

# Tutorial: non-linear dynamics

Winter School on Quantitative Systems Biology:  
Quantitative Approaches in Ecosystem Ecology

Leonardo Pacciani-Mori (University of Padua, Italy)  
November 30th and December 1st, 2020



The Abdus Salam  
**International Centre  
for Theoretical Physics**

# Structure of the tutorial



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- Introduction: why is non-linearity interesting?
  - Examples of non-linearity in ecology

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  - Lyapunov functions
  - Spectral analysis

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## Important

The aim of these tutorials is also to encourage discussion: *please* *don't hesitate to interrupt me and ask questions* if you have them!!!





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## Why are nLDE important?

Every interesting and/or non-trivial phenomenon is described by nLDE.

# Introduction

## Examples



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- 2 Navier-Stokes equations ( $\rightarrow$  fluid dynamics). For an incompressible fluid:

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4 Lotka-Volterra equations:

$$\dot{x} = \alpha x - \beta xy \quad (6a)$$

$$\dot{y} = \delta xy - \gamma y \quad (6b)$$

where:

$x > 0 \rightarrow$  prey's population,  $y > 0 \rightarrow$  predator's population;  $\alpha > 0 \rightarrow$  prey's growth rate,  $\beta > 0 \rightarrow$  predation rate,  $\delta > 0 \rightarrow$  predator's growth rate,  $\gamma > 0 \rightarrow$  predator's death rate.

If written as  $\dot{\vec{z}} = f(\vec{z})$ , with  $\vec{z} = (x, y)$ ,  $f(\vec{z})$  is non-linear.





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(there is no theorem that can help us in general)

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- An equilibrium  $x^*$  is said to be **unstable** if there are solutions  $x(t)$  with  $x_0 = x(0)$  “close enough” to  $x^*$  which go “away” from  $x^*$

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There are several ways we can do so. A very simple yet useful one is drawing *stream plots*, i.e. drawing trajectories of the system in the state space.



Let's see how to do this in a particular case:

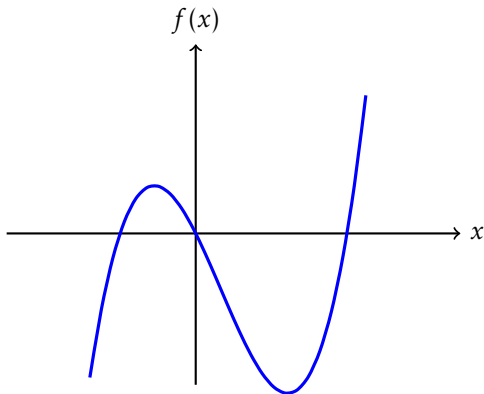
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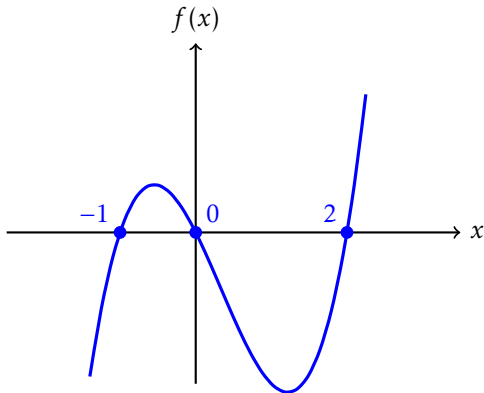
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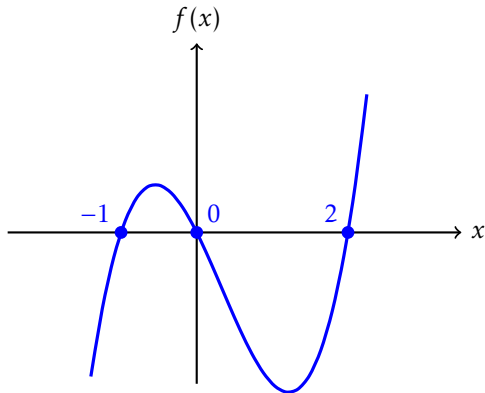
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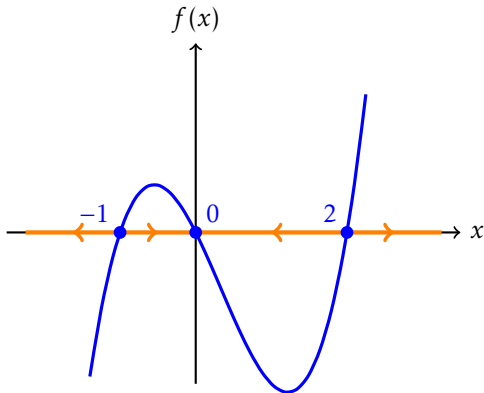
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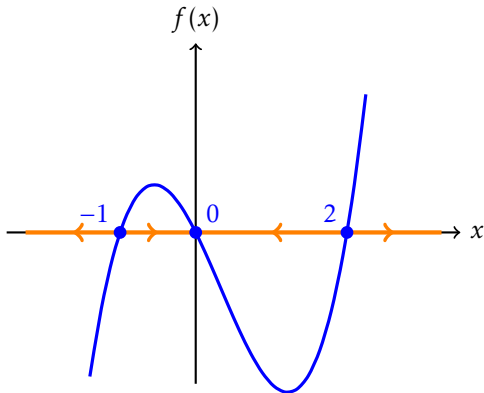
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We can get a sense of which equilibria are stable and which are unstable:

$x^* = 0 \rightarrow$  stable;  $x^* = -1, x^* = 2 \rightarrow$  unstable.



