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Torsten

A Prototype Library for Bayesian Pharmacometrics
Modeling in Stan

User Manual

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Torsten Version 0.83 beta
for Stan Version 2.15.0

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1. INTRODUCTION

1.1. Preface.

Stan is an open source probabilistic language designed primarily to do Bayesian data analysis [1]. Several of its features make it a powerful tool to specify and fit complex models. Notably, its language is extremely flexible and its No U-Turn Sampler (NUTS), an adaptative Hamiltonian Monte Carlo algorithm, has proven more efficient than commonly used Monte Carlo Markov Chains (MCMC) samplers for complex high dimensional problems [2]. Our goal is to harness these innovative features and make Stan a better software for pharmacometrics modeling. Our efforts are twofold:

- (1) We contribute to the development of new mathematical tools, such as functions that support differential equations based models, and implement them directly into Stan's core language.
- (2) We develop Torsten, an extension with specialized pharmacometrics functions.

Throughout the process, we have been working very closely with Stan's development team. We have benefited immensely from their mentoring, advice, and feedback. Just like Stan, Torsten is an open source project that fosters collaborative work. Interested in contributing? Shoot us an e-mail and we will help you help us (charlesm@metrumrg.com and billg@metrumrg.com)!

Torsten is licensed under the BSD 3-clause license.

WARNING: The current version of Torsten is a *prototype*. It is being released for review and comment, and to support limited research applications. It has not been rigorously tested and should not be used for critical applications without further testing or cross-checking by comparison with other methods.

We encourage interested users to try Torsten out and are happy to assist. Please report issues, bugs, and feature requests on our GitHub page: <https://github.com/charlesm93/stan>.

1.2. Installing Torsten.

Installation files are available on GitHub: <https://github.com/charlesm93/example-models/tree/torsten-0.82/PKPD/torsten>

There is currently no mechanism to install Torsten on top of your version of Stan. This is still a work in progress. In the meantime, we offer a version of Stan with Torsten built inside of it. Torsten 0.82 works with Stan 2.14.0. Torsten is built inside the Stan and Stan-math repositories and is agnostic to the interface. We offer support to install Torsten with RStan and CmdStan.

1.2.1. Installing Torsten with RStan. The easiest way to install the RStan interface with Stan and Torsten is to run the script `R/setupRTorsten.R`. You'll need to make a few minor adjustments, notably by specifying the location at which you wish to install the libraries RStan (and its dependency StanHeaders).

If you already have these packages installed, the script will not automatically overwrite them, which is why you should remove them prior to running `setupRTorsten.R`.

The script currently doesn't install all the dependencies for RStan¹. This is to prevent the edited Stan-Headers package from getting overwritten by the `install.packages()` procedure. If you wish to install

¹See <https://github.com/stan-dev/rstan/wiki/RStan-Getting-Started> for details on RStan

RStan's dependencies, you could run `install.package("rstan")`, remove the RStan and the Stan-Headers packages and then run `SetupRTorsten.R`. We realize this is not optimal and are working on a more elegant solution².

1.2.2. *Installing Torsten with CmdStan.* Similarly, you can install the CmdStan interface with Stan and Torsten using the bash file `setupTorsten.sh`³.

1.3. Overview.

Torsten is a prototype Pharmacokinetic/Pharmacodynamic (PKPD) model library for use in Stan 2.14.0. The current version includes:

- Specific linear compartmental models:
 - One compartment model with first order absorption
 - Two compartment model with elimination from and first order absorption into central compartment
- General linear compartmental model described by a system of first-order linear Ordinary Differential Equations (ODEs).
- General compartmental model described by a system of first order ODEs

The models and data format are based on NONMEM®⁴/NMTRAN/PREDPP conventions including:

- Recursive calculation of model predictions
 - This permits piecewise constant covariate values
- Bolus or constant rate inputs into any compartment
- Handles single dose and multiple dose histories
- Handles steady-state dosing histories for specific and general linear models
- Implemented NMTRAN data items include: TIME, EVID, CMT, AMT, RATE, ADDL, II, SS

This library provides Stan language functions that calculate amounts in each compartment, given an event schedule and an ODE system.

1.4. Implementation details.

- Stan version 2.15.0 (<http://mc-stan.org/>)
- All functions are programmed in C++ and are compatible with the Stan-math automatic differentiation library [3]
- All functions can be called directly in a Stan file in a manner identical to other built-in functions
- One and two compartment models: hand-coded analytical solutions
- General linear compartment models with semi-analytical solutions using a built-in Matrix Exponential function (Pade approximation coupled with scaling and squaring [4])
- General compartment models with numerical solutions to ODEs using built-in ODE integrators in Stan (Runge-Kutta 4th/5th and backward differentiation methods from CVODES library), with adjustable tuning parameters
- Mix compartment model, with analytical solutions to the base PK ODE sub-system and numerical solutions to the other ODEs, using built-in ODE integrators, with adjustable tuning parameters

²See the issue tracker: <https://github.com/charlesm93/example-models/issues/3>

³To get the development version of Torsten use `setupTorsten-dev.sh`.

⁴NONMEM® is licensed and distributed by ICON Development Solutions.

1.5. Development plans.

Our current plans for future development of Torsten include the following:

- A system to easily share packages of Stan functions (written in C++ or in the Stan language)
- Steady state calculation for the General compartment model
- Optimize Matrix exponential functions
 - Function for the action of Matrix Exponential on a vector
 - Hand-coded gradients
 - Special algorithm for matrices with special properties
- Fix issue that arises when computing the adjoint of the lag time parameter (in a dosing compartment) evaluated at $t_{lag} = 0$.
- Make the following arguments optional
 - `biovar` and `tlag`, respectively used for the bioavailability fraction and the lag times in each compartment
 - Tuning parameters of the ODE integrators for the general compartmental function.
- Extend formal tests
 - We want more C++ Google unit tests to address cases users may encounter
 - Comparison with simulations from the R package *mrqsolve* and the software NONMEM®
 - Recruit non-developer users to conduct beta testing

1.6. Updates since Torsten 0.82.

- Torsten is now up to date with Stan version 2.15.0
- Add “mix solver” functions
- Add algebraic solver
- Torsten automatically corrects ODE functors when the rates are non-zero. The code carefully distinguishes the case where the rates are fixed data or random parameters.
- Fix bug that prevented Jacobians from being accurately computed for `generalOdeModel_*` when `biovar` was passed as parameters, causing the sampler to dissolve into a quasi-random walk.
- Fix bug that prevented users from using a `print` statement inside a function that specifies an ODE system.
- Fixed minor bugs and report issues.

2. USING TORSTEN

The reader should have a basic understanding of how Stan works before reading this chapter. There are excellent resources online to get started with Stan (<http://mc-stan.org/documentation/>).

In this section we go through the different functions Torsten adds to Stan. It will be helpful to apply these functions to a simple example. We have uploaded code and data on <https://github.com/charlesm93/example-models/tree/torsten-0.82/PKPD/torsten>.

2.1. Example 1: Two Compartment Model.

We model drug absorption in a single patient and simulate plasma drug concentrations:

- Multiple Doses: 1250 mg, every 12 hours, for a total of 15 doses
- PK: plasma concentrations of parent drug (c)
- PK measured at 0.083, 0.167, 0.25, 0.5, 0.75, 1, 1.5, 2, 4, 6, 8, 10 and 12 hours after 1st, 2nd, and 15th dose. In addition, the PK is measured every 12 hours throughout the trial.

The plasma concentration (c) are simulated according to the following equations:

$$\begin{aligned}\log(c) &\sim N(\log(\hat{c}), \sigma^2) \\ \hat{c} &= f_{2cpt}(t, CL, Q, V_2, V_3, k_a) \\ (CL, Q, V_2, V_3, k_a) &= (5 \text{ L/h}, 8 \text{ L/h}, 20 \text{ L}, 70 \text{ L}, 1.2 \text{ h}^{-1}) \\ \sigma^2 &= 0.01\end{aligned}$$

where the mass of drug in the central compartment (y_2) is obtained by solving the system of ordinary differential equations (ODEs):

$$\begin{aligned}(1) \quad \frac{dy_1}{dt} &= -k_a y_1 \\ (2) \quad \frac{dy_2}{dt} &= k_a y_1 - \left(\frac{CL}{V_2} + \frac{Q}{V_2}\right) y_2 + \frac{Q}{V_3} y_3 \\ (3) \quad \frac{dy_3}{dt} &= \frac{Q}{V_2} y_2 - \frac{Q}{V_3} y_3\end{aligned}$$

and the drug concentration is given by $c = \frac{y_2}{V_2}$.

The data are generated using the R package *mrgsolve*⁵, see `TwoCptModelSimulation.R`. We show the results obtained when using the function `PKModelTwoCpt`, which computes solutions to the ODEs analytically.

2.2. Linear One and Two Compartment Model Function.

The one and two compartment model functions have the form:

⁵<https://github.com/metrumresearchgroup/mrgsolve>

```
<model name>(time, amt, rate, ii, evid, cmt, addl, ss,
              theta, biovar, tlag)
```

There is no need to skip a line, but we do so to separate *event* arguments and *model* arguments.

The event arguments describe the event schedule of the clinical trial. `time`, `amt`, `rate`, and `ii` are arrays of real and `evid`, `cmt`, `addl`, and `ss` arrays of integers. All arrays have the same length, which corresponds to the number of events.

Next we have the model arguments: `theta` contains the ODE parameters, `biovar` the bioavailability fraction in each compartment (sometimes denoted as F), and `tlag` the lag times in each compartment. The model arguments may be either one or two dimensional arrays. If they are one dimensional arrays, the parameters are constant for all events. If they are two dimensional arrays then each row should contain the listed parameters, and the number of rows should equal the lengths of the `time`, `amt`, `rate`, `ii`, `evid`, `cmt`, `addl`, and `ss` arrays. The values of the i th row should be the parameter values for the interval $[time[i-1], time[i]]$.

