# Model-based decoding, information estimation, and change-point detection in multi-neuron spike trains

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The neural decoding problem is of fundamental importance in computational and systems neuroscience: given the observed spike trains of a population of cells whose responses are related to a behaviorally-relevant signal $\vec{x}$, how can we estimate, or "decode," $\vec{x}$? Solving this problem experimentally is of basic importance both for our understanding of neural coding and for the design of neural prosthetic devices.

Here we introduce several decoding methods based on point-process neural encoding models (i.e. "forward" models that predict spike responses to novel stimuli). These models incorporate stimulus dependence and spike-history effects (such as refractoriness or bursting), and can also include multineuronal terms corresponding to the excitatory or inhibitory effects between cells. Importantly, these models have concave log-likelihood functions, allowing for simple, efficient fitting of the model parameters via maximum likelihood $[1, 2]$. This concavity property also applies to the stimulus $\vec{x}$, implying that we can tractably perform stimulus decoding by maximizing the likelihood with respect to $\vec{x}$. We present a tractable algorithm for computing the *maximum a posteriori* (MAP) estimate of the stimulus — the most probable stimulus to have generated the observed single- or multiple-spike train response, given some prior distribution over the stimulus. In certain cases we demonstrate that it is possible to decode very high-dimensional stimuli (e.g., $\dim(\vec{x}) \approx 10^4$) with minimal computational effort.

We can further exploit this concavity property by deriving a simple and accurate Gaussian approximation to the posterior distribution $p(\vec{x}|D)$ of the stimulus $\vec{x}$ given the observed spiking data $D$. This Gaussian approximation allows us to: (1) quantify the fidelity with which various stimulus features are encoded; (2) develop an efficient, highly tractable method for estimating the mutual information between the stimulus and the response (interestingly, this estimator indicates that the standard linear reconstruction lower bound technique $[3]$ can lead to significant underestimation of the true information); and (3) establish a framework for the optimal detection of change-point times (e.g. the time at which the stimulus undergoes a change in mean or variance), by marginalizing over the posterior distribution $p(\vec{x}|D)$. We show a variety of examples illustrating the performance of these estimators with simulated data.

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**References**
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