

Dynamical Systems in Problems of Gene Regulation

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CAS-MPG Partner Institute for Computational Biology

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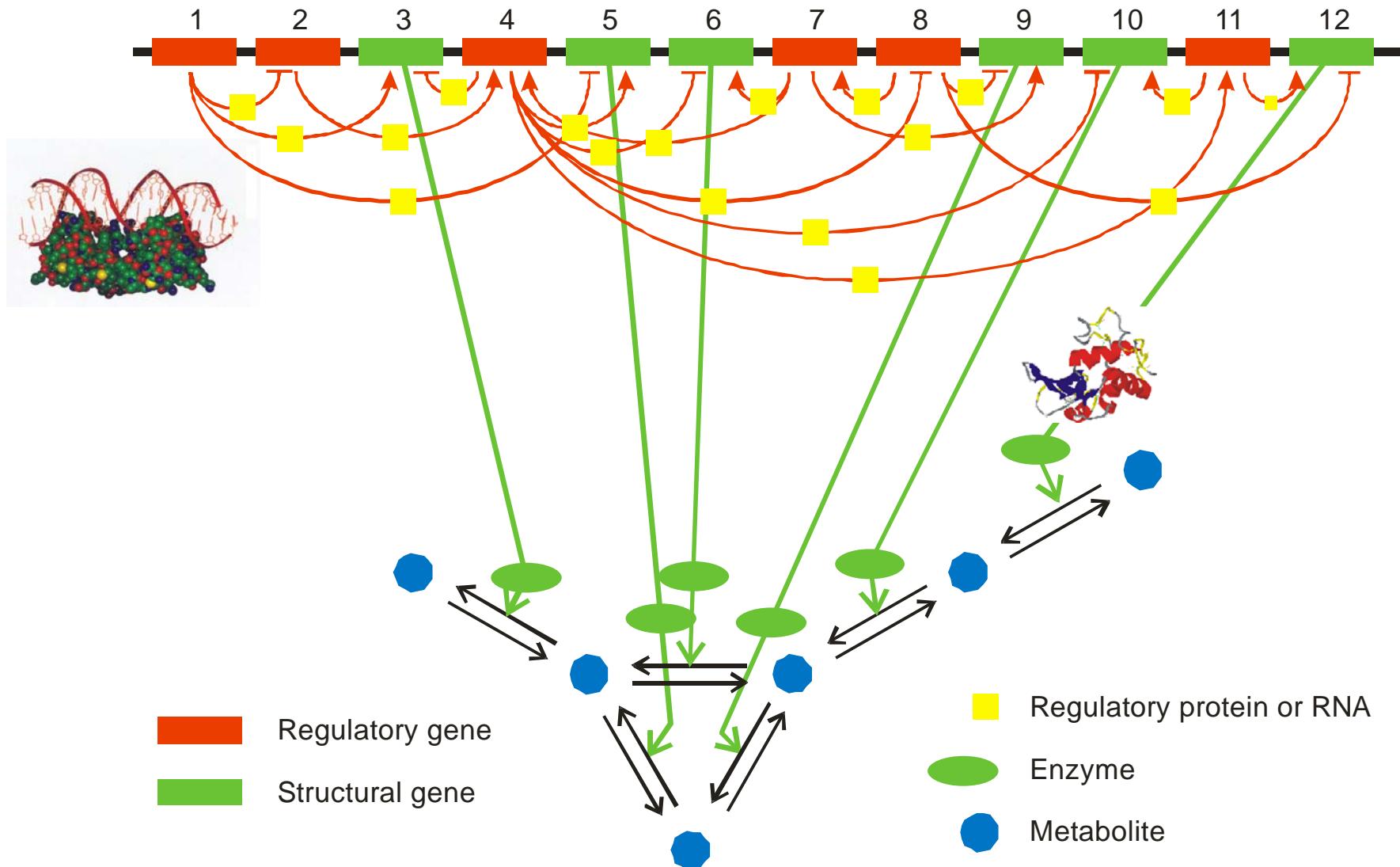
Web-Page for further information:

<http://www.tbi.univie.ac.at/~pks>

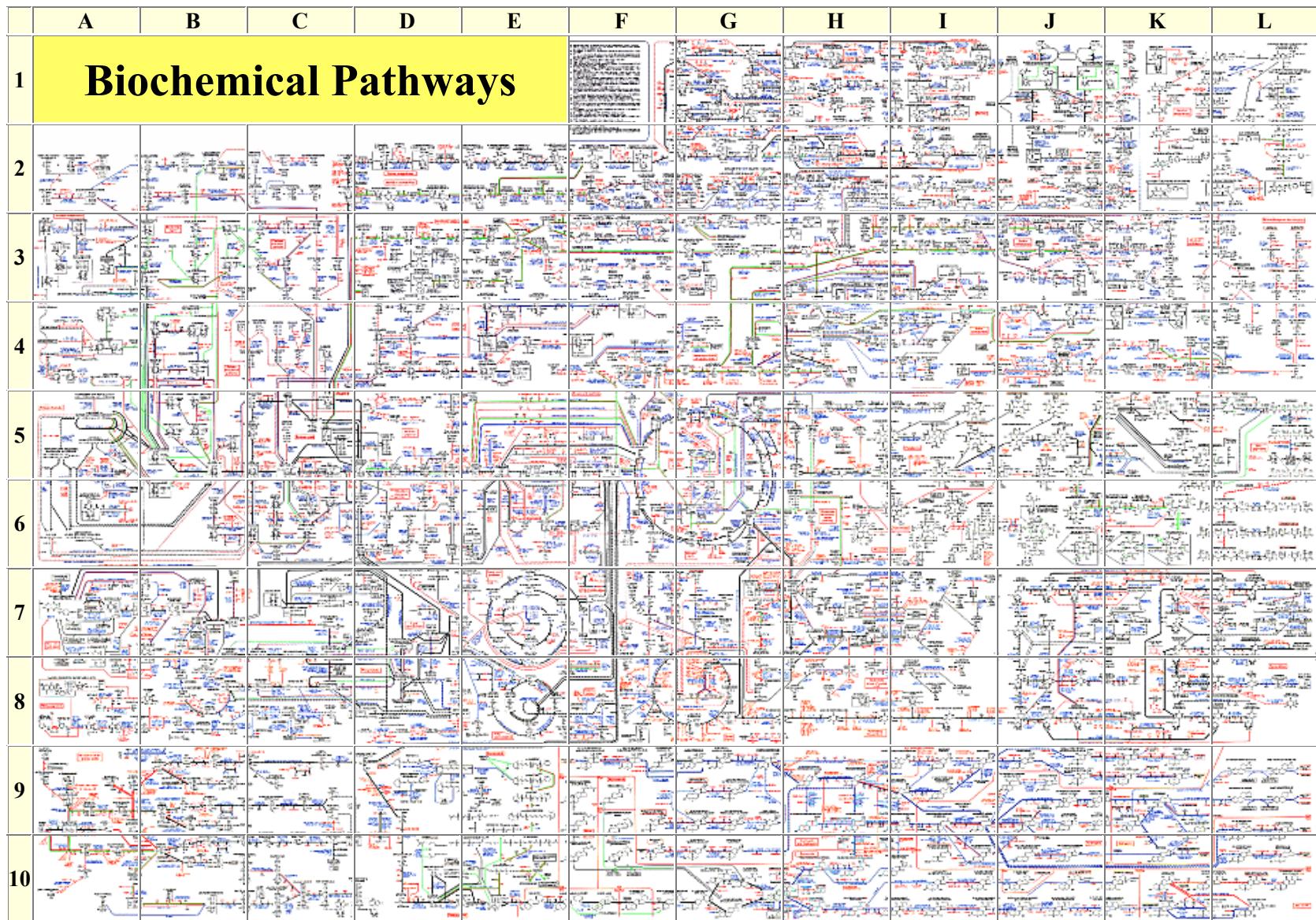
1. The problems of quantitative biology
2. Forward and inverse problems in reaction kinetics
3. Regulation kinetics and bifurcation analysis
4. Reverse engineering of dynamical systems
5. How to upscale from small models to cells?

1. **The problems of quantitative biology**
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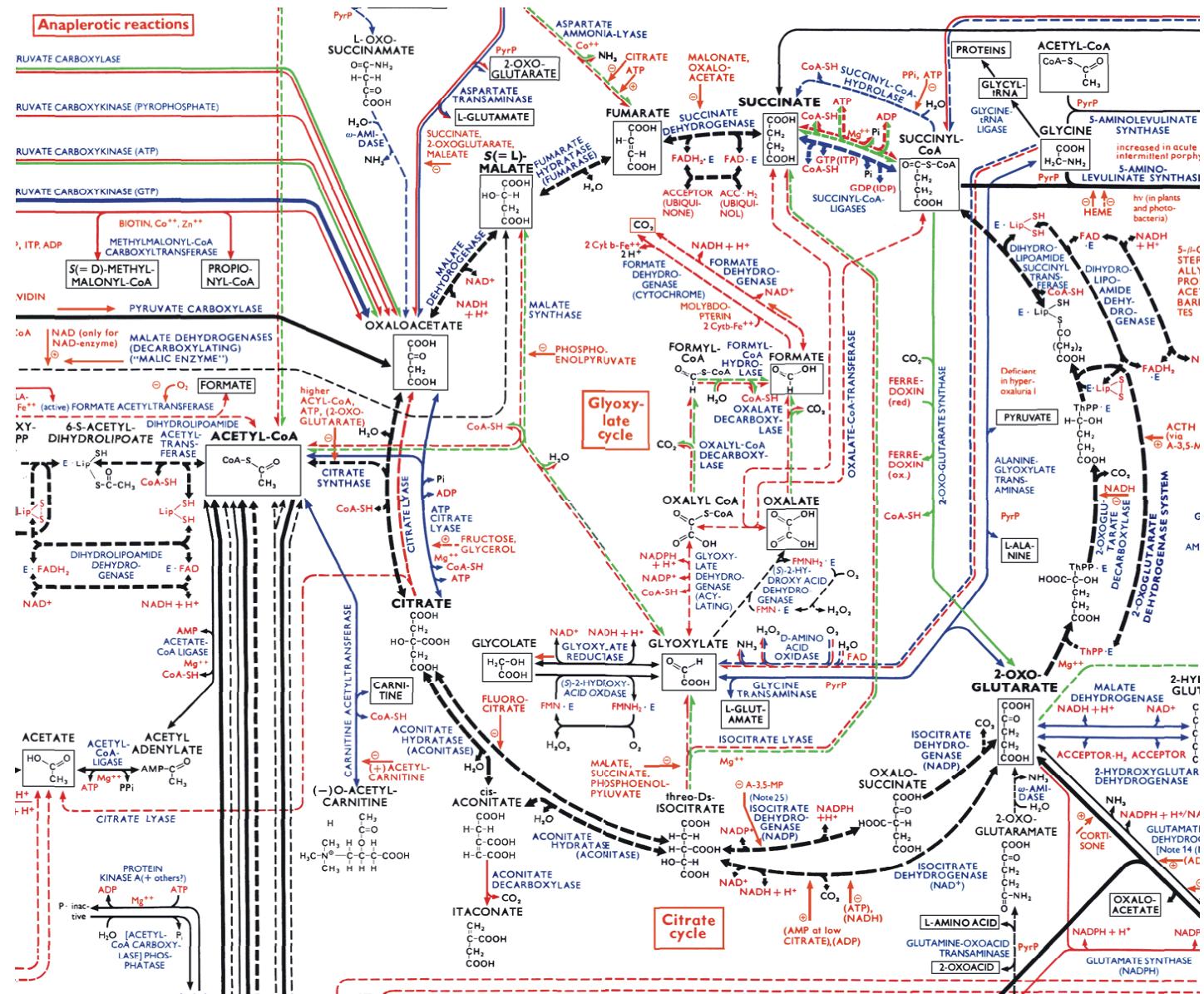
A model genome with 12 genes



Sketch of a genetic and metabolic network



The reaction network of cellular metabolism published by Boehringer-Ingelheim.

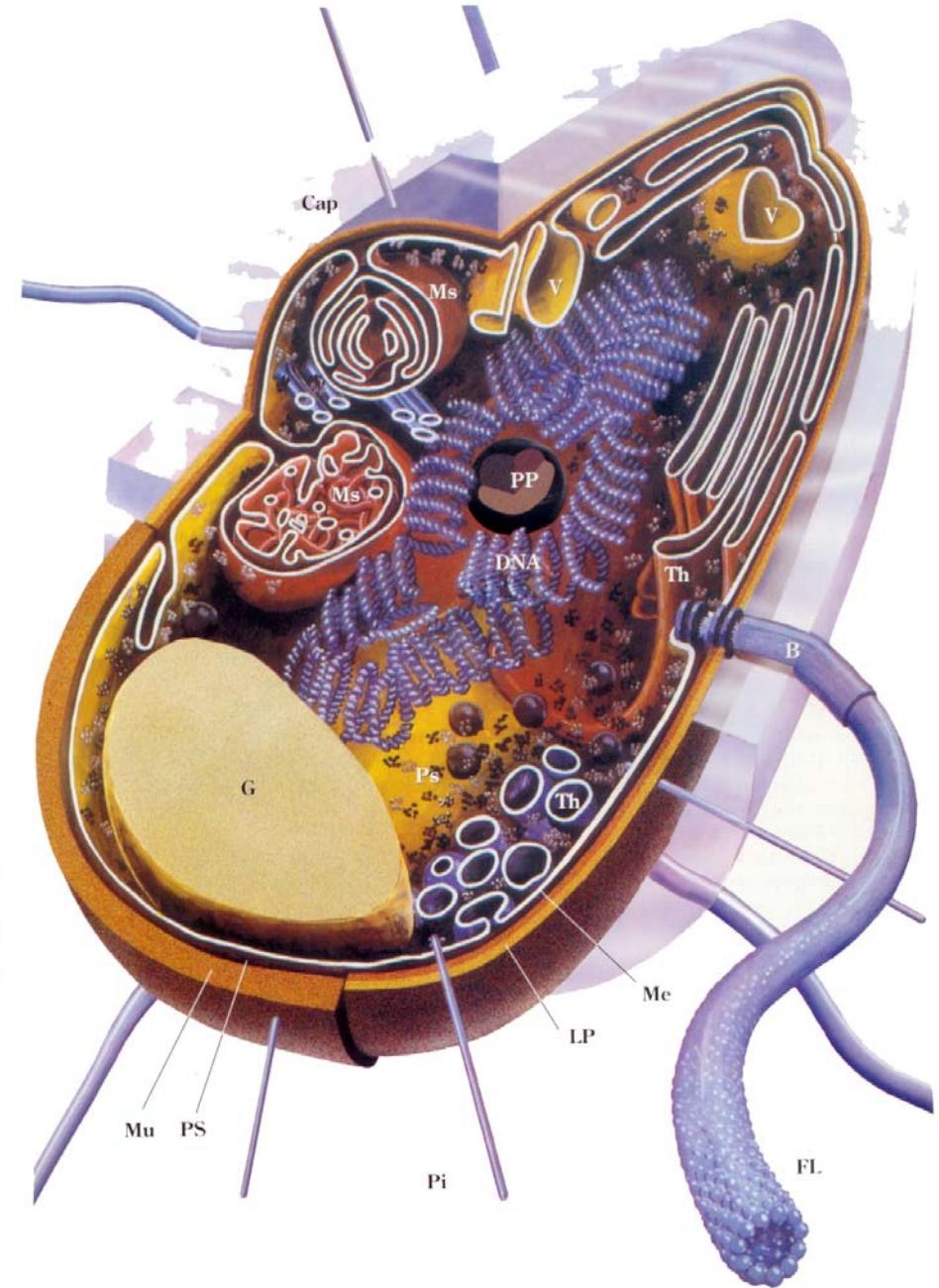


The citric acid
or Krebs cycle
(enlarged from
previous slide).

The bacterial cell as an example for the simplest form of autonomous life

The human body:

10^{14} cells = 10^{13} eukaryotic cells +
 $\approx 9 \times 10^{13}$ bacterial (prokaryotic) cells,
and ≈ 200 eukaryotic cell types



The spatial structure of the bacterium *Escherichia coli*

1. The problems of quantitative biology
2. **Forward and inverse problems in reaction kinetics**
3. Regulation kinetics and bifurcation analysis
4. Reverse engineering of dynamical systems
5. How to upscale from small models to cells?

Kinetic differential equations

$$\frac{dx}{dt} = f(x; k); x = (x_1, \dots, x_n); k = (k_1, \dots, k_m)$$

Reaction diffusion equations

$$\frac{\partial x}{\partial t} = D \nabla^2 x + f(x; k)$$

Parameter set

$$k_j(T, p, \text{pH}, I, \dots); j=1, 2, \dots, m$$

General conditions: T, p, pH, I, ...

