

# Bayesian optimization of protocols for neurostimulation

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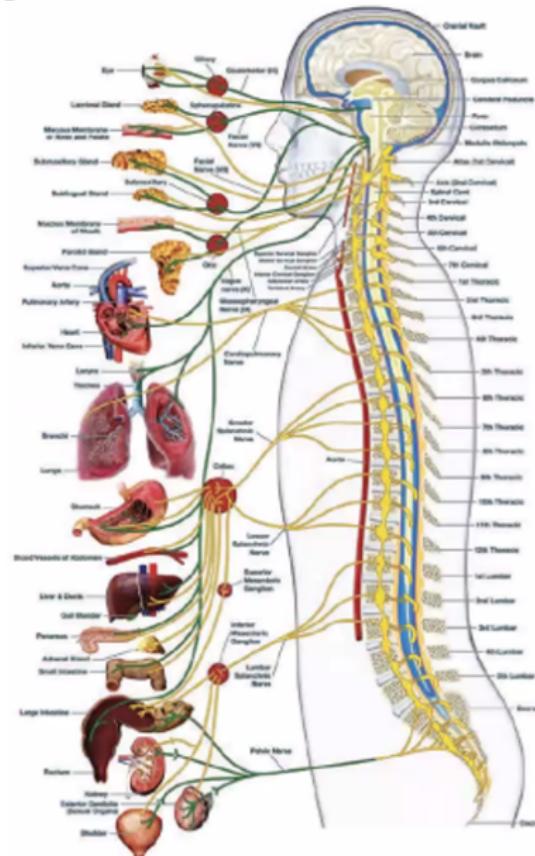
14 Sep 2021

## Bioelectronic therapies

Organs are controlled and regulated by peripheral nervous system

## Traditional **biochemical** interventions

**Bioelectronic** medicines leverage nervous system directly with highly specific, fast and dynamic interventions



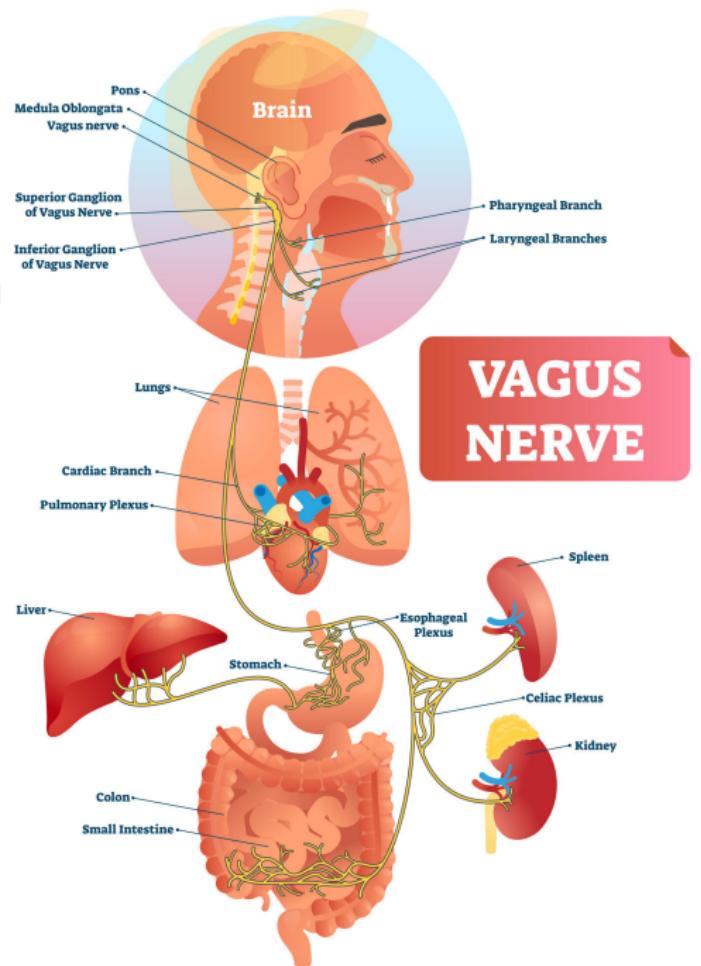
# Vagus nerve

Part of **parasympathetic**  
**(calming)** nervous system

Two way traffic:

**Afferent** messages from  
organs to brain

**Efferent** messages from  
brain to organs



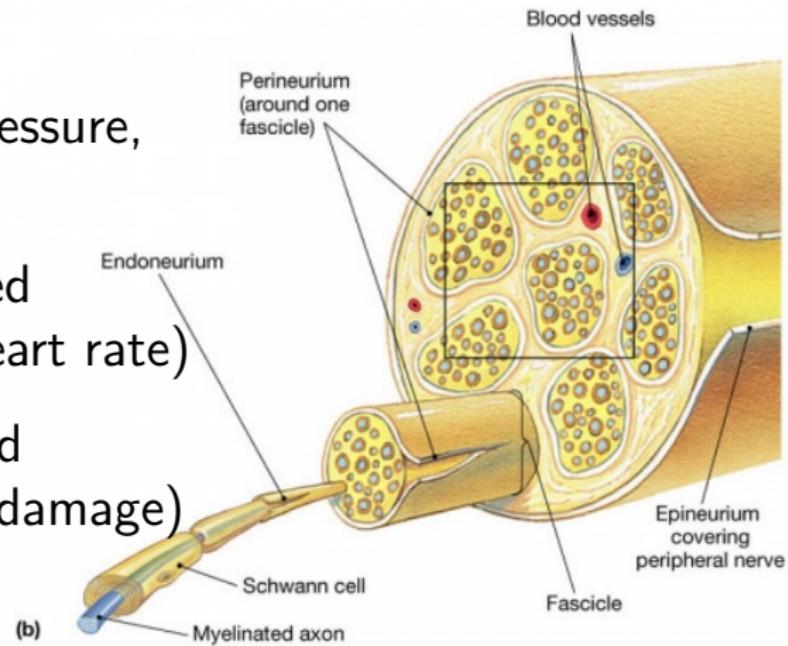
# Cross section of a nerve

Hierarchical organisation into fascicles, types of fibres:

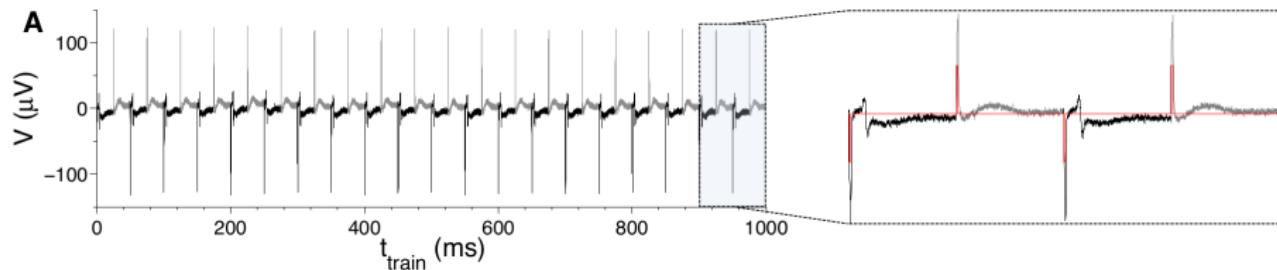
A: large, myelinated  
fast (eg sense lung pressure,  
blood pressure)

B: medium, myelinated  
slower (eg regulate heart rate)

C: small, unmyelinated  
slow (eg sense tissue damage)

