NEST by Example: An Introduction to the Neural Simulation Tool NEST Version 2.12.0

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Abstract

The neural simulation tool NEST can simulate small to very large networks of point-neurons or neurons with a few compartments. In this chapter, we show by example how models are programmed and simulated in NEST.

This document is based on a preprint version of Gewaltig et al. (2012) and has been updated for NEST 2.12.

Converted to Jupyter Notebook and updated to 2.12.0 Håkon Mørk, January 2017

Edited Sacha J. van Albada, May 2015

Updated to 2.6.0 Hans E. Plesser, December 2014

Updated to 2.4.0 Hans E. Plesser, June 2014

Updated to 2.2.2 Hans E. Plesser & Marc-Oliver Gewaltig, December 2012

1 Introduction

NEST is a simulator for networks of point neurons, that is, neuron models that collapse the morphology (geometry) of dendrites, axons, and somata into either a single compartment or a small number of compartments (Gewaltig and Diesmann, 2007). This simplification is useful for questions about the dynamics of large neuronal networks with complex connectivity. In this text, we give a practical introduction to neural simulations with NEST. We describe how network models are defined and simulated, how simulations can be run in parallel, using multiple cores or computer clusters, and how parts of a model can be randomized.

The development of NEST started in 1994 under the name SYNOD to investigate the dynamics of a large cortex model, using integrate-and-fire neurons (Diesmann et al., 1995). At that time the only available simulators were NEURON (Hines and Carnevale, 1997) and GENESIS (Bower and Beeman, 1995) , both focusing on morphologically detailed neuron models, often using data from microscopic reconstructions.

Since then, the simulator has been under constant development. In 2001, the Neural Simulation Technology Initiative was founded to disseminate our knowledge of neural simulation technology. The continuing research of the member institutions into algorithms for the simulation of large spiking networks has resulted in a number of influential publications. The algorithms and techniques developed are not only implemented in the NEST simulator, but

have also found their way into other prominent simulation projects, most notably the NEURON simulator (for the Blue Brain Project: (Migliore et al., 2006)) and IBM's C2 simulator (Ananthanarayanan et al., 2009).

Today, in 2017, there are several simulators for large spiking networks to choose from (Brette et al., 2007), but NEST remains the best established simulator with the the largest developer networks to choose from.

A NEST simulation consists of three main components:

- **Nodes** are all neurons, devices, and also sub-networks. Nodes have a dynamic state that changes over time and that can be influenced by incoming *events*.
- **Events** are pieces of information of a particular type. The most common event is the spike-event. Other event types are voltage events and current events.
- **Connections** are communication channels between nodes. Only if one node is connected to another node, can they exchange events. Connections are weighted, directed, and specific to one event type. Directed means that events can flow only in one direction. The node that sends the event is called *source* and the node that receives the event is called *target*. The weight determines how strongly an event will influence the target node. A second parameter, the *delay*, determines how long an event needs to travel from source to target.

In the next sections, we will illustrate how to use NEST, using examples with increasing complexity. Each of the examples is self-contained.

2 First steps

We begin by starting Python. For interactive sessions, we here use the IPython shell (Pérez and Granger, 2007). It is convenient, because you can edit the command line and access previously typed commands using the up and down keys. However, all examples in this chapter work equally well without IPython. For data analysis and visualization, we also recommend the Python packages Matplotlib (Hunter, 2007) and NumPy (Oliphant, 2006).

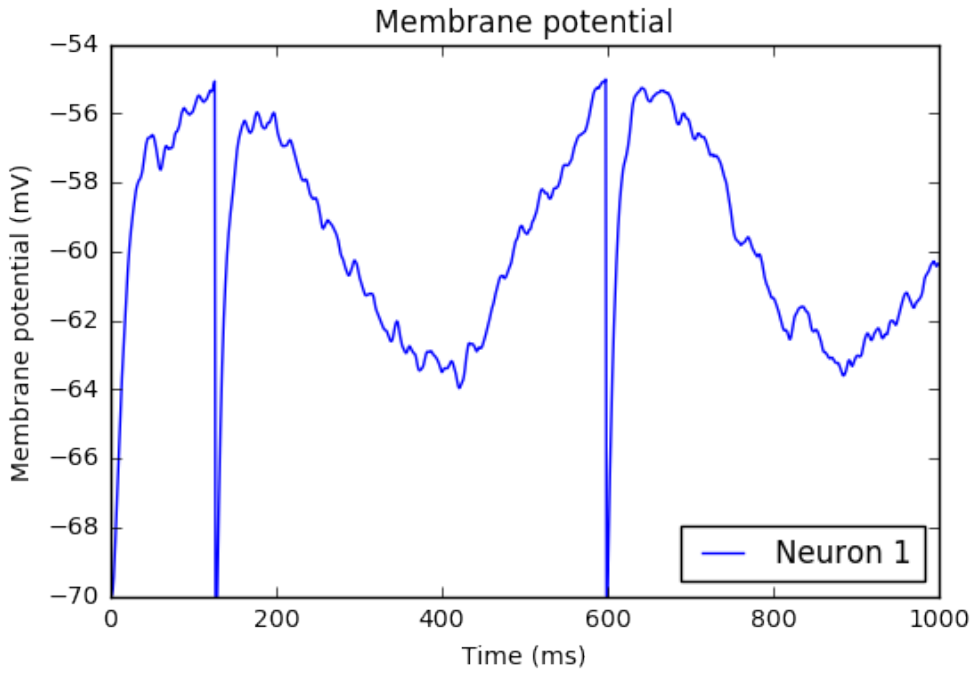
Our first simulation investigates the response of one integrate-and-fire neuron to an alternating current and Poisson spike trains from an excitatory and an inhibitory source. We record the membrane potential of the neuron to observe how the stimuli influence the neuron.

In this model, we inject a sine current with a frequency of 2 Hz and an amplitude of 100 pA into a neuron. At the same time, the neuron receives random spiking input from two sources known as Poisson generators. One Poisson generator represents a large population of excitatory neurons and the other a population of inhibitory neurons. The rate for each Poisson generator is set as the product of the assumed number of synapses per target neuron received from the population and the average firing rate of the source neurons.

The small network is simulated for 1000 milliseconds, after which the time course of the membrane potential during this period is plotted. For this, we use the `pylab` plotting routines of Python's Matplotlib package. The Python code for this small model is shown below.

```
>>> %matplotlib inline
... import nest
... import nest.voltage_trace
... nest.ResetKernel()
... neuron = nest.Create('iaf_psc_alpha')
... sine = nest.Create('ac_generator', 1,
...                    {'amplitude': 100.0,
...                     'frequency': 2.0})
... noise = nest.Create('poisson_generator', 2,
...                     [{'rate': 70000.0},
...                      {'rate': 20000.0}])
```

```
... voltmeter = nest.Create('voltmeter', 1,
...                         {'withgid': True})
... nest.Connect(sine, neuron)
... nest.Connect(voltmeter, neuron)
... nest.Connect(noise[:1], neuron, syn_spec={'weight': 1.0, 'delay': 1.0})
... nest.Connect(noise[1:], neuron, syn_spec={'weight': -1.0, 'delay': 1.0})
... nest.Simulate(1000.0)
... nest.voltage_trace.from_device(voltmeter);
```



We will now go through the simulation script and explain the individual steps. The first two lines `import` the modules `nest` and its sub-module `voltage_trace`. The `nest` module must be imported in every interactive session and in every Python script in which you wish to use NEST. NEST is a C++ library that provides a simulation kernel, many neuron and synapse models, and the simulation language interpreter SLI. The library which links the NEST simulation language interpreter to the Python interpreter is called PyNEST (Eppler et al., 2009).

Importing `nest` as shown above puts all NEST commands in the *namespace* `nest`. Consequently, all commands must be prefixed with the name of this namespace.

