Robust Computation with Neuronal Heterogeneity

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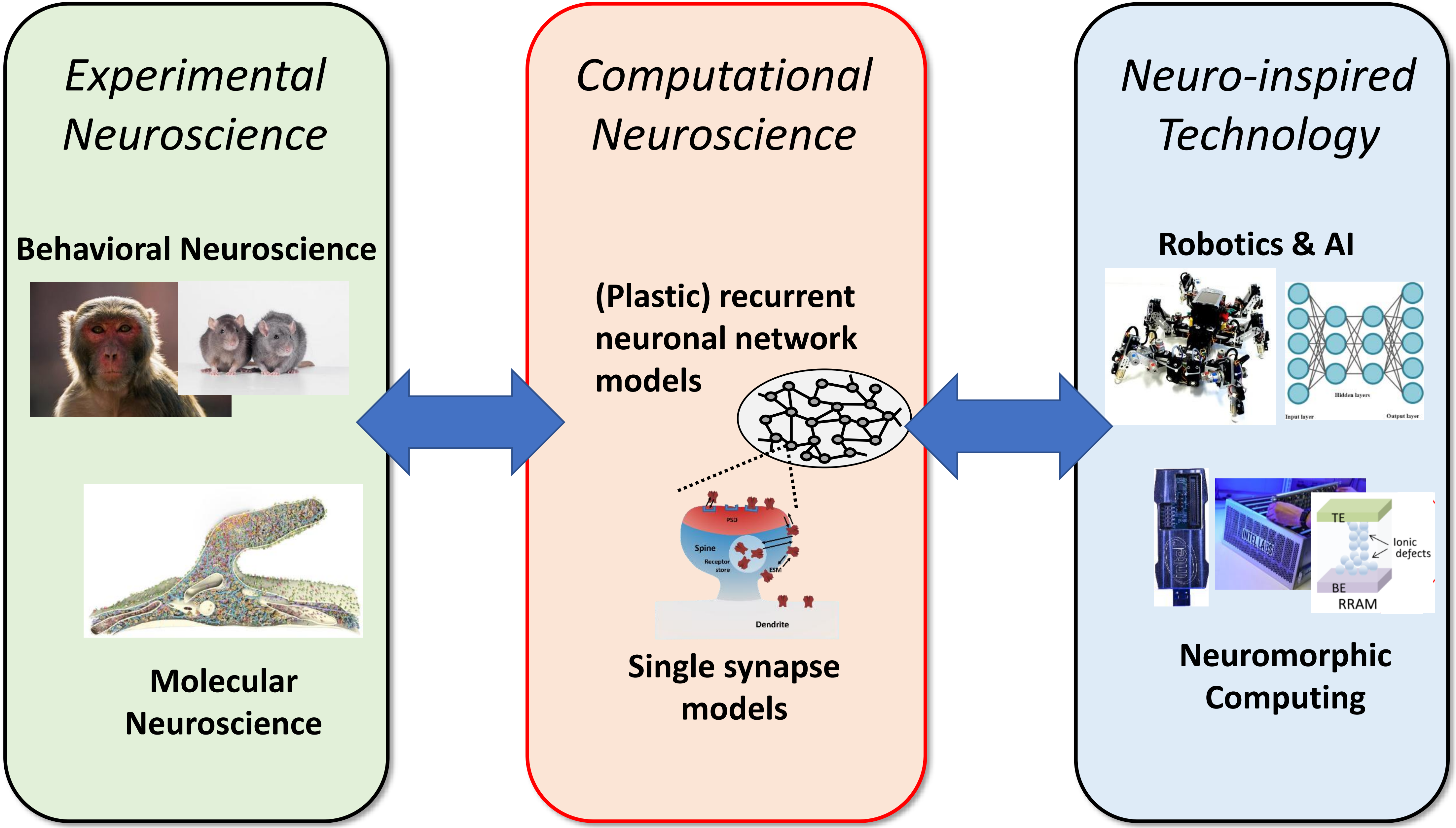
University Medical Center Göttingen



Experimental Neuroscience
Behavioral Neuroscience
Molecular Neuroscience
Computational Neuroscience
(Plastic) recurrent neuronal network models
PSD
Spine
Receptor store
ESM
Dendrite
Single synapse models
Neuro-inspired Technology
Robotics & AI
Input layer
Hidden layers
Output layer
INTEL LABS
TE
Ionic defects
BE
RRAM
Neuromorphic Computing

Experimental Neuroscience

Computational Neuroscience

Neuro-inspired Technology

Part I:

The functional implication and neuromorphic implementation of multi-timescale plasticity

Part II:

The advantages of neuronal heterogeneity for recurrent neural networks

www.sfb1286.de

2017-2029

CRC 1286: Quantitative Synaptology

Speaker: Prof. Rizzoli; Vice-Speaker: Prof. Tetzlaff

UMG

DZNE
Deutsches Zentrum für
Neurodegenerative Erkrankungen

FMP
LEIBNIZ FORSCHUNGSINSTITUT FÜR MOLEKULARE PHARMAKOLOGIE

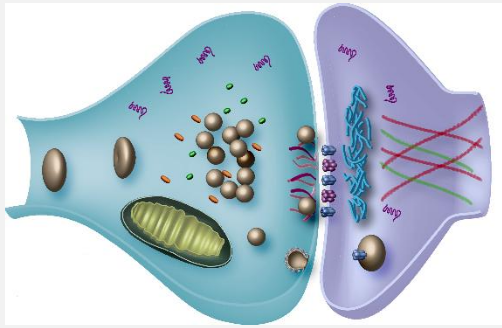
UNIVERSITÄT BONN

UKE
HAMBURG

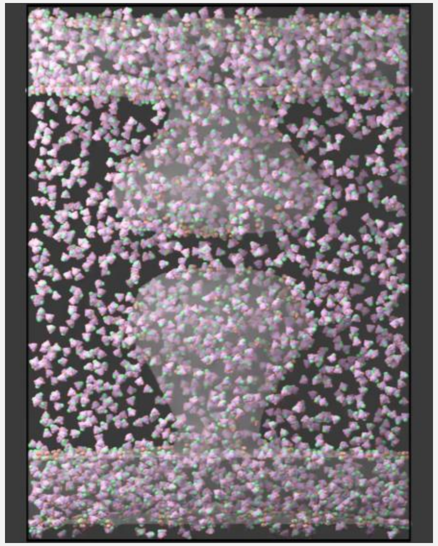
Goal: To analyze the synapse in quantitative detail, to enable computational models of synaptic function.

Deeper understanding of:

- synapse function
- synaptic disease
- single-synapse computation
- differences between synapses
- link between synapse structure and function → connectomics



Outcome:
Computational model of synaptic dynamics

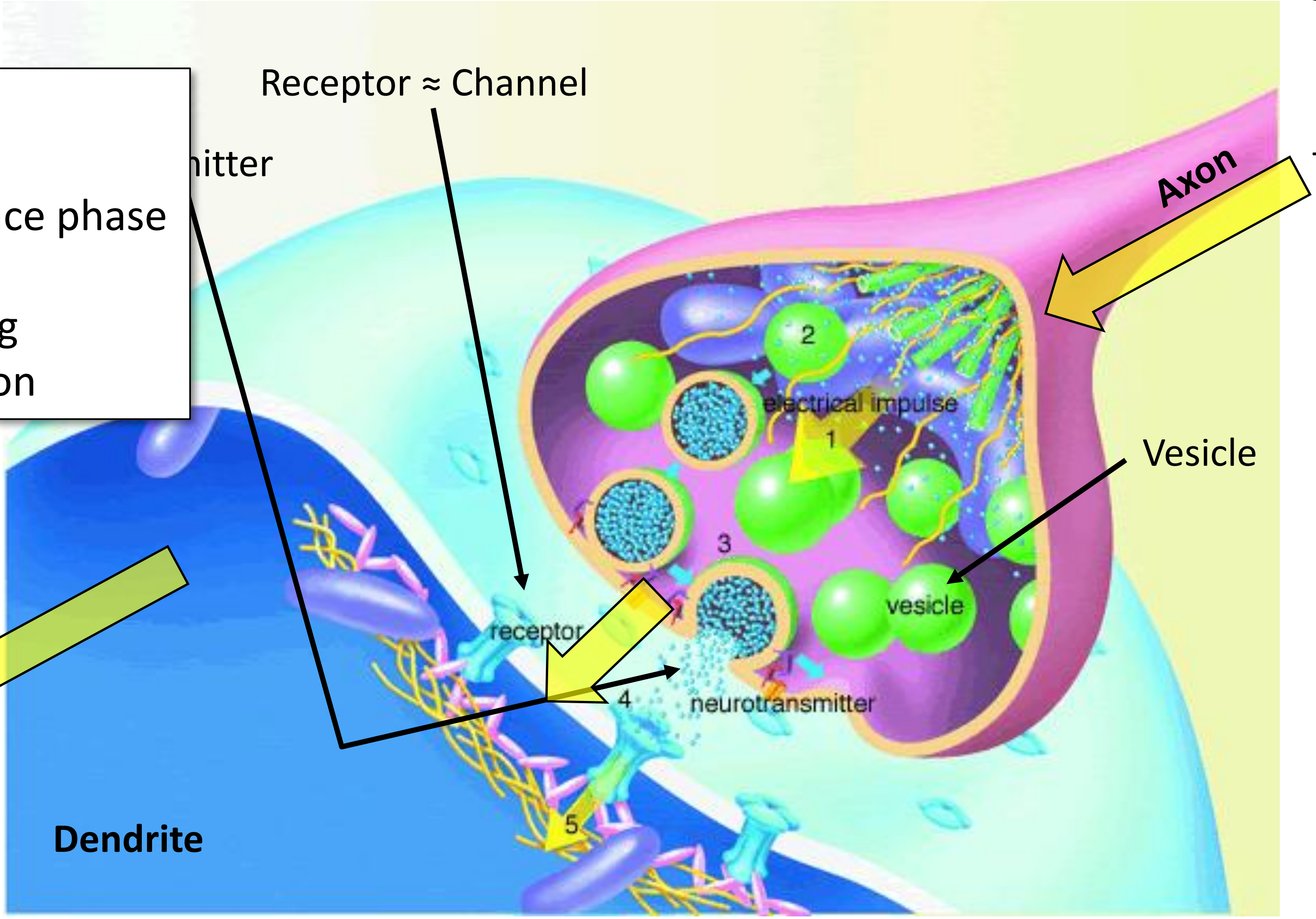


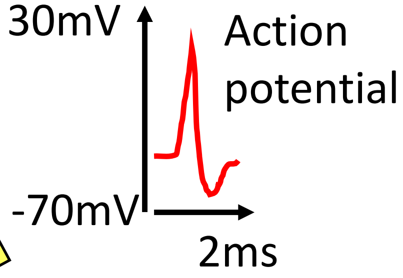
Research Community

Cellular Neurosci., Molecular Neurosci., Computational Neurosci., Systems Neurosci., Neurology, Artifical Intelligence, Neuromorphic Computing, …

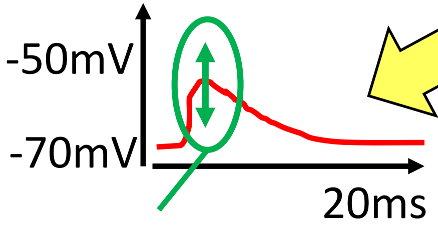
Biological Synapse

General properties:
- No error-signal
- No training/inference phase
- Local variables
- Continuous learning
- Low weight precision





