

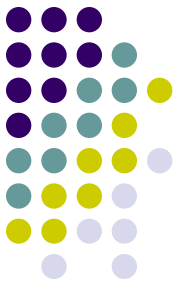
Computing in biomolecular systems



Mikhail Ivanchenko

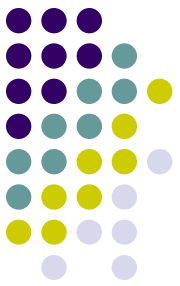
Lobachevsky State University of Nizhny Novgorod





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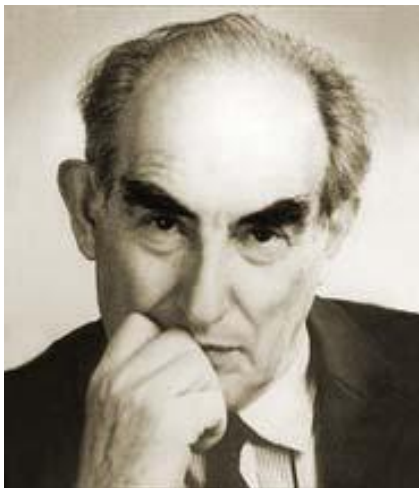
- Introduction: from bio to maths
- Mathematical models of gene regulation
- Dynamics of gene regulation
- Logic circuits
- Synthetic gene classifier



ФИЗИКА НАШИХ ДНЕЙ

**Какие проблемы физики и астрофизики
представляются сейчас особенно важными и интересными
(тридцать лет спустя, причем уже на пороге XXI века)?**

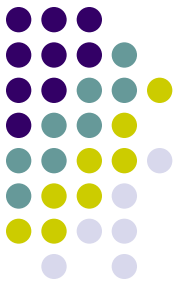
В.Л. Гинзбург



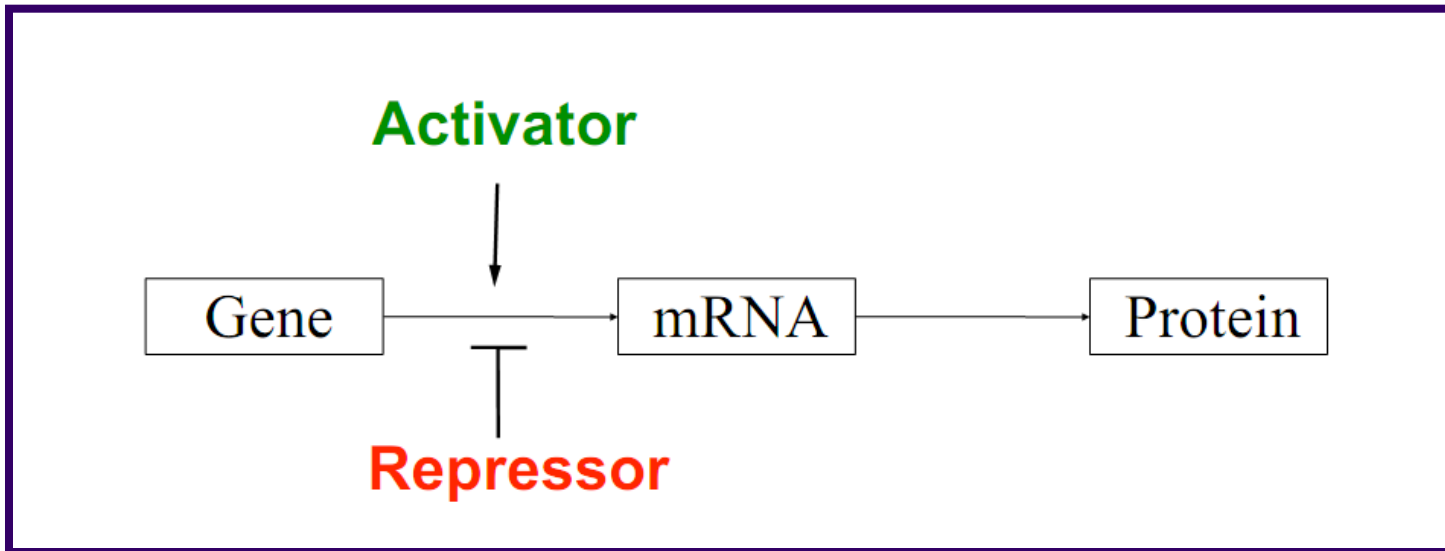
30 + 3 «великих» проблемы науки XXI века

Последняя "великая" проблема, которая будет здесь
затронута, касается связи физики с биологией. С конца

основе физики, уже известной физики. Конкретно, основ-
ными являются вопросы о происхождении жизни и
появлении сознания (мышления). Образование в усло-



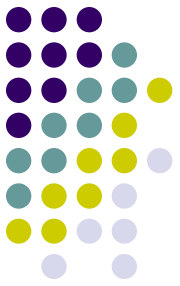
«Newton's Law» for living systems



Transcriptional regulation:

Activator - increases reaction rate

Repressor - decreases reaction rate

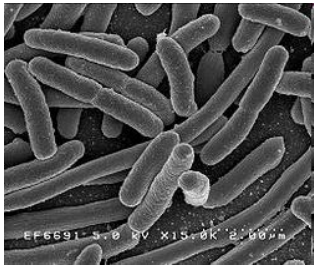
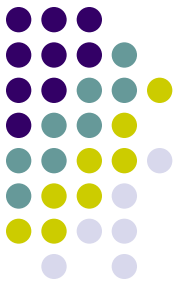


Dynamics

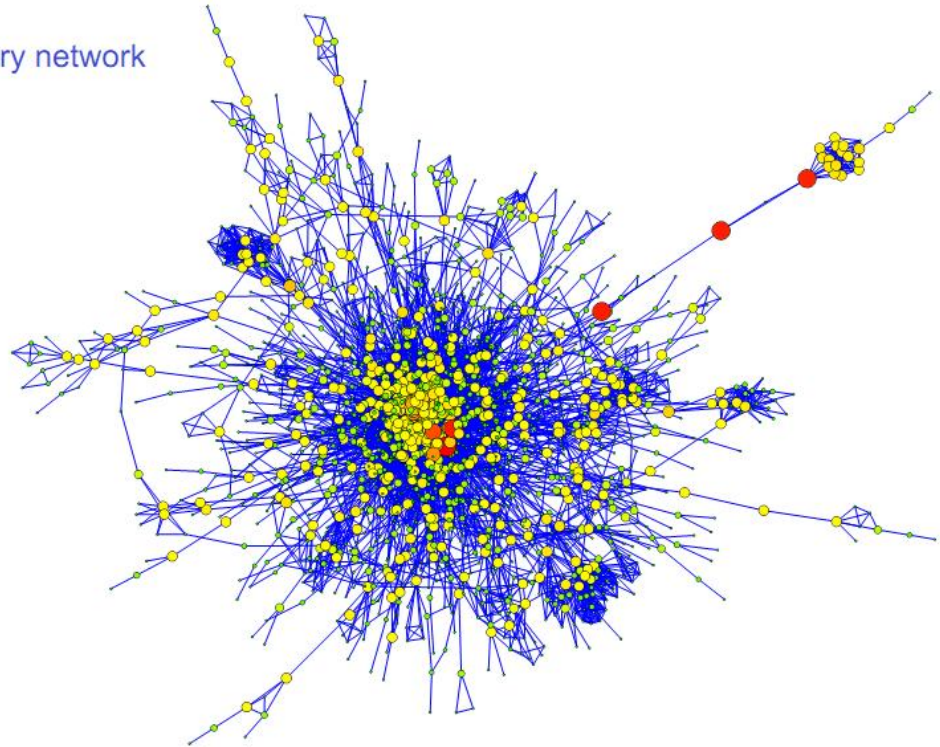
Gene expression is never stationary:

- External signals
- Extrinsic noise
- Intrinsic noise
- Oscillations (circadian and ultradian clocks, cell cycle, etc.)

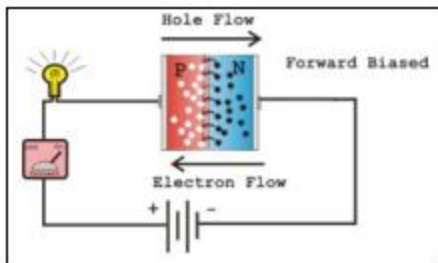
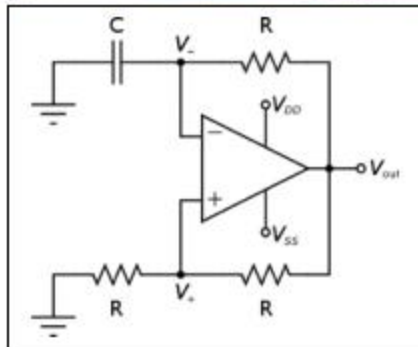
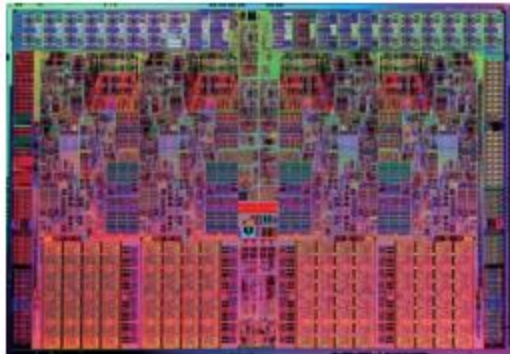
Gene regulation networks



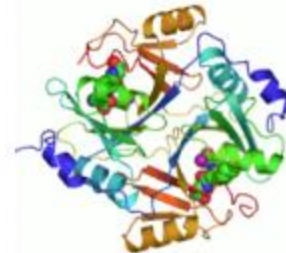
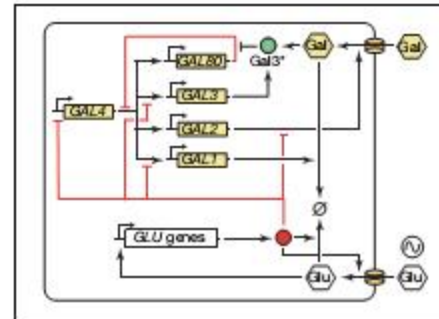
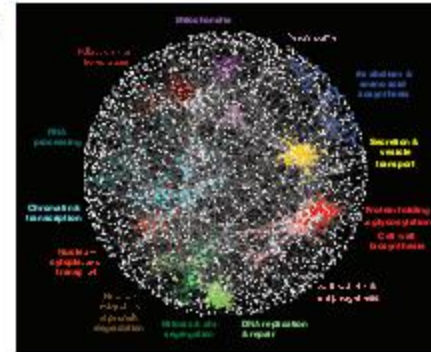
E.Coli regulatory network

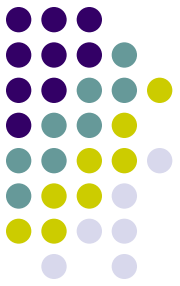


- «read» all genes (genomics)
- determine gene and protein interactions (network reconstruction)
- network dynamics (complex systems)



