# Non-additive processing of synchronous inputs yields enhanced memory storage



### David Breuer <sup>[1]</sup>, Raoul-Martin Memmesheimer <sup>[4]</sup> and Marc Timme <sup>[1-3]</sup>

<sup>[1]</sup> Network Dynamics Group, Max Planck Institute for Dynamics and Self-Organization (MPIDS), 37077 Göttingen, Germany
 <sup>[2]</sup> Bernstein Center for Computational Neuroscience (BCCN), 37077 Göttingen, Germany
 <sup>[3]</sup> Department of Physics, Georg August University Göttingen, 37077 Göttingen, Germany
 <sup>[4]</sup> Donders Institute, Department of Neuroinformatics, Radboud University, 6525 AJ Nijmegen, Netherlands

dbreuer|timme@nld.ds.mpg.de, r.memmesheimer@science.ru.nl

# Motivation

#### How is the memory capacity of the brain ...

Every day we experience that we are (i.e. our brain is) **good at remembering** a large number of facts, faces and other things. Furthermore, we are able, e.g., **to associate** different facts and recognize faces of friends even under complicating conditions. **Simple neural network models** can grasp these capabilities and explain the storage capacity and robustness of memory retrieval <sup>[1,2]</sup>. The following pictures demonstrate both aspects of our memory:



### **Conclusion & Outlook**

#### take home messages

- Hopfield networks provide a simple model for associative memories.
- ▶ The complexity of the brain covers, i.a., **non-additive input processing** and dendritic arbors.
- Dendritic non-additivities increase the robustness of the model against fluctuations.

#### work in progress

How can the couplings w<sub>nbm</sub> be adjusted to optimize storage capacity?



### ... influenced by the complexity of the brain?

The collective dynamics of neural circuits centrally relies on how individual neurons process their inputs <sup>[4]</sup>. Despite a vast literature on neural network dynamics, almost all theoretical studies so far have **assumed linear summation of inputs**. Experimental works, however, have shown that temporally synchronous and spatially close inputs yield a soliton-like excitation and thereby a **supralinear enhancement of the inputs** <sup>[5,6]</sup>. Moreover, commonly studied point-neuron models ignore the richness and **complexity of dendritic arbors** as present in many regions of the brain <sup>[7,8]</sup>.



How do complex biological features of the brain, such as non-additive input processing in multiple dendritic branches, influence its performance as an associative memory?

### **Dendrites provide effective neuronal input**

Do similar gains in memory performance persist in networks of biologically plausible neurons?

### **Dendrites improve robustness of memory**

#### dendritic non-additivities stabilize memorized patterns

• quality of retrieval is measured by the overlap m of the network state with pattern p = 1, w.l.o.g.

$$n = N^{-1} \sum_{n=1}^{N} x_n^1 \left\langle v_n \right\rangle$$

 overlap in the limit PN<sup>-1</sup> → 0 for the standard Hopfield model (black) and increasingly strong non-additivites (gray, orange, red)



effective input *u* to neuron in presence of non-additive dendrites
the neuronal input is split into two contributions of linear and saturated dendrites, respectively



▶ Non-additive **dendrites alter input** *u* to neuron in a non-trivial but **predictable** manner with small deviations  $Std[u] \ll E[u]^{[9]}$ .

## Neuron Model

#### Non-additive dendrites allow successful memory retrieval at higher noise levels <sup>[9]</sup>.

# **Extended Hopfield Model**

#### network architecture

- due to the dendritic branches, **neurons are coupled to branches** of neurons  $w_{nbm}$
- the Hebbian connectivity stores patterns  $x_n^p$  as attractors into the network <sup>[1]</sup>
- this provides the network with the capability to recall and associate memories

 $w_{nm} = N^{-1} \sum_{p=1}^{P} x_n^p x_m^p$  $= N^{-1} \sum_{b=1}^{B} w_{nbm}$ 



#### neuronal dynamics

- ▶ the **binary neurons** are updated stochastically, modeling **noise**<sup>[2]</sup>
- ▶ the non-additive dendrites provide the neuron with an **effective input** *u* (see Effective Input)

#### extended point neurons to two-layer structures

each independent dendritic branch is modeled as a seperate compartment



non-additive dendritic input processing

▶ input summation in dendrites is **non-additive** (see Motivation) but remains linear in neuron



 $v_n (t+1) = \begin{cases} +1, & \text{with probability} \quad p_n \\ -1, & \text{otherwise} \end{cases}$  $p_n (T, u_n) = \left(1 + \exp\left(-2T^{-1}u_n\right)\right)^{-1}$ 

 $v_n$  state of neuron n t time T temperature  $u_n$  effective input to neuron n

# **References & Acknowledgments**

JJ Hopfield (1982) Neural networks and physical systems with emergent collective computational abilities. PNAS, 79(8).
 D Amit (1992) Modeling brain function: The world of attractor neural networks. Cambridge Univ Pr.
 Wikimedia Commons (2012) wiki/Albert\_Einstein, public domain.
 C Koch and I Segev (2000) The role of single neurons in information processing. Nature Neurosci, 3.
 S Gasparini and JC Magee (2006) State-dependent dendritic computation in hippocampal CA1 pyramidal neurons. J Neurosci, 26(7).
 G Ariav (2003) Submillisecond precision of the input-output transformation function [...]. J Neurosci, 23(21).
 B Mel (1994) Information processing in dendritic trees. Neural Comp, 6(6).
 P Poirazi et al (2003) Pyramidal neuron as two-layer neural network. Neuron, 37(6).
 D Breuer et al (unpublished) Non-additive dendritic processing [...]: Impact on single neurons and associative memory networks.

► Financially supported by the BMBF (grant no. 01GQ1005B) and the DFG (grant no. TI 629/3-1).