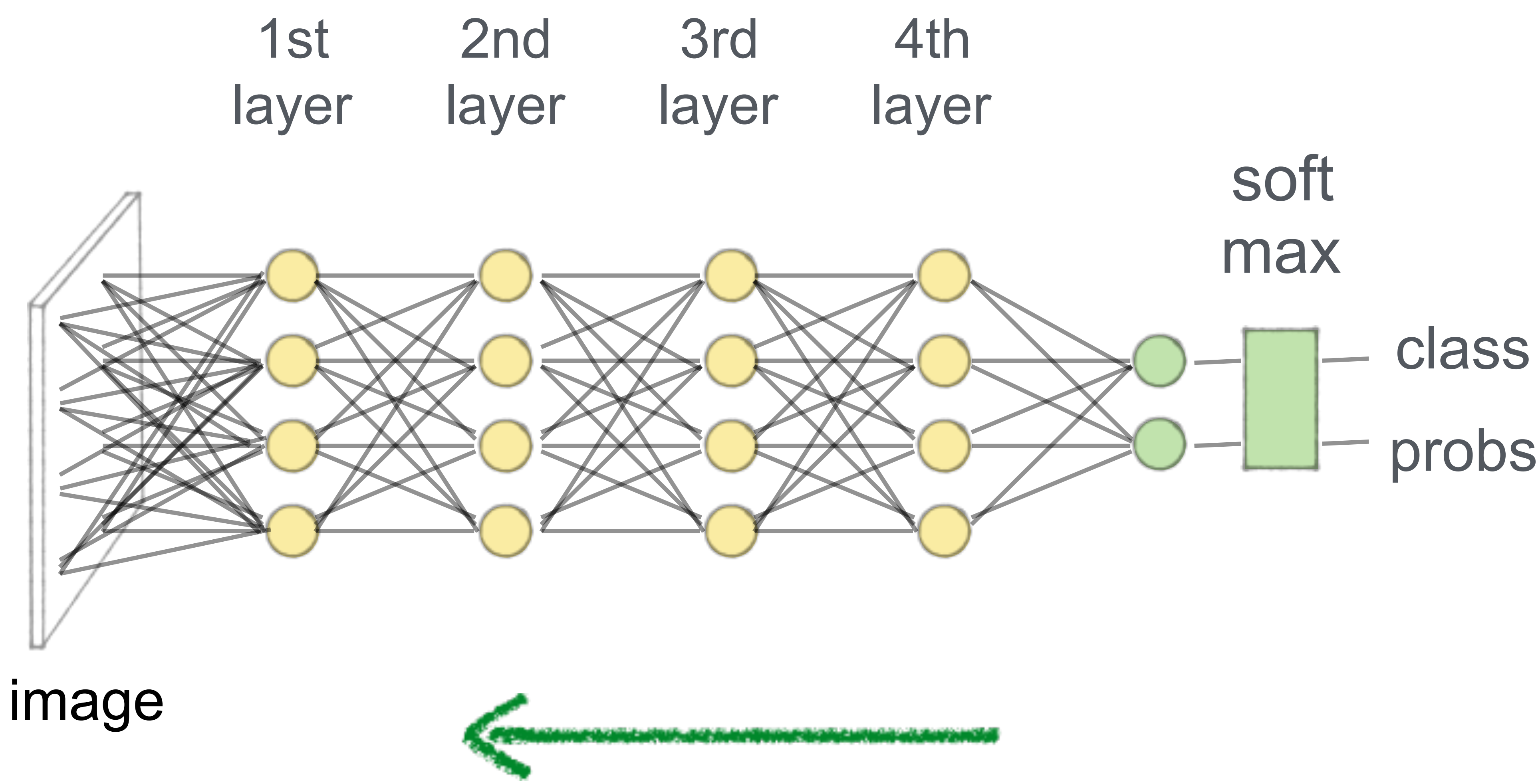
$$\frac{\partial L_i}{\partial w_k} = x_k \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backpropagation



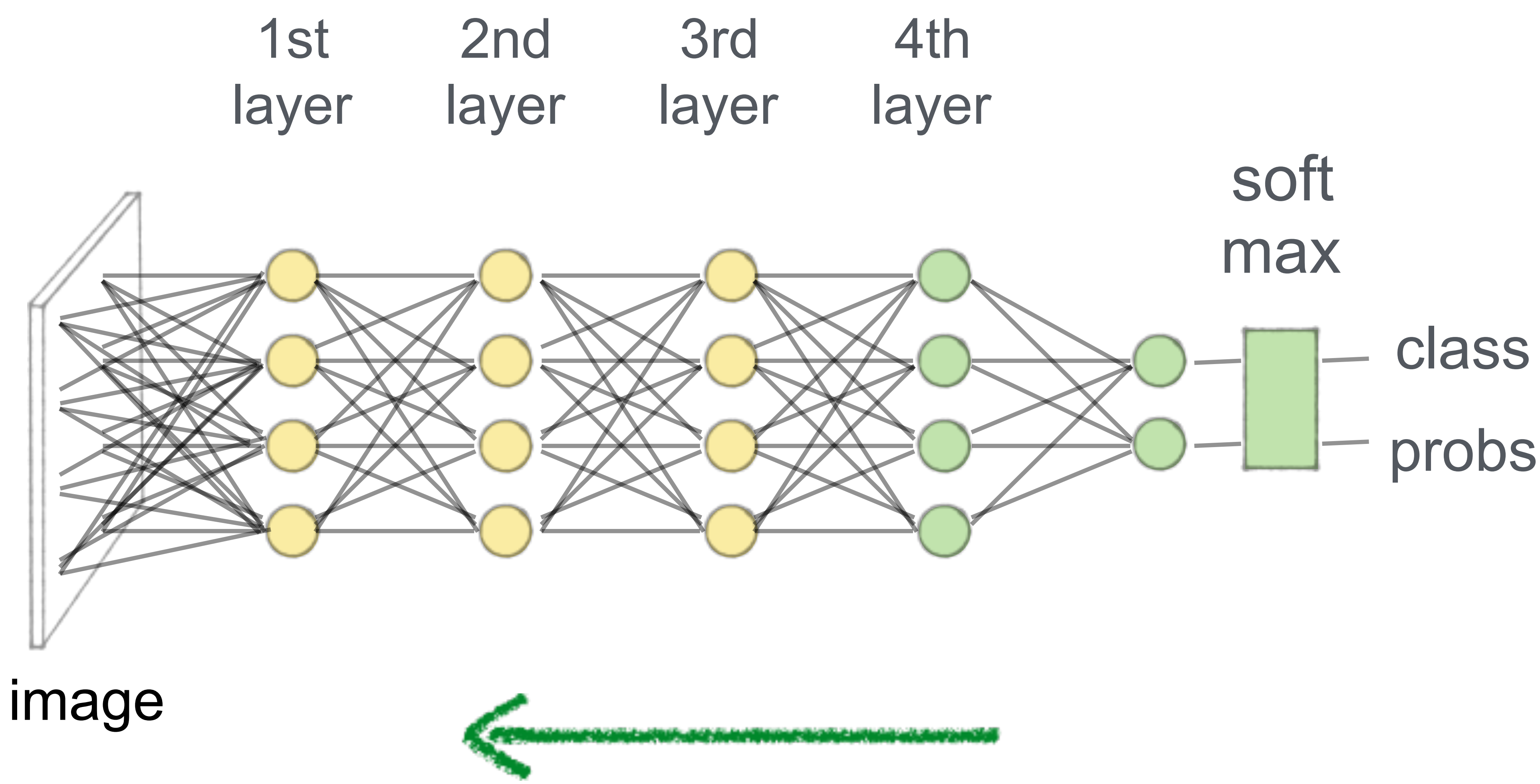
$$\frac{\partial L_i}{\partial w_k} = x_k \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backpropagation



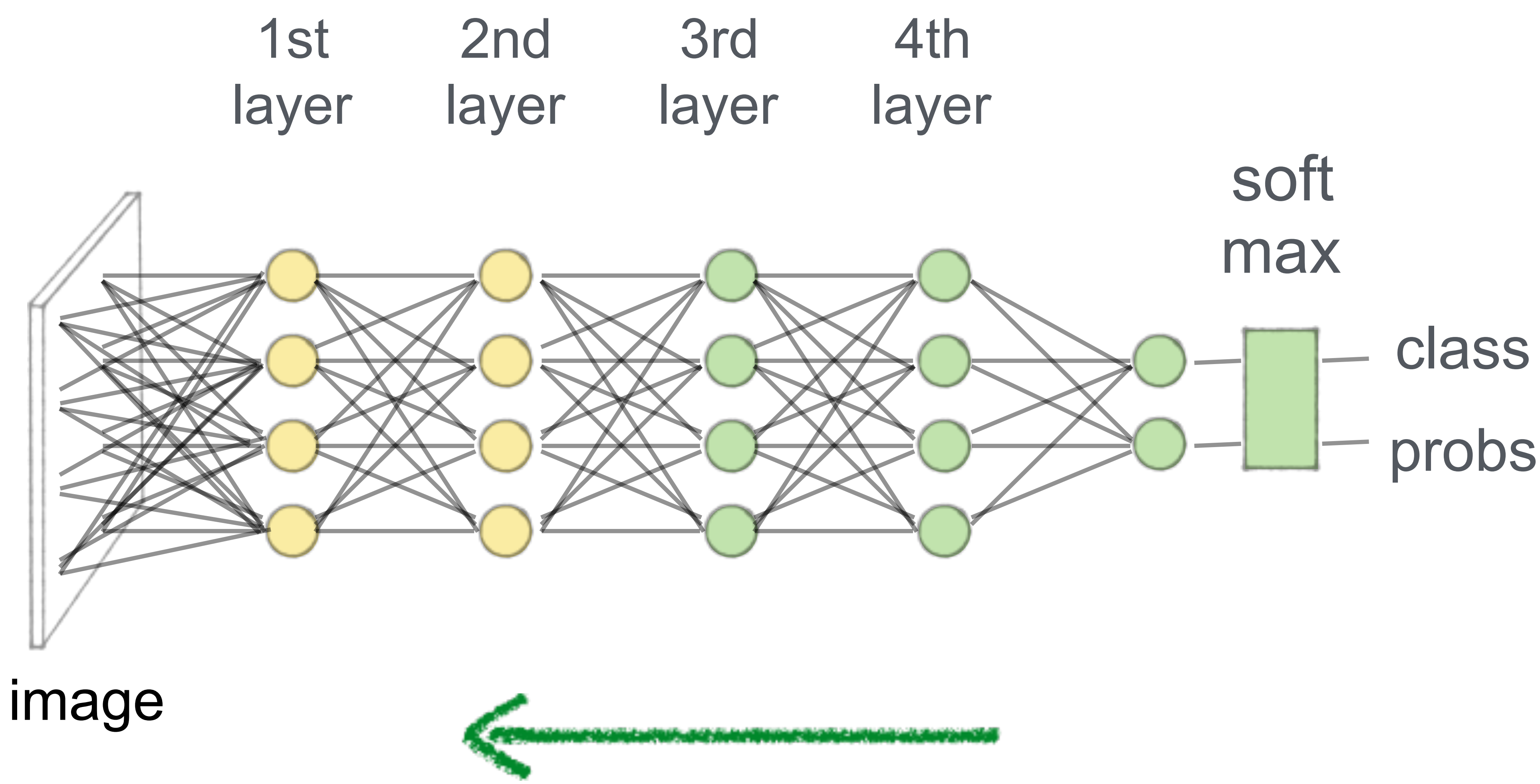
$$\frac{\partial L_i}{\partial w_k} = x_k \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backpropagation



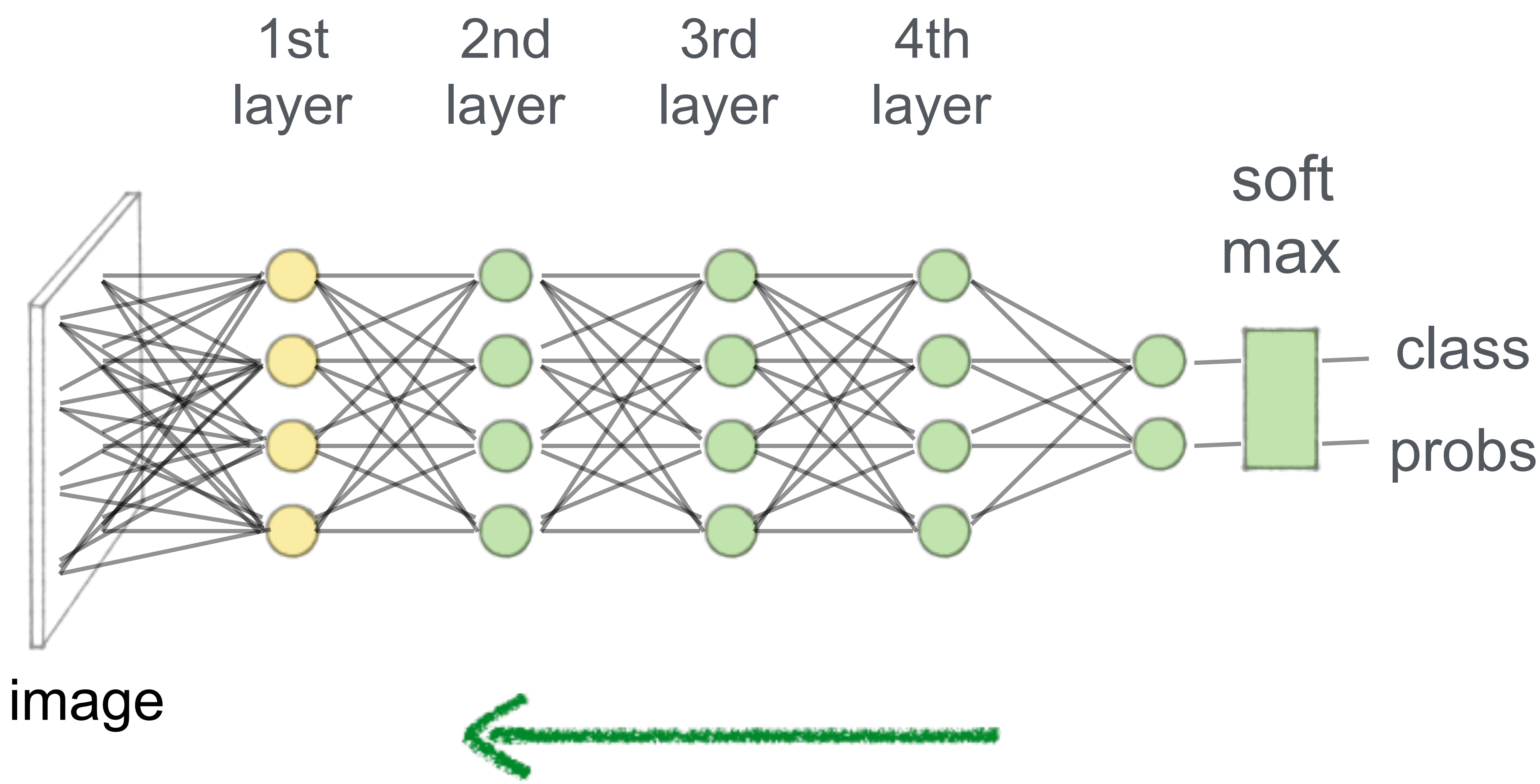
$$\frac{\partial L_i}{\partial w_k} = x_k \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backpropagation



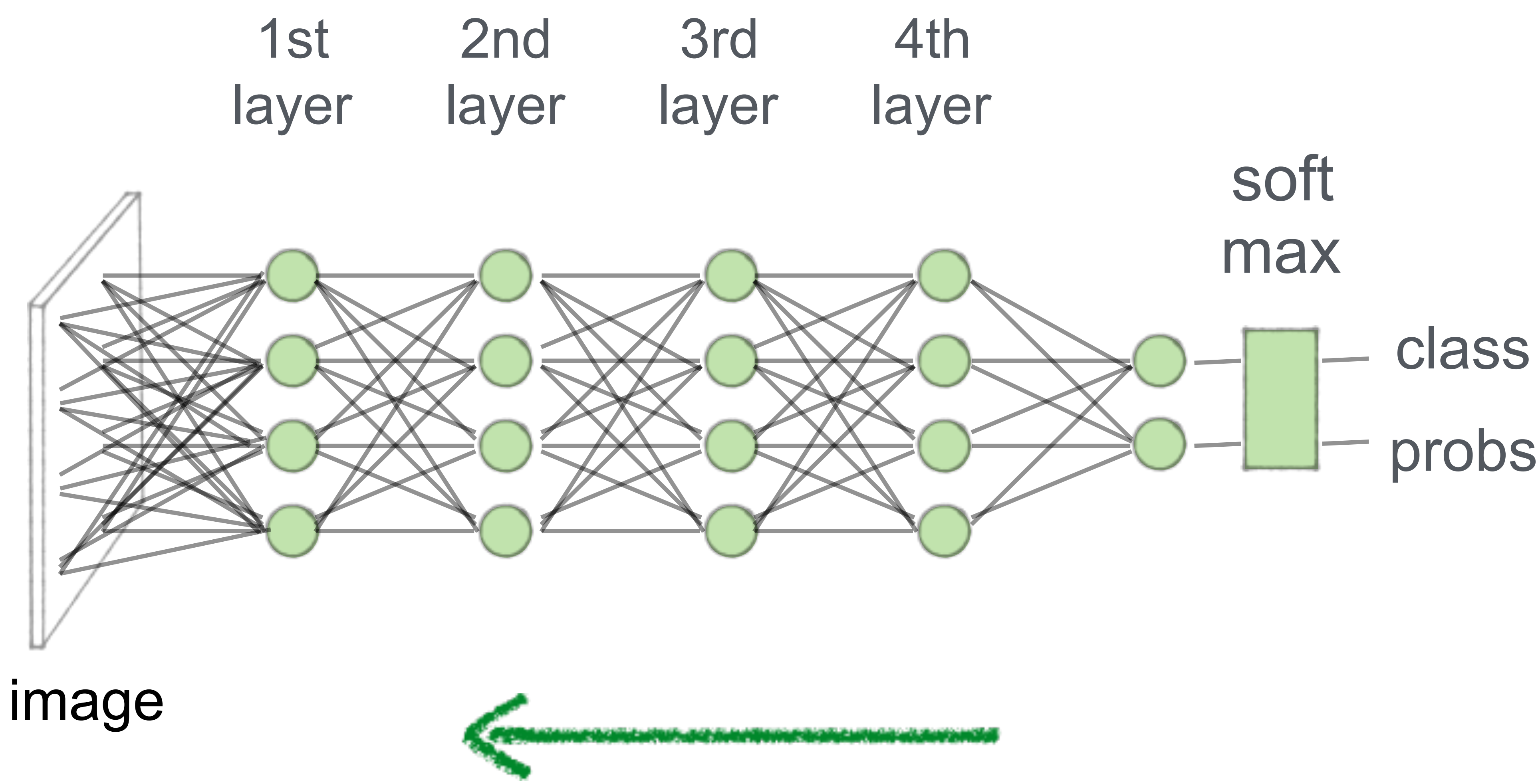
$$\frac{\partial L_i}{\partial w_k} = \underline{x_k} \underline{\xi'} \sum_j \tilde{w}_j \underline{\frac{\partial L_i}{\partial \tilde{y}_j}}$$

Backpropagation



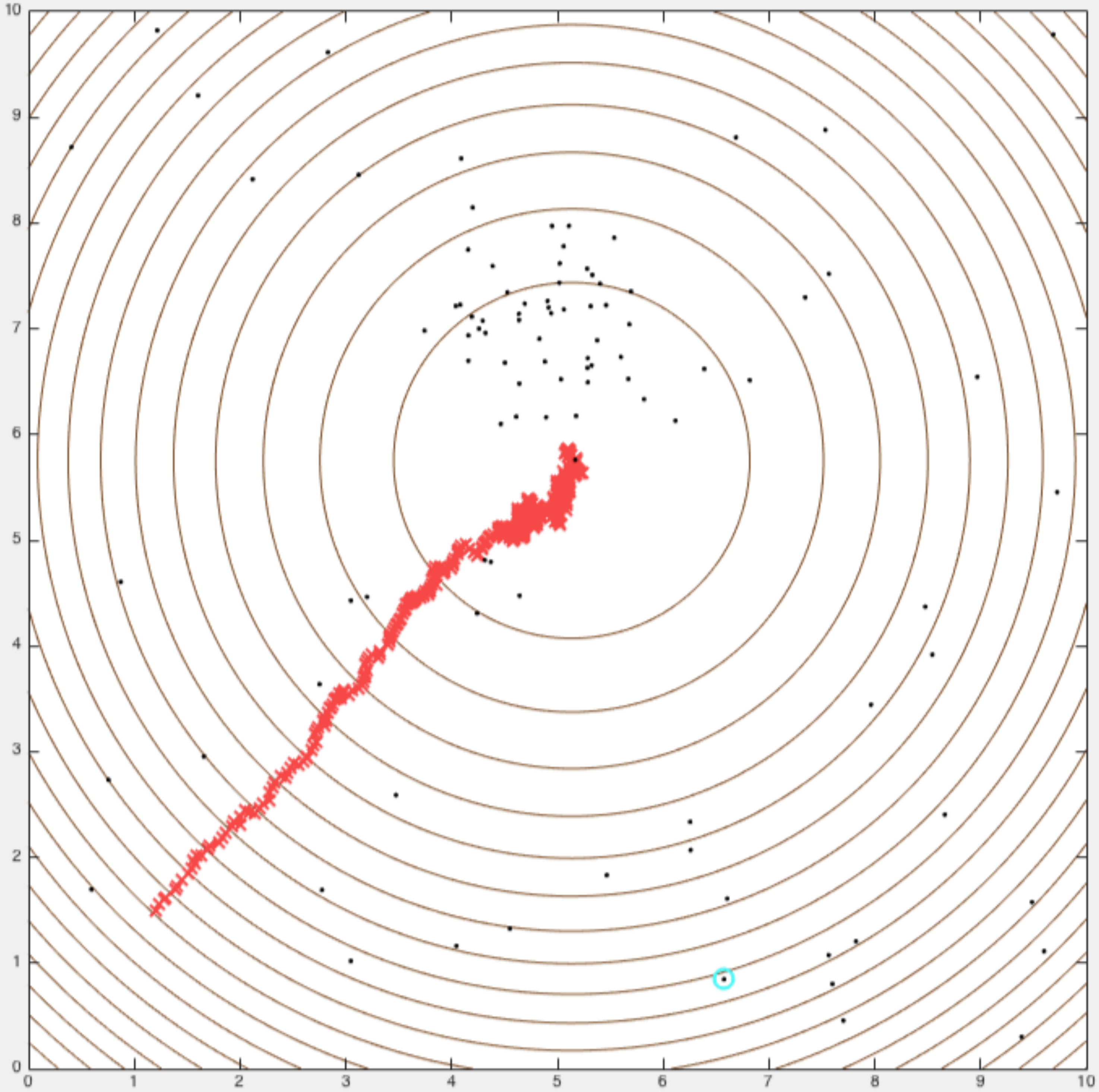
$$\frac{\partial L_i}{\partial w_k} = x_k \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

Backpropagation

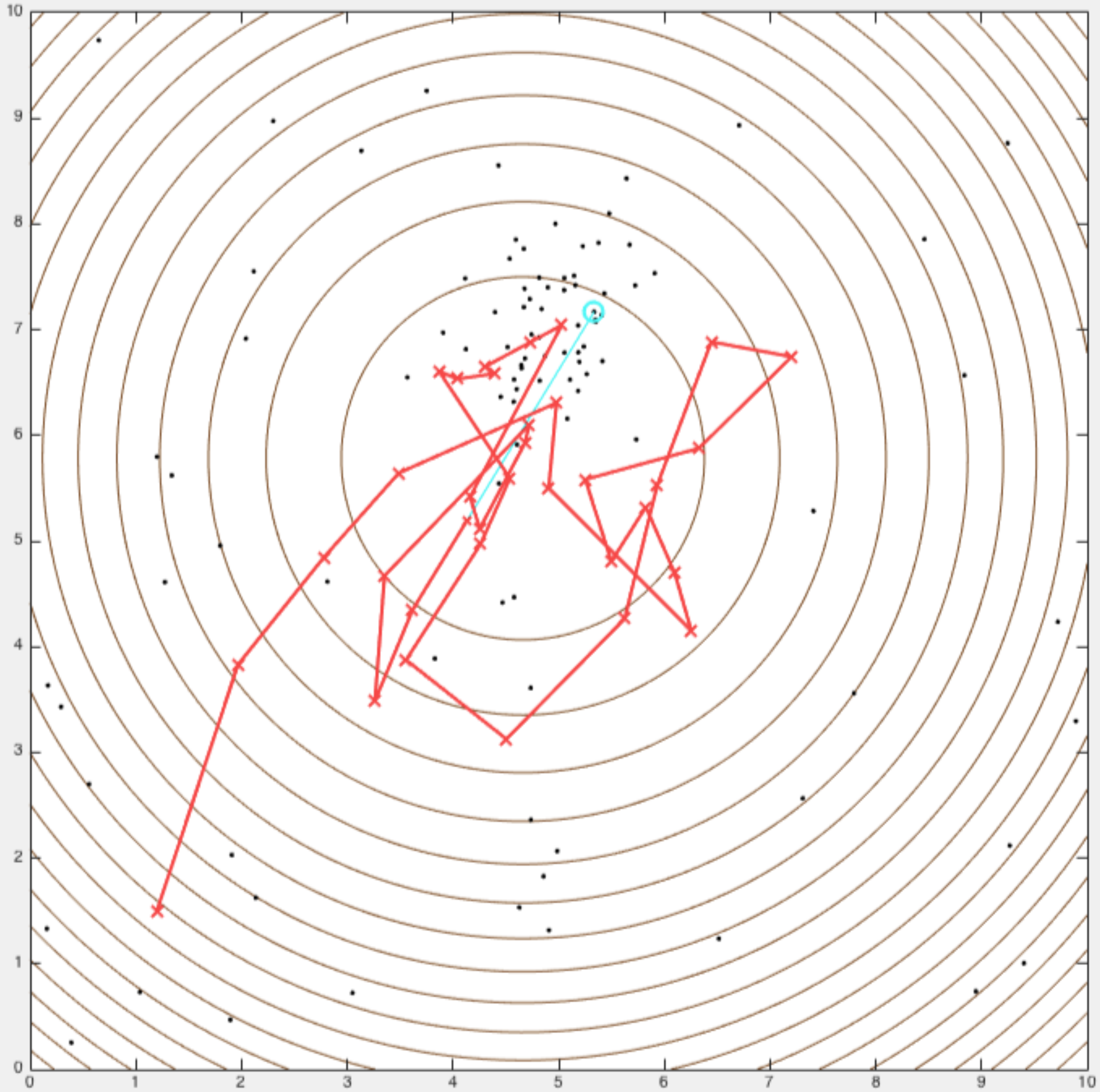


$$\frac{\partial L_i}{\partial w_k} = x_k \xi' \sum_j \tilde{w}_j \frac{\partial L_i}{\partial \tilde{y}_j}$$

