Modeling and simulation of gene regulatory networks 4

Hidde de Jong
IBIS
INRIA Grenoble – Rhône-Alpes
Hidde.de-Jong@inria.fr

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INRIA Grenoble - Rhône-Alpes and IBIS

- IBIS: systems biology group at INRIA/Université Joseph Fourier/CNRS
    - Analysis of bacterial regulatory networks by means of models and experiments
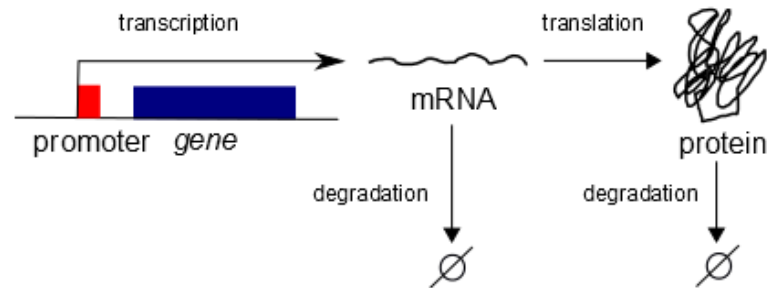   - Biologists, computer scientists, mathematicians, physicists, …

http://ibis.inrialpes.fr

Overview

Gene expression

- Typically, and simplifying quite a bit, **gene expression** in bacteria involves:
    - Transcription by RNAP (mRNA)
    - Translation by ribosomes (proteins)
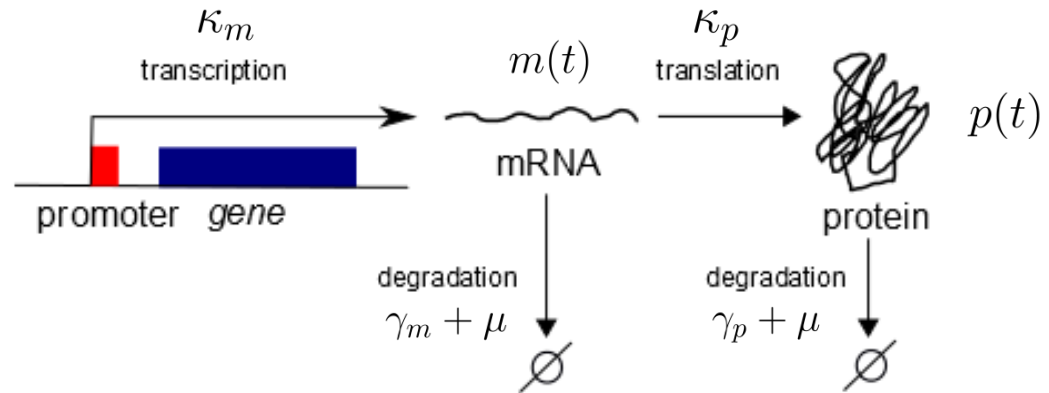   - Degradation of mRNA and protein

Modeling of gene regulatory networks

- ODE model of gene expression, distinguishing **transcription** and **translation**

$$\dot{m} = \kappa_m - (\gamma_m + \mu)\, m$$

$$\dot{p} = \kappa_p\, m - (\gamma_p + \mu)\, p$$

$m(t) \geq 0$, concentration mRNA

$p(t) \geq 0$, concentration protein

$\kappa_m, \kappa_p > 0$, synthesis rate constants

$\gamma_m, \gamma_p > 0$, degradation rate constants

$\mu \geq 0$, growth rate

Stochasticity in gene expression

- ODE models make abstraction of underlying biochemical reaction processes involved in gene expression that may not be warranted
  Kaern *et al.* (2005), *Nat. Rev. Genet.*, 6(6):451-464

- Gene expression is **stochastic** instead of **deterministic** process
  - Underlying biochemical reactions are stochastic processes
  - Probability of reaction to occur depends on random encounters of molecules in cell
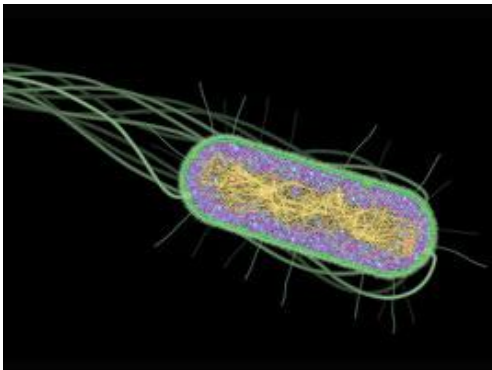
Goodsell (2010), *The Machinery of Life, Springer,* 2nd ed.

Stochasticity in gene expression

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- Gene expression is **stochastic** instead of **deterministic** process
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  - Probability of reaction to occur depends on random encounters of molecules in cell

- **Discrete** number of molecules of reaction species, instead of **continuous** concentrations
  Some reactions species involved in gene expression have very low copy numbers (1-10)

Stochasticity in gene expression

- Stochasticity in gene expression leads to **noise**

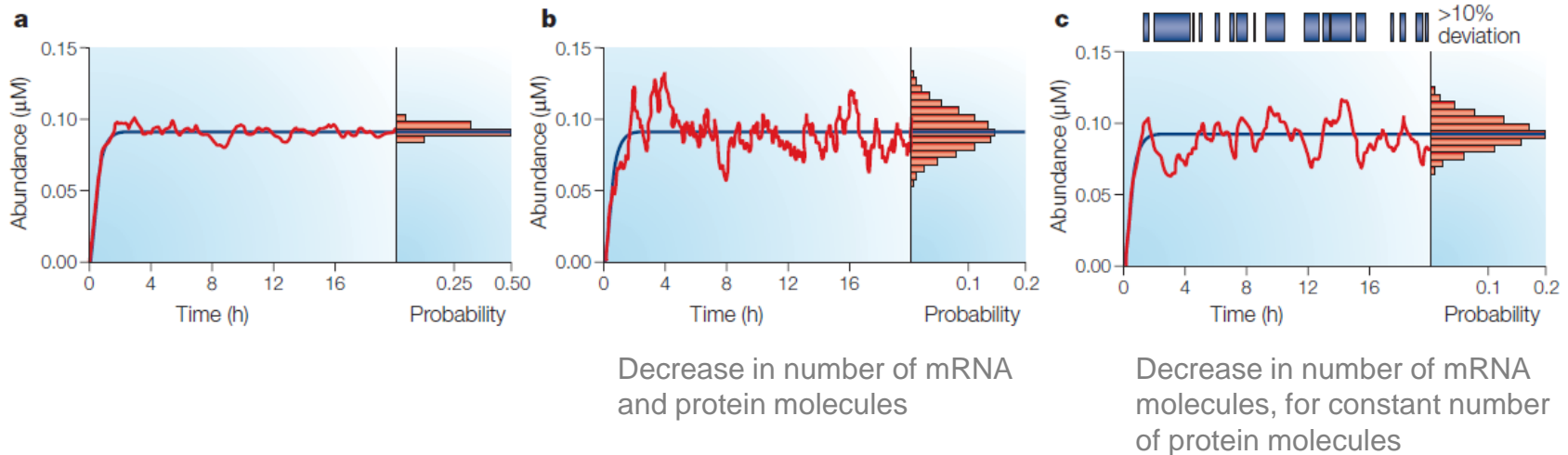 Fluctuations in mRNA and protein concentrations

Kaern *et al.* (2005), *Nat. Rev. Genet.*, 6(6):451-464
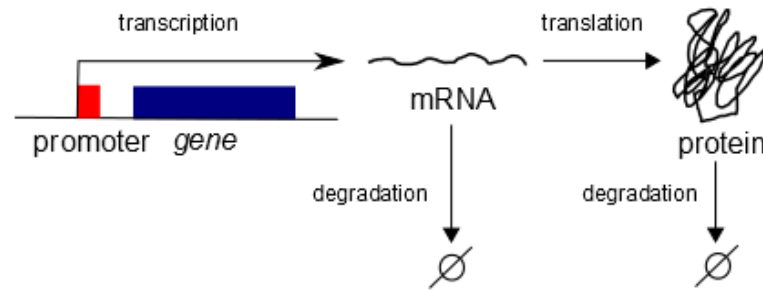
Stochasticity in gene expression

