

# DFT Tutorial

ICANN 2025

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# dynamicfieldtheory.org

- Tutorial documents (end of the week)
- DFT resources
  - Publications
  - Videos
  - Software
  - Book
  - News

The screenshot shows the homepage of the Dynamic Field Theory website. At the top, the navigation bar includes 'DYNAMIC FIELD THEORY' and links for 'NEWS', 'LEARNING DFT', 'EVENTS', 'RESEARCH GROUP', and 'MY APPLICATIONS'. Social media icons for YouTube, Twitter, Facebook, and LinkedIn are also present. The main content area is divided into three columns. The left column features an 'UPCOMING EVENT' section with a large banner for the 'DFT TUTORIAL AT ICANN 2025' on 'SEP 9, 2025', including a 'READ MORE...' button. The middle column has a 'LATEST NEWS' section with a featured article titled 'All you ever wanted to ask about DFT' by Prof. Dr. Gregor Schöner, dated July 31, 2025, and a grid of smaller news items. The right column displays 'LATEST PUBLICATIONS' with three entries, each showing a title, authors, journal information, and download options. At the bottom, a 'WHAT IS DFT?' link is visible.

**DYNAMIC FIELD THEORY** NEWS LEARNING DFT EVENTS RESEARCH GROUP MY APPLICATIONS

UPCOMING EVENT

**DFT TUTORIAL**  
**DFT TUTORIAL AT ICANN 2025**  
**SEP 9, 2025**  
[READ MORE...](#)

LATEST NEWS

**All you ever wanted to ask about DFT**  
Prof. Dr. Gregor Schöner / July 31, 2025  
At the 2025 CogSci conference we ran a tutorial workshop on DFT under the theme "All you ever wanted to ask about DFT". This was less focussed on a technical introduction and hands-on code level exercises, and more concerned with a conceptual introduction (led by [Gregor Schöner](#)), an embedding in...  
[Read More...](#)

Hands-on workshop on DFT at Psychonomics  
November 24, 2024  
BY: Prof. Dr. Gregor Schöner

The Theory of Embodied Cognition group at Ps  
November 15, 2024  
BY: Minseok Kang, M.Sc.

Gregor Schöner's keynote lecture at CogSci 2  
October 15, 2024  
BY: Prof. Dr. Gregor Schöner

A neural dynamic intentional agent  
September 4, 2024  
BY: Prof. Dr. Gregor Schöner

Prof. Dr. Gregor Schöner giving a keynote ta  
July 12, 2024  
BY: Minseok Kang, M.Sc.

A neural process account of visual analogica  
June 21, 2024  
BY: Minseok Kang, M.Sc.

LATEST PUBLICATIONS

Active exploration and working memory synaptic plasticity shapes goal-directed behavior in curiosity-driven learning  
*Cognitive Systems Research*, 91, 101339  
[APA](#)

Toward a neural theory of goal-directed reaching movements  
In Levin, M. F., Petrarca, M., Piscitelli, D., & Summa, S. (Eds.). *Progress in Motor Control: From Neuroscience to Patient Outcomes* (pp. 71–102) Academic Press  
[APA](#) [Downloads](#)

Neural Dynamic Principles for an Intentional Embodied Agent  
*Cognitive Science*, 48(3)  
[APA](#) [Downloads](#)

ROBOVERINE: A human-inspired neural robotic process model of active visual search and scene grammar in naturalistic environments  
In 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) IEEE  
[APA](#) [Downloads](#)

A Neural Process Model of Structure Mapping Accounts for Children's Development of Analogical Mapping by Change in Inhibitory Control  
In L. K. Samuelson, Frank, S. L., Toneva, M., Mackey, A., & Hazeltine, E. (Eds.). *Proceedings of the 45th Annual Conference of the Cognitive Science Society*  
[APA](#) [Downloads](#)

WHAT IS DFT?

# github.com/cedar/juniper

- GPU accelerated version of CEDAR
  - GitHub contains notebooks with demos used here
- Requirements:
  - `jax[cuda12]`
  - `matplotlib`

The screenshot shows the GitHub repository page for `cedar/juniper`. The repository is public and has 17 commits. The file list includes `architectures`, `img`, `src`, `.gitignore`, `DOCS.md`, `LICENSE`, `README.md`, `demo1_detection.ipynb`, `demo2_selection.ipynb`, `demo3_cued_selection.ipynb`, `demo4_Huetchen.ipynb`, `demo5_binding_through_space.ipynb`, `demo6_MemoryGame.ipynb`, `demo7_Corsi_sequence.ipynb`, `demo8_Corsi_query.ipynb`, `juniper.py`, `requirements.txt`, and `run_config.json`. The README file is selected, showing the title **JUNIPER** and the subtitle "Welcome to JUNIPER, the GPU Accelerated Python Implementation of CEDAR". The "Requirements" section lists the following steps:

- Insert your root path (folder that contains `run_config.json`) at the top of `util.py`, or leave it empty if you plan to run the main script from the root path
- Install the required pip packages by running `pip install -r requirements.txt`
- Run `juniper.py` (see Usage)

The repository also shows a sidebar with links to the README, LICENSE, Activity, Custom properties, Stars, Watching, Forks, and Report repository. The "Releases" section shows 1 tag. The "Packages" section shows no packages published. The "Contributors" section lists three contributors: Sehrispk, lars-rub, and moorugi98. The "Languages" section shows a bar chart with Python at 60.0% and Jupyter Notebook at 40.0%.

# Schedule



Building a Neural Dynamic Agent (90 min)



Break and Networking (30 min)



Hybrid Models with DFT (15 min)



Latest DFT Applications (25 min)

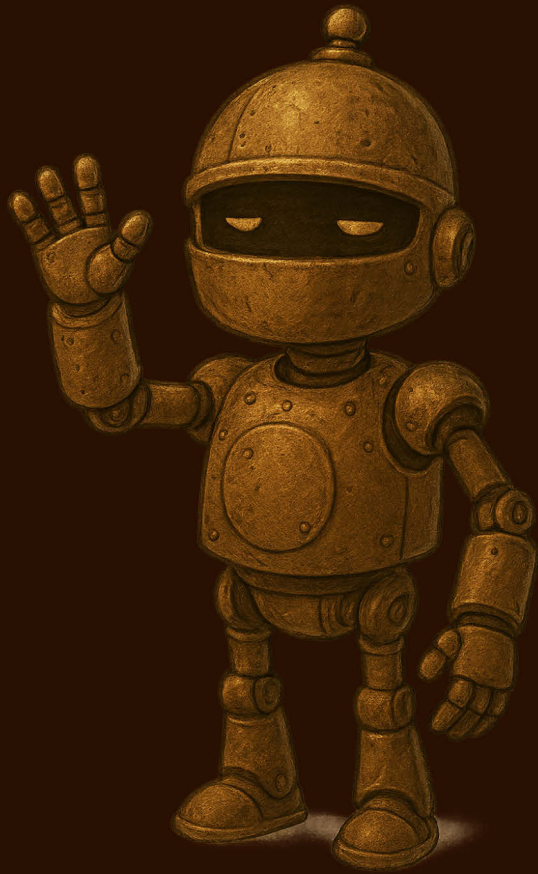


Open Discussion and Q&A (20 min)



How to Build a  
**NEURAL DYNAMIC  
AUTONOMOUS AGENT**  
IN 90 MINUTES

**This is Marvin:**



“Oh God  
I’m so  
depressed”

And his new friend Billy:



“I want to  
play a  
game”





ESCAPE  
ROOM

1



8

2

4

7

3

5

6

# Dynamic Field Theory (DFT)

- Dynamic Field Theory is a mathematical framework that aims to explain how
  - time-continuous evolution of neural population activation leads to cognition
  - discrete events emerge from instabilities in the underlying dynamics

# Foundations

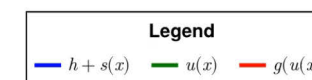
- **Cognition** is best understood at the level of **neural populations**
- Sensory information is transient
  - cognition needs **stable representations**
  - this stability must arise from recurrent connectivity within the neural population
- Neural **representations** needed for cognition are **low-dimensional**
  - they are easier to stabilize
  - enable invariance
- **Instabilities** in the dynamics enable **sequential transitions** between stable states
  - needed for cognition
- **Complex cognitive** functions emerge from interconnected **networks** of neural dynamics

# Dynamic neural field (DNF)

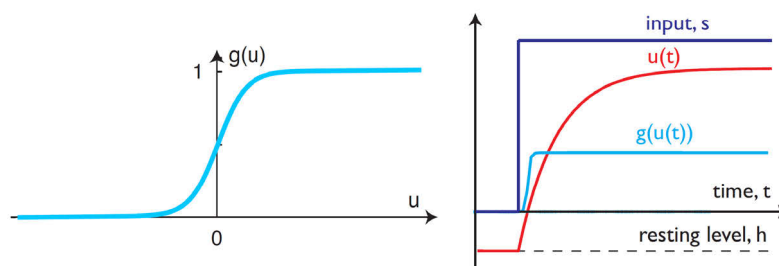
$$\tau \dot{u}(x, t) = -u(x, t) + h + s(x, t) + w_{\xi} \cdot \xi(x, t) + \int \omega(x - x') \cdot g(u(x', t)) dx'$$

Diagram illustrating the components of the Dynamic Neural Field (DNF) equation:

- rate of change** (time scale)  $\tau$
- time**  $t$
- feature value**  $u(x, t)$
- stabilization factor**  $-u(x, t)$
- resting level**  $h$
- external input**  $s(x, t)$
- neural noise**  $w_{\xi} \cdot \xi(x, t)$
- kernel**  $\omega(x - x')$
- sigmoidal threshold**  $g(u(x', t))$



$$g(u) = \frac{1}{1 + \exp(-\beta u)}$$



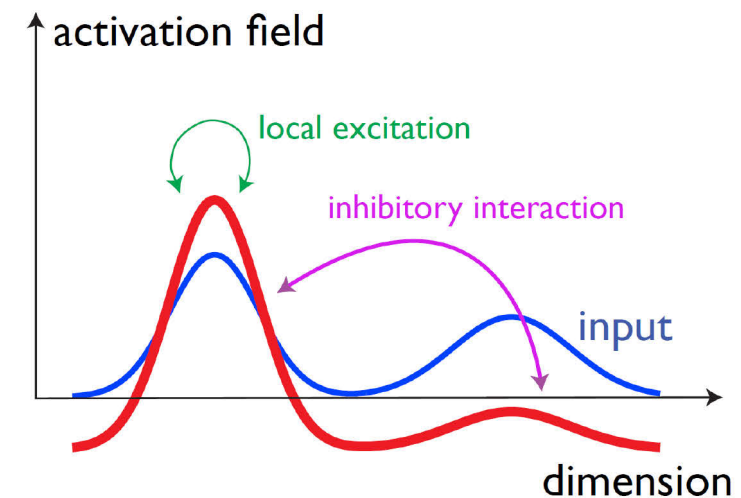
# Underlying Neural Principles:

- Standard **connectionist** assumptions:
  - Continuous activation
  - Nonlinear transfer functions
  - Synaptic connectivity
- Plus:
  - Recurrent dynamics create **stability**
  - Continuous feature **spaces** allow **attention** and **binding**
  - Continuous **time** allows **autonomy**
- Dynamical systems theory is central
  - Stable states = **attractors**
  - Behavioral **robustness** emerges from attractor stability

