An efficient approach for dynamic analysis of neural activity with non-probabilistic guarantees

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The analysis of dynamic neural activity is essential to understanding how neural systems evolve in time their representation to learning, behavior and sensory stimuli. In many approaches to prediction, static and probabilistic assumptions are made on the neural processes. The massively dynamic aspects of brain function can render both of these assumptions invalid in many cases. Typical approaches to address this use a sequence of discrete snapshots in time windows and assume fixed dynamics within a window; however, in many cases this is insufficient to track the evolution on a fine enough time scale. More recently, Bayesian filtering approaches have been developed to track the time-varying representation of neural systems. However, they (a) nonetheless assume a statistical structure and (b) are computationally inefficient to implement exact inference. In this work, we (a) present a general non-probabilistic framework for tracking the time-varying response of neural systems using sequential prediction with expert advice. Our method is universal: for all possible neural sequences, its performance is as good as the best expert in a reference class. We show that point process Bayesian filtering is a special case of this. Secondly, we (b) demonstrate that an efficient algorithm can be constructed for exact inference: this algorithm is an optimal solution to an optimal transportation problem, which can be efficiently solved. The proposed framework was first tested on simulated neural spike data created from time-varying generative models. It showed better goodness-of-fit and tracking performance than other conventional approaches. We also applied the proposed approach in a study of the dynamic properties of neural spike train data from the primary motor cortex of monkey, which was trained to perform a visuomotor task. We constructed a sequential predictor, called Bayesian mixture forecaster (BMF), for tracking the temporal evolution of the neural systems from point process observations. The BMF has a universal guarantee and can be efficiently implemented using the theory of optimal transportation. This enables us to overcome the computational bottleneck of conventional Markov chain Monte Carlo simulation, and instead explicitly construct a map that pushes forward the prior distribution to the posterior. This approach reliably tracked the temporal dynamics of neural systems in a millisecond time scale. Our proposed methodology for dynamic analysis of neural systems enables us to use minimal assumptions to efficiently understand the underlying mechanisms of complex neural systems.