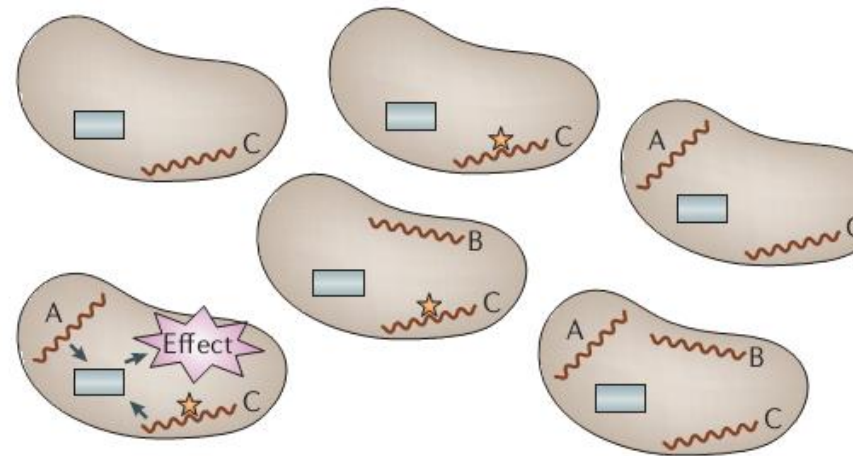
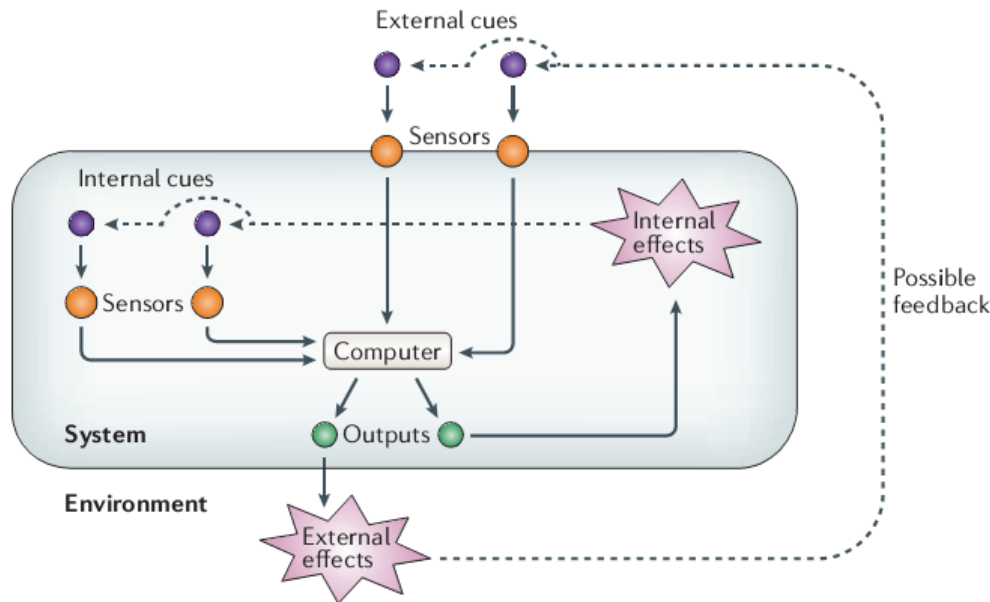
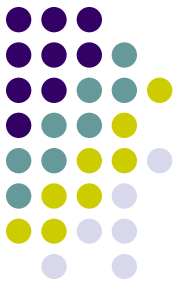
scale





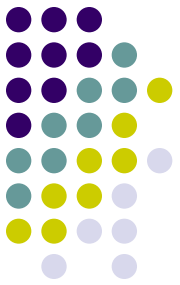
- Do gene networks solve computational tasks?
- Can one construct gene networks for computing?

Do regulatory networks solve computational tasks?



Yes, in the sense of information processing

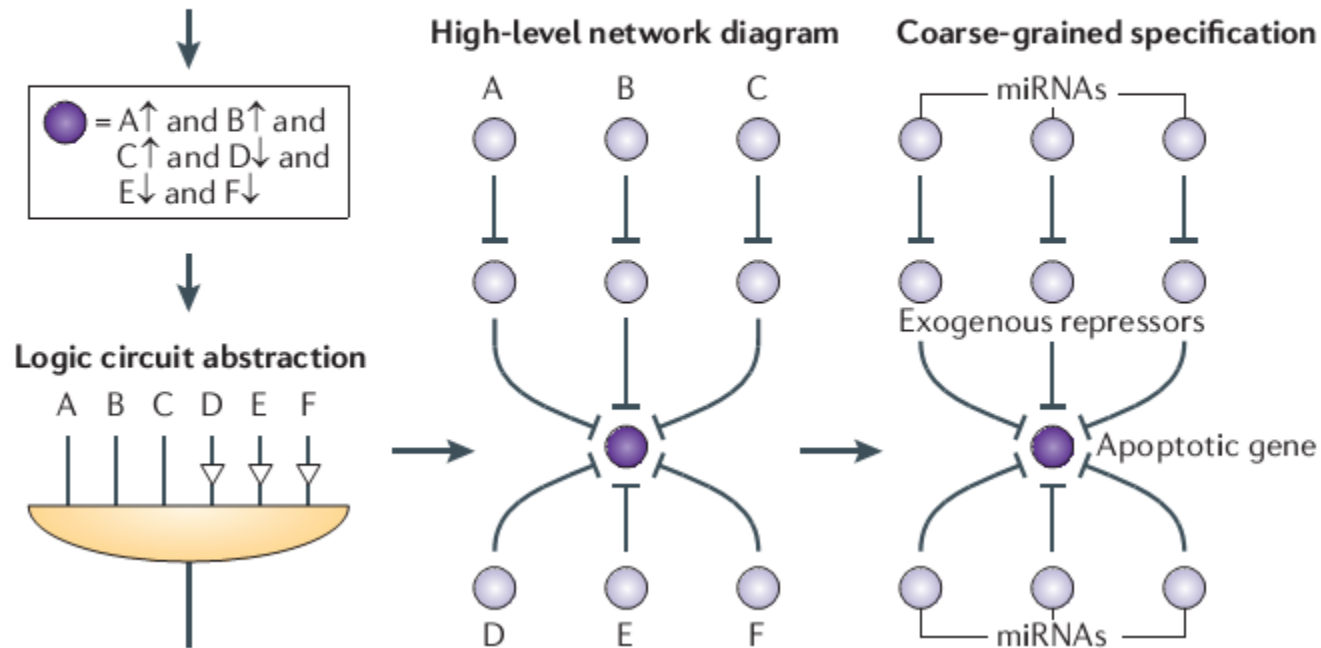
Can one construct gene networks for computing?



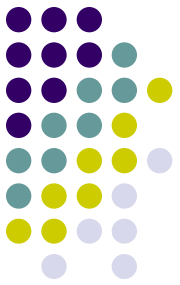
Task: trigger cell death when a certain gene* expression profile[‡] is found in a cell

*Suppose that gene products are negative regulators

[‡]A profile is a combination of highly expressed and unexpressed genes

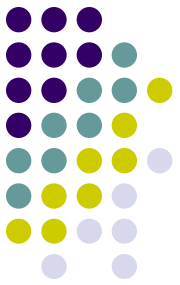


Devil in details: find components!

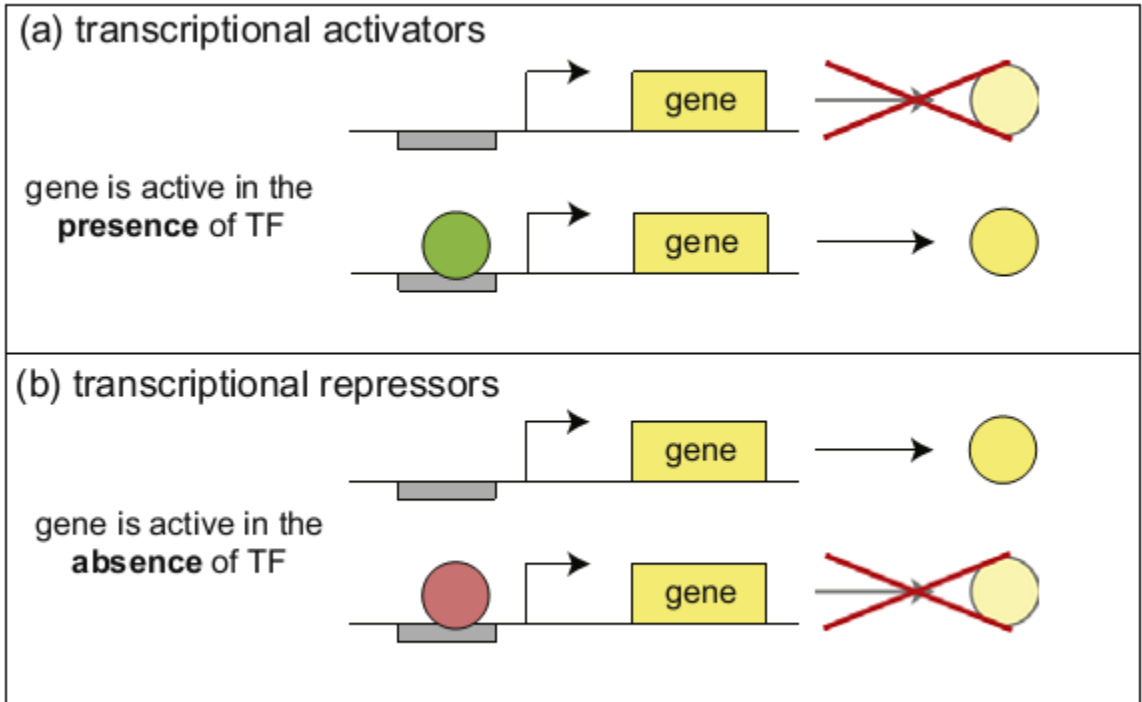
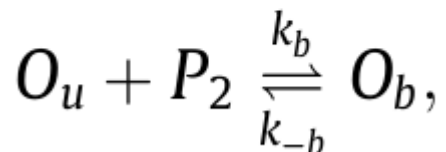
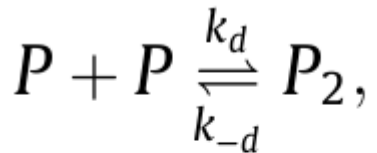


Mathematical models of gene regulation

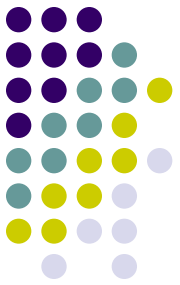
Transcriptional regulation and dynamics



- Let TF be active only as a dimer.
- Let P be a concentration of a monomer TF, P_2 — concentration of a dimer, O_u — concentration of unbound operator sites, O_b — of bound sites.
- Then for equilibrium DNA and TF concentrations one gets:



Transcriptional regulation and dynamics



In the equilibrium state

$$k_d P^2 = k_{-d} P_2,$$
$$k_b O_u P_2 = k_{-b} O_b.$$

Since DNA concentration is constant,
Therefore

$$O_u + O_b = N$$

$$O_u = \frac{N}{1 + (P/K)^2},$$

where $K = \sqrt{k_{-b}k_{-d}/k_bk_d}$

And similarly

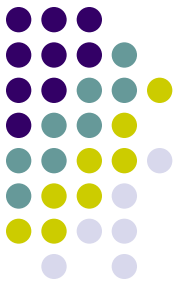
$$O_b = \frac{N(P/K)^2}{1 + (P/K)^2}$$

Hill equations

Hill constant

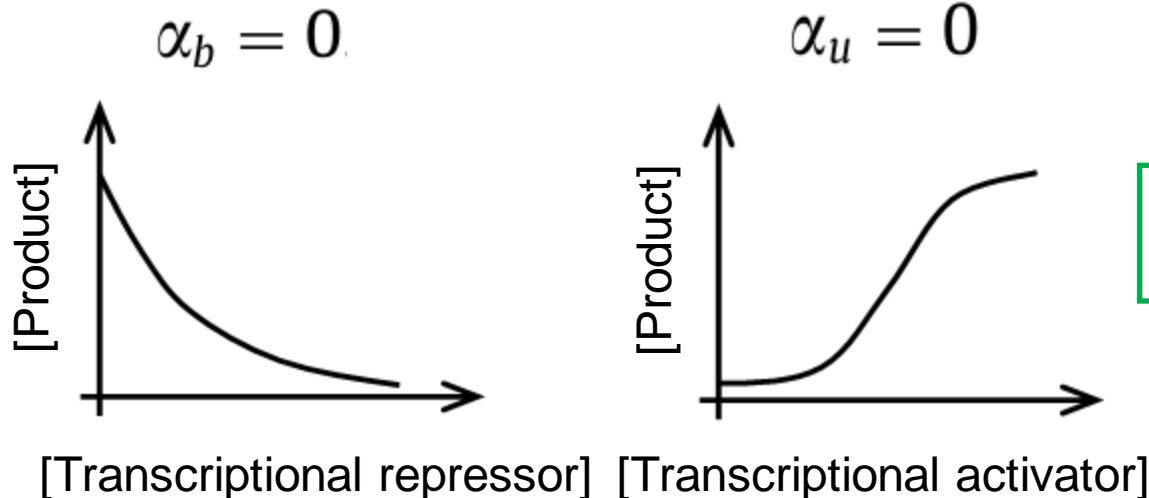
Hill coefficient (not necessarily =2, not even a round number, e.g. in case of simultaneous binding to several operons)

Transcriptional regulation and dynamics



If gene promoter 'works' with rate α_u when unbounded by TF, and with rate α_b when bound, then the net kinetic coefficient of gene expression reads

$$v_{init}(P) = \alpha_u O_u + \alpha_b O_b = \alpha_u \frac{N}{1 + (P/K)^2} + \alpha_b \frac{N(P/K)^2}{1 + (P/K)^2}.$$



Already a sense of a basic threshold (yes/no) detector!



