

# Computer-Aided Systems Biology

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Czech Republic

## 1 Introduction and Motivation

## 2 Methodology

- Biological Networks
- Modelling Problems

## 3 Case Study

## 1 Introduction and Motivation

## 2 Methodology

- Biological Networks
- Modelling Problems

## 3 Case Study

## Biology

- since ancient times
- empirically studies **life** and **living organisms**
- studied aspects: structure, **function**, growth, development and evolution
- used concepts:
  - the **cell** – the unit of life
  - the **gene** – the unit of inherited **information**
  - the **evolution** – the mechanism of species creation

### Biophysics

- since the mid of 19th century
- living organism = open (thermodynamic) **system**
- the goal: **why** and **how** the living matter works?
- uses mathematical apparatus
- a fascinating phenomenon: homeostasis
  - maintain a **stable condition** in a **changing environment**
  - **robust** (up-to certain limits)

# Holistic Thinking and Systems Theory

## Phylosophical Roots



reductionism



# Holistic Thinking and Systems Theory

## Phylosophical Roots

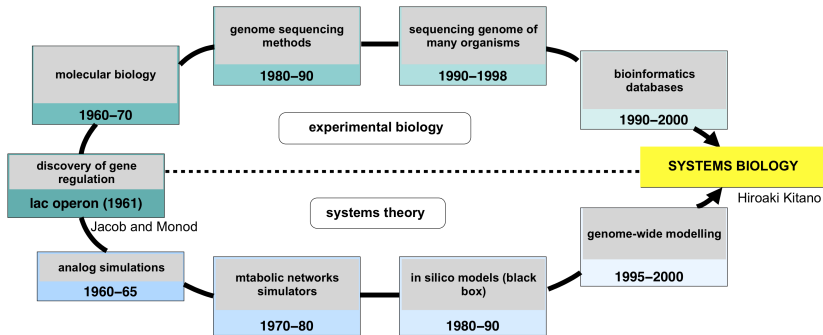
holism



*“A Whole is Greater Than the Sum of Its Parts.”*

– Aristoteles

# Development of Systems Biology



“Does the flap of a butterfly’s wings in Brazil set off a tornado in Texas?”

Philip Merilees



# Motivation: Rigorously Answer Biological Questions

- biology is goal-oriented
- biological problems typically address complex processes

## Examples of biological problems

How the bacteria cell **utilises** particular nutritions?

Which nutritions imply fastest **growth** under given conditions?

# Motivation: Rigorously Answer Biological Questions

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- biological problems typically address complex processes

## Examples of biological problems

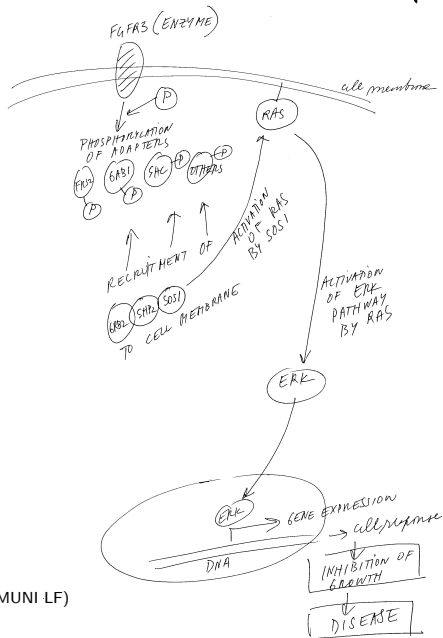
How the bacteria cell **utilises** particular nutritions?

Which nutritions imply fastest **growth** under given conditions?

## The answer should fulfil specific requirements

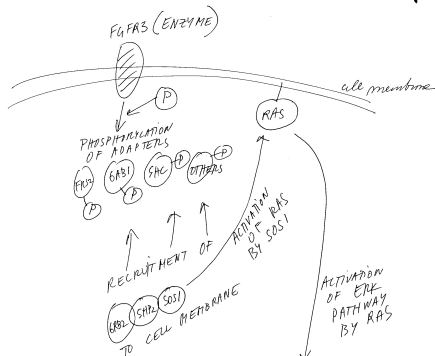
- to formulate and analyse a biological problem **holistically**
- to give mechanistic explanation based on known facts – mechanistic means in the context of laws of physics/chemistry
- to project the mechanistic details onto the genetic information

# From Biologist's Table



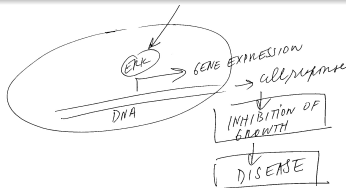
slide credits: Pavel Krejčí (MUNI LF)

# From Biologist's Table



## Biological Problem

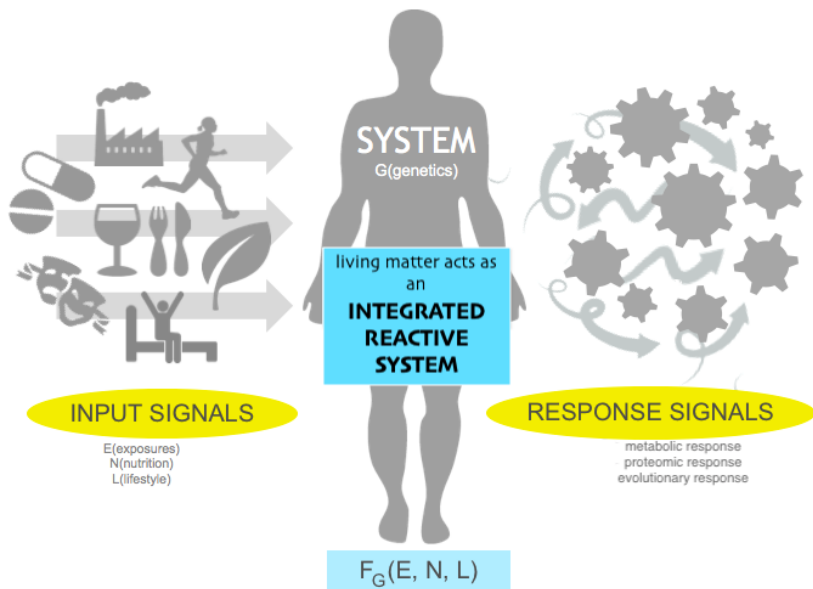
Why a human fibroblast cell misinterprets a certain growth factor?



slide credits: Pavel Krejčí (MUNI LF)

