

Decoding spike ensembles: tracking a moving stimulus

Enrico Rossoni^{*}, Jianfeng Feng^{**}

^{*}University of Sussex, Brighton, UK

^{**}University of Warwick, Coventry, UK

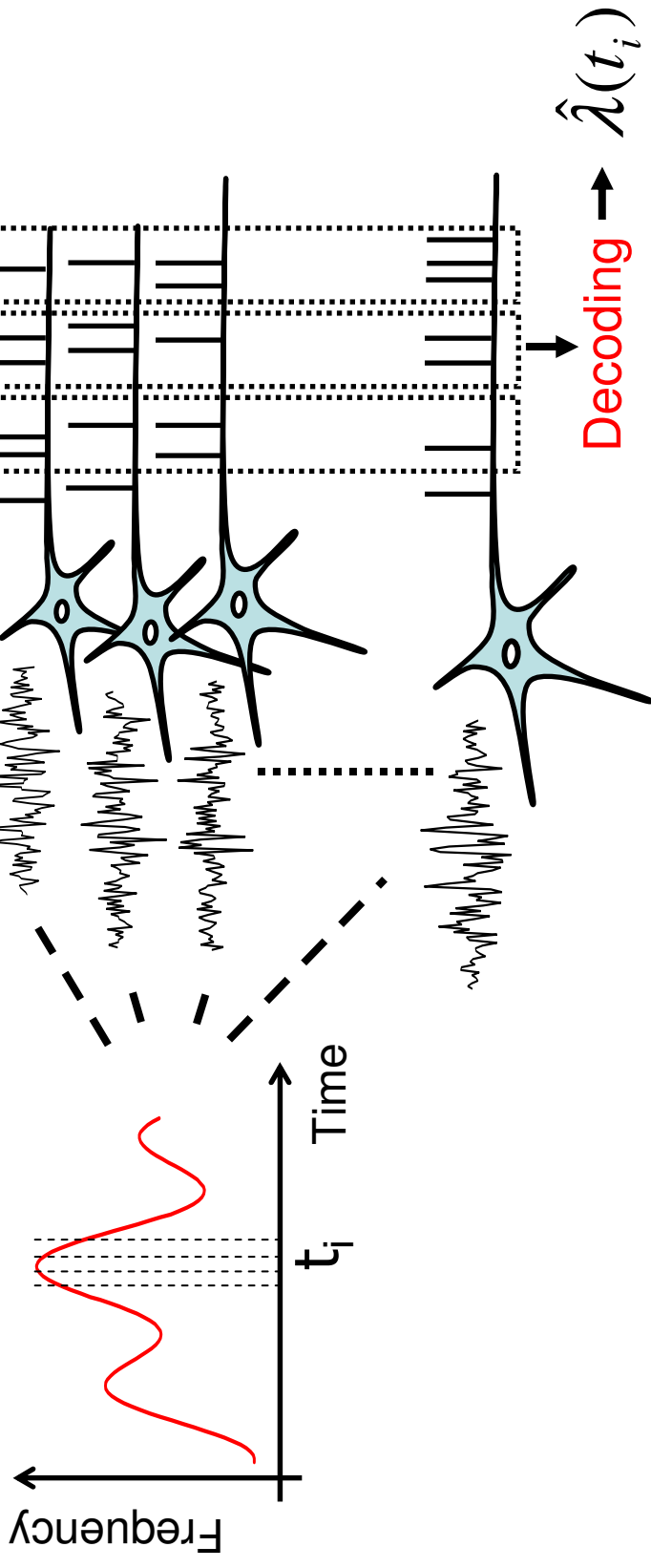
The questions

- Assuming that cortical neurons *in vivo* are 'noisy', how can we read out the information encoded in their spike activity?
- What is the most effective strategy for decoding spiking neurons?
- How accurately/rapidly can we extract information from a spike train ensemble?

