Working Memory and Metastability in a System of Spiking Neurons with Synaptic Plasticity

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Outline

Introduction: delayed responses, working memory, persistent activity and all that

Metastability

Definition of the model

Empirical results

Mean-field analysis

Conclusion and perspective

Where are we?

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It starts with Fuster in 1973

A delayed-response trial typically consists of the presentation of one of two possible visual cues, an ensuing period of enforced delay and, at the end of it, a choice of motor response in accord with the cue. The temporal separation between cue and response is the principal element making the delayed response procedure a test of an operationally defined short-term memory function.

Fuster's paradigm

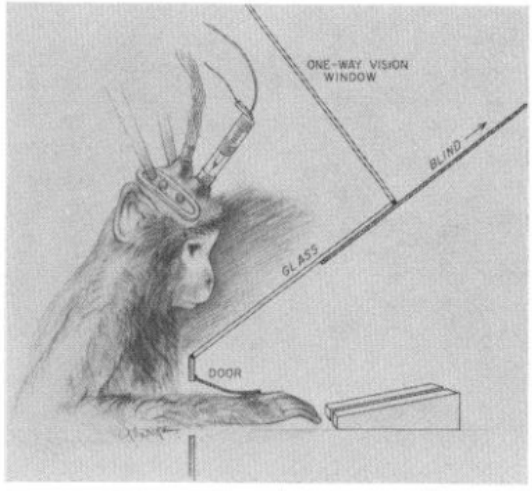


FIG. 1. Diagram of an experimental animal in the testing apparatus.

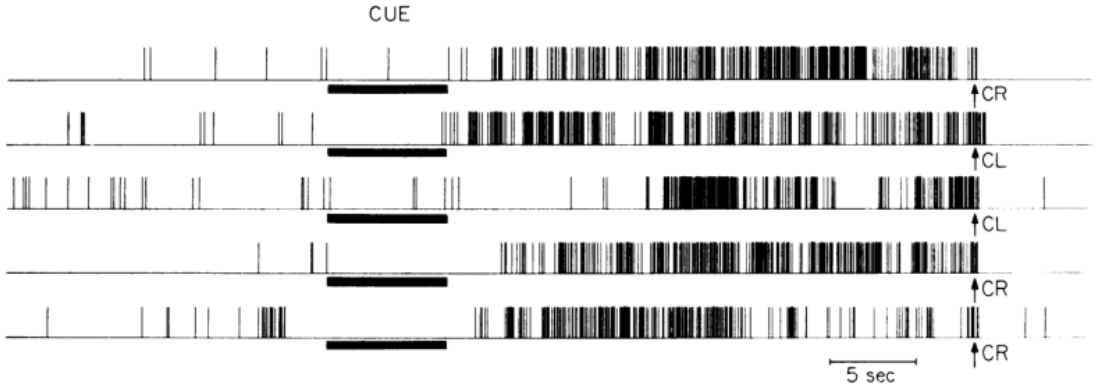


FIG. 4. Unit of type D during five delayed-response trials with 32-sec delay. Spikes are represented by vertical lines in a graphic display obtained by computer method. The notation next to the arrow at the end of each trial's delay refers to the accuracy (C, correct; I, incorrect) and side (R, right; L, left) of the response. The series of single-trial records in this figure—as in subsequent figures—is made of records from consecutive trials.

Figures 1 and 4 of Fuster (1973).

Other delayed activities are observed

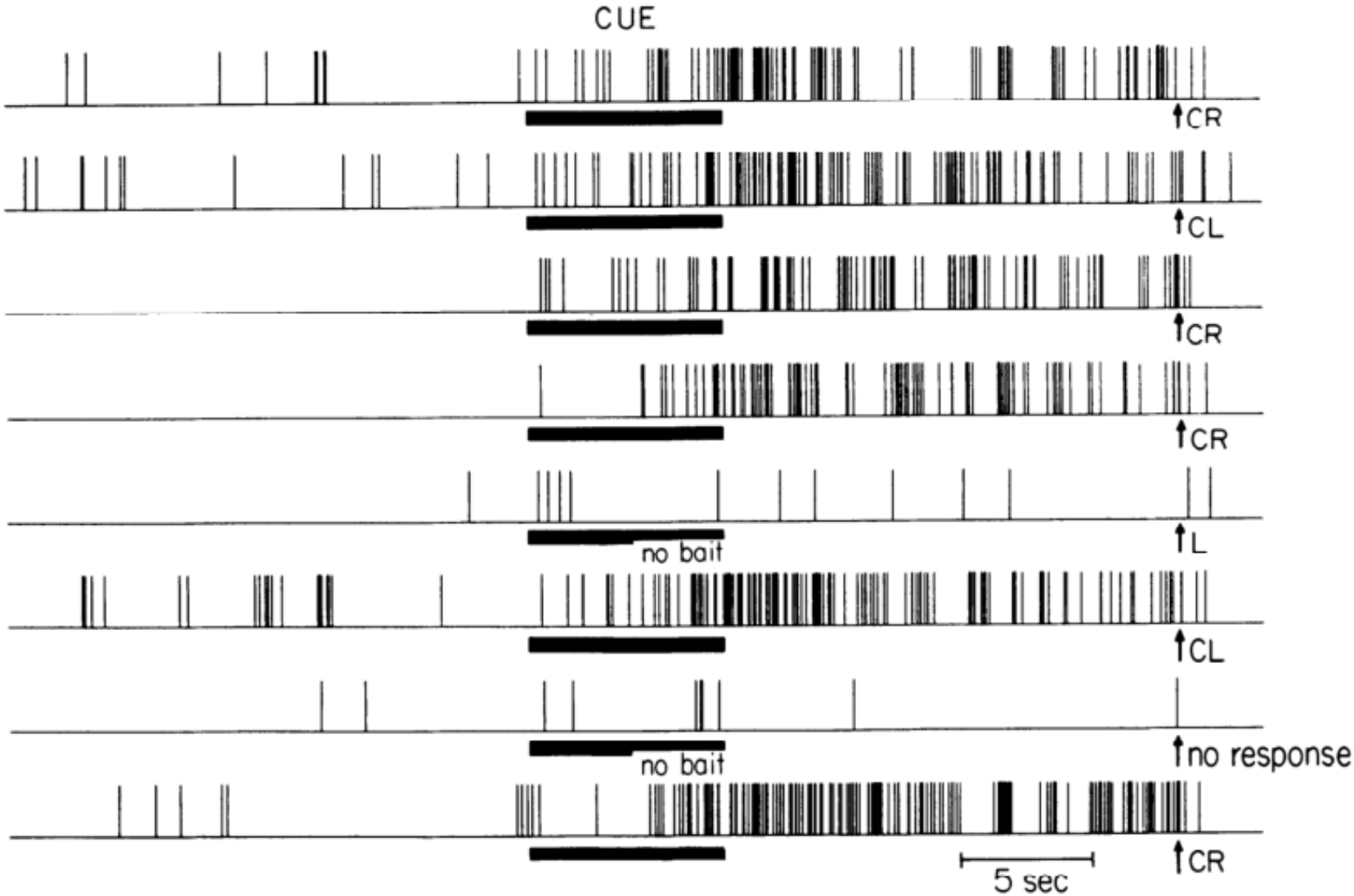


FIG. 6. Unit of type C. Note absence of sustained activation on dry-run trials (fifth and seventh).

Figure 6 of Fuster (1973).

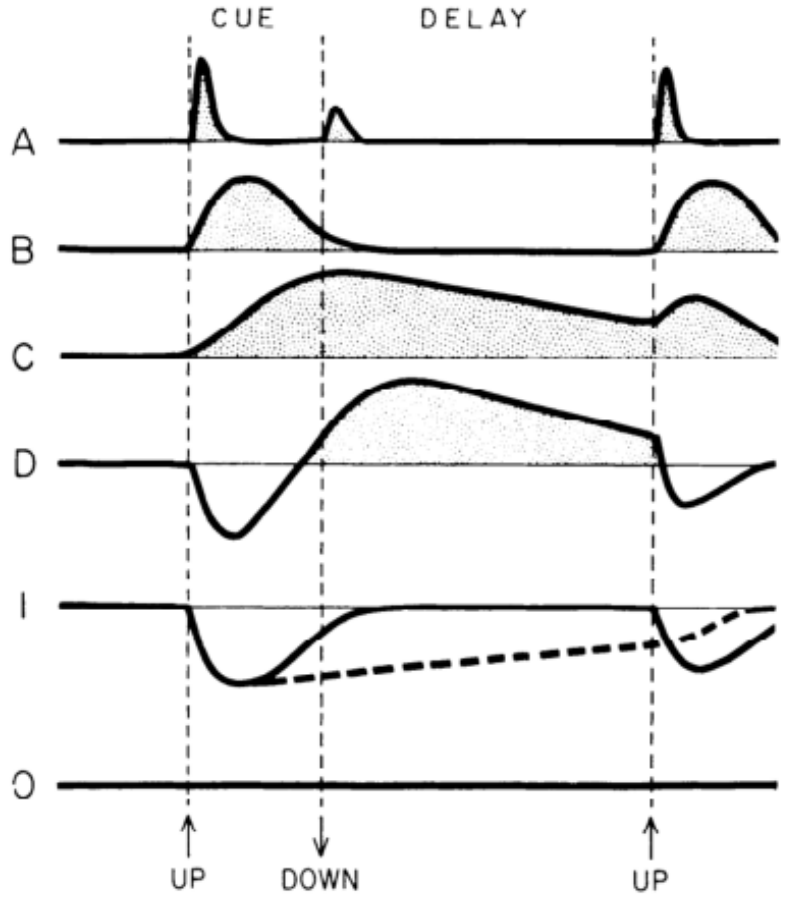
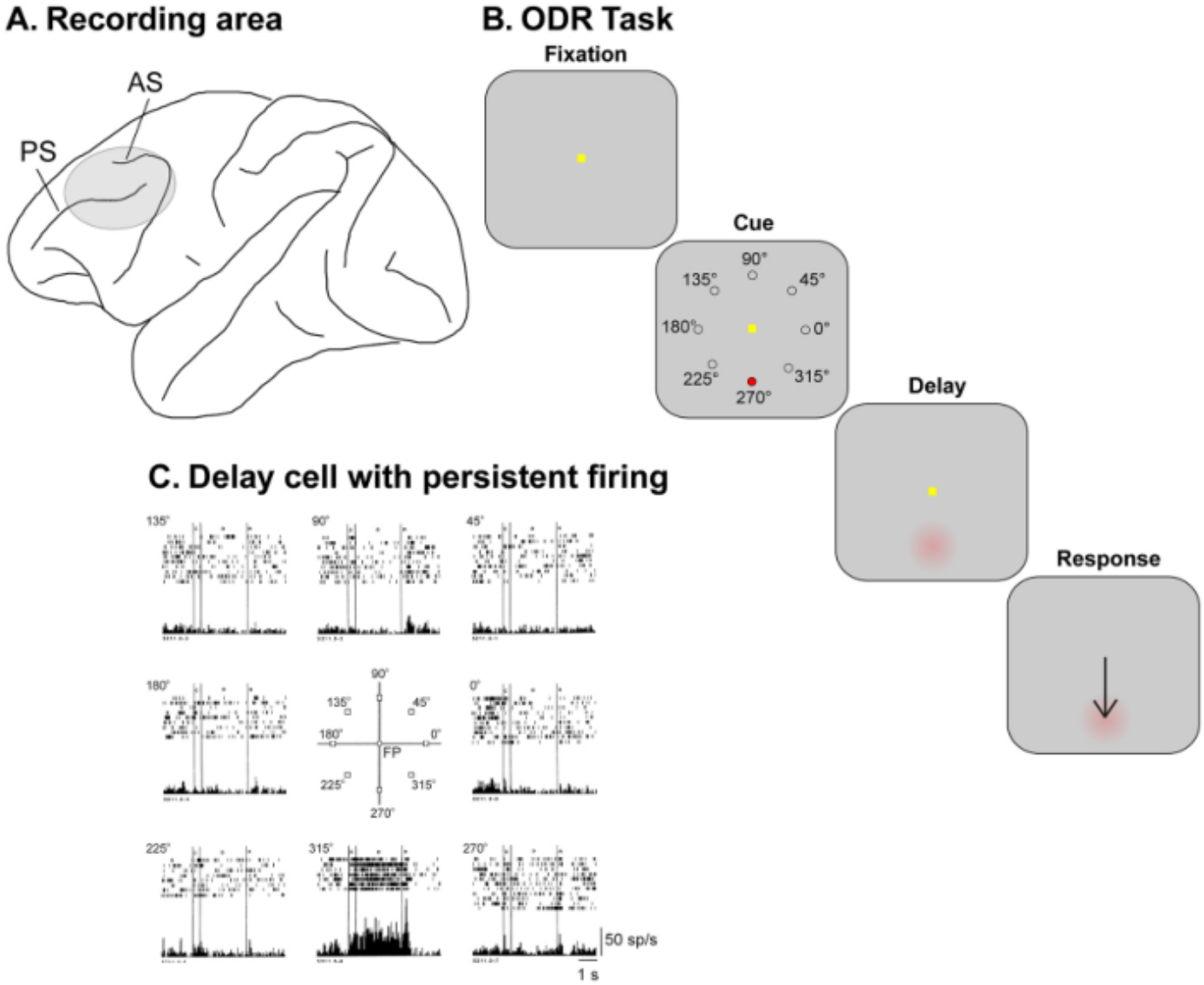


