



# C3

## The mechanistic of local-learning rules for curiosity in neural network models



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### Motivation

- Unsupervised local learning need to adapt to input statistics and task requirements
- Derivation and refinement of those learning rules

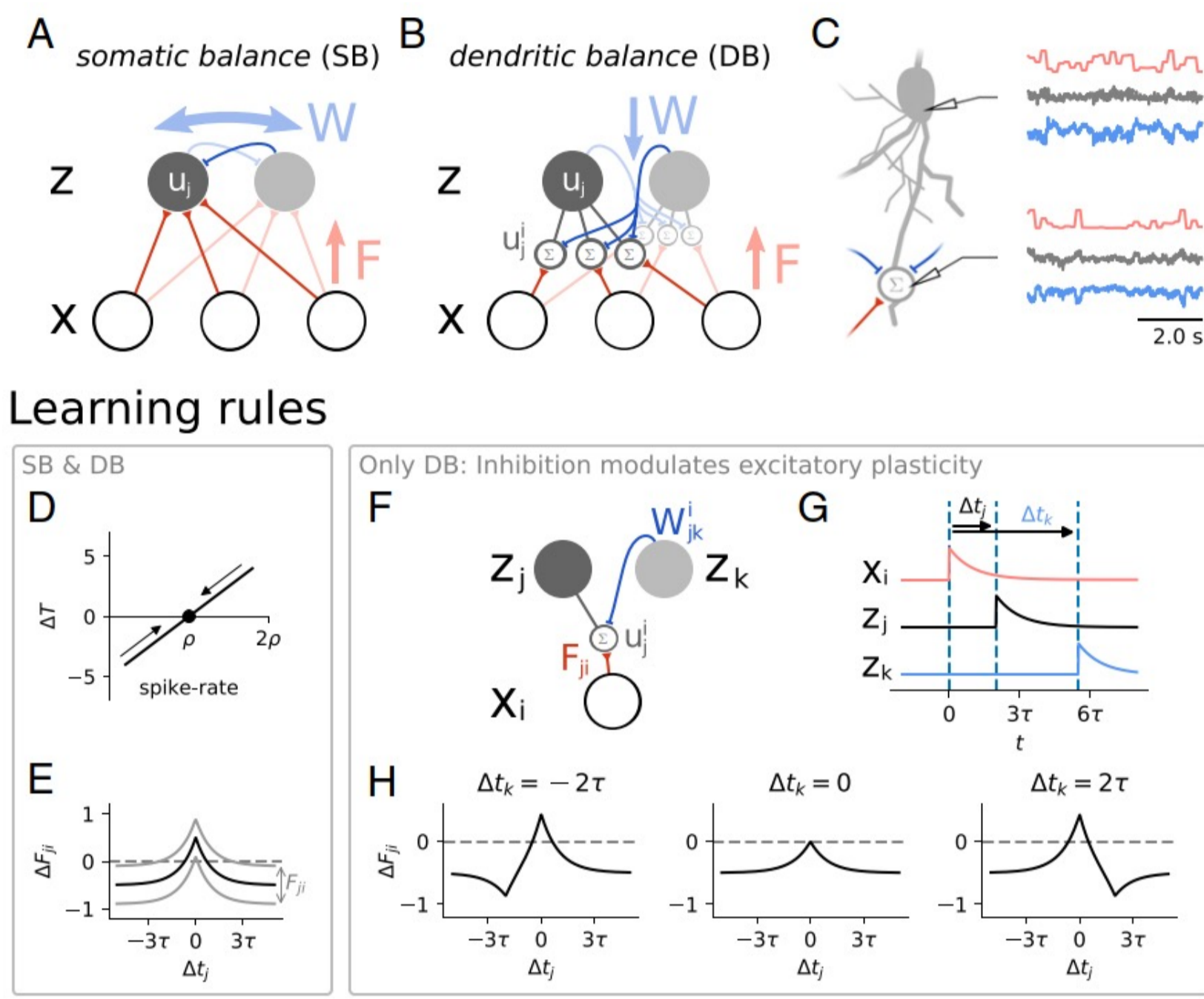


Fig. 1: Local, unsupervised learning rules derived from a goal function of efficient, sparse coding<sup>1</sup>

