A Study for Inference in the Presence of Non-Identifiability:

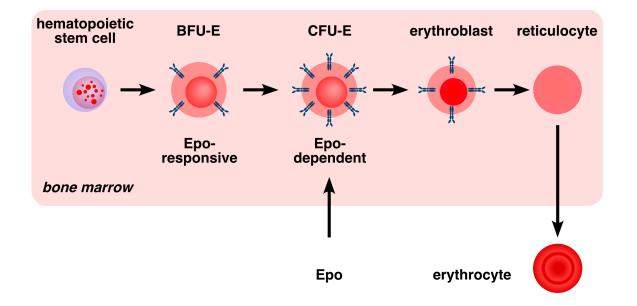
Bayesian MCMC sampling vs. profile likelihood approach

Andreas Raue - University of Freiburg Data Analysis and Modeling of Dynamic Processes in the Life Sciences



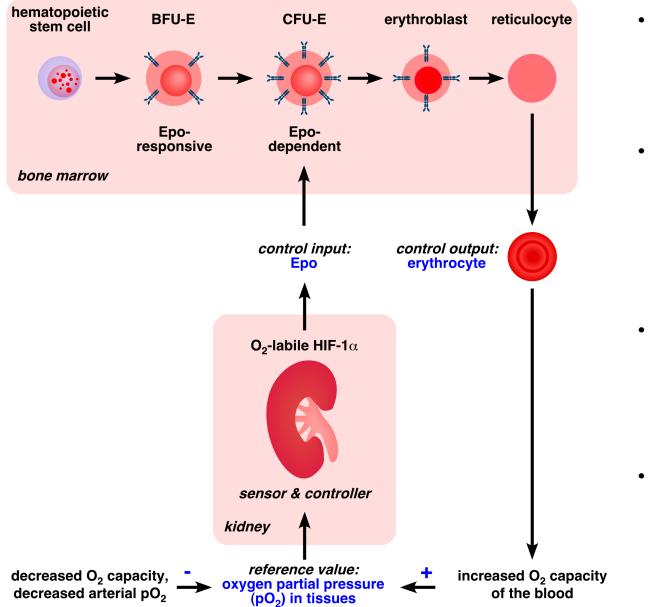
Workshop on Parameter Estimation for Dynamical Systems (II) | Eindhoven, Netherlands | 06.06.2012

Erythropoiesis - A Closed-Loop Control System



• Epo: key regulator of erythropoiesis

Erythropoiesis - A Closed-Loop Control System



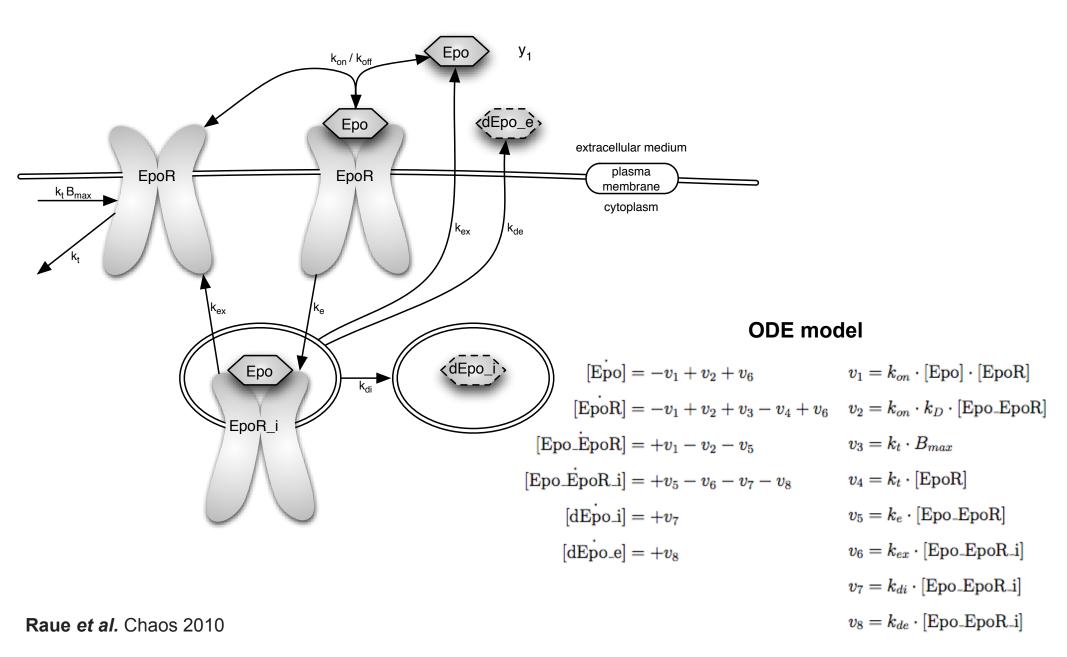
- Epo: key regulator of erythropoiesis
- feedback via red blood cell mass: establishing a closed-loop control circuit
- normal conditions: low levels of plasma Epo

15 mU/ml

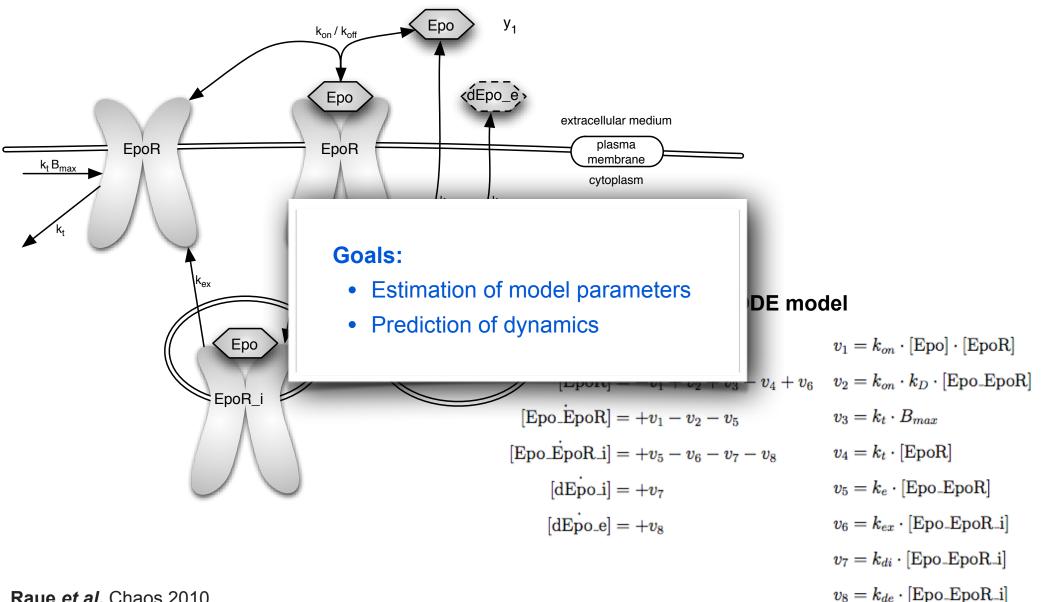
 hypoxic conditions: increased Epo levels

