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Metabolic modelling and synthetic pathway design

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Learning
goals
After this
lecture, you will
be able to...



Describe what are genome-scale metabolic models



Describe how are metabolic phenotype prediction and strain design performed



Describe the steps of synthetic metabolic pathway design

Reading material

Orth JD, Thiele I, Palsson BO (2010) What is flux balance analysis? Nat Biotechnol. 28:245-8. doi: 10.1038/nbt.1614.

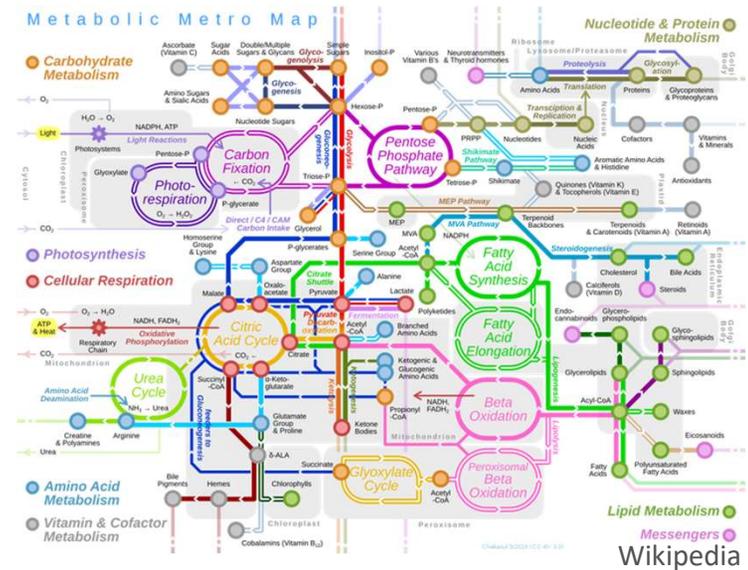
Box 2 outdated, check instead for COBRA toolbox, **COBRApy**, COBRA.jl:
<http://opencobra.github.io/>

Metabolic modelling

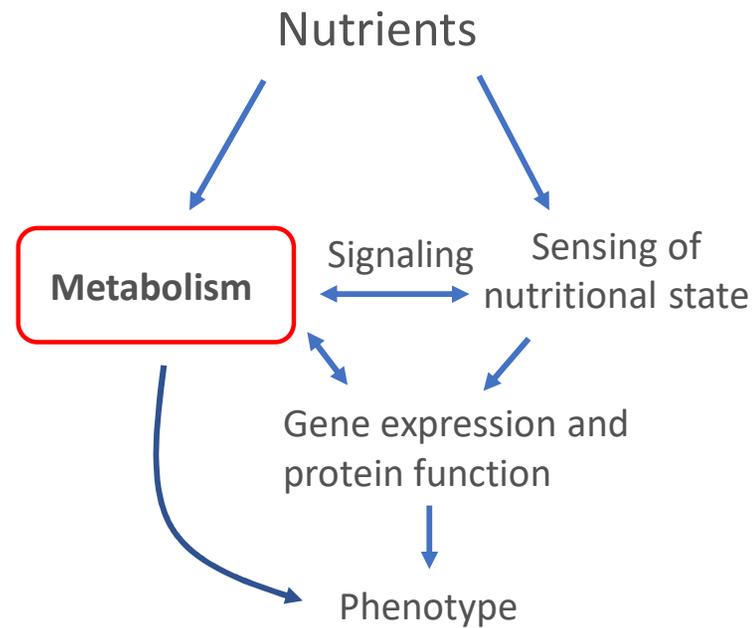
Why is metabolism relevant for synthetic biology?

Metabolism = (bio)chemical reactions involved in sustaining a living state of cells and an organism

- Metabolism generates precursors for product compounds but also for circuit components
- Metabolism generates energy and redox power
- Metabolism is involved in cellular regulation

