Stepped Wedge Cluster Randomized Trials

Kenny Chiu

Supervising Faculty: John Petkau

The University of British Columbia
Department of Statistics

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Outline

1. Introduction
2. Analysis of stepped wedge cluster randomized trials
3. Investigation of simulation study
4. Extensions to basic model
5. Conclusion

Introduction

Hussey and Hughes [1]

Objective

Analysis of stepped wedge cluster randomized trials

Primary SW-CRT setting

Model and methods

Power calculation

Investigation of simulation study

Procedure

Results

Extensions to basic model

Conclusion

Multiple factor analysis

- Factor analysis: estimate latent factors underlying observed data

- *Principal Component Analysis*: given data matrix $A \in \mathbb{R}^{n\times d}$, returns scaled *loadings* $V \in \mathbb{R}^{d\times d}$ and *principal components* (PCs) $S \in \mathbb{R}^{n\times d}$ s.t.

$$S = AV$$

  $\Rightarrow$ Represent and estimate factors by the leading $k \leq d$ PCs

- PCs are (orthogonal) vectors—difficult to interpret if there are many coefficients

Multiple factor analysis

- Factor analysis: estimate latent factors underlying observed data
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  $\Rightarrow$ Represent and estimate factors by the leading $k \leq d$ PCs

- PCs are (orthogonal) vectors—difficult to interpret if there are many coefficients
- **?**]: rotate PCs to make coefficients as sparse as possible (i.e., ≈ 0)

References I

[1] Hussey, M. A. and Hughes, J. P. (2007). Design and analysis of stepped wedge cluster randomized trials. *Contemporary Clinical Trials*, 28(2):182–191.

Key steps of factor rotation procedure

3. **SVD**: apply SVD to data matrix A to obtain

$$A \approx \widehat{U}\widehat{D}\widehat{V}^T$$

   where $\widehat{U} \in \mathbb{R}^{n \times k}$ and $\widehat{V} \in \mathbb{R}^{d \times k}$ contain the first k singular vectors of A and $\widehat{D}$ the first k singular values

4. **Maximize**: given matrix U to rotate, let $g(U, R)$ be the criterion to maximize as a function of R. Compute optimal rotation

$$R_{\widehat{U}} = \arg\max_{R} \ g(U, R)$$

5. **Estimate**: estimate latent matrices

$$\widehat{Z} = \sqrt{n}\widehat{U}R_{\widehat{U}} \ ,$$
$$\widehat{B} = \frac{1}{\sqrt{nd}} R_{\widehat{U}}^T \widehat{D} R_{\widehat{V}}$$