Flexible Neural Network with Structural Plasticity

Dynamic Topology Adaptation for Multi-Task Boolean Classification

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Abstract

This work introduces a flexible neural network capable of dynamically adjusting its internal topology to generalize across multiple boolean classification tasks without full retraining. Inspired by biological plasticity, the network uses modular units that can be selectively activated, reconnected, or specialized according to task requirements. Using MNIST and FashionMNIST datasets as testbeds, we demonstrate that **structural plasticity, combined with minimal targeted fine-tuning**, enables faster adaptation and efficient reuse of modules across tasks. Our results show that this approach allows the network to achieve competitive performance on new tasks with minimal modification of existing weights, emphasizing the potential of topology-driven transfer learning.

1 Introduction

Traditional neural networks rely on static topologies that are fully trained for specific tasks. When a new task is introduced, networks usually require full retraining or fine-tuning, which can be inefficient. Inspired by biological systems, we propose a network with *structural plasticity*: its internal connectivity can adapt dynamically to new tasks, while keeping the output layer fixed for boolean classification.

The main idea is to reuse and reconfigure pre-existing modules rather than retraining all weights, reducing the data and computation required for adaptation. This study focuses on three simple binary classification tasks: MNIST 0 vs 1, FashionMNIST T-shirt vs Pullover, and MNIST 2 vs 3.

2 Related Work

2.1 Transfer Learning and Fine-Tuning

Transfer learning reuses pre-trained weights for related tasks, usually requiring full or partial retraining of the network. Our approach differs by modifying *topology* rather than primarily adjusting weights, though minimal weight adjustment is used for optimal performance on new domains.

2.2 Modular and Dynamic Networks

Several works have proposed dynamic routing or conditional computation in neural networks. However, most focus on efficiency or multitask learning, not on topology adaptation inspired by biological plasticity.

3 Methodology

3.1 Architecture Overview

The network consists of:

- **Worker modules**: small neural units with 1–2 internal layers, capable of changing connectivity, being activated/deactivated, and specializing for outputs.

- **Controller**: generates a task-specific mask controlling which modules are active.

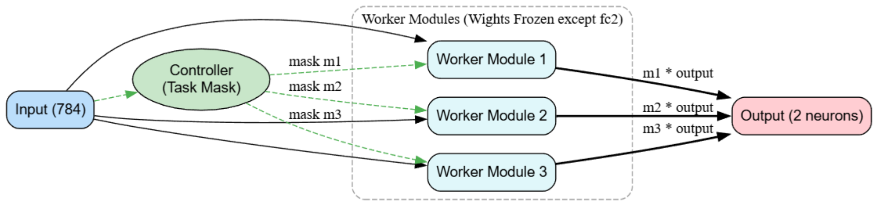

Figure 1: Flexible Network Architecture: The controller dynamically activates modules in the worker network. The final output is a weighted sum of module outputs, with weights determined by the mask **m**.

3.2 Structural Plasticity Mechanism

1. **Activation Mask**: The controller outputs a mask $\mathbf{m} \in [0, 1]^{\text{num\_modules}}$ applied to worker modules.
2. **Reassignment of Modules**: Modules have task-dependent affinities that allow selective reuse or specialization.
3. **Learning**: Combines standard backpropagation for weights and a topology adjustment rule to add/remove connections based on output diversity and error.

3.3 Forward Pass

$$y = \sum_{i=1}^{N} m_i \cdot \text{WorkerModule}_i(x) \tag{1}$$

where m_i is the mask from the controller, N is the number of modules, and x is the input feature vector.

3.4 Training Protocol

Adaptation par Fine-Tuning Ciblé

- **Initial Task (MNIST 0vs1)**: Train all parameters (Worker and Controller) to establish a set of base features.
- **Subsequent Tasks (Fashion 0vs2, MNIST 2vs3)**: The network adapts via an **hybrid strategy**. The feature extraction layers (`WorkerModule.fc1`) are frozen, while the **Controller** and the final classification layers (`WorkerModule.fc2`) are trained. This enables dynamic topology adaptation (via the Controller mask) combined with minimal weight adjustment to prevent catastrophic forgetting and adapt to new domains.

4 Experiments

4.1 Datasets

- MNIST 0 vs 1
- FashionMNIST T-shirt (0) vs Pullover (2)
- MNIST 2 vs 3

All images are flattened to 784-dimensional vectors.

