Modeling the Distillation Process in SEM

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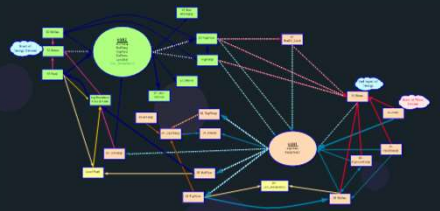
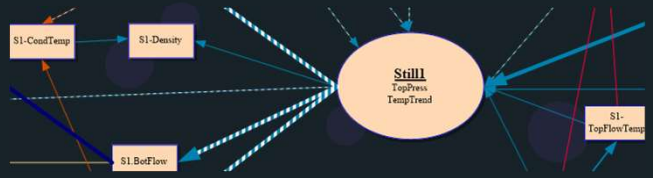
jmp STATISTICAL DISCOVERY FROM SAS

Key Features of Project

1. Clear theory of how processes affect each other



2. Theory stipulates variables have dual roles: inputs (X) and outputs (Y)



3. Each node in diagram is a process measured repeatedly –aka time series

Why Structural Equation Modeling?

General Framework

- Model variances, covariances, and means among variables
- Test theories of multivariate relations among variables
- Test direct and indirect effects
- Account for measurement error
- Specify and model latent (unobserved) variables
- Use cutting edge algorithms for missing data
- Intuitive path diagrams represent statistical models

Structural Equation Modeling

General Framework

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  - E.g., Simple linear regression:

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$$Y_i = \beta_1 X_i + \varepsilon_{yi}$$
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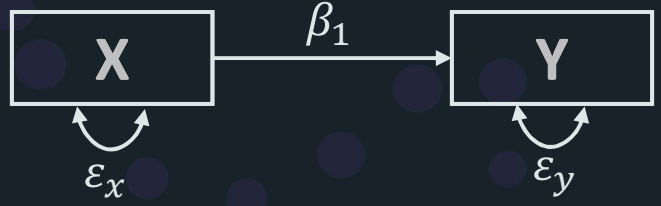
** means/intercepts omitted for simplicity*



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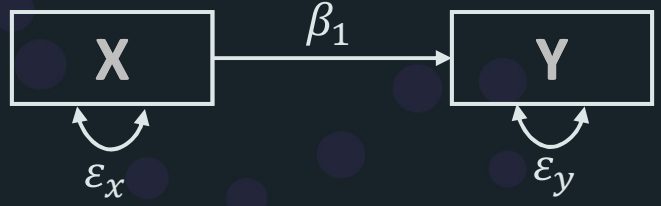

- SEMs imply a covariance structure:

	X	***Y***
X	ε_x	
Y	$\beta_1\varepsilon_x$	$\beta_1^2\varepsilon_x + \varepsilon_y$

- Fit assessed comparing model-implied covariance vs. sample covariance

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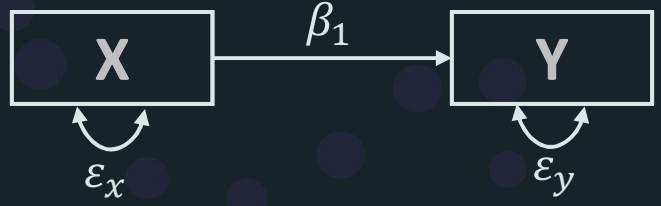

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	X	Y
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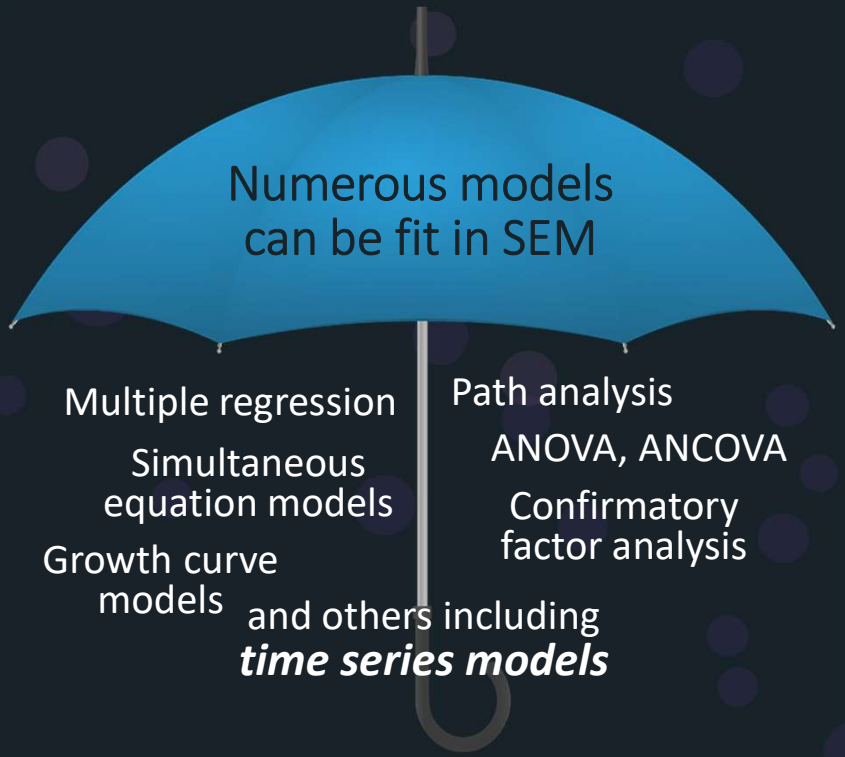
Compare with sample