up to 10000 mU/ml

Epo and Epo receptor interaction and trafficking

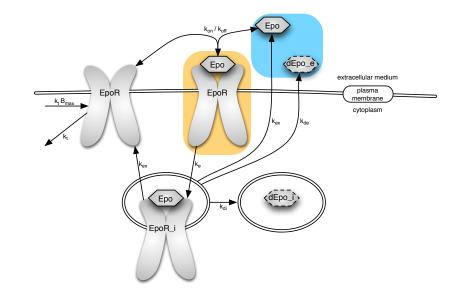


Epo and Epo receptor interaction and trafficking



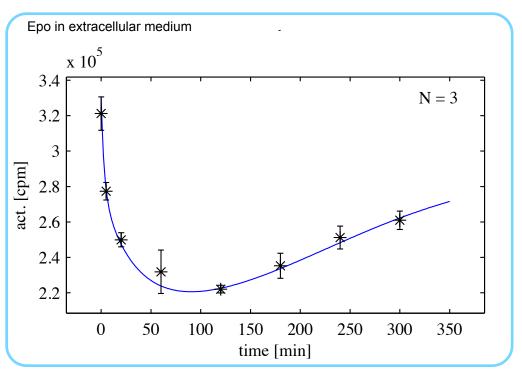
Raue et al. Chaos 2010

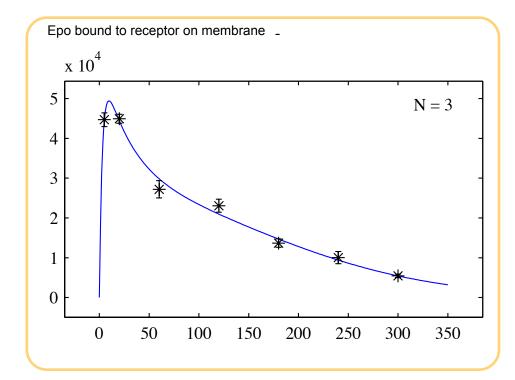
Initial Experimental Setup



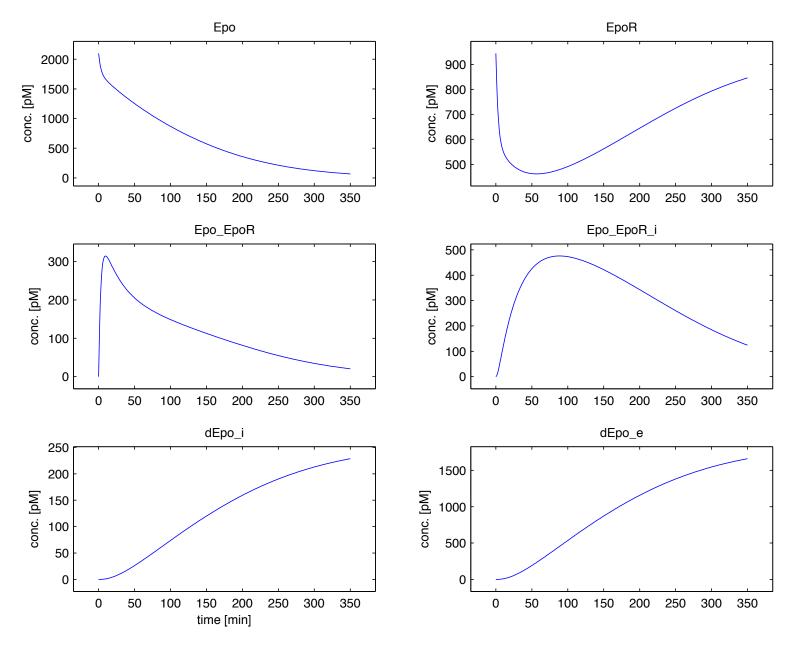
Maximum Likelihood Estimation

$$L(y|\theta) = \prod_{k=1}^{m} \prod_{l=1}^{d_k} \frac{1}{\sqrt{2\pi\sigma_{kl}^2}} \exp\left(-\frac{1}{2}\left(\frac{y_{kl} - y_k(t_l,\theta)}{\sigma_{kl}}\right)^2\right)$$





Predicted Model Dynamics



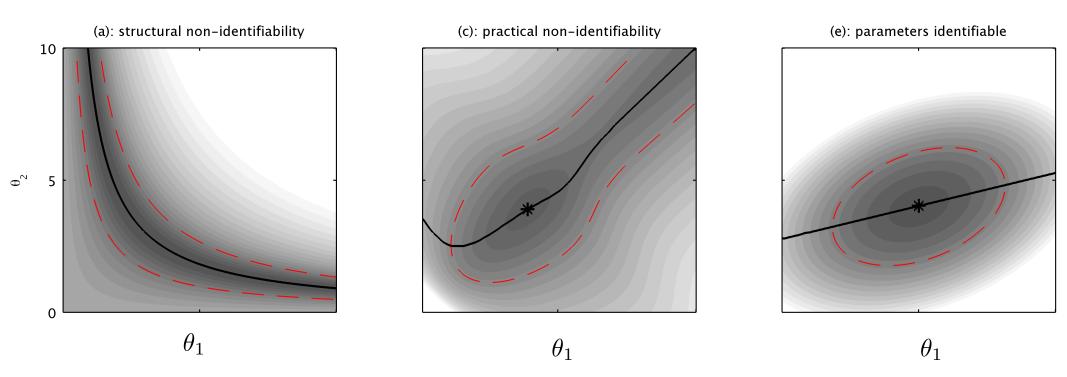
Are the predictions reliable ?

Are the estimated model parameters well constrained / identified ?

Parameter Identifiability

L

Identifiability is a matter of flatness of the likelihood ...

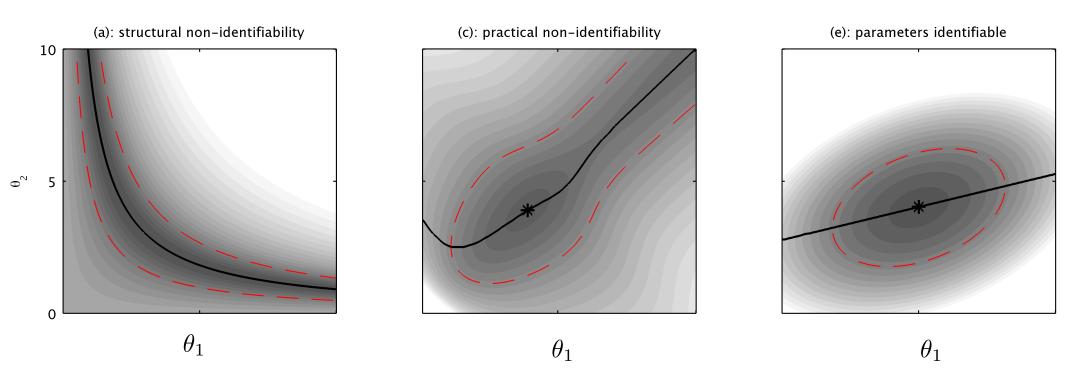


ODE
$$\vec{x}(t) = f(\vec{x}(t), \vec{u}(t), \vec{p}, t)$$

Observables $\vec{y}(t) = g(\vec{x}(t), \vec{s}) + \vec{\epsilon}(t)$
Likelihood $L(y|\theta) = \prod_{k=1}^{m} \prod_{l=1}^{d_k} \frac{1}{\sqrt{2\pi\sigma_{kl}^2}} \exp\left(-\frac{1}{2}\left(\frac{y_{kl} - y_k(t_l, \theta)}{\sigma_{kl}}\right)^2\right)$

Parameter Identifiability

Identifiability is a matter of flatness of the likelihood ...