TABLE 1. *Classification of units in prefrontal cortex by firing changes during delayed-response performance*

Type	No. of Units	Percent
A	20	6.1
B	39	11.9
C	110	33.5
D	55	16.8
I_1	15	4.6
I_2	25	7.6
O	64	19.5
Total	328	100.0

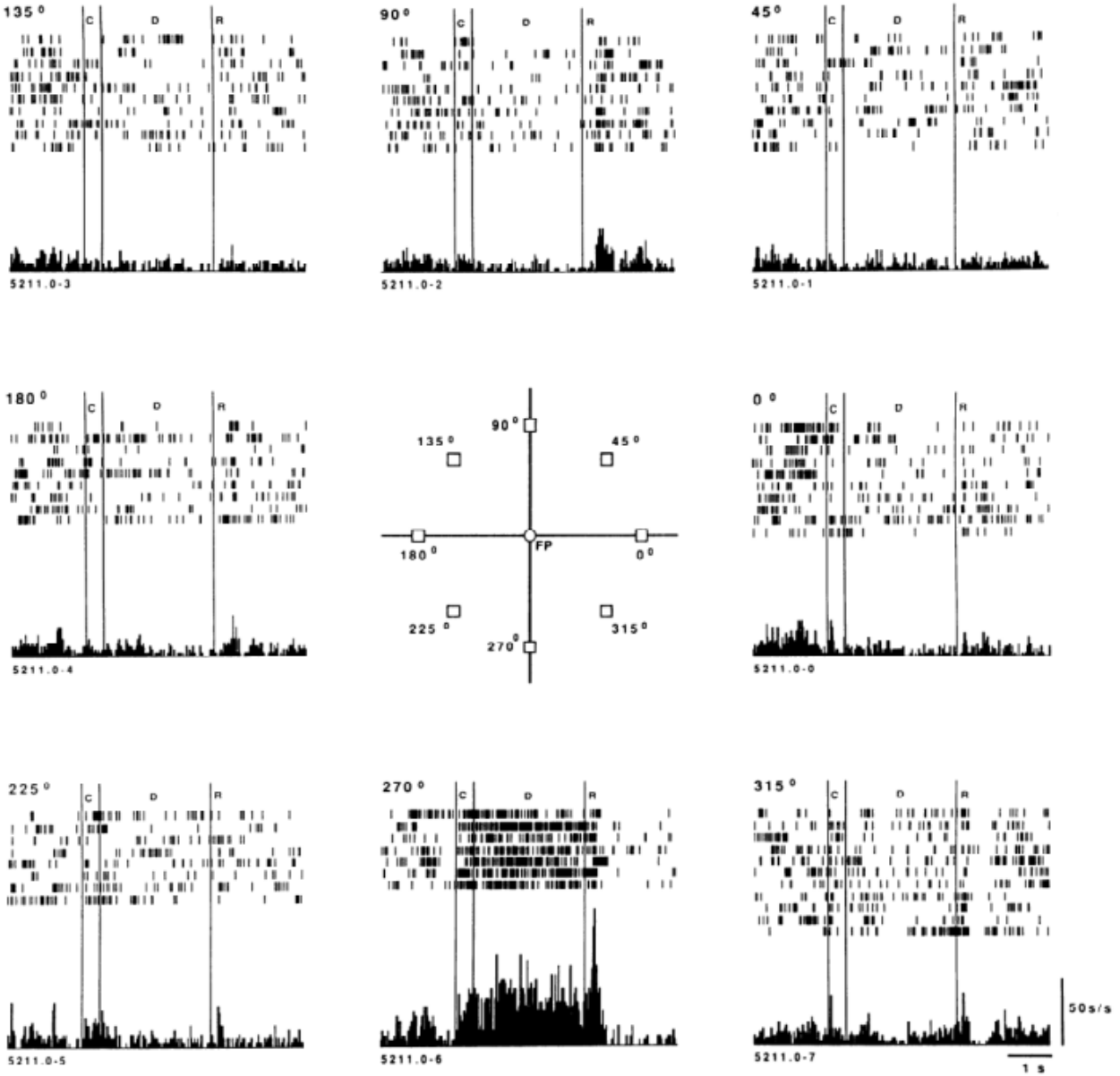
Figure 3 and Table 1 of Fuster (1973).

A "modern" version of Fuster's paradigm



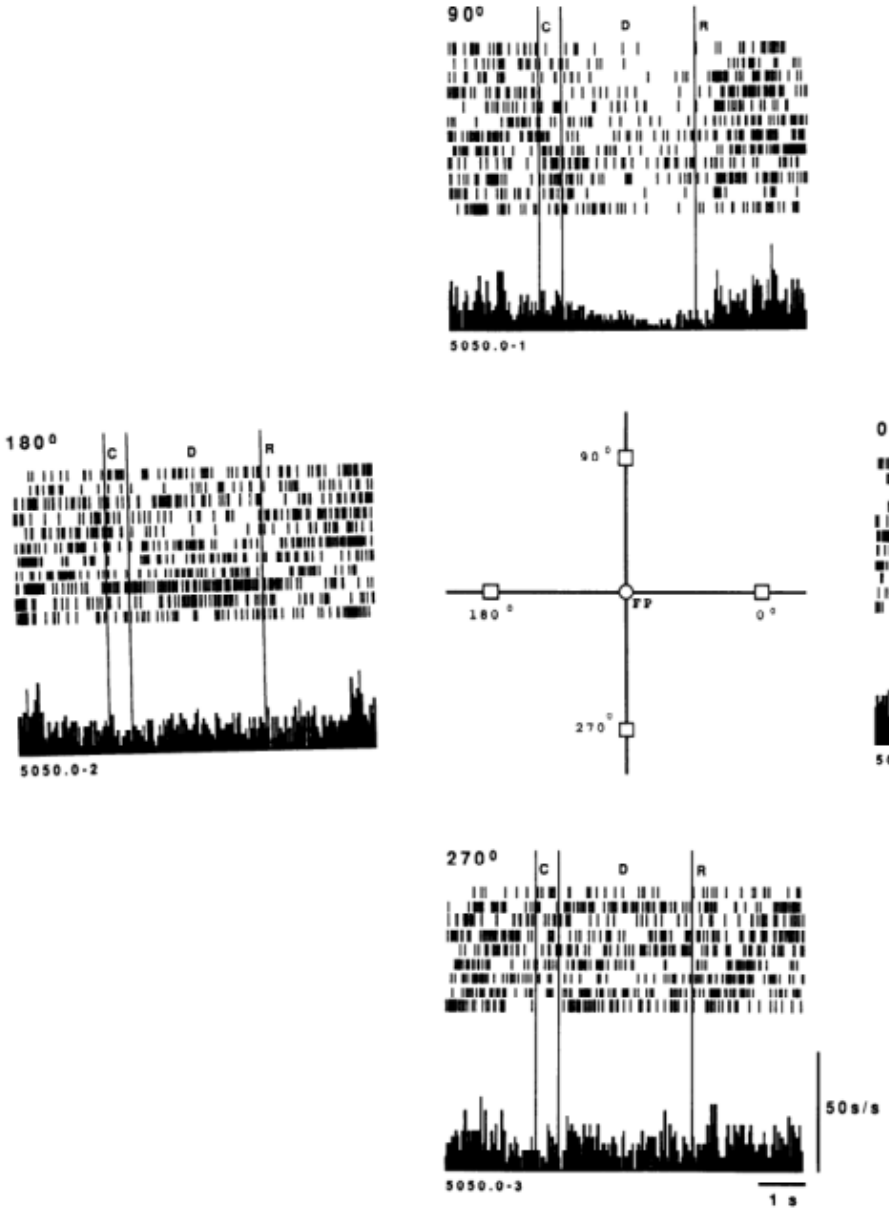
Adaptation of figures from Funahashi et al (1989) by Constantinidis et al (2018).

A better view of the rasters



Funahashi et al (1989) Figure 3.

An example of "inhibition" during the delay



Funahashi et al (1989) Figure 5.