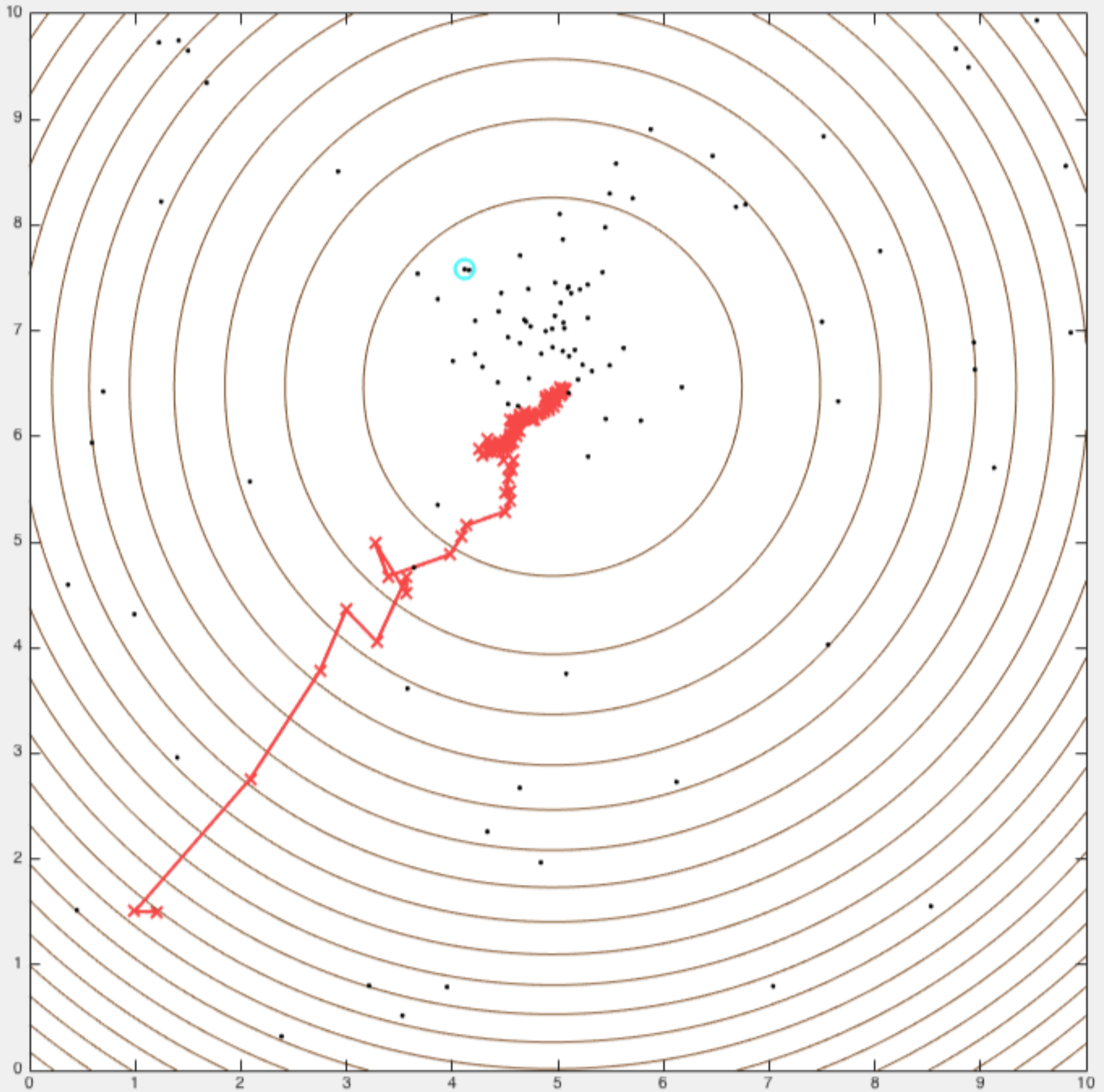
Small Learning Rate



Large Learning Rate

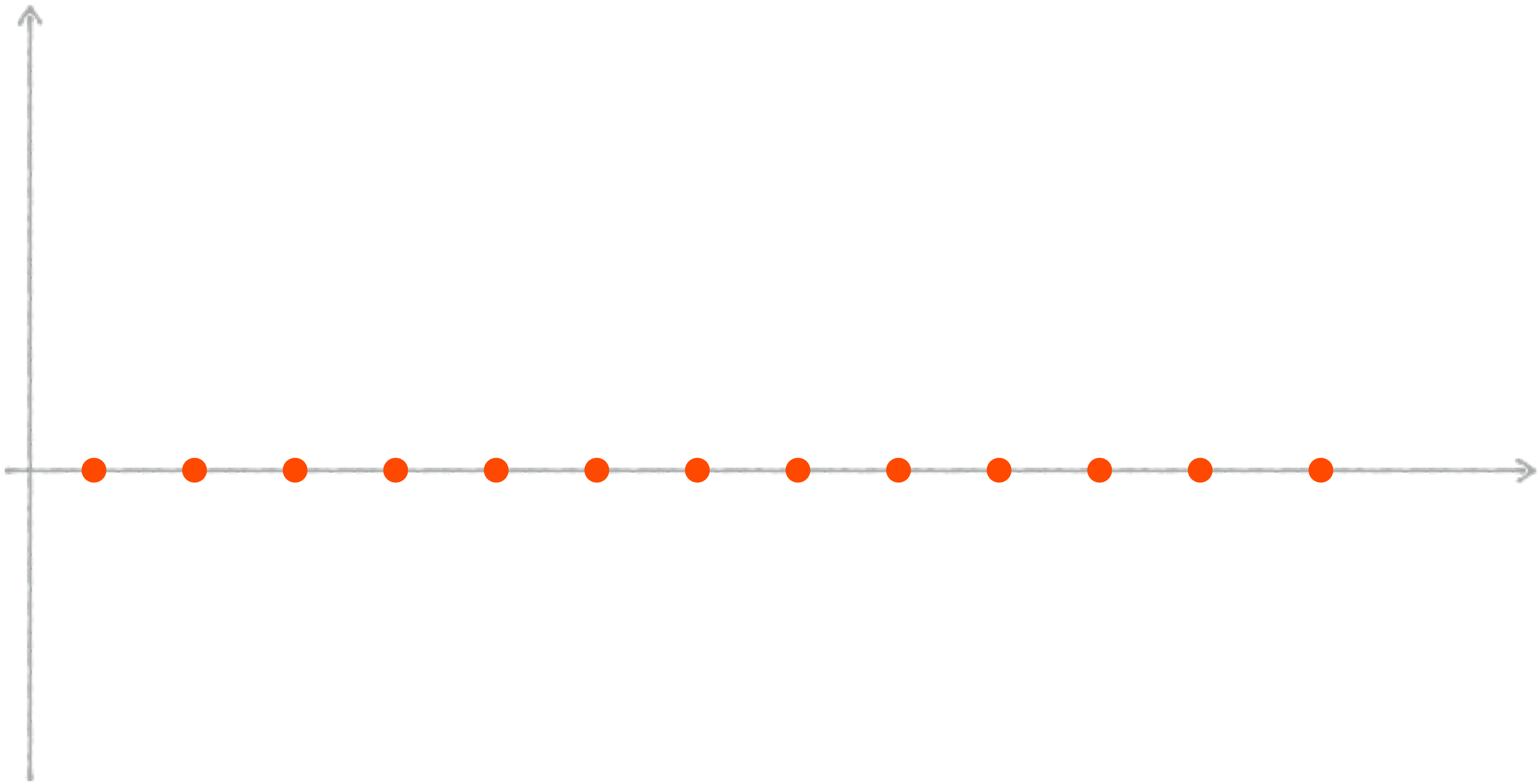


Decreasing Learning Rate

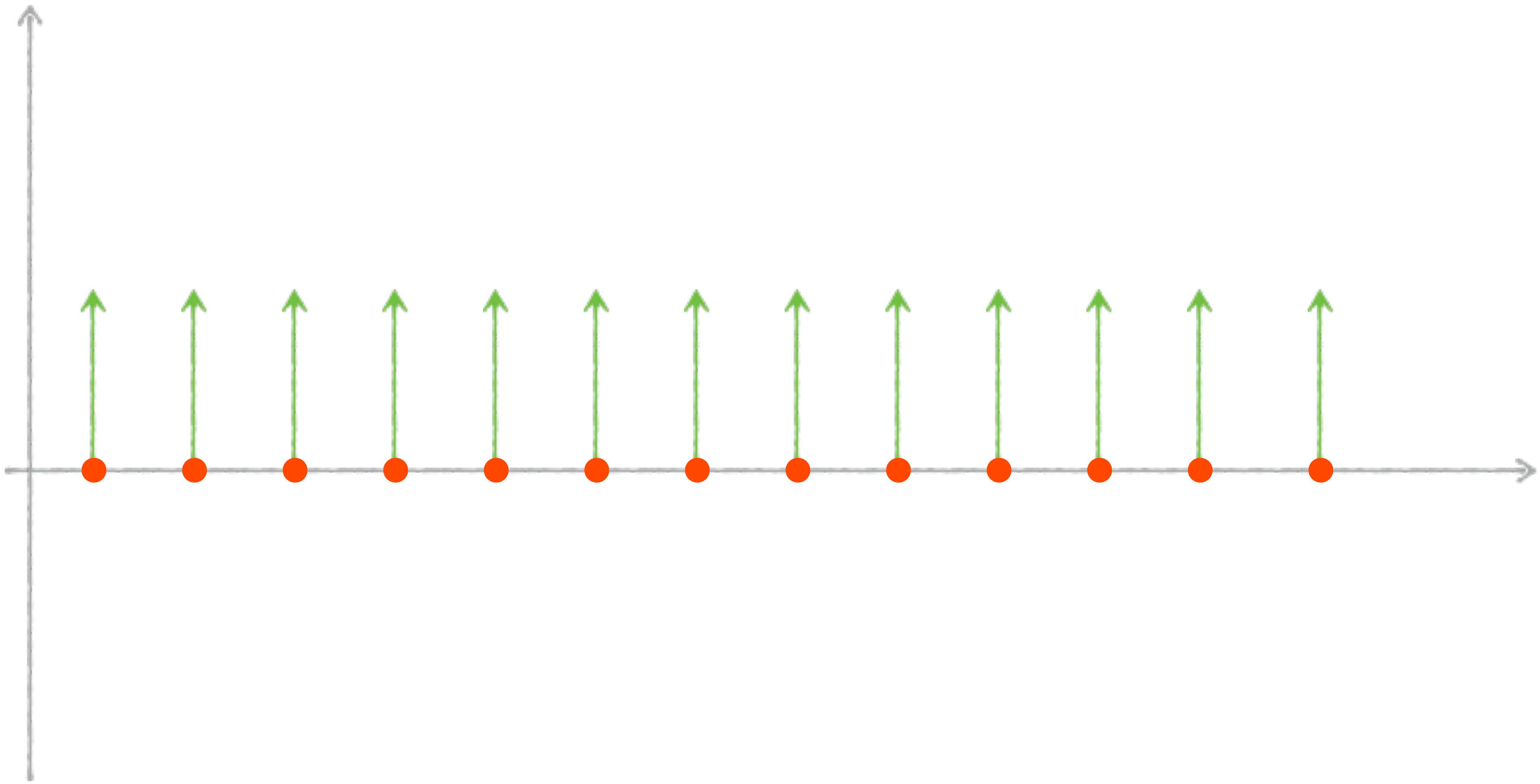


Decrease learning rate over time.

