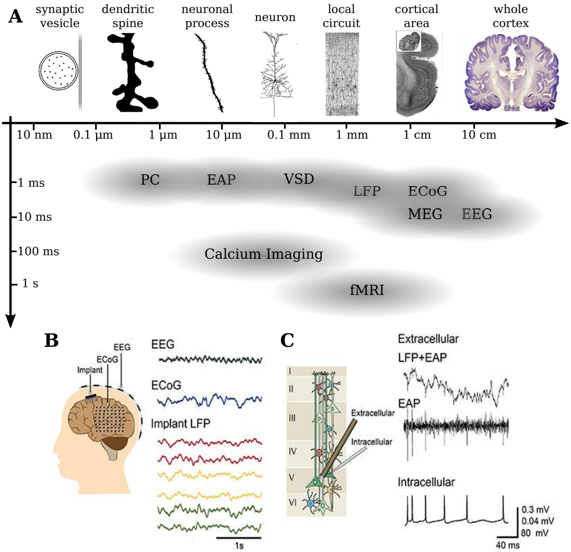
THE NEURAL SIMULATION TOOL NEST

CNS*2023, Leipzig

July 15th, 2023 | Charl Linssen (c.linssen@fz-juelich.de) | SimLab Neuroscience

WHEN TO USE NEST?



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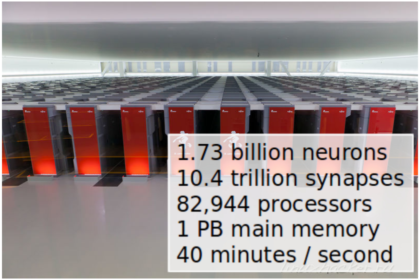
NEST = NEURAL SIMULATION TOOL

- Point neurons and neurons with few electrical compartments
- 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

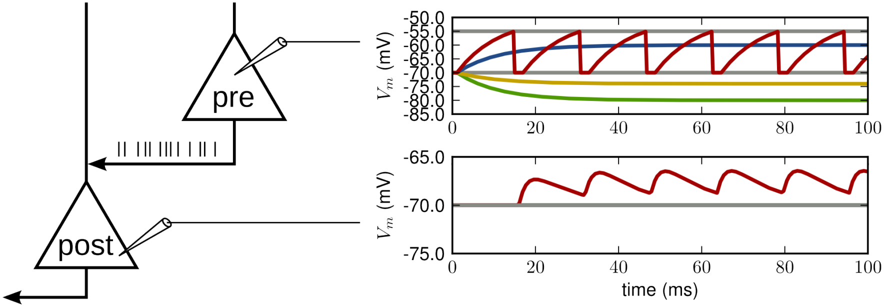
- Exact integration is used for suitable neuron models
- Spike interaction in continuous time available for suitable neuron models
- Extremely scalable: same code from laptop to supercomputers

Constant quality assurance

- Automated unit test suite included in NEST build
- Continuous integration for all repository checkins
- Peer review for all code contributions

NEURONAL SIMULATIONS IN NEST

A simulation in NEST mimics a neuroscientific experiment.

