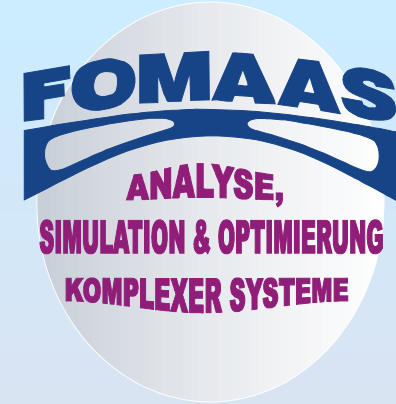
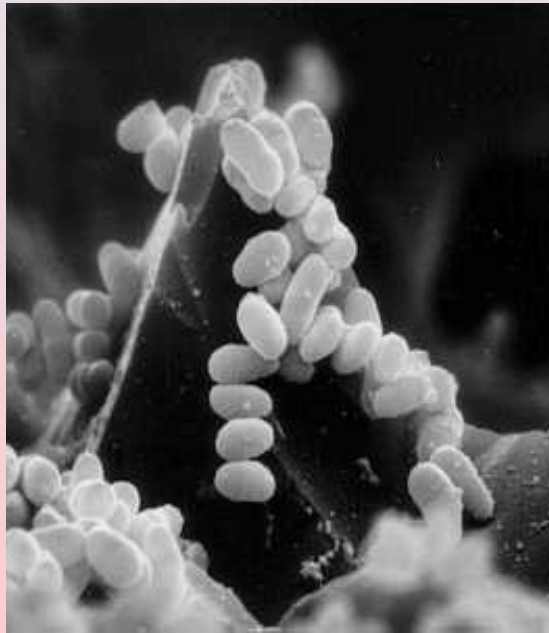


Wolfgang Wiechert
Lehrstuhl für Simulationstechnik
FB 11/12:
Maschinenbau/E-Technik/Informatik
Universität Siegen



Modellierung und Simulation zellulärer Netzwerke



Größenskalen



Partikelmodelle



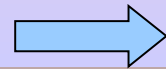
Stochastische Modelle



Räumlich verteilte Modelle

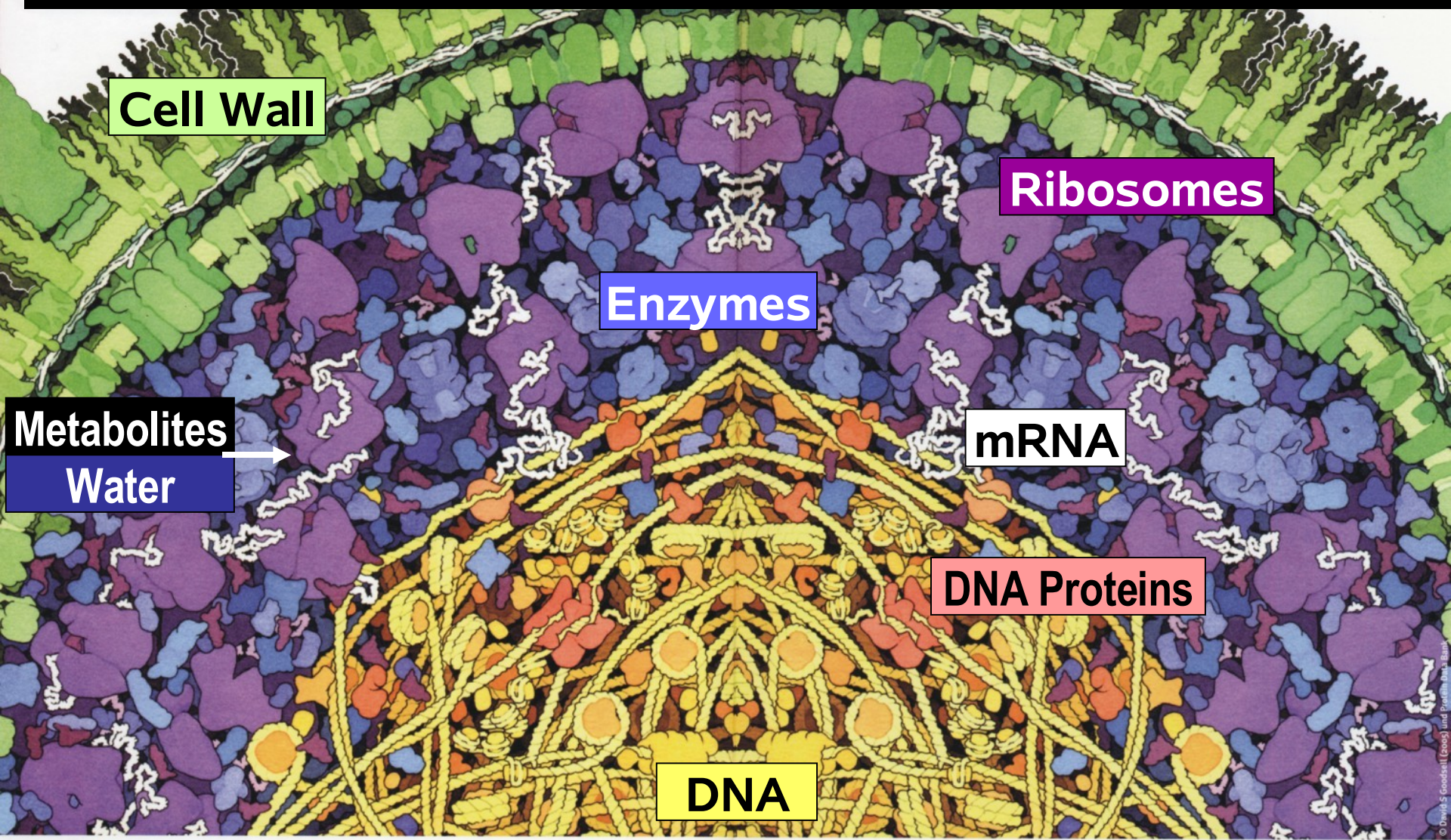


Räumlich homogene Modelle



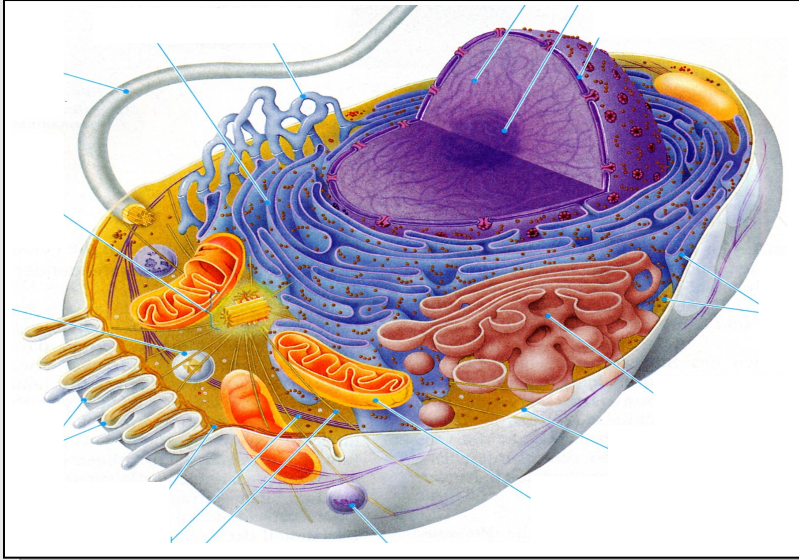
Stöchiometrische Modelle

Cells are Bags of Macromolecules

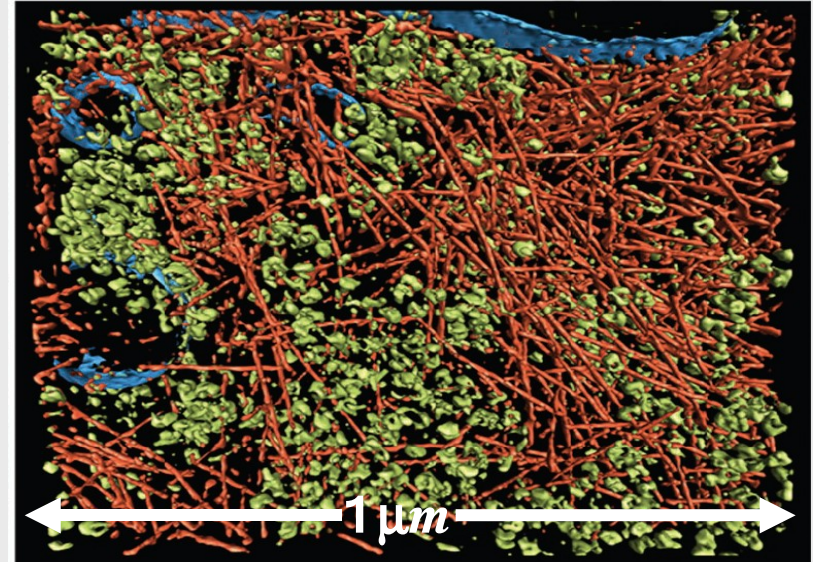


Spatial Structure of Cells

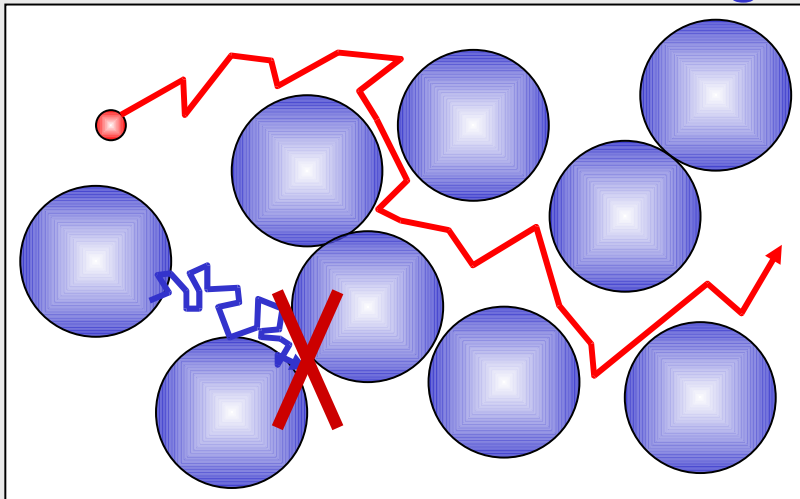
Cellular Compartments



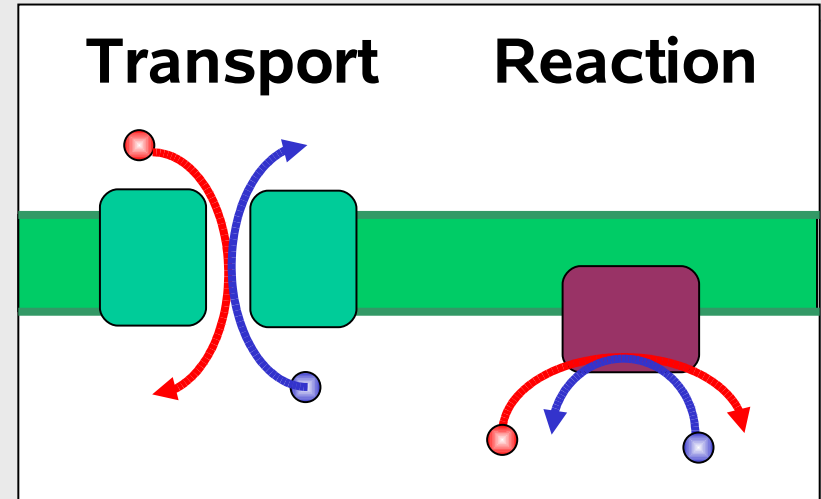
Cytoskeleton



Macromolecular Crowding

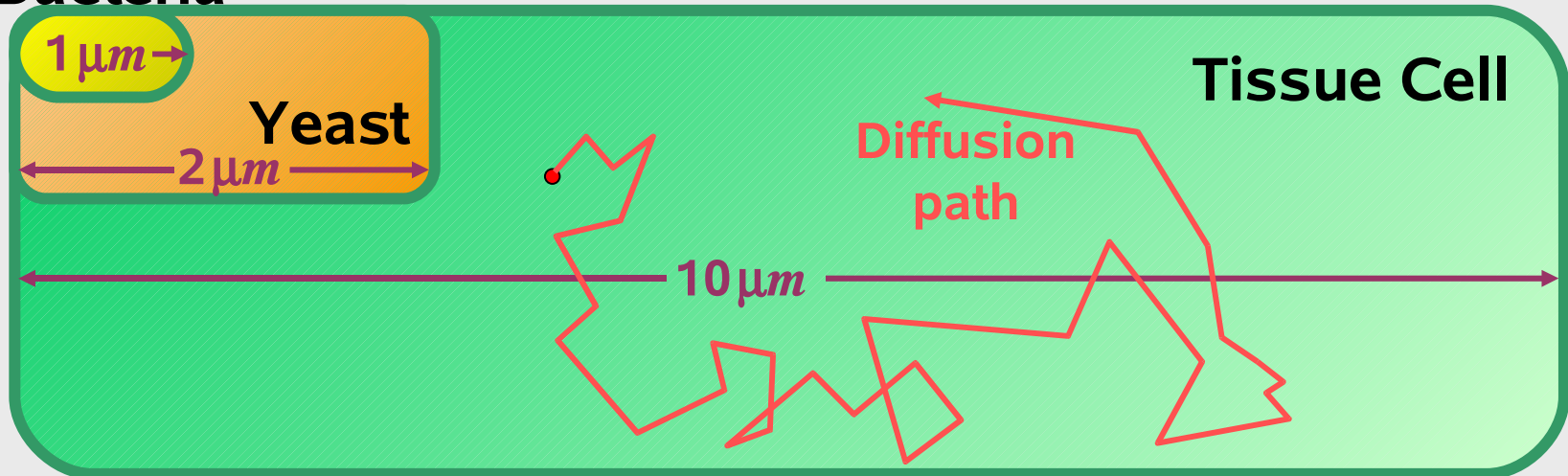


Membrane Processes



Cellular Processes are driven by Molecular Motion

Bacteria



Diffusion time of small molecules in water: $D \sim 10^{-9} \text{ m}^2 \text{ s}$



Crowded environment (hypothetical): $D \sim 10^{-10} \text{ m}^2 \text{ s}$

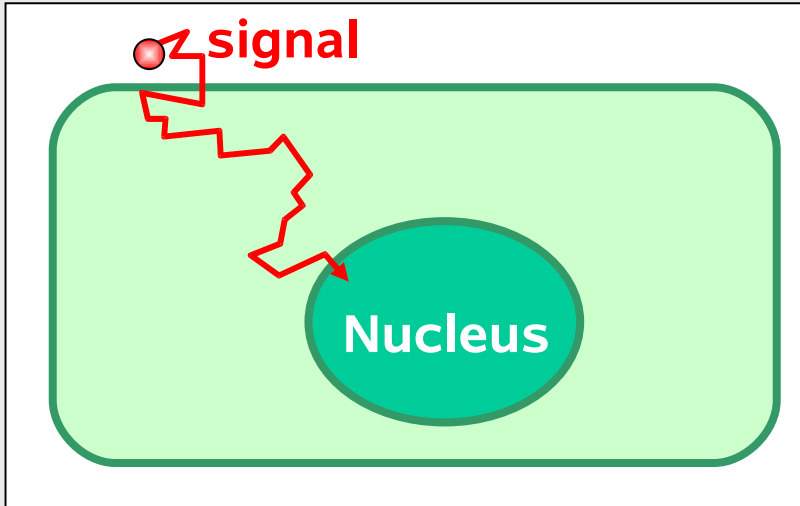


Consequences for cell modeling

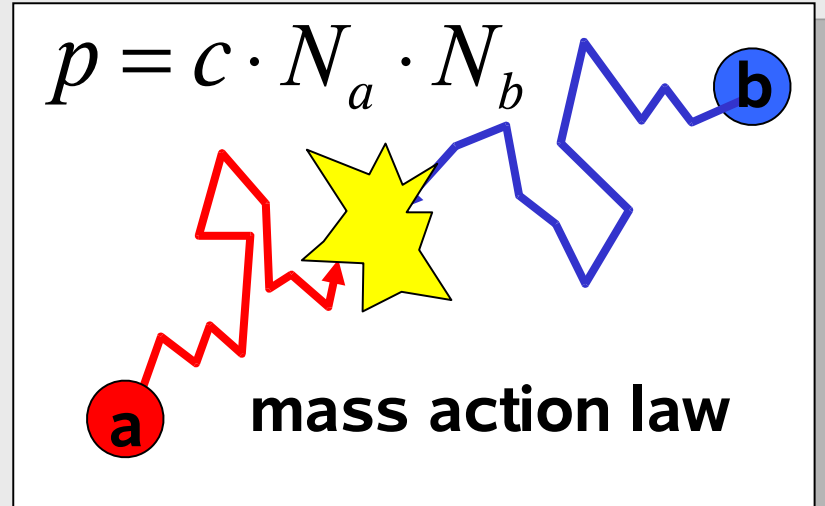
1. Space and diffusion is an issue even for tiny cells
2. Stochastic phenomena are to be expected
3. Reactions interact with diffusion processes

