

A systems approach to biology

SB200

Lecture 3

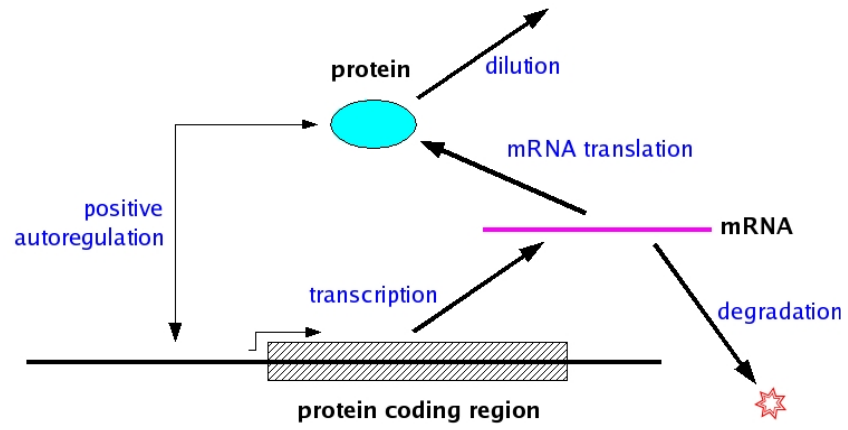
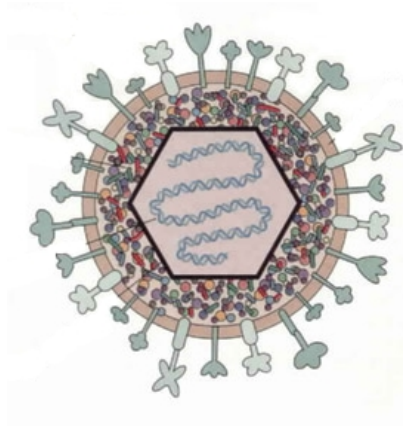
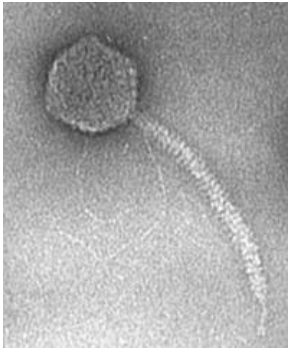
23 September 2008

Jeremy Gunawardena

jeremy@hms.harvard.edu

Recap of Lecture 2

decision making

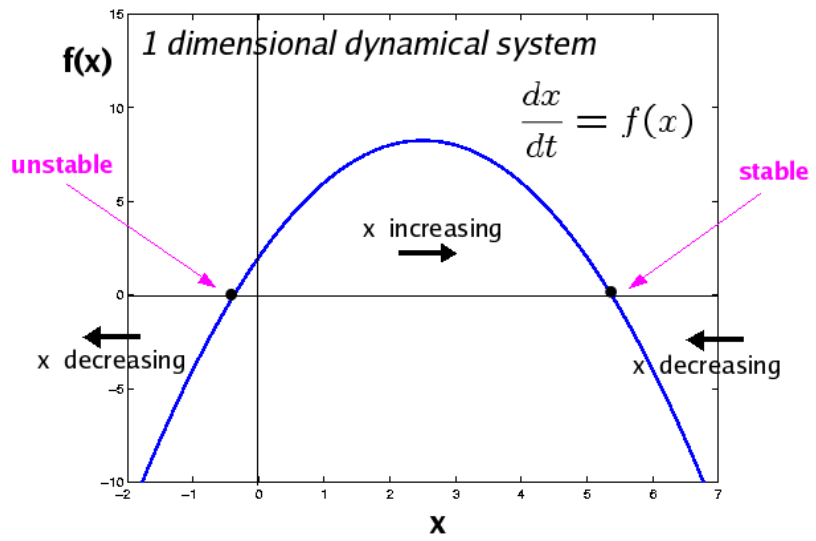


positive feedback

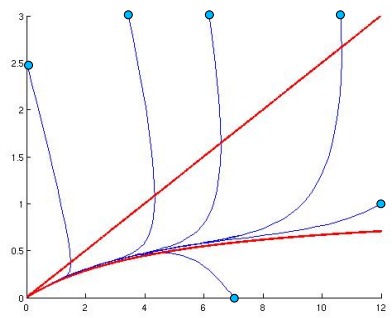
$$\frac{dx_1}{dt} = \lambda x_2 - a x_1$$

