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Poster presentation

Fast inference of couplings between integrate-and-fire neurons from their spiking activity

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Multi-electrode recordings make available the simultaneous spiking activity of tens of neurons for hours [1]. An important issue is to reconstruct the network of connections between the cells from this activity. To be more precise, let us model cells as Leaky Integrate-and-Fire (LIF) neurons (see [2] and references therein) whose membrane potentials obey the differential equation (units are chosen so that the membrane capacitance equals unity),

$$\frac{dV_i}{dt}(t) = -gV_i(t) + \sum_j J_{ij} \sum_k \delta(t - t_{jk}) + I_i + \eta_i(t)$$

$$(1)$$

where g is the leak conductance. J_{ij} is the strength of the connection from neuron j onto neuron i and $t_{j,k}$ the time at which cell j fires its kth spike; we assume that synaptic inputs are instantaneously integrated i.e. the synaptic integration time is much smaller than $1/g$ and the typical inter-spike interval. I_i is a constant external current flowing into cell i, and $\eta_i(t)$ is a fluctuating current, modeled as a Gaussian white noise process with variance σ^2. Neuron i remains silent as long as V_i remains below some threshold potential (equal to 1). If the threshold is reached at some time then a spike is emitted, and the potential is reset to its rest value of zero, and the dynamics resumes.

The above model implicitly defines the likelihood P of the spiking times $\{t_{j,k}\}$ given the currents I_i and synaptic couplings J_{ij}. If we are given the spike times $\{t_{j,k}\}$ we will infer

the couplings and currents by maximizing P. In principle, P can be calculated through the resolution of Fokker-Planck equations (one for each inter-spike interval) for a one-dimensional Orstein-Uhlenbeck process with moving boundaries. However, this approach, or related numerical approximations [3], are inadequate to treat data sets with hundreds of thousands of spikes (such as in recordings of populations of retinal ganglion cells) in a reasonable time.

In our approach, we choose to approximate P from the contribution coming from the most probable trajectory for the potential for each cell i, referred to as $V_i^*(t)$. This approximation is exact when the amplitude σ of the noise is small. The determination of $V_i^*(t)$ was done numerically by Paninski for one cell in [4]. We have found a fast algorithm to determine $V_i^*(t)$ analytically in a time growing linearly with the number of spikes and quadratically with the number of neurons, which allows us to process recordings with tens of neurons easily. The algorithm is based on a detailed and analytical resolution of the coupled equations for the optimal potential $V_i^*(t)$ and the associated optimal noise $\eta_i^*(t)$ through (1), and is too complex to be explained in this abstract.

Once the optimal paths for the potential and noise has been determined, we calculate the log-likelihood of the corresponding couplings and currents through the integral of the squared optimal noise [4]. This log-likelihood is clearly a concave function of the currents and couplings

and can be easily maximized using the Newton-Raphson method. Our algorithm has been tested on artificially generated data, real experimental data (recordings of 32 ganglion cells in the salamander retina submiited to random flickering stimulus, courtesy of M. Meister) and compared to other inference methods based on the Ising model (see abstract by Cocco). To give a flavor of the computational effort required, it takes us about 20 seconds to process a set of 120,000 spikes fired by 32 cells on a personal computer.

References

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