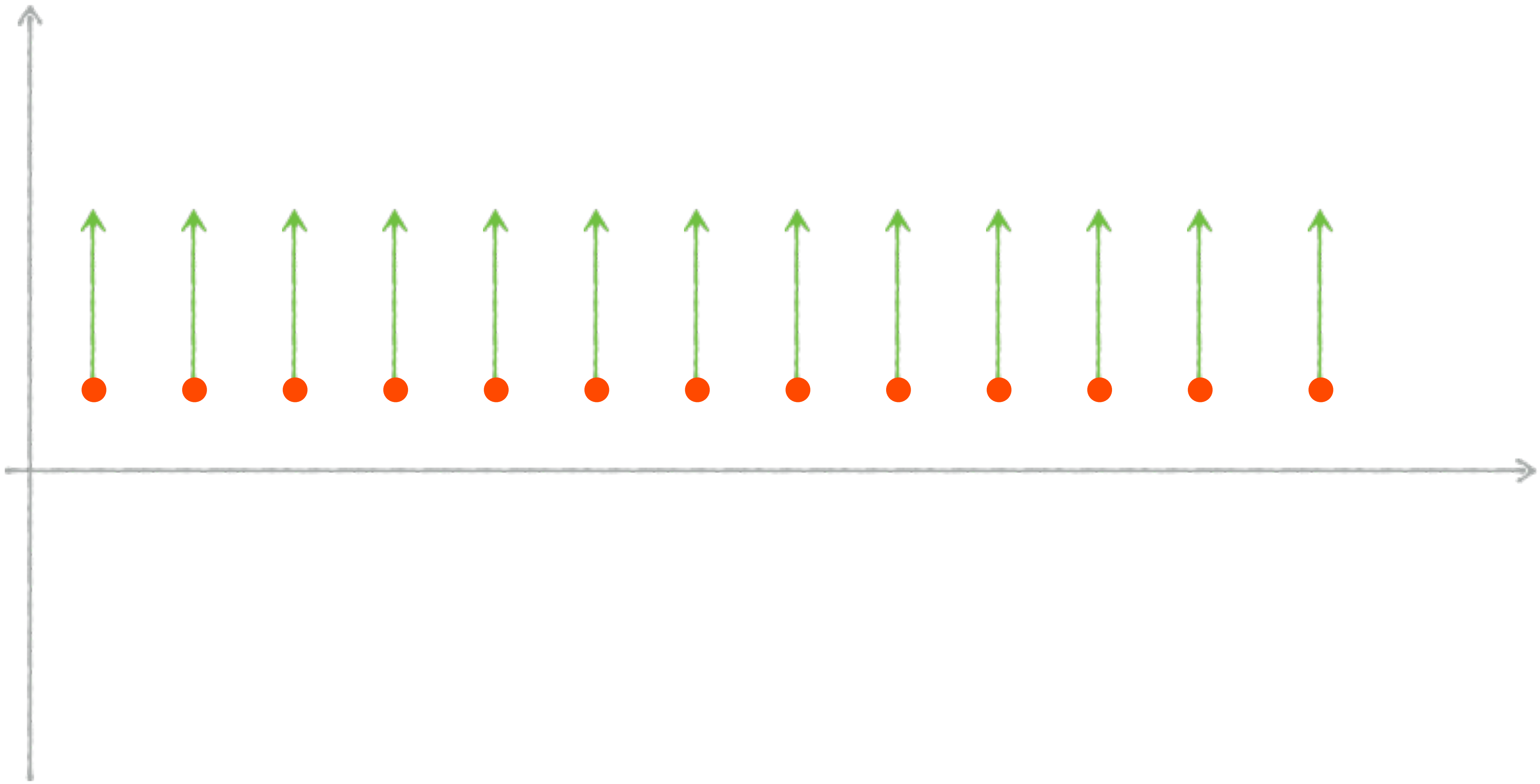
Weight Initialization



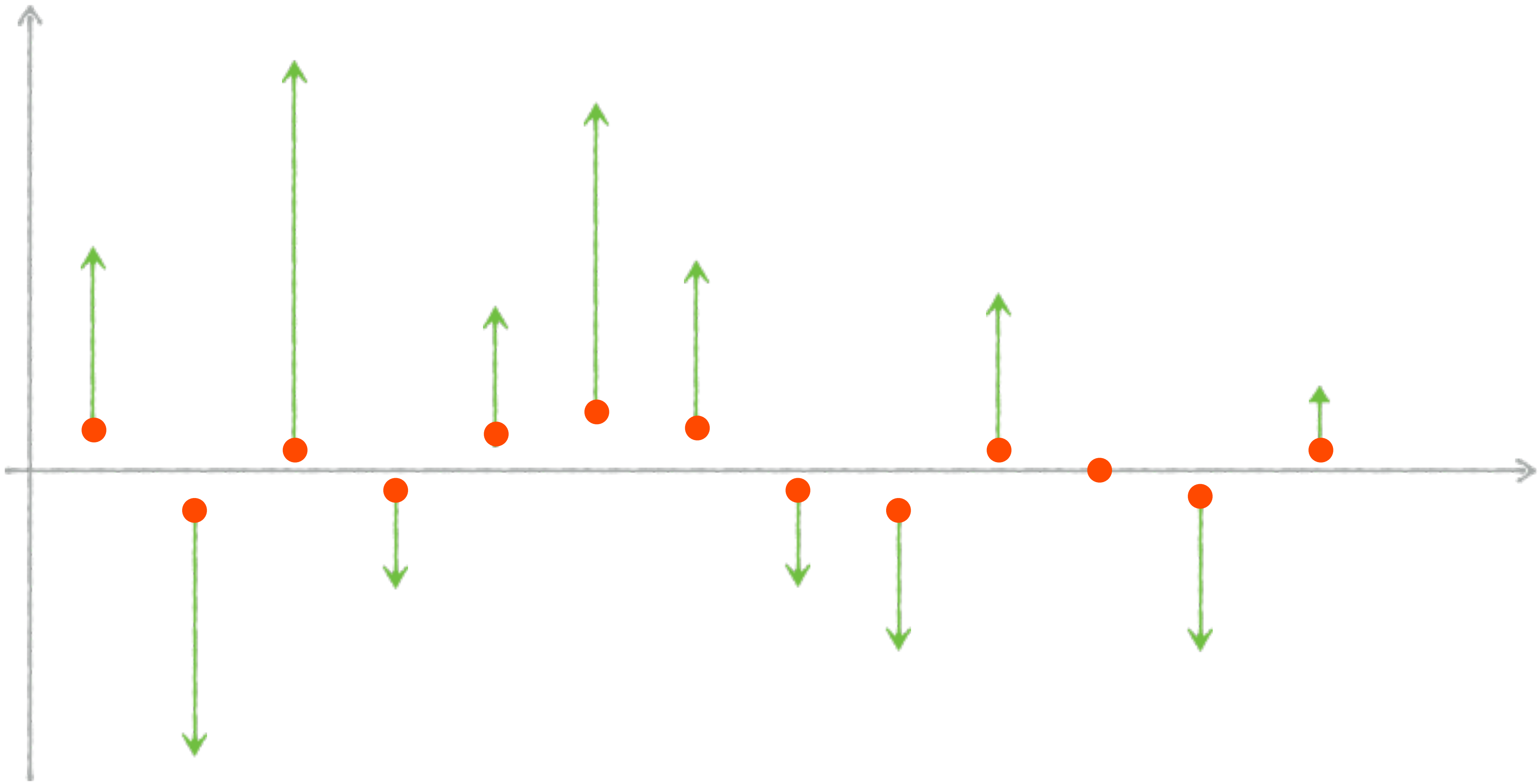
Weight Initialization



Weight Initialization

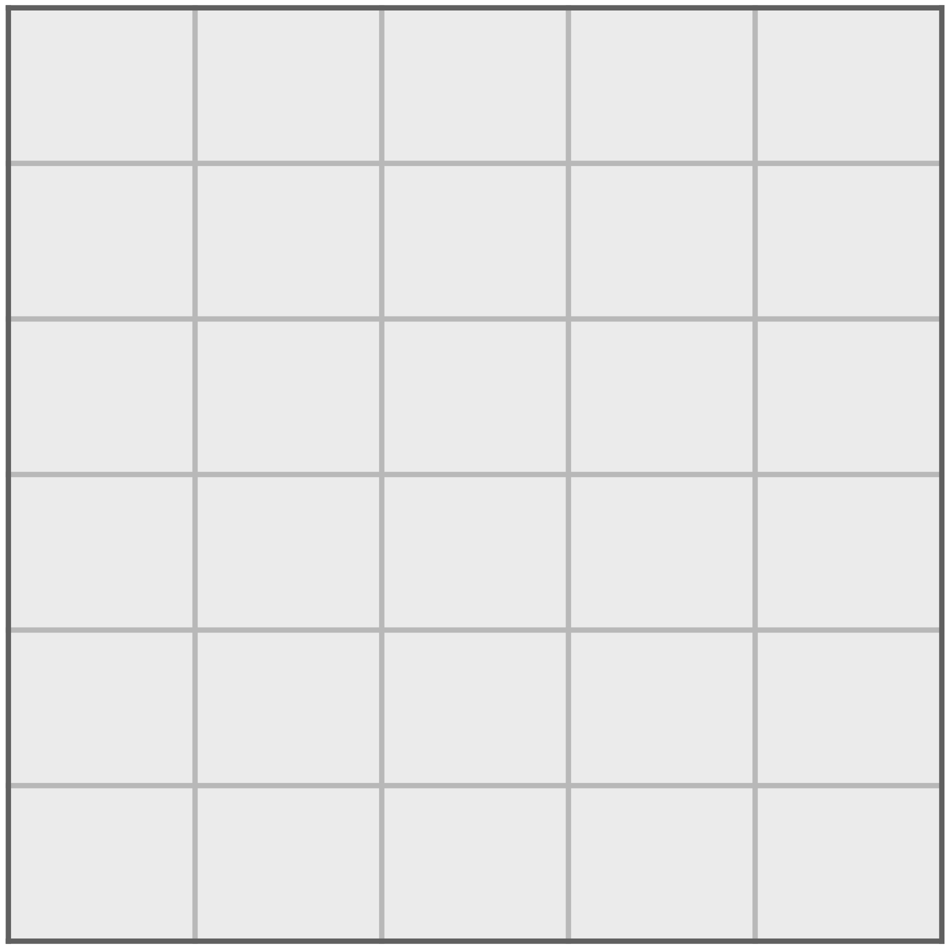


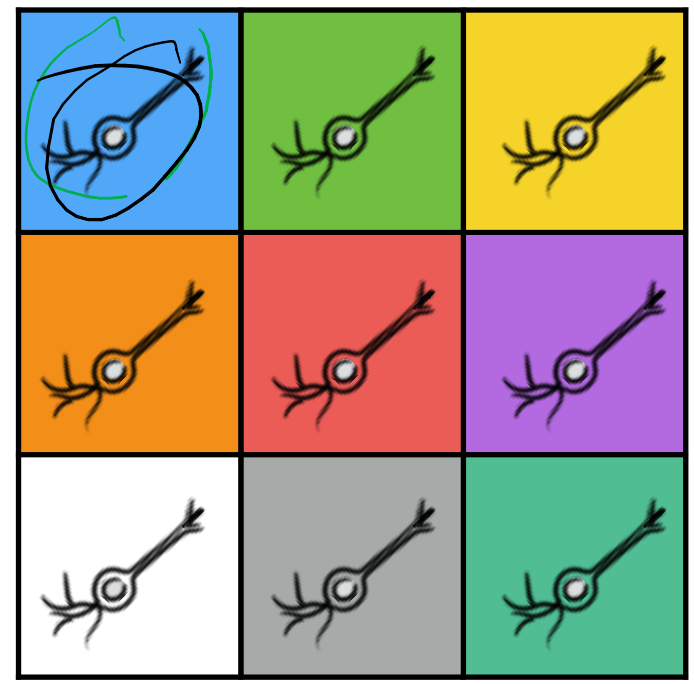
Weight Initialization



<u>Convolutional</u> Neural Networks

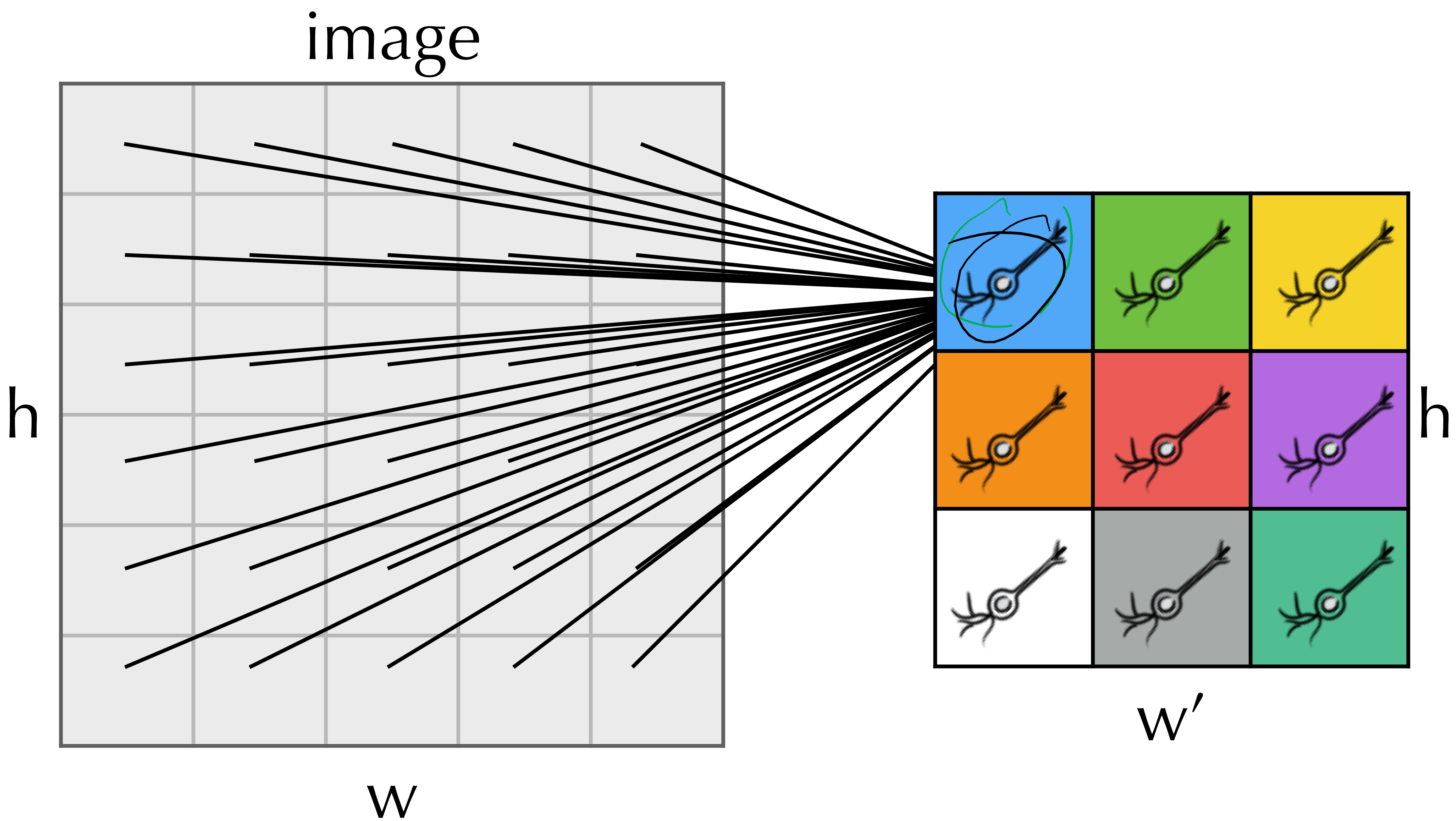
Fully Connected Layers





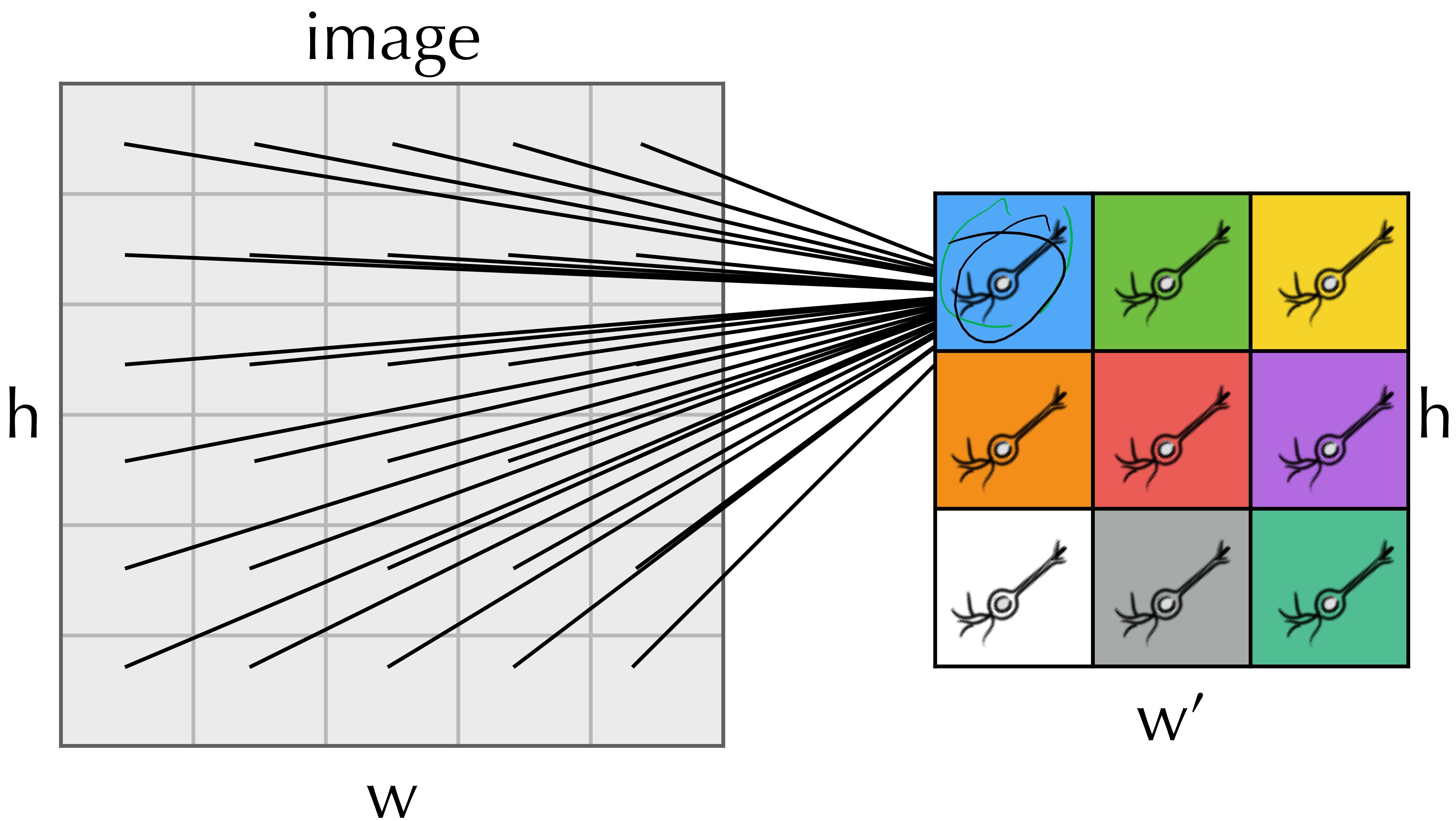
$w \cdot h \cdot w' \cdot h'$

Fully Connected Layers



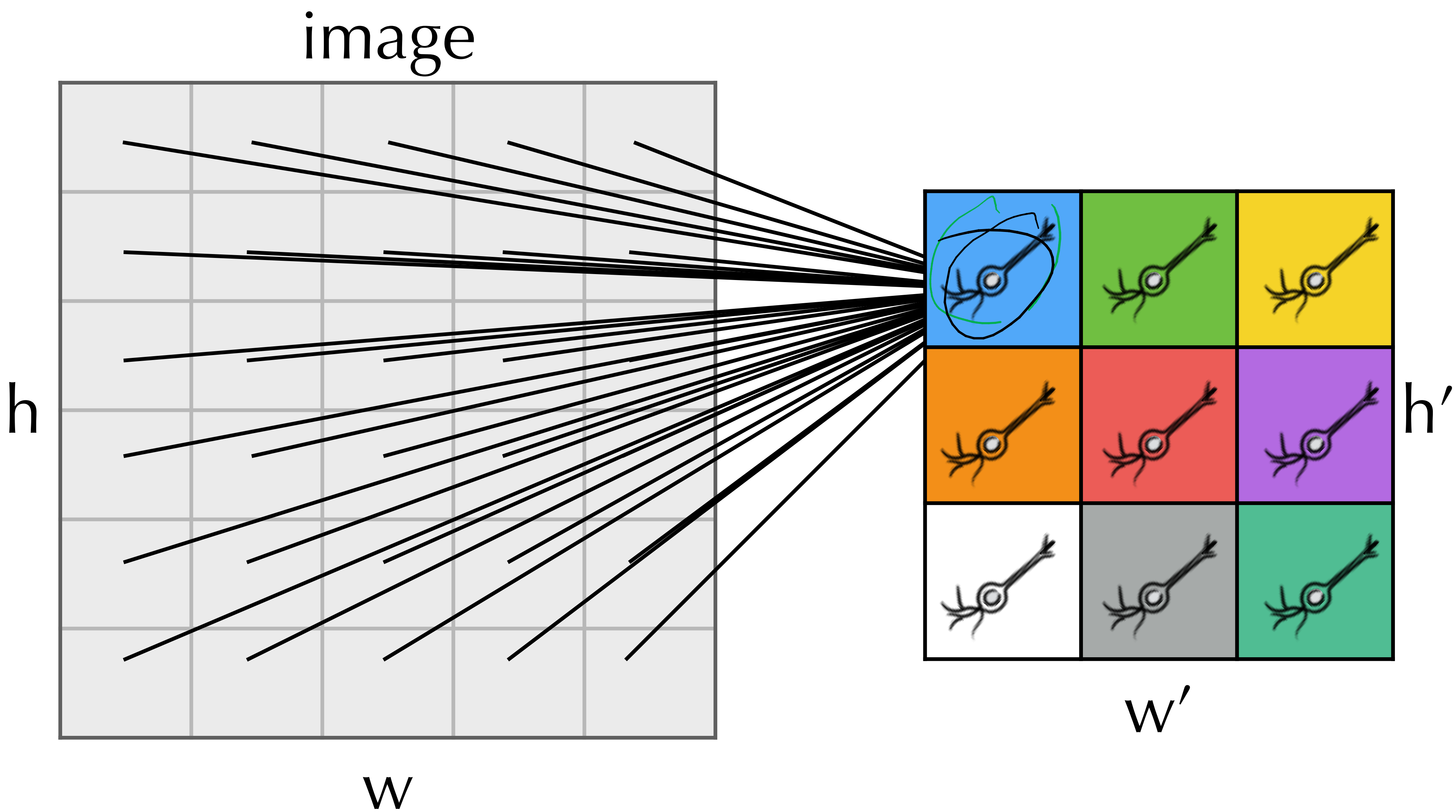
$w \cdot h \cdot w' \cdot h'$

Fully Connected Layers



Number parameters: $w \cdot h \cdot w' \cdot h'$

Fully Connected Layers

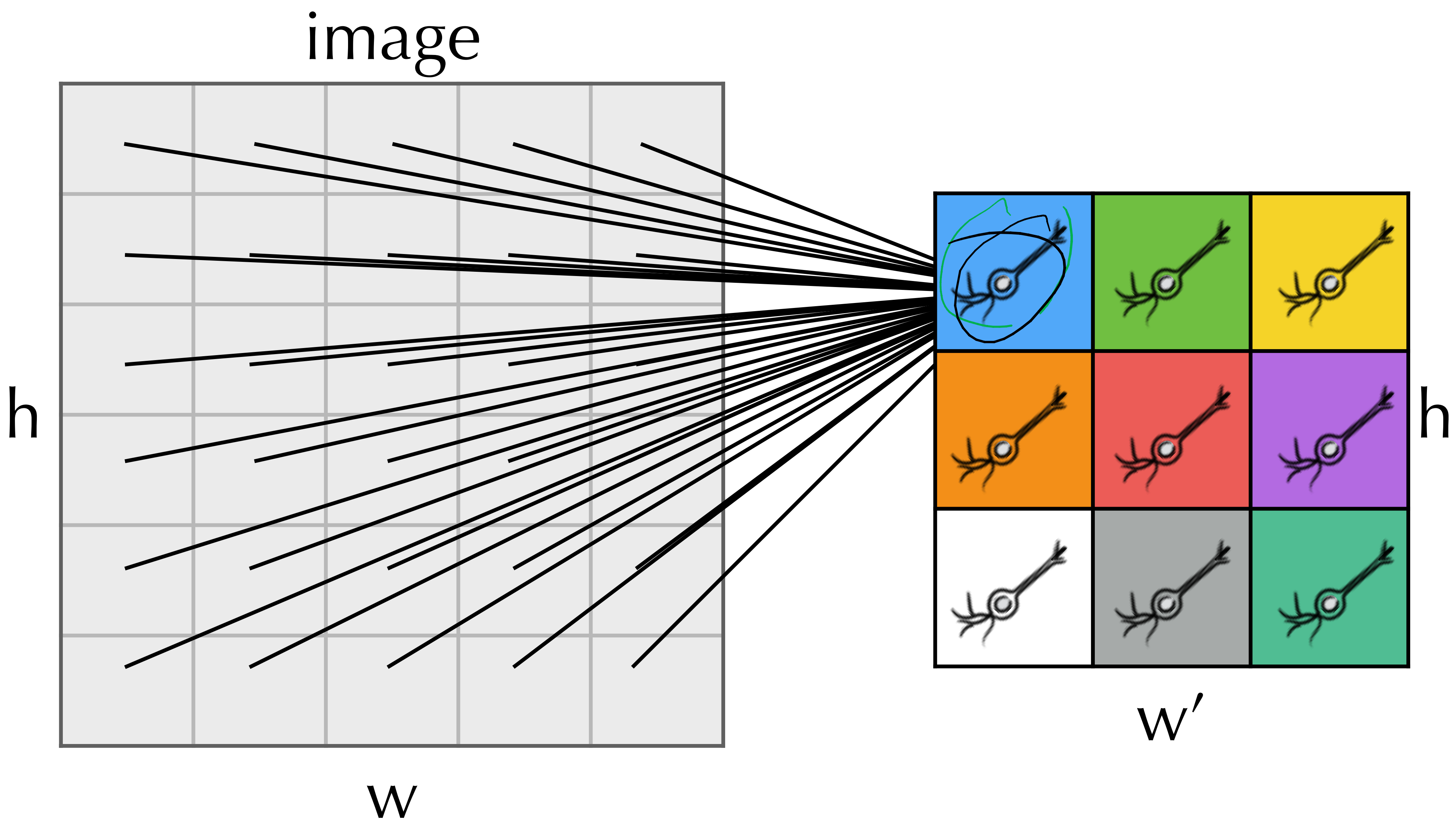


Redundancy? ✓

Number parameters: $w \cdot h \cdot w' \cdot h'$

X

Fully Connected Layers

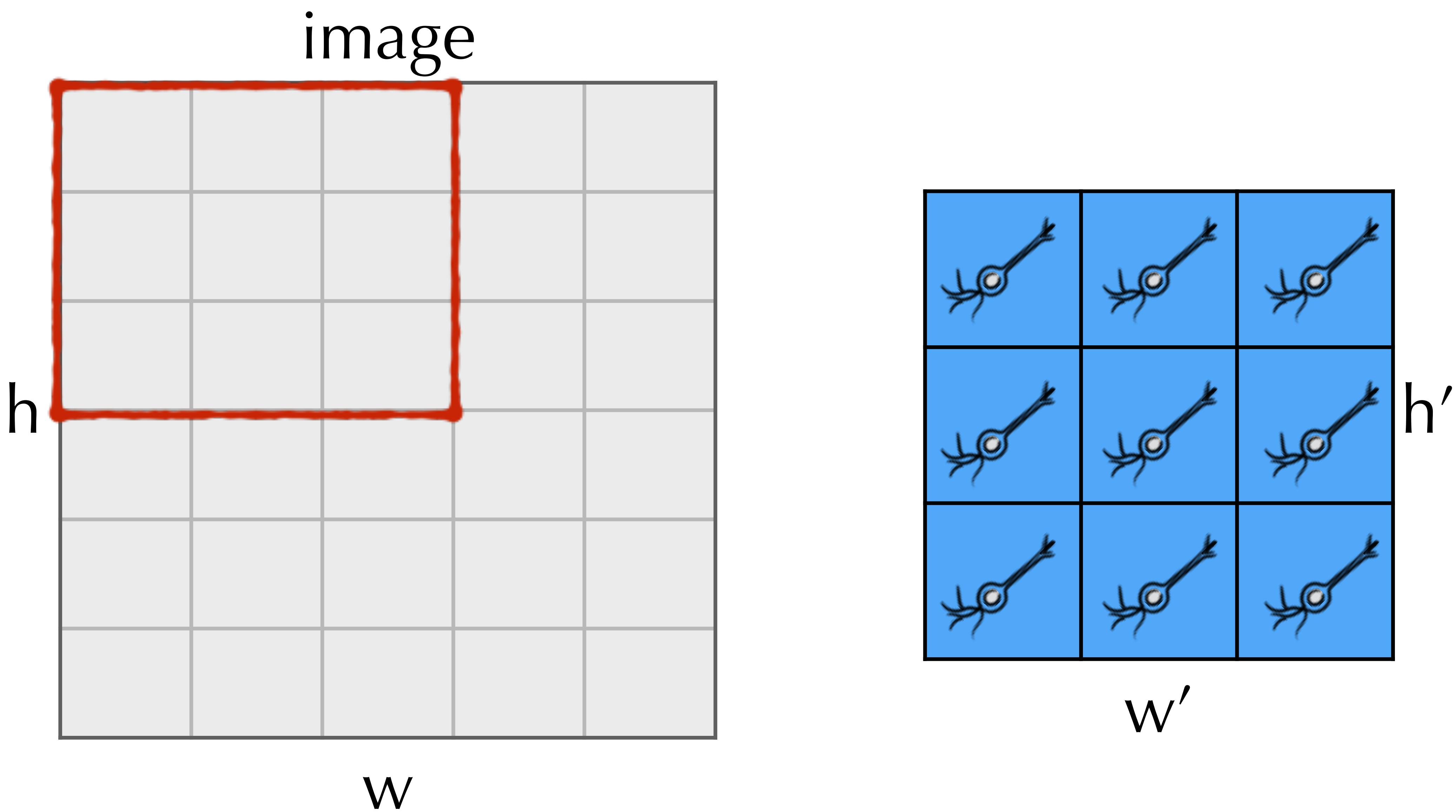


Number parameters: $w \cdot h \cdot w' \cdot h'$

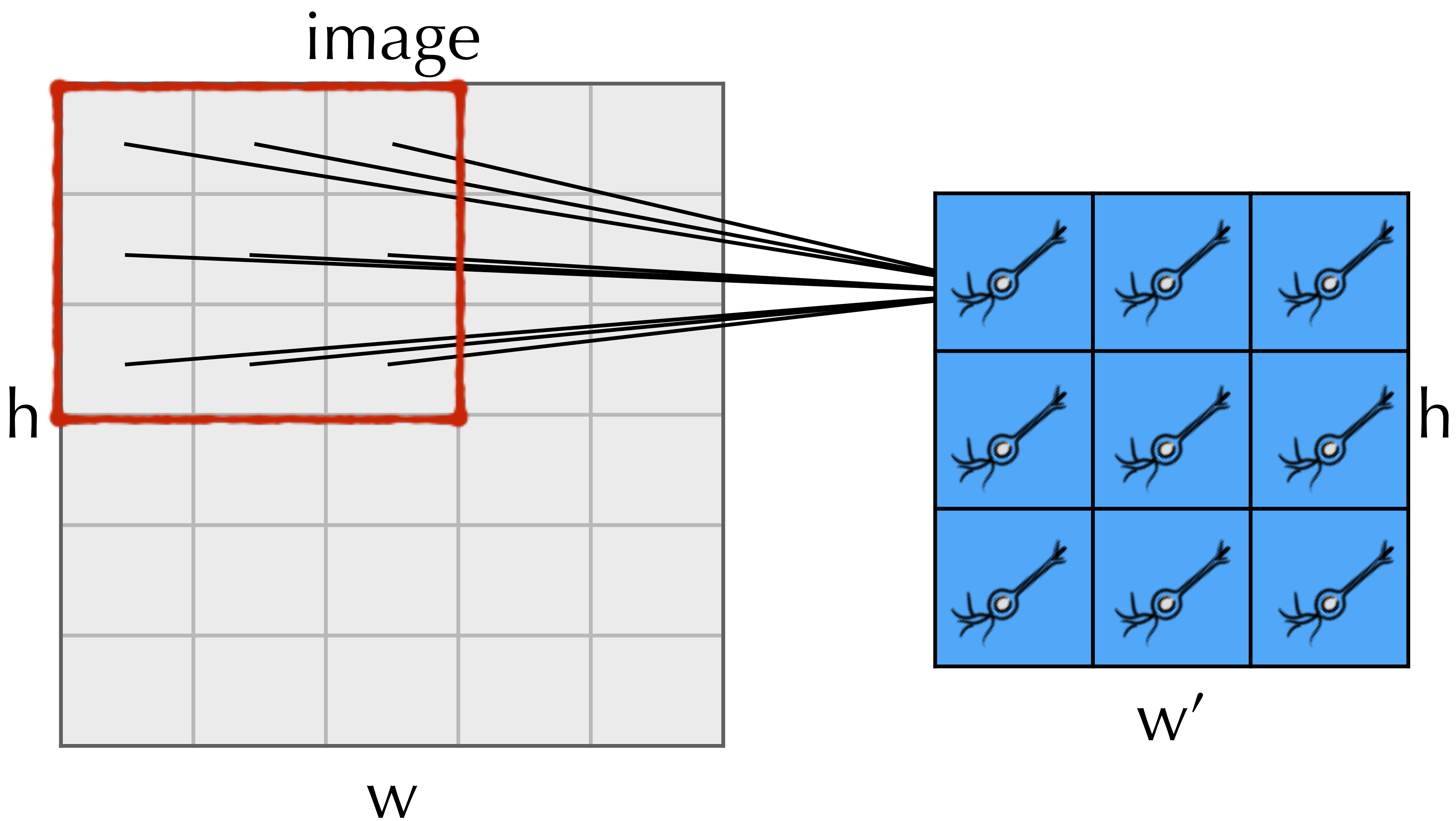
Redundancy? ✓

Locality? ✗

Convolutional Layers

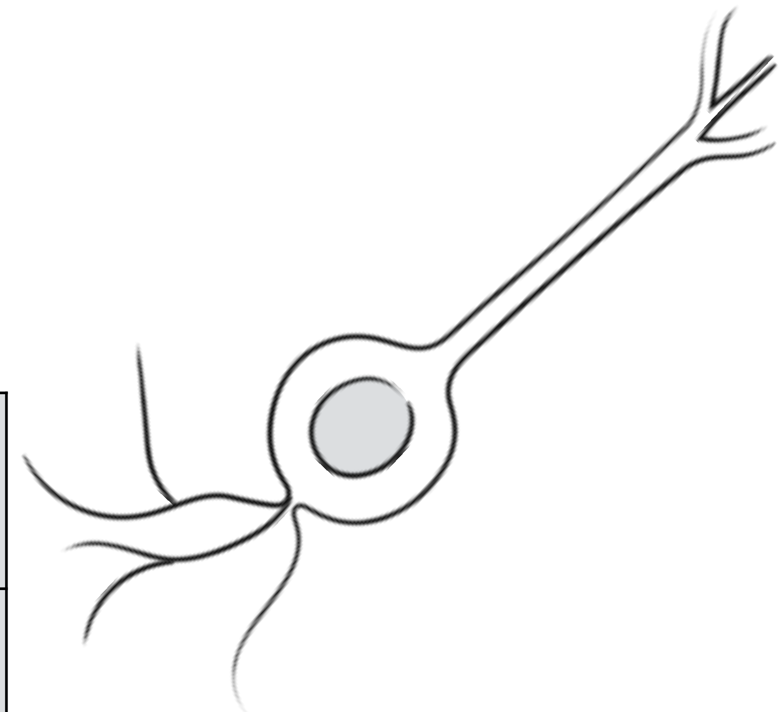


Convolutional Layers



Translation Invariance

2	2	1	2	3
11	21	22	21	14
12	20	45	32	21
11	12	11	16	21
21	22	23	25	35



Translation Invariance

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11	21	22	21	14
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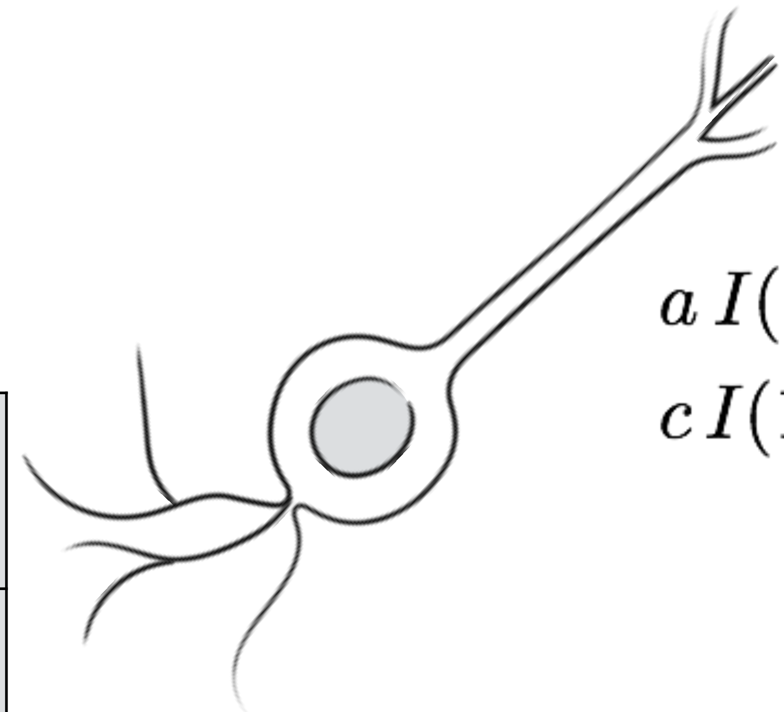
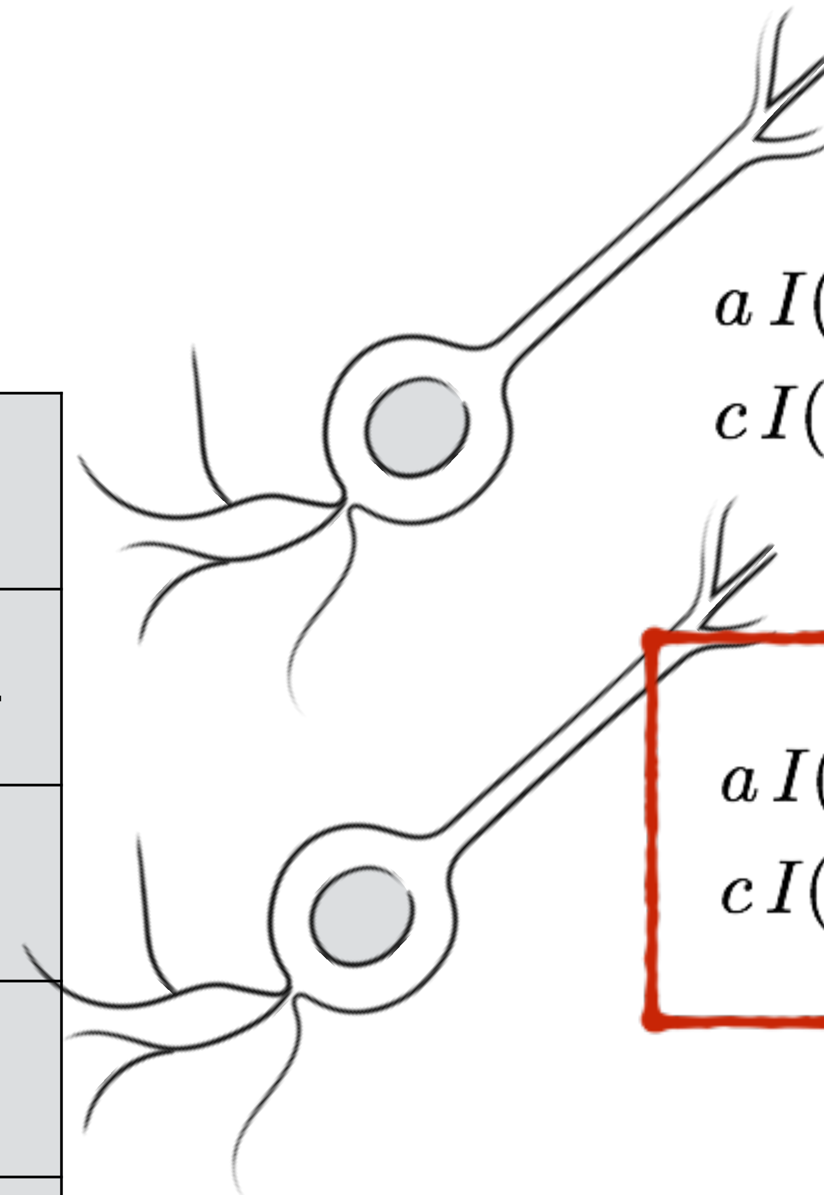


