

# Reminder of Course Aims

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**Course is NOT about memorization, but about training skills, quantitative and critical thinking**

- different from most ETH lectures less new knowledge but ability to use existing knowledge
  - train to operate independently in “unfamiliar” situations with open end (and less precise) questions
- Keep in mind that it is about concepts and NOT the examples we use, they are for illustration*

# 3. ODE Modeling of Metabolic Pathway

- Relate experimental observations to model behaviors via parameters.
- Understand potential biological problems of metabolic dynamics and how regulation can help.
- Understand basic principles of neg and pos feedback.
- Understand biological challenges arising in bi-directional pathways, example of glycolysis/gluconeogenesis.

## Exercise 4

Continuing dynamic analyses, you will be able to:

- understand limitations of simple model to predict response to perturbations, and develop ideas how to overcome the limitations.
- understand effect of basic regulation (neg feedback) on dynamic system - learn to hypothesize and reason on regulatory function.

## Exercise 5

build, analyze and simulate a real (bi-directional) pathway: glycolysis.

## ODE Modeling of a Metabolic Pathway

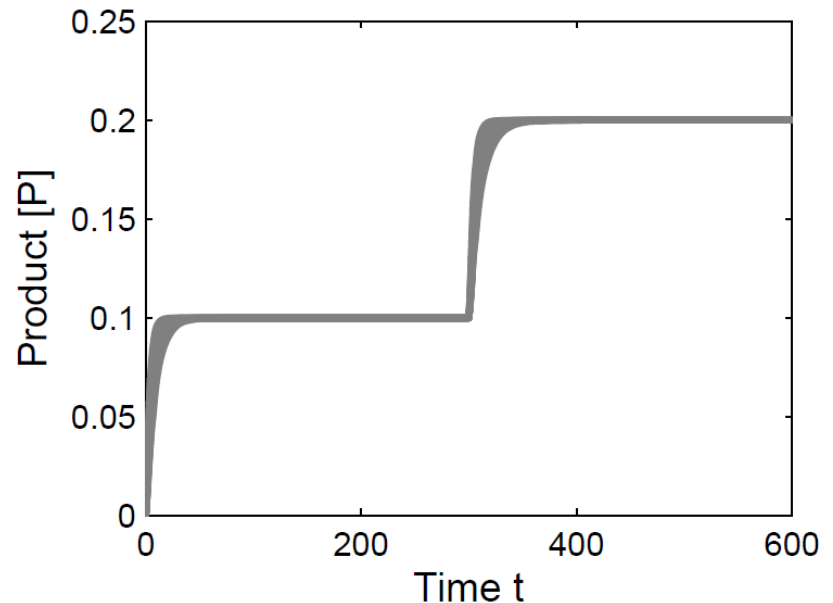
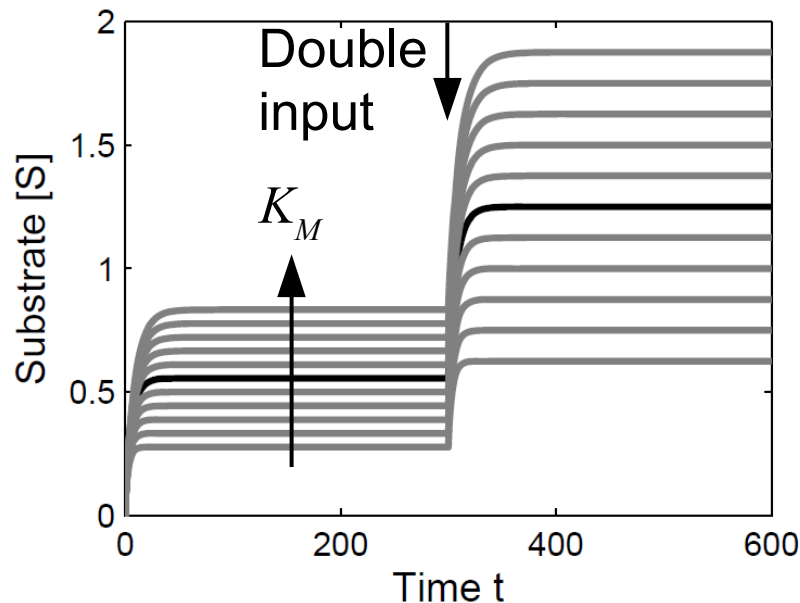
9 March, 2017

Uwe Sauer & Jörg Stelling

### Content:

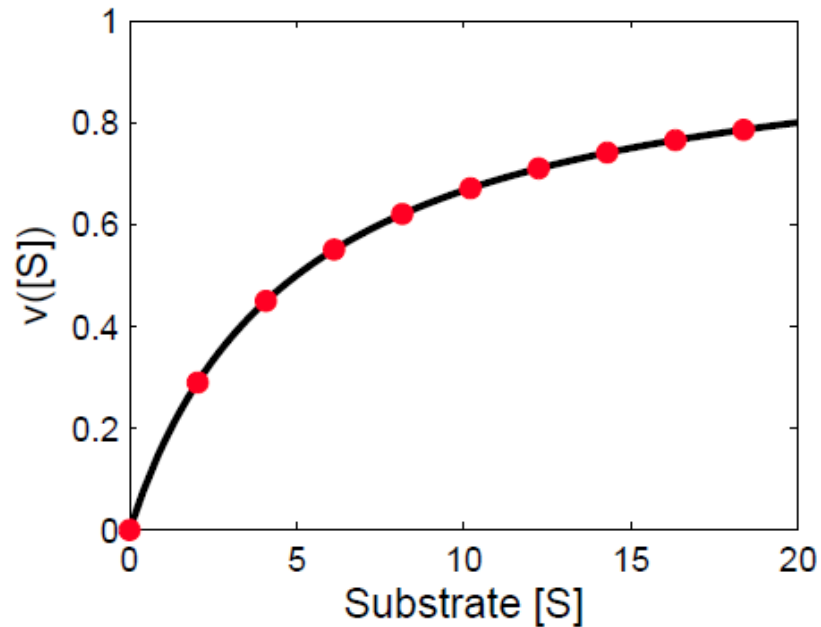
- Concepts: Parameters & model quality (JS)
- Potential biological consequences of metabolic dynamics (US)
- Concepts: Feedback (JS)
- Glycolysis/Gluconeogenesis (US)

# Pathway Dynamics: Example Revisited



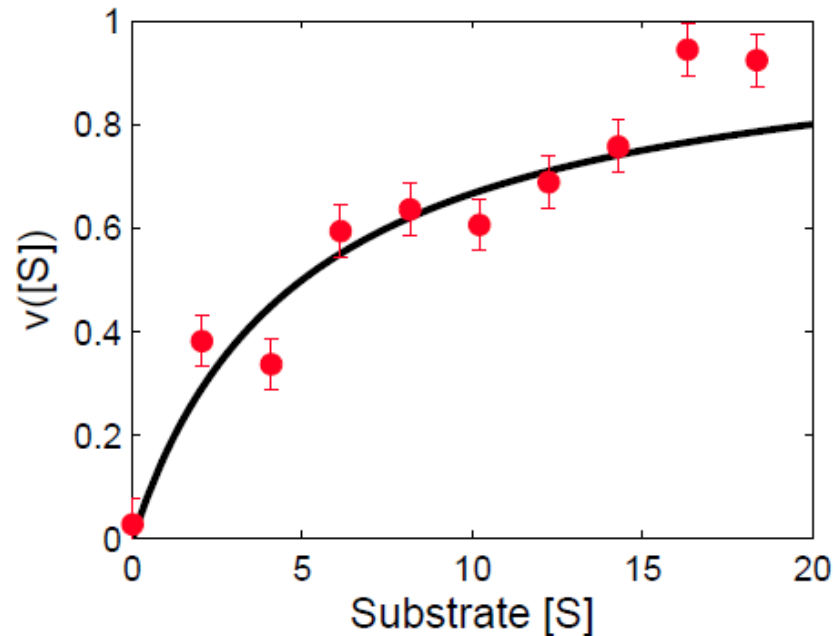
- ❑ **Parameter choices affect predicted dynamics.**
- ❑ Product concentration in steady-state is identical:  
Fluxes through the pathway have to be equal.

# Parameter Values: How to Obtain Them?



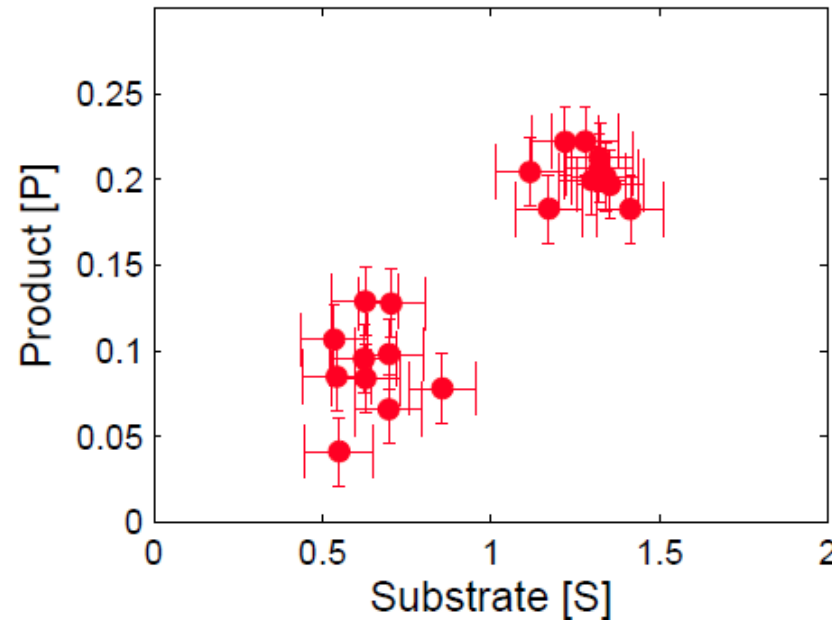
- ❑ **Ideal world:** Databases or measure all quantities exactly.

# Parameter Values: How to Obtain Them?



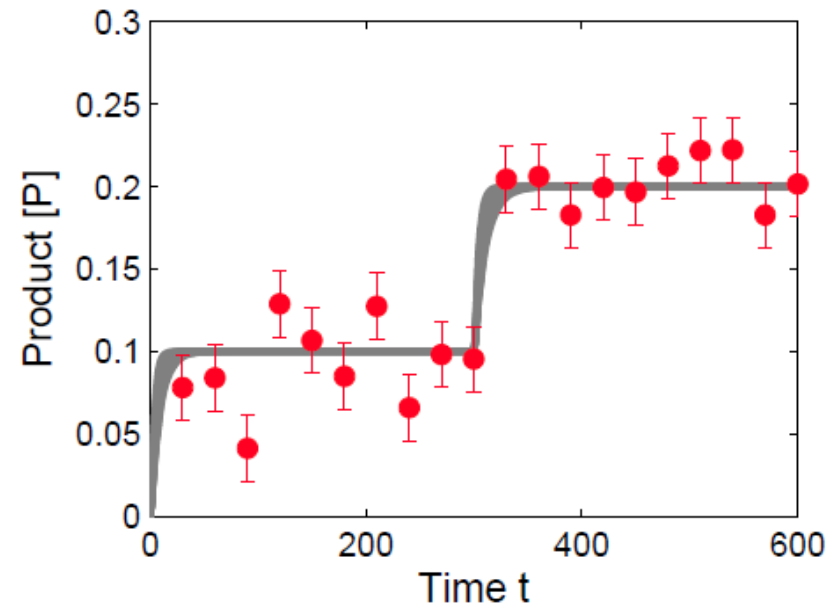
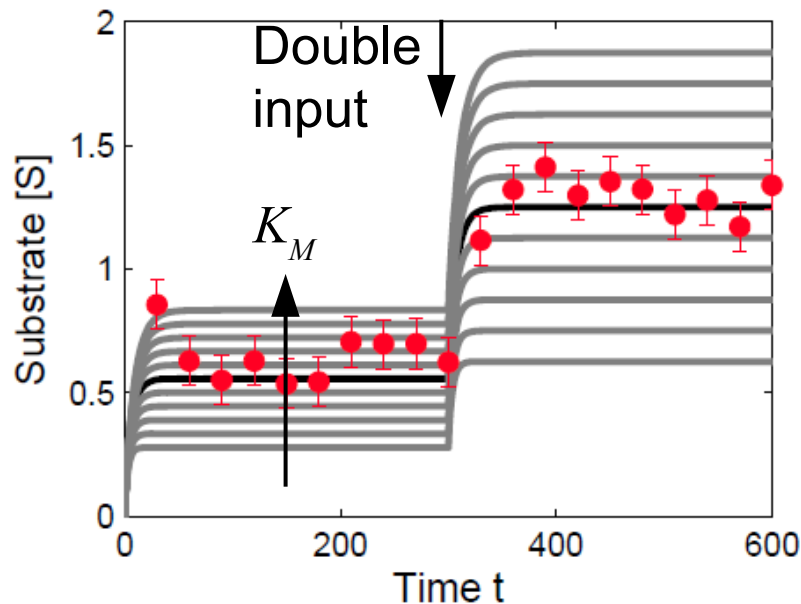
- ❑ **Ideal world:** Databases or measure all quantities exactly.
- ❑ **Reality:** Measurement errors induce uncertainty.

