Brain-Inspired Computing
Class 3
Event-based representations

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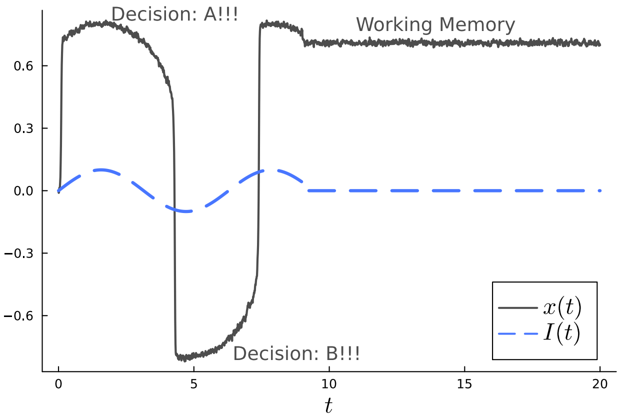
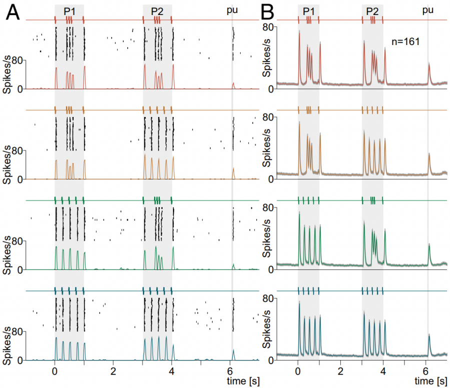
We saw that the emergence of categorical representations is associated with the emergence of working memory, thanks to the underlying multi-stability.



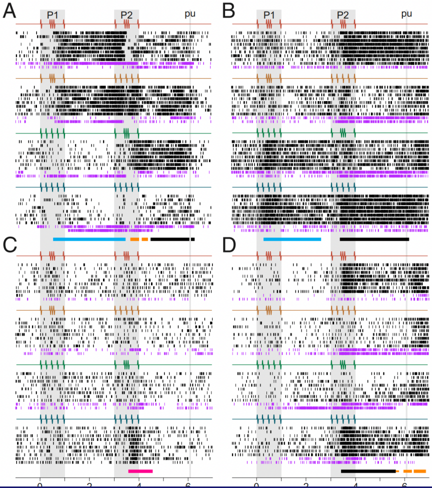
Categorical representations and working memory

This is in line with the transformation of information representation in the cortex [1]

Primary sensory cortex



Dorsal premotor cortex



Categorical representations and working memory

However, categorical representations/decisions must also be "forgot" [1]

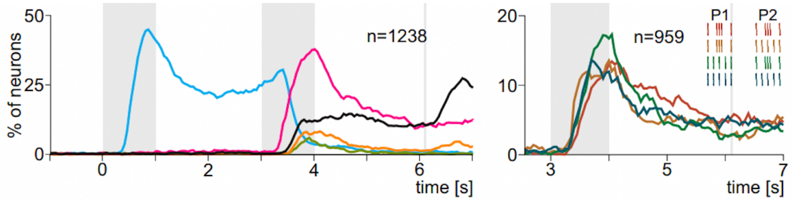
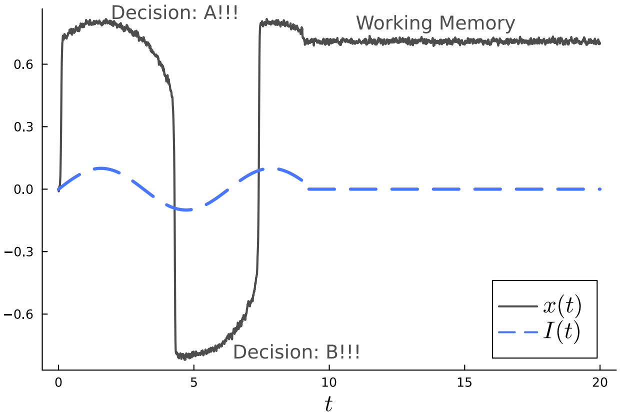


Fig. 7. Population coding dynamics in DPC during pattern discrimination. (*A*) Times at which individual DPC neurons carried a significant signal. Horizontal colored lines indicate time bins encoding (Fig. 4) the first pattern (P1 cyan), the second pattern (P2 light green), the trial class (pink), the decision partially (light orange), or the complete decision (black). Each row corresponds to a single neuron. (*B*) Percentage of neurons with significant encoding as a function of time. (*C*) Results for class-selective neurons sorted according to specific classes: class 1 (red, $n = 241$), class 2 (orange, $n = 219$), class 3 (green, $n = 263$), and class 4 (blue, $n = 236$). (*D*) Percentage of neurons with significant class-selective coding as a function of time.

Stuck in a decision

What makes a representation wanes if it is not used or after it has been used??



[1] Román Rossi-Pool et al. "Emergence of an abstract categorical code enabling the discrimination of temporally structured tactile stimuli". In: *Proceedings of the National Academy of Sciences* 113.49 (2016), E7966–E7975.

Resetting decisions through slow negative feedback: the emergence of excitability

A flexible signal-detection (one category + neutral) model

Let's use model

$$\tau\dot{x}(t) = -x(t) + \tanh(k \cdot x(t) + I(t))$$

(with $k > 1$ to ensure categorical representation) as a tunable detector of large enough positive inputs.

