Dynamic Field Theory (DFT): An introduction

Michael C. Stern

Linguistics Department, Yale University

Purpose of this talk

1. Explain the basic principles of Dynamic Field Theory (DFT)

2. Describe some benefits of DFT for understanding language

3. Provide basis for the rest of the talks in the symposium

DFT resources

Website

dynamicfieldtheory.org

Textbook

Schöner, G., Spencer, J., & DFT Research Group (2016). *Dynamic Thinking: A Primer on Dynamic Field Theory*. Oxford University Press.

Some overview papers

Schöner, G. (2020). The Dynamics of Neural Populations Capture the Laws of the Mind. *Topics in Cognitive Science*, *12*(4), 1257–1271.

Schöner, G. (2023). Dynamical Systems Approaches to Cognition. In R. Sun (Ed.), *The Cambridge Handbook of Computational Cognitive Sciences* (2nd ed., pp. 210–241). Cambridge University Press.

A brief history of DFT

- 1993: first DFT paper (on eye movements)
- Since then: reaching movements, visual perception, development, robotics, word learning, speech articulation, language comprehension
- Theoretical roots in dynamical systems theory (e.g., Newton), as applied to human behavior in the 1980s (e.g., Turvey, Kelso)
- Details come from neuroscientific (e.g., Georgopoulos et al., 1986) and mathematical (e.g., Amari, 1977; Grossberg, 1969) work on dynamics of neural networks in the 1970s and 80s

Basic hypotheses

- Behavior is governed by the nervous system
- **Populations** of neurons constitute a privileged level of description (e.g., Cohen & Newsome, 2009)
- Neural processes exhibit **stability**: a capacity to resist change in the face of noisy and variable inputs
- **Instabilities** allow transitions from one stable state to another

Dynamical systems

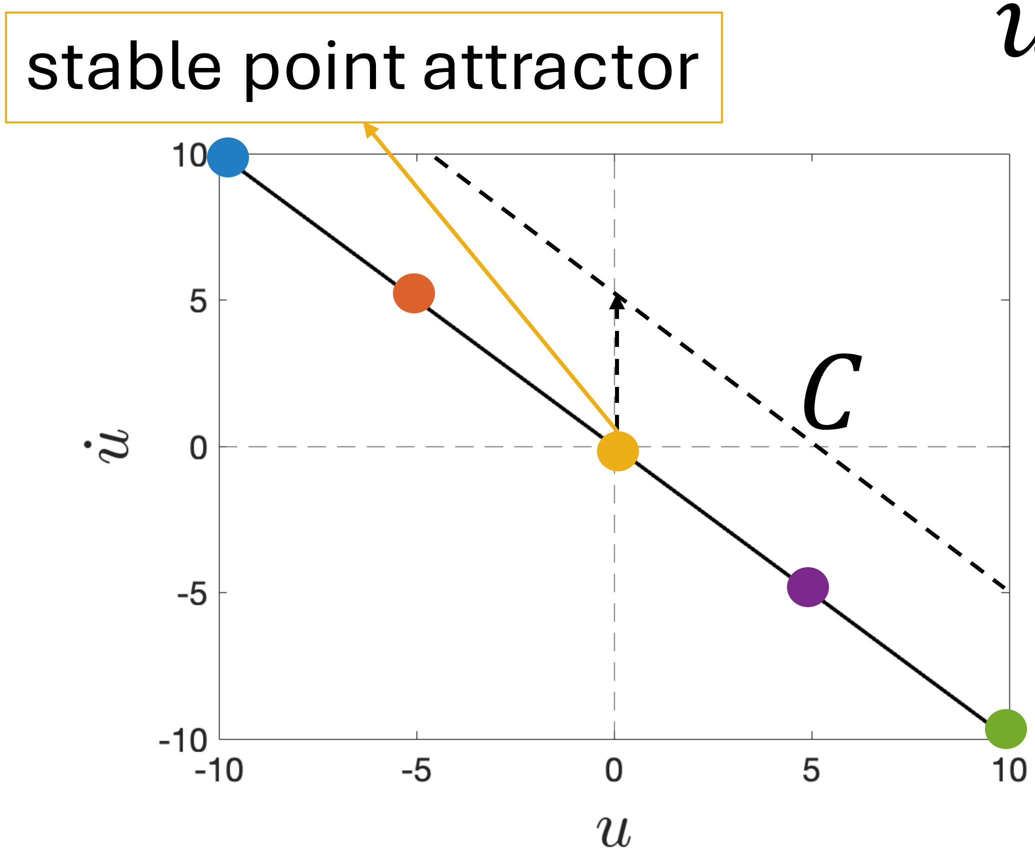
The present predicts the future according to a law of change:

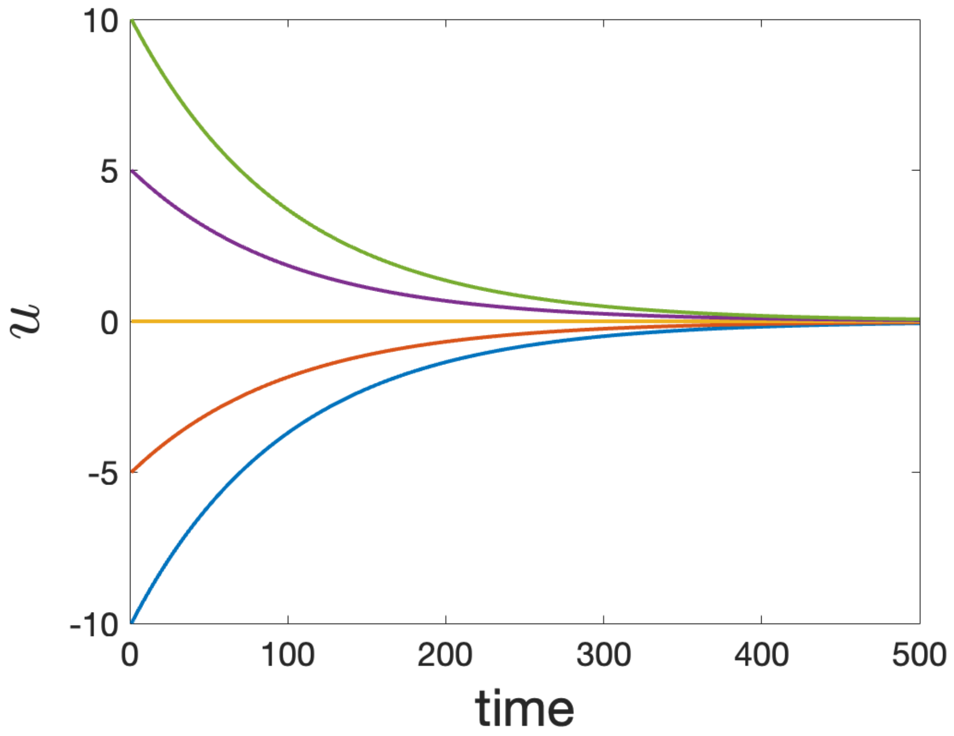
$$\dot{u} = f(u)$$

rate of change	relation between state and change	variable (e.g., neural activation)

