



Shaping the Future of  
Drug Development

# Flexibility of the BLRM in Dose-Escalation Trials

Ursula Garczarek

Cytel Inc. | Hagen (DE)

# Overview

- Bayes logistic regression model (BLRM)
- Why people use **B**LRM
- Application for Dose-Escalation trials and demonstration of flexibility
  - Requirements
  - Prior elicitation
  - Extensions of the basic model

# Bayesian Logistic Regression Model (BLRM)

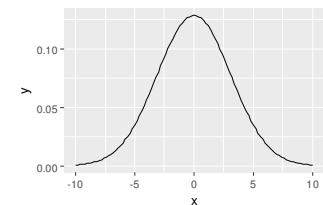
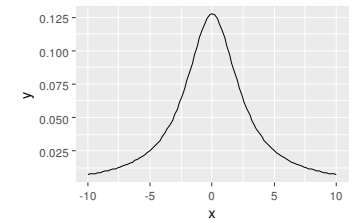
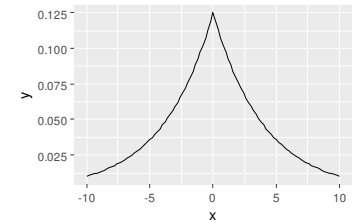
## General Model

- Experimental units:  $n=1, \dots, N$
- $Y_n := 0, 1$  binary outcome,
- $X_{n1}, \dots, X_{nJ} :=$  predictors per experimental unit
- $X_{n1}, \dots, X_{nJ}$  may come from inputs  $Z_{nk}$ ,  $k=1, \dots, K$ ,  $K < J$

$$\begin{aligned} P(Y = 1 | X, \beta) &= \frac{1}{1 + \exp(-\beta_0 - \sum_i \beta_i X_i)} \\ &= \frac{\exp(\beta_0 + \sum_i \beta_i X_i)}{1 + \exp(+\beta_0 + \sum_i \beta_i X_i)} \\ \log\left(\frac{p}{1-p}\right) &= \beta_0 + \sum_i \beta_i X_i \end{aligned}$$

# Why do people use BLRM?

- Variable selection
  - E.g. Multimarker diagnostics (Lasso, ML)
- Coping with sparse data
  - E.g. Analysing adverse events (MBLRM), Epidemiology, Genetics,...
- Coping with missing values/information
  - E.g. presence-only data
- Adaptive experimentation
  - Dose escalation 😊



# Dose-Escalation Trials Phase I

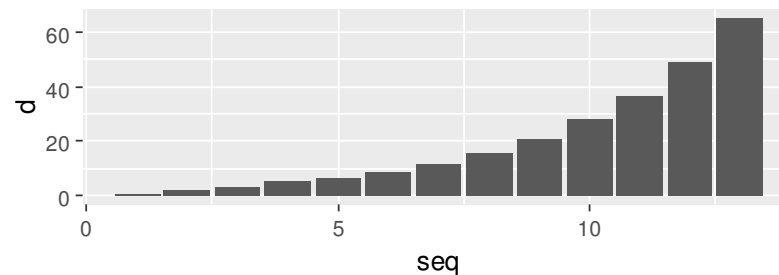
- Assess dose-toxicity relationship
- First-in-human studies
  - Observe Dose limiting toxicities (DLTs)
  - Determine maximum tolerated dose (MTD) or recommended phase II dose (RP2D)
  - MTD := highest dose with toxicity rate lower (or close to) a fixed rate e.g 30%
- Formally:
  - Experimental Units: Patients/Healthy volunteers
  - Binary outcome: experience of a DLT yes/no
  - Other characteristic: controlled drug dose

# Dose-Escalation Trials Phase I

- An sequence of increasing doses  $d_1, d_2, \dots, d_j$

Often: „modified“

Fibonacci:



- Dose  $d_j$  has an unknown toxicity probability  $\pi_j$
- Monotonicity :  $\pi_j < \pi_{j+1}$
- **Goal:** Find MTD
  - $\pi_{\text{MTD}} \leq 0.3, \pi_{\text{D} > \text{MTD}} > 0.3$

# Design requirements

Challenge	Design Requirement
Untested drug in resistant patients	Escalating dose cohorts with small #s patients (e.g. 3-6 patients)
Primary objective: determine MTD	Accurately estimate MTD
High toxicity potential: safety first	Robustly avoid toxic doses („overdosing“)
Most responses occur 80%-120% of MTD*	Avoid sub-therapeutic doses while controlling overdosing
Find best dose for dose expansion	Enroll more patients at acceptable** active doses (flexible cohort sizes)
Complete trial in timely fashion	Use available information efficiently
<b>High toxicity potential: safety first</b>	<b>Medical experts are in control</b>

