



Becoming a multilingual statistician

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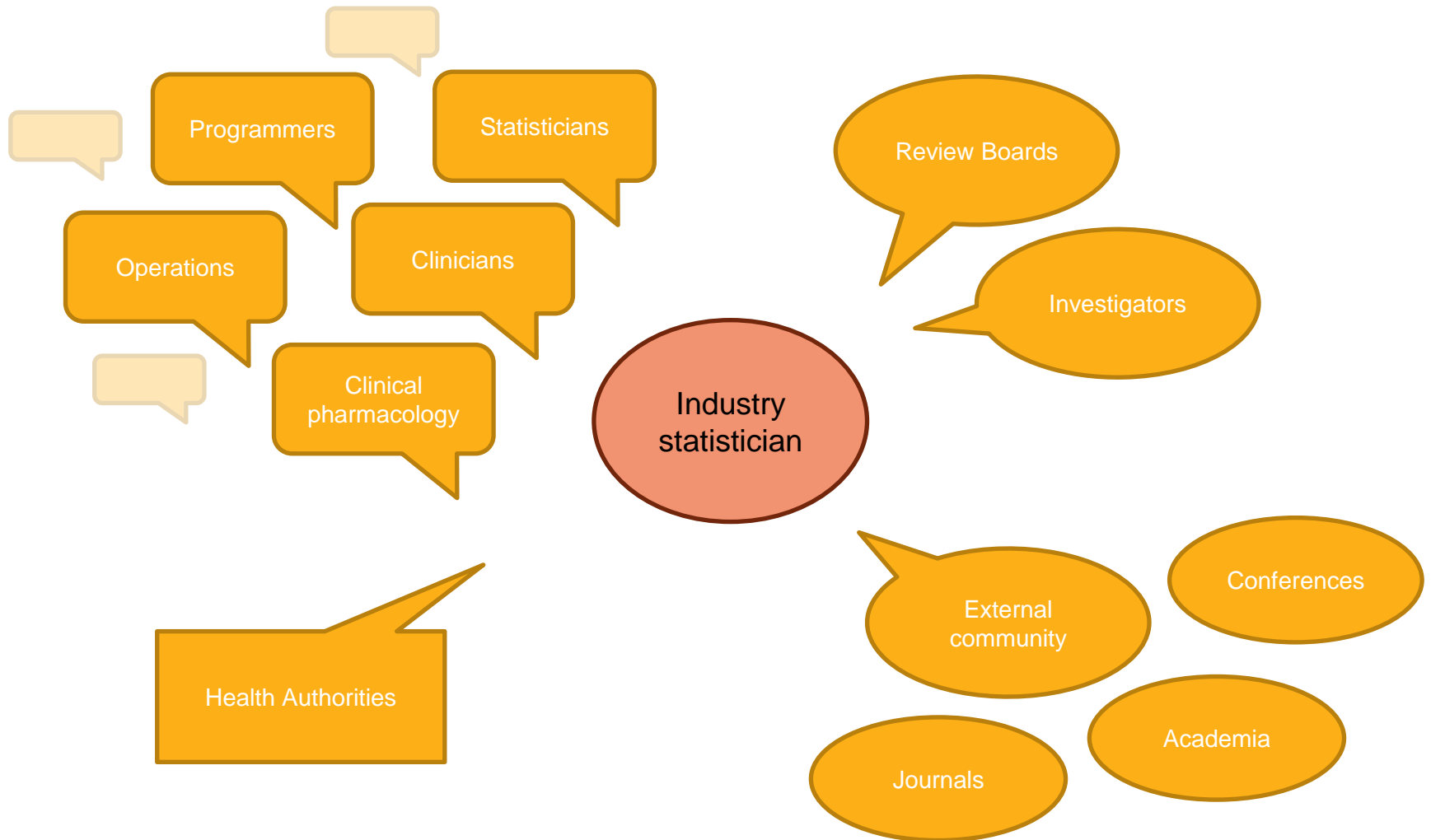
Bayes 2015 Basel

Novartis Oncology Early Clinical Biostatistics

Introduction

- Novartis Oncology Early Clinical Biostatistics
 - Oncology phase 1 (dose finding) and phase 2 (exploration of safety and efficacy)
- We work with (mostly) Bayesian solutions
- Phase I Bayesian model based designs are now our standard approach
- Our phase II designs are increasingly moving to a Bayesian estimation framework

Becoming a multilingual statistician



Presentation Structure

Introduction

- Statistical communication in Novartis Oncology
- In the context of Novartis Oncology's implementation of Bayesian model based dose escalation designs
 - Speaking up: The challenges of moving to a new paradigm
 - Translating ourselves
 - Lost in translation: Some unexpected miscommunications...
 - (Some future challenges)
 - Summary

Speaking up

- 3+3 designs seen as ‘gold standard’
 - Simple algorithmic approach
 - Easy to understand
 - Easy to implement
- Moving out of comfort zone
 - Costs for the team and the organization
 - More complex designs
 - More difficult to understand and communicate
 - More patients enrolled
 - More resources required

Creating internal engagement













Overcoming inertia

- Start with the problem, not the solution
 - Leave the stats to one side initially

- Dose escalation: Find the right dose
 - Accurately assess dose/toxicity relationship
 - Allow flexibility
 - Dose choice is not algorithmically driven
 - Adapt to new information (e.g., intermediate dose levels)
 - Can explore dose range, learn about PK, PD, etc.
 - Gather additional information where there is uncertainty
 - Use available information efficiently
 - Protect patient safety (high toxicity potential)

Creating internal engagement

Overcoming inertia

Design Requirements	3+3 Design	Bayesian Design
Escalating dose cohorts with small numbers of patients (e.g. 3-6 patients)		
Accurately estimate MTD & select recommended dose for expansion (RDE)		
Robustly avoid toxic doses (“overdosing”)		
Avoid sub-therapeutic doses while controlling overdosing		
Enroll more patients at acceptable, active doses (flexible cohort sizes)		
Use available information efficiently		

Creating internal engagement

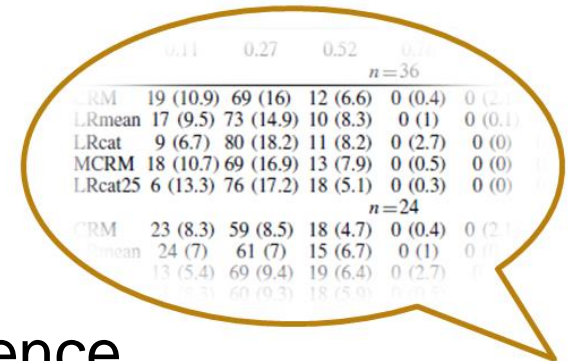
Gaining momentum

- Identifying the issues and knowing we have a statistical solution is only the beginning
- Have to bring the team on the journey
 - Avoid 'black boxes'
- Together we have to:
 - Learn how to speak each others language
 - Helping clinicians understand our approach
 - Learning their language (for example, to help us set up priors)
 - Understand the practical and operational implications

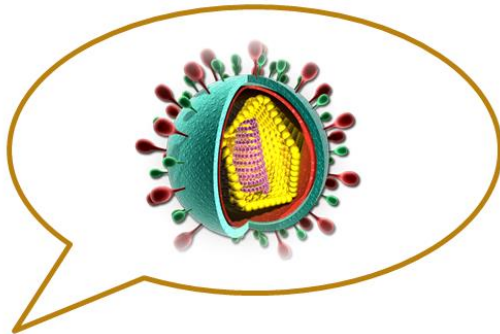
Crossing the language barrier

Translating our language

- Collaboration builds acceptance
 - Openness to questions and concerns
 - Consider and demonstrate benefits and risks
- The right communication for the right audience