Funahashi et al excitation / inhibition summary

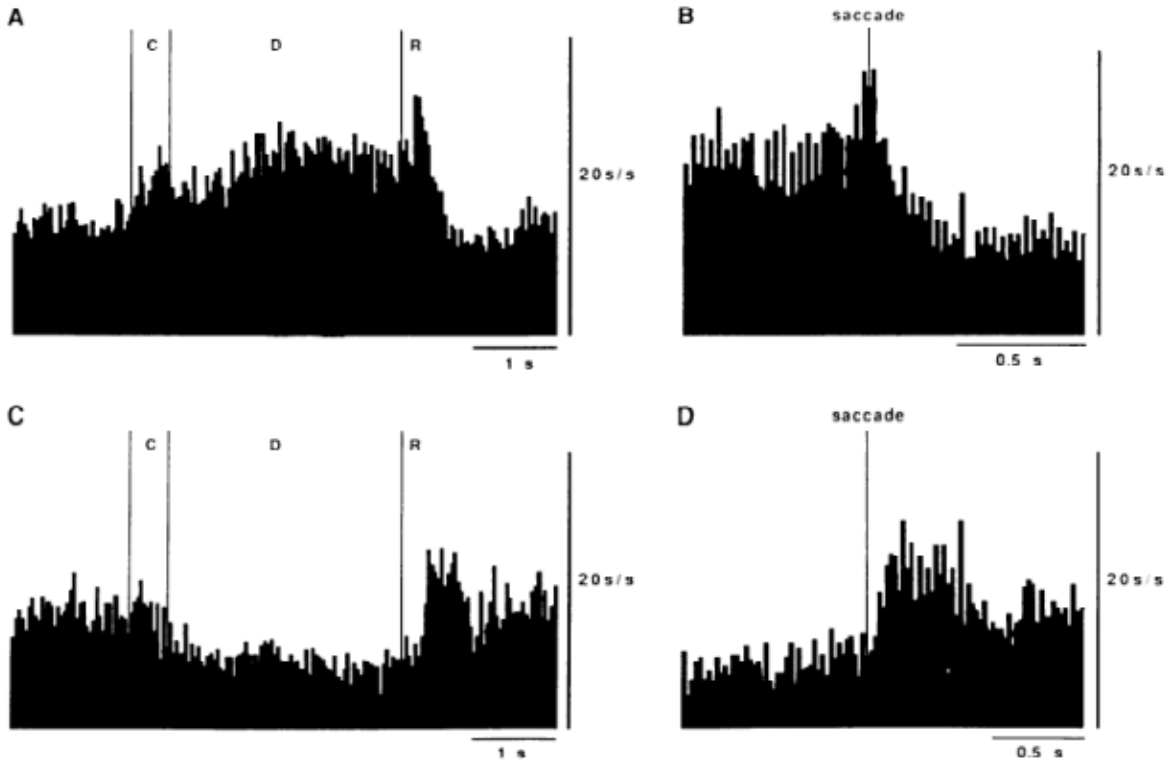
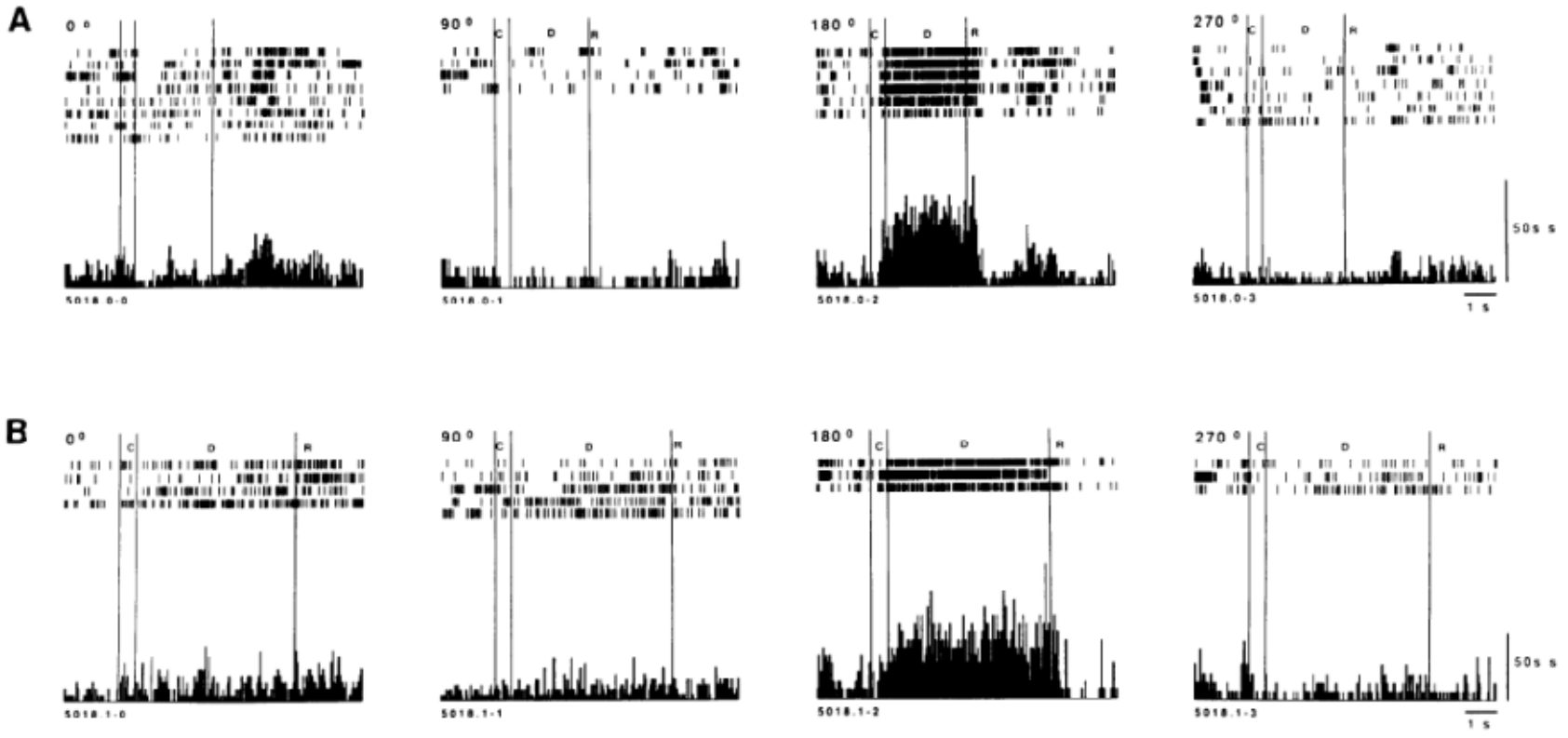


FIG. 10. The time course of excitatory and inhibitory delay period activity. These histograms sum neural activity at the preferred cue direction for all 46 principal sulcus neurons with excitatory directional delay period activity (*A*, *B*) and all 23 principal sulcus neurons with inhibitory directional delay period activity (*C*, *D*). *A* and *C* were aligned at the cue presentation; *B* and *D* were aligned at the initiation of the saccadic eye movements. All delay periods were 3 s.

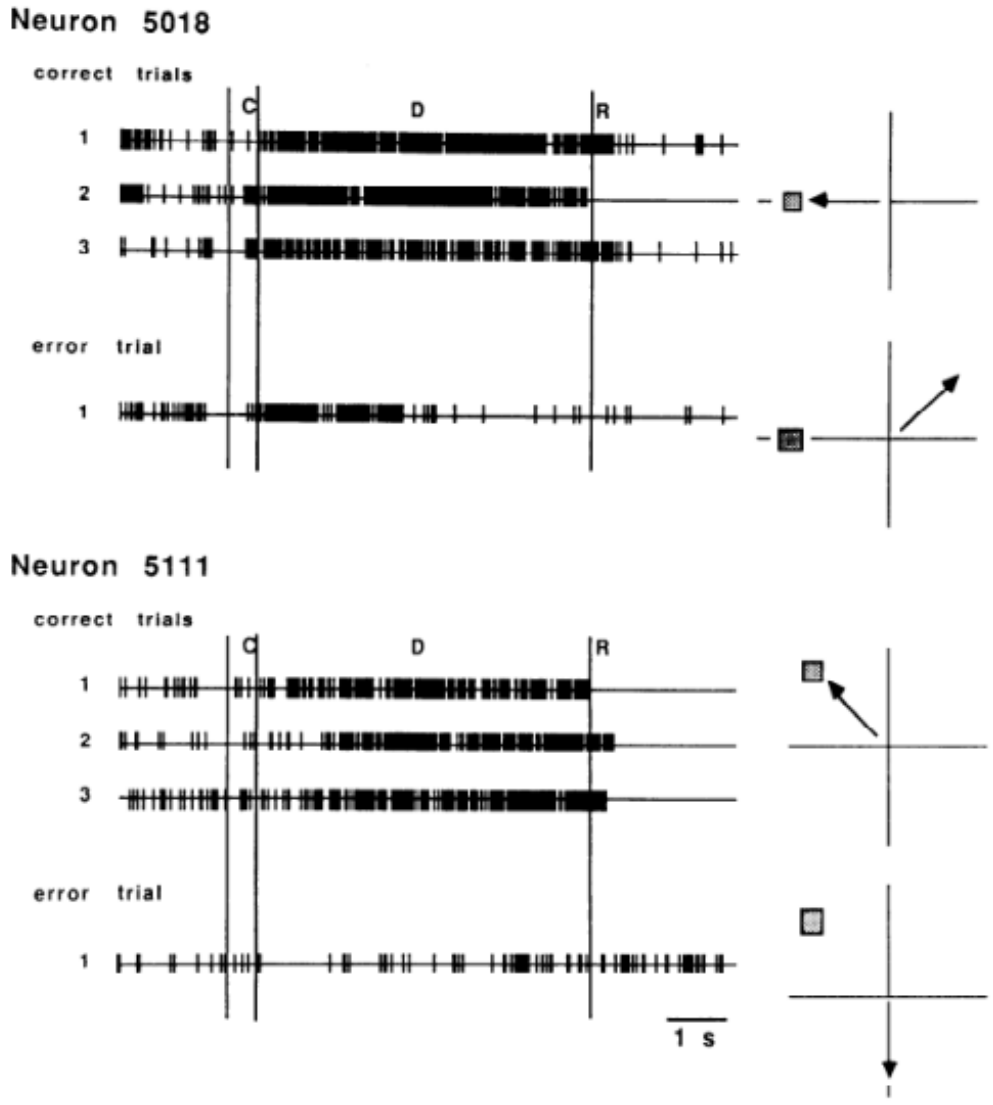
Funahashi et al (1989) Figure 10.

Changing the delay



Funahashi et al (1989) Figure 11.

What happens when mistakes are made?



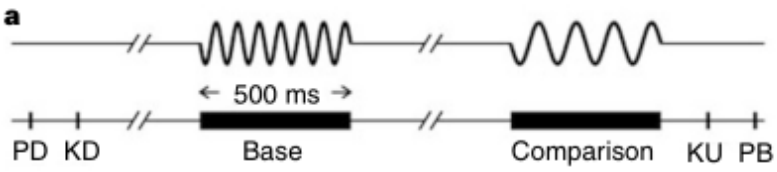
Funahashi et al (1989) Figure 13.

Parametric working memory

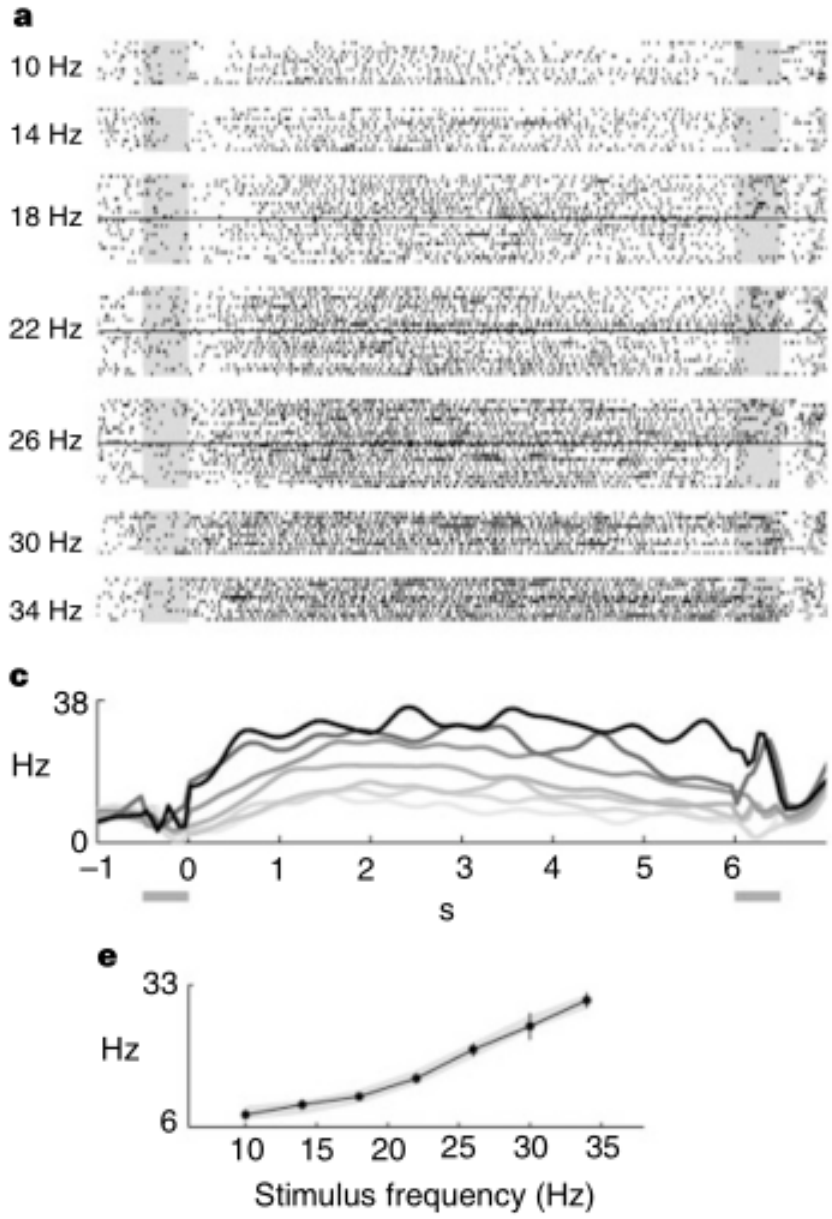
Neuronal correlates of parametric working memory in the prefrontal cortex

Ranulfo Romo, Carlos D. Brody, Adrián Hernández & Luis Lemus

Instituto de Fisiología Celular, Universidad Nacional Autonóma de México, México D.F. 04510, México



Romo et al (1999) title and figure 1a.



