SINGLE NEURON MODEL IN CORTICAL CONTEXT

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NeuroMat Seminar (virtual)

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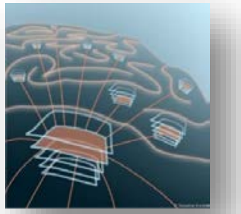


Human Brain Project

EBRAINS

JÜLICH Forschungszentrum

Partially supported by the European Human Brain Project (HBP)

ABSTRACT

In the preparation of the 2023 IHP thematic program "Random Processes in the Brain" the question came up how relevant the single-neuron model is for cortical dynamics and function. Given the plethora of single-neuron models available, insight into their differential effects on the network level would give theoreticians guidance on which model to choose for which research question. The purpose of this talk is to outline a small project approaching this question which could be carried out in the framework of the thematic program in a collaboration of several labs. The talk first presents a well-studied full-density network model of the cortical microcircuit as a suitable reference network. The proposal is to replace the original single-neuron model by alternative common single-neuron models and to quantify the impact on the network level. For this purpose the presentation reviews a range of common single-neuron models as candidates and a set of measures like firing rate, irregularity, and the power spectrum. It seems achievable that all relevant neuron models can be formulated in the domain-specific language NESTML and data analysis be carried out in the Elephant framework such that a reproducible digital workflow for the project can be constructed. A minimal scope of the investigation covers a static network in a stationary state. However, there are indications in the literature that the conventional constraints on network activity are weak. Furthermore, hypotheses on the function of the cortical microcircuit depend on the transient interaction between cortical layers, synaptic plasticity, and a separation of dendritic and somatic compartments. Therefore, we need to carefully debate how the scope of an initial exploration can usefully be restricted.

OUTLINE

- model of cortical microcircuit as building block
- critique of network model
- open network models as research platforms
- benchmark for neuromorphic computers
- potential network model extensions
- alternative single neuron models
- metrics of network activity
- limitations of predictive power of network model
- beyond the stationary state
- potential project design
- references

PEOPLE

this review

- Sacha van Albada
- Simon Essink
- Moritz Helias
- Cordula Huesgen
- Hanjia Jiang
- Alexander Kleinjohann
- Anno Kurth
- Renan Shimoura
- Tom Tetzlaff

nest :: simulated()

- Pooja Babu
- Jochen Eppler
- Steffen Graber
- Tammo Ippen
- Susanne Kunkel
- Anno Kurth
- Charl Linssen
- Jessica Mitchell
- Hakon Mork
- Abigail Morrison
- Hans Ekkehard Plesser
- Jari Pronold
- Jonas Stapmanns
- Dennis Terhorst
- Stine Brekke Vennemo
- …
- Stefan Rotter
- Sebastian Spreizer
- Benjamin Weyers

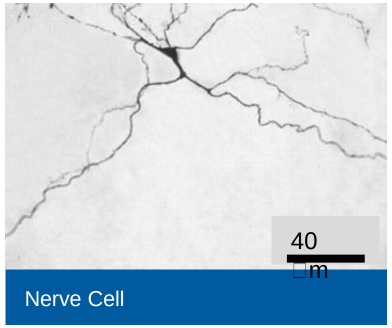
FROM NEURAL COMPUTATION TO NEUROMORPHIC COMPUTING

- modern AI (Deep Learning) excels on tasks with many examples
- but, brains are unbeaten on many natural tasks:
  - learning from few examples
  - eye-hand coordination (robotics)

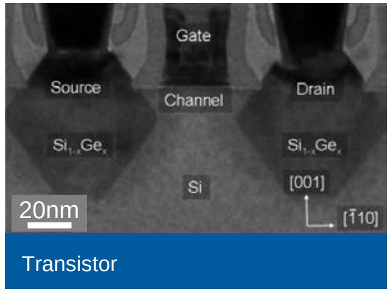
understanding brain function

- modern AI algorithms are optimized for present day computers
- dramatic difference in energy consumption:
  - brain: 20 W
  - supercomputer: 2 Megawatt (2,000,000 W)
- end of Moore's law

novel computers using principles of the brain



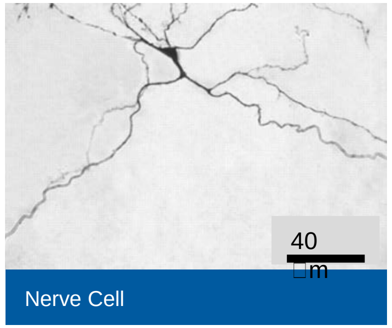
Lin et al. (2003) J Neurophys



http://www.imaging-git.com

DYNAMIC ELEMENTS ARE NOT THE PROBLEM

- size of neurons: 10-100 µm
- size of modern transistor: 10-100 nm
  - in 2d, 1 million transistors fit into 1 neuron
- number of neurons in cortex: about 10^{10}
- number of transistors in modern microprocessor
  (Intel Broadwell-E5): about 10^{10}



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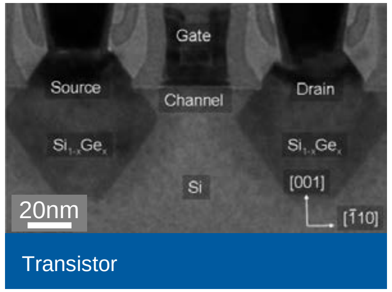


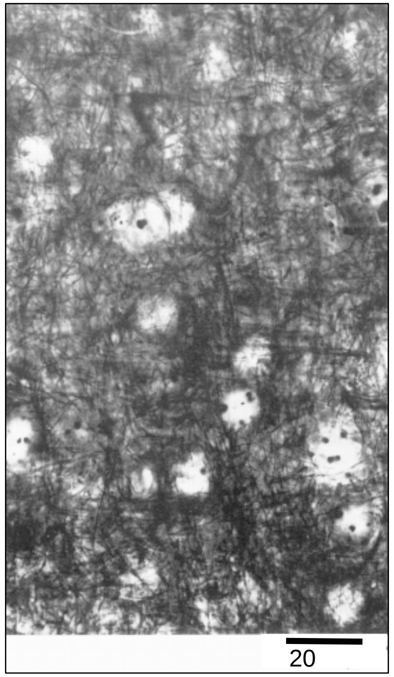
http://www.imaging-git.com

CHALLENGE IS DENSITY OF WIRING

- 100,000 neurons per cubic millimeter
- 10,000 synapses per neuron
- 3 km of axons per cubic millimeter
- densely packed
- in this volume all neurons touch

- difficulty:

  realization of natural density connectivity

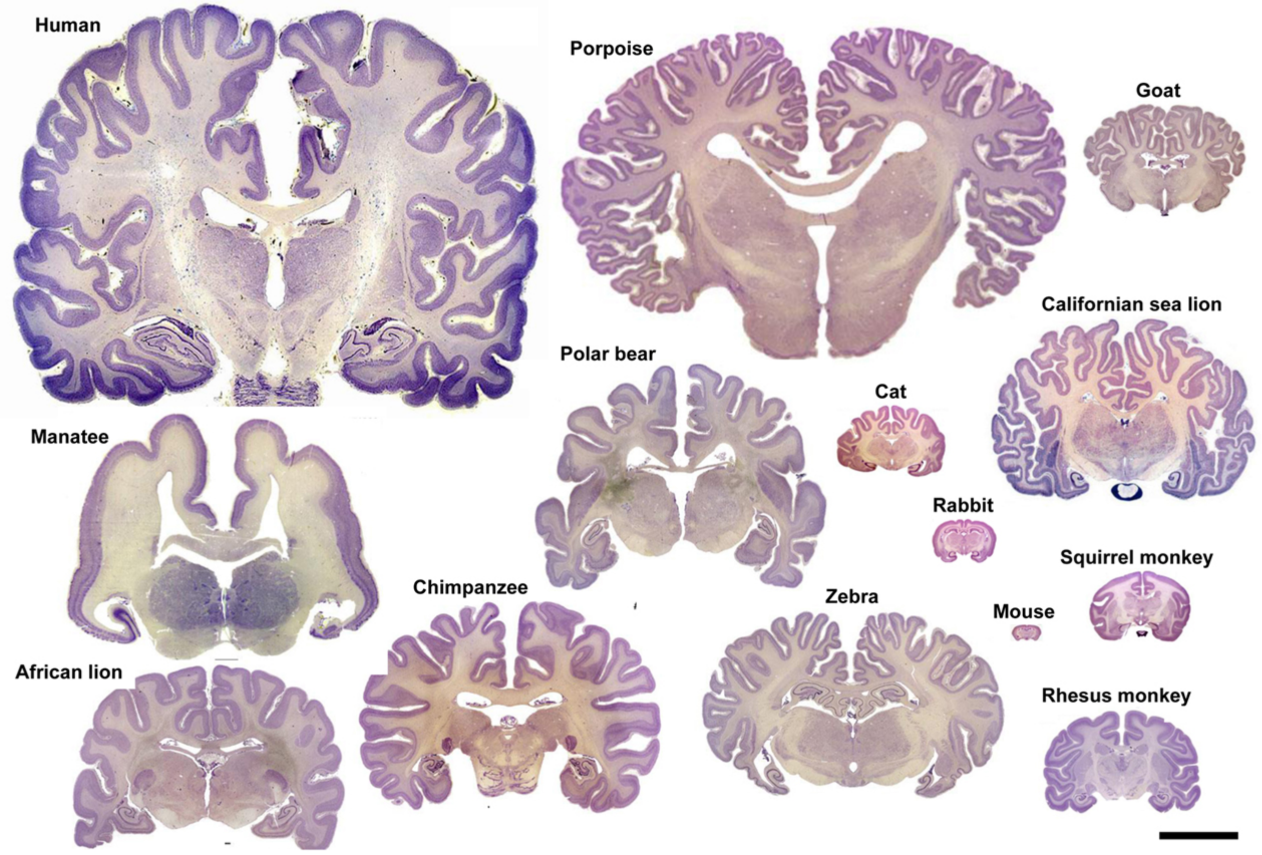


Braitenberg & Schuez (1991)

NEOCORTEX

a universal computational architecture

- nature employs the same local circuitry (microcircuit) across:
  - different species (mouse, ..., men)
  - different functional areas (visual, auditory, …, motor)

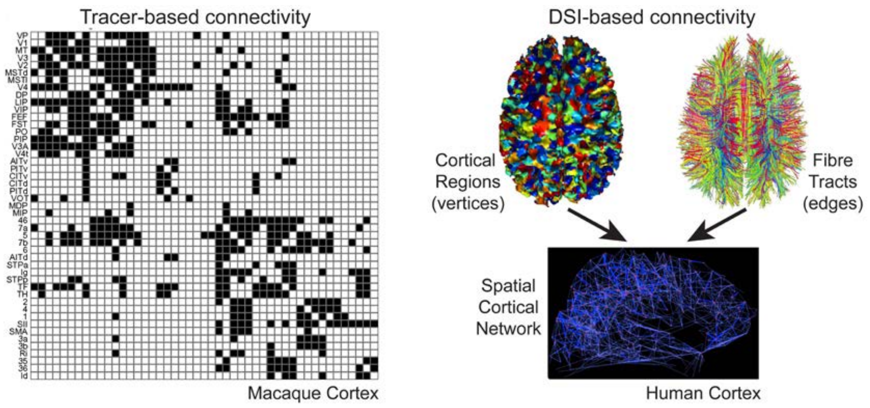


(DeFelipe, 2011)

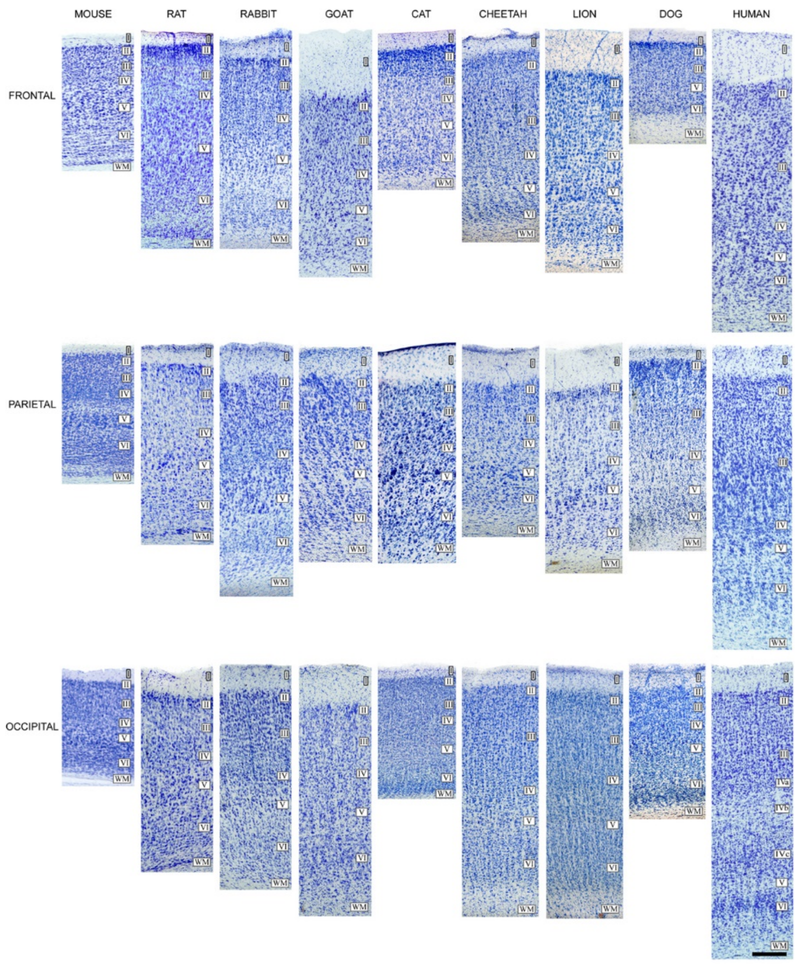
NEOCORTEX

a universal computational architecture

- similarities more striking than differences
- functional specificity arises from
  - specific connectivity between
    - subcortical and cortical areas
    - cortical areas

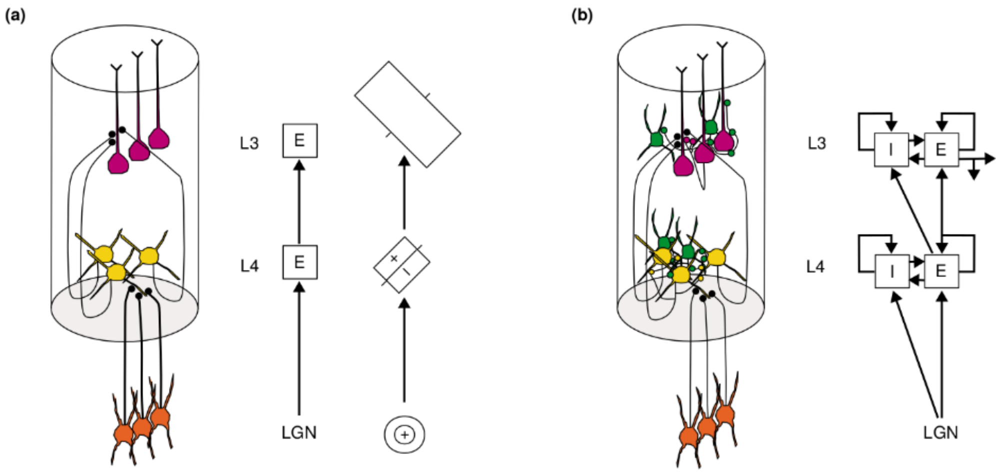


(Budd & Kisvarday, 2012)



(DeFelipe, 2011)

