Computational Neuroscience

Lecture 8: Neural encoding

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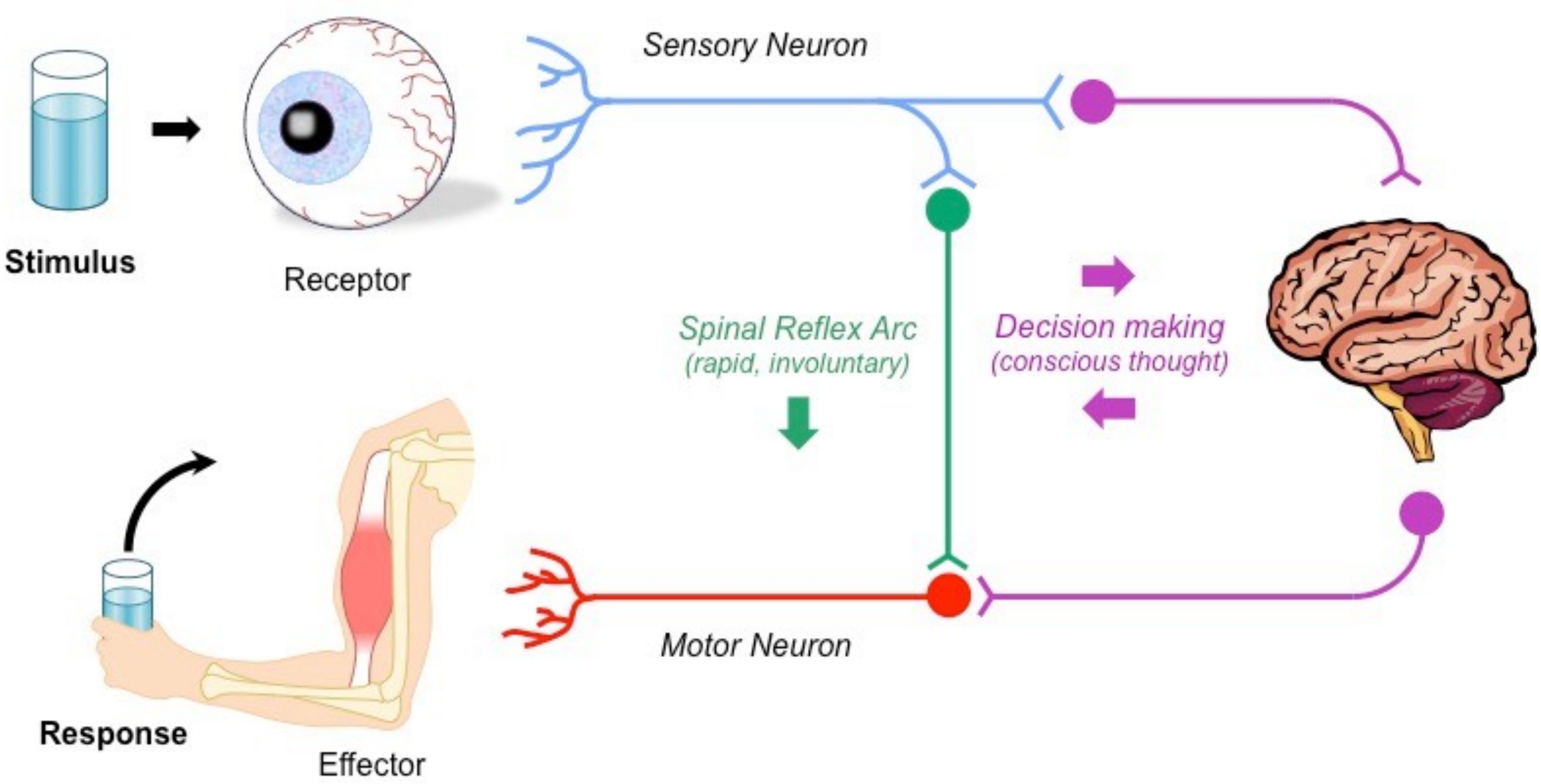
Agenda

- Stimulus, response, spike train
- Spike train statistics
- The neural code

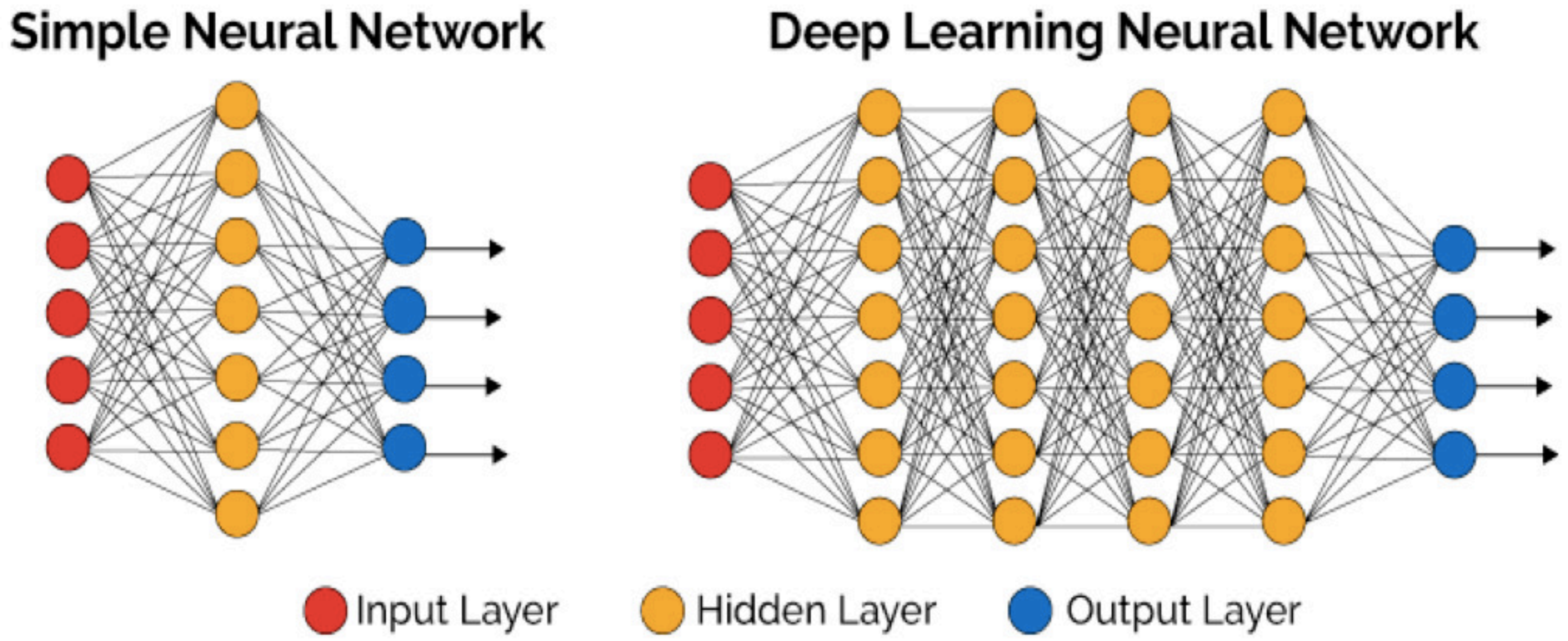
Stimulus, response, spike train

- From stimulus to response
- Spike trains and firing rates
- Variability of spike trains and its source