Next we use the command `Create` to produce one node of the type `iaf_psc_alpha`. As you see in subsequent lines, `Create` is used for all node types. The first argument, `'iaf_psc_alpha'`, is a string, denoting the type of node that you want to create. The second parameter of `Create` is an integer representing the number of nodes you want to create. Thus, whether you want one neuron or 100,000, you only need to call `Create` once. `nest.Models()` provides a list of all available node and connection models.

The third parameter is either a dictionary or a list of dictionaries, specifying the parameter settings for the created nodes. If only one dictionary is given, the same parameters are used for all created nodes. If an array of dictionaries is given, they are used in order and their number must match the number of created nodes. This variant of `Create` is to set the parameters for the Poisson noise generator, the sine generator (for the alternating current), and the voltmeter. All parameters of a model that are not set explicitly are initialized with default values. You can

display them with `nest.GetDefaults(model_name)`. Note that only the first parameter of `Create` is mandatory.

`Create` returns a list of integers, the global identifiers (or GID for short) of each node created. The GIDs are assigned in the order in which nodes are created. The first node is assigned GID 1, the second node GID 2, and so on.

After creating the neuron, sine and noise generators, and voltmeter, we connect the nodes. First we connect the sine generator and the voltmeter to the neuron. The command `Connect` takes two or more arguments. The first argument is a list of source nodes. The second argument is a list of target nodes. `Connect` iterates these two lists and connects the corresponding pairs.

A node appears in the source position of `Connect` if it sends events to the target node. In our example, the sine generator is in the source position because it injects an alternating current into the neuron. The voltmeter is in the source position because it polls the membrane potential of the neuron. Other devices may be in the target position, e.g., the spike detector which receives spike events from a neuron. If in doubt about the order, consult the documentation of the respective nodes using NEST's help system. For example, to read the documentation of the ac_generator you can type `nest.help('ac_generator')`. Dismiss the help by typing `q`.

Next, we use the command `Connect` with the `syn_spec` parameter to connect the two Poisson generators to the neuron. In this example the synapse specification `syn_spec` provides only weight and delay values, in this case ± 1 pA input current amplitude and 1 ms delay. We will see more advanced uses of `syn_spec` below.

After connecting the nodes, the network is ready. We call the NEST function `Simulate` which runs the network for 1000 milliseconds. The function returns after the simulation is finished. Then, function `voltage_trace` is called to plot the membrane potential of the neuron. If you are running the script for the first time, you may have to tell Python to display the figure by typing `pylab.show()`.

If you want to inspect how your network looks so far, you can print it using the command `PrintNodes()`:

```
>>> nest.PrintNodes()

1       iaf_psc_alpha
2       ac_generator
3 .. 4  poisson_generator
5       voltmeter
```

If you run the example a second time, NEST will leave the existing nodes intact and will create a second instance for each node. To start a new NEST session without leaving Python, you can call `nest.ResetKernel()`. This function will erase the existing network so that you can start from scratch.

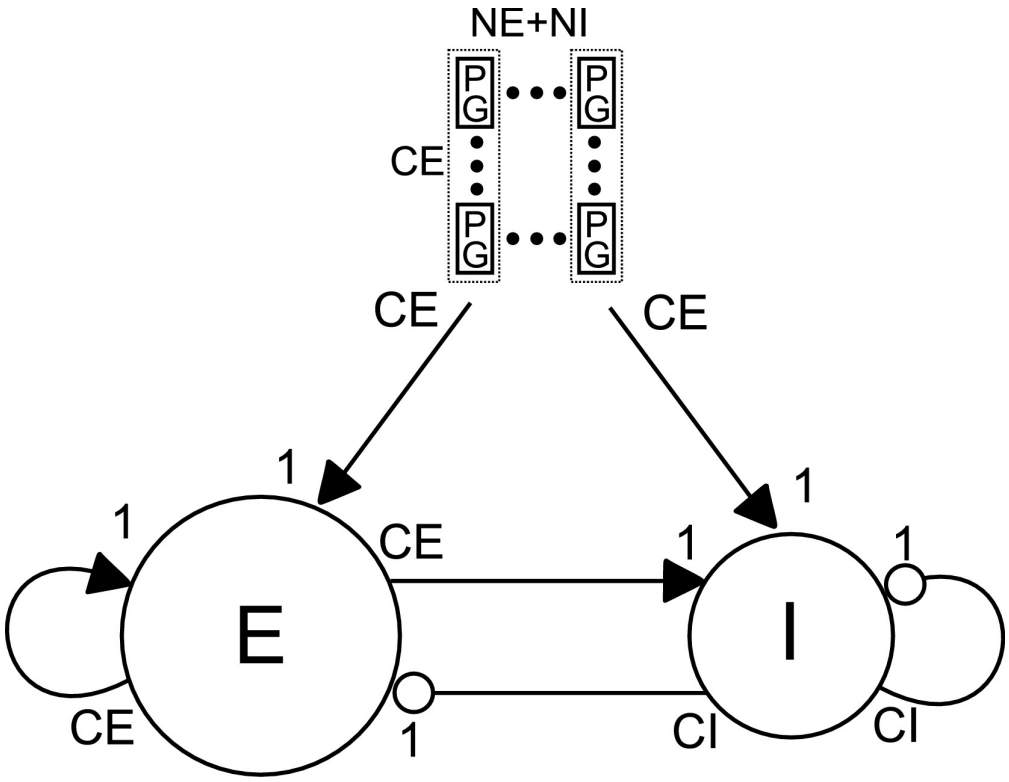
3 Example 1: A sparsely connected recurrent network

Next we discuss a model of activity dynamics in a local cortical network proposed by (Brunel, 2000). We only describe those parts of the model which are necessary to understand its NEST implementation. Please refer to the original paper for further details.

The local cortical network consists of two neuron populations: a population of N_E excitatory neurons and a population of N_I inhibitory neurons. To mimic the cortical ratio of 80% excitatory neurons and 20% inhibitory neurons, we assume that $N_E = 8000$ and $N_I = 2000$. Thus, our local network has a total of 10,000 neurons.

For both the excitatory and the inhibitory population, we use the same integrate-and-fire neuron model with current-based synapses. Incoming excitatory and inhibitory spikes displace the membrane potential V_m by J_E and J_I, respectively. If V_m reaches the threshold value V_{th}, the membrane potential is reset to V_{reset}, a spike is sent with delay $D = 1.5$ ms to all postsynaptic neurons, and the neuron remains refractory for $\tau_{\text{rp}} = 2.0$ ms.

The neurons are mutually connected with a probability of 10%. Specifically, each neuron receives input from $C_E = 0.1 \cdot N_E$ excitatory and $C_I = 0.1 \cdot N_I$ inhibitory neurons (see figure below). The inhibitory synaptic weights J_I are chosen with respect to the excitatory synaptic weights J_E such that $J_I = -g \cdot J_E$, with $g = 5.0$ in this example. In addition to the sparse



Sketch of the network model proposed by (Brunel, 2000). The network consists of three populations: N_E excitatory neurons (circle labelled E), N_I inhibitory neurons (circle labelled I), and a population of identical, independent Poisson processes (PGs) representing activity from outside the network. Arrows represent connections between the network nodes. Triangular arrow-heads represent excitatory and round arrow-heads represent inhibitory connections. The numbers at the start and end of each arrow indicate the multiplicity of the connection.

recurrent inputs from within the local network, each neuron receives randomly timed excitatory input, mimicking the input from the rest of cortex. The random input is modelled as C_E independent and identically distributed Poisson processes with rate ν_{ext}, or equivalently, by a single Poisson process with rate $C_E \cdot \nu_{\text{ext}}$. Here, we set ν_{ext} to twice the rate ν_{th} that is needed to drive a neuron to threshold asymptotically. The details of the model are summarized in the tables below.

