Structural and Practical Identifiability Analysis

of partially observed dynamical systems

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Outline

- Introducing structural and practical identifiability
- I. Profile Likelihood Approach Detecting non-identifiabilities
- JAK-STAT Signaling Pathway
- 2. Mean Optimal Transformation Approach Finding groups of functionally related parameters

ODE models

species:

observables:

$$\dot{\vec{x}}(t) = f(\vec{x}(t), \vec{u}(t), \vec{p}, t) \vec{y}(t) = g(\vec{x}(t), \vec{s}) + \vec{\epsilon}(t)$$

$$\theta = \{\vec{x}_0, \vec{p}, \vec{s}\}$$
$$\in \mathbf{R}^+ \setminus \{0\}$$

Signaling pathways

	species	observables	parameters	data-points	
JAK-STAT	4	2	7	32	
EPO receptor	6	3	10	32	
JAK2-STAT5	13	6	20	213	
TNFα IL-I IL-6	20	6	24	159	
MAPK	24	12	68	168	

ODE models

species: $\dot{\vec{x}}(t) = f(\vec{x}(t), \vec{u}(t), \vec{p}, t)$ observables: $\vec{y}(t) = g(\vec{x}(t), \vec{s}) + \vec{\epsilon}(t)$ $\theta = \{\vec{x}_0, \vec{p}, \vec{s}\} \\ \in \mathbf{R}^+ \setminus \{0\}$

Objective function: Log-Likelihood

$$\chi^2(\theta) = \sum_{k=1}^m \sum_{l=1}^{d_i} \left(\frac{y_{kl}^D - y_k(\theta, t_{kl})}{\sigma_{kl}^D} \right)^2 \qquad \vec{\epsilon}(t) \sim N(0, \sigma^2)$$

$$\hat{\theta} = \arg\min\left[\chi^2(\theta)\right]$$



Structural non-identifiability

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

$$\vec{y}(t) = g(\vec{x}(t), \vec{s}) + \vec{\epsilon}(t)$$

Simple example: A
$$\xrightarrow{k}$$
 B $\dot{A}(t) = -k \cdot A(t)$ $\theta = \{A_0, B_0, k\}$ $\dot{B}(t) = +k \cdot A(t)$

$$y(t) = A(t) + B(t) = A_0 \cdot e^{-k \cdot t} + [B_0 + A_0 \cdot (1 - e^{k \cdot t})] = A_0 + B_0$$

Cobelli, C. and DiStefano, J. (1980). *Parameter and structural identifiability concepts and ambiguities: a critical review and analysis*. American Journal of Physiology- Regulatory, Integrative and Comparative Physiology, 239(1), 7–24.

Structural non-identifiability (data-based view)



Practical non-identifiability & Confidence intervals

Asymptotic confidence intervals

$$\sigma_i^{\pm} = \hat{\theta}_i \pm \sqrt{\chi^2 (1 - \alpha, df) \cdot \mathbf{C}_{ii}}$$

with $\mathbf{C} = \mathbf{H}^{-1}$ and $\mathbf{H} = \nabla^T \nabla \chi^2|_{\hat{\theta}_i}$

Likelihood-based confidence intervals

$$\{\theta \mid \chi^2(\theta) - \chi^2(\hat{\theta}) < \Delta_{\alpha}\}$$

with $\Delta_{\alpha} = \chi^2(1 - \alpha, df)$

Asymptotic vs. likelihood-based confidence intervals





Practical non-identifiability: Likelihood-based confidence region infinitely extended.

Structural non-identifiability \rightarrow Likelihood perfectly flat Practical non-identifiability \rightarrow Likelihood flattens out

Idea: Sample the profile likelihood

$$\chi^2_{PL}(\theta_i) = \min_{\forall \theta_{j \neq i}} \left[\chi^2(\theta) \right]$$

Murphy, S. and van der Vaart, A. (2000). *On profile likelihood*. Journal of the American Statistical Association, 95(450), 449–485.

The profile likelihood

$$\chi^2_{PL}(\theta_i) = \min_{\forall \theta_{j \neq i}} \left[\chi^2(\theta) \right]$$





Raue A., Kreutz C., Maiwald T., Bachmann J., Schilling M., Klingmüller U., Timmer J. *Structural and practical identifiability analysis of partially observed dynamical models by exploiting the profile likelihood*. Bioinformatics, in press

Computational complexity





Swameye, I., Müller, T. G., Timmer, J., Sandra, O., and Klingmüller, U. (2003). *Identification of nucleocytoplasmic cycling as a remote sensor in cellular signaling by databased modeling*. PNAS, 100(3), 1028–1033.



Swameye, I., Müller, T. G., Timmer, J., Sandra, O., and Klingmüller, U. (2003). *Identification of nucleocytoplasmic cycling as a remote sensor in cellular signaling by databased modeling*. PNAS, (3), 1028–1033.



Functional relations between $\{p_2, x_1(0), s_1, s_2\}$



Profile Likelihood Approach Mean Optimal Transformation Approach

Parameter I Parameter 2 Parameter 3 Parameter 4 Parameter 5 Parameter 6 Parameter 7 Parameter 8 Parameter 9

. . .

structurally non-identifiable structurally non-identifiable

structurally non-identifiable

structurally non-identifiable structurally non-identifiable Group I Group 2



Group I Group 2

. . .

. . .

Hengl S., Kreutz C., Timmer J., Maiwald T. *Data-dased identifiability analysis of nonlinear dynamical models*. Bioinformatics 23, 2007, 2612-2618

Idea:

- I. Multiple fitting
- 2. Optimal Transformation

$$\{\Theta, \Phi\} = \sup_{\hat{\Theta}, \hat{\Phi}} |R(\hat{\Theta}(p_i), \hat{\Phi}(p_j))|$$

by Alternating Conditional Expectation algorithm.

3. Bootstrap

Breiman L., Friedman J. H. *Estimating optimal transformations for multiple regression and correlation*. Journal American Statistical Associtation 80, 1985, 580–598





Independency Optimal transformations change every time Not yet decidable

Dependency Optimal transformation is reproduced

Parameter 2	I	I	I	0	0
Parameter 5	I	l		0	0
Parameter 7	I	I		0	0
Parameter 3	0	0	0	I	I
Parameter 8	0	0	0		I

Experimental Design

Structural non-identifiability

 $\{p_2, x_1(0), s_1, s_2\}$

og10(other parameters)

0

-3∟ –3

-2

-1 log10(p₂) 0



Experimental <u>Qesign</u>

Practical non-identifiability

time / min



0 20 40 60 0 time / min

time / min

Summary

- Two data-based approaches to detect and analyse structural and practical nonidentifiabilities
- Facilitating experimental design to build predictive models

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