# Design Principles of a Bacterial Signalling Network

Why is chemotaxis more complicated than needed ?

Jens Timmer

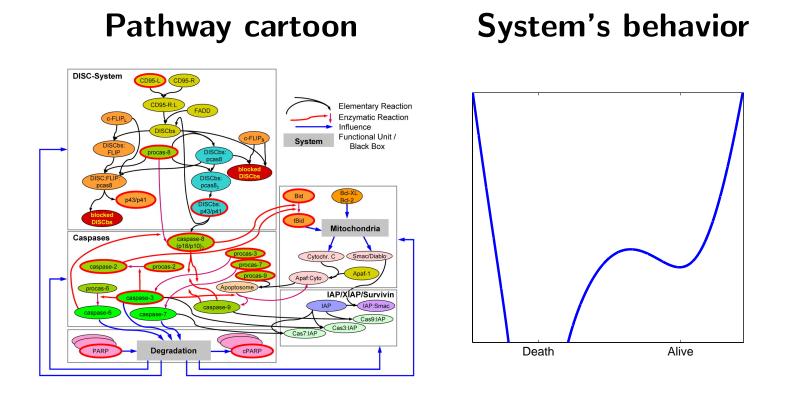
Freiburg Institute for Advanced Studies Center for Systems Biology Center for Data Analysis and Modeling Bernstein Center for Computational Neuroscience Department of Mathematics and Physics University of Freiburg

http://www.fdm.uni-freiburg.de/~jeti/

# Outline

- The Eighth Question
- Bacterial Chemotaxis
- Barkai/Leibler Model
- Cell-to-Cell Variability
- Design Principles of Robustness

# **Examples of Networks I: Apoptosis**



#### Threshold behavior, one-way bistable

# Why Mathematical Modelling in Biology ?

- Make assumptions explicit
- Understand essential properties, failing models
- Condense information, handle complexity
- Understand role of dynamical processes, e.g. feed-back
- Impossible experiments become possible
- Prediction and control
- Understand what is known
- Discover general principles
- "You don't understand it until you can model it"

# Michael Reth's Seven Questions

<b>BIC Question to answer for the understanding of intracellular signaling</b>	
who?	identification
what?	function
with whom?	reaction partner
how?	mechanism
where?	loction in the cell
when?	kinetic
how much?	quantity

**Courtesy of Michael Reth** 

# **Two Differences between Physics and Biology**

**Physics: Understand the empirical world by mathematics** 

- Fundamental laws of nature vs. principles
- In biology there is "function" due to evolution

Physics in biology = Systems Biology:

**Understand function by mathematics** 

# The Eighth Question

#### WHY?

#### Why is chemotaxis more complicated than needed ?

## **Bacterial Chemotaxis – The Phenomenon**

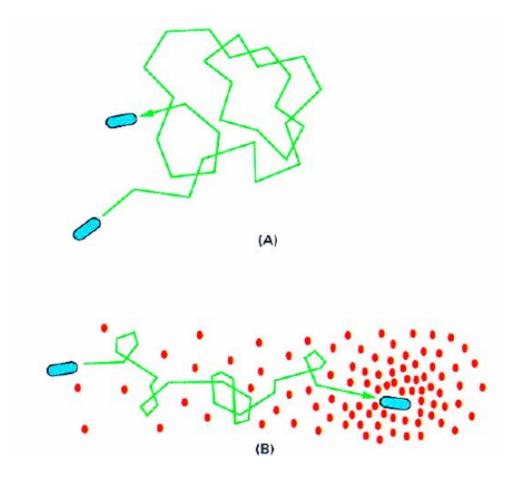
- Bacteria sense nutrient gradients over four orders of magnidute of absolute concentration
- Detect relative changes of 2 %

