Teaching neural networks to be Bayesian without likelihoods

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Bayesian inference is very useful.

The brain might be making use of Bayesian inference.

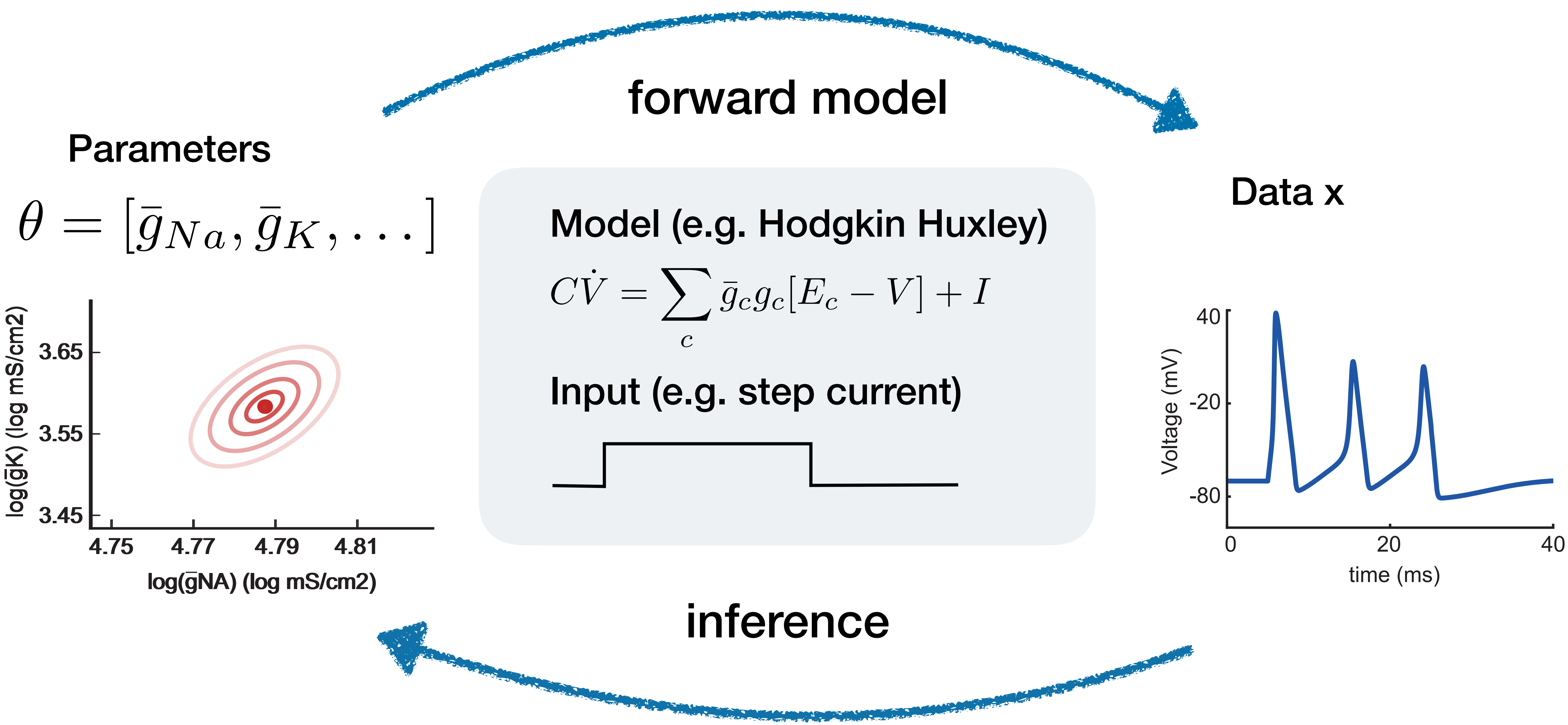
For Bayesian inference, one needs likelihoods.

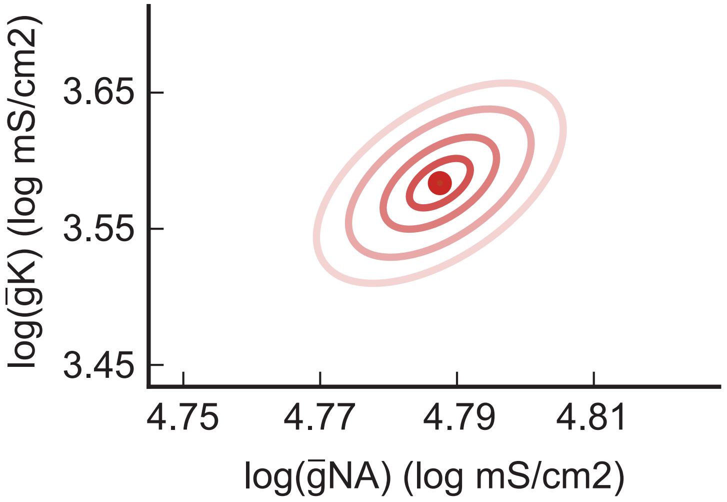
For most models in cognitive science and neuroscience, likelihoods are not tractable.

(How) can we do Bayesian inference without likelihoods?

All we need is a simulator and neural networks.

Bayesian inference: Finding parameters of a model which are consistent with data and prior knowledge



