

Mediation Analysis Using State-Space Modelling in Single-Case Experimental Design Tanoulu Li and Milica Miočević, Department of Psychology, McGill University

#### Introduction

Mediation analysis: the consideration of how a third variable affects the relation between two other variables (MacKinnon, 2008).



# **Example 1: A Basic Lag-One Example**



Fig. 2. Path Diagram of the Basic Lag-One SSM Model

# **Example 3: A Lag-one SSM with** Latent Variables



Fig. 1. Path diagram of the mediation analysis model

*Example*: Self-awareness influences the level of physical activity, and this effect is mediated by mood strength.

State-space modeling (SSM): a modeling framework designed to analyze dynamic systems observed (Shumway and Stoffer, 2000).

# Why SSM in Mediation Analysis?

#### **Structural equation modelling (SEM) Framework:**

- Focus on cross-sectional between-subject design, with homogeneity assumption.
- Unable to capture longitudinal change when the longitudinal data are intensive (Chow, et al. 2010; Molenaar, 2003).

#### **State-Space Modelling Framework:**

 $\begin{pmatrix} X_t \\ M_t \\ Y_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} X_t \\ M_t \\ Y_t \end{pmatrix}, \text{ where } \Theta = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$  $\begin{pmatrix} X_t \\ M_t \\ Y_t \end{pmatrix} = \begin{pmatrix} \rho_X & 0 & 0 \\ a_{t-1} & \rho_M & 0 \\ c'_{t-1} & b_{t-1} & \rho_Y \end{pmatrix} \begin{pmatrix} X_{t-1} \\ M_{t-1} \\ Y_{t-1} \end{pmatrix} + \begin{pmatrix} \zeta_X \\ \zeta_M \\ \zeta_V \end{pmatrix}, \text{ where } \Psi = \begin{pmatrix} \psi_X & 0 \\ 0 & \psi_M \\ 0 & 0 \end{pmatrix}$ 

### **Simulation Studies on Example 1**

	True	T = 50	T = 100	T = 150
	Values			
$\rho_X$	0.6	0.538(0.118)	0.461(0.089)	0.580(0.067)
$ ho_M$	0.4	0.390(0.115)	$0.344_{(0.080)}$	0.343(0.069)
$ ho_Y$	0.5	0.606(0.065)	$0.465_{(0.061)}$	0.559(0.041)
$a_{t-1}$	0.4	0.398(0.098)	0.452(0.080)	0.328(0.060)
$b_{t-1}$	0.4	0.320(0.111)	0.391(0.086)	0.385(0.062)
$c'_{t-1}$	0.5	0.566(0.089)	0.510(0.081)	0.501(0.052)
$\psi_X$	0.5	0.656(0.133)	0.501(0.071)	0.478(0.055)
$\psi_{\scriptscriptstyle M}$	0.4	0.342(0.069)	0.357(0.051)	0.359(0.042)
$\psi_{\scriptscriptstyle Y}$	0.3	0.253(0.051)	0.361(0.051)	0.251(0.029)

	True	T =200	T = 500	T = 1000
	Values			
$\rho_X$	0.6	0.542(0.060)	0.603(0.036)	0.646(0.024)
$ ho_M$	0.4	0.360(0.059)	0.395(0.035)	0.372(0.024)
$ ho_Y$	0.5	0.523(0.042)	0.483(0.025)	0.504(0.017)
$a_{t-1}$	0.4	0.347(0.052)	$0.434_{(0.034)}$	0.436(0.023)
$b_{t-1}$	0.4	0.345(0.058)	$0.433_{(0.035)}$	0.392(0.024)
$c'_{t-1}$	0.5	0.465(0.051)	0.488(0.032)	0.476(0.021)
$\psi_X$	0.5	0.513(0.051)	0.492(0.031)	0.501(0.022)
$\psi_{\scriptscriptstyle M}$	0.4	0.367(0.037)	0.403(0.026)	0.372(0.017)
$\psi_{\scriptscriptstyle Y}$	0.3	0.320(0.032)	0.303(0.019)	0.287(0.013)

Fig. 4. Path Diagram of a SSM Model with a Latent Mediator Measured by Five Manifest Variables

$$\begin{pmatrix} X_t \\ M_{\eta,t} \\ Y_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & \lambda_3 & 0 \\ 0 & \lambda_4 & 0 \\ 0 & \lambda_5 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} X_t \\ M_{1,t} \\ M_{2,t} \\ M_{3,t} \\ M_{4,t} \\ M_{5,t} \\ Y_t \end{pmatrix} + \begin{pmatrix} 0 \\ \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ 0 \end{pmatrix},$$

 $\begin{pmatrix} X_t \\ M_{\eta,t} \\ Y_t \end{pmatrix} = \begin{pmatrix} \rho_X & 0 & 0 \\ a_{t-1} & \rho_{M\eta} & 0 \\ c'_{t-1} & b_{t-1} & \rho_Y \end{pmatrix} \begin{pmatrix} X_{t-1} \\ M_{\eta,t-1} \\ Y_{t-1} \end{pmatrix} + \begin{pmatrix} \zeta_X \\ \zeta_{M\eta} \\ \zeta_Y \end{pmatrix},$ 

- A more accurate and flexible representation in longitudinal within-subject designs with capturing intraindividual variations (Chow, et al. 2010).
- Particularly suitable in Single-Case Experimental Design (SCED).

