

Dynamics of Neural Systems

Local analysis of nonlinear systems II and Lyapunov functions

Martin A. Giese

Martin.giese@uni-tuebingen.de

Jan 13, 2025

Overview

- Topological equivalence
- Lyapunov functions

Overview

- Topological equivalence
- Lyapunov functions

Topological equivalence

- Two subsets A and B of metric spaces are called **topologically equivalent** when there exists a continuous and continuously invertible mapping (homeomorphism) $h: A \rightarrow B$ between them.
- A **differentiable manifold** is a manifold that is locally similar to the Euclidean space and differentiable (detailed definition see Perko).

Center manifold theorem I

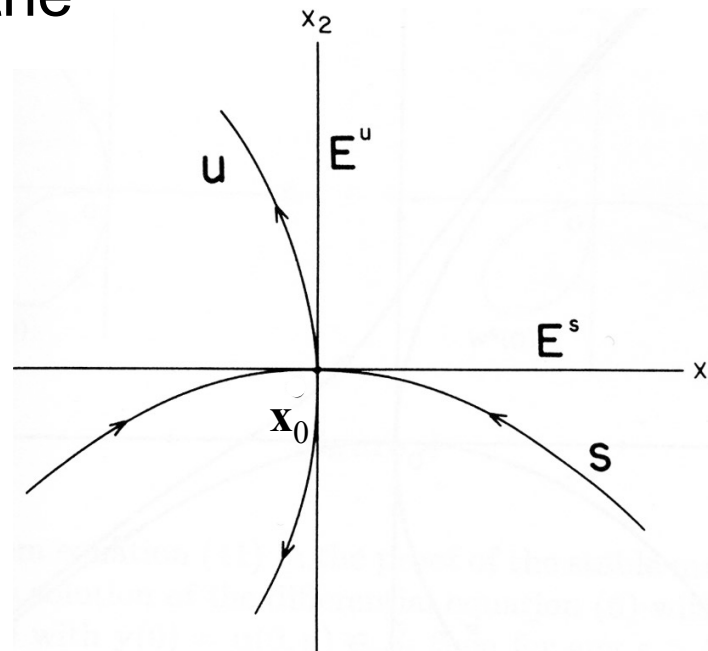
- Assume: $\mathbf{f} \in C^1$ has a fixed point \mathbf{x}_0 , where the matrix $\mathbf{A} = \frac{\partial \mathbf{f}(\mathbf{x}_0)}{\partial \mathbf{x}}$ has k eigenvalues with negative and m with positive real parts, and $n - m - k$ with zero real part; then:
- there exists a k -dimensional **stable manifold** S that is tangent to the stable subspace E^s of the linearized system, which is invariant under the flow of the DEQ, i.e. $\boldsymbol{\varphi}_t(\mathbf{c}) \in S$ for $\mathbf{c} \in S$ and $t \geq 0$, and with: $\lim_{t \rightarrow \infty} \boldsymbol{\varphi}_t(\mathbf{c}) = \mathbf{x}_0$
- there exists an m -dimensional **unstable manifold** U that is tangent to the unstable subspace E^u , which is invariant under the flow ($\boldsymbol{\varphi}_t(\mathbf{c}) \in U$ for $\mathbf{c} \in U$ and $t \leq 0$), and with: $\lim_{t \rightarrow -\infty} \boldsymbol{\varphi}_t(\mathbf{c}) = \mathbf{x}_0$

Center manifold theorem II

- there exists an $(n-m-k)$ -dimensional **center manifold** C that is tangent to the center subspace E^c , which is invariant under the flow of the DEQ.

Center manifold theorem II

- there exists an $(n-m-k)$ -dimensional **center manifold** C that is tangent to the center subspace E^c , which is invariant under the flow of the DEQ.
- Remark: these manifolds are valid locally; it can be shown that they can be extended globally by propagating their points along the flow (global stable and unstable manifold); see Perko book for details.
- Illustration (2D): stable and unstable manifold



Example I

- Assume a system with three coupled nonlinear DEQ:

$$\begin{aligned}\frac{dx_1}{dt} &= -x_1(t) \\ \frac{dx_2}{dt} &= -x_2(t) + x_1^2(t) \\ \frac{dx_3}{dt} &= x_3(t) + x_1^2(t)\end{aligned}$$

- The origin $\mathbf{x} = \mathbf{0}$ is the only fixed point.

