

Influence of Covariance Step Success on Final Parameter Estimates

Henrik B. Nyberg^{1,2}, Andrew C. Hooker¹, Yasunori Aoki¹

UPPSALA Department of Pharmaceutical Biosciences, Uppsala University, Sweden¹ UNIVERSITET Mango Solutions, United Kingdom²



Objective and Hypothesis

To determine if a successful covariance step in NONMEM increases the chance of reaching maximum likelihood, and to investigate the influence of computational stability on final parameter estimates.

Assuming no computational error, the positive-definiteness of the Rmatrix (the Hessian of the OFV) is a necessary condition for the maximum likelihood. Therefore we hypothesize that covariance step success should be a necessary condition for the maximum likelihood.

Conclusions

Covariance step success appears to be a better indication of parameter estimate quality than minimization success.

Estimated parameters are most unlikely to be at ML if the covariance step fails and the initial values were not already close to ML.

Our next step is to expand our exploration to different estimation methods and a wider range of models.

Results: Successful and Unsuccessful Estimations

Introduction

The influence of covariance step completion on the quality of parameter estimates in NONMEM has long been debated. Holford *et al* have shown, for a number of examples, that there is no significant difference in parameter standard errors for different termination statuses in a bootstrap [1].

The work presented here assesses different levels of computational stability and different initial estimates for a model without altering the model, data, or the OFV at maximum likelihood.

Method

Three PK models were examined ten thousand times each using FOCEI estimation in NONMEM 7.3:

- 1. Two-compartment model with simulated data
- 2. One compartment Phenobarbital example model and data included in NONMEM [2]
- 3. Model by Jönsson et al [3] with original data

Computational stability and initial estimates were altered between estimations. To change computational stability the models were linearly reparametrized using the precond [4] script in PsN, to produce an R matrix at ML with condition number between 1 and 10¹⁵.



Fig 2. Percentage of runs that have reached minimum OFV (green) split by group and model. Minimum OFV was accepted as less than the total minimum OFV for that model plus one.

The final OFVs for runs with both minimization and covariance step successful were overwhelmingly reaching the maximum likelihood estimate, although some differences between models could be observed. In Figure 2 we can see the proportions between estimations with acceptable OFV values in green (OFV <= minimum OFV + 1) and estimations that produced a higher OFV in red.

Group 1 consists largely of runs that reach maximum likelihood, while groups 2 and 4 are almost void of successful estimation.

The initial values of the model parameters were randomly perturbed within an order of magnitude around the best estimate in order to investigate initial estimates far from ML.

The result of each estimation was categorized into one of four groups:

- 1. Minimization successful and covariance step successful
- 2. Minimization successful, but failed covariance step
- 3. Failed minimization, but successful covariance step
- 4. Failed minimization and failed covariance step

Results: Local Convergence

The variation in initial estimates and computational stability exposed several local convergence OFVs. In Figure 1 we can see the ML OFV and several clear local convergence OFVs as horizontal lines.



Figure 3 explores the relationship between computational stability and the final OFV for the Phenobarbital model.



Fig 3. Final OFV vs the Optimal Condition Number of the R Matrix. The Phenobarbital model is stable but the pattern with group 2 and 4 failing to reach minimum OFV

The published model by Jönsson *et al* follows the same pattern as the two other included models, but is slightly less stable in this experiment setup as demonstrated by its lower rate of success in Figure 2. In Figure 4 we can see the final OFV versus initial OFV for the Jönsson model.





Fig 1. Final OFV vs Initial OFV for the Two Compartment Model. Red is the respective group highlighted against the grey background of the full data.

References

[1] Holford N *et al*, NONMEM Termination Status is Not an Important Indicator of the Quality of Bootstrap Parameter Estimates, PAGE 15 (2006) Abstr 992 [www.page-meeting.org/?abstract=992]

[2] Beal, S., Sheiner, L.B., Boeckmann, A., & Bauer, R.J., NONMEM User's Guides. (1989-2014), Icon Development Solutions, Ellicott City, MD, USA, 2014.

[3] Jönsson *et al*, Population pharmacokinetic modelling and estimation of dosing strategy for NXY-059, a nitrone being developed for stroke, Clinical Pharmakocinetics (2005), 44(8):863-78

[4] Aoki *et al*, Preconditioning of Nonlinear Mixed Effect model for Stabilisation of Covariance Matrix Computation, PAGE 24 (2015) Abstr 3586 [www.page-meeting.org/default.asp?abstract=3586] Fig 4. Final OFV vs Initial OFV for the Jönsson Model. Local convergence and a minuscule portion of runs reaching maximum likelihood in groups 2 and 4 is evident.

Acknowledgements

donno e fine e f

The research leading to these results has received support from the Innovative Medicines Initiative Joint Undertaking under grant agreement n° 115156, resources of which are composed of financial contribution from the European Union's Seventh Framework Programme (FP7/2007-2013) and EFPIA companies' in kind contribution. The DDMoRe project is also financially supported by contributions from Academic and SME partners.



This research has received support from Mango Solutions Ltd, UK. Mango Solutions provide complex analysis solutions, consulting, training, and application development.