Overcoming model limitations via empirically-tuned parameters

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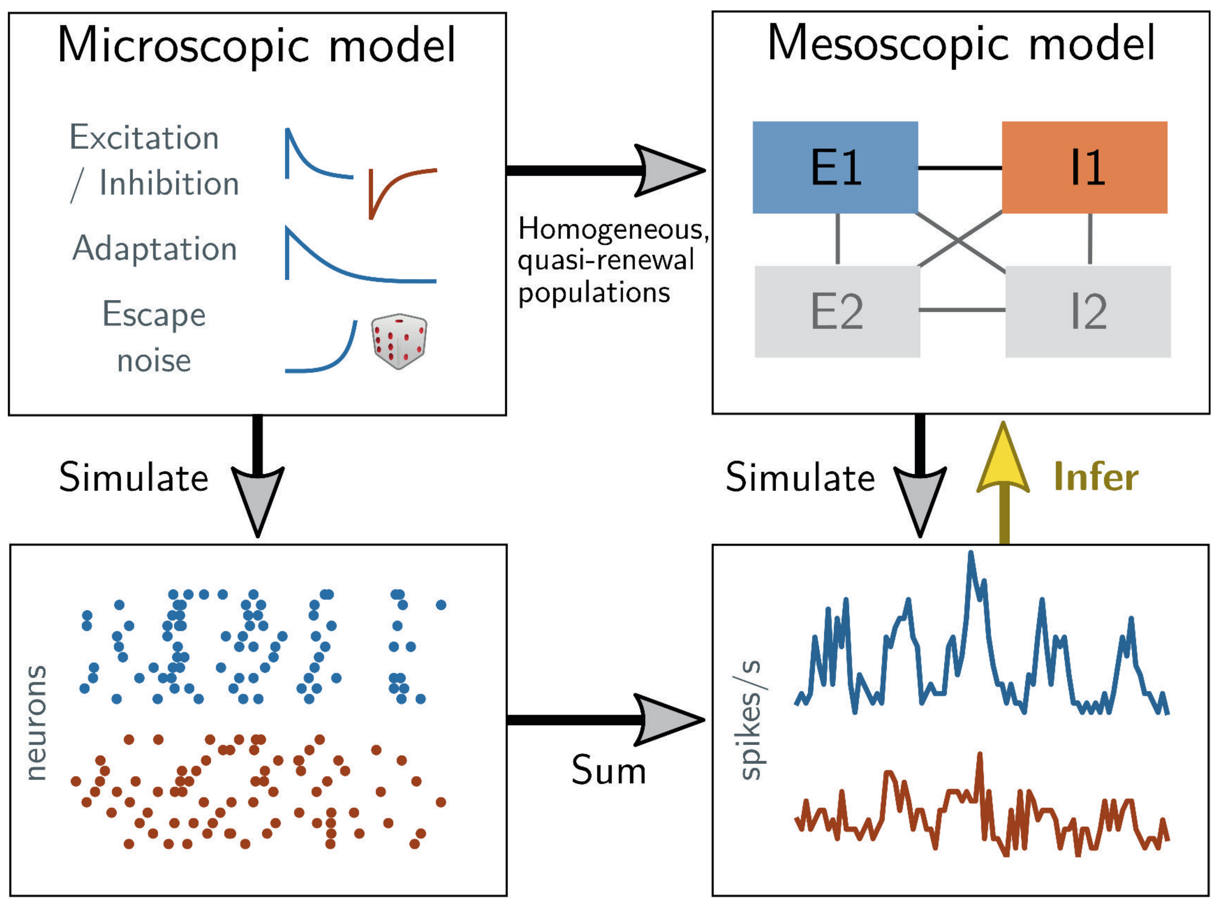
Motivation

