



Dynamical modelling of biological networks

Claudine Chaouiya

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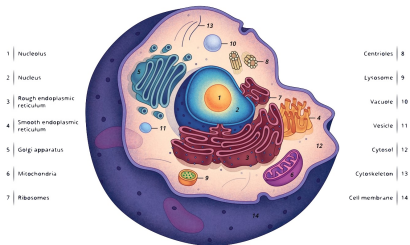
Master Bioinformatics - Marseille Luminy

November 2018

Cell: the structural and functional unit of life

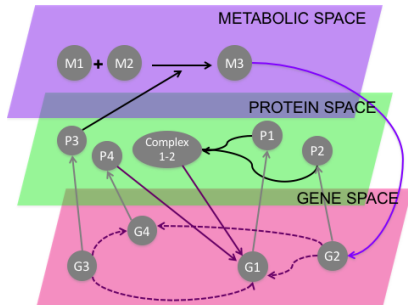
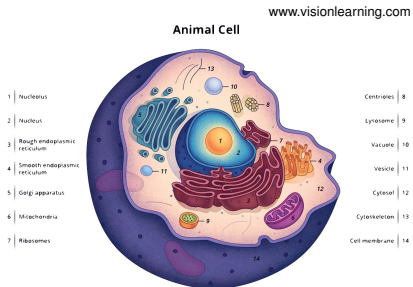
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Animal Cell



Cells are capable of numerous operations: Movement, Energy supply, Signalling, Growth, Division, Death, Decision making (differentiation), etc.

Cell: the structural and functional unit of life



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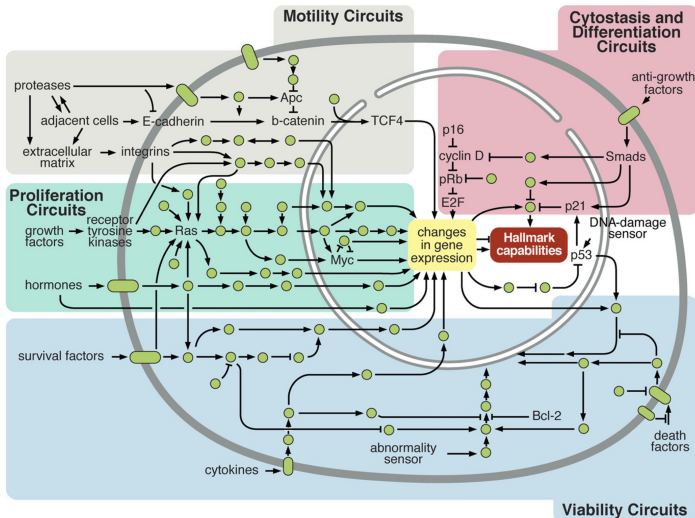
Heterogeneous interaction networks control and drive these operations

→ mostly focus on regulatory networks, *i.e.* interactions between genes and their products (proteins): transcriptional and post-transcriptional regulations

Cell: the structural and functional unit of life

Intracellular Signaling Networks Regulate the Operations of the Cancer Cell

Hanahan & Weinberg (2011) Cell, 144:646-74



Regulatory network modelling

→ *Use of mathematics to study how genes and proteins interact to produce the complex behaviors of a living cell? (J. Tyson)*

Aims

- Understand the role of individual components and interactions
- Suggest missing components and interactions
- Predict behaviours upon perturbations

Advantages of mathematical and computer tools

- Precise and unambiguous description of network
- *In silico* experiments are cheap and easy!
- A computational model is a generator of predictions

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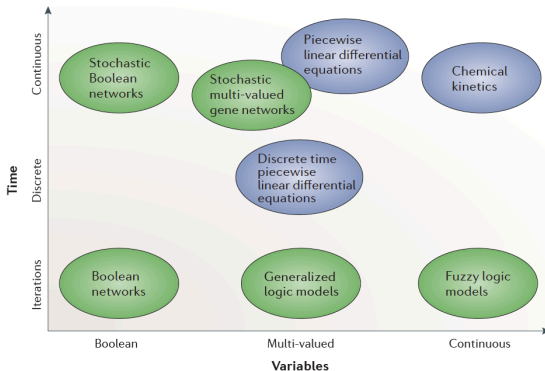
Static vs dynamical models of biological networks

- Static models → topology of the networks (nodes and edges)
- Dynamical models → dynamics of the variables associated with the network nodes (nodes, edges, functions)

Regulatory network modelling

Plenty of modelling frameworks, spanning different levels of details, e.g.

