

[Non]-deterministic dynamics in cells: From multistability to stochastic switching

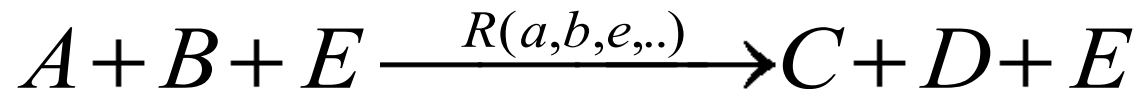
Ádám Halász

Department of Mathematics
West Virginia University

Cells as machines

- We know a lot about the processes that take place in cells
 - Gene expression (transcription, translation)
 - Sensing, signaling, control of gene expression

- Processes can be described as "reactions"



- Molecular species consumed (A,B) produced (C,D), or neither (E)
- Changes are modeled by differential equations

$$\frac{dc}{dt} = -\frac{da}{dt} = R(a,b,e,..)$$

- Issues: **uncertainty**, **parameter variability**, **stochasticity**

Phenotypes and Steady states

- Genetically identical cells can exhibit **different phenotypes**
 - Cell differentiation in multicellular organisms
 - Examples in the bacterial world: alternative phenotypes, possibly with a role in survival, adaptation,..
- Due to the different sets of genes that are “on”
- Multiple phenotypes correspond to **different equilibria** of the dynamical system encoded in the DNA.
- Is phenotype multiplicity always the same as multistability?
- Model predictions may change when including stochastic and spatial effects

Lac system

Network of 5 substances

Example of positive feedback in a genetic network discovered in the 50's

This model due to Yildirim and Mackey, based on MM and Hill reaction rates; **time delays omitted**

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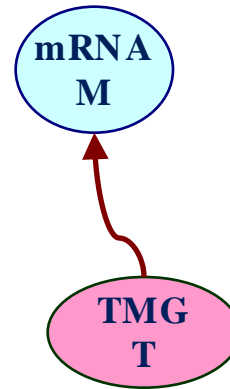


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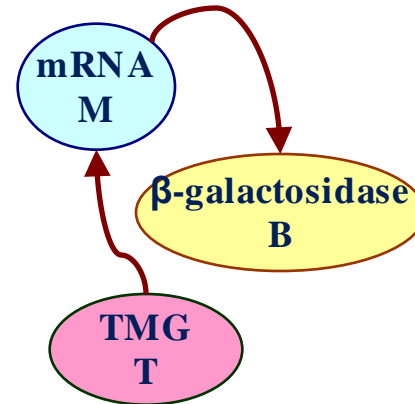


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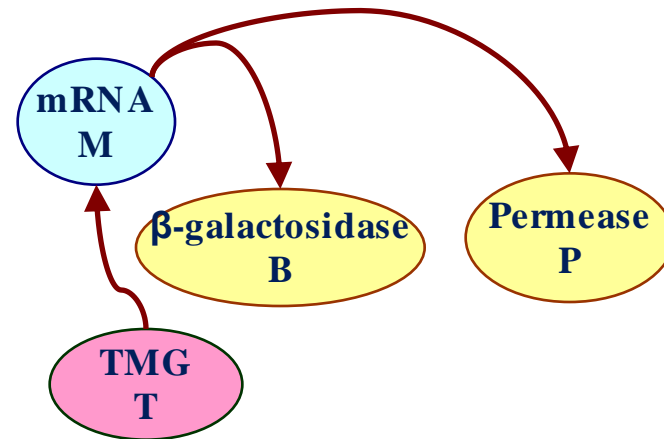


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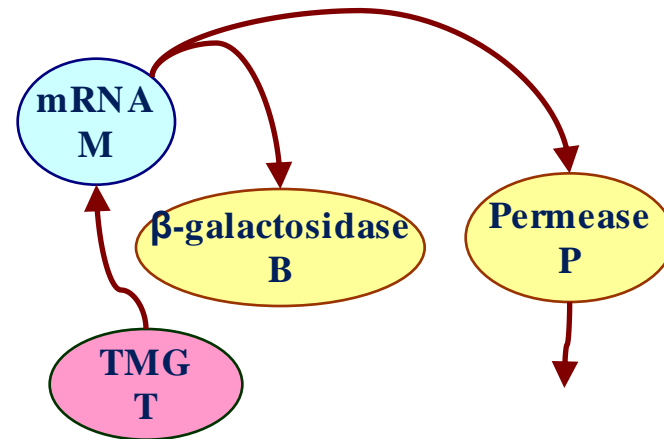


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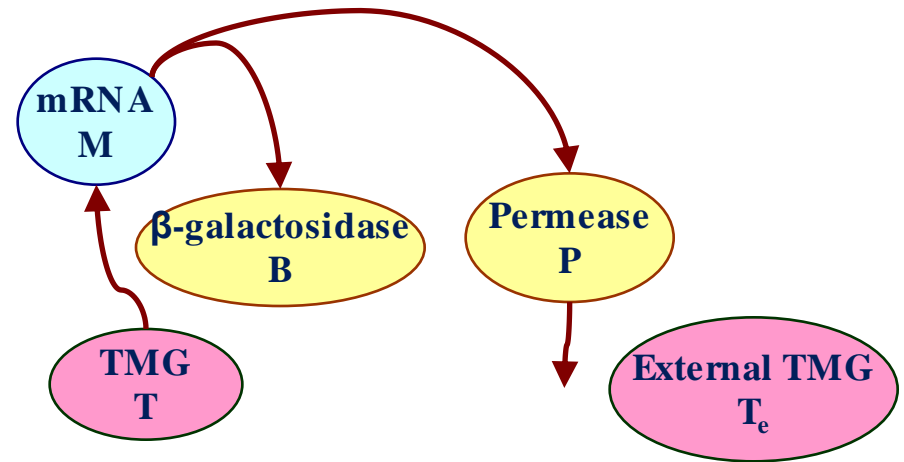


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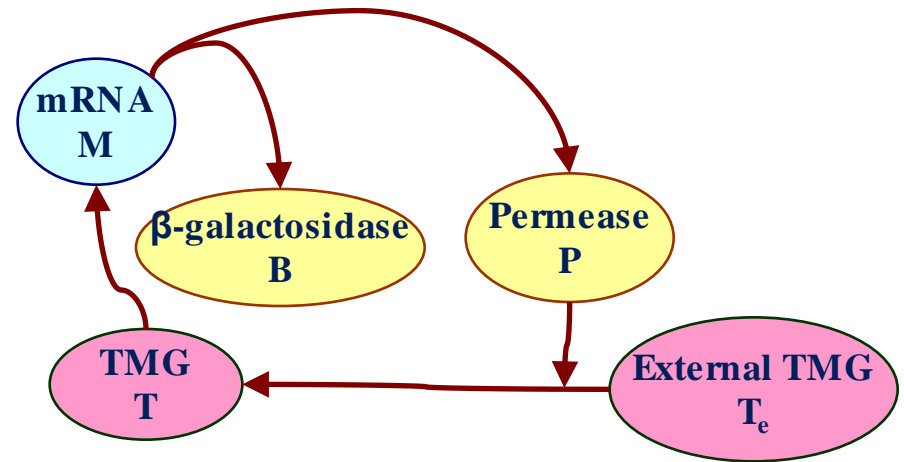


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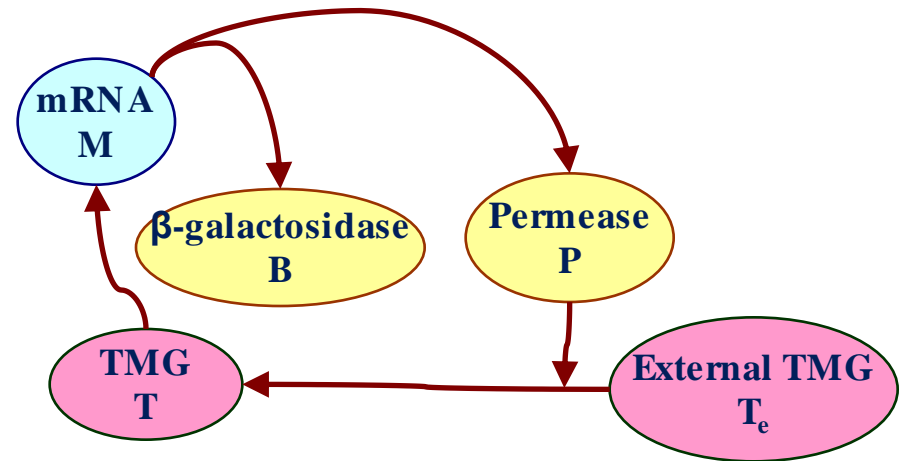


