PAT 463/563 (Fall 2025)

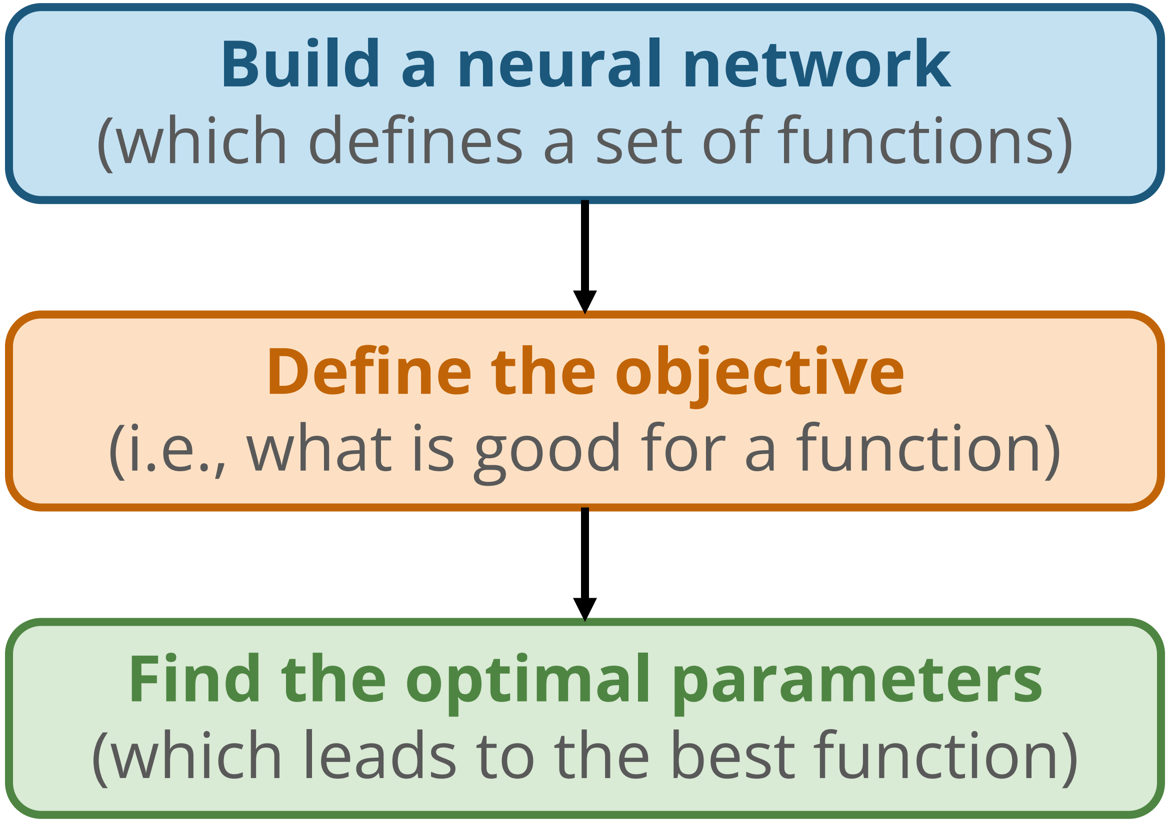
Music & AI

Lecture 7: Deep Learning Fundamentals II

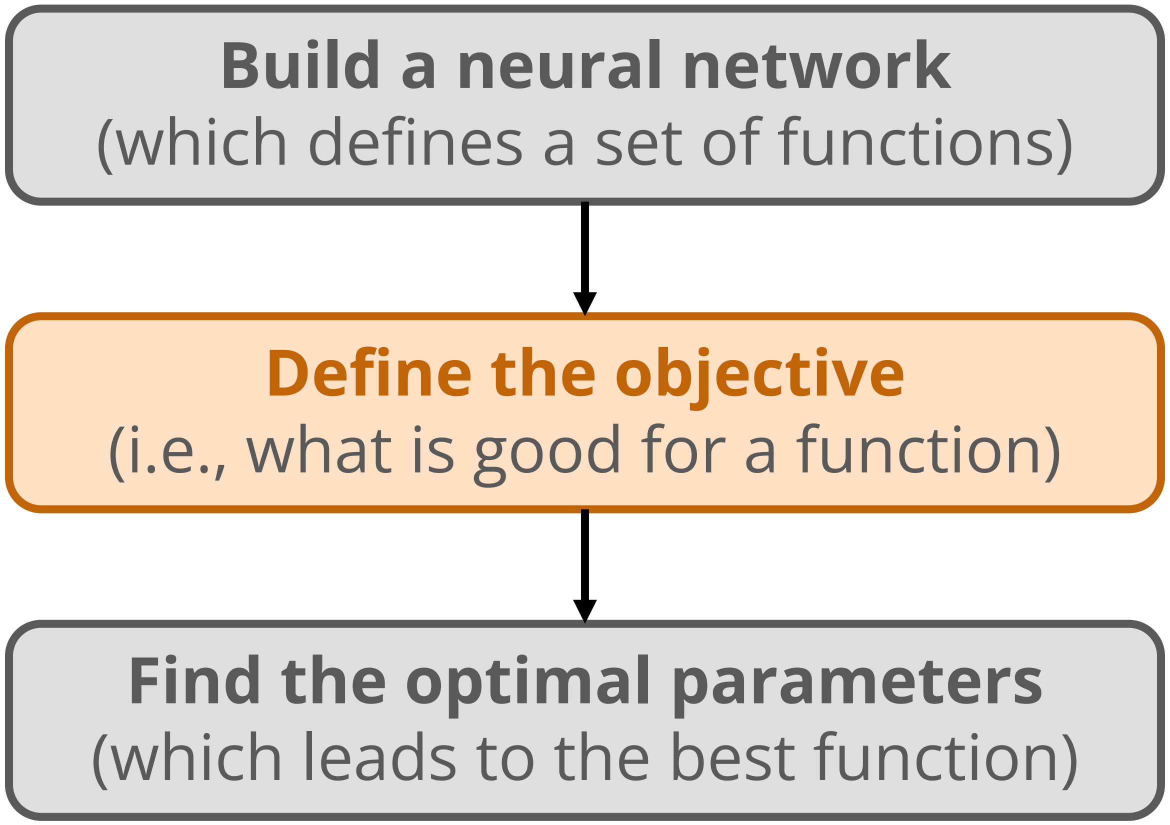
Instructor: Hao-Wen Dong

Training a Neural Network

Training a Neural Network

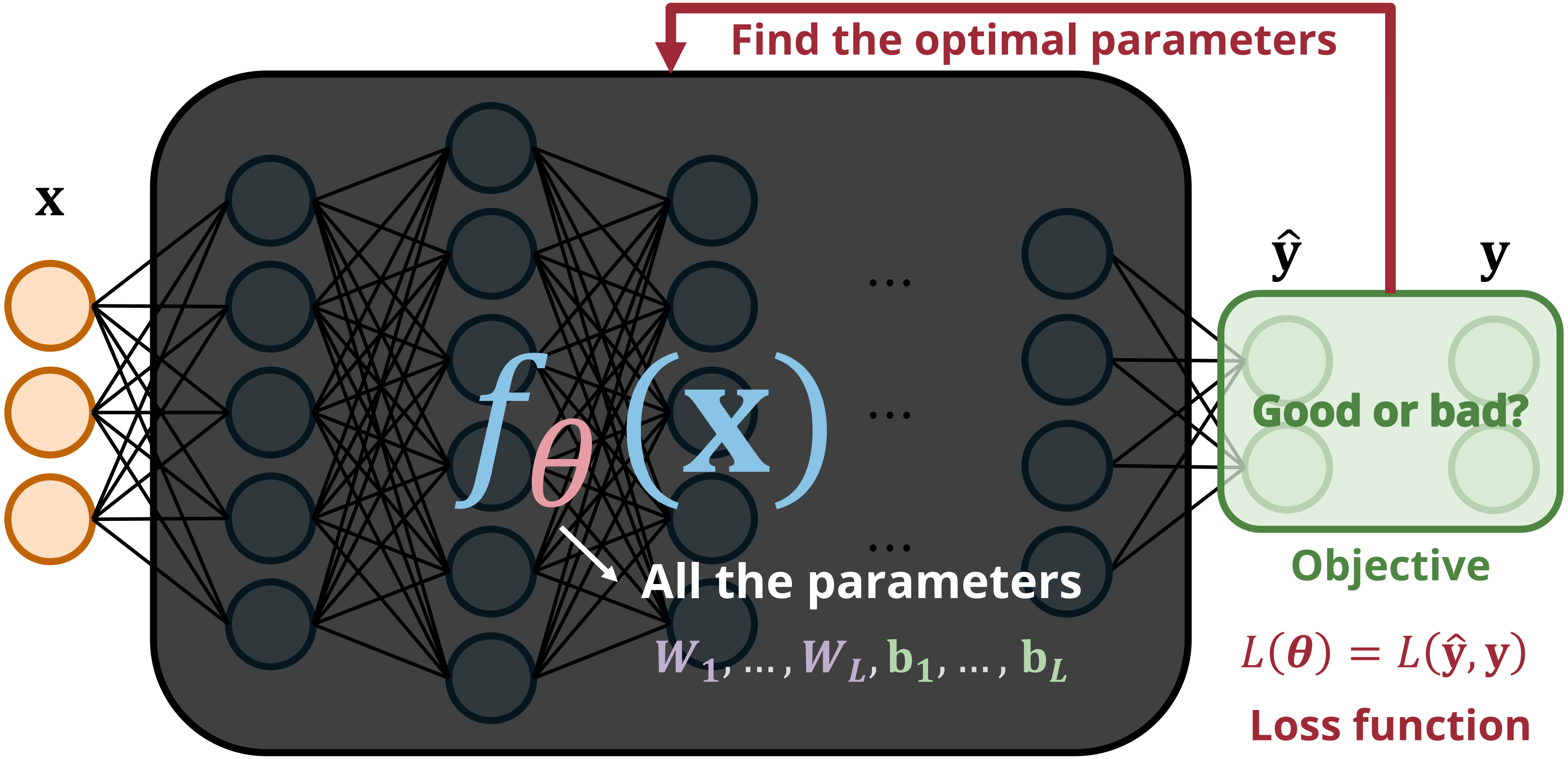


Training a Neural Network



Neural Networks are Parameterized Functions

- A neural network represents **a set of functions**



Loss Function

- Measure **how well the model perform** (in the opposite way)
- The choice of loss function depends on the task and the goals

$$L(\boldsymbol{\theta}) = L(\hat{\mathbf{y}}, \mathbf{y})$$

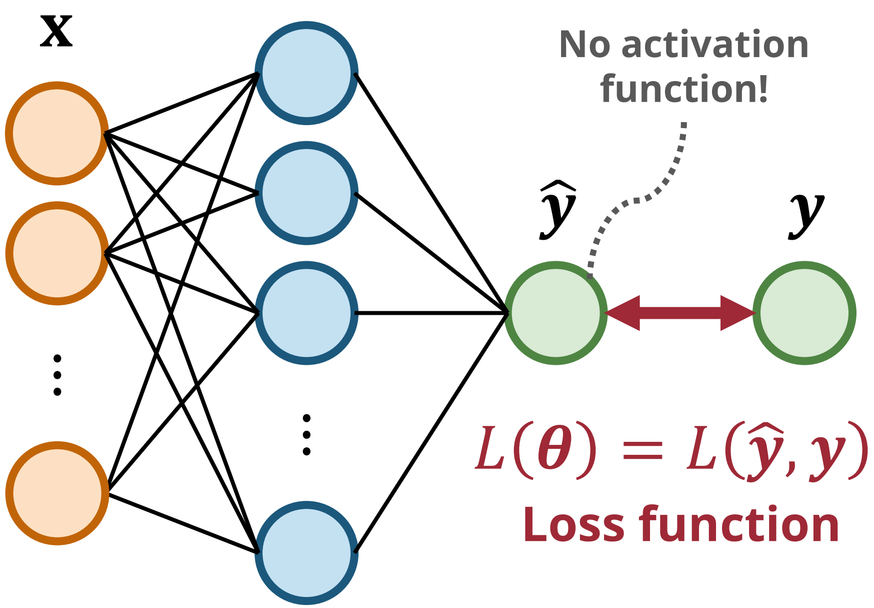
Loss Function: The Many Names

- Sometimes called
  - **Cost** function
  - **Error** function
- The opposite is known as
  - **Objective** function
  - **Reward** function (reinforcement learning)
  - **Fitness** function (evolutionary algorithms & genetic algorithms)
  - **Utility** function (economics)
  - **Profit** function (economics)

Example: Audio Codec

- What would be **a good objective to train a neural audio codec**?
- What do we **care about** for a codec?
  - Reconstruction quality **Trainable**
  - Bit rate (compression rate) **Likely not trainable but searchable**
  - Encoding/decoding speed **Likely not trainable but searchable**
- How do we measure **reconstruction quality**?
  - Difference in raw waveforms?
  - Difference in spectrograms?
  - Perceptual quality (psychoacoustics)?

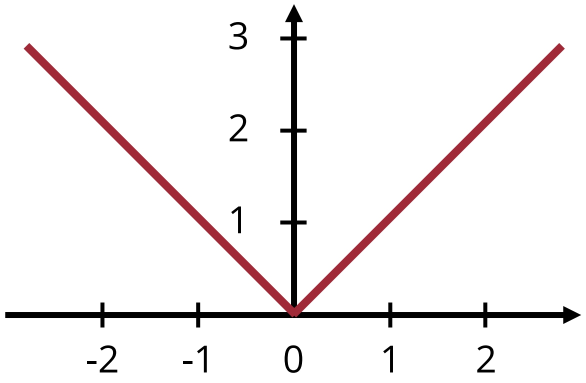
Common Loss Functions for Regression



Why not $L(\hat{y}, y) = \hat{y} - y$?

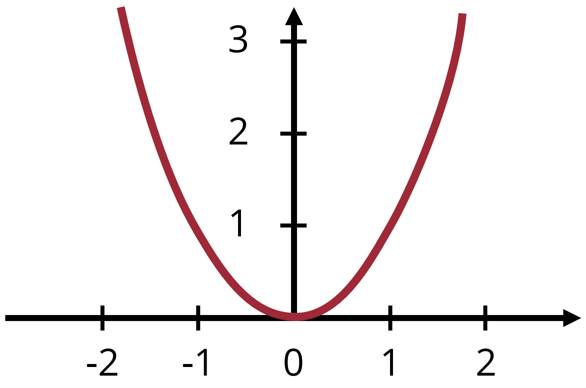
L1 loss

$$L(\hat{y}, y) = |\hat{y} - y|$$



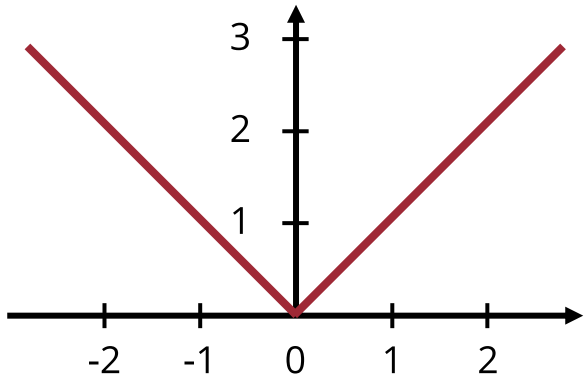
L2 loss

$$L(\hat{y}, y) = (\hat{y} - y)^2$$



L1 vs L2 Losses

L1 loss

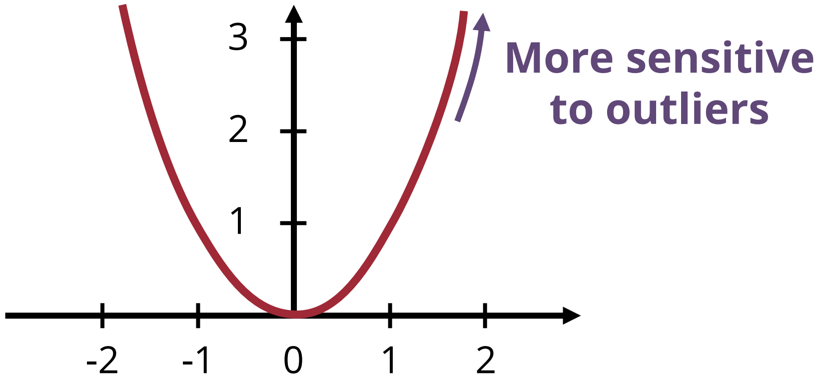


$$L(\hat{y}, y) = |\hat{y} - y|$$

$$L(\hat{\mathbf{y}}, \mathbf{y}) = \mathbf{MAE}(\hat{\mathbf{y}}, \mathbf{y}) = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i|$$

Mean Absolute Error (MAE)

L2 loss



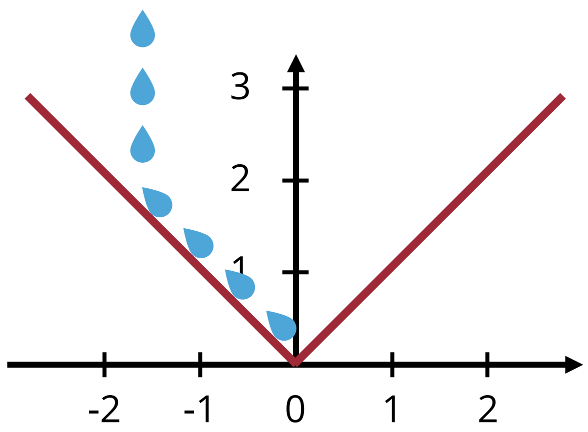
$$L(\hat{y}, y) = (\hat{y} - y)^2$$

$$L(\hat{\mathbf{y}}, \mathbf{y}) = \mathbf{MSE}(\hat{\mathbf{y}}, \mathbf{y}) = \frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2$$

Mean Squared Error (MSE)

L1 vs L2 Losses

L1 loss



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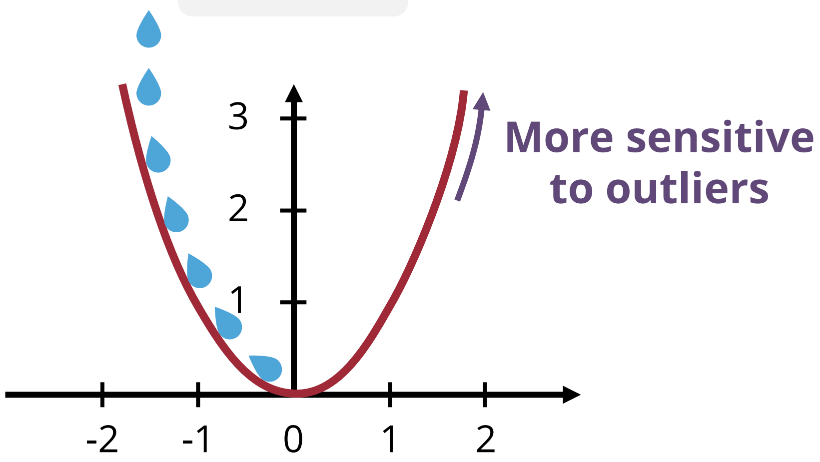
Mean Absolute Error (MAE)

L2 loss



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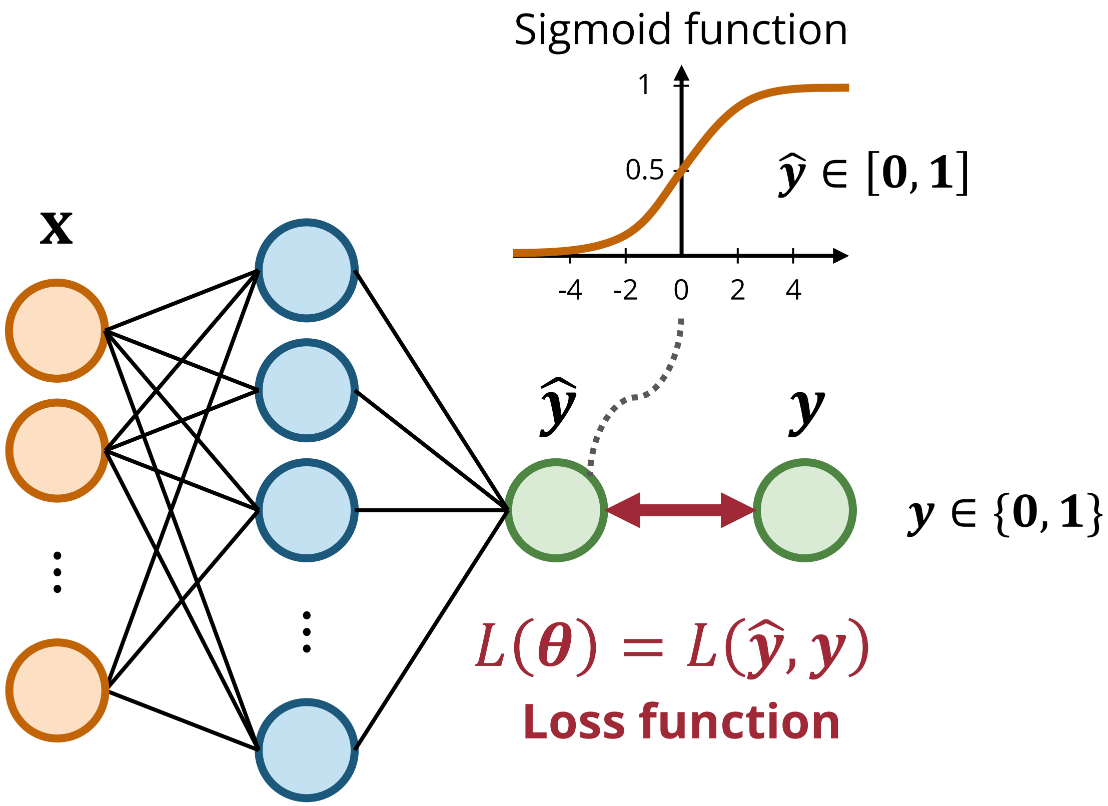
Mean Squared Error (MSE)

