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MICROCOSME: bacterial systems biology

 MICROCOSME: systems biology group at INRIA/Université Grenoble Alpes in Grenoble

Microbiologists, computer scientists, mathematicians, physicists, ...



https://team.inria.fr/microcosme



- **Objective:** analysis, engineering, and control of the growth of bacteria
 - Specific research problems shaped by **biological questions**
 - Problems often addressed by combination of models and experiments



Overview

- Part 1. Systems biology and kinetic modeling
 - Introduction
 - Kinetic modeling of cellular reaction networks
- Part 2. Metabolic network modeling
 - Kinetic modeling of metabolism
 - Metabolic control analysis (MCA)
 - Flux balance analysis (FBA)
 - Practical on flux balance analysis (COBRA)
- Part 3. Gene regulatory network modeling



Biochemical reaction networks

• ODE model for growth of microbial populations:

$$\dot{x} = N \cdot v(x) - \mu \cdot x,$$
$$\mu = \delta \cdot \sum_{i} \alpha_{i} \cdot N_{i} \cdot v(x).$$



• Reaction rates depend on concentrations *x* of substrates, products, effectors



Metabolic networks

- Focus on **subsystems** that can be studied in isolation due to **modular structure** of reaction networks
 (Changing) carbon
 - Time-scale hierarchies
 - Connectivity structure
- Metabolic networks
 - Metabolites and enzymatic reactions
 - Short turn-over times of metabolite pools in comparison with enzyme pools



Kotte et al. (2010), Mol. Syst. Biol., 6: 355



Metabolic networks

- Models describing dynamics of metabolism
 - Effect of growth dilution can often be ignored
 - Variables are metabolites and rates of enzyme-catalyzed reactions
 - Enzyme concentrations constant on time-scale of metabolic dynamics

$$\dot{x} = N v(x)$$



Stoichiometry matrix

- Stoichiometry matrix N describes structure of reaction network

Internal reactions and exchange reactions, reversible and irreversible



Schilling et al. (2000), J. Theor. Biol., 203(3):229-48



• Steady state of metabolic network

Nv = 0

Steady-state reaction rates are called **fluxes**

• **Constraints** on fluxes: upper and lower bounds

$$v^l \le v \le v^u$$

- Bounds on fluxes derived from available information in literature, bounds may be infinite
- For mathematical convenience, all fluxes must be positive $v\geq 0$
- Reversible reaction modeled as pair of irreversible, positive fluxes



• Steady state of metabolic network

Nv = 0

- Stoichiometry matrix and constraints define convex space of possible solutions: flux cone
 - System of steady-state equations underdetermined: more reactions than concentrations variables.
 - Flux cone represents metabolic capabilities of network (possible flux distributions)



Stelling (2004), Curr. Opin. Microbiol., 7:513-8



• Steady state of metabolic network

Nv = 0

- Stoichiometry matrix and constraints define convex space of possible solutions: flux cone
 - System of steady-state equations underdetermined: more reactions than concentrations variables.
 - Every solution can be written as linear combination of rays of flux cone (extreme pathways)

$$C = \left\{ v \mid v = \sum_{i=1}^{n} w_i p^i, \ w_i \ge 0, \ i = 1, \dots, k \right\}$$

- p^i : extreme pathway *i*
- w_i : weigth of *i*th pathway



Stelling (2004), Curr. Opin. Microbiol., 7:513-8

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$$C = \{ v \mid v = \sum_{i=1}^{k} w_i p^i, w_i \ge 0, i = 1, \dots, k \}$$

 Set of extreme pathways unique, but solutions not uniquely defined by extreme pathways



Stelling (2004), Curr. Opin. Microbiol., 7:513-8



 Extreme pathways in example network

> Schilling et al. (2000), J. Theor. Biol., 203(3):229-48

- Extreme pathways provide pathwaybased view of network
- Related concept of elementary modes

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Schilling et al. (1999), Biotechnol. Prog., 15(3):296-303



(c)

(b)

(a)

			- 2		~ ~			
	[1	0	0	0	0	0	0]	v_1
	0	1	1	0	0	0	1	v_2
	0	0	0	1	0	0	1	v_3
	0	0	1	0	0	1	0	v_4
D	0	0	0	1	1	1	0	v5
P =	0	1	0	0	1	0	0	v_6
	-1	0	0	0	0	0	0	$\overline{b_1}$
	1	-1	-1	1	0	0	0	b_2
	0	0	1	-1	-1	0	0	b_3
	0	1	0	0	1	0	0	b_4

D.

p.