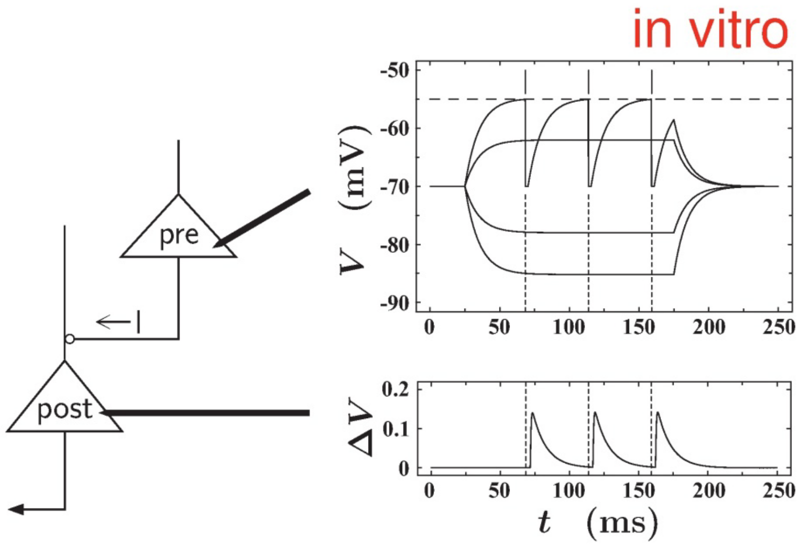
HISTORY OF CORTICAL MICROCIRCUITS

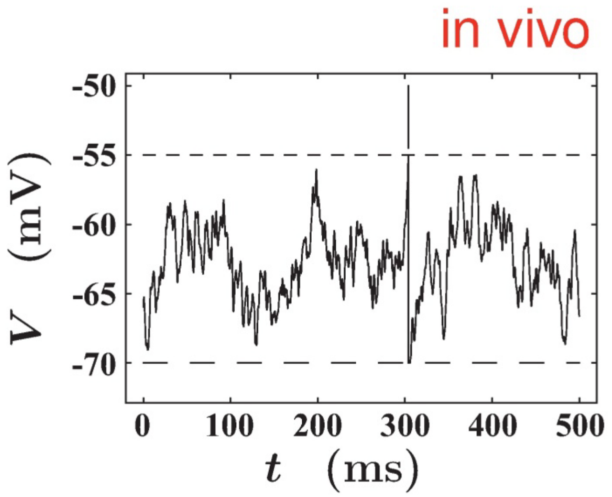


Martin 2002 illustrating the idea of Hubel & Wiesel (a) and the importance of local recurrence (b)

- “canonical” cortical circuits Douglas & Martin 2004
- model of sleep and wakefulness with interactions between multiple microcircuits Hill & Tononi 2005
- single-column thalamocortical network model exhibiting gamma oscillations, sleep spindles, and epileptogenic bursts Traub et al. 2005
- laminar information processing in a computational model with data-based connectivity Haeusler & Maass 2006
- canonical microcircuits for predictive coding Bastos et al. 2012
- stochastic computations in cortical microcircuit models Habenschuss et al. 2013
- microcircuits with minicolumnar organization and attractor dynamics e.g., Lansner et al. 2013
- full-scale point neuron network model with rule-based connectivity Potjans & Diesmann 2014
- full-scale data-based multi-compartment neuron network model Markram et al. 2015

INTERACTIONS BETWEEN NEURONS





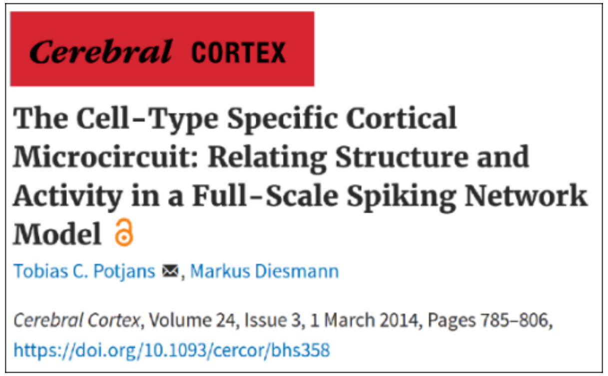
- current injection into pre-synaptic neuron causes excursions of membrane potential
- supra-threshold value causes spike transmitted to post-synaptic neuron
- post-synaptic neuron responds with small excursion of potential after delay
- inhibitory neurons (20%) cause negative excursion

- each neuron receives input from 10,000 other neurons
- causing large fluctuations of membrane potential
- emission rate of 1 to 10 spikes per second

LOCAL CORTICAL MICROCIRCUIT

taking into account layer and neuron-type specific connectivity
is sufficient to reproduce experimentally observed:

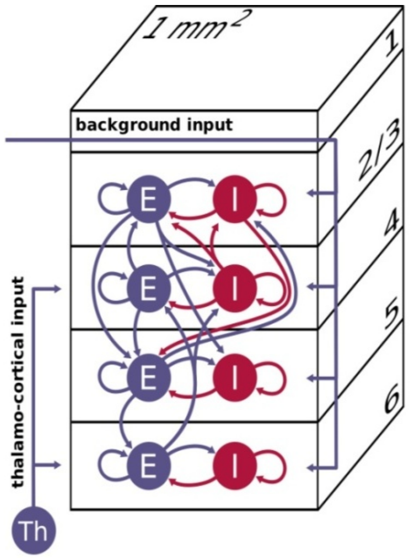
- asynchronous-irregular spiking of neurons
- higher spike rate of inhibitory neurons
- correct distribution of spike rates across layers
- integrates knowledge of more than 50 experimental papers


Cerebral CORTEX

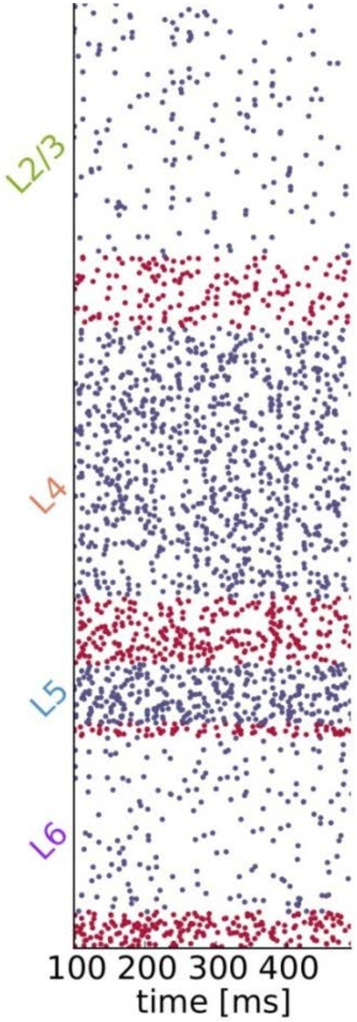
The Cell-Type Specific Cortical Microcircuit: Relating Structure and Activity in a Full-Scale Spiking Network Model

Tobias C. Potjans, Markus Diesmann

Cerebral Cortex, Volume 24, Issue 3, 1 March 2014, Pages 785–806,
https://doi.org/10.1093/cercor/bhs358



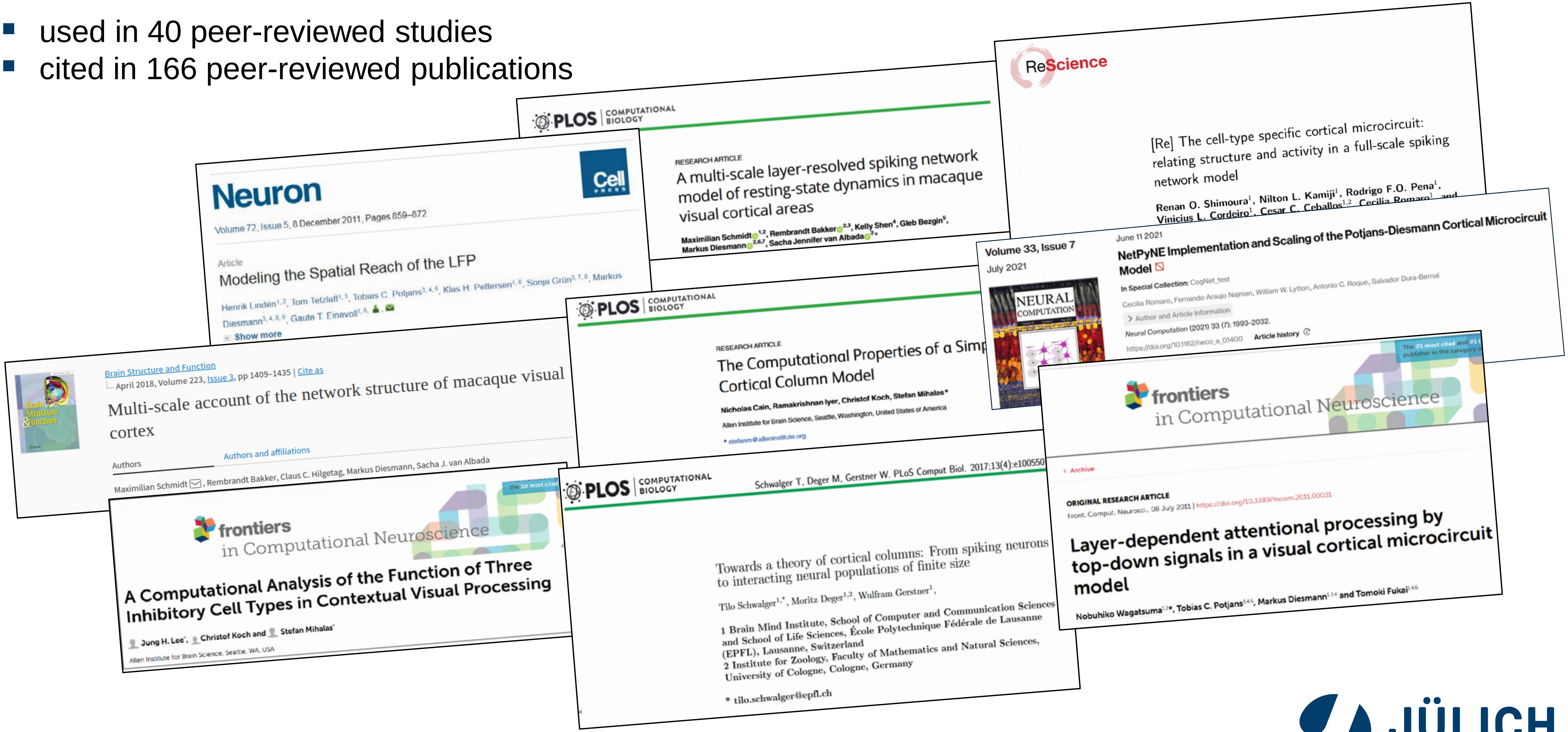
10^5 neurons
10^9 synapses



available at:
www.opensourcebrain.org

BUILDING BLOCK FOR FURTHER STUDIES

- used in 40 peer-reviewed studies
- cited in 166 peer-reviewed publications



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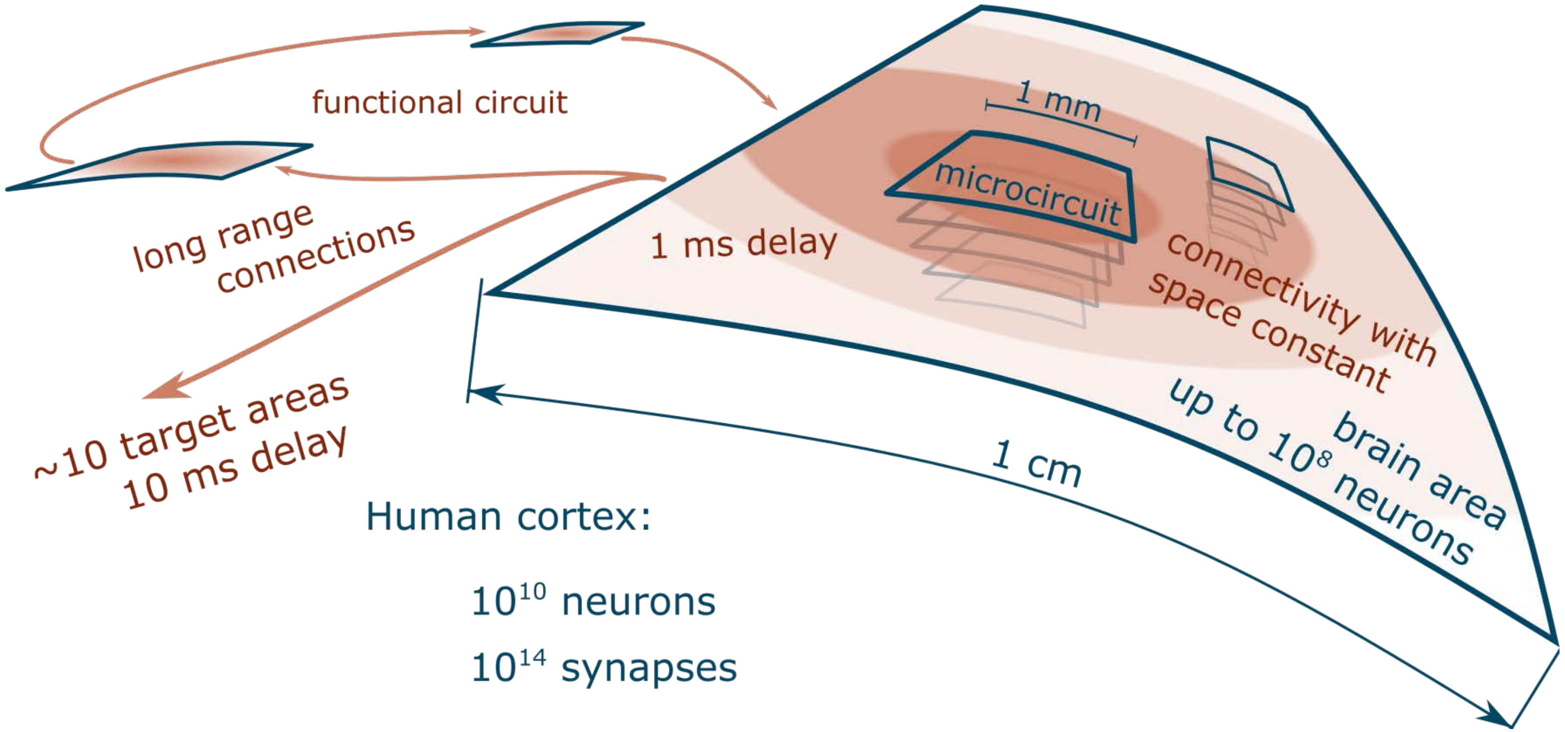
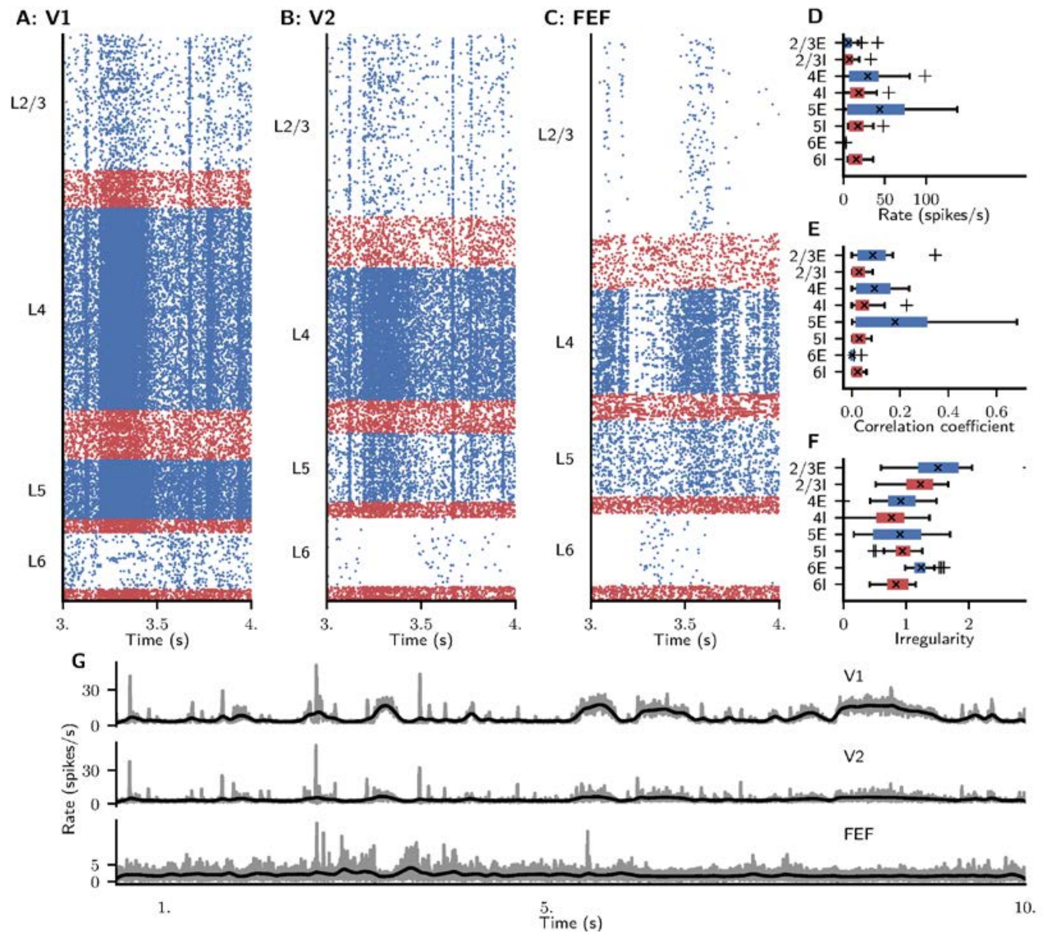
CRITIQUE OF LOCAL NETWORK MODEL

a network of networks with at least three levels of organization:



- neurons in local microcircuit models are missing 50% of synapses
- e.g., power spectrum shows discrepancies, slow oscillations missing
- solution by taking brain-scale anatomy into account

