



# Neural network simulations of simple cognitive functions

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universitetas



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# Materials

Materials for the class: [github.com/acompte/attractors](https://github.com/acompte/attractors).

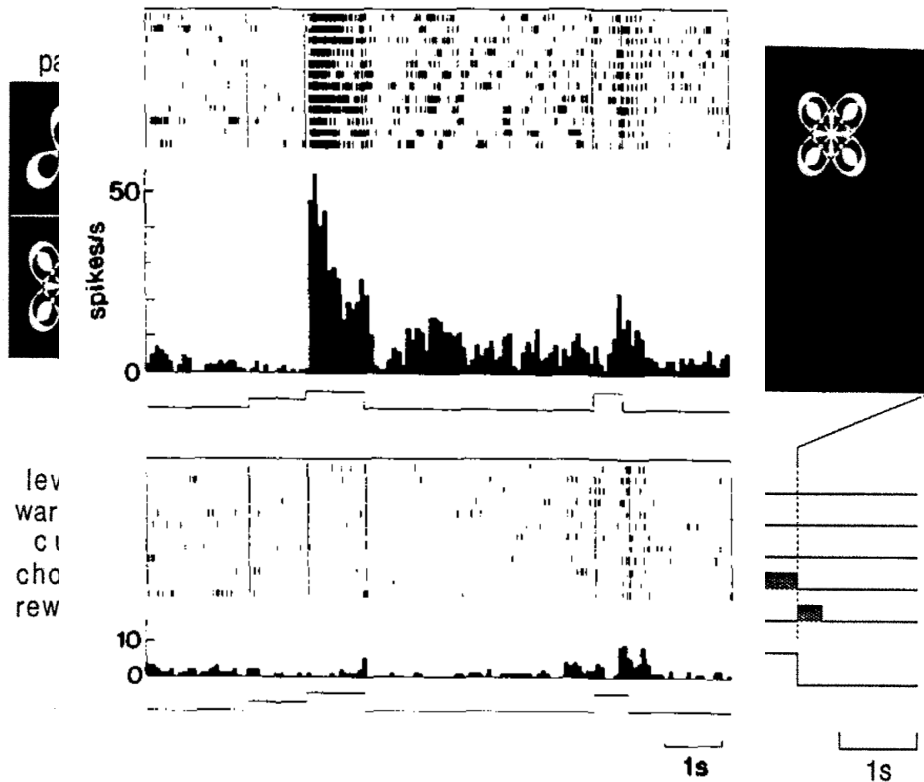
Click  to open exercises

# Contents

- cortical networks:
  - El networks: [Wilson and Cowan, 1972](#)
  - Inhibition-stabilized networks: [Tsodyks et al, 1997](#); [Ozeki et al, 2009](#)
- discrete attractor networks: [Amit and Brunel, 1997](#); [Wang, 2002](#); [Wong and Wang, 2006](#); [Roxin and Ledberg, 2008](#)
- ring attractor networks: [Wilson and Cowan, 1973](#); [Amari, 1977](#); [Hansel and Sompolinsky, 1998](#)
- low-rank RNNs: [Mastrogiuseppe and Ostojic, 2018](#)

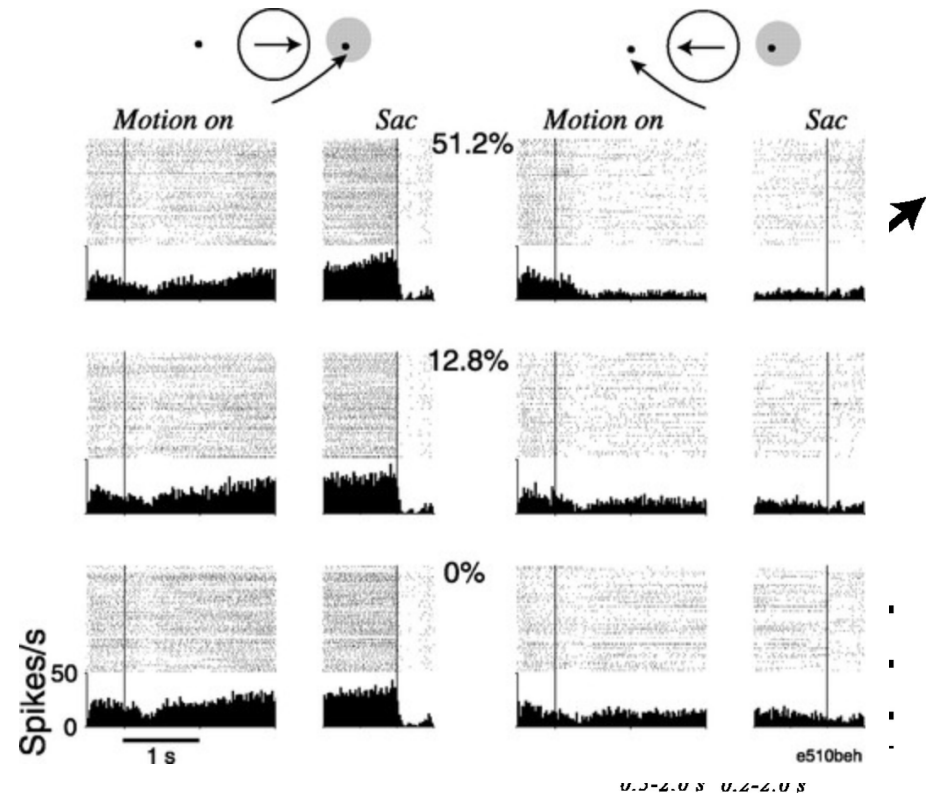
# Neural basis of cognition

## Working memory



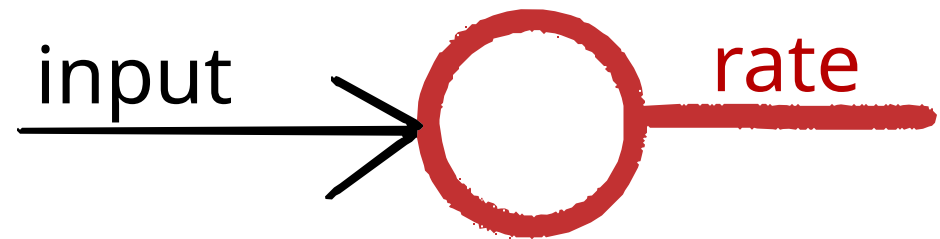
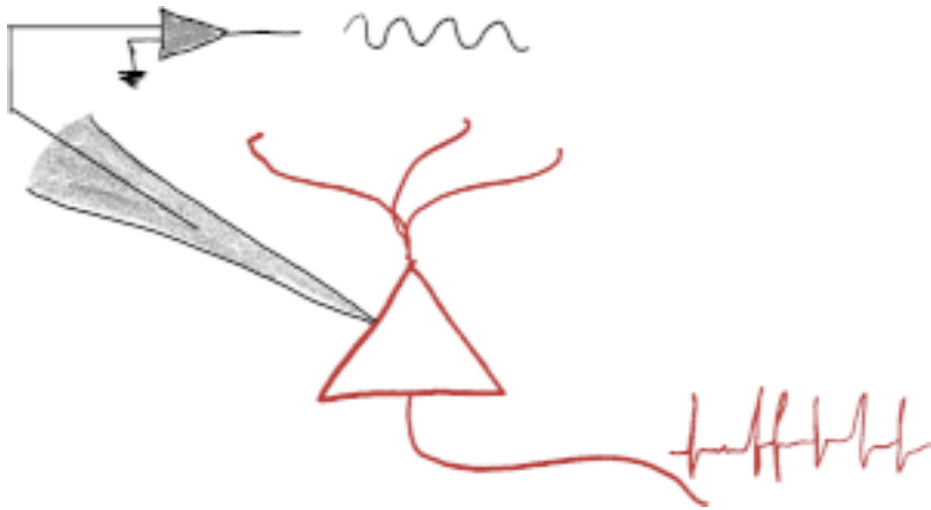
Sakai and Miyashita, 1991