→ Profile Likelihood Approach

Raue et al. Bioinformatics 2009

Likelihood

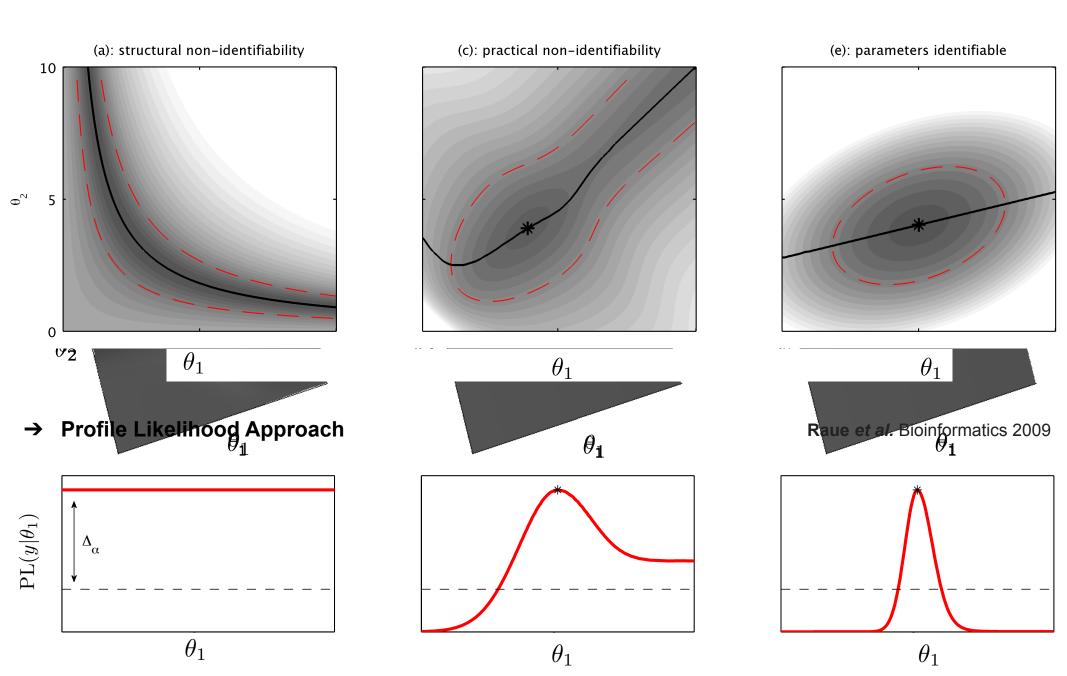
$$L(y|\theta) = \prod_{k=1}^{m} \prod_{l=1}^{d_k} \frac{1}{\sqrt{2\pi\sigma_{kl}^2}} \exp\left(-\frac{1}{2}\left(\frac{y_{kl} - y_k(t_l,\theta)}{\sigma_{kl}}\right)^2\right)$$

Profile Likelihood

$$PL(y|\theta_i) = \max_{\theta_{j\neq i}} [L(y|\theta)]$$

Parameter Identifiability

Identifiability is a matter of flatness of the likelihood ...



Markov chain Monte Carlo

Likelihood Prior
Posterior
$$P(\theta|y) = c \cdot L(y|\theta) \cdot P(\theta)$$

normalisation factor

Markov process with transitions $\theta \rightarrow \theta'$

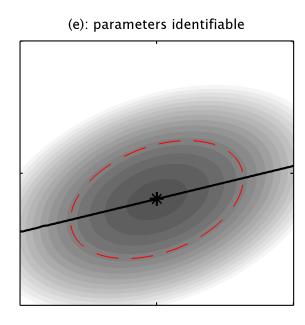
Metropolis-Hastings algorithm

Proposal function $q(\theta'|\theta) \sim N(0, s \cdot \mathbb{I})$

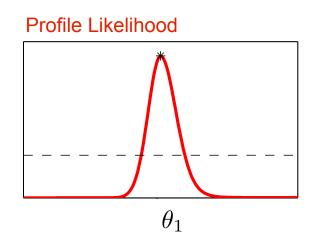
Acceptance probability

 $\alpha(\theta'|\theta) = \min[1, (L(y|\theta')/L(y|\theta)) \cdot (q(\theta|\theta')/q(\theta'|\theta))]$

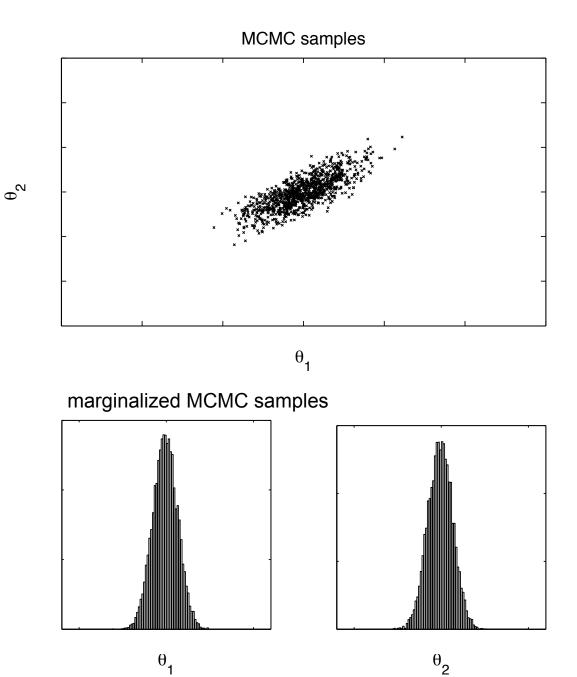
→ simplified MMALA algorithm Girolami et al. J. R. Statist. Soc. B 2011