SLOW FLUCTUATIONS THROUGH METASTABILITY



dynamical slowing near instability

- Schmidt et al. (2018) Brain Struct Func
- Schmidt et al. (2018) PLOS Comput Biol

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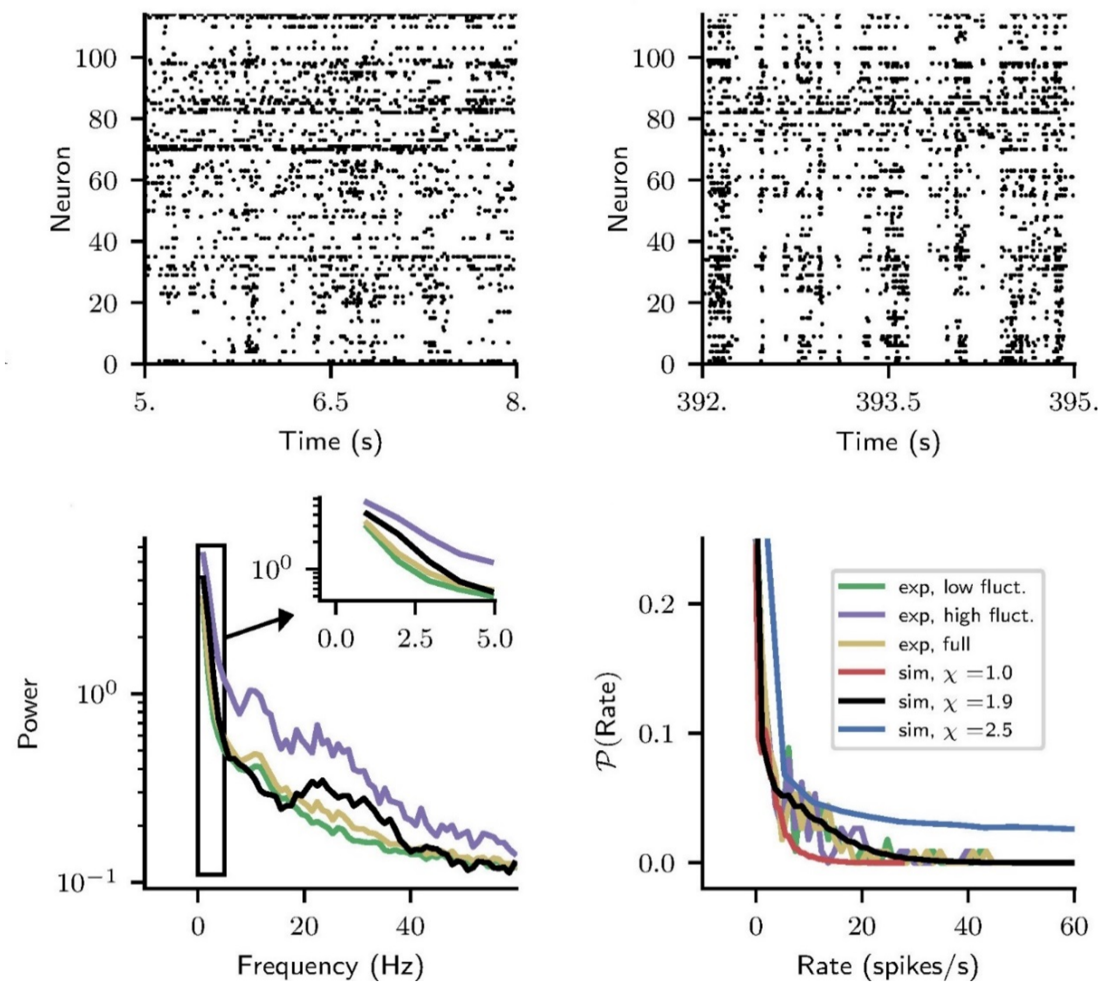
V1 SPIKING STATISTICS



data of Chu et al. (2014)
from all layers in V1

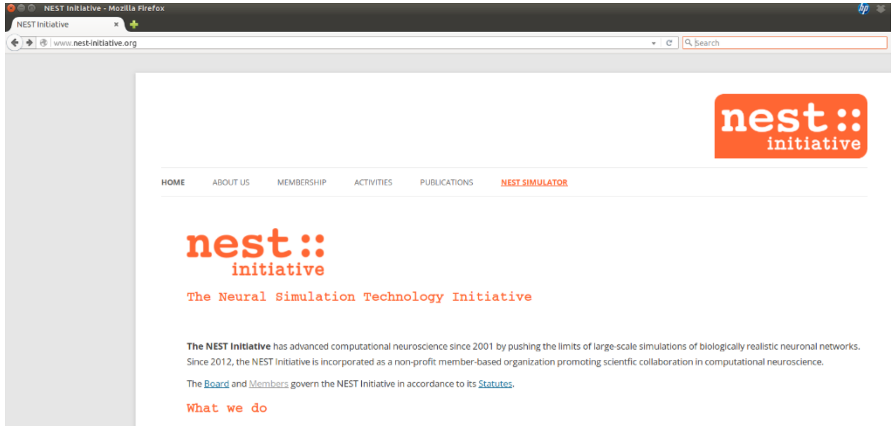
experiment
simulation

simulations with
weak (red), medium
(black/gray), strong (blue)
cortico-cortical interactions

comparison of power spectra and rate distributions between simulation and experiment

SIMULATION TECHNOLOGY: THE NEST INITIATIVE

collaborative effort and community building



network simulator of Human Brain Project

Major goals:

systematically publish new simulation technology

produce public releases under GPL

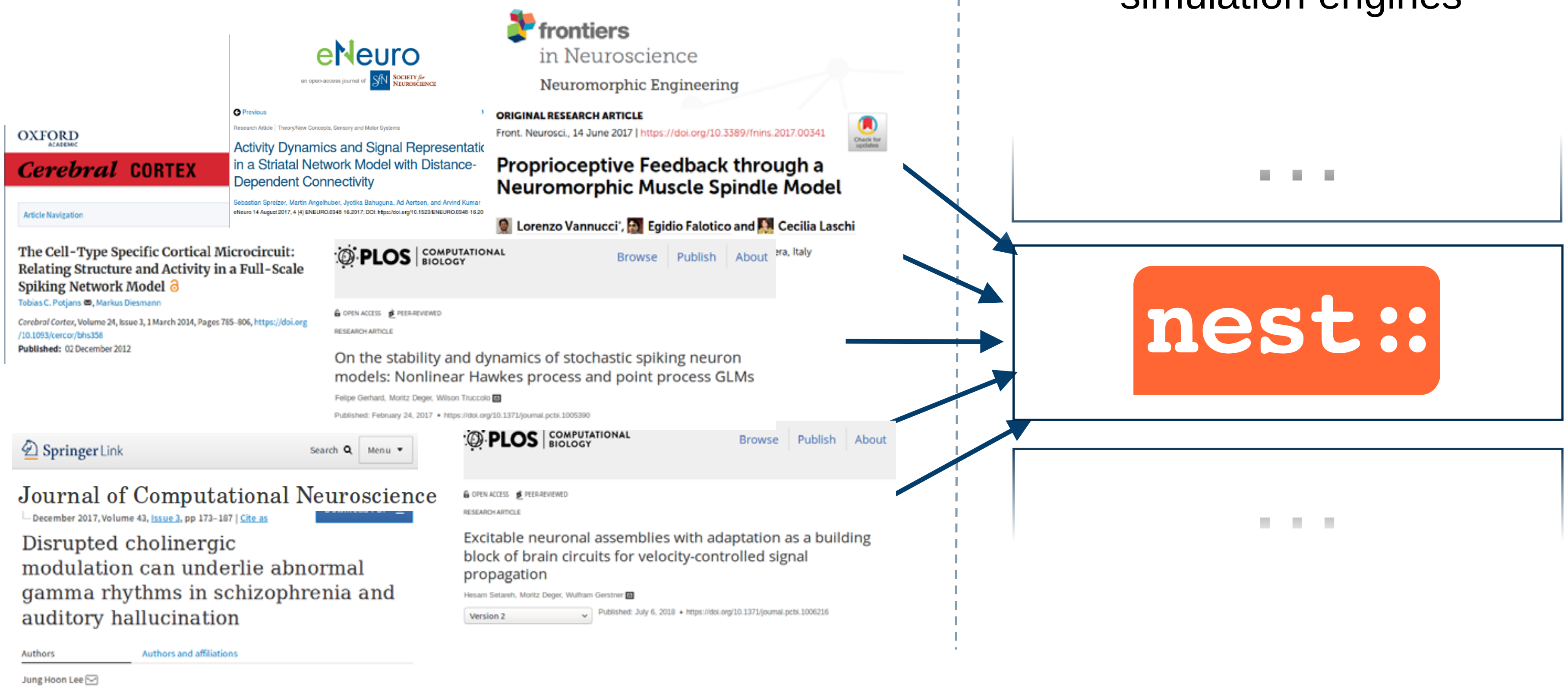
- origins in 1994, registered society (since 2012)
- teaching at international tutorials and advanced courses:
  - Okinawa Computational Neuroscience Course OCNC, OIST, Japan
  - Latin American School on Computational Neuroscience LASCON, Brazil
  - annual NEST Conference, Ås, Norway
  - Computational Neuroscience CNS by OCNS, Melbourne (virtual)

MANY MODELS – ONE SIMULATION ENGINE

concrete mathematical model

JOINT PLATFORM

simulation engines



- enables use of validated and optimized simulation code

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FOR SOME MODELS – SEVERAL SIMULATION ENGINES

concrete mathematical model

Cerebral CORTEX

Article Navigation

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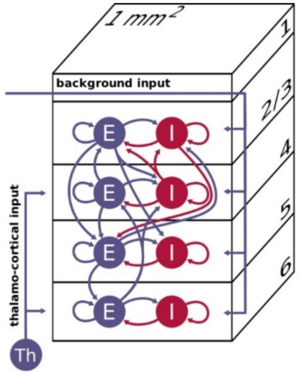
Cerebral Cortex, Volume 24, Issue 3, 1 March 2014, Pages 785–806, https://doi.org/10.1093/cercor/bhs358

Published: 02 December 2012



PyNN

JOINT PLATFORM

simulation engines

nest::

NEURON

SpiNNaker
Biologically Inspired Massively Parallel Architectures

...

- enables cross-validation of results at highest level

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NEUROMORPHIC COMPUTING

- idea to build computers according to principles of the brain

BrainScaleS, Heidelberg

SpiNNaker, Manchester

Human Brain Project

SP9

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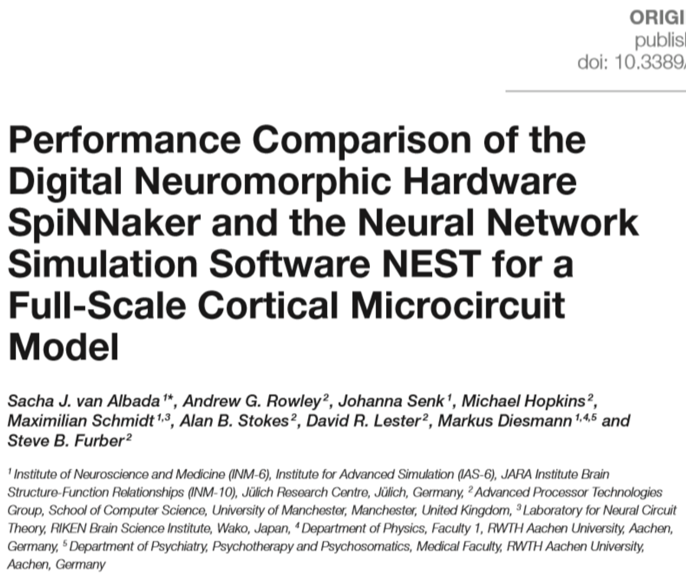
BENCHMARKING OF NEUROMORPHIC SYSTEMS



ORIGINAL RESEARCH
published: 23 May 2018
doi: 10.3389/fnins.2018.00291

Performance Comparison of the Digital Neuromorphic Hardware SpiNNaker and the Neural Network Simulation Software NEST for a Full-Scale Cortical Microcircuit Model

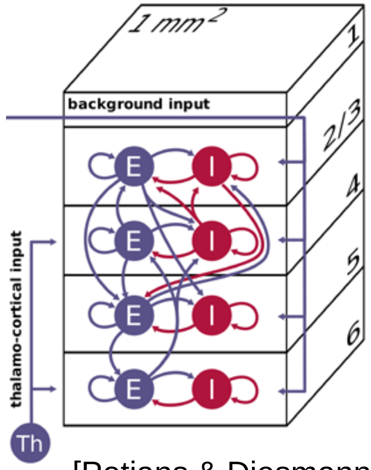
Sacha J. van Albada[1], Andrew G. Rowley[2], Johanna Senk[1], Michael Hopkins[2], Maximilian Schmidt[1,3], Alan B. Stokes[2], David R. Lester[2], Markus Diesmann[1,4,5] and Steve B. Furber[2]*

[1] Institute of Neuroscience and Medicine (INM-6), Institute for Advanced Simulation (IAS-6), JARA Institute Brain Structure-Function Relationships (INM-10), Jülich Research Centre, Jülich, Germany, [2] Advanced Processor Technologies Group, School of Computer Science, University of Manchester, Manchester, United Kingdom, [3] Laboratory for Neural Circuit Theory, RIKEN Brain Science Institute, Wako, Japan, [4] Department of Physics, Faculty 1, RWTH Aachen University, Aachen, Germany, [5] Department of Psychiatry, Psychotherapy and Psychosomatics, Medical Faculty, RWTH Aachen University, Aachen, Germany

Human Brain Project

- 4 year project
- started in EU BrainScaleS
- close collaboration with Manchester
- full-density model on SpiNNaker achieves real time

  (Rhodes et al. (2019), Phil Trans R Soc A, 378:20190160)



[Potjans & Diesmann (2014) Cerebral Cortex]

nest :: simulated()

PyNN

[2022-05-17]

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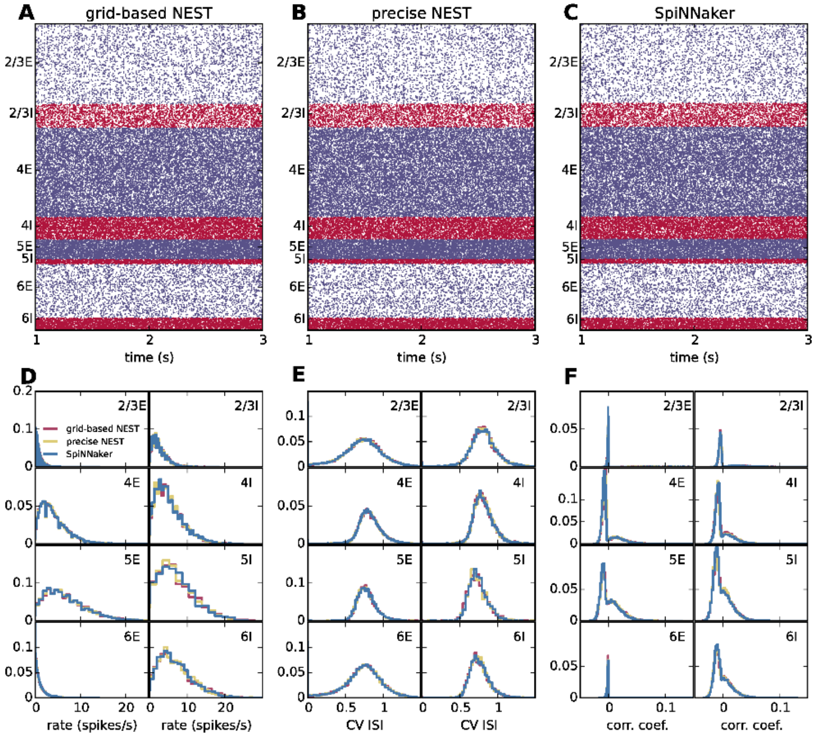
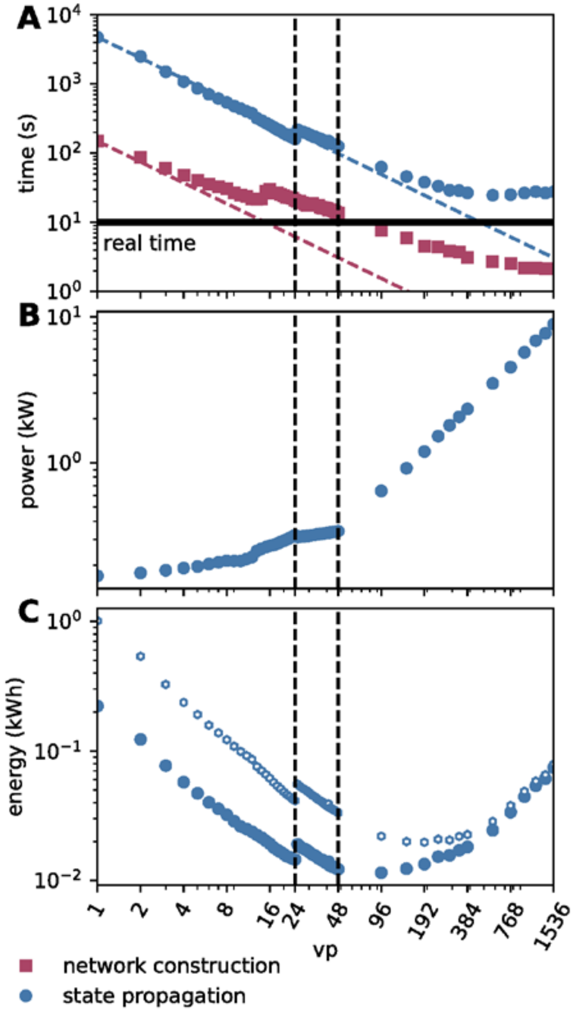
ACCURACY AND TIME- AND ENERGY-TO-SOLUTION





