

Design of preclinical combination studies

Alexander Donev and Bader Almohaimeed

University of Manchester, UK

Talk Outline

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What is a drug combination?

Definition of bioassay

Scientific experiment for determining the effect of a compound or other substance.

Drug combination

Medications which contain two, or more, different compounds.

Combinations of drugs

Combinations of drugs may be useful when:

- using one drug is not sufficient to control a disease;
- the required dose is too high and has undesirable side effects;

Pre-clinical experiments

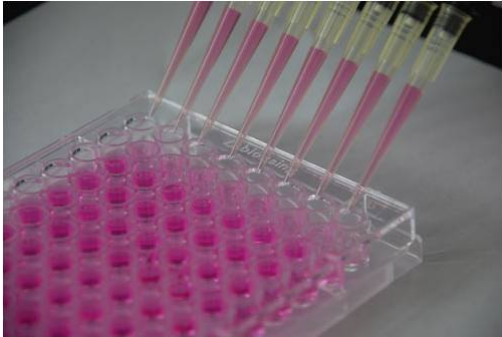
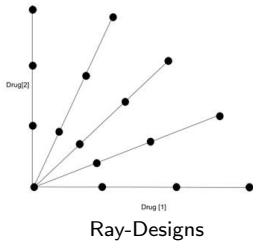


Figure: Typical 96-wells plate

Data structures

- Doses of drugs: d_{ij1} and d_{ij2} , in constant ratios $R_i = d_{ij1}/d_{ij2}$, $i, i = 3, \dots, r, j, j = 1, \dots, c$;
- Response of interest Y_{ij} measured at the doses $x_{ij} = d_{ij1} + d_{ij2}$.

Ray design



The name come from!



Radiating style

Methods for evaluating drug interactions

Combination index

The drug interactions at combination of two drugs can be characterized as

$$\frac{d_1}{D_{y_0,1}} + \dots + \frac{d_2}{D_{y_0,2}} \begin{cases} < 1, & \text{Synergy;} \\ = 1, & \text{Additivity;} \\ > 1, & \text{Antagonism,} \end{cases}$$

- d_i are doses of each drug in the combination of the k drugs resulting in effect y_0 ;
- $D_{y_0,i}$ are the doses of drugs that result in the effect y_0 for each respective drug given alone.

Sources of variability

- occasions
- batches of cultures
- plates
- . . .

Statistical models

Distribution of response

$Y \implies$ Exponential family (EFD)

Nonlinear predictor for each ray

$$\eta(x_{ij}, \boldsymbol{\theta}) = \gamma + \frac{\delta - \gamma}{\left(1 + 10^{(x_{ij} - \alpha_i)\beta_i}\right)^{\lambda_i}},$$

where $\boldsymbol{\theta} = (\alpha_i \beta_i \gamma \delta \lambda_i)$, $i = 1, \dots, r$.

Link function...

between $\eta(x_{ij}, \boldsymbol{\theta})$ and $E[Y] = \mu_{ij} \implies g(\mu_{ij}) = \eta(x_{ij})$.

Hill model (1913)

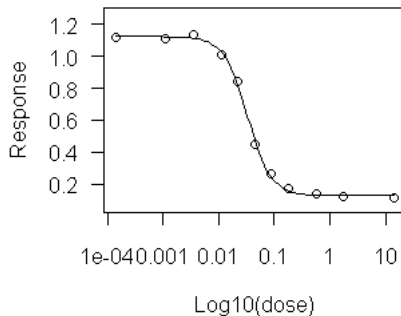
4 parameters

$$Y_{ij} = \gamma + \frac{\delta - \gamma}{1 + 10^{(\alpha_i - x_{ij})\beta_i}} + \varepsilon_{ij}$$

where:

- γ Minimum response
- δ Maximum response
- α LogIC50, or logEC50
- β Hill slope
- ε Experimental error, $\varepsilon \sim N(0, \sigma^2)$

Example of cancer data



Alternative models

Special cases

- Minimum response = 0

$$Y_{ij} = \frac{\delta}{1 + 10^{(x_{ij} - \alpha_i)\beta_i}} + \epsilon_{ij}.$$

- Minimum response = 0 and Maximum response = 1

$$Y_{ij} = \frac{1}{1 + 10^{(x_{ij} - \alpha_i)\beta_i}} + \epsilon_{ij}.$$

- Asymmetric

$$Y_{ij} = \gamma + \frac{\delta - \gamma}{\left(1 + 10^{(x_{ij} - \alpha_i)\beta_i}\right)^{\lambda_i}} + \epsilon_{ij},$$

