OxML 2025 Practical Tutorial: Deep Learning and Representation Learning

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Outline

- Part I: Representation Learning Basics
- Part II: Deep Learning with MNIST and CIFAR-10

Link and Slides

- Link for Part I
- Link for Part II

Objectives for today

• Built a tiny neural-network framework

Trained a PyTorch model on MNIST digits

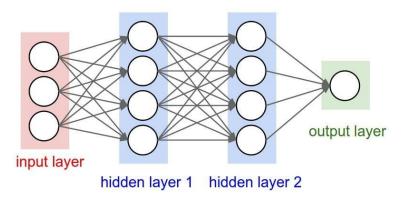
• Extended to a convolutional network on CIFAR-10 images

Part I: Representation Learning Basics

Neural Network Basics

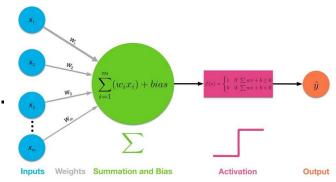
Structure

- Input Layer: Receives raw data.
- Hidden Layers: Perform transformations.
- Output Layer: Produces predictions.



Components/Parameters

- Weights: Parameters learned during training.
- Biases: Allow shifting of activation functions.



 Forward Propagation: Data flows forward, passing through layers, transforming inputs into outputs.

Activation Functions

- Why Activation Functions?
 - Introduce non-linearities to capture complex patterns.
- Common Choices
 - Sigmoid
 - Tanh
 - ReLU (Rectified Linear Unit)

Loss Functions

- Role: Quantify discrepancy between predictions and actual labels.
- Types
 - Mean Squared Error (MSE) $MSE(y, y') = (y - y')^{2}$
 - Cross-Entropy Loss $CE(y, y') = -y\log(y') - (1 - y)\log(1 - y')$

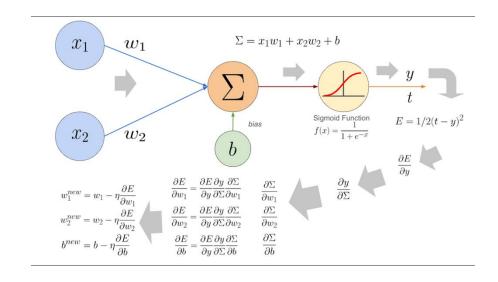
Backpropagation & Gradient Descent

Backpropagation (Day 1)

- Employs chain rule to compute gradients efficiently.
- Gradients propagate backward from output to input layers.

Gradient Descent Process (Day 1)

- Gradients inform parameter updates to reduce loss.
- Optimization strategies: adjusting learning rate, parameter initialization.



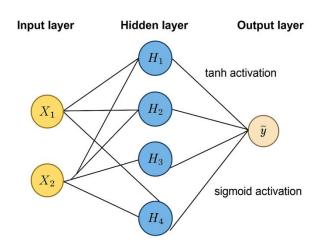
Coding Practical

Hands-on Exercise: Solve XOR binary classification problem step-by-

step.

x_1	x_2	$y = x_1 \oplus x_2$
0	0	0
0	1	1
1	0	1
1	1	0

 $y = x_1 \oplus x_2$



- Visualization of Training Loss over Epochs
- PyTorch Comparison
 - Simplified code structure.
 - Built-in automatic differentiation.

Part II: Deep Learning with MNIST and CIFAR-10