This issues can be addressed theoretically for simple spiking neuronal models

The setup

Stimulus \rightarrow Synaptic input rate $\lambda(t)$

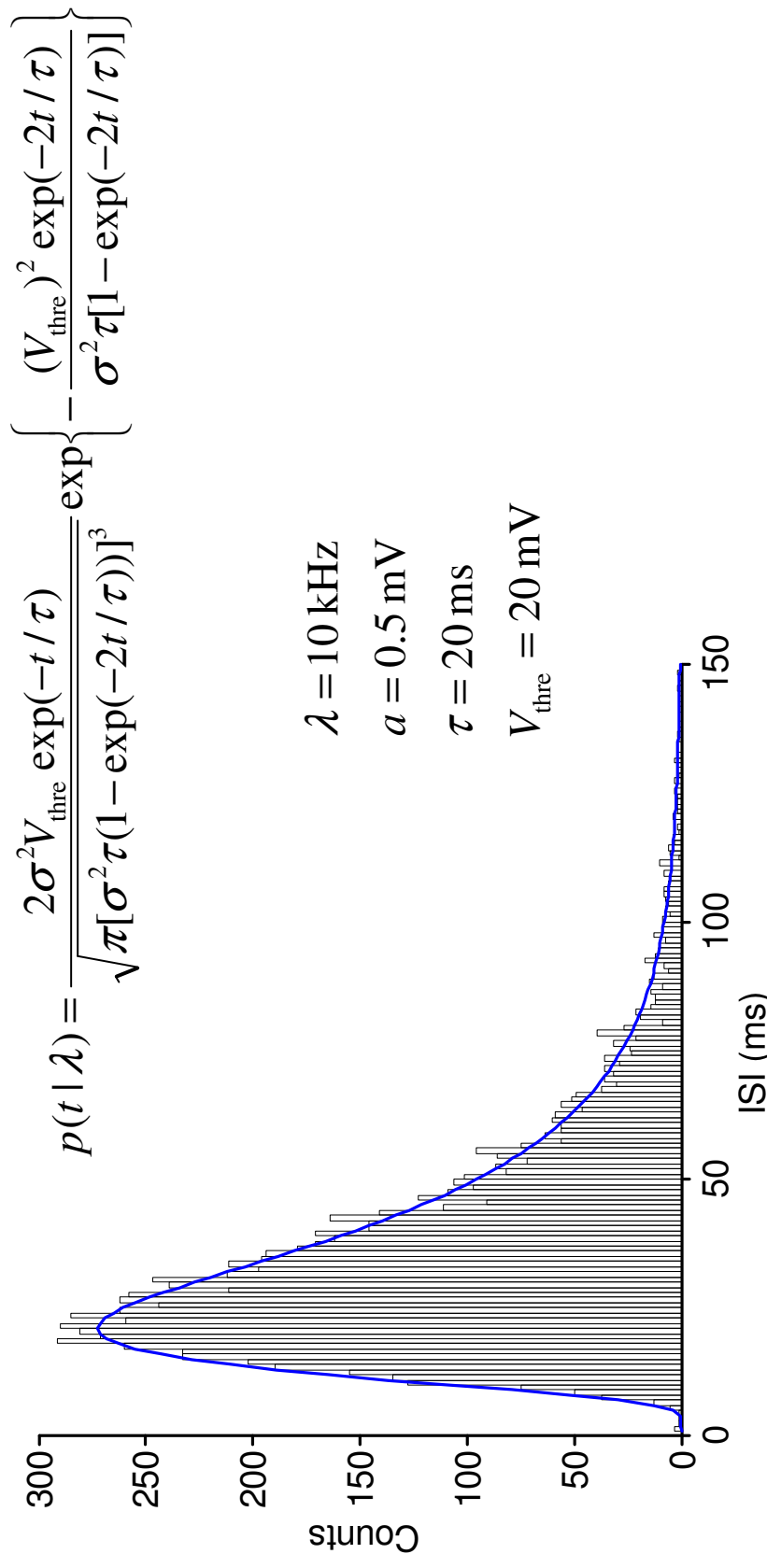


The stimulus is encoded in the time-dependent synaptic input rate $\lambda(t)$. In the decoding stage, the output spike trains are 'parsed' into consecutive time windows and the input is inferred from the observed ISI distribution.

Methods

- Neurons are described by the **leaky Integrate-and-Fire model**
- The synaptic input is given in the **diffusion approximation**
$$dI_t = \mu dt + \sigma dB_t$$
$$\mu = a\lambda(1-r) \quad \sigma = a\sqrt{\lambda(1+r)}$$
- Inputs to different neurons are assumed to be **independent**
- The excitatory vs. inhibitory ratio (r) is adjusted to ensure that the **input is 'balanced'**, i.e. that the mean membrane potential is always at threshold

For this model we derived the **exact ISI probability density**, thus we can adopt an **optimal decoding** strategy using a Maximum-Likelihood estimator.



The histogram of the ISI generated by the LIF model compared with the theoretical ISI distribution (solid blue)

The 'censoring' problem

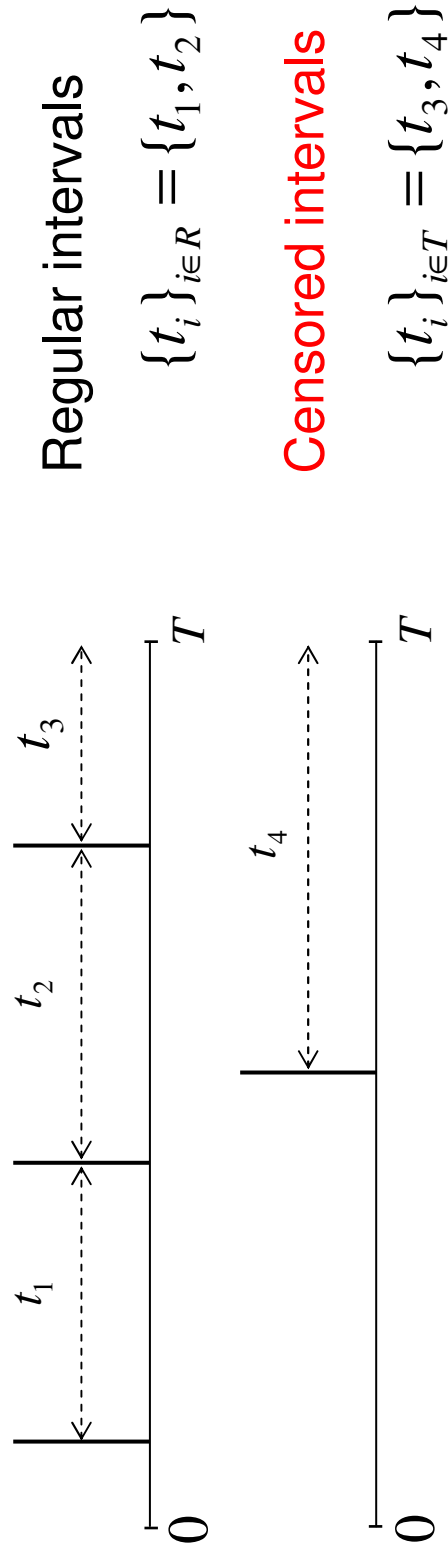
- In the time-dependent case, the input must be inferred from short spike train samples.
- However, when the decoding window length (T) is finite, **the 'standard' ML estimator is biased.**
- Indeed, the presence of a finite window length (**censoring**) modifies the ISI distribution and introduces serial dependencies between consecutive intervals in each window.
- Also, when T is comparable with the 'typical' ISI, only **few intervals** are expected to fall in each window, leading to **poor estimates.**