# Parameter Values: How to Obtain Them?



- ❑ **Ideal world:** Databases or measure all quantities exactly.
- ❑ **Reality:** Measurement errors induce uncertainty.
- ❑ **Biological reality:** Not all quantities can be measured →  
We need (the right) models to **estimate** parameters.

# Pathway Dynamics: Example With Data

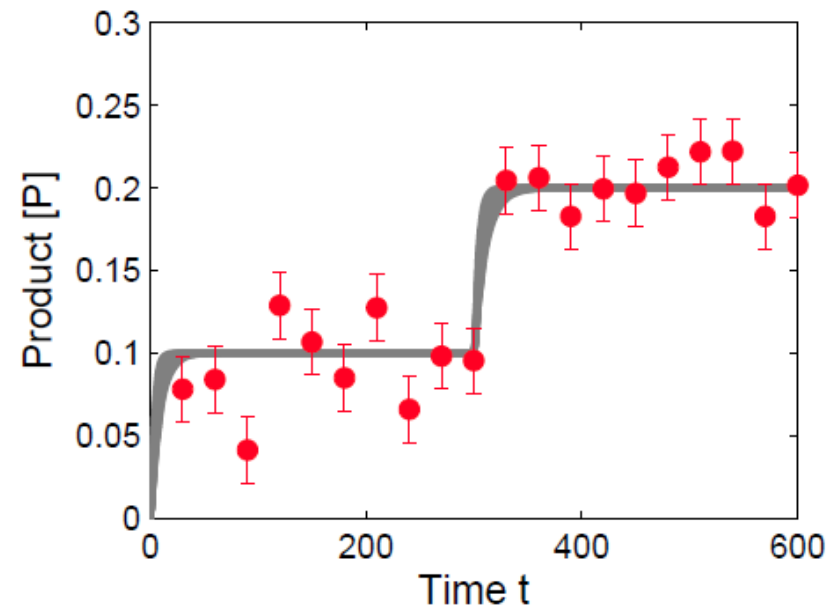
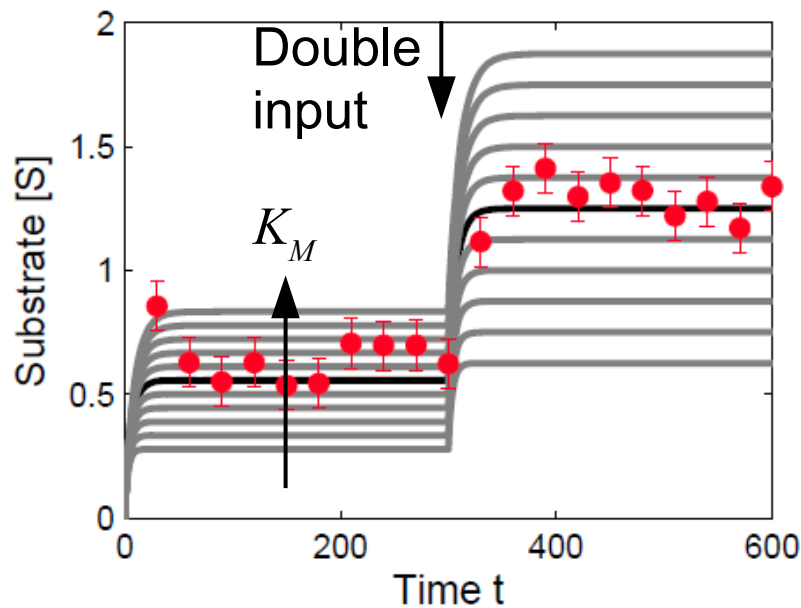


- **Aim:** Select parameter value (for  $K_M$ ) that best fits data.

Is S or P data more informative for  $K_M$  ?



# Concept: Measuring Model Quality

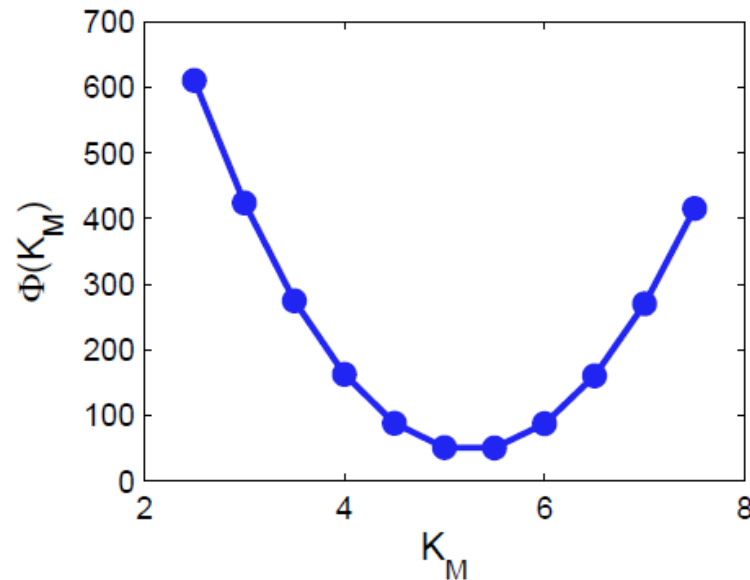


- ❑ **Measure parameter quality:** Distance between simulation ( $x$ ) and experimental ( $x^E$ ) data, taking measurement error ( $\sigma^E$ ) into account:

this formula gives a good approx for  $K_m$

$$\Phi(K_M) = \sum_{i=1}^N \left[ \frac{x(t_i, K_M) - x^E(t_i)}{\sigma^E(t_i)} \right]^2$$

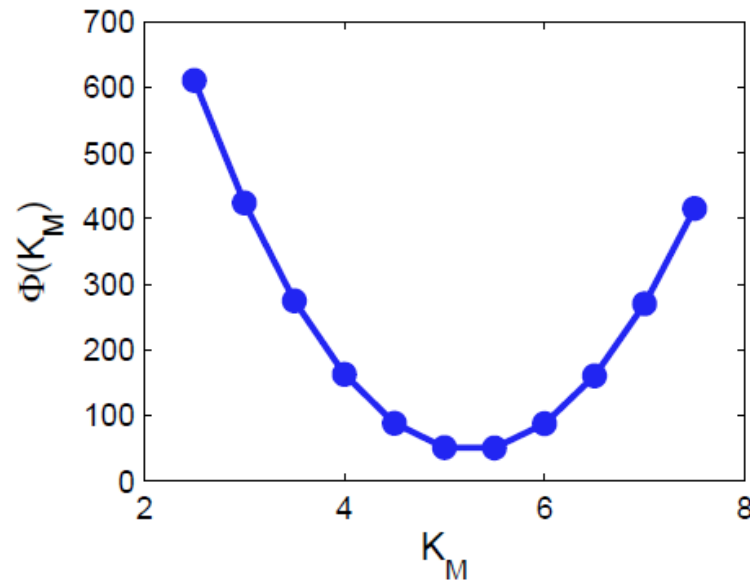
# Concept: Measuring Model Quality



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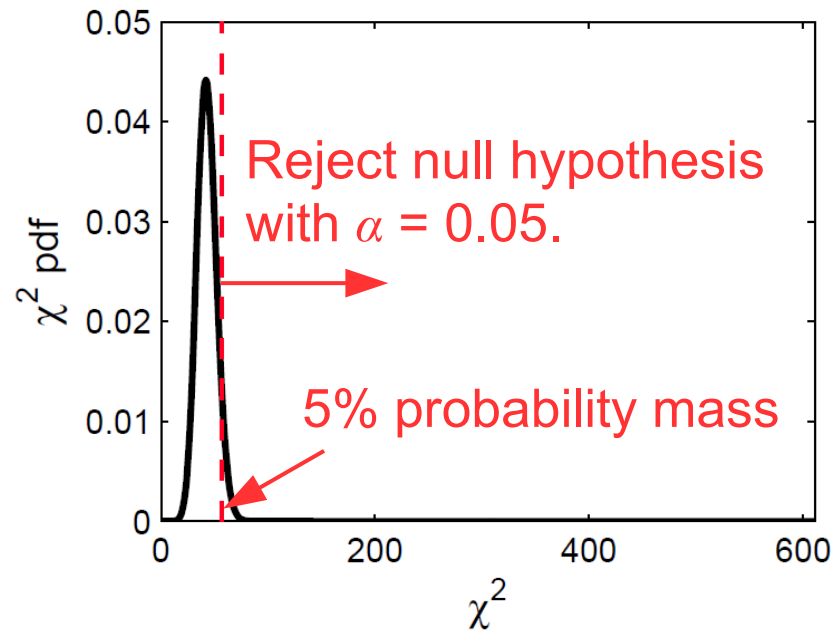
# Concept: Measuring Model Quality



data itself is unsure  
due to background  
noise and limits of  
the measuring  
tools

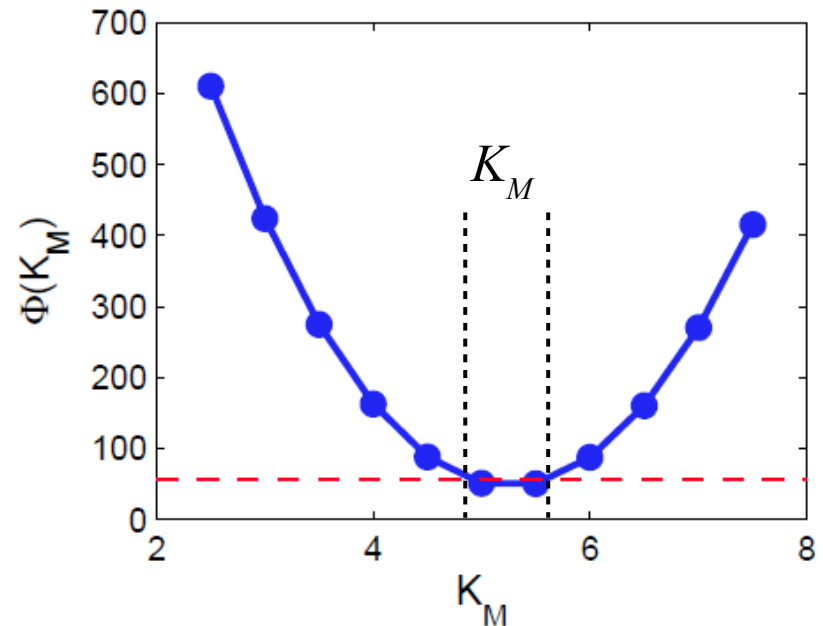
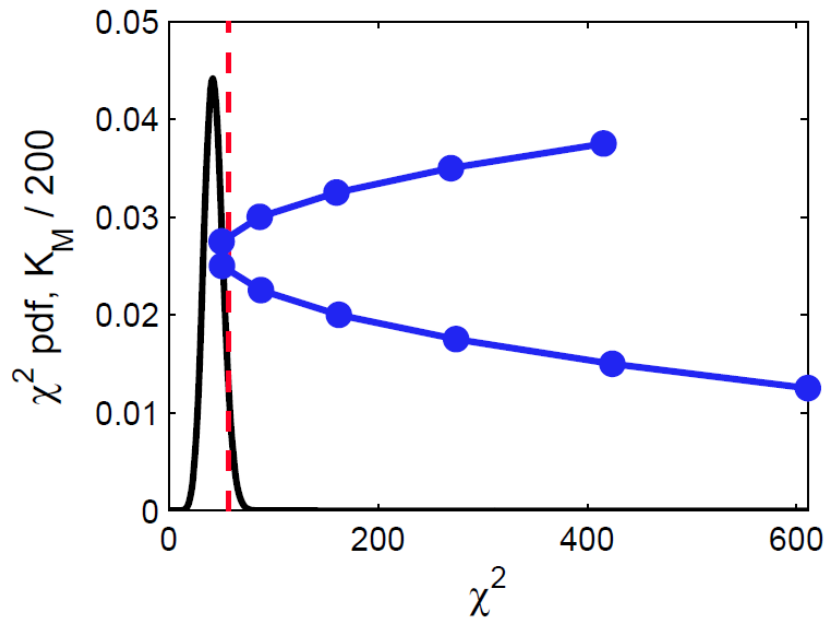
- ❑ **Measure parameter quality:** But which distance between model and data is 'small enough'?
- ❑ **Answer by statistical test:** Is the deviation just caused by measurement noise in the data?

# Concept: Test Statistics



- ❑  **$\chi^2$ -test:** Null hypothesis = deviation is caused by measurement noise with #data points - #estimated parameters degrees of freedom.
- ❑ Select confidence level ( $\alpha$ ) and compare to distance.

# Concept: Uncertain Parameter Values



- ❑  **$\chi^2$ -test:** For the chosen confidence level, several parameter assignments are statistically valid.
- ❑ **General consequence:** Measurement noise leads to uncertainties in parameter values.

