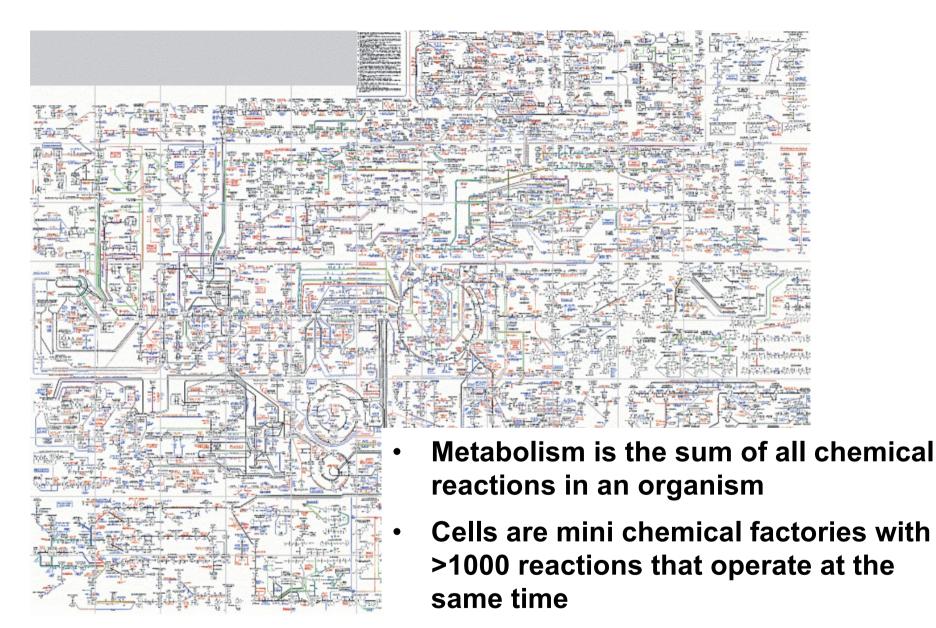
Introduction to Metabolism

Uwe Sauer, ETH Zurich

- Structure & principles of metabolic networks
- Quick glance at key pathways & principles of energy generation
- Mechanisms of regulating metabolic flux
- How to assess metabolic fluxes?





 Highly conserved from bacteria to humans

Two Levels to Aid Understanding Metabolism

Reaction level: kinetics/thermodynamics

 $[E] \bullet k_{cat} \bullet \frac{[S]}{k_m + [S]} = reaction rate (flux)$ Speed

 $\Delta G = \Delta G^{0'} + RT \ln [ATP] / [ADP] \cdot [P_i]$

Direction

The standard free energy of ATP hydrolysis is 30.5 kJ/mol. *In vivo* it is more like 50 kJ/mol.

Network level: structure

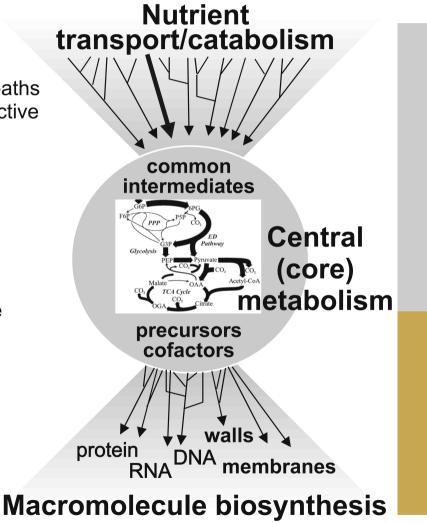
Simple structure from birds eye

Complicated but Structured

- linear
- convergent
- few connections
- typically one or few paths are simultaneously active
- one-way flux

- many cycles
- many connections
- redundant
- flux direction variable
- ubiquitous

- linear
- divergent
- few connections



Catabolism

- Catabolic pathways release energy by breaking down complex molecules into simpler compounds (eg respiration)
- Thermodynamically downhill (mostly!)

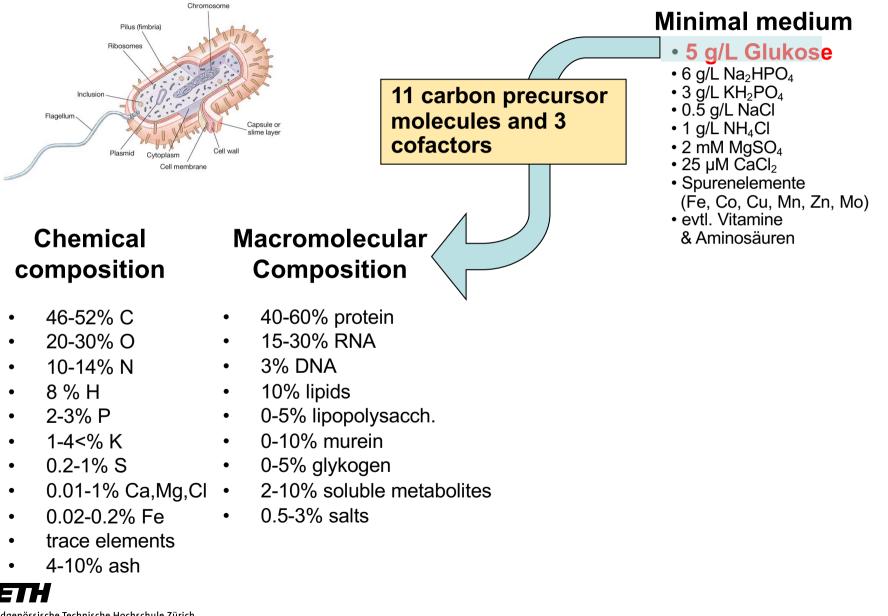
Anabolism

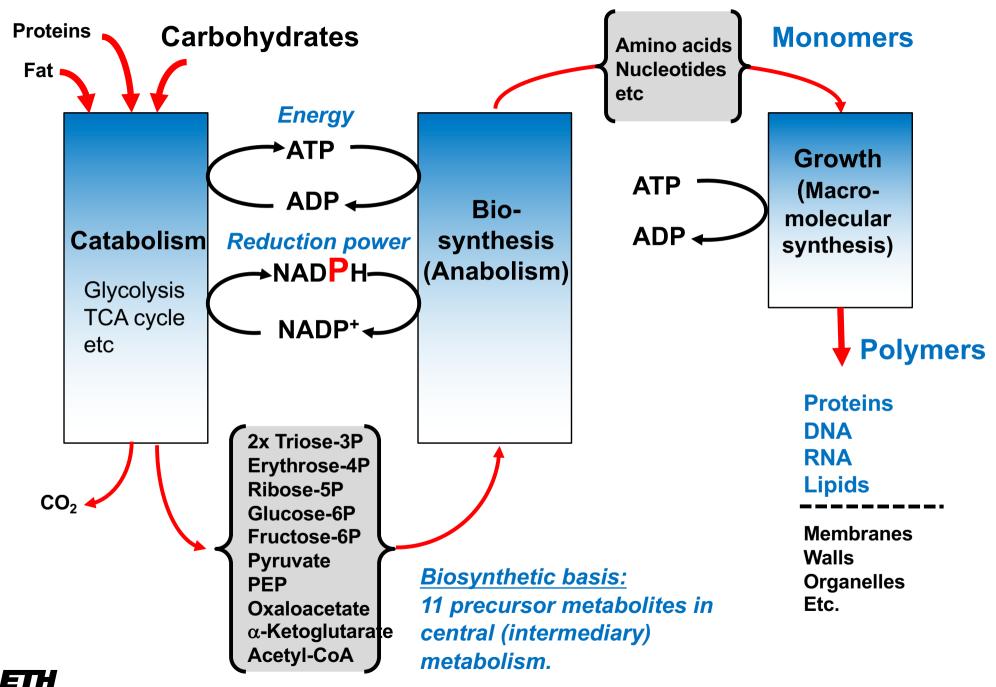
- Anabolic pathways consume energy to build complex molecules from simpler Ones (eg protein synthesis from amino acids)
- Thermodynamically uphill (in general)

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What is Needed to Make a Microbe

(as an example for cells that can make everything from one C source) **Typical Cell Composition**

