

Bayesian Pharmacokinetics/Pharmacodynamics for Personalized Medicine

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Thesis

- ▶ Personalized Medicine
- ▶ Dr. Kim's clinic has concentration/dose/covariate data.
- ▶ Wants predictions for new patients + understanding of which covariates are most important for prediction
- ▶ Tried ML models previously
- ▶ Did not account for repeated observation
- ▶ Lots of unexplained variance

Proposed Direction

- Use PK/PD models and estimate parameters using HMC/hierarchical models

Why Bayesian

As argued in (Wakefield 1996),

- a. PK/PD models are non-linear in parameters. Classical models rely on asymptotic arguments. Tough to validate for this data.
- b. We eventually want to *predict* concentrations for new patients. Bayesian methods are good for this,
- c. We have prior information since hundreds of patients have come through the clinic. This ~~can~~ should be leveraged.
- d. Hierarchical models allow for easy analysis of assumptions to modelling process.
- e. The between subject variability is very high. Variance propagation is crucial.
- f. Want to estimate individual patient's parameters as well as population parameters (this is natural in Bayesian context)

Why Differential Equations

- ▶ Natural, almost canonical, application to PK/PD
- ▶ Depending on the ODE, closed form solutions can be obtained, making inference all the easier
- ▶ Depending on the ODE, numerical integration may be required. Well developed tools to do this effectively and accurately
- ▶ Applied mathematicians don't usually care about inference for parameters
 - ▶ New venues for publication, conference presentations, collaboration

A Thank You

The following examples are based of lectures from Michael Betancourt, a Stan developer and prominent Bayesian.

An Example

- ▶ Stan is an open source project for MCMC.
- ▶ Well developed, widely used, fast.
- ▶ Accessible through numerous languages.

Simulation of a PK Profile

Start with a PK model. Let D be the size of the dose, let V be the volume of the compartment, and let k the elimination rate, and k_a be the dosing rate.

$$\frac{d\mu}{dt} = k_a \frac{D}{V} e^{-k_a t} - k\mu$$

Simulation of a PK Profile

Subject to $\mu(0) = 0$, solution is

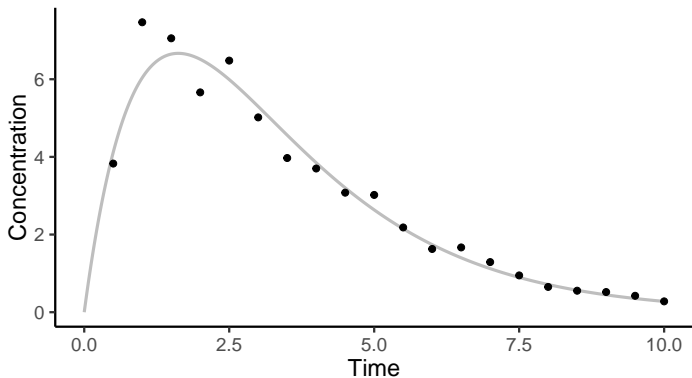
$$\mu(t) = \frac{Dk_a}{(k - k_a)V} (e^{-k_a t} - e^{kt})$$

Simulation of a PK Profile

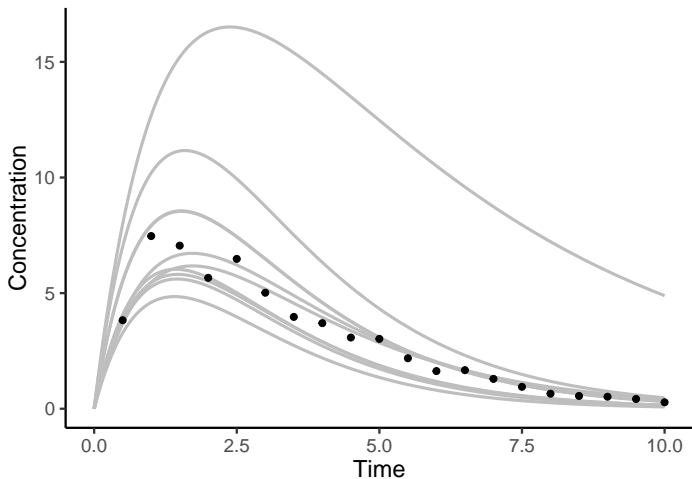
Assume that concentration at time t is

$$\log(Y) \sim \mathcal{N}(\mu(t), \sigma)$$

Simulation of a PK Profile



Our Problem is Really...



