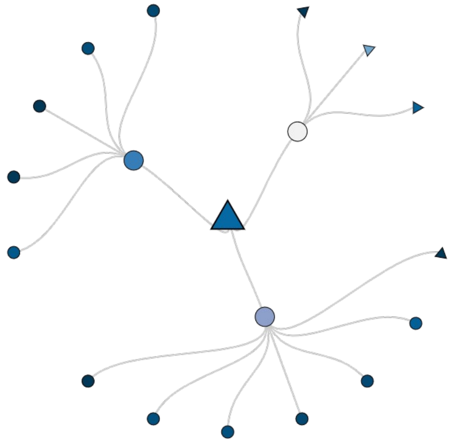
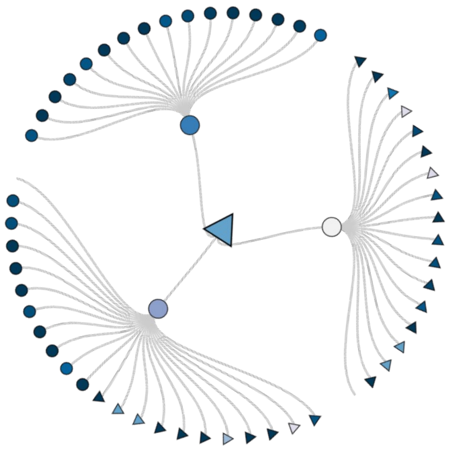
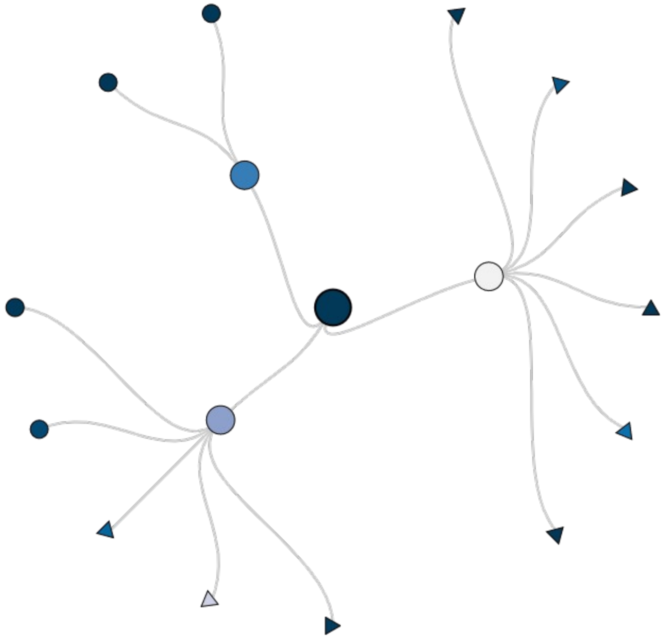




SIMULATING AND ANALYZING THE STRUCTURAL PLASTICITY OF THE BRAIN USING HPC



Sandra Diaz Pier

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Forschungszentrum Jülich, Germany

December 16th, 2021

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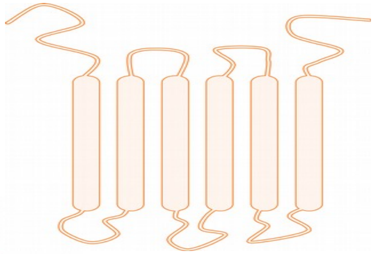
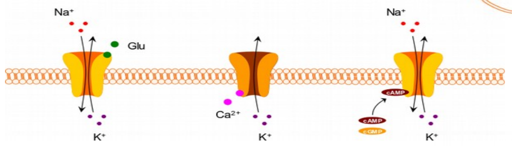
COMPUTATIONAL NEUROSCIENCE TODAY

Plethora of models

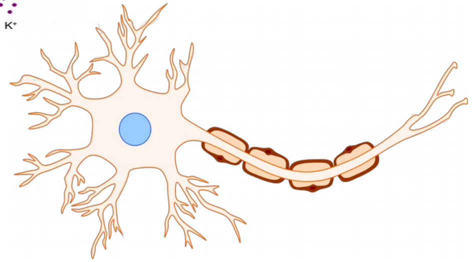
Molecular →

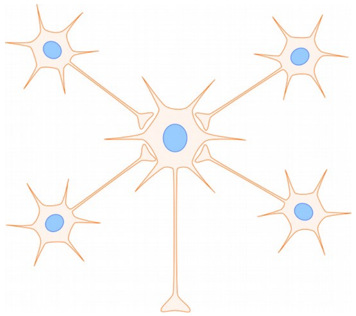




← Channels

Single cell →





← Networks of cells

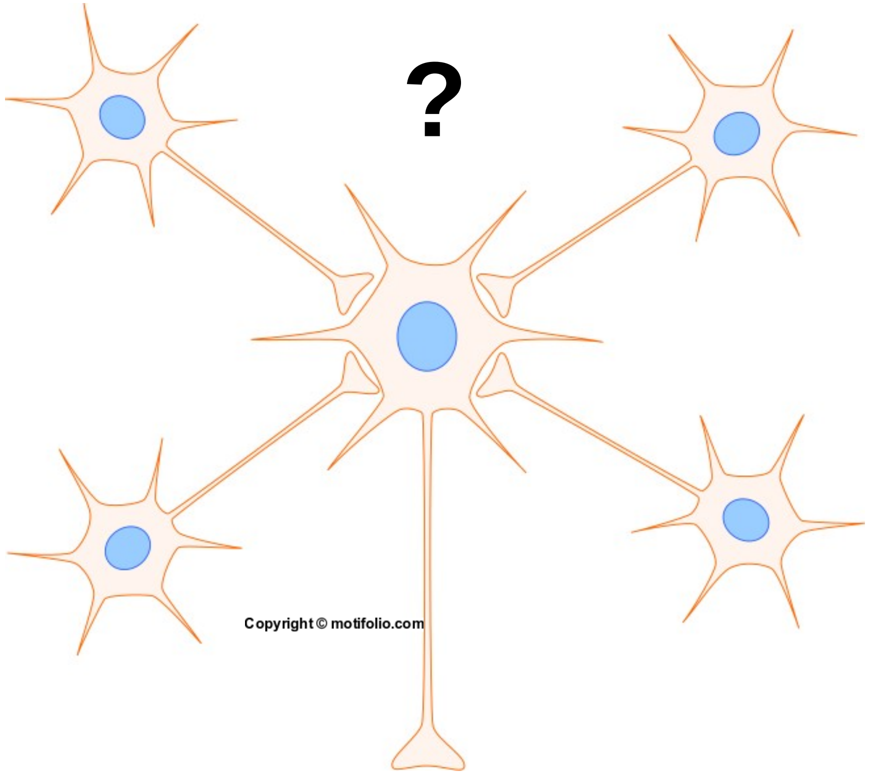
Whole brain →

Large amounts of multimodal experimental data

[Schoffelen, J.M. et. al. 2019]

Increasingly large computational power

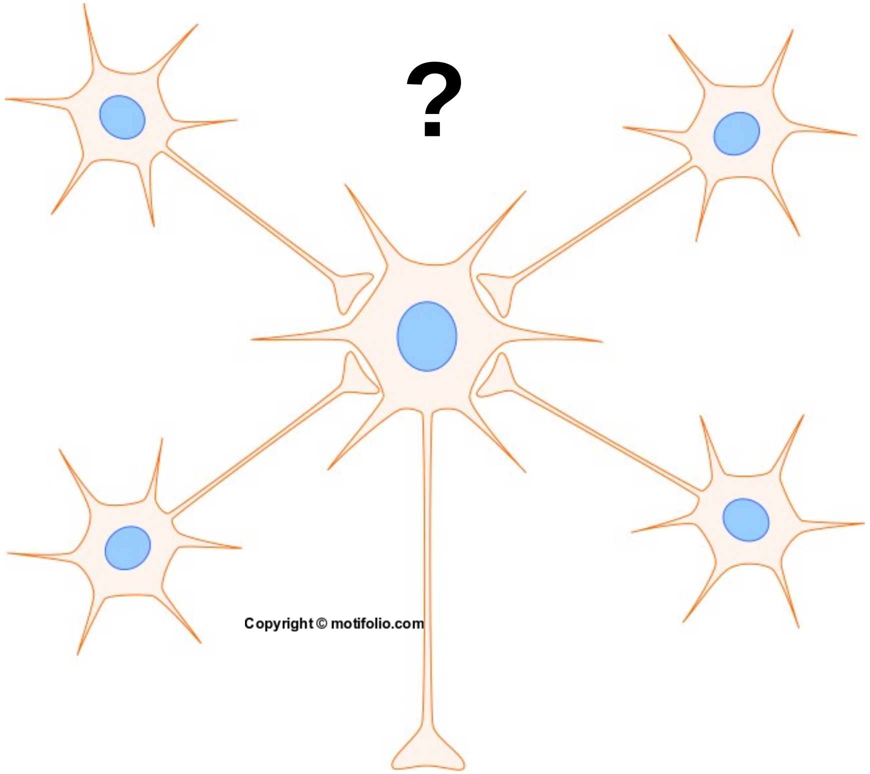
NEURAL NETWORKS



- Each component in the network shows non linear dynamics – chaotic system
- Unknown variables

  → connectivity
- Underconstrained and degenerate system
- Relevant to application fields like AI, robotics, and control

NEURAL NETWORKS



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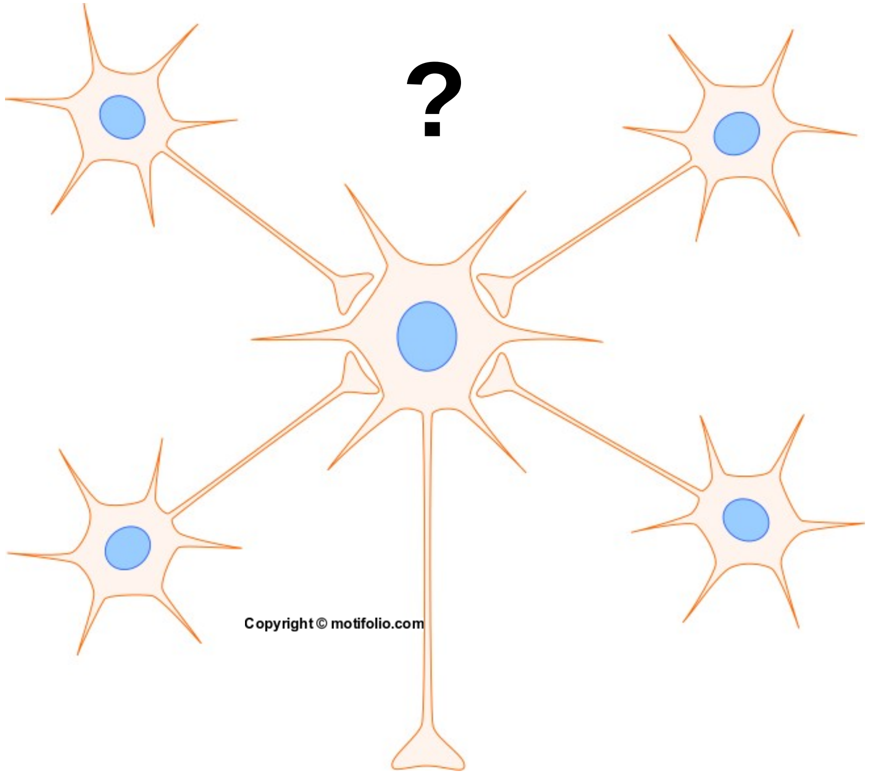
- **How can we efficiently find parameters (connectivity) for this chaotic, underconstrained, dynamic and degenerate system in order to obtain meaningful simulations of brain activity?**