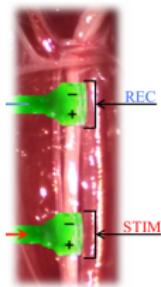


# Stimulation by electric pulses

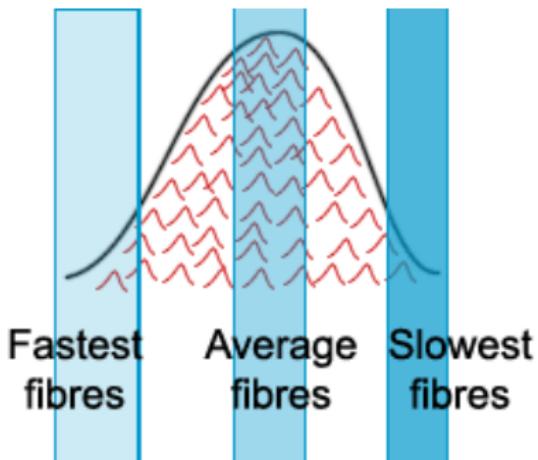


Train of alternating-monophasic stimulation

M Ward et al, A Flexible Platform for  
Biofeedback-driven Control and Personalization  
of Electrical Nerve Stimulation, Therapy, 2015



# Nerve response to stimulation



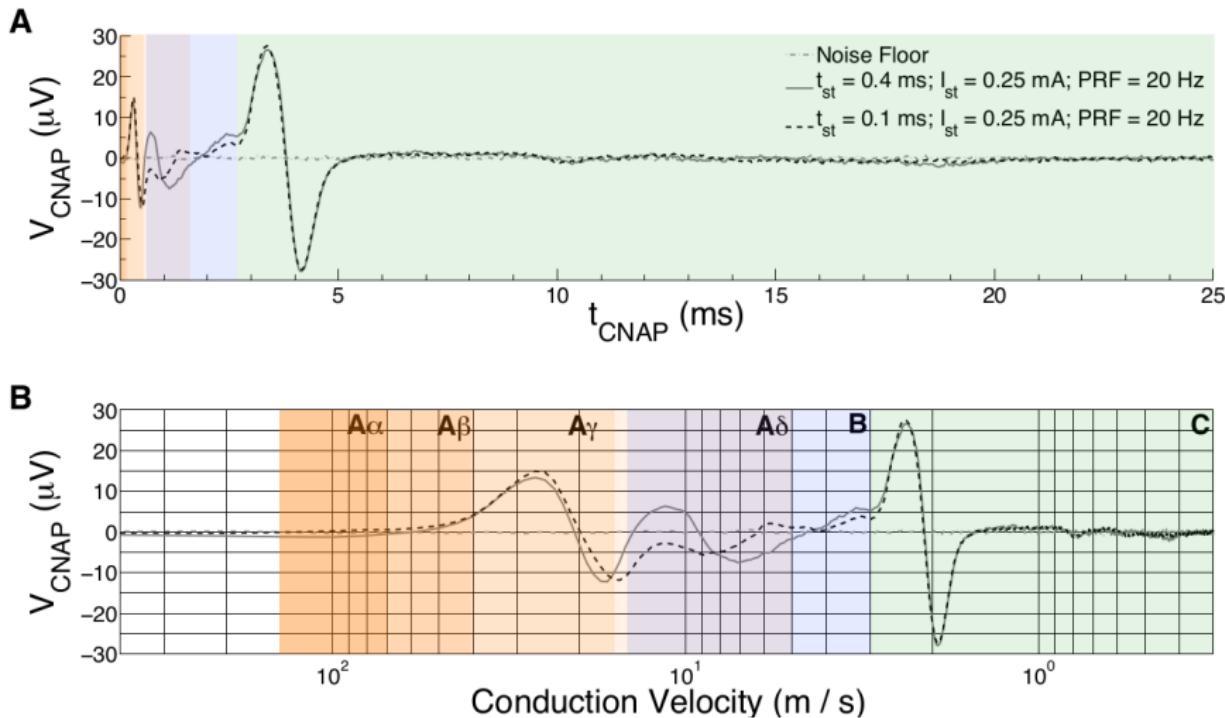
Individual nerve cells triggered by **stimulation** electrodes

Action potentials travel at (slightly) different speeds

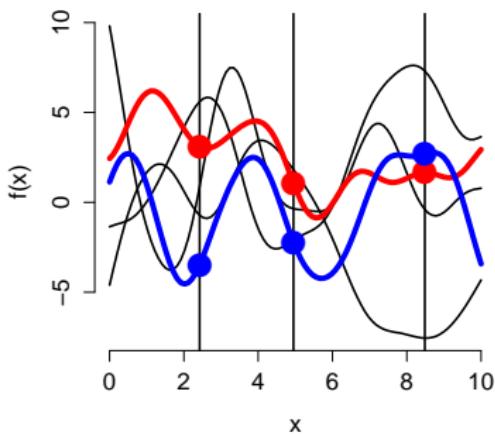
**Response** recorded by **recording** electrodes

Artificial responses affect organs similar to natural ones

# Velocity chart for fibre types



# Gaussian process prior



Family of functions via covariance  $K$  on input points  $x$

$$y \sim N(0, K_{xx})$$

Prediction for  $x^*$  from  $(x, y)$

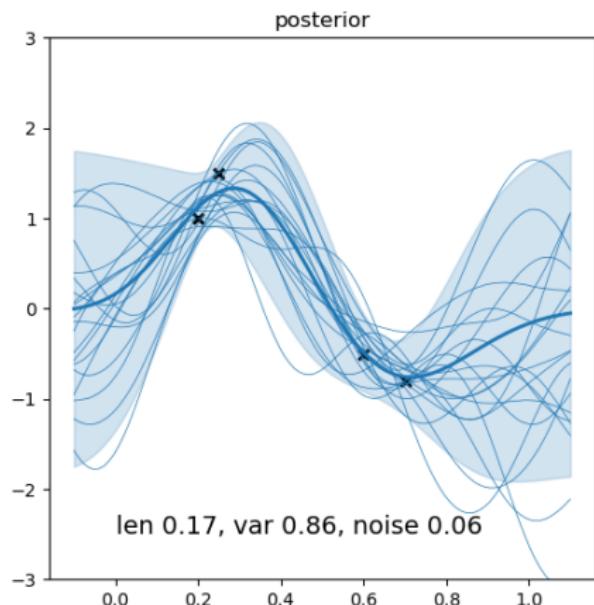
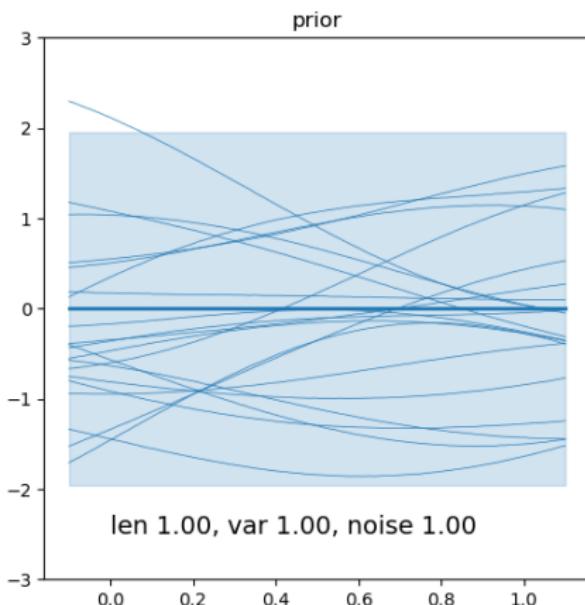
$$y^* \sim N(K_{x^*x} K_{xx}^{-1} y, \Sigma)$$

$$\Sigma = K_{x^*x^*} - K_{x^*x} K_{xx}^{-1} K_{xx^*}$$

$$\text{Gaussian kernel } \text{cov}(x, x^*) = \theta_1 \exp(-\theta_2(x - x^*)^2)$$

Power from flexibility in kernel design and combinations

# GP posterior uncertainty and samples



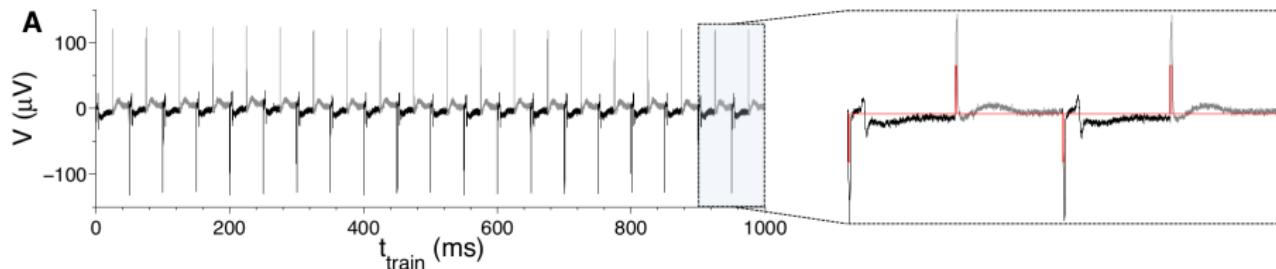
Estimate GP parameters by maximum likelihood

