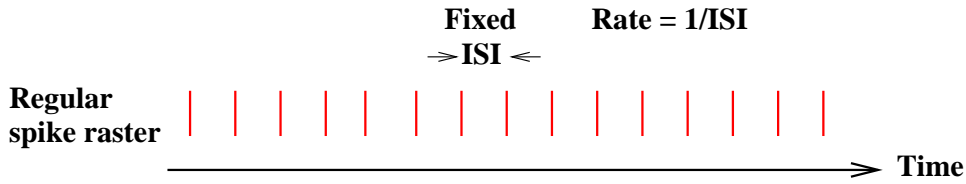


# Spike Train Decoding

## The Problem



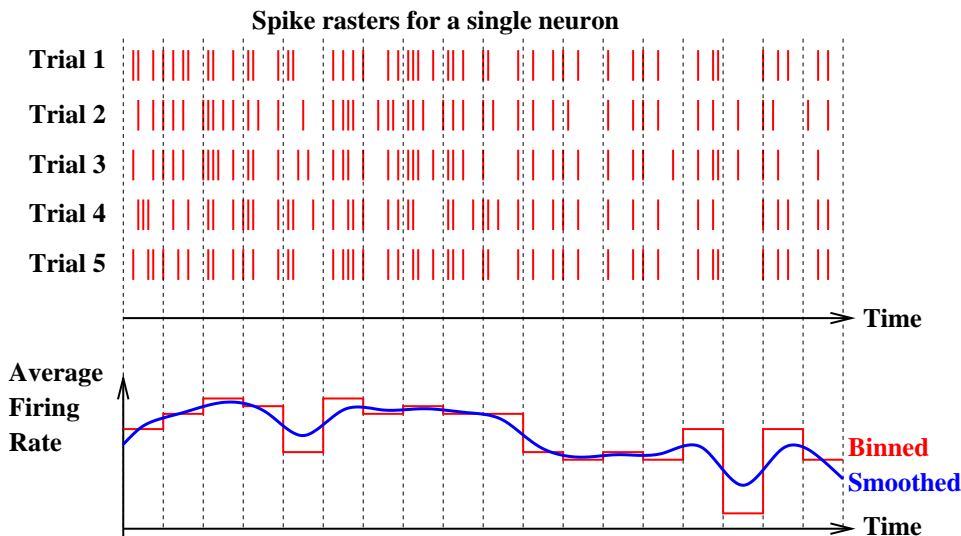
Rather than regular, *in vivo* spike trains are noisy, meaning each inter-spike interval (ISI) is not precisely determined but may be representative of some probabilistic distribution.

Many such ISIs are needed to obtain the distribution which can indicate the most commonly measured statistic, the firing rate of the neuron.

However, when measuring a single neuron, a lot of spikes (and time) may be needed to obtain a good measure of the firing rate,

During this time the firing rate might change ...

## Trial-Averaging



Assumption: given the same stimulus the variation with time of the firing rates of neurons follows a reproducible pattern.

Method: collect spikes from a neuron across repeated presentations of the same stimulus or task (repeated trials).

Average across trials, either using bins (eg all spikes between 2s and 2.1s from the stimulus onset go into the same bin, whichever trial they are on) or using a smoothing kernel (typically Gaussian of unit area).

## Single-Unit Approach

- 1) Use the first 'few' ISIs to estimate the firing rate,  $r_1$ .
- 2) For each timestep calculate the probability of that set of ISIs up until that time,  $t$  — or simply the number,  $N$ , of ISIs if Poisson as:

$$P(N, t|r_1) = \frac{(r_1 t)^N}{N!} \exp(-r_1 t) \quad (1)$$

- 3) If the probability is too low (eg  $P(N, t) < 5\%$ ) assume a change in firing rate.
- 4) Calculate the most likely new firing rate,  $r_2$ , **and** point of transition ( $T_{12}$ ) to a new firing rate by

maximizing the probability:

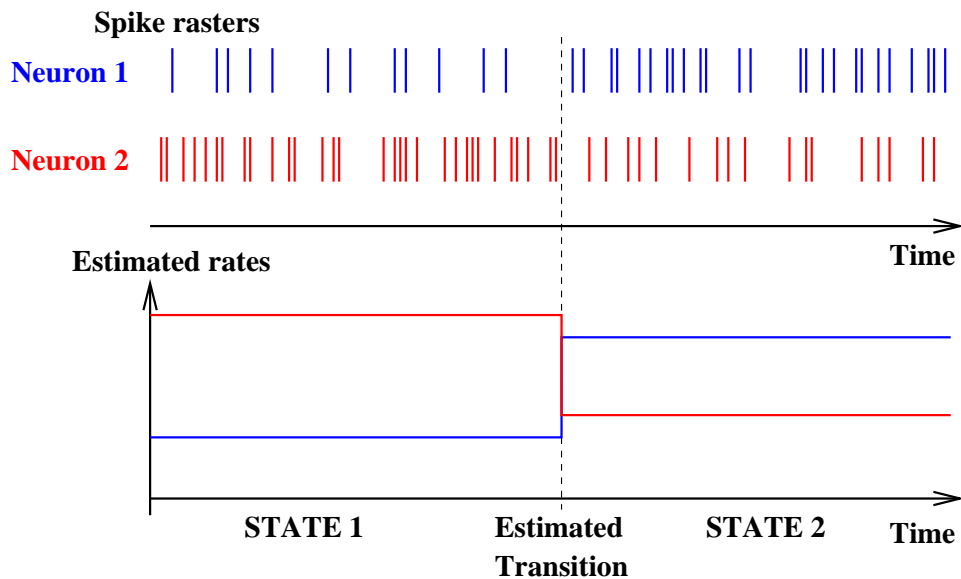
$$P(N_1, T_{12}|r_1) \times P(N_2, t - T_{12}|r_2) = \frac{(r_1(T_{12}))^{N_1}}{N_1!} \exp(-r_1 T_{12}) \frac{[r_2(t - T_{12})]^{N_2}}{N_2!} \exp(-r_2 [t - T_{12}]) \quad (2)$$

where  $N_1$  is the number of spikes before the transition time,  $T_{12}$  and  $N_2$  is the number of spikes after  $T_{12}$  and before  $t$ .

5) Continue with the new firing rate, calculating the probability of the set of ISIs beginning from the transition point.

Notes: this could be improved by incorporating realistic neuronal features such as refractory periods, adaptation etc. into the probabilities, rather than simply assuming Poissonian statistics.

## Hidden Markov Modeling (cf Don Katz's Lab.)



Hidden Markov Modeling assumes spikes are generated as a Markov process (that means a renewal process such as Poisson) according to underlying states with transitions between the underlying (hidden) states occurring probabilistically.

Inputs:

Total number of states.

Initial set of transition probabilities between states.

Method:

Optimizes the set of states (each state has a firing rate for each neuron) and probabilities of transitions between each state.

For each trial produce the likelihood of being in each state at a given time.

Possible results:

Distinct periods with near 100% probability of one state, then fast transitions.

Rapid alternations between states with minimal durations in any one state.

large periods of time with slowly varying probabilities far from 100% in any one state.

Note:

The model allows for transitions from one state to a new one then back.

Duration in a state is given by the probability in each time step of returning to the same state (i.e. remaining there) versus the probability of transition to a new state.