- From the linearized system we compute: $\mathbf{A} = \left. \frac{\partial \mathbf{f}}{\partial \mathbf{u}} \right|_0 = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

- The stable space E^s is this the $x_1 - x_2$ plane, and the unstable space E^u the x_3 axis.

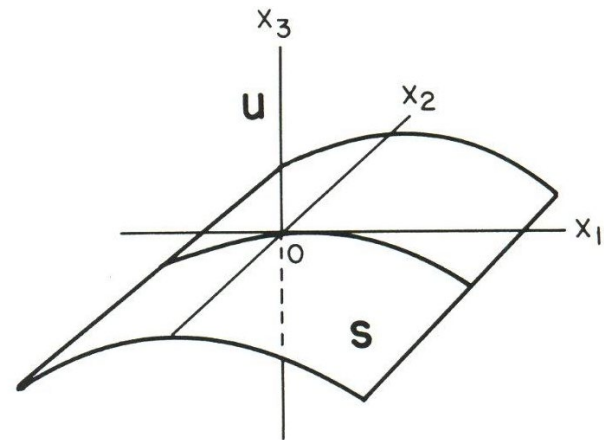
- Solving the first equation one obtains a second non-autonomous linear equations with $x_1^2(t)$ as input.

Example II

- The solution is: $\mathbf{x}(t) = \boldsymbol{\varphi}_t(\mathbf{x}_0) = \begin{pmatrix} x_{0,1}e^{-t} \\ x_{0,2}e^{-t} + x_{0,1}^2(e^{-t} - e^{-2t}) \\ x_{0,3}e^t + \frac{(x_{0,1})^2}{3}(e^t - e^{-2t}) \end{pmatrix}$
- This implies that $\lim_{t \rightarrow \infty} \boldsymbol{\varphi}_t(\mathbf{x}_0) = \mathbf{0}$ iff $x_{0,3} + \frac{(x_{0,1})^2}{3} = 0$,
implying: $S = \left\{ \mathbf{x}_0 \in \mathbb{R}^3 \mid x_{0,3} = -\frac{(x_{0,1})^2}{3} \right\}$ (stable manifold)
- Likewise, it follows that $\lim_{t \rightarrow -\infty} \boldsymbol{\varphi}_t(\mathbf{x}_0) = \mathbf{0}$ only iff $x_{0,1} = x_{0,2} = 0$
implying:

$$U = \left\{ \mathbf{x}_0 \in \mathbb{R}^3 \mid x_{0,1} = x_{0,2} = 0 \right\}$$

(unstable manifold)



Hartman-Grobman theorem

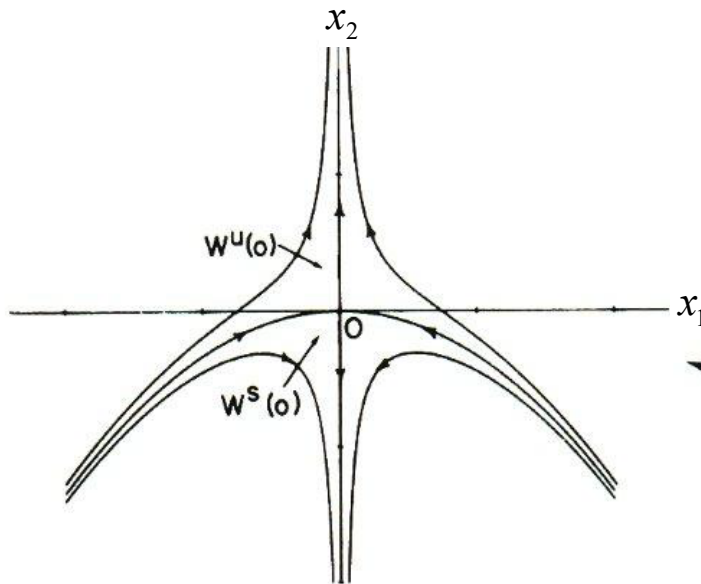
- Differential equations are called **topologically equivalent** if there exists a homeomorphism H (invertible map) that maps the trajectories onto each other.
- Assume: $\mathbf{f} \in C^1$ has a **hyperbolic** fixed point in zero (i.e. $\mathbf{f}(\mathbf{0}) = \mathbf{0}$, and $\mathbf{A} = \frac{\partial \mathbf{f}(\mathbf{0})}{\partial \mathbf{x}}$ has no eigenvalues with zero real part) then the original system $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$ and the linearized system $\dot{\mathbf{y}} = \mathbf{A}\mathbf{y}$ are **topologically equivalent**; this means, for points \mathbf{c} ($= \mathbf{x}_0$) sufficiently near the origin, there exists a homeomorphism H so that:

$$\underbrace{H \circ \varphi_t(\mathbf{c})}_{\mathbf{y}(t)} = e^{\mathbf{A}t} \underbrace{H(\mathbf{c})}_{\mathbf{y}_0} \quad H: \mathbf{x} \rightarrow \mathbf{y}$$

