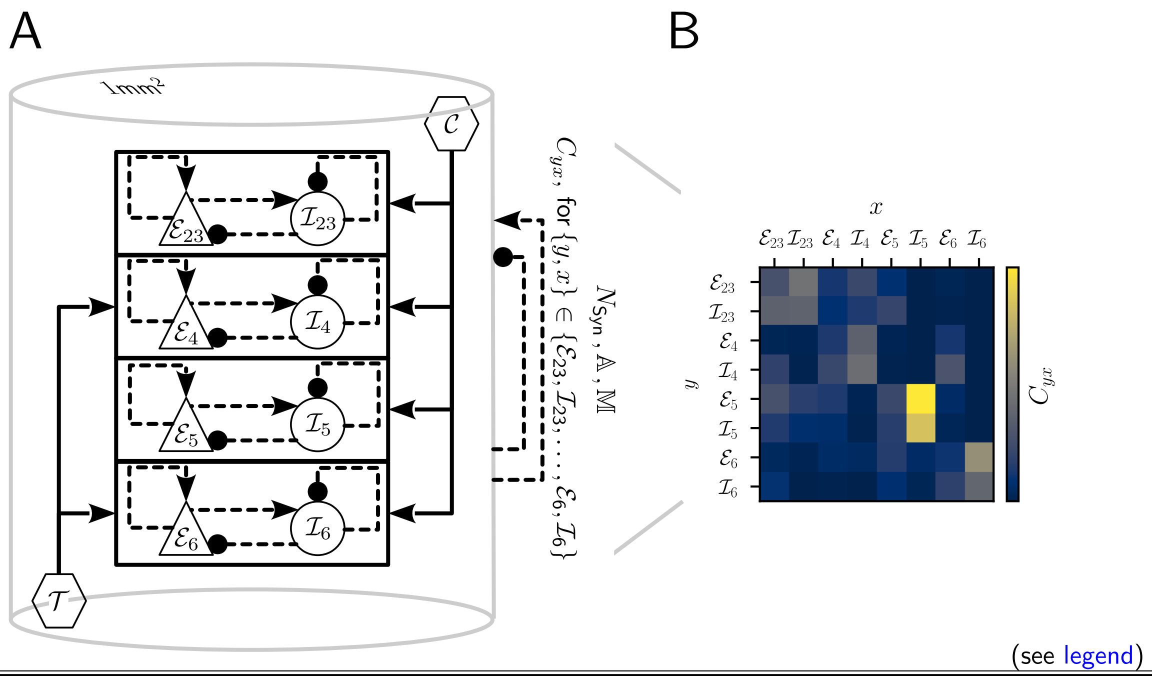
Detailed description of the cortical microcircuit model (Potjans et al., 2014)

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

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

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).

Neurons	
Cortical neurons	
Type	leaky integrate-and-fire (LIF)
Description	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 $V_i(t)$: $$\begin{aligned} &\forall k,\ \forall t \notin \left[t_i^k,\, t_i^k + \tau_{\mathsf{ref}}\right) : \\ &\tau_{\mathsf{m}} \frac{\mathsf{d}V_i(t)}{\mathsf{d}t} = \Big[E_{\mathsf{L}} - V_i(t)\Big] + R_{\mathsf{m}} I_i(t) \end{aligned} \qquad (1)$$ with membrane time constant τ_{m}, membrane resistance R_{m}, resting potential E_{L}, and total synaptic input current $I_i(t)$
Thalamic neurons	
Type	Poisson point process
Description	spike trains $s_i(t)$ $(i \in \mathcal{T})$ modeled as independent realizations of Poisson point process with piece-wise constant rate $$\nu_{\mathcal{T}}(t) = \nu_{\mathcal{T}} \cdot \left(\Theta(t - t_{\mathsf{start}}) - \Theta(t - t_{\mathsf{stop}})\right)$$
Cortico-cortical inputs	
Type	constant (direct) currents (DC)
Description	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 $$I_{\mathcal{C}} = \nu_{\mathcal{C}} \cdot \bar{I} \cdot \tau_{\mathsf{s}}$$ generated by a Poissonian spike train with rate $\nu_{\mathcal{C}}$, convolved with an exponential kernel with amplitude $\bar{I}$ and time constant τ_{s} (see remark 2)

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

<table>
<tr><th colspan="2">Synapses</th></tr>
<tr><td>Type</td><td>exponential postsynaptic currents with static weights and delays</td></tr>
<tr><td>Description</td><td>

- 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:

$$\left(\frac{\mathsf{d}}{\mathsf{d}t} + \frac{1}{\tau_\mathsf{s}}\right) I_i(t) = f_i(t) \tag{2}$$