- Logical models
- Petri nets
- Process algebras
- Constraint-based models
- Ordinary differential equations (ODEs)
- Stochastic master equations
- ...



- Concentration of proteins, mRNAs, and other molecules at time-point t represented by continuous variable $x_i(t) \in IR^+$ (concentration level for individual cell or cell population)
- Regulatory interactions, controlling synthesis and degradation, modelled by ODEs

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

where $x = [x_1, \dots, x_n]$, and $f(x)$ is a **rate law**

- Well-established theory for modeling gene regulatory networks using ODE models \rightarrow Mathematical specification of rate laws

Text books

Cornish-Bowden (1995), Fundamentals of Enzyme Kinetics, Portland Press

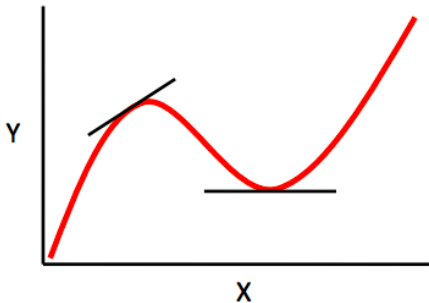
Heinrich and Schuster (1996), The Regulation of Cellular Systems, Chapman & Hall

Interlude!

adapted from E. Gjini

Mathematical equations used to study time-dependent processes

- A *differential equation* is an algebraic equation involving the function and its derivatives
- A *derivative* is a function representing the change of a dependent variable with respect to an independent variable (slope of a curve)
 - . Large derivative: fast change
 - . Small derivative: slow change
 - . Zero derivative: no change
 - . Positive derivative: $Y \uparrow$ if $x \uparrow$
 - . Negative derivative: $Y \downarrow$ if $x \uparrow$



Ordinary differential equation models

Interlude!

adapted from E. Gjini

$Y(t)$: quantity of interest (the dependent variable)
e.g. concentration of a given molecule at time t
or level of expression of a gene at time t

A continuous function of time t (the independent variable)

The change of Y per unit of time : dY/dt Defined by the limit process:

$$\frac{dY}{dt} = \lim_{\Delta t \rightarrow 0} \frac{Y(t + \Delta t) - Y(t)}{\Delta t}$$

the derivative of Y with respect to time.

Interlude!

adapted from E. Gjini

Example of exponential growth: $Y(t)$, number of bacteria over time

r : growth rate of the population per unit of time

$$Y(t + dt) \simeq Y(t) + rY(t)dt$$

$$\frac{Y(t+dt)-Y(t)}{dt} \simeq rY(t)$$

$$\lim_{dt \rightarrow 0} \frac{Y(t+dt)-Y(t)}{dt} \simeq rY(t) \triangleq \frac{dY(t)}{dt} = rY(t)$$

Ordinary differential equation models

Interlude!

