

# Introduction

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- Problem statement
- Opportunity of voltage imaging, core idea of inverting the causal ‘presynaptic spike  $\rightarrow$  postsynaptic PSP’ relation
- Overview of thesis

## 1.1 Connectomics

- Motivation
- Ground-truth connectomics: tracing of electron microscopy and fluorescent injection imaging
- Necessity of connection *inference*
- Mention ‘invasive’ connection testing (stimulate one cell, record possible neighbours)
- Limitations of ‘connectomics’, and of inferred vs ‘actual’ connectomics.  
Terminology, e.g. ‘functional connectomics’

## 1.2 Voltage imaging

- Technologies (from dyes to GEVIs)
- Specs: cell yield, tissue depth, recording duration, SNR, species
- ..and growth of these over time, and comparison with calcium imaging.  
To extrapolate how these might advance in the future
- Comparison with other recording techniques: ephys, calcium imaging, (and briefly mention coarser methods)

## 1.3 Network inference

- Working with events/spikes only, versus working with continuous signals; or a hybrid as here.
- Overview of the spikes-only methods
- The connectomics competition, and the findings about the best methods
- Mention other application domains, like gene regulatory networks
- Conclusion: connection inference by spikes is poor (Ila Fiete etc), and Vm imaging offers unique advantage (causality)

## Simulation details

In this chapter, we describe our experimental setup: the neuron model we simulate, its inputs, and how we simulate voltage imaging.

### 2.1 The AdEx neuron model

We choose to simulate the ‘AdEx’ neuron model, or the ‘adaptive exponential integrate-and-fire’ neuron.[GB09] This is a leaky-integrate-and-fire (LIF) neuron model, with two additions. First, the full upstroke of each spike is simulated, as an exponential runoff. Second, an extra dynamic variable is added: the adaptation current. This current allows the simulation of many non-linear effects of real neurons, like spike-rate adaptation and post-inhibitory rebound.

The AdEx model consists of two differential equations, one to simulate the membrane voltage  $V$ , and one for the adaptation current  $w$ :

$$C \frac{dV}{dt} = -g_L(V - E_L) + g_L \Delta_T \exp\left(\frac{V - V_T}{\Delta_T}\right) - I_{\text{syn}} - w \quad (1)$$

$$\tau_w \frac{dw}{dt} = a(V - E_L) - w \quad (2)$$

$I_{\text{syn}}$  is the synaptic current, explained in [section 2.4](#). We use the sign convention of inter alia Dayan & Abbott<sup>1</sup> where membrane currents are defined as positive when positive charges flow *out* of the cell. I.e. a positive  $I_{\text{syn}}$  decreases the membrane voltage (itself defined as the electric potential inside minus outside the cell).

Other parameters are explained in [table 2.1](#).

In this chapter, we will often analyse  $\frac{dV}{dt}$  as a function of  $V$ , i.e. analyse it as a dynamical system: will the voltage increase or decrease at the current voltage? For conciseness, we will call this function  $F(V)$ . I.e.  $F(V) = \frac{dV}{dt}$  = the right-hand-side of equation (1) here, scaled by  $1/C$ . We’ll mostly analyse  $F$  in the absence of synaptic and adaptation currents, i.e. for  $I_{\text{syn}}$  and  $w$  both zero. [Figure 1](#) shows the  $F(V)$  curve for an AdEx neuron fit to a real neuron.

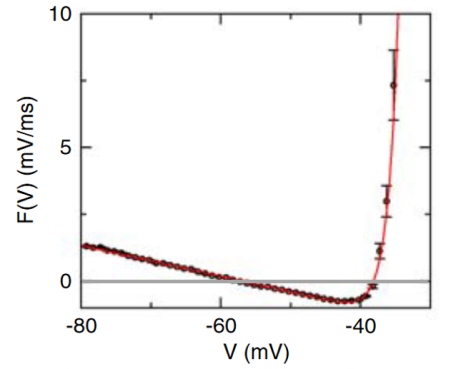


Figure 1: A linear-plus-exponential model (red) fit to data from a cortical pyramidal neuron (black), from [\[Bad+08\]](#)

<sup>1</sup> [\[DA01\]](#), ch. 5.3, p. 162

Name	Description	Units
$V$	Membrane voltage	V
$C$	Membrane capacitance	F
$g_L$	Input / leak conductance	S (V/A)
$E_L$	Resting / leak potential	V
$\Delta_T$	Steepness of $\frac{dV}{dt}$ around the firing threshold	V
$V_T$	Location of minimum of $\frac{dV}{dt}$	V
$w$	Adaptation current	A
$\tau_w$	Time constant of adaptation current	s
$a$	Sensitivity of adaptation current to $V$	S

We solve these equations using first-order (Euler) integration.

