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Bayesian Model Comparison for Dose Response Studies

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- Expository work on recent developments on BMCPMod by Frank Fleischer, Sebastian Bossert, Qiqi Deng, Christina Loley, Jana Gierse (2022) *Pharmaceutical Statistics*.
- MCPMod is well established statistical method. BMCPMod is a Bayesian extension to MCPMod where we assume prior distribution on the mean response.
- No GSK clinical trial data were used. Simulated data has been used for this project.

- 1 Drug Development
- 2 Introduction to Dose Response
 - Pairwise comparison and ANOVA
 - Model-Based comparison
 - Dose Response Models
- 3 Model Comparison Procedure and Modelling method
- 4 Bayesian Model Comparison Procedure and Modelling method
- 5 Simulation Study

Drug Development

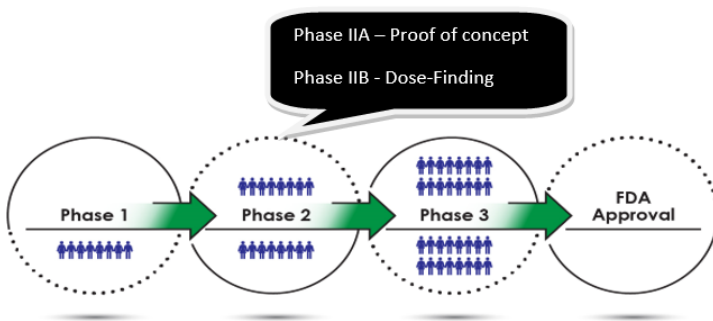


Figure: Drug Development

Why Phase II trials are important?

- Historically initially marketed drugs have later been recognized as excessive doses.
- It is believed by many that high attrition rate in Phase III is largely driven by inadequate dose selection.
- Selection of dose(s) to advance into the Phase III is one of the most challenging decisions during drug development.
- Dose response studies have a huge impact on dose selection process for the success of Phase III trial.
- It reduces the resources/cost/time.

Key Definitions



- **Dose** is the amount of drug administered to achieve a desired benefit (e.g., 500mg paracetamol).
- **Response** is an observation or effect shown by body to the drug.
- **MED** (Minimum Effective Dose) is the smallest dose above which a desired efficacy outcome is obtained.
- **MTD** (Maximum Tolerated Dose) is the dose beyond which the drug cannot be tolerated (due to high safety signals). Doses below the MTD are safe.
- **Therapeutic window:** If $MED < MTD$ then the interval (MED, MTD) is called the Therapeutic window. Doses can be prescribed in this window and optimal dose(s), if any, should lie in this window.

Objectives



- ① To understand the underlying dose response relationship
- ② To identify MED, intermediate dose(s) and MTD.
- ③ To find an optimal dose for Phase III that will be
 - high enough to be effective yet
 - low enough to have acceptable safety

ANOVA



ANOVA Test

- ① Step1: Testing the difference between means of different dose groups.
 - Hypotheses:
 - $H_0 : \mu_1 = \mu_2 = \dots = \mu_4$
 - $H_a : \mu_l \neq \mu_m$, where μ_l and μ_m are two sample means out of all samples.
- ② Step2: Post hoc Tests
 - If H_0 is rejected then proceed with pairwise comparison of mean response and compare it with adjusted critical value.

ANOVA



Limitations of ANOVA approach

- Doses are considered as qualitative factor in traditional ANOVA approach.
- This leads us selecting dose more or less than the actual dose required.
- It has a very vague idea about the shape of the dose response relationship.
- In Anova the means are joined by straight line. We can observe an un-smooth fit.
- For a better understanding of dose response relationship modelling approach is required in Dose Finding.

