Module 2 - Session 2: Loss Functions and Optimizers

Session 2

The Training Sequence

Three lines that make learning happen:

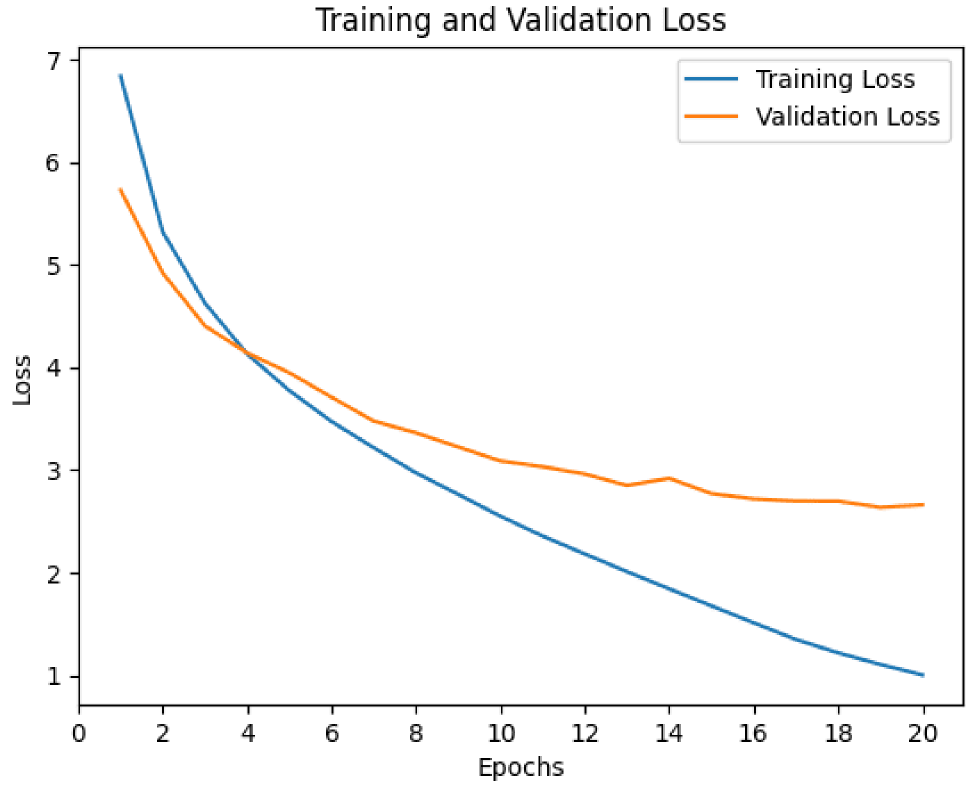
1. **Measure** - How wrong are we?
2. **Diagnose** - What caused the error?
3. **Update** - How do we fix it?

Step 1: Measuring Loss

Loss function: compares predictions to true answers

Higher number = more wrong

Goal: minimize loss



Measuring Error for Regression Tasks

For regression tasks (predicting numbers): temperature, price, distance

Average error = $\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)$

Prediction (minutes)	Actual (minutes)	Error
6	4	$6 - 4 = 2$
3	5	$3 - 5 = -2$

Problem: Average error = 0 (mistakes cancel out!)

Mean Squared Error Loss

Squaring:

- Gets rid of minus signs (all mistakes count)
- Makes bigger mistakes matter more

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

Cross-Entropy Loss

For classification tasks (predicting categories): digit, animal, word

Model outputs: confidence scores (probabilities) for each class

All scores sum to 100%

$$\mathrm{BCE} = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)$$

How Cross-Entropy Works

Punishes overconfident wrong answers

- 95% sure it’s a 7, but it’s actually a 3 → **very high loss**
- 55% sure it’s a 7, but it’s actually a 3 → **smaller loss**