# Example: Michaelis-Menten Parameters

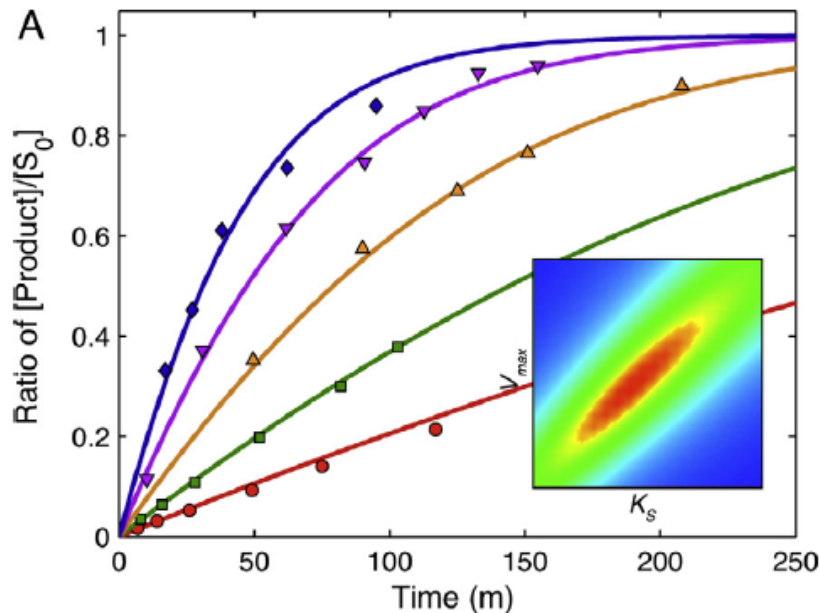
Die Kinetik der Invertinwirkung.

Von

L. Michaelis und Miß Maud L. Menten.

(Eingegangen am 4. Februar 1913.)

$$v = \frac{v_{max} [S]_0}{[S]_0 + K_M}$$



K. A Johnson, *FEBS Letters* 587: 2753 (2013).

- $v_{max}/K_M$  estimation with pen & paper (1913):  
 $0.045 \pm 0.003 \text{ min}^{-1}$
- $v_{max}/K_M$  estimation by computation (2013):  
 $0.046 \pm 0.001 \text{ min}^{-1}$

# Summary: Teaching Goal I

- ❑ Parameter values often have to be estimated indirectly experimental data using a model.
- ❑ Model behaviors and experimental data can be related by measuring the distance between both.
- ❑ This distance depends on parameter values - 'good' parameter values show a low distance.
- ❑ With a statistically defined distance threshold, we obtain parameter estimates and their uncertainties.

# Systems Biology 551-1174-00L

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## ODE Modeling of Metabolic Pathways

9 Mar, 2017

Uwe Sauer, Institute of Molecular Systems Biology

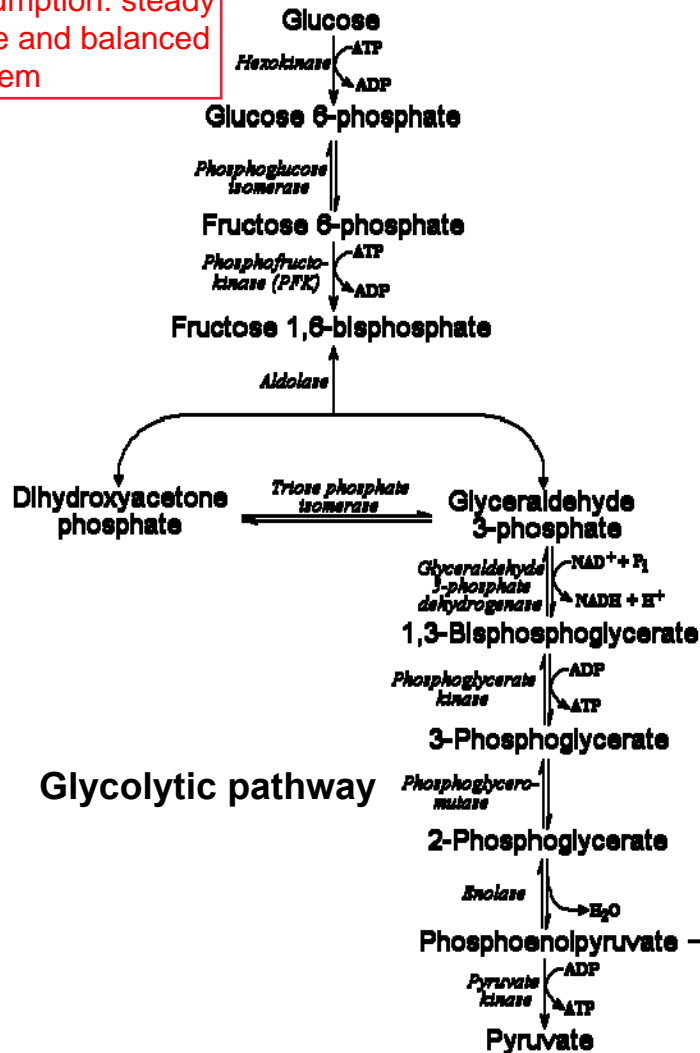
### Content:

- Concepts: Parameters & model quality (JS)
- **Biological consequences of metabolic dynamics (US)**
- Concepts: Feedback for simple systems (JS)
- Glycolysis/gluconeogenesis (US)

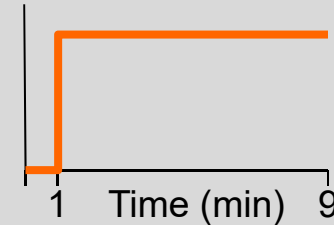


# Metabolite Dynamics Upon Perturbation

assumption: steady state and balanced system

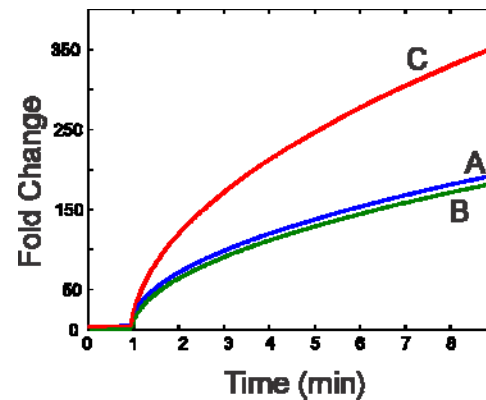


6-fold step increase of INFLUX to A

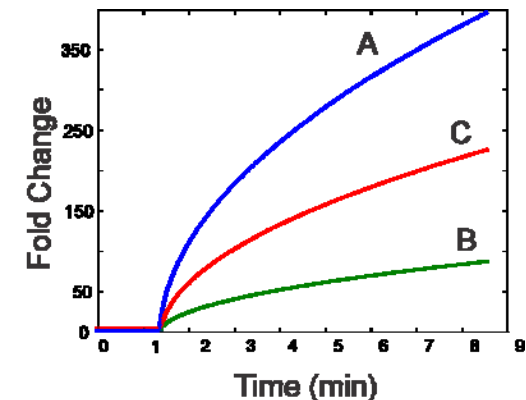


Parameter set 1

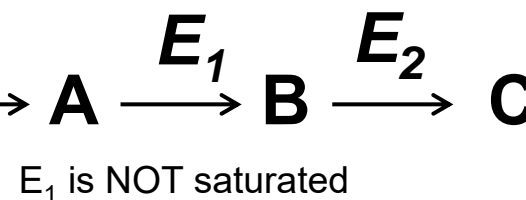
$V_{max}$  and  $K_m$  of  $E_1$  and  $E_2$  similar



Parameter set 2

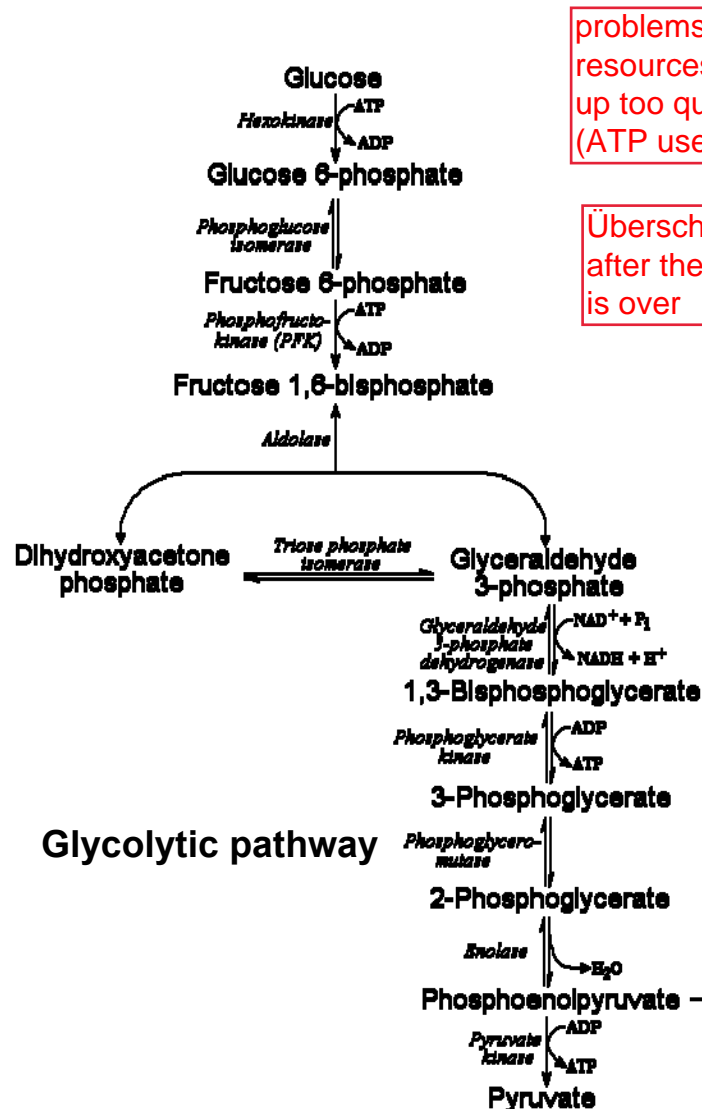


$K_m$  of  $E_1$ , 40 times larger than in set 1



no steady state in both cases

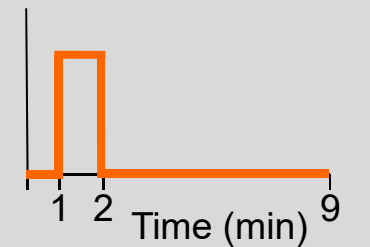
# Metabolite Dynamics Upon Perturbation



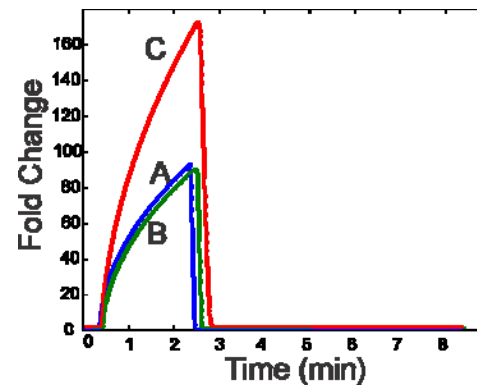
problems: toxicity,  
resources are used  
up too quickly  
(ATP used up)

Überschuss even  
after the pulse (1s)  
is over

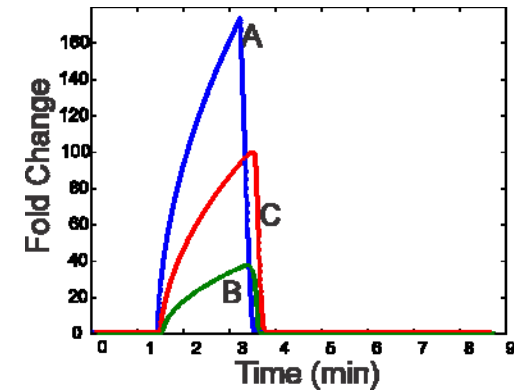
6-fold pulse-like  
increase of INFLUX  
to A



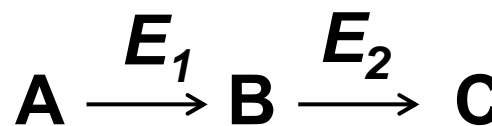
Parameter set 1  
 $V_{\max}$  and  $K_m$  of  $E_1$  and  $E_2$  similar



Parameter set 2



$K_m$  of  $E_1$ , 40 times  
larger than in set 1



What are potential problems for the cell ?

# Consequences of Metabolite Dynamics for the Network

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- Consequences of unregulated pathways:

long time until steady state  
overshoot in metabolite [conc]

- Potential problems of such overshoots ?

metabolite toxicity  
influence other reactions where it participates  
could drain cell of ATP, phosphates etc

*In exercise you will explore how S and P inhibition can alleviate such problems.*

***How can cells avoid/reduce such problems ?***

implement regulation

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Achieving appropriate dynamic responses to perturbations is a general control problem for all biological systems.

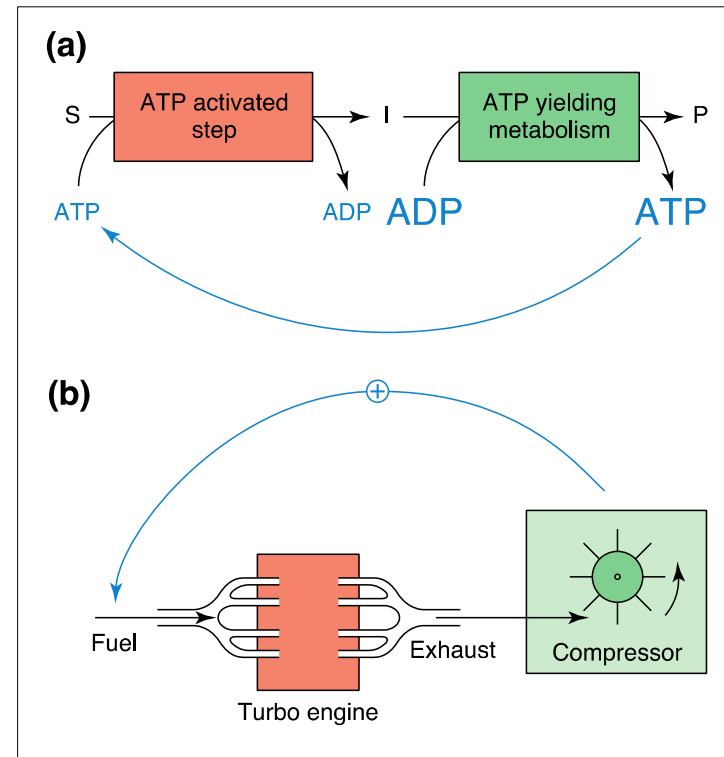
- avoid extreme responses
- quickly achieve a new steady state
- respond flexibly at a time scale that matters
- remain robust to different types, intensities and frequencies of perturbation.
- .....

