

Edge based analysis with edge values

The edge based analysis can be conducted using the function `sem.net.edge`. The idea behind this method is that the edge values can be the unit of analysis if we transform non-network covariates into pair-based values.

Simulated Data Example

To begin with, a random simulated dataset can be used to demonstrate the usage of the node-based network statistics approach. The code below generate a simulated network `net` with four non-network covariates `x1 - x4` which loads on two latent variables `lv1, lv2`.

```
set.seed(100)
nsamp = 100
net <- data.frame(ifelse(matrix(rnorm(nsamp^2), nsamp, nsamp) > 1, 1, 0))
mean(net) # density of simulated network
lv1 <- rnorm(nsamp)
lv2 <- rnorm(nsamp)
nonnet <- data.frame(x1 = lv1*0.5 + rnorm(nsamp),
                    x2 = lv1*0.8 + rnorm(nsamp),
                    x3 = lv2*0.5 + rnorm(nsamp),
                    x4 = lv2*0.8 + rnorm(nsamp))
```

With the simulated data, we can define a `model` string with lavaan syntax that specifies the measurement model as well as the relationship between the network and the non-network variables. In this case, we are using `net` as a mediator between the two latent variables. Since data are generated randomly, the effects should be small overall.

```
model <- '
  lv1 =~ x1 + x2
  lv2 =~ x3 + x4
  lv1 ~ net
  lv2 ~ lv1
'
```

Arguments passed to the `sem.net.edge` function includes the model and the dataset. Note that `data` here should be a list with two elements, one being the named list of all network variables and one being the dataframe containing non-network variables. A `summary` function can be used to look at the output, and the function `path.networksem` can be used to look at mediation effects.

```
data = list(network = list(net = net), nonnetwork = nonnet)
set.seed(100)
res <- sem.net.edge(model = model, data = data, type = 'difference')
summary(res)
path.networksem(res, "net", "lv1", "lv2")
```

The output is shown below.

```
> summary(res)
```

The SEM output:

lavaan 0.6.15 ended normally after 58 iterations

Estimator	ML
Optimization method	NLMINB
Number of model parameters	10
Number of observations	10000

Model Test User Model:

Test statistic	1.584
Degrees of freedom	4
P-value (Chi-square)	0.812

Model Test Baseline Model:

Test statistic	2296.506
Degrees of freedom	10
P-value	0.000

User Model versus Baseline Model:

Comparative Fit Index (CFI)	1.000
Tucker-Lewis Index (TLI)	1.003

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-75480.300
Loglikelihood unrestricted model (H1)	-75479.508
Akaike (AIC)	150980.601
Bayesian (BIC)	151052.704
Sample-size adjusted Bayesian (SABIC)	151020.925

Root Mean Square Error of Approximation:

RMSEA	0.000
90 Percent confidence interval - lower	0.000
90 Percent confidence interval - upper	0.009
P-value H_0: RMSEA <= 0.050	1.000
P-value H_0: RMSEA >= 0.080	0.000

Standardized Root Mean Square Residual:

SRMR	0.003
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Parameter Estimates:

Standard errors	Standard
Information	Expected
Information saturated (h1) model	Structured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
lv1 =~				
x1	1.000			
x2	0.810	0.063	12.894	0.000
lv2 =~				
x3	1.000			
x4	0.302	0.056	5.377	0.000

Regressions:

	Estimate	Std.Err	z-value	P(> z)
lv1 ~				
net	0.053	0.039	1.371	0.170
lv2 ~				

```
lv1          -0.482  0.035 -13.683  0.000
```

Variances:

	Estimate	Std.Err	z-value	P(> z)
.x1	1.964	0.076	25.814	0.000
.x2	2.104	0.055	38.145	0.000
.x3	-0.681	0.527	-1.293	0.196
.x4	2.865	0.063	45.557	0.000
.lv1	0.898	0.077	11.708	0.000
.lv2	2.678	0.529	5.061	0.000

```
> path.networksem(res, "net", "lv1", "lv2")
predictor mediator outcome   apath   bpath indirect
1   net    lv1    lv2 0.05287153 -0.4823857 -0.02550447
indirect_se indirect_z
1 0.01705778 -1.495181
```

Empirical Data Example

As an empirical example, we analyze the the attorney cowork and advice networks. In this example, the advice network is predicted by gender and years in practice, and the cowork network is predicted by the advice network, gender, and years in practice all together. In this case, the advice network acts as a mediator, while gender and years in practice exert indirect effect onto the cowork network through the advice network in addition to having direct effects. The model specification is given below.

```
non_network <- read.table("data/attorney/ELattr.dat")[,c(3,5)]
colnames(non_network) <- c('gender', 'years')
non_network$gender <- non_network$gender - 1
network <- list()
network$advice <- read.table("data/attorney/ELadv.dat")
network$cowork <- read.table("data/attorney/ELwork.dat")

model <- '
  advice ~ gender + years
  cowork ~ advice + gender + years
'
```