# Chemotaxis: One of the best investigated biological systems

# **Bacterial Chemotaxis – The Strategy**

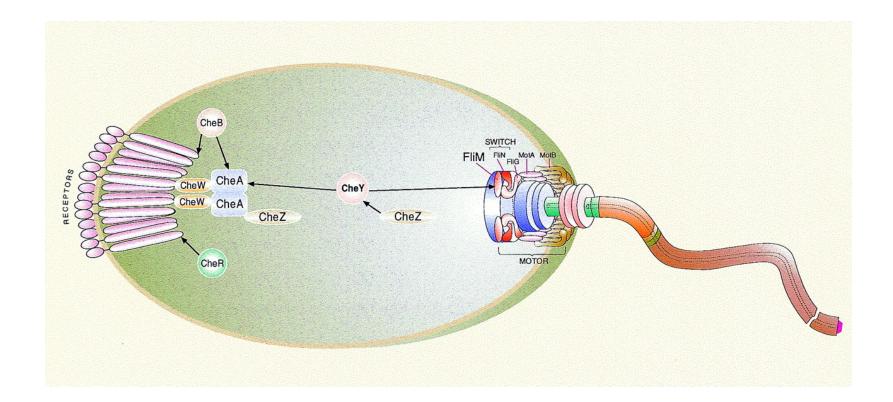
- Bacteria too small to compare front to end
- Strategy:
  - Change direction from time to time (tumble)
  - If concentration increases: reduce tumbling frequency
  - If concentration decrease: increase tumbling frequency
- Sense spatial gradients by temporal changes

## **Chemotaxis – Tumble and Swim**



Random walk vs. biased random walk

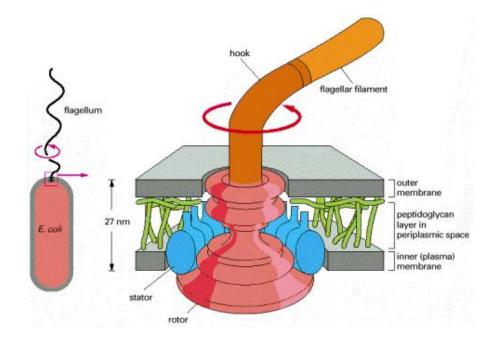
## Chemotaxis in E. coli



# Chemotaxis – Flagella

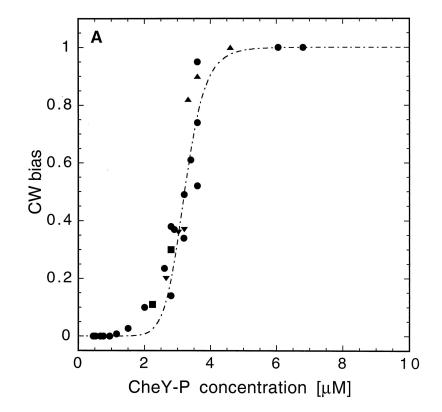
Movement by rotating corkscrew-flagella

- counter-clockwise: form bundle: swim by marine propeller
- clockwise: rotate radially: tumble



# **Chemotaxis – The Task**

**Tumbling/Swimming depends on phosphorylated CheY** 



Important: A small working range

# **Chemotaxis – Adaptation**

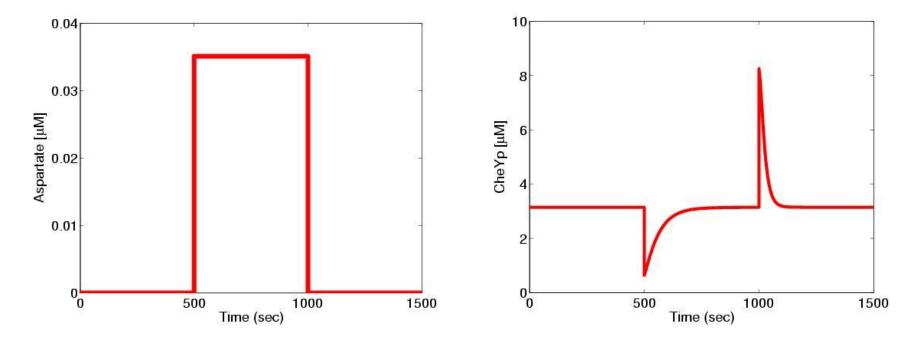
- Motor has a small range of sensitivity
- Cell is chemotactic for a large range of concentrations
- $\implies$  System has to be adaptive:

Steady state of CheYp must be independent from

absolute concentration of ligand

## **Chemotaxis – The Task**

Input: Nutrient concentration Output: Tumbling frequency

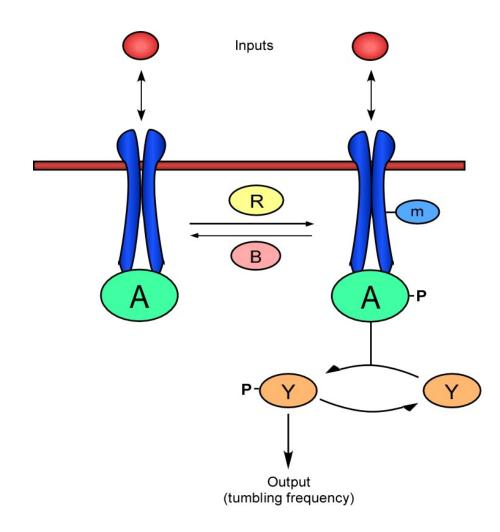


System performs a kind of differentiation

# The Players and their Roles

- T: Receptors
- CheR: Methyltransferase, adds CH<sub>3</sub>
- CheB: Methylesterase, removes CH<sub>3</sub>
- CheA: Kinase, adds PO<sub>4</sub>
- CheZ: Phosphatase, removes PO<sub>4</sub>
- CheY: Signaling protein

# Barkai/Leibler Model – Graphical Version



#### **Barkai/Leibler Model – Mathematical Version**

Probability for activating methylated receptor by ligand L:

$$p = \left(1 - \frac{L}{K_L + L}\right)$$

Concentration of activated receptors  $T_a$ :

$$T_a = p T_m$$

Methylation/demethylation dynamics of receptors:

$$\dot{T}_m = k_R R - k_B B \frac{T_a}{K_B + T_a}$$

**Dynamics of**  $A_p$ :

$$\dot{A}_p = k_A (A_{tot} - A_p) T_a - k_Y A_p (Y_{tot} - Y_p)$$

Dynamics of  $Y_p$ :

$$\dot{Y}_p = k_Y A_p (Y_{tot} - Y_p) - \gamma_Y Y_p$$

# **Perfect Adaptation by** $T_a = p(L) T_m(T_a)$

Steady state of  $T_a$  from

$$\dot{T}_m = k_R R - k_B B \frac{T_a}{K_B + T_a} = 0$$

yields

$$T_a^{ss} = K_B \frac{k_R R}{k_B B - k_R R}$$

- $\bullet$  Independent from ligand concentration L
- Steady state is stable
- The same holds for  $Y_p$

Barkai & Leibler, Nature 387:913, 1997

# The Mechanism: $T_a = p(L) T_m(T_a)$

- Increasing L leads to fast decrease of  $T_a$
- Ap & Yp are fastly dephosphorylated
- $T_m$  is slowly increased
- Turns  $T_a$  and Ap & Yp back to steady state
- Integral negative feedback control

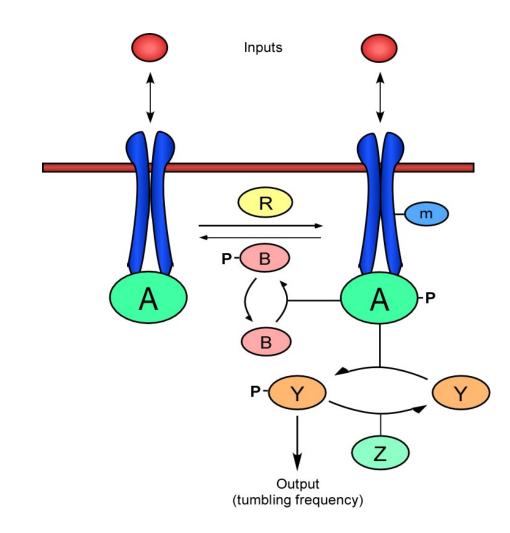
#### In words:

Degree of methylation compensates/remembers absolute concentration of ligand

# But ...

#### ... this model is not realised by nature

# Nature's E. Coli



# **Sources of Variability**

• Intrinsic noise

Differences between identical reporters within one cell

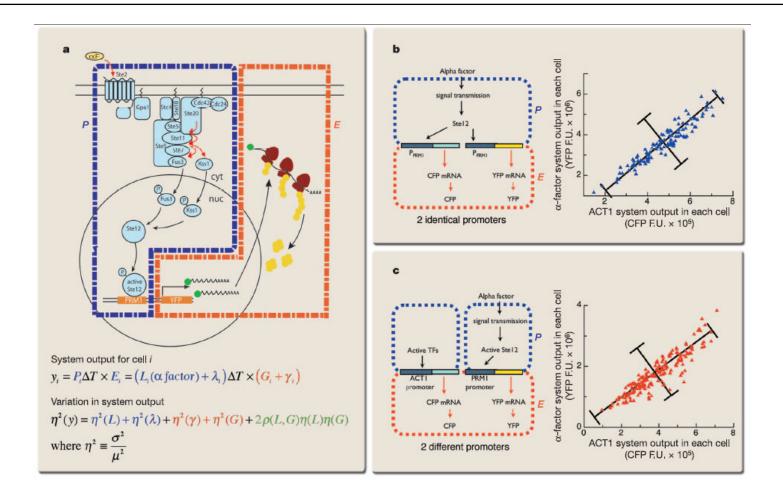
- Stochasticity of reactions
- Extrinsic noise

Differences between identical reporters in different cells

- Expression level of signaling proteins
- Number of ribosomes

**Cell-to-cell variability** 

## **Quantification of Variability**



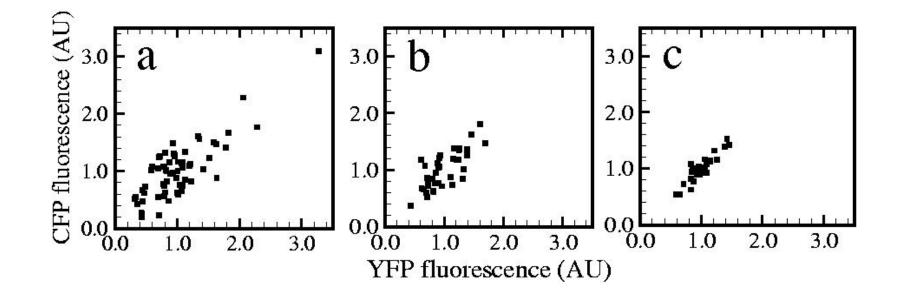
Colman-Lerner et al. Nature 437:699, 2005

# Results

E. coli and yeast:

- Extrinsic noise is larger than intrinsic noise
- Protein concentrations fluctuate in a <u>correlated</u> manner

## **Fluctuations and Chemotaxis**



- Cell-to-cell fluctuations up to factor of ten
- Correlated fluctuations are dominant

# **A** Robustness Principle

# The functionality of a pathway must be robust against fluctuations of protein levels.

For chemotaxis:

- Steady state level  $Y_p$  in [2.2  $\mu$ M, 4.3  $\mu$ M]
- For correlated fluctuation:

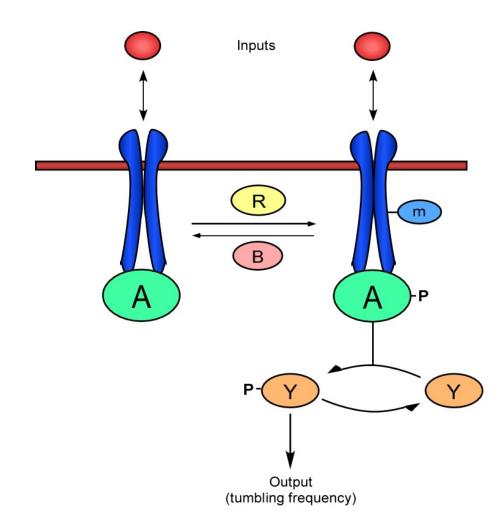
**Steady state invariant under transformation:**  $X_i \rightarrow \lambda X_i$ 

Important quantities may only depend on ratios of concentrations

• For uncorrelated fluctuations:

Use negative feedback-loop to attenuate noise

# Application to Barkai/Leibler Model



### **Robustness of Barkai/Leibler Model**

#### **Steady states:**

$$T_{a}^{ss} = K_{B} \frac{k_{R}R}{k_{B}B - k_{R}R}$$
 o.k.  

