

Introduction to Biological Modeling

Lecture 3: Metabolism
Oct. 6, 2010

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Last week

- modeling cellular dynamics
- minimizing necessary parameters
- eukaryotic cell cycle
- positive feedback, oscillations
- databases



Copasi software

Reading

Covert, Schilling, Famili, Edwards, Goryanin, Selkov, and Palsson
"Metabolic modeling of microbial strains *in silico*" *TRENDS in Biochemical Sciences* 26:179-186, 2001.

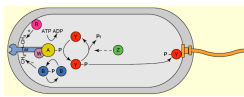
Klamt, Stelling, "Stoichiometric and constraint-based modeling" in *Systems Modeling in Cell Biology* edited by Szallasi, Stelling, and Periwai, MIT Press, Cambridge, MA, 2006.

1

Credit: Alberts, et al. *Molecular Biology of the Cell*, 3rd ed., 1994; http://www.aspencountry.com/product.asp?dept_id=460&pfid=35192.

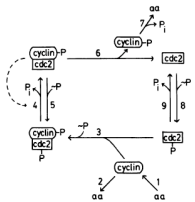
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Small biochemical networks

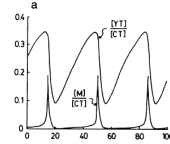


E. coli chemotaxis

few chemical species
few reactions
enough known parameters
simple dynamics
can build model by hand
can understand intuitively



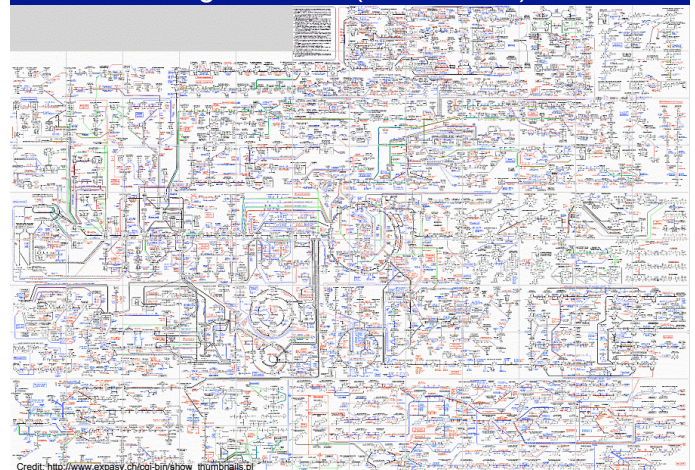
eukaryotic cell cycle



Credit: Andrews and Arkin, *Curr. Biol.* 16:R523, 2006; Tyson, *Proc. Natl. Acad. Sci. USA* 88:7328, 1991.

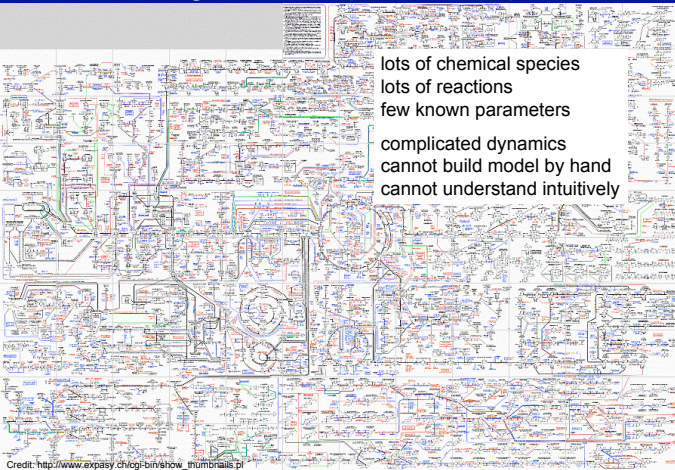
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Big networks (metabolism)



Credit: http://www.expsy.chgigi-bin/show_inumbra1a.pl

Big networks (metabolism)



lots of chemical species
lots of reactions
few known parameters
complicated dynamics
cannot build model by hand
cannot understand intuitively