- runs cortical microcircuit accurately
- largest network on SpiNNaker
- breakthrough: larger networks less dense
- uses less than 1% of SpiNNaker system

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SIMULATION TECHNOLOGY

ORIGINAL RESEARCH
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Sacha J. van Albada… Maximilian Schmidt… Steve B. Furber[2]

[1] Institute of Neuroscience an… Structure-Function Relations… Group, School of Computer… Theory, RIKEN Brain Science… Germany, [5] Department of Ps… Aachen, Germany

GPUs Outperform Current HPC and Neuromorphic Solutions in Terms of Speed and Energy When Simulating a Highly-Connected Cortica…

James C. Knight and Thomas Nowotny*

Centre for Computational Neuroscience and Robotics, School of Engineering and Inf… United Kingdom

frontiers in Neuroscience

ORIGINAL RESEARCH
published: 20 January 2022
doi: 10.3389/fnins.2021.728460

Simulating the Cortical Microcircuit Significantly Faster Than Real Time on the IBM INC-3000 Neural Supercomputer

Arne Heittmann[1], Georgia Psychou[1], Guido Trensch[2], Charles E. Cox[3], Winfried W. Wilcke[3], Markus Diesmann[4,5,6] and Tobias G. Noll[1]*

[1] JARA-Institute Green IT (PGI-10), Jülich Research Centre, Jülich, Germany, [2] Simulation and Data Laboratory Neuroscience, Jülich Supercomputing Centre, Institute for Advanced Simulation, Jülich Research Centre, Jülich, Germany, [3] IBM Research Division, Almaden Research Center, San Jose, CA, United States, [4] Institute of Neuroscience and Medicine (INM-6), Institute for Advanced Simulation (IAS-6), and JARA Institute Brain Structure-Function Relationships (INM-10), Jülich Research Centre, Jülich, Germany, [5] Department of Physics, Faculty 1, RWTH Aachen University, Aachen, Germany, [6] Department of Psychiatry, Psychotherapy and Psychosomatics, School of Medicine, RWTH Aachen University, Aachen, Germany

PHILOSOPHICAL TRANSACTIONS A

rsta.royalsocietypublishing.org

Research

CrossMark click for updates

Article submitted to journal

Subject Areas:
Neuromorphic Computing, Computational Neuroscience, Spiking Neural Networks, Massively-Parallel Computing, Event-Driven Processing

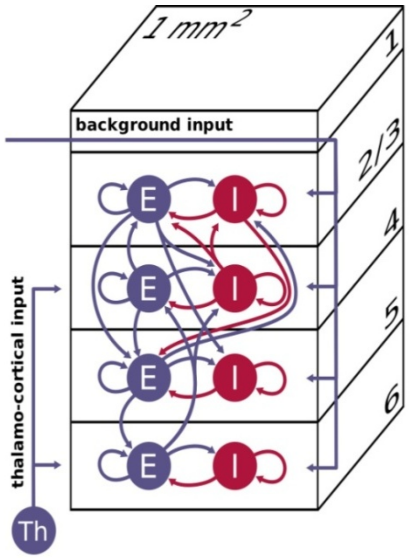
Keywords:
Neuromorphic, SpiNNaker, Cortical

Real-Time Cortical Simulation on Neuromorphic Hardware

Oliver Rhodes[1], Luca Peres[1], Andrew G. D. Rowley[1], Andrew Gait[1], Luis A. Plana[1], Christian Brenninkmeijer[1], and Steve B. Furber[1]

[1] Department of Computer Science, University of Manchester, Manchester, UK

Real-time simulation of a large-scale biologically representative spiking neural network is presented, through the use of a heterogeneous parallelisation scheme and SpiNNaker neuromorphic hardware. A published cortical microcircuit model is used as a benchmark test case, representing $\approx 1\,\mathrm{mm}^2$ of early sensory cortex, containing 77k neurons and 0.3 billion synapses. This is the first true real-time simulation



10^5 neurons
10^9 synapses

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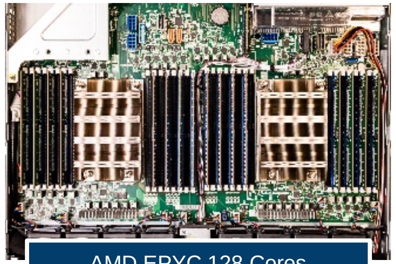
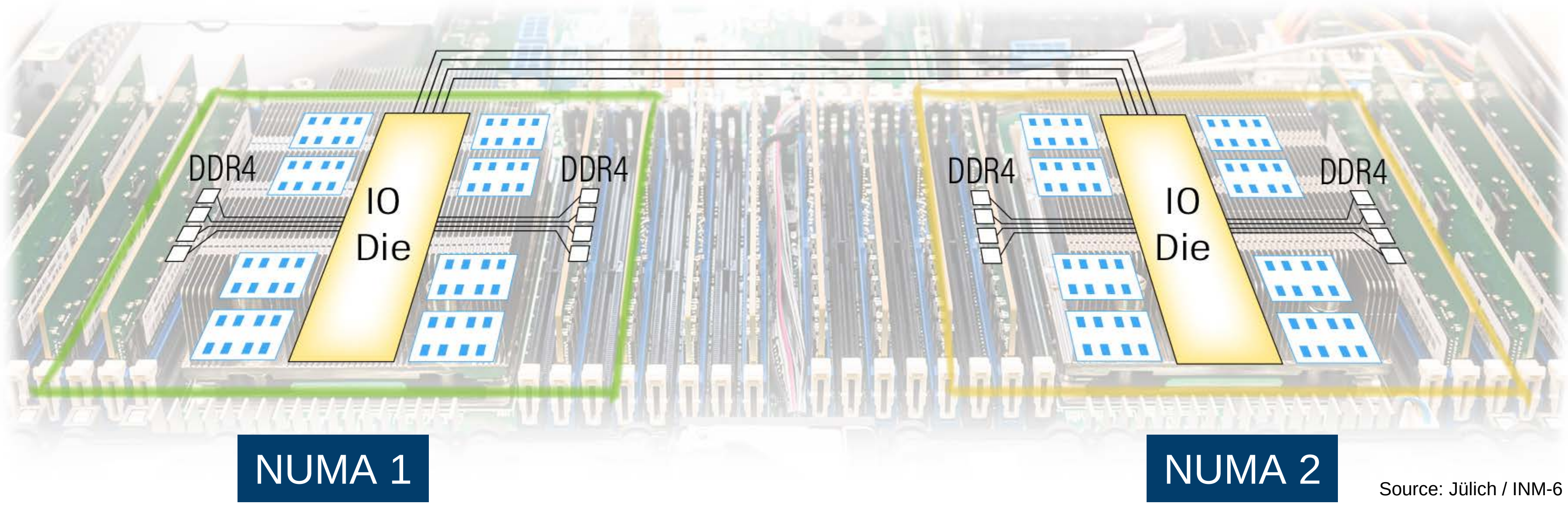
MANY-CORE SYSTEMS


AMD EPYC 128 Cores


IB HDR100 Direct Link

- dual socket AMD EPYC Rome 7702: 128 cores, 2GHz, 256GB RAM
- 2 nodes, IB HDR 100 link



Source: Jülich / INM-6

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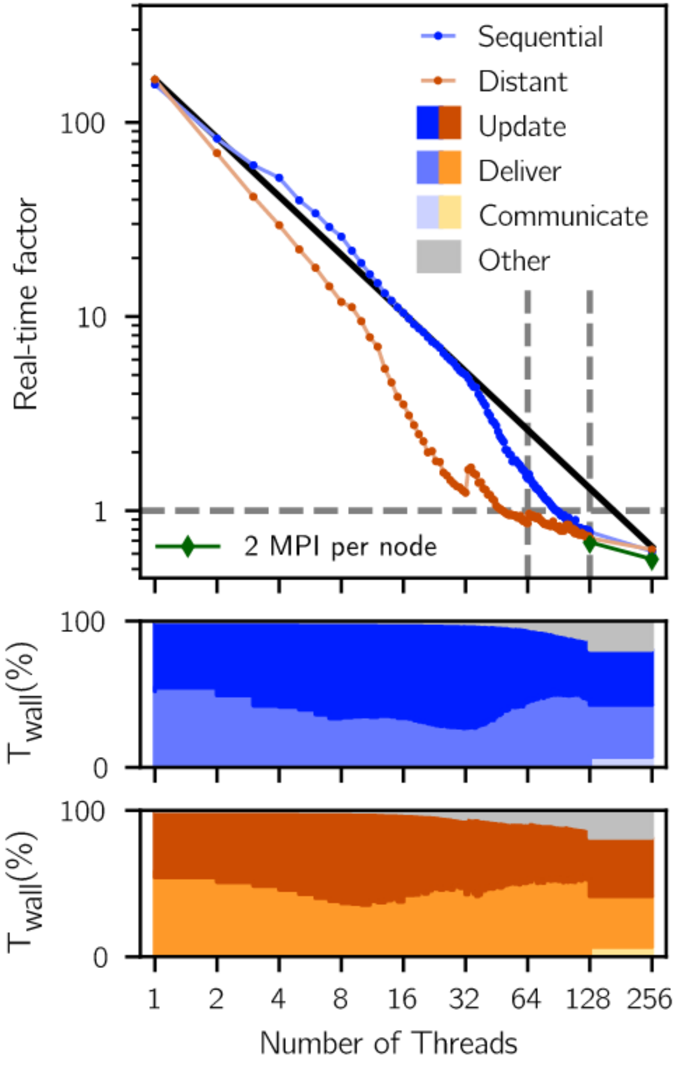
REACHING REAL TIME

- Run cortical microcircuit with NEST on recent conventional compute node
- Use real-time factor $\frac{T_{\text{wall}}}{T_{\text{model}}}$ to assess performance and measure consumed energy
- Observe super-linear scaling and sub realtime performance on single compute node
- NEST exhibits competitive performance at low energy costs

RTF	$E_{\text{syn-event}}$ (μJ)	References
6.29	4.39	2018, NEST [2]
2.47	9.35	2018, NEST [2]
26.08	0.30	2018, GeNN [3]
1.84	0.47[a]	2018, GeNN [3]
1.00	0.60	2019, SpiNNaker [8]
1.06	—	2021, NeuronGPU [9]
0.70	—	2021, GeNN [10]
0.67	0.33	NEST, AMD EPYC Rome (one node, 2 MPI)
0.53	0.48	NEST, AMD EPYC Rome (two nodes, 4 MPI)

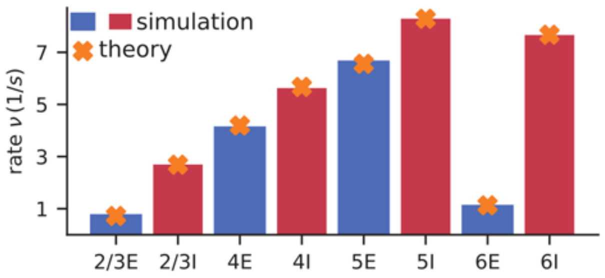
[a]Value estimated by the authors.

Kurth et al. (2022) Neuromorph Comput Eng 2 021001

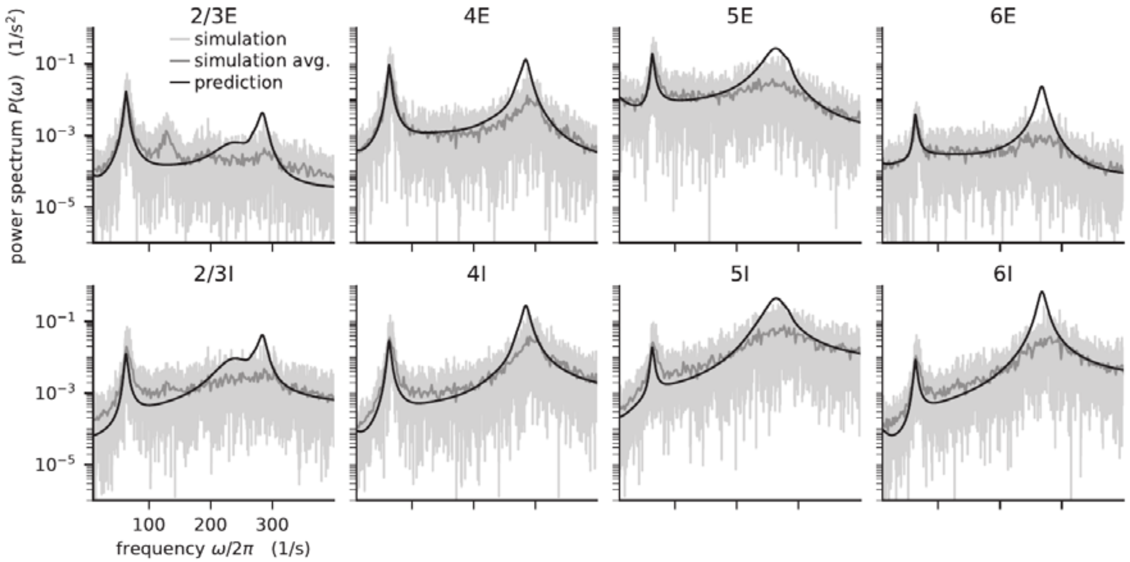


MEAN-FIELD THEORY OF THE MODEL

Firing rates:



Power spectra:



Figures from Layer et al.

