

# Dynamics of the short-term memory

## Full depletion model

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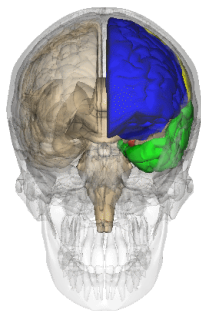
# Overview of the talk

- working memory
- short-term plasticity
- full depletion model
- analytic approximation
- PyDSTool package
- dynamical system view:
  - limit cycle classes
  - bifurcation diagrams
- generalized Taken-Bogdanov system
- discussion

# The human brain

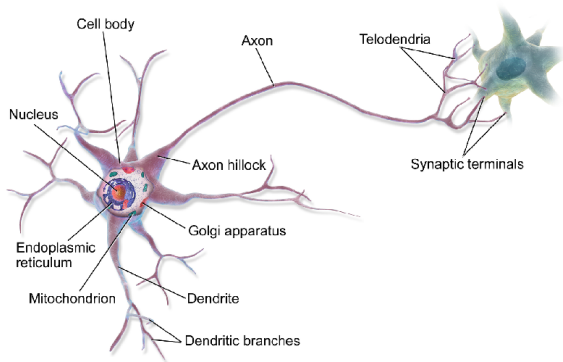
## Numbers:

- weighs on average about 1.5 kg
- volume of around  $1130 \text{ cm}^3$  in women and  $1260 \text{ cm}^3$
- composed of neurons, glial cells, and blood vessels
- $2 \cdot 10^{11}$  neurons  $\sim$  nr. of stars in the Milky Way
- $1.25 \cdot 10^{14}$  synapses in the cerebral cortex alone



# Neurons

- neuron - fundamental structural functional unit of the brain
- discrete cells and not continuous with other cells
- information flows from the dendrites to the axon via the cell body

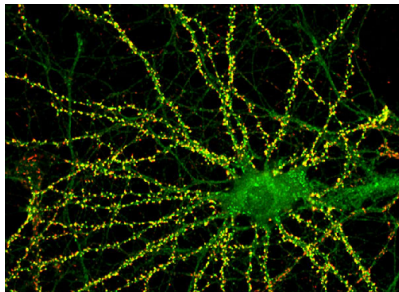


*Image Source: Wikimedia Commons*

# Synapse

Two different types of synapses:

- chemical synapse: electrical activity is converted into the release of a neurotransmitter
- electrical synapse: cell membranes are connected by channels that are capable of passing electric current



*Image Credit: Kennedy lab, Caltech*

# Chemical synapse

Synaptic transmission:

- activation of voltage-gated calcium channels
- release of neurotransmitters
- neurotransmitter receptors
- opening ion channels - postsynaptic potential and/or chemical messengers

Types (neurotransmitter):

- glutamatergic (excitatory)
- GABAergic (inhibitory)
- ...

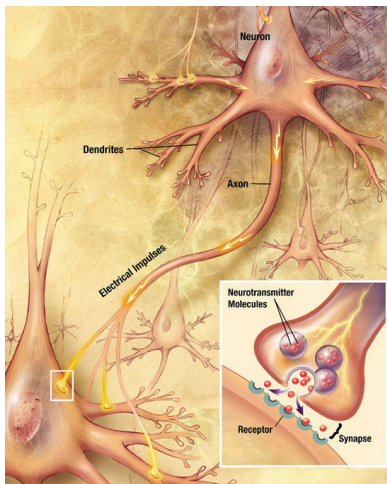


Image Source: *Wikimedia Commons*

# Synaptic plasticity and memory

Plasticity: synapses can strengthen or weaken over time

- long-term plasticity - from minutes to hours
  - long-term potentiation (LTP)
  - long-term depression (LTD)
- short-term or transient synaptic plasticity - from milliseconds to a few minutes