Binary Cross Entropy for Binary Classification

- **Logistic regression** approaches classification like regression

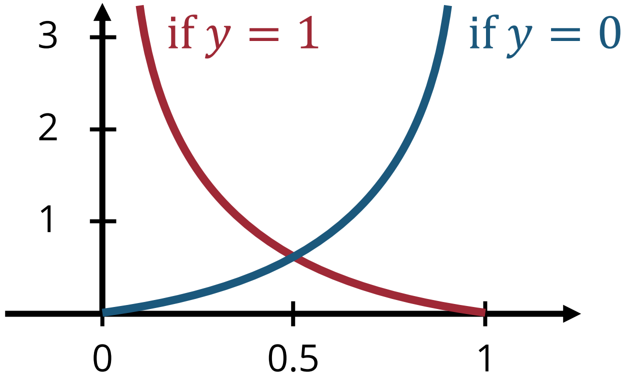


Binary cross entropy

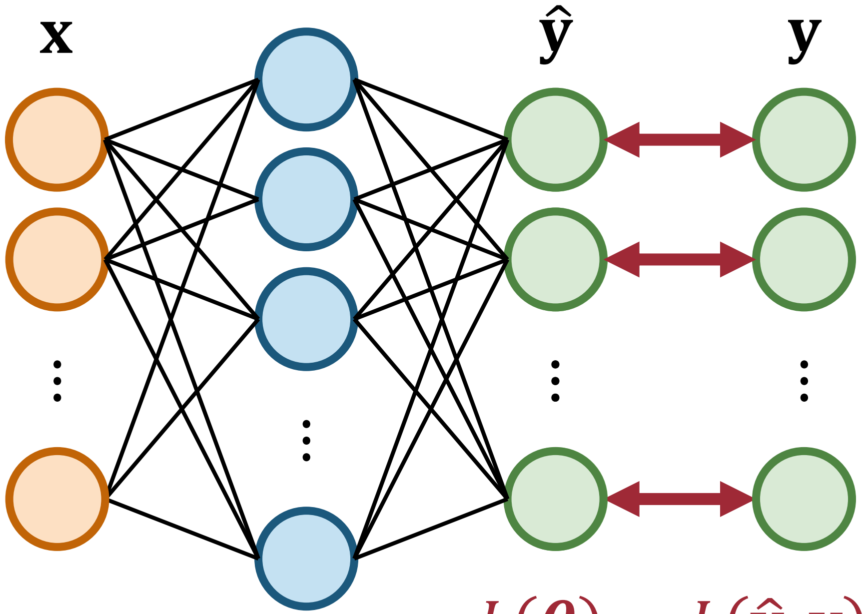
(Also called log loss)

$$L(\hat{y}, y) = \begin{cases} -\log \hat{y}\,, & \text{if } y = 1 \\ -\log(1 - \hat{y})\,, & \text{if } y = 0 \end{cases}$$

$$= -y \log \hat{y} - (1 - y) \log(1 - \hat{y})$$



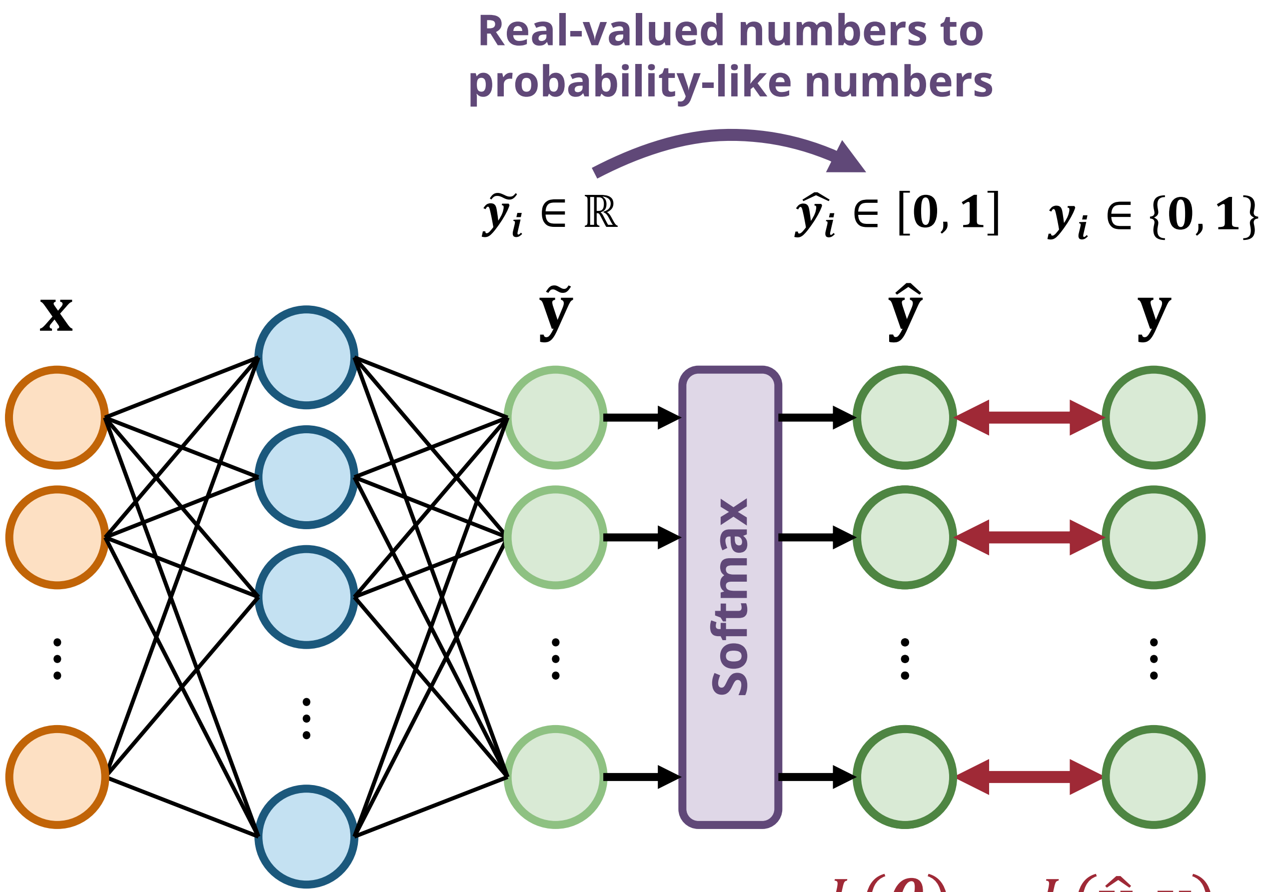
Cross Entropy for Multiclass Classification



$L(\boldsymbol{\theta}) = L(\hat{\mathbf{y}}, \mathbf{y})$

Loss function

Cross Entropy for Multiclass Classification



$$L(\boldsymbol{\theta}) = L(\hat{\mathbf{y}}, \mathbf{y})$$

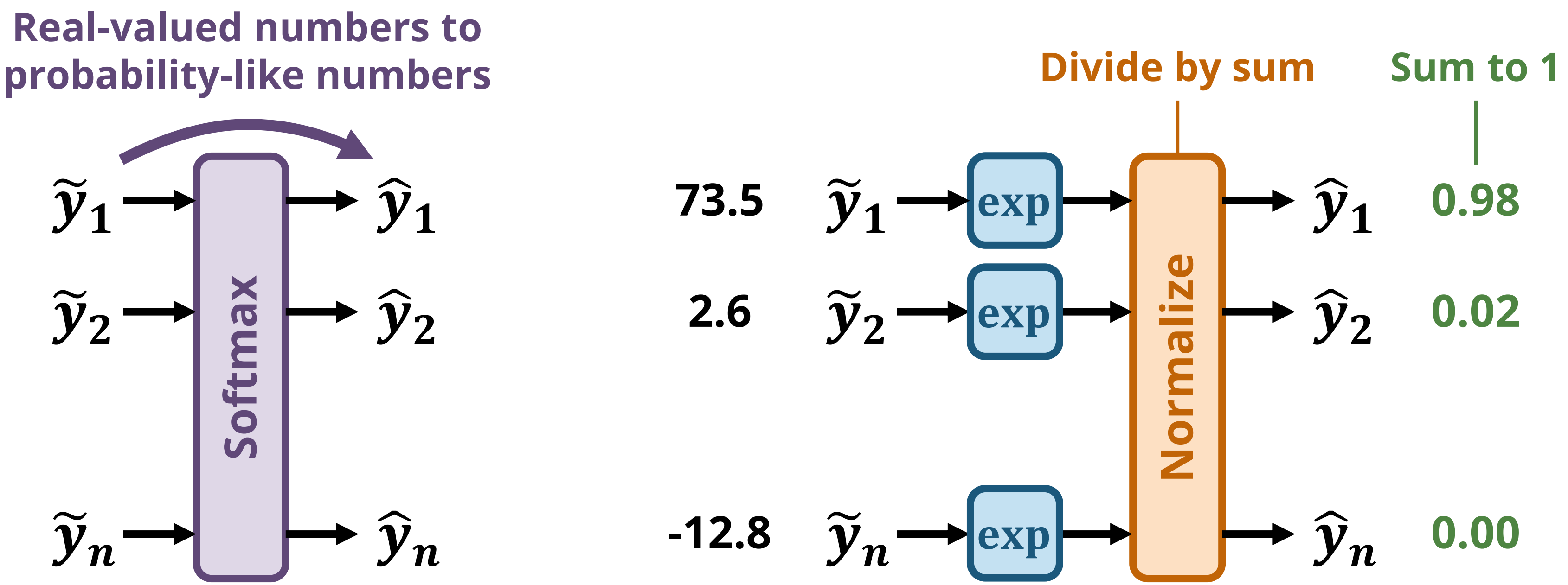
Loss function

Softmax

$$\hat{y}_i = \frac{e^{\tilde{y}_i}}{\sum_{j=1}^{n} e^{\tilde{y}_j}}$$

Softmax

- **Intuition**: Map several numbers to $[0, 1]$ while **keeping their relative magnitude**
  - Softmax is like the **multivariate version of sigmoid**



Cross Entropy for Multiclass Classification

Binary Cross Entropy

Only one of them will be one!

$$L(\hat{y}, y) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y})$$

Cross Entropy

Only one of them will be one!

$$L(\hat{\mathbf{y}}, \mathbf{y}) = -y_1 \log \hat{y}_1 - y_2 \log \hat{y}_2 - \cdots - y_i \log \hat{y}_n$$

$$= -\sum_{i}^{n} y_i \log \hat{y}_i$$

Log likelihood

Optimization

Training a Neural Network

Build a neural network
(which defines a set of functions)

$$\hat{\mathbf{y}} = f_{\boldsymbol{\theta}}(\mathbf{x})$$

Define the objective
(i.e., what is good for a function)

$$L(\boldsymbol{\theta})$$

Find the optimal parameters
(which leads to the best function)

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} L(\boldsymbol{\theta})$$

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↓

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↓

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(which leads to the best function)

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Optimizing the Parameters of a Neural Network

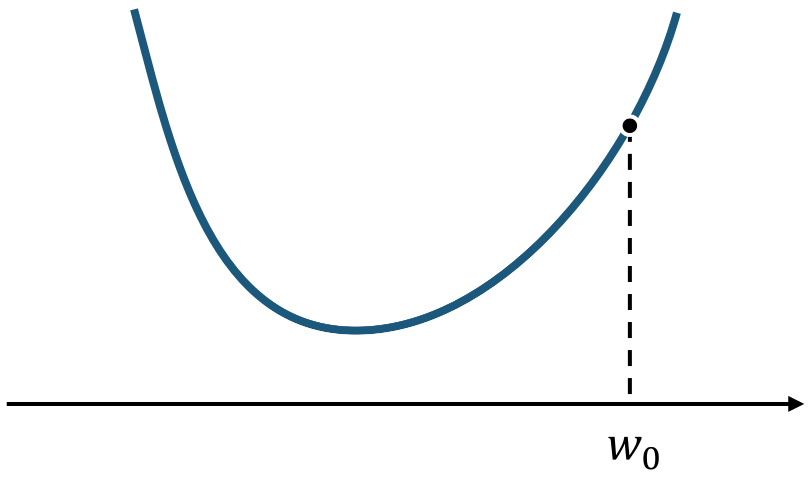
- Many, many ways…
- Most commonly through **gradient descent** in deep learning
- Alternatively, we can use search or genetic algorithm

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} L(\boldsymbol{\theta})$$

Gradient Descent

- **Intuition**: Gradient can suggest a good direction to tune the parameters

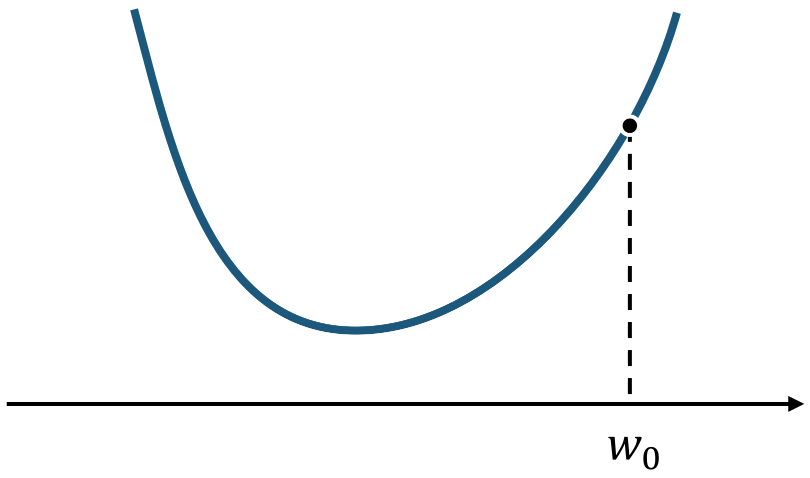
Derivative for a vector, matrix or tensor



Gradient Descent: Pseudocode

- Pick an **initial weight vector** w_0 and **learning rate** η
- Repeat until convergence: $w_{t+1} = w_t - \eta \nabla f(w_t)$

Gradient of function f with respect to weight w



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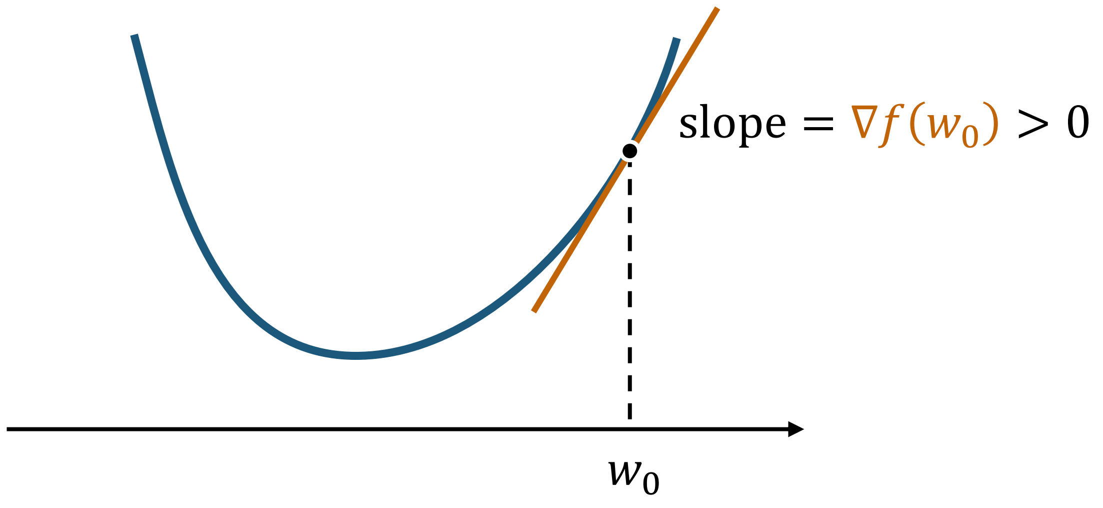

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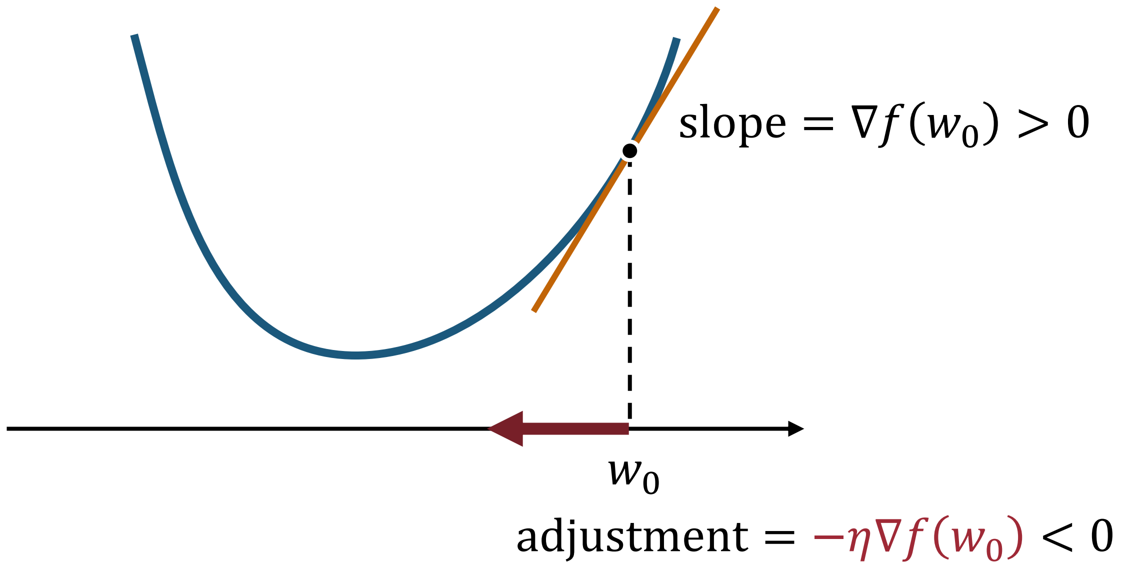

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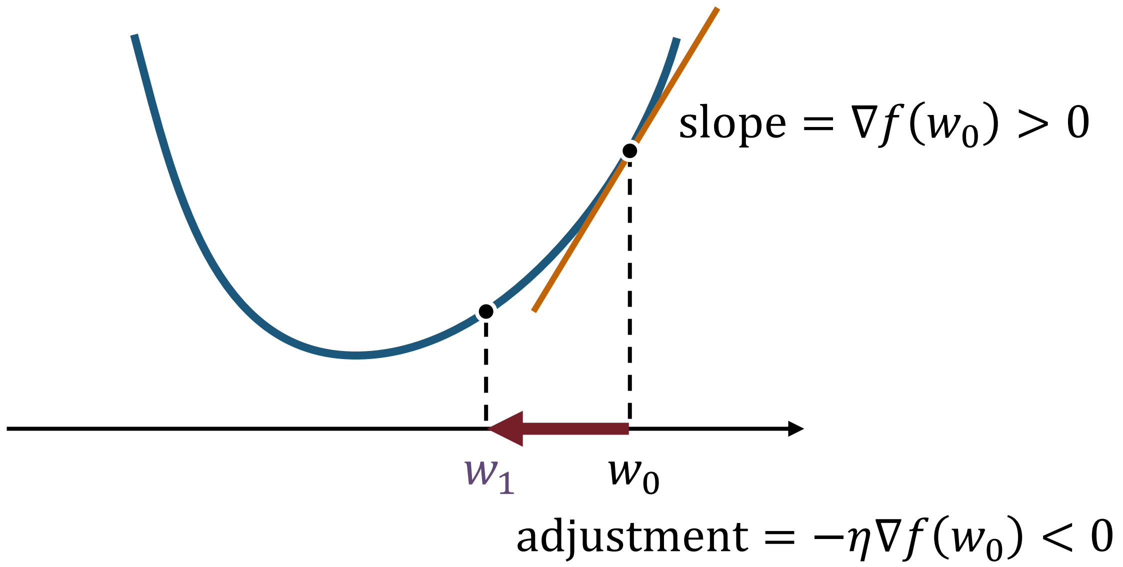