To use the function `sem.net.edge()`, we need to specify whether the covariate values to be run with the social network edge values in SEM should be calculated as the "difference" across two individuals or the "average" across two individuals. Here, the argument `ordered = c("cowork", "advice")`

is used to tell lavaan that the outcome variables cowork and advice are binary.

```
set.seed(100)
res <- sem.net.edge(model = model, data = data,
                    network = network, type = "difference", ordered = c("cowork", "advice"))
```

The output is shown as below.

lavaan 0.6.15 ended normally after 19 iterations

Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	7

Number of observations	5041
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Model Test User Model:

	Standard	Scaled
Test Statistic	0.000	0.000
Degrees of freedom	0	0

Model Test Baseline Model:

Test statistic	1343.292	1343.292
Degrees of freedom	1	1
P-value	0.000	0.000
Scaling correction factor		1.000

User Model versus Baseline Model:

Comparative Fit Index (CFI)	1.000	1.000
Tucker-Lewis Index (TLI)	1.000	1.000
Robust Comparative Fit Index (CFI)		NA
Robust Tucker-Lewis Index (TLI)		NA

Root Mean Square Error of Approximation:

RMSEA	0.000	0.000
90 Percent confidence interval - lower	0.000	0.000

90 Percent confidence interval - upper	0.000	0.000
P-value H_0: RMSEA <= 0.050	NA	NA
P-value H_0: RMSEA >= 0.080	NA	NA

Robust RMSEA	NA	
90 Percent confidence interval - lower		NA
90 Percent confidence interval - upper		NA
P-value H_0: Robust RMSEA <= 0.050		NA
P-value H_0: Robust RMSEA >= 0.080		NA

Standardized Root Mean Square Residual:

SRMR	0.000	0.000
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Parameter Estimates:

Standard errors	Robust.sem
Information	Expected
Information saturated (h1) model	Unstructured

Regressions:

	Estimate	Std.Err	z-value	P(> z)
advice ~				
gender	-0.019	0.040	-0.463	0.643
years	-0.018	0.002	-9.354	0.000
cowork ~				
advice	0.691	0.019	36.651	0.000
gender	0.013	0.040	0.323	0.747
years	0.013	0.002	7.248	0.000

Intercepts:

	Estimate	Std.Err	z-value	P(> z)
.advice	0.000			
.cowork	0.000			

Thresholds:

	Estimate	Std.Err	z-value	P(> z)
advice t1	0.956	0.022	43.812	0.000
cowork t1	1.037	0.022	48.049	0.000

Variances:

	Estimate	Std.Err	z-value	P(> z)
.advice	1.000			
.cowork	0.523			

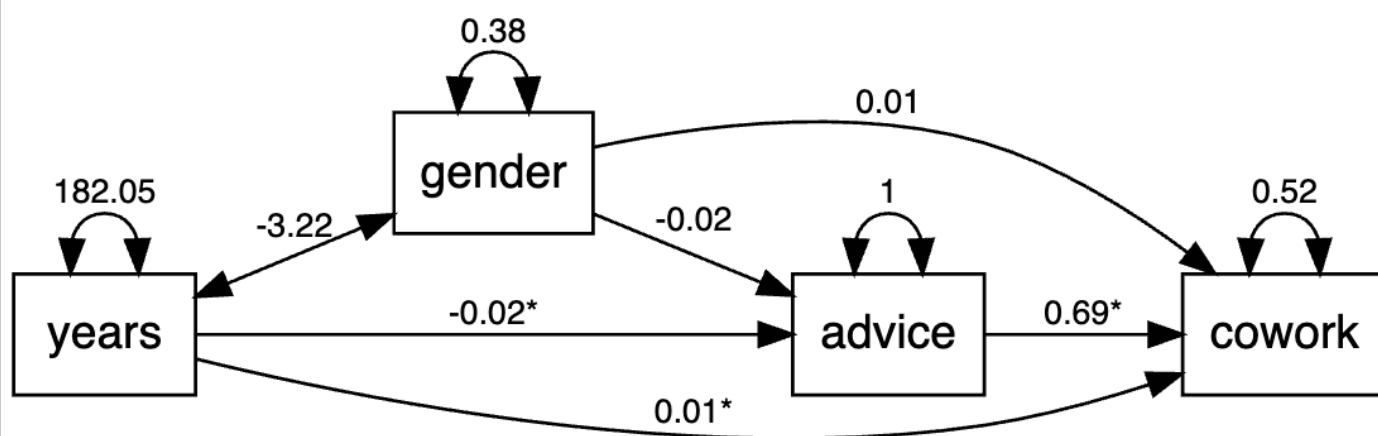
Scales y*:

	Estimate	Std.Err	z-value	P(> z)
advice	1.000			
cowork	1.000			

The indirect effects can be calculated as below.

```
> path.networksem(res, "gender", "advice", "cowork")
predictor mediator outcome   apath   bpath indirect
1  gender  advice cowork -0.01856161 0.6909742 -0.01282559
  indirect_se indirect_z
1  0.01304666 -0.9830558
```

The model is shown in the graph below.



Revision #2

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