From stimulus to response

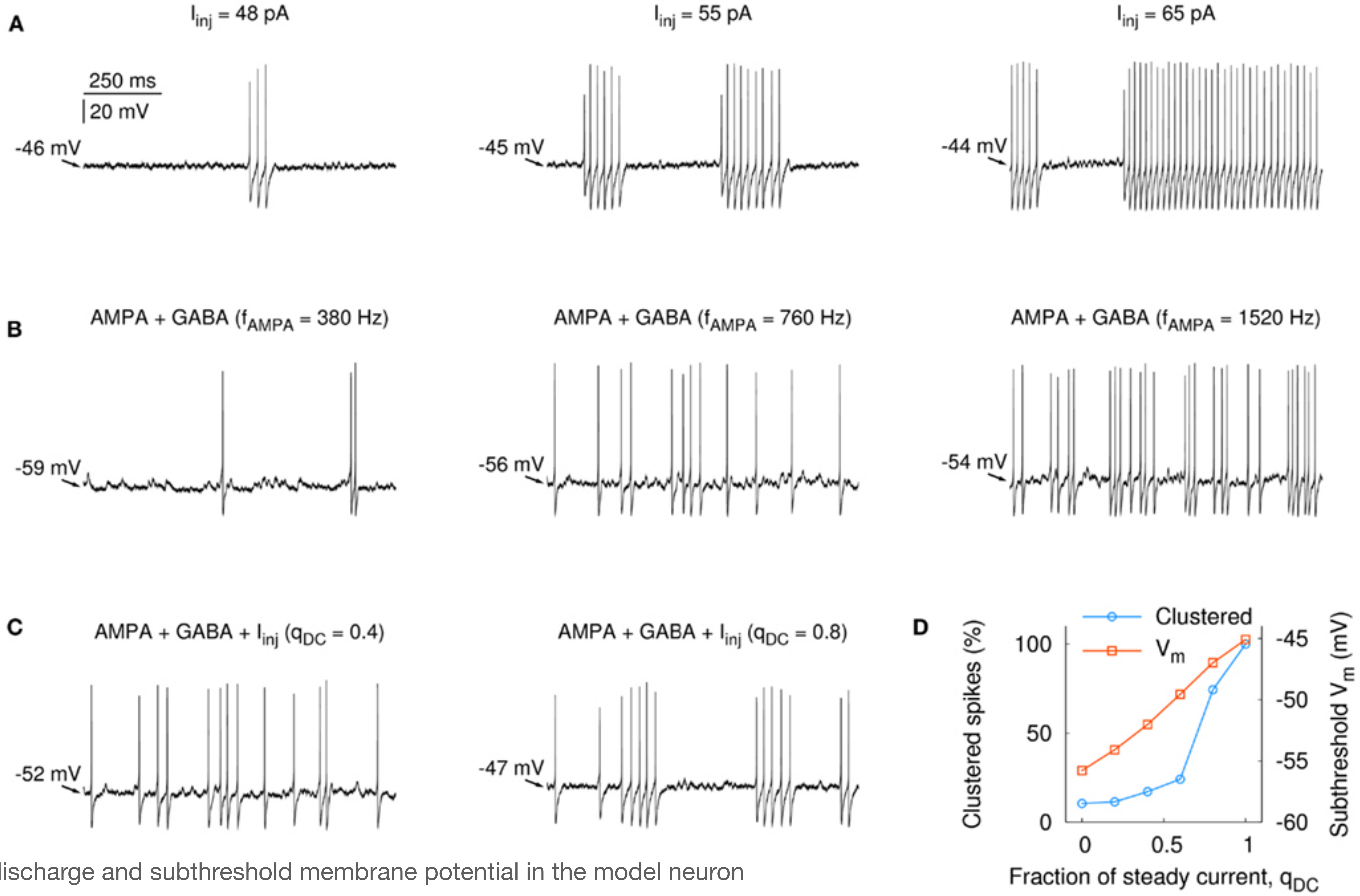


ANN principle architecture

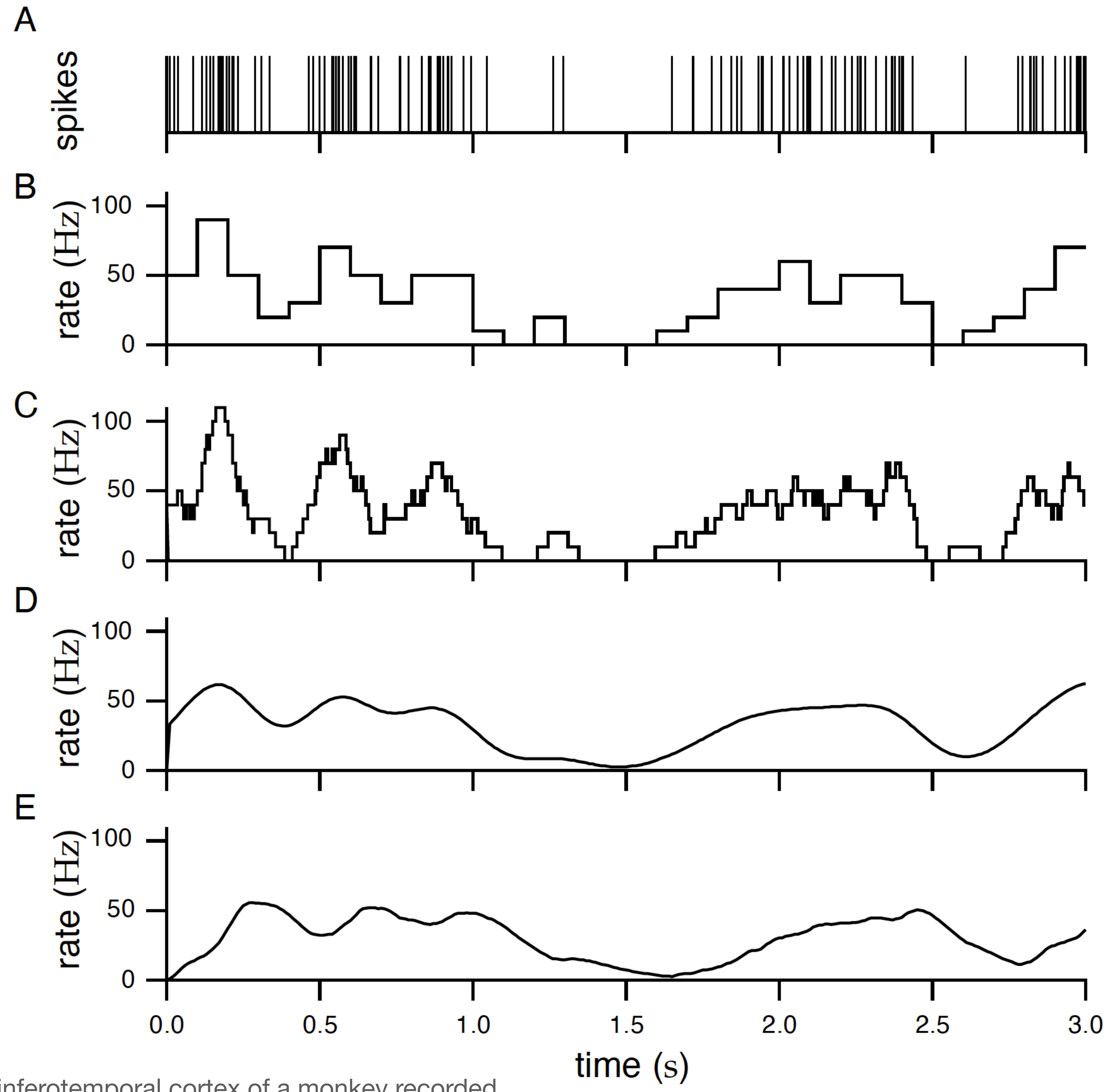



WHAT IF I TOLD YOU
THERE ARE NO OUTPUT LAYERS
IN BIOLOGICAL NEURAL NETWORKS

Spike trains and firing rates

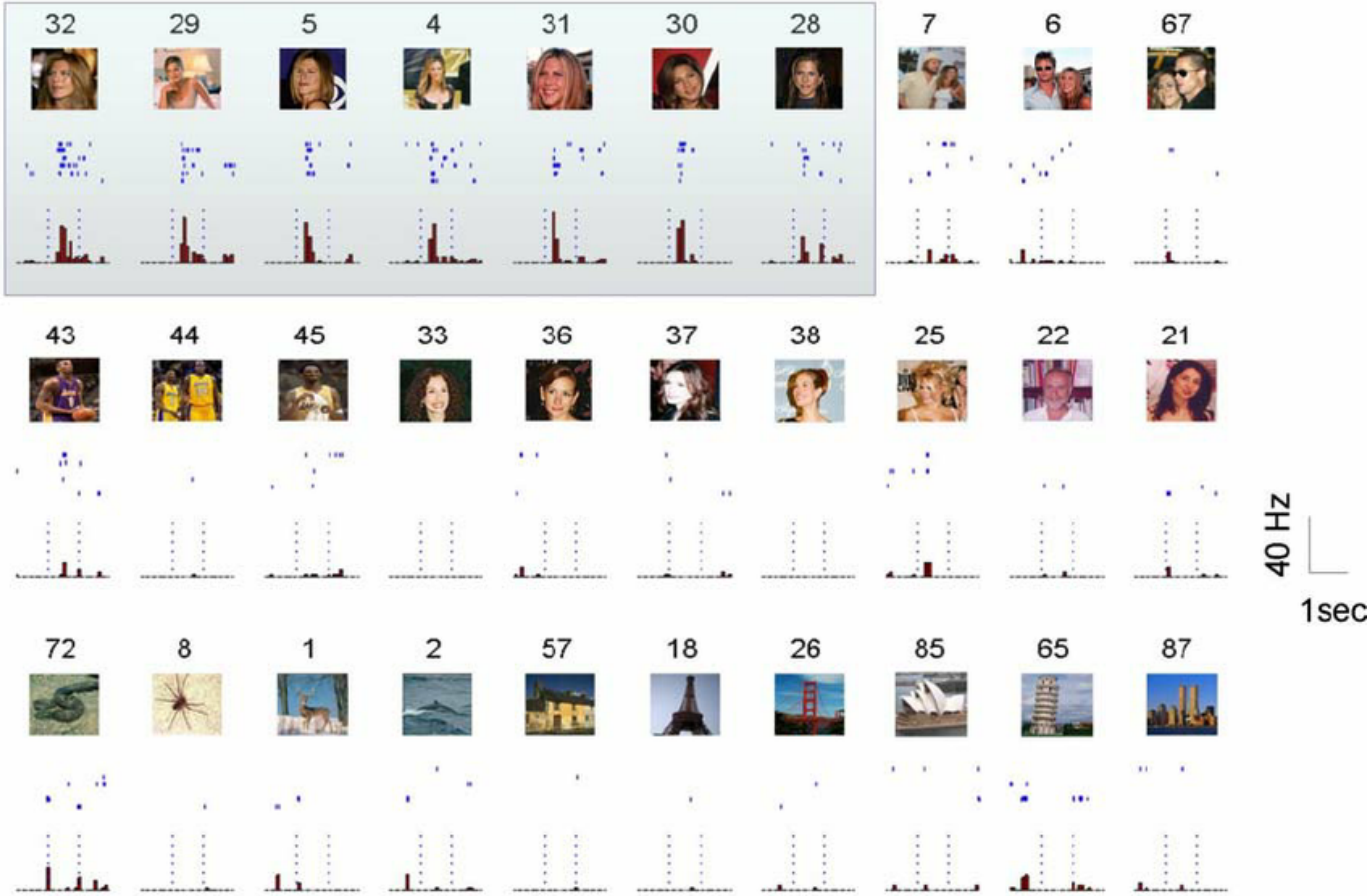


Fast-spiking firing discharge and subthreshold membrane potential in the model neuron



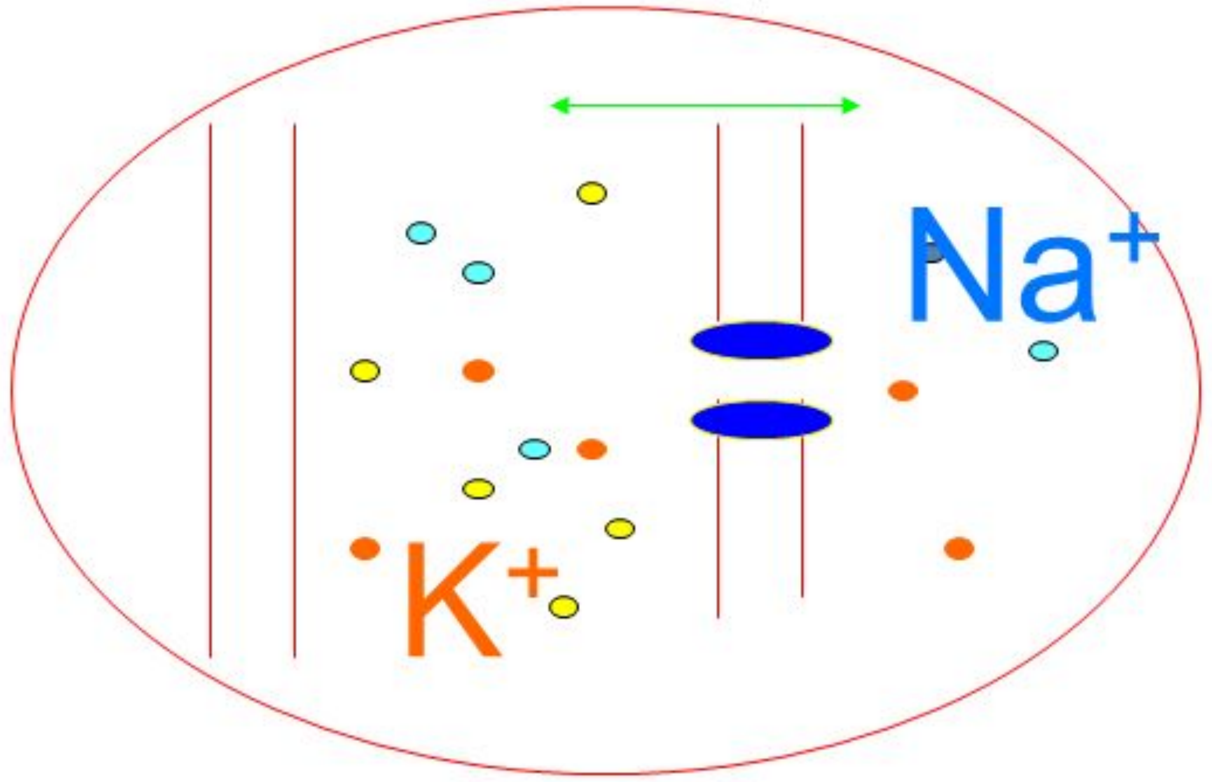
A spike train from a neuron in the inferotemporal cortex of a monkey recorded
while that animal watched a video on a monitor under free viewing conditions

Variability of spike trains



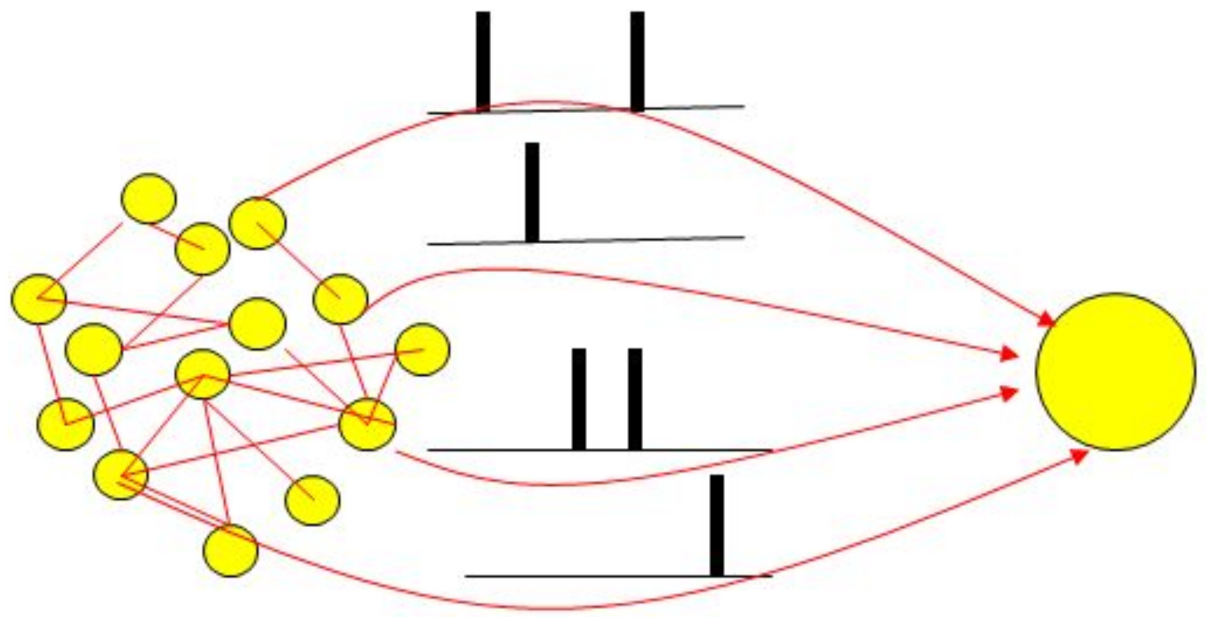
Source of variability

- Intrinsic noise (ion channels)



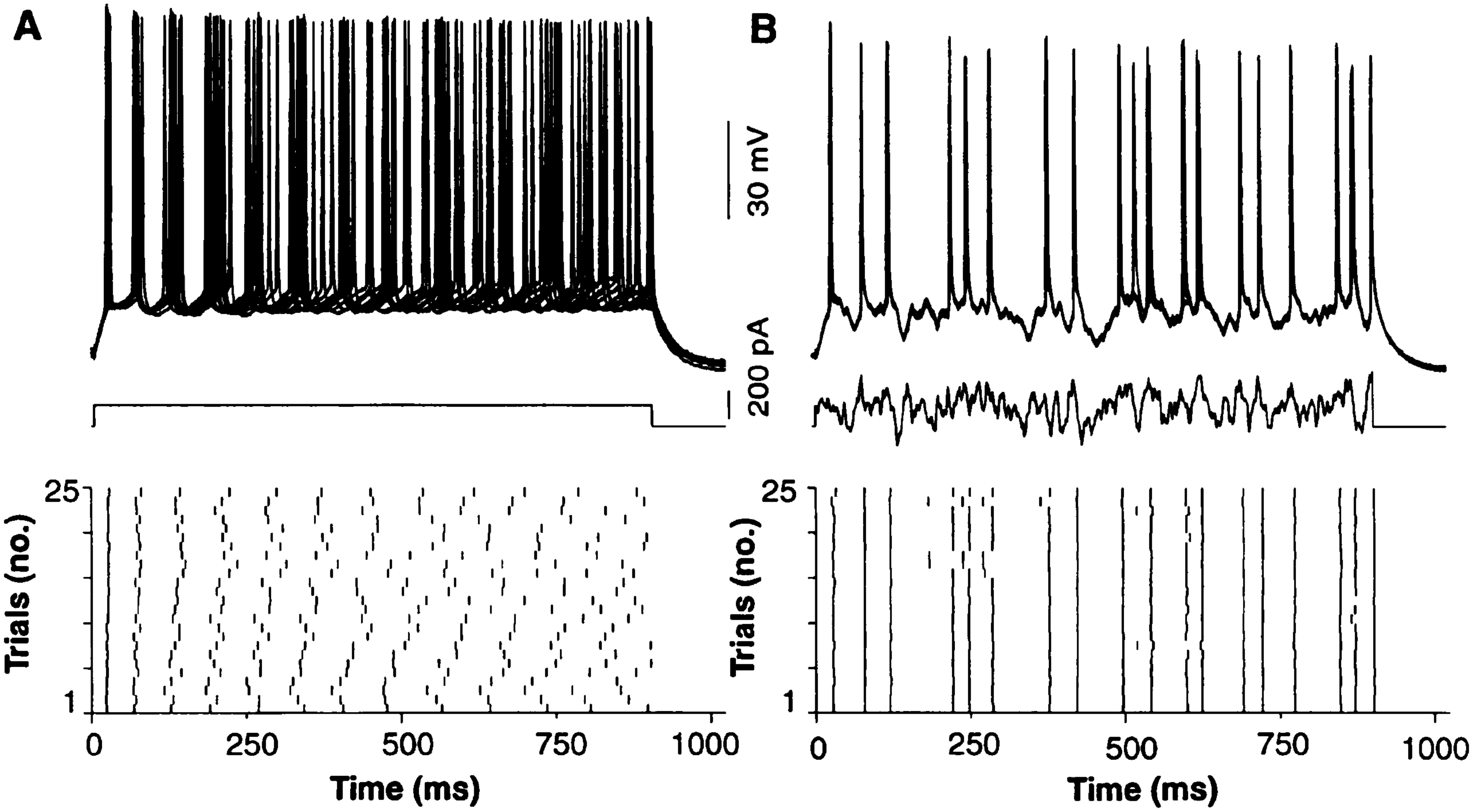
-Finite number of channels
-Finite temperature