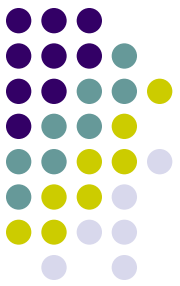
Transcriptional regulation and dynamics

Taking into account protein degradation, we arrive at the differential equation for dynamics of protein concentration

$$\dot{x} = \alpha_u \frac{N}{1 + (P/K)^2} + \alpha_b \frac{N(P/K)^2}{1 + (P/K)^2} - r_{deg}(x)$$

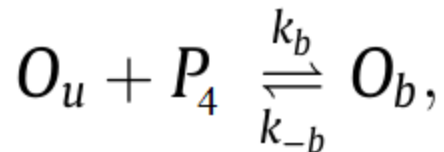
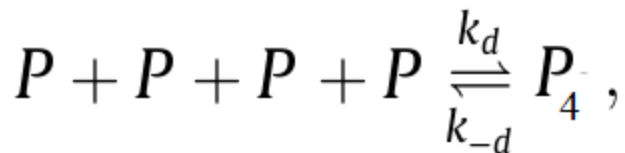
Note:

In fact, the number of molecules is discrete and molecular events are discrete too. Hence ODE gives an approximate description only. A more precise description would employ random processes with probabilities proportional to kinetic coefficients. When the number of molecules is small or production events are rare, that model is much more adequate.



Example 1

- Let TF be active only as a **tetramer**.
- Let P be a concentration of a monomer TF, P_2 — concentration of a dimer, O_u — concentration of unbound operator sites, O_b — of bound sites.
- Then for equilibrium DNA and TF concentrations one gets:



Find equation for the protein dynamics

In equilibrium

$$\begin{aligned} k_d P^4 &= k_{-d} P_4, \\ k_b O_u P_4 &= k_{-b} O_b. \end{aligned} \quad O_u + O_b = N$$

В равновесном состоянии будет выполняться

$$\begin{aligned} k_d P^2 &= k_{-d} P_2, \\ k_b O_u P_2 &= k_{-b} O_b. \end{aligned}$$

Раз суммарная концентрация ДНК постоянна, Отсюда

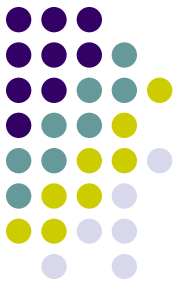
$$O_u = \frac{N}{1 + (P/K)^2},$$

где $K = \sqrt{k_{-b}k_{-d}/k_bk_d}$

$$\text{и аналогично} \quad O_b = \frac{N(P/K)^2}{1 + (P/K)^2}.$$

$r_{deg}(x)$

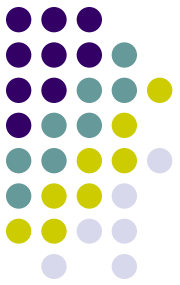
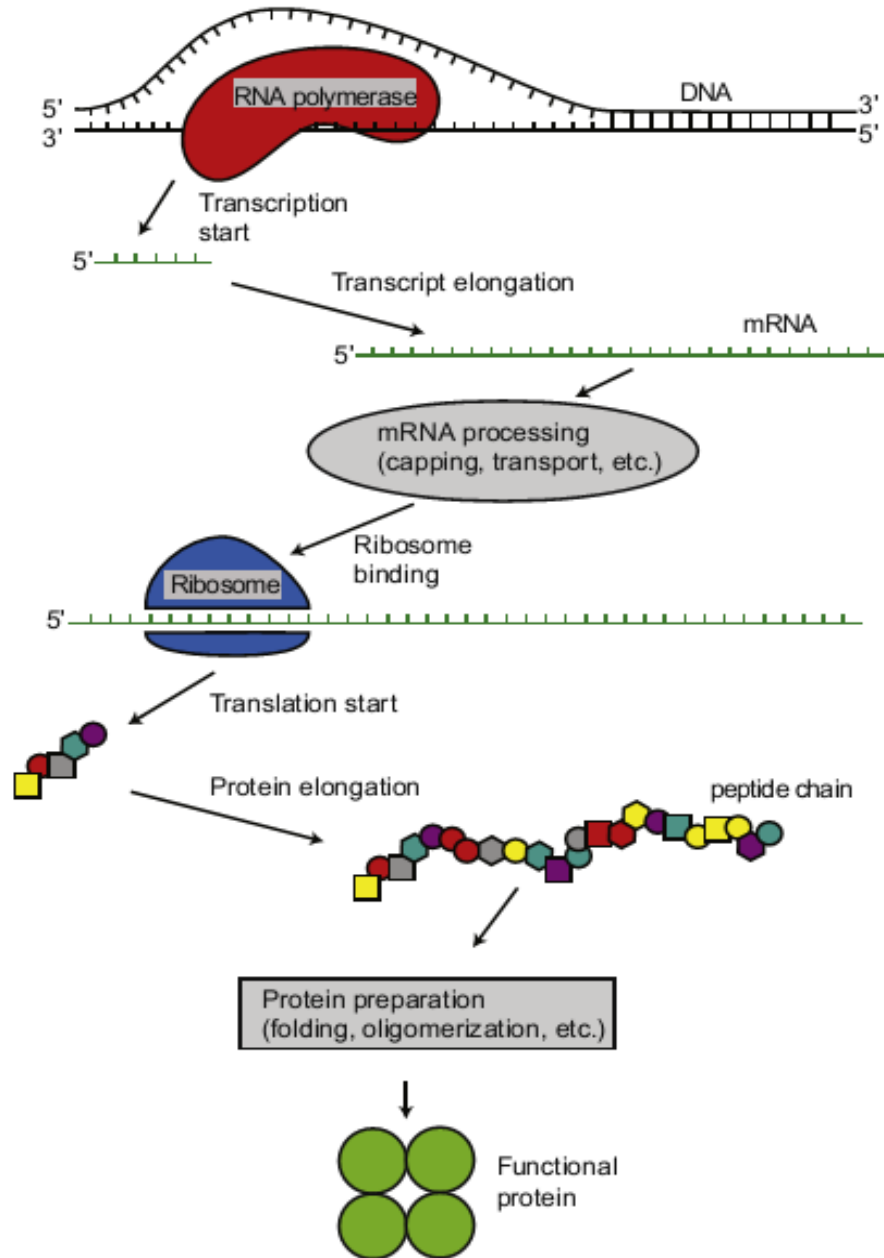
Transcriptional regulation and dynamics

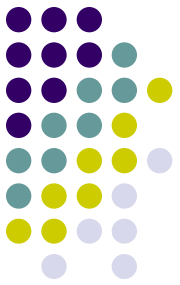


Equations get more complicated if:

- A gene promotor consists of several operators (e.g., a tandem promotor of two operators: for a repressor TF and an activator TF)
- In eucaryotic cells TFs must enter cell nucleus first; coming in and out may add to dynamics
- Often TF are modulated by light active molecules – ligands. E.g. IPTG molecules can bind to TF-repressor LacI – sensitive promotor, and prevent binding of the latter. TF-activator AraC binds to the sensitive promotor only in presence of arabinose.

Detailed protein synthesis scheme





More detailed models

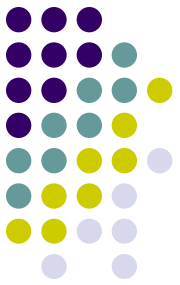
Taking into account mRNA synthesis as a separate process

$$\begin{aligned}\dot{m} &= \frac{\alpha_u N}{1 + (P/K)^2} + \frac{\alpha_b N (P/K)^2}{1 + (P/K)^2} - r_m(m), \\ \dot{x} &= r_{tl}m - r_x(x),\end{aligned}$$

Phenomenological time delay equation

$$\dot{x} = \frac{\alpha_u N}{1 + (P(t - \tau)/K)^2} + \frac{\alpha_b N (P(t - \tau)/K)^2}{1 + (P(t - \tau)/K)^2} - r_{deg}(x)$$

Protein degradation



- «Exponential» (generic mechanisms of cellular degradation)

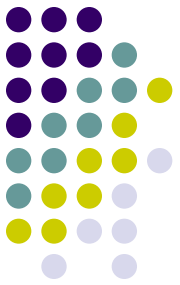
$$r_{deg}(\chi) = \gamma\chi$$

- Enzyme (by a specific enzyme that acts on tagged proteins)

$$r_{deg,enz} = \frac{V_{max}\chi}{K_m + \chi}$$

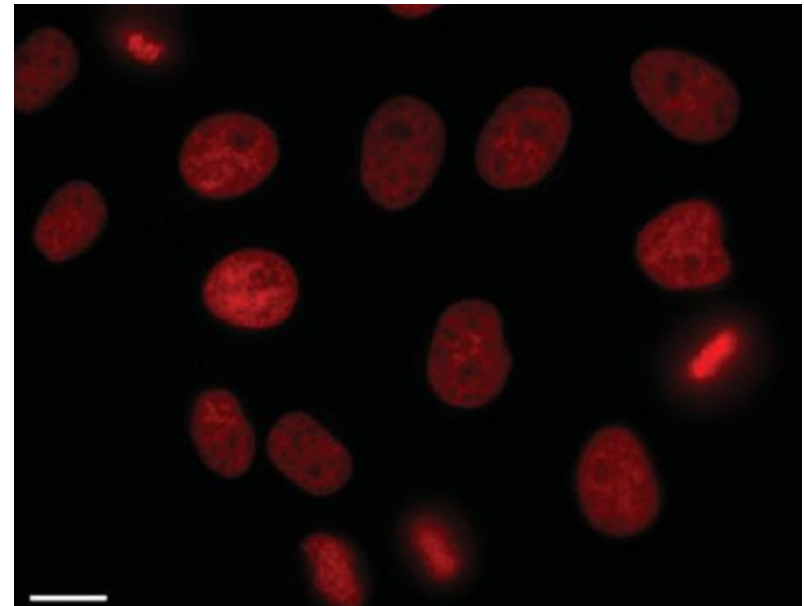
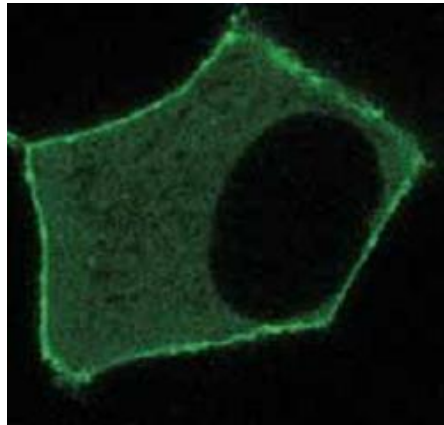
- If an enzyme degrades several proteins, the rate becomes

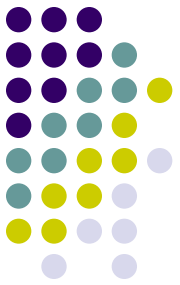
$$r_{deg,i}(\chi_i, T) = \frac{V_{max,i}\chi_i}{K_m + \sum_j \chi_j} - \gamma\chi_i$$



Synthetic biology: plugging in new genes and constructing regulatory networks

- Novel functionality
- «well-orthogonal» signals = an opportunity to study dynamics of networks isolated to a good degree
- Visualising gene expression by fluorescent proteins

