

Spiking network modeling of neuronal dynamics in individual rats

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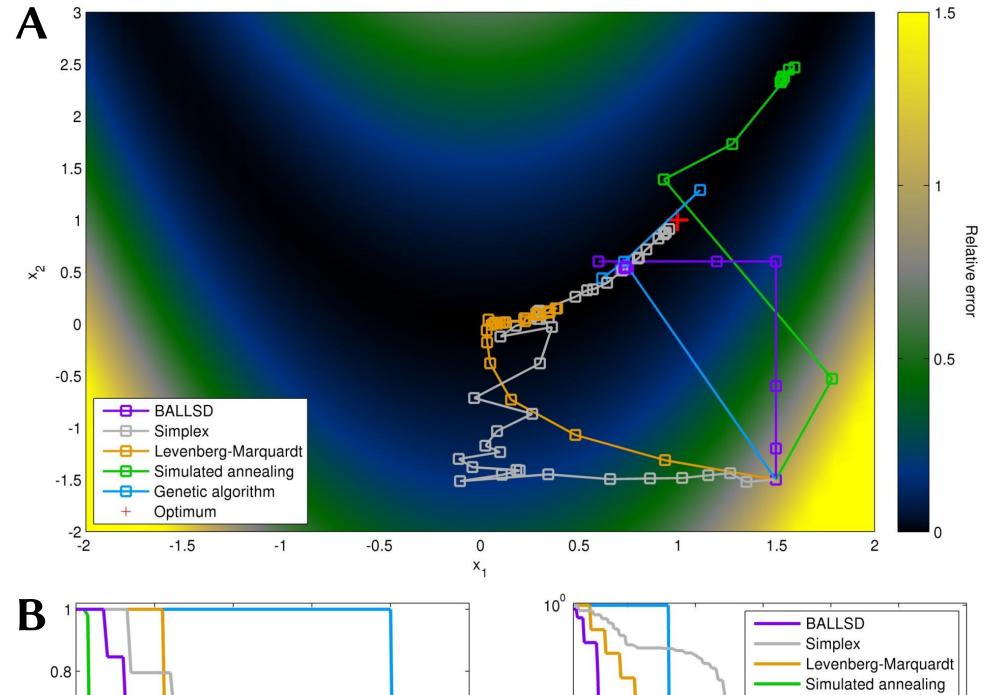


Almost all researchers base their neuronal models on experimental data, but few calibrate their models to it systematically. To our knowledge, no one has previously calibrated spiking network models to individual subjects. In this study, we calibrate and validate a spiking network model against data from individual rats, then use these fits to infer differences in the rats' physiologies.

Data & model

Optimization

- Bayesian adaptive locally linear stochastic descent (BALLSD) [3]: for an objective function $E = f(\mathbf{x})$, BALLSD varies a random parameter *i* and evaluates $E_k^{\pm} = f(\mathbf{x} \pm \delta(i)).$
- If this step is an improvement, BALLSD accepts the changer, increases the probability of selecting this parameter in future, and increases the step size.
- Connection weights, stimulation amplitude, and background input rate were optimized.





Data were recorded from the somatosensory cortices of 9 anesthetized rats, with intrathalamic microstimulation as well as tactile stimulation (Fig. 1). The simulation (Figs. 2– 3) consisted of 2000 spiking Izhikevich neurons [1] representing cortex and thalamus, with connectivities drawn from empirical data [2].

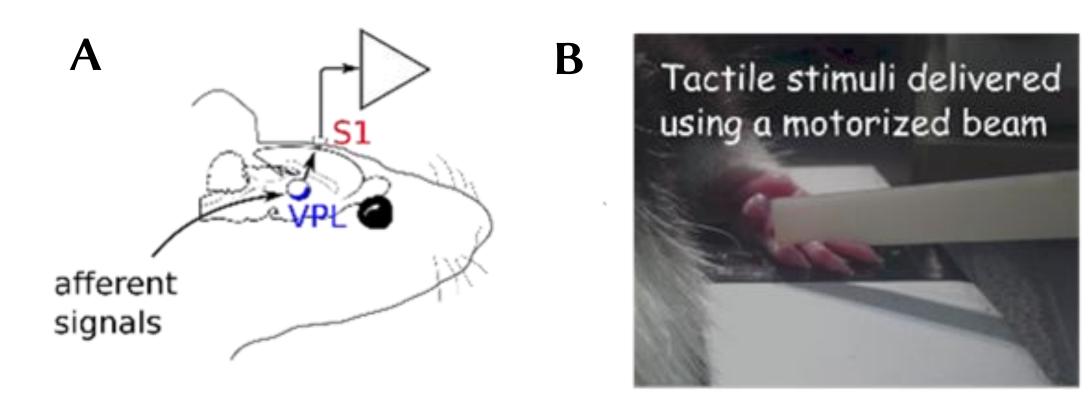


Fig. 1: (A) Natural flow of sensory information. (B) Mechanical actuator delivering tactile stimuli.