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$$\frac{dB}{dt} = \alpha_B M - (\gamma_B + \mu)B$$

$$\frac{dT}{dt} = \alpha_L P \frac{T_e}{K_{T_e} + T_e} - \beta_L P \frac{T}{K_L + T} - (\gamma_T + \mu)T$$

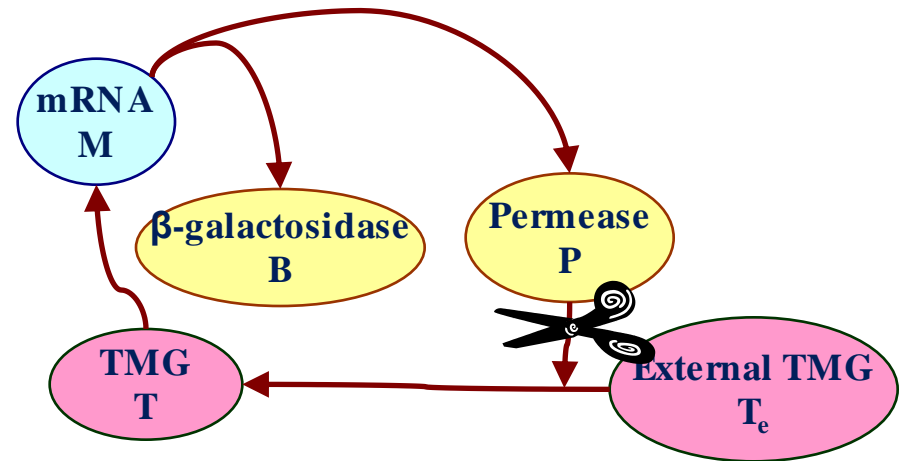
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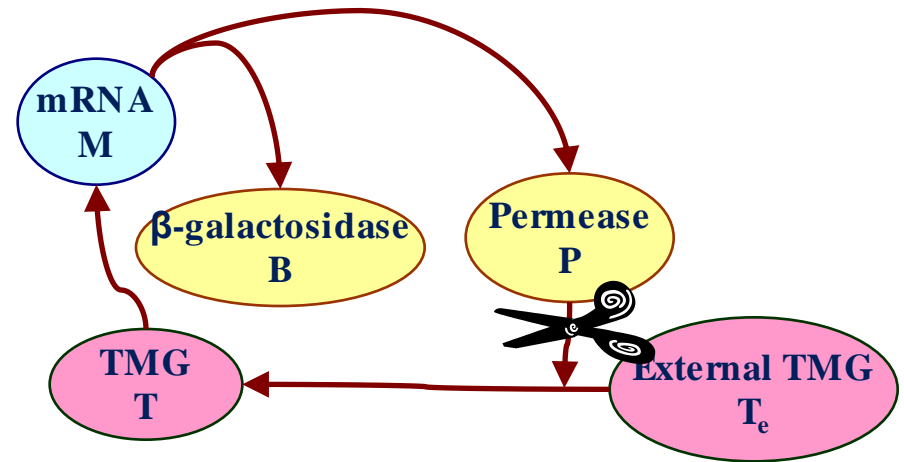
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Because of the positive feedback, the system has an S-shaped steady state structure →

Bistability



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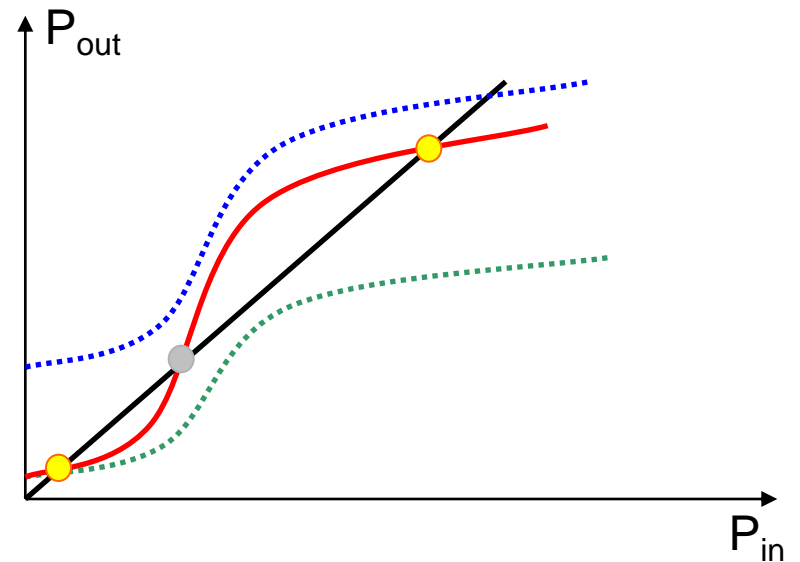
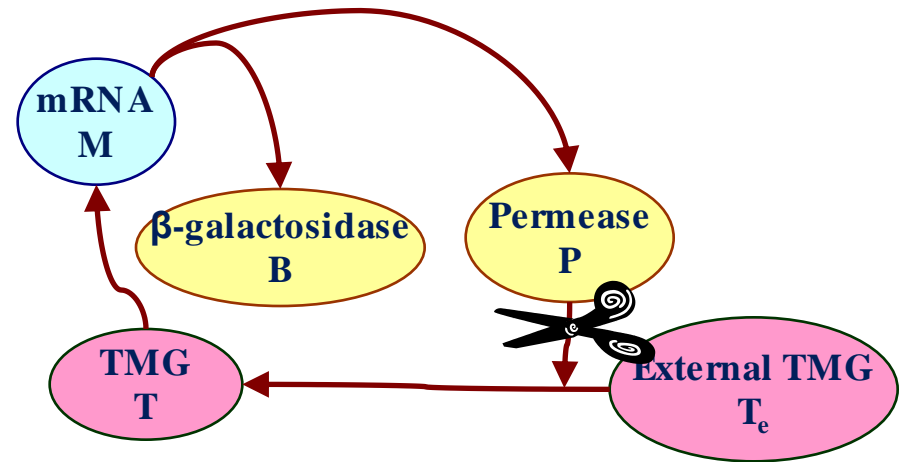
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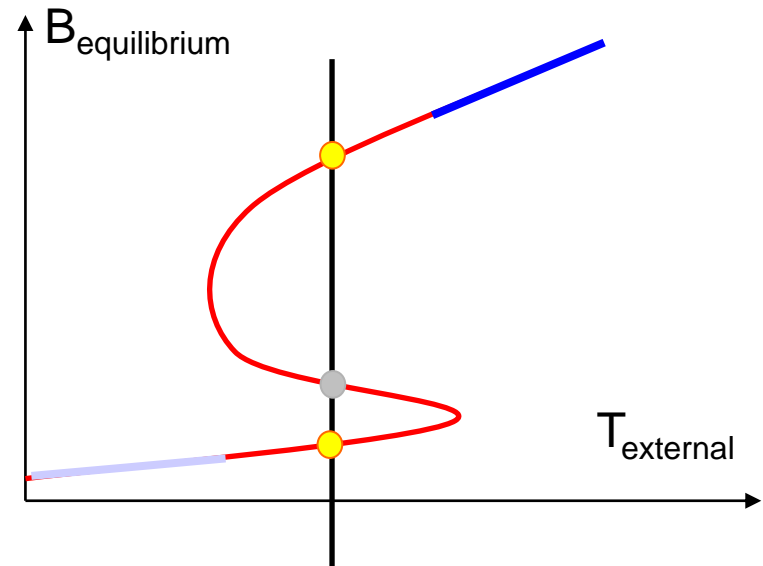
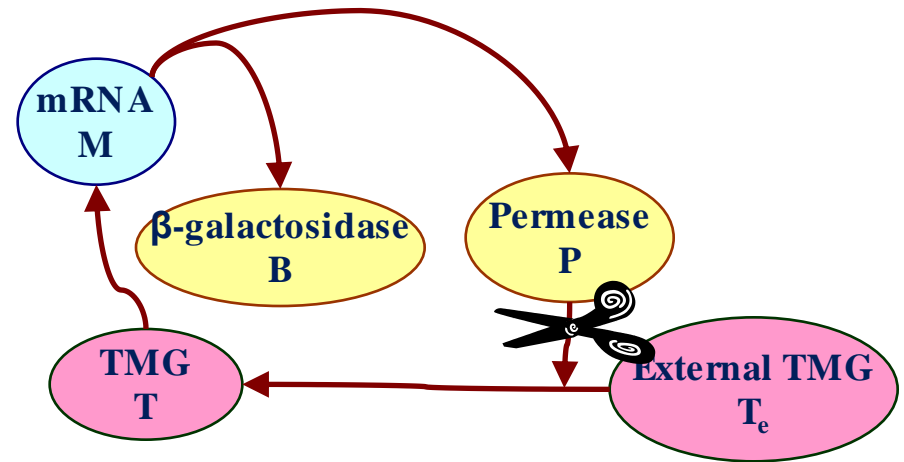
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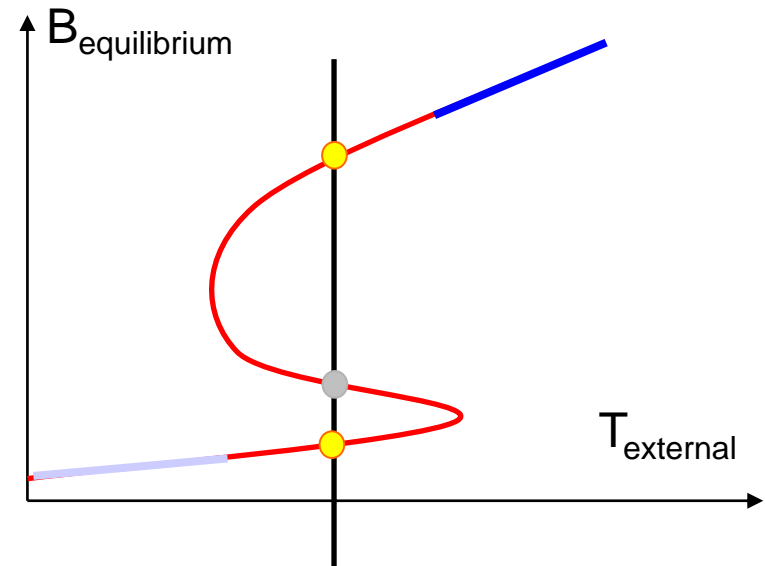
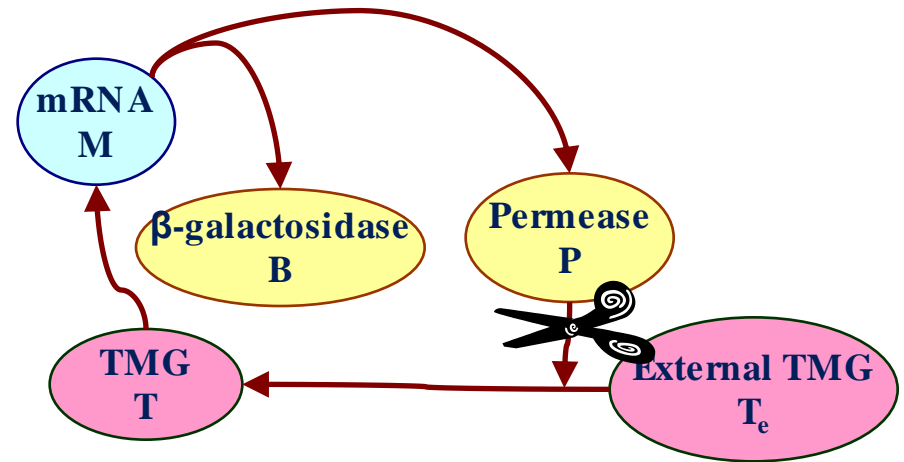
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Bistability provides for switching:



Lac system

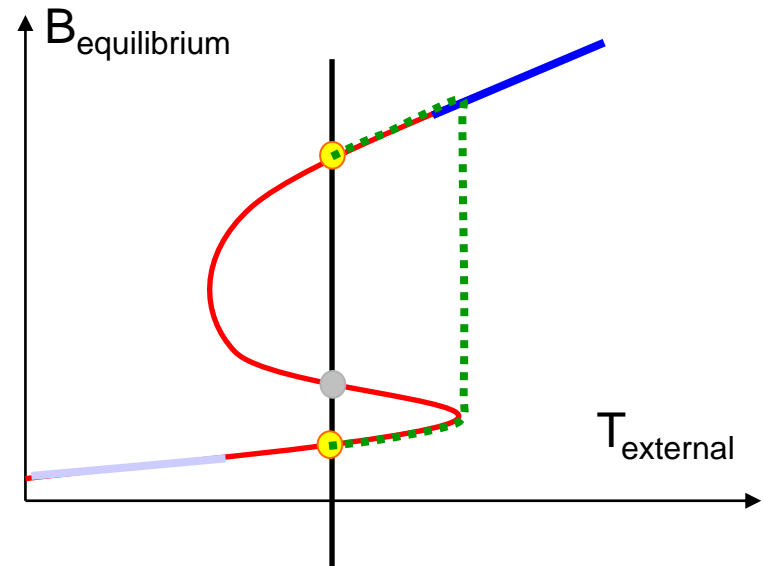
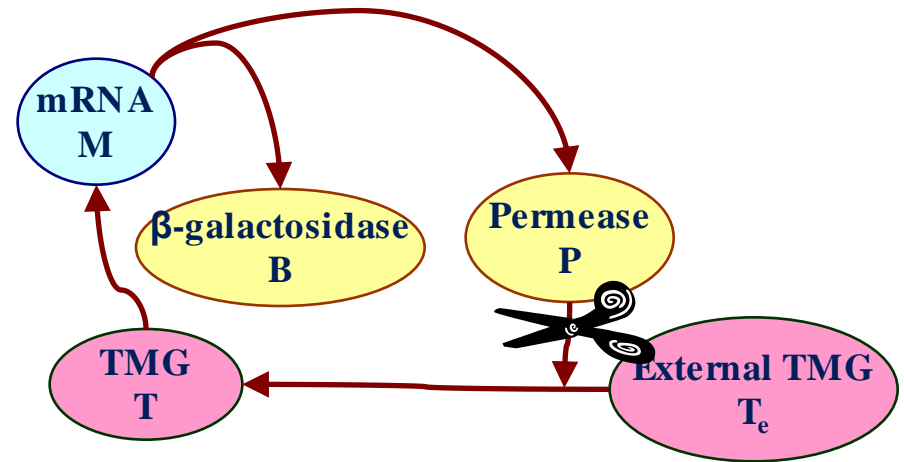
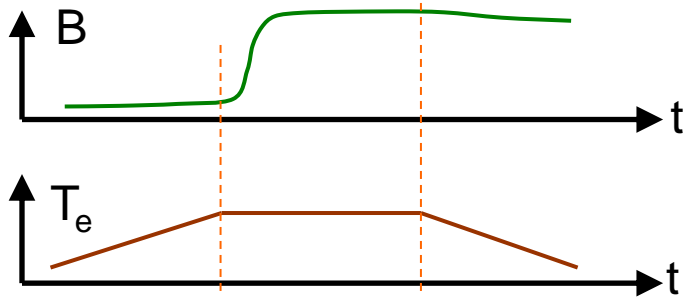
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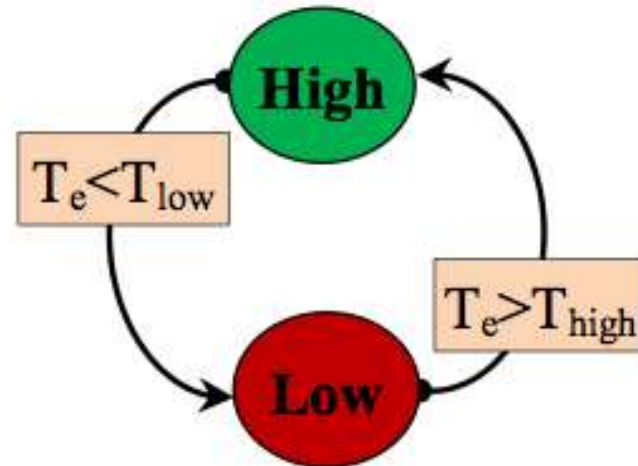
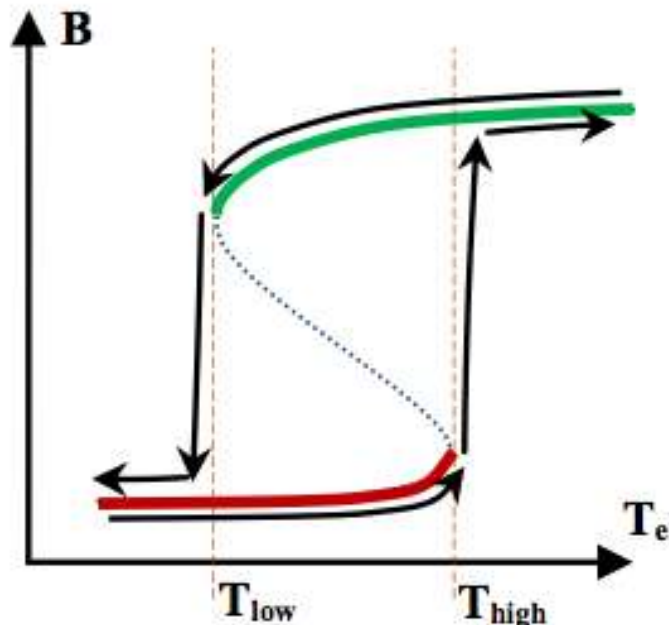
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Bistability provides for switching:



Abstractions

- A **two-state automaton** captures the switching behavior
 - The states can be further characterized, individually
 - More often than not, many details are not important as far as the rest of the system is concerned



Lac system, stochastic model

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The ODE description is not satisfactory:

- once a stable state is attained, the system (cell) should stay there indefinitely
- experimental results show spontaneous transitions and coexistence of two states

(Ozbudak, Thattai, Lim, Shraiman, van Oudenaarden, Nature 2004)

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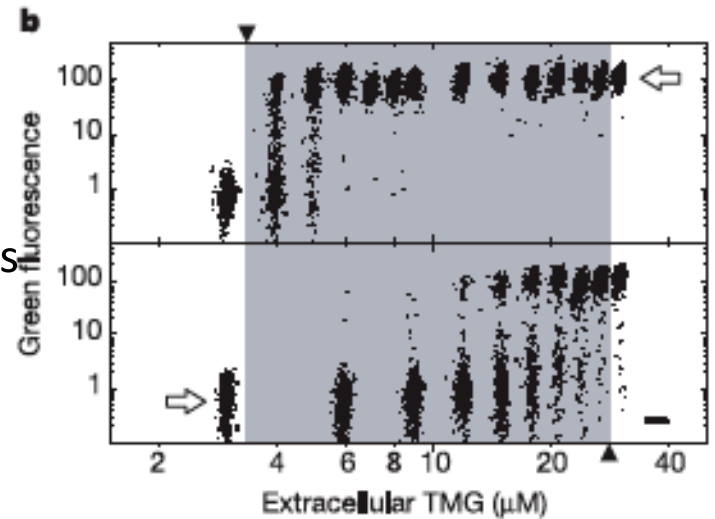
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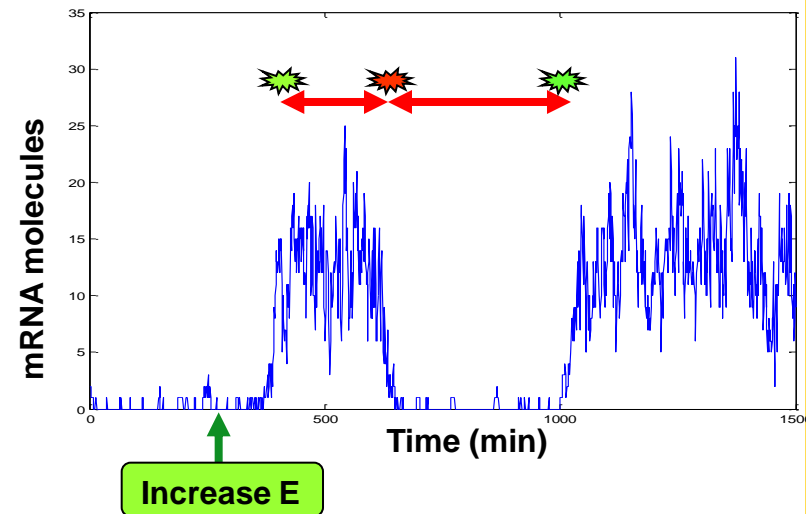
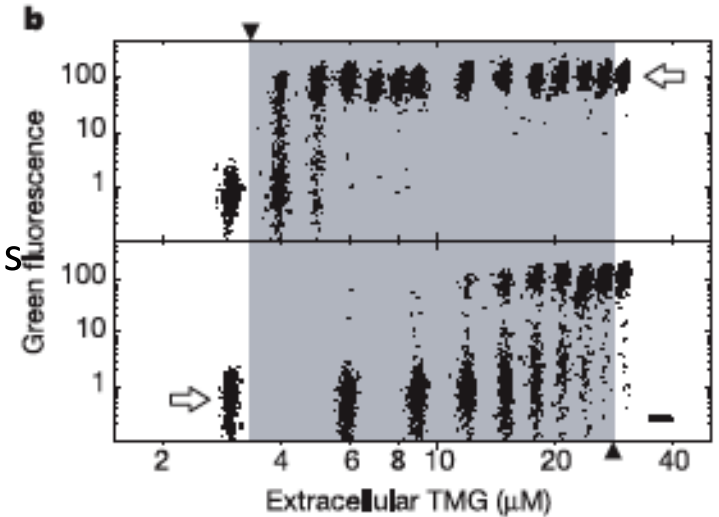
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Discrepancy due to small molecule count:

- first-principles stochastic simulations predict spontaneous transitions



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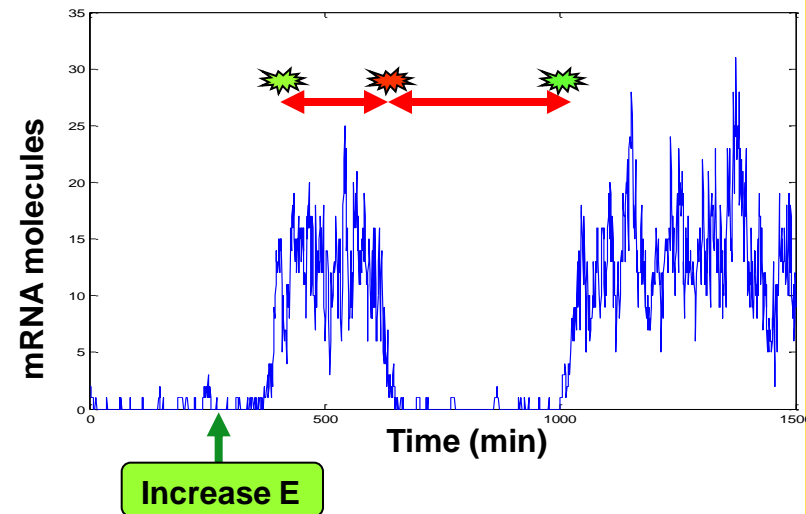
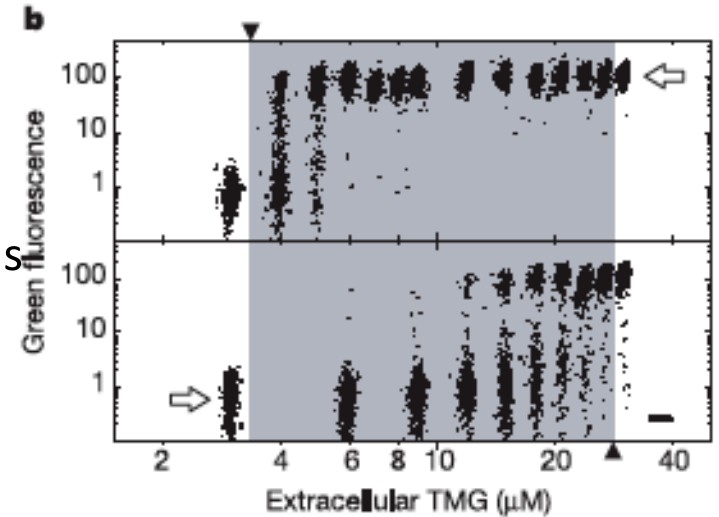
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More efficient 'mixed' simulations:

- can perform aggregate simulations
- equilibrium distributions
- compute transition rates