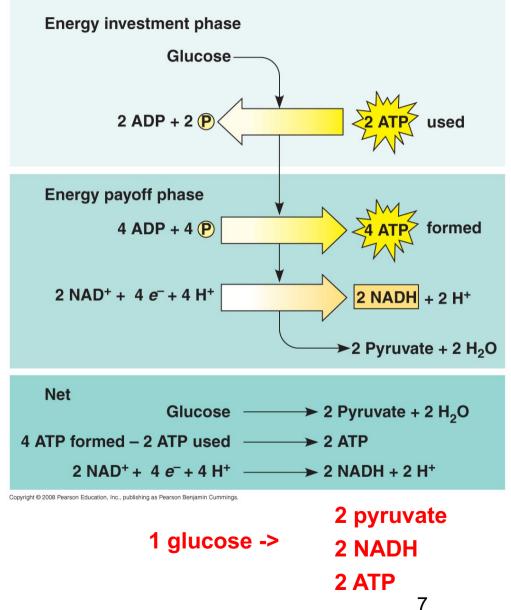


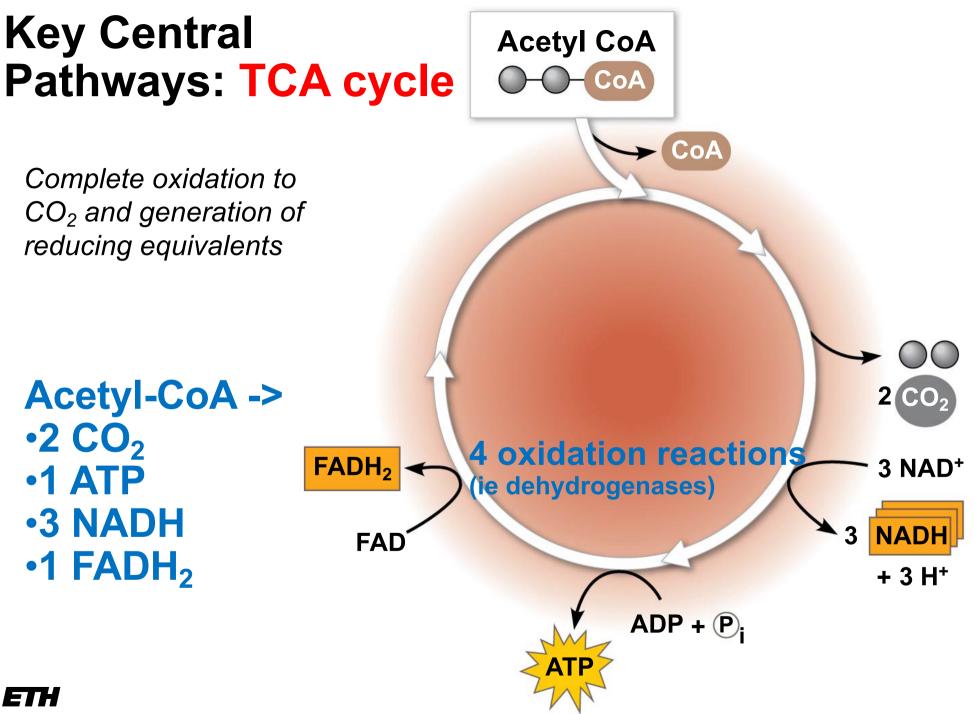


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Key Central Metabolic Pathways: Glycolysis

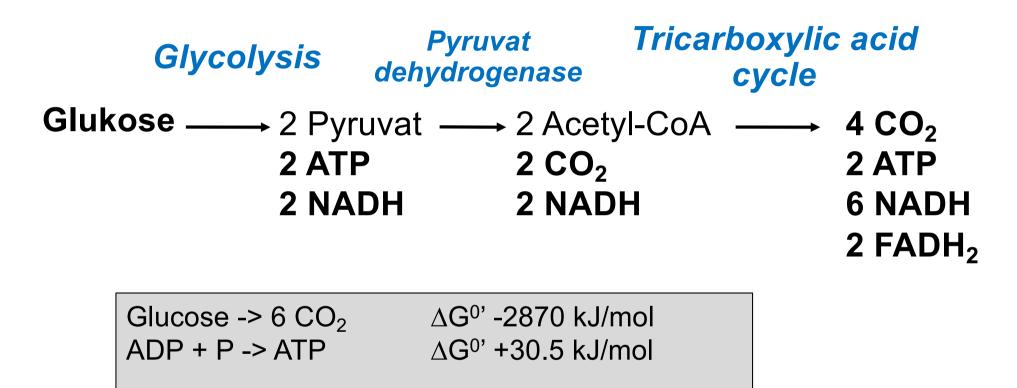
- Glycolysis ("splitting of sugar") breaks down glucose into two molecules of pyruvate
- Has two major phases:
 - Energy investment phase
 - Energy payoff phase
- The immediately generated ATP comes from substrate level phosphorylation !





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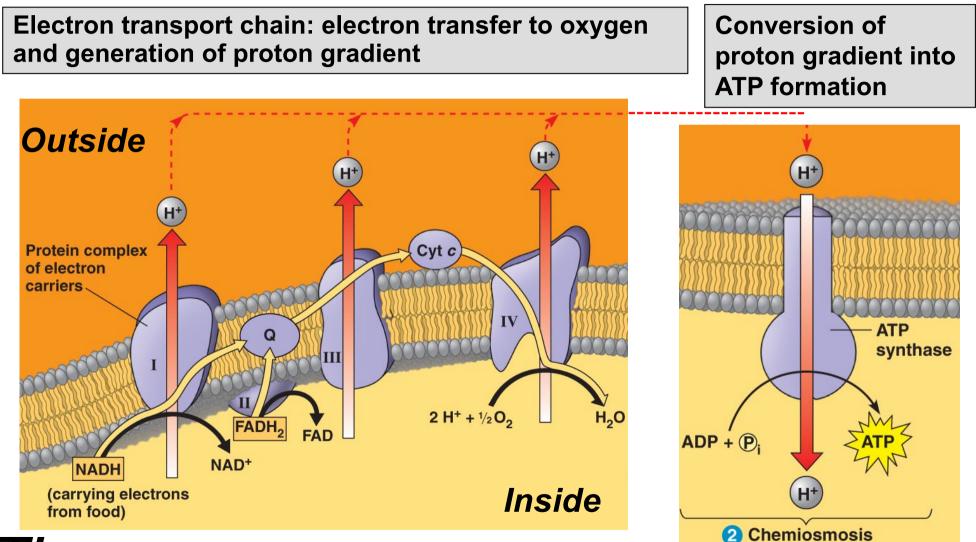
Complete Aerobic Degradation of Glucose



-2870 + 4x 30.5 -> -2748 kJ/mol still unexploited!

How many ATP can be made from one NADH?

Respiration (ie oxidative phosphorylation): **Electron Transport Chain and ATP Synthase**



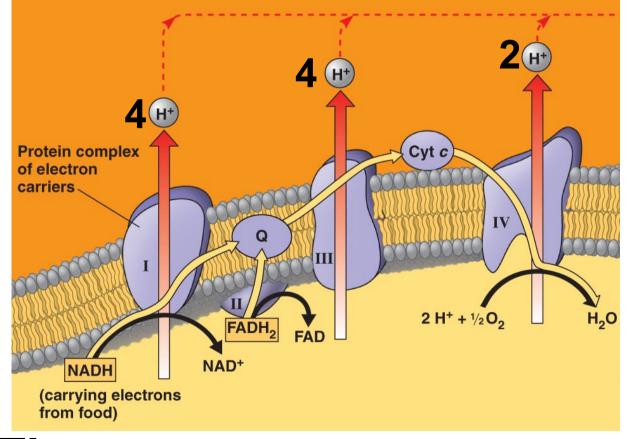
Stoichiometry of Oxidative Phosphorylation

10 H⁺ are maximally exported during respiration.

Bacteria have fewer coupling sites!

