ICLR 2026

Multifidelity simulation-based inference for computationally expensive simulators

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KU LEUVEN

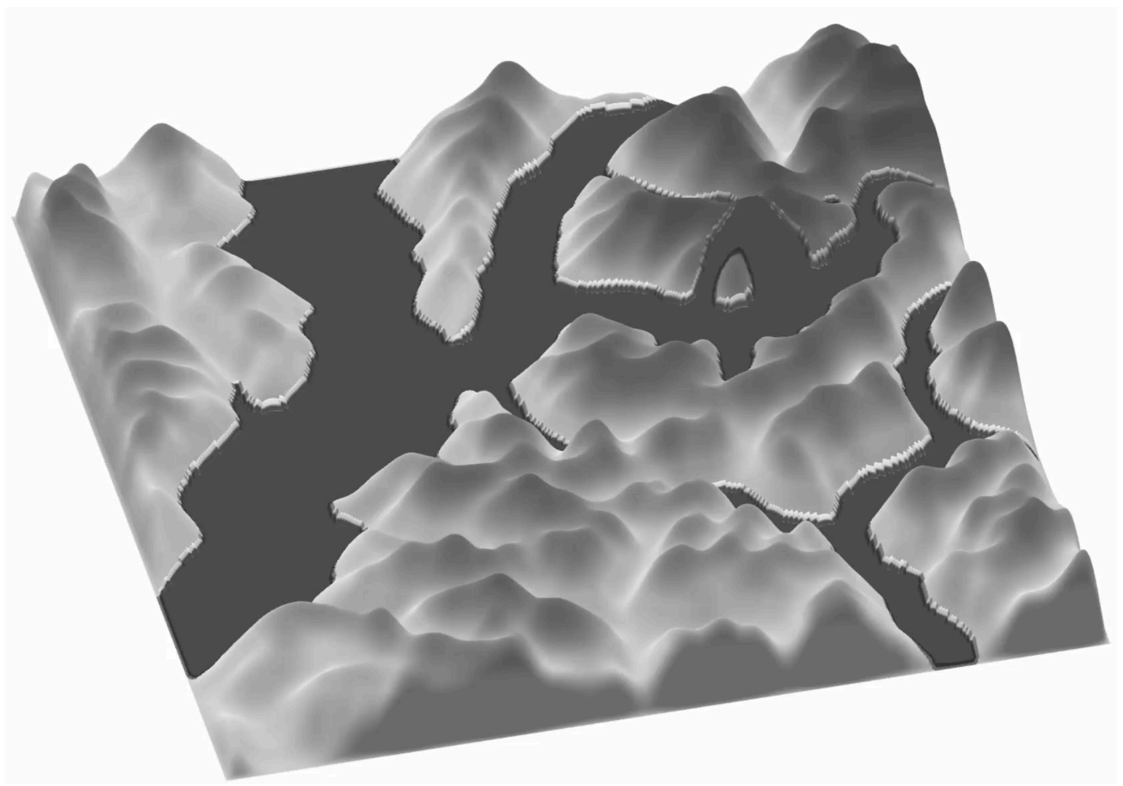
VIB

Problem setting

Stochastic models

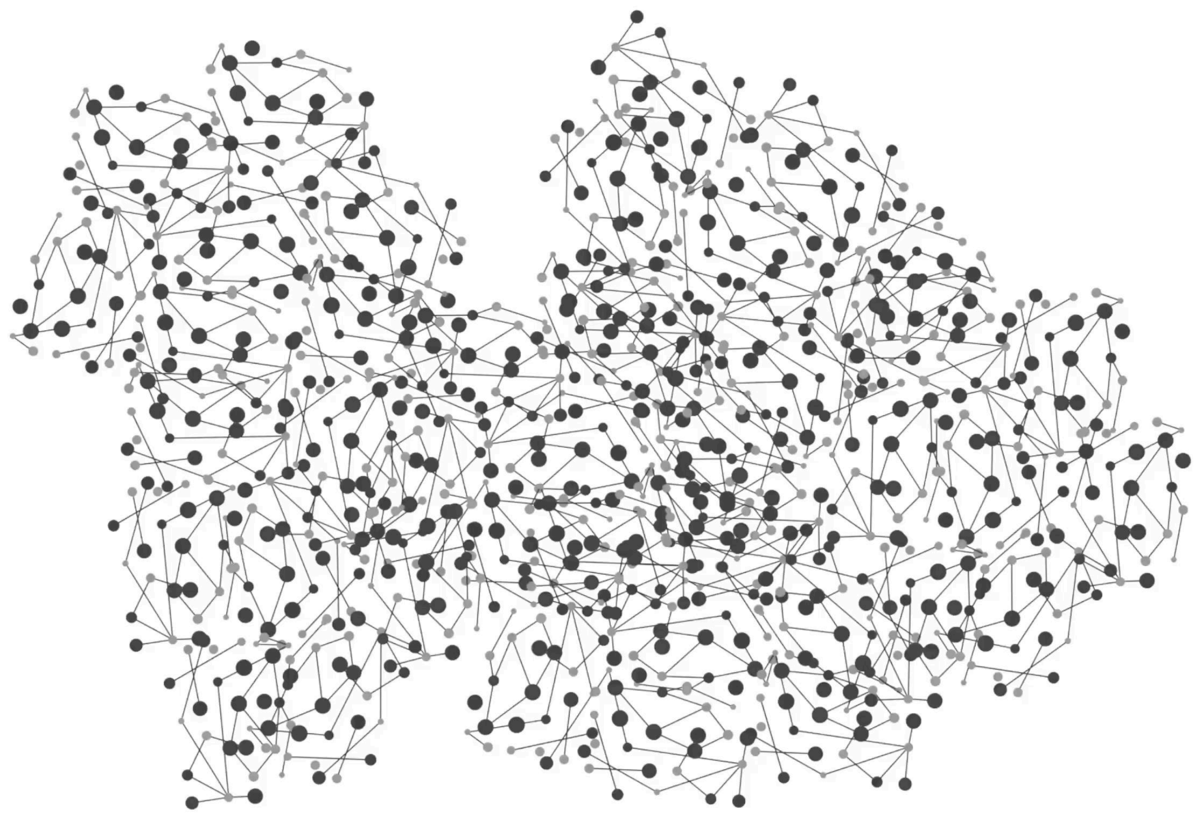
Climate Science

water flow over a landscape



Neuroscience

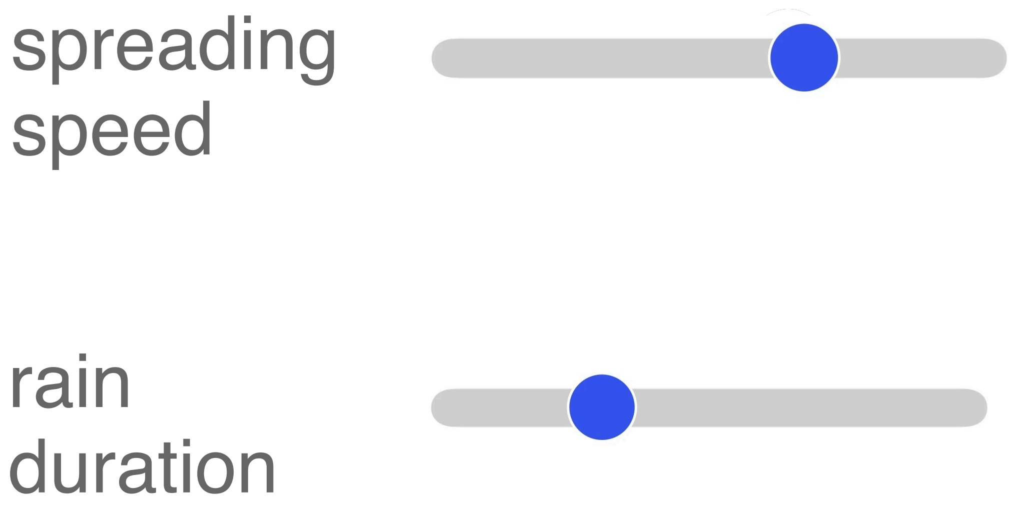
learning plasticity rules

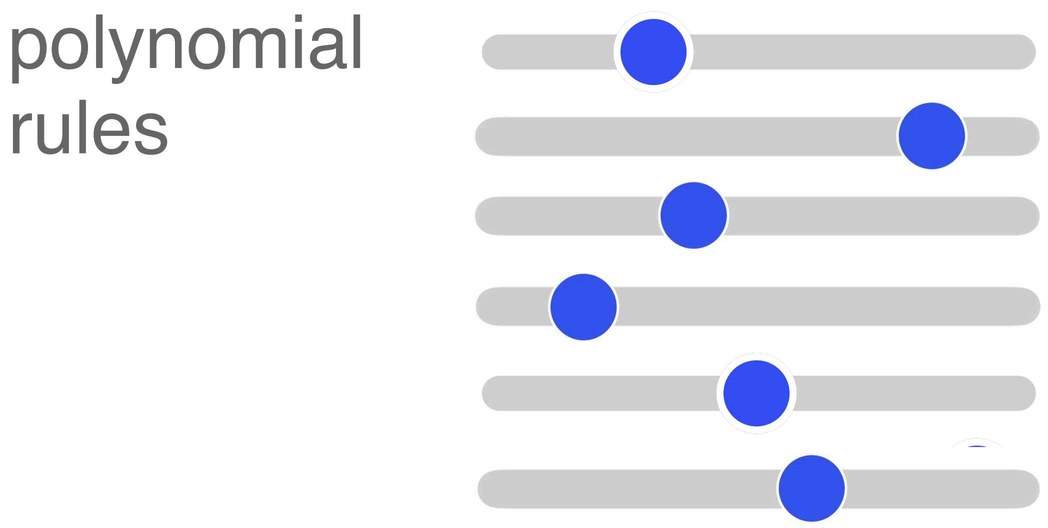


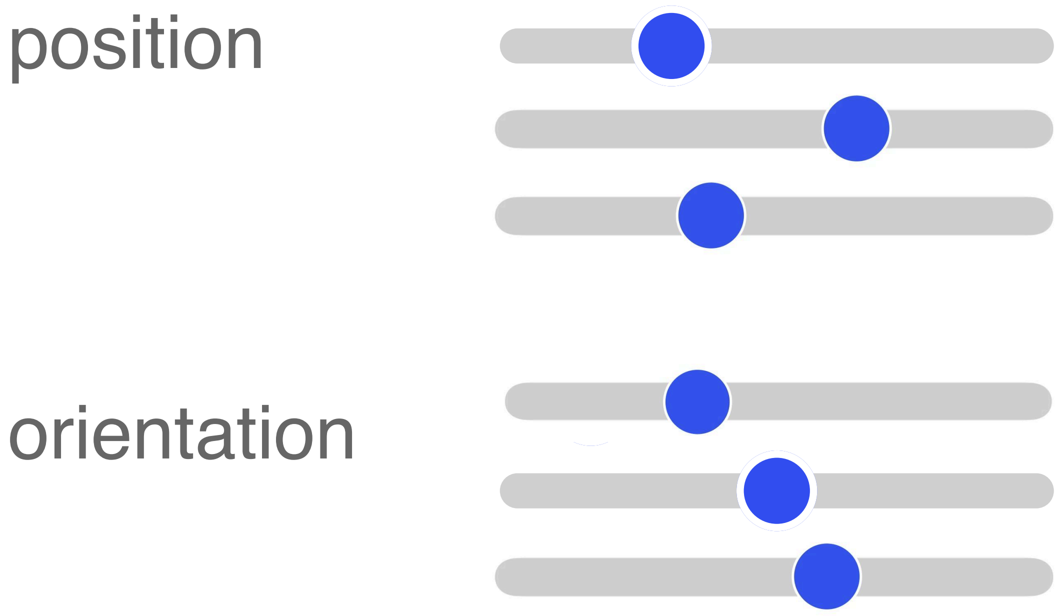
Robotics

multi-fingered robotic grasping