In addition to the two differential equations, the AdEx model also consists of an instantaneous reset condition. When the membrane voltage  $V$  reaches a certain threshold  $\theta$ , a spike is recorded,  $V$  is reset, and  $w$  is increased:

$$\begin{aligned} \text{if } V > \theta \text{ then: } V &\leftarrow V_r \\ w &\leftarrow w + \Delta w \end{aligned} \quad (3)$$

## Analysis

Where are the fixed points of the dynamical system  $\frac{dV}{dt} = F(V)$ ? I.e, where is  $F = 0$ ? Like other neuron models, there are two fixed points: a stable one at the leak potential  $E_L$ , and an unstable one at the instantaneous firing threshold (which we'll call  $E_T$ ).

We see in equation (1) (for  $I_{\text{syn}} = 0$  and  $w = 0$ ) that the leak potential  $E_L$  is indeed a fixed point – or rather lies very close to one: the exponential term is negligibly small at  $V = E_L$ . The second fixed point has no straightforward expression. The exact solutions for  $F$ 's roots need the so called Lambert  $W$  or 'product logarithm' functions  $W_0$  and  $W_{-1}$  (see figure 2). The roots are found at:

$$V = E_L - \Delta_T W_k \left( -\exp \left( \frac{E_L - V_T}{\Delta_T} \right) \right) \quad (4)$$

..where  $k = 0$  gives the resting potential, and  $k = -1$  the instantaneous firing threshold.<sup>2</sup>

Also of interest – especially when comparing with the Izhikevich neuron later – is the slope of AdEx's  $F(V)$ , i.e. its derivative with respect to  $V$ :

$$\begin{aligned} \frac{dF}{dV} &= \frac{d}{dV} \left( -g_L(V - E_L) + g_L \Delta_T \exp \left( \frac{V - V_T}{\Delta_T} \right) \right) \\ &= -g_L + g_L \Delta_T \frac{1}{\Delta_T} \exp \left( \frac{V - V_T}{\Delta_T} \right) \end{aligned} \quad (5)$$

This derivative is zero at  $V = V_T$ . I.e, unlike what is suggested by the 'T' subscript, and the name 'effective threshold potential' given

Table 2.1: Quantities and parameters of the AdEx neuron, equations (1) to (3). By defining the location of  $\frac{dV}{dt}$ 's minimum,  $V_T$  also determines the location of the firing threshold.

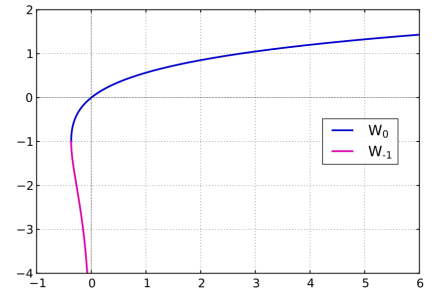


Figure 2: The Lambert  $W$  functions for real numbers.

<sup>2</sup> Here too we see that the true resting potential is almost identical to  $E_L$ :  $W_0$  passes through zero, and its argument is  $\approx 0$ , because the exponential's argument is negative. For  $W_{-1}$  however, figure 2 shows that the second term is not negligible around 0.

to it in [Nau+08],  $V_T$  is not the instantaneous threshold potential (it is not a zero of  $F$ ), but rather the minimum of  $F$  (it is the zero of  $\frac{dF}{dV}$ ).

From equation (5), we also calculate the slope of  $F$  at its two roots. At  $V = E_L$ , the slope (also known as the leak or input conductance here) is  $-g_L$ , plus a negligibly small exponential term. The negative sign shows that this is a stable fixed point: in a linearization of  $F$  around this point, at voltages below the resting potential,  $F$  (i.e.  $C\frac{dV}{dt}$ ) is positive and thus  $V$  will increase. At voltages above  $E_L$ ,  $F$  is negative and  $V$  will decrease. Small deviations on either side of the resting potential will thus decay back to this resting potential.