P-to-O ratio ATP per Oxygen atom Maximum 3

3-4 protons must be translocated to generate an ATP

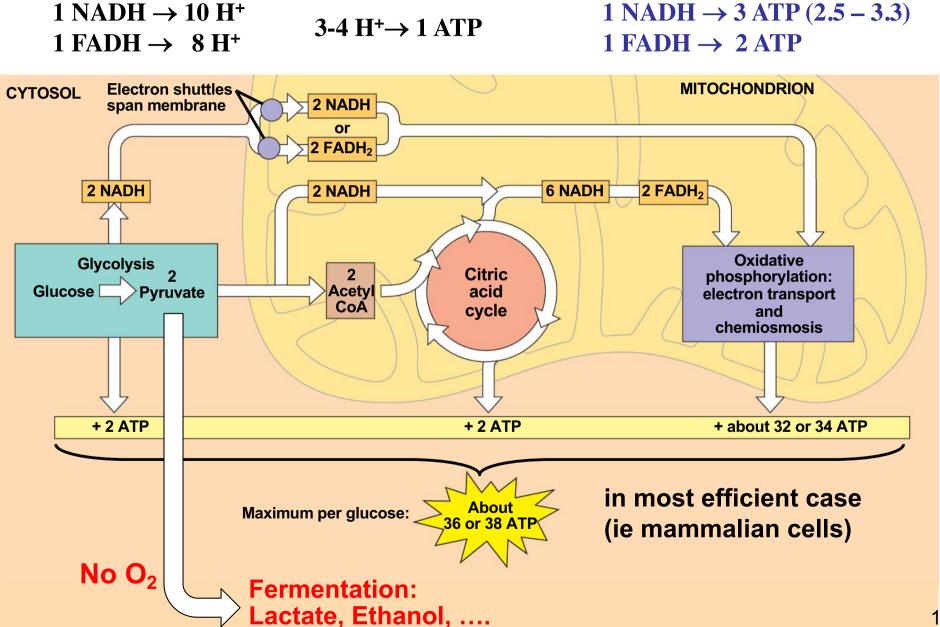


ADP + P_i H⁺

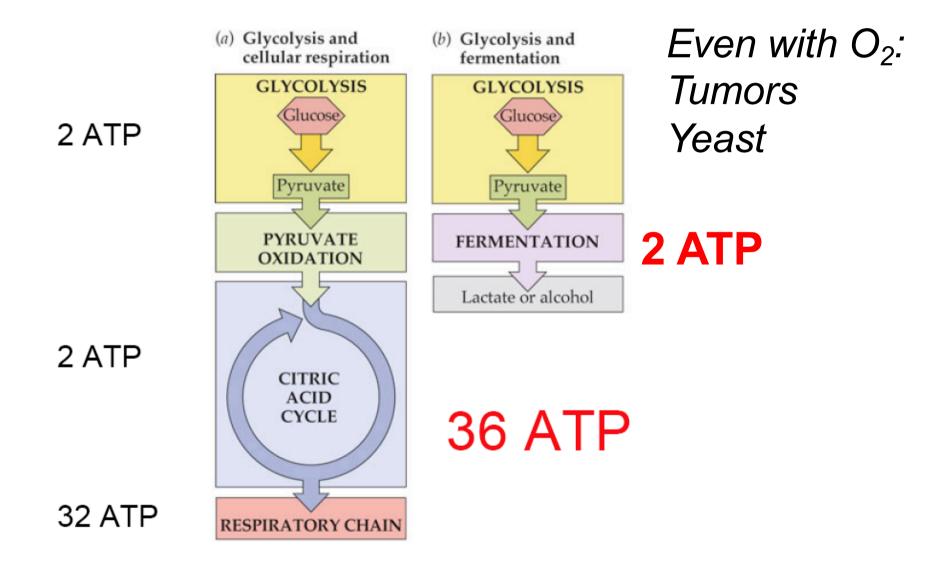
2 Chemiosmosis

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Accounting of ATP Production by Cellular Respiration

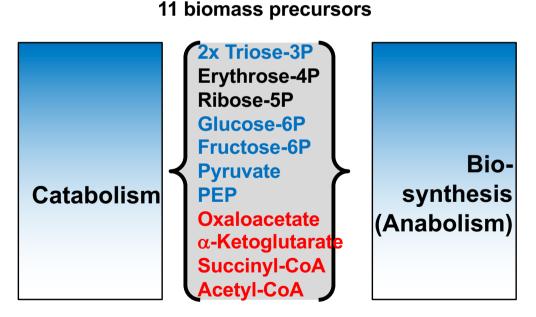


Energetic Consequence of Different Modes of Metabolism



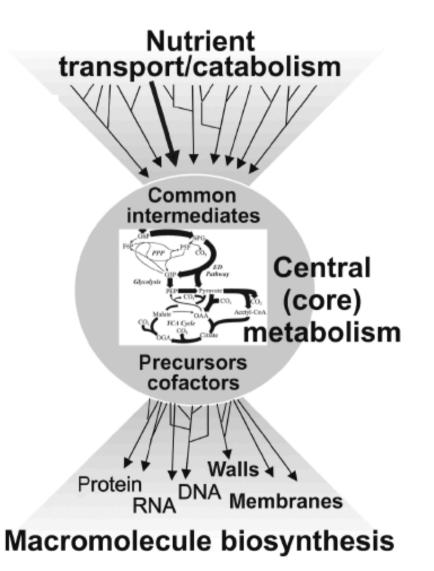
Glycolysis & TCA Cycle: At the Crossroads of Metabolism

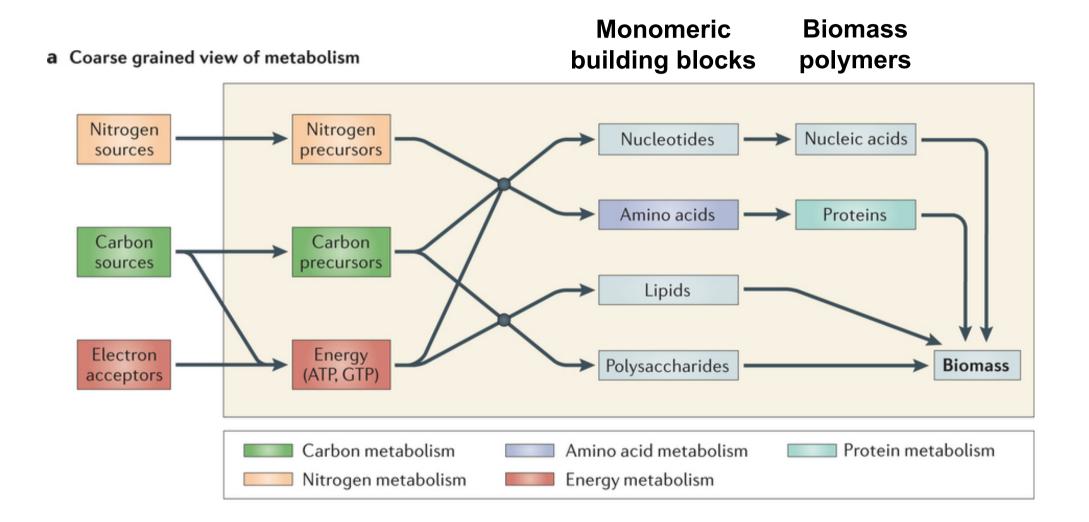
 Glycolysis and the TCA cycle are **THE** key pathways of central (or intermediary) metabolism



Glycolytic intermediate

Citric acid cycle intermediate





Chubukov et al, 2014 Nature Microbiology Reviews

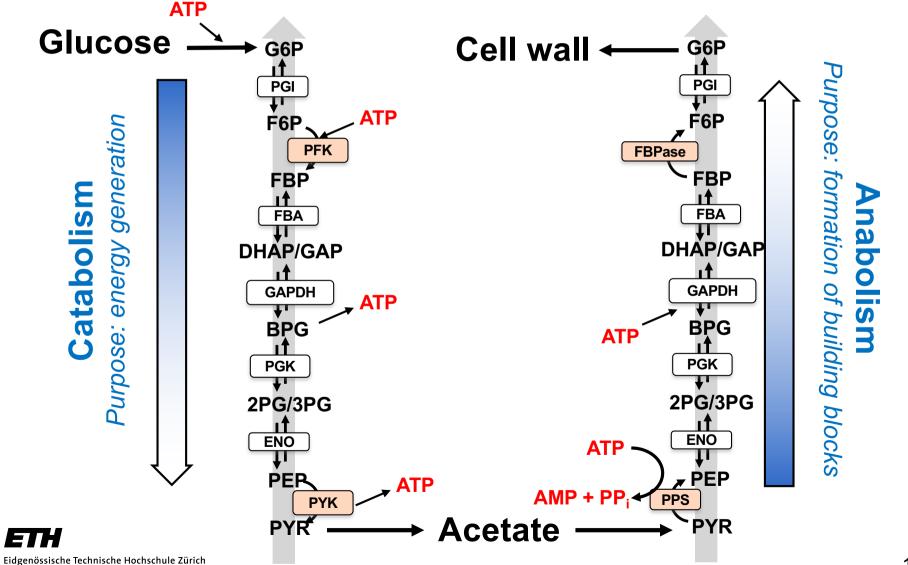
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Take Home Message: Structure of Metabolism is "Simple"

- Catabolic down hill reactions bring various nutrients into central metabolism.
- Anabolic uphill reactions synthesize cellular buildings blocks from 11 central intermediates (driven by catabolically generated ATP).
- Central metabolism is the flexible core of it all, able to run into different directions depending on the environmental conditions.

Central Metabolism Must be Flexible: Glycolysis vs Gluconeogenesis

Mostly the same enzymes, but uphill requires energy



Swiss Federal Institute of Technology Zurich

How is all of this coordinated?

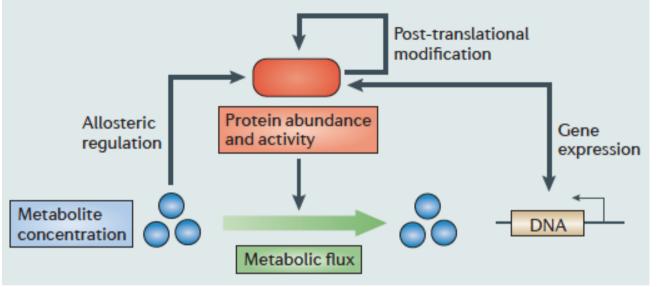
What Matters for a Reaction Flux?

$$[E] \cdot k_{cat} \cdot \frac{[S]}{k_m + [S]} = reaction rate (=flux)$$
Enzyme
conc
Kinetic
parameter
 $K_{cat} - turnover$
 $k_m - affinity$

$$[S]$$

How can cells affect those variables and parameters?

How Cells Influence Reaction Fluxes ?