Nonlinear mixed effects models

Example - all parameters random



$$Y_{ij} = (\gamma + \varepsilon_\gamma) + \frac{(\delta + \varepsilon_\delta) - (\gamma + \varepsilon_\gamma)}{\left(1 + 10^{(x_{ij} - (\alpha + \varepsilon_\alpha))(\beta + \varepsilon_\beta)}\right)^{(\lambda + \varepsilon_\lambda)}} + \epsilon_{ij},$$

- where $\theta_{p_i = \alpha_i, \beta_i, \gamma_i, \delta_i, \lambda_i} \sim EFD(\theta_p, \phi_p)$, and $\epsilon_{ij} \sim EFD(0, \phi)$.
- Related work include: Mentré, Mallet, Baccar (1997), Fedorov, Gagnon, Leonov (2002), Han and Chaloner (2004), Gagnon and Leonov (2005) and Atkinson, A.C. (2008).

Analysis of data

- There are many examples of successful combination studies in the literature, e.g.:
 - ▷ Loewe, S. 1957;
 - ▷ Chou and Talalay, 1984;
 - ▷ Berenbaum MC, 1985;
 - ▷ Faessel, H.M. et al. 1998;
 - ▷ Straetemans R. et al. 2005.
- Extensive discussions of the scientific background of such studies, include:
 - ▷ Berenbaum MC, 1989;
 - ▷ Chou, T. C 1991;
 - ▷ Greco et al. 1995;
 - ▷ Tallarida, R. J. 2000.
 - ▷ Chou, T.C et al. 2006.

Analysis of data

- Recently, there has been substantial interest in the appropriate statistical methods for analysis of data obtained in combination studies including:
 - ▷ Brun YF et al. 2010;
 - ▷ Chou, T. C 2010;
 - ▷ Donev, A. N. 2010;
 - ▷ Fujimoto Junya et. al. 2010;
 - ▷ Kong M et al. 2010;
 - ▷ Lee JJ et al. 2010;
 - ▷ Palomares et al. 2010;
 - ▷ Peterson JJ 2010;
 - ▷ Straetemans R. et al. 2010;
 - ▷ Yan Han et al. 2010;

Analysis of data

- Some of these statistical methods of combination studies have been implemented as statistical packages in the free statistical software R include:
 - ▷ *drc* \implies Analysis of dose-response curves
 - ▷ *grofit* \implies Fitting biological growth curves with R
 - ▷ *dosefinding* \implies Planning and Analyzing Dose Finding experiments
 - ▷ *mixlow* \implies An R Package for Assessing Drug Synergism/Antagonism
- These packages are regularly improved and updated!

Design challenges

- Less attention has been given to the choice of suitable experimental designs for such studies;
- Need to develop the necessary methodology;
- **Need to develop an R package;**

Design challenges

Types of studies

- Single compounds;
- Screening compounds library for combinations - using one design - *population studies*;
- Confirmatory experiments, safety studies, etc;
- Variety of error distributions (normal, binary, Poisson, etc).

Types of models

- Nonlinear (NL);
- Generalized nonlinear (GNL);
- Nonlinear mixed effects (NLME);
- Generalized nonlinear mixed effects (GNLME).

Optimality criteria

- The information matrix

$$\mathbf{M} = \mathbf{X}^T \mathbf{W} \mathbf{X}$$

depends on:

the unknown parameters;

the covariance matrix of the observations \mathbf{W} .

- A common approach is to linearize:

Locally D-optimum design ξ^* :

$$\min |\mathbf{M}^{-1}(\xi, \boldsymbol{\theta})|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

Pseudo-Bayesian D-optimum design ξ^* :

$$\min |\mathbf{M}^{-1}(\xi, \boldsymbol{\theta})|_{\boldsymbol{\theta} \in \boldsymbol{\theta}_0}$$

R package

State

- Early stage of preparation;
- Still developing code;

Search for D-optimum designs for models:

- Nonlinear (NL);
- Generalized nonlinear (GNL);
- Nonlinear mixed effects (NLME);
- Generalized nonlinear mixed effects (GNLME).

Example 1. D-optimum designs for NL and GNL models

Table: Parameters values

| Design | α | β | γ | δ | λ | σ^2 | κ | v | m |
|-----------------|-------------|-------------|----------|----------|-----------|------------|----------|-----|--------------|
| Local | 1.92 | 0.94 | 0.1 | 1.1 | 1.5 | 1 | 0.5 | 1.5 | $2 \times p$ |
| Pseudo-Bayesian | [1.31,3.01] | [0.50,1.15] | 0.1 | 1.1 | 1.5 | 1 | 0.5 | 1.5 | $2 \times p$ |

where

- $\Rightarrow \alpha, \beta, \gamma, \delta$ and λ are models parameters;
- $\Rightarrow \kappa$ and v are parameters of gamma and inverse Gaussian distribution;
- $\Rightarrow m$ is the number of trials in binomial distribution.