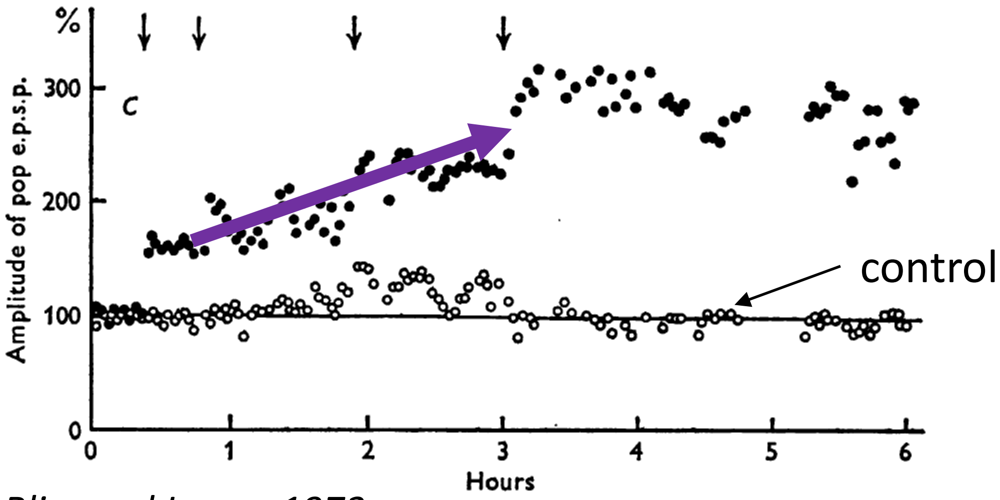
Excitatory
postsynaptic
potential (EPSP)



Synaptic Plasticity

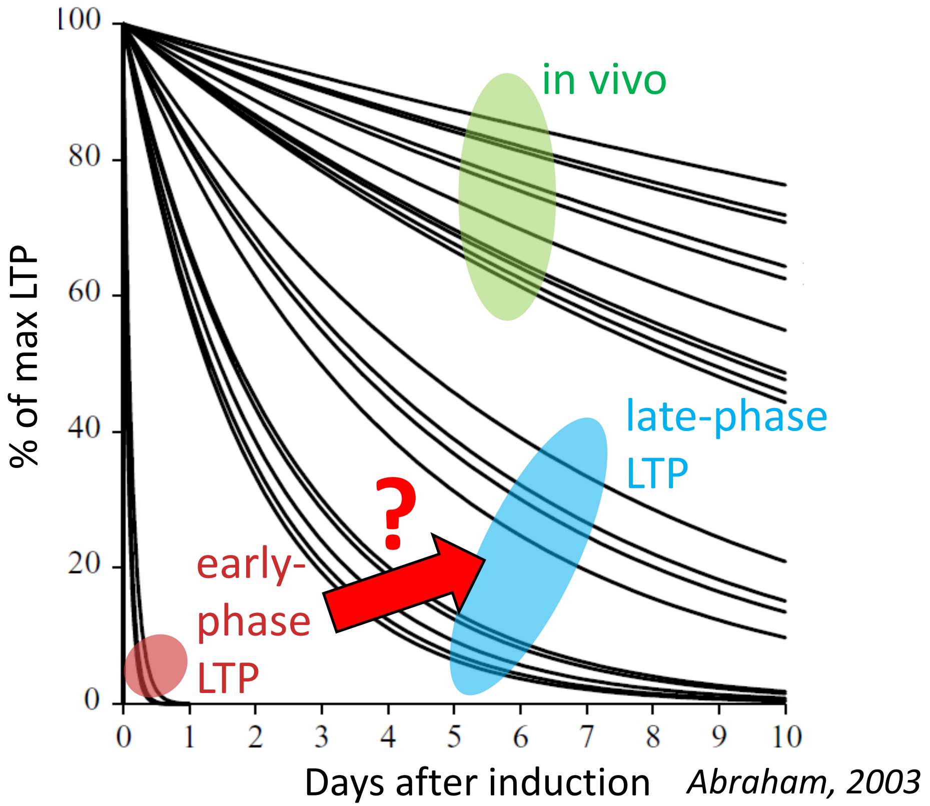
Long-term Synaptic Plasticity

Induction of Long-term Potentiation (LTP):
100 Hz for 1 sec or 10 Hz for 10 sec



Bliss and Lomo, 1973

Maintenance of LTP:



Abraham, 2003

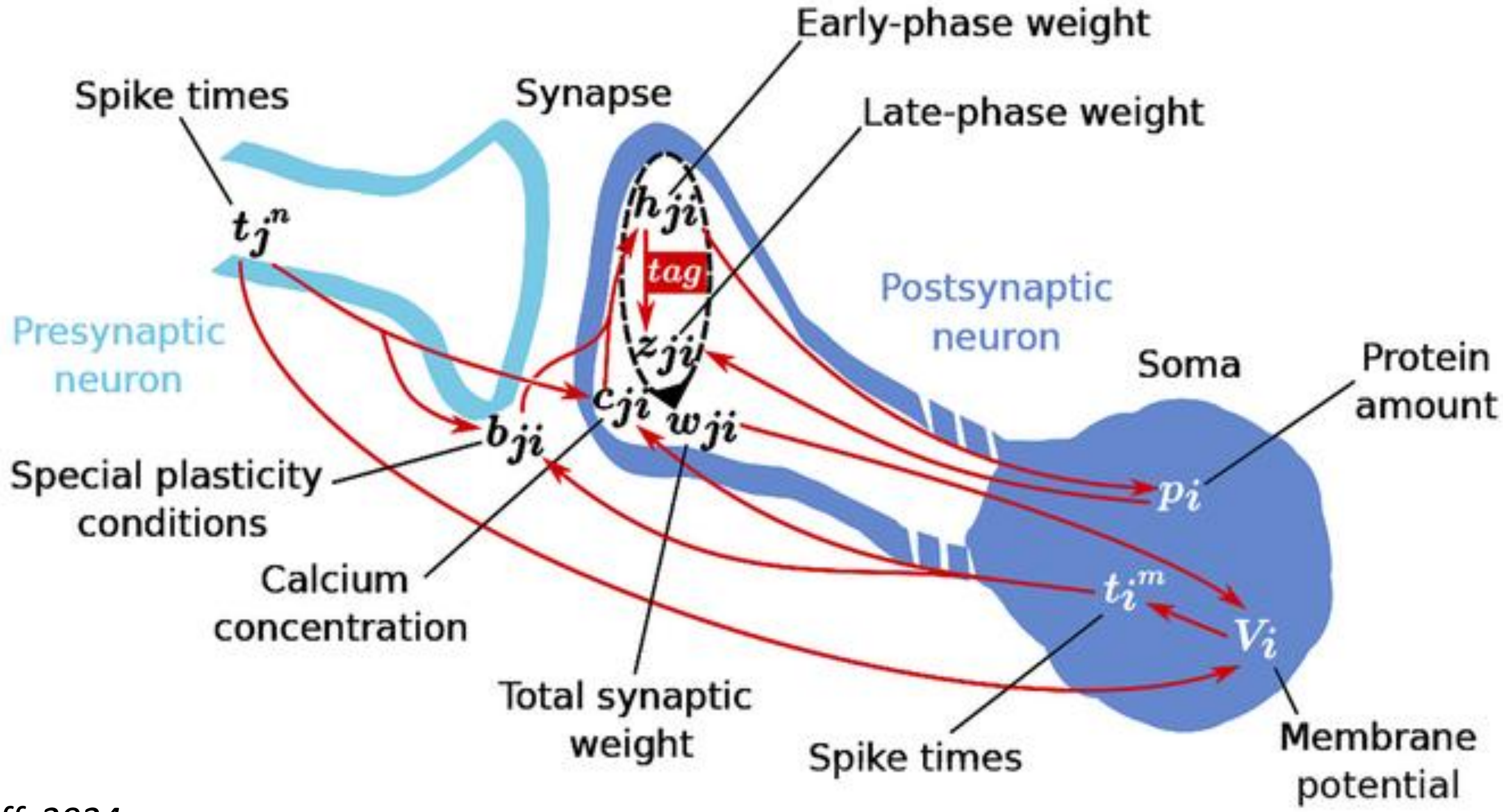
Early- and Late-Phase Plasticity

The synaptic weight consists of two components

i) Early-phase weight (e.g. receptor dynamics)

ii) Late-phase weight (e.g. synthesis of new proteins)

Clopath et al., 2008; Barrett et al., 2009; Li, Kulvicius, Tetzlaff, 2016; Luboeinski & Tetzlaff, 2021; 2022;



Luboeinski & Tetzlaff, 2024

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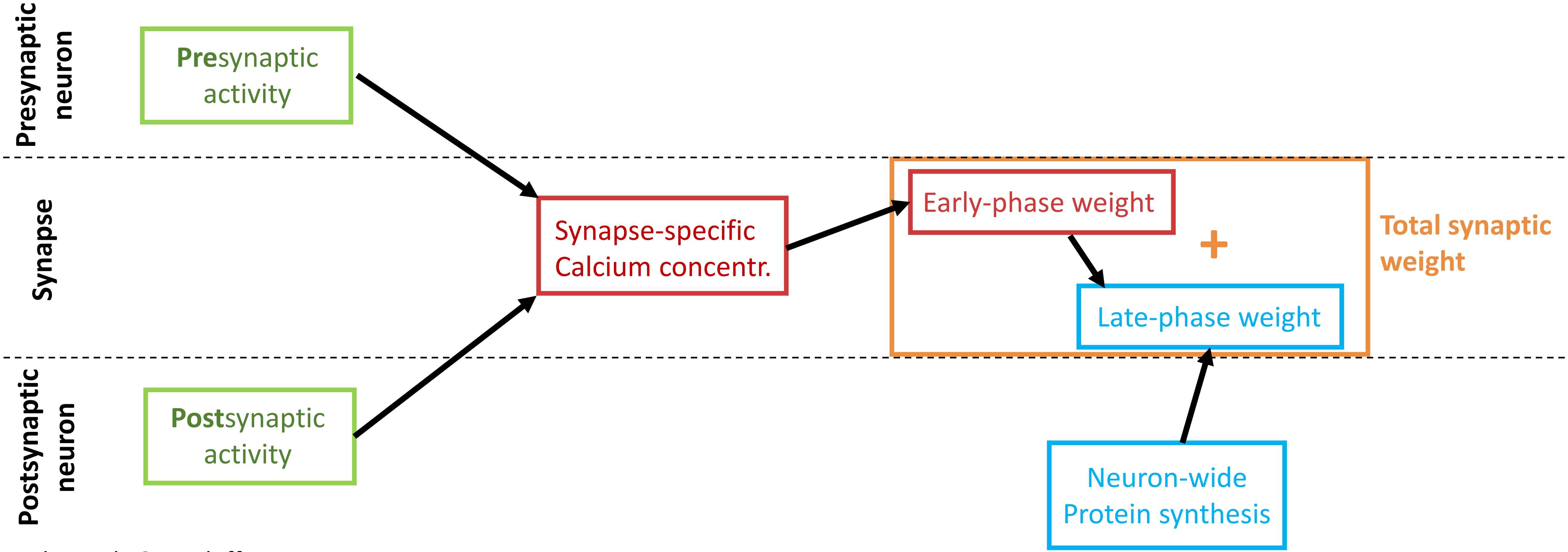