NEURAL NETWORKS



- Each component in the network shows non linear dynamics – chaotic system
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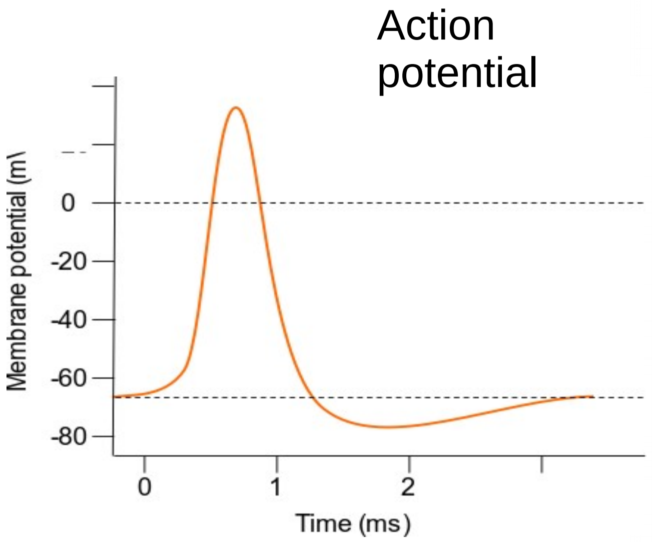
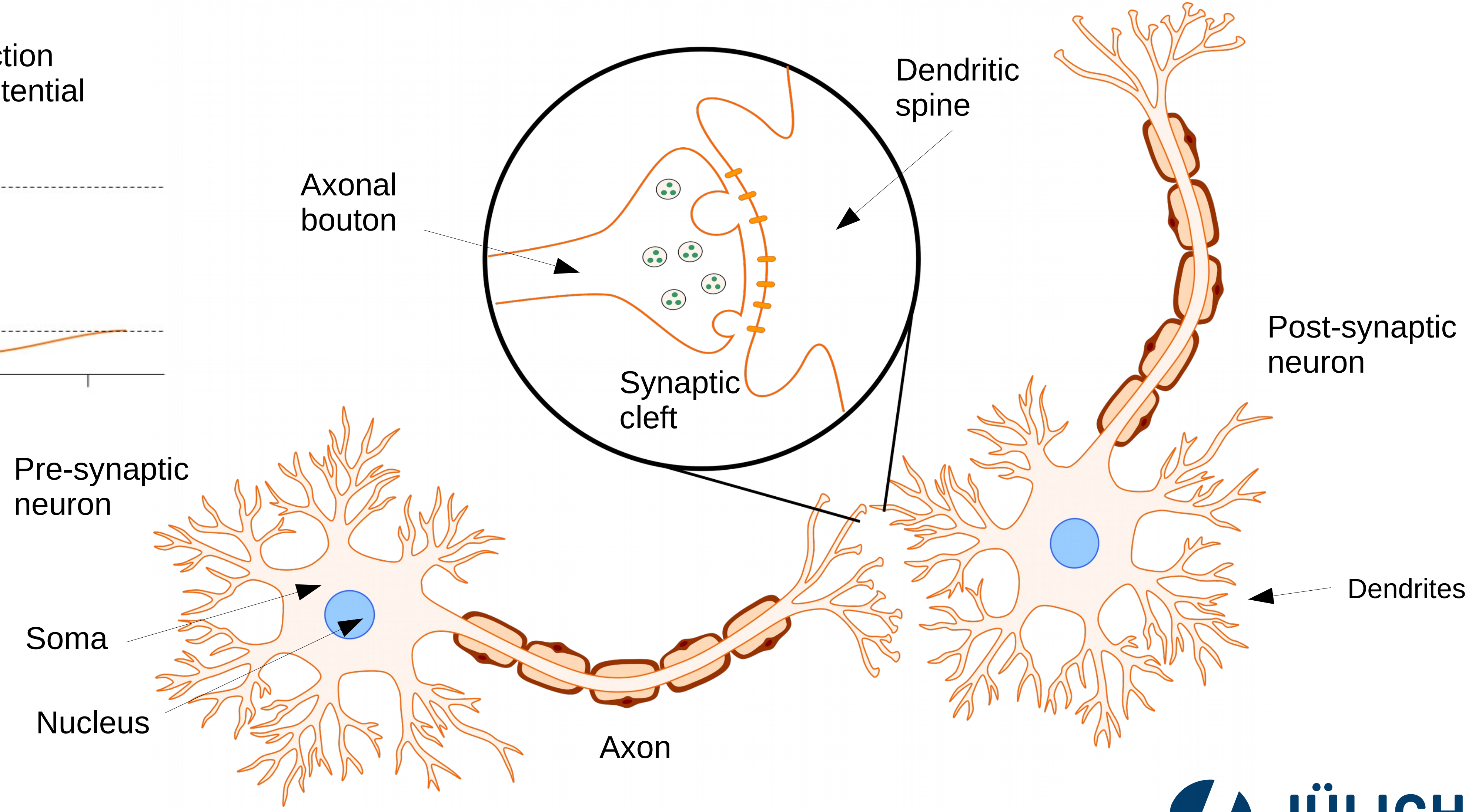
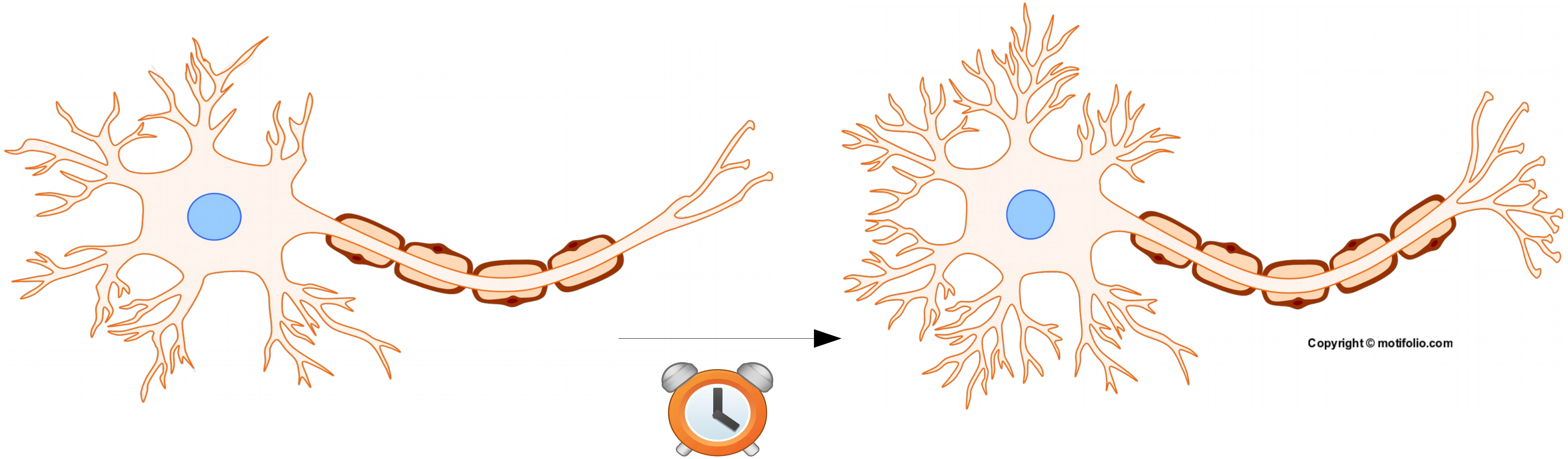
- **How can we efficiently find parameters (connectivity) for this chaotic, underconstrained, dynamic and degenerate system in order to obtain meaningful simulations of brain activity?**
- **Can we get inspiration from the brain to address this problem?**

INTRODUCTION TO NEUROSCIENCE CONCEPTS





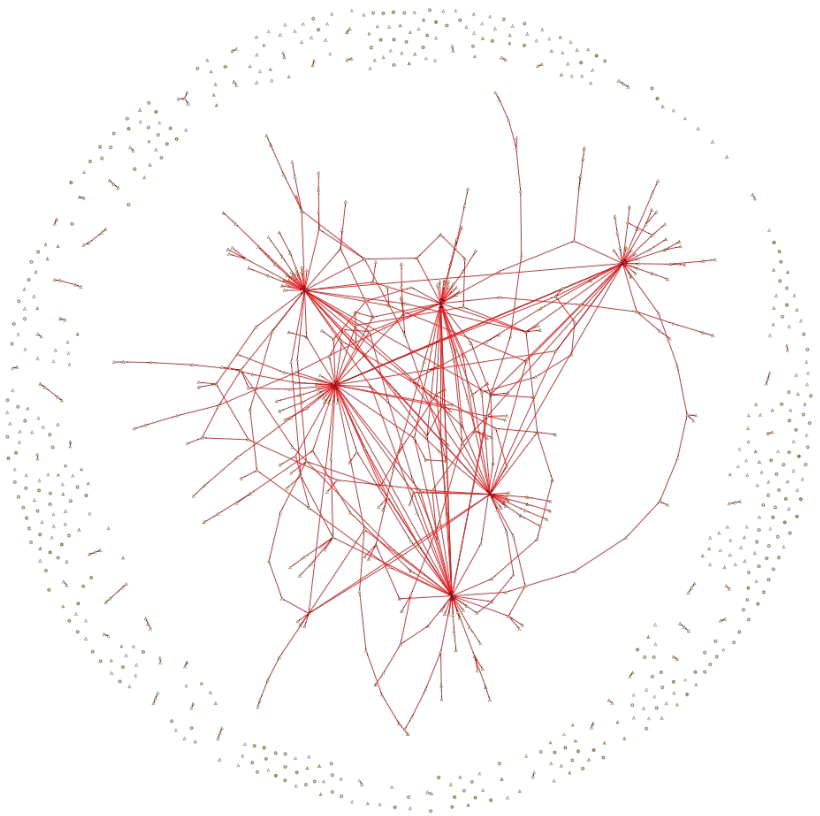
INTRODUCTION TO NEUROSCIENCE CONCEPTS: STRUCTURAL PLASTICITY



Structural plasticity is the ability of neurons to change their structure in order to, among other things, create or rescind synapses with other neurons in a network.
It plays a key role in **development**, **adaptation, healing**, **learning, and memory consolidation.**

FEATURES OF STRUCTURAL PLASTICITY

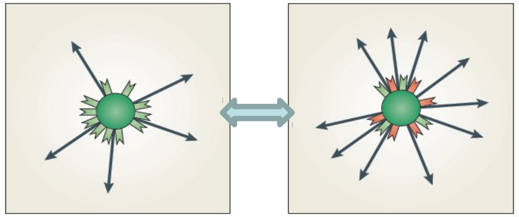
- **Creation** and **deletion** of synapses
- **Slow** process
- Neurons have **local** view and s**hort range connectivity** is more frequent
- Guided by **homeostasis**
  - Metabolic equilibrium → cell-autonomous set point



MODELING STRUCTURAL PLASTICITY

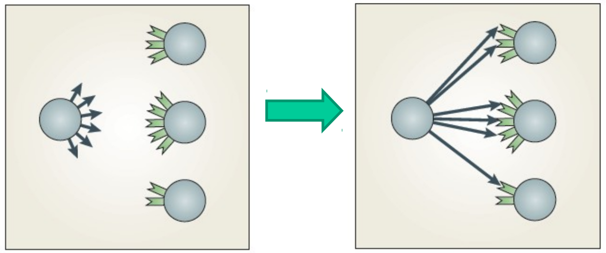
- A model of structural plasticity is described in [Butz & van Ooyen 2013]:

Synaptic elements

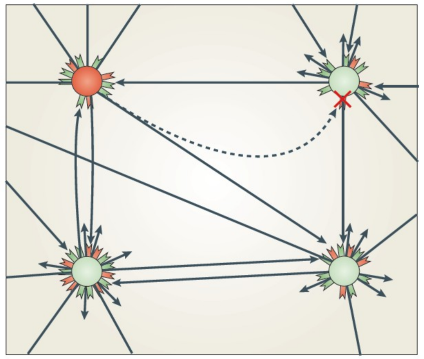


Axonal bouton: presynaptic element
Dendritic spine: exc. postsynaptic element
Dendritic spine: inh. postsynaptic element

Synapse formation / deletion



Network rewiring

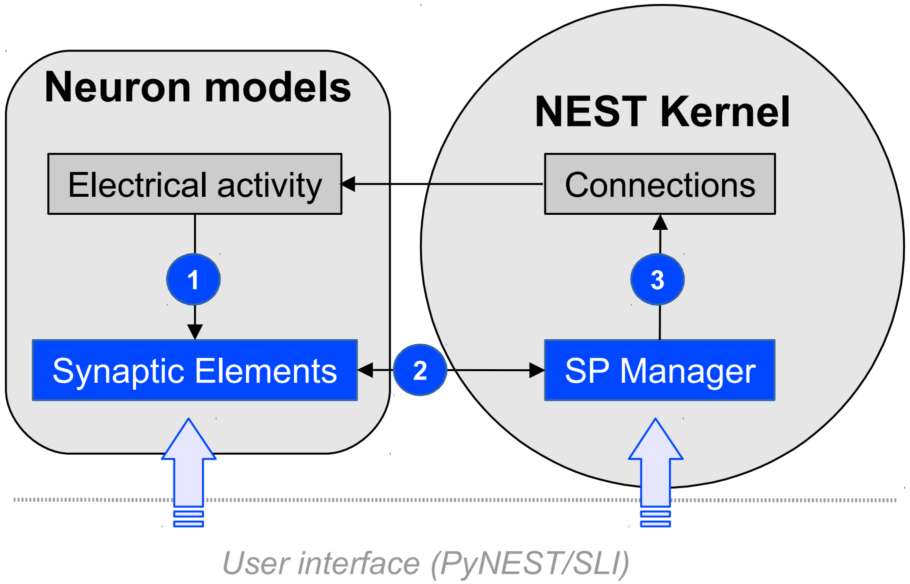


IMPLEMENTING STRUCTURAL PLASTICITY

Diaz-Pier, et al. "Automatic generation of connectivity for large-scale neuronal network models through structural plasticity." Frontiers in neuroanatomy 10 (2016): 57.

nest:: simulated()   EBRAINS

- Based on the model by [Butz & van Ooyen 2013]
- Includes **all abstract features** of structural plasticity *except distance dependency **
- Algorithm implemented with **MPI and multithreading parallelization** in C++
- **Compatible** with all existing neuron and synapse models + other plasticity rules