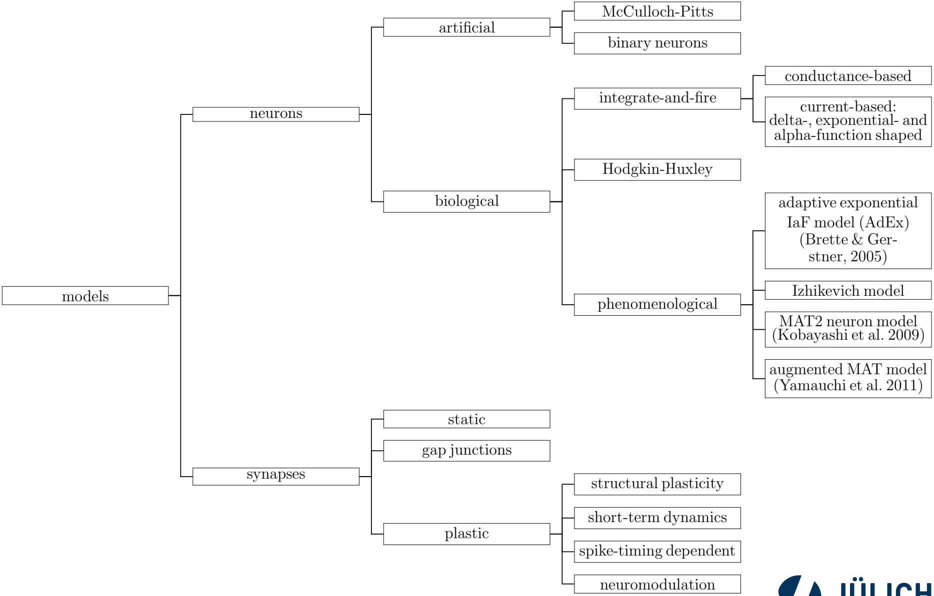


Except that you can easily measure and control every neuron and connection in the network!

THREE MAIN COMPONENTS OF A NEST SIMULATION

- **Nodes**
  - Neurons – Devices (– Sub-networks)
  - Have dynamic state variable(s) that changes over time ($V_{\mathrm{m}}(t)$)
  - Can be affected by events (spikes)
- **Events**
  - Pieces of information of a particular type (e.g., spike, voltage or current event)
  - Recording devices: `‘spike_detector’`, `‘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

NEST NEURON AND SYNAPSE MODELS



NEURON MODELS

- Integrate-and-fire models (`iaf_`)
  - Current-based (`iaf_psc`)
  - Conductance-based (`iaf_cond`)
  - Different post-synaptic shapes (`_alpha`, `_exp`, `_delta`)
- Single compartment Hodgin-Huxley models (`hh_`)
- Adaptive exponential integrate-and-fire models (`aeif_`)
- Allen Institute generalised leaky integrate-and fire family (`gif_`)
- Hill-Tononi model (Hill & Tononi 2005)
- Neuron models with >1 compartments (“mesocompartmental”)
- . . . and many more!

SYNAPSE MODELS

- Gap junctions (electical synapse)
- Short term depression, facilitation
- Spike-timing dependent plasticity (STDP)
  - All-to-all; several nearest-neighbour variants
- Triplet STDP (Pfister & Gerstner 2006)
- Voltage-based STDP (Clopath et al. 2010)
- Dopamine-modulated STDP (Potjans et al. 2010)
- ...and many more!

STIMULATION DEVICES

Spike generators:

- `spike_generator` spikes at prescibed points in time
- `poisson_generator` spikes according to a Poisson distribution
- `gamma_sup_generator` spikes according to a Gamma distribution

Current generators

- `ac_generator` provides a sine-shaped current
- `dc_generator` provices a constant current
- `step_current_generator` provides a step-wise constant current
- `noise_generator` provides a random noise current

RECORDING DEVICES

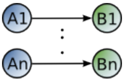
- `spike_detector` records incoming spikes
- `multimeter` records analog quantities (potentials, conductances, …)
- `voltmeter` records the membrane potential
- `correlation_detector` records pairwise cross-correlations between the spiking activity of neurons
- `weight_recorder` records the weight of connections

can record to memory, file, or stream data!

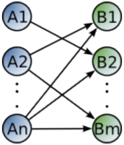
SPECIFICATION OF CONNECTIVITY

- One-to-one
- All-to-all
- Fixed in-, out-degree
- Fixed total number (N)
- Pairwise Bernoulli (p)

```
A = Create('iaf_psc_alpha', n)
B = Create('spike_detector', n)
Connect(A, B, 'one_to_one')
```




```
A = Create("iaf_psc_alpha", n)
B = Create("iaf_psc_alpha", m)
Connect(A, B, {'rule': 'fixed_indegree',
               'indegree': N})
```



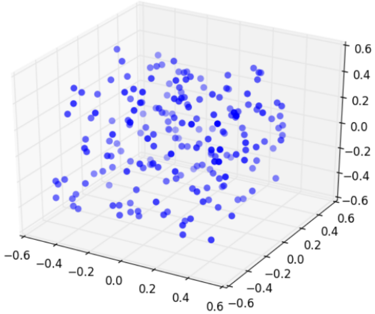
RANDOMIZATION OF SYNAPSE PROPERTIES

Dozens of standard distributions are natively supported.

