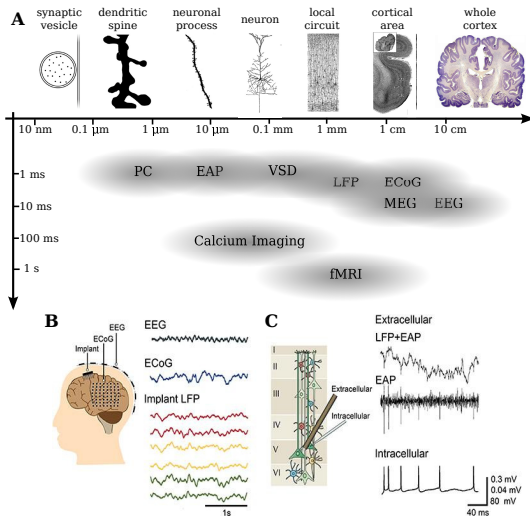




NEST TUTORIAL - EITN FALL SCHOOL 2024

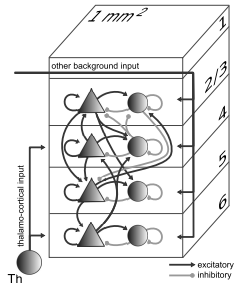
17 October 2024 | Barna Zajzon | IAS-6; Jülich Research Center

Multi-scale brain structure and dynamics



The microcircuit model

- 10^5 identical leaky-integrate and fire neurons
- $3 \cdot 10^8$ exponentially decaying synaptic currents
- Four layers with one excitatory and one inhibitory population each
- Size of populations and connection probabilities deduced from anatomical data

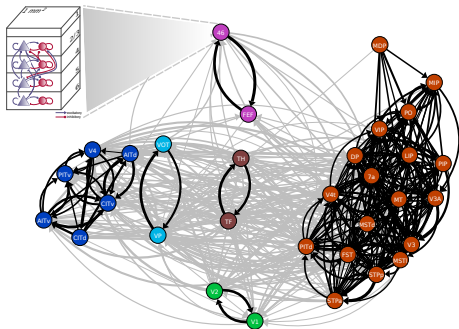


- Asynchronous irregular and cell-type specific firing rates
- Thalamic stimulation elicits flow of activity through cortical layers

Potjans and Diesmann (2014) The Cell-Type Specific Cortical Microcircuit: Relating Structure and Activity in a Full-Scale Spiking Network Model. *Cerebral Cortex* 24(3):785-806

The multi-area model

- Full-density model of macaque visual cortex
- Axonal tracing data from the CoCoMac database, which are systematically refined using dynamical constraints
- Stable asynchronous irregular ground state
- Produces realistic spiking statistics in V1
- Functional connectivity compares to fMRI measurements

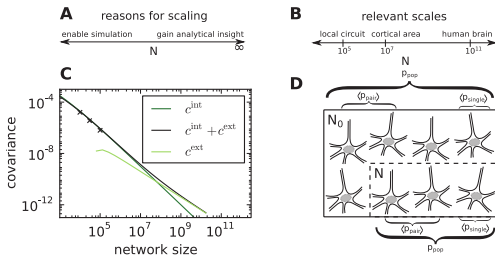


Schmidt et al. (2018) Multi-scale account of the network structure of macaque visual cortex. *Brain Structure and Function* 223(3):1409-1435

Schmidt et al. (2018) A multi-scale layer-resolved spiking network model of resting-state dynamics in macaque visual cortical areas. *PLOS CB* 14(10):e1006359

Importance of the correct network size

- Under which conditions can a small network represent a sub-sampled larger network?
- Analyzes scalability of binary and LIF neuron networks



- Mean activity can be preserved by adjusting the mean and variance of the input
- Temporal structure of pairwise averaged correlations depends on the effective connectivity and cannot always be preserved

van Albada et al. (2015) Scalability of Asynchronous Networks Is Limited by One-to-One Mapping between Effective Connectivity and Correlations. PLOS CB 11(9):e1004490

