Siena Advanced Users' Workshop 2015

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Overview

1. Where to look?

Siena is an evolving endeavour, which may be hard to follow.

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- Follow the Siena/Stocnet discussion list!
- The website
  `http://www.stats.ox.ac.uk/~snijders/siena/`
  notes important matters at the '*News*' page:
  list of incompatibilities and bugs;
  new developments; some interesting papers.
- Most recent versions can be downloaded from
  R-Forge and '*Downloads*' page of website,
  and are announced at the Siena/Stocnet discussion list.
- Website '*News*' page, and Appendix B in the manual,
  give description of changes in the new versions.

Where to look? (2)

- Website ‘*Literature*’ page has a new section ‘Presentations (teaching material)’ including (e.g.) these slides.
- Recent (since late 2014) changes in manual:
  ⇒ elementary effects (treated below);
  ⇒ more about user-defined interaction effects;
  ⇒ changed section about convergence
  and how to use the algorithm options.
- Siena_algorithms.pdf now is at the Siena website (partial explanation of algorithms and code).

2. New convergence criterion

The usual convergence criterion is tmax
the absolute maximum of the *t*-ratios for convergence,
considering simultaneously all parameters in the model.

It has appeared that for some models
(e.g., with non-centered actor covariates)
the usual criterion

$$\text{tmax} \leq 0.10$$

is not sufficient.

Therefore, the overall maximum convergence ratio
(included as tconv.max in *sienaFit* objects since some time)
gets a new importance.

Overall maximum convergence ratio

This is defined as the maximum t-ratio for convergence for any linear combination of the parameters,

$$\text{tconv.max} = \max_b \left\{ \frac{b'(\bar{s}_j - s^{\text{obs}})}{\sqrt{b'\Sigma b}} \right\} .$$

This is equal to (use Cauchy-Schwarz inequality)

$$\max_c \left\{ \frac{c'\Sigma^{-1/2}(\bar{s}_j - s^{\text{obs}})}{\sqrt{c'c}} \right\} = \sqrt{(\bar{s}_j - s^{\text{obs}})'\Sigma^{-1}(\bar{s}_j - s^{\text{obs}})} .$$

The definition implies that

$$\text{tconv.max} \geq \text{tmax} .$$

Illustration:

With one data set & model
with a non-centered actor covariate,
produce several estimates
with different values of tmax and tconv.max,
and see how far they are from the 'true' solution.

1. Produce a rather large set of estimates.

Illustration:

With one data set & model
with a non-centered actor covariate,
produce several estimates
with different values of tmax and tconv.max,
and see how far they are from the 'true' solution.

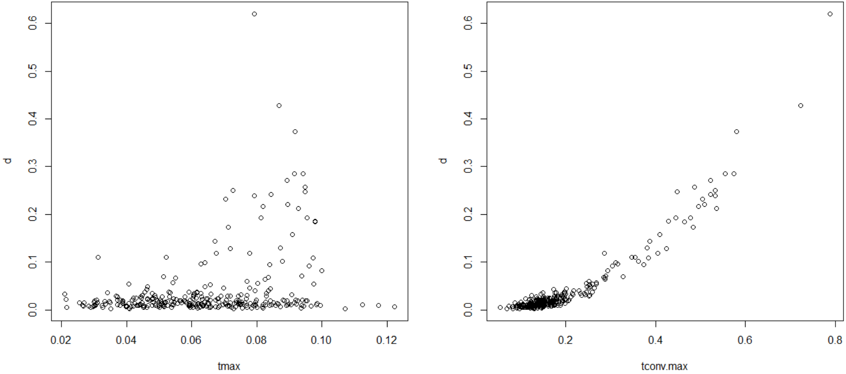
1. Produce a rather large set of estimates.
2. Summarize as follows:
   ⇒ Define 'good' estimates by tconv.max $\leq$ 0.10.
   ⇒ Calculate, from this 'good' set, robust mean $\bar{\mu}$
   and robust mean $\bar{\Sigma}$ of
   estimated covariance matrices $\text{Cov}(\hat{\theta})$.

3. Measure quality of all (good or poor) estimates $\check{\theta}_i$ by

$$d_i = \sqrt{(\check{\theta}_i - \bar{\theta})' \, \bar{\Sigma}^{-1} \, (\check{\theta}_i - \bar{\theta})} \, .$$

This is the standardized distance
from the best estimate $\bar{\theta}$.

Then plot these distances as functions of tmax and tconv.max.



Distances d_i as a function of tmax (left) and tconv.max (right).

