Data Training in Deep Learning

Siu Sai Cheong

About Me

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- Programme Director, Bachelor of Translation with Business Programme
- Programme Director, Master of Arts in Translation (Computer-aided Translation) Programme
- Former Director, Deep Learning Research and Application Centre

My Research Areas

Translation Technology

Artificial Intelligence for Professional Language Services and Creative Industries

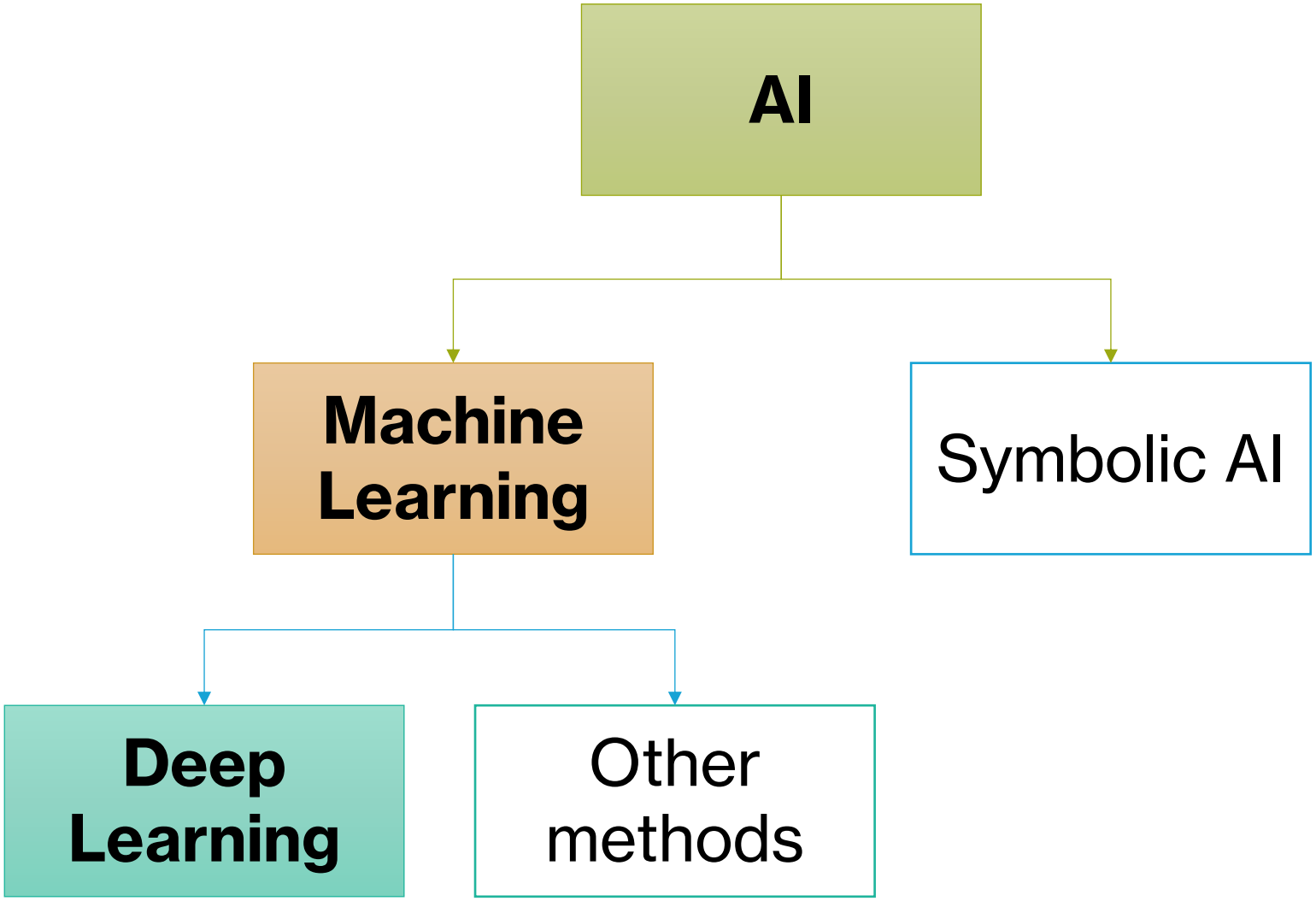
Outline

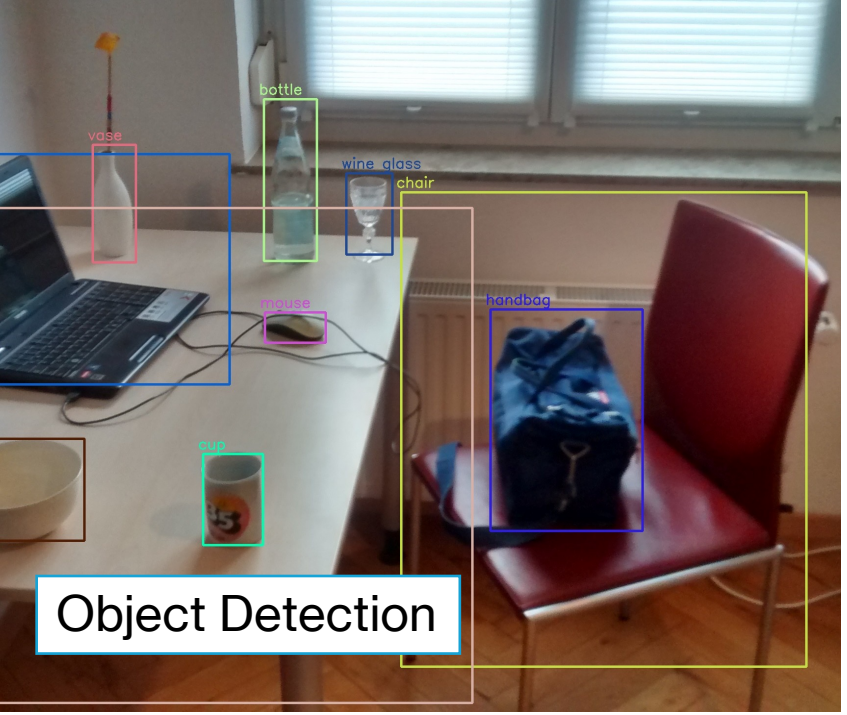
1. Deep Learning: A Brief Introduction

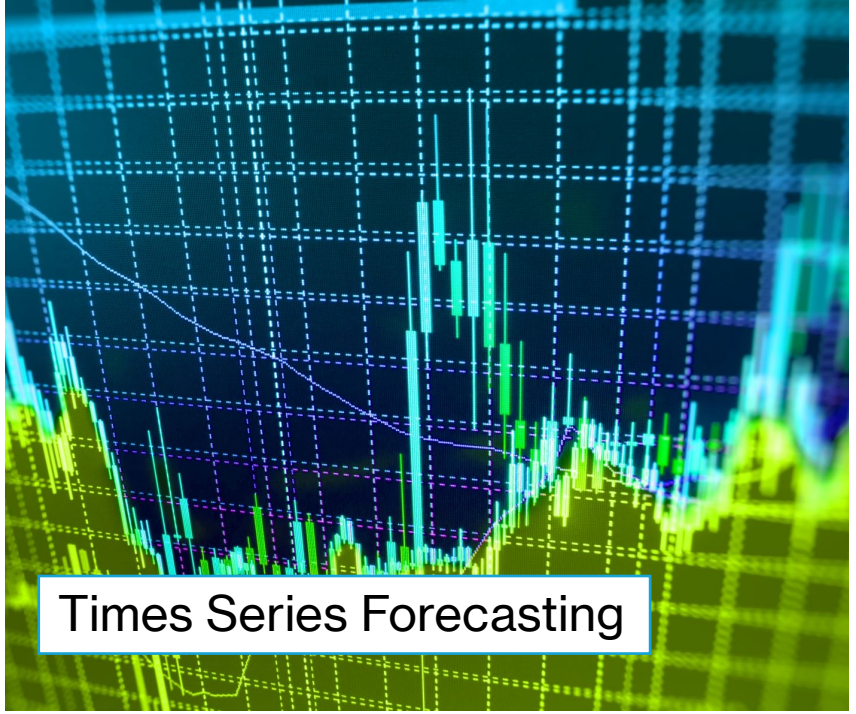
2. Model Training: Key Steps

3. Other Interesting Issues

Deep Learning and Artificial Intelligence


AI
Machine Learning
Symbolic AI
Deep Learning
Other methods


bottle
vase
wine glass
chair
mouse
handbag
cup
Object Detection


Times Series Forecasting


AlphaGo

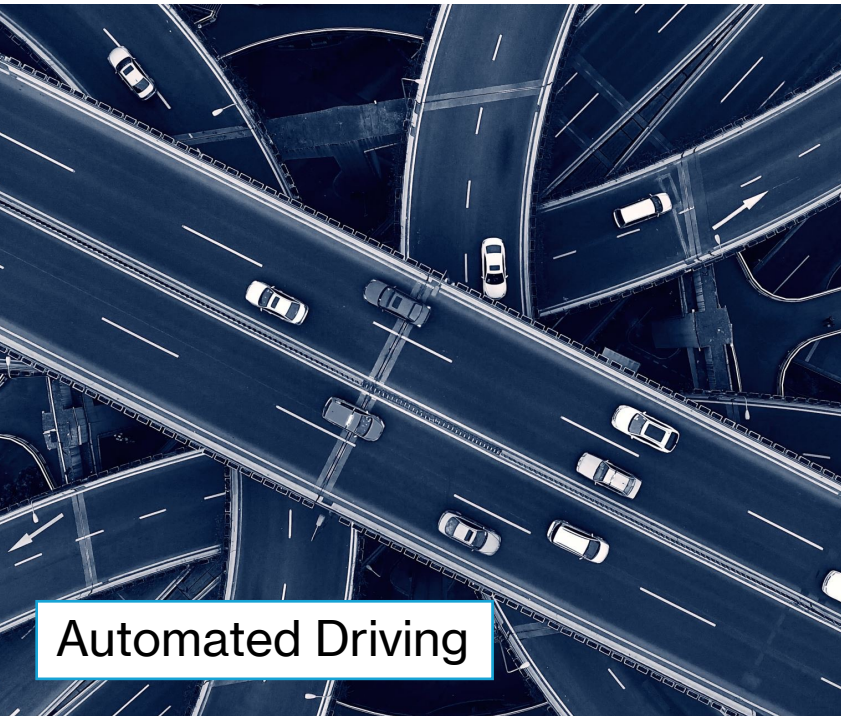
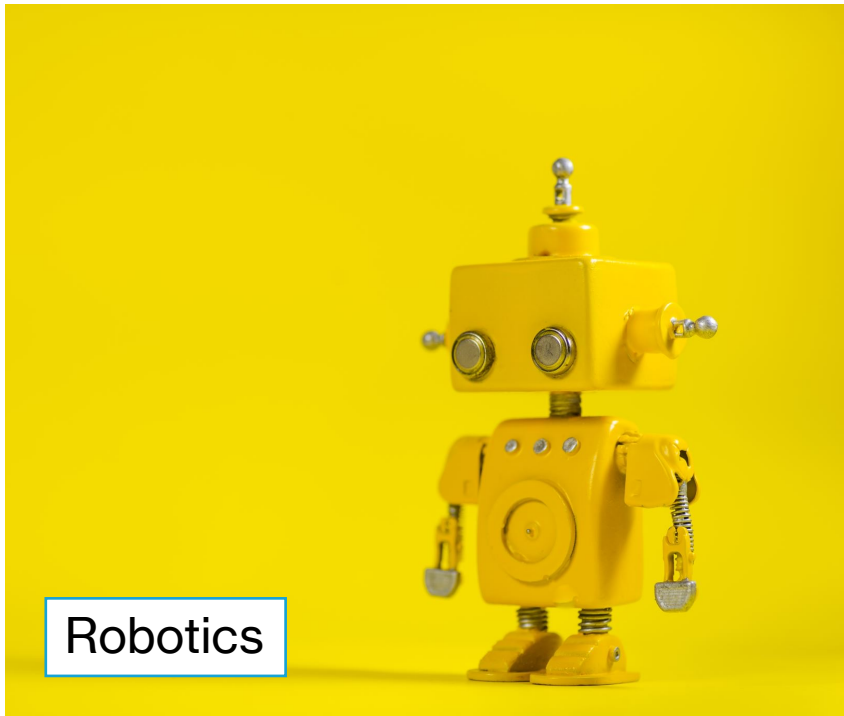

Automated Driving