Goal: Confident about right answers, unsure about wrong ones

Step 2: Diagnosing the Problem

Backward calculates gradients

Gradients = diagnostic scores for each parameter

- Positive gradient $\rightarrow$ increasing weight makes loss worse
- Negative gradient $\rightarrow$ increasing weight helps
- Large gradient $\rightarrow$ big influence
- Small gradient $\rightarrow$ barely mattered

What Backward Does NOT Do

Backward does NOT update weights

It only calculates gradients

Updates happen later with `optimizer.step()`

The Gradient Descent Analogy

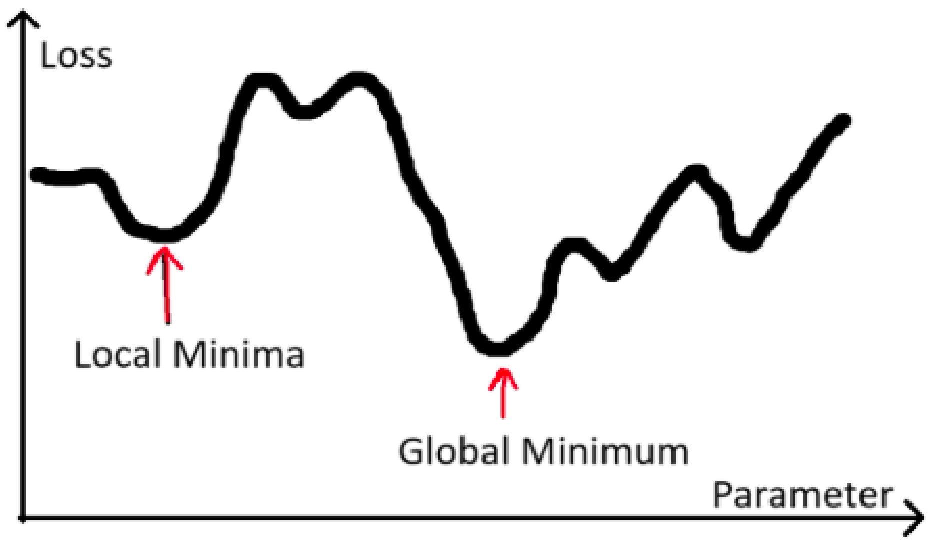


Figure 4. local and global minimum on a parameter-loss curve.

Plos: x-axis: weight, y-axis: loss

Goal: minimize loss (reach bottom of valley)

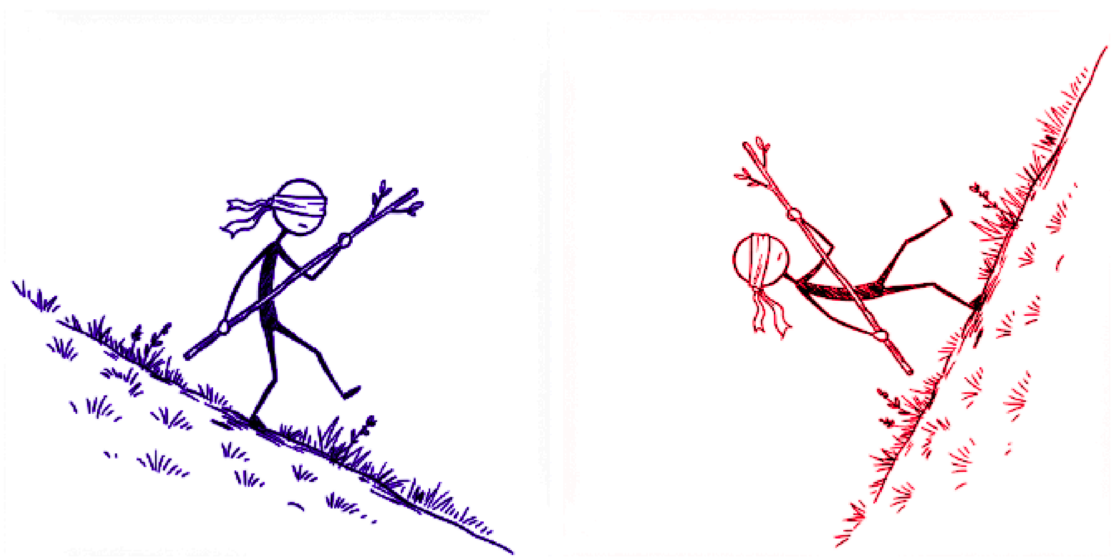
Gradient: tells you the slope (which way is downhill?)