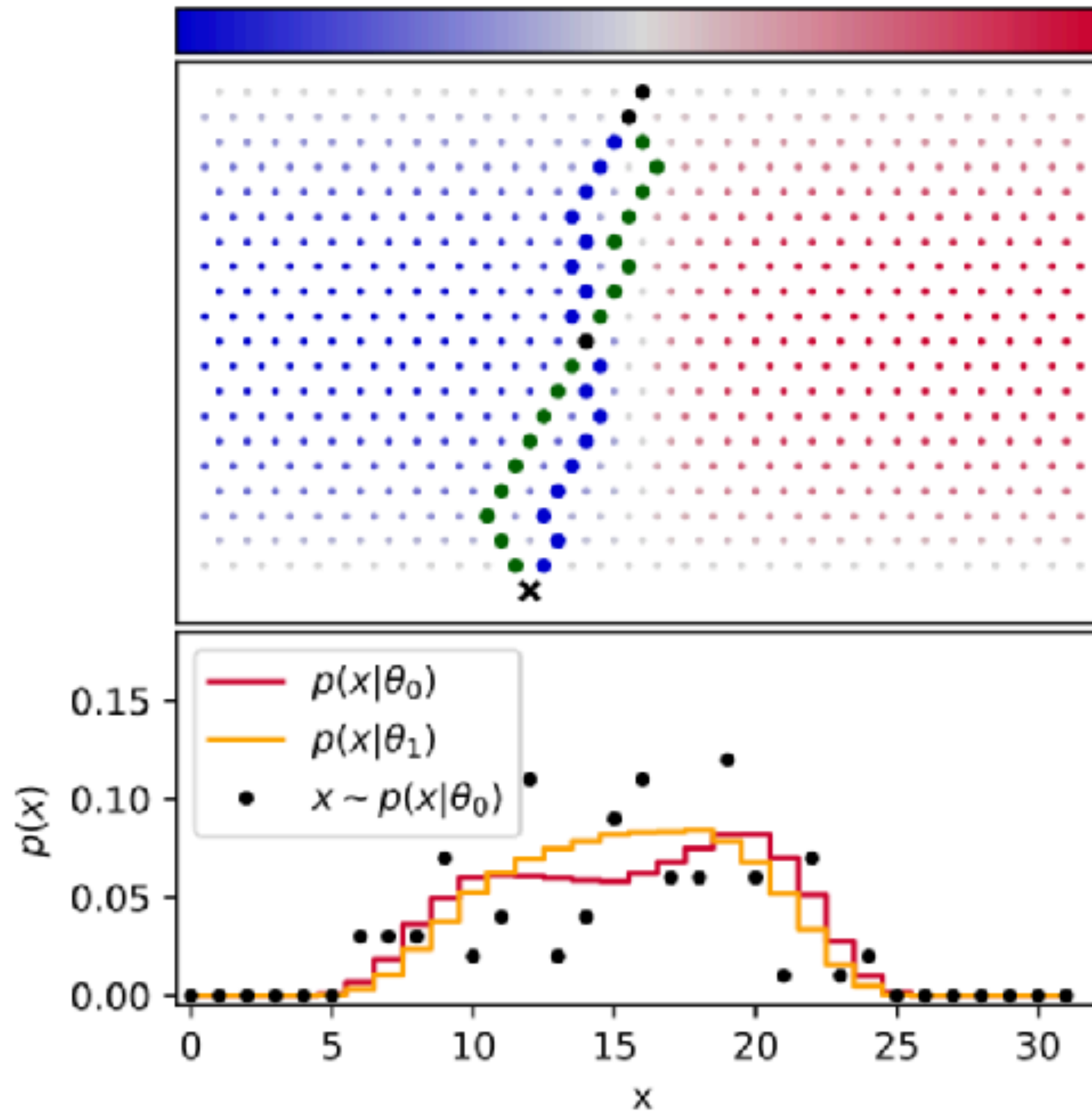


$$p(\theta|x) \propto p(x|\theta)p(\theta)$$

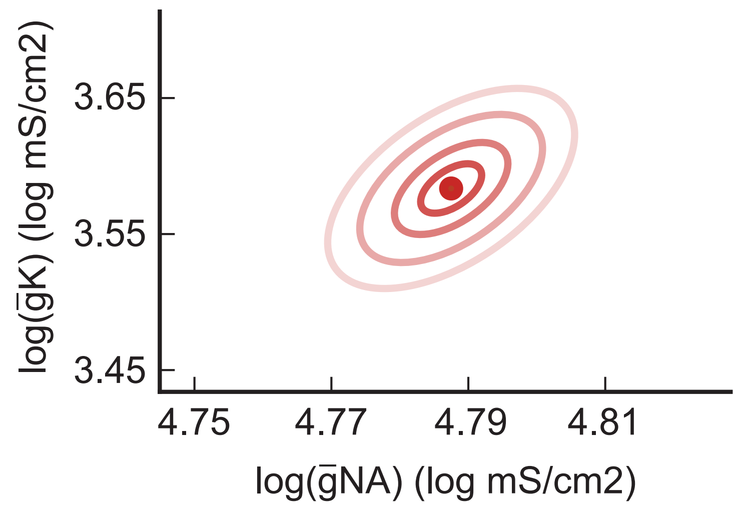
likelihood: often not tractable

posterior: hard to compute

For 'simulation based' models, we can **simulate** x, but we can not **evaluate** the likelihood p(x|params).



Idea and Figures from Brehmer et al 2018



$$p(\theta|x) \propto p(x|\theta)p(\theta)$$

likelihood: often not tractable

posterior: hard to compute

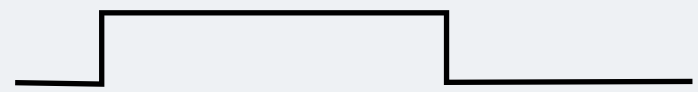
Bayesian inference is intractable for many models in neuroscience and cognitive science.

How can we do **Bayesian inference**, if all we have is a **simulator**, but **no likelihoods**?

Approximate Bayesian Computation (ABC)

Blum & Francois 2010, Papamakarios & Murray 2016

$$C\dot{V} = \sum_c \bar{g}_c g_c [E_c - V] + I$$



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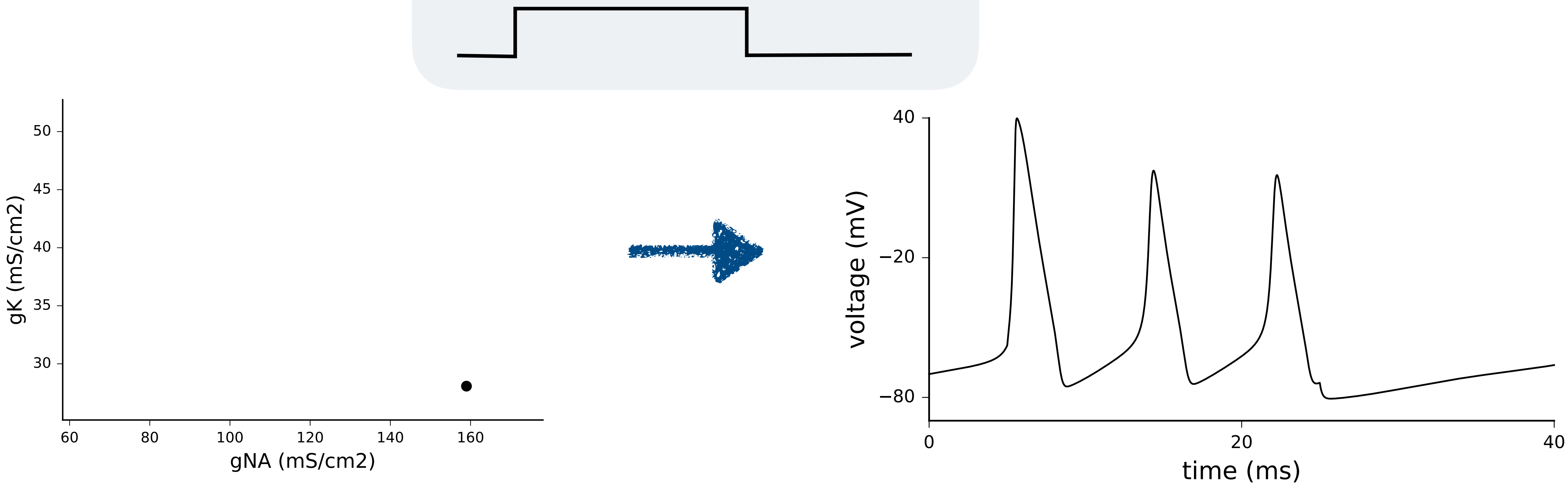

