Bayesian decoding of noisy or incomplete spike trains

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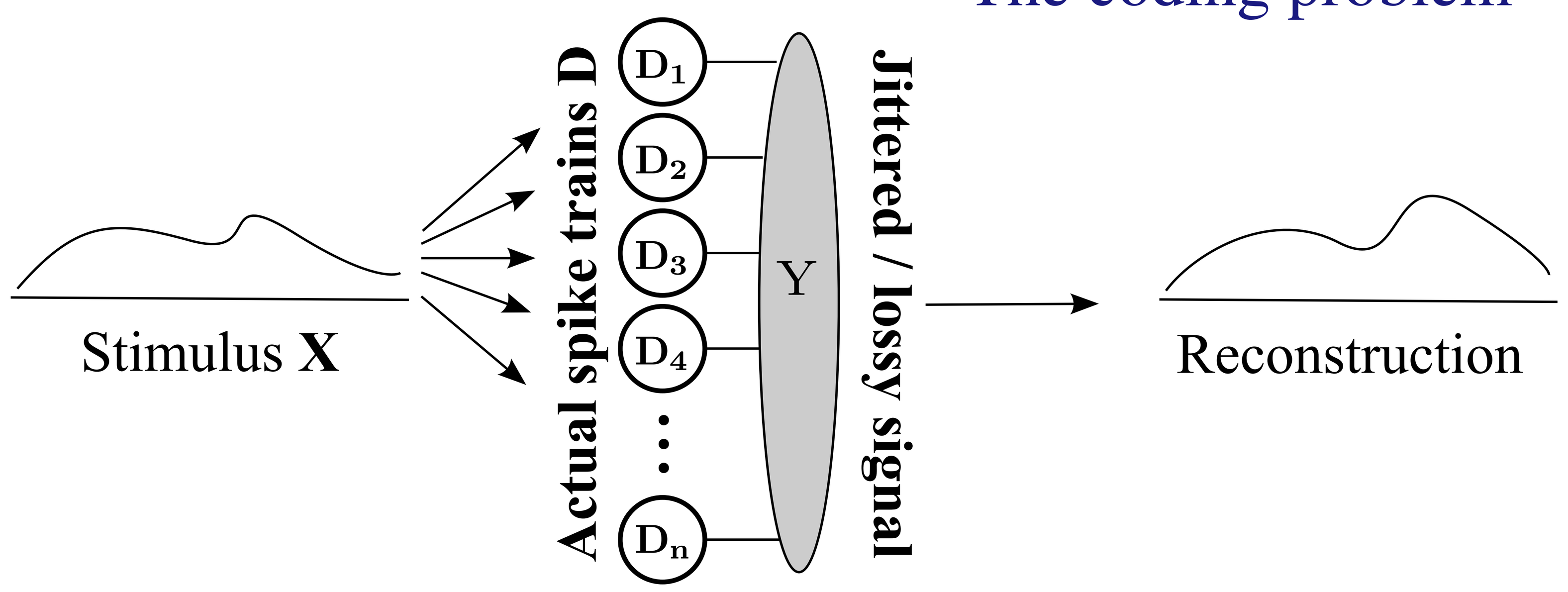
The coding problem



- Consider neurons with a common stimulus emitting spikes.
- Spike train data may be subjected to sources of noise.
- How can we decode in this context?[1]
- We describe computationally efficient decoding of noisy **Markovian neurons**.

Case 1: Spike-time jitter

- Various sources of noise jitter spike times.
- In decoding, spike time jitter is often ignored or averaged over.
- We present a Bayesian treatment of decoding with jitter.
- It is both exact and computationally efficient.
- Decoder input: jittered **discrete time** binary signal.

Case 2: Identity loss

- Electrodes hear multiple cells with varying response properties.
- Spike sorting attributes each spike to some neuron based on waveform characteristics.
- Another framework[5] infers directly on the waveforms.
- We present such a method for our model.
- Decoder input: spike times and waveform feature vectors.