The options for *model name* are:

- PKModelOneCpt
- PKModelTwoCpt

which respectively correspond to the one and two compartment model with first order absorption (figure 1). A vector in `theta` is expected to contain parameters CL , $V2$, and ka for the one compartment case, and CL , Q , $V2$, $V3$, and ka for the two compartments case, in this order. Setting ka to 0 eliminates the first-order absorption. `biovar` contains the bioavailability fraction of each compartment (non-effective if set to 1) and `tlag` the lag time in each compartment (non-effective if set to 0).

PKModelTwoCpt can be used to fit example 1, see `TwoCptModel.stan`. We are interested in evaluating the ODE parameters, stored in `theta`. The bioavailability fraction and the lag times on the other hand are fixed, and we therefore declare `biovar` and `tlag` in the transformed data block. Three MCMC chains of 2000 iterations were simulated. The first 1000 iteration of each chain were discarded. Thus 1000 MCMC samples were used for the subsequent analyses.

Result. The MCMC history plots (figure 3) suggest that the 3 chains have converged to common distributions for all of the key model parameters. The fit to the plasma concentration data (figure 5) are in close agreement with the data, which is not surprising since the fitted model is identical to the one used to simulate the data. Similarly the parameter estimates summarized in Table 1 are consistent with the values used for simulation.

TABLE 1. Summary of the MCMC simulations of the marginal posterior distributions of the model parameters

| | mean | se_mean | sd | 2.5% | 25% | 50% | 75% | 97.5% | n_eff | Rhat |
|-------|-------|---------|--------|--------|--------|-------|-------|-------|---------|------|
| CL | 4.82 | 0.002 | 0.0901 | 4.64 | 4.76 | 4.82 | 4.88 | 5.00 | 2464.73 | 1.00 |
| Q | 7.54 | 0.016 | 0.58 | 6.43 | 7.15 | 7.54 | 7.92 | 8.69 | 1385.75 | 1.00 |
| V2 | 21.14 | 0.069 | 2.45 | 16.37 | 19.44 | 21.19 | 22.78 | 25.89 | 1245.64 | 1.00 |
| V3 | 76.35 | 0.110 | 5.35 | 65.98 | 72.75 | 76.26 | 79.83 | 87.30 | 2379.15 | 1.00 |
| ka | 1.23 | 0.005 | 0.169 | 0.923 | 1.12 | 1.23 | 1.35 | 1.58 | 1295.01 | 1.00 |
| sigma | 0.108 | 0.000 | 0.012 | 0.0887 | 0.0999 | 0.107 | 0.115 | 0.135 | 1973.97 | 1.00 |

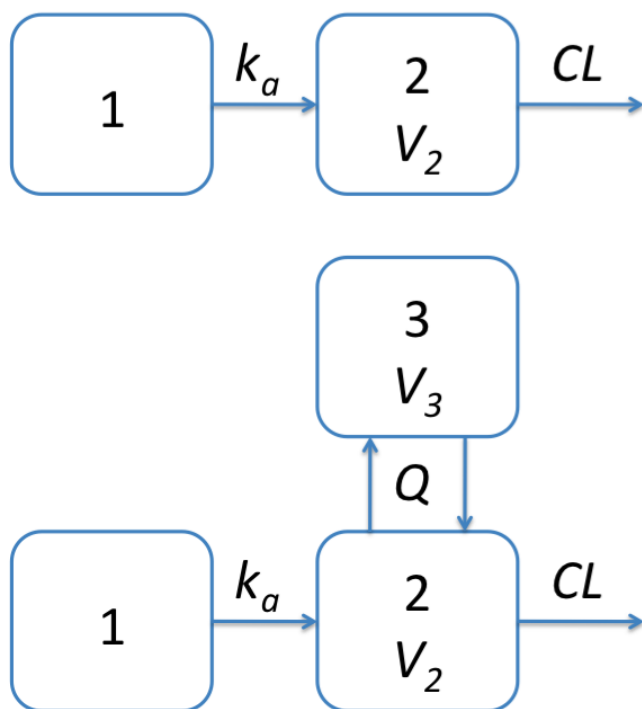


FIGURE 1. One and two compartment models with first order absorption implemented in Torsten.

FIGURE 2. Stan language for fitting a two compartment model using the PKModelTwoCpt function (abstract)

```

data {
  int<lower = 1> nt; # number of events
  int<lower = 1> nObs; # number of observation
  int<lower = 1> iObs[nObs]; # index of observation
  int cmt[nt];
  int evid[nt];
  int addl[nt];
  int ss[nt];
  real amt[nt];
  real time[nt];
  real rate[nt];
  real ii[nt];

  vector<lower = 0>[nObs] cObs; # observed concentration (Dependent Variable)
}

transformed data {
  :
  biovar[1] = 1;
  biovar[2] = 1;
  biovar[3] = 1;

  tlag[1] = 0;
  tlag[2] = 0;
  tlag[3] = 0;

}

:
parameters {
  real<lower = 0> CL;
  real<lower = 0> Q;
  real<lower = 0> V2;
  real<lower = 0> V3;
  real<lower = 0> ka;
  real<lower = 0> sigma;
}

transformed parameters {
  :
  theta[1] = CL;
  theta[2] = Q;
  theta[3] = V2;
  theta[4] = V3;
  theta[5] = ka;

  x = PKModelTwoCpt(time, amt, rate, ii, evid, cmt, addl, ss,
                    theta, biovar, tlag);

  cHat = col(x, 2) ./ V2; # get concentration in the central compartment

  cHatObs = cHat[iObs]; # predictions for observed data records

}

:

```

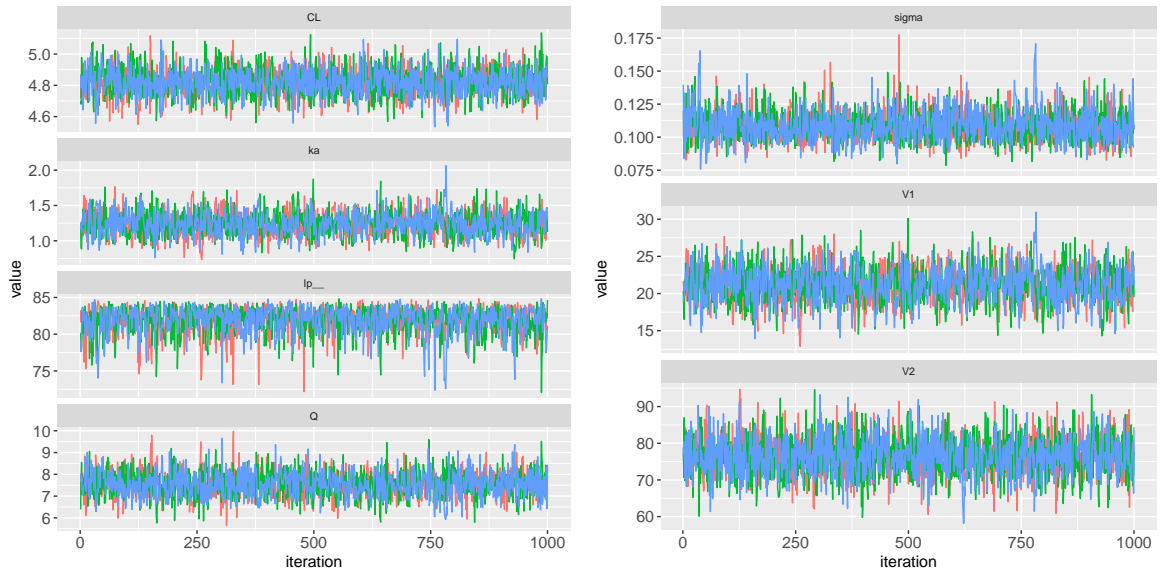


FIGURE 3. MCMC history plots for the parameters of a two compartment model with first order absorption (each color corresponds to a different chain)

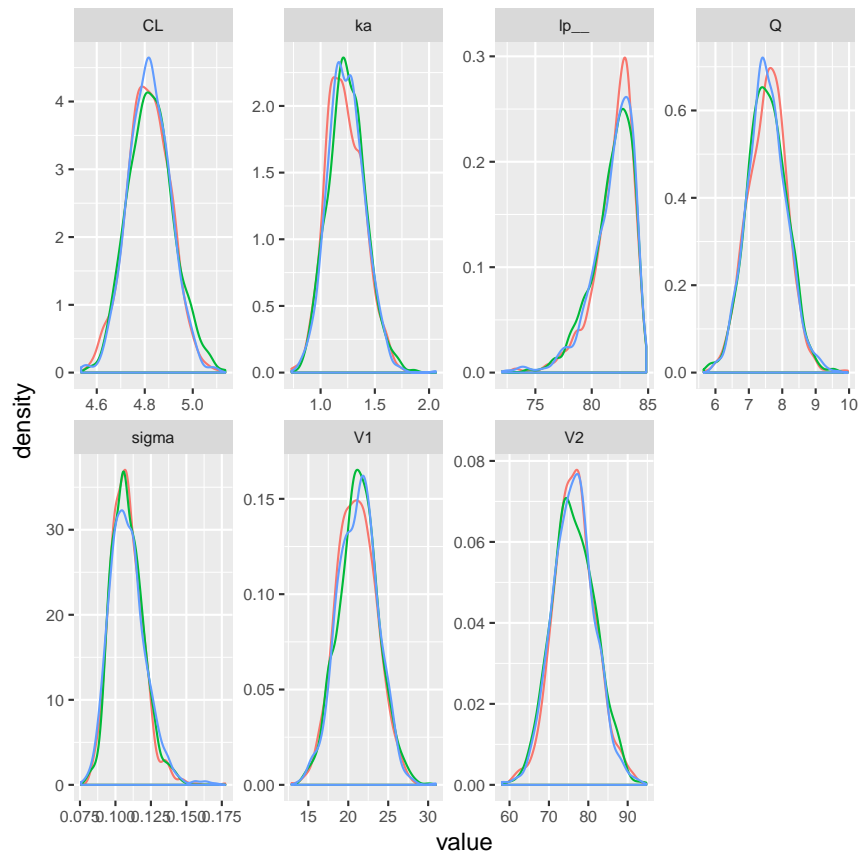


FIGURE 4. Posterior Marginal Densities of the Model Parameters of a two compartment model with first order absorption (each color corresponds to a different chain)

