

# Neural circuits for cognition

**MIT 9.49/9.490/6.S076**

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# Logistics/reminders

- HW # 1 due next week (Tuesday)

# Today

- Quick review
- From single rate-based neuron to networks of rate-based neurons
- Simplest nonlinear network: single neuron with feedback (autapse)
- Graphical and linear stability analysis
- Begin: simplest multi-neuron networks: linear and symmetric

From single neurons to networks

# Rate-based equations

synaptic activation: output

$$\frac{ds_i}{dt} + \frac{s_i}{\tau}$$

Biophysical  
time-constant  
(cell or synapse,  
depending on  
which is slow  
for method of  
averaging)

Total input ( $g_i$ ) or input conductance

$$f \left( \underbrace{\sum_j W_{ij} s_j}_{\text{Network input}} + \underbrace{b_i(t)}_{\text{External input}} \right)$$

Firing rate

External input

$$\equiv r_i(t)$$

# Discrete-time network dynamics (for numerical integration)

$$\frac{ds_i}{dt} + \frac{s_i}{\tau} = f\left(\sum_j W_{ij}s_j + b_i(t)\right) \equiv r_i$$

Replace derivative by discrete time-difference:

$$\frac{s_i(t + \Delta t) - s_i(t)}{\Delta t} = -\frac{1}{\tau}s_i(t) + f(g_i(t))$$

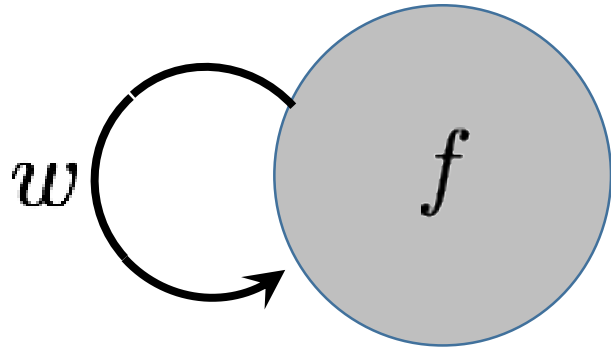
Iteration equation for numerical integration:

$$s_i(t + \Delta t) = \left(1 - \frac{\Delta t}{\tau}\right)s_i(t) + \Delta t f(g_i(t))$$

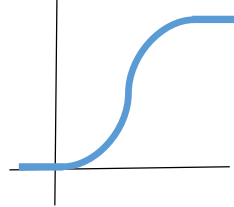
# The simplest nonlinear network

A single-neuron network: the “autapse”

# Bistable switch dynamics with an autapse



$$\tau \frac{ds}{dt} + s = f(ws + b)$$

$$f(x) = \frac{e^x}{1 + e^x}$$


A graph of the sigmoid function  $f(x) = \frac{e^x}{1 + e^x}$ . The curve is blue and S-shaped, starting near 0 for negative  $x$  and approaching 1 for positive  $x$ . It is plotted on a coordinate system with a vertical and horizontal axis.

Fixed point condition:

$$\frac{ds}{dt} = 0$$

$$\Rightarrow \bar{s} = f(w\bar{s} + b)$$

Solve this equation numerically or graphically to find the fixed points.  
And how about the stability of the fixed points?



# Graphical stability analysis

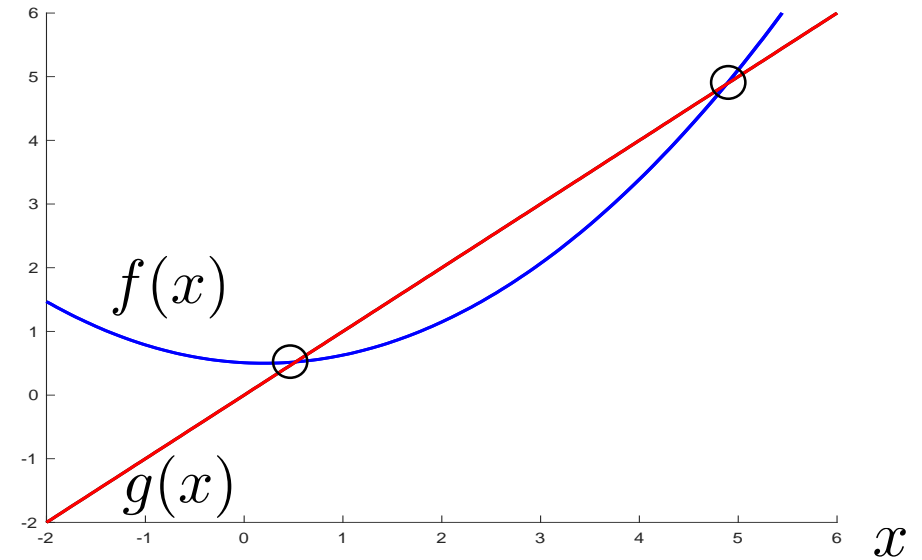
$$\frac{dx}{dt} = f(x) - g(x)$$

Fixed points:

$$f(\bar{x}) = g(\bar{x})$$

# Graphical stability analysis

$$\frac{dx}{dt} = f(x) - g(x)$$



Fixed points:

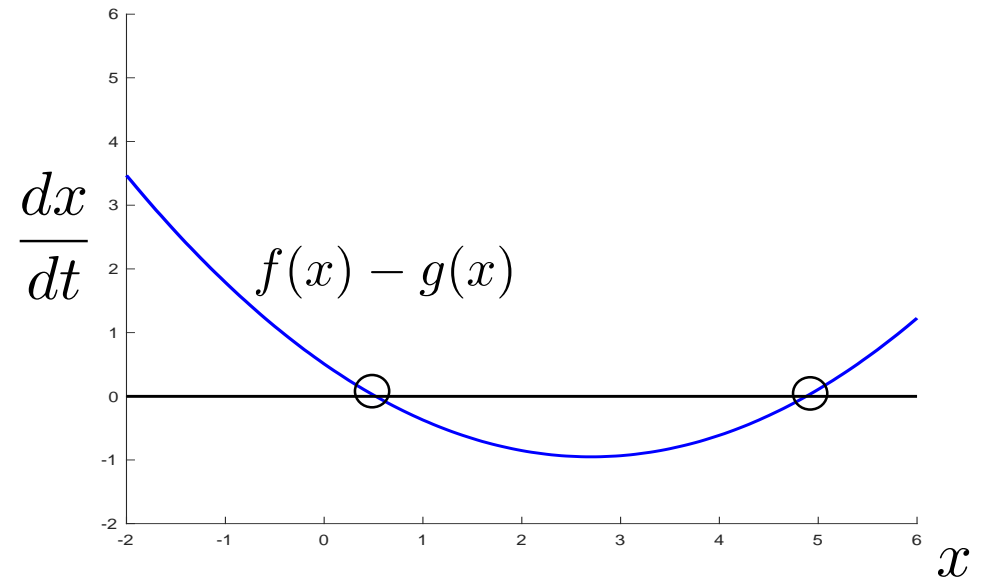
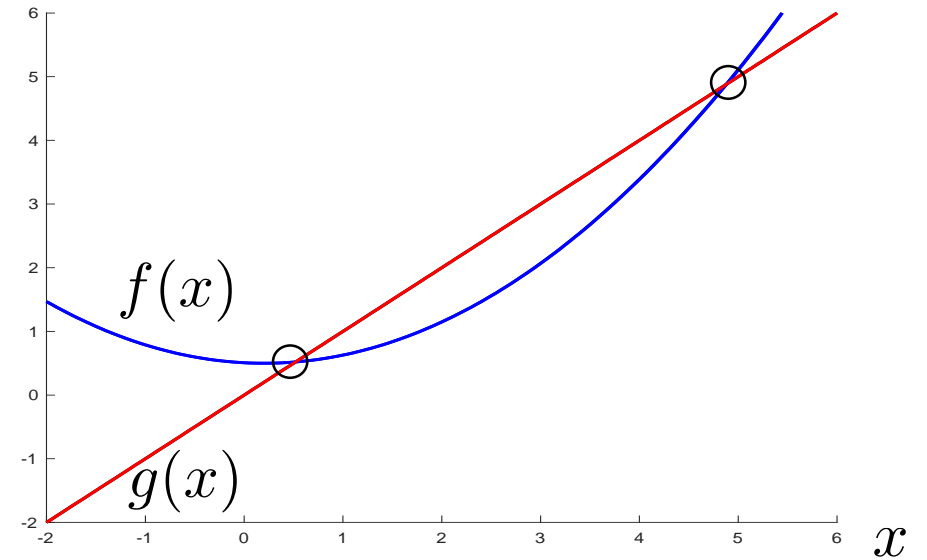
$$f(\bar{x}) = g(\bar{x})$$

# Graphical stability analysis

$$\frac{dx}{dt} = f(x) - g(x)$$

Fixed points:

$$f(\bar{x}) = g(\bar{x})$$

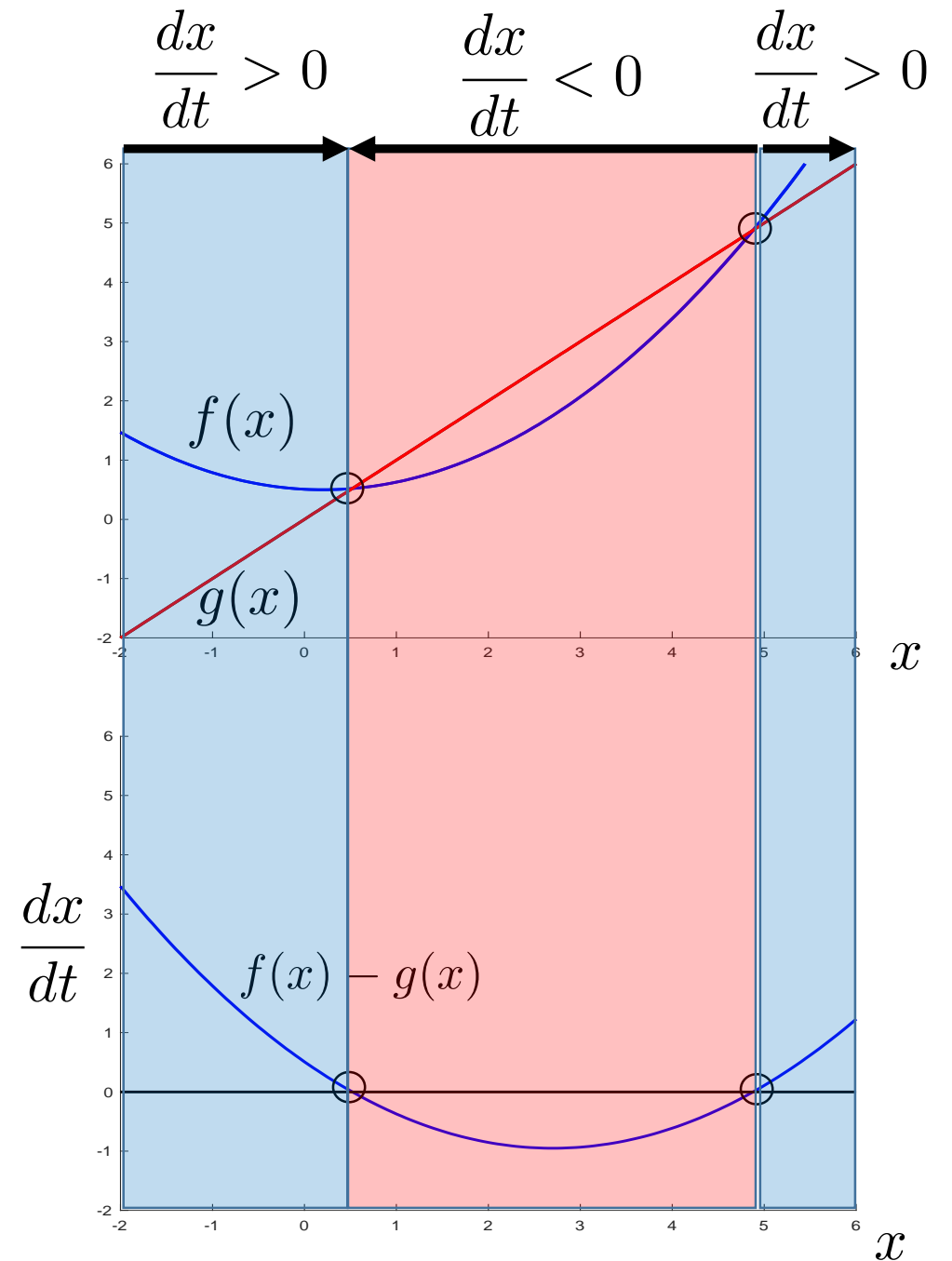


# Graphical stability analysis

$$\frac{dx}{dt} = f(x) - g(x)$$

Fixed points:

$$f(\bar{x}) = g(\bar{x})$$

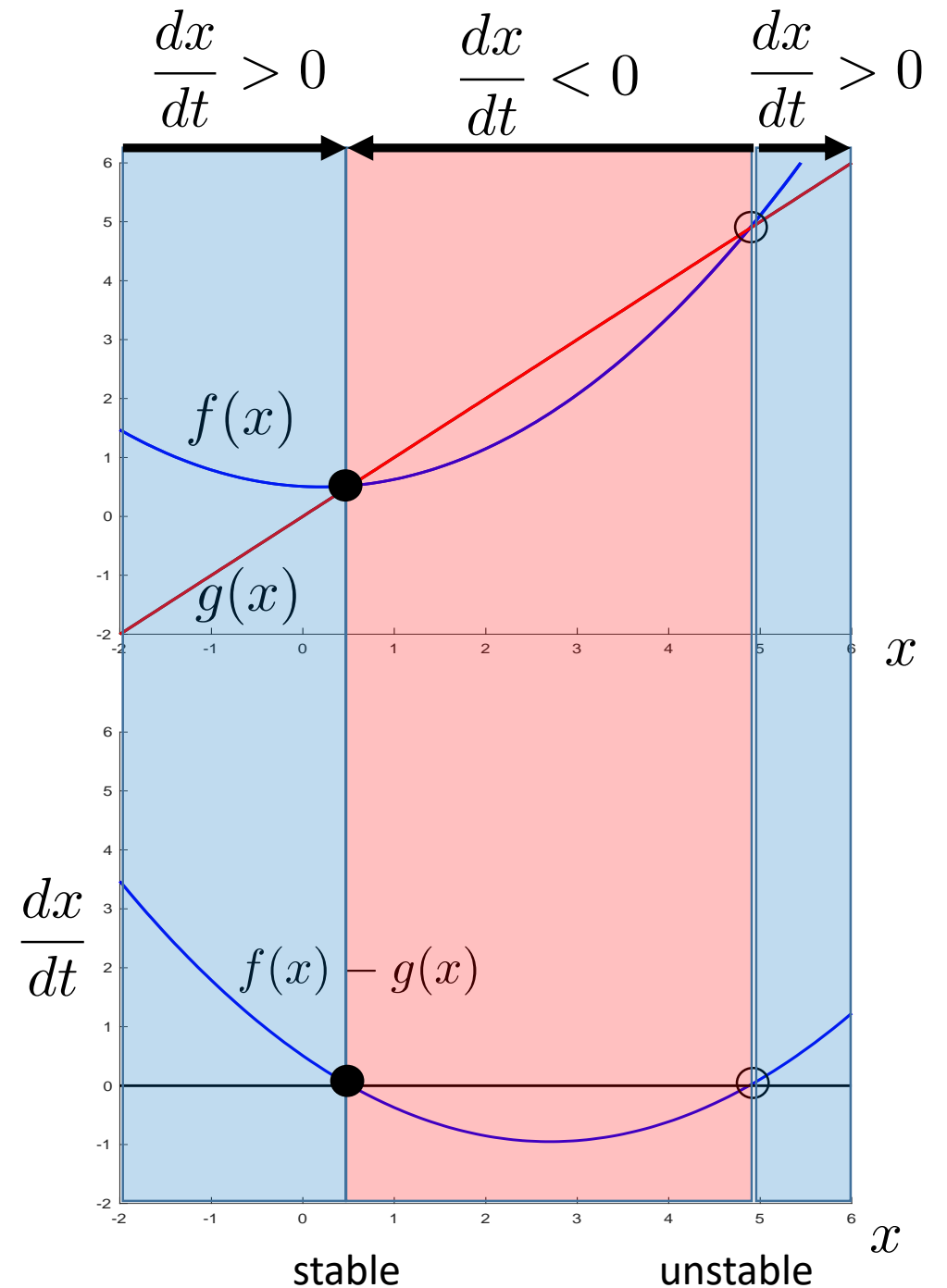


# Graphical stability analysis

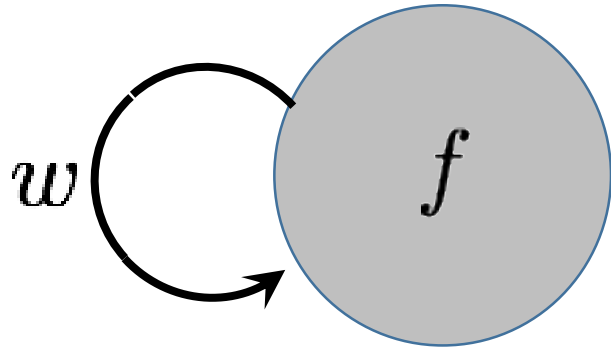
$$\frac{dx}{dt} = f(x) - g(x)$$

Fixed points:

$$f(\bar{x}) = g(\bar{x})$$



# Back to bistable switch: autapse



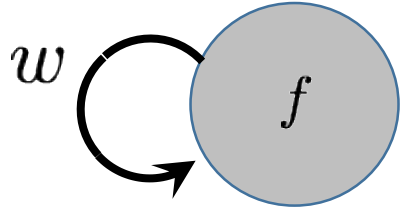
$$\tau \frac{ds}{dt} + s = f(ws + b)$$

$$f(x) = \frac{e^x}{1 + e^x}$$

Fixed point condition:

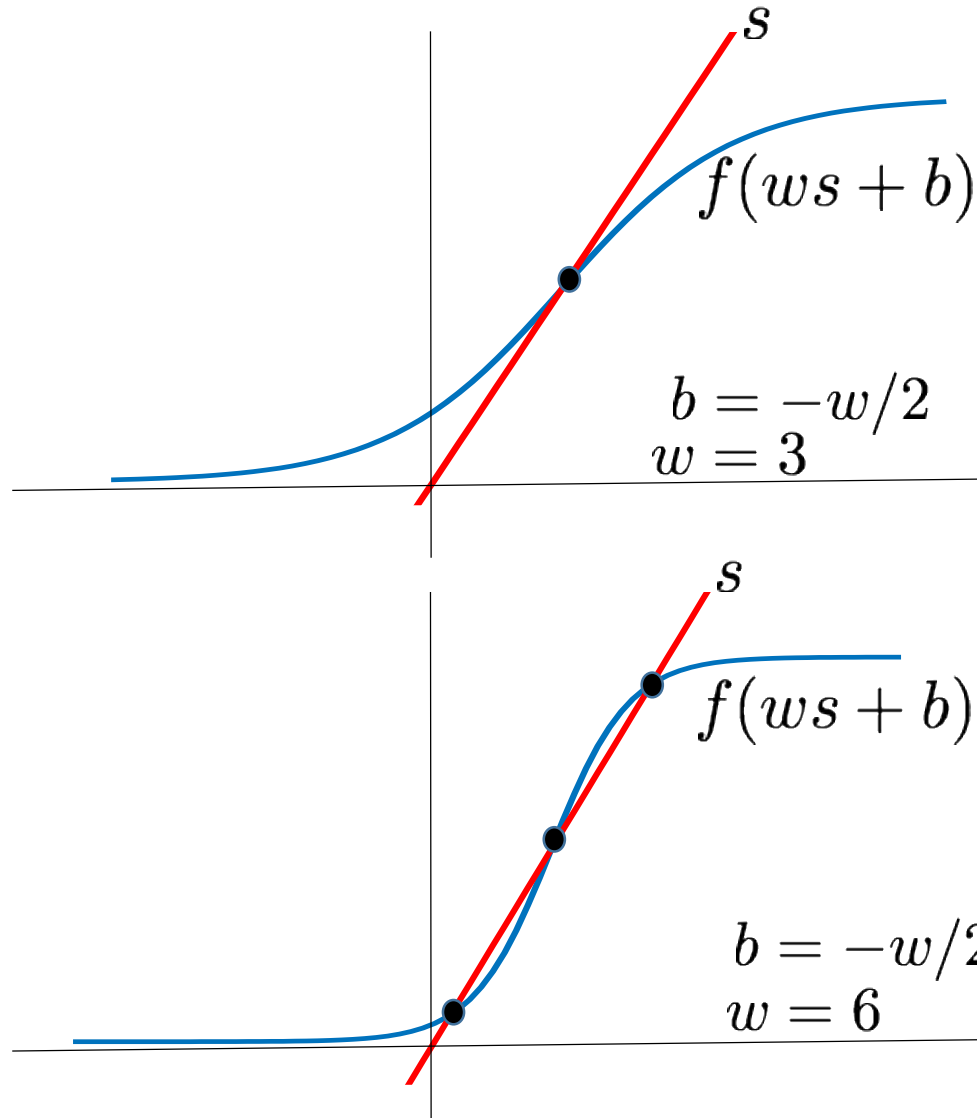
$$\frac{ds}{dt} = 0 \quad \Rightarrow \quad \bar{s} = f(w\bar{s} + b)$$