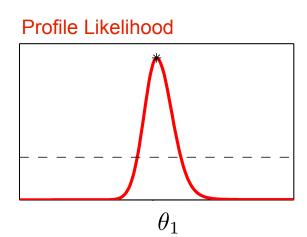


Markov chain Monte Carlo

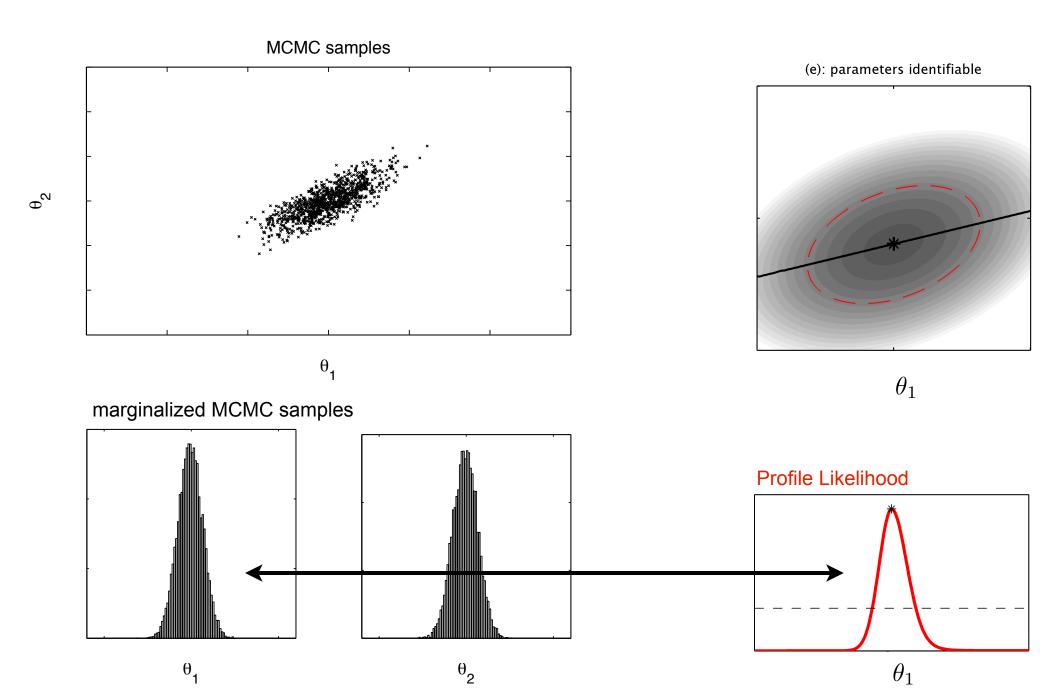


(e): parameters identifiable

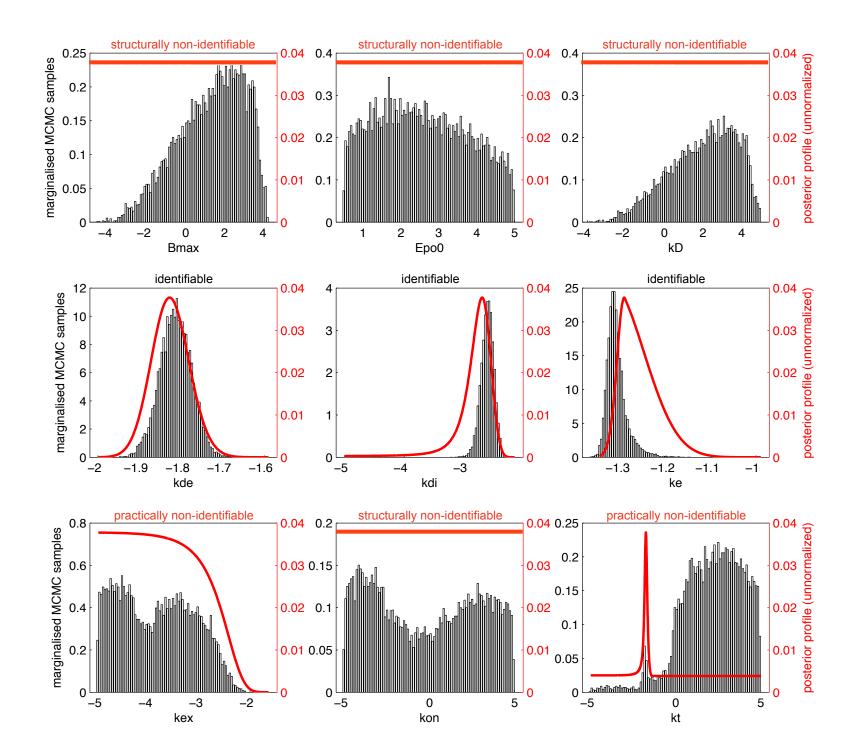
 $heta_1$

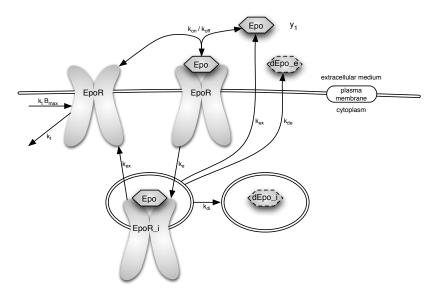


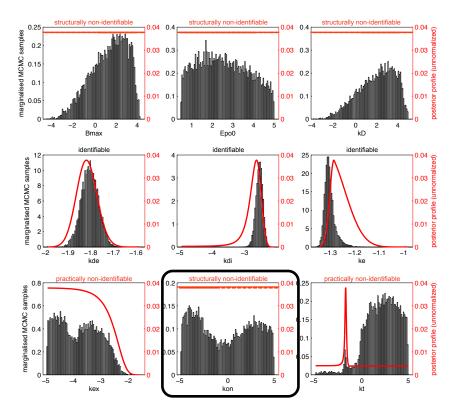
Markov chain Monte Carlo

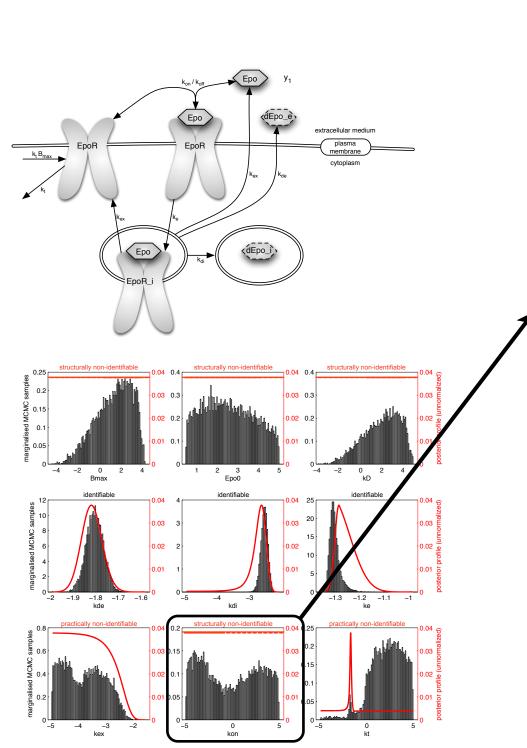


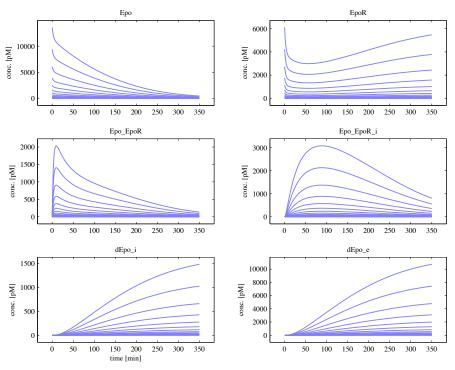
Results for Initial Setup

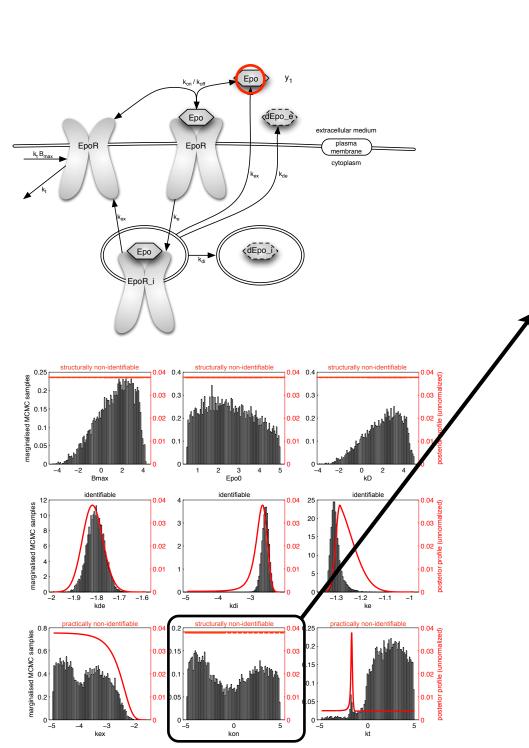


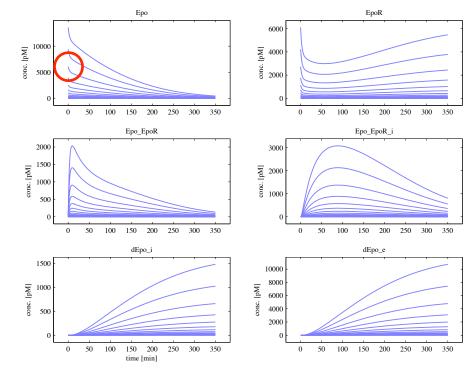


