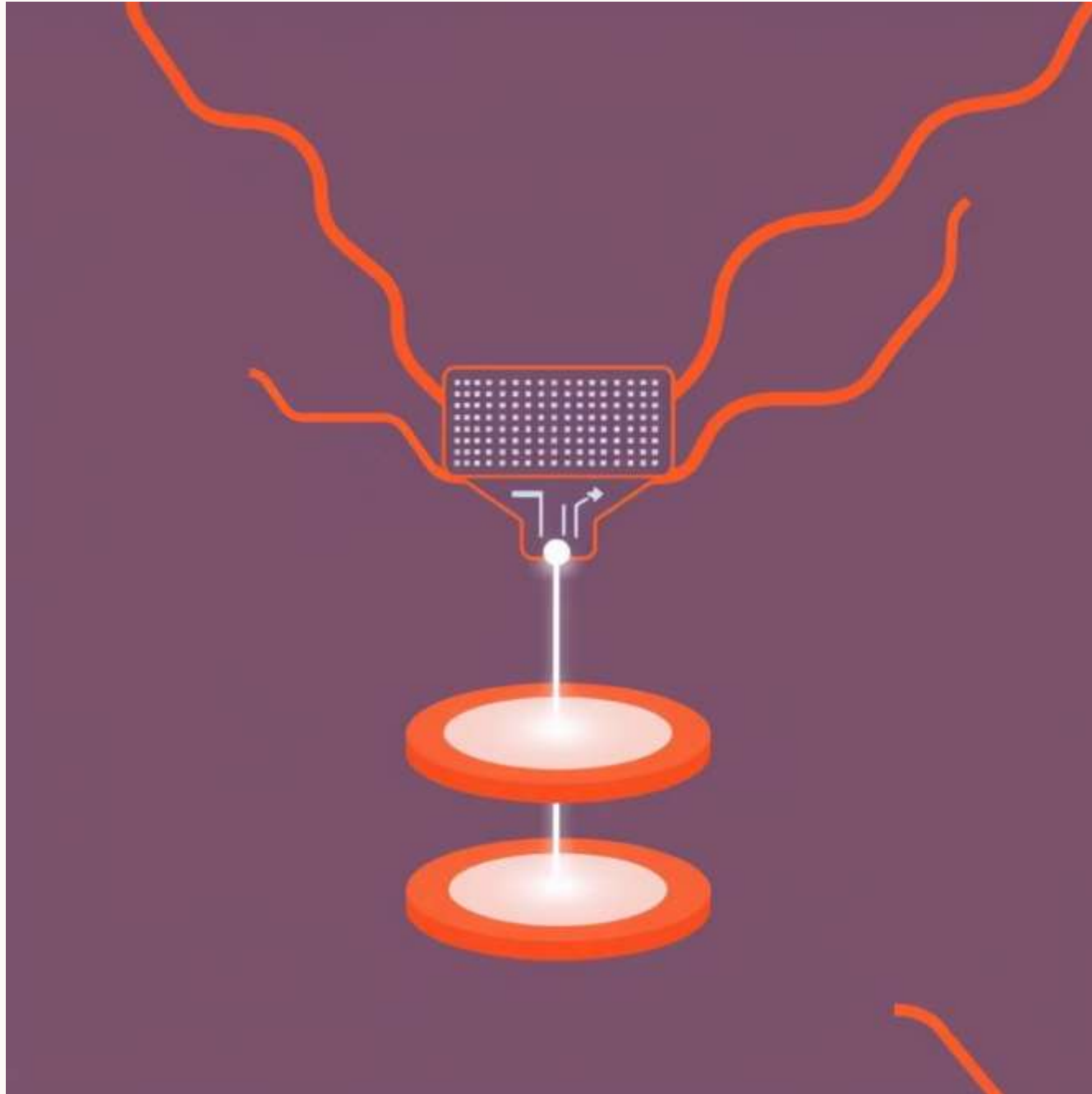




# Training Neural Networks & Optimization

Explore the fundamental processes behind teaching neural networks to learn and improve performance.

# What is Backpropagation?



## Learning Algorithm

The core method for neural network training.