Stochastic Phenomena in Cells

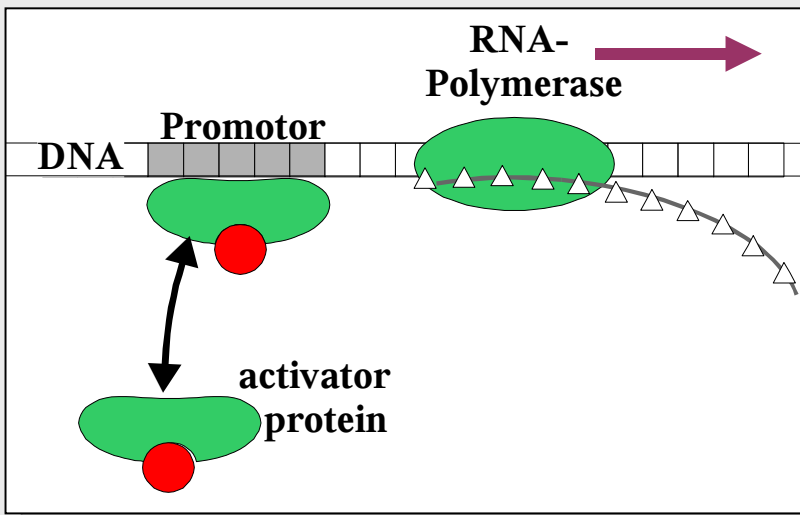
Small particle numbers



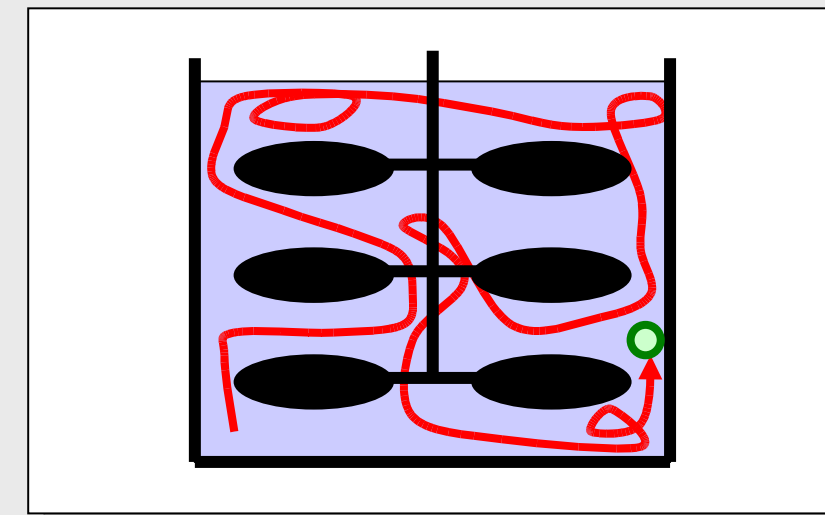
Nonlinearities



Rare molecular events

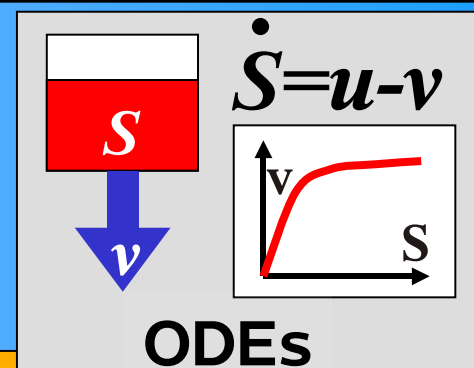
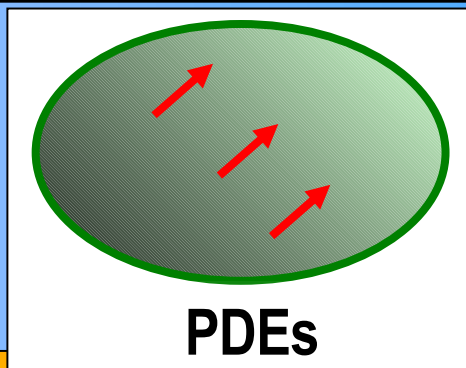


Environmental noise

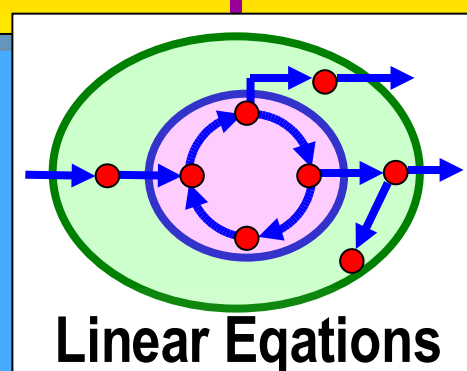
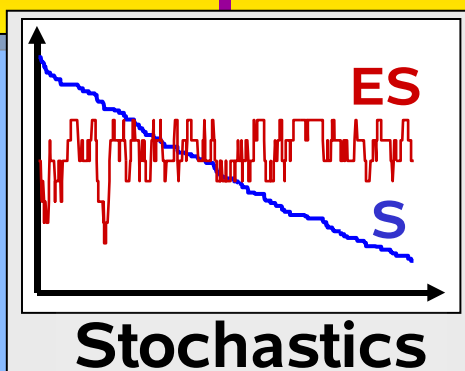
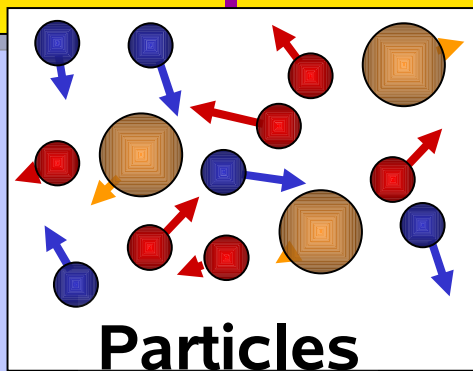


Scales of Cellular Network Modelling

Knowledge
increasing



Spatial Scales

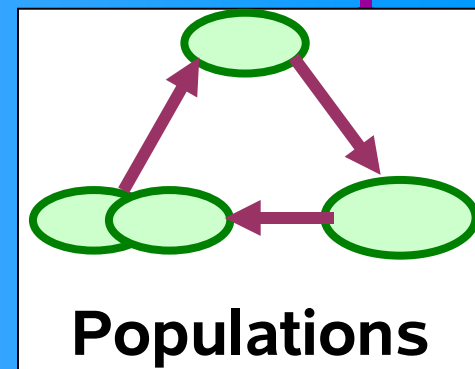


Computational Effort

increasing

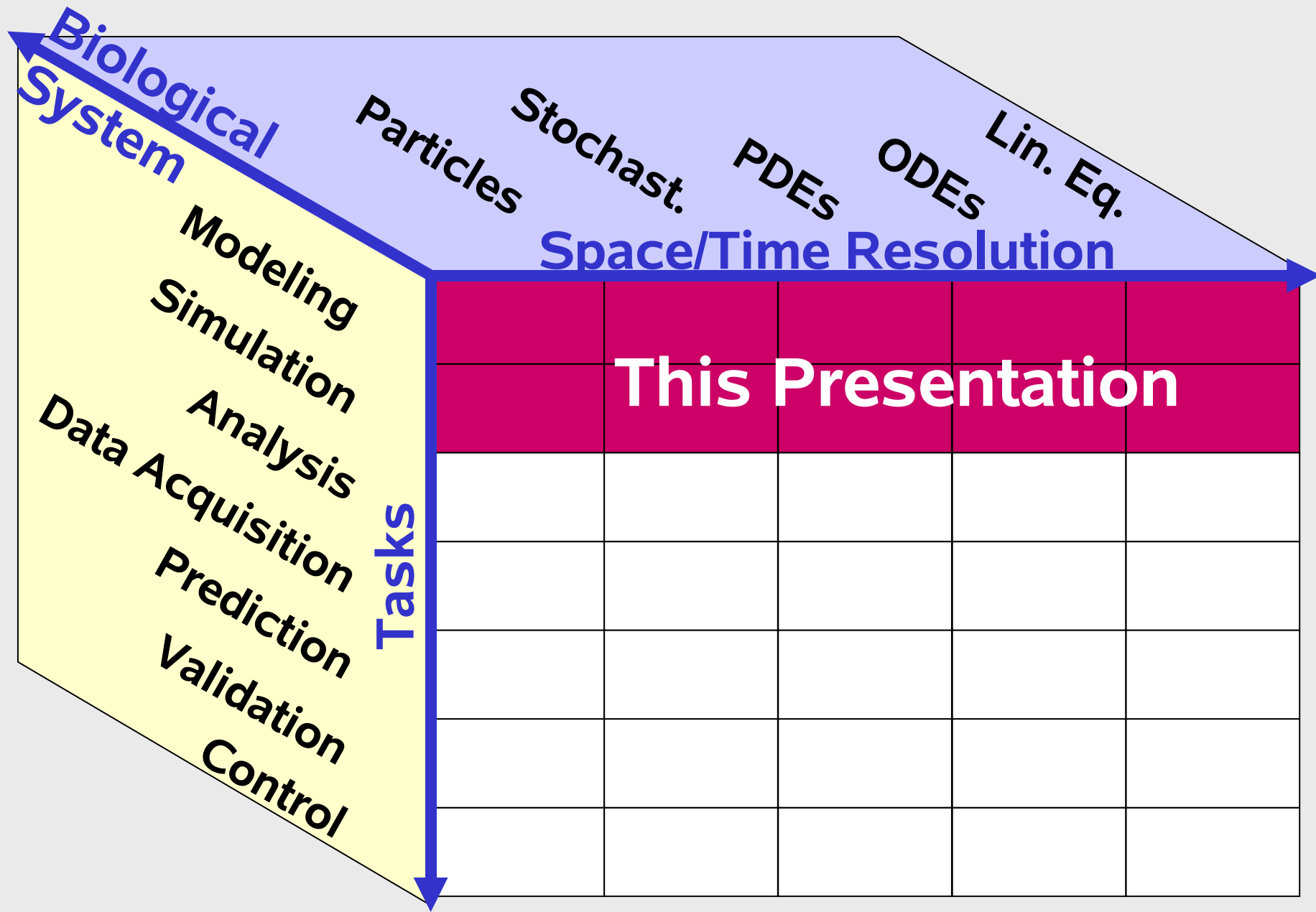
increasing

Available Software Tools



Mol. Dynamics

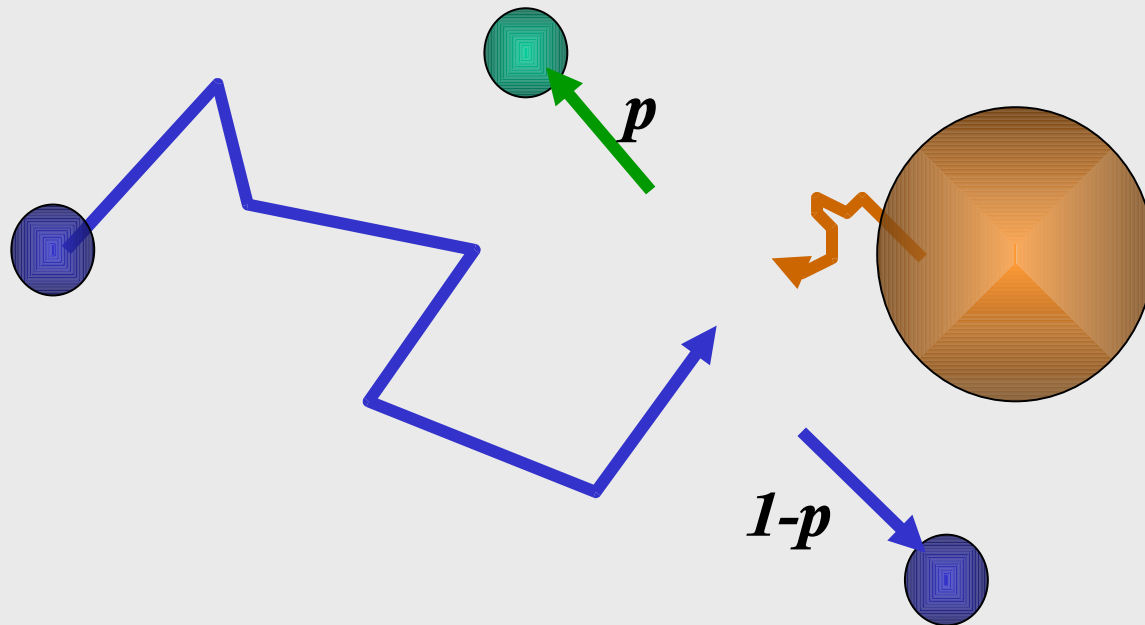
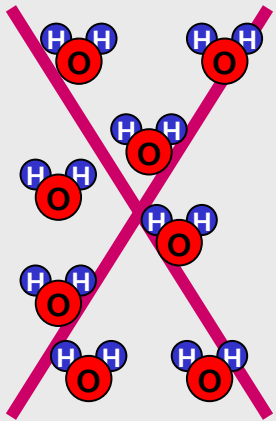
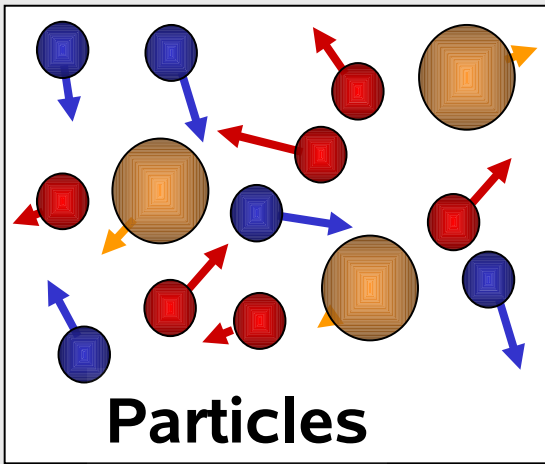
Dimensions of Modeling and Simulation



Particle Approach

Principles

- molecules are discrete particles
- water & other small molecules not considered
- stochastic particle motion
- probability laws for chemical reaction

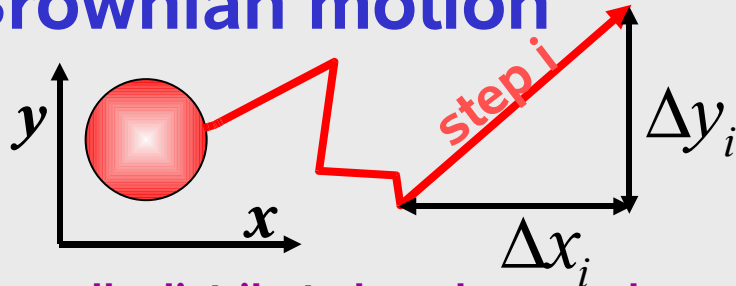


Brownian Dynamics

Principles

- Point particles
- Continuous space
- Discrete time step Δt
- Brownian motion law
- Reaction modeled

