Brain-Inspired Computing
Class 1
Embodied Intelligence and an introduction to the central ideas of the course

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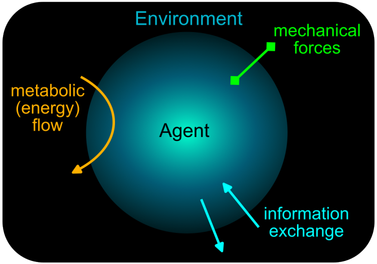
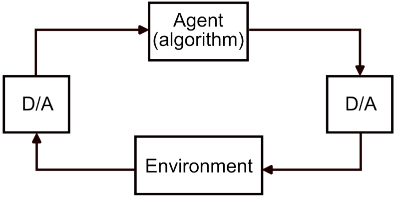


Disembodied



An embodied agent

- has a scope
- makes meaningful decisions
- is analog and dynamical and...
- ... dynamically coupled to the environment

Examples: bacteria, single neurons, robots, humans, fish schools, honeybee societies.

A disembodied agent:

- does not have a scope
- maps digital inputs to digital outputs algorithmically

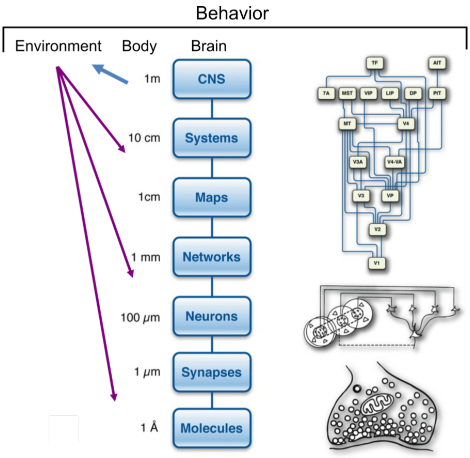
Examples: all machine-learning algorithms.

Embodied agents vs algorithms

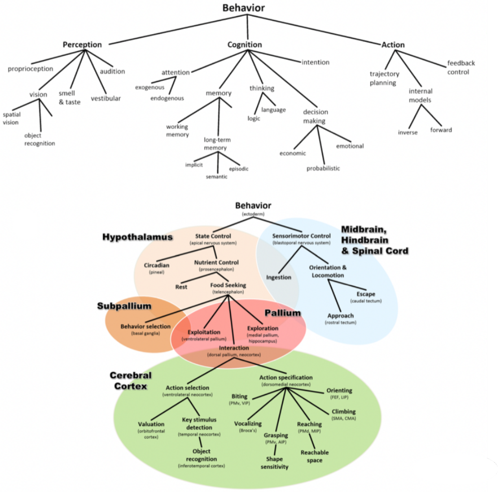
The type of “computations” we want to describe, understand, and reproduce in artificial machines are those observed in **embodied agents**. An embodied agent is an open system, far from equilibrium, in dynamical interaction with the environment it inhabits and with a scope in the environment it inhabits. Example of embodied agents are robots, mammals, and bacteria, both as individuals and as groups. Due to anthropocentric reasons, the course is called “brain-inspired” but as we will discover along the way, a brain is not dissimilar from a molecular regulatory network in a bacterium or from a group of bees when looked through the eyes of embodied computation.

Conversely, disembodied agents do not have a scope and are connected to the environment through immutable and static encoders/decoders (e.g., A/D and D/A converters). The only function of a disembodied agent is to take an input stream of digital information and maps it to an output stream of digital information following algorithmic rules. Disembodied agents are usually designed through machine learning algorithm.

Brains are embodied



Adapted from [6]



Function vs **Purpose** [2].

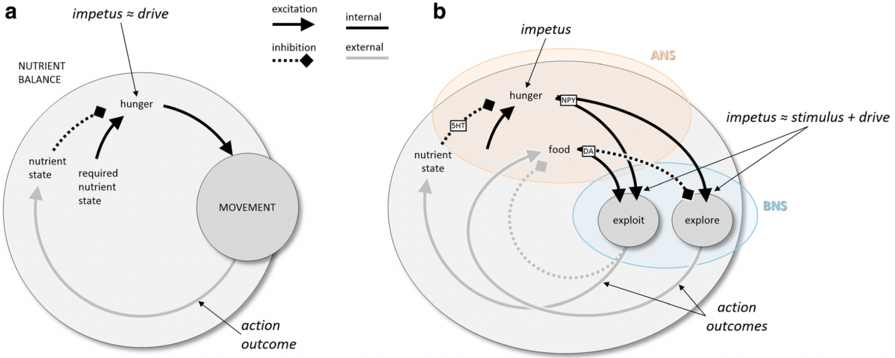
Brains are embodied

Brains are part of an organism that interacts with the environment through a body. The brains are dynamically coupled to the body through electro-molecular signaling and the body is dynamically coupled to the environment, e.g., through mechanical forces or social interactions. The dynamic brain-body-environment interaction determine the organism behavior.