In the resulting plot you should see a raster plot of 50 excitatory neurons during the first 300 ms of simulated time. Time is shown along the x-axis, neuron ID along the y-axis. At $t = 0$, all neurons are in the same state $V_m = 0$ and hence there is no spiking activity. The external stimulus rapidly drives the membrane potentials towards the threshold. Due to the random nature of the external stimulus, not all the neurons reach the threshold at the same time. After a few milliseconds, the neurons start to spike irregularly at roughly 40 spikes/s. In the original paper, this network state is called the *asynchronous irregular state* (Brunel, 2000).

Summary of the network model.

A	Model Summary
Populations	Three: excitatory, inhibitory, external input
Topology	—
Connectivity	Random convergent connections with probability $P = 0.1$ and fixed in-degree of $C_E = PN_E$ and $C_I = PN_I$.
Neuron model	Leaky integrate-and-fire, fixed voltage threshold, fixed absolute refractory time (voltage clamp)
Channel models	—
Synapse model	δ-current inputs (discontinuous voltage jumps)
Plasticity	—
Input	Independent fixed-rate Poisson spike trains to all neurons
Measurements	Spike activity

B	Populations	
Name	**Elements**	**Size**
nodes_E	`iaf_psc_delta` neuron	$N_{\mathrm{E}} = 4N_{\mathrm{I}}$
nodes_I	`iaf_psc_delta` neuron	N_{I}
noise	Poisson generator	1

C	Connectivity		
Name	**Source**	**Target**	**Pattern**
EE	nodes_E	nodes_E	Random convergent $C_{\mathrm{E}} \to 1$, weight J, delay D
IE	nodes_E	nodes_I	Random convergent $C_{\mathrm{E}} \to 1$, weight J, delay D
EI	nodes_I	nodes_E	Random convergent $C_{\mathrm{I}} \to 1$, weight $-gJ$, delay D
II	nodes_I	nodes_I	Random convergent $C_{\mathrm{I}} \to 1$, weight $-gJ$, delay D
Ext	noise	nodes_E $\cup$ nodes_I	Divergent $1 \to N_{\mathrm{E}} + N_{\mathrm{I}}$, weight J, delay D

D	Neuron and Synapse Model
Name	`iaf_psc_delta` neuron
Type	Leaky integrate-and-fire, δ-current input
Sub-threshold dynamics	$\tau_m \dot{V_m}(t) = -V_m(t) + R_m I(t)$ if not refractory $(t > t^* + \tau_{\mathrm{rp}})$ $V_m(t) = V_{\mathrm{r}}$ while refractory $(t^* < t \leq t^* + \tau_{\mathrm{rp}})$ $I(t) = \frac{\tau_m}{R_m} \sum_{\tilde{t}} w \delta(t - (\tilde{t} + D))$
Spiking	If $V_m(t-) < V_\theta \wedge V_m(t+) \geq V_\theta$ 1. set $t^* = t$ 2. emit spike with time-stamp t^*

E	Input
Type	**Description**
Poisson generator	Fixed rate $\nu_{\mathrm{ext}} \cdot C_{\mathrm{E}}$, one generator providing independent input to each target neuron

F	Measurements
Spike activity as raster plots, rates and "global frequencies", no details given	

Summary of the network parameters for the model.

G	Network Parameters
Parameter	**Value**
Number of excitatory neurons N_E	8000
Number of inhibitory neurons N_I	2000
Excitatory synapses per neuron C_E	800
Inhibitory synapses per neuron C_I	200

H	Neuron Parameters
Parameter	**Value**
Membrane time constant τ_m	20 ms
Refractory period τ_{rp}	2 ms
Firing threshold V_{th}	20 mV
Membrane capacitance C_m	1 pF
Resting potential V_E	0 mV
Reset potential V_{reset}	10 mV
Excitatory PSP amplitude J_E	0.1 mV
Inhibitory PSP amplitude J_I	-0.5 mV
Synaptic delay D	1.5 ms
Background rate η	2.0

3.1 NEST Implementation

We now show how this model is implemented in NEST. Along the way, we explain the required steps and NEST commands in more detail so that you can apply them to your own models.

3.1.1 Preparations

The first three lines import NEST, a NEST module for raster plots, and the plotting package `pylab`. We then assign the various model parameters to variables.

```
>>> import nest
... import nest.raster_plot
... import pylab
... nest.ResetKernel()
... g = 5.0
... eta = 2.0
... delay = 1.5
... tau_m = 20.0
... V_th = 20.0
... N_E = 8000
... N_I = 2000
... N_neurons = N_E + N_I
... C_E = int(N_E / 10)
... C_I = int(N_I / 10)
... J_E = 0.1
... J_I = -g * J_E
... nu_ex = eta * V_th / (J_E * C_E * tau_m)
... p_rate = 1000.0 * nu_ex * C_E
```

In the second to last line, we compute the firing rate `nu_ex` (ν_{ext}) of a neuron in the external population. We define `nu_ex` as the product of a constant `eta` times the threshold rate ν_{th},

i.e. the steady state firing rate which is needed to bring a neuron to threshold. The value of the scaling constant is defined with `eta`.

In the final line, we compute the combined input rate due to the external population. With C_E incoming synapses per neuron, the total rate is simply the product `nu_ex*C_E`. The factor 1000.0 in the product changes the units from spikes per ms to spikes per second.

Next, we prepare the simulation kernel of NEST

```
>>> nest.SetKernelStatus({'print_time': True})
```

The command `SetKernelStatus` modifies parameters of the simulation kernel. The argument is a Python dictionary with *key:value* pairs. Here, we set the NEST kernel to print the progress of the simulation time during simulation. Note that the progress is output only to the terminal.

3.1.2 Creating neurons and devices

As a rule of thumb, we recommend that you create all elements in your network, i.e., neurons, stimulating devices and recording devices first, before creating any connections.

```
>>> nest.SetDefaults('iaf_psc_delta',
...                  {'C_m': 1.0,
...                   'tau_m': tau_m,
...                   't_ref': 2.0,
...                   'E_L': 0.0,
...                   'V_th': V_th,
...                   'V_reset': 10.0})
```

Here we change the parameters of the neuron model we want to use from the built-in values to the defaults for our investigation. `SetDefaults` expects two parameters. The first is a string, naming the model for which the default parameters should be changed. Our neuron model for this simulation is the simplest integrate-and-fire model in NEST's repertoire: `'iaf_psc_delta'`. The second parameter is a dictionary with parameters and their new values, entries separated by commas. All parameter values are taken from Brunel's paper (Brunel, 2000) and we insert them directly for brevity. Only the membrane time constant `tau_m` and the threshold potential `V_th` are read from variables, because these values are needed in several places.

```
>>> nodes = nest.Create('iaf_psc_delta', N_neurons)
... nodes_E = nodes[:N_E]
... nodes_I = nodes[N_E:]
...
... noise = nest.Create('poisson_generator', 1, {'rate': p_rate})
...
... nest.SetDefaults('spike_detector', {'to_file': True})
...
... spikes = nest.Create('spike_detector', 2,
...                      [{'label': 'brunel-py-ex'},
...                       {'label': 'brunel-py-in'}])
... spikes_E = spikes[:1]
... spikes_I = spikes[1:]
```

As before we create the neurons with `Create`, which returns a list of the global IDs which are consecutive numbers from 1 to `N_neurons`. We split this range into excitatory and inhibitory neurons. We then select the first `N_E` elements from the list `nodes` and assign them to the variable `nodes_E`. This list now holds the GIDs of the excitatory neurons.

Similarly, in the next line, we assign the range from position `N_E` to the end of the list to the variable `nodes_I`. This list now holds the GIDs of all inhibitory neurons. The selection

is carried out using standard Python list commands. You may want to consult the Python documentation for more details.