Memory: information encoding, storage and retrieval

- sensory memory - less than one second, limited capacity
- short-term memory - several seconds to minutes (without rehearsal), limited capacity
  - acoustic code + visual code
- long-term memory - sometimes a whole life span, immeasurably large capacity
  - encodes information semantically

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# Test

3Xgh1579fT0Bcqm4Ed7La2Xmvt8s



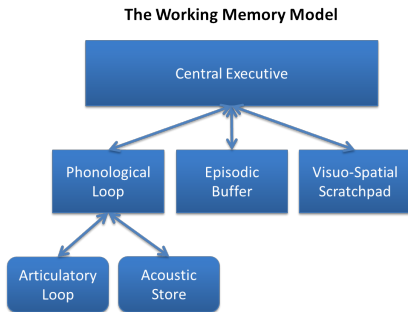
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# Test

?

# Working memory model

- holding and manipulating multiple information in the mind
  - “magical number seven“ (Miller, 1956)
  - link between working memory and learning and attention
- Baddeley’s model (Baddeley and Hitch, 1974):



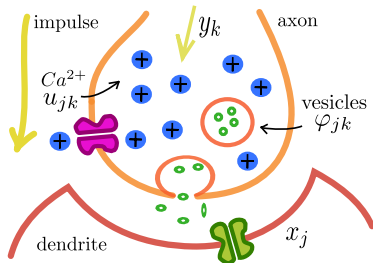
*Image Source: Wikimedia Commons*

# Short-term synaptic plasticity

- Tsodyks-Markram model (5 parameters)
  - the reservoir  $\varphi(t)$  of vesicles with neurotransmitters
  - the Ca-concentration  $u(t)$  influencing the release probability of vesicles

$$\dot{u} = \frac{1-u}{T_u} + \alpha(U-u)y$$

$$\dot{\varphi} = \frac{1-\varphi}{T_\varphi} - \beta\varphi u y$$



- $y \in [0, 1]$  is the pre-synaptic activity level (the firing rate of the other neuron)

# Synaptic theory of working memory

- short-term synaptic plasticity and selective neural populations (Mongillo et al., Science, 2008)

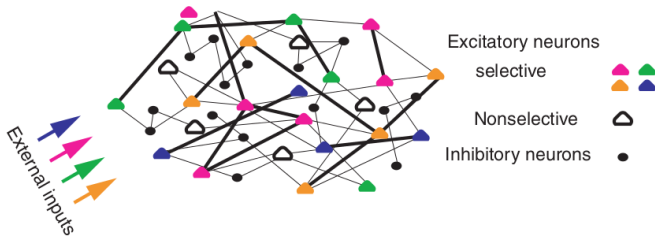


Image Source: Mongillo et al., Science, 2008

# Synaptic theory of working memory

- loading in and reading out memory items (Mongillo et al., Science, 2008)

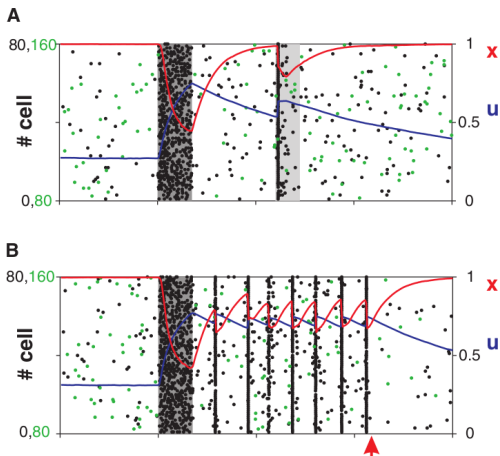


Image Source: Mongillo et al., Science, 2008

## Full depletion model

- for the stricter control of the dynamics (3 parameters)