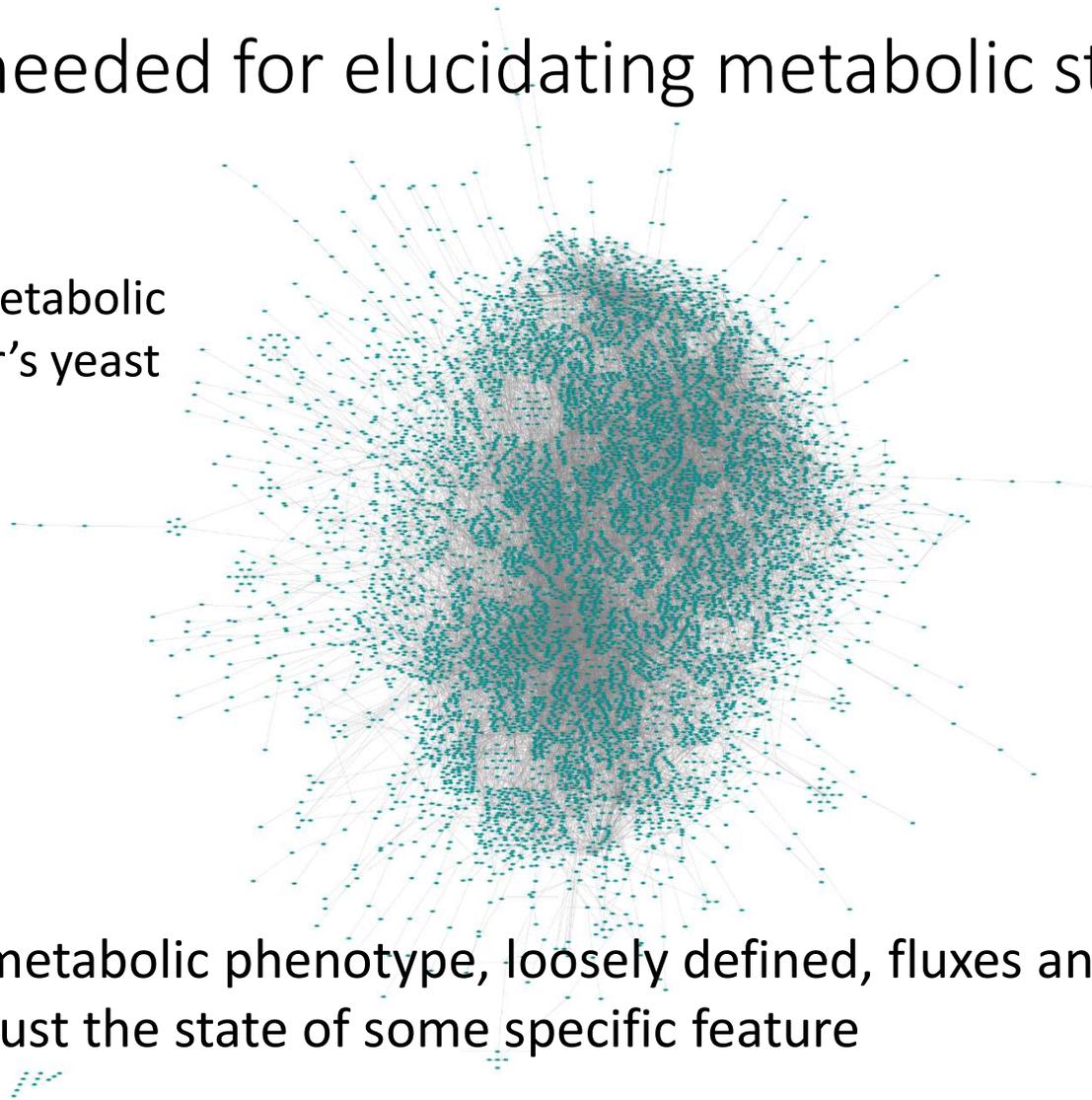


Metabolism is involved in cellular regulation



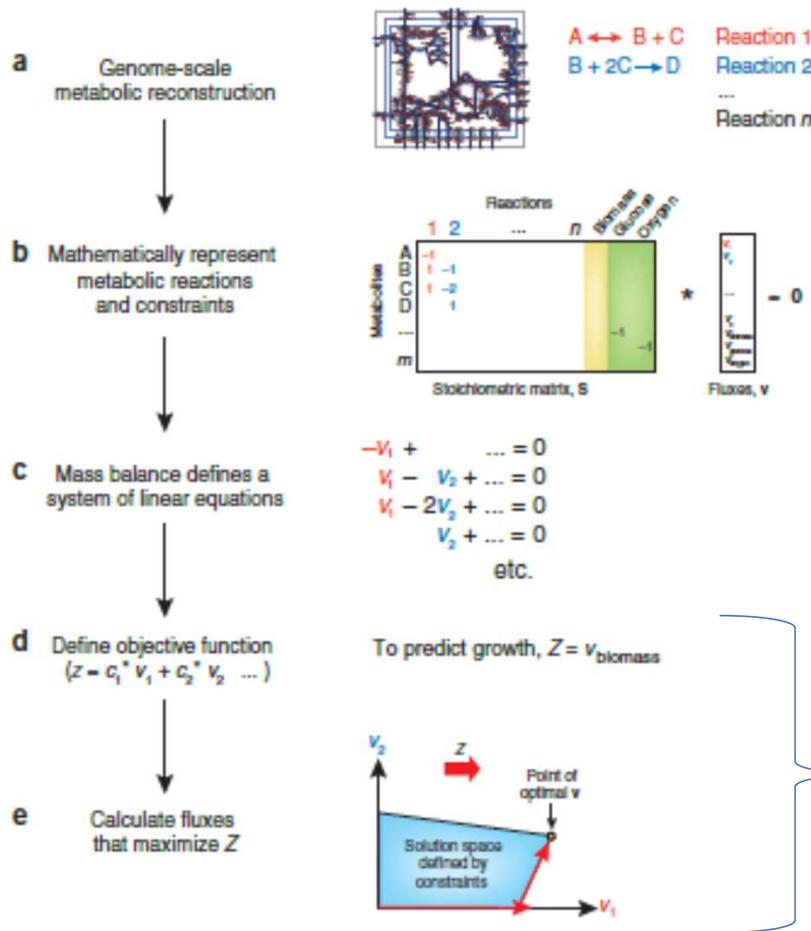
Modelling is needed for elucidating metabolic states

Genome-scale metabolic network of Baker's yeast



Metabolic state = metabolic phenotype, loosely defined, fluxes and metabolite concentrations or just the state of some specific feature

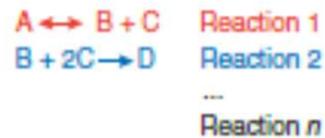
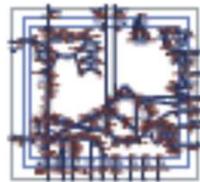
Phenotype prediction using genome-scale metabolic models



Model simulation algorithm:
Flux balance analysis (FBA)

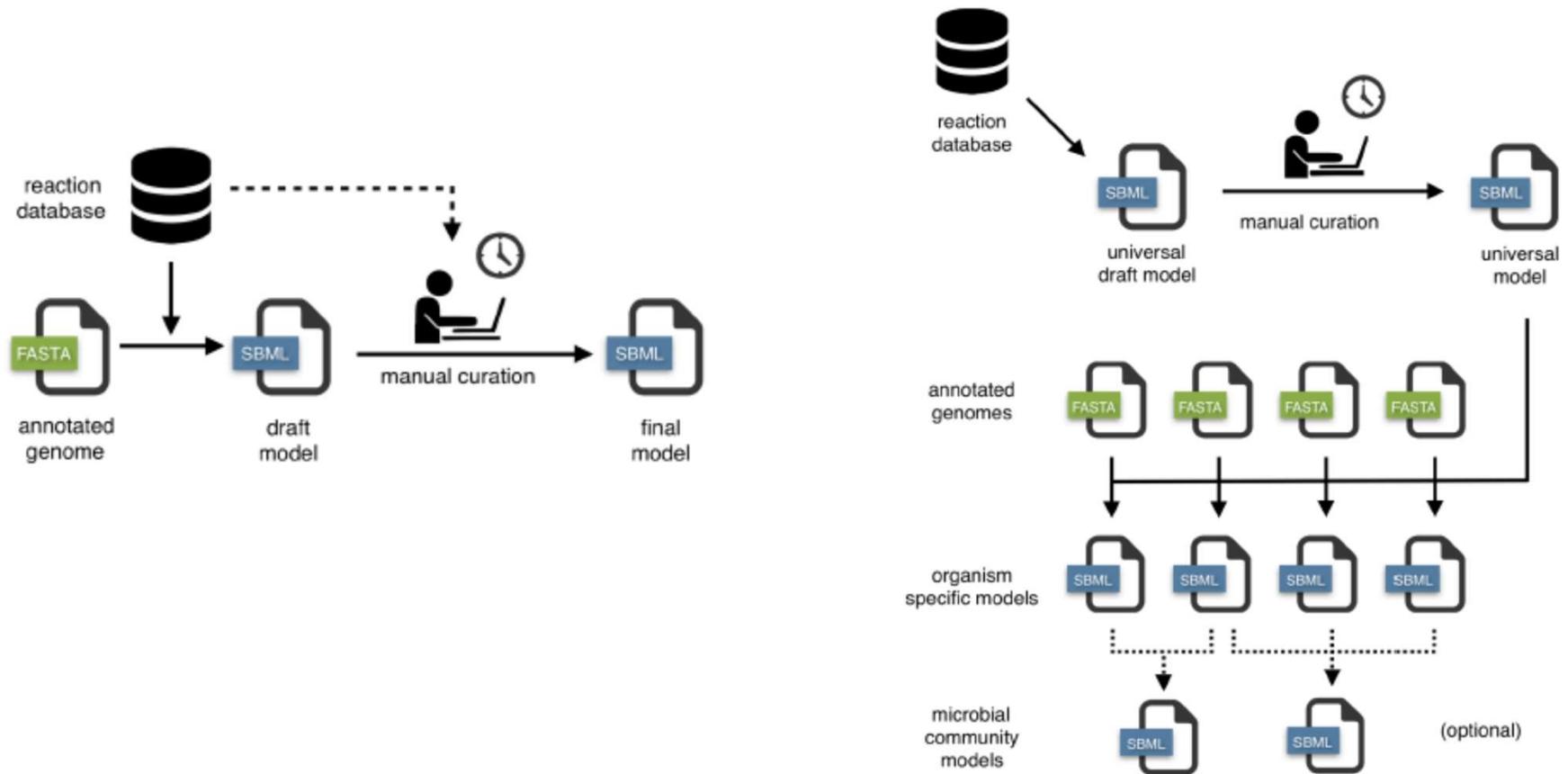
Genome-scale metabolic model reconstruction

a Genome-scale
metabolic reconstruction

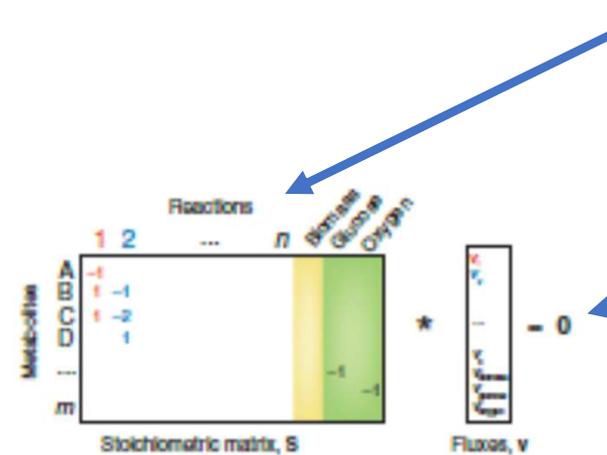
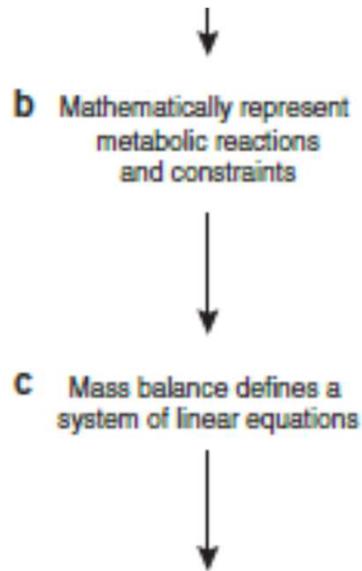


Which reactions can take place in the cells of a species?