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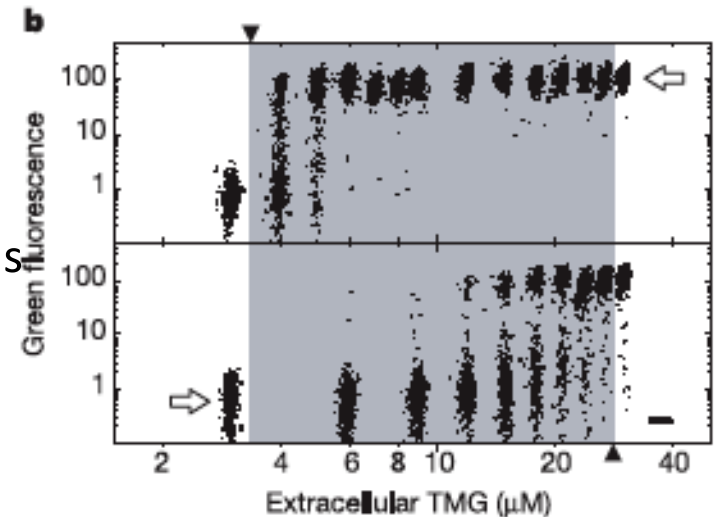
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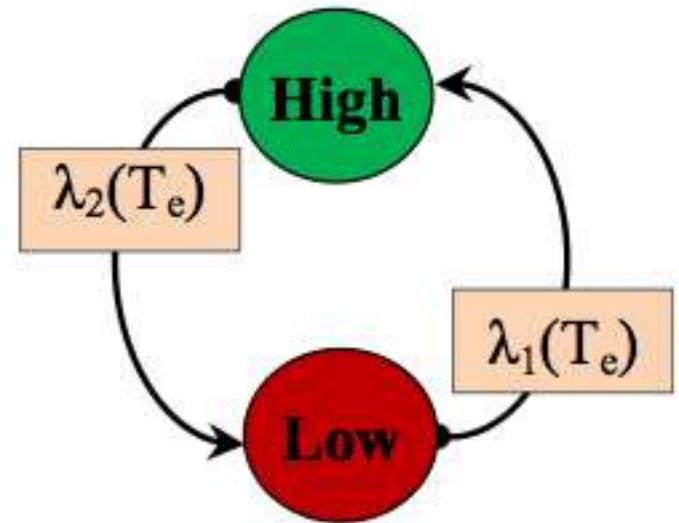
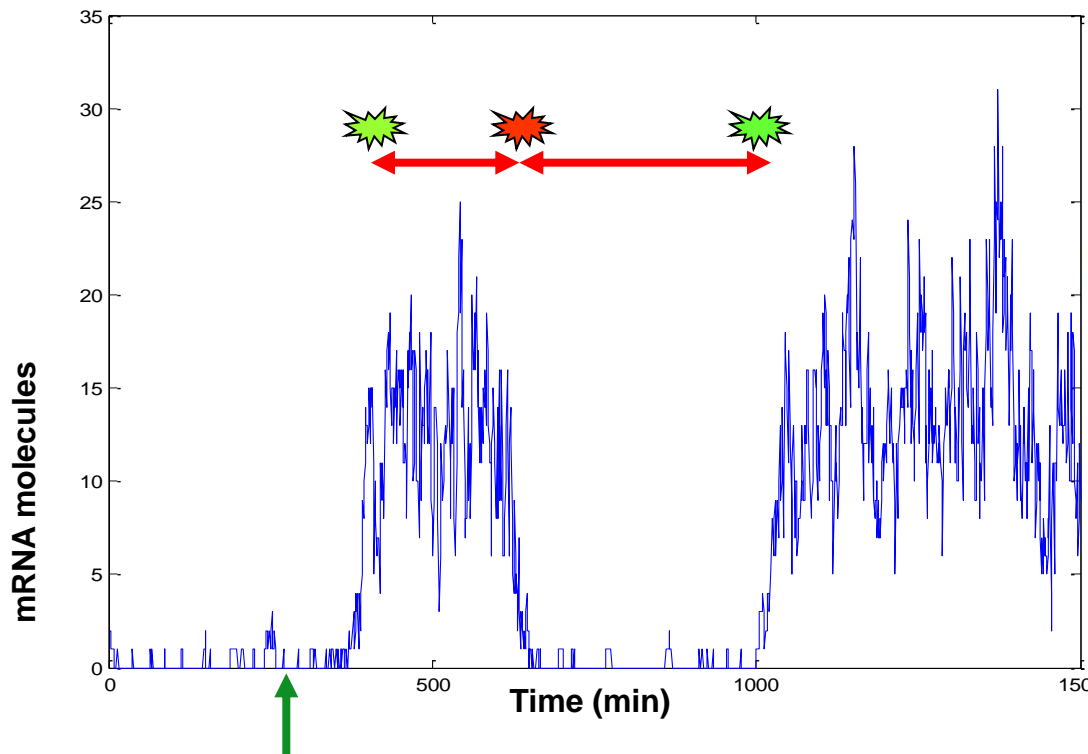
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A stochastic abstraction

- For intermediate values of T_e there is a quantifiable **stochastic switching rate**
- Stochastic transitions occur in addition to the **deterministic switching** triggered by extreme values of T_e



Lac system

System well described by an abstraction:

- two-state Markov chain model
- transition rates depend on external TMG
- can be computed from the full model

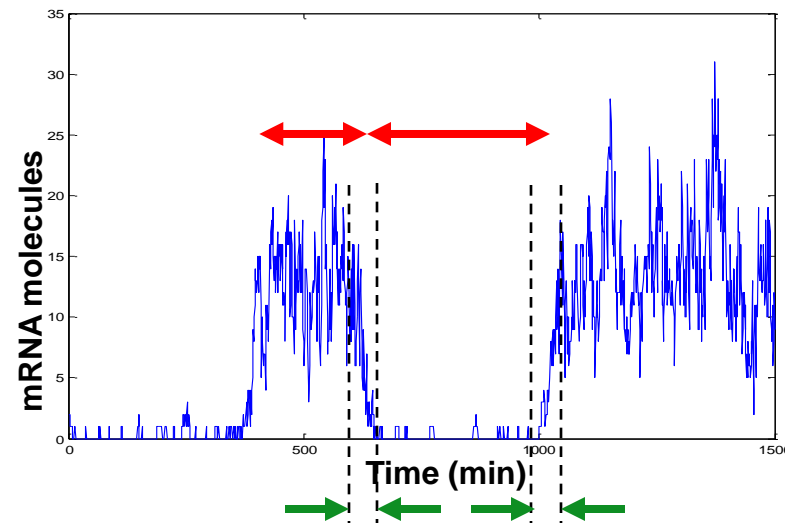
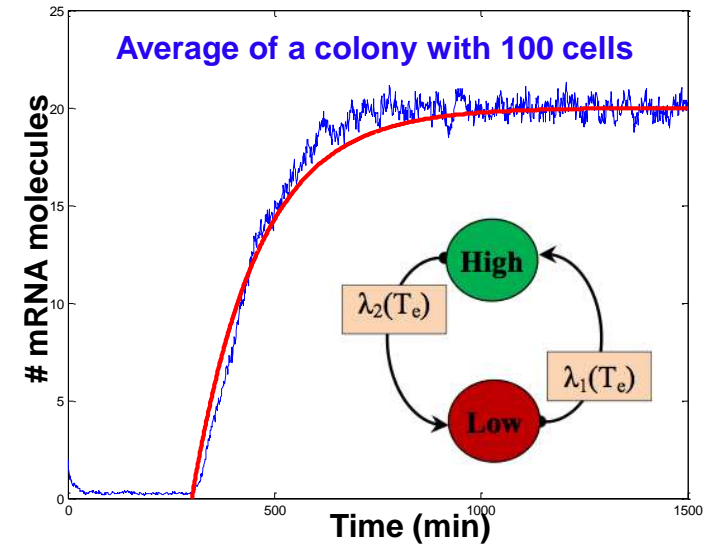
Macroscopic behavior well fitted by this model

- the *timescale of individual transitions* is smaller than the *characteristic time of transition initiation*

Remaining issue:

Model parameters are typically fitted to macroscopic measurements

- need to reconcile microscopic and macroscopic model predictions
- possible new insight into *in vitro* vs. *in vivo* parameters

