Detailed description of the cortical microcircuit model (Potjans et al., 2014)

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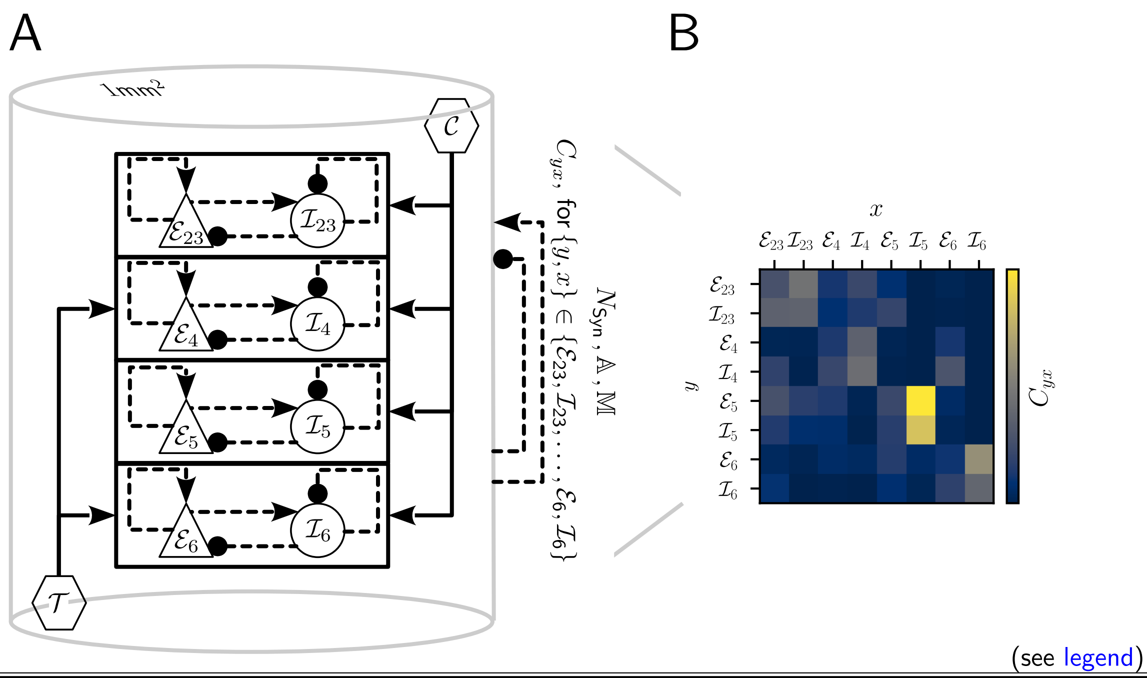
Contents

1 Model description

Summary	
Populations	8 cortical populations in 4 layers (L2/3, L4, L5, L6), driven by a thalamic population ($\mathcal{T}$) and cortico-cortical inputs ($\mathcal{C}$)
Connectivity	random, independent, population specific
Neuron model	cortex: leaky integrate-and-fire (LIF); thalamus, cortico-cortical inputs: Poisson point process
Synapse model	exponential postsynaptic currents with static, normally distributed weights and delays
Predictions	population specific spiking activity



(see legend)

Populations		
Name	**Elements**	**Size**
$x \in \{\mathcal{E}_{23}, \mathcal{E}_4, \mathcal{E}_5, \mathcal{E}_6, \mathcal{I}_{23}, \mathcal{I}_4, \mathcal{I}_5, \mathcal{I}_6\}$	LIF	N_x
$\mathcal{P} = \bigcup_x x$	LIF	$N = \sum_x N_x$ (see remark 1)
$\mathcal{T}$	realizations of Poisson point process	$N_{\mathcal{T}}$
$\mathcal{C} = \bigcup_x \mathcal{C}_x$	population specific currents	$N = \sum_x N_x$

Table 1: Description of the network model (continued on next page).