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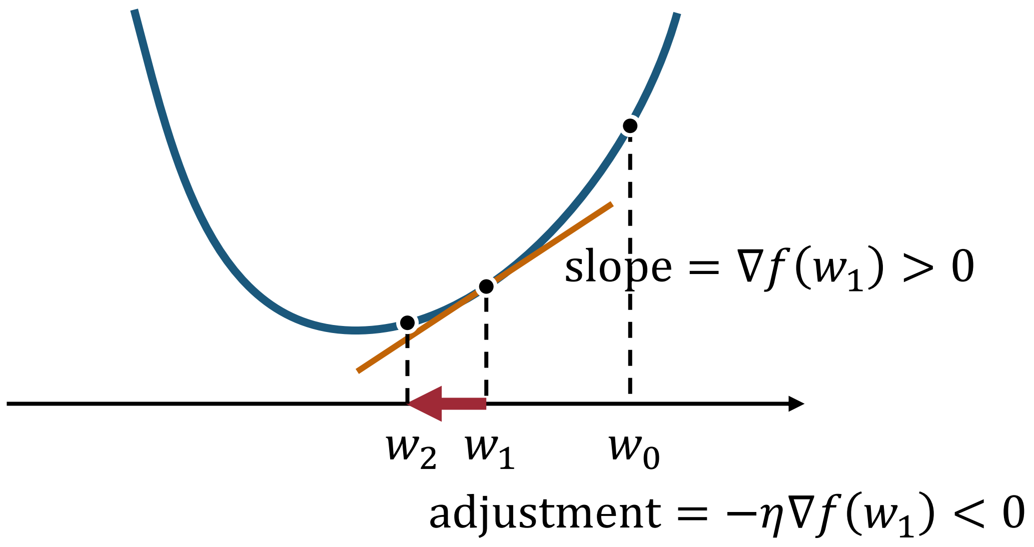

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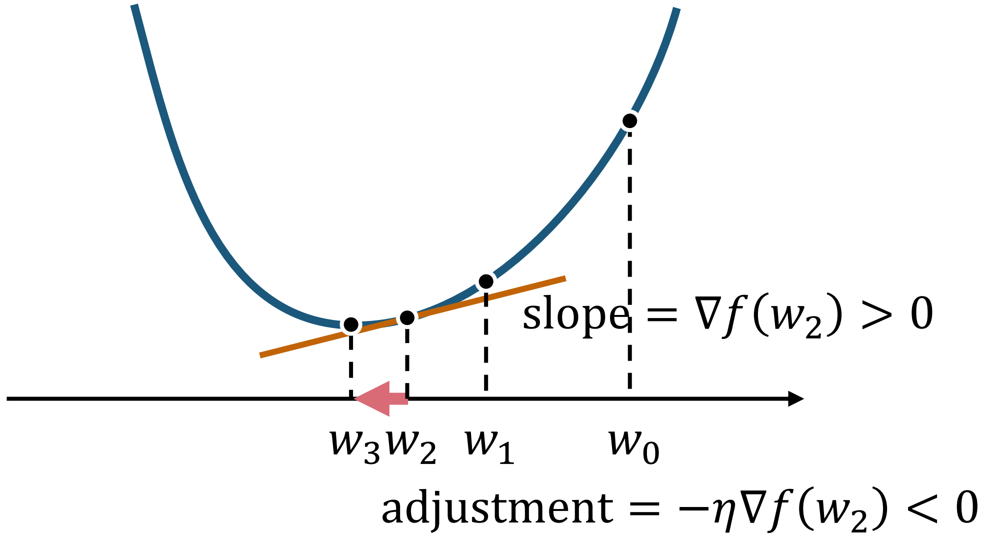

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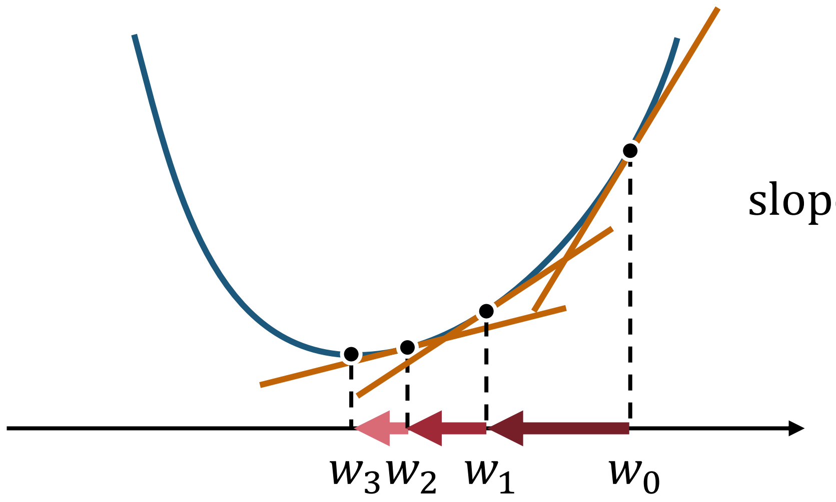
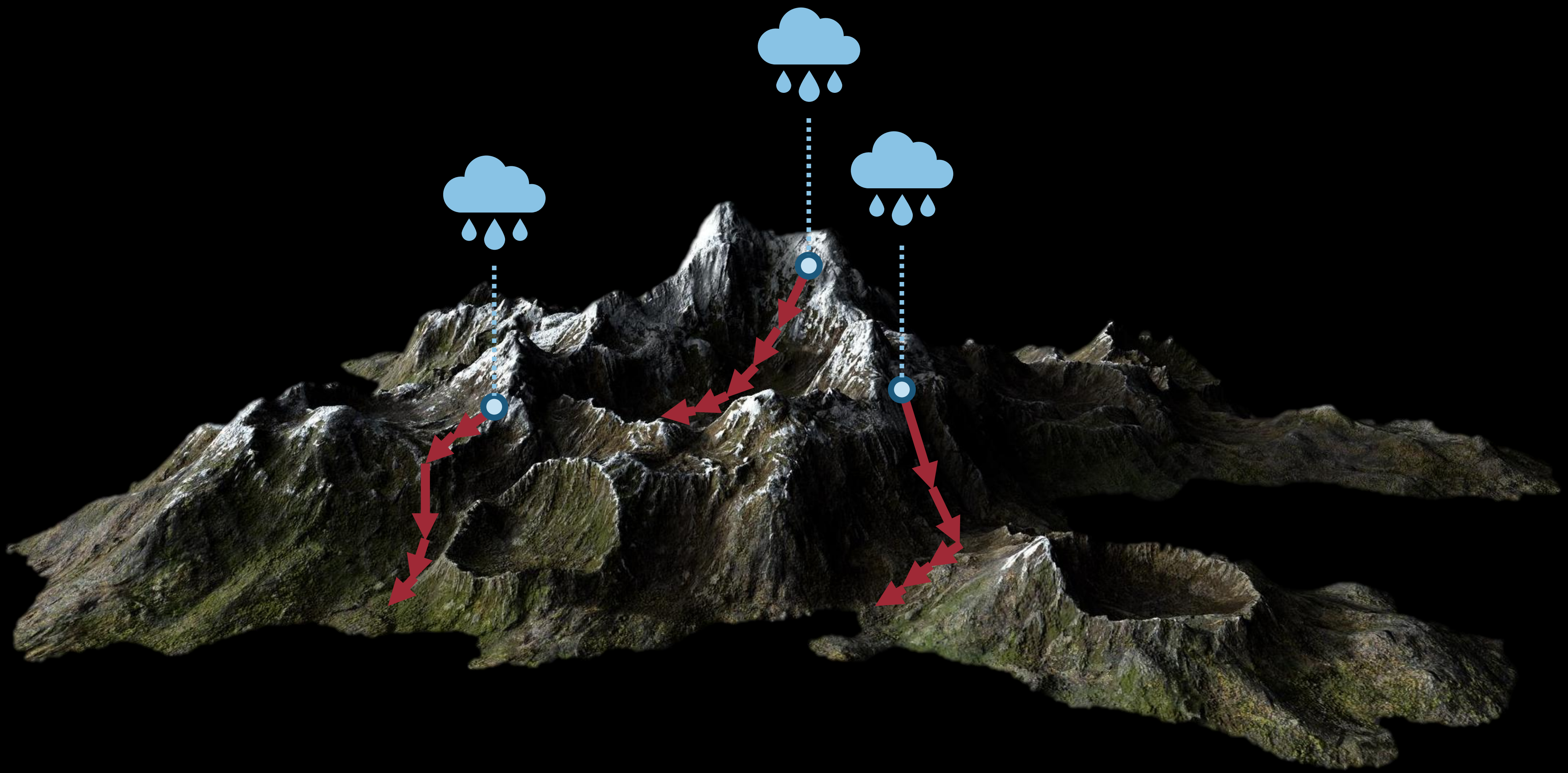


slope $= \nabla f(w_t) > 0$

adjustment $= -\eta \nabla f(w_t) < 0$

Gradient Descent: 3D Case



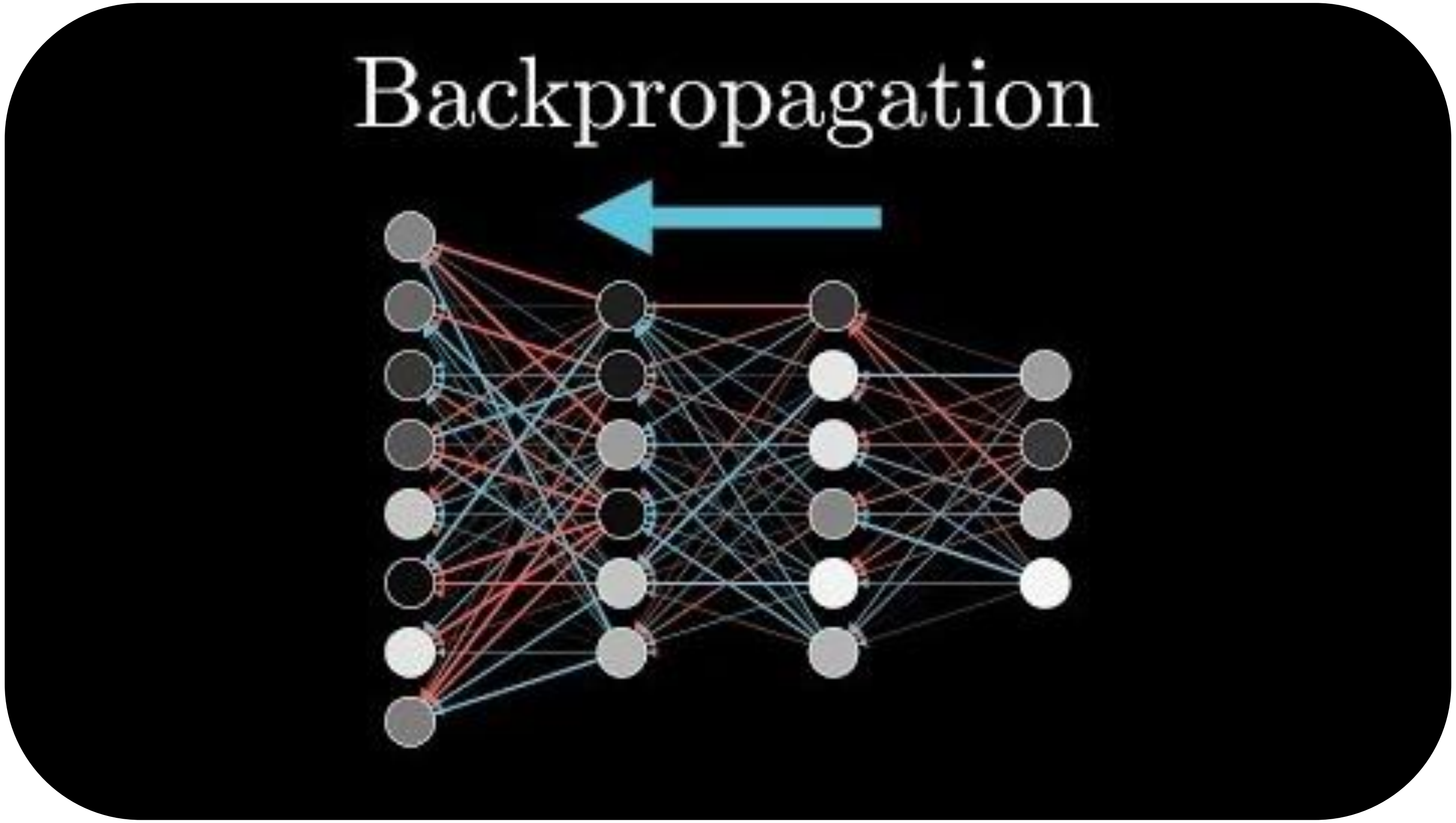
substance3d.adobe.com/community-assets/assets/9fe77d4279e12fe2fbd90b8f7ca18146a565f7ee

Backpropagation: Efficiently Computing the Gradients

- An efficient way of **computing gradients** using chain rule
- The reason why we want **everything to be differentiable** in deep learning

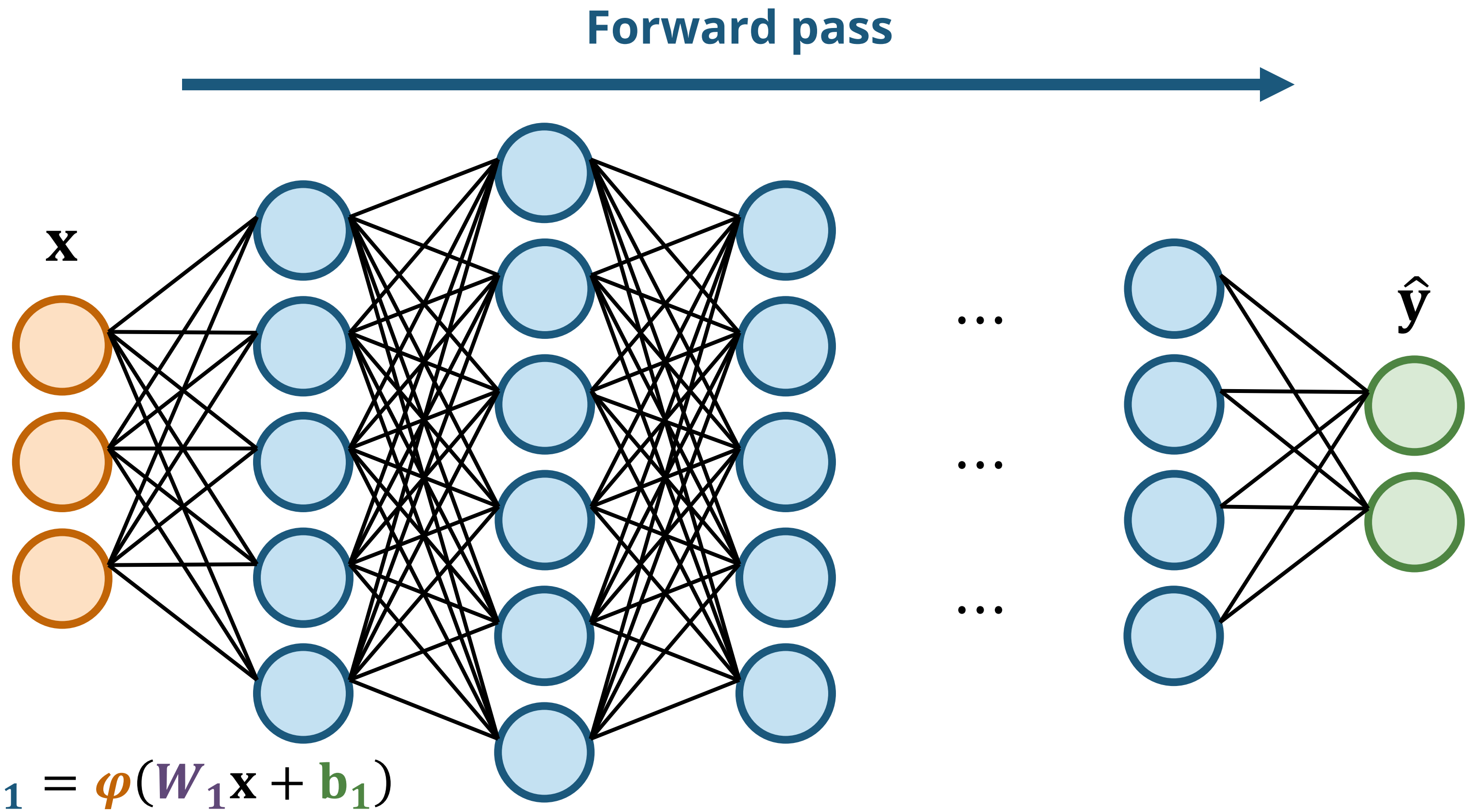
$$w_{t+1} = w_t - \eta \nabla f(w_t)$$

Backpropagation: Efficiently Computing the Gradients



youtu.be/Ilg3gGewQ5U?t=196

Forward Pass & Backward Pass



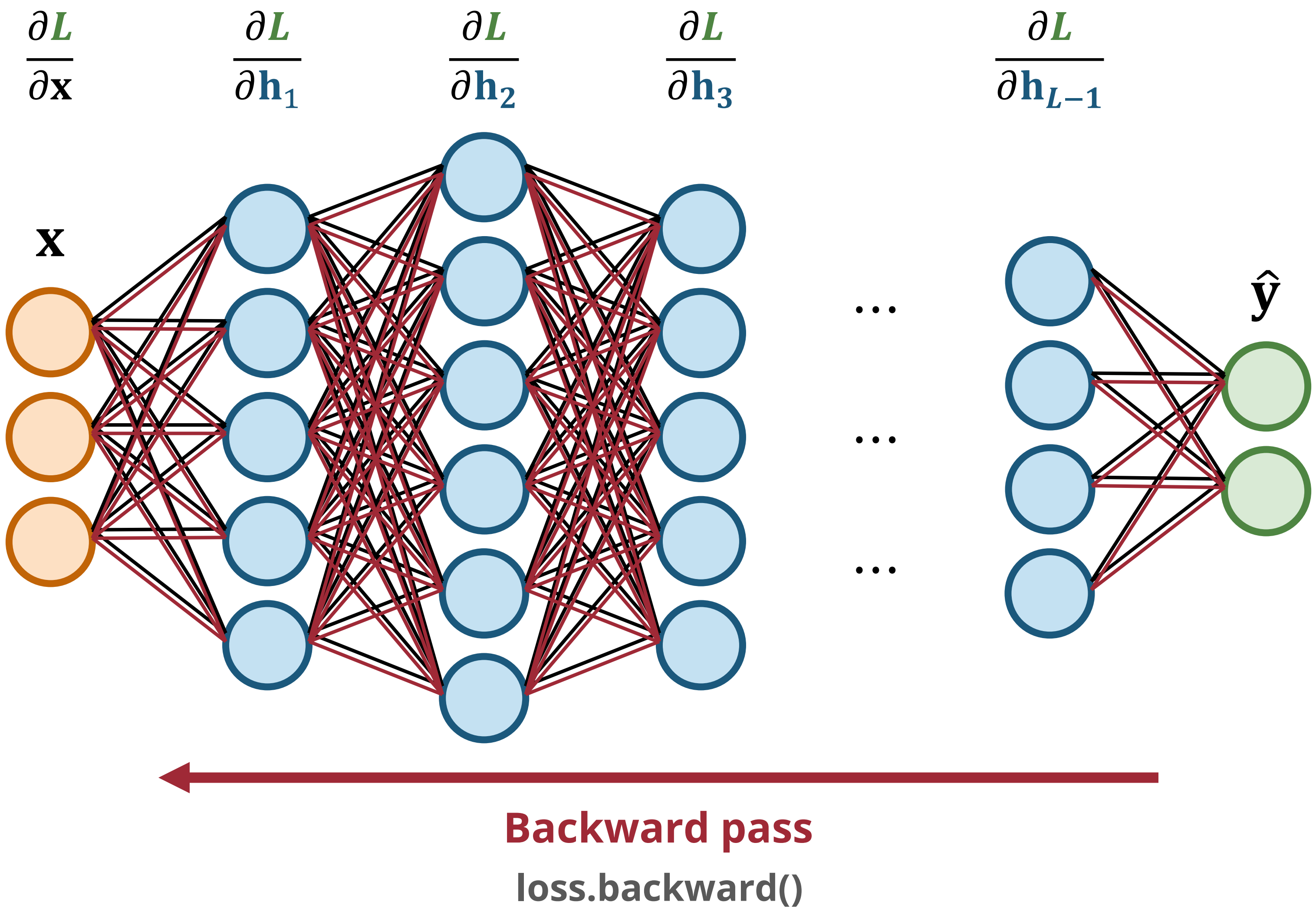
$$\mathbf{h}_1 = \varphi(W_1\mathbf{x} + \mathbf{b}_1)$$