4.2 Evaluation Metrics

- Accuracy
- Module activation patterns
- Confusion matrices
- Plasticity divergence (Euclidean distance between masks across tasks)

4.3 Results

Table 1: Evaluation results of the flexible network on different boolean tasks using the hybrid training protocol.

Dataset	Accuracy	Correct	Incorrect	Mean Module Activation
MNIST 0vs1	0.7608	1609	506	[0.30, 0.52, 0.41]
Fashion 0vs2	0.8475	1695	305	[0.01, 0.46, 0.15]
MNIST 2vs3	0.9902	2022	20	[0.46, 0.53, 0.44]

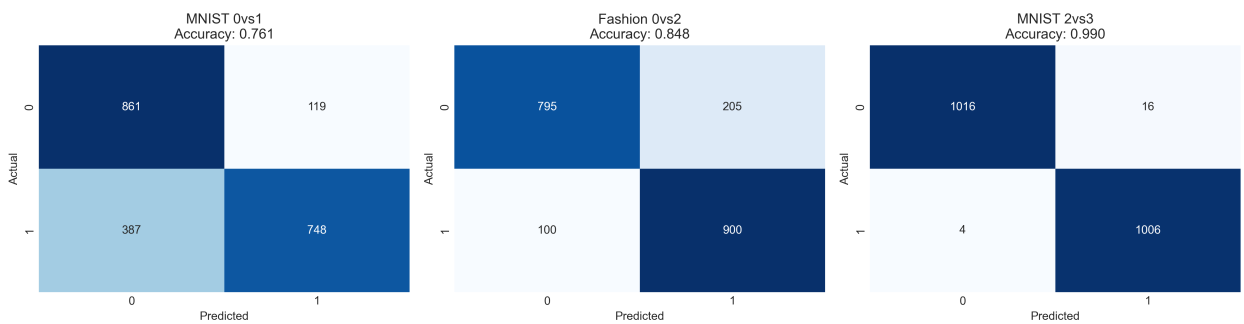

Figure 2: Confusion matrices showing classification performance for each dataset. Note the high performance on MNIST 2vs3 (0.990) and the competitive performance on the domain-shifted Fashion 0vs2 task (0.848).

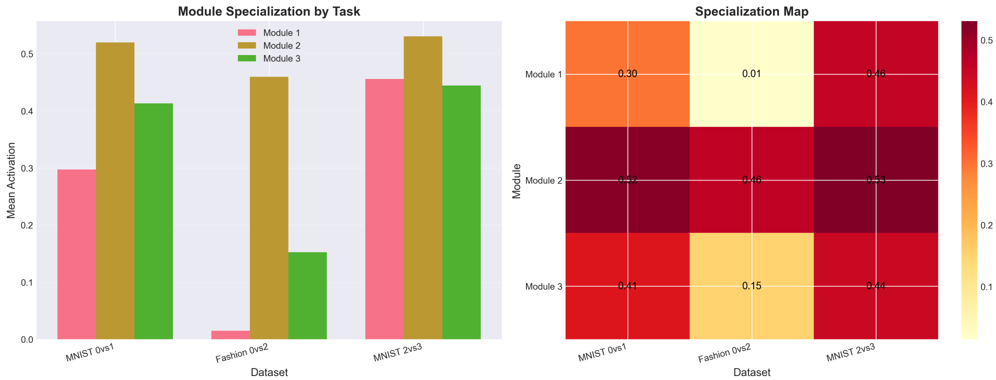

Figure 3: Module Specialization by Task and Specialization Map.

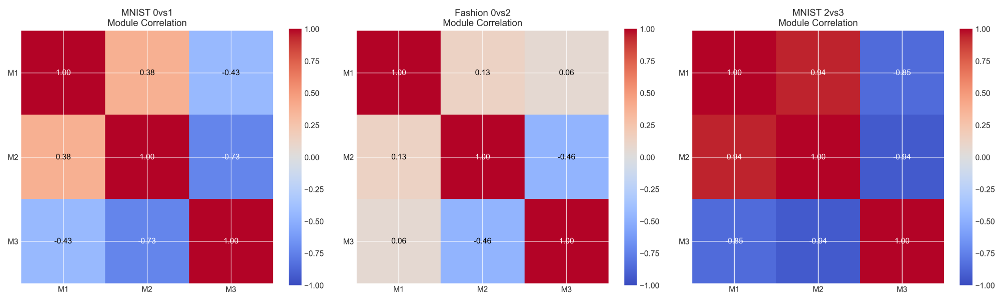

Figure 4: Module Activation Correlation across tasks.