Conclusion:

1. Distance from true estimate is much better indicated by tconv.max than by tmax.
2. When tconv.max exceeds 0.30, distances d_i from the 'true value' $\bar{\theta}$ are larger than 0.1.

New criterion

tmax $\leq$ 0.10 <u>and</u> tconv.max ≤ 0.25 .

Further options for siena07()

To improve the possibilities of `siena07()` to indeed produce estimates satisfying this new criterion,
some new options were developed;
see ?sienaAlgorithmCreate and manual, Section 6.1.3;
also see Siena_algorithms.pdf.

Current advice

1. doubleAveraging = 0
2. diagonalize = 0.2 or other low value (e.g., 0 or 0.5)
   (the 'diagonalize' option was corrected
   and its standardization improved)
3. if this is not sufficient, even with repeated *prevAns* runs:
   tentative: n2start = 500 or higher
   (increases computation time).

What is double averaging?

The regular Robbins-Monro update step is

$$\hat{\theta}_{N+1} = \hat{\theta}_N - a_N \tilde{D}^{-1} (S_N - s)$$

The algorithm with double averaging is

$$\hat{\theta}_{N+1} = \bar{\theta}_N - N a_N \tilde{D}^{-1} (\bar{S}_N - s) ,$$

where

$$\bar{\theta}_N = \frac{1}{N} \sum_{n \leq N} \hat{\theta}_n , \quad \bar{S}_N = \frac{1}{N} \sum_{n \leq N} s_n .$$

See Siena_algorithms.pdf.

3. 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

New effects (1): Influence

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

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

New effects:

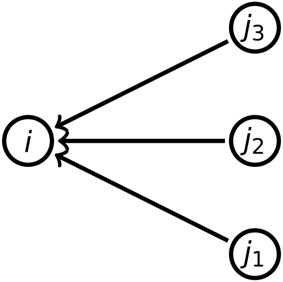
1. totAlt (next to avAlt, totSim, avSim)
2. totRecAlt (next to avRecAlt)
3. totXAlt (next to avXAlt, the old AltsAvAlt)

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

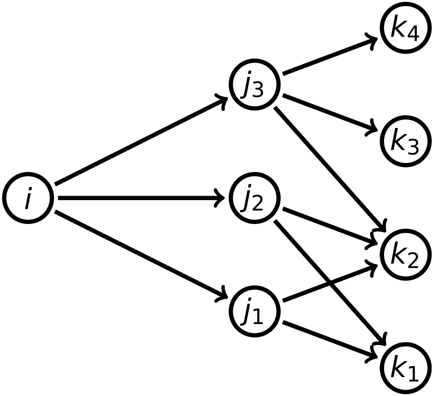
8. maxAlt
9. minAlt

New effects (2): Distance-two

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

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

New effects (5)

16. avTAltDist2 (average of totals) is defined by

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

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

17. totAAltDist2 (total of averages) is defined by

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

New effects (6)

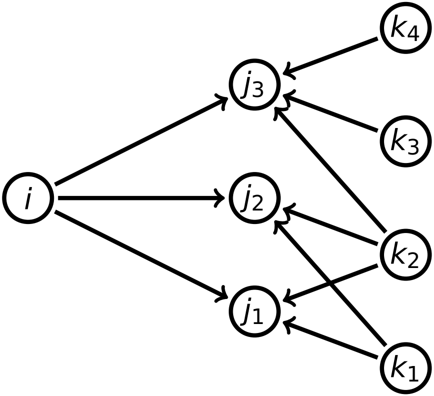
The same for distance-2 averages and totals of covariates:

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

New effects (7): 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

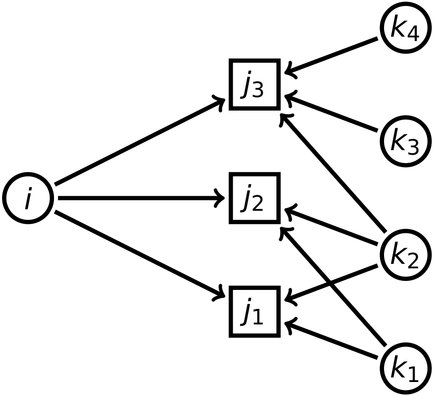


i is influenced by the incoming alter averages of $j_1 - j_3$.

Also ‘sim’ versions (simEgoInDist2 etc.)

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.

Structural equivalence

These distance-two outgoing–incoming effects
can be regarded as representing influence from
actors who are structurally equivalent (w.r.t. outgoing ties).