$$\dot{u} = \frac{U_y - u}{T_u}$$

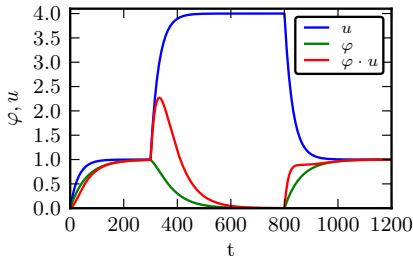
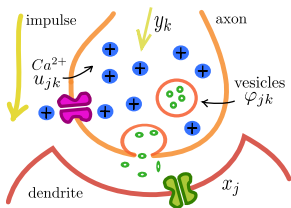
$$U_y = 1 + (U_{max} - 1)y$$

$$\dot{\varphi} = \frac{\Phi_u - \varphi}{T_\varphi}$$

$$\Phi_u = 1 - \frac{uy}{U_{max}}$$

- full depletion after sustained pre-synaptic firing:

- $y(t) = 1$  for  $t \in [300, 800]$
- $T_\varphi = 60, T_u = 30, U_{max} = 4$

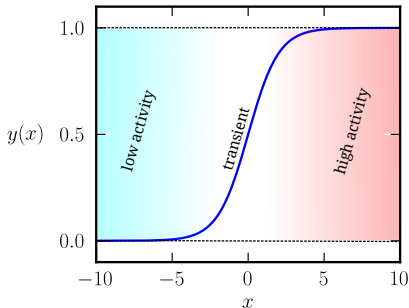
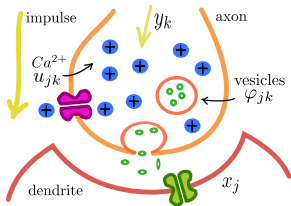


# Neural activity

- dynamics of the neural activity:

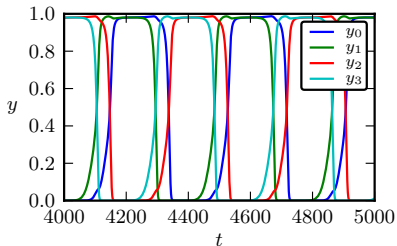
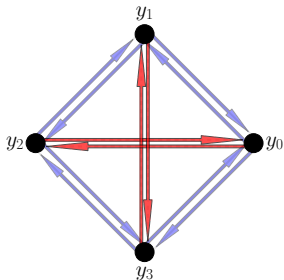
$$\dot{x}_j = -\Gamma x_j + \sum_k (w_{jk} + z_{jk} u_{jk} \varphi_{jk}) y_k$$

$$y_k = y(x_k) = \frac{1}{1 + e^{a(b-x_k)}}$$



# Clique encoding recurrent network

- nearest-neighbours - excitatory weights  $w_0$  (blue arrows)
- others - inhibitory weights  $z_0$  (red arrows)



- $T_\varphi = 60$  are  $T_u = 30$  are kept fixed



## Symmetric approximation

- assume that the initial conditions are the same for all neurons

$$\begin{cases} u_i(t) = u_j(t), \\ \varphi_i(t) = \varphi_j(t), \\ x_i(t) = x_j(t), \end{cases} \quad \forall i, j = \overline{1, N} \quad (1)$$

- dimension reduction:

$$\dot{x} = -\Gamma x + [2w_0 + (N - 3)z_0 u \varphi]y. \quad (2)$$

- fixpoints of the reduced system:

$$\begin{cases} \dot{x} = 0, & \Rightarrow & \Gamma x = [2w_0 + (N - 3)z_0 u \varphi]y \\ \dot{u} = 0, & \Rightarrow & u = 1 + (U_{max} - 1)y \\ \dot{\varphi} = 0, & \Rightarrow & \varphi = 1 - \frac{uy}{U_{max}} \end{cases} \quad (3)$$