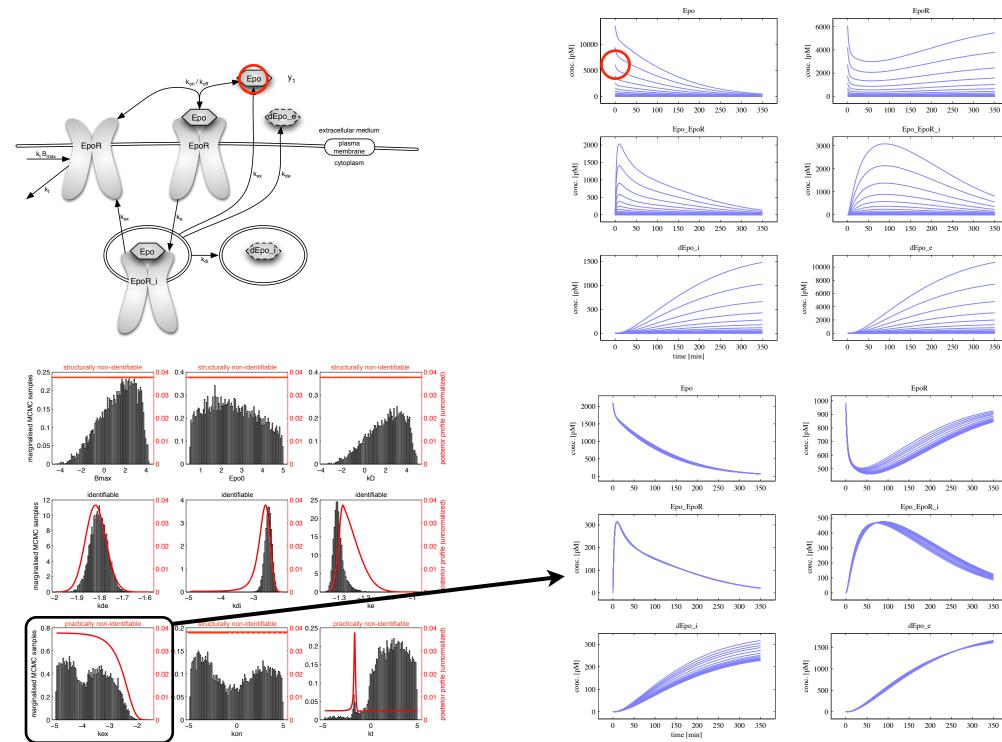


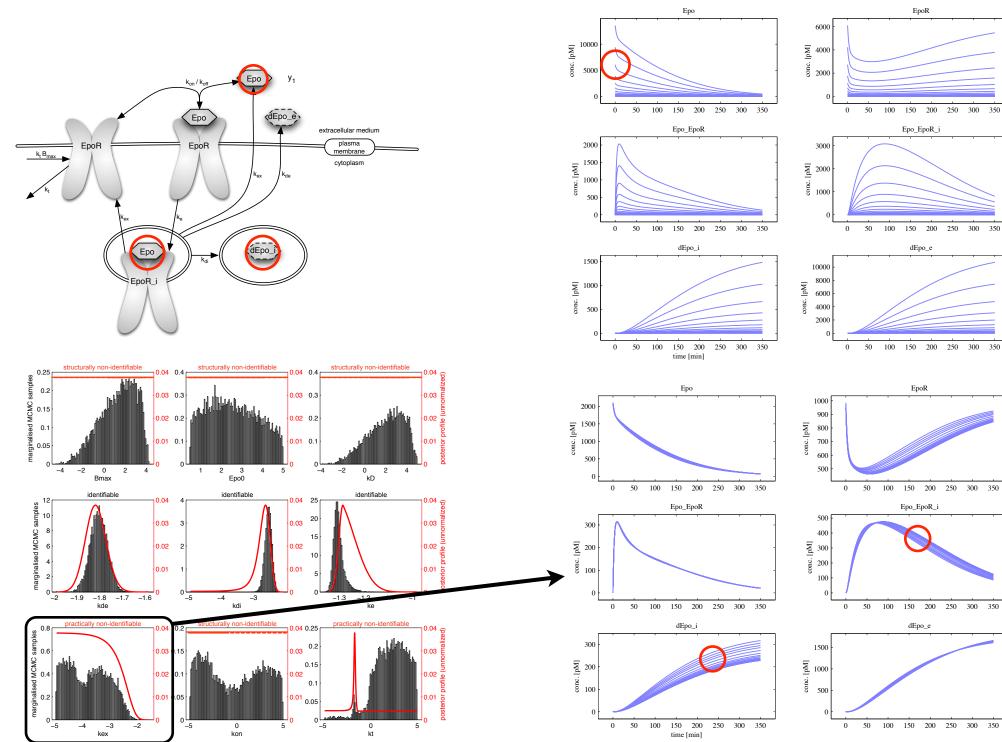




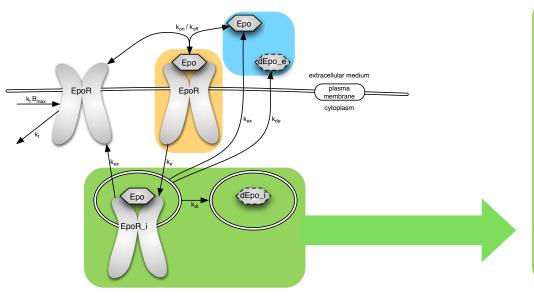


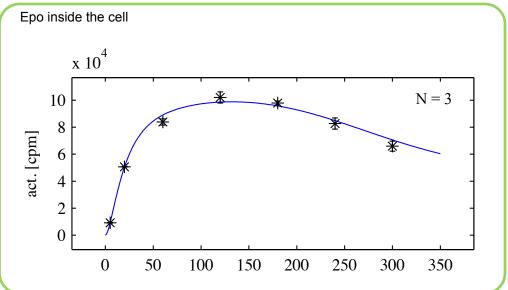


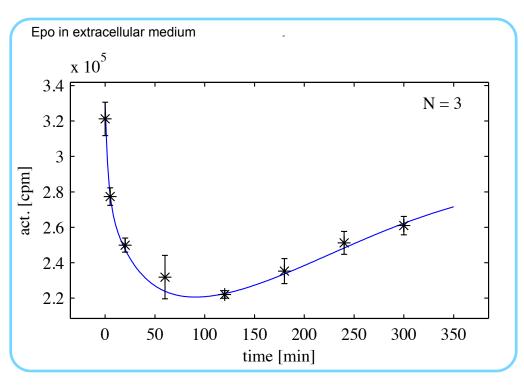


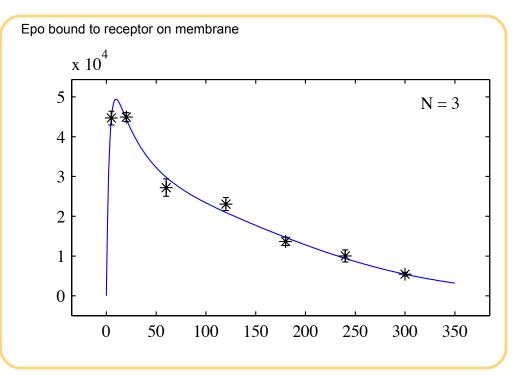


Extended Experimental Setup

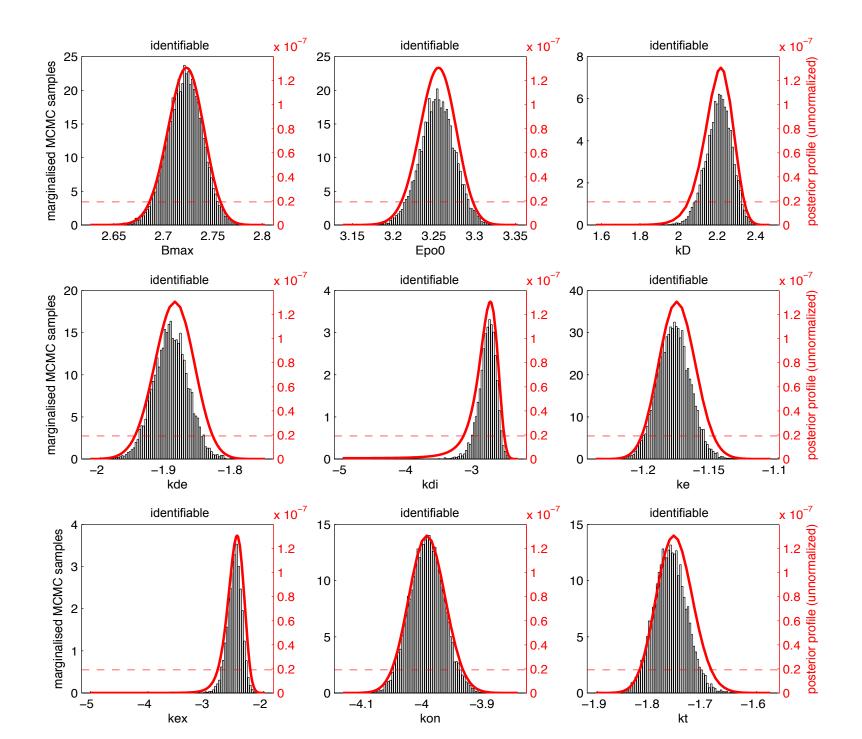






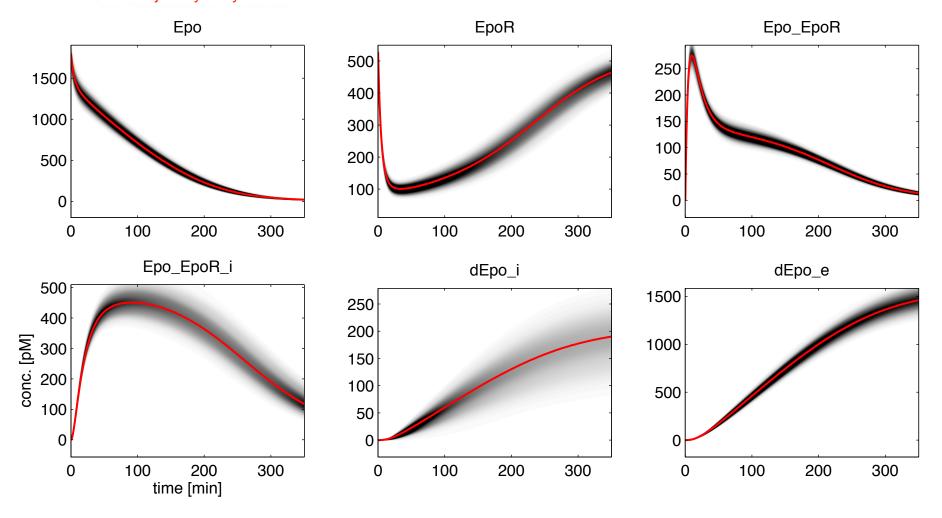


Results for Extended Setup

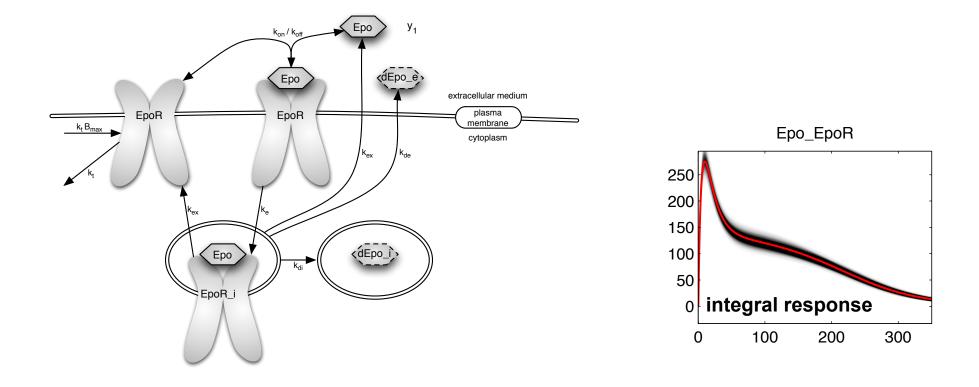


Predicted Model Dynamics

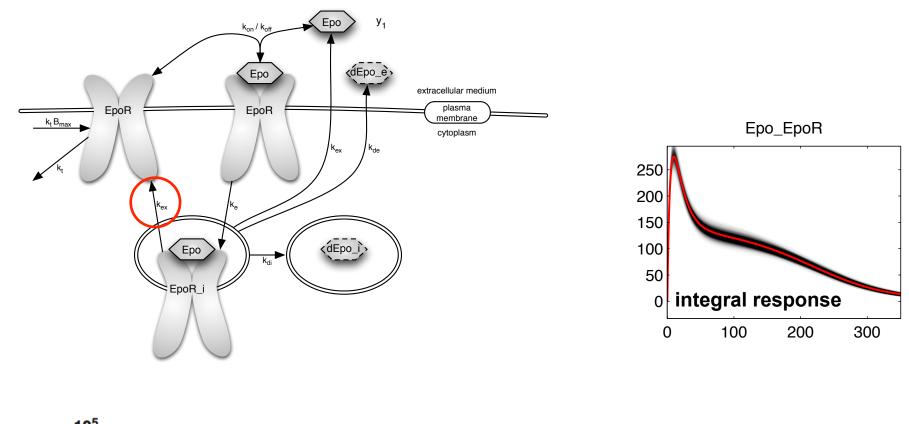