Credit: http://www.expsy.chgigi-bin/show_inumbra1a.pl

What is and isn't known

A lot is known

- 100s of enzymes
- 100s of reactions
- 100s of metabolites

A lot is not known

- lots of enzymes, reactions, and metabolites
- most kinetic parameters
- most gene regulation

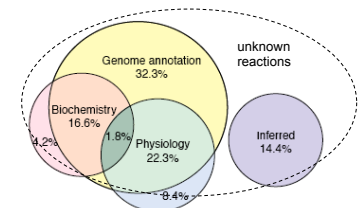
Databases

KEGG

Kyoto Encyclopedia of Genes and Genomes

BRENDA

Braunschweig Enzyme Database



reaction sources in a genome-scale *H. pylori* metabolism model

Credit: Covert et al. *TRENDS in Biochemical Sciences* 26:179, 2001

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Why study metabolism?

Basic science

- how do cells work?
- structure of complex networks

Medical

- metabolic disorders
- biosynthetic drugs (e.g. insulin)

Bioengineering

- biofuels
- bioremediation of waste
- enzyme production



Credits: <http://www.autobiogreen.com/2006/05/29/>; <https://fabibbio.wikispaces.com/Laundry+Detergents+and+Enzymes>

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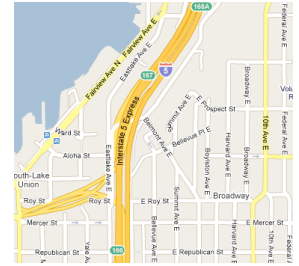
Other complex networks

biological

- food webs
- gene regulatory networks
- signaling networks

non-biological

- road maps
- physical internet (IP addresses)
- internet websites
- electronic circuits



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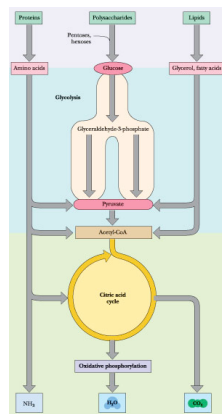
Metabolism quick overview

Anabolism

- biosynthesis of proteins, polysaccharides, lipids, etc.

Catabolism

- breakdown of proteins, polysaccharides, lipids, etc. to make energy



Nomenclature

- Constraint-based modeling
- Pathway analysis
- Metabolic control analysis
- Copasi
- Summary

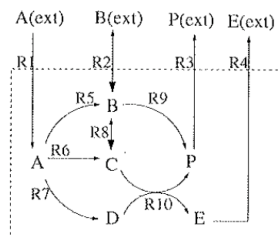
credit: <http://web.virginia.edu/Heidi/chapter18/chp18.htm>

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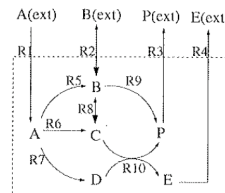
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Terminology

- stoichiometry
- internal, external metabolites
- reversible, irreversible reactions
- enzyme catalysis
- flux

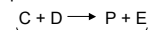


Stoichiometric matrix



Reaction network can be summarized in a matrix

Columns list reaction stoichiometry
Example for reaction R10:



reactions

Rows list internal metabolite sources and sinks

$$N = \begin{bmatrix} 1 & 0 & 0 & 0 & -1 & -1 & -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & -1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & -1 \\ 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \begin{matrix} \leftarrow A \\ \leftarrow B \\ \leftarrow C \text{ internal} \\ \leftarrow D \text{ metabolites} \\ \leftarrow E \\ \leftarrow P \end{matrix}$$

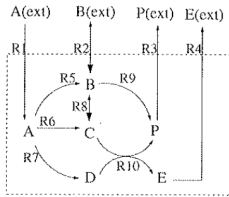
↑ ↑ ↑ ↑ ↑ ↑ ↑ ↑ ↑ ↑
R1 R2 R3 R4 R5 R6 R7 R8 R9 R10

Credit: Klamt and Stelling in *System Modeling in Cellular Biology* ed. Szallasi et al., p. 73, 2006.