Model-Based comparison



- The modelling approach to dose finding is based on an assumed functional relationship between the response and the dose, treated as a quantitative variable.
- The model fitted is used to test for the presence of dose response and to estimate an adequate dose(s) to achieve a desired response



Dose Response Models



- Model: $f(d, \theta) = \theta_0 + \theta_1 f^0(d, \theta^0)$
- Emax Model: $E_0 + E_{\max} \frac{d}{(ED_{50} + d)}$
- Linear Model: $E_0 + \delta d$
- Exponential Model: $E_0 + E_1 \exp(\frac{d}{\delta})$
- Logistic Model:

$$E_0 + E_{\max} \frac{1}{(1 + \exp[\frac{ED_{50} - d}{\delta}])}$$

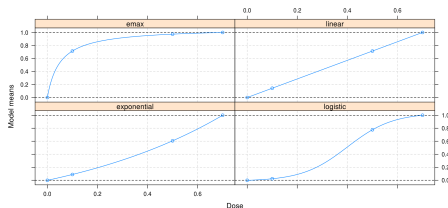


Figure: Dose Response Models

MCP-Mod method



- Multiple Comparison Procedure - Modelling (MCP-Mod) Technique approach was proposed by Bretz, Pinheiro, and Branson (2005) and was approved by FDA.
- **MCP-Mod** combines both into single method
 - 1 MCP Stage: Select best model(s) with appropriate contrasts controlling FWER from a class of candidate models.
 - 2 Mod Stage: Model using best model and find target dose(s) of interest.

MCP-Mod method

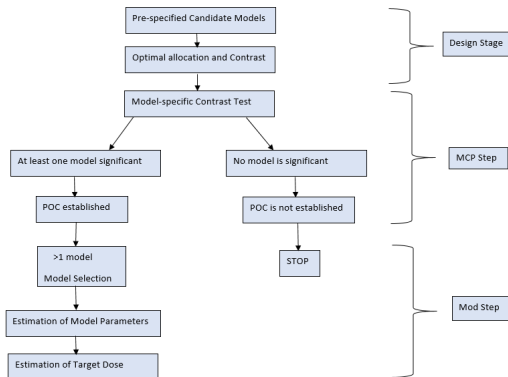


Figure: MCPMod - Overview



MCP-Mod method



- Response Y_{ij} is observed for a set of parallel groups of patients.
- k active doses groups: d_1, \dots, d_k plus placebo dose group: $d_0 \rightarrow k + 1$ groups.

$$Y_{ij} = \mu_{d_i} + \epsilon_{ij}, \quad \epsilon_{ij} \stackrel{\text{i.i.d}}{\sim} N(0, \sigma^2) \quad i = 0, \dots, k, j = 1, \dots, n_i$$

- μ_{d_i} : is the mean dose response at different dose levels d_0, \dots, d_k
- n_i cohort size of each dose group d_i
- ϵ_{ij} : Error term; assumed to be independent and identically distributed.
- Mean dose response is represented as $u_{d_i} = f(d_i, \theta)$ for some dose-response model $f(\cdot)$.
- θ : parameter vector of the unknown dose-response model f .



MCP-Mod method



- The main aim is to find the best-fitting model(s) from the set of candidate models.
- Null hypotheses

$$H_0^m : c'_m \boldsymbol{\mu} = 0$$

for all $m \in \{1, 2, \dots, M\}$ for some contrast c_m such that $\sum c_{mi} = 0$

- Alternative Hypotheses

$$H_1^m : c'_m \boldsymbol{\mu} \neq 0$$

for at least one $m \in \{1, 2, \dots, M\}$

- Single contrast test for testing the m^{th} model:

$$T_m = \frac{c'_m \bar{Y}}{\sqrt{S^2 \sum_{i=1}^k c_{mi}^2 / n_i}}, \quad m = 1, \dots, M$$

MCP-Mod method



- If H_1 is true for any model m then T_m follows non-central t-distribution with non-centrality parameter.
- A significance test for the above hypotheses testing:

$$T_{\max} = \max_{m \in \{1, 2, \dots, M\}} T_m.$$

- If $T_{\max} \geq q$, a significant dose response signal is established.
- q is the adjusted critical value.
- If POC is not established, that is, no significant model \Rightarrow stop.
- If at least one model is significant, we choose the "best" model out the set of candidate models (this the model selection approach, the model averaging approach can also be followed).