$$\mathbf{h}_2 = \varphi(W_2\mathbf{h}_1 + \mathbf{b}_2)$$

$$\mathbf{h}_3 = \varphi(W_2\mathbf{h}_2 + \mathbf{b}_2)$$

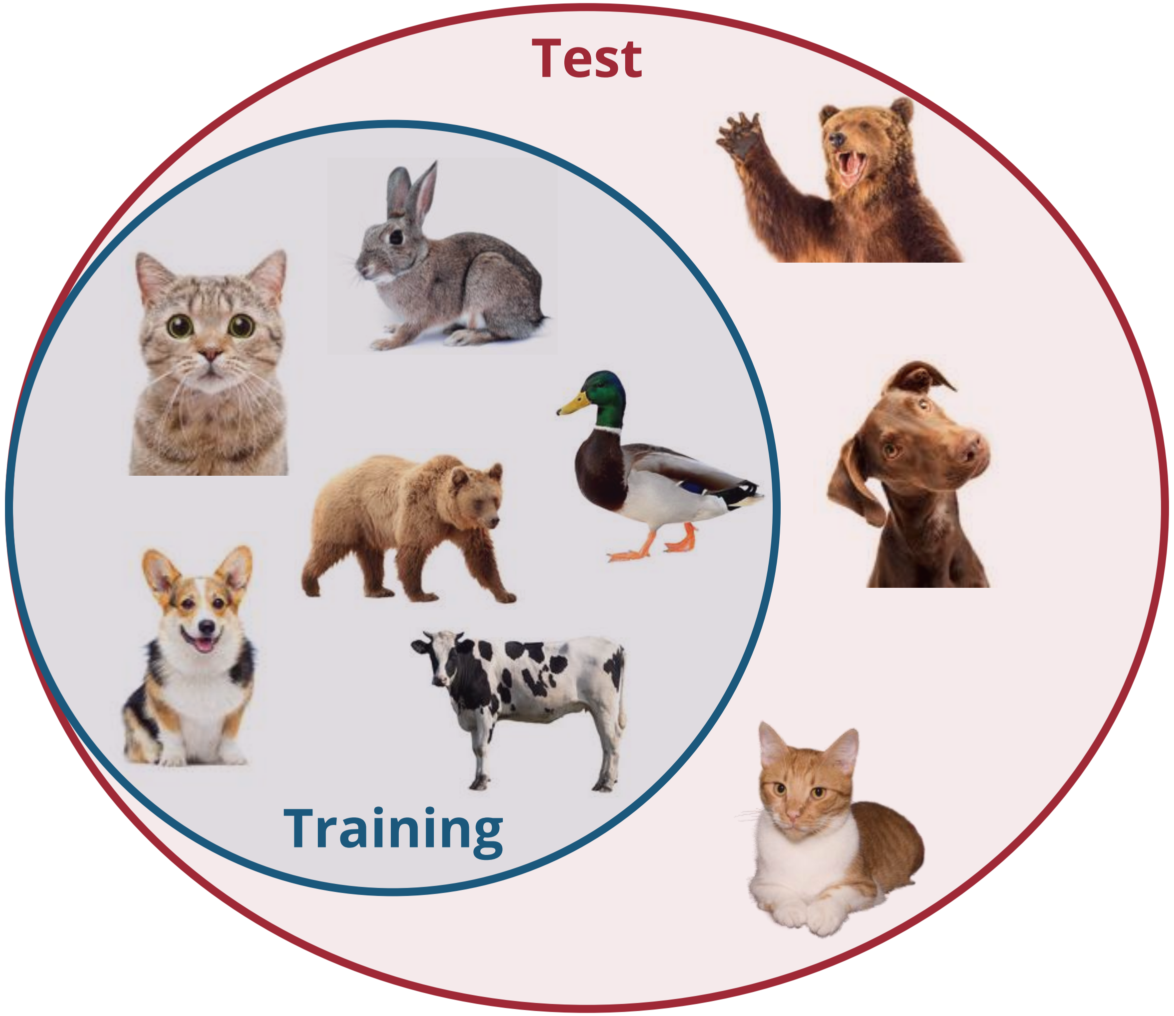
$$\hat{\mathbf{y}} = \varphi(W_L\mathbf{h}_{L-1} + \mathbf{b}_L)$$

Forward Pass & Backward Pass



Training–Validation–Test

In-distribution vs Out-of-distribution



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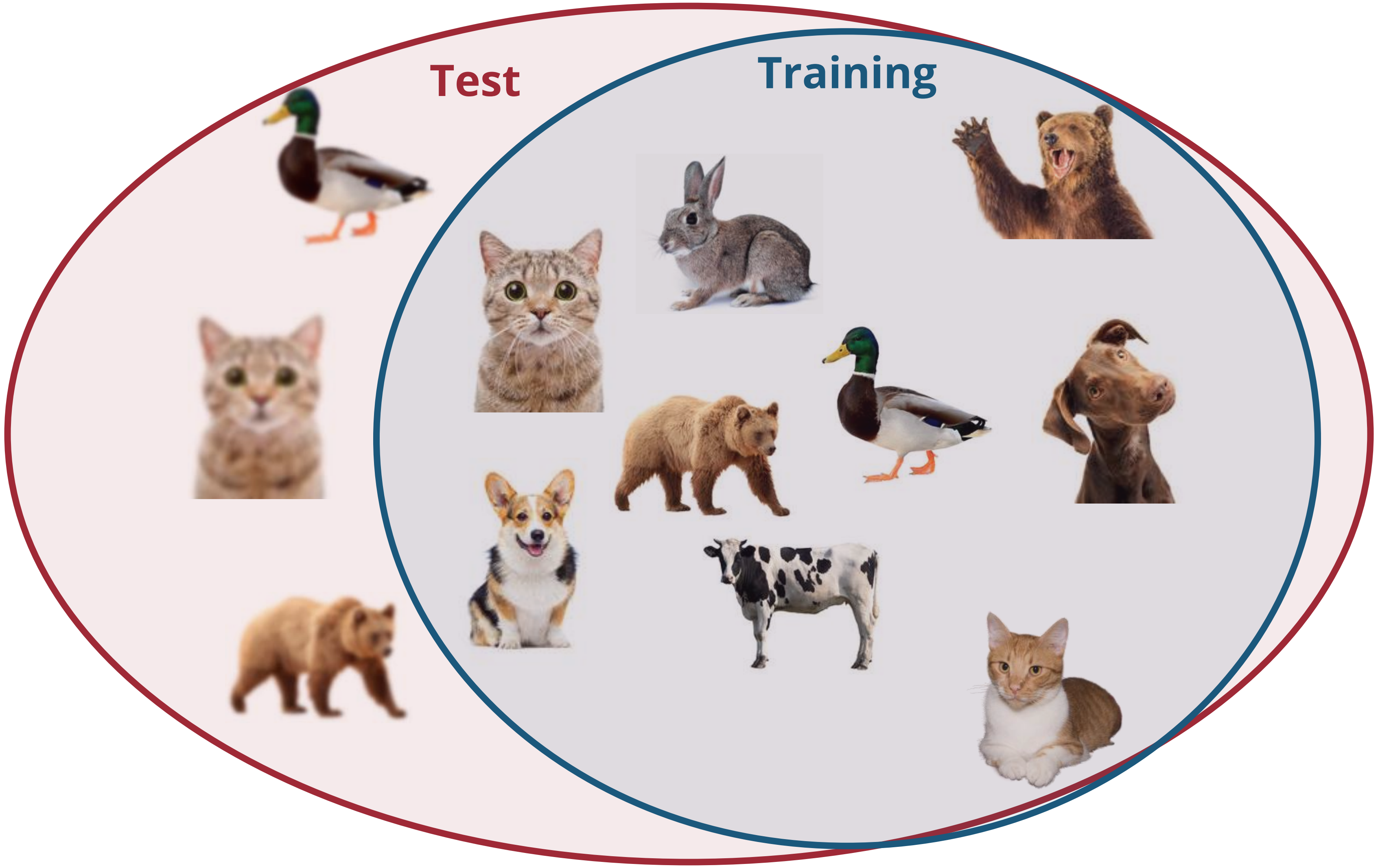


In-distribution vs Out-of-distribution

In-distribution vs Out-of-distribution

- **Key**: Make the training distribution closer to the target distribution
- First, we need to **define our target distribution**
- Then, we can try to
  - Collect a **diverse** dataset covering that covers different parts of the target distribution
  - Apply **data augmentation** to fill the gaps in the distribution

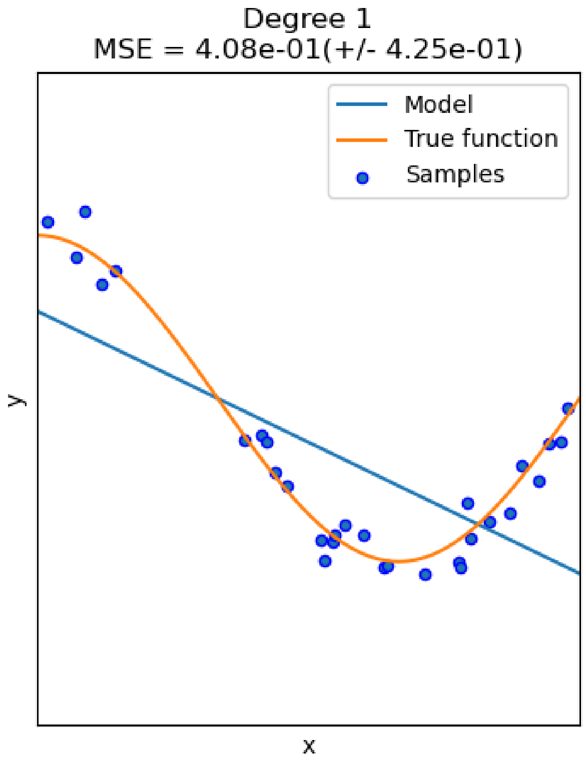
In-distribution vs Out-of-distribution

- What do we really want?
  - Good performance on the **training samples** **We already have their answers**
  - Good performance on **unseen samples in the target distribution** **Yep, we can do this!**
  - Good performance on **out-of-distribution samples** **Hopefully, but not guaranteed**

How to achieve good performance on
unseen samples in the target distribution

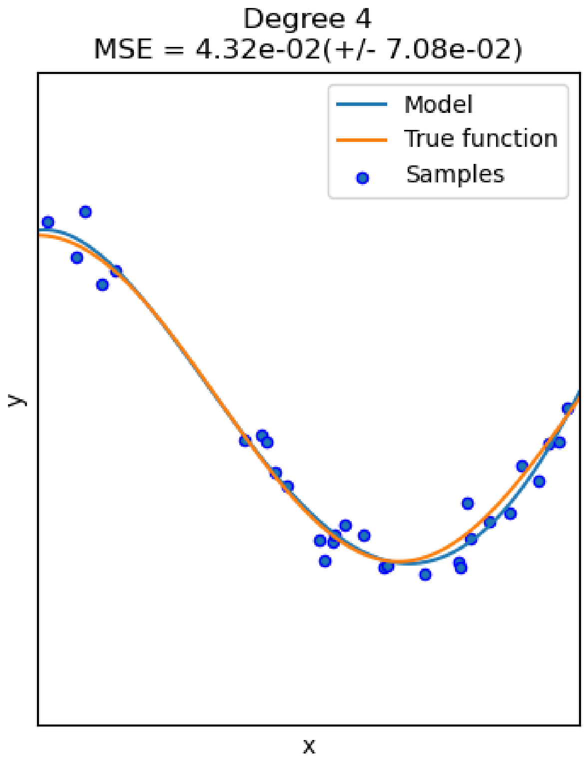
Overfitting & Underfitting

Underfitting

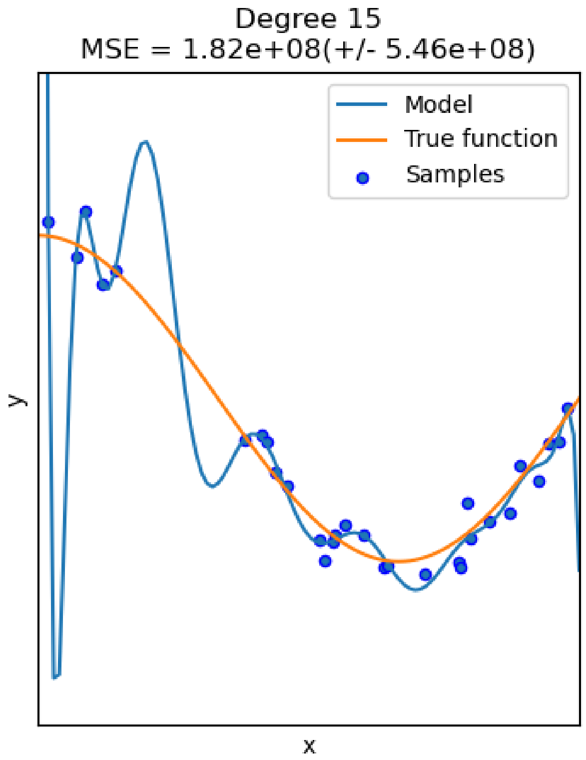


Model too inexpressive

Good fit!



Overfitting

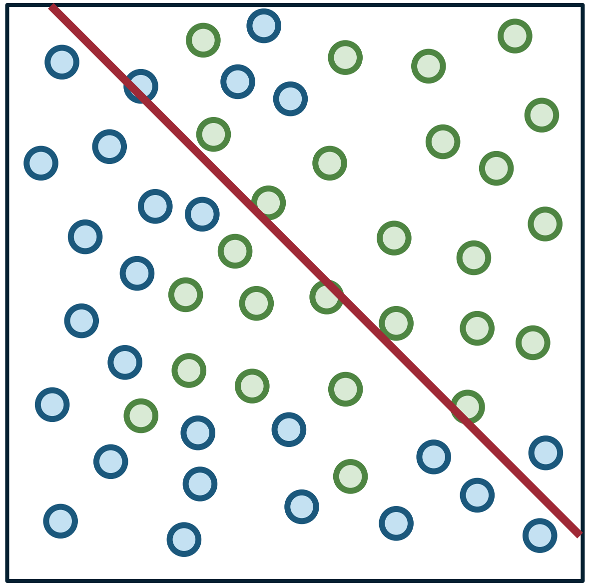


Model too expressive

scikit-learn.org/stable/auto_examples/model_selection/plot_underfitting_overfitting.html

Overfitting & Underfitting

Underfitting



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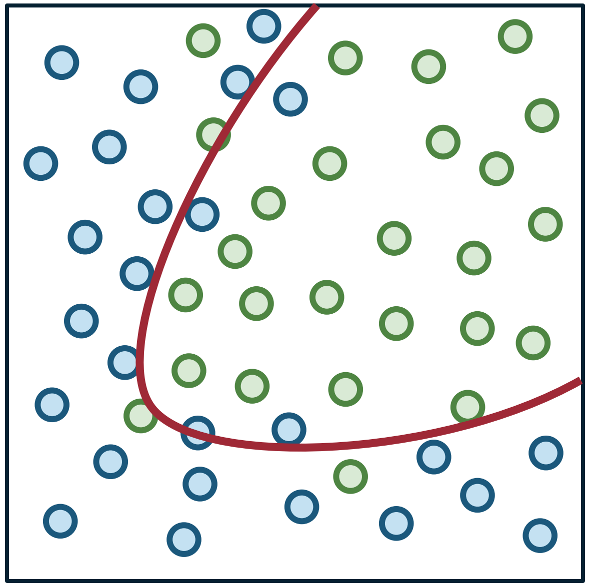

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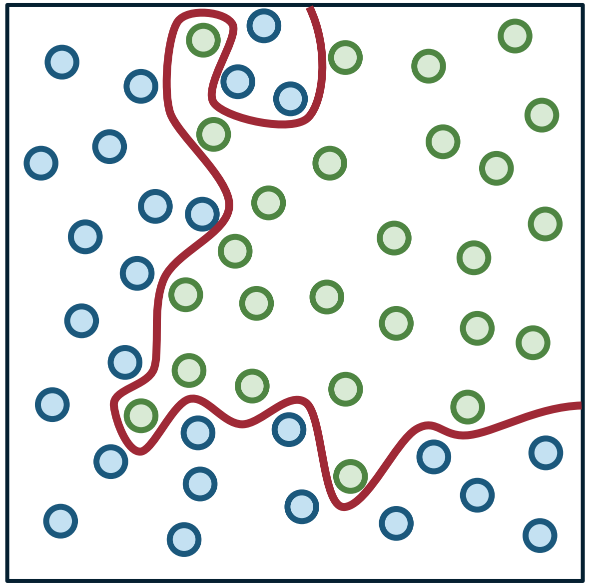

Model too expressive

Train–Test Split

- **Goal**: Good performance on **unseen samples in the target distribution**

Train–Test Split

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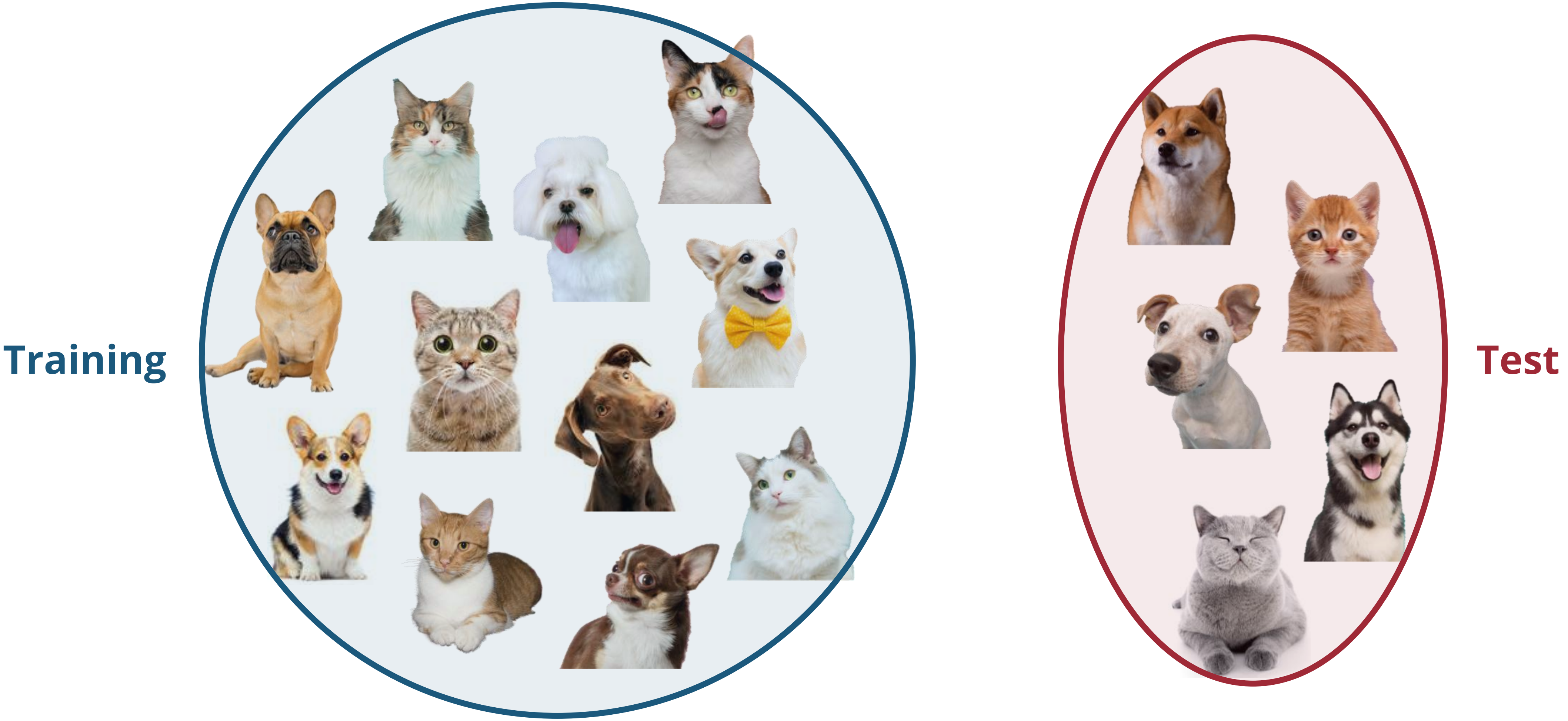
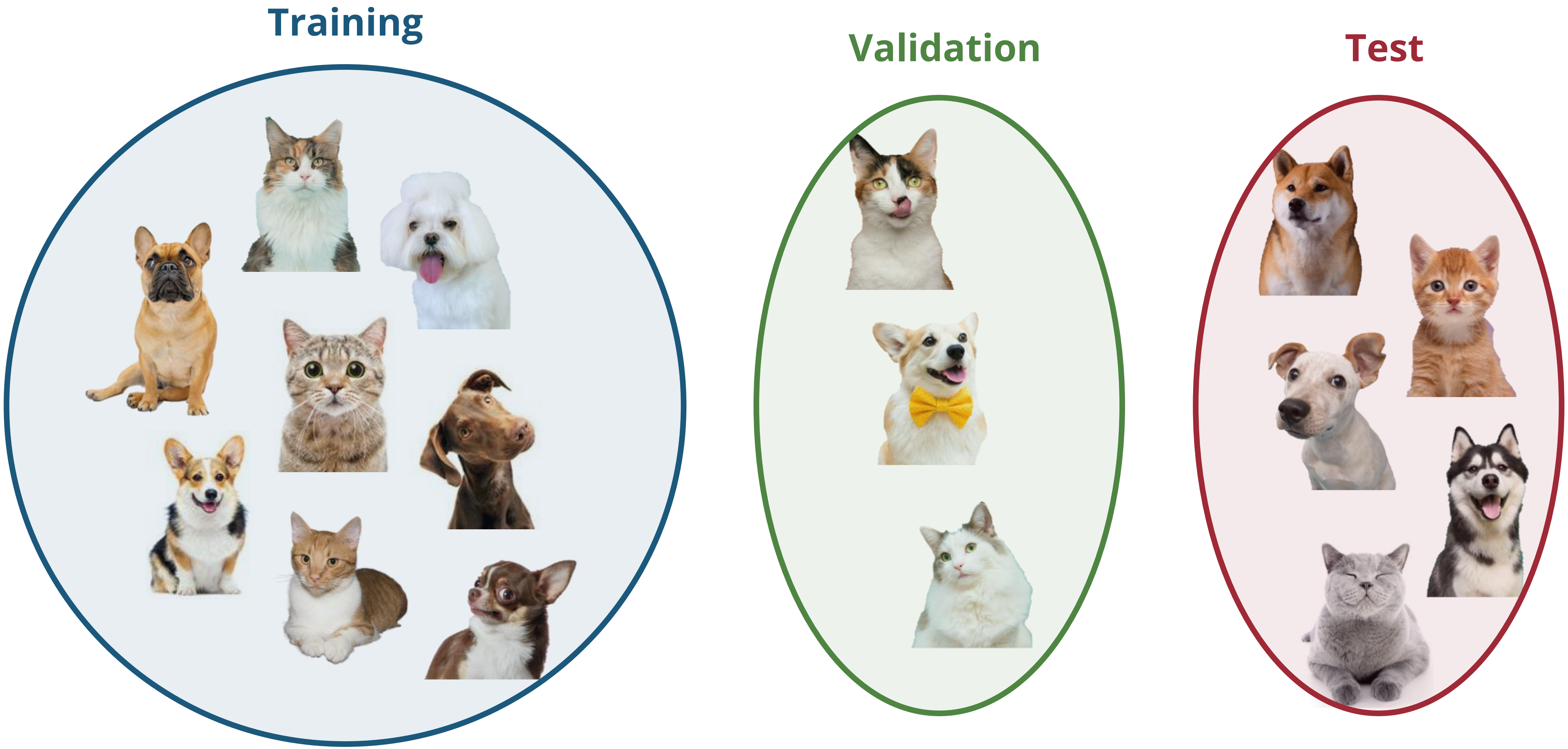