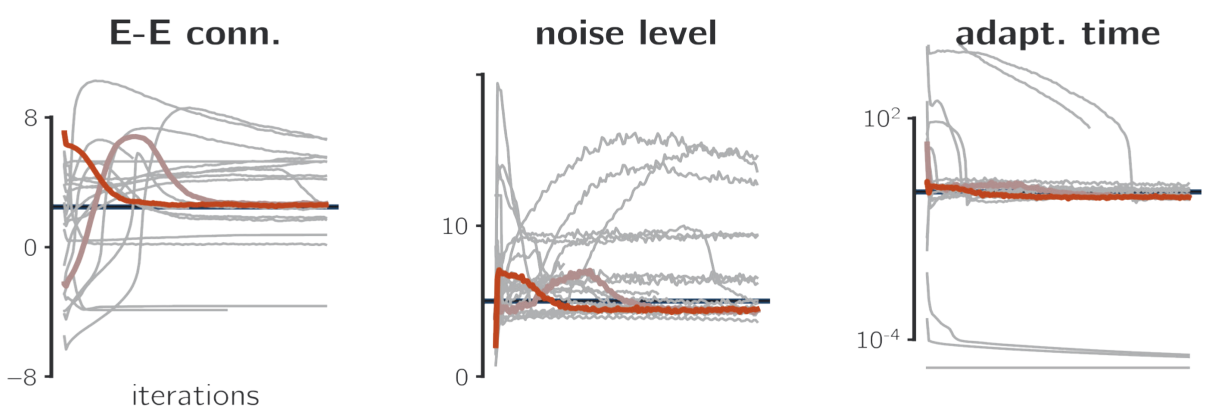
- Even the best neuron population models are still only **approximations** of biological processes.
- **Statistical inference** is already used to fit phenomenological models to data.
- We can **compensate** for approximations by extending statistical inference to mechanistic models.
- This allows us to combine the **interpretability** of mechanistic models with the **predictive power** of data-driven models.

Approach

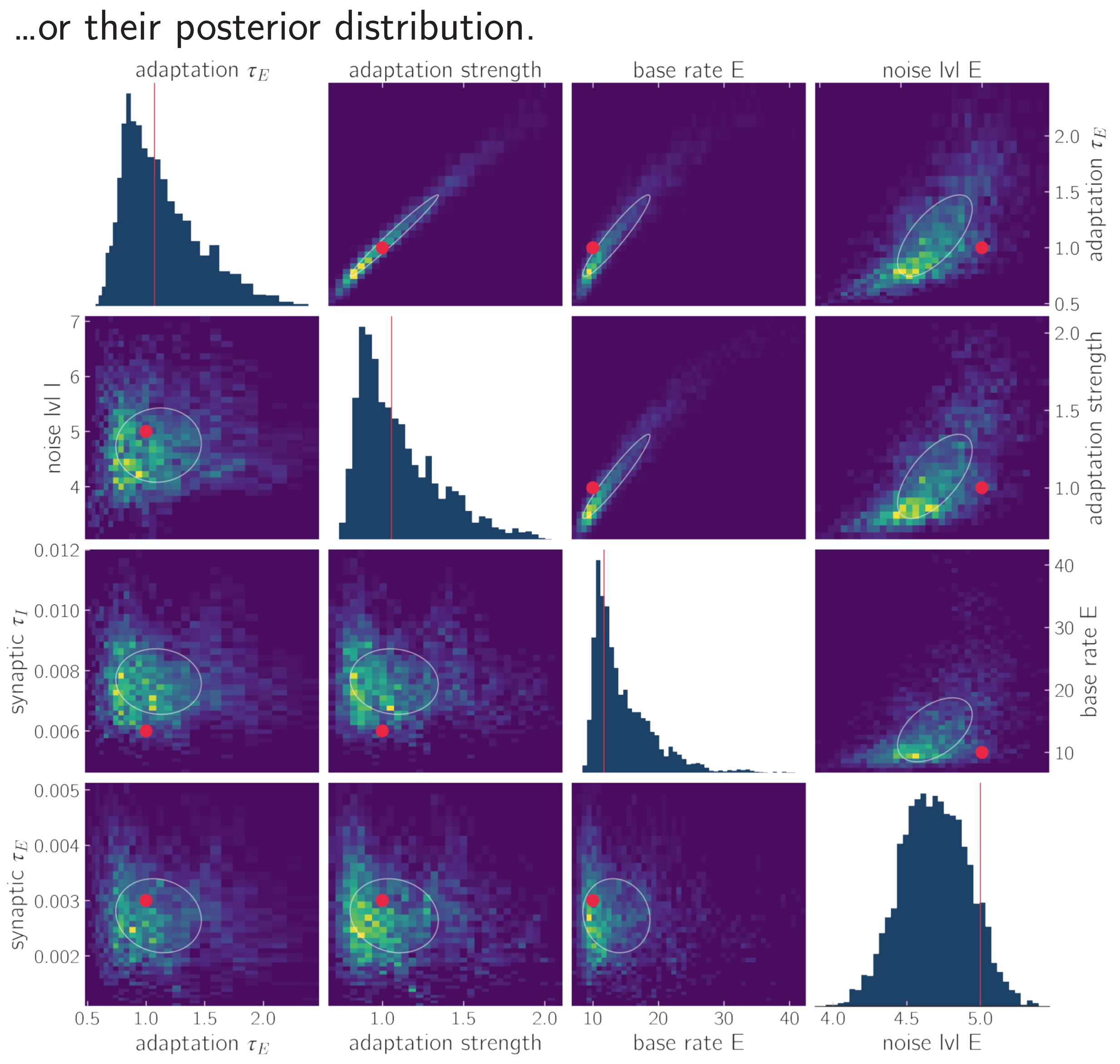
Choose data and model with known mismatch:
- Synthetic data (microscopic)
- Derived model (mesoscopic)[1]