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 $I_{ij}(t = 0) = 0$:

$$\mathsf{PSC}_{ij}(t) = \hat{I}_{ij} \exp(-t/\tau_\mathsf{s}) \Theta(t)$$

with Heaviside function $\Theta(\cdot)$

↷ (exponential decaying) posynaptic current triggered by a single presynaptic spike

- solution of (1) for $I_i(t) = \mathsf{PSC}_{ij}(t)$, $V_i(t = 0) = 0$, and $E_\mathsf{L} = 0$:

$$\mathsf{PSP}_{ij}(t) = \hat{I}_{ij} R_\mathsf{m} \frac{\tau_\mathsf{s}}{\tau_\mathsf{s} - \tau_\mathsf{m}} \left(e^{-t/\tau_\mathsf{s}} - e^{-t/\tau_\mathsf{m}}\right) \Theta(t)$$

- PSC amplitude (synaptic weight):

$$\hat{I}_{ij} = \frac{J_{ij}}{J_\mathsf{unit}(\tau_\mathsf{m}, \tau_\mathsf{s}, R_\mathsf{m})}$$

parameterized by PSP amplitude $J_{ij} = \mathsf{max}_t\big(\mathsf{PSP}_{ij}(t)\big)$

with unit PSP amplitude (PSP amplitude for $\hat{I}_{ij} = 1$):

$$J_\mathsf{unit}(\tau_\mathsf{m}, \tau_\mathsf{s}, R_\mathsf{m}) = R_\mathsf{m} \frac{\tau_\mathsf{s}}{\tau_\mathsf{s} - \tau_\mathsf{m}} \left(\left[\frac{\tau_\mathsf{m}}{\tau_\mathsf{s}}\right]^{-\tau_\mathsf{m}/(\tau_\mathsf{m} - \tau_\mathsf{s})} - \left[\frac{\tau_\mathsf{m}}{\tau_\mathsf{s}}\right]^{-\tau_\mathsf{s}/(\tau_\mathsf{m} - \tau_\mathsf{s})} \right)$$

and time to PSP maximum:

$$t_\mathsf{max} = \frac{\tau_\mathsf{s}\tau_\mathsf{m}}{\tau_\mathsf{m} - \tau_\mathsf{s}} \ln\left(\frac{\tau_\mathsf{m}}{\tau_\mathsf{s}}\right)$$

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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 3) • 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
$I_\mathcal{C}$	$\nu_\mathcal{C} \bar{I}_\mathcal{C} \tau_\mathrm{s} = 0.3\,\mathrm{pA}$	mean amplitude of DC inputs

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 $x_i(t) = \frac{R_\mathsf{m}}{\tau_\mathsf{m}} I_i(t)$:

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

- 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. The implementation contains, besides the original full-scale model of Potjans et al. (2014), a downscaled version, which can run on a desktop computer. This is controlled by the parameters `N_scaling` and `K_scaling` in the network parameters file. The first parameter scales the number of neurons, whereas the second parameter scales the number of synapses per neuron or in-degree. The scaling happens on both, inter-population and external connectivity.

   Downscaling the in-degree K changes the mean and variance of the synaptic input currents. In order to avoid this, one can choose the new synaptic weights J^* in such a way that together with a compensation current these effects are compensated. For the full-scale model we have

   $$\mu = \tau_{\mathsf{s}} K J r \,,$$
   $$\sigma^2 = \tau_{\mathsf{s}} K J^2 r \,,$$

   where K is the in-degree, J the synaptic weight and r the firing rate. For the downscaled model we have

   $$\mu^* = \tau_{\mathsf{s}} K^* J^* r + \mu_0 \,,$$
   $$\sigma^{2*} = \tau_{\mathsf{s}} K^* (J^*)^2 r \,.$$

   Here, $K^* = fK$ with some factor $0 < f < 1$, and μ_0 is a compensation current. Comparing the equations of the variance we find $J^* = J/\sqrt{f}$. Inserting this in the equation of the mean and solving for the compensation current μ_0 we find

   $$\mu_0 = \tau_{\mathsf{s}} \left(1 - \sqrt{f}\right) K J r \,.$$

   There are other ways to downscale the model, for more details see (van Albada et al., 2015).

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 $\bar{I}$. Here, $K_{\mathcal{C}_x}$ denotes the cortico-cortical in-degree and $\nu_{\mathcal{C}}$ a constant rate. DC inputs are computationally less expensive, exactly reproducible, and lead to similar network activity statistics. When replacing Poissonian input spikes $s(t)$ by DC inputs, the current implementation preserves the mean input current

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

3. 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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