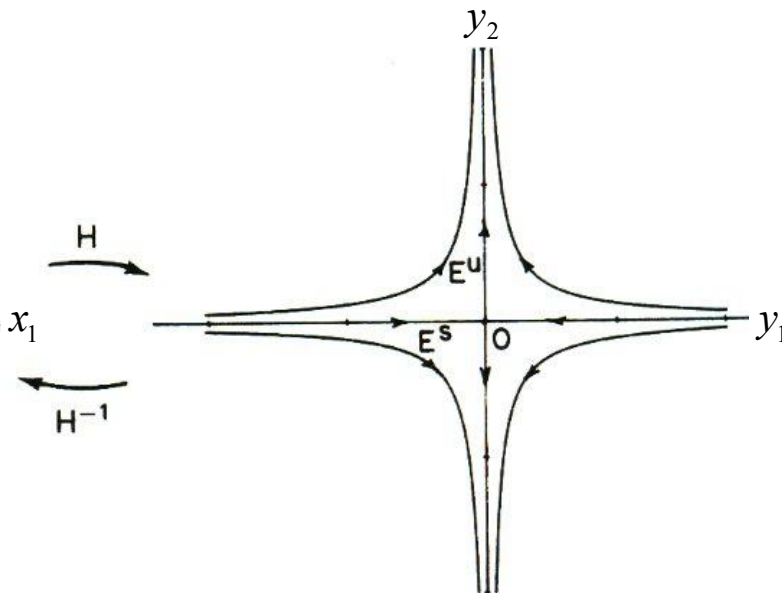
Hartman-Grobman theorem

- Illustration:

Original system



Topologically equiv. linear system

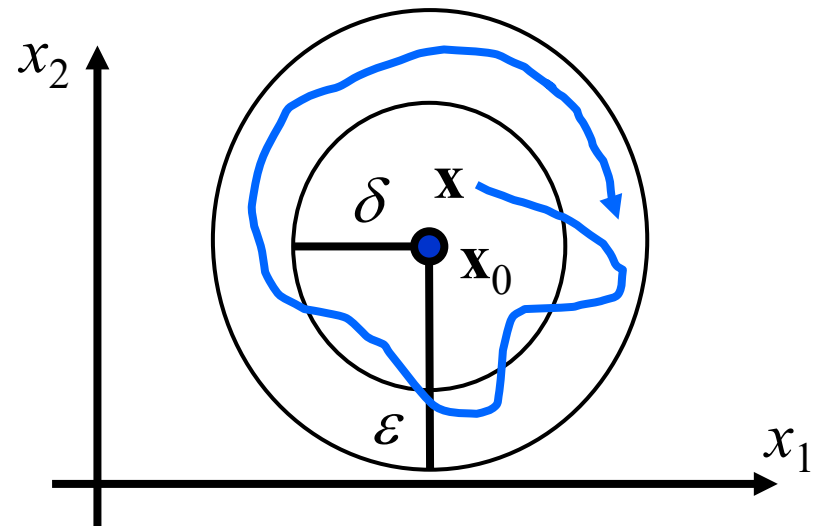


Overview

- Topological equivalence
- Lyapunov functions

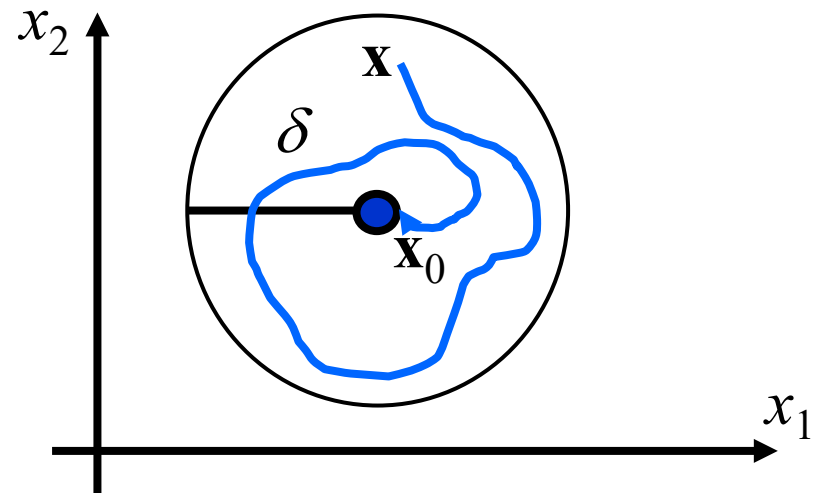
Stability of equilibrium points I

- Lyapunov theory helpful to characterize stability also non-hyperbolic fixed points.
- Assume φ_t is the flow of the differential equation: $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$
- An equilibrium point \mathbf{x}_0 is called **stable** if there exists for all $\varepsilon > 0$ a $\delta > 0$ such that for all $\mathbf{x} \in N_\delta(\mathbf{x}_0)$ and $t \geq 0$ is fulfilled: $\varphi_t(\mathbf{x}) \in N_\varepsilon(\mathbf{x}_0)$ (where $N_\varepsilon(\mathbf{x})$ is a ball with radius ε about \mathbf{x}). \rightarrow 'Solutions for \mathbf{x} close \mathbf{x}_0 remain close.'
- An equilibrium is **unstable** if it is not stable.



Stability of equilibrium points I

- The equilibrium point \mathbf{x}_0 is **asymptotically stable** if there exists $\delta > 0$ such that for all $\mathbf{x} \in N_\delta(\mathbf{x}_0)$: $\lim_{t \rightarrow \infty} \boldsymbol{\varphi}_t(\mathbf{x}) = \mathbf{x}_0$.
- The set of all points for which this condition is fulfilled is called **domain / basin of attraction** of \mathbf{x}_0 .
- Remark that these conditions require a certain behavior for trajectories passing the neighborhood of \mathbf{x}_0 , not only for the ones passing through \mathbf{x}_0 .



Stability of equilibrium points II

- Examples: Linear system:
 - stable node is asymptotically stable.
 - unstable node or a saddle point is unstable.
 - center is stable, but not asymptotically stable.
- A hyperbolic fixed point is obviously unstable if at least one eigenvalue has positive real part.

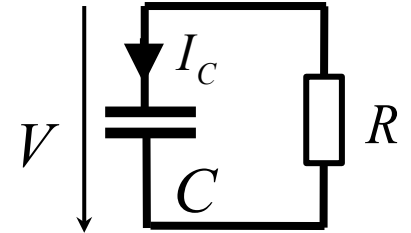
Lyapunov theory: motivation I

Passive membrane circuit

- Assume simple linear model of a membrane (RC circuit) with the DEQ:

$$I_C = C\dot{V}(t) = -V(t)/R$$

$$\dot{V}(t) = \frac{dV}{dt} = \frac{-V(t)}{RC}$$



- Because this system does not contain energy sources and a resistor, eventually the voltage $V(t)$ will converge to zero.
- This implies $V = 0$ is an asymptotically stable fixed point of the dynamics.
- Remark: The electrical energy stored in the capacitor is

$$E(t) = \int_0^t V(t') I_C(t') dt' = C \int_0^t V(t') \frac{dV}{dt'} dt' = C \frac{V^2(t)}{2}$$

(where we assumed $V(0) = 0$).

Lyapunov theory: motivation II

- This energy decays along the trajectories of the system, unless V is already in the fixed point $V = 0$ because:

$$\dot{E}(t) = \frac{d}{dt} C \frac{V^2(t)}{2} = CV(t)\dot{V}(t) = -V^2(t)/R \leq 0$$

- Geometrically, the changes of the system state define a descending motion on the ‘landscape’ that is defined by the function E .
- In general, a passive system that dissipates energy and does not contain energy sources will be stable because the state in which all energy has been dissipated will be stable.