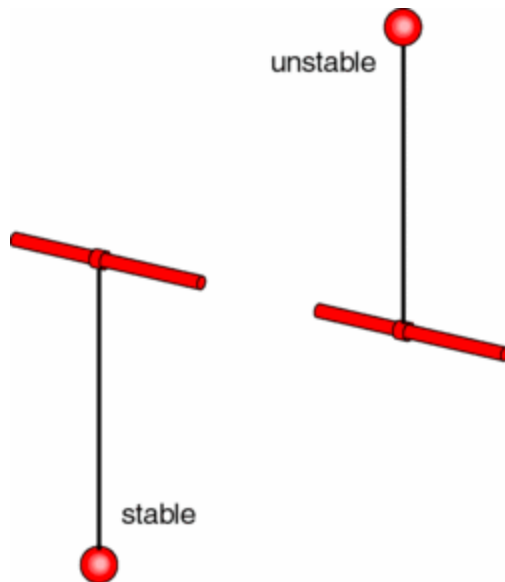




Dynamics of gene regulation



Nonlinear dynamics: equilibrium states



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

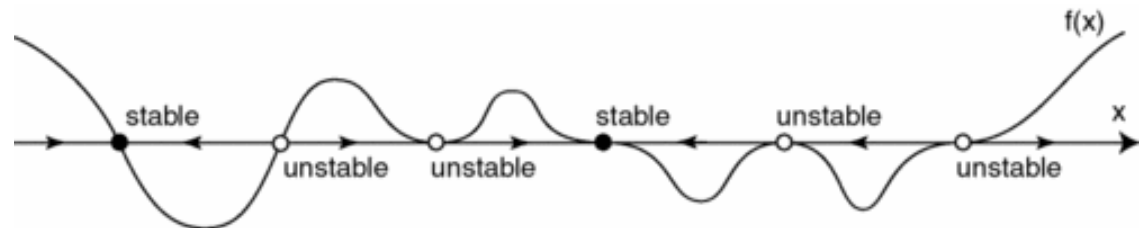
1D dynamical system

$$f(x^*) = 0$$

Equilibrium

$$f'(x^*) < 0$$

Stability criterion





Nonlinear dynamics: equilibrium states

2D dynamical system

$$\dot{x}_1 = f(x_1, x_2)$$

$$\dot{x}_2 = f(x_1, x_2)$$

Equilibrium

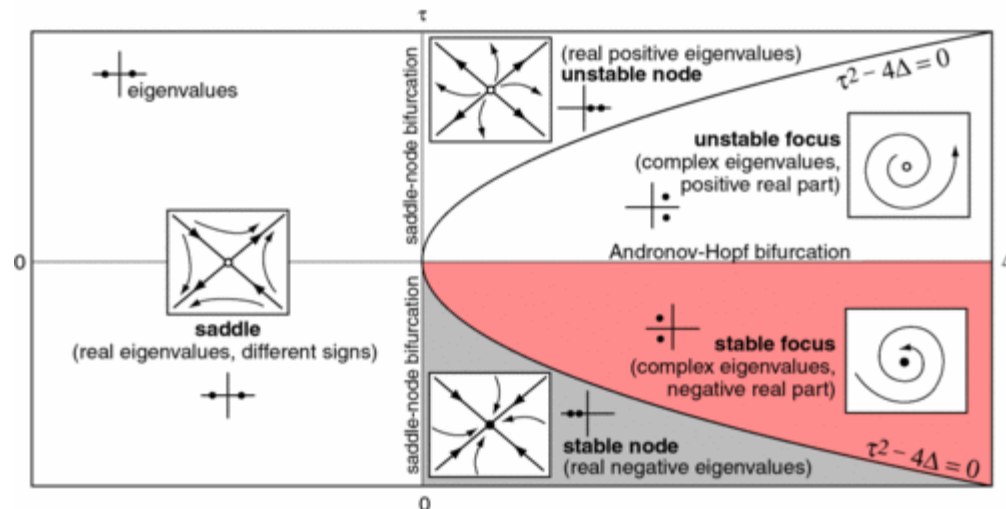
$$f_1(x_1, x_2) = 0$$

$$f_2(x_1, x_2) = 0$$

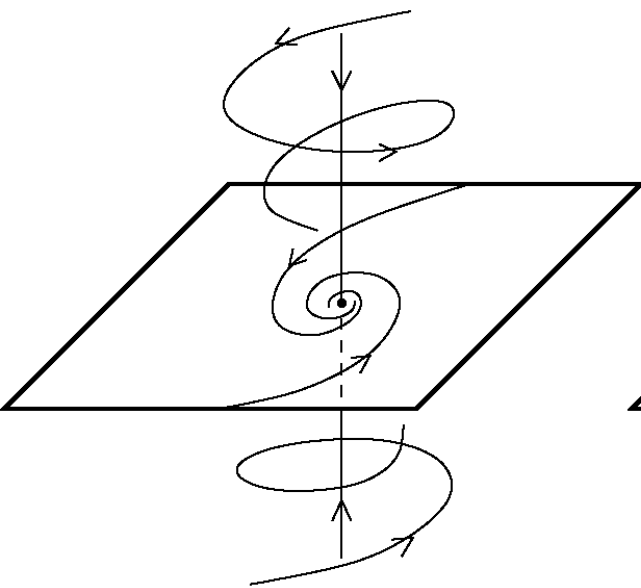
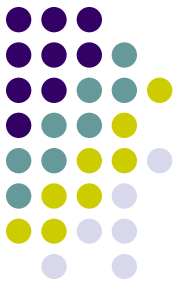
Stability criterion

$$\text{Det} \begin{pmatrix} \partial_{x_1} f_1 - \lambda & \partial_{x_2} f_1 \\ \partial_{x_1} f_2 & \partial_{x_2} f_2 - \lambda \end{pmatrix} = 0$$

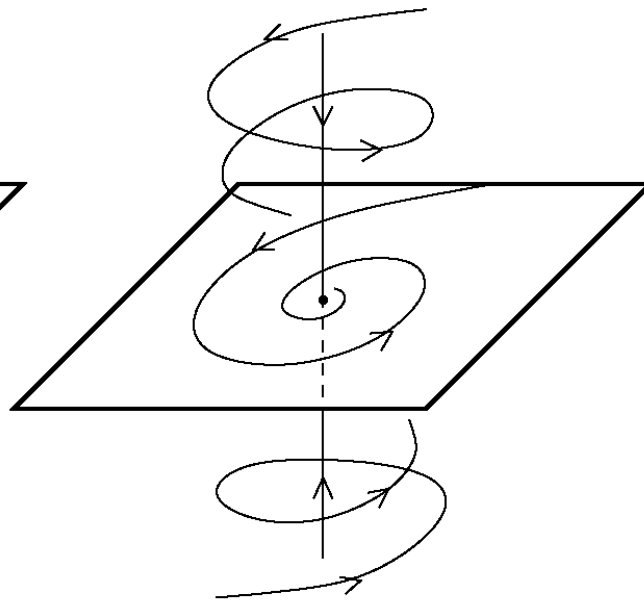
$$\text{Re } \lambda_{1,2} < 0$$



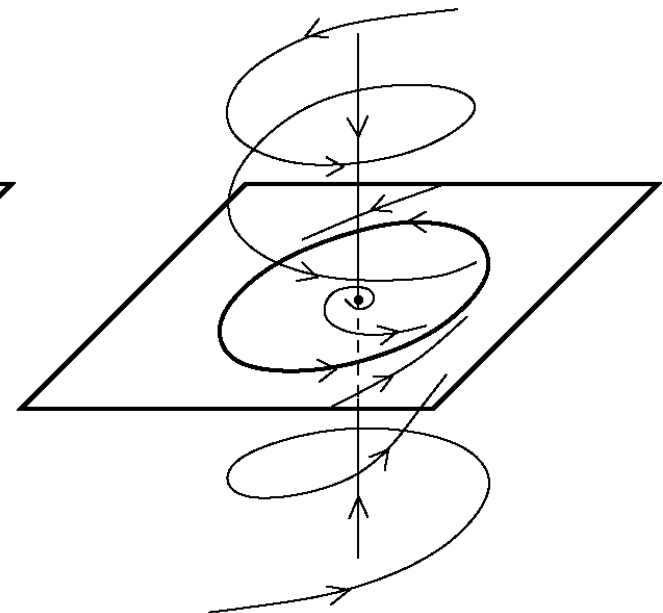
Nonlinear dynamics: oscillations



$\beta < 0$

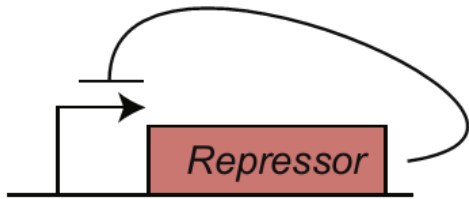
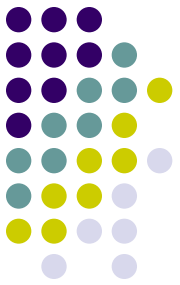


$\beta = 0$



$\beta > 0$

Example 2: self-repressor



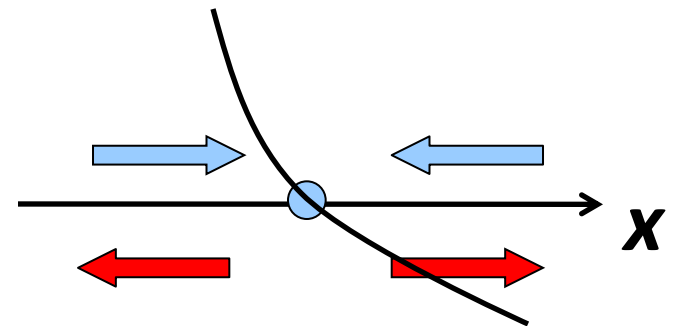
Differential equation

$$\dot{x} = \frac{\alpha}{1 + (x/K)^n} - \gamma x$$

Equilibrium

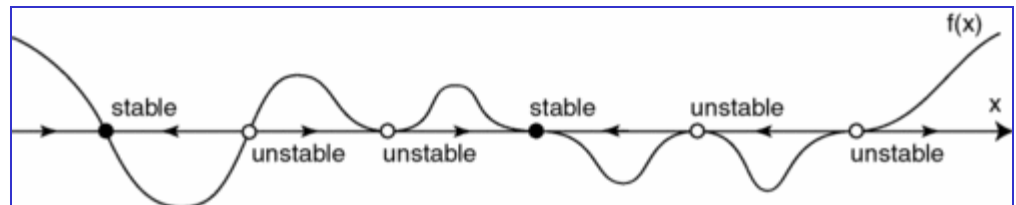
$$\gamma x = \frac{\alpha}{1 + (x/K)^n}$$

Stability

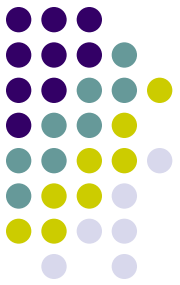


?