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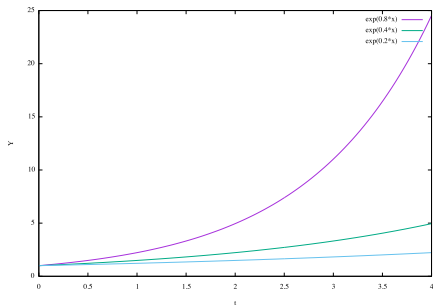
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solution: $Y(t) = Y_0 e^{rt}$



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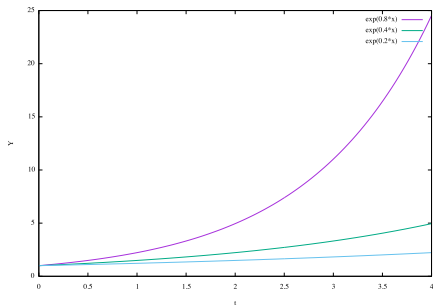
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How long to double the population? δ doubling time

Ordinary differential equation models

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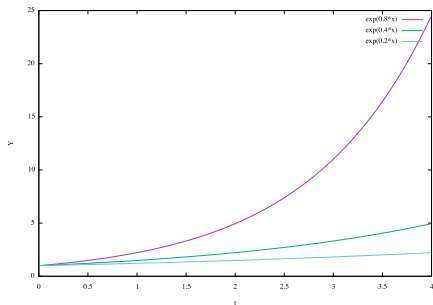
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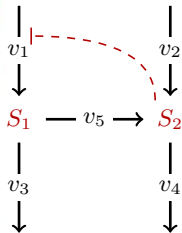
How long to double the population? δ doubling time $2Y_0 = Y_0 e^{r\delta} \Rightarrow \delta = \frac{\ln(2)}{r}$

Ordinary differential equation models

Example of a simple reaction network

adapted from B. Ingalls

Reaction rates follow mass action, production of S_1 allosterically inhibited with a strong cooperative binding of n molecules of S_2 ($s_i = [S_i]$):



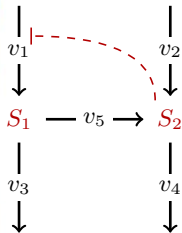
$$\begin{cases} v_1 = \frac{k_1}{1+(s_2/K)^n}, v_3 = k_3 s_1, v_5 = k_5 s_1 \\ v_2 = k_2, v_4 = k_4 s_2 \end{cases}$$

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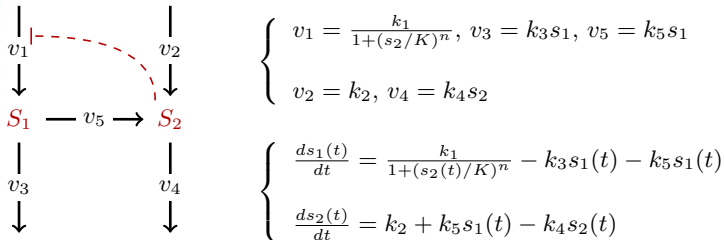
$$\left\{ \begin{array}{l} \frac{ds_1(t)}{dt} = \frac{k_1}{1+(s_2(t)/K)^n} - k_3 s_1(t) - k_5 s_1(t) \\ \frac{ds_2(t)}{dt} = k_2 + k_5 s_1(t) - k_4 s_2(t) \end{array} \right.$$

Ordinary differential equation models

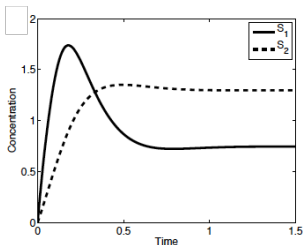
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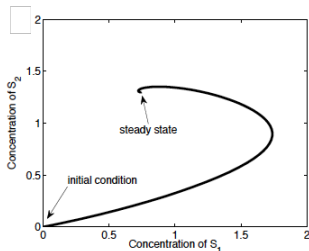
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(conc. time⁻¹) $k_1 = 20$, $k_2 = 5$, (conc.) $K = 1$, (time⁻¹) $k_3 = k_4 = 5$, $k_5 = 2$, and $n = 4$, arbitrary units



Concentrations plotted against time



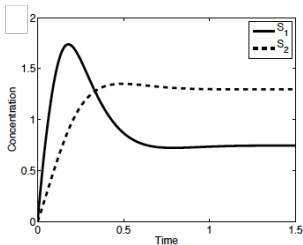
Concentration s_1 plotted against s_2 9/24