Brownian motion

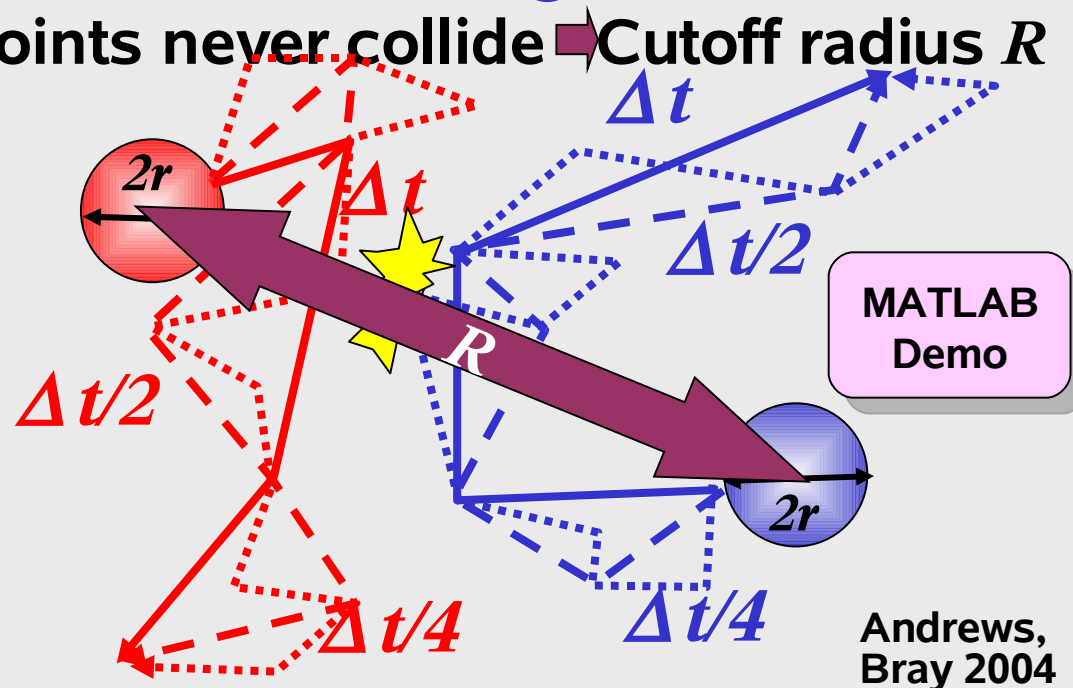


normally distributed random number

$$\Delta x_i = \sqrt{2D \cdot \Delta t} \cdot n(0,1), \\ i = 1, \dots, t/\Delta t$$

Reaction modeling

Points never collide → Cutoff radius R



Andrews,
Bray 2004

Consistent approximation of reaction probability w.r.t. Δt possible from Fokker Planck eqn.

Consistent diffusion step size for $\Delta t \rightarrow 0$

$$\text{Var} \left[\sum_i \Delta x_i \right] = \sum_i \text{Var} [\Delta x_i] = \left(\sqrt{2D \cdot \Delta t} \right)^2 \cdot \sum_i 1 = 2D \cdot \Delta t \cdot t/\Delta t = 2Dt$$

Example: Intracellular Signaling

Steroid Hormones

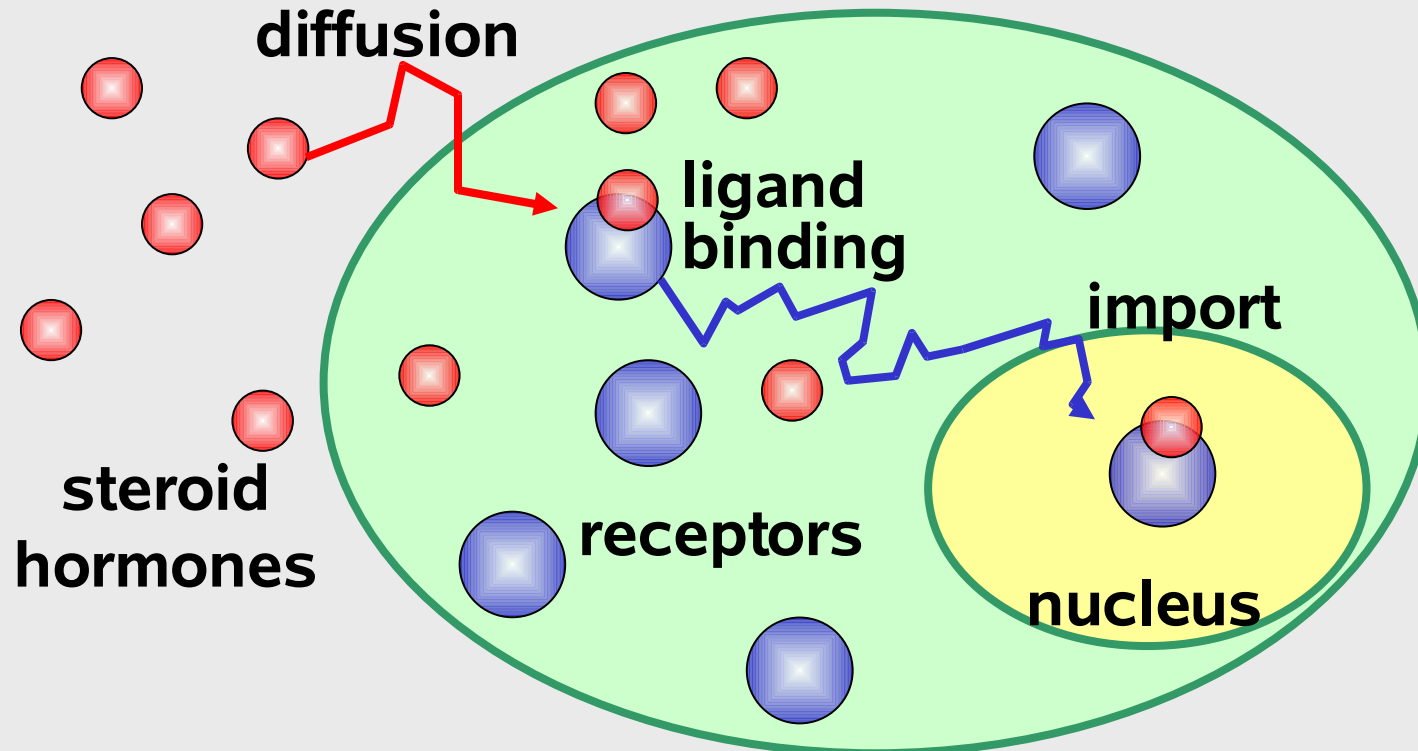
Hormones involved in male phenotype development and maintenance

Characteristics

- small molecule number
- nonlinear binding step
- long diffusion length
- first passage time important

Steroid Hormone Pathway

Lapin, Reuss 2006



Video

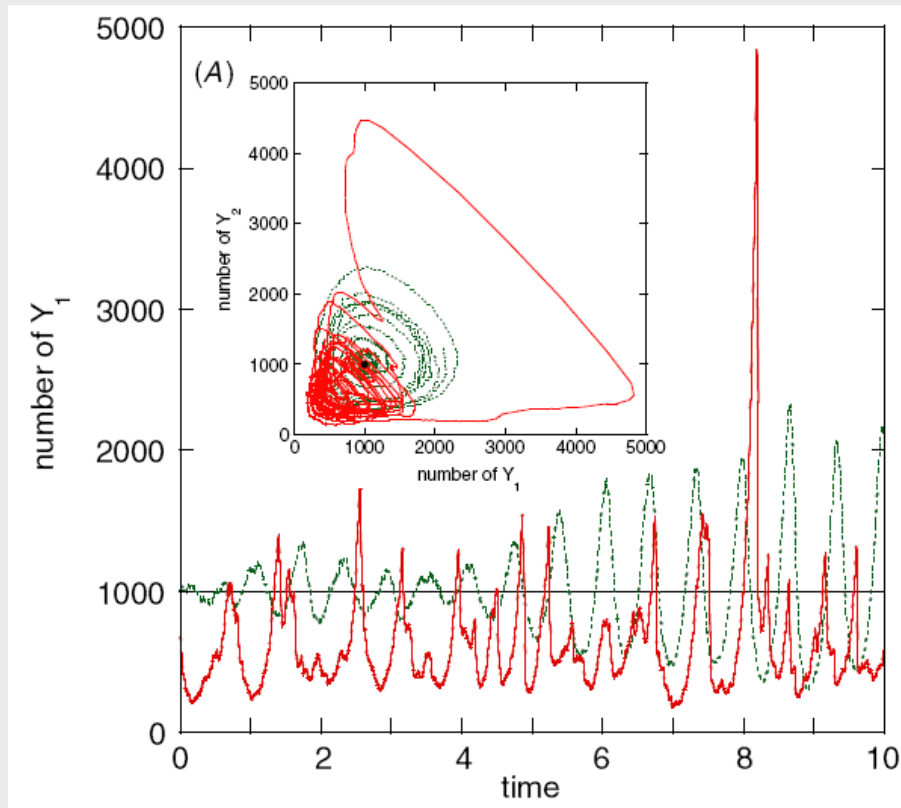
Example: Chemical Lotka Volterra System

Reaction equations

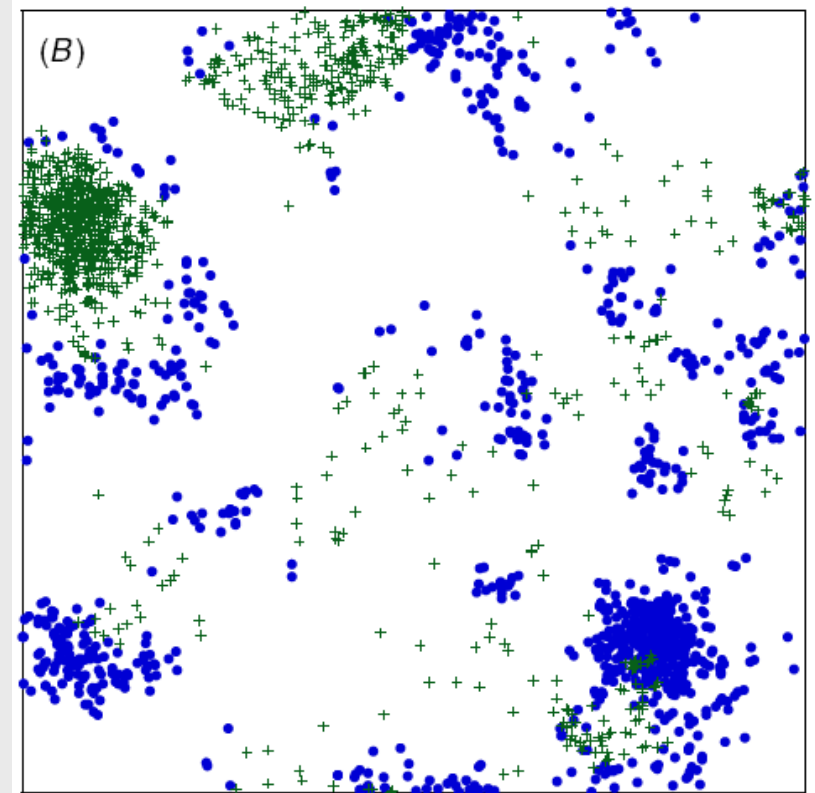


Andrews, Bray 2004

Time course



Spatial distribution



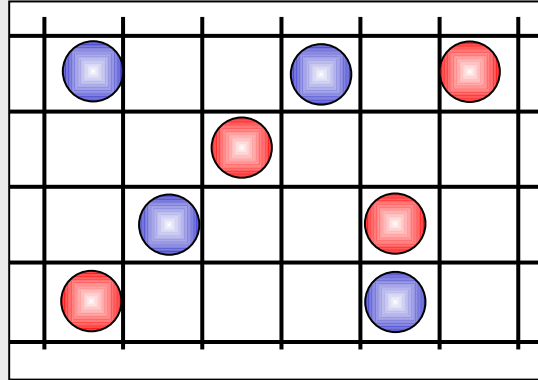
Cellular Automata Approaches

Principles

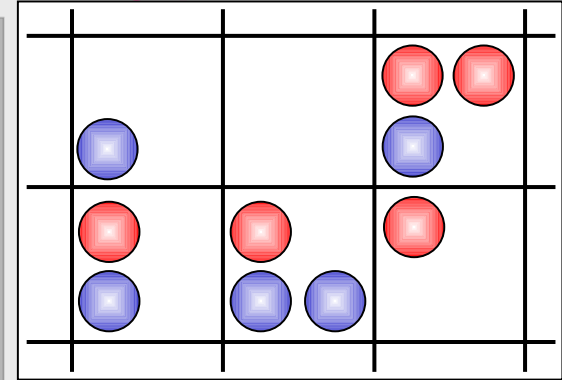
- Discrete space ΔV
- Discrete time Δt
- Particles occupy cells
- Stochastic rules for cell transitions
- Reaction modeled