Behavior can be dissected in terms of **functions** or in terms of **purposes**. The functional dissection is based on our psychological experience and relates to an input-output view of the organism: perception is akin A/D conversion; cognition is akin algorithmic processing; action is akin D/A conversion. Although intuitive, evidence for this dissection have been hard to find in neuronal data [2]. Alternatively, one can dissect behavior in terms of purposes. Purposes are organized hierarchically in such a way that *i)* purposes down the hierarchy are refinements of the purposes above and *ii)* the hierarchy respects the organism phylogeny (see also [5, Chapter 3]). Purposes are naturally embodied as **dynamical control and decision-making subsystem** for the organism behavior and can more easily be mapped to the electrical activity of relevant neuronal structures.

The purpose approach to embodied intelligence is linked to a rich neuroscientific and philosophical discussion about *agency* and the role of *affordances* in understanding cognition (see also [4], [3]). We won't touch this further here but I am happy to discuss it with whomever is interested.

Embodied agents as hierarchical control loops



Single-level behavioral control loop   Low-level/High-level behavioral control loop

From [2]. Low-level purpose: food intake. High-level purpose: explore or exploit food sources.

Embodied agents as hierarchical control loops

The hierarchy of purposes defines a **hierarchy of nested control/decision-making loops**. As illustrated in the food-intake example, a low-level purpose is sufficient to create intelligent behavior in the form of random exploration of the environment under the impetus of the hunger drive. Observe that agent-environment interconnection defines a **negative feedback** loop: the selected action (moving to find food) reduces the cause (hunger). This is a general principle of adaptive behaviors, from homeostasis in all its forms to automatic airplane control. The idea that (negative) feedback is key for brain functioning is the foundation of Wiener's Cybernetics [7].

The feedback interaction, based on extremely simple rules between the agent and the environment (note that the agent does not directly sense the environment, but it indirectly does so though hunger) can lead to much more complex **emergent behaviors**, that is, behaviors that cannot be exhibited by either of the two party in isolation. An organism controlled by a simple food intake regulation mechanism will likely alternate periods of food consumption and periods of movement, interleaved in a complex temporal pattern. Similarly, the food available in the environment will likely exhibit complex spatiotemporal patterns of abundance and scarcity, depending on the agent behavior and how it consumes it. Deprive the animal of the hunger drive that feedback couples it to the environment and the complex behavior will disappear. The idea that simple embodied feedback loop can lead to complex behavior is at the basis of the beautiful book "Vehicles - Experiments in Synthetic Psychology" by V.Braitenberg. It is also at the basis of behavior-based robotics [1].

Embodied agents as hierarchical control loops

Adding a higher-level control loop, with purpose of **deciding** whether to explore or exploit the environment and using a sensor to measure the local food availability further increases the complexity of the emergent behavior and will likely lead to the alternation of exploring phases, in which the agent travels long distances looking for food-rich regions, and exploiting phases, where the local food resources are exploited.

Higher and higher-level control loops could be added in a similar fashion leading to more and more complex emergent behaviors. It is again important to stress that emerging behaviors are never specified *a priori* in the controller (which follows very simple feedback rules) and will very likely be unpredictable (if we try to build such nested control scheme, say, in a Turtlebot).

A missing piece in the explore-exploit control loop is **positive feedback**. Positive feedback makes decision robust to uncertainties through switching mechanisms and allows the control loop to **break indecision** when the cues are unclear, as we will thoroughly see during this course. A natural way to include positive feedback in the explore-exploit controller is in the form of mutual inhibition between the explore and the exploit module

Another example: corridor passing

Let's do it live.

The goal is to reach the other end of the corridor avoiding crashing with the other person. What are the emergent behaviors? Can you feel negative and positive feedback in action?

[1] Rodney A Brooks. "Intelligence without representation". In: *Artificial intelligence* 47.1-3 (1991), pp. 139–159.

[2] Paul Cisek. "Resynthesizing behavior through phylogenetic refinement". In: *Attention, Perception, & Psychophysics* 81 (2019), pp. 2265–2287.

[3] Giovanni Pezzulo and Paul Cisek. "Navigating the affordance landscape: feedback control as a process model of behavior and cognition". In: *Trends in cognitive sciences* 20.6 (2016), pp. 414–424.

[4] Andrea Roli, Johannes Jaeger, and Stuart A Kauffman. "How organisms come to know the world: fundamental limits on artificial general intelligence". In: *Frontiers in Ecology and Evolution* 9 (2022), p. 1035.

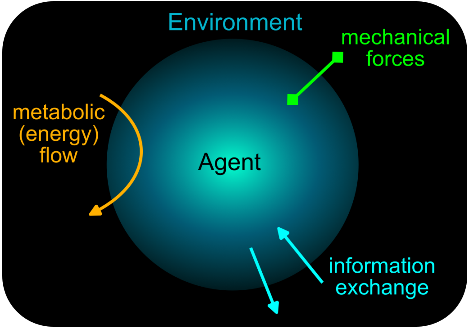
[5] Peter Sterling and Simon Laughlin. *Principles of neural design*. MIT press, 2015.