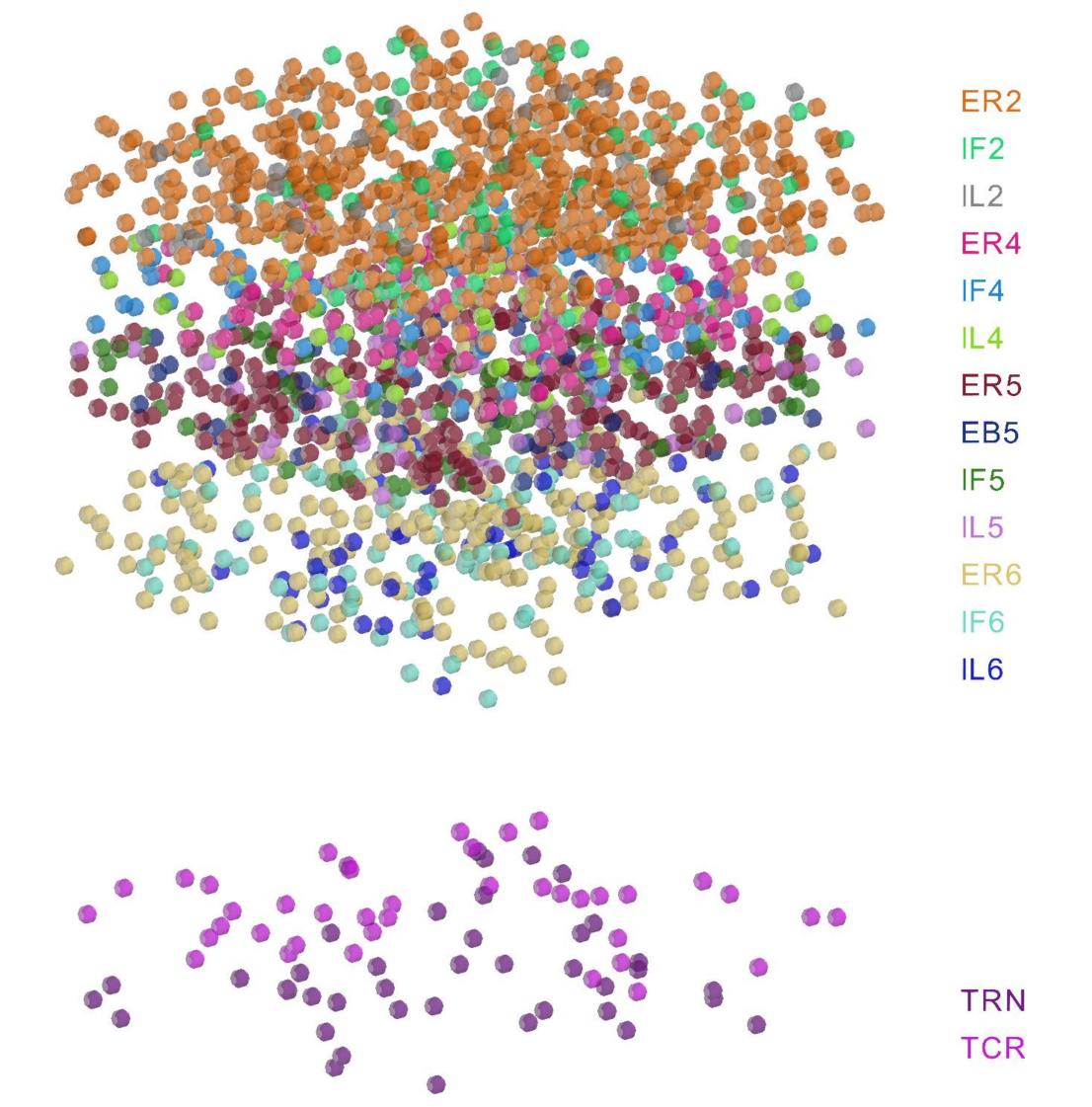
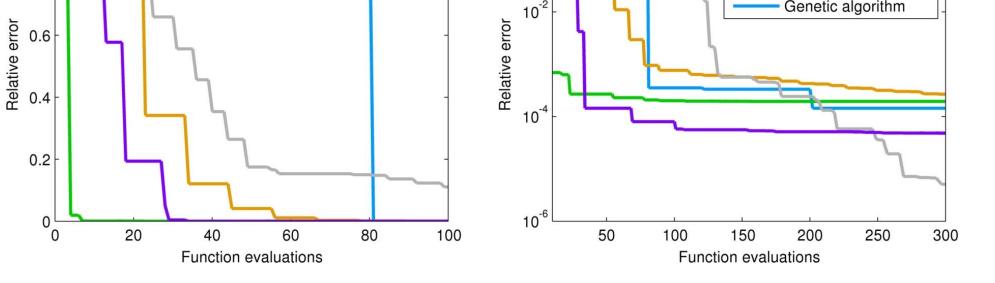