Point attractors and stability

$$\dot{u} = -u + C$$





Neural activation dynamics

point attractor

$$\tau\dot{u} = -u + \boxed{h + s + c \cdot g(u) + \xi}$$

resting level

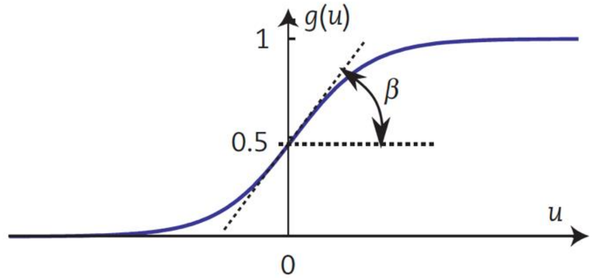
interaction

noise

rate parameter

input

threshold



Neural activation: “feature detectors”

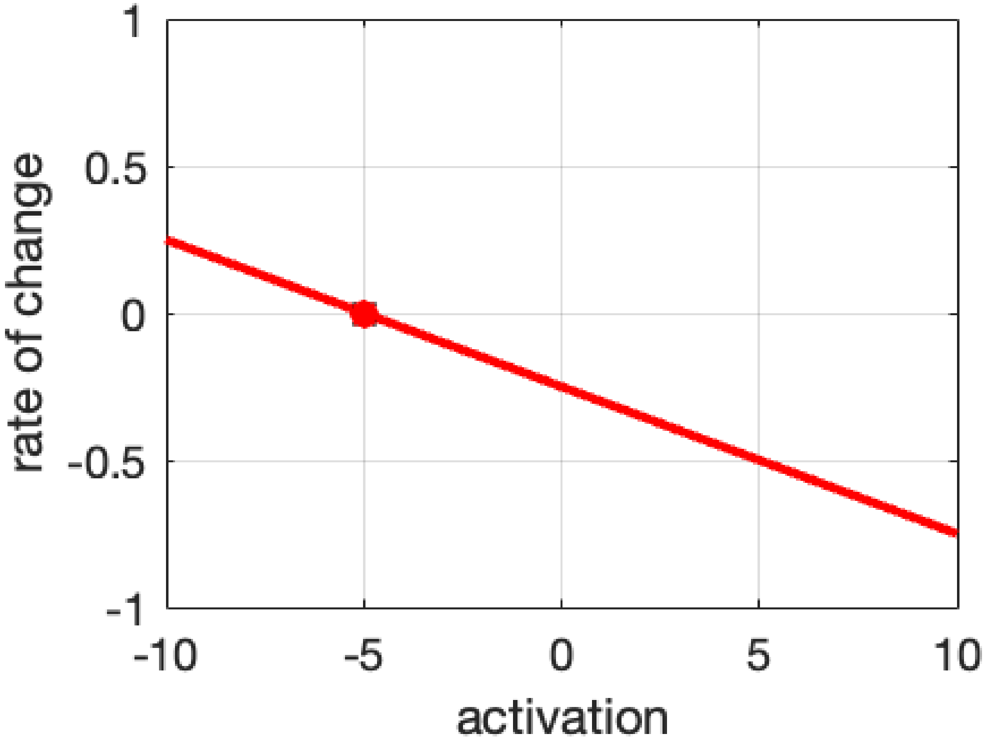
$$\tau\dot{u} = -u + h + s + c \cdot g(u) + \xi$$

$h = -5$

$c = 0$

$s = 0$

$\xi = 0$



plot from COSIVINA (Schneegans et al., 2021)

Neural activation: “feature detectors”

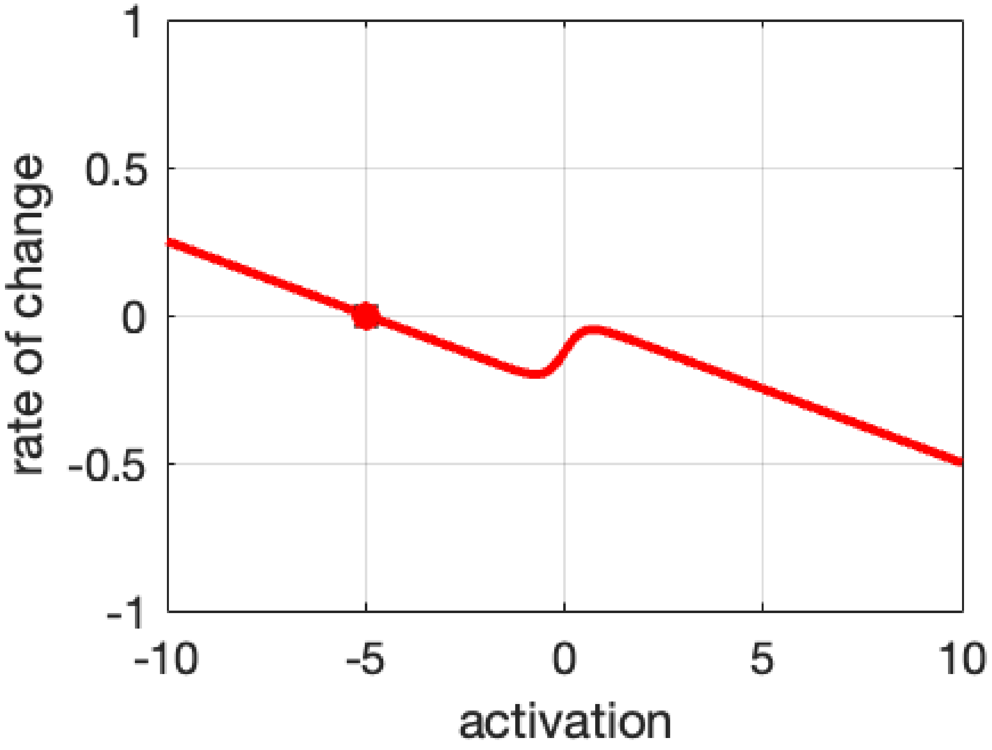
$$\tau\dot{u} = -u + h + s + c \cdot g(u) + \xi$$

$h = -5$

$c = 5$

$s = 0$

$\xi = 0$



Neural activation: "feature detectors"