Initial conditions: $x(0)$

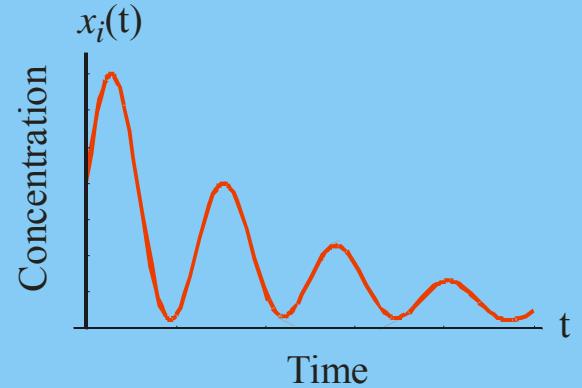
Boundary conditions:

boundary ... S , normal unit vector ... \hat{u}

Dirichlet : $x^S = g(r, t)$

Neumann : $\frac{\partial x}{\partial u} = \hat{u} \cdot \nabla x^S = g(r, t)$

Solution curves: $x(t)$



The forward problem of chemical reaction kinetics (Level I)

Genome: Sequence I_G

Kinetic differential equations

$$\frac{dx}{dt} = f(x; k); x=(x_1, \dots, x_n); k=(k_1, \dots, k_m)$$

Reaction diffusion equations

$$\frac{\partial x}{\partial t} = D \nabla^2 x + f(x; k)$$

Parameter set

$$k_j(I_G; T, p, pH, I, \dots); j=1, 2, \dots, m$$

General conditions: T, p, pH, I, \dots

Initial conditions: $x(0)$

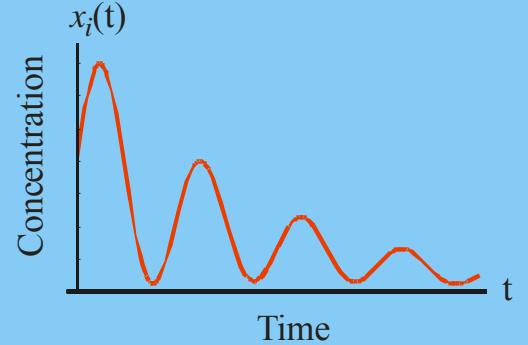
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Solution curves: $x(t)$



The forward problem of biochemical reaction kinetics (Level I)

Genome: Sequence I_G

Parameter set
 $k_j(I_G; T, p, pH, I, \dots); j=1, 2, \dots, m$

Kinetic differential equations

$$\frac{dx}{dt} = f(x; k); x = (x_1, \dots, x_n); k = (k_1, \dots, k_m)$$

Reaction diffusion equations

$$\frac{\partial x}{\partial t} = D \nabla^2 x + f(x; k)$$

General conditions : T, p, pH, I, \dots

Initial conditions : $x(0)$

Boundary conditions :

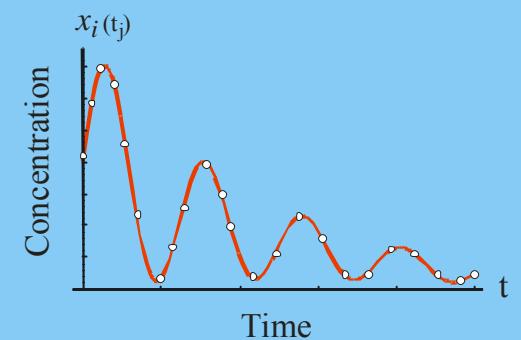
boundary ... S , normal unit vector ... \hat{u}

Dirichlet : $x^S = g(r, t)$

Neumann : $\frac{\partial x}{\partial u} = \hat{u} \cdot \nabla x^S = g(r, t)$

Data from measurements

$$x(t_j); j = 1, 2, \dots, N$$



The inverse problem of biochemical reaction kinetics (Level I)

Genome: Sequence I_G

Kinetic differential equations

$$\frac{dx}{dt} = f(x; k); x = (x_1, \dots, x_n); k = (k_1, \dots, k_m)$$

Reaction diffusion equations

$$\frac{\partial x}{\partial t} = D \nabla^2 x + f(x; k)$$

Parameter set
 $k_j(I_G; T, p, pH, I, \dots); j=1, 2, \dots, m$

General conditions : T, p, pH, I, \dots
Initial conditions : $x(0)$

Boundary conditions :

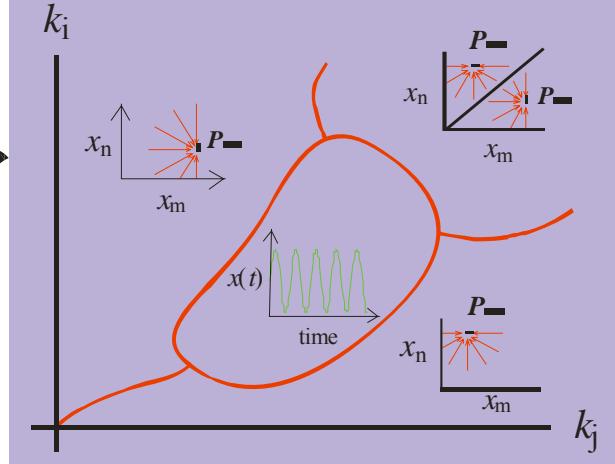
boundary ... S , normal unit vector ... \hat{u}

Dirichlet: $x^S = g(r, t)$

Neumann: $\frac{\partial x}{\partial u} = \hat{u} \cdot \nabla x^S = g(r, t)$

Bifurcation analysis

$$\Upsilon(k_i, k_j; k)$$



The forward problem of bifurcation analysis (Level II)

Genome: Sequence I_G

Sequence I_G

Parameter set
 $k_j(I_G; T, p, pH, I, \dots); j=1, 2, \dots, m$

Kinetic differential equations

$$\frac{dx}{dt} = f(x; k); x=(x_1, \dots, x_n); k=(k_1, \dots, k_m)$$

Reaction diffusion equations

$$\frac{\partial x}{\partial t} = D \nabla^2 x + f(x; k)$$

General conditions: T, p, pH, I, \dots

Initial conditions: $x(0)$

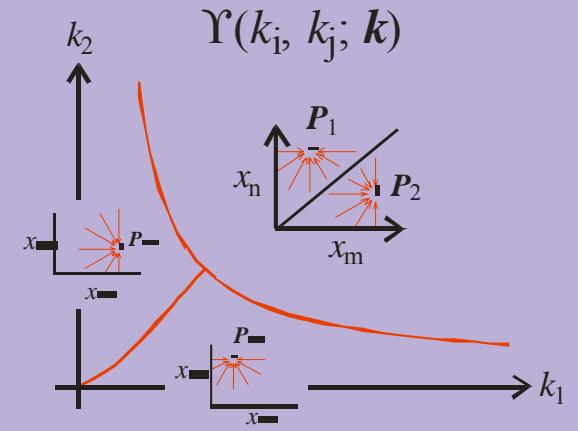
Boundary conditions:

boundary ... S , normal unit vector ... \hat{u}

Dirichlet: $x^S = g(r, t)$

Neumann: $\frac{\partial x}{\partial u} = \hat{u} \cdot \nabla x^S = g(r, t)$

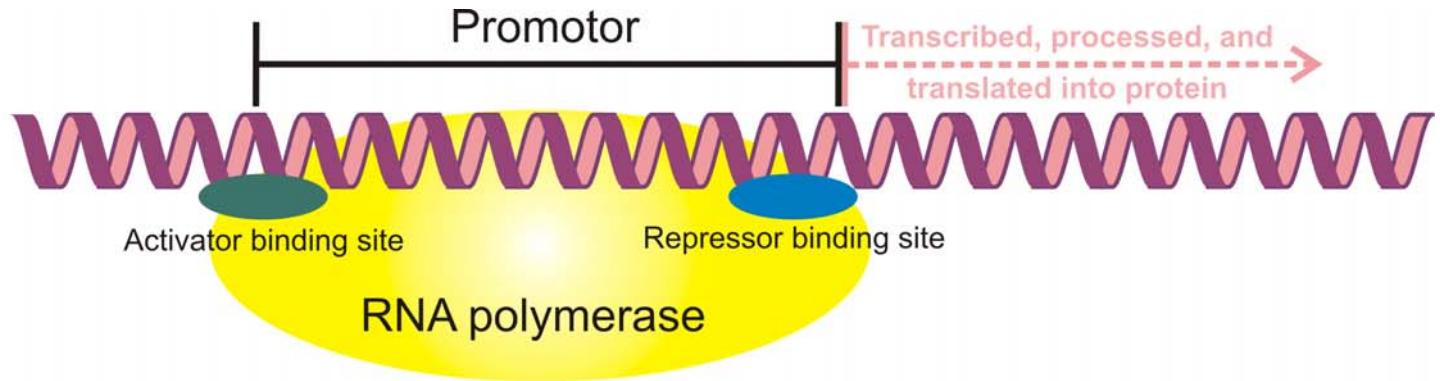
Bifurcation pattern



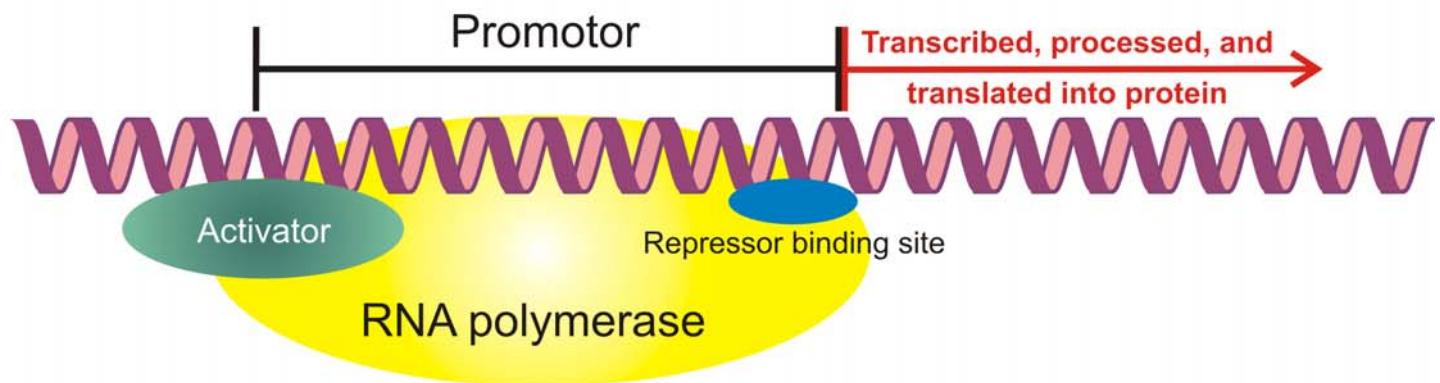
The inverse problem of bifurcation analysis (Level II)

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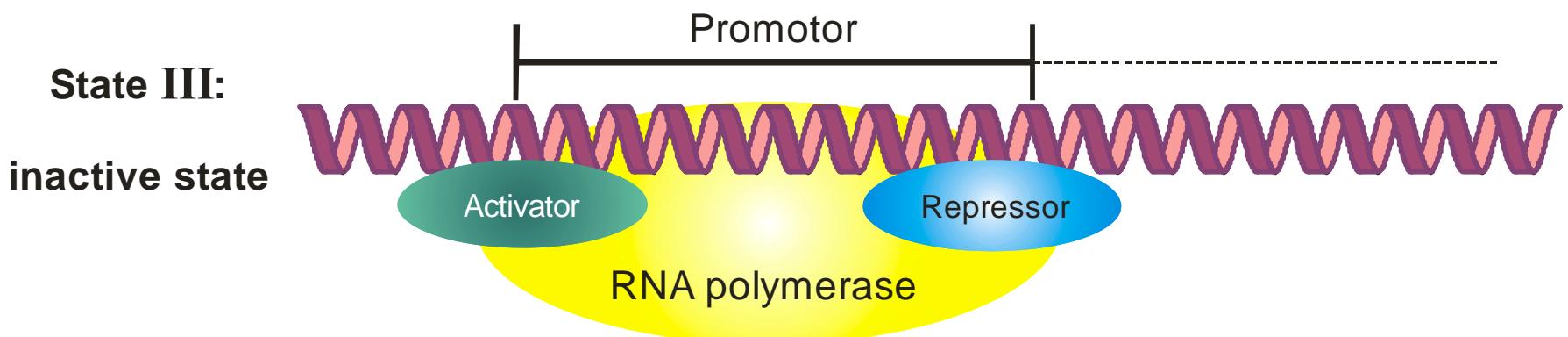
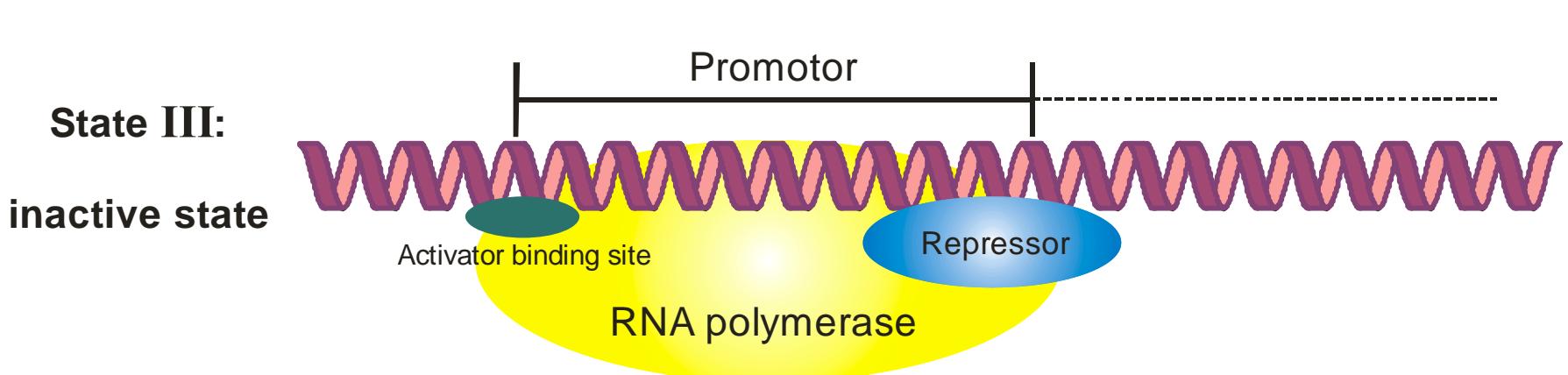
State I:
basal state



State II:
active state



Active states of gene regulation



Inactive states of gene regulation



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Dynamic patterns of gene regulation I: Simple two-gene systems

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Abstract

Regulation of gene activities is studied by means of computer assisted mathematical analysis of ordinary differential equations (ODEs) derived from binding equilibria and chemical reaction kinetics. Here, we present results on cross-regulation of two genes through activator and/or repressor binding. Arbitrary (differentiable) binding function can be used but systematic investigations are presented for gene-regulator complexes with integer valued Hill coefficients up to $n = 4$. The dynamics of gene regulation is derived from bifurcation patterns of the underlying systems of kinetic ODEs. In particular, we present analytical expressions for the parameter values at which one-dimensional (transcritical, saddle-node or pitchfork) and/or two-dimensional (Hopf) bifurcations occur. A classification of regulatory states is introduced, which makes use of the sign of a ‘regulatory determinant’ D (being the determinant of the block in the Jacobian matrix that contains the derivatives of the regulator binding functions): (i) systems with $D < 0$, observed, for example, if both proteins are activators or repressors, to give rise to one-dimensional bifurcations only and lead to bistability for $n \geq 2$ and (ii) systems with $D > 0$, found for combinations of activation and repression, sustain a Hopf bifurcation and undamped oscillations for $n > 2$. The influence of basal transcription activity on the bifurcation patterns is described. Binding of multiple subunits can lead to richer dynamics than pure activation or repression states if intermediates between the unbound state and the fully saturated DNA initiate transcription. Then, the regulatory determinant D can adopt both signs, plus and minus.

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Keywords: Basal transcription; Bifurcation analysis; Cooperative binding; Gene regulation; Hill coefficient; Hopf bifurcation

1. Introduction

Theoretical work on gene regulation goes back to the 1960s (Monod et al., 1963) soon after the first repressor protein had been discovered (Jacob and Monod, 1961). A little later the first paper on oscillatory states in gene regulation was published (Goodwin, 1965). The interest in gene regulation and its mathematical analysis never ceased (Tiwari et al., 1974; Tyson and Othmer, 1978; Smith, 1987) and saw a great variety of different attempts to design models of genetic regulatory networks that can be used in systems biology for computer simulation of *gen*etic and

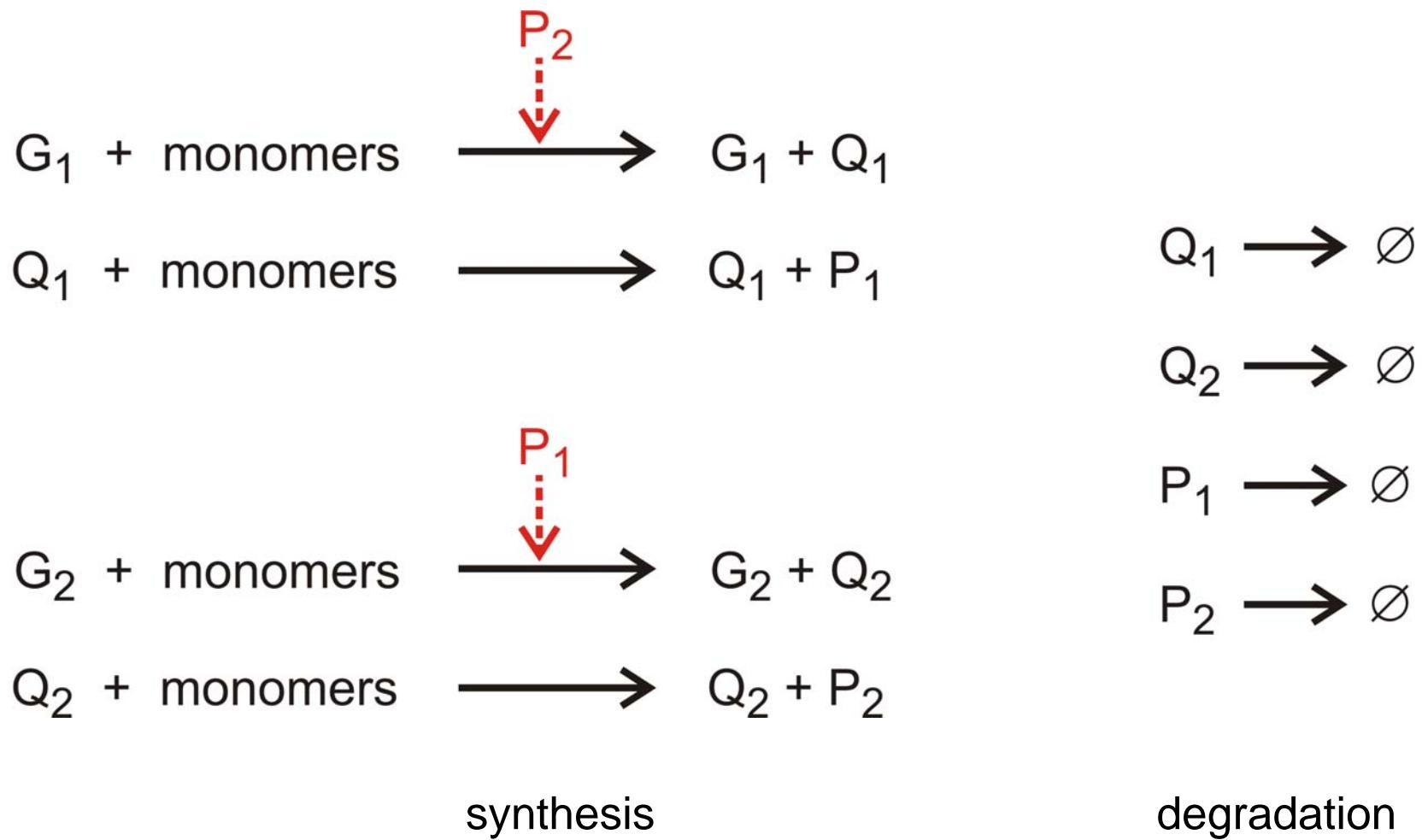
metabolic networks.¹ Most models in the literature aim at a minimalist dynamic description which, nevertheless, tries to account for the basic regulatory functions of large networks in the cell in order to provide a better understanding of cellular dynamics. A classic in general regulatory dynamics is the monograph by Thomas and D'Ari (1990). The currently used mathematical methods comprise application of Boolean logic (Thomas and Kaufman, 2001b; Savageau, 2001; Albert and Othmer, 2003), stochastic processes (Hume, 2000) and deterministic dynamic models, examples are Cherry and Adler (2000), Bindschadler and Sneyd (2001) and Kobayashi et al. (2003) and the recent elegant analysis of bistability (Craciun et al.,

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¹Discussion and analysis of combined genetic and metabolic networks has become so frequent and intense that we suggest to use a separate term, *genabolic networks*, for this class of complex dynamical systems.