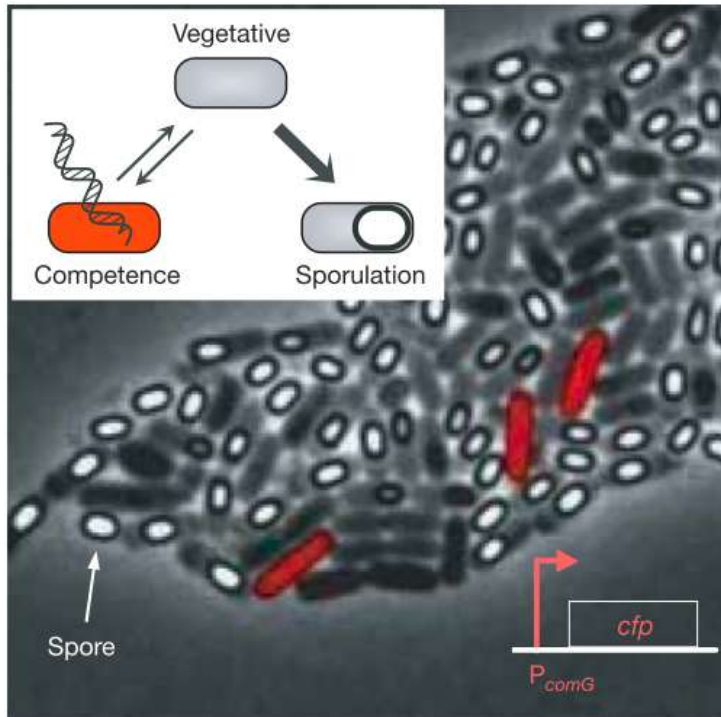


Lac system

- A classic gene switch
- Simple deterministic dynamics
 - **bistability** through **positive feedback**
- Spontaneous **transitions** due to **stochastic effects**
 - fluctuations, finite molecule numbers
- Phenomenologically, the **two modes coexist**
 - the same colony has populations of cells in either state
- Relative population sizes influenced by the characteristic times of the transitions

Competence in *B. subtilis*

(based on a paper from the Elowitz lab)



- A two-prong response to nutritional stress

- Most cells commit to sporulation
- A small minority (<4%) become competent for DNA uptake

- ComK acts as a "master" transcription factor

Vol 440 | 23 March 2006 | doi:10.1038/nature04588

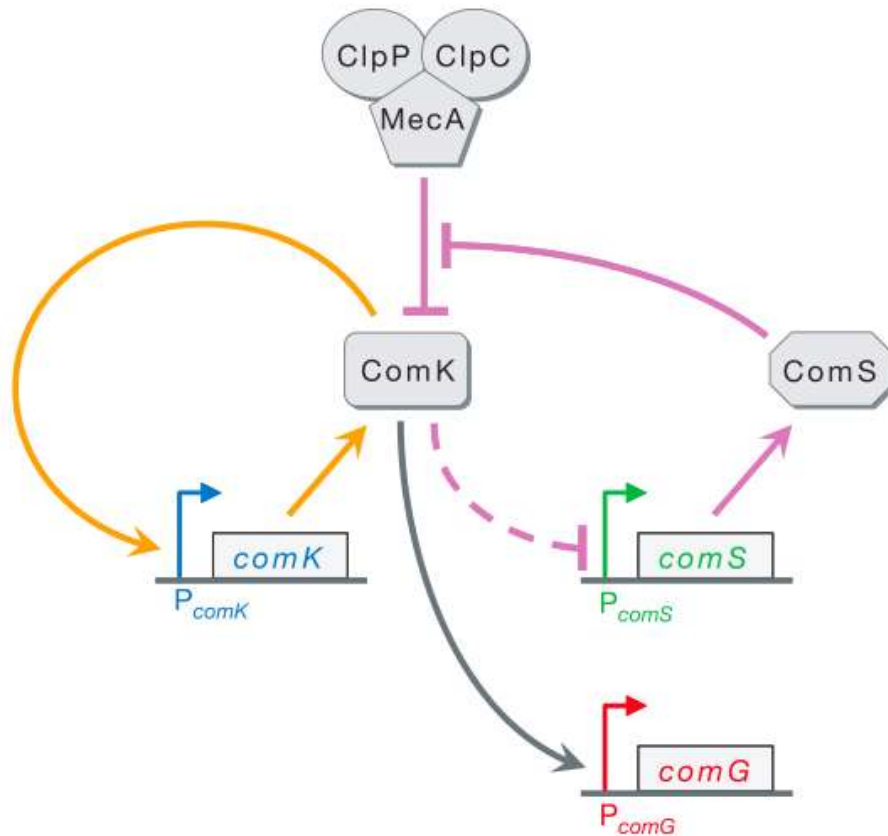
nature

LETTERS

An excitable gene regulatory circuit induces transient cellular differentiation

Gürol M. Süel¹, Jordi Garcia-Ojalvo², Louisa M. Liberman¹ & Michael B. Elowitz¹

Competence in *B. subtilis*

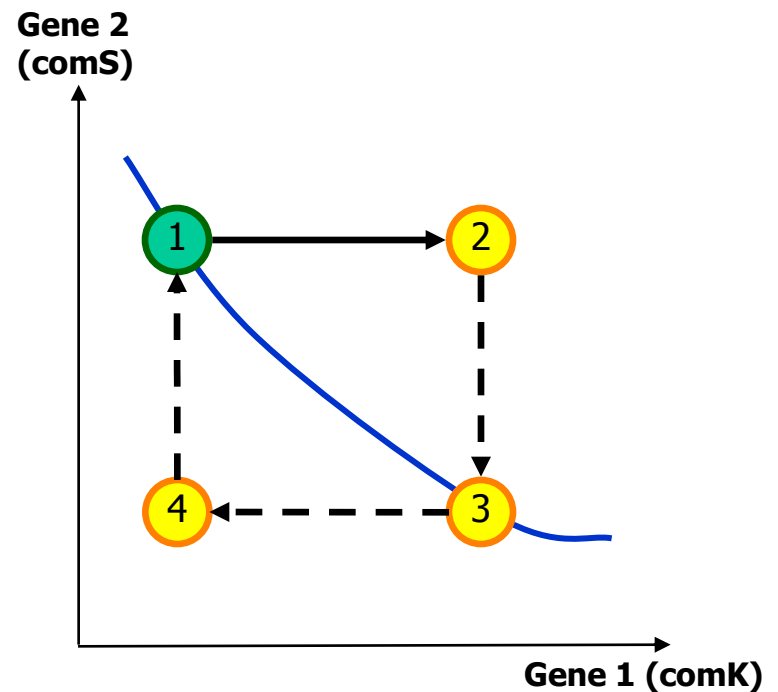
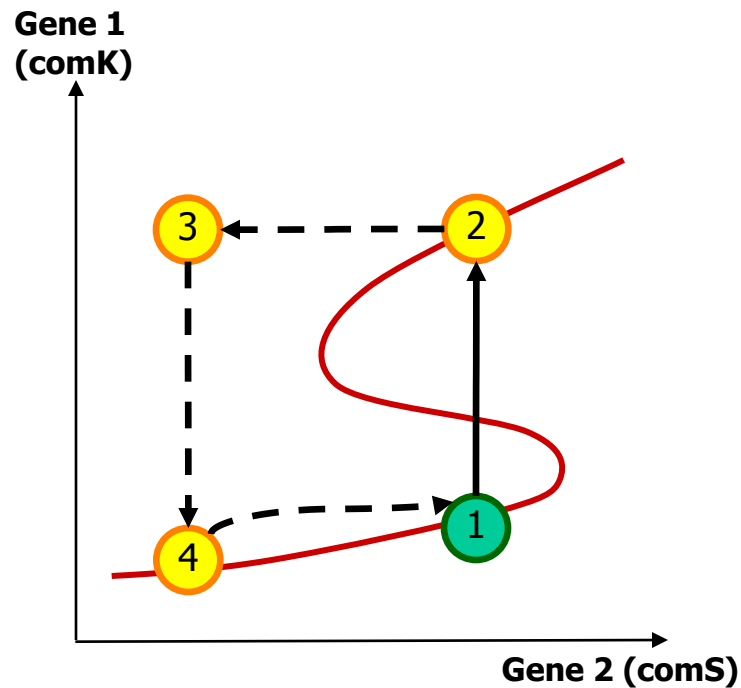


1. *comK* is self-promoting, and is expressed at a basal rate
2. ComK is degraded by MecA
3. ComS competes with MecA, inhibiting ComK degradation
4. *comS* is induced by stress, and is susceptible to noise
5. Overexpression of ComK suppresses *comS*

