

Neural Network Library - Project Report

1. Library Design and Architecture

1. Library Design and Architecture

The neural network library was designed to be modular, readable, and easily extensible, similar to simplified versions of PyTorch or Keras. The core idea is to separate every function of a neural network into clearly defined components:

2. Layer Abstraction (Layer Base Class)

All layers in the library inherit from a simple Layer base class. This ensures every layer implements:

`forward(x)` — computes the output of the layer

`backward(grad_output)` — computes gradients and sends gradient backward

(optional) `update(optimizer)` — updates weights if the layer has parameters

This abstraction allows stacking any sequence of layers inside a Sequential model.

3. Dense Layer (Dense)

The Dense (fully-connected) layer is the main trainable component of the network.

Each Dense layer stores:

Weights W

Biases b

Gradients dW, db

Input cache (needed for backward pass)

Forward pass:

$$y = xW + b$$

Backward pass computes:

Gradient wrt weights

Gradient wrt biases

Gradient wrt inputs

This structure mirrors how professional deep learning frameworks implement linear layers.

4. Activation Functions

Activations are implemented as separate layers (e.g., Tanh, Sigmoid). They do not have weights, only formulas for:

forward activation

backward derivative

This modularity allows replacing activations without modifying the network architecture.

5. Loss Functions (MSELoss)

Loss functions are isolated from the model and only compute:

forward(y_true, y_pred)

backward() → gradient wrt predictions

This design keeps the model focused on learning rather than evaluating error.

6. Optimizer (SGD)

The SGD optimizer handles weight updates:

$W = W - \eta \cdot dW$

7. Model Container (Sequential)

The Sequential class stores a list of layers and manages:

Forward propagation through all layers

Backward propagation from last to first layer

Calling each layer's optimizer update

Running training loops with epochs

It behaves similarly to tf.keras.Sequential.

8. Directory Structure

The library is organized inside the AROGO/ folder:

AROGO/ | — layers.py | — activations.py | — losses.py | — optimizer.py | — network.py

This clean separation makes the codebase:

Easier to maintain

Easy to extend

Structured like real machine-learning libraries

Summary

The core principles of the library are:

Modularity (each component is independent)

Clarity (easy to read and understand)

Extensibility (easy to add new layers/activations)

Realistic design inspired by PyTorch/Keras

2. Gradient Checking

1. Analytical Gradients:

- Computed using the `backward()` methods of our layers.

2. Numerical Gradients:

- Approximated with the formula:
$$[\frac{\partial L}{\partial W} \approx \frac{L(W + \epsilon) - L(W - \epsilon)}{2\epsilon}]$$
- Here, (ϵ) is a very small number (default (1e-5)).

3. Comparison:

- We calculate the maximum difference between analytical and numerical gradients.
- If the difference is very small (e.g., less than (1e-6)), our backpropagation is likely correct.

4. Results:

Analytical: [[-0.00232373 -0.00274231 -0.00977339 0.01306674] [-0.00434791 0.01133584 0.002093

0.01870656]] Numerical: [[-0.00232373 -0.00274231 -0.00977339 0.01306674] [-0.00434791 0.01133584
0.002093 0.01870656]] Max Diff: 2.9750407866402373e-12

3. XOR Experiment

Epoch 0, Loss: 0.2539001108002241 Epoch 2000, Loss: 0.006986212600061806 Epoch 4000, Loss:
0.002426433168836391 Epoch 6000, Loss: 0.00142500829139407 Epoch 8000, Loss: 0.0009993669268076304
Predictions after training: [[0.01332864] [0.97127211] [0.97049072] [0.03451367]]

4. TensorFlow Baseline

1- ease of implementation : our lib has more ease of implementation than tensor flow (keras)

2-training time : our lib has less training time than tensor flow (keras)

3-final predictions :

our lib results : [[0.01332864] [0.97127211] [0.97049072] [0.03451367]]

tensor flow (keras) : [[0.01457623] [0.9690686] [0.97115225] [0.03383316]]