$$\frac{dx_2}{dt} = \frac{\alpha x_1}{k + x_1} - b x_2$$

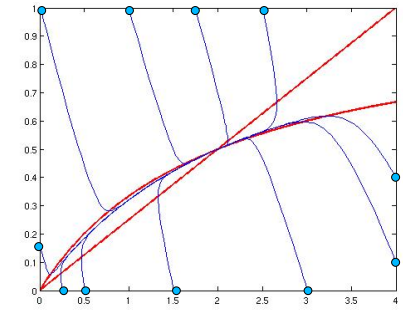
stable & unstable steady states



$$k \geq \alpha\lambda/ab$$



$$k < \alpha\lambda/ab$$



bifurcation

STABILITY THEOREM

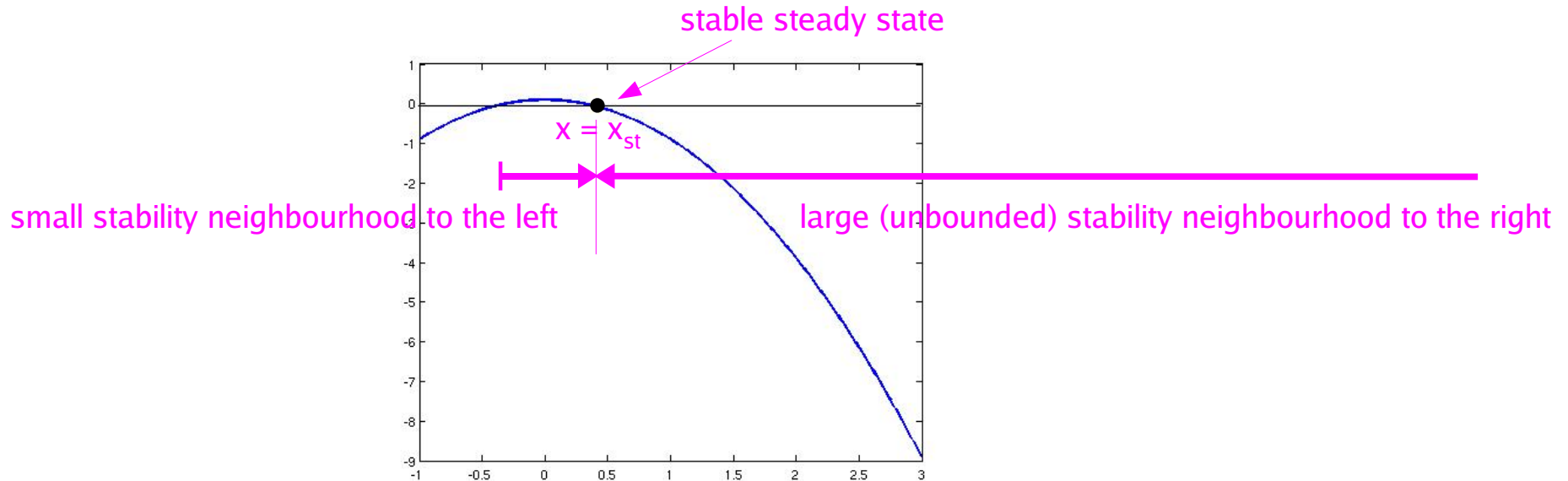
1 dimensional dynamical system $\frac{dx}{dt} = f(x)$

1. find a steady state $x = x_{st}$, so that $\left(\frac{dx}{dt}\right)\Big|_{x=x_{st}} = f(x_{st}) = 0$
2. calculate the **derivative** of f at the steady state $\left(\frac{df}{dx}\right)\Big|_{x=x_{st}}$
3. if the derivative is **negative** then x_{st} is **stable**
4. if the derivative is **positive** then x_{st} is **unstable**
5. if the derivative is **zero** then x_{st} can be stable or unstable

the sign of df/dx only tells us about **local** stability

ie: in some sufficiently small neighbourhood
around the point $x = x_{st}$

these methods do not tell us how “small”