Part of Romo et al (1999) figure 2.

First modelling efforts

Synaptic reverberation underlying mnemonic persistent activity

Xiao-Jing Wang

Stimulus-specific persistent neural activity is the neural process underlying active (working) memory. Since its discovery 30 years ago, mnemonic activity has been hypothesized to be sustained by synaptic reverberation in a recurrent circuit. Recently, experimental and modeling work has begun to test the reverberation hypothesis at the cellular level. Moreover, theory has been developed to describe memory storage of an analog stimulus (such as spatial location or eye position), in terms of continuous 'bump attractors' and 'line attractors'. This review summarizes new studies, and discusses insights and predictions from biophysically based models. The stability of a working memory network is recognized as a serious problem; stability can be achieved if reverberation is largely mediated by NMDA receptors at recurrent synapses.

persistent activity to subserve working memory, it must be stimulus-selective, and therefore information-specific. Moreover, it must be able to be turned on and switched off rapidly (≈100 ms) by transient inputs.

For 30 years, persistent activity in the cortex has been documented by numerous unit recordings from behaving monkeys during working memory tasks (Box 1). How does stimulus-selective persistent activity arise in a neural network? Can we explain persistent activity in terms of the biophysics of neurons and synapses, and circuit connectivity?

Cellular substrate

Heterogeneity in the pyramidal network of the medial prefrontal cortex

Yun Wang[1], Henry Markram[2], Philip H Goodman[3], Thomas K Berger[2], Junying Ma[1] & Patricia S Goldman-Rakic[4,5]

The prefrontal cortex is specially adapted to generate persistent activity that outlasts stimuli and is resistant to distractors, presumed to be the basis of working memory. The pyramidal network that supports this activity is unknown. Multineuron patch-clamp recordings in the ferret medial prefrontal cortex showed a heterogeneity of synapses interconnecting distinct subnetworks of different pyramidal cells. One subnetwork was similar to the pyramidal network commonly found in primary sensory areas, consisting of accommodating pyramidal cells interconnected with depressing synapses. The other subnetwork contained complex pyramidal cells with dual apical dendrites displaying nonaccommodating discharge patterns; these cells were hyper-reciprocally connected with facilitating synapses displaying pronounced synaptic augmentation and post-tetanic potentiation. These cellular, synaptic and network properties could amplify recurrent interactions between pyramidal neurons and support persistent activity in the prefrontal cortex.

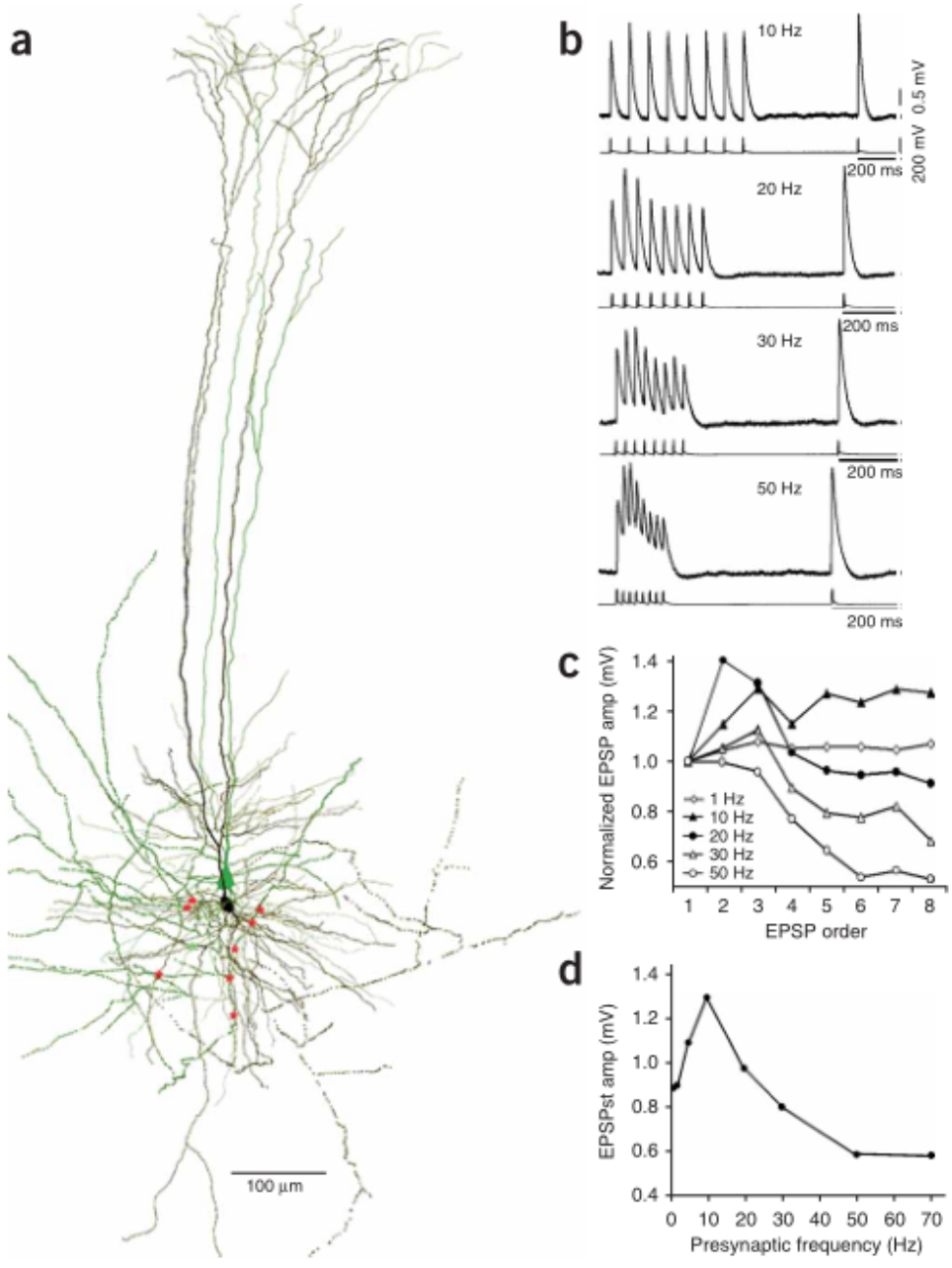


Figure 1 of Wang et al (2006).

Models with short term facilitation

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Current Opinion in Neurobiology

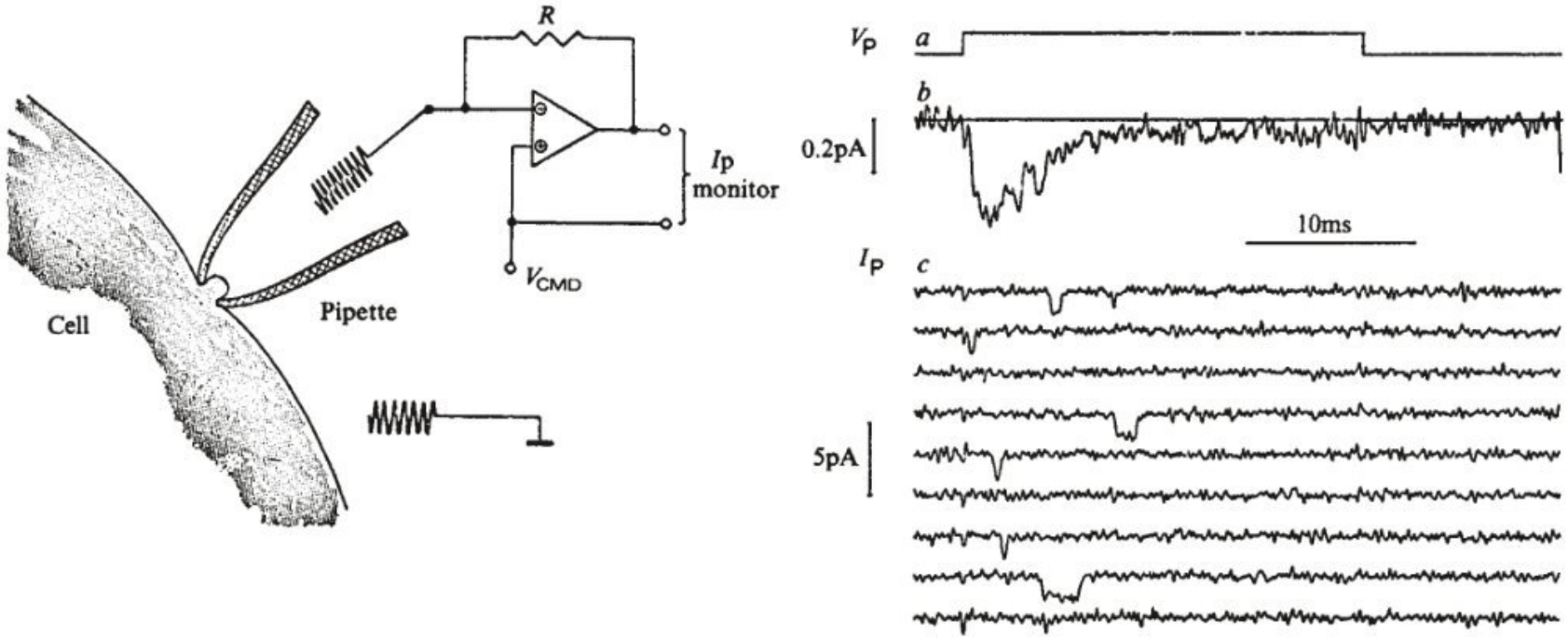
Working models of working memory

Omri Barak[1] and Misha Tsodyks[2]

Working memory is a system that maintains and manipulates information for several seconds during the planning and execution of many cognitive tasks. Traditionally, it was believed that the neuronal underpinning of working memory is stationary persistent firing of selective neuronal populations. Recent advances introduced new ideas regarding possible mechanisms of working memory, such as short-term synaptic facilitation, precise tuning of recurrent excitation and inhibition, and intrinsic network dynamics. These ideas are motivated by computational considerations and careful analysis of experimental data. Taken together, they may indicate the plethora of different processes underlying working memory in the brain.

activity related to storing a fixed item is not stationary, and there is a large heterogeneity in the firing profiles of different neurons [3,4,5•,6]. From the computational side, the network activity representing a memorized item should exhibit a sufficient degree of stability to ensure memory retainment. This requirement is especially challenging for storing continuous variables, such as orientation or spatial position of a visual cue, because of an inevitable drift along the variable's representation. Furthermore, integrating the various data-driven challenges in a self-consistent manner is often a non-trivial computational problem.

Membrane conductances (ion channels) generate fluctuations



Figures 1 and 2 of Sigworth and Neher (1980).