	X	Y
X	1.40	
Y	0.76	1.14

- Fit assessed comparing model-implied covariance vs. sample covariance

Structural Equation Modeling

General Framework



Time Series Analysis

ARIMA Models (Box & Jenkins, 1970)

- Time Series:
  - Collection of data where there is dependence on previous data points
  - Equally spaced time intervals
  - Account for dependence by regressing on the past
- Autoregressive, AR(p), processes:

$$Y_t = \beta_1 Y_{t-1} + \cdots + \beta_p Y_{t-p} + \varepsilon_{yt}$$

- AR(1) process:

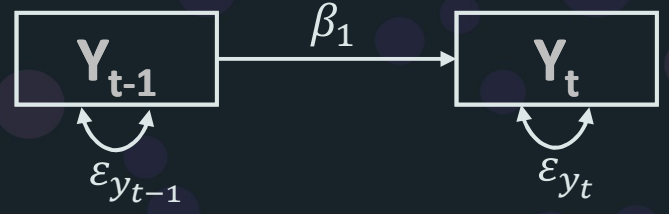
$$Y_t = \beta_1 Y_{t-1} + \varepsilon_{yt}$$

Time Series Analysis

Implemented in SEM

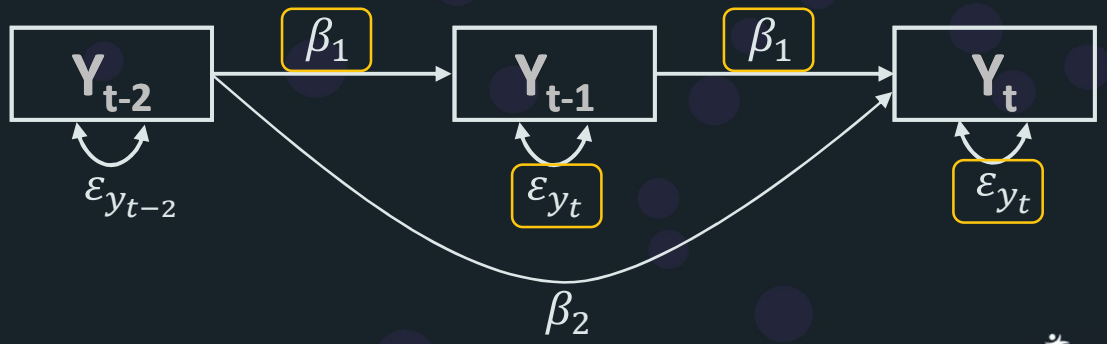
- AR(1) process:

$$Y_t = \beta_1 Y_{t-1} + \varepsilon_{y_t}$$



- AR(2) process:

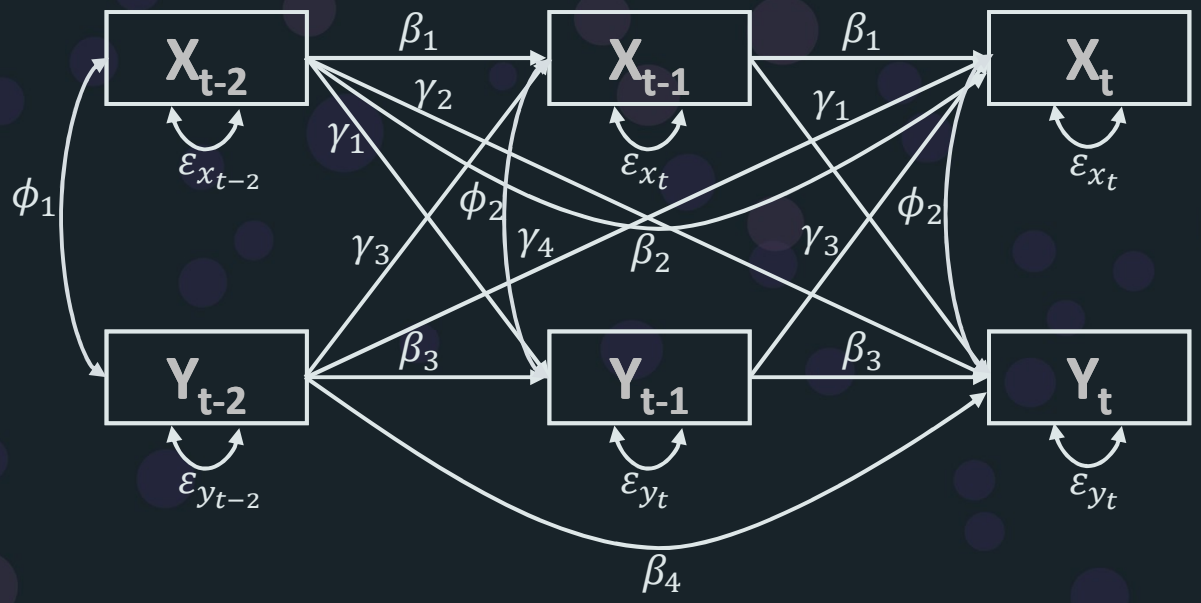
$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \varepsilon_{y_t}$$



Multivariate Time Series Analysis

Implemented in SEM

- Vector Autoregressive Process: VAR(2)



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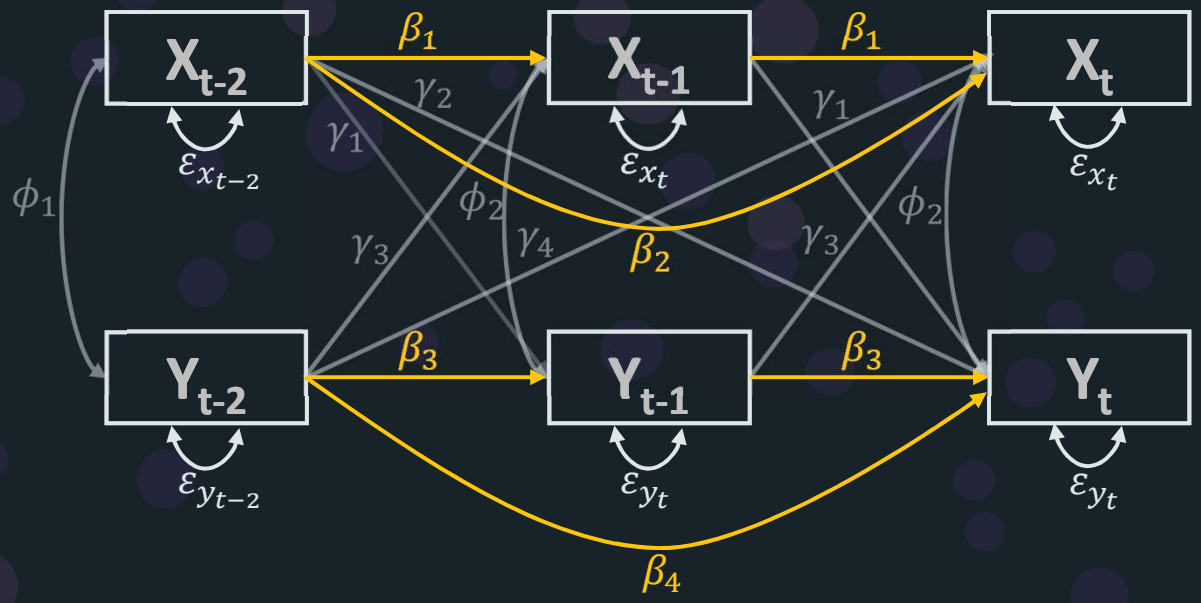