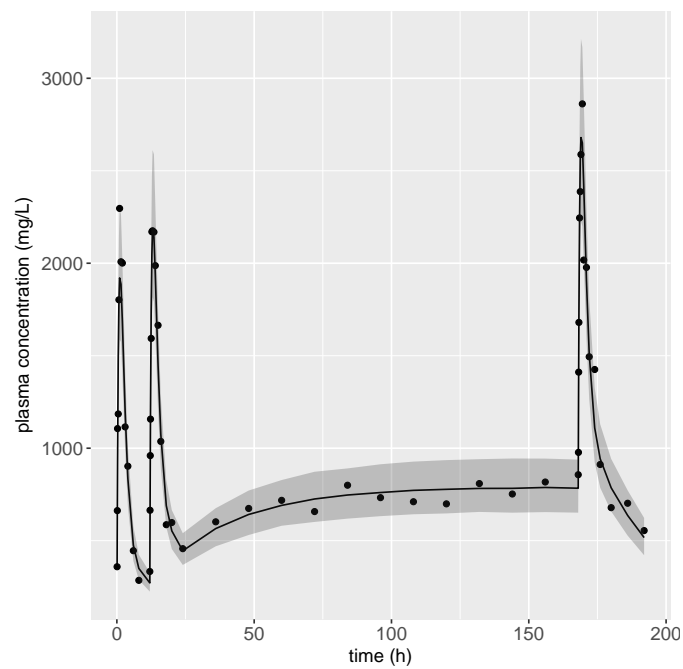


FIGURE 5. Predicted (posterior median and 90 % credible intervals) and observed plasma drug concentrations of a two compartment model with first order absorption

2.3. General Linear ODE Model Function.

A general linear ODE model refers to a model that may be described in terms of a system of first order linear differential equations with (piecewise) constant coefficients, i.e., a differential equation of the form:

$$y'(t) = Ky(t)$$

where K is a matrix. For example K for a two compartment model with first order absorption is:

$$K = \begin{bmatrix} -k_a & 0 & 0 \\ k_a & -(k_{10} + k_{12}) & k_{21} \\ 0 & k_{12} & -k_{21} \end{bmatrix}$$

where $k_{10} = CL/V2$, $k_{12} = Q/V2$, and $k_{21} = Q/V3$.

The linear ODE model function has the form:

```
linOdeModel(time, amt, rate, ii, evid, cmt, addl, ss,
            system, biovar, tlag)
```

system can be:

- the matrix K , if the constant rate matrix is the same for all events.
- an array of constant rate matrices. The length of the array is the number of events and each element corresponds to the matrix at the interval $[time[i-1], time[i]]$.

system contains all the ODE parameters, so we no longer need theta.

FIGURE 6. Stan language for fitting a two compartment model using the `linOdeModel` function (abstract)

```
transformed parameters {
  matrix[3, 3] K;
  real k10 = CL / V2;
  real k12 = Q / V2;
  real k21 = Q / V3;
  vector<lower = 0>[nTheta] theta[1];
  vector<lower = 0>[nt] cHat;
  vector<lower = 0>[nObs] cHatObs;
  matrix<lower = 0>[nt, 3] x;

  K = rep_matrix(0, 3, 3);

  K[1, 1] = -ka;
  K[2, 1] = ka;
  K[2, 2] = -(k10 + k12);
  K[2, 3] = k21;
  K[3, 2] = k12;
  K[3, 3] = -k21;

  x = linOdeModel(time, amt, rate, ii, evid, cmt, addl, ss,
                  K, biovar, tlag);

  cHat = col(x, 2) ./ V1;

  cHatObs = cHat[iObs]; # predictions for observed data records
}

model{
  logCObs ~ normal(log(cHatObs), sigma);
}
```

2.4. General ODE Model Function.

Torsten may be used to fit models described by a system of first-order ODEs, i.e., differential equations of the form:

$$y'(t) = f(t, y(t))$$

In the case where the rate vector R is non-zero, this equation becomes:

$$y'(t) = f(t, y(t)) + R$$

The general ODE model functions have the form:

```
<model_name>(ODE_system, nCmt,
              time, amt, rate, ii, evid, cmt, addl, ss,
              theta, biovar, tlag,
              rel_tol, abs_tol, max_step)
```

where `ODE_system` specifies $f(t, y(t))$, which the user defines inside the **functions** block (see section 19.2 of the Stan reference manual for details and figure 7 for an example). The user does NOT include the rates in their definition of f . Torsten automatically corrects the derivatives when the rates are non-zero.

`nCmt` is the number of compartments (or, equivalently, the number of ODEs) in the model. `rel_tol`, `abs_tol`, and `max_step` are tuning parameters for the ODE integrator: respectively the relative tolerance, the absolute tolerance, and the maximum number of steps.

The options for `model_name` are:

- `generalOdeModel_rk45`
- `generalOdeModel_bdf`

They respectively call the built-in Runge-Kutta 4th/5th order (rk45) integrator, recommended for non-stiff ODEs, and the Backward Differentiation (BDF) integrator, recommended for stiff ODEs. Which value to use for the tuning parameters depends on the integrator and the specifics of the ODE system. Reducing the tolerance parameters and increasing the number of steps make for a more robust integrator but can significantly slow down the algorithm. The following can be used as a starting point: `rel_tol = 1e-6`, `abs_tol = 1e-6` and `max_step = 1e+6` for the rk45 integrator and `rel_tol = 1e-10`, `abs_tol = 1e-10` and `max_step = 1e+8` for the bdf integrator⁶. Users should be prepared to adjust these values. For additional information, see Stan's reference manual (section 19).

⁶These are the default tuning parameters for `integrate_ode_rk45()` and `integrate_ode_bdf()`. Torsten functions do not have a default values for these parameters. The user must explicitly pass the tuning parameters to `generalOdeModel_*`.

FIGURE 7. Stan language for fitting a two compartment model using the `genOdeModel_rk45` function (abstract)

```

functions{
  # define ODE system for two compartment model
  real[] twoCptModelODE(real t,
                        real[] y,
                        real[] theta,
                        real[] dummy_real,
                        int[] dummy_int){

    real Q = theta[1];
    real CL = theta[2];
    real V2 = theta[3];
    real V3 = theta[4];
    real ka = theta[5];
    real k12 = Q / V2;
    real k21 = Q / V3;
    real k10 = CL / V2;
    real y[3];

    dydt[1] = -ka * y[1];
    dydt[2] = ka * y[1] - (k10 + k12)*y[2] + k21*y[3];
    dydy[3] = k12 * y[2] - k21 * y[3];

    return dydt;
  }
}

transformed parameters {

  theta[1] = CL;
  theta[2] = Q;
  theta[3] = V1;
  theta[4] = V2;
  theta[5] = ka;

  x = generalCptModel_rk45(twoCptModelODE, 3,
                          time, amt, rate, ii, evid, cmt, addl, ss,
                          theta, biovar, tlag,
                          1e-8, 1e-8, 1e8);
}

```

2.5. Mix ODE Model Function.

In certain cases, an ODE system can be divided in two subsystems:

$$\begin{aligned}
 y_1' &= f_1(t, y_1) \\
 y_2' &= f_2(t, y_1, y_2)
 \end{aligned}$$

where y_1 , y_2 , f_1 , and f_2 are vector-valued functions, and y_1' is independent of y_2 . This structure arises, for instance, in PKPD models, where y_1 describes the PK of the drug and y_2 the PD effects. If y_1 has an analytical solution, we can construct a *mix solver*, which analytically solves y_1 and numerically integrates y_2 . This approach leads to an appreciable gain in computational efficiency. In the example of a Friberg-Karlsson semi-mechanistic model [5], we observe an average $\sim 44\%$ speedup when using the mix solver in lieu of the numerical integrator⁷.

Torsten supports the mix solver for cases where y_1 is either a One or Two Compartment model with a first-order absorption.

The mix ODE model functions have the form:

```
<model_name>(reduced_ODE_system, nOde,
              time, amt, rate, ii, evid, cmt, addl, ss,
              theta, biovar, tlag,
              reltol, abstol, max_step)
```

where `reduced_ODE_system` specifies the system we numerically solve (y_2 in the above discussion) and `nOde` the number of equations in that system. Section 19.2 of the Stan user manual explains how to code an ODE system in the **functions** block. The function that defines a *reduced system* has an almost identical signature but takes one additional argument: y_1 , the solution to the base PK ODEs (figure 8).

FIGURE 8. Stan language for defining a reduced ODE system

```
functions{
  real[] reducedODE(real t, // time
                    real[] y, // reduced state
                    real[] y1, // solution to the base PK states
                    real[] theta, // parameters
                    real[] x_r, // data (real)
                    int[] x_int) { // data (integer)
    :
  }
}
```

Again, the user does not specify the rates. Torsten automatically corrects the derivatives for non-zero rates.

The options for `modelName` are:

- `mixOde1CptModel_rk45`
- `mixOde1CptModel_bdf`
- `mixOde2CptModel_rk45`
- `mixOde2CptModel_bdf`

These four functions correspond to all the permutations we can obtain when using either a base One or Two Compartment function, and the Runge-Kutta 4th/5th order (rk45) or Backward Differentiation (BDF) integration method.