Synapses generate even more fluctuations

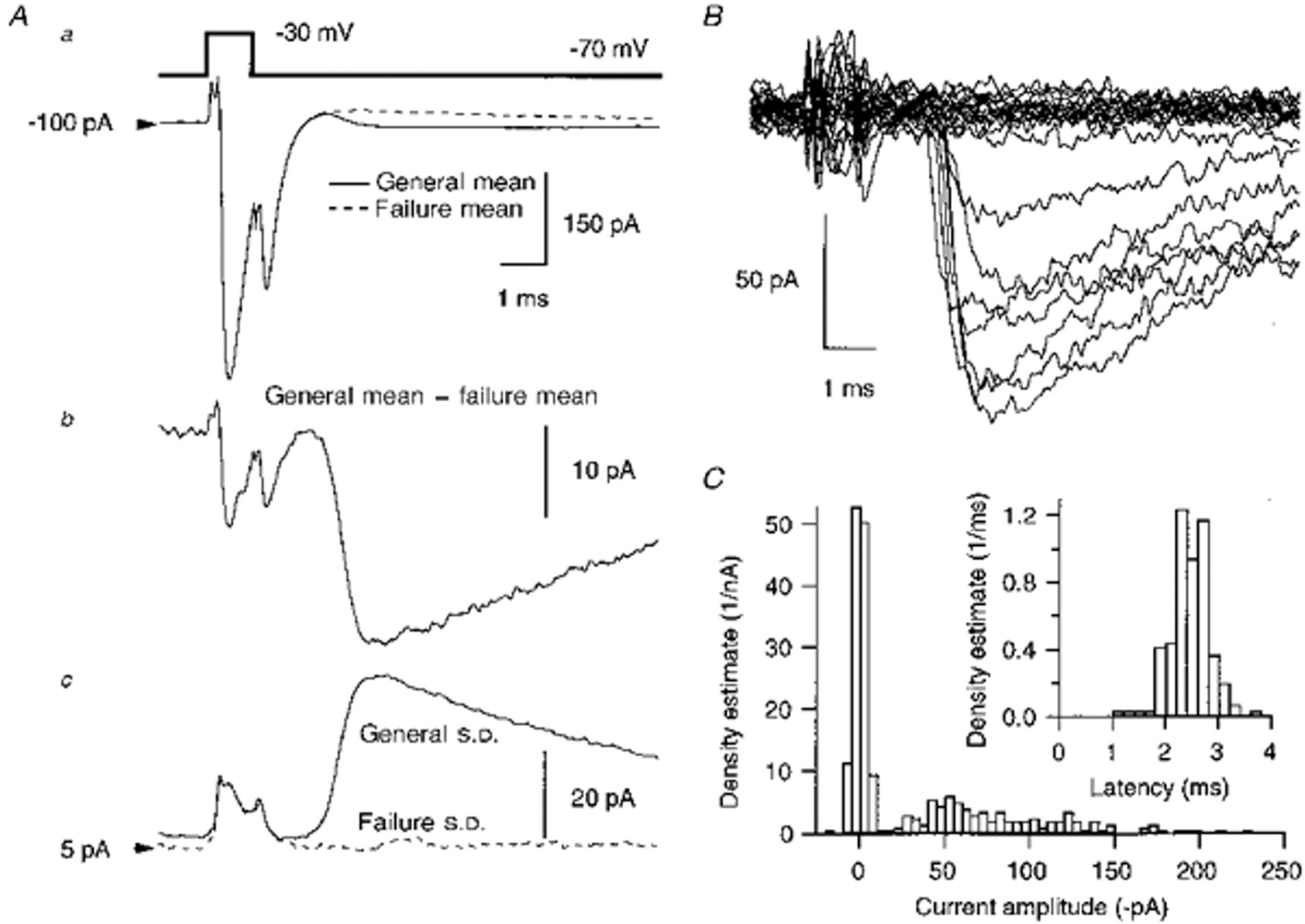


Figure 1 of Pouzat and Marty (1998).

Where are we?

Metastability: general view

Metastability is a notion which initially came from statistical physics, and which has now been studied in a wide range of fields to explain various phenomenons. Examples: Supercooling water, avalanche, nuclear physics etc.

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Informally a system is metastable if, under the right conditions,it tends to persist in a seemingly stable (but in fact precarious) equilibrium for a long time, before falling into the actual equilibrium because of an unusually big (but statistically unavoidable) deviation from this pseudo-equilibrium.

Metastability: a little bit more specific

In the specific field of *interacting particle systems*, metastability is characterized by the following two properties (Cassandro et al. 1984):

- the time it takes for the system to get to the actual equilibrium (quiescent state) is asymptotically memory-less,
- and before reaching this equilibrium the system behave as if it were in a stationary regime.

Where are we?

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- When a neuron spikes its membrane potential is reset to zero. That's the only way the membrane potential can decrease.

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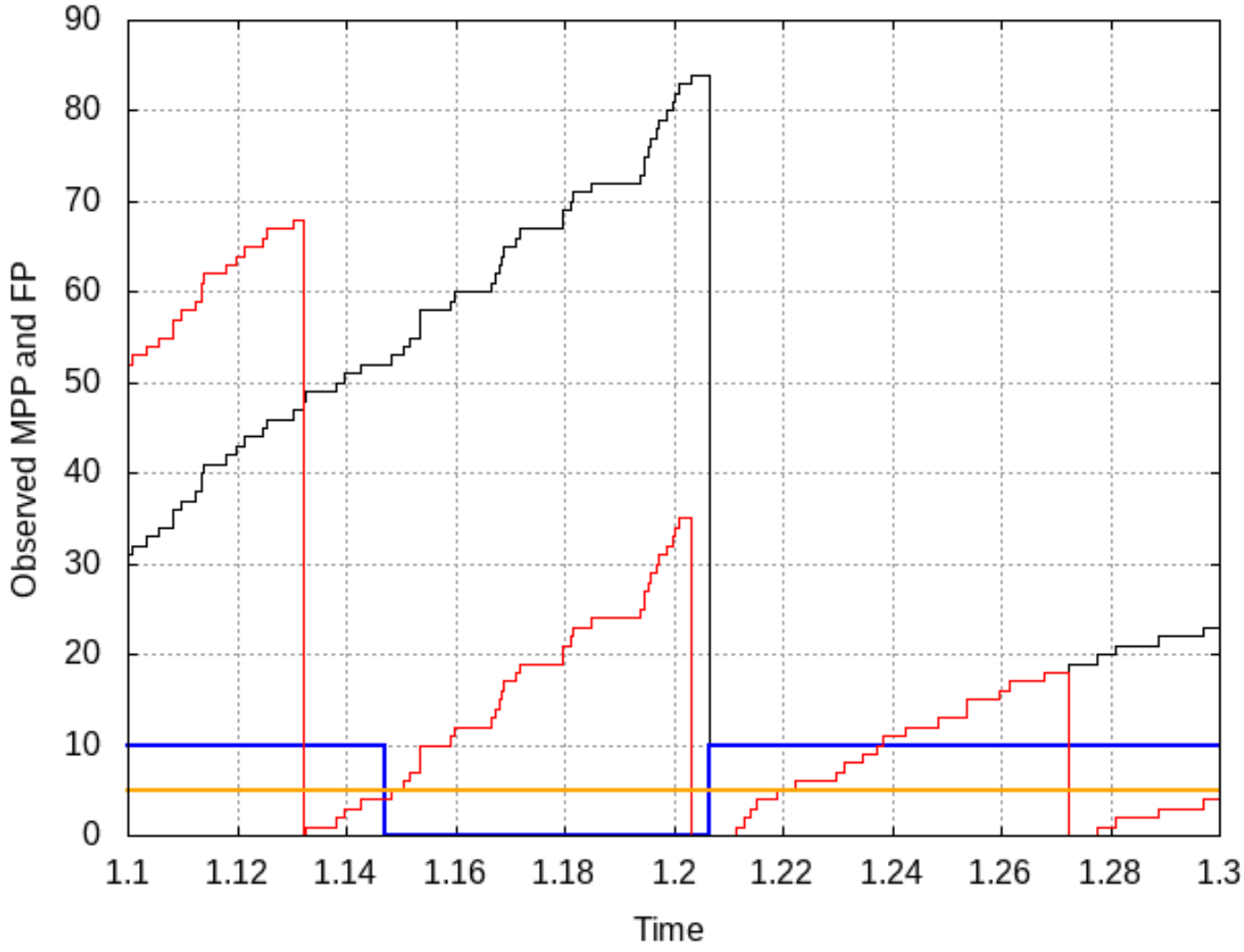
- We are here modelling the sub-network of strongly interconnected pyramidal cells with facilitating synapses described by Wang et al (2006) in the prefrontal cortex.

In picture



Simulation with $N = 50$, $\beta = 10$, $\lambda = 10$ and $\theta = 5$.

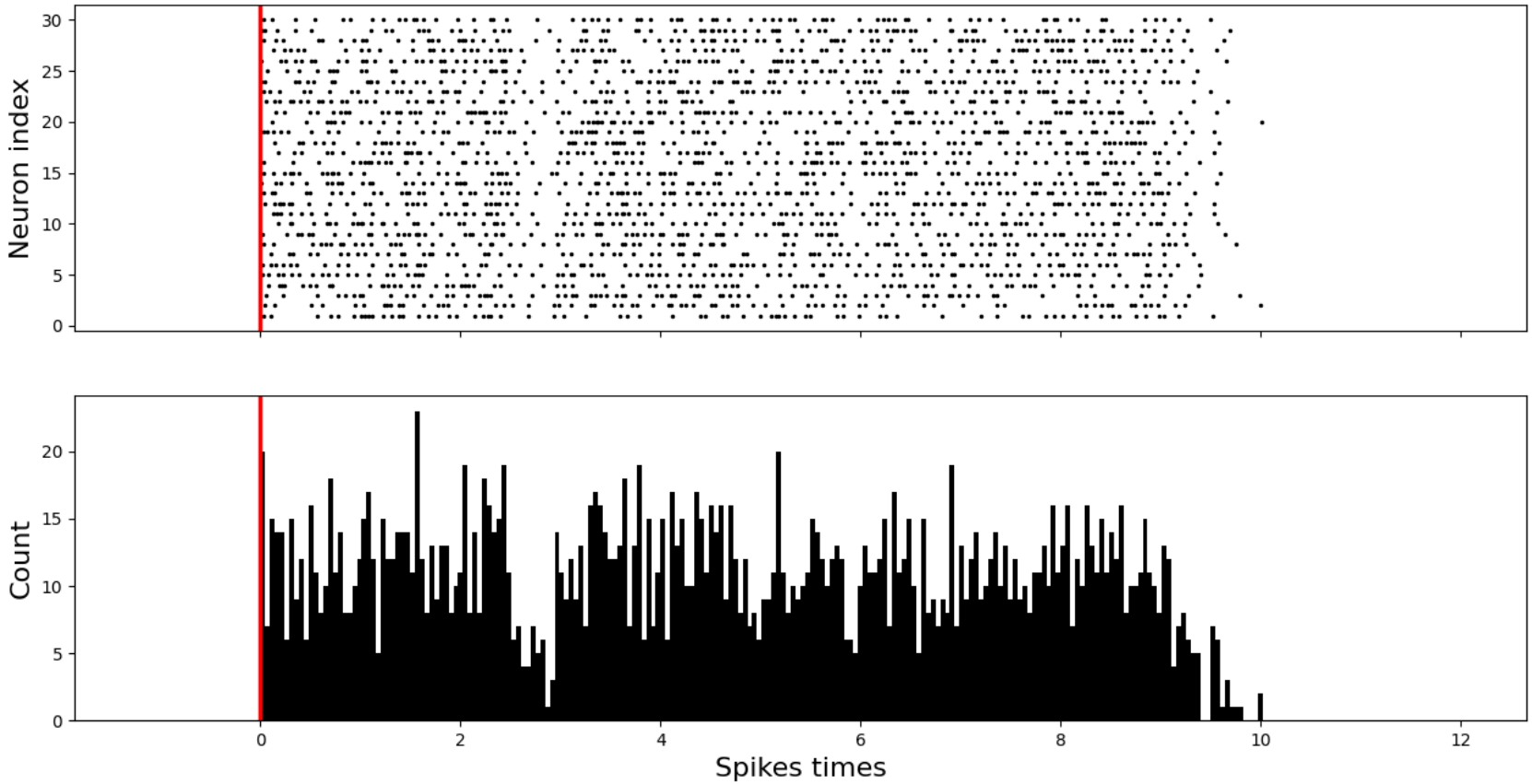
Where are we?