Autoregressive effects

Multivariate Time Series Analysis

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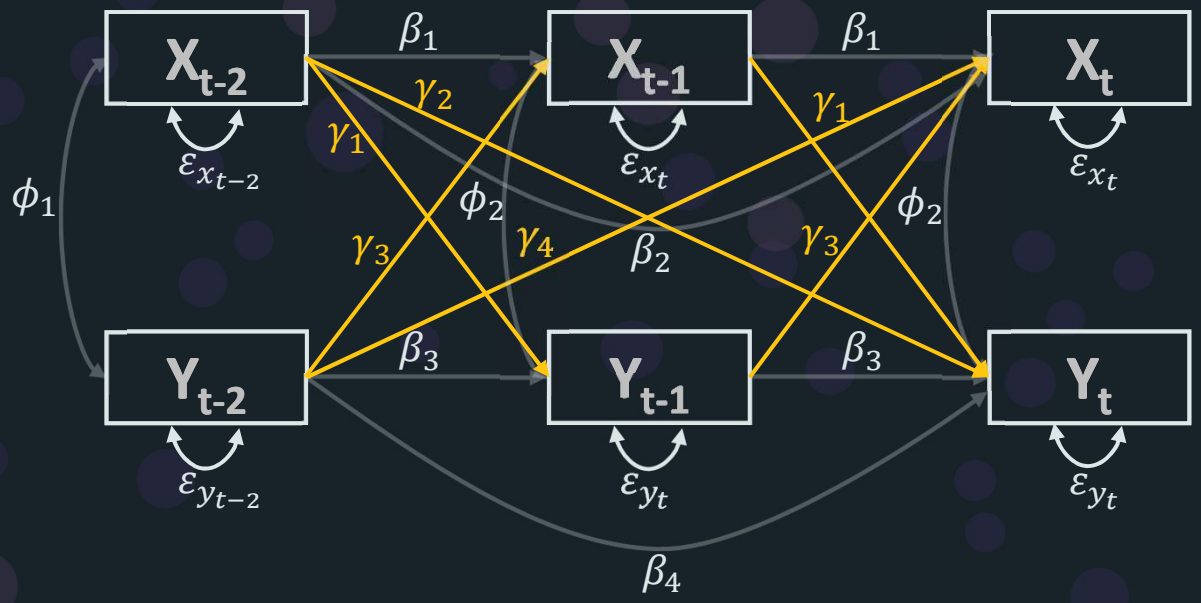

Cross-lagged effects

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Multivariate Time Series Analysis