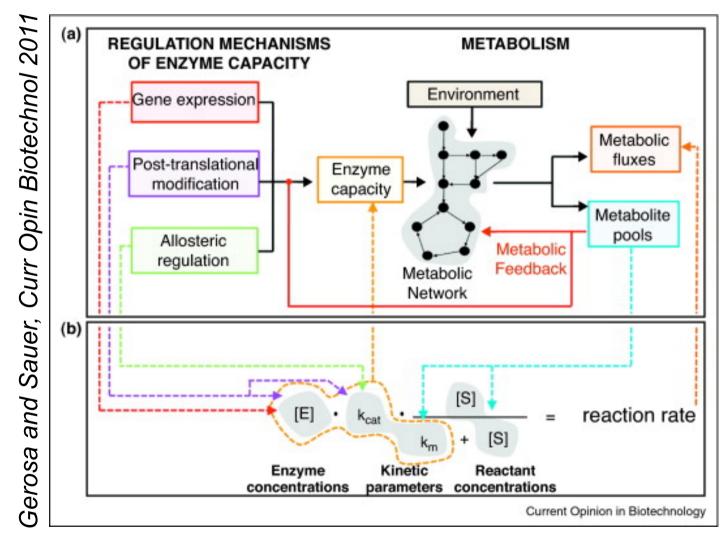


Chubukov et al, 2014 Nature Microbiology Reviews

Given the relatively slow response time and stochastic nature of transcription and translation events, expression of individual enzymes is not fine-tuned in accordance to changes in metabolic flux, but rather to set the scope of possible fluxes (Kochanowski, Sauer and Noor 2015 Curr Opin Microbiol)

Which fluxes are realized depends more on enzyme kinetics & regulatory small molecule-protein interactions: either through stable covalent binding (post-translational modification) or through fleeting non-covalent interactions (allostery).

In Networks All is Intertwined



We still cannot understand network behavior from the individual (parameterized) reactions

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Key Experimental Methods for Metabolic Research in Sys Bio

Classically it was enzymology; ie in vitro enzyme assays

Proteomics

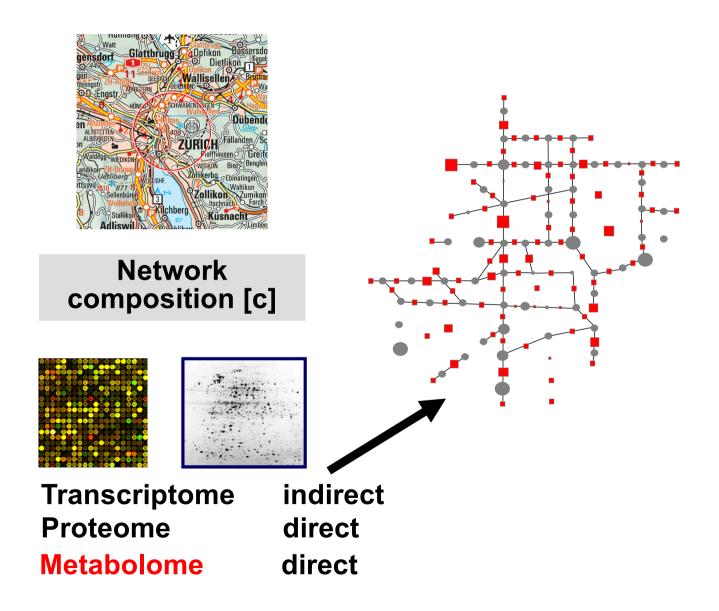
(or transcriptomics since easier)

- Metabolomics
- Flux analysis

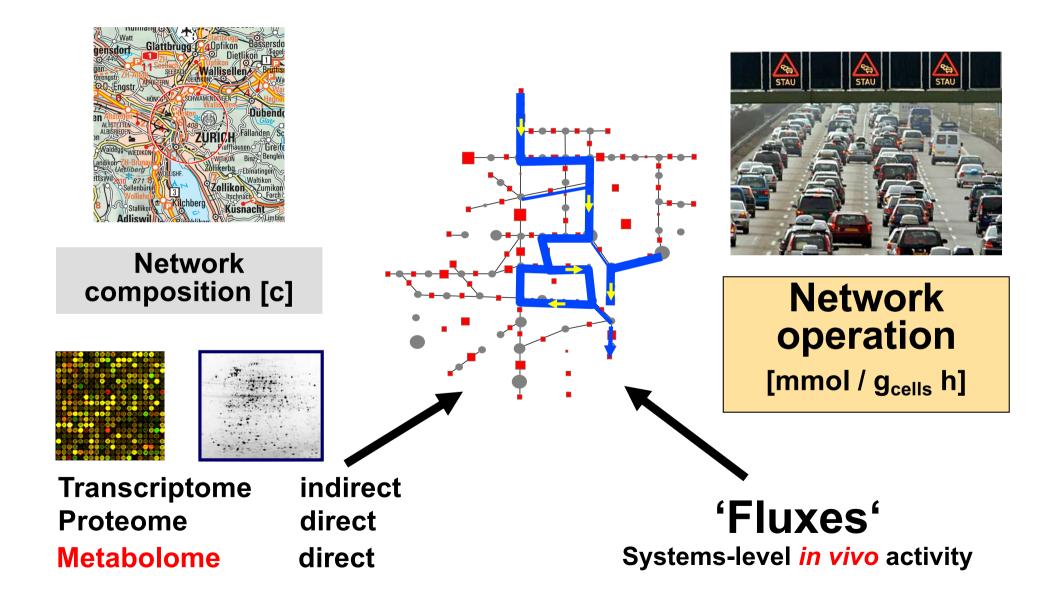
Mass spectrometry the key enabling technology!



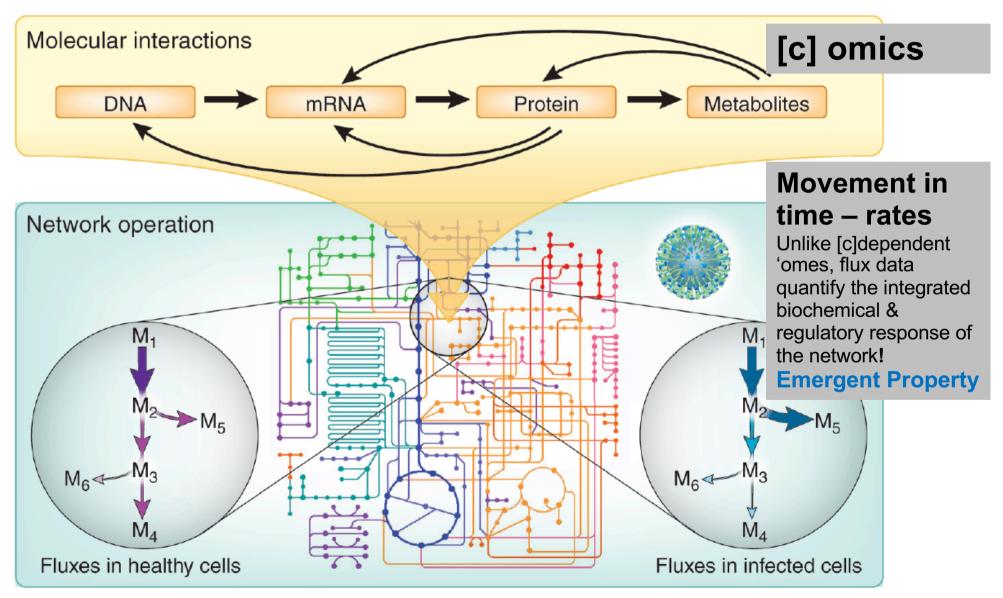
Experimental Analysis of Metabolic Networks as Systems



Experimental Analysis of Metabolic Networks as Systems



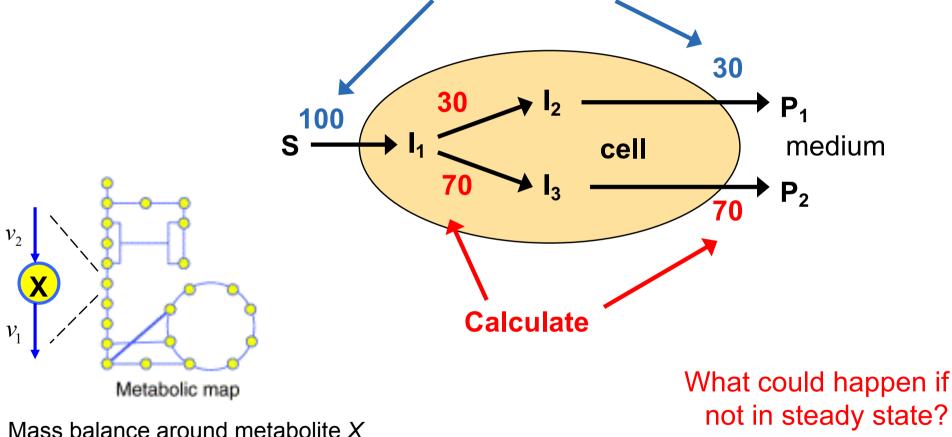
From Components to the Functional State: Metabolic Flux Analysis



Sauer & Zamboni 2008. Nature Biotech

Infer a Non-Measurable Quantity Stoichiometric Flux Analysis

Measure uptake/excretion over time



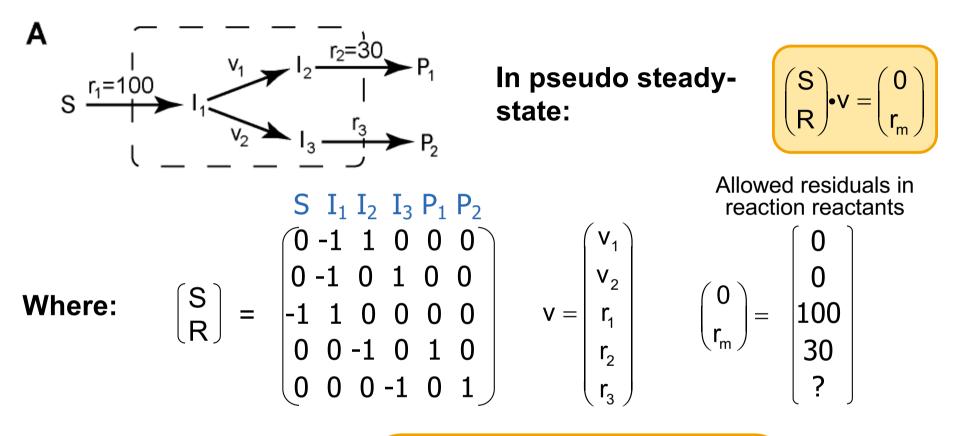
Assumption: Steady state for intracellular metabolite concentrations