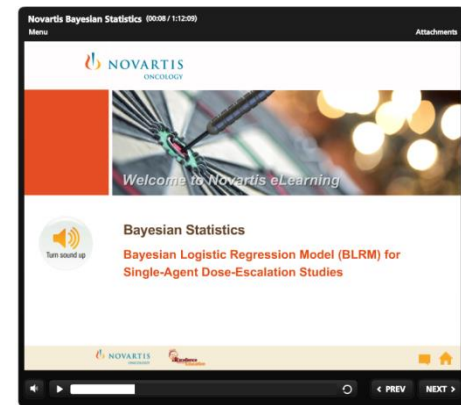
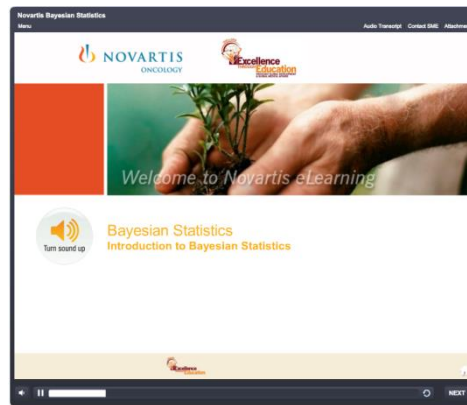
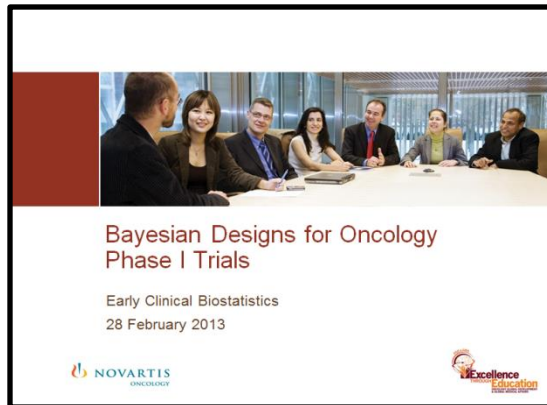
	0.11	0.27	0.52	0.75	0.90	0.95
	n=36					
CRM	19 (10.9)	69 (16)	12 (6.6)	0 (0.4)	0 (0)	0 (0)
LRmean	17 (9.5)	73 (14.9)	10 (8.3)	0 (1)	0 (0.1)	0 (0)
LRcat	9 (6.7)	80 (18.2)	11 (8.2)	0 (2.7)	0 (0)	0 (0)
MCRM	18 (10.7)	69 (16.9)	13 (7.9)	0 (0.5)	0 (0)	0 (0)
LRcat25	6 (13.3)	76 (17.2)	18 (5.1)	0 (0.3)	0 (0)	0 (0)
	n=24					
CRM	23 (8.3)	59 (8.5)	18 (4.7)	0 (0.4)	0 (2.1)	0 (0)
LRmean	24 (7)	61 (7)	15 (6.7)	0 (1)	0 (0)	0 (0)
LRcat	13 (5.4)	69 (9.4)	19 (6.4)	0 (2.7)	0 (0)	0 (0)
MCRM	13 (5.4)	60 (10.3)	18 (5.0)	0 (0.3)	0 (0)	0 (0)



- Think conceptually
 - Simple, clear, non-technical, consistent
 - A picture is worth a thousand words
- Educate (and be educated)
 - Broad education in common concepts
 - Specific education in our commonly used designs

Building engagement

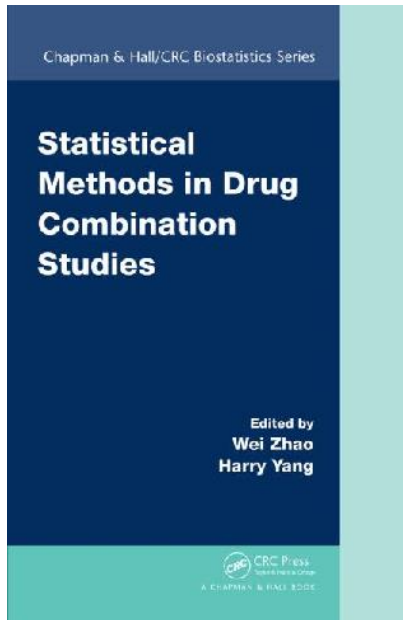
Internal training



- Face to face, and online
- Statistical training
- Non-statistical training
 - Discuss design issues, and clinical questions
 - Implementation and operation
 - Offer statistical solutions
 - Case studies to provide context

Building engagement

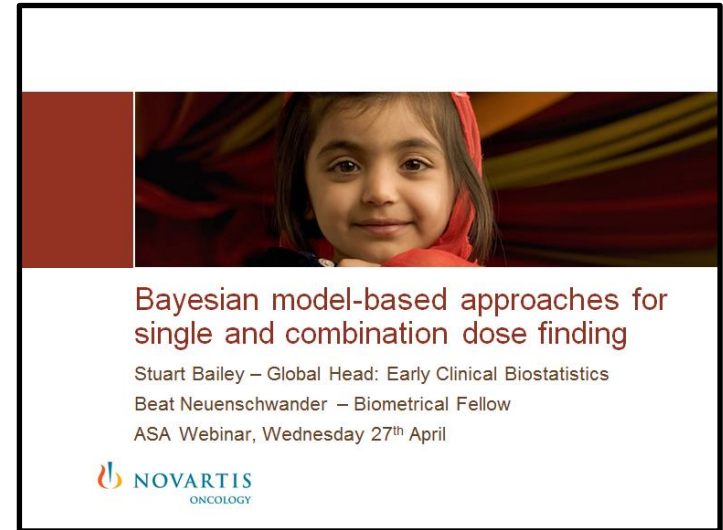
External: Publications and presentations



Neuenschwander et al (2014)
Chapter: A Bayesian Industry
Approach to Phase I
Combination Trials



Neuenschwander et al (2008)
Critical aspects of the Bayesian
approach to phase I cancer trials
Statistics in Medicine



Bailey & Neuenschwander (2011)
ASA Webinar

Building engagement

External: Publications and external presentations



Sessa et al (2013)
 First in human Phase I Dose-Escalation Study of the HSP90 Inhibitor AUY922 in Patients with Advanced Solid Tumors



Demetri et al (2009)
 A phase I Study of Single-Agent Nilotinib or in Combination with imatinib in Patients with Imatinib-Resistant Gastrointestinal Stromal Tumors

Building engagement

External: Health authority interactions

■ **FDA**

- Critical Path Initiative seeks to promote “new and innovative scientific approaches, such as the use of Bayesian Statistics”
- Committee for Medicinal Products for Human Use (**CHMP**) guideline for Clinical Trials in Small Populations
 - “Model-based approaches have been shown to provide better estimation of true MTDs compared to standard algorithmic approaches”

Building engagement

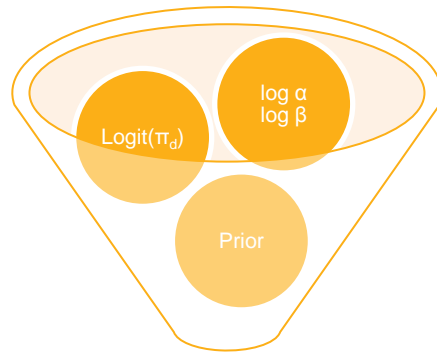
External: Health authority interactions

■ **FDA**

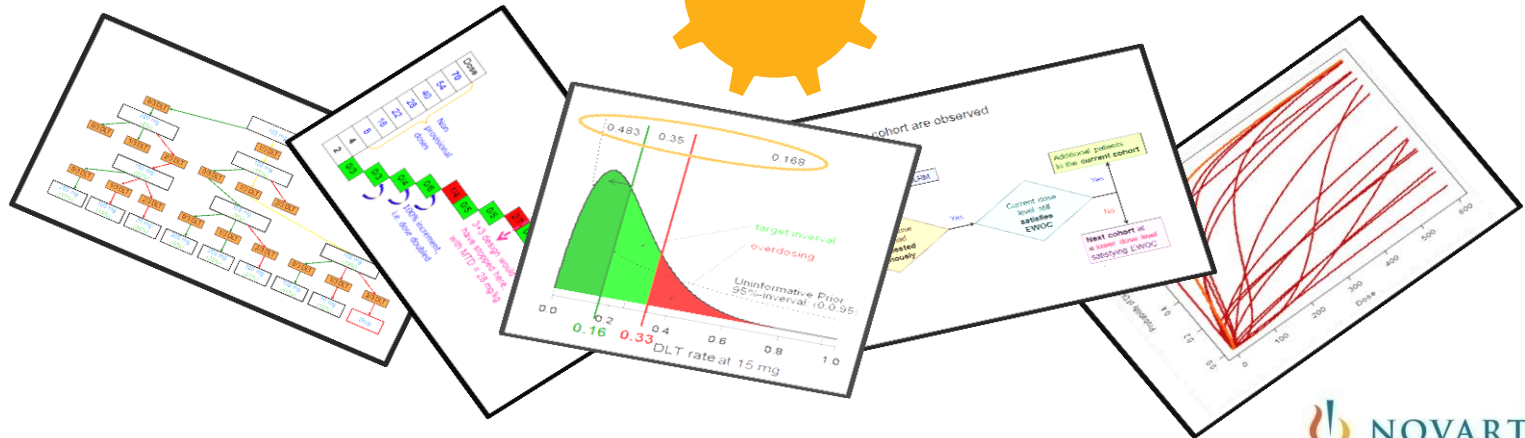
- Presentation to FDA Biostatisticians and Oncologists in Jun 2009
- Novartis commented on Draft FDA Adaptive Design Guidance in May 2010