Marlier et al.,2024





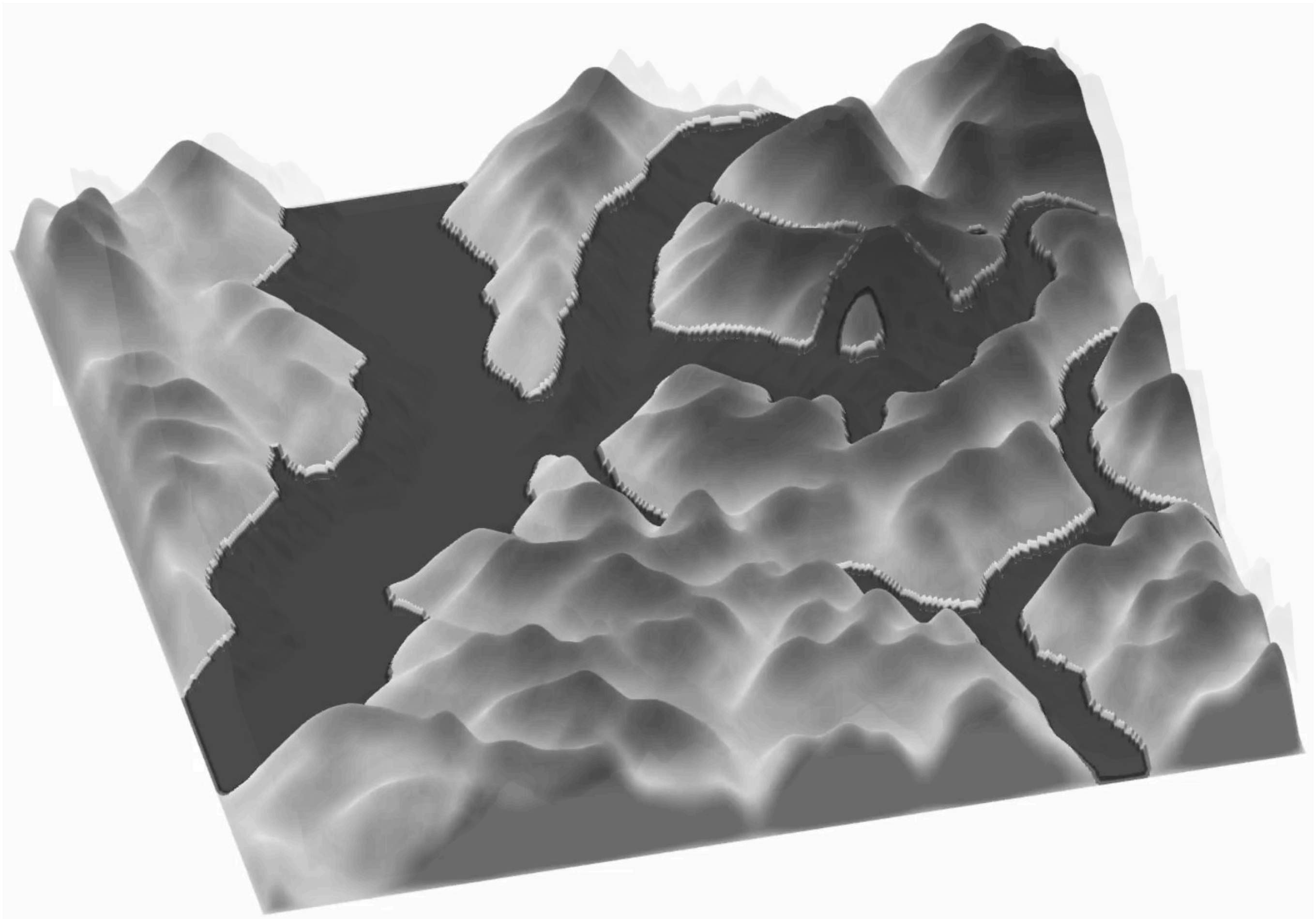


Problem setting

Stochastic models

2 types of problems

- **Forward simulation**
- Inference over parameters



Parameters

Spreading speed

Rain duration

Problem setting

Stochastic models

2 types of problems

- Forward simulation
- **Inference over parameters**

Parameters

Spreading speed

Rain duration

Problem setting

Stochastic models

2 types of problems

- Forward simulation
- **Inference over parameters**
    - Empirical observations are variable