Next, we create and connect the external population and some devices to measure the spiking activity in the network.

We create a device known as a `poisson_generator`, which produces a spike train governed by a Poisson process at a given rate. We use the third parameter of `Create` to initialize the rate of the Poisson process to the population rate `p_rate` which we have previously computed.

If a Poisson generator is connected to n targets, it generates n independent and identically distributed spike trains. Thus, we only need one generator to model an entire population of randomly firing neurons.

To observe how the neurons in the recurrent network respond to the random spikes from the external population, we create two spike detectors. By default, spike detectors record to memory but not to file. We override this default behaviour to also record to file. Then we create one detector for the excitatory neurons and one for the inhibitory neurons. The default file names are automatically generated from the device type and its global ID. We use the third argument of `Create` to give each spike detector a `'label'`, which will be part of the name of the output file written by the detector. Since two devices are created, we supply a list of dictionaries.

In the second to last line, we store the GID of the first spike detector in a one-element list and assign it to the variable `spikes_E`. In the next line, we do the same for the second spike detector that is dedicated to the inhibitory population.

3.1.3 Connecting the network

Once all network elements are in place, we connect them.

```
>>> nest.CopyModel('static_synapse_hom_w',
...                'excitatory',
...                {'weight': J_E,
...                 'delay': delay})
... nest.Connect(nodes_E, nodes,
...              {'rule': 'fixed_indegree',
...               'indegree': C_E},
...              'excitatory')
... nest.CopyModel('static_synapse_hom_w',
...                'inhibitory',
...                {'weight': J_I,
...                 'delay':delay})
... nest.Connect(nodes_I, nodes,
...              {'rule': 'fixed_indegree',
...               'indegree': C_I},
...              'inhibitory')
```

We create a new connection type `'excitatory'` by copying the built-in connection type `'static_synapse_hom_w'` while changing its default values for *weight* and *delay*. The command `CopyModel` expects either two or three arguments: the name of an existing neuron or synapse model, the name of the new model, and optionally a dictionary with the new default values of the new model.

The connection type `'static_synapse_hom_w'` uses the same values of weight for all synapses. This saves memory for networks in which these values are identical for all connections. Later (in 'Randomness in NEST') we will use a different connection model to implement randomized weights and delays.

Having created and parameterized an appropriate synapse model, we draw the incoming excitatory connections for each neuron. The function `Connect` expects four arguments:

a list of source nodes, a list of target nodes, a connection rule, and a synapse specification. Some connection rules, in particular `'one_to_one'` and `'all_to_all'` require no parameters and can be specified as strings. All other connection rules must be specified as a dictionary, which at least must contain the key `'rule'` specifying a connection rule; `nest.ConnectionRules()` shows all connection rules. The remaining dictionary entries depend on the particular rule. We use the `'fixed_indegree'` rule, which creates exactly `indegree` connections to each target neuron; in previous versions of NEST, this connectivity was provided by `RandomConvergentConnect`.

The final argument specifies the synapse model to be used, here the `'excitatory'` model we defined previously.

In the final lines we repeat the same steps for the inhibitory connections: we create a new connection type and draw the incoming inhibitory connections for all neurons.

```
>>> nest.Connect(noise, nodes, syn_spec='excitatory')
...
... N_rec = 50
... nest.Connect(nodes_E[:N_rec], spikes_E)
... nest.Connect(nodes_I[:N_rec], spikes_I)
```

Here we use `Connect` to connect the Poisson generator to all nodes of the local network. Since these connections are excitatory, we use the `'excitatory'` connection type. Finally, we connect a subset of excitatory and inhibitory neurons to the spike detectors to record from them. If no connection rule is given, `Connect` connects all sources to all targets (`all_to_all` rule), i.e., the noise generator is connected to all neurons (previously `DivergentConnect`), while in the second to last line, all recorded excitatory neurons are connected to the `spikes_E` spike detector (previously `ConvergentConnect`).

Our network consists of 10,000 neurons, all of which have the same activity statistics due to the random connectivity. Thus, it suffices to record from a representative sample of neurons, rather than from the entire network. Here, we choose to record from 50 neurons and assign this number to the variable `N_rec`. We then connect the first 50 excitatory neurons to their spike detector. Again, we use standard Python list operations to select `N_rec` neurons from the list of all excitatory nodes. Alternatively, we could select 50 neurons at random, but since the neuron order has no meaning in this model, the two approaches would yield qualitatively the same results. Finally, we repeat this step for the inhibitory neurons.

3.1.4 Simulating the network

Now everything is set up and we can run the simulation.

```
>>> simtime = 300
... nest.Simulate(simtime)
... ex_events, in_events = nest.GetStatus(spikes, 'n_events')
... events_to_rate = 1000. / simtime / N_rec
... rate_ex = ex_events * events_to_rate
... print('Excitatory rate: {:.2f} Hz'.format(rate_ex))
... rate_in = in_events * events_to_rate
... print('Inhibitory rate: {:.2f} Hz'.format(rate_in))
... nest.raster_plot.from_device(spikes_E, hist=True);
```

First we select a simulation time of 300 milliseconds and assign it to a variable. Next, we call the NEST command `Simulate` to run the simulation for 300 ms. During simulation, the Poisson generators send spikes into the network and cause the neurons to fire. The spike detectors receive spikes from the neurons and write them to a file and to memory.

When the function returns, the simulation time has progressed by 300 ms. You can call `Simulate` as often as you like and with different arguments. NEST will resume the simulation

at the point where it was last stopped. Thus, you can partition your simulation time into small epochs to regularly inspect the progress of your model.

After the simulation is finished, we compute the firing rate of the excitatory neurons and the inhibitory neurons. Finally, we call the NEST function `raster_plot` to produce the raster plot. `raster_plot` has two modes. `raster_plot.from_device` expects the global ID of a spike detector. `raster_plot.from_file` expects the name of a data file. This is useful to plot data without repeating a simulation.

4 Parallel simulation

Large network models often require too much time or computer memory to be conveniently simulated on a single computer. For example, if we increase the number of neurons in the previous model to 100,000, there will be a total of 10^9 connections, which won't fit into the memory of most computers. Similarly, if we use plastic synapses (see Example 3: plastic networks) and run the model for minutes or hours of simulated time, the execution times become uncomfortably long.

To address this issue, NEST has two modes of parallelization: multi-threading and distribution. Multi-threaded and distributed simulation can be used in isolation or in combination (Plesser et al., 2007) , and both modes allow you to connect and run networks more quickly than in the serial case.

Multi-threading means that NEST uses all available processors or cores of the computer. Today, most desktop computers and even laptops have at least two processing cores. Thus, you can use NEST's multi-threaded mode to make your simulations execute more quickly whilst still maintaining the convenience of interactive sessions. Since a given computer has a fixed memory size, multi-threaded simulation can only reduce execution times. It cannot solve the problem that large models exhaust the computer's memory.

Distribution means that NEST uses many computers in a network or computer cluster. Since each computer contributes memory, distributed simulation allows you to simulate models that are too large for a single computer. However, in distributed mode it is not currently possible to use NEST interactively.

In most cases, writing a simulation script to be run in parallel is as easy as writing one to be executed on a single processor. Only minimal changes are required, as described below, and you can ignore the fact that the simulation is actually executed by more than one core or computer. However, in some cases your knowledge about the distributed nature of the simulation can help you improve efficiency even further. For example, in the distributed mode, all computers execute the same simulation script. We can improve performance if the script running on a specific computer only tries to execute commands relating to nodes that are represented on the same computer. An example of this technique is shown below in Example 2.

To switch NEST into multi-threaded mode, you only have to add one line to your simulation script:

```
>>> nest.ResetKernel()
... n = 4  # number of threads
... nest.SetKernelStatus({'local_num_threads': n})
```

Here, `n` is the number of threads you want to use. It is important that you set the number of threads *before* you create any nodes. If you try to change the number of threads after nodes were created, NEST will issue an error.