At the firing threshold  $V = E_T$  (i.e. the second solution to equation (4)), the slope is:

$$g_L \left( \exp \left( \frac{E_T - V_T}{\Delta_T} \right) - 1 \right) \quad (6)$$

..which is positive (as  $E_T > V_T$ ), indicating that this is an unstable fixed point: a small deviation of the voltage above  $E_T$  will blow up to infinity (i.e, a spike is generated).

## 2.2 Alternative neuron models

Why did we choose the AdEx model to simulate neuron voltages? In short, because it strikes a good balance between realism and complexity. We briefly consider here two alternative neuron models: the simple leaky-integrate-and-fire (LIF) neuron, and the more complex Hodgkin-Huxley (HH) neuron. In the next section, we go into more depth on a third alternative, the very similar Izhikevich neuron.

A simpler model than AdEx would be the well-known LIF neuron:

$$C \frac{dV}{dt} = -g_L(V - E_L) - I_{\text{syn}}$$

$$\text{if } V > \theta, \text{ then: } V \leftarrow V_r$$

As is apparent from comparing this with equations (1) and (3), the AdEx model is an extension of the LIF model. The LIF neuron lacks a simulation of the upstroke of spikes (the exponential term in equation (1)), and the slower time-scale adaptation current (equation (2)), which allows the simulation of many qualitatively different real neuron types. It is especially this first addition, the full upstroke simulation, that seems relevant in generating realistic voltage traces.

Would this thesis have been very different had we used LIF neurons instead? Probably not, though it might depend on the mean voltage level of the simulated neuron: if it is well below the firing threshold, both LIF and AdEx are linear (the exponential term is negligible), and they behave quasi identically. When a spike is generated in the AdEx model, the exponential feedback makes the upstroke very fast,

and thus not many timesteps in the simulation are spent on it, versus the linear regime.

On the other hand, when the neuron would continuously teeter just below its firing threshold, the LIF and AdEx models do not behave similarly. LIF's  $F(V)$  curve is still fully linear, while AdEx's is not, and AdEx will behave more like a real neuron – see [figure 1](#).

Another well-known alternative neuron model is the class of Hodgkin-Huxley (HH)-like neurons. These models simulate the full trajectory of a spike: both its upstroke and its downstroke. Unfortunately they also have many free parameters. They also take a bit longer to simulate, being higher dimensional (having more differential equations), and containing many more exponential terms, which take the brunt of the time when numerically evaluating a differential expression.

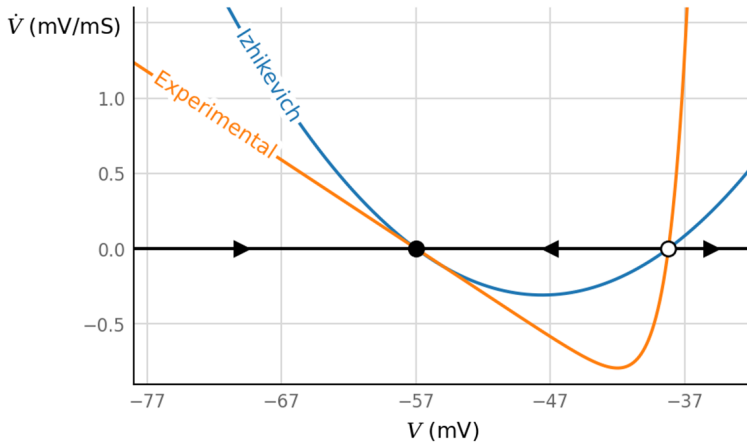


Figure 3: Neuron models as dynamical systems: a comparison of the  $F(V)$  curves of the Izhikevich and AdEx neurons. ‘Experimental’ is an AdEx neuron fit to a cortical pyramidal neuron (using data from [\[Bad+08\]](#)). The Izhikevich neuron’s parameters were chosen to match the fixed points and the leak conductance. Arrows indicate whether the voltage will increase or decrease (1D flow field).  $\rightarrow \bullet \leftarrow$  is a stable fixed point (resting potential),  $\leftarrow \circ \rightarrow$  is an unstable fixed point (spike threshold).  $\dot{V} \equiv \frac{dV}{dt}$ .