Fig. 4: Example of BALLSD. (A) Trajectories of BALLSD vs. traditional algorithms. (B) Relative error of each method, showing the initial and asymptotic stages of the algorithms.



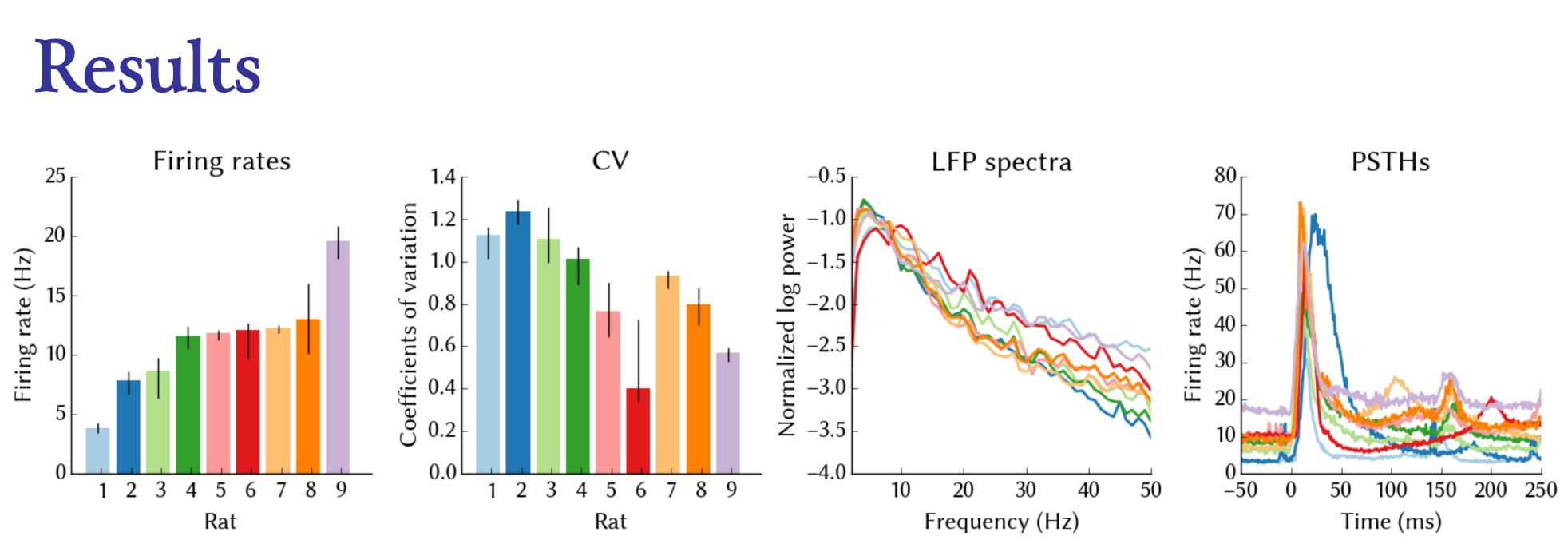
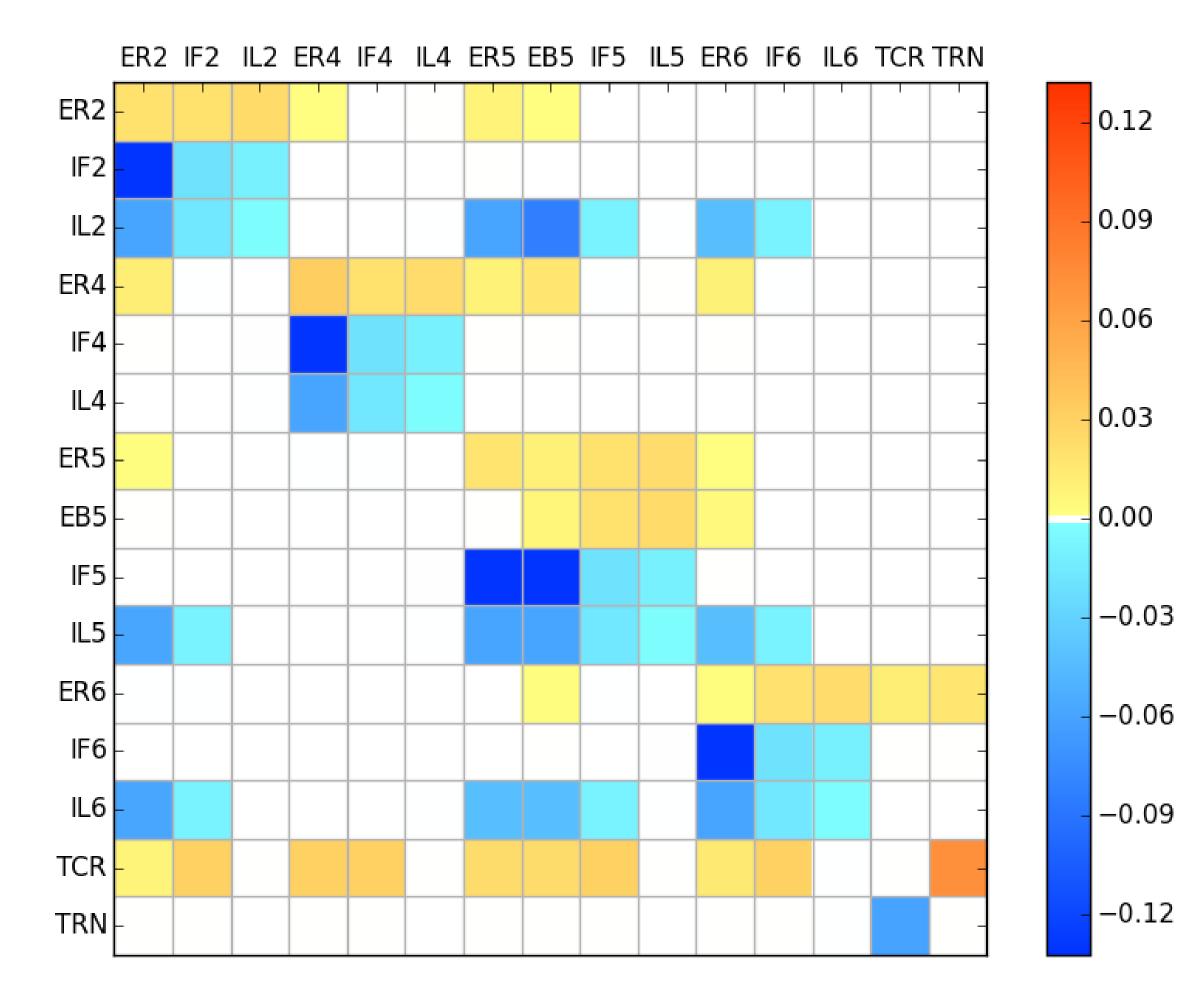