$$\frac{\alpha}{1 + (x/K)^n} - \gamma x$$



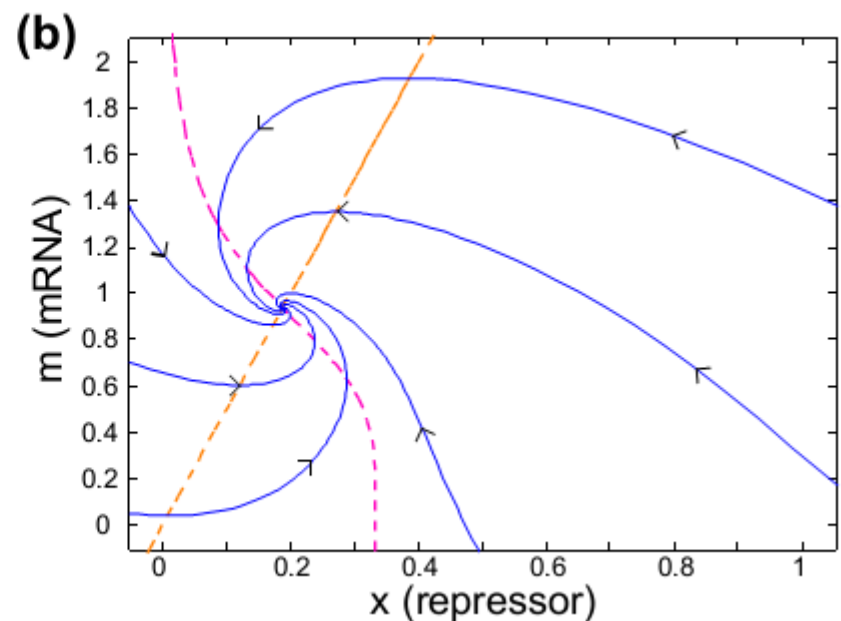
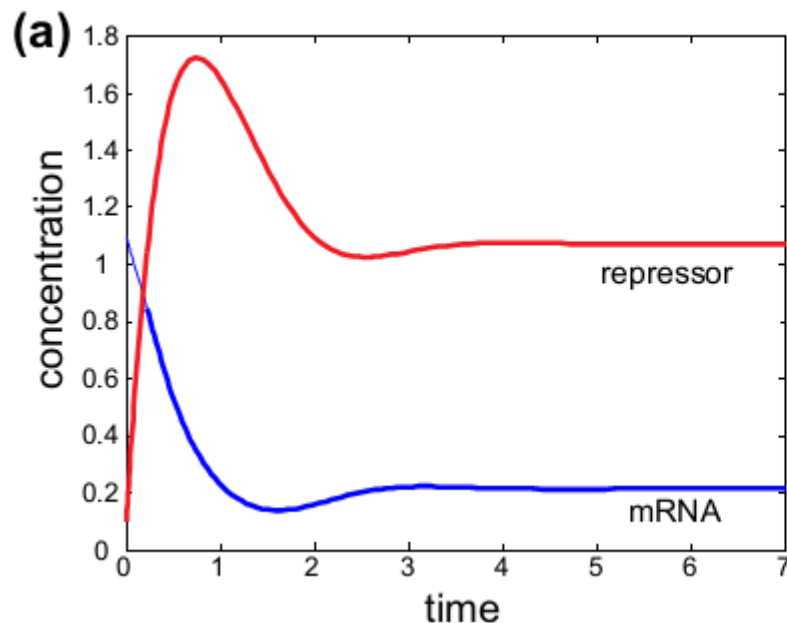
Self-repressor: more complex dynamics?



- mRNA dynamics:

$$\dot{m} = \frac{\alpha}{1 + (x/K)^n} - \delta m,$$
$$\dot{x} = \beta m - \gamma x,$$

- Still an equilibrium, though with oscillatory approach (stable focus)

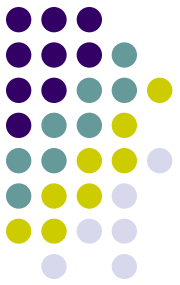
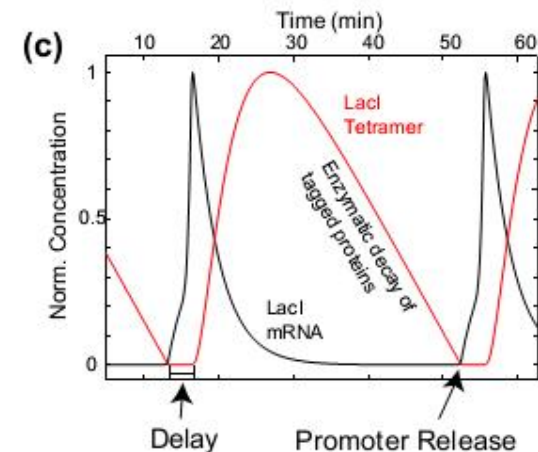
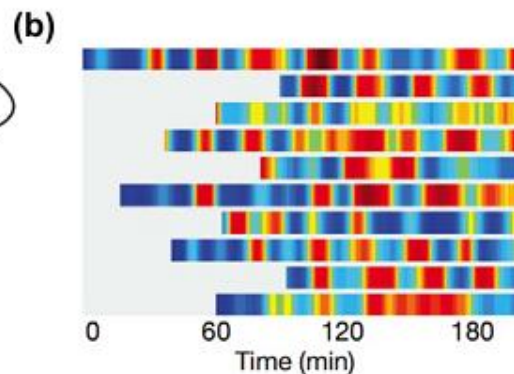
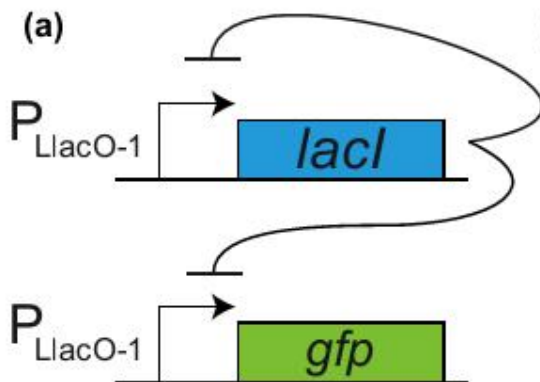


Self-repressor with time-delay: self-sustained oscillations!

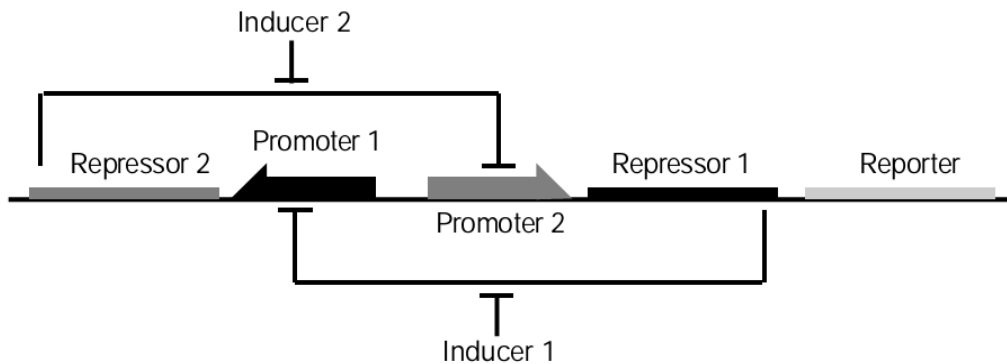
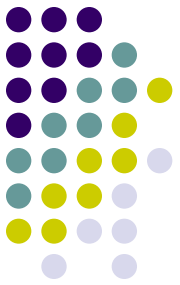
- Mathematical model and biological experiment
(Striker et al., Nature, 2008)
- Biological clocks

$$\dot{x} = \frac{\alpha'}{1 + (x_\tau/K)^\beta} - \frac{Vx}{K_m + x} - \gamma x$$

$$x_\tau = x(t - \tau)$$



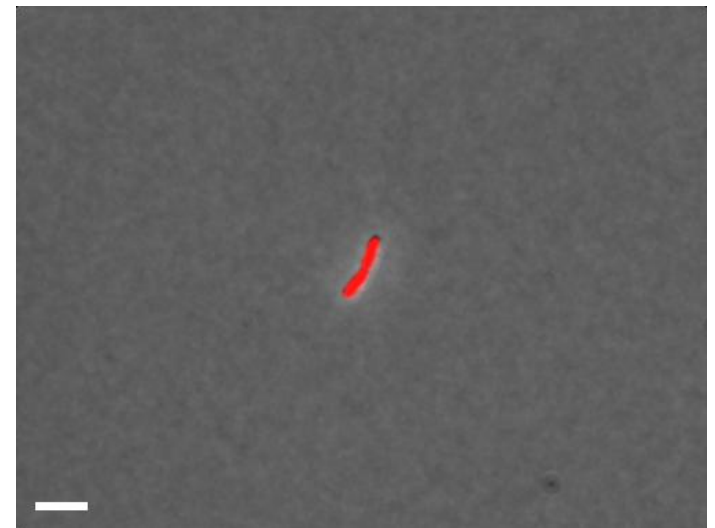
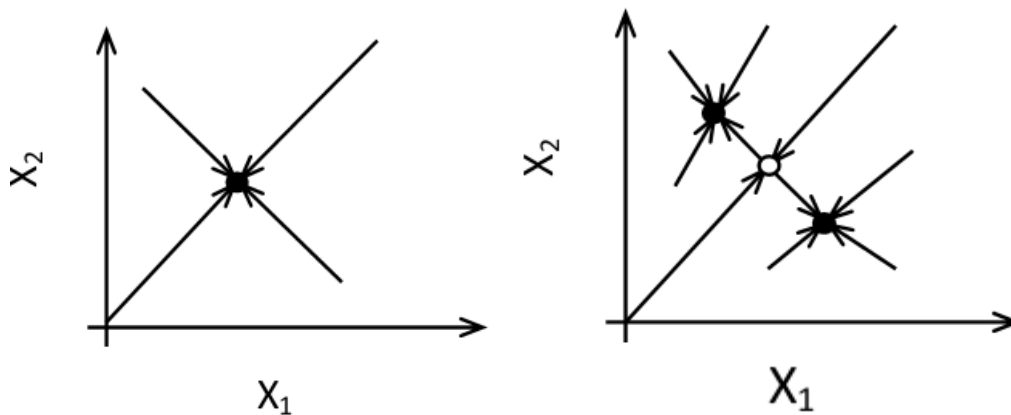
Genetic toggle-switch



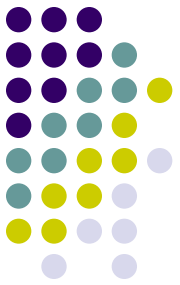
$$\dot{x}_1 = \frac{K_1}{1 + x_2^{n_2}} - x_1$$

$$\dot{x}_2 = \frac{K_2}{1 + x_1^{n_1}} - x_2$$

(Gardner, Kantor & Collins, *Nature*, 2000)



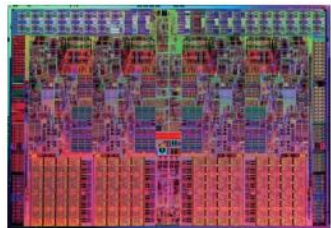
Noise-driven separation



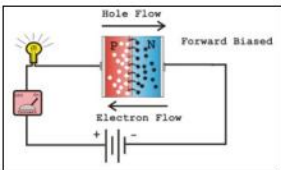
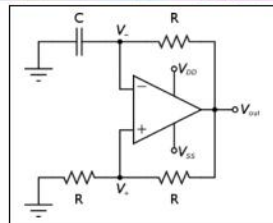
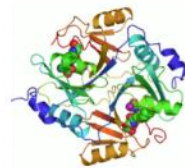
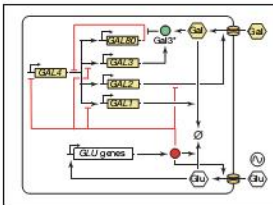
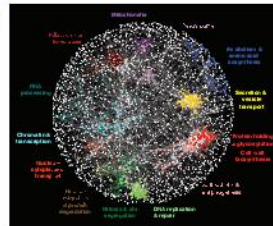
Collective dynamics



Towards distributed circuits



Systems Biology



Synthetic Biology

scale

Single cell limitations:

- Number of exogenous constructs (robustness of circuit, cell viability)
- Complexity of circuit
- Useful functionality, regulated by the circuit (e.g. oscillatory)