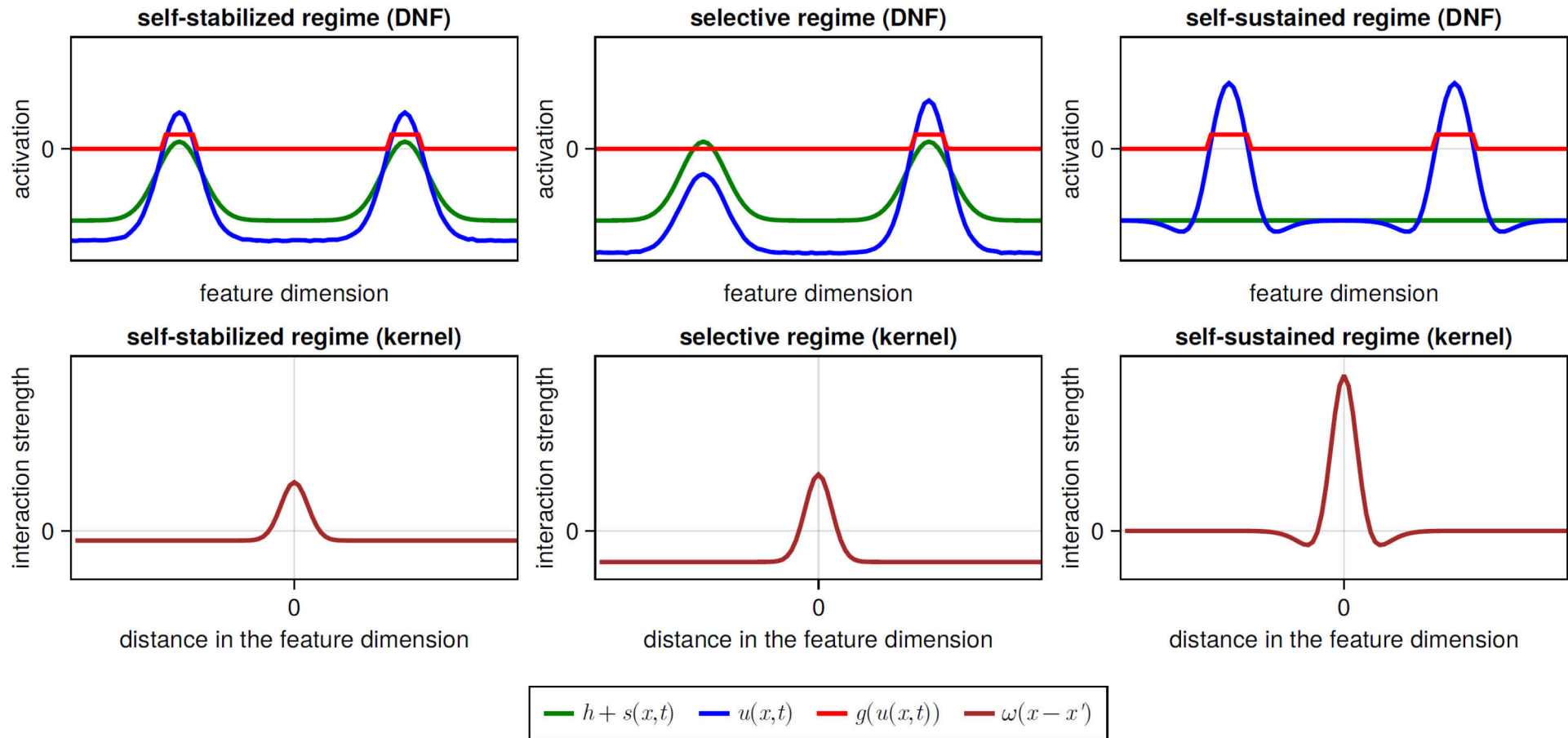
# Neural interaction kernel

$$\omega(\Delta x) = \underbrace{\phi(\Delta x, a_{lex}, 0, \sigma_{lex})}_{\text{lateral excitation}} \underbrace{- \phi(\Delta x, a_{lin}, 0, \sigma_{lin})}_{\text{lateral inhibition}} \underbrace{- \psi}_{\text{global inhibition}}$$

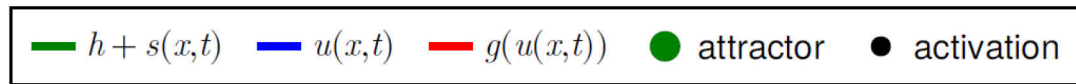
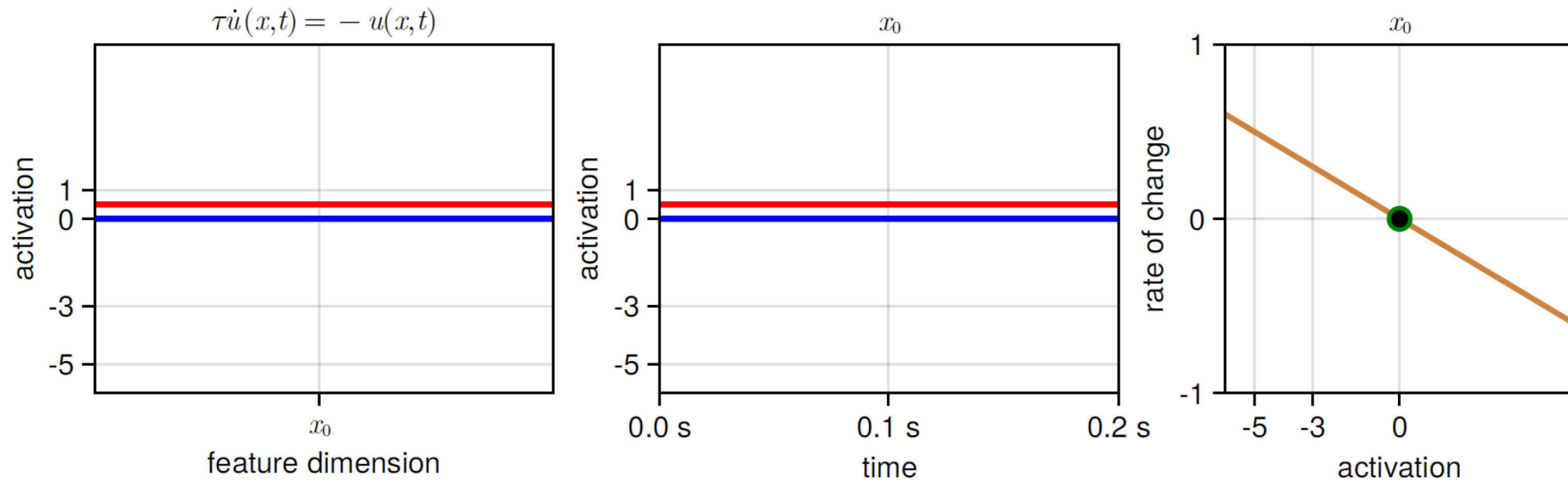
$$\phi(\Delta x, a, \mu, \sigma) = a \cdot \exp\left(-\frac{(\Delta x - \mu)^2}{2\sigma^2}\right)$$



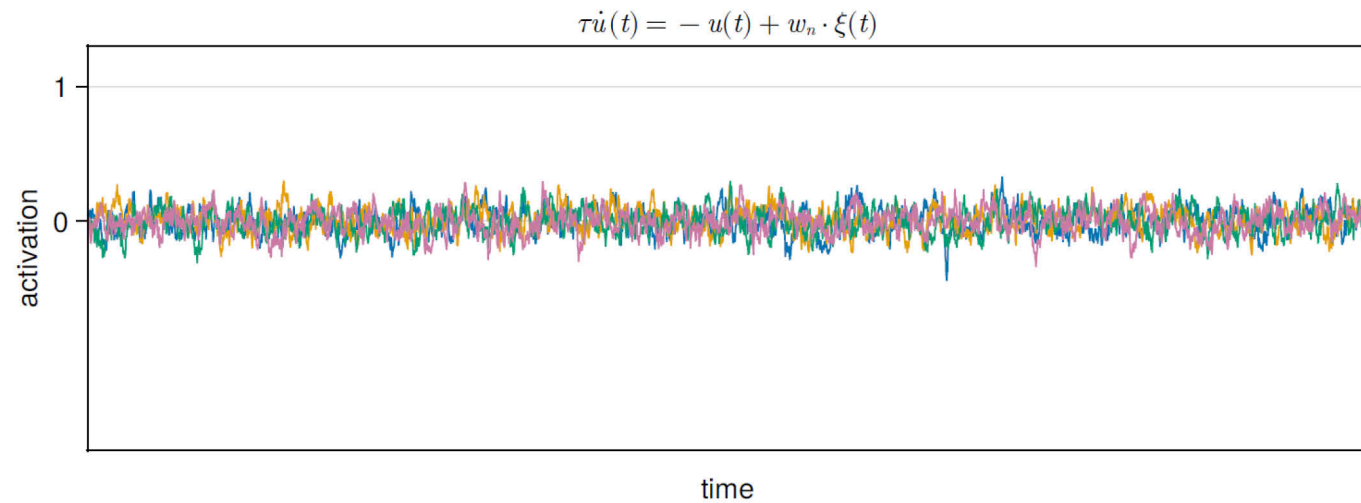
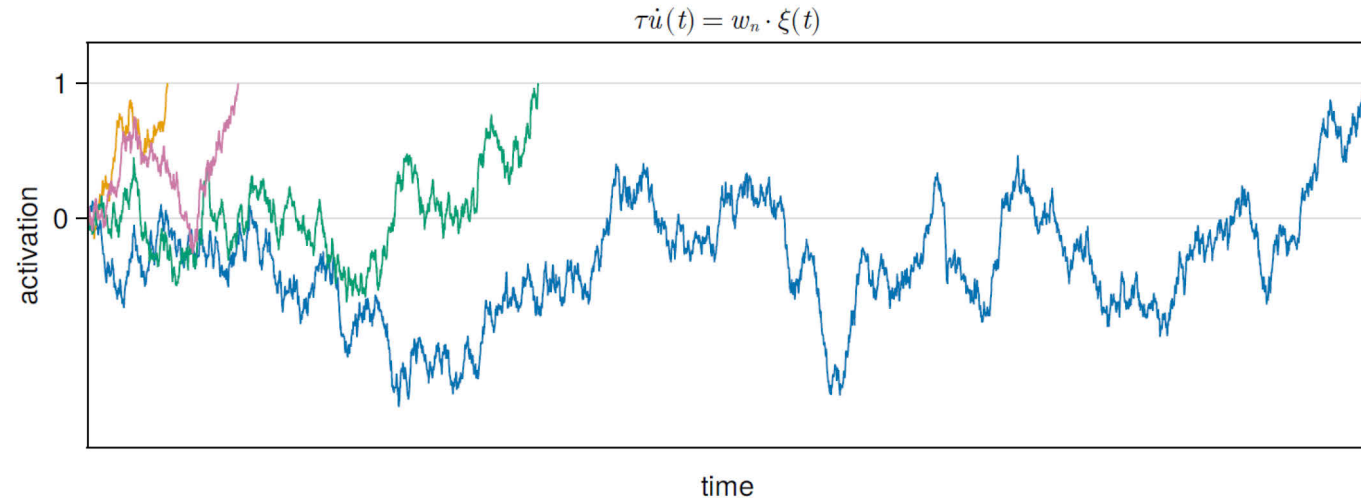
# Neural dynamic regimes



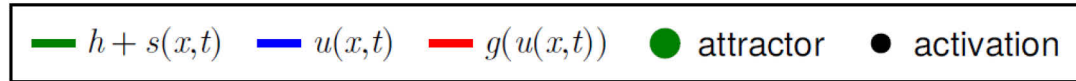
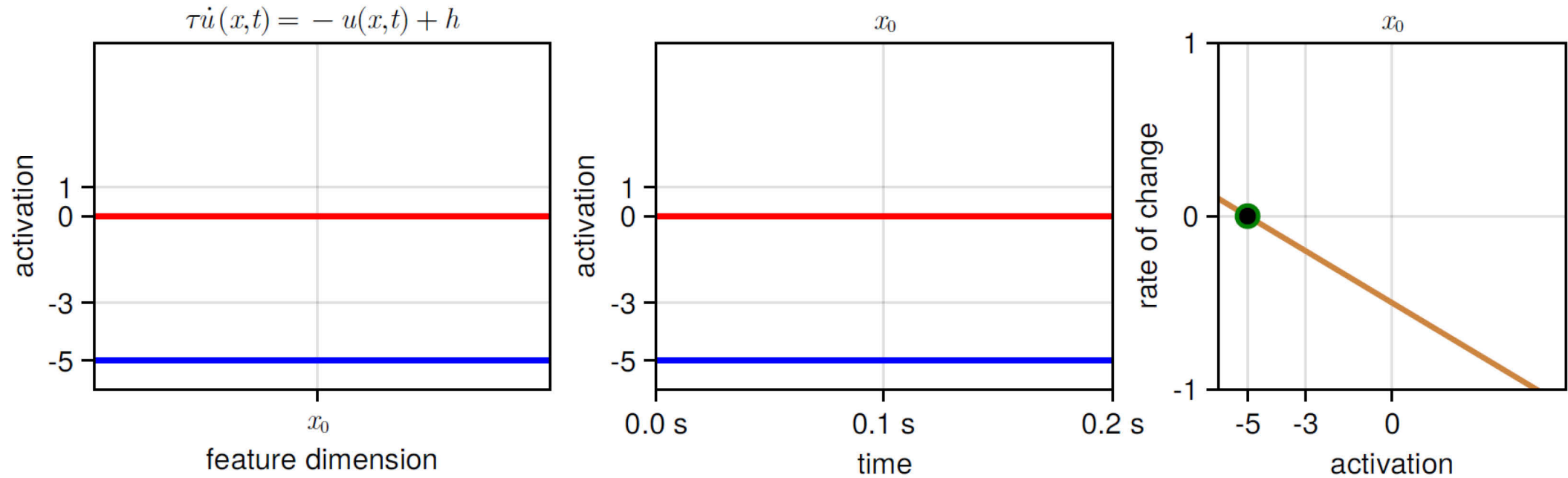
# Attractor states and instabilities