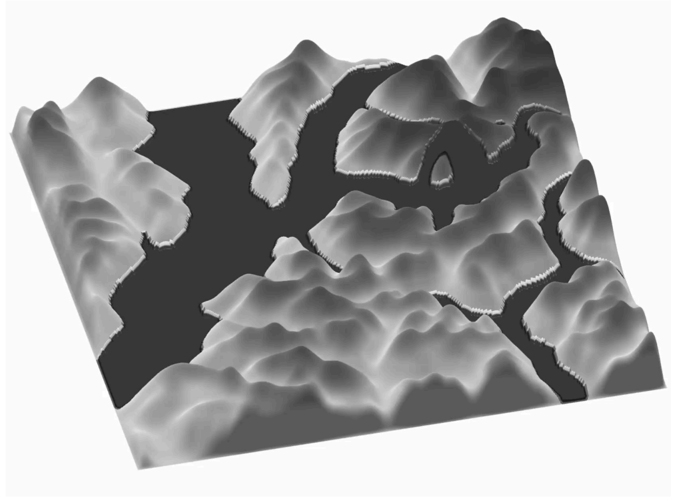
Parameters

Background

Simulation-based inference (SBI), a framework for parameter inference

Prior over parameters

$x|\theta$



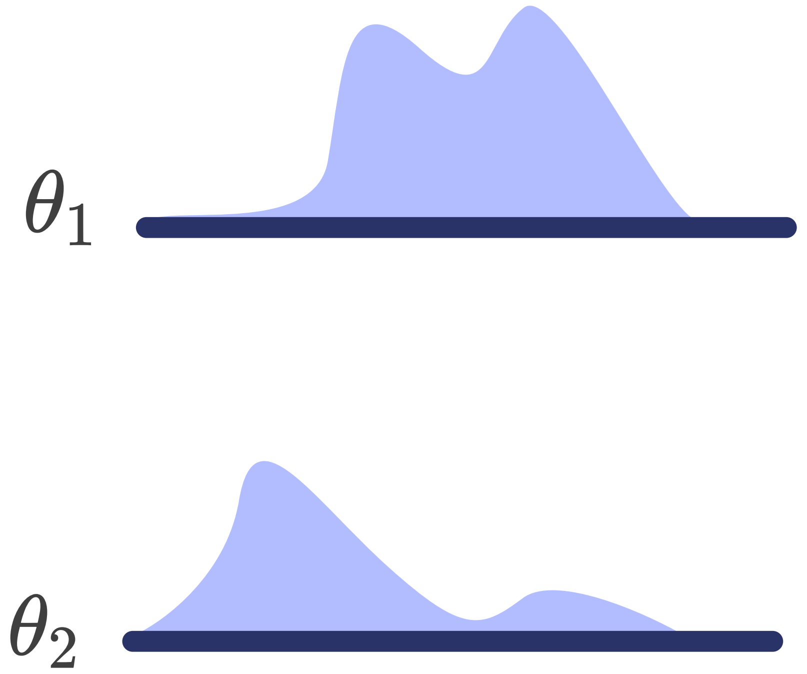
High-fidelity simulations

Empirical observation x_o

sbi

Boelts, 2025, JOSS
Cranmer, 2019, PNAS

$p(\theta|x_o)$



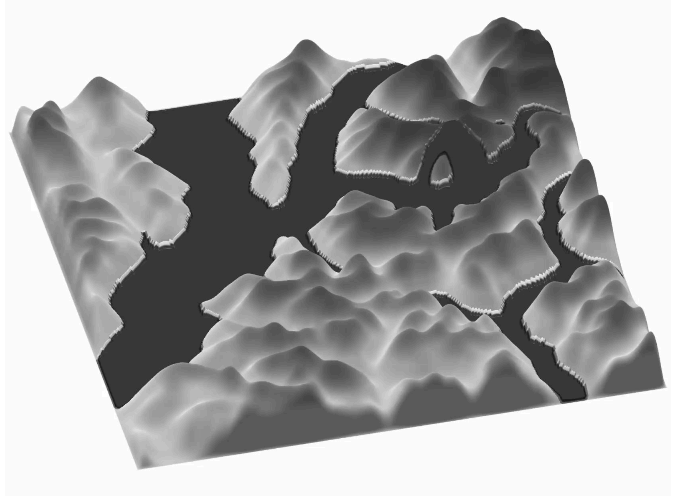
Posterior over parameters given x_o

Related work

Simulation-based inference (SBI), a framework for parameter inference

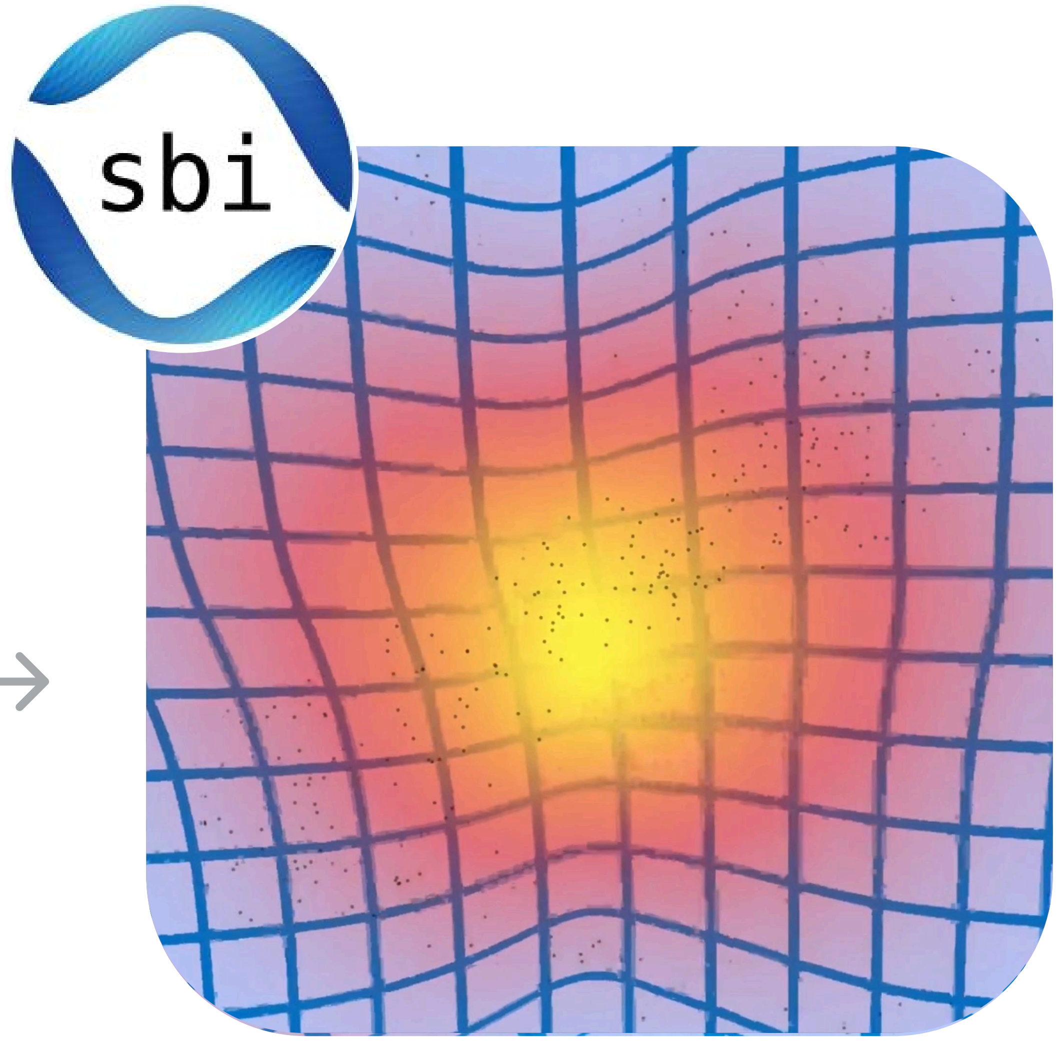
Prior over parameters

$x|\theta$



High-fidelity simulations

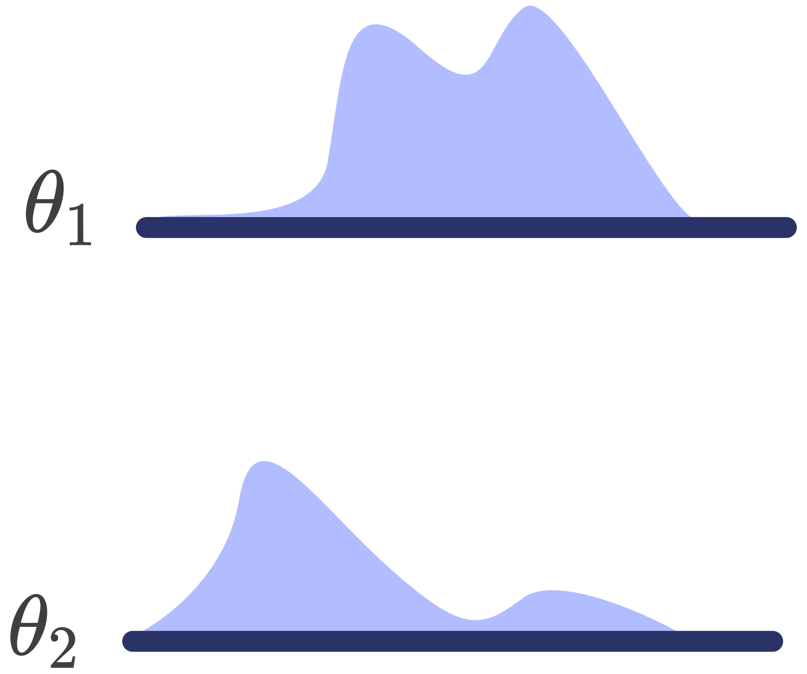
Empirical observation x_o



Neural Posterior Estimation (NPE)