4. 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

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

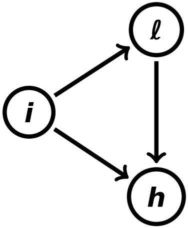
$$\Delta^-\big(x, x^*\big) = \begin{cases} 1 & \text{if tie is dropped } (x^* = x^{-ij}) \\ 0 & \text{if tie is created, or no change.} \end{cases}$$

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 ($i \rightarrow j = \ell$).

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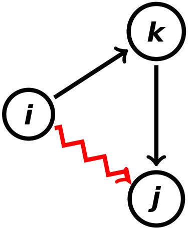
elementary effect

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^-).

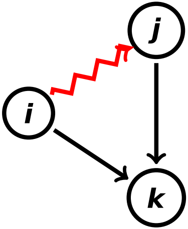
Example : transTrip1 and transTrip2

transTrip1 (transitive closure)



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

transTrip2
(structural equivalence outgoing ties)



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

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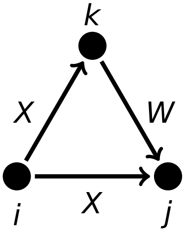
However, they can be be distinguished empirically by estimation by the Generalized Method of Moments (under development) and by likelihood-based methods (Maximum Likelihood, Bayes).

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)

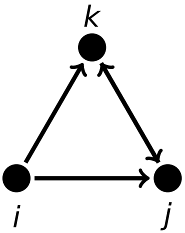
32. cl.XWX1: like XWX1 but for dependent network.
33. cl.XWX2: like XWX2 but for dependent network.

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") .
39. And various others
    (e.g., interactions between networks and covariates).

5. Co-evolution

Evolution of multiple networks is studied more and more.

Various new effects have been constructed for this purpose: see Section 12.1.2 of the manual.

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When a monadic or dyadic variable is regarded
as a control variable,
it still may be advisable to use it as a dependent variable
in the SAOM analysis, rather than as a covariate,
because this will allow the 'control' variable much better
to maintain its correspondence during the simulations
with the focal dependent variables.

Results using a ‘control network’ as a covariate
will differ quite appreciably from results obtained
while using it as a co-evolving dependent network;
and similarly for monadic variables.

Example: acquaintance or communication
as a control network variable for advice
to study the properties of the ‘purified’ advice relation,
conditional on the condition of acquaintance.

6. Multilevel Analysis of Networks

See MultiMetaSAOM_s.pdf, at website.

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:

$$\begin{array}{cc} & \begin{array}{cc} A & B \end{array} \\ \begin{array}{c} A \\ B \end{array} & \left(\begin{array}{cc} \text{internal } A & 0 \\ 0 & \text{internal } B \end{array} \right) \\ & \text{networks } A,\ B \end{array} \quad \begin{array}{c} \begin{array}{cc} A & B \end{array} \\ \left(\begin{array}{cc} 0 & \text{two-mode } A \times B \\ \text{two-mode } B \times A & 0 \end{array} \right) \\ \begin{array}{cc} \text{network } X_2 & \text{network } X_1 \end{array} \end{array}$$

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.

For the ‘Analysis of Multilevel Networks’ using RSiena, possibilities exist in principle, as indicated above;

a first example is
Tom A.B. Snijders, Alessandro Lomi, and Vanina Torlò (2013). A model for the multiplex dynamics of two-mode and one-mode networks, with an application to employment preference, friendship, and advice.
Social Networks, 35, 265-276;

the research program has been continued by James Hollway in his DPhil thesis (Oxford – Zürich – Genève);

further relevant effects have to be elaborated;

and the field is open!

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For Analysis of Multilevel Networks generally:

7. Missing Data

- ⇒ Sometimes there is enough information to make some imputations with a high degree of confidence.
If possible, do this!
- ⇒ There was an error in the treatment of missings in *non-centered* monadic covariates
until and including version 1.1-284.

Missing Data (contd.)

⇒ New option *imputationValues* in *coCovar*, *varCovar* :
these values will be used for imputation of missings for the simulations,
but (like always happens for missings) are not taken into account for the statistics used for estimation.

Can be used if there are reasonable, not completely reliable values for imputation,

8. Relative Importance of Effects

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

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

`sienaRI()` also gives (not explicitly used in her paper)
the raw/total importance of effects.

`sienaRIDynamics()` still has difficulties
(temporarily withdrawn).

Expected importance of a parameter is defined as
the change in choice probabilities
if this parameter would be changed to the value 0.

Expected relative importance is the same,
relative to all effects
(i.e., rescaled to have sum = 1).

`sienaRI()` also produces entropies
(cf. Snijders, *Maths. and Soc. Sci.*, 2004).