Genome-scale metabolic model reconstruction



Conversion into mathematical representation

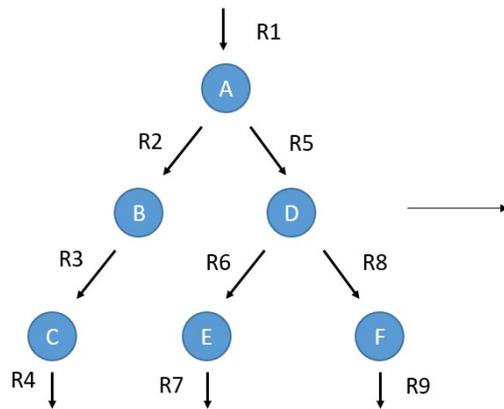


Stoichiometric matrix

Metabolite mass balances are zeros only as a metabolic steady state is assumed

$$\begin{aligned}
 -v_1 + \dots &= 0 \\
 v_1 - v_2 + \dots &= 0 \\
 v_1 - 2v_2 + \dots &= 0 \\
 v_2 + \dots &= 0 \\
 \text{etc.}
 \end{aligned}$$

Toy model example



Stoichiometric matrix

Metabolites	R1	R2	R3	R4	R5	R6	R7	R8	R9
A	1	-1			-1				
B		1	-1						
C			1	-1					
D					1	-1		-1	
E						1	-1		
F								1	-1

Obeying the law of conservation of mass,
metabolite mass balances constrain metabolic phenotypes

$$\frac{dX}{dt} = \mathbf{S} \cdot \mathbf{v} = \mathbf{S} \cdot \mathbf{f}(\mathbf{e}(t), \mathbf{s}(t), \mathbf{p})$$

Figure modified by
Tuula Tenkanen from
O'Brien et al. 2015

Steady state assumption linearizes the mass balances

$$\frac{dX}{dt} = \mathbf{S} \cdot \mathbf{v} = \mathbf{S} \cdot \mathbf{f}(\mathbf{e}(t), \mathbf{s}(t), \mathbf{p}) = 0$$

Constraints:

1) $\mathbf{S}\mathbf{v} = 0$

2) $\mathbf{v}, lb < \mathbf{v} < \mathbf{v}, ub$

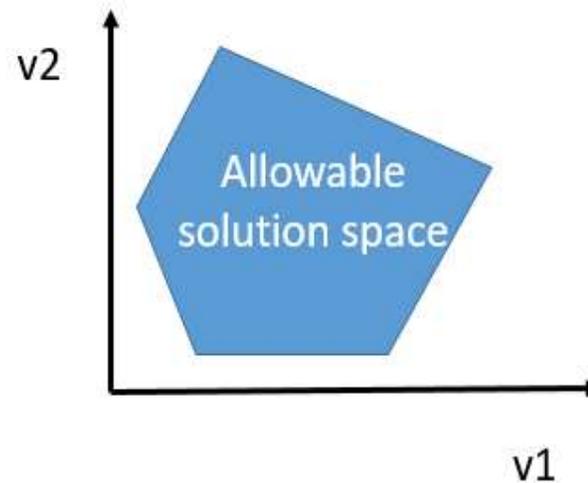


Figure modified by
Tuula Tenkanen from
O'Brien et al. 2015

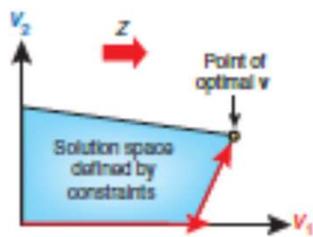
The linear system is lighter to solve and free of kinetic equations and parameters
Additional constraints introduced to obey the second law of thermodynamics

Defining an objective function for forming an optimization problem

d Define objective function
($Z = c_1 \cdot v_1 + c_2 \cdot v_2 \dots$)

e Calculate fluxes that maximize Z

To predict growth, $Z = v_{\text{biomass}}$



Choice of the objective function depends on the question

After the optimization problem is defined it can be solved using any linear optimization solver

Linear optimization can be used to identify different optimal metabolic states

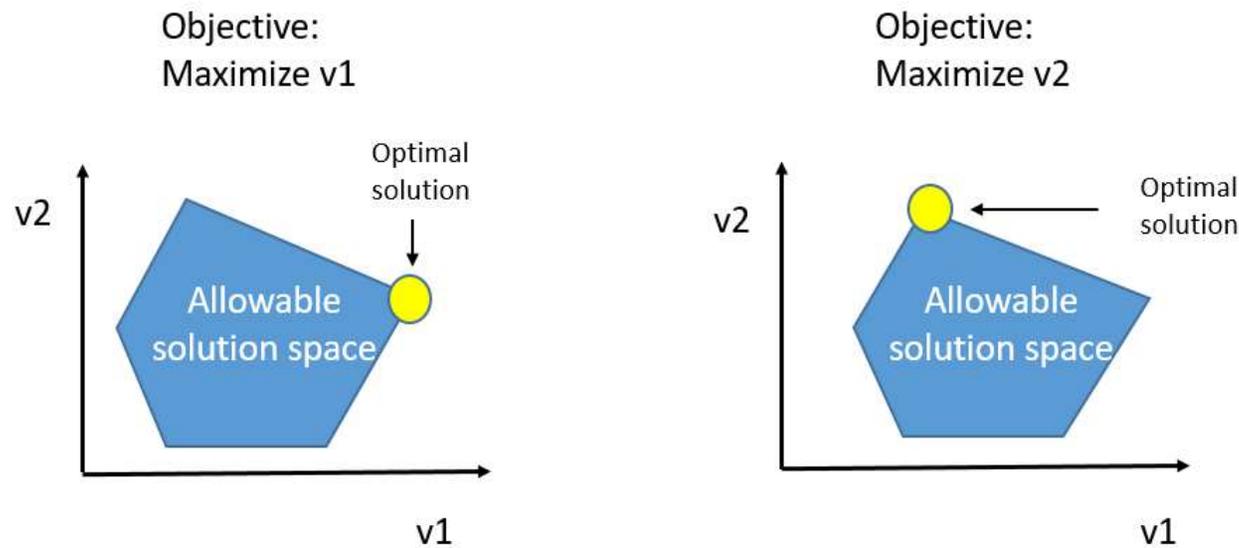


Figure modified by Tuula Tenkanen from O'Brien et al. 2015

Flux Balance Analysis (FBA)

Varma and Palsson, 1993; Varma and Palsson, 1994

maximize (or minimize) $c' \cdot v$

subject to

$$S \cdot v = 0$$

$$v, lb < v < v, ub$$

Linear optimization can be used to identify optimal metabolic states

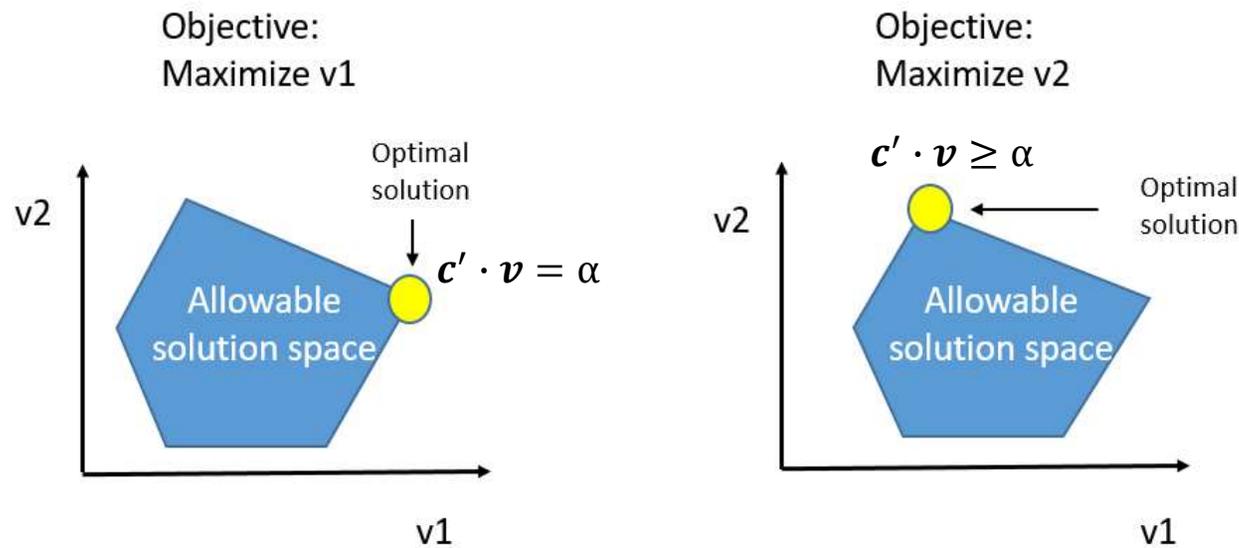


Figure modified by Tuula Tenkanen from O'Brien et al. 2015

Flux Variability Analysis (FVA)