### Preliminary work:

- Derivation of learning rules<sup>1-3</sup>
- Homeostasis and input shape network state<sup>4</sup>
- Adapting networks to task requirements<sup>5, 6</sup>

### Objectives

- Optimize the neural implementation of efficient, curious learning, based on learning rules derived from theoretic principles
- Thus, derive how learning rules need to be adapted, depending familiar or curious sampling (i.e., at higher rates of novel input)
- Investigate how this translates into differences in the processing of novel and familiar input.
- In understanding how learning rules change for curious sampling, we contribute to the question **How are we curious?**
- If we can show that curiosity-dependent learning rules improve learning, we contribute also the question **Why are we curious?**



How do neural networks update learning rules and strategies to implement curious learning?

### Methods

- Deriving mechanism that enables one to adapt learning rules that are specialized to conservative and curious sampling
- Optimizing network performance and simulation efficiency via pruning and structural plasticity
- Information-theory to formulate goal functions, and guide the derivation of the learning rules

### Hypotheses:

- Increased variance of firing threshold may facilitate curious learning, and increased synaptic variability may facilitate acquisition of novel features.
- Adaptation of learning rates.
- Under synaptic and structural plasticity, differentiation between novel and old synapses may facilitate acquisition of novel information and maintenance of old ones.

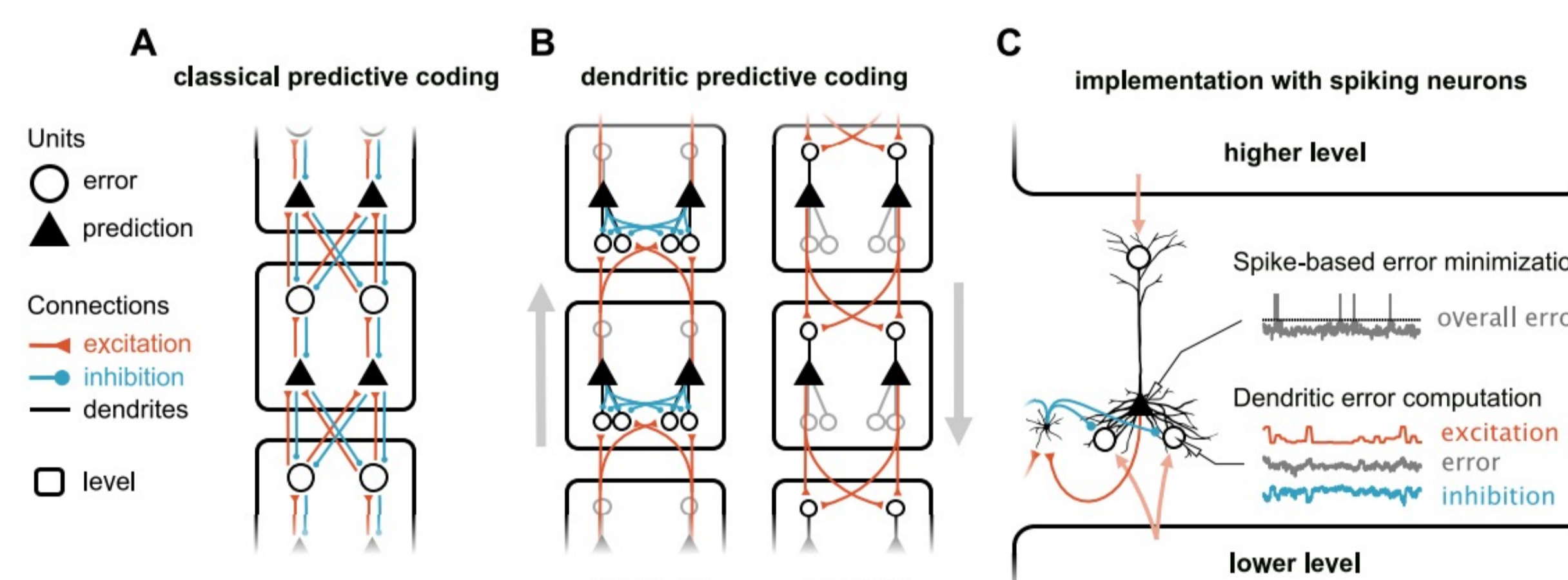


Fig. 2: Network architecture for the learning rules implemented via dendritic balance for hierarchical predictive coding<sup>2</sup>