Example 1: Locally D-optimum designs

Table: Locally D-optimum designs for Ray 4

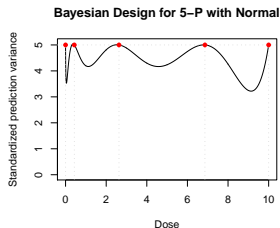
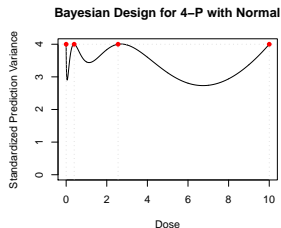
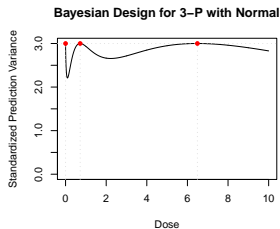
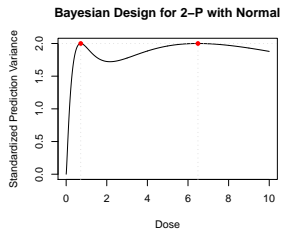
| Model parameter | Design point | Error | | | | |
|-----------------|--------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| | | Normal | Poisson | Binomial | Gamma | I-Gaussian |
| 2-P | 1 | 0.45 | 0.24 | 0.67 | 1.17 | 0.94 |
| | 2 | 5.55 | 2.71 | 7.19 | 10 (<i>max</i>) | 10 (<i>max</i>) |
| 3-P | 1 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0.45 | 0.22 | 0.71 | 1.17 | 0.94 |
| | 3 | 5.56 | 2.52 | 7.51 | 10 (<i>max</i>) | 10 (<i>max</i>) |
| 4-P | 1 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0.24 | 0.15 | 0.25 | 0.41 | 0.36 |
| | 3 | 2.07 | 1.41 | 2.17 | 3.39 | 3.03 |
| | 4 | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) |
| 5-P | 1 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0.24 | 0.14 | 0.10 | 0.16 | 0.13 |
| | 3 | 2.05 | 1.48 | 0.71 | 1.28 | 1.17 |
| | 4 | 6.39 | 5.96 | 2.21 | 5.04 | 4.93 |
| | 5 | 10 (<i>max</i>) | 10 (<i>max</i>) | 5.10 | 10 (<i>max</i>) | 10 (<i>max</i>) |

Example 2: Pseudo-Bayesian D-optimum designs

Table: Pseudo-Bayesian D-optimal designs for Ray 4

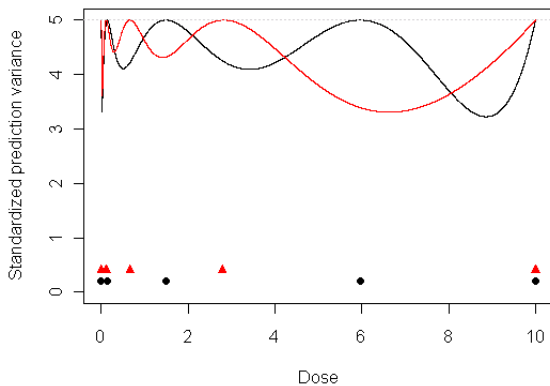
| Model parameter | Design point | Error | | | | |
|-----------------|--------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| | | Normal | Poisson | Binomial | Gamma | I-Gaussian |
| 2-P | 1 | 0.72 | 0.41 | 1.02 | 1.58 | 1.31 |
| | 2 | 6.49 | 3.47 | 8.13 | 10 (<i>max</i>) | 10 (<i>max</i>) |
| 3-P | 1 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0.72 | 0.40 | 1.08 | 1.58 | 1.31 |
| | 3 | 6.49 | 3.27 | 8.45 | 10 (<i>max</i>) | 10 (<i>max</i>) |
| 4-P | 1 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0.40 | 0.27 | 0.42 | 0.65 | 0.57 |
| | 3 | 2.56 | 1.85 | 2.66 | 3.88 | 3.52 |
| | 4 | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) |
| 5-P | 1 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0.43 | 0.15 | 0.18 | 0.28 | 0.25 |
| | 3 | 2.63 | 0.87 | 1.02 | 1.61 | 1.42 |
| | 4 | 6.86 | 3.56 | 3.79 | 5.15 | 4.81 |
| | 5 | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (max) | 10 (<i>max</i>) | 10 (<i>max</i>) |