Image Classification


Robotics

My Deep Learning Projects

- Text and Speech Translation
- Image Translation
- Other Natural Language Processing (NLP) Tasks

IPO Translate (English-Chinese Translation)

Source Text

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Load Sample | Translate

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Translation 1	Translation 2
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Translation 1	Translation 2
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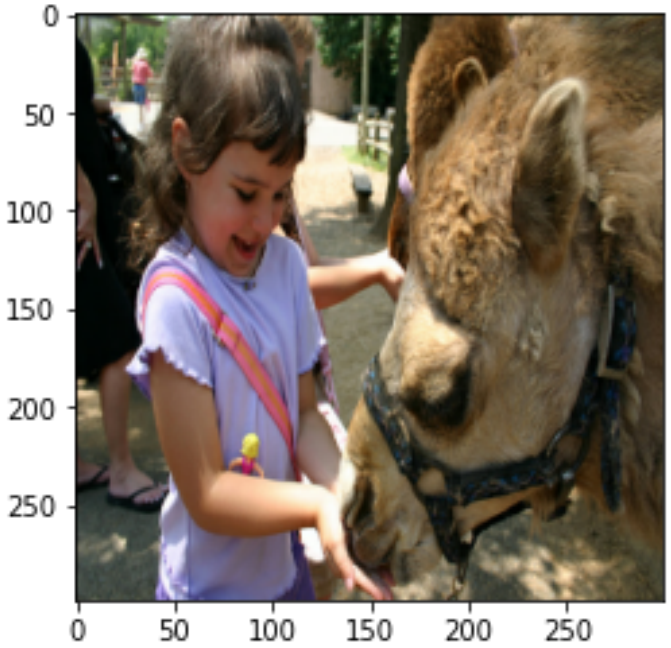
Technology for the Translation of Government Press Releases

Website for the Project "A Hybrid Approach to the Translation of Government Press Releases: Integration of Translation Memories and Neural Machine Translation"

The work described in this website was fully supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. UGC/FDS14/H16/18).

Image-to-text translation



女孩餵駱駝

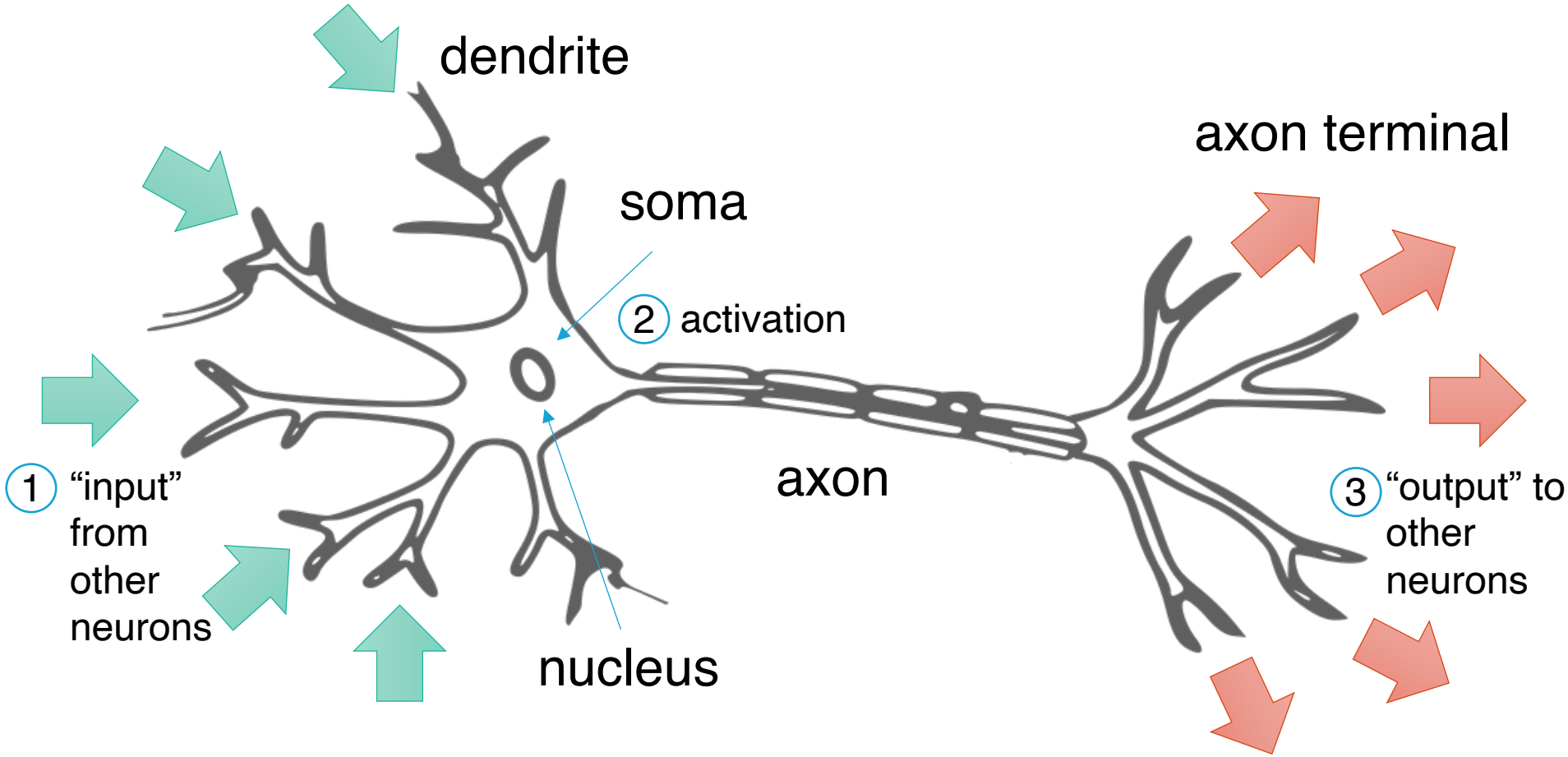
How does Deep Learning work?