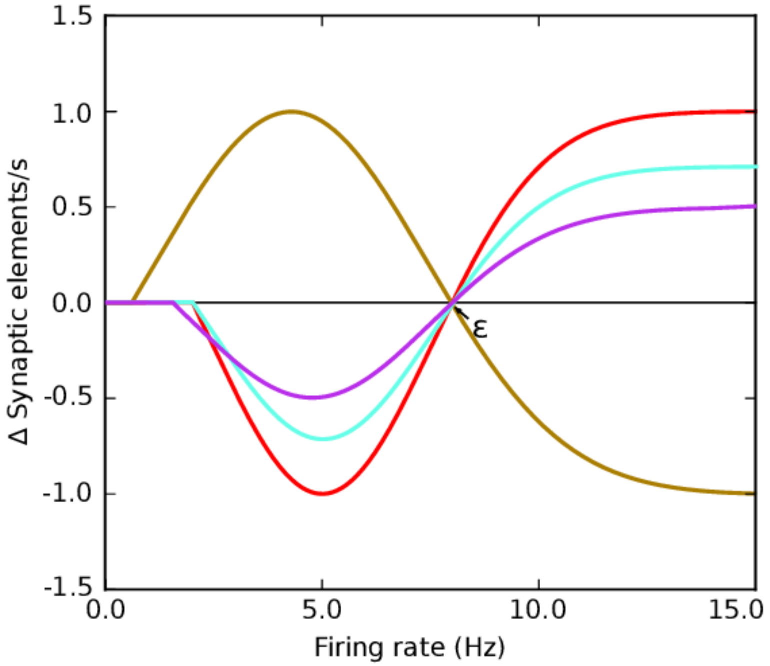
1. The number of **synaptic elements** is updated depending on the electrical activity of the neurons

The **SP manager**:

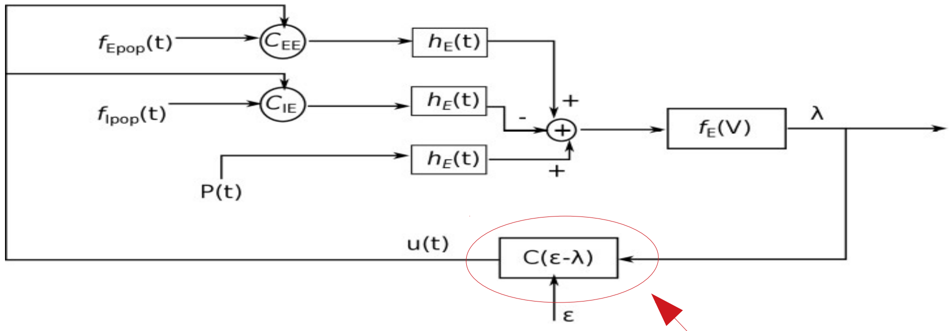
2. Gathers the number of synaptic elements per neuron
3. Creates/deletes synapses to update the connections between the neurons

IMPLEMENTING STRUCTURAL PLASTICITY

Growth curves for synaptic elements

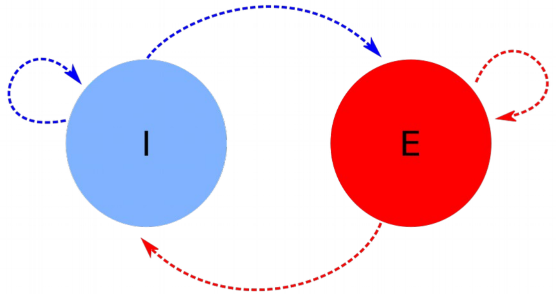


- Updating the number of synaptic elements with **homeostatic growth** curves
- Change in synaptic elements **depending on the firing rate** of the neuron at time t
- Shape is **important for stability** of the system and ε indicates the **target firing rate** of the neuron
- **Progressively** introduce disturbances in the system in the form of **slow structural changes**

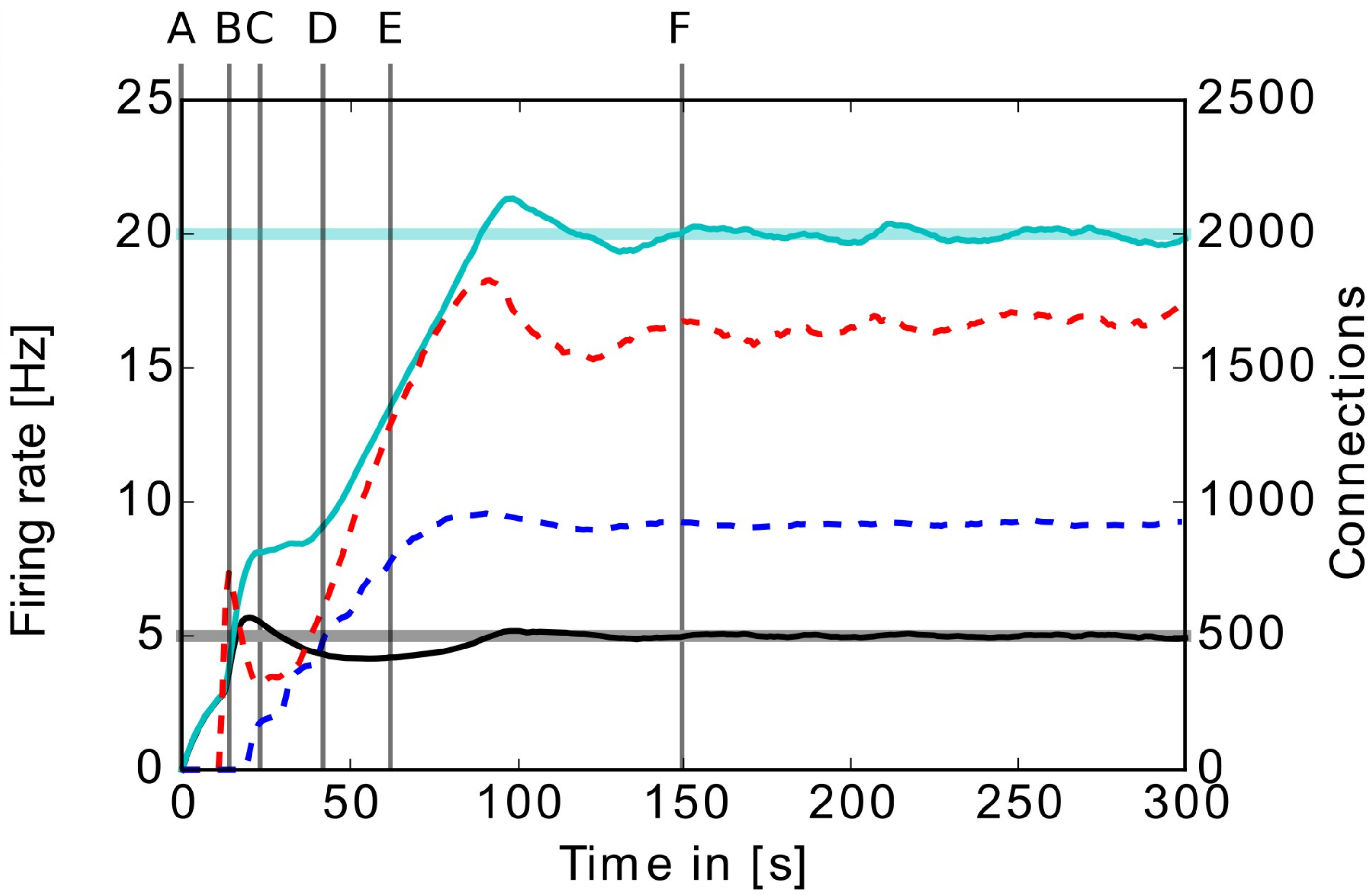


Structural plasticty

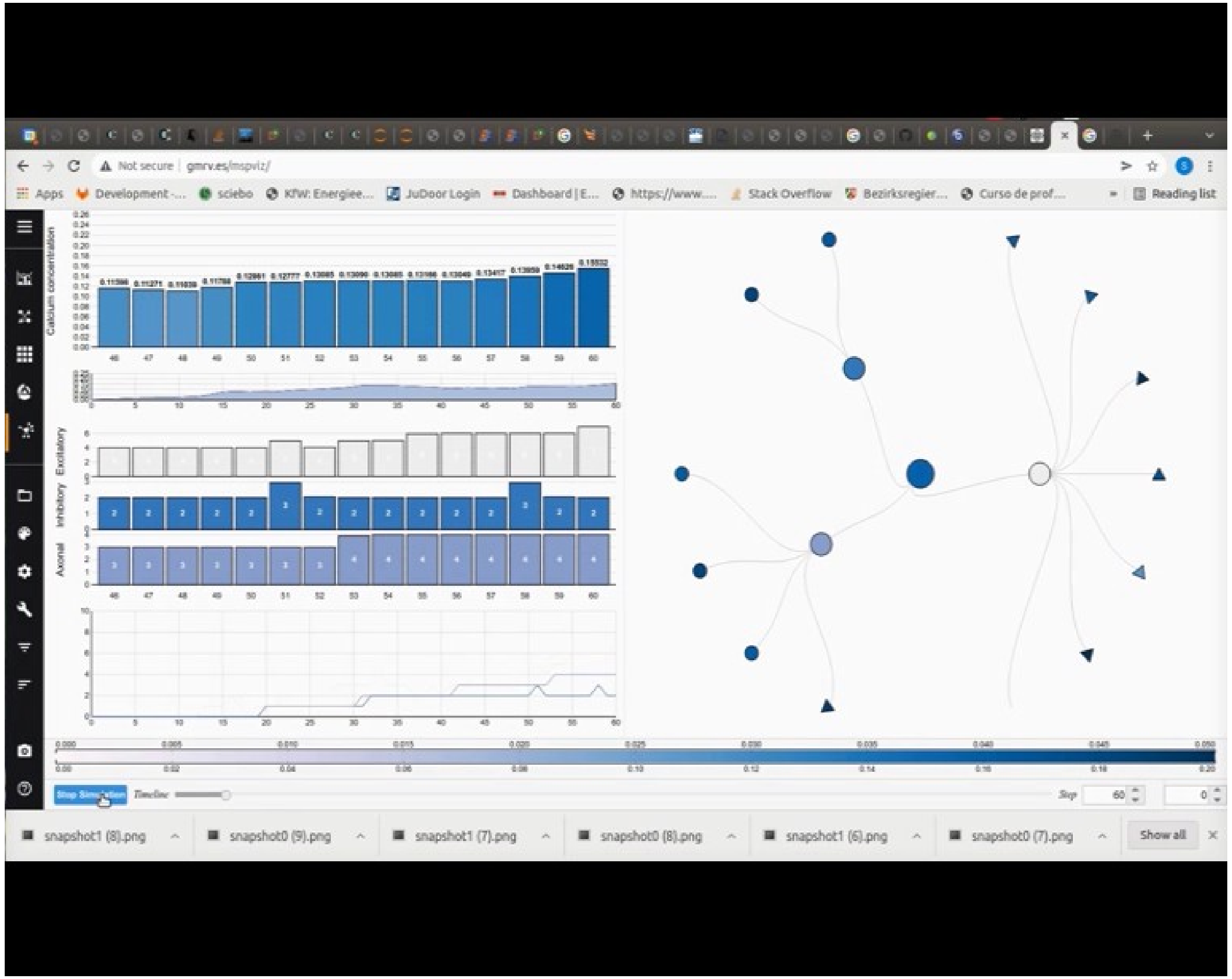
STRUCTURAL PLASTICITY IN NEST



- Two population network (800 excitatory neurons, 200 inhibitory neurons)
- Target activity 5Hz and 20Hz respectively



STRUCTURAL PLASTICITY IN NEST

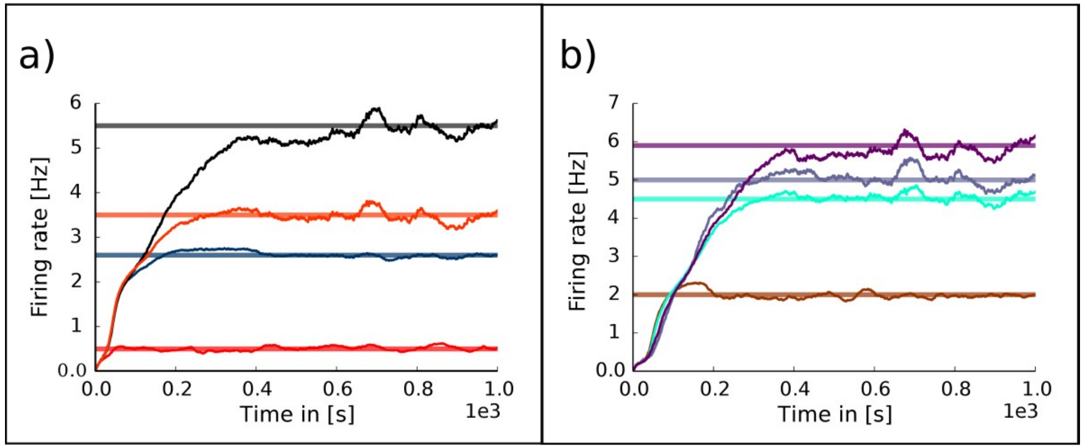


MSPViz

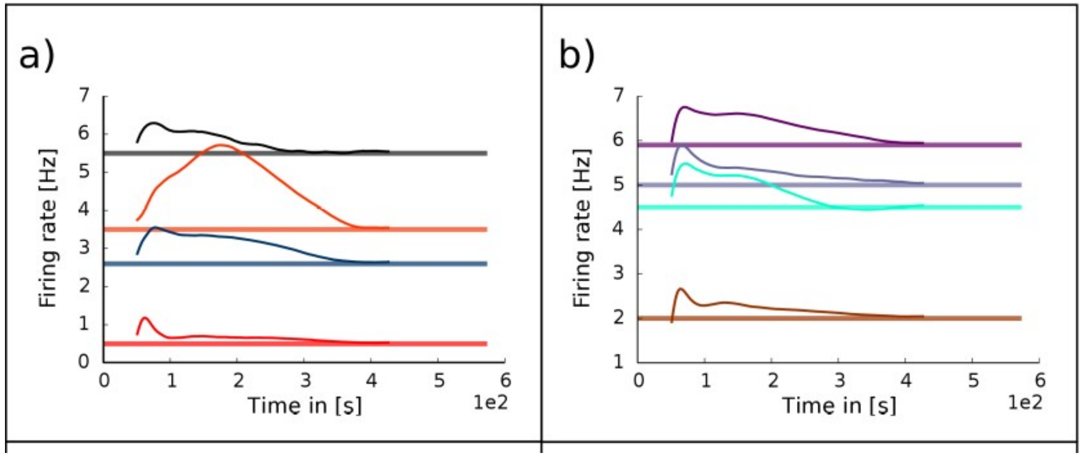
- Web based tool for structural plasticity analysis
- **Offline analysis** of the evolution of the network through time
- **Visualization** at the neuron, sub-network and network level