⁷A manuscript on the subject is in progress.

We cannot apply the mix solver to the Two Compartment example we have been using so far. Instead, we'll consider the very model which motivated the implementation of the method in the first place.

2.6. Example 2: Friberg-Karlsson Semi-Mechanistic Model [5].

In this second example, we add to our two Compartment model a PD effect, described by a system of nonlinear ODEs.

Neutropenia is observed in patients receiving an ME-2 drug. Our goal is to model the relation between neutrophil counts and drug exposure. Using a feedback mechanism, the body maintains the number of neutrophils at a baseline value (figure 9). While in the patient's blood, the drug impedes the production of neutrophils. As a result, the neutrophil count goes down, and after the drug clears out, the feedback mechanism kicks in and brings the neutrophil count back to baseline.

Friberg-Karlsson Model for drug-induced myelosuppression (ANC)

$$\begin{aligned} \log(ANC_i) &\sim N(\log(Circ), \sigma_{ANC}^2) \\ Circ &= f_{FK}(MTT, Circ_0, \alpha, \gamma, c) \\ (MTT, Circ_0, \alpha, \gamma, ktr) &= (125, 5.0, 3 \times 10^{-4}, 0.17) \\ \sigma_{ANC}^2 &= 0.001 \end{aligned}$$

where c is the drug concentration in the blood we get from the Two Compartment model, and $Circ$ is obtained by solving the following system of nonlinear ODEs:

$$(4) \quad \frac{dy_{\text{prol}}}{dt} = k_{\text{prol}} y_{\text{prol}} (1 - E_{\text{drug}}) \left(\frac{Circ_0}{y_{\text{circ}}} \right)^{\gamma} - k_{\text{tr}} y_{\text{prol}}$$

$$(5) \quad \frac{dy_{\text{trans1}}}{dt} = k_{\text{tr}} y_{\text{prol}} - k_{\text{tr}} y_{\text{trans1}}$$

$$(6) \quad \frac{dy_{\text{trans2}}}{dt} = k_{\text{tr}} y_{\text{trans1}} - k_{\text{tr}} y_{\text{trans2}}$$

$$(7) \quad \frac{dy_{\text{trans3}}}{dt} = k_{\text{tr}} y_{\text{trans2}} - k_{\text{tr}} y_{\text{trans3}}$$

$$(8) \quad \frac{dy_{\text{circ}}}{dt} = k_{\text{tr}} y_{\text{trans3}} - k_{\text{tr}} y_{\text{circ}}$$

where $E_{\text{drug}} = \alpha c$.

The ODEs specifying the Two Compartment Model (equations 1 - 3) do not depend on the PD ODEs (equations 4 - 8) and can be solved analytically by Torsten. We therefore specify our model using a mix solver function. We do not expect our system to be stiff and use the Runge-Kutta 4th/5th order integrator.

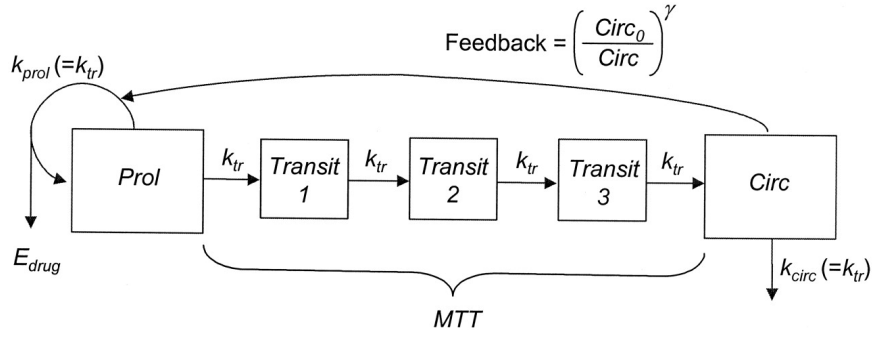


FIGURE 9. Friberg-Karlsson semi-mechanistic Model [5]

FIGURE 10. Stan language to define a reduced ODE system

```

functions{
  # define reduced ODE system for two compartment model
  real[] FK_ODE(real t,
    real[] y,
    real[] y_pk,
    real[] theta,
    real[] dummy_real,
    int[] dummy_int){
    real V2 = theta[3];

    ## PK variables
    real VC = parms[3];

    ## PD variables
    real MTT = parms[6];
    real circ0 = parms[7];
    real alpha = parms[8];
    real gamma = parms[9];
    real ktr = 4 / MTT;
    real prol = y[1] + circ0;
    real transit1 = y[2] + circ0;
    real transit2 = y[3] + circ0;
    real transit3 = y[4] + circ0;
    real circ = fmax(machine_precision(), y[5] + circ0);
    real conc = y_pk[2] / VC;
    real Edrug = alpha * conc;
    real dydt[5];

    conc = y_pk[2] / VC;
    Edrug = alpha * conc;

    dydt[1] = ktr * prol * ((1 - Edrug) * ((circ0 / circ)^gamma) - 1);
    dydt[2] = ktr * (prol - transit1);
    dydt[3] = ktr * (transit1 - transit2);
    dydt[4] = ktr * (transit2 - transit3);
    dydt[5] = ktr * (transit3 - circ);

    return dydt;
  }
}

```

FIGURE 11. Stan language for fitting a Friberg-Karlsson model using `mixOde2CptModel_rk45`

```

transformed parameters {
  vector[nt] cHat;
  vector[nObsPK] cHatObs;
  vector[nt] neutHat;
  vector<lower = 0>[nObsPD] neutHatObs;
  real theta[nParms]; # ODE parameters
  matrix[nt, nCmt] x;

  theta[1] = CL;
  theta[2] = Q;
  theta[3] = VC;
  theta[4] = VP;
  theta[5] = ka;
  theta[6] = mtt;
  theta[7] = circ0;
  theta[8] = alpha;
  theta[9] = gamma;

  x = mixOde2CptModel_rk45(FK_ODE, nOde,
                           time, amt, rate, ii, evid, cmt, addl, ss,
                           theta, biovar, tlag,
                           1e-6, 1e-6, 1e+6);

  cHat = x[ , 2] / VC;
  neutHat = x[ , 8] + circ0;

  cHatObs = cHat[iObsPK];
  neutHatObs = neutHat[iObsPD];
}

```

TABLE 2. Summary: Arguments of Torsten functions.

| model | function name | argument names | parameters in theta |
|---|------------------|--|---|
| one compartment model with first order absorption | PKModelOneCpt | time, amt, rate, ii, evid, cmt, addl, ss, theta, biovar, tlag | CL, V_2, k_a |
| two compartment model with first order absorption | PKModelTwoCpt | time, amt, rate, ii, evid, cmt, addl, ss, theta, biovar, tlag | CL, Q, V_2, V_3, k_a |
| general linear compartment model | linOdeModel | time, amt, rate, ii, evid, cmt, addl, ss, system, biovar, tlag | NA: pass in constant rate matrix instead of theta |
| general compartment models | genOdeModel_* | ODE.system, nCmt, time, amt, rate, ii, evid, cmt, addl, ss, theta, biovar, tlag, rel_tol, abs_tol, max_num_steps | Parameters that get passed to ODE system |
| mix 1 compartment model | mixOde1Cpt_* | reduced.ODE.system, nOde, time, amt, rate, ii, evid, cmt, addl, ss, theta, biovar, tlag, rel_tol, abs_tol, max_num_steps | CL, V_2, k_a , followed by the parameters that get passed to the re- duced ODE system |
| mix 2 compartment model | mixOde2Cpt_* | reduced.ODE.system, nOde, time, amt, rate, ii, evid, cmt, addl, ss, theta, biovar, tlag, rel_tol, abs_tol, max_num_steps | CL, Q, V_2, V_3, k_a , fol- lowed by the parame- ters that get passed to the reduced ODE sys- tem |

3. ADDITIONAL EXAMPLES

Code for examples can be found on GitHub: <https://github.com/charlesm93/example-models/tree/torsten-0.82/PKPD/torsten>.

All the files to run a model are stored under the directory that bears the model's name. There are four files per example:

- `<model name>.stan`
- `<model name>.data.R`
- `<model name>.init.R`
- `<model name>Simulation.R`

`data.R` contains the data we fit the model to and `init.R` the initial estimates of the parameters. These two files are generated using `Simulation.R`. The `R` folder contains `R` scripts to compile and run the models, as well as code to output diagnostic plots and statistics.

3.1. Example 3: Effect Compartment Population Model.

Let us expand example 1 to a population model fitted to the combined data from phase I and phase IIa studies. The parameters exhibit inter-individual variations (IIV), due to both random effects and to the patients' body weight, treated as a covariate and denoted bw :

Population Model for Plasma Drug Concentration (c).

$$\begin{aligned}
 \log(c_{ij}) &\sim N(\log(\hat{c}_{ij}), \sigma^2) \\
 \hat{c}_{ij} &= f_{2cpt}(t_{ij}, D_j, \tau_j, CL_j, Q_j, V_{1j}, V_{2j}, k_{aj}) \\
 \log(CL_j, Q_j, V_{ssj}, k_{aj}) &\sim N\left(\log\left(\widehat{CL}\left(\frac{bw_j}{70}\right)^{0.75}, \widehat{Q}\left(\frac{bw_j}{70}\right)^{0.75}, \widehat{V}_{ss}\left(\frac{bw_j}{70}\right), \widehat{k}_a\right), \Omega\right) \\
 V_{1j} &= f_{V_1} V_{ssj} \quad V_{2j} = (1 - f_{V_1}) V_{ssj} \\
 (\widehat{CL}, \widehat{Q}, \widehat{V}_{ss}, \widehat{k}_a, f_{V_1}) &= (10 \text{ L/h}, 15 \text{ L/h}, 140 \text{ L}, 2 \text{ h}^{-1}, 0.25) \\
 \Omega &= \begin{pmatrix} 0.25^2 & 0 & 0 & 0 \\ 0 & 0.25^2 & 0 & 0 \\ 0 & 0 & 0.25^2 & 0 \\ 0 & 0 & 0 & 0.25^2 \end{pmatrix}, \quad \sigma = 0.1
 \end{aligned}$$

Furthermore we add a fourth compartment in which we measure a PD effect (figure 12).