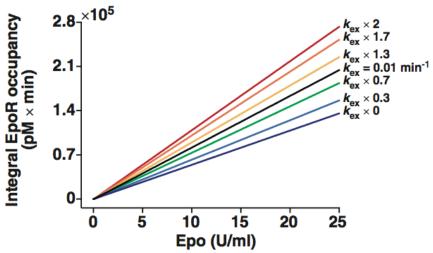


Predicted Model Dynamics - Biological Interpretation

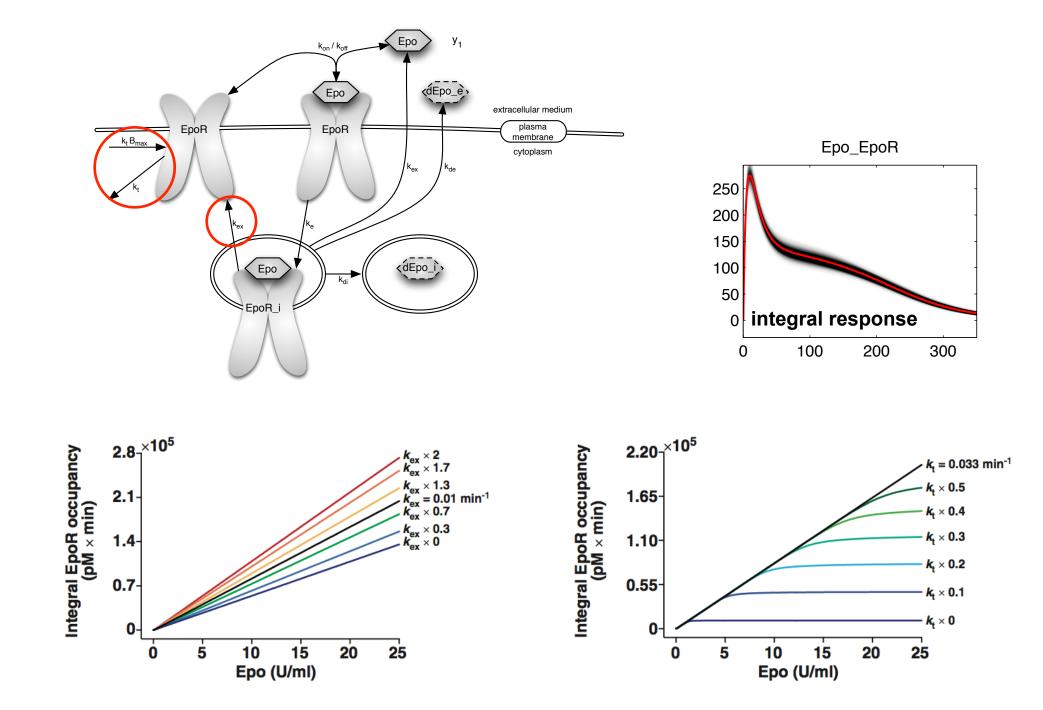


Predicted Model Dynamics - Biological Interpretation





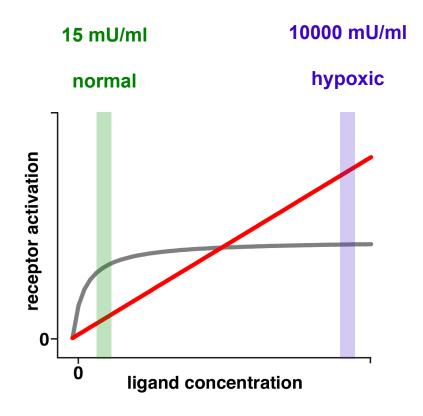
Predicted Model Dynamics - Biological Interpretation



Summary 1 Cellular information processing through EpoR

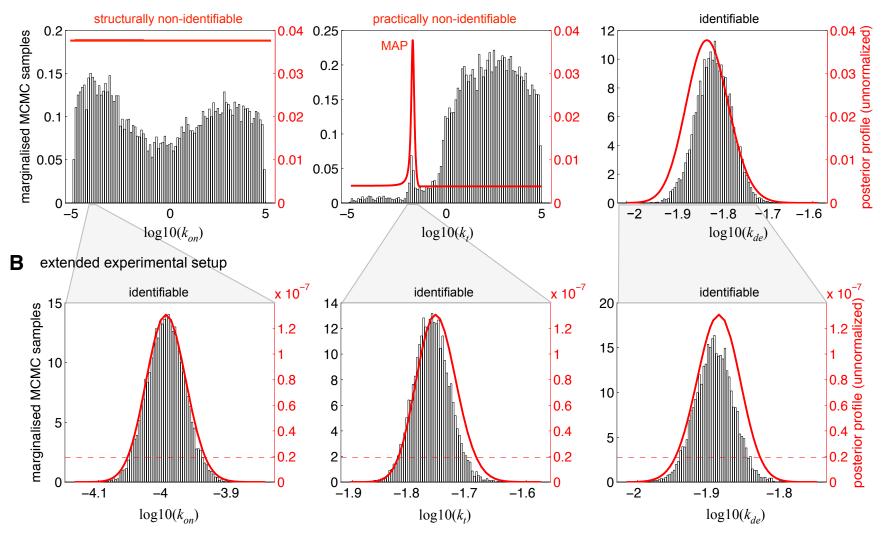
- → linear relation of Epo levels and integral EpoR activation over a broad range of ligand concentrations