## Decision making



Shadlen and Newsome, 2001

# The basic unit: the neuron

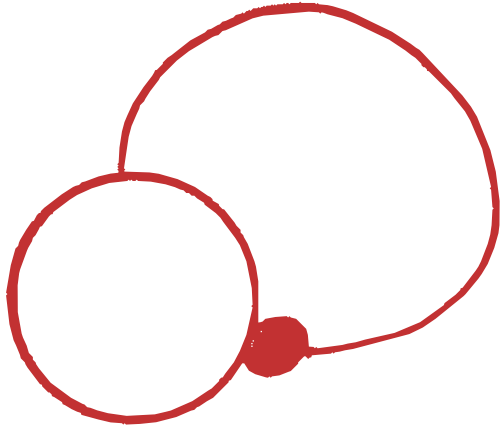


$$\tau \frac{dr(t)}{dt} = -r(t) + I(t)$$

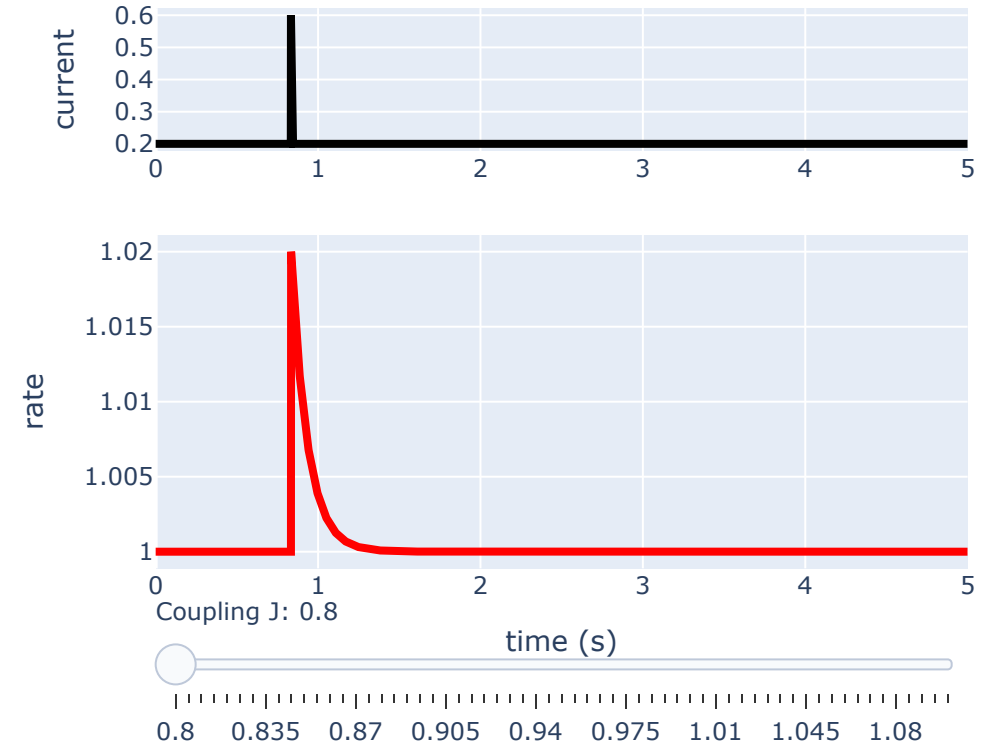
Euler method:

$$\tau \frac{r(t + dt) - r(t)}{dt} = -r(t) + I(t) \quad \Rightarrow \quad r(t + dt) = r(t) + \frac{dt}{\tau} [-r(t) + I(t)]$$

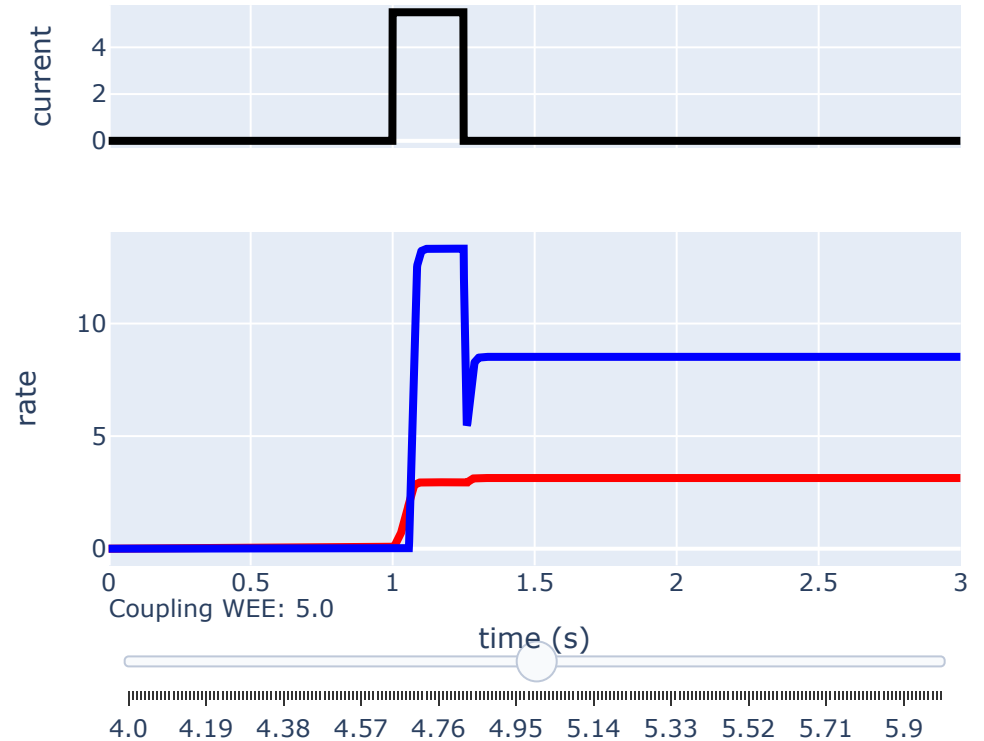
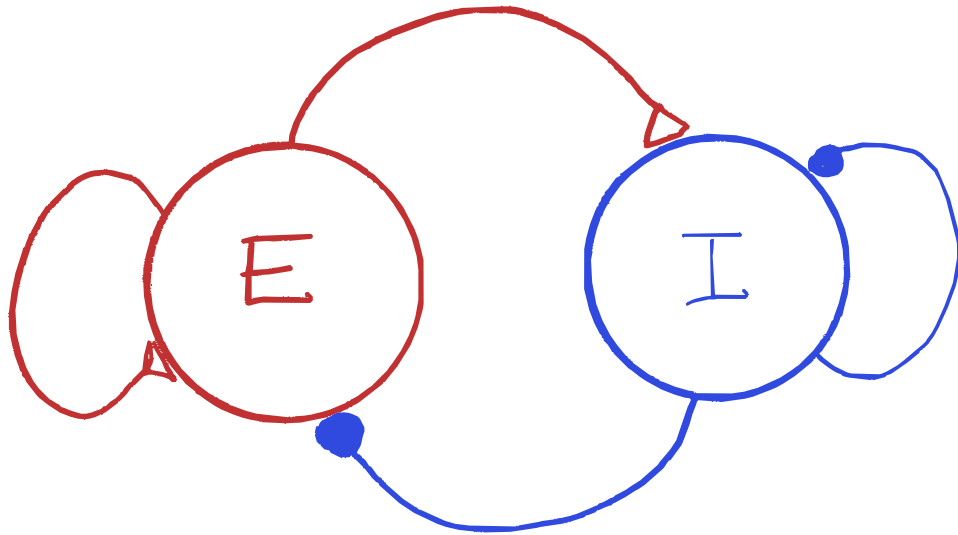
# Recurrent excitation in cortex