- Stochasticity in gene expression leads to **noise**

  Fluctuations in mRNA and protein concentrations

- Noise amplified by small number of molecules

Decrease in number of mRNA and protein molecules
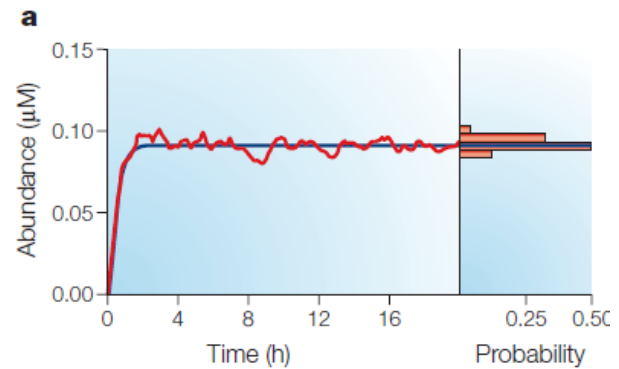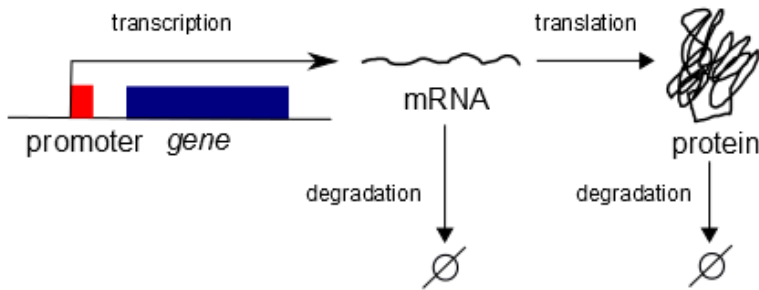
Decrease in number of mRNA molecules, for constant number of protein molecules

Kaern *et al.* (2005), *Nat. Rev. Genet.*, 6(6):451-464

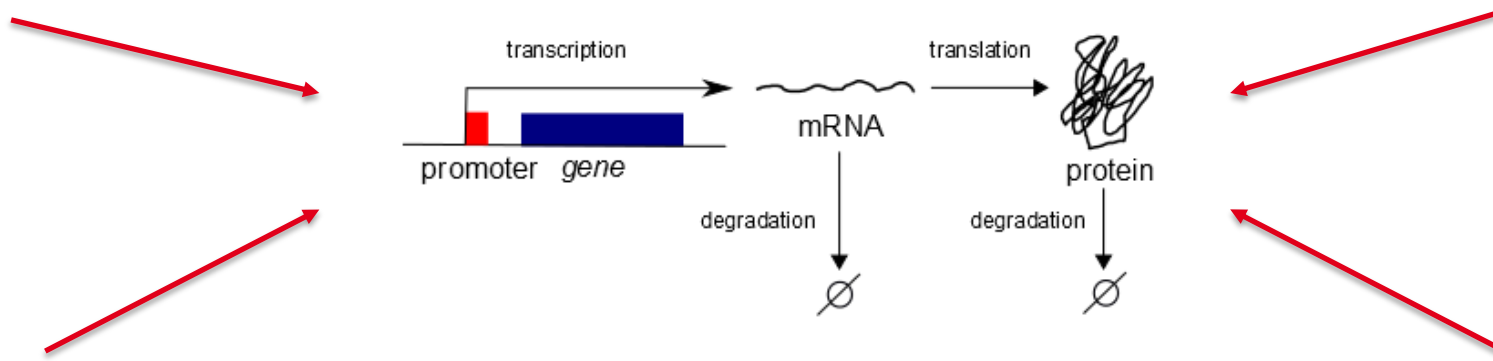# Stochasticity in gene expression

- Stochasticity in gene expression leads to **noise**

  Fluctuations in mRNA and protein concentrations

- Noise amplified by small number of molecules

- Different types of noise:

  – **Intrinsic noise:** fluctutations due to stochasticity of processes involved in gene expression (transcription, translation, …)

Stochasticity in gene expression

- Stochasticity in gene expression leads to **noise**

    Fluctuations in mRNA and protein concentrations

- Noise amplified by small number of molecules

- Different types of noise:

    - **Intrinsic noise:** fluctutations due to stochasticity of processes involved in gene expression (transcription, translation, …)

    - **Extrinsic noise:** fluctutations due to variability in external factors (temperature, ribosome availability, …). Impact on rate constants.
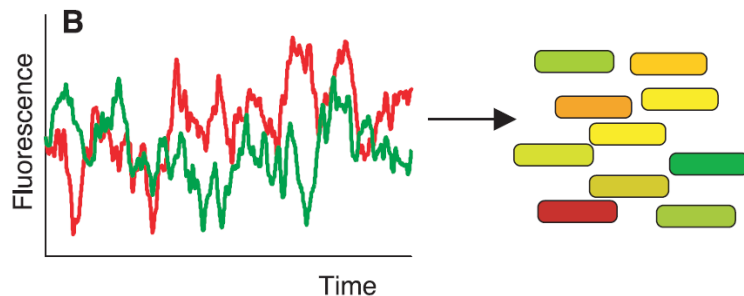
Stochasticity in gene expression

- Experimental discrimination between intrinsic and extrinsic noise

  Expression in a single cell with two different reporter genes (*gfp* and *cfp*) controlled by same promoter
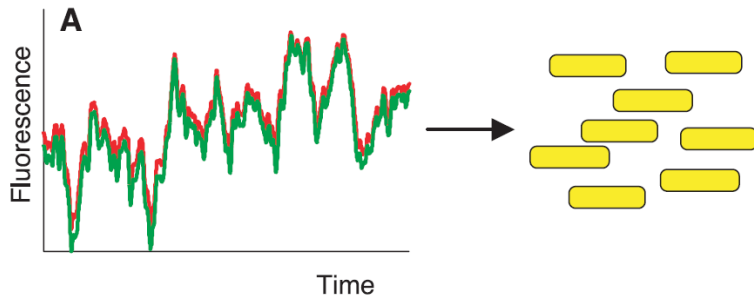
No intrinsic noise, so relative amount of both proteins is constant over time and across individual cells in population
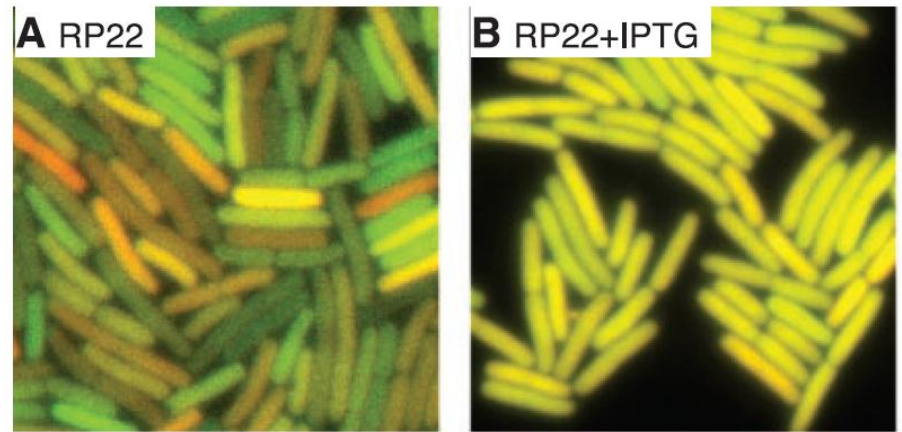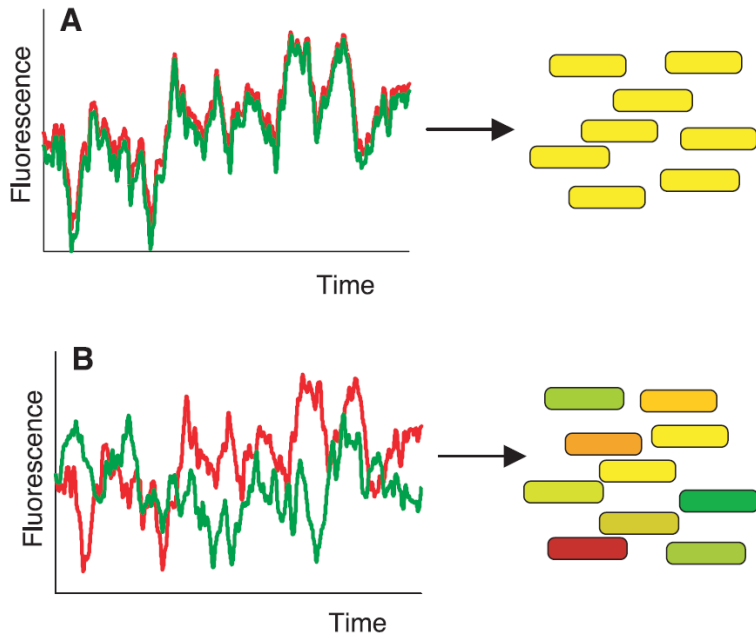
Intrinsic noise, so relative amount of both proteins varies over time and across individual cells in population