- Theory developed in

  Bos, Diesmann, and Helias (2016)
  PLOS CB (https://doi.org/10.1371/journal.pcbi.1005132)

- Implementation available as part of the

  Neuronal Network Mean-field Toolbox NNMT
  (https://github.com/INM-6/nnmt)

  presented in

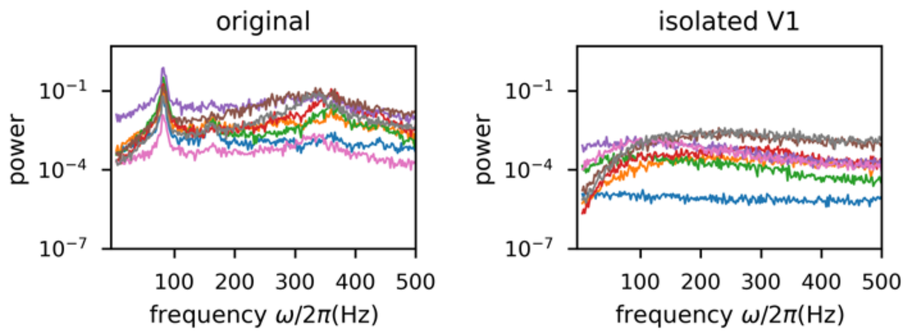
  Layer, Senk, Essink, van Meegen, Bos, and Helias (accepted)
  Frontiers in Neuroinformatics
  (https://doi.org/10.3389/fninf.2022.835657)

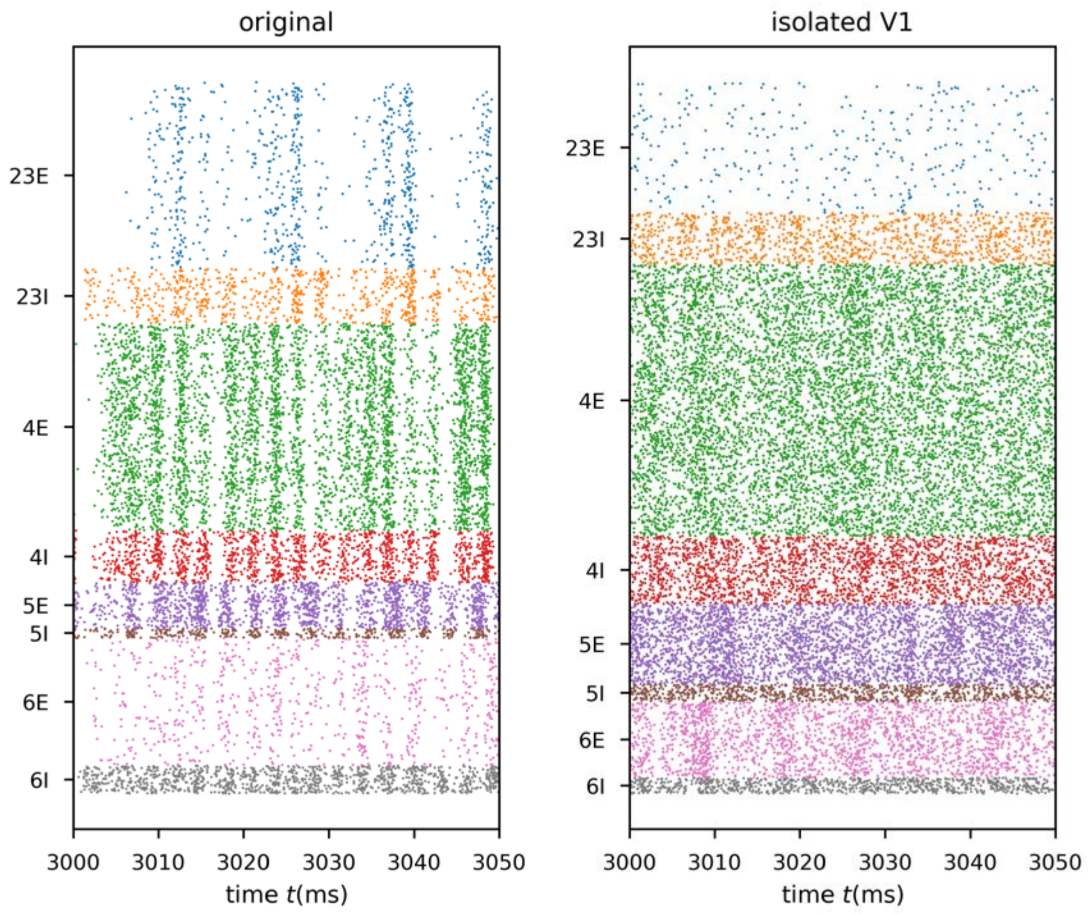
  Preprint available at:
  https://www.biorxiv.org/content/10.1101/2021.12.14.472584v1

CRITIQUE VSTRIPES, ISOLATED V1 AS IMPROVED MODEL

- original microcircuit exhibits population synchronization at ~64Hz and >300 Hz visible as stripes in raster plot and peaks in power spectra

- microcircuit with up-to-date connectivity of isolated V1 from MAM-model does not show oscillatory behavior
  - neuron density increased
  - synaptic density kept constant
    - → **weaker coupling**





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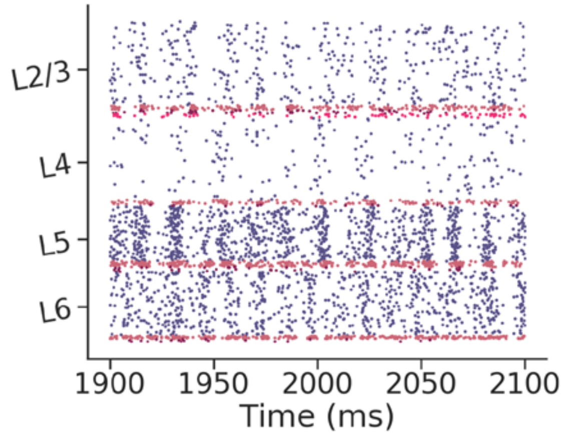
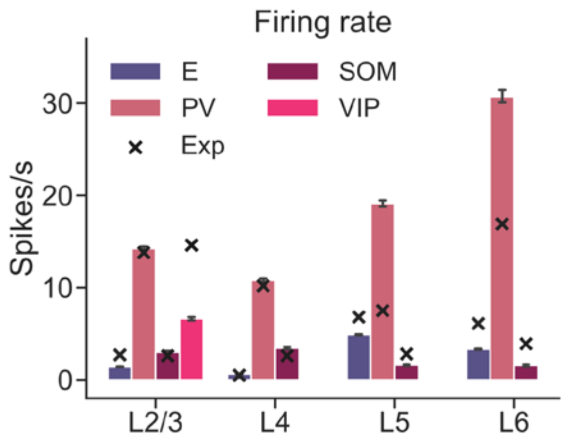
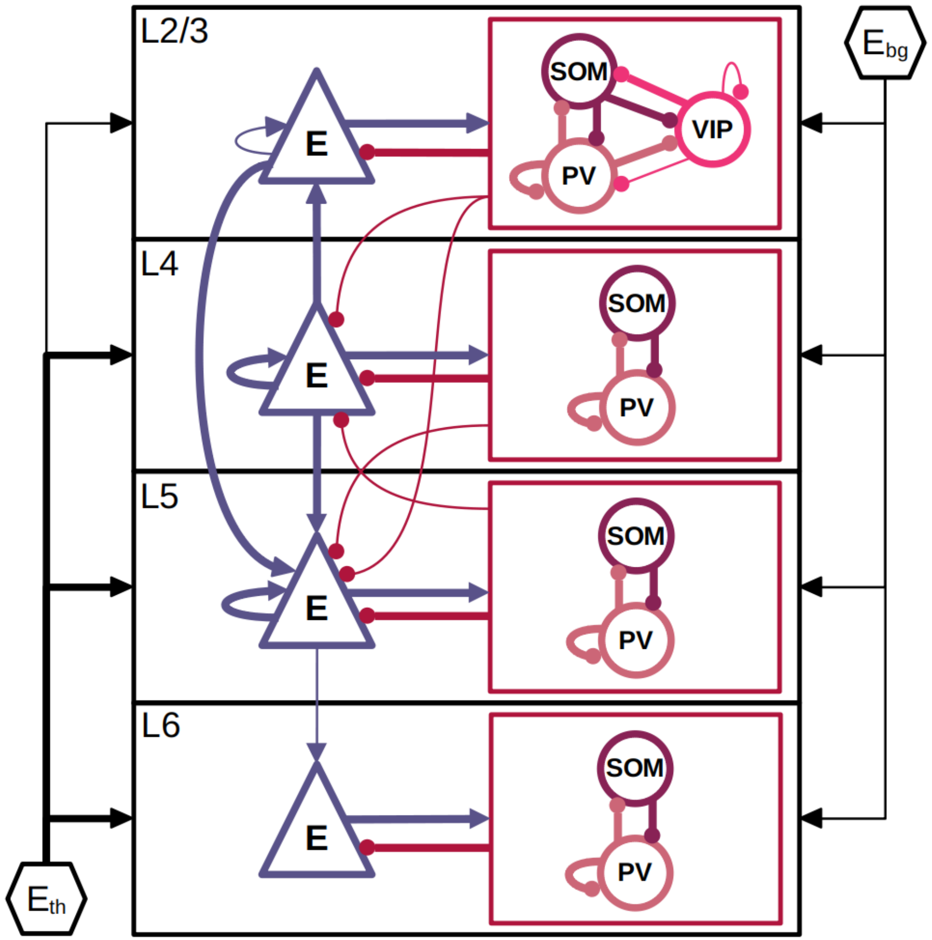
MICROCIRCUIT WITH INHIBITORY CELL TYPES

- Distinct cell properties and connectivity (e.g. different targets and STP)
    - Fast-spiking, non-adapting PV interneurons
    - Facilitating inhibition with SOM interneurons as source
    - Disinhibitory VIP interneurons

Jiang, H. J., & van Albada, S. J. (2019). A Cortical Microcircuit Model with Three Critical Interneuron Groups. In Bernstein Conference Abstract Booklet.







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ALTERNATIVE SINGLE NEURON DYNAMICS

Model	Model name in NEST
LIF coba synapses	iaf_cond_exp
AdEx coba synapses	aeif_cond_exp
HH point-neuron model	hh_psc_alpha
Izhikevich	izhikevich
MAT2	mat2_psc_exp
GLIF class (Allen Institute)	glif_psc
GIF spike-response model (Gerstner)	gif_psc_exp
Galves-Loecherbach	under construction

```
neuron iaf_psc_exp:
  state:
    V_m mV = 0 mV

  equations:
    shape G = exp(-t / tau_syn)
    V_m' = -V_abs / tau_m
           + (I_ext + convolve(G, spikes)) / C_m

  update:
    integrate_odes()
    if V_abs >= V_threshold:
      V_abs = 0 mV
      emit_spike()
```

- many models can be expressed in domain specific language NESTML (Plotnikov et al. 2016)
  - exposes differences in formal definitions
  - supports build-up of a catalogue of models

ALTERNATIVE SINGLE NEURON DYNAMICS

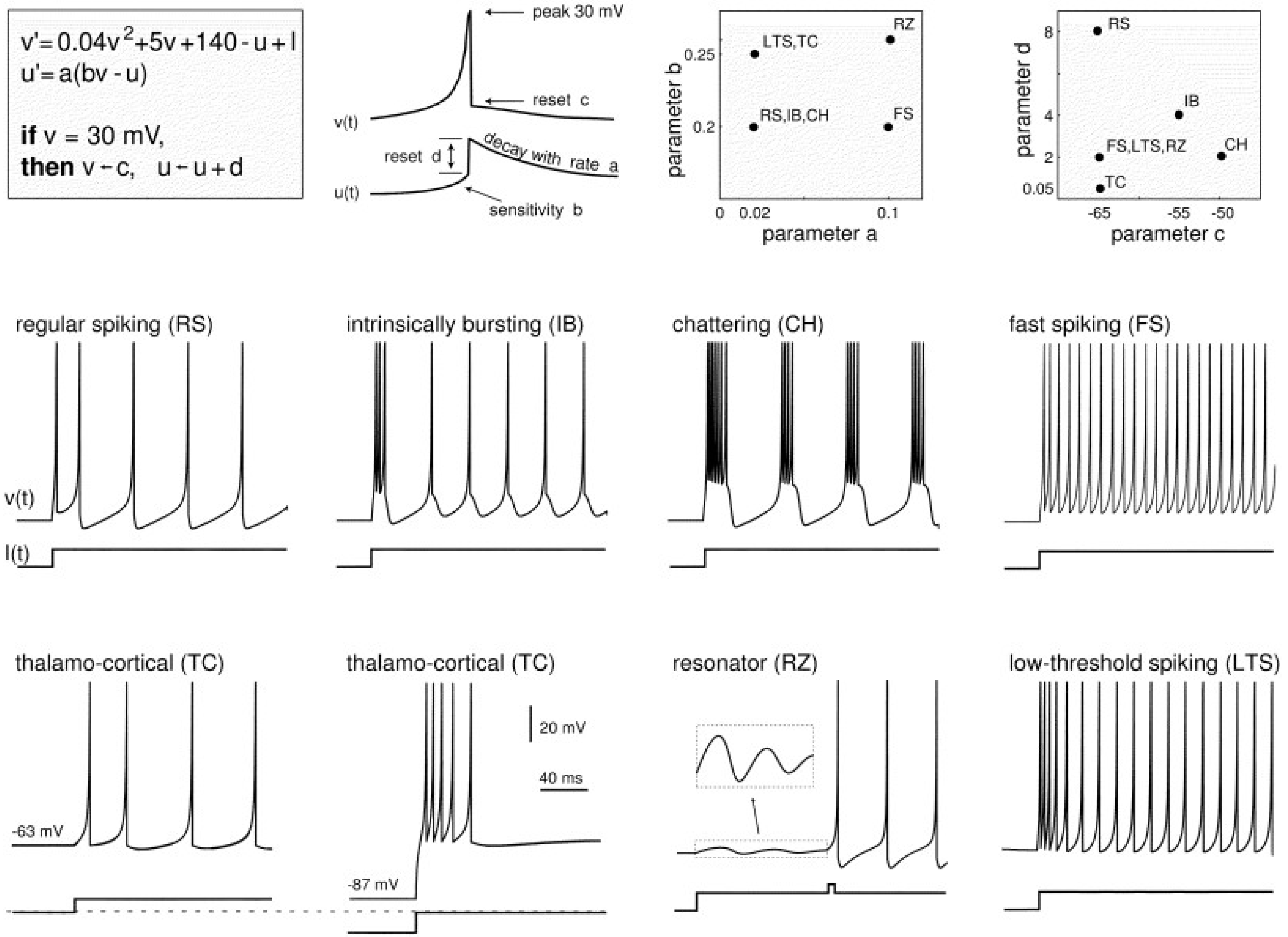
- Izhikevich model

IEEE TRANSACTIONS ON NEURAL NETWORKS, VOL. 14, NO. 6, NOVEMBER 2003

Simple Model of Spiking Neurons

Eugene M. Izhikevich

- Implemented in NEST:
  - izhikevich



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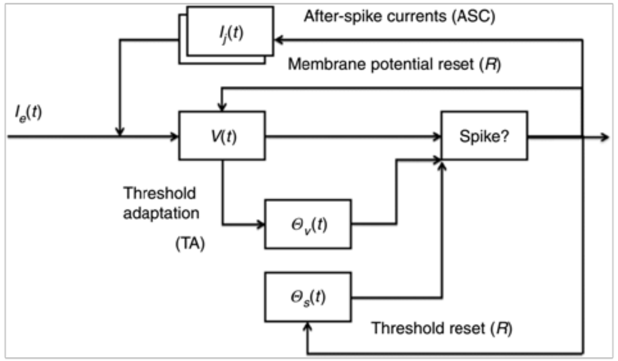
ALTERNATIVE SINGLE NEURON DYNAMICS

- GLIF model

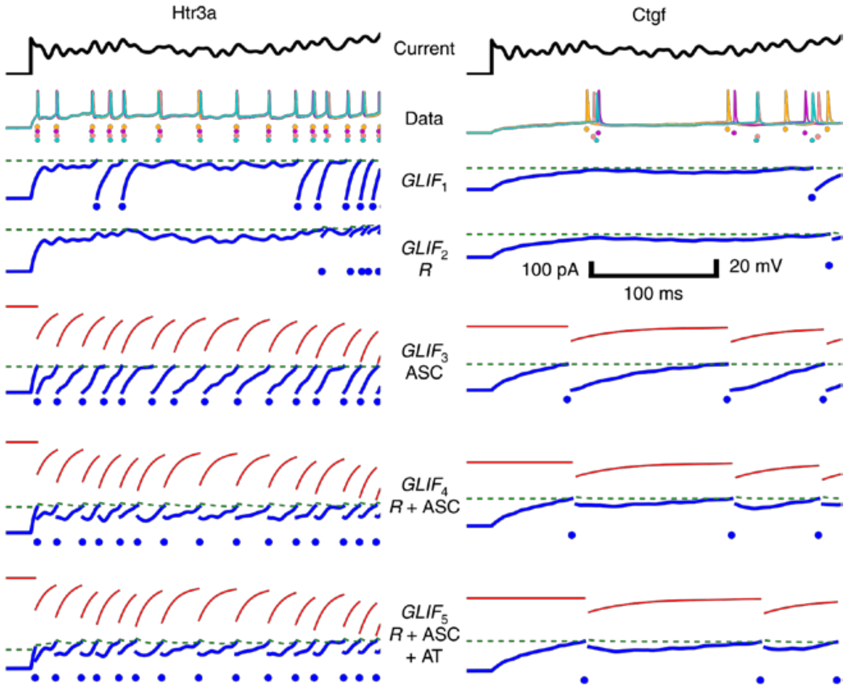
DOI: 10.1038/s41467-017-02717-4 OPEN

Generalized leaky integrate-and-fire models classify multiple neuron types

Corinne Teeter[1], Ramakrishnan Iyer[1], Vilas Menon[1,2], Nathan Gouwens[1], David Feng[1], Jim Berg[1], Aaron Szafer[1], Nicholas Cain[1], Hongkui Zeng[1], Michael Hawrylycz[1], Christof Koch[1] & Stefan Mihalas[1]



- Implemented in NEST:
  - glif_psc
  - glif_cond



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ALTERNATIVE SINGLE NEURON DYNAMICS