Luboeinski & Tetzlaff, 2024

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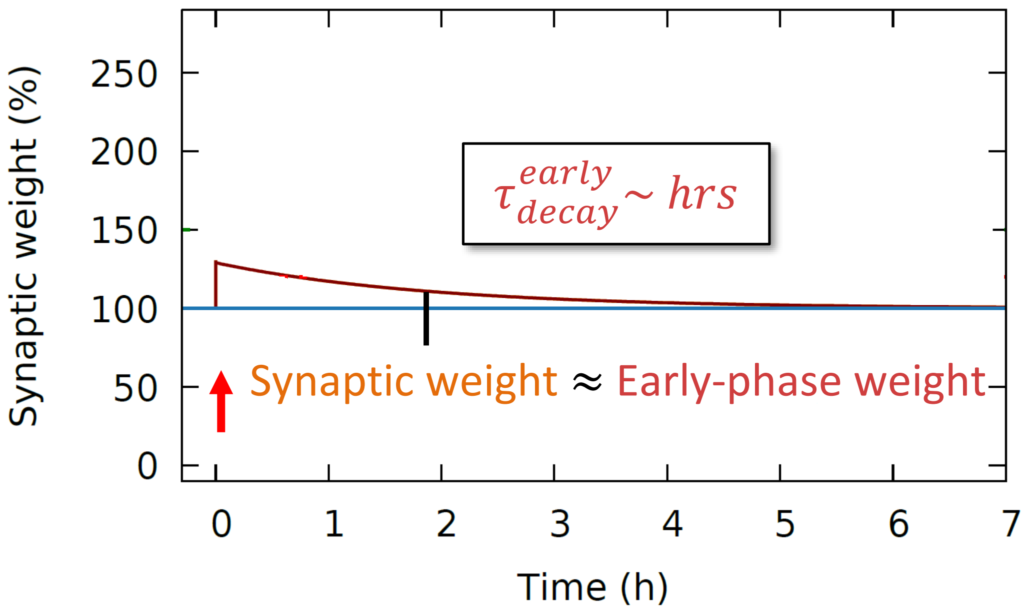
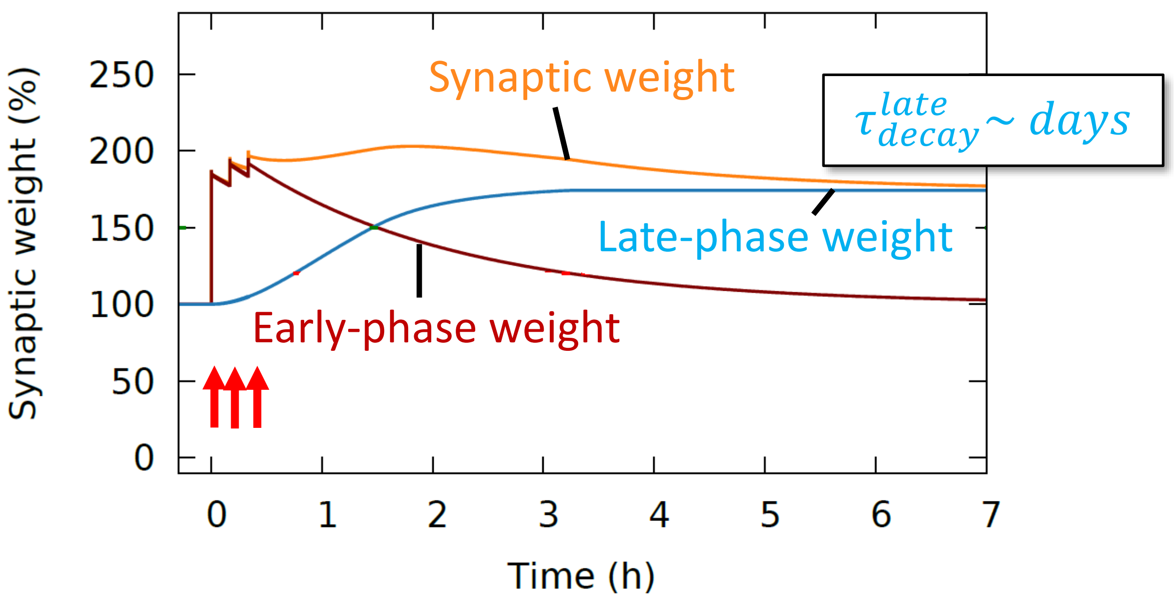
Only calcium-based plasticity

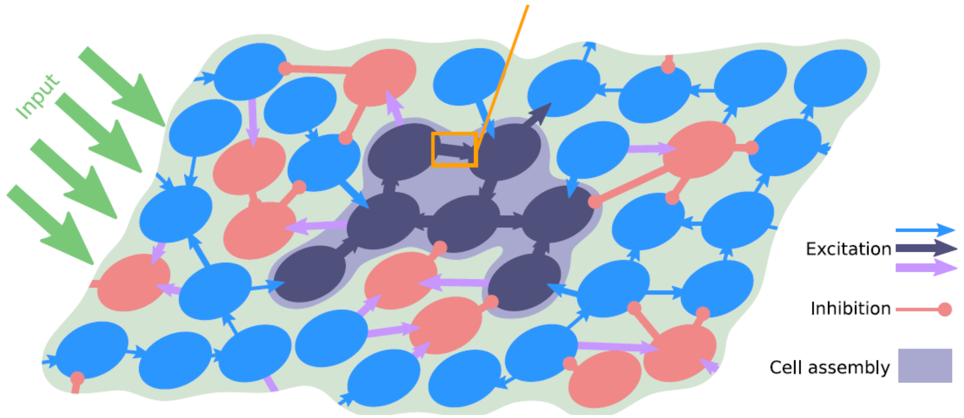


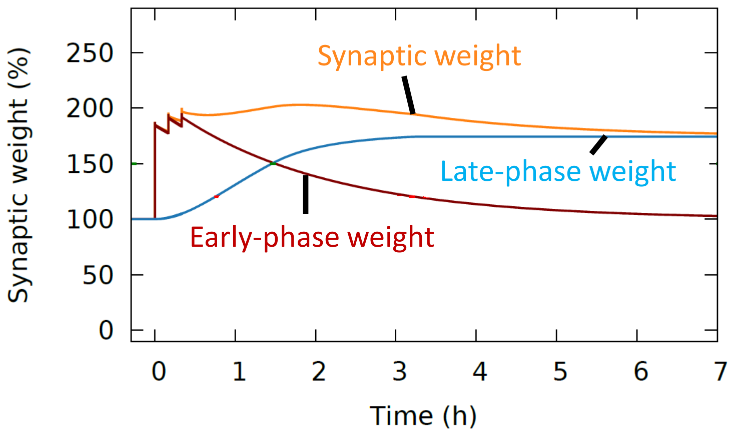
Calcium-based plasticity + Protein-synthesis triggered

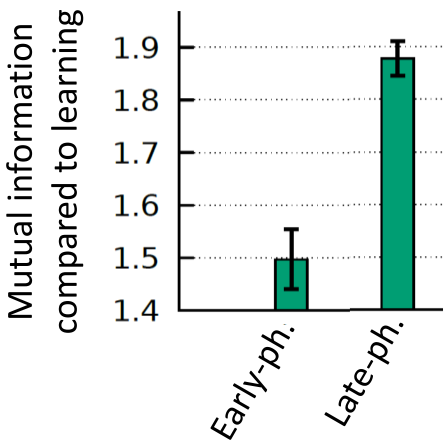


Luboeinski & Tetzlaff, 2021; 2022

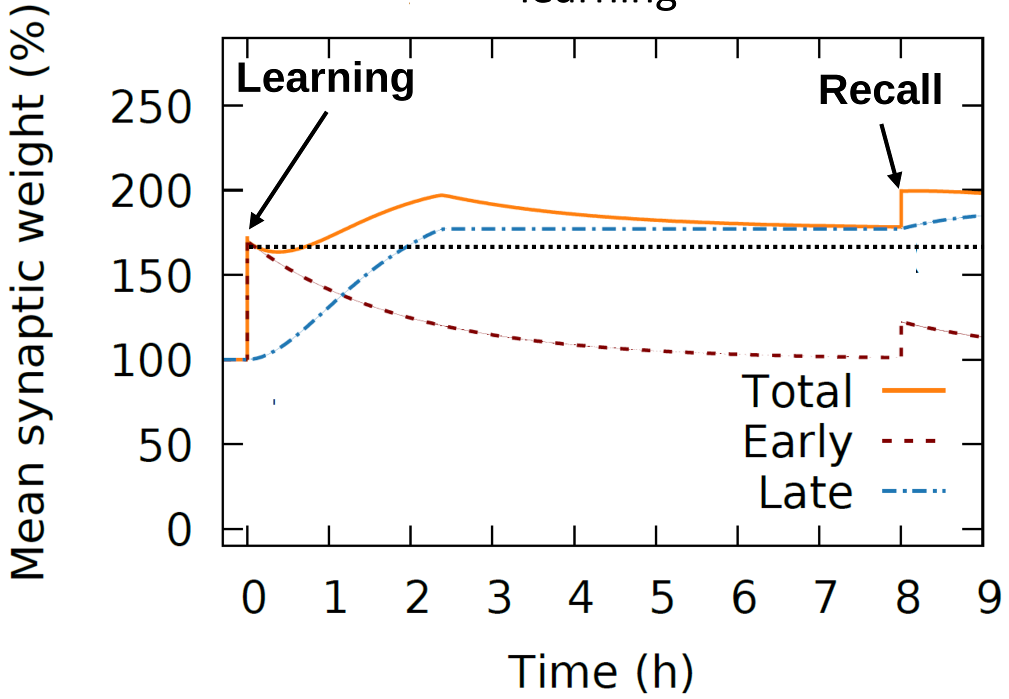
Functional Implications







About 20% stronger synaptic weights several hours **after** learning



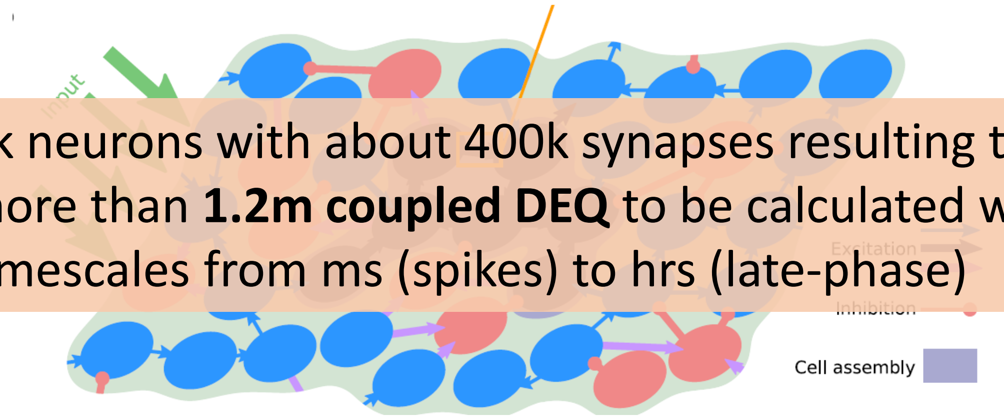
✓ Consolidation or stabilization of memory representations

Luboeinksi & Tetzlaff, 2021

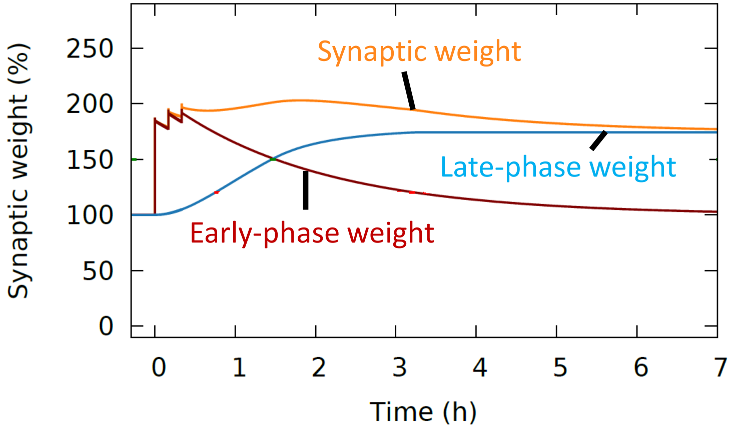
✓ Automatic improvement of memory representations

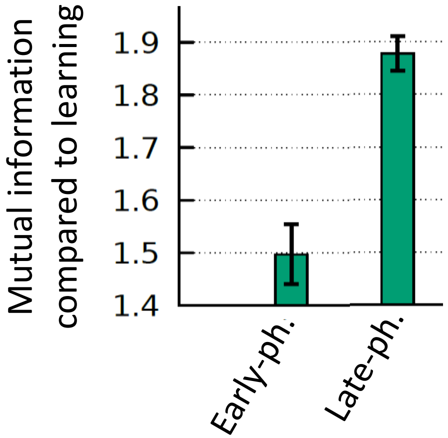
Luboeinksi & Tetzlaff, 2021

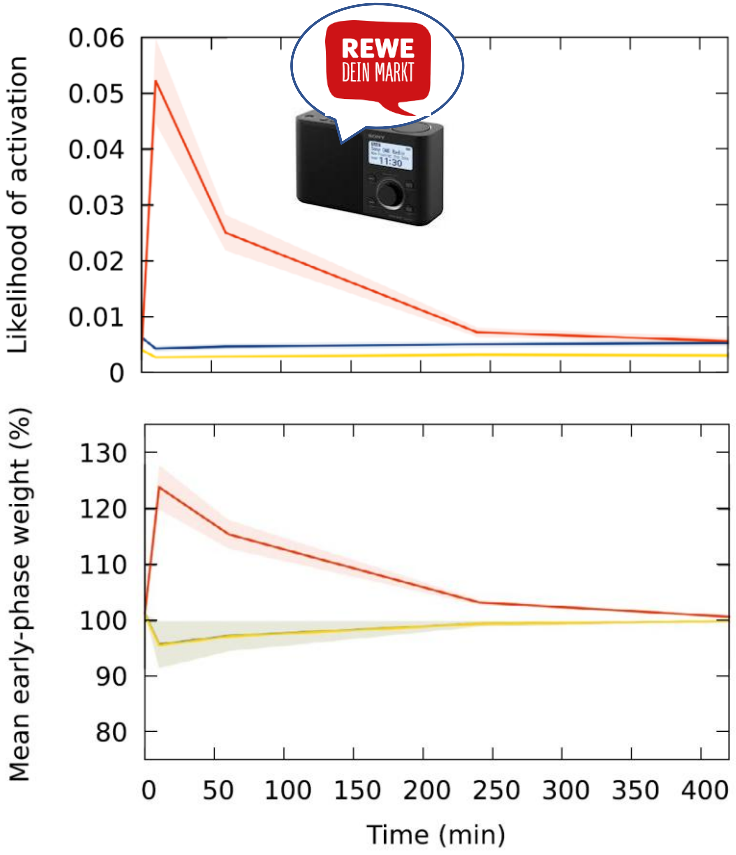
Functional Implications



2k neurons with about 400k synapses resulting to more than **1.2m coupled DEQ** to be calculated with timescales from ms (spikes) to hrs (late-phase)