Two variants

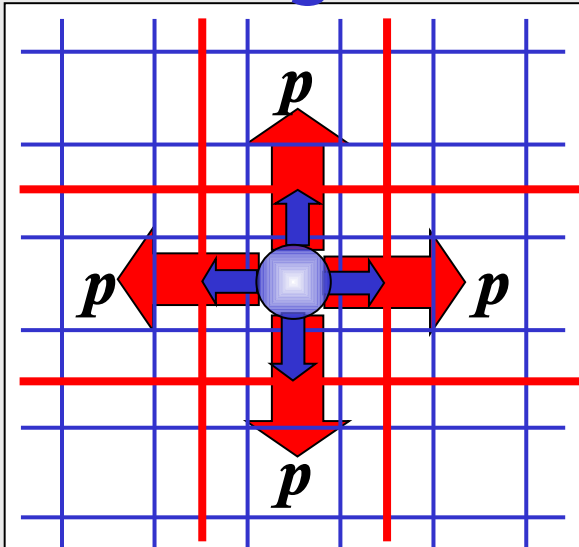
one particle per cell



many particles per cell



Consistent diffusion modeling



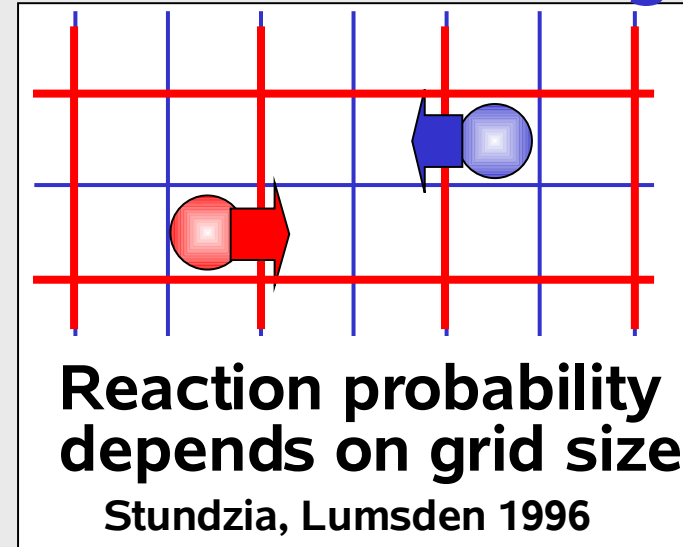
Result for
1D Lattice gas

$$p = p(\Delta t, \Delta x)$$

$$\frac{p}{1-p} = 2D \cdot \frac{\Delta t}{\Delta x^2}$$

Szopard, Drosz 1998

Consistent reaction modeling

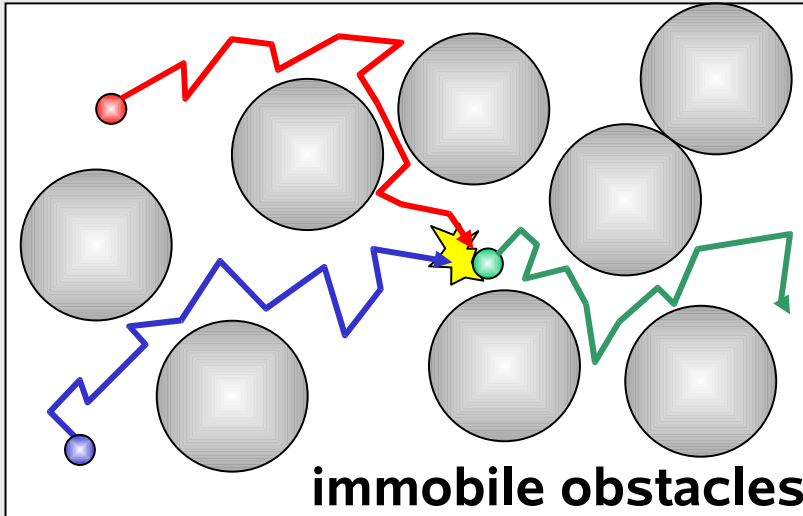


Reaction probability
depends on grid size

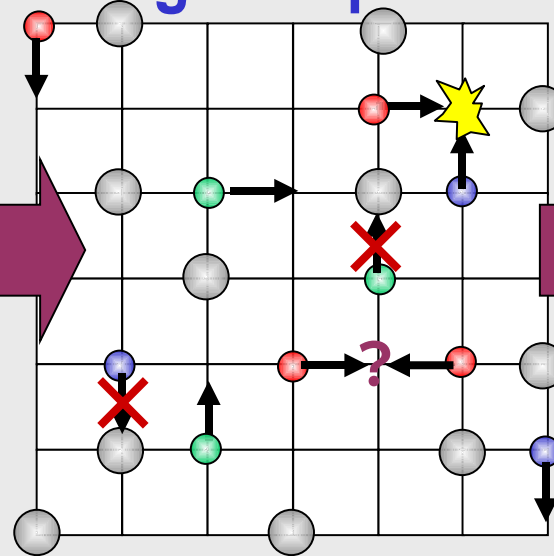
Stundzia, Lumsden 1996

Example: Macromolecular Crowding

Macromolecular Crowding



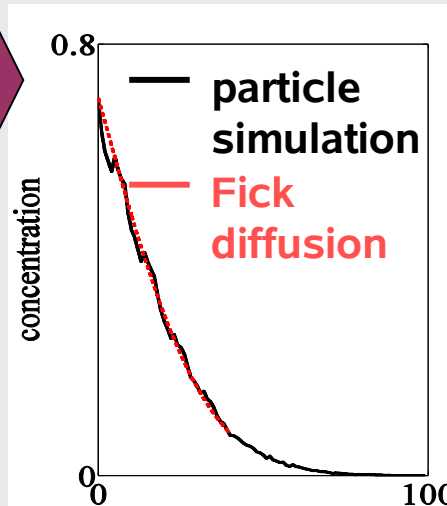
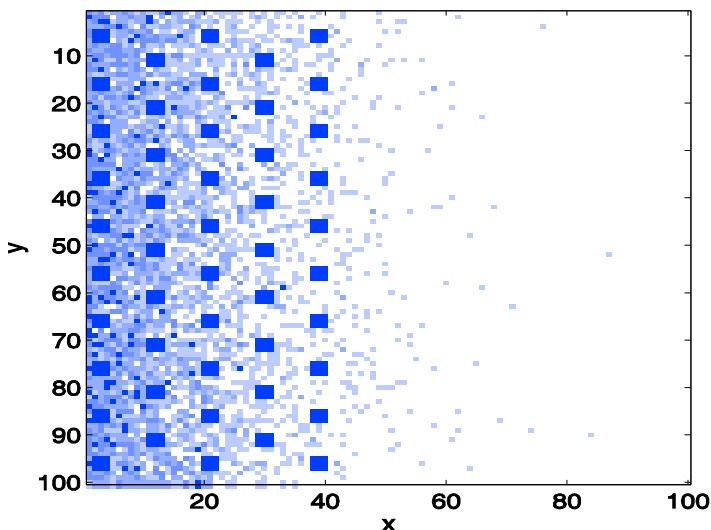
Lattice gas implementation



Fractal Kinetics

Schnell,
Turner 2004

Hindered diffusion

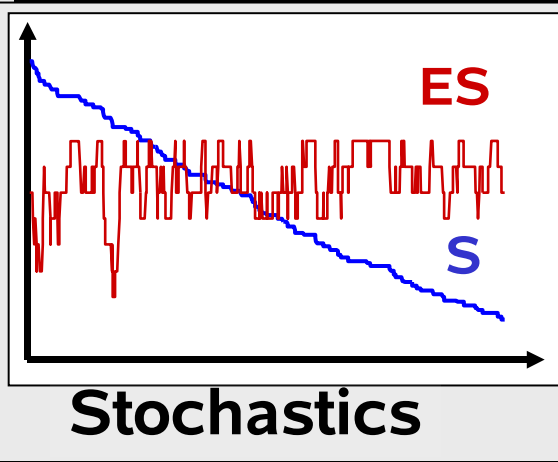


Effective Diffusion Coefficient

Buschmann
2004
Lipkow 2005

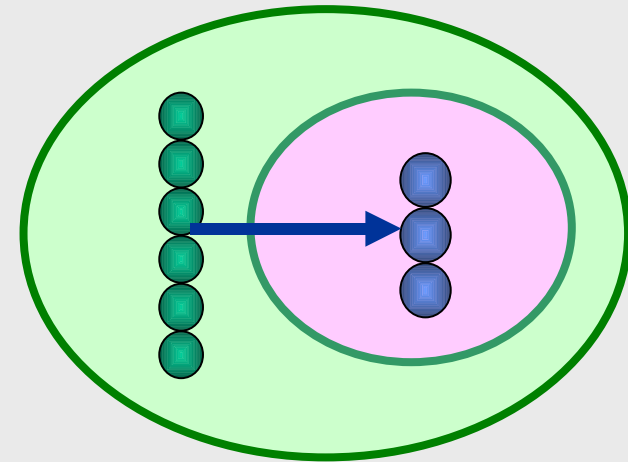
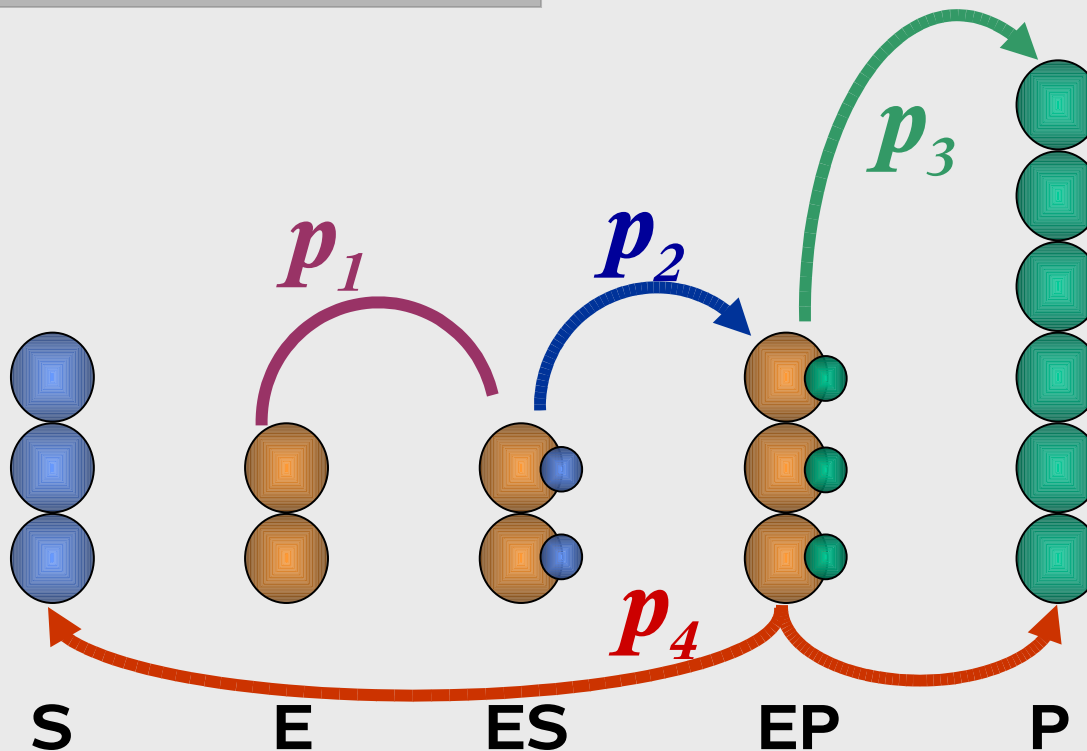
video

Spatially homogeneous Stochastic Models



Principles

- integer number of molecules
- spatially homogeneous
- probability laws for chemical reaction



MATLAB
demo

Gillespie's Stochastic Simulation Algorithm (SSA)

Principles

- Species $1, \dots, N$
- Discrete state vector x
- Propensity functions $a_i(x)$:
Reaction probability per time
- Stoichiometry vectors v_i
- Discrete event time stepping

Algorithm

Initialize $t \leftarrow t_0$ and $x \leftarrow x_0$

loop

Evaluate $a_i(x)$, $i=1, \dots, N$

Sample from Δt_i

Compute $I = \arg \min \Delta t_i$

$t \leftarrow t + \Delta t_I$ and $x \leftarrow x + v_I$

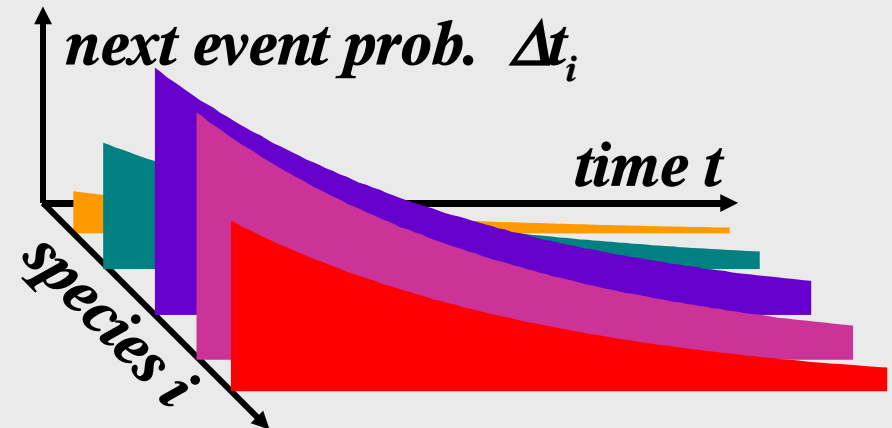
end loop

Next reaction event for specie i

Assuming that no other event happens until time Δt , i.e. $a_i(x) = \text{const}$.

$$\Delta t_i : a_i \cdot \exp\left(-\sum_{j=1}^N a_j \cdot \Delta t\right)$$

exponential distribution

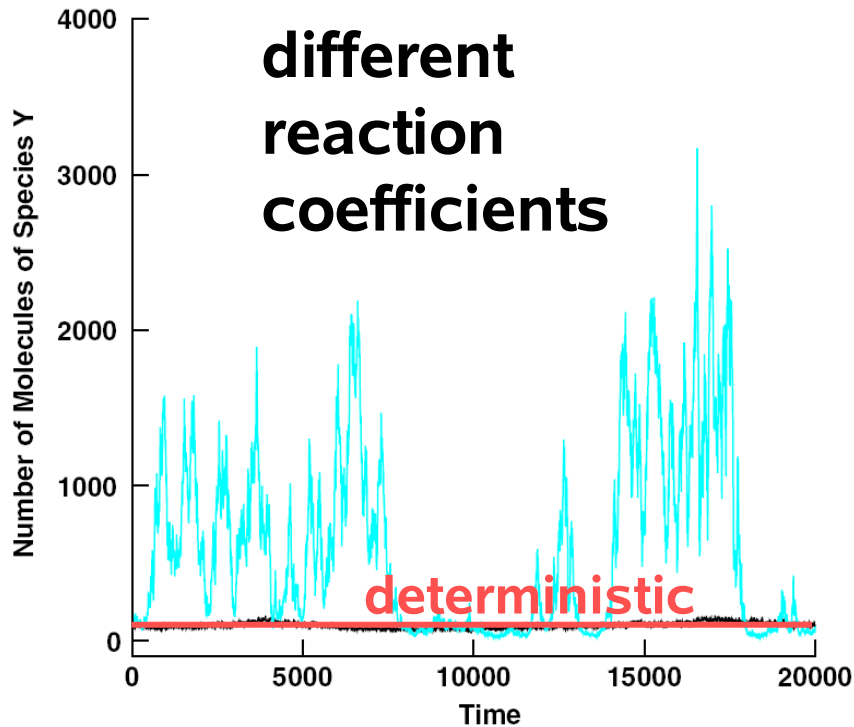
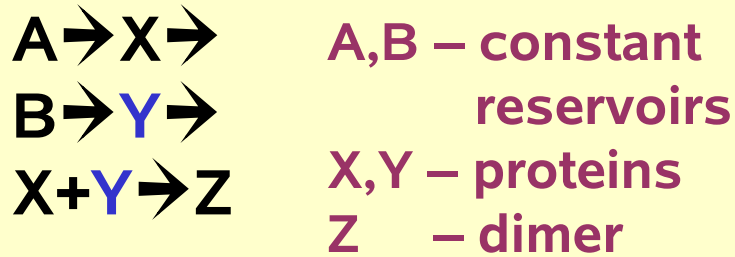


Exactness property

SSA computes an exact realization of the process with given propensities.