$$\tau \frac{dr}{dt} = -r + Jr$$



# E-I network



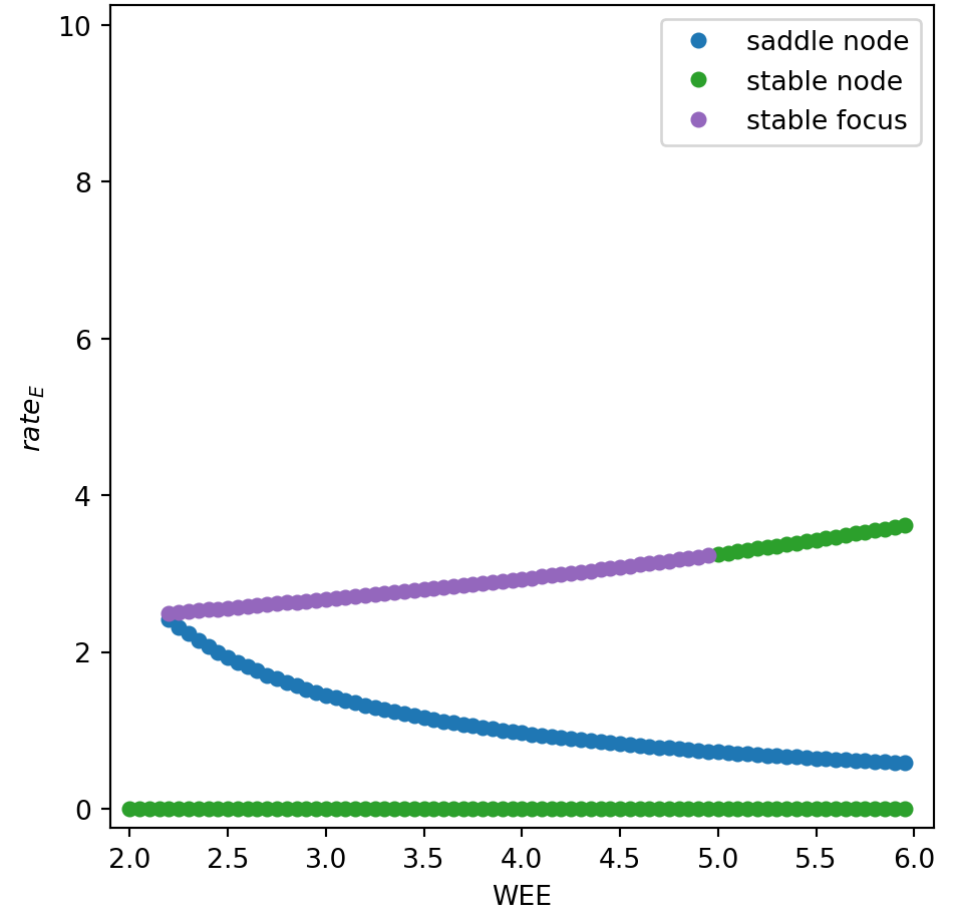
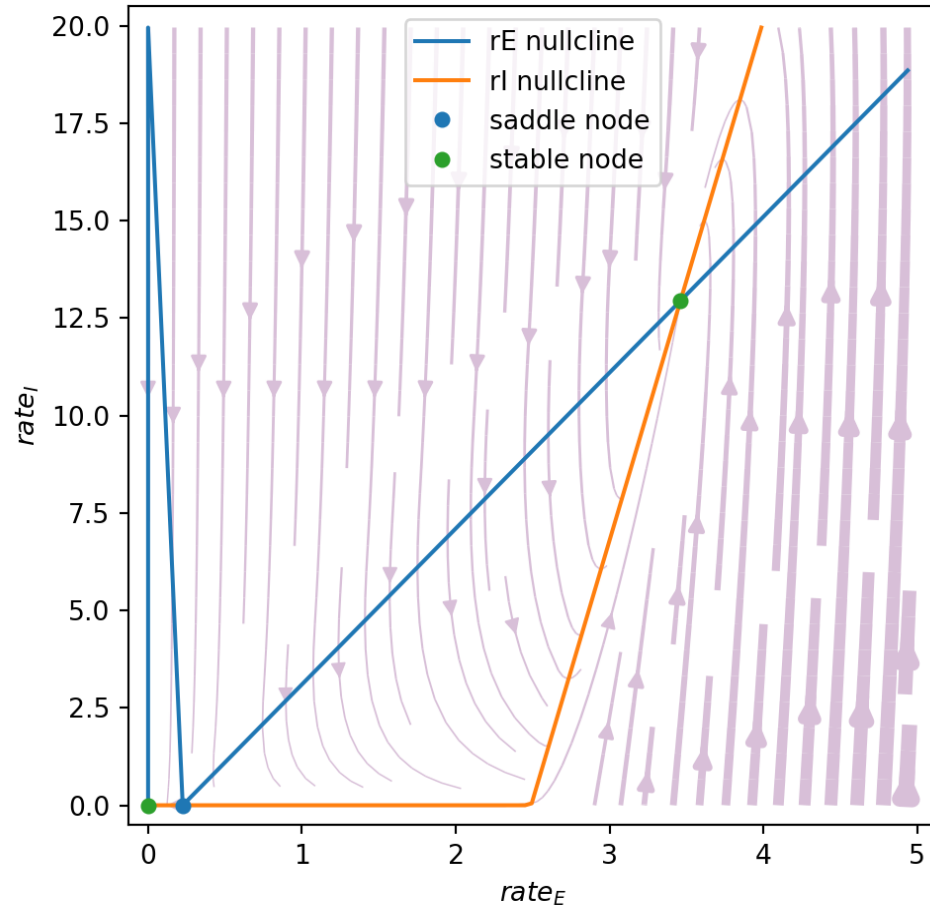
$$\tau_E \frac{dr_E(t)}{dt} = -r_E(t) + G_E[\mathbf{W}_{EE}r_E(t) - \mathbf{W}_{EI}r_I(t) + I_E(t) - \theta_E]_+$$

$$\tau_I \frac{dr_I(t)}{dt} = -r_I(t) + G_I[\mathbf{W}_{IE}r_E(t) - \mathbf{W}_{II}r_I(t) + I_I(t) - \theta_I]_+$$