-Network noise (background activity)



-Spike arrival from other neurons
-Beyond control of experimentalist

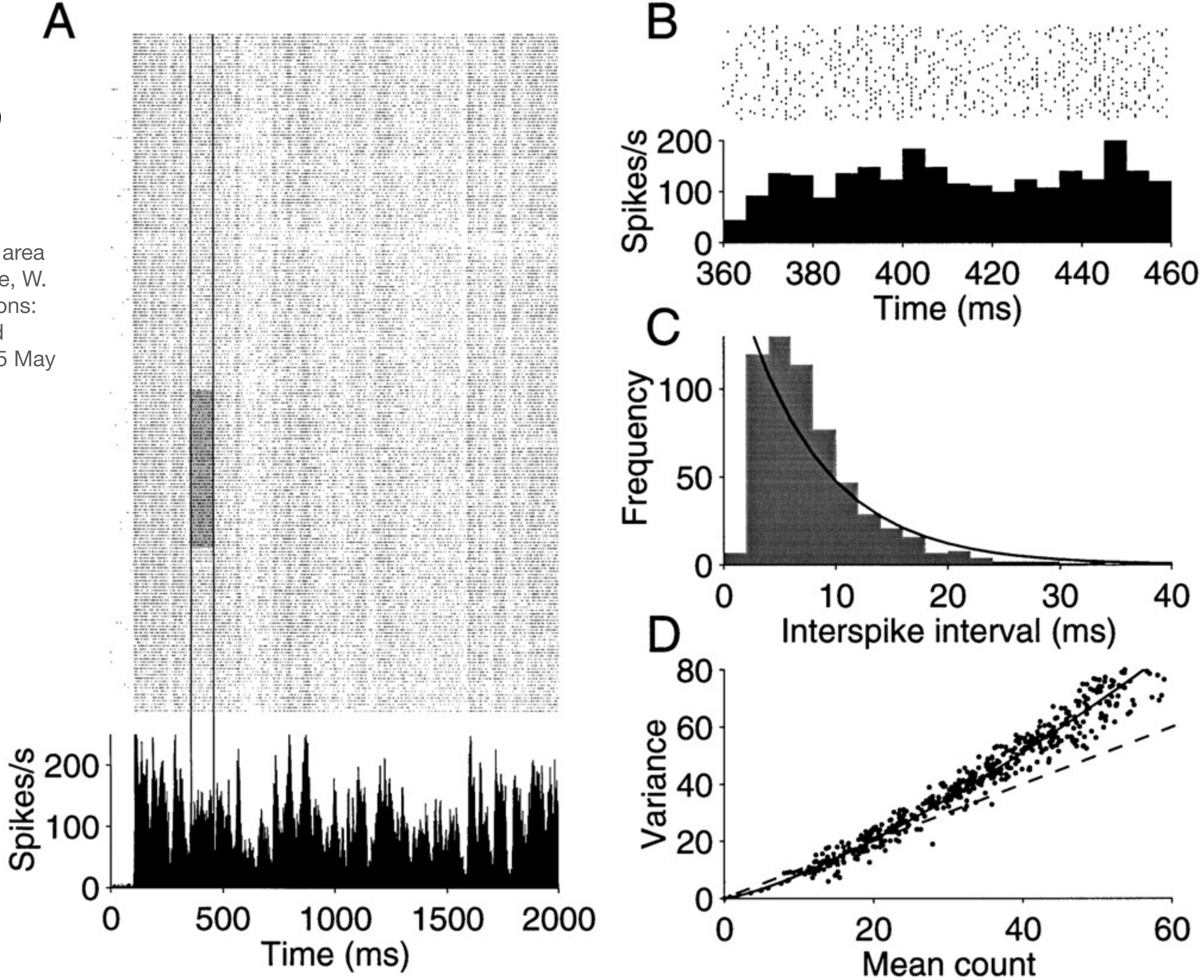
Variability *in-vitro*



Mainen, Z., & Sejnowski, T. (1995). Reliability of spike timing in neocortical neurons. Science, 268(5216), 1503–1506. doi:10.1126/science.7770778

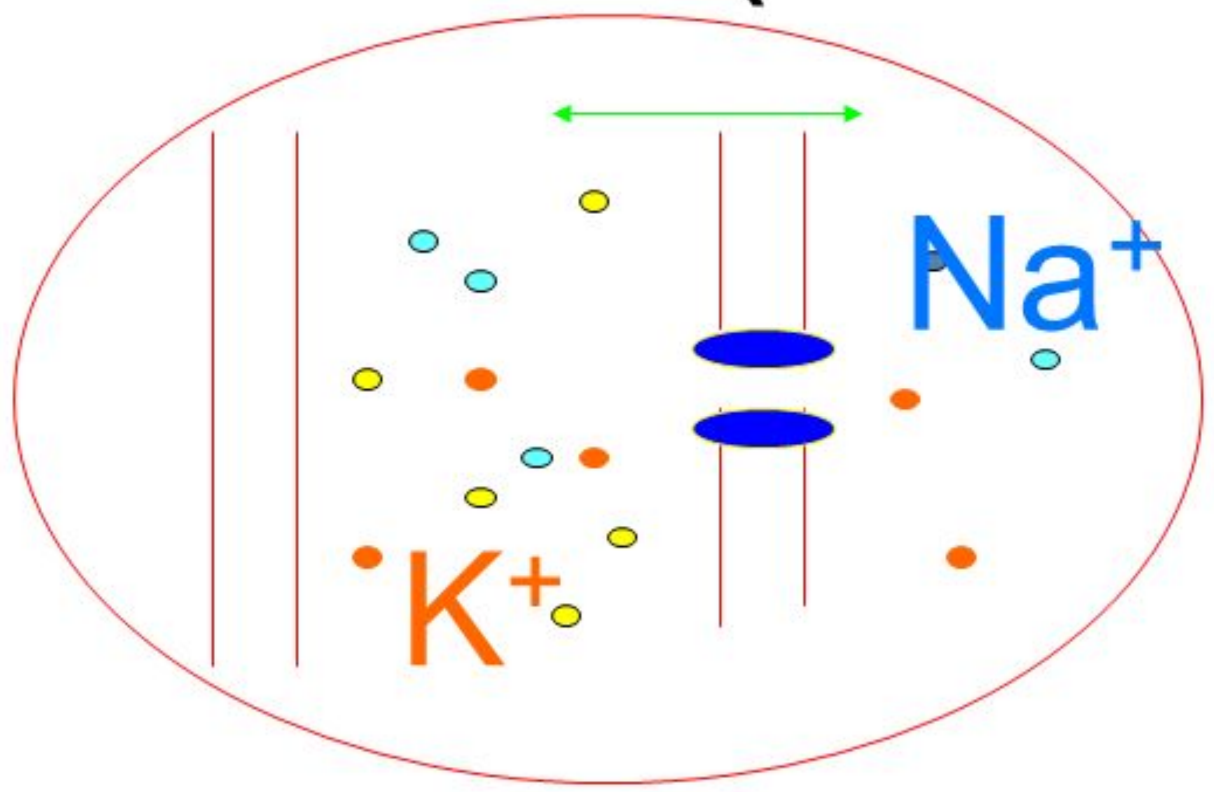
Variability *in-vivo*

Response variability of a neuron recorded from area MT of an alert monkey. Shadlen, M. & Newsome, W. (1998). The Variable Discharge of Cortical Neurons: Implications for Connectivity, Computation, and Information Coding. Journal of Neuroscience 15 May 1998, 18 (10) 3870-3896; DOI: https://doi.org/10.1523/JNEUROSCI.18-10-03870.1998



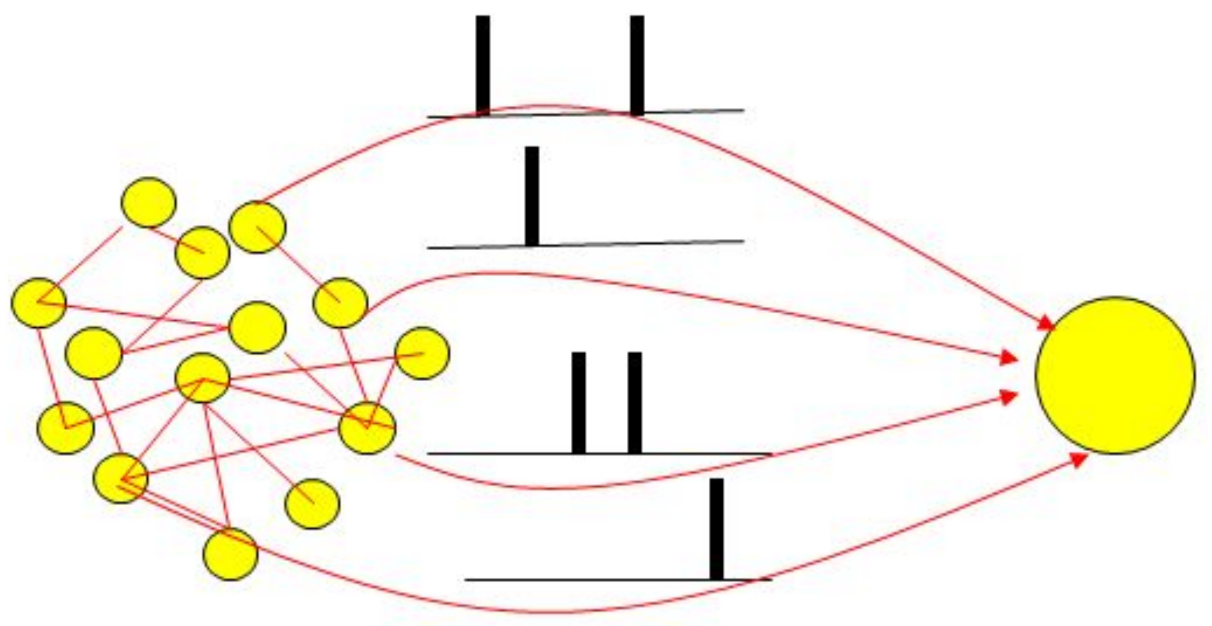
Source of variability

- Intrinsic noise (ion channels)



-Finite number of channels
-Finite temperature

-Network noise (background activity)



-Spike arrival from other neurons
-Beyond control of experimentalist

Spike train statistics

- Poisson model
- Membrane potential fluctuations
- Stochastic spikes

Poisson process

The Poisson process provides an extremely useful approximation of stochastic neuronal firing.