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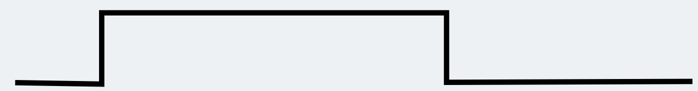
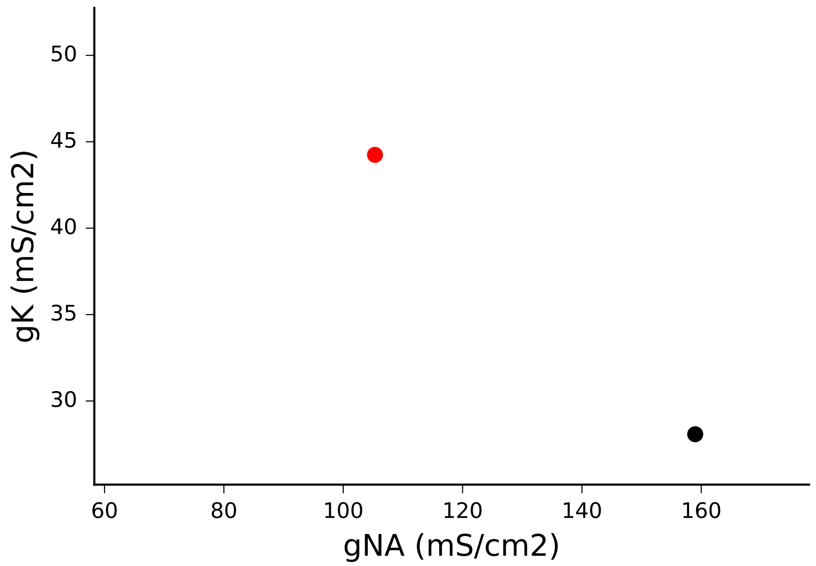
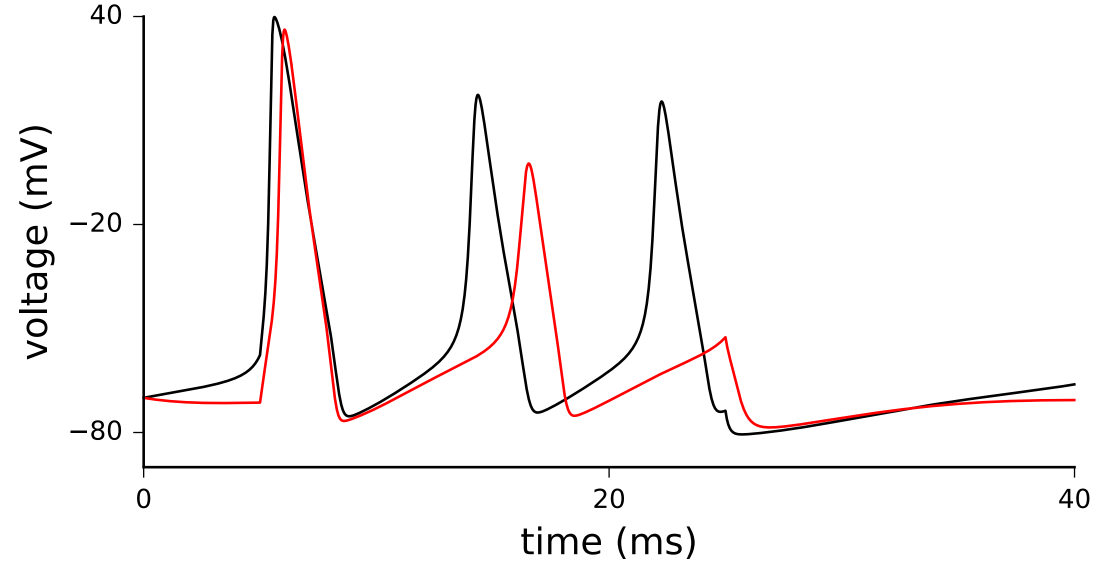
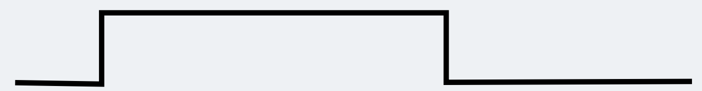