LINEARISATION THEOREM

the dynamics of

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

is **qualitatively similar** to that of its linearisation

$$\frac{dx}{dt} = \left[\left. \left(\frac{df}{dx} \right) \right|_{x=x_{st}} \right] x$$

derivative of f at $x = x_{st}$

in the **local vicinity** of a steady state $x = x_{st}$

provided that

$$\left[\left. \left(\frac{df}{dx} \right) \right|_{x=x_{st}} \right] \neq 0$$

1 dimensional systems provide excellent intuition for n dimensional systems

The STABILITY and LINEARISATION THEOREMS hold in n dimensions

but we need to understand

the **derivative** (in n dimensions)

what it means for an n-dimensional derivative to be “**negative**”



Jacobian matrix



eigenvalues

From this point we will need to use some matrix algebra. You will find everything needed for the lectures explained in the handouts

“Matrix algebra for beginners, Parts I, II and III”

Matrix algebra for beginners, Part I
matrices, determinants, inverses

Jeremy Gunawardena
Department of Systems Biology
Harvard Medical School
200 Longwood Avenue, Cambridge, MA 02115, USA
jeremy@hms.harvard.edu

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STABILITY THEOREM

n dimensional dynamical system $\frac{dx}{dt} = f(x)$ *x is a vector !!!*

1. find a steady state $x = x_{st}$, so that $\left(\frac{dx}{dt}\right)\Big|_{x=x_{st}} = f(x_{st}) = 0$
2. calculate the **Jacobian matrix** at the steady state $A = (Df)\Big|_{x=x_{st}}$
3. if all the eigenvalues of A have **negative real part** then x_{st} is **stable**
4. if none of the eigenvalues of A are **zero** and at least one of the eigenvalues has **positive real part** then x_{st} is **unstable**
5. if at least one of the eigenvalues of A is **zero** then x_{st} can be either **stable or unstable**

Jacobian matrix

$$Df = \left(\frac{\partial f_i}{\partial x_j} \right) \quad n \times n \text{ matrix}$$

$$f_1(x_1, x_2) = \lambda x_2 - a x_1$$

$$f_2(x_1, x_2) = \frac{\alpha x_1}{k + x_1} - b x_2$$

$$Df = \begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{pmatrix} = \begin{pmatrix} -a & \lambda \\ \frac{\alpha k}{(k+x_1)^2} & -b \end{pmatrix} \quad \text{Jacobian matrix}$$

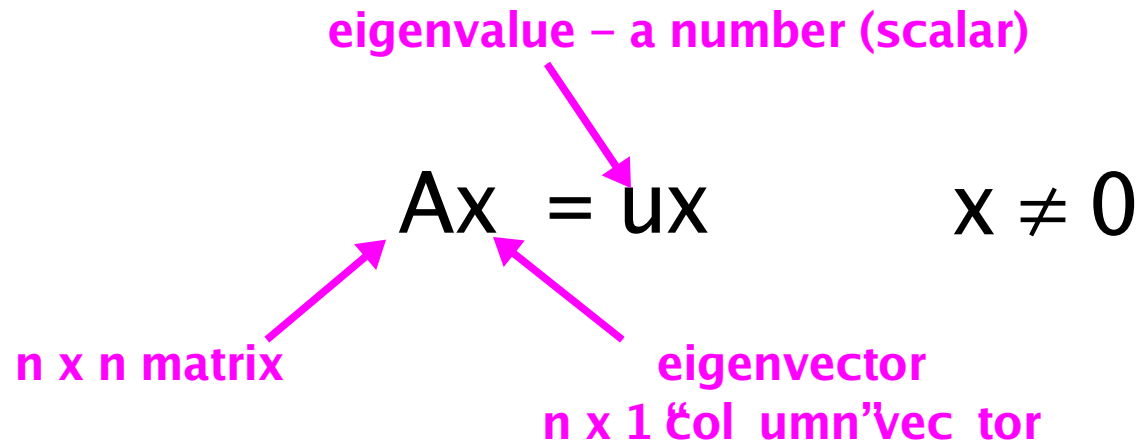
Eigenvalues

$$Ax = \lambda x \quad x \neq 0$$

eigenvalue – a number (scalar)