STRUCTURAL PLASTICITY IN NEST

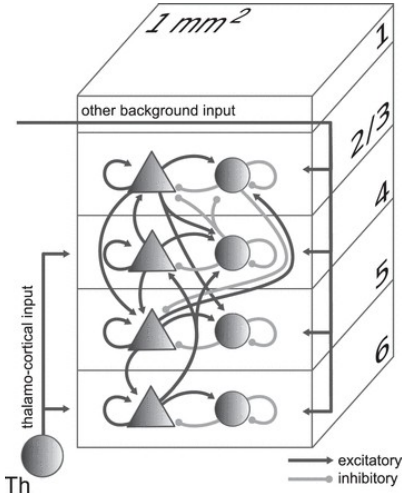
No initial connectivity



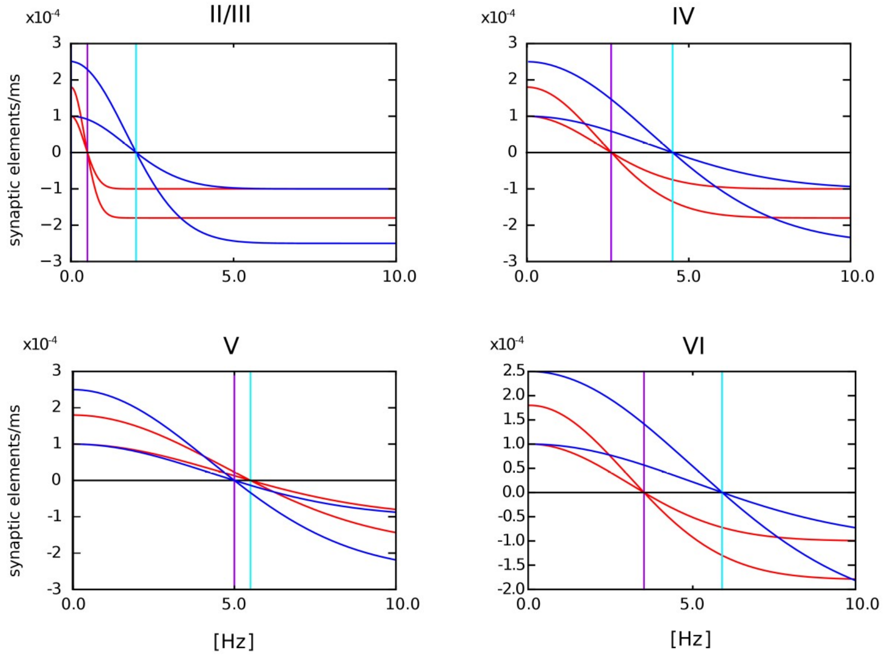
With initial connectivity (10% error)



[Potjans and Diesmann, 2014]

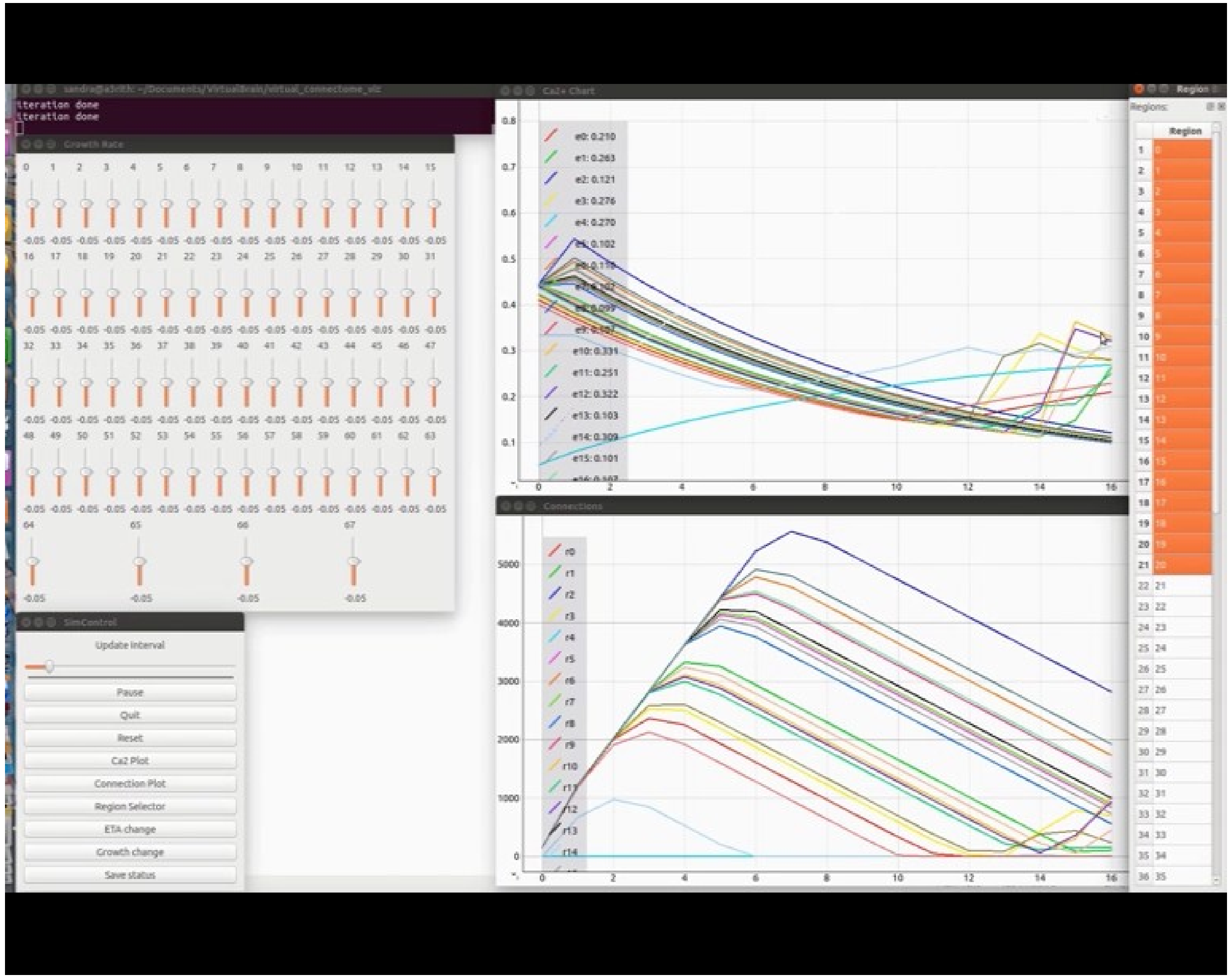


Growth curves



INTERACTIVE STEERING AND VISUALIZATION

Observing the dynamics of the connectivity in a network is not simple

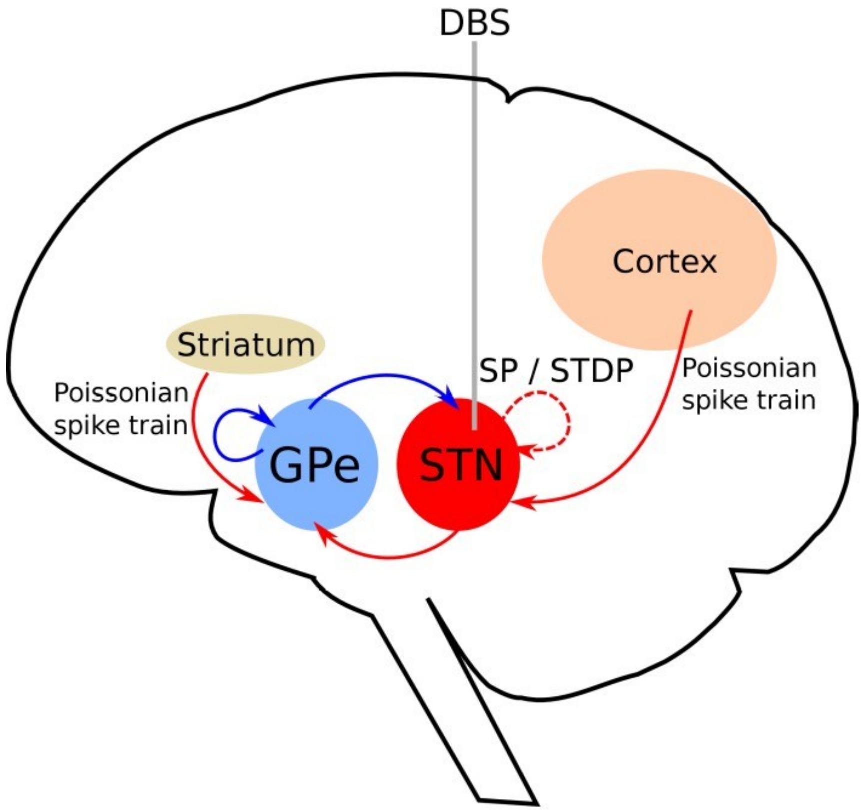


- **First** interactive steering and visualization simulations with NEST **on HPC**
- The user can **define the growth trajectory** of the network
- **Interactive exploration** of the parameter space
- **Insight** on higher level plasticity dependencies

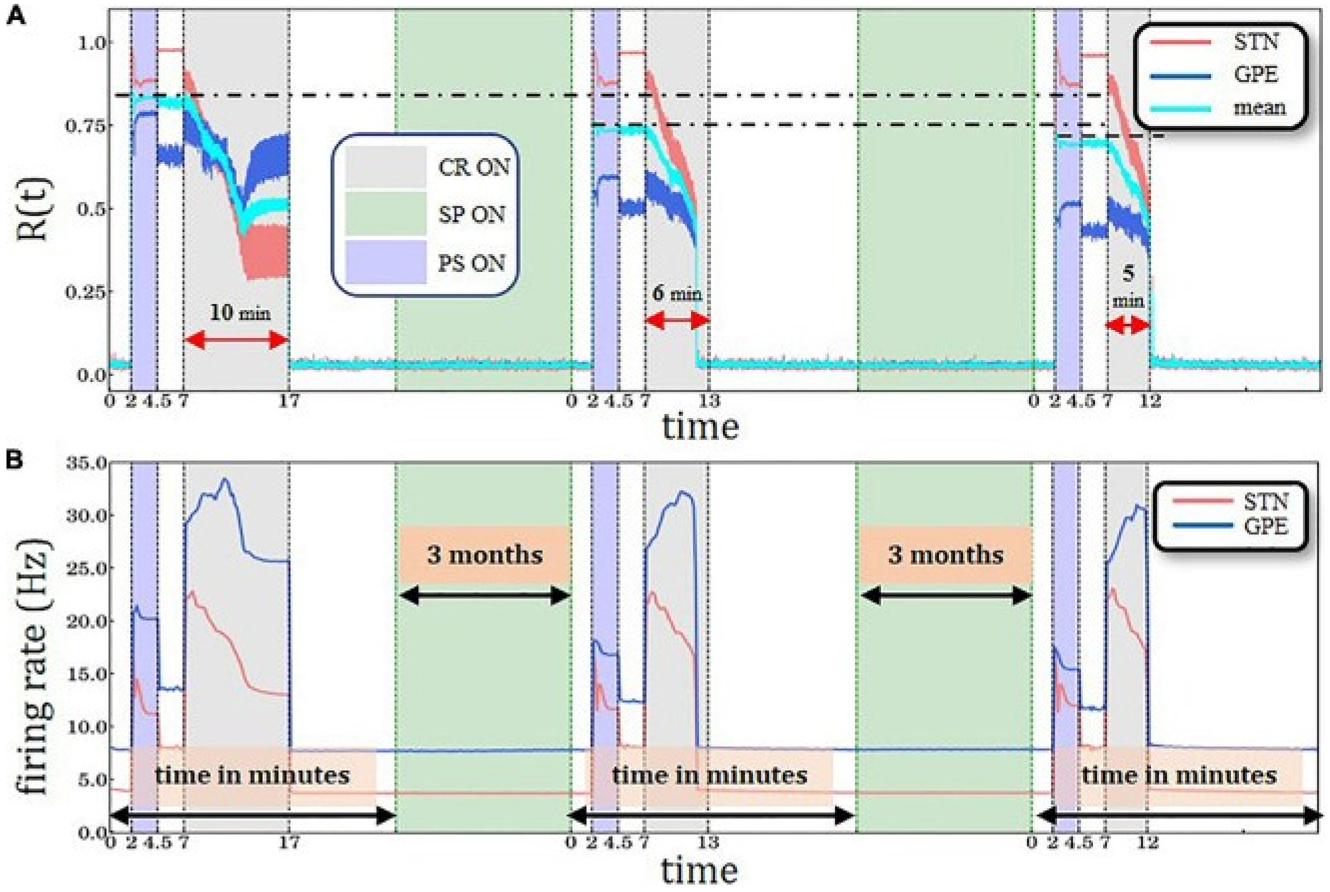
Nowke, Diaz-Pier, et al. "Toward rigorous parameterization of underconstrained neural network models through interactive visualization and steering of connectivity generation." Frontiers in neuroinformatics 12 (2018): 32.