A good choice for the number of threads is the number of cores or processors on your computer. If your processor supports hyperthreading, you can select an even higher number of threads.

The distributed mode of NEST is particularly useful for large simulations for which not only the processing speed, but also the memory of a single computer are insufficient. The distributed mode of NEST uses the Message Passing Interface (MPI Forum, 2009), a library

that must be installed on your computer network when you install NEST. For details, please refer to NEST documentation at www.nest-simulator.org.

The distributed mode of NEST is also easy to use. All you need to do is start NEST with the MPI command `mpirun`:

```
mpirun -np m python script.py
```

where `m` is the number of MPI processes that should be started. One sensible choice for `m` is the total number of cores available on the cluster. Another reasonable choice is the number of physically distinct machines, utilizing their cores through multithreading as described above. This can be useful on clusters of multi-core computers.

In NEST, processes and threads are both mapped to *virtual processes* (Plesser et al., 2007) . If a simulation is started with `m` MPI processes and `n` threads on each process, then there are `m×n` virtual processes. You can obtain the number of virtual processes in a simulation with

```
>>> nest.GetKernelStatus('total_num_virtual_procs')
```

The virtual process concept is reflected in the labelling of output files. For example, the data files for the excitatory spikes produced by the network discussed here follow the form `brunel-py-ex-x-y.gdf`, where `x` is the ID of the data recording node and `y` is the ID of the virtual process.

5 Randomness in NEST

NEST has built-in random number sources that can be used for tasks such as randomizing spike trains or network connectivity. In this section, we discuss some of the issues related to the use of random numbers in parallel simulations. In example 2, we illustrate how to randomize parameters in a network.

Let us first consider the case that a simulation script does not explicitly generate random numbers. In this case, NEST produces identical simulation results for a given number of virtual processes, irrespective of how the virtual processes are partitioned into threads and MPI processes. The only difference between the output of two simulations with different configurations of threads and processes resulting in the same number of virtual processes is the result of query commands such as `GetStatus`. These commands gather data over threads on the local machine, but not over remote machines.

In the case that random numbers are explicitly generated in the simulation script, more care must be taken to produce results that are independent of the parallel configuration. Consider, for example, a simulation where two threads have to draw a random number from a single random number generator. Since only one thread can access the random number generator at a time, the outcome of the simulation will depend on the access order.

Ideally, all random numbers in a simulation should come from a single source. In a serial simulation this is trivial to implement, but in parallel simulations this would require shipping a large number of random numbers from a central random number generator (RNG) to all processes. This is impractical. Therefore, NEST uses one independent random number generator on each virtual process. Not all random number generators can be used in parallel simulations, because many cannot reliably produce uncorrelated parallel streams. Fortunately, recent years have seen great progress in RNG research and there is a range of random number generators that can be used with great fidelity in parallel applications.

Based on this knowledge, each virtual process (VP) in NEST has its own RNG. Numbers from these RNGs are used to

- choose random connections
- create random spike trains (e.g., `poisson_generator`) or random currents (e.g., `noise_generator`).

In order to randomize model parameters in a PyNEST script, it is convenient to use the random number generators provided by NumPy. To ensure consistent results for a given num-

ber of virtual processes, each virtual process should use a separate Python RNG. Thus, in a simulation running on N_{vp} virtual processes, there should be $2N_{vp} + 1$ RNGs in total:

- the global NEST RNG;
- one RNG per VP in NEST;
- one RNG per VP in Python.

We need to provide separate seed values for each of these generators. Modern random number generators work equally well for all seed values. We thus suggest the following approach to choosing seeds: For each simulation run, choose a master seed msd and seed the RNGs with seeds msd, $msd + 1$, $\ldots$ $msd + 2N_{vp}$. Any two master seeds must differ by at least $2N_{vp} + 1$ to avoid correlations between simulations.

By default, NEST uses Knuth's lagged Fibonacci RNG, which has the nice property that each seed value provides a different sequence of some 2^{70} random numbers (Knuth, 1998). Python uses the Mersenne Twister MT19937 generator (Matsumoto and Nishimura, 1998), which provides no explicit guarantees, but given the enormous state space of this generator it appears astronomically unlikely that neighbouring integer seeds would yield overlapping number sequences. For a recent overview of RNGs, see (L'Ecuyer and Simard, 2007). For general introductions to random number generation, see (Gentle, 2003), (Knuth, 1998) or (Plesser, 2010).

6 Example 2: Randomizing neurons and synapses

Let us now consider how to randomize some neuron and synapse parameters in the sparsely connected network model introduced in Example 1. We shall

- explicitly seed the random number generators;
- randomize the initial membrane potential of all neurons;
- randomize the weights of the recurrent excitatory connections.

We begin by setting up the parameters

```
>>> import numpy
... import nest
... nest.ResetKernel()
... # Network parameters. These are given in Brunel (2000) J.Comp.Neuro.
... g = 5.0  # Ratio of IPSP to EPSP amplitude: J_I/J_E
... eta = 2.0  # rate of external population in multiples of threshold rate
... delay = 1.5  # synaptic delay in ms
... tau_m = 20.0  # Membrane time constant in mV
... V_th = 20.0  # Spike threshold in mV
...
... N_E = 8000
... N_I = 2000
... N_neurons = N_E + N_I
...
... C_E = int(N_E / 10)  # number of excitatory synapses per neuron
... C_I = int(N_I / 10)  # number of inhibitory synapses per neuron
...
... J_E = 0.1
... J_I = -g * J_E
...
... nu_ex = eta * V_th / (J_E * C_E * tau_m)  # rate of an external neuron in ms^-1
... p_rate = 1000.0 * nu_ex * C_E  # rate of the external population in s^-1
...
```

```
... # Set parameters of the NEST simulation kernel
... nest.SetKernelStatus({'print_time': True,
...                       'local_num_threads': 2})
```

So far the code is similar to Example 1, but now we insert code to seed the random number generators:

```
>>> # Create and seed RNGs
... msd = 1000   # master seed
... n_vp = nest.GetKernelStatus('total_num_virtual_procs')
... msdrange1 = range(msd, msd + n_vp)
... pyrngs = [numpy.random.RandomState(s) for s in msdrange1]
... msdrange2 = range(msd + n_vp + 1, msd + 1 + 2 * n_vp)
... nest.SetKernelStatus({'grng_seed': msd + n_vp,
...                       'rng_seeds': msdrange2})
```

We first define the master seed `msd` and then obtain the number of virtual processes `n_vp`. Then we create a list of `n_vp` NumPy random number generators with seeds `msd`, `msd+1`, ... `msd+n_vp-1`. The next two lines set new seeds for the built-in NEST RNGs: the global RNG is seeded with `msd+n_vp`, the per-virtual-process RNGs with `msd+n_vp+1`, ..., `msd+2*n_vp`. Note that the seeds for the per-virtual-process RNGs must always be passed as a list, even in a serial simulation.