References

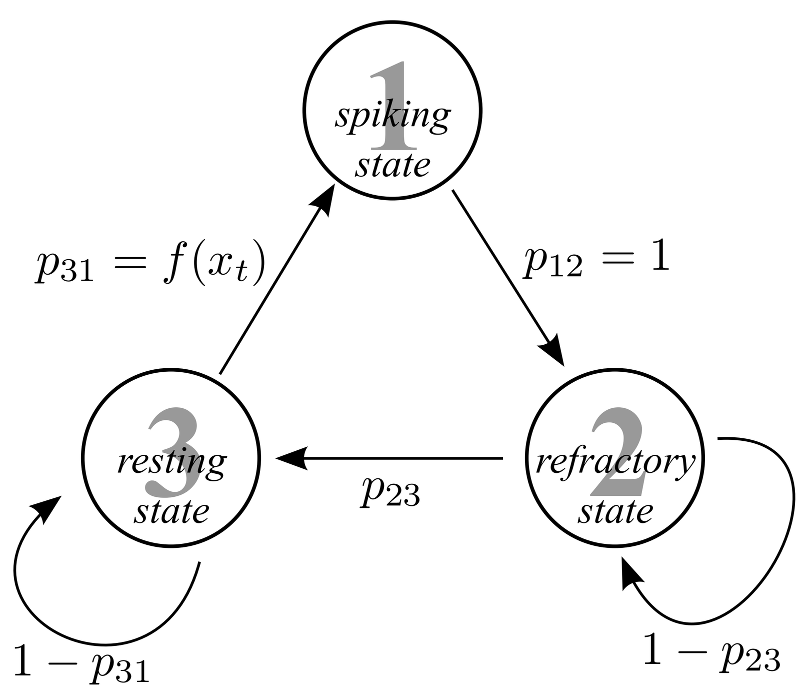
1) Bialek et al., 1991, *Reading a Neural Code*, Science 252
2) Kass et al., 2005, *Statistical Issues in the Analysis of Neuronal Data*, J Neurophysiol 94
3) Aldworth et al., 2005, *Dejittered Spike-Conditioned Stimulus . . .*, J Neuroscience, 25
4) Gollisch, 2006, *Estimating Receptive Fields in the Presence of Spike-time Jitter*, Network, 17
5) Ventura, 2008, *Spike Train Decoding Without Spike Sorting*, Neural Computation 20
6) Ahmadian et al., 2008, *Analyzing the Primate Retinal Code with Efficient Model-based Decoding Methods*, Society for Neuroscience, Poster
7) Smith and Paninski, 2011, *Tractable inference on continuous-space Markov chains*, In preparation
8) Escola et al., 2010, *Hidden Markov models for the stimulus-response relationships of multistate neural systems*

Stimulus reconstruction

- The heart of this method is an optimal decoding algorithm that scales linearly with time and with number of neurons.
- We use Gibbs sampling to reconstruct stimuli from noisy data, in which samples are drawn from a joint distribution by sequentially sampling from the corresponding marginals.
- For log-concave response function f, we can quickly compute MAP estimate of stimulus.
- In our particular model, we can analytically compute the posterior mean, so we can use Rao-Blackwellization, in which the posterior mean is tallied instead of the sampled stimulus.

A simple model neuron

- Neurons follow some Markov dynamics
- The stimulus-dependence is in the transition probabilities
- We focus on three-state neuron, considered elsewhere[8], simple but reasonable



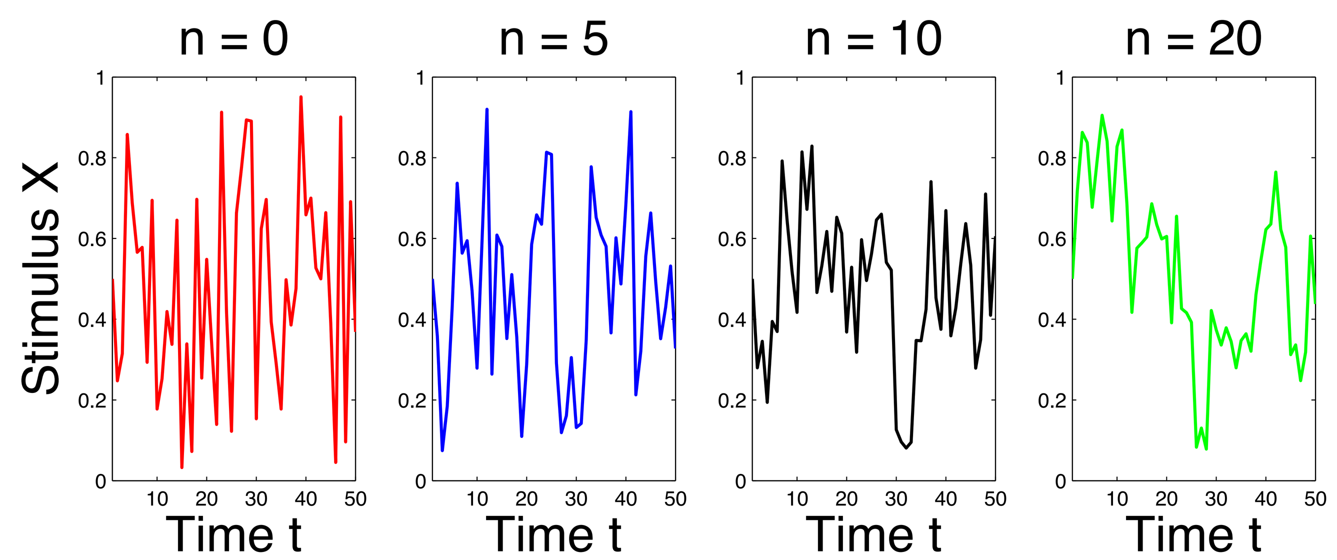
State sequence **Q**
`333122223333122312 2...`