Mass balance around metabolite X

$$\frac{dX}{dt} = -1 \cdot v_1 + 1 \cdot v_2 = 0$$

$$\uparrow$$
Steady state assumption

The Mathematical Framework



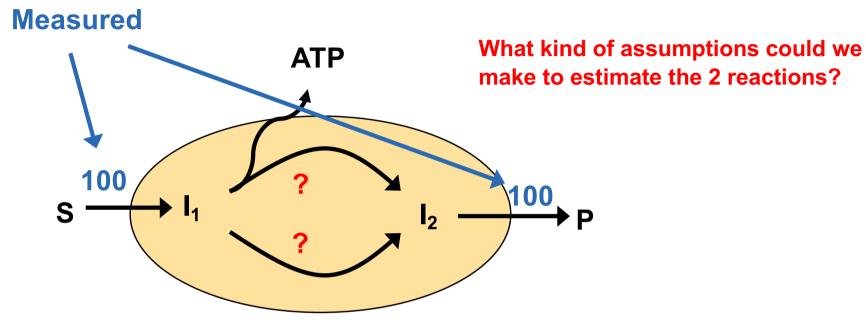
v – intracellular flux

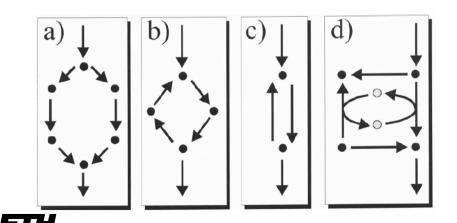
- r extracellular (exchange) flux
- S stoichiometric matrix
- R reactant residuals

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 $\operatorname{pinv} \begin{pmatrix} \mathbf{S} \\ \mathbf{R} \end{pmatrix} \begin{pmatrix} \mathbf{0} \\ \mathbf{r}_{\mathrm{m}} \end{pmatrix} \Longrightarrow \begin{vmatrix} \mathbf{v}_{2} \\ \mathbf{r}_{1} \\ \mathbf{r}_{2} \end{vmatrix} = \begin{vmatrix} 70 \\ 100 \\ 30 \end{vmatrix}$ 70

Why don't we just rely on this computational analysis?



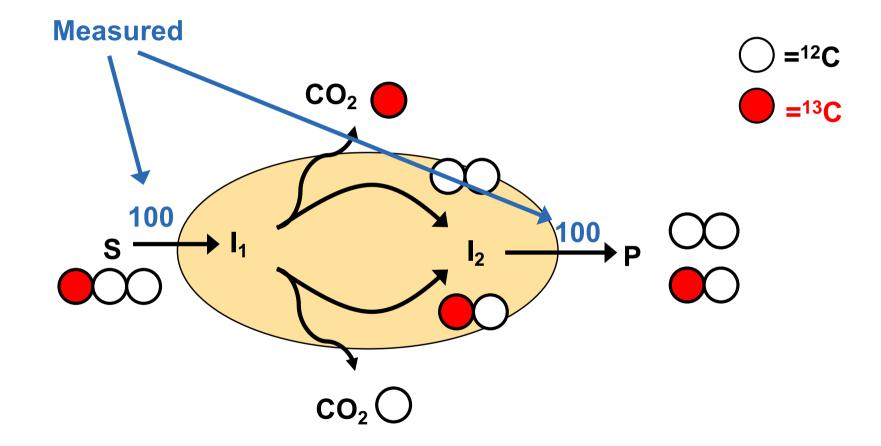


Typical situations where stoichiometric flux analysis fails: (a) parallel pathways without any related flux measurement, (b) certain metabolic (futile) cycles, (c) bidirectional reactions, and (d) split pathways when cofactors (gray circles) are not balanced.

To deal with such **underdetermined systems**, typically strong biological assumptions are made (e.g. on ATP production, cofactor balancing or cellular objective), which severely limit the value of obtained results.

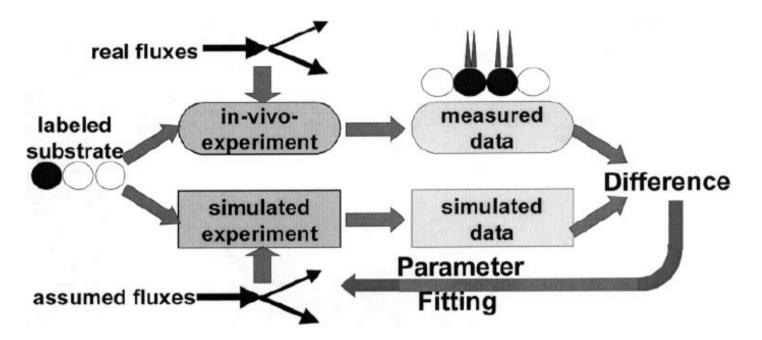
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The Basics: ¹³C-based MFA



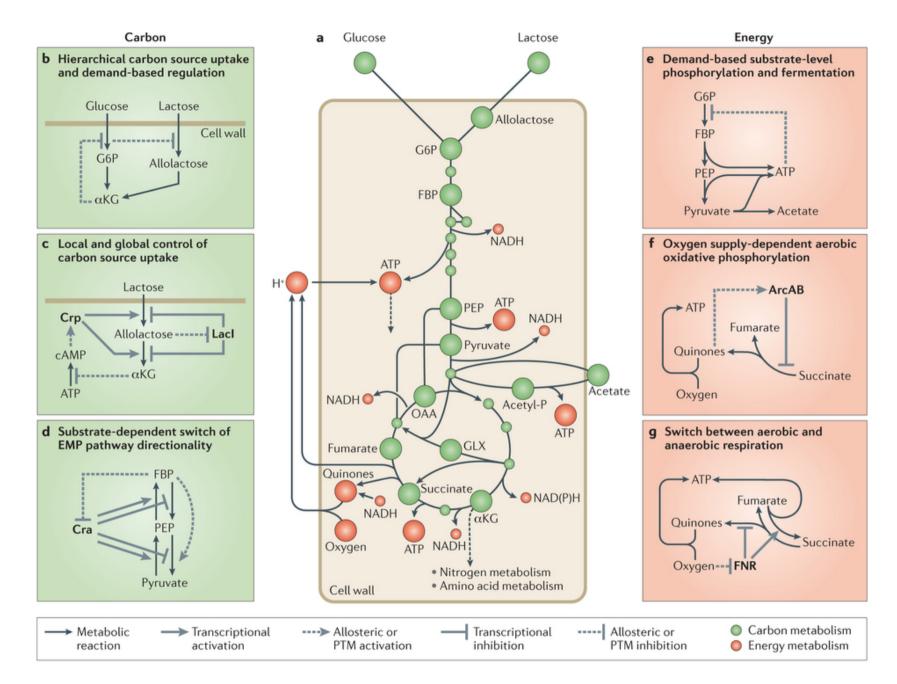
Iterative Isotopologue Balancing How to fit fluxes to data ?

Using a reaction and atom resolved model of metabolism



- Global isotopologue balancing:
 - provides a single flux solution for the network
 - provides flux number for each reaction in the network
 - is computation intensive (non linear problem)

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Chubukov et al, 2014 Nature Microbiology Reviews

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ЕТН

Summary

- Metabolic networks are structured into mostly linear anabolic (& catabolic) pathways and an interconnected and flexible central metabolism.
- Most energy is conserved in redox cofactors which respiration converts into ATP (with varying stoichiometries!).
- Flux regulation: gene expression sets more the scope, while PTMs and metabolite binding actually regulate the fluxes.
- Intracellular fluxes cannot be measured, but need to be inferred computationally. Some methods exploit isotopic tracing for higher confidence inference.

Institute of Molecular Systems Biology

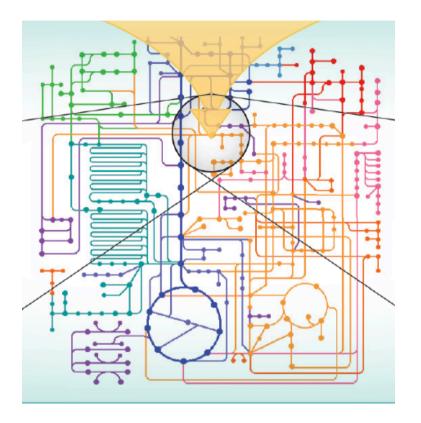
Central Metabolism and Growth-Lag Tradeoffs

Uwe Sauer, ETH Zurich

- Allosteric regulation topology
- Growth-lag tradeoff



Metabolism



After decades of discovery and detailed mechanisms: metabolism is the furthest in terms of knowledge.

