



December 6, 2025

Understand how neural networks learn by iteratively adjusting weights to reduce error.

This slide establishes the learning objective for this topic

Gradient descent is the algorithm that trains neural networks. The core idea is simple: calculate which direction reduces the error, then take a small step in that direction. Repeat until you reach a minimum.

The **gradient** tells us the slope of the loss landscape at our current position. It points "uphill" toward higher error. By stepping in the opposite direction (downhill), we reduce the loss.

Understanding this concept is crucial for neural network fundamentals

Key Concept (2/2)

The **learning rate** controls how big each step is. Too large, and we might overshoot the minimum. Too small, and training takes forever. Finding the right learning rate is crucial for effective training.

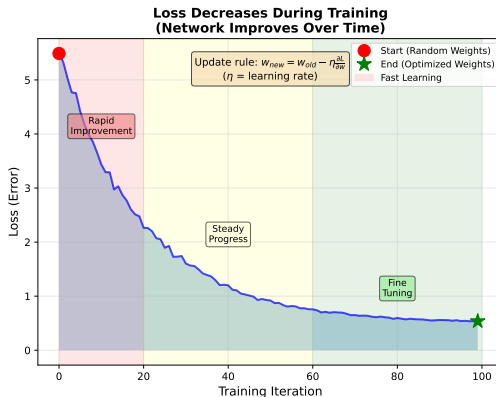
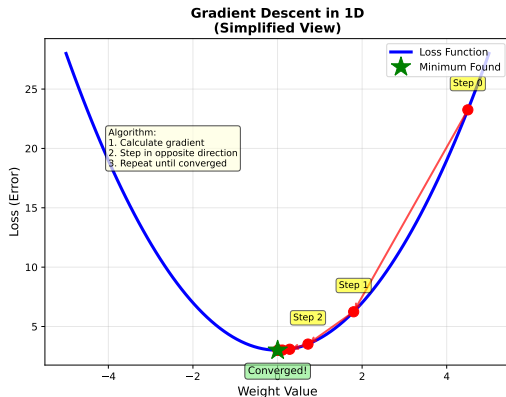
Each update follows:

$$w_{new} = w_{old} - \eta \cdot \frac{\partial L}{\partial w}$$

This simple rule, applied to all weights simultaneously, enables networks to learn complex patterns from data.

Understanding this concept is crucial for neural network fundamentals

Gradient Descent: Learning by Stepping Downhill



Visual representations help solidify abstract concepts

Weight update rule:

$$w := w - \eta \cdot \nabla_w L$$

Expanded for a single weight:

$$w_{new} = w_{old} - \eta \cdot \frac{\partial L}{\partial w}$$

Where: - **w** = weight value - **eta** = learning rate (typically 0.001 to 0.1) - **dL/dw** = gradient (partial derivative of loss with respect to weight) - **:=** means "update to"

Mathematical formalization provides precision

Imagine rolling a ball down a hill to find the lowest point:

1. **Calculate slope**: Which way is downhill? (gradient) 2. **Take a step**: Move in that direction (weight update) 3.

Repeat: Keep going until you stop descending (convergence)

The learning rate is like the ball's momentum: - **Too high**: Ball bounces over valleys, never settling - **Too low**: Ball creeps slowly, taking ages to reach bottom - **Just right**: Ball rolls smoothly into the lowest valley

Intuitive explanations bridge theory and practice

Practice Problem 1

Problem 1

Current weight $w = 2.5$, learning rate $\eta = 0.1$, gradient $dL/dw = 0.8$. Calculate the new weight after one update.

Solution

$$w_{new} = w_{old} - \eta \cdot \frac{\partial L}{\partial w}$$

$$w_{new} = 2.5 - 0.1 \cdot 0.8$$

$$w_{new} = 2.5 - 0.08 = 2.42$$

The weight decreased from 2.5 to **2.42**. The positive gradient meant we were on an uphill slope (with respect to w), so we moved w downward.

Practice problems reinforce understanding

Practice Problem 2

Problem 2

After many iterations, the gradient becomes very small ($dL/dw = 0.001$). What does this indicate about the training?

Solution

A very small gradient indicates:

1. **Near a minimum:** The loss landscape is nearly flat, suggesting we're close to a minimum (either local or global)
2. **Convergence:** The weights are stabilizing; further updates will be tiny
3. **Possible plateau:** The network may have reached its best performance given the architecture and data
4. **Training completion:** This is often used as a stopping criterion

With $\eta = 0.1$ and $\text{gradient} = 0.001$:

$$\Delta w = 0.1 \times 0.001 = 0.0001$$

Each update changes weights by only 0.01% - training is essentially complete.

Practice problems reinforce understanding

Key Takeaways

- Gradient descent iteratively reduces loss by following downhill direction
- Learning rate controls step size - crucial hyperparameter
- Too high = divergence, too low = slow convergence
- Small gradients indicate convergence (near minimum)
- This is the "learning" in machine learning

These key points summarize the essential learnings