

# Adapting to time: why nature chose to evolve a diverse set of neurons

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## Abstract

Neurons are morphologically diverse, but the evolutionary advantage of this is unclear. In addition, neurons spike and exploit time in their computations, outputs and learning. However, most work on artificial neural networks (ANNs) abstract over these details and restrict learning and adaptation to the spatial parameters of weights and biases. Even when time is introduced, it is introduced through recurrency at a fixed time step (synchronous computation), and again, learning is restricted to weights and biases. Here we adapt weights, time constants and delays in an evolutionary context in an attempt to gain some insights into why neurons are so diverse. We show that nature might have evolved a morphologically diverse set of neurons to i) map spatio-temporal spike trains and ii) ease the evolutionary search for high performing solutions.

## Introduction

Through the course of evolution, nature has produced a diverse set of neurons to meet the computational demands facing adapting organisms, with the mammalian brain evolving about 5,000 types (Yao et al., 2023). In addition, neurons utilize spike-timing in their computations (Lorenzo et al., 2009; Birznieks and Vickery, 2017), with axonal transmission speeds varying by over an order of magnitude (Stoelzel et al., 2017) and neuronal time constants by almost two orders of magnitude (Beggs et al., 2000). This diversity is relevant to various problems, like sound localization by barn owls (Carr and Konishi, 1988), and it may also contribute to in-life learning of temporally correlated parameters, through myelin plasticity (Lakhani et al., 2016). Despite these striking observations, most ANNs abstract over these features and restrict learning and computations to the spatial parameters of weights and biases.

At earlier stages, some work has been done to explore the interaction of a temporal parameter, namely time constants, with weights and biases in the framework of continuous-time recurrent neural networks to solve an associate learning task (Izquierdo et al., 2008). Recently however, and in the context of spiking neural networks, research has investigated the benefits of in-life learning of single temporal parameters

(Perez-Nieves et al., 2021; Hammouamri et al., 2023; Grapolini and Subramoney, 2023; Farner et al., 2024). Here, we expand on this work by co-adapting weights with two temporal parameters, namely time constants and delays, in an evolutionary context to solve a diverse set of spatio-temporal problems. From these investigations, we show the limitations of weight-only solutions, demonstrate the significance of temporal parameters like delays, and show that delays and time constants alone can learn all fundamental logic gates when the weights are fixed.

## Weights are neither sufficient nor necessary in mapping spatio-temporal logic problems

Spatio-temporal logic problems offer a tractable context for investigating the properties of various neuronal parameters and their role in neural computation across a wide range of input-output mappings. The problems include a temporal dimension embodied in the input spike train as shown on the  $x$ -axis of Figure 1a. For example, the first entry on the  $x$ -axis shows 001(NO) and 011(YES) for the input encodings, which means that the spike trains might take the form (.....|.....) for NO, and (.....||.....) for YES, and these inputs are applied to all combinations of each logic problem. Conversely, the output code is simply the spike count from the output-layer neuron.

Figures Figure 1a&b show the number of generations needed to reach a perfect solution (zero loss) for a given combination of i) co-evolved parameters, ii) input-output encoding, iii) logic problem type, and iv) weight clipping range. The weight clipping range is a hyperparameter that is used during evolution to restrict the values that a parameter, in this case weights, can take. We use  $[-1, 1]$  mV and  $[2, -2]$  mV clipping ranges as they exemplify networks that are restricted to values below or, below and above the threshold of 1.1 mV. The number of generations was employed as an indirect measure of the ease of finding a perfect solution. Thus, from an evolutionary perspective, fewer generations suggests that co-evolving the given set of neuronal parameters increases the chances of survival of an individual relative to other parameter sets.