If the number of events per unit time:

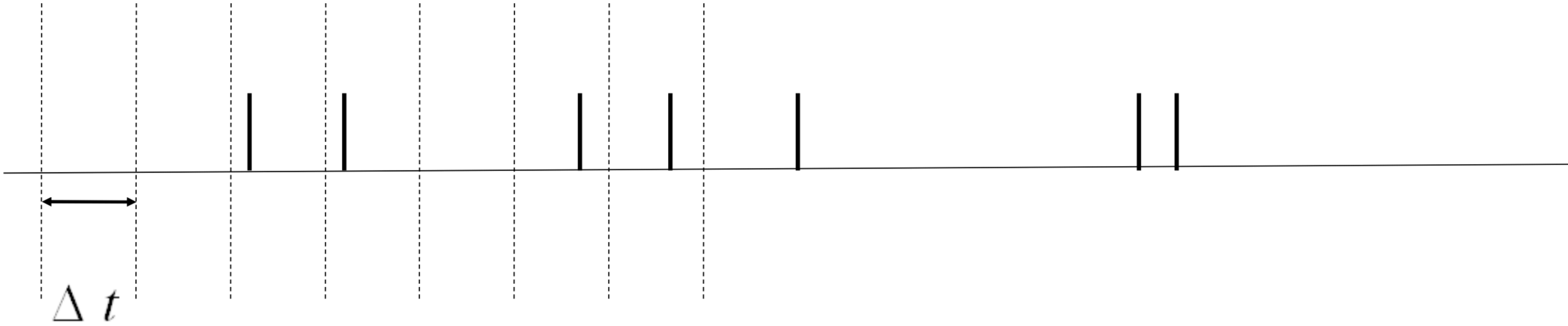
- ρ is constant, then it's homogenous Poisson process (HPP)
- ρ changes over time, then it's non-homogenous Poisson process (NHPP)

Homogenous Poisson process (HPP)

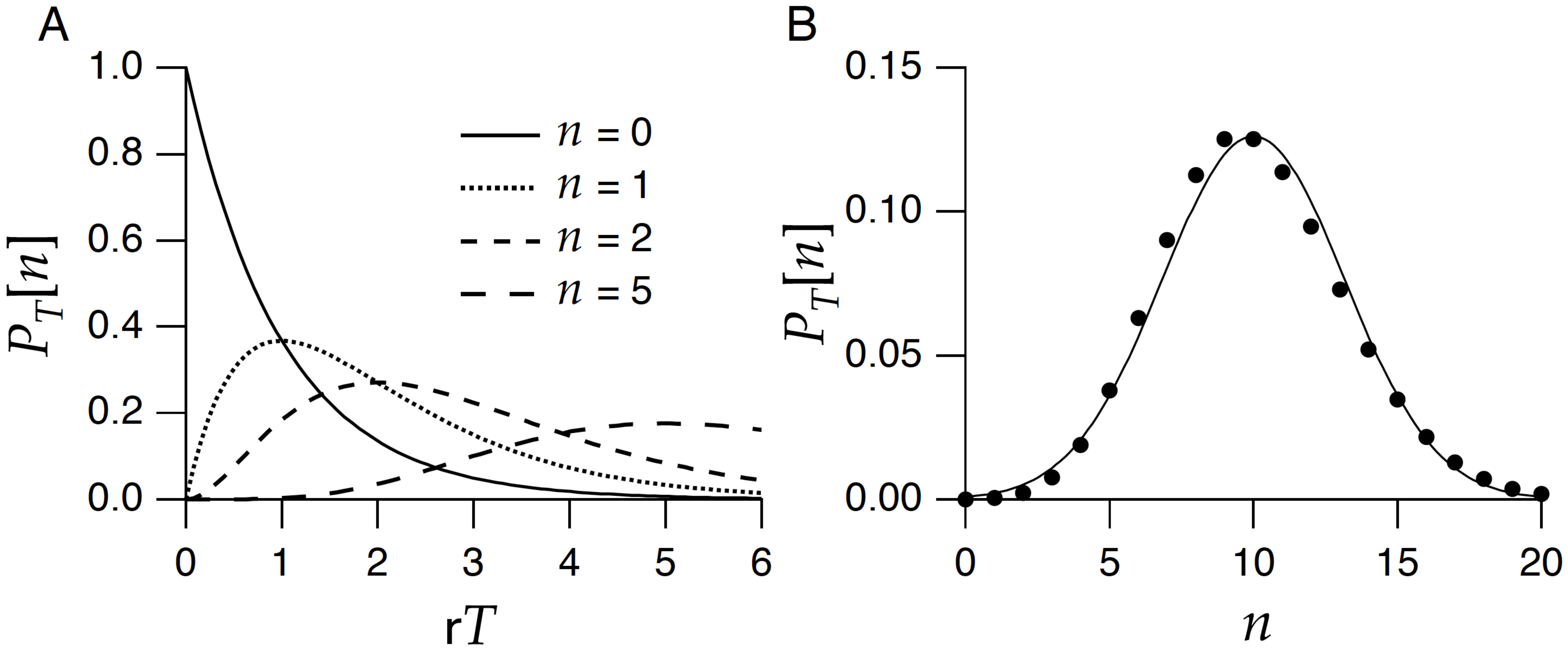
Rate is constant

Probability of firing: $P_F = \rho_0 \Delta t$

Survival function: $\frac{d}{dt} S(t_1 \mid t_0) = -\rho_0 S(t_1 \mid t_0)$



Homogenous Poisson process (HPP)



(A) The probability that a homogeneous Poisson process generates n spikes in a time period of duration T plotted for $n = 0$,1,2, and 5. The probability is plotted as function of the rate times the duration of the interval, rT, to make the plot applicable for any rate. (B) The probability of finding n spikes during a time period for which r$T = 10$ (dots) compared with a Gaussian distribution with mean and variance equal to 10 (line).

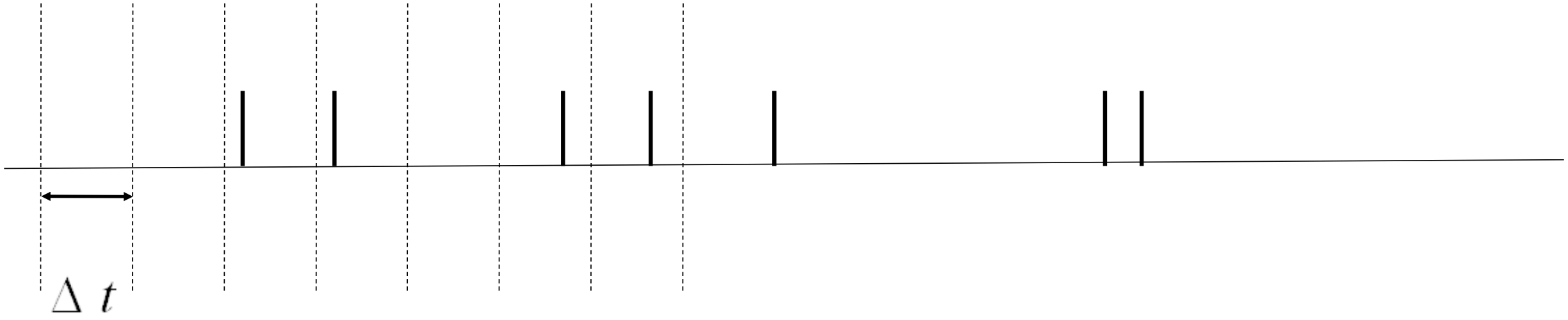
Non-homogenous Poisson process (NHPP)

Rate changes

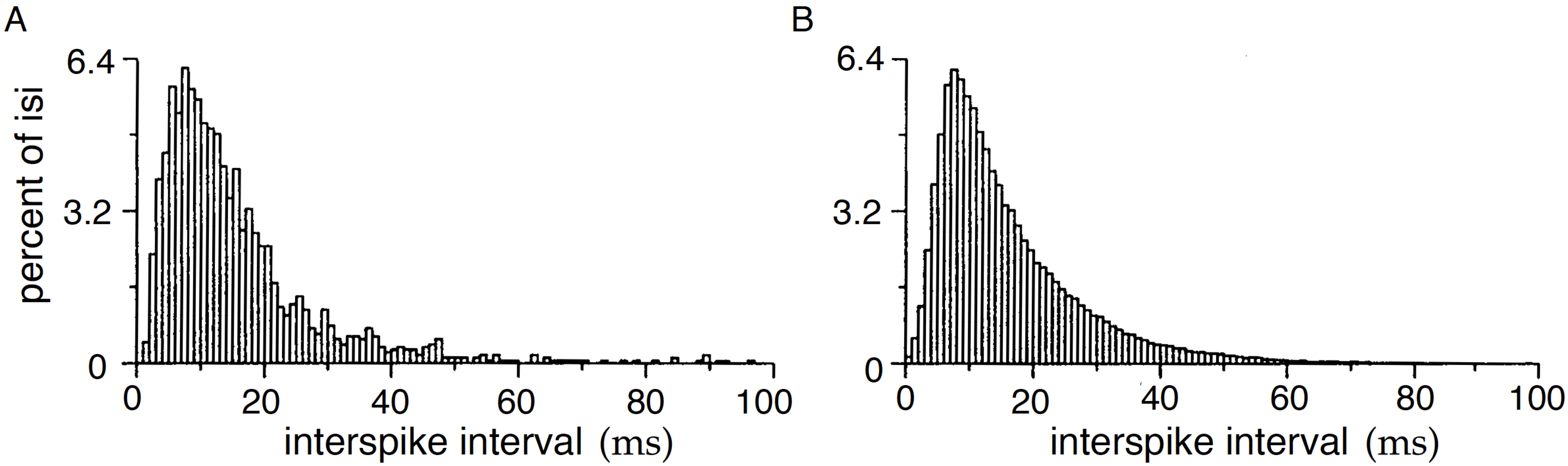
Probability of firing: $P_F = \rho(t)\Delta t$

Survival function: $S(t \mid \hat{t}) = exp(-\int_{\hat{t}}^{t} \rho(t')dt')$

Interval distribution: $P(t \mid \hat{t}) = \rho(t)S(t \mid \hat{t})$

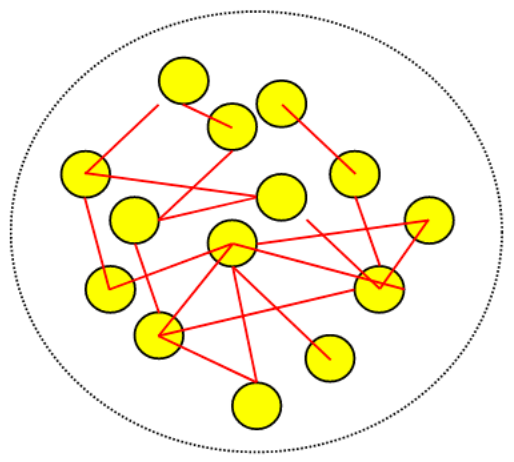


Comparison with data

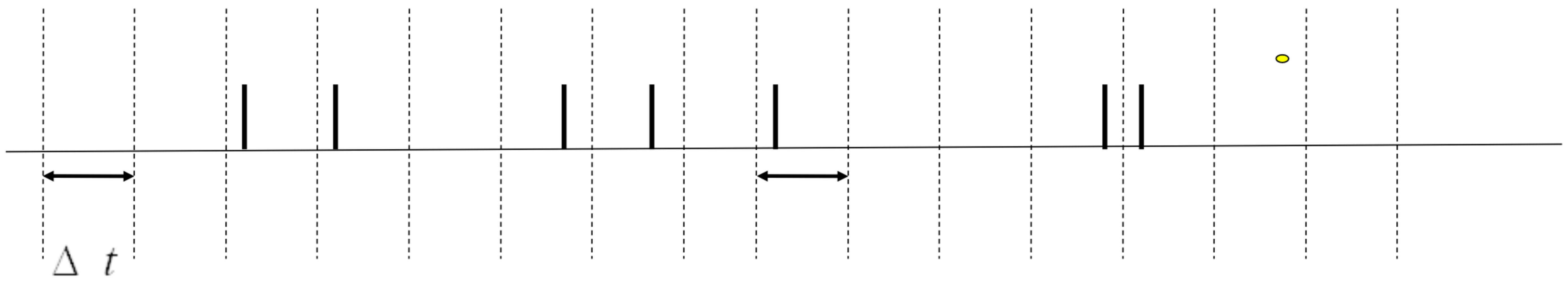


(A) Interspike interval distribution from an MT neuron responding to a moving, random-dot image. The probability of interspike intervals falling into the different bins, expressed as a percentage, is plotted against interspike interval. (B) Interspike interval histogram generated from a Poisson model with a stochastic refractory period. (Adapted from Bair et al., 1994.)

