Edge based analysis with latent space model

The R function `sem.net.edge.lsm` can be used to conduct edge based analysis with latent space model. In this case, the latent distance between each pair of individuals is used along with the transformed non-network covariates in SEM.

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(10)
nsamp = 50
lv1 <- rnorm(nsamp)
net <- ifelse(matrix(rnorm(nsamp^2) , nsamp, nsamp) > 1, 1, 0)
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
  net ~ lv1
  lv2 ~ net
'
```

Arguments passed to the `sem.net.edge.lsm` function includes the model, the dataset, and the latent dimensions. 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.

```
data = list(network = list(net = net), nonnetwork = nonnet)
set.seed(100)
res <- sem.net.edge.lsm(model = model, data = data, latent.dim = 1)
summary(res)
path.networksem(res, 'lv2', c('net.dists'), 'lv1')
```

The output is shown below:

```
Model Fit InformationSEM Test statistics:  492.628 on 4 df with p-value:  0
network 1 LSM BIC:  2244.546
==========================================
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The SEM output:
lavaan 0.6.15 ended normally after 29 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        11

  Number of observations                          2500

Model Test User Model:

  Test statistic                               492.628
  Degrees of freedom                                 4
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                               958.550
  Degrees of freedom                                10
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.485
```

```
  Tucker-Lewis Index (TLI)                      -0.288

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -22209.465
  Loglikelihood unrestricted model (H1)             NA

  Akaike (AIC)                               44440.930
  Bayesian (BIC)                             44504.994
  Sample-size adjusted Bayesian (SABIC)      44470.045

Root Mean Square Error of Approximation:

  RMSEA                                          0.221
  90 Percent confidence interval - lower         0.205
  90 Percent confidence interval - upper         0.238
  P-value H_0: RMSEA <= 0.050                    0.000
  P-value H_0: RMSEA >= 0.080                    1.000

Standardized Root Mean Square Residual:

  SRMR                                           0.109

Parameter Estimates:

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

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)
  lv2 =~
    x4                1.000
    x3                0.976       NA
  lv1 =~
    x2                1.000
    x1                0.642       NA

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)
```

```
  net.dists ~
    lv1              -0.000       NA
  lv2 ~
    net.dists        -0.000       NA

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)
   .x4              2.856       NA
   .x3              1.501       NA
   .x2              1.722       NA
   .x1              2.490       NA
   .net.dists       0.553       NA
   .lv2             1.315       NA
    lv1             0.715       NA

The LSM output:


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Summary of model fit
==========================

Formula:   network::network(data$network[[latent.network[i]]]) ~ euclidean(d = latent.dim)
<environment: 0x7fc473af4960>
Attribute: edges
Model:     Bernoulli
MCMC sample of size 4000, draws are 10 iterations apart, after burnin of 10000 iterations.
Covariate coefficients posterior means:
            Estimate     2.5%   97.5% 2*min(Pr(>0),Pr(<0))
(Intercept) -0.67923 -0.83587 -0.5504            < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Overall BIC:        2244.546
Likelihood BIC:     2184.507
Latent space/clustering BIC:     60.03918

Covariate coefficients MKL:
             Estimate
(Intercept) -1.117408
```

Empirical Data Example

When embedding the LSM into the edge-based approach, one thing that needs to be considered is whether to model covariates predicting the social networks in the LSM framework or in the SEM framework. This is only a concern in the edge-based model since covariates need to be edge-based as well if using the LSM method, and it defies the purpose of simplicity if we consider the LSM in the actor-based approach. In this example, we will accommodate the covariates in the LSM framework within the edge-based approach. The dataset used in this example is the Florentine marriage dataset. The model is quite simple as shown below. Essentially, the observed marriage network is hypothesized to be based not only on the latent positions, but also on the non-network variable of wealth. Additionally, priorates is viewed as a predictor of the distance between latent positrons of the marriage networks.

```
load("data/flomarriage.RData")


network <- list()
network$flo <- flomarriage.network
nonnetwork <- flomarriage.nonnetwork



model <- '
  flo ~  wealth
  priorates ~ flo + wealth
'
```

When fitting the model using the `sem.net.edge.lsm` function, the argument `type` and `latent.dim` are needed. Here, although the marriage network contains binary edges, the ordered argument is not needed since only the continuous latent distances will be used in the SEM.

```
data = list(network=network, nonnetwork=nonnetwork)
set.seed(100)
res <- sem.net.edge.lsm(model=model,data=data, type = "difference", latent.dim = 2, netstats.rescale = T,
data.rescale = T)
## results
summary(res)
```

In this model, the `latentnet` package is first used to estimate the LSM with the covariate of wealth. Then, the resulting latent positions of the marriage network, taking apart the effect of wealth, is hypothesized to be influenced by priorates and the effect is estimated through `lavaan`. Thus, the latent distances of the marriage network acts like a mediator between priorates and the observed network. The resulting estimates from both the SEM component and the LSM component are shown below.