- → accurate translation of ligand input into erythrocyte production

Becker et al. Science 2010



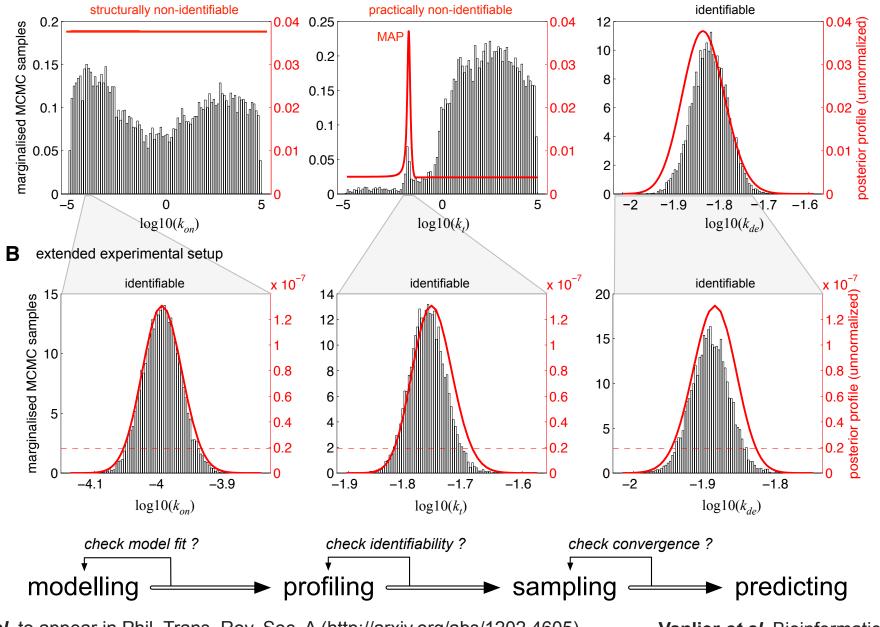
Comparison of profile likelihood and MCMC sampling

A initial experimental setup



Comparison of profile likelihood and MCMC sampling

A initial experimental setup



Raue et al. to appear in Phil. Trans. Roy. Soc. A (http://arxiv.org/abs/1202.4605)

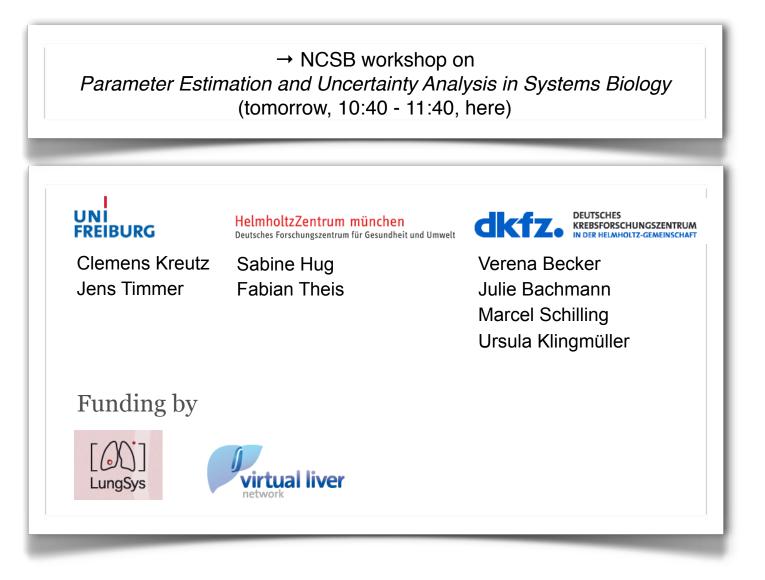
Vanlier et al. Bioinformatics 2012

Approach is applicable for larger models (24 x 25 ODEs, 113 parameters)