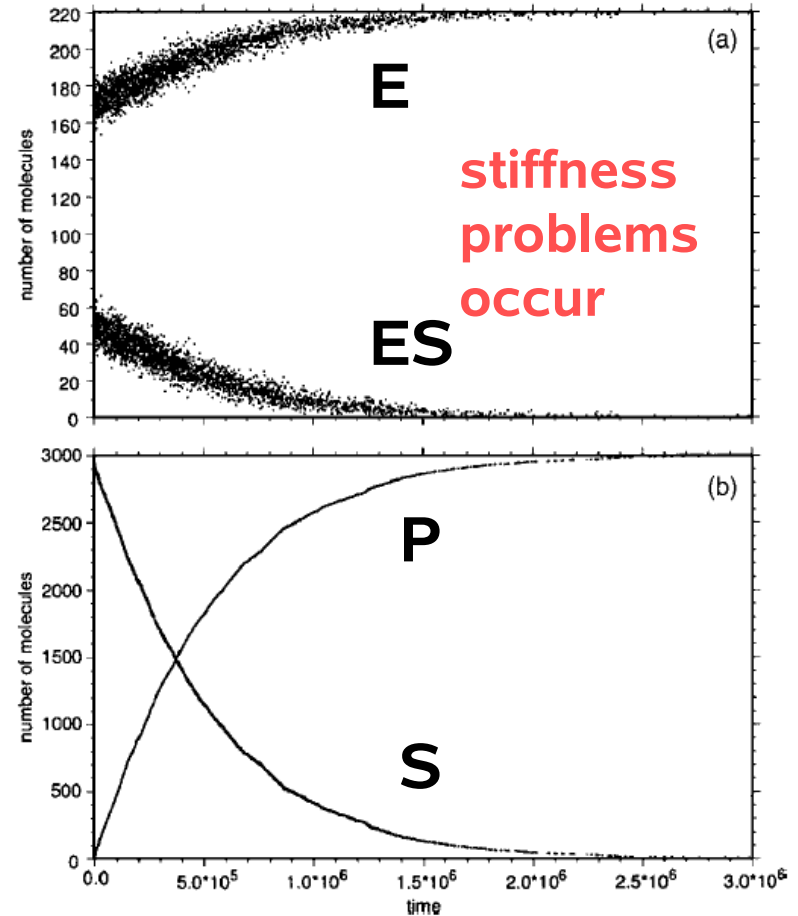
Example: Nonlinear Reactions

Monostable system



Samad, 2005

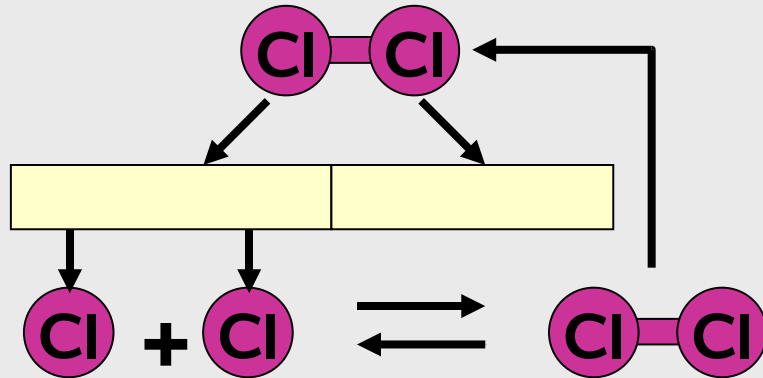
Michaelis Menten system



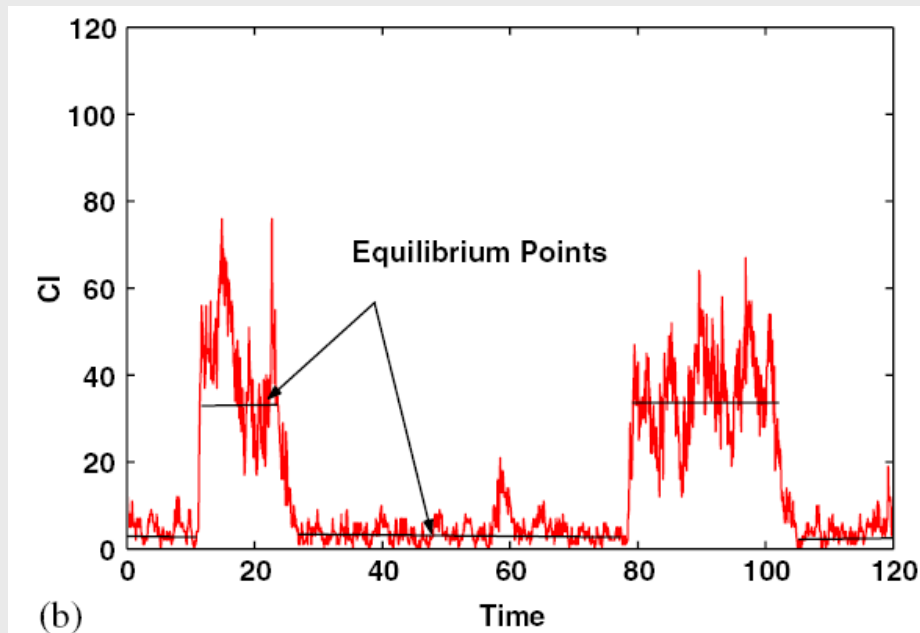
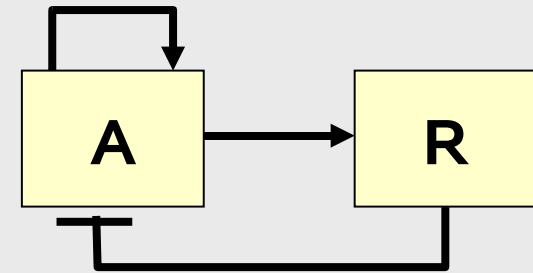
Cao, 2005

Example: Genetic Regulation

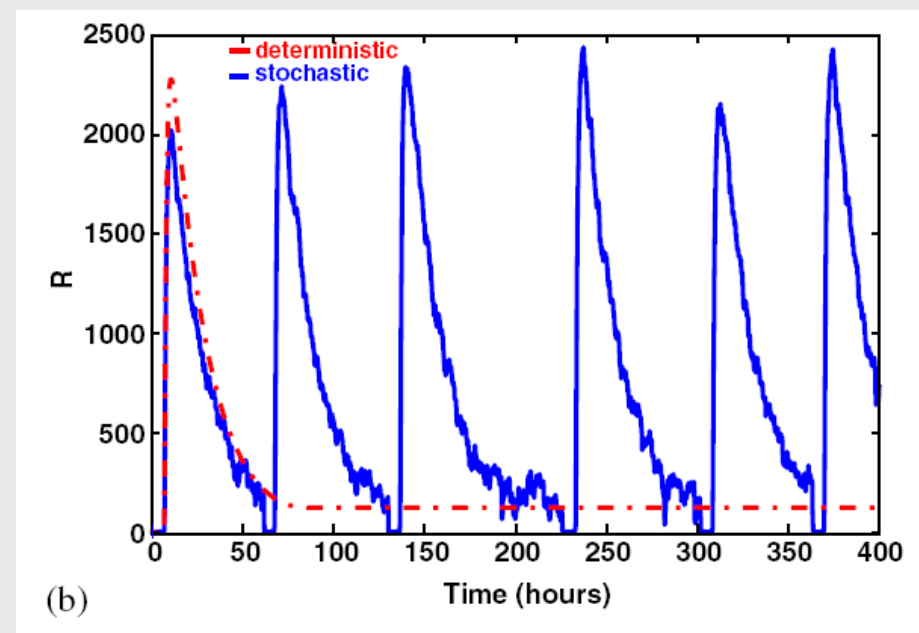
Genetic switch



Circadian oscillator



Samad, 2005



Samad, 2005

Improvements to Gillespie's Algorithm

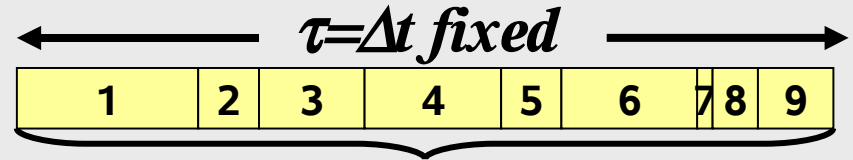
Speedup

- next reaction method
- tau leaping
- chemical Langevin SDE
- classical reaction ODE

Gibson,
Bruck 2000

Gillespie
2001

Gillespie
2000



Poisson distribution (discrete)

large particle numbers

Normal distribution (continuous)

expectations + $\Delta t \rightarrow 0$

deterministic model (ODE)

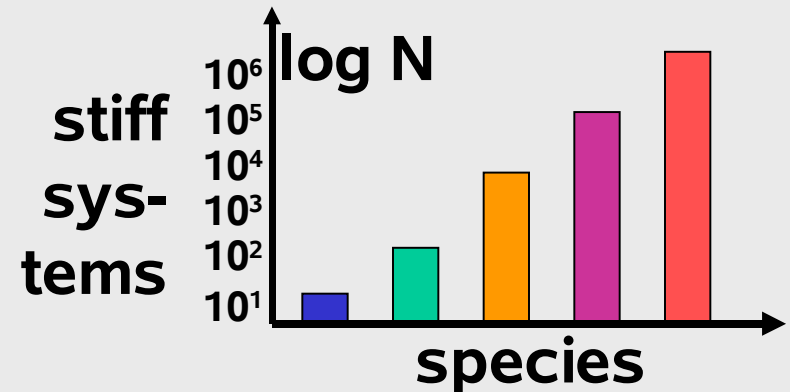
Precision & Stability

- higher order methods
- implicit tau leaping
- slow reaction method

Cao 2006

Rathinam
2003

Cao 2005

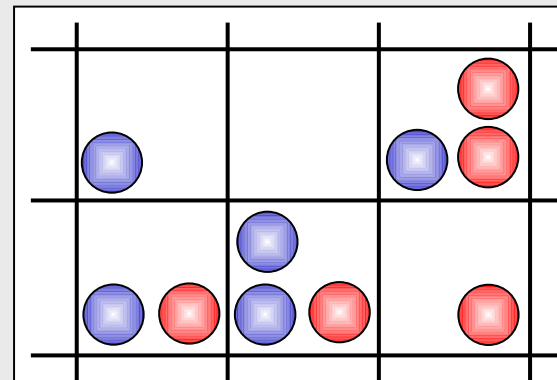


Space

- consistent spatial discretization with SSA
- classical diffusion reaction PDE

Elf,
Ehrenberg
2004

Kholodenko
2006



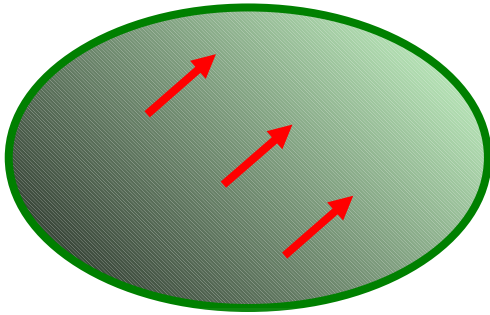
expectations

+ $\Delta T \rightarrow 0$

+ $\Delta V \rightarrow 0$

deterministic
model (PDE)

PDE Models

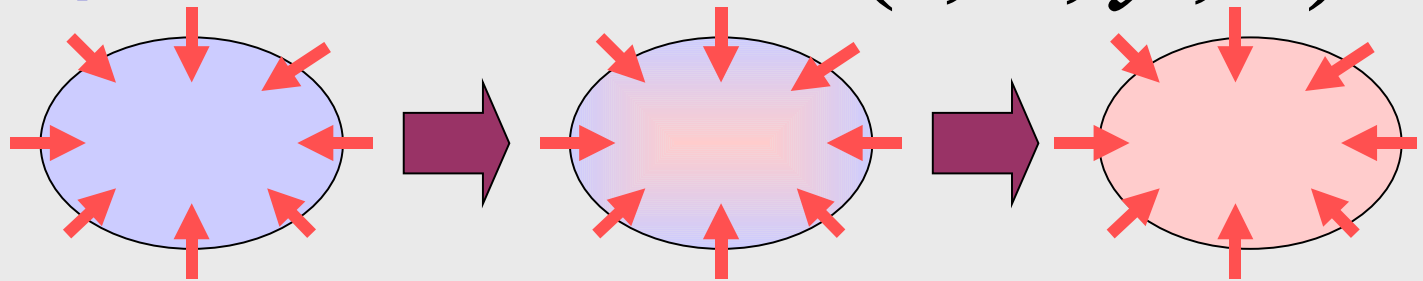


PDEs

Principles

- species given by concentrations
- spatio-temporal distribution
- diffusion model (particle average)
- reaction model (particle average)

Spatio-temporal concentration $c(t, x, y, z)$



Reaction
Diffusion
Equation

$$\dot{c} =$$

temporal change

$$\nabla$$

effective
coefficient

$$D$$

$$\cdot \nabla c$$

diffusion
flow

$$+$$

$$r(c)$$

reaction

Example: Phosphoprotein Signals

Phosphorylation of Signaling Proteins

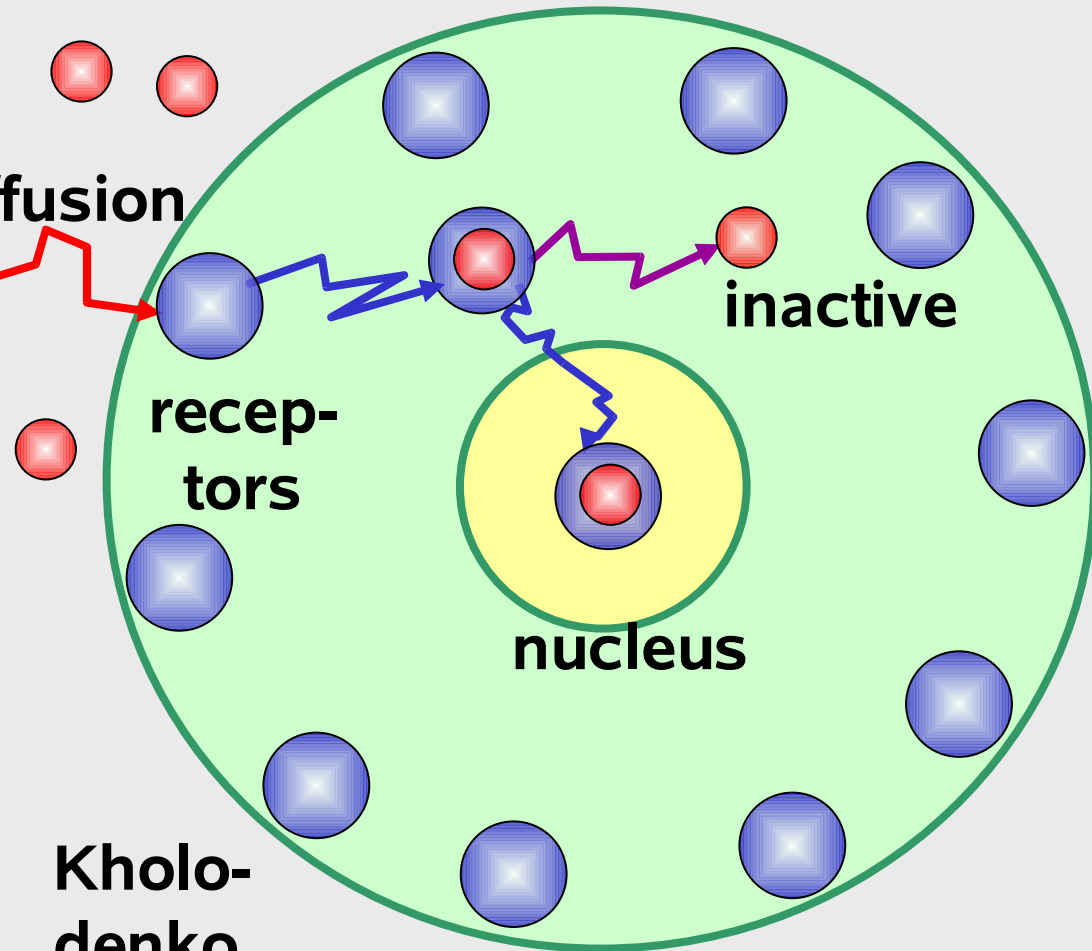
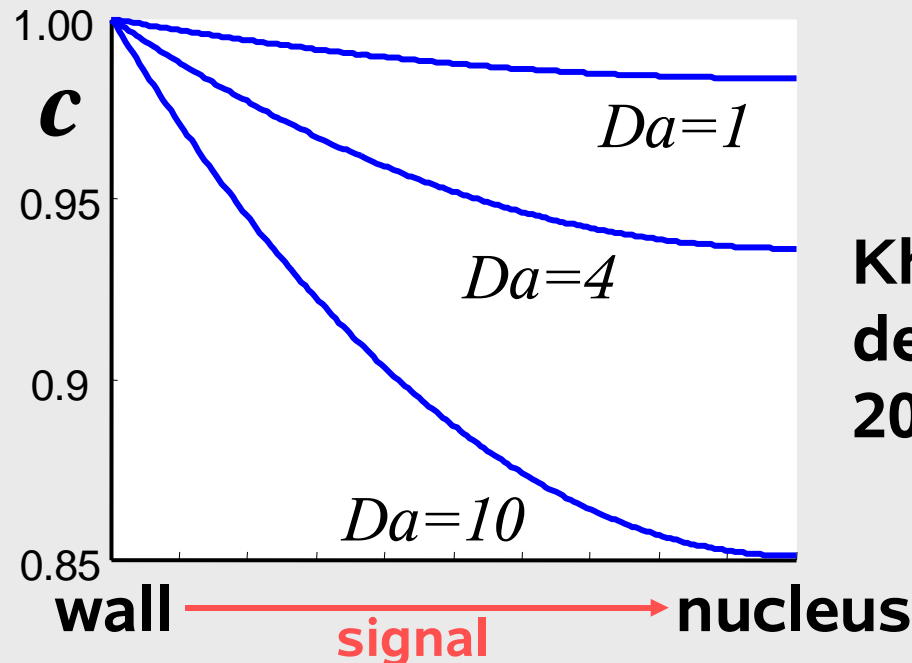
signal

