project proposal:

Effect of homeostatic regulation on dynamics of recurrent neuronal networks

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https://github.com/tomtetzlaff/2023_eitnfallschool

Outline

Background

Questions and hypotheses

Proposed work plan

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- both in nature and in Computational Neuroscience, neuronal network dynamics can become unstable, leading either
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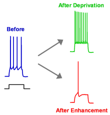
- typical countermeasures
  - Computational Neuroscience: laborious parameter tuning and/or unrealistic assumptions
  - (healthy) brains: **homeostatic regulation**

Background

Known forms of homeostasis in biological neuronal networks

- intrinsic plasticity (hours–days): regulation of cell-intrinsic excitability (e.g., thresholds; “slow adaptation”) (Naudé et al. 2012)

Intrinsic plasticity



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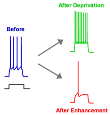

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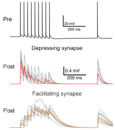

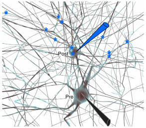

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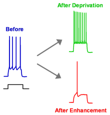

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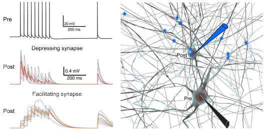

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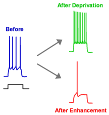

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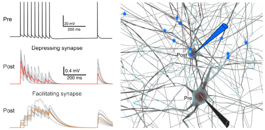

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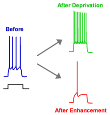

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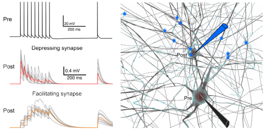

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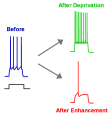

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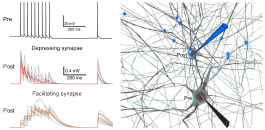

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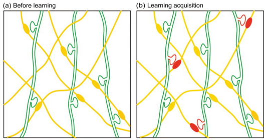

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- ...and certainly many more

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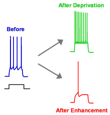

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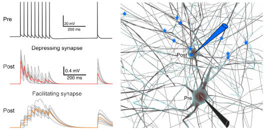

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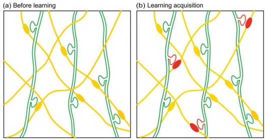

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Questions and hypotheses

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2) How does the presence of such mechanisms alter network dynamics, such as the dynamics in response to perturbations?

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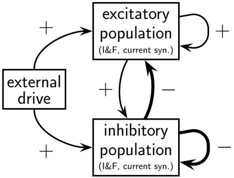

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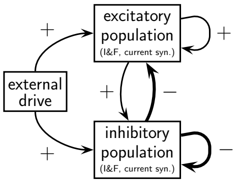

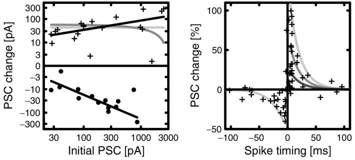

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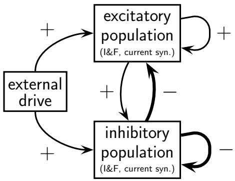

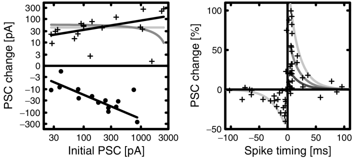

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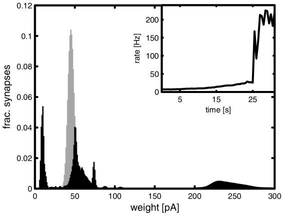

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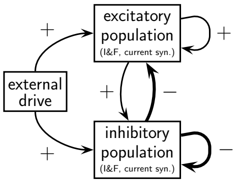

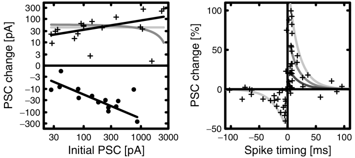

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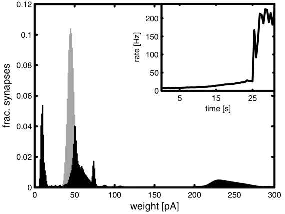

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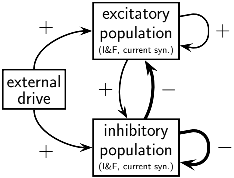