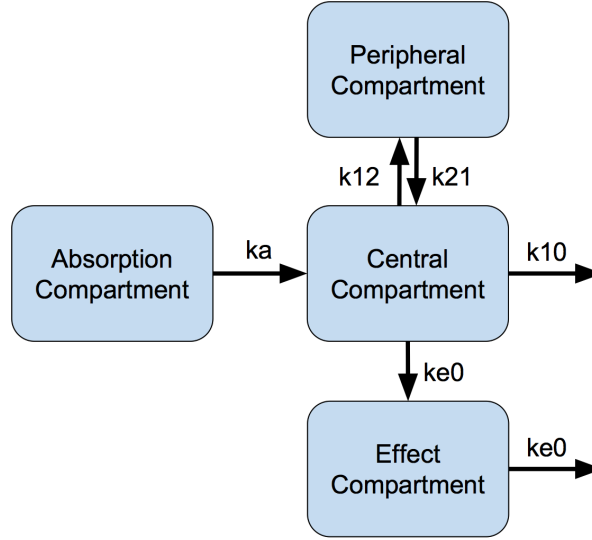


FIGURE 12. Effect Compartment Model

Effect Compartment Model for PD response (R).

$$\begin{aligned}
 R_{ij} &\sim N\left(\hat{R}_{ij}, \sigma_R^2\right) \\
 \hat{R}_{ij} &= \frac{E_{max} c_{eij}}{EC_{50j} + c_{eij}} \\
 c'_{e,j} &= k_{e0j} (c_{\cdot,j} - c_{e,j}) \\
 \log(EC_{50j}, k_{e0j}) &\sim N\left(\log\left(\widehat{EC}_{50}, \widehat{k}_{e0}\right), \Omega_R\right) \\
 \left(E_{max}, \widehat{EC}_{50}, \widehat{k}_{e0}\right) &= (100, 100.7, 1) \\
 \Omega_R &= \begin{pmatrix} 0.2^2 & 0 \\ 0 & 0.25^2 \end{pmatrix}, \quad \sigma_R = 10
 \end{aligned}$$

The PK and the PD data are simulated using the following treatment.

- Phase I study
 - Single dose and multiple doses
 - Parallel dose escalation design
 - 25 subjects per dose
 - Single doses: 1.25, 5, 10, 20, and 40 mg
 - PK: plasma concentration of parent drug (c)
 - PD response: Emax function of effect compartment concentration (R)
 - PK and PD measured at 0.083, 0.167, 0.25, 0.5, 0.75, 1, 2, 3, 4, 6, 8, 12, 18, and 24 hours
- Phase IIa trial in patients
 - 100 subjects
 - Multiple doses: 20 mg
 - sparse PK and PD data (3-6 samples per patient)

FIGURE 13. Stan language for fitting an effect compartment model using `linOdeModel` (abstract)

```

transformed parameters {
  for(j in 1:nSubjects){
    :
    :
    Omega = quad_form_diag(rho, omega);

    for(j in 1:nSubjects){
      CL[j] = exp(logtheta[j, 1]) * (weight[j] / 70)^0.75;
      Q[j] = exp(logtheta[j, 2]) * (weight[j] / 70)^0.75;
      V1[j] = exp(logtheta[j, 3]) * weight[j] / 70;
      V2[j] = exp(logtheta[j, 4]) * weight[j] / 70;
      ka[j] = exp(logtheta[j, 5]);
      ke0[j] = exp(logKe0[j]);
      EC50[j] = exp(logEC50[j]);

      k10 = CL[j] / V1[j];
      k12 = Q[j] / V1[j];
      k21 = Q[j] / V2[j];
      ke0[j] = exp(logKe0[j]);
      EC50[j] = exp(logEC50[j]);

      K = rep_matrix(0, 4, 4);

      K[1, 1] = -ka[j];
      K[2, 1] = ka[j];
      K[2, 2] = -(k10 + k12);
      K[2, 3] = k21;
      K[3, 2] = k12;
      K[3, 3] = -k21;
      K[4, 2] = ke0[j];
      K[4, 4] = -ke0[j];

      x[start[j]:end[j],] = linOdeModel(time[start[j]:end[j]],
                                         amt[start[j]:end[j]],
                                         rate[start[j]:end[j]],
                                         ii[start[j]:end[j]],
                                         evid[start[j]:end[j]],
                                         cmt[start[j]:end[j]],
                                         addl[start[j]:end[j]],
                                         ss[start[j]:end[j]],
                                         K, biovar, tlag);

      cHat[start[j]:end[j]] = 1000 * x[start[j]:end[j], 2] ./ V1[j];
      ceHat[start[j]:end[j]] = 1000 * x[start[j]:end[j], 4] ./ V1[j];
      respHat[start[j]:end[j]] = 100 * ceHat[start[j]:end[j]] ./
        (EC50[j] + ceHat[start[j]:end[j]]);
    }

    cHatObs = cHat[iObs];
    respHatObs = respHat[iObs];
  }
  :
  :
}

```

The model is simultaneously fitted to the PK and the PD data. For this effect compartment model, we construct a constant rate matrix and use `linOdeModel`. Correct use of `Torsten` requires the user pass the entire event history (observation and dosing events) for an individual to the function. Thus the Stan model shows the call to `linOdeModel` within a loop over the individual subjects rather than over the individual observations.

Results. We use the same diagnosis tools as for the previous example. The MCMC history plots (figure 14) suggest the 4 chains have converged to common distributions. We note some minor auto-correlations for lp_{-} (the log posterior) and for IIV parameters: specifically Ω_{ke_0} and ρ . The correlation matrix ρ does not explicitly appear in the model, but it is used to construct Ω , which parametrizes the PK IIV. The fits to the plasma concentration (figure 16) are in close agreement with the data, notably for the sparse data

case (phase IIa study). The fits to the PD data (figure 17) look good, though the data is more noisy. The model reflects the noise by producing larger credible intervals. The estimated values of the parameters are consistent with the values used to simulate the data.

TABLE 3. Summary of the MCMC simulations of the marginal posterior distributions of the model parameters for example 2

| | mean | se_mean | sd | 2.5% | 25% | 50% | 75% | 97.5% | n_eff | Rhat |
|-----------|---------|---------|-------|---------|---------|---------|---------|---------|----------|-------|
| CLHat | 10.523 | 0.003 | 0.201 | 9.712 | 9.958 | 10.096 | 10.231 | 10.483 | 4000.000 | 0.999 |
| QHat | 14.867 | 0.014 | 0.357 | 14.182 | 14.620 | 14.862 | 15.106 | 15.563 | 678.208 | 1.007 |
| V1Hat | 34.188 | 0.067 | 1.089 | 31.940 | 33.494 | 34.214 | 34.918 | 36.251 | 267.748 | 1.016 |
| V2Hat | 103.562 | 0.076 | 2.925 | 98.031 | 101.600 | 103.455 | 105.472 | 109.583 | 488.296 | 1.001 |
| kaHat | 1.930 | 0.004 | 0.077 | 1.771 | 1.880 | 1.933 | 1.982 | 2.076 | 334.888 | 1.014 |
| ke0Hat | 1.050 | 0.001 | 0.044 | 0.967 | 1.020 | 1.051 | 1.078 | 1.137 | 164.741 | 1.000 |
| EC50Hat | 104.337 | 0.040 | 2.100 | 100.169 | 102.909 | 104.345 | 105.768 | 108.351 | 744.041 | 1.000 |
| sigma | 0.099 | 0.000 | 0.002 | 0.095 | 0.097 | 0.099 | 0.100 | 0.103 | 906.342 | 1.002 |
| sigmaResp | 10.156 | 0.003 | 0.197 | 9.779 | 10.023 | 10.154 | 10.286 | 10.552 | 4000.000 | 1.000 |
| omega[1] | 0.270 | 0.000 | 0.016 | 0.241 | 0.259 | 0.269 | 0.280 | 0.302 | 4000.000 | 1.001 |
| omega[2] | 0.231 | 0.001 | 0.021 | 0.192 | 0.217 | 0.230 | 0.245 | 0.275 | 531.512 | 1.006 |
| omega[3] | 0.219 | 0.002 | 0.031 | 0.158 | 0.199 | 0.218 | 0.238 | 0.281 | 158.198 | 1.017 |
| omega[4] | 0.267 | 0.001 | 0.026 | 0.218 | 0.249 | 0.266 | 0.284 | 0.319 | 684.870 | 1.001 |
| omega[5] | 0.285 | 0.002 | 0.037 | 0.214 | 0.259 | 0.284 | 0.309 | 0.361 | 284.545 | 1.009 |
| omegaKe0 | 0.271 | 0.003 | 0.047 | 0.183 | 0.239 | 0.271 | 0.303 | 0.363 | 217.350 | 1.007 |
| omegaEC50 | 0.213 | 0.001 | 0.021 | 0.174 | 0.199 | 0.213 | 0.227 | 0.255 | 190.193 | 1.000 |