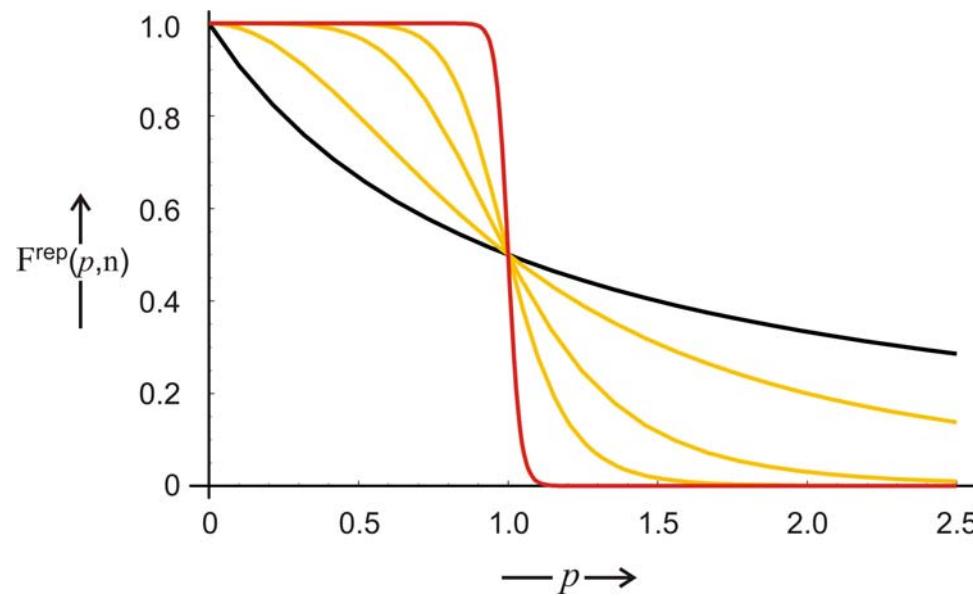
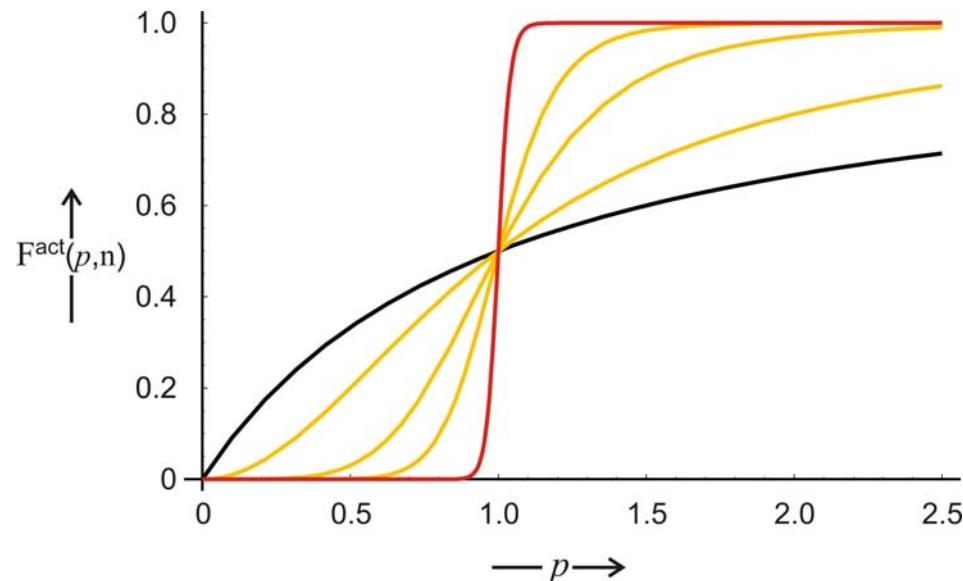


Cross-regulation of two genes

Activation: $F_i(p_j) = \frac{p_j^n}{K + p_j^n}$

Repression: $F_i(p_j) = \frac{K}{K + p_j^n}$

$$i, j = 1, 2$$



Gene regulatory binding functions

$$[G_1] = [G_2] = g_0 = \text{const.}$$

$$[Q_1] = q_1, [Q_2] = q_2,$$

$$[P_1] = p_1, [P_2] = p_2$$

$$\text{Activation: } F_i(p_j) = \frac{p_j^n}{K + p_j^n}$$

$$\text{Repression: } F_i(p_j) = \frac{K}{K + p_j^n}$$
$$i, j = 1, 2$$

$$\frac{dq_1}{dt} = k_1^Q F_1(p_2) - d_1^Q q_1$$

$$\frac{dq_2}{dt} = k_2^Q F_2(p_1) - d_2^Q q_2$$

$$\frac{dp_1}{dt} = k_1^P q_1 - d_2^P p_1$$

$$\frac{dp_2}{dt} = k_2^P q_2 - d_2^P p_2$$

$$\text{Stationary points: } \bar{p}_1 - \vartheta_1 F_1(\vartheta_2 F_2(\bar{p}_1)) = 0, \bar{p}_2 = \vartheta_2 F_2(\bar{p}_1)$$

$$\vartheta_1 = \frac{k_1^Q k_1^P}{d_1^Q d_1^P}, \vartheta_2 = \frac{k_2^Q k_2^P}{d_2^Q d_2^P}$$

Qualitative analysis of **cross-regulation** of two genes: Stationary points

$$A = \left\{ a_{ij} = \frac{\partial \dot{x}_i}{\partial x_j} \right\} = \begin{pmatrix} -d_1^Q & 0 & k_1^Q \frac{\partial F_1}{\partial p_1} & k_1^Q \frac{\partial F_1}{\partial p_2} \\ 0 & -d_2^Q & k_2^Q \frac{\partial F_2}{\partial p_1} & k_2^Q \frac{\partial F_2}{\partial p_2} \\ k_1^P & 0 & -d_1^P & 0 \\ 0 & k_2^P & 0 & -d_2^P \end{pmatrix}$$

Cross regulation : $\frac{\partial F_1}{\partial p_1} = \frac{\partial F_2}{\partial p_2} = 0$

$$|A - \varepsilon I| = \begin{vmatrix} -d_1^Q - \varepsilon & 0 & 0 & k_1^Q \frac{\partial F_1}{\partial p_2} \\ 0 & -d_2^Q - \varepsilon & k_2^Q \frac{\partial F_2}{\partial p_1} & 0 \\ k_1^P & 0 & -d_1^P - \varepsilon & 0 \\ 0 & k_2^P & 0 & -d_2^P - \varepsilon \end{vmatrix} = \begin{vmatrix} Q_D & Q_K \\ P_D & P_K \end{vmatrix}$$

Qualitative analysis of **cross-regulation** of two genes: Jacobian matrix

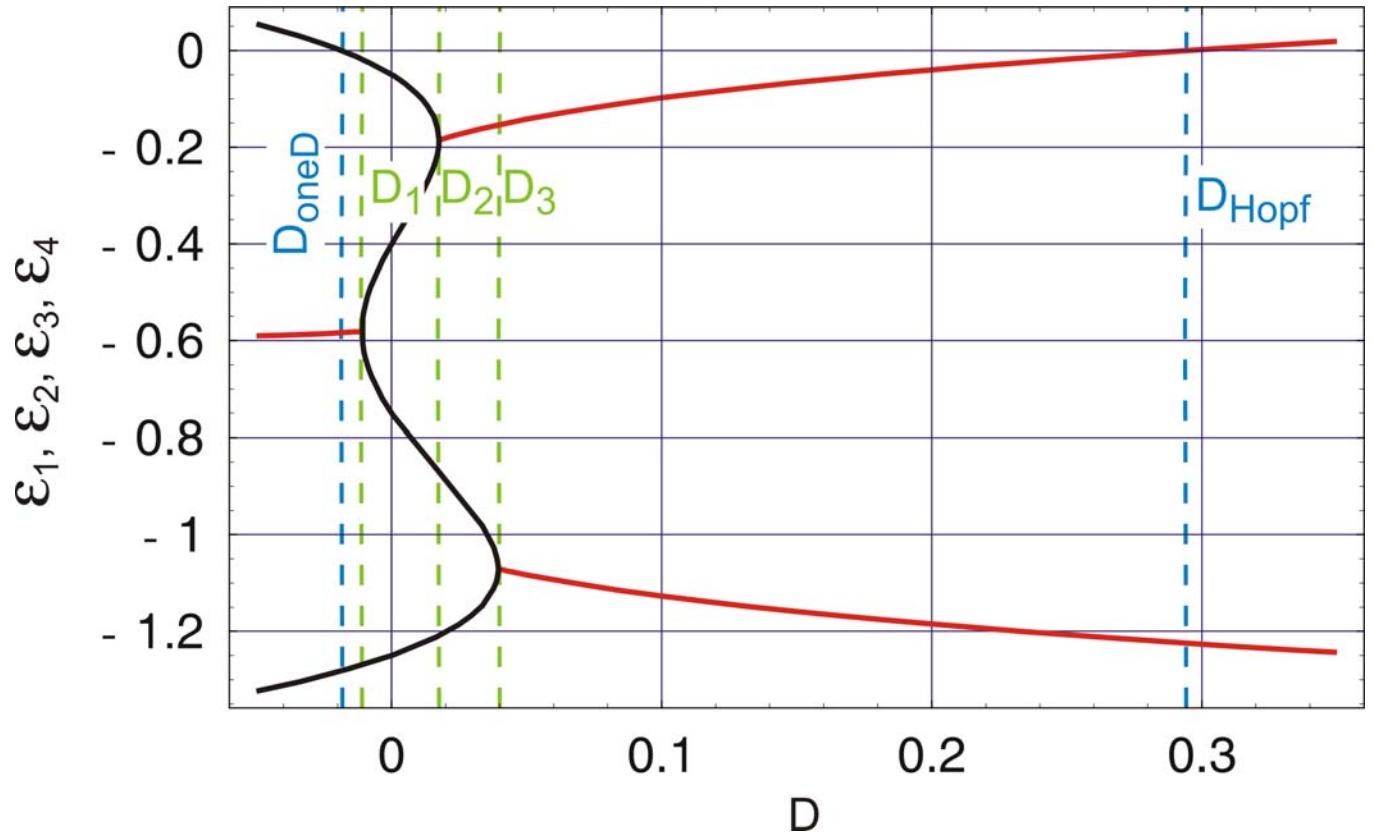
$$Q_D\cdot P_K=P_K\cdot Q_D \quad \text{and hence} \quad \begin{vmatrix} Q_D & Q_K \\ P_K & P_D \end{vmatrix}=\left|Q_D\cdot P_D-Q_K\cdot P_K\right|$$

$$\left|\mathbf{Q}_D\cdot\mathbf{P}_D-\mathbf{Q}_K\cdot\mathbf{P}_K\right|=\begin{vmatrix}\left(-d_1^Q-\varepsilon\right)\left(-d_1^P-\varepsilon\right) & -k_1^Q\frac{\partial F_1}{\partial p_2}k_1^P \\ -k_2^Q\frac{\partial F_2}{\partial p_1}k_2^P & \left(-d_2^Q-\varepsilon\right)\left(-d_2^P-\varepsilon\right)\end{vmatrix}=$$

$$=\Bigl(-d_1^Q-\varepsilon\Bigr)\Bigl(-d_1^P-\varepsilon\Bigr)\Bigl(-d_2^Q-\varepsilon\Bigr)\Bigl(-d_2^P-\varepsilon\Bigr)-k_1^Qk_2^Qk_1^Pk_2^P\frac{\partial F_1}{\partial p_2}\frac{\partial F_2}{\partial p_1}=0$$

$$(\varepsilon+d_1^Q)(\varepsilon+d_2^Q)(\varepsilon+d_1^P)(\varepsilon+d_2^P)+D=0$$

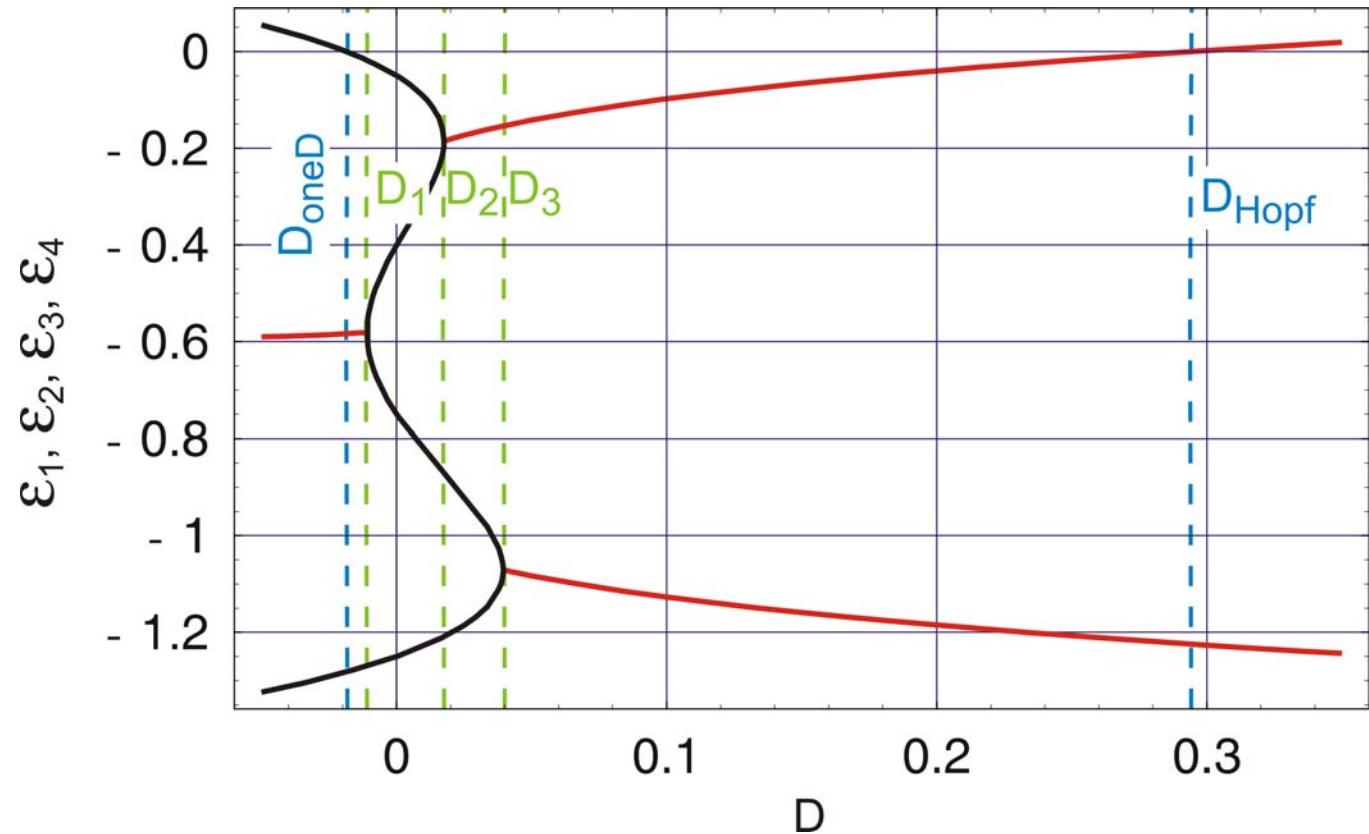
$$D=-k_1^Qk_2^Qk_1^Pk_2^P\,\frac{\partial F_1}{\partial x_2}\frac{\partial F_2}{\partial x_1}$$



$$(\varepsilon + d_1^Q)(\varepsilon + d_2^Q)(\varepsilon + d_1^P)(\varepsilon + d_2^P) + D = 0$$

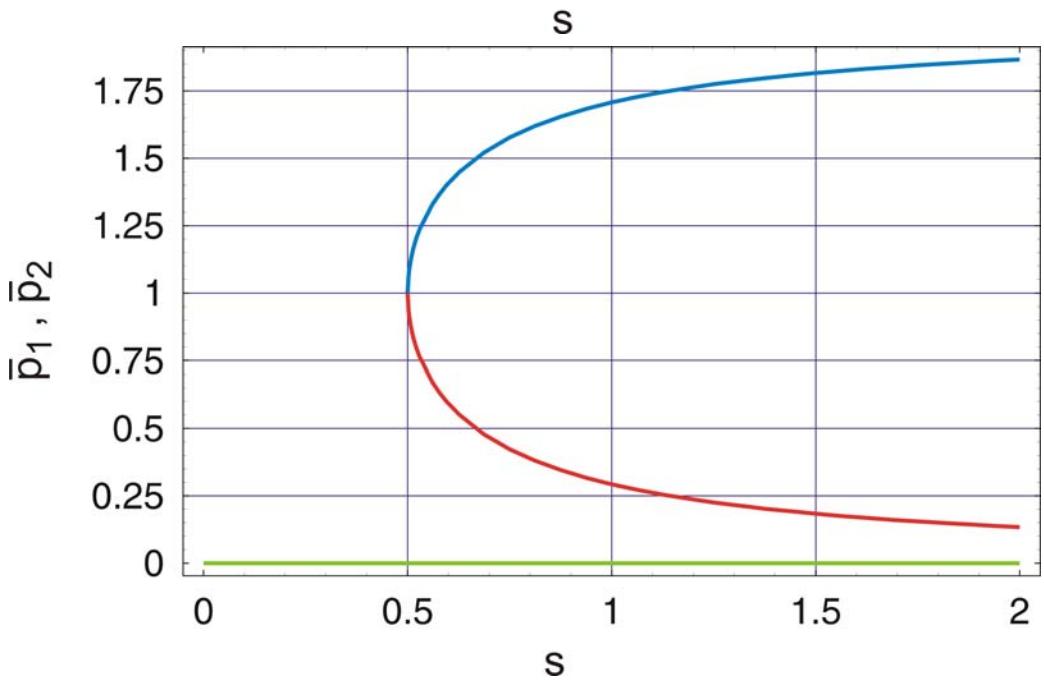
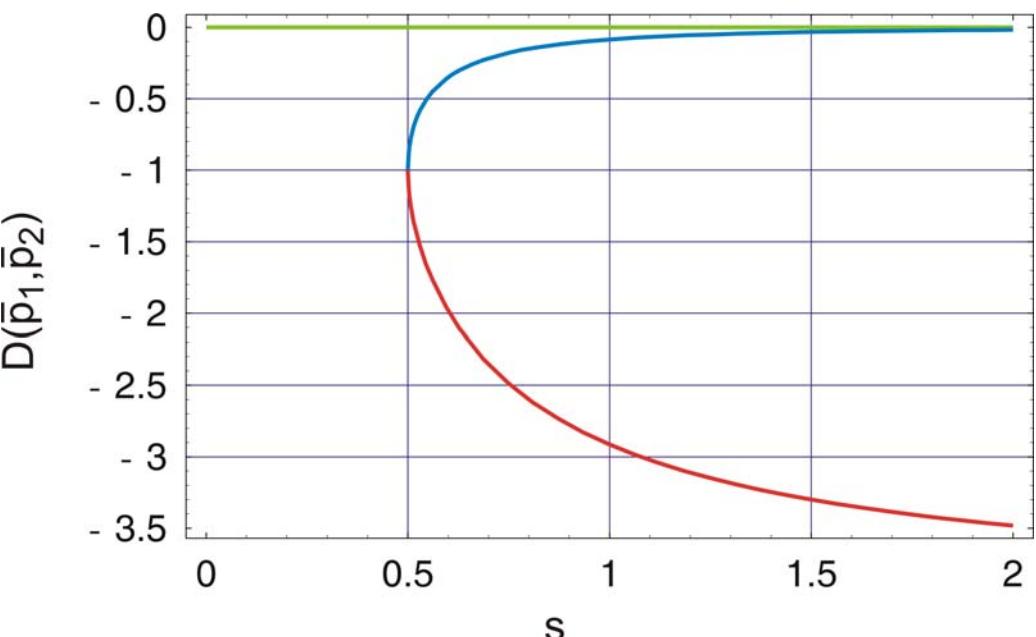
Eigenvalues of the Jacobian of the cross-regulatory two gene system

$$D = -k_1^Q k_2^Q k_1^P k_2^P \frac{\partial F_1}{\partial x_2} \frac{\partial F_2}{\partial x_1}$$