1. Sample data from multiple parameters





$$C\dot{V} = \sum_c \bar{g}_c g_c [E_c - V] + I$$



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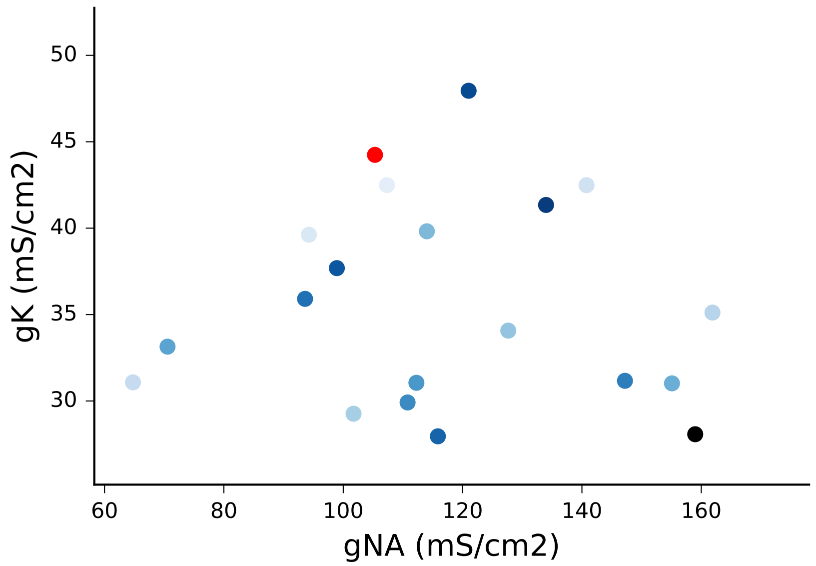
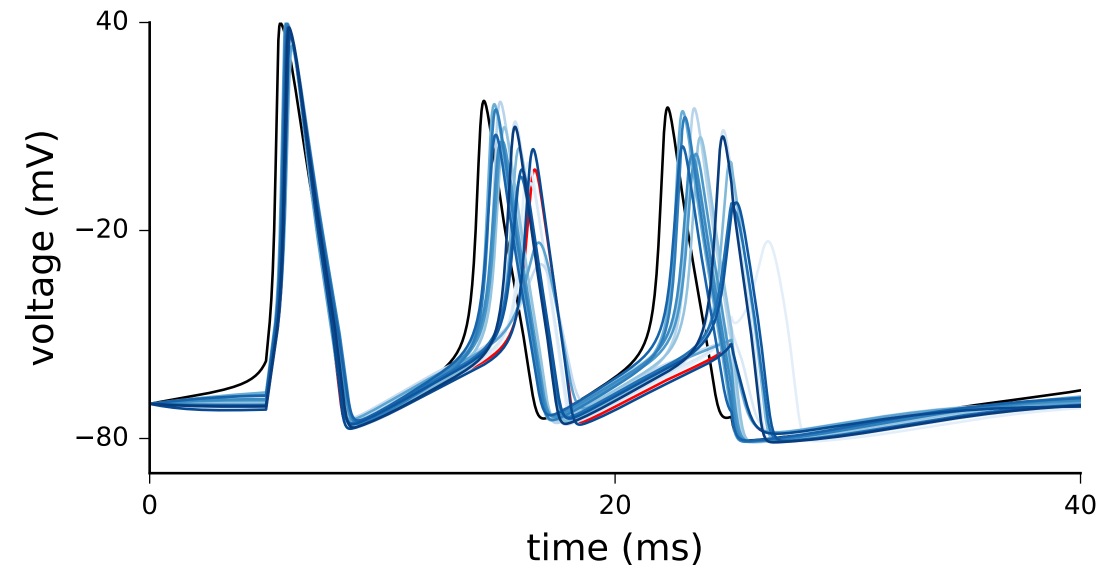
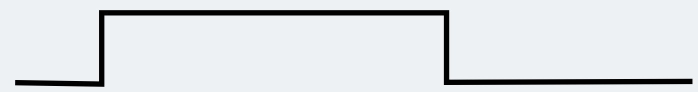
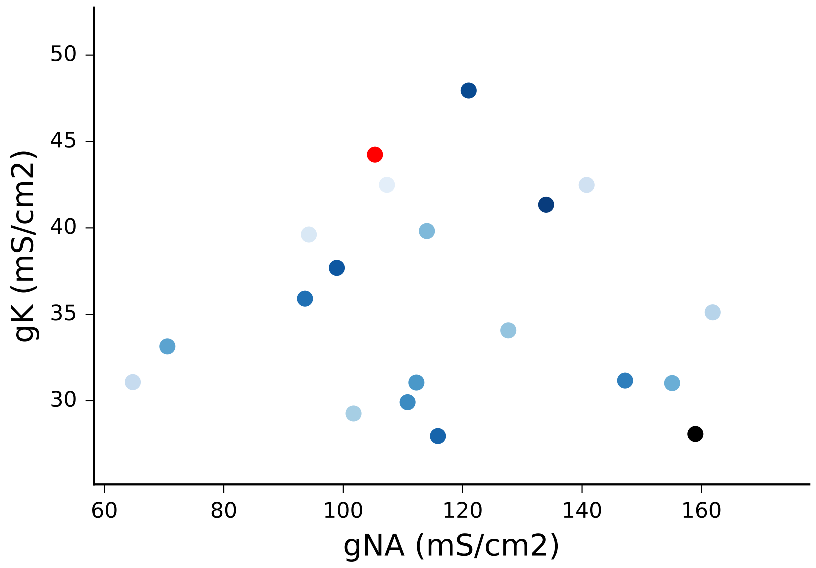
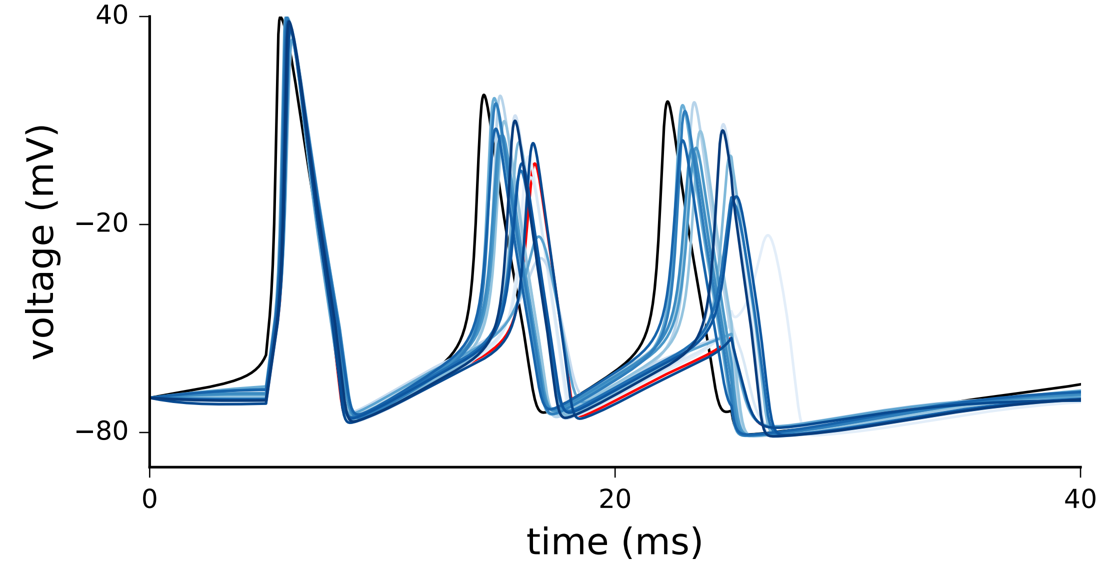


