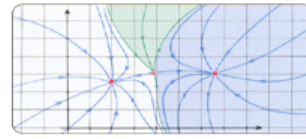
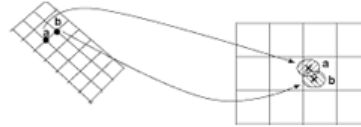


## Part 1: Dynamics

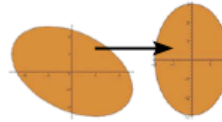
Jan 10 (01) **2-Dimensional flow geometries**. HW1



Jan 12 (02) **Discrete dynamics & Mappings**.



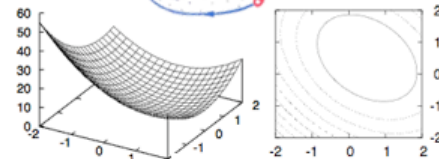
Jan 17 (03) **Diagonalization & eigenvalues**. HW2



Jan 19 (04) **Higher dimensional dynamics & linearization**.



Jan 24 (05) **Stability & Gradient systems**. HW3



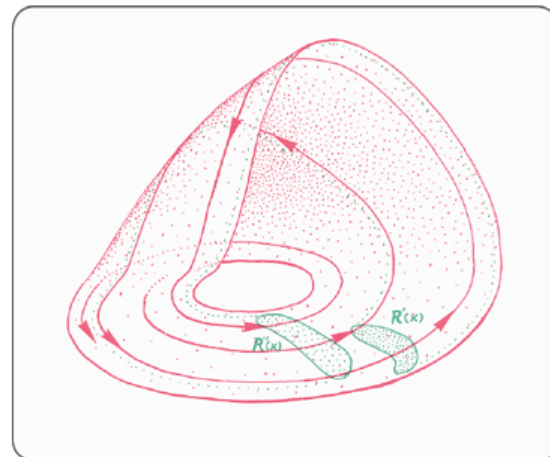
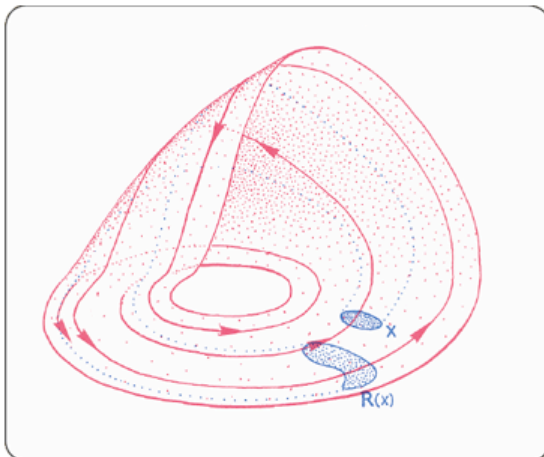
*Dynamics: The Geometry of Behavior*, Ralph Abraham and Chris Shaw (2005)

*Nonlinear dynamics and chaos*, Steven H. Strogatz (1994)

*Mathematical Models in Biology*, Leah Edelstein-Keshet (1988)

01\_Dynamics.psd

## Expansion of Regions After Each Cycle



*Any small error in the measurement of the current state (inevitable) eventually leads to total ignorance of the position of the trajectory within the chaotic attractor.*

*Dynamics: The Geometry of Behavior*, Ralph Abraham and Chris Shaw (2005)

02\_RosslerExpand.psd

## Lyapunov Exponent

The Lyapunov exponent is a measure of how much two neighboring initial points will diverge in the dynamics flow.

**1-dimensional system:** an initial separation,  $\Delta x_0$ .  
The separation at a much later time will be given by

$$\Delta x_t = \Delta x_0 e^{\lambda t}$$

Where the Lyapunov exponent of the system is defined by

$$\lambda = \lim_{t \rightarrow \infty} \frac{1}{t} \ln(\Delta x(t))$$

Typo?

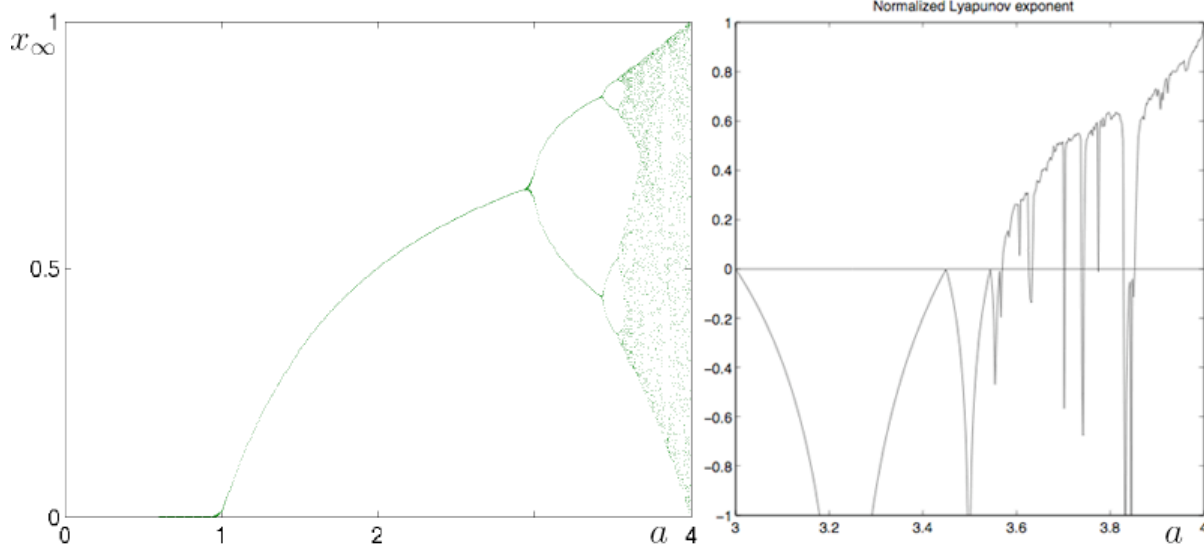
and  $\Delta x(t)$  is the average deviation of a perturbed trajectory.

