

Bayesian
model choice

J. O'Quigley

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Bayesian model choice for generalized CRM models

John O'Quigley

Bayesian model choice/model selection/model adaptive/assessment/diagnostic

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Refs: Kass and Raftery, Gelfand, Gelfand and Ghosh, others

- Model averaging (Yin and Yuan 2009)
- Patient heterogeneity
- Bridging studies
- Multi-drug problem, partial ordering
- Graded toxicities

Continual Reassessment Method

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- Typically a unique working model is assumed for the underlying true dose-toxicity relationship before the start of the trial:

$$\Pr(Y_j = 1 | X_j = x_j) = \psi(d_i, a) = \alpha_i^a.$$

- Model parameter(s) a sequentially updated after observations on each subject or group of subjects.
- Subject allocation uses current running estimate of MTD.

Simple patient heterogeneity: 2 groups

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- A dose finding study for breast cancer treatment at UVA CC.
- Goal: to determine the MTD of dasatinib.
- Two groups of patients
 - Dasatinib plus capecitabine for paclitaxel-refractory metastatic breast cancer patients (G1)
 - Dasatinib plus fulvestrant for hormone-sensitive, progressive metastatic breast cancer patients (G2)
- G1 patients are more sensitive to dasatinib and may have a higher probability of toxicity.
- G2 patients may have higher MTD than G1 patients.
- It is believed the difference in MTD would not exceed 2 doses.

A 2-group CRM shift model

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Power model for the one-sample CRM model:

$$\psi(x_j, \mathbf{a}) = \alpha_j^{\mathbf{a}} \quad (1)$$

Power model for the two-sample CRM shift model:

$$\psi(x_j, \mathbf{a}) = \alpha_{\phi(i)}^{\mathbf{a}}, i = 1, \dots, k, \phi(i) = i + z_j \Delta(i) \quad (2)$$

where:

- $\Delta(i)$ denotes the doses shifted from dose i and it takes integer value between $-k + 1$ and $k - 1$.
- z_j is an indicator for groups and takes value of 0 or 1.
- $0 < \alpha_m < \alpha_n < 1$ for $m < n$.
- $0 < \mathbf{a} < \infty$.

- If the order of the difference is known, the sign of $\Delta(i)$ is known.
- If $z_j = 0$ group is more sensitive to the treatment, $\Delta(i) \leq 0$.
- If $z_j = 1$ group is less sensitive to the treatment, $\Delta(i) \geq 0$.
- We may be able to limit $\Delta(i)$ to very few values.

Particular situations

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- Bridging studies
- Several prognostic groups: $\Delta_1, \Delta_2, \Delta_3, \dots$,
- Several groups, some having known orderings
- Continuous prognostic variable broken into classes
- Different treatment schedules
- Schedules \times prognostic groups

Illustration of the 2-group CRM shift model

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Log-likelihood for power model is:

$$L_j(\mathbf{a})_{\Delta} = \sum_{i=1}^6 n_{1i(1)} \mathbf{a} \log(\alpha_i) + n_{1i(0)} \log(1 - \alpha_i^{\mathbf{a}}) \\ + \sum_{i=1}^6 n_{2i(1)} \mathbf{a} \log(\alpha_{i-\Delta}) + n_{2i(0)} \log(1 - \alpha_{i-\Delta}^{\mathbf{a}}) \quad (3)$$

where $\Delta=0,1$ or 2 .

$n_{1i(1)}$ = # DLT from G1 patients on dose i

$n_{1i(0)}$ = # non-DLT from G1 patients on dose i

$n_{2i(1)}$ = # DLT from G2 patients on dose i

$n_{2i(0)}$ = # non-DLT from G2 patients on dose i

Sample of trial history from the two-group CRM shift design

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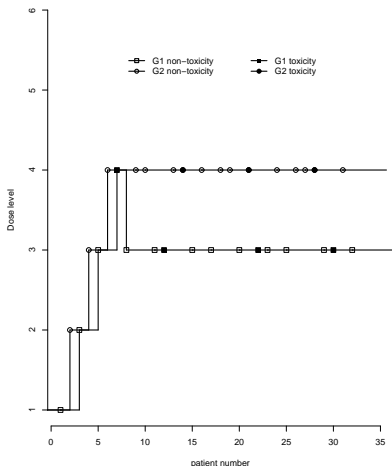
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Four schemes