Deep Learning

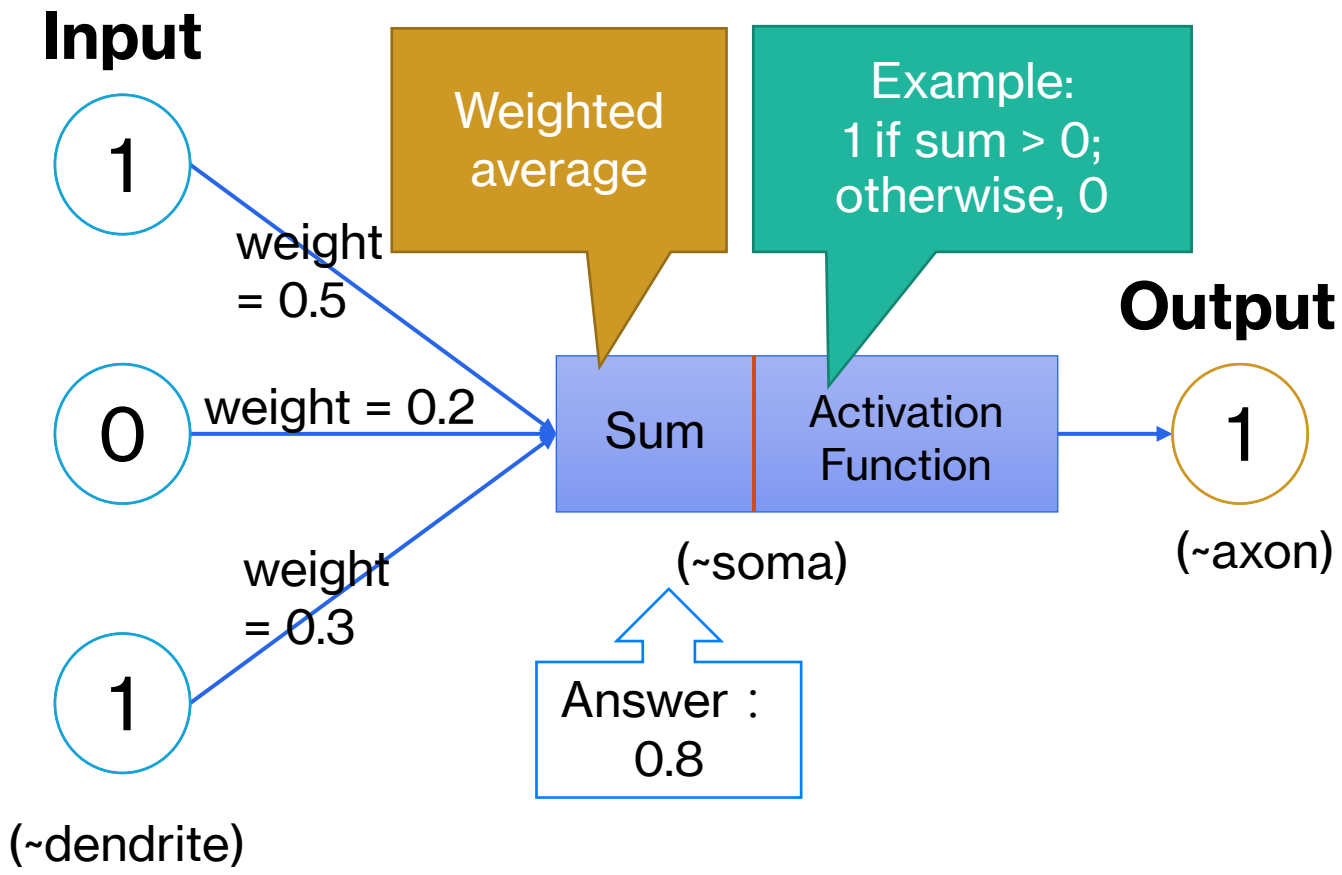
Artificial Neural Network

Artificial Neuron

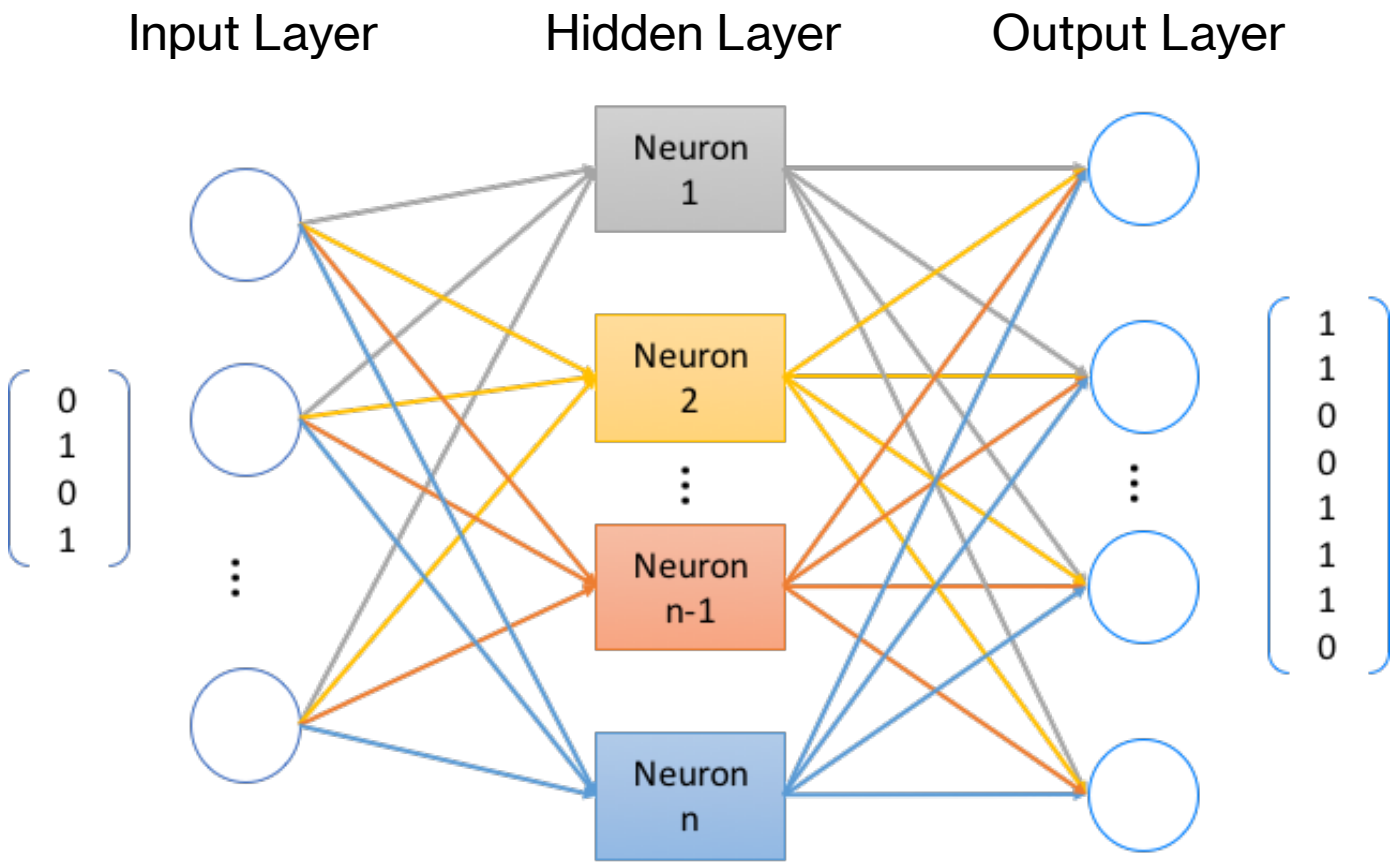
Biological Neuron



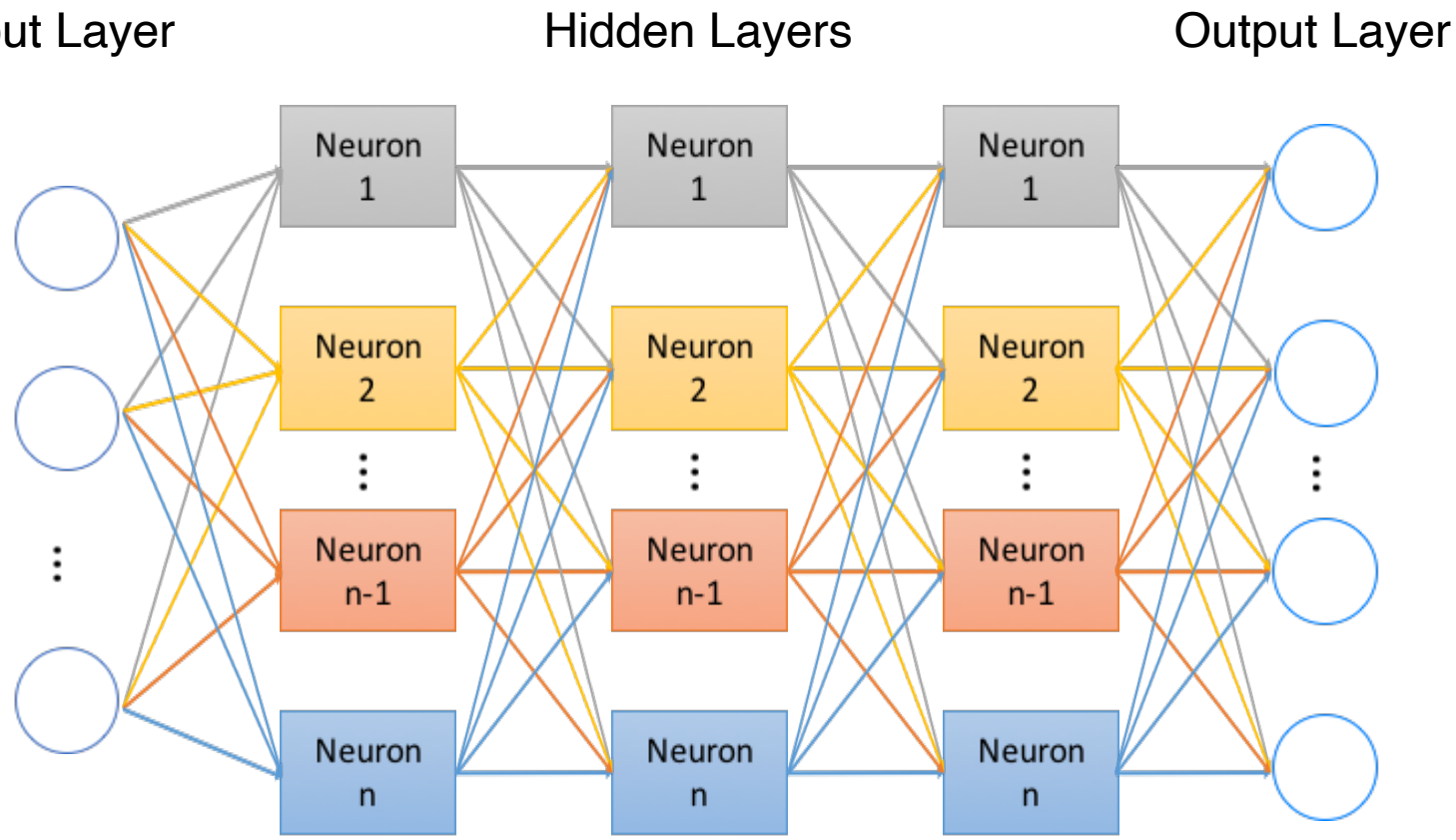
Artificial Neuron



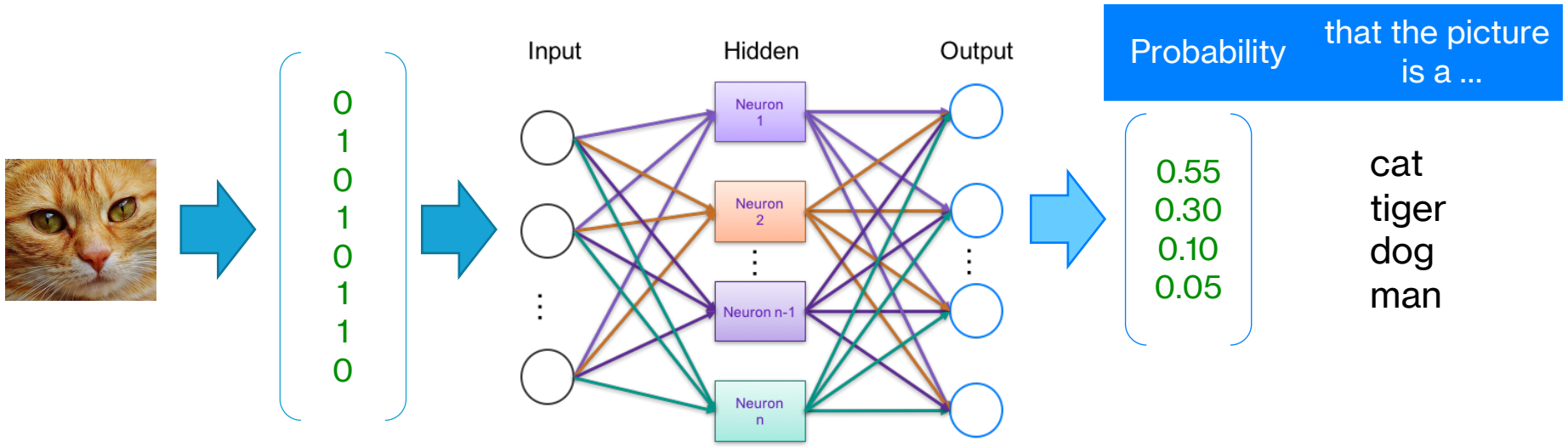
Artificial Neural Network



Deep Neural Network



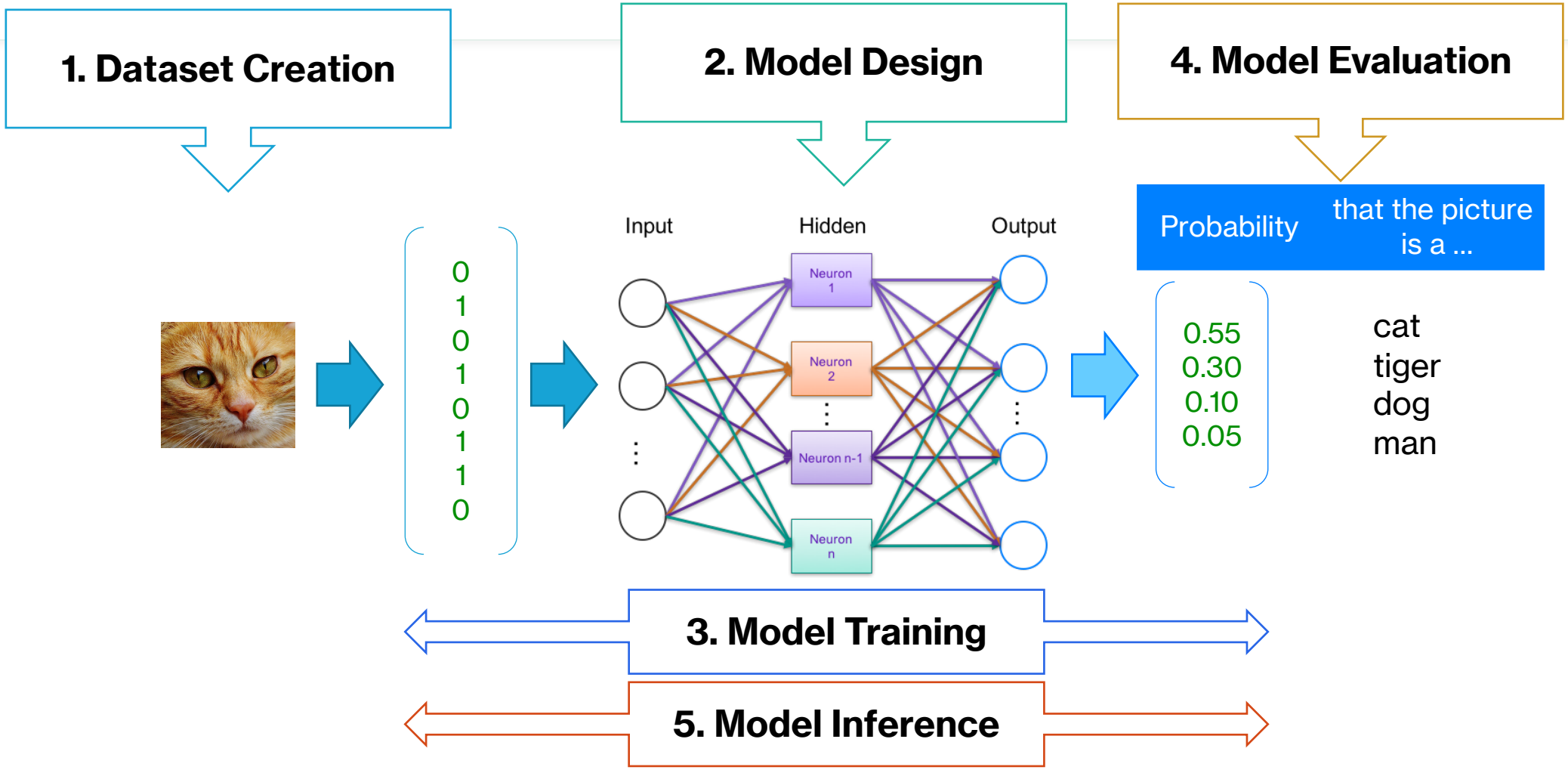
Example: Image Classification



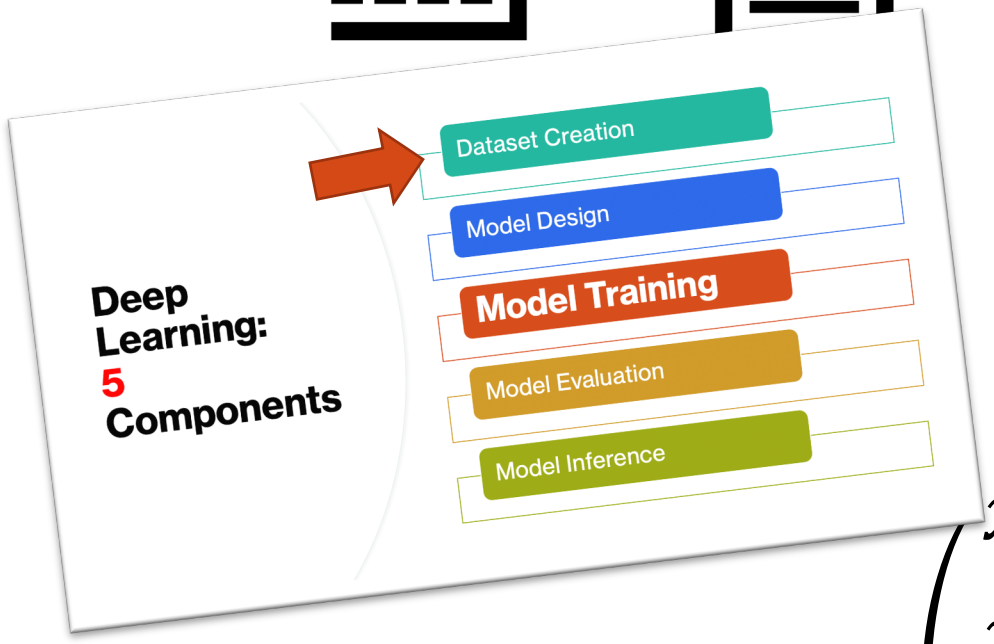
Deep Learning: 5 Components

- Dataset Creation
- Model Design
- **Model Training**
- Model Evaluation
- Model Inference

Example: Image Classification



How can we train a model?

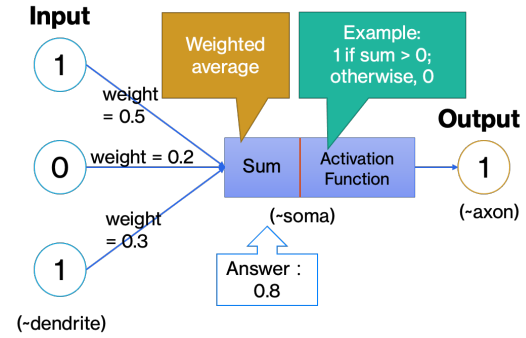