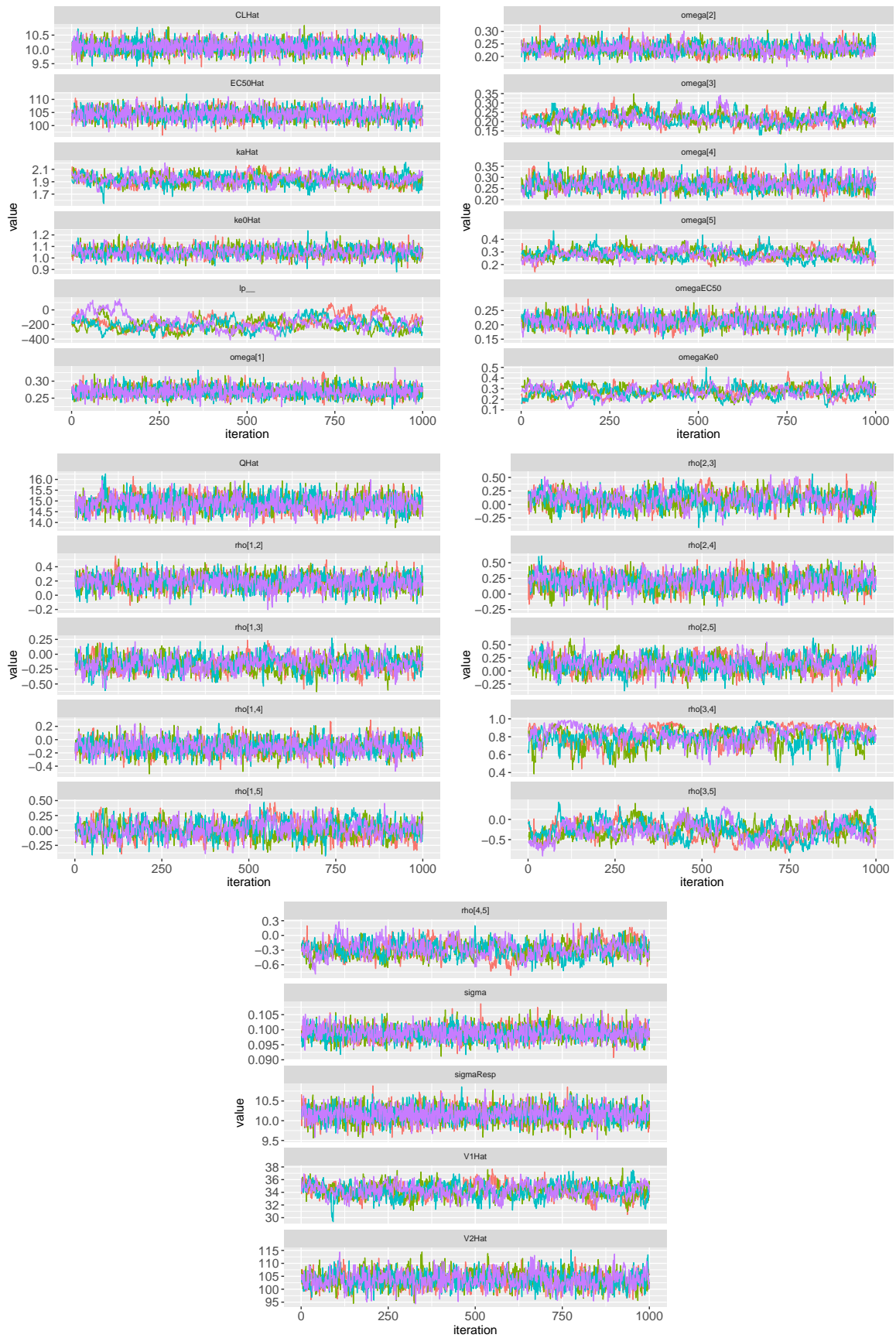


FIGURE 14. MCMC history plots for the parameters of an Effect Compartment Model (each color corresponds to a different chain) for example 2

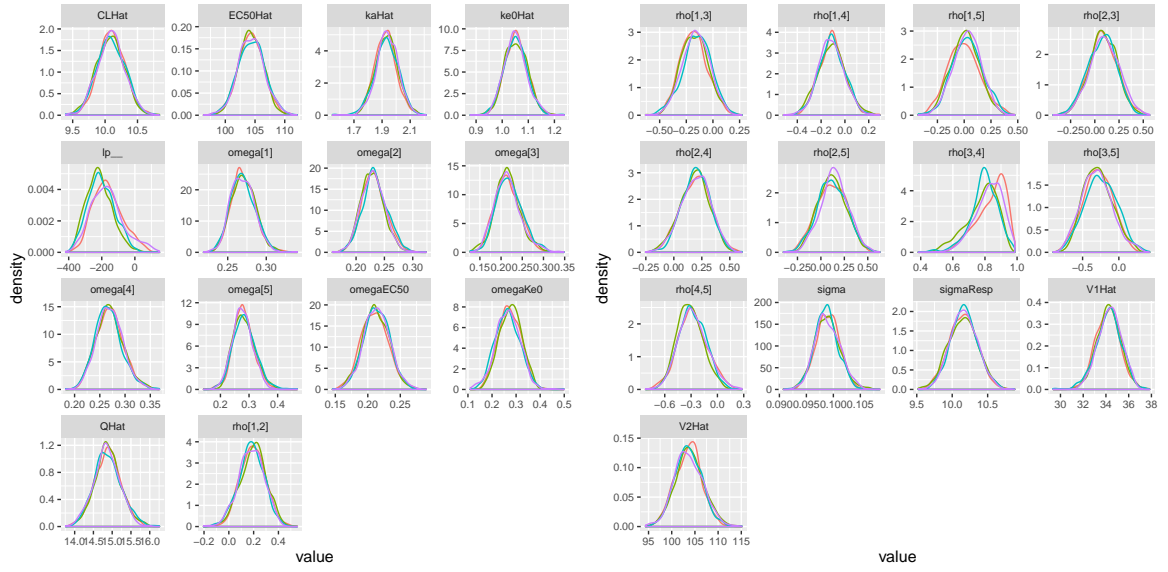


FIGURE 15. Posterior Marginal Densities of the Model Parameters of an Effect Compartment Model (each color corresponds to a different chain) for example 2

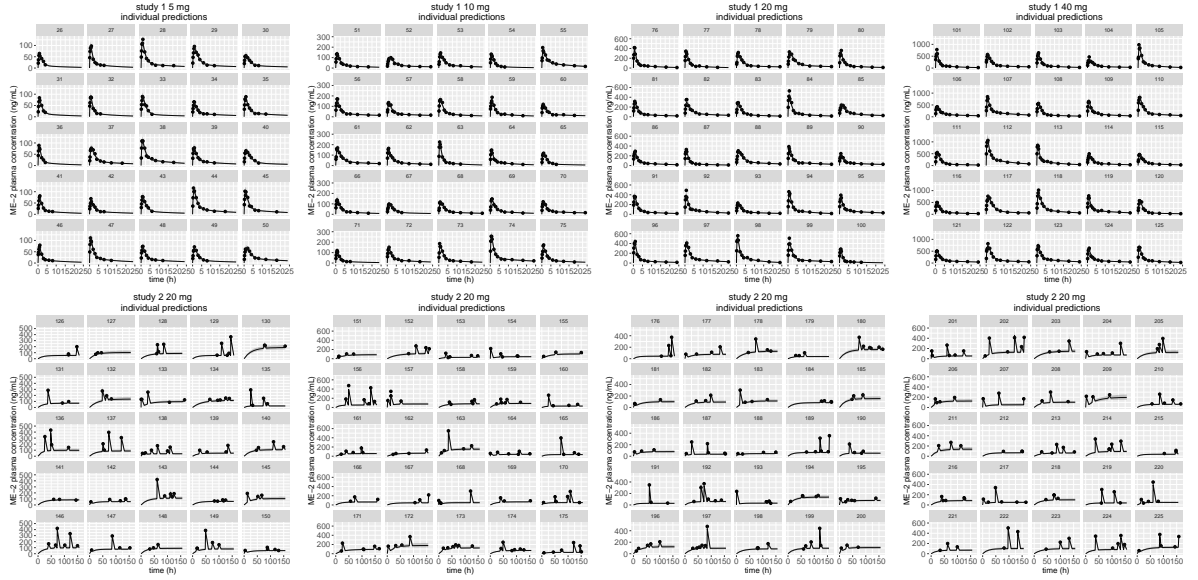


FIGURE 16. Predicted (posterior median and 90 % credible intervals) and observed plasma drug concentrations for example 2 for an Effect Compartment Model



FIGURE 17. Predicted (posterior median and 90 % credible intervals) and observed PD Response for example 2

3.2. Example 4: Friberg-Karlsson Semi-Mechanistic Population Model.

We now return to example 2 and extend it to a population model. While we recommend using the `mix` solver, for completeness we'll show how to specify the model with the `generalOdeModel_*` function. We leave it as a (trivial) exercise to the reader to rewrite the model with `mixOde2CptModel_*`.

Friberg-Karlsson Population Model for drug-induced myelosuppression (*ANC*)

$$\begin{aligned}
 \log(ANC_{ij}) &\sim N(Circ_{ij}, \sigma_{ANC}^2) \\
 \log(MTT_j, Circ_{0j}, \alpha_j) &\sim N\left(\log\left(\widehat{MTT}, \widehat{Circ_0}, \widehat{\alpha}\right), \Omega_{ANC}\right) \\
 \left(\widehat{MTT}, \widehat{Circ_0}, \widehat{\alpha}, \gamma\right) &= (125, 5, 2, 0.17) \\
 \Omega_{ANC} &= \begin{pmatrix} 0.2^2 & 0 & 0 \\ 0 & 0.35^2 & 0 \\ 0 & 0 & 0.2^2 \end{pmatrix}, \quad \sigma_{ANC} = 0.1 \\
 \Omega_{PK} &= \begin{pmatrix} 0.25^2 & 0 & a0 & 0 & 0 \\ 0 & 0.4^2 & 0 & 0 & 0 \\ 0 & 0 & 0.25^2 & 0 & 0 \\ 0 & 0 & 0 & 0.4^2 & 0 \\ 0 & 0 & 0 & 0 & 0.25^2 \end{pmatrix}
 \end{aligned}$$

The PK and the PD data are simulated using the following treatment.