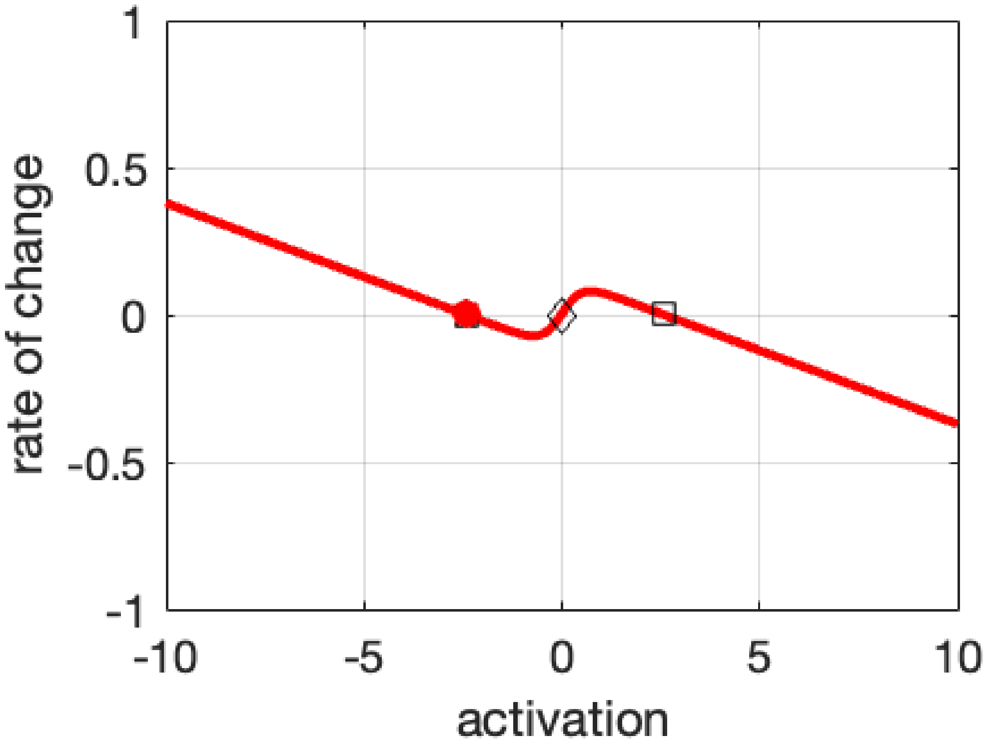
$$\tau\dot{u} = -u + h + s + c \cdot g(u) + \xi$$

$h = -5$

$c = 5$

$s = 2.5$

$\xi = 0$



From one stable state to two: **bifurcation**

Neural activation: "feature detectors"

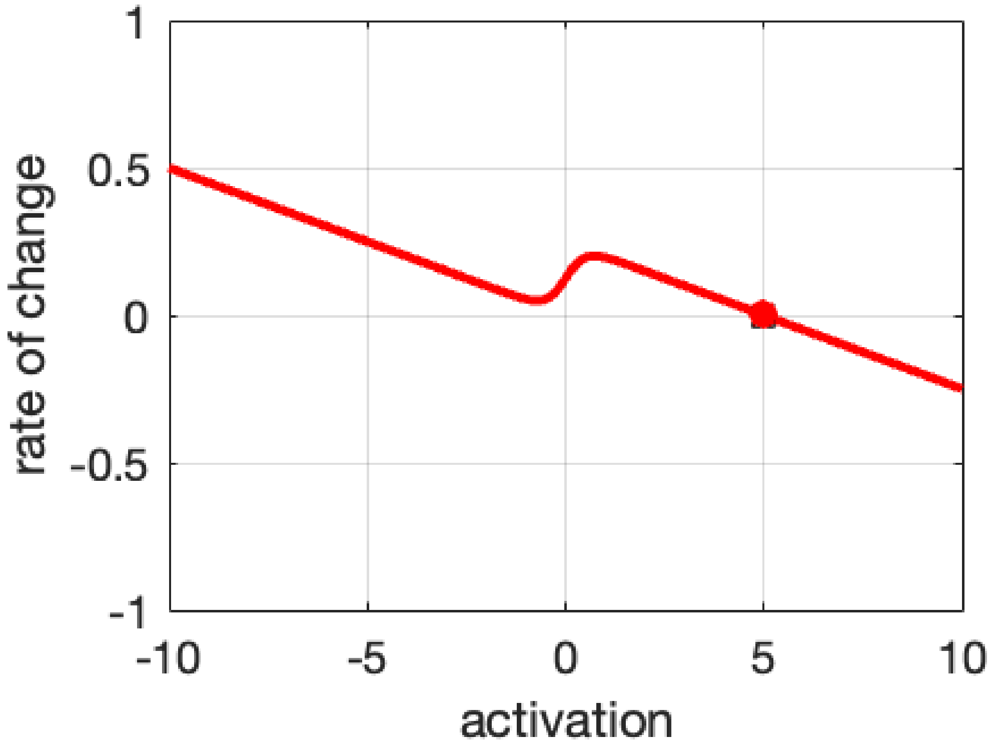
$$\tau\dot{u} = -u + h + s + c \cdot g(u) + \xi$$

$h = -5$

$c = 5$

$s = 5$

$\xi = 0$



Activation jumps to a positive state: **detection instability**

Neural activation: “feature detectors”

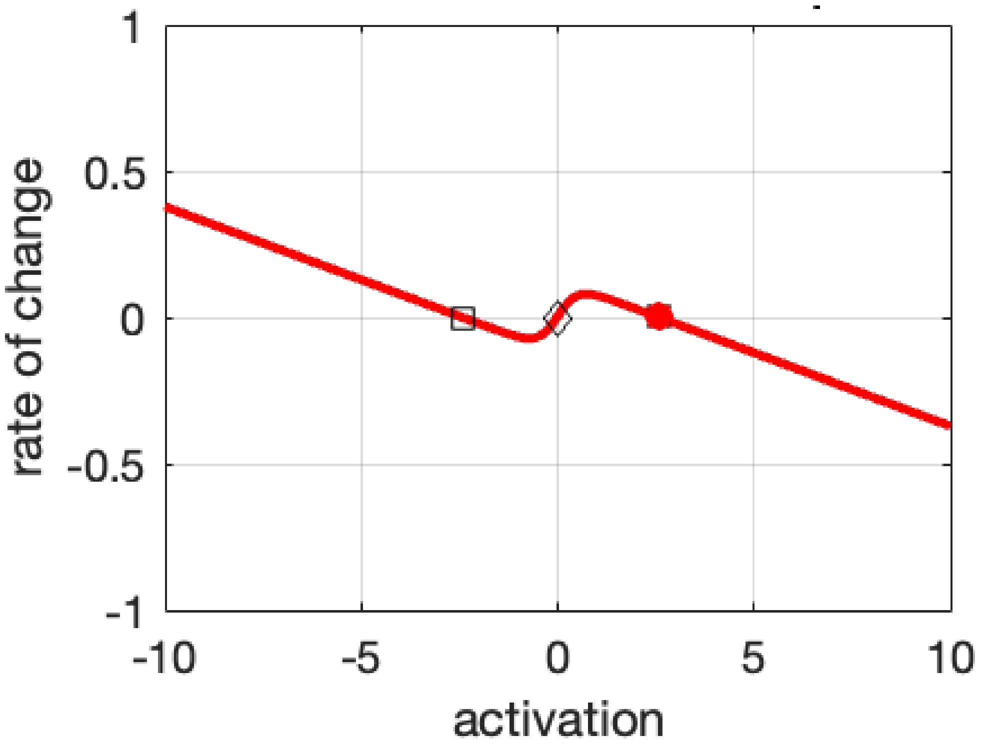
$$\tau\dot{u} = -u + h + s + c \cdot g(u) + \xi$$