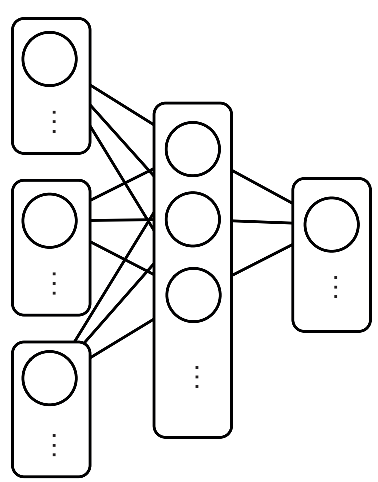


$$C\dot{V} = \sum_c \bar{g}_c g_c [E_c - V] + I$$





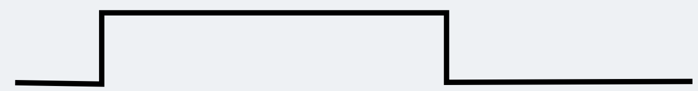


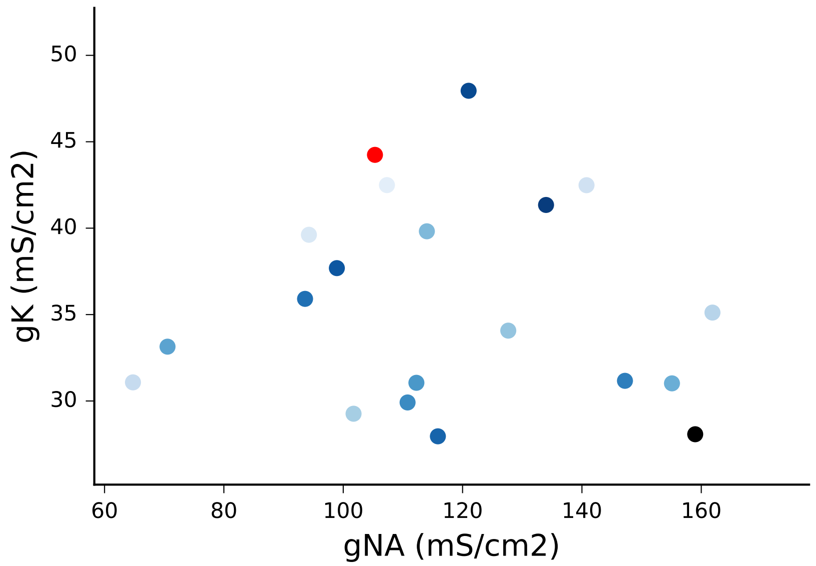


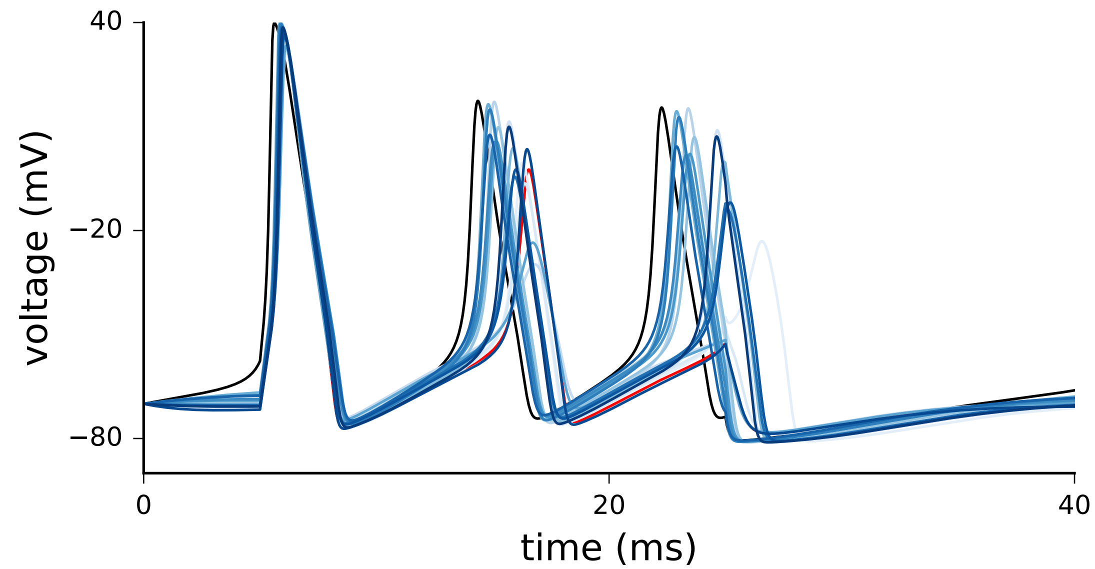
2. Train Neural network (NN) to predict parameters from samples

$$P(\theta|x_o) = \mathrm{NN}_\phi(x = x_o)$$

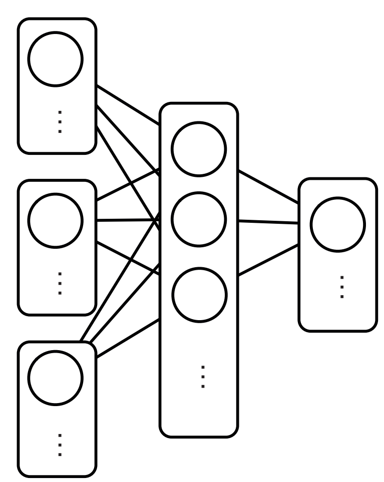
$$C\dot{V} = \sum_c \bar{g}_c g_c [E_c - V] + I$$