Simulations outline

Simulations are easily performed since the "global" network rate is constant between two successive events (spike or facilitation loss). Our `C` code writes to disk:

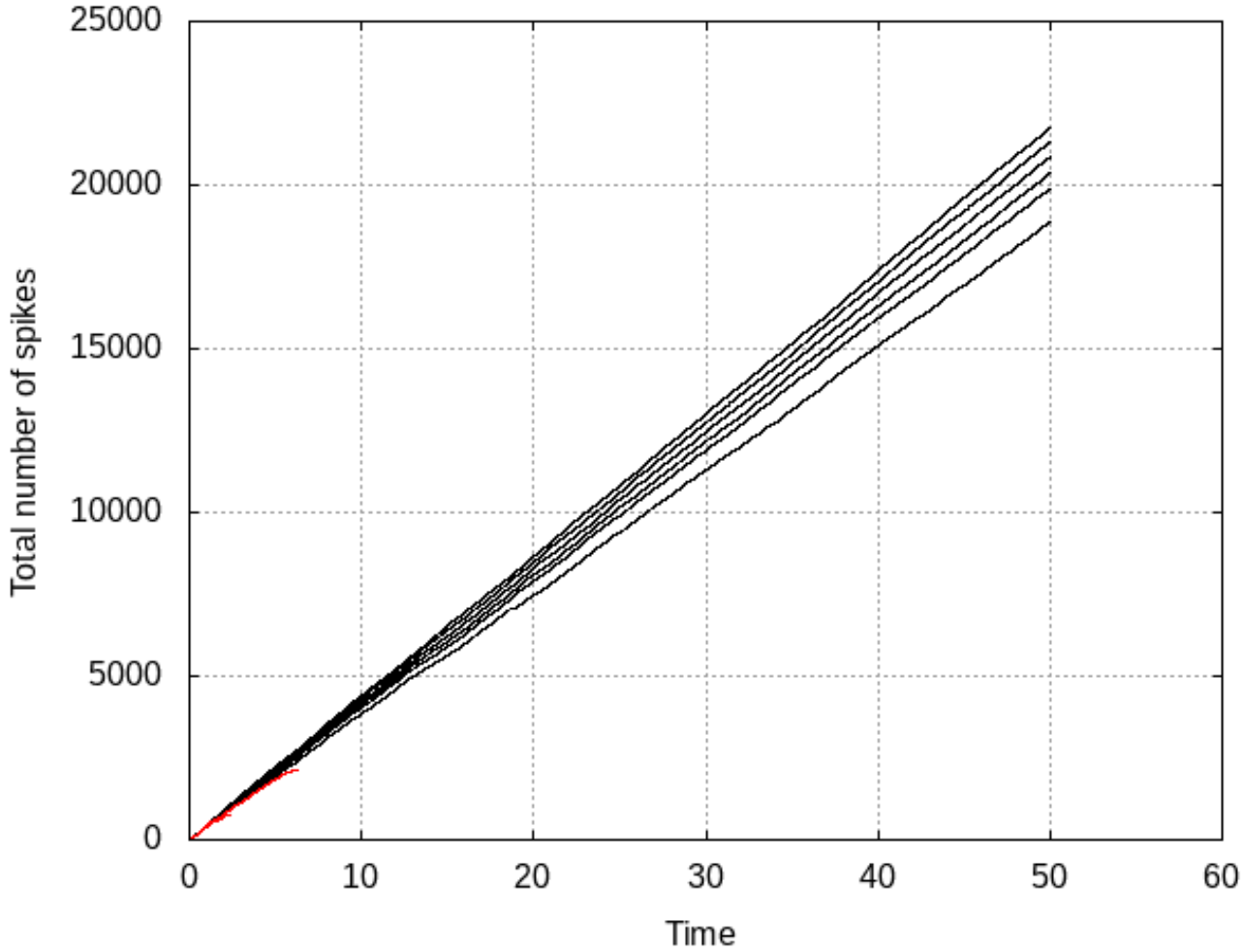
```
# Simulation of a networks with 50 neurons
# Xoroshiro128+ PRNG seeds set at 20061001 and 19731004
# The initial max membrane potential was set to 50
# The initial probability for a synapse to be active was set to 0.750000
# Parameter theta = 5.000000
# Parameter beta = 10.000000
# Parameter lambda = 10.000000
# Simulation duration = 50.000000

# Spike time  Total nb of spikes  Neuron of origin
0.0012163964                   1                11
0.0015877227                   2                39
0.0021882591                   3                 4
0.0046765785                   4                18
0.0065390698                   5                33
...
```

Tiny network example



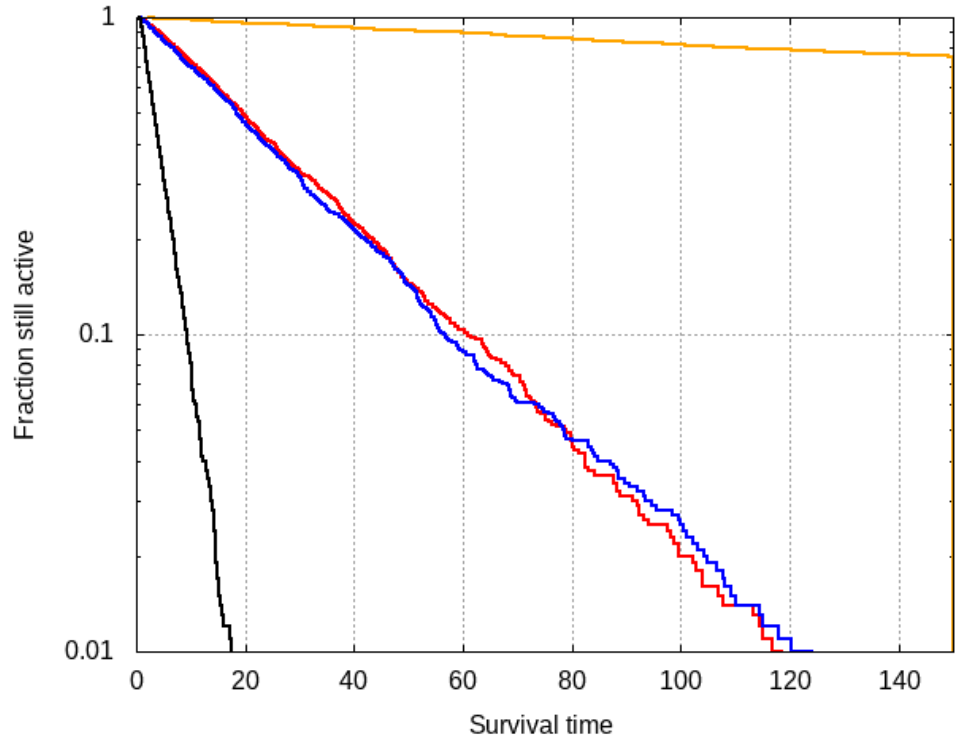
Trajectory of an entire system composed of 30 neurons, with $\lambda = 5$, $\beta = 10$ and $\theta = 5$. The initial probability for the synapses to be active was 0.75, the initial membrane potentials were drawn uniformly on $\{0, 1, \ldots, 29\}$.

Increasing λ



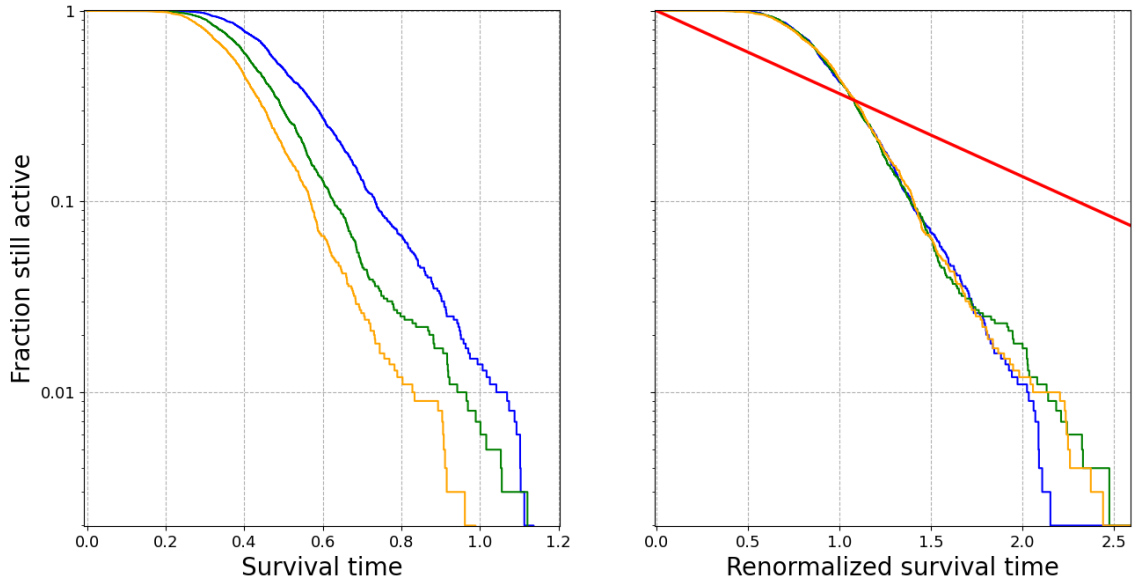
Observed counting processes of a network made of 50 neurons with increasing values of λ from 1 to 9. In black, "top to bottom", $\lambda \in \{1, 2, \ldots, 6\}$; in red, $\lambda > 6$.

Survival time distribution



Empirical survival functions for 1000 replicates with $\theta = 5$, $\lambda = 6$ (blue and red), $\lambda = 7$ (black) and $\lambda = 5$ (orange), $\beta = 10$ and a network with 50 neurons. The initial probability for the synapses to be active was 0.75, the initial membrane potentials were drawn uniformly on $\{0, 1, \ldots, 49\}$. All simulations except the blue and red start from *the same* random initial state. **A log scale is used for the ordinate**.

Survival time when λ is "too" large



Empirical survival functions for 1000 replicates with $\lambda = 15$ (blue), $\lambda = 30$ (green), $\lambda = 60$ (orange), $\beta = 10$ and a network with 50 neurons. The initial probability for the synapses to be active was 0.75, the initial membrane potentials were drawn uniformly on $\{0, 1, \ldots, 49\}$. All simulations start from *the same* random initial state.

Where are we?

What can we do, what do we want?

- We cannot yet prove that the metastable state exists.
- We will therefore postulate that it does: that's what the simulations show.
- We will use the intrinsic symmetry of the model: the neurons are all equivalent.
- We will try to get network properties in the metastable state:
  - network firing rate
  - number of neurons in each state
  - number of facilitated synapses
  - ...

  from the 4 network parameters: N, θ, β, λ.

Notations and remarks

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- We obviously have: $\sum_{i=0}^{\theta} N_i(t) = N$ at all times.
- Then under our assumption of quasi-stationarity, the expectations of the N_i should be almost constant in the metastable phase.
- Thus we let $\mu_0, \mu_1, \ldots \mu_\theta$ be the constants such that $\mathbb{E}(N_0(t)) \approx \mu_0, \ \ldots, \ \mathbb{E}(N_\theta(t)) \approx \mu_\theta$, where t is any time before the extinction of the system.