Connectivity		
Source	**Target**	**Pattern**
$x \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$	$y \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$	• random, fixed total number K_{yx} of connections[1] (see remark 1) • synaptic weights J_{ij} $(\forall i \in y, j \in x)$ • spike-transmission delays d_{ij} $(\forall i \in y, j \in x)$
$\mathcal{T}$	$y \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$	• random, fixed total number $K_{y\mathcal{T}}$ of connections[1] • synaptic weights J_{ij} $(\forall i \in y, j \in \mathcal{T})$ • spike-transmission delays d_{ij} $(\forall i \in y, j \in \mathcal{T})$
$\mathcal{C}_y$	$y \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$	• one-to-one[2]

Connectivity patterns:

[1] *random, fixed total number* (N_{Syn}): This rule establishes a total number of

$$K_{yx} = \frac{\ln\left(1 - C_{yx}\right)}{\ln\left(1 - (N_x N_y)^{-1}\right)},$$

connections between a source population x of size N_x and a target population y of size N_y. C_{yx} denotes the connection probability. Sources and targets are randomly and independently drawn from x and y with replacement. Multiple connections between two neurons and self-connections are permitted ($\mathbb{M}$, $\mathbb{A}$).

[2] *one-to-one* (δ): Each neuron in the source population is connected to one corresponding neuron in the target population (bijection).

(see "Network sketch" above and Senk et al., 2022)

Table 1: Description of the network model (continued).

<table>
<tr><th colspan="2">Neurons</th></tr>
<tr><th colspan="2">Cortical neurons</th></tr>
<tr><td>Type</td><td>leaky integrate-and-fire (LIF)</td></tr>
<tr><td>Description</td><td>dynamics of membrane potential $V_i(t)$ and spiking activity $s_i(t)$ of neuron $i \in x$ for $x \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$:

• emission of kth $(k = 1, 2, \ldots)$ spike of neuron i at time t_i^k if
$$V_i\left(t_i^k\right) \geq \theta$$
with spike threshold θ

• reset and refractoriness:
$$\forall k,\ \forall t \in \left[t_k^i,\, t_k^i + \tau_{\mathsf{ref}}\right] : \quad V_i(t) = V_{\mathsf{reset}}$$
with refractory period τ_{ref} and reset potential V_{reset}

• spike train $s_i(t) = \sum_k \delta(t - t_i^k)$

• subthreshold dynamics of membrane potential $V_i(t)$:
$$\begin{aligned} &\forall k,\ \forall t \notin \left[t_i^k,\, t_i^k + \tau_{\mathsf{ref}}\right) : \\ &\tau_{\mathsf{m}} \frac{\mathsf{d}V_i(t)}{\mathsf{d}t} = \left[E_{\mathsf{L}} - V_i(t)\right] + R_{\mathsf{m}} I_i(t) \end{aligned} \tag{1}$$
with membrane time constant τ_{m}, membrane resistance R_{m}, resting potential E_{L}, and total synaptic input current $I_i(t)$</td></tr>
<tr><th colspan="2">Thalamic neurons</th></tr>
<tr><td>Type</td><td>Poisson point process</td></tr>
<tr><td>Description</td><td>spike trains $s_i(t)$ $(i \in \mathcal{T})$ modeled as independent realizations of Poisson point process with piece-wise constant rate
$$\nu_{\mathcal{T}}(t) = \nu_{\mathcal{T}} \cdot (\Theta(t - t_{\mathsf{start}}) - \Theta(t - t_{\mathsf{stop}}))$$</td></tr>
<tr><th colspan="2">Cortico-cortical inputs</th></tr>
<tr><td>Type</td><td>constant (direct) currents (DC)</td></tr>
<tr><td>Description</td><td>population specific constant input current of magnitude
$$I_{\mathcal{C}_x} = K_{\mathcal{C}_x} \cdot I_{\mathcal{C}} \quad (\forall x \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}),$$
with cortico-cortical in-degree $K_{\mathcal{C}_x}$, and mean current
$$I_{\mathcal{C}} = \nu_{\mathcal{C}} \cdot \bar{I}_{y,\mathcal{C}} \cdot \tau_{\mathsf{s}} \quad (\forall y \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\})$$
generated by a Poissonian spike train with rate $\nu_{\mathcal{C}}$, convolved with an exponential kernel with amplitude $\bar{I}_{y,\mathcal{C}}$ and time constant τ_{s} (see remark 2)</td></tr>
</table>

Table 2: Description of the network model (continued).