diffusion

Damköhler Number

$$Da = R^2 k / D$$

Steady State Profiles



Kholodenko
2006

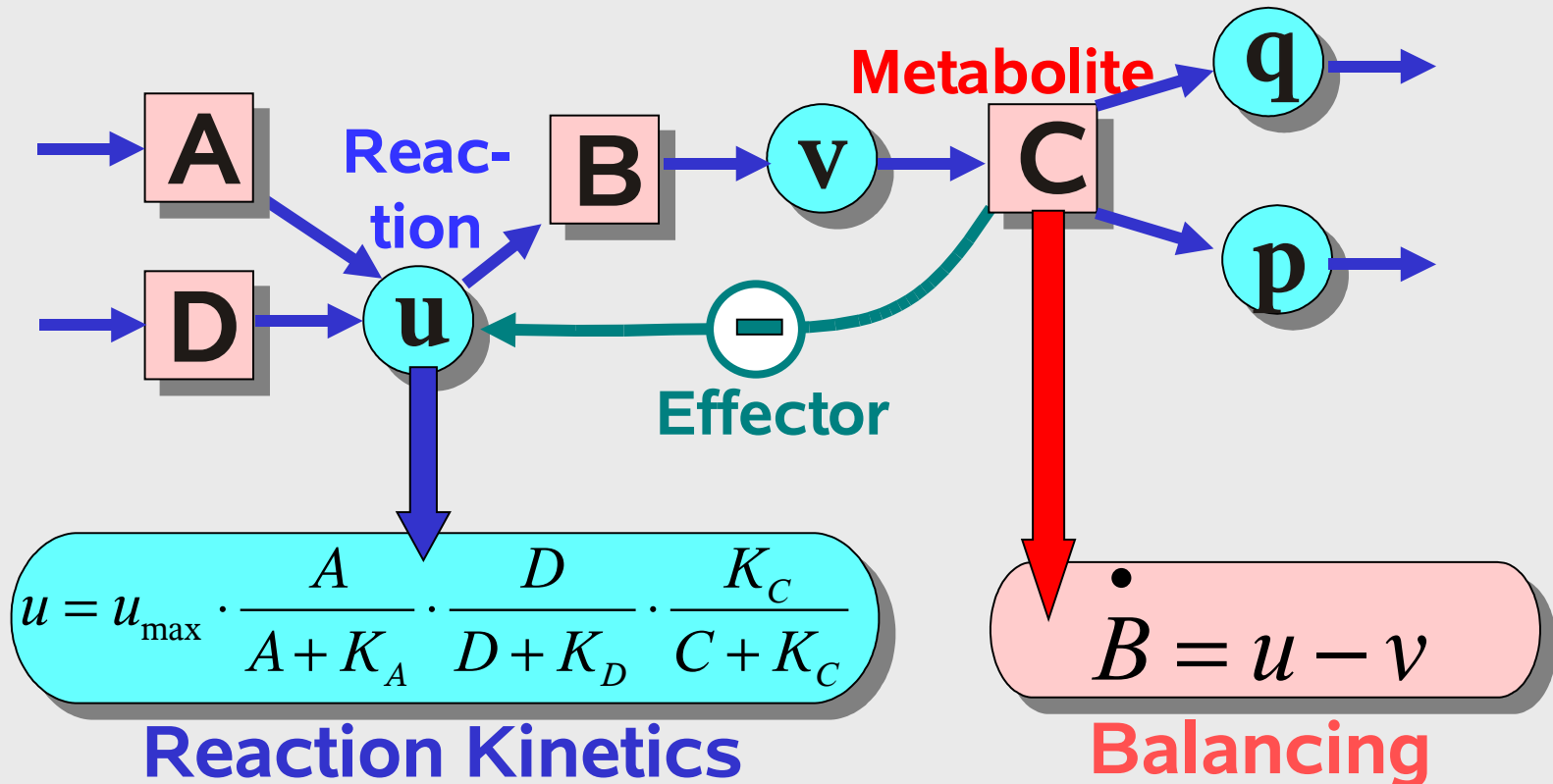
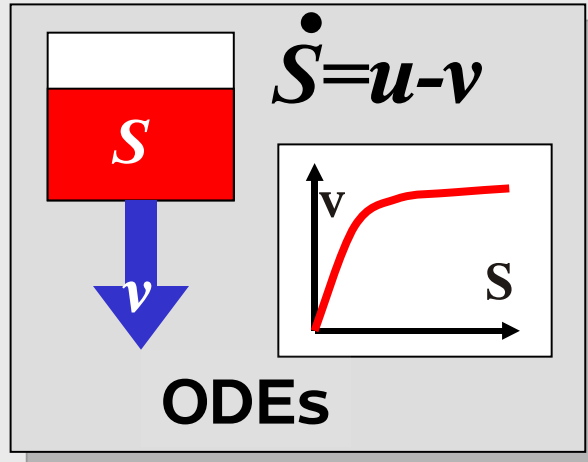
Radial RD Reaction

$$\frac{D}{r^2} \frac{d}{dr} \left(r^2 \frac{dc}{dr} \right) - kc = 0$$

ODE Models

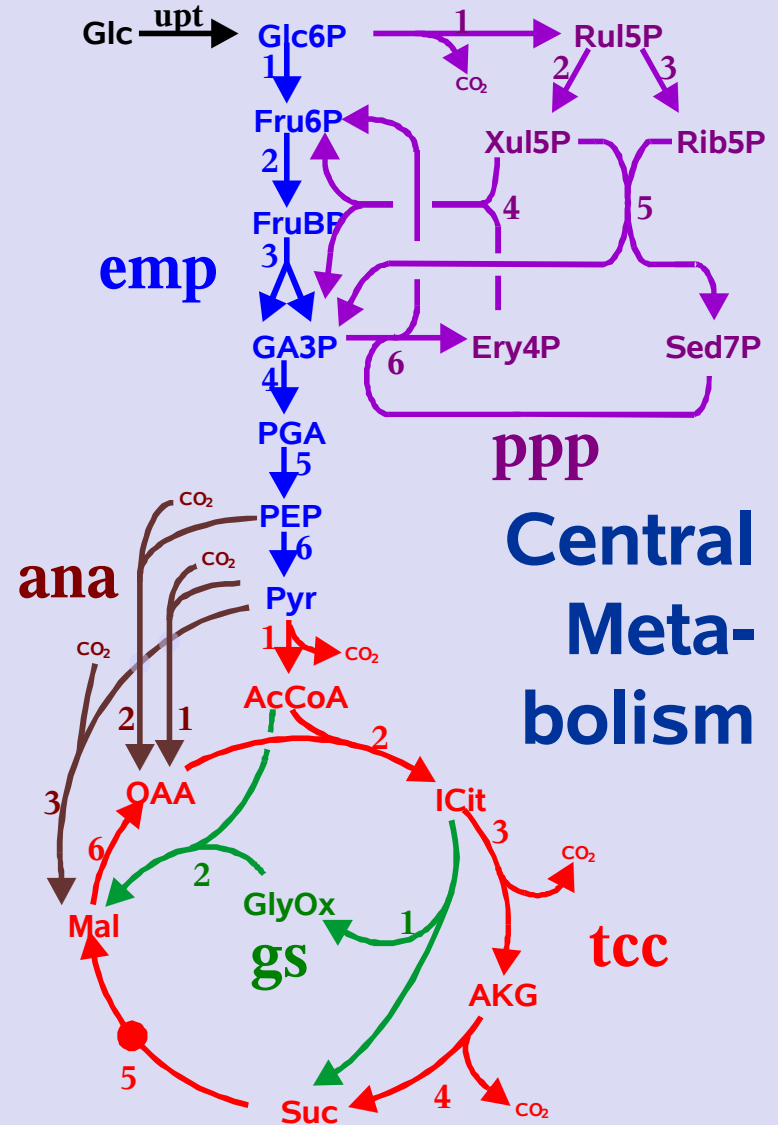
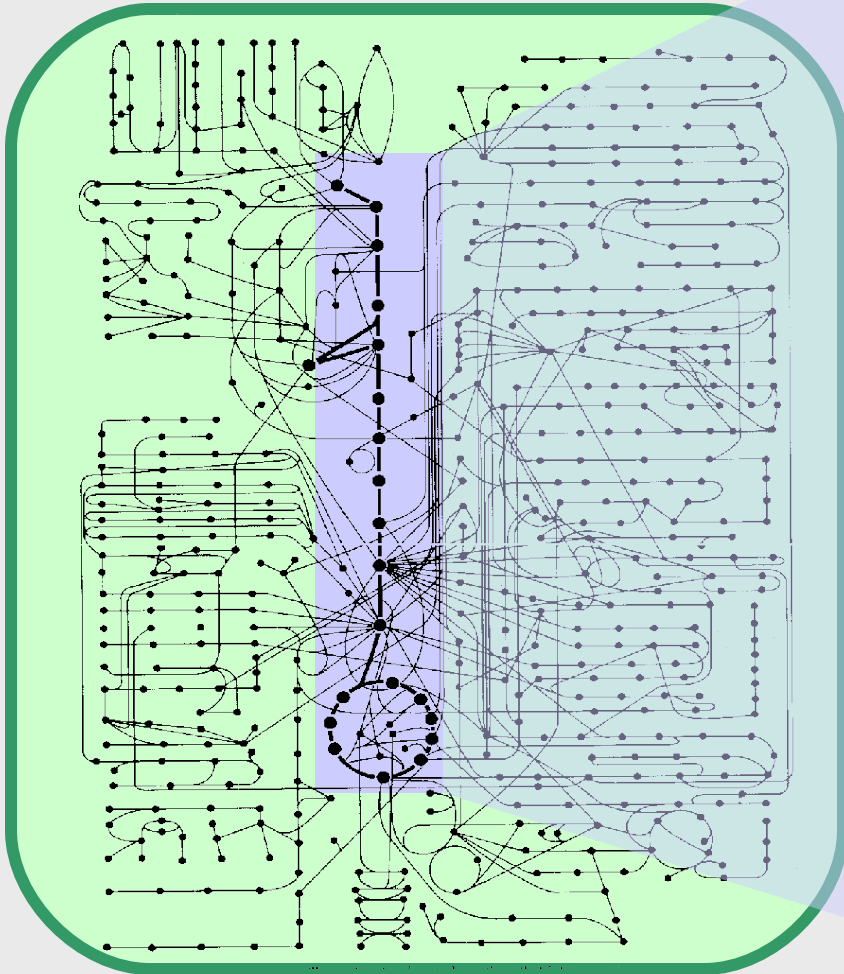
Principles

- homogeneous concentrations
- biochemical reaction network
- enzyme kinetic reaction models
- balance equations



Genome Scale Networks and Central Pathways

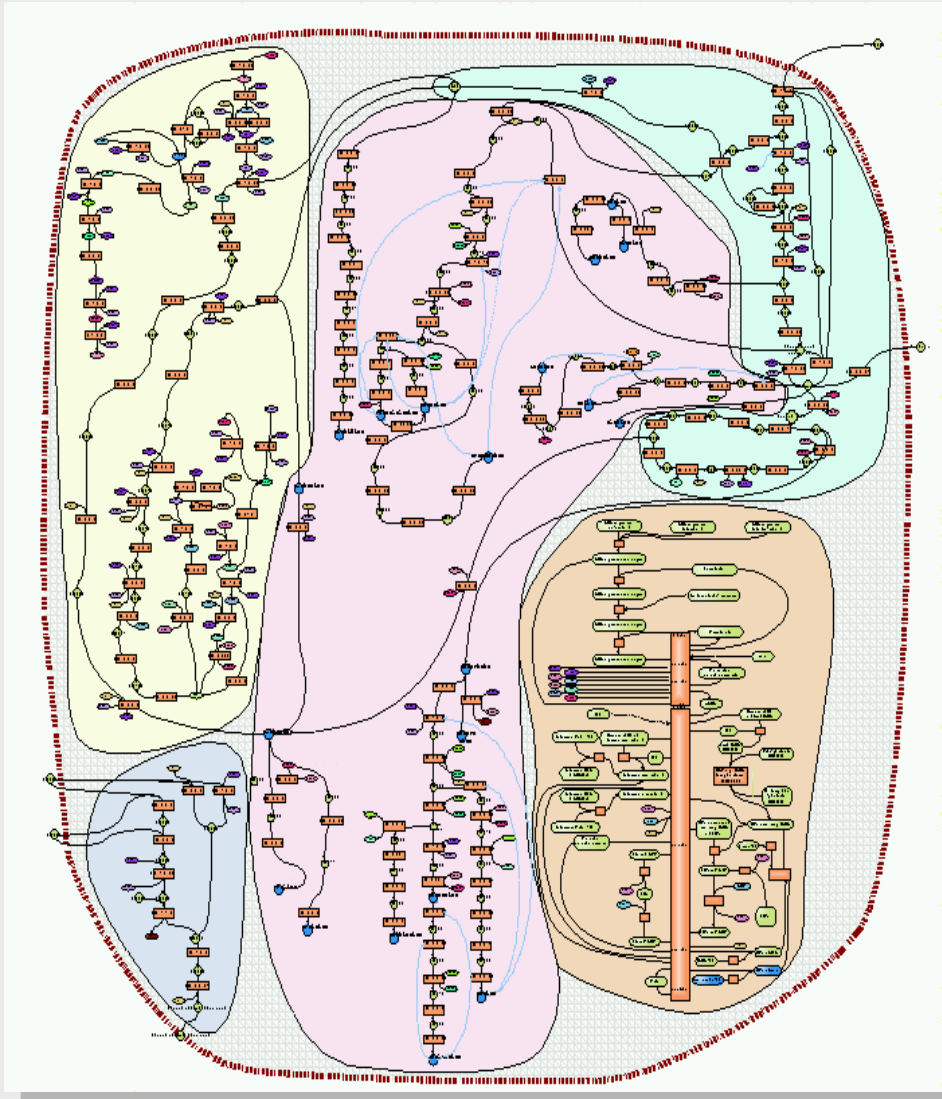
Total:
> 1000 Reactions



Tools for Network Simulation

E-Cell

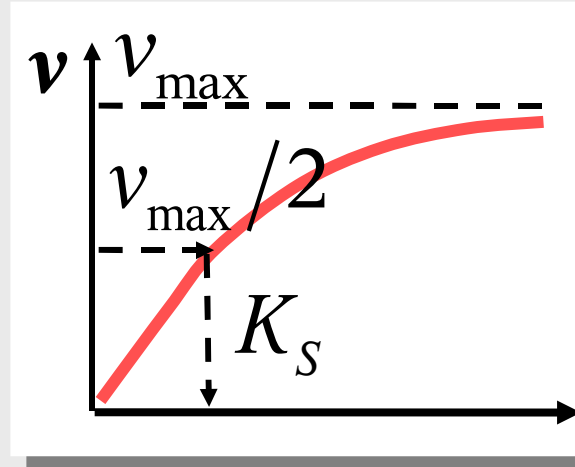
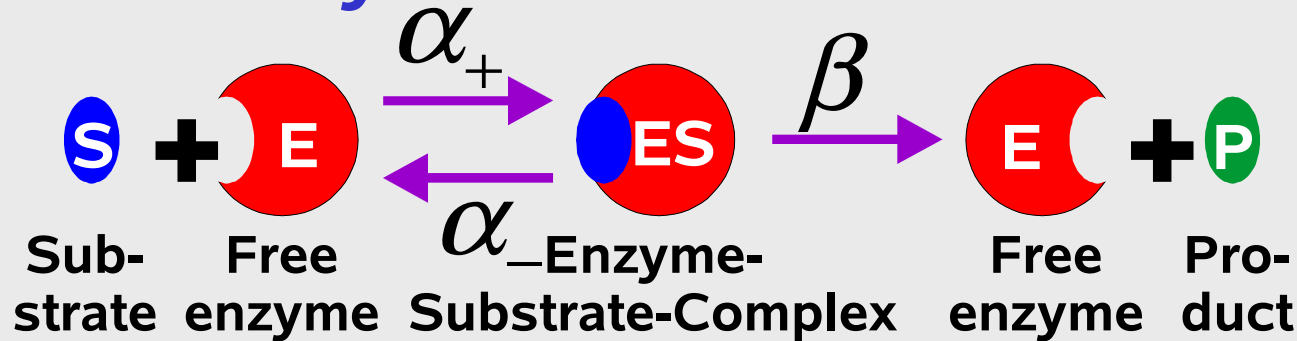
... and other tools



