Gaussian process based nonlinear latent structure discovery in multivariate spike train data

Abstract

A large body of recent work has focused on methods for identifying low-dimensional latent structure in multi-neuron spike train data. Most such methods have employed either linear latent dynamics or linear (or log-linear) mappings from a latent space to spike rates. Here we propose a doubly nonlinear latent variable model for population spike trains that can identify nonlinear low-dimensional structure underlying apparently high-dimensional spike train data. Our model, the Poisson Gaussian Process Latent Variable Model (P-GPLVM), is defined by a low-dimensional latent variable governed by a Gaussian process, nonlinear tuning curves parametrized as exponentiated samples from a second Gaussian process, and Poisson observations. The nonlinear tuning curves allow for the discovery of low-dimensional latent embeddings, even when spike rates span a high-dimensional subspace (as in, e.g., hippocampal place cell codes). To learn the model, we introduce the decoupled Laplace approximation, a fast approximate inference method that allows us to efficiently maximize marginal likelihood for the latent path while integrating over tuning curves. We show that this method outperforms previous approaches to maximizing Laplace approximation-based marginal likelihoods in both the convergence speed and value of the final objective. We apply the model to spike trains recorded from hippocampal place cells and show that it outperforms a variety of previous methods for latent structure discovery, including variational auto-encoder based methods that parametrize the nonlinear mapping from latent space to spike rates with a deep neural network.