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- 1 Two-sample CRM shift design
- 2 Two-group two-parameter CRM design
- 3 Two separate studies design
- 4 One single study design, ignoring the group difference

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Target rate =0.20

$\Delta = 0, 1, \text{ or } 2$

Table: Scenarios of probability of toxicity

Scenario	Gr. <i>i</i>	Probability of toxicity $R_i(d_k)$					
A	1	.07	.23	.31	.35	.45	.57
	2	.07	.23	.31	.35	.45	.57
B	1	.08	.20	.35	.50	.70	.80
	2	.01	.05	.18	.40	.55	.70
C	1	.02	.19	.31	.45	.51	.63
	2	.03	.05	.11	.21	.39	.50

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Table: MTD recommendation and in-trial allocation for scenario A

	Group 1						Group 2				
	<i>d</i> 1	<i>d</i> 2	<i>d</i> 3	<i>d</i> 4	<i>d</i> 5	<i>d</i> 6	<i>d</i> 1	<i>d</i> 2	<i>d</i> 3	<i>d</i> 4	<i>d</i> 5
$R_i(d_k)$.07	.23	.31	.35	.45	.57	.07	.23	.31	.35	.45
Proportion of MTD											
Scheme I	.27	.49	.19	.04	.00	.00	.12	.45	.28	.13	.02
Scheme II	.27	.47	.19	.05	.00	.00	.09	.40	.29	.16	.04
Scheme III	.22	.38	.23	.11	.04	.01	.22	.39	.22	.12	.04
Scheme IV	.17	.51	.23	.09	.01	.00	.17	.51	.23	.09	.01
Proportion of Patients											
Scheme I	.35	.38	.19	.06	.02	.00	.19	.33	.25	.15	.06
Scheme II	.35	.33	.19	.07	.03	.02	.17	.29	.26	.15	.08
Scheme III	.31	.29	.20	.11	.06	.03	.31	.29	.20	.11	.06
Scheme IV	.25	.37	.22	.11	.04	.01	.25	.37	.22	.11	.04

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Table: Recommendation and in-trial allocation for scenario B

	Group 1						Group 2				
	$d1$	$d2$	$d3$	$d4$	$d5$	$d6$	$d1$	$d2$	$d3$	$d4$	$d5$
$R_i(d_k)$.08	.20	.35	.50	.70	.80	.01	.05	.18	.40	.55
Proportion of MTD											
Scheme I	.18	.54	.27	.01	.00	.00	.00	.19	.61	.19	.01
Scheme II	.23	.49	.26	.01	.00	.00	.00	.12	.63	.21	.03
Scheme III	.22	.47	.26	.04	.00	.00	.00	.15	.62	.21	.02
Scheme IV	.02	.43	.53	.03	.00	.00	.02	.43	.53	.03	.00
Proportion of Patients											
Scheme I	.24	.40	.29	.06	.01	.00	.07	.22	.43	.22	.05
Scheme III	.32	.35	.25	.05	.02	.01	.06	.17	.44	.23	.08
Scheme II	.30	.33	.24	.09	.03	.01	.10	.20	.41	.20	.07
Scheme IV	.11	.35	.42	.09	.02	.01	.11	.35	.42	.09	.02

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Table: Recommendation and in-trial allocation for scenario C