## 2.3 The Izhikevich neuron

Another alternative neuron model is the Izhikevich neuron, which is exceedingly similar to the AdEx neuron. These are the Izhikevich equations, using the same symbols as used before (in [equations \(1\) to \(3\)](#)):

$$C \frac{dV}{dt} = k(V - E_L)(V - E_T) - I_{\text{syn}} - w \quad (7)$$

$$\tau_w \frac{dw}{dt} = a(V - E_L) - w \quad (8)$$

$$\text{if } V > \theta, \text{ then:} \quad (9)$$

$$V \leftarrow V_r$$

$$w \leftarrow w + \Delta w$$

We have introduced two new parameters not present in the AdEx equations: the steepness of the parabola,  $k$ ; and  $E_T$ , the instantaneous firing threshold (the firing threshold in the absence of any synaptic or adaptation currents).

The only difference with AdEx is in equation (7), where the  $F(V)$  curve is not made by a linear plus exponential term, as in AdEx; but rather by a quadratic (a parabola). Its two zeros (the fixed points) are readily apparent, as  $E_L$  and  $E_T$ .

### Correspondences with AdEx

In Izhikevich's book<sup>3</sup>, different names are used for the same quantities:

<sup>3</sup> [Izh07], section 5.2.4, equations 5.7 & 5.8

$$C \frac{dv}{dt} = k(v - v_r)(v - v_t) - u + I \quad (10)$$

$$\frac{du}{dt} = a(b(v - v_r) - u) \quad (11)$$

$$\text{if } v > v_{\text{peak}}, \text{ then:} \quad (12)$$

$$v \leftarrow c$$

$$u \leftarrow u + d$$

Table 2.2 compares both notation conventions.

AdEx	Izh	Description	Units
$V$	$v$	Membrane voltage	V
$w$	$u$	Adaptation current	A
$\tau_w$	$1/a$	Time constant of adaptation current	s
$E_L$	$v_r$	Resting / leak potential	V
$V_r$	$c$	Reset voltage after spike	V
$a$	$b$	Sensitivity of adapt. current to $V$	S
$b$	$d$	Adaptation current bump after spike	A

Table 2.2: Different symbols used for the same quantities in [Nau+08] ('AdEx') and [Izh07] ('Izh'). Membrane capacitance  $C$  (in farad) is the same in both notations.

Beside these straightforward correspondences, there are some parameters in either model that have no direct equivalent in the other:  $k$  and  $v_t$  in Izhikevich, and  $g_L$ ,  $\Delta_T$ , and  $V_T$  in AdEx. For those, we'll look at the shape of Izhikevich's  $F(V)$ , as we've done for the AdEx neuron before.

First, the AdEx parameter  $g_L$ . This is the input conductance, a.k.a. the leak conductance, and the slope of  $F(V)$  around the leak potential. We can find this same conductance for the Izhikevich neuron by taking the derivative with respect to  $v$  of the right hand side of equation (10), at  $w = 0$ ,  $I_{\text{syn}} = 0$ , and  $v = v_r$ . We find:

$$\left. \frac{d}{dv} (k(v - v_r)(v - v_t)) \right|_{v=v_r} = k(v_r - v_t) \quad (13)$$

(this value is negative: the leak potential is a stable fixed point. This corresponds to equation (1), where we find ' $-g_L$ '). Thus, our first nontrivial correspondence:

$$g_L = k(v_t - v_r) \quad (14)$$

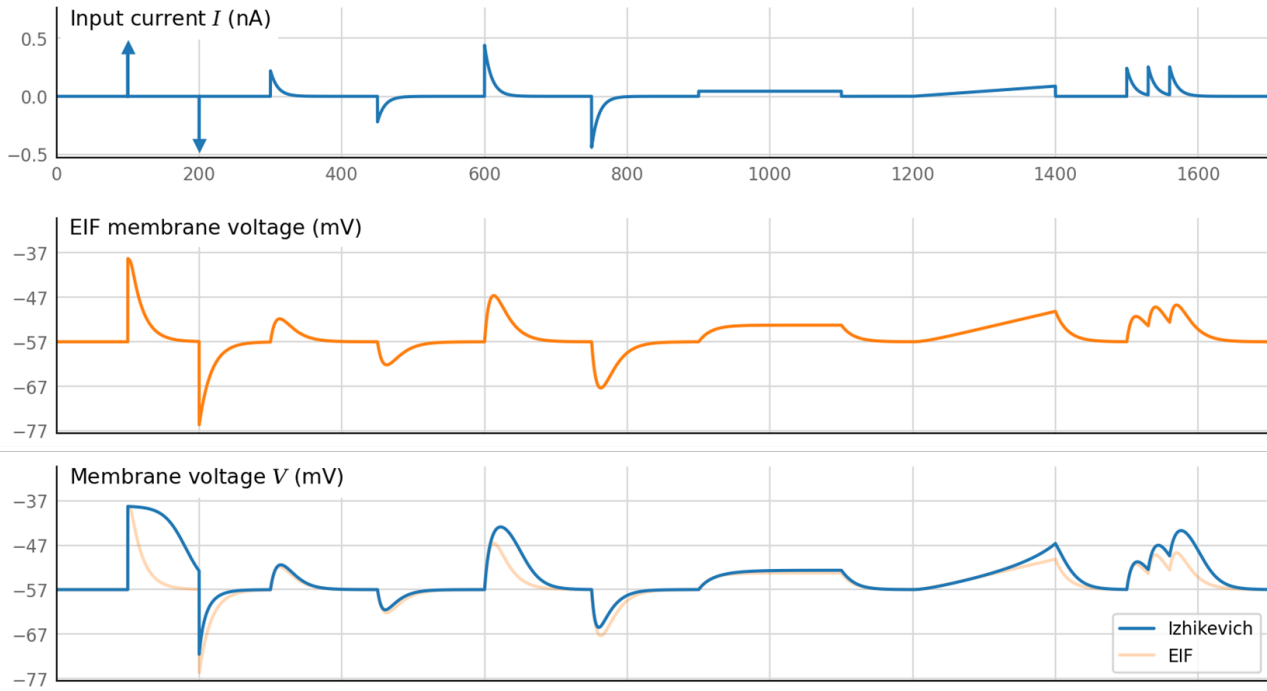


Figure 4: The nonlinear response of Izhikevich neurons to subthreshold input currents. ‘EIF’ stands for exponential integrate-and-fire; it has the same  $\frac{dV}{dt}$  as an AdEx neuron. Adaptation currents are negligibly small for both models in this test scenario.

We’ve seen that  $V_T$  is the minimum of AdEx’s  $F$ . The minimum of Izhikevich’s  $F$  is easily found as the average of the parabola’s two zeros. I.e,  $V_T$  corresponds to  $(v_r + v_t)/2$ .

Finally,  $\Delta_T$  co-determines the slope of AdEx’s  $F$  at the firing threshold (equation (6)). Given that Izhikevich’s  $F$  is a parabola, with slopes equal in magnitude at both roots, we already know the firing threshold slope: it is the same as the leak conductance, equation (14). Here, the AdEx model is more expressive than Izhikevich’s: the slope of  $\frac{dV}{dt}$  at the firing threshold can be independently tweaked from the leak conductance; in Izhikevich these two are clung together by the form of the quadratic equation.

## Comparison with AdEx

The Izhikevich and AdEx models are very similar. Their phase spaces are topologically identical: the adaptive current equation is identical (up to a renaming of the variables); and the  $F(V)$ -graph has the same shape, with two fixed points: a stable fixed point at the resting potential, and an unstable one at the firing threshold (figure 3).

They differ in the exact shape: Izhikevich’s  $F(V)$  is a parabola, while AdEx is the more realistic ‘linear subthreshold, and then transitioning to an exponential’ (see figures 1 and 3). As a result, Izhikevich neurons have an unrealistically slow spike upstroke.



A second issue is Izhikevich's subthreshold nonlinearity. The effects of this can be seen in [figure 4](#). Positive input currents produce stronger responses than equally large negative input currents. This is explained by the quadratic  $\frac{dV}{dt}$  shape: positive deviations are attenuated less, and negative deviations more, than a linear neuron would. Real and AdEx neurons do not suffer this asymmetry.

This nonlinearity is not visible for small voltage deviations, which is what the postsynaptic potentials we are interested in in this thesis tend to be. There is however an effect of the neuron's average voltage: if this voltage is constantly on the higher side, then inputs – both negative and positive – will cause larger responses than if the median voltage was lower.