$$x = x_1 \quad \boldsymbol{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix} \quad \boldsymbol{X} = \begin{pmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{pmatrix}$$

Manipulation of numbers: scalars, vectors, matrices, and tensors

To get started, let’s revisit the following

A Simple Neuron



Given the input

$$\boldsymbol{x} \in \mathbb{R}^d$$

$$\boldsymbol{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix}$$

We have

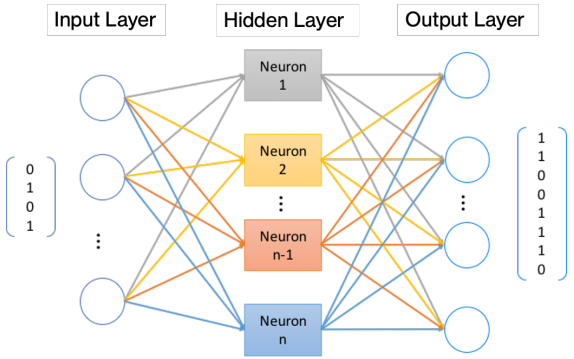
$$\boldsymbol{w} \in \mathbb{R}^d \quad b \in \mathbb{R} \quad \text{and} \quad \sigma(z) = \frac{1}{1+e^{-z}}, \text{ where } z \in \mathbb{R}$$

A sigmoid function as an example

The output is

$$\hat{y} = \sigma(\boldsymbol{w}^T\boldsymbol{x} + b), \text{where } \hat{y} \in \mathbb{R}$$

A Simple Network



Given the input