	Group 1						Group 2				
	<i>d</i> 1	<i>d</i> 2	<i>d</i> 3	<i>d</i> 4	<i>d</i> 5	<i>d</i> 6	<i>d</i> 1	<i>d</i> 2	<i>d</i> 3	<i>d</i> 4	<i>d</i> 5
$R_i(d_k)$.02	.19	.31	.45	.51	.63	.03	.05	.11	.21	.39
Proportion of MTD											
Scheme I	.07	.47	.39	.07	.01	.00	.00	.07	.32	.48	.12
Scheme II	.11	.47	.32	.08	.02	.00	.01	.06	.32	.38	.20
Scheme III	.11	.46	.34	.07	.01	.00	.00	.04	.30	.43	.20
Scheme IV	.01	.23	.55	.19	.02	.00	.01	.23	.55	.19	.02
Proportion of Patients											
Scheme I	.16	.38	.34	.09	.03	.00	.05	.13	.29	.35	.15
Scheme II	.23	.34	.28	.10	.03	.02	.06	.11	.27	.30	.18
Scheme II	.24	.34	.25	.10	.05	.02	.10	.14	.26	.26	.16
Scheme IV	.08	.24	.39	.20	.06	.02	.08	.24	.39	.20	.06

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Table: Simulation results for the shift model with prior probabilities of shifted doses Δ

	Group 1						Group 2					
	d1	d2	d3	d4	d5	d6	d1	d2	d3	d4	d5	d6
$R_i(d_k)$.08	.20	.35	.50	.70	.80	.01	.05	.18	.40	.55	.70
	<i>prior = .33, .33, .33</i>											
% of MTD	.18	.54	.27	.01	.00	.00	.00	.19	.61	.19	.01	.00
% of Patients	.24	.40	.29	.06	.01	.00	.07	.22	.43	.22	.05	.01
	<i>prior = .25, .50, .25</i>											
% of MTD	.10	.56	.32	.01	.00	.00	.00	.12	.66	.21	.01	.00
% of Patients	.22	.44	.29	.04	.01	.00	.06	.19	.48	.22	.04	.01
	<i>prior = .29, .43, .29</i>											
% of MTD	.11	.57	.31	.01	.00	.00	.00	.14	.65	.20	.01	.00
% of Patients	.21	.43	.30	.04	.01	.00	.06	.21	.45	.22	.05	.01
	<i>prior = .17, .50, .33</i>											
% of MTD	.12	.62	.25	.00	.00	.00	.00	.09	.68	.22	.01	.00
% of Patients	.24	.47	.25	.04	.01	.00	.06	.18	.47	.24	.05	.01
	<i>prior = .33, .50, .17</i>											
% of MTD	.09	.58	.33	.01	.00	.00	.00	.15	.65	.19	.01	.00
% of Patients	.20	.44	.31	.04	.01	.00	.06	.22	.46	.22	.04	.00

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Table: Simulation results to compare the shift model and the optimal design for Scenario A

d_k	Group 1						Group 2				
	1	2	3	4	5	6	1	2	3	4	5
R_k	0.07	0.23	0.31	0.35	0.45	0.57	0.07	0.23	0.31	0.35	0.45
$p_k(16)$	0.27	0.49	0.19	0.04	0.00	0.00	0.12	0.45	0.28	0.13	0.02
$q_k(16)$	0.23	0.50	0.14	0.10	0.03	0.00	0.23	0.50	0.14	0.10	0.03

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Table: Simulation results to compare the shift model and the optimal design for scenario B

d_k	Group 1						Group 2				
	1	2	3	4	5	6	1	2	3	4	5
R_k	0.08	0.20	0.35	0.50	0.70	0.80	0.01	0.05	0.18	0.40	0.55
$p_k(16)$	0.18	0.53	0.27	0.01	0.00	0.00	0.00	0.19	0.61	0.19	0.01
$q_k(16)$	0.24	0.55	0.20	0.01	0.00	0.00	0.02	0.13	0.68	0.17	0.00

Phase I study of a combination

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Table: Drug combinations used in Phase 1 trial of Samarium Lexidronam and Bortezomib DLT defined by as a grade 3+ neutropenia (Berenson et al. 2009)

Agent	Drug Combination					
	d_1	d_2	d_3	d_4	d_5	d_6
Sm (mCi/kg)	0.25	0.5	1.0	0.25	0.5	1.0
Bortezomib (mg/m ²)	1.0	1.0	1.0	1.3	1.3	1.3

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- Consider two drugs, A and B , resulting in the treatment combinations.