## Dynamical systems view: fixpoints

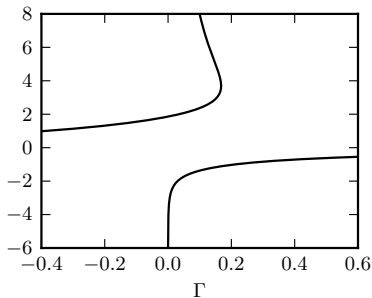
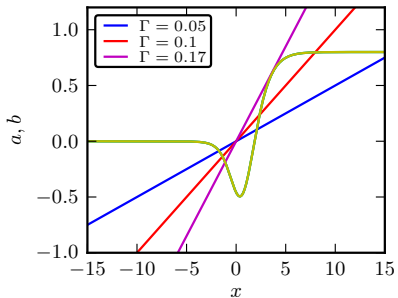
- substituting the  $u$  and  $\varphi$  variables

$$\Gamma x = y(x) \cdot \left\{ \underbrace{2w_0 + (N - 3)z_0 \left[ 1 + (U_{max} - 1)y(x) \right]}_u \cdot \underbrace{\left[ 1 - \frac{y(x) + (U_{max} - 1)y^2(x)}{U_{max}} \right]}_\varphi \right\}$$

- solutions can be found grafically
- note that the left hand side is always a straight line

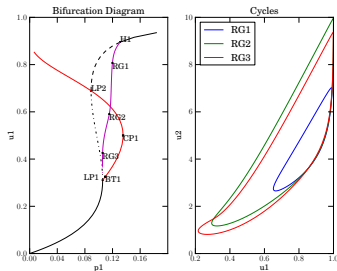
# Dynamical systems view: $\Gamma$ parameter

- fixpoints and bifurcation diagram
- parameters:  $w_0 = 0.4$ ,  $z_0 = -1$ ,  $U_{max} = 4$



# PyDSTool package

- supports:
  - symbolic math
  - optimization
  - phase plane analysis
  - continuation and bifurcation analysis
  - data analysis, etc.

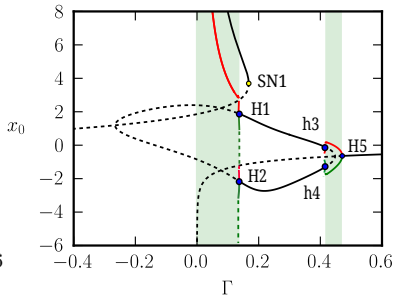
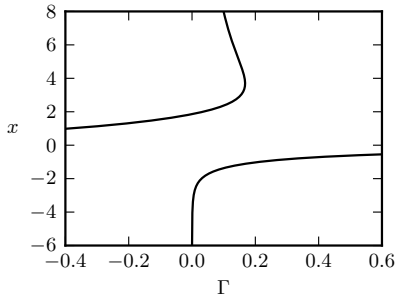


Left: Bifurcation diagram.  
Right: Limit cycles.

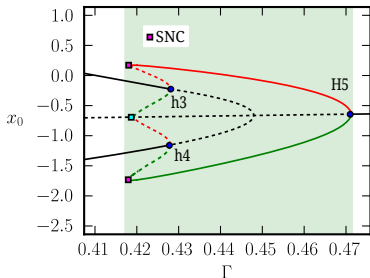
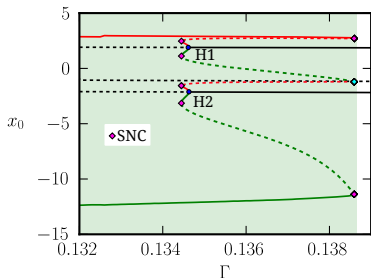
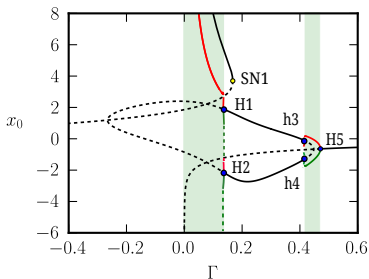
*Clewley RH, Sherwood WE, LaMar MD, Guckenheimer JM (2007)  
PyDSTool, a software environment for dynamical systems modeling.  
URL <http://pydstool.sourceforge.net>*