n x n matrix

eigenvector
n x 1 'column' vector



The eigenvalues satisfy the **characteristic equation** of the matrix A

$$\det(A - \lambda I) = 0$$

This is a polynomial equation in λ , of degree n .

By the Fundamental Theorem of Algebra, this equation has n solutions **but some of them may be complex numbers (of the form $a + ib$)**

An $n \times n$ matrix always has n (possibly complex) eigenvalues

*Matrices are like numbers –
they can be added and multiplied together*

**except that multiplication is not commutative
and not all non-zero matrices have an inverse**

for any $n \times n$ matrix A

A is invertible A^{-1} exists – if and only if $\det \neq 0$

$\det A =$ product of the eigenvalues of A

$\text{Tr } A =$ sum of the eigenvalues of A

$$\det AB = (\det A)(\det B)$$

At the steady state $(x_1, x_2) = (0, 0)$

$$\det \begin{pmatrix} -a - u & \lambda \\ \frac{\alpha}{k} & -b - u \end{pmatrix} = (a + u)(b + u) - \frac{\lambda\alpha}{k}$$

Characteristic equation is

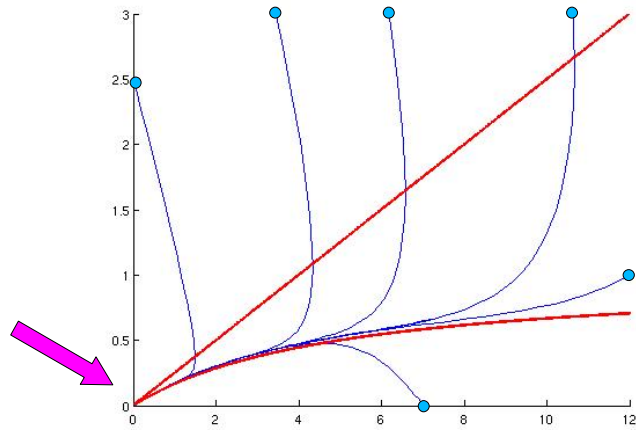
$$u^2 + (a + b)u + \left(ab - \frac{\lambda\alpha}{k}\right) = 0$$

(Note: In the original image, blue arrows point from '- Tr A' to the coefficient (a+b) and from 'det A' to the constant term ab - λα/k.)

Eigenvalues are

$$u = \frac{-(a + b) \pm [(a + b)^2 - 4(ab - \frac{\lambda\alpha}{k})]^{1/2}}{2}$$

(Note: In the original image, a blue arrow points from 'disc A = (Tr A)² - 4 det A' to the discriminant term.)



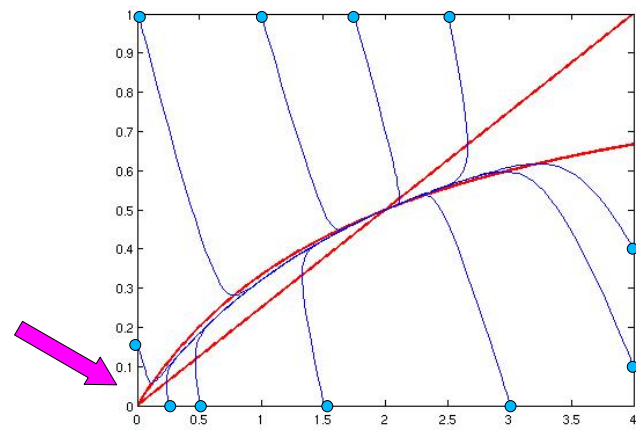
λ	0.08	(sec) ⁻¹
a	0.02	(sec) ⁻¹
b	0.1	(sec) ⁻¹
α	0.1	(μM)(sec) ⁻¹
k	5	(μM)

