Design Considerations for Comparing Dynamic Treatment Regimens in a Longitudinal SMART

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Joint with D. Almirall

ENAR 2020 23 March 2020

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This is a question about a sequence of treatments.

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Dynamic treatment regimens (DTRs) operationalize clinical decision-making by recommending particular treatments to certain subsets of patients at specific times.



- MI-IOP: 2 motivational interviews to re-engage patient in intensive outpatient program
- **MI-PC**: 2 motivational interviews to engage patient in treatment of their choice.

[.] Chakraborty, B., and E. E. M. Moodie (2013). Statistical Methods for Dynamic Treatment Regimes.

A **SMART** is one type of randomized trial design that can be used to answer questions at multiple stages of the development of a high-quality DTR.

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The key feature of a SMART is that some (or all) participants are randomized *more than once*.

Motivating Example: The ENGAGE Study



. McKay, J. R., et al. (2015). Journal of Consulting and Clinical Psychology.









Primary Aim



6

Example Model: Continuous Longitudinal Outcome in ENGAGE



$$\mathsf{E} \left[Y_{t}^{(d)} \mid \mathbf{X} \right] := \mu^{(d)}(\beta)$$

$$= \beta_{0}$$

$$+ \mathbb{1} \left\{ t \leq t^{*} \right\} \left\{ \beta_{1}t + \beta_{2}a_{1}t \right\}$$

$$+ \mathbb{1} \left\{ t > t^{*} \right\} \left\{ t^{*}\beta_{1} + t^{*}\beta_{2}a_{1} \right.$$

$$+ \beta_{3}(t - t^{*}) + \beta_{4}(t - t^{*})a_{1}$$

$$+ \beta_{5}(t - t^{*})a_{2NR}$$

$$+ \beta_{6}(t - t^{*})a_{1}a_{2NR} \right\}$$

. Lu, X., et al. (2016). Statistics in Medicine.

"GEE-Type" Estimating Equations for Model Parameters

$$0 = \sum_{i=1}^{N} \sum_{d} \left[\underbrace{\frac{I^{(d)}(A_{1,i}, R_{i}, A_{2,i})}{P(A_{1,i} = a_{1})P(A_{2,i} = a_{2} \mid A_{1,i} = a_{1}, R_{i})}_{W^{(d)}(A_{1,i}, R_{i}, A_{2,i})} \cdot \left(\mathbf{D}^{(d)} \right)^{\top} \cdot \mathbf{V}^{(d)} (\tau)^{-1} \cdot \left(\mathbf{Y}_{i} - \mu^{(d)}(\beta) \right) \right],$$

- d specifies an embedded DTR,
- $I^{(d)}(A_{1,i}, R_i, A_{2,i}) = \mathbb{1}\{A_{1,i} = a_1\}(R_i + (1 R_i)\mathbb{1}\{A_{2,i} = a_2\})$
- $\mathbf{D}^{(d)} = rac{\partial}{\partial eta^{ op}} \mu^{(d)}(eta)$
- $m{V}^{(d)}\left(au
 ight)$ is a working model for $m{Var}\left(m{Y}^{(d)}-\mu^{(d)}(m{eta})
 ight)$

[.] Lu, X., et al. (2016). Statistics in Medicine.

Variance of Parameter Estimates

- Call the solution to the estimating equations $\hat{oldsymbol{eta}}$
- Under usual regularity conditions:

•
$$\hat{\boldsymbol{\beta}} \xrightarrow{\boldsymbol{p}} \boldsymbol{\beta}^*$$

• $\sqrt{n} \left(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}^* \right) \Rightarrow \mathcal{N} \left(\mathbf{0}, \mathbf{B}^{-1} \mathbf{M} \mathbf{B}^{-1} \right)$

where

$$\boldsymbol{B} := \mathsf{E}\left[\sum_{d \in \mathcal{D}} W^{(d)}\left(A_{1}, R, A_{2}\right) \left(\boldsymbol{D}^{(d)}\right)^{\top} \left(\boldsymbol{V}^{(d)}(\boldsymbol{\tau})\right)^{-1} \boldsymbol{D}^{(d)}\right]$$

$$\boldsymbol{M} := \mathsf{E}\left[\left(\sum_{d \in \mathcal{D}} W^{(d)}\left(\mathsf{A}_{1,i}, \mathsf{R}_{i}, \mathsf{A}_{2,i}\right) \left(\boldsymbol{D}^{(d)}\right)^{\top} \left(\boldsymbol{V}^{(d)}(\boldsymbol{\tau})\right)^{-1} \left(\boldsymbol{Y} - \boldsymbol{\mu}^{(d)}(\boldsymbol{\theta})\right)\right)^{\otimes 2}\right]$$

. Vaart, A. W. van der (1998). Asymptotic statistics.