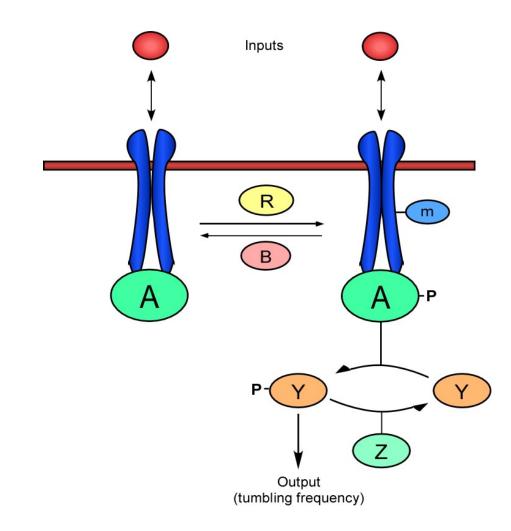
$$A_{p}^{ss} \approx \frac{k_{A}T_{a}^{ss}}{k_{Y}} \frac{A_{tot}}{Y_{tot}}$$
 o.k. (w.o.a)  

$$Y_{p}^{ss} = \frac{k_{y}A_{p}^{ss}}{k_{Y}A_{p}^{ss} + \gamma_{Y}}Y_{tot}$$
 not o.k.

Cure:  $Y_p$  must have a phosphatase (*CheZ*)

$$Y_p^{ss} = \frac{k_y A_p^{ss}}{k_Z} \frac{Y_{tot}}{Z_{tot}}$$
 o.k.

## **Extension of the Model**



# **Robustness Against Correlated Fluctuations**

- $Y_p$  must have a phosphatase (*CheZ*)
- Methyltransferase CheR has to work at saturation
- The pathway must be weakly activated,  $X_p \ll X_{tot}$

# **Robustness Against Uncorrelated Fluctuations**

Diminish uncorrelated noise by a classical negative feedback

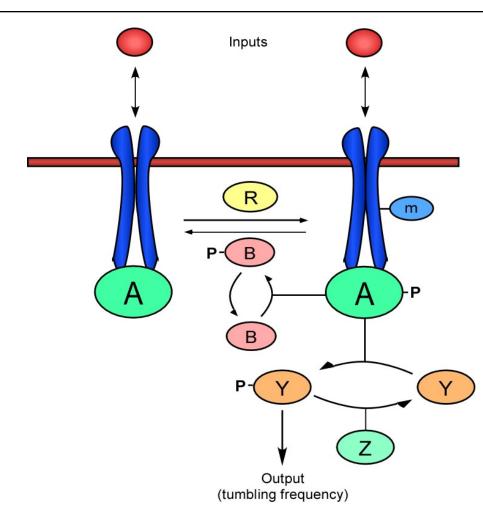
- Methylesterase B can be phoshorylated by  $A_p$
- Only  $B_p$  can demethylate receptors

$$\Delta Y_p = -\frac{\frac{\partial f}{\partial T_a} \frac{\partial T_a}{\partial R}}{\alpha + \beta \frac{\partial B_p}{\partial A_p}} \Delta R$$

• Robustness against correlated fluctuations:

 $\implies B_p \text{ must } \underline{\text{not}} \text{ have a phosphatase}$ 

# **Final Model**



#### And this is how E. coli looks like

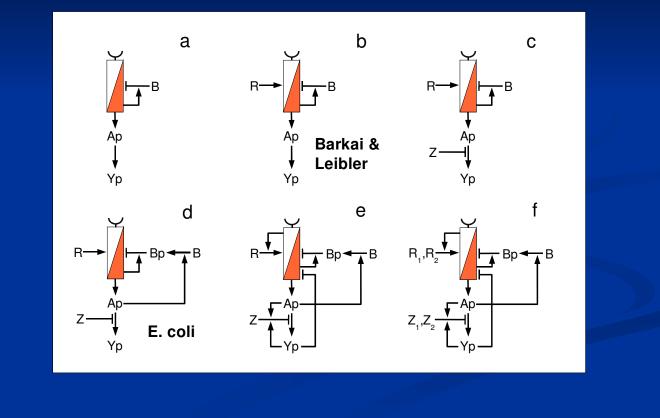
# In silico Biology

Is nature's solution optimal ?