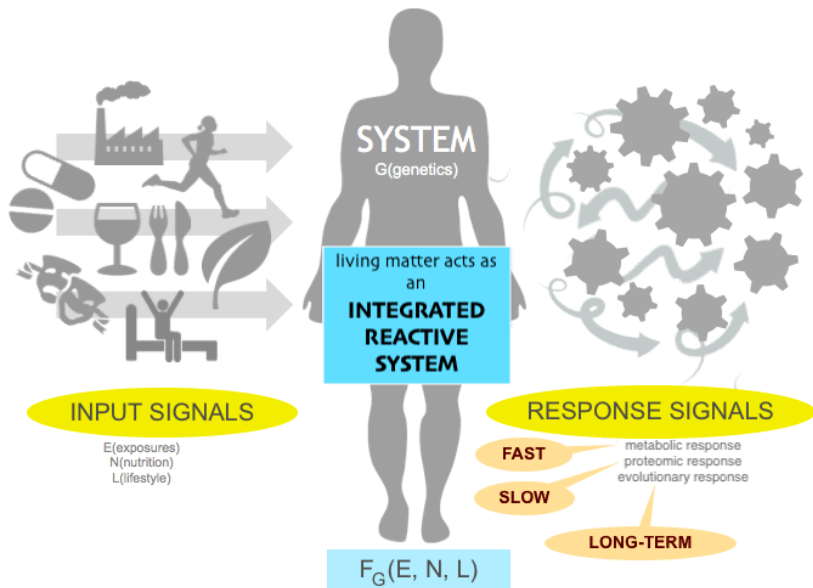
# Systems Approach: The Grand Challenge

Complex Organism as a System



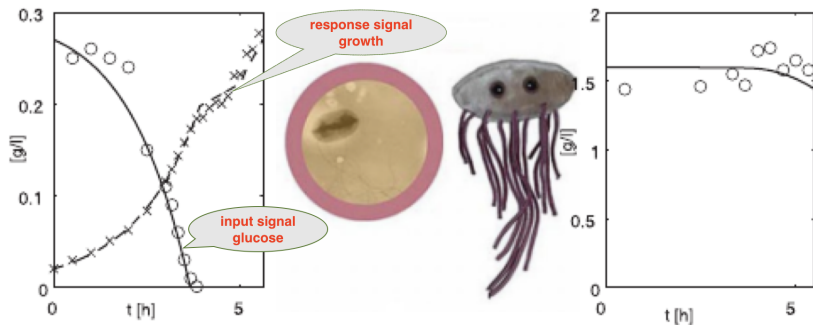
# Systems Approach: The Grand Challenge

Complex Organism as a System



# Systems Approach: A Moderate Challenge

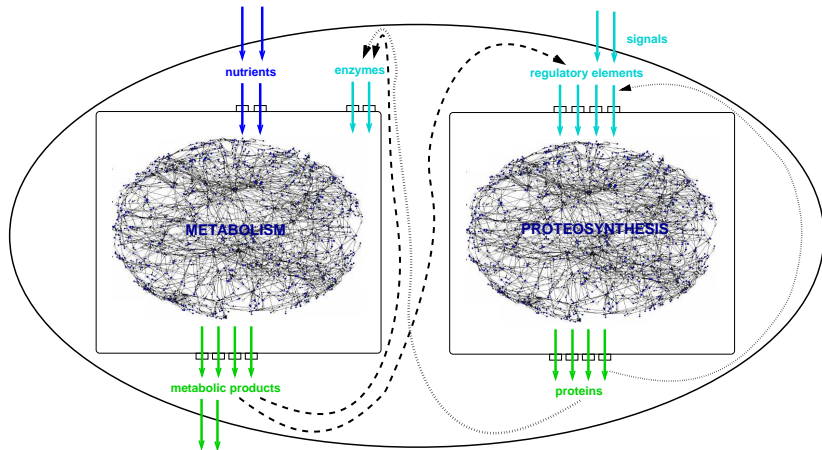
## Population of Bacteria as a System



for a particular set of genes  $G$

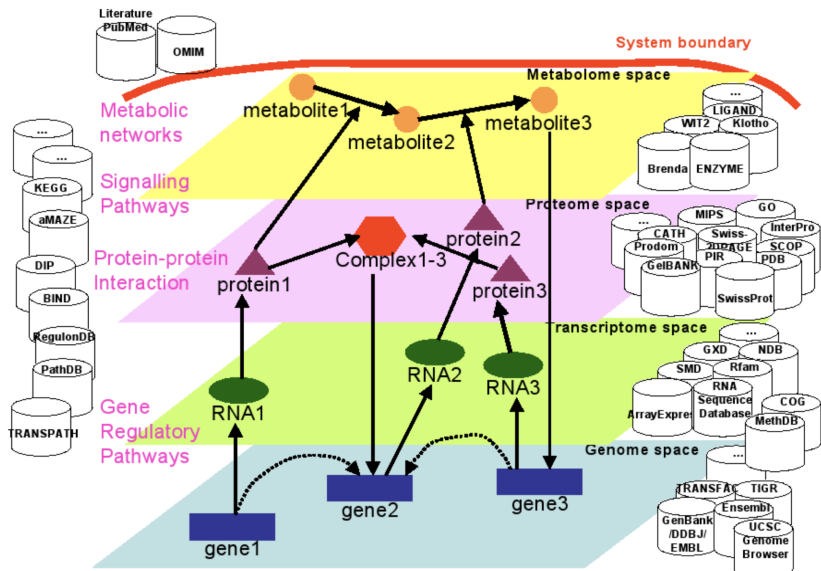
$F_G : (\text{environment exposure, nutrition}) \rightarrow \text{growth profile}$

# Systems View of Processes Driving the Cell





# The Cell as a Complex Interaction Network



slide credits: David Gilbert (Brunel Univ.)

1 Introduction and Motivation

2 Methodology

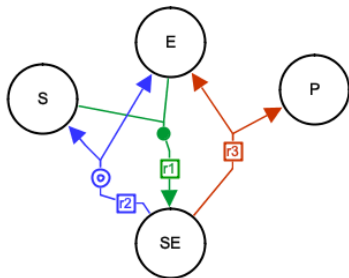
- Biological Networks
- Modelling Problems

3 Case Study

## Assumptions

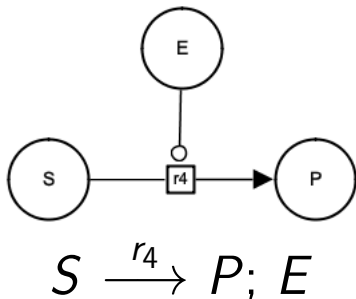
- The biological reality (a biophysical process) is understood as a **biological system**.
- A biological system is given as a **network**  $\mathcal{N}$  of biochemical **components** connected by chemical/physical **interactions**.
- The components include relevant genes and gene products.