```
Model Fit InformationSEM Test statistics:  0 on 0 df with p-value:  NA
network 1 LSM BIC:  259.7975
==========================================
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The SEM output:
lavaan 0.6.15 ended normally after 6 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                         5

  Number of observations                           256

Model Test User Model:

  Test statistic                                 0.000
  Degrees of freedom                                 0

Model Test Baseline Model:

  Test statistic                                50.126
  Degrees of freedom                                 3
  P-value                                        0.000

User Model versus Baseline Model:

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

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)               -700.431
  Loglikelihood unrestricted model (H1)       -700.431

  Akaike (AIC)                                1410.863
  Bayesian (BIC)                              1428.589
  Sample-size adjusted Bayesian (SABIC)       1412.737

Root Mean Square Error of Approximation:
```

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

Standardized Root Mean Square Residual:

  SRMR                                           0.000

Parameter Estimates:

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

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)
  priorates ~
    wealth            0.422    0.057    7.441    0.000
  flo.dists ~
    wealth            0.000    0.063    0.000    1.000
  priorates ~
    flo.dists        -0.000    0.057   -0.000    1.000

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)
   .priorates         0.819    0.072   11.314    0.000
   .flo.dists         0.996    0.088   11.314    0.000
```

The LSM output:

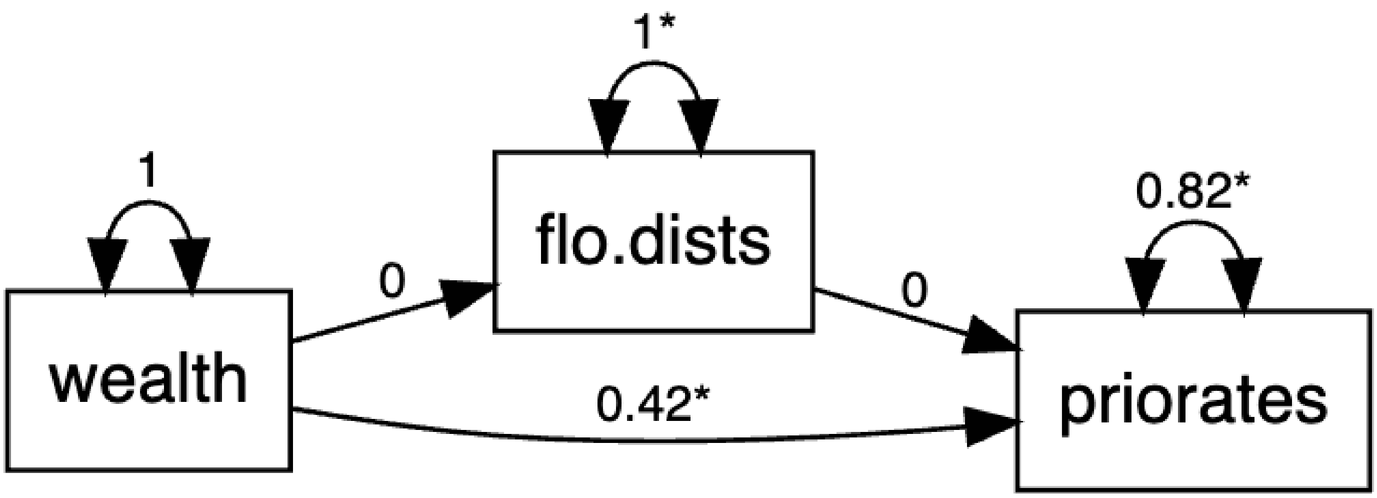
```
==========================
Summary of model fit
==========================

Formula:   network::network(data$network[[latent.network[i]]]) ~ euclidean(d = latent.dim)
<environment: 0x7fc434ed5160>
Attribute: edges
```

```
Model:     Bernoulli
MCMC sample of size 4000, draws are 10 iterations apart, after burnin of 10000 iterations.
Covariate coefficients posterior means:
            Estimate   2.5%  97.5% 2*min(Pr(>0),Pr(<0))
(Intercept)   5.0133 2.5627 7.9665            < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Overall BIC:        259.7975
Likelihood BIC:     85.53086
Latent space/clustering BIC:     174.2666

Covariate coefficients MKL:
            Estimate
(Intercept) 2.861026
```

To look at indirect effects, the following code can be used.

```
> path.networksem(res, "wealth","flo.dists", "priorates")
  predictor  mediator   outcome        apath         bpath      indirect
1    wealth flo.dists priorates 2.976241e-21 -4.047181e-22 -1.204539e-42
   indirect_se   indirect_z
1 1.874237e-22 -6.42682e-21
```

The model is shown in this diagram below.



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