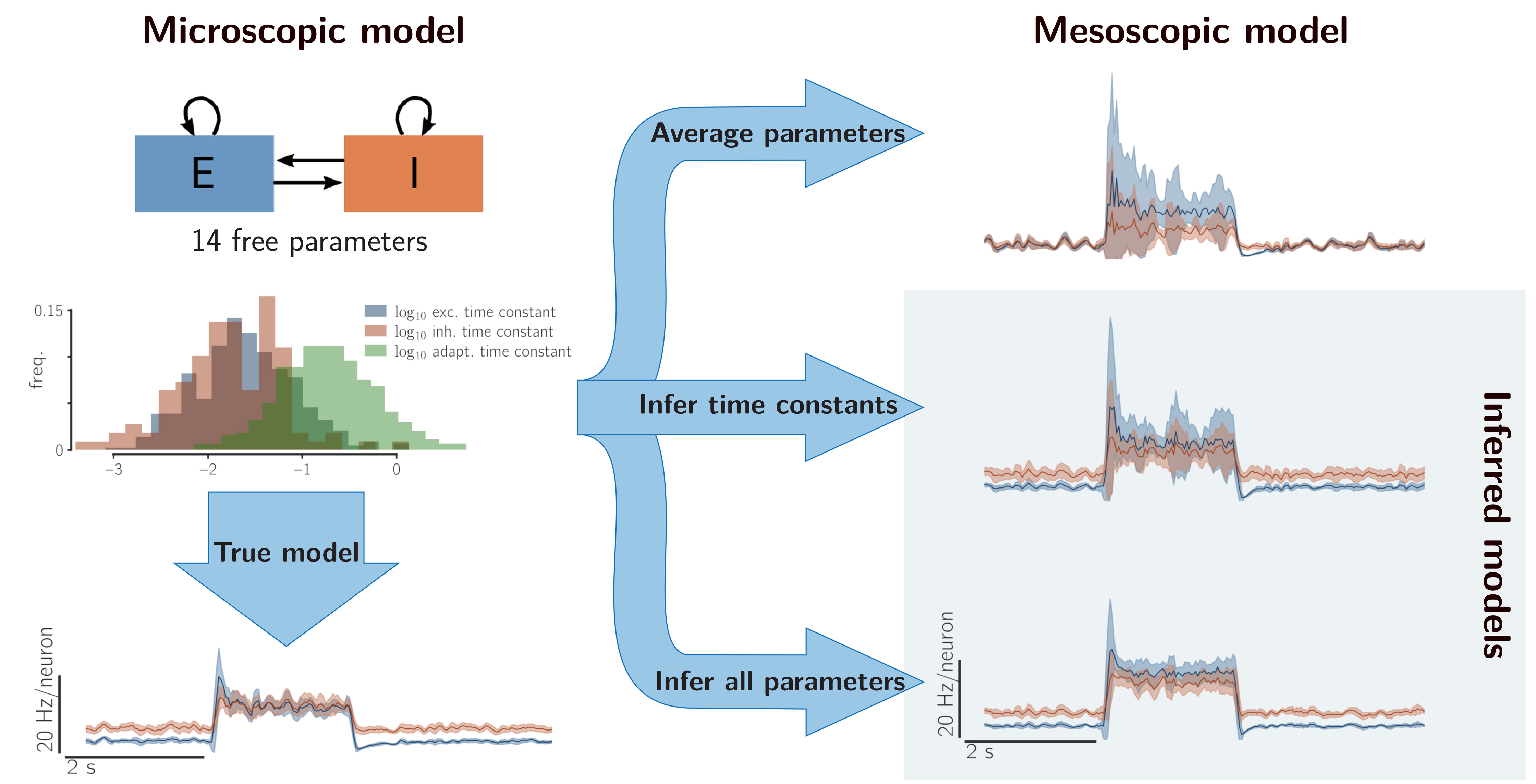
Use statistical inference to recover parameter point estimates...