NEST = NEural Simulation Tool

- Focus on the dynamics, size and structure of neural systems rather than on the exact morphology of individual neurons
 - Phenomenological synapse models (STDP, STP)
 - + gap junctions, neuromodulation and structural plasticity
 - Frameworks for rate models and binary neurons
 - Support for neuroscience interfaces (MUSIC, libneurosim)
-
- Highly efficient C++ core with a Python frontend
 - Hybrid parallelization (OpenMP+MPI)
 - Same code from laptops to supercomputers



NEST design goals

- NEST development is always driven by scientific needs
- High accuracy and flexibility
 - Exact integration is used for suitable neuron models
 - Spike interaction in continuous time available for suitable neuron models
 - Extremely scalable: same code from laptop to supercomputers
- Constant quality assurance
 - Automated unit test suite included in NEST build
 - Continuous integration for all repository checkins
 - Peer review for all code contributions

Main components of a NEST simulation

■ Nodes

- Neurons – Devices (– Sub-networks)
- Have dynamic state variable(s) that changes over time ($V_m(t)$)
- Can be affected by events (spikes)

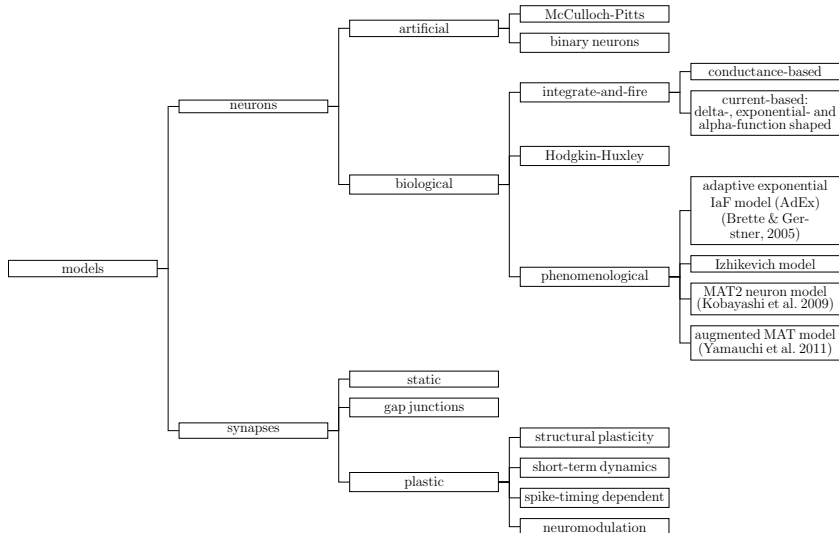
■ Events

- Pieces of information of a particular type (e.g., spike, voltage or current event)
- Recording devices: 'spike_recorder', 'voltmeter', 'multimeter'

■ Connections

- Communication channels for the exchange of events
- Directed (from source node to target node)
- Weighted (how strongly does an event influence the target node)
- Delayed (length of transmission duration between source and target)
- Connections are created using one global `Connect` function

Neuron and synapse models in NEST



Event-driven vs. time-driven simulation

	Event-driven	Time-driven
Pros	<ul style="list-style-type: none">■ more efficient for low input rates■ 'correct' solution for invertible neuron models	<ul style="list-style-type: none">■ more efficient for high input rates■ works for all neuron models■ scales well
Cons	<ul style="list-style-type: none">■ only works for neurons with invertible dynamics■ event queue does not scale well	<ul style="list-style-type: none">■ only 'approximate' solution even for analytically solvable models■ spikes can be missed due to discrete sampling of membrane potential