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

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

Example: Results for Glasgow data

Effect	par.	(s.e.)
basic rate parameter friendship	11.207	(1.025)
outdegree (density)	–2.023***	(0.249)
reciprocity	2.563***	(0.190)
transitive recipr. triplets	–0.323***	(0.086)
GWESP I -> K -> J (69)	2.172***	(0.145)
indegree - popularity	–0.016	(0.031)
outdegree - popularity	–0.135†	(0.076)
outdegree - activity	–0.146***	(0.026)
sex alter	–0.101	(0.118)
sex ego	0.076	(0.150)
same sex	0.691***	(0.118)

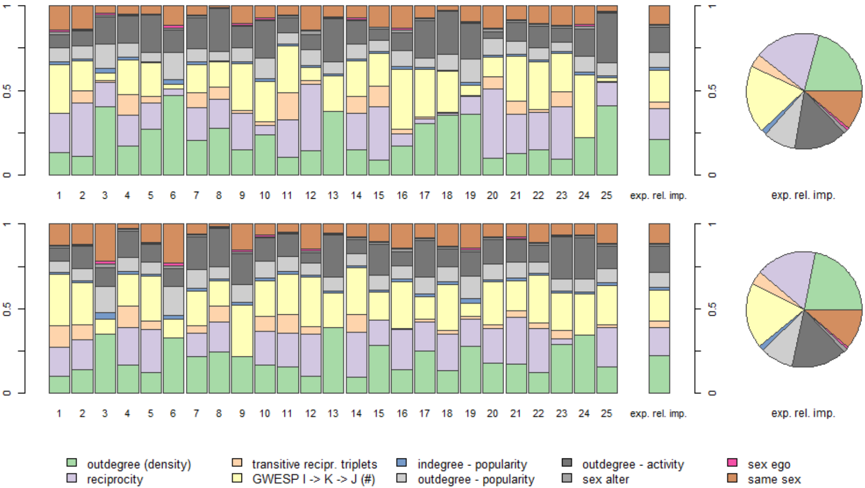
† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

convergence t ratios all < 0.07.

Overall maximum convergence ratio 0.15.

Example: Results for Glasgow data

	Exp. rel. importance		Exp. importance	
Effect	wave 1	wave 2	wave 1	wave 2
outdegree (density)	0.2075	0.2193	0.8656	0.9122
reciprocity	0.1857	0.1691	0.7154	0.6701
transitive recipr. triplets	0.0369	0.0381	0.1650	0.1696
GWESP I -> K -> J (69)	0.1889	0.1831	0.8079	0.7839
outdegree - popularity	0.0145	0.0149	0.0543	0.0551
outdegree - activity	0.0900	0.0922	0.3361	0.3500
sex alter	0.1486	0.1541	0.6608	0.6791
sex ego	0.0113	0.0109	0.0373	0.0365
same sex	0.0062	0.0063	0.0244	0.0248
Entropy			0.3798	0.3860



Plot of relative importance of effects for first 25 actors and averaged for all actors (pie-chart).

The graph was produced by

```
plot(RI, actors=1:25, addPieChart = TRUE, legendColumns=5)
```

where RI was the object produced by `sienaRI()`;
`plot.sienaRI()` was slightly improved in version 1.1-288,
with a new argument *actors*,
and better proportions of the pie chart.

Note: you can get the code of such a function by
`RSIenaTest:::plot.sienaRI`
(no parentheses!) and then, if you know enough R,
modify as desired.

9a. Developments in current models

There still is much more to do and explore within the confines of what has already been developed and implemented.

1. The topics mentioned above are open for application / elaboration.
2. Evaluation / creation / maintenance / elementary effects
3. Evaluation / creation / maintenance / effects for behaviour
4. Variants of non-directed models.
5. Comparability of effects across models, data sets
   $\sim$ 'marginal' effects

Developments in current models (contd.)

6. Model selection
7. Importance of GoF for validity of results
8. Extended auxiliary functions for GoF
9. avAlt ⇔ avSim ⇔ totAlt ⇔ totSim
10. Diffusion of innovations – event history analysis
11. Two-mode networks
12. Multivariate (e.g., signed) networks
13. Ordered networks

9b. Hot Issues

- Analysis of Multilevel Networks (see above!)
- Comparison SAOM $\longleftrightarrow$ ERGM
  (Per Block, Friday 10.00am)
- JSiena (poster Felix Schönenberger, Saturday 5.30pm)
- Generalized Method of Moments
  (Viviana Amati, Friday 10.00am)
- Continuous dependent actor variables
  (Nynke Niezink, Friday 9.40am)
- Settings model (Tom Snijders, Friday 9.20am)


The horse race of Siena,
il Palio, was originated in year