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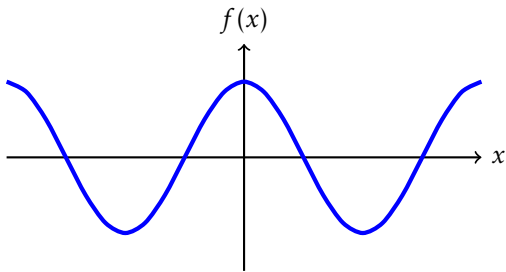
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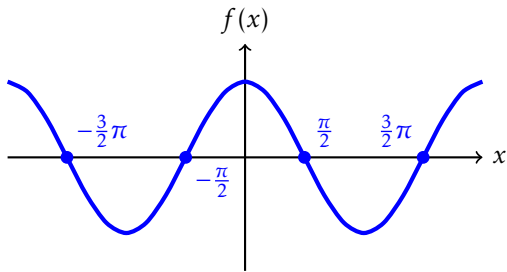
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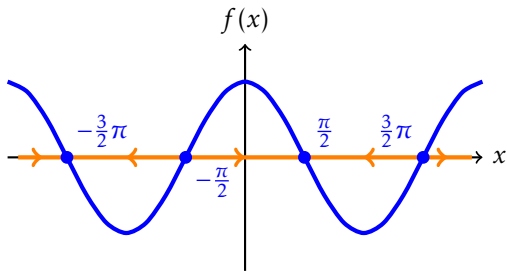
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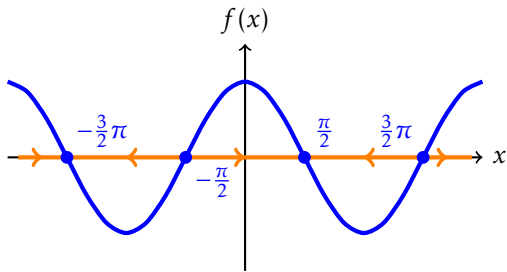
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$k$  even and  $x^* > 0$ , or  $k$  odd and  $x^* < 0 \rightarrow$  stable;  
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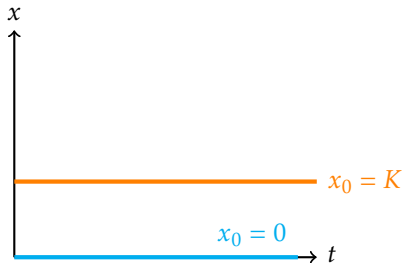
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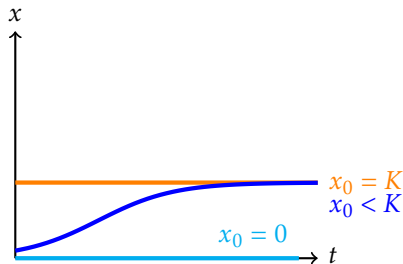
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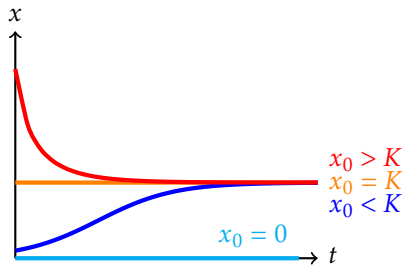
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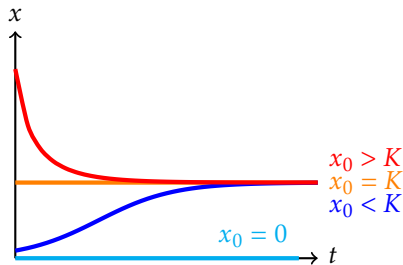
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The maximal population that the system can sustain is  $K$  ( $\rightarrow$  carrying capacity).

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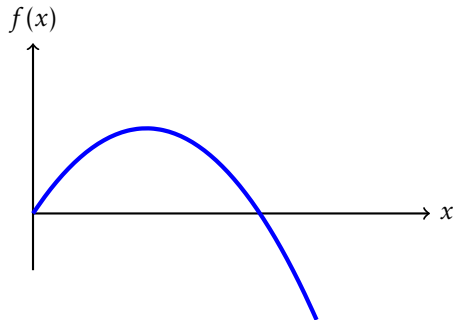


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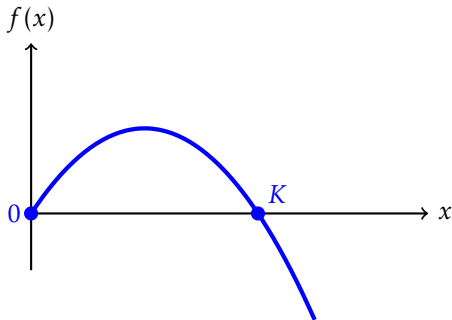
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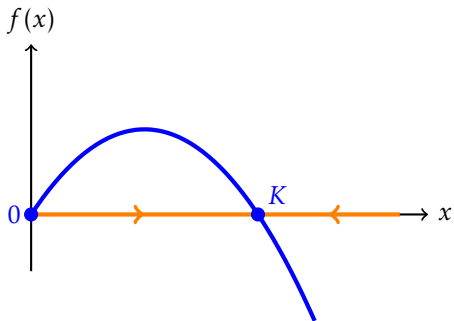
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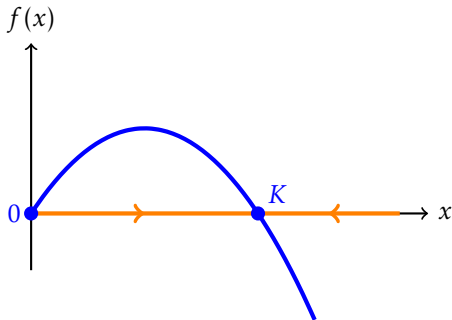
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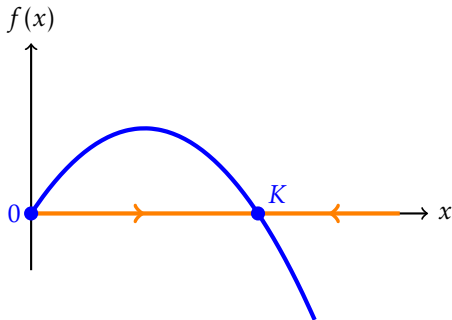
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$x^* = 0 \rightarrow$  unstable;  $x^* = K \rightarrow$  stable.

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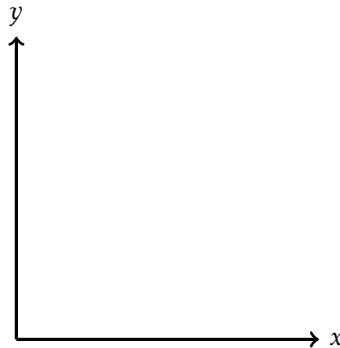
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## Conclusion

We have indeed recovered the same behavior!