Table rows 1-7 from:

Satrajit Roychoudhury, Novartis, <https://www.slideshare.net/JamesCahill3/eugm-2014-roychoudhuri-phase-1-combination>

\* Joffe and Miller 2008 JCO

\*\* Less than or equal to the MTD determined on study

# The 3+3 design (schematic)

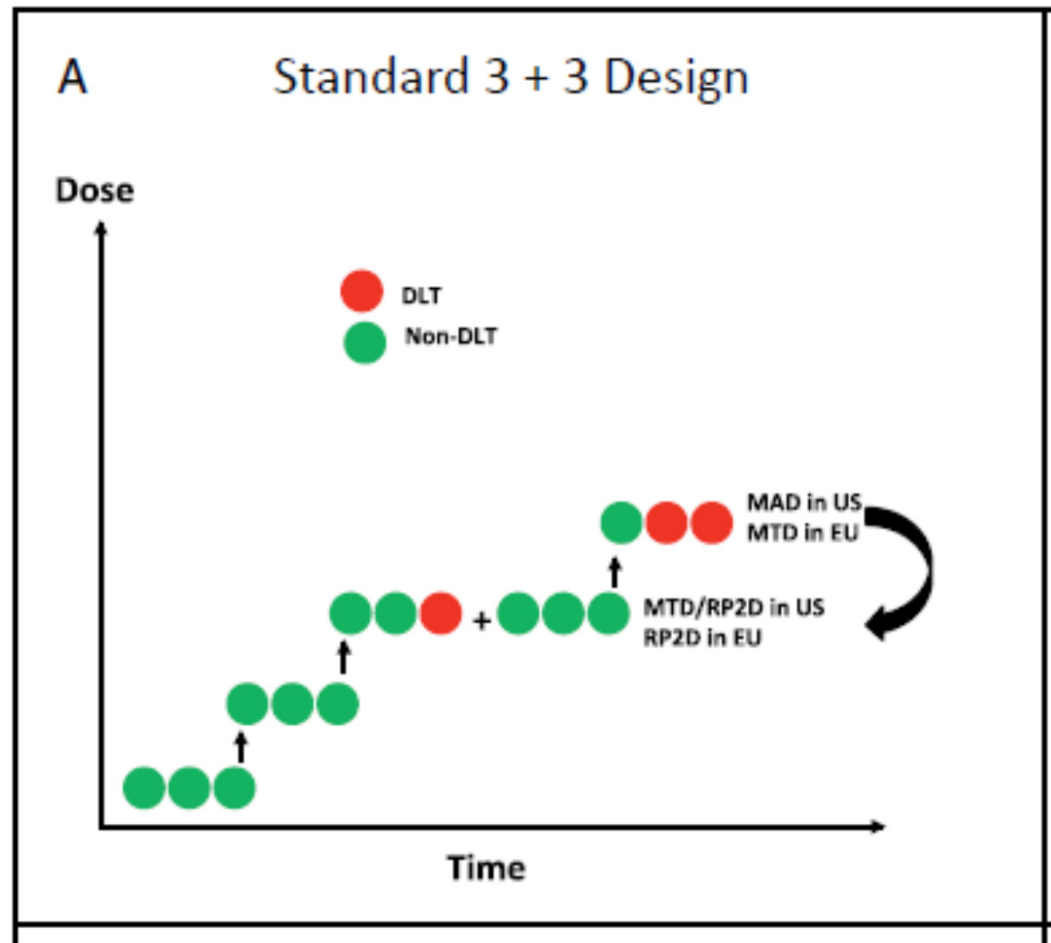


Image from Hansen et al 2014.