- basic form: **chemical reaction networks (CRNs)**
  - elementary chemical reactions
  - represent the flow of the mass
- example:



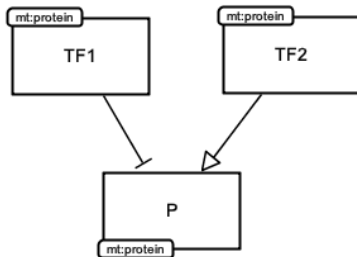
SBGN standard notation, see <https://www.sbgn.org>

- simplified form: **reaction-influence networks (RINs)**
  - chemical reactions influenced by other molecules
  - represent the modulated flow of the mass
- example:



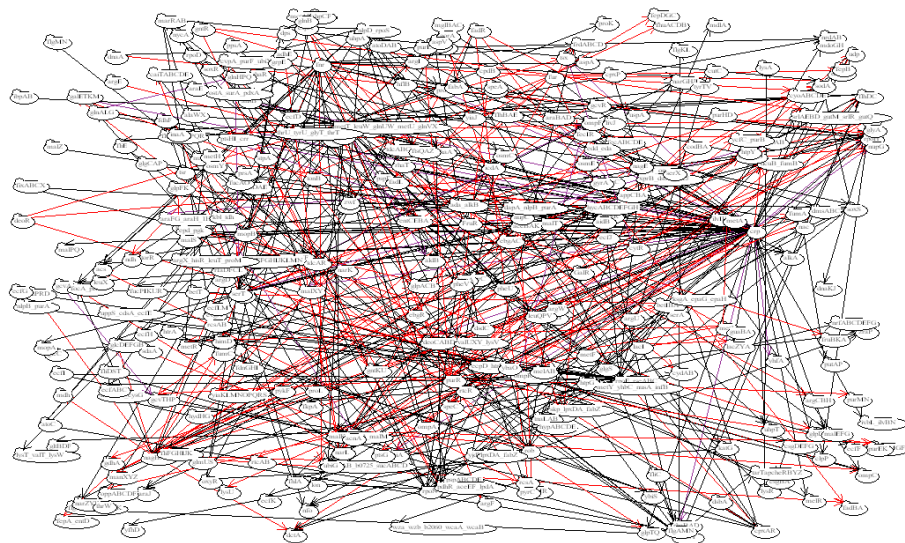
SBGN standard notation, see <https://www.sbgn.org>

- abstract form: **influence networks (INs)**
  - represent positive/negative influences among molecules
  - well fit incomplete knowledge
  - typically gene regulatory networks, signalling pathways
- example:



SBGN standard notation, see <https://www.sbgm.org>

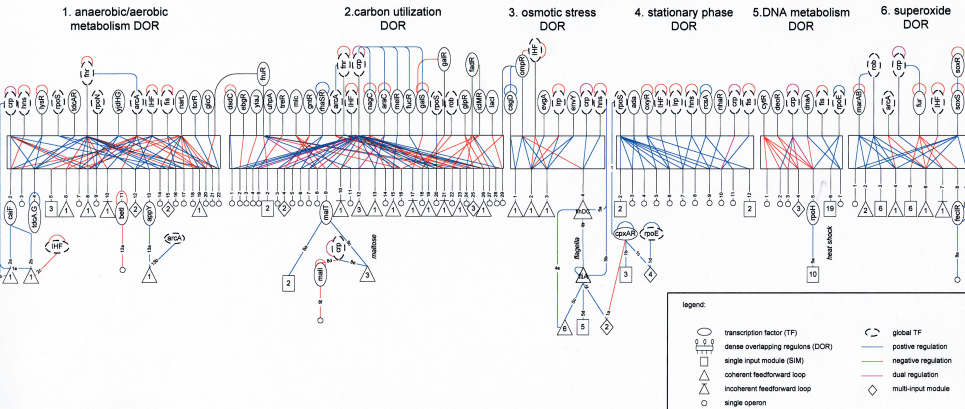
# Biological Networks are Large



genetic regulatory network of *E. coli*

see <https://reactome.org> for more...

# ...But Organised



genetic regulatory network of *E. coli*



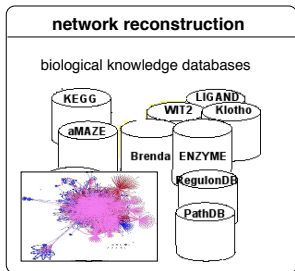
## The General Goal

For a biological system given by a network  $\mathcal{N}$  **reconstruct** the system's **dynamics**:

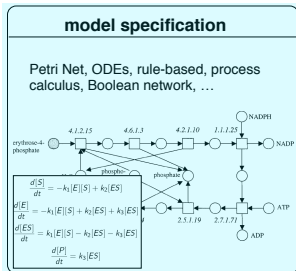
*Define a function that encodes the information (signal) processing occurring in **all** components of the system in time.*

$$F_{\mathcal{N}} : (\text{input stimuli, environment signals}) \rightarrow \text{response signals}$$

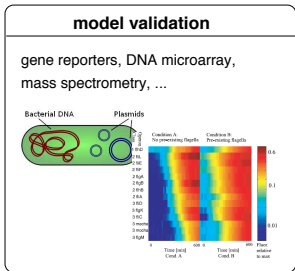
# Model-Based Workflow



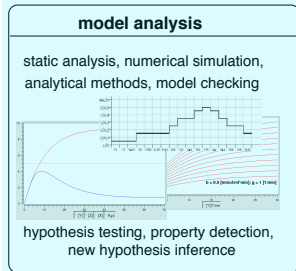
biological network  
 hypothesis



computer lab



emergent properties  
 model questions



How to reconstruct the dynamics  $F_{\mathcal{N}}$  of a network  $\mathcal{N}$ ?

- 1 choose a modelling framework
- 2 associate every interaction in  $\mathcal{N}$  with a suitable **kinetic rule**
  - describes how a **state** of affected components changes in time
- 3 build a computational **model** by combining kinetic rules

# Modelling Frameworks

state-transition systems

states: discrete molecule numbers or qualities (on/off)

qualitative model

abstraction

abstraction

abstracted  
time  
modeled

stochastic model

approximation

continuous model

Continuous-Time Markov Chains  
states: discrete molecule numbers

Ordinary Differential Equations  
states: continuous concentrations

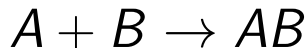
states  
← discrete      continuous →

# Model Construction

## Continuous View of CRNs

deterministic continuous-time dynamics of molecule population  
molecules dissolved in the cell volume (a well-stirred “pool”)

molar concentration  $[M]=[mol \cdot l^{-1}]$



biophysical law of **mass action kinetics**:

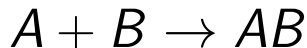
$$v = k[A][B] \quad [M \cdot s^{-1}]$$

# Model Construction

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molar concentration  $[M]=[mol \cdot l^{-1}]$



biophysical law of **mass action kinetics**:

$$v = k[A][B] \quad [M \cdot s^{-1}]$$

$$\frac{d[A]}{dt} = -v$$

$$\frac{d[B]}{dt} = -v$$

$$\frac{d[AB]}{dt} = v$$

$k [s^{-1}]$  is a reaction-specific **parameter**

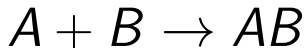
Waage, P.; Guldberg, C.M. (1864). Studier over Affiniteten. Forhandlinger i Videnskabs-selskabet i Christiania (Transactions of the Scientific Society in Christiania) (in Danish): 35–45.