# Finding fixed points of autapse graphically



$$\bar{s} = f(ws + b)$$

Fixed points equation

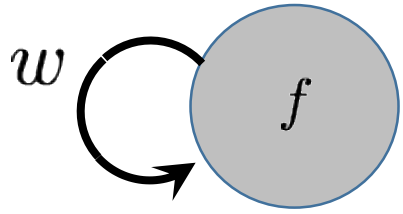


Shallow sigmoid:  
one fixed point

Steep sigmoid:  
three fixed points

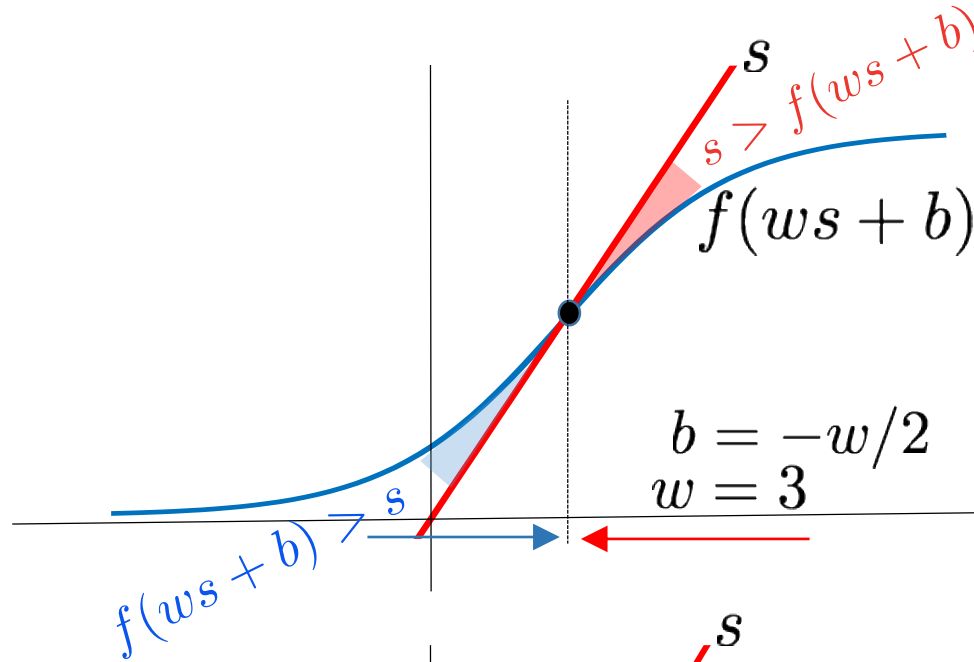
“Pitchfork bifurcation” as a function of parameter  $w$ : from 1 to 3 fixed points.

# Stability of fixed points: graphical analysis

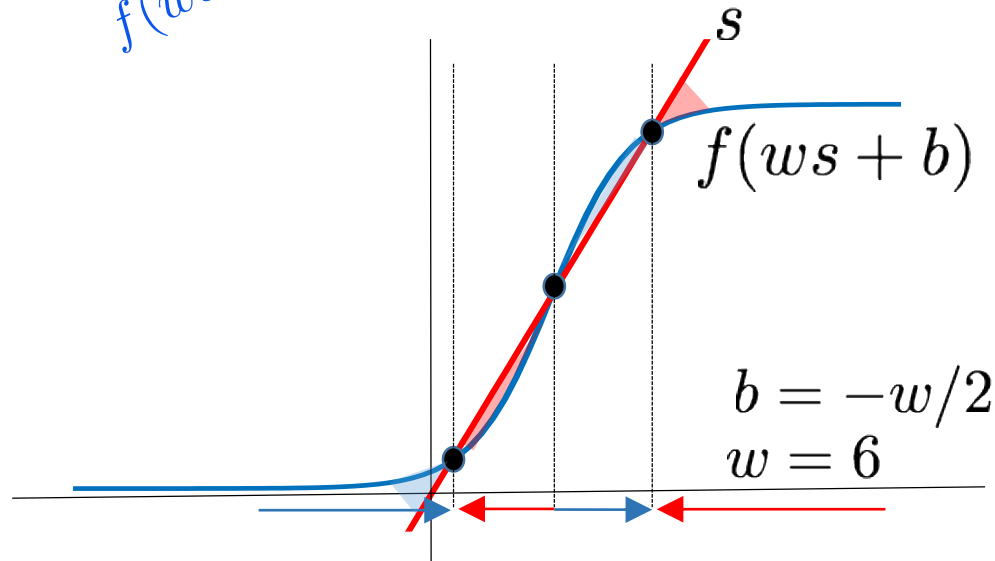


$$\bar{s} = f(ws + b)$$

$$\tau \frac{ds}{dt} + s = f(ws + b)$$



fixed point is stable



central fixed point becomes unstable; other two are stable.



Linear stability analysis of non-linear systems

# Linear (local) stability analysis

Arbitrary autonomous nonlinear dynamical system (autonomous – no driving term  $g(t)$ ):

(single variable for now; will generalize to multi-dimensional case later)

$$\frac{dx}{dt} = -x + f(x)$$

# Linear (local) stability analysis

Arbitrary autonomous nonlinear dynamical system (autonomous – no driving term  $g(t)$ ):  
(single variable for now; will generalize to multi-dimensional case later)

$$\frac{dx}{dt} = -x + f(x)$$

Suppose there is a set of fixed points, indexed by  $i$ :

$$\bar{x}_i = f(\bar{x}_i)$$

# Linear (local) stability analysis

Arbitrary autonomous nonlinear dynamical system (autonomous – no driving term  $g(t)$ ):

$$\frac{dx}{dt} = -x + f(x)$$

Suppose there is at least one fixed point:

$$\bar{x} = f(\bar{x})$$

We can examine the dynamics equation at values of  $x$  near this fixed point:

$$x = \bar{x} + \delta x$$

where  $\delta x$  is very small ( $\delta x \rightarrow 0$ ). This is why the approach is called “local”. Idea: Taylor expand the non-linear function  $f$  around the fixed point to lowest order to get linear equation.