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$$\begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix} = \begin{pmatrix} \alpha x - \beta xy \\ \delta xy - \gamma y \end{pmatrix} := f \begin{pmatrix} x \\ y \end{pmatrix}, \quad \begin{matrix} x, y > 0 \\ \alpha, \beta, \gamma, \delta > 0 \end{matrix} \quad (16)$$

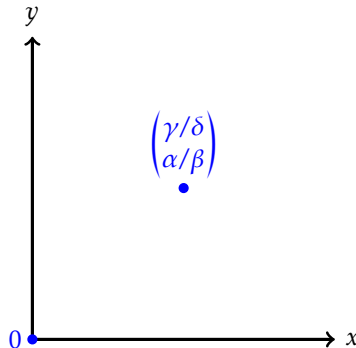


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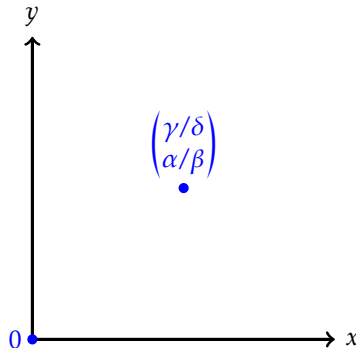
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We can see immediately that:

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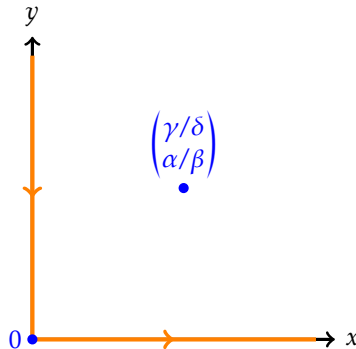
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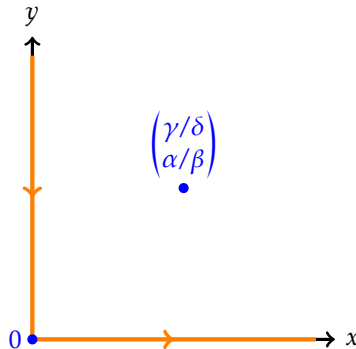
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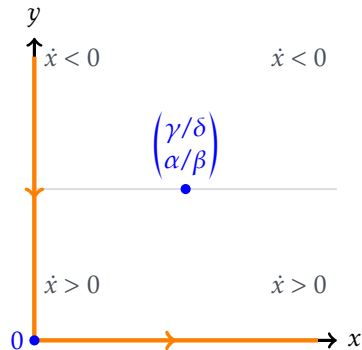
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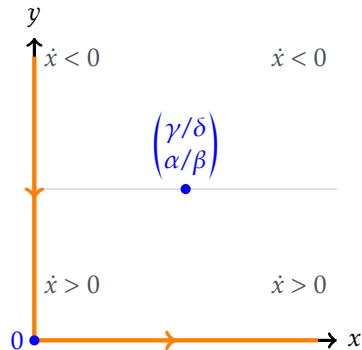
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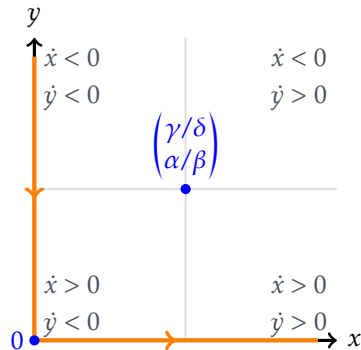
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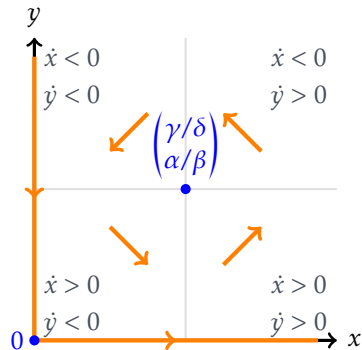
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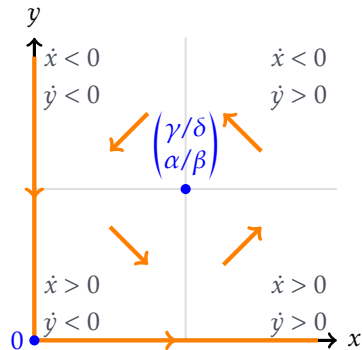
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The trajectories oscillate around the equilibrium  $(\gamma/\delta, \alpha/\beta)$ !



# Stability in non-linear systems



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There are two possible approaches:

- Using Lyapunov functions
- Spectral analysis

# Some formal definitions



Let  $x^*$  be an equilibrium for the system  $\dot{x} = f(x)$ , with  $x \in \mathbb{R}^n$  and  $f : \mathcal{D} \subset \mathbb{R}^n \rightarrow \mathbb{R}^n$  is continuous.

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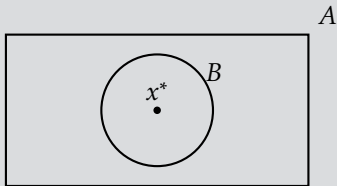
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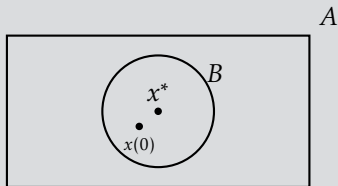
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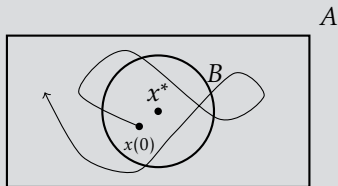




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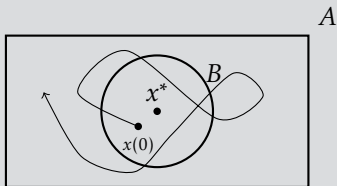
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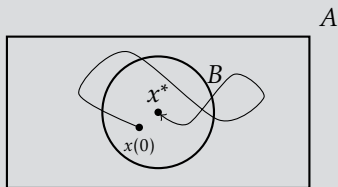


If  $x^*$  is stable not only  $\forall t \geq 0$ , but  $\forall t \in \mathbb{R}$ ,  $x^*$  is said to be **stable at all times**.

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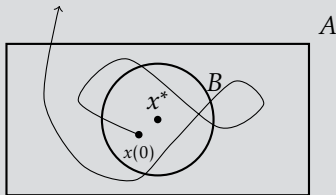
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# Lyapunov functions

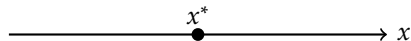


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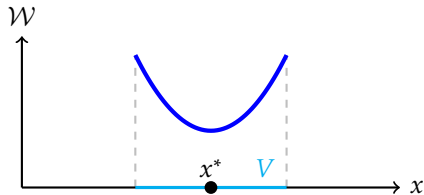
The principle behind this approach is the following:

- Assume we have a system  $\dot{x} = f(x)$  and  $x^*$  is an equilibrium



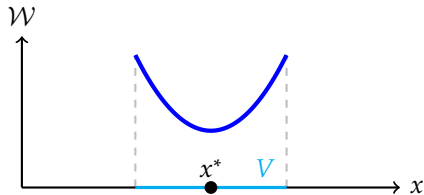
The principle behind this approach is the following:

- Assume we have a system  $\dot{x} = f(x)$  and  $x^*$  is an equilibrium
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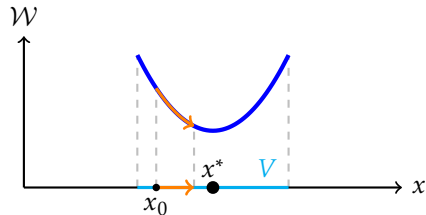
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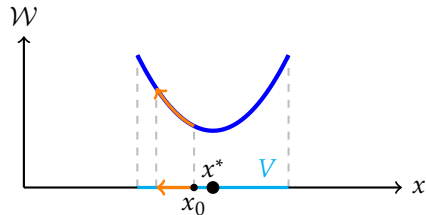
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  - if  $\mathcal{W}(x(t))$  decreases, i.e.  $\dot{\mathcal{W}} < 0$ ,  $x(t)$  will move towards  $x^*$ , so  $x^*$  is asymptotically stable



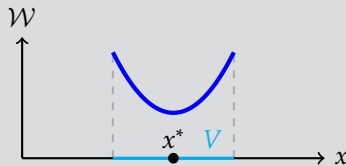
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  - if  $\mathcal{W}(x(t))$  increases, i.e.  $\dot{\mathcal{W}} > 0$ , then  $x(t)$  will move away from  $x^*$ , and so  $x^*$  is unstable



## Lyapunov's second theorem

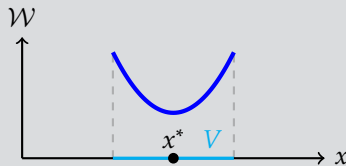
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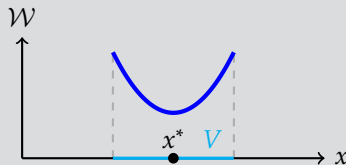
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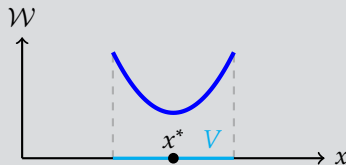




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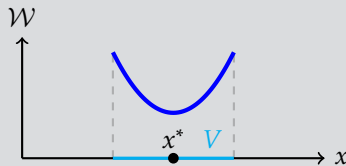
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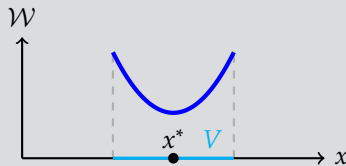
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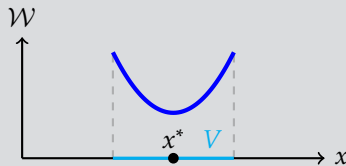


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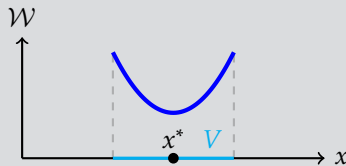
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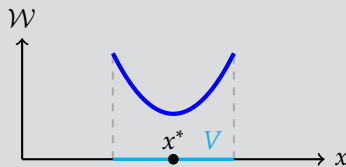
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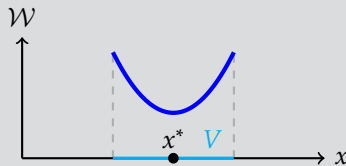
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- This method can give a lot of information on equilibria
- It only gives sufficient and not necessary conditions for (in)stability: an equilibrium can be (un)stable without having a Lyapunov function
- It is not always easy to find Lyapunov functions (exception: conserved quantities)

# Lyapunov functions

Example



The Abdus Salam  
International Centre  
for Theoretical Physics



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## Important

There is no “general recipe” to find a system's Lyapunov function!

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## Conclusion

The equilibrium  $(\gamma/\delta, \alpha/\beta)$  of the Lotka-Volterra equations is ***stable at all times***.

We can't say anything on the equilibrium  $(0, 0)$ .

# Lyapunov functions

## Example



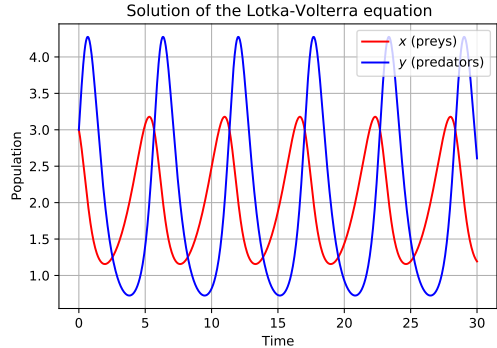
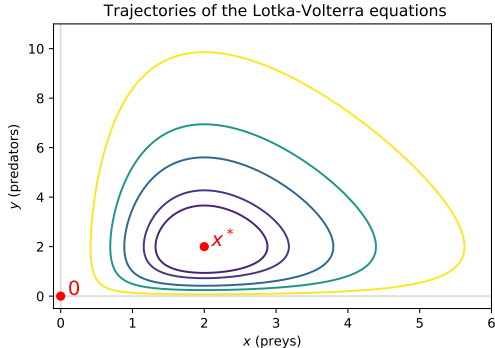
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Let's take a look at the trajectories of the Lotka-Volterra equations:



$$x_0 = y_0 = 3$$

Simulations with  $\alpha = 2/3$ ,  $\beta = 1/3$ ,  $\gamma = 2$ ,  $\delta = 1$ .



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The eigenvalues of the jacobian matrix give us valuable information on the stability of  $x^*$ .



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## Marginal stability

An equilibrium is said to be *marginally stable* if it is neither asymptotically stable nor unstable.

## Lyapunov's first theorem

Let  $x^*$  be an equilibrium of the non-linear system  $\dot{x} = f(x)$ ,  $x \in \mathbb{R}^n$ . Then:

- 1 All eigenvalues of  $J$  have negative real part  $\Rightarrow x^*$  is ***asymptotically stable***
- 2 At least *one* eigenvalue of  $J$  has positive real part  $\Rightarrow x^*$  is ***unstable***

## Pros and cons

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# Spectral analysis

## Examples



The Abdus Salam  
International Centre  
for Theoretical Physics

Let's see a couple of general examples.