Ordinary differential equation models

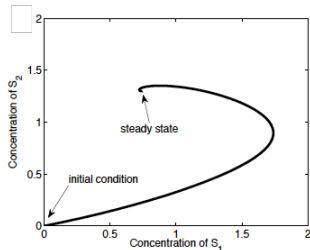
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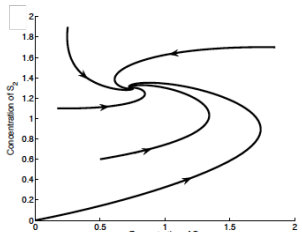
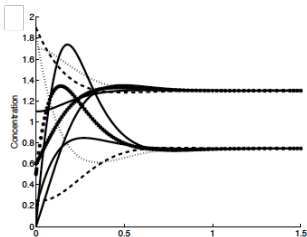
($\text{conc.} \cdot \text{time}^{-1}$) $k_1 = 20$, $k_2 = 5$, (conc.) $K = 1$, (time^{-1}) $k_3 = k_4 = 5$, $k_5 = 2$, and $n = 4$, arbitrary units



Concentrations plotted against time



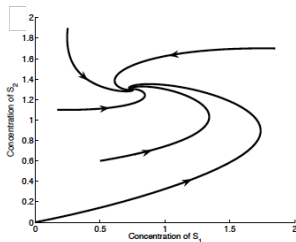
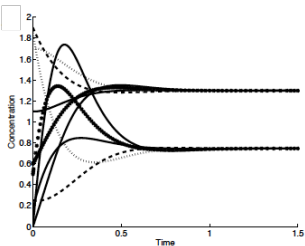
Concentration s_1 plotted against s_2
Phase portrait



Ordinary differential equation models

Example of a simple reaction network

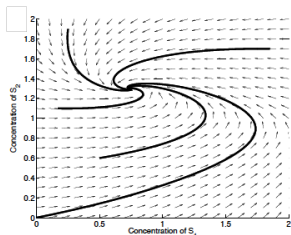
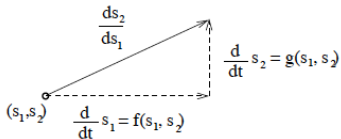
adapted from B. Ingalls



Phase portrait

$$\begin{cases} \frac{ds_1(t)}{dt} = f(s_1(t), s_2(t)) \\ \frac{ds_2(t)}{dt} = g(s_1(t), s_2(t)) \end{cases}$$

The motion in the phase plane at (s_1, s_2) is given by $(f(s_1, s_2), g(s_1, s_2))$



Direction field

Ordinary differential equation models

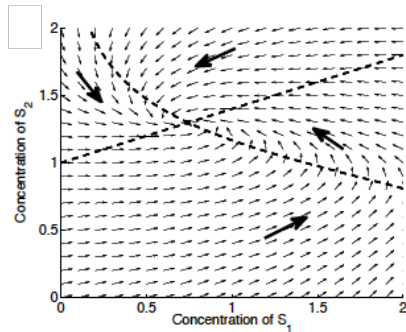
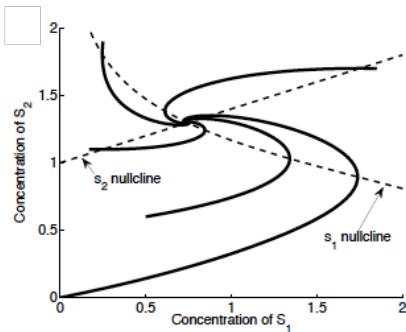
Example of a simple reaction network

adapted from B. Ingalls

The s_1 -nullcline (or zero-growth isocline) is the curve $\frac{ds_1}{dt} = 0$

The **steady state** (or fixed point) of the system is located where all of the nullclines intersect: $\frac{ds_1(t)}{dt} = \frac{ds_2(t)}{dt} = 0$

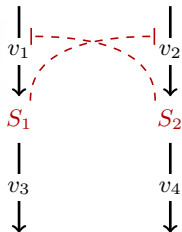
It is stable, because if we move a bit away, the system will return to it.