Arbeitstagung IBS-DR & DVFFA, Hannover



# Limitations of 3+3

- Fixed cohort sizes (either 3 or 6)
- Pre-defined dose levels to be potentially tested
- Ignores dosage history other than previous cohort
- Ignores uncertainty:
  - True DLT rate  $p=0.5$  -> 11% chance of 0 or 1 DLT in 6 patients
  - True DLT rate  $p=0.166$ , 26% chance of  $\geq 2$  DLT in 6 patients
- Cannot re-escalate
- Low probability of selecting true MTD (e.g. Thall and Lee. 2003)
- High variability in MTD estimates (Goodman et al. 1995)

# Design requirements

Challenge	Design Requirement
Untested drug in resistant patients	Escalating dose cohorts with small #s patients (e.g. 3-6 patients)
Primary objective: determine MTD	Accurately estimate MTD
High toxicity potential: safety first	Robustly avoid toxic doses („overdosing“)
Most responses occur 80%-120% of MTD*	Avoid sub-therapeutic doses while controlling overdosing
Find best dose for dose expansion	Enroll more patients at acceptable** active doses (flexible cohort sizes)
Complete trial in timely fashion	Use available information efficiently
High toxicity potential: safety first	Medical experts are in control

Table rows 1-7 from:

Alessandro Matano, Novartis, <http://www.smi-online.co.uk/pharmaceuticals/archive/4-2013/conference/adaptive-designs>