According to the theory of censored data in statistics, an **unbiased estimator** of λ is given by

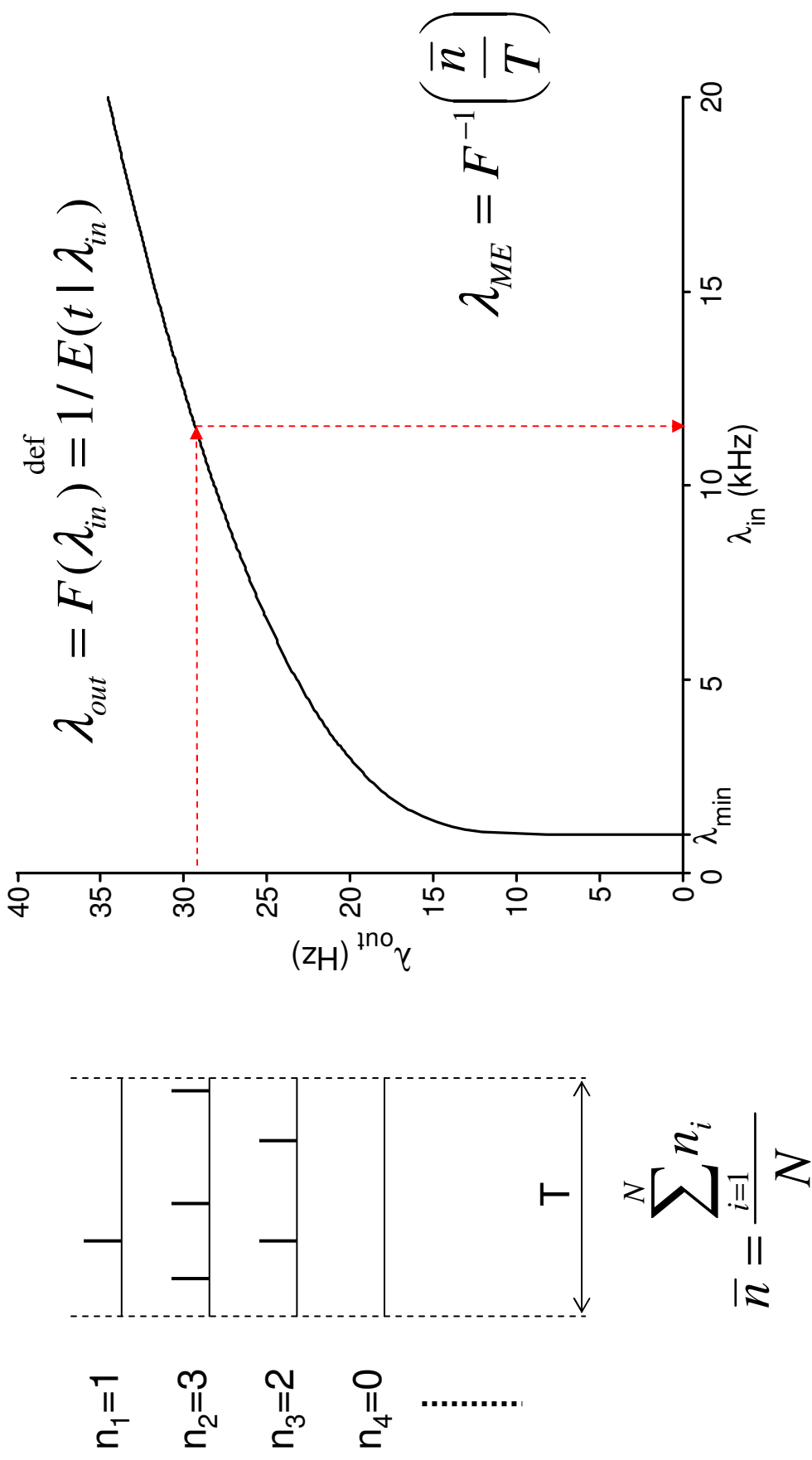
$$\lambda_{CMLE} = \arg \max L_C(\lambda)$$