Stochastic spike arrival

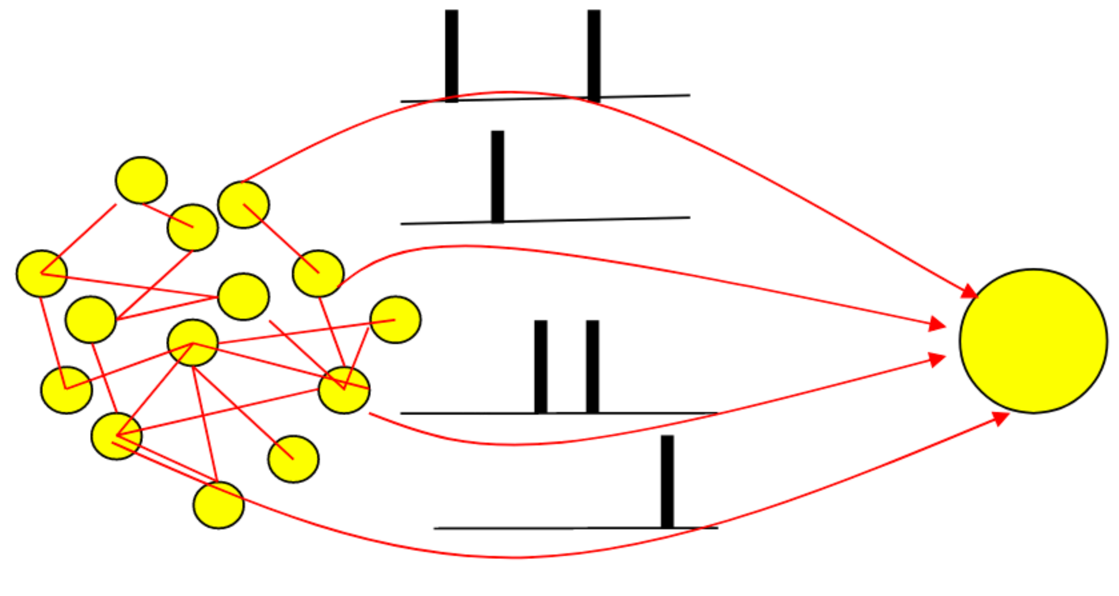


Total spike train of K presynaptic neurons



spike train

Pull out one neuron



Probability of spike arrival:

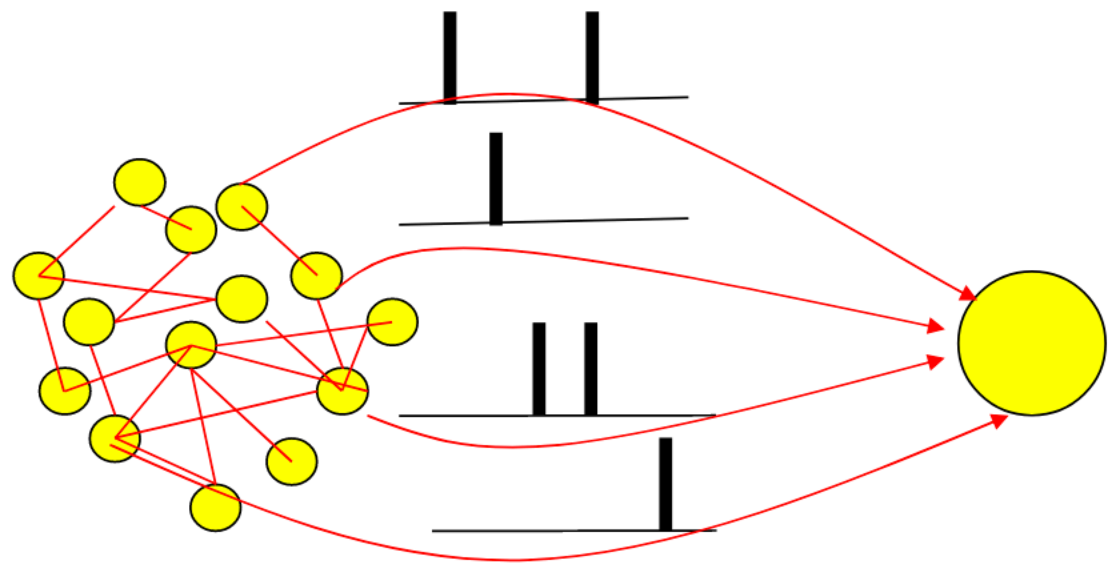
$$P_F = K \rho_0 \, \Delta t$$

Take $\Delta t \to 0$

expectation

$$S(t) = \sum_{k=1}^{K} \sum_{f} \delta(t - t_k^f)$$

Membrane potential fluctuations



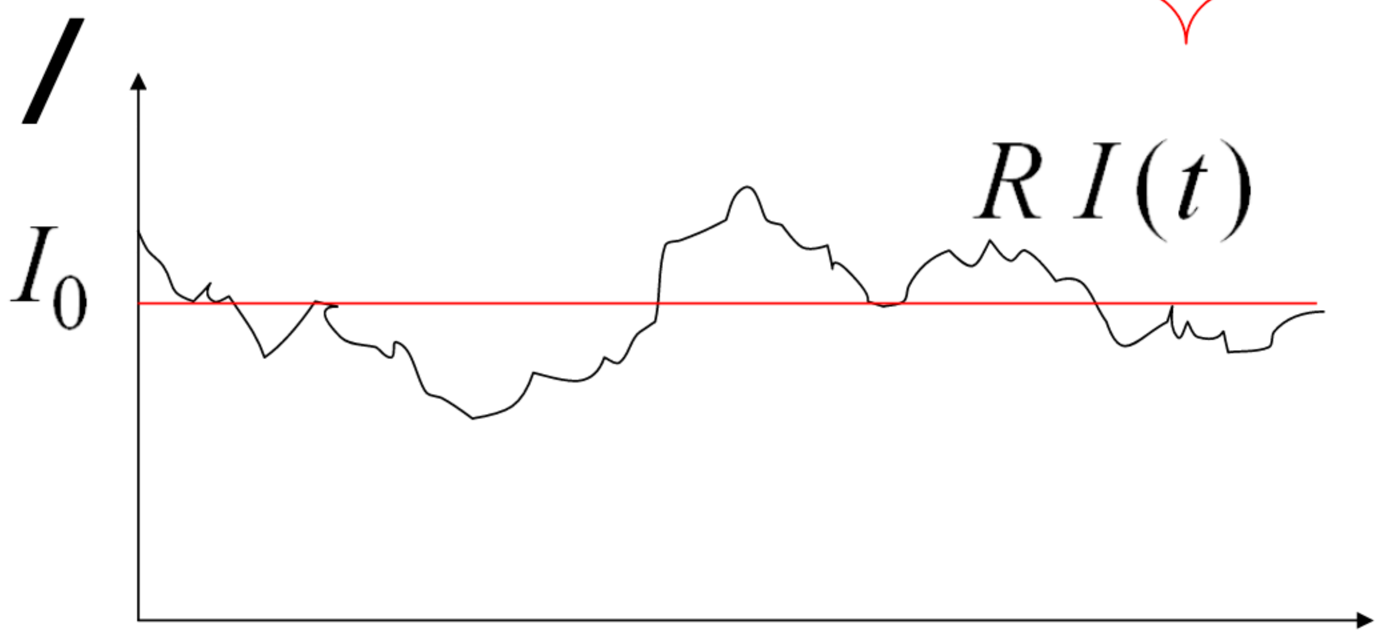
Synaptic current pulses of shape α

$$RI^{syn}(t) = \sum_k w_k \sum_f \alpha(t - t_k^f)$$

EPSC

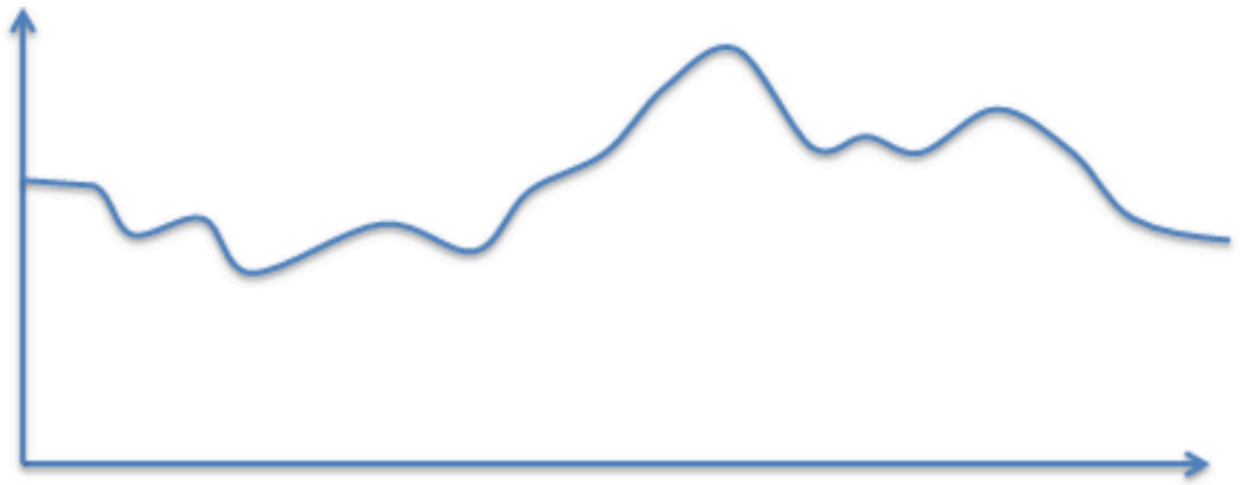
Passive membrane

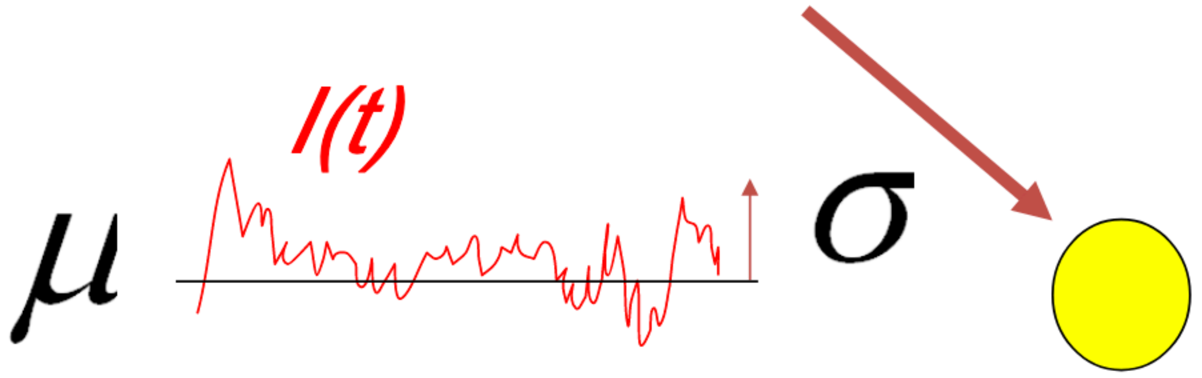
$$\tau \frac{d}{dt}u = -(u - u_{rest}) \quad + RI^{syn}(t)$$