$$u^2 + 0.12u + 0.0014 = 0$$

$$u = -0.12 \pm 0.094$$

$$u = -0.214$$

$$u = -0.026$$



λ	0.08	(sec) ⁻¹
a	0.02	(sec) ⁻¹
b	0.1	(sec) ⁻¹
α	0.1	(μM)(sec) ⁻¹
k	2	(μM)

$$u^2 + 0.12u - 0.002 = 0$$

$$u = -0.12 \pm 0.1497$$

$$u = -0.2697$$

$$u = +0.0297$$

A simple theorem about stability and instability in feedback loops.

Details in the handout.

Stability of steady states for a general autoregulatory loop

Jeremy Gunawardena

24 September 2007

This is a handout for SB200, "A systems approach to biology". It provides details of the theorem proved in the lectures, which gives a graphical method for determining the stability of a steady state for a general autoregulatory loop. If you have any comments or questions, and especially if you notice any misprints or errors, please send me a message at jeremy@hms.harvard.edu.

The autoregulatory loop is shown schematically in Figure 1, where x_1 and x_2 are the concentrations of protein and mRNA, respectively. This scheme allows for first-order degradation of mRNA and protein, with (positive) rate constants b and a , respectively, but the rate of mRNA translation can be an arbitrary function, $f(x_2)$, of mRNA concentration and the rate of gene expression can be an arbitrary function, $g(x_1)$, of protein concentration. This translates into the following system of differential equations

$$\begin{aligned} dx_1/dt &= f(x_2) - ax_1 \\ dx_2/dt &= g(x_1) - bx_2, \end{aligned} \quad (1)$$

which defines a two-dimensional dynamical system. We assume throughout that $a, b > 0$.

We want to work out the stability of a steady state of this system. As we discussed in Lectures 2 and 3, the stability a steady state depends on the eigenvalues of the Jacobian matrix at that steady state. Since this is a two-dimensional system, we can work out the stability more quickly by calculating the determinant and the trace of the Jacobian (as summarized in the Determinant/Trace diagram for two-dimensional dynamical systems). It is easy to work out the Jacobian matrix at any state $x = (x_1, x_2)$. Let us call this $J(x)$. Calculating the partial derivatives, we find that

$$J(x) = \begin{pmatrix} -a & \frac{df}{dx_2} \\ \frac{dg}{dx_1} & -b \end{pmatrix}. \quad (2)$$

Note that the partial derivatives in the Jacobian can be replaced by ordinary derivatives because f and g are each functions of only a single state variable. We see from (2) that $\text{Tr}J(x) = -(a+b) < 0$, independently of x . It follows that the stability of any steady state will depend solely on the sign of

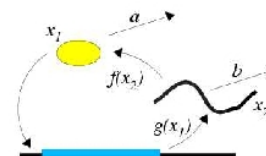
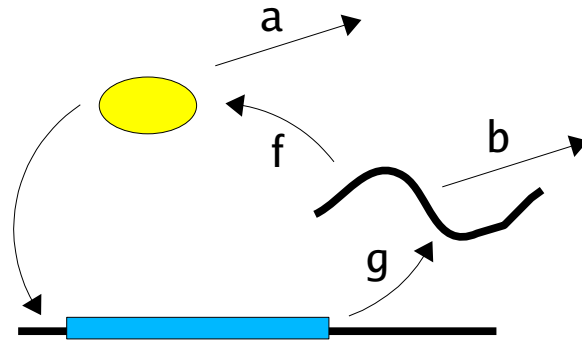


Figure 1: The general autoregulatory loop. A single gene is transcribed into mRNA which is translated into protein which feeds back on its own expression. Both mRNA and protein are degraded.