[6] X-J. Wang. *Theoretical Neuroscience of Cognition*. 2023.

[7] Norbert Wiener. *Cybernetics or Control and Communication in the Animal and the Machine*. MIT press, 2019.

Agents' state as representation

The agent-environment control dynamical system

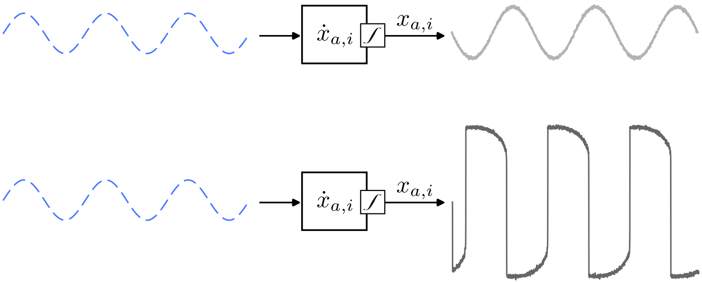


$$
\begin{aligned}
\dot{\boldsymbol{x}}_e &= f(\boldsymbol{x}_e, h^{\text{inf}}_{a\to e}(\boldsymbol{x}_a), h^{\text{mf}}_{a\to e}(\boldsymbol{x}_a)) \\
0 &= h^{\text{mec}}(\boldsymbol{x}_e, \boldsymbol{x}_a) \\
\dot{\boldsymbol{x}}_a &= g(\boldsymbol{x}_a, h^{\text{inf}}_{e\to a}(\boldsymbol{x}_e), h^{\text{mf}}_{e\to a}(\boldsymbol{x}_e))
\end{aligned} \quad \dagger
$$

The interaction between the agent and the environment can mathematically be described control dynamical system obtained by the (input-output, algebraic, or other) interconnection of a dynamical system describing the evolution of the environment state $\boldsymbol{x}_e$ and a dynamical system describing the evolution of the agent state $\boldsymbol{x}_a$.

† **Disclaimer:** no worries, we are not gonna use such kind of equations again in the course! They are here just to make the point below :)

Agents' state as embodied representation



(the $\int$ block will be omitted for clarity in the rest of the course)

When state variables are suitably chosen, the evolution of the agent state $\boldsymbol{x}_a$ provides an embodied representation of the behavior. Each variable $x_{a,i}$ evolves accordingly to the differential equation

$$\dot{x}_{a,i} = f_i(\boldsymbol{x}_e, h^{\text{inf}}_{a\to e}(\boldsymbol{x}_a), h^{\text{mf}}_{a\to e}(\boldsymbol{x}_a))$$

and, possibly, some algebraic constraints defined by $0 = h^{\text{mec}}(\boldsymbol{x}_e, \boldsymbol{x}_a)$. Thus, $x_{a,i}$ nonlinearly integrates its inputs (both other agent's state variables and environment's state variables) into a time trajectory $x_{a,i}(t)$.

Agents' state as embodied representation

When building a model of the environment-agent interaction, a *constraint we put on the way we chose the agent's state variables* is that the nonlinear integration performed by each state variable over its inputs is purposeful for the agent's behavior. In analogy with signal processing, in which a signal is transformed using a suitable basis or by digital sampling in a way that is purposeful for the engineer (detecting pick frequencies, denoising, etc.), we call this dynamical and behaviorally purposeful input-to-state transformation a **representation**. The representation is embodied because $x_{a,i}$ is a dynamical state of the agent.

Agents' state as embodied representation

In the food intake regulation example, x_a can be chosen to be a vector $x_a = (p, m, n, h)$ where p is the position of the agent in the environment, m is its movement state, n is its nutrient state, h is its hunger state. Let's illustrate the representation idea by deriving a simple model for the time evolution of m. The agent should be prone to move (m increases) when hunger is high while the propensity to move should go down when hunger is low. A possible model of this behavior is

$$\tau\dot{m} = -m + S(k \cdot m + h)$$

where τ determines how fast m reacts to changes in h, k is a tunable feedback gain, and S is a monotone increasing function that maps variations of h to variations of m.

The variable m creates a behaviorally purposeful representation of the hunger state by mapping it to movement behavior. Depending on τ, k, and the function S the representation can have various properties.

It could resemble the action of an analog filter, i.e., when S is roughly linear, in which case the movement state will be a filtered (e.g., lagged) version of the hunger state (top plot above). Such a representation would lead to smooth and slow changes in m as a function of h. Conversely, the representation could resemble a switch, which would lead to much more abrupt, almost discrete (digital), changes in m (bottom plot above). The representation could have memory or not.

Connection with the "no representation" motto of embodied intelligence

A motto of embodied intelligence, both in behavioral robotics [1] and cognitive science [2], is that "representations" are not needed to obtain intelligent behavior and that they do not exist in the brain. But this viewpoint clashes strongly with our own experience, full of symbols and either kind of abstract representations that we routinely use to interact with the environment.