Not only a workhorse network but also an internal **signal generator** !

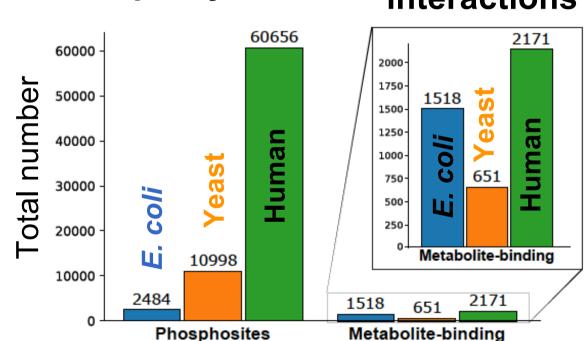
Metabolite-protein interactions are the basis of these signals and drivers of network coordination

Non-Covalent vs Covalent (Post-Translational) Metabolite Regulation

- Both are fast and reversible
- But PTMs can achieve lasting changes and combinatorics, however, at a cost of additional, modifying enzymes

Hypothesis: non-covalent metabolite-protein interactions are are more ancient and mainly used to regulate **conserved biological processes that maintain cellular homeostasis**, for example metabolism and transcription in Pro- and Eukaryotes alike.

Non-Covalent vs Covalent (Post-Translational) Metabolite Regulation in Enzymes of Pro- and Eukaryotes



Metabolite-protein interactions

Non-covalent interactions are equally abundant across kingdoms



Gruber, Diether & Sauer unpublished

1.7 in E. coli and 36 in human reactions

Average phosphorylation:

Phosphorylation

What Is Our Present Knowledge of **Metabolite-Enzyme Regulation?**

- In contrast to metabolic networks, there is no equivalent regulation • network let alone a model
- Developed a framework leveraging the vast, but fragmented, • biochemical literature to reconstruct metabolite-protein regulatory network
- Genome-scale architecture of *E. coli* small molecule regulatory • network:
 - **1,669 unique regulatory interactions** between 321 metabolites and 364 enzymes
 - > 83% interactions are inhibitory
 - $\approx 50\%$ of enzymes regulated

Collaboration with Ed Reznik & Daniel Segre Boston University



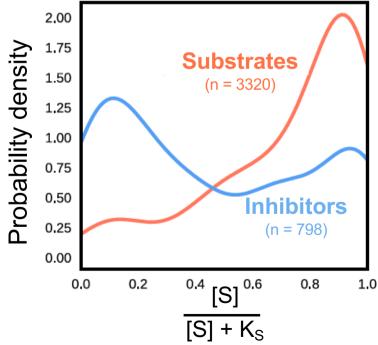
Elad Noor



Reznik*, Christodoulou*, Sauer, Segre & Noor 2017 Cell Reports

Combining metabolomics data from many conditions with metabolic control analysis, we showed:

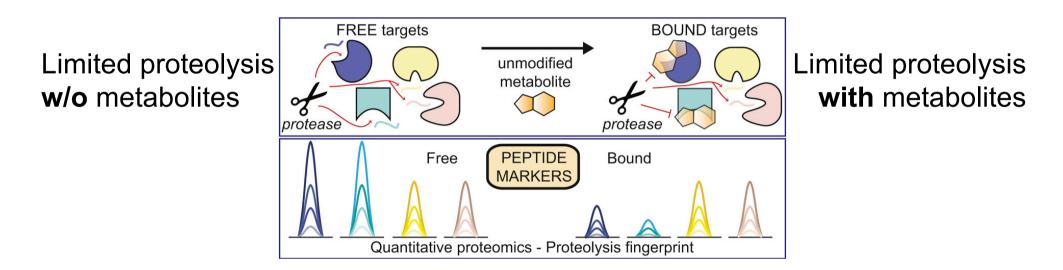
- fundamental trade-off between regulation and enzymatic activity,
- an inherent cost associated with metabolite regulation,
- Under physiological conditions, most enzymes operate at or near saturation.



 $K_{\rm S} = K_{\rm M} \, or \, K_{\rm I}$

A Chemoproteomic Map of Metabolite-Protein Interactions

A method developed by the Picotti Lab @ ETH



Captures different interactions:

- catalytic
- allosteric
- protein complex

E. coli interactome atlas for 20 metabolites (*CCM, 4 amino acids, 7 nucleotides, cAMP*)

1678 interactions; ³/₄ unknown (!)

Chemoproteomic Mapping of Metabolite-Protein Interactions

collaboration with Picotti Lab @ ETH

Strength

- Proteome-wide discovery !!!
- All types of interactions (... but regulatory ones need to be inferred indirectly)

Weakness

Metabolite centric: no comprehensive mapping of a specific subnetwork

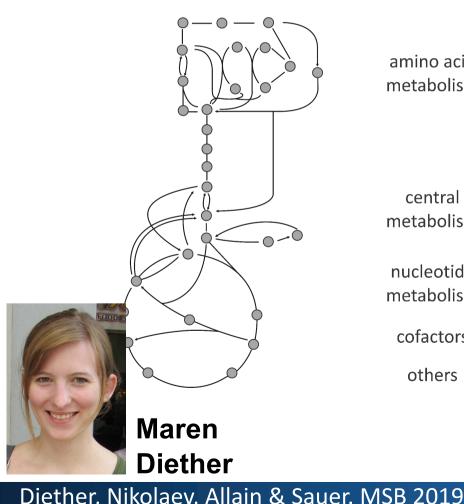
How deep is our knowledge of regulatory metabolite-protein interactions ?

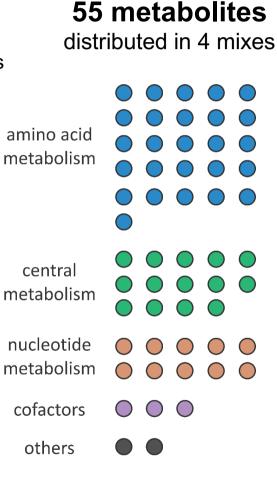
How Many Met-Prot Interactions are in Central Metabolism?

collaboration with Allain Lab @ ETH

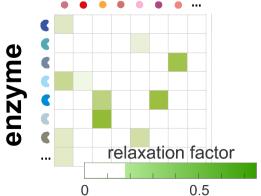
Purified 29 central enzymes of *E. coli*