#### Infobox 2.1: Mathematical details of hierarchical predictive coding

**Predictive coding with error units.** The goal in hPC is to maximize the model log-likelihood  $\mathcal{L}$  (for a detailed tutorial see [1]).

$$\mathcal{L} = \sum_{t=1}^T \log p_{\theta}(r^t | r^{t-1}), \quad (1)$$

where  $\theta$  are the model parameters,  $r^t$  is neural activity of a neural network at level  $i$ , and inputs are provided by the previous level  $r^{t-1}$ . This defines a hierarchy of processing stages that for example can be associated with different visual cortical areas (e.g. V1, V2, etc.), where  $r^0$  are visual inputs from LGN [8]. Typically, a linear model is assumed, where inputs are modelled according to

$$r^{t-1} = \mathbf{D}^T r^t + \mathbf{n}^{t-1}, \quad (2)$$

with decoding matrix  $\mathbf{D}^T$  and Gaussian white noise  $\mathbf{n}^{t-1}$  with zero mean and variance  $\sigma_{\mathbf{n}}^2$ . With this model, for a single level  $i$ , the relevant contributions of the negative log-likelihood  $-\mathcal{L}$  take the intuitive form of the square sum of coding errors for bottom-up inputs and errors of top-down predictions:

$$\begin{aligned} \text{bottom-up error: } & e^{t-1} = r^{t-1} - \mathbf{D}^T r^t, \quad (3) \\ \text{top-down error: } & e^t = r^t - \mathbf{D}^{T+1} r^{t+1}, \end{aligned} \quad (4)$$

$$-\mathcal{L}^i = \frac{1}{2\sigma_{\mathbf{e}}^2} e^{t-1T} e^{t-1} + \frac{1}{2\sigma_{\mathbf{e}}^2} e^{tT} e^t. \quad (5)$$

The goal is then to minimize the sum of coding errors on a fast timescale  $\tau_c$  via neural dynamics  $\frac{d}{dt} r^t$ , and with a slow learning rate  $\eta_D$  via neural plasticity on the weights  $\mathbf{D}^T$  by performing gradient ascent on  $\mathcal{L}$ :

$$\begin{aligned} \text{dynamics: } & \tau_c \frac{d}{dt} r^t = \frac{1}{\sigma_{\mathbf{e}}^2} \mathbf{D}^T r^t e^{t-1} - \frac{1}{\sigma_{\mathbf{e}}^2} e^t, \quad (6) \\ \text{plasticity: } & \eta_D \frac{d}{dt} \mathbf{D}^T = \frac{1}{\sigma_{\mathbf{e}}^2} e^{t-1T} r^t. \end{aligned} \quad (7)$$

To yield a neural implementation, the key innovation in classical hPC was to represent prediction errors within a distinct neural population of error units, that integrate inputs of prediction units within the same level, and subtract top-down predictions according to

$$\tau_c \frac{d}{dt} e^t = -e^t + r^t - \mathbf{D}^{T+1} r^{t+1}, \quad (8)$$

where decoding weights  $\mathbf{D}^T$  now correspond directly to weights of neural connections [1]. Together with the dynamics of prediction units, this results in the hierarchical neural circuit shown in Fig 2A.

**Predictive coding with dendritic errors.** In dendritic hPC, the computation of errors in Eq. (8) is accomplished by the leaky voltage dynamics of dendritic compartments [12, 13]. To this end, for each prediction neuron  $j$  one introduces basal dendritic compartments  $b_{j,k} \approx D_{j,k} e^{t-1}$ , which are each innervated by a single synapse of a prediction neuron  $k$  of the previous level, as well as an apical compartment  $a_j \approx -e^t$  that is innervated by prediction neurons of a higher level (Fig 2B). The error computation is then performed by voltage dynamics according to