# Linear (local) stability analysis

$$\frac{d(\bar{x} + \delta x)}{dt} = -\bar{x} - \delta x + f(\bar{x} + \delta x)$$

Linear Taylor approximation:  $f(\bar{x} + \delta x) \approx f(\bar{x}) + f'(\bar{x})\delta x$

Obtain linear equation for the dynamics near the fixed point:

$$\frac{d\delta x}{dt} = \cancel{-\bar{x}} + \cancel{f(\bar{x})} - \delta x + f'(\bar{x})\delta x = -\underbrace{(1 - f'(\bar{x}))}_{\text{constant}} \delta x$$

Gives a simple solution for how the perturbations  $\delta x$  will evolve:

$$\delta x(t) = \delta x(0)e^{-(1-f'(\bar{x}))t}$$

# Linear (local) stability analysis of $\bar{x}$

Linearization around  $\bar{x}$

$$\frac{dx}{dt} = -x + f(x) \quad \longrightarrow \quad \frac{d\delta x}{dt} = -(1 - f'(\bar{x})) \delta x$$

Simple exponential growth/decay solution describing how the perturbations  $\delta x$  evolve:

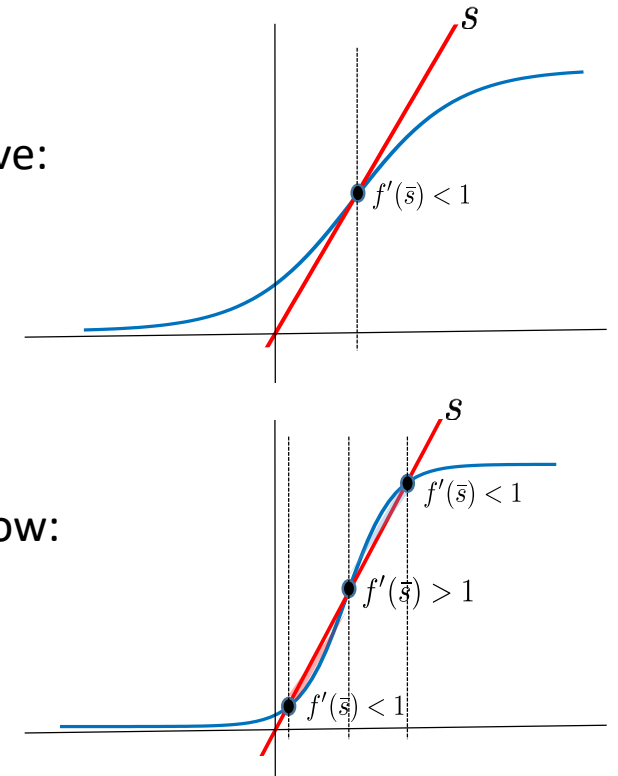
$$\delta x(t) = \delta x(0)e^{-(1-f'(\bar{x}))t}$$

$\bar{x}$  STABLE if perturbations decay:

$$(1 - f'(\bar{x})) > 0$$

$\bar{x}$  UNSTABLE if perturbations grow:

$$(1 - f'(\bar{x})) < 0$$



# Relative merits: graphical vs linear stability analysis

Graphical	Linear
Global; can get basins	Local
Low-dimensional systems	High-dimensional systems
Not easy to use in general	Easy to use
Qualitative	Quantitative

# Bistable switch summary

- A system with nonlinear positive feedback that is superlinear/accelerating, with saturation, can exhibit bistability.
- Bistability occurs for a sufficiently steep positive feedback curve, out of a pitchfork bifurcation as a function of the steepness parameter.
- A single neuron exciting itself is a “cartoon” of positive feedback within a network: it can exhibit switch dynamics.
- Graphical stability analysis and linear stability analysis are tools to examine stability of fixed points.
- Further analysis of this system: homework.



Simplest multi-neuron networks:  
linear networks

# Notation

- Matrices: upper-case  $A, B, U, W$  **A, B, U, W**
- Column vector: **bold**, (usually) lower-case  $\mathbf{x}, \mathbf{y}, \mathbf{v}, \mathbf{w}$   
(handwriting:  $\mathbf{x} \rightarrow \underline{x}$ )
- Scalars  $a, b, c, \gamma, \alpha$
- Discrete indices  $i, j, k, l, m, n; \alpha, \beta$

The rate-based network equation (vector-matrix form)

$$\frac{ds_i}{dt} + \frac{s_i}{\tau} = f\left(\sum_j W_{ij}s_j + b_i(t)\right)$$

$$\frac{d\mathbf{s}}{dt} + \frac{\mathbf{s}}{\tau} = f(\mathbf{W}\mathbf{s} + \mathbf{b})$$

# Some notation: vectors and matrices

$$\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix}$$

size  $(m \times 1)$  column vector

$$v_i \in \mathbb{R}$$

$$\mathbf{v} \in \mathbb{R}^m$$

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix}$$

size  $(n \times m)$  matrix

$$A \in \mathbb{R}^{n \times m}$$

# Some more notation

- Matrices: upper-case  $A, B, U, W$
- Column vector: **bold**, (usually) lower-case  $\mathbf{x}, \mathbf{y}, \mathbf{v}, \mathbf{w}$   
(handwriting:  $\mathbf{x} \rightarrow \underline{x}$ )
- Scalars  $a, b, c, \gamma, \alpha$
- Discrete indices  $i, j, k, l, m, n; \alpha, \beta$

The rate-based network equation (vector-matrix form)

$$\frac{ds_i}{dt} + \frac{s_i}{\tau} = f\left(\sum_j W_{ij}s_j + b_i(t)\right)$$

$$\frac{d\mathbf{s}}{dt} + \frac{\mathbf{s}}{\tau} = f(\mathbf{W}\mathbf{s} + \mathbf{b})$$

# Linear algebra: basics to review

Please look at linear algebra slides and primer on course website if you'd like a quick refresher/introduction to some basic definitions and concepts for vectors and matrices.

