Applying a Reduced Model of Apical and Basal Dendritic Compartments to Sequence Learning in Recurrent Neural Networks

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Introduction

- Experiments suggest that, depending on the amount of apical (distal) and basal dendritic synaptic drive, layer 5 pyramidal neurons can exhibit quietness, low frequency spiking and high frequency bursting [1, 2].
- The latter only occurs when distal and basal inputs coincide in time. A simplified, rate based compartment model of this effect has been used to gate plasticity of basal connections by means of distal synaptic inputs [3].
- We use this mechanism for sequence prediction. In our framework, coincidence detection of distal and basal input modulates plasticity to extract a predictive signal from a recurrent dynamic reservoir.
- This approach is similar to echo state networks [4], but readout and external input are now collected by the same units (see Fig. 1). Combining both streams of information in the previously described manner, the error signal for learning is thus implicitly expressed as the nonlinear response to basal and distal input.

Model Description

We used a discrete time non-binary rate encoding neuron model, whose output frequency is given by

$$x\left(I_p, I_d\right) = 2\left[\sigma\left(I_p - \theta_{p1}\right)\sigma\left(I_d - \theta_d\right) + \alpha\sigma\left(I_p - \theta_{p0}\right)\sigma\left(-\left(I_d - \theta_d\right)\right)\right] - 1$$

$$\sigma(x) = \frac{1}{1 + \exp(-g \cdot x)}$$

$$I_p(t) = \sum_{k=1}^{n} w_{p,k}(t) x_{p,k}(t), \quad I_d(t) = \sum_{k=1}^{n} w_{d,k}(t) x_{d,k}(t)$$

Proximal and distal weights were subject to Hebbian plasticity and weight normalization.

$$\Delta w_{p/d,i}(t) = \epsilon_w \left(x(t) - \langle x \rangle\right)\left(x_{p/d,i}(t) - \langle x_{p/d,i} \rangle\right)$$

$$w_{p/d,i}(t+1) = w_{p/d,\mathrm{total}} \frac{w_{p/d,i}(t) + \Delta w_{p/d,i}(t)}{\sqrt{\sum_{k=1}^{np/nd}\left[w_{pk}(t) + \Delta w_{pk}(t)\right]^2}}$$

A Single Distal Input Stream Acts as a Guiding Signal for Proximal Plasticity

- We fed a single neuron with 10 randomly fluctuating proximal inputs and one distal input that was perfectly correlated with one of the proximal signals.
- As a "distraction", the standard deviation of another proximal input was increased, such that proximal inputs had a dominant principal component.
- As shown in Fig. 2, the distal input acts as a guiding input, such that the proximal input that maximizes correlation with the distal input is selected.
- If the distal input is uncorrelated, proximal weights select the principal component (Fig. 3).

Conclusions

- The model allows for the reproduction of a wide range of dynamical properties of spiking neurons.
- Characteristic properties such as the spike height and width can be controlled very well by certain model parameters.
- Good usability as a rate encoding model with a sigmoid activation function.
- Further investigations should compare how spiking and rate network dynamics map onto each other under the same synaptic coupling.