Verifying D-optimal designs for NLMs using GET

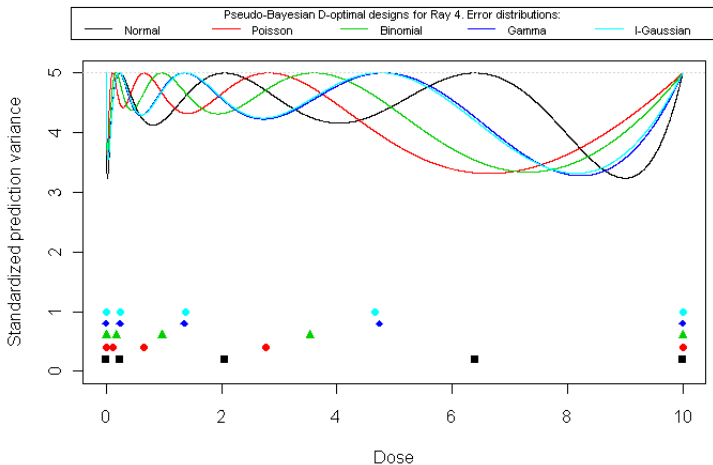


Optimum designs for GNLM with Poisson errors

Local (—) and pseudo-Bayesian (—) D-optimum designs with Poisson distribution



Optimum designs for GNLM models



Example 2. D-optimum designs for NLME and GNLME models

Model assumption:

- the model can be given as

$$Y_{ij} = (\gamma + \varepsilon_\gamma) + \frac{(\delta + \varepsilon_\delta) - (\gamma + \varepsilon_\gamma)}{\left(1 + 10^{(x_{ij} - (\alpha + \varepsilon_\alpha))(\beta + \varepsilon_\beta)}\right)^{(\lambda + \varepsilon_\lambda)}} + \varepsilon_{ij}, \quad (1)$$

- where $\theta_{p_i = \alpha_i, \beta_i, \gamma_i, \delta_i, \lambda_i} \sim EFD(\theta_p, \phi_p)$, and $\varepsilon_{ij} \sim EFD(0, \phi)$.

Optimum designs for GNLME models

5 cases:

- 1 Case 1:
 $\theta_{p_i} \sim N(\theta_p, \sigma_p^2) = ((1.69, 0.84, 2.90, 0.20, 1.5), (0.26, 0.03, 0.76, 0.01, 0.02))$
 $\epsilon_{ij} \sim N(0, \sigma^2) = (0, 0.25)$
- 2 Case 2:
 $\theta_{p_i} \sim \ln N(\theta_p, \sigma_p^2) = ((1.69, 0.84, 2.90, 0.20, 1.5), (0.26, 0.03, 0.76, 0.01, 0.02))$
 $\epsilon_{ij} \sim \ln N(0, \sigma^2) = (0, 0.25)$
- 3 Case 3:
 $\theta_{p_i} \sim \Gamma(\kappa_{\theta_p}, \vartheta_{\theta_p}) = ((1, 0.9, 1, 1, 1), (0.2, 0.3, 1, 0.02, 0.5))$
 $\epsilon_{ij} \sim \Gamma(\kappa_{\epsilon}, \vartheta_{\epsilon}) = (1, 0.5)$
- 4 Case 4:
 $\theta_{p_i} \sim \text{I-G}(\mu_{\theta_p}, \kappa_{\theta_p}) = ((1, 0.9, 1, 0.1, 0.5), (0.1, 0.3, 1, 0.01, 0.02))$
 $\epsilon_{ij} \sim \text{I-G}(\mu_{\epsilon}, \kappa_{\epsilon}) = (0.1, 0.3)$
- 5 Case 5:
 $\theta_{p_i} \sim \ln N(\theta_p, \sigma_p^2)$
 $\theta_{\alpha} \sim \text{Exp}(\lambda_{\alpha}) = (3.2)$

Example 3: Locally D-optimum designs for NLMEM

Table: Locally D-optimal designs for ray 4

| Model parameter | Design point | Case | | | | |
|-----------------|--------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| | | 1 | 2 | 3 | 4 | 5 |
| 4-P | 1 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0.98 | 1.01 | 0.99 | 1.00 | 1.01 |
| | 3 | 5.36 | 5.45 | 5.40 | 5.43 | 5.44 |
| | 4 | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) |
| 5-P | 1 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0.24 | 0.29 | 0.24 | 0.33 | 0.29 |
| | 3 | 1.67 | 1.92 | 1.68 | 2.31 | 1.92 |
| | 4 | 5.47 | 5.92 | 5.28 | 6.67 | 5.95 |
| | 5 | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) | 10 (<i>max</i>) |

Discussion

- Challenges ahead!

Note: This work is part of Bader's PhD thesis and is currently been written up for submission to a journal.

References

- ▶ 96-well picture was taken from:
<http://www.sz-wholesaler.com/p/893/905-1/96-well-cell-culture-plate-406392.html>