3. Use NN to propose new samples

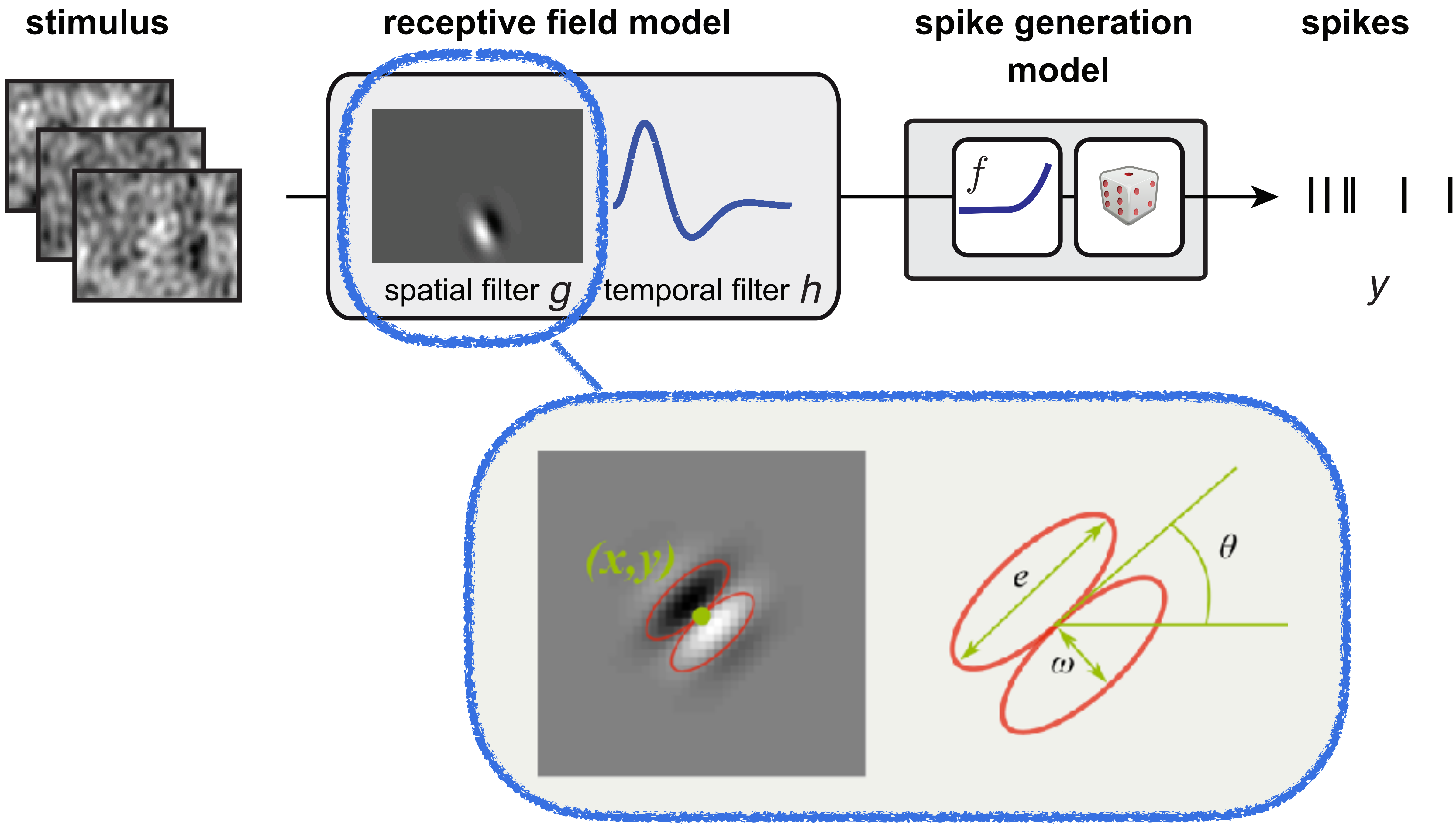


2. Train Neural network (NN) to predict parameters from samples

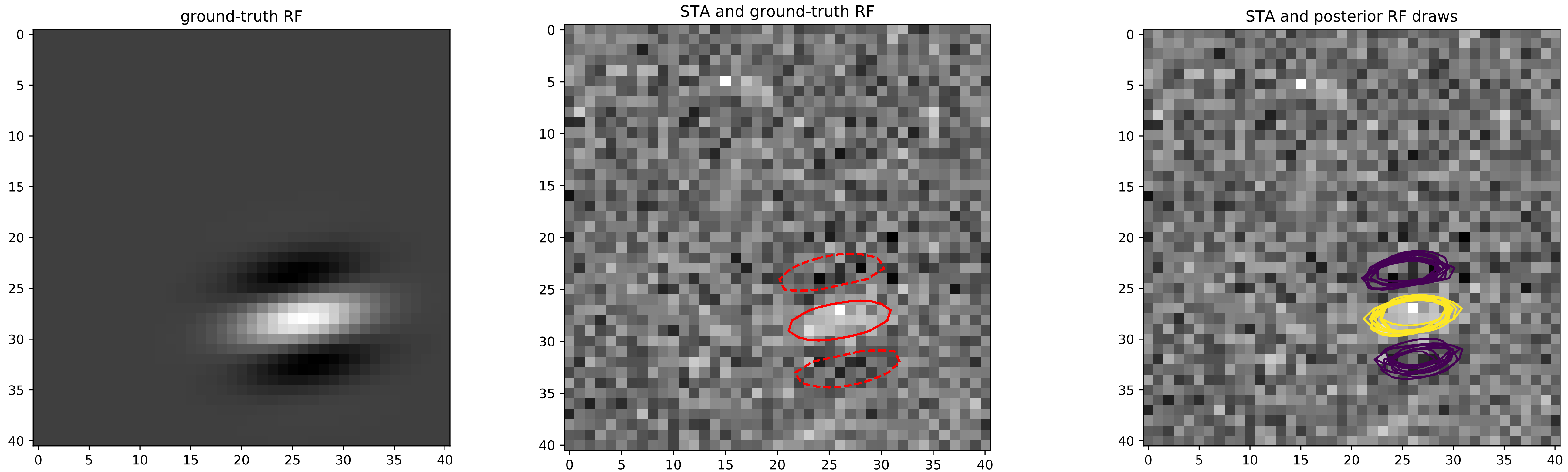
$$P(\theta | x_o) = \mathrm{NN}_\phi(x = x_o)$$

Lückmann, Goncalves et al, NIPS 2017

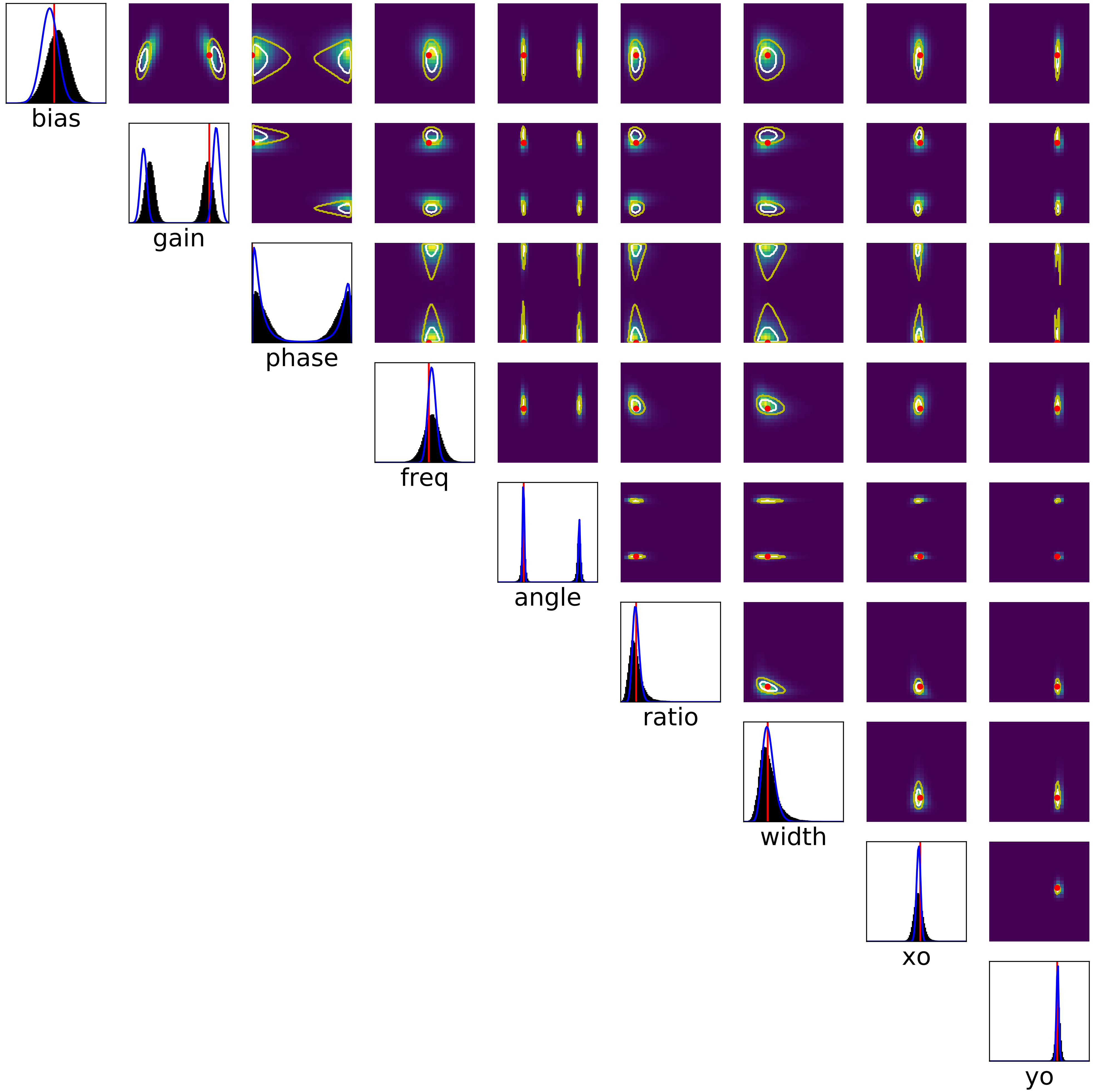
Application I: Estimating receptive fields of neurons in primary visual cortex