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Dynamical model



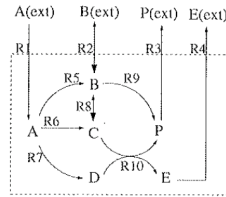
Dynamics for A

$$\frac{d[A]}{dt} = 1 \cdot r_1(t) - 1 \cdot r_5(t) - 1 \cdot r_6(t) - 1 \cdot r_7(t)$$

reaction rates (fluxes)

$r_1(t)$ = rate of reaction R1
 $r_2(t)$ = rate of reaction R2
 ...
 $r_{10}(t)$ = rate of reaction R10

Dynamical model



Dynamics for A

$$\frac{d[A]}{dt} = 1 \cdot r_1(t) - 1 \cdot r_5(t) - 1 \cdot r_6(t) - 1 \cdot r_7(t)$$

reaction rates (fluxes)

$r_1(t)$ = rate of reaction R1
 $r_2(t)$ = rate of reaction R2
 ...
 $r_{10}(t)$ = rate of reaction R10

math

$$\frac{d}{dt} \begin{bmatrix} [A] \\ [B] \\ [C] \\ [D] \\ [E] \\ [P] \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & -1 & -1 & -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & -1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} r_1(t) \\ r_2(t) \\ r_3(t) \\ r_4(t) \\ r_5(t) \\ r_6(t) \\ r_7(t) \\ r_8(t) \\ r_9(t) \\ r_{10}(t) \end{bmatrix}$$

stoichiometric matrix

$$\frac{dc}{dt} = N \cdot r(t)$$

c = metabolite concentrations
N = stoichiometric matrix
r(t) = reaction rate vector

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Nomenclature

Constraint-based modeling

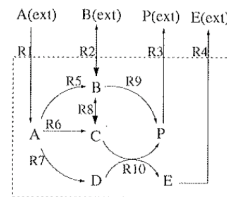
Pathway analysis

Metabolic control analysis

Copasi

Summary

Constraint-based modeling



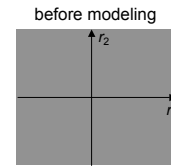
Main idea

We can infer a lot about the fluxes, just from the diagram (and assumptions).

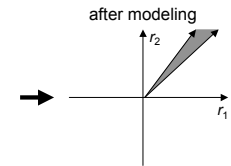
- can predict metabolite production rates
- can infer missing reactions
- improves network understanding

flux space

1 dimension for each reaction (10 here)



everything is possible



a few things are possible

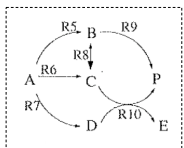
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Constraint 0: conservation relations

Some metabolite concentrations always change together

Biology



$$[A] + [B] + [C] + [D] + [E] + [P] = \text{constant}$$

6 metabolites
5 degrees of freedom

traffic analogy



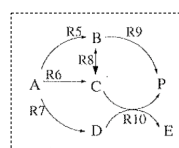
total number of cars on island is constant

Conservation relations are always true (regardless of dynamics, reaction directionality, etc.)

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Constraint 0: conservation relations - math

Example



$$[A] + [B] + [C] + [D] + [E] + [P] = \text{constant}$$

6 metabolites
5 degrees of freedom

Conservation relations arise when rows of the stoichiometric matrix are linearly dependent

$$N = \begin{bmatrix} R5 & R6 & R7 & R8 & R9 & R10 \\ -1 & -1 & -1 & 0 & 0 & 0 \\ 1 & 0 & 0 & -1 & -1 & 0 \\ 0 & 1 & 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \begin{matrix} A \\ B \\ C \\ D \\ E \\ P \end{matrix}$$

i.e. there exists y^T for which:

$$y^T N = 0$$

In this case, the only solution is

$$y^T = [1 \ 1 \ 1 \ 1 \ 1 \ 1]$$

which implies

$$[A] + [B] + [C] + [D] + [E] + [P] = \text{constant}$$

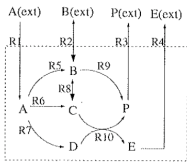
y^T is the left null-space of **N**

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Constraint 1: steady-state assumption

If system is at steady state, fluxes into and out of each metabolite are equal.