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- if the next spike of j happens at time $s + \tau$, do we still have $F_j(s + \tau) = 1$?
- By our model definition and our quasi-stationarity assumption we have: $\mathbb{E}\left[F_j(s + \tau)|\tau\right] = e^{-\lambda\tau}$.

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- μ_E is the "mean probability" that the synapse is still facilitated when the neuron spikes.

Circulation among U states

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- For the two extrem states, we have:

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leading to

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- We can also obtain a new expression for the rate of "effective" spikes:

$$\mu_\theta \beta \mu_E = \left(N - \frac{\theta}{\mu_E}\right) \beta \mu_E = \beta(\mu_E N - \theta)\,.$$

Getting an implicit equation for μ_E

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- Once threshold has been reach, the rate at which a spike is generated is β so the interval between two successive spikes of a given neuron is approximately

$$T \approx \frac{\theta}{\beta(\mu_E N - \theta)} + Y\,,$$

where Y is an exponential random variable with rate parameter β.

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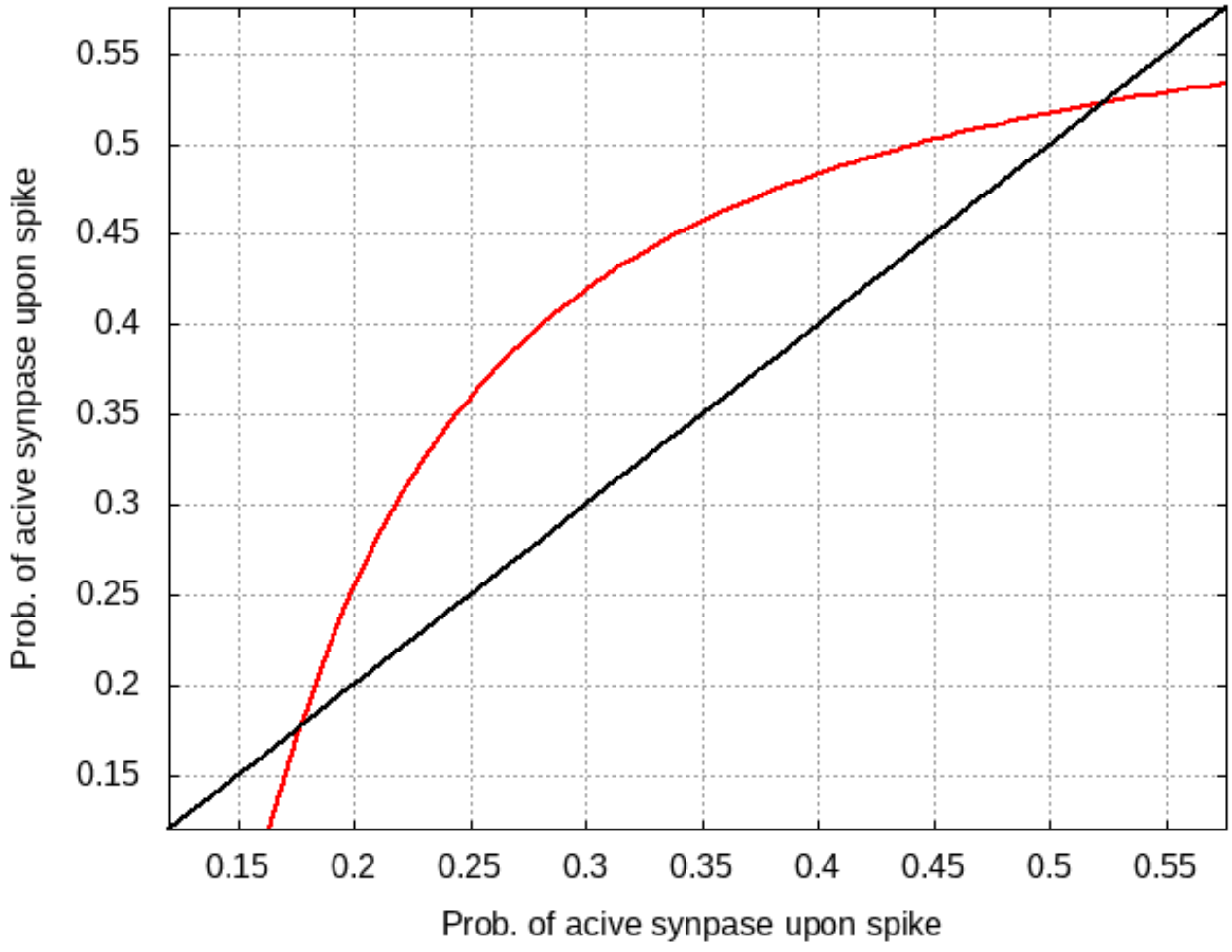
- This requires a numerical integration whose precision we can check.
- Looking at:

$$\mu_E \approx \frac{\beta}{\lambda+\beta} \exp\left(-\frac{\lambda\theta}{\beta(\mu_E N-\theta)}\right),$$

we see that the right hand side is a decreasing function of λ, so if λ is too large the equation could have no solution implying that there is no metastable state as we saw in the simulations.

Graphical solution of the implicit equation



Example with $N = 50$, $\theta = 6$, $\beta = 10$, $\lambda = 6$.

Comparison between mean-field solution and simulations

The implicit equation solution gives:

```
With N=500, beta=10.0, lambda=6.0, theta=51 we get:
  [...]
  mu_E        = 0.54435,
  nu_N        = 4063.10,
  mu_theta    = 406.31,
  mu_A        = 308.56.
```

One numerical simulation gives:

```
Dealing with sim_n500_u50_f0p75_b10_l6_sim1_neuron:
[...]
*** Network level statistics ****
Ignoring 10 time unit(s) at both ends we get:
  nu_N = 4056.3, with a 95% CI of [4045.4,4067.3].
The mean nb of neurons above threshold is: 405.861
The mean nb of active synapse is: 308.909
```

Where are we?

A conclusion for the mathematicians in the room

Remains the question of whether or not it is possible to establish rigorous results for this model, and if so how to do it?

Asymptotic memorylessness

If you write τ_N for the time of extinction of a system containing N neurons, the standard way to obtain the asymptotic memorylessness is to show:

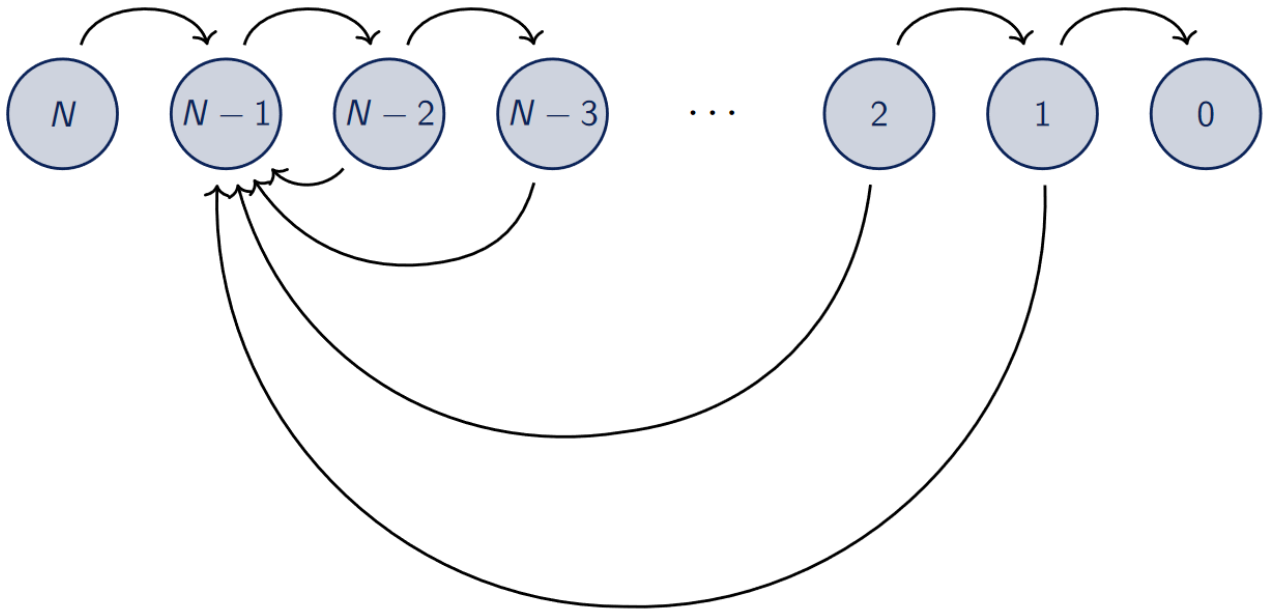
$$\lim_{N\to\infty} \left| \mathbb{P}\left(\frac{\tau_N}{\beta_N} > s+t\right) - \mathbb{P}\left(\frac{\tau_N}{\beta_N} > s\right)\mathbb{P}\left(\frac{\tau_N}{\beta_N} > t\right) \right| = 0,$$

where β_N is some time scale satisfying $\mathbb{E}(\tau_N) \underset{N\to\infty}{\sim} \beta_N$.

See for example:
Cassandro et al. (1984)
Andre (2019)
Andre and Planche (2021)

Asymptotic memorylessness

In the setting of André and Planche (2021), which is close to our model, a simple technique is to consider only the number of active neurons at any time t.



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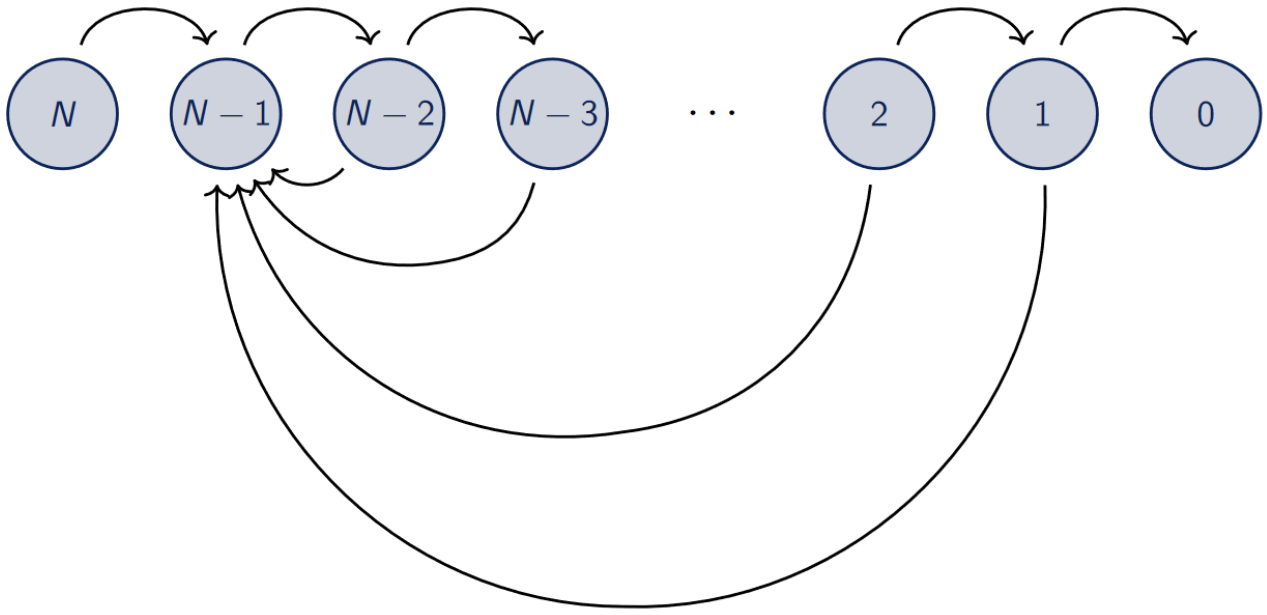

