GEORG-AUGUST-UNIVERSITÄT GÖTTINGEN IN PUBLICA COMMODA SEIT 1737

C3

The mechanistics 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

Preliminary work:

- Derivation of learning rules[1-3]
- Homeostasis and input shape network state[4]
- Adapting networks to task requirements[5, 6]

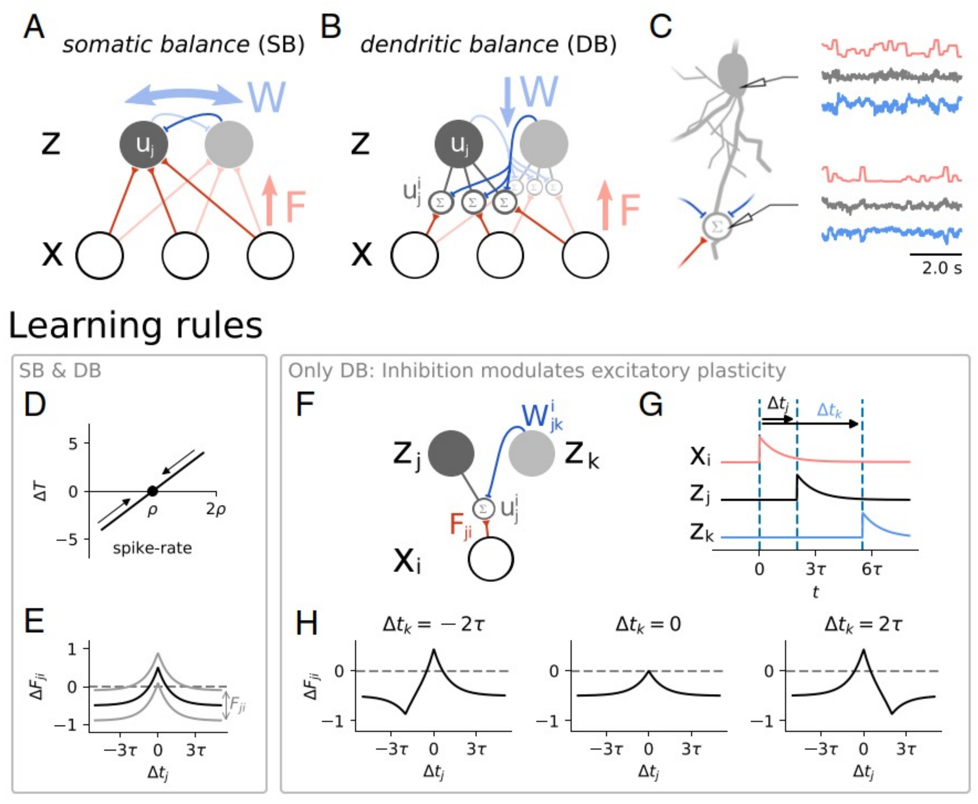

Fig. 1: Local, unsupervised learning rules derived from a goal function of efficient, sparse coding[1]

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.

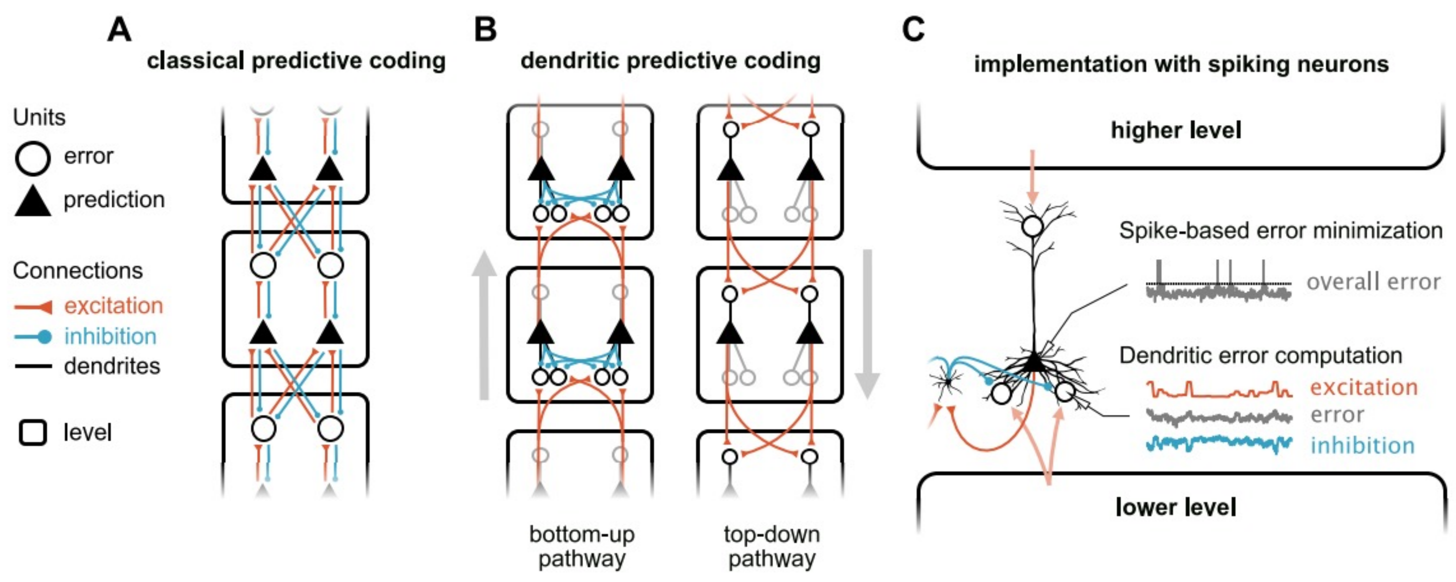

Fig. 2: Network architecture for the learning rules implemented via dendritic balance for hierarchical predictive coding[2]