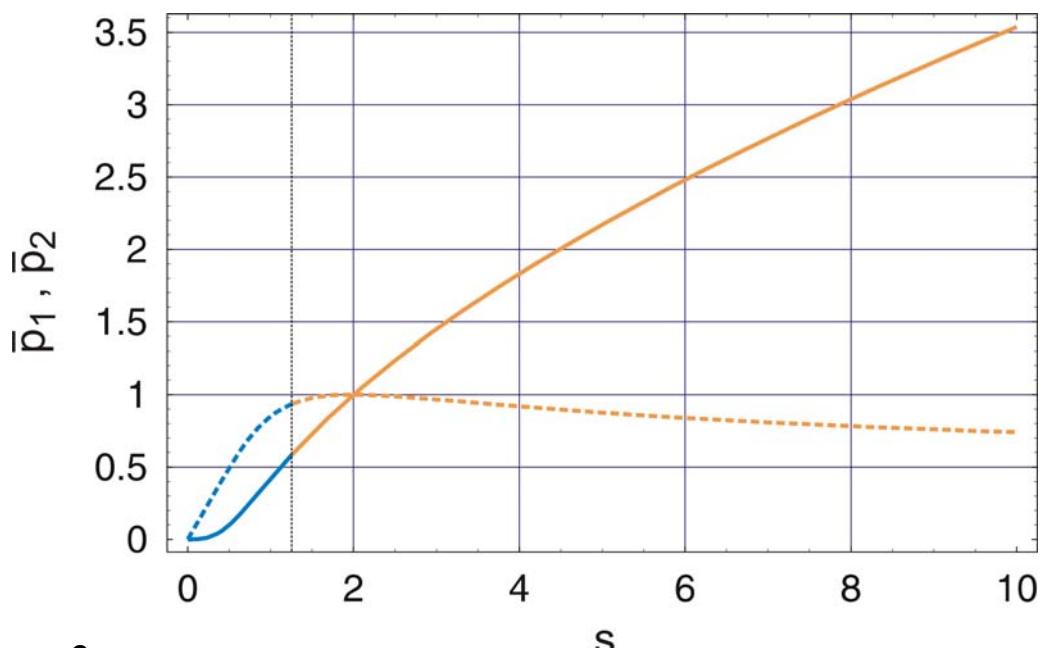
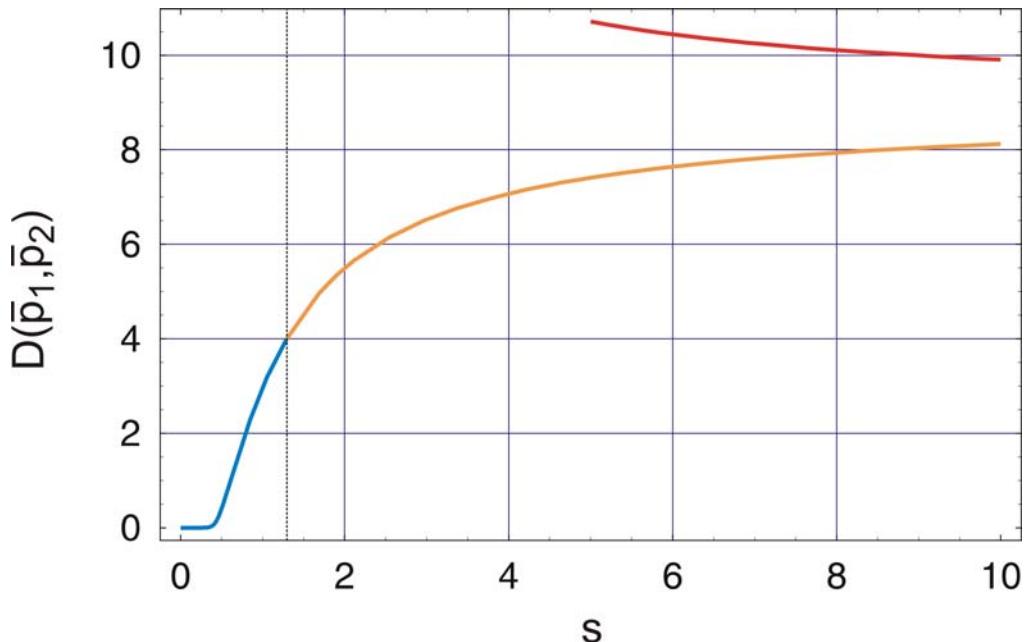


$$D_{\text{OneD}} = -d_1^Q d_2^Q d_1^P d_2^P$$

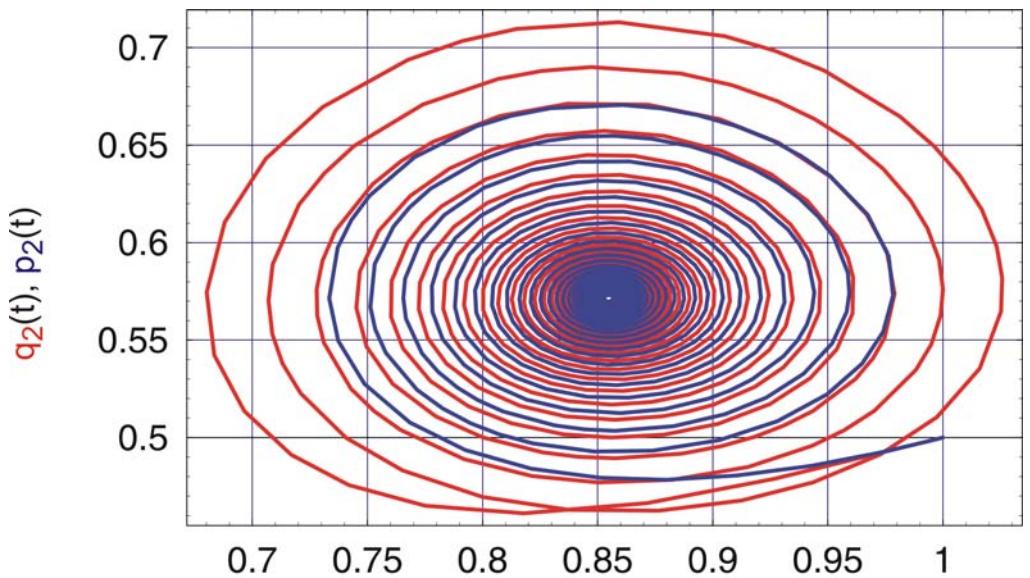
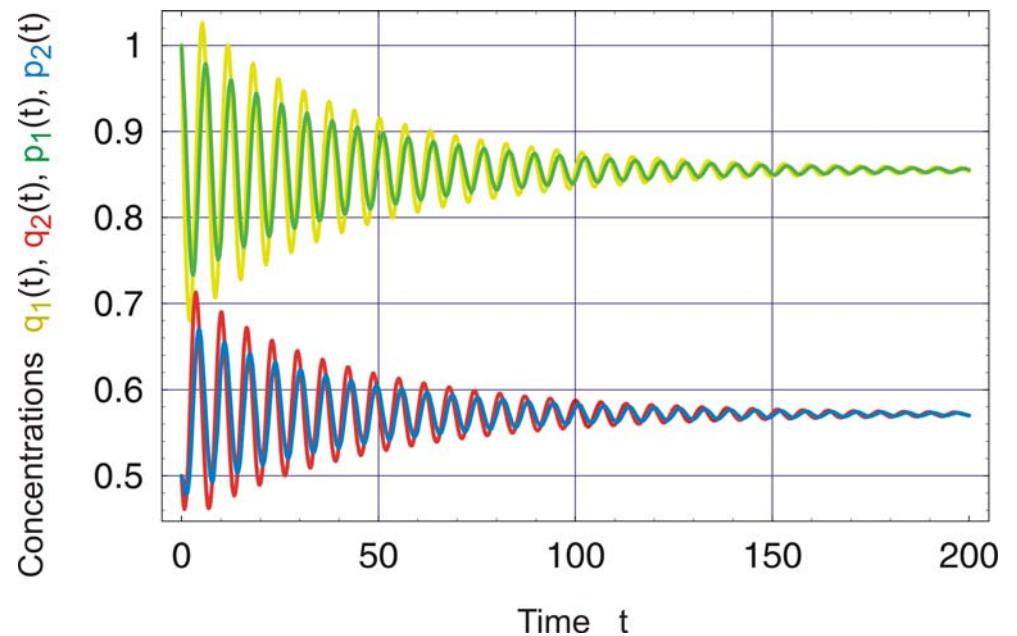
$$D_{\text{Hopf}} = \frac{(d_1^Q + d_2^Q)(d_1^Q + d_1^P)(d_1^Q + d_2^P)(d_2^Q + d_1^P)(d_2^Q + d_2^P)(d_1^P + d_2^P)}{(d_1^Q + d_2^Q + d_1^P + d_2^P)^2}$$



Regulatory dynamics at $D \leq 0$, act.-act., $n=2$

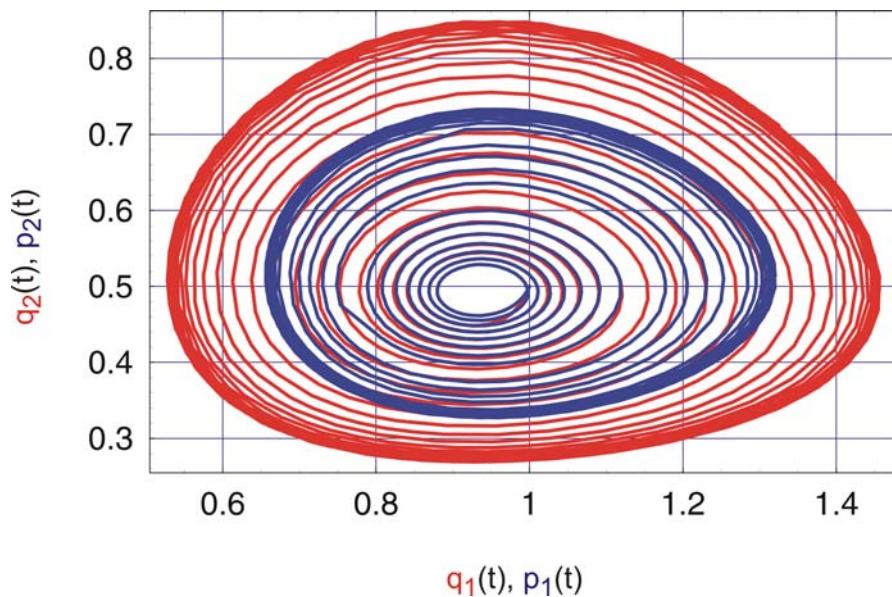
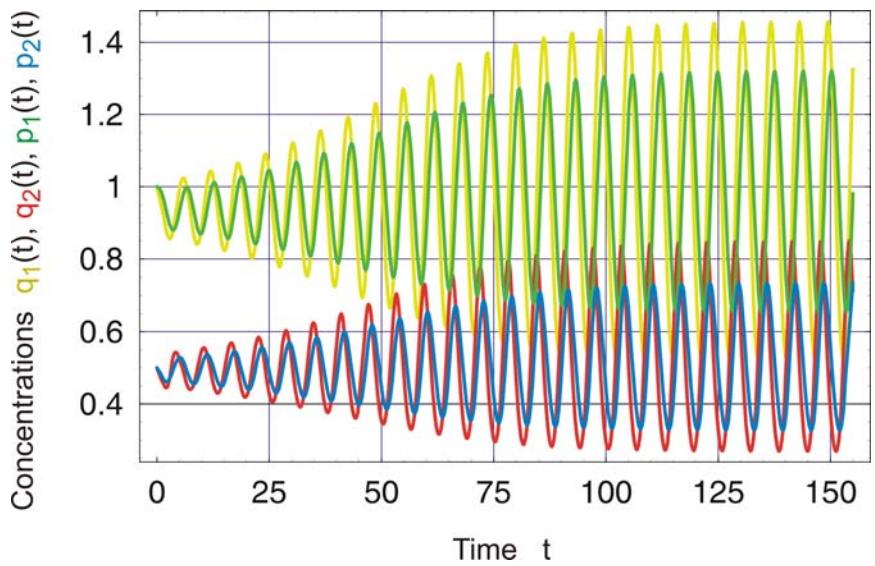
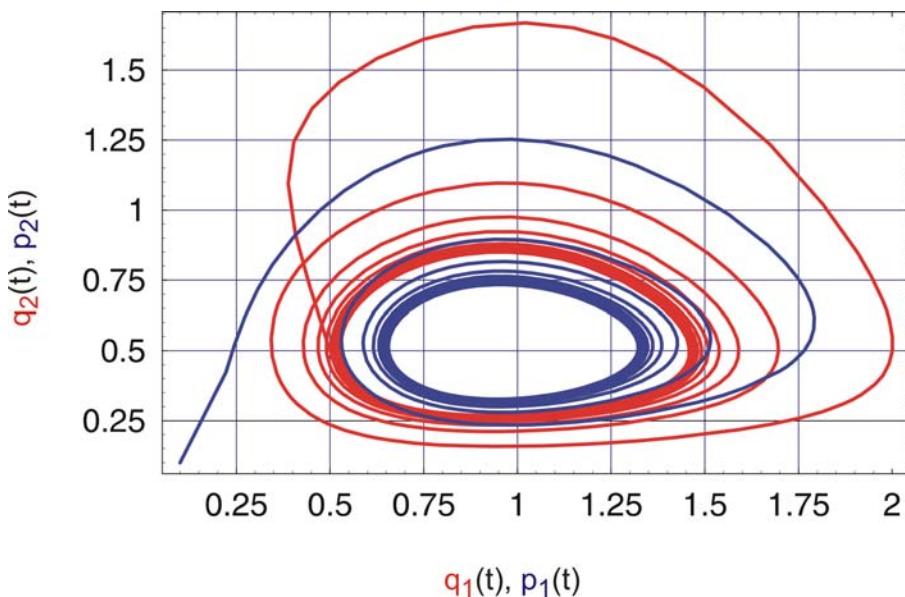
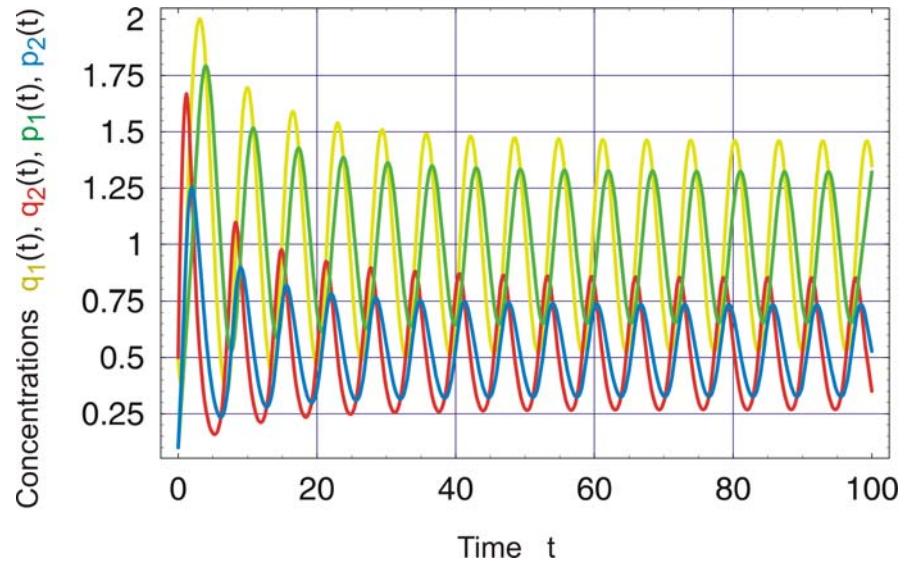


Regulatory dynamics at $D \geq 0$, act.-rep., $n=3$

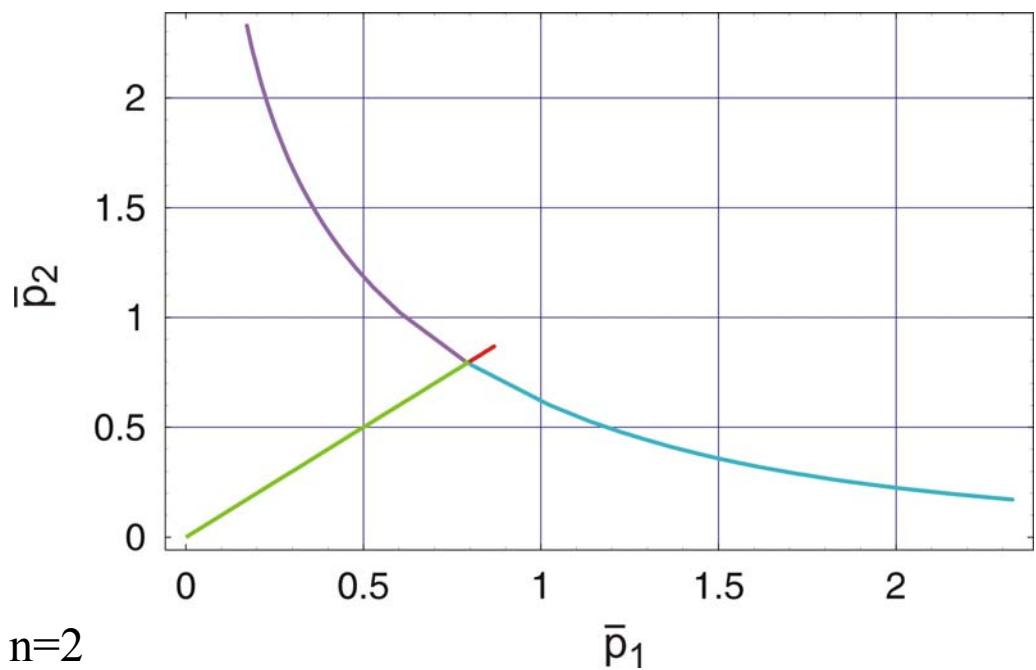
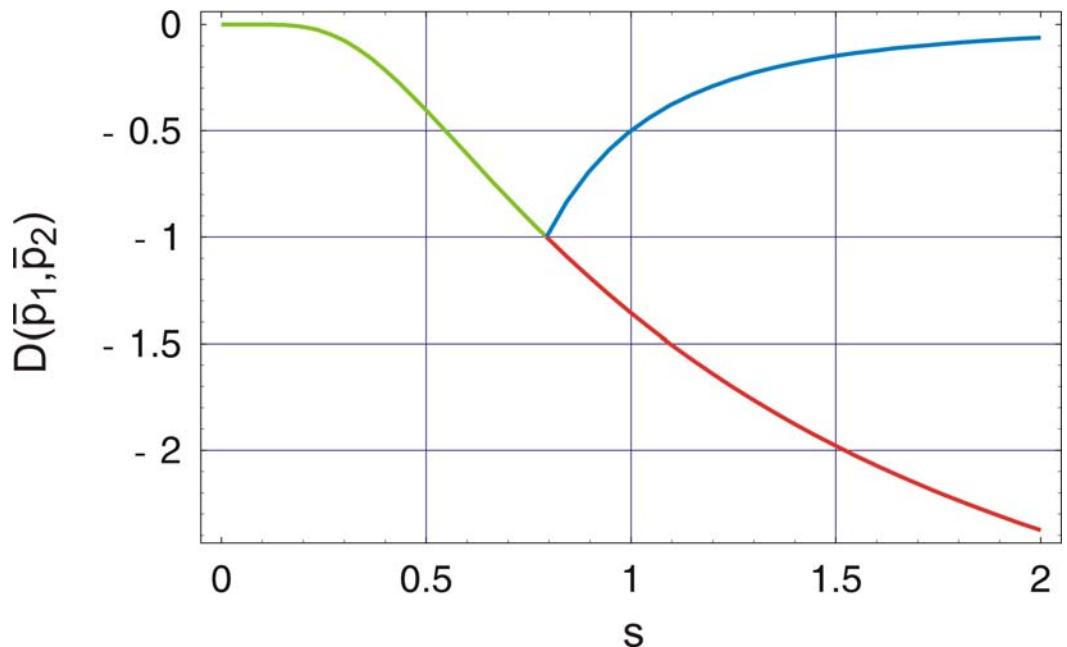