Test Set is an Estimation of the Test Distribution

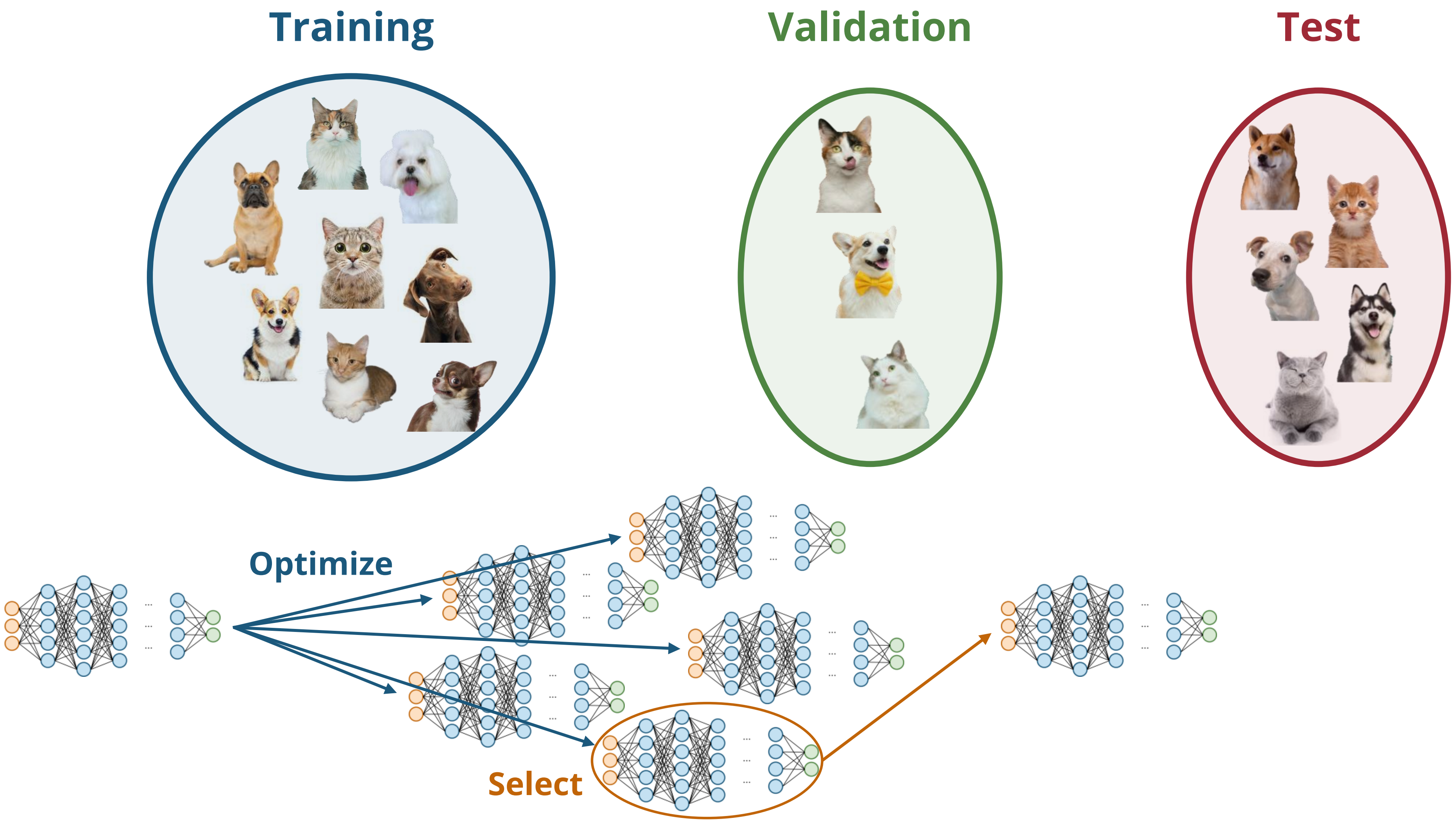
- We create a test set because we want to **estimate the performance when the model is applied to an interested distribution**

Train–Validation–Test Split

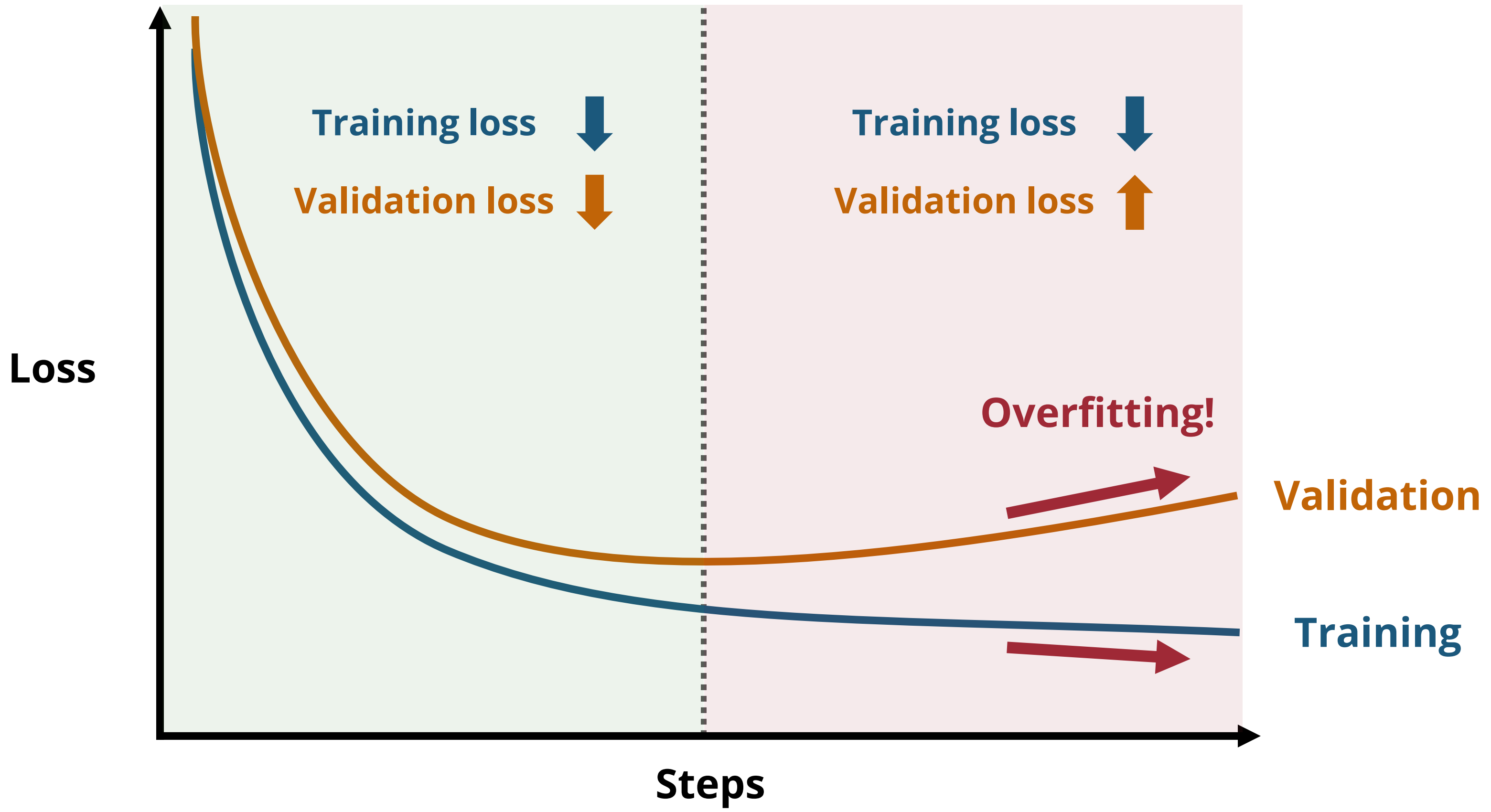
Train–Validation–Test Split



Training–Validation–Test Pipeline



Training vs Validation Losses



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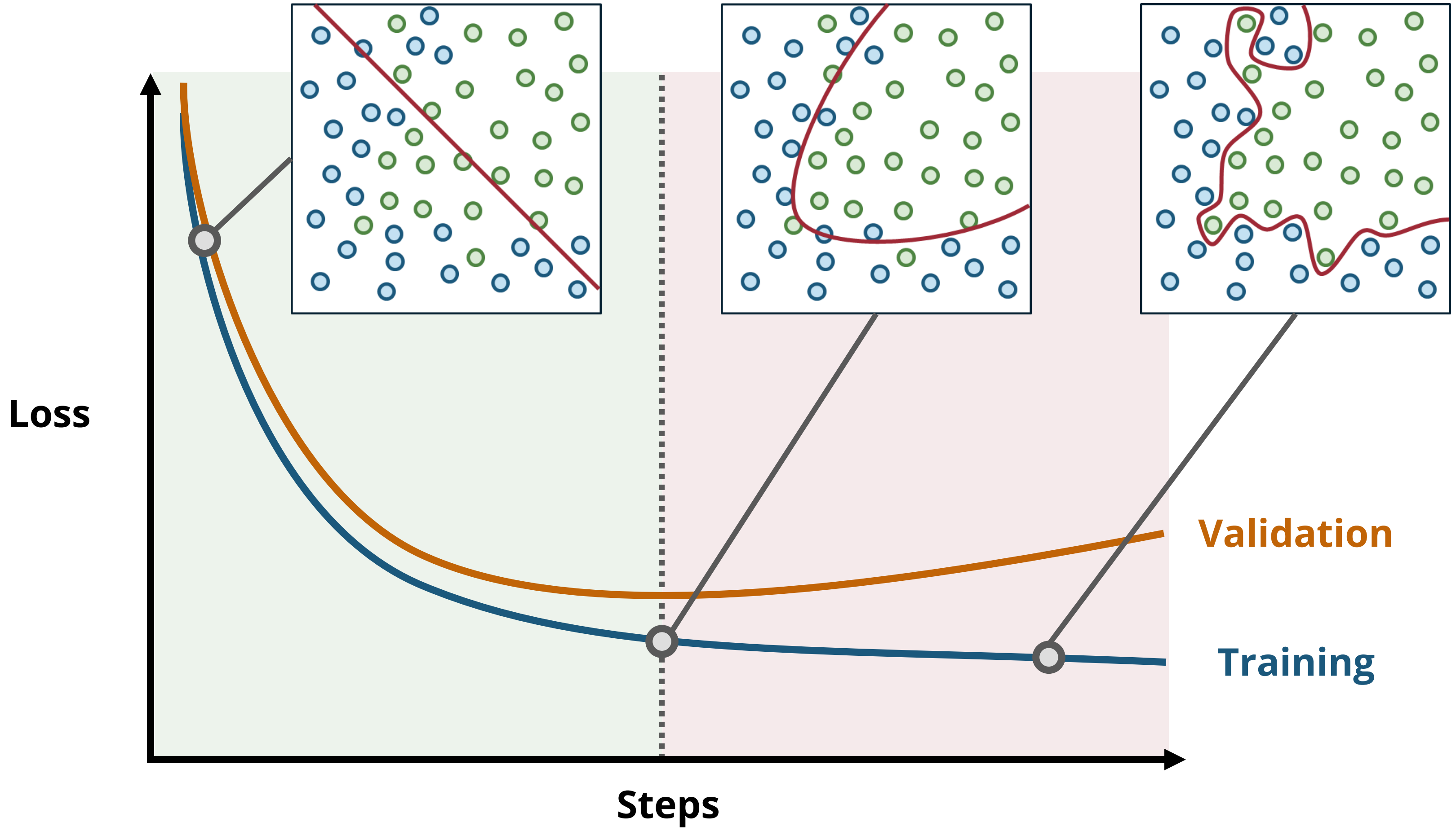

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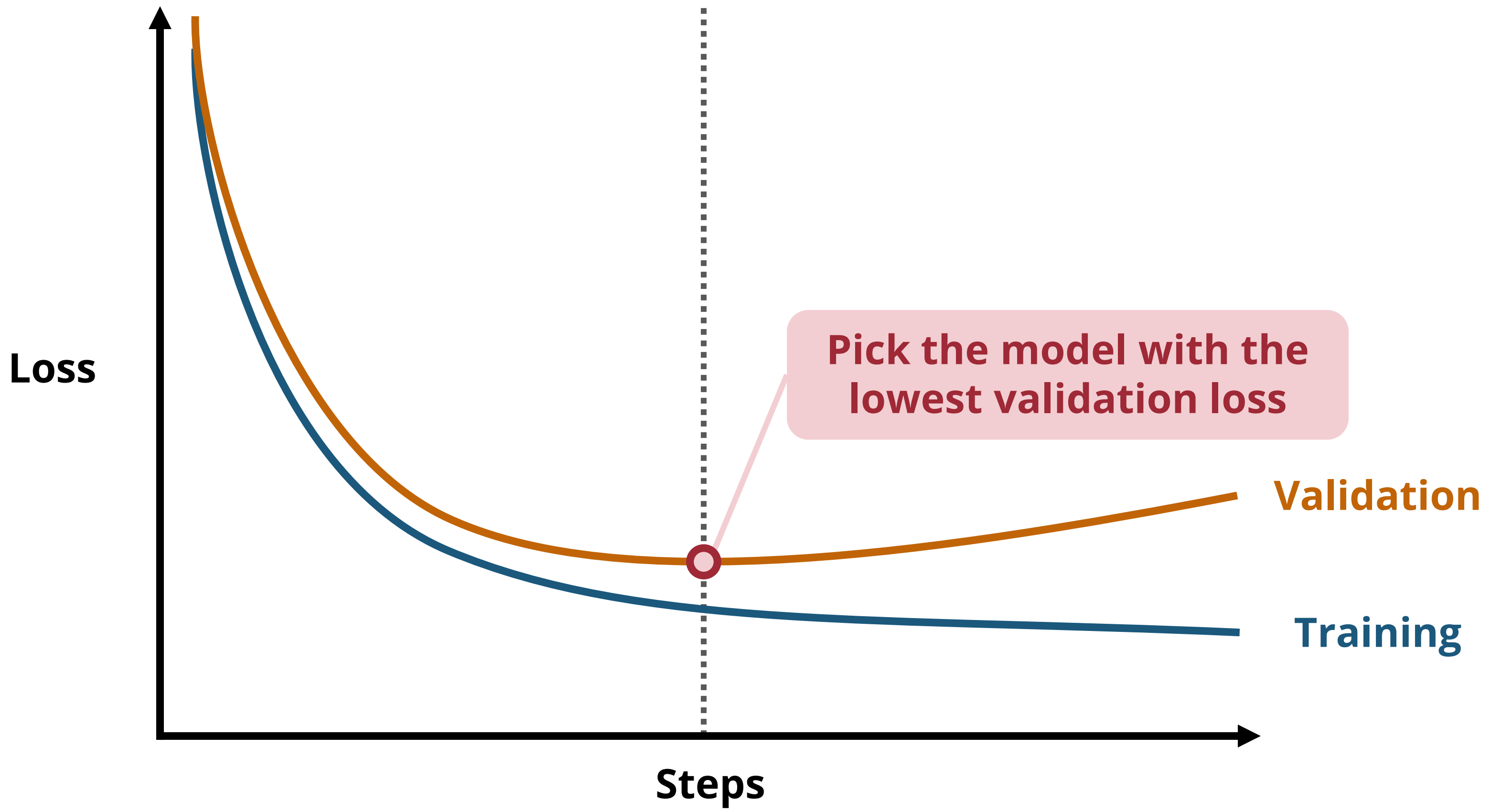

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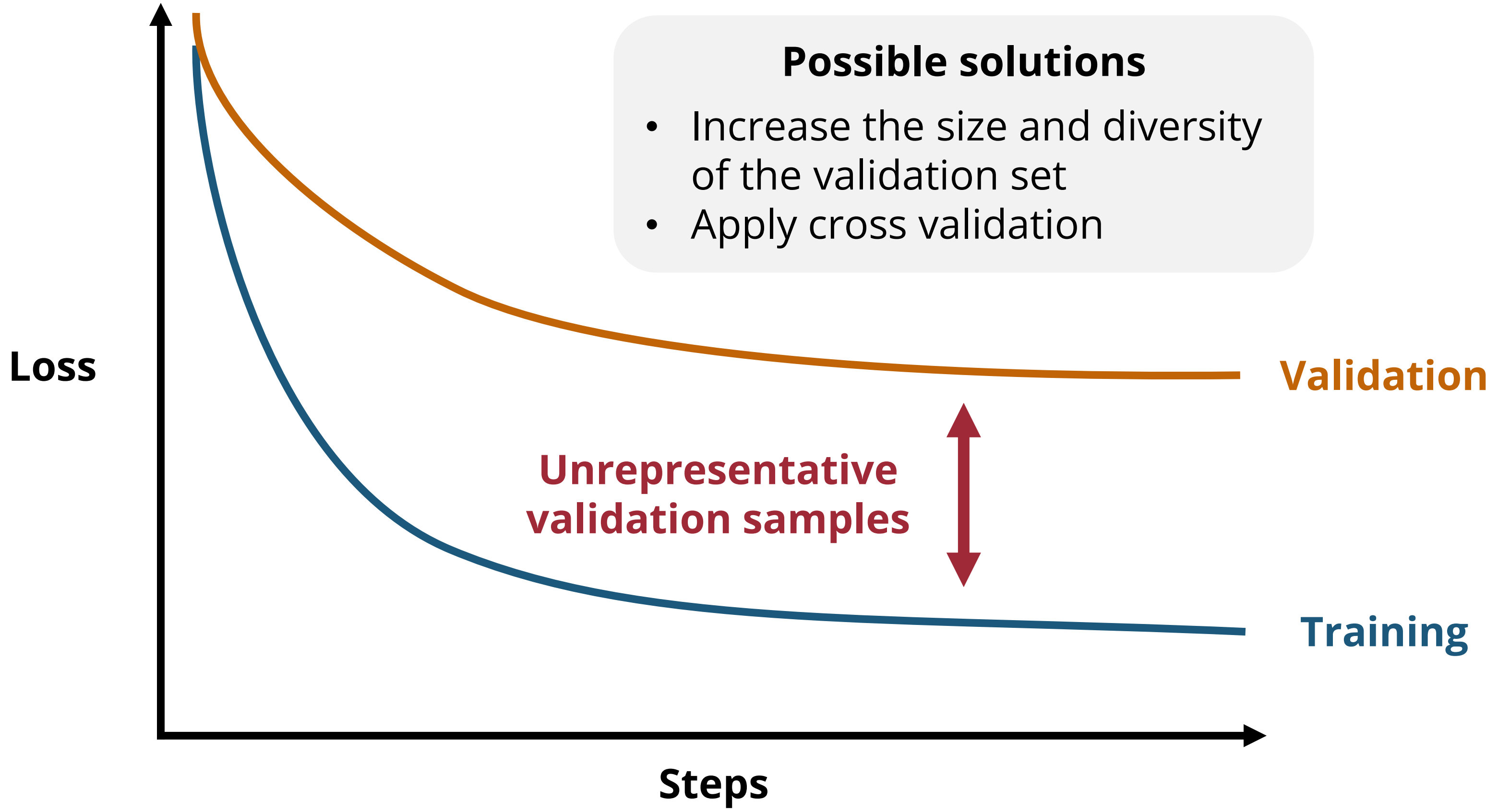