$$I^{syn}(t) = I_0 + I^{fluct}(t)$$

→ Fluctuating potential

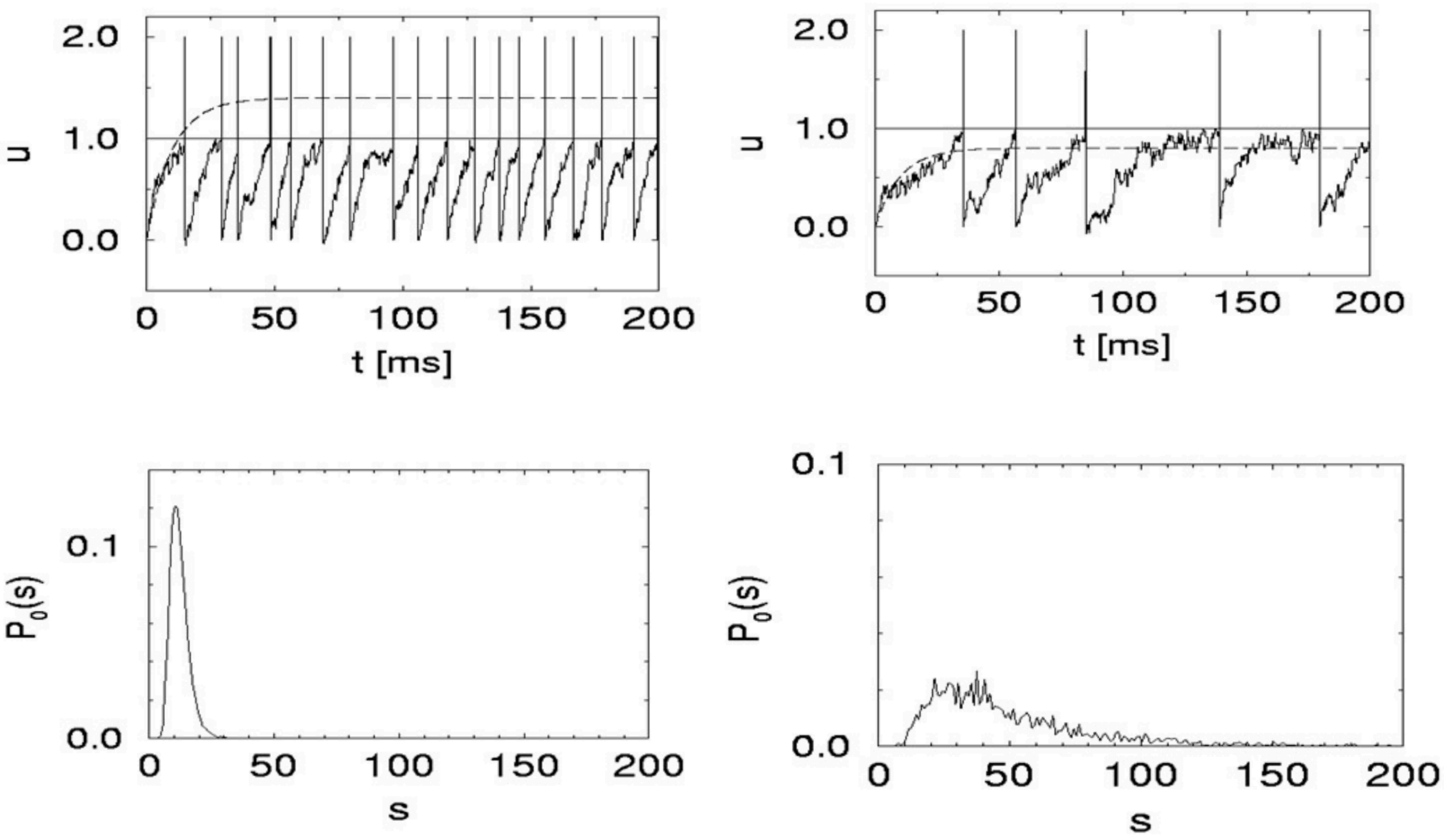




Fluctuating input current

Stochastic spikes in IF models

Superthreshold vs. Subthreshold regime



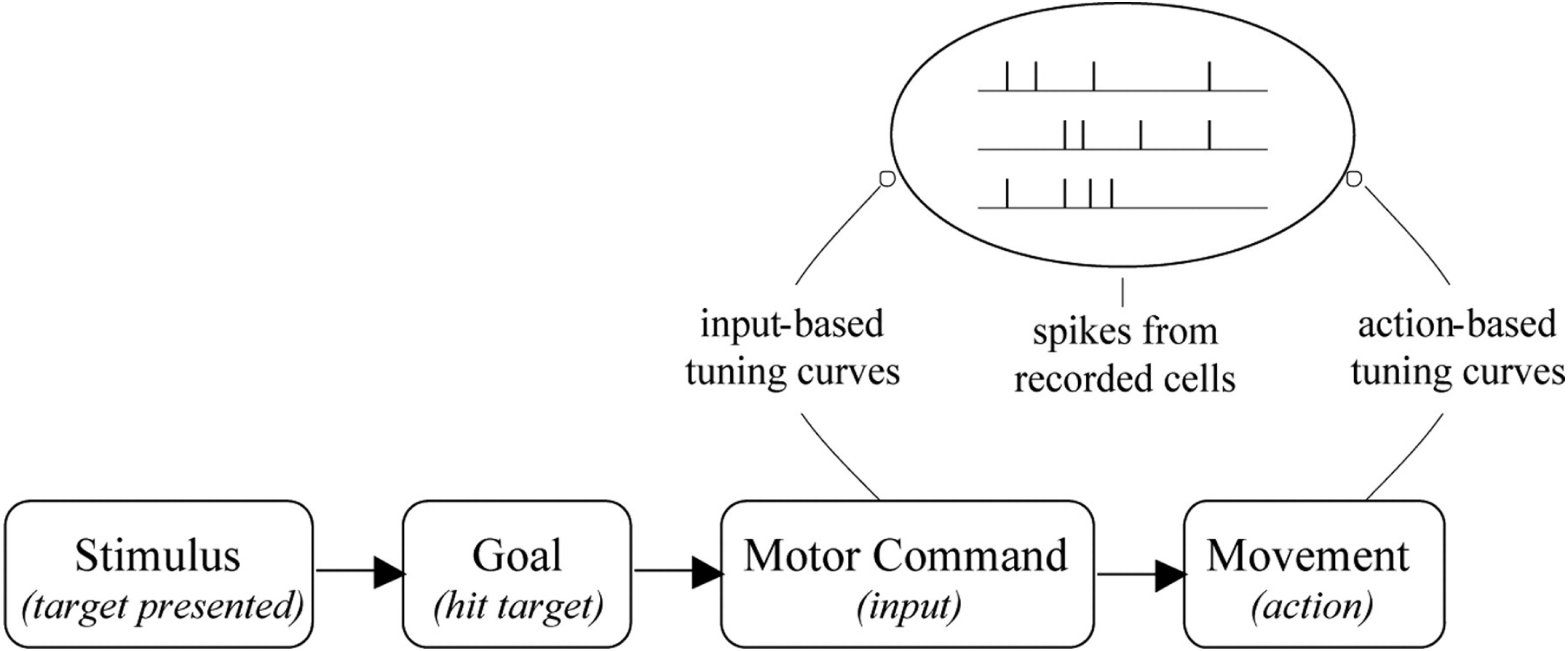
The neural code

- What is neural code?
- Encoding/decoding
- Types of neural code

Neural code

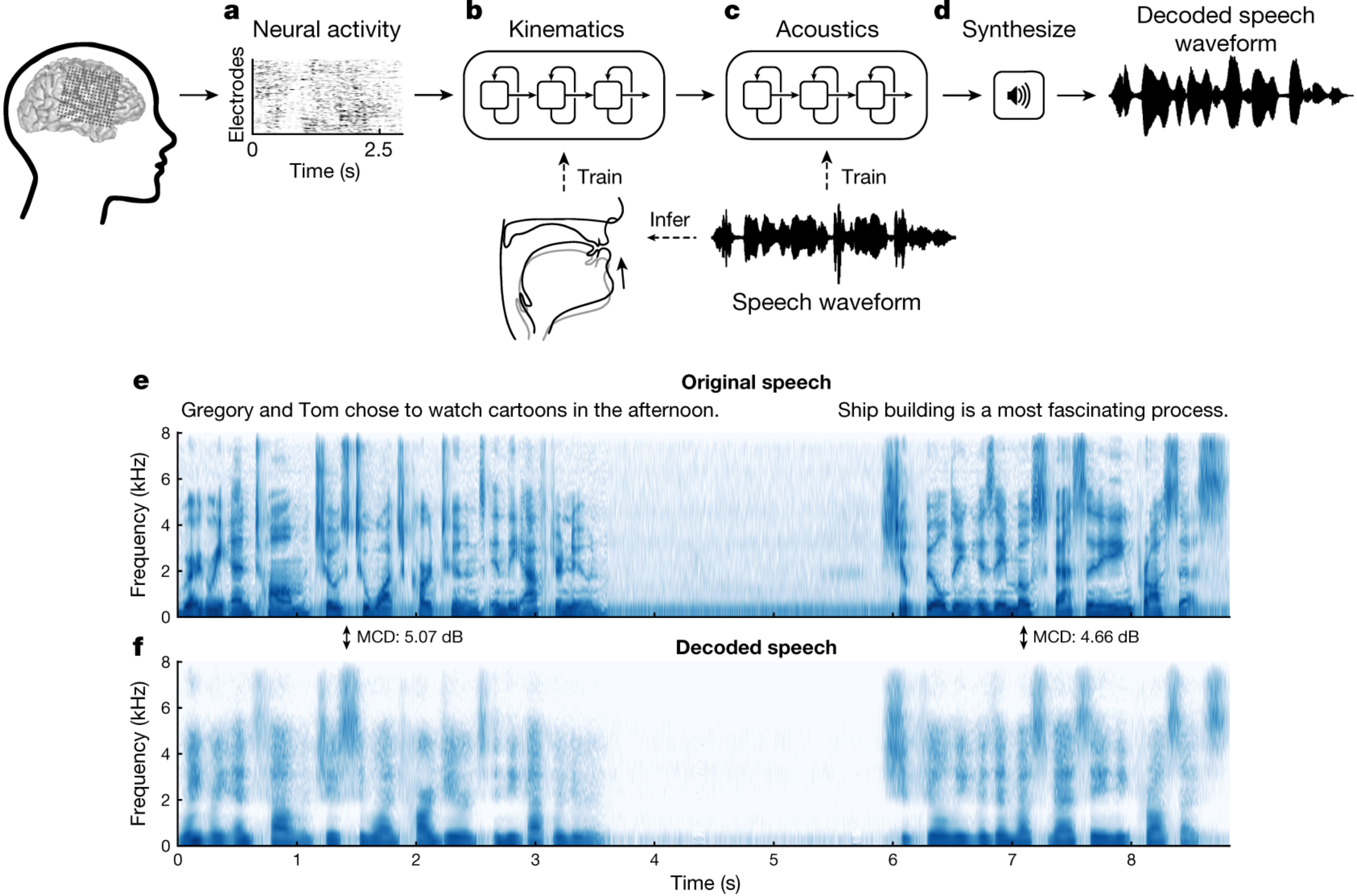
encoding
decoding
encoding most
frequent stimuli
perception
of stimuli
learning
statistical
model
reproducing
the stimuli
thinking
behavior

Encoding


input-based
tuning curves
spikes from
recorded cells
action-based
tuning curves
Stimulus
(target presented)
Goal
(hit target)
Motor Command
(input)
Movement
(action)

Decoding

- Neural decoding is the process of taking statistical consistencies, a statistical model of the world, and reproducing the stimuli
- Maps to the process of thinking and acting, which in turn guide what stimuli we receive
- Completes the "*stimuli → response → behavior → stimuli → ...*" loop



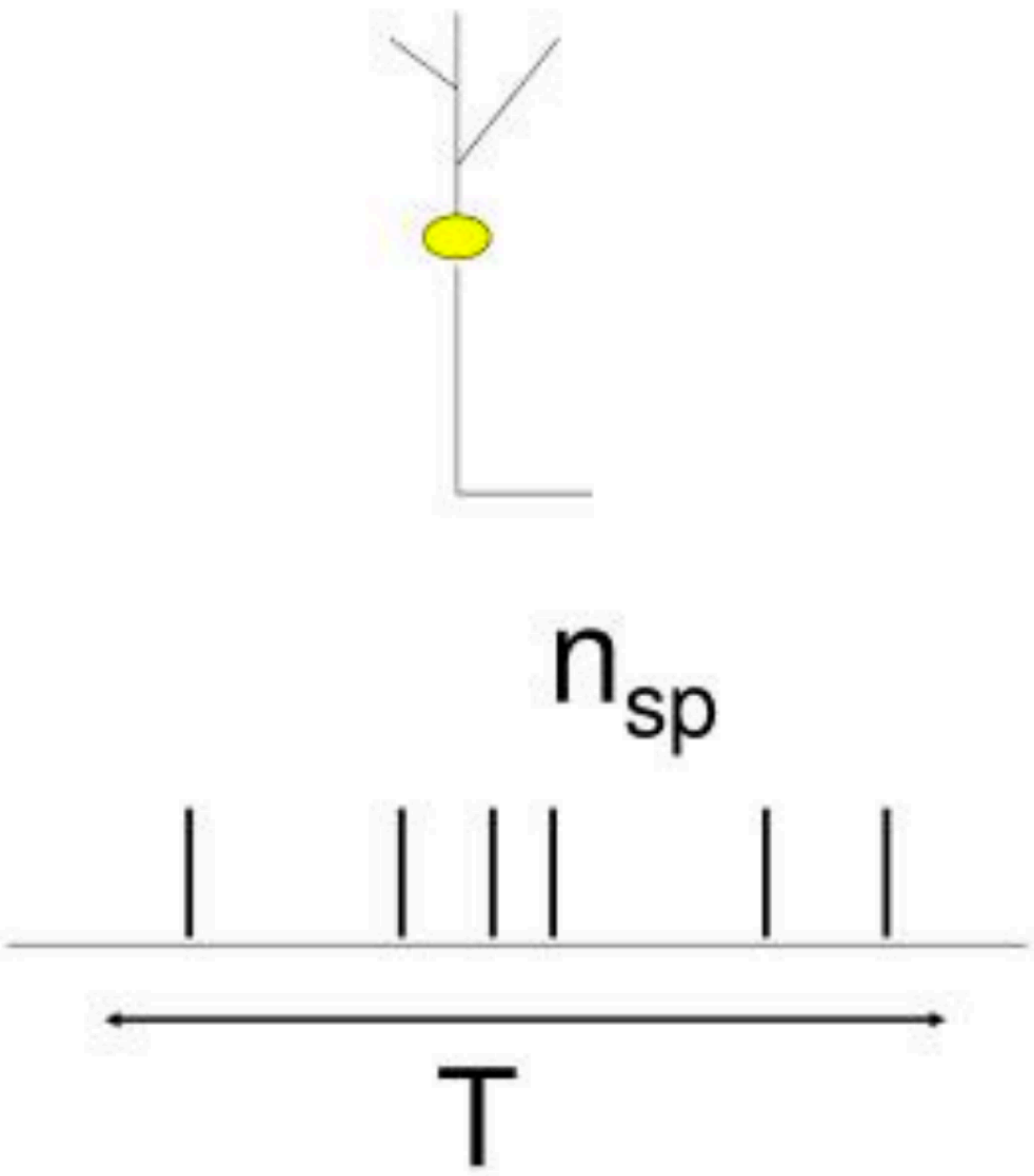
Anumanchipalli, G.K., Chartier, J. & Chang, E.F. Speech synthesis from neural decoding of spoken sentences. *Nature* **568,** 493–498 (2019). https://doi.org/10.1038/s41586-019-1119-1