Ordinary differential equation models

Another case of a reaction network

adapted from B. Ingalls

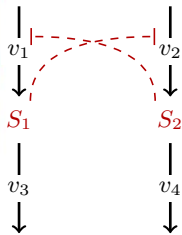


$$\left\{ \begin{array}{l} \frac{ds_1(t)}{dt} = \frac{k_1}{1+(s_2(t)/K_2)^{n_1}} - k_3 s_1(t) \\ \frac{ds_2(t)}{dt} = \frac{k_2}{1+(s_1(t)/K_1)^{n_2}} - k_4 s_2(t) \end{array} \right.$$

Ordinary differential equation models

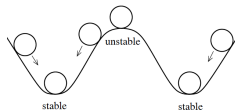
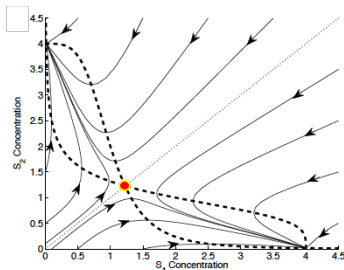
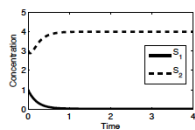
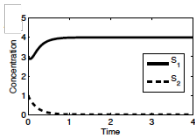
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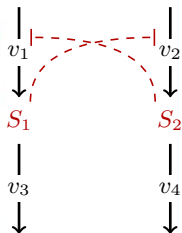
with **balanced** inhibition strength, $k_1 = k_2 = 20$, $K_1 = K_2 = 1$, $k_3 = k_4 = 5$, $n_1 = n_2 = 4$.



Ordinary differential equation models

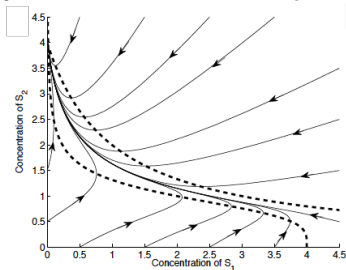
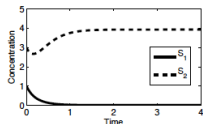
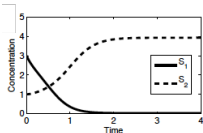
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with **unbalanced** inhibition strength, $k_1 = k_2 = 20$, $K_1 = K_2 = 1$, $k_3 = k_4 = 5$, $n_1 = 4$, $n_2 = 1$.



Exercise

from B. Ingalls

Consider the following system:

$$\begin{cases} \frac{dx(t)}{dt} = -y(t) \\ \frac{dy(t)}{dt} = x(t) \end{cases}$$

What are the nullclines? The steady state?

Sketch the direction field by drawing the direction vectors in the $x - y$ phase plane for $(1, 0)$, $(1, 1)$, $(0, 1)$, $(-1, 1)$, $(-1, 0)$, $(-1, -1)$, $(0, -1)$, $(1, -1)$.

Ordinary differential equation models

Exercise

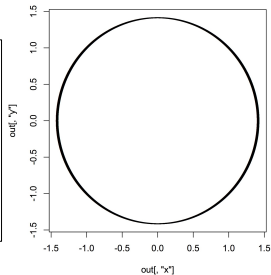
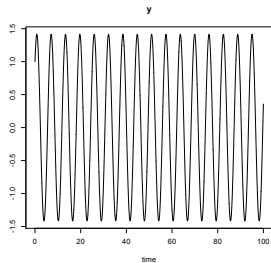
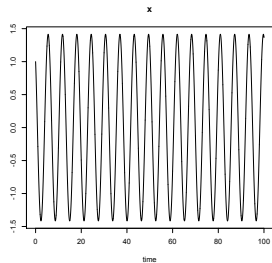
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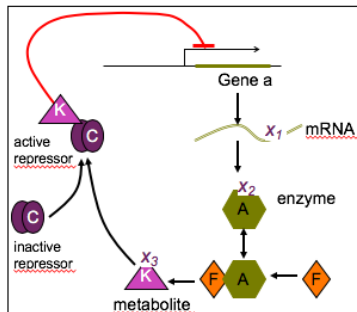
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Ordinary differential equation models