Optimal Contrast



- Optimal contrast maximizes the chance of rejecting the associated null hypothesis, that is maximizes the non-centrality.
- Under balanced sample size allocation $n_i = n$, $i = 0, 1, \dots, k$

$$\begin{aligned}c_m &= \frac{\mu - \bar{\mu}\mathbf{1}}{\|\mu - \bar{\mu}\mathbf{1}\|} \\ &= \frac{\mu^0 - \bar{\mu}^0\mathbf{1}}{\|\mu^0 - \bar{\mu}^0\mathbf{1}\|}\end{aligned}$$

- μ^0 is vector of standardized mean dose response.



BMCP-Mod method



- Bayesian-MCPMod approach

$$Y_{ij} = \mu(d_i) + \epsilon_{ij}, \quad \epsilon_{ij} \stackrel{\text{i.i.d}}{\sim} N(0, \sigma^2) \quad i = 0, \dots, k, j = 1, \dots, n_i$$

- Prior is considered as normal distribution

$$\mu \sim \mathcal{N}_{K+1} \left(\theta_0, \frac{\sigma^2}{n_0} I \right)$$

- Posterior μ is

$$\mu_i \mid \mathcal{Y} \sim \mathcal{N} \left(\frac{\frac{\theta_0}{\sigma^2/n_{0,i}} + \frac{\bar{Y}_i}{\sigma^2/n_i}}{\frac{n_{0,i}}{\sigma^2} + \frac{n_i}{\sigma^2}}, \frac{1}{\frac{n_{0,i}}{\sigma^2} + \frac{n_i}{\sigma^2}} \right) = \mathcal{N} \left(\frac{n_{0,i}\theta_{0,i} + n_i\bar{y}_i}{n_{0,i} + n_i}, \frac{\sigma^2}{n_{0,i} + n_i} \right)$$



BMCP-Mod method



- Placebo group: $\mu_{d_0} \sim w_1 N(\theta_{0,0,1}, \sigma^2/n_{0,0,1}) + \dots + w_4 N(\theta_{0,0,4}, \sigma^2/n_{0,0,4})$
- Active dose groups: one component conjugate normal prior

$$\mu \sim w_1 \cdot \mathcal{N} \left(\begin{pmatrix} \theta_{0,0,1} \\ \theta_{0,1} \\ \vdots \\ \theta_{0,K} \end{pmatrix}, \begin{pmatrix} \frac{\sigma^2}{n_{0,0,1}} & \frac{\sigma^2}{n_{0,1}} & \dots & \frac{\sigma^2}{n_{0,K}} \end{pmatrix} I \right) + \dots +$$

$$w_L \cdot \mathcal{N} \left(\begin{pmatrix} \theta_{0,0,4} \\ \theta_{0,1} \\ \vdots \\ \theta_{0,K} \end{pmatrix}, \begin{pmatrix} \frac{\sigma^2}{n_{0,0,4}} & \frac{\sigma^2}{n_{0,1}} & \dots & \frac{\sigma^2}{n_{0,K}} \end{pmatrix} I \right)$$



BMCP-Mod method



$$\mu \mid \mathcal{Y} \sim w_1^* \mathcal{N} \left(\begin{pmatrix} \frac{n_{0,0,1}\theta_{0,0,1}+n_0\bar{Y}_0}{n_{0,0,1}+n_0} \\ \frac{n_{0,1}\theta_{0,1}+n_1\bar{Y}_1}{n_{0,1}+n_1} \\ \vdots \\ \frac{n_{0,K}\theta_{0,K}+n_K\bar{Y}_K}{n_{0,K}+n_K} \end{pmatrix}, \left(\frac{\sigma^2}{n_{0,0,1}+n_0} \cdots \frac{\sigma^2}{n_{0,K}+n_K} \right) I \right) + \dots +$$