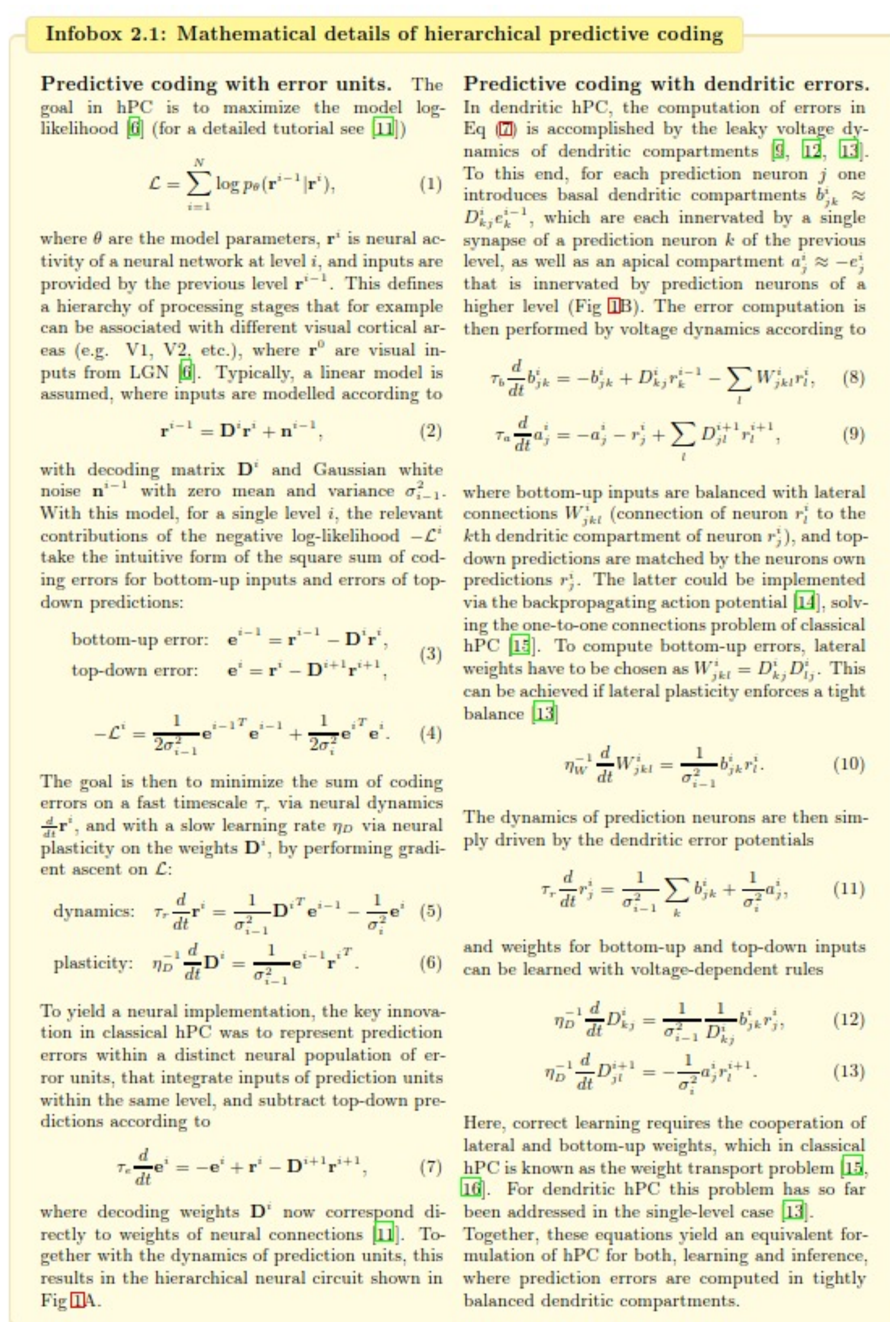

Fig. 3: Derivation of learning rules for hierarchical predictive coding via dendritic balance[2]

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

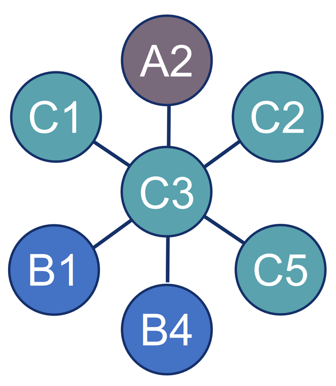

Fig. 4: Key collaboration partners of doctoral researcher working on Project C3

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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2. Mikulasch, F. A., Rudelt, L., **Wibral, M.** & **Priesemann, V.** (2022). Where is the error? Hierarchical predictive coding through dendritic error computation. *Trends in Neurosciences*, 46(1), 45-59.
3. **Wibral, M., Priesemann, V.,** Kay, J. W., Lizer, J. T. & Phillips, W. A. (2017). Partial information decomposition as a unified approach to the specification of neural goal functions. *Brain and Cognition*, 112, 25-38.
4. Zierenberg, J., Wilting, J. & **Priesemann, V.** (2018). Homeostatic plasticity and external input shape neural network dynamics. *Physical Review X*, 8, 031018.
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