EMNN: PyTorch-based Evolutionary Mini Neural Network

A Novel Paradigm of Neural Evolution Inspired by Genetic Algorithms

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Abstract

This paper proposes the EMNN (Evolutionary Mini Neural Network) system - an innovative intersection between Genetic Algorithms (GAs) and neural networks. Instead of backpropagation-based gradient descent, EMNN simulates evolution: populations of minimal neural architectures (PyTorch-based) undergo selection, crossover, and mutation to solve supervised tasks. Using a basic regression task (Y = 2X + 3), this research highlights the emergence of optimal weights purely through evolutionary pressure.

The experiment successfully demonstrates convergence toward target weight and bias values across generations, highlighting the potential of evolution as a computationally creative paradigm for learning systems.

1. Introduction

Traditional neural networks are dominantly optimized using gradient descent and backpropagation. However, biological evolution predated backpropagation by billions of years, shaping complex learning systems via natural selection, crossover, and mutation.

EMNN draws inspiration from this primordial intelligence. We question - what if weights could evolve? Can minimal networks self-organize toward a solution without ever seeing a gradient? This study explores this question by implementing evolutionary operations directly on weights and biases using PyTorch.

2. System Architecture

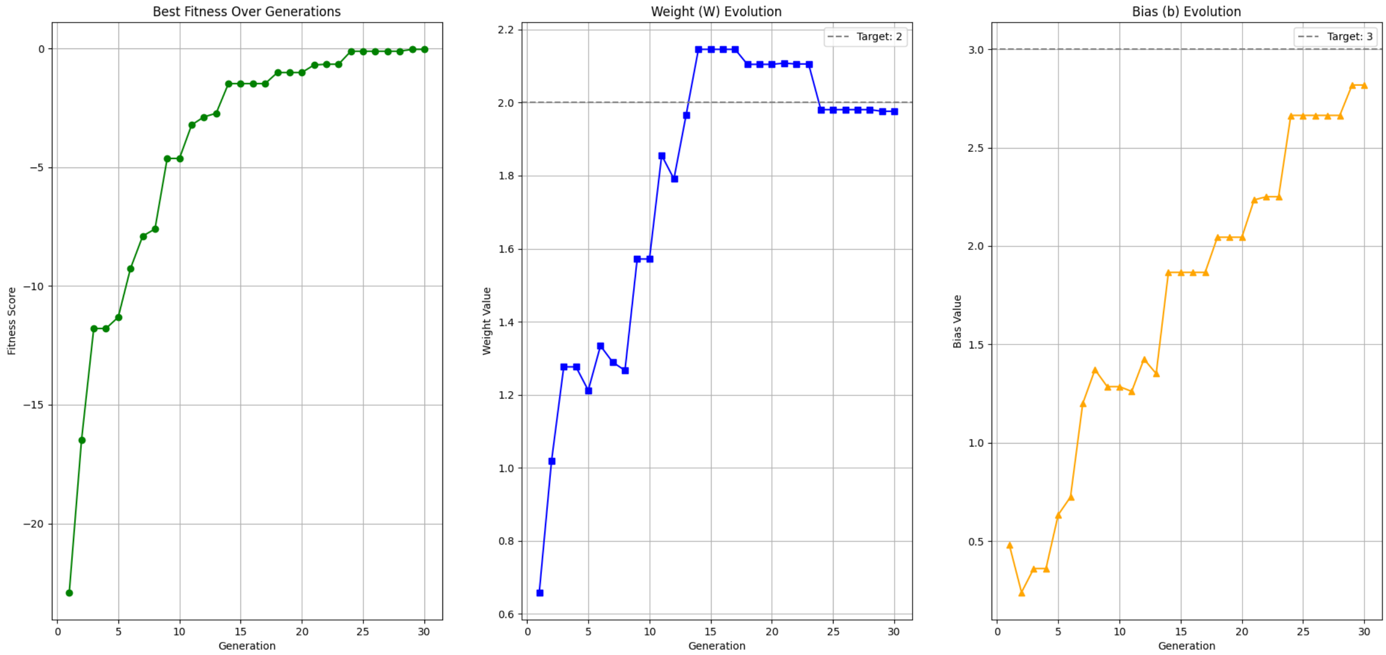
Each individual in the population is a minimal neural network model: a single-layer linear system with parameters W and b. The evolutionary cycle proceeds as follows:

1. Initialization: Random population of neural models.
2. Evaluation: Fitness is evaluated using negative Mean Squared Error (MSE).
3. Selection: Top individuals are selected based on fitness.
4. Crossover: New offspring are generated by combining weights and biases from parents.
5. Mutation: Small perturbations are introduced to avoid local stagnation.
6. Iteration: The new population repeats this cycle for multiple generations.

3. Visual Evolution of Fitness, Weight, and Bias

The following figure illustrates the evolutionary trajectory of best fitness, weight (W), and bias (b) across 30 generations.

As can be observed, W converges toward 2 and b toward 3, while fitness approaches 0 (perfect prediction).



4. Analysis and Interpretation

The fitness curve exhibits a logarithmic improvement - rapid early gains followed by diminishing returns as parameters converge near optima.

Weight and bias evolution show discrete jumps indicating crossovers and minor oscillations due to mutation noise.

Importantly, this system demonstrated that evolution, even without backpropagation, can discover high-quality solutions.

This opens a new space for hybrid algorithms that mix biologically inspired search with deep learning.

5. Use Cases and Implications

- Resource-limited learning where gradients are unavailable.
- Meta-learning and neural architecture evolution.
- Exploration of creative solutions in noisy environments.

- Combining EMNN with reinforcement learning environments.

6. Future Work Directions

- Evolving multi-layer or recurrent models.
- Incorporating self-adaptive mutation strategies.
- Hybrid GA-backprop methods.
- Real-time visual animation of weight gene transfer.
- Co-evolution of loss functions and activation functions.

7. Conclusion

EMNN is not merely an engineering experiment - it is a philosophical lens.

This work reminds us that intelligence is not a property of gradients alone but of dynamics, diversity, and selection pressure.

This exploration invites further investigation into evolution as computation, and computation as evolution.