■ **PMDA**

- Presentation to PMDA in Nov 2010
- Novartis Bayesian Phase I designs are generally well accepted and challenges/questions from Health Authorities are more on the specifics of the application than on the general approach



Translating ourselves



Communication with Stats users

Difficult concepts and complex data

- Need to enable clinicians and others to understand
- Now a few examples taken from the model based approach we use for dose escalation studies in Novartis
 - Understanding priors
 - The EWOC (Escalation With Overdose Control) criterion
 - Dose escalation decision making

Phase I Dose escalations

Bayesian Logistic Regression

$$r_d \sim \text{Bin}(\pi_d, n_d)$$

$$\text{logit}(\pi_d) = \log(\alpha) + \beta \log(d/d^*)$$

- Model specifications
 - d is dose
 - r_d is the number of patients with DLT at dose d
 - π_d is $P(\text{DLT at dose } d)$
 - n_d is the total number of patients at dose d
 - Logistic regression
 - α and β are the logistic parameters
 - d^* is a fixed reference dose

Phase I Dose escalations

- Want to communicate to others
 - The principals underlying our model
 - Some key concepts that can help us to interpret the model
 - How we can use our model to guide dose escalation
- Need to think about key message
 - Might depend on circumstance
 - Will influence the way in which we share information

Phase I Dose escalations

- Perhaps we want to discuss with the team the set of curves the model is describing
 - This might be the case during study set up
 - Perhaps we want to demonstrate what our prior tells us about the dose/toxicity relationship
 - Or to help teams understand the flexibility of the model we are using
- Alternatively, we want to communicate with the team what the model is telling us about which doses are safe to use
 - This might be used to confirm the safety of the starting dose (prior)
 - Or to identify the maximum dose to which we can escalate for our next cohort (posterior)

Priors

- One of the first things we need to do it to build a prior for the logistic parameters
- If this is a first in human trial, we might want to use a non-informative prior
- If we have data from previous trials (perhaps in other indications) with the same drug then we may incorporate that data to produce a more informative prior

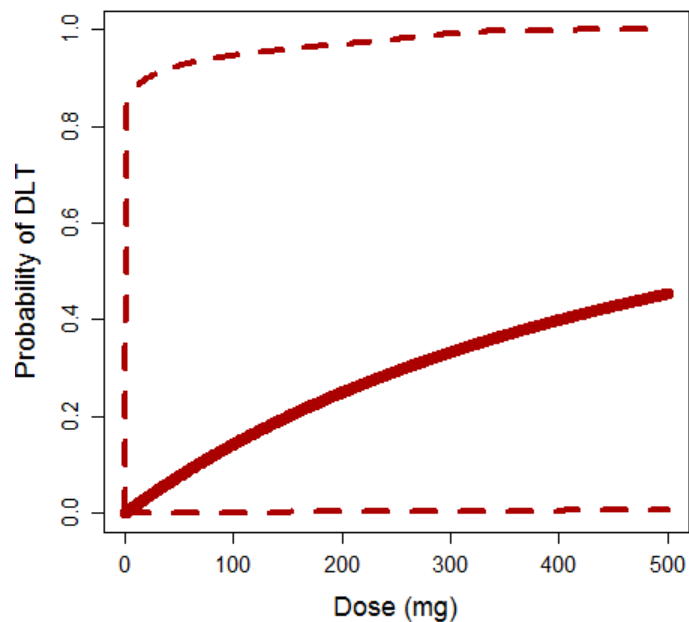
$$\begin{array}{ccc} \text{Non-informative prior} & & \text{Informative prior} \\ \left(\begin{array}{c} \log \alpha \\ \log \beta \end{array} \right) \sim \text{BVN} \left(\left(\begin{array}{c} 0.33 \\ 0 \end{array} \right), \left(\begin{array}{c} 2, 0 \\ 0, 1 \end{array} \right) \right) & \text{BVN} & \left(\left(\begin{array}{c} -1.96 \\ 0.479 \end{array} \right), \left(\begin{array}{c} 0.910, -0.235 \\ -0.235, 0.634 \end{array} \right) \right) \end{array}$$

- How can we help our colleagues understand what this means?
 - Does our prior match their prior beliefs about the dose/toxicity relationship

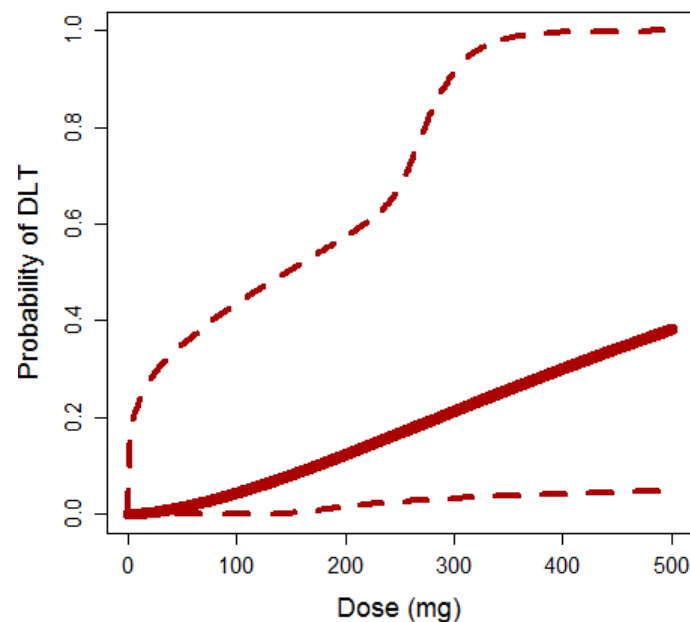
Priors

- Simple graphical summary to describe the 'space' of possible curves
- Simple explanation, clear and intuitive interpretation