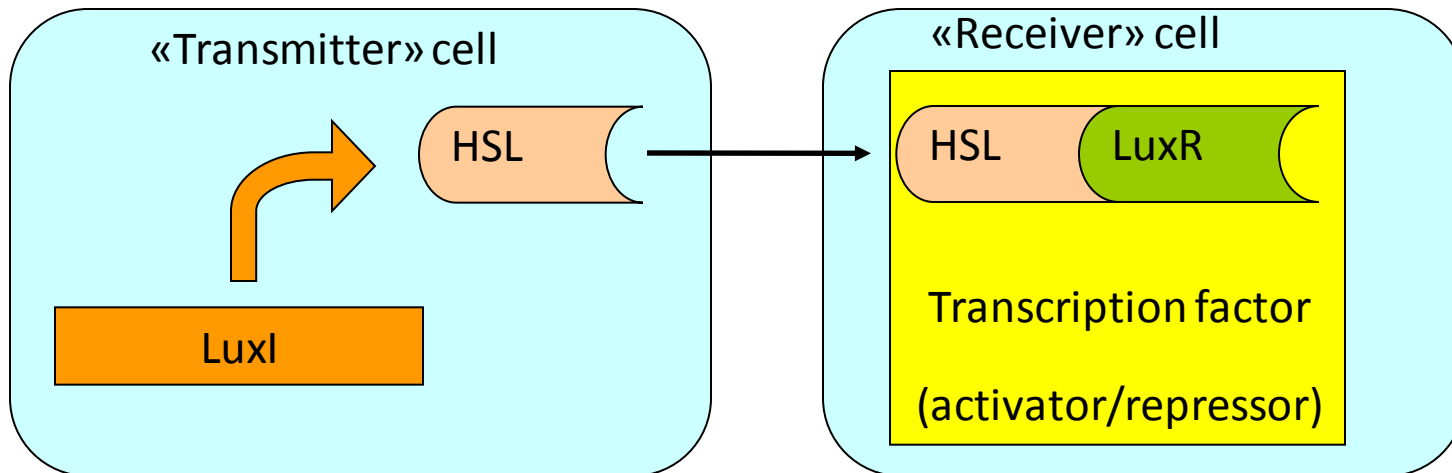
Solution:

- Distributed circuits and intercellular communication

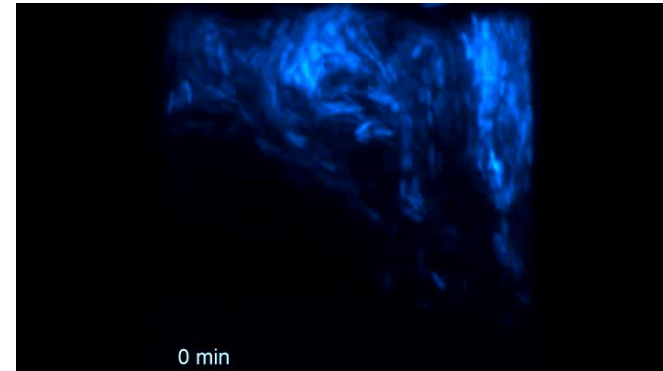
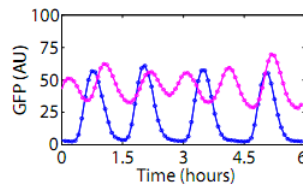
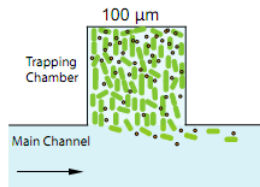
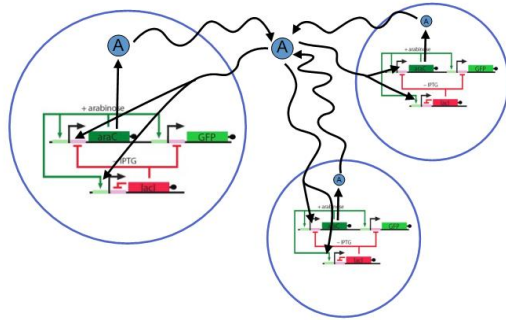
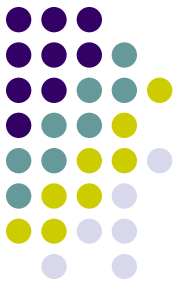


Intercellular communication

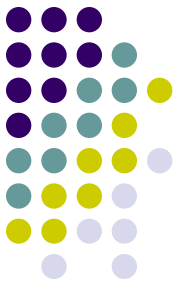
Quorum-sensing mechanisms:
HSL (homoserine-lacton) family ligands



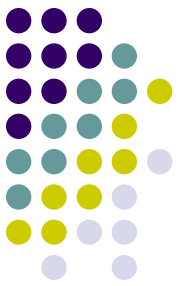
Intercellular communication: synchronization of genetic clocks



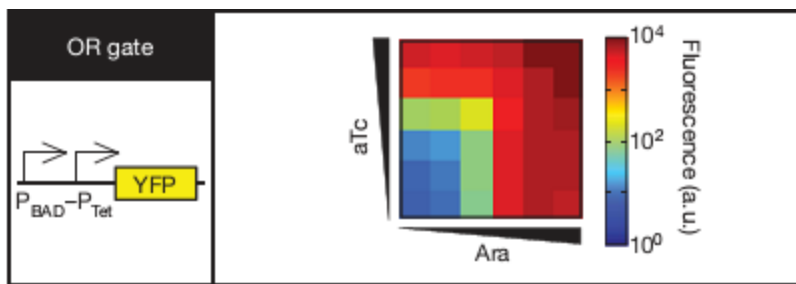
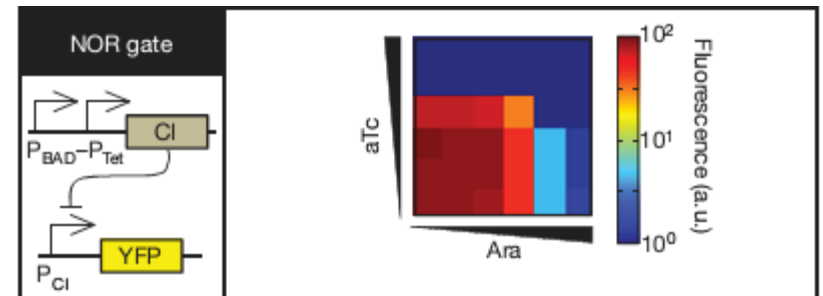
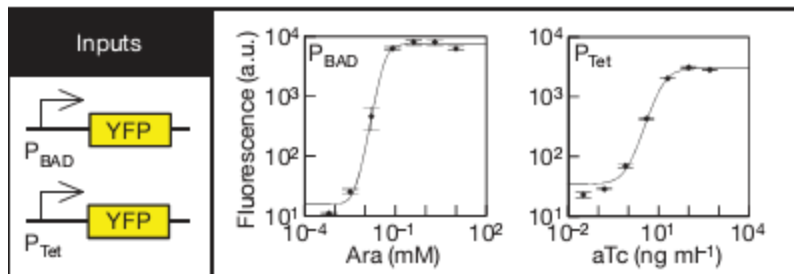
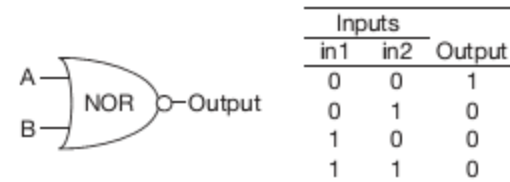
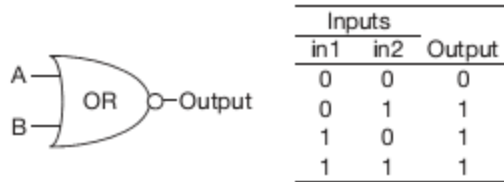
Danino et al., Nature, 2010



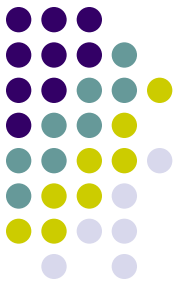
Logic circuits



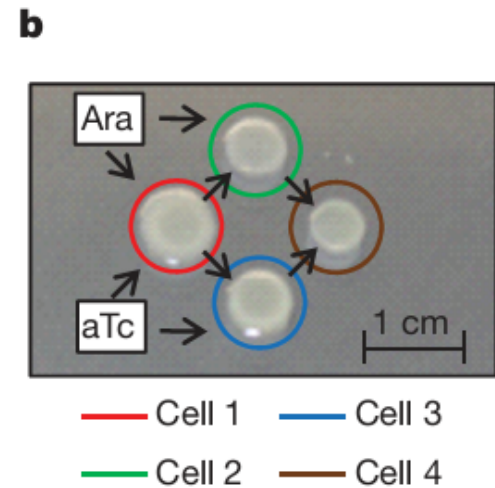
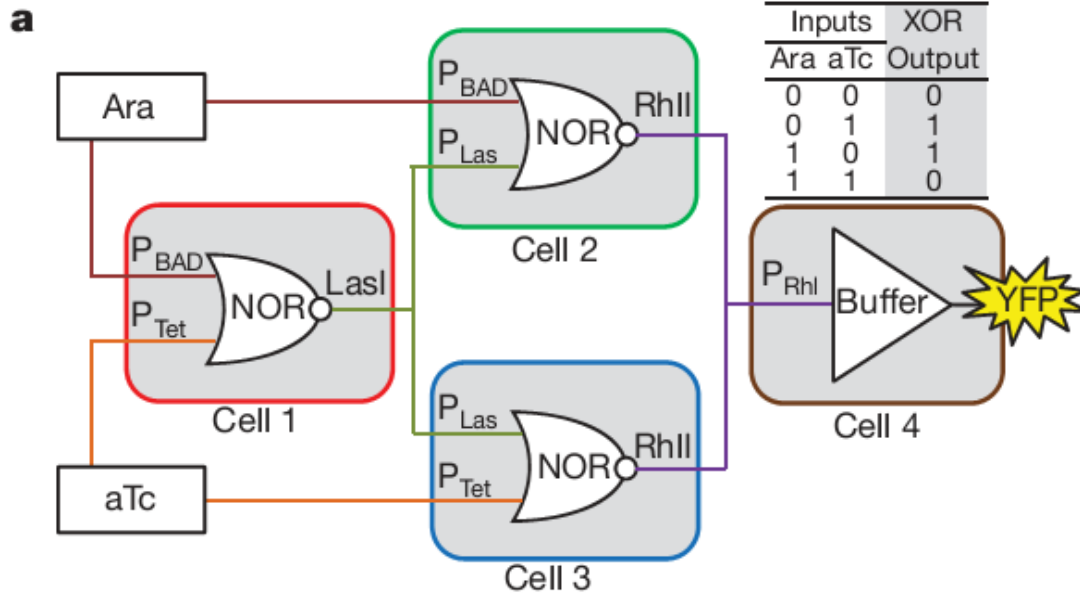
Example 3. Logic circuits



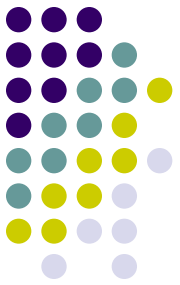
Tamsir, Tabor & Voigt, Nature, 2011



Distributed logic circuits



Tamsir, Tabor & Voigt, Nature, 2011



Next generation gene computing: learning

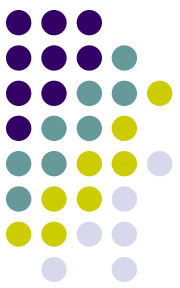
Distributed genetic classifier

<http://arxiv.org/abs/1405.5328>

Andriy Didovyk,[†] Oleg I. Kanakov,[‡] Mikhail V. Ivanchenko,[¶] Jeff Hasty,^{†,§,||}

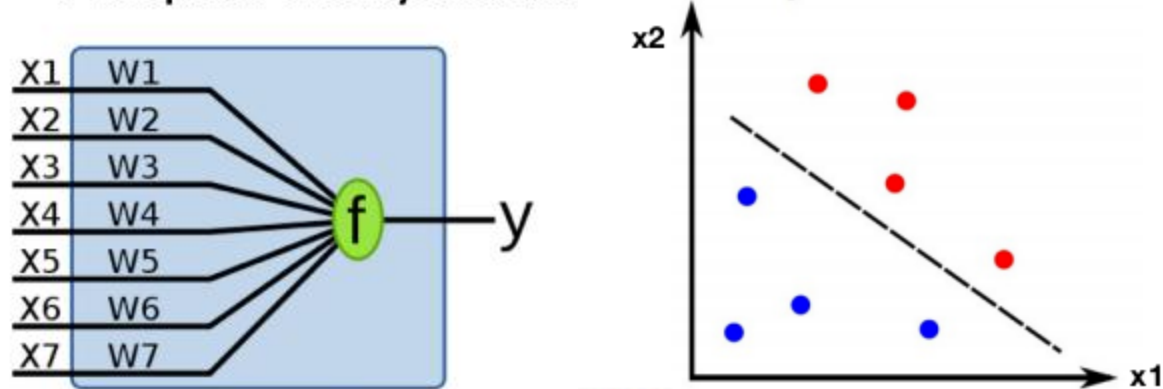
Ramón Huerta,^{*,†} and Lev Tsimring^{*,†}

*BioCircuits Institute, University of California San Diego, La Jolla CA, USA, Department
of Radiophysics, Lobachevsky State University of Nizhniy Novgorod, Nizhniy Novgorod,
Russia, Department for Bioinformatics, Lobachevsky State University of Nizhniy Novgorod,
Nizhniy Novgorod, Russia, Department of Bioengineering, University of California San
Diego, La Jolla CA, USA, and Molecular Biology Section, Division of Biological Science,
University of California San Diego, La Jolla CA, USA*



Machine learning: classical ideas

Perceptron- one layer feedforward neural network



1. Initialise weights and threshold. Note that weights may be initialised by setting each weight node $w_i(0)$ to 0 or to a small random value. In the example below, we choose the former.