$$\left( \frac{\Delta x_t}{\Delta x_0} \right) ?$$

03a\_LyExp.psd

## Lyapunov Exponent for the Logistic Map

$$x_{n+1} = ax_n(1 - x_n)$$



<http://courses.physics.kth.se/5A1352/>

03b\_LyExpLogistic.psd

## Lyapunov's Stability Theorem

To show that a system is stable, construct a **Lyapunov function**.

Lyapunov's stability theorem: If there is a Lyapunov function  $V$  such that:

$$\dot{x} = f(x) \text{ with } x \in \mathbb{R}^n \text{ and } f(\bar{x}) = 0, \bar{x} \text{ is a fixed point.}$$

$$V : \mathbb{R}^n \rightarrow \mathbb{R} \text{ is a } C^2 \text{ function defined on some neighborhood } U \text{ of } \bar{x}.$$

$$V(\bar{x}) = 0 \text{ and } V(x) > 0 \forall x \in (U - \bar{x}).$$

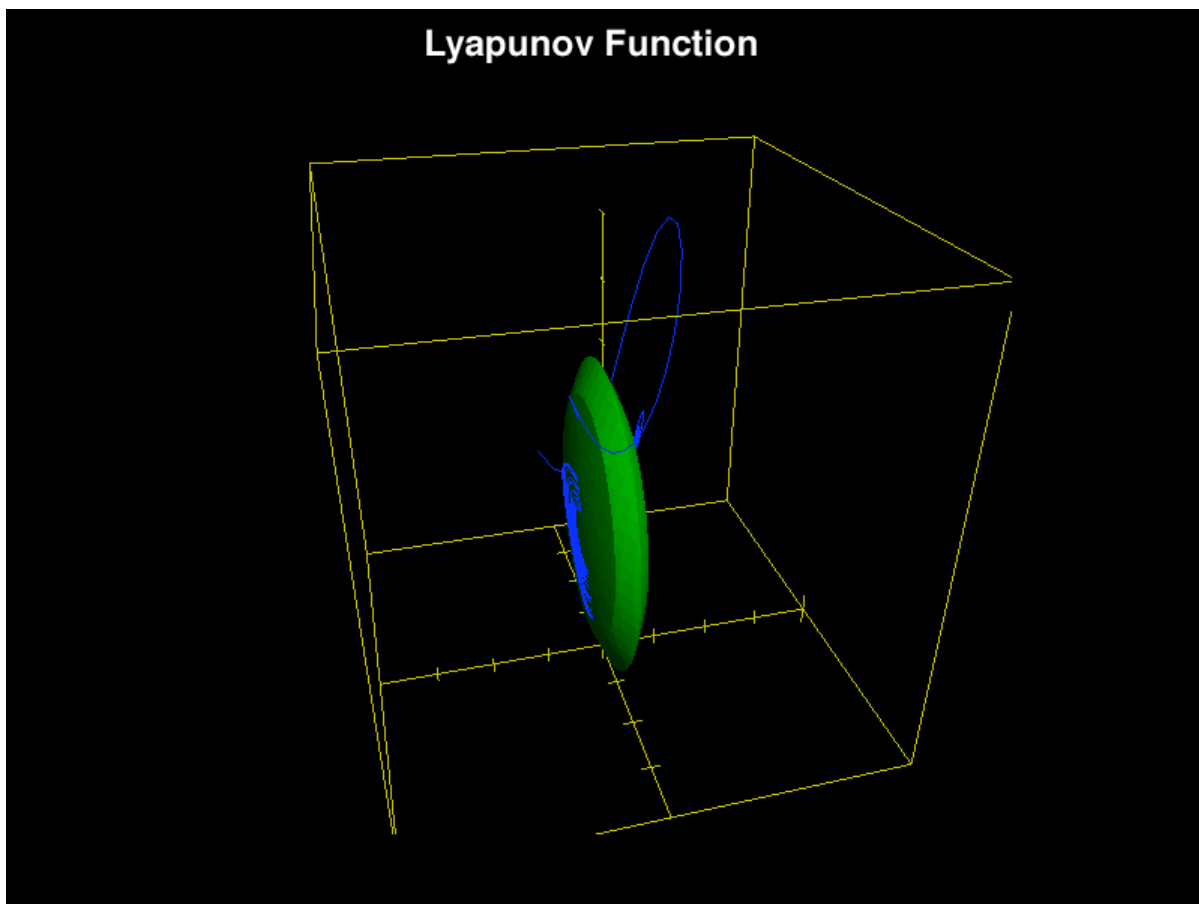
$$\dot{V} \leq 0 \forall x \in (U - \bar{x})$$

then  $\bar{x}$  is stable.

If  $\dot{V} < 0 \forall x \in (U - \bar{x})$ , then  $\bar{x}$  is asymptotically stable.