*Just like in technical control systems (eg air condition), biological control systems are not perfect. In the following we'll discuss an example: Turbo Design*

# Dynamic Problems of Pathways with Turbo-Design

Teusink et al. 1998 Trends Biochem. Sci

- many catabolic pathways begin with an ATP-requiring activation reaction
- net ATP generation occurs further down the pathway
- biologically useful when there is a continuous supply of substrate (eg in higher organisms)
- *perturbation: what happens upon substrate fluctuations?*



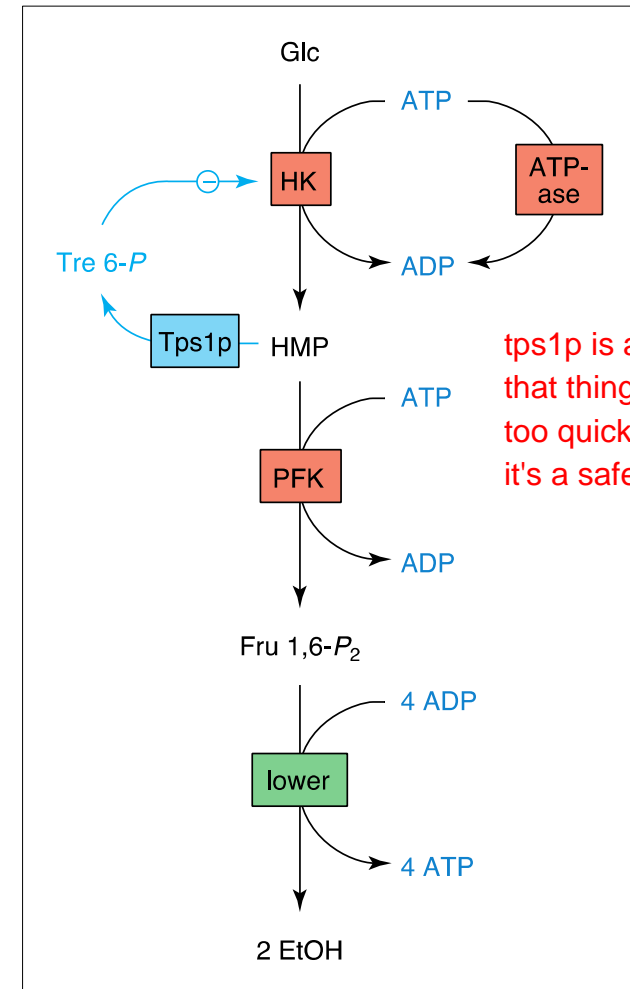
**Comparison of an activated catabolic pathway with a turbo engine.** (a) General scheme for a catabolic pathway in which the first step involves coupling of ATP hydrolysis to activation of a substrate (S). Downstream, the conversion of an intermediate (I) to a product (P) generates a surplus of ATP. (b) Schematic representation of a turbo engine, in which exhaust gases are used to increase the influx of fuel.

# Turbo-Design: Example Glycolysis

- In bacteria and yeasts, sudden excess of substrate supply can lead to **substrate-accelerated death** (eg maltose supply in *S. cerevisiae*)
- With glucose it does not occur, unless *tps1* is deleted, which encodes the trehalose-6-P synthetase
- Although trehalose-6-P has no role in glycolysis, one function of Tps1-p is to inhibit the first step of glycolysis to reduce the initial flux (ie **guard** the initiation of glycolytic flux)

Schematic representation of the core model of glycolysis. In the model the lower part of glycolysis is represented as a single step. Glc, glucose; HMP, hexose monophosphate; Fru 1,6-P<sub>2</sub>, fructose 1,6-bisphosphate; Tre 6-P, trehalose 6-phosphate; EtOH, ethanol; HK, hexokinase; PFK, phosphofructokinase; Tps1p, Tre 6-P synthase; lower, lower part of glycolysis.

pool of ATP drops and the next reaction cant even start due to little ATP present (lots of ADP)



*tps1p* is a regulating step so that things are not used up too quickly. it's a safety system.

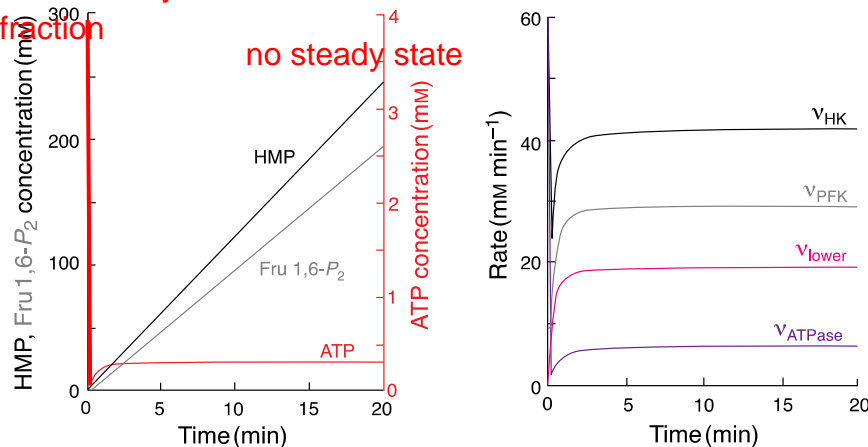
Teusink et al. 1998 Trends Biochem. Sci

# Turbo-Design Glycolysis: What is the Problem?

Time course simulations with a kinetic model of yeast glycolysis of a glucose pulse at  $T_0$  (only the core reactions shown on the figure before)

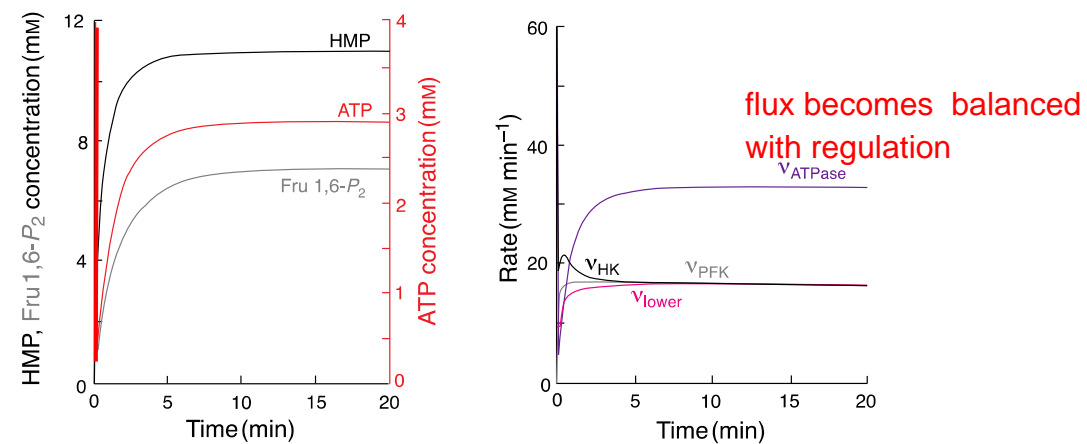
## Unguarded glycolysis

ATP drops extremely, trapped in low ATP state!  
then recovers only a small fraction



## Guarded glycolysis

these find their steady state elater on



Guarded means a feedback inhibition of hexokinase by hexose-P (for example through the trehalose-6-P loop)

Teusink et al. 1998  
Trends Biochem. Sci

## ODE Modeling of a Metabolic Pathway

9 March, 2017

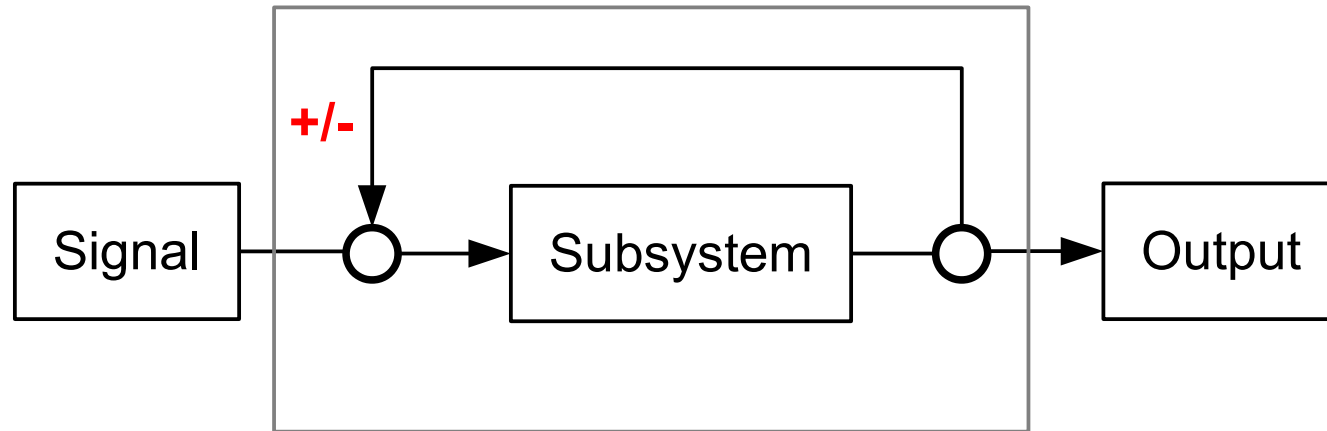
Uwe Sauer & Jörg Stelling

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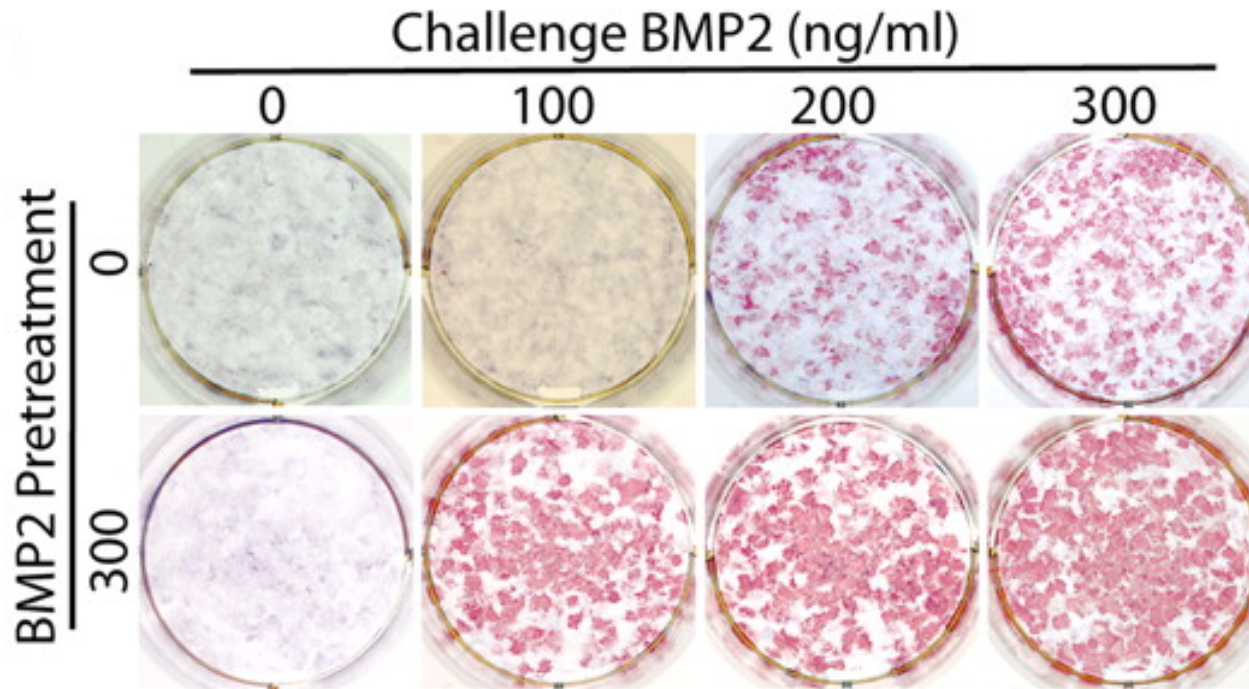


# Concept: Feedback Systems



- ❑ **Circular patterns of interactions can establish feedback loops with positive or negative net effect.**
- ❑ Intertwined feedback loops → **Complex dynamics.**

# Example: Memory in Cell Differentiation



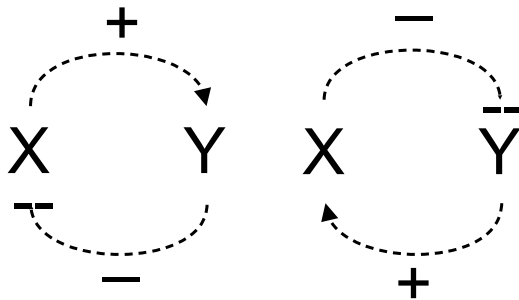
From: Wang et al. (2009) PNAS 106: 6638-6643.