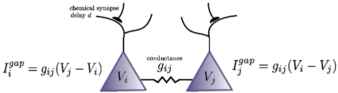
```
delay_dist = {'distribution': 'uniform',
              'low': 0.8, 'high': 2.5}

alpha_dist = {'distribution': 'normal_clipped',
              'low': 0.5, 'mu': 5.0,
              'sigma': 1.0}

syn_dict = {'model': 'stdp_synapse',
            'weight': 2.5,
            'delay': delay_dist,
            'alpha': alpha_dist}
```

STRUCTURED NETWORKS USING TOPOLOGY

- Set node positions on grids or arbitrary points in space (1D, 2D, 3D)
- Nodes can be neurons or combinations of neurons and devices
- Connect nodes in a position- and distance-dependent manner
- Set boundary condition (periodic or not)



GAP JUNCTIONS

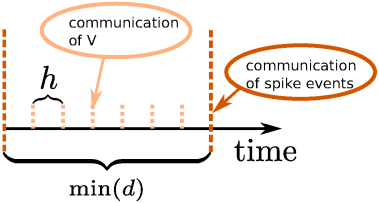


Neuron i (hh_psc_alpha_gap)

$y_i'(t) = f_i(y_i(t))$, $y_i(t_0)$ given

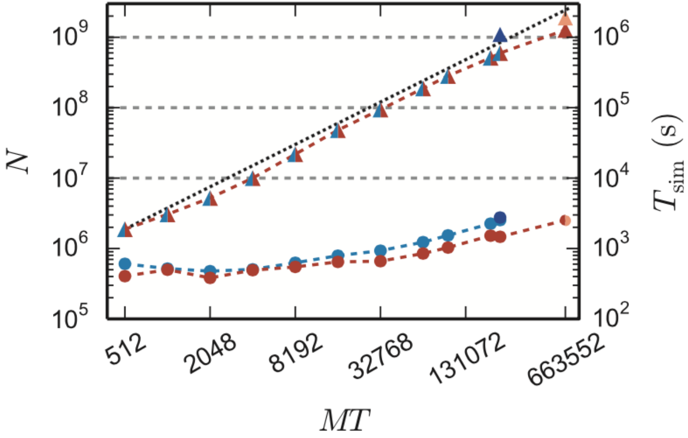
$$\frac{V_i'}{C_m} = -I_i^{ionic}(V_i, m_i, h_i, n_i, p_i)$$
$$+I_i^{applied}(I_i^{ex}, I_i^{in})$$
$$+I_i^{gap}(V_i, V_j)$$

- at each time point neuron i needs membrane potential of neuron j
- large system of differential equations
- naïve: communication of V in each step
- better: Jacobi waveform relaxation



Hahne et al. (2015). A unified framework for spiking and gap-junction interactions in distributed neural network simulations. Frontiers in Neuroinformatics. 9:22

NEST PERFORMANCE



Maximum network size and corresponding run time as function of number of virtual processes on the K computer (red) and JUQUEEN (blue). Taken from Kunkel et al., (2014), Front Neuroinf. DOI: 10.3389/fninf.2014.00078

HOW TO USE NEST?

- The Python interface PyNEST

```
import nest
n = nest.Create("iaf_psc_exp", 8000, {"V_m": -65.})
sd = nest.Create("spike_detector")
nest.Connect(n, sd)
...
nest.Simulate(1000.)
```

- The multi-simulator Python interface PyNN

```
from pyNN import nest
nest.setup()
neuron_t = nest.native_cell_type("iaf_psc_exp")
pop_exc = nest.Population(8000, neuron_t, {})
pop_exc.initialize(V_m=-65.)
...
nest.run(1000.)
```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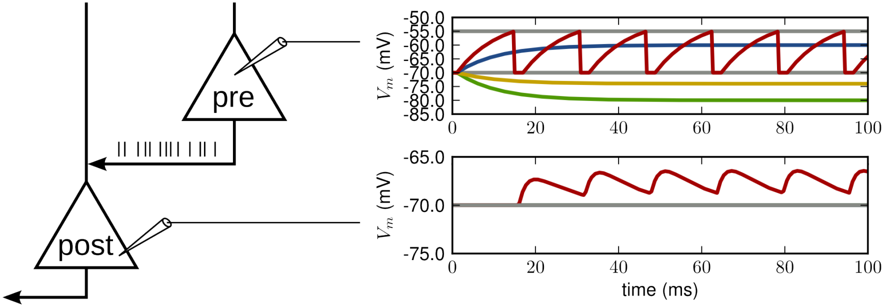


Except that you can easily measure and control every neuron and connection in the network!