\* Joffe and Miller 2008 JCO

\*\* Less than or equal to the MTD determined on study

# Alternatives to 3+3

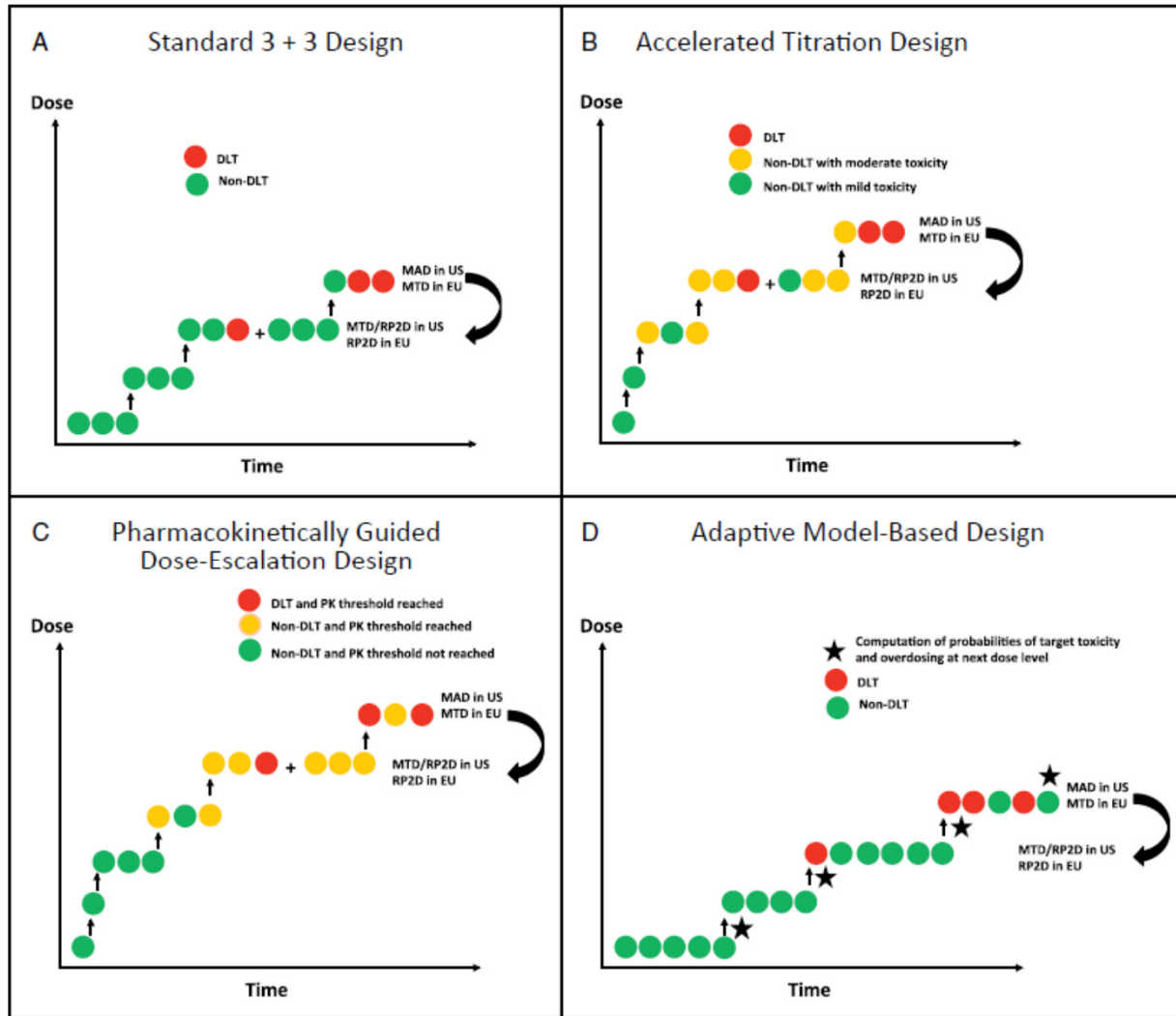


Fig 1. — (A) Schematic of the standard 3 + 3 design. (B) Schematic of the rule-based accelerated titration design. (C) Schematic of the pharmacokinetically guided dose-escalation design. (D) Schematic of an adaptive model-based design (eg, escalation with overdose control). DLT = dose-limiting toxicity, EU = European Union, MAD = maximum administered dose, MTD = maximum tolerated dose, PK = pharmacokinetics, RP2D = recommended phase 2 dose, US = United States.

Image from Hansen et al 2014.

# Why Bayesian in Dose-Escalation

Bayesian solution	Design Requirement
Information can be updated for as small and larger groups as one wants	Escalating dose cohorts with small #s patients (e.g. 3-6 patients)
Assessable by posterior	Accurately estimate MTD
Choose next dose based on posterior	Robustly avoid toxic doses („overdosing“)
Choose next dose based on posterior	Avoid sub-therapeutic doses while controlling overdosing
Choose next dose based on posterior	Enroll more patients at acceptable** active doses (flexible cohort sizes)
All information is used + „prior“	Use available information efficiently
High toxicity potential: safety first	Medical experts are in control

# Theoretical and Practical Loss „function“

## Dose escalation

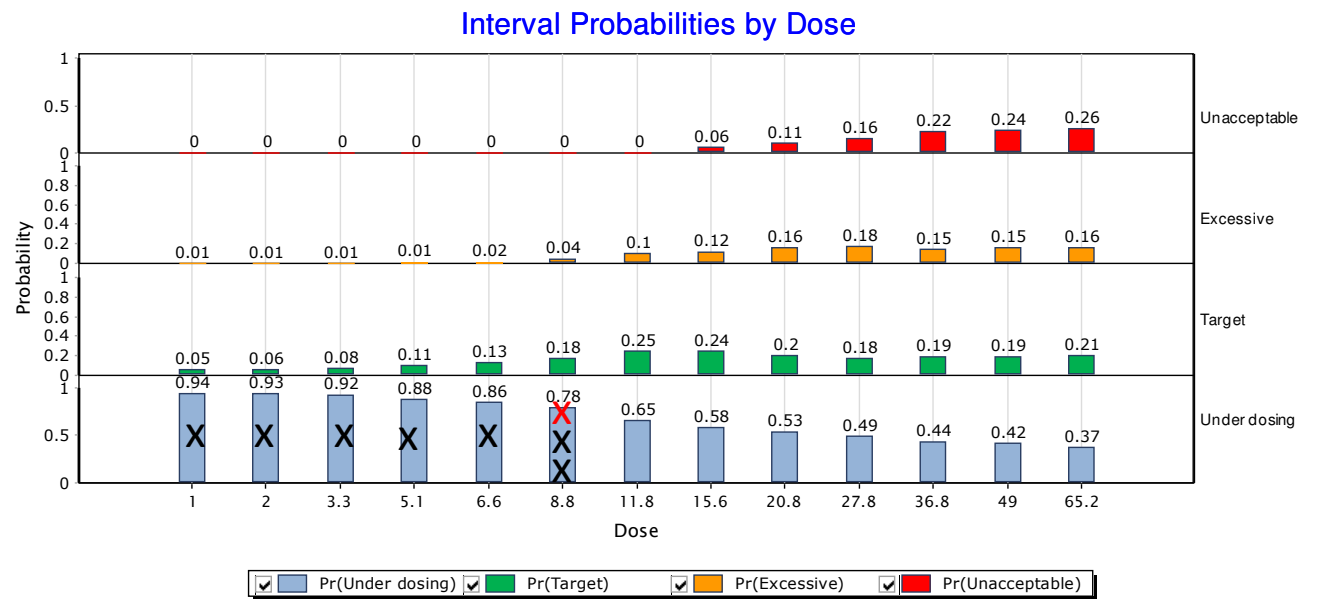


Algorithm  
in control

$$L(\theta, d) = \begin{cases} l_1 = 1 & \pi_{d|\theta} \in (0, 0.2] & \text{under - dosing} \\ l_2 = 0 & \pi_{d|\theta} \in (0.2, 0.35] & \text{targeted tox} \\ l_3 = 1 & \pi_{d|\theta} \in (0.35, 0.6] & \text{excessive tox} \\ l_4 = 2 & \pi_{d|\theta} \in (0.6, 0.1] & \text{unacceptable tox} \end{cases}$$