- ❑ Human bone marrow cells exhibit memory of bone morphogenetic protein 2 (BMP2) pretreatment.

What could be mechanisms for memory?

# Two Basic Types of Feedback Systems

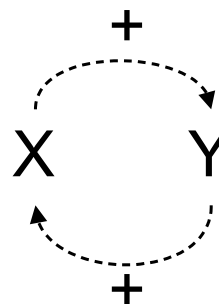
Negative  
Feedback



X activates Y, Y  
inhibits/inactivates  
X

vix e versa

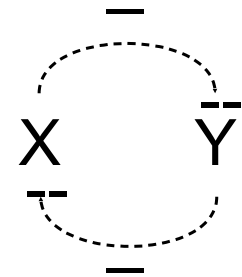
Positive  
Feedback



X activates Y, Y activates X  
Turbo example from before, e.g.

$\approx$

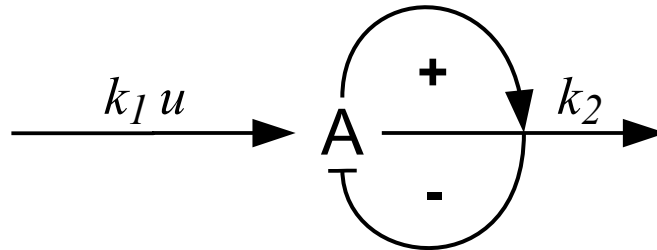
Mutual  
Antagonism



X inhibits Y, Y inhibits X

- Patterns of interactions between two components  
→ **Qualitatively different feedback structures.**

# Negative Feedback: Production-Degradation

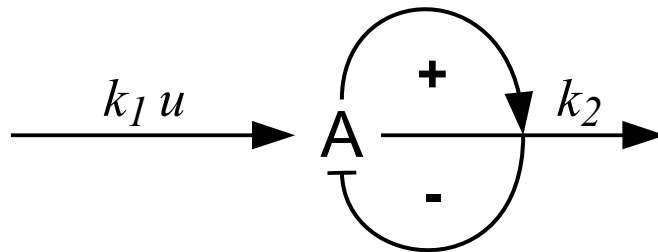


$$\frac{d[A]}{dt} = +k_1 \cdot u - k_2 [A] \Rightarrow [A] = \frac{k_1 \cdot u}{k_2} (1 - e^{-k_2 \cdot t})$$

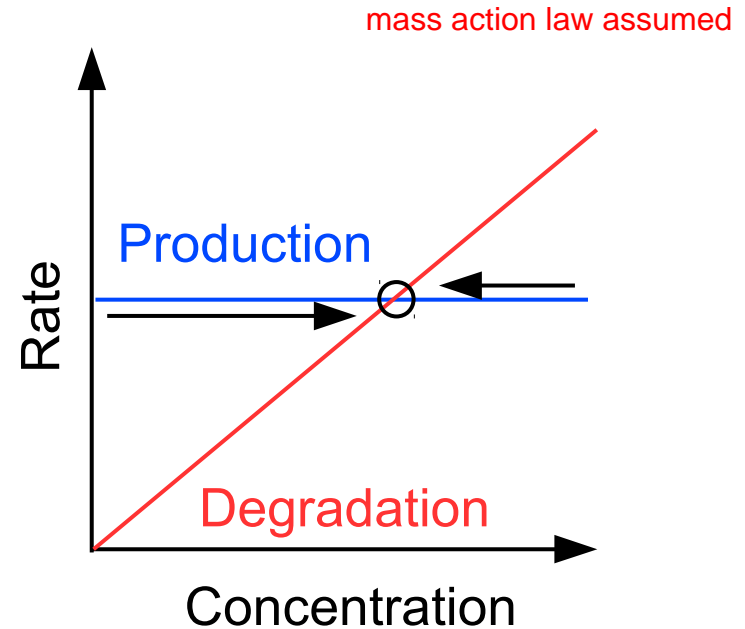
- Increased A accelerates degradation, leading to reduced concentration of A → **Negative feedback**.
- From analytic solution: After perturbation, the system will return to (a) steady-state again → **Homeostasis**.

Can we analyze the behavior graphically?

# Negative Feedback: Production-Degradation

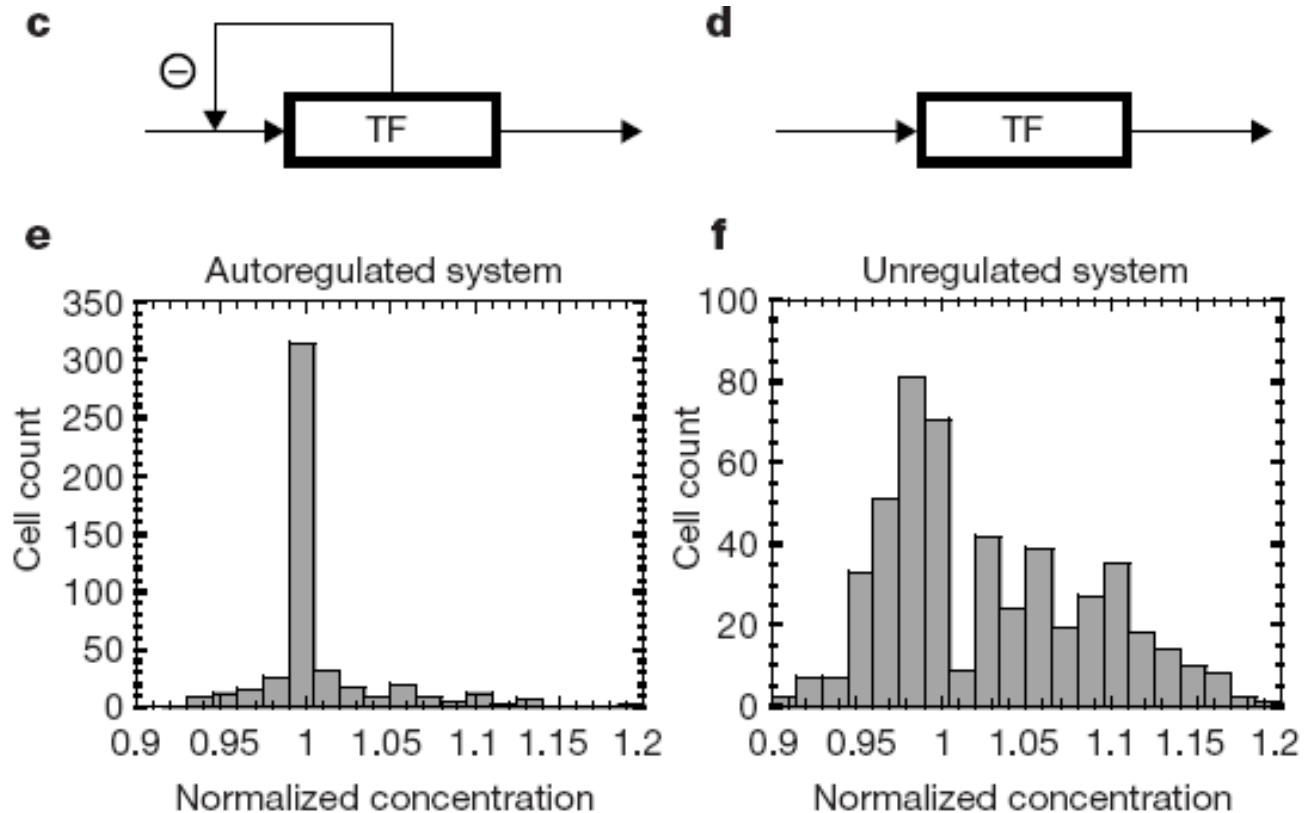


the system will reach a steady state through negative feedback eventually. degradation will rise until it crosses production and it is in homeostasis



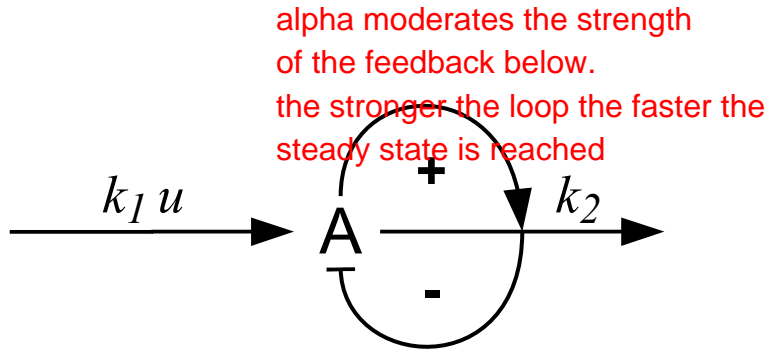
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- Graphically: After perturbation, the system will return to (a) steady-state again → **Homeostasis**.

# Negative Feedback: Example #1



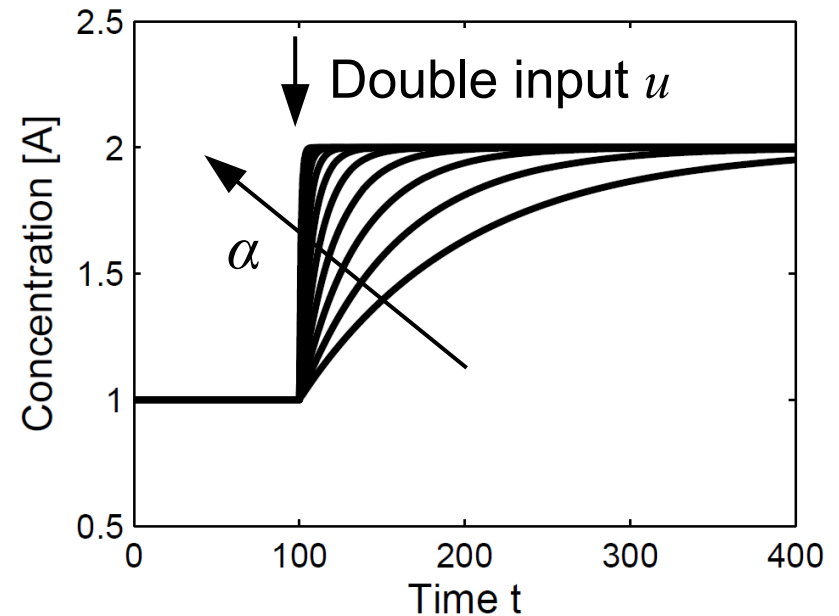
From: Becskei & Serrano (2000) Nature 405: 591-593.

# Negative Feedback: Production-Degradation



$$\frac{d[A]}{dt} = \alpha(k_1 \cdot u - k_2[A])$$

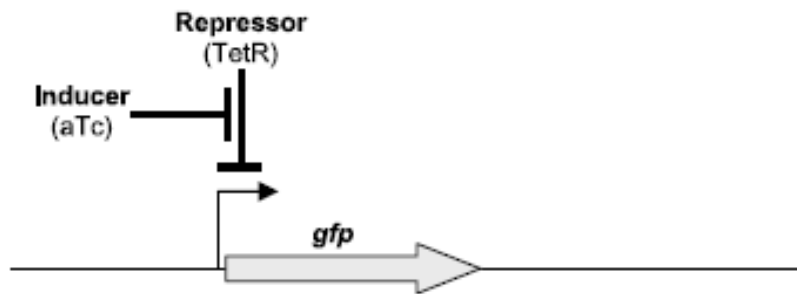
alpha changes how quickly steady state is reached



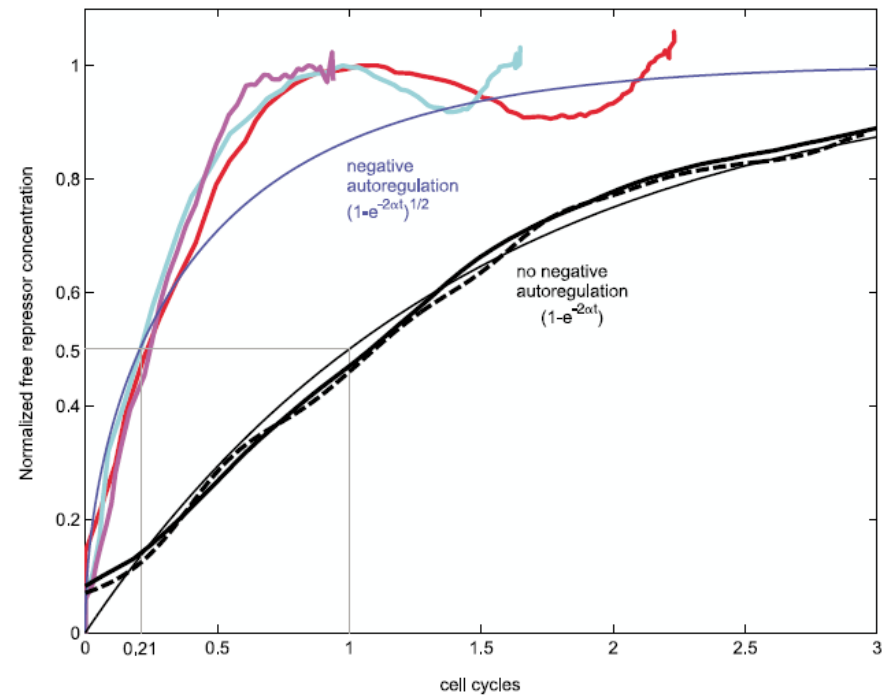
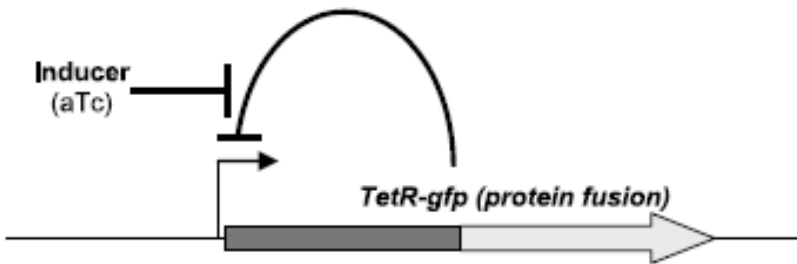
- Assume modified feedback and identical steady-state by scaling of both rates with factor  $\alpha$ .
- Increased feedback gain  $\rightarrow$  **Faster responses.**

# Negative Feedback: Example #2

A. Simple transcription unit (open loop)



B. Negative autoregulatory circuit



From: Rosenfeld et al. (2002) J. Mol. Biol. 323: 785-793.