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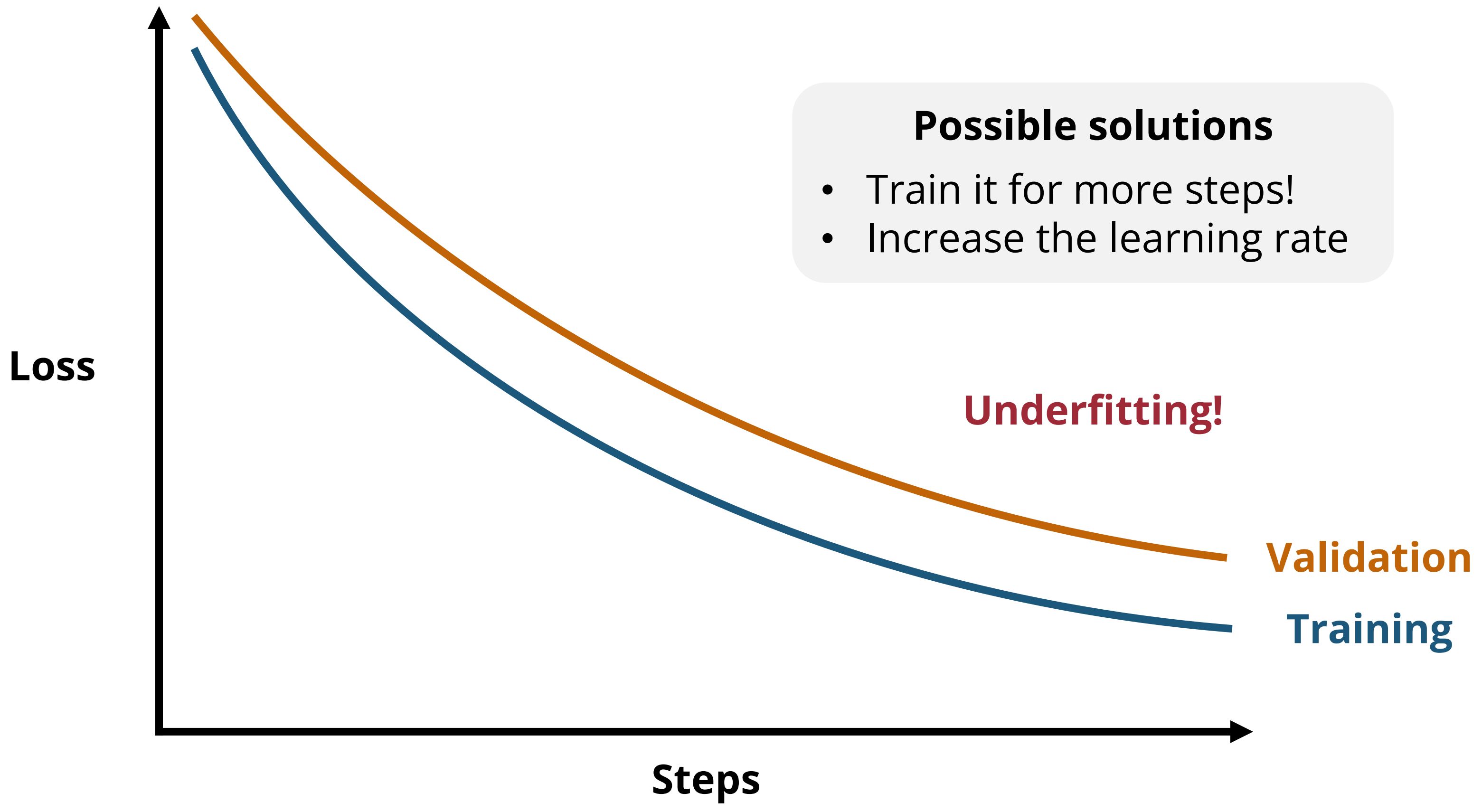
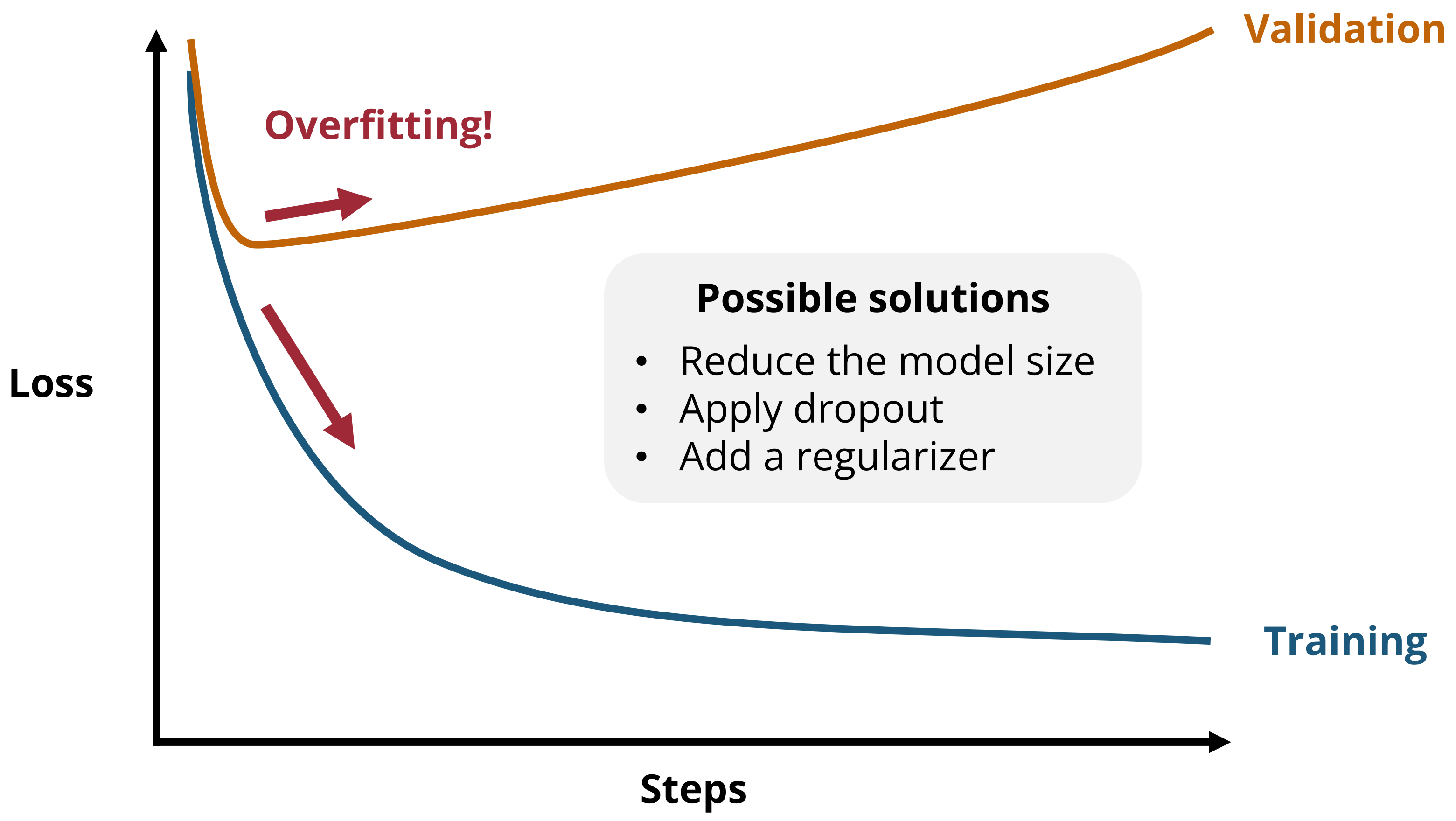


Training vs Validation Losses



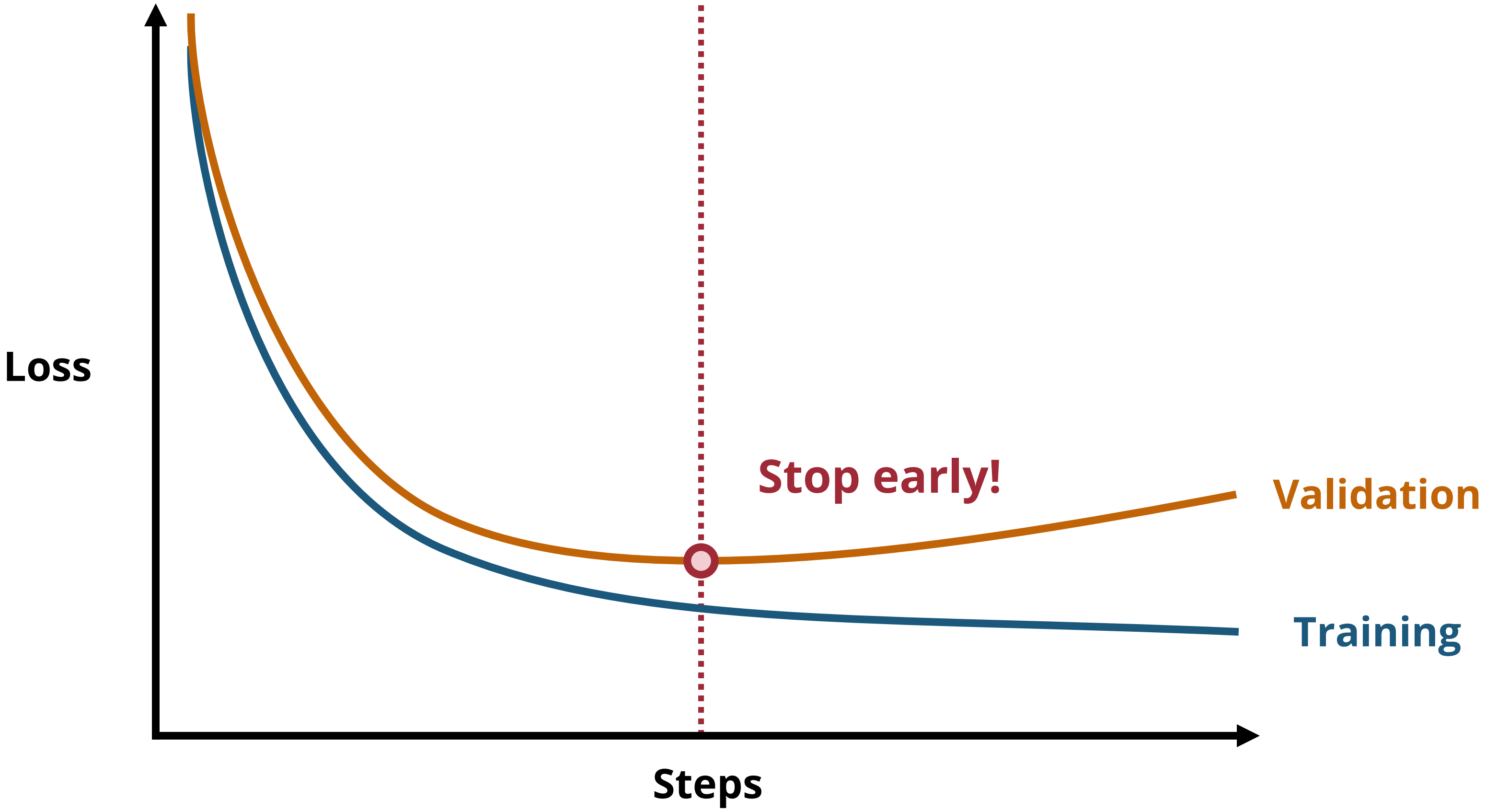
Train–Validation–Test Split

- **Keys**
  - **Never train or select your model on test samples!**
  - Don't over-select your model on the validation set

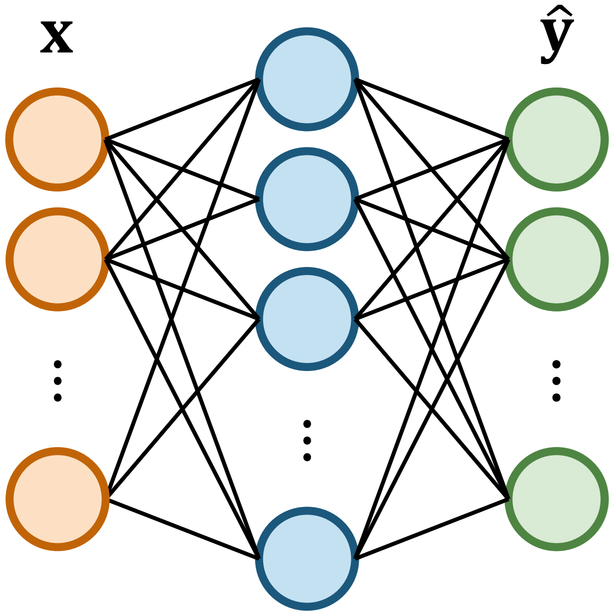
- What's the **best ratio**?
  - Most common: **8:1:1** or 9:0.5:0.5
  - For smaller dataset, you might even want 6:2:2

Overcoming Overfitting

Early Stopping

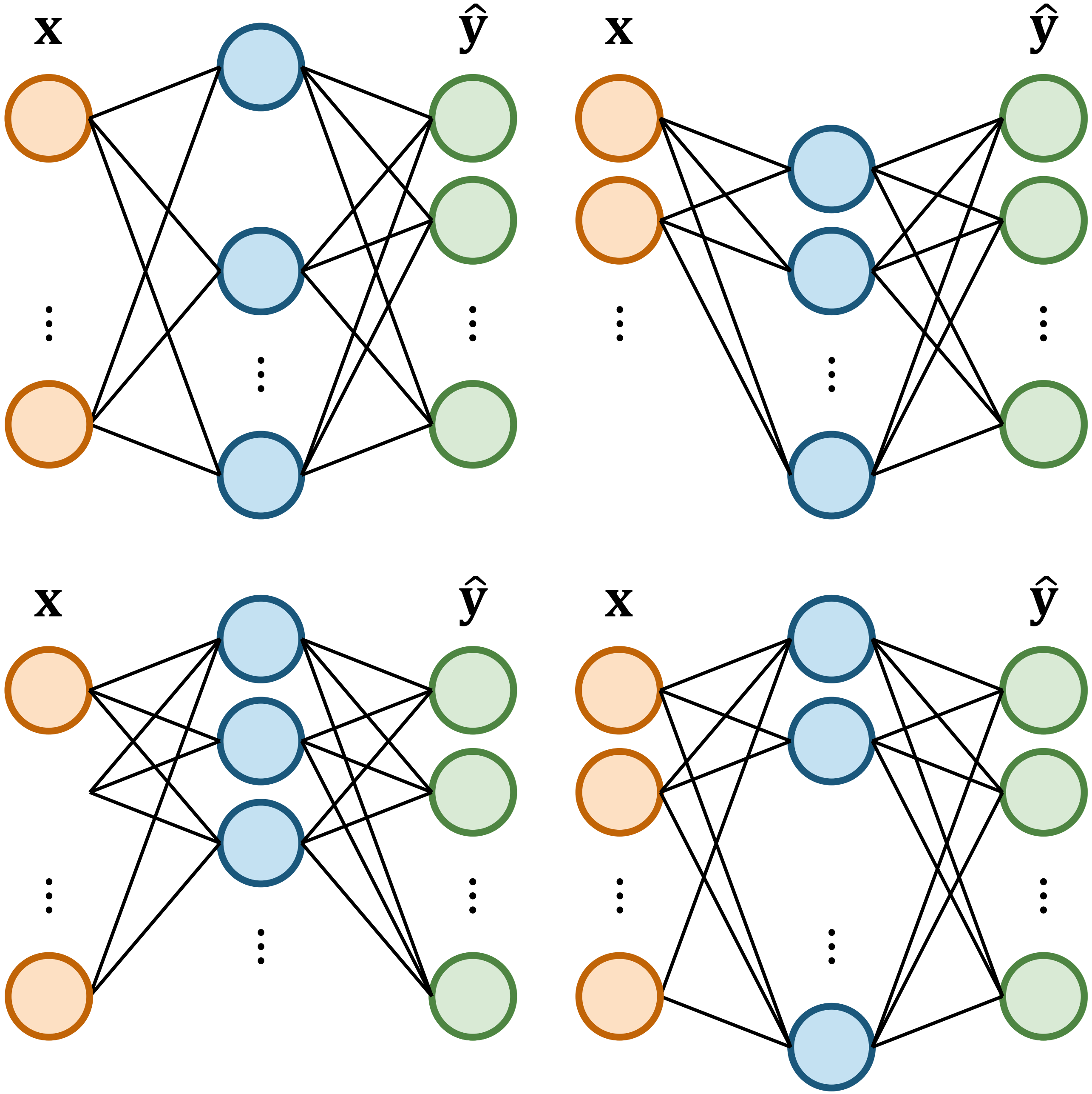


Dropout



Each neuron may be removed
with probability p during training

Dropout rate



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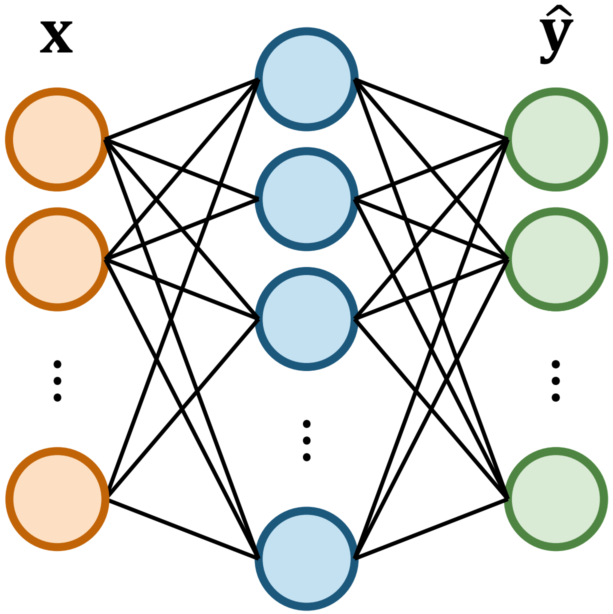
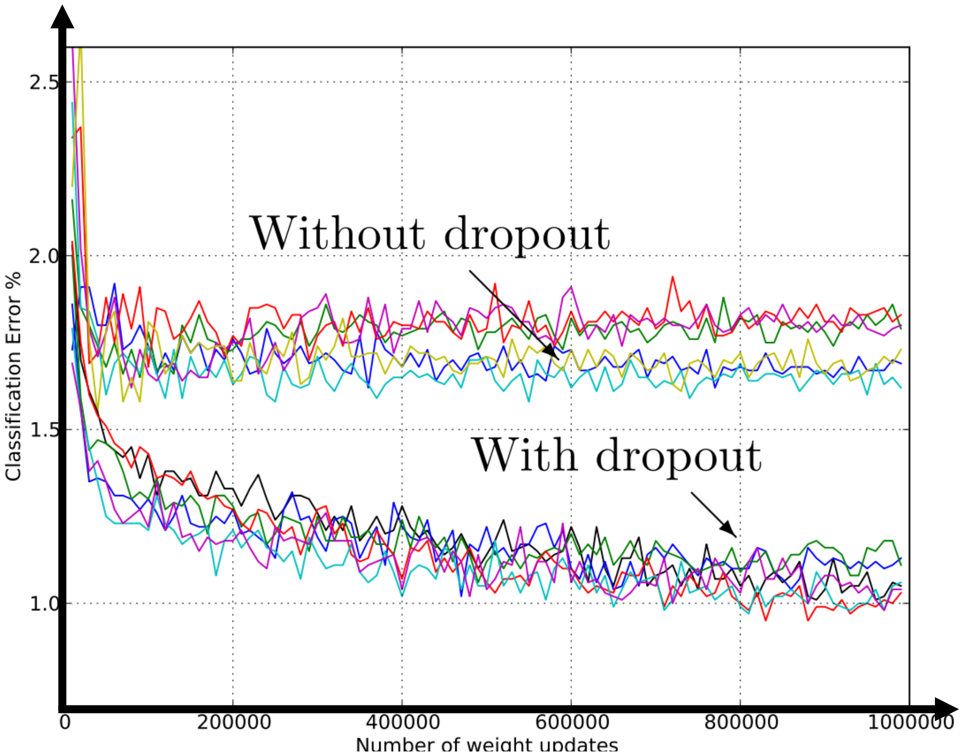


Each neuron may be removed with probability p during training

Test error rate



Weight updates

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," *JMLR*, 2014.\

Regularization Term

- A regularization term can help alleviate overfitting
  - **L1 regularization** (LASSO)

$$L' = L + \lambda(|w_1| + |w_2| + \cdots + |w_K|)$$

  - **L2 regularization** (ridge regression)

$$L' = L + \lambda\left(w_1^2 + w_2^2 + \cdots + w_K^2\right)$$

Both L1 and L2 regularizations encourage smaller weights

Recap

Training a Neural Network

Build a neural network
(which defines a set of functions)