(from Andy Fraser's notes)

04\_LyapunovFun.psd



05\_LyapunovLorenz.psd

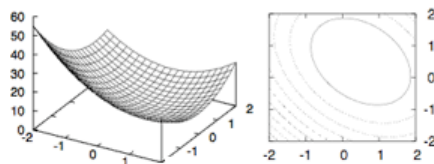
## Lyapunov Function for Gradient Systems

$$\dot{x} = -\frac{\partial V}{\partial x} \quad \text{and} \quad \dot{y} = -\frac{\partial V}{\partial y}$$

07\_LyapunovGradient.psd

### Why study gradient systems?

1. Especially “easy” systems to study.  
A generalization of one-dimensional flows.
2. Historically important (physics).  
Many laws of physics can be expressed as gradient systems.
3. Advantageous for applications in optimization problems.  
Convergence theorems for optimization procedures.



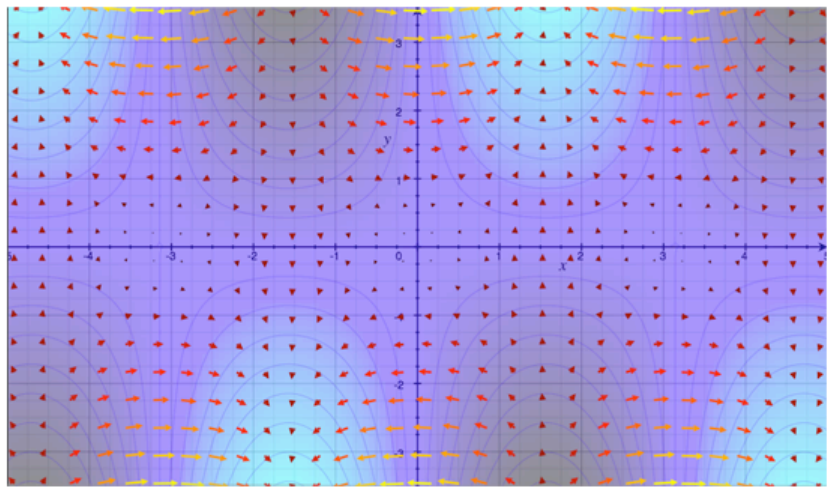
12\_WhyGradientSys.psd

## Gradient Systems: Gradient of a Potential Functions

Vector fields associated to a scalar potential:  $V : \mathbb{R}^n \rightarrow \mathbb{R}$

$$\frac{d}{dt}\vec{x} = \vec{f}(x) = -\nabla V(x)$$

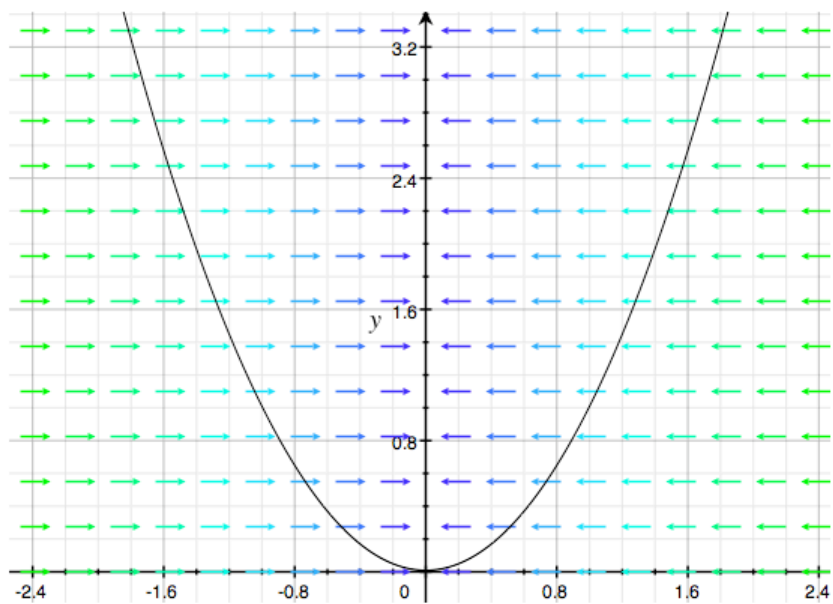
The gradient is the maximal directional derivative:  $\nabla V(x) = \begin{bmatrix} \partial/\partial x_1 \\ \partial/\partial x_2 \\ \vdots \\ \partial/\partial x_N \end{bmatrix} V(x)$