To do so, let $\pm I_{SN}$, $I_{SN} > 0$, be the input values at which the saddle-node bifurcations happen in the $\{(I, x)\}$-bifurcation diagram. Let $-I_{SN} < I_0 < I_{SN}$ be a constant bias input and let x_0 be the lower stable equilibrium for $I(t) \equiv I_0$. Let the detector dynamics be

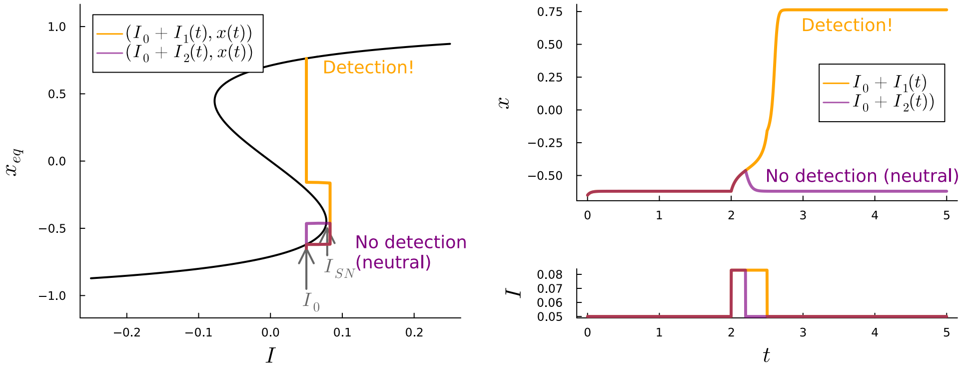
$$\tau\dot{x}(t) = -x(t) + \tanh(k \cdot x(t) + I_0 + I(t)), \quad x(0) \approx x_0$$

When the input $I(t)$ crosses an implicitly defined threshold $I_{th} = I_{SN} - I_0$ (i.e., the saddle-node bifurcation is crossed) the state switches to the up state: a sufficiently large input was detected! The parameter I_0 serves to shift the implicit threshold.

(Parenthesis: receptive fields)

The input $I(t)$ can be the output of a filter with (possibly MISO) transfer function $F(s)$ that pre-processes the actual input to the agent. The transfer function $F(s)$ is called a "receptive field".

A flexible signal-detection (one category + neutral) model



Resetting the decision through slow negative feedback: one-option excitable dynamics

If we want our system to forget its decision after a while, i.e., after the decision's representation is used for some cognitive process or if it is not used at all, we can achieve it through **slow negative feedback**. The effect of slow negative feedback is to bring the state back to a neutral or nominal state. The **decision becomes an event**, which happens at a given time and lasts a finite amount of time.

Adding a slow negative feedback variable on x, we obtain dynamics

$$\tau\dot{x}(t) = -x(t) + \tanh(k \cdot x(t) + \bar{I}_0 + I(t) - x_s(t)) + \sigma \cdot n(t), \quad x(0) \approx x_0$$
$$\dot{x}_s(t) = \varepsilon(x(t) - x_s(t)), \quad x_s(0) \approx x_0$$

where $0 < \varepsilon \ll 1$.

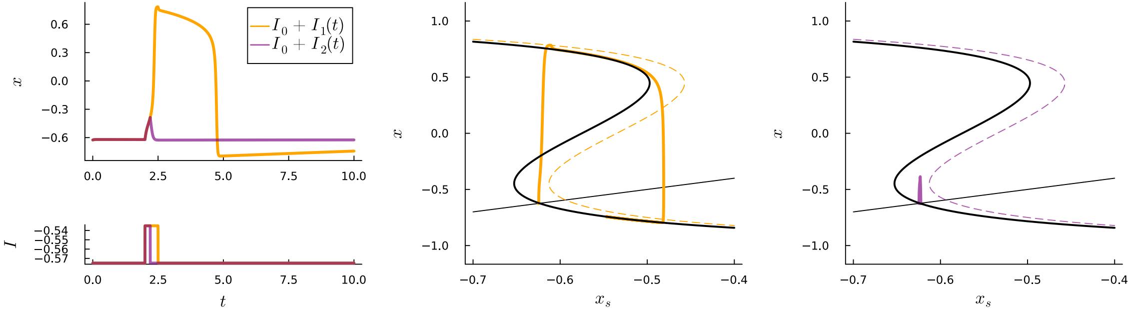
Resetting the decision through slow negative feedback: one-option excitable dynamics

To ensure that $(x, x_s) = (x_0, x_0)$ is an equilibrium for $I(t) = 0$ and for a desired threshold shift I_0, we let $\bar{I}_0 = I_0 + x_0$. In this way, the **fast subsystem**

$$\tau \dot{x}(t) = -x(t) + \tanh(k \cdot x(t) + \bar{I}_0 + I(t) - x_s(t)) + \sigma \cdot n(t), \quad x(0) \approx x_0$$
$$\dot{x}_s(t) = 0, \quad x(0) \approx x_0$$

(in which for analysis purpose we have “frozen” the slow variable x_s by approximating $\varepsilon \approx 0$) is still $I_{SN} - I_0$ input units away from the detection threshold.

The resulting dynamics is a **one-option (stimulus detected!) excitable dynamics**.



$I_0 + I_1(t)$
$I_0 + I_2(t)$
x
I
t
x_s
0.6
0.3
0.0
−0.3
−0.6
−0.54
−0.55
−0.56
−0.57
0.0
2.5
5.0
7.5
10.0
1.0
0.5
−0.5
−1.0
−0.7
−0.6
−0.5
−0.4

Toward generalization to multiple options

Toward generalized excitability

Interpreting excitable dynamics as nature's solution to reset a decision variable after the represented decision is no more useful to the agent's behavior provides a vantage viewpoint to generalize the notion of excitable events (restricted to one option in the classical setting) to multiple decision dimensions.

We will do this by suitably including slow negative feedback in multi-option representations (decision-making dynamics), and using geometric analysis to guide our model building.

The recipe will always be to add adaptation (through slow negative feedback) around a suitably chosen hysteresis.