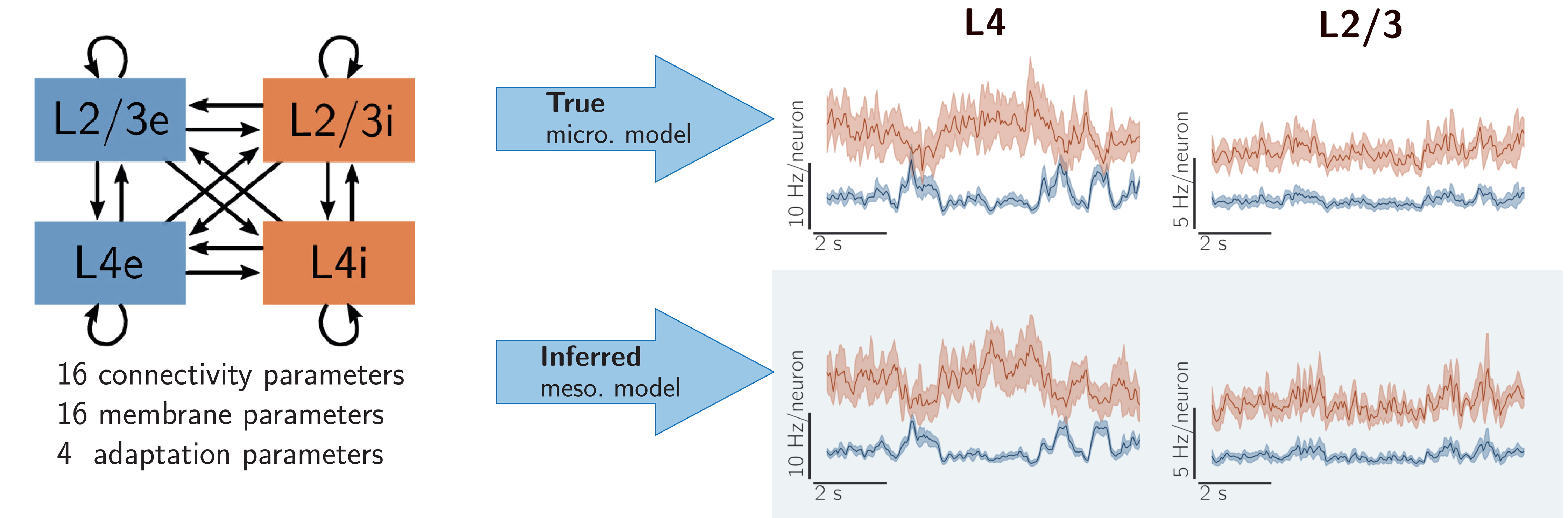
...or their posterior distribution.