Event-driven vs. time-driven

NEST uses a hybrid approach to simulation

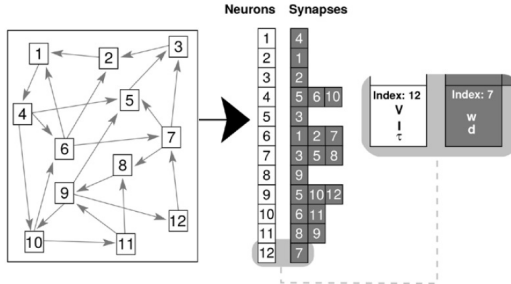
- Input events to neurons are frequent: time-driven algorithm
 - If the dynamics is nonlinear, we need a numerical method to solve it, e.g.:
 - Forward Euler: $y([i + 1]h) = y(ih) + h \cdot \dot{y}(ih)$
 - Runge-Kutta (k -th order)
 - Runge-Kutte-Fehlberg with adaptive step size
 - ...
- Use a pre-implemented solver, for example, from the GNU Scientific Library (GSL)
- If the dynamics is linear (e.g. leaky integrate-and-fire), we can solve it exactly

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 - ...
 - Use a pre-implemented solver, for example, from the GNU Scientific Library (GSL)
 - If the dynamics is linear (e.g. leaky integrate-and-fire), we can solve it exactly
- Events at synapses are rare: event driven component
 - Exception: gap junctions

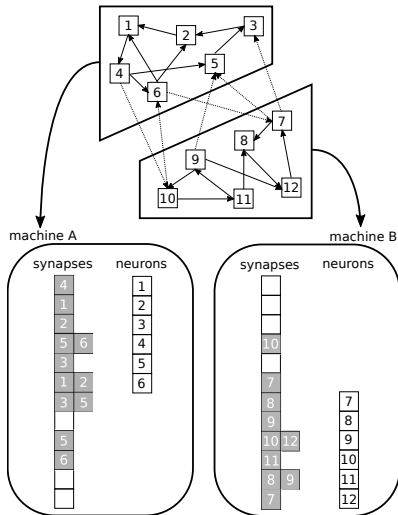
Representation of network structure: serial



- Each neuron and synapse maintains its own parameters
- Synapses save the index of the target neuron

Representation of network structure: distributed

- modulo operation distributes neurons
- one target list for every neuron on each machine
- synapse stored on machine that hosts the target neuron
- connections are established on each machine and the connectivity information subsequently propagated to other machines
 - wiring is a parallelizable task



Creating custom models

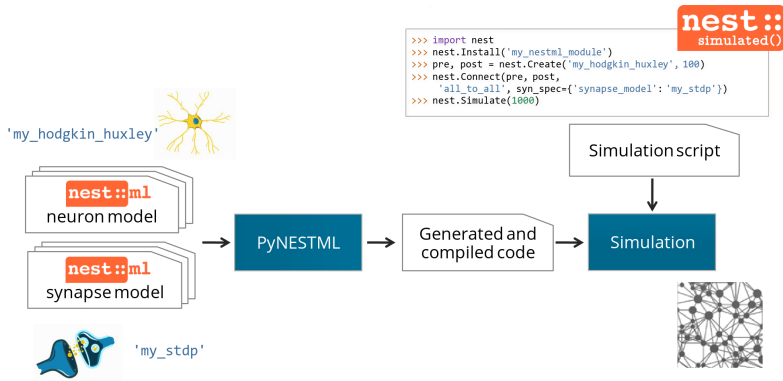
- Discuss with developers via user mailing list
 - If your idea makes sense
 - If it has not yet been implemented
 - Start from most similar existing model
 - It may end up in a release!
- Extension modules (C++ knowledge required)
 - Loaded dynamically
- Inside NEST (C++ knowledge required)
 - Re-compile and re-install after each change

Recommended:

- **NESTML (NEST Modeling Language)**

NESTML

NESTML is a domain-specific language for neuron and synapse models



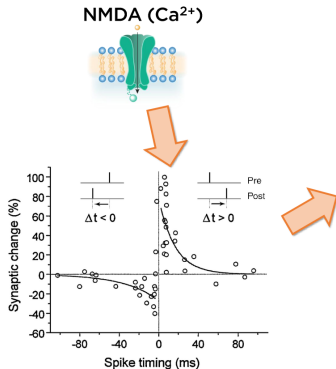
NESTML: Design principles

- Concise; low on boilerplate
- Speak in the vernacular of the neuroscientist (keywords such as `neuron`, `synapse`)
- Easy (dynamical) equation handling coupled with imperative-style programming (`if V_m >= threshold: ...`)

NESTML comes with a code generation toolbox.