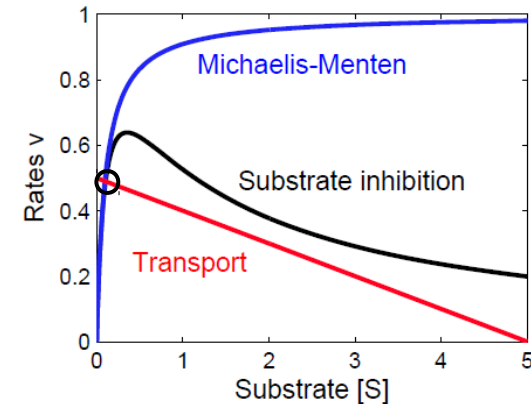
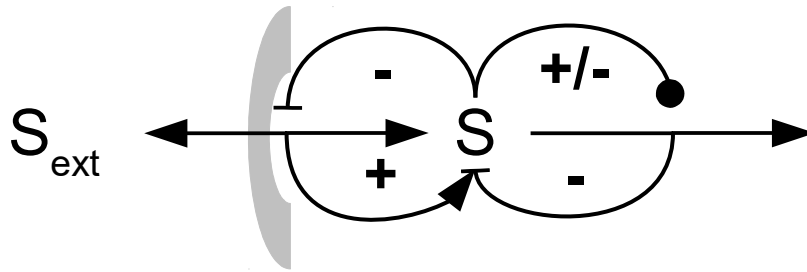
# Negative Feedback: Functions

- ❑ **Simple negative feedback systems:**
  - Eventually approaching steady state.
  - Existence of a unique steady state.
  
- ❑ **Functions in biological networks:**
  - Set point regulation → Homeostasis.
  - Perturbation rejection, fast responses.

Biological examples?

glycolysis

# Positive Feedback in Substrate Inhibition



- Diffusion of extracellular substrate  $S_{ext}$  with rate:

$$v_{Transport}([S_{ext}], [S]) = D \cdot ([S_{ext}] - [S])$$

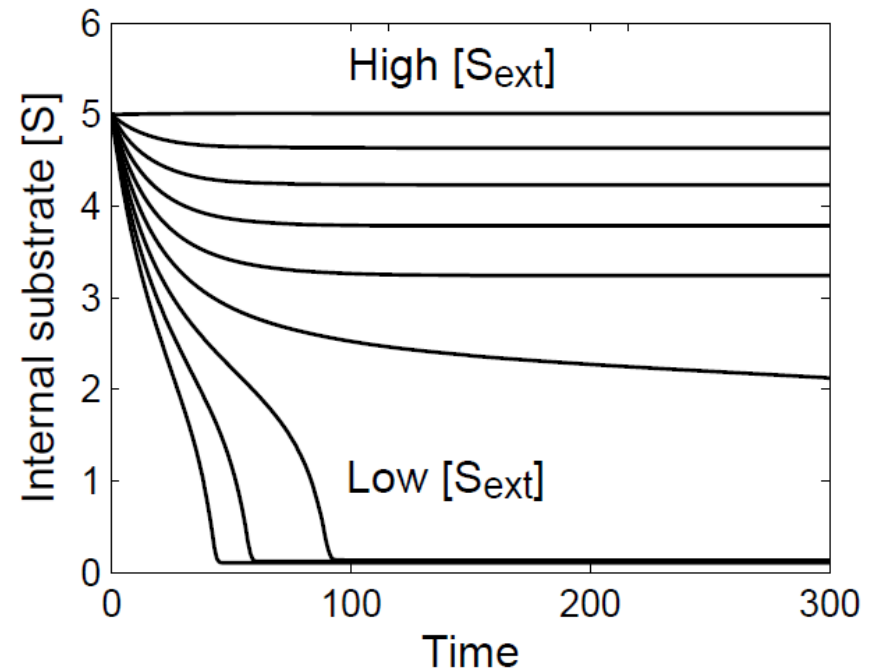
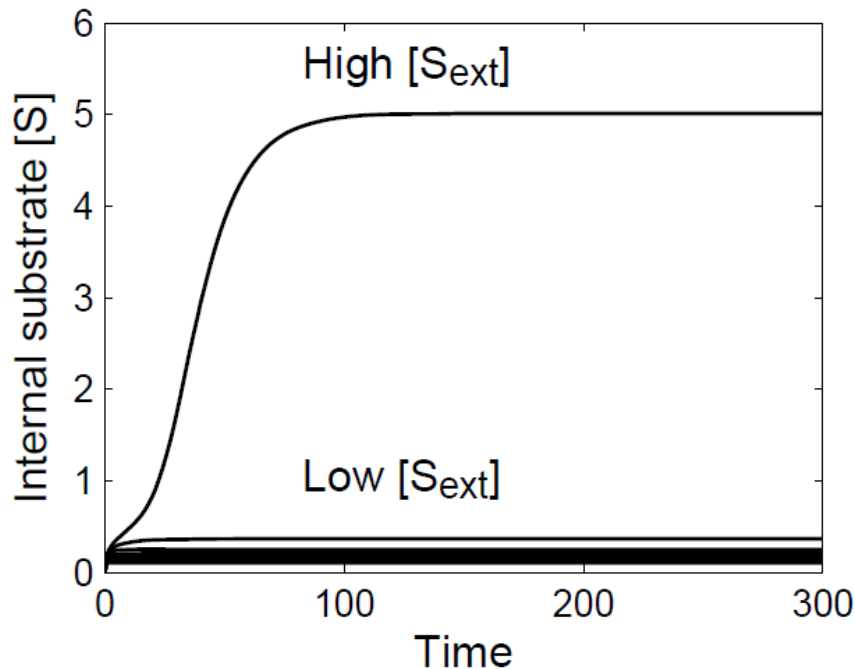
and degradation of substrate with substrate inhibition:

$$v_{Degradation}([S]) = \frac{v_{max}[S]}{[S] + K_M + \frac{[S]^2}{K_I}}$$

- **Positive feedback possible** (depending on state).

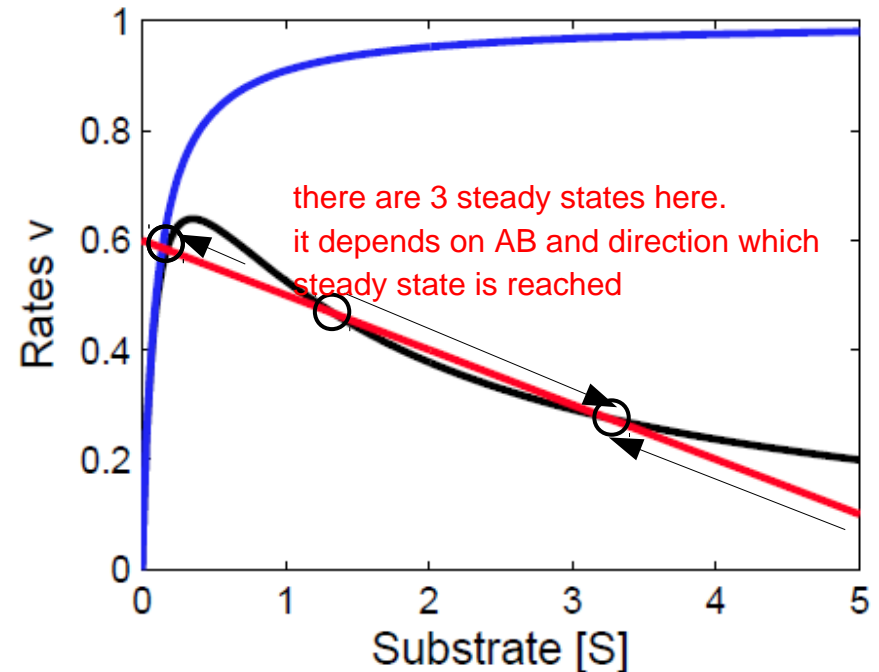
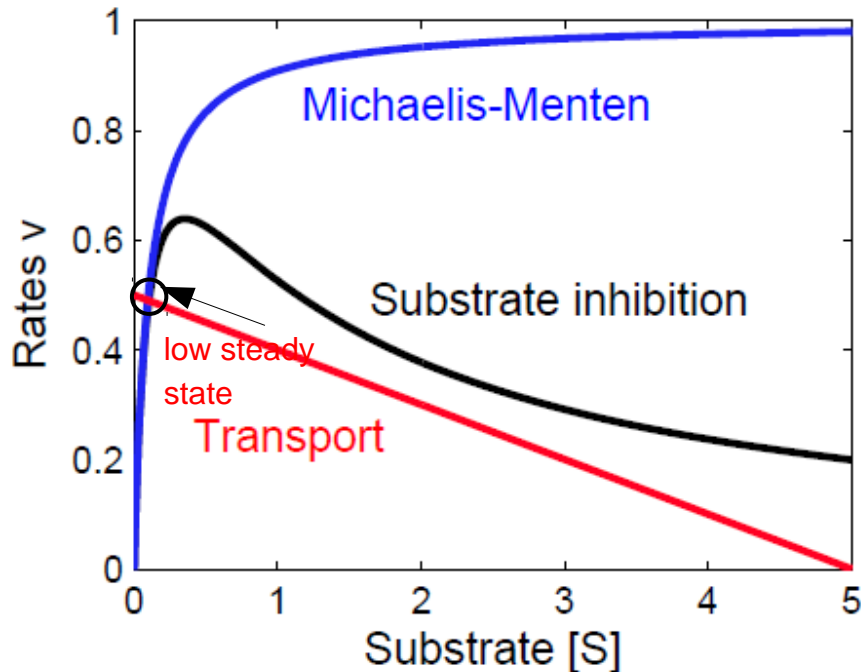
# Substrate Inhibition: Dynamic Memory

AB are different



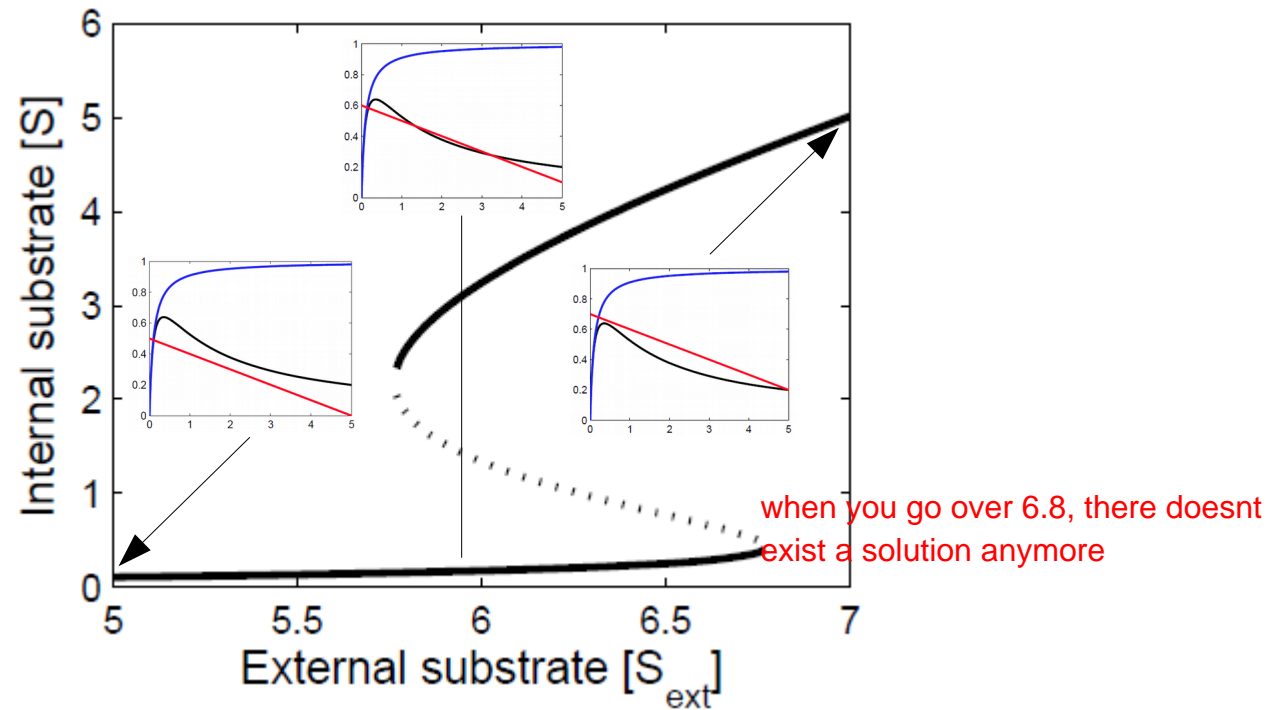
- For the same (constant) external substrate concentrations and low or high initial internal state:  
**The system 'remembers' its internal state.**

# Substrate Inhibition: Dynamic Memory



- **Explanation:** For certain external substrate concentrations more than one steady-state exists  
→ Path depends on the initial internal substrate.