A FULL EXAMPLE

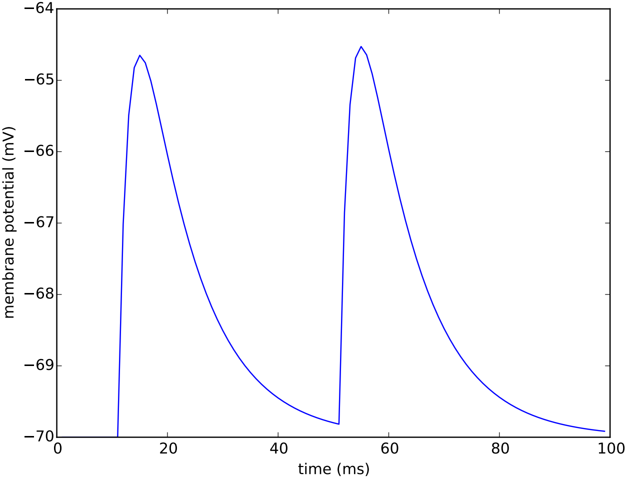
```
import nest                                    # import NEST module
neuron = nest.Create('iaf_psc_exp')            # create a neuron
voltmeter = nest.Create('voltmeter')           # create a voltmeter
spikegenerator = nest.Create('spike_generator') # create a spike generator
nest.SetStatus(spikegenerator, {'spike_times': [10., 50.]}) # let it spike

# connect spike generator and voltmeter to the neuron
nest.Connect(spikegenerator, neuron, syn_spec={'weight' : 1E3})
nest.Connect(voltmeter, neuron)

nest.Simulate(100.) # run the simulation

# read out recording time and voltage from voltmeter and plot them
times = nest.GetStatus(voltmeter)[0]['events']['times']
voltage = nest.GetStatus(voltmeter)[0]['events']['V_m']
pl.plot(times, voltage)
pl.xlabel('time (ms)'); pl.ylabel('membrane potential (mV)')
pl.show()
```

A FULL EXAMPLE



EVENT-DRIVEN VS. TIME-DRIVEN

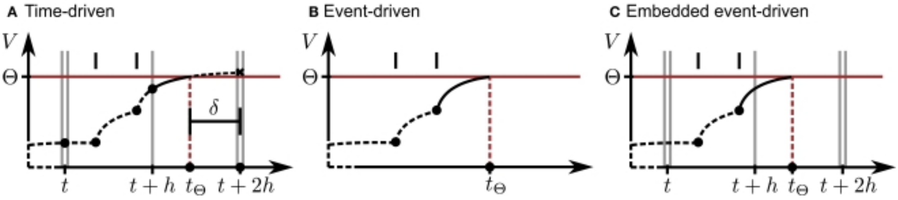
Event-driven simulation:

- Visit a neuron only when it receives an event (e.g. a spike)
- From $y(t_i)$, calculate $y(t_{i+1})$

Time-driven simulation:

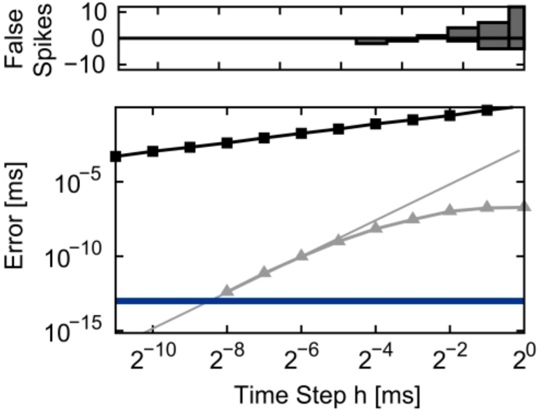
- Visit each neuron in each time step h
- From $y(ih)$, calculate $y([i+1]h)$

EVENT-DRIVEN VS. TIME-DRIVEN



Hanuschkin et al. Front. Neuroinf. 2010

EVENT-DRIVEN VS. TIME-DRIVEN



Hanuschkin et al. Front. Neuroinf. 2010

EVENT-DRIVEN VS. TIME-DRIVEN

	Event-driven	Time-driven
Pros	■ more efficient for low input rates ■ 'correct' solution for invertible neuron models	■ more efficient for high input rates ■ works for all neuron models ■ scales well
Cons	■ only works for neurons with invertible dynamics ■ event queue does not scale well	■ 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
    - ...