Agent	Drug Combination					
	d_1	d_2	d_3	d_4	d_5	d_6
A	54	67.5	75	79	84.5	89.5
B	6	6	6	5	7.5	9

- Level d_3 may be more or less toxic than d_4
- There are two possible simple orders (models) consistent with the partial order.
- We index the models by M where M takes value M_h under the h^{th} possible ordering

$$M_1: d_1 \rightarrow d_2 \rightarrow d_3 \rightarrow d_4 \rightarrow d_5 \rightarrow d_6$$

$$M_2: d_1 \rightarrow d_2 \rightarrow d_4 \rightarrow d_3 \rightarrow d_5 \rightarrow d_6$$

Set of possible orders of toxicity probabilities

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Ordering	Simple Order										
M_1	$R(d_1)$	\leq	$R(d_2)$	\leq	$R(d_3)$	\leq	$R(d_4)$	\leq	$R(d_5)$	\leq	$R(d_6)$
M_2	$R(d_1)$	\leq	$R(d_2)$	\leq	$R(d_4)$	\leq	$R(d_3)$	\leq	$R(d_5)$	\leq	$R(d_6)$
M_3	$R(d_1)$	\leq	$R(d_2)$	\leq	$R(d_4)$	\leq	$R(d_5)$	\leq	$R(d_3)$	\leq	$R(d_6)$
M_4	$R(d_1)$	\leq	$R(d_4)$	\leq	$R(d_2)$	\leq	$R(d_3)$	\leq	$R(d_5)$	\leq	$R(d_6)$
M_5	$R(d_1)$	\leq	$R(d_4)$	\leq	$R(d_2)$	\leq	$R(d_5)$	\leq	$R(d_3)$	\leq	$R(d_6)$

Escalation rules

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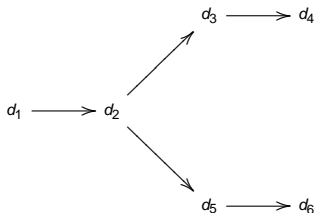
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Agent	Drug Combination					
	1	2	3	4	5	6
Paclitaxel	54	67.5	81	94.5	67.5	67.5
Carboplatin	6	6	6	6	7.5	9



Probability Model

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- Let d_{hi} be the dose combination at level i under ordering h
- We model true probability of toxicity at dose d_{hi} , $d_{hi} \in \{d_1, \dots, d_k\}$ via

$$R(d_{hi}) = \Pr(Y_j = 1 \mid d_{hi}) = E(Y_j \mid d_{hi}) = \psi_h(d_{hi}, \mathbf{a}_h)$$

- Using simple power model:

$$\psi_h(d_{hi}, \mathbf{a}_h) = \alpha_{hi}^{a_h}$$

where $0 < \alpha_{hi} < 1$ and $0 < a_h < \infty$.

- For each ordering, "model", M_h , find \hat{a}_h
- Choose model which maximizes likelihood.
- Can put priors on particular models (orderings).

Inference

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Likelihood under ordering M_h is



$$\phi(\Omega_j | M_h, \mathbf{a}_h) = \prod_{\ell=1}^j \Psi_h^{y_\ell}(\mathbf{x}_\ell, \mathbf{a}_h) \{1 - \Psi_h(\mathbf{x}_\ell, \mathbf{a}_h)\}^{(1-y_\ell)}$$

- For each M_h , $h = 1, \dots, H$, likelihood can be maximized in order to obtain $\hat{\mathbf{a}}_h$, for \mathbf{a}_h .
- Can use informative priors on M_h or discrete uniform



$$f(M_h, \mathbf{a}_h | \Omega_j) \propto \phi(\Omega_j | M_h, \mathbf{a}_h) g(\mathbf{a}_h | M_h) p(M_h)$$

where

$$C = \sum_{h=1}^H \int_{u \in \mathcal{A}} \phi(\Omega_j | M_h, u) g(u | M_h) p(M_h) d(u)$$

Marginal posterior distribution of the ordering, M , by integrating out over \mathbf{a}_h

$$f(M_h | \Omega_j) = \frac{1}{C} p(M_h) \int_{\mathcal{A}} \phi(\Omega_j | M_h, \mathbf{a}_h) g(\mathbf{a}_h | M_h) d\mathbf{a}_h.$$

- Update in the usual way given Ω_j .
- Can use $f(M_h | \Omega_j)$ to sample an ordering (model).