$$w_L^* \cdot \mathcal{N} \left(\begin{pmatrix} \frac{n_{0,0,4}\theta_{0,0,4}+n_0\bar{Y}_0}{n_{0,0,1}+n_0} \\ \frac{n_{0,1}\theta_{0,1}+n_1\bar{Y}_1}{n_{0,1}+n_1} \\ \vdots \\ \underbrace{\frac{n_{0,K}\theta_{0,K}+n_K\bar{Y}_K}{n_{0,K}+n_K}}_{\theta_4} \end{pmatrix}, \underbrace{\left(\frac{\sigma^2}{n_{0,0,4}+n_0} \cdots \frac{\sigma^2}{n_{0,K}+n_K} \right) I}_{\tau_4} \right)$$



BMCP-Mod method



$$\mathbf{c}_m^T \boldsymbol{\mu} \mid \mathcal{Y} \sim \underbrace{w_1^* \mathcal{N} \left(\mathbf{c}_m^T \boldsymbol{\theta}_y^1, \sum_{i=0}^K c_{m,i}^2 \tau_1[i, i] \right)}_{\sim Z_1} + \cdots + \underbrace{w_4^* \mathcal{N} \left(\mathbf{c}_m^T \boldsymbol{\theta}_y^4, \sum_{i=0}^K c_{m,i}^2 \tau_4[i, i] \right)}_{\sim Z_4}$$

$$\begin{aligned} P(\mathbf{c}_m^T \boldsymbol{\theta} > 0 \mid \mathcal{Y}) &= \sum_{l=1}^4 w_l^* \cdot P(Z_l > 0), \\ &= \sum_{l=1}^4 w_l^* \Phi \left(\frac{\mathbf{c}_m^T \boldsymbol{\theta}_y^l}{\sqrt{\sum_{i=0}^K c_{m,i}^2 \tau_l^2[i, i]}} \right) = p_m^y. \end{aligned}$$

Significant test is established if $p^* = \max_{m=1, \dots, M} p_m^y$ is greater than an adjusted critical value $1 - \alpha^*$.

Simulation Study



Example:

- $k = 4$ active dose groups and a placebo group:
 $d_0 = 0, d_1 = \frac{1}{30}, d_2 = \frac{3}{30}, d_3 = \frac{10}{30}, d_4 = 1$
- Standard deviation $\sigma = 1.1$
- $M = 6$ candidate models
 - Three different Emax models
 - One Exponential model
 - One Linear model
 - One Logistic model
- $\alpha = 0.05$
- Overall sample size $n = 300$

Simulation Study

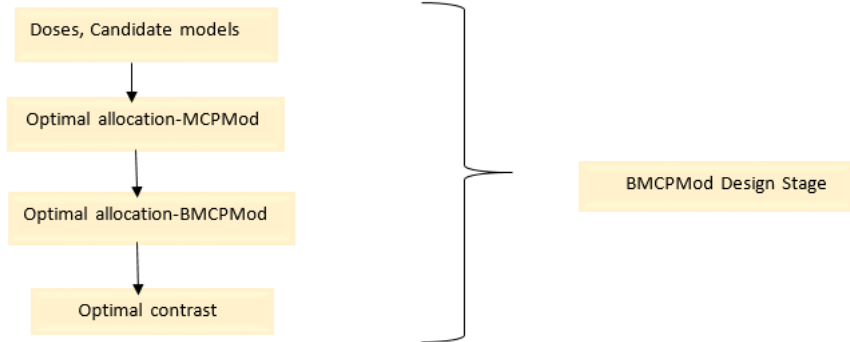


Figure: BMCPMod Design Stage

Simulation Study



Prior Information:

- **Placebo group** has three different conjugate priors

prior	weights	Mean($\theta_{0,0,i}$)	ESS($n_{0,0,i}$)	ESS_{elir}
informative	0.5	0	30	9.5
weakly informative 1	0.25	0.25	2	
weakly informative 2	0.25	-0.25	2	

Table: Placebo prior information

- We consider vaguely informative prior for active groups.
- **active dose groups:** prior mean: $\theta_{0,i} = 0$, ESS: $n_{0,i} = 1$

Expected local-information-ratio effective sample size

- $ESS_{elir} = E_{\mu} \left(\frac{i(p(\mu))}{i_F(\mu)} \right)$
- $i_F(\mu) = - \sum_i n_i E \left(\frac{\partial^2}{\partial \mu^2} \log f(y_{i1} | \mu) \right)$ is the Fisher information of the sampling model
- $i(p(\mu)) = - \frac{d^2 \log p(\mu)}{d\mu^2}$ is the prior distribution of μ .
- If the prior is a k components mixture distribution, $p(\mu) = \sum_{j=1}^K w_j p_j(\mu)$
- ESS_{elir} is calculated using function `ess` of RBest package in R.

Optimal allocation



- Experimental optimal design is represented as

$$\xi = \{(d_1 \cdots d_k), (w_1 \cdots w_k)\}$$

- Fishers Information matrix is $M(\xi, \theta) = \sum_{i=1}^k w_i \frac{\partial f(d, \theta)}{\partial \theta} \frac{\partial f(d, \theta)^T}{\partial \theta}$
- D-optimal Design using General Equivalence Theorem (GET)
 - Design maximizes $\log\{\det[\mathbf{M}(\xi)]\}$
 - $d(x, \xi) = f(x)^T [\mathbf{M}(\xi)]^{-1} f(x) \leq p$
- Optimal allocation is calculated using function `optDesign` of `DoseFinding` package in R.

Simulation Study



- Optimal allocation for MCPMod:

Dose	0	$\frac{1}{30}$	$\frac{3}{30}$	$\frac{10}{30}$	1
N=300	80	33	44	48	95

- Optimal allocation for BMCPMod:

Dose	0	$\frac{1}{30}$	$\frac{3}{30}$	$\frac{10}{30}$	1
N=300	72	34	46	50	98

Optimal Contrast



- Optimal contrast for unbalanced sample size:

$$\mathbf{c}_m \propto \mathbf{S}^{-1} \left(\boldsymbol{\mu}_m^0 - \frac{\boldsymbol{\mu}_m^{0'} \mathbf{S}^{-1} \mathbf{1}}{\mathbf{1}' \mathbf{S}^{-1} \mathbf{1}} \mathbf{1} \right)$$

- $\boldsymbol{\mu}_m^0$ is the vector of standardized mean dose response.
- $\mathbf{S} = \text{diag}(n_0, n_1, \dots, n_k)$ is the matrix of inverse of the cohort sizes.
- We normalize the optimal contrast so that $\|\mathbf{c}_m\| = 1$.

Simulation Study



Optimal contrast for BMCPMod allocation:

	E _{max1}	E _{max2}	E _{max3}	exponential	logistic	linear
0	-0.685	-0.837	-0.613	-0.379	-0.499	-0.425
0.03	-0.182	-0.006	-0.204	-0.172	-0.229	-0.186
0.1	-0.021	0.142	-0.094	-0.206	-0.262	-0.201
0.33	0.215	0.221	0.174	-0.120	0.231	-0.050
1	0.672	0.480	0.737	0.877	0.759	0.861

Table: BMCPMod Optimal Contrast

Simulation Study



- The posterior probabilities for $M = 6$ models

Models	posterior probabilities
E _{max} 1	0.3107429
E _{max} 2	0.4103961
E _{max} 3	0.2813772
Exponential	0.2122869
Linear	0.2528265
Logistic	0.2225135

Table: Posterior Probabilities

- Adjusted critical value is 0.14823
- $0.4103961 \geq 0.14823$ POC is established.

References



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Thank You