Non-informative prior



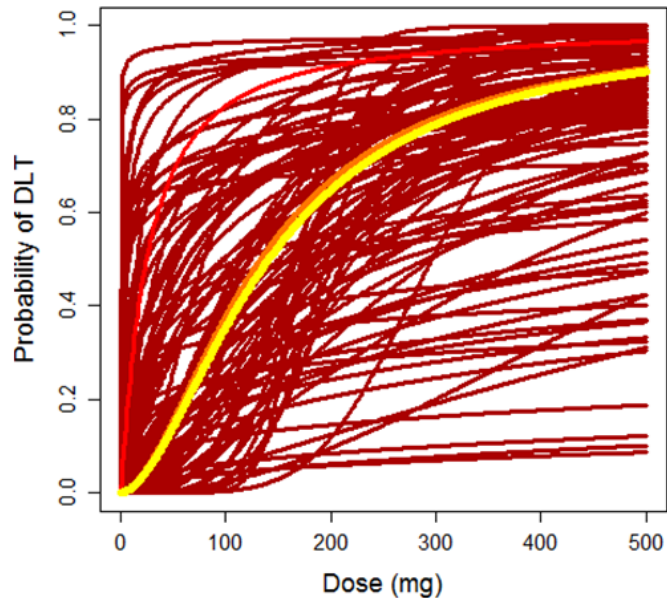
Informative prior



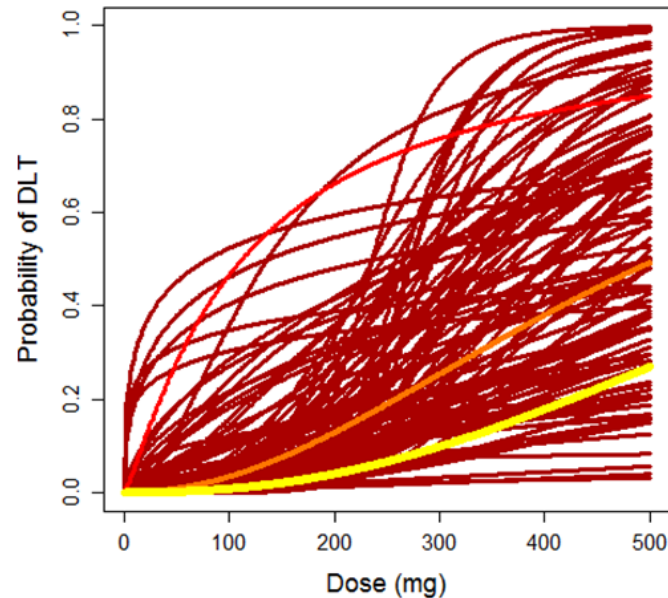
Priors

- We can illustrate further...
- What sort of curves are 'possible' based on our prior?

Non-informative prior



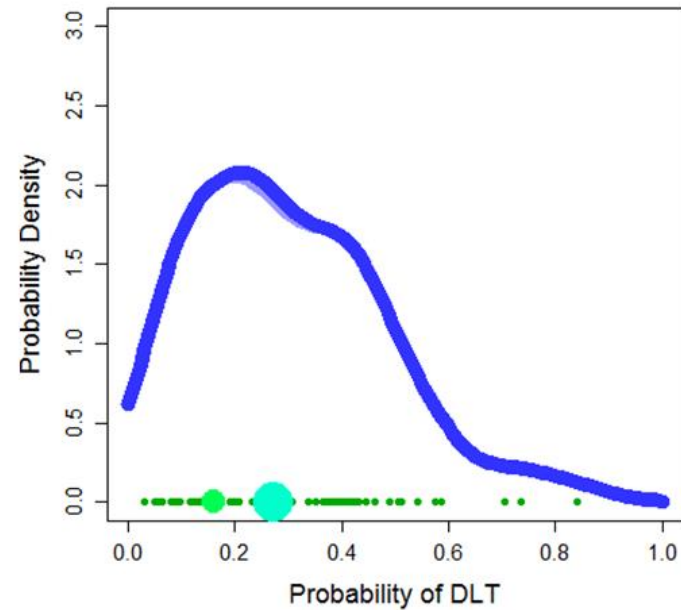
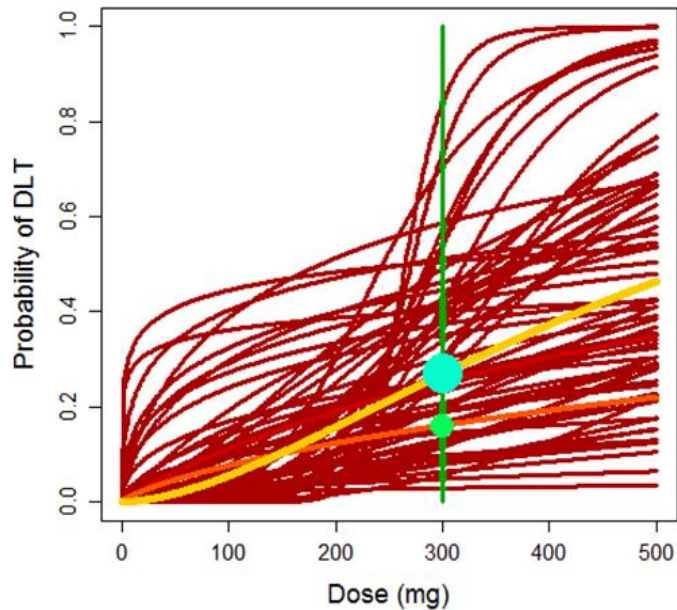
Informative prior



Learning about toxicity at a given dose

- And how do we turn these random curves into information about toxicity at a given dose?

Informative prior



EWOC: Understanding a concept

Escalation with overdose control

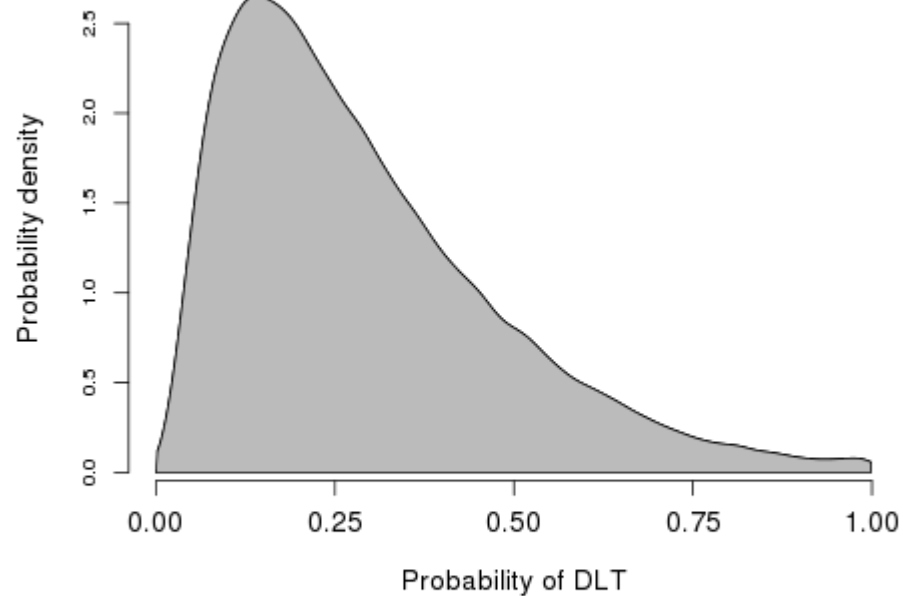
- Patients will not receive a dose for which there is a posterior probability greater than 25% that the probability of DLT will exceed 33%
- Tricky concept: ‘Probability of a probability’, ‘25%’, ‘33%’?
- Break into manageable chunks
 - Define ‘excessive toxicity’
 - If risk of DLT exceeds 33%, dose is excessively toxic
 - But we’re never sure of the true risk, we only have an estimate with error

Reference: Babb et al.