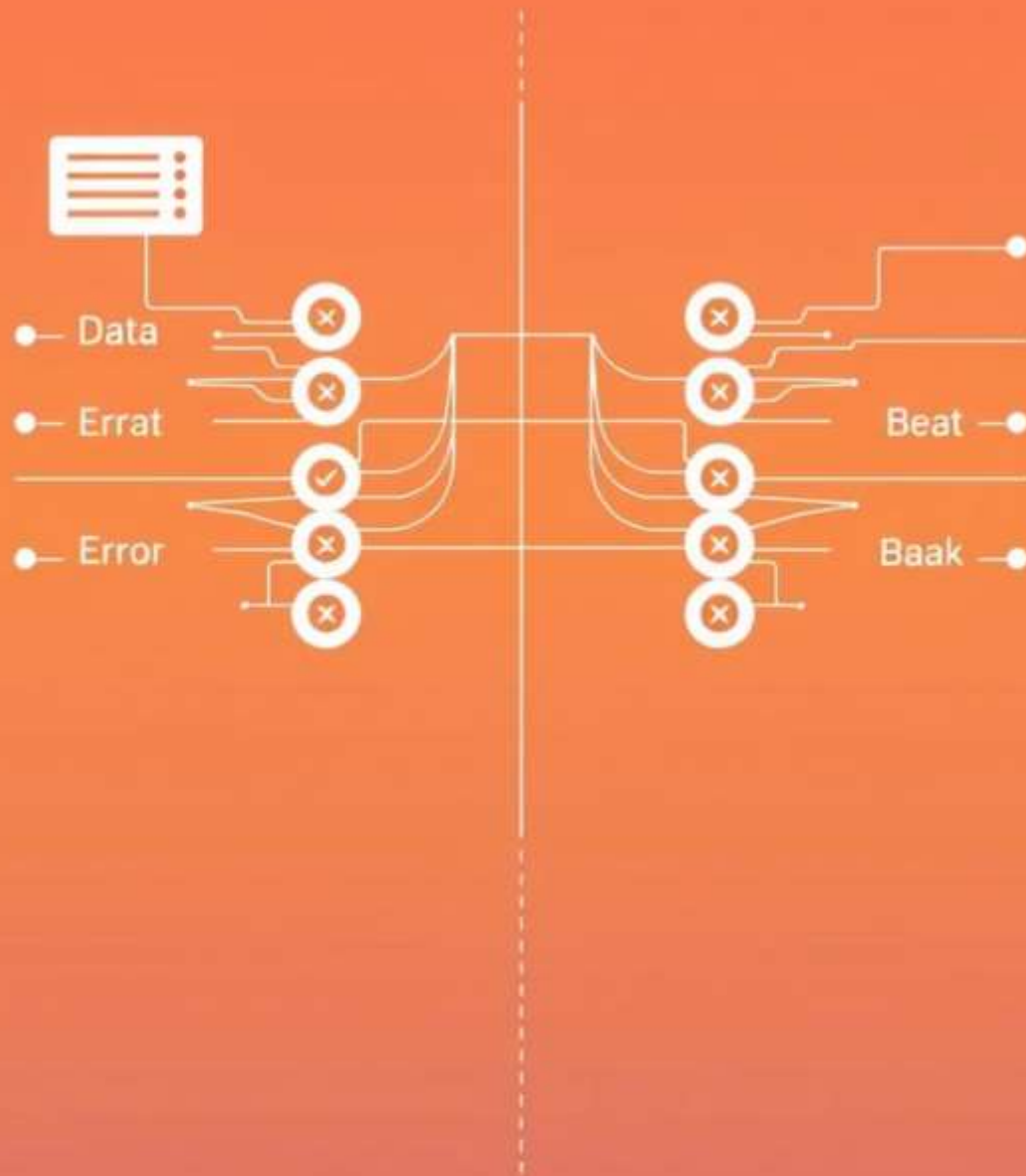
## Error Measurement

Calculates how far off predictions are.

## Weight Adjustment

Fine-tunes connections to reduce errors.

# How Backpropagation Works



1

## Forward Pass

Input data moves through the network to generate an output.

2

## Calculate Loss

Compare predicted output with the actual target.

3

## Backward Pass

Error signals are sent back through the network.