Then we create the nodes

```
>>> nest.SetDefaults('iaf_psc_delta',
...                  {'C_m': 1.0,
...                   'tau_m': tau_m,
...                   't_ref': 2.0,
...                   'E_L': 0.0,
...                   'V_th': V_th,
...                   'V_reset': 10.0})
... nodes = nest.Create('iaf_psc_delta', N_neurons)
... nodes_E = nodes[:N_E]
... nodes_I = nodes[N_E:]
...
... noise = nest.Create('poisson_generator', 1, {'rate': p_rate})
...
... spikes = nest.Create('spike_detector', 2,
...                      [{'label': 'brunel-py-ex'},
...                       {'label': 'brunel-py-in'}])
... spikes_E = spikes[:1]
... spikes_I = spikes[1:]
```

After creating the neurons as before, we insert the following code to randomize the membrane potential of all neurons:

```
>>> node_info = nest.GetStatus(nodes)
... local_nodes = [(ni['global_id'], ni['vp'])
...                for ni in node_info if ni['local']]
... for gid, vp in local_nodes:
...     nest.SetStatus([gid], {'V_m': pyrngs[vp].uniform(-V_th, V_th)})
```

In this code, we meet the concept of *local* nodes for the first time (Plesser et al. 2007). In serial and multi-threaded simulations, all nodes are local. In an MPI-based simulation with m MPI processes, each MPI process represents and is responsible for updating (approximately) $1/m$-th of all nodes—these are the local nodes for each process. We obtain status information for each node; for local nodes, this will be full information, for non-local nodes this will only be

minimal information. We then use a list comprehension to create a list of `gid` and `vp` tuples for all local nodes. The `for`-loop then iterates over this list and draws for each node a membrane potential value uniformly distributed in $[-V_{\text{th}}, V_{\text{th}})$, i.e., $[-20\text{mV}, 20\text{mV})$. We draw the initial membrane potential for each node from the NumPy RNG assigned to the virtual process `vp` responsible for updating that node.

As the next step, we create excitatory recurrent connections with the same connection rule as in the original script, but with randomized weights.

```
>>> nest.CopyModel('static_synapse', 'excitatory')
... nest.Connect(nodes_E, nodes,
...              {'rule': 'fixed_indegree',
...               'indegree': C_E},
...              {'model': 'excitatory',
...               'delay': delay,
...               'weight': {'distribution': 'uniform',
...                          'low': 0.5 * J_E,
...                          'high': 1.5 * J_E}})
```

The first difference to the original is that we base the excitatory synapse model on the built-in `static_synapse` model instead of `static_synapse_hom_w`, as the latter implies equal weights for all synapses. The second difference is that we randomize the initial weights. To this end, we have replaced the simple synapse specification `'excitatory'` with a subsequent synapse specification dictionary. Such a dictionary must always contain the key `'model'` providing the synapse model to use. In addition, we specify a fixed delay, and a distribution from which to draw the weights, here a uniform distribution over $[J_E/2, 3J_E/2)$. NEST will automatically use the correct random number generator for each weight.

To see all available random distributions, please run `nest.sli_run('rdevdict info')`. To access documentation for an individual distribution, run, e.g., `nest.help('rdevdict::binomial')`. These distributions can be used for all parameters of a synapse.

We then make the rest of the connections.

```
>>> nest.CopyModel('static_synapse_hom_w',
...                'inhibitory',
...                {'weight': J_I,
...                 'delay': delay})
... nest.Connect(nodes_I, nodes,
...              {'rule': 'fixed_indegree',
...               'indegree': C_I},
...              'inhibitory')
...
... # connect one noise generator to all neurons
... nest.CopyModel('static_synapse_hom_w',
...                'excitatory_input',
...                {'weight': J_E,
...                 'delay': delay})
... nest.Connect(noise, nodes, syn_spec='excitatory_input')
...
... # connect all recorded E/I neurons to the respective detector
... N_rec = 50  # Number of neurons to record from
... nest.Connect(nodes_E[:N_rec], spikes_E)
... nest.Connect(nodes_I[:N_rec], spikes_I)
```

Before starting our simulation, we want to visualize the randomized initial membrane potentials and weights. To this end, we insert the following code just before we start the simulation:

```
>>> pylab.figure(figsize=(12,3))
... pylab.subplot(121)
... V_E = nest.GetStatus(nodes_E[:N_rec], 'V_m')
... pylab.hist(V_E, bins=10)
... pylab.xlabel('Membrane potential V_m [mV]')
... pylab.title('Initial distribution of membrane potentials')
... pylab.subplot(122)
... ex_conns = nest.GetConnections(nodes_E[:N_rec],
...                                synapse_model='excitatory')
... w = nest.GetStatus(ex_conns, 'weight')
... pylab.hist(w, bins=100)
... pylab.xlabel('Synaptic weight [pA]')
... pylab.title(
...     'Distribution of synaptic weights ({:d} synapses)'.format(len(w)));
```

Here, `nest.GetStatus` retrieves the membrane potentials of all 50 recorded neurons. The data is then displayed as a histogram with 10 bins. The function `nest.GetConnections` here finds all connections that

- have one of the 50 recorded excitatory neurons as source;
- have any local node as target;
- and are of type `excitatory`.

Next, we then use `GetStatus()` to obtain the weights of these connections. Running the script in a single MPI process, we record approximately 50,000 weights, which we display in a histogram with 100 bins.

Note that the code above will return complete results only when run in a single MPI process. Otherwise, only data from local neurons or connections with local targets will be obtained. It is currently not possible to collect recorded data across MPI processes in NEST. In distributed simulations, you should thus let recording devices write data to files and collect the data after the simulation is complete.

Comparing the raster plot from the simulation with randomized initial membrane potentials with the same plot for the original network reveals that the membrane potential randomization has prevented the synchronous onset of activity in the network.

We now run the simulation.

```
>>> simtime = 300.  # how long shall we simulate [ms]
... nest.Simulate(simtime)
```

As a final point, we make a slight improvement to the rate computation of the original script. Spike detectors count only spikes from neurons on the local MPI process. Thus, the original computation is correct only for a single MPI process. To obtain meaningful results when simulating on several MPI processes, we count how many of the `N_rec` recorded nodes are local and use that number to compute the rates:

```
>>> events = nest.GetStatus(spikes, 'n_events')
...
... N_rec_local_E = sum(nest.GetStatus(nodes_E[:N_rec], 'local'))
... rate_ex = events[0] / simtime * 1000.0 / N_rec_local_E
... print('Excitatory rate   : {:.2f} Hz'.format(rate_ex))
...
... N_rec_local_I = sum(nest.GetStatus(nodes_I[:N_rec], 'local'))
... rate_in = events[1] / simtime * 1000.0 / N_rec_local_I
... print('Inhibitory rate   : {:.2f} Hz'.format(rate_in))
```

Each MPI process then reports the rate of activity of its locally recorded nodes.

7 Example 3: Plastic Networks

NEST provides synapse models with a variety of short-term and long-term dynamics. To illustrate this, we extend the sparsely connected network introduced in Example 1 with randomized synaptic weights as described in section 'Randomness in NEST' to incorporate spike-timing-dependent plasticity (Bi and Poo, 1998) at its recurrent excitatory-excitatory synapses.