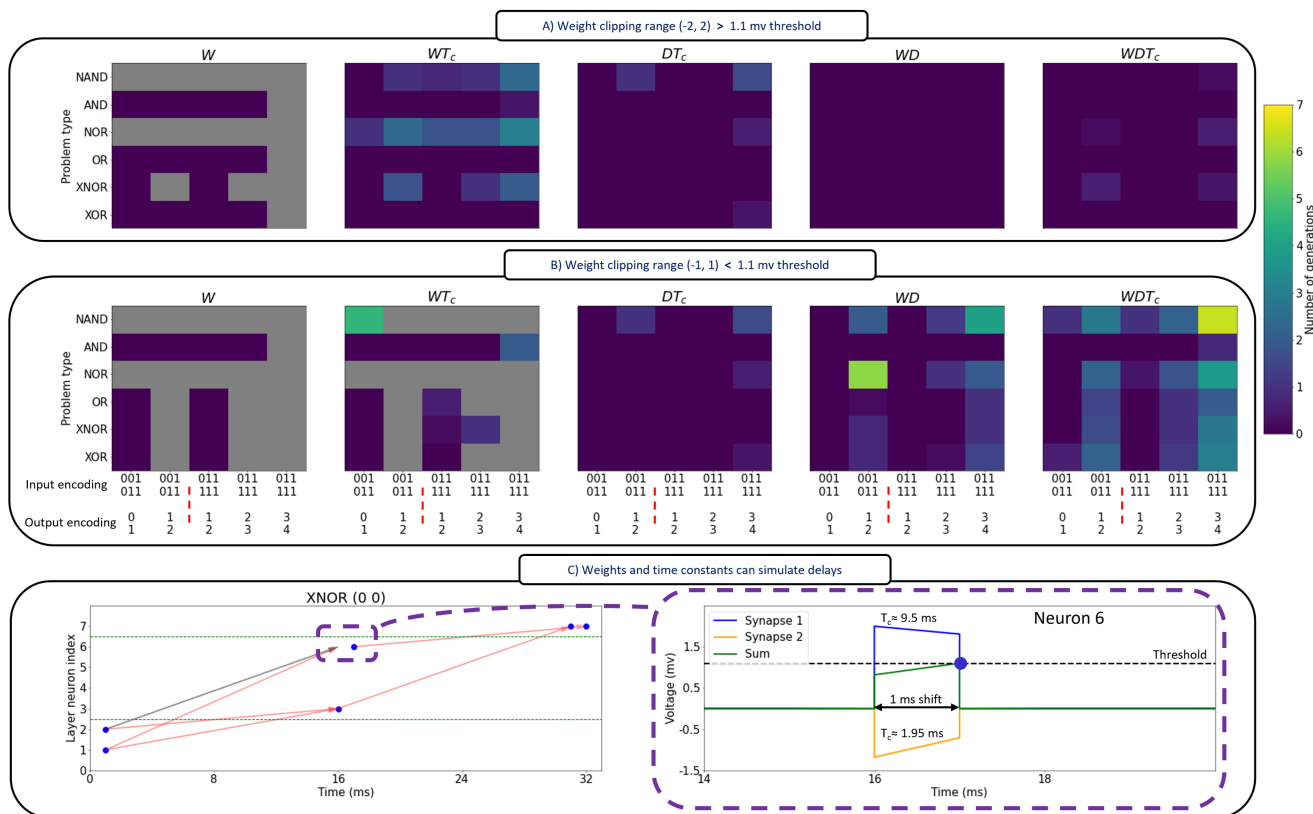


Figure 1: Effect of the input-output encoding and the co-evolved parameters on the search speed and availability of solutions for various logic problems. This is conveyed through the number of generations needed to find a solution, where grey means no solutions found. This is performed for A)  $[-2, 2]$  mV and B)  $[-1, 1]$  mV weights clipping range during evolution. C)  $WT_c$  only solutions can simulate delays. Left, the spiking plot for a sample XNOR problem and right, a zoomed-in view of the voltage traces with their sum. Abbreviations code, W: weights,  $T_c$ : time constants, D: delays.

A close inspection of Figure 1a&b shows that weights alone cannot solve all logic problems. Weights are a spatial adaptation parameter, and when faced with a temporal input (a spike train), we observe that weight-only mutated networks have the lowest performance. Conversely, it seems that the biggest contributors to performance are delays. Thus, when they are combined with other parameters, like weights or time constants, they can greatly enhance the ability of neural networks to successfully map input spike trains to diverse output encodings. The usefulness of delays in this context helps to explain why there is a performance increase when time constants are co-trained with weights (although slight for the  $[-1, 1]$  mV weight clipping case). This performance increase is possible because weights and time constants can simulate delays as shown in Figure 1c. This result is achieved through the integration of postsynaptic potentials of different time constants, most often a slow excitation and a fast inhibition. For Figure 1c, the left image is a spiking raster plot, which shows the spike arrival times (arrow heads) and spiking times (blue dots) for each neuron in the network, including the input neurons, namely 1 and 2.

The purple-dashed rectangle emphasizes a case where neuron 6 spikes one millisecond after the spikes from neurons 1 and 2 arrive. This process is enlarged in the right image of Figure 1c, where the voltage traces of each synapse are shown beside their sum. Finally, it should be noted that delays and time constants can solve all logic problems as illustrated by the middle image of Figure 1b. It should be emphasized that there are countless neuronal types, depending on the temporal constraints, and they are limited by the extent of the problem the network is trying to solve.

Our findings highlight the important role that adaptive temporal parameters play in solving simple spatio-temporal problems, and that their complex interactions alter the nature of the solutions obtained in the different co-adaptation conditions. This not only provides a possible explanation for why the brain evolved morphologically diverse neurons that can exploit the fine temporal structure of spike trains, it also highlights the problem of ignoring the adaptive role that time plays when building neural network models of brain function, as is the standard with current ANNs that rely on rate coding.

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