# Vagus nerve stimulation in rats

M Ward et al, A Flexible Platform for Biofeedback-driven Control and Personalization of Electrical Nerve Stimulation, Therapy, 2015

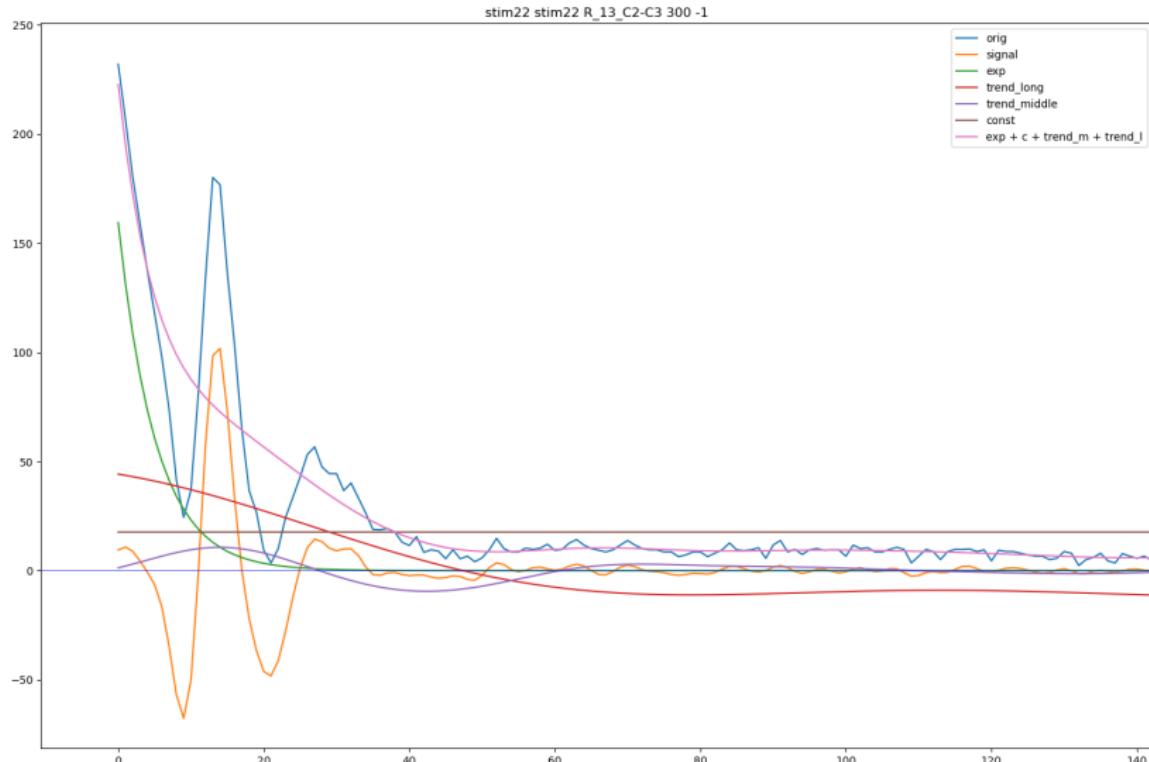
- ▶ Trials with 12 subjects
- ▶ Left cervical branch of vagus nerve
- ▶ 7 pulse currents 0, 0.2,..., 1.2
- ▶ 4 pulse durations 0.1, 0.2, 0.4, 0.8, for 20 secs
- ▶ Alternating monophasic, 10Hz, for 1 second
- ▶ Responses recorded

# Stimulation by electric pulses



1s train of alternating-monophasic stimulation, 10Hz

# Response decomposition by GP



Kernels: exponential decay, trends, signal, noise

BIOS

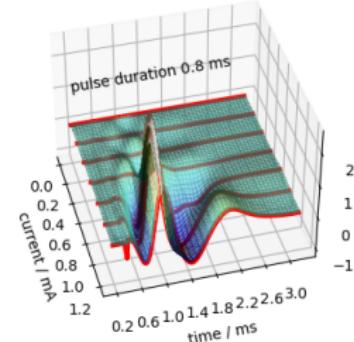
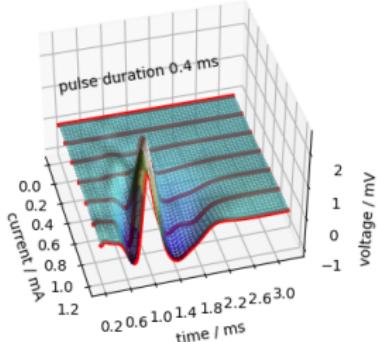
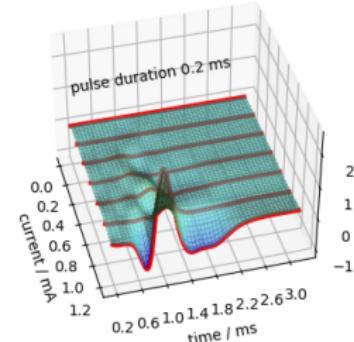
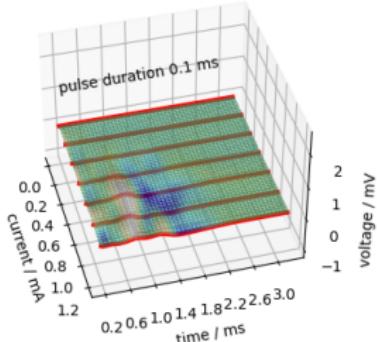
# Modelling nerve responses by GPs

gp for cnap data sub-SA2p1\_2\_SPARC\_10Hz\_LcVNS

Stimulation:  
pulse duration,  
current

Response:  
time series

GP model:  
Input:  
 $\text{curr} \times \text{dur} \times \text{time}$   
Output:  
voltage



# Finding optimal stimulation parameters

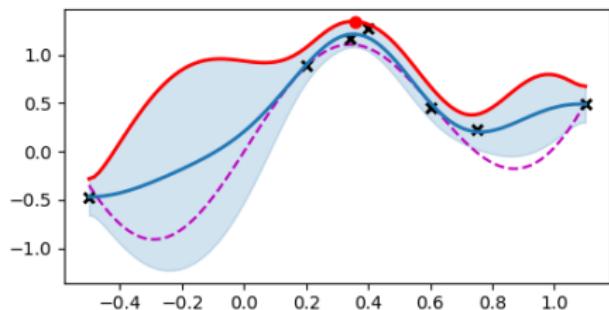
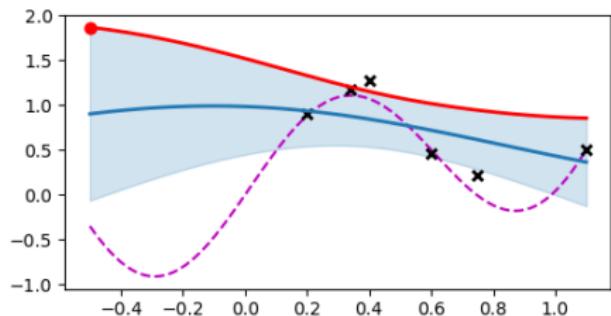
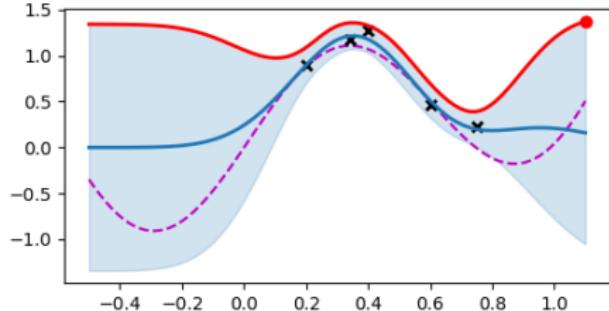
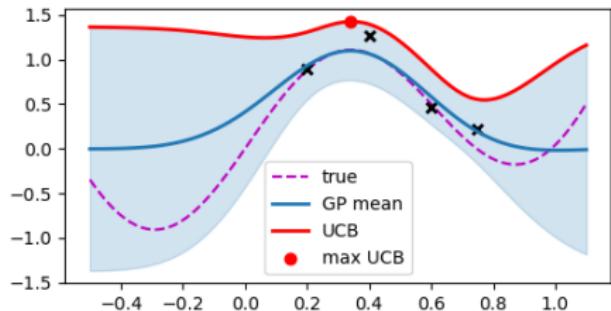
- ▶ Maximise overall nerve or physiological response
- ▶ Minimize distance of response to target setpoint
- ▶ Need to adjust stimulation parameters to changes
- ▶ Exploit previous trials or data