$$a\, I(1,1) + b\, I(2,1) +$$
$$c\, I(1,2) + d\, I(2,2)$$

Translation Invariance

2	2	1	2	3
11	21	22	21	14
12	20	45	32	21
11	12	11	16	21
21	22	23	25	35

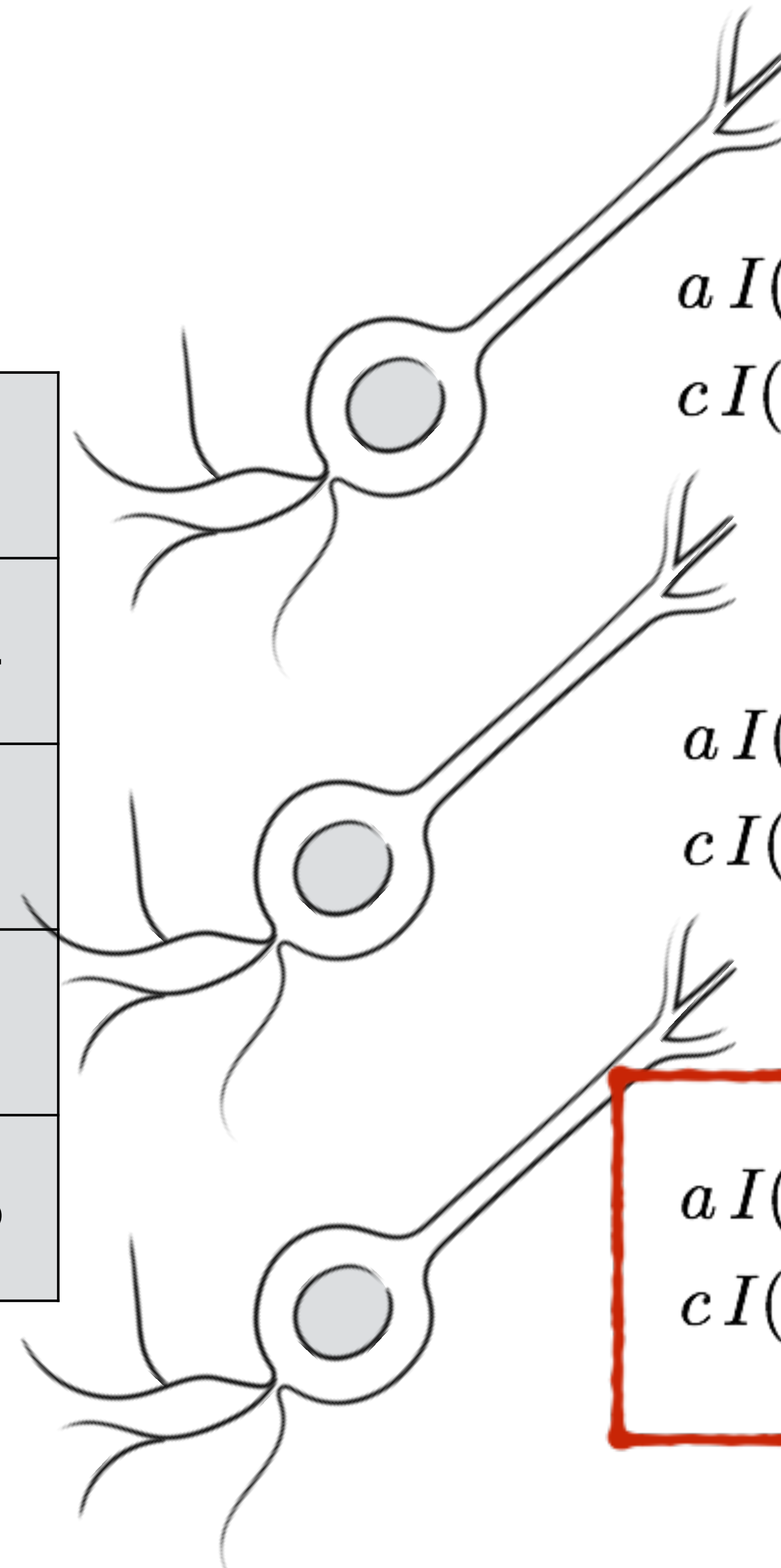


$$a\,I(1,1) + b\,I(2,1) + c\,I(1,2) + d\,I(2,2)$$

$$\boxed{a\,I(2,1) + b\,I(3,1) + c\,I(2,2) + d\,I(3,2)}$$

Translation Invariance

2	2	1	2	3
11	21	22	21	14
12	20	45	32	21
11	12	11	16	21
21	22	23	25	35

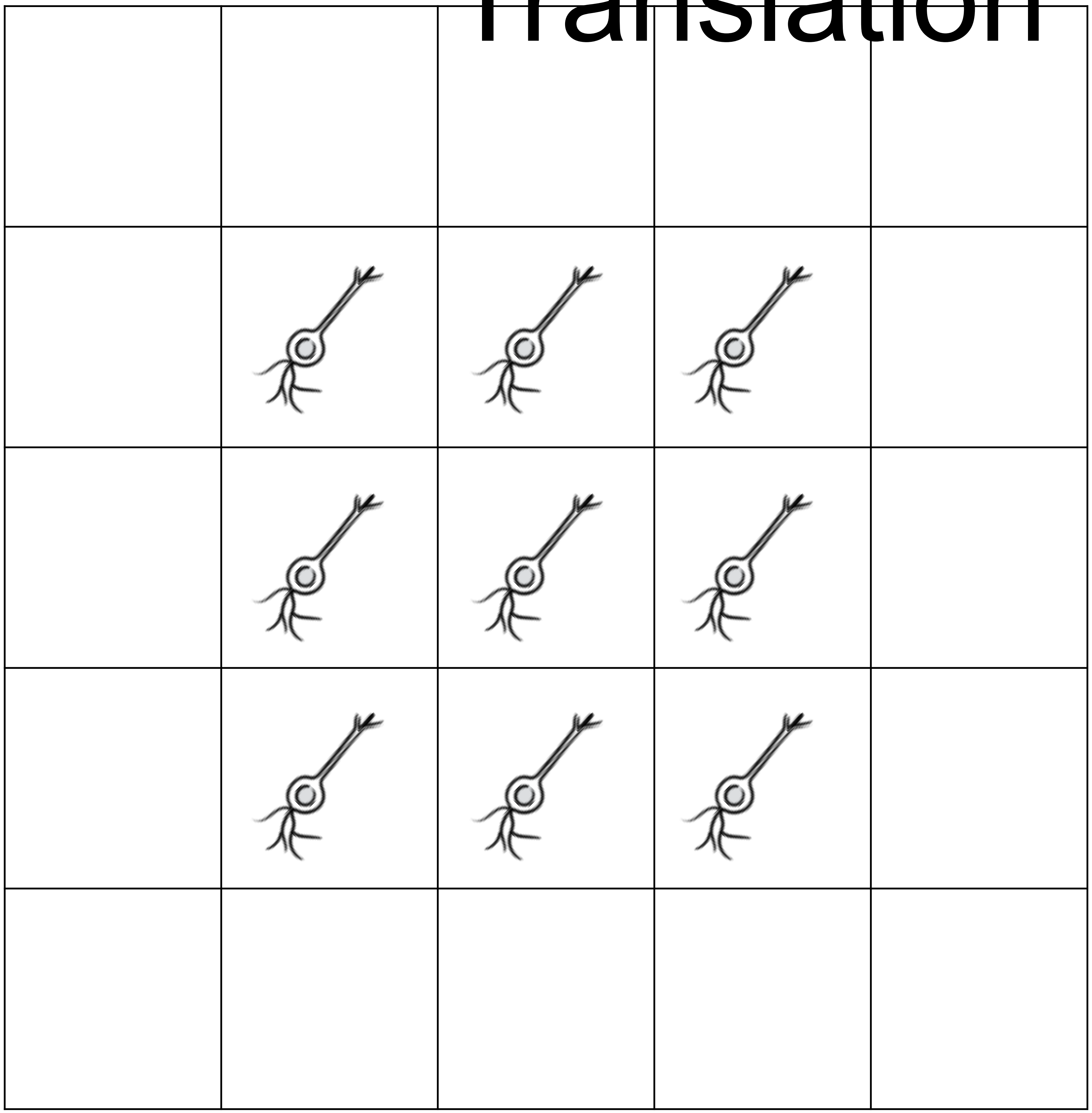


$$a\,I(1,1) + b\,I(2,1) + c\,I(1,2) + d\,I(2,2)$$

$$a\,I(2,1) + b\,I(3,1) + c\,I(2,2) + d\,I(3,2)$$

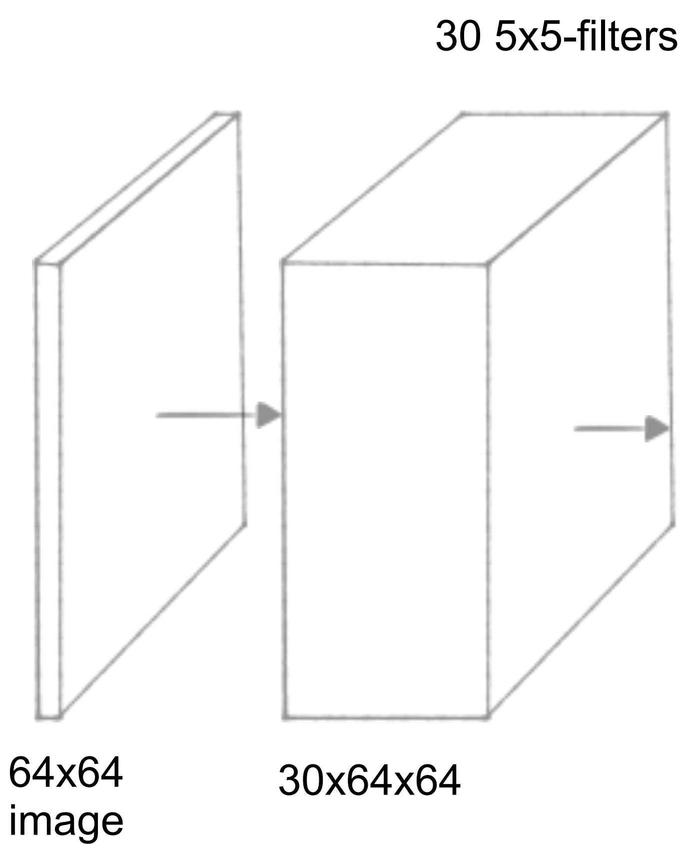
$$a\,I(3,1) + b\,I(4,1) + c\,I(3,2) + d\,I(4,2)$$

Translation Invariance



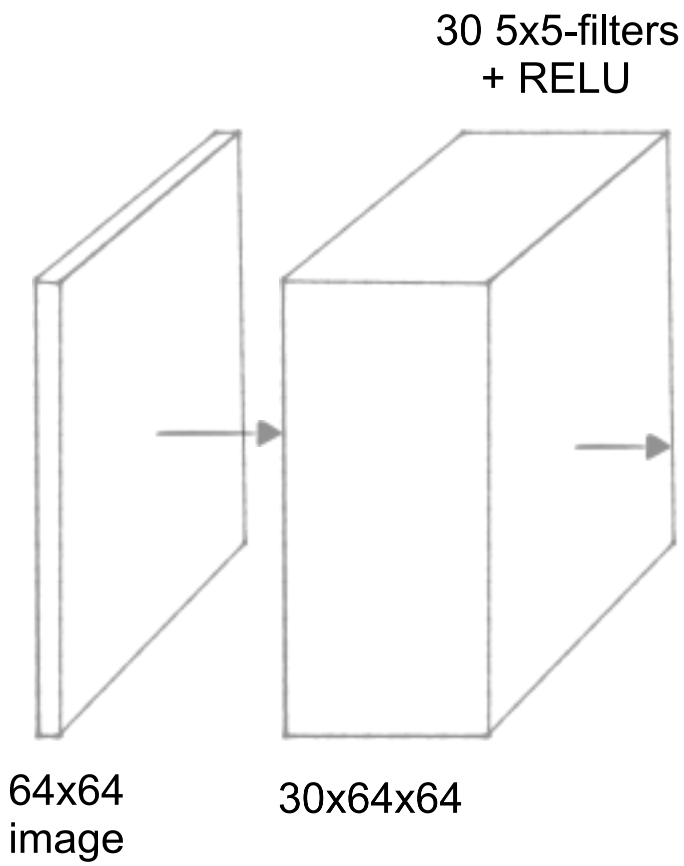
$$I \star \begin{pmatrix} a & b \\ c & d \end{pmatrix}$$