no isomerases, no hetero complexes



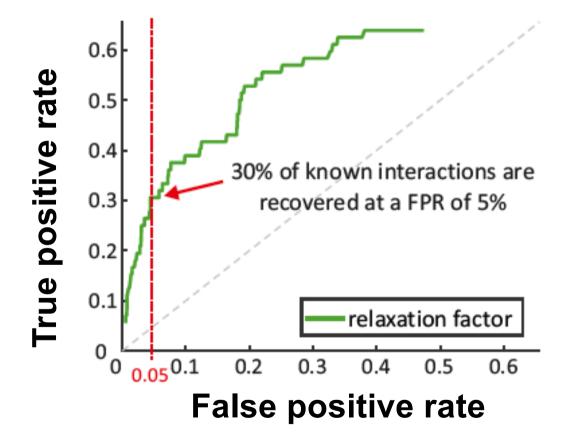


1D ¹H NMR (T1rho) spectroscopy enzyme metabolites NMR metabolites



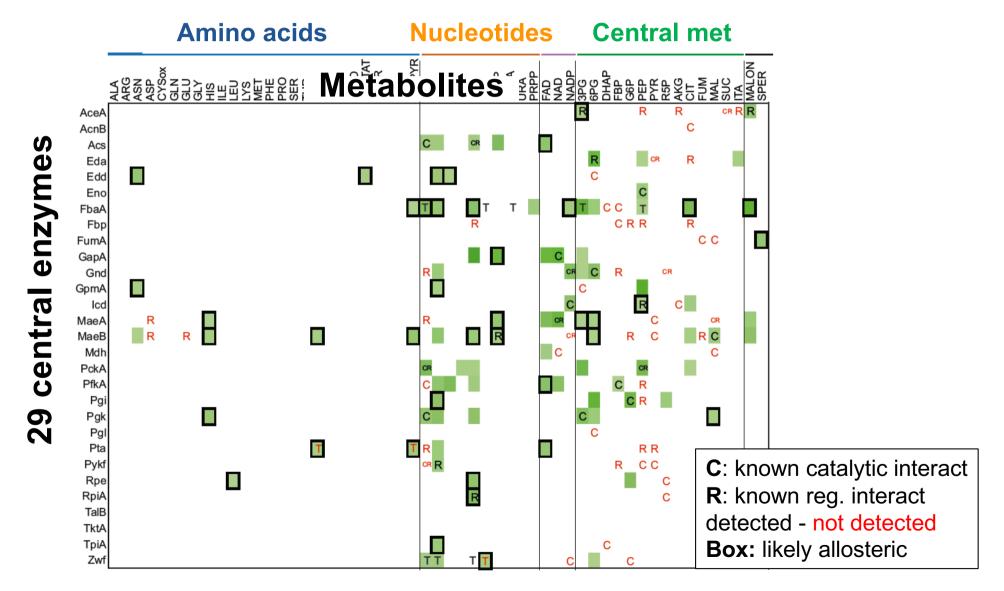
9

Subnetwork Focused Mapping of Metabolite-Protein Interactions

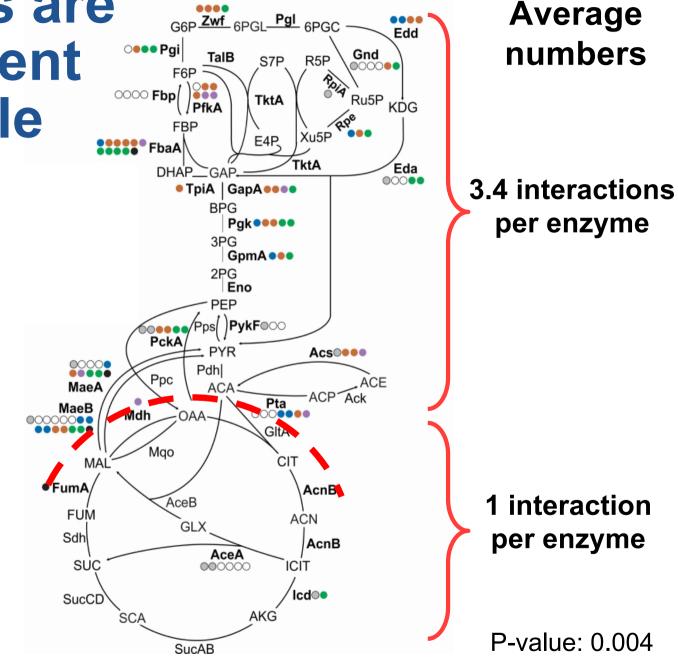


40 regulatory, 43 catalytic interactions were known already **Cutoffs set for low false positive rate** (30% recovery)

Subnetwork Focused Mapping of Metabolite-Protein Interactions



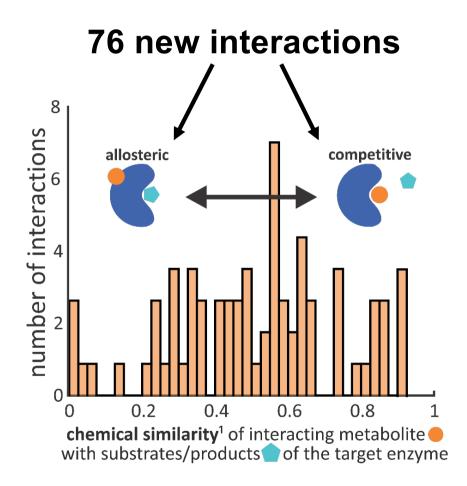
Interactions are Less Frequent in TCA Cycle



known regulatory interactions detected not detected new interactions amino acid biosynthesis nucleotide biosynthesis redox central metabolism other

Diether, Nikolaev, Allain & Sauer. MSB 2019

NMR Detects 'Likely' Allosteric and Competitive Interactions



Equally distributed between 'likely allosteric' and 'likely competitive'

Hattori et al. (2010) Nucleic Acids Res.

Conclusion

- ~ 100 interactions detected 76 are novel (!)
- Doubled number of regulatory interactions in central metabolism -> much larger interaction network than currently known
- Based on chemical similarity ~ about 50% of novel interactions are allosteric!
- So far, 8 out of 11 tested interactions functionally validated

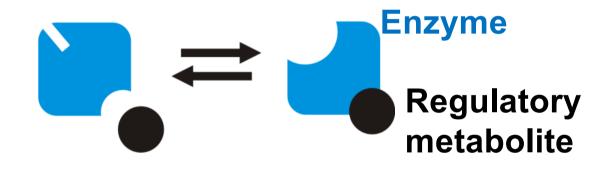
From to Topology to Function

Working towards a "comprehensive" metprot interaction map of central metabolism.

But a long way from network topology to understand *in vivo* function in cellular context

Which regulatory interactions govern a given adaption, and precisely how do they do it?

Avoiding Confounding (other) Regulation When Assessing Allosteric Metabolite-Protein Regulation





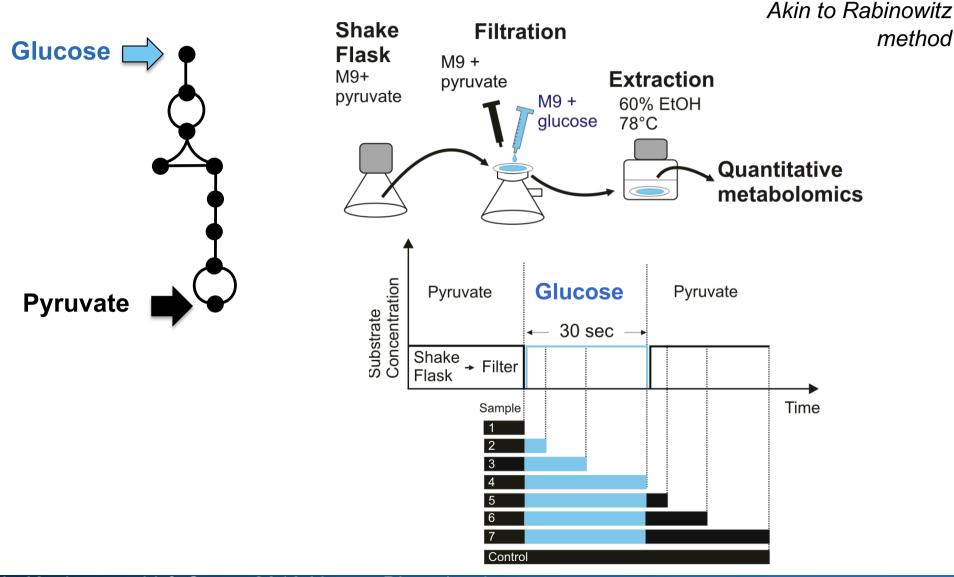
Assumption: allosteric effects dominate very rapid (!) responses



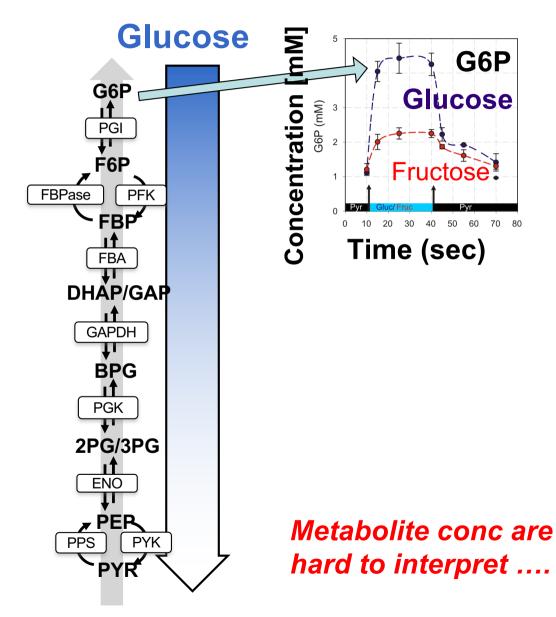
Karl Kochanowski

Hannes Link

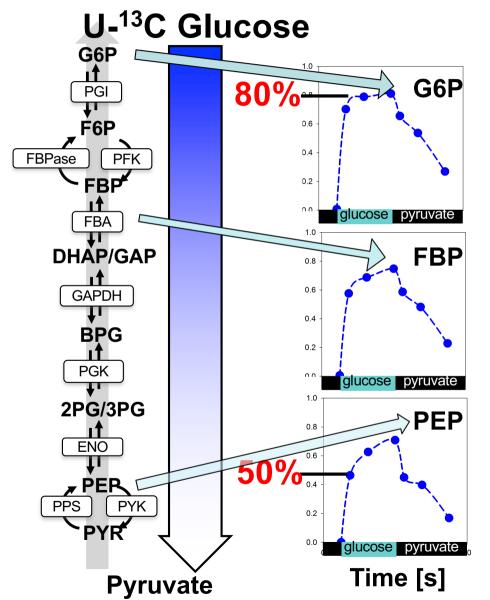
Gluconeogenesis to Glycolysis Switch of *E. coli* within 30 Seconds



Dynamic [Metabolite] Response (30 s)



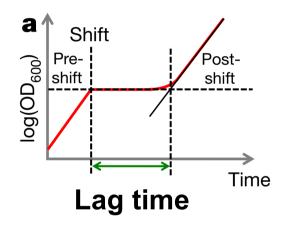
Dynamic ¹³C-Experiments Demonstrate: Flux Reversion within 5 Seconds



Fully ¹³C-labelled fraction

- Combine short-term metabolite dynamics with ODE modeling
- Infer allosteric regulation relevant for a given adaptation
- Identify novel allostery

Can *E. coli* always shift rapidly between glycolytic & gluconeogenic C-sources?