Bayesian optimization

# Bayesian optimization

- ▶ Optimize unknown function: evaluation at given test points
- ▶ Model current function by GP
- ▶ Use current GP mean and variance to find new test point:
  - ▶ to reduce uncertainty about true function
  - ▶ to optimize function
- ▶ Iterate until stopping criterion met  
(eg little change in optimum, enough reduction in uncertainty)

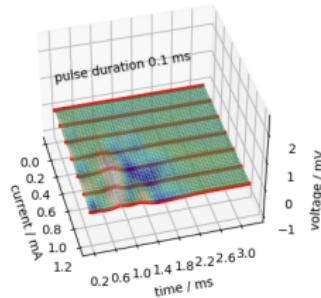
# Bayesian optimization



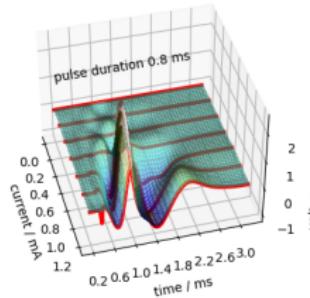
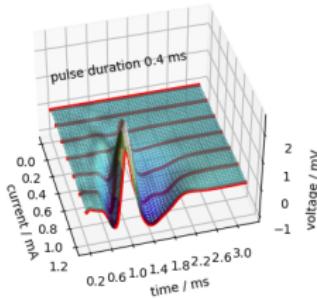
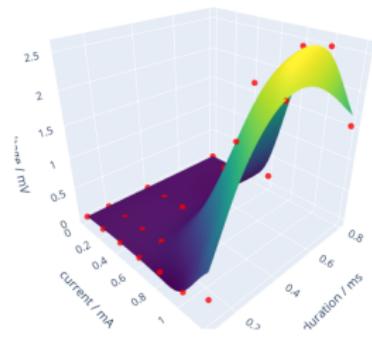
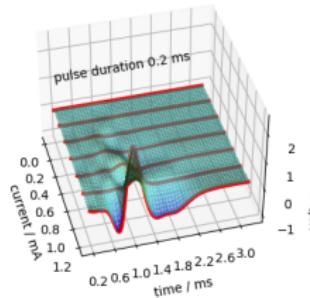
Upper Confidence Bound or Expected Improvement

# Bayesian optimization of max response

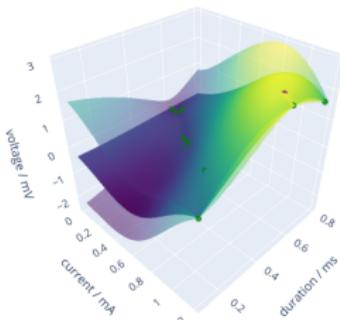
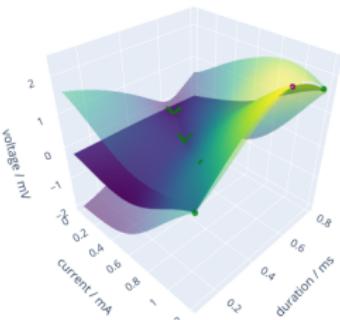
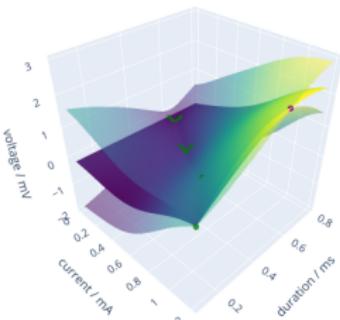
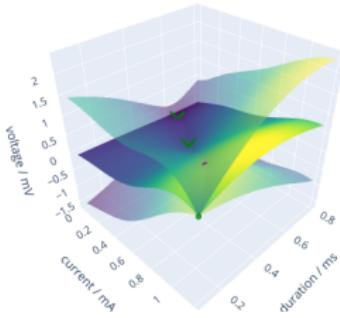
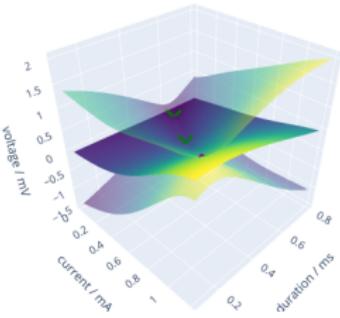
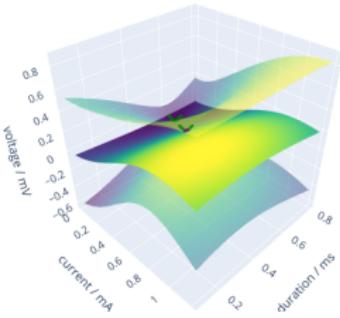
gp for cnap data sub-SA2p1\_2\_SPARC\_10Hz\_LcVNS



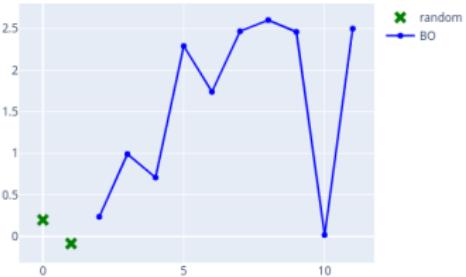
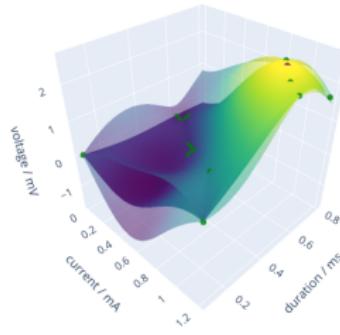
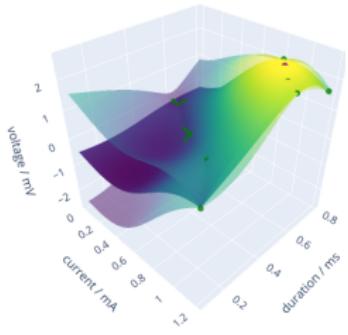
sub-SA2p1\_2\_SPARC\_10Hz\_LcVNS



Build GP simulator  
from max nerve  
response in trial



# BO of max nerve response



Typically acceptable maximum reached in less than a dozen of steps

# Joint GP for multiple trials?

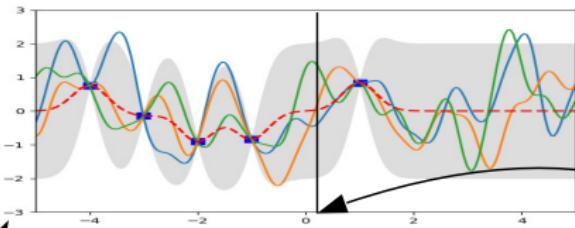
Update with consecutive data points from the same trial works fine

Increased stability and efficiency of BO from multiple trials as priors?