4

## Update Weights

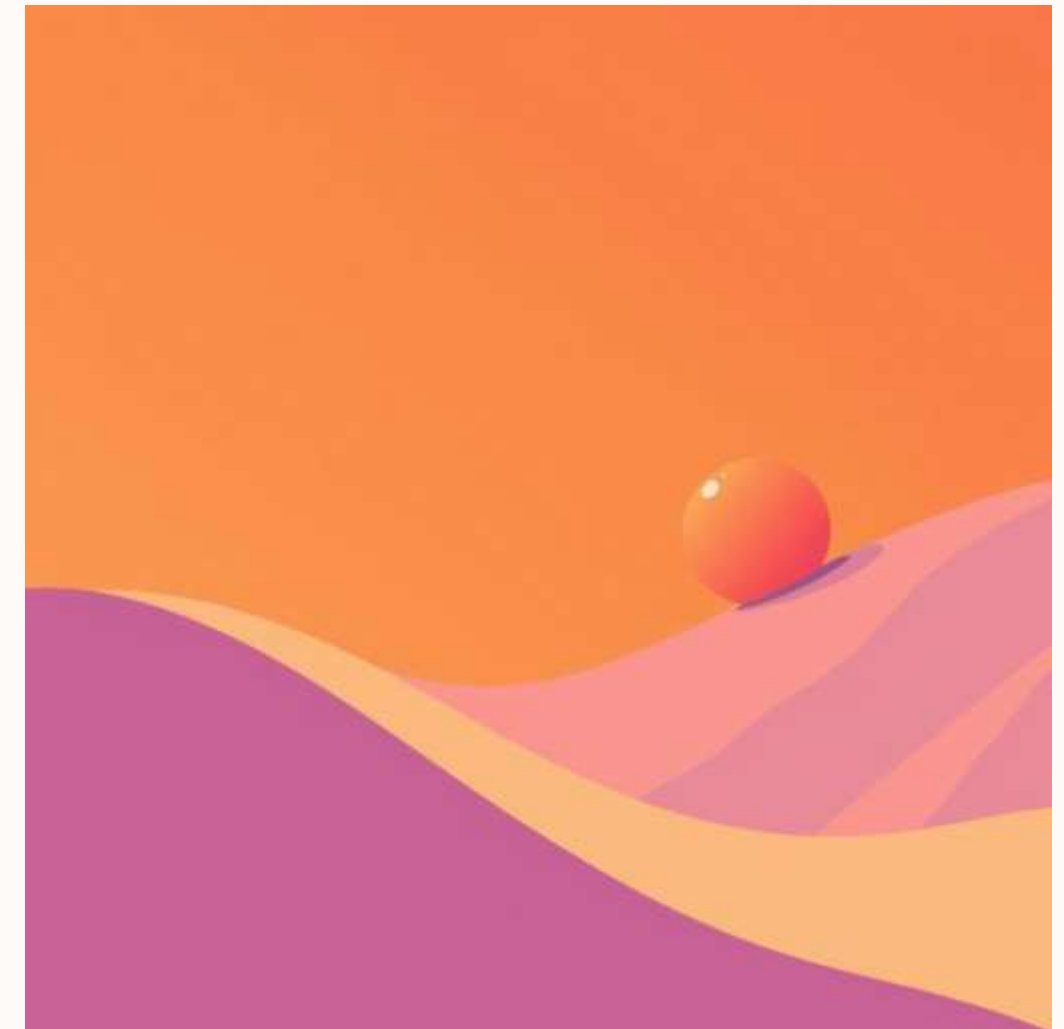
Adjust network connections based on error signals.

# Introduction to Gradient Descent

An optimization algorithm that helps minimize the "loss" or error in a neural network. It iteratively adjusts the network's weights to find the lowest point of the loss function.

$$w := w - \eta \nabla L(w)$$

- $w$ : network weights
- $\eta$ : learning rate
- $\nabla L$ : gradient of the loss function



# Understanding the Gradient



## Slope of Loss

Indicates the steepest direction of the error curve.

## Direction & Magnitude

Tells how much and in which way to change weights.

## Minimize Error

The ultimate goal is to reach the lowest error point.

# Variants of Gradient Descent

Different approaches to updating weights, each with trade-offs.



## Batch GD

Uses all data for one update.



## Stochastic GD

Updates per single data point.



## Mini-Batch GD

Updates per small group of data.