We create all nodes and randomize their initial membrane potentials as before. We then generate a plastic synapse model for the excitatory-excitatory connections and a static synapse model for the excitatory-inhibitory connections:

```
>>> nest.ResetKernel()
... # Synaptic parameters
... STDP_alpha = 2.02  # relative strength of STDP depression w.r.t potentiation
... STDP_Wmax = 3 * J_E  # maximum weight of plastic synapse
...
... # Simulation parameters
... N_vp = 8  # number of virtual processes to use
... base_seed = 10000  # increase in intervals of at least 2*n_vp+1
... N_rec = 50  # Number of neurons to record from
... data2file = True  # whether to record data to file
... simtime = 300.  # how long shall we simulate [ms]
... # Set parameters of the NEST simulation kernel
... nest.SetKernelStatus({'print_time': True,
...                       'local_num_threads': 2})
...
... # Create and seed RNGs
... ms = 1000  # master seed
... n_vp = nest.GetKernelStatus('total_num_virtual_procs')
... pyrngs = [numpy.random.RandomState(s) for s in range(ms, ms + n_vp)]
... nest.SetKernelStatus({'grng_seed': ms + n_vp,
...                       'rng_seeds': range(ms + n_vp + 1, ms + 1 + 2 * n_vp)})
...
... # Create nodes --------------------------------------------------
...
... nest.SetDefaults('iaf_psc_delta',
...                  {'C_m': 1.0,
...                   'tau_m': tau_m,
...                   't_ref': 2.0,
...                   'E_L': 0.0,
...                   'V_th': V_th,
...                   'V_reset': 10.0})
...
... nodes = nest.Create('iaf_psc_delta', N_neurons)
... nodes_E = nodes[:N_E]
... nodes_I = nodes[N_E:]
...
... noise = nest.Create('poisson_generator', 1, {'rate': p_rate})
...
... spikes = nest.Create('spike_detector', 2,
...                      [{'label': 'brunel_py_ex'},
...                       {'label': 'brunel_py_in'}])
... spikes_E = spikes[:1]
... spikes_I = spikes[1:]
...
```

```
... # randomize membrane potential
... node_info = nest.GetStatus(nodes, ['global_id', 'vp', 'local'])
... local_nodes = [(gid, vp) for gid, vp, islocal in node_info if islocal]
... for gid, vp in local_nodes:
...     nest.SetStatus([gid], {'V_m': pyrngs[vp].uniform(-V_th, V_th)})
...
... nest.CopyModel('stdp_synapse_hom',
...                'excitatory_plastic',
...                {'alpha': STDP_alpha,
...                 'Wmax': STDP_Wmax})
... nest.CopyModel('static_synapse', 'excitatory_static')
```

Here, we set the parameters `alpha` and `Wmax` of the synapse model but use the default settings for all its other parameters. The `_hom` suffix in the synapse model name indicates that all plasticity parameters such as `alpha` and `Wmax` are shared by all synapses of this model.

We again use `nest.Connect` to create connections with randomized weights:

```
>>> nest.Connect(nodes_E, nodes_E,
...              {'rule': 'fixed_indegree',
...               'indegree': C_E},
...              {'model': 'excitatory_plastic',
...               'delay': delay,
...               'weight': {'distribution': 'uniform',
...                          'low': 0.5 * J_E,
...                          'high': 1.5 * J_E}})
...
... nest.Connect(nodes_E, nodes_I,
...              {'rule': 'fixed_indegree',
...               'indegree': C_E},
...              {'model': 'excitatory_static',
...               'delay': delay,
...               'weight': {'distribution': 'uniform',
...                          'low': 0.5 * J_E,
...                          'high': 1.5 * J_E}})
... nest.CopyModel('static_synapse',
...                'inhibitory',
...                {'weight': J_I,
...                 'delay': delay})
... nest.Connect(nodes_I, nodes,
...              {'rule': 'fixed_indegree',
...               'indegree': C_I},
...              'inhibitory')
...
... # connect noise generator to all neurons
... nest.CopyModel('static_synapse_hom_w',
...                'excitatory_input',
...                {'weight': J_E,
...                 'delay': delay})
... nest.Connect(noise, nodes, syn_spec='excitatory_input')
...
... # connect all recorded E/I neurons to the respective detector
... nest.Connect(nodes_E[:N_rec], spikes_E)
... nest.Connect(nodes_I[:N_rec], spikes_I)
...
... # Simulate ------------------------------------------------------
```

```
...
... # Visualization of initial membrane potential and initial weight
... # distribution only if we run on single MPI process
... if nest.NumProcesses() == 1:
...
...     pylab.figure(figsize=(12,3))
...
...     # membrane potential
...     V_E = nest.GetStatus(nodes_E[:N_rec], 'V_m')
...     V_I = nest.GetStatus(nodes_I[:N_rec], 'V_m')
...     pylab.subplot(121)
...     pylab.hist([V_E, V_I], bins=10)
...     pylab.xlabel('Membrane potential V_m [mV]')
...     pylab.legend(('Excitatory', 'Inibitory'))
...     pylab.title('Initial distribution of membrane potentials')
...     pylab.draw()
...
...     # weight of excitatory connections
...     w = nest.GetStatus(nest.GetConnections(nodes_E[:N_rec],
...                                            synapse_model='excitatory_plastic'),
...                        'weight')
...
...     pylab.subplot(122)
...     pylab.hist(w, bins=100)
...     pylab.xlabel('Synaptic weight w [pA]')
...     pylab.title('Initial distribution of excitatory synaptic weights')
...     pylab.draw()
...
... else:
...     print('Multiple MPI processes, skipping graphical output')
...
... nest.Simulate(simtime)
...
... events = nest.GetStatus(spikes, 'n_events')
...
... # Before we compute the rates, we need to know how many of the recorded
... # neurons are on the local MPI process
... N_rec_local_E = sum(nest.GetStatus(nodes_E[:N_rec], 'local'))
... rate_ex = events[0] / simtime * 1000.0 / N_rec_local_E
... print('Excitatory rate   : {:.2f} Hz'.format(rate_ex))
...
... N_rec_local_I = sum(nest.GetStatus(nodes_I[:N_rec], 'local'))
... rate_in = events[1] / simtime * 1000.0 / N_rec_local_I
... print('Inhibitory rate   : {:.2f} Hz'.format(rate_in))
```

After a period of simulation, we can access the plastic synaptic weights for analysis:

```
>>> if nest.NumProcesses() == 1:
...     nest.raster_plot.from_device(spikes_E, hist=True)
...     # weight of excitatory connections
...     w = nest.GetStatus(nest.GetConnections(nodes_E[:N_rec],
...                                            synapse_model='excitatory_plastic'),
...                        'weight')
...     pylab.figure(figsize=(12,4))
...     pylab.hist(w, bins=100)
```

```
...     pylab.xlabel('Synaptic weight [pA]')
...     # pylab.savefig('../figures/rand_plas_w.eps')
...     # pylab.show()
...
... else:
...     print('Multiple MPI processes, skipping graphical output')
```

Plotting a histogram of the synaptic weights reveals that the initial uniform distribution has begun to soften, as we can see in the plots resulting from the simulation above. Simulation for a longer period results in an approximately Gaussian distribution of weights.

8 Example 4: Classes and Automatization Techniques

Running the examples line for line is possible in interactive sessions, but if you want to run a simulation several times, possibly with different parameters, it is more practical to write a script that can be loaded from Python.

Python offers a number of mechanisms to structure and organize not only your simulations, but also your simulation data. The first step is to re-write a model as a *class*. In Python, and other object-oriented languages, a class is a data structure which groups data and functions into a single entity. In our case, data are the different parameters of a model, and functions are what you can do with a model. Classes allow you to solve various common problems in simulations:

- **Parameter sets** Classes are data structures and so are ideally suited to hold the parameter set for a model. Class inheritance allows you to modify one, a few, or all parameters while maintaining the relation to the original model.
- **Model variations** Often, we want to change minor aspects of a model. For example, in one version we have homogeneous connections and in another we want randomized weights. Again, we can use class inheritance to express both cases while maintaining the conceptual relation between the models.
- **Data management** Often, we run simulations with different parameters or other variations and forget to record which data file belonged to which simulation. Python's class mechanisms provide a simple solution.

We organize the model from Example 1 into a class, by realizing that each simulation has five steps which can be factored into separate functions:

1. Define all independent parameters of the model. Independent parameters are those that have concrete values which do not depend on any other parameter. For example, in the Brunel model, the parameter g is an independent parameter.
2. Compute all dependent parameters of the model. These are all parameters or variables that have to be computed from other quantities (e.g., the total number of neurons).
3. Create all nodes (neurons, devices, etc.)
4. Connect the nodes.
5. Simulate the model.