Medical  
experts in  
control



# Bayesian Logistic Regression Model

## Flex 1: Meaningful parametrization

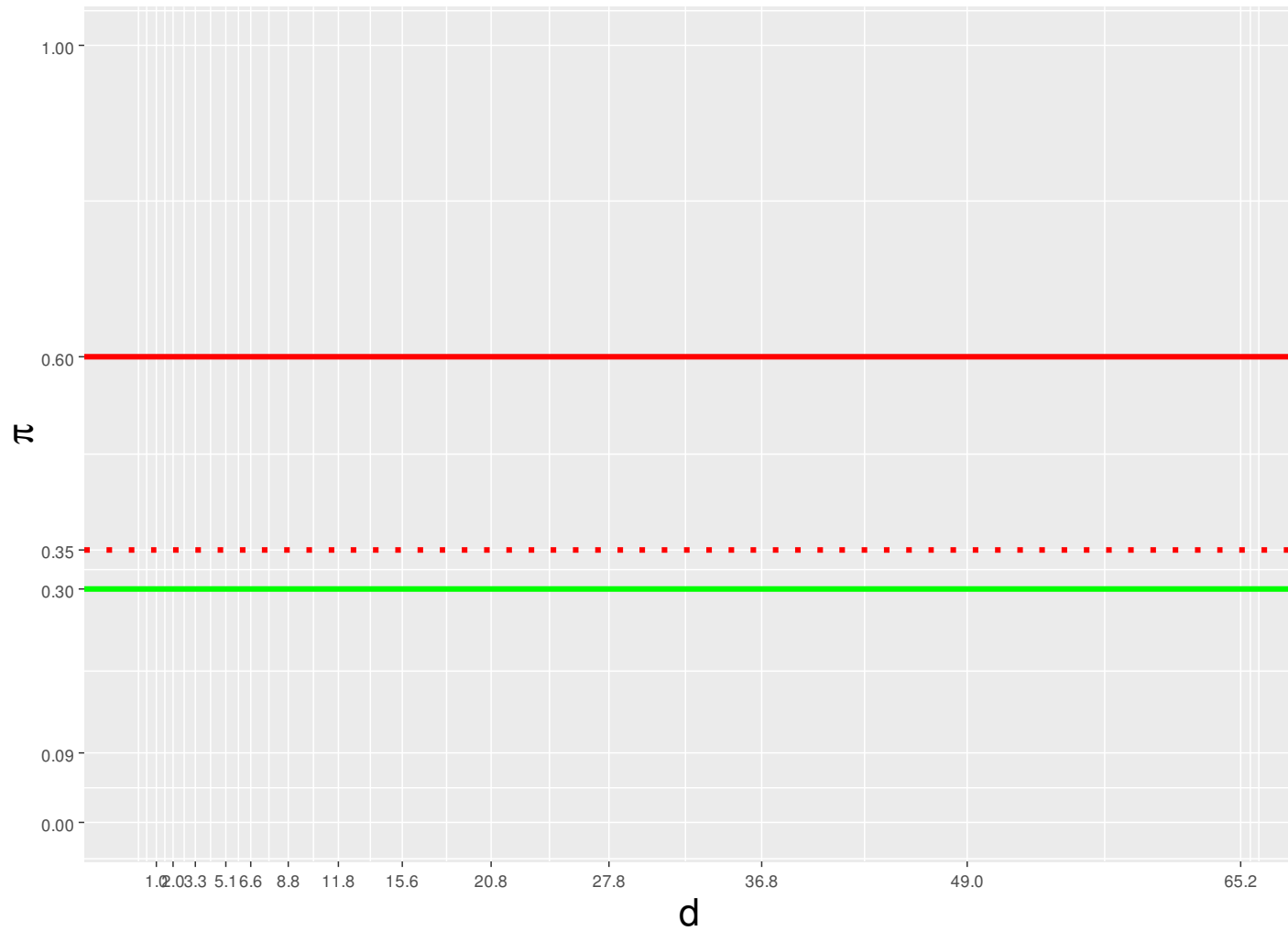
- Data:
  - #DLT/#Patients:  $r_d \sim \text{Binomial}(\pi_d, n_d)$
- Parameter Model:
  - $\text{logit}(\pi_d) = \log(\alpha) + \beta(\log(d/d^*))$
- Prior:
  - $(\log(\alpha), \log(\beta)) \sim \mathcal{N}_2(\mu_1, \mu_2, \sigma_1, \sigma_2, \rho)$