Spike train **D**
`000100000000100010 0...`

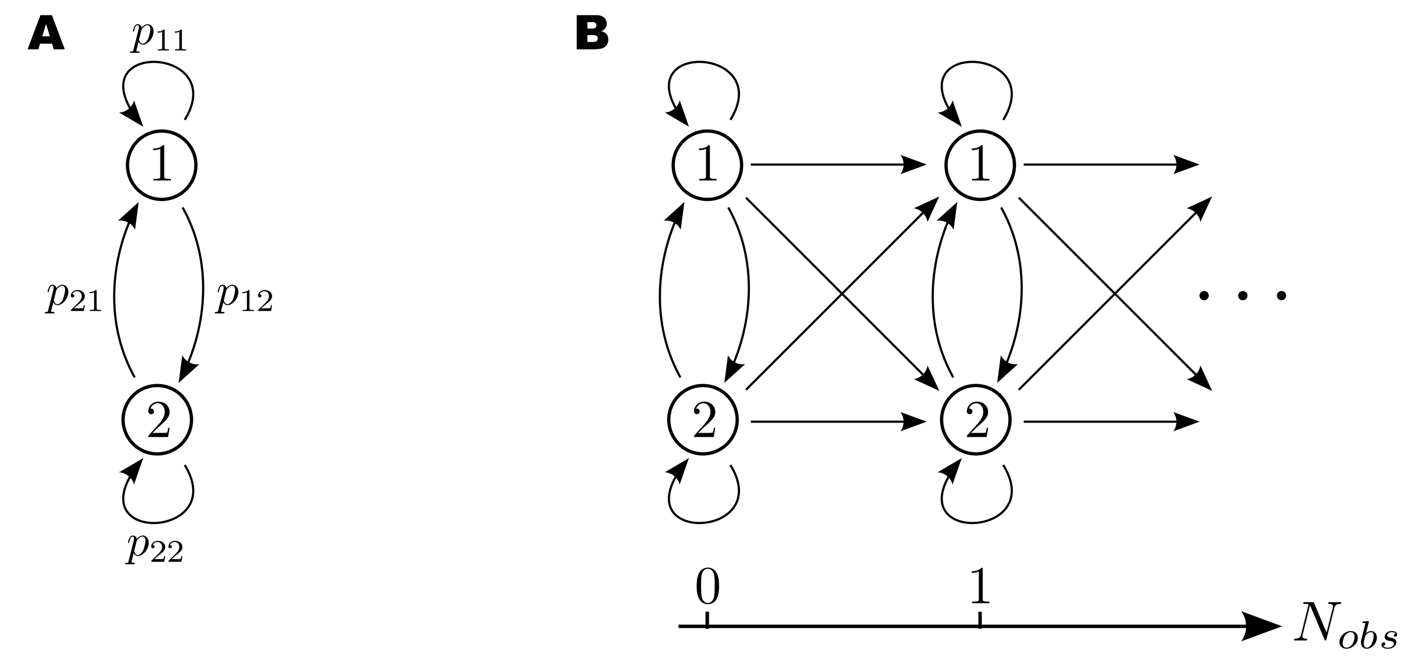
Jittered spike train **Y**
`000001000001001000...`