Network Structure



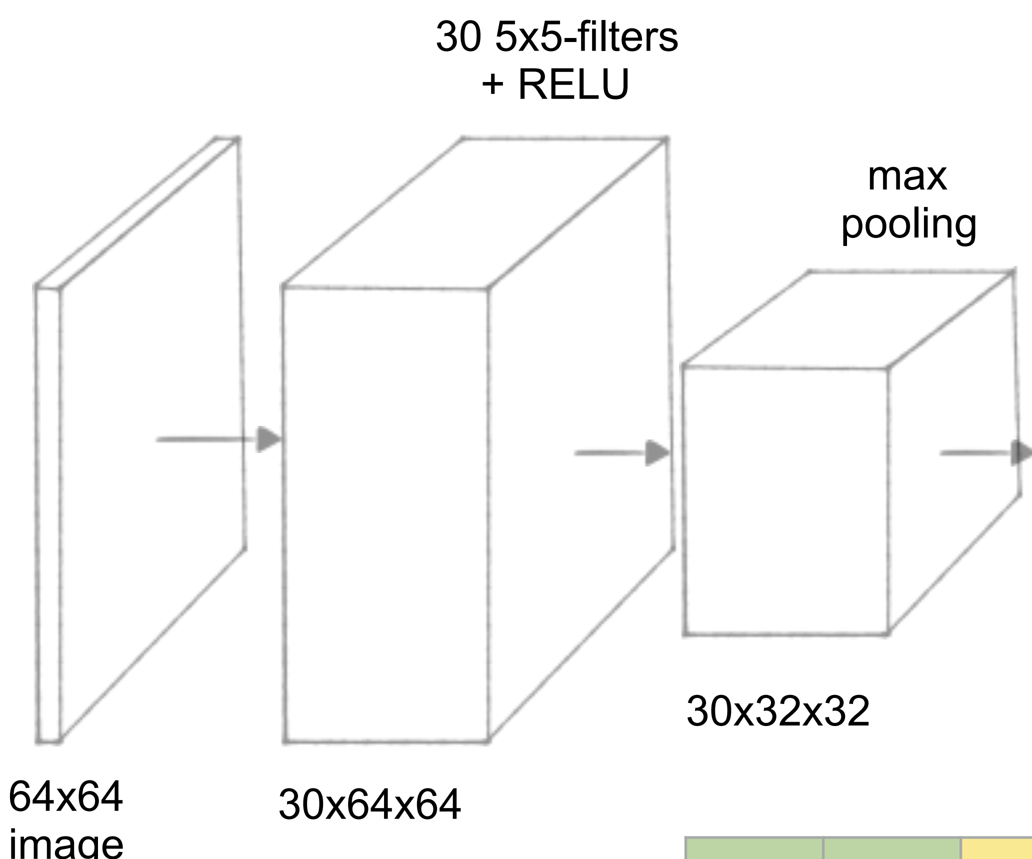
$$I \star w$$

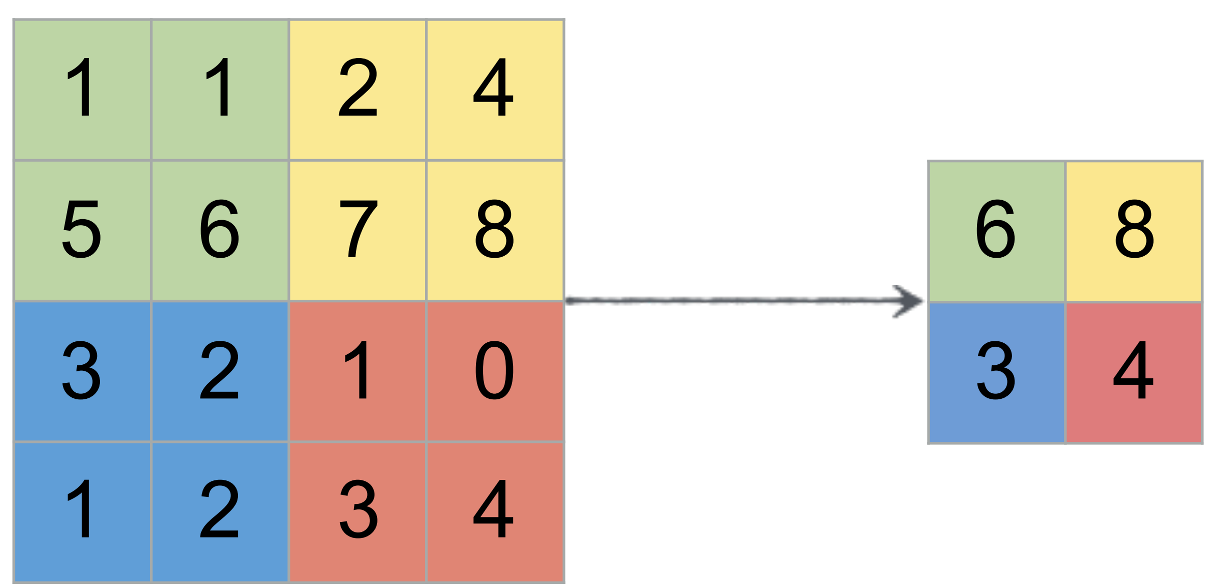
Network Structure



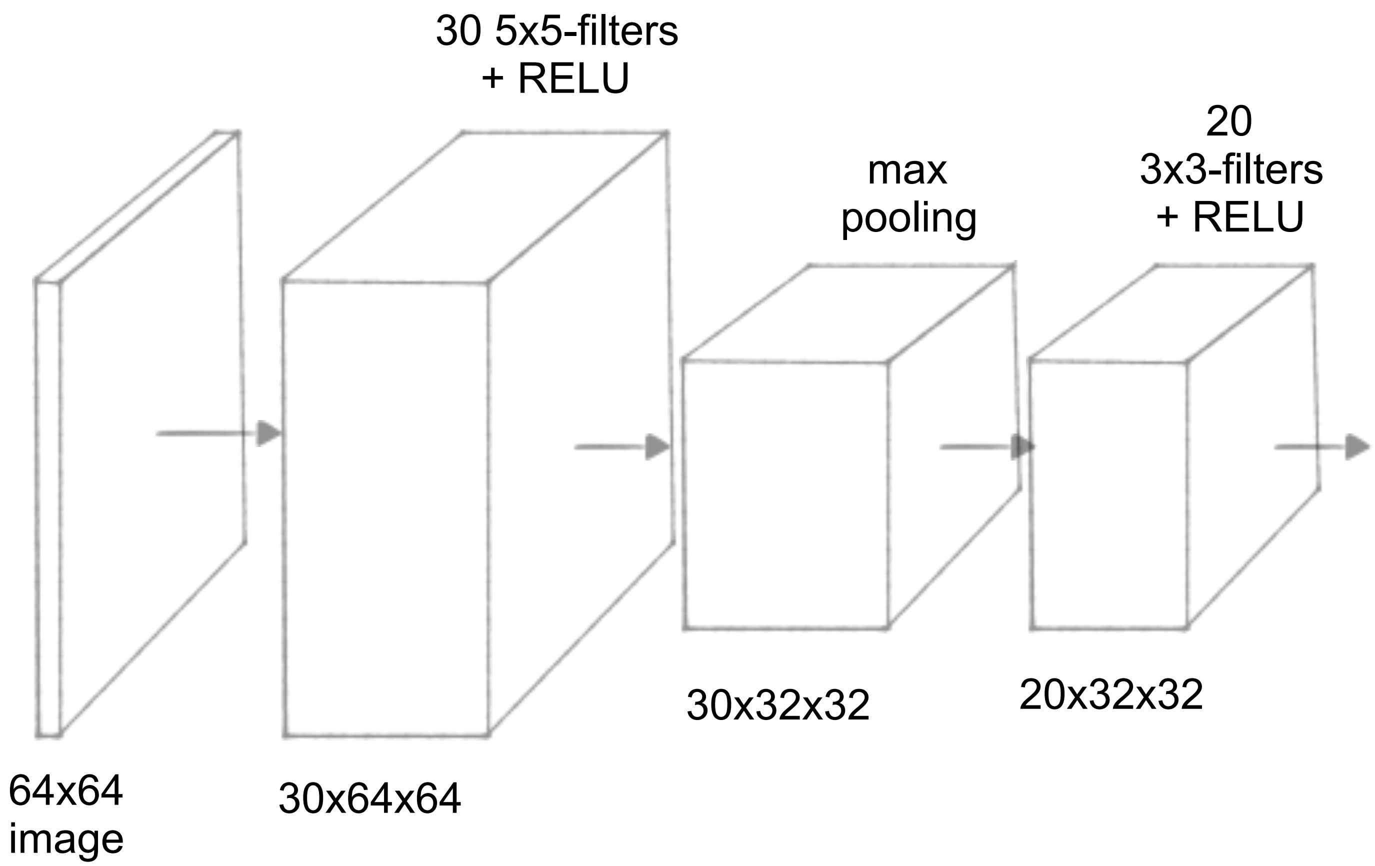
$$\max\{I \star w, 0\}$$

Network Structure

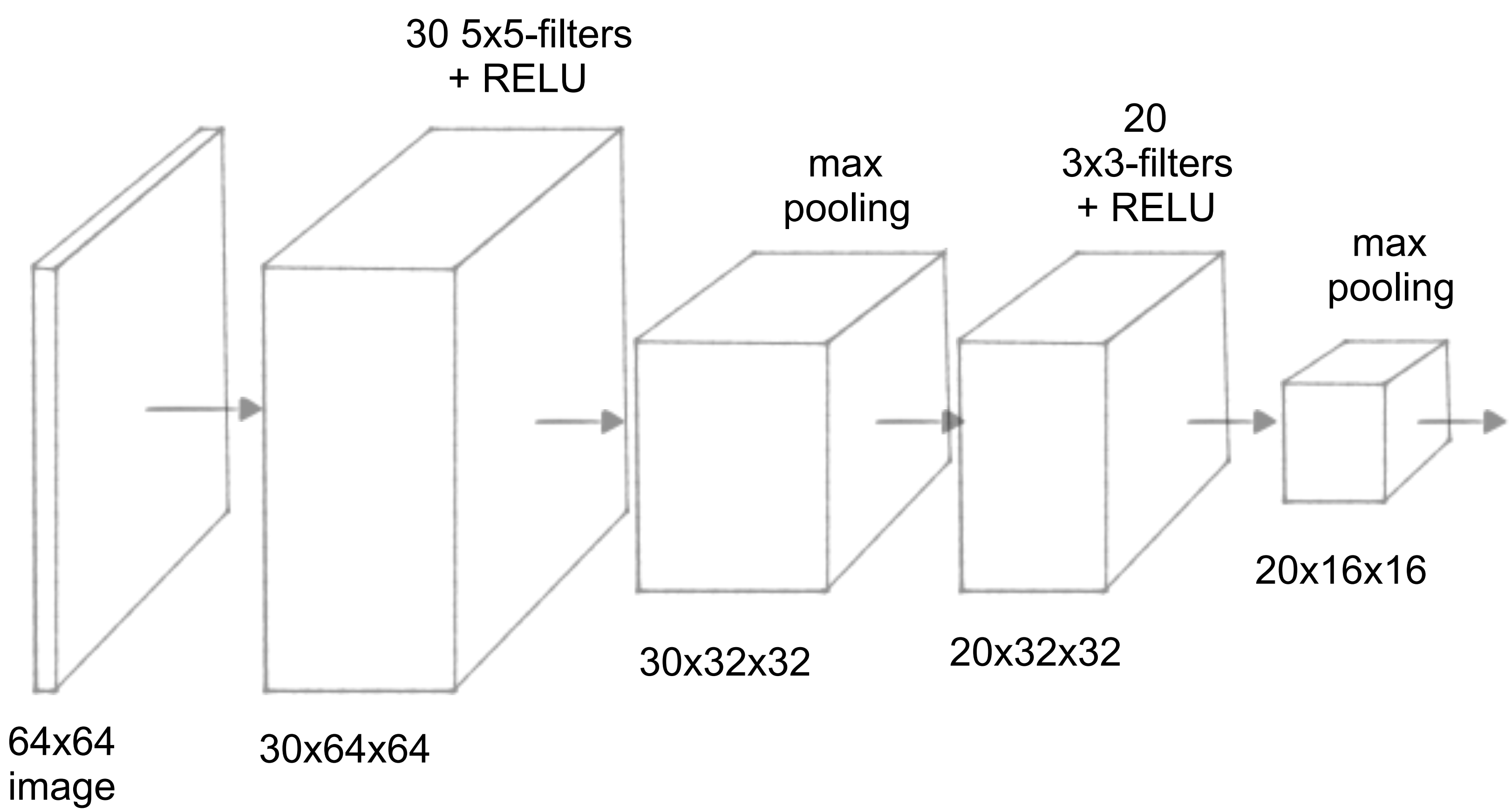




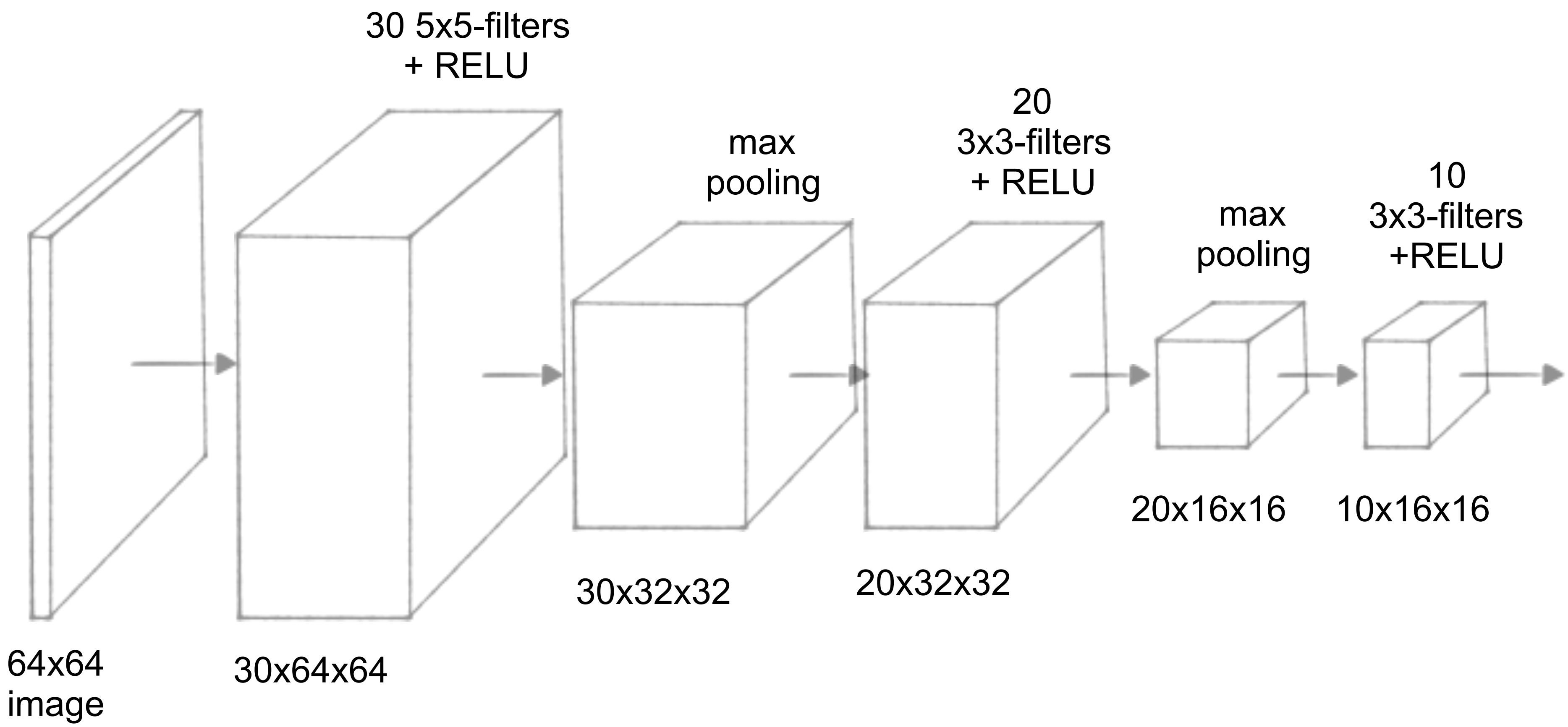
Network Structure



Network Structure

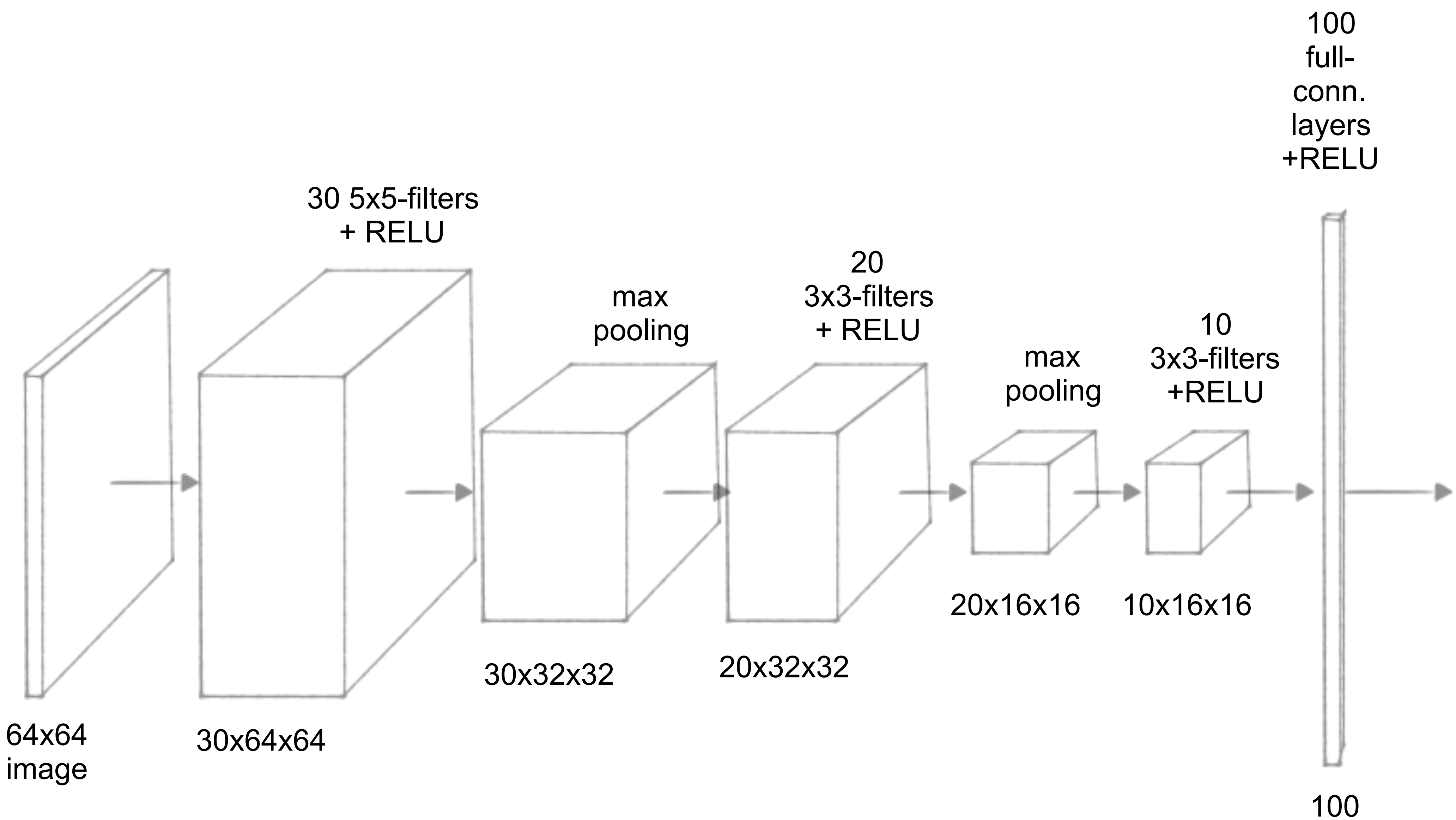


Network Structure



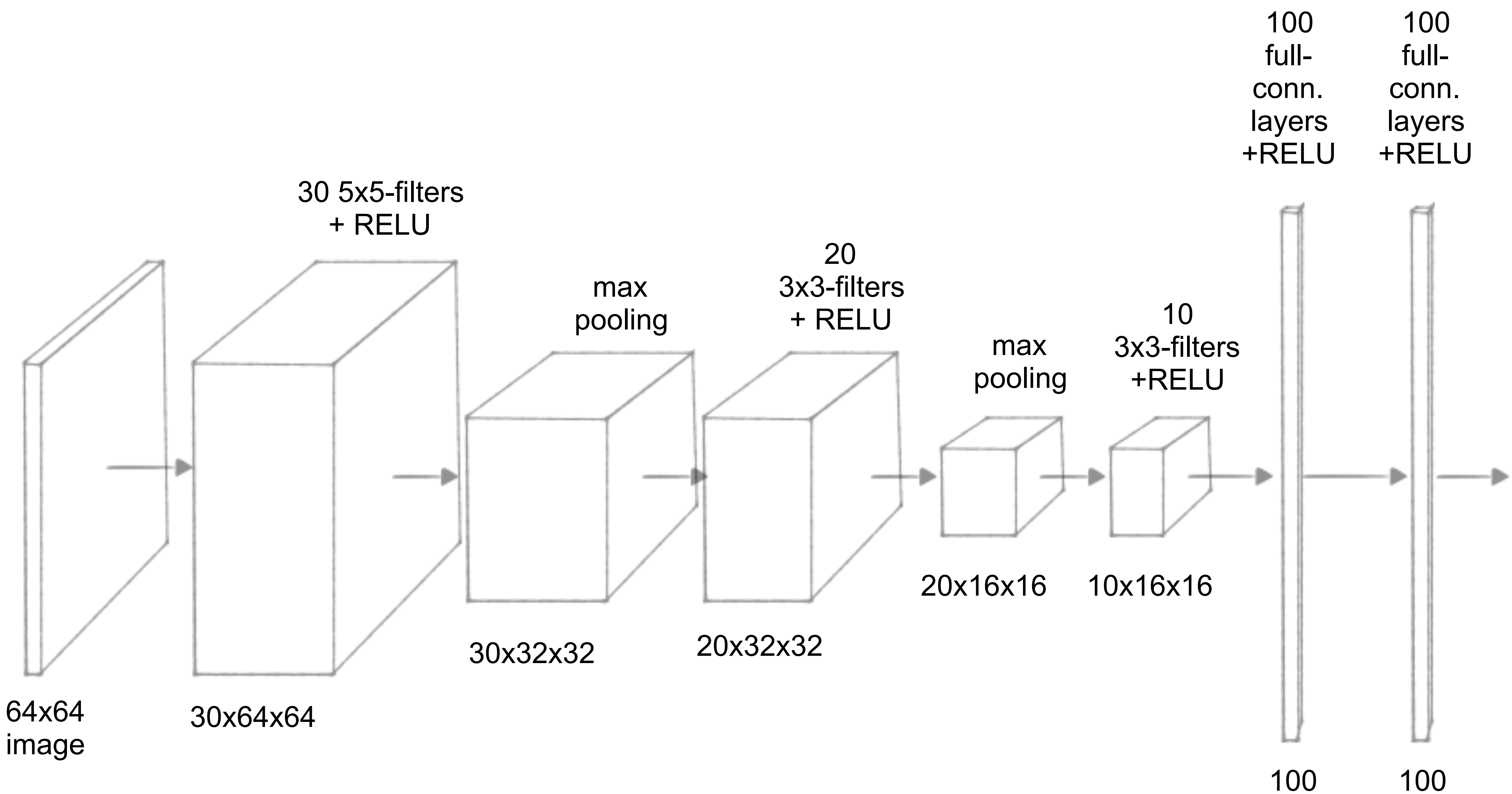
$$\max\{I \otimes f, 0\}$$

Network Structure

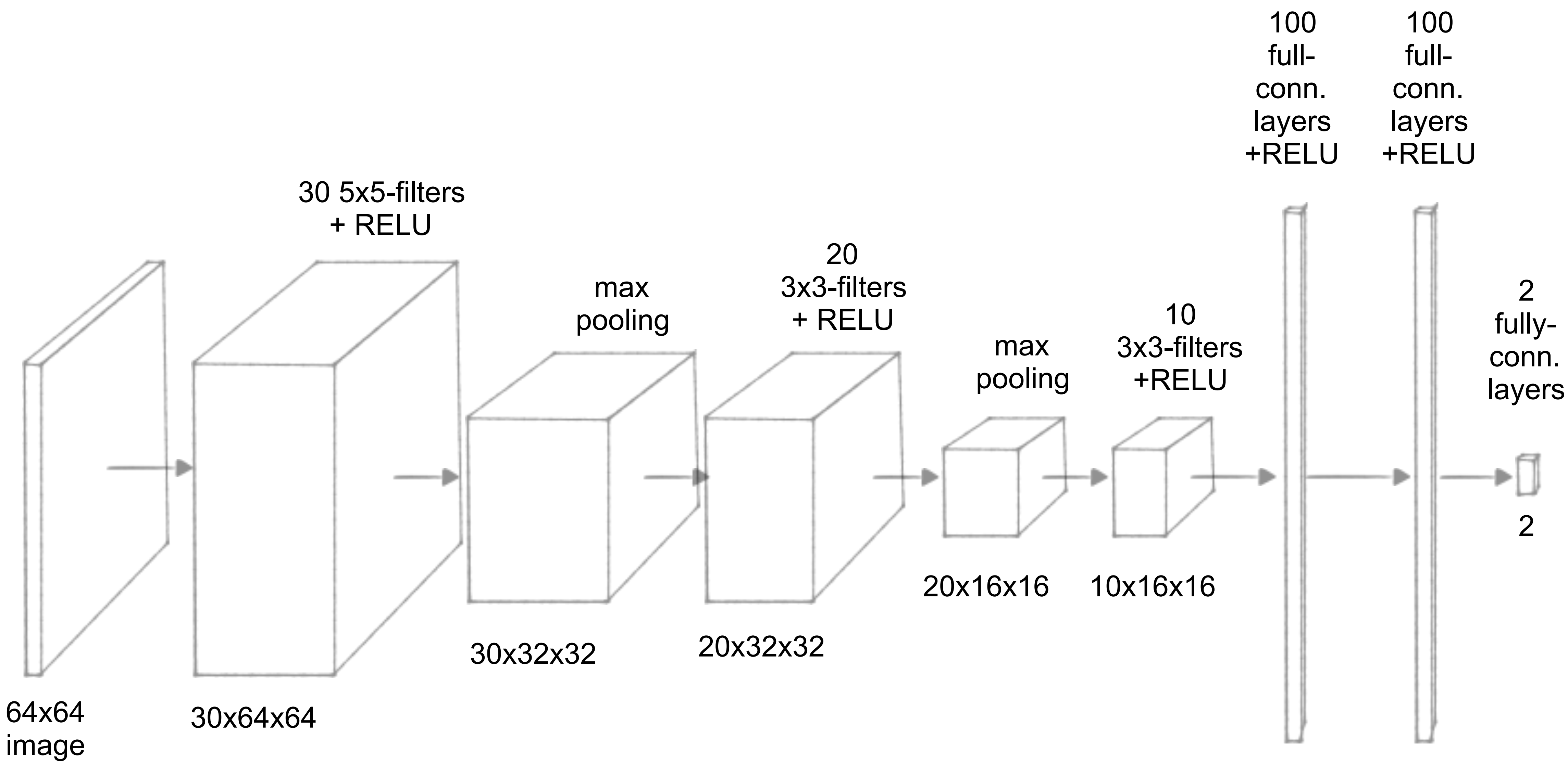


$$\sum_{i=1}^{10} \sum_{u=1}^{16} \sum_{v=1}^{16} w_{ijk} x_{ijk}$$

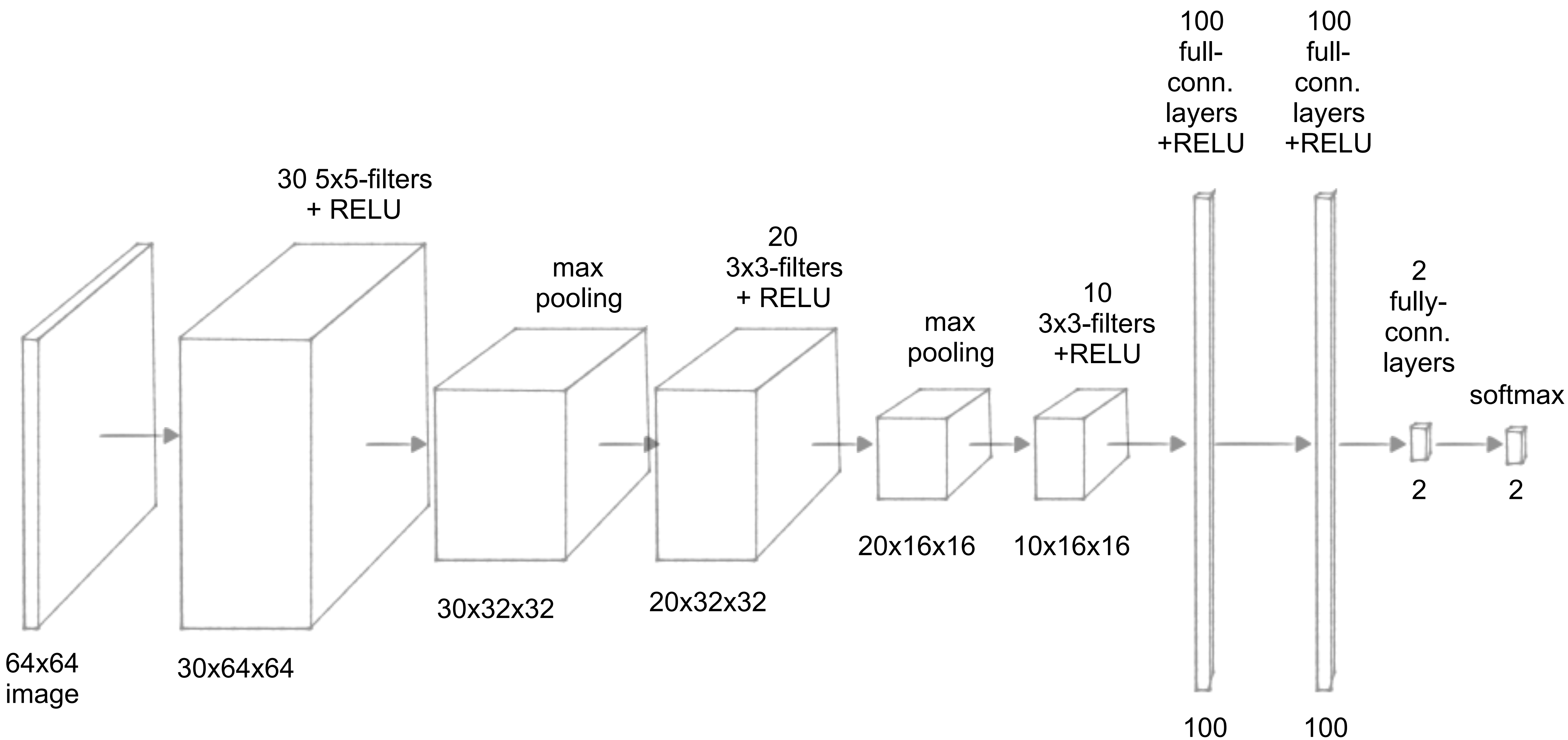
Network Structure



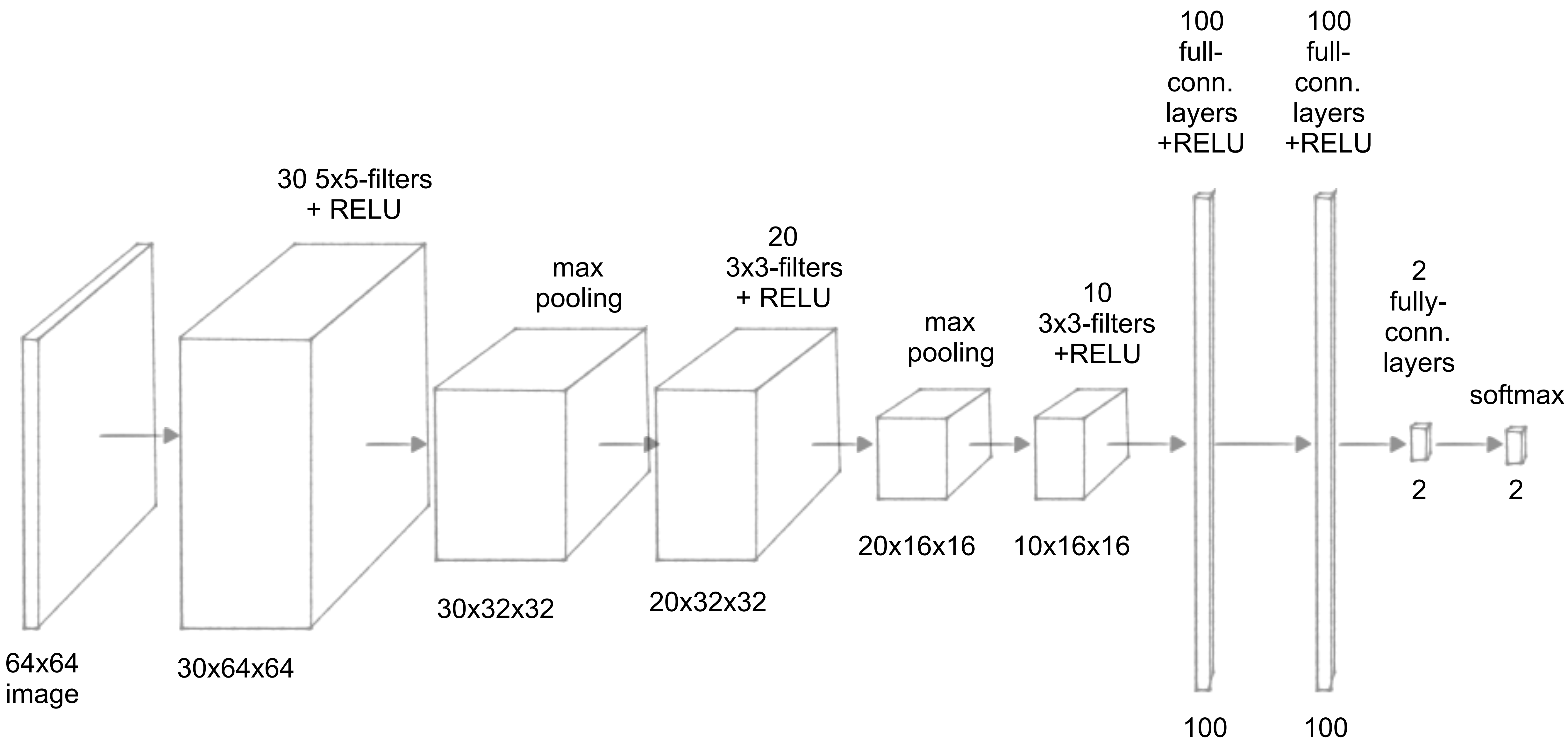
Network Structure



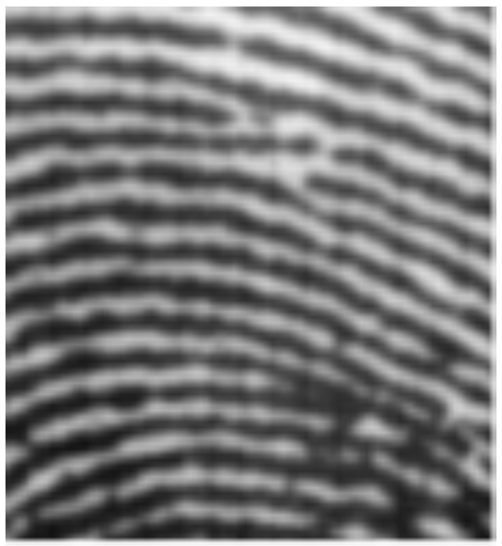
Network Structure

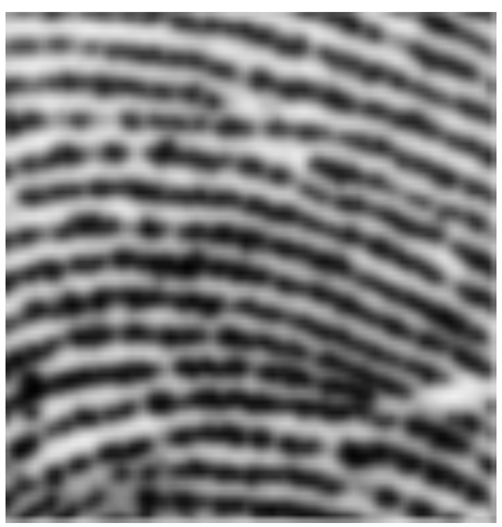


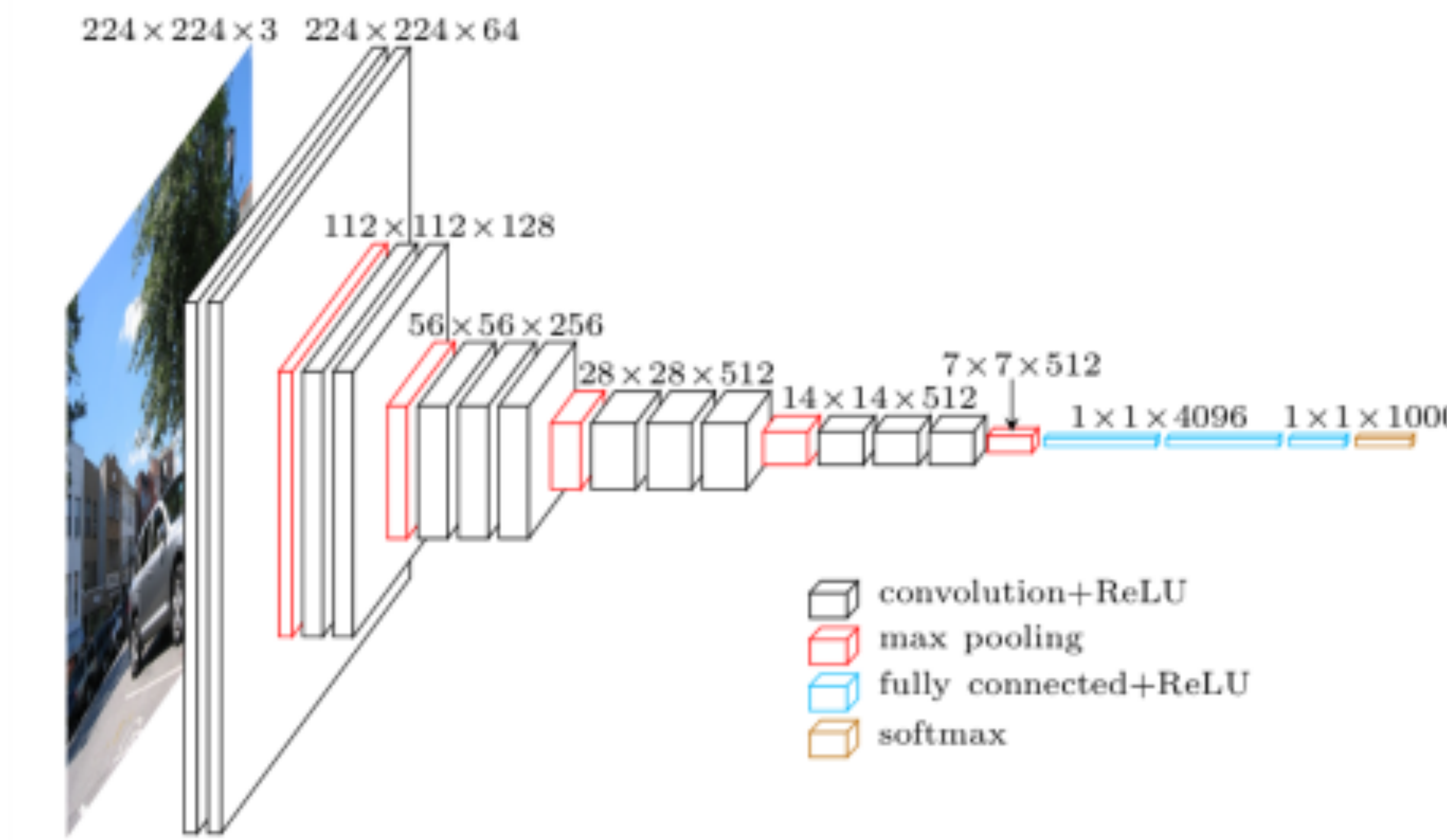
Number Parameters?



