Adaptive incorporation of animal data into phase I trials: a robust Bayesian meta-analytic approach

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Motivation



- * Current approaches use preclinical data only to determine a maximum starting dose
- * Goal: Formal incorporation of preclinical data into phase I first-in-man trials



Context:

- \star Let *i* label the historical animal studies, *i* = 1, ..., *M*
- * J_i doses for evaluation: d_{i1}, \ldots, d_{iJ_i}
- * binary endpoint: toxicity or no-toxicity

Two-parameter logistic regression model: for $j = 1, \ldots, J_i$,

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- * **Historical data** \Rightarrow predict for **new** dose-toxicity parameters $\theta_{i^*} = (\theta_{1i}, \theta_{2i})$
 - Exchangeability: $\theta_{i^{\star}}, \theta_{1}, \dots, \theta_{M} | \mu, \Psi \sim \mathsf{BVN}(\mu, \Psi)$
- ★ Main challenge for using historical animal data \Rightarrow new $\theta_{i^{\star}}$ in a human trial
 - ► the "interesting" region may be defined on very different dose intervals



Translating an animal dose-toxicity curve



* Solution: translate the animal dose-toxicity data onto a common scale



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Thus, for *M* historical animal studies,

$$\operatorname{logit}(p_{ij}) = \theta_{1i} + \exp(\theta_{2i}) \log(\frac{\delta_{A_i}}{d_{ij}} d_{Ref}),$$

where δ_{A_i} index the species used in historical study $i = 1, \ldots, M$.

Let i^* label the **new first-in-man trial**. We have

$$\operatorname{logit}(p_{i^{\star}j}) = \theta_{1i^{\star}} + \exp(\theta_{2i^{\star}}) \log(d_{i^{\star}j}/d_{\operatorname{Ref}}).$$

This translation parameter δ_{A_i} leads to a feasible assumption of exchangeability:

$$\boldsymbol{\theta}_1,\ldots,\boldsymbol{\theta}_M,\boldsymbol{\theta}_{i^\star}|\boldsymbol{\mu},\boldsymbol{\Psi}\sim\mathsf{BVN}(\boldsymbol{\mu},\boldsymbol{\Psi})$$



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However, knowing $A_i \in \{S_1, \ldots, S_K\}$, what if predictability of the human toxicity may vary across animal species?

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$$\begin{split} \theta_1 | \boldsymbol{\mu}_{S_1}, \Psi &\sim \mathsf{BVN}(\boldsymbol{\mu}_{S_1}, \Psi), \\ \theta_2, \theta_3, \theta_4 | \boldsymbol{\mu}_{S_2}, \Psi &\sim \mathsf{BVN}(\boldsymbol{\mu}_{S_2}, \Psi), \\ \theta_5, \theta_6 | \boldsymbol{\mu}_{S_3}, \Psi &\sim \mathsf{BVN}(\boldsymbol{\mu}_{S_3}, \Psi). \end{split}$$

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Moreover,

 $\boldsymbol{\mu}_{\mathcal{S}_1}, \boldsymbol{\mu}_{\mathcal{S}_2}, \boldsymbol{\mu}_{\mathcal{S}_3} | \boldsymbol{\textit{m}}, \boldsymbol{\Sigma} \sim \mathsf{BVN}(\boldsymbol{\textit{m}}, \boldsymbol{\Sigma}).$

- \star K random-effects distributions for sharing info between studies
- * One 'supra-species' random-effects distribution for sharing info across species



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- \star K random-effects distributions for sharing info between studies
- * One 'supra-species' random-effects distribution for sharing info across species
- * This model accounts for both between-study and between-species heterogeneity

Relating the new parameters θ_{i^*} with historical parameters θ_i s:

* Permitting borrowing from each animal species S_k , we define

 $\theta_{i^{\star}}|\mu_{S_{k}},\Psi\sim \mathsf{BVN}(\mu_{S_{k}},\Psi)$ with prior probability $w_{S_{k}}$.

 $\star\,$ For the purpose of robustification, we stipulate

 $\theta_{i^{\star}} \sim \text{BVN}(\boldsymbol{m}_0, R_0)$ with prior probability w_R ,

where $w_R = 1 - \sum_{k=1}^{K} w_{S_k}$.