↓

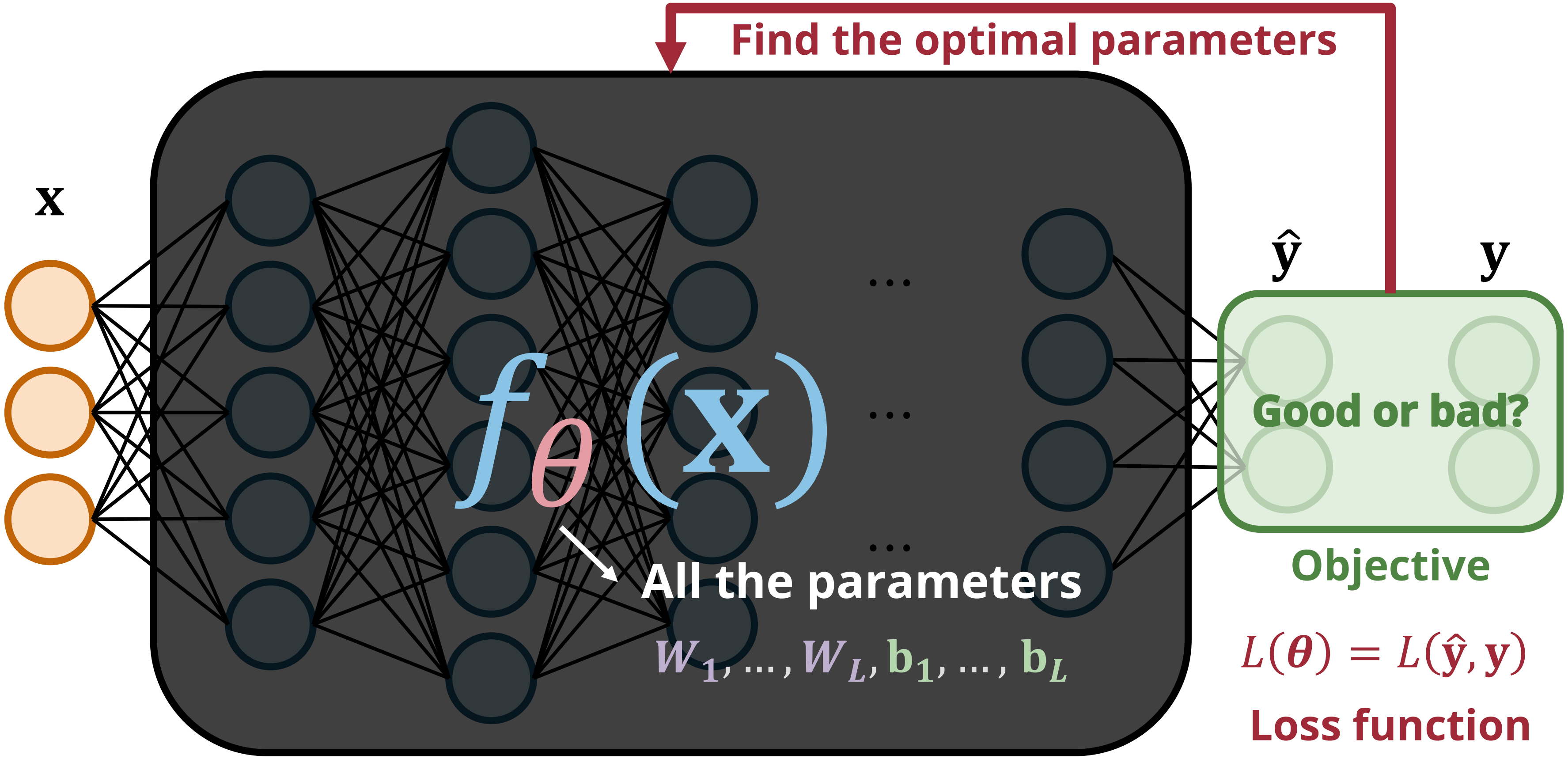
Define the objective
(i.e., what is good for a function)

↓

Find the optimal parameters
(which leads to the best function)

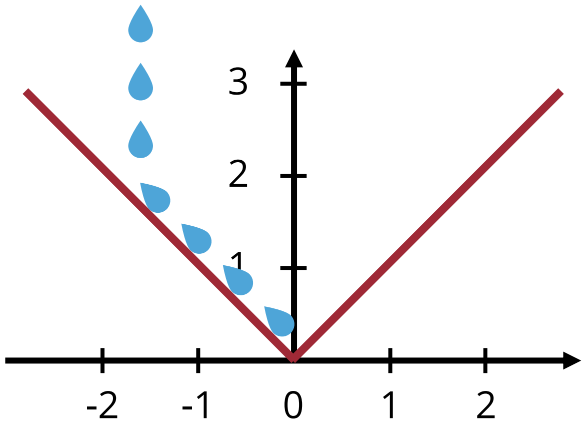
Neural Networks are Parameterized Functions

- A neural network represents **a set of functions**



L1 vs L2 Losses

L1 loss

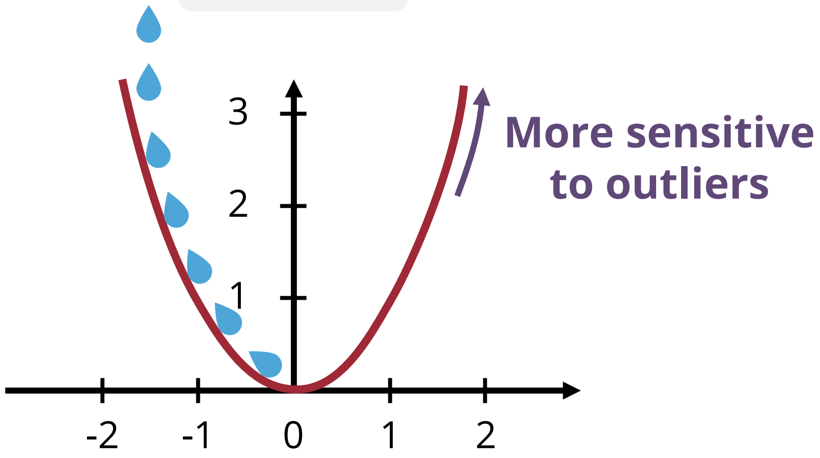


$$L(\hat{y}, y) = |\hat{y} - y|$$

$$L(\hat{\mathbf{y}}, \mathbf{y}) = \mathbf{MAE}(\hat{\mathbf{y}}, \mathbf{y}) = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i|$$

Mean Absolute Error (MAE)

L2 loss

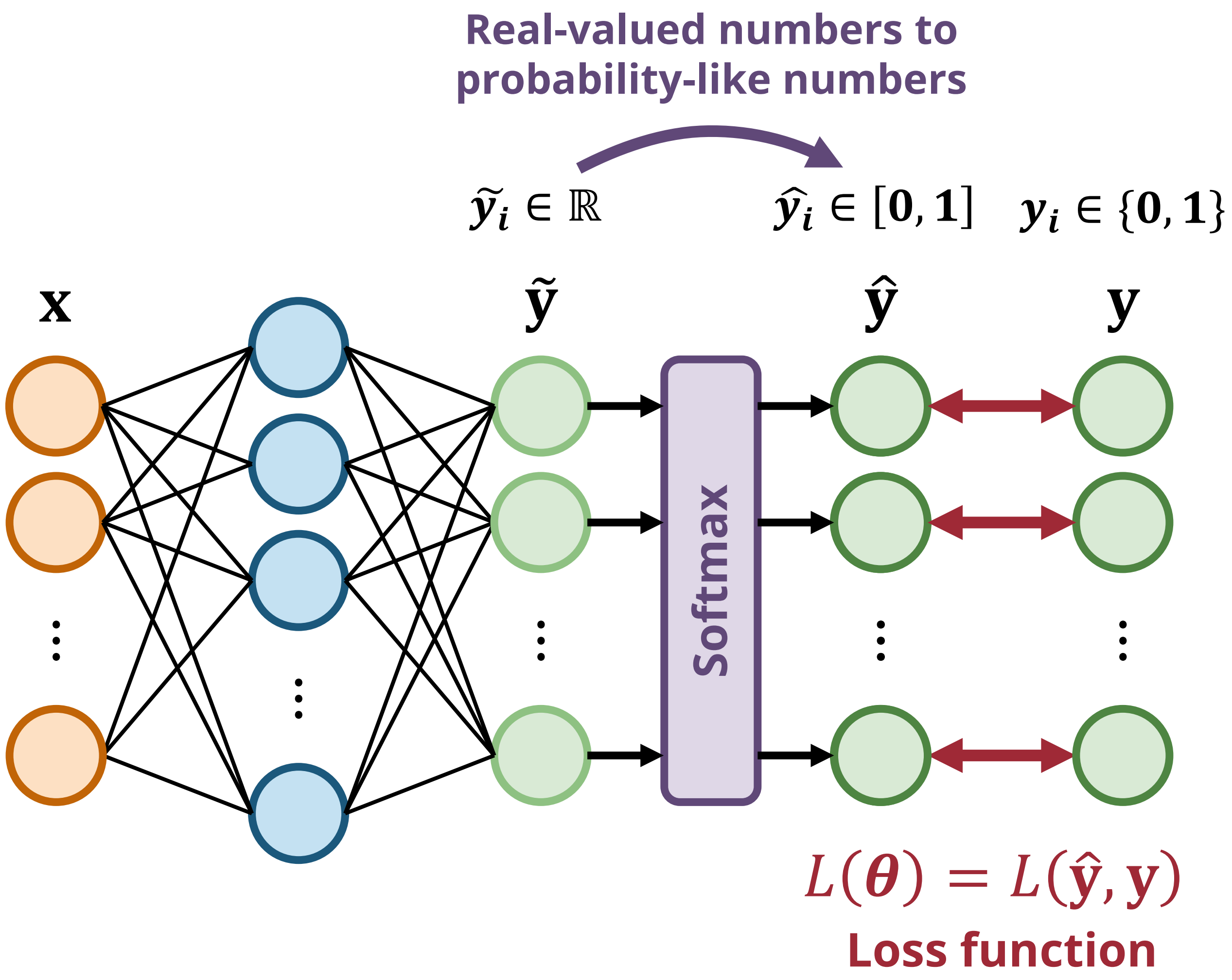


$$L(\hat{y}, y) = (\hat{y} - y)^2$$

$$L(\hat{\mathbf{y}}, \mathbf{y}) = \mathbf{MSE}(\hat{\mathbf{y}}, \mathbf{y}) = \frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2$$

Mean Squared Error (MSE)

Cross Entropy for Multiclass Classification

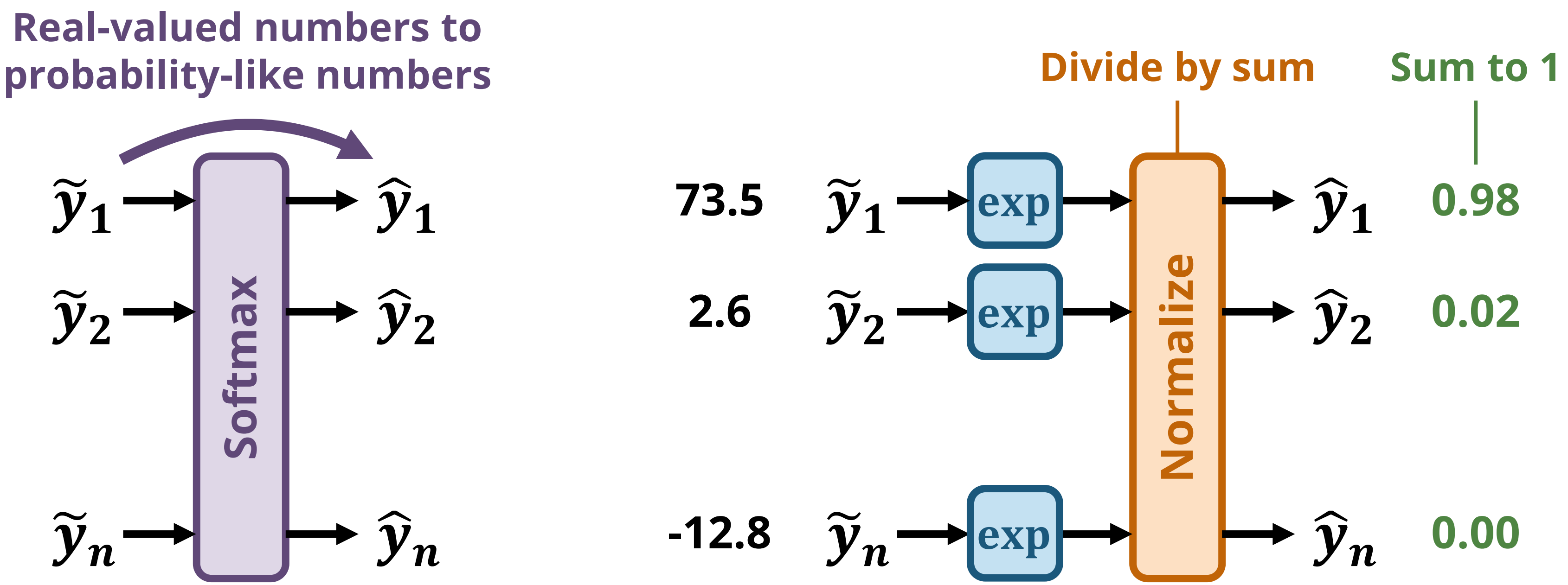


Softmax

$$\hat{y}_i = \frac{e^{\tilde{y}_i}}{\sum_{j=1}^{n} e^{\tilde{y}_j}}$$

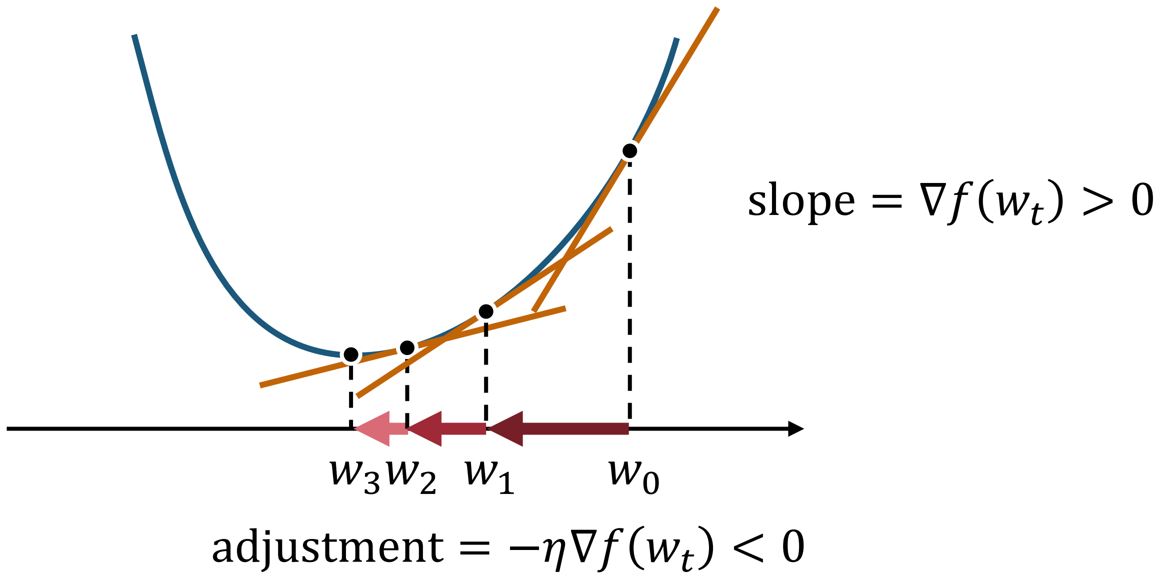
Softmax

- **Intuition**: Map several numbers to $[0, 1]$ while **keeping their relative magnitude**
  - Softmax is like the **multivariate version of sigmoid**

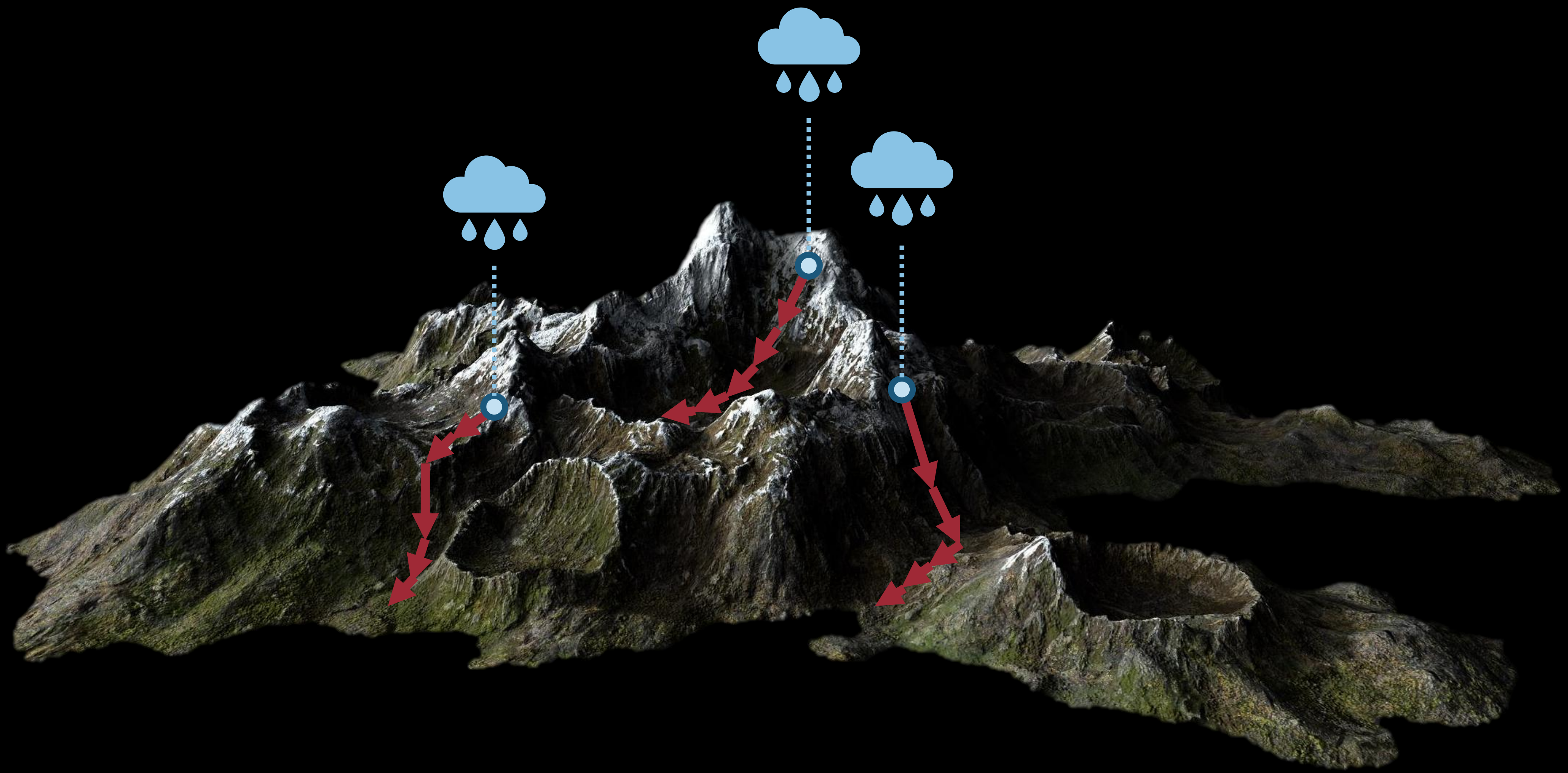


Gradient Descent: Pseudocode

- Pick an initial weight vector w_0 and learning rate η
- Repeat until convergence: $w_{t+1} = w_t - \eta \nabla f(w_t)$