Mahadevan et al. 2003

maximize and minimize v_i

subject to

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

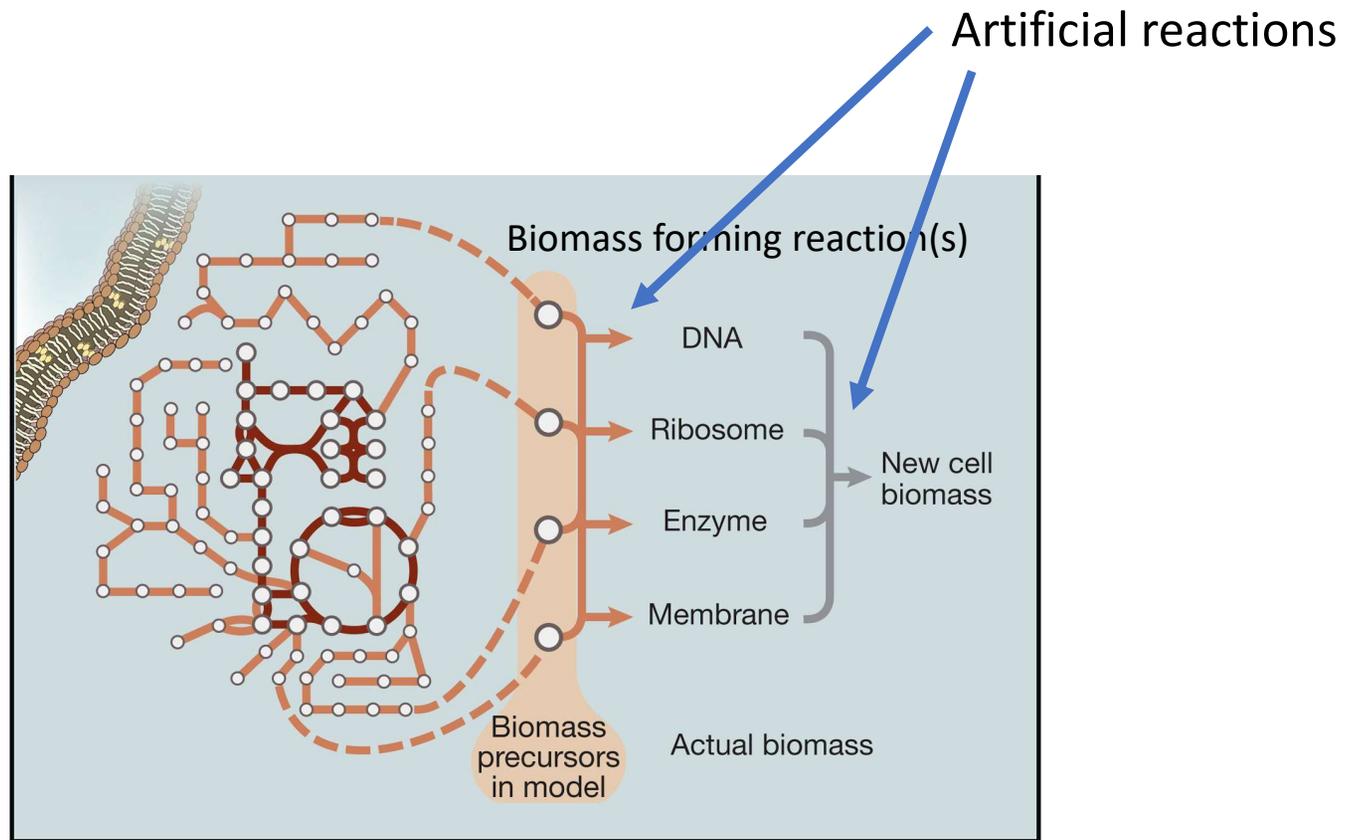
$$\mathbf{c}' \cdot \mathbf{v} \geq \alpha$$

$$\mathbf{v}, \mathbf{lb} < \mathbf{v} < \mathbf{v}, \mathbf{ub}$$

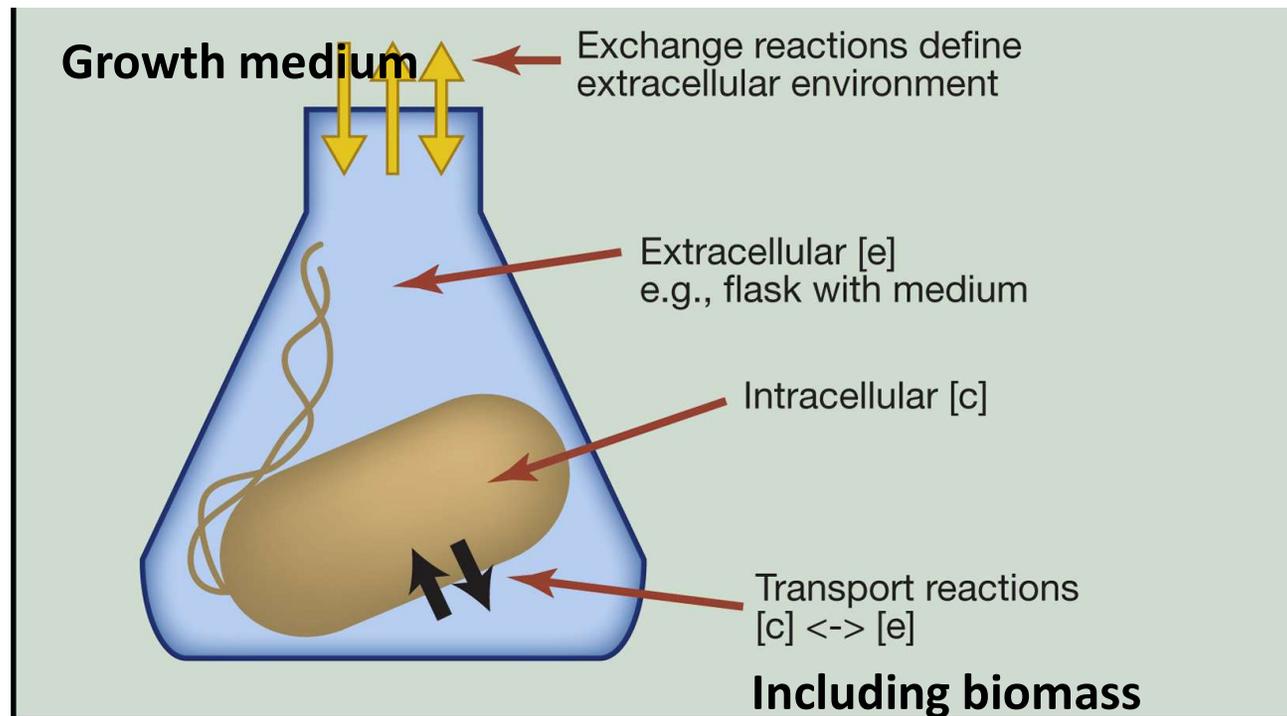
α is the optimal value of the initial objective

- ⇒ While the objective has the optimal value other fluxes may vary
- ⇒ The ones that are non-zero are essential for the optimal value of the objective