✓ Consolidation or stabilization of memory representations

Luboeinksi & Tetzlaff, 2021

✓ Automatic improvement of memory representations

Luboeinksi & Tetzlaff, 2021

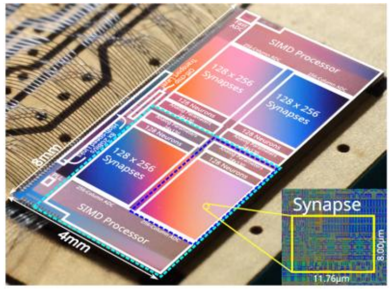
✓ Priming of memory representations for several hours

Luboeinksi & Tetzlaff, 2022

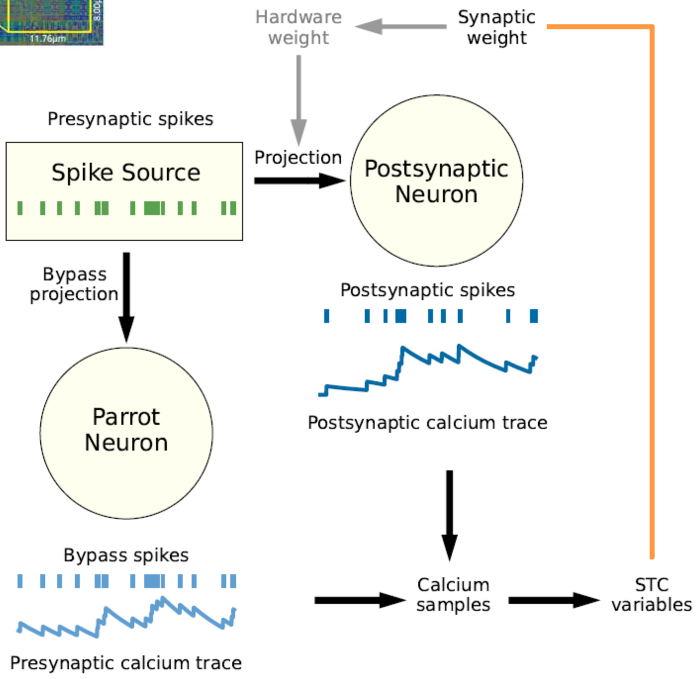
Neuromorphic Implementation of Multi-timescale Plasticity

BrainScaleS-2 Implementation

Goal: Utilizing the accelerated calculation of neuronal dynamics by BrainScaleS-2 to enable



long-term investigations of memory dynamics, being relevant for neuroscience and medicine



In cooperation with Schemmel lab (A. Atoui, J. Kaiser, et al.)

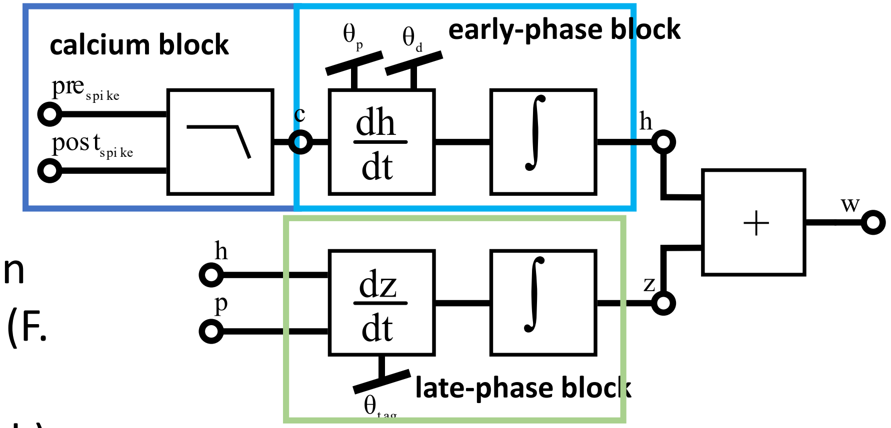
UNIVERSITÄT HEIDELBERG
ZUKUNFT
SEIT 1386

Atoui et al., 2024, arXiv

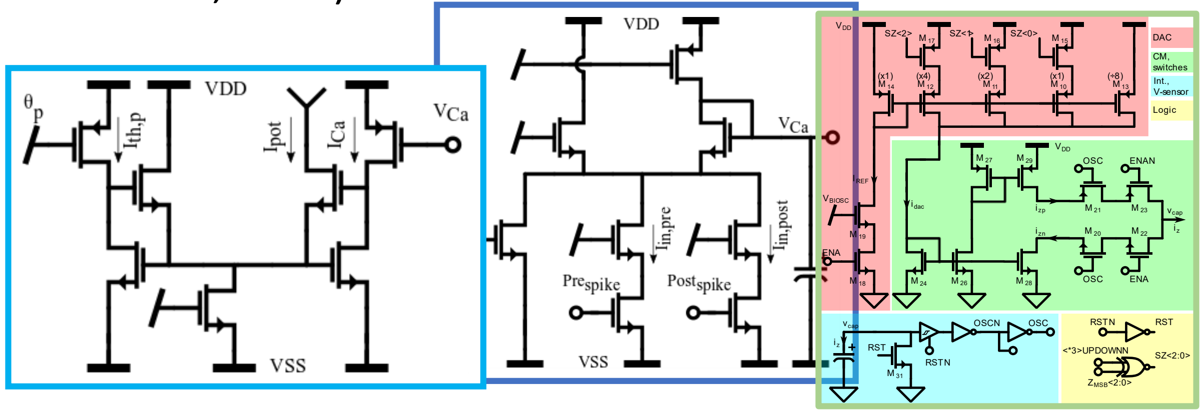
CMOS-based Implementation

Goal: Obtain a hardware system that is optimized to store information on the biological timescales of several hours

university of groningen



In cooperation with Covi lab (F. Quintana, P. Gibertini, et al.)



Experimental Neuroscience

Computational Neuroscience

Neuro-inspired Technology

Part I:

The functional implication and neuromorphic implementation of multi-timescale plasticity

Part II:

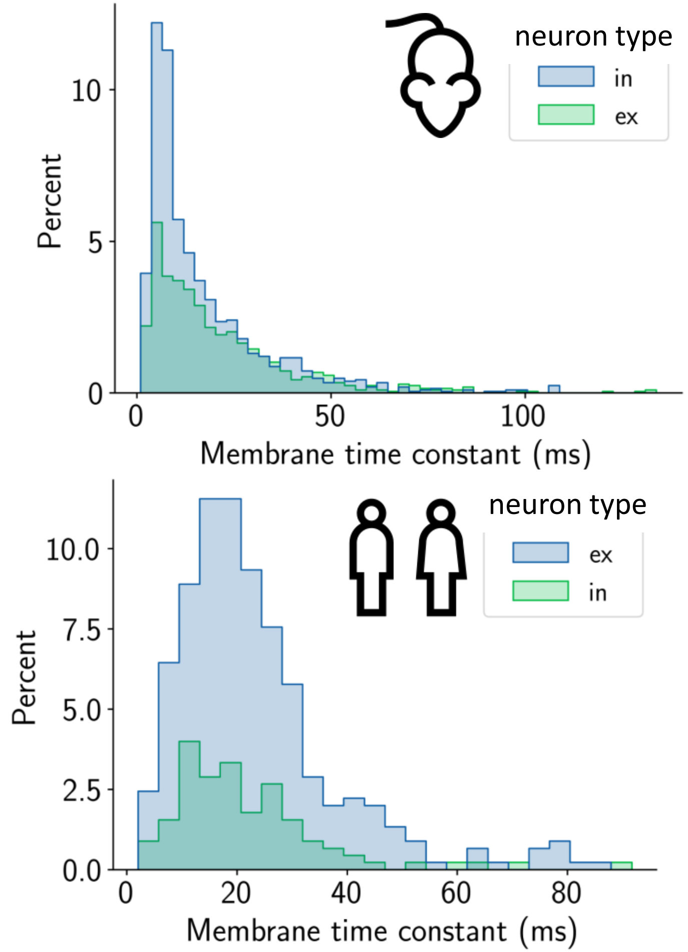
The advantages of neuronal heterogeneity for recurrent neural networks

“Precision” of components

LEGO bricks are accurate to within 2 micrometers

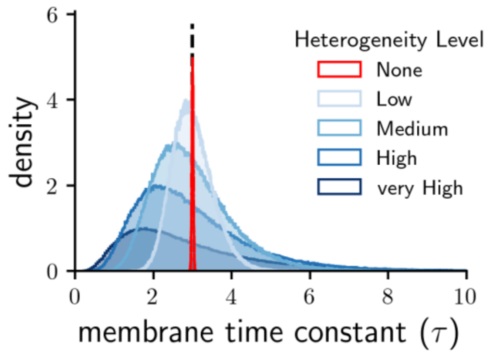
https://www.natgeokids.com/uk/kids-club/entertainment/general-entertainment/ten-top-lego-facts/

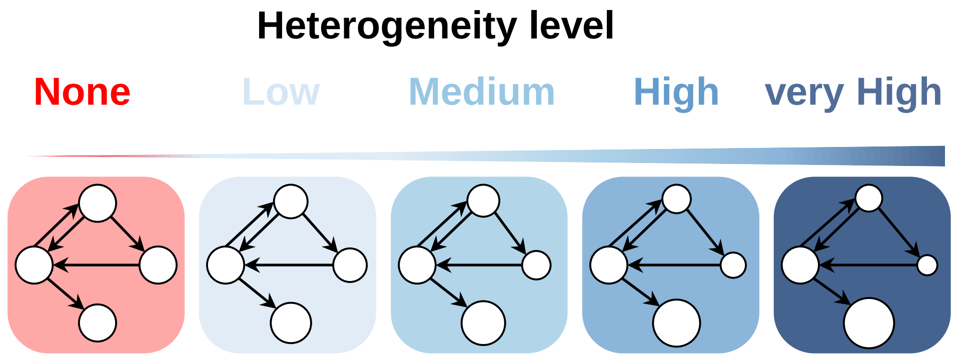
“memory of a neuron”



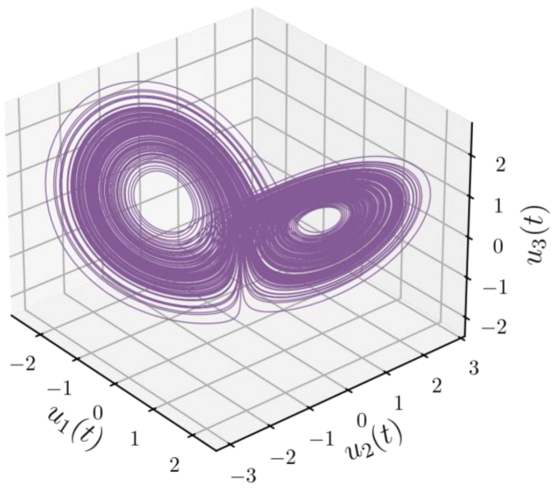
Allen Institute for Brain Science. Synaptic Physiology Coarse Matrix dataset (2019)

