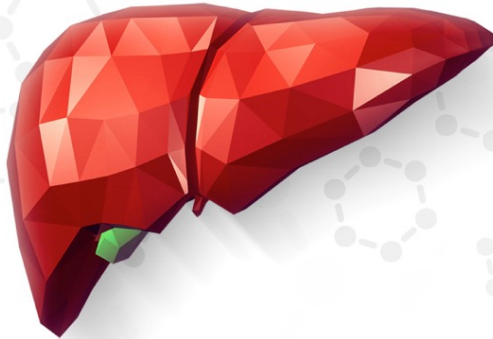
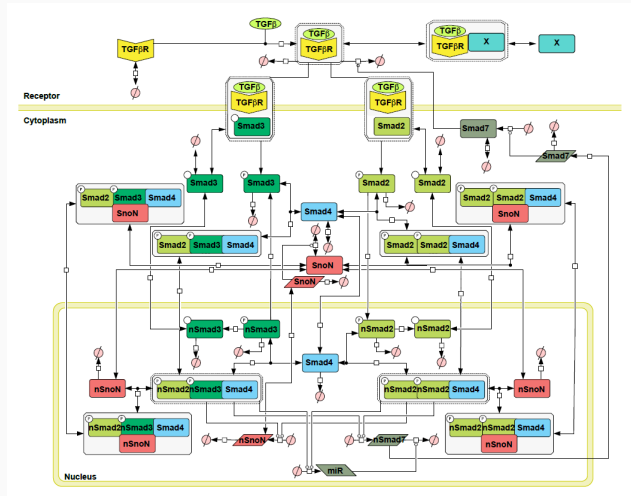


Model-based detection of progression-caused alterations in cellular information processing



First LiSyM Jamboree & SAB Meeting
16 th May 2017 | Jens Timmer | University of Freiburg

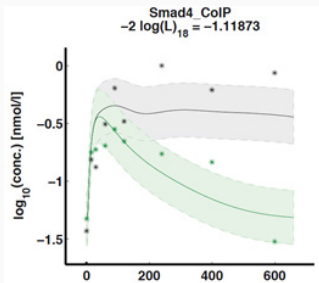
Chronic Liver Disease Progression - The Modeller's Perspective



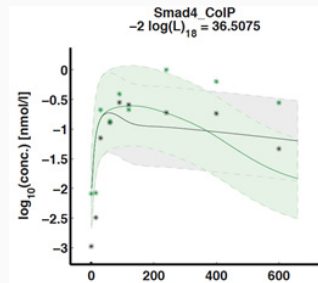
Chronic Liver Disease Progression - The Modeller's Perspective

Same model structure but different behaviors

Primary hepatocytes



Hepa 1-6



Parameter Estimation in Nonlinear, Partially Observed, Noisy, Non-autonomous, Stiff, Sparse Dynamical Systems

Dynamics:

$$\dot{\vec{x}} = \vec{f}(\vec{x}, \vec{p}, \vec{u}), \quad \vec{x}(t_0) = \vec{x}_0 \quad \vec{x} \in \mathbb{R}_+^n$$

Observations:

$$\vec{y}(t_i) = \vec{g}(\vec{x}(t_i), \vec{p}) + \vec{\epsilon}(t_i), \quad \vec{\epsilon}(t_i) \sim \mathbf{N}(\mathbf{0}, \Sigma_i), \quad \vec{y} \in \mathbb{R}_+^m$$

Negative log-likelihood:

$$\chi^2(\vec{p}, \vec{x}_0) = \sum_{i=1}^N \sum_{j=1}^M \left(\frac{(y_j^D(t_i) - g_j(\vec{x}(t_i; \vec{p}, \vec{x}_0)))^2}{\sigma_{ij}} \right)^2$$

Parameters fitted on logarithmic scale

Chronic Liver Disease Progression - The Modeller's Perspective

Hypothesis:

Disease progression = Alterations in cellular information processing

Hierarchy of possibilities to reflect this in the models

- ▶ Changes in initial values \vec{x}_0 : Different expression levels of involved proteins
- ▶ Changes in kinetic parameters \vec{p} : Different expression levels of enzymes, scaffolds or transporters
- ▶ Changes in topological structure of pathway $f(\cdot)$: Other proteins involved

All alterations in the model can be related to biology

Strategy

- ▶ Fit models for different stages of disease progression
- ▶ Look for differences in initial values, parameters, model structure
- ▶ Challenge: Experimental data \implies there will always be differences
- ▶ Required: A systematic procedure to detect "real" differences
- ▶ Since differences are related to biology:

Model-based functional genomics/proteomics

Finding the Differences

- ▶ Performing a plethora of t -tests is not an option
- ▶ Idea:
For parameter p_i^j at disease stage j write parameter $p_i^{j'}$ at disease stage j' as

$$p_i^{j'} = \tilde{r}_i p_i^j$$

On log-scale:

$r_i = \log \tilde{r}_i$, $r_i = 0$ means no difference for parameter p_i between stages j and j'

- ▶ Challenge: How to find the real differences

Regularisation

Extend the log-likelihood

$$\chi_{k,\lambda}^2 = \chi^2 + \lambda \sum_i |r_i|^k$$

Goal:

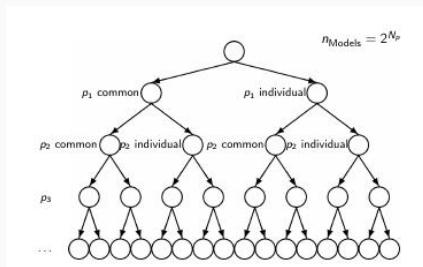
- ▶ The statistically minimum number of necessary differences, a sparse solution
- ▶ numerically efficient

How to choose k and λ ?

Choosing k

$$\chi_{k,\lambda}^2 = \chi^2 + \lambda \sum_i |r_i|^k$$

- ▶ $k = 0$: gives sparsity, but NP-hard
- ▶ $k = 2$: efficient, but not sparse
- ▶ $k = 1$: also sparse, but treatable



A lot of numerical details ...

- ▶ Non-differentiable objective function at $\mathbf{r}_i = \mathbf{0}$: sub-gradients
- ▶ Constrained optimisation: Karush-Kuhn-Tucker criterion
- ▶ Uniqueness of reduction: profile likelihood

Choosing λ

$$\chi_{1,\lambda}^2 = \chi^2 + \lambda \sum_i |r_i|^1$$

- ▶ Estimate parameters individually for all disease stages from $\chi_{1,0}^2$
- ▶ Scan λ from **0** to higher values
- ▶ Estimate parameters based on regularised $\chi_{1,\lambda}^2$
- ▶ Will lead to increasing number of $r_i = \mathbf{0}$
- ▶ Apply likelihood ratio test between $\chi_{1,0}^2$ and $\chi_{1,\lambda}^2$
- ▶ If not significant $r_i = \mathbf{0}$ is justified, otherwise: stop
- ▶ Use profile likelihood to find out whether reduction is unique

Merkle et al. 2016, PLoS Comput Biol 12(8): e1005049.