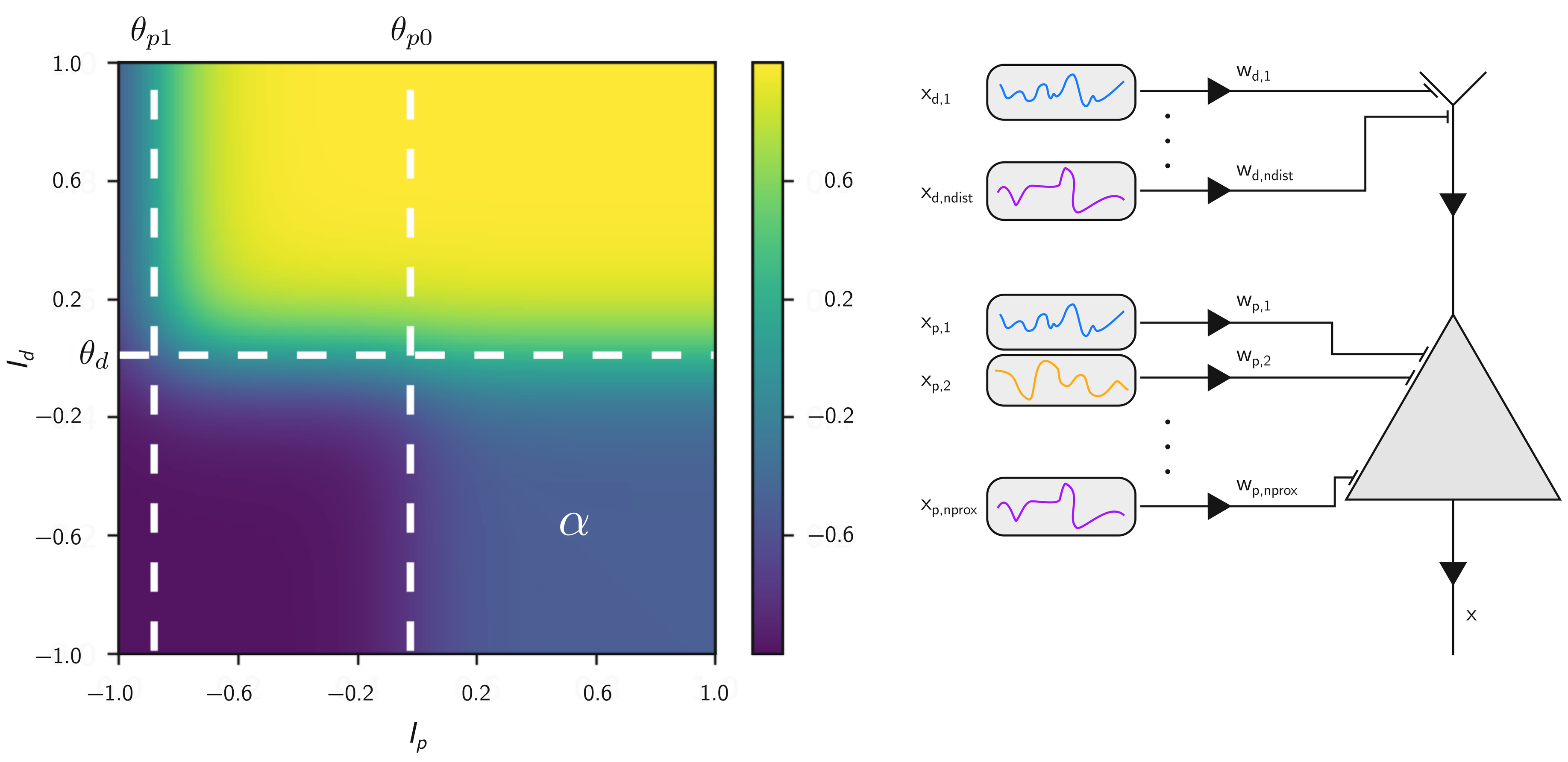

Figure 1: Output rate model a function of proximal (basal) and distal (apical) dendritic input (left) and an illustration of the accumulation of inputs in the neuron model.

