A PYTHON Package for Kernel Smoothing via Diffusion: Estimation of Firing Rate from Spike Trains

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Kernel smoothing is a powerful methodology to gain insight into data. It has wide applications in many different fields, ranging from Economics to Neurosciences. The most important basic application of kernel smoothing in Neuroscience is estimation of time-dependent firing rates from neuronal spike trains. Traditionally, this is achieved by the PSTH (Peri-Stimulus Time Histogram) or, alternatively, smoothing with a fixed kernel. The PSTH relies on the availability of multiple trials for averaging out trial-to-trial fluctuations. However, one can obtain a plausible estimate from a single trial as well, using kernel smoothing methods, where the bandwidth of the kernel is a parameter to be selected in analogy to the bin size of the histogram. The form of the kernel is rather unimportant, provided it is smooth, unimodal and normalized. Its bandwidth, in contrast, defines how smooth the resultant rate would be (Nawrot et al., 1999). A suboptimal kernel may result in over-smoothing or under-smoothing, where the optimal kernel is defined by a minimal deviation from the true rate profile. There may be no globally optimal kernel for strongly changing Poisson rates, though. As a cure to this problem one can optimize the estimate by locally adaptive bandwidth selection. To this end, Shimazaki and Shinomoto (2009) suggested a combinatorial way of optimizing MISE (mean square integrated error) as a method of local bandwidth estimation. This method, although effective, is computationally very costly and biased. Instead, we suggest an application of a new method by Botev et al. (2010), namely Kernel Density Estimation via Diffusion. The diffusion method offers a fast completely data driven algorithm for local bandwidth selection, avoiding the boundary bias and the assumption of Gaussianity. An implementation of the new method as a PYTHON package is made available.

References

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