Live or Spoof?





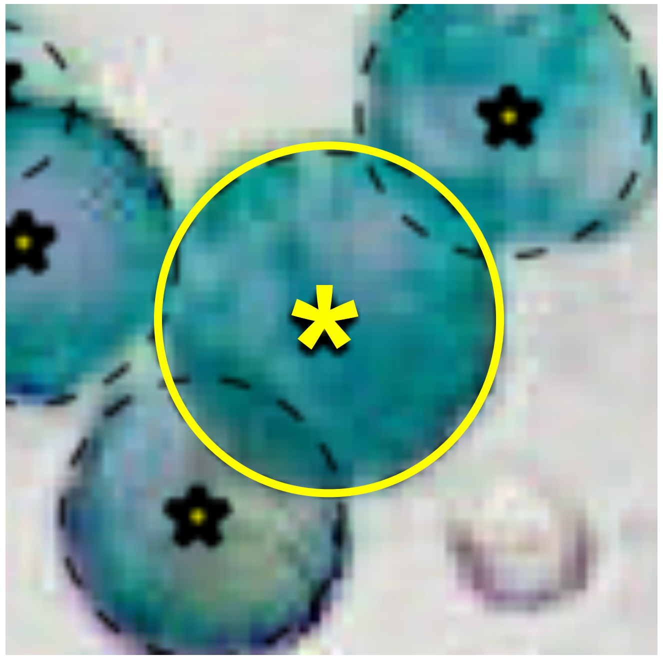


VGG-16

[Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

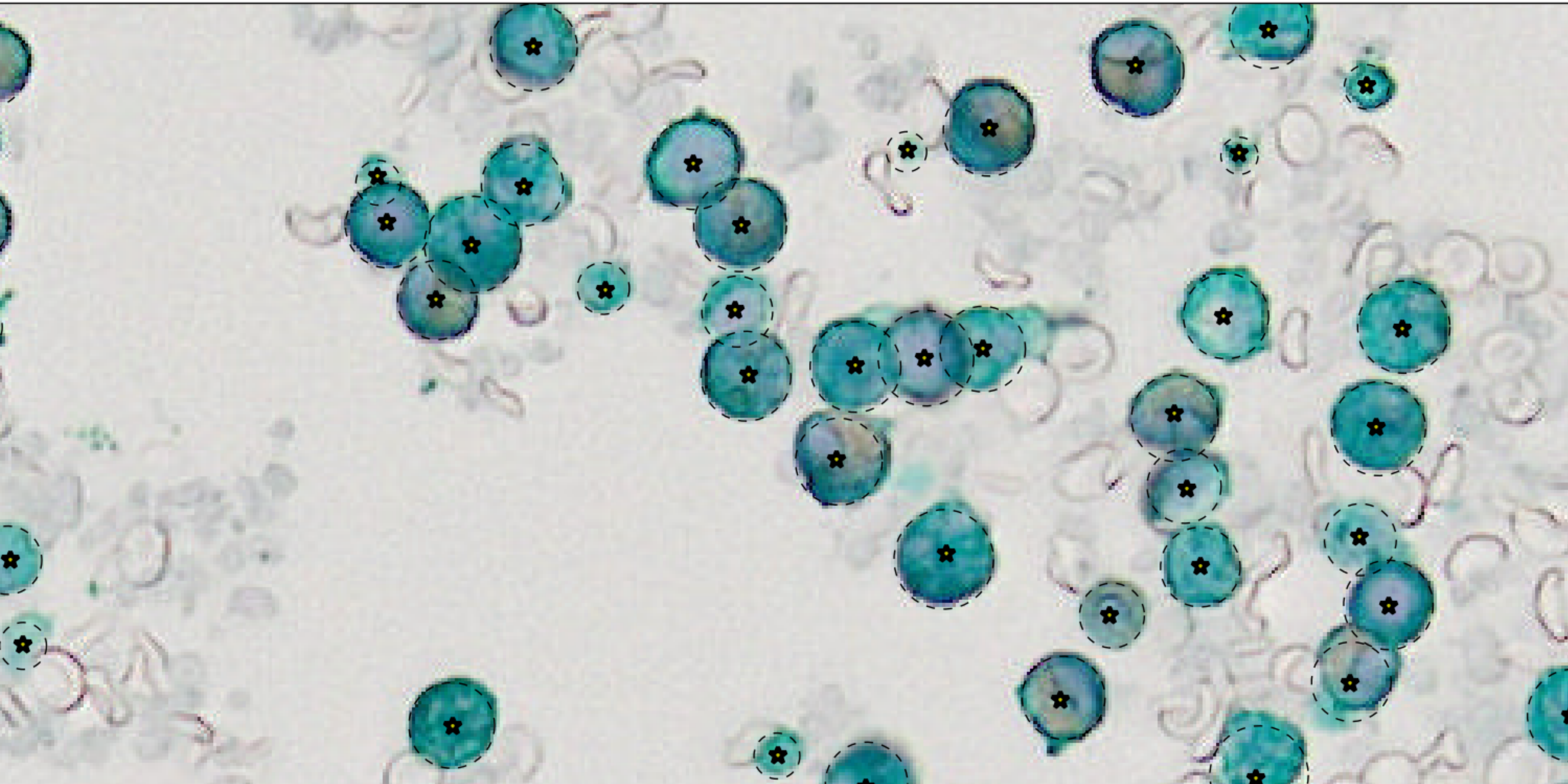
Regression: Centre and Radius

- No softmax
- Quadratic loss function

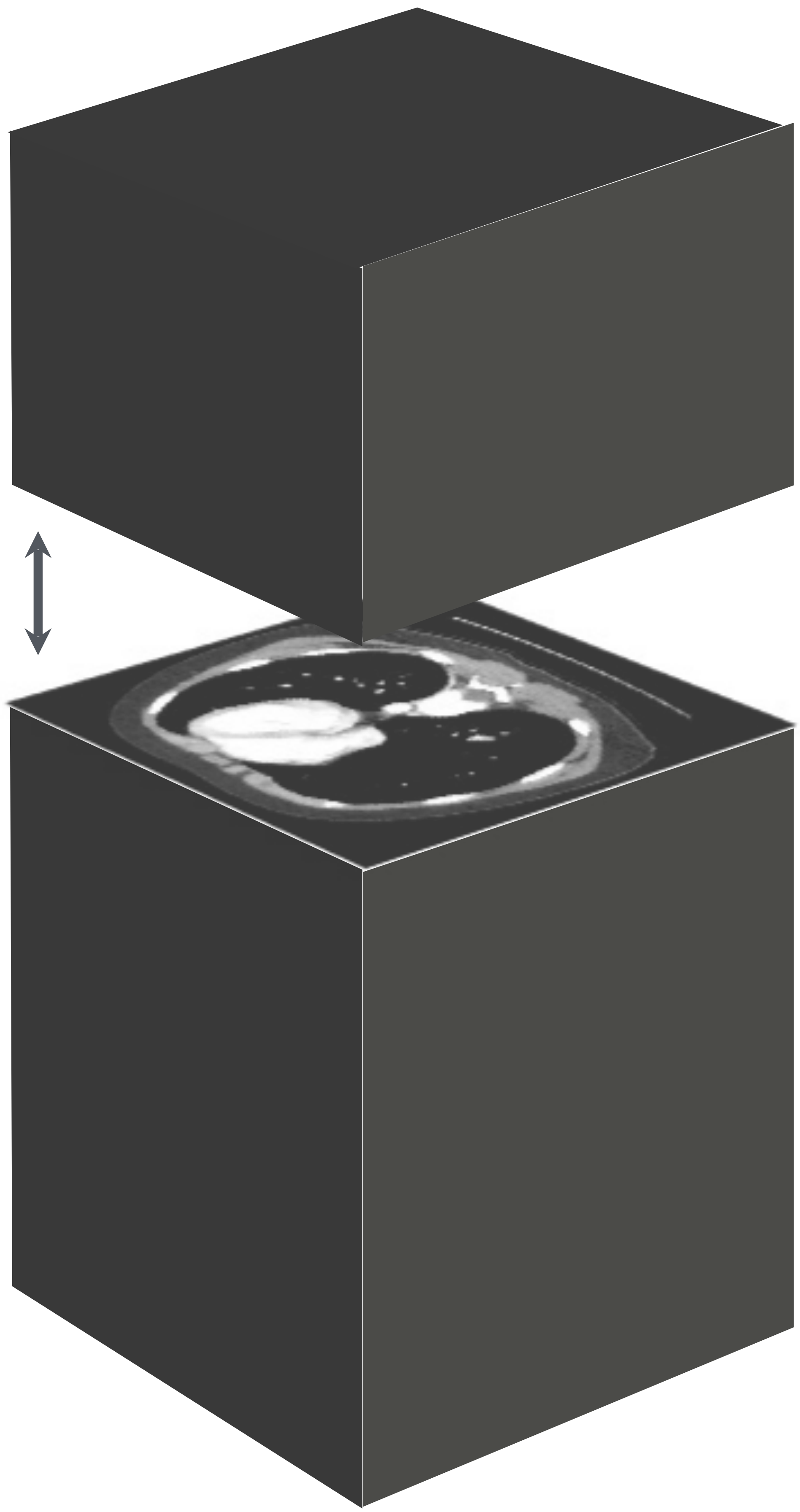


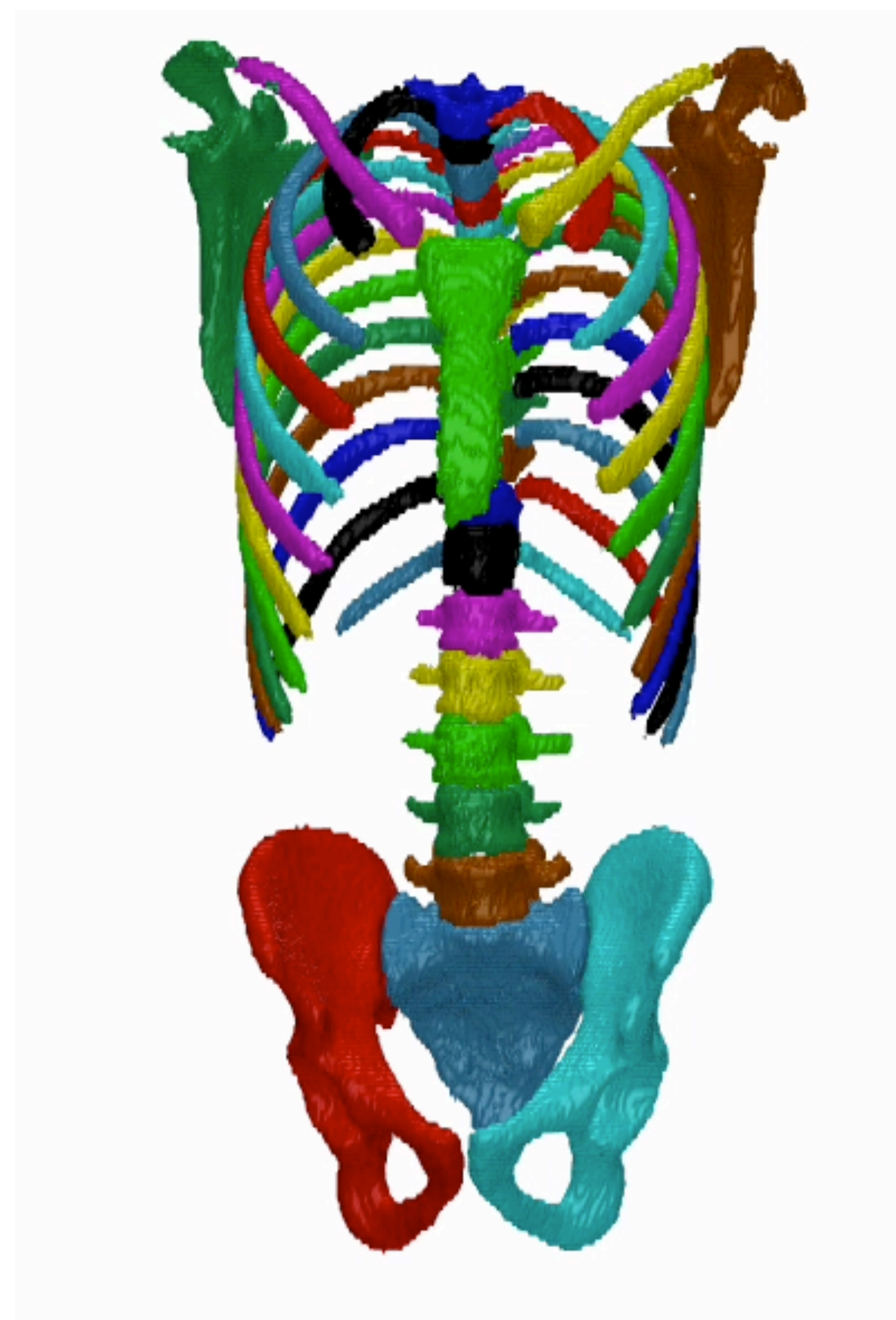
Centre and Radius

- No softmax
- Quadratic loss function

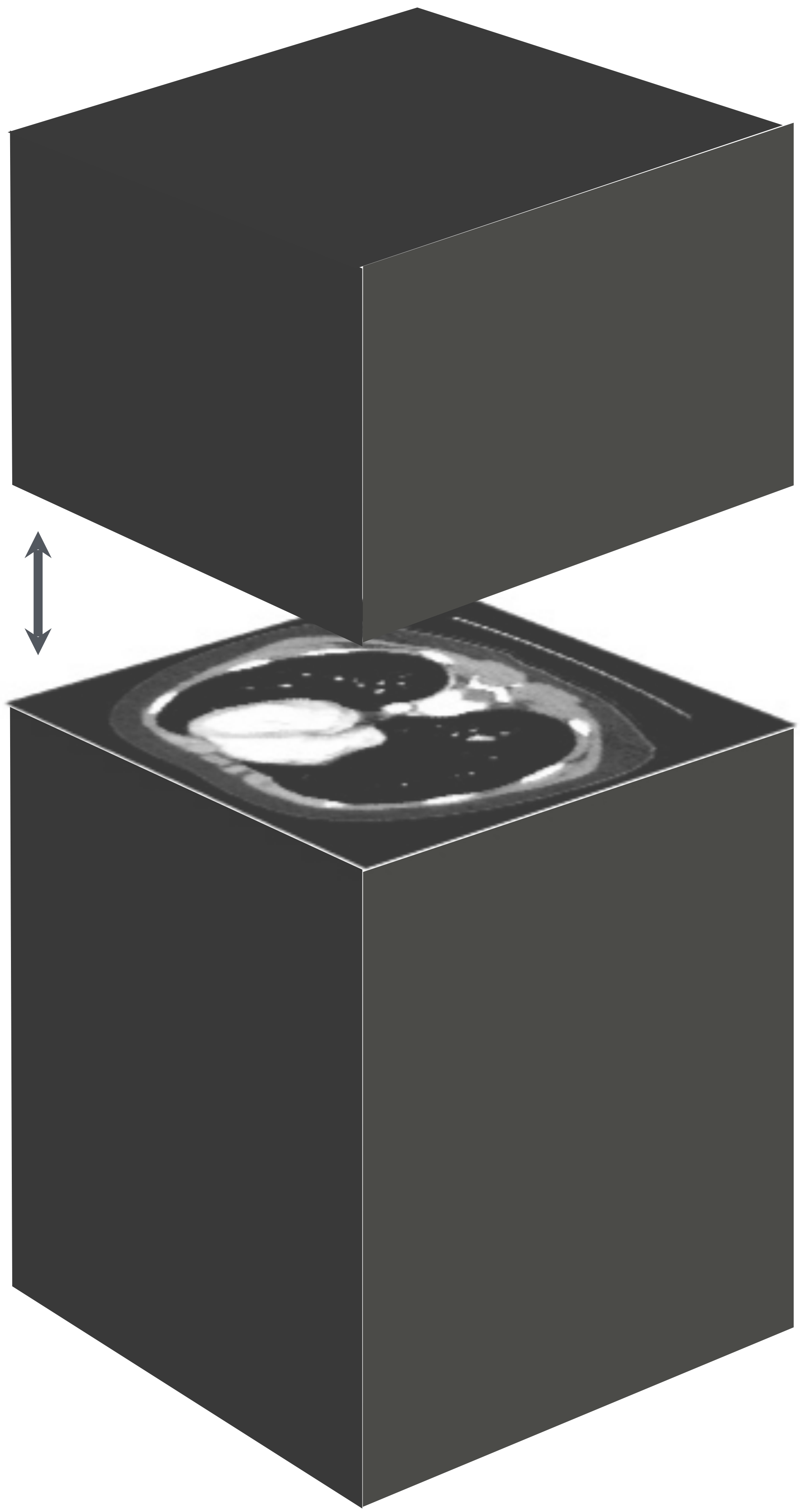


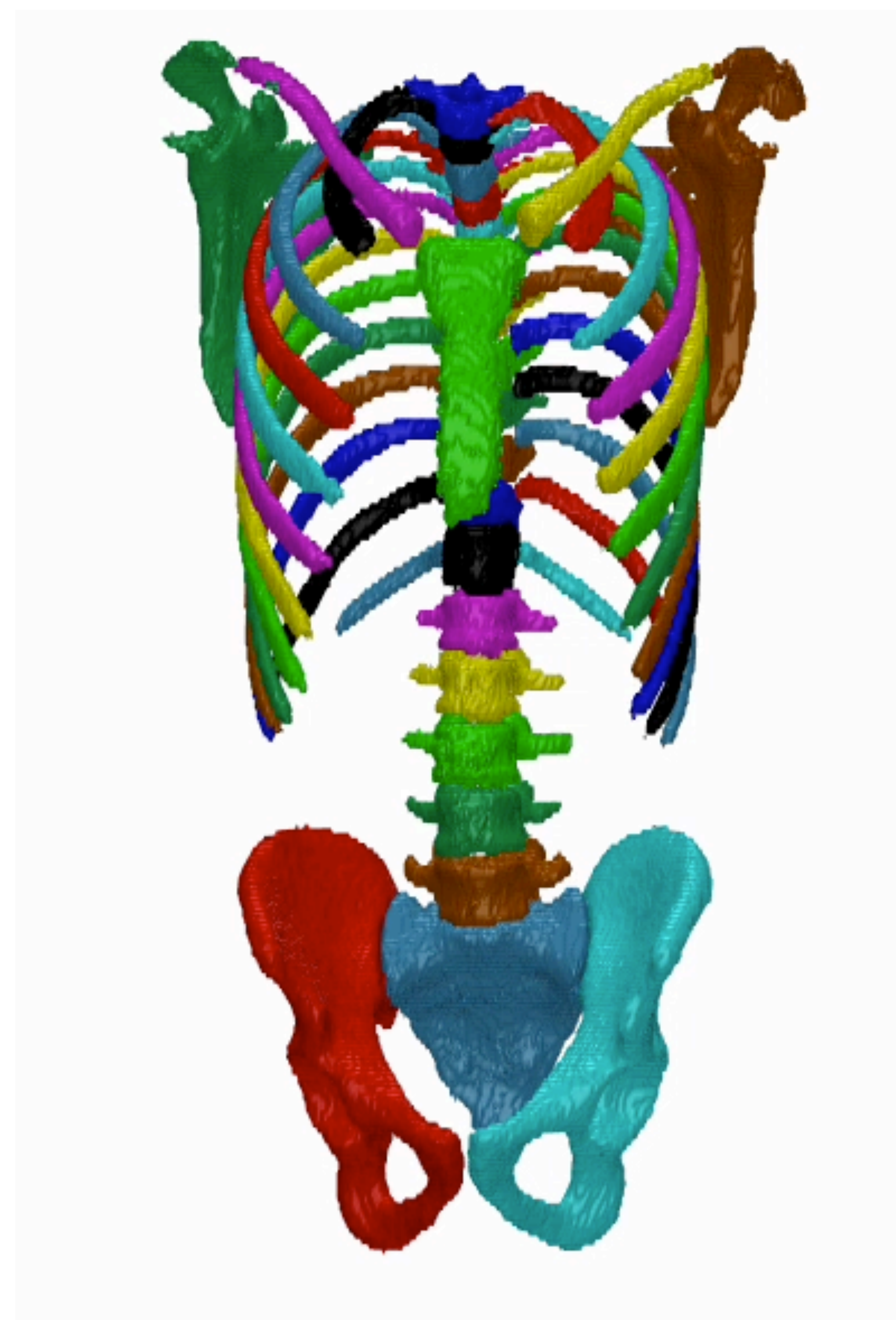
Segmentation



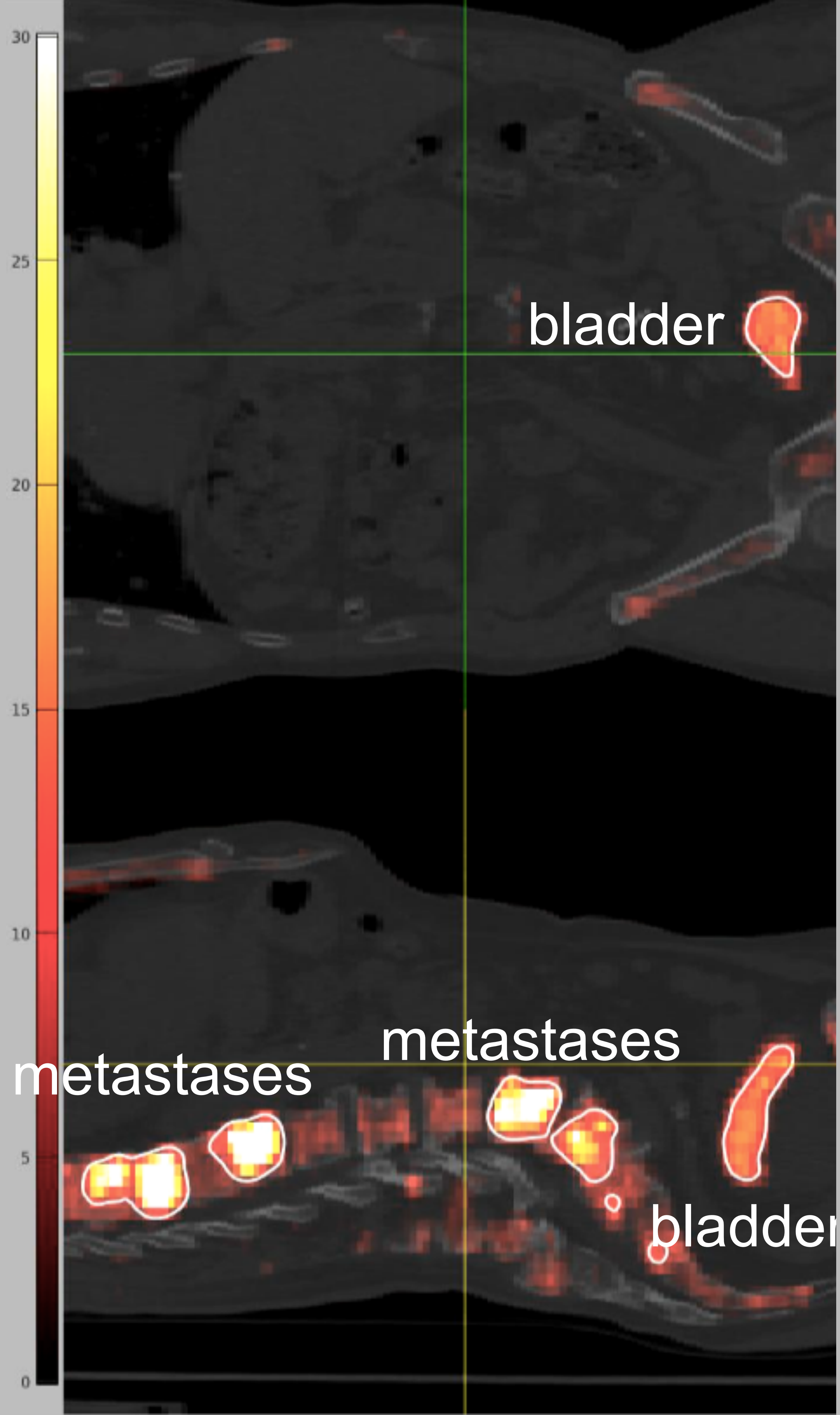


Segmentation

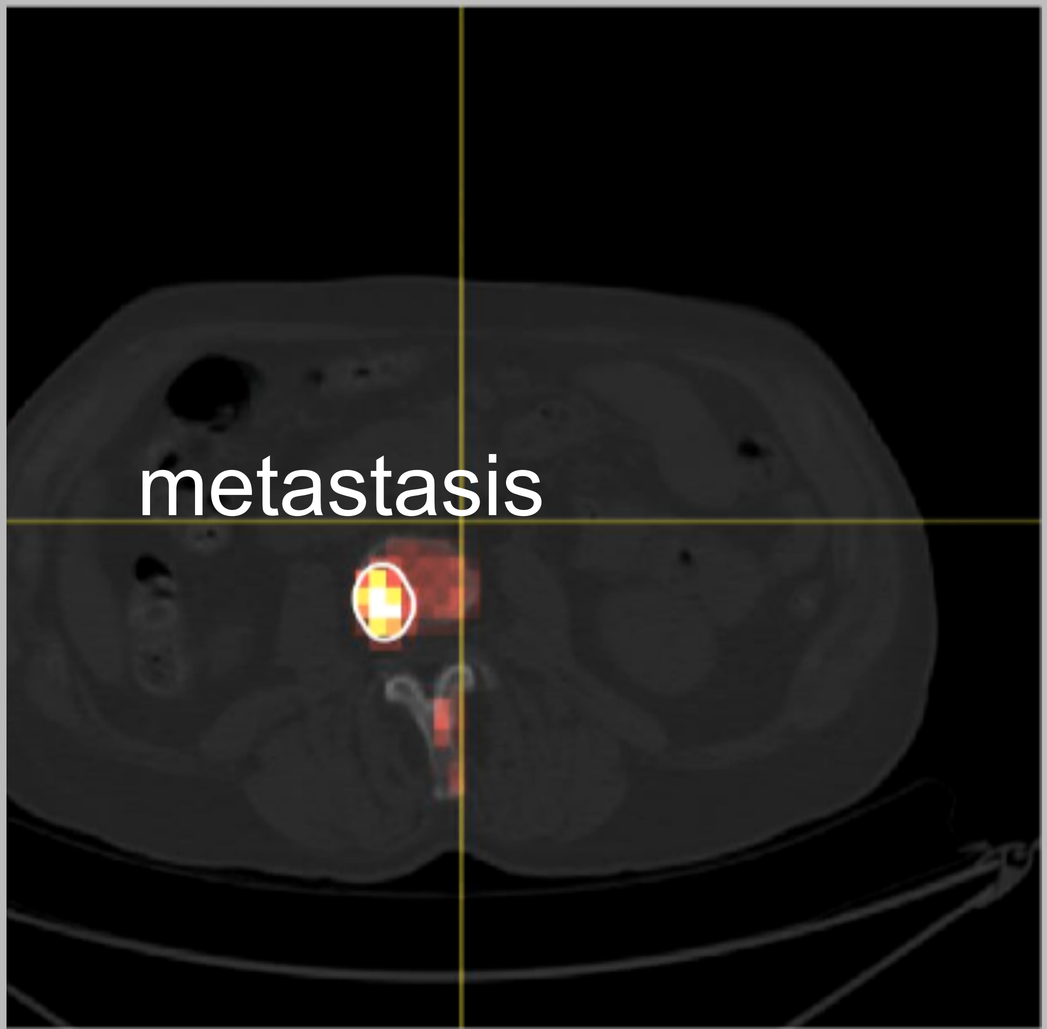




Diagnosis



30
25
20
15
10
5
0
bladder
metastases
metastases
bladder

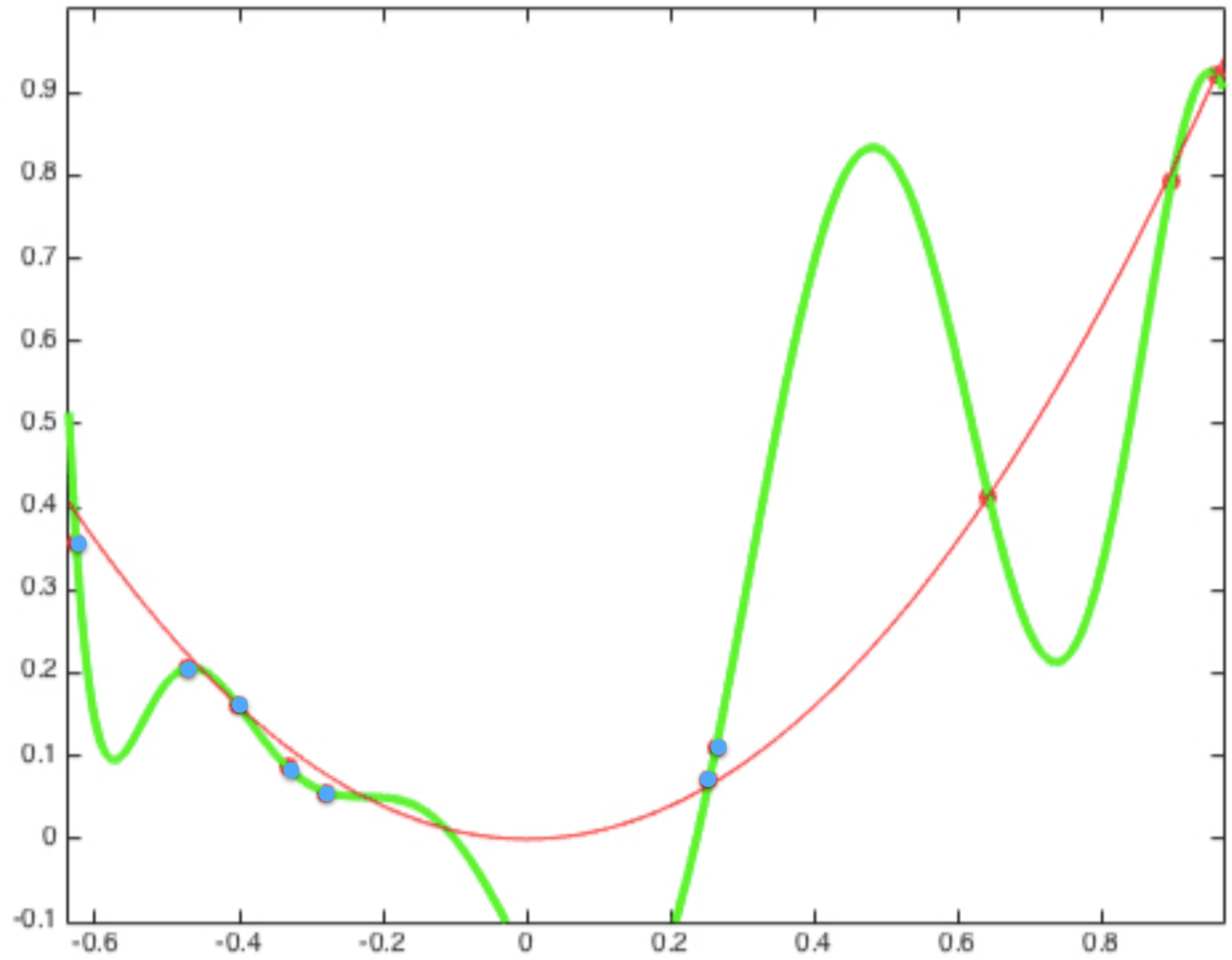


metastasis

Overfitting, Part II

Overfitting

10 data points - Fitting 10th degree polynomial



$$y = x^2$$

Overfitting

VGG-16 architecture

[Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

Overfitting

VGG-16 architecture

224

224

Conv 64 3x3

Conv 64 3x3

max pooling

conv 1

[Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

Overfitting

VGG-16 architecture

224

224

Conv 64 3x3	Conv 64 3x3	max pooling	**conv 1**
Conv 128 3x3	Conv 128 3x3	max pooling	**conv 2**

[Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

Overfitting

VGG-16 architecture

224

224

Conv 64 3x3	Conv 64 3x3	max pooling		**conv 1**
Conv 128 3x3	Conv 128 3x3	max pooling		**conv 2**
Conv 256 3x3	Conv 256 3x3	Conv 256 3x3	max pooling	**conv 3**

[Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

Overfitting

VGG-16 architecture

224

224

Conv 64 3x3	Conv 64 3x3	max pooling		**conv 1**
Conv 128 3x3	Conv 128 3x3	max pooling		**conv 2**
Conv 256 3x3	Conv 256 3x3	Conv 256 3x3	max pooling	**conv 3**
Conv 512 3x3	Conv 512 3x3	Conv 512 3x3	max pooling	**conv 4**

[Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

Overfitting

VGG-16 architecture

224

224

Conv 64 3x3	Conv 64 3x3	max pooling		**conv 1**
Conv 128 3x3	Conv 128 3x3	max pooling		**conv 2**
Conv 256 3x3	Conv 256 3x3	Conv 256 3x3	max pooling	**conv 3**
Conv 512 3x3	Conv 512 3x3	Conv 512 3x3	max pooling	**conv 4**
Conv 512 3x3	Conv 512 3x3	Conv 512 3x3	max pooling	**conv 5**

[Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

Overfitting

VGG-16 architecture

224

224

Conv 64 3x3	Conv 64 3x3	max pooling		**conv 1**
Conv 128 3x3	Conv 128 3x3	max pooling		**conv 2**
Conv 256 3x3	Conv 256 3x3	Conv 256 3x3	max pooling	**conv 3**
Conv 512 3x3	Conv 512 3x3	Conv 512 3x3	max pooling	**conv 4**
Conv 512 3x3	Conv 512 3x3	Conv 512 3x3	max pooling	**conv 5**
FC 4096	FC 4096	FC 1000	soft max	

[Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

Overfitting

VGG-16 architecture

224

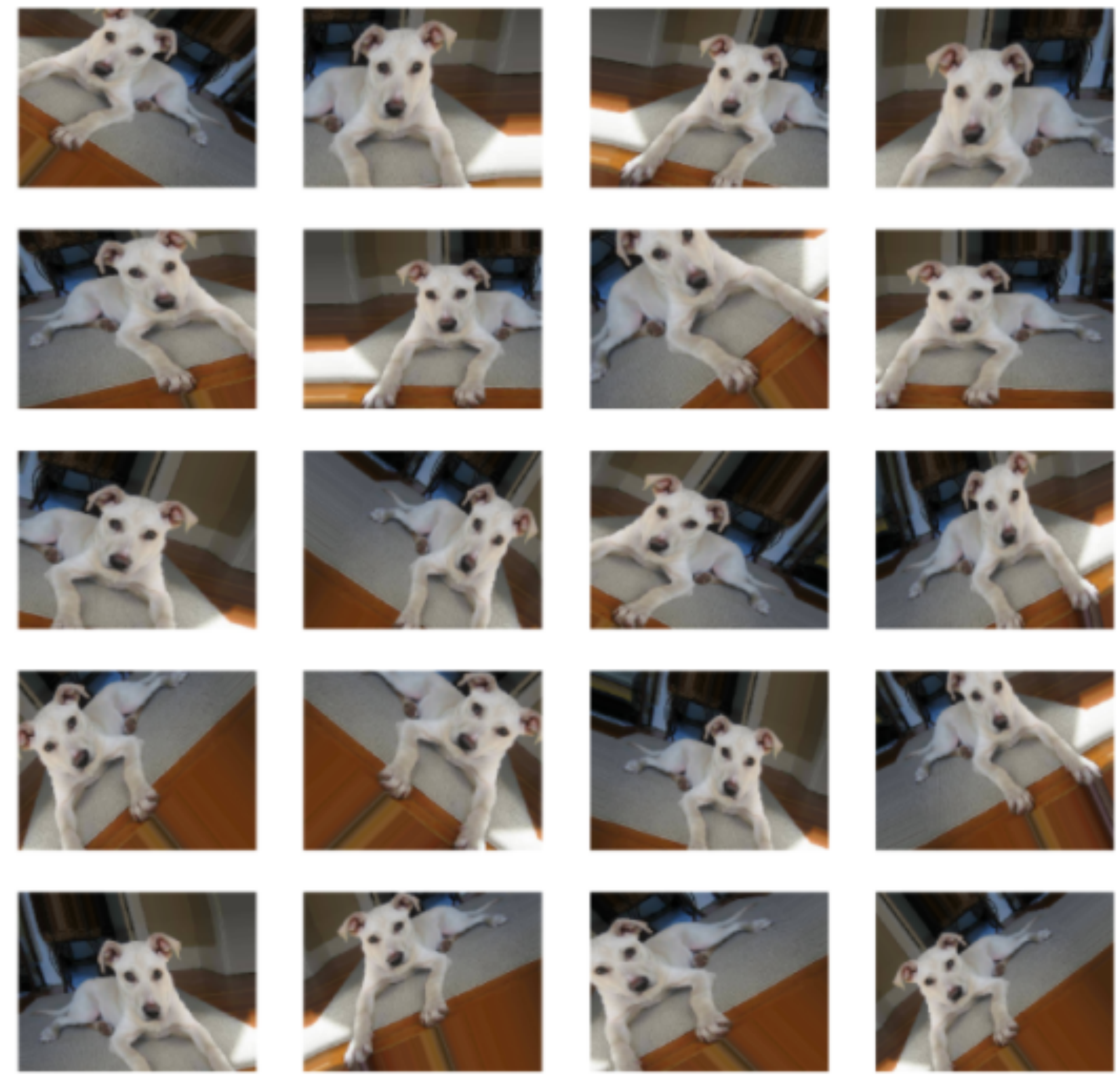
224

~138M parameters!

Conv 64 3x3	Conv 64 3x3	max pooling		**conv 1**
Conv 128 3x3	Conv 128 3x3	max pooling		**conv 2**
Conv 256 3x3	Conv 256 3x3	Conv 256 3x3	max pooling	**conv 3**
Conv 512 3x3	Conv 512 3x3	Conv 512 3x3	max pooling	**conv 4**
Conv 512 3x3	Conv 512 3x3	Conv 512 3x3	max pooling	**conv 5**
FC 4096	FC 4096	FC 1000	soft max	

[Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015]

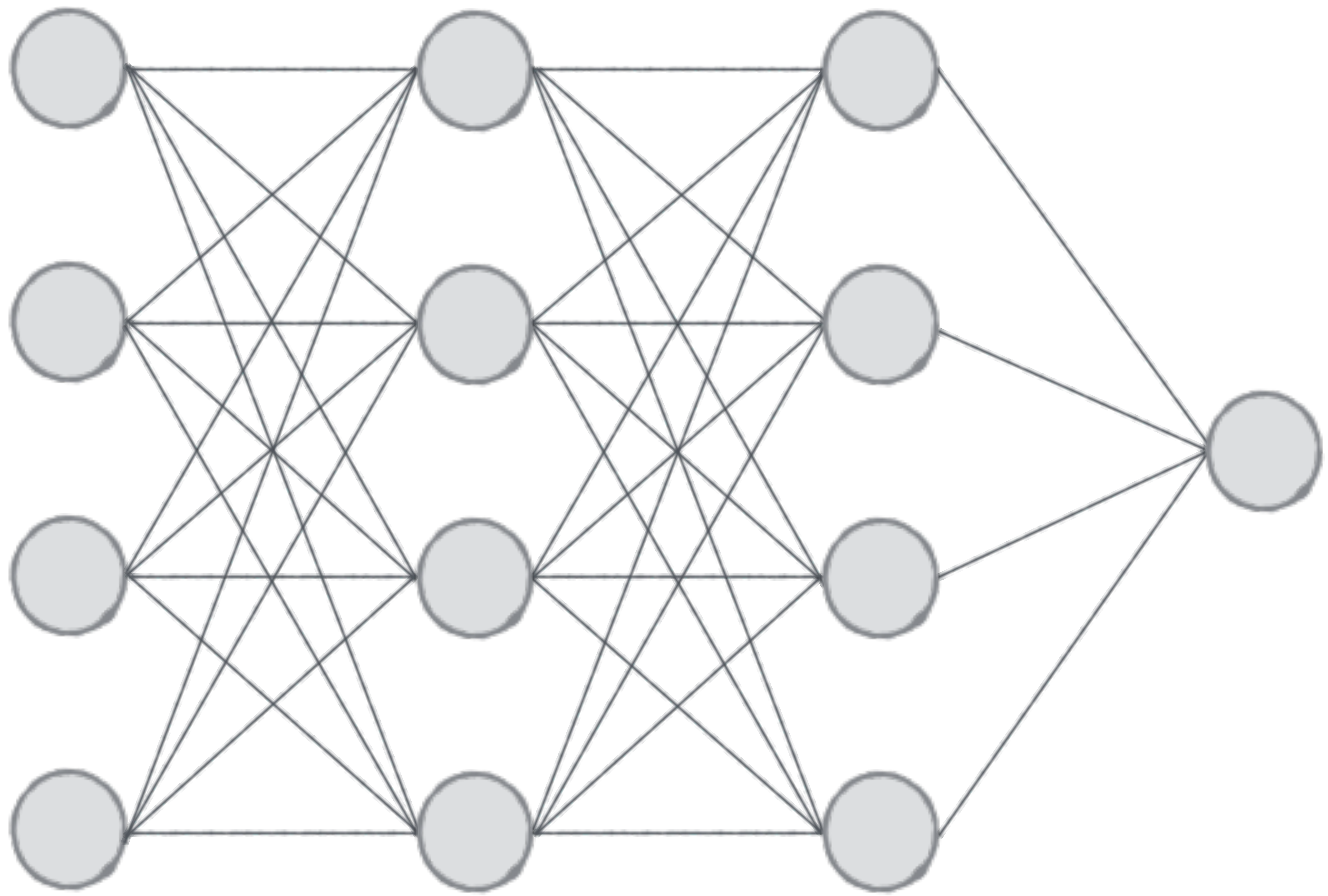
Data Augmentation



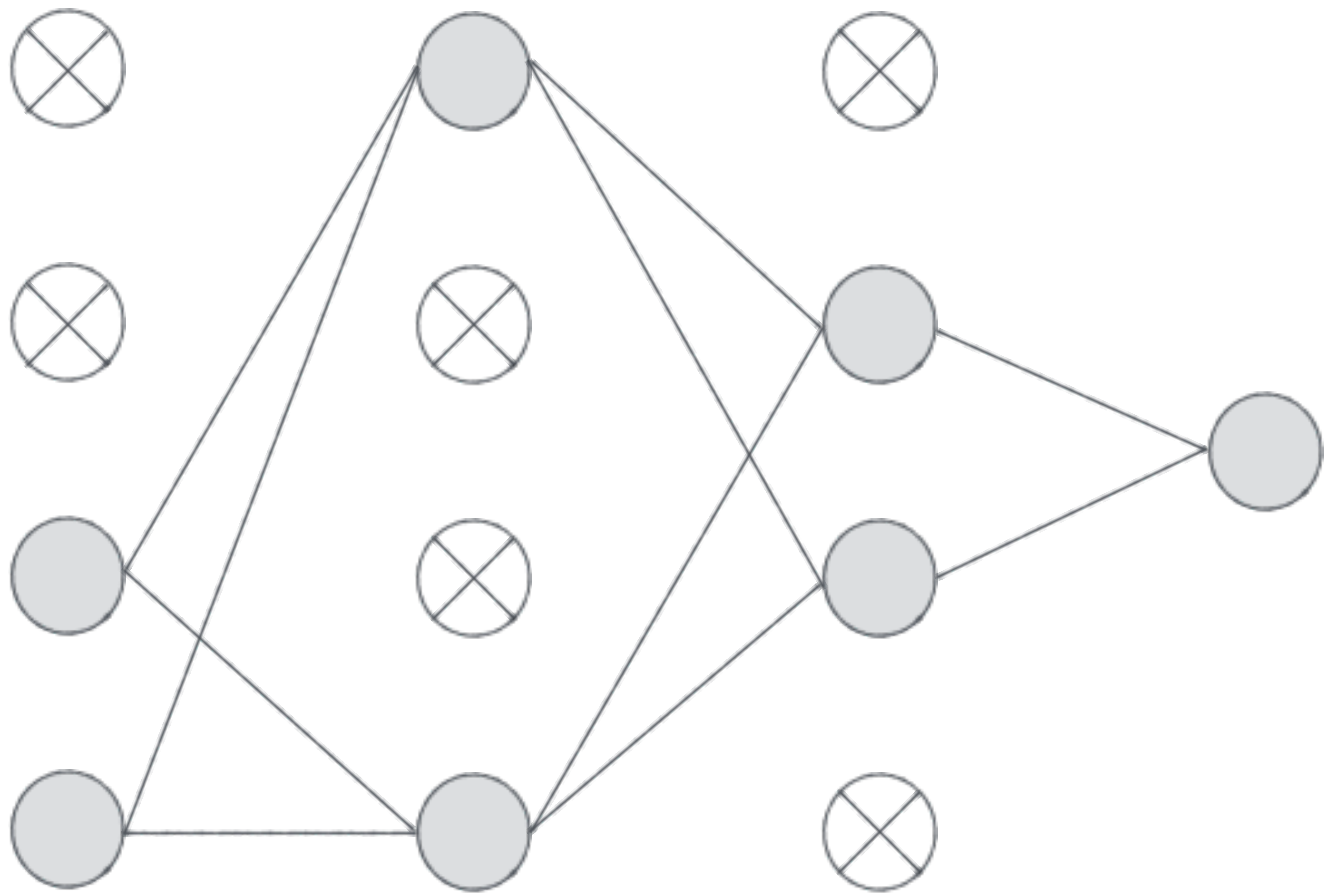
Regularization

$$L(w_1, \ldots, w_n) + c \sum_i w_i^2$$

Dropout



Dropout



Randomly disable neurons for each minibatch

Dropout

Transfer Learning

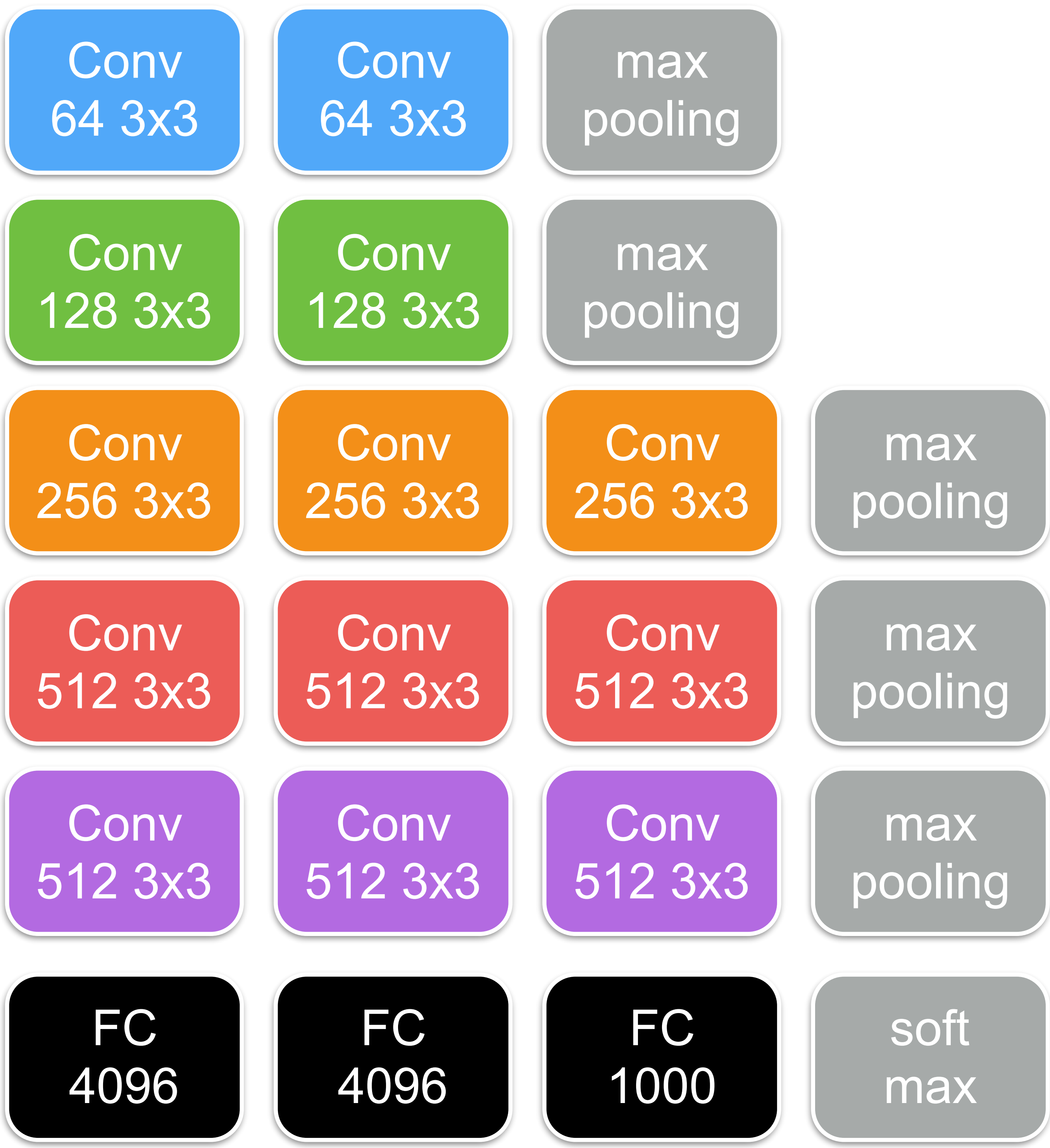
IMAGENET

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., ... & Fei-Fei, L. (2015). Imagenet large scale visual recognition challenge. *arXiv preprint arXiv:1409.0575*. [web]