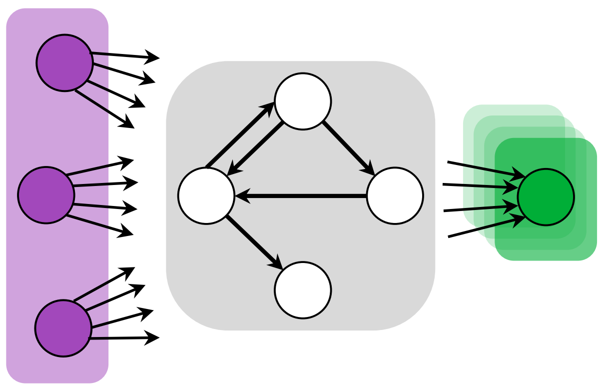
Testing Neuronal Heterogeneity in RNNs

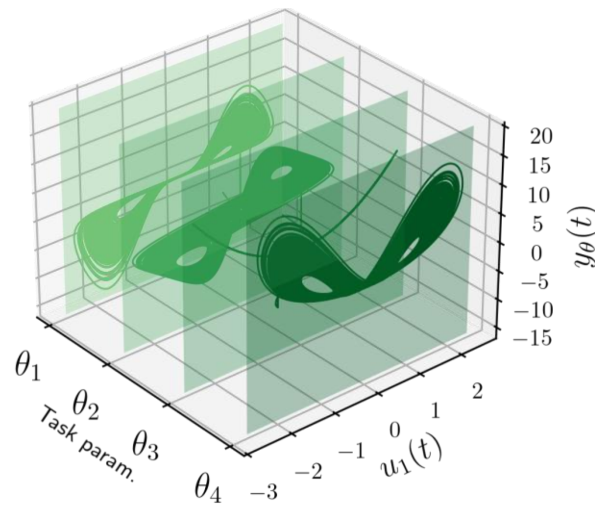




Same network architecture, with different levels of heterogeneity



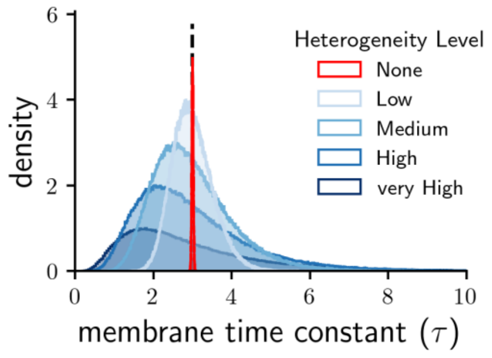


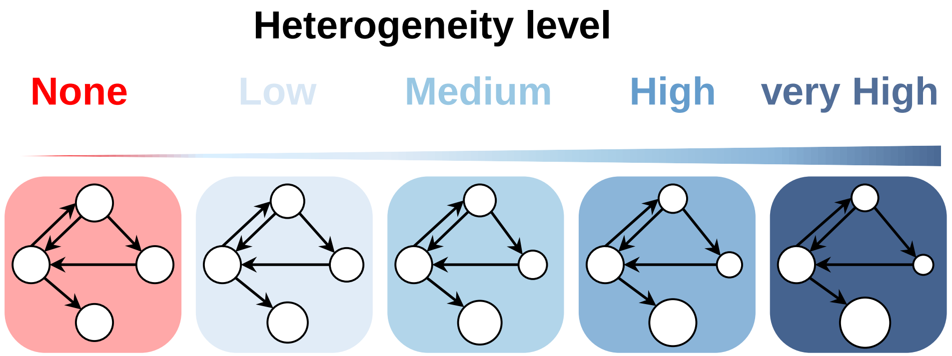


Multi-dimensional, partially predictable (sensory) input

Multiple tasks or target functions

Testing Neuronal Heterogeneity in RNNs





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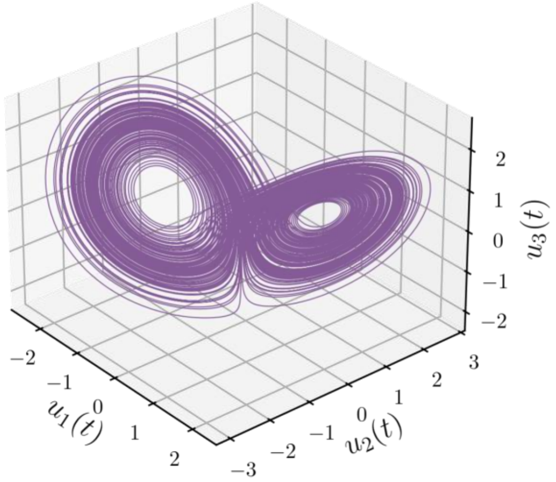
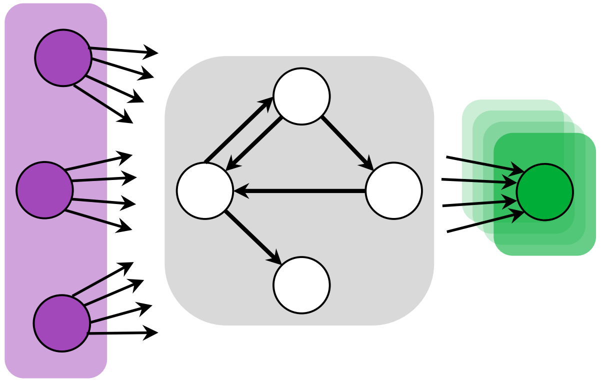




Desired Output

Multi-dim. Input

Time shift (memory/prediction)

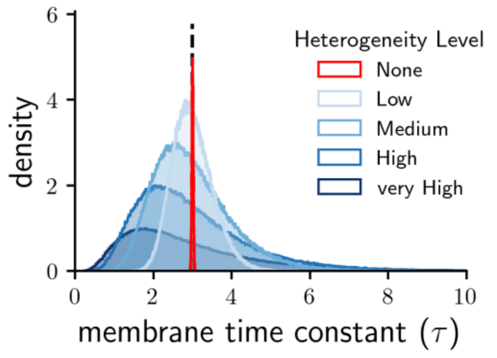
$$y_\theta(t) = \mathcal{F}_\theta[\mathbf{u}(t)] = u_k(t+\Delta)^d$$

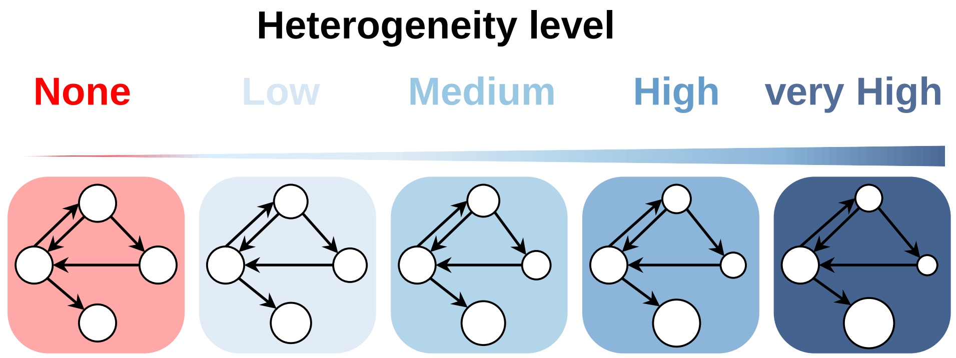
Input Dimension

Nonlinear Computing

Multi-dimensional, partially predictable (sensory) input

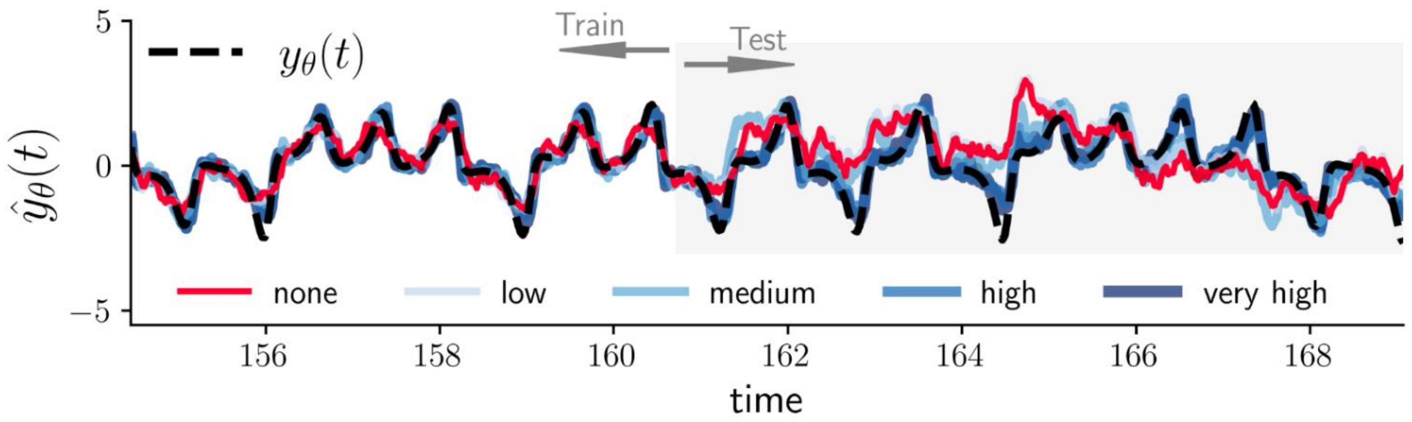
Testing Neuronal Heterogeneity in RNNs





Same network architecture, with different levels of heterogeneity

One examplary task



Desired Output

Multi-dim. Input

Time shift (memory/prediction)

$$y_\theta(t) = \mathcal{F}_\theta[\mathbf{u}(t)] = u_k(t+\Delta)^d$$

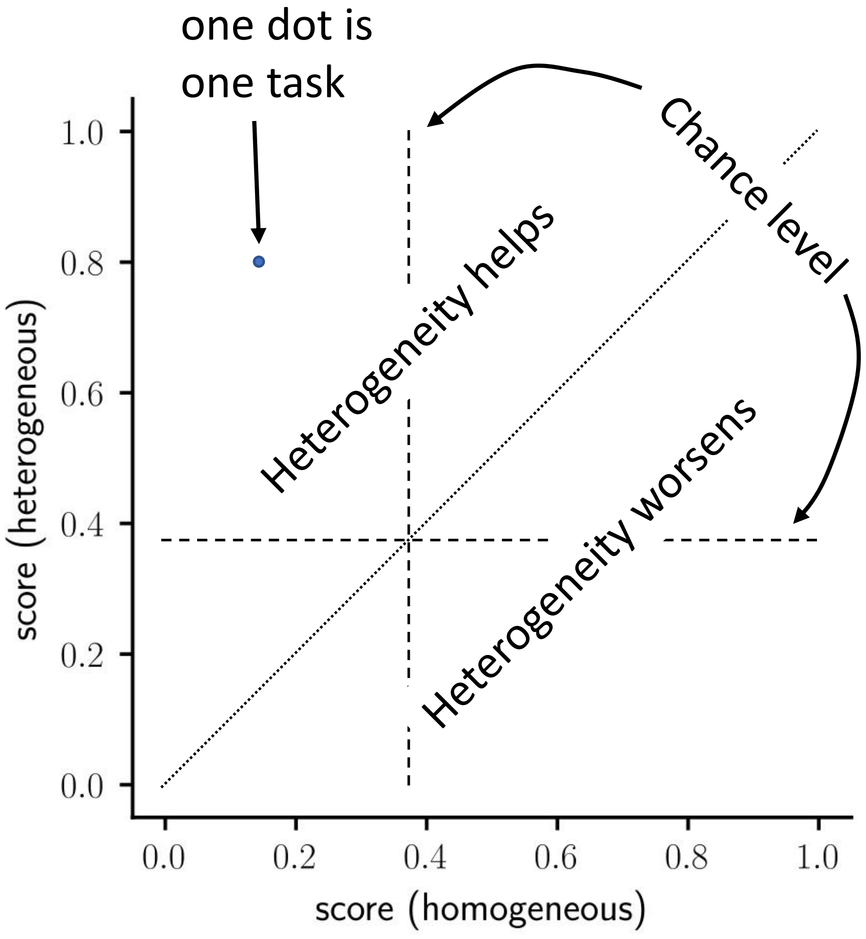
Input Dimension

Nonlinear Computing

By varying the task parameters, we obtained in total **435 different tasks**.