$f(x,y) = y \cdot \sin x$

13\_WhatGradientSys.psd

## Geometry of Gradient Systems: 1-Dimension



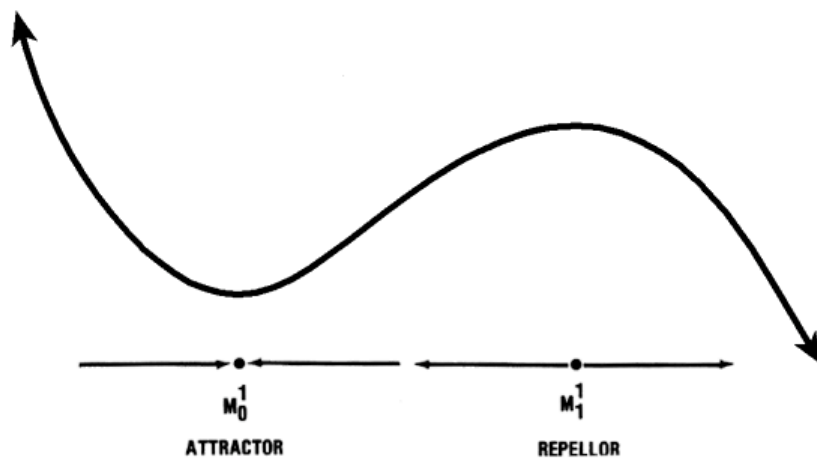
14\_1D\_levelSets.psd

## Attractor versus Repeller: Second Derivative at Fixed Point

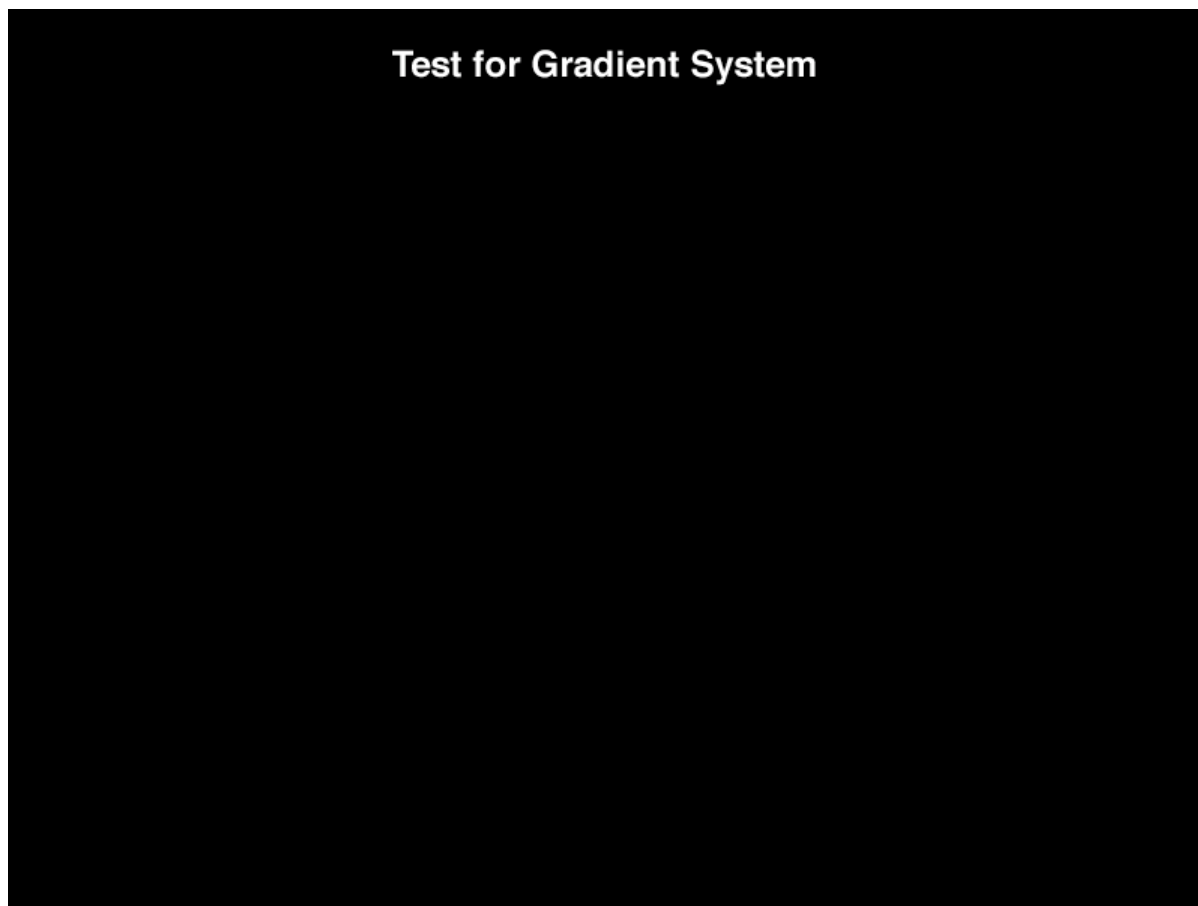
The *Hessian* of the potential at each fixed point

$$H_{i,j}(x) \equiv \frac{\partial^2}{\partial x_i \partial x_j} V(x) \Big|_{x=x_0}$$

determines whether the fixed point is an attractor or repeller:

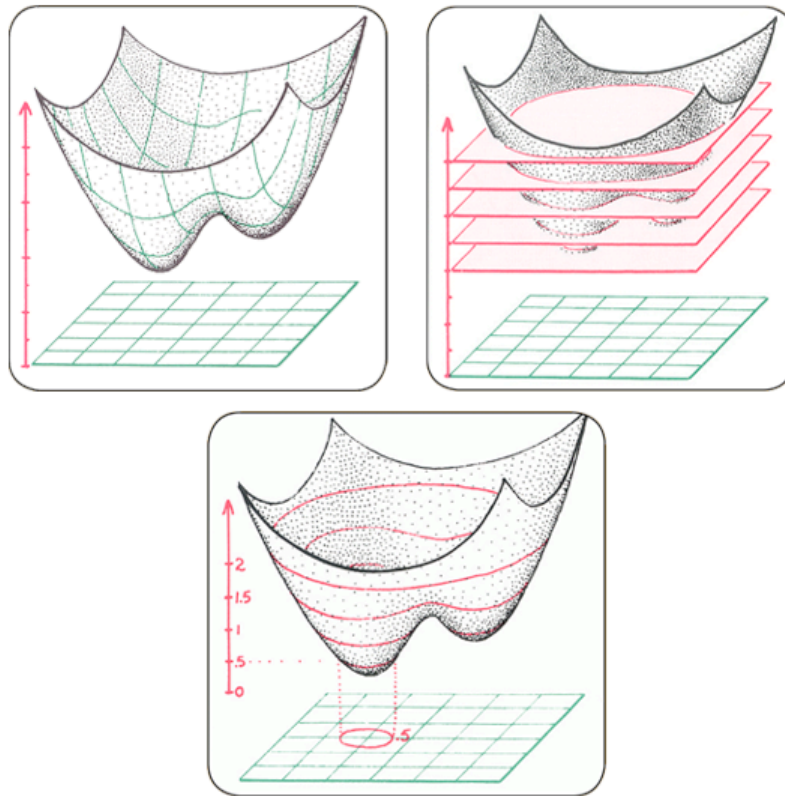


15\_criticalValue.psd



16\_gradient\_test.psd

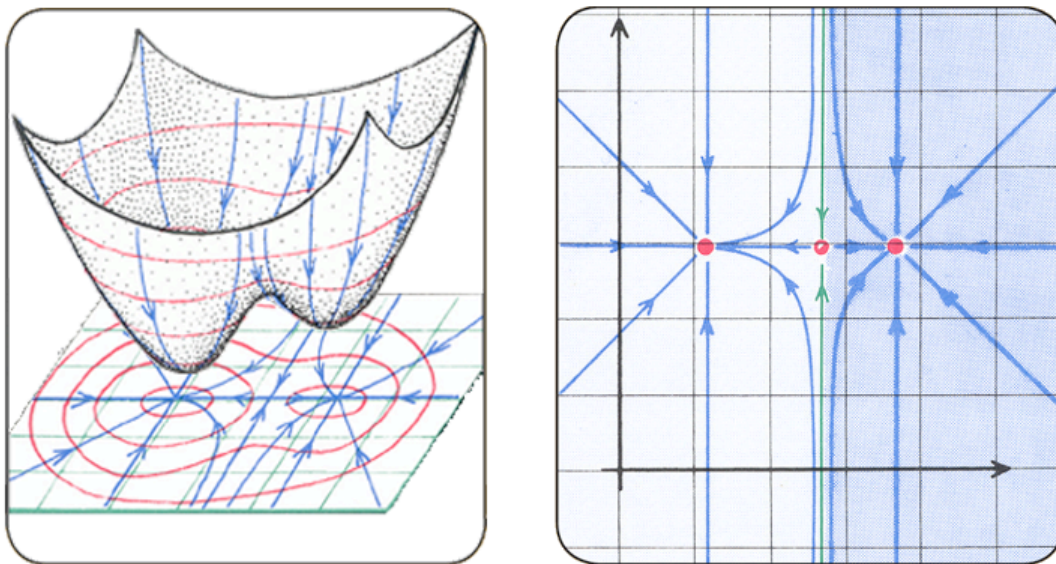
### Gradient Systems: Level Sets



*Dynamics: The Geometry of Behavior*, Ralph Abraham and Chris Shaw (2005)

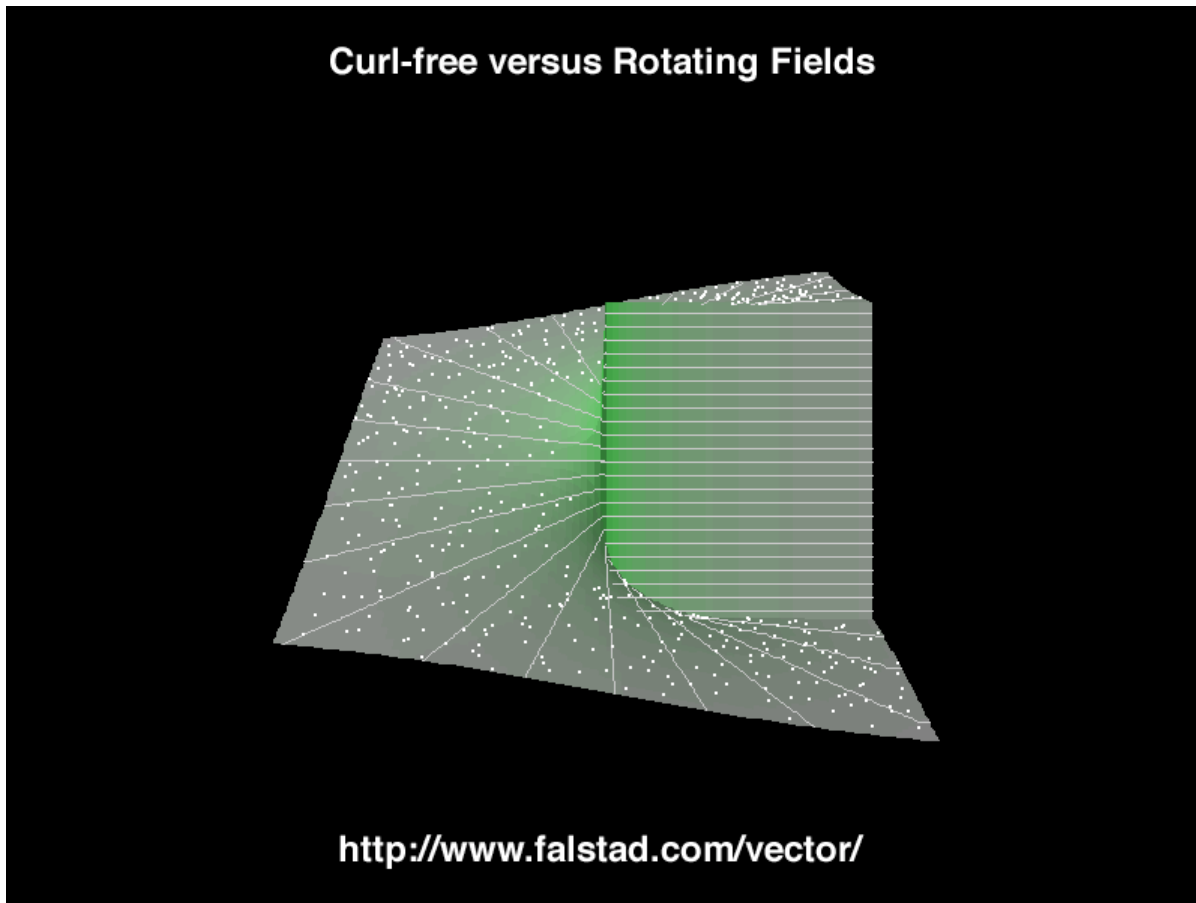
17\_levelSets.psd

### Gradient Systems: Forces from Potential Function



*Dynamics: The Geometry of Behavior*, Ralph Abraham and Chris Shaw (2005)