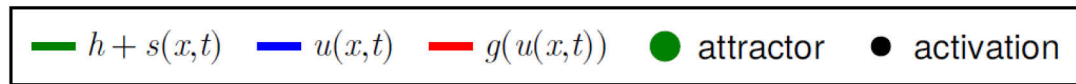
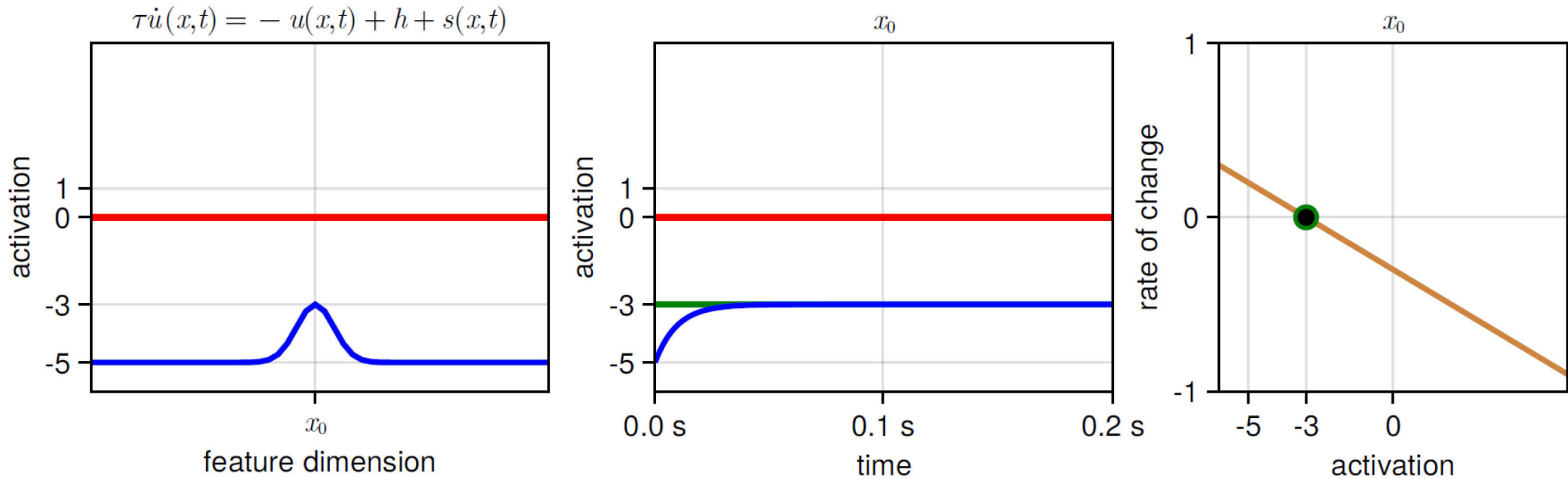
# Attractor states and instabilities



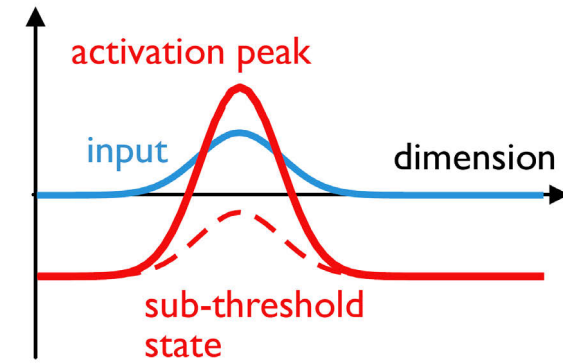
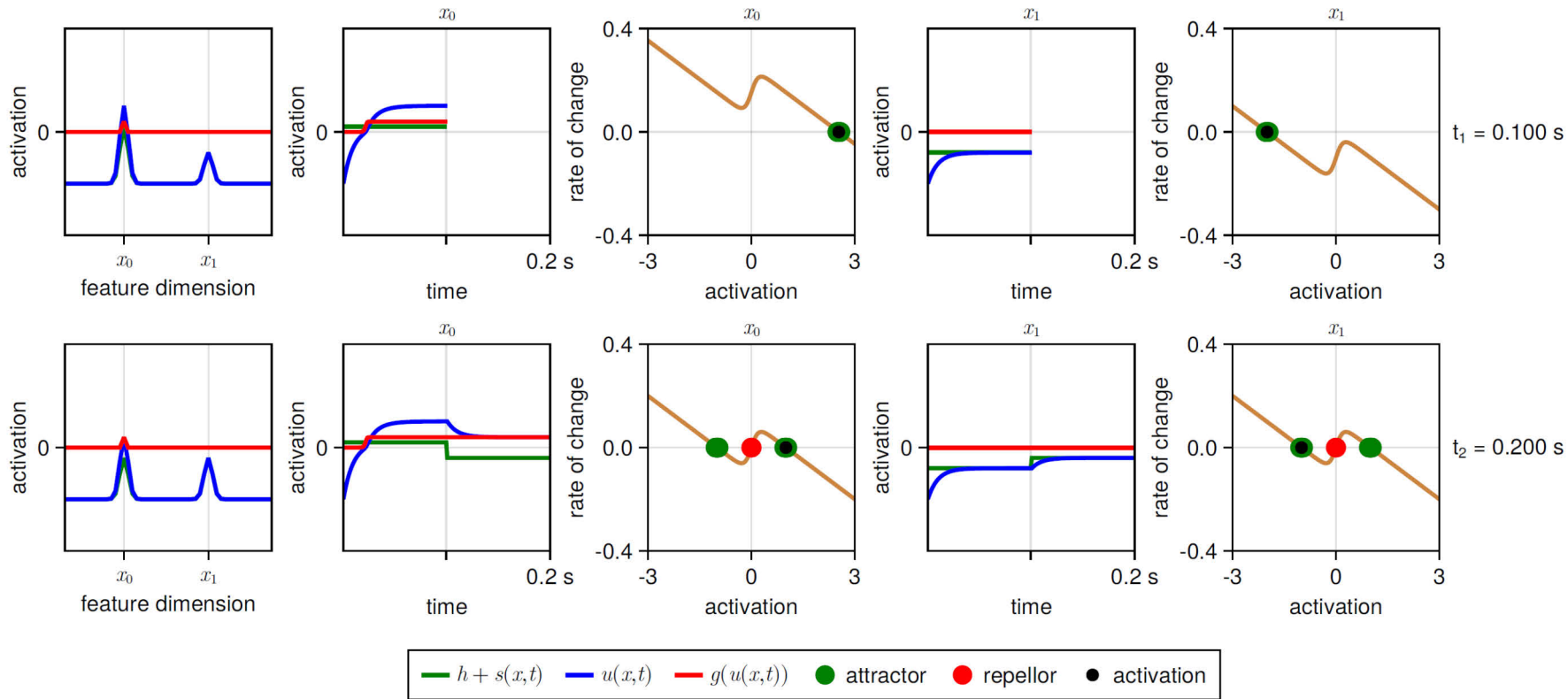
# Attractor states and instabilities



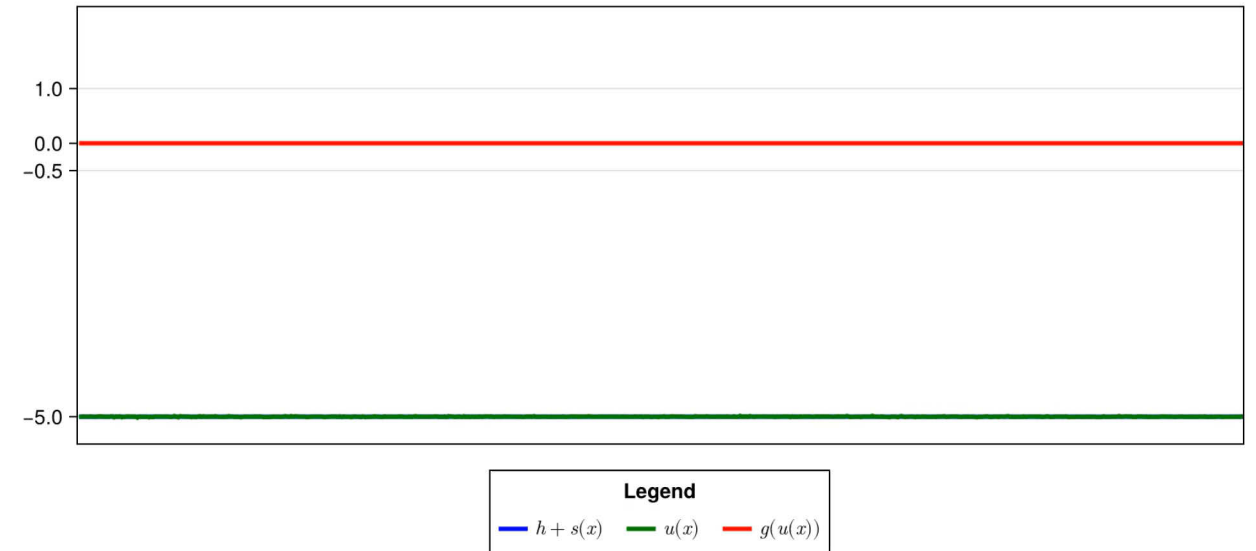
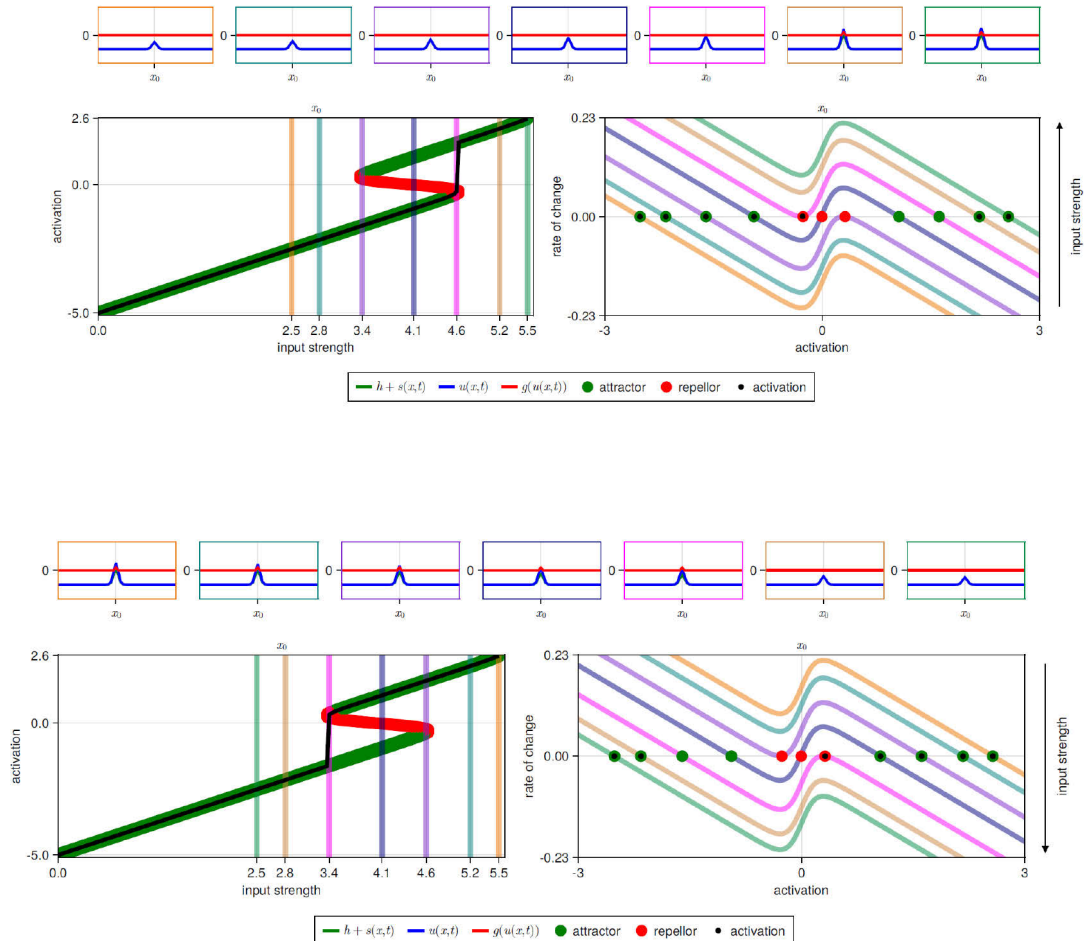
# Attractor states and instabilities