Artificial reactions forming biomass allow growth simulations

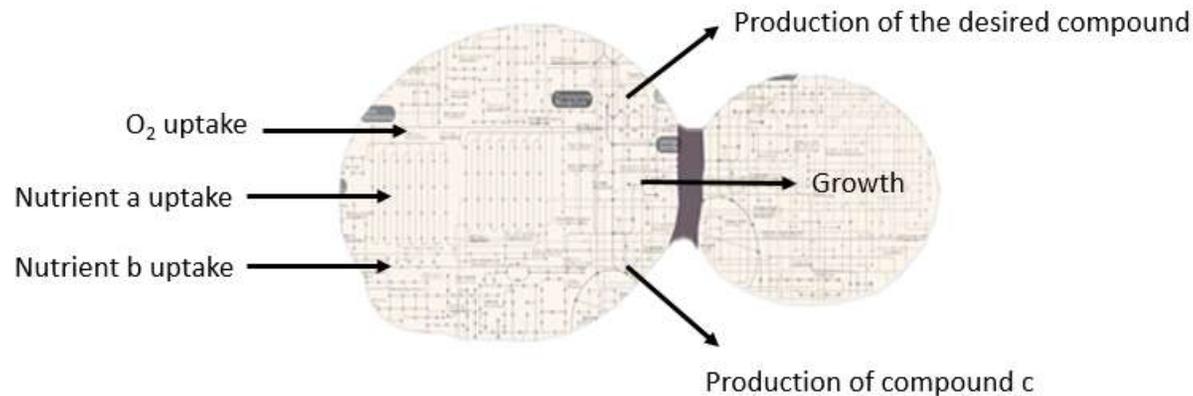


Metabolic states depend on environment

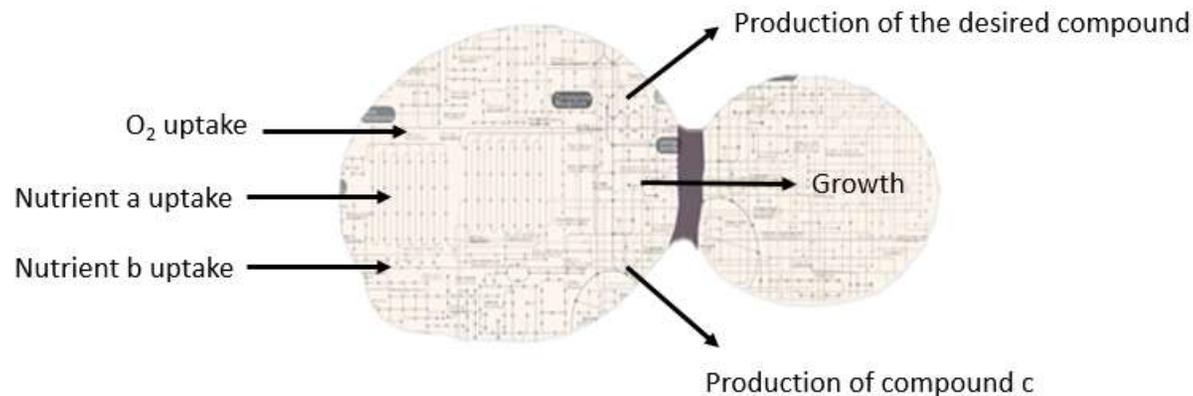


Specific fluxes

- Flux units depend on how the artificial biomass producing reaction is defined
- If it is defined as mmol of precursors for generating 1 g cell dry weight (CDW), then flux units are $\text{mmol}/(\text{g CDW} * \text{h})$



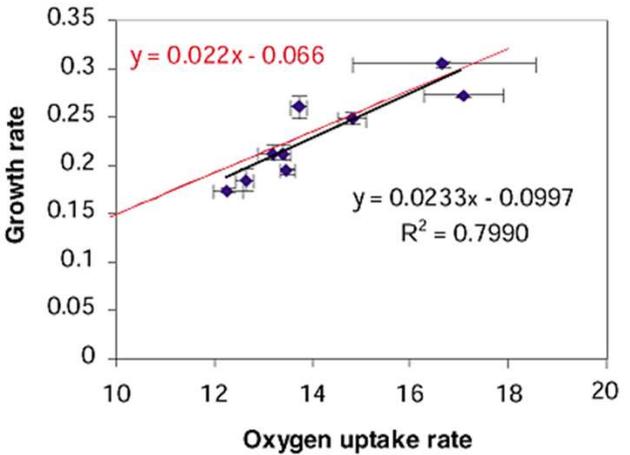
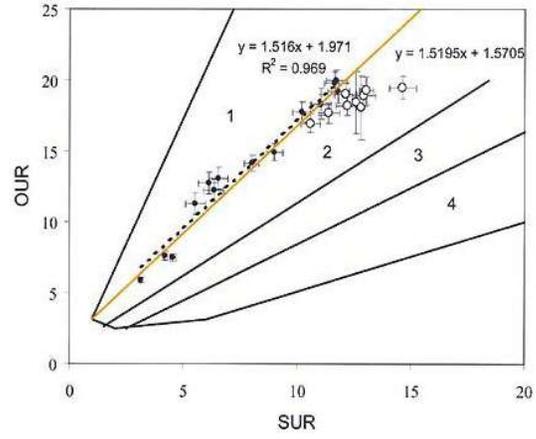
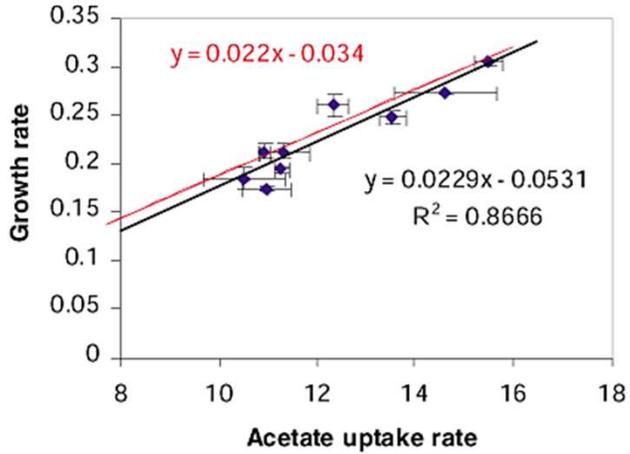
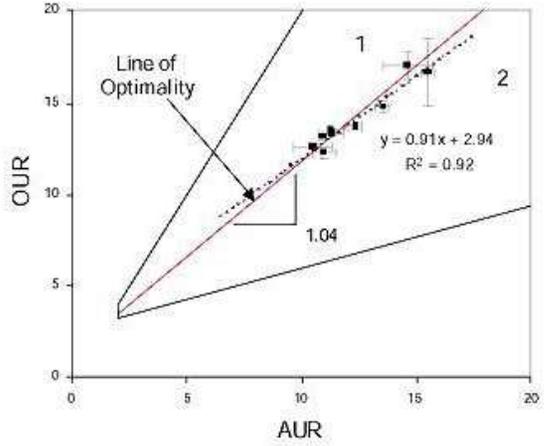
Prediction vs estimation of metabolic state?



When arbitrary constraints are used, yields can be predicted

When empirical rates are used as constraints, other rates can be estimated or predicted

FBA simulations optimizing growth predict well experimental phenotypes



In silico predictions of *Escherichia coli* metabolic capabilities are consistent with experimental data

Jeremy S. Edwards^{1,2}, Rafael U. Ibarra¹, and Bernhard O. Palsson^{1*}

¹Department of Bioengineering, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093-0412. ²Current address: Department of Chemical Engineering, University of Delaware, Newark, DE 19716. *Corresponding author (palsson@ucsd.edu).

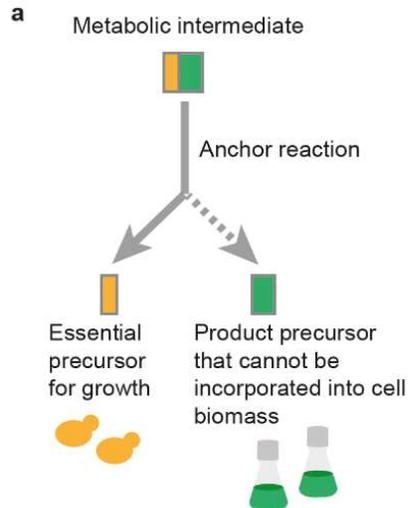
Design of strain engineering strategies

In silico design of engineering strategies using genome-scale metabolic models

- Growth-product coupling: the cells can only grow if they produce
- Push-pull strategies: expression levels are modified to push and pull more resources to production

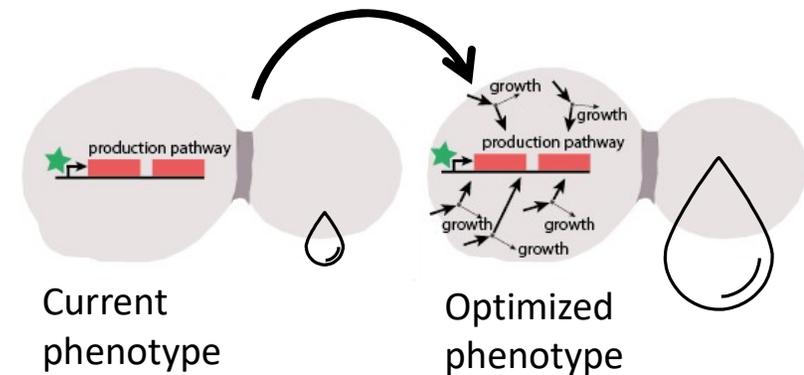
Growth-product coupling

Algorithms use genome-scale metabolic models for identifying knock-out targets



Push-pull strategies

Algorithms use genome-scale metabolic models for identifying deletion and re-regulation targets