USING STRUCTURAL PLASTICITY

- Coordinated Reset Therapy is simulated on a model of the Sub Thalamic Nucelus (STN) and the Globus Palidus externus (GPe)
- Simulated **unhealthy synchronization and stimulation protocols**
- Model considers both synaptic (STDP) and structural plasticity
- Able to simulate **long lasting effects of CR therapy**

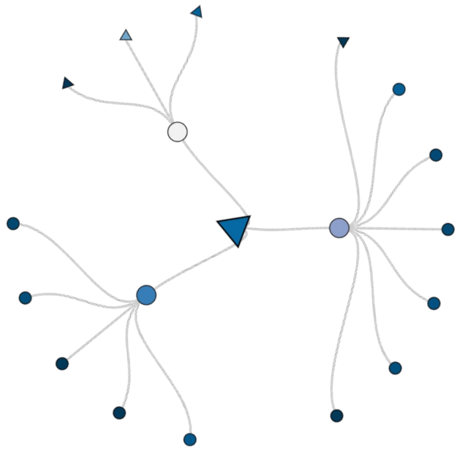


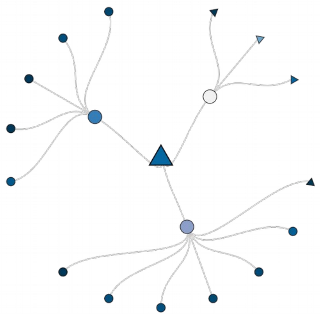
USING STRUCTURAL PLASTICITY

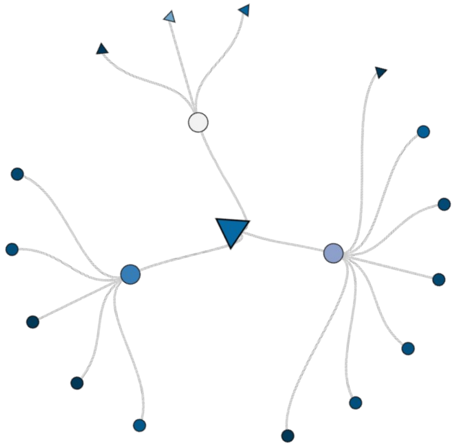


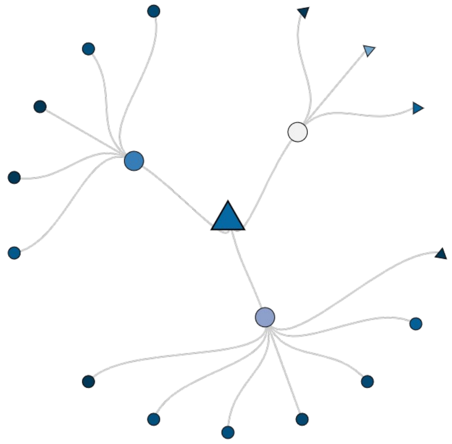
* Manos, Thanos, Sandra Diaz-Pier, and Peter A. Tass. "Long-Term Desynchronization by Coordinated Reset Stimulation in a Neural Network Model With Synaptic and Structural Plasticity." Frontiers in physiology 12 (2021).

HOMEOSTATIC GROWTH RULES









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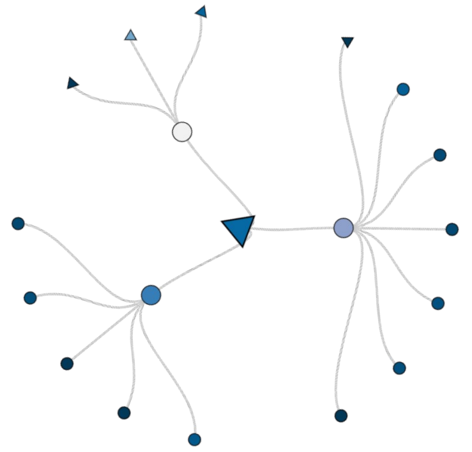
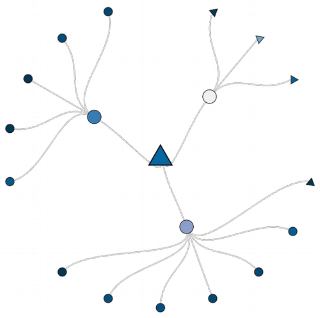
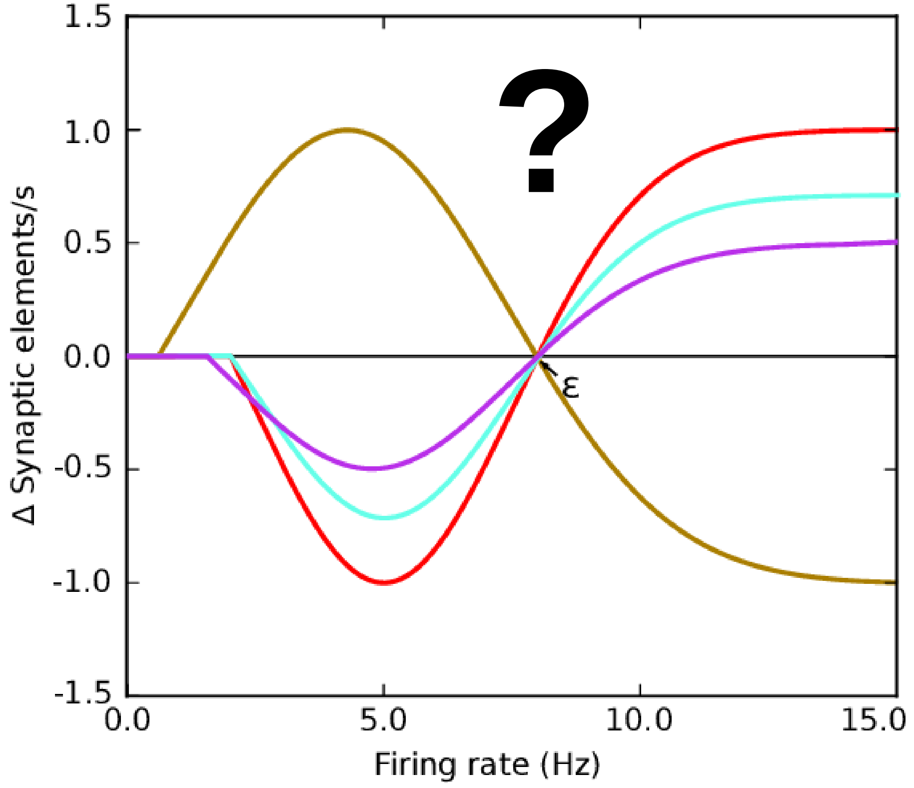
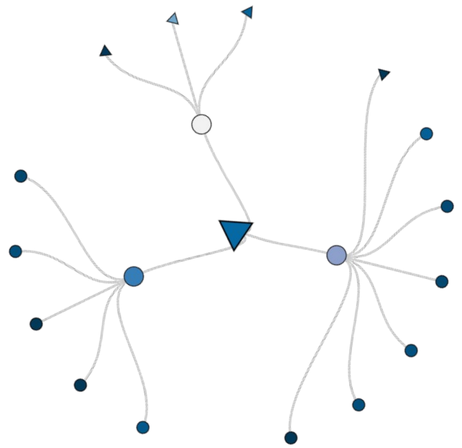
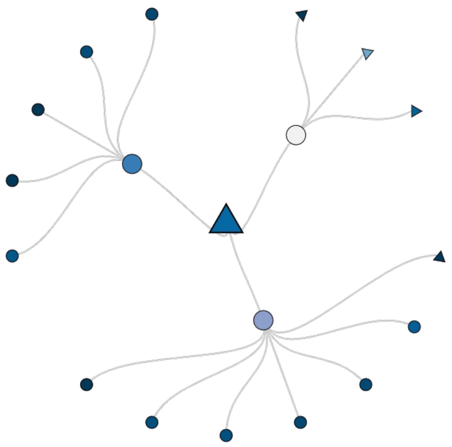




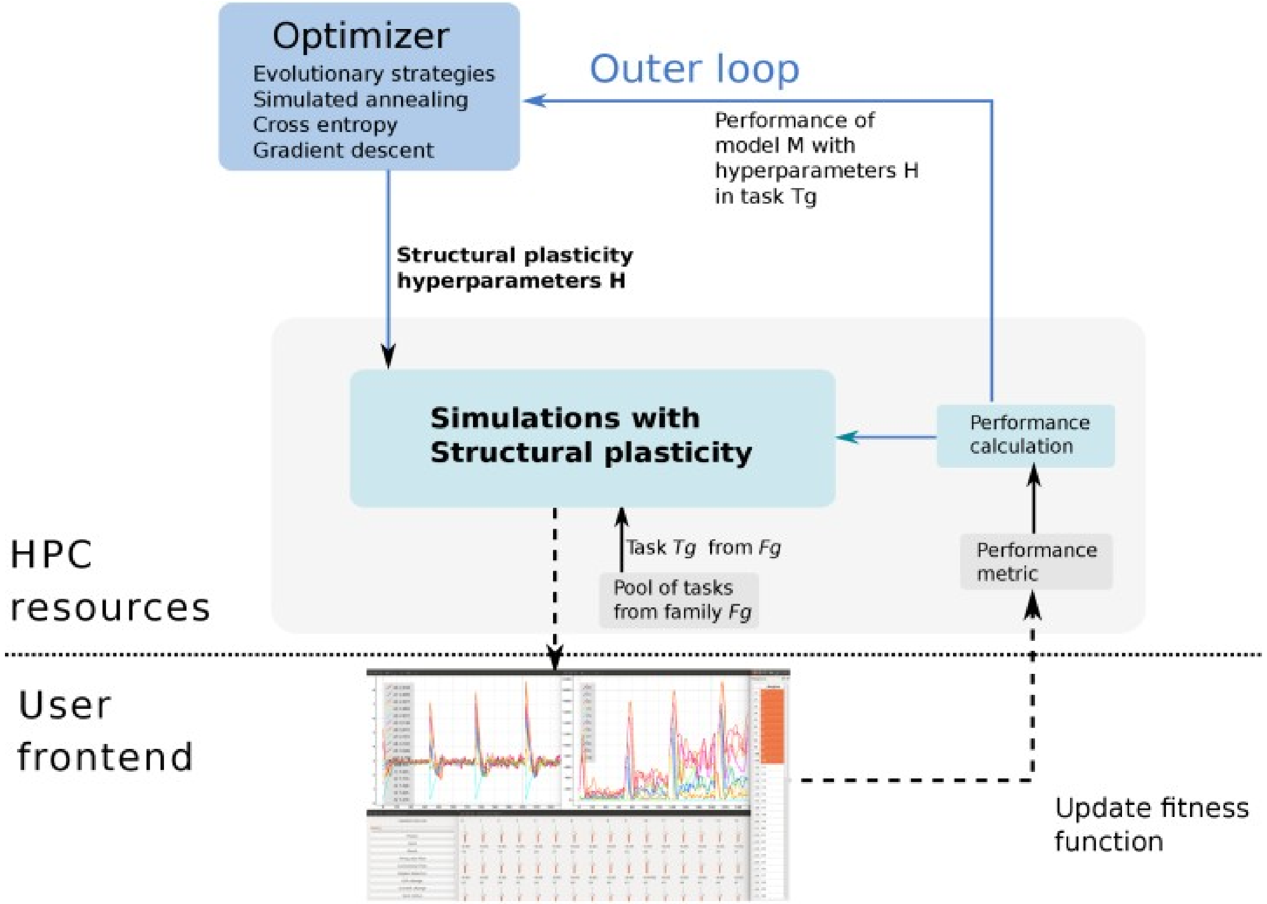
Growth curves for synaptic elements





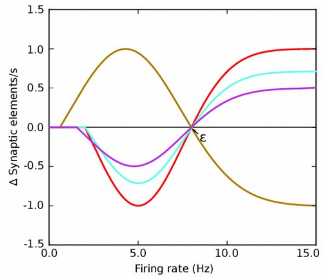


LEARNING HOMEOSTATIC RULES

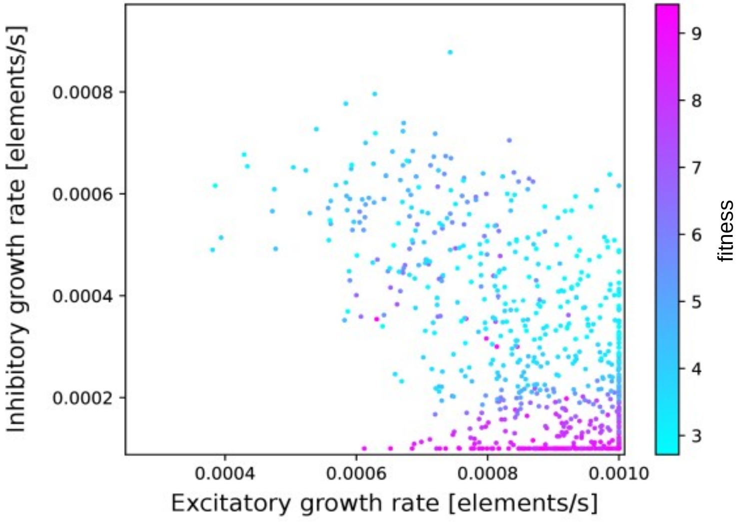


- **Meta optimization** of homeostatic rules
- Learning the rules which allow a network to optimally generate connectivity for different target functions
- Integrated and developed with the Learning to learn [L2L] framework