# Sub- and suprathreshold attractor states



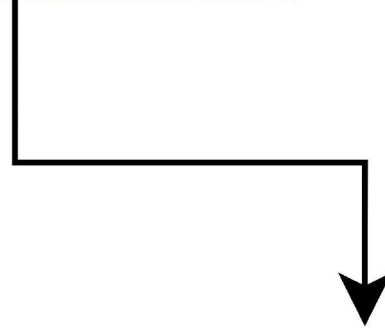
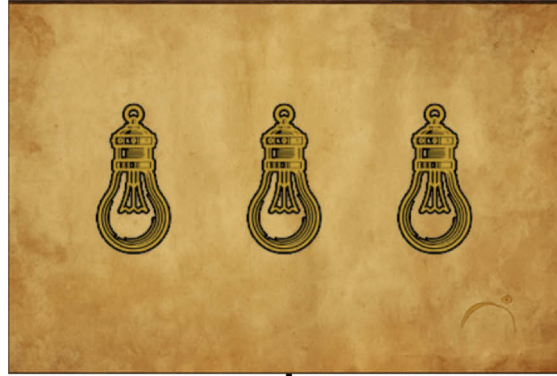
# Detection and reverse detection





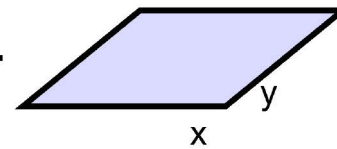
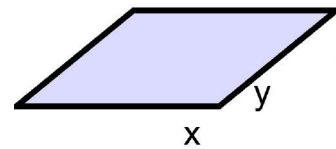


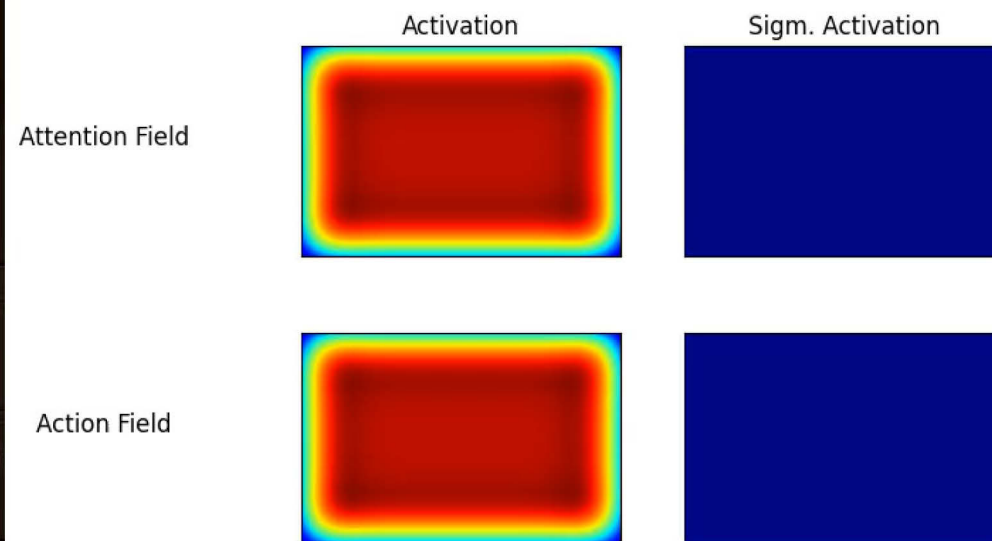
Scene



Action Field

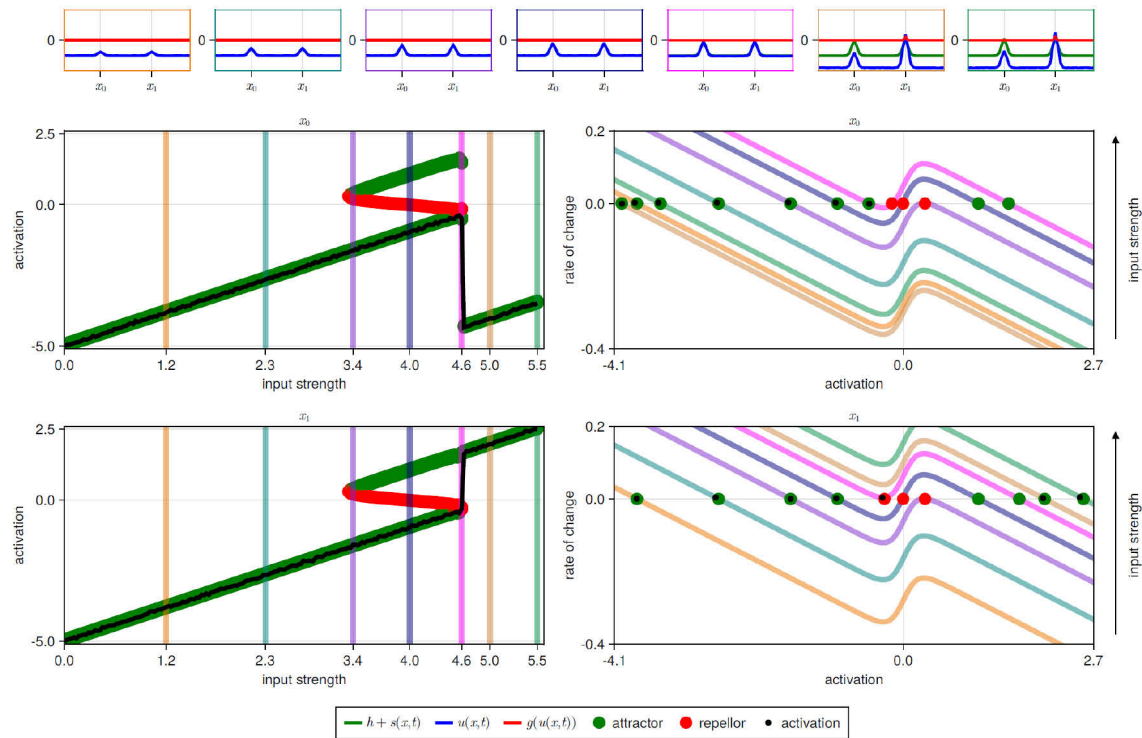
Attention Field





[https://github.com/cedar/juniper/blob/main/demo1\\_detection.ipynb](https://github.com/cedar/juniper/blob/main/demo1_detection.ipynb)

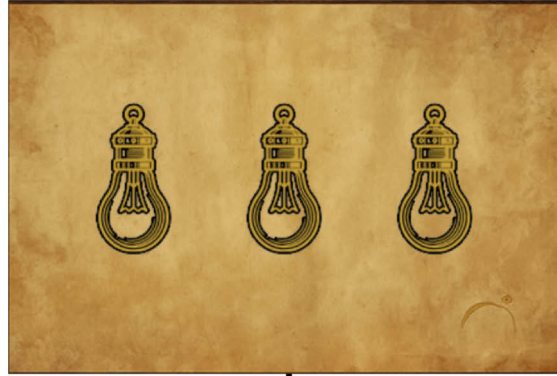
# Selection



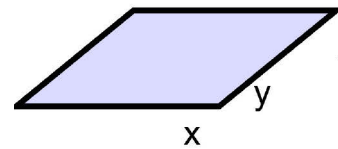




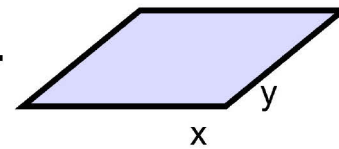
Scene



Action Field



Attention Field



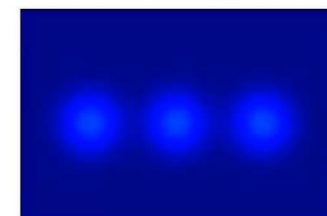


Attention Field

Action Field

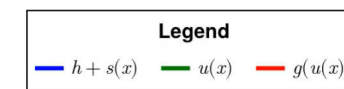
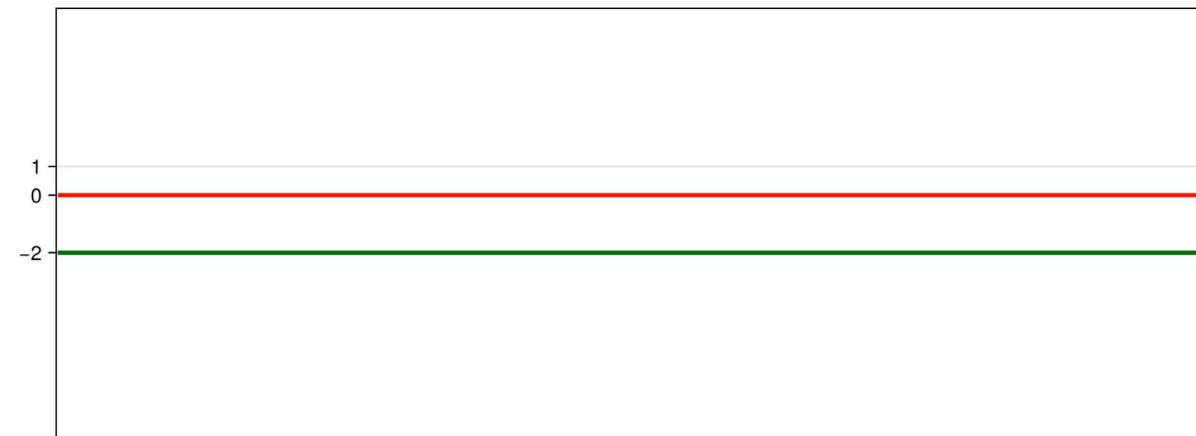
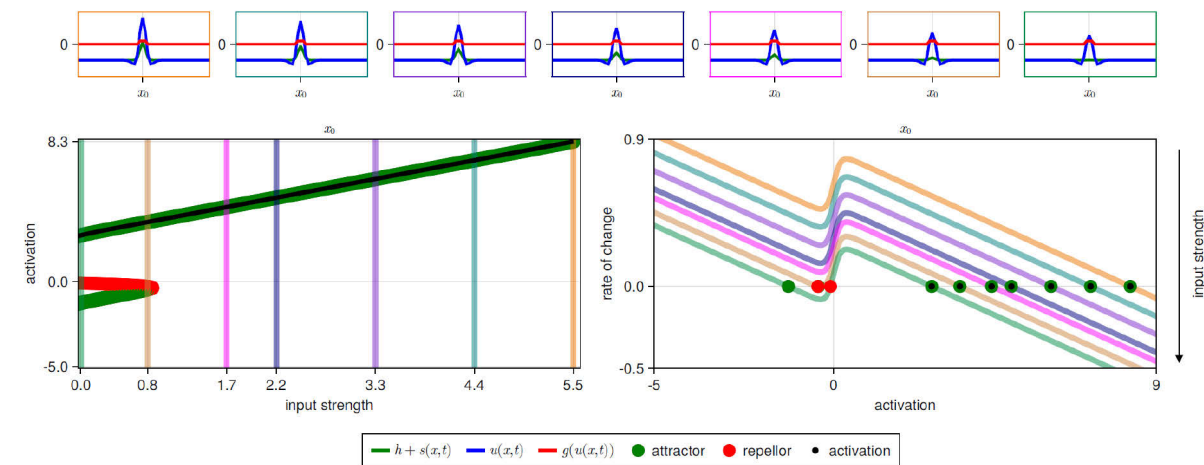
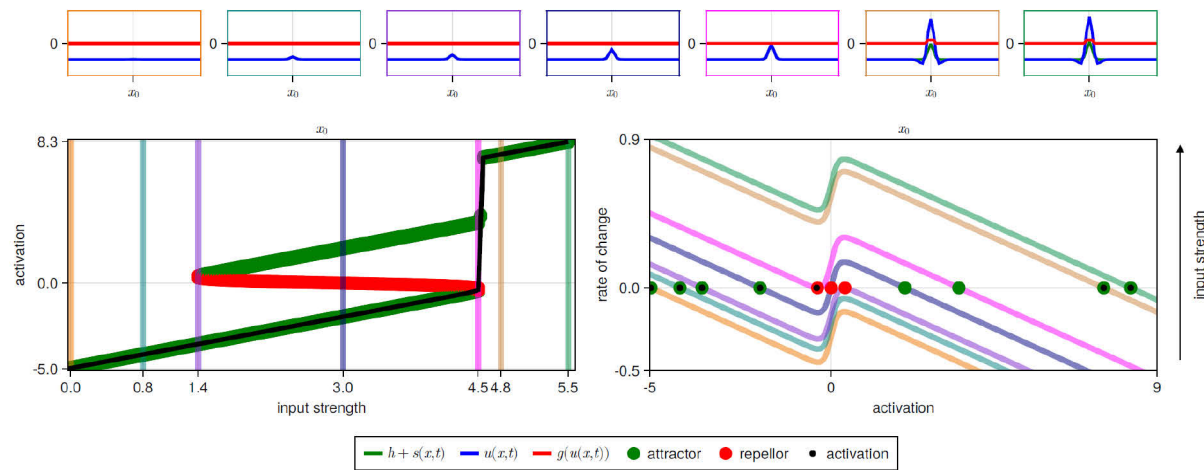
Activation