Synapses	
Type	exponential postsynaptic currents with static weights and delays
Description	• total synaptic input current $I_i(t)$ to neuron i ($\forall i \in y \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$) is governed by: $$\left(\frac{\mathrm{d}}{\mathrm{d}t} + \frac{1}{\tau_\mathrm{s}}\right) I_i(t) = f_i(t) \quad (2)$$ with superposition from all neurons $j \in x$, $\forall x \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6, \mathcal{T}, \mathcal{C}\}$ $$f_i(t) = \sum_x \sum_j f_{ij}(t) = \sum_x \sum_j \hat{I}_{ij} s_j(t - d_{ij})$$ of weighted spike trains with static synaptic weigths $\hat{I}_{ij}$, synaptic time constant τ_s, and spike transmission delays d_{ij} • solution of (2) for $f_{ij}(t) = \hat{I}_{ij} s_j(t)$ and $I_{ij}(t=0) = 0$: $$\mathrm{PSC}_{ij}(t) = \hat{I}_{ij} \exp(-t/\tau_\mathrm{s}) \Theta(t)$$ with Heaviside function $\Theta(\cdot)$ $\curvearrowright$ (exponential decaying) posynaptic current triggered by a single presynaptic spike • solution of (1) for $I_i(t) = \mathrm{PSC}_{ij}(t)$, $V_i(t=0) = 0$, and $E_\mathrm{L} = 0$: $$\mathrm{PSP}_{ij}(t) = \hat{I}_{ij} R_\mathrm{m} \frac{\tau_\mathrm{s}}{\tau_\mathrm{s} - \tau_\mathrm{m}} \left(e^{-t/\tau_\mathrm{s}} - e^{-t/\tau_\mathrm{m}}\right) \Theta(t)$$ • PSC amplitude (synaptic weight): $$\hat{I}_{ij} = \frac{J_{ij}}{J_\mathrm{unit}(\tau_\mathrm{m}, \tau_\mathrm{s}, R_\mathrm{m})}$$ parameterized by PSP amplitude $J_{ij} = \mathrm{max}_t\big(\mathrm{PSP}_{ij}(t)\big)$ with unit PSP amplitude (PSP amplitude for $\hat{I}_{ij} = 1$): $$J_\mathrm{unit}(\tau_\mathrm{m}, \tau_\mathrm{s}, R_\mathrm{m}) = R_\mathrm{m} \frac{\tau_\mathrm{s}}{\tau_\mathrm{s} - \tau_\mathrm{m}} \left(\left[\frac{\tau_\mathrm{m}}{\tau_\mathrm{s}}\right]^{-\tau_\mathrm{m}/(\tau_\mathrm{m} - \tau_\mathrm{s})} - \left[\frac{\tau_\mathrm{m}}{\tau_\mathrm{s}}\right]^{-\tau_\mathrm{s}/(\tau_\mathrm{m} - \tau_\mathrm{s})} \right)$$ and time to PSP maximum: $$t_\mathrm{max} = \frac{\tau_\mathrm{s}\tau_\mathrm{m}}{\tau_\mathrm{m} - \tau_\mathrm{s}} \ln\left(\frac{\tau_\mathrm{m}}{\tau_\mathrm{s}}\right)$$

Table 3: Description of the network model (continued).

Synapses (continued)	
Description	• synaptic weights $$\hat{I}_{ij} = \begin{cases} \mathsf{max}(0, z_{yx}), & j \in x \in \{\mathcal{E}_{23}, \mathcal{E}_4, \mathcal{E}_5, \mathcal{E}_6, \mathcal{T}\} \\ \mathsf{min}(0, z_{yx}), & j \in x \in \{\mathcal{I}_{23}, \mathcal{I}_4, \mathcal{I}_5, \mathcal{I}_6\} \\ \bar{I}_{yx}, & j \in x = \mathcal{C} \end{cases}$$ with $$z_{yx} \sim \mathcal{N}\left\{\bar{I}_{yx}, \sigma^2_{\mathsf{s},yx}\right\}$$ drawn from a normal distribution with mean $\bar{I}_{yx}$, variance $\sigma^2_{\mathsf{s},yx}$ note: clipping of synaptic weights leads to a deviation of the total number of synapses with non-zero weights from K_{yx} (see "Connectivity") • distributed synaptic delays $$d_{ij} = \begin{cases} \mathsf{max}(d_{\mathsf{min}}, z_x), & j \in x \in \{\mathcal{E}_{23}, \dots, \mathcal{I}_6, \mathcal{T}\} \\ \bar{d}_x, & j \in x = \mathcal{C} \end{cases}$$ with $$z_x \sim \mathcal{N}\left\{\bar{d}_x, \sigma^2_{\mathsf{d},x}\right\}$$ drawn from a normal distribution with mean $\bar{d}_x$, variance $\sigma^2_{\mathsf{d},x}$, and minimal delay $d_{\mathsf{min}} > 0$