# Dynamical systems view: $\Gamma$ parameter

- full bifurcation diagram

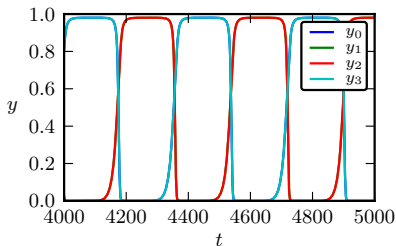
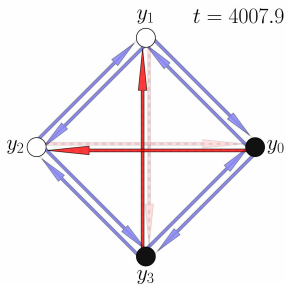


# Dynamical systems view: $\Gamma$ parameter



# Dynamical systems view: $\Gamma$ parameter - limit cycles (class I.)

- synchronised dynamics



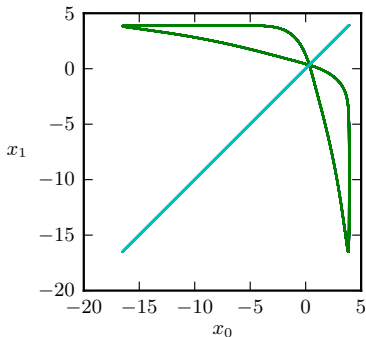
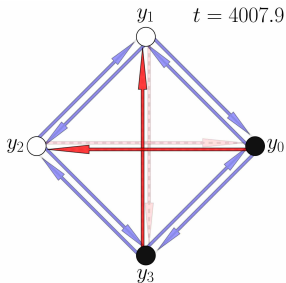
Neural activity.

Parameters:  $\Gamma = 0.1$ ,  
 $w_0 = 0.4$ ,  $z_0 = -1$ ,  $U_{max} = 4$ .

## Dynamical systems view:

### $\Gamma$ parameter - limit cycles (class I.)

- synchronised dynamics



Limit cycles.

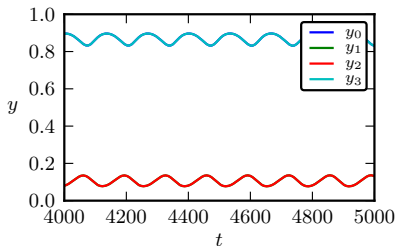
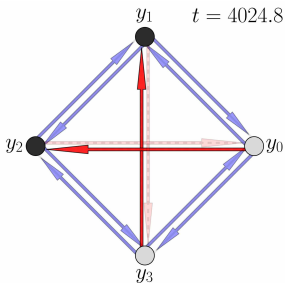
Parameters:  $\Gamma = 0.1$ ,

$w_0 = 0.4$ ,  $z_0 = -1$ ,  $U_{max} = 4$ .



# Dynamical systems view: $\Gamma$ parameter - limit cycles (class IV.)

- small amplitude synchronised dynamics

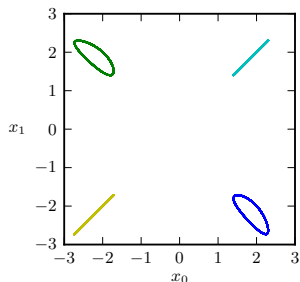
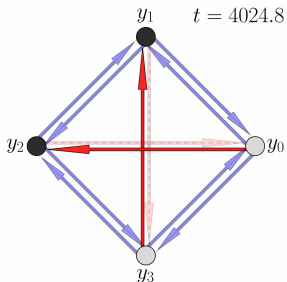


Neural activity.

Parameters:  $\Gamma = 0.1345$ ,  
 $w_0 = 0.4$ ,  $z_0 = -1$ ,  $U_{max} = 4$ .

# Dynamical systems view: $\Gamma$ parameter - limit cycles (class IV.)

- small amplitude synchronised dynamics



Limit cycles.