Use multitask GP

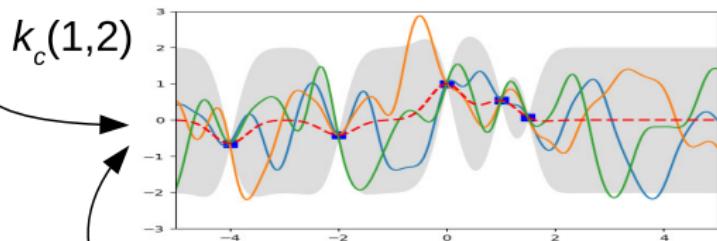
# Multitask GP

Task 1



$$k_c(1,3) \quad k_t(t_1, t_2)$$

Task 2

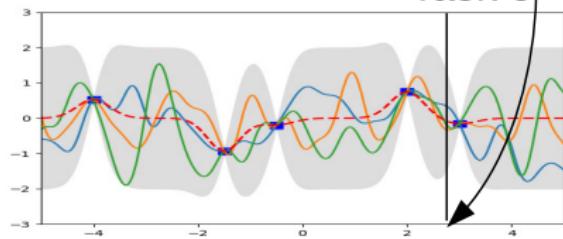


$$k_c(1,2)$$

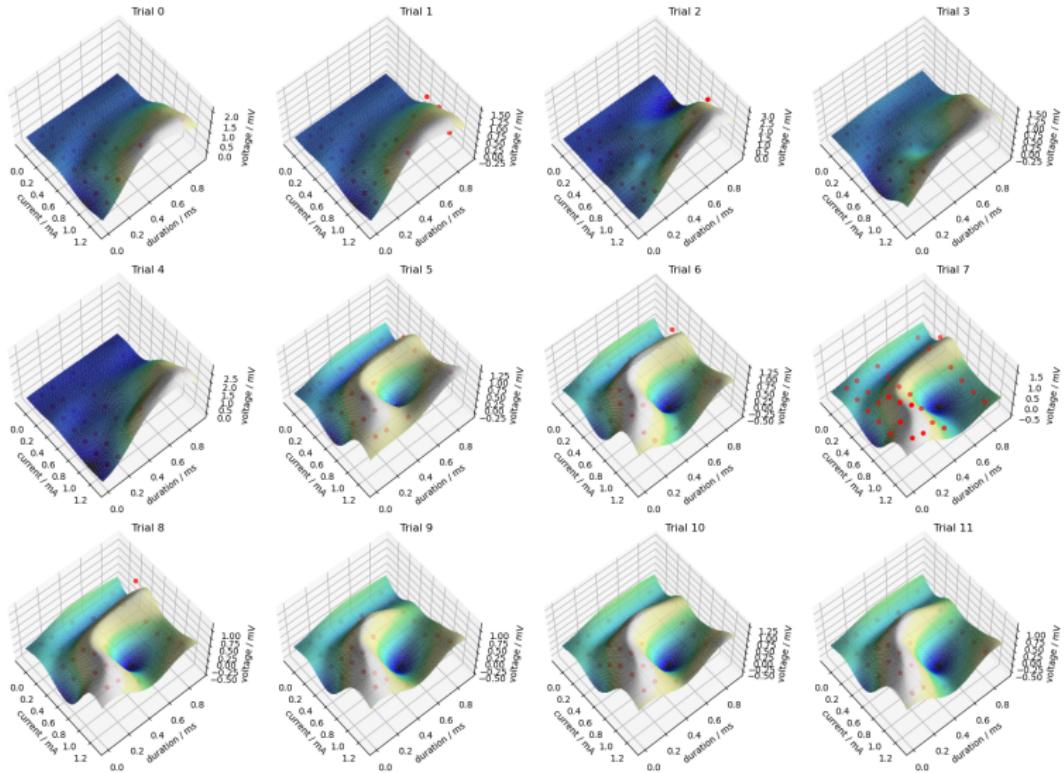
$$k_c(1,3)$$

$$k_c(2,3)$$

Task 3

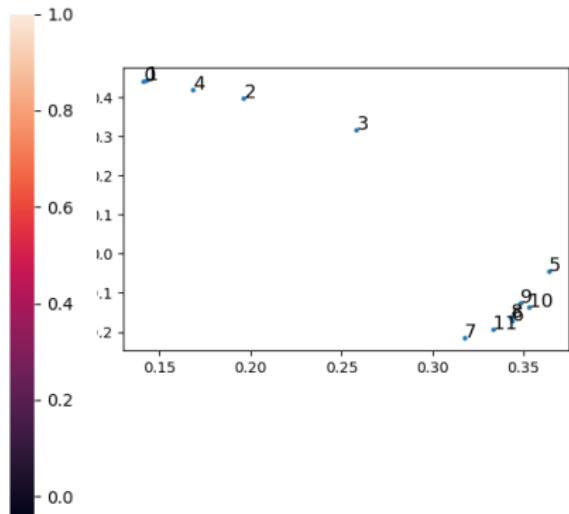


# Maximum nerve response trials



# Coregionalisation kernel of multitask GP

0	-1.00	1.00	0.89	0.84	0.90	0.30	0.03	-0.03	0.06	0.10	0.10	-0.03
1	-1.00	1.00	0.90	0.85	0.91	0.30	0.03	-0.03	0.07	0.11	0.11	-0.03
2	-0.89	0.90	1.00	0.87	0.97	0.42	0.21	0.03	0.17	0.33	0.29	0.19
3	-0.84	0.85	0.87	1.00	0.82	0.58	0.37	0.37	0.45	0.48	0.45	0.34
4	-0.90	0.91	0.97	0.82	1.00	0.38	0.15	-0.04	0.11	0.20	0.20	0.07
5	0.30	0.30	0.42	0.58	0.38	1.00	0.96	0.88	0.94	0.90	0.94	0.89
6	-0.03	0.03	0.21	0.37	0.15	0.96	1.00	0.92	0.96	0.94	0.97	0.96
7	-0.03	-0.03	0.03	0.37	-0.04	0.88	0.92	1.00	0.98	0.86	0.89	0.89
8	-0.06	0.07	0.17	0.45	0.11	0.94	0.96	0.98	1.00	0.90	0.94	0.92
9	-0.10	0.11	0.33	0.48	0.20	0.90	0.94	0.86	0.90	1.00	0.98	0.99
10	-0.10	0.11	0.29	0.45	0.20	0.94	0.97	0.89	0.94	0.98	1.00	0.98
11	-0.03	-0.03	0.19	0.34	0.07	0.89	0.96	0.89	0.92	0.99	0.98	1.00



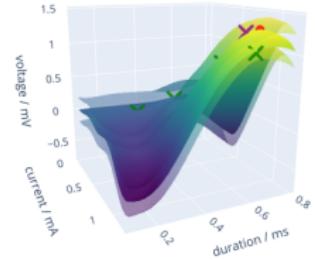
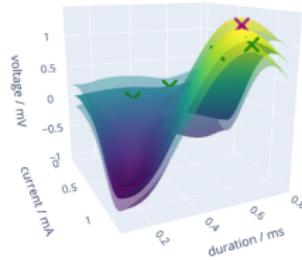
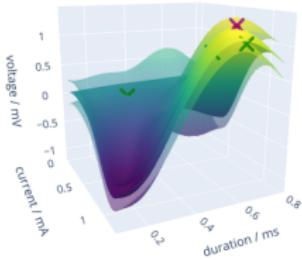
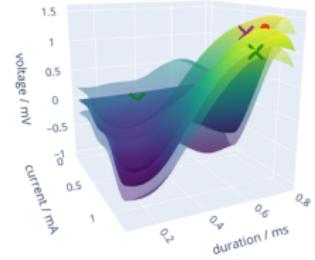
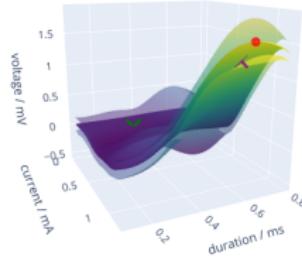
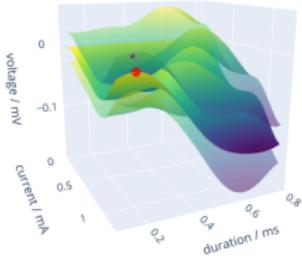
GP estimation of kernel by Cholesky parametrization