# Model Construction

## Stochastic View of CRNs

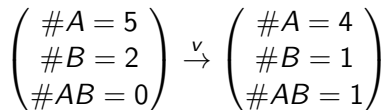
stochastic continuous-time dynamics of molecule population  
molecules distributed uniformly in the cell volume (well-stirred)

states describe molecules number (#)



biophysical law of **stochastic mass action** describes an expected  
rate of reaction event occurrence:

$$v = k \cdot \#A \cdot \#B \quad [s^{-1}]$$

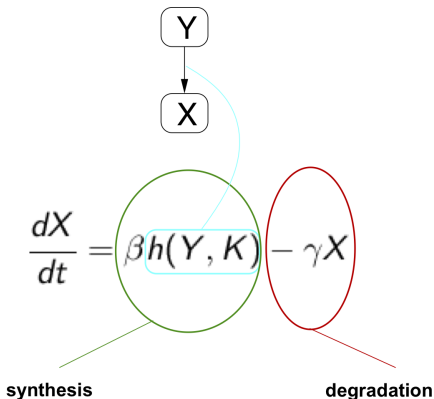


$k [s^{-1}]$  is a reaction-specific **parameter**, depends on cell volume

# Model Construction

## Continuous View of INs

controlled synthesis of  $X$  and its spontaneous degradation  
so-called (sigmoidal) Hill kinetics



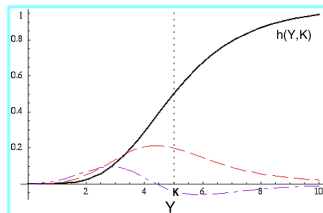
$\beta, \gamma$  ... production and degradation parameters;



# Model Construction

## Continuous View of INs

controlled synthesis of  $X$  and its spontaneous degradation  
so-called (sigmoidal) Hill kinetics



$$\frac{dX}{dt} = \beta h(Y, K) - \gamma X$$

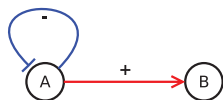
synthesis

degradation

$\beta, \gamma$  ... production and degradation parameters;  
 $K$  ... parameter of the influence

# Model Construction

## Qualitative View of Influence Nets – Discrete Regulatory Networks



$$A \in \{0, 1, 2\}, B \in \{0, 1\}$$

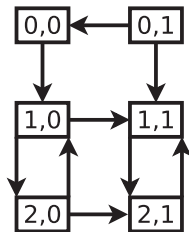
$$t_{AA} = 2, t_{AB} = 1$$

$$K_{A,\emptyset} = 2$$

$$K_{A,\{A\}} = 0$$

$$K_{B,\emptyset} = 0$$

$$K_{B,\{A\}} = 1$$



- introduced by René Thomas [1973]
- refined by Chaouiya et al. [2003]

- for a given network a model is built on first principles
- continuous models
  - **denotational** semantics defines the continuous flow

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

- stochastic and qualitative models
  - **operational** semantics defines events execution
  - quantitative or discrete parameters

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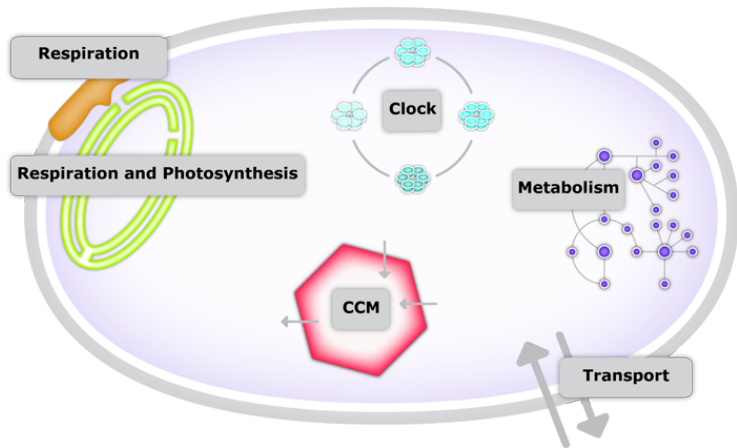
### Challenges (for Computer Science!)

How to deal with large, potentially infinite networks?

How to deal with unknown parameters?

# Model Specification

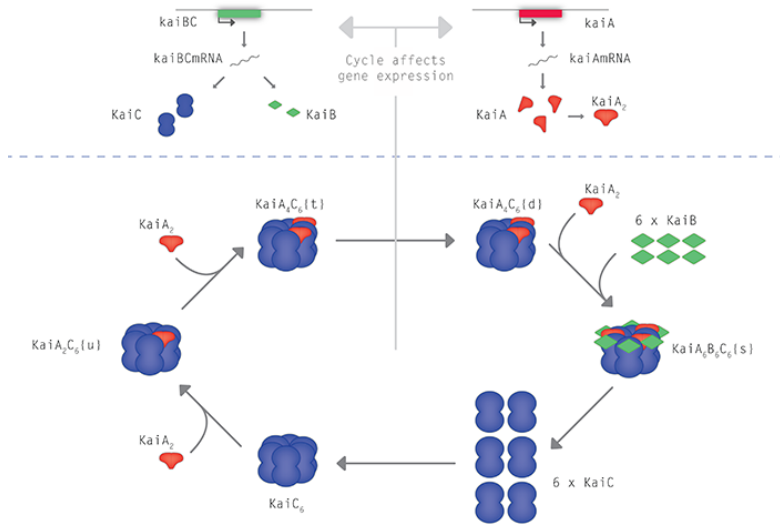
Comprehensive Modelling Platform (CMP)



<https://e-cyanobacterium.org>

# Model Specification

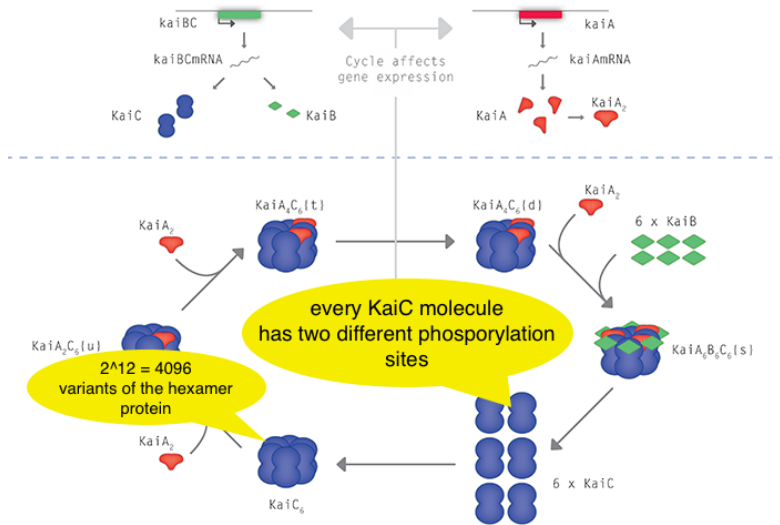
Example: Cyanobacteria Clock



<https://e-cyanobacterium.org>

# Model Specification

Example: Cyanobacteria Clock



<https://e-cyanobacterium.org>

- rule-based: generalise reactions to rules
- components have states (e.g., phosphorylated sites)
- rules are executed in a solution (soup of entities) in a context-free manner (match  $\rightarrow$  apply)
- all kind of models can be generated
- BCSL example:

```
S{u}::KaiC::KaiC6::cyt <=> S{p}::KaiC::KaiC6::cyt
```