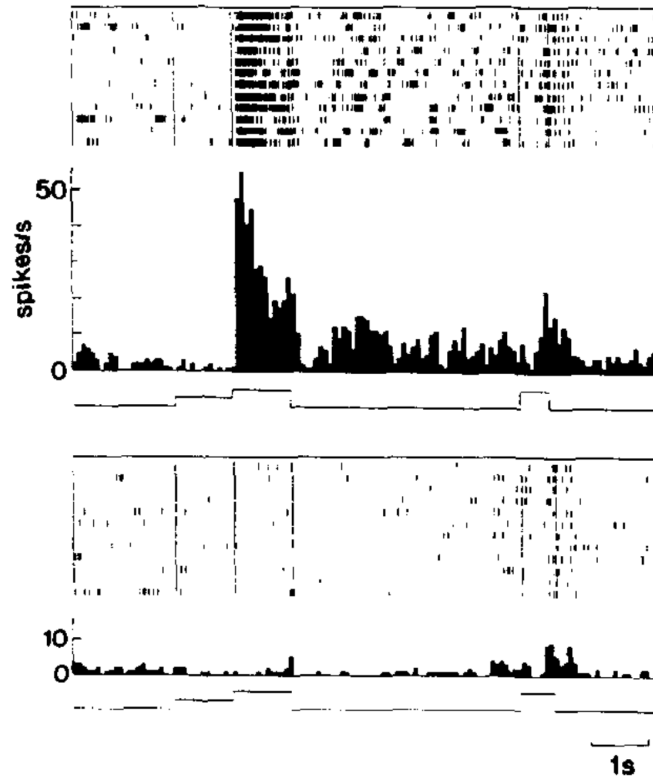


# Phase-space analysis

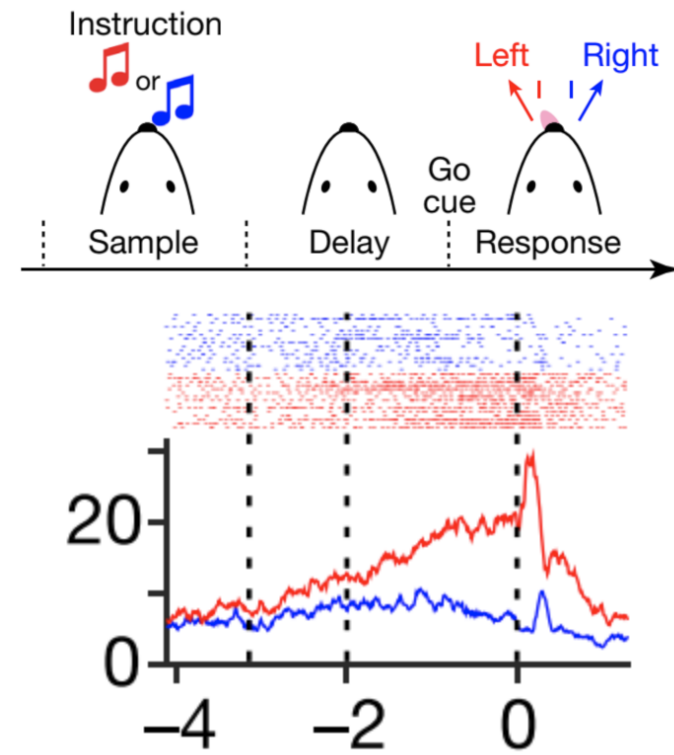


Brainpy: [Wang et al 2023](#)

# Discrete working memory

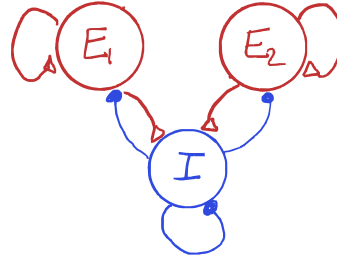


Sakai and Miyashita, 1991



Inagaki et al, 2019

# The double-well model

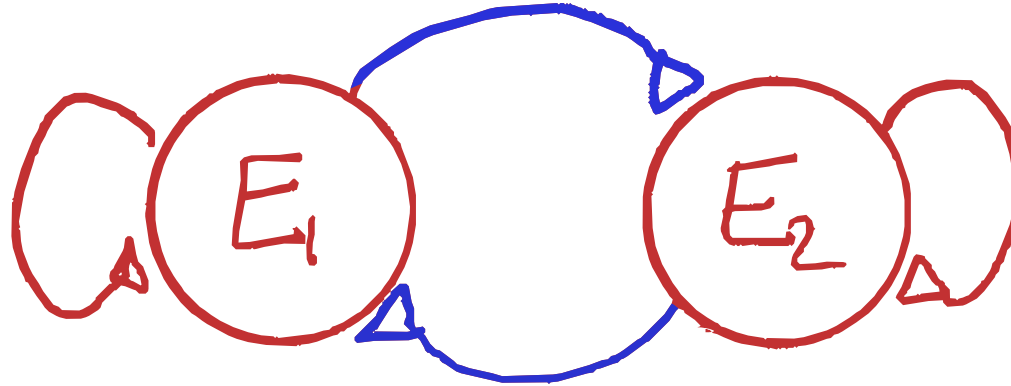


$$\tau_E \frac{dI_{E1}(t)}{dt} = -I_{E1}(t) + \mathbf{W_{EE}} g_E(I_{E1}(t)) - \mathbf{W_{EI}} g_I(I_I(t)) + S_1(t)$$

$$\tau_E \frac{dI_{E2}(t)}{dt} = -I_{E2}(t) + \mathbf{W_{EE}} g_E(I_{E2}(t)) - \mathbf{W_{EI}} g_I(I_I(t)) + S_2(t)$$

$$\tau_I \frac{dI_I(t)}{dt} = -I_I(t) + \mathbf{W_{IE}} g_E(I_{E1}(t)) + \mathbf{W_{IE}} g_E(I_{E2}(t)) - \mathbf{W_{II}} I_I(t)$$

# The double-well model

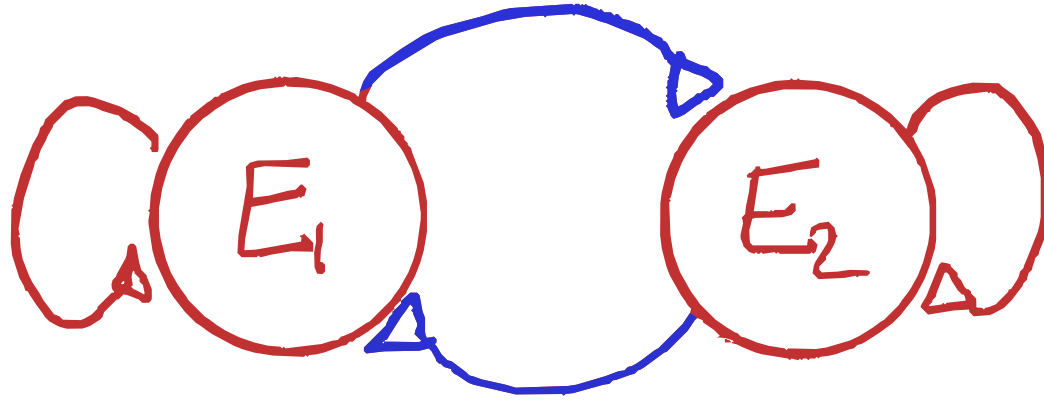


$$\tau_E \frac{dI_{E1}}{dt} = -I_{E1} + (W_{EE} - \alpha)g_E(I_{E1}) - \alpha g_E(I_{E2}) + S_1$$

$$\tau_E \frac{dI_{E2}}{dt} = -I_{E2} + (W_{EE} - \alpha)g_E(I_{E2}) - \alpha g_E(I_{E1}) + S_2$$