$$\boldsymbol{x} \in \mathbb{R}^d$$

We have

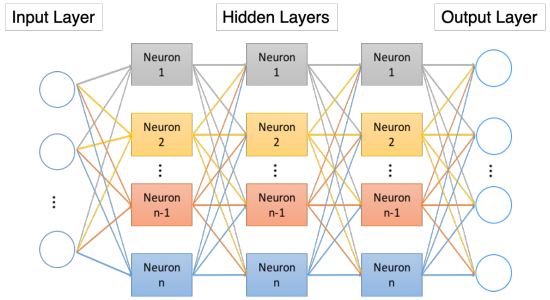
Element-wise operation here

$\boldsymbol{W} \in \mathbb{R}^{d \times h}$ $\boldsymbol{b} \in \mathbb{R}^h$ and $\sigma(\boldsymbol{z}) = \frac{1}{1+e^{-z}}$, where $\boldsymbol{z} \in \mathbb{R}^h$

The output is

$$\hat{\boldsymbol{y}} = \sigma(\boldsymbol{W}^T\boldsymbol{x} + \boldsymbol{b}), \text{where } \hat{\boldsymbol{y}} \in \mathbb{R}^h$$

A Simple Deep Neural Network



Given the input $\boldsymbol{x} \in \mathbb{R}^d$

We have

$\boldsymbol{W_1} \in \mathbb{R}^{d \times h_1}$ $\quad \boldsymbol{b_1} \in \mathbb{R}^{h_1}$

$\boldsymbol{W_2} \in \mathbb{R}^{h_1 \times h_2}$ $\quad \boldsymbol{b_2} \in \mathbb{R}^{h_2}$

... ...