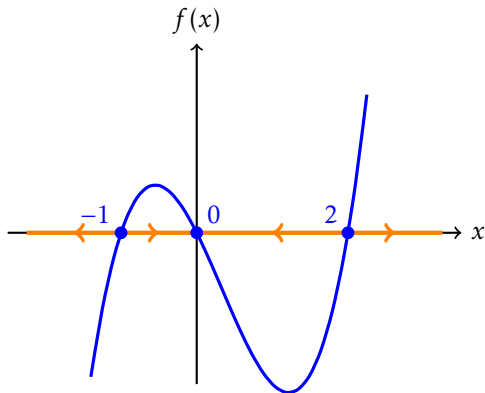
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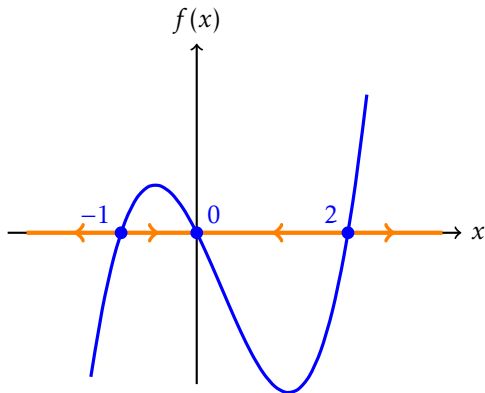
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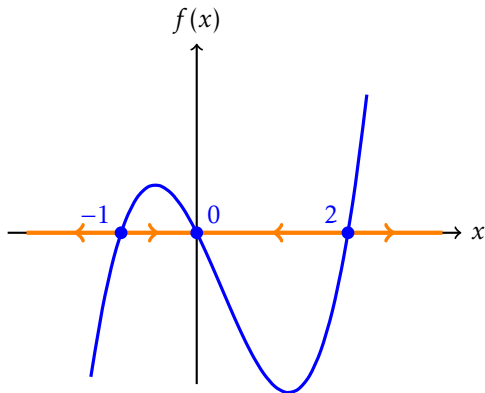
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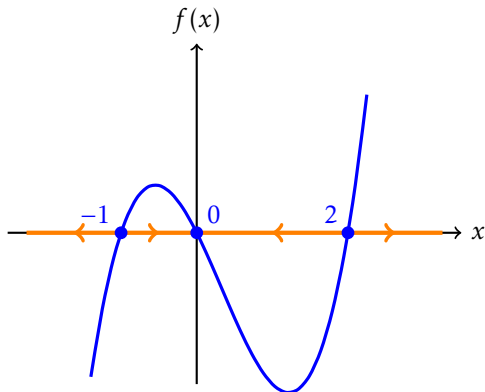
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Therefore:

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$$x^* = 0 \rightarrow \text{asymptotically stable}$$

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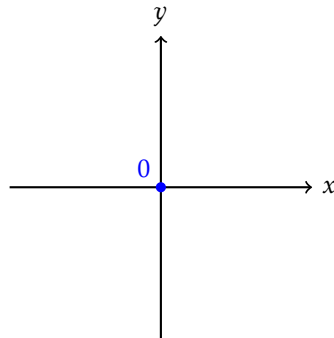
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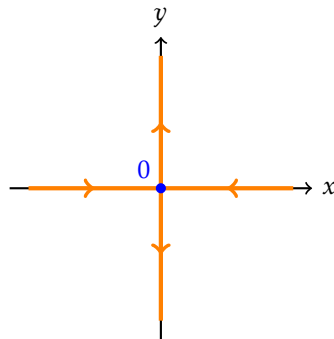
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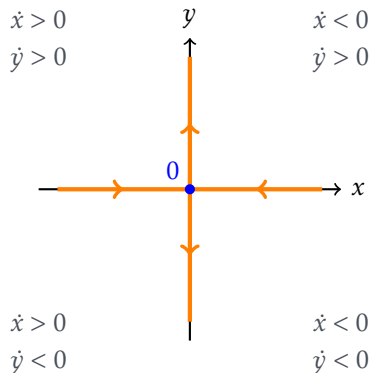
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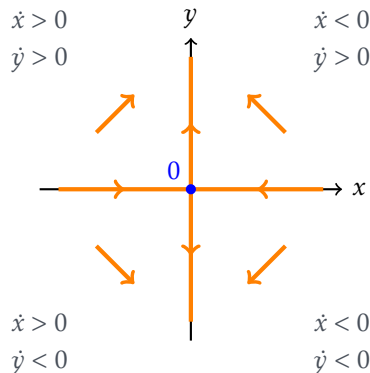
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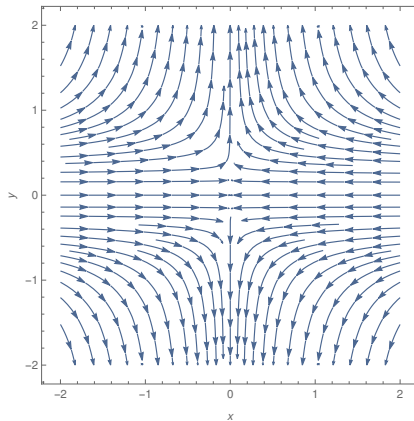
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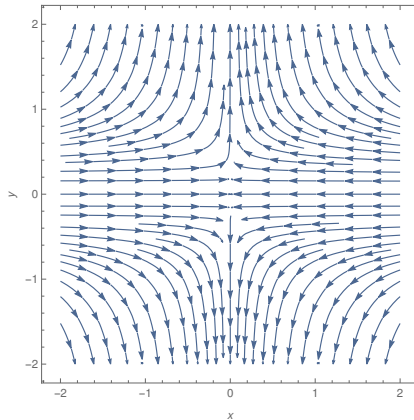
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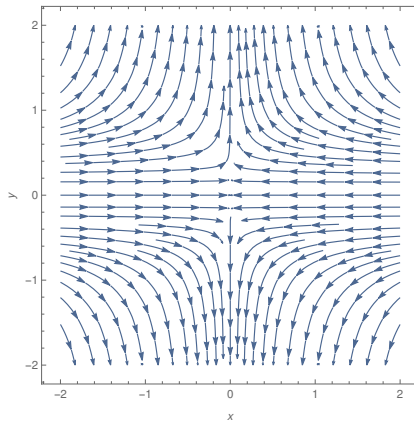
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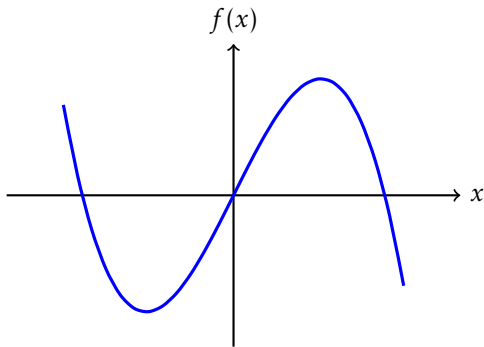
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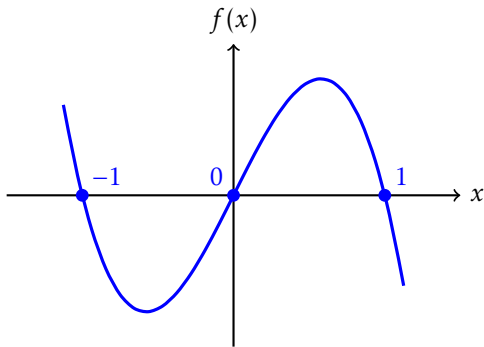