PC 1 and 2 of Eigendecomposition of kernel

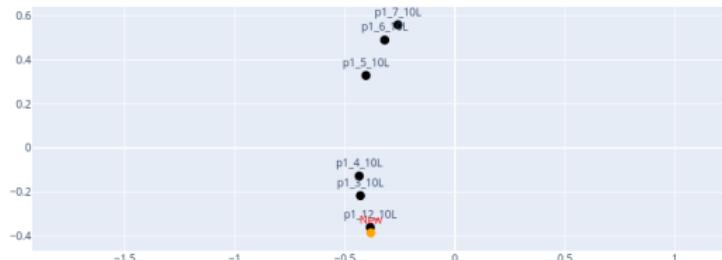
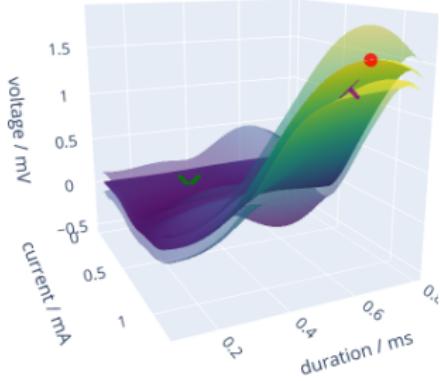
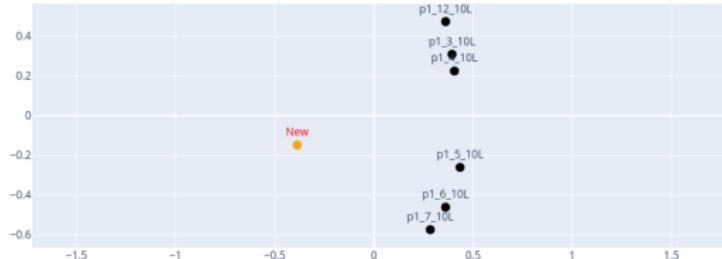
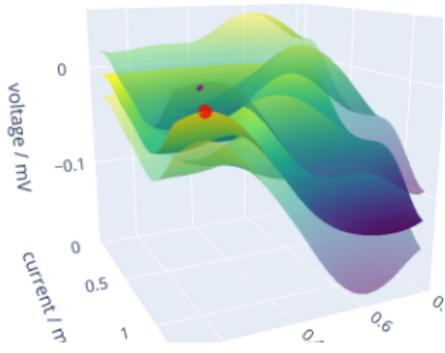
# Bayesian optimization with priors

- ▶ Select suitable prior trials
- ▶ Extend kernel to new trial
- ▶ No need even for initial query points, prior trials typically suggest good starting points

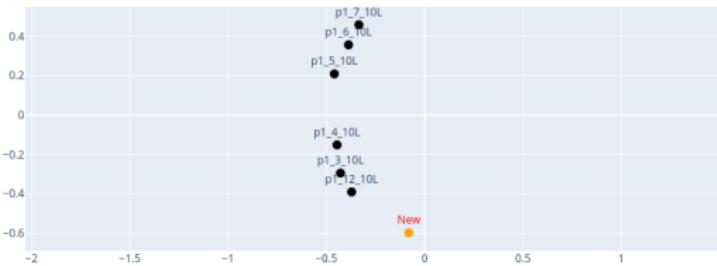
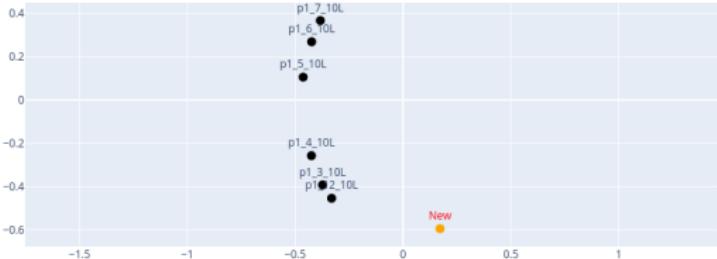
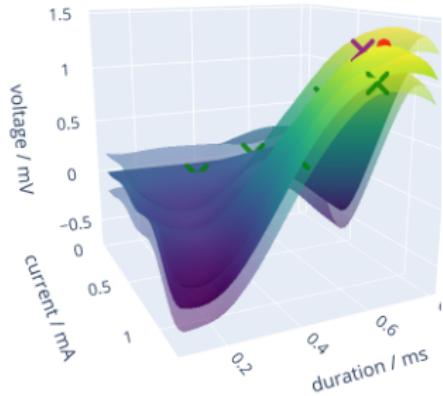
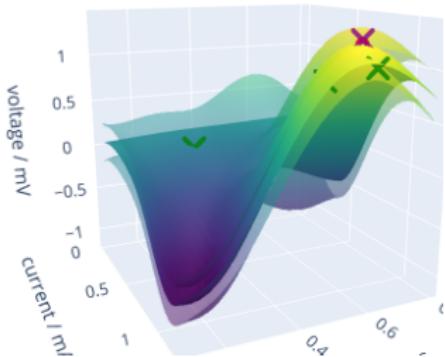
Demo: select 6 previous trials



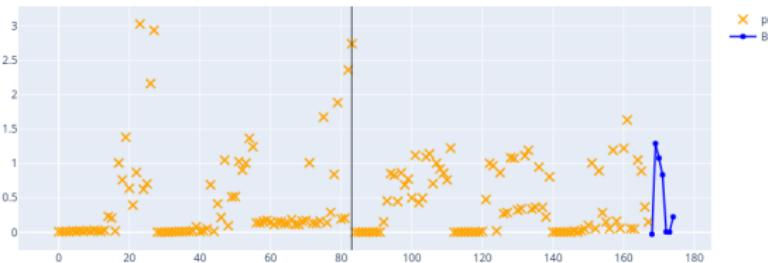
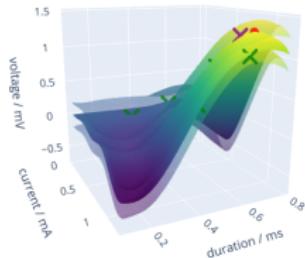
# BO with prior



# BO with prior



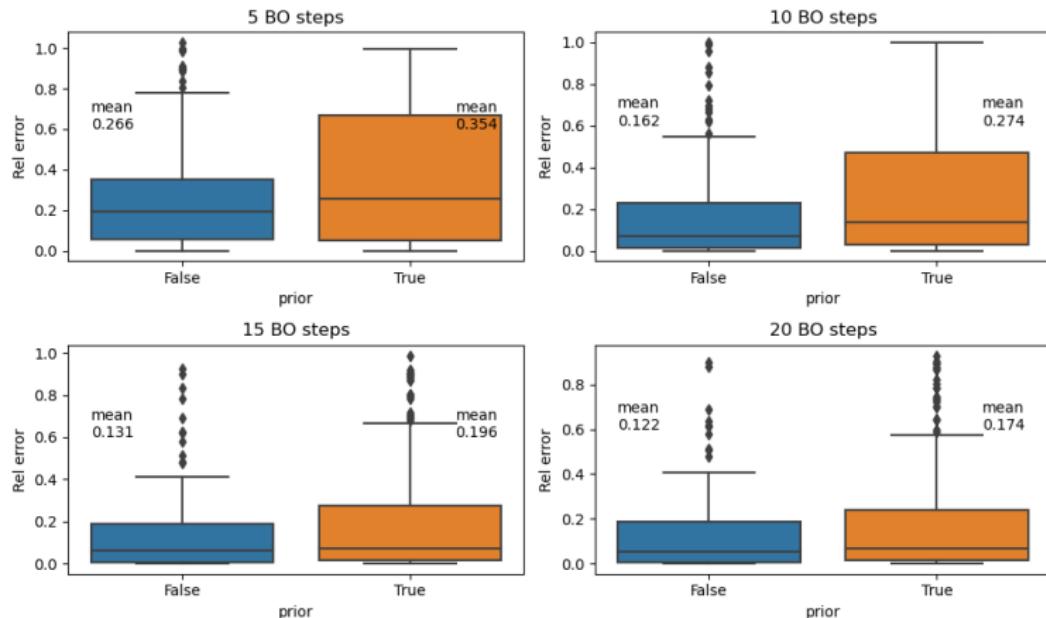
# BO of max nerve response



# Systematic test of BO with prior

- ▶ Obtain true maximum of simulator
- ▶ Simulator provides noisy data for BO and BO with prior
- ▶ Evaluate maximum input suggested by BOs on simulator
- ▶ Compare how close to true maximum
- ▶ Variables:
  - ▶ noise-signal ratio NSR
  - ▶ number of priors
  - ▶ number of queries

