RSiena: Remarks and Developments

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Overview

- ⇒ New version RSiena 1.1-282
- ⇒ New effects: influence from incoming ties,
- ⇒ New effects: two-step influence
- ⇒ Influence through direct ties $\looparrowleft\looparrowright$ influence from those who have similar affiliations: structural equivalence

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- ⇒ Evaluation effects $\rightleftharpoons$ Elementary effects
- ⇒ Diagnostic in case of multicollinearity
- ⇒ Effect sizes (*sienaRI*)

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- ⇒ Analysis of Multilevel Networks
- ⇒ Centering is optional
- ⇒ Attention for website and some recent papers.

Incompatibilities

1. Effects object no longer used as argument for print01Report().
2. Effect AltsAvAlt renamed to avXAlt (it is like avAlt but for covariates).
3. Parameter ‘priorRatesFromData’ in *sienaBayes* now has values 0-1-2 instead of TRUE-FALSE.

New effects

There are a lot of new effects.

1. Influence effects
2. Influence from incoming alters
3. Distance-two effects
4. Elementary effects
5. Miscellaneous

Influence effects

The triple avSim – totSim – avAlt
now is a quartet with a 2×2 structure:
{ sim , alt } × { av, tot }

This was implemented for regular influence effects,
influence from reciprocated alters, and
influence from other covariates (non-dependent / exogenous).

New effects:

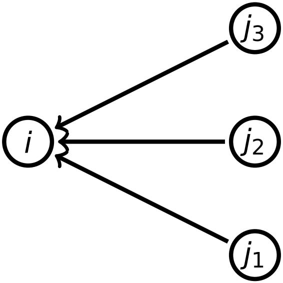
1. totAlt
2. totRecAlt
3. totXAlt

Incoming influence effects

The effects avAlt – totAlt – avXAlt – totXAlt
now also have analogues for influence from incoming ties:

4. avInAlt
5. totInAlt
6. avXInAlt
7. totXInAlt

i is influenced by
incoming ties $j_1 - j_3$



Extreme influence effects

8. maxAlt
9. minAlt

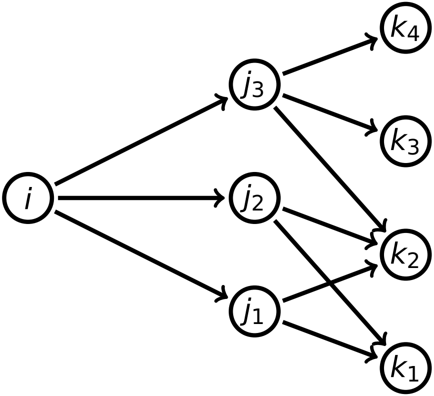
Distance-two effects

There now is the possibility to express influence at distance 2.

With the distinction average/total this leads to 4 possibilities: average vs. total at step 1 or step 2.

10. avAltDist2
11. totAltDist2
12. avTAltDist2
13. totAAltDist2

i is influenced by the average/total of the alter averages/totals of $j_1 - j_3$



New effects (3)

14. The formula for avAltDist2 (average at both steps) uses

$$\check{z}_j^{(-i)} = \begin{cases} \dfrac{\sum_{h \neq i} x_{jh}\, z_h}{x_{j+} - x_{ji}} & \text{if } x_{j+} - x_{ji} > 0 \\ 0 & \text{if } x_{j+} - x_{ji} = 0. \end{cases}$$

The effect is

$$s_{i14}^{\text{beh}}(x, z) = z_i \times \frac{\sum_j x_{ij}\, \check{z}_j^{(-i)}}{\sum_j x_{ij}}$$

(and the mean behavior, i.e. 0, if the ratio is 0/0).

New effects (4)

15. totAltDist2 (total at both steps) is defined by

$$s^{\mathrm{beh}}_{i15}(x,z) = z_i \sum_j x_{ij} \sum_{h \neq i} x_{jh}\, z_h = z_i \sum_j x_{ij}\,(x_{j+} - x_{ji})\,\check{z}_j^{(-i)} \ .$$

New effects (5)

16. avTAltDist2 (average of totals) is defined by

$$s^{\text{beh}}_{i16}(x,z) = z_i \times \frac{\sum_j x_{ij}\,(x_{j+} - x_{ji})\,\check{z}_j^{(-i)}}{\sum_j x_{ij}}$$
$$= z_i \times \frac{\sum_j x_{ij}\,\sum_{h \neq i} x_{jh}\,z_h}{\sum_j x_{ij}}$$

and the mean behavior, i.e. 0, if the ratio is 0/0.