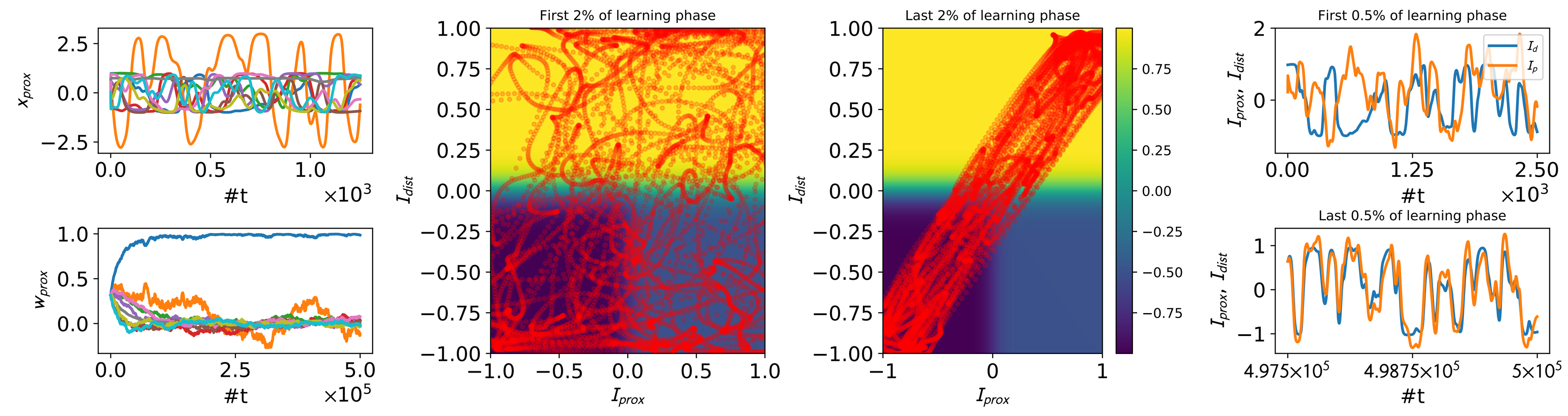

Figure 2: Results for a single distal input, correlated with one proximal input

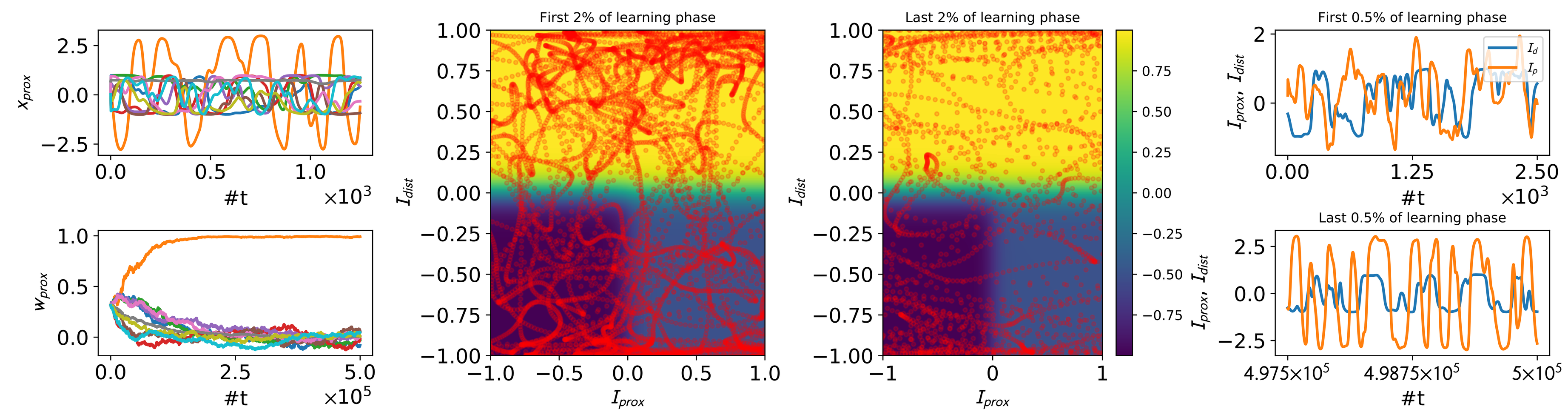

Figure 3: Single distal input, uncorrelated

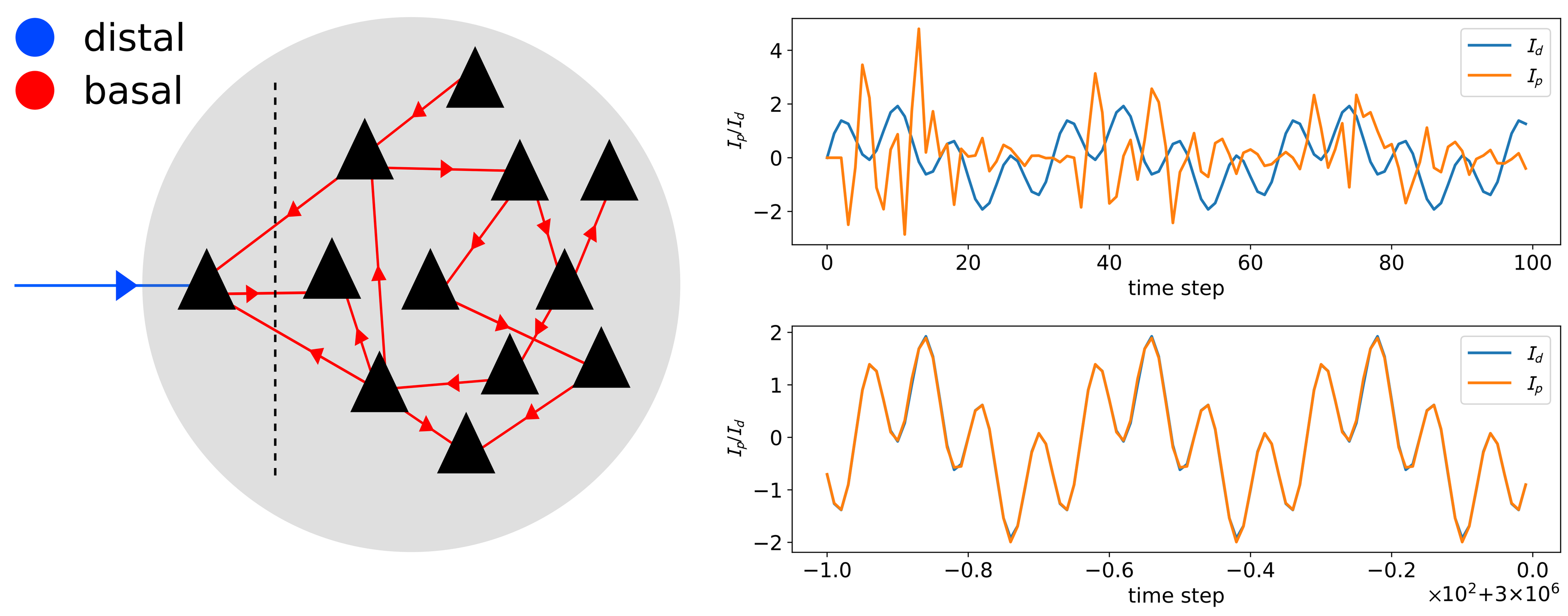

Figure 4: Echo state network

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[2] Adam S. Shai, Costas A. Anastassiou, Matthew E. Larkum, and Christof Koch. Physiology of Layer 5 Pyramidal Neurons in Mouse Primary Visual Cortex: Coincidence Detection through Bursting. *PLOS Computational Biology*, 11(3):1–18, 03 2015.

[3] J. Bono and C. Clopath. Modeling somatic and dendritic spike mediated plasticity at the single neuron and network level. *nature communications*, 2017.

[4] Herbert Jaeger. The "echo state" approach to analysing and training recurrent neural networks – with an Erratum note. 2010.