Statistical inference for mechanistic models of neural populations based on spike-train data

Multi-neuronal spike-train data recorded in vivo typically exhibit rich dynamics as well as considerable variability across cells and repetitions of identical experimental conditions (trials). The interpretation of such data often relies on abstract statistical models that allow for principled parameter estimation and model selection; however, the interpretive power of these models is limited by the low extent to which prior biophysical constraints are incorporated. In contrast, mechanistic models are useful to interpret neurocircuit dynamics, but are rarely quantitatively matched to experimental data due to methodological challenges.

In my talk I will present analytical, likelihood-based tools to efficiently fit spiking population models to single-trial spike trains. I will first focus on coupled stochastic integrate-and-fire neurons, for which we infer the statistics of hidden inputs, neuronal adaptation properties and synaptic connectivity. Then, to infer the low-dimensional collective dynamics I will consider a doubly-stochastic model that accounts for fast independent and slower shared input fluctuations. We reconstruct the shared variations, classify their dynamics, obtain precise spike rate estimates, and quantify how individual neurons contribute to the population activity, all from a single trial.

Extensive evaluations based on simulated data, and validations using ground truth recordings in vitro and in vivo demonstrate that our methods efficiently yield accurate results and outperform classical approaches. Altogether, these tools enable a quantitative, mechanistic interpretation of recorded neuronal population activity.