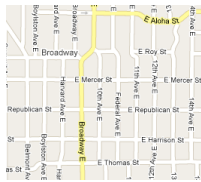
biology



true when metabolic reactions are much faster than:

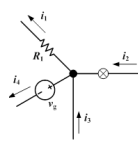
- external metabolite changes
- internal gene regulation

traffic analogy



the same number of cars enter and leave each intersection.

electronics

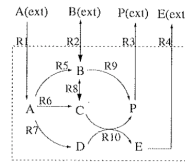


current entering and leaving a junction are equal (Kirchhoff's law)

Constraint 1: steady-state assumption

If system is at steady state, fluxes into and out of each metabolite are equal.

biology



Uses:

- identifies "dead-end" metabolites, which show network mistakes
- in computer modeling

math

$$\frac{d[A]}{dt} = 0 \quad 0 = \frac{dc}{dt} = N \cdot r(t)$$

$$\frac{d[B]}{dt} = 0 \quad N \cdot r = 0$$

$$\frac{d[P]}{dt} = 0 \quad r \text{ is null-space of } N$$

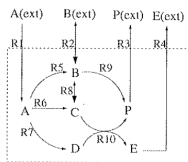
$$r = \begin{bmatrix} 2 & 0 & -1 & 1 \\ 0 & 1 & 1 & -1 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & -1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \begin{matrix} R1 \\ R2 \\ R3 \\ R4 \\ R5 \\ R6 \\ R7 \\ R8 \\ R9 \\ R10 \end{matrix}$$

Only possible fluxes are proportional to a column of r , or a sum of columns.

Constraint 2: reaction direction, capacity

flux *signs* are known for irreversible reactions
flux *values* may be limited

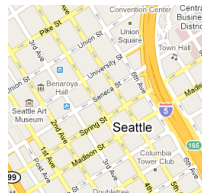
biology



irreversible reactions
 V_{max} for enzymes
max. transport rates

e.g. $r_1 > 0$

traffic analogy

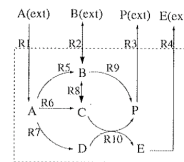


traffic is limited by:
one-way roads
maximum road capacity

Constraint 2: reaction direction, capacity

flux *signs* are known for irreversible reactions
flux *values* may be limited

biology



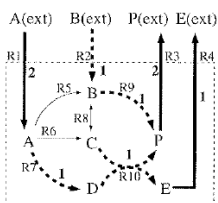
irreversible reactions
 V_{max} for enzymes
max. transport rates

math

$$\begin{bmatrix} 0 \\ -\infty \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ -\infty \\ 0 \end{bmatrix} \leq r \leq \begin{bmatrix} 1 \\ 0 \\ \infty \\ \infty \\ \infty \\ \infty \\ \infty \\ \infty \\ \infty \\ \infty \end{bmatrix} \begin{matrix} R1 \\ R2 \\ R3 \\ R4 \\ R5 \\ R6 \\ R7 \\ R8 \\ R9 \\ R10 \end{matrix} \quad \left. \vphantom{\begin{matrix} 0 \\ -\infty \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ -\infty \\ 0 \end{matrix}} \right\} \text{assumes only A is available}$$

Constraint 3: experimental data

Flux measurements can constrain system



Measure (bold lines):
 $R1 = R3 = 2, R4 = 1$

Infer (dashed lines):
 $R2 = R7 = R9 = R10 = 1$

Don't know (thin lines):
 $R5, R6, \text{ or } R8$

traffic analogy



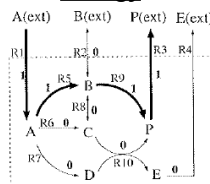
"Constraint" 4: optimization

Assume network has evolved to be "optimal"