Model parameters  $\alpha$  and  $\beta$  can be interpreted as:

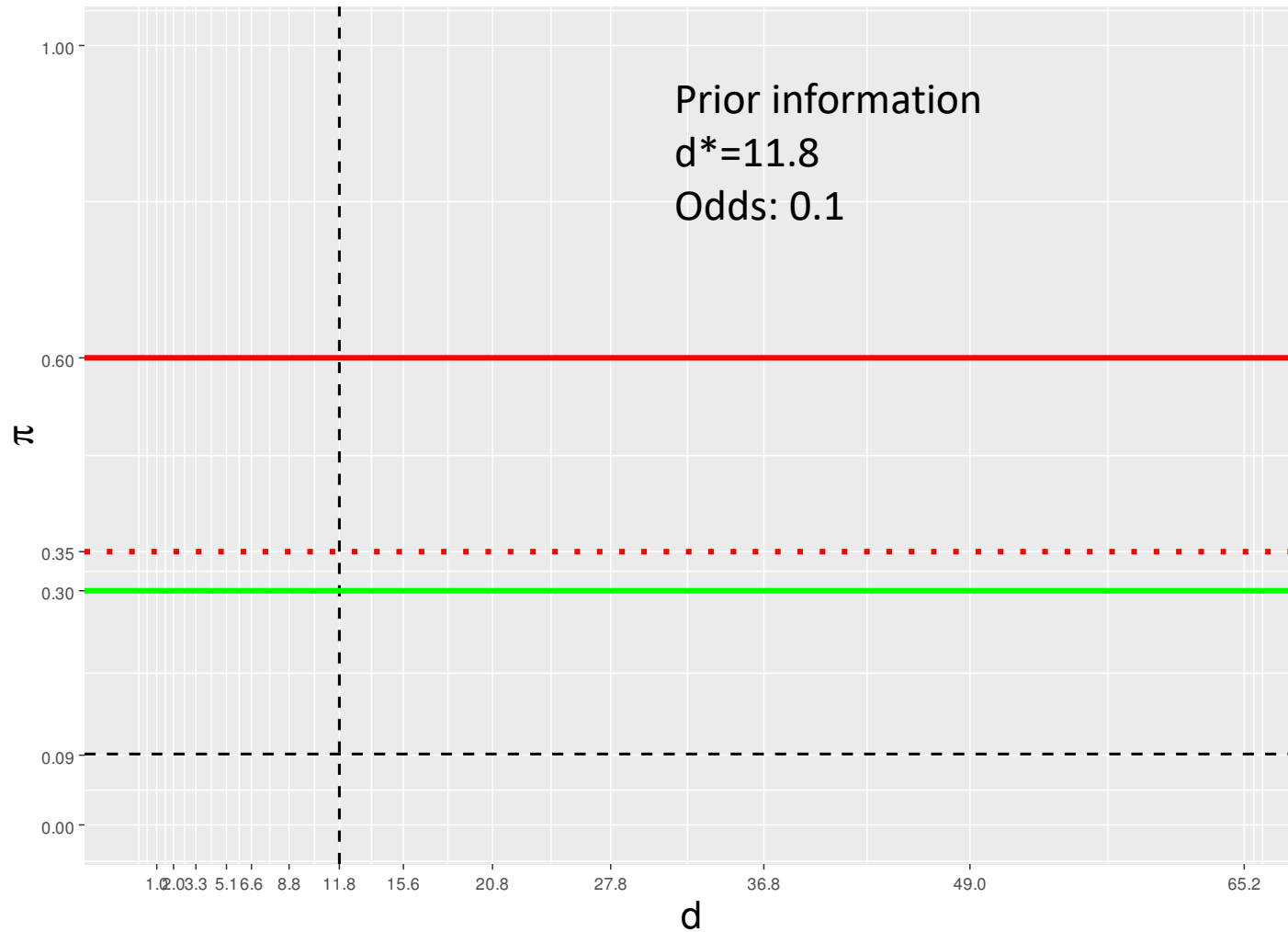
$\alpha$ : odds of a DLT at  $d^*$  (reference dose)

