Simple benchmark for planning and evaluating complex dose finding designs

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Cheung (2014). Biometrics 70, 389-397

Agenda

- Dose Finding Trials
 - General background
 - Example: A phase 1/2, Eff-Tox design
- Dose Finding benchmark
 - Applications: Design diagnostic
 - (method comparison; sample size calculation)
 - Discussion

Dose Finding Trials

- Phase I and phase I/II
- Not parallel randomized
- Small-group-sequential: Adapt after every small cohort (e.g. 3)
- General design and analysis strategy
 - Observe a few
 - Estimate a "good" dose (model-based, myopic or not)
 - Treat at the good dose, and observe

Dose Finding Trials

Challenge in planning: Complexity

- Assume programming correct without theoretical guidance
- Pathological properties may not be detected by simulation
- Difficult to reproduce by another statistician, and review the plausibility of the simulation results

Some generality and notation

- A pre-specified set of test levels {1, ..., K}
- Multinomial outcome Y:
 - $-Y_i(k) =$ Outcome for patient *i* at dose level k
 - Take values on L+1 possible values $\{w_0, w_1, ..., w_L\}$
 - Tail distribution $\pi_l(k) = Pr\{Y(k) \ge w_l\}$ for l = 1, ..., L
- Objective: Estimate the target dose $d(\pi)$ in $\{1, ..., K\}$
- Example 1: Phase I trial with binary toxicity Y = 0, 1
 - $-\pi_1(k)$ denotes toxicity probability at dose k
 - $d(\pi) = arg \min_k |\pi_1(k) p|$ for some target *p*.

Example 2:Thrombolytic agent for acute stroke

- Phase 1/2 study
- Trinary outcome (Efficacy-toxicity):
 - Intracranial hemorrhage (Toxicity; Y=2)
 - Reperfusion without hemorrhage (Response; Y=1)
 - Neither (Y=0)
- Thall and Cook (2004):
 - Define desirability $\delta(\pi_E, \pi_T)$ as a function of response rate π_E and toxicity rate π_T
 - Aim to find a dose that maximizes $\delta(\pi_E, \pi_T)$
 - $d_{TC}(\pi) = arg max_k \delta_k$

Example 2: Thrombolytic agent for acute stroke



Example 2:Thrombolytic agent for acute stroke

Thall and Cook (2004):

- Outcome-adaptive
- Bayesian, model-based dose finding method
 - Assign patients at dose with maximum desirability based on interim data, subject to acceptability criteria
 - Consider two dose-response-toxicity models:
 Proportional odds (PO) and Continuation ratio (CR)
- Use simulation at planning: compare models

Simulation results: Which model to use?

Scenario 3

Model	Dose 1	Dose 2	Dose 3	Dose 4	Dose 5
Desirability	-0.48	-0.13	0.22	0.32	-0.26
PO	0	0	20	72	7
CR	0	2	32	49	16

Scenario 4

Model	Dose 1	Dose 2	Dose 3	Dose 4	Dose 5
Desirability	0.12	0.29	0.45	0.58	0.69
РО	0	2	10	34	54
CR✔	0	0	1	5	94
benchmark					9

Which model to use?

- Motivation:
 - Numerical performance from simulation can be difficult to interpret without a benchmark
- Proposal:
 - Dose Finding Benchmark Design

Dose Finding Benchmark

- Goal: A theoretical dose finding design that provides an upper limit of accuracy for any dose finding methods for a given design objective under a given scenario.
- Definition:
 - Recall $d(\pi)$ is the target dose (estimand)
 - Benchmark design: $d(\pi^*)$ where π^* is a nonparametric optimal estimate of π based on <u>complete outcome</u> <u>profile</u>

Complete outcome profile: Example 1

• In an actual trial, we observe a partial outcome profile, e.g., a patient at dose 3 with toxicity

Dose 1	Dose 2	Dose 3	Dose 4	Dose 5
?	?	Toxicity	Toxicity	Toxicity

• In <u>computer simulation</u>, we can observe a complete profile by generating a uniform tolerance

Dose 1	Dose 2	Dose 3	Dose 4	Dose 5
No toxicity	Toxicity	Toxicity	Toxicity	Toxicity

• The nonparametric optimal estimate $\pi^*(k)$ is evaluated by the proportion of toxicity at dose k in a simulated trial

Complete outcome profile: General (inc. Example 2)

- Ordinal outcome Y: Takes values on L+1 possible values $\{w_0, w_1, ..., w_L\}$ with tail distribution $\pi(k)$ at dose k
- $Y_i(k)$ = Outcome for patient *i* at dose level *k*
- In simulation, randomly draw a tolerance profile: U_{il} , U_{i2} , ... U_{iL} iid Uniform(0,1)
- Generate complete outcome profile *Y_i(k)* for patient *i* at dose level *k* as follows:
 - $Y_{i}(k) = w_{l} \text{ if } U_{i,l+1} > r_{l+1}(k) \text{ and } U_{ij} \le r_{j} \text{ for all } j=1,...,l$ - $r_{j}(k) = \pi_{j}(k) / \pi_{j-1}(k)$
- Nonparametric optimal $\pi^*(k)$ = average of $I\{Y_i(k) \ge w_i\}$ benchmark

Thall and Cook (2004), revisit

Scenario 3

Model	Dose 1	Dose 2	Dose 3	Dose 4	Dose 5
Desirability	-0.48	-0.13	0.22	0.32	-0.26
PO	0	0	20	72	7
CR	0	2	32	49	16
d(π*)	0	0	13	85	1

Scenario 4

Model	Dose 1	Dose 2	Dose 3	Dose 4	Dose 5
Desirability	0.12	0.29	0.45	0.58	0.69
РО	0	2	10	34	54
CR✔	0	0	1	5	94
d(π*)	0	0	0	5	95
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Thall and Cook (2004), revisit

Benchmark as "effect size"

- Benchmark d(π*) performs better in S4 than in S3 suggesting S4 is an "easier" scenario than S3; analogous to large effect size in hypothesis test
- Eff-tox using proportional odds model is idiosyncratic in that it does comparatively poorly in an easy scenario (S4).
- Continuation ratio model wins in this example

Benchmark for Method Comparison



Benchmark for "Power" Calculation



Cheung (2013): Sample size formulae for CRM

Summary & Discussion

- The proposed benchmark is applicable to general early phase dose finding settings:
 - Discrete test levels, including combination therapy
 - Multinomial outcome (multiple tox; bivariate; etc)
- Applications: effect size; method comparison; power calculation
- Features of a good benchmark:
 - Easy and quick to compute (not error prone)
 - Nonparametric: not favoring one model over another
 - Upper bound of accuracy for parametric methods