Popular choices:

- maximum growth rate per substrate consumed
- total flux is minimized (to minimize enzyme synthesis)
- for mutants, least change from wild type

biology



We believe the network evolved to maximize P output. Thus, if it's just fed A, the fluxes must be as shown (except for $R5, R6, R8$ uncertainty).

traffic analogy



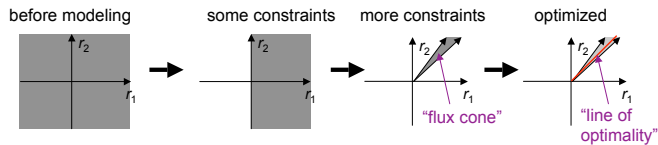
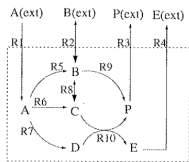
Assume everyone drives the shortest route possible.

i.e. total flux is minimized

Constraint-based modeling summary

Constraints

0. conservation relations
1. steady state assumption
2. max. and min. fluxes
3. experimental data
4. optimization

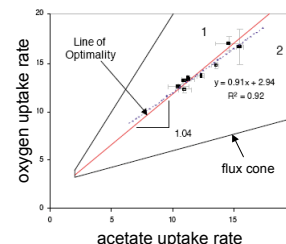
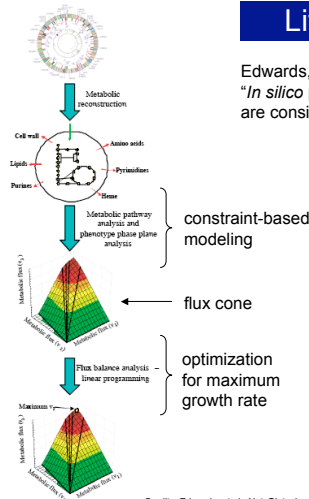


From the reaction network, and some assumptions, we can estimate most reaction fluxes.

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Literature example

Edwards, Ibarra, and Palsson, 2001
 "In silico predictions of *E. coli* metabolic capabilities are consistent with experimental data"



Result

- constraint-based modeling and optimization based on growth rate yields fluxes that agree with experiment

Credits: Edwards, et al., Nat. Biotechnol. 19:125, 2001.

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Nomenclature

Constraint-based modeling

Pathway analysis

Metabolic control analysis

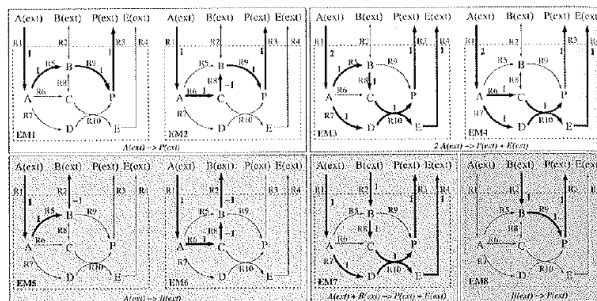
Copasi

Summary

Pathways

Elementary flux mode

a path through the network that cannot be simplified (and obeys constraints like steady-state, reaction directionality, etc.)



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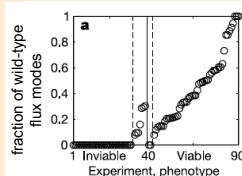
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Pathway applications

Removing all essential pathways leads to inviability

- helpful for understanding mutants
- good for designing drug targets

Stelling et al. (2002) showed high correlation between fraction of flux modes available in mutants and viability. No flux modes implied inviable.