Regulatory dynamics at $D < D_{\text{Hopf}}$, act.-repr., $n=3$

$q_1(t), p_1(t)$



Regulatory dynamics at $D > D_{\text{Hopf}}$, act.-repr., $n=3$



Regulatory dynamics at $D \leq 0$, rep.-rep., $n=2$

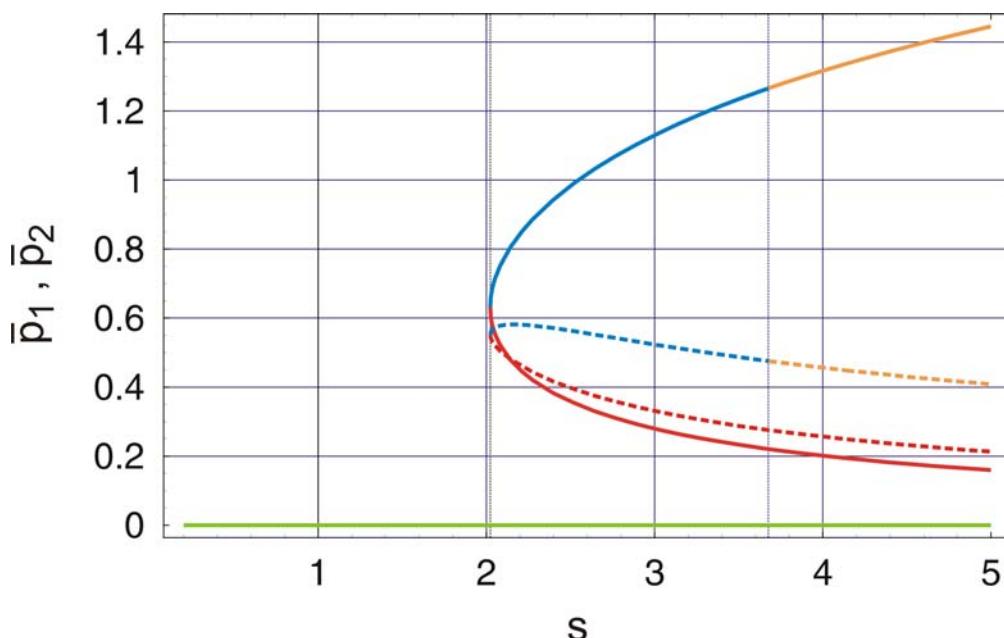
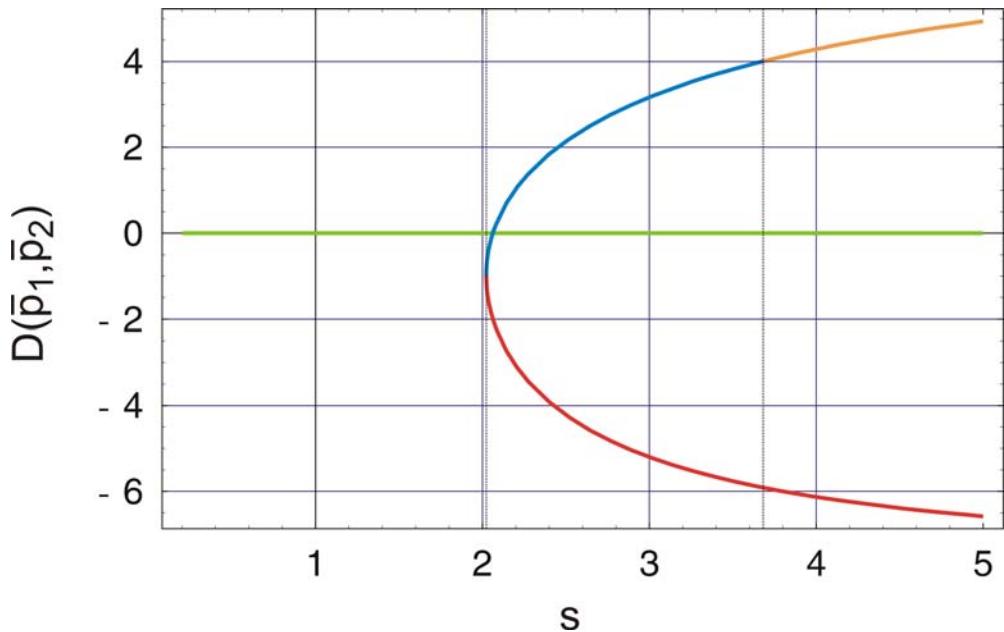
Hill coefficient: n	Act.-Act.	Act.-Rep.	Rep.-Rep.
1	S , E	S	S
2	E , B(E,P)	S	S , B(P_1, P_2)
3	E , B(E,P)	S , O	S , B(P_1, P_2)
4	E , B(E,P)	S , O	S , B(P_1, P_2)

$$\text{Activation : } F_i(p_j) = \frac{p_j^n}{K + p_j^n}$$

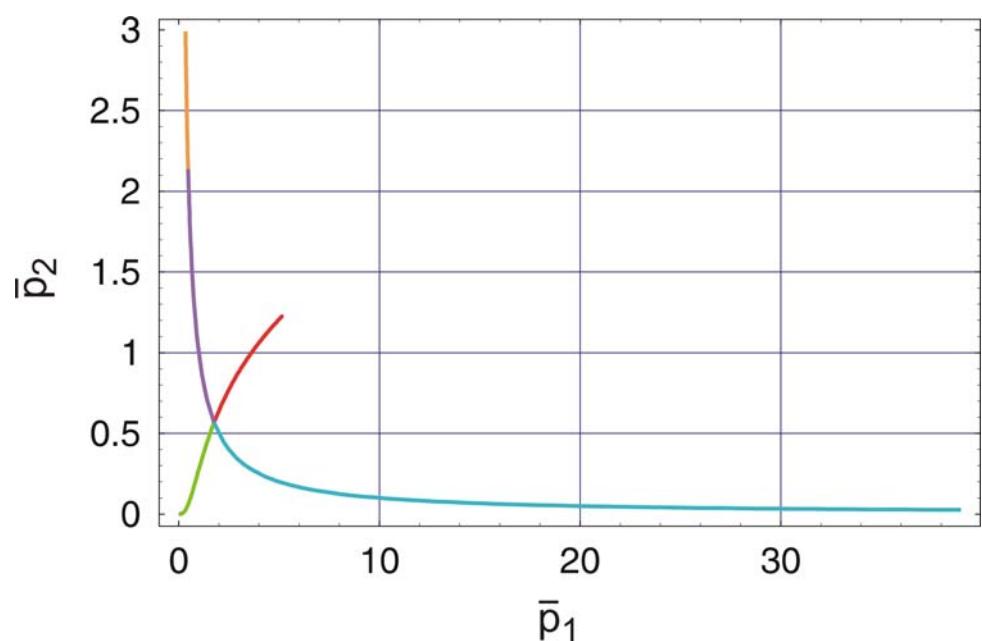
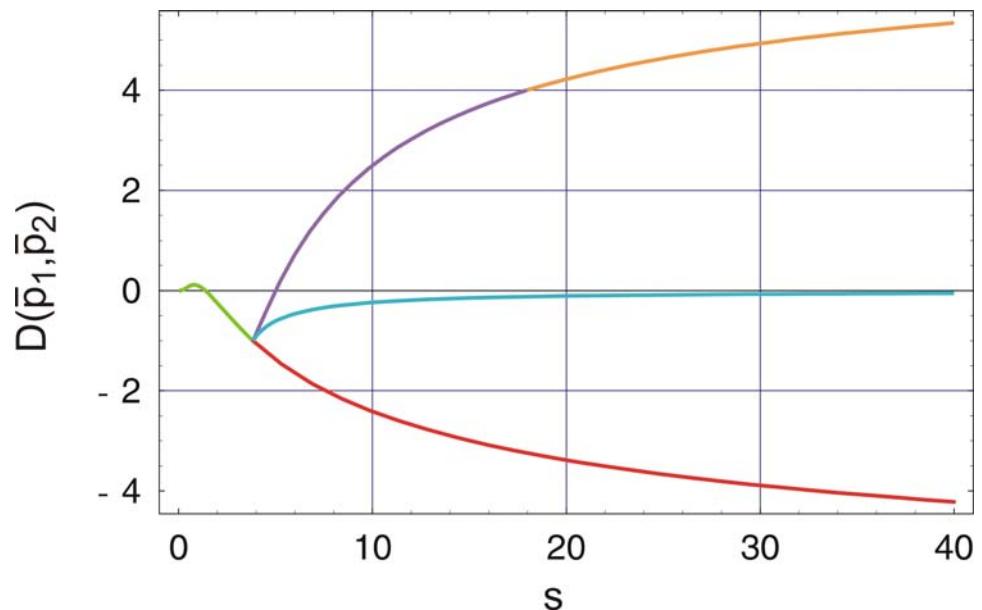
$$\text{Repression : } F_i(p_j) = \frac{K}{K + p_j^n}$$

$$\text{Intermediate : } F_i(p_j) = \frac{p_j^m}{\kappa_1 + \kappa_2 p_j + \kappa_3 p_j^2 + \dots + p_j^n}$$

$$i, j = 1, 2; \quad 1 \leq m \leq n - 1$$



Regulatory dynamics, int.-act., m=2, n=4

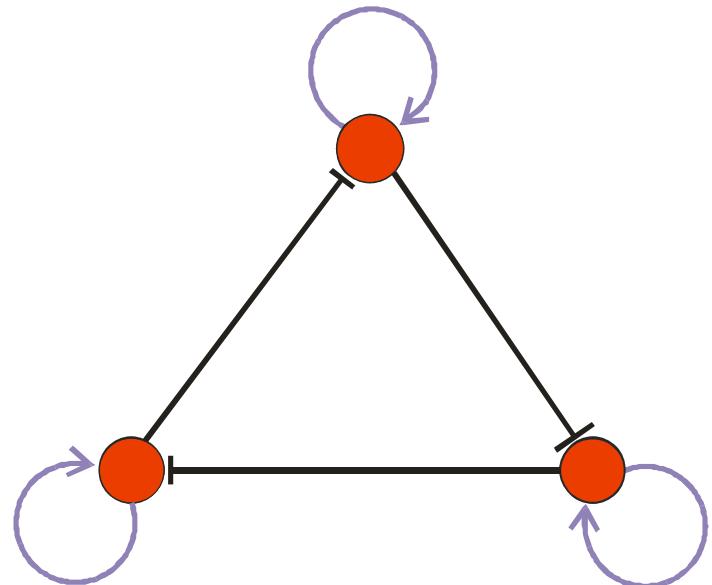
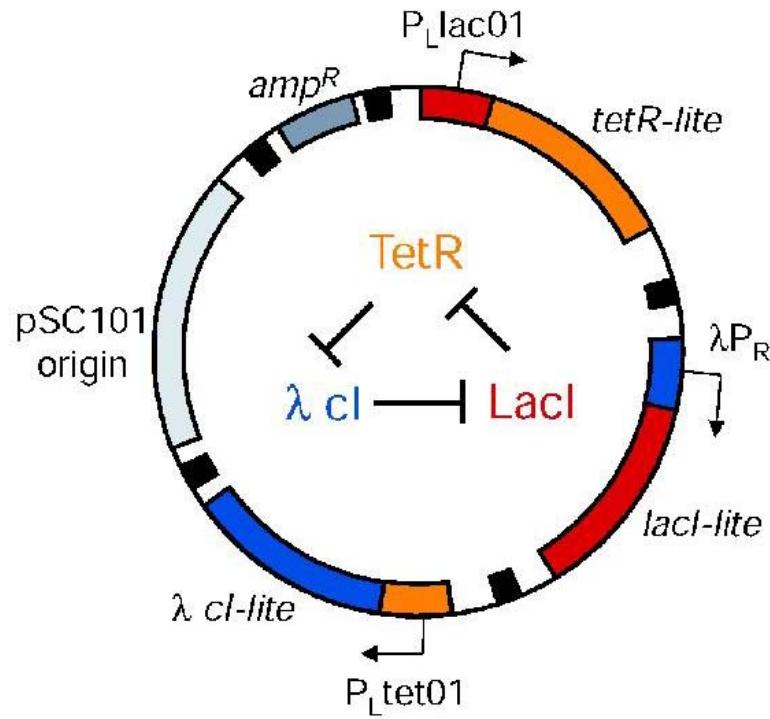


Regulatory dynamics, rep.-int., m=2, n=4

$$| \mathbf{Q}_d \cdot \mathbf{P}_d - \mathbf{Q}_k \cdot \mathbf{P}_k | = \begin{vmatrix} (-d_1^Q - \varepsilon)(-d_1^P - \varepsilon) & 0 & -k_1^P k_1^Q \frac{\partial F_1}{\partial p_3} \\ -k_2^P k_2^Q \frac{\partial F_2}{\partial p_1} & (-d_2^Q - \varepsilon)(-d_2^P - \varepsilon) & 0 \\ 0 & -k_3^P k_3^Q \frac{\partial F_3}{\partial p_2} & (-d_3^Q - \varepsilon)(-d_3^P - \varepsilon) \end{vmatrix}$$

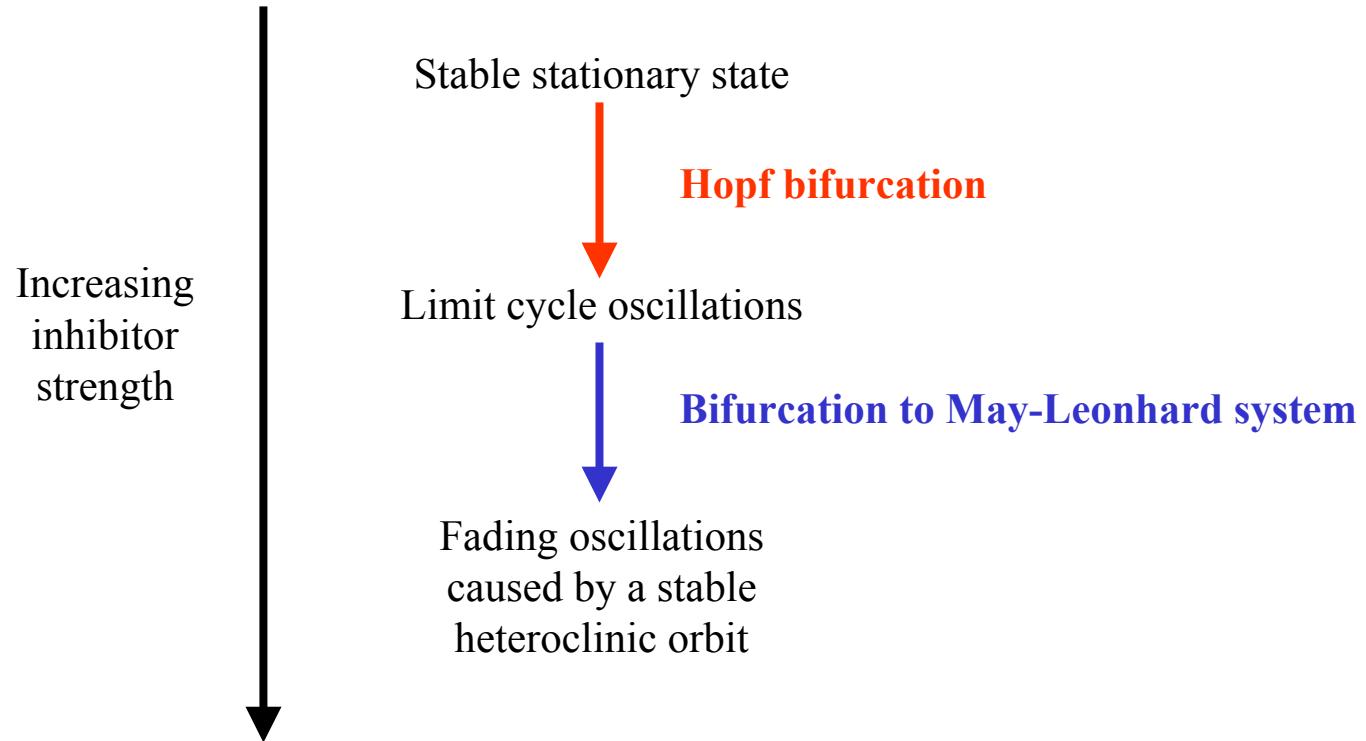
$$D=-k_1^Q\,k_2^Q\,k_3^Q\,k_1^P\,k_2^P\,k_3^P\,\frac{\partial F_1}{\partial p_3}\frac{\partial F_2}{\partial p_1}\frac{\partial F_3}{\partial p_2}$$