The stance taken here is a mid point between the 'no representation' and 'full-blown representation' viewpoints, or, better said, it is an effort to try reconciling them. By focusing on embodied agents described by control dynamical systems with certain purposes, we will see that there is a continuum between analog representations, i.e., filters, that are fully compatible with the 'no representation' viewpoint, and digital representations, i.e., discrete categories, in line with the 'full-blown representation' approach.

Again, these are almost philosophical topics that go beyond the course content, but I am happy to discuss this further with whomever is interested :)

[1] Rodney A Brooks. "Intelligence without representation". In: *Artificial intelligence* 47.1-3 (1991), pp. 139–159.

[2] Anthony Chemero. "Radical embodied cognitive science". In: *Review of General Psychology* 17.2 (2013), pp. 145–150.

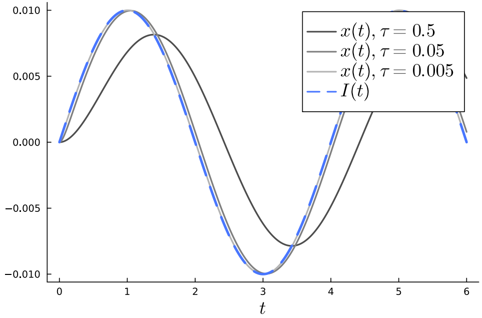
Flexible representations

Faithful/analog representations

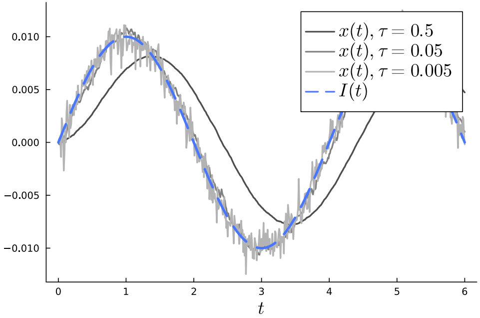
Let's consider the simple model of a representing state variable derived in the last example

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

where I is the input. When $k = 0$ the model is linear in x. In the absence (presence) of noise, its response to a small sinusoidal input for various τ is shown in the left (right) plot.



$\|I(t) - x(t)\|^2 \approx 0.1$, $\|I(t) - x(t)\|^2 \approx 0.013$, $\|I(t) - x(t)\|^2 \approx 0.0013$



$\|I(t) - x(t)\|^2 \approx 0.1$, $\|I(t) - x(t)\|^2 \approx 0.016$, $\|I(t) - x(t)\|^2 \approx 0.025$

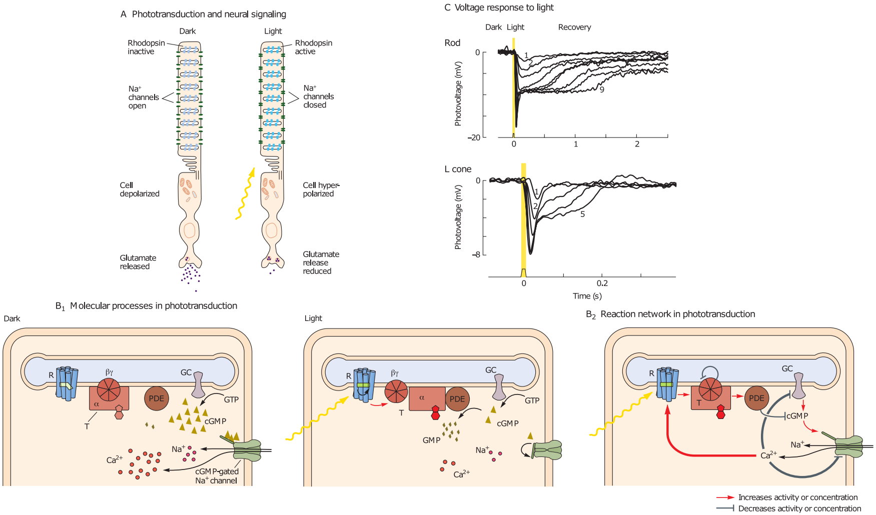
Faithful/analog representations

In the absence of noise, making the representing dynamics faster lets the state $x(t)$ track the input with arbitrary precision. The analog representation is **faithful**. An engineering example of a dynamical system that aims at faithfully representing its input is a microphone, which uses, e.g., a capacitor to represent air pressure waves into an electrical signal.

High faithfulness comes however at the price of making the representation highly sensitive to noise. In the presence of noise, a slightly less faithful representation can achieve much better performances. Analog filter design with desired filtering (or, in this context, representational) properties is a fundamental engineering problem.

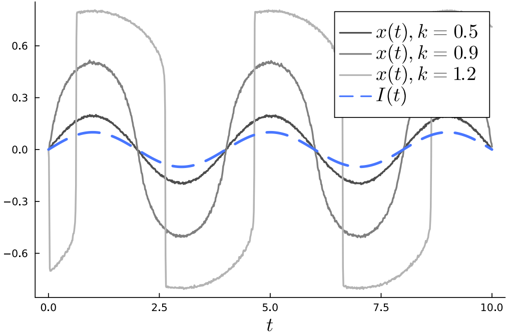
A biological example of a dynamical system that aims at faithfully representing its input is a retinal photo-receptor, which uses a complicated electromolecular dynamics to represent the rate of incoming photos into an electrical signal.