Sigm. Activation



[https://github.com/cedar/juniper/blob/main/demo2\\_selection.ipynb](https://github.com/cedar/juniper/blob/main/demo2_selection.ipynb)

# Memory





# ESCAPE ROOM



8



4

7



5

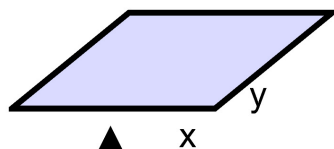
6



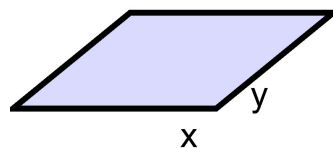
Scene



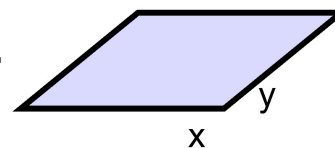
Action Field



Memory Field



Attention Field





Attention Field

Memory Field

Action Field

Activation

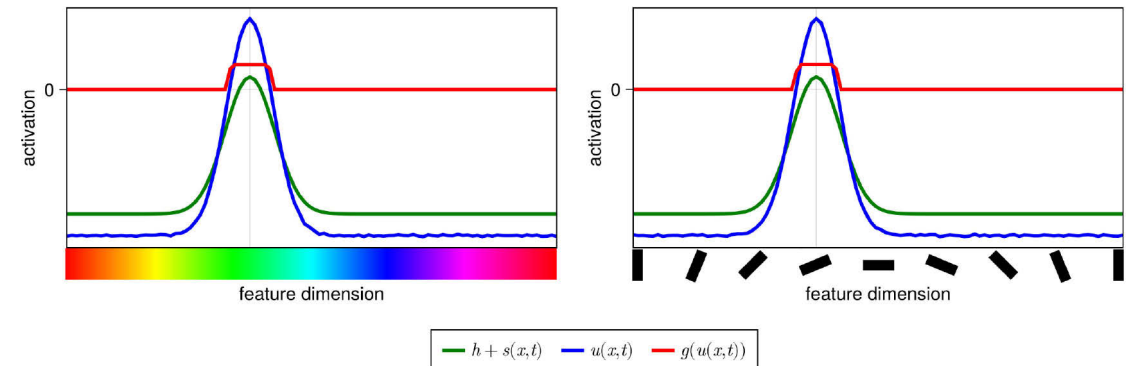
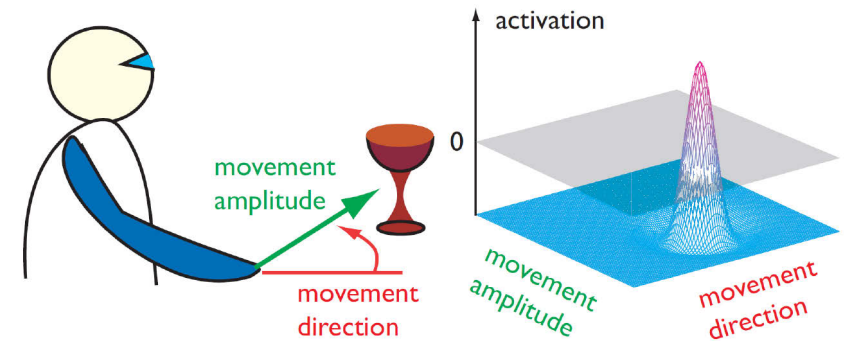
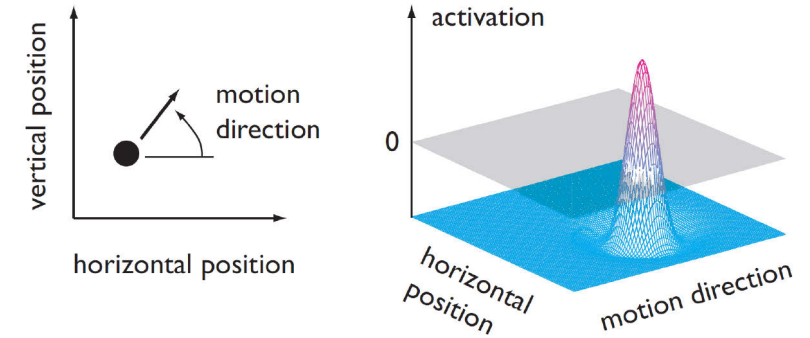
Sigm. Activation



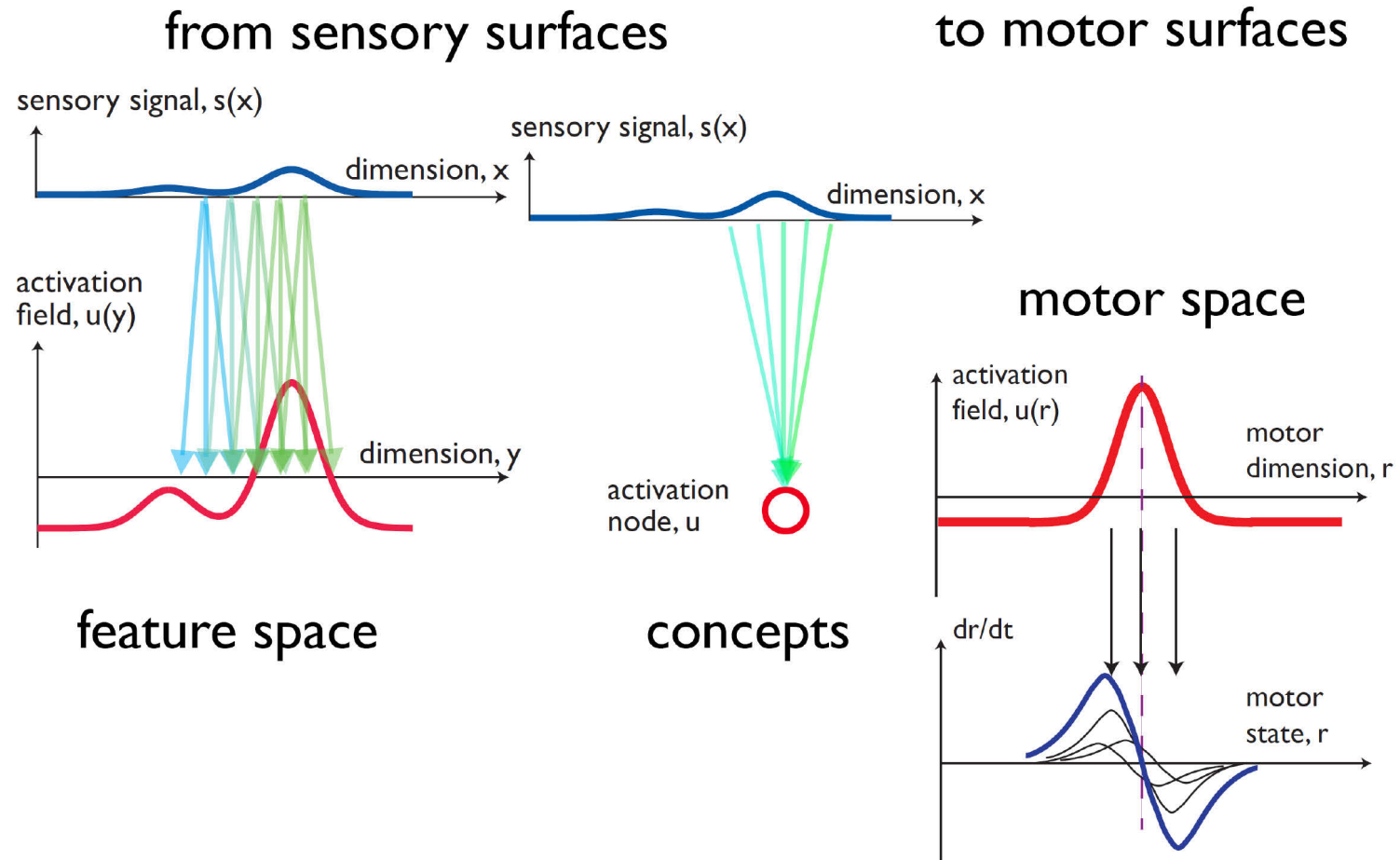
[https://github.com/cedar/juniper/blob/main/demo4\\_Huetchen.ipynb](https://github.com/cedar/juniper/blob/main/demo4_Huetchen.ipynb)

# Continuous Feature Spaces

- Fields are defined over low-dimensional continuous spaces
- Facilitates:
  - Attention
  - Decision making
  - Binding
  - Generalization
  - Grounding
  - Compositional representation
  - ...