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Our hierarchical model is completed by specifying priors for the hyperparameters

- \star Weakly informative priors for the population means in μ_{S_k} , $m{m}$
- $\star\,$ Half-normal priors for the variance parameters in $\Psi,\,\Sigma$
- $\star\,$ Uniform priors for the correlation coefficients in $\Psi,\,\Sigma$



One common practice for dose conversion is to perform Allometric scaling.

- * Normalise body weight (BW) to body surface area (BSA)
- * FDA fomulated the calculation of human equivalent dose (HED)

$$\mathsf{HED} \; (\mathsf{mg/kg}) = \mathsf{Animal \; dose \; } (\mathsf{mg/kg}) \times \frac{(\mathsf{BW/BSA})_{\mathcal{A}}}{(\mathsf{BW/BSA})_{\mathcal{H}}}$$



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- \star Uncertainty usually surrounds the translation factor when treated as a fixed constant
- * We consider a log-normal prior, $\delta_{\mathcal{A}_i} \sim LN(\lambda, \gamma^2)$



Prior specification for δ_{A_i}

Species	B	W (kg)	BSA (m ²)	HED in	mg/kg	HED in	${\rm mg}/{\rm m}^2$
•	Reference	Working range	- ()	λ	γ	λ	γ
Mouse	0.02	(0.011, 0.034)	0.007				
Rabbit	1.80	(0.900, 3.000)	0.150				
Dog	10	(5, 17)	0.500				



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Specifying $\delta_{A_i} \sim LN(\lambda, \gamma)$ based on an optimiser:

- BW is commonly modelled using log-normal distribution in Biometrics literature
- We then calibrate the log-normal distributions so that the 2.5th, 50th and 97.5th percentiles are in good agreement with the reference and working range
- SSA is assumed to have negligible variation in adult animals and humans
- Find the log-normal distributions for both $(BW/BSA)_A$ and $(BW/BSA)_H$
- Depending on the unit of human dose, $\delta_{A_i} \sim LN(\lambda, \gamma^2)$ is therefore determined



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Species	B	W (kg)	BSA (m ²)	HED in	mg/kg	HED in	${\rm mg}/{\rm m}^2$
	Reference	Working range		λ	γ	λ	γ
Mouse	0.02	(0.011, 0.034)	0.007	-2.562	0.298	1.050	0.283
Rabbit	1.80	(0.900, 3.000)	0.150	-1.127	0.290	2.485	0.274
Dog	10	(5, 17)	0.500	-0.616	0.301	2.996	0.286

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- BW is commonly modelled using log-normal distribution in Biometrics literature
- We then calibrate the log-normal distributions so that the 2.5th, 50th and 97.5th percentiles are in good agreement with the reference and working range
- BSA is assumed to have negligible variation in adult animals and humans
- Find the log-normal distributions for both $(BW/BSA)_A$ and $(BW/BSA)_H$
- Depending on the unit of human dose, $\delta_{A_i} \sim LN(\lambda, \gamma^2)$ is therefore determined



An anti-cancer therapy AUY922 is to be evaluated with a phase I first-in-man trial.

- \star Aim: augment the phase I trial with animal data to estimate the target dose, TD25
- * Historical animal data were collected from 3 dog studies
- $\star\,$ Available human doses include 2, 4, 8, 16, 22, 28, 40, 54, 70 $\rm mg/m^2$





Prior and toxicity scenarios



- * Simulated 2000 phase I dose-escalation trials (15 cohorts of 3 patients per trial)
- * Interim dose recommendations using animal & accumulating human toxicity data

IDEAS

We are interested in 4 analysis models for the comparison

- (i) Model A: Fully exchangeability between θ_i s and θ_{i^*} ($w_R = 0$)
- (ii) Model B: High level of prior confidence in exchangeability assumption ($w_R = 0.3$)
- (iii) Model C: Prior ambivalence about exchangeability assumption ($w_R = 0.5$)
- (iv) Model D: No borrowing of information from preclinical data ($w_R = 1$)



Analysis model 🔺 A 🔺 B 🔺 C 🔹 D





Simulation results

Analysis model 🔺 A 🔺 B 🔺 C 🔹 D





- \star We proposed a Bayesian meta-analytic approach for data augmentation
- $\star\,$ By introducing the possibility of non-exchangeability, our proposal can
 - alleviate potential prior-data conflict
 - ► allow for robust borrowing of information from animals to humans
- \star Dose-escalation procedure based on the proposed model is safe and ethical
- * It is not limited to a particular setup, but can be applied more broadly
 - ▶ synthesising data that have been recorded on a different measurement scale.



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