Photoreceptor: a biological example of faithful/analog representation



From [1].

Categorical/digital representations



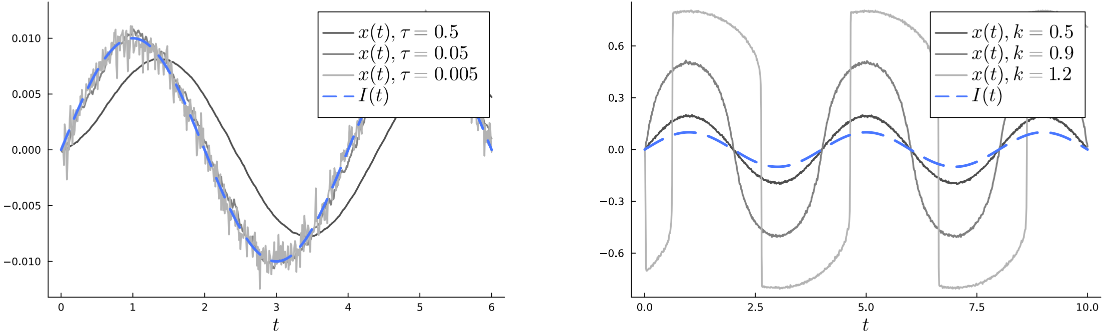
Cranking up the feedback gain k initially leads to a nonlinear amplification of the input ($k < 1$). For even larger values of the feedback gain ($k > 1$) the response to input acquires a **switch-like** behavior: for sufficiently positive inputs, the trajectory converges to a roughly constant high state; for sufficiently negative inputs the trajectory switches to a low state. The switching between high and low state exhibit hysteresis.

The low and high state are akin the bits of a digital switch and represent a low and a high **category**, respectively.

A biological example of categorical switching

Flexible representations

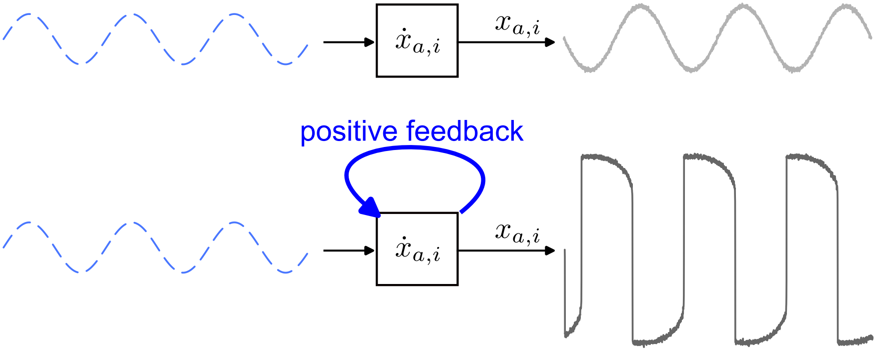
small k $\longleftrightarrow$ large k



As an example: whn we raed somehting fast, we use categorical representation to map noisy (i.e., orthographically wrong) inputs to the correct categories; but reading the same sentence slowly we can create a faithful representation of the input (and correct the errors).

Flexible representations

The tuner of the transition between analog/faithful and digital/categorical representation is the positive feedback gain.



Exercise: Write a model for the mutual inhibition between the explore-exploit modules under the drive of the hunger stimulus and show that it exhibits flexible representation as a function of the mutual inhibition strength. Explain in terms of positive feedback.

Flexible representations

Purely analog/faithful and purely digital/categorical representations are just the extreme of a continuum (as it can be appreciated by gradually increasing the positive feedback gain k in the simple model above). The possibility of gradually changing the representation along the analog and digital continuum makes the representation **flexible**. A flexible representation can be adapted to the context and to the agent experience.

As an another example, take the process of learning a high-coordination activity like juggling. At the beginning we work in an analog way, creating a faithful (but slow) representation of the ball dynamics (i.e., paying a lot of attention to them) and of all the movements we need to do in order to execute them. With learning, movements sequences are consolidated into categories (three-ball cascade, three-ball shower, three-ball columns, etc.) that we can activate automatically, without any precise mental representation and by drastically reducing the attention we need to pay to the balls.