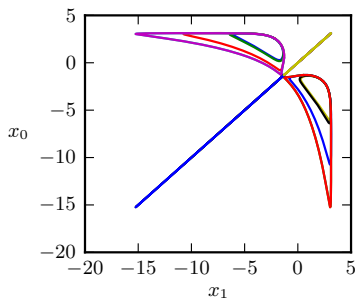
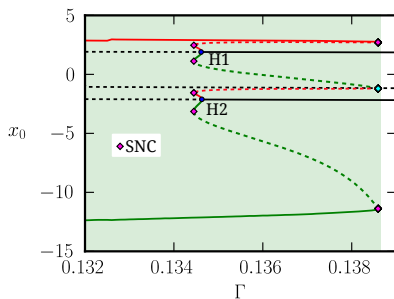
Parameters:  $\Gamma = 0.1345$ ,

$w_0 = 0.4$ ,  $z_0 = -1$ ,

$U_{max} = 4$ .

# Bifurcations with limit cycles

- small limit cycles appear by Hopf-bifurcation ( $H$ )
- saddle-node bifurcation of limit cycles ( $SNC$ )
- limit cycles merge by homoclinic bifurcation



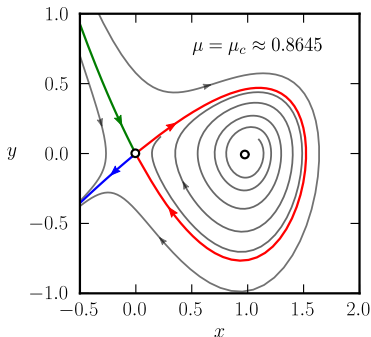
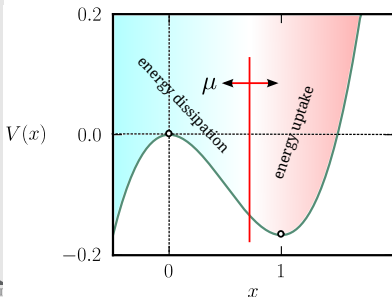
# Taken-Bogdanov system

- example for Homoclinic bifurcation
- mechanical system with a potential  $V(x)$  and adaptive velocity-dependent forces:

$$\ddot{x} = (x - \mu)\dot{x} - V'(x) \quad \dot{x} = y$$

$$V(x) = x^3/3 - x^2/2$$

$$\dot{y} = (x - \mu)y + x(1 - x)$$



## Generalized Taken-Bogdanov systems

- dissipation changes to anti-dissipation when  $\mu = V(\mathbf{x})$ :

$$\ddot{\mathbf{x}} = \alpha(\mu - V(\mathbf{x}))\dot{\mathbf{x}} - \nabla V(\mathbf{x})$$

- fixpoints at the minima and maxima of  $V(\mathbf{x})$ :

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{y} & \mathbf{y}^* &= 0 \\ \dot{\mathbf{y}} &= \alpha(\mu - V(\mathbf{x}))\mathbf{y} - \nabla V(\mathbf{x}) & \nabla V(\mathbf{x}^*) &= 0\end{aligned}$$

- potential with predefined minima  $V(\mathbf{x}_n^*) \approx V_n$ ,  $n = \overline{1, M}$ :

$$V(\mathbf{x}) = \prod_n \left( g_n(\mathbf{x} - \mathbf{x}_n^*) + \frac{V_n}{p_n} \right)$$

$$g_n(\mathbf{z}) = \tanh(\mathbf{z}^2/z_n^2), \quad p_n = \prod_{j \neq n} \left( g_n(\mathbf{x}_n - \mathbf{x}_j^*) + \frac{V_j}{p_j} \right)$$