- MAT model

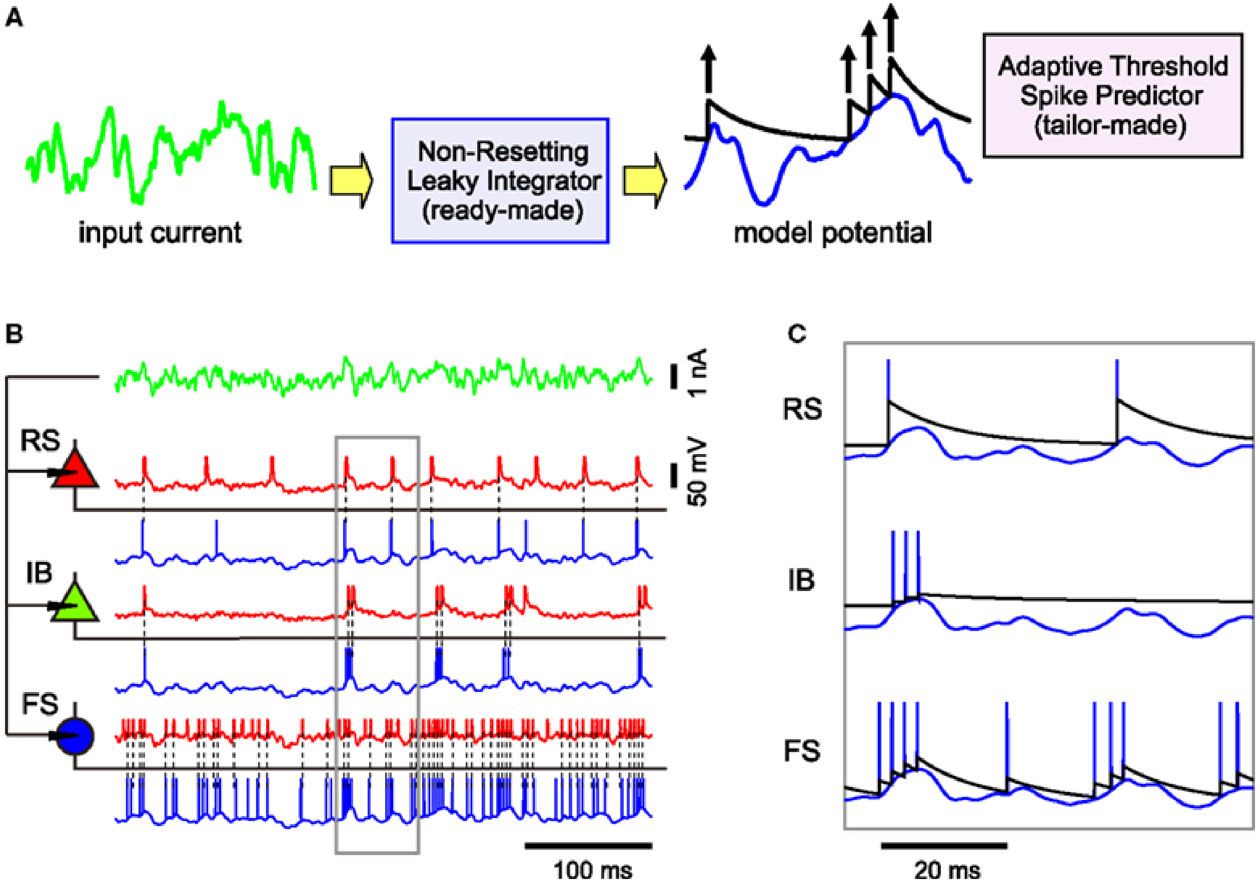
frontiers in
COMPUTATIONAL NEUROSCIENCE

ORIGINAL RESEARCH ARTICLE
published: 30 July 2009
doi: 10.3389/neuro.10.009.2009

Made-to-order spiking neuron model equipped with a multi-timescale adaptive threshold

Ryota Kobayashi[1†], Yasuhiro Tsubo[2†] and Shigeru Shinomoto[3]*

[1] Department of Human and Computer Intelligence, Ritsumeikan University, Shiga, Japan
[2] Laboratory for Neural Circuit Theory, RIKEN Brain Science Institute, Saitama, Japan
[3] Department of Physics, Graduate School of Science, Kyoto University, Kyoto, Japan

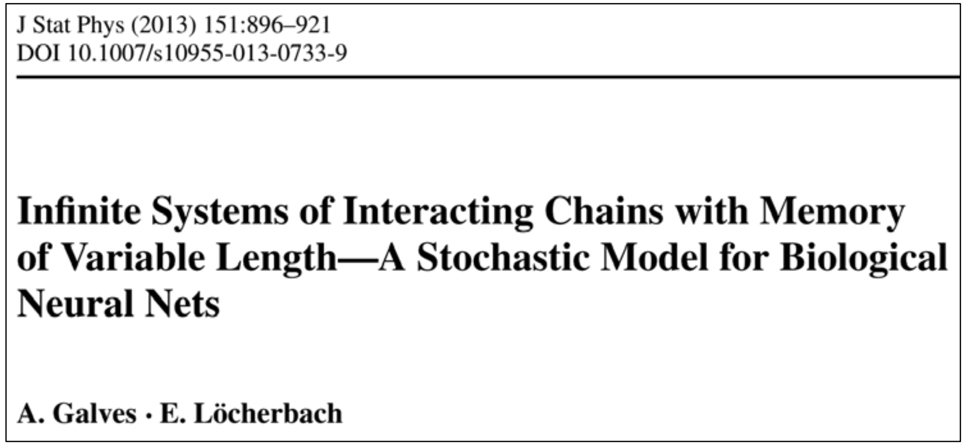


- Implemented in NEST:
  - mat2_psc_exp

- winner of International Competition on Quantitative Single-Neuron Modeling [INCF 2009], Gerstner & Naud 2009

ALTERNATIVE SINGLE NEURON DYNAMICS

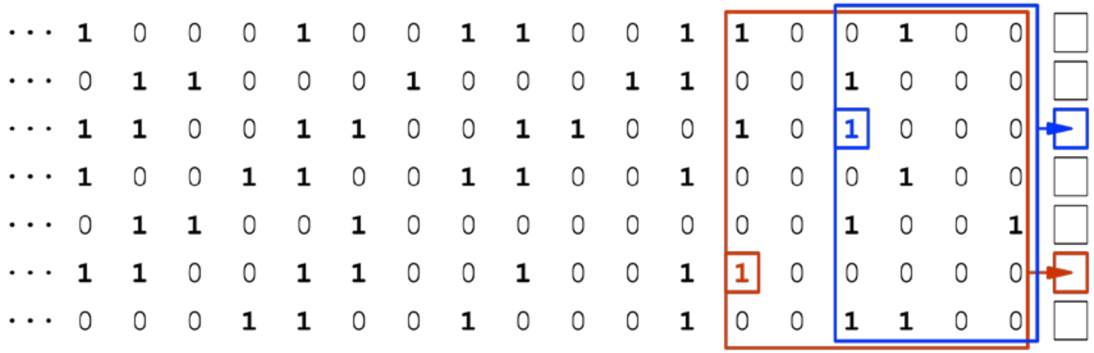
- Galves-Loecherbach model



J Stat Phys (2013) 151:896–921
DOI 10.1007/s10955-013-0733-9

Infinite Systems of Interacting Chains with Memory of Variable Length—A Stochastic Model for Biological Neural Nets

A. Galves · E. Löcherbach



$$\text{Prob}\left(\bigcap_{k\in K}\{X_k[t]=a_k\}\;\Big|\;X[-\infty:t-1]\right)=\prod_{k\in K}\text{Prob}\left(X_k[t]=a_k\;\Big|\;X[\tau_k[t]:t-1]\right)$$

- team already working on NEST implementation (Galves, Pouzat, Linssen, Babu, Shimoura…)
- spiking in this model can be stochastic (delta model with escape noise)

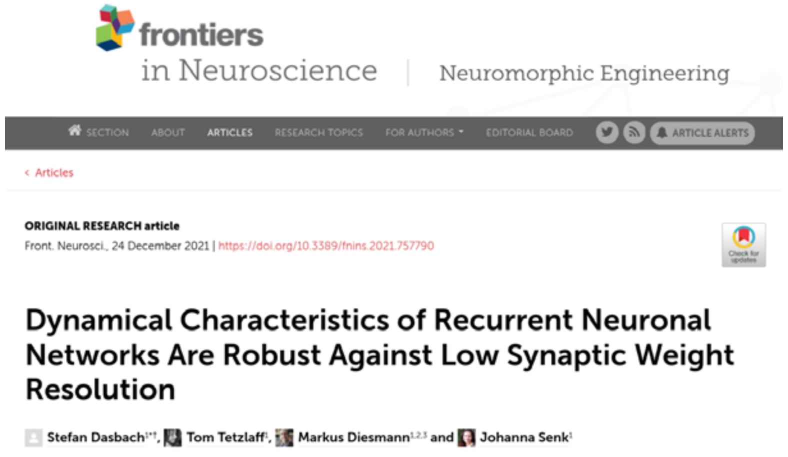
WHAT ARE RELEVANT METRICS?

- distribution of spikes rates
- distribution of correlation coefficients
- single spike train irregularity (CV ISI)
- network synchrony
- power spectrum of neuronal activity
- functional metrics:
  - Haeussler & Maass 2006
  - separability

Limitations

- large amounts of data may be required for higher-order measures (Dasbach et al. 2021)
- prominent measures already captured by mean field theories (Bos et al. 2016, Dasbach et al. 2021)
- neglect any dendritic computation and plasticity

DISTRIBUTED SYNAPTIC WEIGHTS


frontiers in Neuroscience | Neuromorphic Engineering

SECTION ABOUT ARTICLES RESEARCH TOPICS FOR AUTHORS EDITORIAL BOARD ARTICLE ALERTS

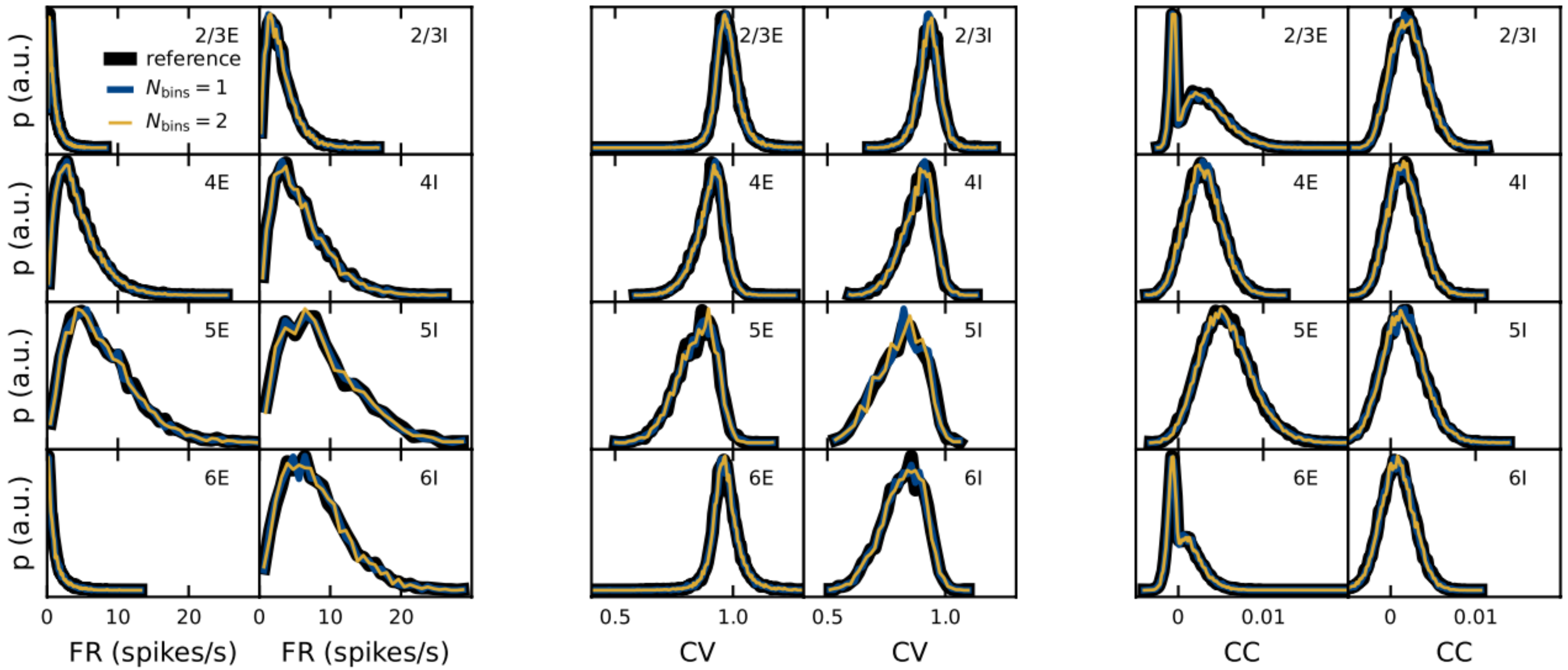
‹ Articles

ORIGINAL RESEARCH article

Front. Neurosci., 24 December 2021 | https://doi.org/10.3389/fnins.2021.757790

Dynamical Characteristics of Recurrent Neuronal Networks Are Robust Against Low Synaptic Weight Resolution

Stefan Dasbach[1*†], Tom Tetzlaff[1], Markus Diesmann[1,2,3] and Johanna Senk[1]



firing rates | spike train irregularity | spike correlation

- weight quantization preserving synaptic input statistics preserves overall firing statistics
- microcircuit model with sufficiently heterogeneous in-degrees: firing statistics preserved even when replacing all normally distributed weights (reference) by the mean weight
- **metrics FR, CV, and CC are not sufficient to constrain weight distribution**
- practical consequence: substantial reduction of memory demands in simulations possible

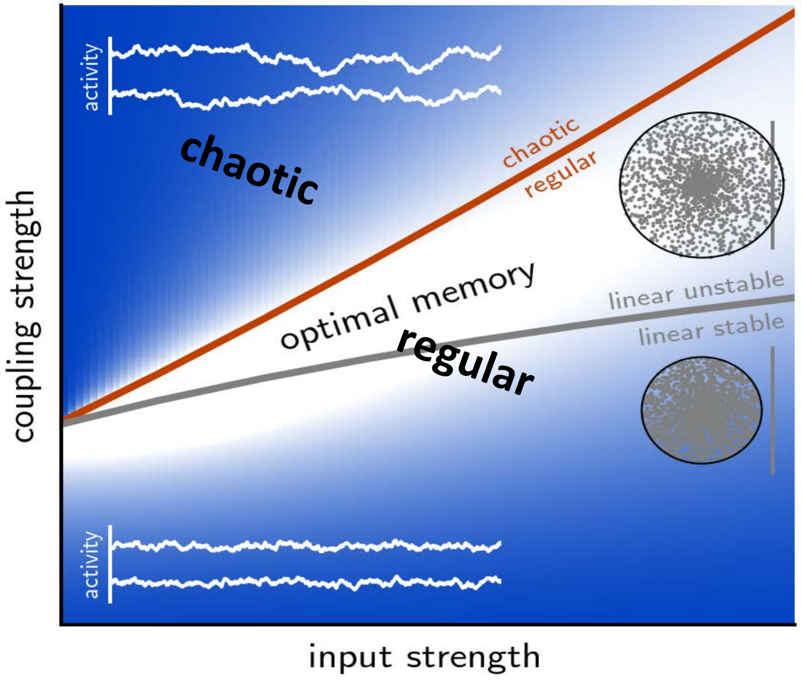
CHAOS AND MEMORY IN RATE NETWORKS

nonlinear network: $$\tau \frac{dx_i(t)}{dt} = -x_i(t) + \sum_{j=1}^{N} W_{ij}\phi(x_j(t)) + \xi_i(t)$$

continuous in time

continuous in value

"rate network"



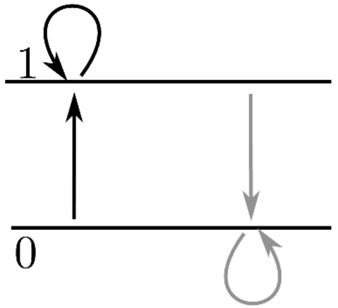
new dynamical state between loss of linear stability and onset of chaos with optimal memory

Schuecker, Goedeke, Helias (2018) Optimal Sequence Memory in Driven Random Networks, Phys Rev X