Papamakarios, 2019, PMLR

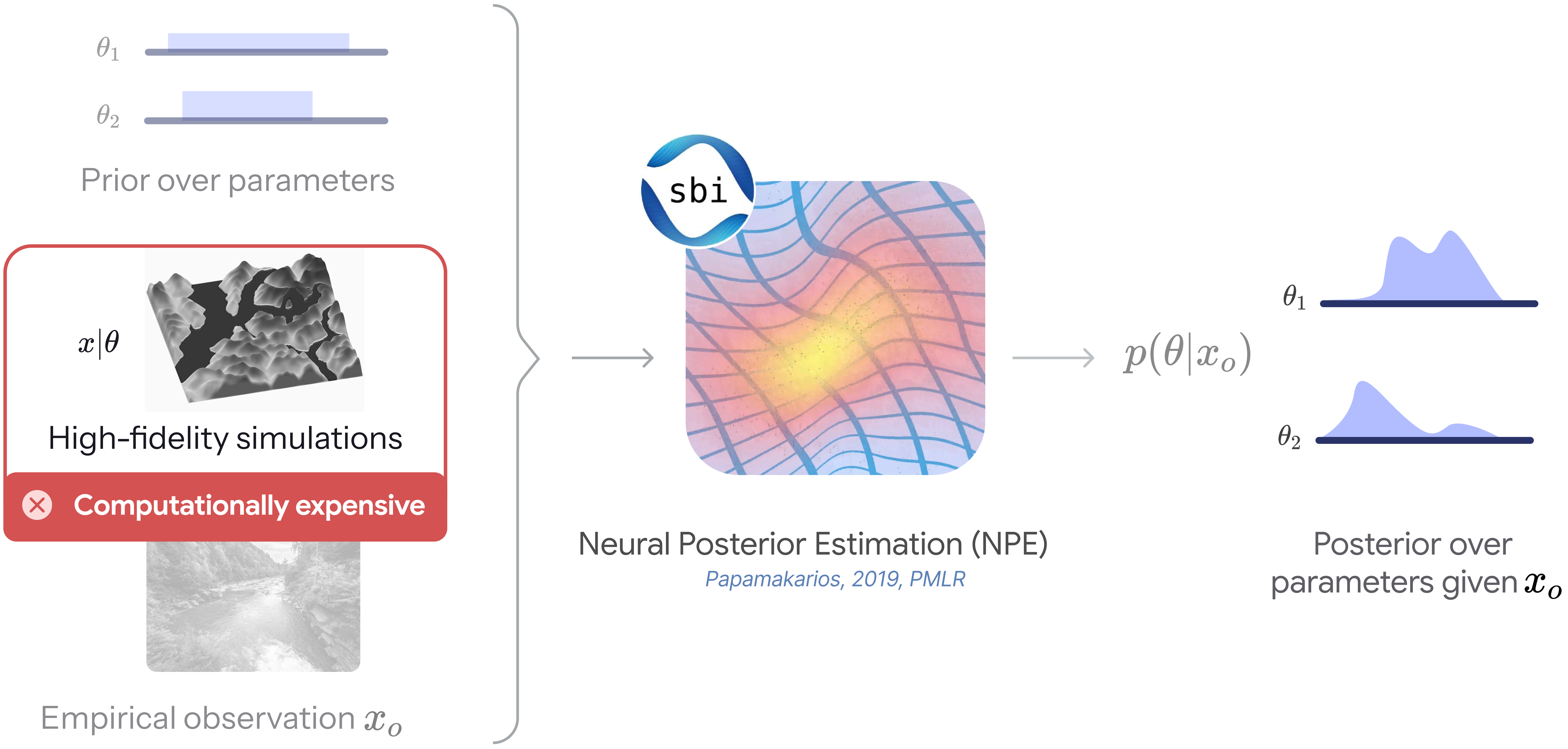
$p(\theta|x_o)$



Posterior over parameters given x_o

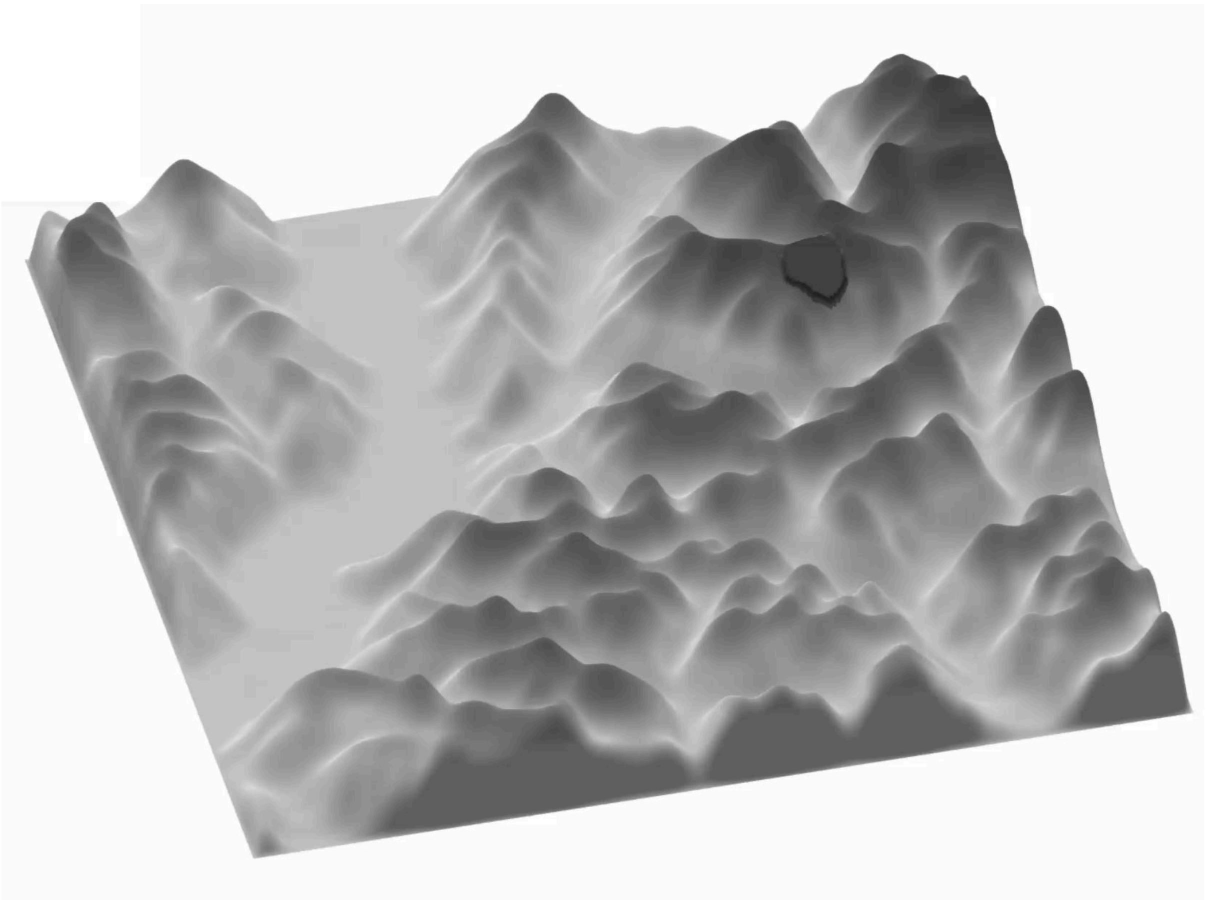
Related work

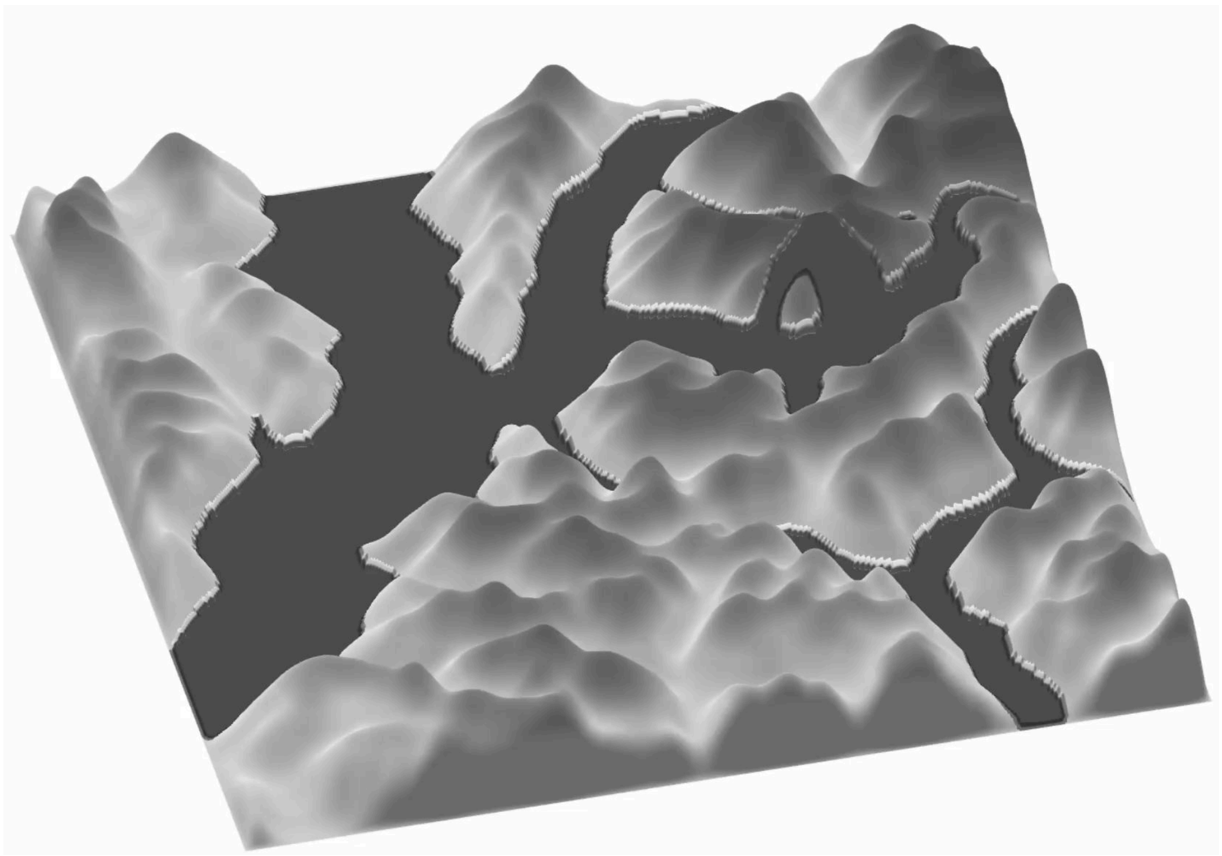
Simulation-based inference (SBI), a framework for parameter inference