Elowitz *et al.* (2002), *Science*, 297(5584):1183-6

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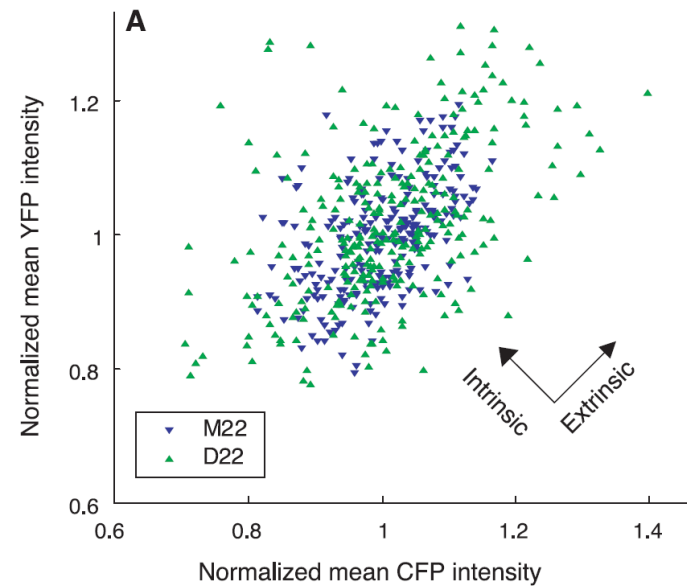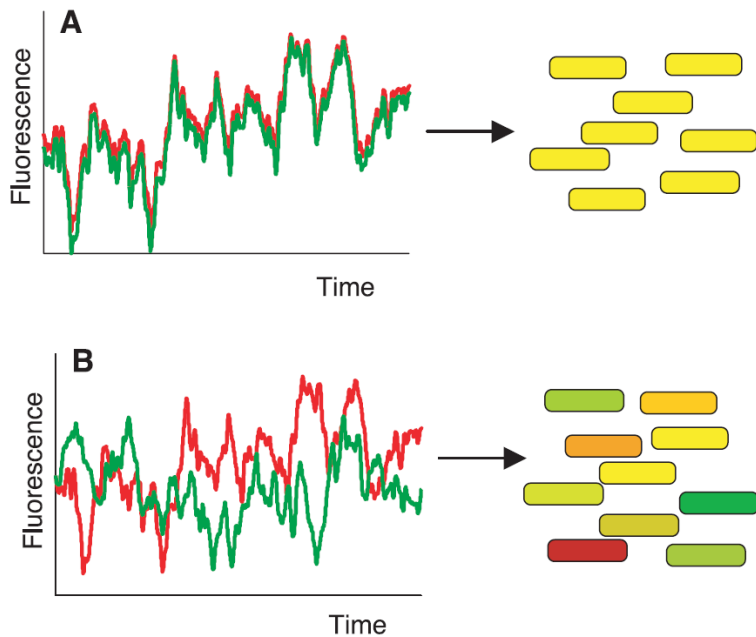

Elowitz *et al.* (2002), *Science*, 297(5584):1183-6

Stochasticity in gene expression

- Experimental discrimination between intrinsic and extrinsic noise

    Expression in a single cell with two different reporter genes controlled by same promoter

Elowitz *et al.* (2002), *Science*, 297(5584):1183-6

Stochasticity in gene expression

- Major question is how cells both **tolerate and exploit** noise.

   Rao *et al.* (2002), *Nature*, 420(6912):231-237

    Raj and van Oudenaarden (2008), *Cell*, 135(2):216-26

- Most cellular processes are **robust** to noise, despite stochasticity of underlying system of biochemical reactions

- Sometimes, intracellular noise drives **population heterogeneity** that may be beneficial for a species
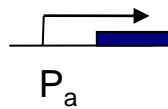
    After infection, only fraction of cells lyse

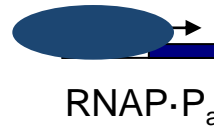- ODE models are not suitable for studying origin and effects of noise
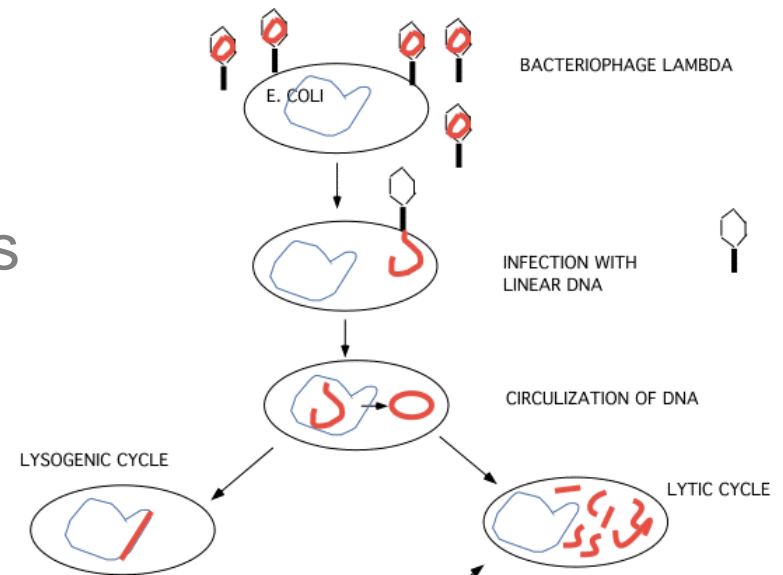
Stochastic models

- **Stochastic models** of gene regulation are more appropriate

- Number of molecules of each species i at time-point t represented by discrete variable $X_i(t) \in \mathbb{N}$

P_a	RNAP	RNAP·P_a	RBS_a
X_1	X_2	X_3	X_4

Stochastic models

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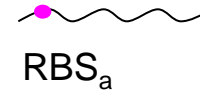
- Reactions between molecular species lead to change in state of system from $X(t)$ to $X(t+\Delta t)$ over time-interval Δt, where
$$X = [X_1, \ldots, X_n]'$$

Change of state by reaction k described by vector ν_k

Reaction 1: $\nu_1 = [-1 \ -1 \ 1 \ 0]$

P_a + RNAP ⇌ RNAP·P_a

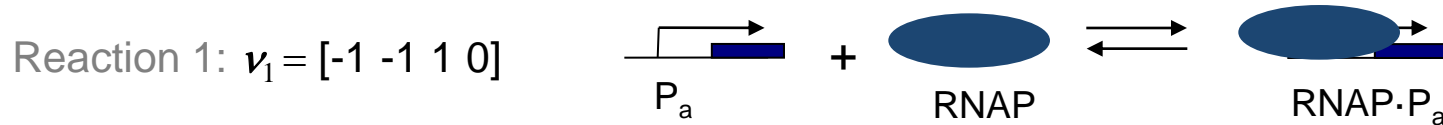Reaction 2: $\nu_2 = [1 \ 1 \ -1 \ 1]$

RNAP·P_a → RNAP + P_a + RBS$_a$
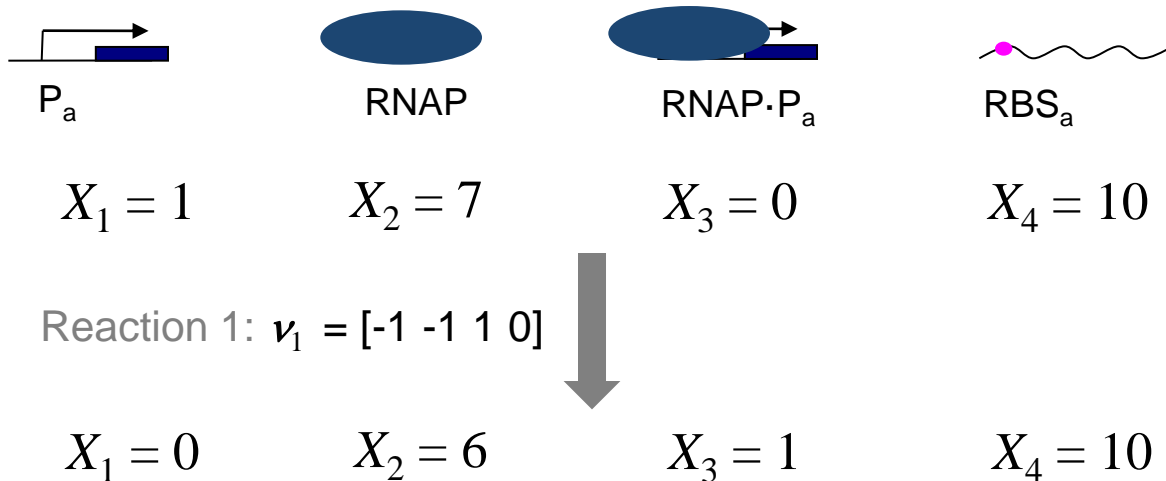
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- Reactions between molecular species lead to change in state of system from $X(t)$ to $X(t+\Delta t)$ over time-interval Δt, where $X = [X_1, \ldots, X_n]'$

P_a	RNAP	RNAP·P_a	RBS$_a$
$X_1 = 1$	$X_2 = 7$	$X_3 = 0$	$X_4 = 10$

Reaction 1: ν_1 = [-1 -1 1 0]