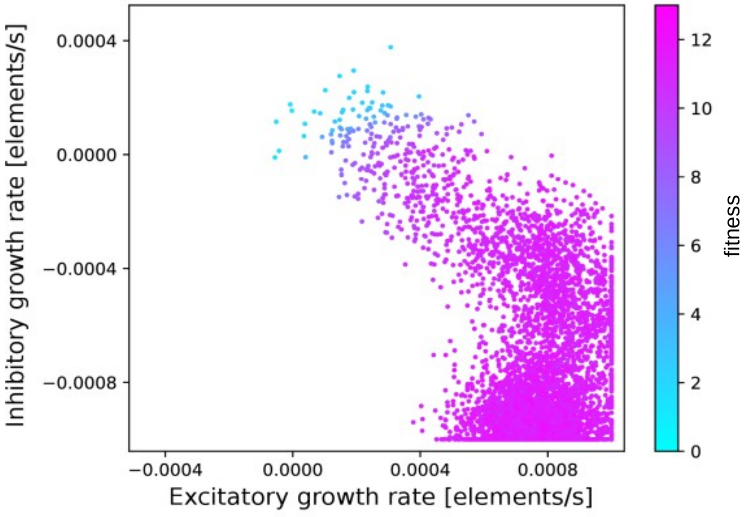
LEARNING HOMEOSTATIC RULES



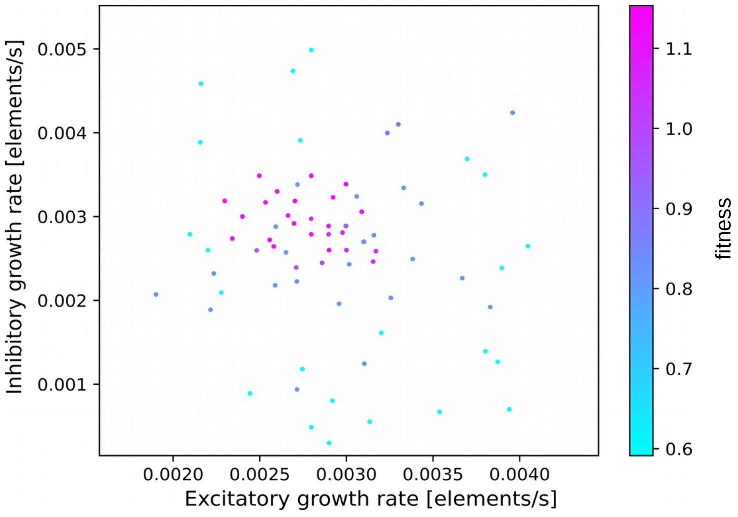
Without negative growth rates



With negative growth rates

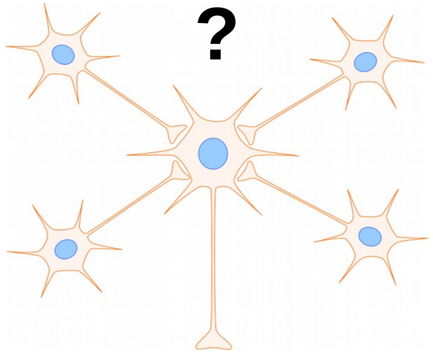


Cortical microcircuit



- **Identify** homeostatic rules and relationships between them
- Critical features of homeostatic development towards **stable** system

GOING BACK TO THE INITIAL QUESTIONS...



- **How can we efficiently find parameters (connectivity) for this chaotic, underconstrained, dynamic and degenerate system in order to obtain meaningful simulations of brain activity?**
- **Can we get inspiration from the brain to address this problem?**

With **structural plasticity** we can **generate, modify and optimize connectivity** in simulations of spiking neural networks **inspired by neurobiology**

SUMMARY OF THE WORK

- The implemented software infrastructure can be used for **simulating**, **visualizing** and **analyzing** structural plasticity useful to **modify**, **generate** and **optimize** connectivity in simulations of neural networks
- **Meta optimization** of structural plasticity rules provides insight on network development dynamics
- New way to study the relationship between **structure** and **function** in spiking neural networks

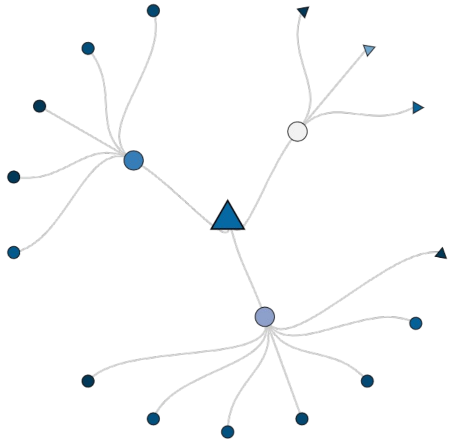
FUTURE WORK

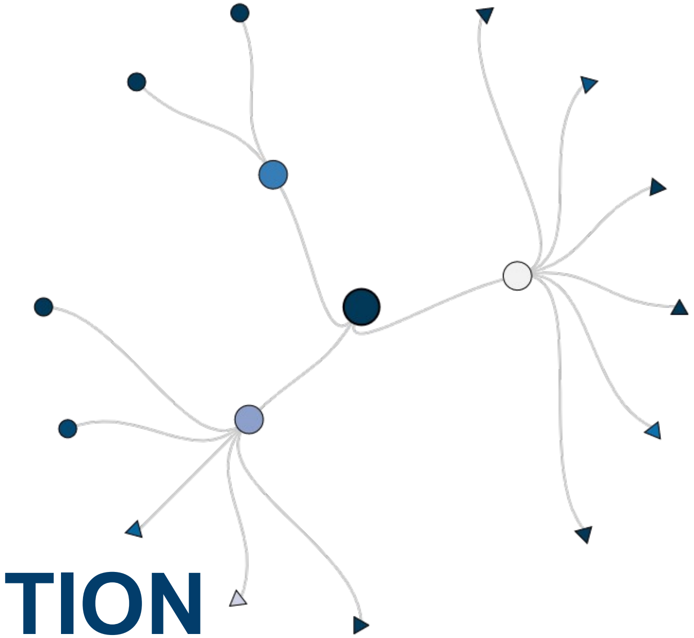
- Applications in clinical neuroscience, design of brain computer interfaces, and treatment planning
- Extensions of the algorithm
- Compatibility with other simulators and neuromorphic hardware
- Usage of emerging computational architectures by co-simulation ł

ł Klijn, W.; Diaz, S. ; Morrison, A. ; Peyser. "A.Staged deployment of interactive multi-application HPC workflows". HPCS 2019 [10.1109/HPCS48598.2019.9188104]

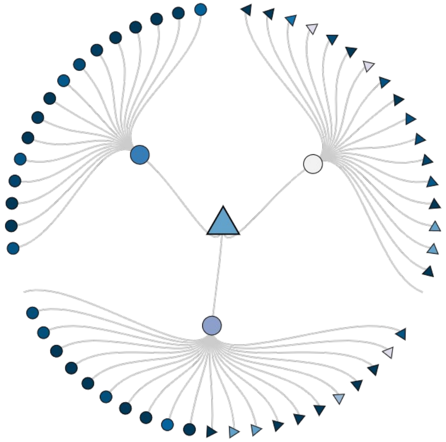
ACKNOWLEDGEMENTS

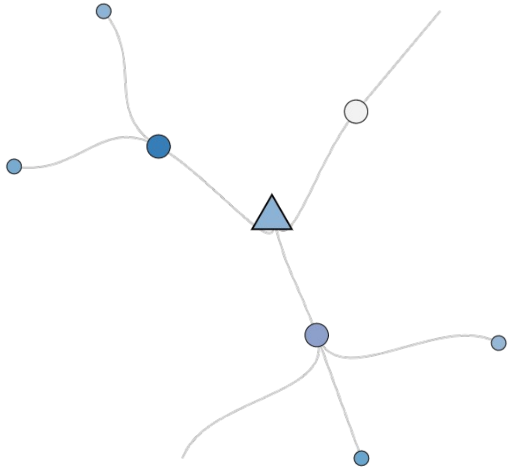
- Abigail Morrison, Alexander Peyser and the whole SimLab Neuroscience
- My co-authors in the different papers discussed in this presentation
- Collaborators and users of the structural plasticity tools





THANK YOU FOR YOUR ATTENTION AND HAPPY HOLIDAYS





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[Lappalainen, J. et. al. 2019] Lappalainen, Janne, Juliane Herpich, and Christian Tetzlaff. "A theoretical framework to derive simple, Firing-Rate-Dependent mathematical models of synaptic plasticity." Frontiers in computational neuroscience 13 (2019): 26.

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[Butz & van Ooyen 2013] Butz, Markus, and Arjen van Ooyen. "A simple rule for dendritic spine and axonal bouton formation can account for cortical reorganization after focal retinal lesions." PLoS computational biology 9.10 (2013).

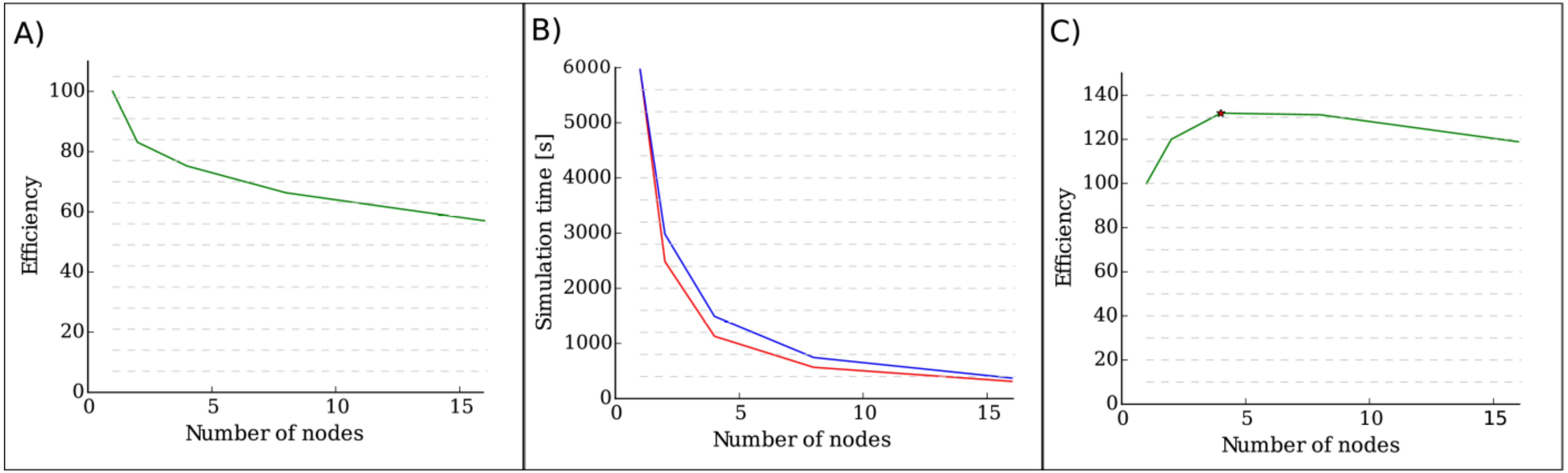
[Potjans and Diesmann, 2014] Potjans, Tobias C., and Markus Diesmann. "The cell-type specific cortical microcircuit: relating structure and activity in a full-scale spiking network model." Cerebral cortex 24.3 (2014): 785-806.

[Plesser et. al. 2007] Hans E Plesser, Jochen M Eppler, Abigail Morrison, Markus Diesmann, and Marc-Oliver Gewaltig. Efficient parallel simulation of large-scale neuronal networks on clusters of multiprocessor computers. In Euro-Par 2007 parallel processing, pages 672–681. Springer, 2007.