Inference can compensate for homogeneous approximation



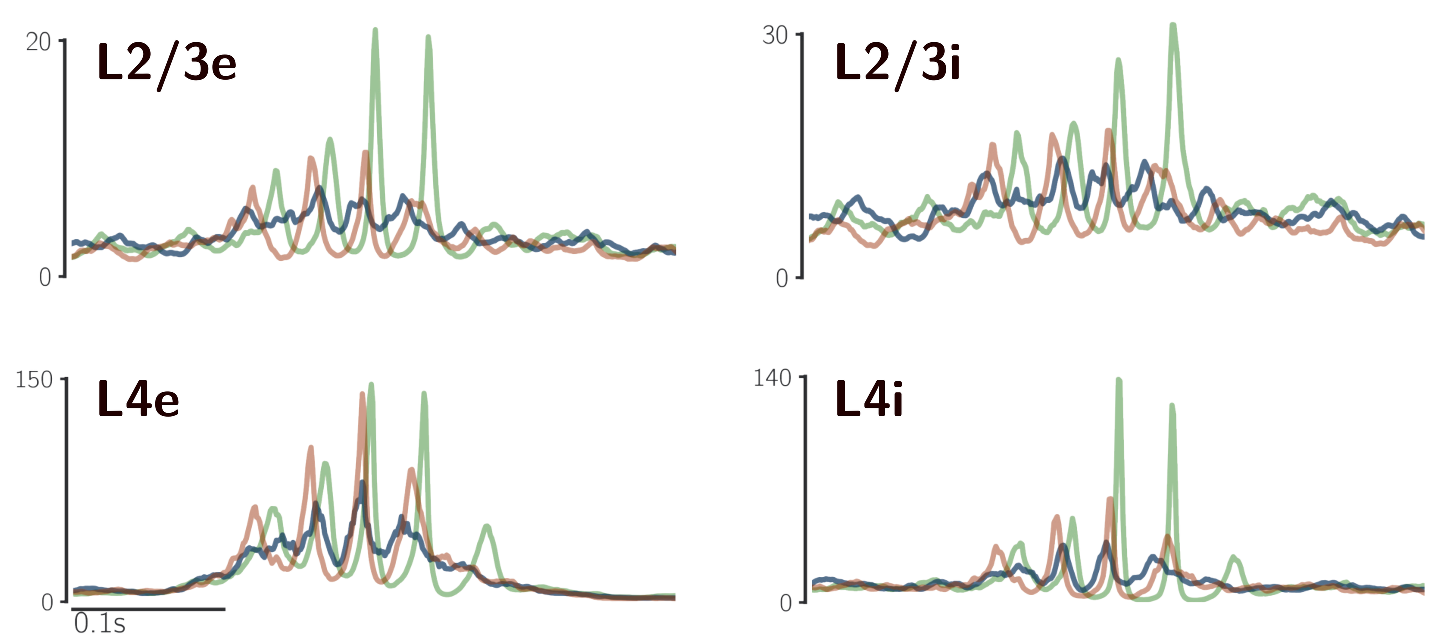
We can infer dozens of parameters simultaneously