State functions

- Electrical energy is an example of a **state function**, which depends on the dynamical state of the system.
- For a general DS $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$, we require that state functions $E(\mathbf{x})$ are scalar and have continuous spatial derivatives (C^1 functions).
- A state function is called **positive definite** in a region R of the neighborhood of a singular point \mathbf{x}_0 if:
$$E(\mathbf{x}_0) = 0 \text{ and}$$
$$E(\mathbf{x}) > 0 \text{ for } \mathbf{x} \neq \mathbf{x}_0$$
- In general, the time derivative of the state function is then given by:
$$\dot{E}(\mathbf{x}) = \left(\frac{\partial E}{\partial \mathbf{x}} \right)^T \mathbf{f}(\mathbf{x})$$

Lyapunov theorem

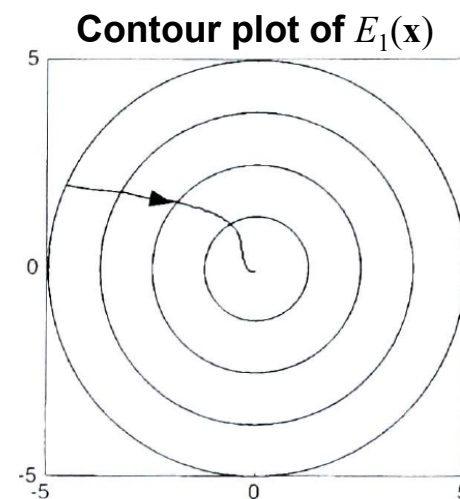
- Direct method of Lyapunov proven in his thesis (1892).
- Core idea: definition of a generalized energy function (Lyapunov function) $E(\mathbf{x})$ that decreases on the trajectories of the dynamics.
- **Theorem:** If in region R there exists a (C^1) positive definite state function (with $E(\mathbf{x}_0) = 0$ and $E(\mathbf{x}) > 0$ if $\mathbf{x} \neq \mathbf{x}_0$) then:
 - a) if $\dot{E}(\mathbf{x}) \leq 0$ everywhere then \mathbf{x}_0 is stable.
 - b) if $\dot{E}(\mathbf{x}) < 0$ everywhere (in region R) except for \mathbf{x}_0 then \mathbf{x}_0 is asymptotically stable.
 - c) if $\dot{E}(\mathbf{x}) > 0$ everywhere (in region R) except for \mathbf{x}_0 then \mathbf{x}_0 is unstable.



A.M. Lyapunov

Example

- Consider the system:
$$\begin{aligned}\dot{x}_1 &= -x_1 - x_2 - 3x_1x_2^2 \\ \dot{x}_2 &= -x_2 + x_1\end{aligned}$$
- Lyapunov functions: $E_1(\mathbf{x}) = x_2^2 + x_1^2$
(see Wilson book)
$$E_2(\mathbf{x}) = x_1^2 + x_2^2 - x_2^4$$
- Around the singular point $\mathbf{x} = \mathbf{0}$ both functions are positive definite.
- E_1 proves stability in the whole phase space, E_2 only in the strip $|x_2| < 1$.
- Lyapunov functions are thus **not unique**; the proven stability region depends on the chosen function.



Finding Lyapunov functions I

- No principled approach; often simple techniques work.
- Example: divisive feedback (see Lecture 7):

$$\begin{aligned}\tau \frac{du_1}{dt} &= -u_1(t) + \frac{s}{1+u_2(t)} \\ \tau \frac{du_2}{dt} &= -u_2(t) + 2u_1(t)\end{aligned}$$
- Lyapunov function can be found using following **theorem**:
If the C^1 functions $F(x_1, x_2)$ and $G(x_1, x_2)$ have only a finite number of joint zeros (points with $F(x_1, x_2) = G(x_1, x_2) = 0$) then the following function with $|\varepsilon| < 1$

$$E(\mathbf{x}) = (1/2)F^2(\mathbf{x}) + \varepsilon F(\mathbf{x})G(\mathbf{x}) + (1/2)G^2(\mathbf{x}) \quad \mathbf{x} = [x_1, x_2]^T$$

is **positive definite** in regions around each zero.
- **Corollary:** For $a, c < 0$ and $|b| < 2\sqrt{ac}$ the function

$$aF^2(\mathbf{x}) + bF(\mathbf{x})G(\mathbf{x}) + cG^2(\mathbf{x})$$

is **negative definite** in these regions.

Finding Lyapunov functions II

- For the example choose $\varepsilon = 0$ and resulting Lyapunov function:
$$\begin{cases} F(u_1, u_2) = \frac{1}{\tau} \left(-u_1 + \frac{s}{1+u_2} \right) \\ G(u_1, u_2) = \frac{1}{\tau} (-u_2 + 2u_1) \end{cases}$$

$$E(u_1, u_2) = \frac{1}{2} (F^2 + G^2) = \frac{1}{2\tau} \left(\left(-u_1 + \frac{s}{1+u_2} \right)^2 + (-u_2 + 2u_1)^2 \right)$$

Positive definite according to
the theorem (with $\varepsilon = 0$)!