$$\alpha = -\gamma W_{EI} W_{IE}$$

# The double-well model

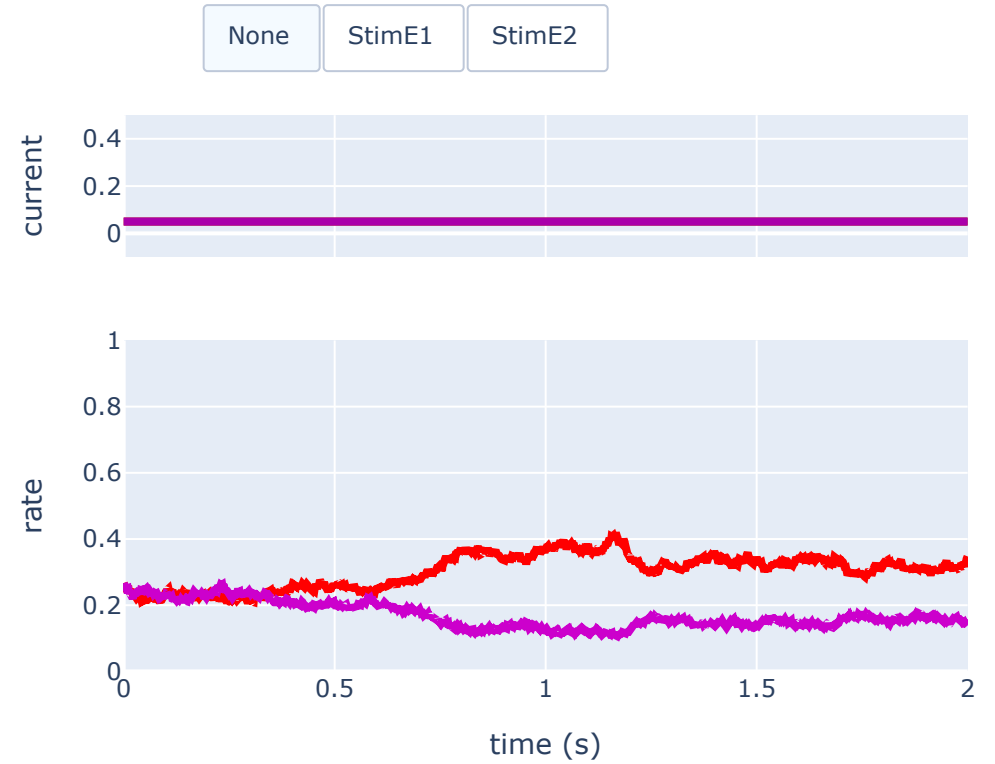
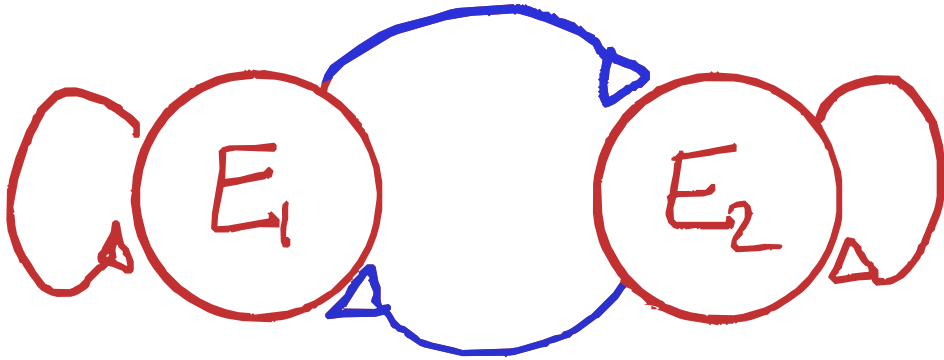


$$\tau_E \frac{dI_{E1}}{dt} = -I_{E1} + \mathbf{J_E} g_E(I_{E1}) - \mathbf{J_I} g_E(I_{E2}) + S_1$$

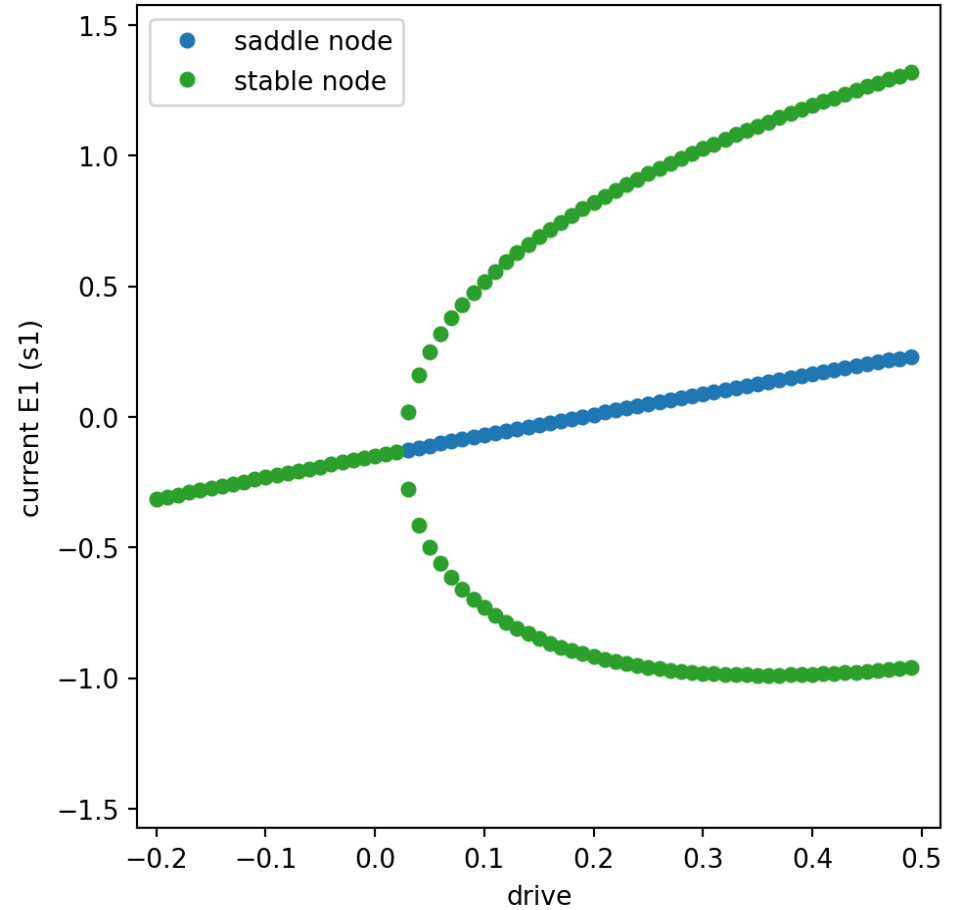
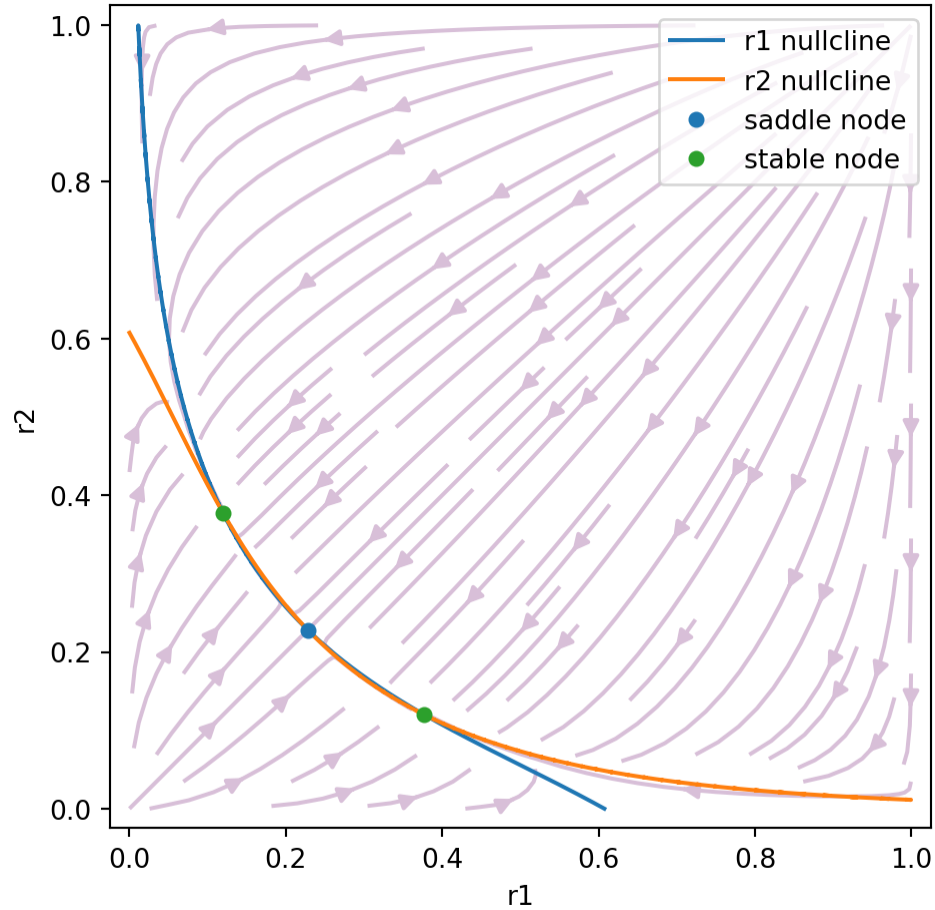
$$\tau_E \frac{dI_{E2}}{dt} = -I_{E2} + \mathbf{J_E} g_E(I_{E2}) - \mathbf{J_I} g_E(I_{E1}) + S_2$$