$$h = -5$$

$$c = 5$$

$$s = 2.5$$

$$\xi = 0$$



Activation stays positive despite decrease in input: **hysteresis**

Neural activation: “feature detectors”

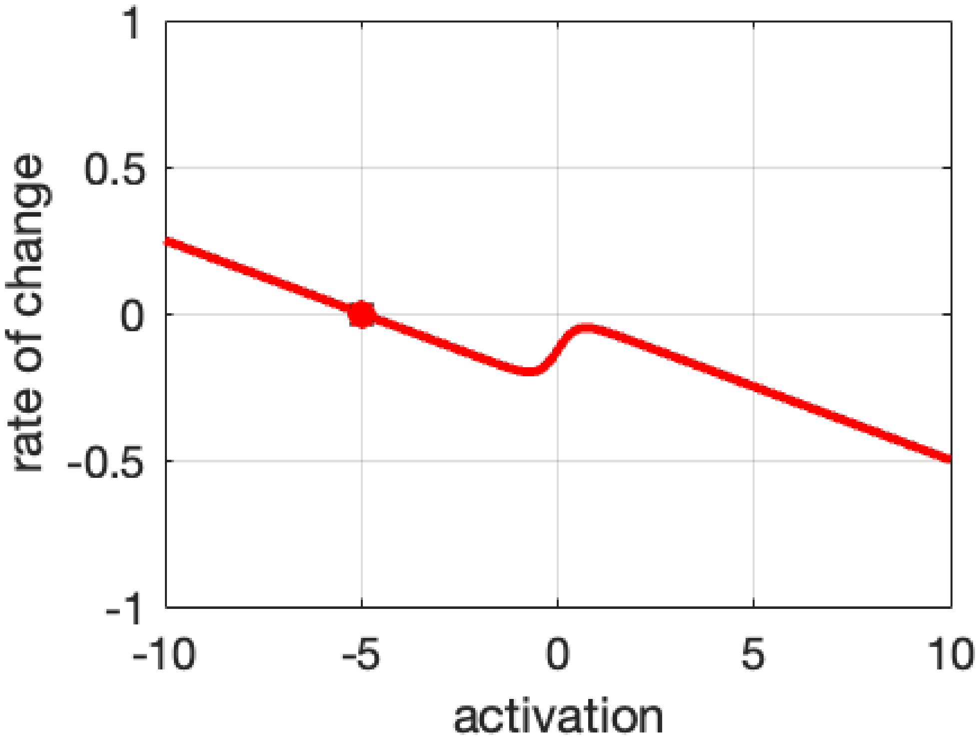
$$\tau \dot{u} = -u + h + s + c \cdot g(u) + \xi$$

$h = -5$

$c = 5$

$s = 0$

$\xi = 0$

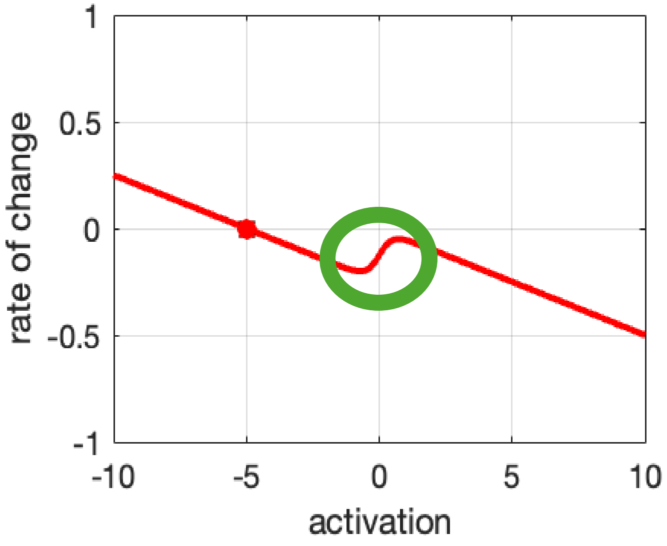


Activation jumps to negative state: **reverse detection instability**

Emergent categoriality

As s changes gradually, u **jumps** from off to on state, or vice versa

Nonlinearity allows categorical behavior to emerge from system that is fundamentally continuous in time and (activation) space



Neural fields (Amari, 1977)

- $u =$ **average** spiking activity **across** neural population

  → neural population activation represents **categorical** feature

  → **node** of activation value

- Some neural populations have **internal structure**

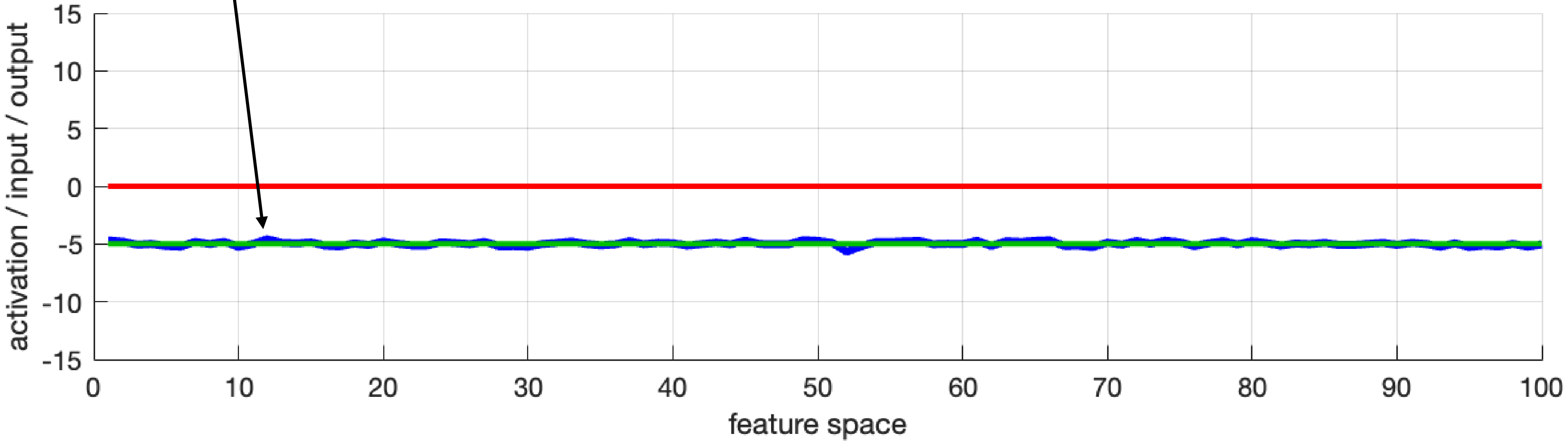
  → activation represents **continuous** feature