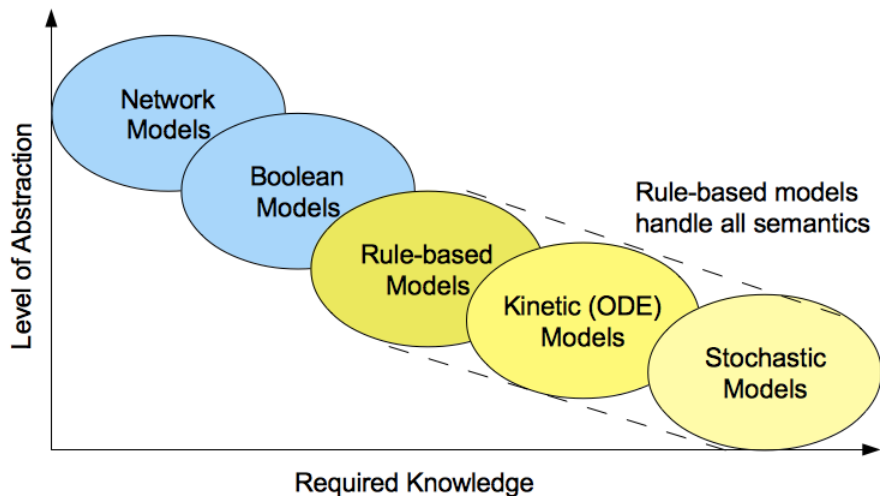
executes on any serine site of any KaiC in a hexamer

### Other Languages

- Kappa, BNGL, Chromar, LBS, ... (rule-based)
- SPiM, BioSPI, ... (process-algebraic)



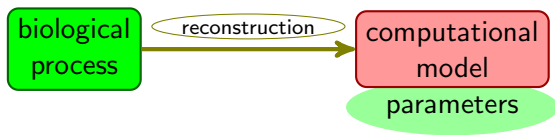
# Required Knowledge



# Model Construction

## Dealing with Unknown Parameters

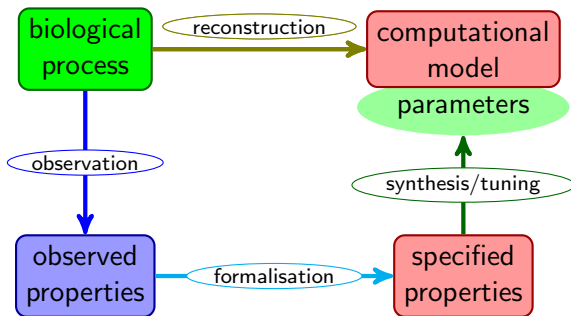
- traditional approaches – parameter estimation  
⇒ finding a single “optimal” value fitting experimental data



# Model Construction

## Dealing with Unknown Parameters

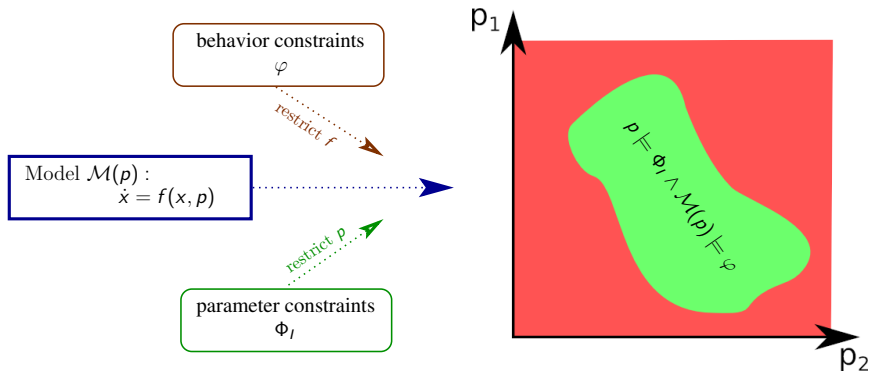
- traditional approaches – parameter estimation  
⇒ finding a single “optimal” value fitting experimental data
- computer science approach – **parameter synthesis**  
⇒ finding values satisfying given dynamical properties/hypotheses



- qualitative properties (LTL, CTL, HCTL)
  - modalities (possibilities/necessities in future behaviour)
  - reachability of particular (sets of) states
  - temporal ordering of events, monotonicity
  - temporal correlations of model variables
  - stability (attractors, basins of attraction)
- quantitative properties
  - deterministic (MTL, MITL, STL, STL\*)
    - enhance modalities with (dense) time information
    - exact timing of events, time-bounds
    - value-freezing (HSB 2012)
  - stochastic (PLTL, PCTL, CSL)
    - probability of property satisfaction
    - stochasticity combined with time

# Problem Formulation

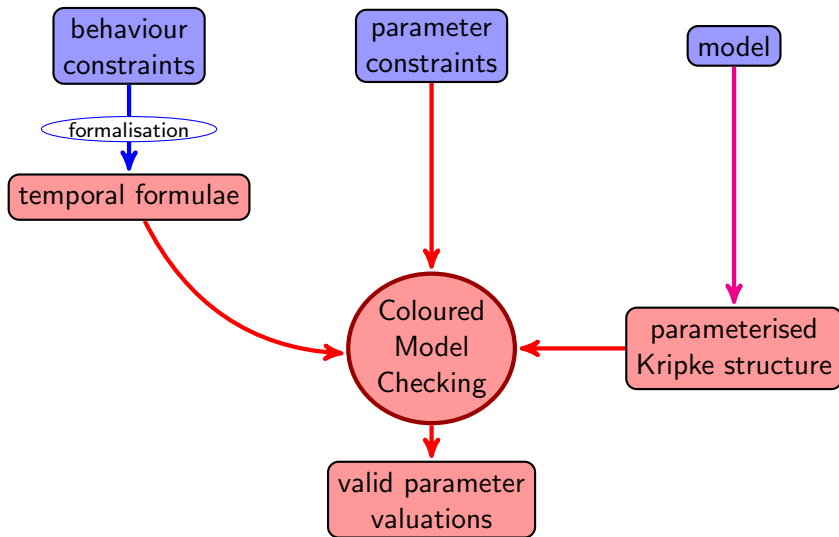
## Parameter Synthesis for Dynamical Systems



### Parameter Synthesis Problem

Assume  $\mathcal{P}$  is the admissible **parameter space**. Given a *behaviour constraint*  $\varphi$ , *parameter constraint*  $\Phi_I$ , and a *parameterised model*  $\mathcal{M}$ , **find the maximal set**  $P \subseteq \mathcal{P}$  **of parameterisations** such that  $p \models \Phi_I$  and  $\mathcal{M}(p) \models \varphi$  for all  $p \in P$ .