Upscaling to more genes: $n = 3$

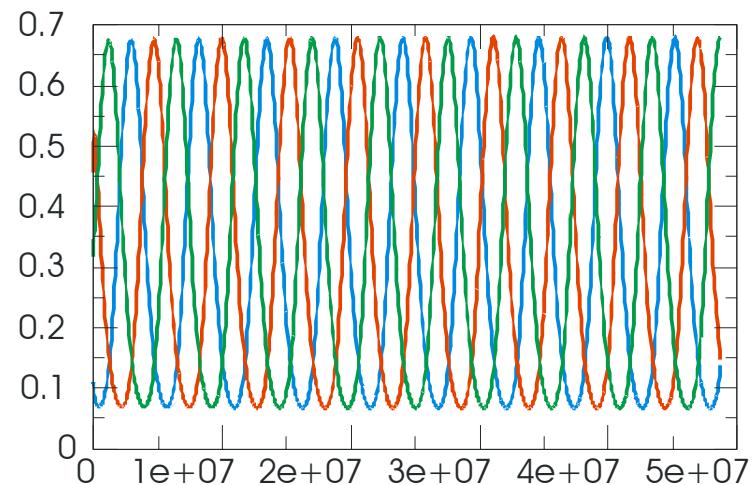


An example analyzed and simulated by MiniCellSim

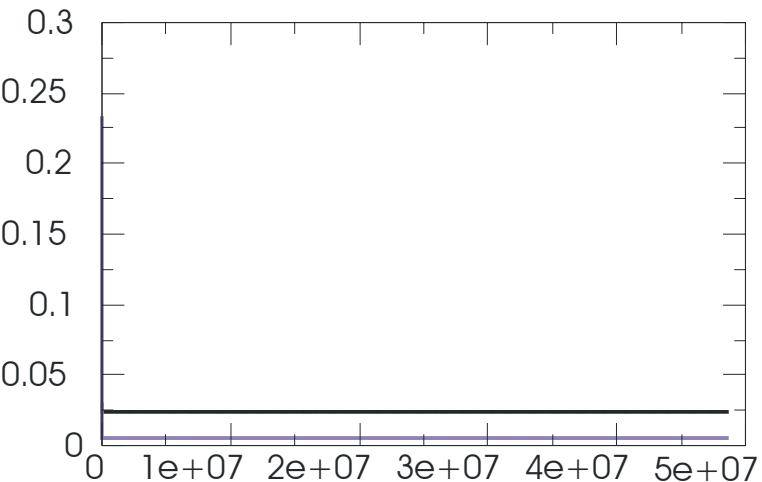
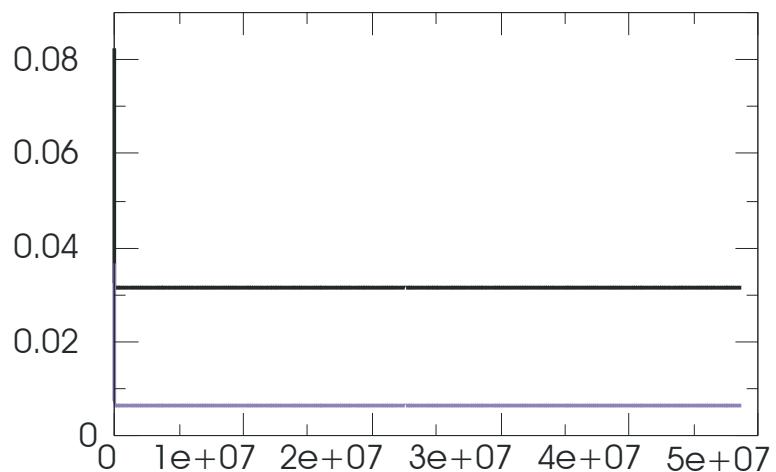
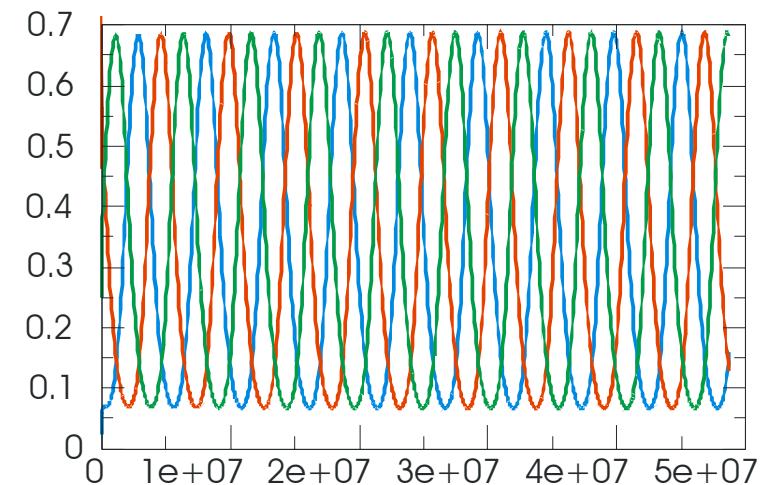
The repressilator: M.B. Elowitz, S. Leibler. A synthetic oscillatory network of transcriptional regulators. *Nature* **403**:335-338, 2002



Proteins

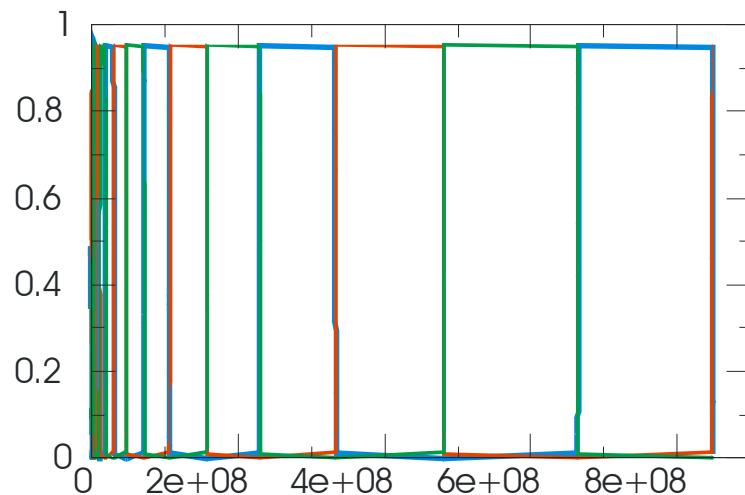


mRNAs

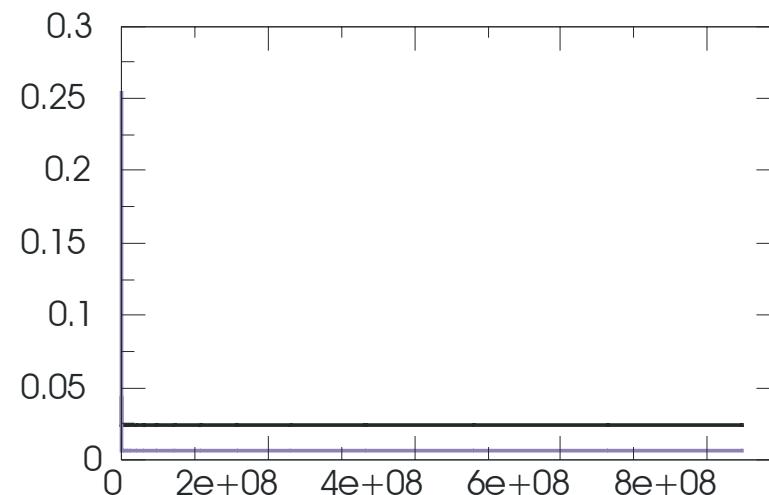
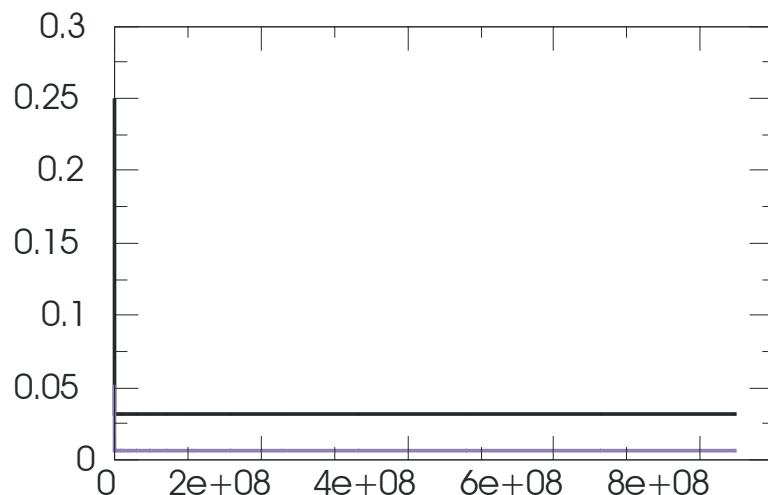
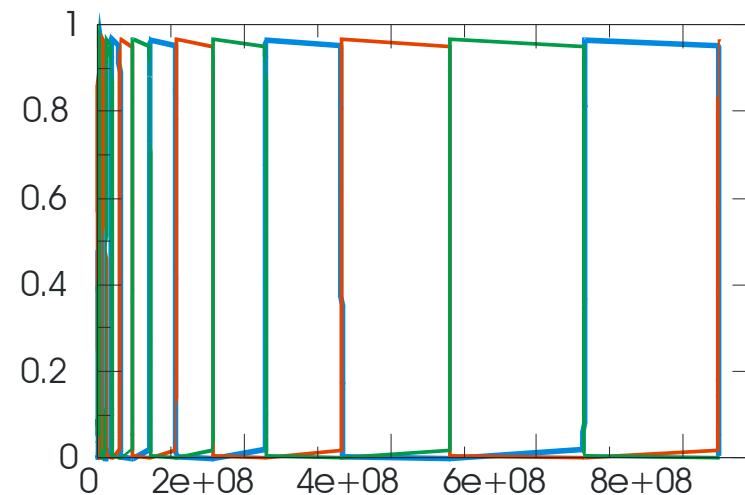


The repressilator limit cycle

Proteins

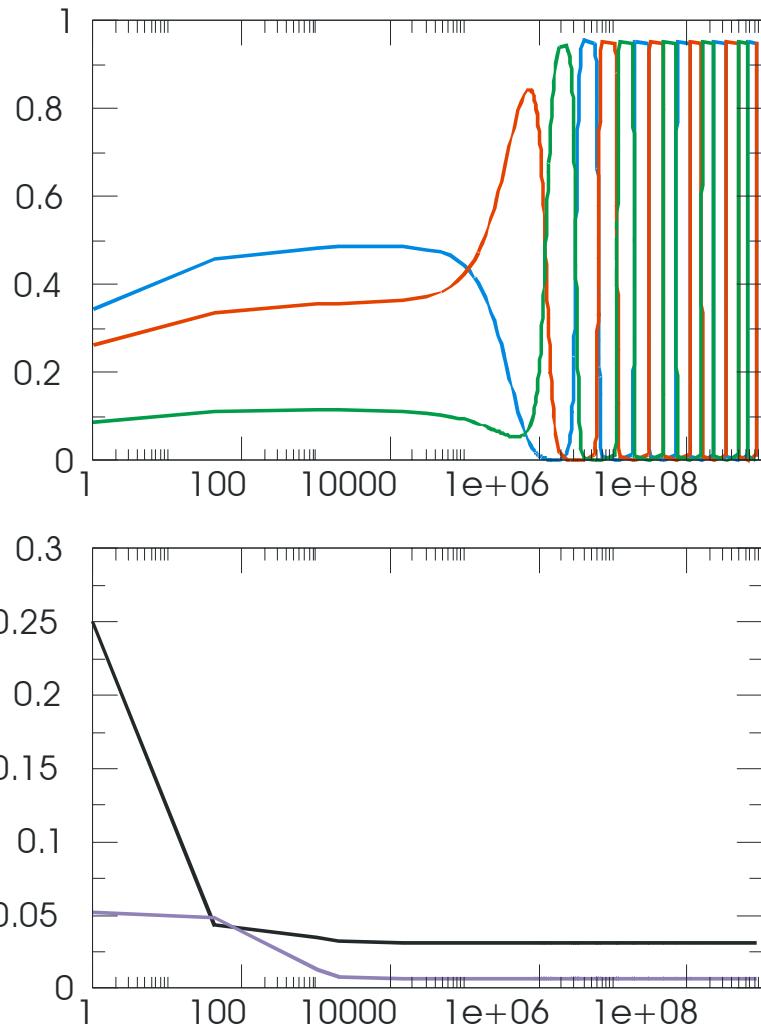


mRNAs

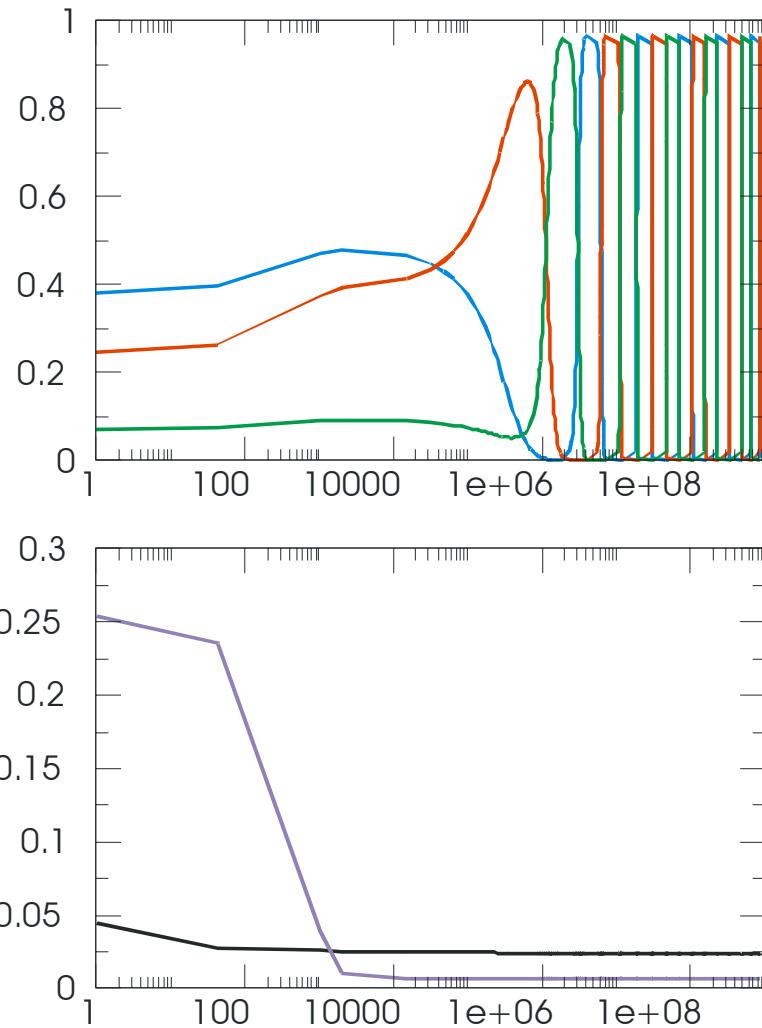


The repressilator heteroclinic orbit

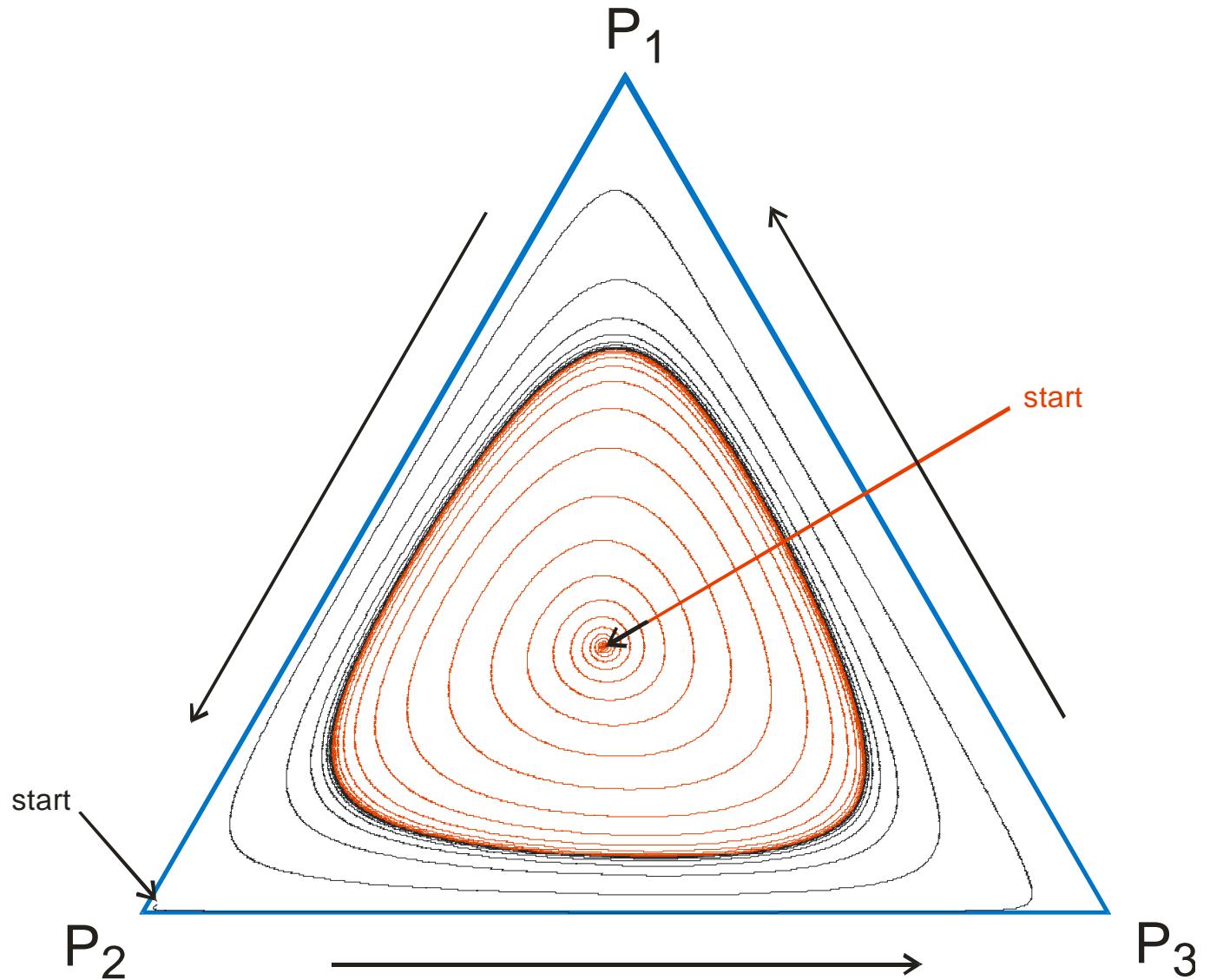
Proteins



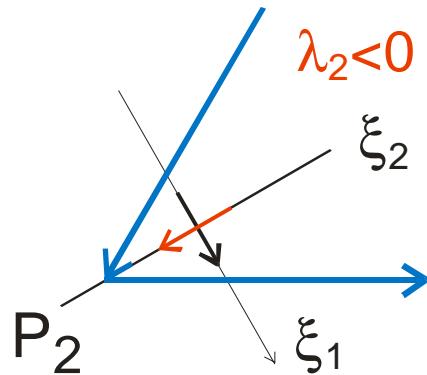
mRNAs



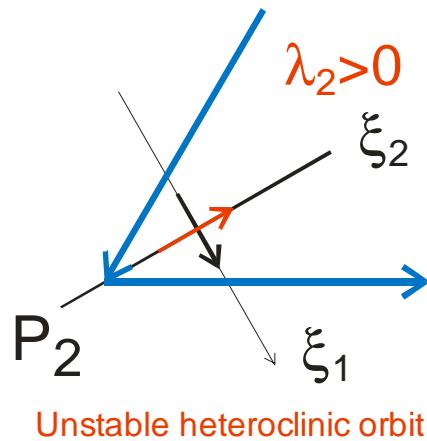
The repressilator heteroclinic orbit (logarithmic time scale)