Example: ODE model of a genetic regulatory system w/ end-product inhibition

from H. de Jong

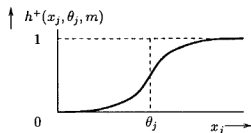


$$\begin{cases} \frac{dx_1}{dt} = \kappa_1 r(x_3) - \gamma_1 x_1 \\ \frac{dx_2}{dt} = \kappa_2 x_1 - \gamma_2 x_2 \\ \frac{dx_3}{dt} = \kappa_3 x_2 - \gamma_3 x_3 \end{cases}$$

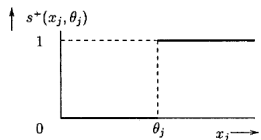
x_1 : concentration of mRNA
 x_2 : concentration of protein A
 x_3 : concentration of metabolite K
 κ_i : production constants
 γ_i : degradation constants
 r : a decreasing non-linear regulatory function ranging from 0 to 1

Genetic regulatory networks

Non linear regulatory functions



$$h^+(x, \theta, m) = \frac{x^m}{x^m + \theta^m}$$

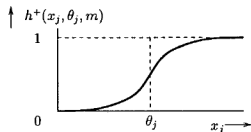


$$\begin{aligned} x < \theta, s^+(x, \theta) &= 0 \\ x > \theta, s^+(x, \theta) &= 1 \end{aligned}$$

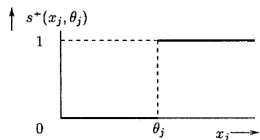
Ordinary differential equation models

Genetic regulatory networks

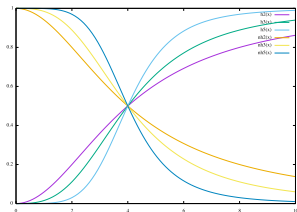
Non linear regulatory functions



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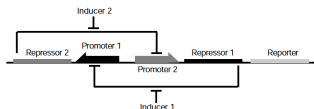


$$x < \theta, s^+(x, \theta) = 0$$
$$x > \theta, s^+(x, \theta) = 1$$



Exercise: Give the expression for the inhibitory Hill function
What is the effect when increasing m ?
 m is called the cooperativity parameter

Genetic regulatory networks: the toggle switch



Toggle switch design: Repressor 1 inhibits transcription from Promoter 1 and is induced by Inducer 1. Repressor 2 inhibits transcription from Promoter 2 and is induced by Inducer 2.

$$\frac{du}{dt} = \frac{\alpha_1}{1+v^\beta} - u$$

$$\frac{dv}{dt} = \frac{\alpha_2}{1+u^\gamma} - v$$

- u concentration of rep. 1
- v concentration of rep. 2
- α_1 rate of synthesis of rep. 1
- α_2 rate of synthesis of rep. 2
- β cooperativity of repression of prom. 2
- γ cooperativity of repression of prom. 1

Genetic regulatory networks: the toggle switch

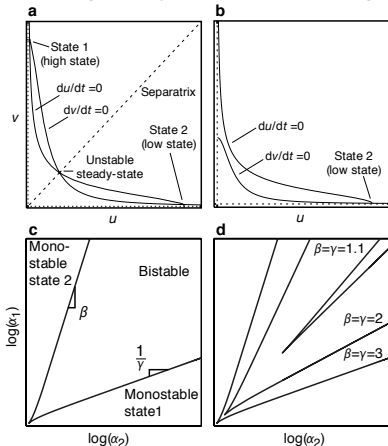
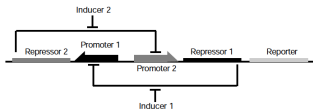


Figure 2 Geometric structure of the toggle equations. **a**, A bistable toggle network with balanced promoter strengths. **b**, A monostable toggle network with imbalanced promoter strengths. **c**, The bistable region. The lines mark the transition (bifurcation) between bistability and monostability. The slopes of the bifurcation lines are determined by the exponents β and γ for large α_1 and α_2 . **d**, Reducing the cooperativity of repression (β and γ) reduces the size of the bistable region. Bifurcation lines are illustrated for three different values of β and γ . The bistable region lies inside of each pair of curves.



