

Part II: Building Robust PK/PD Population Models with Bayesian Inference

Clinical neonate example in scientific collaboration with M. Pfister, university children's hospital Basel (UKBB)

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Example: Acetaminophen in Neonates Very sparse sampling and well-established adult data

Neonates

- Newly born babies
- Very sparse sampling
- Organ maturation
- Pain management in given and the second secon
- Acetaminophen
 - Extensive adult data
 - Parent-Metabolite kinetics

Relevant external information Human renal function maturation N=923



Source: Rhodin et. al, Pediatr Nephrol (2009) 24:67-76

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Context for Acetaminophen in Neonates

Extensive adult data, metabolites are essential

- Adult literature data
 - PK: parent V and CI are known from IV data
 - Main metabolites formed mostly in the liver
 ~60% glucuronidation & ~30% sulfation → G/S ratio ~ 2:1
 - Elimination via kidney \rightarrow Cl ~ 7.2 l/h/70kg

Metabolism vastly different in neonates

- Kidney mature at ~1y after birth
- Glucuronidation (G) quickly matures around birth
- Sulfation (S) mature long before birth
- Key challenge is to account for changing metabolism

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Experimental Data

IV infusions & sparse sampling for (pre-)term neonates

- Joint work with Dept. of Paediatric Research Center, University Children's Hospital Basel see for details poster <u>II-57</u> & II-56
- Patient population N=35

	Mean	Min - Max	Unit
Pma	35	23 - 41	weeks
Weight	2.2	0.46 - 4.2	kg
# Obs per pat.	7.2	3 - 11	

- Dosing regimen
 - 30min IV infusions
 - GA ≤ 28: 5x 15mg/kg every 12h
 - GA > 28: 7x 15mg/kg every 8h



Modelling Considerations

Bayesian modelling reflects a quantitative model context with the prior

- Key modeling questions in general
 - 1. What is the objective of the M&S?
 - 2. In what aspect is the data at hand informative?
 - 3. Model checking
- The Bayesian extra is the prior:
 Formulation of the quantitative model context
 - What external information is relevant for the objective and can (or must) be taken into account?
 - How can we parametrize the model to optimally mirror prior information?
 - Different sources of information can vary in relevance and quality
 → Prior elicitation, see references

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The Quantitative Model Context: The Prior

Bayes puts data into a context via the prior

Priors

- Use of correct units
- Are part of the model
- Often useful to consider plausible 95% Crl

- Technical aspects of priors
 - Similar to regularization
 - Remove non-identifiability if chosen proper
 - Parameterization dependent

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Prior	Usage	Example for $(\log(\omega_{cl}))$ »
Improper	Easy to use can be problematic	∝ 1
Non- Informative	Minimize impact on results can also be problematic	~ Normal(0, 10^2) $\omega_{Cl} \sim (10^{-85}, 10^{85})_{95}$
Weakly- Informative	Identify scale minimal impact, stable inference	~ Normal(log(0.5), 2) $\omega_{Cl} \sim (0.01, 25)_{95}$
Informative	Contextual domain knowledge (renal clearance)	~ Normal(log(0.2), log(3)/1.96) $\omega_{Cl} \sim (0.06, 0.6)_{95}$

7 | PAGE 2015 | M. Betancourt & S. Weber | June 4th 2015 | Bayesian PK/PD | Public

Parametrization is Key in Bayesian Modeling Model parameters must mirror prior knowledge

- Objective for neonate model *Quantify impact of developing metabolism on PK*
- Strategy: Relate to adult data with allometric '1/4' power scaling and use known GFR maturation function
- Key facts identified and choices made
 - Metabolites G and S constitute ~90% of Acetaminophen elimination $logit(\pi_{G+S}) \sim (logit(0.85), logit(0.95))_{95}$
 - Clearance of metabolites via the kidney (~7.2 l/h/70kg) $\log C l_{\rm G,ref} \sim (\log(5), \log(10))_{95}$
 - Glucuronidation formation capacity developing with pma

$$Cl_{\text{APAP,G},j} = Cl_{\text{APAP,G},\text{ref}} \pi_{34} \left(\frac{w_j}{70}\right)^{3/4} \exp(\lambda_G \left(pma_j - 34\right))$$

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The Developing Metabolism in Neonates Fast clearance maturation slows down $T_{\frac{1}{2}}$ decrease with age

- Increase by CI maturation slows T_{1/2} weight scaling $T_{\frac{1}{2}} = \log(2) \frac{V}{Cl} \left(\frac{w}{70}\right)^{\frac{1}{4}}$
- Considerable uncertainty & variability
- Metabolism changes quickly and is very different from 2:1 G/S adult ratio



Doing Bayesian PK/PD

The operational & computational hurdles are vanishing

- NONMEM / Monolix (hybrid approach, not full Bayes)
 - No HMC/NuTS available (yet?) → convergence critical
 - Very restrictive in prior choices
- Stan, <u>http://mc-stan.org/</u>
 - PK/PD support growing (stiff ODE solver on Stan GitHub)
 - HMC/NuTS can deal very efficiently with non-linear PK/PD
 - Active community, very responsive user mailinglist
 - Excellent user manual with introductory material
 - ACOP 2015: Workshop from Bill Gillespie on «Getting Started with Bayesian PK/PD Modeling Using Stan»

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WinBUGS/PKBUGS/WBDiff

Key Benefits of a Bayesian Approach

Probabilistic knowledge integration facilitates quantitative decisions

- Bayes provides a quantitative framework to statistically model uncertain knowledge (including external to dataset)
 - The prior reflects a quantitative model context
 - External information make models more robust, yet accounting for uncertainty is key
 - Model parameterization must mirror prior knowledge
- Results become **conditional** on the **totality of evidence** $p(\theta|D) \propto p(D|\theta) p(\theta)$

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 Neonate example clinical relevance: Maturation alters weight scaling, impacting dosing



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References I Applied Bayesian introduction material

Stan

- Stan Dev Team 2015, Version 2.6. <u>http://mc-stan.org</u>
- Stan User Manual (great introduction, very applied)
- Applied Bayesian Statistics Books
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Neonate example

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