- Phase IIa trial in patients
 - Multiple doses: 80,000 mg
 - Parallel dose escalation design
 - 15 subjects
 - PK: plasma concentration of parent drug (*c*)
 - PD response: Neutrophil count (*ANC*)
 - PK measured at 0.083, 0.167, 0.25, 0.5, 0.75, 1, 2, 3, 4, 6, 8, 12, 18, and 24 hours
 - PD measured once every two days for 28 days.

Once again, we simultaneously fit the model to the PK and the PD data. From a computational perspective, this is a much more difficult problem than the one we dealt with in previous example. The nonlinear nature of the ODEs forces us to use a numerical solver, which is significantly slower than the linear methods we have employed so far. Because the ODE system of interest is non-stiff, we use the *rk45* version of `genOdeModel`.

It pays off to construct informative priors. For instance, we could fit the PK data first, as was done in example 1, and get informative priors on the PK parameters. The PD parameters are drug independent, so we can use information from the neutropenia literature. In this example, we choose to use weakly informative priors on the PK parameters and strongly informative priors on the PD parameters.

Since it takes a long time to run the model, we only use 100 iterations per chain, and study what we can learn from this less than optimal scenario. It is worth noting that Stan, because of its highly efficient MCMC sampler, still does a reasonable job estimating the posterior distribution.

FIGURE 18. Stan language for coding an ODE system describing a Friberg-Karlsson Mechanism

```

real[] twoCptNeutModelODE(real t,
    real[] x,
    real[] parms,
    real[] rdummy,
    int[] idummy){
  real CL = parms[1];
  real Q = parms[2];
  real V2 = parms[3];
  real V3 = parms[4];
  real ka = parms[5];
  real mtt = parms[6];
  real circ0 = parms[7];
  real gamma = parms[8];
  real alpha = parms[9];
  real k10 = CL / V2;
  real k12 = Q / V2;
  real k21 = Q / V3;
  real ktr = 4 / mtt;
  real dxdt[8];
  real conc;
  real EDrug;
  real transit1;
  real transit2;
  real transit3;
  real circ;
  real prol;

  dxdt[1] = -ka * x[1];
  dxdt[2] = ka * x[1] - (k10 + k12) * x[2] + k21 * x[3];
  dxdt[3] = k12 * x[2] - k21 * x[3];
  conc = x[2]/V1;
  EDrug = alpha * conc;
  // x[4], x[5], x[6], x[7] and x[8] are differences from circ0.
  prol = x[4] + circ0;
  transit1 = x[5] + circ0;
  transit2 = x[6] + circ0;
  transit3 = x[7] + circ0;
  circ = fmax(machine_precision(), x[8] + circ0); // Device for implementing a modeled
                                                    // initial condition
  dxdt[4] = ktr * prol * ((1 - EDrug) * ((circ0 / circ)^gamma) - 1);
  dxdt[5] = ktr * (prol - transit1);
  dxdt[6] = ktr * (transit1 - transit2);
  dxdt[7] = ktr * (transit2 - transit3);
  dxdt[8] = ktr * (transit3 - circ);

  return dxdt;
}

```

Results. The MCMC history plots are not as convincing as in the previous examples, mostly because the number of iterations is small (100 versus 1000 in the previous example). It does however look as though the chains are converging to a common distribution, and we see little auto-correlation (in particular, we expect that if we had run the model for 1000 iterations, we would obtain the desired "fuzzy caterpillar" look). The plots of the marginal posterior distributions clearly show that the chains have not (yet) converged to a common distribution, but they do not disagree significantly. Still, the need for more iterations is evident. The model fits the data, and the credible interval reflect the noise in the data. The parameters estimation reflects the real value of the parameters.

FIGURE 19. Stan language for fitting a Friberg-Karlsson model using `genCptModel_rk45` (abstract)

```

transformed parameters {
  :
  for(i in 1:nSubjects) {

    parms[1] = thetaM[i, 1] * (weight[i] / 70)^0.75; # CL
    parms[2] = thetaM[i, 2] * (weight[i] / 70)^0.75; # Q
    parms[3] = thetaM[i, 3] * (weight[i] / 70); # V1
    parms[4] = thetaM[i, 4] * (weight[i] / 70); # V2
    parms[5] = kaHat; # ka
    parms[6] = thetaM[i, 5]; # mtt
    parms[7] = thetaM[i, 6]; # circ0
    parms[8] = gamma;
    parms[9] = thetaM[i, 7]; # alpha

    x[start[i]:end[i]] = generalOdeModel_rk45(twoCptNeutModelODE, 8,
                                              time[start[i]:end[i]],
                                              amt[start[i]:end[i]],
                                              rate[start[i]:end[i]],
                                              ii[start[i]:end[i]],
                                              evid[start[i]:end[i]],
                                              cmt[start[i]:end[i]],
                                              addl[start[i]:end[i]],
                                              ss[start[i]:end[i]],
                                              parms, biovar, tlag,
                                              1e-6, 1e-6, 1e6);

    cHat[start[i]:end[i]] = x[start[i]:end[i], 2] / parms[1][3]; # divide by V1
    neutHat[start[i]:end[i]] = x[start[i]:end[i], 8] + parms[1][7]; # Add baseline
  }

  cHatObs = cHat[iObsPK];
  neutHatObs = neutHat[iObsPD];

  :
}

```

TABLE 4. Summary of the MCMC simulations of the marginal posterior distributions of the model parameters for example 3

| | mean | se_mean | sd | 2.5% | 25% | 50% | 75% | 97.5% | n_eff | Rhat |
|-----------|---------|---------|---------|---------|---------|---------|---------|---------|---------|-------|
| CL | 9.986 | 0.009 | 0.174 | 9.641 | 9.872 | 9.982 | 10.107 | 10.331 | 400.000 | 0.997 |
| Q | 14.633 | 0.055 | 1.106 | 12.505 | 13.992 | 14.623 | 15.296 | 16.948 | 400.000 | 0.996 |
| V1 | 32.909 | 0.174 | 2.439 | 28.203 | 31.186 | 32.836 | 34.762 | 37.750 | 195.828 | 1.008 |
| V2 | 106.631 | 0.311 | 6.226 | 95.234 | 102.269 | 106.403 | 111.000 | 118.533 | 400.000 | 0.999 |
| ka | 1.882 | 0.012 | 0.175 | 1.582 | 1.756 | 1.871 | 2.006 | 2.223 | 196.052 | 1.007 |
| sigma | 0.106 | 0.001 | 0.010 | 0.089 | 0.098 | 0.105 | 0.112 | 0.132 | 259.693 | 1.009 |
| alpha | 3.3E-04 | 1.4E-06 | 2.2E-05 | 2.9E-04 | 3.2E-04 | 3.3E-04 | 3.5E-04 | 3.8E-04 | 247 | 1.01 |
| mtt | 132.763 | 0.515 | 6.498 | 120.843 | 128.082 | 132.223 | 136.694 | 146.845 | 159.372 | 1.024 |
| circ0 | 5.014 | 0.009 | 0.172 | 4.711 | 4.888 | 5.000 | 5.138 | 5.334 | 400.000 | 1.000 |
| gamma | 0.190 | 0.002 | 0.022 | 0.153 | 0.175 | 0.187 | 0.202 | 0.239 | 139.485 | 1.025 |
| sigmaNeut | 0.092 | 0.001 | 0.014 | 0.068 | 0.082 | 0.090 | 0.100 | 0.125 | 161.199 | 1.010 |