EWOC: Understanding a concept

Escalation with overdose control

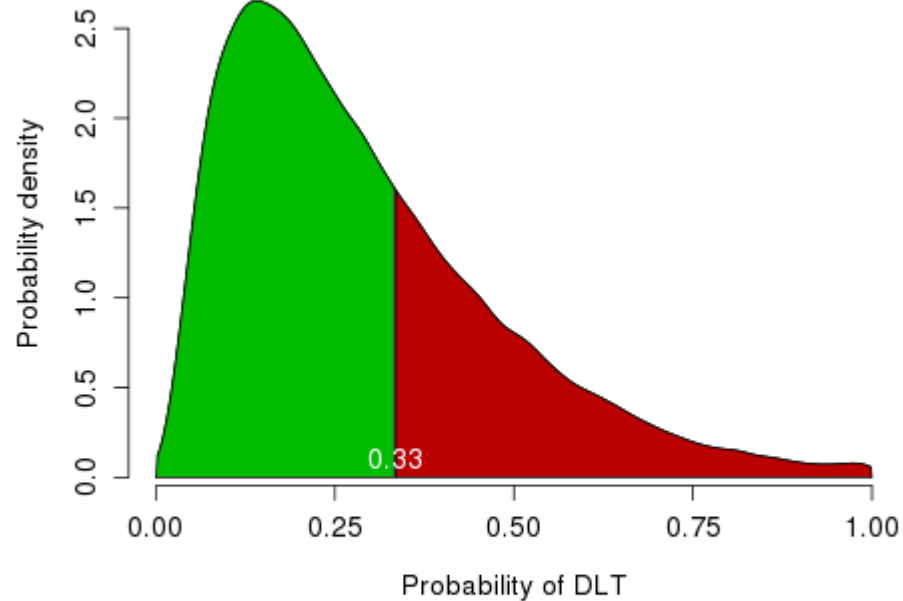
300mg



EWOC: Understanding a concept

Escalation with overdose control

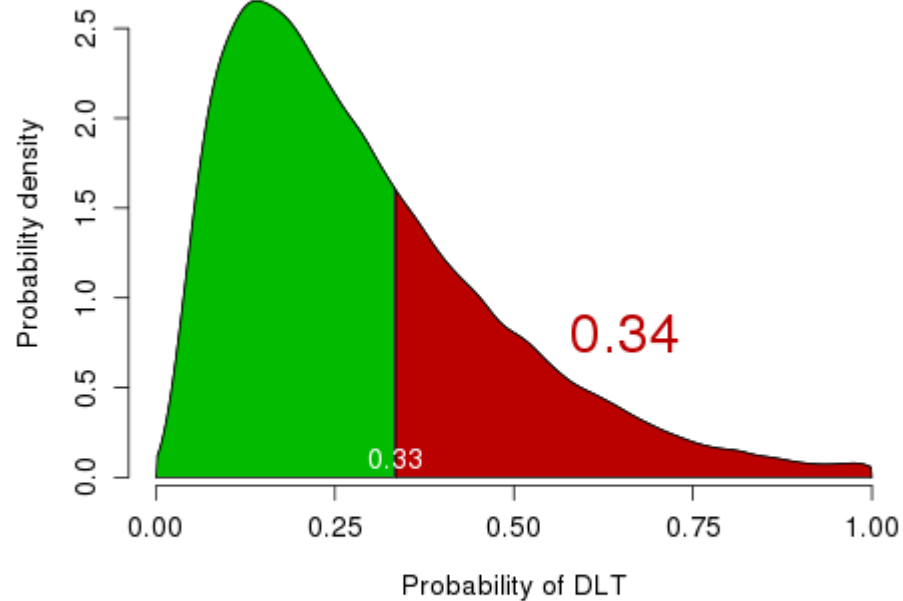
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EWOC: Understanding a concept

Escalation with overdose control

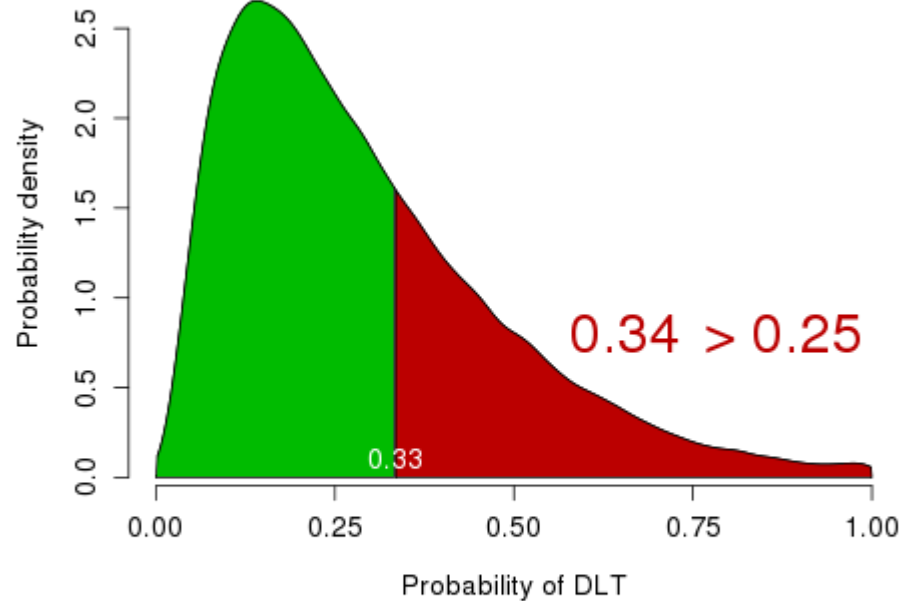
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EWOC: Understanding a concept

Escalation with overdose control

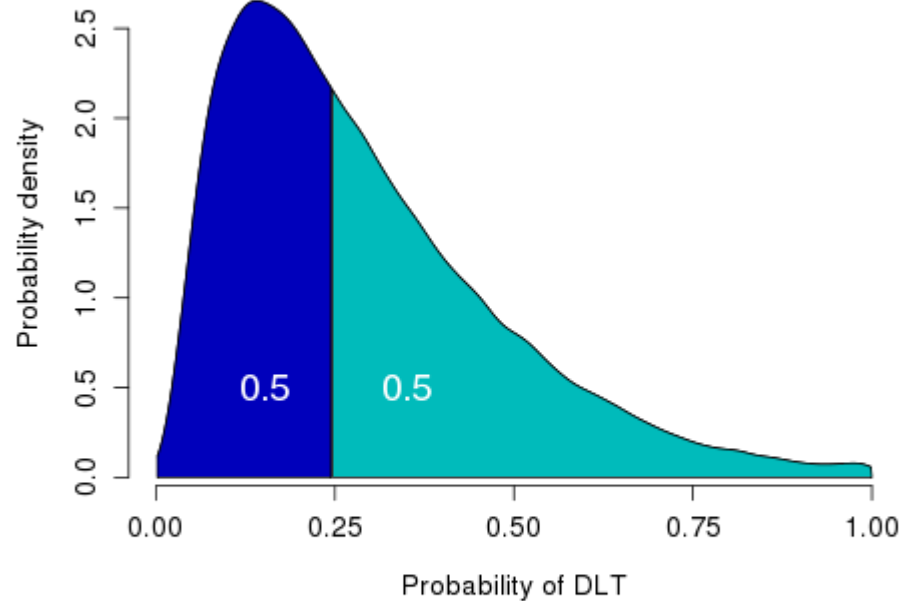
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EWOC: Understanding a concept

Escalation with overdose control

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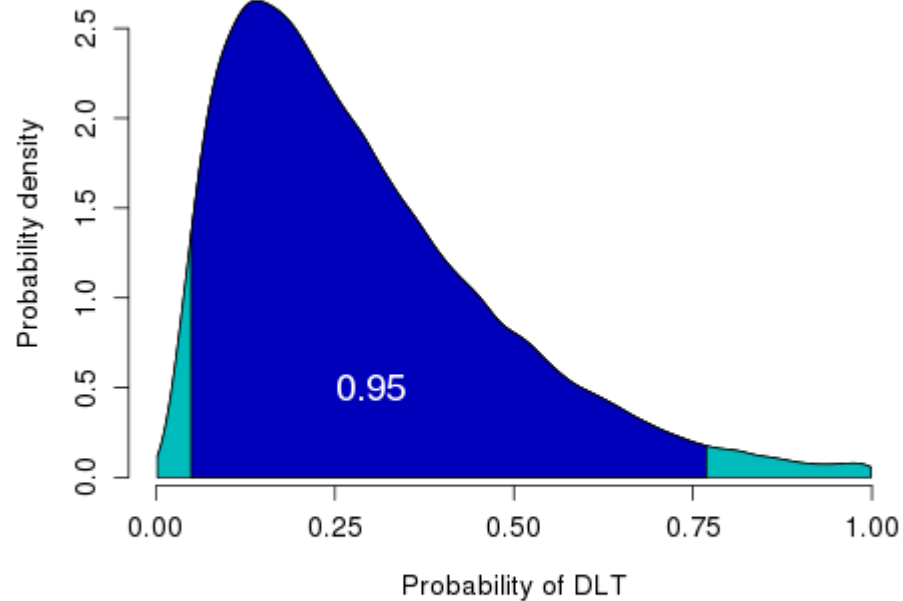