Toggle switch design: Repressor 1 inhibits transcription from Promoter 1 and is induced by Inducer 1. Repressor 2 inhibits transcription from Promoter 2 and is induced by Inducer 2.

$$\frac{du}{dt} = \frac{\alpha_1}{1+v^\beta} - u$$

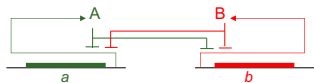
$$\frac{dv}{dt} = \frac{\alpha_2}{1+u^\gamma} - v$$

- u concentration of rep. 1
- v concentration of rep. 2
- α_1 rate of synthesis of rep. 1
- α_2 rate of synthesis of rep. 2
- β cooperativity of repression of prom. 2
- γ cooperativity of repression of prom. 1

Ordinary differential equation models

Exercise: ODE model of a genetic cross-inhibition

adapted from H. de Jong



Can you devise the remaining model equations?

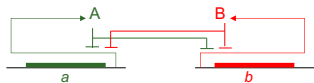
$$\left\{ \begin{array}{l} \frac{dx_{ra}}{dt} = \kappa_{ra} h_2^-(x_{pb}, \theta_{pb}) h_2^-(x_{pa}, \theta_{pa}) - \gamma_{ra} x_{ra} \\ \frac{dx_{pa}}{dt} = \\ \frac{dx_{rb}}{dt} = \\ \frac{dx_{pb}}{dt} = \end{array} \right.$$

$$h_2^-(x, \theta) = \frac{\theta^2}{x^2 + \theta^2}$$

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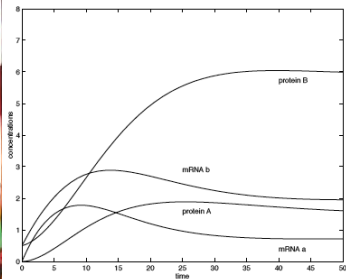
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Ordinary differential equation models

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- ODEs are valid for homogeneous systems and large numbers of molecules
- Stochasticity arises due to the small number of molecules
- Consider discrete amounts of molecules, homogeneous system, no spatial restrictions

β_j : transition probability that reaction j brings the system to state X ,

α_j : transition probability to leave state X with the occurrence of reaction j

the master equation gives the evolution of X

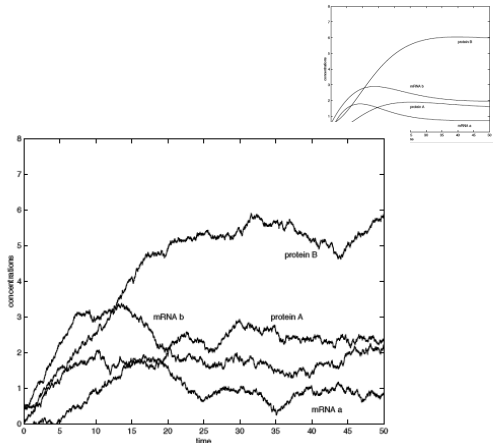
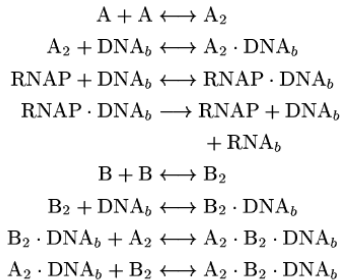
$$\frac{\delta}{\delta t} p(X, t) = \sum_{j=1}^m (\beta_j - \alpha_j p(X, t)).$$

hard to solve \rightarrow stochastic simulation algorithm (Gillespie 77)