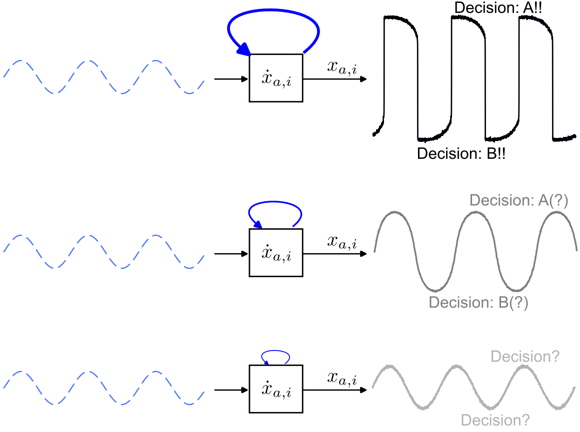
The idea of flexible representation is tightly related to the idea of mixed-feedback (i.e., positive *and* negative) representation introduced in [2]. Its potential for embodied artificial intelligence is still largely unexplored. For disembodied applications, see the work of Prof. Drion.

[1] Eric R Kandel et al. *Principles of neural science*. McGraw-hill New York.

[2] Rodolphe Sepulchre, G Drion, and A Franci. "Control across scales by positive and negative feedback". In: *Annual Review of Control, Robotics, and Autonomous Systems* 2 (2019), pp. 89–113.

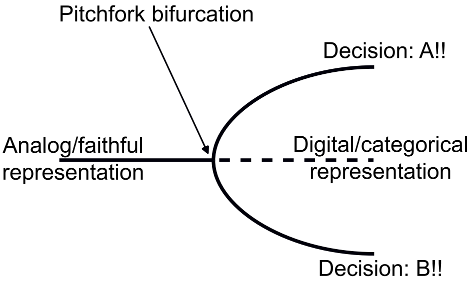
Flexible decision making

Flexible representations as flexible decision-making



- When the representation is digital/categorical the category to which the state converge can be interpreted as a *decision*. The decision can be sensory, motor, or higher-level, depending on the layer that makes it.
- When the representation is halfway between digital/categorical and analog/faithful, the layer is still communicating a decision, but the communicated strength of the decision is weaker.
- When the representation is analog/faithful no marked decision can be distinguished.

Connection between decision-making and bifurcations



The pitchfork bifurcation is the **organizing center** of two-option decision-making and the transition from analog/faithful representation to digital/categorical representation of a scalar signal is captured by the pitchfork bifurcation diagram.

Multi-option decision-making and the associated analog/faithful to digital/categorical representations are similarly modeled by higher-dimensional generalizations of the pitchfork [3, 2, 1]

[1] Anastasia Bizyaeva, Alessio Franci, and Naomi Ehrich Leonard. "Nonlinear opinion dynamics with tunable sensitivity". In: *IEEE Transactions on Automatic Control* (2022).

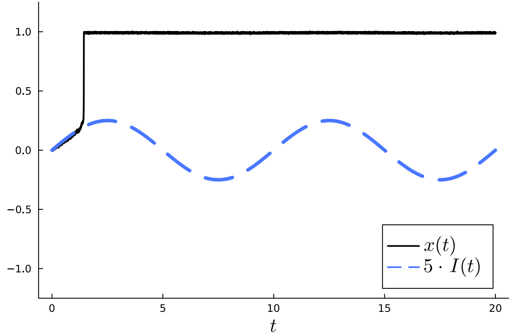
[2] Anastasia Sergeyevna Bizyaeva. "Nonlinear dynamics of multi-agent multi-option belief and opinion formation". PhD thesis. Princeton University, 2022.

[3] Alessio Franci et al. "Breaking indecision in multi-agent, multi-option dynamics". In: *arXiv preprint arXiv:2206.14893* (2022).

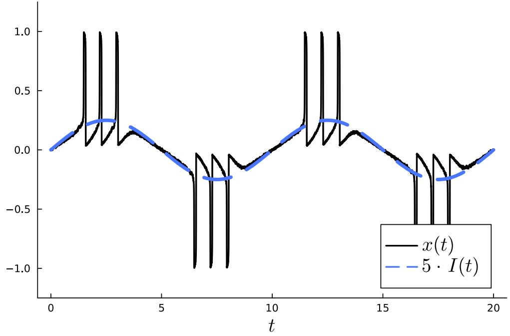
Generalized excitability:
making representations event-based

From decisions to events

A problem of decision-making dynamics is that they might get stuck in a decision despite inputs point in the opposite direction.

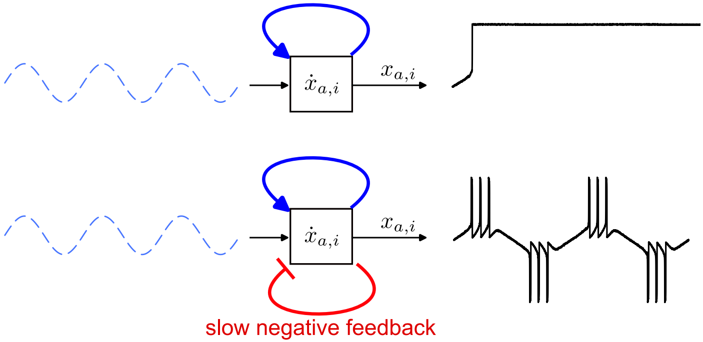


A solution to this problem that does not compromise the decisive/categorical nature of the communication is by adding a**slow negative feedback** loop that resets the decision state.