17. totAAltDist2 (total of averages) is defined by

$$s^{\text{beh}}_{i17}(x,z) = z_i \times \Big(\sum_j x_{ij}\,\check{z}_j^{(-i)}\Big)\,.$$

New effects (6)

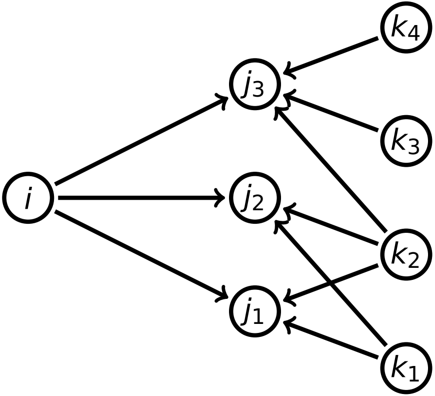
The same for distance-2 averages and totals of covariates:

18. avXAltDist2
19. totXAltDist2
20. avTXAltDist2
21. totAXAltDist2

New effects: outgoing - incoming

The same for distance-2 averages and totals
where the second step is for incoming ties:

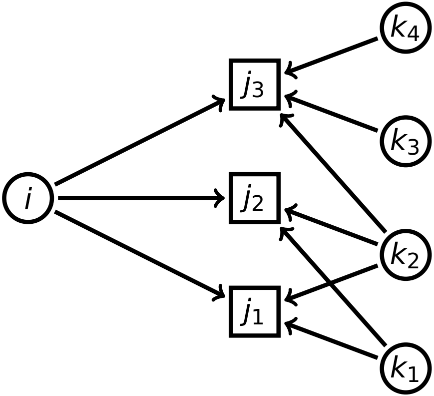
22. avInAltDist2
23. totInAltDist2
24. avTInAltDist2
25. totAInAltDist2
26. avXInAltDist
27. totXInAltDist2
28. avTXInAltDist2
29. totAXInAltDist2



i is influenced by
the incoming alter averages of $j_1 - j_3$

New effects (8)

The *InAltDist2 effects are
also available
for two-mode networks.



This means that it is now possible to model influence
from those out-alters
who have the same affiliations as the focal actor.

Elementary effects

SAOM effects have been framed in the triple

1. evaluation
2. maintenance/endowment
3. creation

effects.

The contributions to probabilities are based on differences in
evaluation function f^{ev}
maintenance function f^{mt}
creation function f^{cr}
which play the following role in the definition of a ministep:

The probability that, given a current network x and actor i making the ministep, the network changes to $x^{\pm ij}$, is

$$\frac{\exp\Big(u_i\big(x, x^{\pm ij}\big)\Big)}{1 + \sum_{h \neq i} \exp\Big(u_i\big(x, x^{\pm ih}\big)\Big)}$$

where the objective function is

$$\begin{aligned} u_i\big(x, x^*\big) = f_i^{\text{ev}}(x^*) - f_i^{\text{ev}}(x) &+ \Delta^+\big(x, x^*\big)\big(f_i^{\text{cr}}(x^*) - f_i^{\text{cr}}(x)\big) \\ &+ \Delta^-\big(x, x^*\big)\big(f_i^{\text{mt}}(x^*) - f_i^{\text{mt}}(x)\big) \end{aligned}$$

and

$$\Delta^+\big(x, x^*\big) = \begin{cases} 1 & \text{if tie is created } (x^* = x^{+ij}) \\ 0 & \text{if tie is dropped, or no change} \end{cases}$$

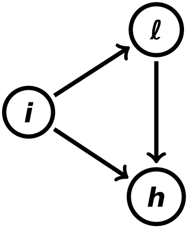
$$\Delta^-\big(x, x^*\big) = \begin{cases} 1 & \text{if tie is dropped } (x^* = x^{-ij}) \\ 0 & \text{if tie is created, or no change.} \end{cases}$$

However, not all probabilities of change can be based on changes in some (evaluation-type) function.