The repressilator limit cycle

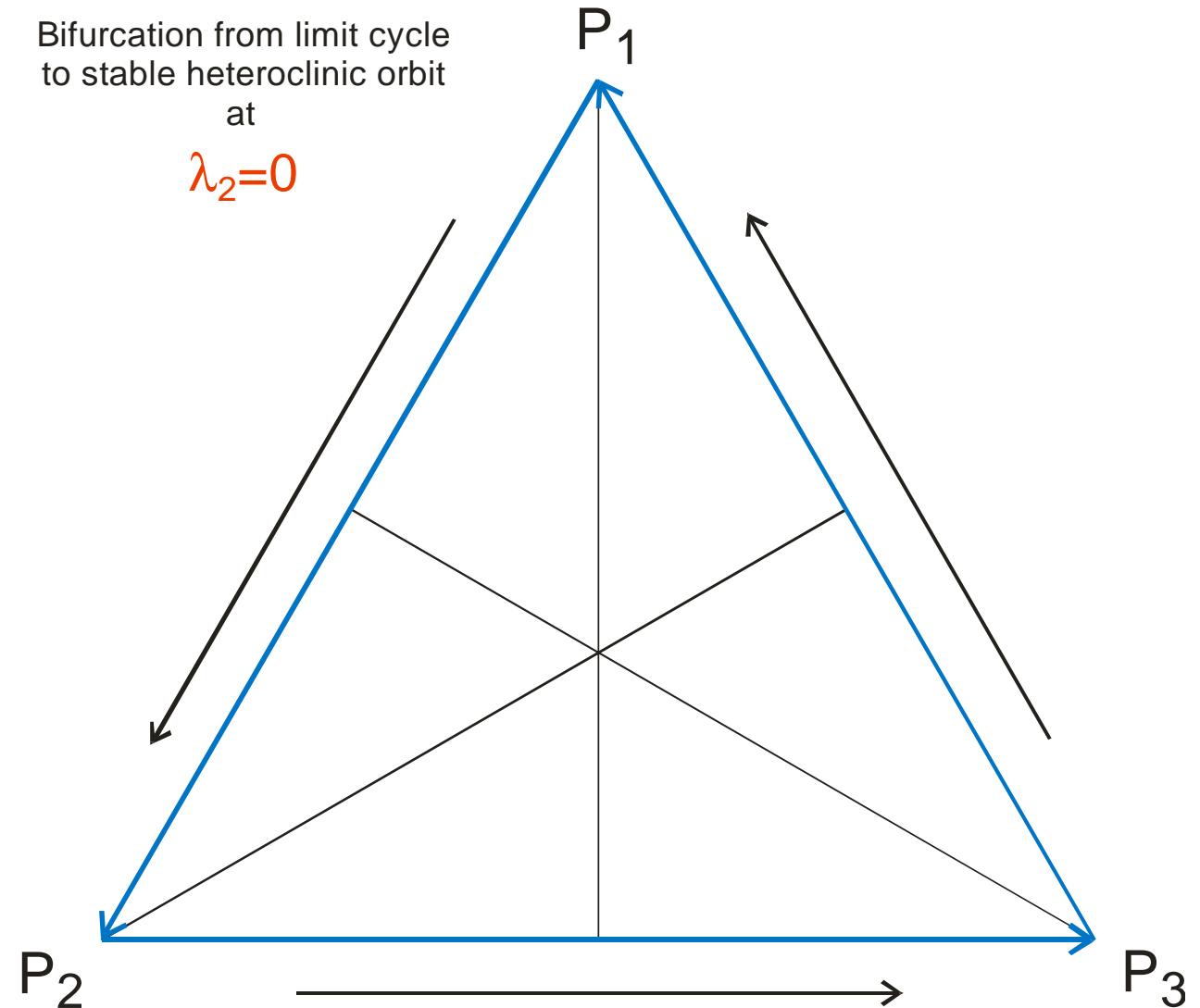


Stable heteroclinic orbit

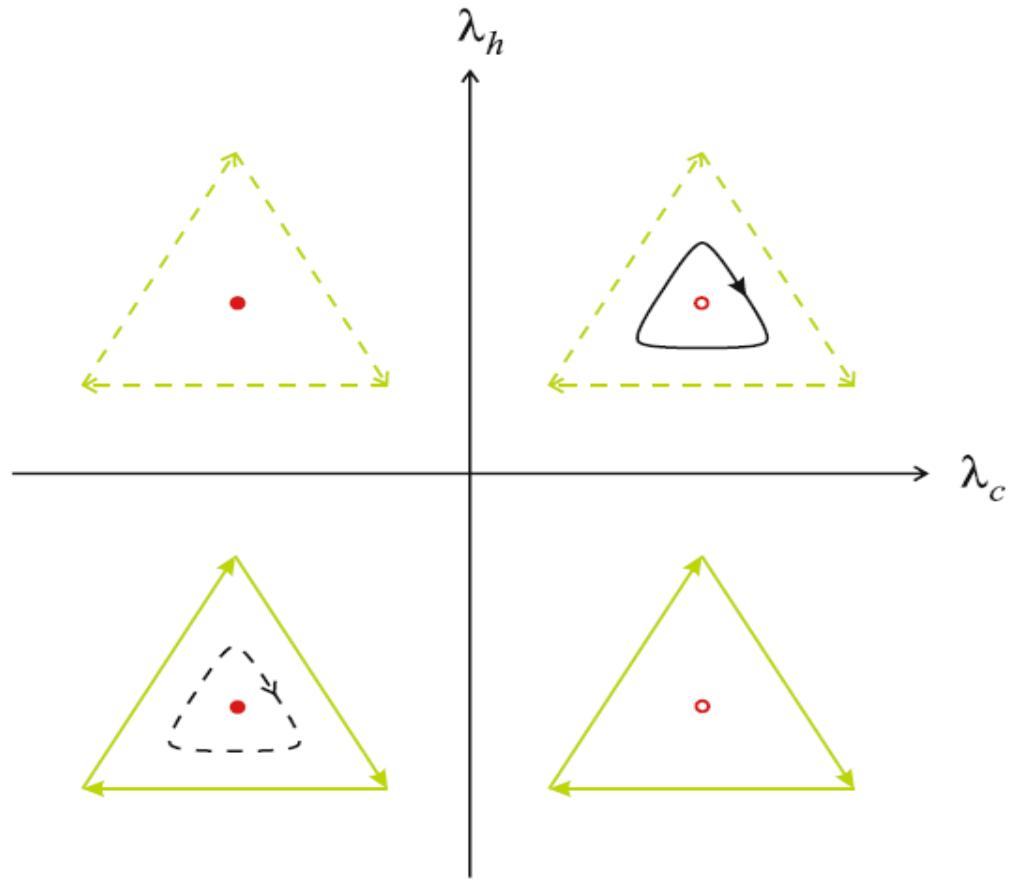


Unstable heteroclinic orbit

Bifurcation from limit cycle
to stable heteroclinic orbit
at
 $\lambda_2=0$



The repressilator heteroclinic orbit



$$(\varepsilon + d_1^Q) \dots (\varepsilon + d_n^Q)(\varepsilon + d_1^P) \dots (\varepsilon + d_n^P) + D = 0$$

$$D = - k_1^Q k_2^Q \dots k_n^Q k_1^P k_2^P \dots k_n^P \frac{\partial F_1}{\partial p_n} \frac{\partial F_2}{\partial p_1} \dots \frac{\partial F_n}{\partial p_{n-1}}$$

Upscaling to n genes with cyclic symmetry

1. The problems of quantitative biology
2. Forward and inverse problems in reaction kinetics
3. Regulation kinetics and bifurcation analysis
4. **Reverse engineering of dynamical systems**
5. How to upscale from small models to cells?

$$\dot{x} = f(x; p); \quad x = (x_1, \dots, x_n); \quad p = (p_1, \dots, p_m); \quad p \in P \subset \mathbf{R}^m$$

Σ ... bifurcation manifold

$$p = (p_i, p_s) \in P_i \times P_s; \quad P = P_i \oplus P_s; \quad \Sigma(p_s) \equiv \Sigma \cap \{p_s\}$$

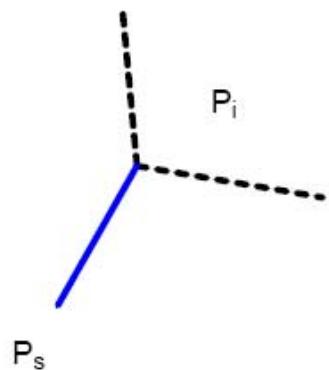
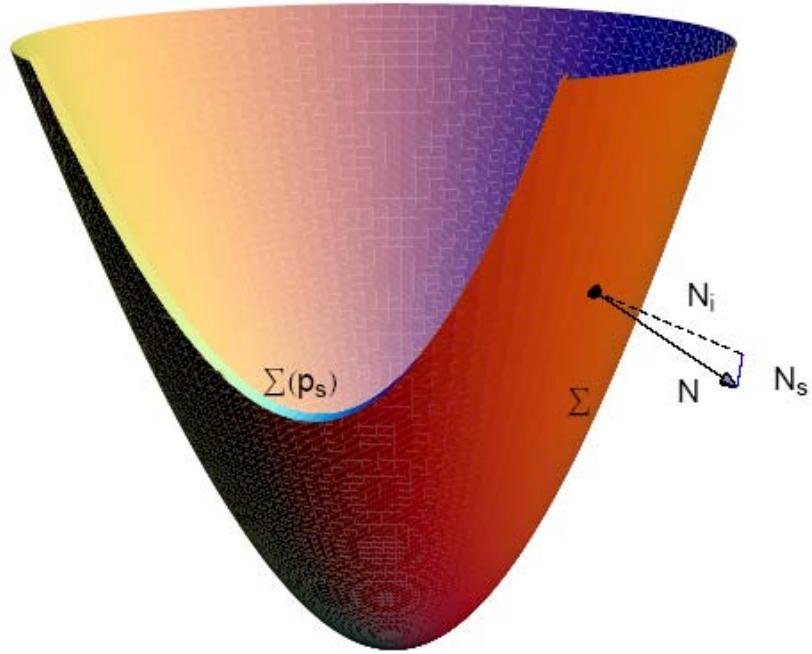
$$F(p) \equiv (F(p)_i, F(p_s)) = (\pi_{\perp \Sigma(p_s)} p_i, p_s) \quad \dots \text{forward operator}$$

$$\min_{p_s} J(p) = \min_{p_s} \|F(p)_i - p_i\| \quad \dots \text{formulation of the inverse problem}$$

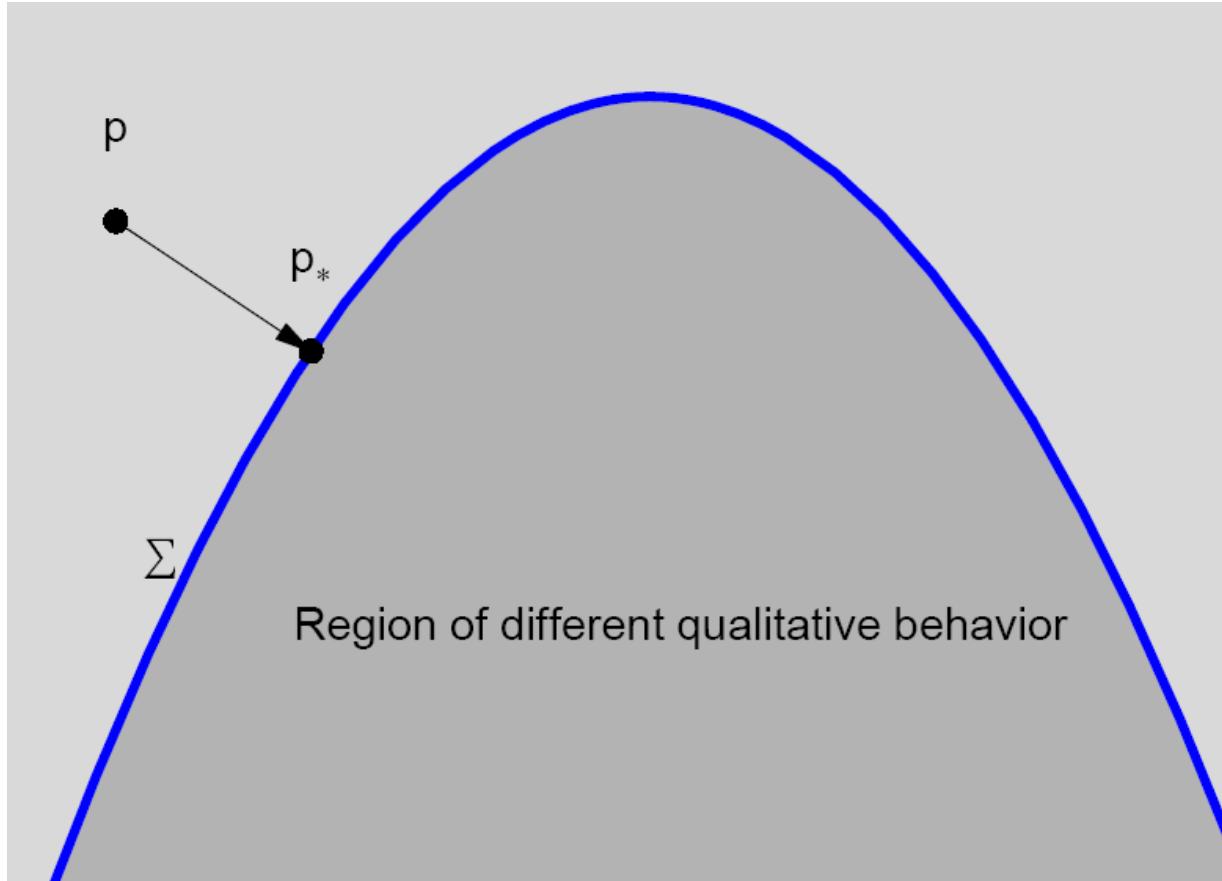
subject to $p_{\text{low}} \leq p \leq p_{\text{upp}}$

and $0 \leq c(F(p)_i)$

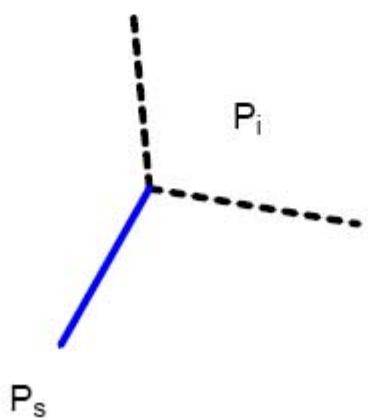
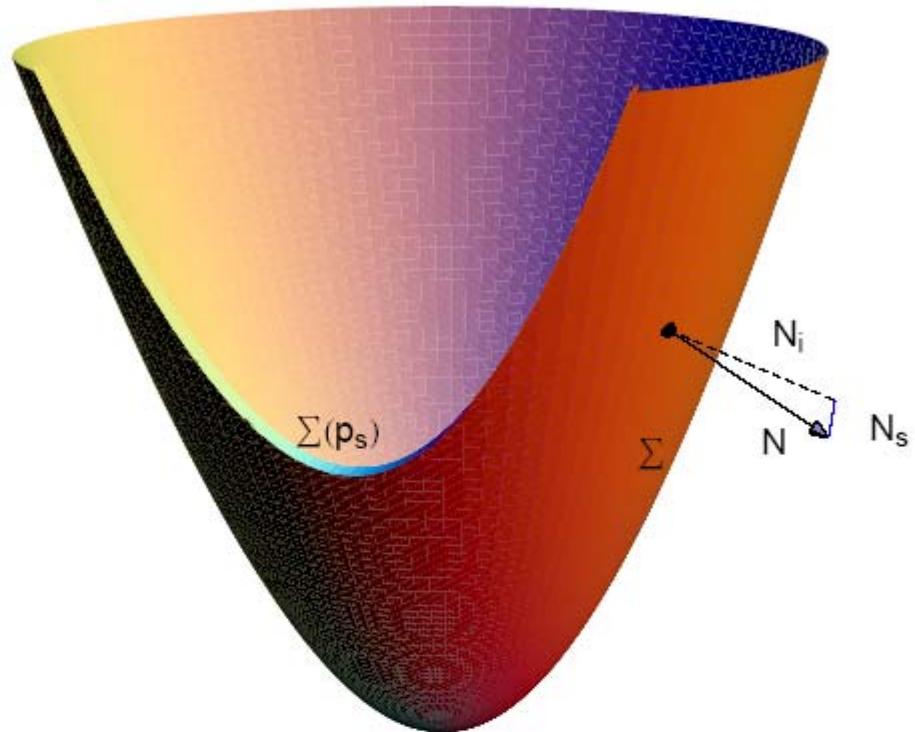
J. Lu, H.W. Engl, P. Schuster. Inverse bifurcation analysis: Application to simple gene systems.
AMB Algorithms for Molecular Biology 1, no.11, 2006.

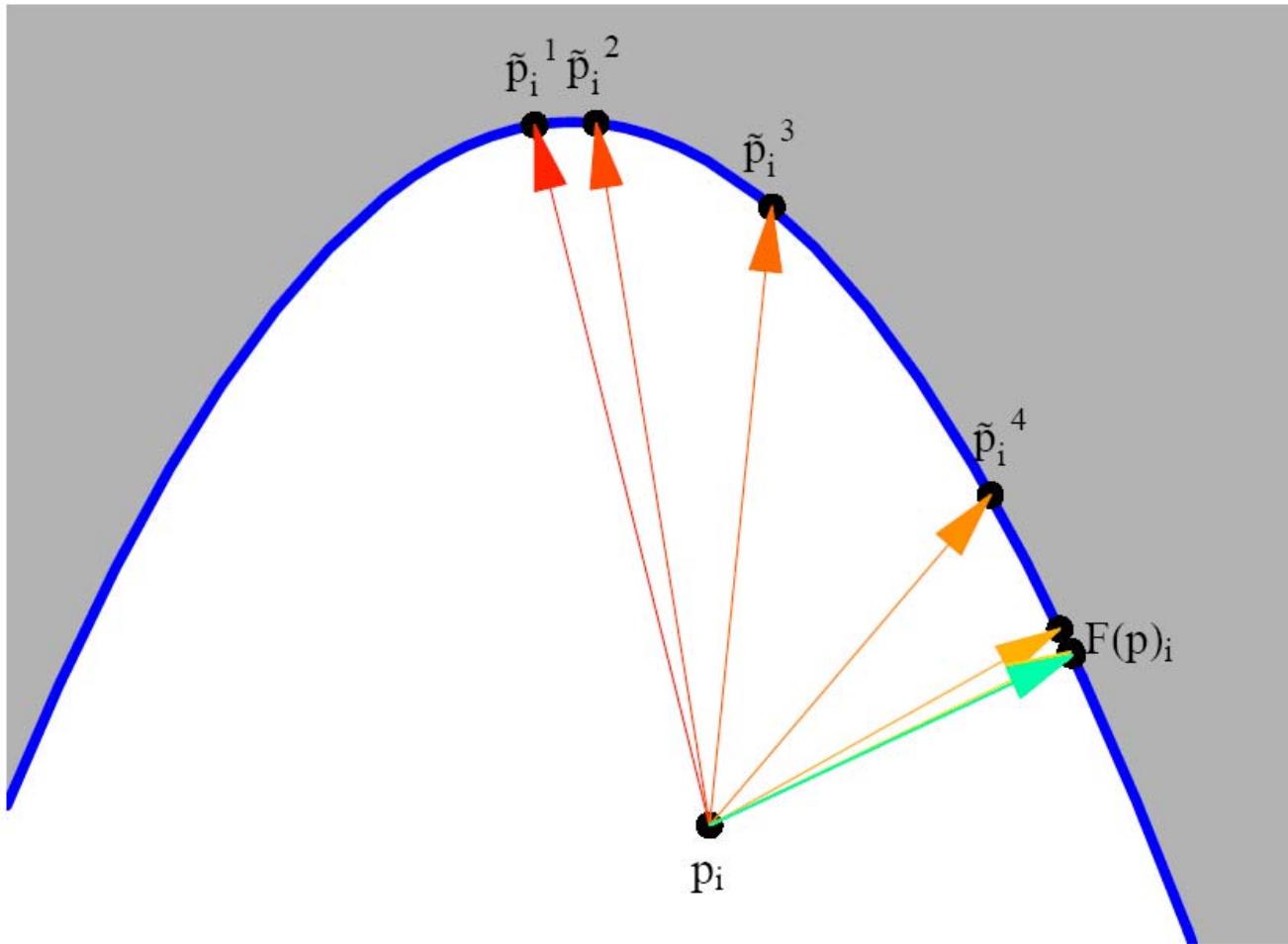


The bifurcation manifold



Definition of the forward operator $F(p)$





Iterative solution for $\min J(p)$

ALGORITHM: LOCMINDIST($x, (p_i, p_s), v, \epsilon,$)