Steiert et al. 2016, Bioinformatics 32, 2016, i718-i726

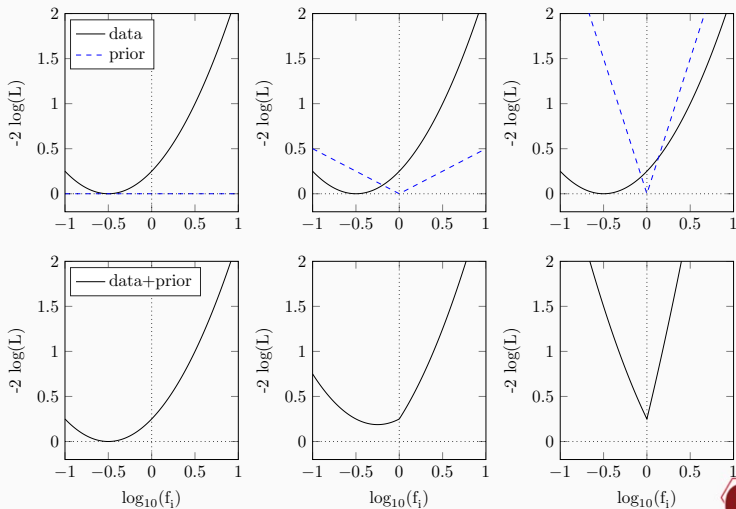
Summary

- ▶ There is still need to develop new modeling techniques in systems medicine
- ▶ Since differences in parameters at different disease stages reflect biology
 - ▶ understand mechanisms
 - ▶ identify biomarkers
 - ▶ identify intervention points
- ▶ Systems are non-linear: points of maximal differences are not necessarily points of most effective interactions
- ▶ It needs the model

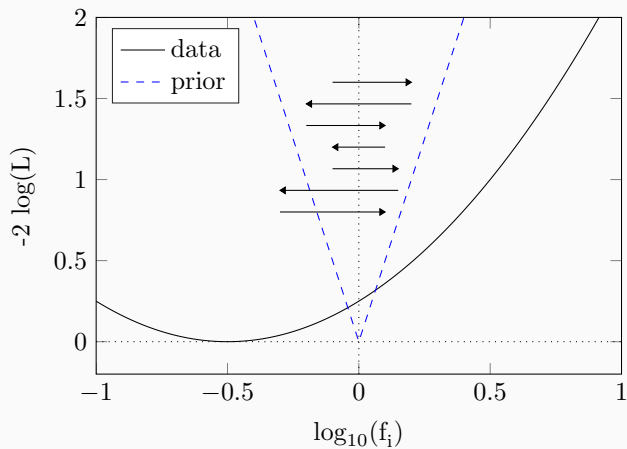
Acknowledgements

- ▶ Bernhard Steiert
- ▶ Wolfgang Mader
- ▶ Clemens Kreutz
- ▶ Andreas Raue
- ▶ Ruth Merkle
- ▶ Florian Salopiata
- ▶ Marcel Schilling
- ▶ Ursula Klingmüller

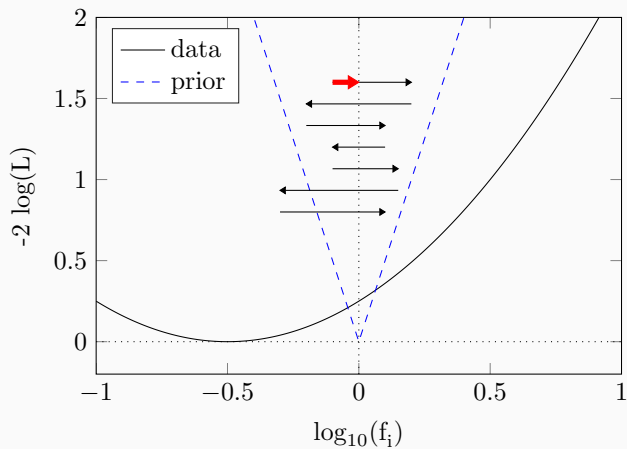
Regularization: example



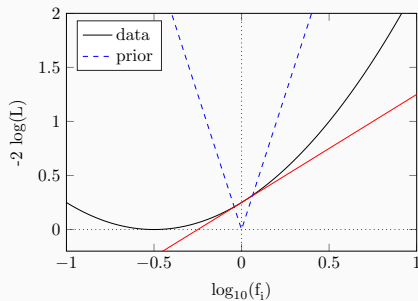
Regularization: step size



Regularization: step size



Regularization: convergence



Karush–Kuhn–Tucker convergence criterion

$$\begin{cases} \nabla_i \chi^2(\hat{\rho}_i) + \lambda \operatorname{sign}(\hat{\rho}_i) = 0, & |\hat{\rho}_i| > 0 \\ |\nabla_i \chi^2(\hat{\rho}_i)| \leq \lambda, & \hat{\rho}_i = 0 \end{cases}$$