$\beta > 0$ : increase log-odds of DLT by unit increase log dose

# BLRM Flex 2: Plausible functional shapes

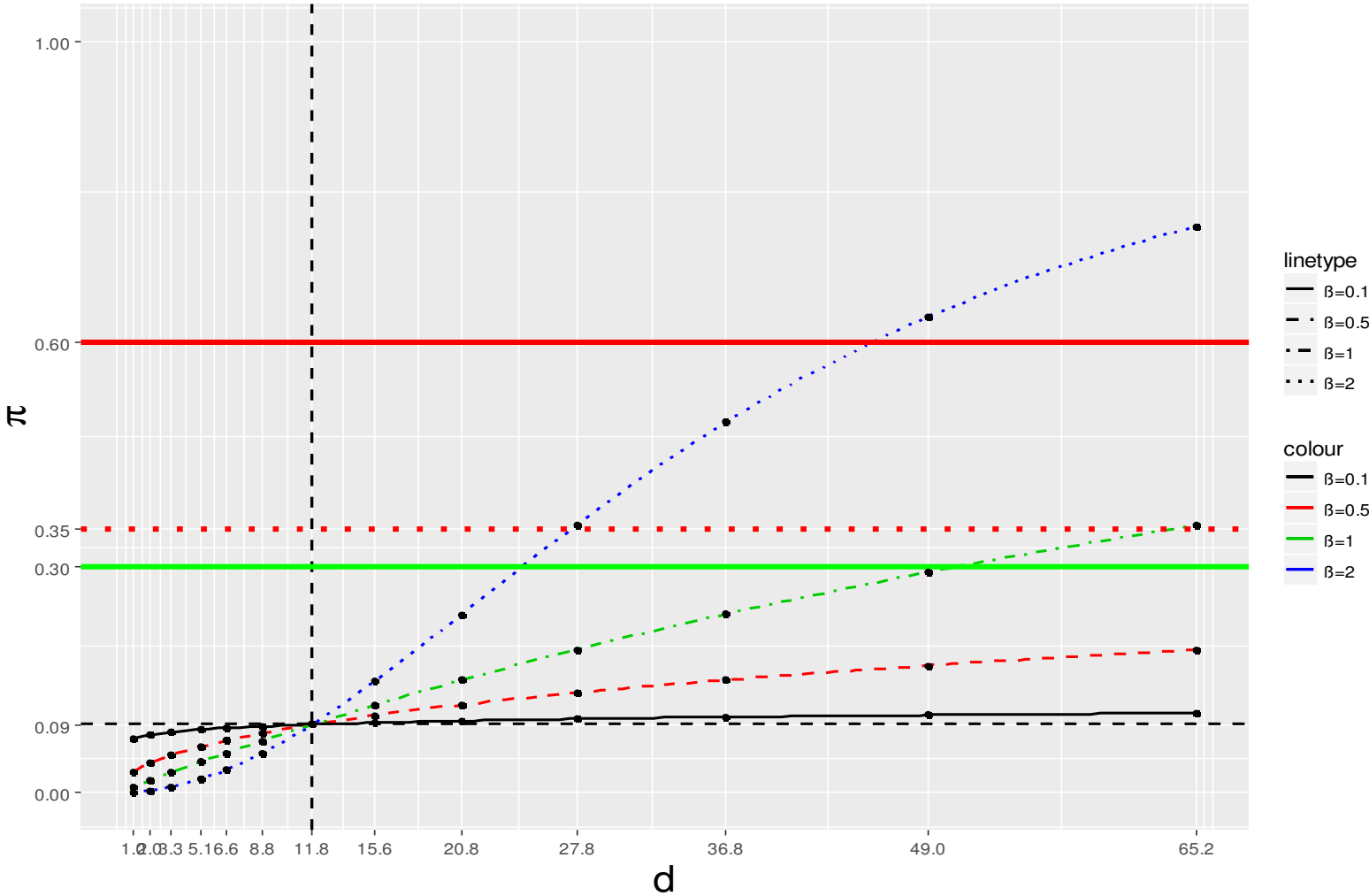


# BLRM Flex 2: Plausible functional shapes





# BLRM Flex 2: Plausible functional shapes



# BLRM Flex 3=1+2: Prior elicitation

There has to be knowledge on lowest dose and on dose range

## 1. Minimal informative

- $P(\pi_{d_1} \leq 0.6) = 0.95$ 
    - $\mathcal{B}(1, \log(0.05/0.4))$
  - $P(\pi_{d_j} \leq 0.2) = 0.05$ 
    - $\mathcal{B}(\log(0.05/0.2), 1)$
- Prior medians for the other doses by basic model
- $\mathcal{B}(a, b), j=2, \dots, J-1$
- Best approximating
- $$\mathcal{N}_2(\mu_1, \mu_2, \sigma_1, \sigma_2, \rho)$$