- Eigenvalues, eigenvectors
- Orthogonality
- Properties of real, symmetric matrices ( $\mathbf{M}=\mathbf{M}^T$ )
- Notes available: Linear algebra primer

# Eigenvectors and eigenvalues

If for a linear operator (matrix)  $M$ , there exists a non-zero vector  $\mathbf{v}$  such that:

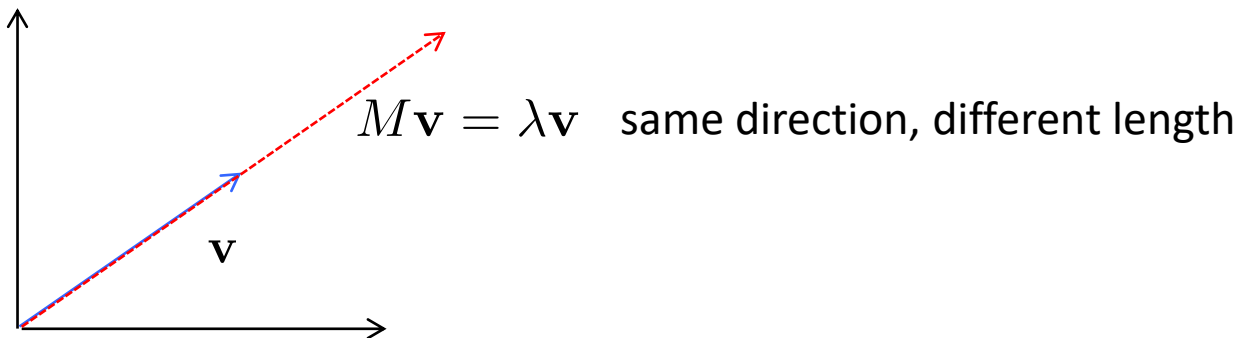
$$M\mathbf{v} = \lambda\mathbf{v}$$

where  $\lambda$  is a scalar, then  $\mathbf{v}$  is an eigenvector of  $M$ , with eigenvalue  $\lambda$ .

Eigenvalues are given by the roots of the characteristic equation:  $|M - \lambda I| = 0$

In other words, the eigenvectors of a matrix are a special set of vectors for which the matrix product acts simply as a scalar product:

geometric view





# Eigenvectors and eigenvalues of square matrices

- The eigenvalues of real-valued matrices are generally complex and eigenvectors need not be orthogonal.
- The eigenvalues of real symmetric matrices are real eigenvalues and their eigenvectors are orthogonal.
- Asymmetric matrices in general have different left and right eigenvectors, but have a common set of eigenvalues.

Linear and linearized networks,  
relationship to linear systems

# Linear(ized) neural networks

Linearized dynamics of a *nonlinear neural network* around a point  $\bar{\mathbf{s}}$ :

$$\frac{d\delta\mathbf{s}}{dt} + \frac{\delta\mathbf{s}}{\tau} = \mathbf{D}\mathbf{W}\delta\mathbf{s}$$

$$\mathbf{D}_{ij} = \left( \frac{\partial f}{\partial g_i} \bigg|_{\bar{\mathbf{s}}} \right) \delta_{ij}$$

A linear neural network:

$$\tau \frac{d\mathbf{s}}{dt} + \mathbf{s} = \mathbf{W}\mathbf{s} + \mathbf{b}$$

$$(\mathbf{D} = \mathbb{I})$$

# The rate-based network equation (vector-matrix form)

$$\frac{ds_i}{dt} + \frac{s_i}{\tau} = f\left(\sum_j W_{ij}s_j + b_i\right)$$

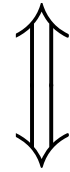
Linearized dynamics in the vicinity of some state  $\bar{\mathbf{s}}$ :  $\mathbf{s} = \bar{\mathbf{s}} + \delta\mathbf{s}$

$$\frac{d\delta s_i}{dt} + \frac{\delta s_i}{\tau} = \left(\frac{\partial f}{\partial g_i}\bigg|_{\bar{\mathbf{s}}}\right) \sum_j W_{ij}\delta s_j$$

$$\frac{d\delta\mathbf{s}}{dt} + \frac{\delta\mathbf{s}}{\tau} = \mathbf{DW}\delta\mathbf{s} \qquad \mathbf{D}_{ij} = \left(\frac{\partial f}{\partial g_i}\bigg|_{\bar{\mathbf{s}}}\right)\delta_{ij}$$

Linear(ized) dynamical system fixed points correspond to the roots of corresponding linear systems

Fixed points of  $\frac{d\mathbf{x}}{dt} = W\mathbf{x}$



Solutions of  $W\mathbf{x} = 0$

# Linear systems review

$n$  equations in  $m$  unknowns ( $v_1, \dots, v_m$ ):

$$a_{11}v_1 + \cdots + a_{1m}v_m = b_1$$

$$a_{21}v_1 + \cdots + a_{2m}v_m = b_2$$

.....

$$a_{n1}v_1 + \cdots + a_{nm}v_m = b_n$$

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$

$(n \times m)$                        $(m \times 1)$                        $(n \times 1)$

$$\mathbf{A}\mathbf{v} = \mathbf{b}$$

# System of equations: when does unique solution exist?

$n$  equations (constraints) in  $m$  unknowns: *generically (though not exactly always!)*, a unique solution exists when,  $n=m$  or  $A$  is square.

$$\begin{bmatrix} a_{11} & \cdots & a_{1m} \\ a_{21} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots \\ a_{m1} & \cdots & a_{mm} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

$(m \times m)$   $(m \times 1)$   $(n \times 1)$

$$A \mathbf{v} = \mathbf{b}$$

$(m \times m)$   $(m \times 1)$   $(m \times 1)$

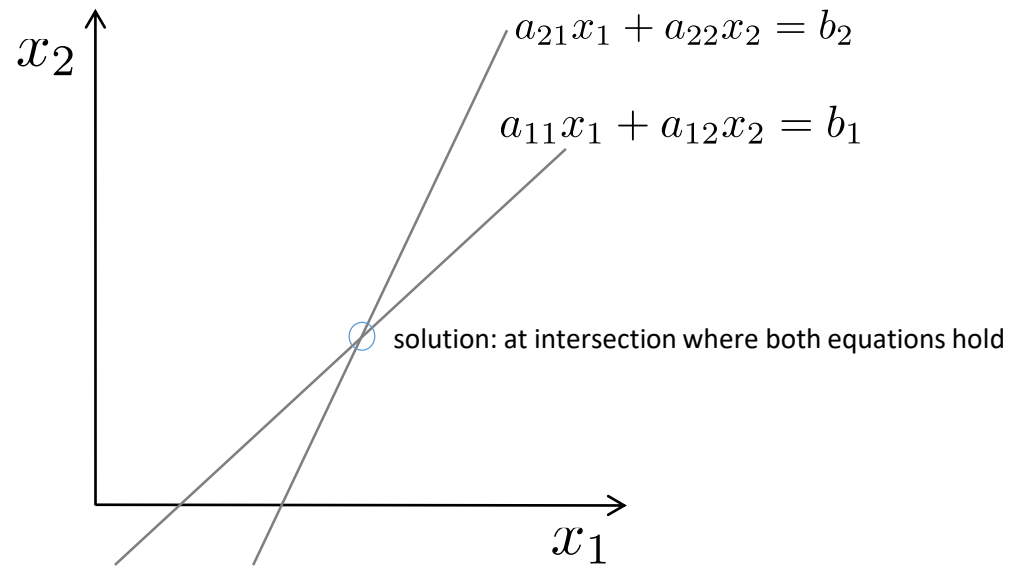
The diagram consists of three blue rectangular blocks. The first block is a square, with a blue 'm' written above it and another blue 'm' written to its left. To its right is a thin vertical rectangle. An equals sign is placed between this second rectangle and a third, identical thin vertical rectangle on the right.