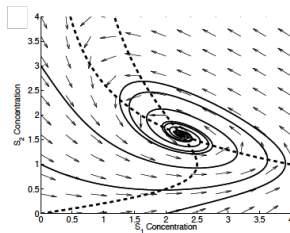
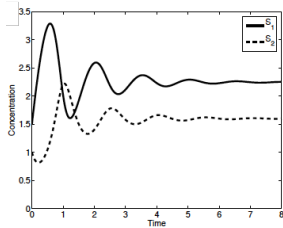
A note on stochastic models

adapted from H. de Jong

Kierzek et al. 2001 proposed 10 elementary reactions for the transcription and translation of a prokaryotic gene



Oscillatory behaviours

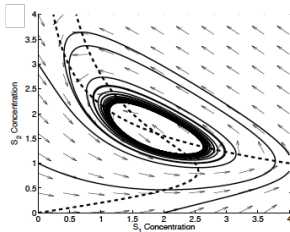
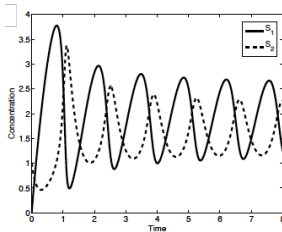
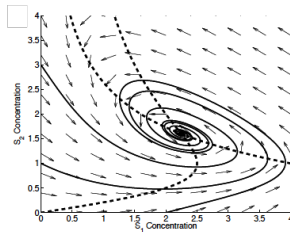
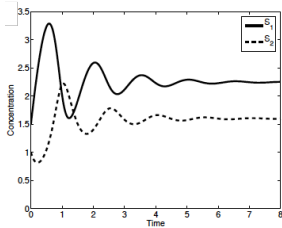


from B. Ingalls

Ordinary differential equation models

Oscillatory behaviours

from B. Ingalls



A note on bifurcation analysis

from B. Ingalls

- Variation in parameter values can cause qualitative changes in long-term system behaviour (e.g. location and/or number of steady states)
- Parameter values at which such changes occur are called bifurcation points

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$$\frac{dx(t)}{dt} = (a - 1)x(t)$$

What is the sign of the rate of change dx/dt for positive and negative values of x ?
Under which condition the steady state at $x = 0$ is stable?

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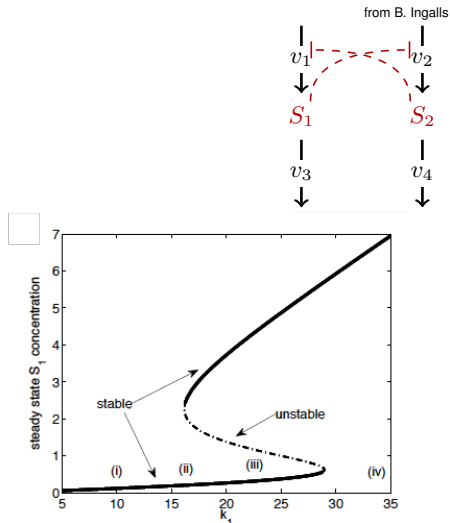
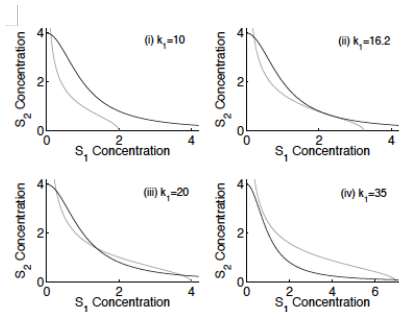
Under which condition the steady state at $x = 0$ is stable?

the steady state is stable if $a < 1$, unstable if $a > 1$.

The parameter value $a = 1$ is thus a bifurcation point for this system.

Ordinary differential equation models

A note on bifurcation analysis



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