Jouhten P. et al. *unpublished work* with Kiran Patil, EMBL Heidelberg

Growth-product coupling aligns biological and engineering objectives

Bi-level optimization

Design Objective

Find k deletions such that maximum product yield is achieved:

such that,

Biological Objective

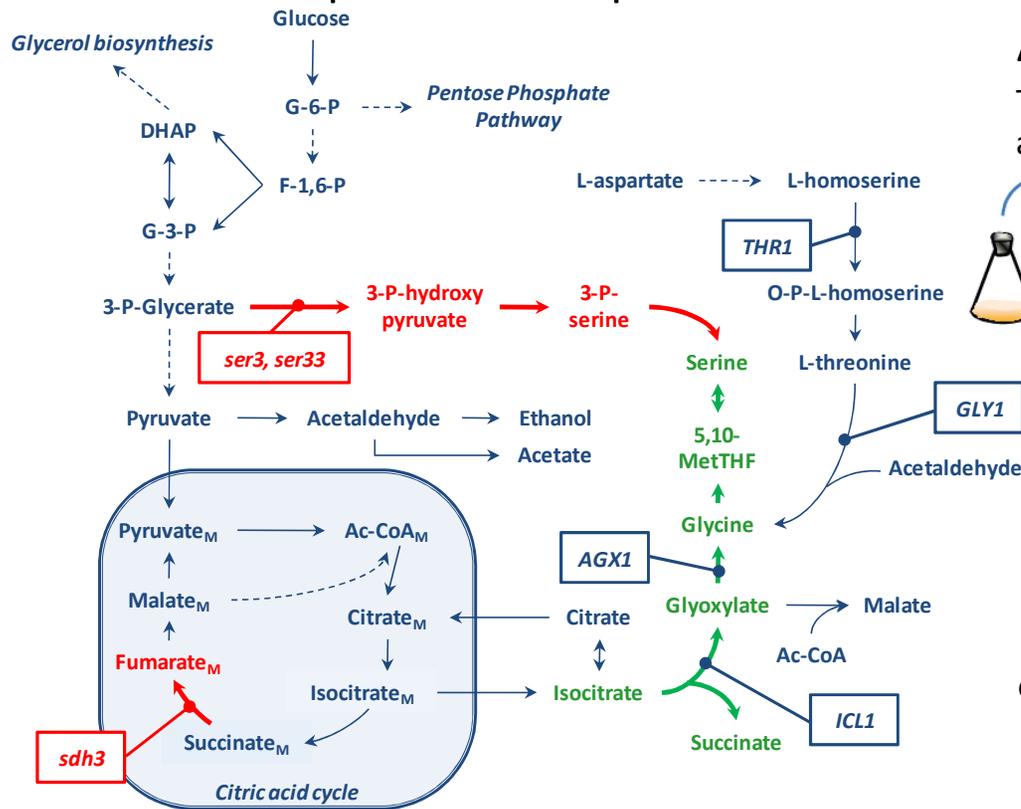
e.g. *flux is distributed for maximum growth*

Evolution driven objective

OptKnock: Burgard et al. (2003)
OptGene: Patil et al. (2005)

Growth-product coupling allows using adaptive laboratory evolution for improving production

Proof of concept: succinate production in *S. cerevisiae*

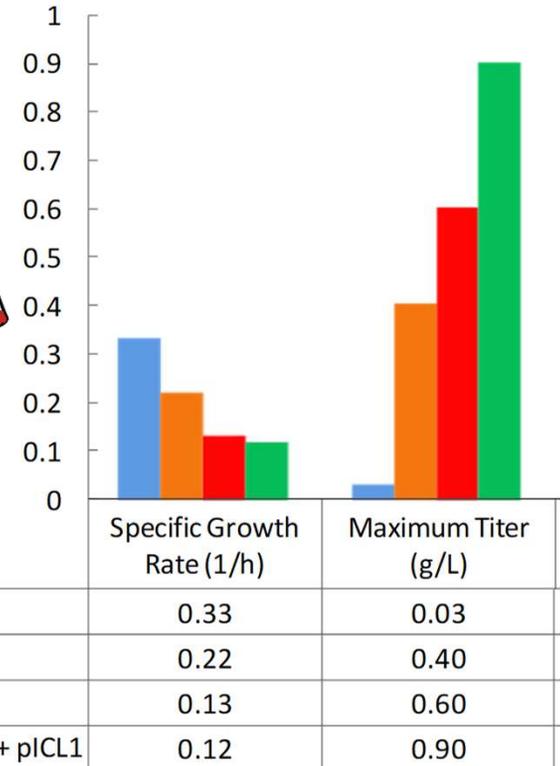


ALE

To recover from Gly auxotrophy



Gly auxotrophic
Gly prototrophic



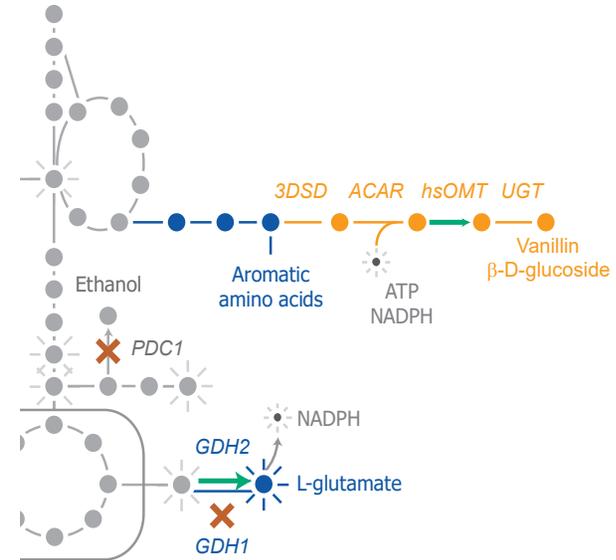
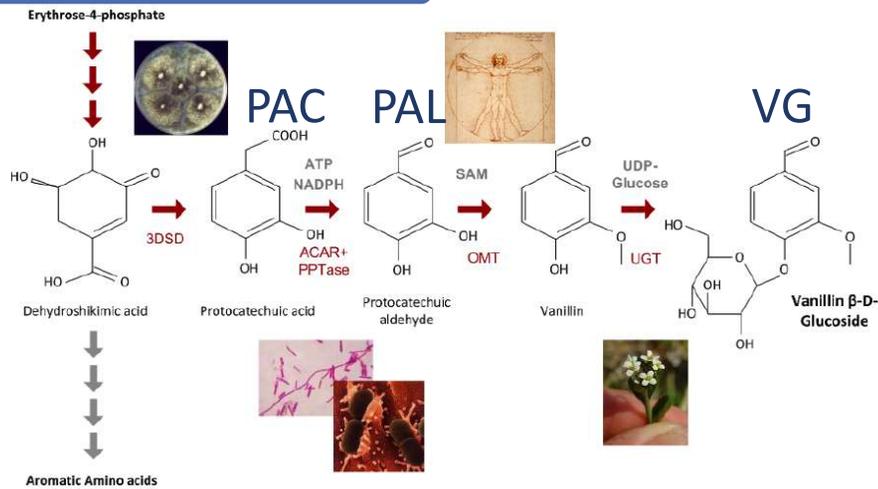
Otero *et al.* PLoS One. (2013) 8:e54144.

Slide from Kiran Patil

Pathway optimization improved vanillin production only after designed optimization of network