$$\tau_c \frac{d}{dt} b_{j,k} = -b_{j,k} + D_{j,k} r_k^{t-1} - \sum_l W_{j,l} r_l^t, \quad (9)$$

$$\tau_c \frac{d}{dt} a_j = -a_j - r_j^t + \sum_l D_{j,l}^{T+1} r_l^{t+1}, \quad (10)$$

where bottom-up inputs are balanced with lateral connections  $W_{j,l}$  (connection of neuron  $j$  to the  $l$ th dendritic compartment of neuron  $j$ ), and top-down predictions are matched by the neurons own predictions  $r_j^t$ . The latter could be implemented via the backpropagating action potential [14], solving the one-to-one connections problem of classical hPC [12]. To compute bottom-up errors, lateral weights have to be chosen as  $W_{j,l} = D_{j,l}^T$ . This can be achieved if lateral plasticity enforces a tight balance [13]

$$\eta_W \frac{d}{dt} W_{j,l} = \frac{1}{\sigma_{\mathbf{e}}^2} b_{j,k} r_l^t. \quad (11)$$

The dynamics of prediction neurons are then simply driven by the dendritic error potentials

$$\tau_c \frac{d}{dt} r_j^t = \frac{1}{\sigma_{\mathbf{e}}^2} \sum_k b_{j,k} + \frac{1}{\sigma_{\mathbf{e}}^2} a_j, \quad (12)$$

and weights for bottom-up and top-down inputs can be learned with voltage-dependent rules

$$\eta_D \frac{d}{dt} D_{j,k} = \frac{1}{\sigma_{\mathbf{e}}^2} b_{j,k} r_k^{t-1}, \quad (13)$$

$$\eta_D \frac{d}{dt} D_{j,l}^{T+1} = \frac{1}{\sigma_{\mathbf{e}}^2} a_j r_l^{t+1}. \quad (14)$$

Here, correct learning requires the cooperation of lateral and bottom-up weights, which in classical hPC is known as the weight transport problem [12, 13]. For dendritic hPC this problem has so far been addressed in the single-level case [13]. Together, these equations yield an equivalent formulation of hPC for both, learning and inference, where prediction errors are computed in tightly balanced dendritic compartments.

Fig. 3: Derivation of learning rules for hierarchical predictive coding via dendritic balance<sup>2</sup>

### Cross-project collaborations

- We will test whether the model's prediction on higher baseline variability during blocks of curious (versus familiar) sampling manifests in electrophysiological data (B1, C1)
- The information-theoretic approach to optimal curious sampling (C5) can guide us to optimize the conditions when learning rules should be adapted.
- We will draw on insights of A2, B1, B4, C2 & C5 on the question of under which conditions humans, animals and machines are curious, to adapt and optimize our stimulus set

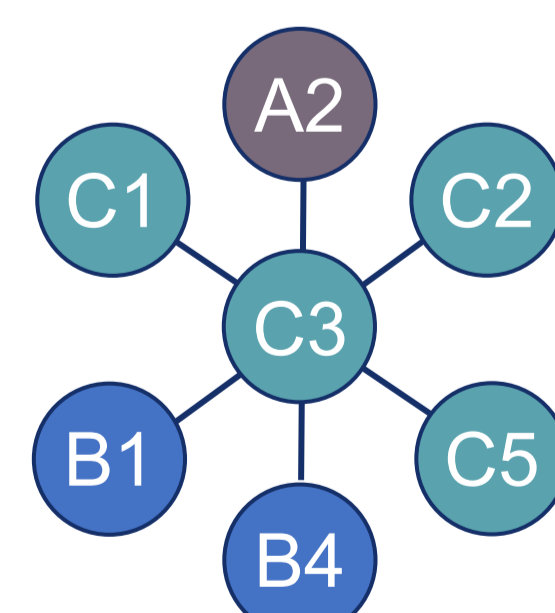


Fig. 4: Key collaboration partners of doctoral researcher working on Project C3

### Potential PhD projects

1. Unsupervised efficient encoding of features in spiking neural networks with structural plasticity
2. Tuning learning rules to conservative and curious exploration of stimulus environments
3. Learning predictive encoding in neural networks, and using its responses to dynamically select learning rules for curious sampling of stimuli

### References

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