Batch Gradient Descent



Mini-Batch Gradient Descent

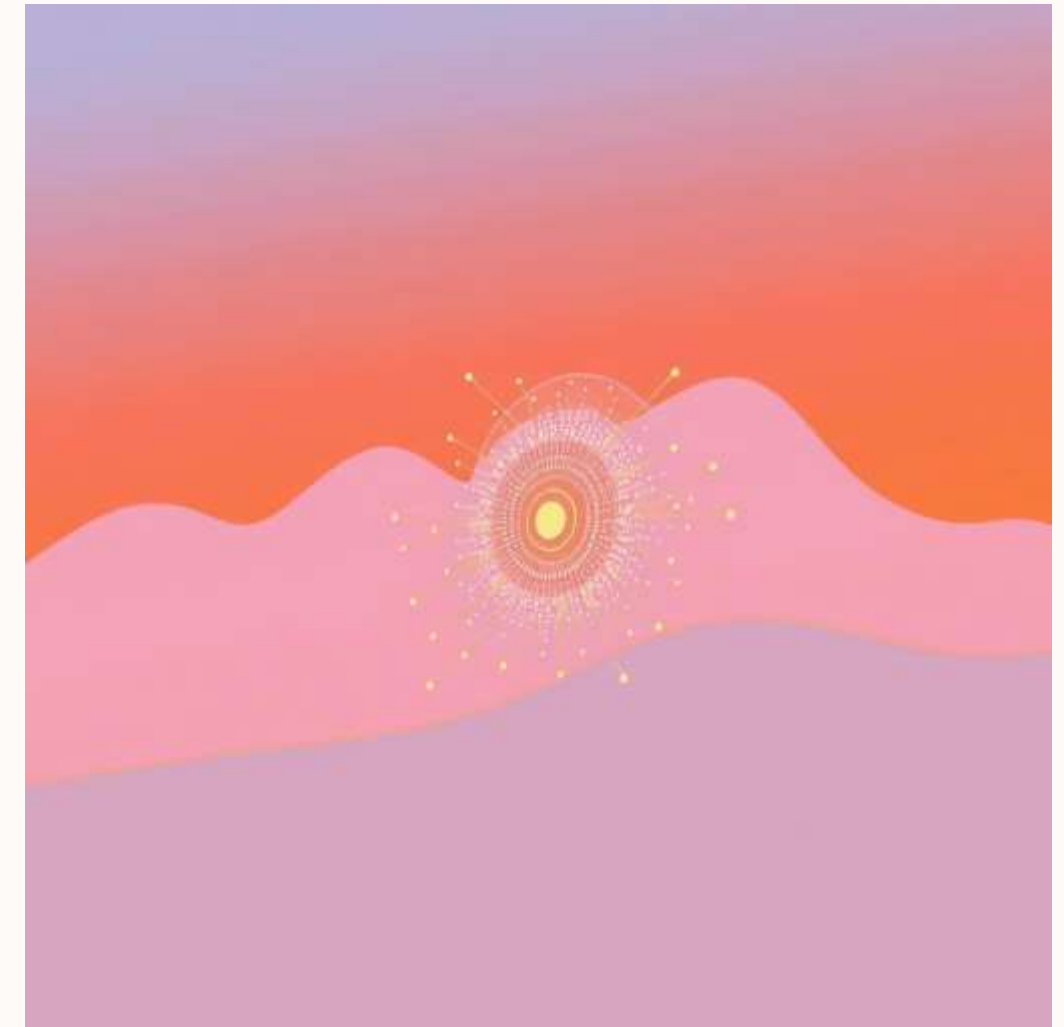


# Batch Gradient Descent

Calculates the gradient using the **entire training dataset** before updating the weights. This leads to a very stable convergence.

$$w := w - \eta \frac{1}{N} \sum_{i=1}^N \nabla L_i(w)$$

**N**: Total number of training samples. Each **L<sub>i</sub>** is the loss for one sample.



**i** Stable, but can be very slow for large datasets.



# Stochastic & Mini-Batch Gradient Descent

1

## Stochastic GD

**Update per sample:** Weights updated after processing just one training example.

⚠ Noisy updates, but very fast.

2

## Mini-Batch GD

**Update per small batch:** Updates weights after processing a small subset of training data (e.g., 32-256 samples).

✅ Balances speed and stability, widely used.



# Learning Rate: Key Hyperparameter



The learning rate ( $\eta$ ) controls the size of the steps taken during weight updates.

## High Learning Rate

May overshoot the optimal solution, causing instability.

## Low Learning Rate

Leads to very slow convergence, extending training time.

Finding the right balance is crucial for efficient training.



# Summary & Takeaways



## Backpropagation

The engine for calculating error gradients.



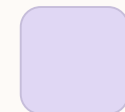
## Gradient Descent

The optimizer for adjusting network weights.



## GD Variants

Batch, Stochastic, Mini-Batch offer different speeds/stabilities.



## Learning Rate

Crucial for effective and efficient training.

Mastering these basics unlocks the power of neural networks!