18\_potential.psd



19\_gradient\_test2.psd

### Gradient Systems: No Closed Orbits

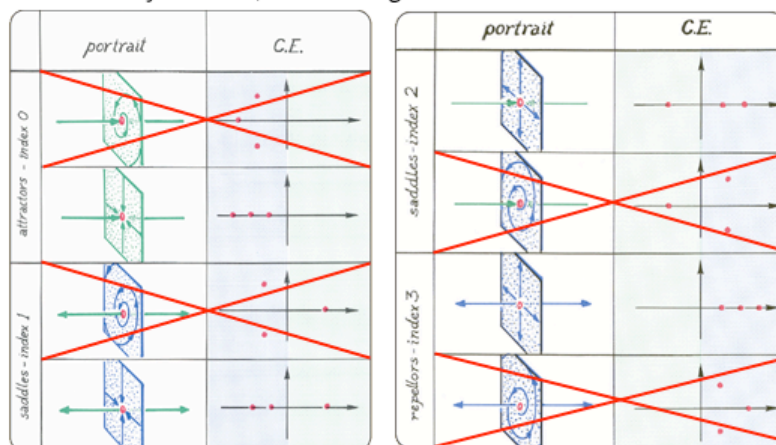
The *Jacobian* of the dynamical system,

$$\frac{d}{dt} \vec{x} = \vec{f}(\vec{x}) = -\nabla V(\vec{x})$$

is the *Hessian* of the potential:

$$H_{i,j}(x) \equiv \frac{\partial^2}{\partial x_i \partial x_j} V(x)$$

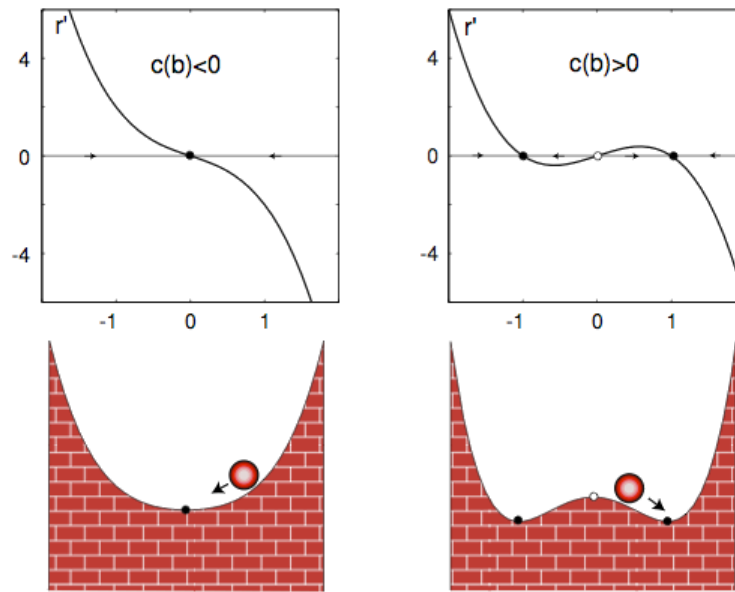
Then the Jacobian is symmetric, and the *eigenvalues* are real.



19\_NoClosedOrbits.psd



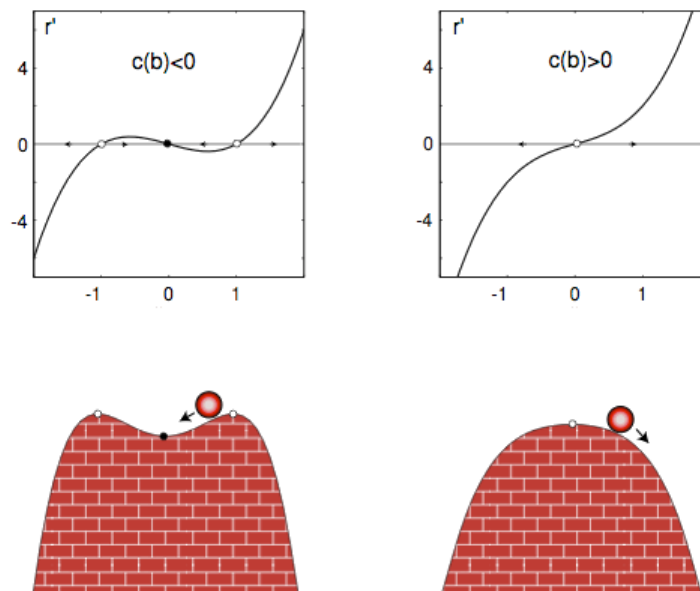
## Bifurcations in 1-Dimensional Gradient Systems