2. For each sample j in our training set D , perform the following steps over the input \mathbf{x}_j and desired output d_j :

2a. Calculate the actual output:

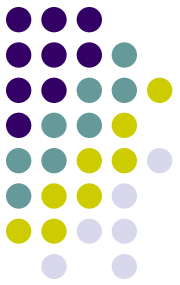
$$y_j(t) = f[\mathbf{w}(t) \cdot \mathbf{x}_j] = f[w_0(t) + w_1(t)x_{j,1} + w_2(t)x_{j,2} + \cdots + w_n(t)x_{j,n}]$$

2b. Adapt weights:

$$w_i(t+1) = w_i(t) + \alpha(d_j - y_j(t))x_{j,i}, \text{ for all nodes } 0 \leq i \leq n.$$

Step 2 is repeated until the iteration error $d_j - y_j(t)$ is less than a user-specified error

Molecular perceptron?



Proc. Natl. Acad. Sci. USA
Vol. 88, pp. 10983–10987, December 1991
Chemistry

Perceptron inside the cell??

Chemical implementation of neural networks and Turing machines

ALLEN HJELMFELT[†], EDWARD D. WEINBERGER[†], AND JOHN ROSS[‡]

[†]Max-Planck-Institut für Biophysikalische Chemie, D-3400 Göttingen, Federal Republic of Germany; and [‡]Department of Chemistry, Stanford University, Stanford, CA 94305

972

Biophysical Journal Volume 66 April 1994 972–977

Computer Simulated Evolution of a Network of Cell-Signaling Molecules

Dennis Bray^{*} and Steven Lay[†]

^{*}Department of Zoology and [†]Department of Applied Mathematics and Theoretical Physics, University of Cambridge, Cambridge, United Kingdom

Journal of Theoretical Biology 249 (2007) 58–66


www.elsevier.com

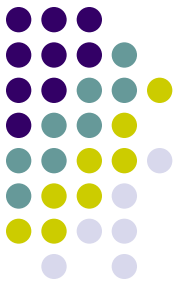
Associative learning in biochemical networks

Nikhil Gandhi^a, Gonen Ashkenasy^{b,*}, Emmanuel Tannenbaum^{b,*}

^aCollege of Computing, Georgia Institute of Technology, Atlanta, GA 30332, USA

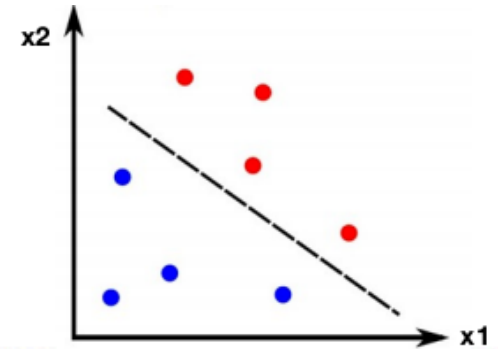
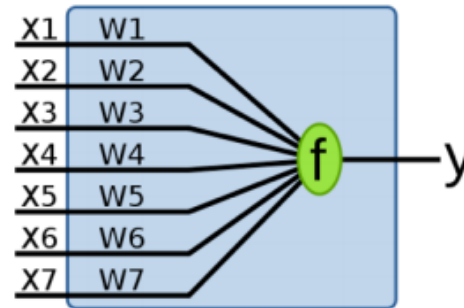
^bDepartment of Chemistry, Ben-Gurion University of the Negev, Be'er-Sheva 84105, Israel

Molecular classifier?

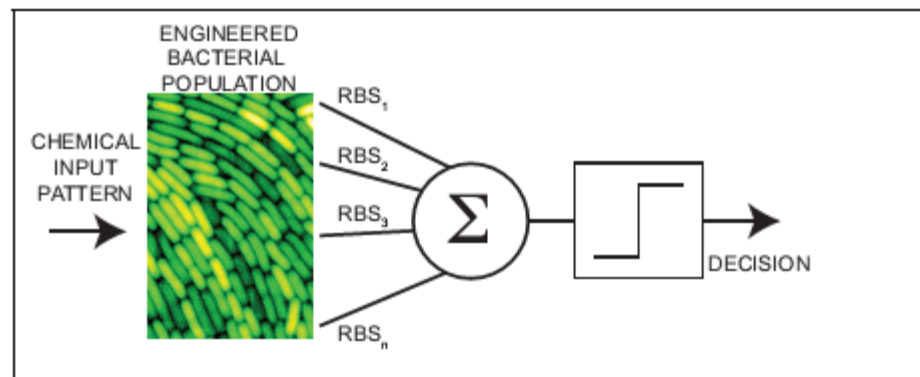


Weak points:

- Actual constructs
- Memory



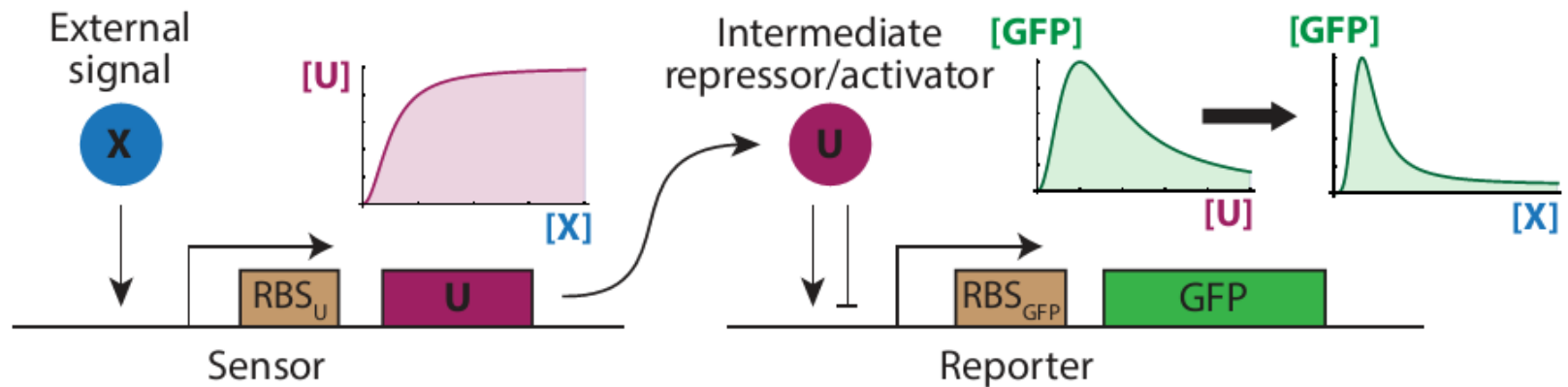
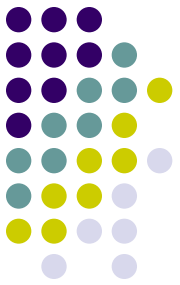
- Our solution: population classifier





Single-input classifier

Single cell synthetic circuit



$$\begin{aligned} \frac{du}{dt} &= r_u(x; m_u) - \mu_u u & r_u(x; m_u) &= m_u \cdot \frac{\alpha A_u^{p_u} + x^{p_u}}{A_u^{p_u} + x^{p_u}} \\ \frac{dz}{dt} &= r_g(u; m_g) - \mu_g z & r_g(u; m_g) &= m_g \cdot \frac{A_g^{p_g} u^{p_g}}{(A_g^{p_g} + u^{p_g})^2} \end{aligned}$$

Ensemble of cells – ‘pixel’ classifier

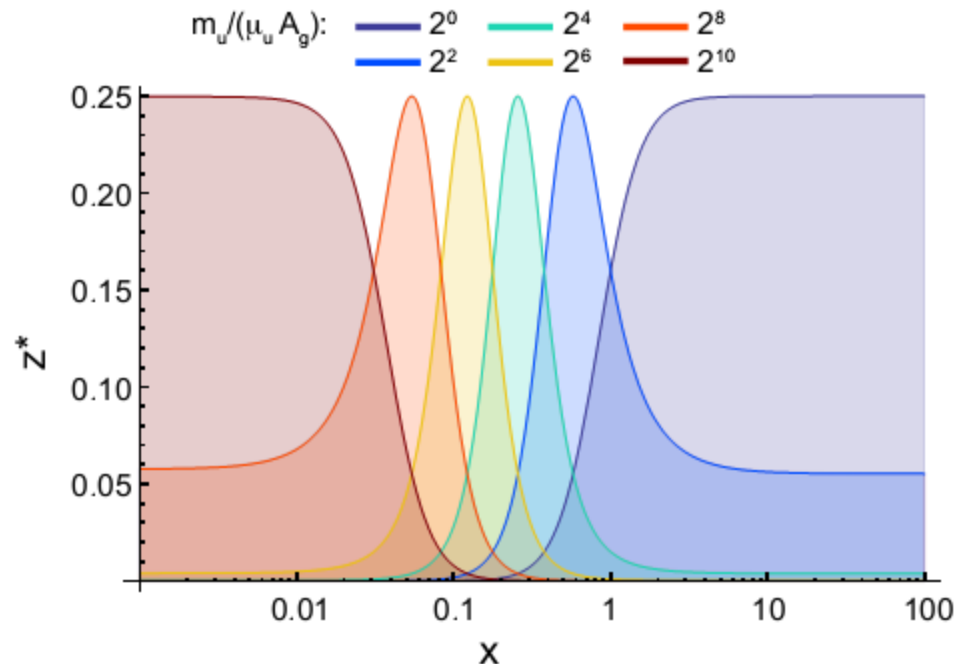
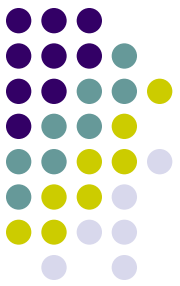
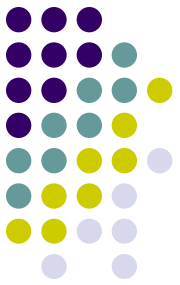
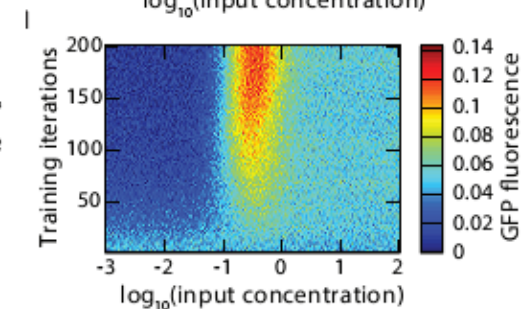
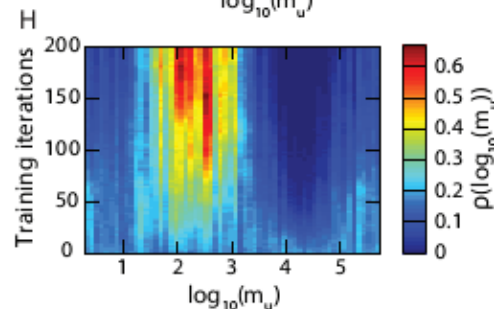
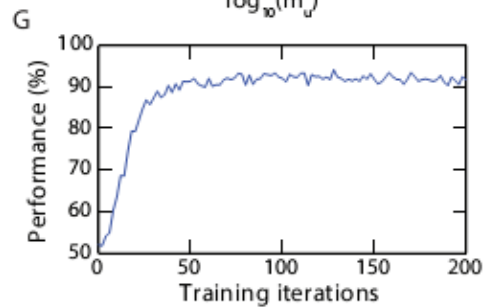
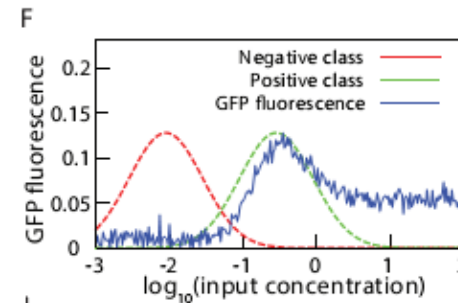
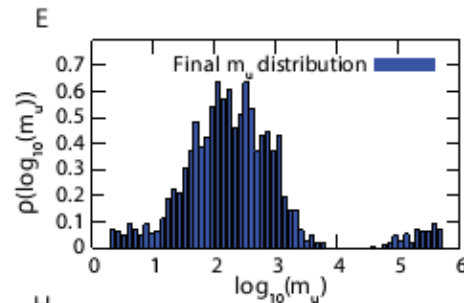
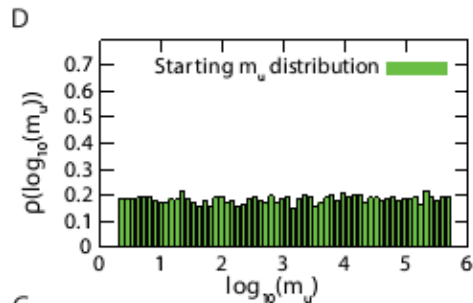
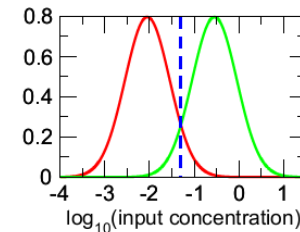