arbitrary functions

- $\frac{dx_1}{dt} = f(x_2) - ax_1$

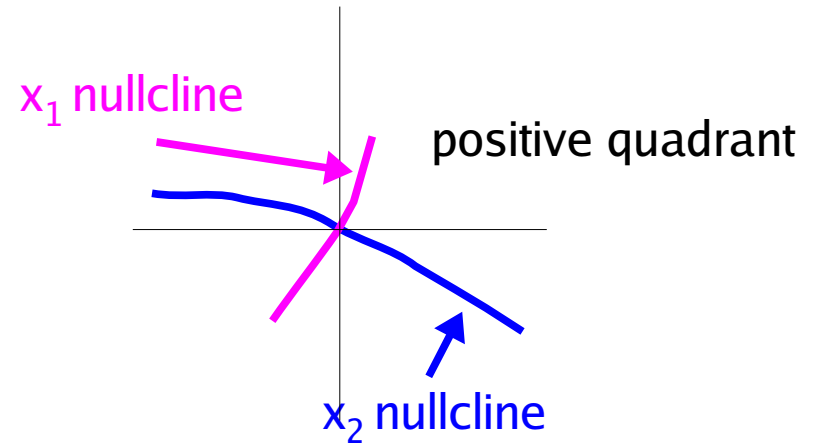
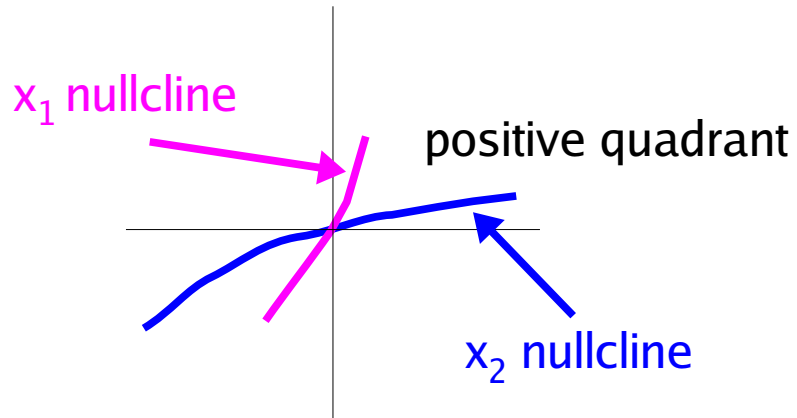
- $\frac{dx_2}{dt} = g(x_1) - bx_2$