# Feature space

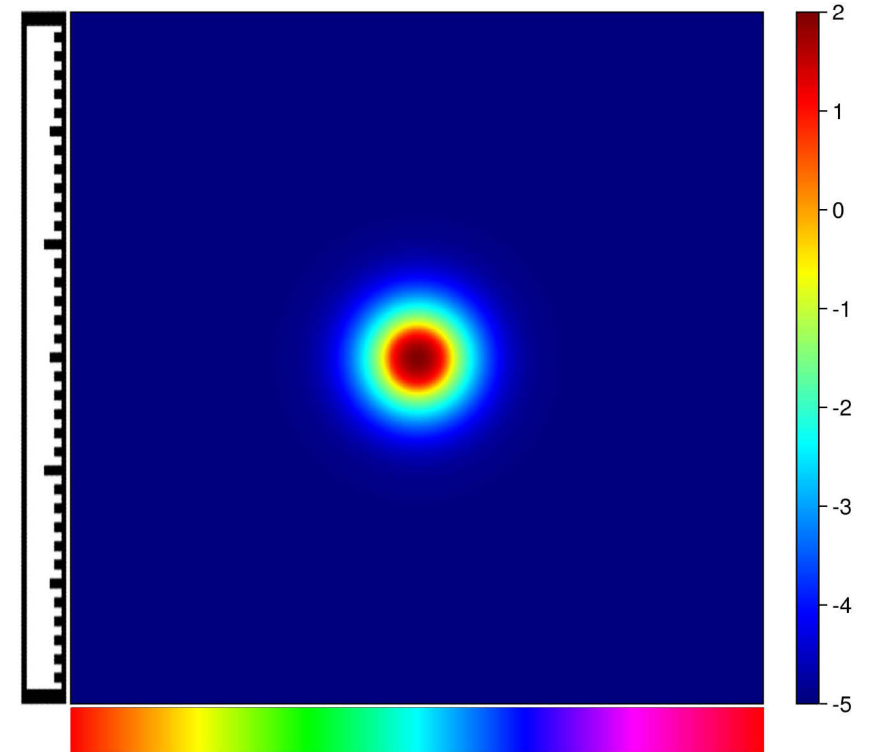


# Dimensionality

$$\begin{aligned}\tau \dot{u}(\chi, t) = & -u(\chi, t) + h + s(\chi, t) + w_\xi \cdot \xi(\chi, t) \\ & + \int \cdots \int \omega(\chi - \chi') \cdot g(u(\chi', t)) \, dx'_1 \dots dx'_n\end{aligned}$$

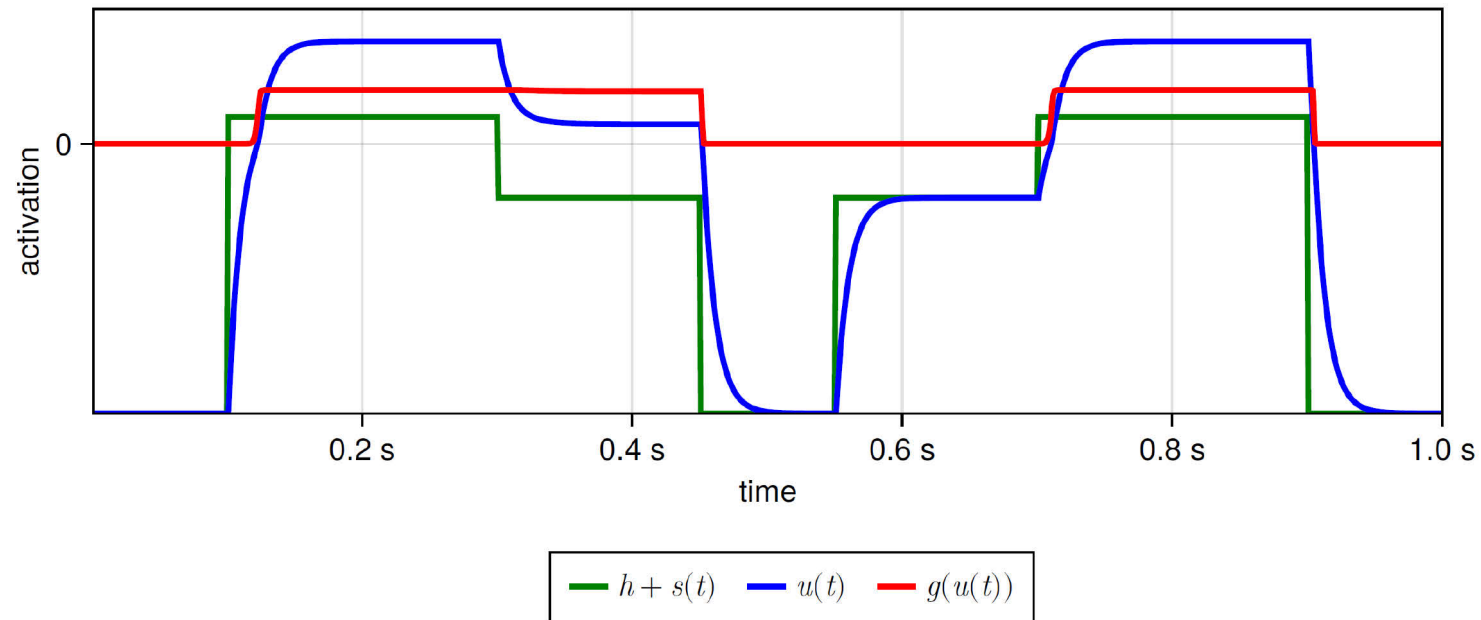
$$\omega(\Delta\chi) = \phi(\Delta\chi, a_{lex}, \vec{0}, \sigma_{lex} \vec{0}) - \phi(\Delta\chi, a_{lin}, \vec{0}, \sigma_{lin} \vec{0}) - \psi$$

$$\phi(\Delta\chi, a, \vec{\mu}, \vec{\sigma}) = a \cdot \exp \left( - \sum_{i=1}^{|\Delta\chi|} \frac{(\Delta x_i - \mu_i)^2}{2\sigma_i^2} \right)$$



# Dynamic neural node (DNN)

$$\overset{\text{time scale}}{\tau} \overset{\text{rate of change}}{\dot{u}(t)} = \overset{\text{stabilization factor}}{-u(t)} + \overset{\text{resting level}}{h} + \overset{\text{external input}}{s(t)} + \overset{\text{self excitation strength}}{w_{\xi} \cdot \xi(t)} + \overset{\text{neural noise}}{w_e} \cdot \overset{\text{sigmoidal threshold}}{g(u(t))}$$

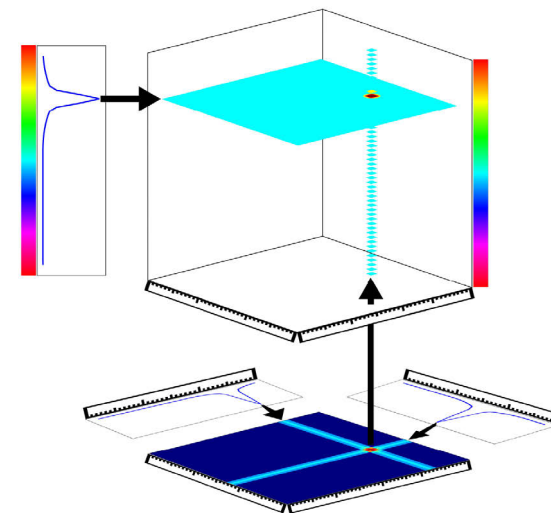
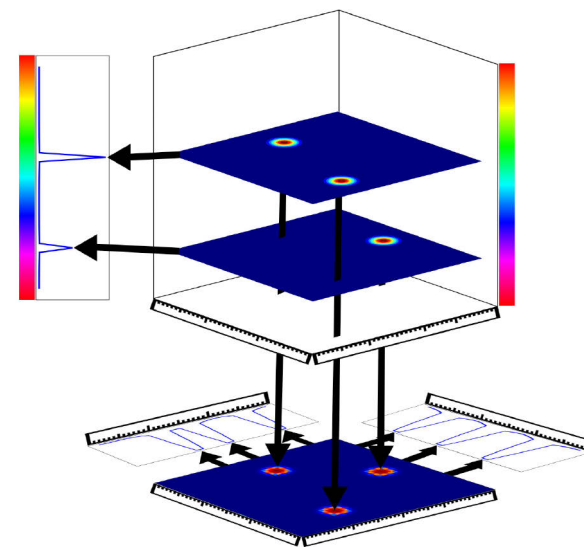


# Connections between DNFs

$$\begin{aligned}
 \tau_T \dot{u}_T(\chi^T, t) = & -u_T(\chi^T, t) + h_T + w_{T,\xi} \cdot \xi_T(\chi^T, t) \\
 & + \int \cdots \int \omega_T(\chi^T - \chi^{T'}) \cdot g(u_T(\chi^{T'}, t)) \, dx_1^{T'} \dots dx_n^{T'} \\
 & + w_{S,T} \left( \int \cdots \int w_{S,T}^\gamma \cdot \gamma_{S,T}(\chi^S, \chi^T, t) \cdot \kappa_{S,T}(\chi^S - \chi^\kappa) \right. \\
 & \quad \left. \cdot g(u_S(\chi^\kappa, t)) \, dx_1^\kappa \dots dx_m^\kappa \, dx_1^S \dots dx_m^S \right)
 \end{aligned}$$

$$\gamma_{S,T}^{\text{fix}}(\chi^S, \chi^T, t) = \begin{cases} 1, & \text{if } x_i^S = x_i^T, \forall i \in \mathbb{N}_{>0}, i \leq \min\{|\chi^S|, |\chi^T|\} \\ 0, & \text{otherwise} \end{cases}$$

$$\kappa_{S,T}(\Delta\chi) = \phi(\Delta\chi, a_{ex}, \vec{0}, \vec{\sigma}_{ex}) - \phi(\Delta\chi, a_{in}, \vec{0}, \vec{\sigma}_{in})$$



# Hebbian connections between DNFs

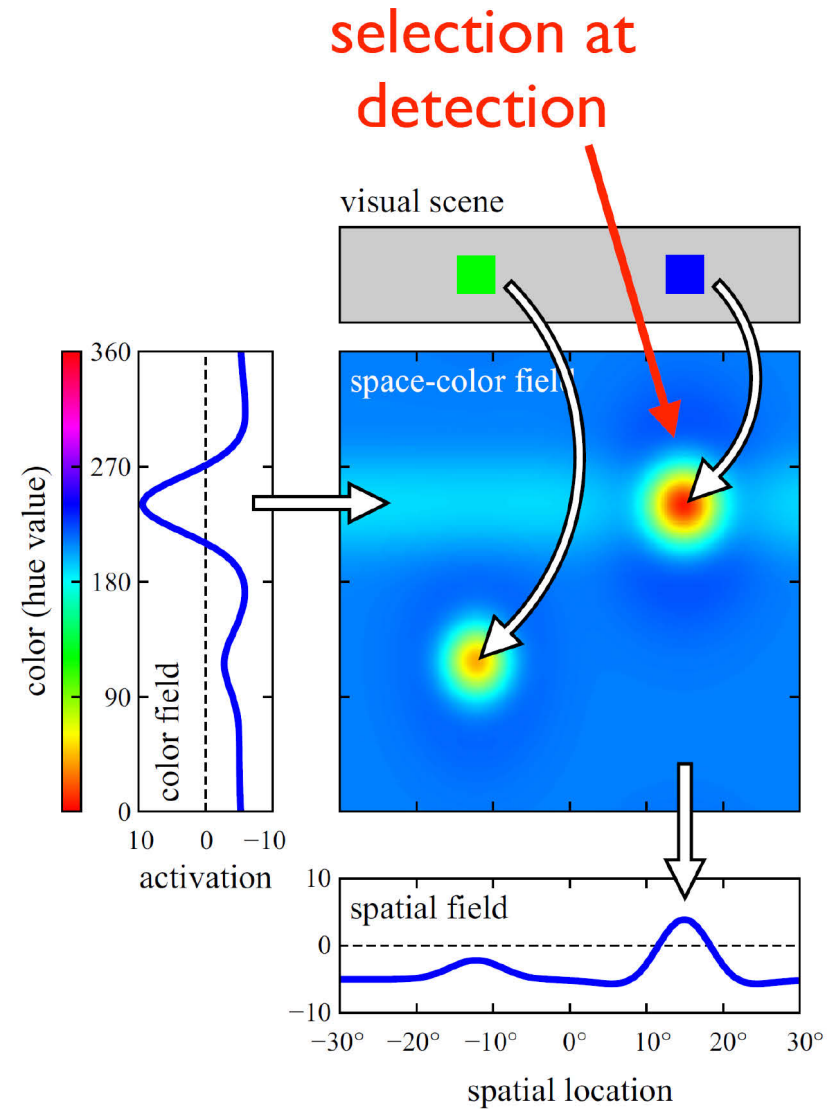
$$\begin{aligned}
 \tau_T \dot{u}_T(\chi^T, t) = & -u_T(\chi^T, t) + h_T + w_{T,\xi} \cdot \xi_T(\chi^T, t) \\
 & + \int \cdots \int \omega_T(\chi^T - \chi^{T'}) \cdot g(u_T(\chi^{T'}, t)) \, dx_1^{T'} \dots dx_n^{T'} \\
 & + w_{S,T} \left( \int \cdots \int w_{S,T}^\gamma \cdot \gamma_{S,T}(\chi^S, \chi^T, t) \cdot \kappa_{S,T}(\chi^S - \chi^\kappa) \right. \\
 & \quad \left. \cdot g(u_S(\chi^\kappa, t)) \, dx_1^\kappa \dots dx_m^\kappa \, dx_1^S \dots dx_m^S \right)
 \end{aligned}$$

$$\gamma_{S,T}^{\text{heb}}(\chi^S, \chi^T, t) = w_{S,T}^{\gamma*}(\chi^S, \chi^T, t)$$

$$\tau \dot{w}_{S,T}^{\gamma*}(\chi^S, \chi^T, t) = \eta \cdot g(u_{\text{learn}}(t)) \cdot g(u_S(\chi^S, t)) \cdot (g(u_T(\chi^T, t)) - w_{S,T}^{\gamma*}(\chi^S, \chi^T, t))$$

$$\kappa_{S,T}(\Delta\chi) = \phi(\Delta\chi, a_{ex}, \vec{0}, \sigma_{ex}) - \phi(\Delta\chi, a_{in}, \vec{0}, \sigma_{in})$$

