Demo Taylor and Francis template

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ARTICLE HISTORY
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ABSTRACT
This document is only a demo explaining how to use the template.

KEYWORDS
template; demo

1. Introduction

2. Methods

2.1. *Causal Models*

For all simulations, the following data generating mechanism will be simulated:

$$\mathbf{X}_t = \Phi \mathbf{X}_{t-1} + \mathbf{B}_{ct}\mathbf{C}^T + \mathbf{1u}_t + \mathbf{E}_t \tag{1}$$

$$\mathbf{X}_1 = \mathbf{B}_{c1}\mathbf{C}^T + \mathbf{1u}_1 + \mathbf{E}_1$$

$$\begin{bmatrix} x_{it} \\ y_{it} \end{bmatrix} = \begin{bmatrix} \phi_{xx} & \phi_{xy} \\ \phi_{yx} & \phi_{yy} \end{bmatrix} \begin{bmatrix} x_{i,t-1} \\ y_{i,t-1} \end{bmatrix} + \begin{bmatrix} \beta_{xc_1t} & \beta_{xc_2t} \\ \beta_{yc_1t} & \beta_{yc_2t} \end{bmatrix} \begin{bmatrix} C_{1i} \\ C_{2i} \end{bmatrix} + U_{it} + \begin{bmatrix} \epsilon_{xit} \\ \epsilon_{yit} \end{bmatrix} \tag{2}$$

For $t = 2, ..., T$ and

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$$\begin{bmatrix} x_{i1} \\ y_{i1} \end{bmatrix} = \begin{bmatrix} \beta_{xc_1 1} & \beta_{xc_2 1} \\ \beta_{yc_1 1} & \beta_{yc_2 1} \end{bmatrix} \begin{bmatrix} C_{1i} \\ C_{2i} \end{bmatrix} + U_{i1} + \begin{bmatrix} \epsilon_{xi1} \\ \epsilon_{yi1} \end{bmatrix}$$

$$\begin{bmatrix} \epsilon_{xit} \\ \epsilon_{yit} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \psi_x & 0 \\ 0 & \psi_y \end{bmatrix} \right)$$

$$\begin{bmatrix} C_{1i} \\ C_{2i} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \psi_{C_1} & 0 \\ 0 & \psi_{C_2} \end{bmatrix} \right)$$

$$U_{it} \sim \mathcal{N}\left(0, \psi_u\right)$$

For $i = 1, ..., N$.

This SCM is similar to the DPM as it does not have an explicit decomposition of within and between effects and it is thus an observation based model, rather than a residual based model. One way that it differs from the DPM, other than having an observed confounder instead of a latent factor, is that the DPM includes covariances between the residuals at each timepoint. Because our model is specified as a DAG, two-headed arrows are not included, and this is thus expressed as a latent confounder between the residuals at each timepoint. It can be shown that when these the effect of these confounders on the residuals are 1, this specification using a confounder u_t with $\sigma^2_{u_t} = \psi_u$ is equivalent to specifying a covariance between the residuals where $\sigma_{x_t y_t} = \psi_u$. Furthermore, the variance of the residuals at each timepoint, ψ_x and ψ_y are equal to the residual variances in the DPM, minus the variance of the unique factor u_t at that timepoint. The SCMs that will be simulated are described below.

2.1.1. One confounder, time-invariant effects. (Model 1)

When there is only one confounder C, Equation 1 reduces to:

$$\mathbf{X}_t = \Phi \mathbf{X}_{t-1} + \beta_{ct} \mathbf{c}^T + \mathbf{1} \mathbf{u}_t + \mathbf{E}_t$$

Equation 2 reduces to:

$$\begin{bmatrix} x_{it} \\ y_{it} \end{bmatrix} = \begin{bmatrix} \phi_{xx} & \phi_{xy} \\ \phi_{yx} & \phi_{yy} \end{bmatrix} \begin{bmatrix} x_{i,t-1} \\ y_{i,t-1} \end{bmatrix} + \begin{bmatrix} \beta_{xct} \\ \beta_{yct} \end{bmatrix} C_i + U_{it} + \begin{bmatrix} \epsilon_{xit} \\ \epsilon_{yit} \end{bmatrix}$$

The following choices were made for the parameters for the simulation: $\Phi = \begin{bmatrix} \phi_{xx} & \phi_{xy} \\ \phi_{yx} & \phi_{yy} \end{bmatrix} = \begin{bmatrix} 0.1 & 0.15 \\ 0.1 & 0.6 \end{bmatrix}$, $\beta_{ct} = \begin{bmatrix} 0.10 \\ 0.12 \end{bmatrix}$, $\psi_u = 0.6$, $\psi_x = \psi_y = 1 - \psi_u = 0.4$, and $psi_C = 5$.

3. Results

4. Discussion

References