Wong and Wang 2006

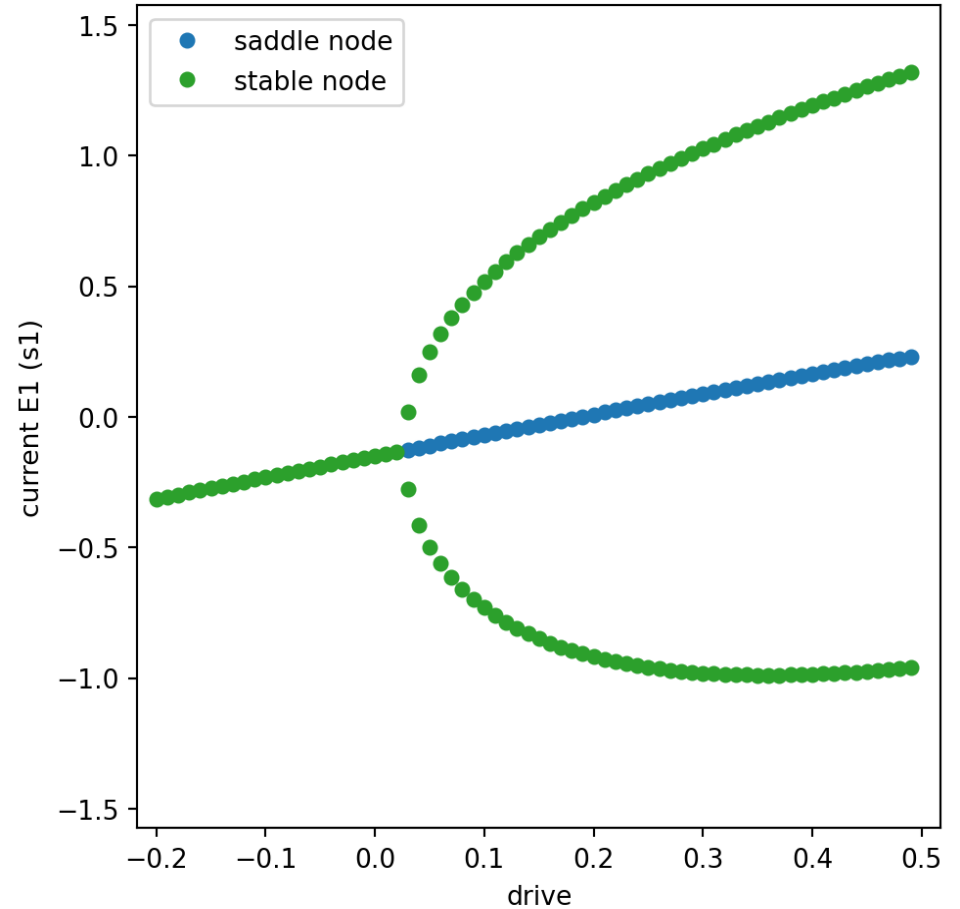
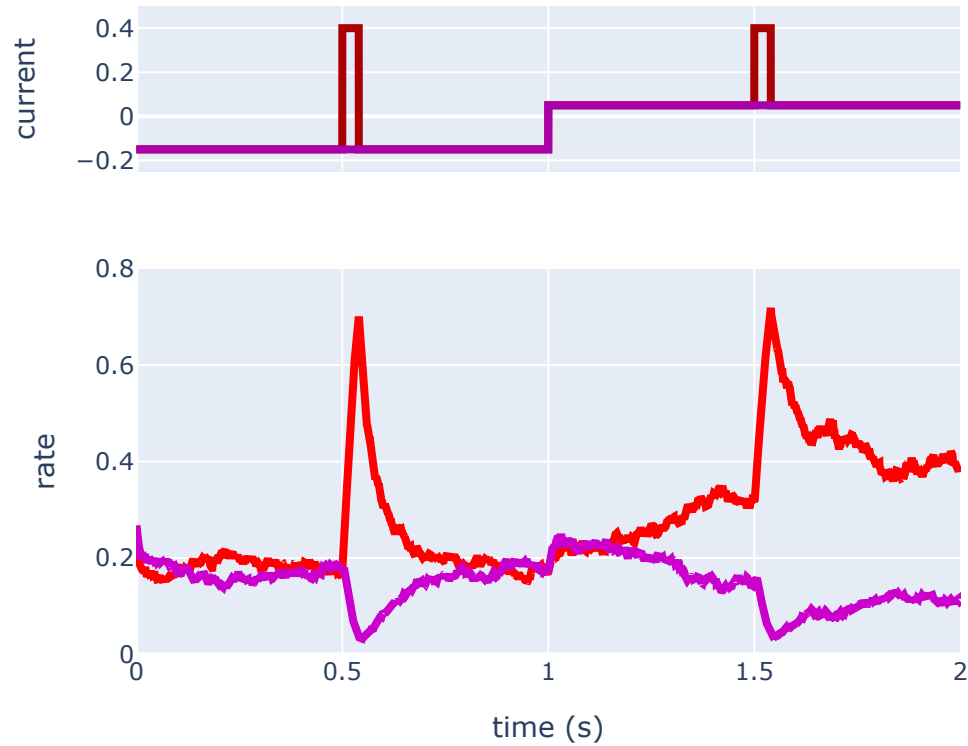
# Selective memory