Shift from sugars to acetate alucose 8-Normalized OD₆₀₀ mannitol - maltose 4glycerol galactose 2--O- mannose 6 8 Time after shift [hrs]



In collaboration with Terry Hwa (UCSD) and Johan Paulsson (Harvard)



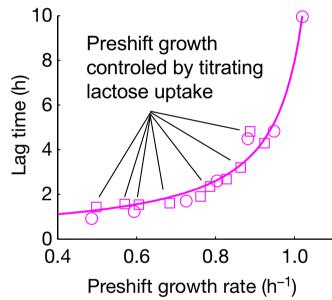
Dimitris Christodoulou

20

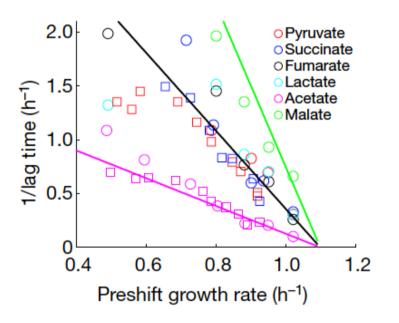
Markus Basan Basan, Honda Paulsson, Hwa & Sauer 2020 Nature

Fast Growth Rate -> Long Lag Phase

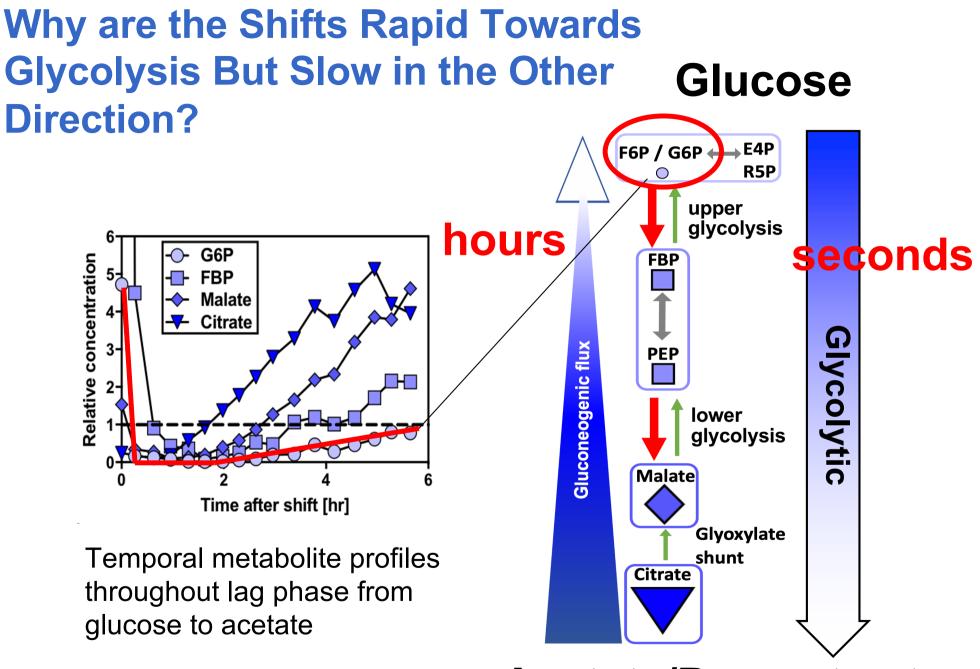
Shift from various Csources to acetate



Growth-lag relationship depends on influx rather than specifics of C-source



- Linear relationship btw inverse lag time (1/T_{lag}) (ie adaptability) and preshift growth rate
- Found a general linear relationship for shifts from 6 glycolytic to 6 gluconeogenic C-sources

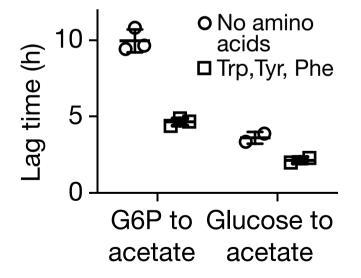


Acetate/Pyruvate etc

Why are the Shifts Rapid Towards Glycolysis But Slow in the Other Direction?

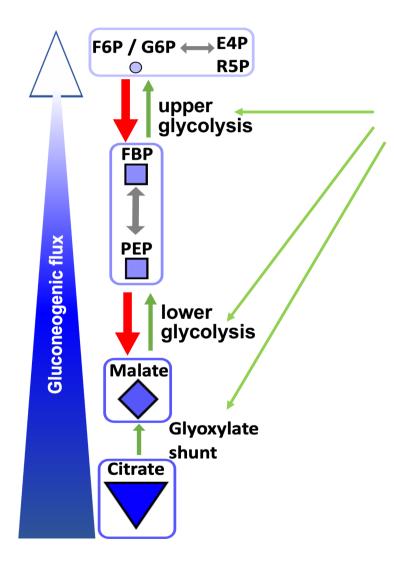
- Metabolites in upper glycolysis increase very late
- Typically when growth resumes (eg FBP drops 200x from growth on glucose in the lag phase)
- ¹³C-flux tracing confirms almost no gluconeogenic flux, while TCA cycle flux is rapid during lag

Hypothesis: Gluconeogenic flux limits biosynthesis of biomass components derived from upper glycolysis.



Supplementing AA from upper glycolysis & PP pathway reduces lag phase!

Why do Cells Have Such a Hard Time to Revert Glycolysis?

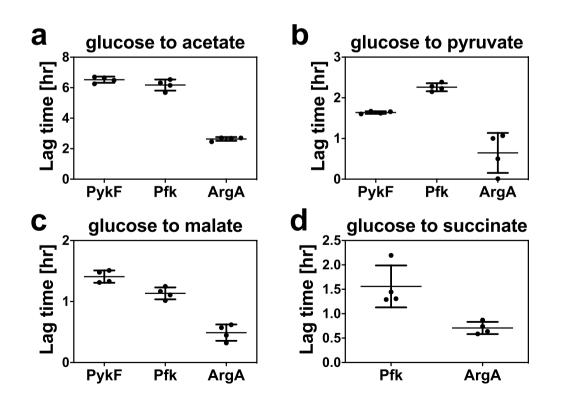


- Dedicated gluconeogenic enzymes must be synthesized in the lag phase
- But their glycolytic counterparts are still present – the faster cells grew before the shift the more of them are present!!!!
- The lingering huge glycolytic capacity counteracts the upward flux

After the shift, cells are trapped in state where gluconeogenesis limits synthesis of AA, which in turn limits production of the very enzymes needed to alleviate the bottleneck

Why can *E. coli* not Avoid Depletion of Gluconegenic Metabolites?

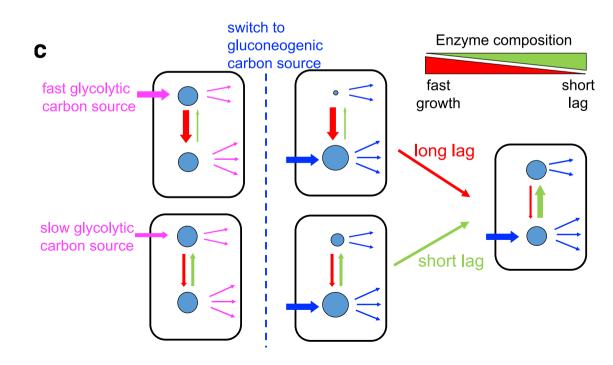
Hypothesis: Allosteric regulation of opposing glycolytic enzymes does not achieve complete inhibition



Consistently, overexpression of irreversible glycolytic enzymes increases lag phase over the control (ArgA)

Conclusion

- A series of low metabolite pools in upper gluconeogenesis causes long lag phases
- Because for fast glycolytic growth the distribution of enzymes strongly favors glycolysis of gluconeogenesis
- Classical tradeoff between the fitness measures optimal growth and adaptability: Maximum growth in one condition increases time to adapt to other conditions.



Tradeoff Between Maximum Growth and Adaptability

• A unique perspective on why cells grow at a certain rate in a given condition:

Can be advantageous to grow slower for the benefit of shorter adaptation

- Growth rate is a reflection of ecological likelihood that conditions will change:
 - eg although chemically very similar, *E. coli* grows slow on fructose and mannose but fast on glucose. Deleting Cra – the TF that activates gluconeogenesis and represses glycolysis – increases the growth rate on fructose and mannose BUT prevents shift to many gluconeogenic substrates!
 - Thus Cra may be designed to slow growth on glycolytic substrates to enable adaptation to gluconeogenesis
- We found similar tradeoffs in other respiro-fermentative microbes, eg *B. subtilis* and *S. cerevisiae*
- In contrast, anaerobes that do not grow on gluconeogenic C-sources do not show this tradeoff; ie. the gut microbe *B. thetaiotaomicron* grew equally fast on all tested C-sources

Take Home Messages

- Non-covalent met-prot interactions regulate conserved homeostatic processes (in pro- and eukaryotes).
- Still largely unknown met-prot interaction network. "Comprehensive" interaction map on horizon for *E. coli.*
- Understanding the function of allosteric regulation requires dynamic data and computer models.
- Allosteric regulation works not «perfectly», eg cannot entirely shut off an unnecessary activity.
- Consequently there is a fundamental tradeoff btw the fitness traits of maximum growth and adaptability.
- A series of low metabolite pools in upper gluconeogenesis causes long lag phases after shifts from sugars to organic acids



Collaboration: Paola Picotti (ETH) Fred Allain (ETH) Reznik/Segre Lab (BU) Johan Paulsson (Harvard) Terry Hwa (UCSD)





Karl Kochanowski



Hannes Link



Dimitris Christodoulou



Markus Basan



Maren Diether



Elad Noor





SystemsX The Swiss Initiative in Systems Biology