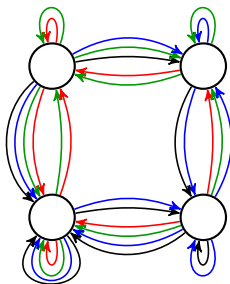
# Parameter Synthesis Workflow



# Parameterised Kripke Structures

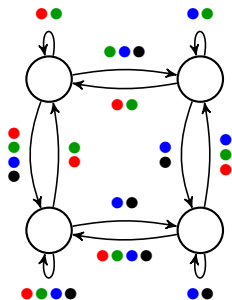
## State Transition Systems with Parameters

### Transitions with Parameters (coloured transitions)



- each parameter valuation represents one Kripke structure
- shared state space, different transition space

### Transitions with Parameters (coloured transitions)



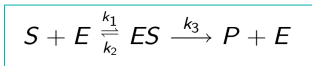
- each parameter valuation represents one Kripke structure
- shared state space, different transition space
- symbolic representation of parameters
- symbolic PKS: every transition is associated with a formula



# From ODE Models to Kripke Structures

## Rectangular Abstraction of Reaction Kinetics

[Belta, Habets, Schuppen]



mass action kinetics

with limitation of 1 molecule per each reactant species

multi-affine ODEs

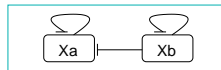
$$\begin{aligned} \frac{d[S]}{dt} &= -k_1[E][S] + k_2[ES] \\ \frac{d[E]}{dt} &= -k_1[E][S] + k_2[ES] + k_3[ES] \\ \frac{d[ES]}{dt} &= k_1[E][S] - k_2[ES] - k_3[ES] \\ \frac{d[P]}{dt} &= k_3[ES] \end{aligned}$$

set discrete value domains per each variable



## Rectangular Abstraction of Regulatory Kinetics

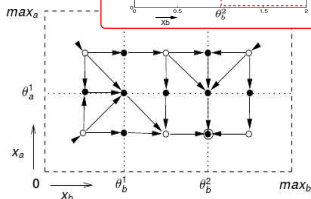
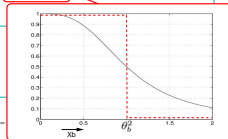
[de Jong, Batt]



Hill kinetics

piece-wise affine ODEs

$$\begin{aligned} \frac{dx_a}{dt} &= \kappa_a s^-(x_a, \theta_a^1) s^-(x_b, \theta_b^1) - \gamma_a x_a \\ \frac{dx_b}{dt} &= \kappa_b s^-(x_b, \theta_b^2) - \gamma_b x_b \end{aligned}$$



# Coloured Model Checking

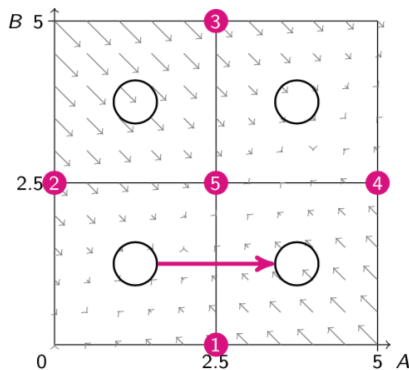
## Symbolic Parameter Space

$$\frac{dA}{dt} = -k_1 \cdot A + k_2 \cdot B$$

$$\frac{dB}{dt} = k_1 \cdot A - k_2 \cdot B$$

$$k_2 = 0.8$$

$$k_1 = ?$$



$$\Phi_{\text{state00} \rightarrow \text{state10}} := -2.5 \cdot k_1 > 0 \vee -2.5 \cdot k_1 + 2.5 \cdot k_2 > 0$$

The transition exists if and only if the formula is **satisfiable**.

Local parameter constraints are **predicates over reals**.

# Pithya Tool

The screenshot displays the Pithya Tool web interface. At the top, there are several control panels:

- number of arrows:** A slider ranging from 10 to 100, currently set at 30.
- parameter  $\gamma_{pRB}$ :** A slider ranging from 0 to 1.0, currently set at 0.014.
- parameter  $\gamma_{pEF1}$ :** A slider ranging from 0 to 1.0, currently set at 0.014.
- height of plots:** A slider ranging from 200 to 300, currently set at 250.
- horizontal axis in plot 1:** A dropdown menu set to "pRB".
- vertical axis in plot 1:** A dropdown menu set to "EF1".
- horizontal axis in plot 2:** A dropdown menu set to "pRB".
- vertical axis in plot 2:** A dropdown menu set to "EF1".

Below these panels are additional controls:

- coloring threshold:** A slider ranging from 0 to 1.0, currently set at 0.1.
- coloring direction:** Radio buttons for "horizontal", "vertical", and "both", with "both" selected.
- choose .bio file:** A file selection area showing "s/haide1\_1P\_0002.bio" and an "Upload complete" button.
- choose .psm file:** A file selection area showing "bb/resisttime.psm" and an "Upload complete" button.
- Download image:** A button to download the current plot.

The main area contains two plots:

- Left Plot:** A large plot showing a grid of arrows. The horizontal axis is labeled "pRB" and the vertical axis is labeled "EF1". The plot is divided into two regions: a green region on the left and a red region on the right, separated by a diagonal boundary.
- Right Plot:** A zoomed-in plot of the same data. The horizontal axis is labeled "pRB" and the vertical axis is labeled "EF1". The plot shows a grid of arrows with a blue rectangular box highlighting a specific region.

<http://pithya.ics.muni.cz>

[CAV 2017]

## 1 Introduction and Motivation

## 2 Methodology

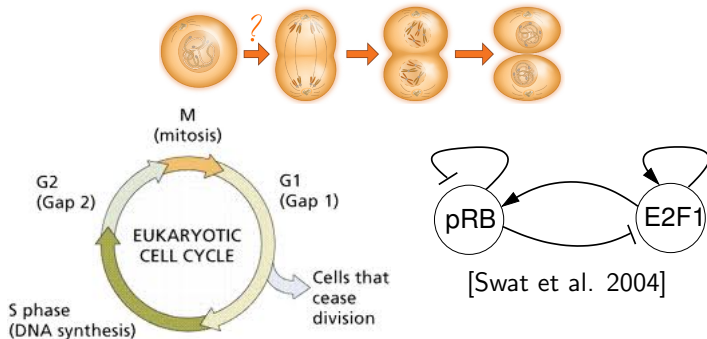
- Biological Networks
- Modelling Problems

## 3 Case Study

# Case Study: Cell Cycle Control System

*Example:* decision making in living cells

— *to divide or not to divide?*



decisions implemented by circuits of positive and negative interactions  
modelling of cell cycle since 1970 [Goldbetter et al.]