# Cued selection





# ESCAPE ROOM

|                                                                                      |                                                                                     |   |
|--------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|---|
|    |  | 8 |
|    |  | 7 |
|  | 5                                                                                   | 6 |

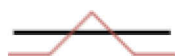
RED



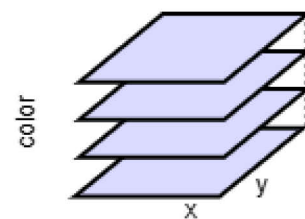
Scene



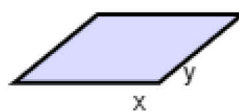
Feature Cue



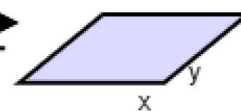
Feature Map



Action Field

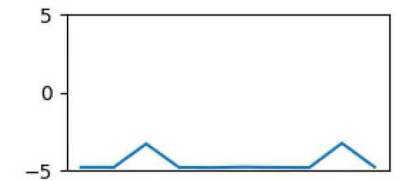
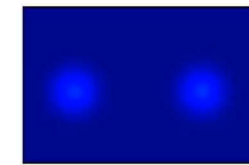


Attention Field

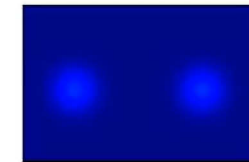




Feature Map Field



Attention Field

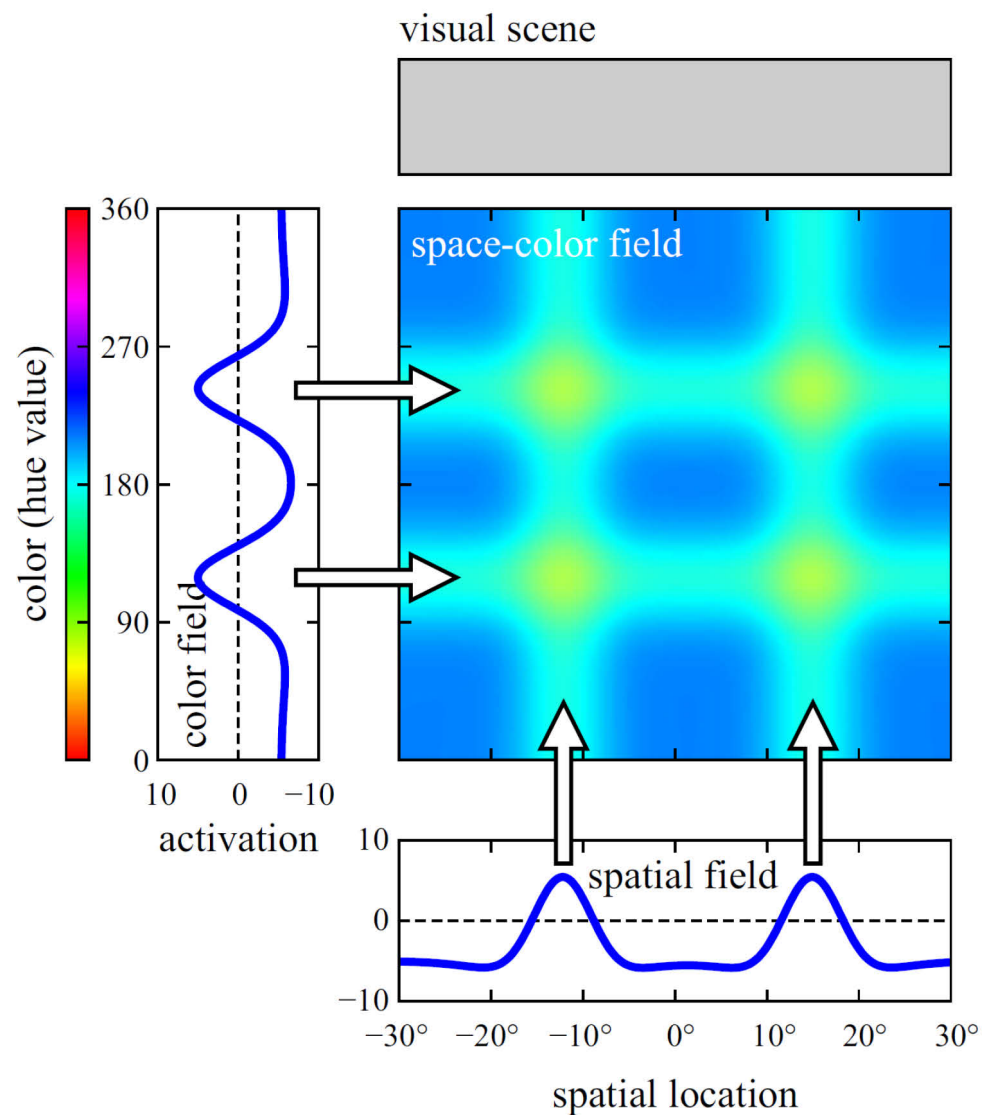


Action Field

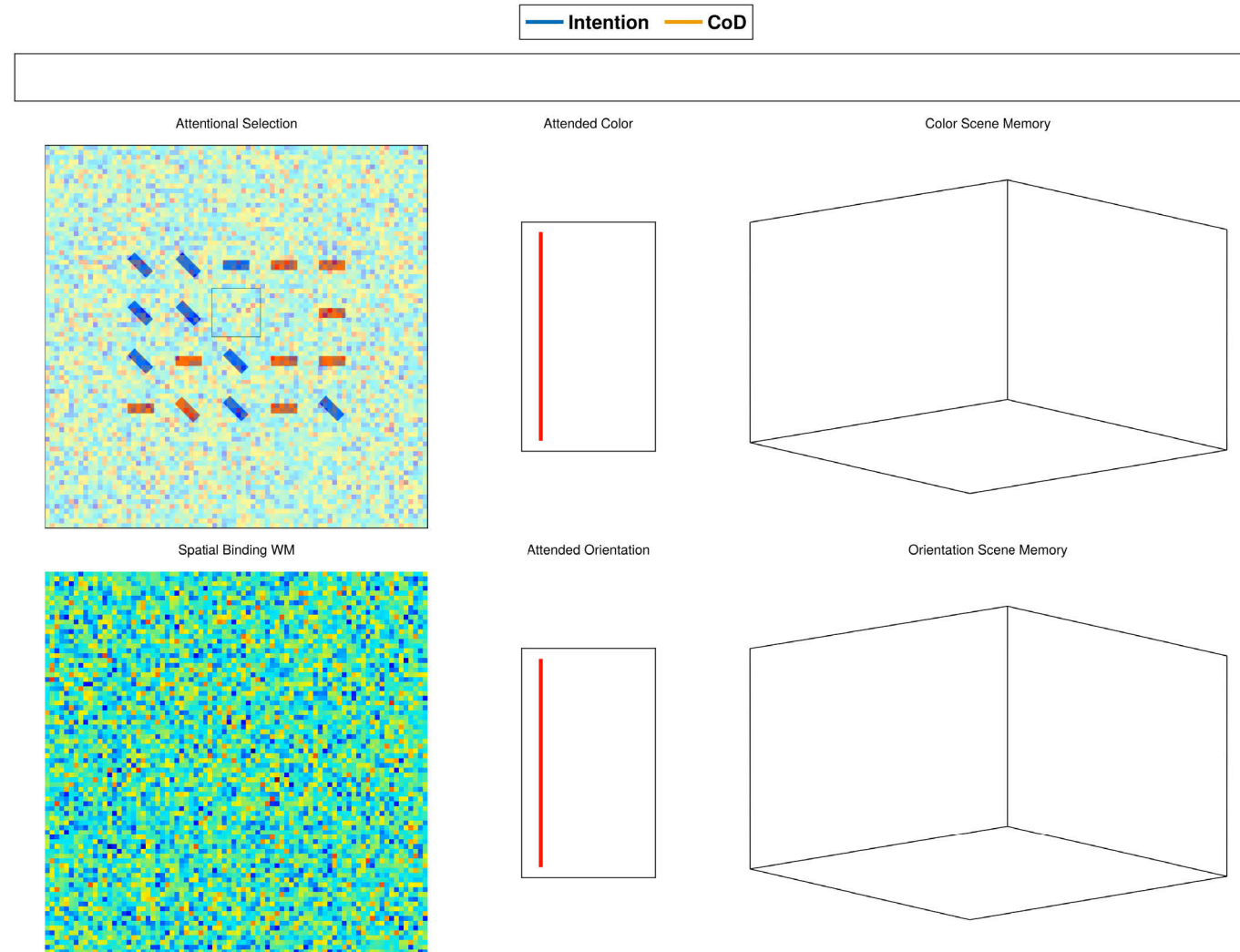


[https://github.com/cedar/juniper/blob/main/demo3\\_cued\\_selection.ipynb](https://github.com/cedar/juniper/blob/main/demo3_cued_selection.ipynb)