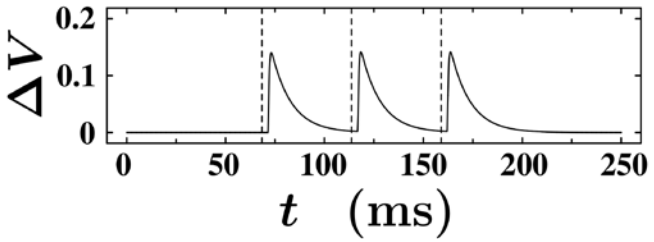
SPIKING INTERACTION

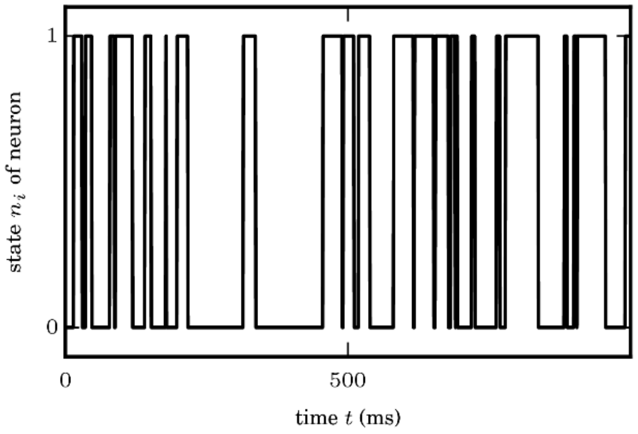
Taking into account discrete coupling

Binary neurons (kinetic noneq. Ising model)



binary, all-or-nothing signal





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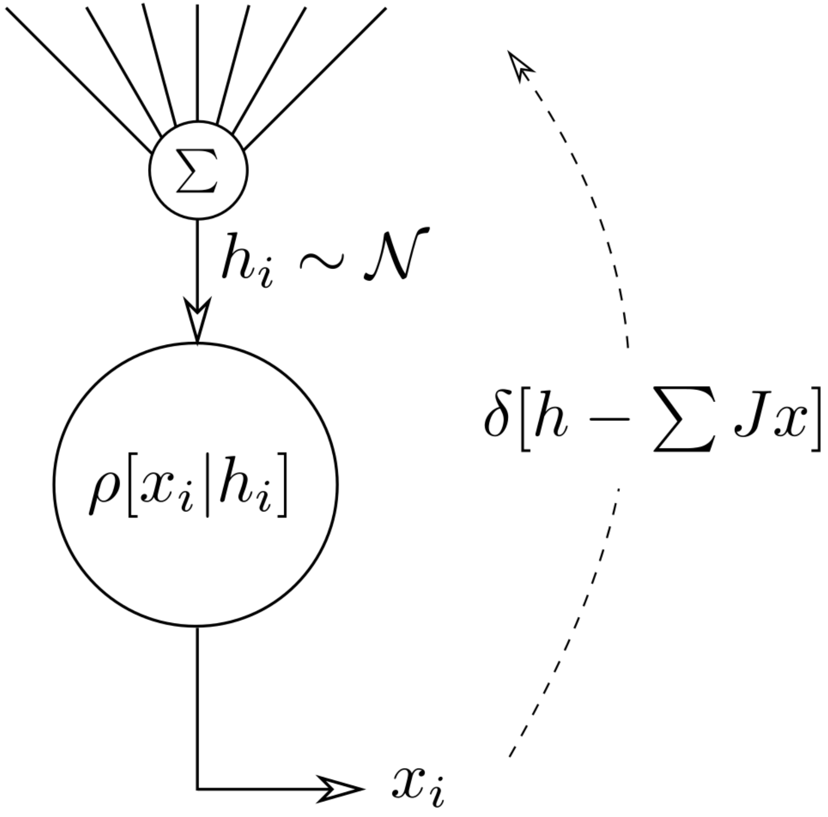
NEURON MODEL INDEPENDENT FIELD THEORY

... uncovers equivalent activity statistics in binary and stochastic rate networks

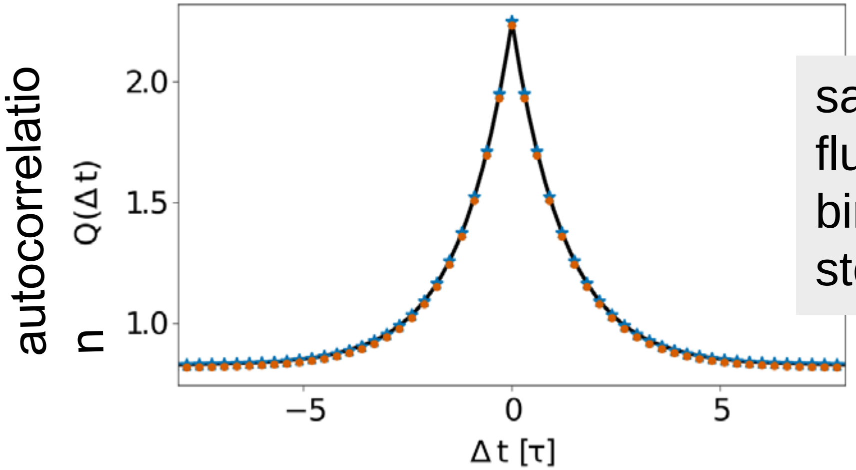


- self-consistency equation for autocorrelation function Q (dynamical MFT)

$$\tau^2 \ddot{Q}(\Delta t) = -V'_{R,Q(0)}(Q(\Delta t))$$

Effective noise:

$$\sigma^2_{\mathrm{eff}} = \frac{2}{\tau}\sqrt{2(V_\infty - V_{g^2})}$$

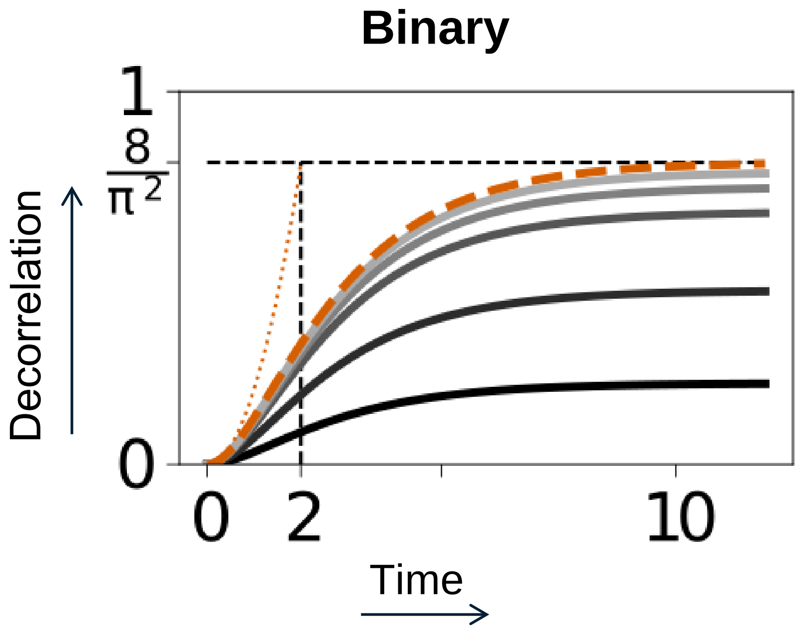


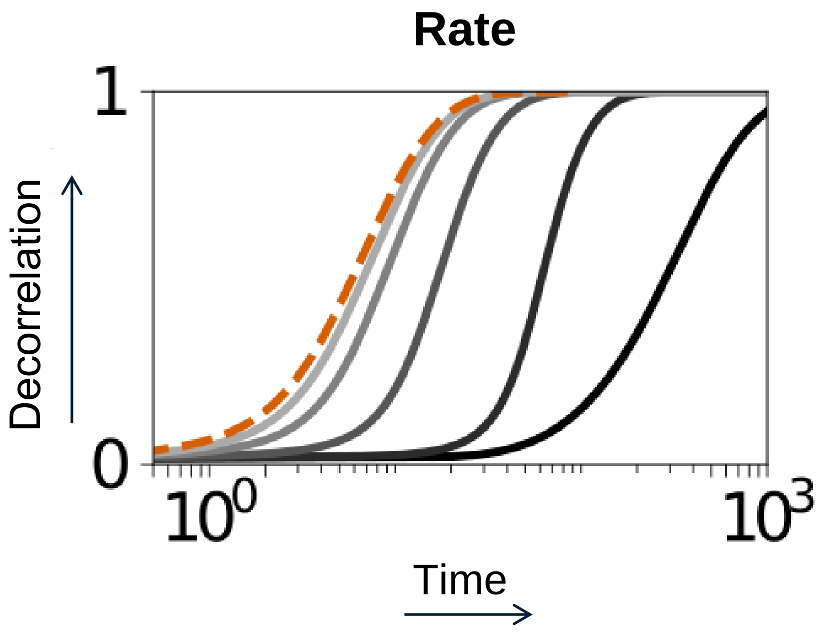
same statistics of fluctuations in binary and stochastic rate nets!

CHAOS IN BINARY NETWORKS

Differences to rate nets:

1. Mutually exclusive regimes.
2. Limited chaotic attractor.
3. No critical slowing down.

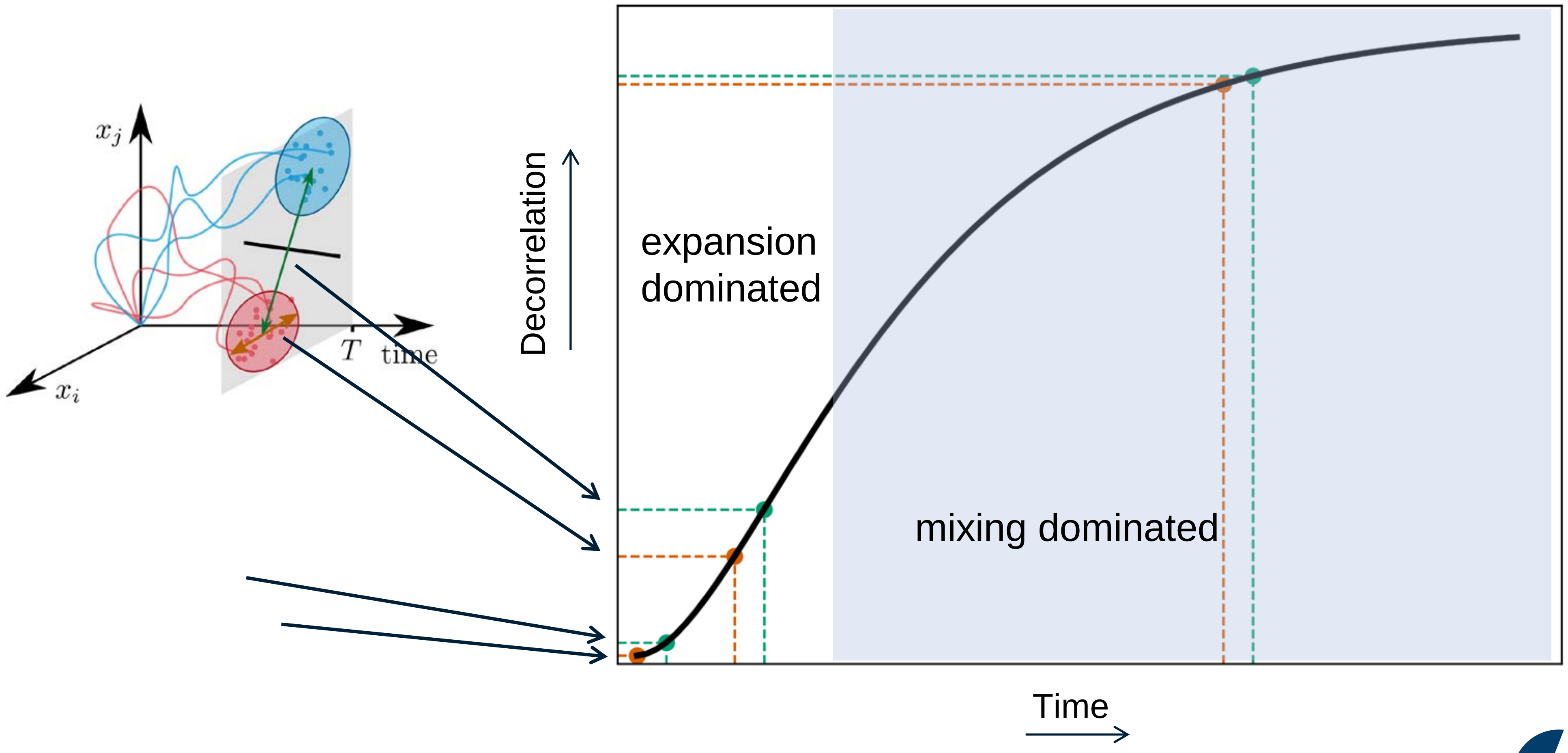




Keup, Kuehn, Dahmen, Helias (2021) Transient Chaotic Dimensionality Expansion by Recurrent Networks. Phys Rev X

DECORRELATION CURVE

Inter-class distance increases compared to intra-class distance



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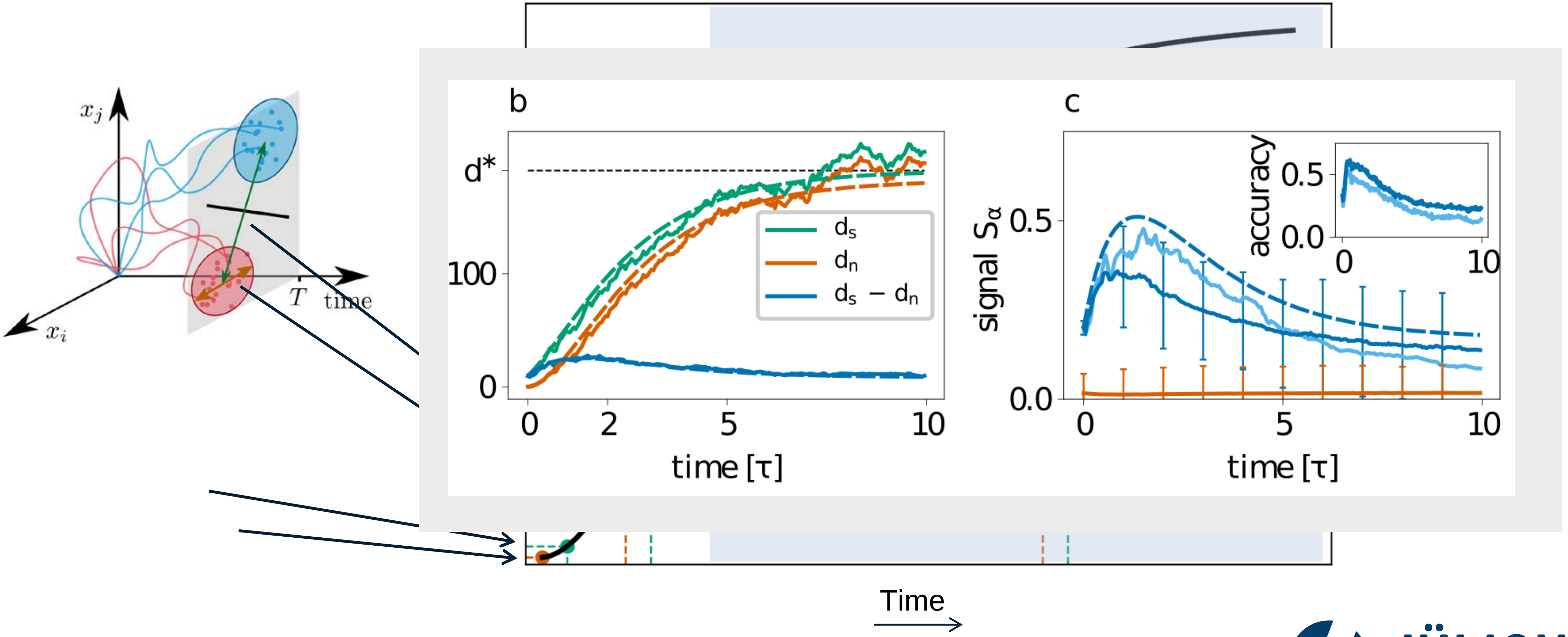
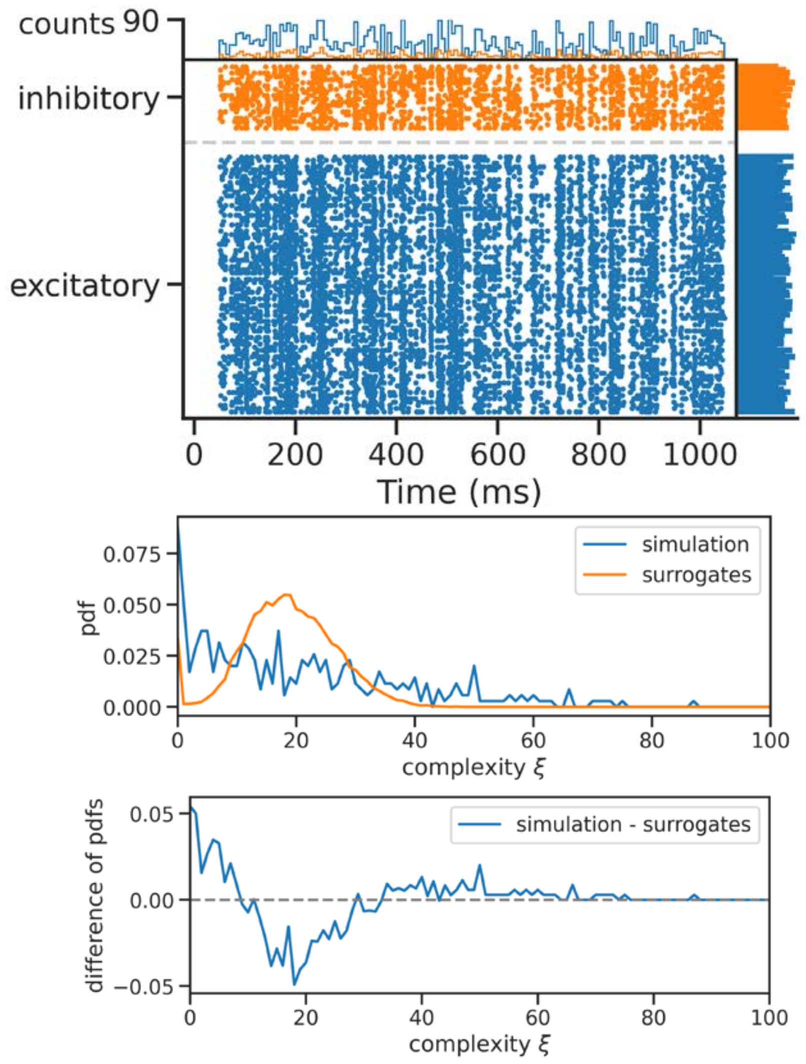
DECORRELATION CURVE