Initial conditions	
Type	random initial membrane potentials and homogeneous initial synaptic currents
Description	• membrane potentials $$V_i(t=0) \sim \mathcal{N}(\bar{V}_{0,x}, \sigma^2_{\mathsf{v},x})$$ randomly and independently drawn from a normal distribution with mean $\bar{V}_{0,x}$ and variance $\sigma^2_{\mathsf{v},x}$ ($\forall i \in x \in \{\mathcal{E}_{23}, \dots, \mathcal{I}_6\}$; see remark 4) • synaptic currents: $I_i(t=0) = 0\,\mathsf{pA}$ ($\forall i \in y \in \{\mathcal{E}_{23}, \dots, \mathcal{I}_6\}$)

Table 4: Description of the network model (continued).

2 Model parameters

Network and connectivity
Population sizes

x	$\mathcal{E}_{23}$	$\mathcal{I}_{23}$	$\mathcal{E}_4$	$\mathcal{I}_4$	$\mathcal{E}_5$	$\mathcal{I}_5$	$\mathcal{E}_6$	$\mathcal{I}_6$	$\mathcal{T}$
N_x	$20,683$	$5,834$	$21,915$	$5,479$	$4,850$	$1,065$	$14,395$	$2,948$	902

Connection probabilities C_{yx}

y \ x	$\mathcal{E}_{23}$	$\mathcal{I}_{23}$	$\mathcal{E}_4$	$\mathcal{I}_4$	$\mathcal{E}_5$	$\mathcal{I}_5$	$\mathcal{E}_6$	$\mathcal{I}_6$	$\mathcal{T}$
$\mathcal{E}_{23}$	0.1009	0.1689	0.0437	0.0818	0.0323	0.0	0.0076	0.0	0.0
$\mathcal{I}_{23}$	0.1346	0.1371	0.0316	0.0515	0.0755	0.0	0.0042	0.0	0.0
$\mathcal{E}_4$	0.0077	0.0059	0.0497	0.1350	0.0067	0.0003	0.0453	0.0	0.0983
$\mathcal{I}_4$	0.0691	0.0029	0.0794	0.1597	0.0033	0.0	0.1057	0.0	0.0619
$\mathcal{E}_5$	0.1004	0.0622	0.0505	0.0057	0.0831	0.3726	0.0204	0.0	0.0
$\mathcal{I}_5$	0.0548	0.0269	0.0257	0.0022	0.0600	0.3158	0.0086	0.0	0.0
$\mathcal{E}_6$	0.0156	0.0066	0.0211	0.0166	0.0572	0.0197	0.0396	0.2252	0.0512
$\mathcal{I}_6$	0.0364	0.0010	0.0034	0.0005	0.0277	0.0080	0.0658	0.1443	0.0196

Neuron		
Name	**Value**	**Description**
θ	$-50\,\mathrm{mV}$	spike threshold
E_L	$-65\,\mathrm{mV}$	resting potential
τ_m	$10\,\mathrm{ms}$	membrane time constant
C_m	$250\,\mathrm{pF}$	membrane capacitance
R_m	$\tau_\mathrm{m}/C_\mathrm{m} = 40\,\mathrm{M}\Omega$	membrane resistance
V_reset	$-65\,\mathrm{mV}$	reset potential
τ_ref	$2\,\mathrm{ms}$	absolute refractory period
τ_s	$0.5\,\mathrm{ms}$	postsynaptic current time constant
$\nu_\mathcal{T}$	$120\,\mathrm{s}^{-1}$	rate of thalamic neurons
t_start	$700\,\mathrm{ms}$	start time of thalamic input
$\Delta t_\mathcal{T}$	$10\,\mathrm{ms}$	duration of thalamic input
t_stop	$t_\mathrm{start}+\Delta t_\mathcal{T} = 710\,\mathrm{ms}$	stop time of thalamic input
$\nu_\mathcal{C}$	$8\,\mathrm{s}^{-1}$	rate of cortico-cortical inputs
$I_\mathcal{C}$	$\nu_\mathcal{C}\bar{I}_{y,\mathcal{C}}\tau_\mathrm{s} = 0.3\,\mathrm{pA}$	mean amplitude of DC inputs ($\forall y \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$)