Low-fidelity simulator

High-fidelity simulator





✅ **cheap**

❌ inaccurate

❌ expensive

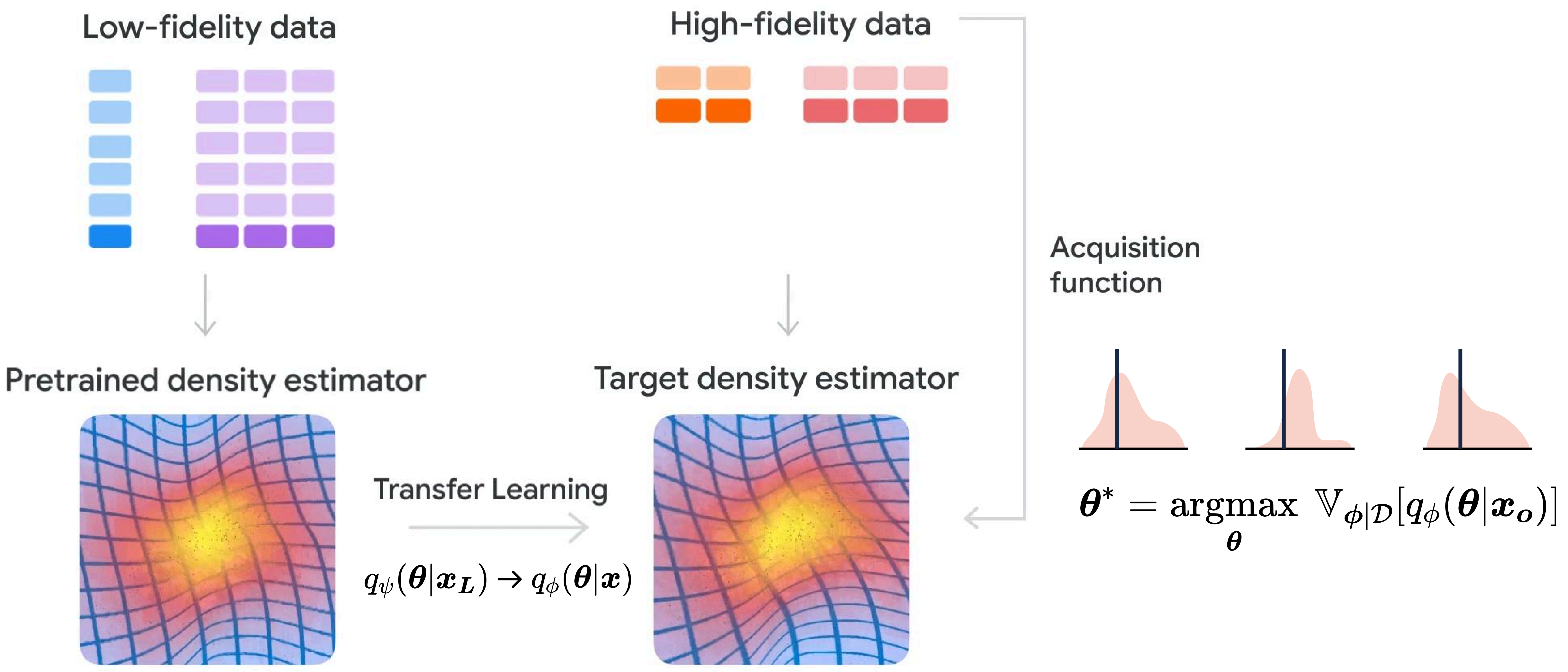
✅ **accurate**

Method

Multifidelity NPE

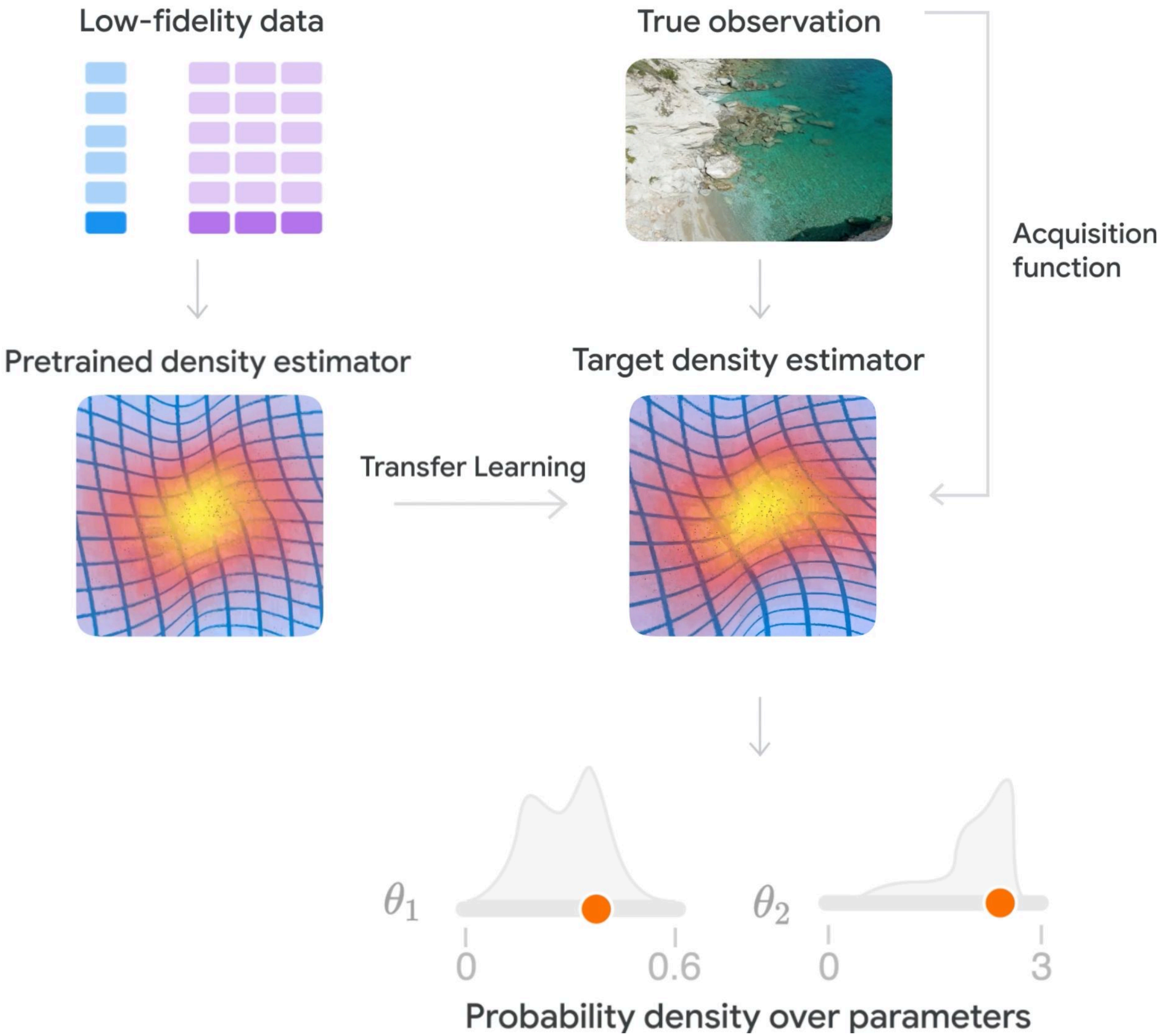
Method