From decisions to events

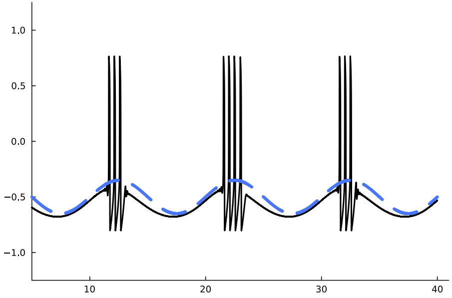
By resetting the decision state, slow negative feedback leads to communication **event-based communication**: an event is generated each time a decision is made and the state is reset. Event-based communication is a form of **excitable behavior**: when the decision threshold is crossed the system transiently visit an excited (decision) state. The role of positive and negative feedback on multiple timescales for neuronal excitability and its robustness is thoroughly discussed in a series of papers [1, 5, 3, 2, 4, 6].



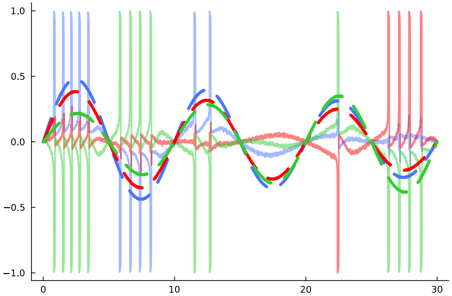
Decisions + Excitability = Generalized Excitability

By providing with excitability the dynamics of possibly high-dimensional (i.e., with many options to chose from) decision variables, what we obtain by joining dynamical decision making and excitability is a generalization of classical (spike) excitability.

Classical (spike) excitability is 1-option event-based communication.



Generalized excitability is multi-option event-based communication.



[1] Guillaume Drion et al. "A novel phase portrait for neuronal excitability". In: *PLoS One* (2012).

[2] Guillaume Drion et al. "Dynamic input conductances shape neuronal spiking". In: *eneuro* 2.1 (2015).

[3] Alessio Franci, Guillaume Drion, and Rodolphe Sepulchre. "Modeling the modulation of neuronal bursting: a singularity theory approach". In: *SIAM Journal on Applied Dynamical Systems* 13.2 (2014), pp. 798–829.

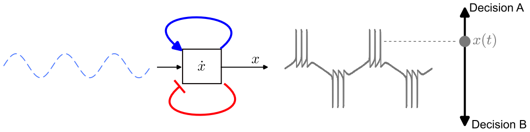
[4] Alessio Franci, Guillaume Drion, and Rodolphe Sepulchre. "Robust and tunable bursting requires slow positive feedback". In: *Journal of neurophysiology* 119.3 (2018), pp. 1222–1234.

[5] Alessio Franci et al. "A balance equation determines a switch in neuronal excitability". In: *PLoS computational biology* 9.5 (2013), e1003040.

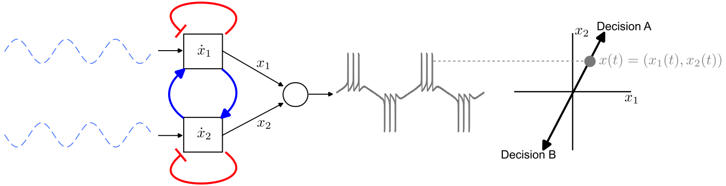
[6] Rodolphe Sepulchre, G Drion, and A Franci. "Control across scales by positive and negative feedback". In: *Annual Review of Control, Robotics, and Autonomous Systems* 2 (2019), pp. 89–113.