- Code generation (model definition but not instantiation)
- Automated ODE analysis and solver selection
- Flexible addition of targets using Jinja2 templates

Creating custom models with NESTML



nest::ml

```
synapse stdp:
state:
  w real = 1
  tr_post real = 0
  tr_pre real = 0

equations:
  tr_pre' = -tr_pre / tau_tr
  tr_post' = -tr_post / tau_tr

input:
  pre_spikes real <- spike
  post_spikes real <- spike

onReceive(pre_spikes):
  w -= alpha * tr_post      # depress synapse
  tr_pre += 1              # update presynaptic trace
  deliver_spike(w, delay)  # to postsynaptic partner

onReceive(post_spikes):
  w += alpha * tr_pre      # potentiate synapse
  tr_post += 1             # update postsynaptic trace

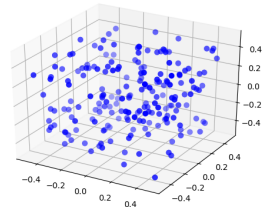
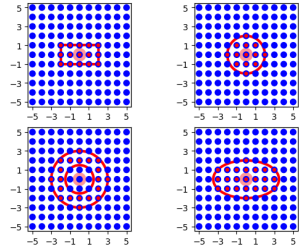
parameters:
  delay ms = 1 ms          # dendritic delay
  tau_tr ms = 50 ms        # pre/post trace time const.
  alpha real = .02         # learning rate
```

Image credit: (c) S.B.C. Lehmann, FZ Jülich; (m) C. Linssen; Bl & Poo 2001

Topologically structured networks

■ Functionality

- Lay out elements on grids or at arbitrary points in space (2D or 3D)
- Elements can be neurons or combinations of neurons and devices
- Connect neurons in a position- and distance-dependent manner
- Set periodic boundary conditions
- Choose whether to allow self-connections (autapses) or multiple connections (multapses)
- Distance-dependent or random weights and delays



Why should I use NEST?

- 1 NEST provides over 50 neuron models
- 2 NEST provides over 10 synapse models, including short-term plasticity (Tsodyks & Markram) and different variants of STDP
- 3 NEST provides many examples that help you getting started
- 4 NEST lets you inspect and modify the state of each neuron and each connection at any time during a simulation
- 5 NEST is fast and memory efficient; it makes best use of your multi-core computer and compute clusters
- 6 NEST has a large and experienced developer community
- 7 NEST was first released in 1994 under the name SYNOD and has been extended and improved ever since
- 8 NEST is open source software and is licensed under the GPL 2

Acknowledgments

This presentation is based on previous work by many people.

- Hannah Bos
- David Dahmen
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- Jannis Schuecker
- Johanna Senk
- Tom Tetzlaff
- Sacha van Albada
- Charl Linssen
- Anno Kurth

Getting help

Within Python:

```
nest.help('iaf_psc_exp')  
nest.help('Connect')
```

Online documentation:

NEST: <https://nest-simulator.readthedocs.io/>

NESTML: <https://nestml.readthedocs.io/en/latest/>

Community:

- NEST and NESTML user mailing lists
- Bi-weekly open video conference
- <http://github.com/nest/nest-simulator/>
- <https://github.com/nest/nestml>
- Annual NEST Conference: a forum for users and developers

Please tell us about problems. We can only fix what we know of!

Now hands-on

1 Check out the Github repo on EBRAINS



2 Get the exercises

- Go to https://github.com/zbarni/nest_tutorial_eitn_24
- Download as zip (or clone)

3 Enjoy the ride

- Open `0_hello_world.ipynb` for a first glance
- Get started with `1_first_steps.ipynb`