Giacomo Bassetto, Marcel Nonnenmacher



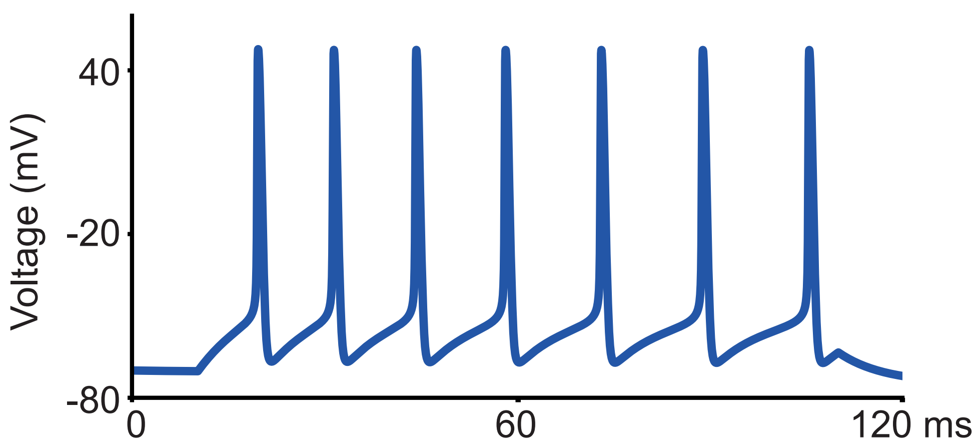
ground-truth RF
STA and ground-truth RF
STA and posterior RF draws
0
5
10
15
20
25
30
35
40


bias
gain
phase
freq
angle
ratio
width
xo
yo

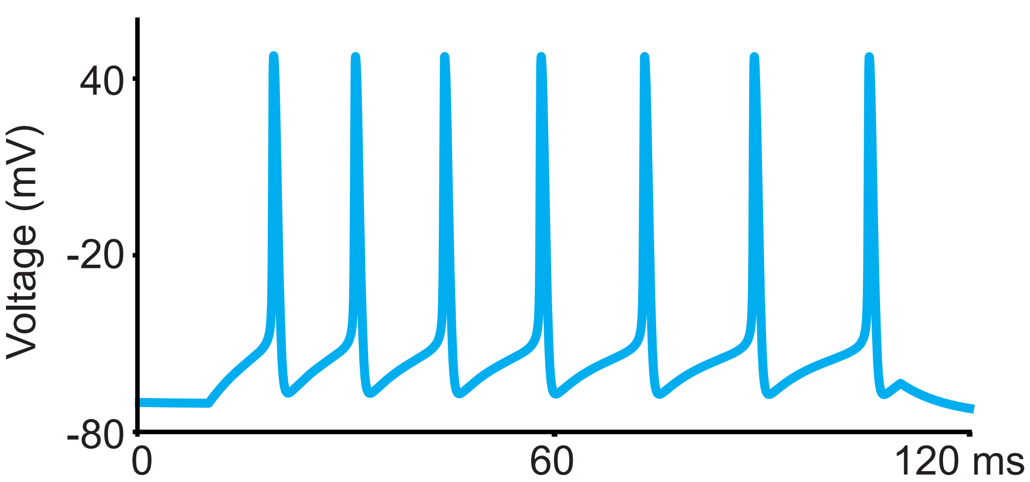
Application II: Inferring parameters of biophysical neurons models

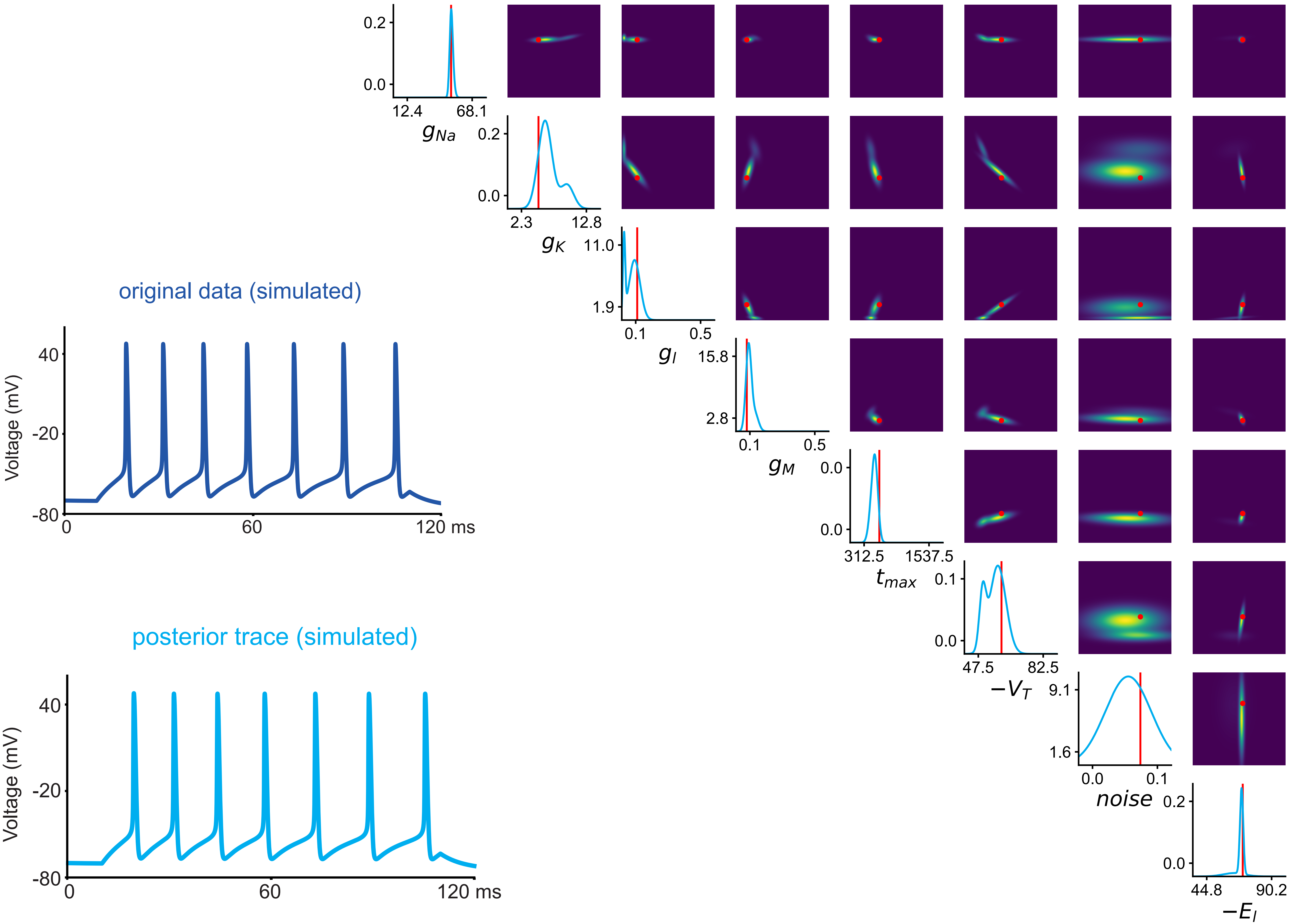
$$C_m \frac{dV}{dt} = g_{\text{leak}}(E_{\text{leak}} - V) + \bar{g}_{\text{Na}} m^3 h (E_{\text{Na}} - V) + \bar{g}_{\text{K}} n^4 (E_{\text{K}} - V) + \bar{g}_M p (E_{\text{K}} - V) + I_{\text{inj}} + \sigma(t)$$

original data (simulated)



posterior trace (simulated)



