Computing loss of efficiency in optimal Bayesian decoders given noisy or incomplete spike trains

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The problem of optimal Bayesian decoding of spike trains has received a great deal of previous attention., In many cases we are particularly interested in performing optimal decoding when spike trains are not fully available: for example, information about neural identity or correlations may be lost during spike sorting, or spike times may be corrupted with noise due to stochastic membrane channel effects. In this work we present methods for efficiently computing the impact of such perturbations on the performance of the optimal decoder.

We focus on a Markovian model of spiking dynamics which is closely related to the spike-response/generalized-linear model framework that has been quite popular in the recent computational and statistical neuroscience literature. This model is sufficiently flexible that we may incorporate realistic stimulus encoding and spiking dynamics, but nonetheless permits exact computation via efficient forward-backward methods familiar from the theory of hidden Markov models. We also introduce a novel prior distribution on smoothly varying stimulus signals; this prior is conditionally conjugate to the likelihood in our encoding model, implying that the posterior expectation of stimuli given the model's sufficient statistics can be computed exactly, further enabling efficient computation.

We analyze two important problems within this framework. First, we quantify the loss of decoding efficiency when the identities of the observed neurons are discarded or corrupted. A concrete example involves spike sorting in low-SNR regimes, where overlaps in spike clusters can lead to errors or excessive uncertainty in the identity of the neuron contributing any observed spike. Second, we examine the impact of errors in the timing of each observed spike., In each case, our methods allow us to compute the loss in decoding performance efficiently over a range of parameter values, contributing to a more systematic understanding of the importance of these effects.

References

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