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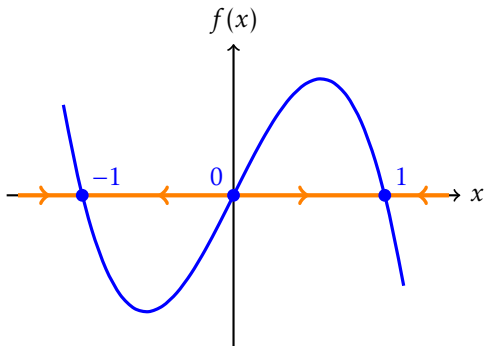


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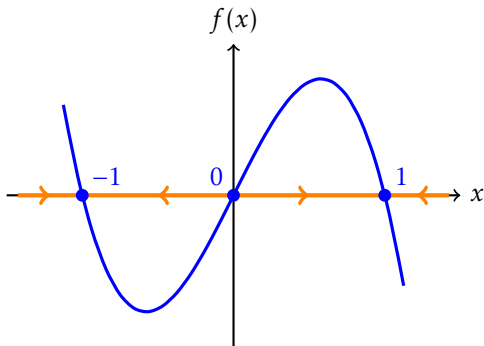
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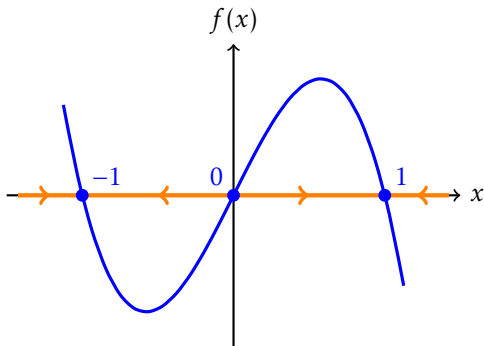
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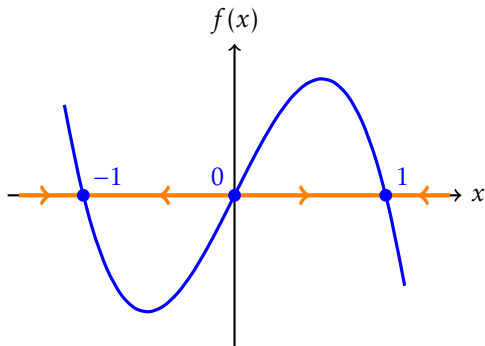
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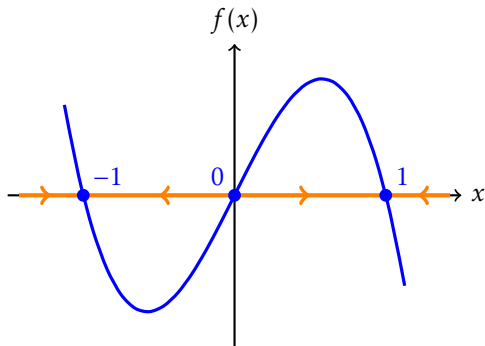
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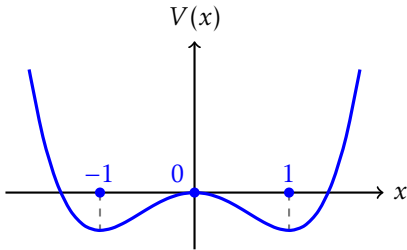
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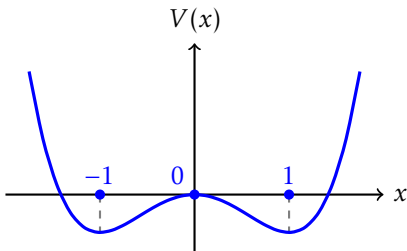
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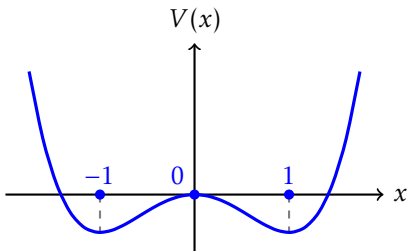
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External perturbations can move the system from one equilibrium to the other.

# Timescale separation



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## Notice

The validity of this approach depends on the system considered. We need some phenomenological knowledge on the system to justify this separation of timescales.

# Timescale separation

## Examples



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# Timescale separation

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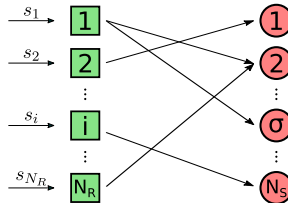
# Timescale separation

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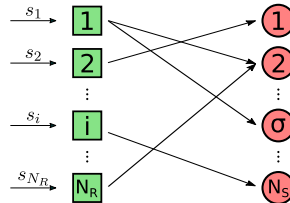
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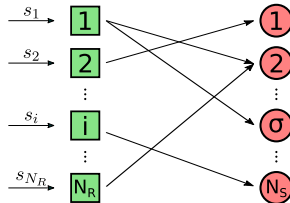
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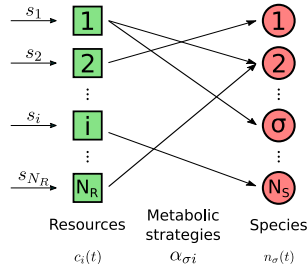
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The equations of the model are:

$$\dot{n}_\sigma = n_\sigma \left( \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} r_i(c_i) - \delta_\sigma \right) \quad \dot{c}_i = s_i - \sum_{\sigma=1}^{N_S} n_\sigma \alpha_{\sigma i} r_i(c_i) \quad (41)$$

where:

$$r_i(c_i) = \frac{c_i}{c_i + K_i} \quad \text{and} \quad \sigma = 1, \dots, N_S \quad \text{and} \quad i = 1, \dots, N_R \quad (42)$$

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We can therefore describe the system using only the species' populations.