Multifidelity NPE



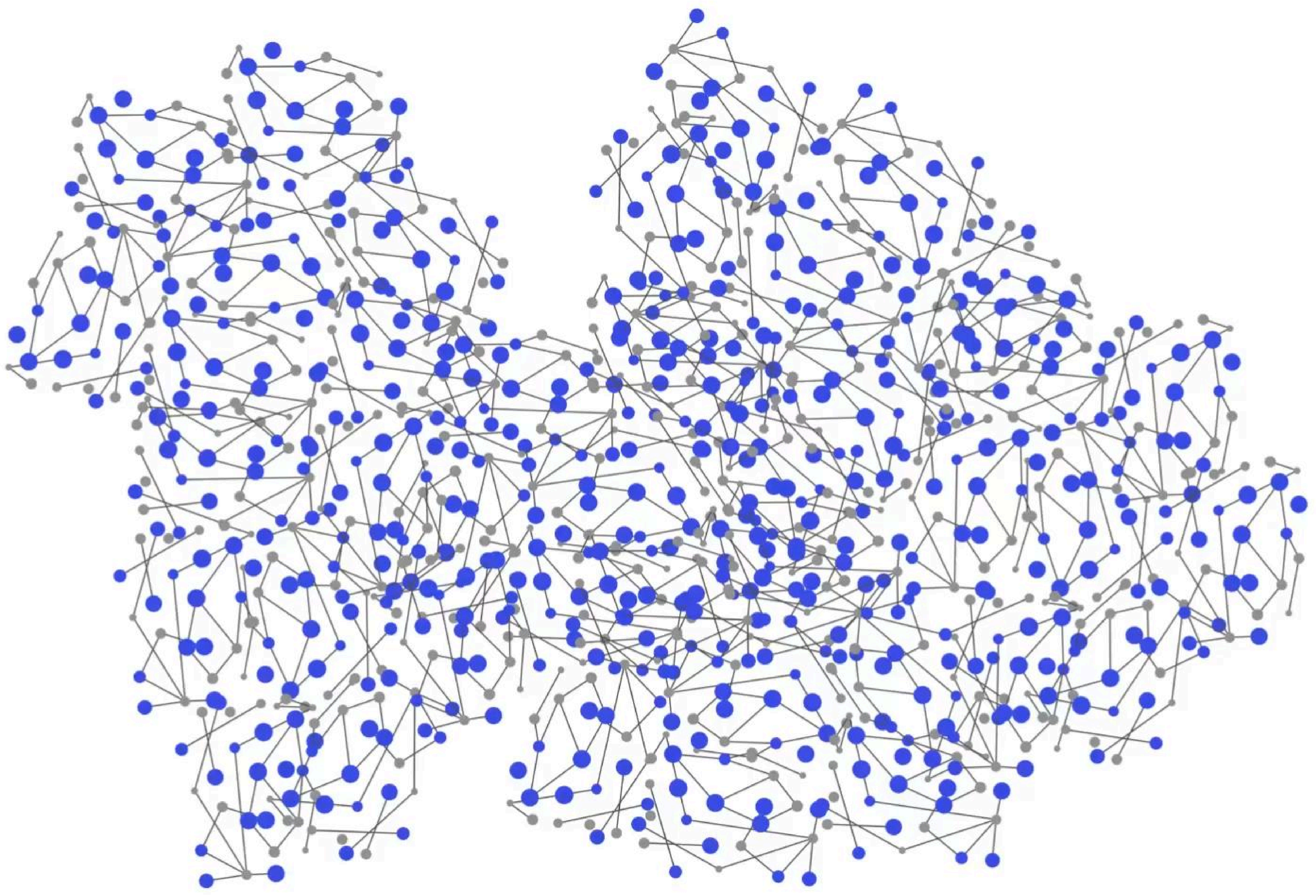
Method

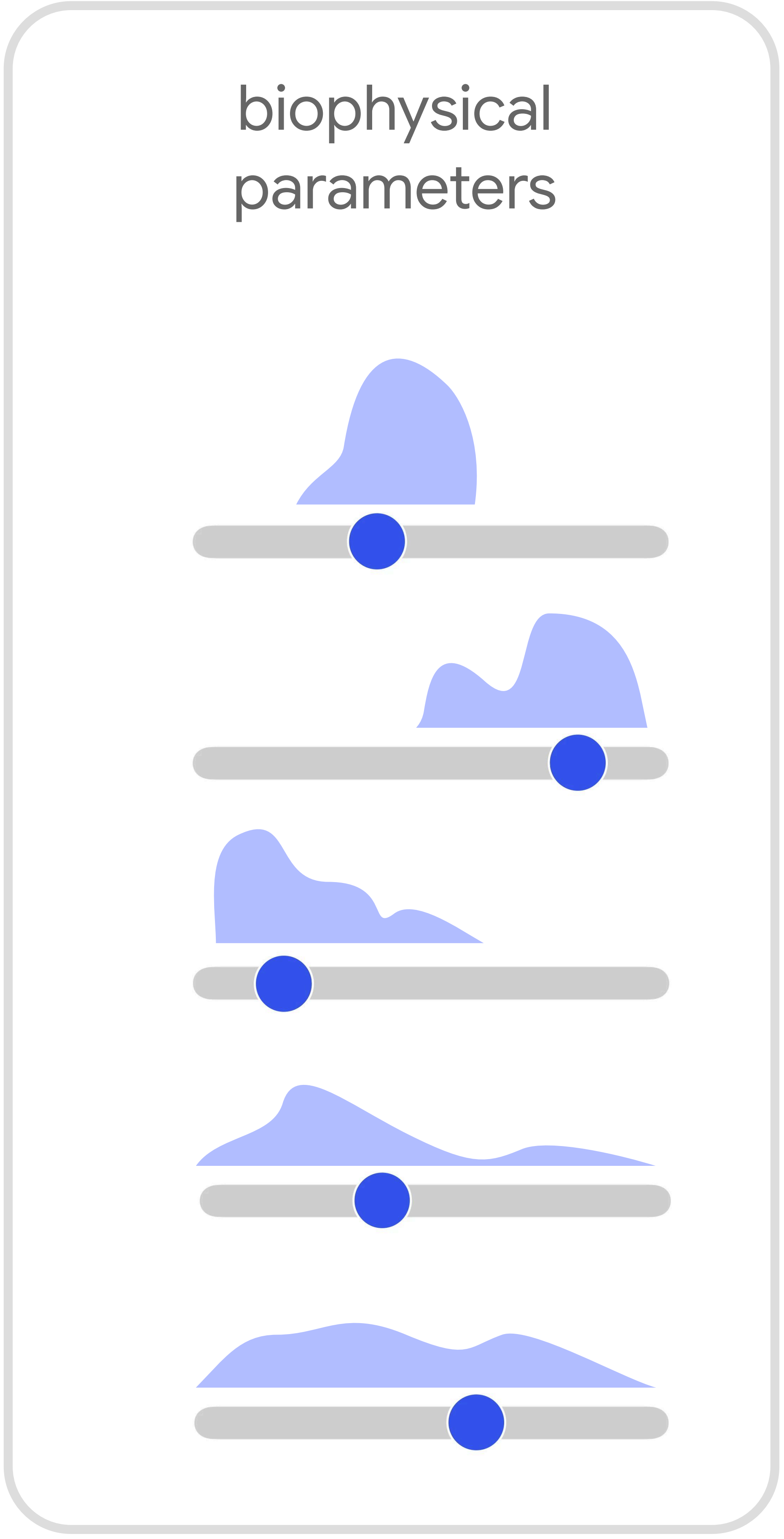
Multifidelity NPE



Results

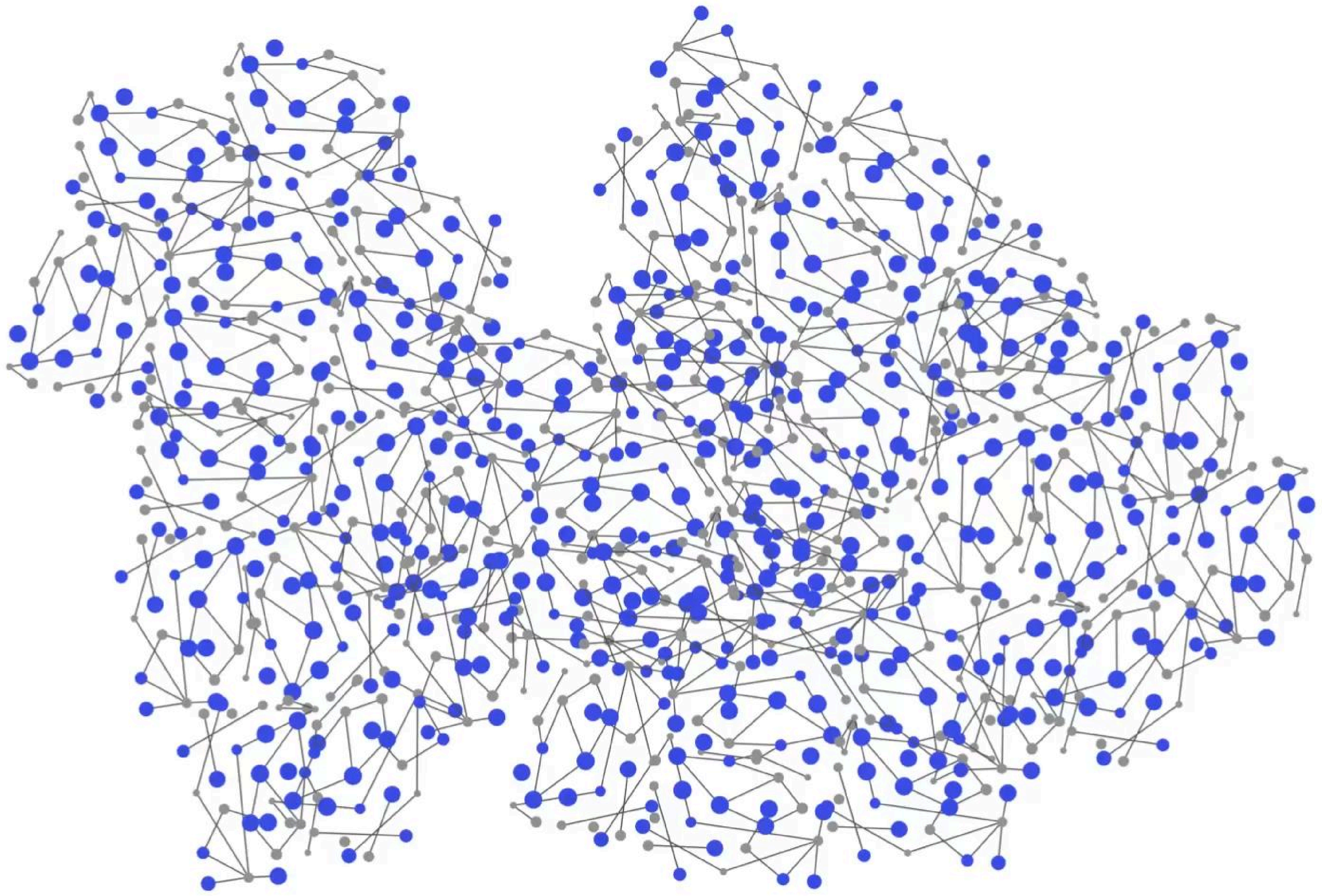
Inferring plasticity rules from a biological neural network