$\boldsymbol{W_n} \in \mathbb{R}^{h_{n-1} \times h_n}$ $\quad \boldsymbol{b_n} \in \mathbb{R}^{h_n}$

and $\sigma(\boldsymbol{z}) = \frac{1}{1+e^{-\boldsymbol{z}}}$, where $\boldsymbol{z} \in \mathbb{R}^{h_i}$

We usually have more than one $\sigma(x)$

The output is

$$\hat{\boldsymbol{y}} = \sigma(\boldsymbol{W_n^T}\left(\ldots\sigma\left(\boldsymbol{W_2^T}\left(\sigma\left(\boldsymbol{W_1^T x} + \boldsymbol{b_1}\right)\right) + \boldsymbol{b_2}\right)\ldots\right) + \boldsymbol{b_n}), \text{ where } \hat{\boldsymbol{y}} \in \mathbb{R}^{h_n}$$

$$\hat{y} = \sigma(\boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{x} + b), \text{where } \hat{y} \in \mathbb{R}$$

$$\hat{\boldsymbol{y}} = \sigma(\boldsymbol{W}^{\boldsymbol{T}}\boldsymbol{x} + \boldsymbol{b}), \text{where } \hat{\boldsymbol{y}} \in \mathbb{R}^{h}$$

$$\hat{\boldsymbol{y}} = \sigma(\boldsymbol{W}_{\boldsymbol{n}}^{\boldsymbol{T}}\left(\ldots\sigma\left(\boldsymbol{W}_{\boldsymbol{2}}^{\boldsymbol{T}}\left(\sigma\left(\boldsymbol{W}_{\boldsymbol{1}}^{\boldsymbol{T}}\boldsymbol{x} + \boldsymbol{b}_{\boldsymbol{1}}\right)\right) + \boldsymbol{b}_{\boldsymbol{2}}\right)\ldots\right) + \boldsymbol{b}_{\boldsymbol{n}}), \text{where } \hat{\boldsymbol{y}} \in \mathbb{R}^{h_n}$$

As we'd like to focus on model training rather than model design, we have

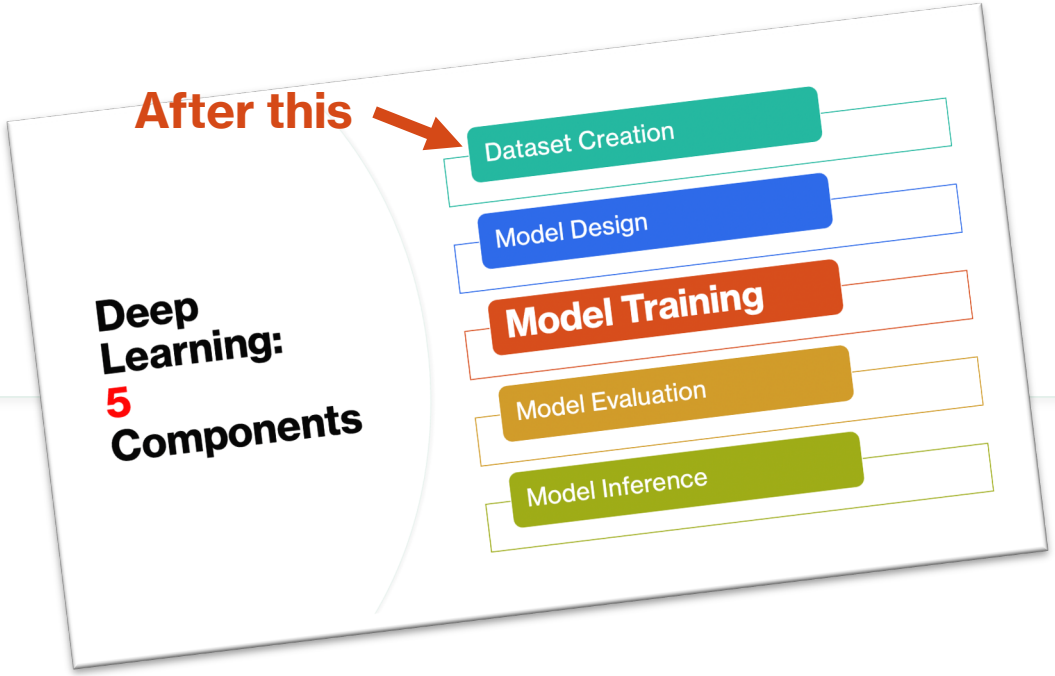
$$\hat{\boldsymbol{y}} = f_{\theta}(\boldsymbol{x}), \text{where } \theta = (\boldsymbol{W}_{\boldsymbol{1}}, \boldsymbol{b}_{\boldsymbol{1}}, \boldsymbol{W}_{\boldsymbol{2}}, \boldsymbol{b}_{\boldsymbol{2}}, \ldots, \boldsymbol{W}_{\boldsymbol{n}}, \boldsymbol{b}_{\boldsymbol{n}})$$

Model Design:
How is f like

Model Training:
Find our parameters ☺

We’re ready to train our model!

Data First!



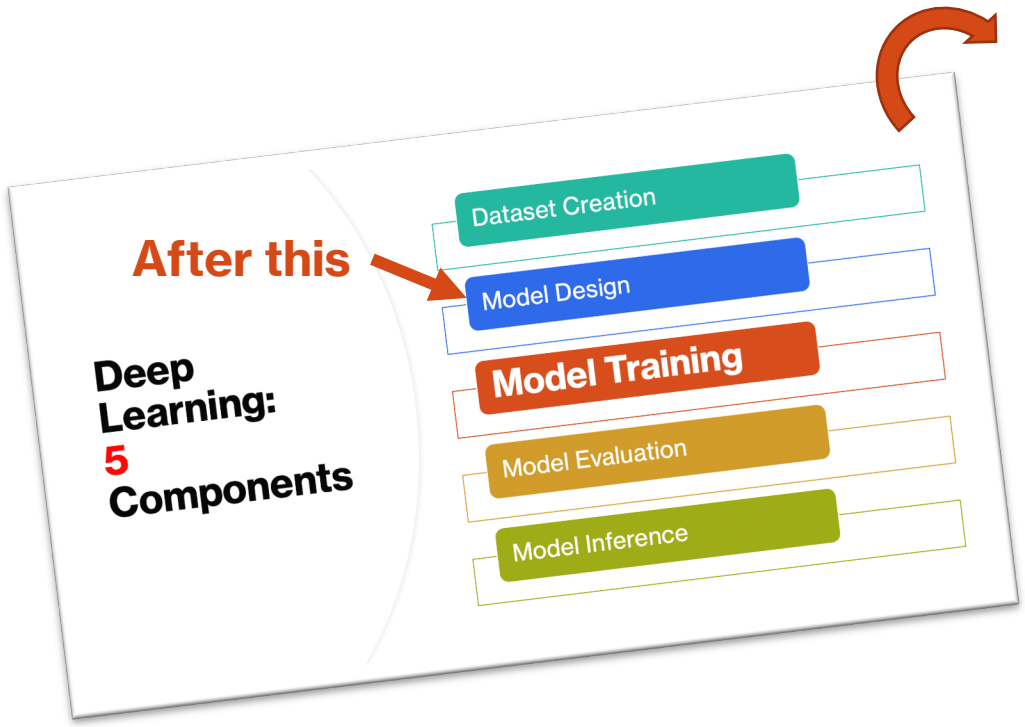
For example, we have

$$\{(\boldsymbol{x_i}, \boldsymbol{y_i})\}_{i=1}^{m} = \{(\boldsymbol{x_1}, \boldsymbol{y_1}), (\boldsymbol{x_2}, \boldsymbol{y_2}), \dots, (\boldsymbol{x_m}, \boldsymbol{y_m})\}$$

(e.g., $x_i \in \mathbb{R}^d$ and $y_i \in \mathbb{R}^h$ for all i)

We can also have other options like $x_i \in [0,255]^d$ and $y_i \in \{0, \dots, |class|\}$, depending on the nature of our task.

Initialize our parameters



We have

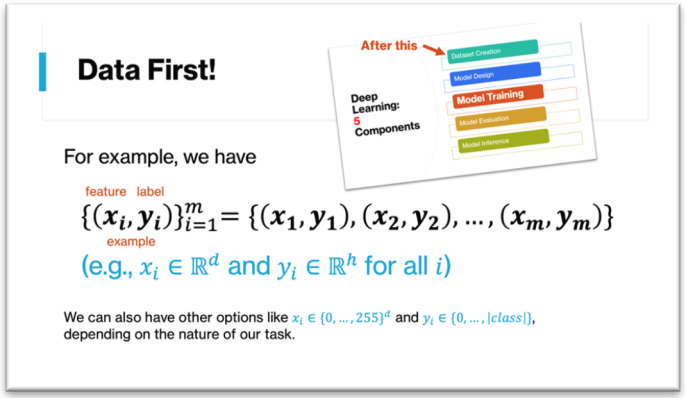
$$\hat{\boldsymbol{y}} = f_\theta(\boldsymbol{x}),$$
where $\theta = (\boldsymbol{W_1}, \boldsymbol{b_1}, \boldsymbol{W_2}, \boldsymbol{b_2}, \ldots, \boldsymbol{W_n}, \boldsymbol{b_n})$