●
Median

EWOC: Understanding a concept

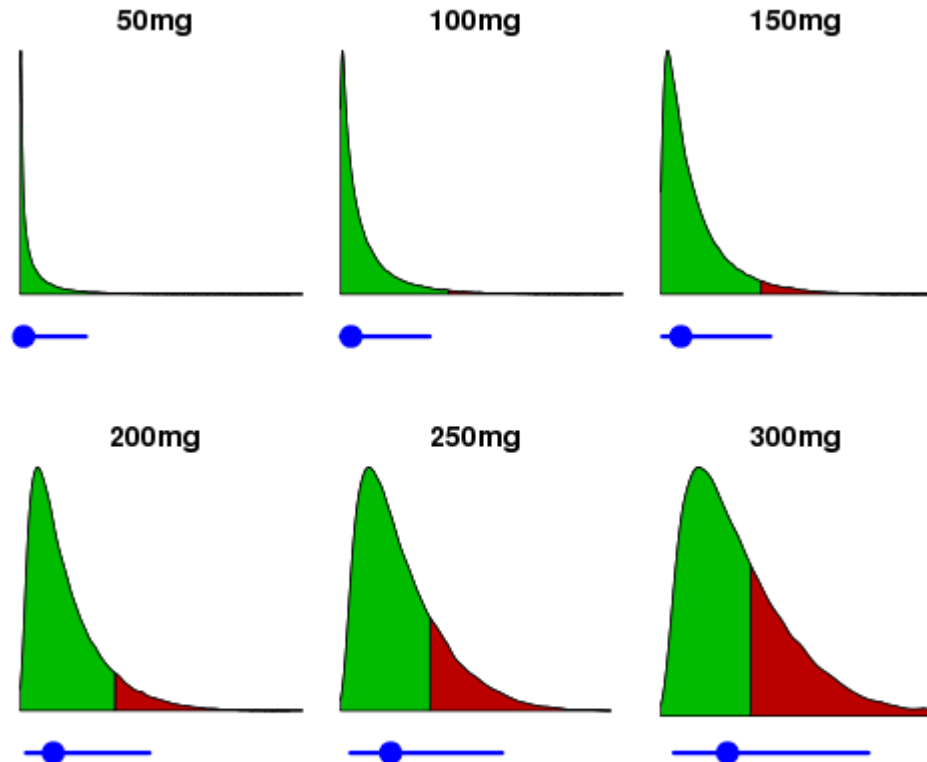
Escalation with overdose control

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EWOC: Understanding a concept

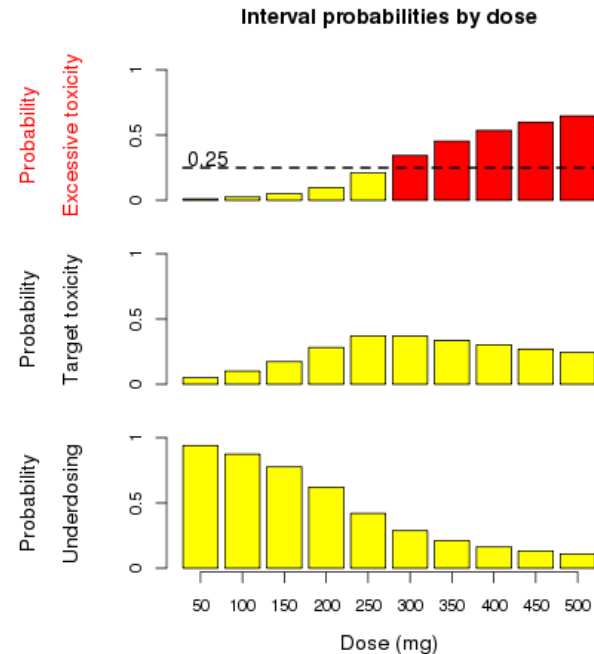
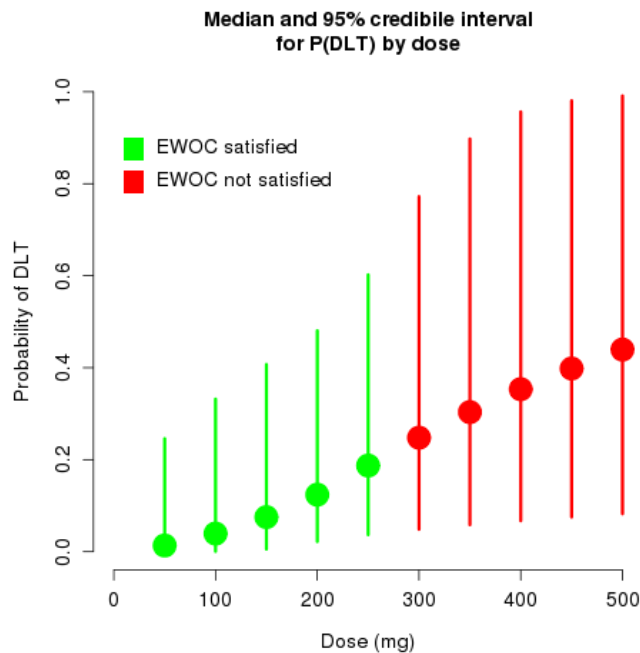
Escalation with overdose control



Dose decisions

Supporting a dose recommendation

- Graphical summaries used to support dose escalation decisions
 - To the point – what doses may be safely used?



Communication with Statisticians

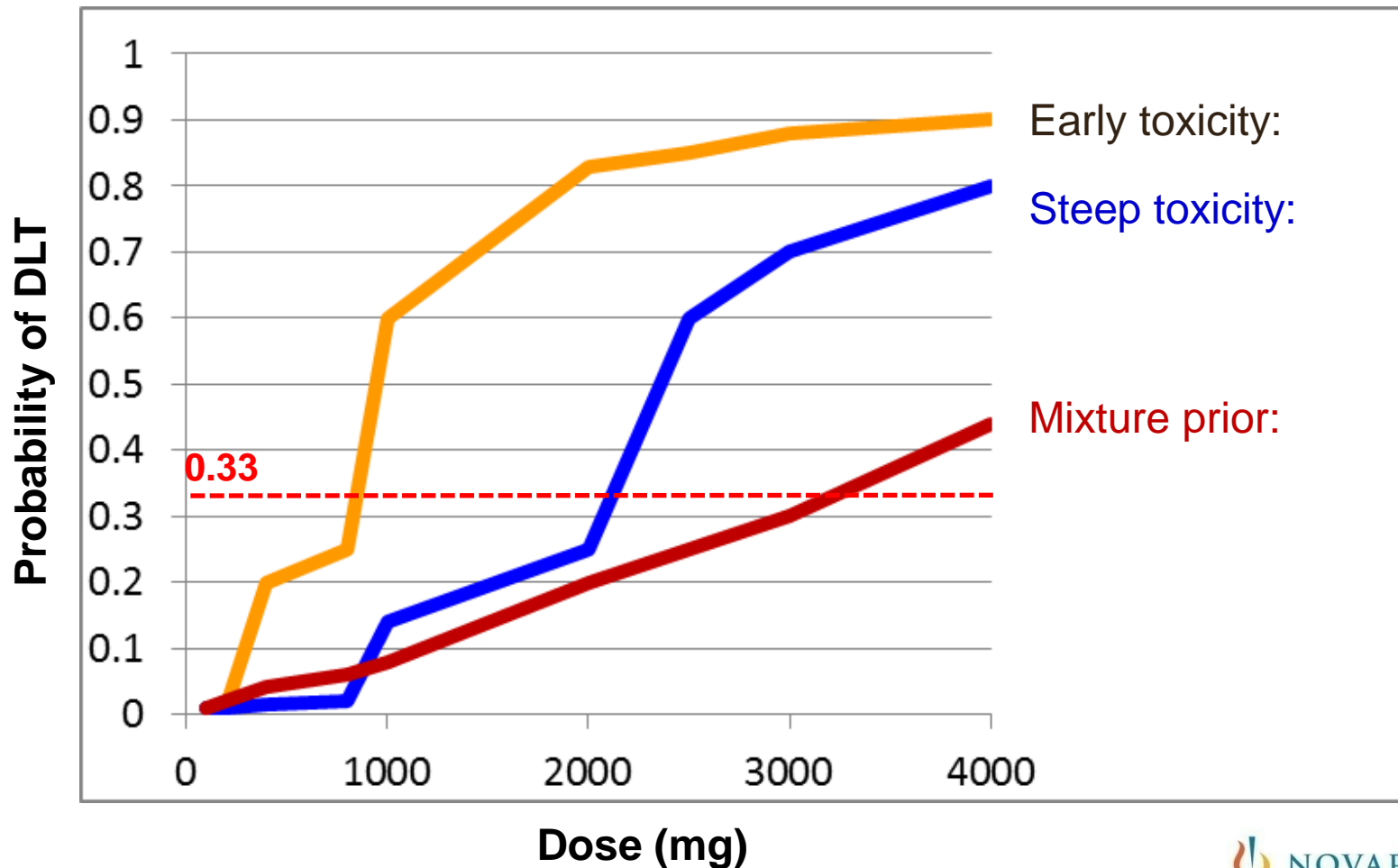
Statistically bilingual

- We need to be statistically bilingual
- Enable a frequentist to understand the properties of our Bayesian design
 - For our model based Phase I approach this typically includes an investigation of operating characteristics