BALSA	E-CELL	Monod	SBMLSim
BASIS	ecellJ	Narrator	SBMLTB
BIOCHAM	ESS	NetBuilder	SBlID
BioCharon	FluxAnalyzer	Oscill8	SBToolbox
ByoDyn	Fluxor	PANTHER	SBW
BioCyc	Gepasi	PathArt	SCIpath
BioGrid	Gillespie2	PathScout	Sigmoid*
BioModels	HSMB	Pathway An.	SigPath
BioNetGen	HybridSBML	PathwayLab	SigTran
BioPathwise	INSILICO	Pathway Tools	SIMBA
Bio Sketch Pad	JACOBIAN	PathwayBuilder	SimBiology
BioSens	Jarnac	PATIKAwEB	Simpathica
BioSPICE	JDesigner	PaVESy	SimPheny*
BioSpreadsheet	JigCell	PET	SimWiz
BioTapestry	JSim	PNK	SloppyCell
BioUML	JWS Online	PottersWheel	SmartCell
BSTLab	Karyote*	Reactome	SRS P. Ed.
CADLIVE	KEGG2SBML	ProcessDB	StochSim
CellDesigner	Kineticon	PROTON	StochKit
Cellerator	Kinsolver*	pysbml	STOCKS
CellML2SBML	libSBML	PySCeS	TERANODE
Cellware	MathSBML	runSBML	Trelis
CL-SBML	MesoRD	SABIO-RK	Virtual Cell
CLEML	Meta-All	SBML ODE	WebCell
COPASI	MetaboLogica	SBML-PET	WinSCAMP
Cyto-Sim	MetaFluxNet	SBMLeditor	XPPAUT
Cytoscape	MMT2	SBMLmerge	
DBsolve	Modesto	SBMLR	
Dizzy	Moleculizer	SBMLSim	

Quasi Stationary Reaction Kinetics

Michaelis Menten Model of an enzyme reaction



Assumptions

1. Large particle number
2. Spatial homogeneity
3. Slowly changing substrate concentration
4. Substrate binding fast compared to reaction

$$\alpha_+, \alpha_- \gg \beta$$

Quasi stationary rate

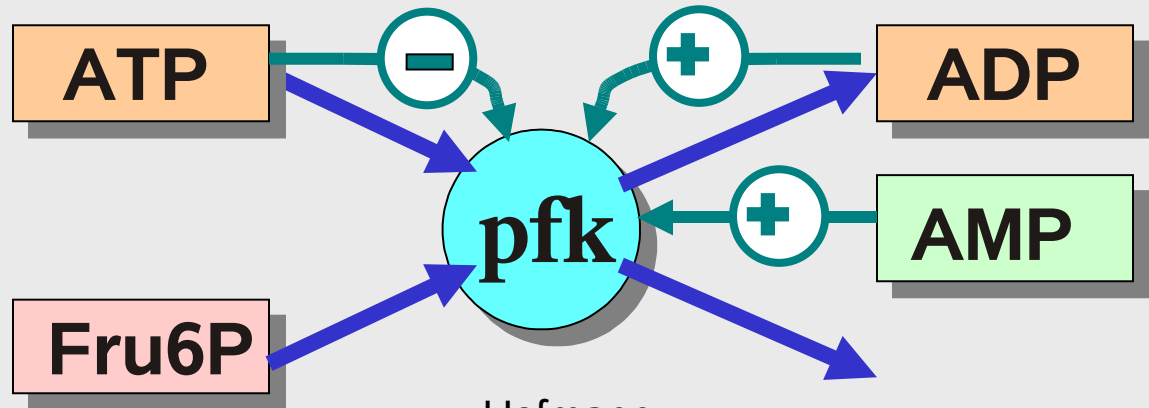
$$\begin{aligned}
 v(S) &= E_0 \cdot \beta \cdot \frac{S}{S + \frac{\alpha_- + \beta}{\alpha_+}} \\
 &= v_{\max} \cdot \frac{S}{S + K_S}
 \end{aligned}$$

Michaelis
Menten
Kinetics

Many other reaction mechanisms are known.

Reaktion Kinetic Data

Simplified Phosphofructokinase-Model



Hofmann
et al. 1982

Kinetics of PFK

$$v(F6P, ATP, ADP, AMP) = v_{\max} \cdot \dots \text{ Enzyme activity}$$

$$\frac{ATP}{ATP + K_{ATPS} \left[1 + \frac{ADP}{K_{ADPC}} \right]} \cdot \frac{1}{1 + L_0 / \left[1 + \frac{F6P}{K_{F6P}} \right]^8} \cdot \dots$$

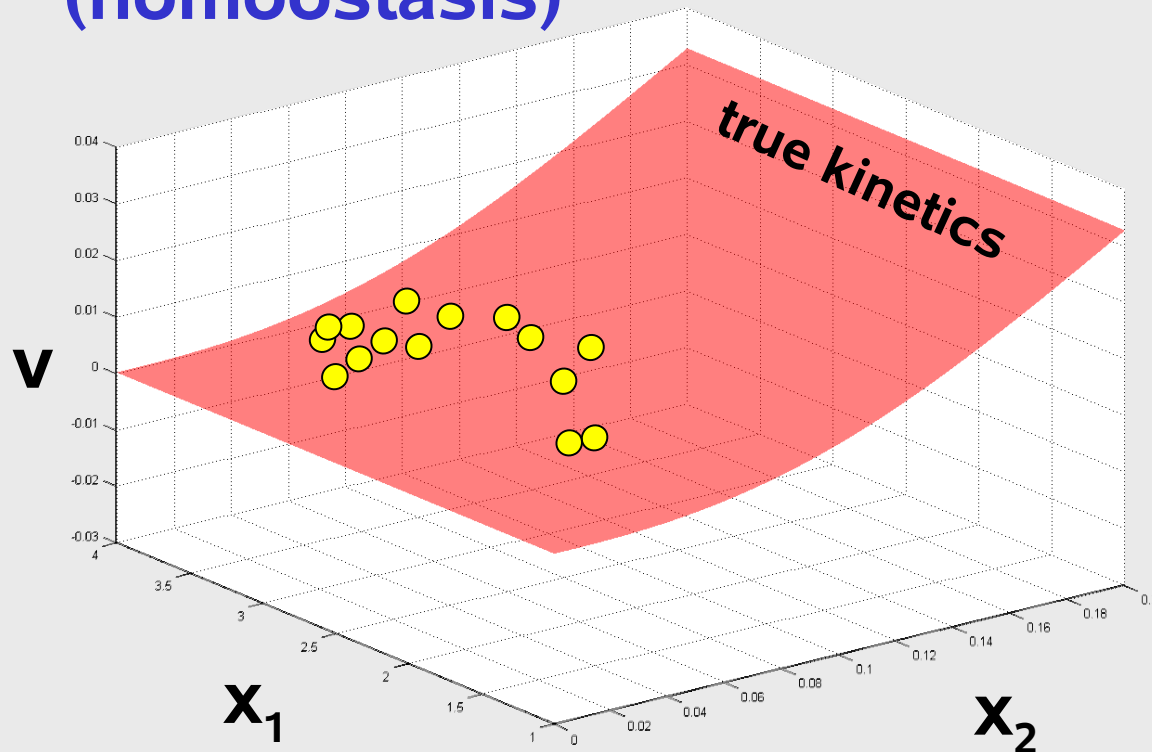
10 kinetic Parameters

$$F6P + K_{F6PS} \cdot \left[1 + \frac{ATP}{K_{ATP1}} + \frac{ADP}{K_{ADP2}} + \frac{AMP}{K_{AMP2}} \right] / \left[1 + \frac{ADP}{K_{ADP1}} + \frac{AMP}{K_{AMP1}} \right]$$

Number of parameters increases faster than number of reactands.

Approximate Kinetic Formats

Typical in vivo concentrations (homöostasis)



Requirements for approximations

- biologically reasonable
- nonlinear
- good approximation properties
- one parameter per reactand/effector
- good computational properties

Proposed kinetic formats

- **power laws** Savageau, Voit
- **lin-log** Heijnen
- **fuzzy** Liao

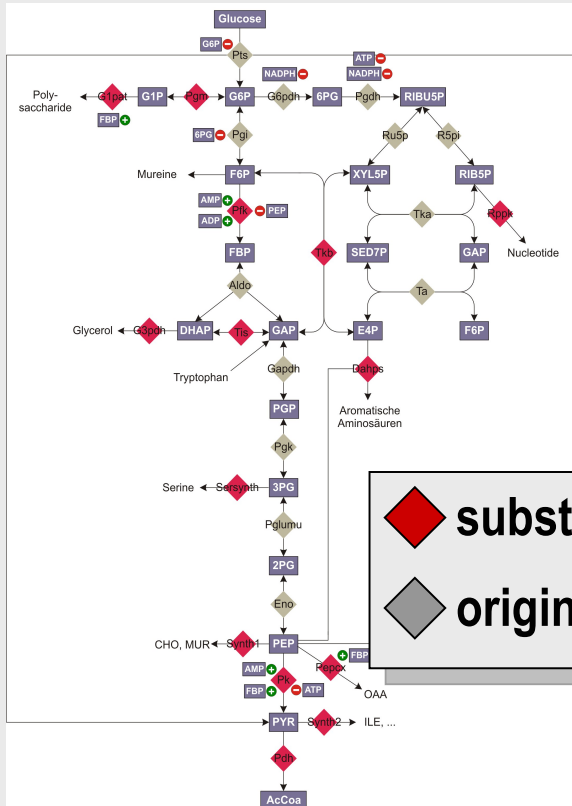
- **generic** Wiechert
- **convenience** Klipp

Example: Substitution of Kinetic Terms

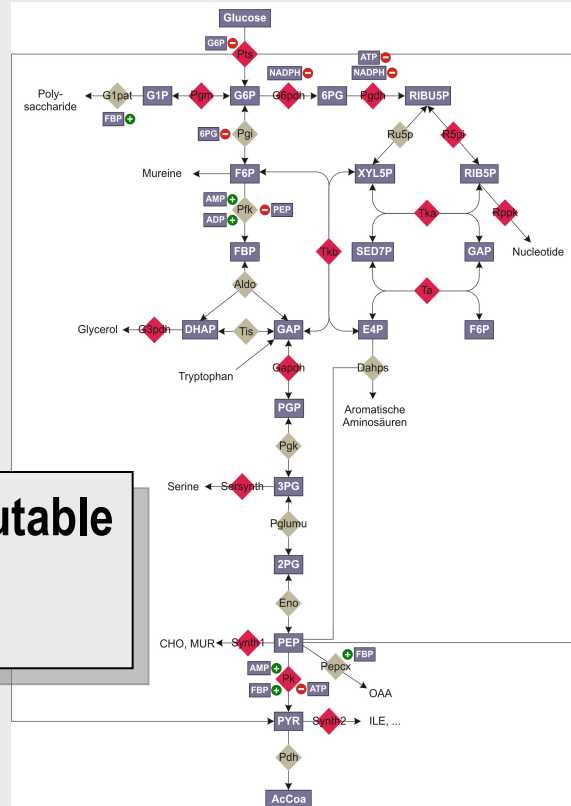
Substituting kinetic terms in an E. coli model
original model has 116 parameters

Chassagnole 2004

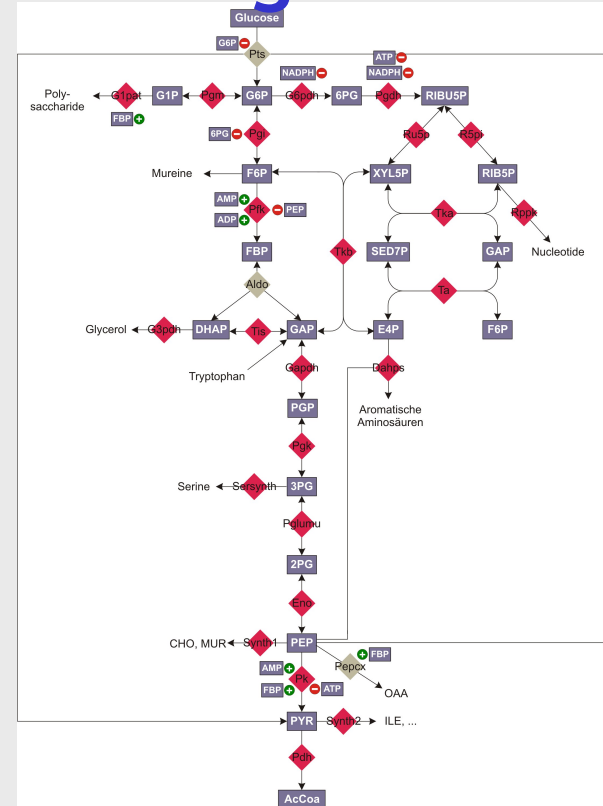
Power Law



Generic



Lin-Log



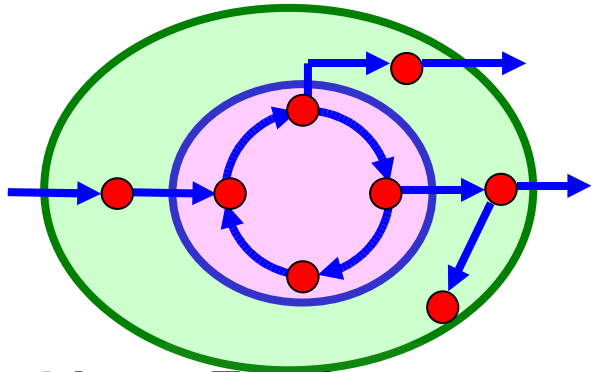
14 Substitutions (87)

15 Substitutions (93)

24 Substitutions (81)

All simplified models reproduce the same experimental data.

Stoichiometric Models

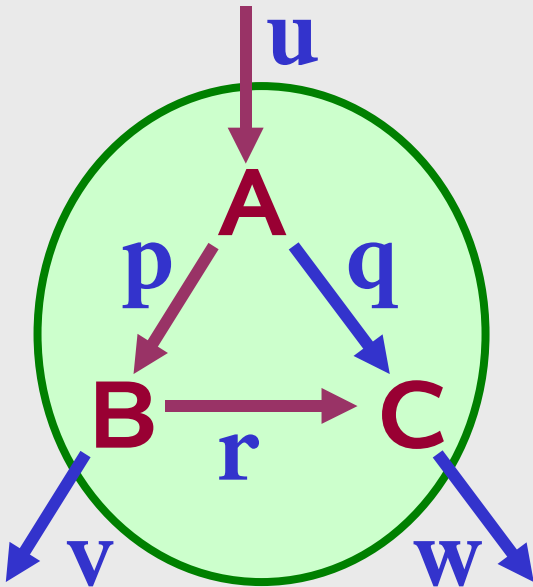


Linear Equations

Principles

- spatially homogeneous
- steady state (constant fluxes)
- reduced to metabolic fluxes

Stoichiometry

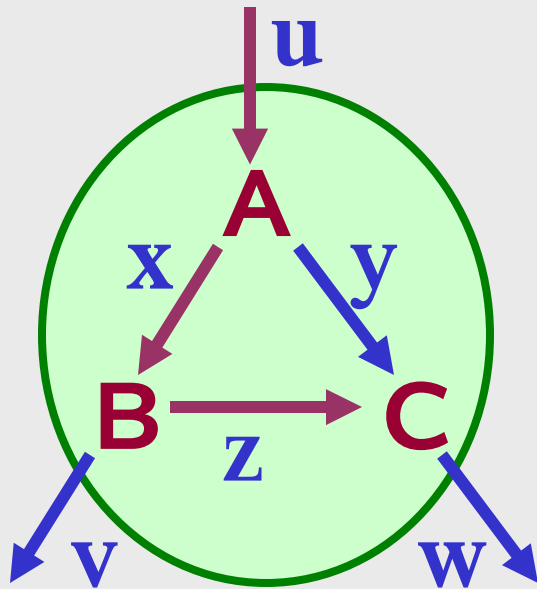


$$\begin{pmatrix} 1 & \cdot & \cdot & -1 & -1 & \cdot \\ \cdot & -1 & \cdot & 1 & \cdot & -1 \\ \cdot & \cdot & -1 & \cdot & 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} u \\ v \\ w \\ p \\ q \\ r \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