## 2. Somewhat informative

- $P(\pi_{d_1} \leq 0.05) = 0.5$ 
    - $\mathcal{B}(1, \log(0.05/0.5))$
  - $P(\pi_{\text{MTD}} \leq 0.3) = 0.5$ 
    - $\mathcal{B}(\log(0.3/0.5), 1)$
- Prior medians for the other doses by basic model
- $\mathcal{B}(a, b), j=2, \dots, J$  without  $d=\text{MTD}$
- Best approximating
- $$\mathcal{N}_2(\mu_1, \mu_2, \sigma_1, \sigma_2, \rho)$$

# Dose-Escalation Trials Phase I

- Assess dose-toxicity relationship
- First-in-human (FIH) studies – single agent
  - Determine maximum tolerated dose (MTD) or recommended phase II dose (RP2D)
  - Observe Dose limiting toxicities (DLTs)
- Combination dose finding studies (Phase Ib)
  - Same primary objective as FIH studies
    - Combination of two (or more) drugs
    - Addition of a new drug to a registered treatment to increase efficacy

<http://www.bayes-pharma.org/bayes2014docs/Day1/Jullion.pdf>

# Bayesian Logistic Regression Model

## Flex 4: Extending

For each single agent we assume:

- $\text{logit}(\pi_i(d_i)) = \log(\alpha_i) + \beta_i (\log(d_i))$ ,  $i=1,2$

Note: „standardized“  $d_1$  ( $d_1/d_1^*$ , agent1) and  $d_2$  ( $d_2/d_2^*$  agent2)

With a bit of probability calculus and under independence:

- $\text{odds}_{12}^0(d_1, d_2) = \text{odds}_1(d_1) + \text{odds}_2(d_2) + \text{odds}_1(d_1) * \text{odds}_2(d_2)$

Assign one new parameter  $\eta$  for interaction:

- $\text{odds}_{12}(d_1, d_2) = \text{odds}_{12}^0(d_1, d_2) * \exp(\eta d_1 d_2)$

# BLRM Flex 5: Prior elicitation

There is typically knowledge on at least one agent

Meta-Analytic-Predictive Prior for agent with historical study:

Historical:  $\text{logit}(\pi_h(d_h)) = \log(\alpha_h) + \beta_h(\log(d_h))$

Comb trial:  $\text{logit}(\pi_1(d_1)) = \log(\alpha_1) + \beta_1(\log(d_1))$

Assumption of similarity:

$\log(\alpha_h), \log(\alpha_1) \sim \mathcal{N}(\mu_\alpha, \tau)$

$\log(\beta_h), \log(\beta_1) \sim \mathcal{N}(\mu_\beta, \tau)$

Choice of  $\tau$  based on heterogeneity (or hyperprior):

$\tau = 2$  (very large),  $1$  (large),  $0.5$  (substantial),  $0.25$  (moderate),  $0.125$  (small) variability.

Prior on interaction  $\eta$ :

e.g.  $N(0, 1.121)$ : no interaction expected but allowing up to 9-fold increase in 95% increase or decrease in prior interval

All suggestions from Neuenschwandner et al 2016

# References

## MBLRM

William DuMouchel. Multivariate Bayesian Logistic Regression for Analysis of Clinical Study Safety. *Statistical Science*, 27:319–339, 2012

## BLRM

B. Neuenschwander, M. Branson, and T. Gsponer. Clinical aspects of the Bayesian approach to phase I cancer trials. *Statistics in Medicine*, 27:2420-2439, 2008.

F. Divino, N. Golini, G.J. Lasinio, A. Penttinen. Bayesian logistic regression for presence-only data. *Stoch Environ Res Risk Assess*, 2015

## Combination

B. Neuenschwander, et al. A Bayesian Industry Approach to Phase I Combination Trials in Oncology. *Statistical Methods in Drug Combination Studies*, 95-135, 2015

B. Neuenschwander, S. Roychoudhury & H. Schmidli: On the use of co-data in clinical trials, *Statistics in Biopharmaceutical Research*, 2016

## 3+3

A. Hansen et al. Is 3+3 the best? *Cancer control* 21, 200-208, 2014