# Substrate Inhibition: Dynamic Memory



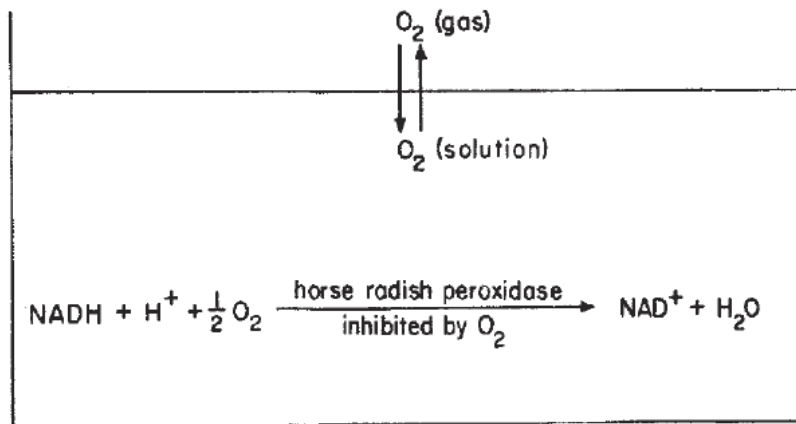
- ❑ Qualitatively different internal steady-states are possible, for the same external conditions → **Memory through a purely dynamic process.**

Similarities to turbo design?

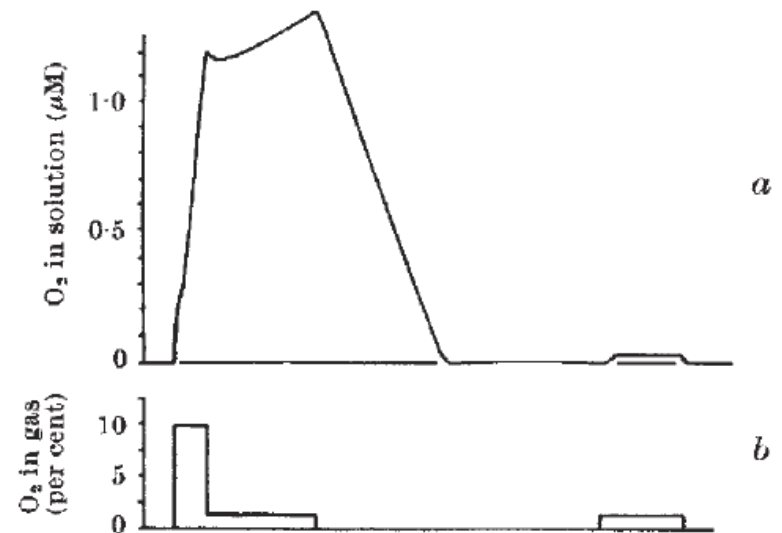
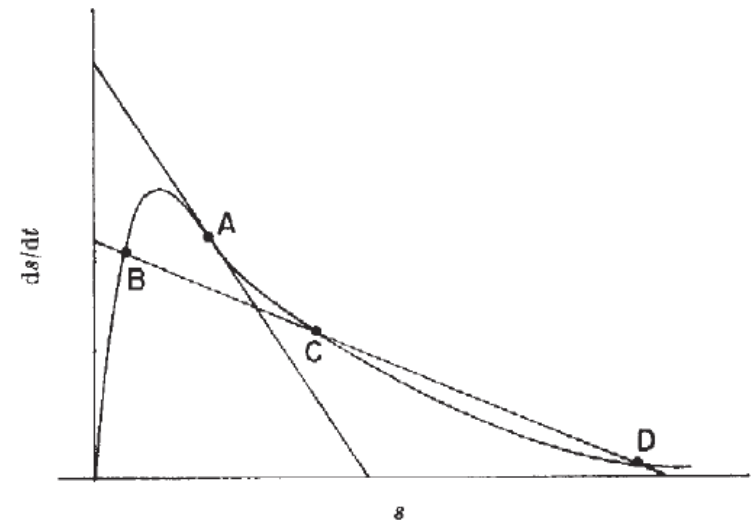
# Example #1: Substrate Inhibition Kinetics

## Bistability caused by Substrate Inhibition of Peroxidase in an Open Reaction System

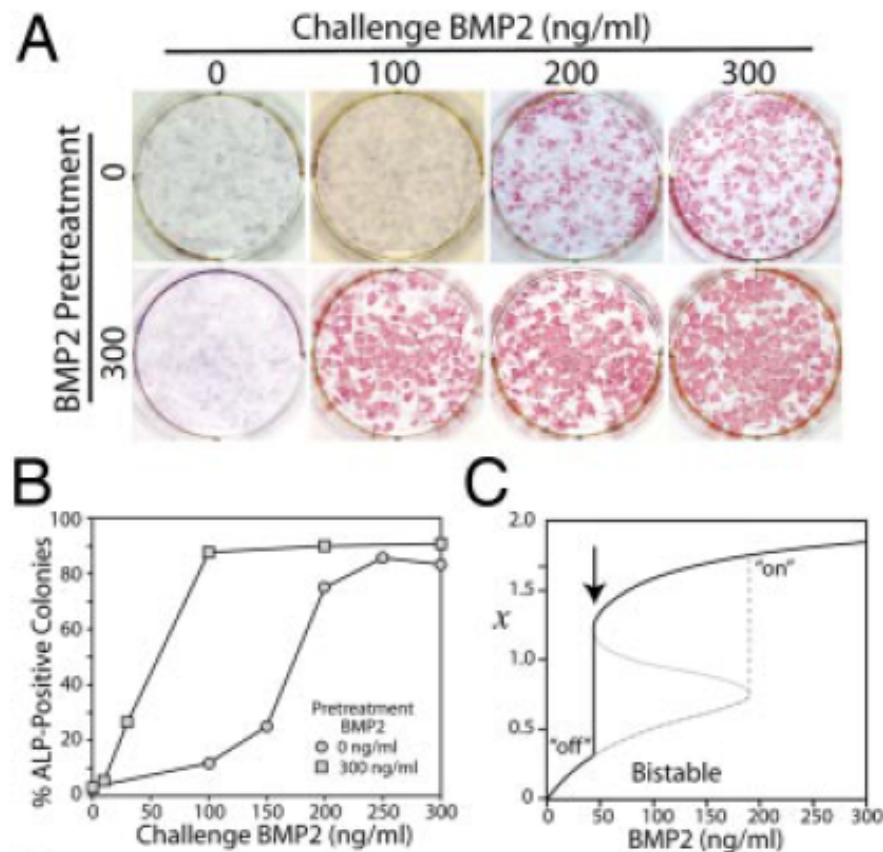
NATURE, VOL. 217, MARCH 16, 1968



- **Example:** Horseradish peroxidase with substrate inhibition.



## Example #2: Memory in Cell Differentiation



From: Wang et al. (2009) PNAS 106: 6638-6643.

- **Example:** Human bone marrow cells exhibit memory of bone morphogenetic protein 2 (BMP2) treatment.

# Positive Feedback: Functions

- ❑ **'Simple' positive feedback systems:**
  - Multiple steady states may be possible.
  - Phenomenon in nonlinear systems: Memory.
  
- ❑ **Functions in biological networks:**
  - Discrete decisions from continuous signals.
  - Possibly irreversible decisions (development).

How can decisions become irreversible?



## Summary: Teaching Goal III

- ❑ Negative and positive feedback have distinct functions such as homeostasis vs. memory.
- ❑ Dynamic behaviors can be analyzed graphically by plotting rates as a function of states and reasoning about the the impact of rates on states.
- ❑ Memory can be established dynamically, provided that more than one steady-state exists in a system.

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## ODE Modeling of a Metabolic Pathway

9 Mar, 2017

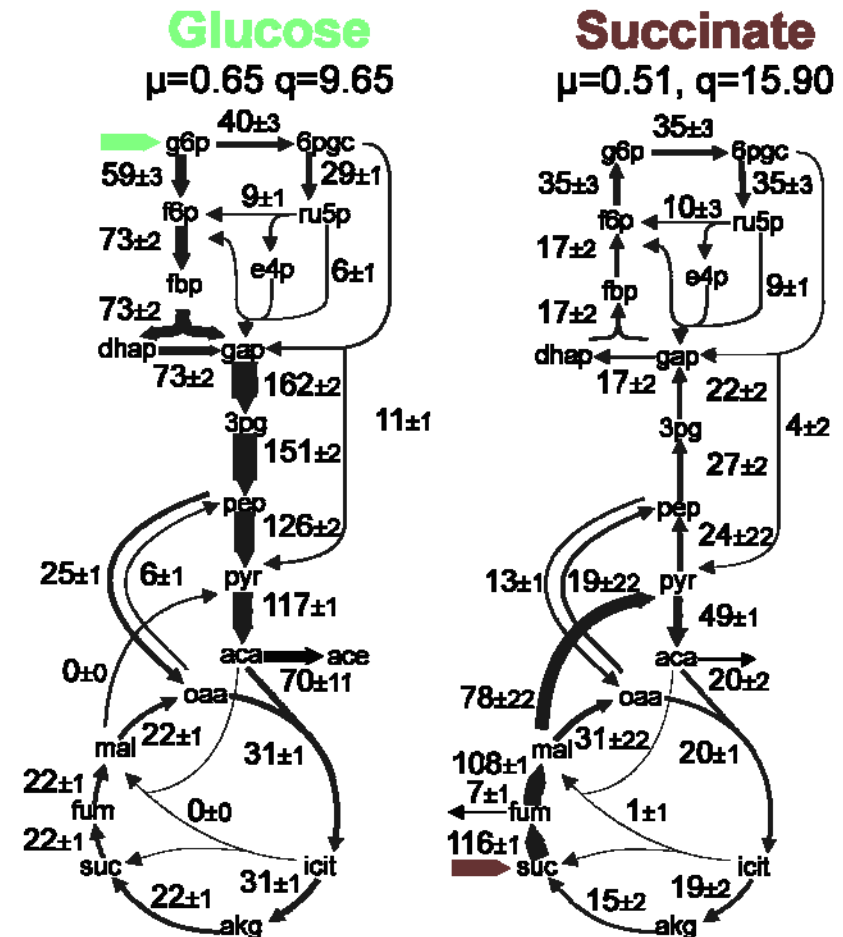
Uwe Sauer, Institute of Molecular Systems Biology

### Content:

- Concepts: Parameters & model quality (JS)
- Biological consequences of metabolic dynamics (US)
- Concepts: Feedback for simple systems (JS)
- **Glycolysis/Gluconeogenesis (US)**