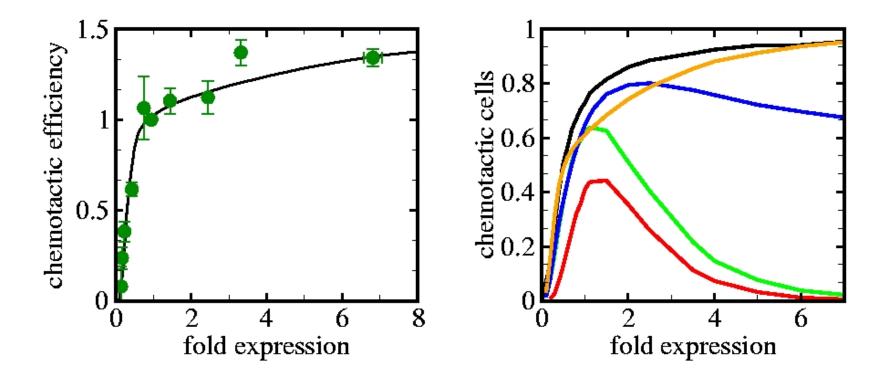
- Choose different chemotactic pathway topologies
- Protein concentrations from experimental distributions

**Compare chemotactic behaviour of** *in silico* **mutants to** *in vivo* **E. coli for different expression levels of proteins** 

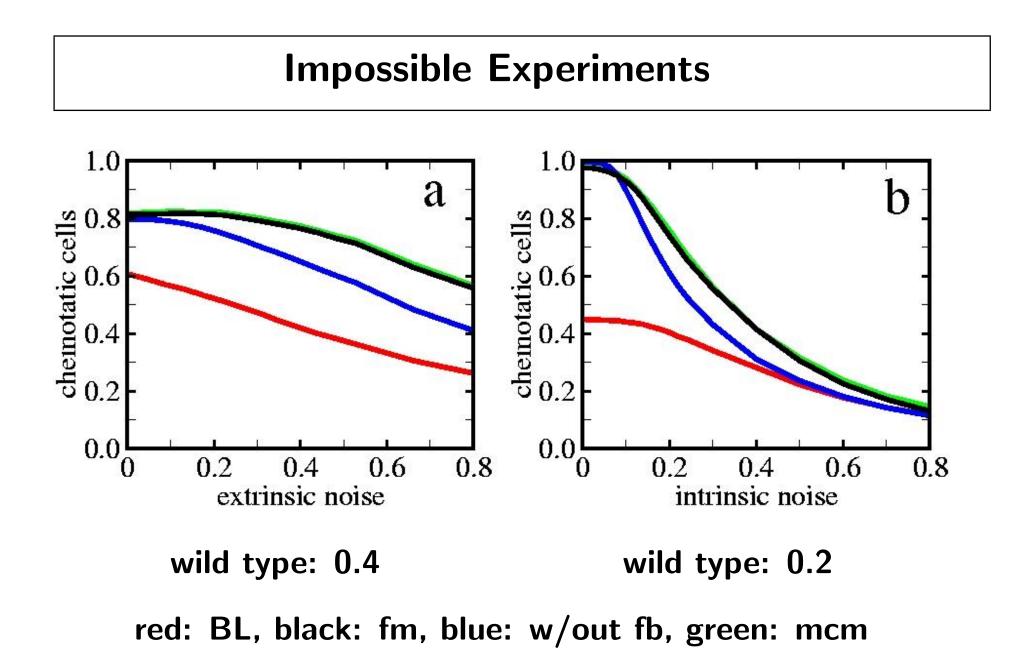
# Cartoons of Perfect Adaptive Pathways



### Results: in vivo vs. in silico



red: Barkai/Leibler, black: final model, cyan: without feedback blue: CheR not in saturation, green: CheBp with phosphatase



# Conclusions

- E. coli has to be adaptive <u>and</u> robust
- E. coli seems to be optimised to deal with fluctuations:
  - Uncorrelated noise: Feedback control
  - Correlated noise: Phosphatase here, saturation there
- Deals with noise on protein level, not in expression process
- E. coli is as complex as necessary but as simple as possible

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M. Kollmann, L. Lovdok, K. Bartholomé, J. Timmer, V. Sourjik. Design principles of a bacterial signalling network, Nature 438:504, 2005

# Number of Players per Cell

- Receptors: 40.000
- CheB: 400
- CheR: 300
- CheY: 14000
- CheZ: 6000