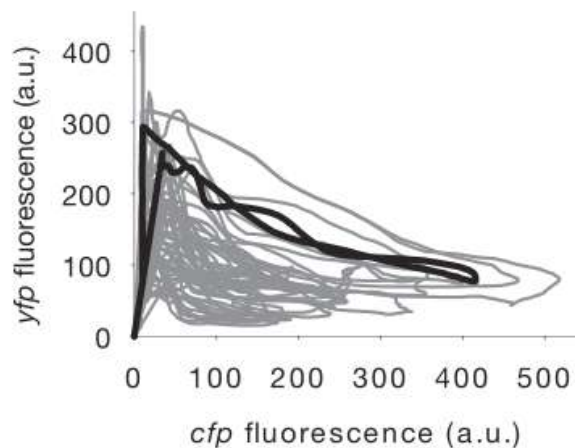
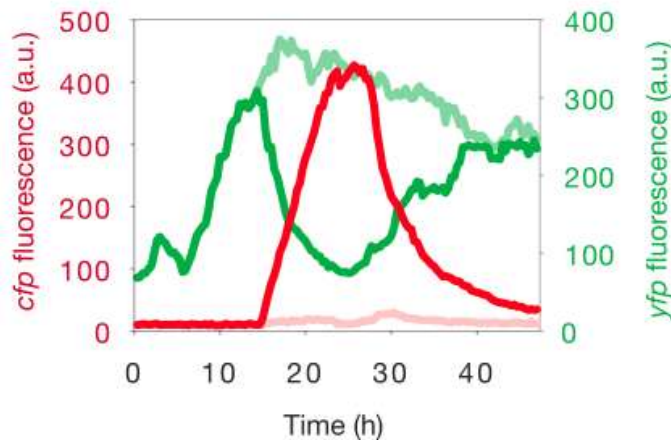
[Suel et al., Nature, 2006]

Bistability and slow return

- Two genes with mutual influence:
 - A fluctuation induces Gene 1 (comK)
 - Gene 2 (comS) is inhibited; drops below the threshold for Gene 1
 - Gene 1 returns to its low state, and Gene 2 slowly increases



Competence in *B. subtilis*



ComS (red) and **ComK (green)** activities during a competence event

[From Suel et al., Nature, 2006]

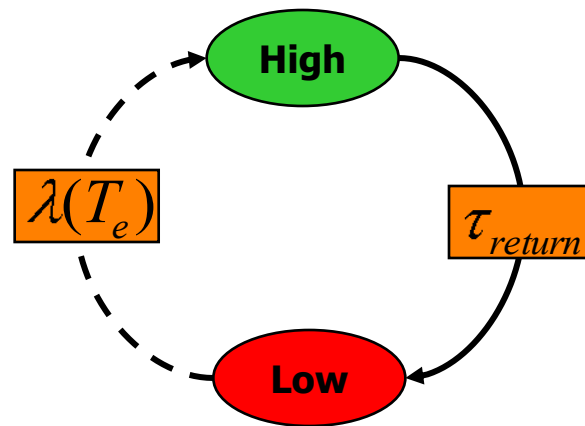
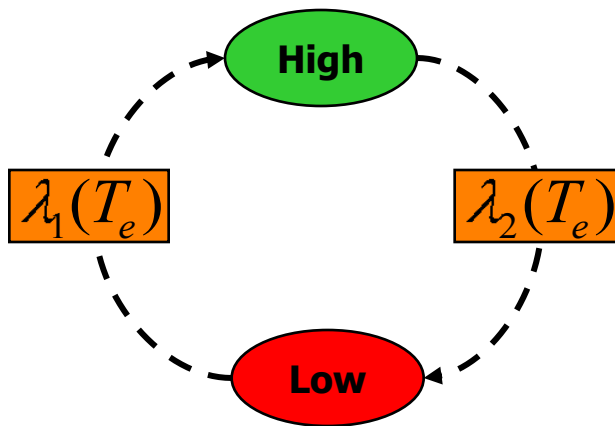
- A fluctuation in **ComS** blocks the degradation of **ComK**
- Increased ComK induces *comK* and the module "flips" into the high mode
- Eventually, the high level of ComK suppresses *comS*
- Lack of ComS leads to increased degradation of ComK
- *comK* "flips" back into the low mode

The competence example

- **Two phenotypes**, with identifiable roles in the survival of the species
- Entry into competence is **triggered stochastically**, similarly to "spontaneous induction" in the *lac* system.
- However, exit from competence is **deterministic**; it is guaranteed by the dynamics of the network
- Even though a bistability motif is present (self-promotion of *comK*), the system is **not** bistable

A different abstraction

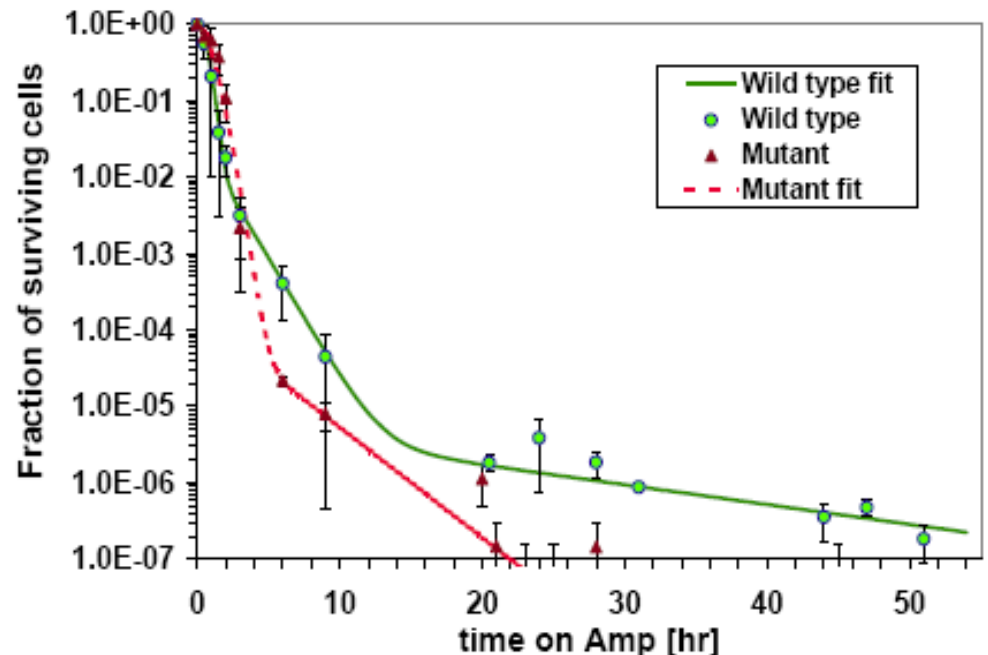
- Only one **steady state** and a **transient**
 - Stochastic transition in one direction
 - Deterministic trajectory on the way back
- Similar long-term population distributions



Bacterial persistence

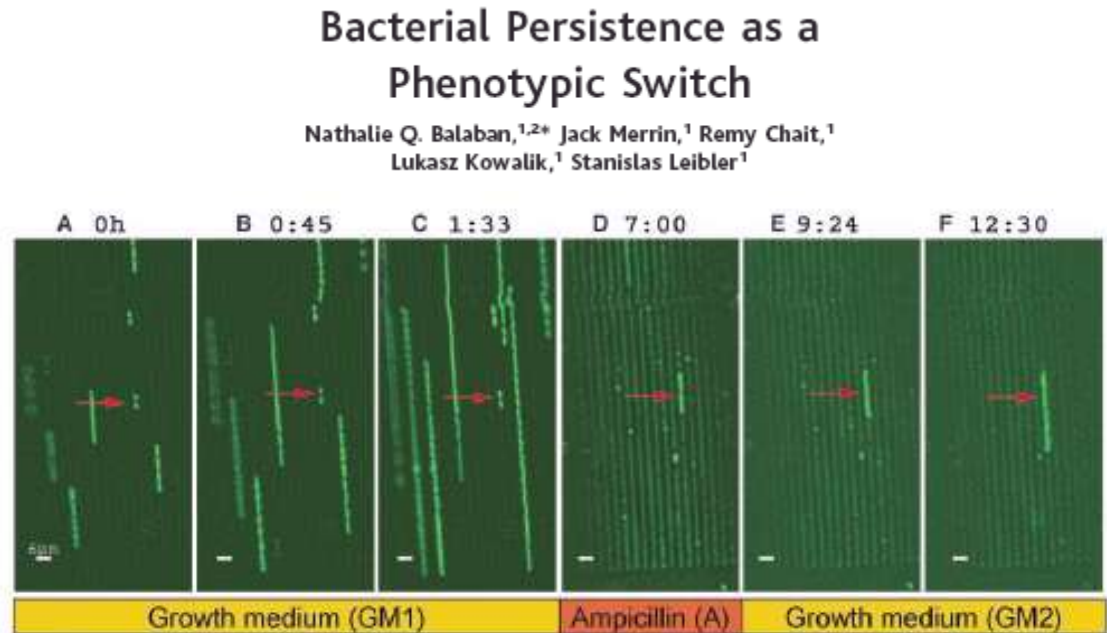
Discovered in the 1940's during the first large scale administration of antibiotics

- Small fraction survive therapy at a higher rate than the rest of the colony
- Persistence opens the door to the emergence of resistant strains
- Persisters are genetically identical to the rest
- They give rise to a colony identical to the old one