# Central Metabolism Must Be Flexible

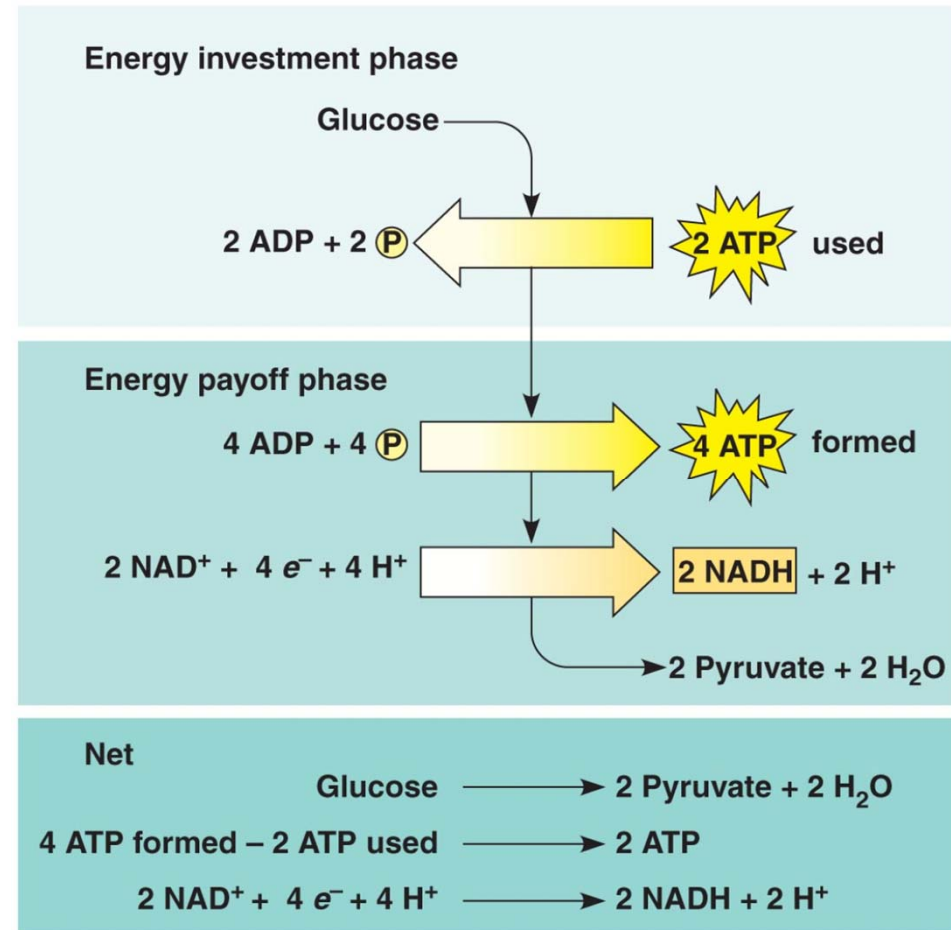
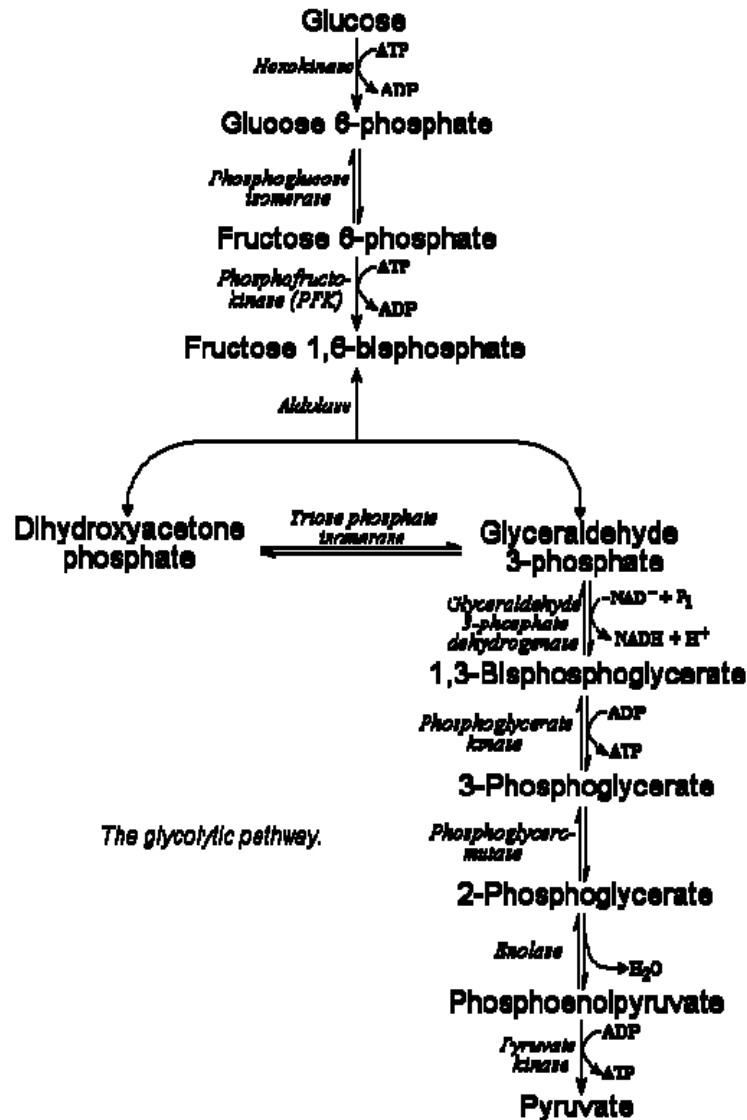
- To accommodate different carbon inputs
- Is amphibolic; ie serves both catabolic and anabolic functions
- Provide suitable supply of ATP, redox cofactors, and carbon precursors for different cellular needs (eg rapid growth, survival, stress responses etc)
- **Is therefore highly interconnected and can operate in multiple directions**
- In the following example we focus on the specific flexibility problem of **changing flux direction** in a pathway



# Glycolysis

Perhaps THE most central pathway throughout all species

Function: catabolism of hexoses




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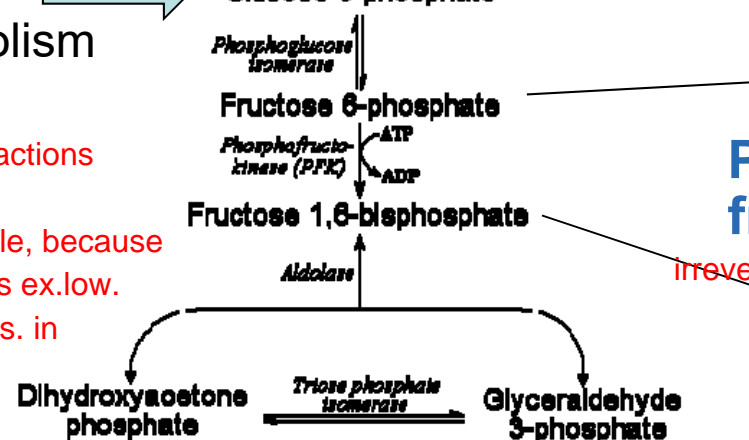
Why is that necessary?

# Glycolysis - Gluconeogenesis

Except for 2, all reactions are freely reversible

Glucose  Glucose 6-phosphate  
metabolism

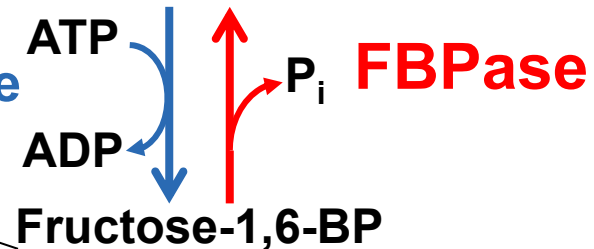
why are the two reactions irreversible?  
Practically irreversible, because  $K$  for ATP to ADP is ex. low.  
Realistically irrevers. in the cell.



Phospho-  
fructokinase

irreversible


Fructose-6-P

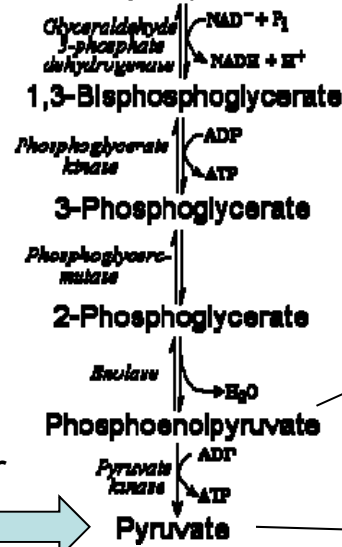


glycolytic

gluconeogenic

The glycolytic pathway.

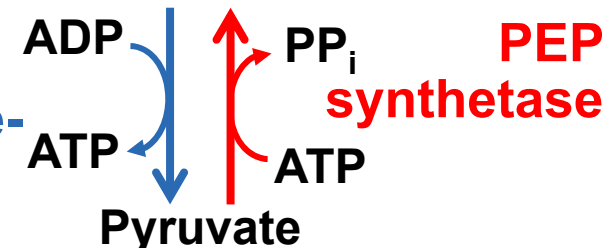
Lipid degradation,  
metabolism of C2, C3 or  
C4 compounds 



Pyruvate-  
kinase

PEP

irreversible too.



# Which Challenges Arise When Pathways Must Operate in 2 Directions ?

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direction determined by metabolite conc.

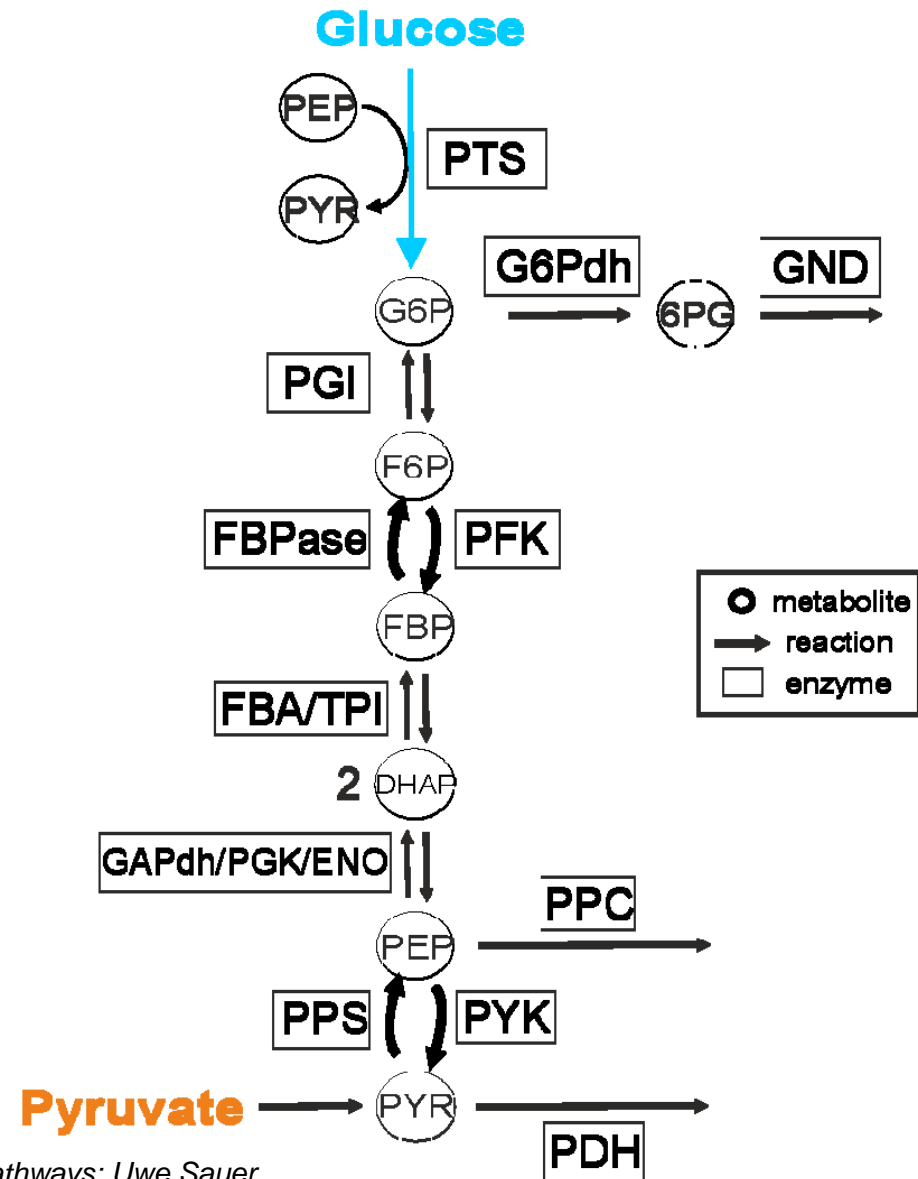
genetic regulation necessary to reduce protein cost

when conditions change alternative reactions are necessary, but genetic reg. take times

simultaneous presence/activity of enzymes catalyzing opposing reactions leads to futile cycling

# Simplified Model of Glycolysis/Gluconeogenesis

An abstraction of the whole system. *What is missing?*



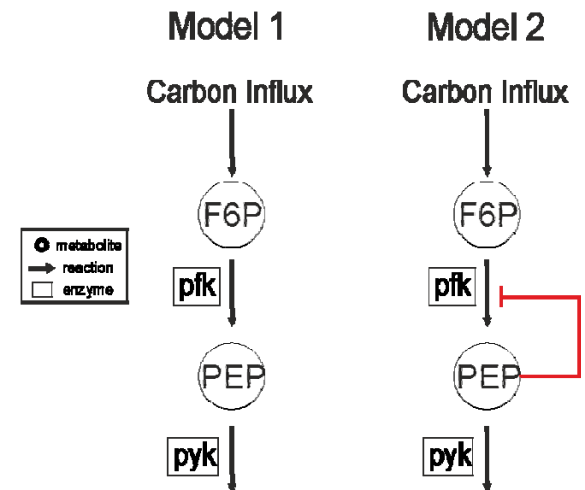
# Exercise 4: Two Reaction Model

## Greatly simplified model(s) of glycolysis

- 2 key (irreversible) reactions of glycolysis
- PEP (nearly) at end of glycolysis, a high energy compound
- PEP is generally positioned at a metabolic decision point

### Goal of exercise 4:

- Formulate and implement a simple kinetic model of 2 metabolic reactions (with and w/o regulation)
- Implement and simulate models. Study system behavior under different parameters and perturbations.
- Understand why a biological system would need to develop such feedback?
- What does feedback achieve in this case?



**Phosphofructokinase**  
**Pyruvate kinase**



# Teaching Goals Lecture 3

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- Understand potential biological problems of metabolic dynamics and how regulation can help.
- Understand basic principles of neg and pos feedback.
- Understand biological challenges arising in bi-directional pathways, example of glycolysis/gluconeogenesis.
- Relate experimental observations to model behaviors via parameters.

Generally explain problems arising from metabolite dynamics. Be able to explain on an example.

Identify types of feedback. Be able to analyze effects of feedback graphically.

Be able to rationalize and explain need for feedback on a reversible linear pathway

Explain measures and statistics to compare models to data. Rationalize uncertainty in parameters.