# Timescale separation

## Examples

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If we apply again the separation of timescales so that  $c_i$  are the fast variables:

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Substituting in  $n_\sigma$  and [rearranging](#), we get:

$$\dot{n}_\sigma = n_\sigma \lambda_\sigma \left( 1 - \sum_{\rho=1}^{N_S} \beta_{\rho\sigma} n_\rho \right) \quad \text{where:} \quad \lambda_\sigma = \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma \quad \beta_{\rho\sigma} = \frac{1}{\lambda_\sigma} \sum_{i=1}^{N_R} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \quad (47)$$

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$$\dot{c}_i = 0 \quad \Rightarrow \quad c_i = Q_i \left( 1 - \frac{1}{g_i} \sum_{\sigma=1}^{N_S} n_\sigma \alpha_{\sigma i} \right) \quad (46)$$

Substituting in  $n_\sigma$  and **rearranging**, we get:

$$\dot{n}_\sigma = n_\sigma \lambda_\sigma \left( 1 - \sum_{\rho=1}^{N_S} \beta_{\rho\sigma} n_\rho \right) \quad \text{where:} \quad \lambda_\sigma = \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma \quad \beta_{\rho\sigma} = \frac{1}{\lambda_\sigma} \sum_{i=1}^{N_R} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \quad (47)$$

These are called *generalized Lotka-Volterra equations*.



# That's all!

Questions?



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Backup slides



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# Solution of the logistic equation

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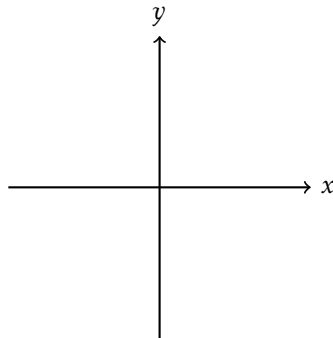
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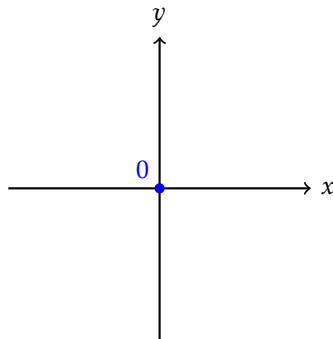
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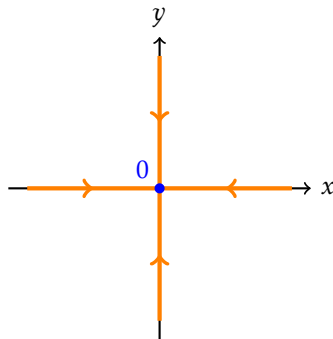
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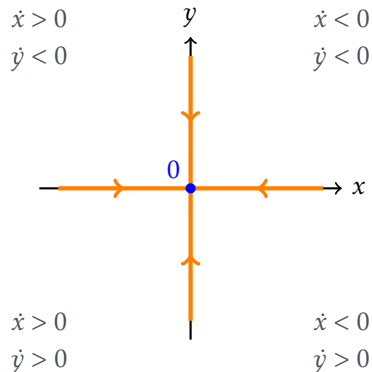
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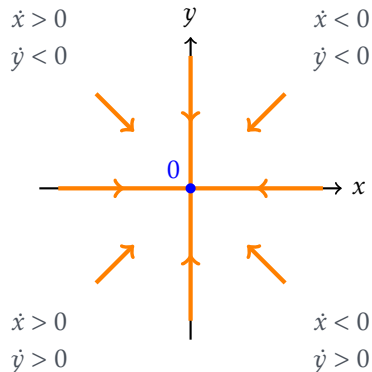
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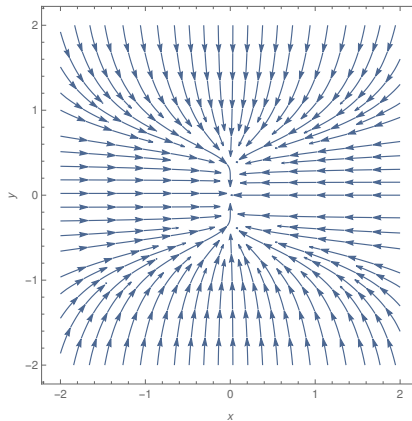
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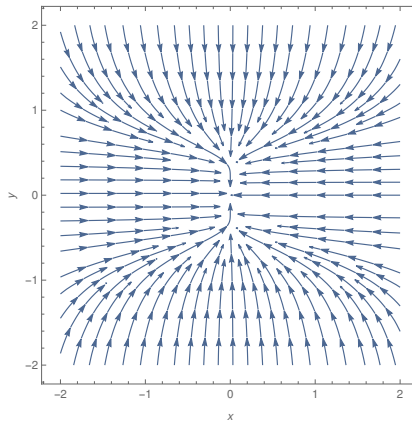
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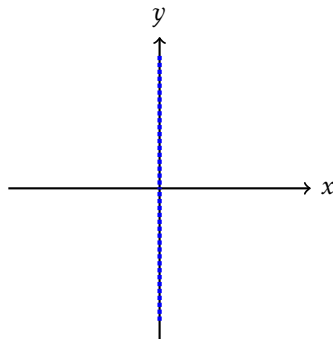
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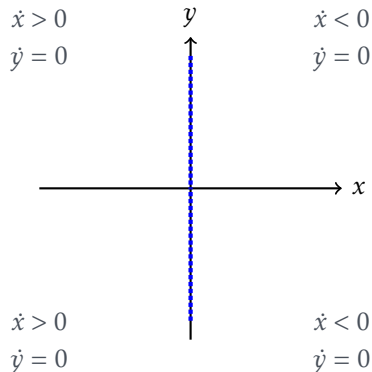
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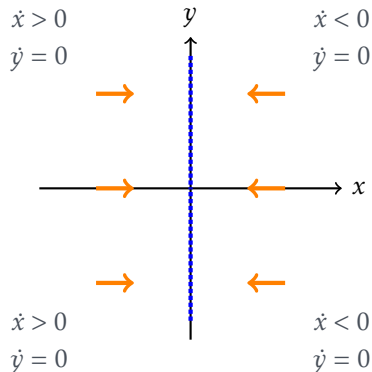
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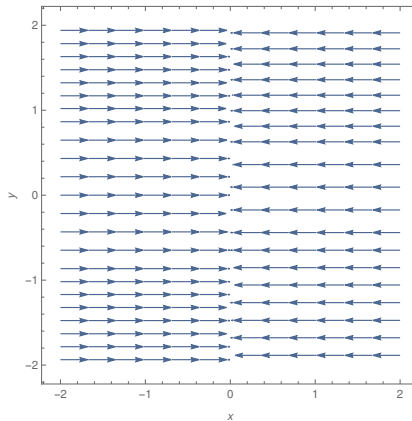
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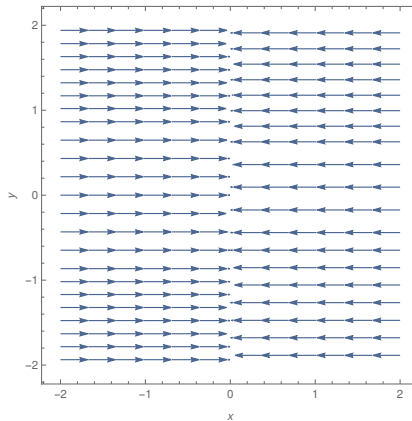
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# The consumer-resource model