- From this follows:

Has the form assumed
in the corollary!

$$\begin{aligned} \dot{E}(u_1, u_2) &= F \left(\frac{\partial F}{\partial u_1} F + \frac{\partial F}{\partial u_2} G \right) + G \left(\frac{\partial G}{\partial u_1} F + \frac{\partial G}{\partial u_2} G \right) \\ &= F^2 \frac{\partial F}{\partial u_1} + FG \left(\frac{\partial F}{\partial u_2} + \frac{\partial G}{\partial u_1} \right) + G^2 \frac{\partial G}{\partial u_2} \end{aligned}$$

Finding Lyapunov functions II

- Taking into account $a = c = \frac{\partial F}{\partial u_1} = \frac{\partial G}{\partial u_2} = -\frac{1}{\tau}$ and using the corollary follows the negative definiteness of the last function if $|b| = \left| \frac{\partial F}{\partial u_2} + \frac{\partial G}{\partial u_1} \right| = \frac{1}{\tau} \left| \frac{-s}{(1+u_2)^2} + 2 \right| < \frac{2}{\tau}$.

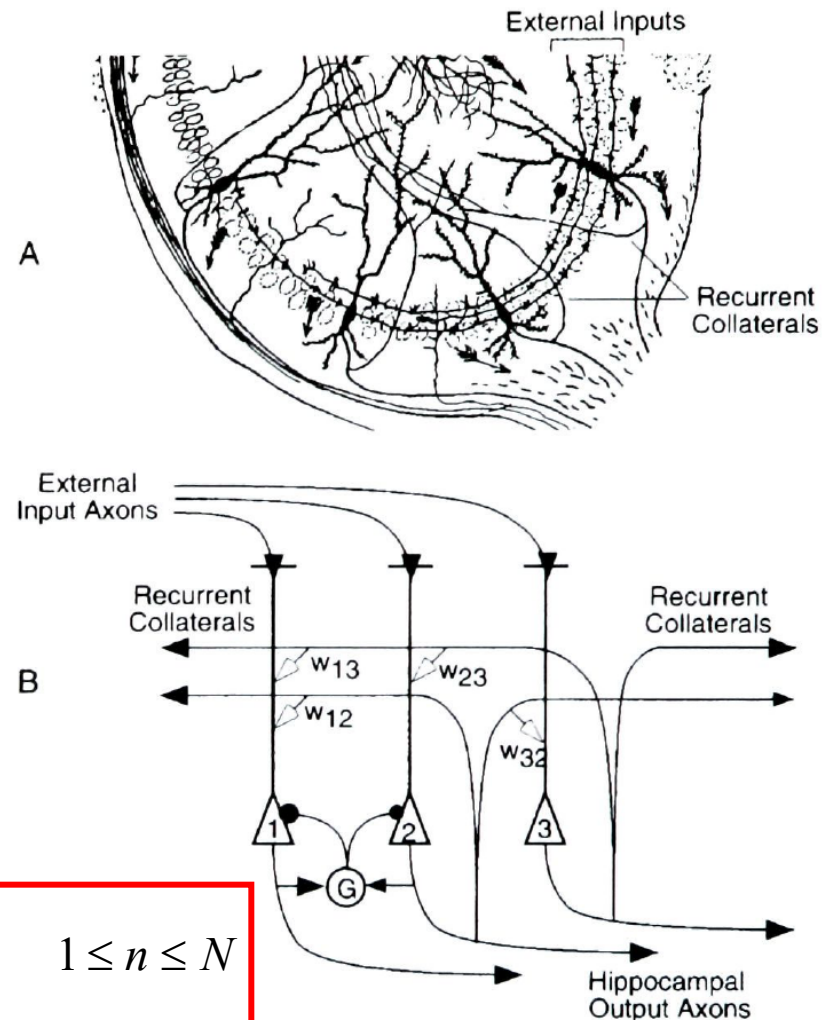
This condition is fulfilled for $u_2 > \frac{\sqrt{s}}{2} - 1$.

- This implies that the fixed point $u_{0,2} = 2u_{0,1} = \frac{-1+\sqrt{1+8s}}{2}$ is within that region because $u_{0,2} > \frac{\sqrt{s}}{2} - 1$ for any $s \geq 0$. Therefore, E is really a Lyapunov function that is valid in the relevant region $u_{0,2} \geq 0$.