Not all approximations can be compensated by inference

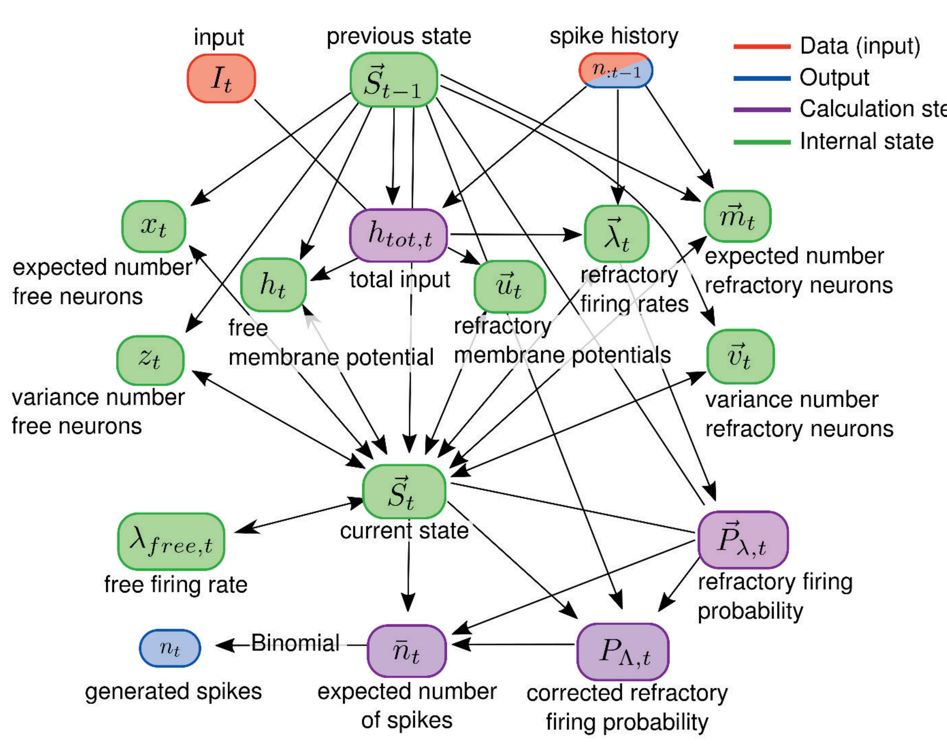
- Extreme inputs can break the quasi-renewal renewal approximation
- Inference can only work within model constraints
- More flexible models → more compensation possibilities

True micro. model
Theoretical meso. model
Inferred meso. model



Method

Mesoscopic generalized integrate-and-fire model[1]

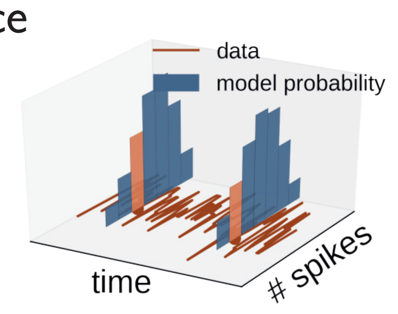


- Adaptation via dynamic threshold;
- Number of parameters $\approx 5N_{pop} + N_{pop}^2$.

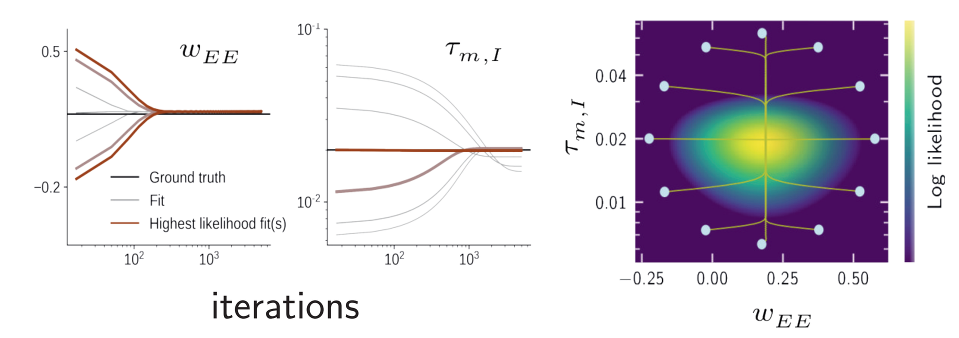
Maximum likelihood inference

Likelihood function

- parameters: θ
- current state: $S(t)$
- data (# spikes): $n(t)$
- model: • $P(n(t)|S(t-1),\theta)$
  • $S(t-1) \to S(t)$
- likelihood: $L(\theta) = \prod_t P(n(t)|S(t-1),\theta)$



Optimization via stochastic gradient ascent



Why use inference to determine parameters ?

- **Systematic**: no hand-tuning of parameters
- **Principled**: recovered parameters maximize the likelihood
- **Scalable**: can infer dozens of parameters
- **Flexible**: model equations do not change
- **Ready**: code library available on github

Computational tools

Gradient ascent fits performed with ADAM[2] algorithm, using Theano[3] for automatic differentiation and optimization. Posteriors obtained via Hamiltonian Markov Chain Monte Carlo, using PyMC3.[4]

References

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[2] D. P. Kingma, J. Ba, arXiv:1412.6980 (2014)
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