- $u(x) =$ average spiking activity organized by **cognitive dimension $\boldsymbol{x}$**

  → **field** of activation values

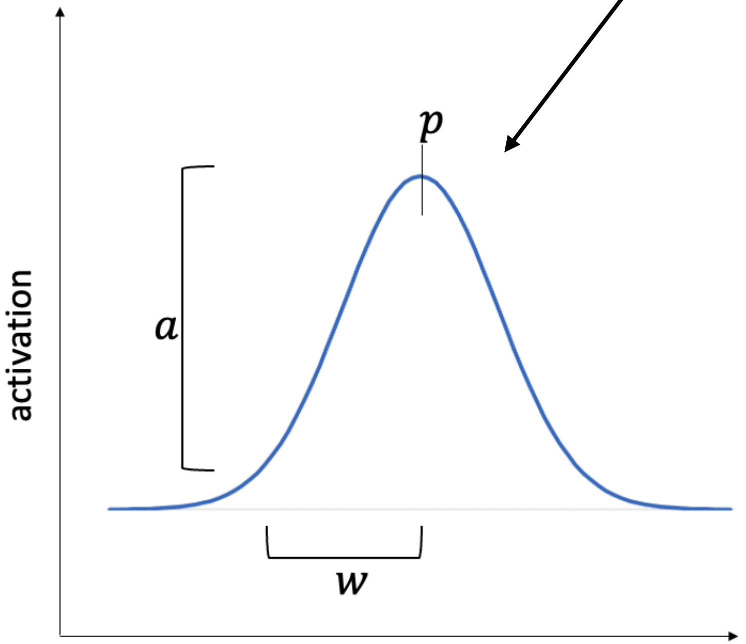
Neural fields: continuous features x

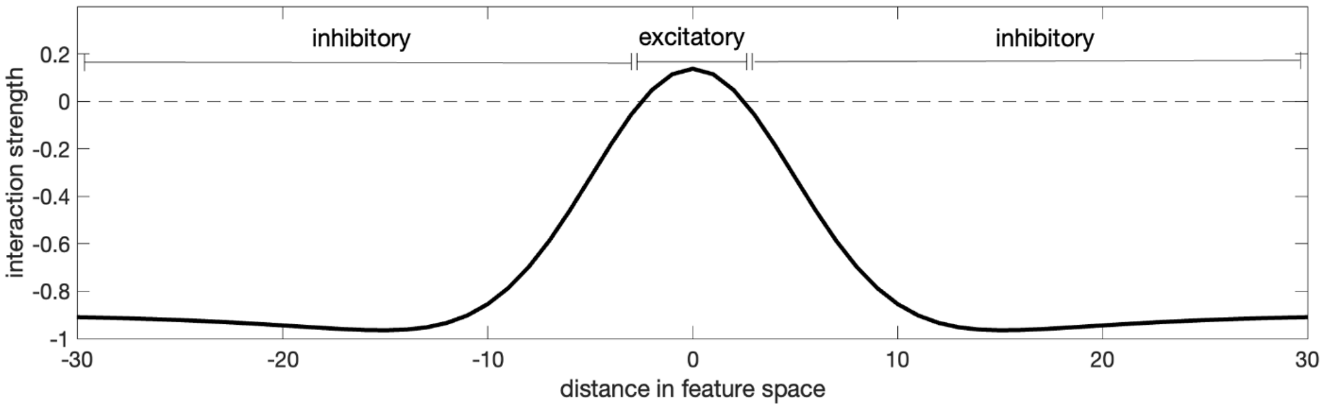
$$\tau\dot{u}(x) = -u(x) + h + s(x) + \int k(x - x')g\big(u(x')\big)dx' + q\xi(x)$$



Neural fields: continuous features x

$$\tau\dot{u}(x) = -u(x) + h + s(x) + \int k(x - x')g\big(u(x')\big)dx' + q\xi(x)$$



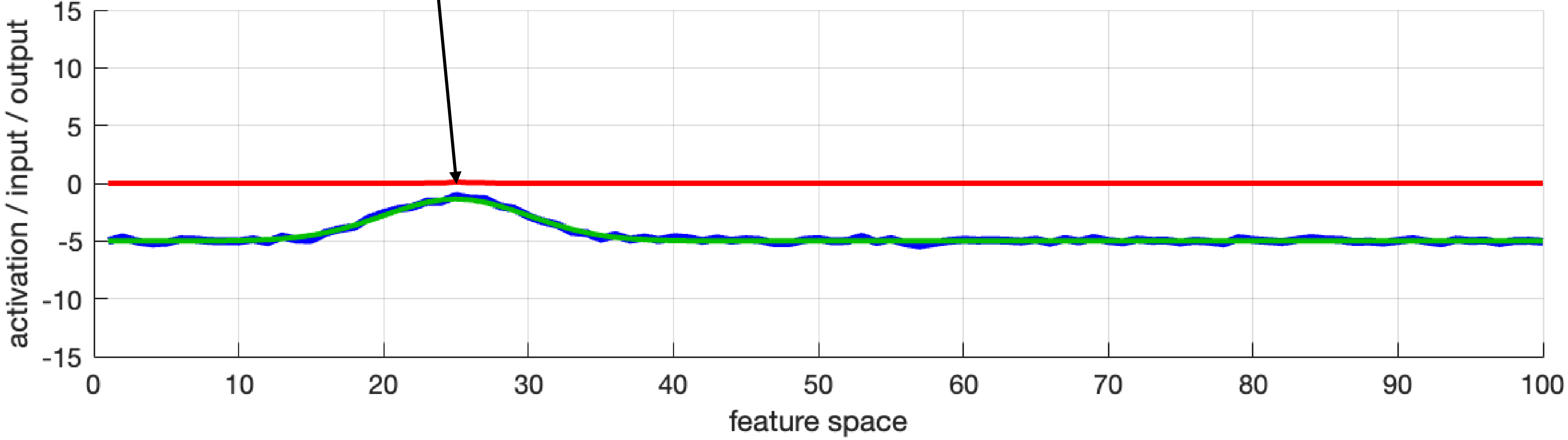


(e.g., Jancke et al., 1999)