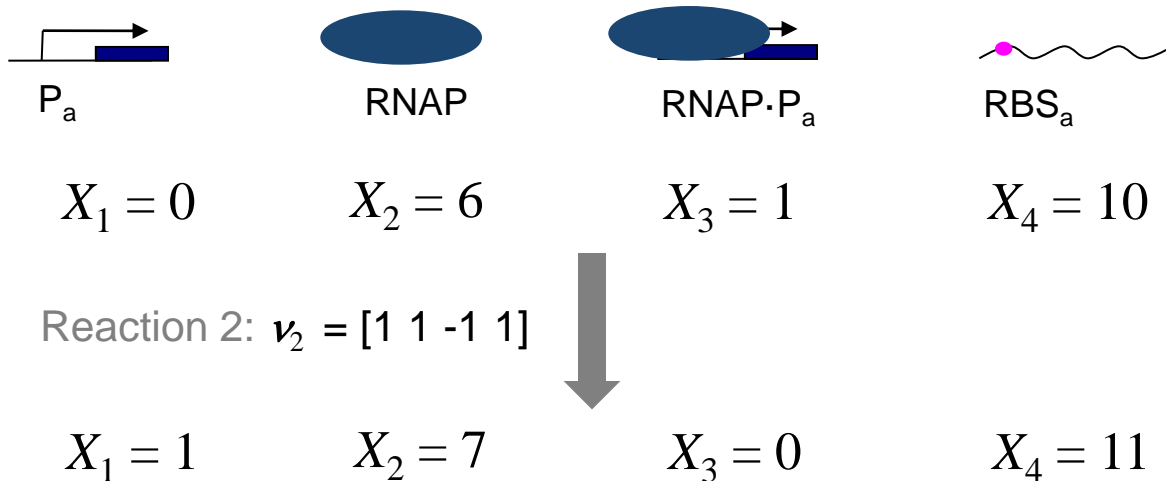| $X_1 = 0$	$X_2 = 6$	$X_3 = 1$	$X_4 = 10$

Stochastic models

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$X_1 = 0$	$X_2 = 6$	$X_3 = 1$	$X_4 = 10$

Reaction 2: ν_2 = [1 1 -1 1]

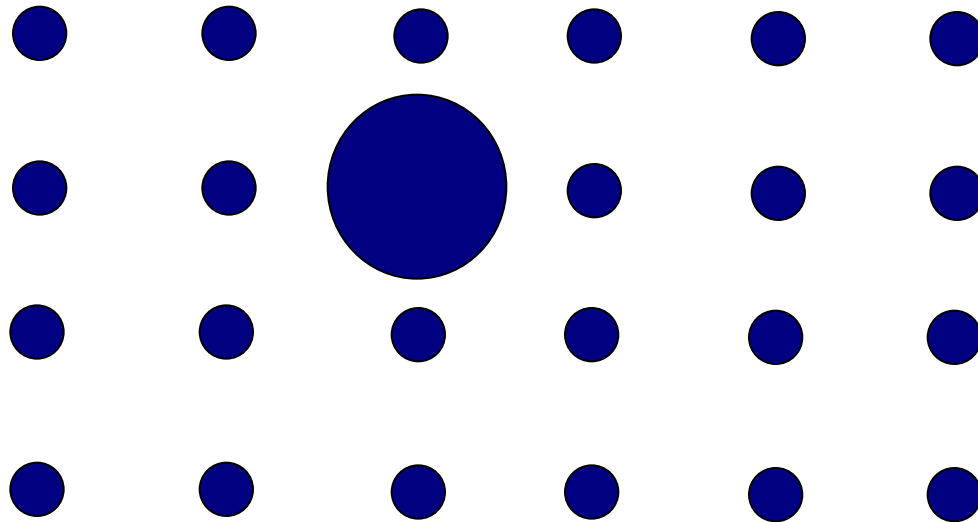|			
$X_1 = 1$	$X_2 = 7$	$X_3 = 0$	$X_4 = 11$

Stochastic models

- Possible states are given by possible value combinations for variables: $X = V$, with $V = [V_1, \ldots, V_n]'$

- Transitions between states are given by possible reactions k
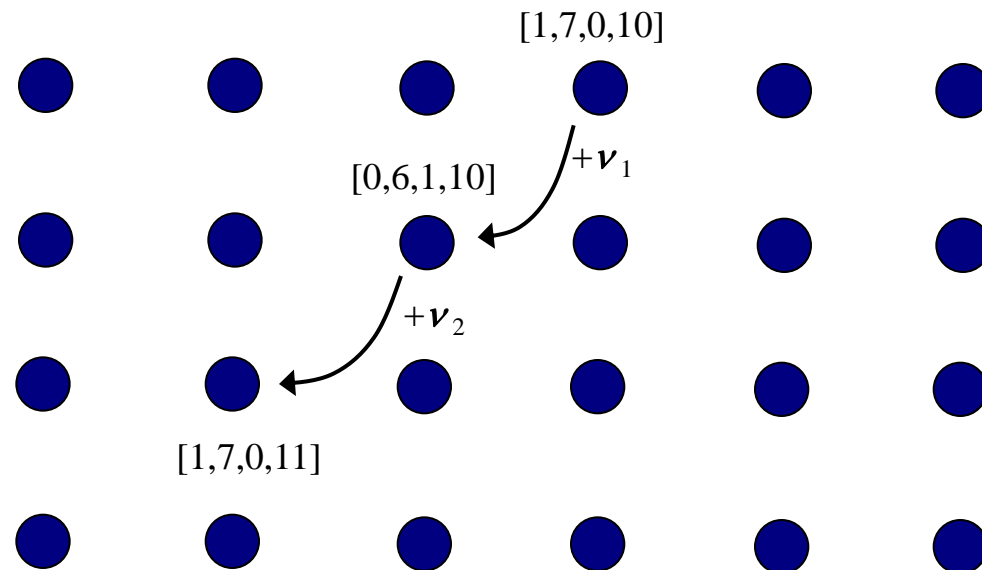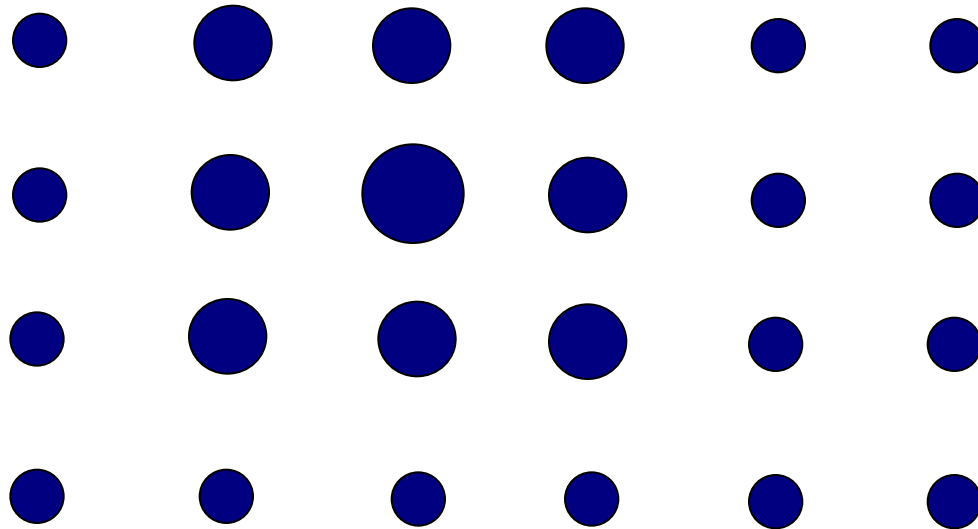
[1,7,0,10]

[0,6,1,10]

$+\nu_1$

$+\nu_2$

[1,7,0,11]

Stochastic models

- Probability distribution $p[X(t)=V]$ describes probability that at time-point t there are $V = [V_1, \ldots, V_n]'$ molecules

Time t_0

Stochastic models

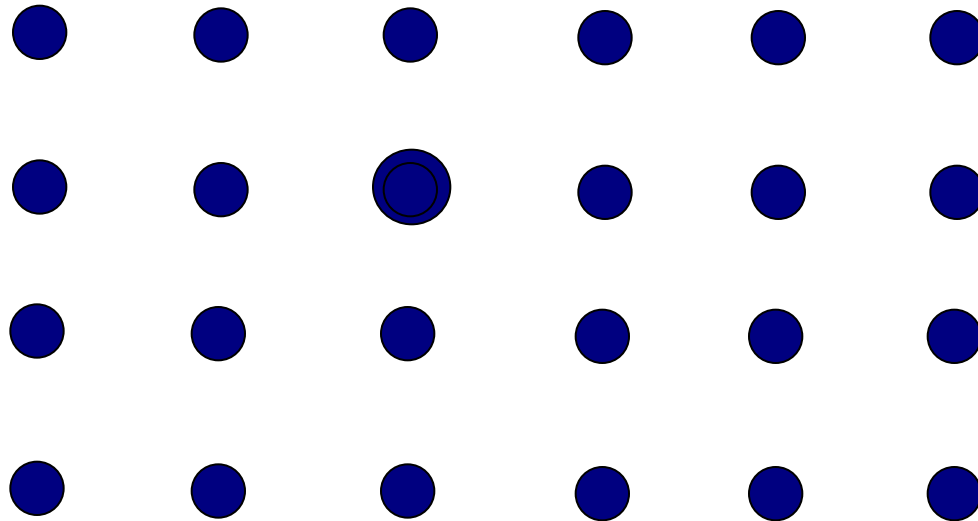- Probability distribution $p[X(t) = V]$ describes probability that at time-point t there are $V = [V_1, \ldots, V_n]'$ molecules