- Set initial parameter: $p^0 \leftarrow p, x^0 \leftarrow x$
- FOR $j = 1, \dots, j_{max}$
 1. From p and x , continue along parameter ray $\{(p_i + rv, p_s) : r \in \mathbb{R}_+\}$, until bifurcation point p^b detected
 2. Compute normal vector at bifurcation point p^b : $v \leftarrow N_i(p^b)$
 3. Update: parameter iterate $p^j \leftarrow p^b$
ODE solution at bifurcation point $x^j \leftarrow x(p^b)$
 4. Terminate if $\|p^j - p^{j-1}\| / \|p^0\| < \epsilon$
- END
- Return $[(p_i^j, p_s), x^j]$

ALGORITHM: APPLYF($x_{init}, (p_i, p_s), \epsilon$)

- $x_{init} \leftarrow \text{INITODESOLN}(x_{init}, p)$
- Generate initial search vectors $V \leftarrow \{v_1, v_2, \dots, v_{\max}\}$
- FOR $j = 1, \dots, \dim(V)$
$$\begin{aligned}[F^j, x^j] &\leftarrow \text{LOCMINDIST}(x_{init}, p, v_j, \epsilon) \\ d_j &\leftarrow \|F^j - p\|\end{aligned}$$
- END
- $j_m \leftarrow \arg \min_{j=1, \dots, \dim(V)} d_j$
- Return $[F^{j_m}, x^{j_m}, x_{init}]$

ALGORITHM: INVERSE BIFURCATION

- Inputs:

- SBML document
- Initial parameter $p_i \in P_i$, $p_s \in P_s$, ODE solution x_{init}
- Parameter bounds $p_{\text{low}}, p_{\text{upp}} \in \mathbb{R}^m$
- Tolerances $\epsilon_{\text{proj}}, \epsilon_{\text{optim}} > 0$
- Step-size constraint $\Delta p_{\text{max}} \in \mathbb{R}^m$
- Nonlinear constraints $c : P_i \rightarrow \mathbb{R}^k$

- Constrained optimization step:

FOR $j = 1, \dots, j_{\text{max}}$

- $[F, x, x_{\text{init}}] \leftarrow \text{APPLYF}(x_{\text{init}}, (p_i, p_s), \epsilon)$
- $F'^* \leftarrow \text{APPLYFDERIVADJ}(F, x)$
- $c \leftarrow \text{APPLYC}(F, x)$
- $c'^* \leftarrow \text{APPLYCDERIVADJ}(F, F'^*, x)$
- $[p_s, \tilde{H}] \leftarrow \text{SQPSTEP}(F, F'^*, p_{\text{low}}, p_{\text{upp}}, c, c'^*, \tilde{H}, \Delta p_{\text{max}})$
- $J_{j+1} \leftarrow \|F(p) - p\|$
- Terminate if $|(J_{j+1} - J_j)/J_0| \leq \epsilon_{\text{optim}}$

END

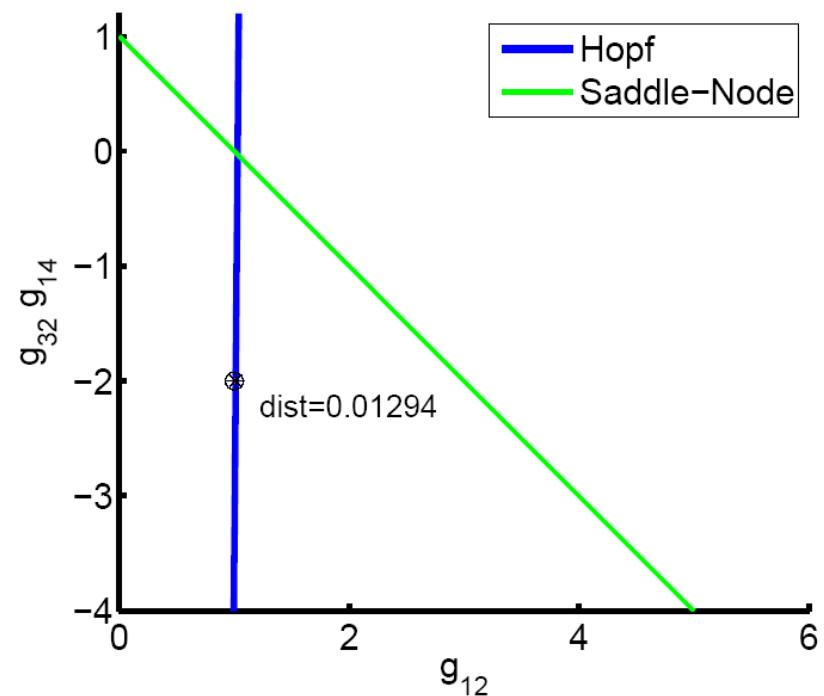
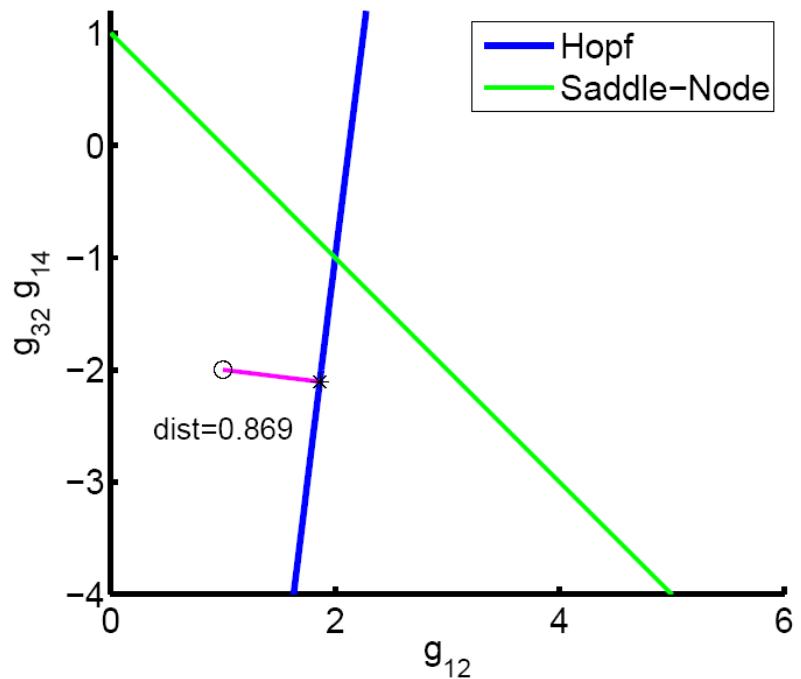
$$\begin{aligned}\frac{dx_{2k-1}}{dt} &= \beta_{2k-1}(f_{2k-1} - x_{2k-1}) \\ \frac{dx_{2k}}{dt} &= \beta_{2k}(x_{2k-1} - x_{2k}), \\ k &= 1, 2, 3\end{aligned}$$

$$\begin{aligned}f_1 &= \begin{cases} B & \text{for } x_2^{g_{12}} x_4^{g_{14}} \leq B \\ x_2^{g_{12}} x_4^{g_{14}} & \text{for } B < x_2^{g_{12}} x_4^{g_{14}} < M \\ M & \text{for } x_2^{g_{12}} x_4^{g_{14}} \geq M \end{cases} \\ f_3 &= \begin{cases} B & \text{for } x_2^{g_{32}} \leq B \\ x_2^{g_{32}} & \text{for } B < x_2^{g_{32}} < M \\ M & \text{for } x_2^{g_{32}} \geq M \end{cases} \\ f_5 &= \begin{cases} 1/M & \text{for } x_4^{g_{54}} \leq 1/M \\ x_4^{g_{54}} & \text{for } 1/M < x_4^{g_{54}} < 1/B, \\ 1/B & \text{for } x_4^{g_{54}} \geq 1/B \end{cases}\end{aligned}$$

Switch or oscillatory behavior in Escherichia coli

T.S. Gardner, C.R. Cantor, J.J. Collins. Construction of a genetic toggle switch in Escherichia coli. *Nature* **403**:339-342, 2000.

M.R. Atkinson, M.A. Savageau, T.J. Myers, A.J. Ninfa. Development of genetic circuitry exhibiting toggle switch or oscillatory behavior in Escherichia coli. *Cell* **113**:597-607, 2003.



Inverse bifurcation analysis of switch or oscillatory behavior in *Escherichia coli*

J. Lu, H.W. Engl, P. Schuster. Inverse bifurcation analysis: Application to simple gene systems. *AMB Algorithms for Molecular Biology* 1:11, 2006.

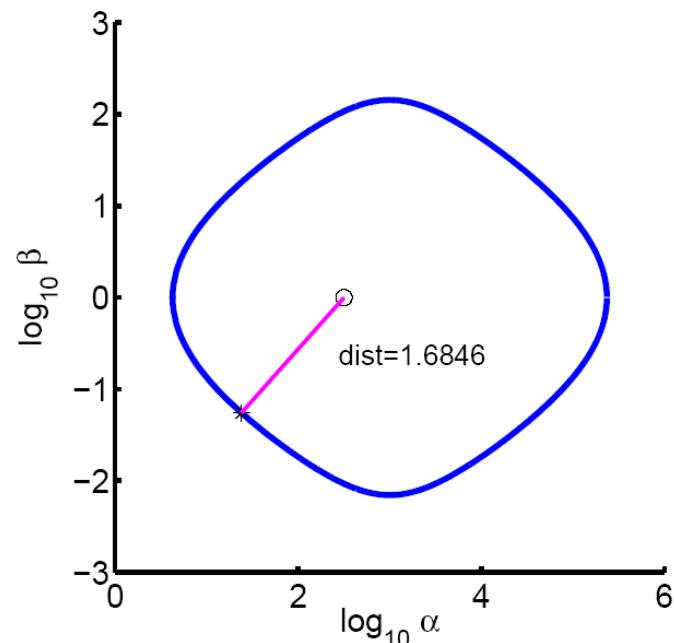
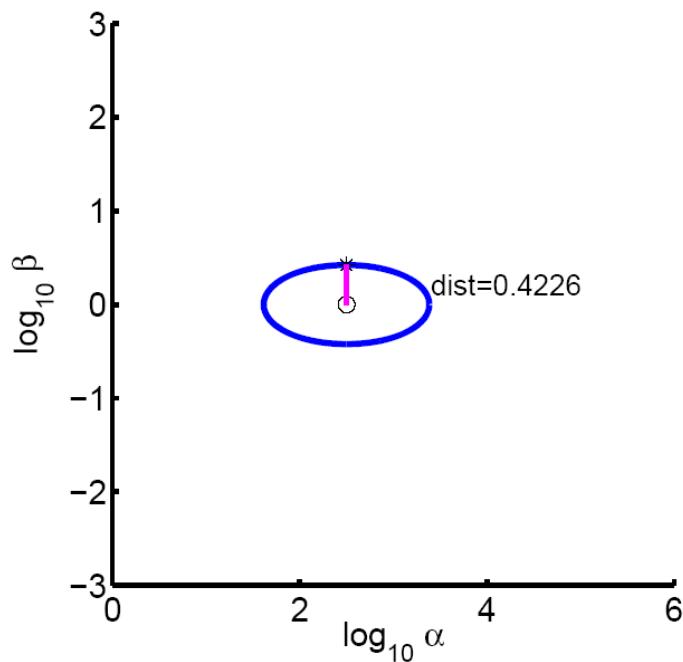
$$\begin{aligned}\dot{x}_i &= \beta_i(y_i - x_i) \\ \dot{y}_i &= \alpha_i \left(\frac{1 - \delta_i}{1 + x_{i-1 \mod n}^{h_i}} + \delta_i \right) - y_i, \quad i = 0, \dots, n-1\end{aligned}$$

$$\alpha_i = \alpha, \beta_i = \beta, h_i = h, \delta_i = \delta$$

$$\begin{aligned}p_i &= (\alpha, \beta) & (10^{-4}, 0) \leq (\delta, h) \leq (10^{-1}, 2) \\ p_s &= (\delta, h)\end{aligned}$$

Inverse bifurcation analysis of the repressilator model

S. Müller, J. Hofbauer, L. Endler, C. Flamm, S. Widder, P. Schuster. A generalized model of the repressilator. *J. Math. Biol.* **53**:905-937, 2006.



Inverse bifurcation analysis of the repressilator model

J. Lu, H.W. Engl, P. Schuster. Inverse bifurcation analysis: Application to simple gene systems. *AMB Algorithms for Molecular Biology* 1:11, 2006.

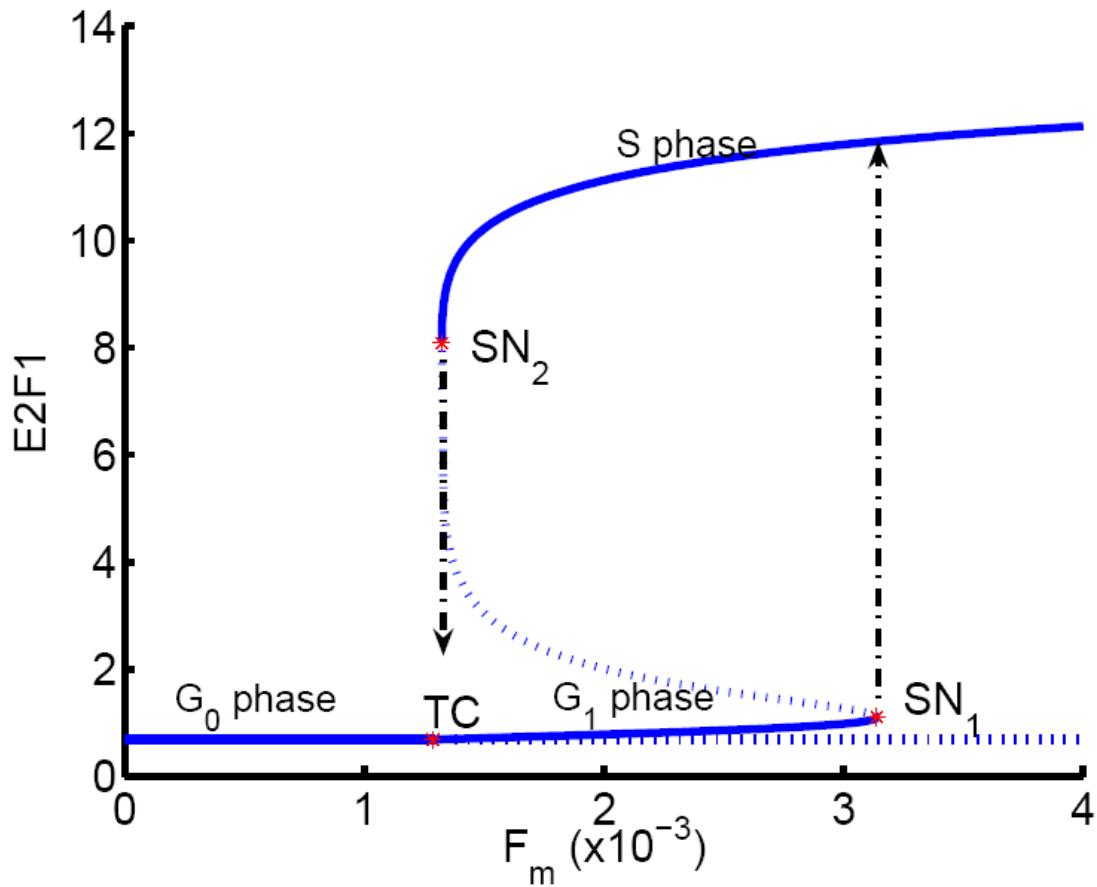
$$\frac{d}{dt} [\text{pRB}] = k_1 \frac{[\text{E2F1}]}{K_{m1} + [\text{E2F1}]} \frac{J_{11}}{J_{11} + [\text{pRB}]} - \phi_{\text{pRB}} [\text{pRB}]$$

$$\frac{d}{dt} [\text{E2F1}] = k_p + k_1 \frac{a^2 + [\text{E2F1}]^2}{K_{m2}^2 + [\text{E2F1}]^2} \frac{J_{12}}{J_{12} + [\text{pRB}]} - \phi_{\text{E2F1}} [\text{E2F1}]$$

$$\frac{d}{dt} [\text{AP1}] = F_m + k_{25} [\text{E2F1}] \frac{J_{15}}{J_{15} + [\text{pRB}]} \frac{J_{65}}{J_{11} + [\text{pRB}']} - \phi_{\text{AP1}} [\text{AP1}]$$

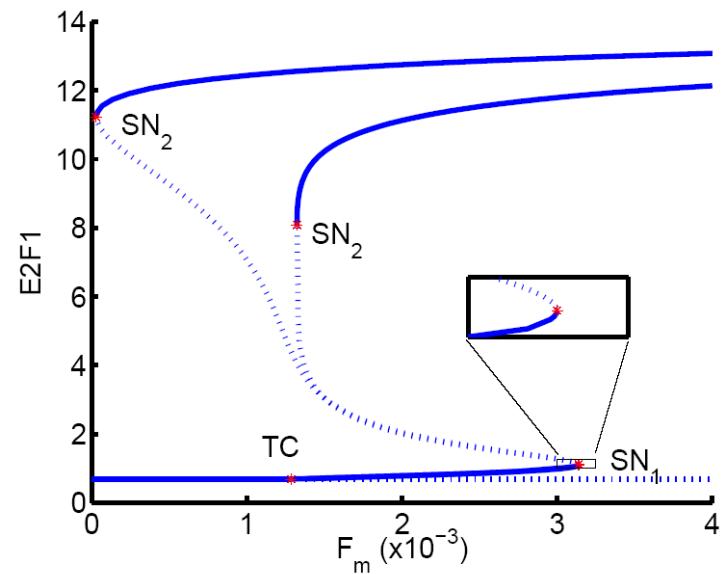
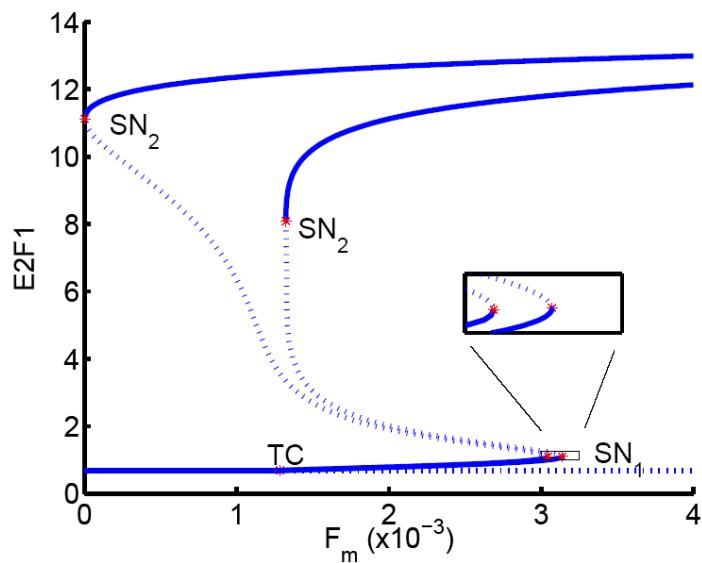
A simple dynamical cell cycle model

J.J. Tyson, A. Csikasz-Nagy, B. Novak. The dynamics of cell cycle regulation. *Bioessays* **24**:1095-1109, 2002



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4. Reverse engineering of dynamical systems
5. How to upscale from small models to cells?

Suitable systems for upscaling:

1. Linear systems via large eigenvalue problems
2. Cascades
3. Cyclic systems in case of high symmetry
4. Sufficiently simple networks ???

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