Golmohammadi & Tetzlaff, 2024, arXiv

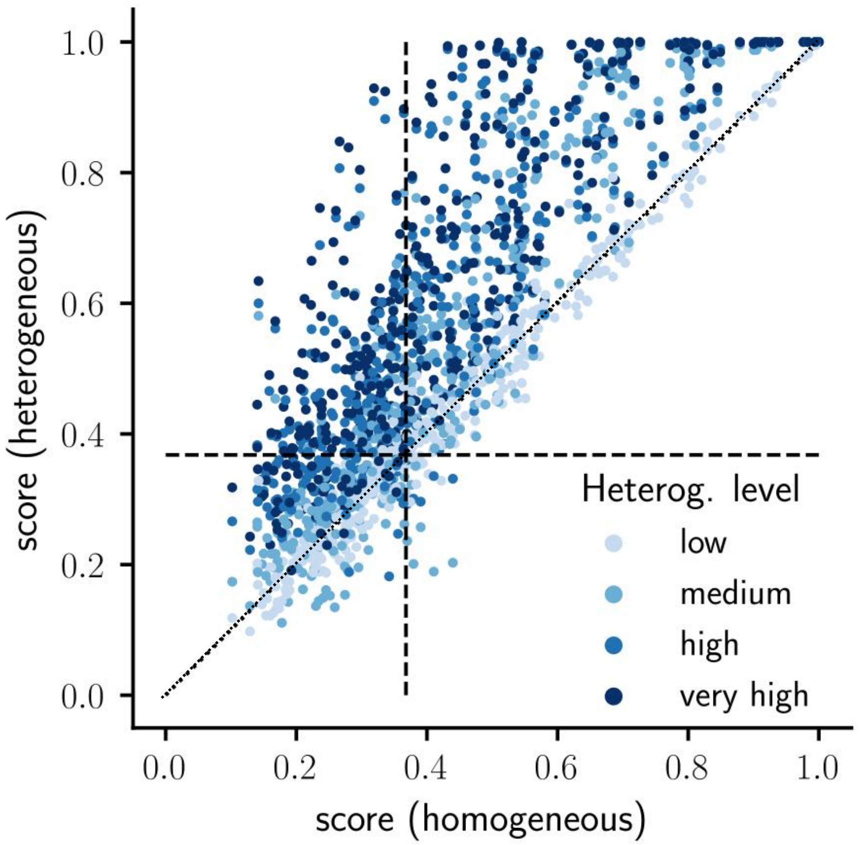
The Influence of Heterogeneity on Task Performance



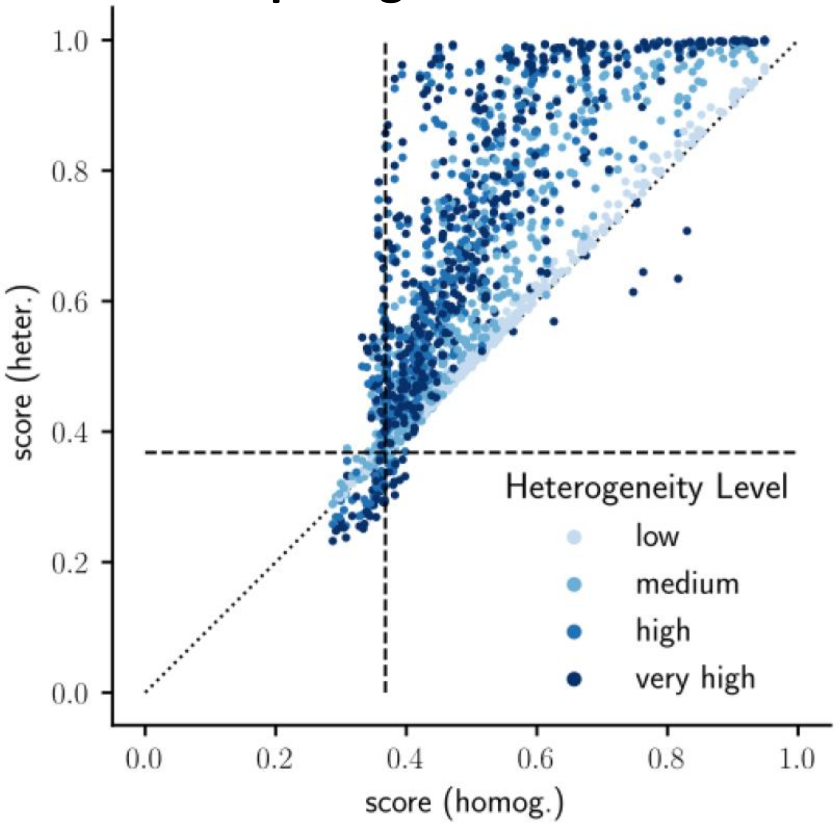
Golmohammadi & Tetzlaff, 2024, arXiv

The Influence of Heterogeneity on Task Performance

Rate-coded Neurons

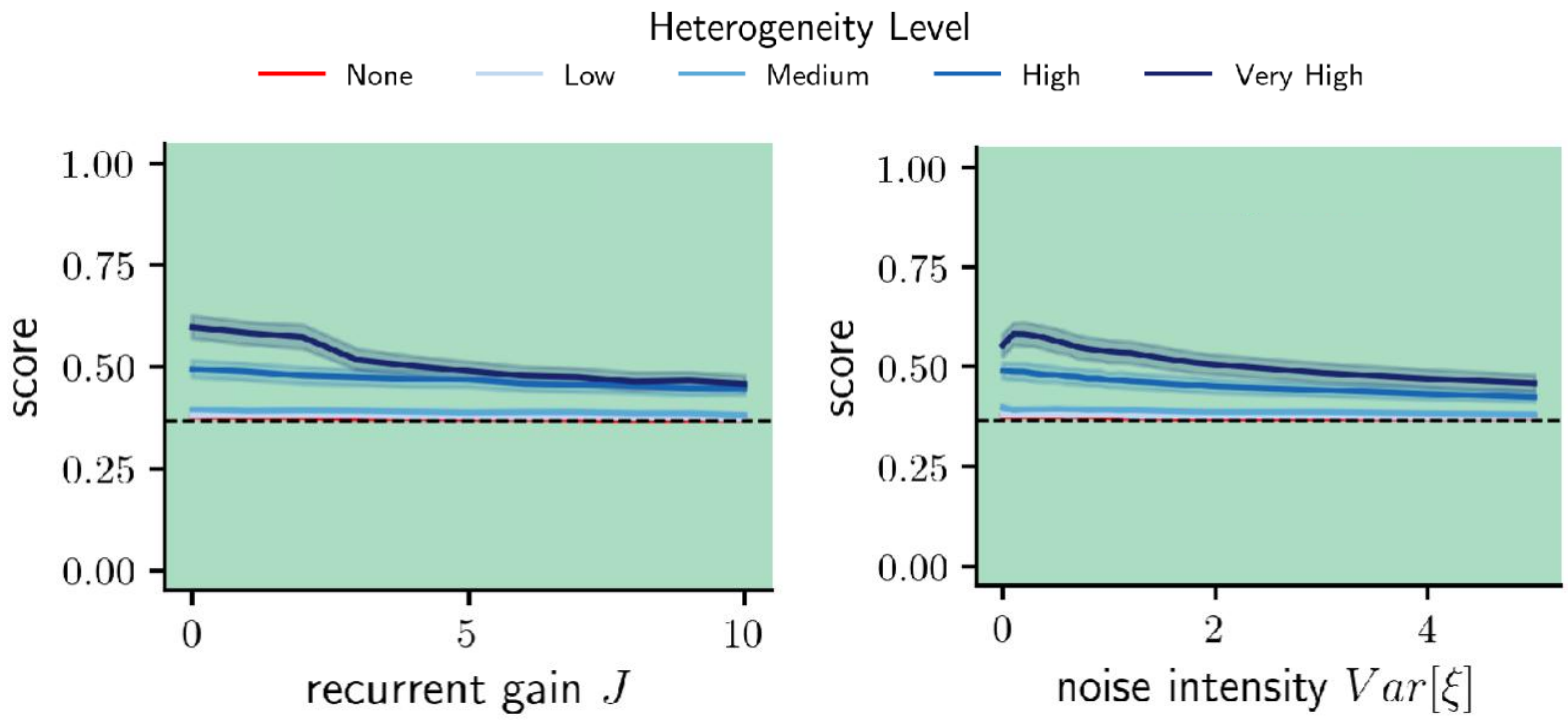


Spiking Neurons



Golmohammadi & Tetzlaff, 2024, arXiv

Heterogeneity improves Performance across Hyperparameters

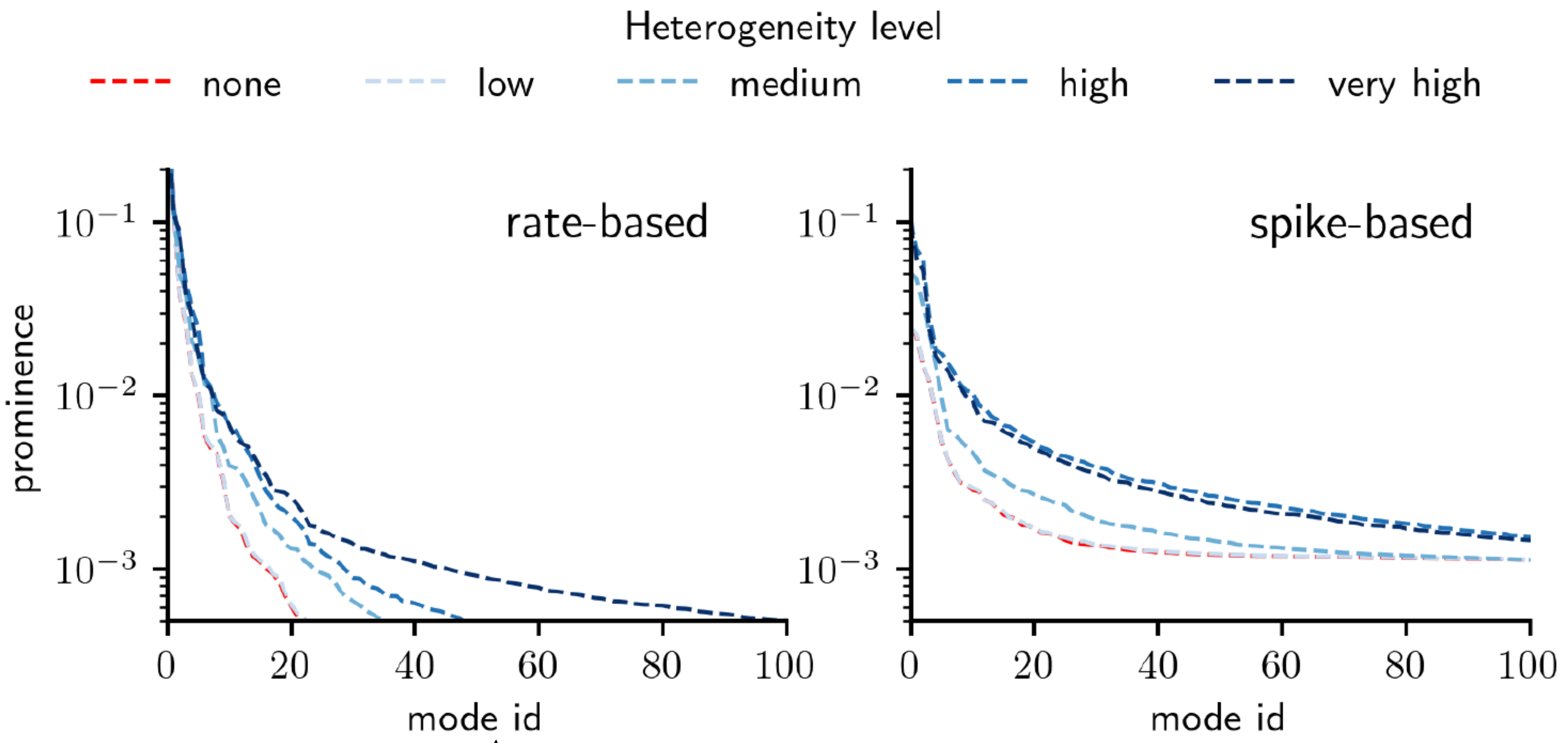


Different Average Synaptic Weight

Different Noise Levels

Golmohammadi & Tetzlaff, 2024, arXiv

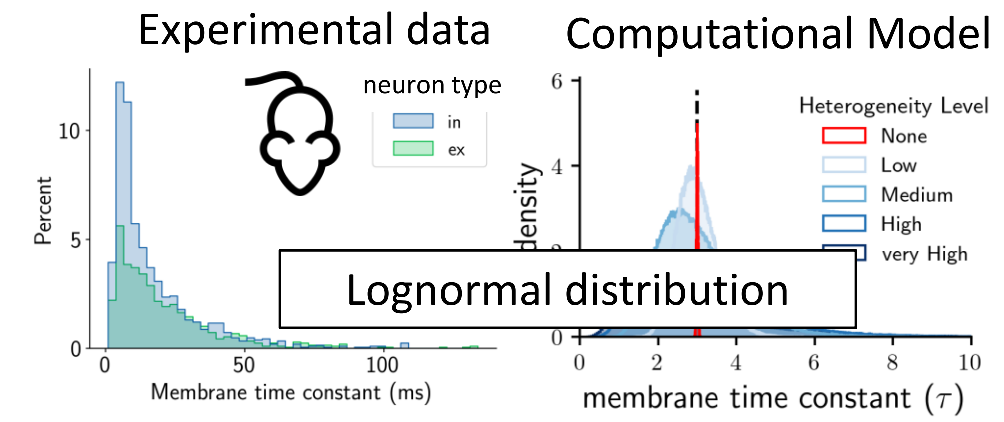
Heterogeneity enriches the information processing capacity of neural networks