# **Model Formulation: State and Measurement Equations**

#### **Measurement/Observation Equation**:

 $\eta_t = B\eta_{t-1} + \zeta_t, \zeta_t \sim \text{MVN}(0, \Psi)$ 

**State/Transition Equation**:

 $y_t = \Lambda \eta_t + \epsilon_t, \epsilon_t \sim \text{MVN}(0, \Theta)$ 

### **Estimation Method: Kalman Filter**

• A recursive algorithm used to estimate the hidden states

Table 1. The Estimates with Standard Errors for Simulated Data Using Lag-One Model

## **Example 2: A Lag-Two Model**





#### Discussion

Lag-P Model: Broadly, we can extend the lag-2 SSM model in Example 2 to lag-p, where  $\eta_t$  is influenced by previous lags up to  $\eta_{t-1}$ 

 $\eta'_t = B_1 \eta'_{t-1} + B_2 \eta'_{t-2} + \dots + B_p \eta'_{t-p} + \zeta_t, \text{ where } \zeta_t \sim \text{MVN}(0, \Psi)$ 

 $\eta_t = \begin{pmatrix} \eta'_t \\ \eta'_{t-1} \\ \vdots \\ \eta'_{t-n} \end{pmatrix}, B = \begin{pmatrix} B_1 & B_2 & \dots & B_p \\ I_3 & 0 & \dots & 0 \\ 0 & I_3 & \dots & 0 \\ 0 & 0 & \ddots & \vdots \\ 0 & 0 & \ddots & \vdots \end{pmatrix}, \zeta = \begin{pmatrix} \zeta'_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \Psi = \begin{pmatrix} \psi'_t & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & \ddots & \vdots \\ 0 & 0 & 0 & \ddots & \vdots \end{pmatrix}$ 

**Covariates:** SSM's flexibility permits the inclusion of covariates (input/control variables) in both measurement and state equations, as described below.

(latent variables).

• Operate in two primary phases: prediction and update.

**Prediction Phase**  
$$\hat{\eta}_{t|t-1} = B\hat{\eta}_{t-1} + \zeta_t$$
  $P_{t|t-1} = BP_{t-1}B' + \Psi$ 

Update Phase  

$$\epsilon_t = (y_t - \Lambda \hat{\eta}_{t|t-1}) \qquad \hat{\eta}_t = \hat{\eta}_{t|t-1} + K_t \epsilon_t$$

$$K_t = P_{t|t-1} \Lambda' (\Lambda P_{t|t-1} \Lambda' + \Theta)^{-1} \qquad P_t = (I - K_t \Lambda_t) P_{t|t-1}$$

#### Reference

Chow, S. M., Ho, M. H. R., Hamaker, E. L., & Dolan, C. V. (2010). Equivalence and differences between structural equation modeling and state-space modeling techniques. Structural Equation Modeling, 17(2), 303-332. MacKinnon D. P. (2008). Introduction to statistical mediation analysis. Erlbaum. Molenaar P. C. (2003). State space techniques in structural equation modeling. Retrieved from the Pennsylvania State Department of Human Development and Family Studies website: http://www.hhdev.psu.edu/hdfs/faculty/docs/StateSpaceTechniques.pdf Shumway, R. H., & Stoffer, D. S. (2000). Time series analysis and its applications (Vol. 3). New York: springer.

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Fig. 3. Path Diagram of the Lag-Two SSM Model

 $\begin{pmatrix} X_t \\ M_t \\ Y_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} X_t \\ M_t \\ Y_t \\ X_{t-1} \\ M_{t-1} \end{pmatrix}, \text{ where } \Theta = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$ 

$(X_t)$		$\rho_X$	0	0	0	0	0	$X_{t-1}$		$(\zeta_X)$	
$M_t$		$a_{t-1}$	$ ho_M$	0	0	0	0	$\left( M_{t-1} \right)$		$\zeta_M$	
$Y_t$	=	$c'_{t-1}$	$b_{t-1}$	$ ho_Y$	$c'_{t-2}$	0	0	$Y_{t-1}$	+	$\zeta_Y$	
$X_{t-1}$		1	0	0	0	0	0	$X_{t-2}$		0	
$M_{t-1}$	/	0	1	0	0	0	0 /	$M_{t-2}$		0	
$\langle Y_{t-1} \rangle$		\ 0	0	1	0	0	0/	$\langle Y_{t-2} /$		\0/	

	$/\psi_X$	0	0	0	0	0
	0	$\psi_M$	0	0	0	0
,where $\Psi =$	0	0	$\psi_Y$	0	0	0
	0	0	0	0	0	0
	0	0	0	0	0	0 /
	\ 0	0	0	0	0	0/

 $\eta_t = B\eta_{t-1} + Cf_t + \zeta_t, \zeta_t \sim \text{MVN}(0, \Psi)$  $y_t = \Lambda \eta_t + A x_t + \epsilon_t, \epsilon_t \sim \text{MVN}(0, \Theta)$ *Examples*: Social Interactions, Health Status Changes **Missing Values:** With the Expectation-Maximization (EM) algorithm, SSM excels at handling missing data by iterating between estimating the missing data given the model parameters (E-step) and optimizing the model parameters given the estimated data (M-step).

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