## 2.4 Synapse model

One unexplained term in our neuron model, equation (1), is the synaptic current  $I_{\text{syn}}$ . This is the following sum over all input synapses  $i$  of the neuron:

$$I_{\text{syn}} = \sum_i g_i (V - E_i) \quad (15)$$

where  $V$  is the global membrane voltage of the neuron,  $E_i$  is the reversal potential of that synapse, and  $g_i$  is the local synaptic conductance, which is modulated by presynaptic spikes.

For an excitatory synapse,  $V < E_i$ , making  $g_i(V - E_i)$  negative, increasing the membrane voltage according to the sign convention for  $I_{\text{syn}}$  in equation (1).

We simulate the synaptic conductances  $g_i$  as exponentially decaying signals (with time constant  $\tau$ ), and bump them up instantaneously on arrival of a presynaptic spike:

$$\frac{dg_i}{dt} = -g_i/\tau \quad (16)$$

On incoming presynaptic spike:

$$g_i \leftarrow g_i + \Delta g_i \quad (17)$$

Note that these are not the so called alpha-synapses. Those are two dimensional and also have an exponential rise, instead of just an exponential decay. (For an infinitely fast rise though, these models are of course the same). Simulating a full alpha synapse might increase the realism of our voltage traces, for a small simulation cost. We did not try this however. Foremost because alpha synapses fit to real data often have very fast rise times that are almost indistinguishable from instantaneous jumps.

For efficiency, we give all our excitatory synapses the same reversal potential,  $E_{\text{exc}}$ . Idem for the inhibitory synapses, with  $E_{\text{inh}}$ . This allows us to factor the synaptic current sum (equation (15)) as follows:

$$I_{\text{syn}} = (V - E_{\text{exc}}) \sum_{\text{exc } i} g_i + (V - E_{\text{inh}}) \sum_{\text{inh } i} g_i \quad (18)$$

The sums of conductance signals  $g_i(t)$  can also be simplified. Say that the values of  $g_i$  at  $t = 0$  are  $G_i$ . The solution to equation (16) (at least in the time until a new presynaptic spike arrives) is then

$$g_i(t) = G_i e^{-t/\tau} \quad (19)$$

With this, and when all synapses have the same time constant  $\tau$ , the two sums in equation (18) can be factored as follows:<sup>4</sup>

$$\sum_i g_i(t) = \sum_i \left( G_i e^{-t/\tau} \right) = \left( \sum_i G_i \right) e^{-t/\tau} \quad (20)$$

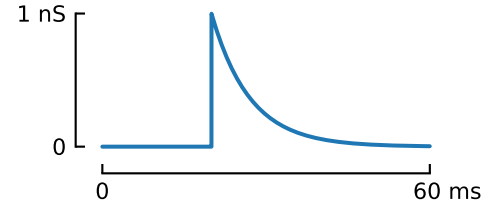


Figure 5: Example synaptic conductance trace  $g_1(t)$ , with a single incoming spike at  $t = 20$  ms.

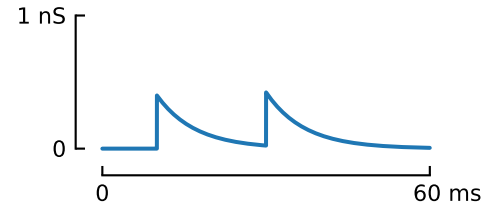


Figure 6: Another example trace  $g_2(t)$ , with spikes at  $t = 10$  ms and  $30$  ms, and a smaller  $\Delta g$ .

<sup>4</sup> This is only valid in the time before any new spikes arrive. But the ‘summability’ still holds after a new spike. To see this, the given reasoning can be repeated, but simply with different values for the  $G_i$  (all decayed by an amount  $e^{-t_{\text{spike}}/\tau}$ , and one increased by a bump  $\Delta g_i$ ), and then redefining  $t_{\text{spike}}$  to be  $t = 0$ .

This means that we need to only keep track of two conductance signals:  $g_{\text{exc}}$  and  $g_{\text{inh}}$ , each the sum of all excitatory or all inhibitory synaptic conductances.

Our synaptic current sum then becomes simply:

$$I_{\text{syn}} = (V - E_{\text{exc}}) g_{\text{exc}} + (V - E_{\text{inh}}) g_{\text{inh}}, \quad (21)$$

and we only need to simulate two differential equations, instead of one for every synapse:

$$\begin{aligned} \frac{dg_{\text{exc}}}{dt} &= -g_{\text{exc}}/\tau \\ \frac{dg_{\text{inh}}}{dt} &= -g_{\text{inh}}/\tau, \end{aligned}$$

where on arrival of a spike at synapse  $i$  either  $g_{\text{exc}}$  or  $g_{\text{inh}}$  is instantaneously increased by a value  $\Delta g_i$ , depending on whether that synapse is excitatory or inhibitory.