Time t_1

Stochastic models

- Probability distribution $\mathsf{p}[X(t){=}V]$ describes probability that at time-point t there are $V = [V_1,\ldots, V_n]'$ molecules

Time t_2

Stochastic master equation

- Evolution of probability distribution $p[X(t)=V]$ given by

$$p[X(t+\Delta t)=V] = p[X(t)=V]\left(1 - \sum_{j=1}^{m} \alpha_j \Delta t\right) +$$

$$\sum_{k=1}^{m} p[X(t)=V-\nu_k]\, \beta_k\, \Delta t$$

  - m is the number of reactions that can occur in the system

  - $\alpha_j \Delta t$ is the probability that reaction j will occur in $[t,\, t+\Delta t]$ given that $X(t)=V$

  - $\beta_k \Delta t$ is the probability that reaction k will bring the system from $X(t)=V-\nu_k$ to $X(t+\Delta t)=V$ in $[t,\, t+\Delta t]$

Van Kampen (1997), *Stochastic Processes in Physics and Chemistry*, Elsevier

Stochastic master equation

- For $\Delta t \to 0$ we obtain **stochastic master equation**

$$\mathrm{dp}[\boldsymbol{X}(t){=}\boldsymbol{V}] \,/\, \mathrm{d}t = \sum_{j=1}^{m} \mathrm{p}[\boldsymbol{X}(t){=}\boldsymbol{V}{-}\boldsymbol{\nu}_j]\,\beta_j - \mathrm{p}[\boldsymbol{X}(t){=}\boldsymbol{V}]\,\alpha_j$$

- Probabilities $\alpha_j,\ \beta_j$ are defined in terms of kinetic constants of reactions and number of reactant molecules

- Unimolecular reaction j : $S_1 \to$ product(s)

$$\alpha_j = k_j\, X_1\, (X_1\text{-}1)/2$$

- Bimolecular reaction j : $S_1 + S_2 \to$ product(s)

$$\alpha_j = k_j\, X_1\, X_2/\Omega \qquad\qquad \Omega : \text{cell volume}$$

Gillespie (2007), *Annu. Rev. Phys. Chem.*, 58:35-55

Stochastic master equation

- For $\Delta t \rightarrow 0$ we obtain **stochastic master equation**

$$\mathrm{dp}[X(t){=}V] \,/\, \mathrm{d}t = \sum_{j=1}^{m} \mathrm{p}[X(t){=}V{-}\nu_j]\,\beta_j - \mathrm{p}[X(t){=}V]\,\alpha_j$$

- Probabilities α_j, β_j are defined in terms of kinetic constants of reactions and number of reactant molecules

- Analytical solution of master equation is not possible in most situations of practical interest

Van Kampen (1997), *Stochastic Processes in Physics and Chemistry*, Elsevier

Stochastic simulation

- Analytical solution of master equations is not possible in most situations of practical interest

- **Stochastic simulation** predicts sequences of reactions that change state of system, starting from initial state $X(0) = V_0$

  - Stochastic simulation samples joint probability density function

    $$\mathrm{p}[\tau, j / X(t) = V]$$

    $\tau =$ time until occurrence of next reaction

    $j =$ index of next reaction

  - **Interpretation:** $\mathrm{p}[\tau, j / X(t) = V]\mathrm{d}\tau$ is probability, given $X(t) = V$, that next reaction will occur in $[t + \tau, t + \tau + \mathrm{d}\tau]$ and is reaction j

Gillespie (2002), *J. Phys. Chem.*, 81(25): 2340-61

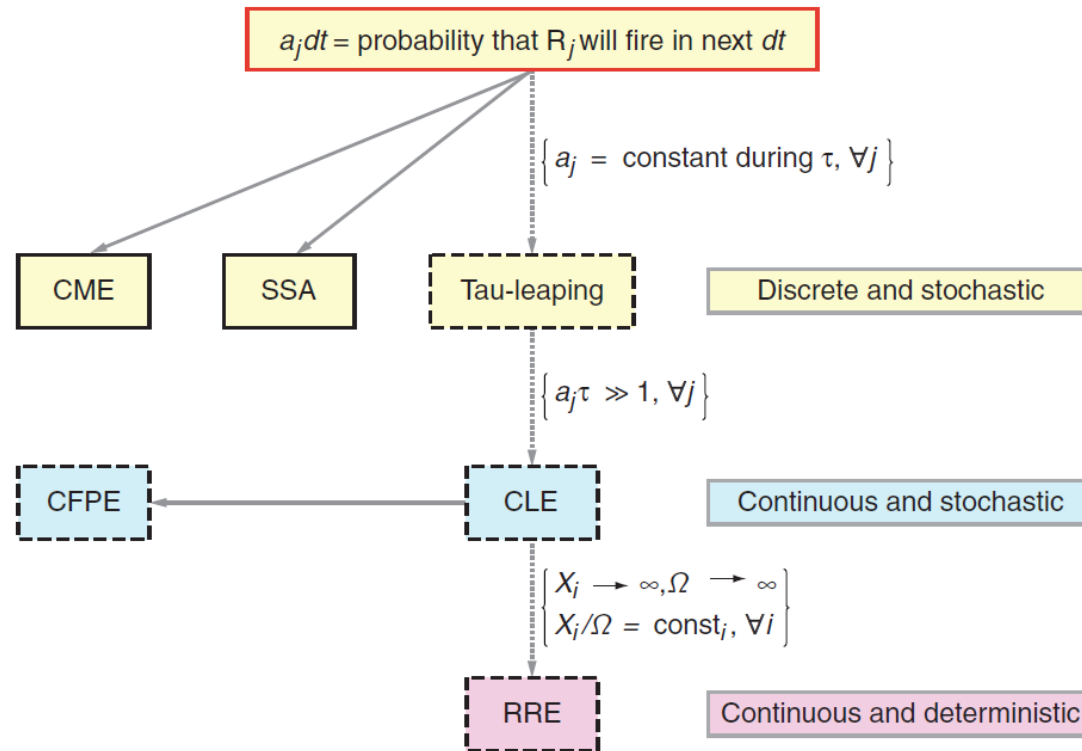Gillespie (2007), *Annu. Rev. Phys. Chem.*, 58:35-55

Stochastic simulation

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Stochastic simulation samples joint probability density function

$$p[\tau, j/X(t) = V]$$

τ = time until occurrence of next reaction

j = index of next reaction

Probability density function defined in terms of α_j, β_k (reaction constants)

Gillespie (2002), *J. Phys. Chem.*, 81(25): 2340-61

Gillespie (2007), *Annu. Rev. Phys. Chem.*, 58:35-55

Stochastic simulation

- Analytical solution of master equations is not possible in most situations of practical interest

- **Stochastic simulation** generates sequences of reactions that change state of system, starting from initial state $X(0) = V_0$

- Stochastic simulation based on sampling of $p[\tau, j/X(t) = V]$ generates sequences in exact accordance with stochastic master equations

- Repeating stochastic simulation many times (Monte-Carlo procedure) yields approximation of probability distribution $p(X(t) = V)$

Gillespie (2002), *J. Phys. Chem.*, 81(25): 2340-61

Gillespie (2007), *Annu. Rev. Phys. Chem.*, 58:35-55

Stochastic simulation

- Analytical solution of master equations is not possible in most situations of practical interest

- **Stochastic simulation** generates sequences of reactions that change state of system, starting from initial state $X(0) = V_0$

- Various approximations of basic stochastic simulation algorithm, trading exactness for simulation speed:

  – Tau-leaping approaches: choose τ such that α_j, β_j remain approximately constant over time interval (encapsulate several reactions in one step)

  – Quasi-steady-state approximations (distinguish between slow and fast reactions)