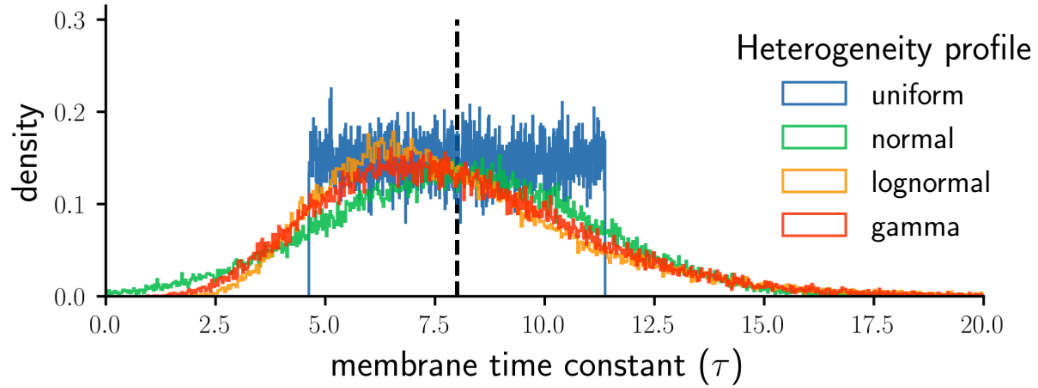


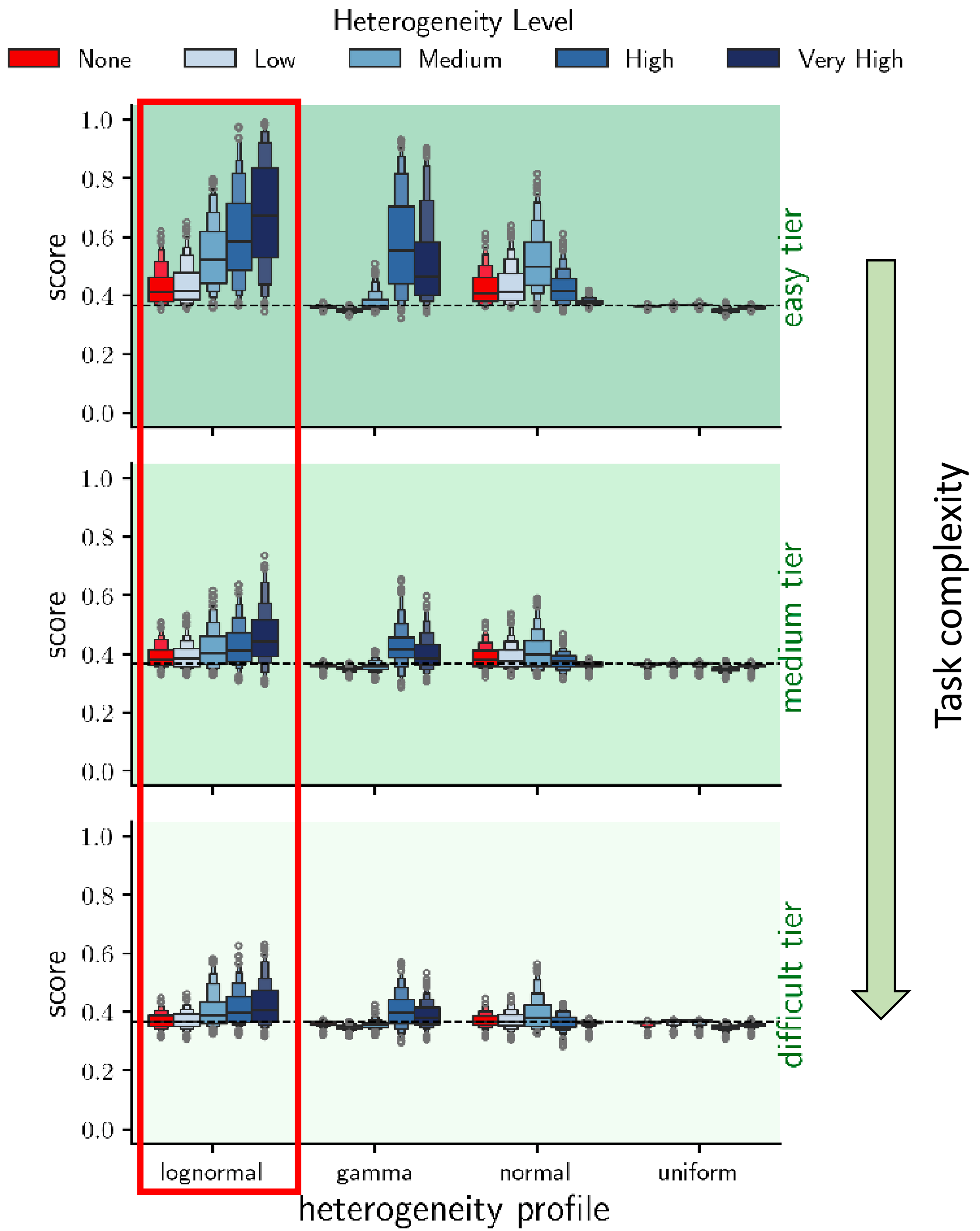
Independent (linear) temporal modes of the network