Exactly computable, temporally correlated conjugate prior

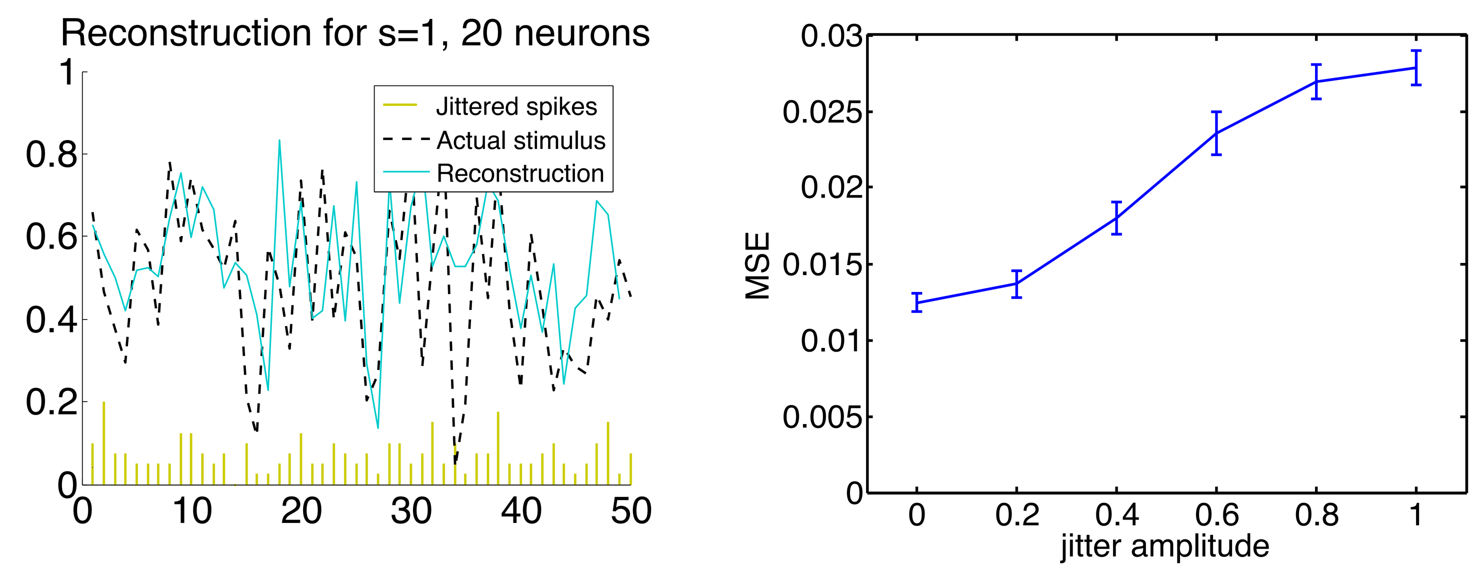
- We found a class of smoothing priors on our reconstructions for which inference is still in linear time.[7]



Reconstruction with spike-time jitter

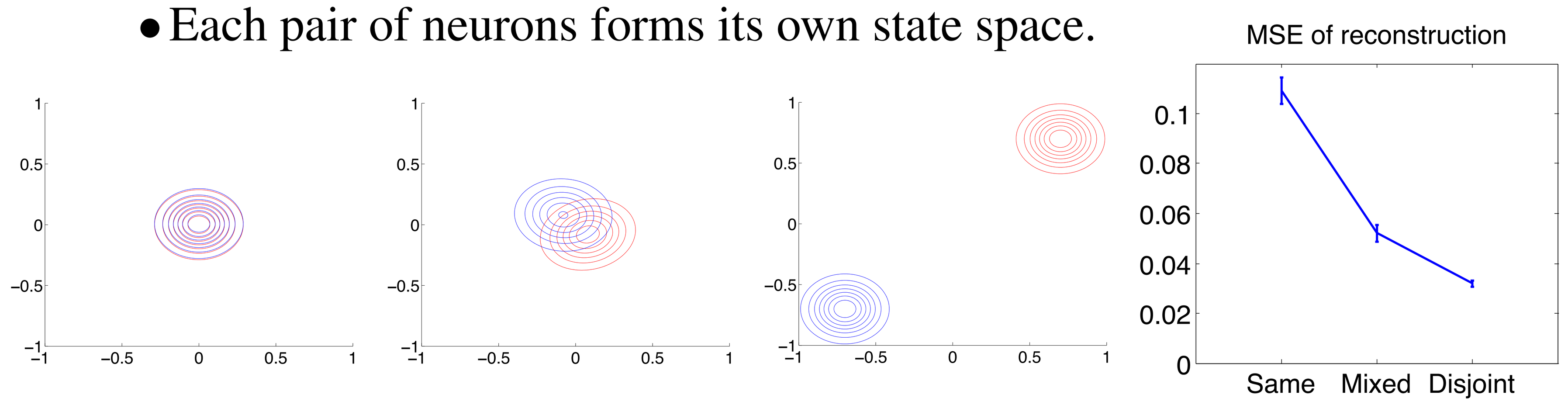


- Spikes are independently subjected to some jitter distribution.
- A HMM is constructed whose observations are jittered spikes.
- This involves an expansion of the state space.
- The variable matrices are banded so we preserve efficiency.
- The signal is reconstructed by Gibbs sampling between path Q and stimulus X.



Reconstruction with neuron identity loss

- An array of electrodes, each hearing one ON and one OFF cell.
- Spikes are vectors in a feature space.
- The two cells' feature distributions may overlap.
- We infer on the noisy data directly without prior sorting.
- Each pair of neurons forms its own state space.



This figure shows the average MSE over 25 full reconstructions using 40 neurons for the three situations depicted to the left. As there is more overlap of characteristic spike features, more information is lost.