  – …

Gillespie (2007), *Annu. Rev. Phys. Chem.*, 58:35-55

Stochastic simulation

- Relation of stochastic simulation models with other modeling approaches

Gillespie (2007), *Annu. Rev. Phys. Chem.*, 58:35-55

Stochastic simulation

- **Stochastic simulation** generates sequences of reactions that change state of system, starting from initial state $X(0) = V_0$
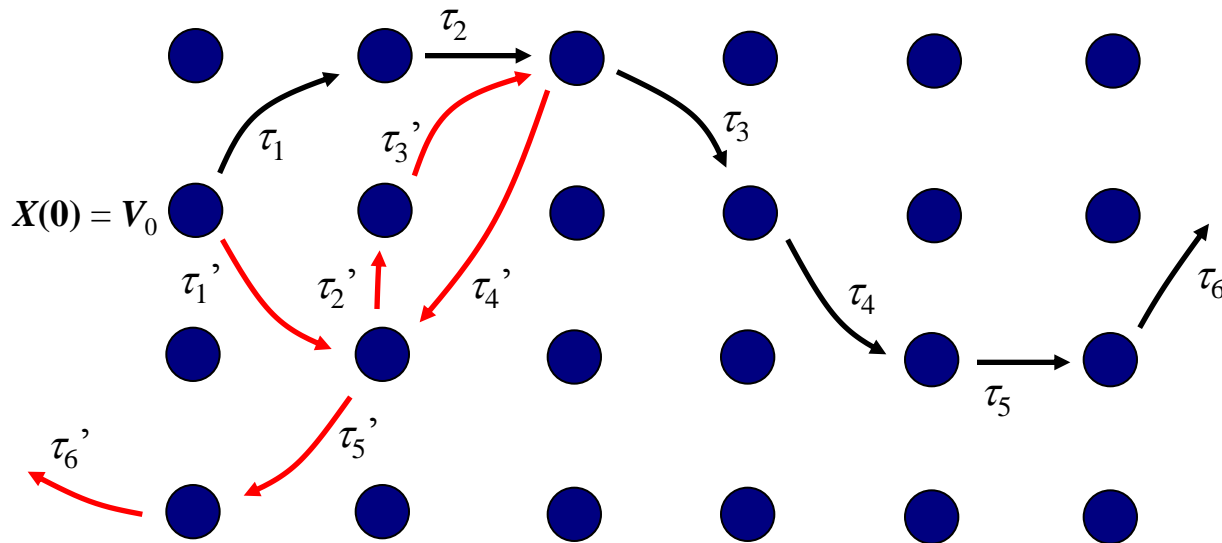
- Stochastic simulation may lead to different dynamical behaviors starting from identical initial conditions: **heterogeneity**

Auto-inhibition network

- **Auto-inhibition** network consists of a single gene, coding for transcription regulator inhibiting expression of its own gene
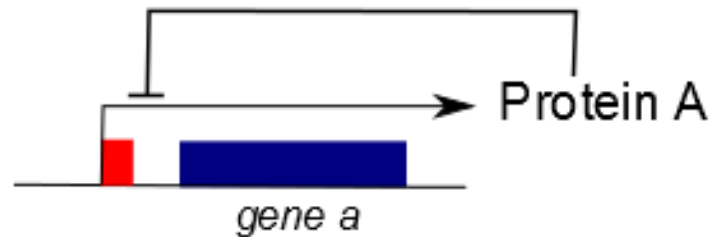
- Auto-inhibition is example of **negative feedback**, and frequently occurs in bacterial regulatory networks

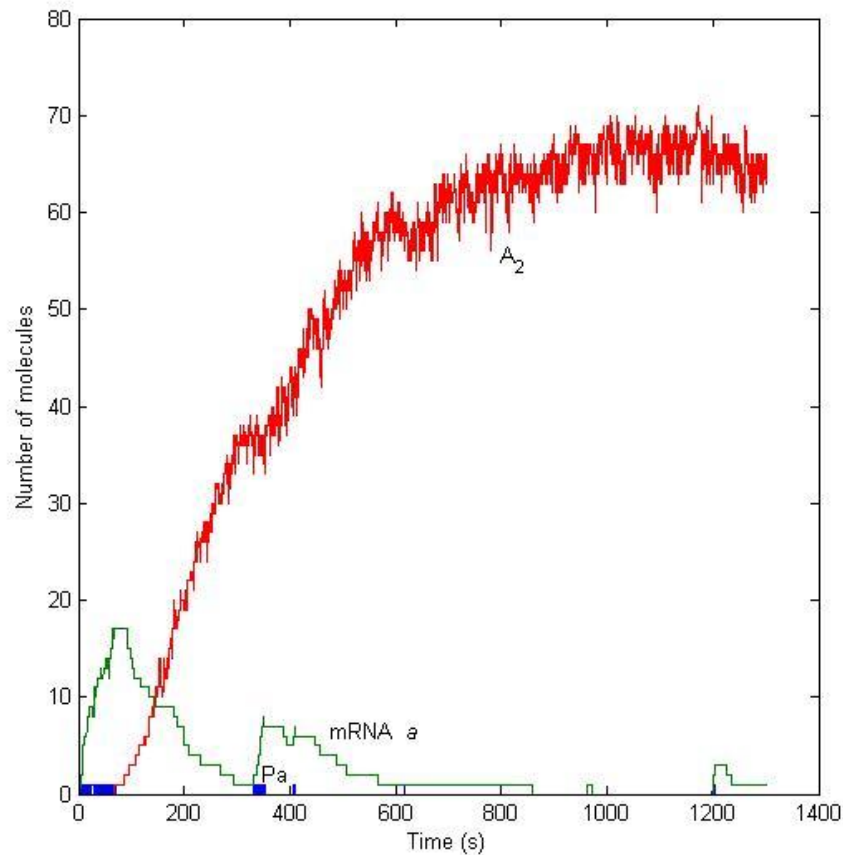Thieffry *et al.* (1998), *BioEssays*, 20(5):433-440

- Development of stochastic model requires list of species, reactions, and kinetic constants
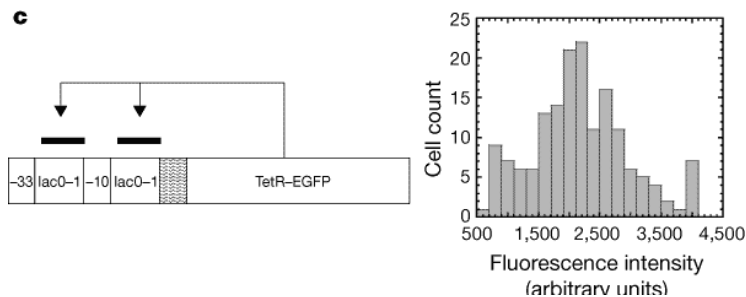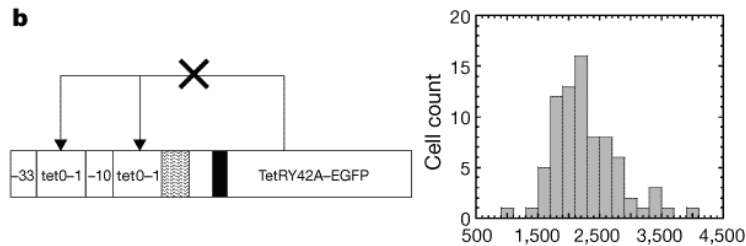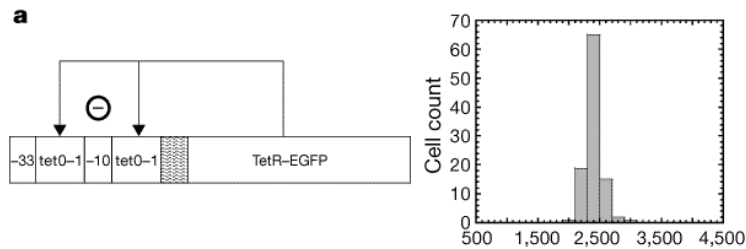
Reactions and species
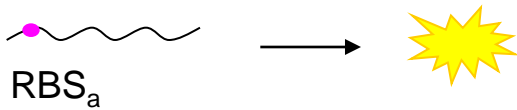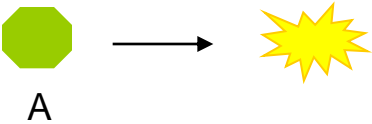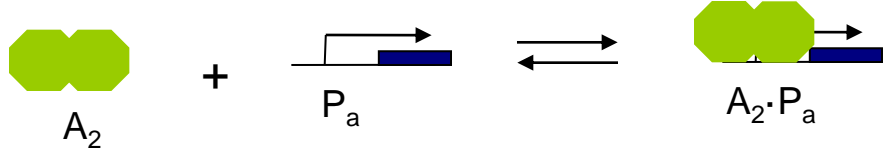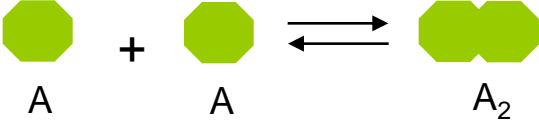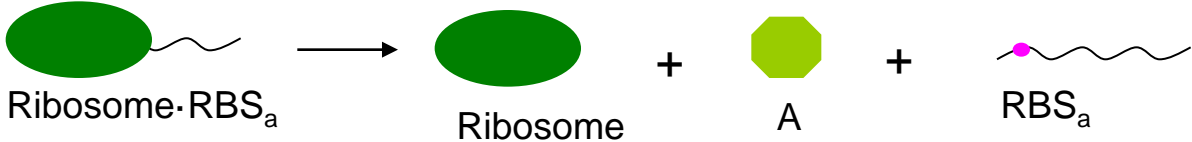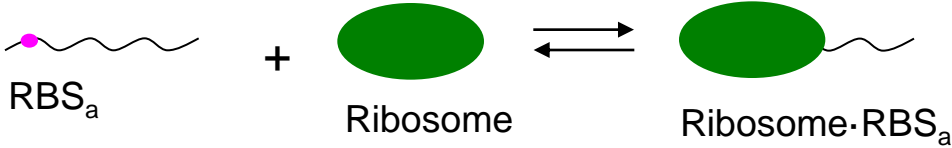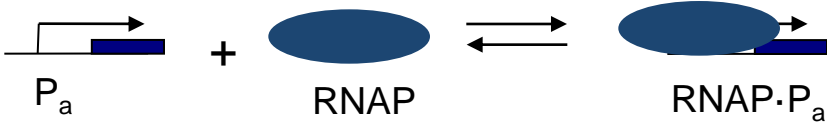
Stochastic simulation of auto-inhibition