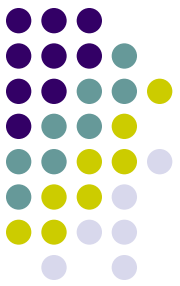
Figure 2: Steady state GFP concentration (z^*) as a function of the concentration of the external chemical signal X for the modular classifier circuit shown for a range of m_u values representing a range of the relative strengths of the sensor promoter (Fig. 1). Non-dimensional circuit parameters are $\mu_u = \mu_g = m_g = A_u = 1$, $A_g = 20$, $p_g = p_u = 2$, $\alpha = 10^{-3}$.

Training by examples through cell elimination

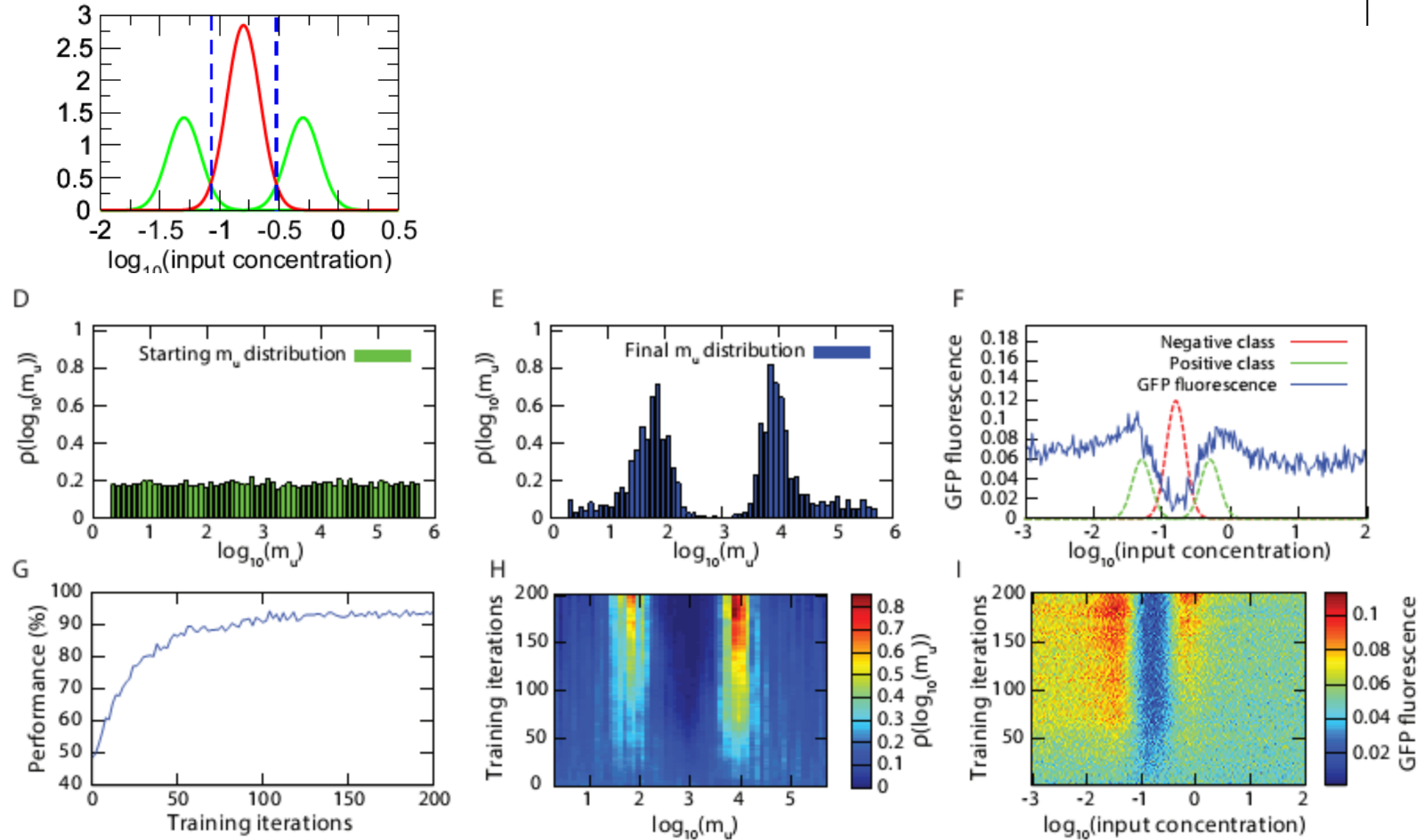


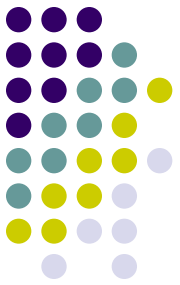
Discrimination of two unimodal (overlapping!) classes





Unimodal vs. Bimodal classes





Two- (multiple) input classifier

Two- (multiple) input classifier

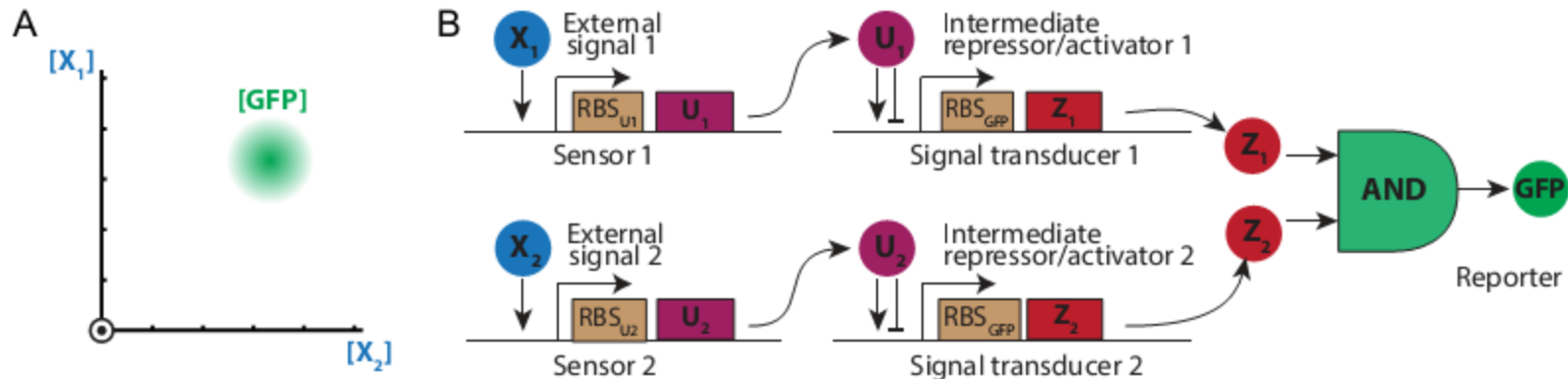
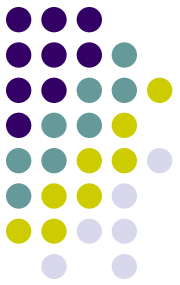
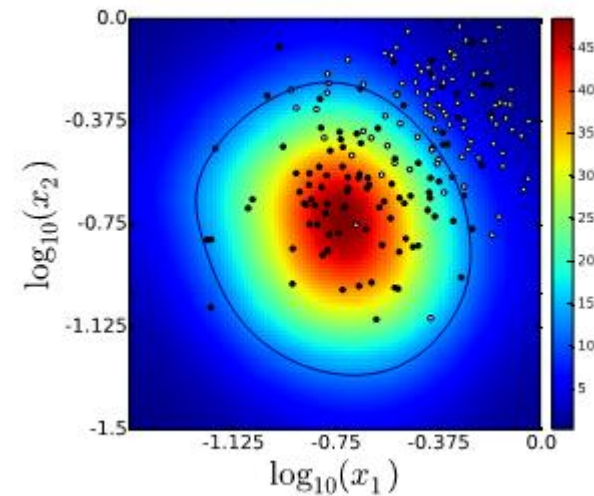
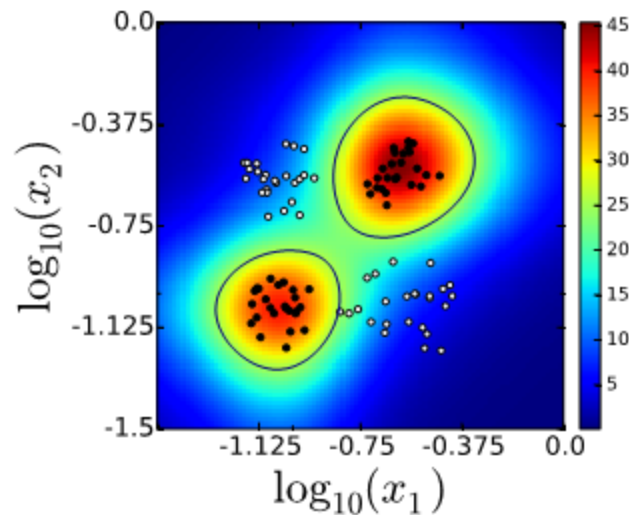


Figure 8: (A) The desired bell-shaped response of the multidimensional classification circuit. (B) The genetic circuit proposed for use in a distributed genetic classifier with multiple inputs per cell. Independent sensing and response functionalities are combined using an appropriate biological AND gate. The resulting response function of the entire two-promoter circuit is bell-shaped with respect to the inputs X_1 and X_2 for the relevant choice of parameters.



Results

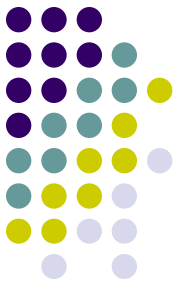
- Linearly non-separable classes
- Overlapping classes





Conclusions

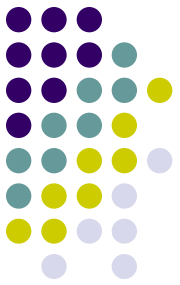
- Synthetic gene regulatory network – a powerful approach in biocomputing
- Equations of molecular kinetics
- Already minimal gene circuits display stationary states, oscillations, bistability
- Distributed regulation networks through quorum sensing communications
- Logical circuits
- Learning. Distributed synthetic gene classifier.



Collaborations

- Lev Tsimring, UCSD
- Alexey Zaikin, UCL
- Oleg Kanakov, UNN





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- The Ministry of education and science of the Russian Federation grant 02.B.49.21.0003