## 2.5 Input spikes

In our simplest experimental setup, we simulate just one AdEx neuron. Its input is provided by an array of  $N$  Poisson neurons, i.e. they each generate spike trains according to a Poisson process. We call this the ‘N-to-1’ setup.

The firing rates of real neurons often follow a long-tailed distribution: most neurons do not fire much at all, while a few fire a lot. We recapitulate this in the firing rates of our Poisson input neurons, by drawing their firing rates from a log-normal distribution. We look to the literature for realistic parameters for this distribution, namely to the modelling paper of Roxin et al. [Rox+11], and the experimental sources it cites [HDZ08; OCo+10].

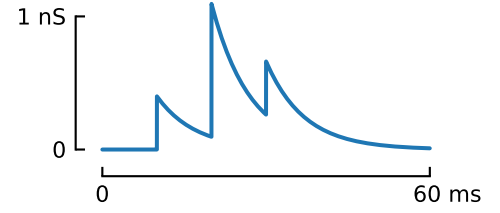


Figure 7: A third synaptic conductance trace  $g_3(t)$ , with three input spikes at the same times and strengths as in figures 5 and 6. This signal is simulated independently, but turns out to be equal to the sum of the two others:  $g_3(t) \equiv g_1(t) + g_2(t)$ .

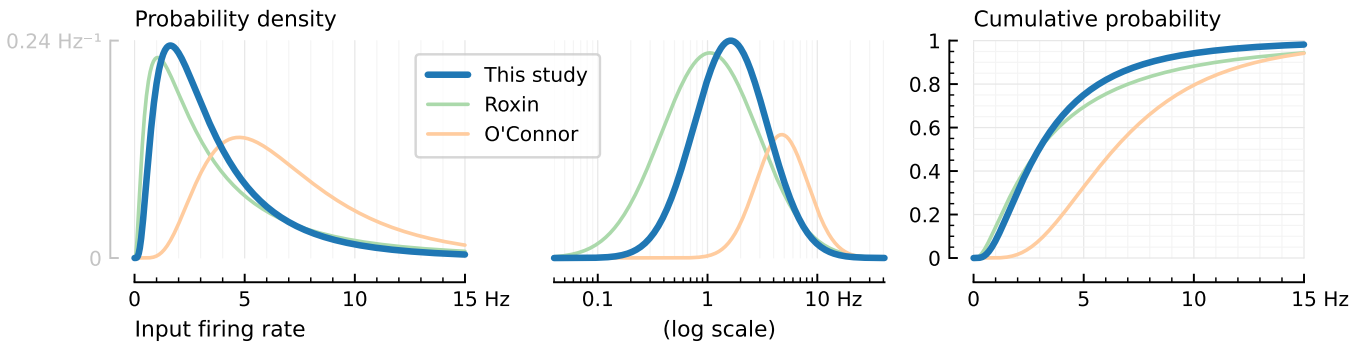


Figure 8: **Input spike trains are given log-normally distributed firing rates.**

The distribution used in our simulations is shown in bold. It has mean  $\mu_L = 4$  Hz and variance of the underlying Gaussian  $\sigma^2 = 0.6$ . The two light distributions are from the literature. Note that the Roxin et al. distribution is slightly more heavy tailed than this study’s: it has both more low firing and more high firing neurons.

Log-normal distributions are usually parametrized with  $\mu$  and  $\sigma$ : the location and scale of the underlying normal distribution, i.e. after log-transforming the input domain. In the above sources however, the mean  $\mu_L$  of the data distribution itself is given. We can find  $\mu$ , if  $\sigma$  is known, as  $\mu = \ln(\mu_L) - \sigma^2/2$ .