High-fidelity model

Recurrent spiking network model



$$\tau_m \frac{\mathrm{d}V_j}{\mathrm{d}t} = -(V_j - V_{\mathrm{rest}}) - g_j^{\mathrm{E}}(t)(V_j - E_{\mathrm{E}}) - g_j^{\mathrm{I}}(t)(V_j - E_{\mathrm{I}})$$

Cost per simulation (CPU)

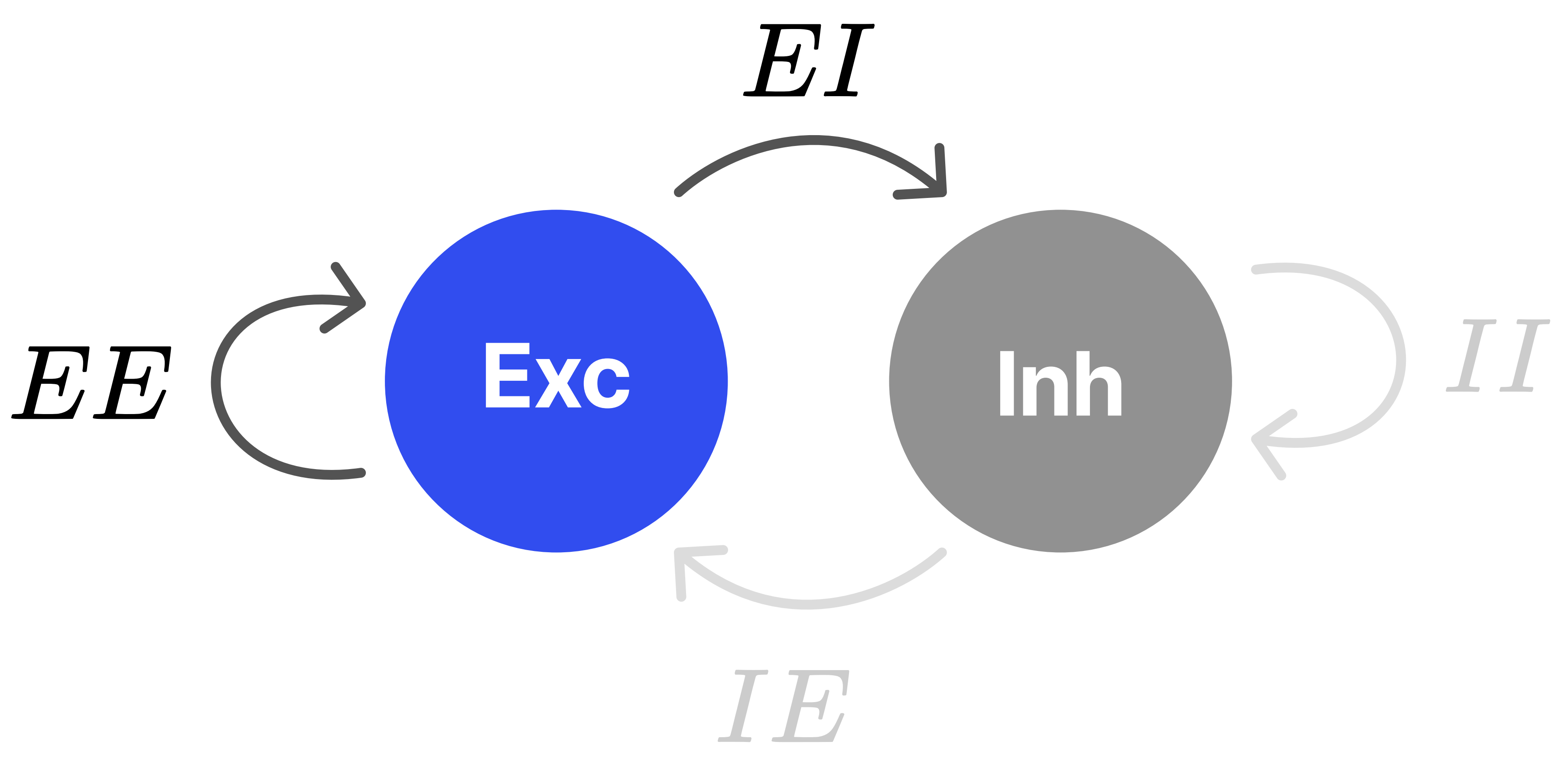
5 minutes

Number of parameters

24

Low-fidelity model

Mean-field model



Cost per simulation (CPU)