Neural fields: continuous features x

$$\tau\dot{u}(x) = -u(x) + h + s(x) + \int k(x - x')g\big(u(x')\big)dx' + q\xi(x)$$

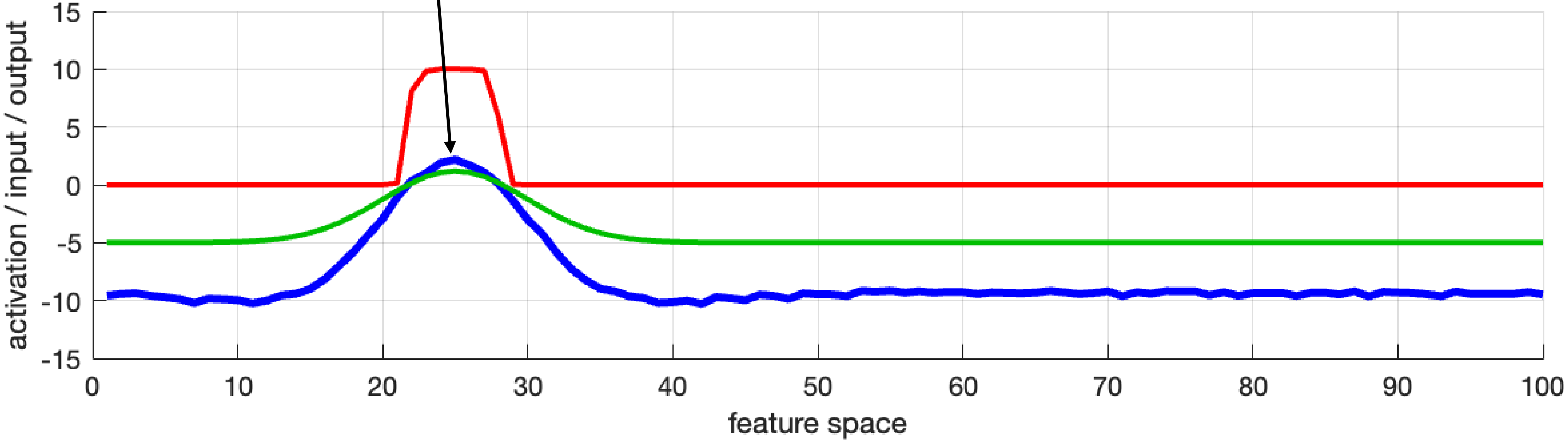
$a = 3.5$



Neural fields: continuous features x

$$\tau\dot{u}(x) = -u(x) + h + s(x) + \int k(x - x')g\big(u(x')\big)dx' + q\xi(x)$$

$$\boxed{a = 6}$$

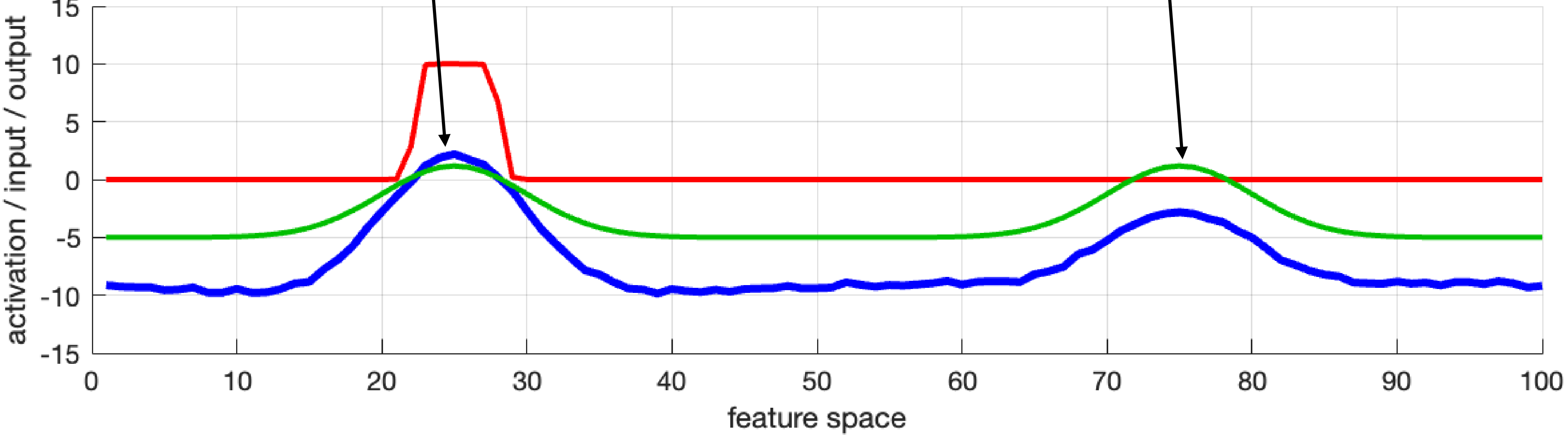


Neural fields: continuous features x

$$\tau\dot{u}(x) = -u(x) + h + s(x) + \int k(x - x')g\big(u(x')\big)dx' + q\xi(x)$$