Excitable Network representations

Excitable Network representations



- Single agent representation

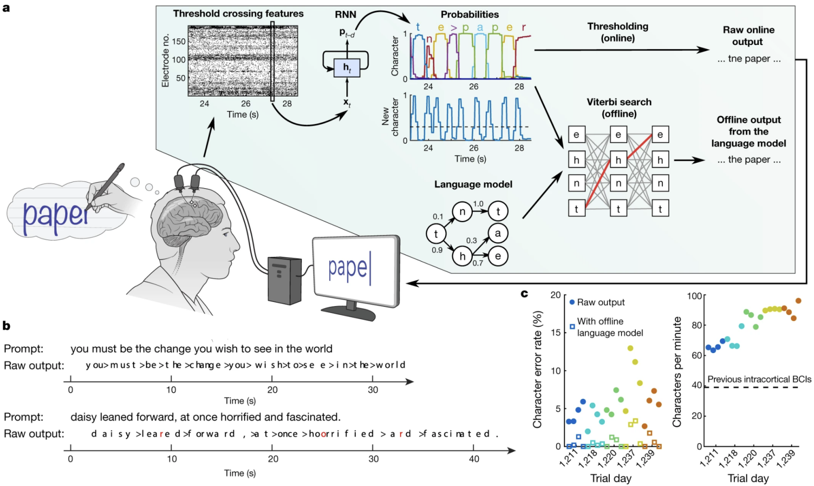


- Network representation

Excitable Network representations

The decision-making model derived in [1, 3] is for an arbitrary number of deciding agents (cells, organisms, robots, layers) and an arbitrary number of options among which the agents are deciding. The model is defined as an **opinion network** in which the nodes are the values assigned by the agents to the different options.
Augmenting this model with the fast-positive, slow-negative feedback motif of excitability, we obtain a generalized excitable dynamics in the high-dimensional multi-agent multi-option space. Excitable events are characterized by a direction in the option space, indicating which option are favored/disfavored, and a direction in the agent space, indicating which agents favor/disfavor which options.
The multi-agent nature of the excitable event leads to **shared representations**, that is, in which the signal is represented across many nodes of the representing network and, conversely, in which the same node can represent different incoming signals simultaneously.

Shared representations in biology population dynamics



Motor decision-making (which letter to write?) decoded through an RNN from the population activity of many thousands of neuron in the precentral gyrus premotor area. The decision representation is shared. From [6].

Shared representations in biology population dynamics

When a layer, like our premotor or prefrontal cortices, must represent huge amount of possible sensor and motor behaviors, shared representations are a natural way to ensure **robustness and flexibility of the representation**. Because a same category, i.e., the letter *a* is represented across many neurons, failure of some of them is not crucial. On the other hand, the high dimension of the network allows representations to evolve through learning and experience. Furthermore, representations of some categories can be recycle to represent new similar ones. In such a high-dimensional setting it can be difficult, if not impossible, to decipher the representation without the help of ML techniques. The marriage of neuroscience and ML, mostly through RNN, has already a relatively long history [5, 4, 2, 7] but a rigorous control-theoretical framework to make sense of those kinds of results is still missing. Generalized excitability might provide such a framework. Something we can explore through an ongoing collaboration with ▸ Roman Rossi-Pool, who studies primate cognitive electrophysiology (both experimentally and through ML methods) at the Cellular Physiology Institute of UNAM.

[1] Anastasia Bizyaeva, Alessio Franci, and Naomi Ehrich Leonard. "Nonlinear opinion dynamics with tunable sensitivity". In: *IEEE Transactions on Automatic Control* (2022).

[2] Angus Chadwick et al. "Learning shapes cortical dynamics to enhance integration of relevant sensory input". In: *Neuron* 111.1 (2023), pp. 106–120.

[3] Alessio Franci et al. "Breaking indecision in multi-agent, multi-option dynamics". In: *arXiv preprint arXiv:2206.14893* (2022).

[4] Valerio Mante et al. "Context-dependent computation by recurrent dynamics in prefrontal cortex". In: *nature* 503.7474 (2013), pp. 78–84.

[5] Ben Sorscher et al. "A unified theory for the computational and mechanistic origins of grid cells". In: *Neuron* 111.1 (2023), pp. 121–137.

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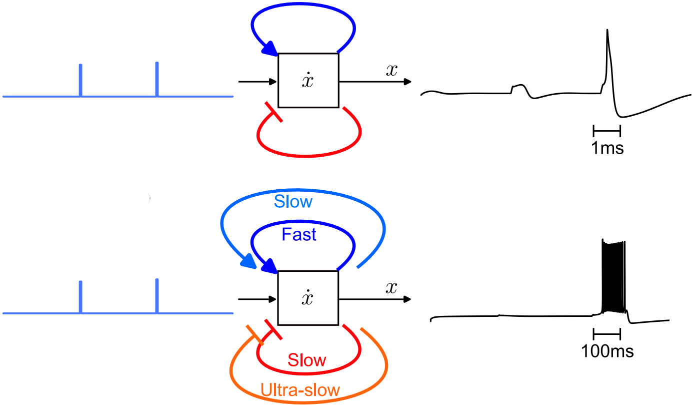
Multi-scale excitability

Multi-scale excitability

Another key properties of generalized excitability is its **multi-scale nature**. The fast-positive/slow-negative feedback motif can be repeated at slower scales to generate *multi-scale events in the form of events-of-events*. The most well-studied form of multi-scale excitability is bursting (see, again, [1, 5, 3, 2, 4, 6] and references therein).



Despite its existence and fundamental role for brain functioning are evident, the precise roles of multi-scale excitability are still largely unknown. Here, we will rapidly touch at two of them: generating **robust and tunable event-based oscillations** and **tuning the dynamics of learning**.

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Event-based oscillations and CPGs

Event-based oscillations and CPGs

The role of bursting for the generation of robust and tunable oscillations has been explored in a number of works [3, 2, 1]. Let's illustrate here with a sensorimotor example: quadruped CPG control (on keynote). Note the emergent behavioral properties of the resulting sensorimotor loop.

The key point is that bursts constitute tunable temporal decisions: when actuation should take place? The decision is tunable because the temporal properties of the burst can be tuned: number of spikes, frequency of the spikes, etc. This is a general property of signaling through events-of-events.

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*Making sense of electrophysiological data

*Elements of plasticity and learning