For a square matrix, when is a unique solution guaranteed to exist?  
Time for some geometric insight.

# Geometric view: when does a unique solution exist?

E.g. 2-dimensional problem: 2 unknowns, 2 equations

equation of a line  $\begin{cases} a_{11}x_1 + a_{12}x_2 = b_1 \\ a_{21}x_1 + a_{22}x_2 = b_2 \end{cases}$  unknowns  $x_1, x_2$



Two lines in 2D *generically* intersect at a (single) location thus generically a unique solution exists.

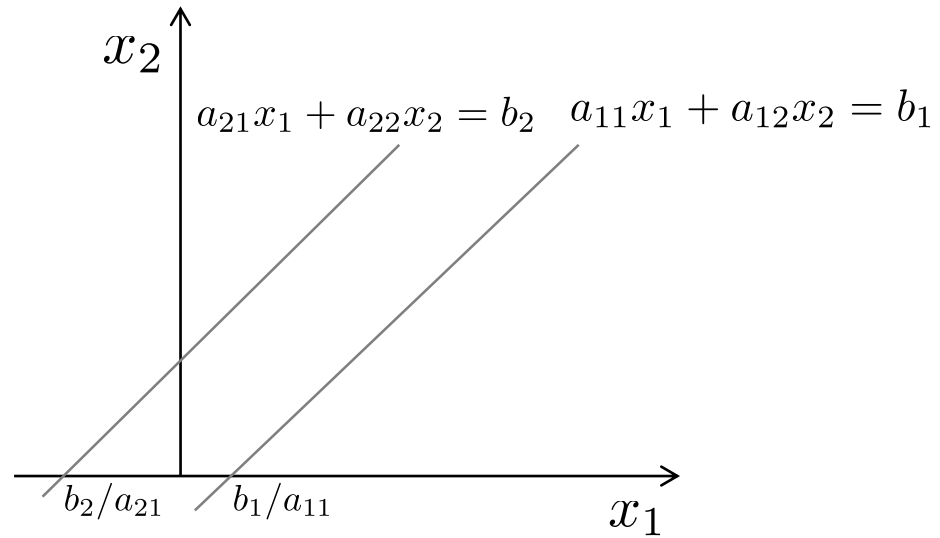


Geometric view: Two ways that a unique solution *does not* exist in 2D

What are these?

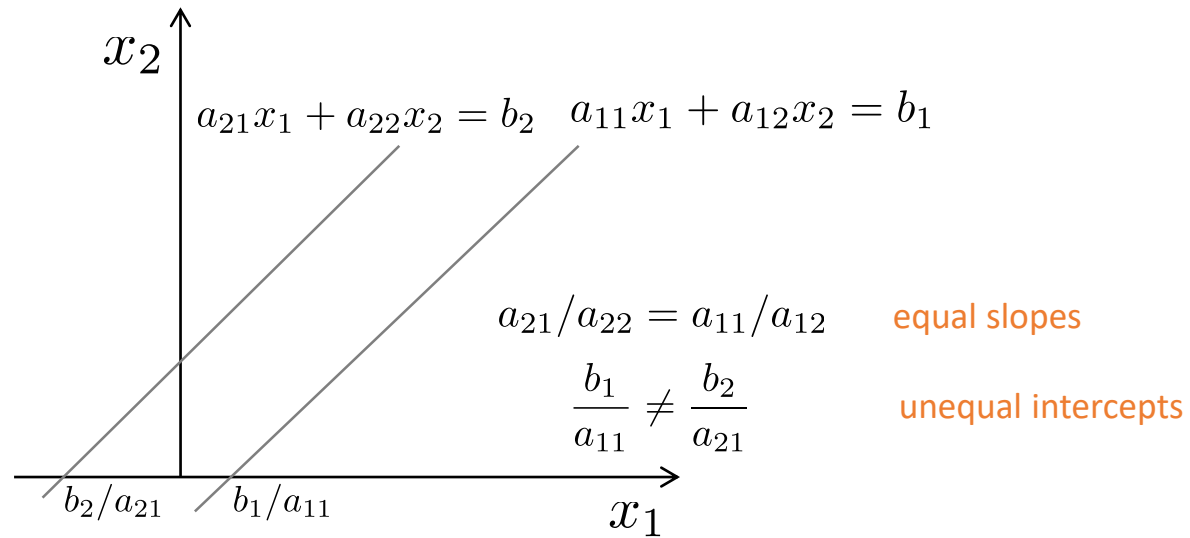
Geometric view: Two ways a unique solution *does not* exist in 2D