 \mathbf{p}_{s} \mathbf{p}_{6}

 \mathbf{p}_7

$\mathbf{v}^{\mathrm{T}} = [4\ 2\ 0\ 1\ 0\ 1 -$	421	1]

$${\bf p_1, p_2, p_3}$$

Null space dimensions of Smod:

$$d(\mathbf{S}_{mod}) = n - r(\mathbf{S}_{mod}) = 8 - 5 = 3$$

Unique decomposition of v: $w^{T} = [4 \ 1 \ 1 \ 0 \ 0 \ 0 \ 0]$ OF $\mathbf{v} = (4) \cdot \mathbf{p}_1 + (1) \cdot \mathbf{p}_2 + (1) \cdot \mathbf{p}_3$



• Steady state of metabolic network

Nv = 0

- Stoichiometry matrix and constraints define convex space of possible solutions: **flux cone**
- FBA aims at finding solutions maximising or minimising linear combination of fluxes: **objective function**

$$Z = c^T v \qquad \qquad c \in \mathbb{R}^n$$

- Typical objective function: biomass production
- Optimal solution: maximum growth rate under constraints on uptake rates





• Steady state of metabolic network

Nv = 0

- Stoichiometry matrix and constraints define convex space of possible solutions: **flux cone**
- FBA aims at finding solutions maximising or minimising linear combination of fluxes: **objective function**
- Constrained optimisation problem in mathematics
 - Use of LP (linear programming) for solving optimisation problem
 - COBRA toolbox for building and analysing FBA models

Palsson (2006), *Systems Biology: Properties of Reconstructed Networks*, Cambridge University Press Orth *et al.* (2010), *Nat. Biotechnol.*, 28(3):245-8



• Genome-scale reconstruction of *E. coli* metabolism



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- Genome-scale reconstruction of *E. coli* metabolism
- FBA predictions of flux distributions maximizing growth rate with acetate as carbon source
 - Given acetate and oxygen uptake rates, compute optimal growth rate
 - Experimental test of predicted line of optimality: control of acetate uptake rate → measurement of growth rate and oxygen uptake rate





Edwards et al. (2001), Nat. Biotechnol, 19(2):125-30



- Genome-scale reconstruction of *E. coli* metabolism
- FBA predictions of flux distributions maximising growth rate with acetate as carbon source
- Good correspondence of FBA predictions and experimental data suggests that *E. coli* metabolic network is optimised to maximise growth rate on acetate





Edwards et al. (2001), Nat. Biotechnol, 19(2):125-30



- In other cases, predicted optimal growth rate larger than observed growth rate
- However, experiments show that *E. coli* mutant undergoes adaptive evolution to achieve predicted optimal growth rate

Growth rate increases on different substrates



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Grenoble Alpe

Ibarra et al. (2002), Nature, 420(6912):186-9



- Genome-scale reconstruction of *E. coli* metabolism
- FBA predictions of flux distributions maximising growth rate with glucose as carbon source and fixed oxygen uptake rate
- Effect on growth rate when deleting genes in central carbon metabolism: essential genes and robustness



Edwards et al. (2000), Proc. Natl. Acad. Sci. USA, 97(10):5528-33



- Genome-scale reconstruction of *E. coli* metabolism
- FBA predictions of flux distributions maximising growth rate with glucose as carbon source and fixed oxygen uptake rate
- Good correspondence with data for gene deletions examined (86%), but less so for broader range of conditions (60%)
 Observed growth rate lower than predicted growth rate
- Not surprising: regulatory network of wild-type cells may not be optimal in mutant backgrounds!

