Optimal Designs for Prediction in Random Coefficient Regression with One Observation per Individual

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Optimal Designs in RCR with One Observation per Unit

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Motivation

- RCR model with
 - *n* observational units (individuals)
 - One observation per unit
- OD for prediction of *random effects*
- Earlier works
 - P. & Schwabe (2016), etc.:
 number of observations > number of parameters
 - Graßhoff et al. (2012): OD for *fixed effects*

RCR model with one observation per individual MSE for prediction of individual effects

RCR model with one observation per individual

$$Y_i = \mathbf{f}(x_i)^\top \boldsymbol{\beta}_i + \varepsilon_i, \qquad i = 1, .., n, \qquad x_i \in \mathcal{X}$$

- $\mathbf{f} = (f_1, .., f_p)^\top$
- $\boldsymbol{\beta}_i = (\beta_{i1}, ..., \beta_{ip})^\top$ random
 - $E(\beta_i) = \beta_0 \ unknown$
 - $Cov(\beta_i) = \sigma^2 \mathbf{D}$, **D** known, non-singular

•
$$E(\varepsilon_i) = 0$$
, $Var(\varepsilon_i) = \sigma^2$

• All β_i and all $\varepsilon_{i'}$ uncorrelated

Graßhoff et al. (2012): OD for estimation of β_0

This work: OD for prediction of $\mathbf{b}_i = \beta_i - \beta_0$

RCR model with one observation per individual MSE for prediction of individual effects

MSE for prediction of individual effects

Main interest - k selected individuals, $k \in [p, n - p]$

 \rightarrow OD for prediction of $\Psi = \frac{1}{k} \sum_{i=1}^{k} \mathbf{b}_i$

MSE of BLUP $\hat{\Psi}$ for Ψ :

$$\operatorname{Cov}(\hat{\Psi} - \Psi) = \sigma^2 \left(\frac{1}{k} \mathsf{D} - \frac{1}{k^2} \mathsf{D} \mathsf{M}_k \mathsf{D} + \frac{1}{k^2} \mathsf{D} \mathsf{M}_k \mathsf{M}^{-1} \mathsf{M}_k \mathsf{D} \right)$$

$$\mathbf{M} = \sum_{i=1}^{n} \mathbf{M}(x_i) \quad \& \quad \mathbf{M}_k = \sum_{i=1}^{k} \mathbf{M}(x_i)$$
$$\mathbf{M}(x_i) = \mathbf{g}(x_i)\mathbf{g}(x_i)^{\top} \quad \& \quad \mathbf{g}(x_i) = \frac{\mathbf{f}(x_i)}{\sqrt{\mathbf{f}(x_i)^{\top}\mathbf{D}\mathbf{f}(x_i) + 1}}$$

Group designs Linear criterion Linear criterion: The same design in both groups

Two groups of individuals



 $\mathcal{X}_1 = \mathcal{X}_2 = \mathcal{X}$ - particular case

Group designs Linear criterion Linear criterion: The same design in both groups

Group designs

Exact designs

Group 1

Group 2

$$\xi_{1,e} = \begin{pmatrix} x_{11}, \dots, x_{1N_1} \\ m_{11}, \dots, m_{1N_1} \end{pmatrix} \& \xi_{2,e} = \begin{pmatrix} x_{21}, \dots, x_{2N_2} \\ m_{21}, \dots, m_{2N_2} \end{pmatrix}$$

 $x_{1j} \in \mathcal{X}_1$ support of $\xi_{1,e}$ & $x_{2j} \in \mathcal{X}_2$ support of $\xi_{2,e}$

$$\sum_{j=1}^{N_1} m_{1j} = k$$
 & $\sum_{j=1}^{N_2} m_{2j} = n - k$

 $N_1 = |\{x_{11}, \dots, x_{1N_1}\}|$ & $N_2 = |\{x_{21}, \dots, x_{2N_2}\}|$

Group designs Linear criterion Linear criterion: The same design in both groups

Group designs

Approximate designs

$$\begin{array}{ccc} & \text{Group 1} & \text{Group 2} \\ \xi_1 = \begin{pmatrix} x_{11}, \dots, x_{1\tilde{N}_1} \\ w_{11}, \dots, w_{1\tilde{N}_1} \end{pmatrix} & \& & \xi_2 = \begin{pmatrix} x_{21}, \dots, x_{2\tilde{N}_2} \\ w_{21}, \dots, w_{2\tilde{N}_2} \end{pmatrix} \\ \sum_{j=1}^{\tilde{N}_1} w_{1j} = 1, \ \tilde{N}_1 = |\{x_{11}, \dots, x_{1\tilde{N}_1}\}| & \& & \sum_{j=1}^{\tilde{N}_2} w_{2j} = 1, \ \tilde{N}_2 = |\{x_{21}, \dots, x_{2\tilde{N}_2}\}| \end{array}$$

Information matrices

$$\mathsf{M}_{1,\xi} = \sum_{j=1}^{\tilde{N}_1} w_{1j} \mathsf{M}(x_{1j})$$
 & $\mathsf{M}_{2,\xi} = \sum_{j=1}^{\tilde{N}_2} w_{2j} \mathsf{M}(x_{2j})$