Bacterial persistence

- Persisters are non-growing cells
 - Some are generated during stationary phase
 - There is spontaneous persister generation
- Persistence is an alternative phenotype
 - “Hedging strategy”
- Mechanism not well understood
- Likely an example of spontaneous entry and slow, deterministic return to growth

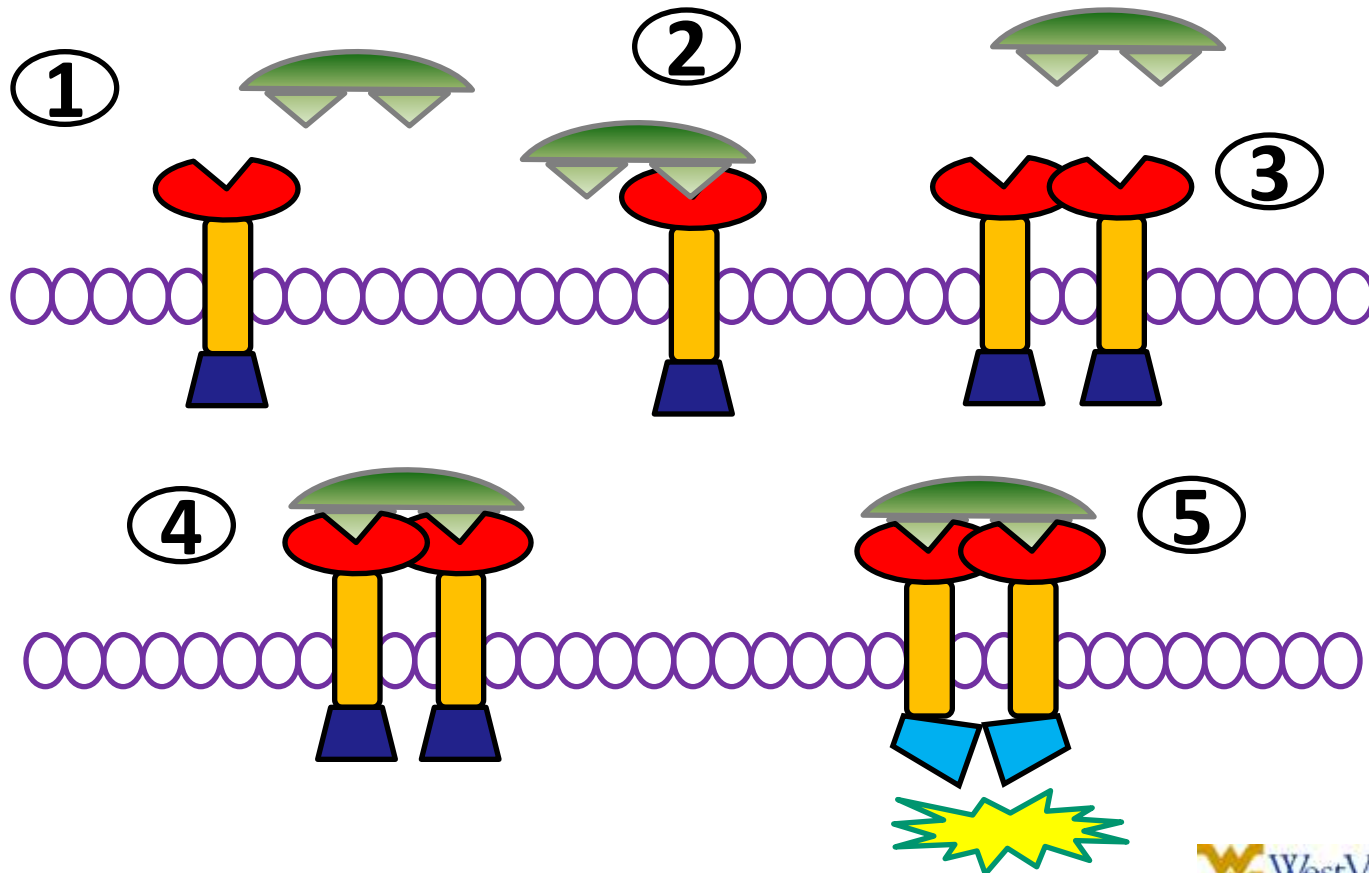


Spatial effects in cell signaling

- Cells must coordinate in multicellular organisms
 - This is achieved through signaling; signals are special substances
 - Specialized receptors on the cell membrane, some inside the cell
- Receptor tyrosine kinase (RTK) receptors have to dimerize in order to signal
 - These are membrane receptors; they can move more or less freely on the membrane
 - Dimerization is more likely if the receptors are located in high density patches, rather than being uniformly distributed
 - Such patches have been observed; the mechanism behind their formation is unclear
- Spatial self-organization contributes to the dynamics of signal initiation

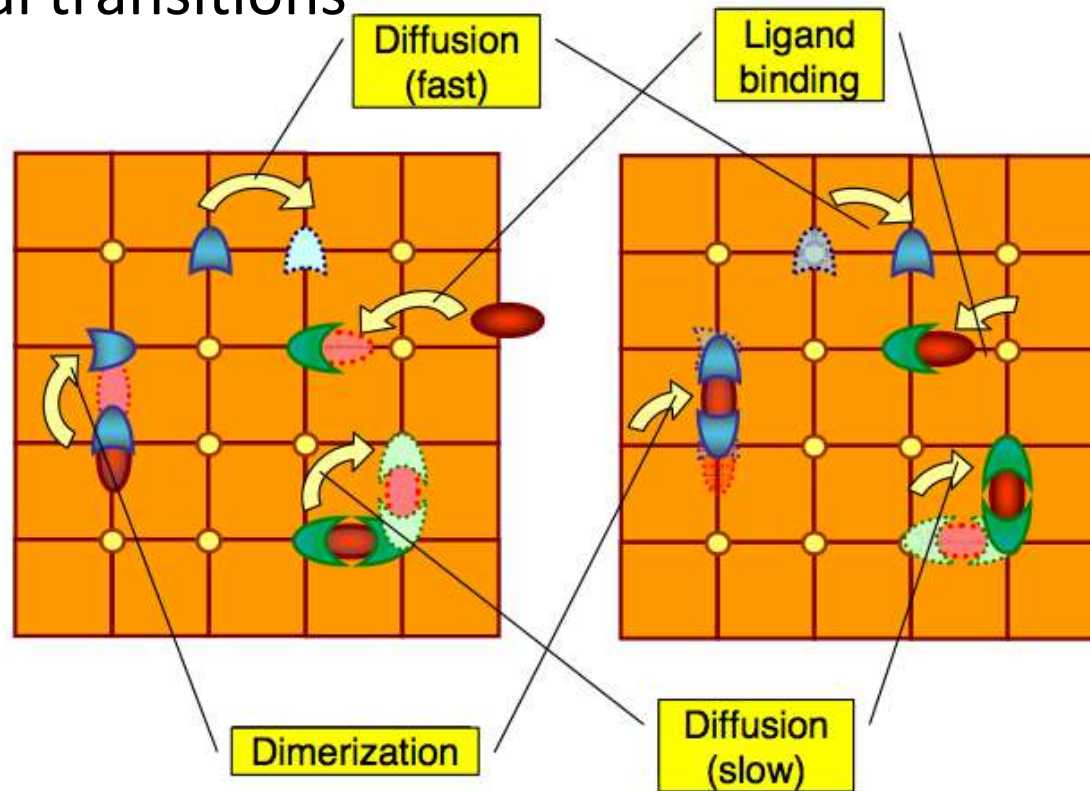
Membrane receptors

- Large molecules which straddle the cell membrane
- Ligand binding and dimerization are required for signal initiation



Spatial Monte-Carlo simulation

- Sometimes the only approach to signal initiation
- Molecules are simulated individually
- The system evolves as a Markov chain with spatial and chemical transitions



Summary

- Cellular processes can usually be described by ODE-based rate laws
- Two apparently conflicting challenges
 - The complexity of the networks requires **simplifications** (abstractions)
 - The ODE approach is itself an idealization of a richer underlying phenomenology of **stochastic effects** and **spatial structure**
- There are good mathematical methods for abstraction, and good algorithms for simulation

Acknowledgments

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 - Harvey Rubin, Vijay Kumar, Junhyong Kim
 - Marcin Imielinski (HMS), Agung Julius (RPI), Selman Sakar
 - Jeremy Edwards (UNM)
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 - Penn Genomics Frontiers Institute / Commonwealth of Pennsylvania
 - State of West Virginia