*Dynamical Systems in Neuroscience* (2006) E.M. Izhikevich

20\_1dBifur.psd

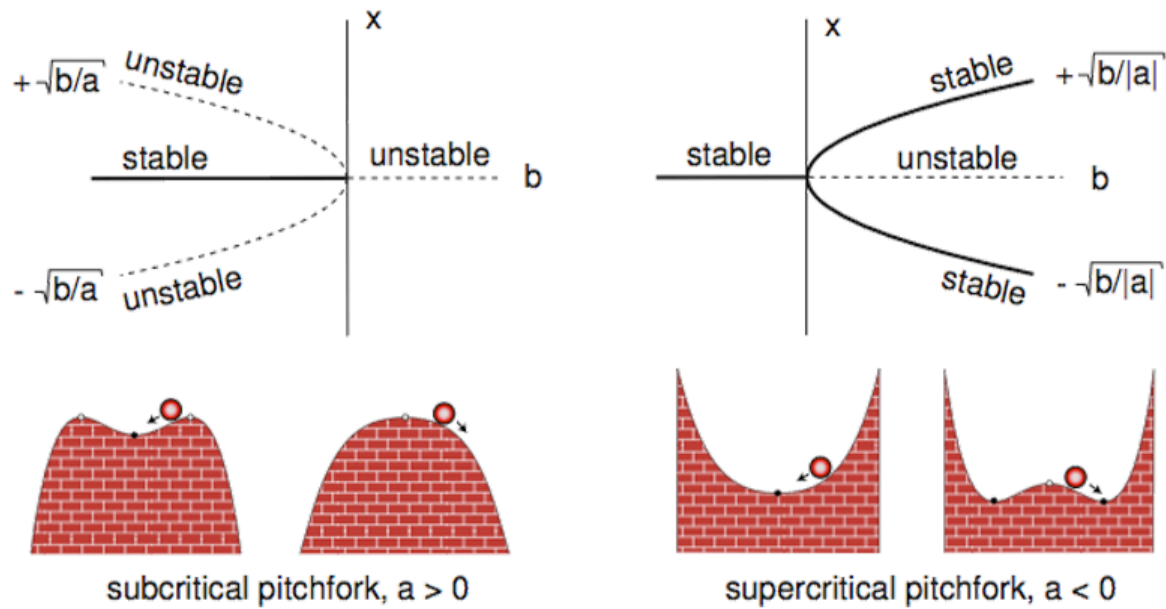
## Bifurcations in 1-Dimensional Gradient Systems



*Dynamical Systems in Neuroscience* (2006) E.M. Izhikevich

21\_1dBifur.psd

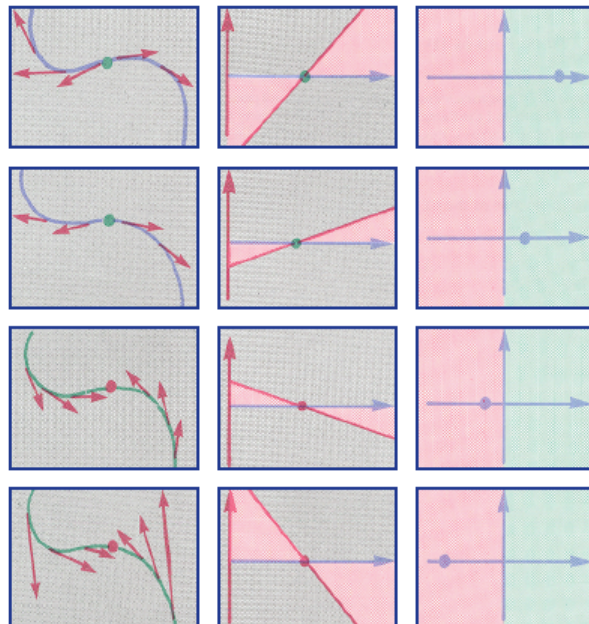
## Bifurcations in 1-Dimensional Gradient Systems



*Dynamical Systems in Neuroscience* (2006) E.M. Izhikevich

22\_1dBifur.psd

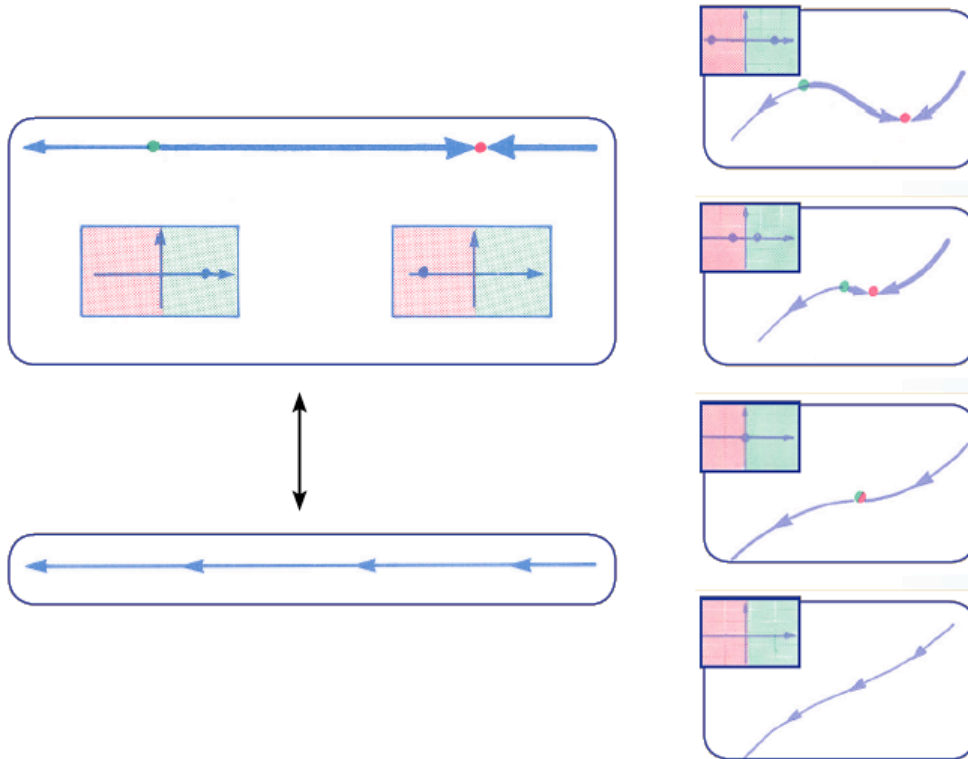
## Elementary Catastrophes: Fold



*Dynamics: The Geometry of Behavior*, Ralph Abraham and Chris Shaw (2005)