$a = 6$

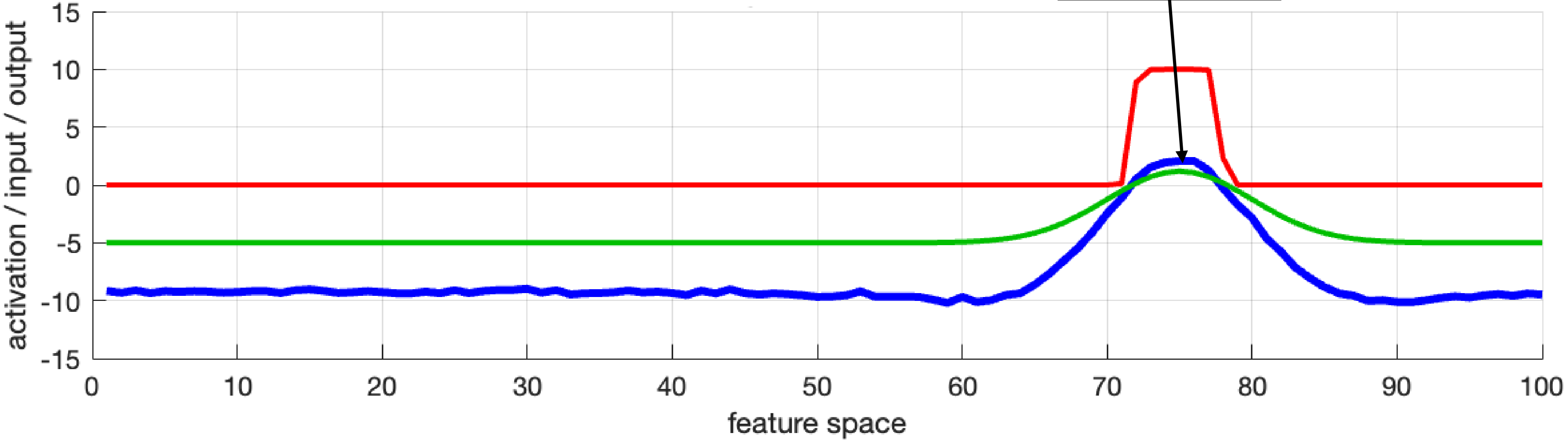
$a = 6$



Neural fields: continuous features x

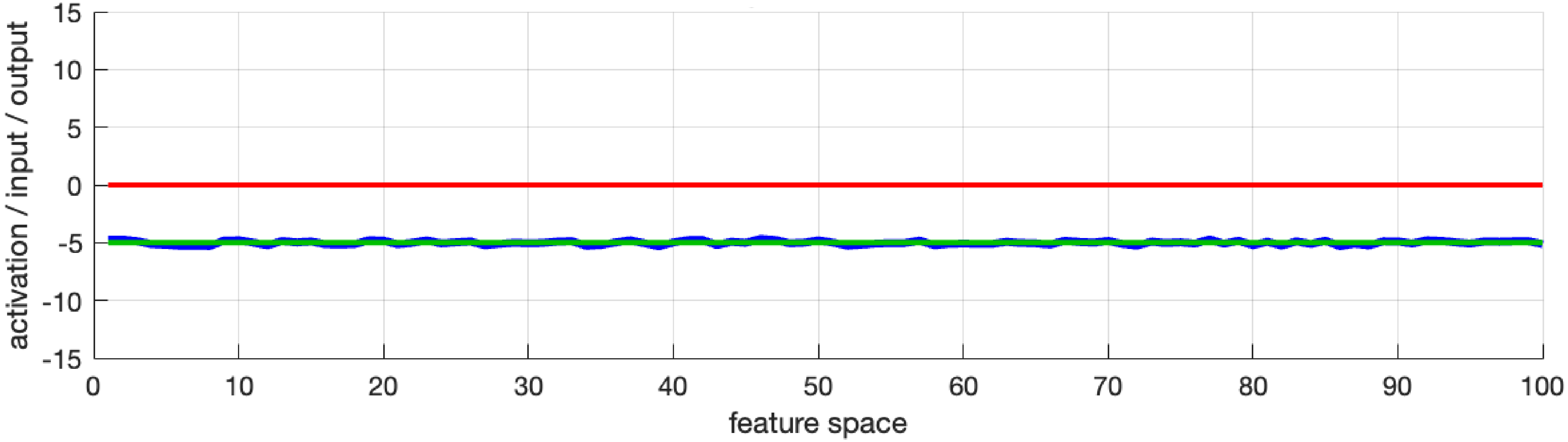
$$\tau\dot{u}(x) = -u(x) + h + s(x) + \int k(x - x')g\big(u(x')\big)dx' + q\xi(x)$$

$$\boxed{a = 6}$$



Neural fields: continuous features x

$$\tau\dot{u}(x) = -u(x) + h + s(x) + \int k(x - x')g\big(u(x')\big)dx' + q\xi(x)$$



Activation peaks as cognitive events

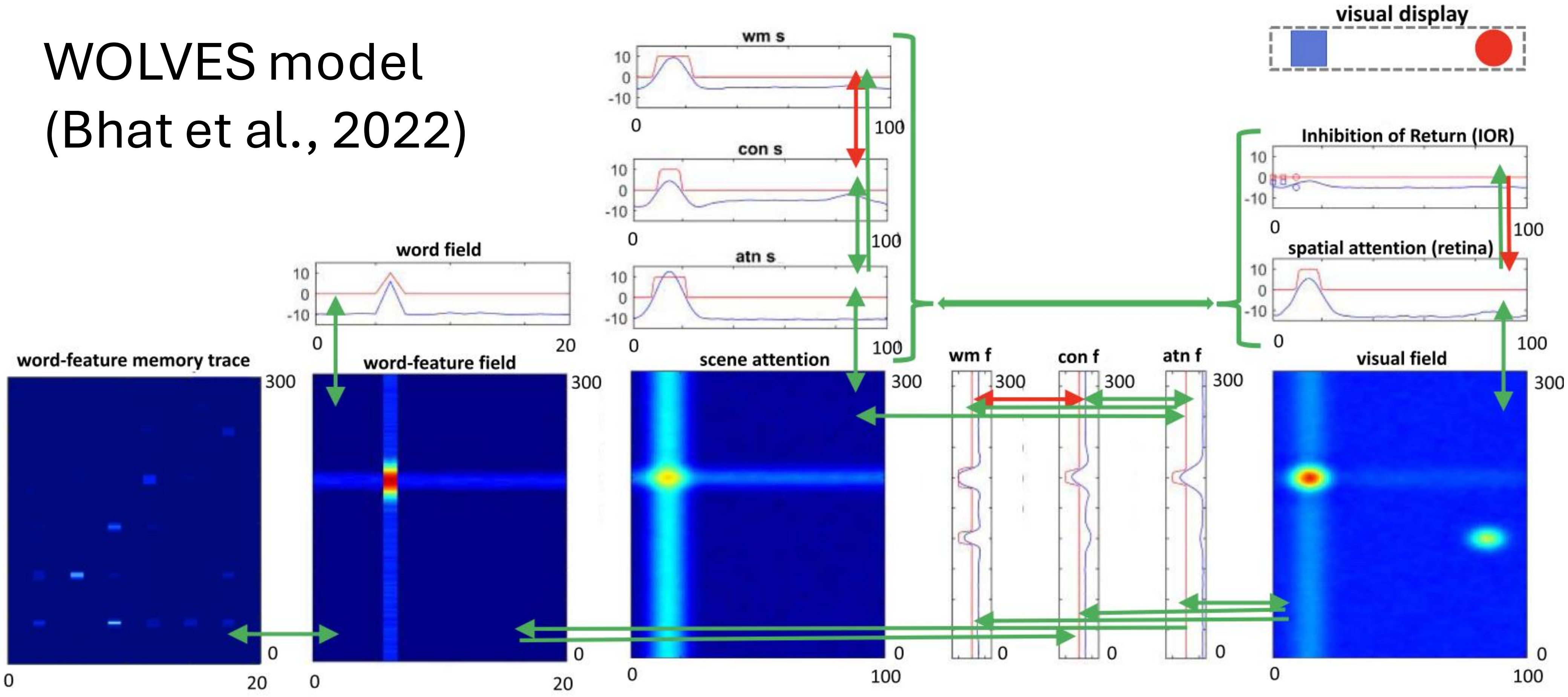
Activation peaks form and dissipate as **instabilities**