where the **censored likelihood** function is

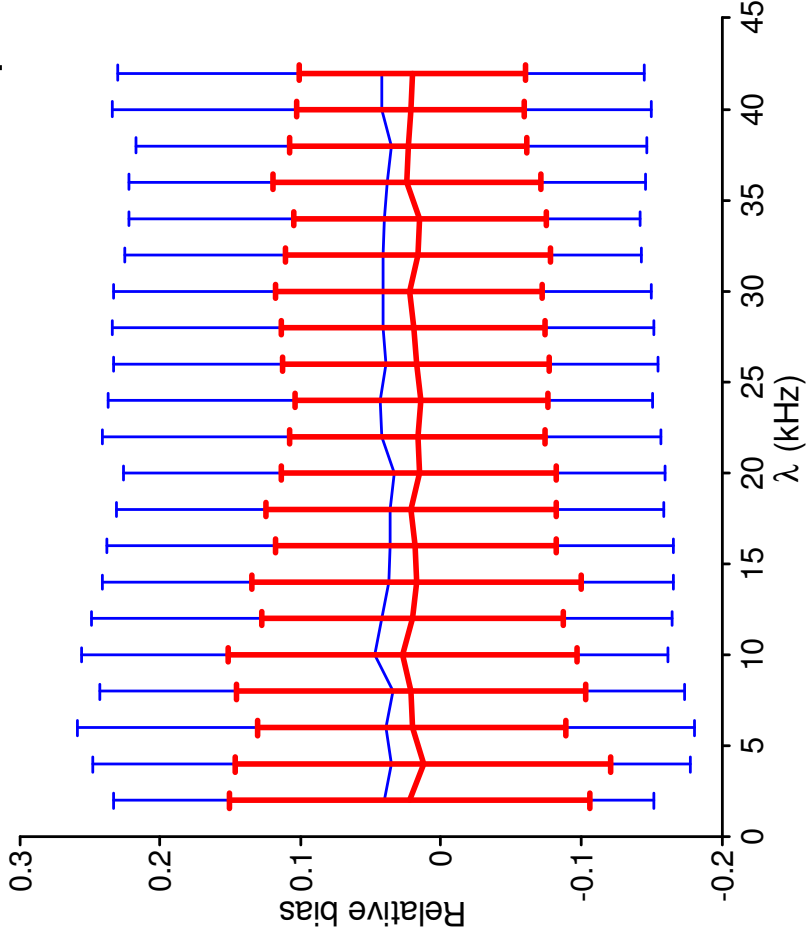
$$L_C(\lambda) = \sum_{i \in R} \log p(t_i | \lambda) + \sum_{i \in T} \log S(t_i | \lambda) \quad S(t | \lambda) = \int_t^{+\infty} p(t' | \lambda) dt'$$



In the **rate-coding** approach, a **Moment Estimate (ME)** of the stimulus is obtained from the **mean spike count**,



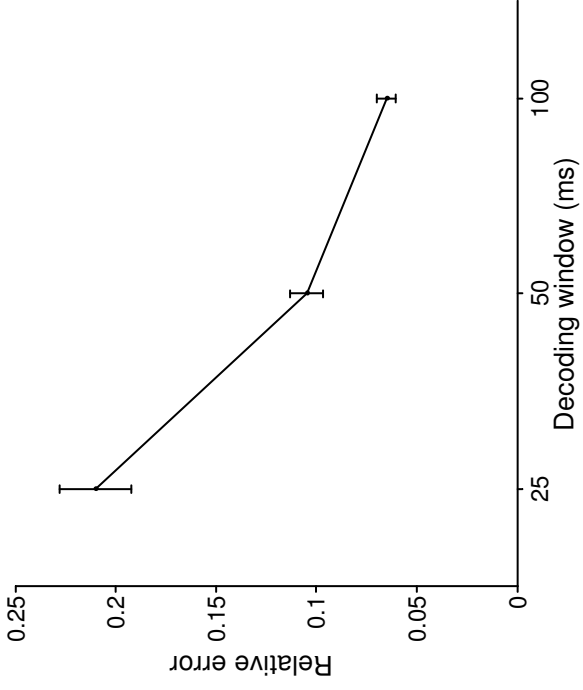
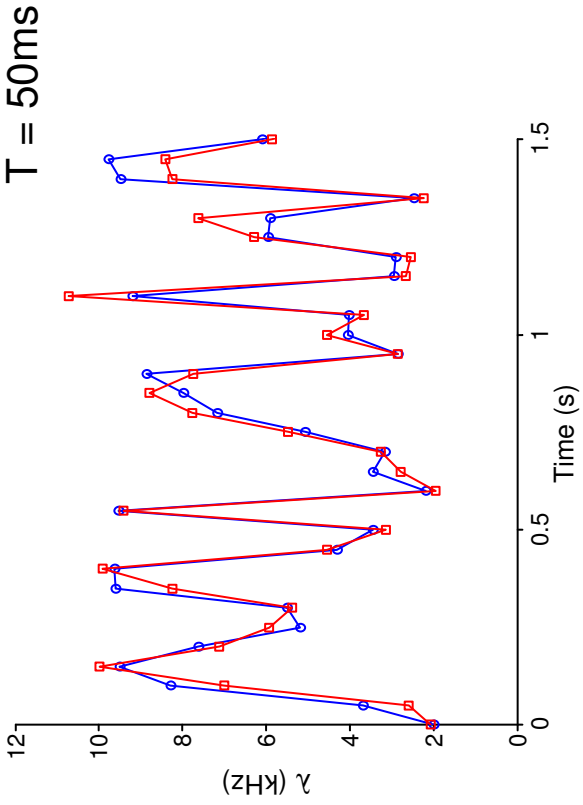
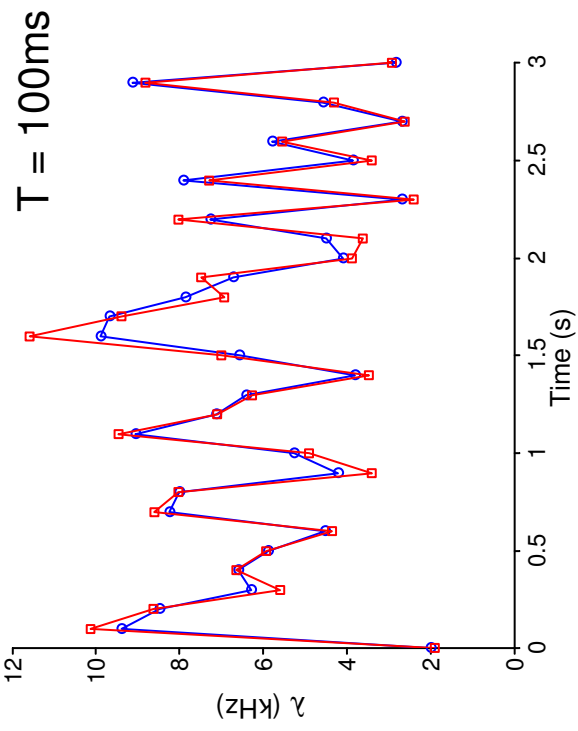
T = 50ms