Example : transitive triplets

The transitive triplets effect is defined as

$$s_i(x) = \sum_{j,k} x_{ij}\, x_{ik}\, x_{kj}$$



with change statistic
(change when adding tie $i \rightarrow j$)

$$\delta_{ij}(x) = \sum_{k} x_{ik}\big(x_{kj} + x_{jk}\big) \; .$$

The first part refers to creating the tie $i \rightarrow j = h$,
the second part to creating the tie $i \rightarrow j = \ell$.

But one could be interested in only transitive closure,
as defined by closing of an open two-path ($i \rightarrow j = h$),
as distinct from creating ties
to those with the same out-choices,
which is a kind of structural equivalence ($i \rightarrow j = \ell$).

This cannot be represented
as a change in an evaluation function.

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elementary effect

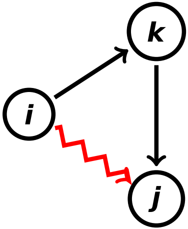
Elementary effect

An elementary effect is simply an effect that is a term
of the objective function $u_i\big(x, x^*\big)$
used to define change probabilities for ministeps,
referring to creation and/or maintenance of a tie $i \rightarrow j$,
without being necessarily a difference $f_i(x^{\pm ij}) - f_i(x)$
of some function f_i
(or similar with multiplication by Δ^+ or Δ^-).

Example : transTrip1 and transTrip2

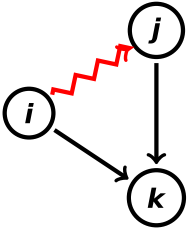
transTrip1 (transitive closure)

$$s_{ij}(x) = x_{ij} \sum_k x_{ik} \, x_{kj}$$



transTrip2
(structural equivalence outgoing ties)

$$s_{ij}(x) = x_{ij} \sum_k x_{ik} \, x_{jk}$$



Elementary effects can lead to the same configuration and therefore have the same target statistic
(such as transTrip1 and transTrip2).

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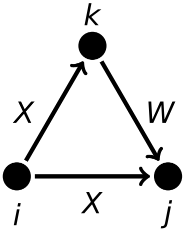
However, they can be be distinguished empirically by estimation by the Generalized Method of Moments and by likelihood-based methods (Maximum Likelihood, Bayes).

Incidentally, the gwesp effects have also been implemented as elementary effects.

New effects (continued)

30. XWX1: like XWX, dependent variable is only one of the XWX ties: $i \rightarrow j$.
31. XWX2: dependent variable here is $i \rightarrow k$.



XWX1 and XWX2 are elementary effects.

New effects (still continued)

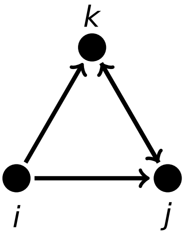
32. cl.XWX1: like XWX1 but for dependent network.
33. cl.XWX2: like XWX2 but for dependent network.

cl.XWX1 and cl.XWX2 also are elementary effects.

34 sameXInPop, *indegree popularity from same covariate*
number of incoming ties received by those
to whom i is tied and sent by others
who have the same covariate value as i,

$$s^{\text{net}}_{i34}(x) = \sum_j x_{ij} \sum_h x_{hj} I\{v_i = v_h\} \ .$$

35 transRecTrip2,
another
reciprocity × transTrip interaction.



36. reciPop: reciprocal degree popularity
37. reciAct: reciprocal degree activity
38. gwesp.. effects obtain endowment and creation effects. They now also are allowed to interact with other effects (interactionType = "dyadic") .

Warning for collinearities between effects

E.g: use transTrip together with transMedTrip effects:

```
Estimates, standard errors and convergence t-ratios
                                   Estimate   Standard   Conv.
                                                Error     t-ratio
1. eval outdegree (density)         -2.6538  ( 0.1198   ) 0.0833
2. eval reciprocity                  2.3836  ( 0.2008   ) 0.0326
3. eval transitive triplets          0.3535  ( 0.0545   ) 0.0592
4. eval transitive mediated triplets 0.5624  ( 0.0545   ) 0.0592
Warning: ** Warning: Noninvertible estimated covariance matrix **
```

Note that a standard error is given. This is wrong.