# Case Study: Cell Cycle Control System

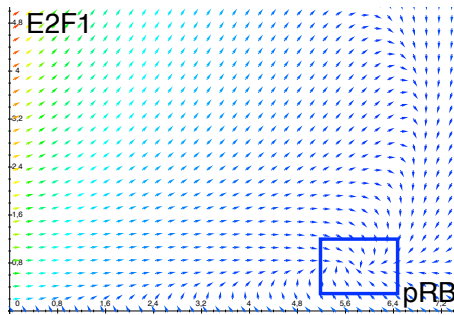
## Parameterised Non-Linear Mathematical Model

$f$  ... phase space (vector field),  $f : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n$

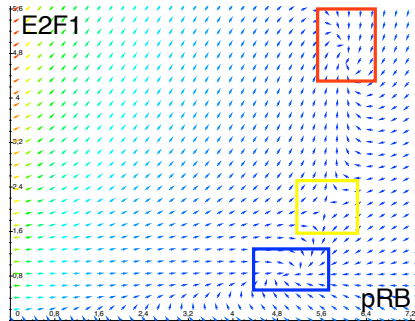
$$\dot{x} = f(x(t), p)$$

$x$  ... state vector ( $\mathbb{R}^n$ )

$p$  ... parameter vector ( $\mathbb{R}^m$ )



$p = 0.006$



$p = 0.012$

# Properties Specification: HCTL

- HCTL — hybrid CTL with past
- state formulae

$$\varphi ::= \text{true} \mid p \mid \neg\varphi \mid \varphi \wedge \varphi \mid \mathbf{E}\psi \mid \mathbf{A}\psi \mid \\ \hat{\mathbf{E}}\psi \mid \hat{\mathbf{A}}\psi \mid x \mid \downarrow x.\varphi \mid @x.\varphi \mid \exists x.\varphi$$

- path formulae

$$\psi ::= \mathbf{X}\varphi \mid \varphi \mathbf{U}\varphi$$

## *Single-state patterns*

- sink (stable steady state):  $\downarrow s. \mathbf{AX} s$
- source (only self-loops, no other incoming):  $\downarrow s. \hat{\mathbf{A}}\mathbf{X} s$

## *Multi-state patterns*

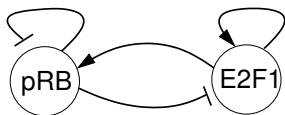
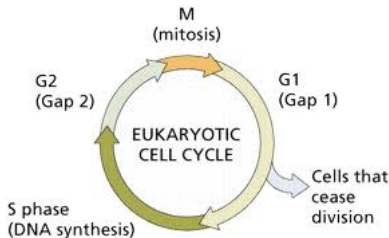
- state in a nontrivial SCC:  $\downarrow s. \mathbf{EX EF} s$
- state in a final SCC (generalised sink):  $\downarrow s. \mathbf{AG EF} s$

## *Relations among patterns*

- at least two sinks in the whole system:  
 $\exists s. \exists t. (\@s. \neg t \wedge \mathbf{AX} s) \wedge (\@t. \mathbf{AX} t)$



# Case Study: Regulation of $G_1/S$ Cell Cycle Transition



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

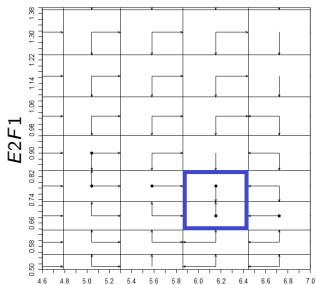
$$\frac{d[E2F1]}{dt} = k_p + k_2 \frac{a^2 + [E2F1]^2}{K_{m2}^2 + [E2F1]^2} \frac{J_{12}}{J_{12} + [pRB]} - \phi_{E2F1} [E2F1]$$

[Swat et al. 2004]

unknown parameter:  $\phi_{pRB}$

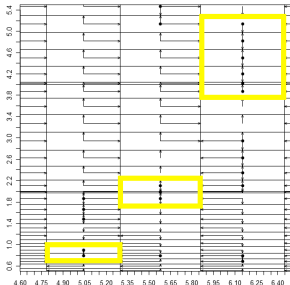
- $\varphi_1 := \exists s. \exists t. (\textcircled{s}. \mathbf{AG EF s}) \wedge (\textcircled{t}. \neg \mathbf{EF s} \wedge \mathbf{AG EF t})$
- $\varphi_2 := \neg \varphi_1 \wedge \downarrow s. \mathbf{AG EF s} \wedge E2F1 < 4$
- $\varphi_3 := \neg \varphi_1 \wedge \downarrow s. \mathbf{AG EF s} \wedge E2F1 > 4$

# Case Study: Results



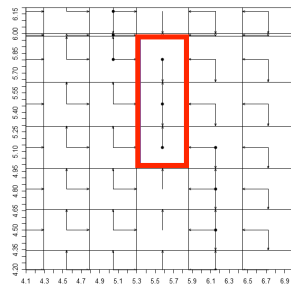
$\varphi_2$

$$\phi_{pRB} = 0.0075 \\ [0.002, 0.011]$$



$\varphi_1$

$$\phi_{pRB} = 0.0115 \\ [0.011, 0.0136]$$



$\varphi_3$

$$\phi_{pRB} = 0.014 \\ [0.0136, 0.5]$$

results agree with numerical methods up-to precision of approximation/discretisation

## Related Work

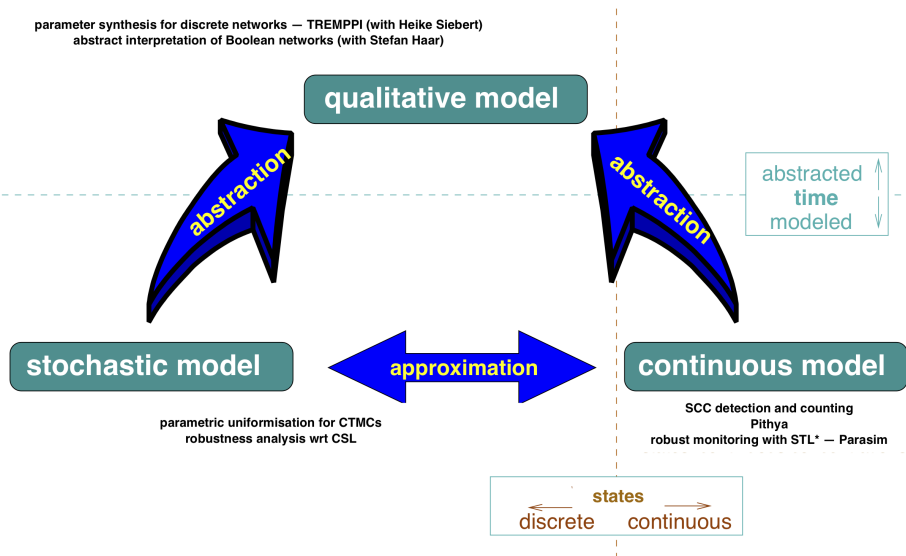
- Batt et al. 2007: *RoverGene*, BDD/Polytopes-based approach
- Batt et al. 2010: *GNA*, symbolic approach, piecewise affine
- Grosu et al. 2011: *RoverGene* revisited, approximation improved
- Bogomolov et al. 2015, *SpaceEx*, multi-affine hybrid automata