[Schoffelen, J.M. et. al. 2019] Schoffelen, JM., Oostenveld, R., Lam, N.H.L. et al. A 204-subject multimodal neuroimaging dataset to study language processing. Sci Data 6, 17 (2019). https://doi.org/10.1038/s41597-019-0020-y

[L2L] https://github.com/Meta-optimization/L2L/tree/master/l2l

SCALING NETWORKS WITH SP ON HPC



- Benchmarks performed with NEST 2.10 and two networks 5,000 (A) and 100,000 neurons (B & C)
- The 100,000 neuron network shows supralinear scaling (increasingly efficient caching Plesser et. al. 2007)
- Largest simulations done of up to 68*76,000 neurons on 70 nodes with sparse connectivity

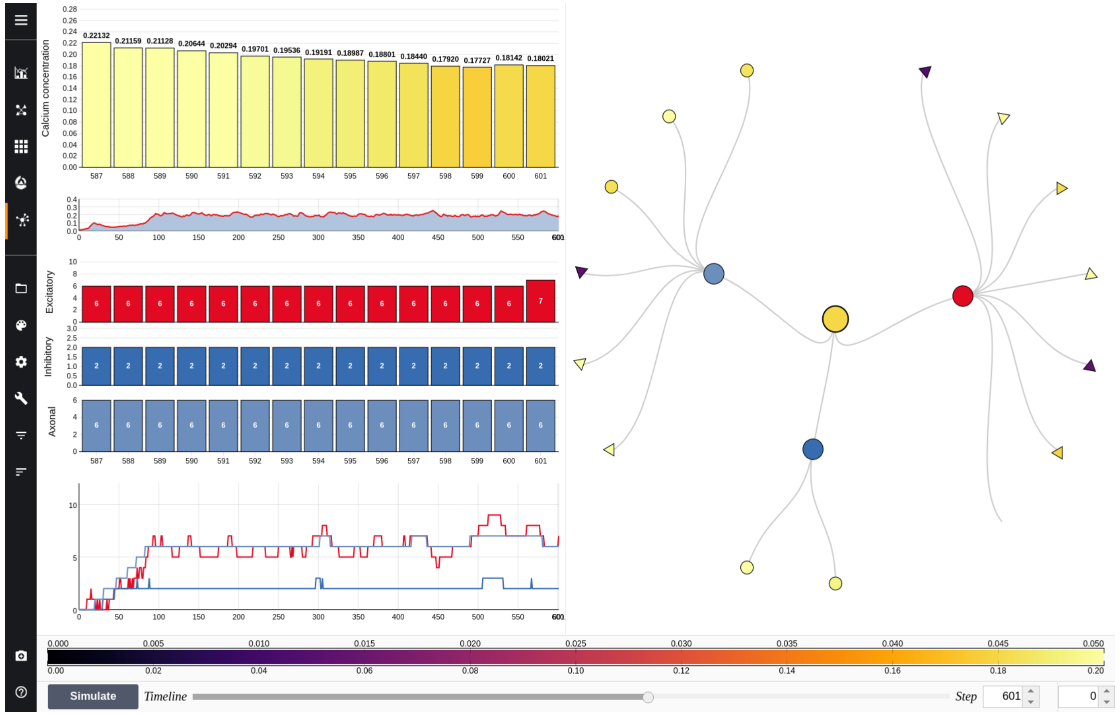
[Plesser et. al. 2007] Hans E Plesser, Jochen M Eppler, Abigail Morrison, Markus Diesmann, and Marc-Oliver Gewaltig. Efficient parallel simulation of large-scale neuronal networks on clusters of multiprocessor computers. In Euro-Par 2007 parallel processing, pages 672–681. Springer, 2007.

VISUALIZATION

Observing the dynamics of the connectivity in a network is not simple

Requirements for visualization and analysis of simulations with structural plasticity:

1. Observe changes of the network in time
2. Visualize the balance between different types of connections
3. Easily identify important structural components in the network



MSPViz

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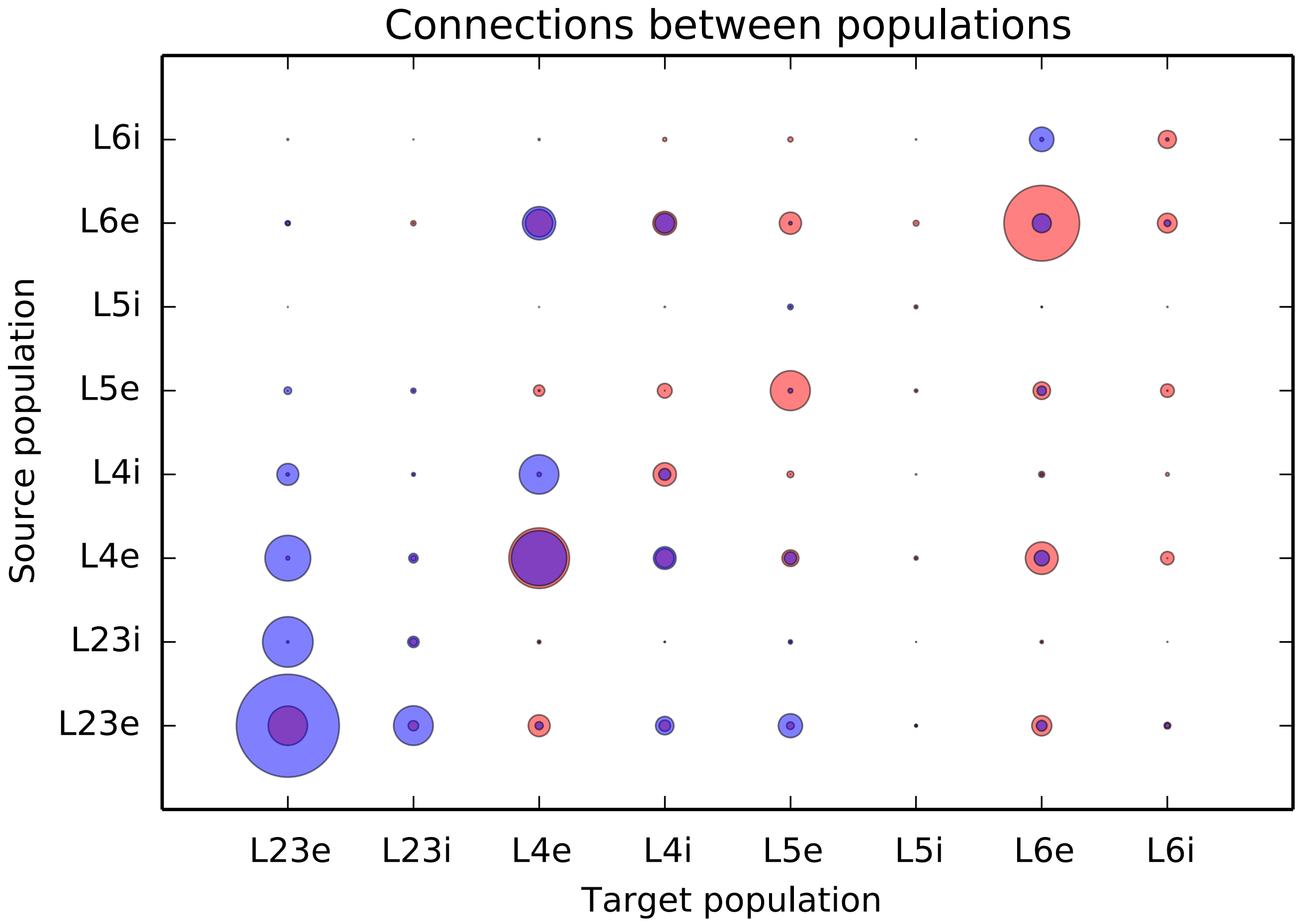
Connections between populations



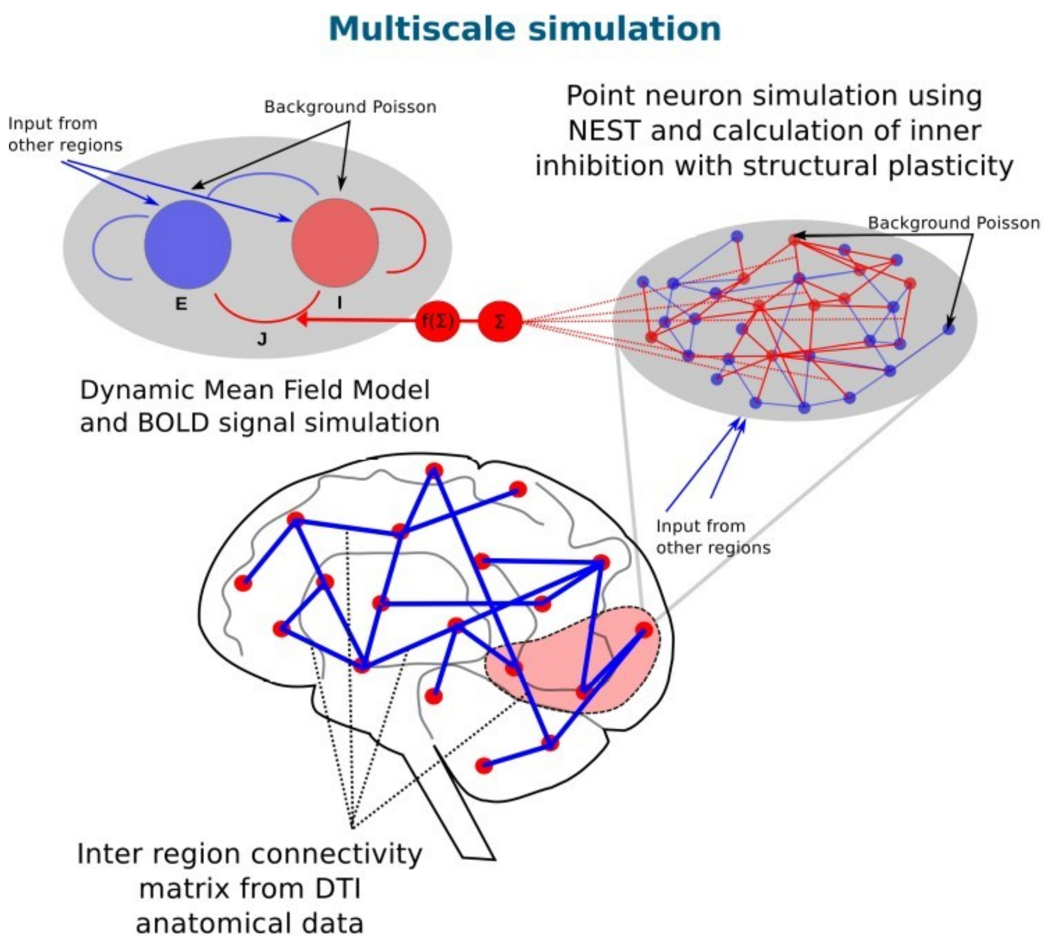
STRUCTURAL PLASTICITY BEYOND NEUROSCIENCE

Applications:

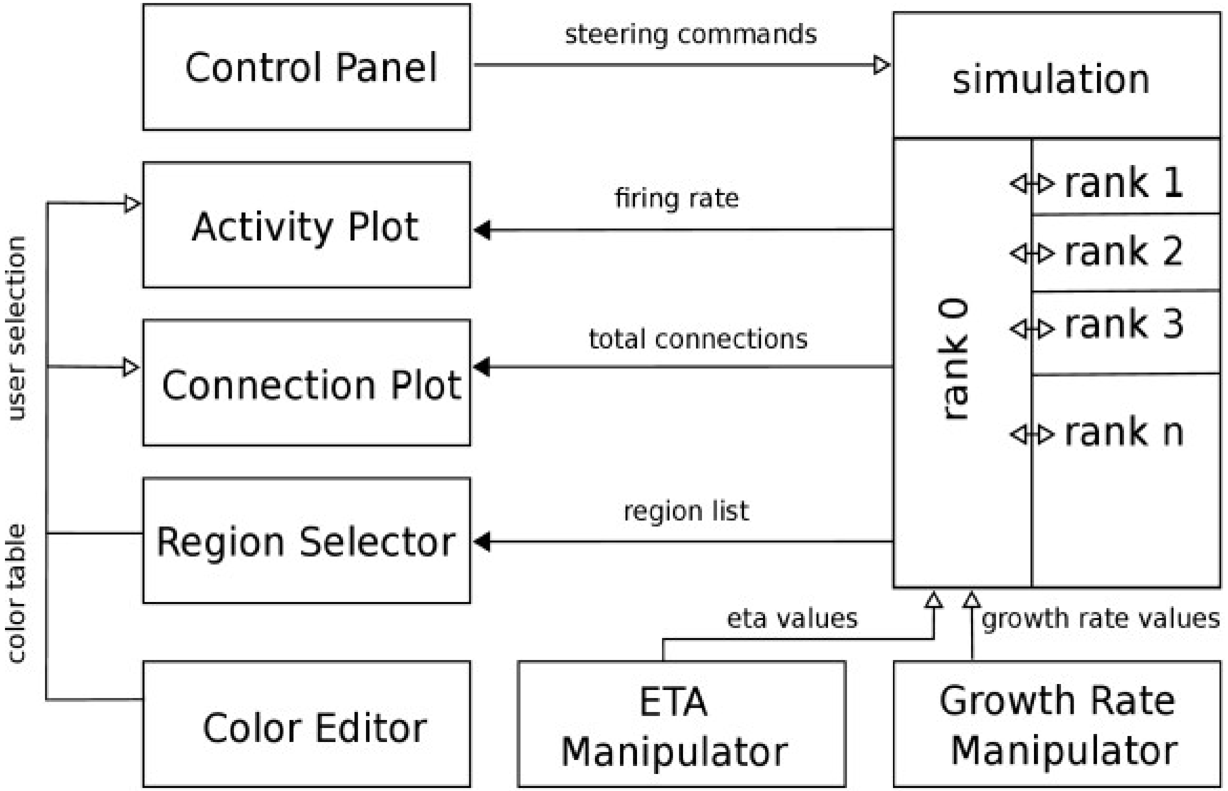
- Optimization of **connectivity** in spiking neural networks
- Finding **optimal architectures** to ML problems
- Solving **multiobjective optimization** problems in other scientific fields e.g.
  - Economics
  - Ecology
  - Information networks
- New applications where the relatively static **structure encodes the solution to an initial problem**