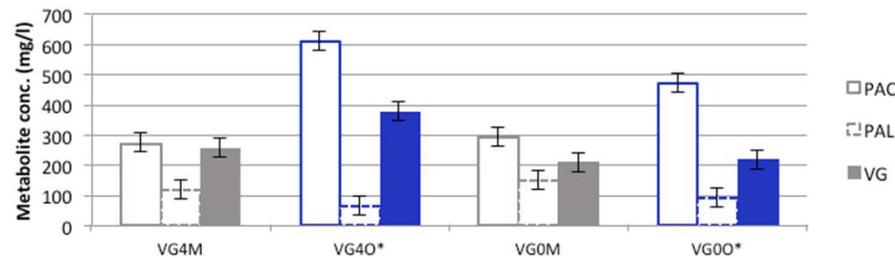
Synthetic vanillin pathway



Experimental validation



Overall 5-fold productivity improvement



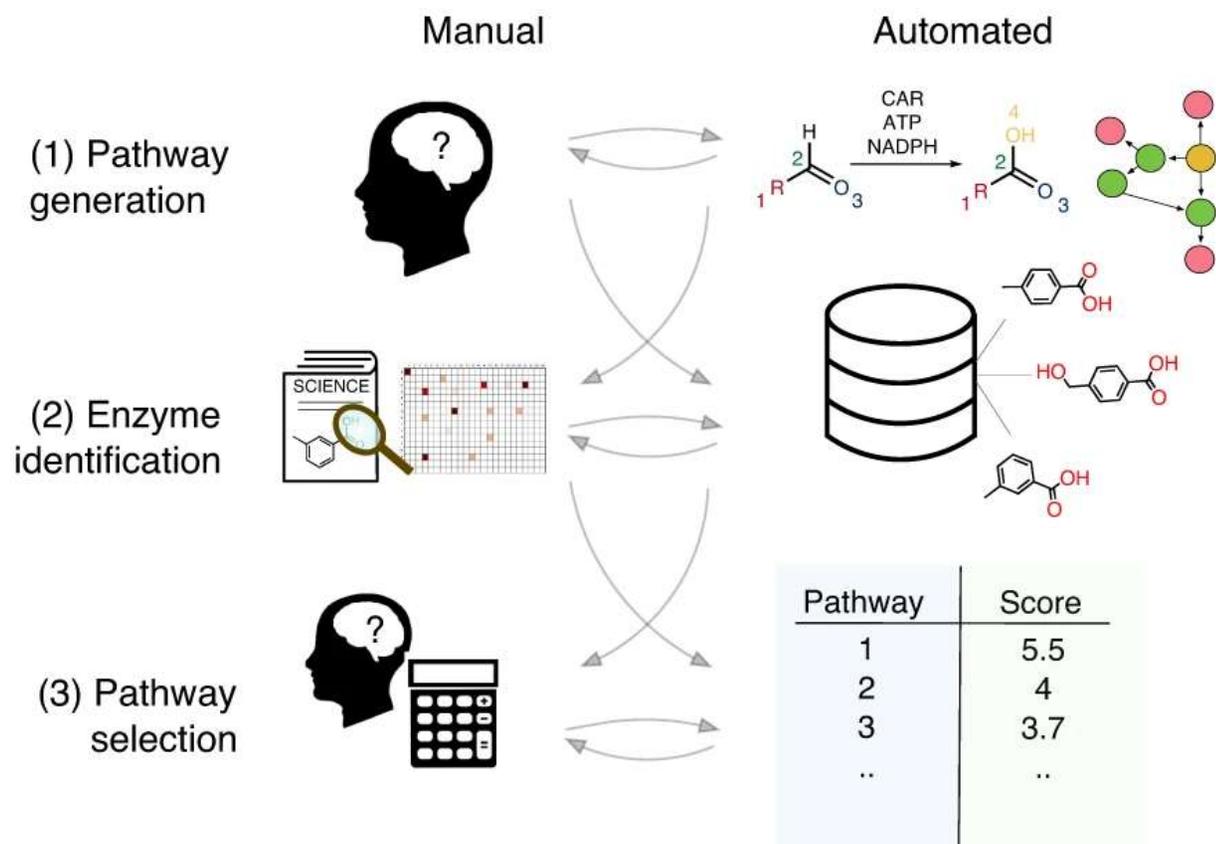
Strains with overexpressed O-methyltransferase in blue

Brochado et al. (2011, 2013). Dr. Kiran Patil in collaboration with Evolva A/S (Denmark)

Slide from Kiran Patil

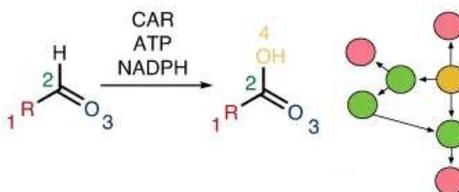
Synthetic pathway design

Synthetic pathway design



Biochemical pathway generation

(1) Pathway generation



- Can be defined as a retrosynthesis problem from desired compound back to precursors in microbial cells
- Such pathways can be searched through known biochemical reactions from data bases like Kegg, Metacyc, Rhea
- They can also be searched through potential reactions that enzymes could catalyze defined by reaction rules



Finnigan et al. (2021) Nat Catal 4:98-104. doi: 10.1038/s41929-020-00556-z.

Reaction rules model possible enzyme catalyzed reactions

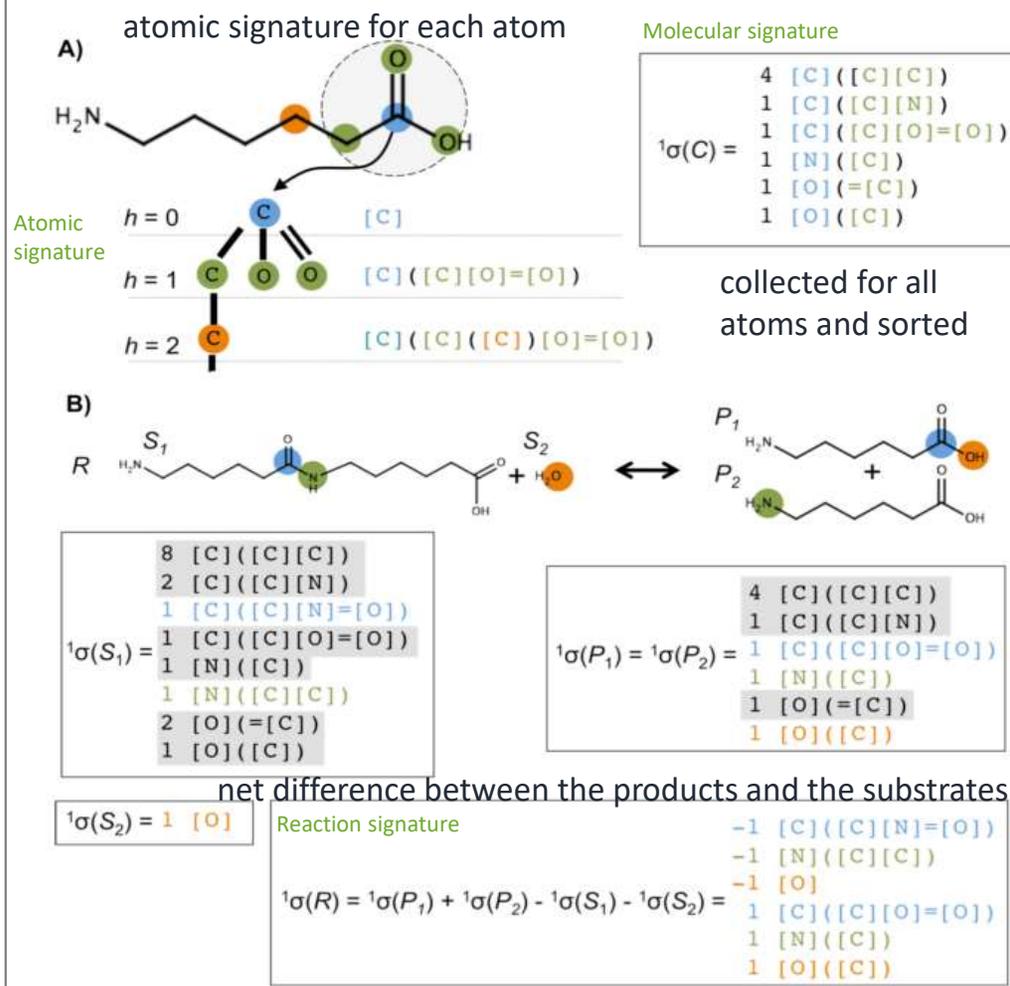
- Rules model similarities to known reactions (i.e. similarities of reactants)
- Assume that if the core of the reaction (where the bonds break) remains the same then an enzyme could be found/built for the novel reaction
- Define different dimensions of the core
- Reaction rules create extended metabolic space

Table 1 Reactions in the EMRS

height h	reactions	% increase from canonical
2	9083	17.72%
3	7882	2.15%
4	7800	1.09%
5	7752	0.47%
6	7725	0.12%
canonical	7716	0%

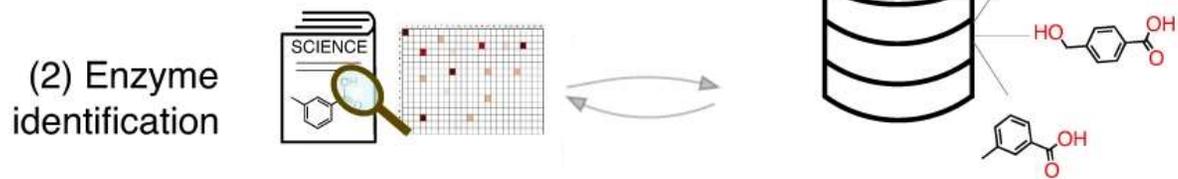
Number of novel generated putative reactions in the EMRS for different heights h .

Retropath method reaction signature



Carbonell, P., Planson, A.-G., Fichera, D., & Faulon, J.-L. (2011). A retrosynthetic biology approach to metabolic pathway design for therapeutic production. *BMC Systems Biology*, 5(1), 122.