Doing Bayesian Inference

One possible model is

$$k_a \sim \text{Cauchy}(0, 1)$$

$$k \sim \text{Cauchy}(0, 1)$$

$$\sigma \sim \text{Cauchy}(0, 1)$$

$$\mu|t, k, k_a, D, V = \left(\frac{Dk_a e^{t(k-k_a)}}{(k-k_a)V} - \frac{Dk_a}{(k-k_a)V} \right) e^{-kt}$$

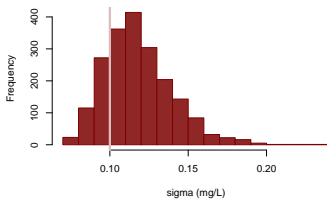
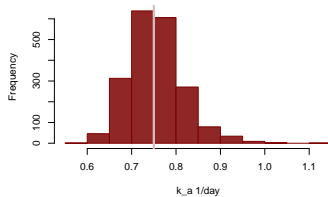
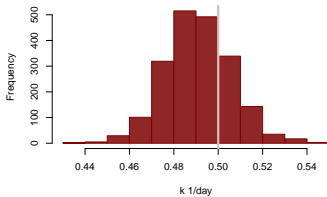
$$\log(Y)|\mu \sim \mathcal{N}(\mu, \sigma)$$

Stan Does the Rest

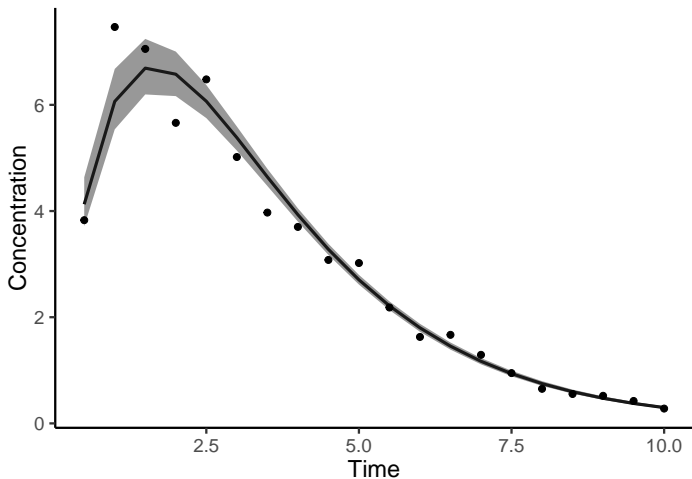
Code the model in Stan (not shown here) and sample from the posterior.

```
input_data <- read_rdump("one_comp_lin_elim_abs.data.R")  
  
fit <- stan(file='one_comp_lin_elim_abs_ode.stan', data=input_data,  
            iter=2000, chains=2, seed=4938483)
```

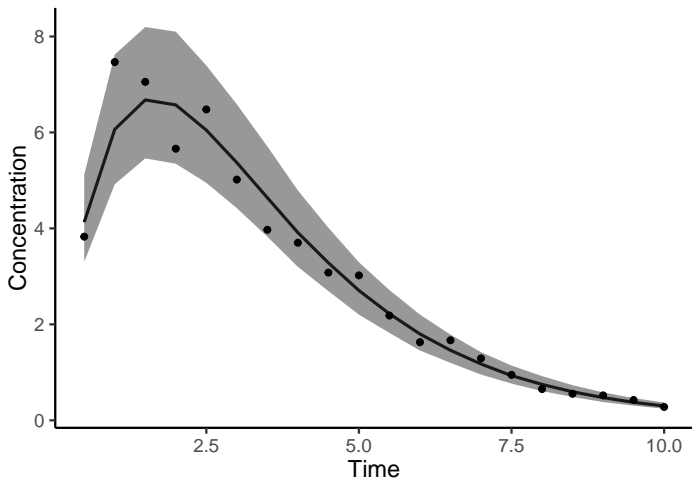
Marginal Posterior Distributions



Credible Interval for $\mu(t)$



Posterior Predictive Check



Extensions

Extend by:

- ▶ Include more compartments
- ▶ More complicated dynamics
- ▶ Non-uniformly sampled times
- ▶ Hierarchy

What I Would Like To Do

- ▶ Determine exactly the population we are studying
- ▶ Determine the model for the dynamics
- ▶ Hierarchical generalized linear model for effect of clinical variables on PK/PD variables
- ▶ Determine how dosing influences concentration levels (therapy vs. poison)
- ▶ Cross validate predictive performance
- ▶ Hopefully show that Bayesian approach is better than any current practice
- ▶ Write an OSS library for Bayesian PK/PD (maybe)

Questions

Ask me how I made this presentation in R

References

Wakefield, Jon. 1996. "The Bayesian analysis of population pharmacokinetic models." *J. Am. Stat. Assoc.* 91 (433): 62–75.