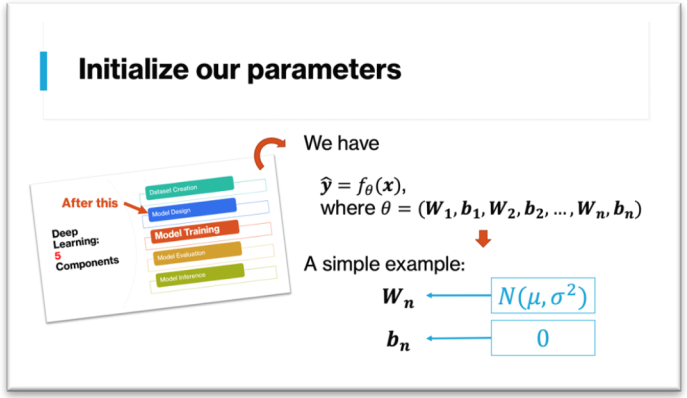
A simple example:

$\boldsymbol{W_n}$ ← $N(\mu, \sigma^2)$

$\boldsymbol{b_n}$ ← 0

Forward propagation





$$\{(x_i, y_i)\}_{i=1}^{m} \Rightarrow f_\theta(x), \text{ where } \theta = (W_1, b_1, W_2, b_2, \dots, W_n, b_n) \Rightarrow \hat{y}_i$$

Initialized

Loss computation

$\{(\boldsymbol{x_i}, \boldsymbol{y_i})\}_{i=1}^{m}$ → $f_\theta(\boldsymbol{x})$, where $\theta = (\boldsymbol{W_1}, \boldsymbol{b_1}, \boldsymbol{W_2}, \boldsymbol{b_2}, \ldots, \boldsymbol{W_n}, \boldsymbol{b_n})$ → $\hat{\boldsymbol{y}}_i$

↓

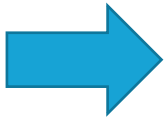
$$L(\hat{\boldsymbol{y}}, \boldsymbol{y}) = \frac{1}{m}\sum_{i}^{m} l(\hat{\boldsymbol{y}}_i, \boldsymbol{y}_i)$$

Mean Absolute Error (MAE), Mean Squared Error (MSE), Cross-entropy Loss and more

Parameter adjustment

Let's use this

$$L(\hat{\boldsymbol{y}}, \boldsymbol{y})$$

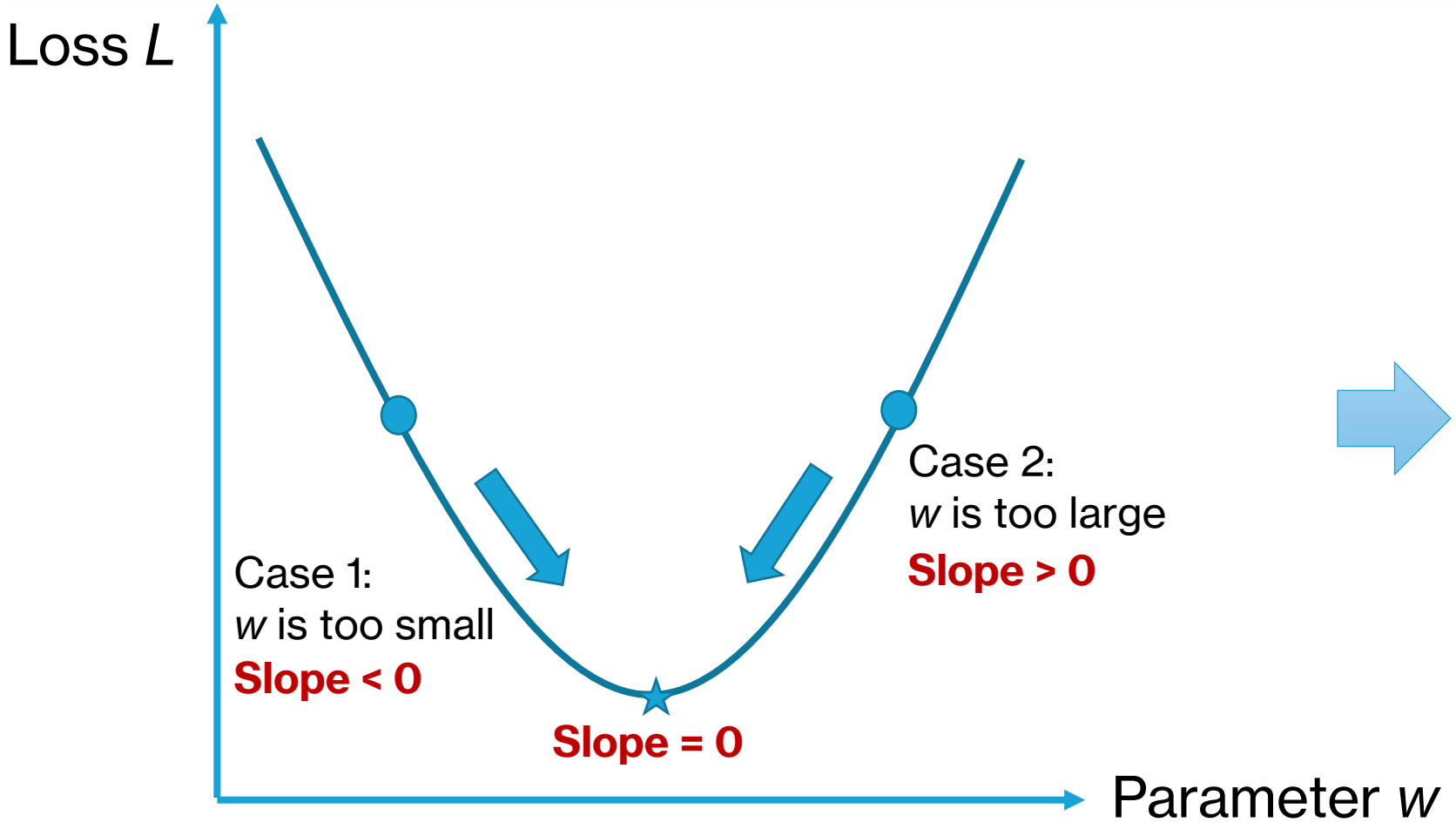


How?

To "improve" our parameters

$$\theta = (\boldsymbol{W_1}, \boldsymbol{b_1}, \boldsymbol{W_2}, \boldsymbol{b_2}, \ldots, \boldsymbol{W_n}, \boldsymbol{b_n})$$

Consider this

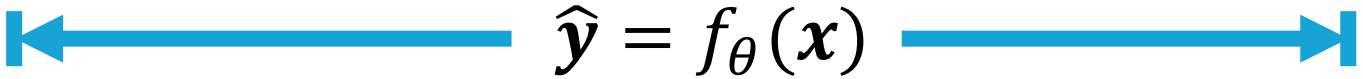


1. Find $\frac{\partial L(\hat{\boldsymbol{y}}, \boldsymbol{y})}{\partial \theta}$

2. Adjust θ

Back propagation

An Example



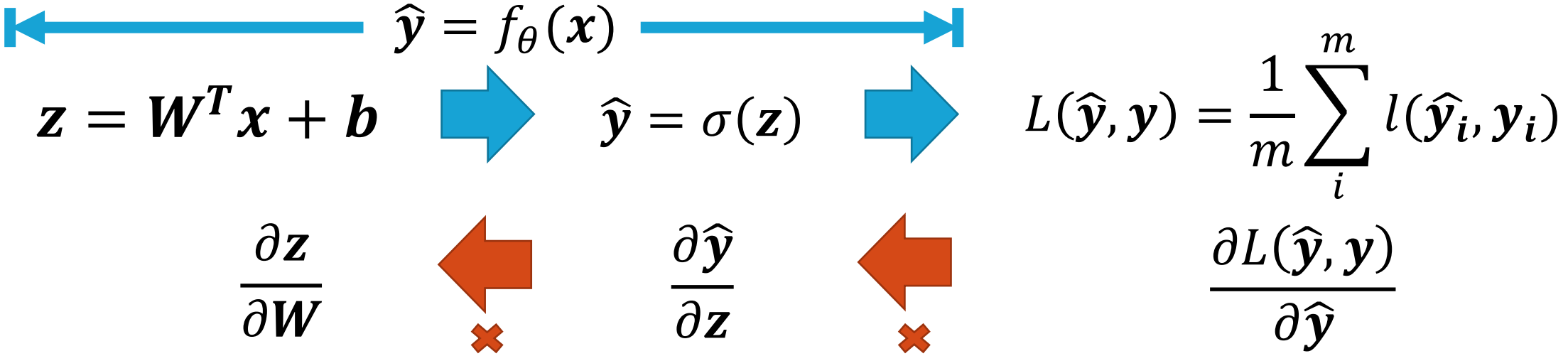
$$z = W^T x + b \Rightarrow \hat{y} = \sigma(z) \Rightarrow L(\hat{y}, y) = \frac{1}{m}\sum_{i}^{m} l(\hat{y}_i, y_i)$$

How can we find $\frac{\partial L(\hat{y}, y)}{\partial W}$?