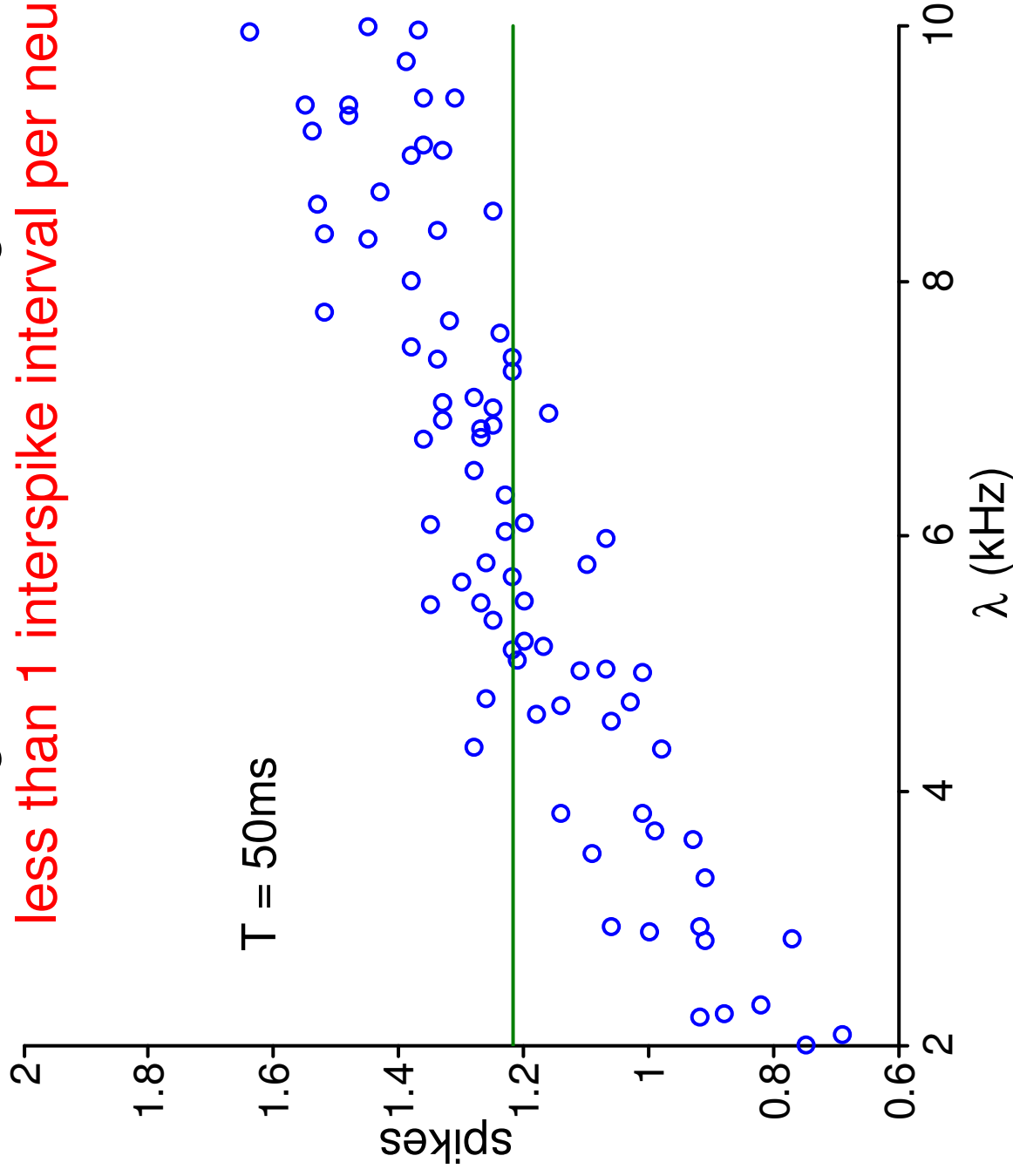
The Censored Maximum Likelihood Estimator (red) is **more efficient** than the Moment Estimator (blue) as indicated by the smaller SD of the estimates (bars). The bias is almost entirely removed.

Example

A random steplike signal (red) is estimated via CMLE (blue) using decoding windows of length T .