Position of peak in feature space determines content of cognitive event (e.g., phonetic target in articulation)

Nonlinearity allows discrete cognitive events to occur in continuous space (continuous time, continuous activation, continuous features)

Networks/architectures through coupling

WOLVES model
(Bhat et al., 2022)



DFT models of language

- Speech production (Roon & Gafos, 2016; Stern et al., 2022; Stern & Shaw 2023a,b)
- Long-term change in phonological representations (Gafos & Kirov, 2009; Shaw & Tang, 2023)
- Individual differences in phonological representation (Harper, 2021)
- Word learning via visual exploration (WOLVES: Bhat et al., 2022)
- Noun phrases guiding visual search (Sabinasz et al., 2023)
- Negation processing (Kati et al., 2024)

Today

- Speech errors (Manasvi Chaturvedi)
- Code-switching (Alessandra Pintado-Urbanc)
- Phonological neighborhood effects (Miranda Zhu)
- Sibilant-vowel phonotactics (Ayla Karakaş)
- Structural priming (Herbert Zhou)

Benefits of DFT: single framework

- Coupled differential equations all the way down
- Different models can, in theory, be slotted together (e.g., WOLVES = WOL + VES)
- Hypotheses in one domain generate hypotheses in other domains

Modeling choices → theoretical claims

- What are the feature dimensions represented by fields?

- What are the categories represented by nodes?

→ **linguistic theory**

- Mechanisms/parameters: coupling, inputs, resting level, evolution rate, lateral interaction

  → **few** and **interpretable**

- Goal: generative model, not data-fitting

Thank you!

Website

dynamicfieldtheory.org

Textbook

Schöner, G., Spencer, J., & DFT Research Group (2016). *Dynamic Thinking: A Primer on Dynamic Field Theory*. Oxford University Press.

Some overview papers

Schöner, G. (2020). The Dynamics of Neural Populations Capture the Laws of the Mind. *Topics in Cognitive Science*, *12*(4), 1257–1271.

Schöner, G. (2023). Dynamical Systems Approaches to Cognition. In R. Sun (Ed.), *The Cambridge Handbook of Computational Cognitive Sciences* (2nd ed., pp. 210–241). Cambridge University Press.

References

Amari, S. (1977). Dynamics of pattern formation in lateral-inhibition type neural fields. *Biological Cybernetics*, *27*(2), 77–87.

Bhat, A. A., Spencer, J. P., & Samuelson, L. K. (2022). Word-Object Learning via Visual Exploration in Space (WOLVES): A neural process model of cross-situational word learning. *Psychological Review*, *129*(4), 640–695.

Cohen, M. R., & Newsome, W. T. (2009). Estimates of the Contribution of Single Neurons to Perception Depend on Timescale and Noise Correlation. *Journal of Neuroscience*, *29*(20), 6635–6648.

Gafos, A. I., & Kirov, C. (2009). A dynamical model of change in phonological representations: The case of lenition. *Approaches to Phonological Complexity*, 219–240.

Georgopoulos, A. P., Schwartz, A. B., & Kettner, R. E. (1986). Neuronal population coding of movement direction. *Science*, *233*, 1416–1419.

Grossberg, S. (1969). On learning, information, lateral inhibition, and transmitters. *Mathematical Biosciences*, *4*(3), 255–310.

Harper, S. (2021). *Individual Differences in Phonetic Variability and Phonological Representation* [PhD thesis]. University of Southern California.

Jancke, D., Erlhagen, W., Dinse, H. R., Akhavan, A. C., Giese, M., Steinhage, A., & Schöner, G. (1999). Parametric population representation of retinal location: Neuronal interaction dynamics in cat primary visual cortex. *Journal of Neuroscience*, *19*(20), 9016–9028.

Kati, L., Sabinasz, D., Schöner, G., & Kaup, B. (2024). Interaction of polarity and truth value—A neural dynamic architecture of negation processing. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *46*.

Roon, K. D., & Gafos, A. I. (2016). Perceiving while producing: Modeling the dynamics of phonological planning. *Journal of Memory and Language*, *89*, 222–243.

Sabinasz, D., Richter, M., & Schöner, G. (2023). Neural dynamic foundations of a theory of higher cognition: The case of grounding nested phrases. *Cognitive Neurodynamics*, 1–23.

Schöner, G. (2020). The Dynamics of Neural Populations Capture the Laws of the Mind. *Topics in Cognitive Science*, *12*(4), 1257–1271.

Schöner, G. (2023). Dynamical Systems Approaches to Cognition. In R. Sun (Ed.), *The Cambridge Handbook of Computational Cognitive Sciences* (2nd ed., pp. 210–241). Cambridge University Press.

Schöner, G., Spencer, J., & Group, D. R. (2016). *Dynamic Thinking: A Primer on Dynamic Field Theory*. Oxford University Press.

Schneegans, S. (2021). *COSIVINA: A Matlab Toolbox to Compose, Simulate, and Visualize Neurodynamic Architectures* [Computer software]. https://github.com/cosivina/cosivina

Shaw, J. A., & Tang, K. (2023). A dynamic neural field model of leaky prosody: Proof of concept. *Proceedings of the 2022 Annual Meeting on Phonology (AMP)*.

Stern, M. C., Chaturvedi, M., & Shaw, J. A. (2022). A dynamic neural field model of phonetic trace effects in speech errors. *Proceedings of the Annual Meeting of the Cognitive Science Society, 44*.

Stern, M. C., & Shaw, J. A. (2023a). Neural inhibition during speech planning contributes to contrastive hyperarticulation. *Journal of Memory and Language*, *132*, 104443.

Stern, M. C., & Shaw, J. A. (2023b). Not all phonological neighbors affect production equivalently: Predictions from a neural dynamic model. *Proceedings of the 20th International Congress of Phonetic Sciences (ICPhS)*, 4002–4006.