Title: Beyond the Perceptron: A Dendritic Neuron Model for Solving Nonlinear Problems

Abstract: This paper introduces and analyzes a biologically inspired computational model that extends the classical artificial neuron by incorporating dendritic compartments. These compartments serve as intermediate nonlinear processors before the soma, mimicking dendritic integration in biological neurons. We evaluate this model against a standard perceptron on the XOR problem, demonstrating that a single dendritic neuron with multiple compartments can solve linearly inseparable problems without requiring multiple layers.

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1. Introduction

Classical artificial neurons, such as the McCulloch-Pitts model or sigmoid units, perform a single-stage weighted sum followed by a nonlinear activation. While sufficient for linearly separable problems, they fail to solve nonlinearly separable tasks like XOR without multiple layers. Biological neurons, in contrast, are known to perform complex local computations within dendritic compartments before integration at the soma. Inspired by this, we construct a two-stage neuron architecture with dendritic compartments and demonstrate its expressiveness on the canonical XOR task.

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2. Model Description

Our dendritic neuron consists of multiple dendritic compartments. Each compartment independently performs a weighted sum of the input vector followed by a nonlinearity (`tanh`). The outputs of all compartments are then aggregated at the soma using a weighted sum and passed through a sigmoid activation.

Formally:

- Each compartment: $h_i = \tanh(\sum_j w_{ij} x_j + b_i)$
- Soma output: $y = \sigma(\sum_i v_i h_i + b_s)$

Where:

- x_j : input features
- w_{ij} : weights for compartment i
- v_i : soma weights
- σ : sigmoid activation

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3. Comparison to Standard Artificial Neuron

A standard artificial neuron fails on the XOR problem due to its inability to create the necessary nonlinear decision boundary in a single layer. In contrast, the dendritic neuron succeeds without additional layers.

This is due to its local nonlinearity in each compartment, effectively simulating a mini hidden layer inside a single unit.

Model	Layers	Solves XOR?	Nonlinearity Location
Perceptron	1	No	After weighted sum
Dendritic Neuron	1	Yes	In each compartment + soma

This demonstrates that dendritic compartmentalization serves as an inductive bias that enables more complex representations in shallow models.

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4. Experimental Setup

We implemented the model in Go and trained it on the XOR dataset. The neuron was initialized with 2 inputs and 4 compartments. Training used standard stochastic gradient descent with MSE loss and derivative backpropagation through both the soma and compartments.

Key settings:

- Epochs: 10,000
- Learning rate: 0.1
- Activation functions: `tanh` (compartments), `sigmoid` (soma)

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5. Results

The dendritic neuron reliably learned the XOR function. By epoch 10,000, the prediction error converged, and the rounded outputs matched the expected labels.

Example:

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Input: [0, 1], Expected: 1, Prediction: 0.97, Rounded: 1
Input: [1, 1], Expected: 0, Prediction: 0.04, Rounded: 0
```

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6. Discussion and Future Directions

This model demonstrates that dendritic nonlinearity can significantly increase the representational power of shallow networks. While simple, it opens doors for integrating bio-inspired inductive biases into modern architectures.

Future work includes:

- Integrating dendritic neurons into transformers or MLP blocks
- Exploring compartment-wise gating or inhibition
- Hardware acceleration for compartmentalized processing

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7. Conclusion

We presented a dendritically inspired neuron model that surpasses classical perceptrons in expressiveness without adding layers. This lightweight enhancement aligns with emerging trends in neuromorphic computing and offers promising pathways for efficient neural modeling.