Inter-class distance increases compared to intra-class distance

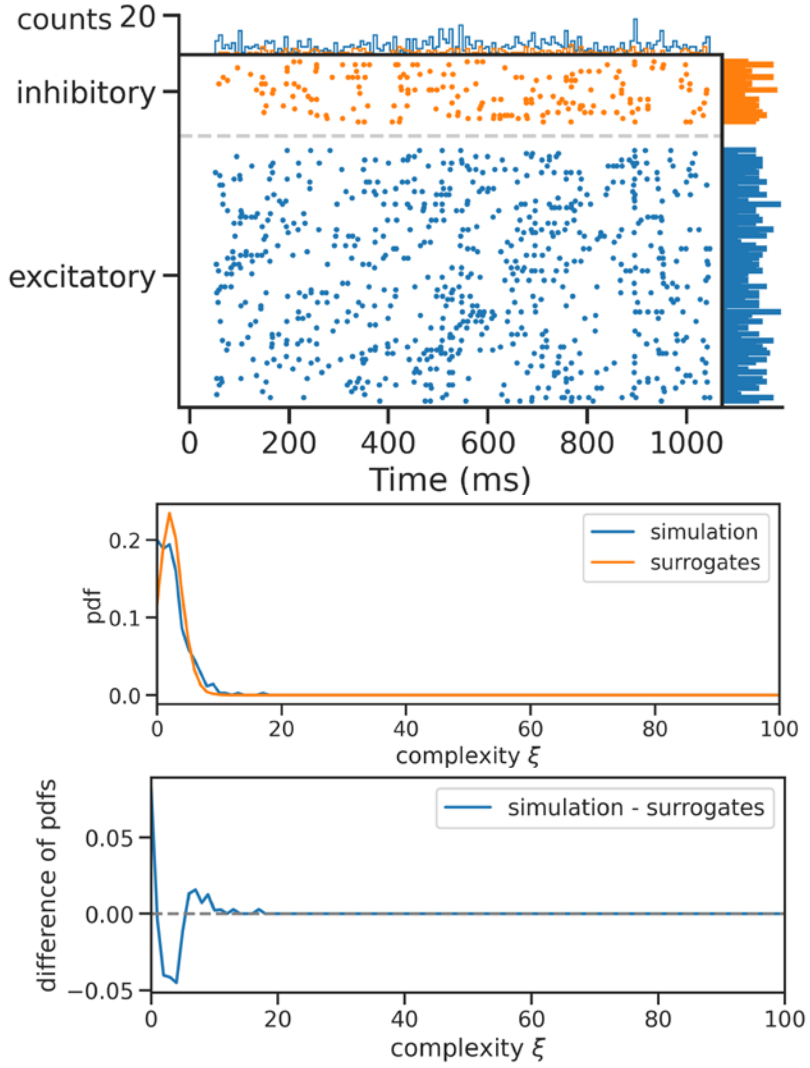


COMPLEXITY DISTRIBUTION

synchronous irregular



asynchronous irregular

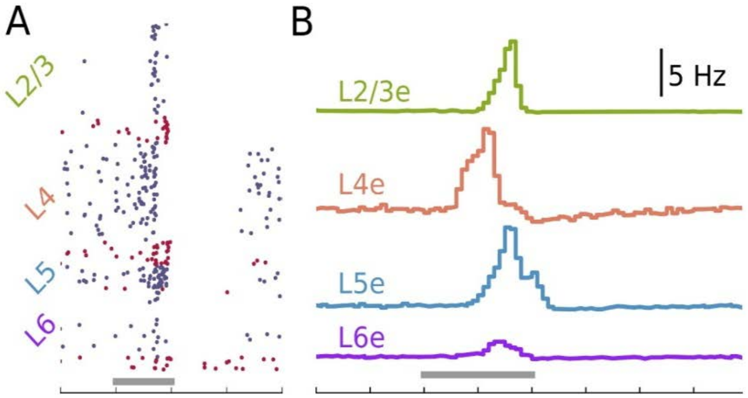


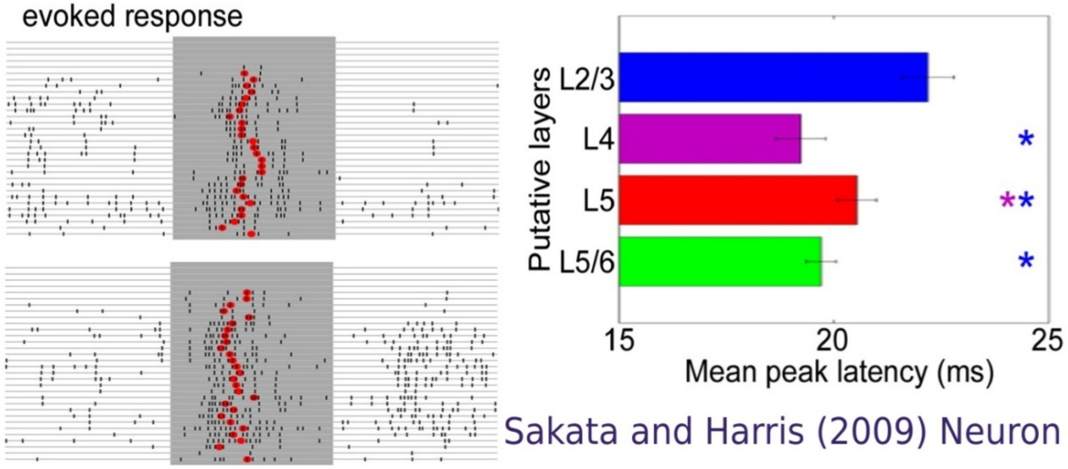
- **Complexity distribution is a measure to evaluate synchrony in network activity**

Grün, S., Abeles, M. & Diesmann, M. Impact of Higher-Order Correlations on Coincidence Distributions of Massively Parallel Data. Lecture Notes in Computer Science 5286, 96–114 (2008)

Brunel, N. Dynamics of sparsely connected networls of excitatory and inhibitory neurons. Computational Neuroscience 8, 183–208 (2000)

RESPONSE TO TRANSIENT INPUTS

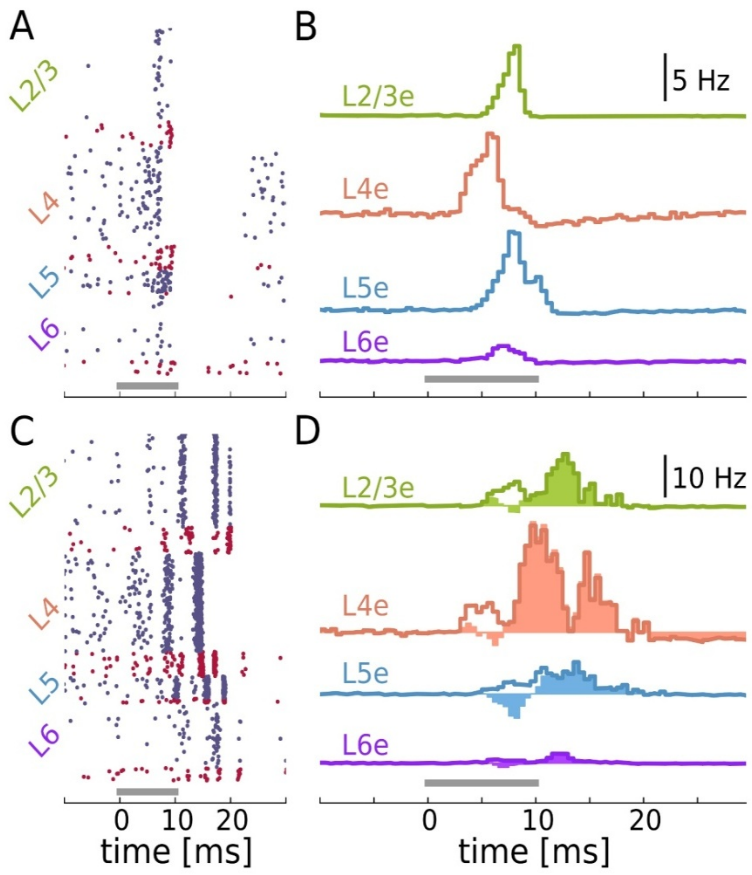




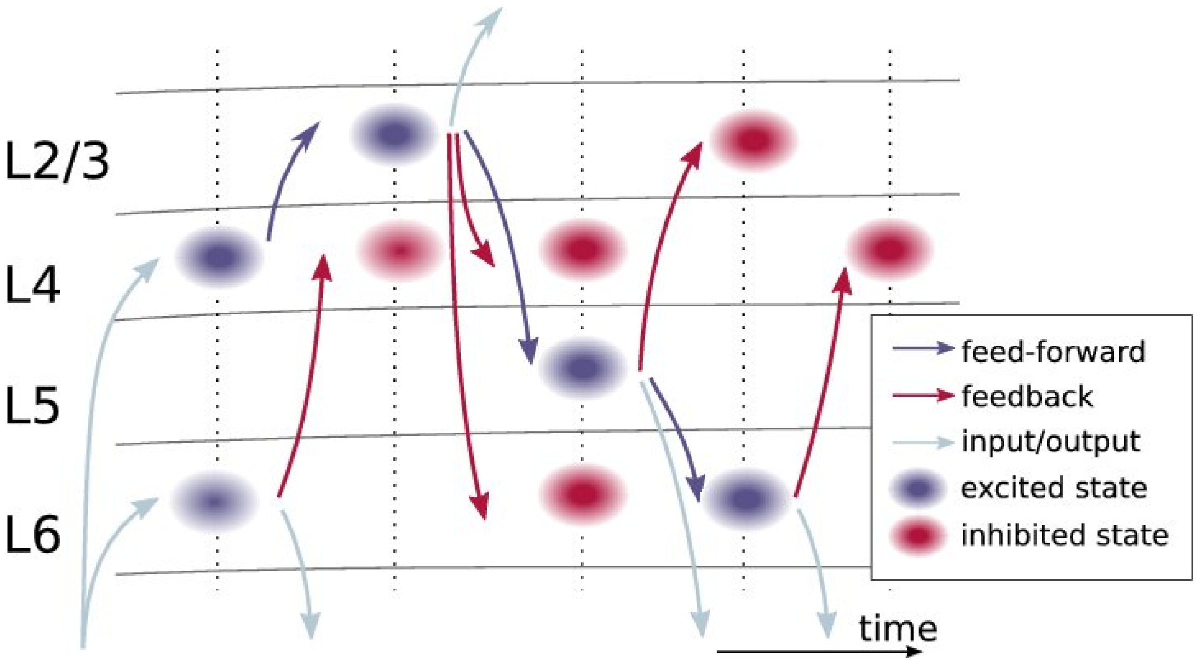
Sakata and Harris (2009) Neuron

RESPONSE TO TRANSIENT INPUTS

- T = -0.4
- T = +0.4



HYPOTHESIS ON CORTICAL FLOW OF ACTIVITY



- handshaking between layers

Potjans TC & Diesmann M (2014) The cell-type specific connectivity of the local cortical network explains prominent features of neuronal activity. *Cerebral Cortex* 24 (3): 785-806

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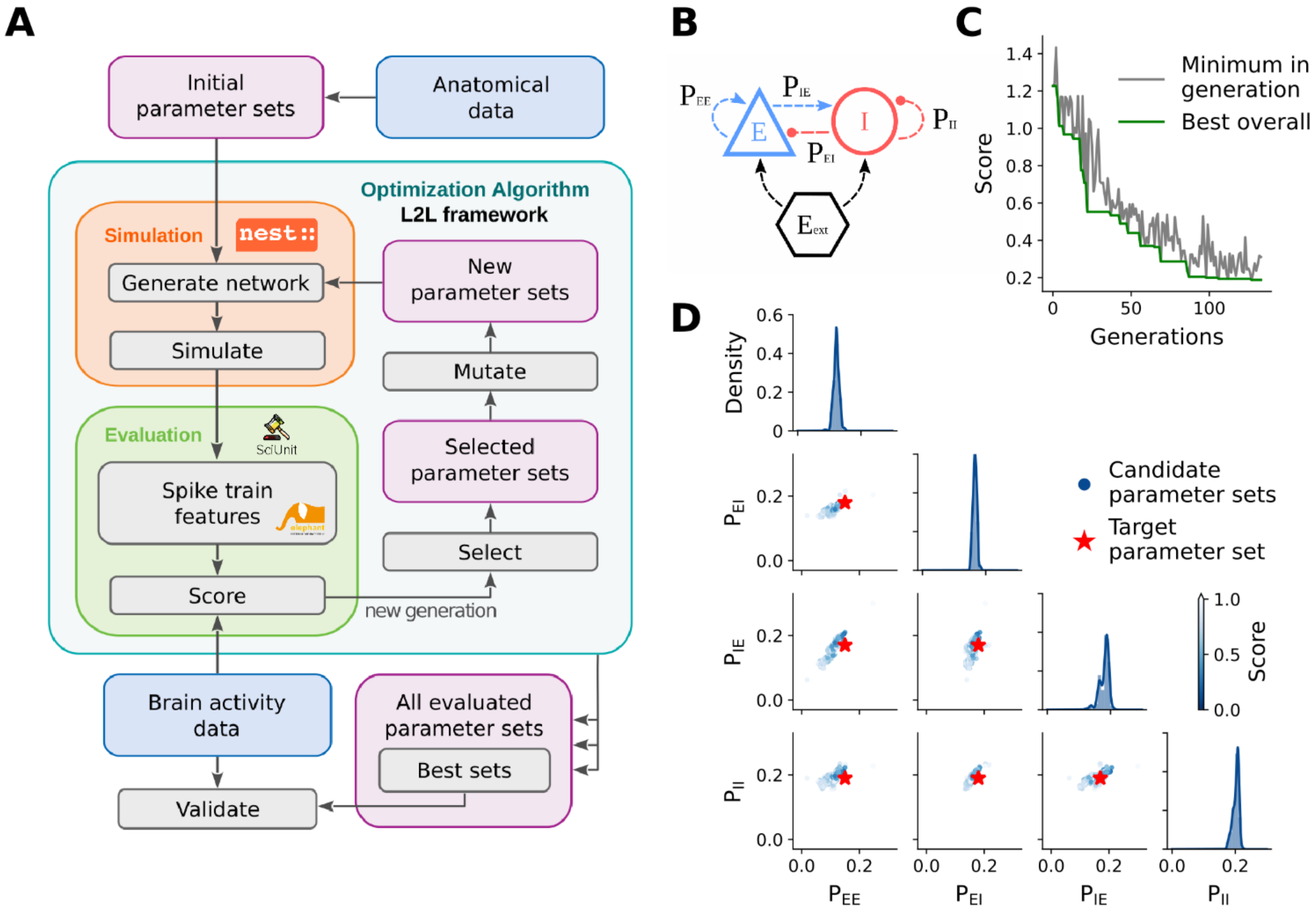
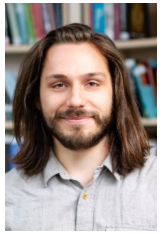
FIT OF PARAMETERS, VALIDATION FRAMEWORK



Aitor Morales-Gregorio



Robin Gutzen

- Development and implementation of stochastic optimization algorithm
- Implementation of data comparison framework with NetworkUnit (Gutzen et al. Front Neuroinform 2018)
- Proof of concept successfully run, applying the parameter estimation to synthetic data from a small balanced random network

- some prior work on CUBA vs COBA comparison: Cavallari et al. 2014

POTENTIAL PROJECT DESIGN

- agree on a specific variant of the network model
- agree on a dynamical state of the model as a reference
- agree on a set of metrics to fit to reference (rates, irregularity, correlation)
- agree on whether we want to go into cell type specific models or not
- assign interested researchers or groups to specific neuron models
- use Elephant and Validation Framework for consistent analysis
- Juelich and the SimLabs at Juelich and NeuroMat help with NEST implementations of the neuron models and use of the analysis software
- agree on further metrics to expose differences (complexity, transients, chaos, function)
- communicate over the year to sort out problems
- gather in March 2023 and discuss the results in Paris

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