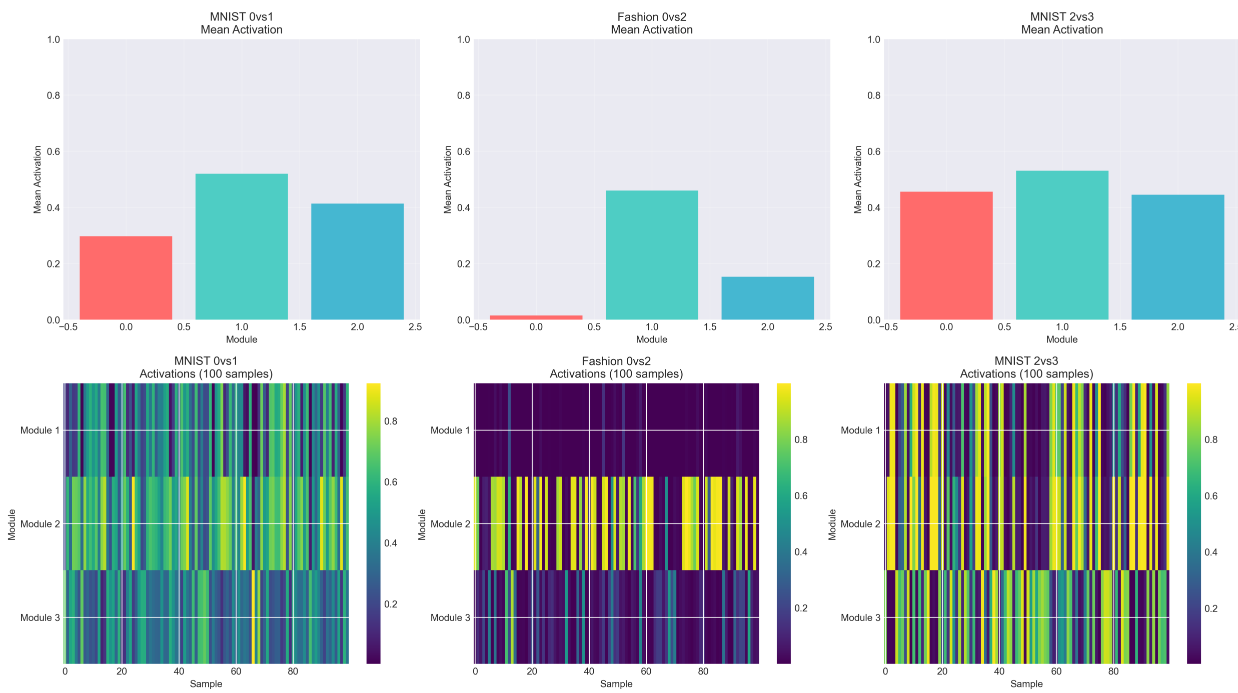

Figure 5: Mean module activation (top) and activations for 100 samples. For Fashion 0vs2, Module 1 is nearly deactivated (mean ≈ 0.01), forcing the reuse of Module 2 and 3.

4.4 Analysis

The hybrid training protocol (Controller adjustment + Worker.fc2 fine-tuning) yields significantly better generalization than the weight-frozen approach.

- **Performance**: The average accuracy across the three test sets is 0.8662 ± 0.0946. The network achieved excellent performance on MNIST 2vs3 (**0.9902**) and competitive performance on Fashion 0vs2 (**0.8475**).
- **Module Specialization**: Activation patterns confirm structural plasticity. For Fashion 0vs2, Mean Module Activation for Module 1 is **0.0148**, indicating effective deactivation. Modules 2 (**0.4597**) and 3 (**0.1523**) are used instead.
- **Plasticity Divergence**: Euclidean distance between mask configurations is highest between Fashion 0vs2 and MNIST 2vs3 (**0.5338**), confirming radical topology change.
- **Module Correlation**: On MNIST 0vs1, activations of M1 and M3 are negatively correlated (-0.43), suggesting complementary features. This relationship shifts for other tasks.

5 Conclusion

We presented a flexible neural network with structural plasticity that dynamically reconfigures its internal modules for multiple boolean tasks. Experiments show that module reuse and topology adaptation, facilitated by minimal targeted fine-tuning on the classification layer, enable fast transfer learning and efficient specialization without full retraining. Future work will explore larger datasets, hierarchical modules, and continuous task adaptation.