We translate these steps into a simple class layout that will fit most models:

```
>>> class Model(object):
...     """Model description."""
...     # Define all independent variables.
...
...     def __init__(self):
...         """Initialize the simulation, set up data directory"""
...
...     def calibrate(self):
```

```
...         """Compute all dependent variables"""
...
...     def build(self):
...         """Create all nodes"""
...
...     def connect(self):
...         """Connect all nodes"""
...
...     def run(self, simtime):
...         """Build, connect, and simulate the model"""
```

In the following, we illustrate how to fit the model from Example 1 into this scaffold. The complete and commented listing can be found in your NEST distribution.

```
>>> class Brunel2000(object):
...     """
...     Implementation of the sparsely connected random network,
...     described by Brunel (2000) J. Comp. Neurosci.
...     Parameters are chosen for the asynchronous irregular
...     state (AI).
...     """
...     g = 5.0
...     eta = 2.0
...     delay = 1.5
...     tau_m = 20.0
...     V_th = 20.0
...     N_E = 8000
...     N_I = 2000
...     J_E = 0.1
...     N_rec = 50
...     threads = 2       # Number of threads for parallel simulation
...     built = False     # True, if build() was called
...     connected = False  # True, if connect() was called
...     # more definitions follow...
...
...     def __init__(self):
...         """
...         Initialize an object of this class.
...         """
...         self.name = self.__class__.__name__
...         self.data_path = self.name + '/'
...         nest.ResetKernel()
...         if not os.path.exists(self.data_path):
...             os.makedirs(self.data_path)
...         print("Writing data to: " + self.data_path)
...         nest.SetKernelStatus({'data_path': self.data_path})
...
...     def calibrate(self):
...         """
...         Compute all parameter dependent variables of the
...         model.
...         """
...         self.N_neurons = self.N_E + self.N_I
...         self.C_E = self.N_E / 10
...         self.C_I = self.N_I / 10
```

```
...         self.J_I = -self.g * self.J_E
...         self.nu_ex = self.eta * self.V_th / (self.J_E * self.C_E * self.tau_m)
...         self.p_rate = 1000.0 * self.nu_ex * self.C_E
...         nest.SetKernelStatus({"print_time": True,
...                               "local_num_threads": self.threads})
...         nest.SetDefaults("iaf_psc_delta",
...                          {"C_m": 1.0,
...                           "tau_m": self.tau_m,
...                           "t_ref": 2.0,
...                           "E_L": 0.0,
...                           "V_th": self.V_th,
...                           "V_reset": 10.0})
...
...     def build(self):
...         """
...         Create all nodes, used in the model.
...         """
...         if self.built:
...             return
...         self.calibrate()
...         # remaining code to create nodes
...         self.built = True
...
...     def connect(self):
...         """
...         Connect all nodes in the model.
...         """
...         if self.connected:
...             return
...         if not self.built:
...             self.build()
...         # remaining connection code
...         self.connected = True
...
...     def run(self, simtime=300):
...         """
...         Simulate the model for simtime milliseconds and print the
...         firing rates of the network during this period.
...         """
...         if not self.connected:
...             self.connect()
...         nest.Simulate(simtime)
...         # more code, e.g., to compute and print rates
```

A Python class is defined by the keyword `class` followed by the class name, `Brunel2000` in this example. The parameter `object` indicates that our class is a subclass of a general Python Object. After the colon, we can supply a documentation string, encased in triple quotes, which will be printed if we type `help(Brunel2000)`. After the documentation string, we define all independent parameters of the model as well as some global variables for our simulation. We also introduce two Boolean variables `built` and `connected` to ensure that the functions `build()` and `connect()` are executed exactly once.

Next, we define the class functions. Each function has at least the parameter `self`, which is a reference to the current class object. It is used to access the functions and variables of the object.

The first function from the code above is also the first one that is called for every class object. It has the somewhat cryptic name `__init__()`. `__init__()` is automatically called by Python whenever a new object of a class is created and before any other class function is called. We use it to initialize the NEST simulation kernel and to set up a directory where the simulation data will be stored.

The general idea is this: each simulation with a specific parameter set gets its own Python class. We can then use the class name to define the name of a data directory where all simulation data are stored.

In Python it is possible to read out the name of a class from an object. This is done with `self.name=self.__class__.__name__`. Don't worry about the many underscores, they tell us that these names are provided by Python. In the next line, we assign the class name plus a trailing slash to the new object variable `data_path`. Note how all class variables are prefixed with `self`.

Next we reset the NEST simulation kernel to remove any leftovers from previous simulations, using `nest.ResetKernel()`.

The following two lines use functions from the Python library `os` which provides functions related to the operating system. In the `if`-test we check whether a directory with the same name as the class already exists. If not, we create a new directory with this name. Finally, we set the data path property of the simulation kernel. All recording devices use this location to store their data. This does not mean that this directory is automatically used for any other Python output functions. However, since we have stored the data path in an object variable, we can use it whenever we want to write data to file.

The other class functions are quite straightforward. `Brunel2000.build()` accumulates all commands that relate to creating nodes. The only addition is a piece of code that checks whether the nodes were already created. The last line in this function sets the variable `self.built` to `True` so that other functions know that all nodes were created.

In function `Brunel2000.connect()` we first ensure that all nodes are created before we attempt to draw any connection. Again, the last line sets a variable, telling other functions that the connections were drawn successfully.

`Brunel2000.built` and `Brunel2000.connected` are state variables that help you to make dependencies between functions explicit and to enforce an order in which certain functions are called.

The main function `Brunel2000.run()` uses both state variables to build and connect the network.

In order to use the class we have to create an object of the class (after loading the file with the class definition, if it is in another file):

```
>>> import os
... net = Brunel2000()
... net.run(500)
```

Finally, we demonstrate how to use Python's class inheritance to express different parameter configurations and versions of a model. In the following listing, we derive a new class that simulates a network where excitation and inhibition are exactly balanced, i.e. $g = 4$:

```
>>> class Brunel_balanced(Brunel2000):
...     """
...     Exact balance of excitation and inhibition
...     """
...     g = 4
```

Class `Brunel_balanced` is defined with class `Brunel2000` as parameter. This means the new class inherits all parameters and functions from class `Brunel2000`. Then, we redefine the value of the parameter `g`. When we create an object of this class, it will create its new data directory.

We can use the same mechanism to implement an alternative version of the model. For example, instead of re-implementing the model with randomized connection weights, we can use inheritance to change just the way nodes are connected:

```
>>> class Brunel_randomized(Brunel2000):
...     """
...     Like Brunel2000, but with randomized connection weights.
...     """
...
...     def connect(self):
...         """
...         Connect nodes with randomized weights.
...         """
...         # Code for randomized connections follows
```

Thus, using inheritance, we can easily keep track of different parameter sets and model versions and their associated simulation data. Moreover, since we keep all alternative versions, we also have a simple versioning system that only depends on Python features, rather than on third party tools or libraries. The full implementation of the model using classes can be found in the examples directory of your NEST distribution.

9 How to continue from here

In this chapter we have presented a step-by-step introduction to NEST, using concrete examples. The simulation scripts and more examples are part of the examples included in the NEST distribution. Information about individual PyNEST functions can be obtained with Python's `help()` function (in iPython it suffices to append `?` to the function). For example:

```
>>> help(nest.Connect)
```

To learn more about NEST's node and synapse types, you can access NEST's help system. NEST's online help still uses a lot of syntax of SLI, NEST's native simulation language. However, the general information is also valid for PyNEST.

Help and advice can also be found on NEST's user mailing list where developers and users exchange their experience, problems, and ideas. And finally, we encourage you to visit the web site of the NEST Initiative at www.nest-initiative.org.

10 Acknowledgements

AM partially funded by BMBF grant 01GQ0420 to BCCN Freiburg, Helmholtz Alliance on Systems Biology (Germany), Neurex, and the Junior Professor Program of Baden-Württemberg. HEP partially supported by RCN grant 178892/V30 eNeuro. HEP and MOG were partially supported by EU grant FP7-269921 (BrainScaleS).

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