Go downhill → lower loss

Zooming in on a single parameter taking a step against the gradient

Multiple parameters

If we have two parameters (θ_0 and θ_1):



Stochastic Gradient Descent (SGD)

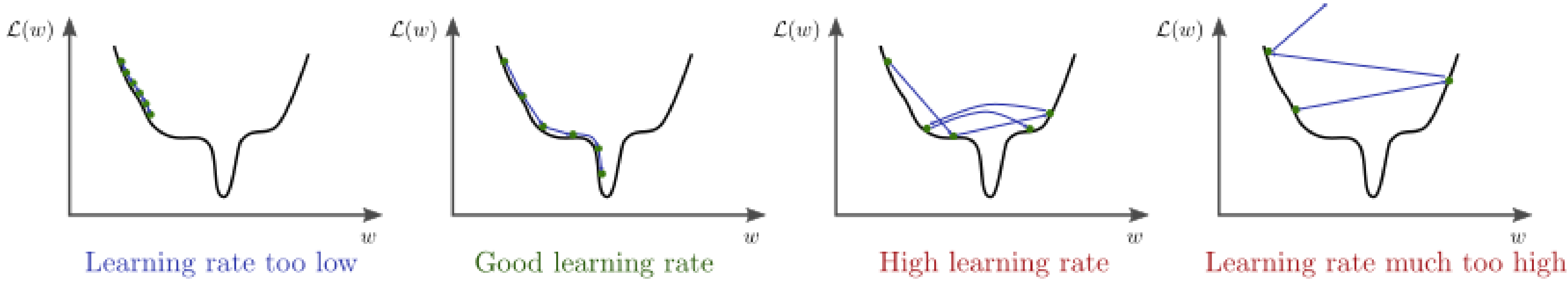
Strategy:

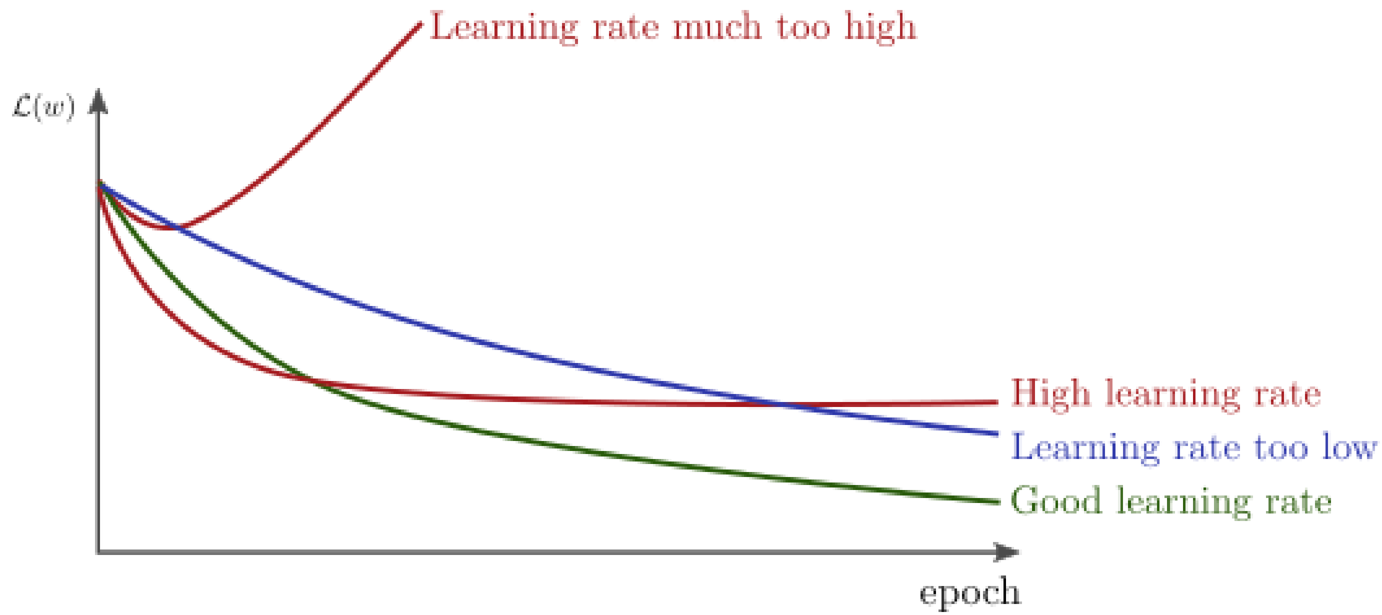
- Negative gradient ($\frac{\partial \text{loss}}{\partial w_0}$) $\rightarrow$ increase weight (w_0)
- Positive gradient ($\frac{\partial \text{loss}}{\partial w_1}$) $\rightarrow$ decrease weight (w_1)
- Big gradient ($\frac{\partial \text{loss}}{\partial w_0}$) $\rightarrow$ big change (w_0)
- Small gradient ($\frac{\partial \text{loss}}{\partial w_1}$) $\rightarrow$ small change (w_1)