  $\rightarrow$ 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.

EVENT-DRIVEN VS. TIME-DRIVEN

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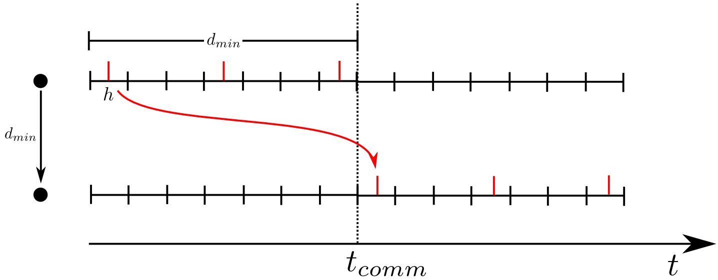
    - Runge-Kutte-Fehlberg with adaptive step size
    - $\ldots$

  $\rightarrow$ 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

MINIMUM SYNAPTIC DELAY

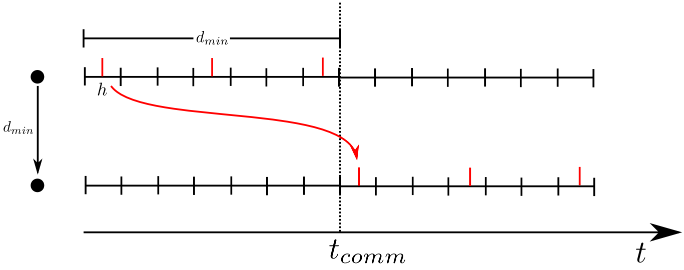
During an interval of the minimal transmission delay in the network (Δ), neurons are effectively decoupled.



Input events to neurons are frequent: time-driven updates.
Events at synapses are rare: event driven.

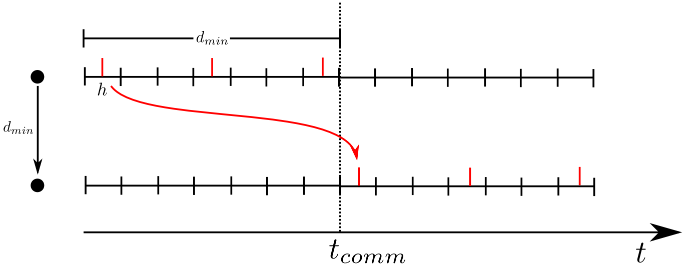
COMMUNICATION OF EVENTS

- communication only required in intervals of the minimal delay between neurons



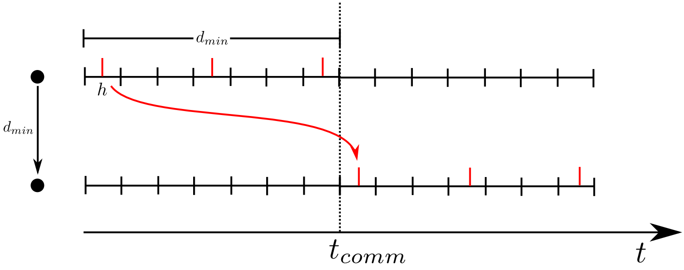
COMMUNICATION OF EVENTS

- communication only required in intervals of the minimal delay between neurons
- communication frequency independent of step size h



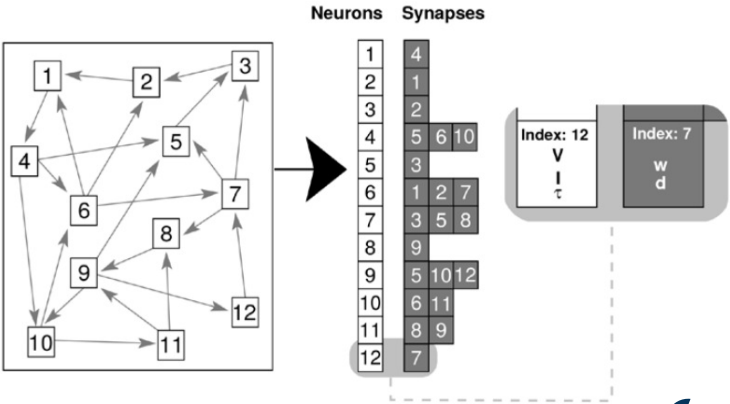
COMMUNICATION OF EVENTS

- communication only required in intervals of the minimal delay between neurons
- communication frequency independent of step size h
- less communications containing more data is more efficient due to overhead of communication between machines