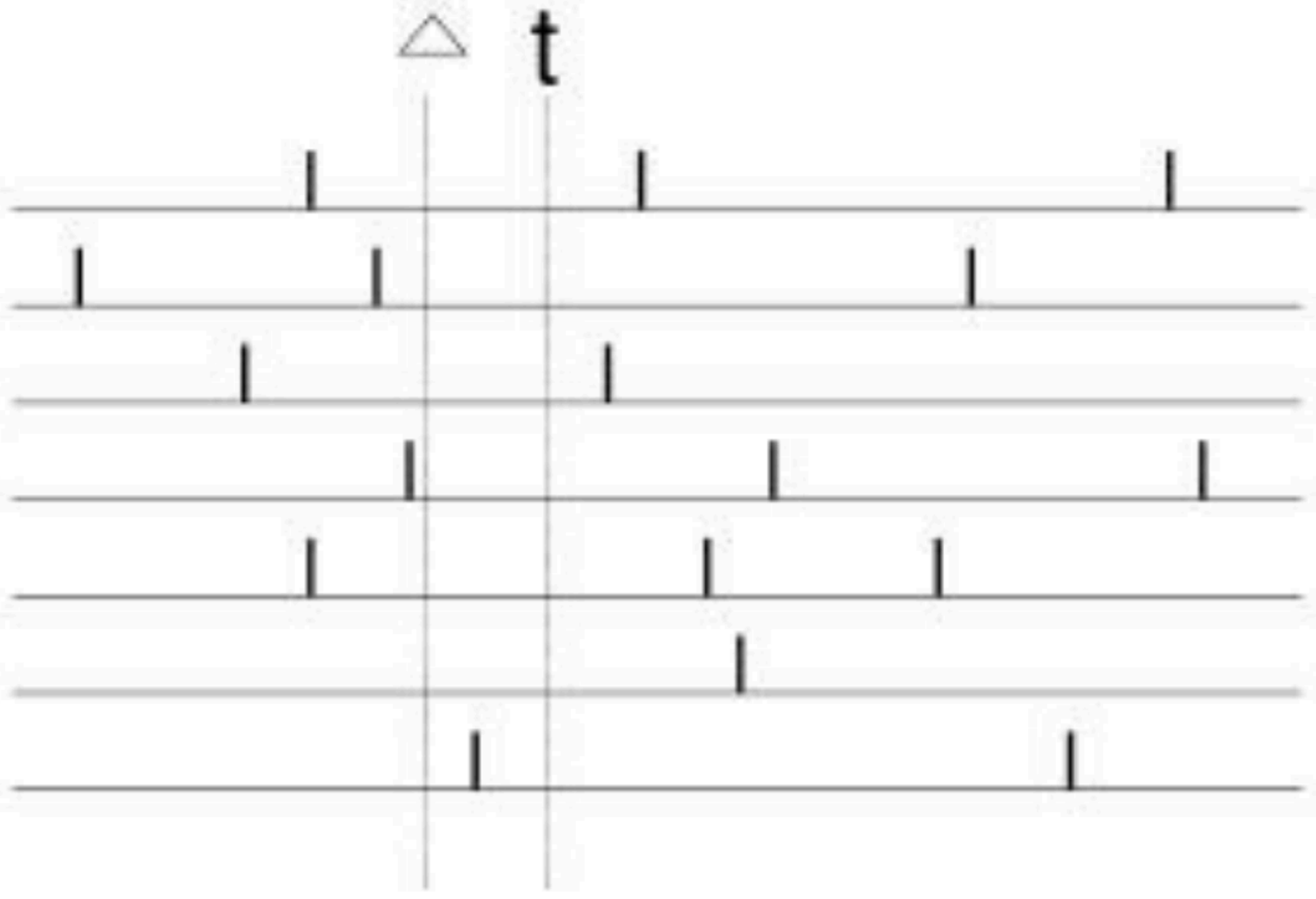
Speech synthesis decoding

Neural coding scheme (hypothesized)

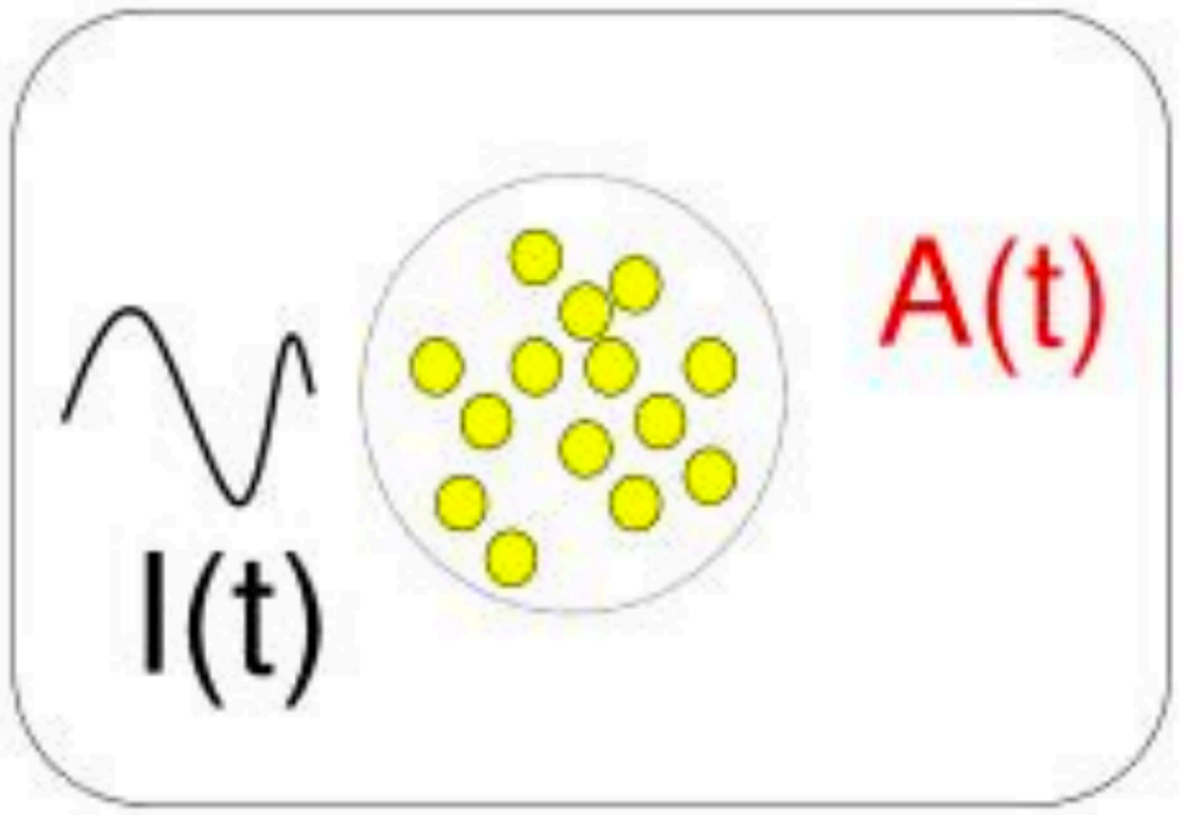
- **Rate** coding
- **Temporal** code
- **Population** code
- **Sparse** code

Rate coding





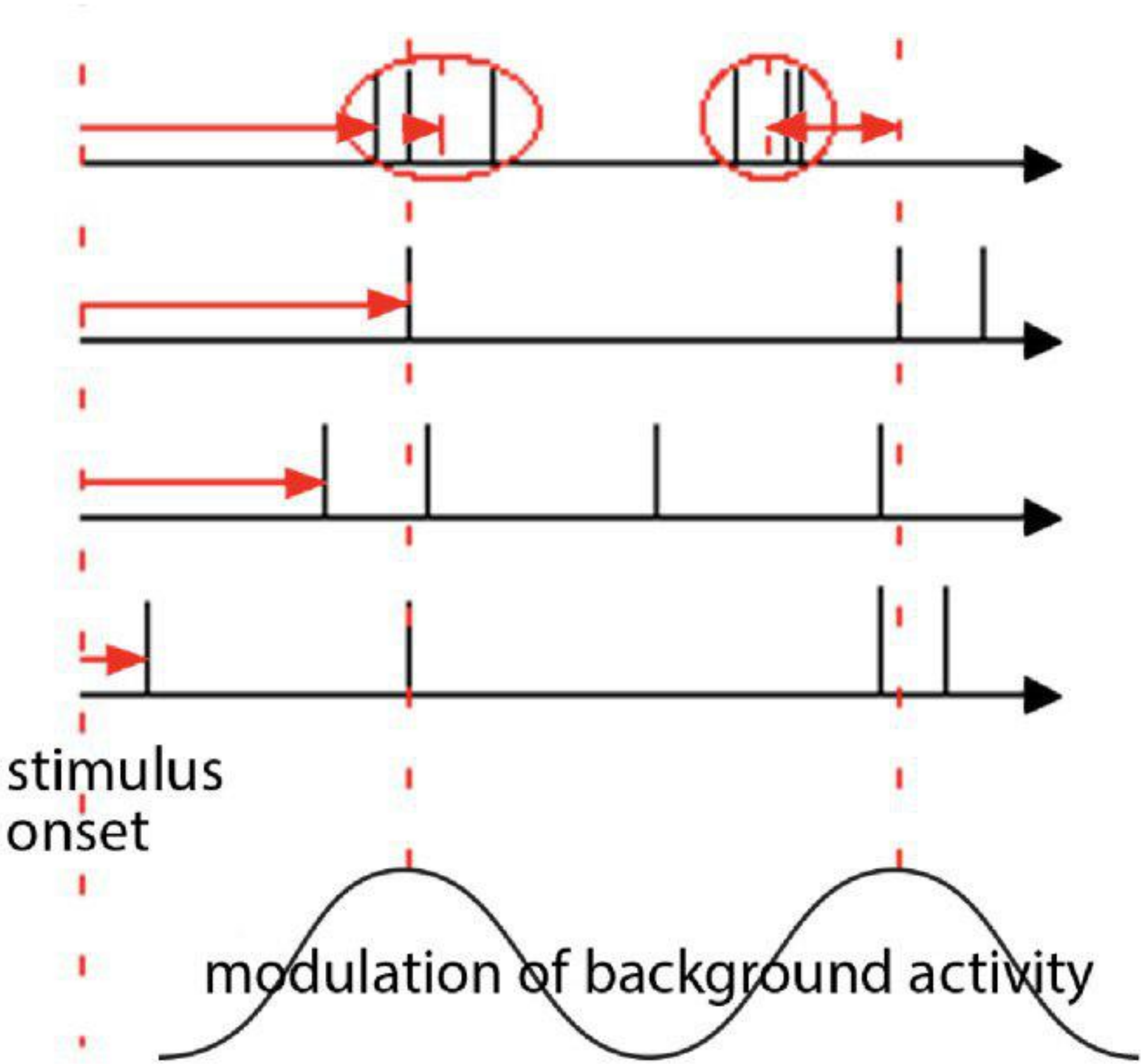
$$PSTH(t) = \frac{n(t;t+\Delta t)}{K\,\Delta t}$$