Communication with Statisticians

Statistically bilingual

- How does our model operate under a number of 'true' scenarios

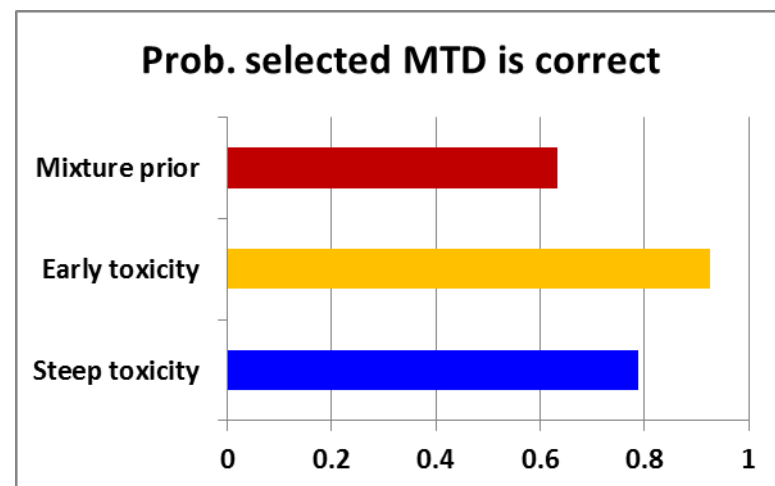


Communication with Statisticians

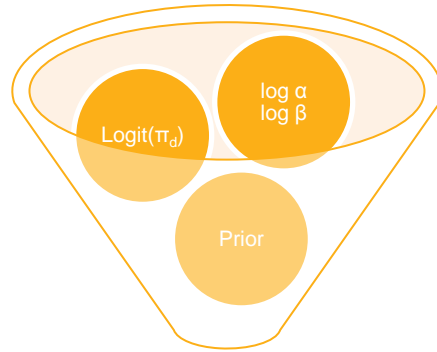
Statistically bilingual

■ Summary metrics:

- Do we have a high (long run) probability of correctly identifying the MTD?
- Is our approach successful at minimizing the risk of a patient being exposed to an excessively toxic dose?



True Scenario	I	II	III	IV	V	VI	VII
Mixture prior	63.3	8.1	28.6	28.0	5.1	25.2	3.5
Early toxicity	92.5	4.3	3.2	58.4	13.5	24.7	5.2
Steep toxicity	78.8	0.6	20.6	36.8	9.9	25.7	3.8

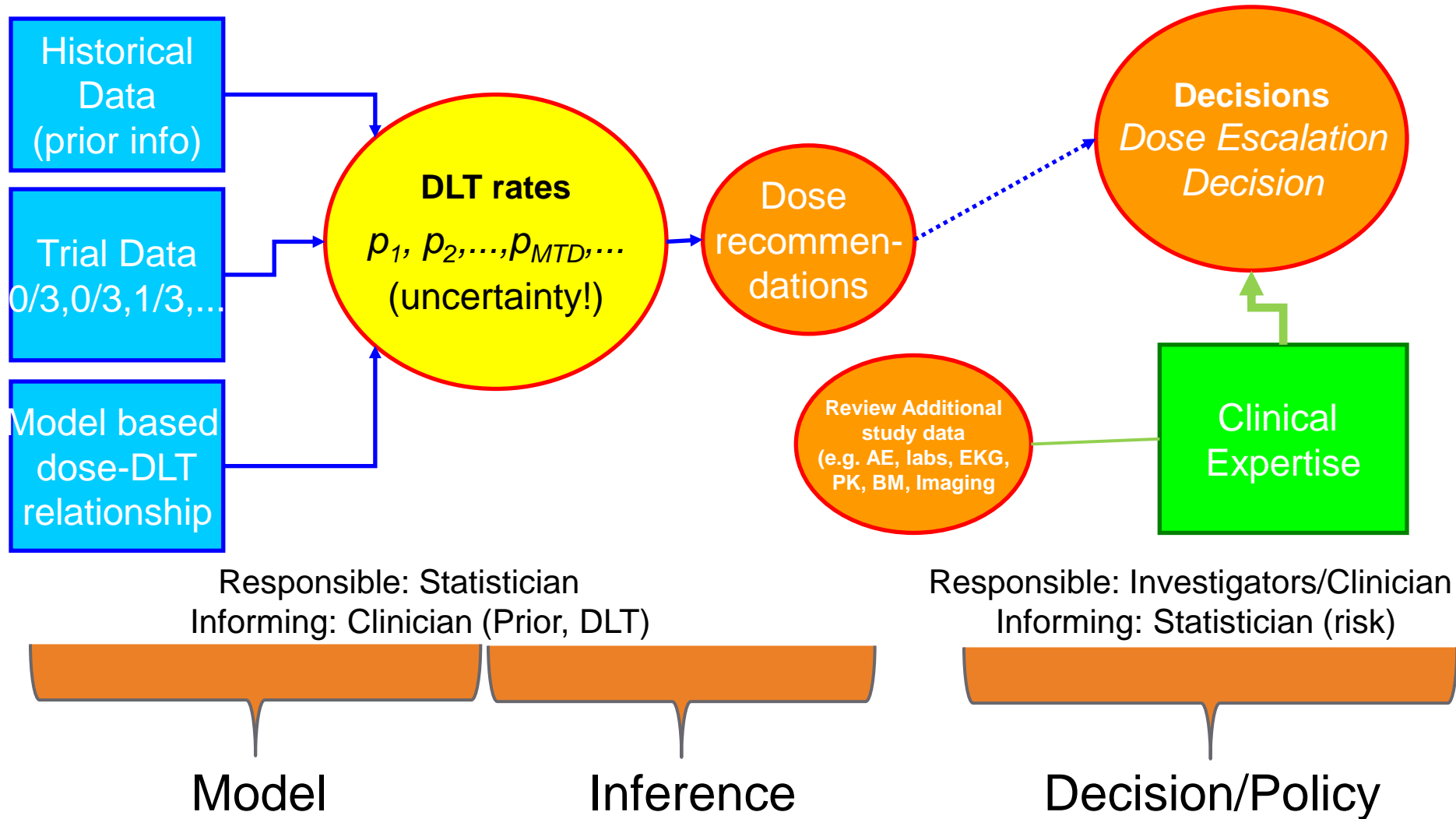


Lost in translation



Dose decisions

Clinically driven, statistically supported decisions



Dose decisions

Clinically driven, statistically supported decisions

- Maximum dose **recommended** by the Bayesian logistic regression model
- Statistician thinks:
 - I've run the model using the latest data. I've applied the EWOC criterion, and considered the protocol specified rules for dose escalation. Taking all of this into account tells us that this is the maximum dose that can safely be given to future patients. Now it's up to the team to make an informed choice about which dose to investigate next...
- Clinician thinks:
 - This is the dose

Efficiency

- We aim to use the available information **efficiently**
- To a statistician this is shorthand for many things:
 - We won't make decisions based purely on the current cohort
 - We will formally incorporate prior information into the analysis
 - The team will have flexibility to consider other data to make an informed decision
 - We can recruit additional patients if we need to explore further
- The clinicians response:
 - But my dose escalation has enrolled more than 50 patients
 - If I used 3+3 I could do this with just 12 patients!
 - **This approach is not efficient!**