N

$$\cdot \mathbf{v} = \mathbf{0}$$

Stoichiometrically Feasible Fluxes



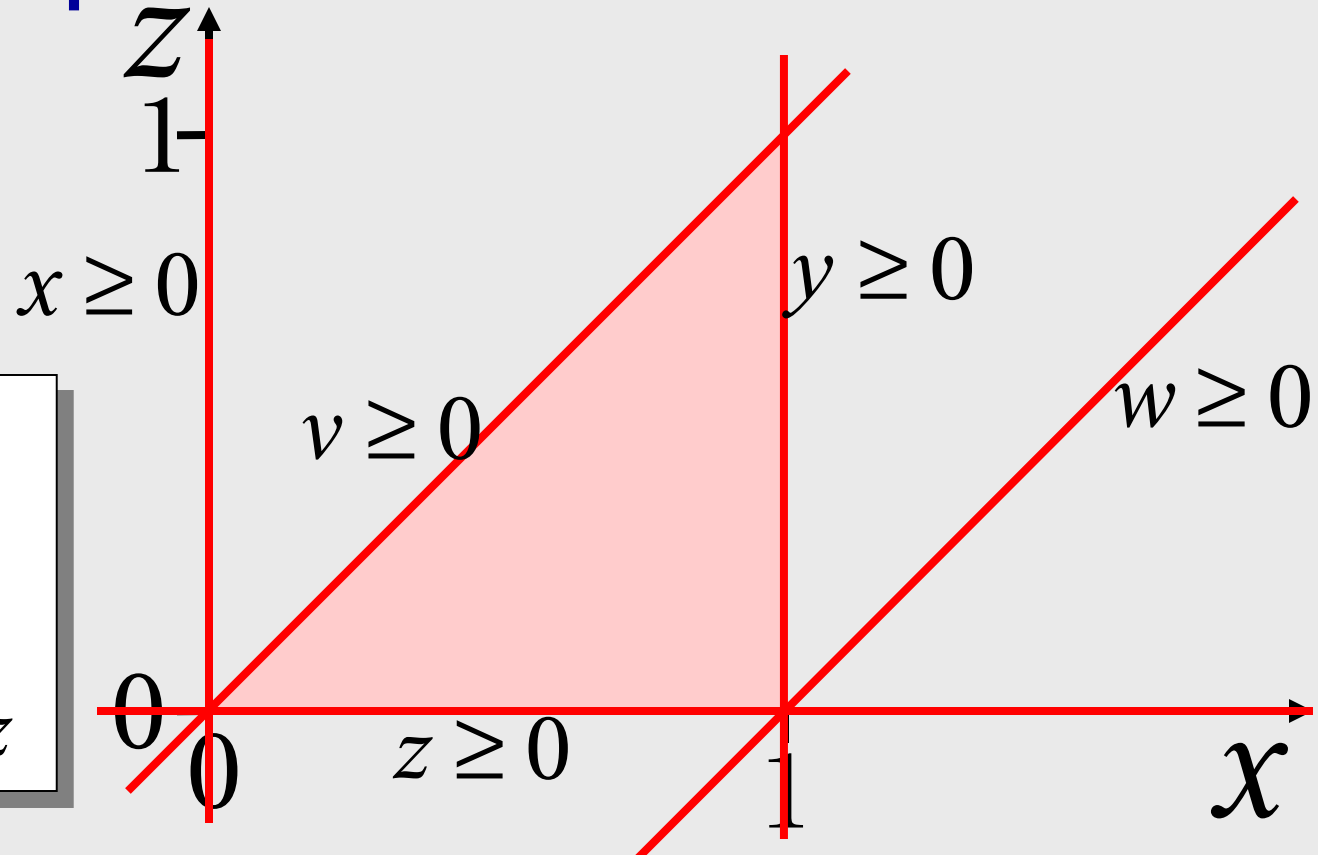
Relative fluxes:

$$u = 1$$

Unidirectionality :

$$v, w, x, y, z \geq 0$$

Space of feasible fluxes :



Stoichiometry:

$$A: y = u - x$$

$$B: v = x - z$$

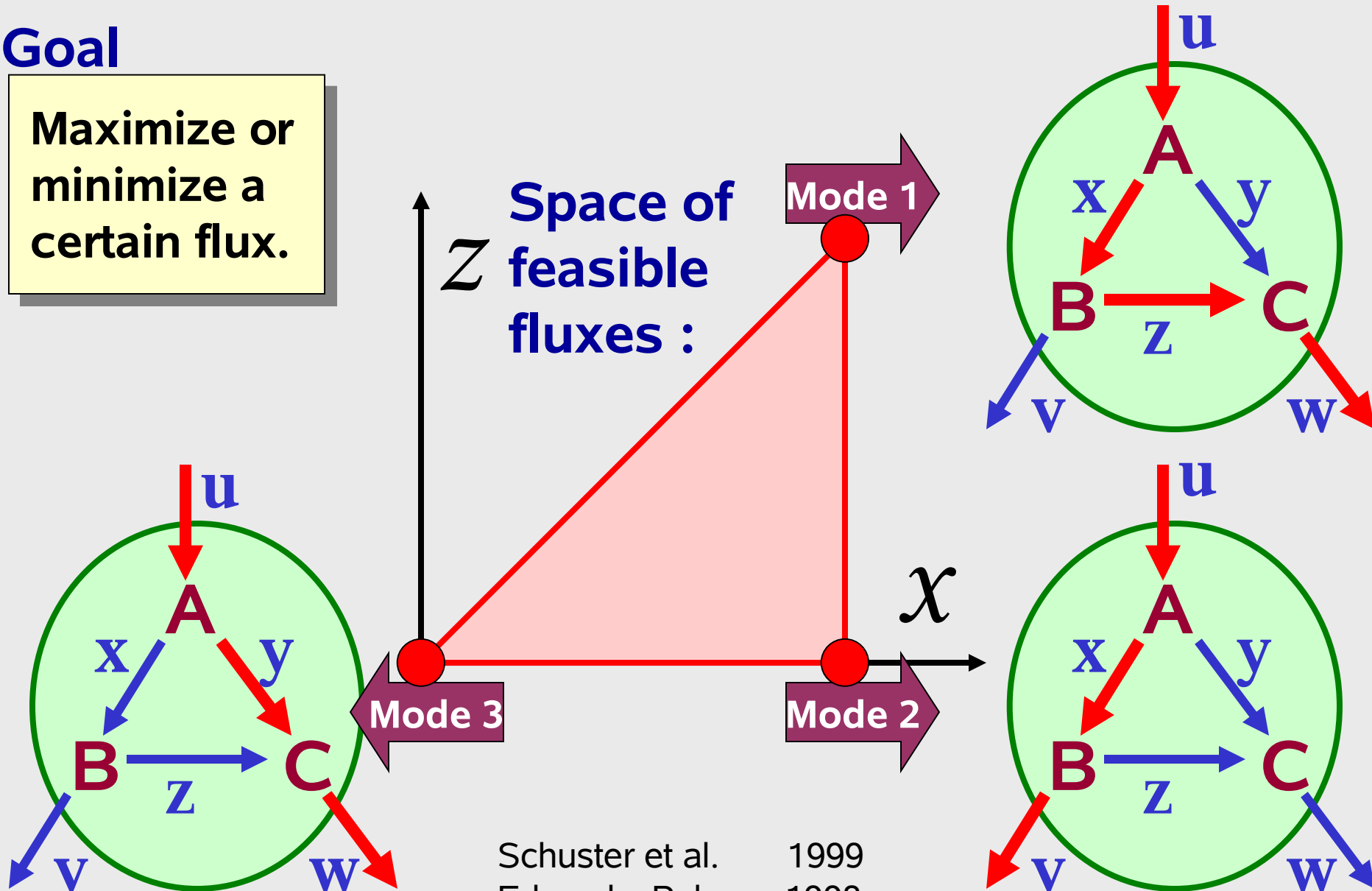
$$C: w = y + z$$

$$= u - x + z$$

Flux Balance Analysis: Extremal Fluxes

Goal

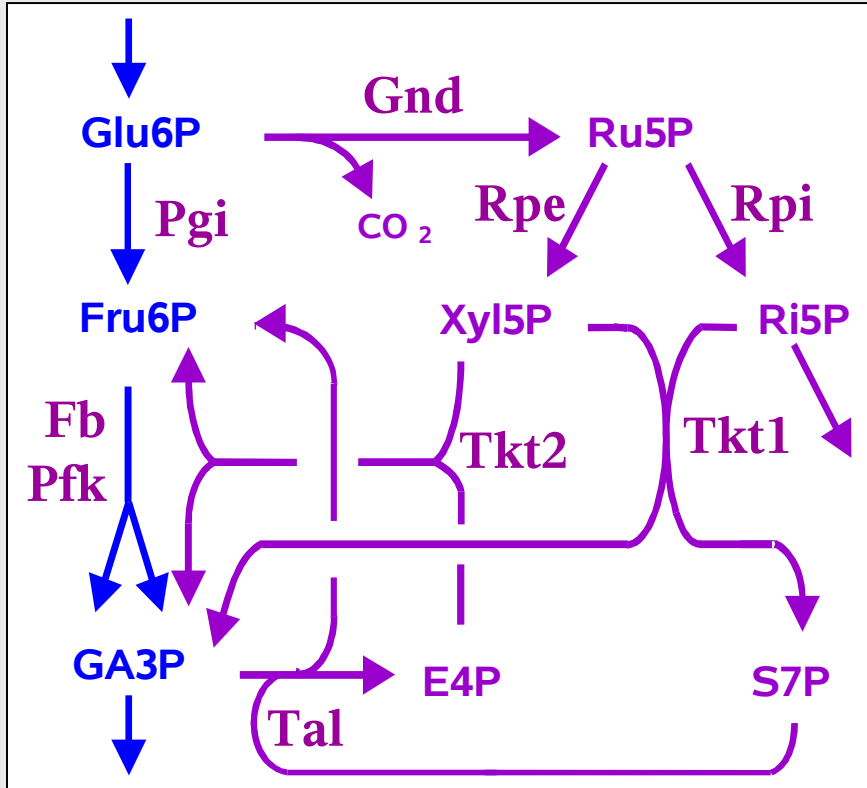
Maximize or minimize a certain flux.



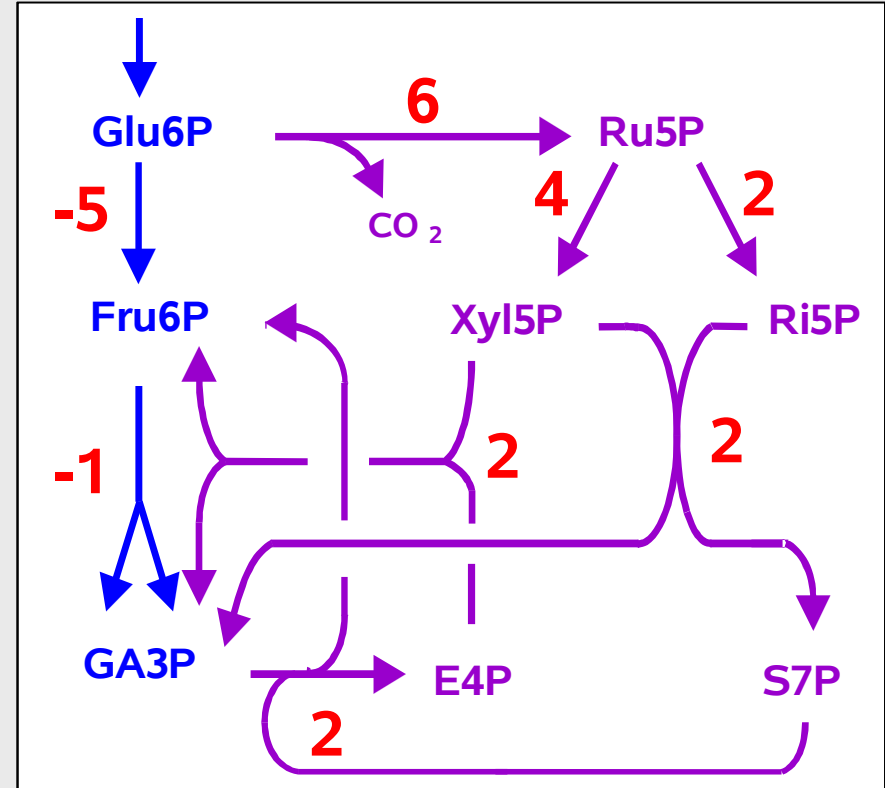
Schuster et al. 1999
Edwards, Palsson 1998

Example: Sugar Metabolism

Reactions and Pools



Mode 6: „PPP Cycle“

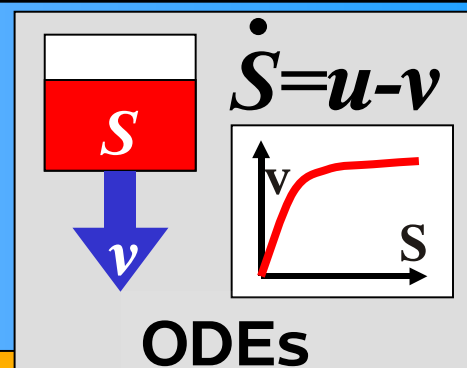
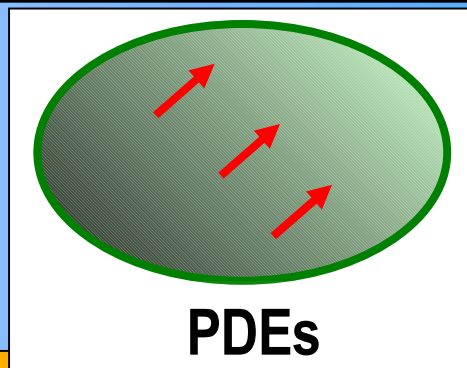


Applications

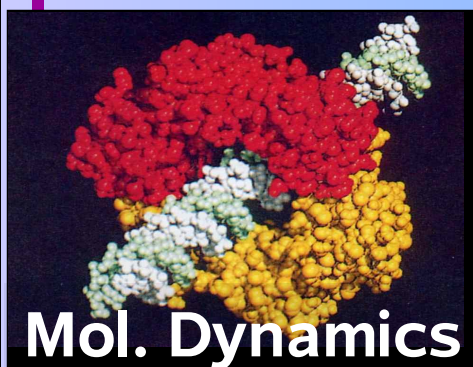
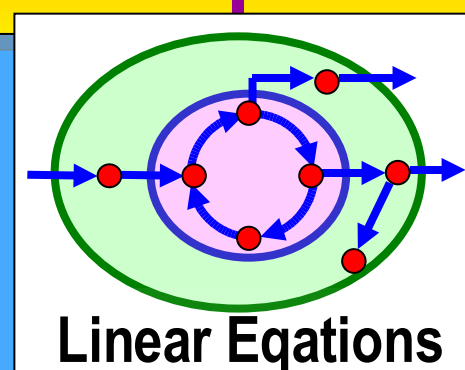
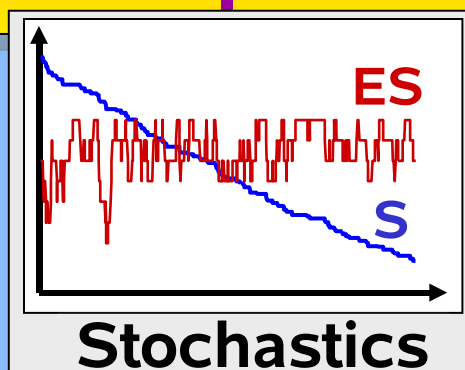
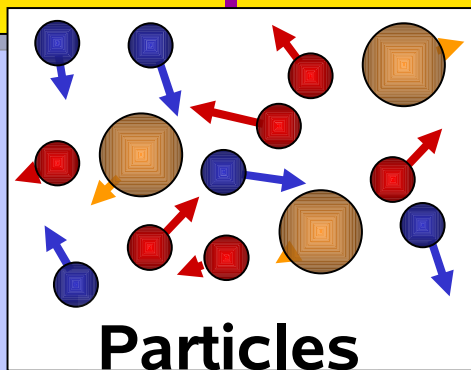
Schuster et al. 2000

- Maximal Yields
- Screening
- Funct. Genomics
- Knockout Targets
- Drug Targets

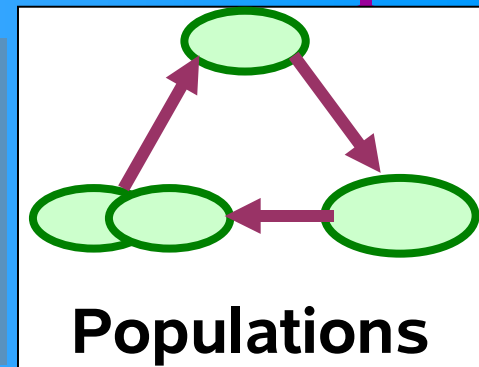
Scales of Cellular Network Modelling



Spatial Scales



How to reduce the effort ?
How to obtain the data ?
How to validate the model ?
How to predict experiments ?



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