Hippocampal CA3 network

Memory networks I

- Important application of Lyapunov functions in neuroscience (Hopfield; Grossberg, ...)
- Modeling long-term memory, e.g. in hippocampus.
- Model: Recurrent neural network with hebbian learning; example:



$$\tau \frac{du_n}{dt} = -u_n(t) + \Theta \left(-v(t) + \sum_{m=1}^N w_{mn} u_m(t) \right) \quad 1 \leq n \leq N$$

Inhibition dynamics:

$$\tau \frac{dv}{dt} = -v(t) + c \sum_{m=1}^N u_m(t) \quad \text{with} \quad \Theta(u) = K_1 \frac{u^2 1(u)}{K_2^2 + u^2}$$

← Sigmoidal threshold

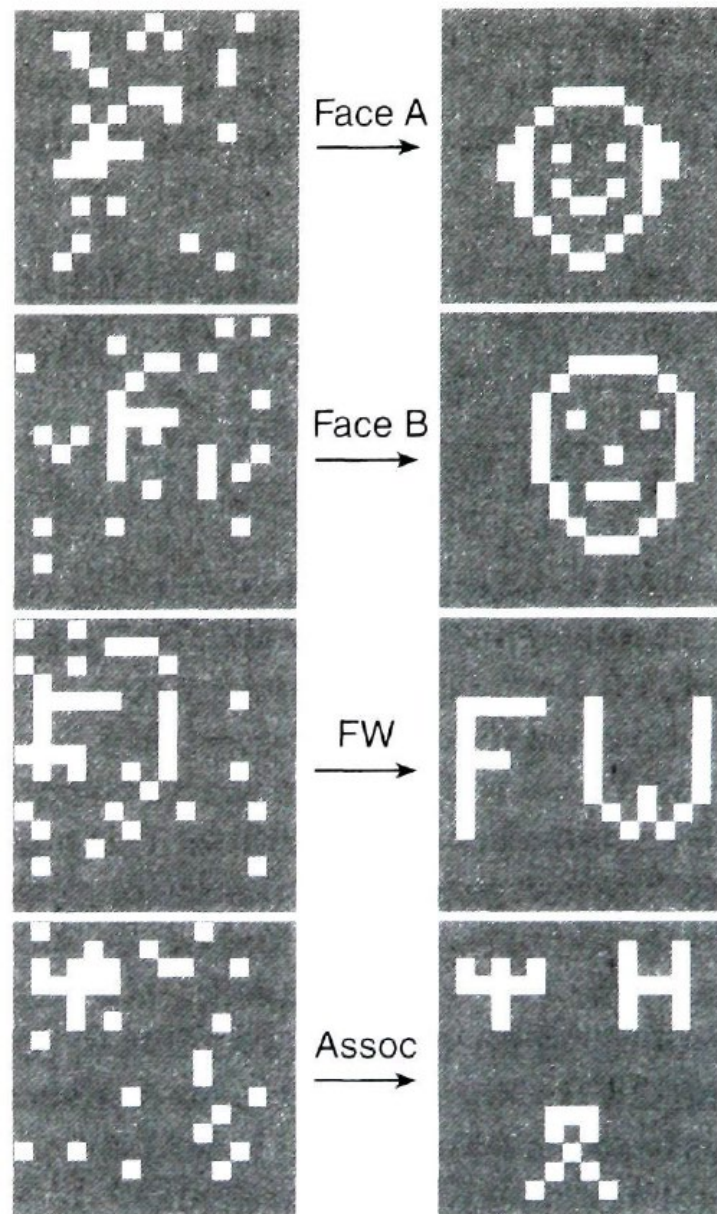
Memory networks II

- **Hebbian learning rule:**

$$\tau_w \frac{dw_{mn}}{dt} = -w_{mn} + 1 \left(u_m(t) - \frac{K_1}{2} \right) \left(u_n(t) - \frac{K_1}{2} \right)$$

- We assume that the learning dynamics is much slower than the activation dynamics; this allows us to treat the weights as quasi-constant.
- The network is an **auto-associative memory**: stored patterns can be completed by the recurrent dynamics.
- Suboptimal patterns suppressed by inhibition.