# Generalized Taken-Bogdanov systems

- 2 dimensional example

$$\dot{x} = y$$

$$\dot{y} = \alpha(\mu - V(x))y - V'(x)$$

$$y^* = 0$$

$$V'(x^*) = 0$$

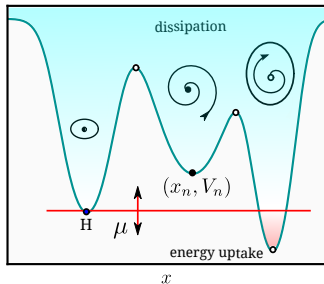
- stability of fixpoints:

$$J = \begin{pmatrix} 0 & 1 \\ V''(x^*) & \alpha(\mu - V(x^*)) \end{pmatrix}$$

$$d = \det(J) = V''(x^*) \Rightarrow \text{saddles}$$

$$t = \text{Tr}(J) = \alpha(\mu - V(x^*))$$

$$\lambda_{1,2} = \frac{t \pm \sqrt{t^2 - 4d}}{2} \Rightarrow$$



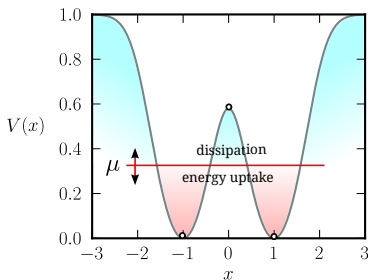
when  $\mu \rightarrow V(x^*) \Rightarrow t \rightarrow 0 \Rightarrow$  series of Hopf-bifurcations at  $x_n^*$

# Double potential well

- system with a symmetric double potential well:

$$\ddot{x} = \alpha(\mu - V(x))\dot{x} - V'(x)$$

$$V(x) = \left( g_1(x - x_1^*) + \frac{V_1}{p_1} \right) \cdot \left( g_2(x - x_2^*) + \frac{V_2}{p_2} \right)$$



$$x_1 = -1$$

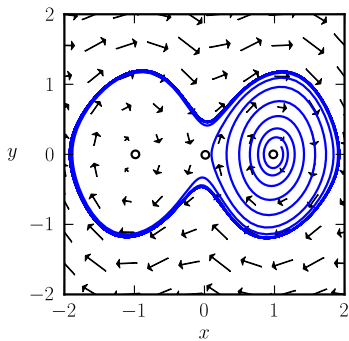
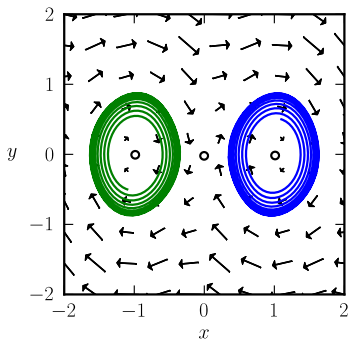
$$x_2 = +1$$

$$V_1 = V_2 = 0$$

$$z_1 = z_2 = 1$$

$$p_1 = p_2 = 1$$

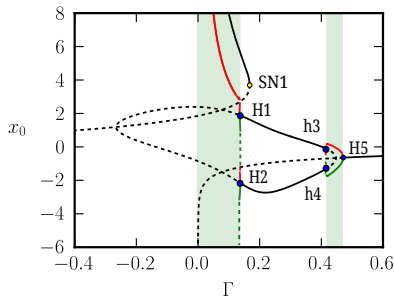
# Merging limit cycles





# Possible interpretations

- full bifurcation diagram




3Xgh1579fT0Bcqm4Ed7La2Xmvt8s

- phonological loop + phonological store
  - 3Xgh-3Xgh-3Xgh...
  - 3Xgh-1579-3Xgh-1579-3Xgh-1579...

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## Summary

- 
- memory and synaptic plasticity
  - working memory
  - new model for transient synaptic plasticity
  - implemented in a recurrent neural network
  - dynamical systems type study
  - analytic method for fixpoint analysis
    - parameter regions
    - limit cycles classes
  - merging limit cycles
  - new example system
  - interpretations