## Our Contribution

- HIBI 2010, TCCB 2012: **coloured LTL model checking**, piecewise multi-affine, parallel algorithm
- CMSB 2015: **coloured CTL model checking**, piecewise multi-affine, parallel algorithm
- ATVA 2016, CMSB 2016: parameters represented in first order logic, SMT solver employed, interdependent parameters
- HSB 2015, FM 2016: **discrete bifurcation analysis**
- CMSB 2017, ICCTCS 2018: analysis of terminal SCCs, application to cyanobacteria models
- TACAS 2019: application to bifurcation analysis of TCP

# Contribution Overview

parameter synthesis for discrete networks — TREMPPI (with Heike Siebert)  
abstract interpretation of Boolean networks (with Stefan Haar)



- using methods of computer science we can specify biological systems rigorously
- formal methods allow exhaustive exploration of models under parameter uncertainty
- use of formal methods is important for synthetic biology – we want to know what we construct!
- analysis becomes a push-button technology
- applications in cyber-physical systems
- problems:
  - the grand challenge not yet targeted
  - modellers trained in biophysics and computer science needed
  - scalability
  - we need methods giving results up to given precision instead of insisting on exact results
- Machine Learning to learn  $F_N$ ?

## Computer Science

Luboš Brim, Marta Kwiatkowska, Jiří Barnat, Thomas Henzinger, Loïc Paulevé, Ezio Bartocci, Luca Bortolussi, Jérôme Feret, Andrzej Mizera, Alessandro Abate, Jan Van Schuppen, Milan Češka, Nikola Beneš, Stefan Haar, Heike Siebert, Hidde de Jong, Ivana Černá

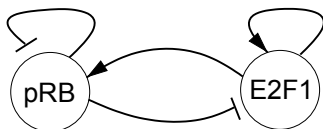
## Biology

Ralf Steuer, Louis Mahadevan, Jan Červený, Dušan Lazár, Pavel Krejčí, Stefanie Hertel, Christoff Flamm

## Students

- Samuel Pastva, Matej Troják, Sven Dražan, Jana Dražanová, Martin Demko, Matej Hajnal
- Tomáš Vejpustek, Juraj Kolčák, Jan Papoušek, Vojtěch Brůža, Juraj Nižnan, Lukrécia Mertová, Petr Dluhoš, Simon Van Goethem

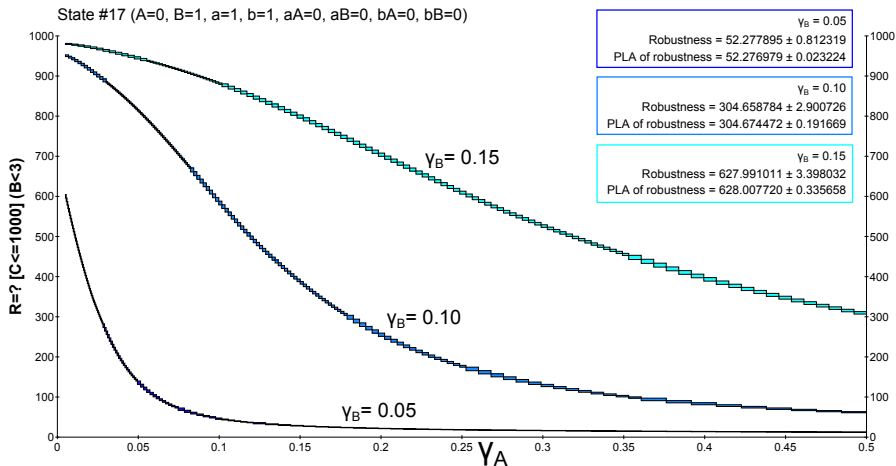
# Parameter Exploration of Stochastic Models



Gene a interactions		Gene b interactions	
$a \rightarrow a + A$	1	$b \rightarrow b + B$	0.05
$aB \rightarrow aB + A$	1	$bB \rightarrow bB + B$	1
$A + a \leftrightarrow aA$	100; 10	$A + b \leftrightarrow bA$	100; 10
$B + a \leftrightarrow aB$	100; 10	$B + b \leftrightarrow bB$	100; 10
Proteins degradation			
$A \rightarrow$	$\gamma_A$	$B \rightarrow$	$\gamma_B$

- CTMC with 1078 states and 5919 transitions
- hypothesis about stability of B in low/high population
  - expected time spent in states with low/high population of B
  - formalization in CSL using cumulative rewards
  - $R_{=?}[C^{\leq 1000}](B < 3)$ ,  $R_{=?}[C^{\leq 1000}](B > 7)$

## Robustness analysis - stability in low population of B

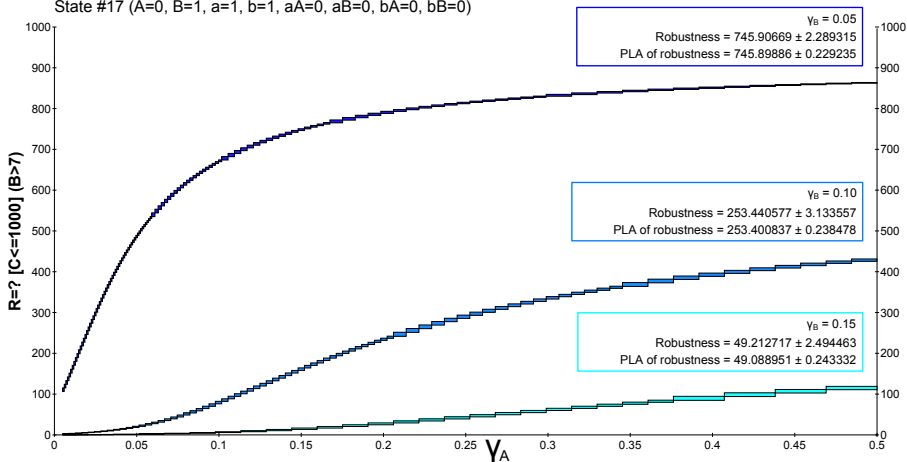


- in average  $3.0 \cdot 10^6$  reaction steps, 100 subspaces, 7 hours



## Robustness analysis - stability in high population of B

State #17 (A=0, B=1, a=1, b=1, aA=0, aB=0, bA=0, bB=0)



● in average  $3.0 \cdot 10^6$  reaction steps, 100 subspaces, 7 hours