14 million images of 1000 classes

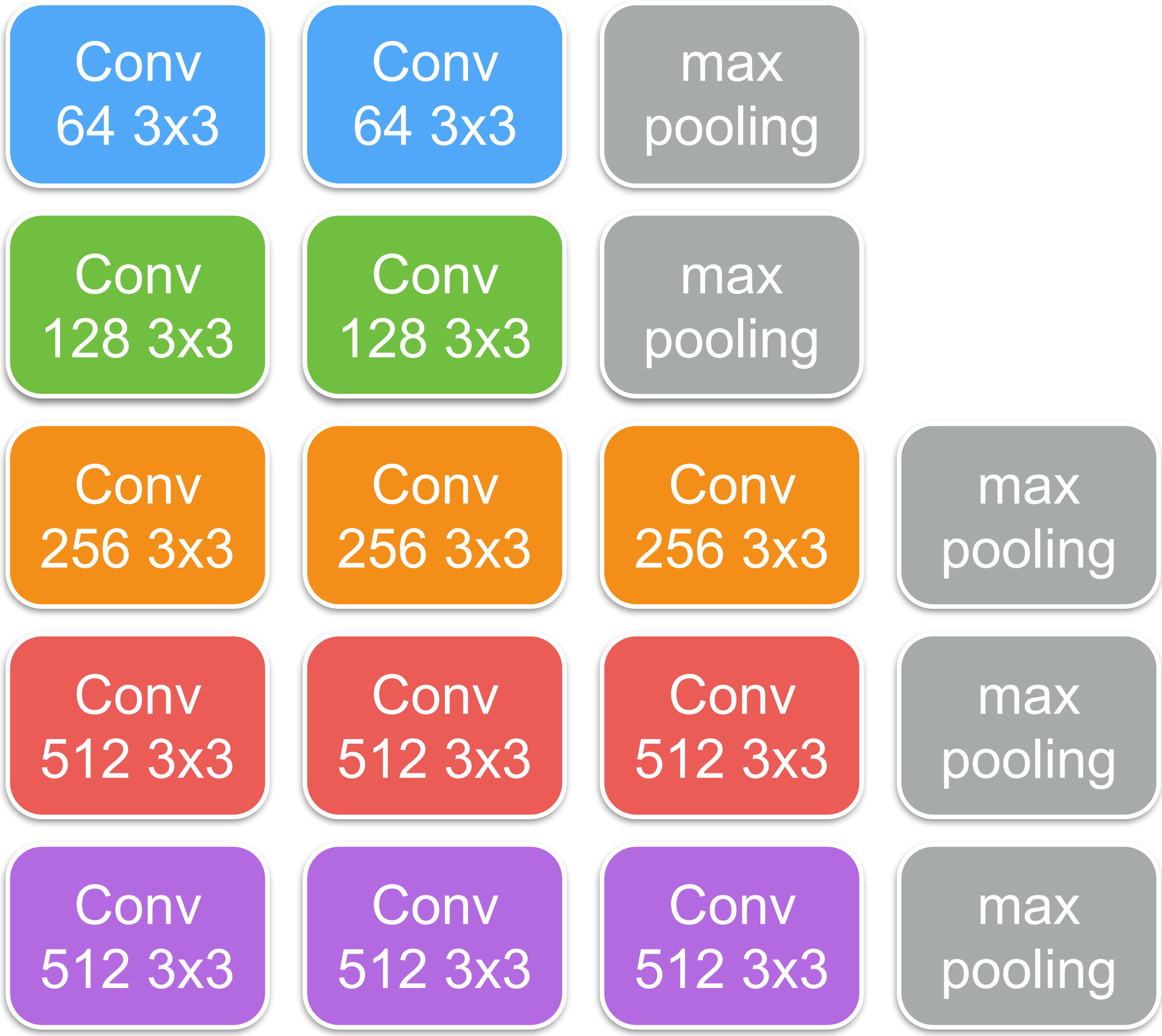
Transfer Learning

VGG-16 architecture



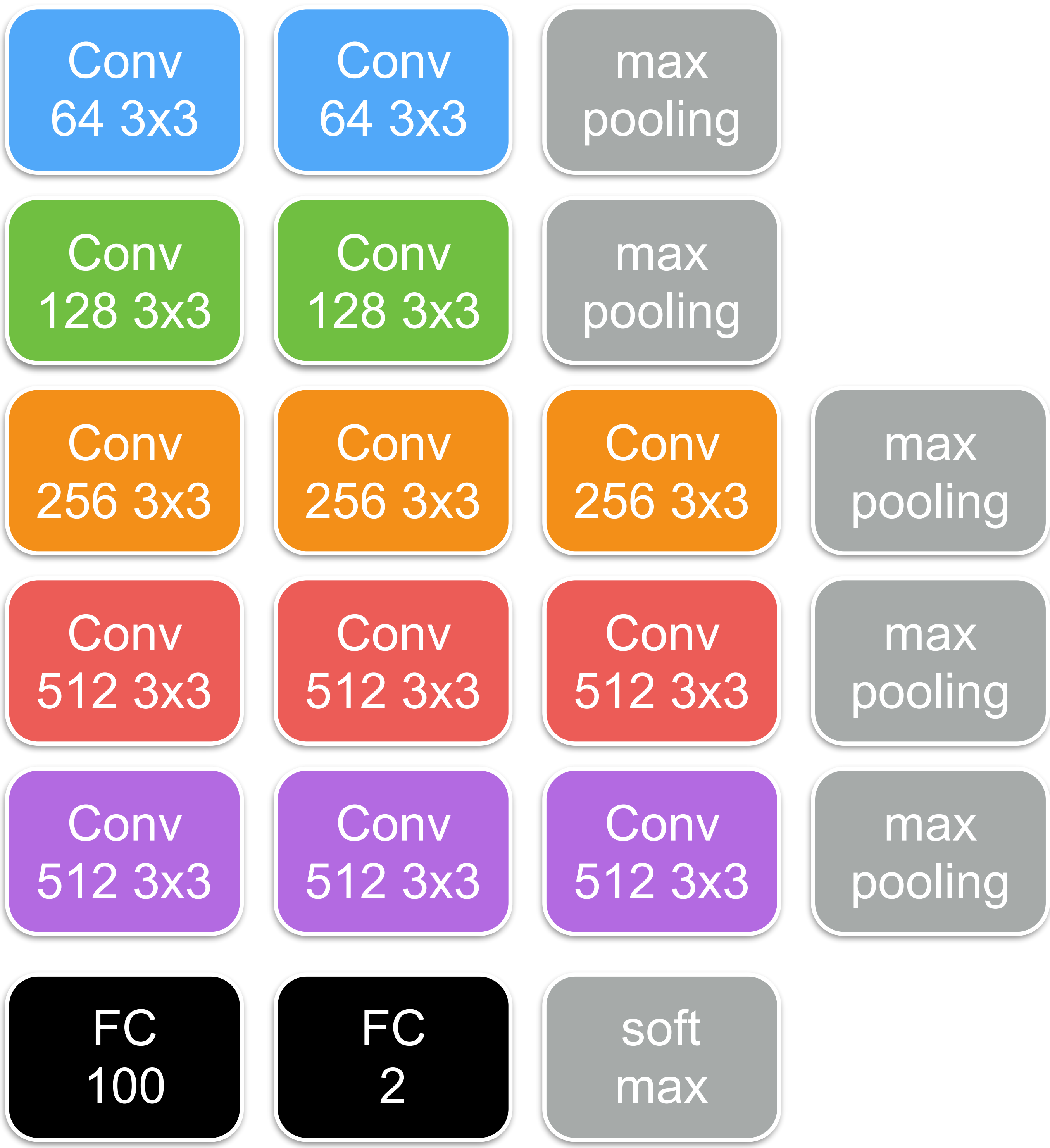
Transfer Learning

VGG-16 architecture



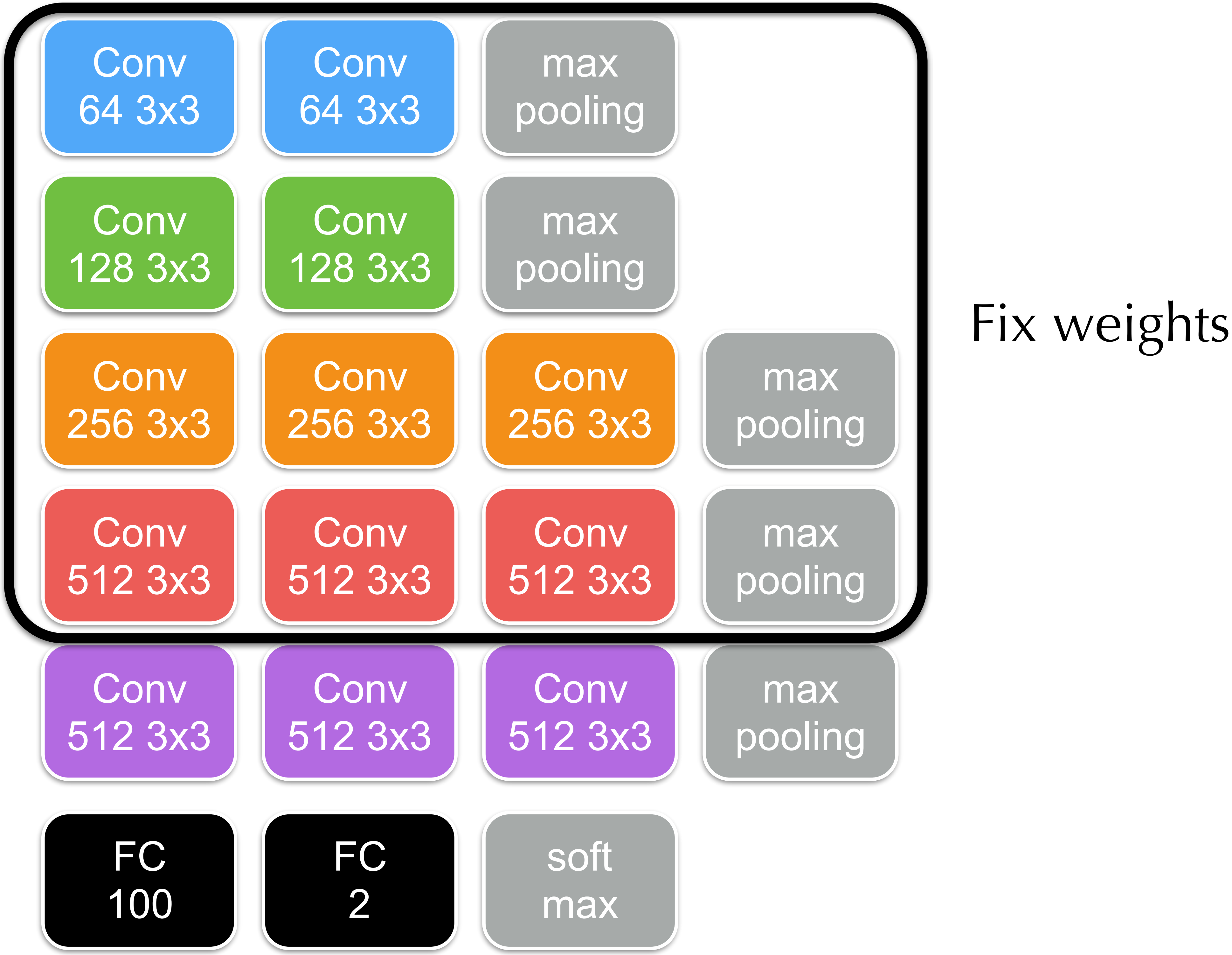
Transfer Learning

VGG-16 architecture



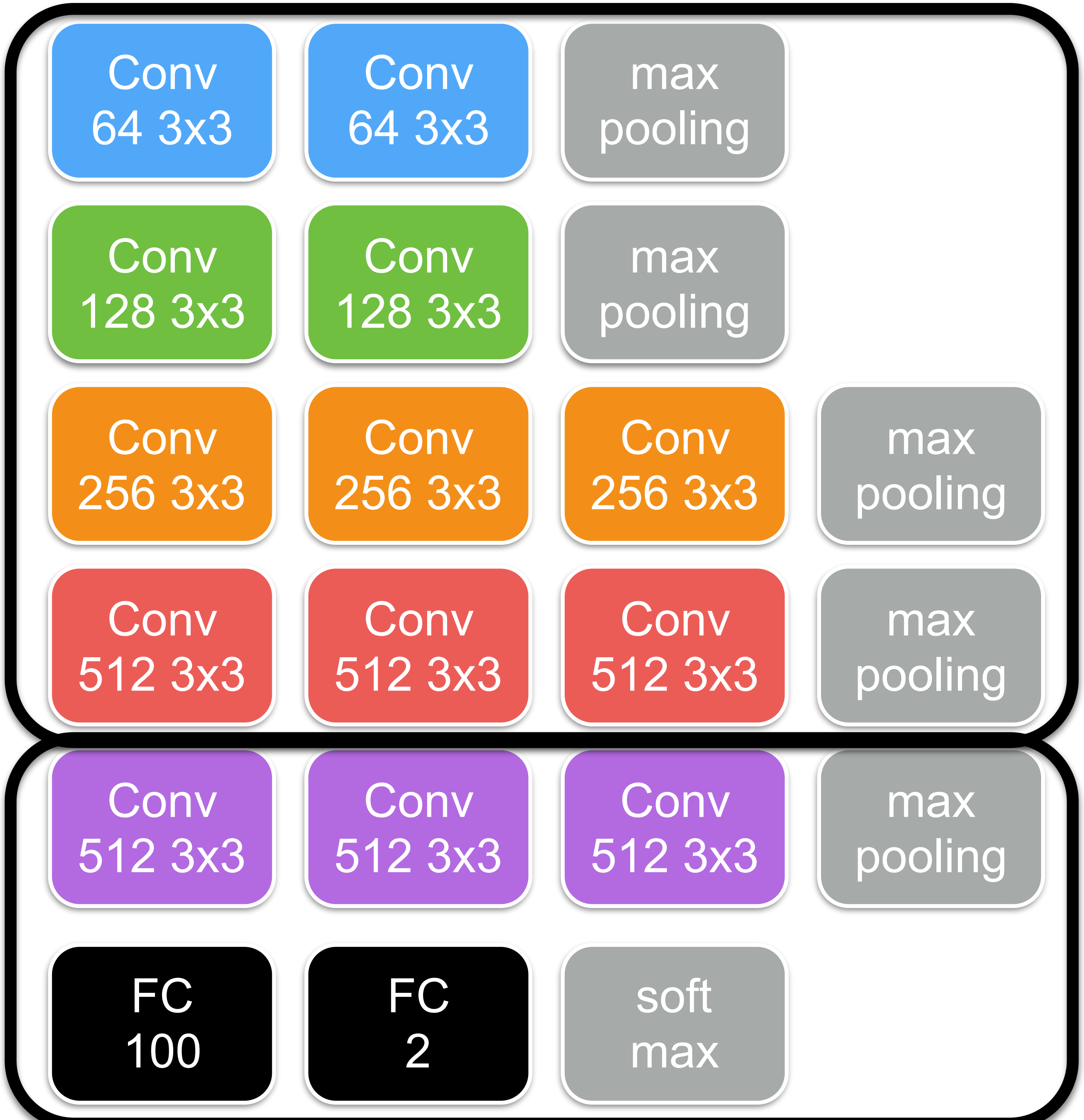
Transfer Learning

VGG-16 architecture



Transfer Learning

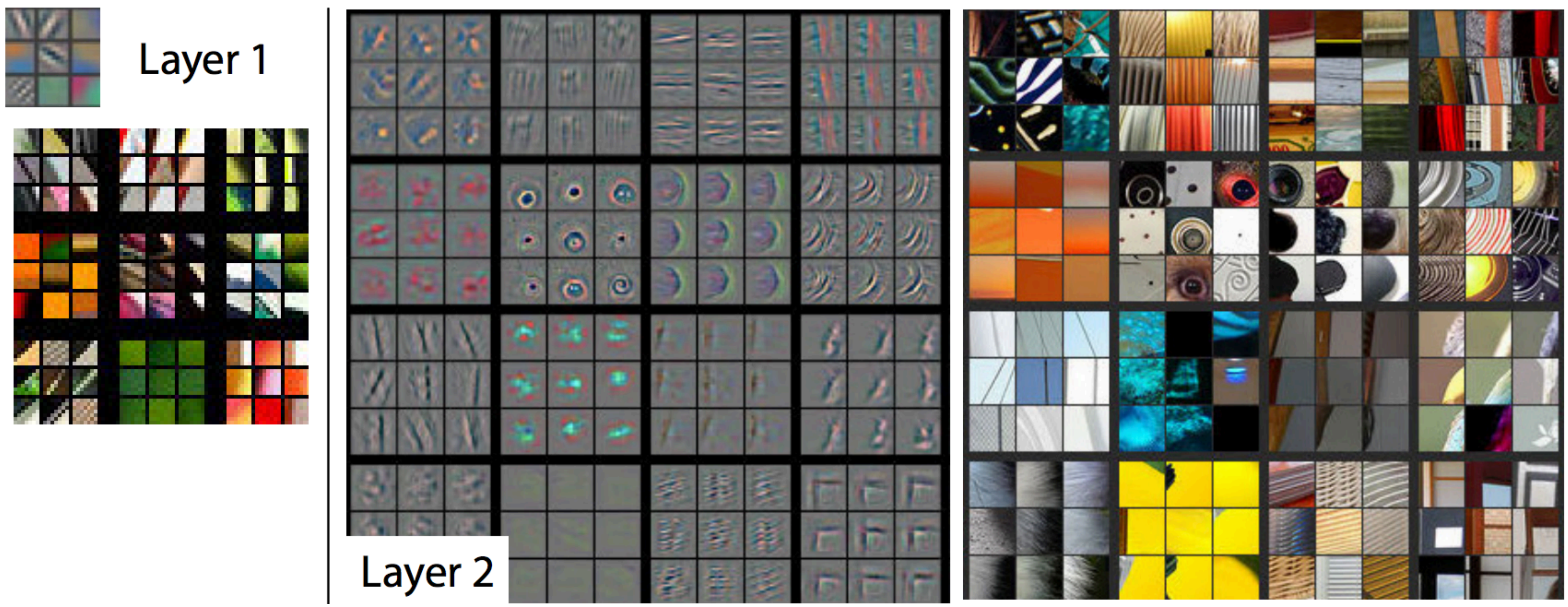
VGG-16 architecture



Fix weights

Train on limited data

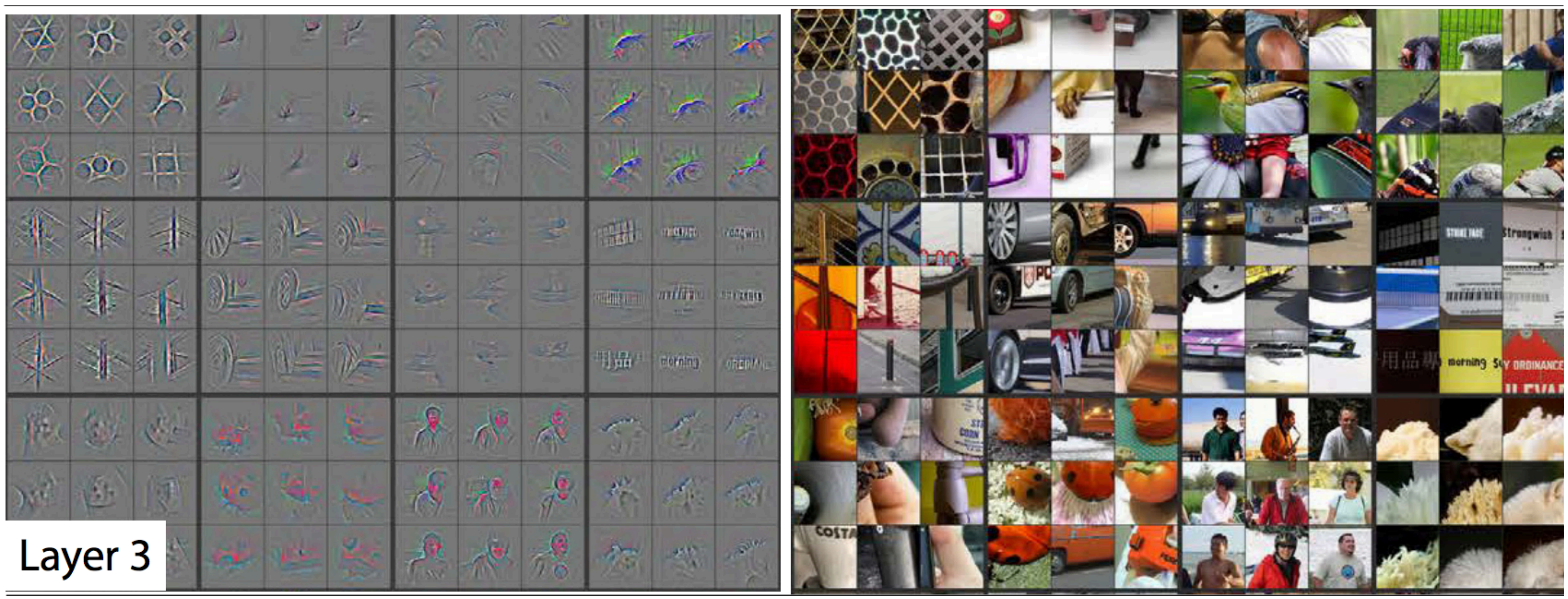
Transfer Learning



Low-level features: corners, edges, ...

[Zeiler & Fergus, Visualizing and Understanding Convolutional Networks, ECCV 2014]

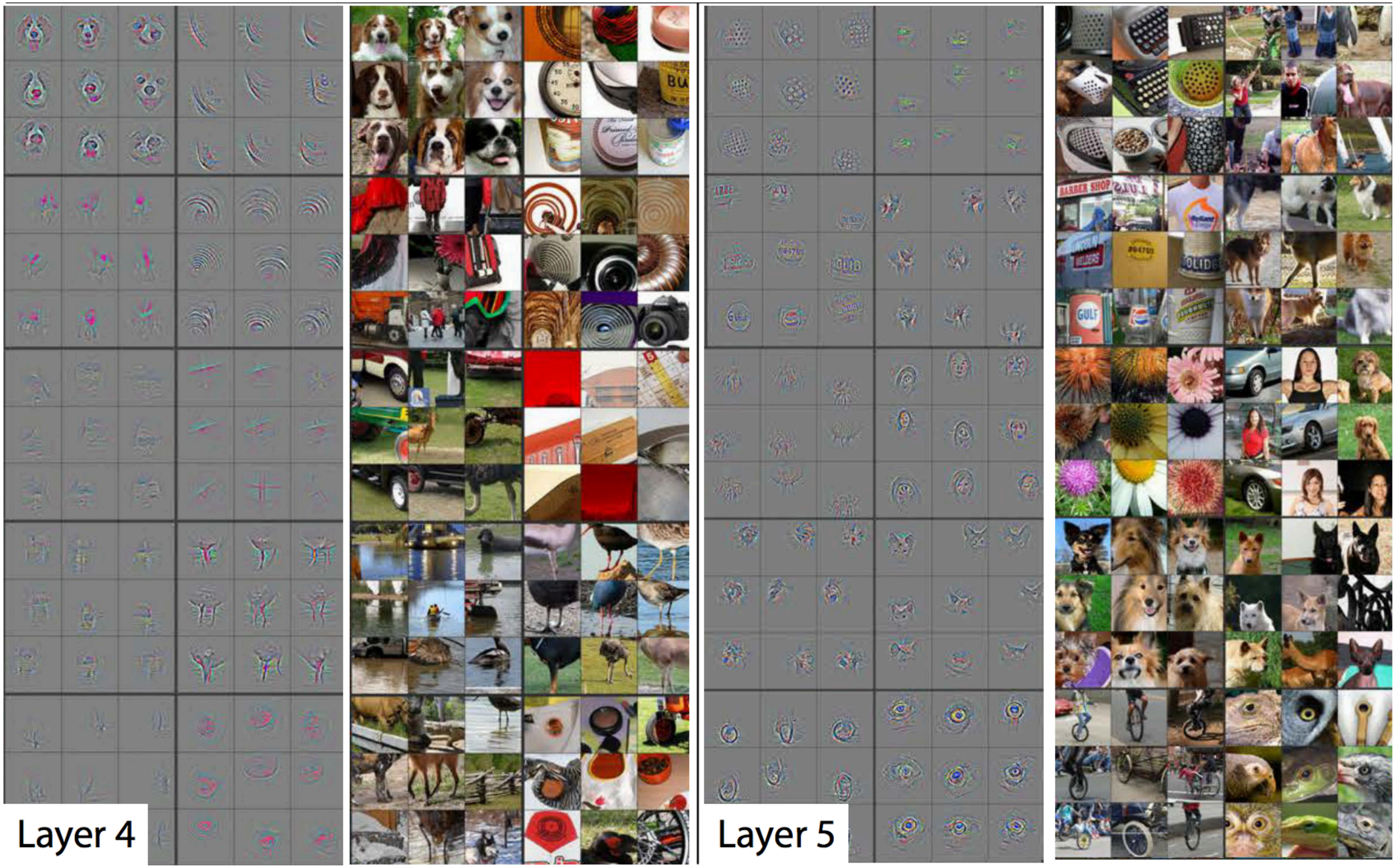
Transfer Learning



Low-level features: mid-level features

[Zeiler & Fergus, Visualizing and Understanding Convolutional Networks, ECCV 2014]

Transfer Learning



Higher-level features: object parts & objects

[Zeiler & Fergus, Visualizing and Understanding Convolutional Networks, ECCV 2014]

Lessons Learned

- Main lessons from this lecture
  - Convolutional neural networks
  - Layers: Fully connected, convolutional, activation functions, max pooling
  - Backpropagation
  - Handling overfitting

Lessons Learned

- Main lessons from this lecture
  - Convolutional neural networks
  - Layers: Fully connected, convolutional, activation functions, max pooling
  - Backpropagation
  - Handling overfitting
- Next lecture: More convolutional Neural Networks