- Occurrence of fluctuations and bursts in gene expression

Auto-inhibition and noise reduction

- Auto-inhibition reduces fluctuations in gene expression level
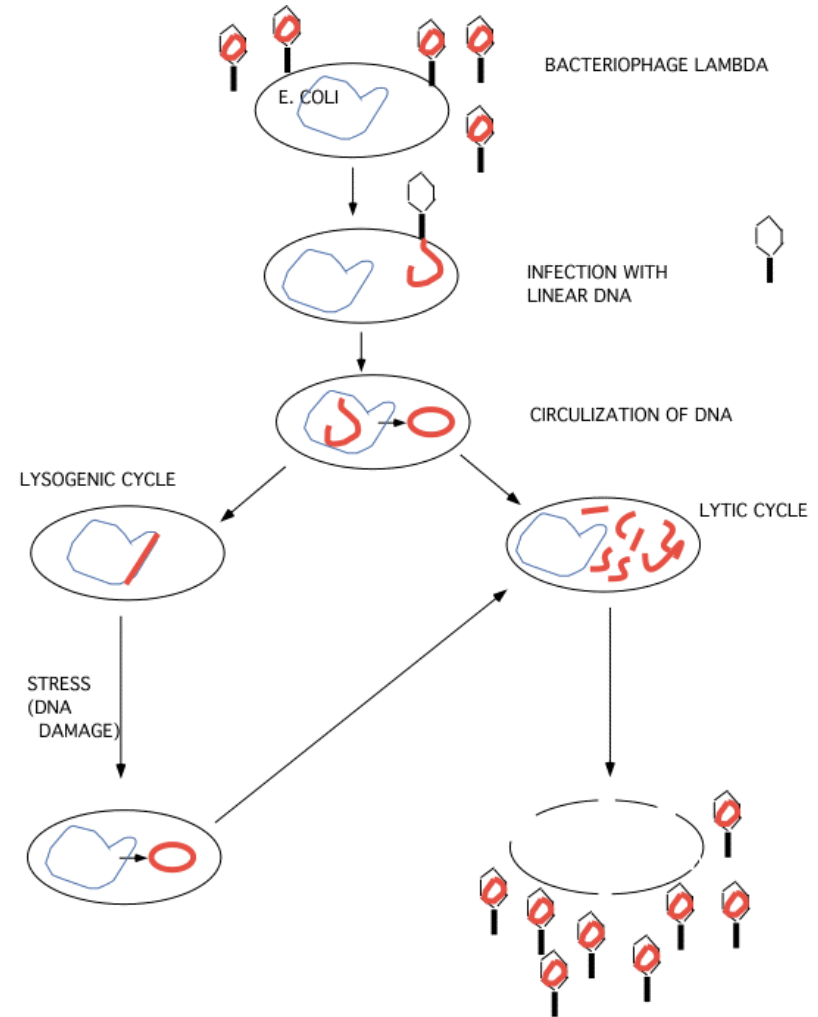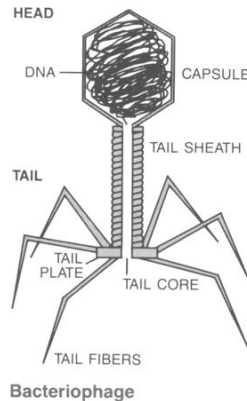

Becskei and Serrano (2000), *Nature*, 405(6785):590-591
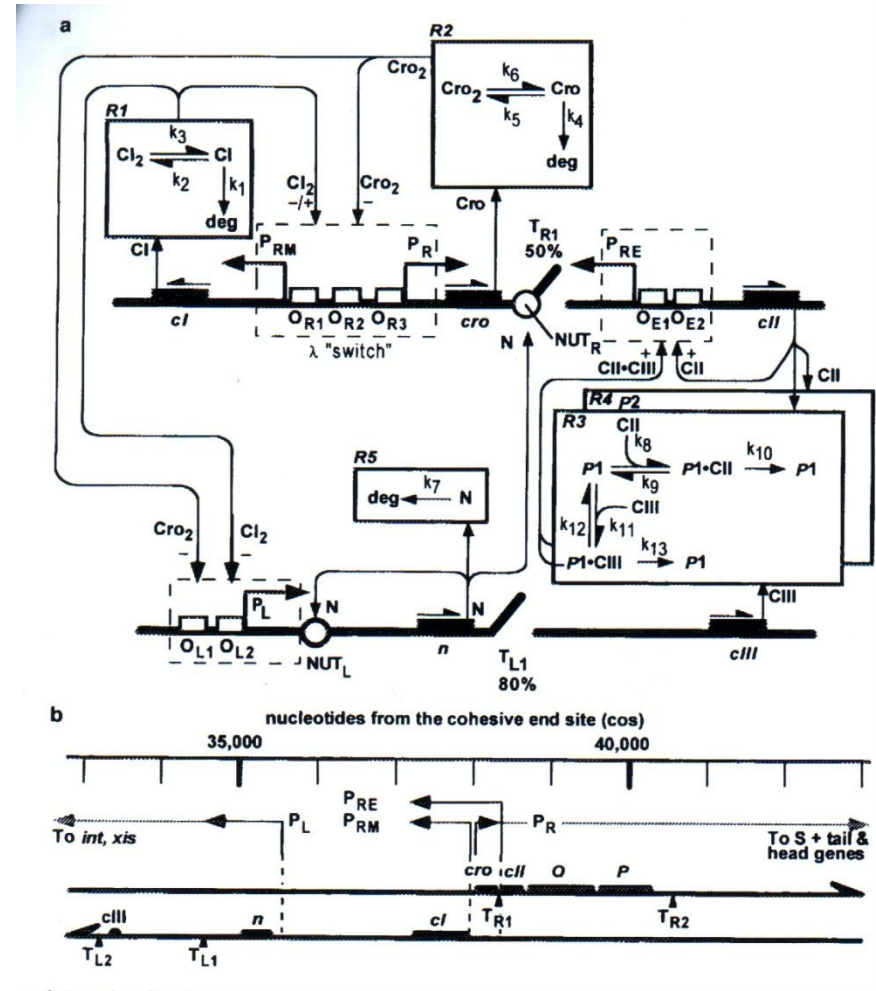
Bacteriophage λ infection of *E. coli*

- Response of *E. coli* to phage λ infection involves decision between alternative developmental pathways: **lytic cycle** and **lysogeny**

  Ptashne (1997), *A Genetic Switch: Phage λ and Higher Organisms*, Cell Press

Stochastic analysis of phage λ infection
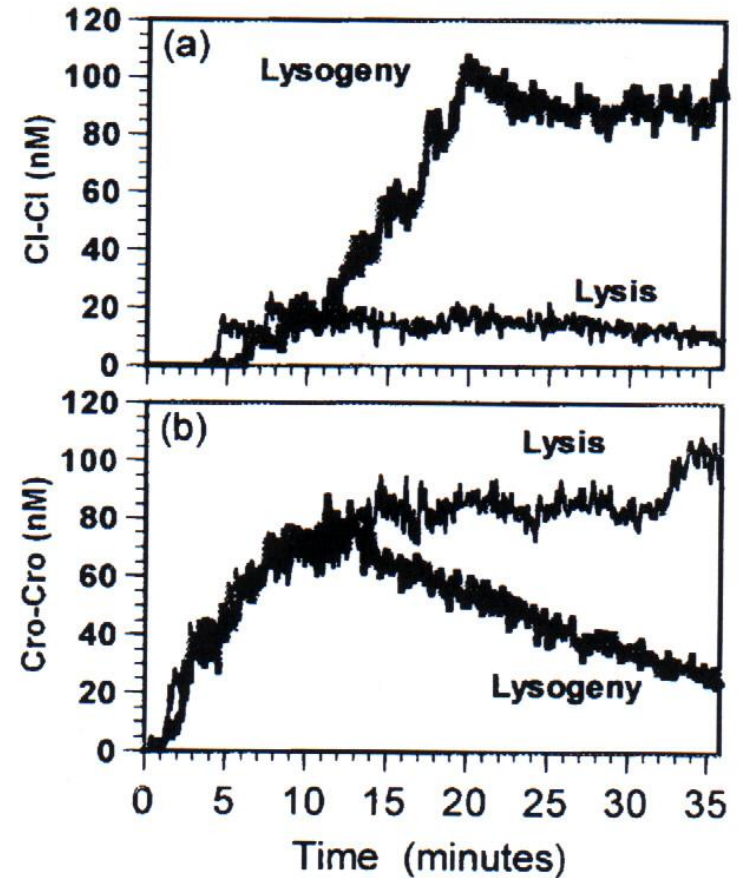
- Stochastic model of λ lysis-lysogeny decision network