Goal: Develop a tractable sample size formula for the test

$$H_{o}: \mathbf{c}^{ op} oldsymbol{eta} = o$$
 vs. $H_{1}: \mathbf{c}^{ op} oldsymbol{eta} = \Delta$

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We choose **c** such that

$$\mathbf{c}^{\top}\boldsymbol{\beta} = \mathsf{E}\left[\mathsf{Y}_{\mathsf{T}}^{(1,a_{2\mathsf{R}},a_{2\mathsf{N}\mathsf{R}})} - \mathsf{Y}_{\mathsf{T}}^{(-1,a_{2\mathsf{R}}',a_{2\mathsf{N}\mathsf{R}}')}\right]$$

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We use a 1-degree of freedom (asymptotic) Wald test with test statistic

$$Z = \frac{\sqrt{n}\mathbf{c}^{\top}\hat{\boldsymbol{\beta}}}{\sigma_{\mathsf{c}}},$$

where $\sigma_{c} = \mathbf{c}^{\top} \mathbf{B}^{-1} \mathbf{M} \mathbf{B}^{-1}$.

$$N \geq \frac{4\left(Z_{1-\alpha/2} + Z_{1-\gamma}\right)^2}{\delta^2} \cdot (1-\rho^2) \cdot \left(2 - P(R_i = 1)\right)$$

•
$$\delta = E[Y_T^{(d)} - Y_T^{(d')}] / \sqrt{\left(Var(Y_T^{(d)}) + Var(Y_T^{(d')})\right) / 2}$$
 is the targeted standardized effect size

- + α is the desired type-I error
- + 1 γ is the desired power
- $\rho = cor(Y_t, Y_{t'})$ for $t \neq t'$

[.] Seewald, N. J., et al. (2019). Statistical Methods in Medical Research.

$$N \geq \underbrace{\frac{4\left(\mathbf{Z}_{1-\alpha/2} + \mathbf{Z}_{1-\gamma}\right)^{2}}{\delta^{2}}}_{\text{Standard sample size for a 2-arm trial}} \cdot (1-\rho^{2}) \cdot \left(2 - P(R_{i} = 1)\right)$$

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Table 1: Example sample sizes for comparison of two embedded DTRs. r = 0.4, α = 0.05 (two-sided), and 1 – γ = 0.8.

	W	Within-Person Correlation		
Std. Effect Size	$\rho = 0$	ho= 0.3	ho= 0.6	
$\delta=$ 0.3	559	508	358	
$\delta=$ 0.5	201	183	129	

Preliminary Results for Adding Timepoints in Stage 2



Sample size multiplier vs. Exchangeable ρ , assuming P(R=1)=0.3. m_2 is num. timepoints after second randomization.

Extension to More than Three Timepoints

- A work in progress!
- Challenges:
 - When should we add timepoints? First stage? Second stage? Both?
 - Working assumptions needed for partial ordering on variance matrices
 - Intuition behind non-monotone relationship between sample size and ρ

Sample size considerations for comparing dynamic treatment regimens in a sequential multiple-assignment randomized trial with a continuous longitudinal outcome

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Statistical Methods in Medical Research 0(0) 1-22 © The Author(s) 2019 Article reuse guidelines: sagepub.com/journals-permissions DOI: 10.1177/0962280219877520 journals.sagepub.com/home/smm





Funding

This work was supported by the National Institutes of Health (R01HD073975, U54EB020404, R03MH097954, R01MH114203, P01AA016821, RC1AA019092, R01DA039901, P50DA039838, R01DA047279, U01CA229437) and the Institute of Education Sciences (R324B180003).The content of this presentation is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.



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