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Dose	d_1	d_2	d_3	d_4	d_5	d_6	n	tox
$R(d_j)$	0.26	0.33	0.51	0.62	0.78	0.86	-	-
Conaway et al.	0.35	0.52	0.11	0.02	0.00	0.00	21.3	8.5
POCRM	0.29	0.50	0.16	0.04	0.01	0.00	22.0	8.4
CRM	0.27	0.49	0.23	0.01	0.00	0.00	22.0	7.9
$R(d_j)$	0.12	0.21	0.34	0.50	0.66	0.79	-	-
Conaway et al.	0.07	0.29	0.42	0.21	0.01	0.00	25.6	9.0
POCRM	0.02	0.23	0.55	0.11	0.10	0.00	26.0	10.0
CRM	0.01	0.18	0.63	0.17	0.01	0.00	25.0	7.5
$R(d_j)$	0.04	0.07	0.20	0.33	0.55	0.70		-
Conaway et al.	0.00	0.02	0.38	0.51	0.08	0.02	28.5	8.8
POCRM	0.00	0.00	0.26	0.50	0.23	0.01	29.0	10.8
CRM	0.00	0.01	0.19	0.67	0.13	0.00	28.0	8.0
$R(d_j)$	0.01	0.04	0.05	0.17	0.33	0.67		-
Conaway et al.	0.00	0.00	0.06	0.25	0.64	0.05	29.0	7.8
POCRM	0.00	0.00	0.01	0.29	0.61	0.09	29.0	9.4
CRM	0.00	0.00	0.00	0.18	0.76	0.06	28.0	6.3
$R(d_j)$	0.01	0.02	0.05	0.15	0.20	0.33		-
Conaway et al.	0.00	0.00	0.01	0.04	0.37	0.59	26.2	5.8
POCRM	0.00	0.00	0.00	0.20	0.12	0.68	27.0	6.4
CRM	0.00	0.00	0.00	0.05	0.26	0.69	27.0	4.3

Probability model for grades

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Using information on grades

- Model $R(d_j)$, the true probability of dose-limiting toxic response for the j^{th} patient via:

$$R(d_j) = \Pr(Y_j = 3|d_j) = \psi(d_j, a) = \alpha_i^a$$

- Model the probability of a grade 2 or grade 3 response by implementing the parameter b :

$$\Pr(Y_j = 2 \text{ or } Y_j = 3|d_j) = \xi(d_j, a, b) = [\alpha_i^a]^b$$

- From which the probability of a grade 2 toxicity is obtained

$$\Pr(Y_j = 2|d_j) = \xi(d_j, a, b) - \psi(d_j, a) = [\alpha_i^a]^b - \alpha_i^a$$

- The probability of a grade 1 toxicity follows:

$$\Pr(Y_j = 1|d_j) = 1 - \xi(d_j, a, b) = 1 - [\alpha_i^a]^b$$

Simulation Results

Bayesian
model choice

J. O'Quigley

Overview

Continual
reassessment
method
Subject
heterogeneity
2 group model

Simulations

Impact of prior

Comparison
with optimal
design

Combination
therapies

Partial ordering of
doses

Models

Simulations

Using information on
grades

Table: Compared Frequency of Final Recommendation of a Standard CRM and a Design Using Known Information on Graded Toxicities ($\theta=0.25$, $n=25$)

	d_1	d_2	d_3	d_4	d_5	d_6
R_k	0.05	0.11	0.22	0.35	0.45	0.60
Standard CRM	0.00	0.13	0.53	0.30	0.04	0.00
CRM using grades	0.00	0.09	0.60	0.29	0.02	0.00