Arkin *et al.* (1998), *Genetics*, 149(4): 1633-1648

Stochastic analysis of phage λ infection

- Time evolution of Cro and CI dimer concentrations

- Due to stochastic fluctuations, under identical conditions cells follow one or other pathway (with some probability)

Arkin *et al.* (1998), *Genetics*, 149(4): 1633-1648

Comparison with deterministic approach

- Deterministic models can be seen as predicting **average behavior** of cell population

  Gillespie. (2000), *J. Chem. Phys.*, 113(1): 297-306

- Analysis of average behavior may obscure that one part of population chooses one pathway rather than another

  Arkin *et al.* (1998), *Genetics*, 149(4): 1633-1648

- However, under some conditions deterministic models yield good approximation
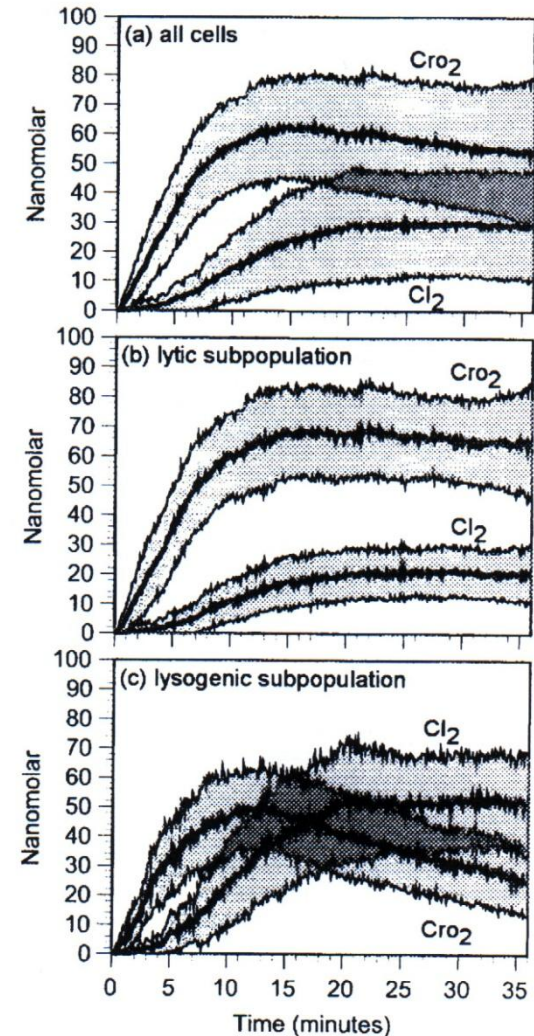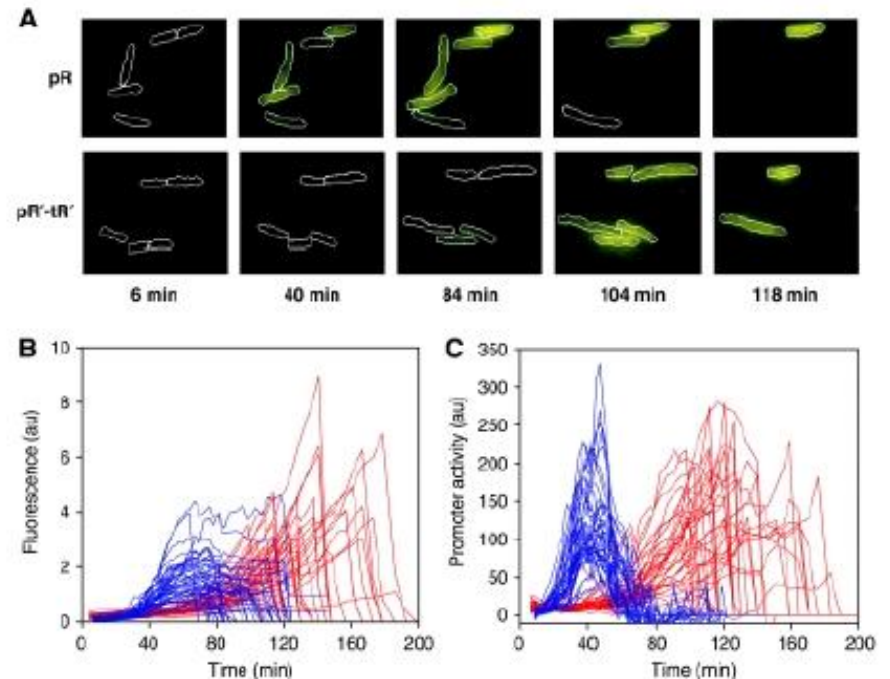
Measurements of phage λ infection

- New measurement techniques allow real-time and *in-vivo* monitoring of the execution of lytic and lysogenic pathways in individual cells

   Use of reporter genes in combination with fluorescence microscopy

Amir *et al.* (2007), *Mol. Syst. Biol.*, 3:71

Stochasticity and hidden variables

- Is observed population heterogeneity entirely due to stochastic dynamics of biochemical reactions?

- **Hidden variables** that deterministically set outcome of what seems noisy decision process

    Deterministic voting of stochastic decision in single phages
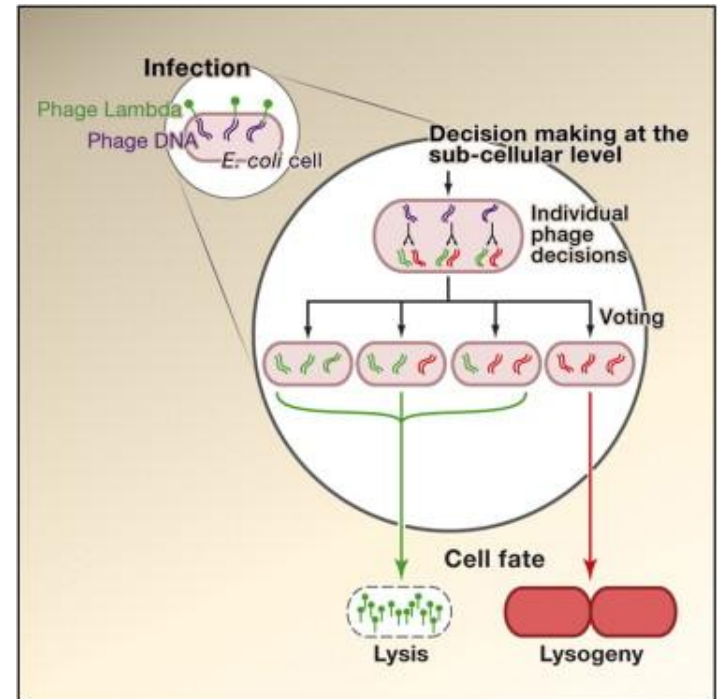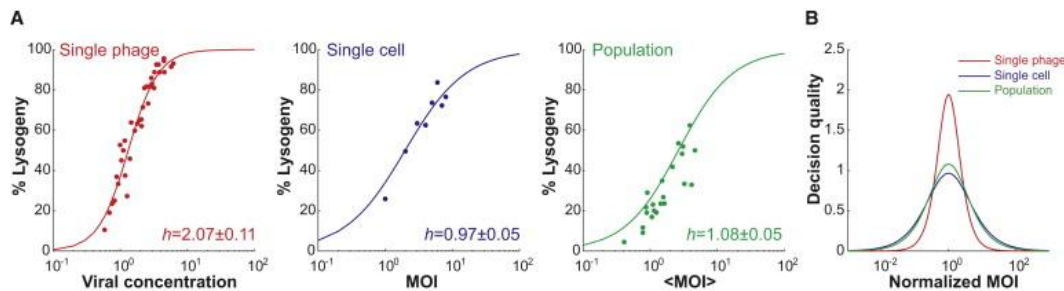
Zeng *et al.* (2010), *Cell*, 141(4):682-91

Conclusions

- Stochastic models provide more realistic picture of gene expression

- Difficulty of stochastic models is that required information on regulatory mechanisms on molecular level usually not available

  Reaction schemas and kinetic constants, necessary for generating values of parameters τ and ρ, are not or incompletely known

- Another difficulty is that stochastic simulation is computationally expensive

  Large networks cannot currently be handled, but a host of extensions and approximations have been developed

Merci !

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