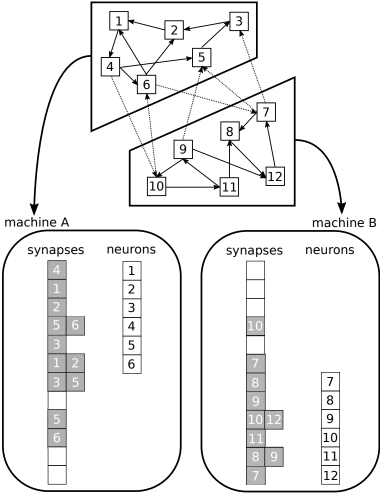
REPRESENTATION OF NETWORK STRUCTURE: SERIAL

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



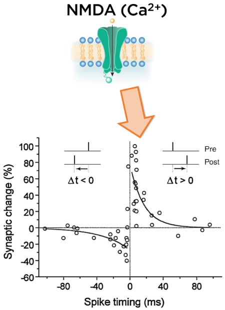
REPRESENTATION OF NETWORK STRUCTURE: DISTRIBUTED

- neurons are distributed round robin onto processes
- one target list for every neuron on each machine
- synapse stored on machine that hosts the target neuron
- wiring is a parallel operation



NESTML

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



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
```

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

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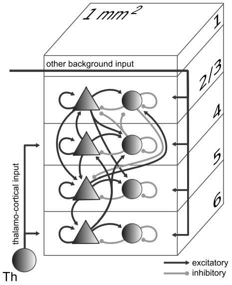
THE MICROCIRCUIT MODEL

- 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 sets

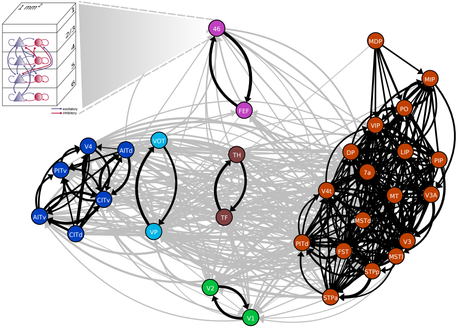


- asynchronous irregular and cell-type specific firing rates
- thalamic stimulation elicits flow of activity through cortical layers

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
- stable asynchronous irregular ground state

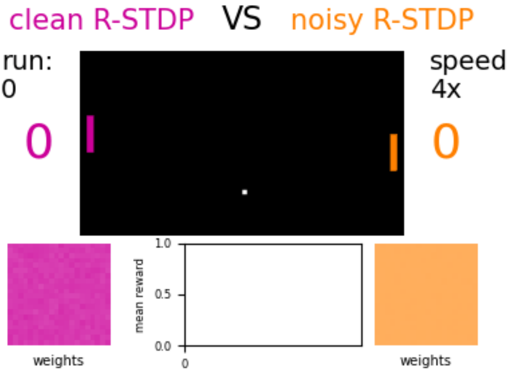


- produces realistic spiking statistics in V1
- functional connectivity compares to fMRI measurements

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

LEARNING TO PLAY PONG

Two spiking neural networks of two layers each compete by encoding an input-output mapping in their weights using reward-modulated STDP



Wunderlich T., et al (2019). Demonstrating advantages of neuromorphic computation: a pilot study. Frontiers in neuroscience, 13, 260

GETTING HELP

Within Python:

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

Online documentation:

`https://nest-simulator.readthedocs.io/`

Community:

- NEST user mailing list
- Bi-weekly open video conference
- `http://github.com/nest/nest-simulator/`
- Annual NEST Conference: a forum for users and developers

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

REFERENCES AND FURTHER READING

- The NEST Simulator documentation at https://nest-simulator.readthedocs.io/
- Gewaltig et al. (2012) NEST by example: An introduction to the neural simulation tool NEST. doi:10.1007/978-94-007-3858-4_18
- Hanuschkin et al. (2010) A general and efficient method for incorporating precise spike times in globally time-driven simulations. doi:10.3389/fninf.2010.00113
- Jordan et al. (2018) Extremely Scalable Spiking Neuronal Network Simulation Code: From Laptops to Exascale Computers. doi:10.3389/fninf.2018.00002

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