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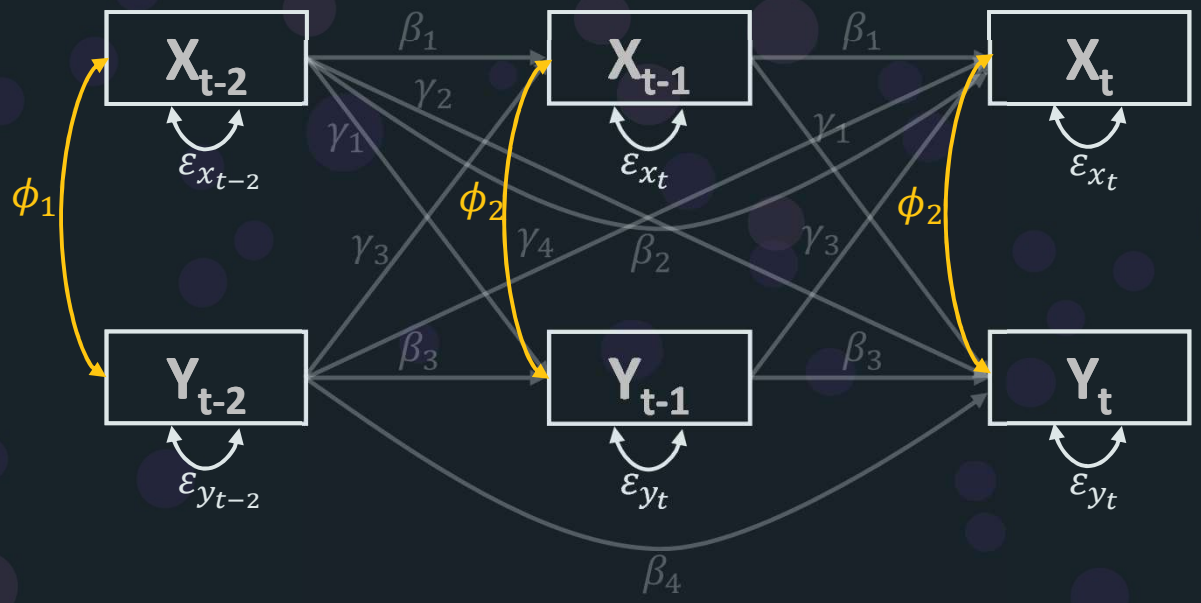
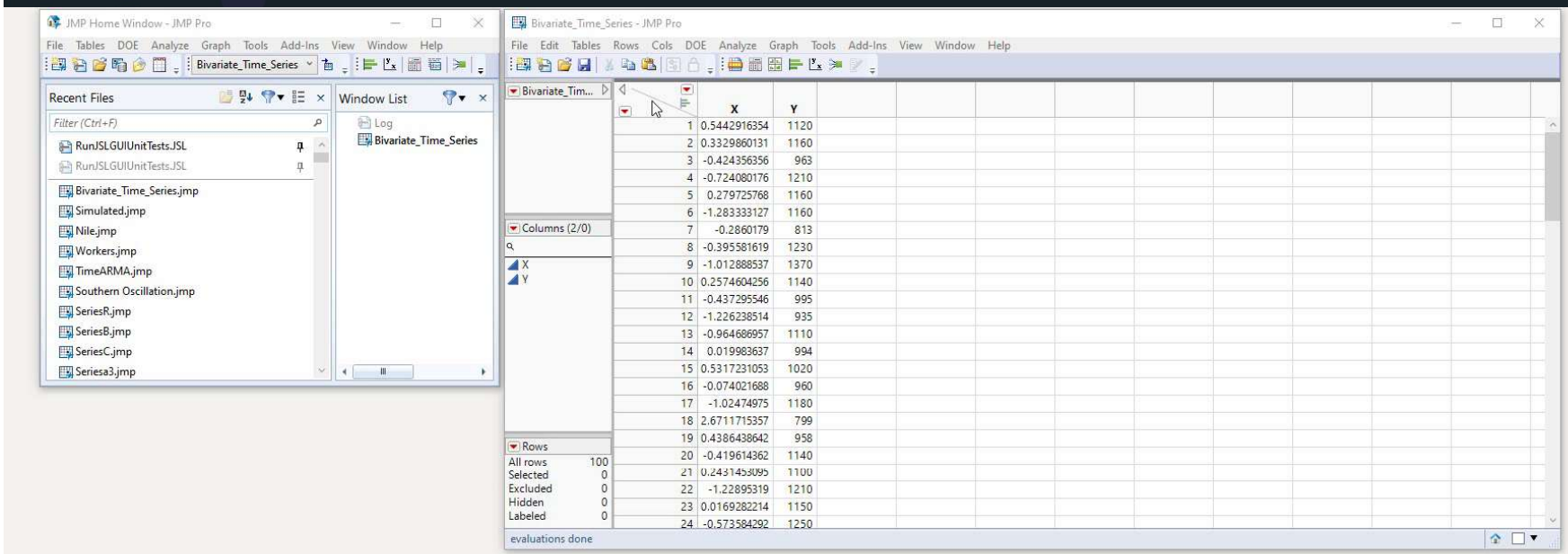


Within-time covariances and residual covariances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File Tables DOE Analyze Graph Tools Add-Ins View Window Help
Bivariate_Time_Series
Recent Files
Filter (Ctrl+F)
RunJSLGUIUnitTests.JSL
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Simulated.jmp
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TimeARMA.jmp
Southern Oscillation.jmp
SeriesR.jmp
SeriesB.jmp
SeriesC.jmp
Seriesa3.jmp
Window List
Log
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Bivariate_Time_Series - JMP Pro
File Edit Tables Rows Cols DOE Analyze Graph Tools Add-Ins View Window Help
Bivariate_Tim...
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Y
Rows
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Selected 0
Excluded 0
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Labeled 0
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4 -0.724080176 1210
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7 -0.2860179 813
8 -0.395581619 1230
9 -1.012888537 1370
10 0.2574604256 1140
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12 -1.226238514 935
13 -0.964686957 1110
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15 0.5317231053 1020
16 -0.074021688 960
17 -1.02474975 1180
18 2.6711715357 799
19 0.4386438642 958
20 -0.419614362 1140
22 -1.22895319 1210
23 0.0169282214 1150
24 -0.573584292 1250
evaluations done

Multivariate Time Series Analysis

Distillation Process Data

- 26 processes, ~45k measurements (10-minute intervals)
- Explore univariate time series models in JMP:
  - AR(1) or AR(2) fit best for most processes
  - VAR(2) for SEM
- Data pre-processing:
  - Missing data
    - SEM estimation can handle it BUT computationally intensive
    - Selected subset of complete data: ~13k
  - Large scale differences
    - Standardized all processes
  - Create lagged variables
- Model specification
  - Equality constraints are a challenge (tedious and error prone)
  - JSL script to generate JSL for SEM

Multivariate Time Series Analysis

Distillation Process Data