Population specific cortico-cortical in-degree $K_{\mathcal{C}_x}$

$\mathcal{C}_x$	$\mathcal{C}_{\mathcal{E}_{23}}$	$\mathcal{C}_{\mathcal{I}_{23}}$	$\mathcal{C}_{\mathcal{E}_4}$	$\mathcal{C}_{\mathcal{I}_4}$	$\mathcal{C}_{\mathcal{E}_5}$	$\mathcal{C}_{\mathcal{I}_5}$	$\mathcal{C}_{\mathcal{E}_6}$	$\mathcal{C}_{\mathcal{I}_6}$	$\mathcal{C}_\mathcal{T}$
$K_{\mathcal{C}_x}$	1600	1500	2100	1900	2000	1900	2900	2100	–

Table 5: Model parameters (continued on next page).

Synapse		
Name	**Value**	**Description**
J	$0.15\,\mathrm{mV}$	(mean) weight (PSP amplitude) of excitatory synapses
$\bar{I}_{yx}$		synaptic weights:
	$J/J_{\mathsf{unit}} \approx 87.81\,\mathrm{pA}$	$x \in \{\mathcal{E}_{23}, \mathcal{E}_4, \mathcal{E}_5, \mathcal{E}_6, \mathcal{T}, \mathcal{C}\}$
	$-4J/J_{\mathsf{unit}}$	$x \in \{\mathcal{I}_{23}, \mathcal{I}_4, \mathcal{I}_5, \mathcal{I}_6\}$, except for:
	$2J/J_{\mathsf{unit}}$	$(x, y) = (\mathcal{E}_{23}, \mathcal{E}_4)$
$\sigma_{\mathsf{s},yx}$	$0.1 \cdot \bar{I}_{yx}$	standard deviation of weight distribution
$\bar{d}_x$		mean spike transmission delays:
	$1.5\,\mathrm{ms}$	$x \in \{\mathcal{E}_{23}, \mathcal{E}_4, \mathcal{E}_5, \mathcal{E}_6, \mathcal{T}, \mathcal{C}\}$
	$0.75\,\mathrm{ms}$	$x \in \{\mathcal{I}_{23}, \mathcal{I}_4, \mathcal{I}_5, \mathcal{I}_6\}$
$\sigma_{\mathsf{d},x}$	$0.5 \cdot \bar{d}_x$	standard deviation of spike transmission delays
d_{min}	$0.1\,\mathrm{ms}$	minimal spike transmission delay
Initial conditions		
Population specific mean and standard deviation of initial membrane-potential distributions		

population x	$\mathcal{E}_{23}$	$\mathcal{I}_{23}$	$\mathcal{E}_4$	$\mathcal{I}_4$	$\mathcal{E}_5$	$\mathcal{I}_5$	$\mathcal{E}_6$	$\mathcal{I}_6$
$\bar{V}_{0,x}$ (mV)	-68.28	-63.16	-63.33	-63.45	-63.11	-61.66	-66.72	-61.45
$\sigma_{\mathsf{v},x}$ (mV)	5.36	4.57	4.74	4.94	4.94	4.55	5.46	4.48

Table 6: Model parameters (continued).

A Single-neuron dynamics in normal form (subthreshold)

- linear, inhomogeneous dynamics of synaptic input currents and (subthreshold) membrane potential for neuron $i \in y \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$ (cf. eqs. (1) and (2)):

$$\begin{aligned} \dot{I}_i + \frac{1}{\tau_\mathsf{s}} I_i &= f_i(t) \\ \dot{V}_i + \frac{1}{\tau_\mathsf{m}} \Big[V_i - E_\mathsf{L}\Big] - \frac{R_\mathsf{m}}{\tau_\mathsf{m}} I_i &= 0 \end{aligned} \tag{3}$$

with

$$f_i(t) = \sum_x \sum_{j \in x} \hat{I}_{ij} s_j(t - d_{ij}) \qquad (x \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6, \mathcal{T}, \mathcal{C}\}) \tag{4}$$