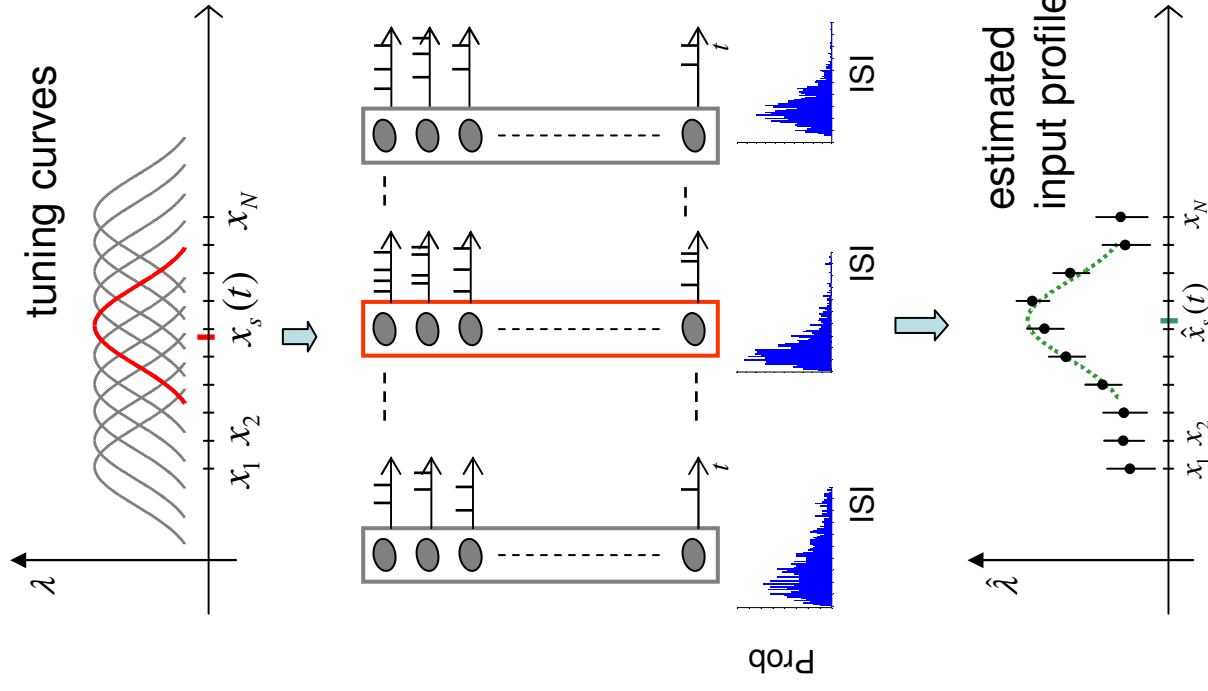


The signal is decoded using an average of
less than 1 interspike interval per neuron

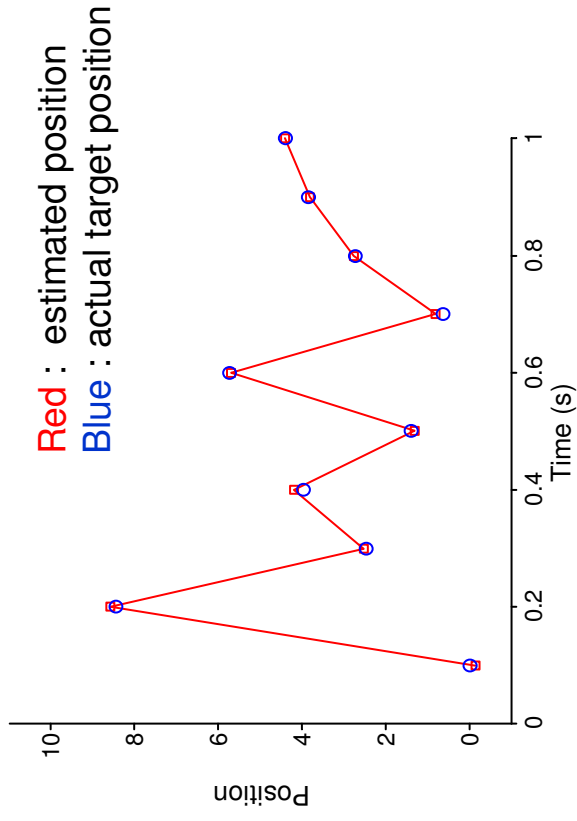


The tracking task

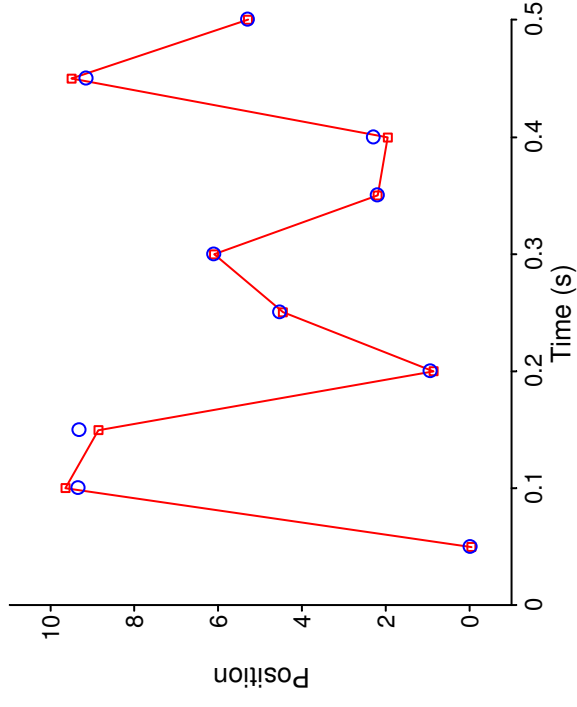
- The position of a target (x_s) is changed randomly at regular intervals of time.
- Neurons are grouped in columns and tuned to specific stimulus locations (x_i) to create a 'topographical map'
- Using CMLE/ME, the input to each column is inferred from the spike activity observed during the latest decoding window.
- The estimated input profile is fitted to determine the most likely position of the target.