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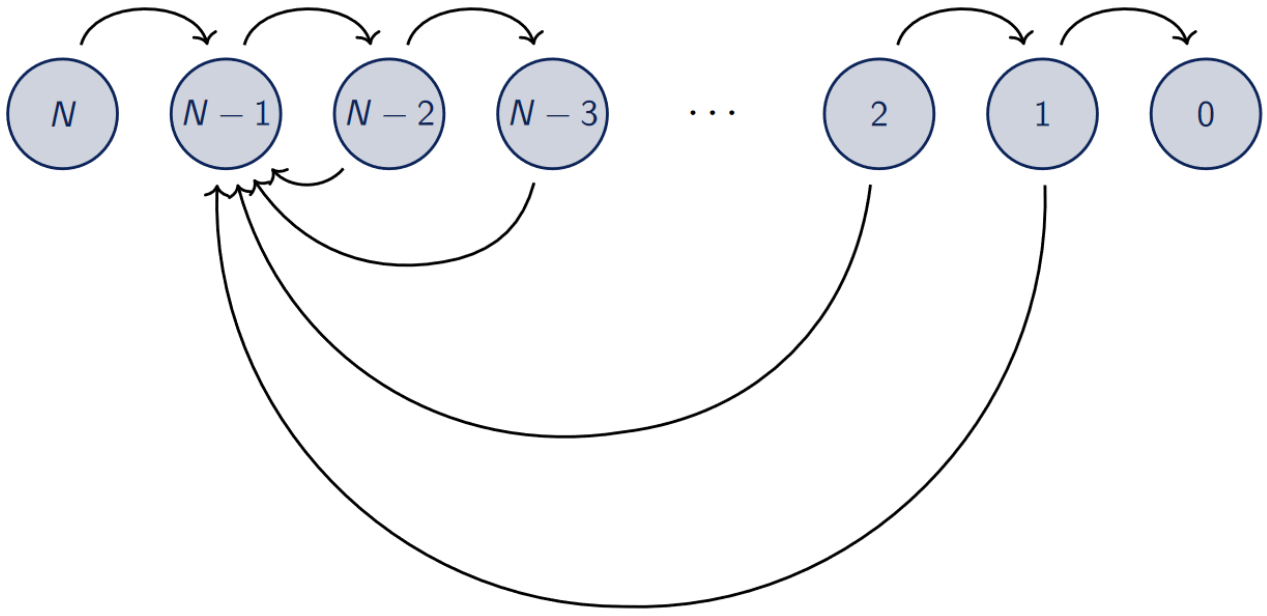

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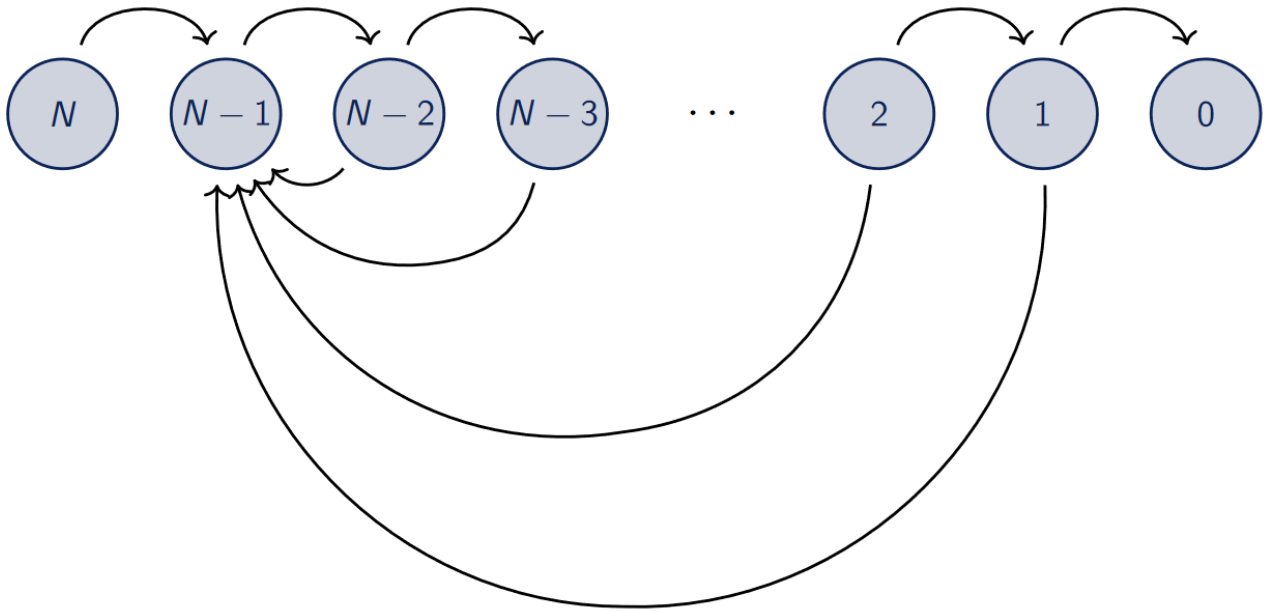

This is a (continuous time) Markov chain
$\rightarrow$ compute the invariant measure explicitly
$\rightarrow$ use it to conclude.

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Indeed if for any $t \geq 0$ we write $X(t)$ for the number of neurons above the threshold in our model, then $(X(t))_{t \geq 0}$ is not a Markov chain.

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An alternative approach would to define $(X(t))_{t\geq 0}$ as the process that gives the count of neurons for each possible value of the membrane potential.

Asymptotic memorylessness

That is, for any $t \geq 0$

$$X(t) = \left(X_0(t), X_1(t), \ldots, X_{\theta-1}(t), X_\theta^F(t), X_\theta^{NF}(t) \right).$$

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Then $(X(t))_{t\geq 0}$ is a Markov chain on $\{0, \ldots N\}^{\theta+2}$, but it is also far less tractable than the previous case...

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Remains the question of how to give a precise mathematical formulation of the second point in the characterization of metastability.

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Finally prove that, for any suitable $f : X^{\mathbb{Z}} \mapsto \mathbb{R}$, we have

$$\frac{1}{R}\int_s^{s+R} f(\xi_N(t))dt \approx \int f d\mu.$$

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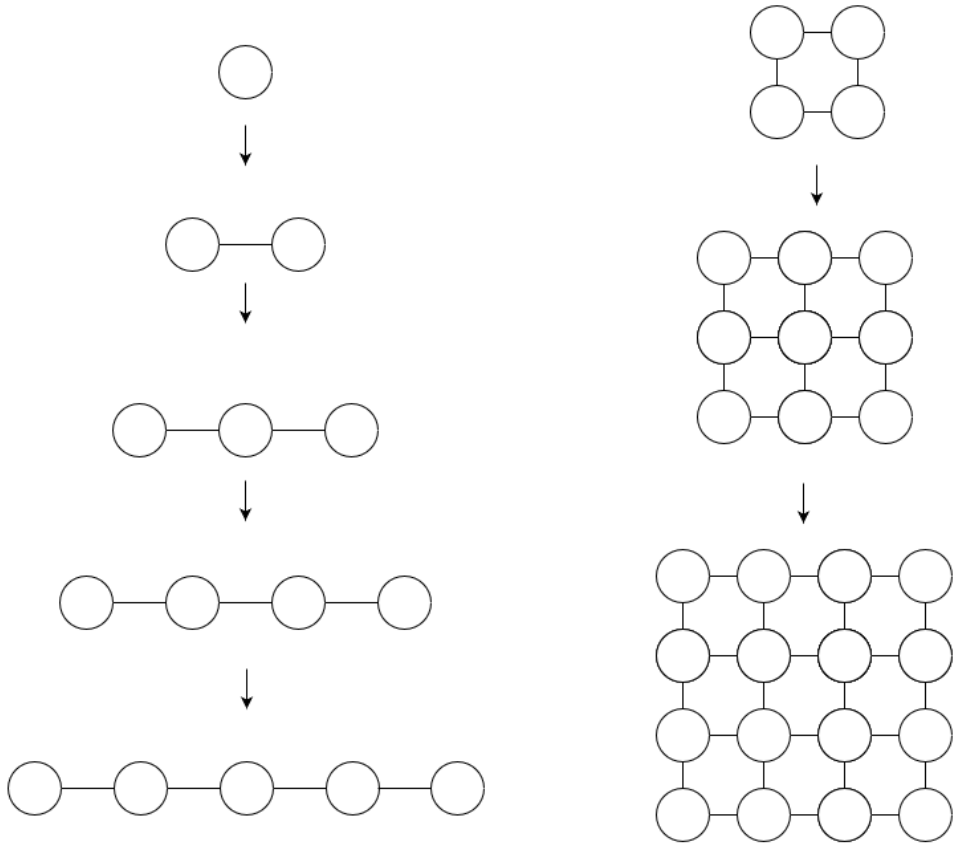

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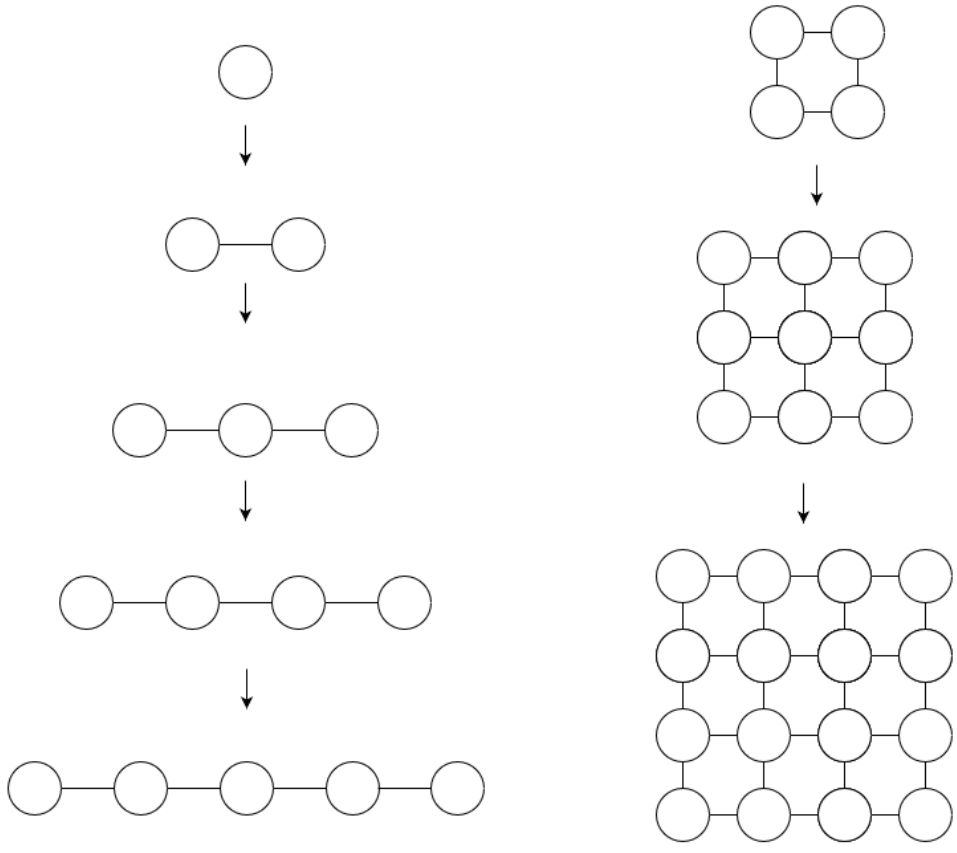

Problem: a sequence of complete graphs doesn't preserve the local structure!

The end