INTERACTIVE STEERING AND VISUALIZATION

- Use structural plasticity to optimize connectivity from one scale to the next
- 68 regions of the brain
- Each region has 2 populations
- Plasticity is enabled only within regions
- Connections between regions are defined by experimental data



INTERACTIVE STEERING AND VISUALIZATION



FUTURE WORK

Comment on this paper

Growth Rules for the Repair of Asynchronous Irregular Neuronal Networks after Peripheral Lesions

Ankur Sinha, Christoph Metzner, Neil Davey, Roderick Adams, Michael Schmuker, Volker Steuber

doi: https://doi.org/10.1101/810846

Article | Open Access | Published: 28 February 2018

Associative properties of structural plasticity based on firing rate homeostasis in recurrent neuronal networks

Júlia V. Gallinaro & Stefan Rotter

Network remodeling induced by transcranial brain stimulation: A computational model of tDCS-triggered cell assembly formation

Han Lu, Júlia V. Gallinaro and Stefan Rotter

Homeostatic structural plasticity leads to the formation of memory engrams through synaptic rewiring in recurrent networks

Nebojša Gašparović*, Júlia V. Gallinaro* & Stefan Rotter

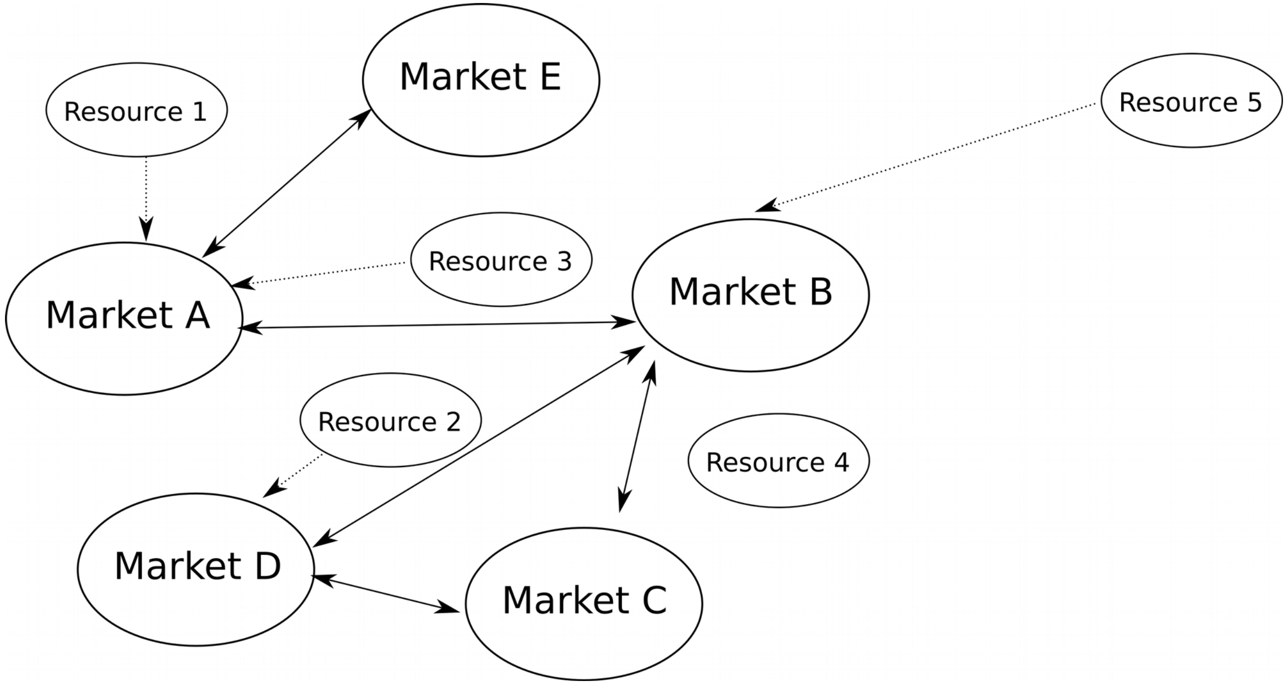
March 8, 2020

A scalable algorithm for simulating the structural plasticity of the brain

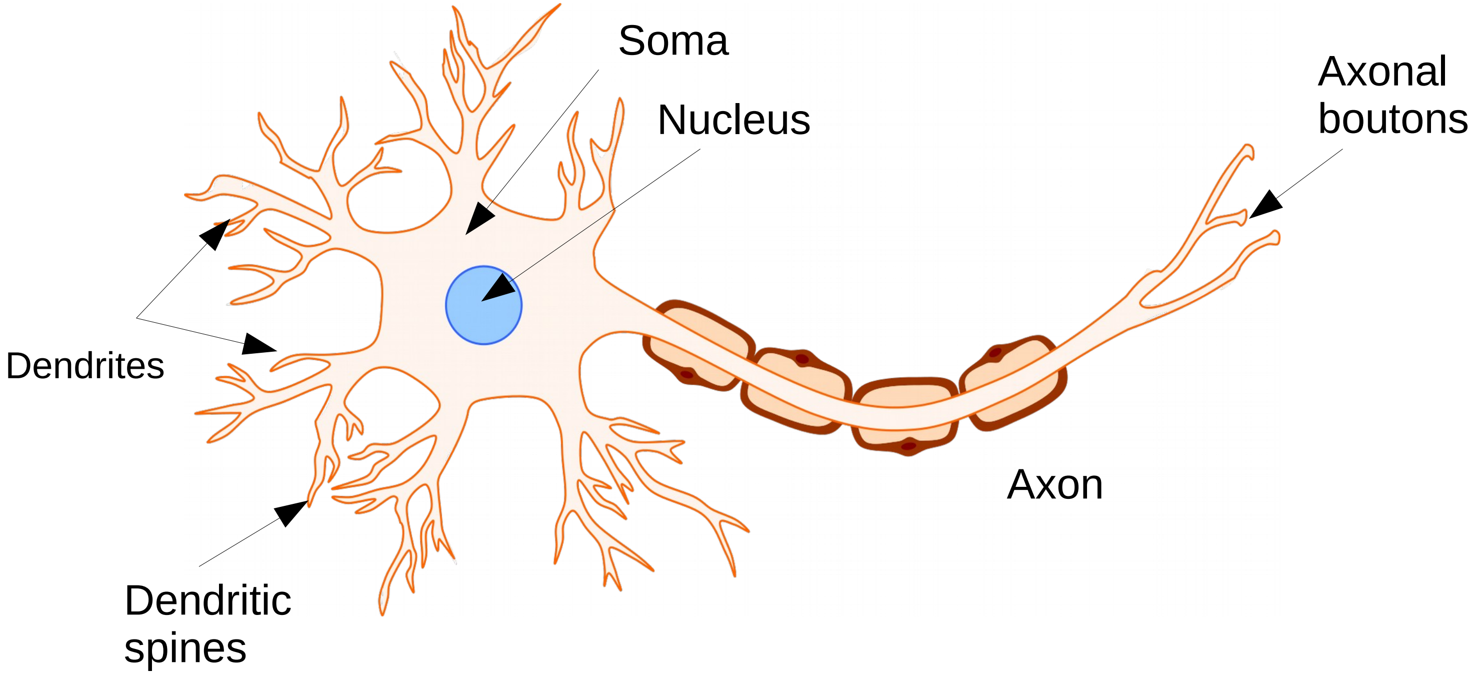
Sebastian Rinke [a], Markus Butz-Ostendorf [b], Marc-André Hermanns [c], Mikaël Naveau [d, 1], Felix Wolf [a]

CONCLUSIONS

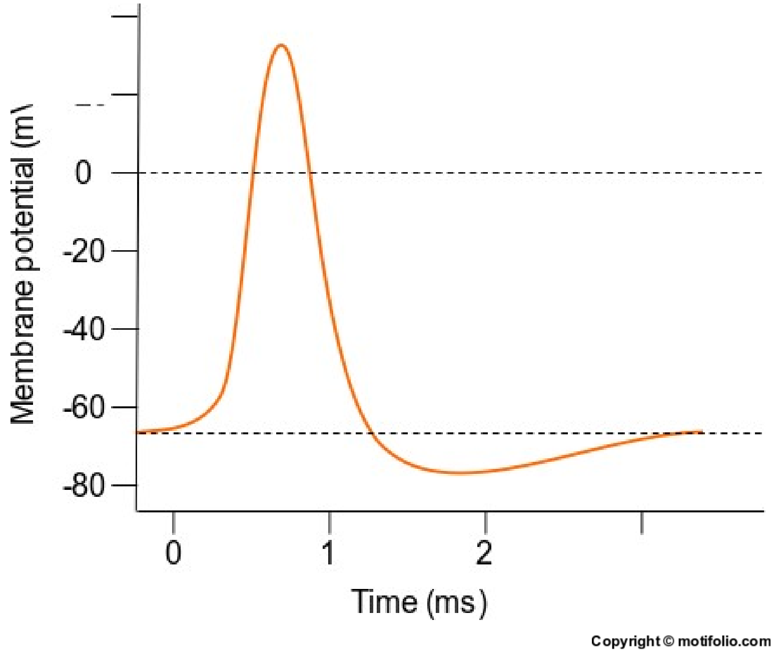
- Potential as new way to solve problems with a brain inspired algorithm



INTRODUCTION TO NEUROSCIENCE CONCEPTS: NEURONAL STRUCTURE

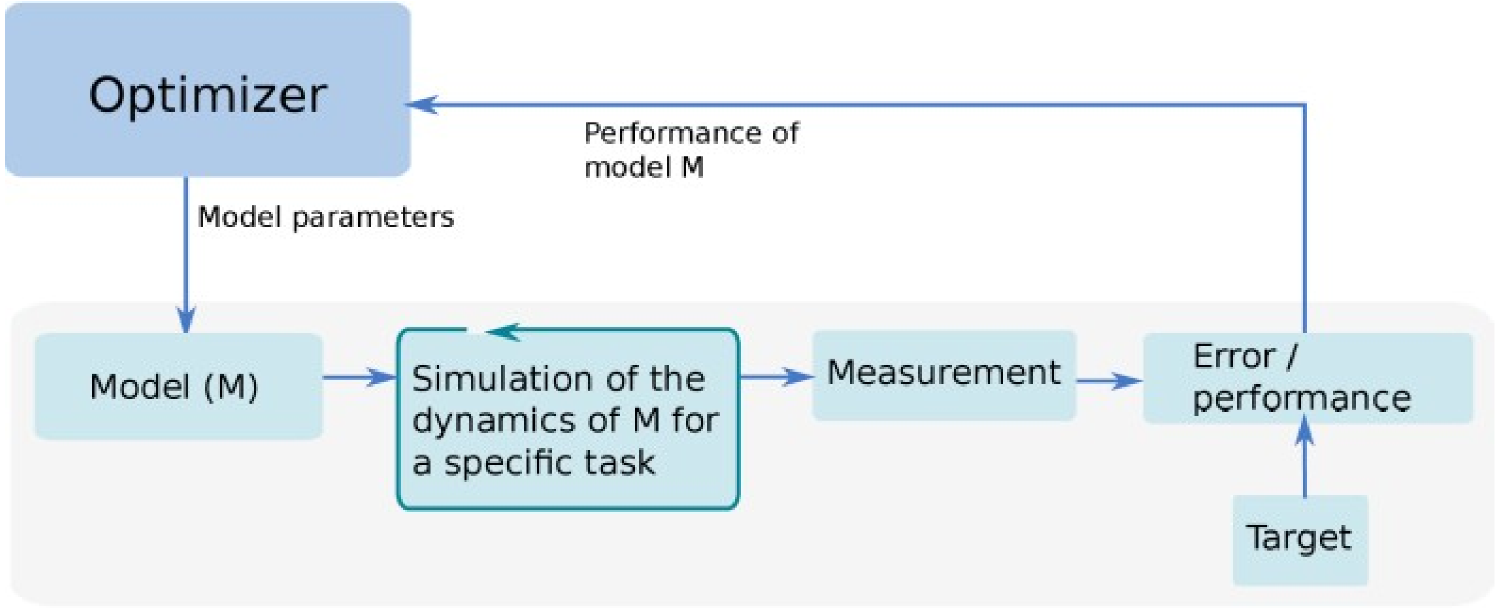


Action potential



OPTIMIZING MODELS TO FIT EXPERIMENTAL DATA

How do we search vast parameter spaces?



- Models based on sets of differential equations
- Fit to match expected behavior or experimental data
- Search vast parameter spaces