Gradient Descent: 3D Case



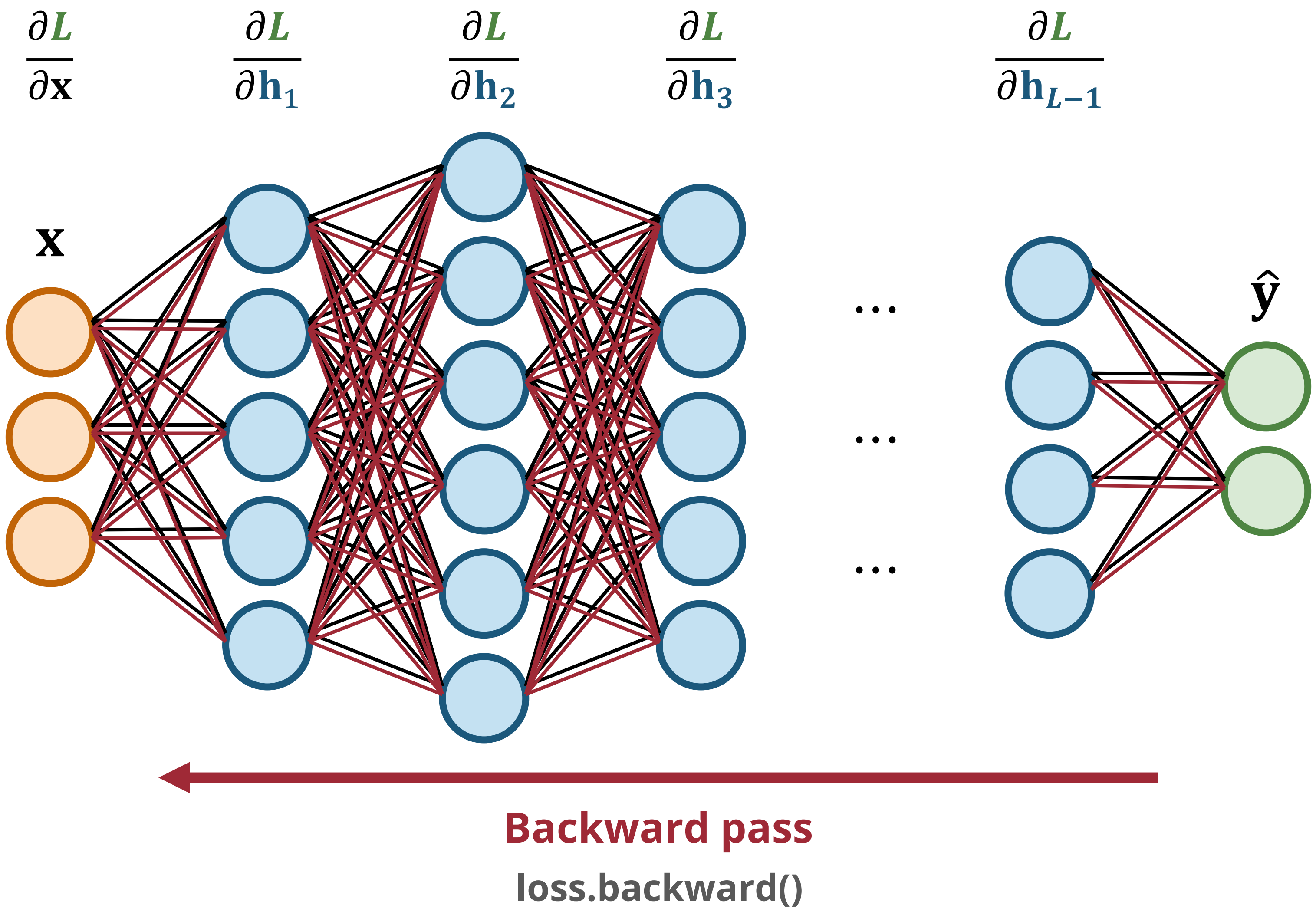
substance3d.adobe.com/community-assets/assets/9fe77d4279e12fe2fbd90b8f7ca18146a565f7ee

Backpropagation: Efficiently Computing the Gradients

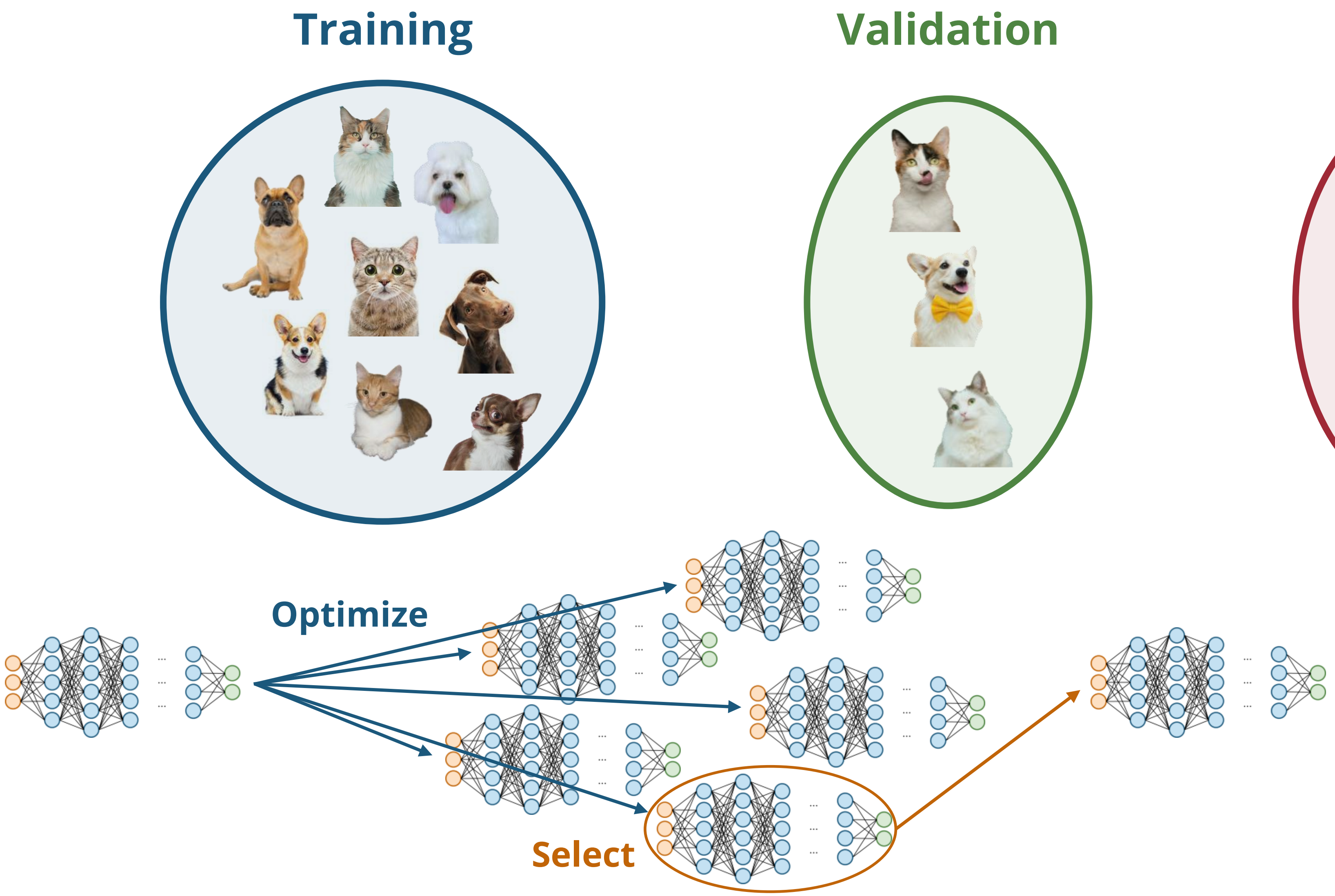
- An efficient way of **computing gradients** using chain rule
- The reason why we want **everything to be differentiable** in deep learning

$$w_{t+1} = w_t - \eta \nabla f(w_t)$$

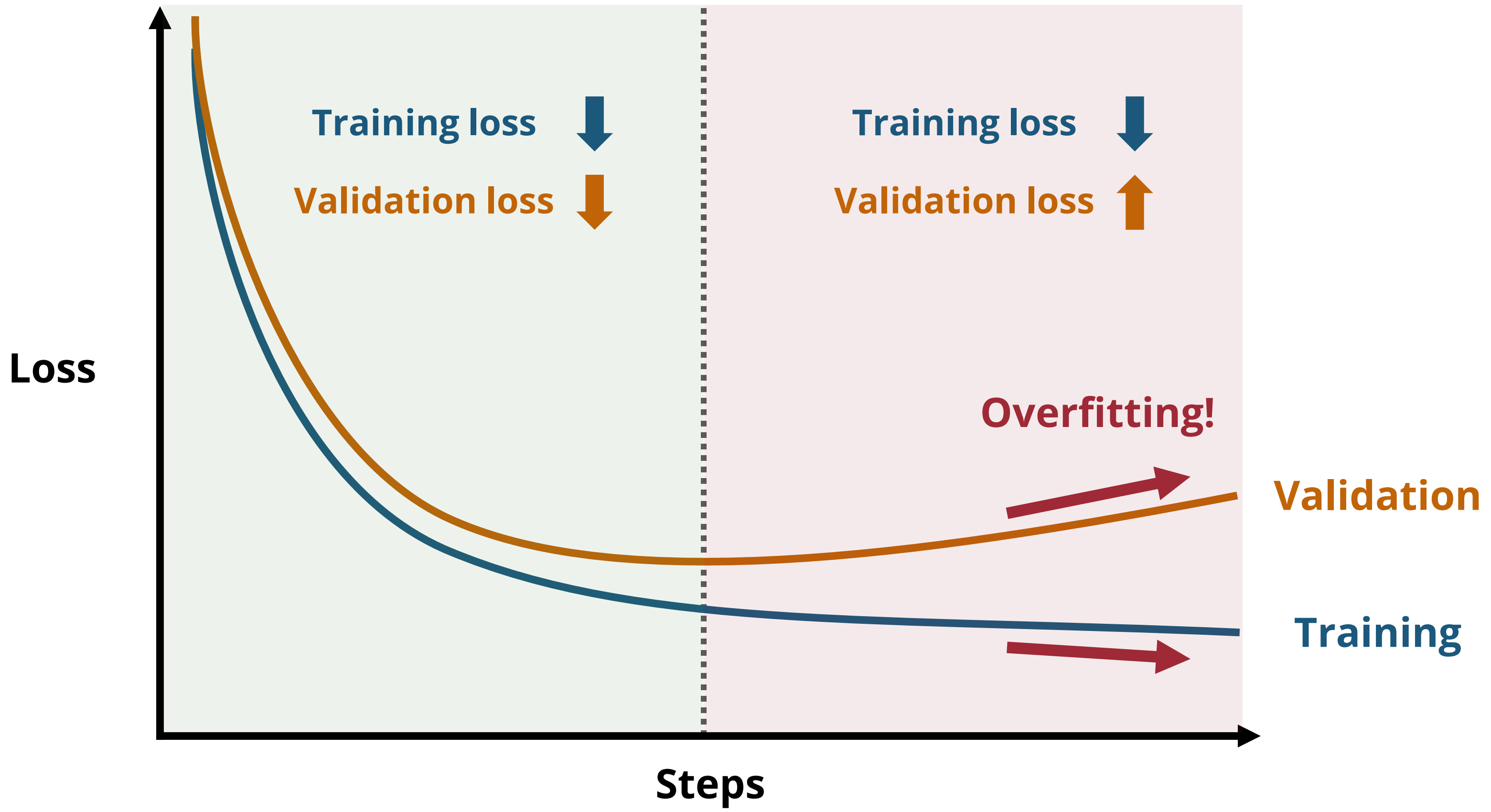
Forward Pass & Backward Pass



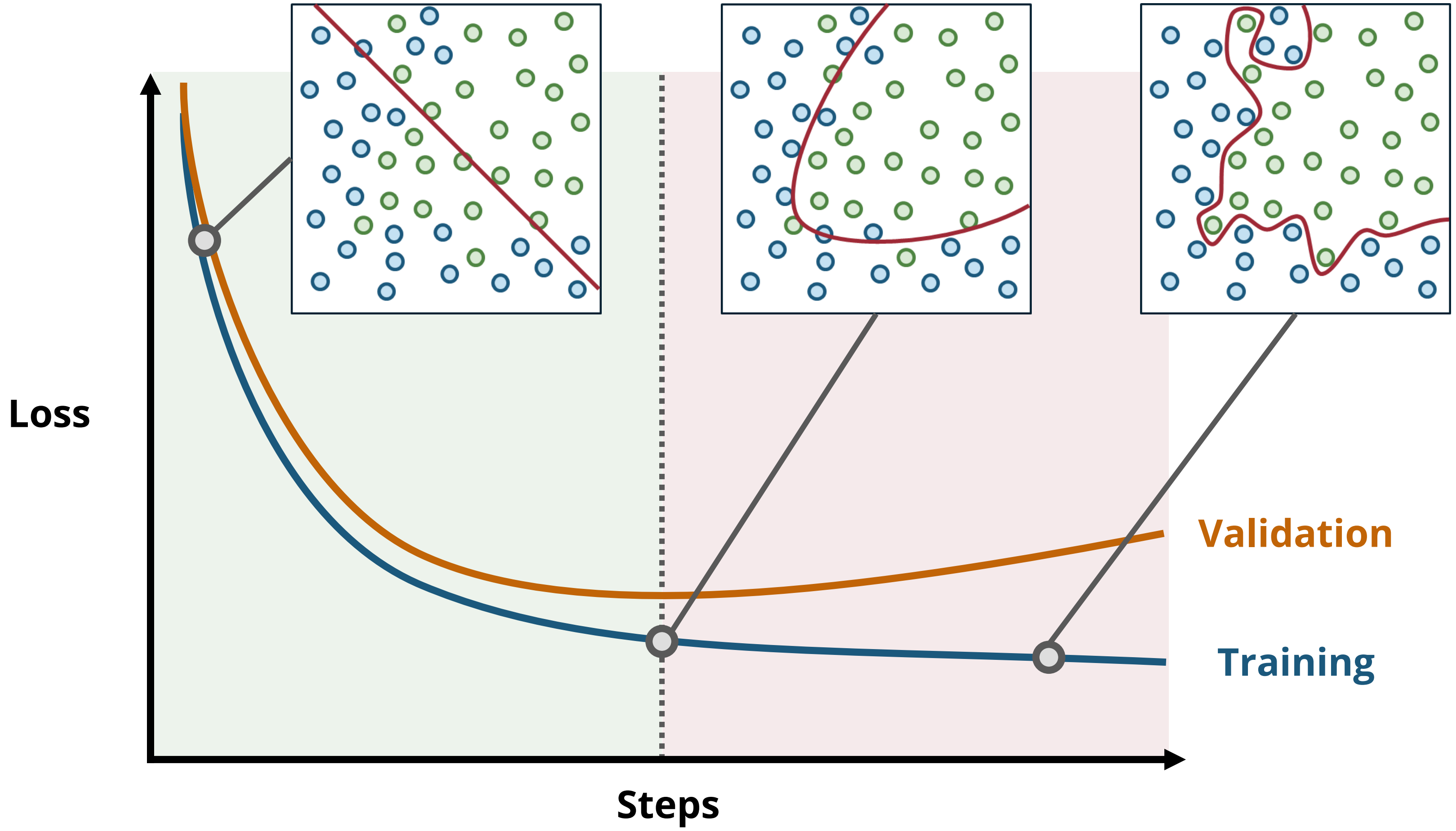
Training–Validation–Test Pipeline



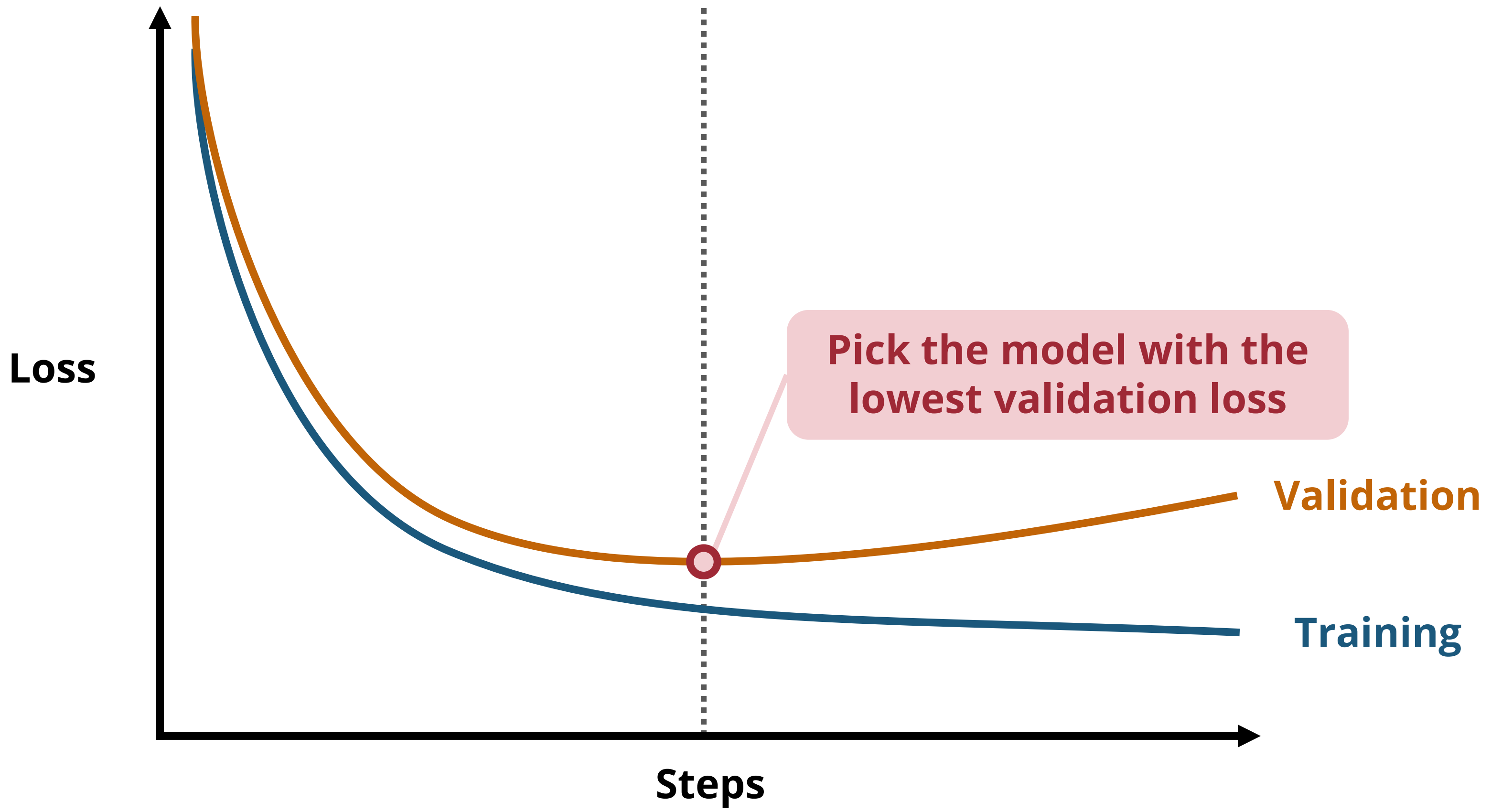
Training vs Validation Losses



Training vs Validation Losses

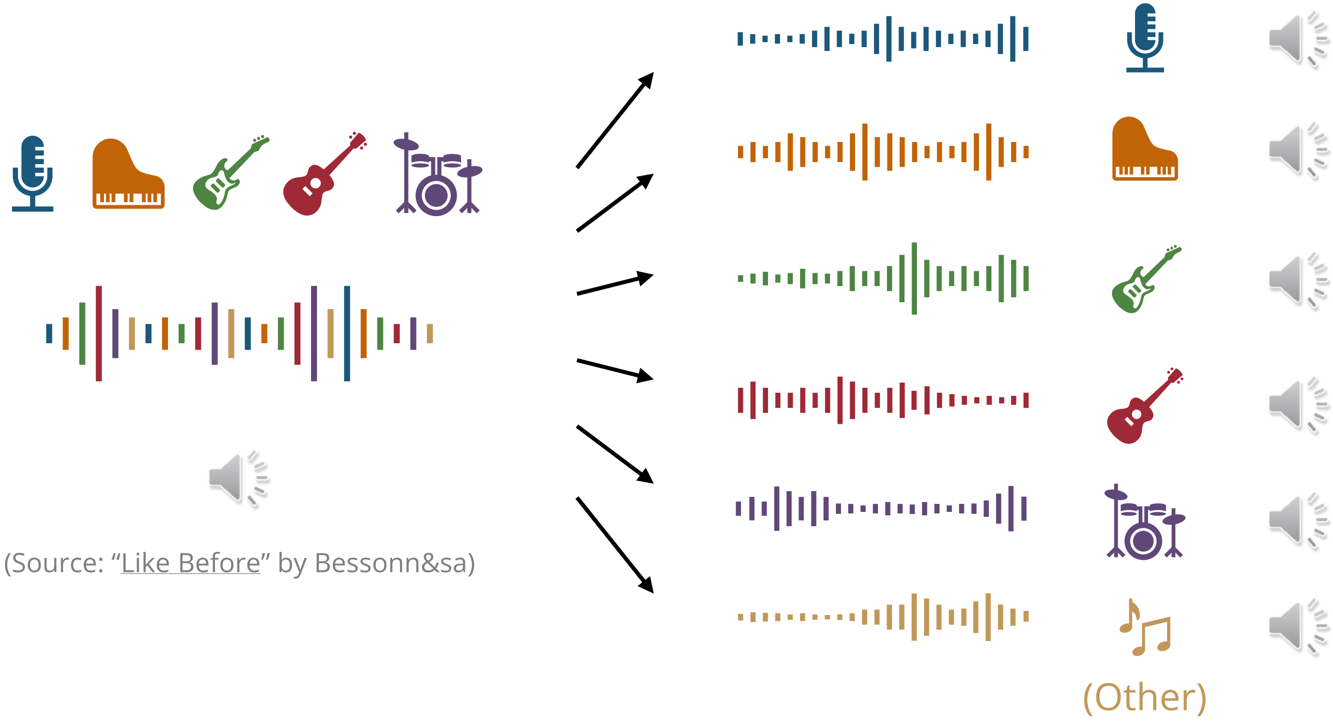


Training vs Validation Losses



Next Lecture

Source Separation



(Source: "Like Before" by Bessonn&sa)