Lost in translation

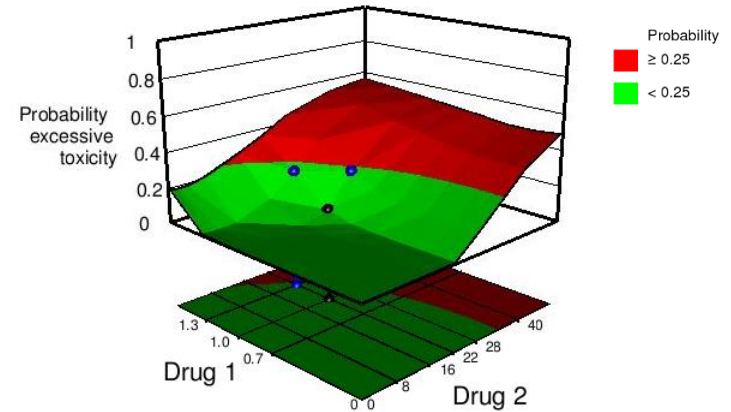
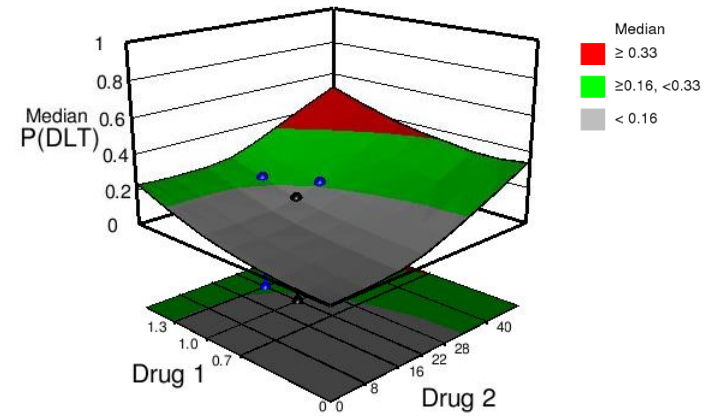
- Don't assume we have a common understanding
- Need to develop a shared vocabulary
- These aren't necessarily statistical concepts
- But clear communication is important

Beyond single agent

- Dual combination
 - More complex visualizations
- Triple (or more!) combinations
 - How to maintain simplicity and clarity of communication?

P(Excessive toxicity)

		Drug 2 (mg)				
		8	16	22	28	40
Drug 1 (mg)	0.7	0.00	0.00	0.01	0.15	0.40
	1.0	0.00	0.00	0.05	0.23	0.45
	1.3	0.01	0.09	0.21	0.35	0.50



Combination dose escalation

Drug-drug interaction

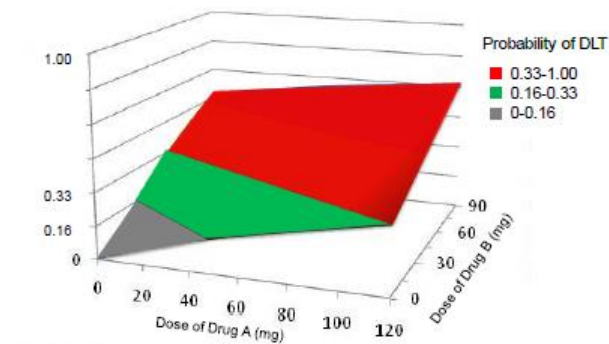
$$odds(\pi_{A(dA)B(dB)}) = odds(\pi^0_{A(dA)B(dB)}) \exp(\eta)$$

- Flexible model, allowing for DDI
- DDI is modeled as an odds multiplier
 - How to translate this concept for a non-statistical audience?

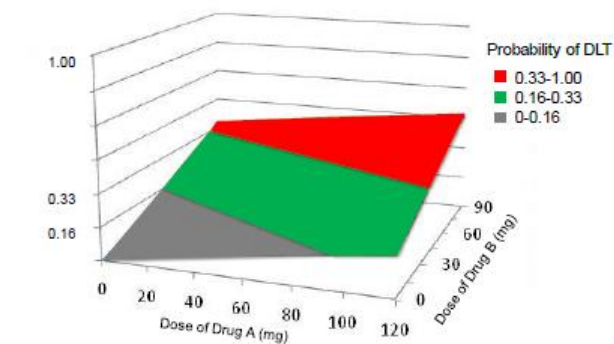
Combination dose escalation

Drug-drug interaction

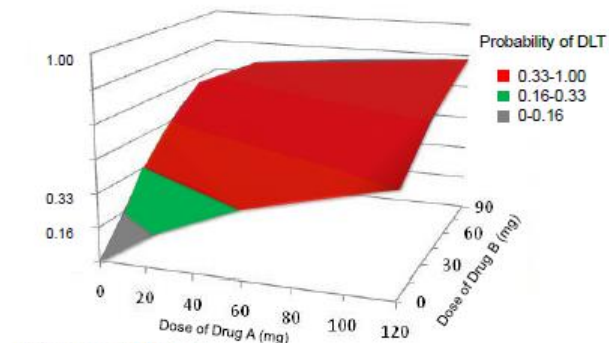
$$\text{odds}(\pi_{A(dA)B(dB)}) = \text{odds}(\pi^0_{A(dA)B(dB)}) \exp(\eta)$$



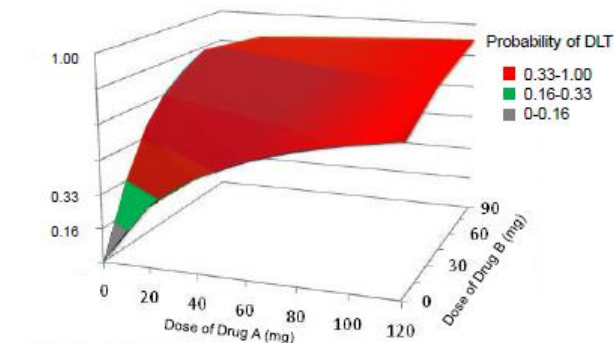
No interaction, $\eta = 0$



Antagonism, $\eta = -0.5$



Moderate synergism, $\eta = 2$



Strong synergism, $\eta = 5$

Combination dose escalation

Drug-drug interaction

$$odds(\pi_{A(dA)B(dB)}) = odds(\pi^0_{A(dA)B(dB)}) \exp(\eta)$$

- Here DDI is introduced on a safety scale
 - Perhaps our colleagues are more accustomed to thinking of DDI in terms of PK rather than safety
 - Not the same, but not unrelated - PK interaction may inform safety interaction

Combination dose escalation

Drug-drug interaction

$$odds(\pi_{A(dA)B(dB)}) = odds(\pi^0_{A(dA)B(dB)}) \exp(\eta)$$

■ New challenge:

- How do we help teams better understand and interpret our interaction parameter?
- How do we elicit prior distributions
- Do we look for more complex statistical solutions?
 - Do we even need to 'tease apart' PK and safety interaction? Or is it enough that we have a flexible model to guide escalation?

Summary

- The move to Bayesian model based dose escalations shows how we can motivate change by:
 - Engaging colleagues
 - Demonstrating tangible advantages for the team, and for patients
 - Use conceptual thinking to help the team understand a more challenging design
- Good communication requires:
 - Engagement
 - Ingenuity
 - Constant refinement
 - Hard work!

References

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- Bailey, Neuenschwander, Laird, Branson. A Bayesian case study in oncology phase I combination dose-finding using logistic regression with covariates. *JBS* 2009
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- Sessa C, Shapiro GI, Bhalla KN, Britten C, Jacks KS, Mita M, Papadimitrakopoulou V, Pluard T, Samuel TA, Akimov M, Quadt C, Fernandez-Ibarra C, Lu H, Bailey S, Chica S, Banerji U. First-in-human phase I dose-escalation study of the HSP90 inhibitor AUY922 in patients with advanced solid tumors. *Clin Cancer Res.* 2013 Jul 1;19(13):3671-80.