Pattern completion



Memory networks III

- Two neurons without inhibition:

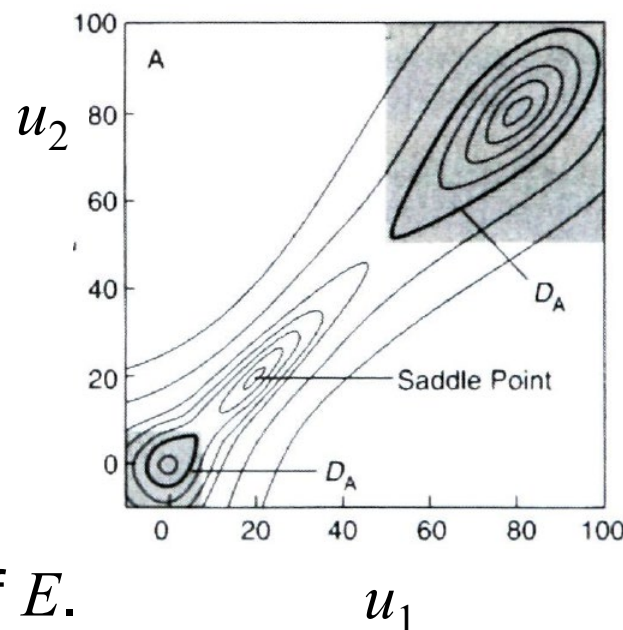
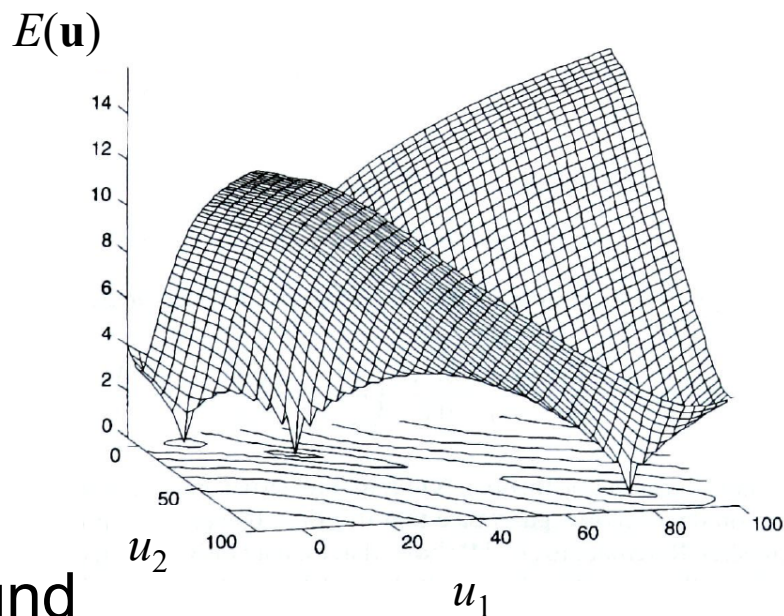
$$\begin{aligned}\frac{du_1}{dt} &= \frac{1}{\tau}(-u_1(t) + \Theta(u_2(t))) = f_1(u_1, u_2) \\ \frac{du_2}{dt} &= \frac{1}{\tau}(-u_2(t) + \Theta(u_1(t))) = f_2(u_1, u_2)\end{aligned}$$

- A Lyapunov function can be found using the last theorem:

$$E(\mathbf{u}) = (1/2)(f_1^2(u_1, u_2) + f_2^2(u_1, u_2))$$

- From $\dot{E}(\mathbf{u}) = -\frac{f_1^2}{\tau} - \frac{f_2^2}{\tau} + f_1 f_2 \left(\frac{\partial f_1}{\partial u_2} + \frac{\partial f_2}{\partial u_1} \right)$ follows $\dot{E}(\mathbf{u}) < 0$ for $\frac{\partial f_1}{\partial u_2} + \frac{\partial f_2}{\partial u_1} = \frac{\Theta'(u_2) + \Theta'(u_1)}{\tau} < \frac{2}{\tau}$. This is fulfilled in the gray regions.

- Stable states correspond to minima of E .



Things to remember

- Center manifold theorem $\rightarrow 2)$
- Hartman-Grobman theorem $\rightarrow 2)$
- Lyapunov theory $\rightarrow 2,3)$

Literature (for this lecture)

- 1) Dayan, P. & Abbott, L.F. (2001 / 2005) *Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems*. MIT Press, Cambridge MA, USA. Chapter 7.
- 2) Perko, L. (1998) *Differential Equations and Dynamical Systems*. Springer-Verlag, Berlin. Chapter 2.
- 3) Wilson, H.R. (1999) *Spikes, Decisions, and Actions*. Oxford University Press, UK. Chapters 6 and 14.