1. Offset parallel lines: **no solution**



# Algebra: when does a unique solution *not* exist?

## 1. Offset parallel lines: **no solution**

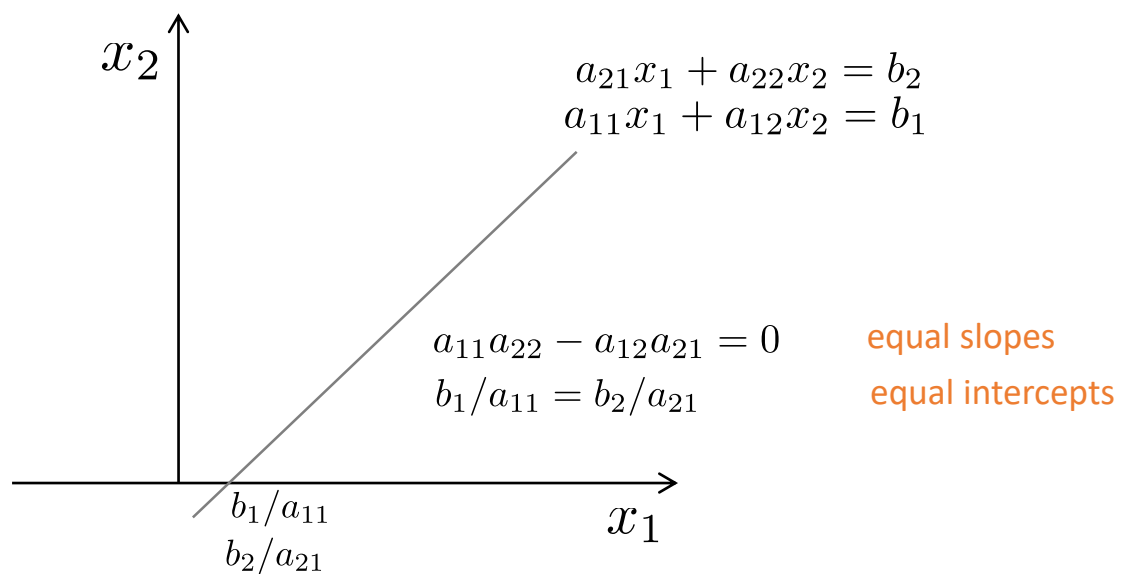


$$a_{11}a_{22} - a_{12}a_{21} = 0$$

$$\det(A) \equiv a_{11}a_{22} - a_{12}a_{21}$$

# Algebra: when does a unique solution *not* exist?

## 2. Aligned parallel lines: **infinitely many solutions**



Back to algebraic view: existence of unique solution in terms of coefficient matrix  $A$

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

determinant:  $\det(A) \equiv a_{11}a_{22} - a_{12}a_{21}$

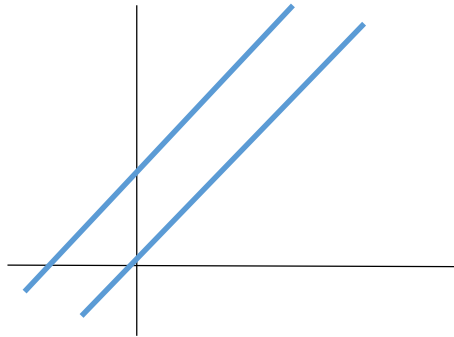
2-dim system of equations with square coefficient matrix  $A$  has a unique solution when:

$$\det(A) \neq 0$$

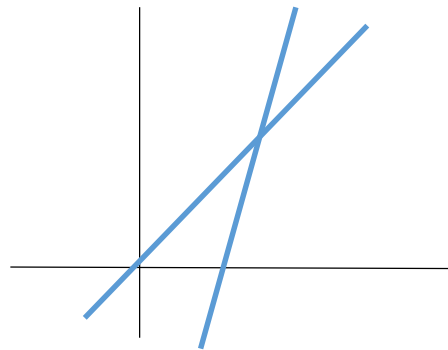
Same condition for  $m$ -dim system of equations with square coefficient matrix: need non-singular determinant.

# Fixed points of any linear dynamical system

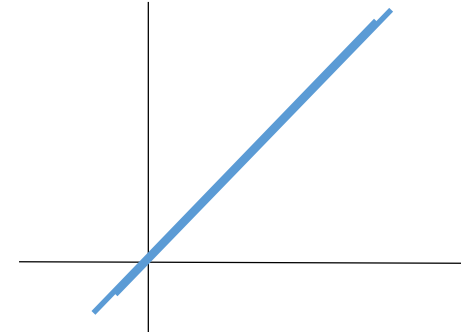
- A linear system (of any dimension) admits exactly 0, 1, or infinitely many fixed points.



0 solutions  
NOT generic



1 solution  
(generic case)  
square matrix, non-zero determinant

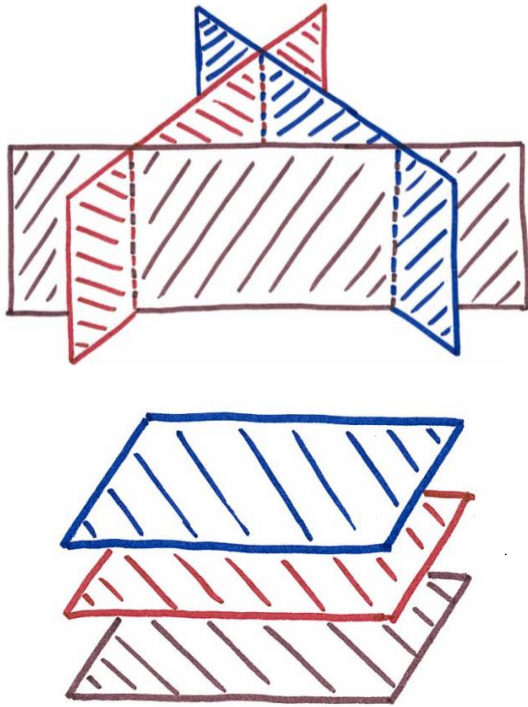


Infinitely many solutions  
NOT generic

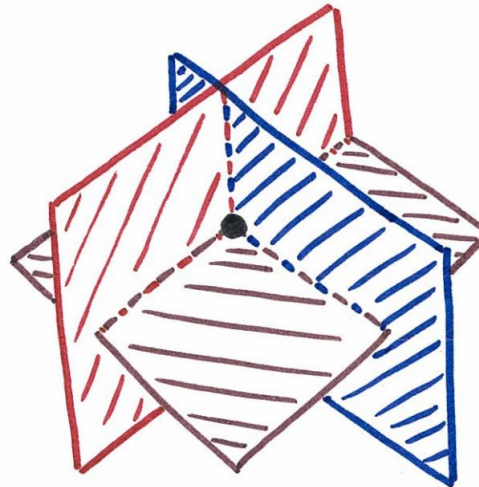
Corollary: A linear system cannot exhibit a finite number  $>1$  of fixed points (cf. our bistable switch)

# Linear dynamical systems: all possibilities

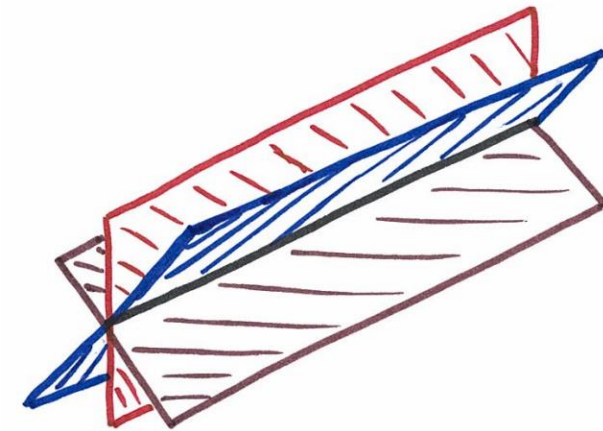
- A linear system admits 0, 1, or infinitely many fixed points.
- **Regardless of system dimension:** these are the only possibilities.



0 solutions  
NOT generic



1 solution  
(generic case)  
square matrix, non-zero determinant



Infinitely many solutions  
NOT generic

# Summary

- Global and linear stability analysis
- Accelerating positive feedback + saturation  $\rightarrow$  bistability
- Linear dynamical systems and relationship with linear systems of equations: fixed points of dynamical system are roots of linear system
- Linear dynamical systems admit 0,1, or infinitely many fixed points