Chain rule!

Back propagation

An Example



$$= \frac{\partial L(\hat{y}, y)}{\partial W}$$

Optimization

A Simple Example: Stochastic/Mini-batch Gradient Descent

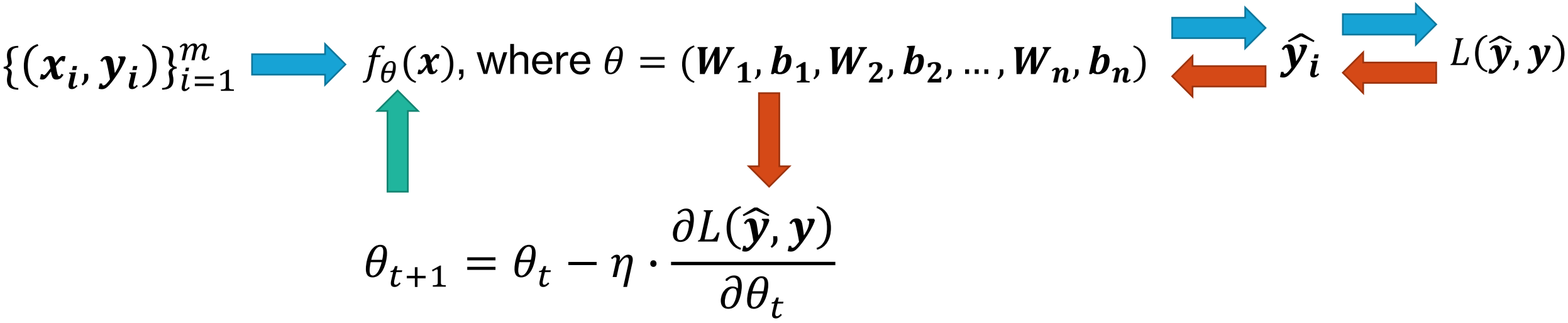
For all $\theta = (\boldsymbol{W_1}, \boldsymbol{b_1}, \boldsymbol{W_2}, \boldsymbol{b_2}, \dots, \boldsymbol{W_n}, \boldsymbol{b_n})$ at step t, we have

Learning rate

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\partial L(\hat{\boldsymbol{y}}, \boldsymbol{y})}{\partial \theta_t}$$

From back propagation

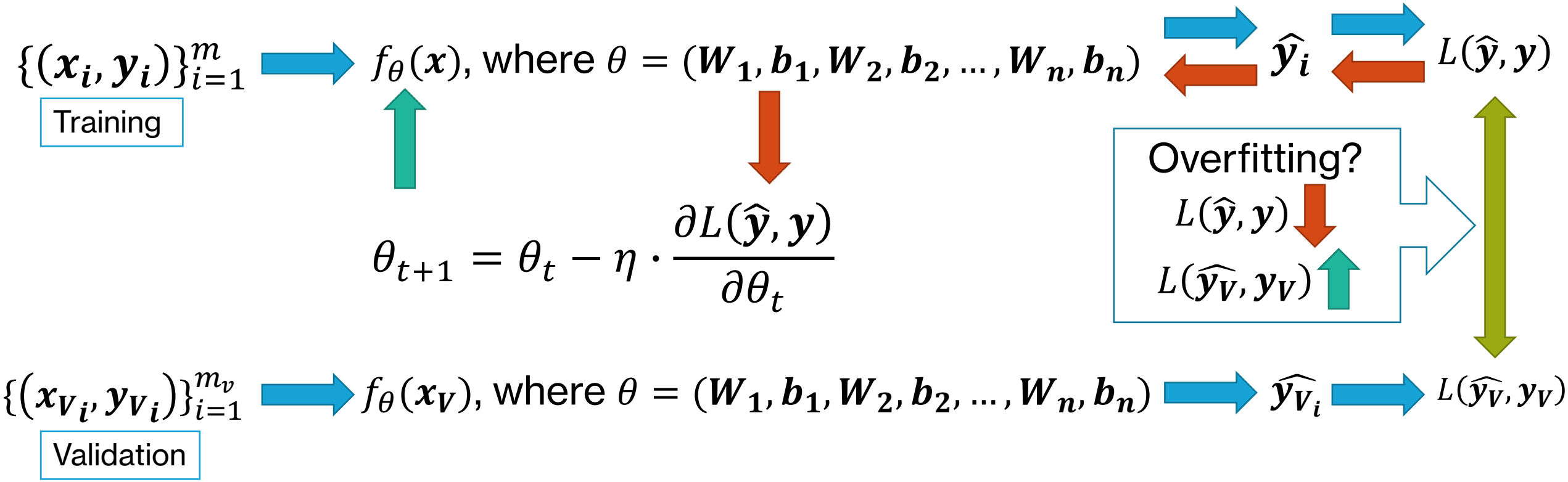
Iteration


$\{(x_i, y_i)\}_{i=1}^{m}$
$f_\theta(x)$, where $\theta = (W_1, b_1, W_2, b_2, \ldots, W_n, b_n)$
$\hat{y}_i$
$L(\hat{y}, y)$
$\theta_{t+1} = \theta_t - \eta \cdot \frac{\partial L(\hat{y}, y)}{\partial \theta_t}$

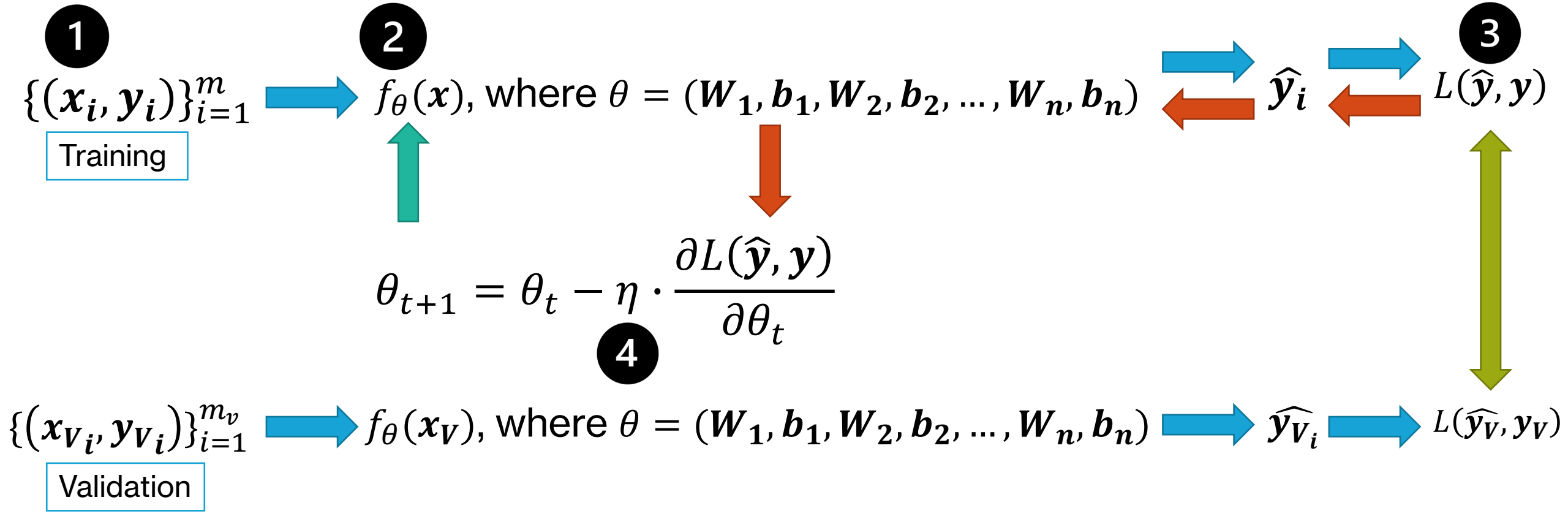
When should we stop training?

- No. of steps
- No. of epochs
- Early stopping

Early Stopping



Deep Learning Tasks



Other Interesting Issues

- Programming for Data Training
- Different Modes of Training: Supervised Training and Beyond
- Optimization Algorithms
- Design of Training Tasks
- Advanced Training Methods (e.g., training using trained models)
- Specific Examples of Training (e.g., translation, image processing, regression, time series forecasting, and more): To be explored in conjunction with dataset creation and model building

Thank you!