$$A(t) = \frac{n(t;t+\Delta t)}{N\Delta t}$$

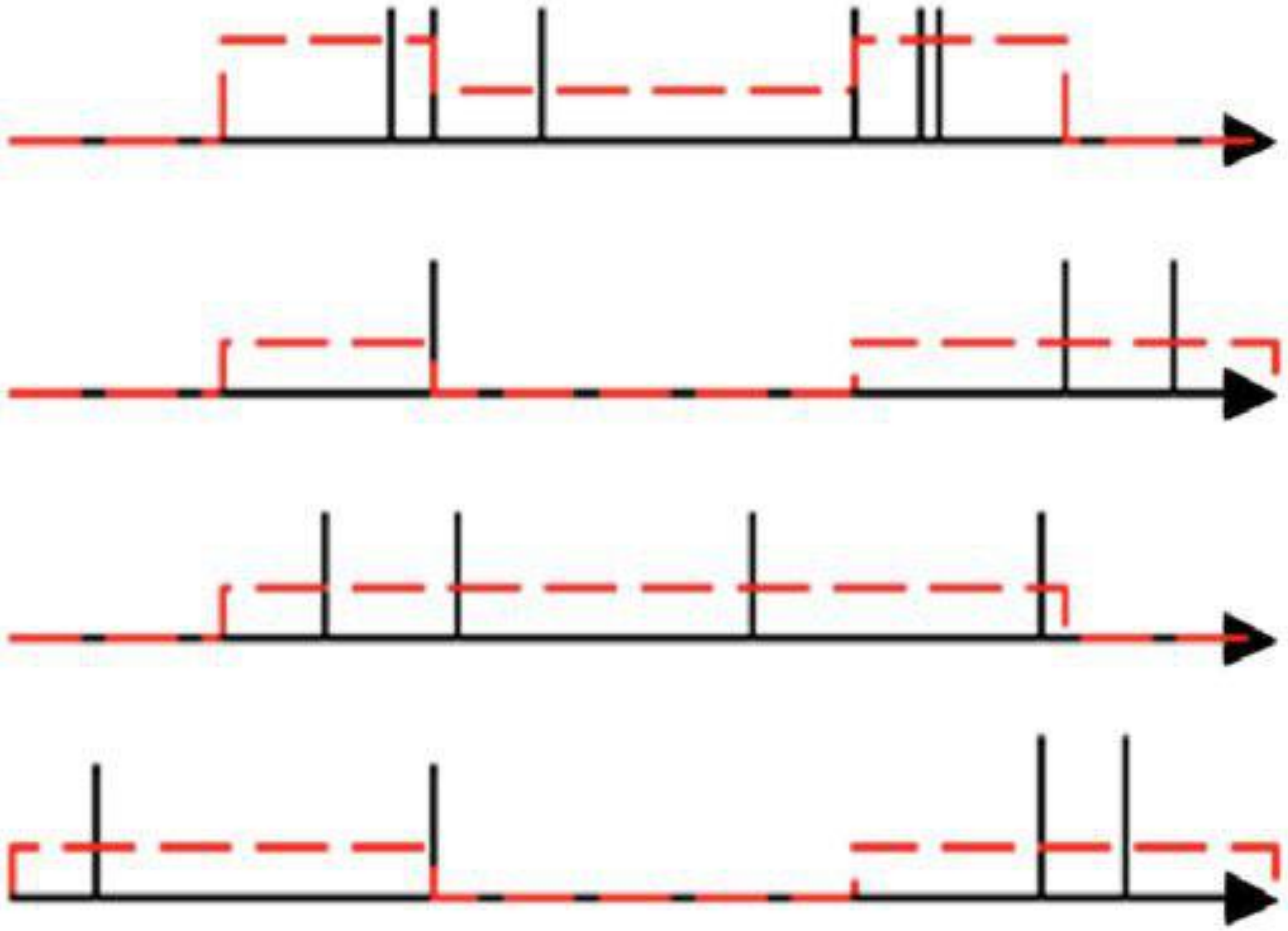
population activity

Temporal coding



Patterns across time and space

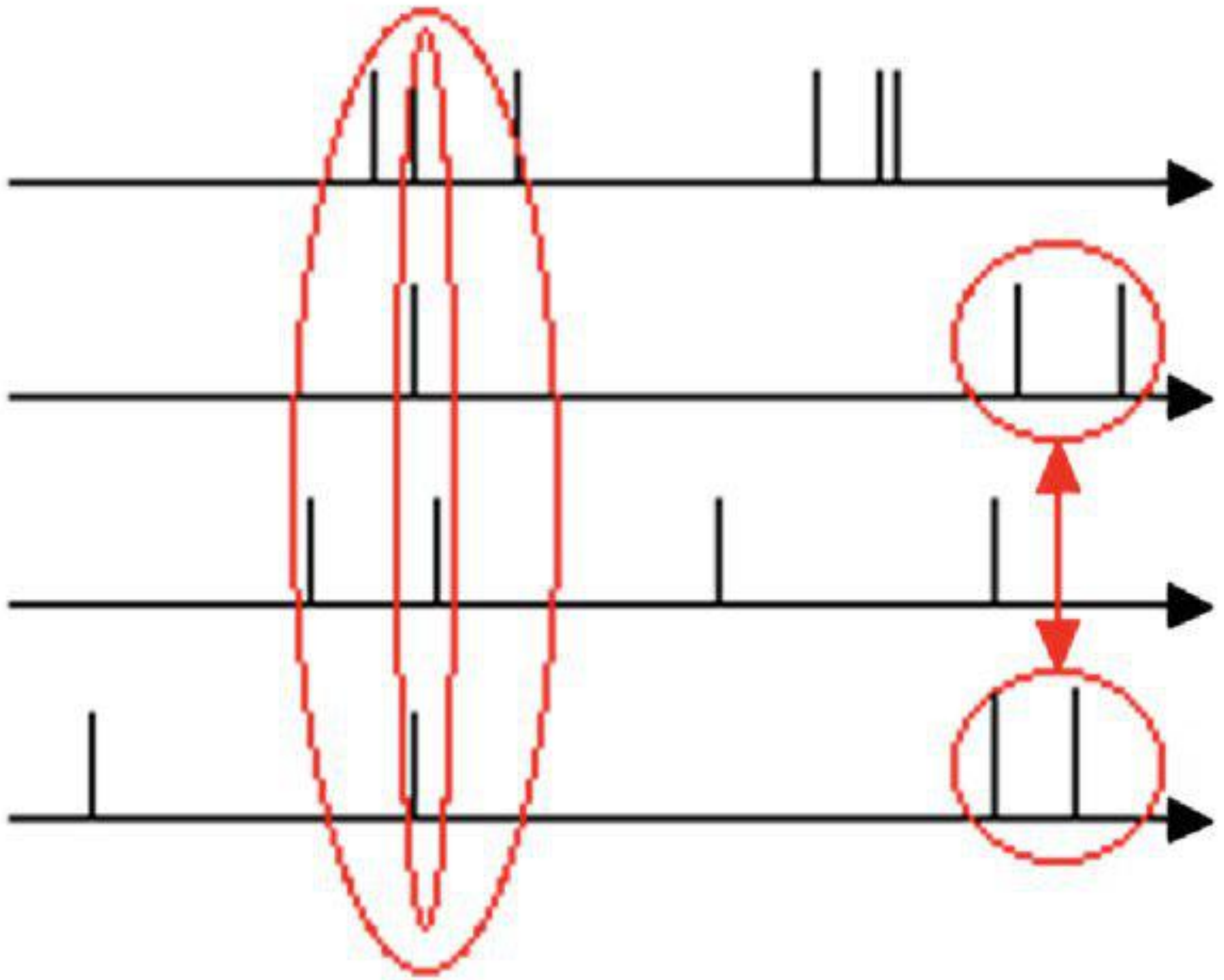
Temporal vs rate coding



Temporal: no averaging over time

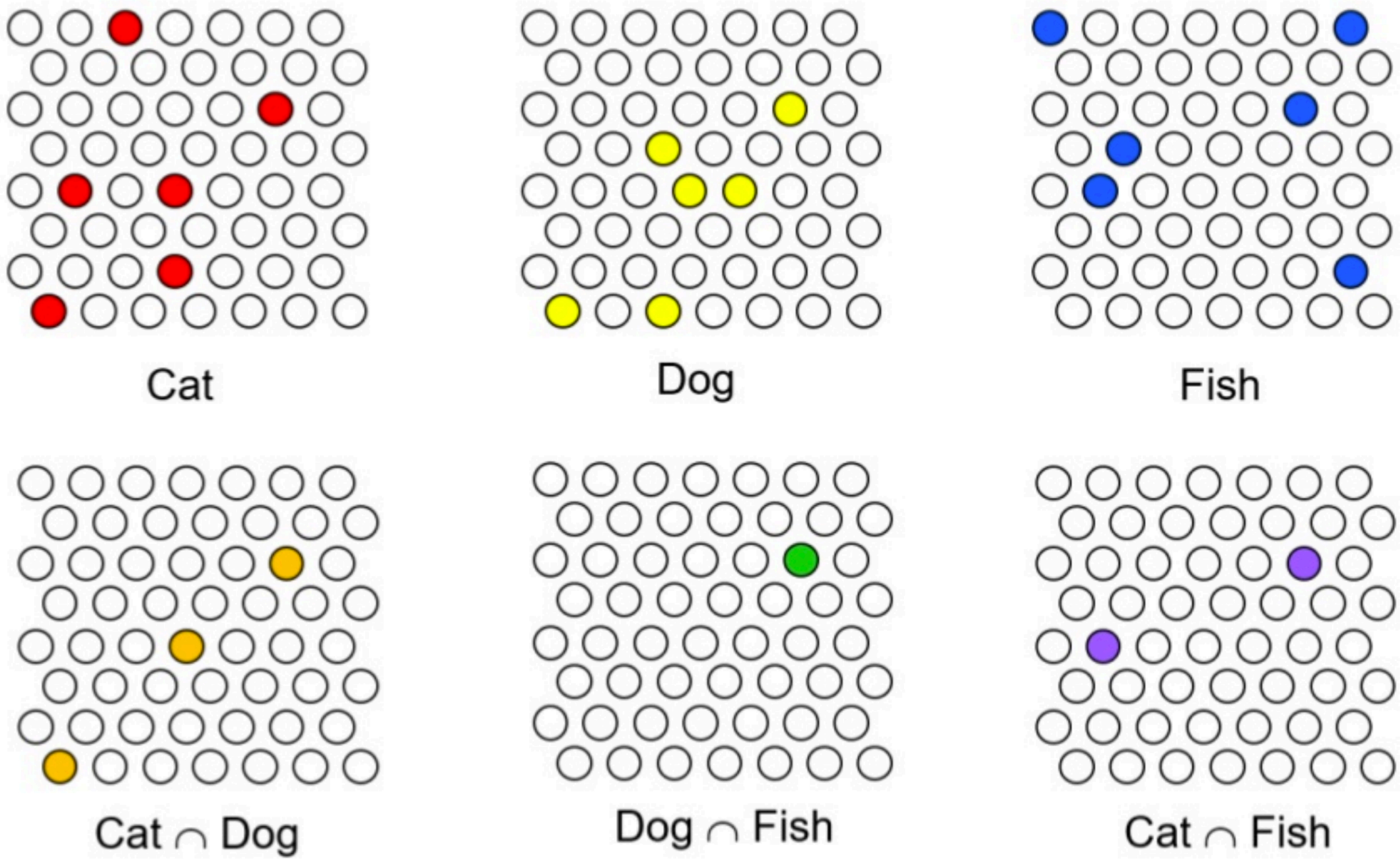
Rate: averaging over time (e.g. a few 100 ms)

Population coding

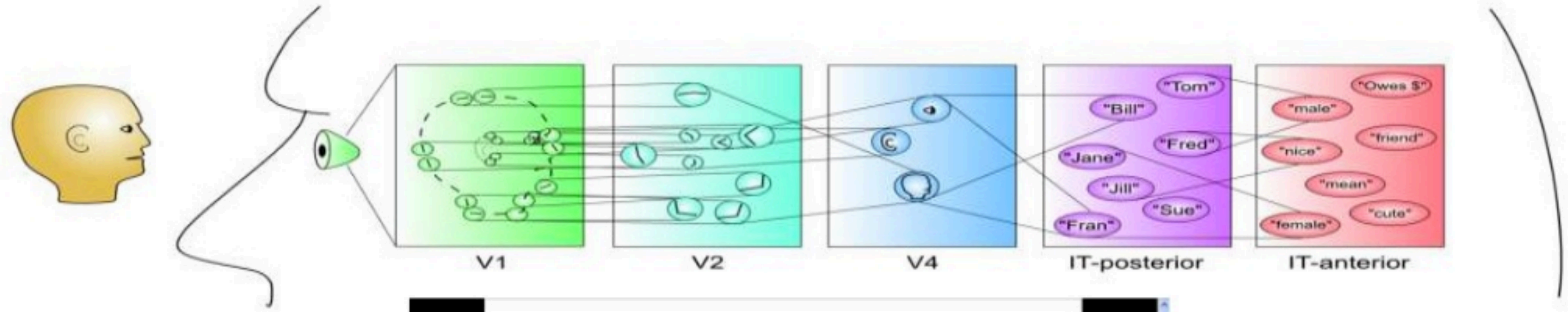


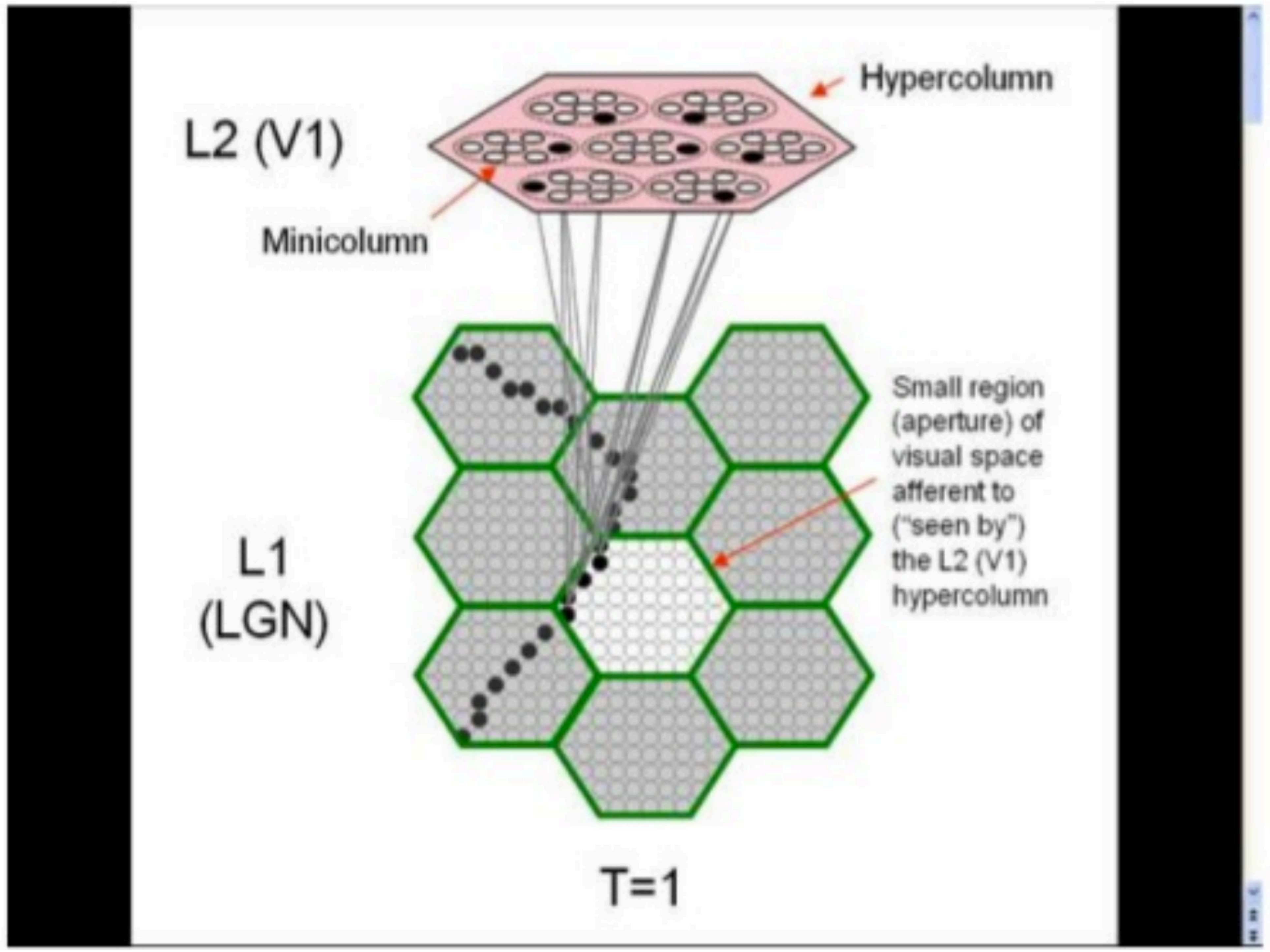
Population: averaging over space
Synchrony: patterns across space

Sparse coding



Hierarchical sparse distributed representations in VC





Conclusions

- Random single spikes are useless to analyse
- Spike trains give us statistics
- Neurons are robust
- Different neurons can use different coding scheme
- Some encoding schemes are just good for analysis