Roxin et al. use a mean rate  $\mu_L$  of 5 Hz and a variance of the logarithm of the rate  $\sigma^2 = 1.04$  in their figure 2. Hromádka et al. [HDZ08] recorded neurons in the auditory cortex of awake rats during acoustic stimulation. They find a mean firing rate  $\mu_L$  of 6.2 Hz and a median of 2.4 Hz; no numeric variances are given. O'Connor et al. [OCO+10] recorded neurons in the barrel (whisker) cortex of behaving mice. Ensembled over all layers of the cortex they recorded from, they report  $\mu_L = 7.4$  Hz,  $\sigma_L = 12.6$  Hz, a median of 1.5 Hz, and an interquartile range of 9.5 Hz. This corresponds to a Gaussian variance of  $\sigma^2 = \ln(1 + \sigma_L^2/\mu_L^2) = 0.30$ . The Roxin and O'Connor distributions are also shown in figure 8.

Given these data, we choose our parameters  $\mu$  and  $\sigma$  so that the distribution lies roughly halfway O'Connor's and Roxin's, while making sure our firing rates are rather low than high: as our idea rests on the number of spikes that can be used to calculate spike-triggered averages, we don't want to overestimate the number of available input spikes and obtain overly optimistic results.

Our log-normal distribution has a median of 2.96 Hz, very close to Roxin's 2.97 Hz. O'Connor's has 6.4 Hz, which is markedly different from the median of 1.5 Hz they reported (hinting that their data distribution might not be log-normal).

## 2.6 Voltage imaging

The signals detected by a light microscope in a voltage imaging setup are not the same as the real membrane voltage signals of which they are a reflection.

We model this lossy transformation by simply adding Gaussian noise to our simulated membrane voltage. As in the voltage imaging literature, we quantify the amount of this noise by a 'spike-SNR' measure (spike signal-to-noise ratio). This is defined as the height of an average spike relative to the standard deviation of the noise.

A more realistic model of the voltage-imaging transformation would also incorporate the exponential decay over time of the SNR, and the short-term 'smearing in time' of voltage indicators. The latter could be done by passing the voltage signal through a linear filter with some non-instantaneous impulse response.

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# Spike-triggered averaging

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- Principle, example STAs
- Influence on STA of E/I balance, output firing rate, reversal potentials
- Use as connection test: shuffled spike trains and height of STA, p-values, and the 'area-over-start' heuristic for E vs I classification.
- Evaluation of a connection test: 'ternary' classification, summary measures, AUROC
- Performance of the simple STA-height test, for different N
- Influence of window length
- What about Vm imaging affects detection the most?

# New connection inference methods

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## 4.1 STA Template correlation

- Idea for the two-pass test
- Template examples. Both ideal and template found with first-pass (STA height-only)
- Performance for different  $N$ , & comparison with previous method

## 4.2 Linear regression of the upstroke

- Non-STA method: concatenated individual windows as  $(X, y)$
- Examples of pooled windows, and fits
- Mention the problem of unknown transmission delays
- Performance for different  $N$ , & comparison with previous methods

## 4.3 Fitting a full STA model

- Model design
- Iterative model fitting
- Problem of overfitting, and parameter-constraints to solve it
- An advantage: fit parameters (like transmission delay and time constants) are biologically meaningful
- Performance for different  $N$ , & comparison with previous methods

## 4.4 Clustering, & Hierarchical model fitting

- (Time-permitting)

## 4.5 Zhou/Cai's 'Spike-triggered regression'

- (Time-permitting)

## 4.6 Computational cost

- Timings of each method, extrapolation for larger number of tested connections

## 4.7 Summary

- Conclusions of the N-to-1 experiment
- Leadup to the network experiments: what we could not yet test (the problem of indirect connections, as e.g. identified in the connectomics challenge)

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## Network model

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- Network connectivity, E/I balance, raster plots
- Too many possible connections to test them all → Subsampling
- Performance of last chapter's methods
- If time: experiment with a network that is less densely connected than our current fully-random one. Why? To better examine the effect of indirect connections / colliders (For the current connectivity, there are too many of those. But in a more realistic, 'localized' network, there are less, and so it seems easier to isolate and examine their effect).



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# Discussion

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## 6.1 Summary & conclusions

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## 6.2 Future work

- Test on real data
- Direct comparison with spikes-only methods
- More complexity in the testing setup: different transmission delays and time constants per synapse / neuron, plus:
- Short term synaptic plasticity. Bursting. Oscillations.
- Simulate different brain areas (different cell types and connectivity patterns). Simulate the same area, but in different states (up vs down, e.g.)
- New connection test method to try: something deep learning-based (we have infinite training data, given our simulation)