# Double-well: Phase-space analysis



# Drive modulates network function

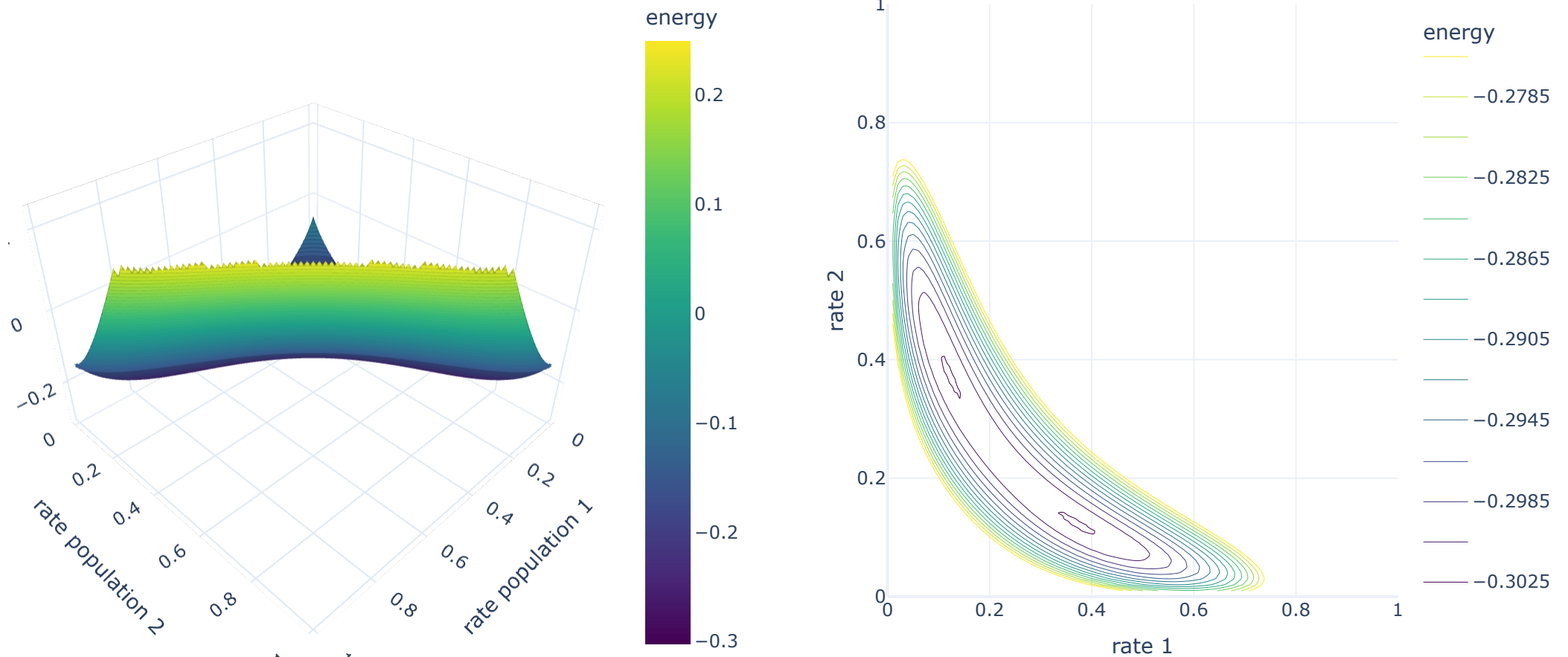




# Double-well: Energy landscape

$$E(r_1, r_2) = -\frac{J_E}{2}(r_1^2 + r_2^2) + J_I r_1 r_2 - S(r_1 + r_2) + \int_0^{r_1} g_E^{-1}(x) dx + \int_0^{r_2} g_E^{-1}(x) dx$$

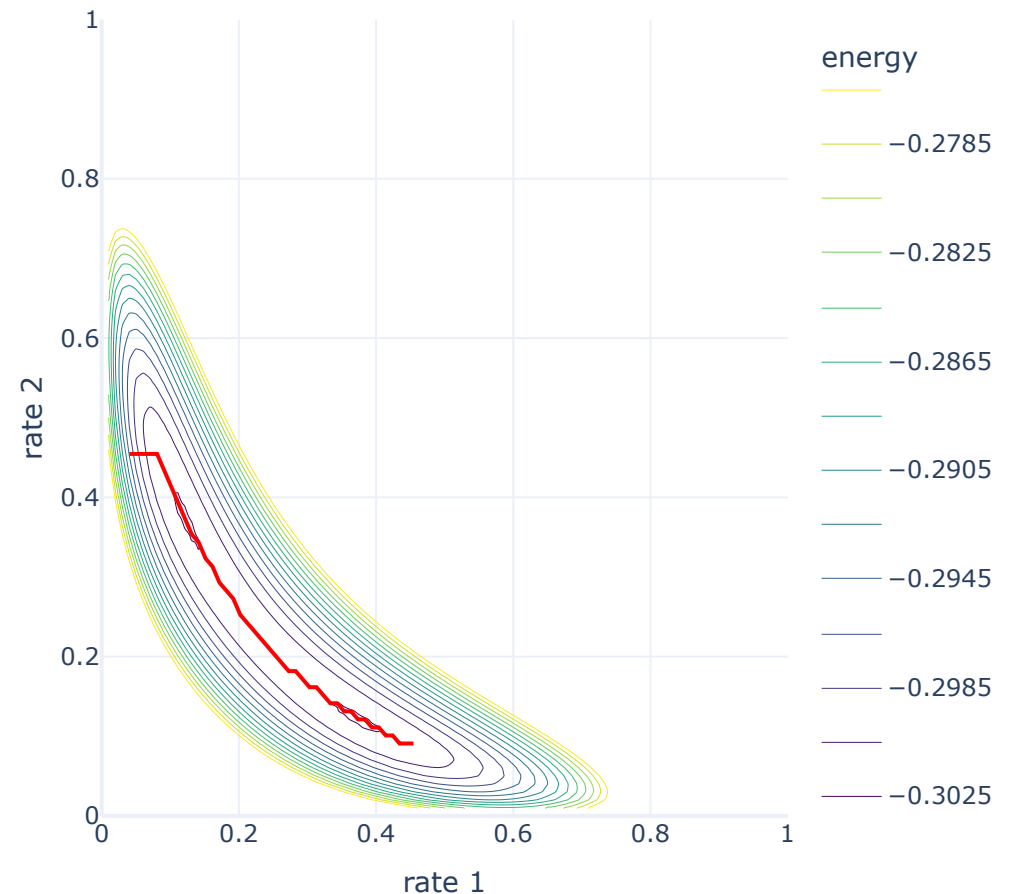
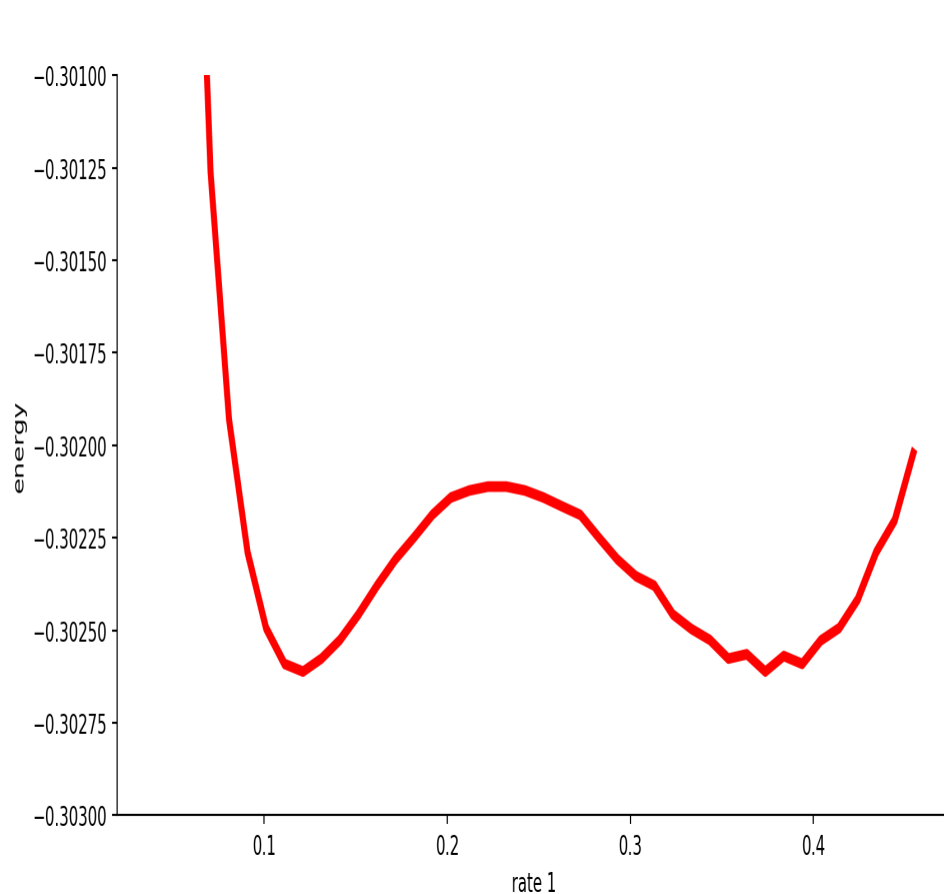
Gerstner et al, 2014



