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

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

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

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
```

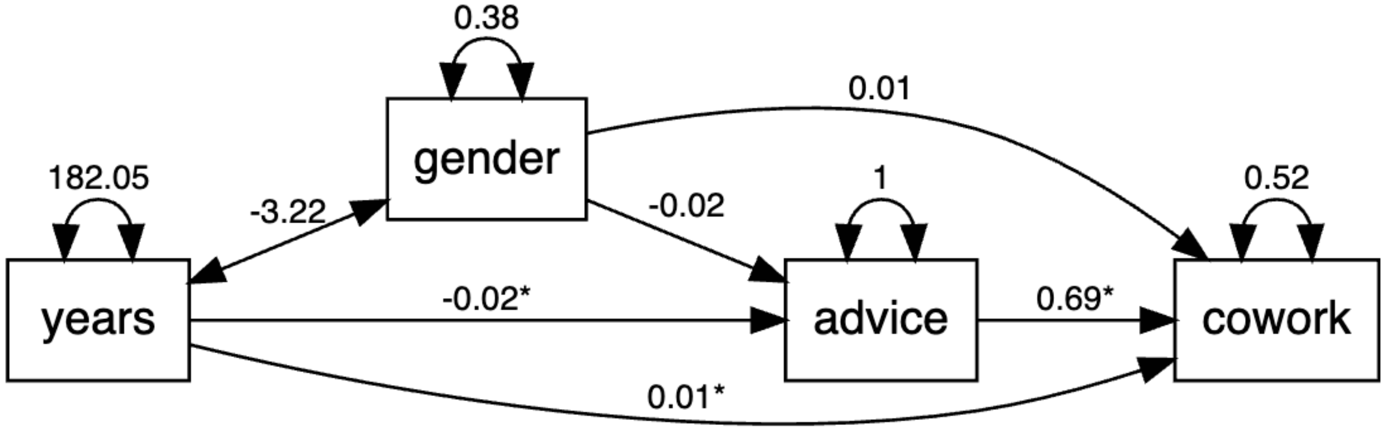
```
Variances:
                   Estimate  Std.Err  z-value  P(>|z|)
   .advice          1.000
   .cowork          0.523

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
Created 24 October 2024 15:09:37 by Admin
Updated 14 November 2024 01:04:11 by ziqian