Regulatory network selects actual flux distribution from possible flux distributions in flux cone



Regulatory flux balance analysis

• Steady-state dynamics of metabolic network

Nv = 0

- Stoichiometry matrix and constraints define convex space of possible solutions: flux cone
- Refinement of flux cone using additional constraints

Regulation of enzyme activity or expression, switching on/off extreme pathways



Covert et al. (2003), J. Theor. Biol., 221(3):309-25



- Regulatory network of wild-type cells may not be optimal in mutant backgrounds
- How do predictions change when including regulatory network?
- Genome-scale model of *E. coli* metabolism, including regulation of enzymatic genes
 - Boolean models relating expression of enzymatic genes to growth conditions



Covert et al. (2004), Nature, 429(6987):92-6



- Regulatory network of wild-type cells may not be optimal in mutant backgrounds
- Genome-scale model of *E. coli* metabolism, including regulation of enzymatic genes
- Prediction of growth rate in different mutants and growth conditions improved

60% vs 78%



Covert et al. (2004), Nature, 429(6987):92-6



Dynamic flux balance analysis

Dynamics of metabolic network through interactions with
 environment
 Substrate

$$\dot{s} = -v_{ext}(t) \cdot B, \quad s(0) = s_0$$

 $\dot{B} = \mu(t) \cdot B, \quad B(0) = B_0$

- *B* : biomass concentration in medium
- s : substrate concentration in medium
- μ : growth rate
- *v_{ext}* : substrate uptake rate
- Dynamics predicted by means of dynamic FBA
 - Metabolic network at quasi-steady state with respect to environment
 - Computation of exchange rates and growth rate by means of FBA at each time-point t
 - Change in substrate concentrations puts bounds on uptake rates





Dynamic flux balance analysis

Dynamics predicted by means of dynamic FBA
 Sequential growth of *E. coli* on different carbon sources (glucose, acetate)
 Orth *et al.* (2002), *Nat. Protocols*, 2(3):727-38





Monte-Carlo sampling of FBA solutions

- Stoichiometry matrix and constraints define convex space of possible solutions: **flux cone**
- FBA selects solutions from flux cone optimizing objective function, but no single solution
- Alternative approach: Monte-Carlo sampling of optimal solutions

Distributions for individual fluxes in network





Monte-Carlo sampling of FBA solutions

Analysis of glycolysis pathway in *E. coli* during growth on glucose





Monte-Carlo sampling of FBA solutions

- Analysis of glycolysis pathway in *E. coli* during growth on glucose
 - Tight distributions
 - Correlations between fluxes



Becker et al. (2007), Nat. Protocols, 2(3):727-38



Conclusion FBA

- FBA models provide genome-scale picture of metabolism and yield experimentally-testable predictions
 - Predictions of flux distributions in different growth conditions c and genetic backgrounds



Orth et al. (2010), Nat. Biotechnol., 28(3):245-8



Conclusion FBA

- FBA models provide genome-scale picture of metabolism and yield experimentally-testable predictions
 - Predictions of flux distributions in different growth conditions and genetic backgrounds
 - Tool for metabolic engineering
 - In *E. coli* and other (less well-characterised) organisms



Conclusion FBA

- But FBA has problems as well!
 - Practical question: which objective function works best for problem considered?
 - Fundamental question: what do microorganisms optimise?
 Schuetz et al. (2007), Mol. Syst. Biol., 3:119
 - Integration of regulatory mechanisms on metabolic and genetic level is not easy to achieve in FBA formalism
 - No predictions on dynamics on time-scale of metabolism



Internships in MICROCOSME

- Challenging problems for biologists, physicists, computer scientists, mathematicians, ...
- ... in a multidisciplinary working environment
- Contact: Hidde.de-Jong@inria.fr and https://team.inria.fr/ microcosme





Courtesy Antrea Pavlou (2021)



Thanks!



team.inria.fr/microcosme



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