Scales updates with learning rate:

$$\text{step size} = \text{learning rate} \times \text{gradient}$$

Learning Rate Matters





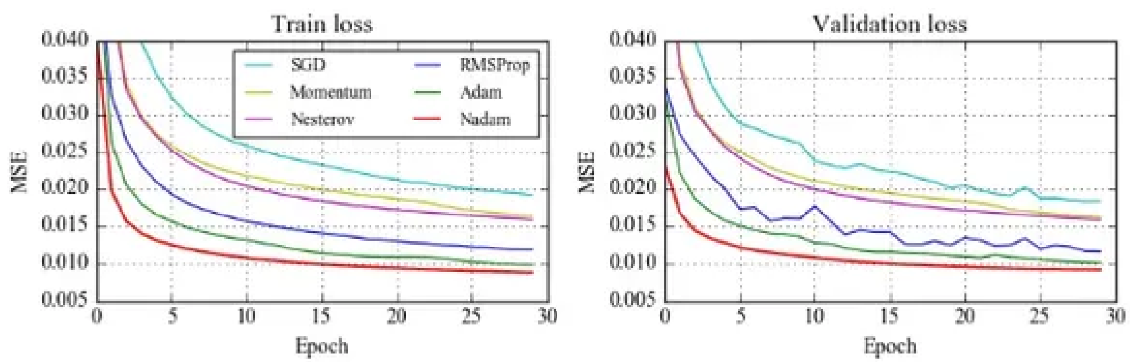
Adam Optimizer

Adapts learning rate for each weight individually

Like having an assistant:

- Knows which weights need big adjustments
- Knows which need fine-tuning

Popular first choice: reliable, flexible, often faster



Optimizers’ loss curves

Why `zero_grad()`?

Every `backward()` call adds to existing gradients

Without `zero_grad()`: gradients accumulate incorrectly

Result: training breaks

Complete Training Loop

```python
for batch in dataloader:
    optimizer.zero_grad()       # Clear gradients
    outputs = model(inputs)      # Forward pass
    loss = loss_fn(outputs, targets)  # Measure
    loss.backward()             # Diagnose
    optimizer.step()            # Update
```

Measure → Diagnose → Update

What’s Next?

In **Session 3: Device Management and Image Classification Setup**, you learn:

- Running on GPUs vs CPUs
- Moving models and data to devices
- Setting up MNIST data pipeline
- Building your first image classifier architecture