23a\_fold.psd

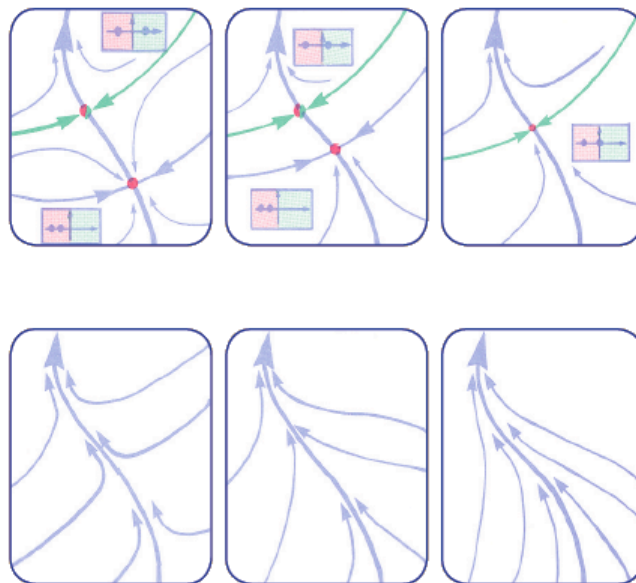
### Elementary Catastrophes: Fold



*Dynamics: The Geometry of Behavior*, Ralph Abraham and Chris Shaw (2005)

23b\_fold2.psd

### Elementary Catastrophes: 2-D Fold Saddle-Node Bifurcation



*Dynamics: The Geometry of Behavior*, Ralph Abraham and Chris Shaw (2005)

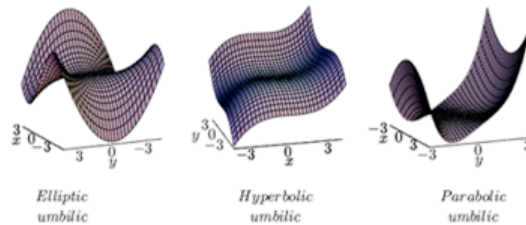
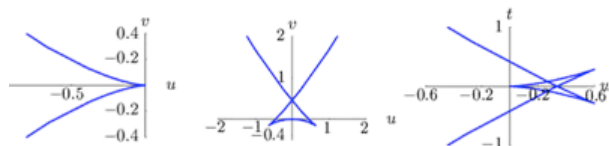
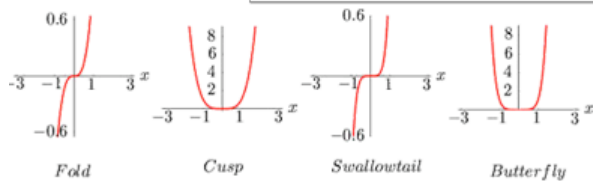
24\_2D\_fold.psd

## Elementary Catastrophes: 2-D Fold Saddle-Node Bifurcation

25a\_fold.psd

### The First Seven Elementary Catastrophes

Germ	Corank	Codim	Universal Unfolding	Name
$x^3$	1	1	$x^3 + ux$	Fold
$x^4$	1	2	$x^4 + ux^2 + vx$	Cusp
$x^5$	1	3	$x^5 + ux^3 + vx^2 + wx$	Swallowtail
$x^6$	1	4	$x^6 + ux^4 + vx^3 + wx^2 + tx$	Butterfly
$x^3 + y^3$	2	3	$x^3 + y^3 + uxy + vx + wy$	Hyperbolic umbilic
$x^3 - xy^2$	2	3	$x^3 - xy^2 + \frac{u}{-1}(x^2 + y^2) + vx + wy$	Elliptic umbilic
$x^2 + y^4$	2	4	$x^2y + y^4 + ux^2 + vy^2 + wx + ty$	Parabolic umbilic



<http://www-wales.ch.cam.ac.uk/~tvb20/elcat.htm>

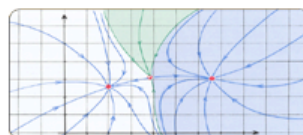
30\_unfoldings.psd

# Hamiltonian Systems

31\_hamiltonian.psd

## Part 1: Dynamics

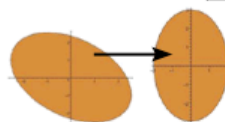
Jan 10 (01) **2-Dimensional flow geometries.** HW1



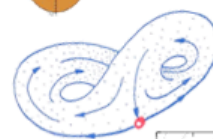
Jan 12 (02) **Discrete dynamics & Mappings.**



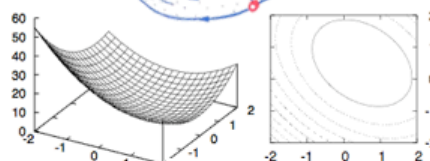
Jan 17 (03) **Diagonalization & eigenvalues.** HW2



Jan 19 (04) **Higher dimensional dynamics & linearization.**



Jan 24 (05) **Stability & Gradient systems.** HW3



*Dynamics: The Geometry of Behavior*, Ralph Abraham and Chris Shaw (2005)  
*Nonlinear dynamics and chaos*, Steven H. Strogatz (1994)  
*Mathematical Models in Biology*, Leah Edelstein-Keshet (1988)

32\_Dynamics.psd