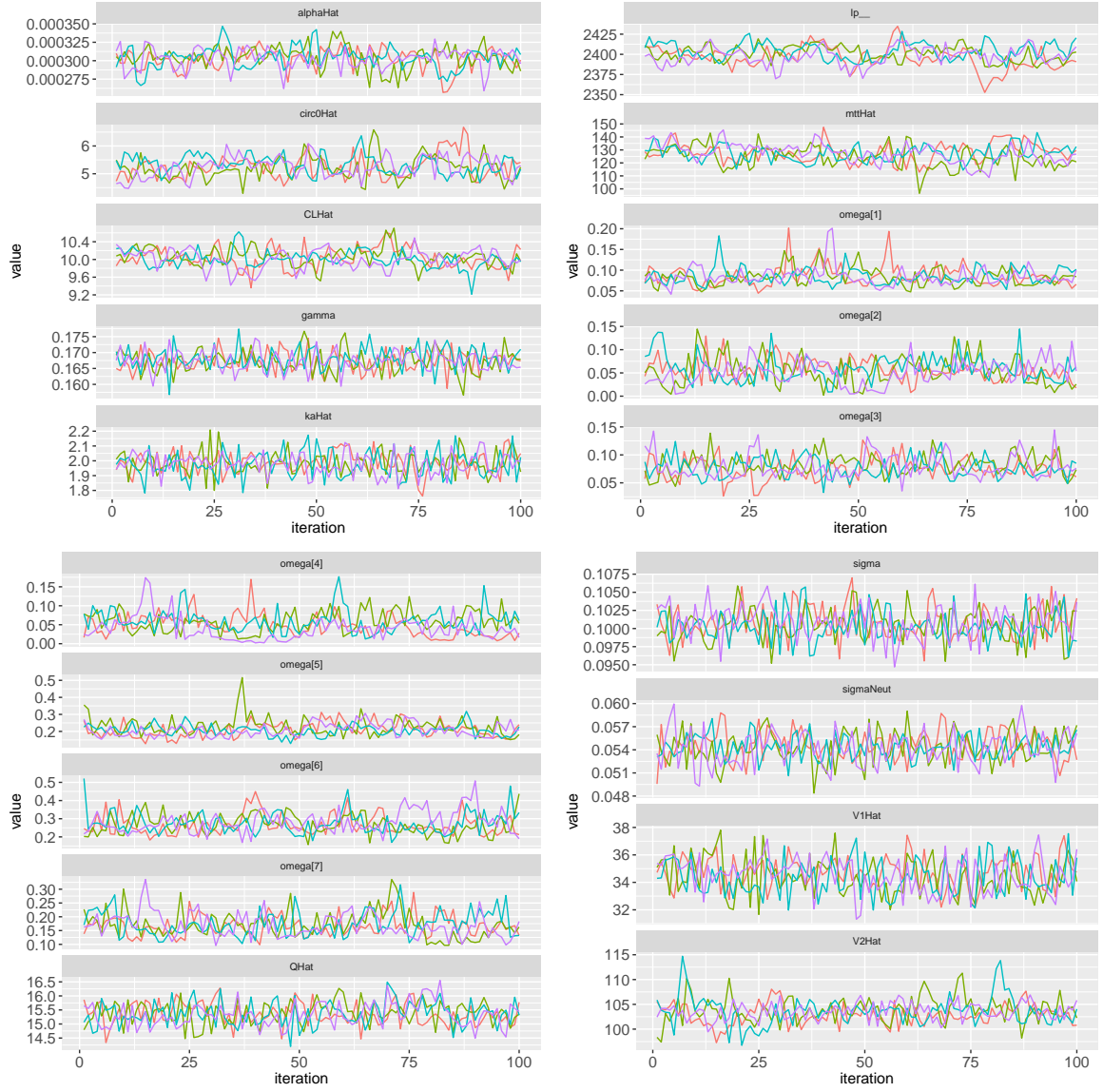


FIGURE 20. MCMC history plots for the parameters of a Friberg-Karlsson semi-mechanistic model (each color corresponds to a different chain) for example 3

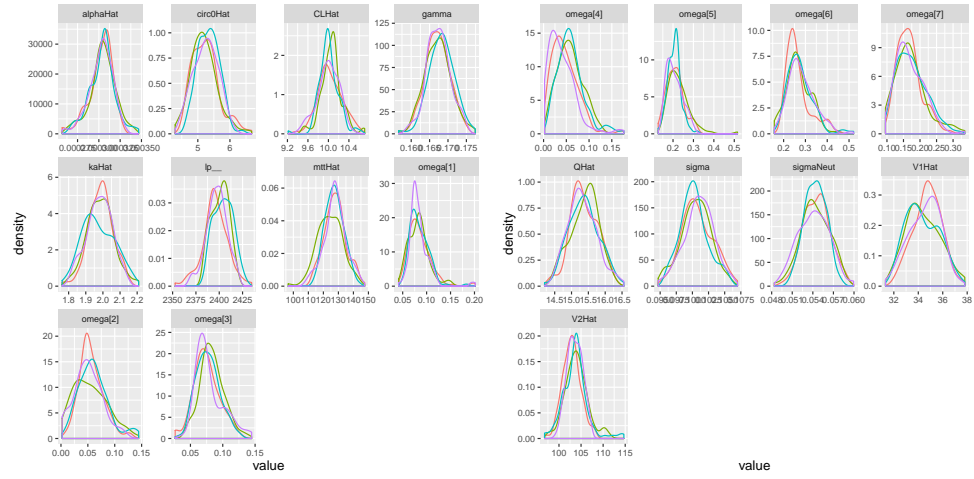


FIGURE 21. Posterior Marginal Densities of the Model Parameters of a Friberg-Karlsson semi-mechanistic model (each color corresponds to a different chain)

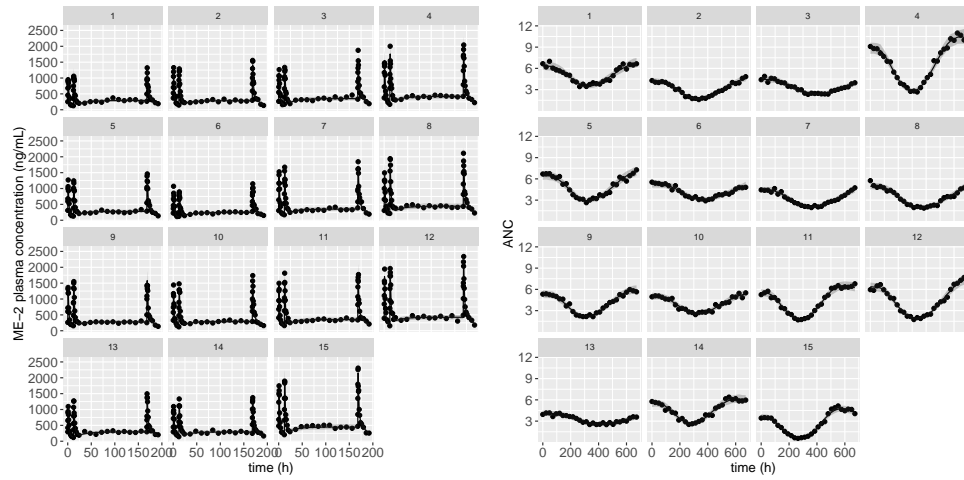


FIGURE 22. Predicted (posterior median and 90 % credible intervals) and observed plasma drug concentrations, and Neutrophil counts, for a Friberg-Karlsson semi-mechanistic model

4. APPENDIX

(Note: this section is still being worked on and is far from finished)

4.1. Solving Systems of Algebraic Equations.

In order to compute a steady state solution for a general compartment model, we need an algebraic solver. Such a solver will be added to Stan’s core language⁸. A prototype is available in Torsten’s development branch on GitHub.

The `algebra_solver` function uses the Powell hybrid method (also called the “dogleg” method)[8] to find the solution to a system of nonlinear algebraic equations. In other words, we wish to solve:

$$f(x) = 0$$

for x , where f and x are vector valued functions.

The user first defines f , the algebraic system, in the **functions** block, using a pre-specified signature:

```
real[] f(vector x, // unknown
          vector y, // parameters
          real[] dat_r, // data (real)
          int[] dat_int) // data (integer)
```

The algebraic solver has the form:

```
algebra_solver(f, x, theta, x_r, x_i
              rel_tol, f_tol, max_step)
```

where f is the algebraic system defined in the function block, x a vector which contains the initial guesses for the solution, y a vector of parameters, dat_r an array of real data, and dat_int an array of integer data.

The last three arguments are optional and specify the tuning parameters of the solver. The relative tolerance (`rel_tol`, default value 1×10^{-10}) sets an upper bound for the error in the computed solution relative to the real solution. Given an estimated solution θ , the function tolerance (`f_tol`, default value 1×10^{-6}) specifies the maximum value of $\|f(\theta)\|$ ⁹. The maximum number of steps (`max_num_steps`, default value 1000) is the maximum number of times the solver will compute $f(x)$ before “giving up”. While these parameters have default values, the user should be prepared to adjust them.

4.1.1. Example.

Let’s suppose we wish to solve the following algebraic system:

⁸A pull request has been submitted on Stan’s gitHub page. This prototype builds on the Hybrid Nonlinear solver from the C++ *Eigen* library[6]. Their implementation follows closely the one in MINPACK-1[7].

⁹It helps to think geometrically about this. Ideally we would want the point $f(\theta)$ to be at the origin; the norm represents deviations from this ideal. Users should keep in mind the norm scales up with the square-root of x ’s dimension.

$$\begin{aligned} z_1 &= x_1 - y_1 \\ z_2 &= x_2 - y_2 \end{aligned}$$

where $(y_1, y_2) = (0.9, 1.1)$. We would code this in Stan as follows:

FIGURE 23. Stan language for solving an algebraic system

```

functions{
  real[] algebraSystem(vector x,
                        vector y,
                        real[] dat,
                        int[] dat_int) {

    vector[2] f_x;
    f_x[1] = x[1] - y[1];
    f_x[2] = x[2] - y[2];
    return f_x;
  }
}

:

transformed data {
  vector[2] x;
  vector[2] y;
  real dat[0];
  int dat_int[0];

  x[1] = 1;
  x[2] = 1;
}

transformed parameters{
  vector y[2];
  vector theta[2];

  y_p[1] = 0.9;
  y_p[2] = 1.1;

  theta = algebra_solver(algebra_system, x, y, dat, dat_int);
}

:

```

4.2. Implementing Torsten.

Stan's math library is written in C++, which offers a great deal of speed and flexibility. The Stan language provides a very handy interface that allows us to focus on statistical modeling and saves us the trouble of doing extensive coding in C++. At run time, a *make* file translates our Stan model into C++, which then gets compiled and executed. Accordingly, there are two steps to add a function to Stan: (1) write the procedure in C++, (2) expose the procedure to the language so users may use it in a Stan file.

The Stan code is open-source and available on GitHub. It is compartmentalized into several repos: *math* contains the mathematical functions, *stan* exposes these functions. Other repos provide code to interface

Stan with higher level languages, such as R and Python. Torsten exists as a forked version of `math` and `stan`. Other repos remain unchanged.

Regularly, we merge Stan's latest release into Torsten.

Modifications in math. All Torsten files are located in the Torsten directory, under `stan/math`. The code can be found on GitHub: <https://github.com/charlesm93/math>

Modifications in Stan. We do further modifications in `stan` to expose Torsten's functions. We edit `function_signatures.h` to expose `PKModelOneCpt`, `PKModelTwoCpt`, and `linOdeModel`. The general ODE model functions are higher-order functions (i.e. they take another function as one of their arguments). They are exposed by directly modifying the grammar files, following closely the example of `integrate_ode_rk45` and `integrate_ode_bdf`.

The code can be found on GitHub: <https://github.com/charlesm93/stan>.

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