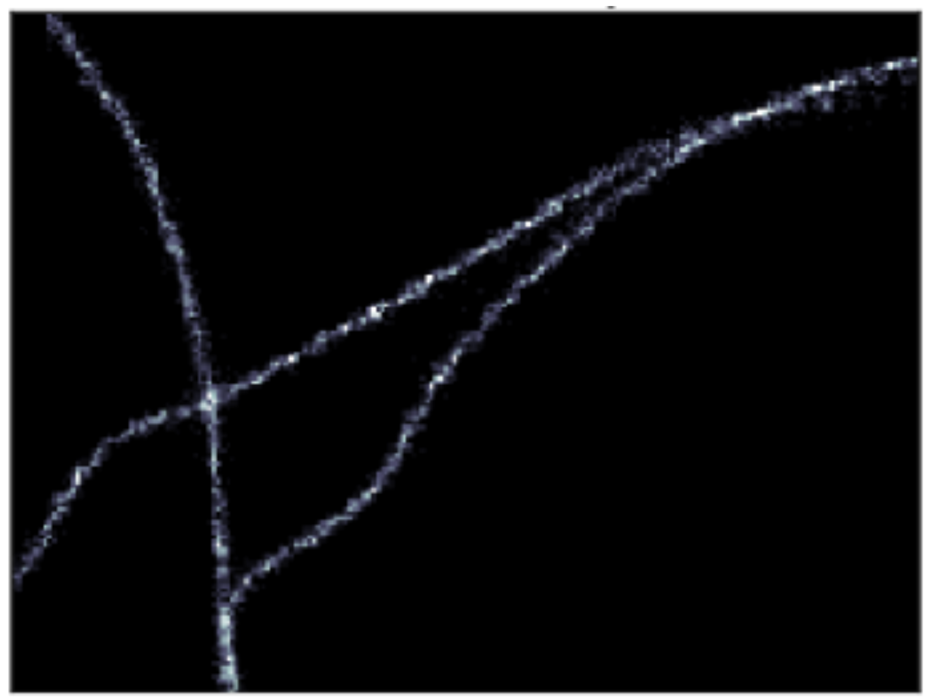

original data (simulated)
posterior trace (simulated)
Voltage (mV)
40
-20
-80
0
60
120 ms
0.2
0.0
12.4
68.1
g_{Na}
2.3
12.8
g_K
11.0
1.9
0.1
0.5
g_l
15.8
2.8
g_M
312.5
1537.5
t_{max}
47.5
82.5
$-V_T$
9.1
1.6
noise
44.8
90.2
$-E_l$

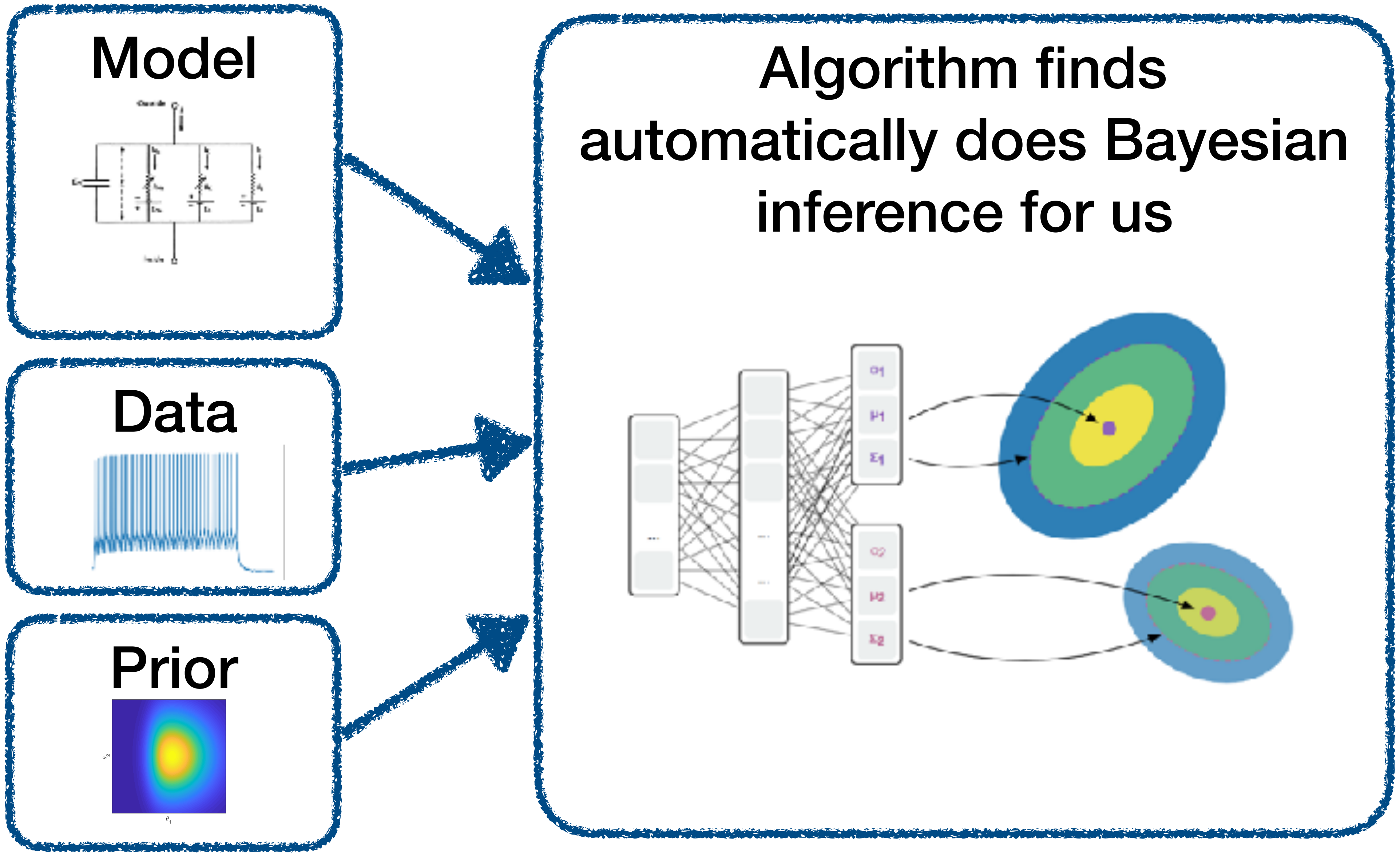
Inferring connectivity rules in cortical circuits (with M. Oberlaender, caesar Bonn, DFG SPP Connectomics)

Effects of prior expectation on probabilistic computations (DFG SFB Robust Vision with H Nienborg and F Wichmann)

Inferring action potentials from 2photon imaging data (Speiser et al, NIPS 2017)

Source reconstruction for super-resolution microscopy (Speiser et al, in prep., leaderboard on EPFL challenge)





- **Flexibility:** Inference approach does not depend on specifics of forward model.
- **Amortized inference:** Once the network is trained, inference is very fast.
- A strategy for **efficient inference** in the brain?
- Lots of work to be done to make this user-friendly.

Thanks to ....

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Dr. Pedro Goncalves

Jan-Matthis Lückmann

SFB 1089

SPP 2041 Computational Connectomics

ROBUST VISION

Human Frontier Science Program

Bundesministerium für Bildung und Forschung

IKT 2020 Machine Learning

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S Remy, DZNE Bonn
S Turaga, HHMI Janelia
G Zeck, D Rathbun, E Zrenner, K Stingl, Tübingen
D Zoccolan, A Laio, SISSA Trieste

code and preprints at www.mackelab.org