- rescale membrane potential $v_i(t) = V_i(t) - E_\mathsf{L}$ and total current $x_i(t) = \dfrac{R_\mathsf{m}}{\tau_\mathsf{m}} I_i(t)$:

$$\begin{aligned} \dot{x}_i + \frac{1}{\tau_\mathsf{s}} x_i &= \frac{R_\mathsf{m}}{\tau_\mathsf{m}} f_i(t) \\ \dot{v}_i + \frac{1}{\tau_\mathsf{m}} v_i - x_i &= 0 \end{aligned} \tag{5}$$

- normal form of neuron-i dynamics (5):

$$\frac{\mathsf{d}}{\mathsf{d}t} \boldsymbol{y}_i = \boldsymbol{A} \boldsymbol{y}_i + \boldsymbol{f}_i(t) \tag{6}$$

with $D = 2$ dimensional state vector

$$\boldsymbol{y}_i(t) = \Big(x_i(t)\,,\, v_i(t)\Big)^\mathsf{T}, \tag{7}$$

with constant $(D \times D)$ matrix

$$\boldsymbol{A} = \begin{bmatrix} -1/\tau_\mathsf{s} & 0 \\ 1 & -1/\tau_\mathsf{m} \end{bmatrix}, \tag{8}$$

and inhomogeneity vector

$$\boldsymbol{f}_i(t) = \left(\frac{R_\mathsf{m}}{\tau_\mathsf{m}} f_i(t)\,,\, 0\right)^\mathsf{T} \tag{9}$$

(see Sec. 3.2.2 in Rotter & Diesmann, 1999)

- see App. B for an efficient, exact integration scheme of (6)
- back-transform to physical quantities:

$$\begin{aligned} V_i(t) &= v_i(t) + E_\mathsf{L} \\ I_i(t) &= \frac{\tau_\mathsf{m}}{R_\mathsf{m}} x_i(t) \end{aligned} \tag{10}$$

B Exact integration of single-neuron dynamics (subthreshold)

- exact integration of (6) for spikes arriving at the target neuron i on a time grid $\mathcal{T}_\Delta = \{t_k = k\Delta | k \in \mathbb{N}, \Delta \in \mathbb{R}^+\}$, i.e., for spike trains $s_j(t) = \sum_l \delta(t - t_j^l)$ with $t_j^l \in \mathcal{T}_\Delta$ (Rotter & Diesmann, 1999):

$$\boldsymbol{y}_i(t_{k+1}) = \boldsymbol{P}\boldsymbol{y}_i(t_k) + \boldsymbol{f}_i(t_{k+1}) \tag{11}$$

with $(D \times D)$ propagator matrix (matrix exponential)

$$\boldsymbol{P} = e^{\boldsymbol{A}\Delta} \tag{12}$$

with components

$$\boldsymbol{P} = \begin{bmatrix} e^{-\Delta/\tau_\mathsf{s}} & 0 \\ \frac{e^{-\Delta/\tau_\mathsf{m}} - e^{-\Delta/\tau_\mathsf{s}}}{1/\tau_\mathsf{s} - 1/\tau_\mathsf{m}} & e^{-\Delta/\tau_\mathsf{m}} \end{bmatrix} \tag{13}$$

(see Sec. 3.2.2 in Rotter & Diesmann, 1999)

C Remarks

1. In the PyNEST implementation, the model size can be configured by the parameters `N_scaling` and `K_scaling`, which scale the number of neurons in the network and the number of synapses per neuron (in-degree), respectively. The original full-scale model corresponds to `N_scaling=1` and `K_scaling=1` (default). Downscaling the model enables running the model on a desktop computer. The scaling of the synapse number affects both connections within the local network and external (cortico-cortical) inputs.

