Sora Owada

# Neural Network Experimental Report

## Overview

This report summarizes two neural network experiments conducted using a visual neural network simulator. Different network architectures, activation functions, and learning rates were tested on synthetic classification datasets to observe model behavior and decision boundary formation.

---

## Experiment 1

**Configuration:**

- Dataset: Two-class synthetic dataset (top left option)
- Features: $x_1$, $x_2$
- Training/test split: 50%
- Noise: 0
- Batch size: 10
- Hidden layers: 2 hidden layers (4 neurons in the first, 2 neurons in the second)
- Activation function: Tanh
- Learning rate: 0.03
- Regularization: None
- Problem type: Classification

**Results:**

- Epochs: Approximately 1147
- Training loss: 0.000
- Test loss: 0.035

**Observations:**

- The decision boundary smoothly separated the two classes.
- Despite using a simple two-layer architecture with few neurons, the model fit the data accurately.
- The Tanh activation helped by squashing inputs between -1 and 1, enabling non-linear decision boundaries.
- A small learning rate of 0.03 allowed for stable and gradual convergence without overshooting.

---

# Experiment 2

**Configuration:**

- Dataset: Grid pattern synthetic dataset (second option)
- Features: $x_1$, $x_2$
- Training/test split: 50%
- Noise: 0
- Batch size: 10
- Hidden layers: 3 hidden layers (5 neurons, 3 neurons, 2 neurons respectively)
- Activation function: ReLU
- Learning rate: 0.01
- Regularization: None
- Problem type: Classification

**Results:**

- Epochs: Approximately 871
- Training loss: 0.000
- Test loss: 0.000

**Observations:**

- The complex grid structure required a deeper network to correctly classify the four regions.
- ReLU activation was effective in creating sharp and distinct decision boundaries.
- Achieving both zero training and testing loss indicates the model generalized extremely well without overfitting.
- The lower learning rate of 0.01 contributed to very stable and precise learning.

---

# Key Takeaways

- Simple decision boundaries can be learned effectively with a small network and Tanh activations.
- Complex, multi-region classification tasks benefit from deeper networks and ReLU activations.
- Proper tuning of the learning rate is crucial for smooth convergence and high model accuracy.
- Both experiments demonstrated successful training and generalization with low final losses.