# The binding problem



# Binding through space





# ESCAPE ROOM

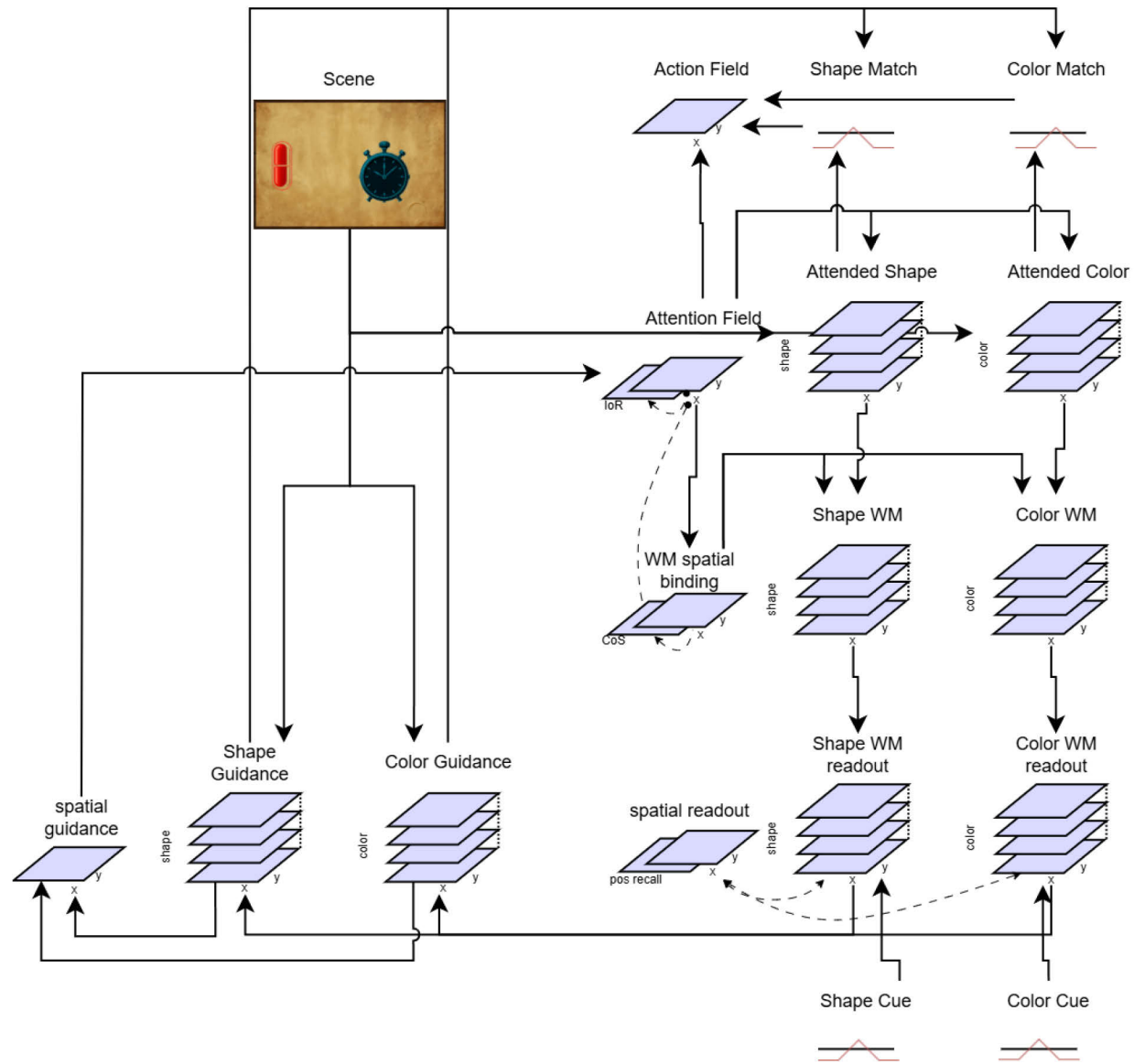
8

7

6

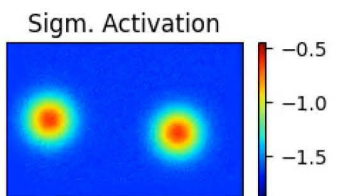








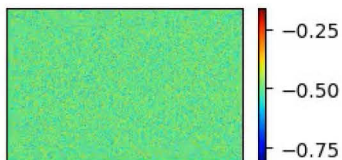
Attention Field



Action Field

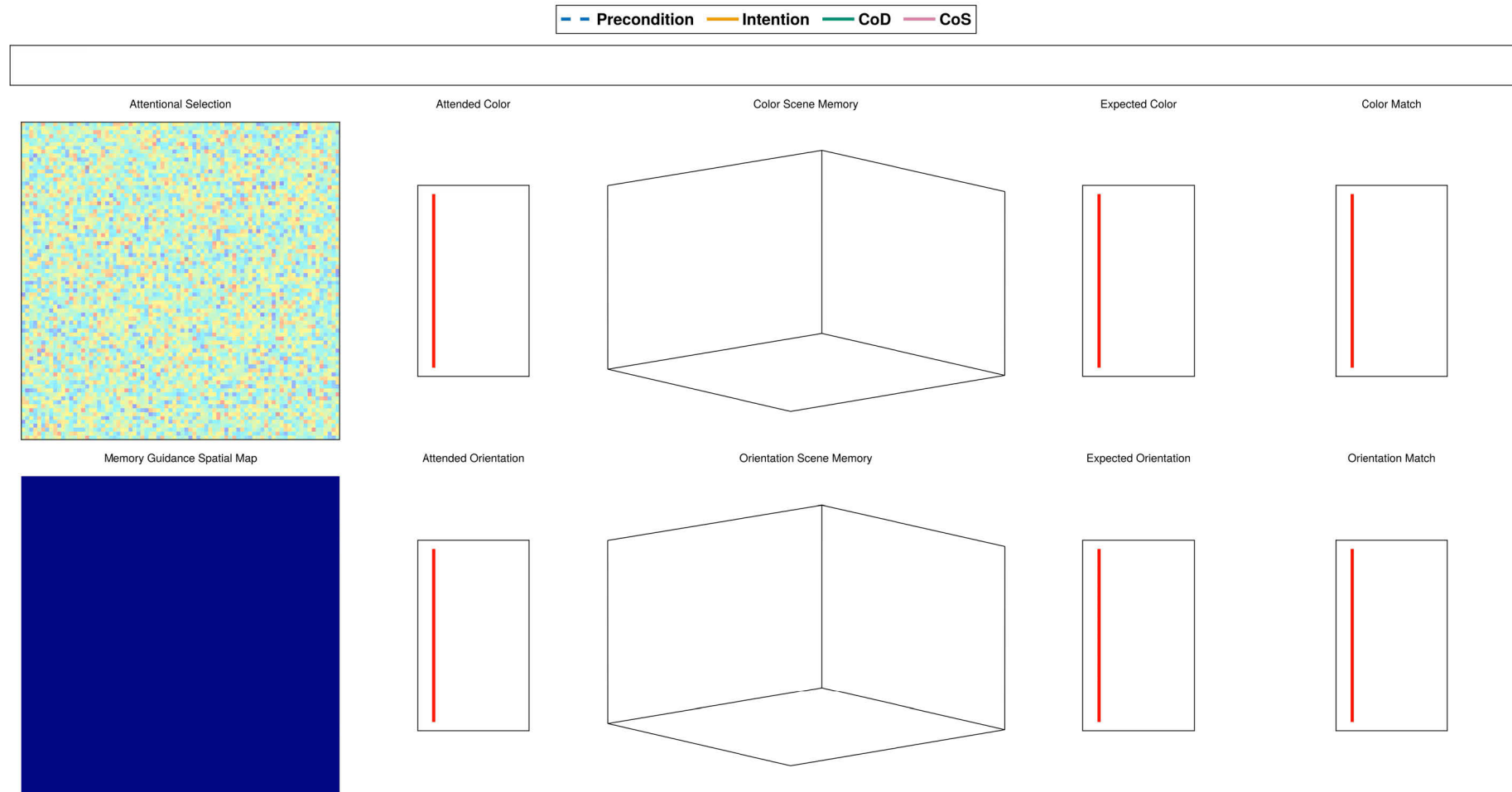


Guidance Field



[https://github.com/cedar/juniper/blob/main/demo5\\_binding\\_through\\_space.ipynb](https://github.com/cedar/juniper/blob/main/demo5_binding_through_space.ipynb)

# Visual exploration / scene memory guidance





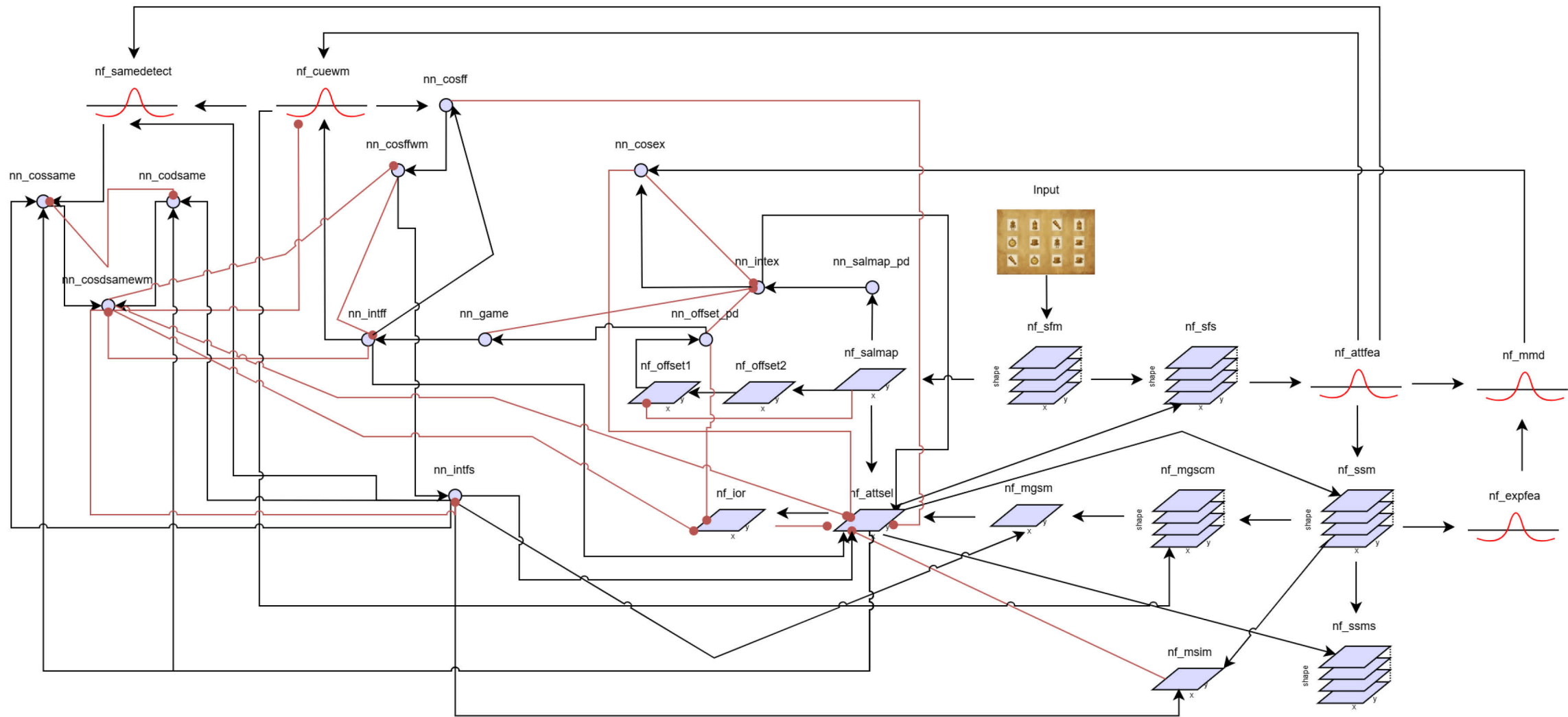
# ESCAPE ROOM

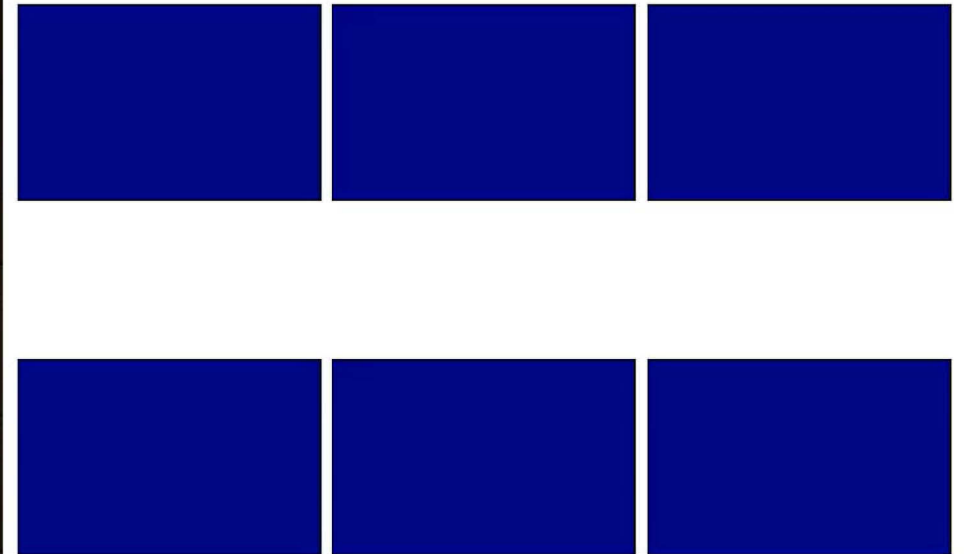
8

7









[https://github.com/cedar/juniper/blob/main/demo6\\_MemoryGame.ipynb](https://github.com/cedar/juniper/blob/main/demo6_MemoryGame.ipynb)



[https://github.com/cedar/juniper/blob/main/demo6\\_MemoryGame.ipynb](https://github.com/cedar/juniper/blob/main/demo6_MemoryGame.ipynb)

# Coordinate transformation