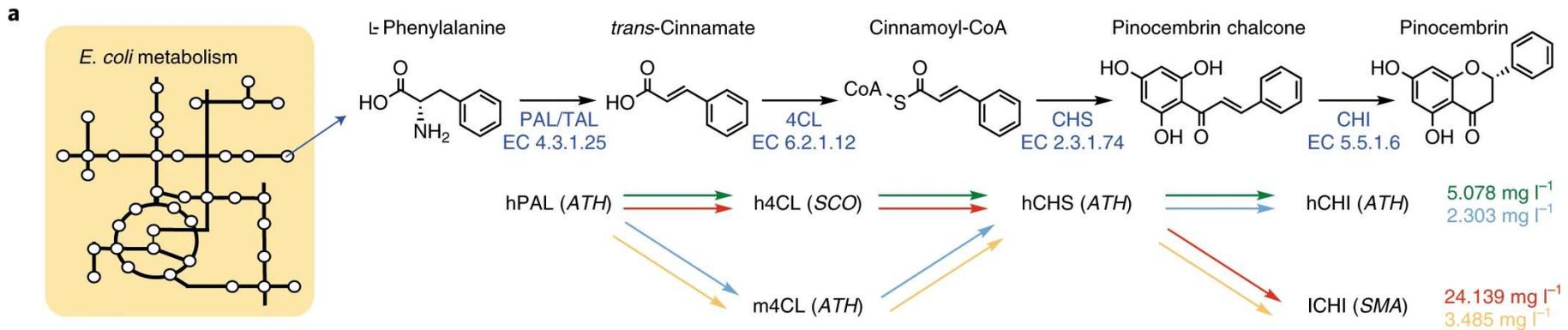
Finding enzymes



- If the reactions were already known and annotated with enzyme sequences, more candidate sequences found from sequence resources using similarity-based search
- If many sequences encoding the desired enzymatic activity are known, likely important sequence features for the activity can be identified
- If no sequence is known, reaction rules can be used for identifying sequences that may encode also the desired activity (i.e. due to promiscuity)

If substantial **sequence similarity** is observed, the sequences are likely **homologous (i.e. share ancestry in evolution)**

Synthetic pathway to pinocembrin to *E.coli*



Alternative enzyme options result in different pinocembrin titers
 Pathway optimization could involve optimizing the enzyme levels or the actual enzymes

Figure from Lee et al. Nature Catalysis 2,18–33(2019) but data from Feher, T. et al. Biotechnol. J. 9, 1446–1457 (2014).

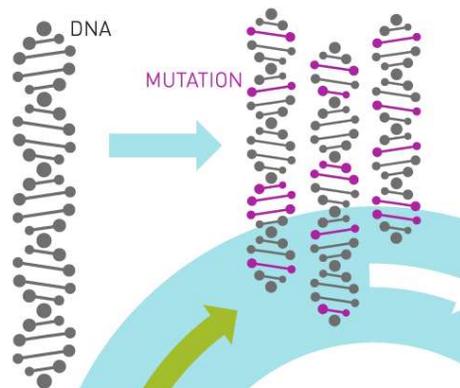
Frances H. Arnold
received the Noble prize
for directed evolution of
proteins in 2018



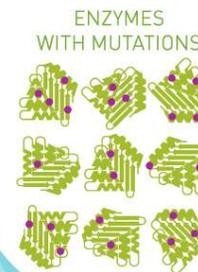
<https://www.quantamagazine.org/frances-arnold-george-smith-and-gregory-winter-win-chemistry-nobel-for-directing-evolution-20181003/>

THE WORK FLOW FOR THE DIRECTED EVOLUTION OF ENZYMES

1 Random mutations are introduced in the gene for the enzyme that will be changed.

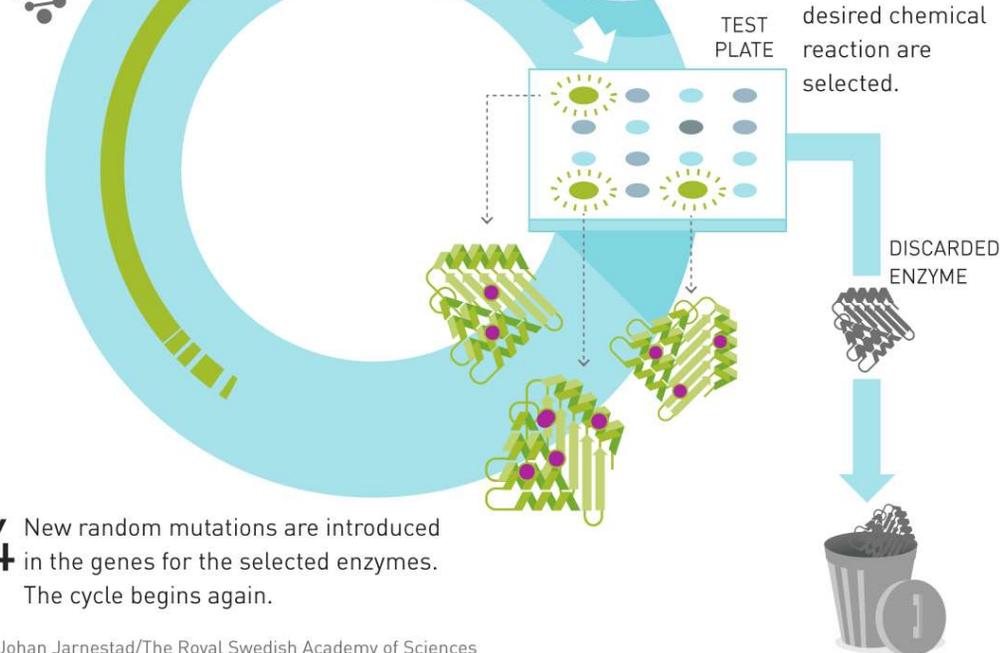


2 The genes are inserted in bacteria, which use them as templates and produce randomly mutated enzymes.



3 The changed enzymes are tested. Those that are most efficient at catalysing the desired chemical reaction are selected.

4 New random mutations are introduced in the genes for the selected enzymes. The cycle begins again.



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Novel protein design is coming within reach

AlphaFold by DeepMind is a breakthrough in natural protein folding prediction

Article

Improved protein structure prediction using potentials from deep learning

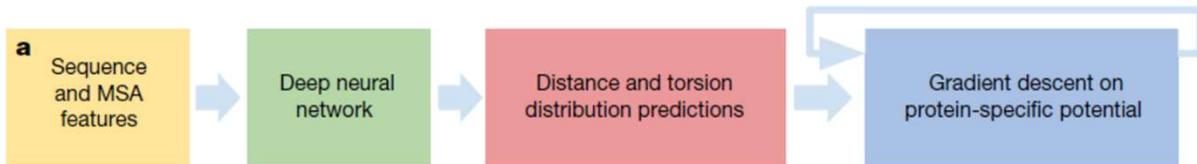
<https://doi.org/10.1038/s41586-019-1923-7>

Received: 2 April 2019

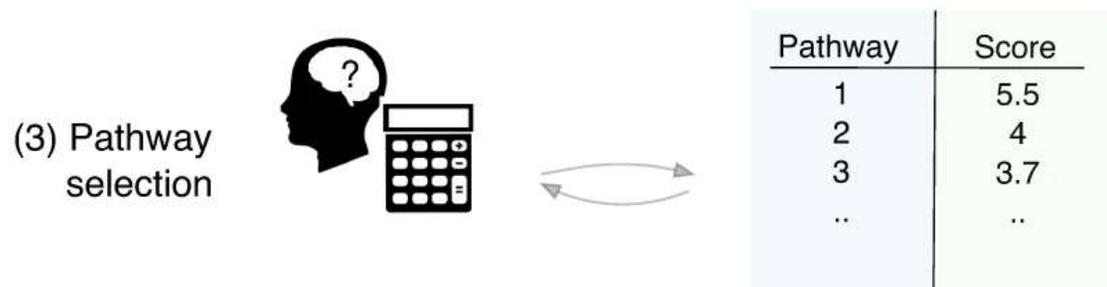
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Andrew W. Senior^{1,2*}, Richard Evans^{1,4}, John Jumper^{1,4}, James Kirkpatrick^{1,4}, Laurent Sifre^{1,4}, Tim Green¹, Chongli Qin¹, Augustin Židek¹, Alexander W. R. Nelson¹, Alex Bridgland¹, Hugo Penedones², Stig Petersen¹, Karen Simonyan¹, Steve Crossan¹, Pushmeet Kohli¹, David T. Jones^{2,3}, David Silver¹, Koray Kavukcuoglu¹ & Demis Hassabis¹



Synthetic pathway design



- Criteria e.g. theoretical yield, thermodynamics of reactions, pathway length, number of new-to-nature reactions, toxicity