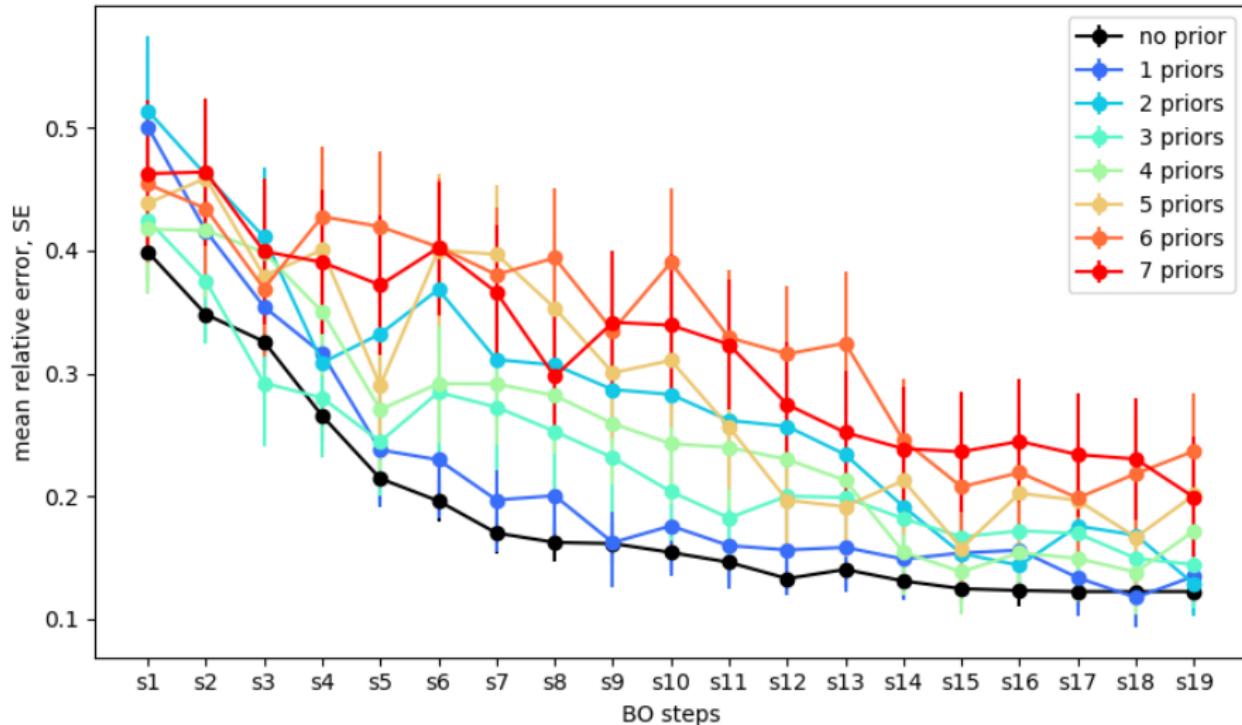
# Relative error with unweighted BO priors



Compared to BO without prior BO with prior performs worse particularly for small numbers of BO queries

# Relative error with unweighted BO priors

Mean relative error of BO estimate, prior weight 1.0



# Weighted likelihood

$$f \sim N(0, K_{xx}), (y - f) | f \sim N(0, \sigma^2 I)$$

Points weighted by  $W = \text{diag}(w_1, \dots, w_n)$   
results in likelihood term  $(y - f)^T W(y - f) / \sigma^2$

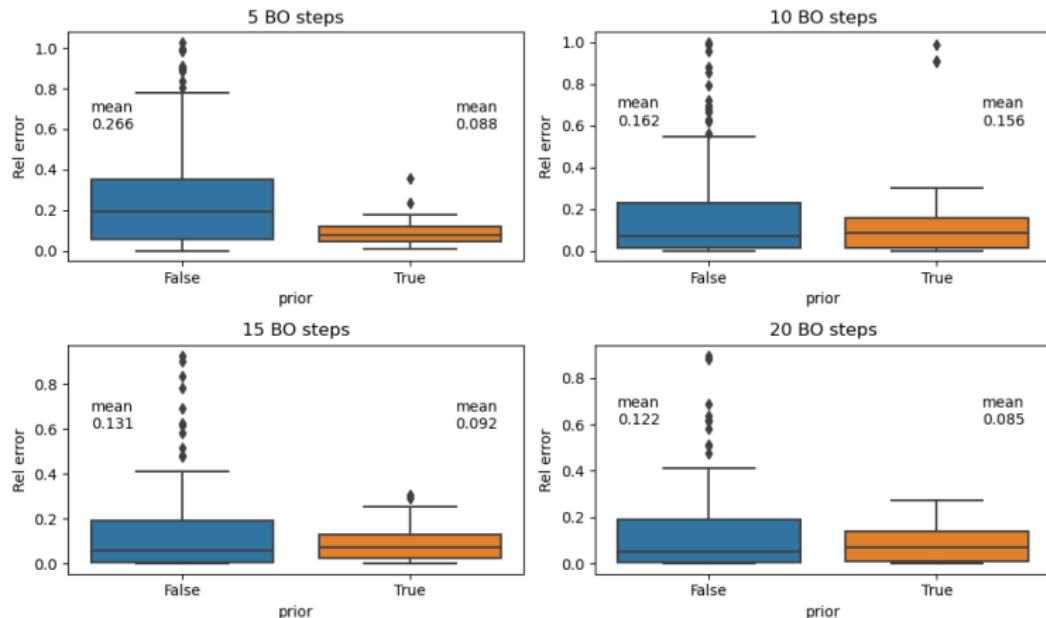
$$\text{cov}(y) = K_{xx} + \sigma^2 I \text{ to } \text{cov}(y) = K_{xx} + \sigma^2 W^{-1}$$

Equivalently, rescale kernels and data:

$$f^* = K_{x^*x}(K_{xx} + \sigma^2 W^{-1})^{-1}y = \tilde{K}_{x^*x}(\tilde{K}_{xx} + \sigma^2 I)^{-1}\tilde{y}$$