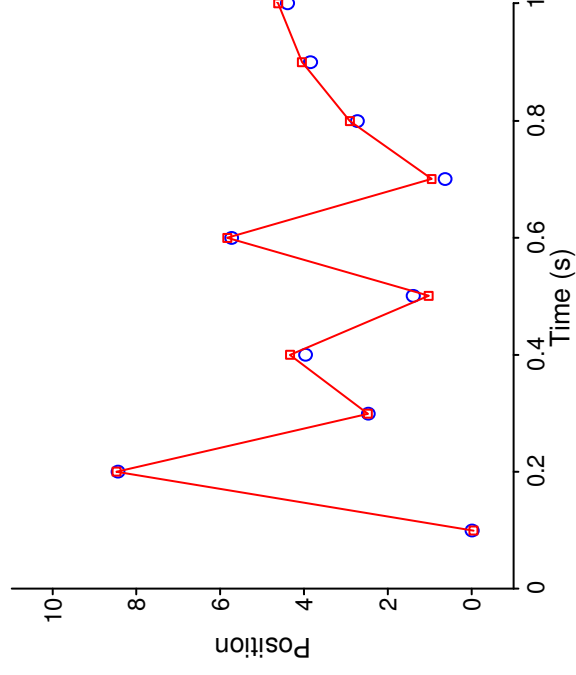
CMLE (100 ms) Error = 0.11



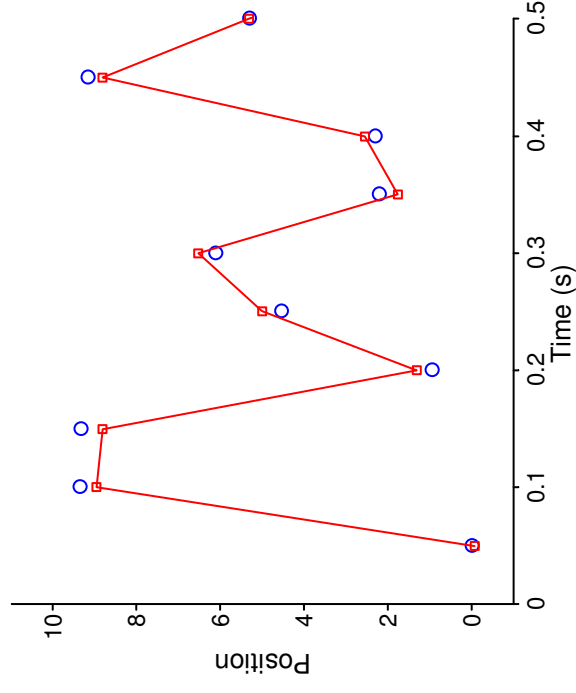
CMLE (50 ms) Error = 0.24

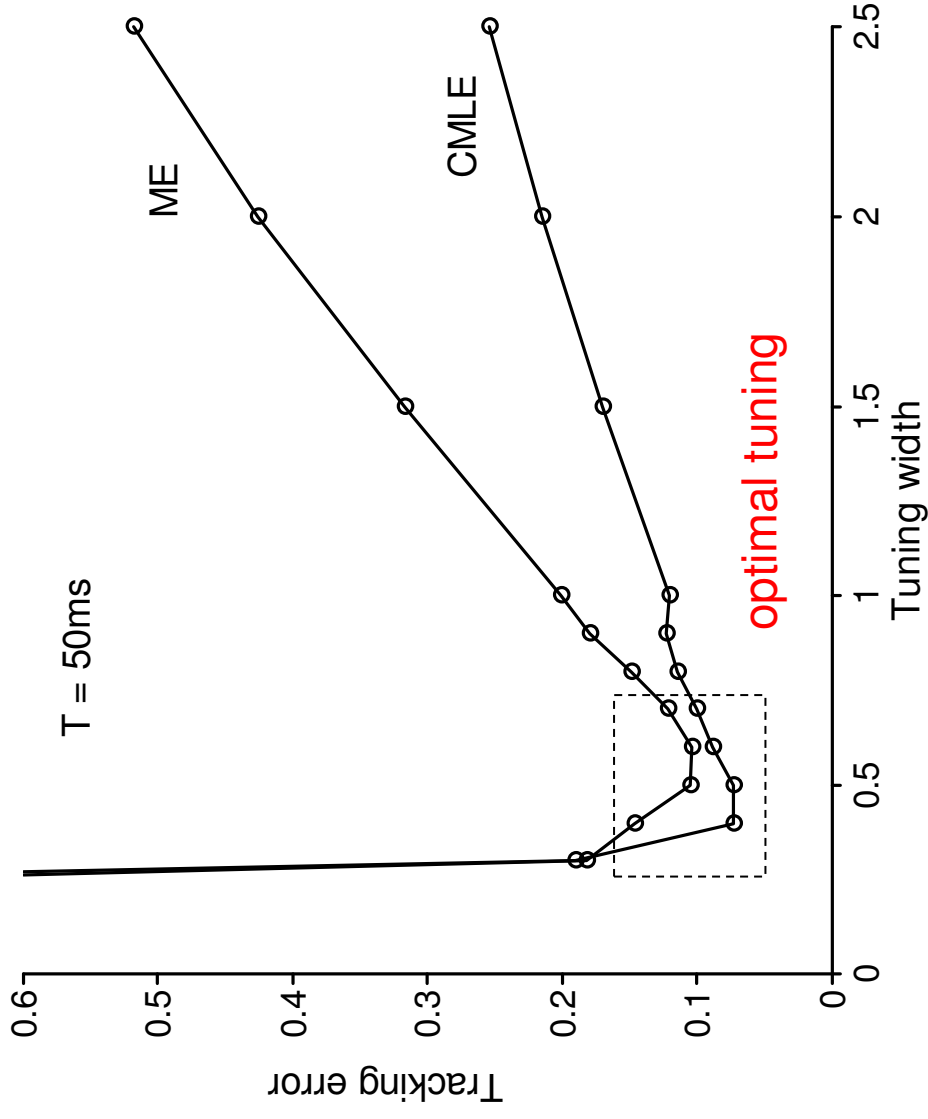


ME (100 ms) Error = 0.19



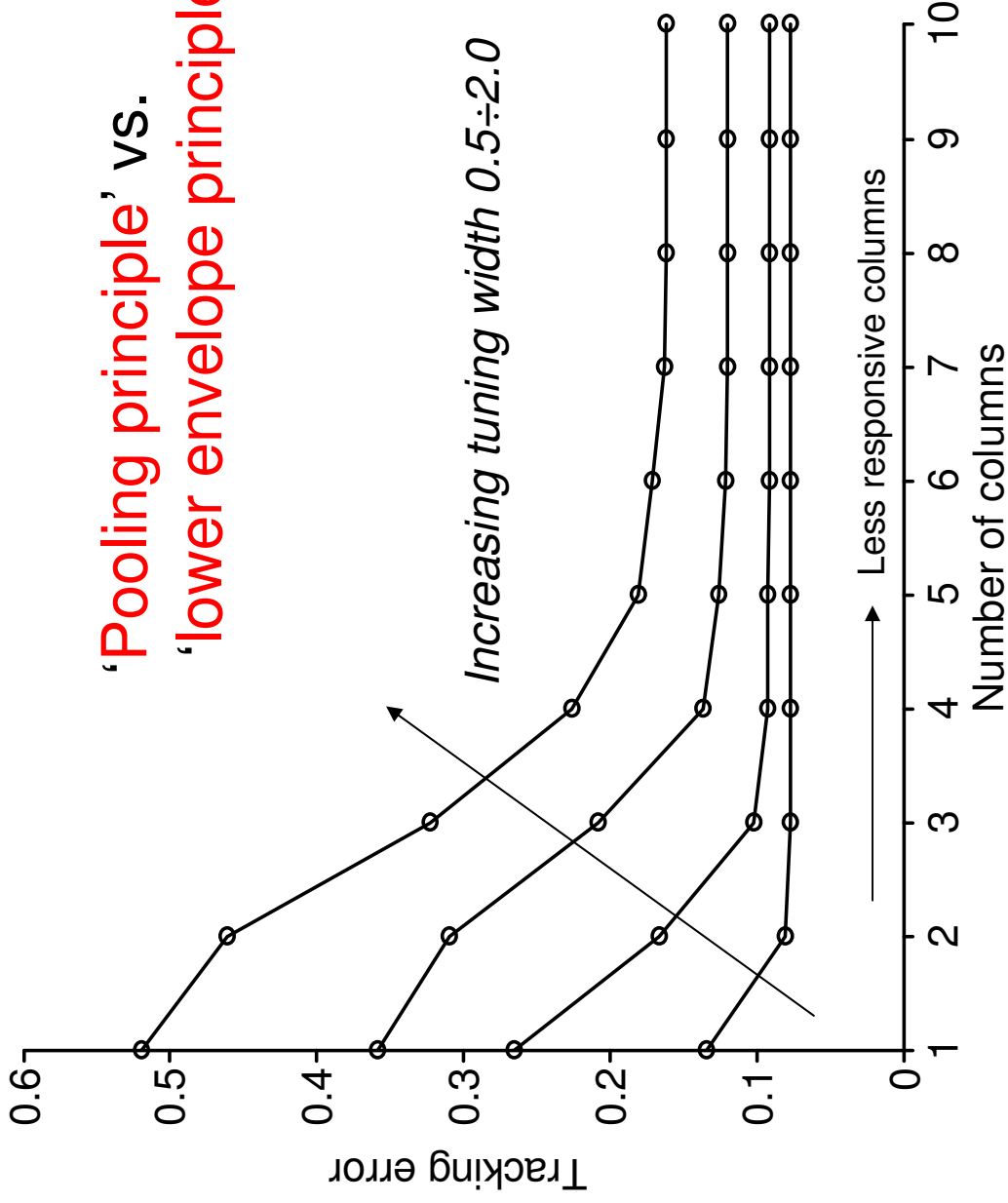
ME (50 ms) Error = 0.32





How does the tuning width affect the tracking accuracy?

**‘Pooling principle’ vs.
‘lower envelope principle’**



Is the tracking accuracy increased by considering also less responsive columns for decoding? Would this increase noise instead?

Conclusions

- We present an optimal unbiased strategy to decode the input information from spike train ensembles
- We have applied such approach to a spiking neuronal network in order to perform a tracking task
- We suggest that general issues regarding population coding can be addressed within this framework