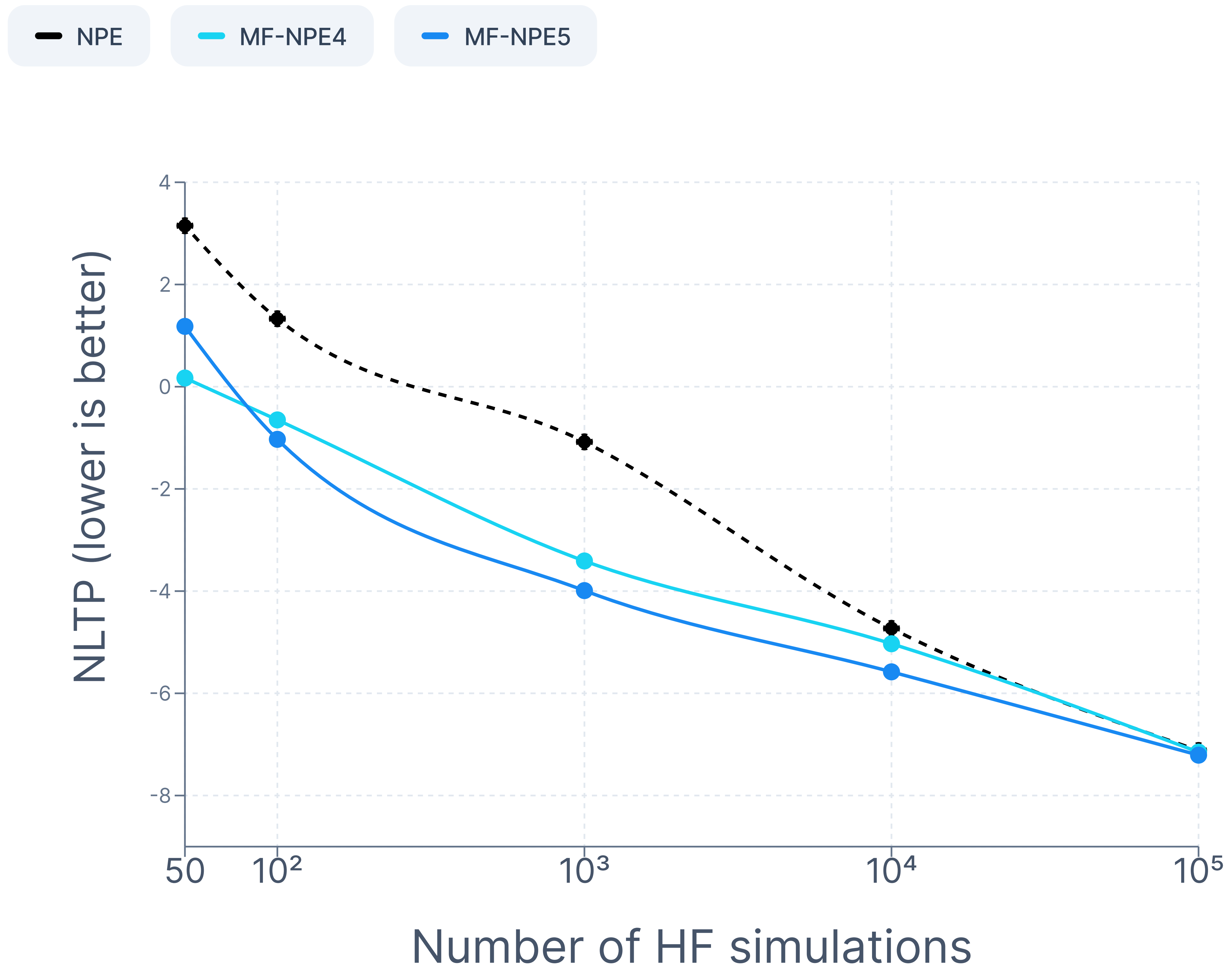
instantaneous

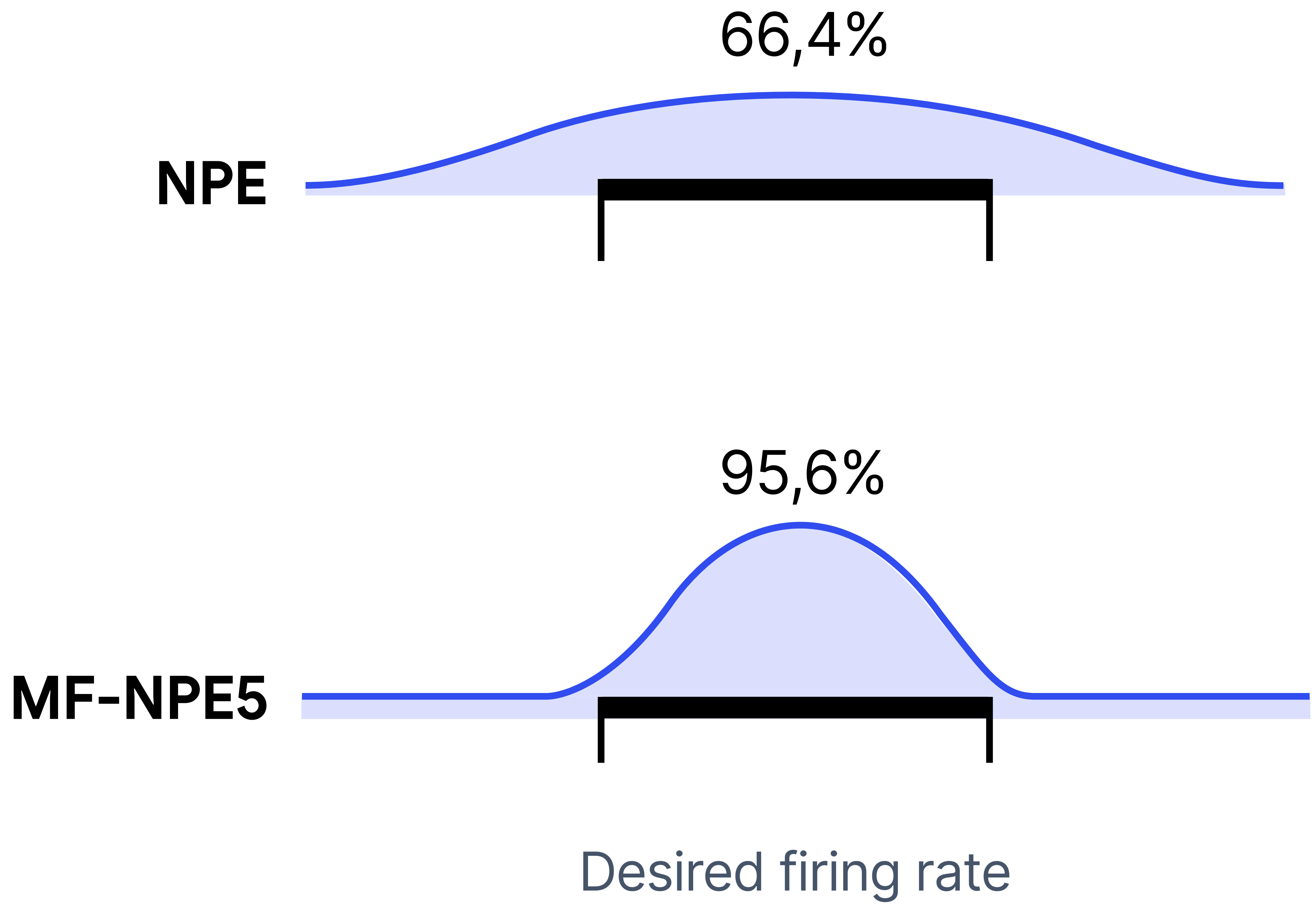
Number of parameters

12

Method comparison between NPE and Multifidelity NPE (MF-NPE)

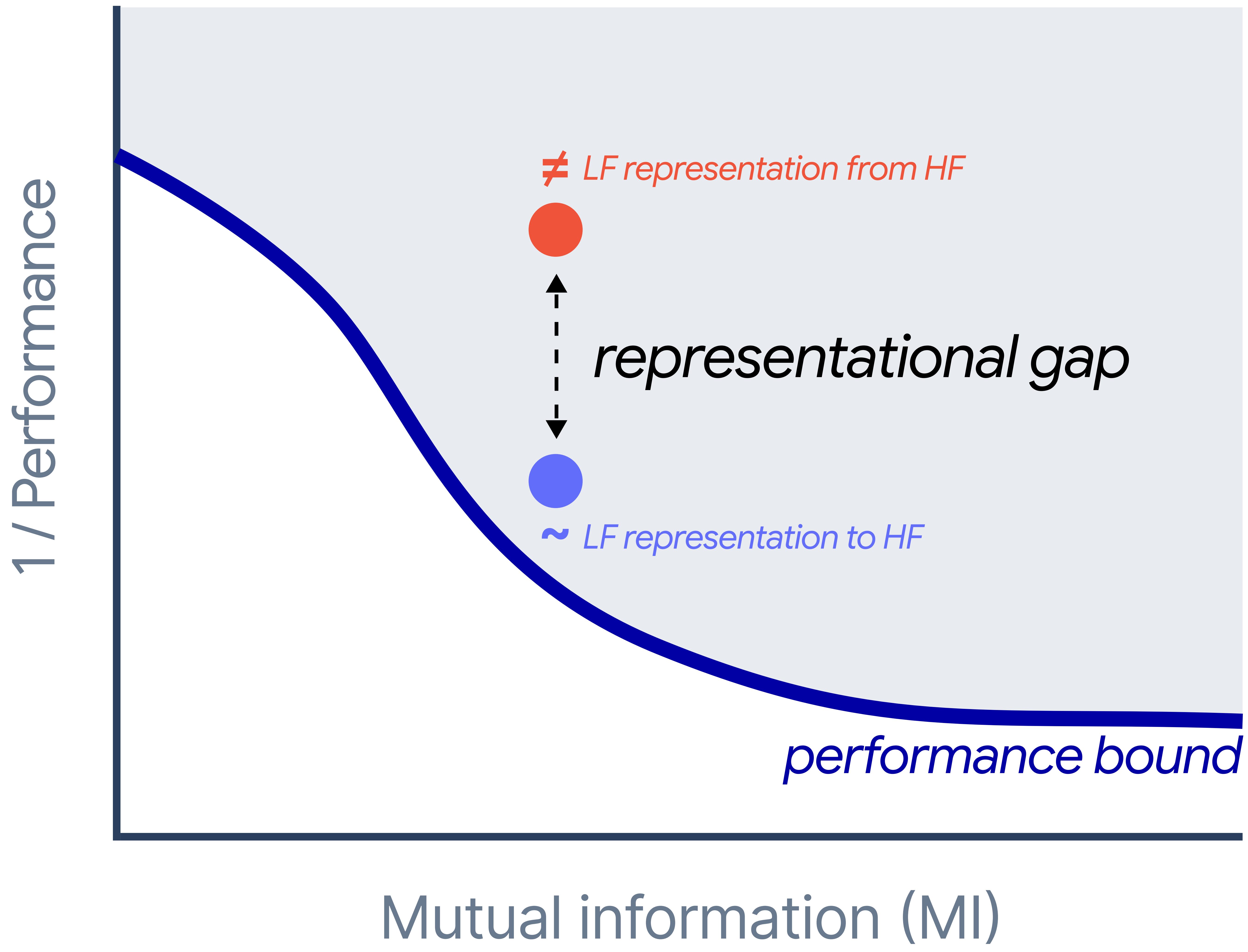
Recurrent Spiking Network model





Already used in (Confavreux et al., 2025) to learn plasticity rules

Why does it work?



Contributions

Multifidelity NPE (MF-NPE)

Can reduce the simulation budget by up to

~100 times

Allows simulation-based inference over computationally

expensive simulators

Multifidelity Simulation-based Inference for Computationally Expensive Simulators

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GitHub

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