For exact designs: $M_k = k M_{1,\xi} \& M = k M_{1,\xi} + (n-k) M_{2,\xi}$ $w_{1j} = m_{1j}/k \& w_{2j} = m_{2j}/(n-k) \& \tilde{N}_\ell = N_\ell, \ell = 1, 2$

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Group designs Linear criterion Linear criterion: The same design in both groups

Linear criterion

L-criterion for prediction of Ψ :

$$\Phi_L = \operatorname{tr}\left(\operatorname{Cov}(\mathcal{L}\hat{\Psi} - \mathcal{L}\Psi)\right)$$

For approximate designs

$$\Phi_{L}(\xi) = -\operatorname{tr}\left[\tilde{\mathsf{L}}\left(\frac{1}{k}\mathsf{M}_{1,\xi}^{-1} + \frac{1}{n-k}\mathsf{M}_{2,\xi}^{-1}\right)^{-1}\right]$$
$$\tilde{\mathsf{L}} = \mathsf{D}\mathsf{L}\mathsf{D} \quad \& \quad \mathsf{L} = \mathcal{L}^{\top}\mathcal{L}$$

The L-criterion is convex with respect to $(M_{1,\xi}, M_{2,\xi})$

Group designs Linear criterion Linear criterion: The same design in both groups

Optimality condition

Design criterion

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Equivalence theorem for multiple-design problems ¹

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Optimality condition



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Group designs Linear criterion Linear criterion: The same design in both groups

Linear criterion: The same design in both groups

If $\mathcal{X}_1 = \mathcal{X}_2 = \mathcal{X}$

Design with $\xi_1 = \xi_2$ may be optimal

L-criterion:

$$\Phi_L(\xi) = -\mathrm{tr}\left[\tilde{\mathsf{L}}\mathsf{M}_{1,\xi}
ight]$$

Optimality condition:

$$\mathbf{g}(x)^{\top} \tilde{\mathbf{L}} \mathbf{g}(x) \leq \operatorname{tr} \left(\tilde{\mathbf{L}} \mathbf{M}_{1,\xi^*} \right), \quad \forall x \in \mathcal{X}$$

- 1) All designs with $\xi_1 = \xi_2$ optimal
- 2) Singular design optimal
- 3) No optimal designs with $\xi_1 = \xi_2$

Example 1: The same design region in both groups Example 2: Different design regions

Examples: Straight line regression

$$Y_i = \beta_{i1} + \beta_{i2} x_i + \varepsilon_i$$

- $f(x) = (1, x)^{\top}$
- $D = \operatorname{diag}(d_1, d_2)$
- A-criterion: $L = \mathbb{I}_p$

Examples:

- Example 1: The same design region in both groups
- Example 2: Different design regions

Example 1: The same design region in both groups Example 2: Different design regions

Example 1: The same design region in both groups

$$Y_i = \beta_{i1} + \beta_{i2} x_i + \varepsilon_i$$

- $\mathcal{X}_1 = \mathcal{X}_2 = [-a, a], a > 0$
- $\xi_1 = \xi_2$

• All observations at endpoints: -a & a

Designs:

$$\xi_1 = \left(\begin{array}{cc} -a & a \\ 1 - w & w \end{array}\right)$$

Example 1: The same design region in both groups Example 2: Different design regions

Example 1: The same design region in both groups

A-criterion:

$$\Phi_{A}(\xi) = -\frac{d_{2}a^{2} + d_{1}^{2}}{d_{2}a^{2} + d_{1} + 1}$$

Ind. of designs

Optimality condition satisfied $\begin{array}{c} \updownarrow \\ \{d_2 \geq \frac{d_1^2}{d_1 + 1}\} \cup \{d_2 = 0\} \\ & \uparrow \\ & \\ All \ w \in [0, 1] \text{ optimal} \end{array}$

Otherwise, no optimal endpoints designs with $\xi_1 = \xi_2$

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Example 1: The same design region in both groups Example 2: Different design regions

Example 2: Different design regions

$$Y_i = \beta_{i1} + \beta_{i2} x_i + \varepsilon_i$$

- $\mathcal{X}_1 = [-1, 1]$ & $\mathcal{X}_2 = [-a, a], a > 0$
- All observations at endpoints: -1 & 1 or -a & a
- In general $\xi_1 \neq \xi_2$

Designs:

$$\xi_1=\left(egin{array}{cc} -1&1\ 1-w_1&w_1\end{array}
ight)$$
 & & $\xi_2=\left(egin{array}{cc} -a&a\ 1-w_2&w_2\end{array}
ight)$

Example 1: The same design region in both groups Example 2: Different design regions

Example 2: Different design regions

• Case 1: $d_1 = d$ & $d_2 = 0$ - random intercept

Optimal designs:

$$w_1^* = aw_2^* - rac{a}{2} + rac{1}{2}$$

with $(w_1^*, w_2^*) \in [0, 1]^2$

• Case 2: $d_1 = 0$ & $d_2 = d$ - random slope

Optimal designs:

$$w_1^* = \frac{a + 2w_2^* - 1}{2a}$$

with $(w_1^*, w_2^*) \in [0, 1]^2$

For a = 1: $w_1^* = w_2^*$ - same OD as in Example 1

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Literature

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Thank you for your attention!