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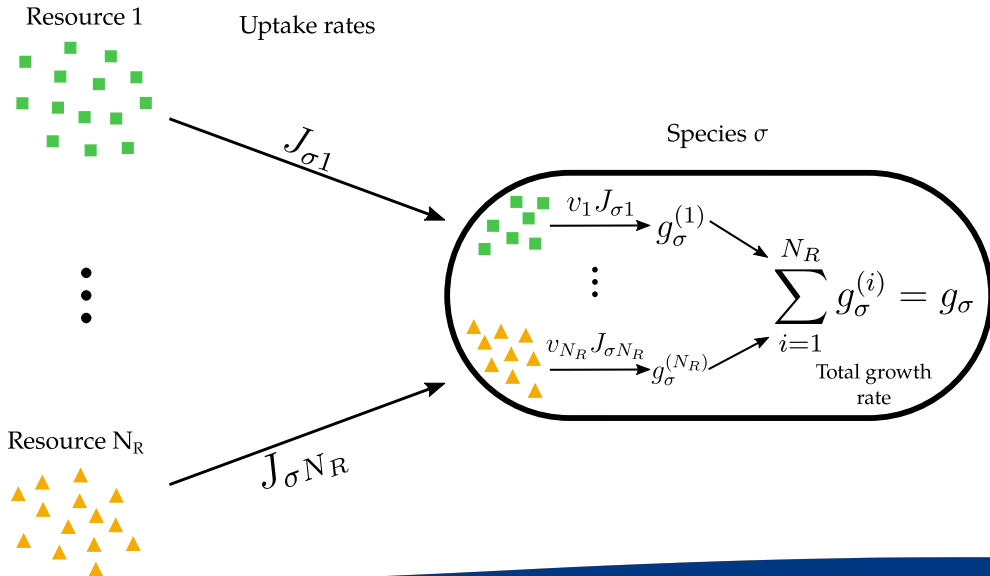
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Therefore:

$$\dot{n}_\sigma = n_\sigma \left( \sum_{i=1}^{N_R} v_i J_{\sigma i} - \delta_\sigma \right) \qquad \dot{c}_i = s_i - \sum_{\sigma=1}^{N_S} J_{\sigma i} n_\sigma \qquad (55)$$

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Alternatively, we can assume  $J_{\sigma i} = \alpha_{\sigma i} c_i$ , but we need a logistic term instead of  $s_i$  to limit the uptake rates:

$$\dot{n}_{\sigma} = n_{\sigma} \left( \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} c_i - \delta_{\sigma} \right) \quad \dot{c}_i = g_i c_i \left( 1 - \frac{c_i}{Q_i} \right) - \sum_{\sigma=1}^{N_S} n_{\sigma} \alpha_{\sigma i} c_i , \quad (58)$$



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Substituting in  $\dot{n}_\sigma$ :

$$\begin{aligned}
 \dot{n}_\sigma &= \left( \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} \frac{Q_i}{g_i} \sum_{\rho=1}^{N_S} n_\rho \alpha_{\rho i} - \delta_\sigma \right) = \\
 &= n_\sigma \left( \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma \right) \left( 1 - \frac{1}{\sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma} \sum_{\rho=1}^{N_S} n_\rho \sum_{i=1}^{N_S} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \right) \quad (60)
 \end{aligned}$$

$$\dot{n}_\sigma = n_\sigma \left( \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma \right) \left( 1 - \frac{1}{\sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma} \sum_{\rho=1}^{N_S} n_\rho \sum_{i=1}^{N_S} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \right) \quad (61)$$

$$\dot{n}_\sigma = n_\sigma \left( \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma \right) \left( 1 - \frac{1}{\sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma} \sum_{\rho=1}^{N_S} n_\rho \sum_{i=1}^{N_S} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \right) \quad (61)$$

Then:

$$\lambda_\sigma := \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma$$

$$\dot{n}_\sigma = n_\sigma \left( \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma \right) \left( 1 - \frac{1}{\sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma} \sum_{\rho=1}^{N_S} n_\rho \sum_{i=1}^{N_S} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \right) \quad (61)$$

Then:

$$\lambda_\sigma := \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma \quad \Rightarrow \quad \dot{n}_\sigma = n_\sigma \lambda_\sigma \left( 1 - \frac{1}{\lambda_\sigma} \sum_{\rho=1}^{N_S} n_\rho \sum_{i=1}^{N_S} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \right) \quad (62)$$

$$\dot{n}_\sigma = n_\sigma \left( \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma \right) \left( 1 - \frac{1}{\sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma} \sum_{\rho=1}^{N_S} n_\rho \sum_{i=1}^{N_S} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \right) \quad (61)$$

Then:

$$\lambda_\sigma := \sum_{i=1}^{N_R} v_i \alpha_{\sigma i} Q_i - \delta_\sigma \quad \Rightarrow \quad \dot{n}_\sigma = n_\sigma \lambda_\sigma \left( 1 - \frac{1}{\lambda_\sigma} \sum_{\rho=1}^{N_S} n_\rho \sum_{i=1}^{N_S} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \right) \quad (62)$$

Finally:

$$\beta_{\rho\sigma} := \frac{1}{\lambda_\sigma} \sum_{i=1}^{N_S} v_i \frac{Q_i}{g_i} \alpha_{\sigma i} \alpha_{\rho i} \quad \Rightarrow \quad \dot{n}_\sigma = n_\sigma \lambda_\sigma \left( 1 - \sum_{\rho=1}^{N_S} \beta_{\rho\sigma} n_\rho \right) \quad (63)$$