This now gives the warning:

```
*** Warning: Covariance matrix not positive definite ***
*** Standard errors not reliable ***
The following is approximately a linear combination
for which the data carries no information:
 -1 * beta[3] + 1 * beta[4]
It is advisable to drop one or more of these effects.
```

Relative Importance of Effects

Natalie Indlekofer has contributed the function `sienaRI()`,
which assesses the relative importance of effects.
From version 1.1-270.

Indlekofer, Natalie, and Brandes, Ulrik, (2013).
Relative importance of effects
in stochastic actor-oriented models.
Network Science 1.3, 278–304.

Now including dynamic importance (over the period);
but this still/again runs into a crash;
and also (not explicitly given in her paper)
the raw/total importance of effects.

Indlekofer & Brandes (2013), formulae (3, 4):

π_i is the vector of probabilities for actor i in mext ministep, and $\pi_i^{(-k)}$ is the same if effect k obtains a weight of 0;

$$I_k(X, i) = \frac{\left\|\pi_i - \pi_i^{(-k)}\right\|_1}{\sum_{\ell=1}^{K} \left\|\pi_i - \pi_i^{(-\ell)}\right\|_1} \ ;$$

expected relative importance then is

$$\frac{1}{N} \sum_{i=1}^{N} I_k(X, i) \ .$$

Expected (raw / total) importance can then be defined as

$$\frac{1}{N} \sum_{i=1}^{N} \left\|\pi_i - \pi_i^{(-k)}\right\|_1 \ .$$

Multilevel Analysis of Networks

Analysis of multilevel network dynamics (Koskinen - Snijders)
(‘random coefficient Siena’) is now available;
still experimental, paper still needs to be finished,
but can be used.

The analysis is Bayesian (MCMC) and time-consuming.

See the manual!

Especially meaningful for many small groups,
where ‘borrowing strength’ is important.

Convergence assessment still needs to be further codified;
various options and parameters are being added,
e.g., to help convergence.

For example:
now possible to estimate parameters for elementary effects
that have the same target statistic.

Analysis of Multilevel Networks

Multilevel network (Wang, Robins, Pattison, Lazega, 2013):

Network with nodes of several types,
distinguishing between types of ties
according to types of nodes they connect.

Thus, if types of nodes are A, B, C,
distinguish between $A - A$, $B - B$, $C - C$ ties, etc., (*within-type*)
and between $A - B$, $A - C$, etc., ties (*between-type*).

Some may be networks of interest,
others may be fixed constraints,
still others may be non-existent or non-considered.

Analysis of multilevel networks with several actor sets is possible by a sleight of hand, (thanks to James Hollway).

Consider multilevel network with two node sets, A and B.

There are two one-mode networks internal to A and B,
and two two-mode networks X_1 from A to B; X_2 from B to A.

Specification for RSiena possible by employing
one joint node set $A \cup B$ and two dependent networks:

$$
\begin{array}{cc}
 & \begin{array}{cc} A & B \end{array} \\
\begin{array}{c} A \\ B \end{array} & \begin{pmatrix} \text{internal } A & 0 \\ 0 & \text{internal } B \end{pmatrix}
\end{array}
\qquad
\begin{array}{c}
\begin{array}{cc} A & B \end{array} \\
\begin{pmatrix} 0 & \text{two-mode } A \times B \\ \text{two-mode } B \times A & 0 \end{pmatrix}
\end{array}
$$

networks $A,\ B$ network X_2 network X_1

For example:

A a set of organizations, B a set of individuals,
X_2 is a fixed membership relation, X_1 is not there;

networks A and B could be taken apart
in two distinct networks;

if there are only ties between individuals within organizations,
B will be a network of diagonal blocks
and structural zeros between different organizations;

if there are essential differences between individual ties
within organizations or across organizations,
B can be decomposed in two further distinct networks.

Further to be developed....

Centering

Note that centering of monadic and dyadic covariates now is optional.

Sometimes centering is more, sometimes less suitable.

(E.g., do not center if you wish to use an interaction to specify some effect for only some category of an actor covariate.)

Think of this choice!

Website - documentation

Note the website:

at the ‘*news*’ tab,
there is a list of incompatibilities and bugs;
also some interesting papers are mentioned.

- Manual explains elementary effects.
- Section in manual about user-defined interaction effects extended.
- Siena_algorithms.pdf is put at the Siena website (partial explanation of algorithms and code).