# Joining Forces of Bayesian and Frequentist Methodology: A Study for Inference in the Presence of Non-Identifiability

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### The "Systems Biology" Approach





Identification of potential drug targets

### 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 model parameters well identified? Are the predictions reliable?

## Parameter Identifiability

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



ODE Observables

Likelihood

$$\begin{aligned} \dot{\vec{x}}(t) &= f(\vec{x}(t), \vec{u}(t), \vec{p}, t) \\ \vec{y}(t) &= g(\vec{x}(t), \vec{s}) + \vec{\epsilon}(t) \end{aligned}$$
$$L(y|\theta) = \prod_{k=1}^{m} \prod_{l=1}^{d_k} \frac{1}{\sqrt{2\pi\sigma_{kl}^2}} \exp\left(-\frac{1}{2}\left(\frac{y_{kl} - y_k(t_l, \theta)}{\sigma_{kl}}\right)^2\right) \end{aligned}$$

## Parameter Identifiability

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



→ Profile Likelihood Approach



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

Profile Likelihood

Likelihood

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

## Parameter Identifiability

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



## MCMC Sampling



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





## MCMC Sampling











## MCMC Sampling



## **Results for Initial Setup**











-5 -4 -3

kex

-2

-5

0

kon

5

\_5

0

kt

5



#### EpoR 6000 편 <sup>1000</sup> <u> 전</u> 4000 conc. 500 2000 150 200 250 150 200 250 50 100 300 350 100 300 350 0 0 50 Epo\_EpoR Epo\_EpoR\_i 2000 3000 [Wd] 1500 1000 500 <u>¥</u> 2000 9 8 1000 500 50 100 150 200 250 300 350 50 100 150 200 250 300 350 0 0 dEpo\_i dEpo\_e 1500 10000 8000 편 1000 [Md] 6000 500 conc. 4000 2000 100 150 200 250 300 350 50 150 200 250 300 350 0 100 0 50 time [min] Еро EpoR 1000 2000 90 된 <sup>1500</sup> [M] 800 i 1000 700 conc. 600 500 50 0 50 100 150 200 250 300 350 0 50 100 150 200 250 300 350 Epo\_EpoR Epo\_EpoR\_i 50 300 400 <u>전</u> 300 Md 200 200 100 0 50 100 150 200 250 300 350 0 50 100 150 200 250 300 350 dEpo\_i dEpo\_e 300 1500 <u>전</u> 200 M 1000 9 100

50

0

100 150 200 250 300 350

50 100

150 200

time [min]

250 300 350

0

#### Non-observability of model dynamics:



#### Non-observability of model dynamics:



0.04 📻 0.03 marginalised MCMC sc 0.02 💆 0.02 0.02 10 0.01 0.01 b 0.01 5 0 <u>-</u>2 0 0 -1.9 -1.8 -1.7 -1.6 -3 -4 -1.3 kdi kde ke practically non-identifiable practically 0.04 <del>g</del> 0.8 0.04 0.25 marginalised MCMC samples 0.2 0.03 0.03 0.0 0.15 0.02 0.1 .05 0.01 0.05 ال⊔₀ ٥٢ 0 ٥, -5 -4 -3 -2 -5 0 5 \_5 0 5

kon

kt

kex

### Extended Experimental Setup









## **Results for Extended Setup**



## **Predicted Model Dynamics**



## Predicted Model Dynamics - Biological Interpretation



Becker et al. Science 2010

## Predicted Model Dynamics - Biological Interpretation



Becker et al. Science 2010



## Predicted Model Dynamics - Biological Interpretation







## Summary

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



## Summary

Comparison of profile likelihood and MCMC sampling



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Comparison of profile likelihood and MCMC sampling



## Acknowledgements



## 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)

## 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 115 free parameters

~10 minutes per profile

Bachmann et al. Molecular Systems Biology 2011

## **Model-Based Experimentation**

(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