   Without any compensation, downscaling the in-degree would change the mean and the variance of the synaptic input currents. In order to avoid this, one can choose the new synaptic weights $\bar{I}^*_{i,x}$ ($\forall i \in y \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}, x \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6, \mathcal{C}_y\}$) in such a way that together with a compensation current these effects are compensated. For the full-scale model we have

$$\mu_i = I_{\text{rec},i} + I_{\text{ext},i} = \tau_\text{s} \sum_x K_{i,x} \bar{I}_{i,x} \nu_x \,,$$
$$\sigma_i^2 = \sigma^2_{\text{rec},i} + \sigma^2_{\text{ext},i} = \tau_\text{s} \sum_x K_{i,x} \bar{I}^2_{i,x} \nu_x \,,$$

   where $K_{i,x}$ is the in-degree, $\bar{I}_{i,x}$ the synaptic weight and ν_x the mean firing rate. For the downscaled model we have

$$\mu_i^* = \tau_\text{s} \sum_x K^*_{i,x} \bar{I}^*_{i,x} \nu_x + \mu_{i,0} \,,$$
$$(\sigma^*)^2 = \tau_\text{s} \sum_x K^*_{i,x} (\bar{I}^*_{i,x})^2 \nu_x \,.$$

   Here, $K^*_{i,x} = f K_{i,x}$ with some factor $0 < f < 1$. Comparing the equations of the variance we find $\bar{I}^*_{i,x} = \bar{I}_{i,x}/\sqrt{f}$, if we want to leave fluctuations invariant. We have also a constant compensation current $\mu_{i,0}$ to leave also the mean input current invariant. Inserting this in the equation of the mean and solving for the compensation current $\mu_{i,0}$ we find

$$\mu_{i,0} = \tau_\text{s} \left(1 - \sqrt{f}\right) \sum_x K_{i,x} \bar{I}_{i,x} \nu_x \,.$$

   There are other ways to downscale the model, for more details see (van Albada et al., 2015). Note that this derivation assumes that all spike-trains are stationary Poissonian inputs (for downscaling with DC inputs see remark 3).
   The scaling and compensation current are implemented in the PyNEST implementation provided here.

2. In the original model of Potjans et al. (2014), the cortico-cortical inputs are modeled as independent realizations $s_i(t)$ ($i \in \mathcal{C}_x$ for $x \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$) of a Poisson point process with constant rate $\nu_{\mathcal{C}_x} = K_{\mathcal{C}_x} \nu_\mathcal{C}$, filtered by an exponential kernel PSC(t) with time constant τ_s and amplitude $\bar{I}_{y,\mathcal{C}}$ ($\forall y \in \{\mathcal{E}_{23}, \ldots, \mathcal{I}_6\}$). Here, $K_{\mathcal{C}_x}$ denotes the cortico-cortical in-degree and $\nu_\mathcal{C}$ a constant rate. In the implementation provided here, these Poissonian inputs are replaced by constant external currents (DC). DC inputs are computationally less expensive, exactly reproducible, and lead to similar network activity statistics. When replacing cortico-cortical input spikes $s(t)$ by DC inputs, the current implementation preserves the mean input current

$$I_\mathcal{C} = (\langle s \rangle * \text{PSC})(t) = \bar{I}_{y,\mathcal{C}} \nu_\mathcal{C} \tau_\text{s} \,.$$

3. With cortico-cortical inputs modeled as DC currents, the DC amplitude of the downscaled model is given by

$$I^*_{\text{DC},i} = I_{\text{DC},i} + (1 - \sqrt{f}) I_{\text{rec},i} \,,$$

   (see remark 1). To ensure the downscaled network is activated by the cortico-cortical input, the DC amplitude $I^*_{\text{DC},i}$ of the downscaled model needs to exceed the rheobase current, i.e.

$$I_{\text{rh},i} = \frac{\Theta - E_\text{L}}{R_\text{m}} \leq I^*_{\text{DC},i} \,.$$

   All populations i with

$$f < f_{\text{min},i} = \left(1 - \frac{I_{\text{rh},i} - I_{\text{ext},i}}{-|I_{\text{rec},i}|}\right)^2 \,,$$

   are not activated by the cortico-cortical inputs (neurons in these populations may still fire due to local inputs from other populations of the microcircuit).

4. The original model of Potjans et al. (2014) uses population *unspecific* normal distributions of initial membrane potentials. By default, the current implementation uses population *specific* initial membrane potential distributions instead to speed up convergence to the stationary state. In the reference implementation, the type of initial conditions can be set by the parameter `V0_type` (`"optimized"` [default] or `"original"`). In (Senk et al., 2025), the population specific initial conditions are refered to as *amended* initial conditions.

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