Fig. 5: There was considerable variability between subjects in terms of mean firing rates, coefficients of variation, local field potential spectra, and peristimulus time histograms.

Fig. 2: Schematic diagram of the model showing cell locations and types. Number = layer; \mathbf{E} = excitatory; \mathbf{I} = inhibitory; \mathbf{R} = regular firing; \mathbf{B} = bursting; \mathbf{F} = fast-spiking; \mathbf{L} = low-threshold spiking; **TCR** = thalamocortical relay; **TRN** = thalamic reticular nucleus.



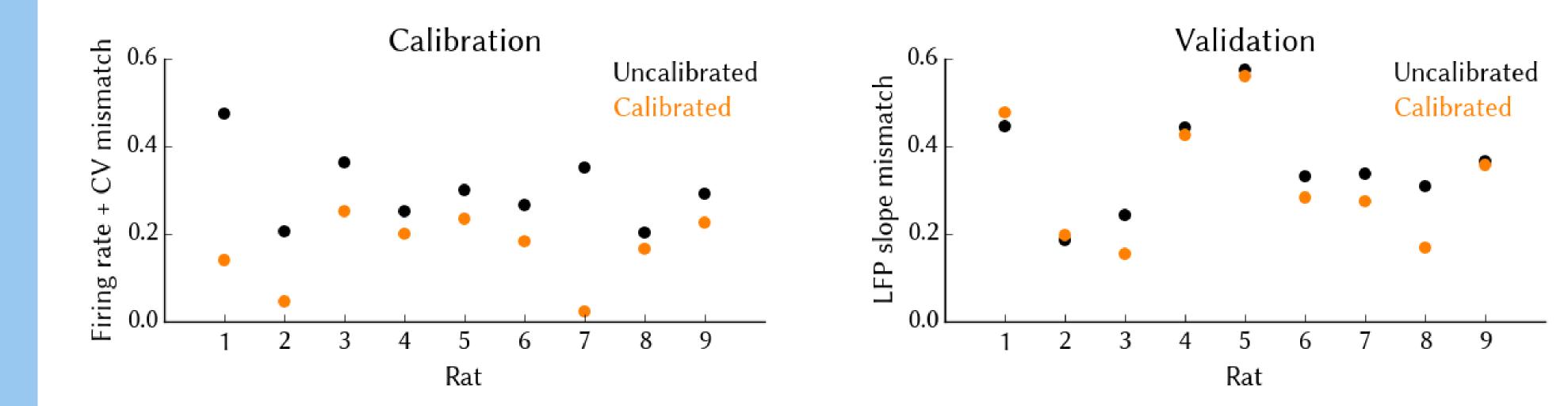


Fig. 6: Calibration reduced the average mismatch for firing rate and coefficient of variation from 30% to 16% on average. This reduced mismatch in the LFP slope in 7 of the 9 subjects, albeit by a small amount (from 36% to 34%).

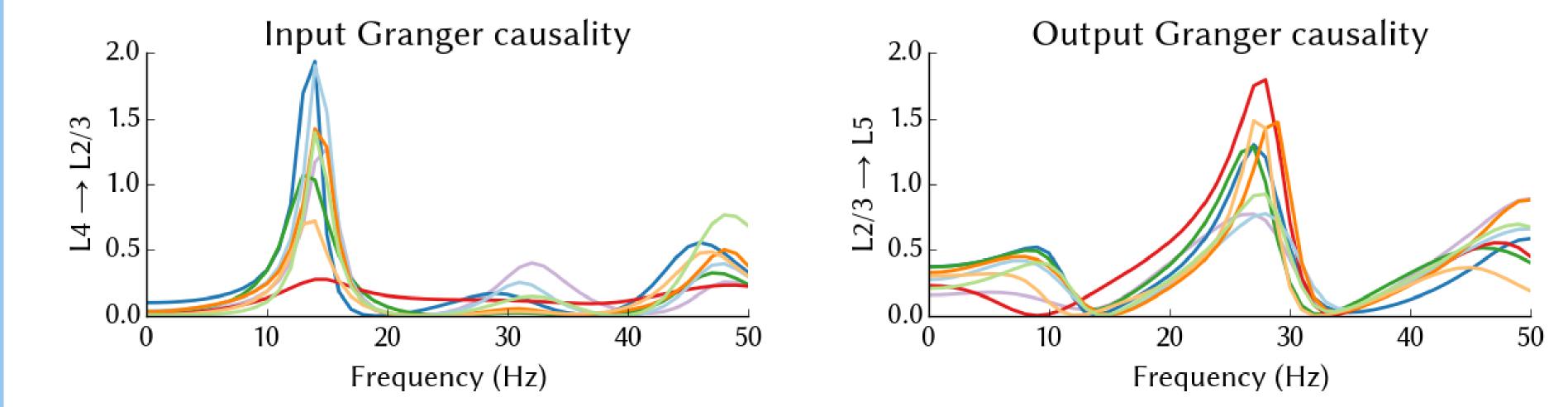


Fig. 3: Connectivity of the model, showing effective connectivity from rows to columns. Red = excitation, blue = inhibition.

Fig. 7: Model-derived interlaminar spectral Granger causality. Peak Granger causality differed between individuals by factors of 10 and 3 in key input and output pathways, respectively.

Summary

- We used a novel optimization method to calibrate spiking network models to data from individual rats.
- Inter-subject differences can be related to differences in model parameters and thence to differences in computation.
- Future work will investigate other fitting methods, and will relate modeled differences in computation to differences in behavior.

References

[1] Izhikevich EM, Edelman GM (2008). Proc Natl Acad *USA* **105**:3593–8. [2] Kerr CC, et al. (2013). *Front Comput Neurosci* **7**:1–14. [3] Kerr CC, et al. (under review).

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Further information

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