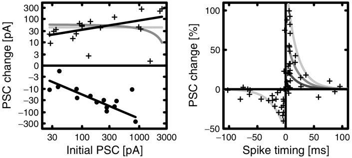

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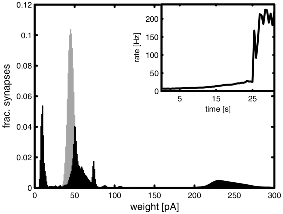

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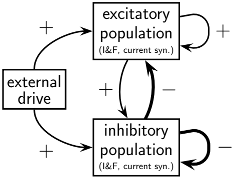
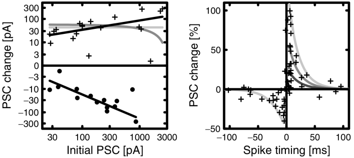
6. investigate how the implemented form of homeostasis affects network dynamics in the absence or presence of external perturbations (such as average firing rates, level of correlations in firing activity, power spectra of population activity, sensitivity to perturbations)

(Bachmann et al. 2020)





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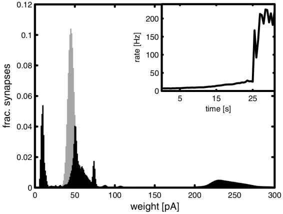

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References I

Abbott, L. F. and S. B. Nelson (2000). “Synaptic plasticity: taming the beast”. In: **Nature Neuroscience** 3, pp. 1178–1183. DOI: `10.1038/81453`.

Bachmann, Claudia et al. (2020). “Firing rate homeostasis counteracts changes in stability of recurrent neural networks caused by synapse loss in Alzheimer’s disease”. In: **PLoS Computational Biology** 16.8, e1007790. DOI: `10.1371/journal.pcbi.1007790`.

Butz, Markus and Arjen van Ooyen (2013). “A simple rule for dendritic spine and axonal bouton formation can account for cortical reorganization after focal retinal lesions”. In: **PLoS Computational Biology** 9.10, e1003259. DOI: `10.1371/journal.pcbi.1003259`.

Fu, Min and Yi Zuo (2011). “Experience-dependent structural plasticity in the cortex”. In: **Trends in Neuroscience** 34.4, pp. 177–187.

Gallinaro, Júlia V., Nebojša Gašparović, and Stefan Rotter (2022). “Homeostatic control of synaptic rewiring in recurrent networks induces the formation of stable memory engrams”. In: **PloS Computational Biology** 18.2, e1009836. DOI: `10.1371/journal.pcbi.1009836`.

Gallinaro, Júlia V. and Stefan Rotter (2018). “Associative properties of structural plasticity based on firing rate homeostasis in recurrent neuronal networks”. In: **Scientific Reports** 8.1. DOI: `10.1038/s41598-018-22077-3`.

Hartmann, Christoph et al. (2015). “Where’s the noise? Key features of spontaneous activity and neural variability arise through learning in a deterministic network”. In: **PLoS Computational Biology** 11.12, e1004640.

Hennequin, Guillaume, Everton J Agnes, and Tim P Vogels (2017). “Inhibitory plasticity: balance, control, and codependence”. In: **Annual review of Neuroscience** 40, pp. 557–579. DOI: `10.1146/annurev-neuro-072116-031005`.

Markram, Henry et al. (2015). “Reconstruction and simulation of neocortical microcircuitry”. In: **Cell** 163.2, pp. 456–492. DOI: `10.1016/j.cell.2015.09.029`.

References II

Morrison, A., A. Aertsen, and M. Diesmann (2007). "Spike-Timing Dependent Plasticity in Balanced Random Networks". In: **Neural Computation** 19, pp. 1437–1467. DOI: `10.1162/neco.2007.19.6.1437`.

Naudé, Jérémie et al. (2012). "A theory of rate coding control by intrinsic plasticity effects". In: **PLoS Computational Biology** 8.1, e1002349.

Tetzlaff, Christian et al. (2011). "Synaptic scaling in combination with many generic plasticity mechanisms stabilizes circuit connectivity". In: **Frontiers in Computational Neuroscience** 5, p. 47.

Tsodyks, Misha V. and Henry Markram (1997). "The neural code between neocortical pyramidal neurons depends on neurotransmitter release probability". In: **Proceedings of the National Academy of Sciences USA** 94, pp. 719–723.

Watt, Alanna J and Niraj S Desai (2010). "Homeostatic plasticity and STDP: keeping a neuron's cool in a fluctuating world". In: **Frontiers in Synaptic Neuroscience** 2, p. 1486.