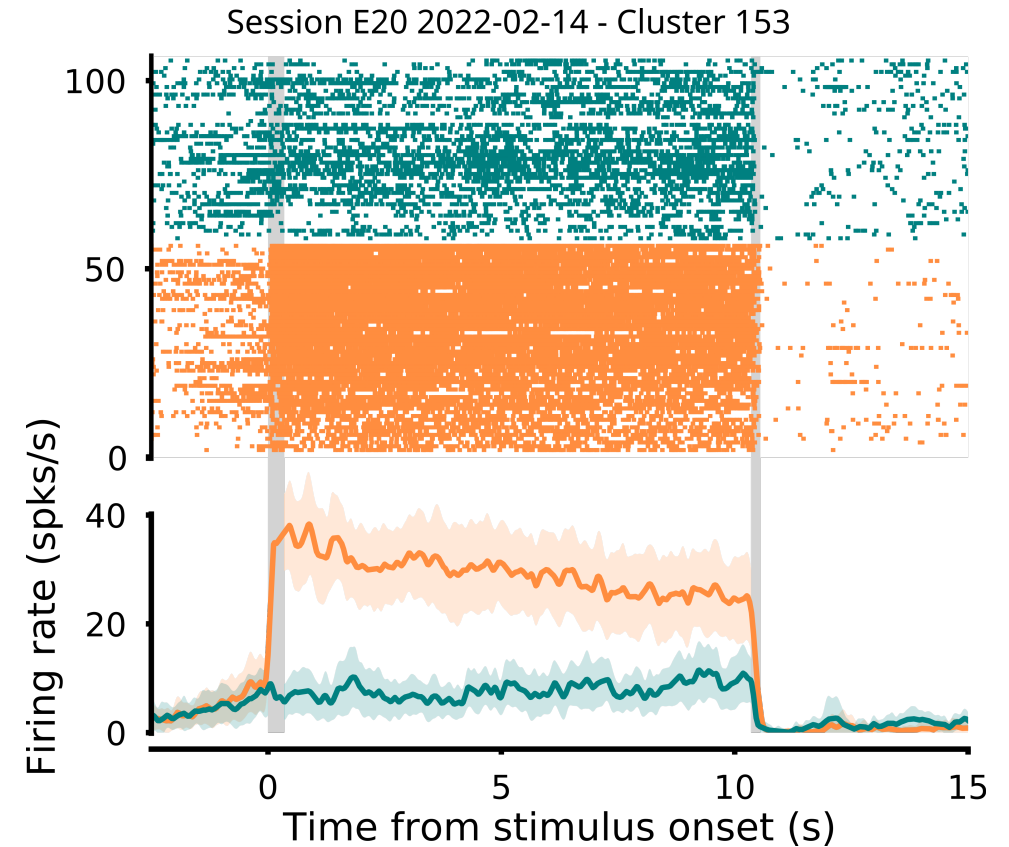
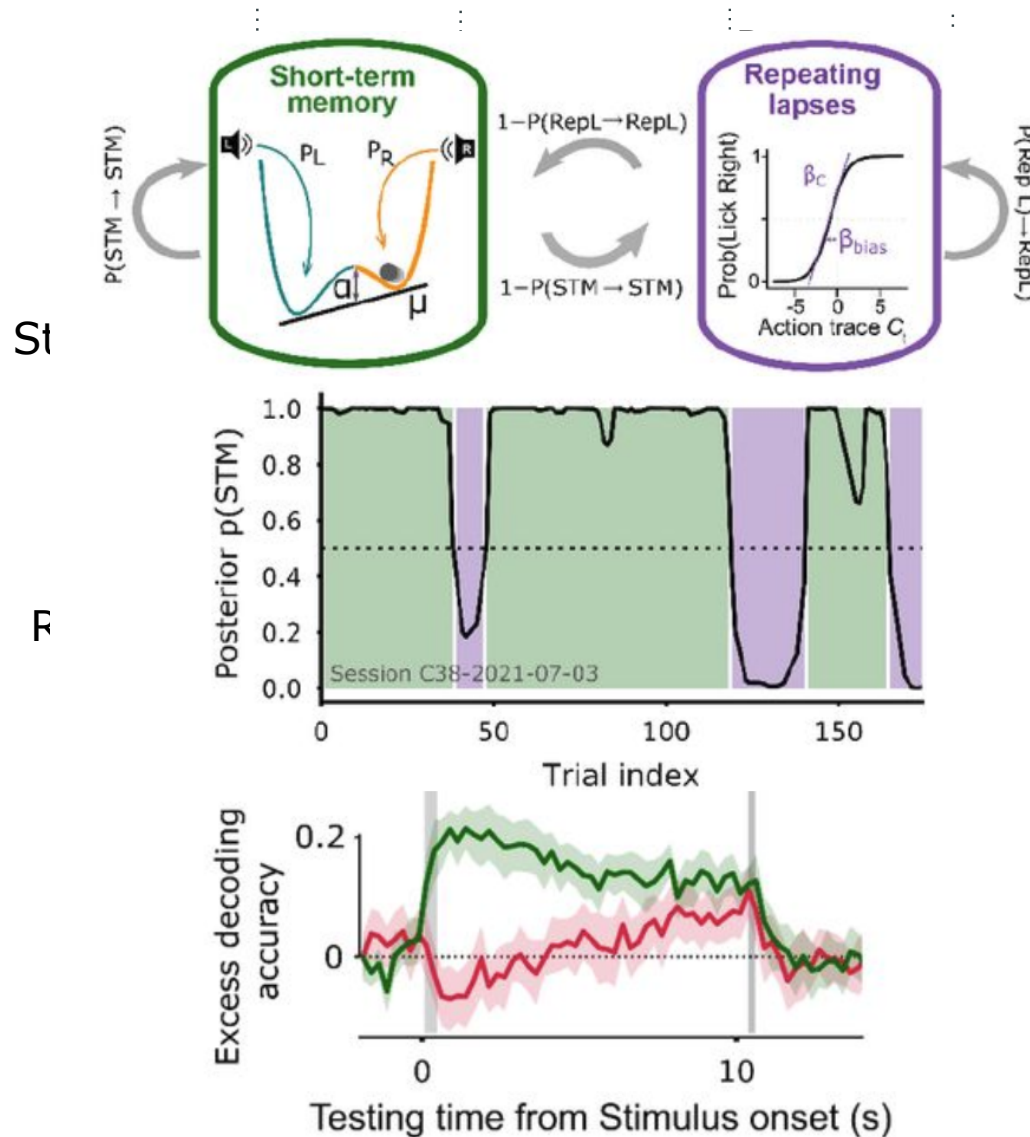
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$$E(r_1, r_2) = -\frac{J_E}{2}(r_1^2 + r_2^2) + J_I r_1 r_2 - S(r_1 + r_2) + \int_0^{r_1} g_E^{-1}(x) dx + \int_0^{r_2} g_E^{-1}(x) dx$$

Gerstner et al, 2014



# Experimental evidence



(Ona-Jodar et al. bioRxiv 2025)

# End of part 1!