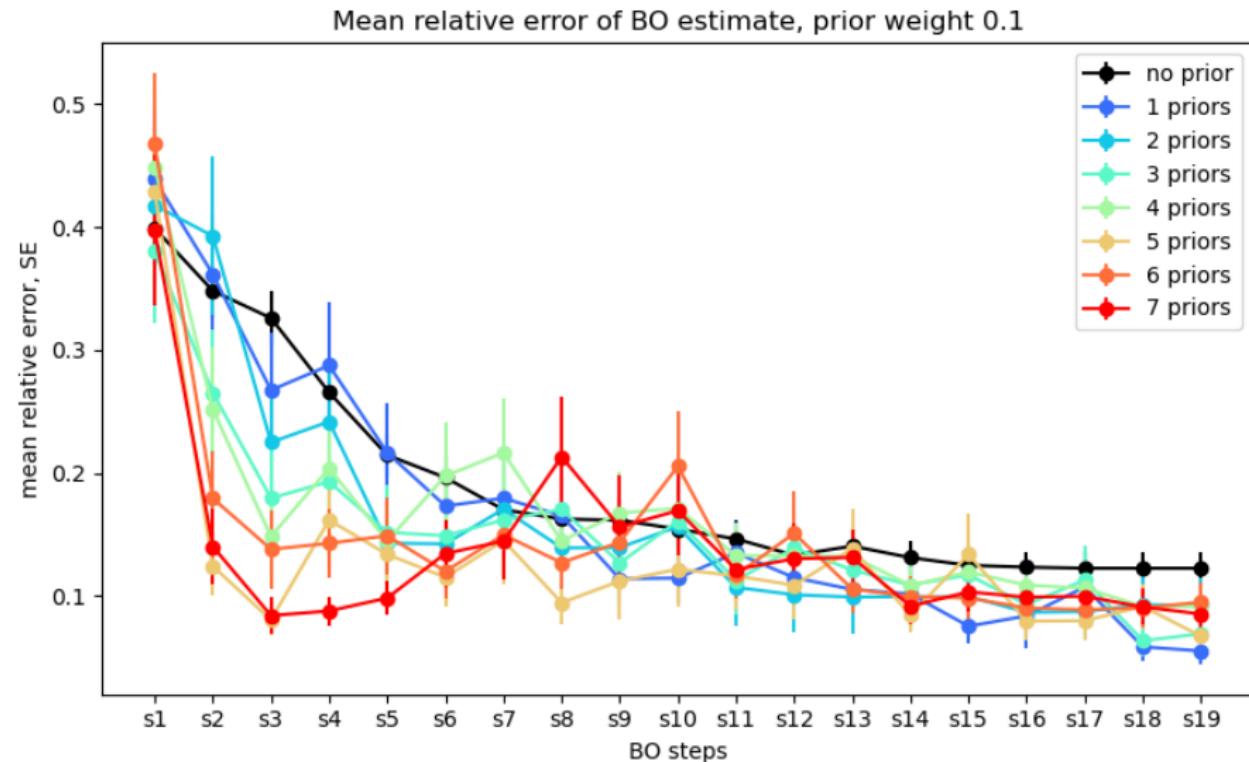
$$\tilde{K}_{x^*x} = K_{x^*x}W^{1/2}, \tilde{K}_{xx} = W^{1/2}K_{xx}W^{1/2}, \tilde{y} = W^{1/2}y$$

# Relative error with weighted BO priors

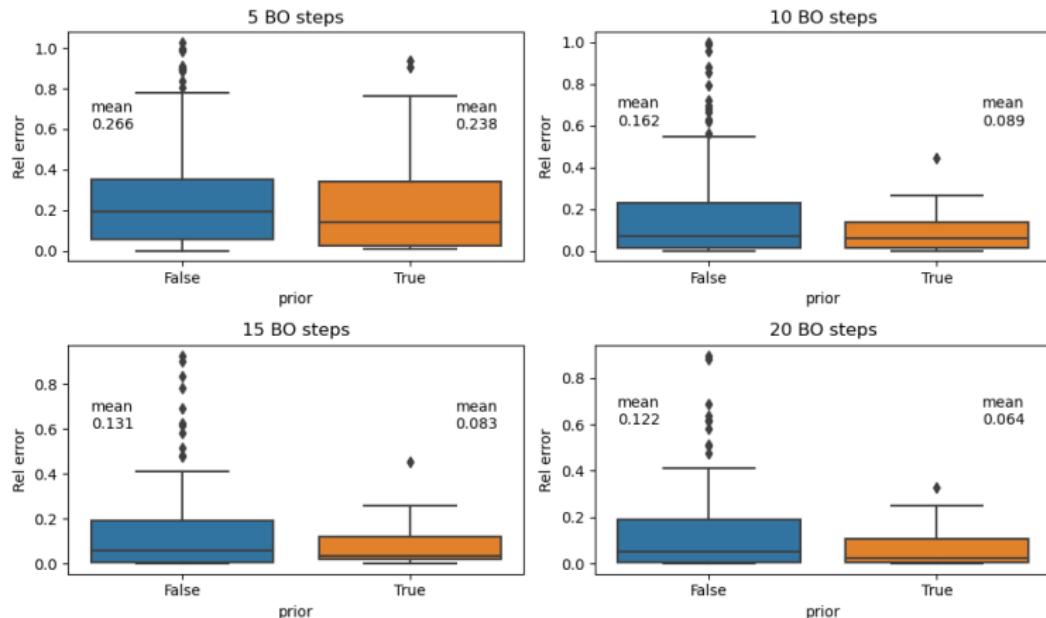


Excellent performance of BO with weighted priors (0.1) and many prior trials (7) for few steps

# Relative error with weighted BO priors

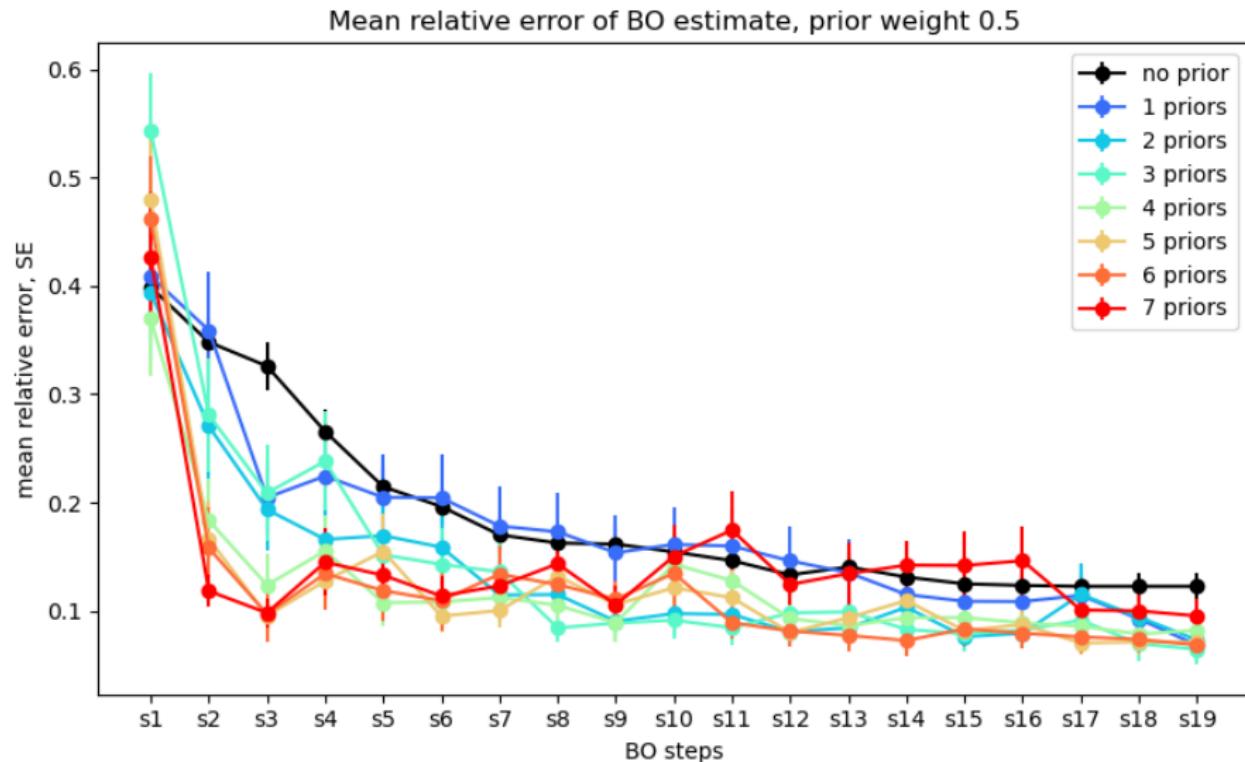


# Relative error with weighted BO priors



Excellent performance of BO with weighted priors (0.5) and fewer prior trials (3) for more steps

# Relative error with weighted BO priors



# Final thoughts

- ▶ Bioelectronic treatments are highly dynamic and time critical compared to traditional therapies
- ▶ Full stack solutions required: surgery, electronics, data management, algorithms tightly interlinked
- ▶ Bayesian approaches provide stability and robustness through controlled regularisation
- ▶ Theoretical considerations of statistical and ML methods directly inspired by practical experience

# We are recruiting

If you are interested in working in this kind of environment, get in touch:

<https://www.bios.health/careers>

[careers@bios.health](mailto:cCareers@bios.health)