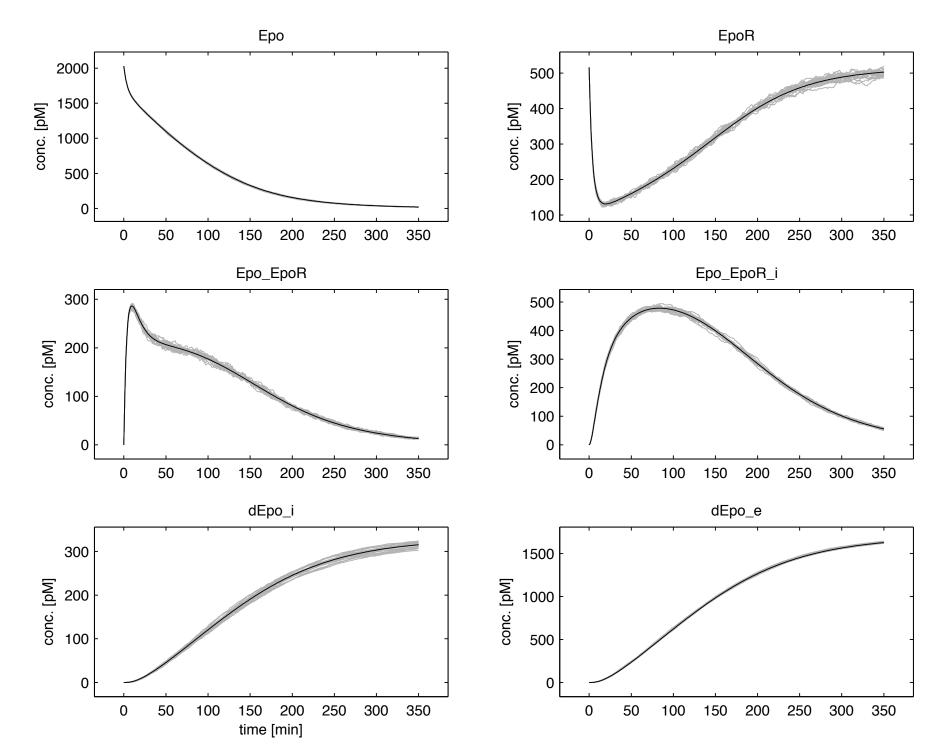
Approach is applicable for larger models (24 x 25 ODEs, 113 parameters)

→ NCSB workshop on Parameter Estimation and Uncertainty Analysis in Systems Biology (tomorrow, 10:40 - 11:40, here)

Acknowledgements



Comparison of ODE and SSA

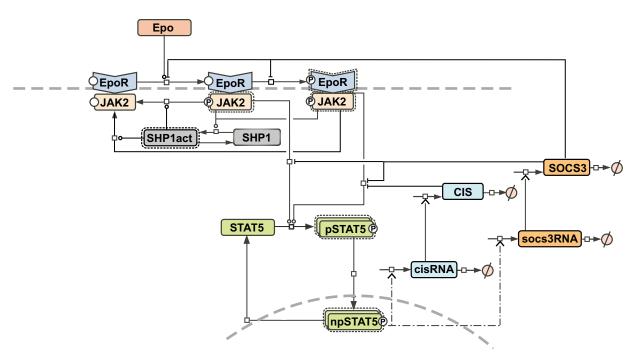


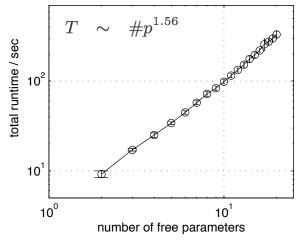
Scaling of Profile Likelihood Approach

Runtime analysis for increasing number of parameters:

Calculation can also be parallelized perfectly!

Model of downstream signaling events:



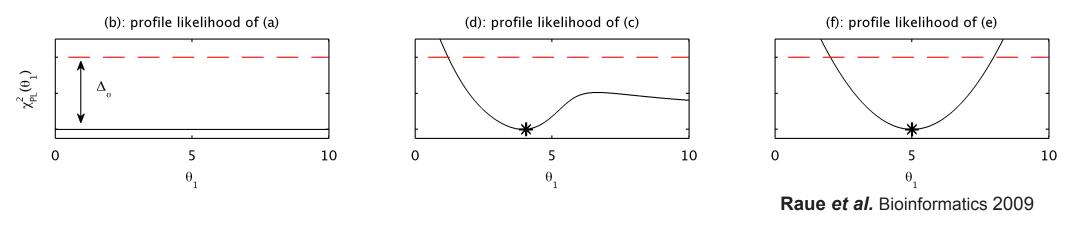


25 ODEs 24 experimental conditions 541 data points 113 free parameters

~10 minutes per profile

Bachmann et al. Molecular Systems Biology 2011

Requirements for Profile Likelihood Approach

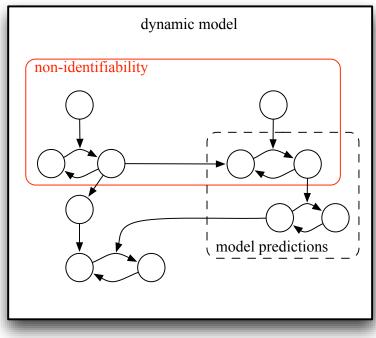


- Profile Likelihood Approach is not limited to ODE models
- Only requirement: a working Maximum Likelihood Estimation
- Freely available software implementation:

PottersWheel Toolbox (MATLAB)

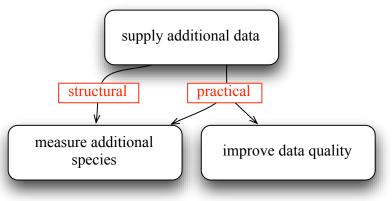
Experimental Design vs. Model Reduction

(a) scenario 1

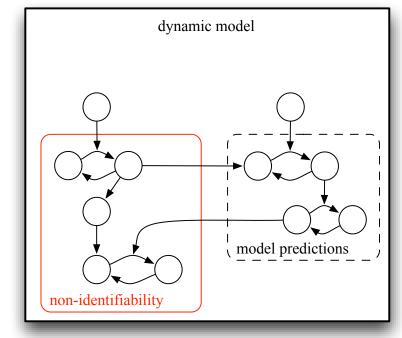


model predictions affected by non-identifiability → model predictions not reliable

experimental design:

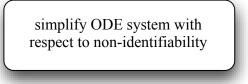


(b) scenario 2



model predictions not or only negliglibly affected by non-identifiability

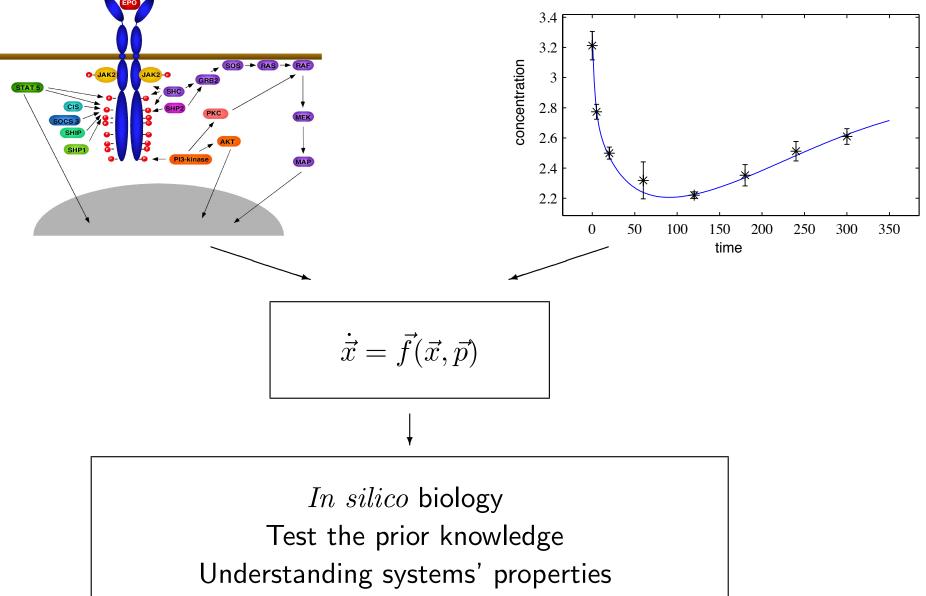
model reduction:



Raue et al. IET Systems Biology 2011

The "Systems Biology" Approach





Identification of potential drug targets