Pathways help build intuition

- in all biochemistry texts

For further analysis

- The minimal set of elementary flux modes are the "eigenvectors" of the network

Nomenclature

Constraint-based modeling

Pathway analysis

Metabolic control analysis

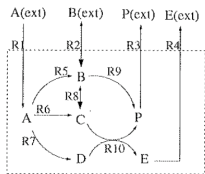
Copasi

Summary

Metabolic control analysis

Metabolic control analysis is sensitivity analysis of the reaction network. Same constraints (steady-state, reaction directionality, etc.)

biology



we want to make E from A, will doubling enzyme 10 help? what about knocking out enzyme 9?

traffic analogy



if Mercer Street is widened, will that fix congestion? Or just move it to the next traffic light?

Credit: http://www.cityofseattle.net/transportation/ppmp_mercer.htm

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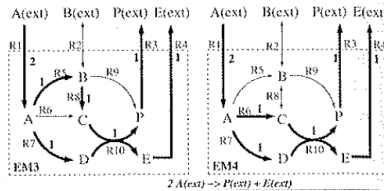
Metabolic control analysis

Common misconception

- There is one rate-limiting step

Truth

- Lots of reactions affect total production rate
 - upstream reactions in pathway
 - downstream reactions due to product inhibition



Math

Flux control coefficient is effect of enzyme amount on flux:

$$C_{R_{10}}^{R_4} = \frac{\partial \ln r_4}{\partial \ln [E_{10}]}$$

r_4 is flux in reaction R4, $[E_{10}]$ is enzyme amount in R10.

Flux control coefficients are usually between 0 and 1:
 $C_{R_{10}}^{R_4} = 0$ R10 has no effect
 $C_{R_{10}}^{R_4} = 1$ R10 is rate-limiting

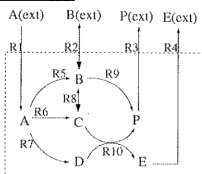
Typical flux control coefficients are 0 to 0.5, with several enzymes sharing most of the control on any flux.

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Metabolic control analysis - substrate conc.

What happens if an external metabolite concentration changes?

biology



we want to make E from A, should we increase [A]? does [P] matter?

Response coefficient: $R_{[A(ext)]}^{R_4} = \frac{\partial \ln r_4}{\partial \ln [A]}$

Found by summing control coefficients and "enzyme elasticities" for each enzyme

traffic analogy



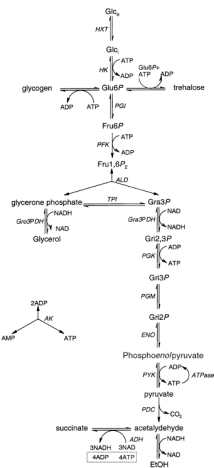
how will traffic change after a football game ends?

- Nomenclature
- Constraint-based modeling
- Pathway analysis
- Metabolic control analysis
- Copasi**
- Summary

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Metabolic modeling example



Pritchard and Kell (2002) investigated flux control in yeast glycolysis

They used Gepasi (predecessor to Copasi). This is a Copasi example file: YeastGlycolysis.cps

In Copasi, it's easy to find:

- stoichiometric matrix
- constraint 0: mass conservation
- steady-state concentrations
- elementary flux modes
- metabolic control analysis coefficients

Credit: Pritchard, Kell, Eur. J. Biochem. 269:3894, 2002.

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- Nomenclature
- Constraint-based modeling
- Pathway analysis
- Metabolic control analysis
- Copasi
- Summary**

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Summary

Big networks

Useful databases for metabolism
KEGG, BRENDA

Stoichiometric matrix

math representation of network

Constraint-based modeling

0. mass conservation
1. steady-state assumption
2. reaction min. & max. fluxes
3. experimental data
4. optimize

Metabolic Control Analysis

sensitivity of fluxes to parameters

Simulation tools

Copasi does many of these tasks

Homework

Next week's class is on gene regulatory networks.

Class will be in room B1-072/074

Read

Milo, Shen-Orr, Itzkovitz, Kashtan, Chklovskii, and Alon,
"Network motifs: Simple building blocks of complex networks"
Science 298:824, 2002.