

# semmcci: Monte Carlo Confidence Intervals

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## Installation

You can install the CRAN release of `semmcci` with:

```
install.packages("semmcci")
```

You can install the development version of `semmcci` from [GitHub](#) with:

```
install.packages("remotes")  
remotes::install_github("jeksterslab/semmcci")
```

## Documentation

See [GitHub Pages](#) for package documentation.

## Description

In the Monte Carlo method, a sampling distribution of parameter estimates is generated from the multivariate normal distribution using the parameter estimates and the sampling variance-covariance matrix. Confidence intervals for defined parameters are generated by obtaining percentiles corresponding to  $100(1 - \alpha)\%$  from the generated sampling distribution, where  $\alpha$  is the significance level.

Monte Carlo confidence intervals for free and defined parameters in models fitted in the structural equation modeling package `lavaan` can be generated using the `semmcci` package. The package has two main functions, namely, `MC()` and `MCStd()`. The output of `lavaan` is passed as the first argument to the `MC()` function to generate Monte Carlo confidence intervals. Monte Carlo confidence intervals for the standardized estimates can also be generated by passing the output of the `MC()` function to the `MCStd()` function.

## Example

A common application of the Monte Carlo method is to generate confidence intervals for the indirect effect. In the simple mediation model, variable **X** has an effect on variable **Y**, through a mediating variable **M**. This mediating or indirect effect is a product of path coefficients from the fitted model.

```
library(semmcci)
library(lavaan)
```

## Data

```
n <- 1000
X <- rnorm(n = n)
M <- 0.50 * X + rnorm(n = n)
Y <- 0.25 * X + 0.50 * M + rnorm(n = n)
data <- data.frame(X, M, Y)
```

## Model Specification

The indirect effect is defined by the product of the slopes of paths **X** to **M** labeled as **a** and **M** to **Y** labeled as **b**. In this example, we are interested in the confidence intervals of `indirect` defined as the product of **a** and **b** using the `:=` operator in the `lavaan` model syntax.

```

model <- "
  Y ~ cp * X + b * M
  M ~ a * X
  indirect := a * b
  direct := cp
  total := cp + (a * b)
"

```

## Model Fitting

We can now fit the model using the `sem()` function from `lavaan`.

```
fit <- sem(data = data, model = model)
```

## Monte Carlo Confidence Intervals

The `fit` `lavaan` object can then be passed to the `MC()` function to generate Monte Carlo confidence intervals.

```

MC(fit, R = 20000L, alpha = c(0.001, 0.01, 0.05))

#> Monte Carlo Confidence Intervals
#>      est      se      R 0.05%  0.5%  2.5% 97.5% 99.5% 99.95%
#> cp      0.2008 0.0336 20000 0.0934 0.1143 0.1352 0.2667 0.2858 0.3102
#> b      0.5243 0.0301 20000 0.4218 0.4473 0.4656 0.5833 0.6024 0.6228
#> a      0.4594 0.0321 20000 0.3579 0.3781 0.3969 0.5228 0.5418 0.5671
#> Y~~Y    0.9278 0.0415 20000 0.7870 0.8197 0.8461 1.0091 1.0342 1.0548
#> M~~M    1.0161 0.0455 20000 0.8660 0.9004 0.9265 1.1051 1.1322 1.1716
#> indirect 0.2409 0.0218 20000 0.1724 0.1869 0.1998 0.2851 0.3000 0.3168
#> direct  0.2008 0.0336 20000 0.0934 0.1143 0.1352 0.2667 0.2858 0.3102

```

```
#> total      0.4417 0.0348 20000 0.3292 0.3517 0.3745 0.5099 0.5290 0.5530
```

## Standardized Monte Carlo Confidence Intervals

Standardized Monte Carlo Confidence intervals can be generated by passing the result of the `MC()` function to `MCStd()`.

**Note:** We recommend setting `fixed.x = FALSE` when generating standardized estimates and confidence intervals to model the variances and covariances of the predictors if they are assumed to be random.

```
fit <- sem(data = data, model = model, fixed.x = FALSE)
unstd <- MC(fit, R = 20000L, alpha = c(0.001, 0.01, 0.05))
```

```
MCStd(unstd)
```

```
#> Standardized Monte Carlo Confidence Intervals
```

#>	est	se	R	0.05%	0.5%	2.5%	97.5%	99.5%	99.95%
#> cp	0.1689	0.0280	20000	0.0744	0.0964	0.1145	0.2247	0.2411	0.2578
#> b	0.4904	0.0254	20000	0.4030	0.4248	0.4399	0.5392	0.5543	0.5675
#> a	0.4131	0.0263	20000	0.3191	0.3440	0.3611	0.4636	0.4797	0.4978
#> Y~~Y	0.6625	0.0243	20000	0.5840	0.5978	0.6138	0.7096	0.7232	0.7361
#> M~~M	0.8293	0.0217	20000	0.7522	0.7699	0.7851	0.8696	0.8817	0.8982
#> X~~X	1.0000	0.0000	20000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
#> indirect	0.2026	0.0170	20000	0.1475	0.1599	0.1700	0.2364	0.2477	0.2610
#> direct	0.1689	0.0280	20000	0.0744	0.0964	0.1145	0.2247	0.2411	0.2578
#> total	0.3715	0.0273	20000	0.2777	0.2984	0.3164	0.4241	0.4390	0.4581

## References

- MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate Behavioral Research*, 39(1), 99–128. [https://doi.org/10.1207/s15327906mbr3901\\_4](https://doi.org/10.1207/s15327906mbr3901_4)
- Preacher, K. J., & Selig, J. P. (2012). Advantages of Monte Carlo confidence intervals for indirect effects. *Communication Methods and Measures*, 6(2), 77–98. <https://doi.org/10.1080/19312458.2012.679848>
- R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Vienna, Austria. <https://www.R-project.org/>
- Tofighi, D., & Kelley, K. (2019). Indirect effects in sequential mediation models: Evaluating methods for hypothesis testing and confidence interval formation. *Multivariate Behavioral Research*, 55(2), 188–210. <https://doi.org/10.1080/00273171.2019.1618545>
- Tofighi, D., & MacKinnon, D. P. (2015). Monte Carlo confidence intervals for complex functions of indirect effects. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(2), 194–205. <https://doi.org/10.1080/10705511.2015.1057284>