$a, b > 0$

x_1 nullcline lies above x_2 nullcline,
both in the positive quadrant

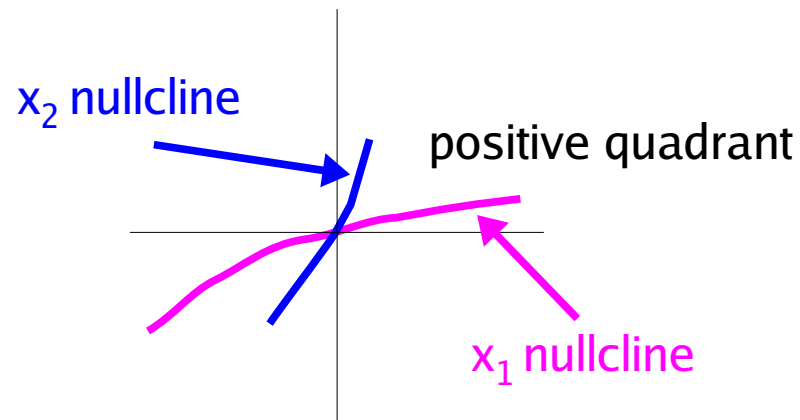
OR

x_1 nullcline in positive quadrant
 x_2 nullcline in fourth quadrant

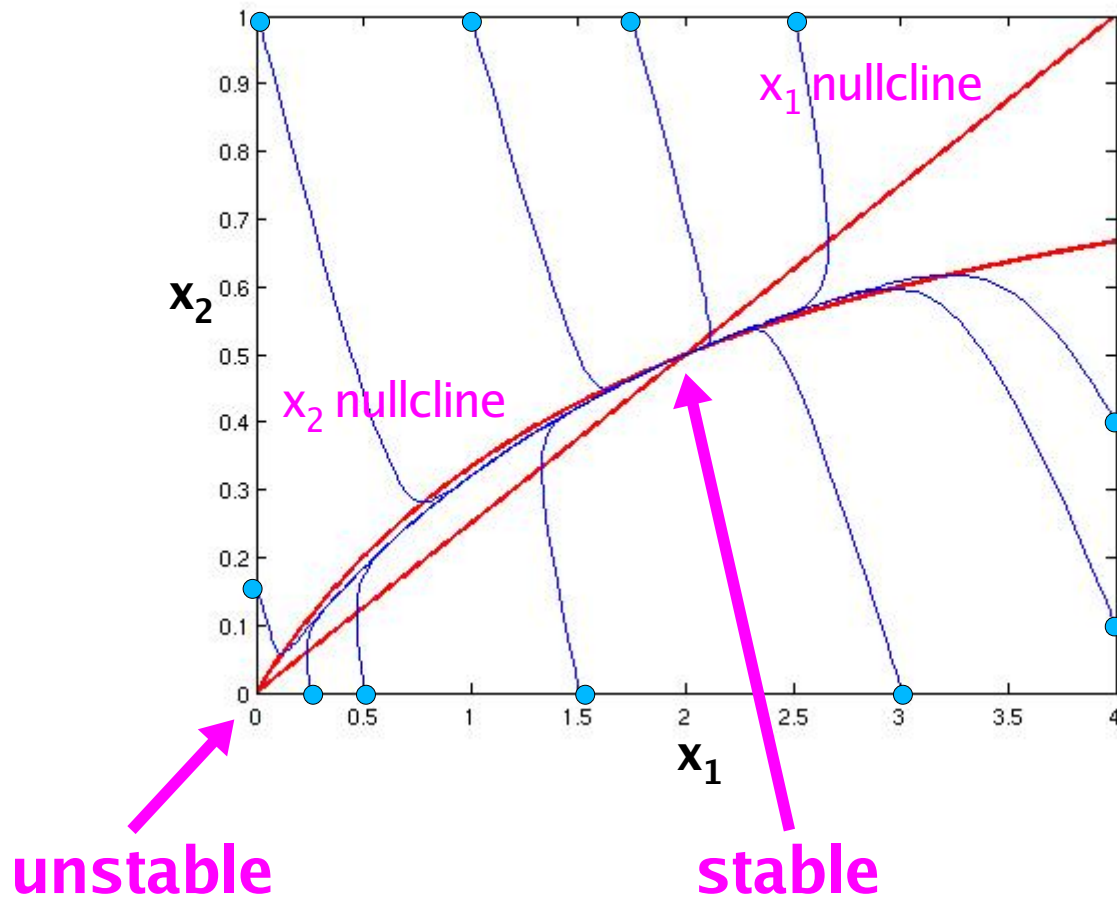


STABLE

x_2 nullcline lies above x_1 nullcline
both in the positive quadrant



UNSTABLE



LINEARISATION THEOREM

in n dimensions the dynamics of

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

is **qualitatively similar** to that of its linearisation

$$\frac{dx}{dt} = \left[(Df)|_{x=x_{st}} \right] x$$

Jacobian of f at $x = x_{st}$

in the **local vicinity** of a steady state $x = x_{st}$

provided that none of the eigenvalues of the Jacobian matrix

$$\left[(Df)|_{x=x_{st}} \right]$$

are 0

$$\frac{dx}{dt} = f(x) \quad \text{with steady state at } x = x_{st}$$

1 dimensional

$$a = \left. \left(\frac{df}{dx} \right) \right|_{x=x_{st}}$$

$$dx/dt = ax$$

$$x(t) = \exp(at)x_0$$

$$\exp(a) = 1 + a + a^2/2 + a^3/3! + \dots$$

exponential

$$\exp(a+b) = \exp(a)\exp(b)$$

$n > 1$ dimensional

$$A = (Df)|_{x=x_{st}}$$

$$dx/dt = Ax$$

$$x(t) = \exp(At)x_0$$

$$\exp(A) = I + A + A^2/2 + A^3/3! + \dots$$

matrix exponential

$$\exp(A+B) = \exp(A).\exp(B)$$

provided $AB = BA$