Golmohammadi & Tetzlaff, 2024, arXiv

The Influence of the Heterogeneity Distribution

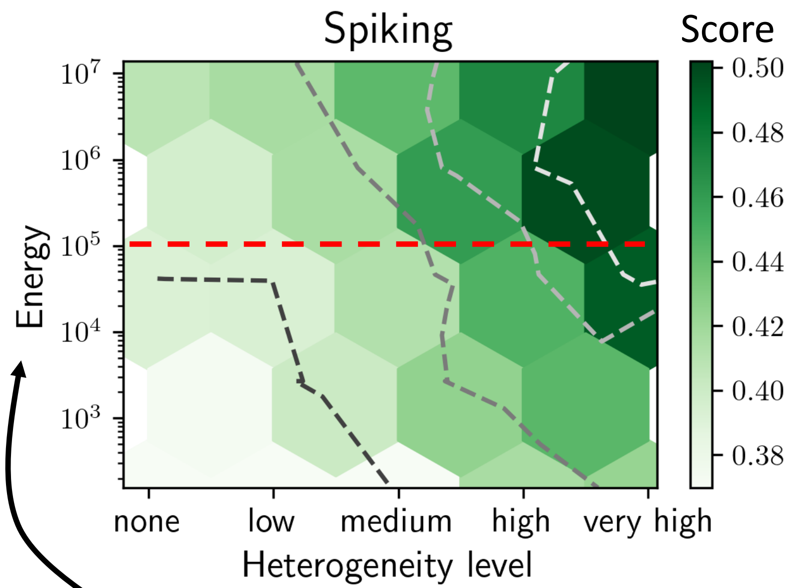


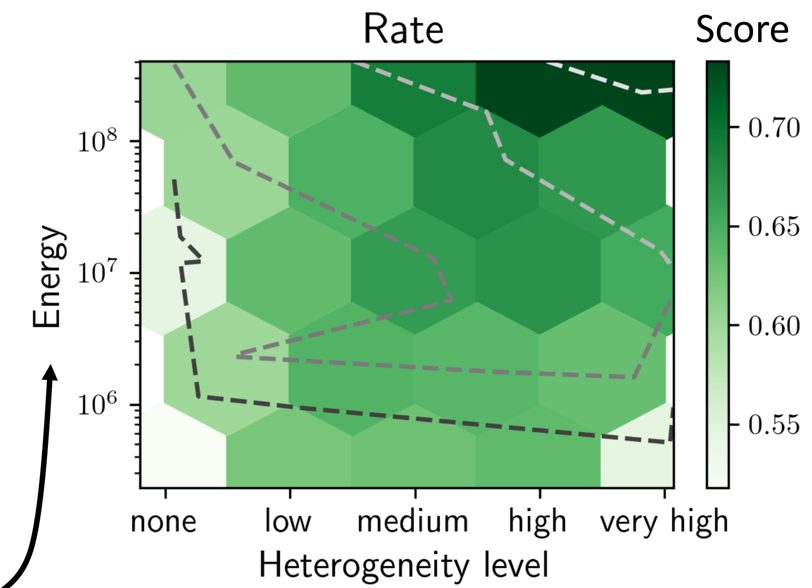


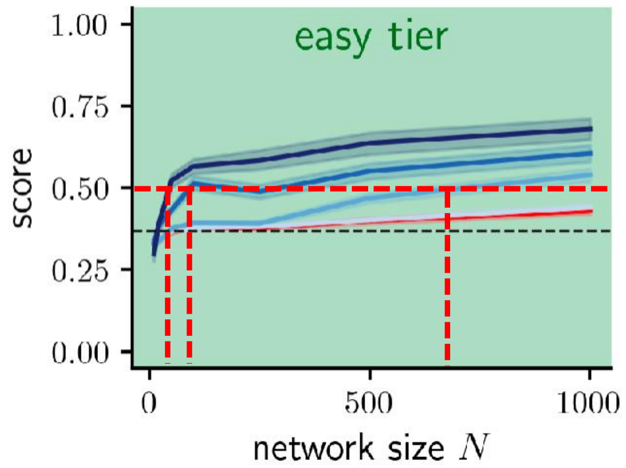


Golmohammadi & Tetzlaff, 2024, arXiv

Heterogeneity yield Energy-efficient Networks



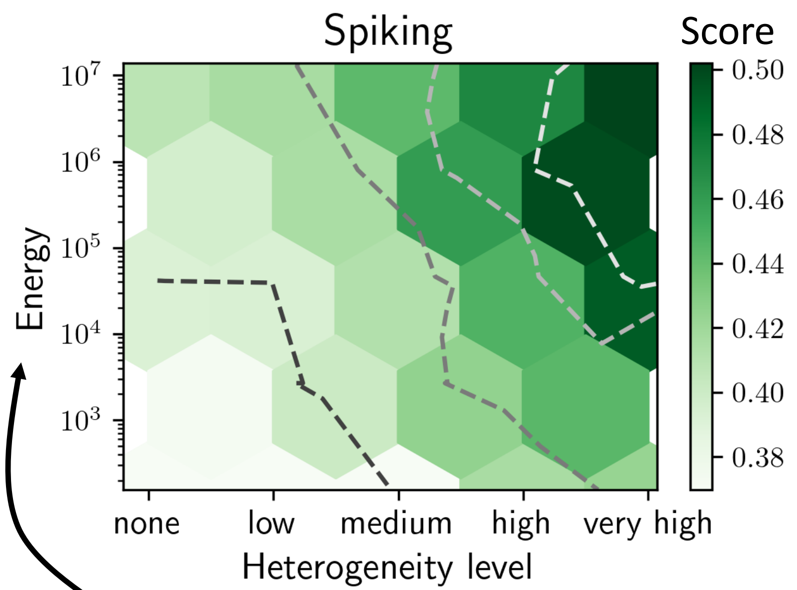


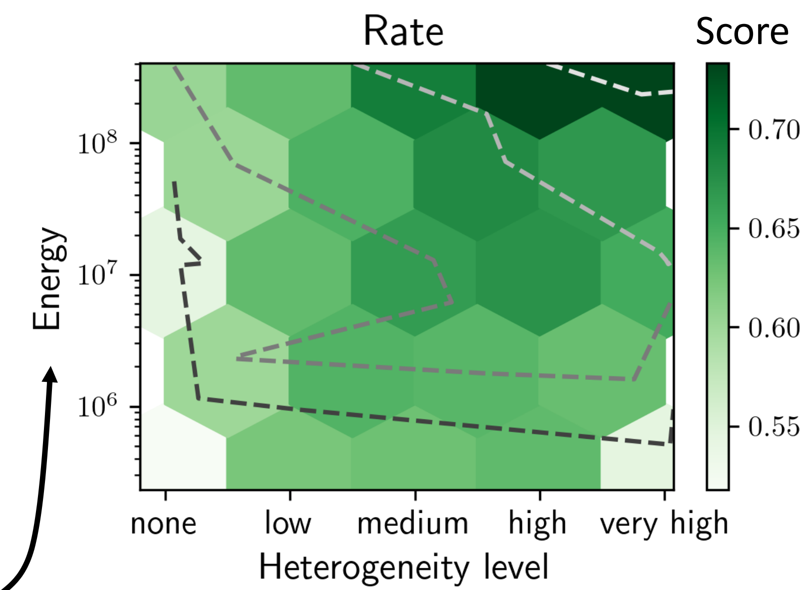


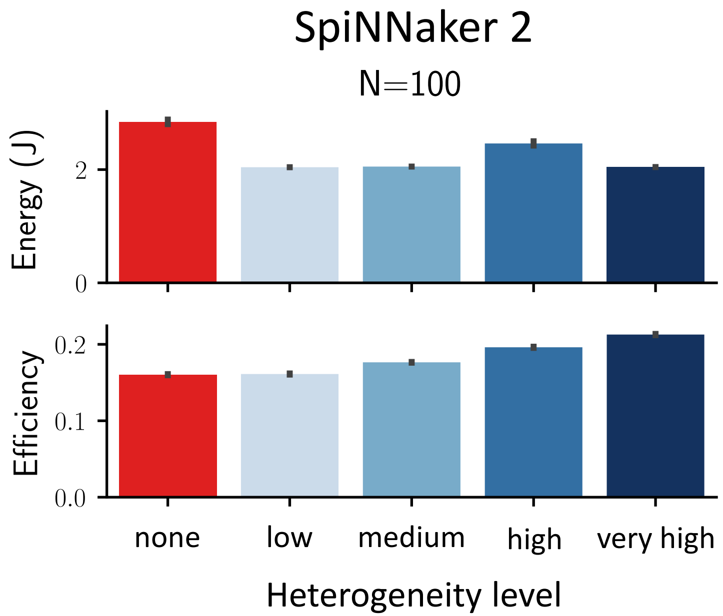
Energy = Function(Activity, #Synapses, #Neurons)

Howarth et al., 2012

Heterogeneity yield Energy-efficient Networks







Energy = Function(Activity, #Synapses, #Neurons)

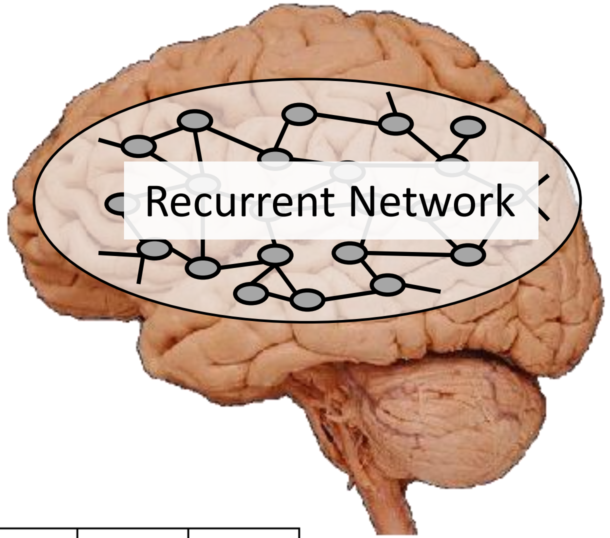
Howarth et al., 2012

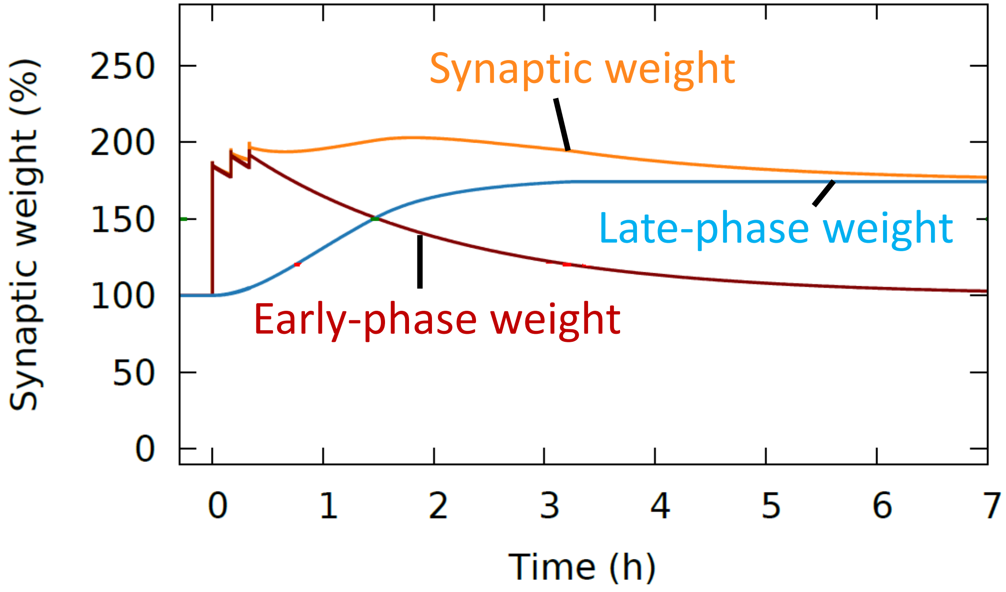
Score per energy

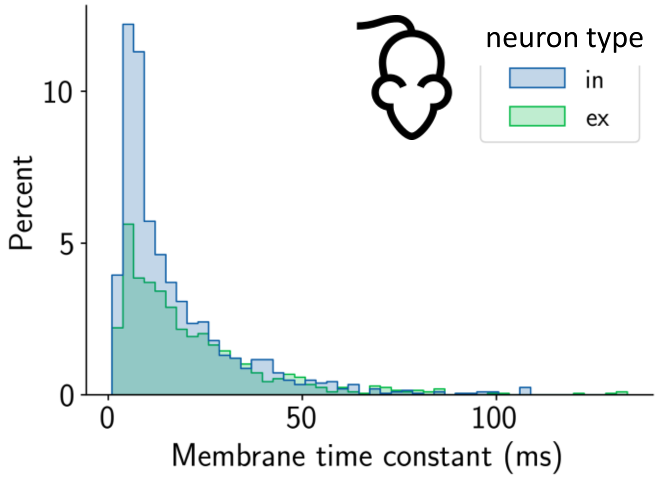
The Dynamic, Heterogeneous, Multi-timescale Brain

"Static" System

Dynamic System



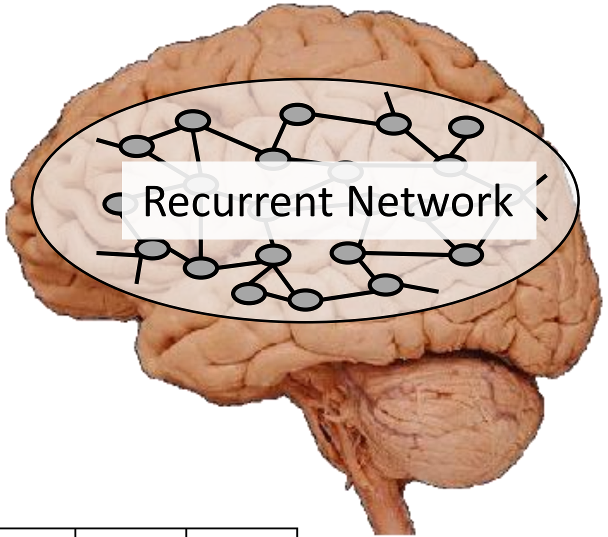


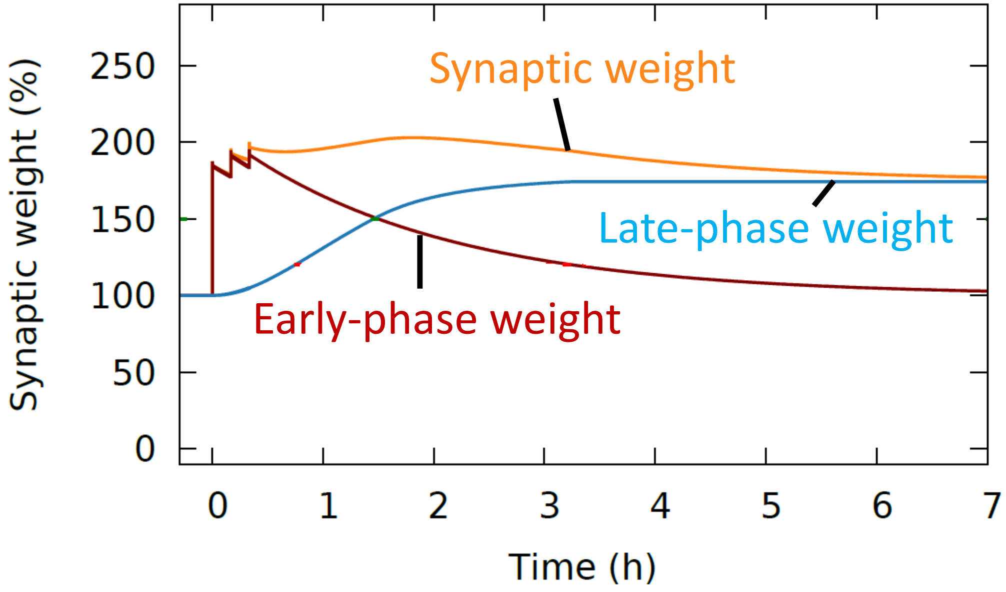


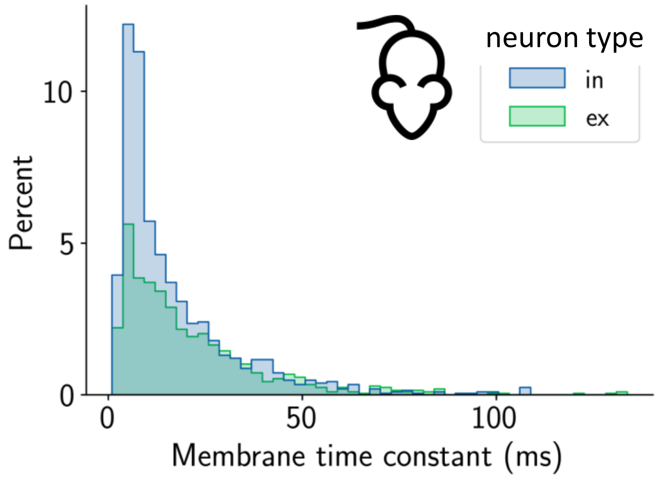
The Dynamic, Heterogeneous, Multi-timescale Chip?

Dynamic Chip

Dynamic System







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Group for Computational Synaptic Physiology

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Arash Golmohammadi *Dr. Jannik Luboeinski*

Bundesministerium für Bildung und Forschung

MemrisTec

DFG

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CIDAS
Campus-Institut Data Science

KISSKI
KI-Servicezentrum für sensible und kritische Infrastrukturen

SFB 1286
Quantitative Synaptology