StOCNET in development: An update

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StOCNET is an open software system in a Windows environment for the advanced statistical analysis of social networks. It provides a platform to make a number of statistical methods that are presently still privately proposed available to a wider audience. A flexible user interface utilizing an easily accessible data structure is developed such that new methods can readily be included in the future. As such, it will allow researchers to develop new statistical tools by combining their own programs with routines of the StOCNET system, providing a faster availability of newly developed methods.

In this paper we show the current state of the developments with an emphasis on the implementation and operation of the programs that are already included in StOCNET : BLOCKS (for stochastic blockmodeling) and SIENA (for analyzing repeated measurements of social networks). Moreover, we present an overview of future contributions, which will be available within the near future, and of planned activities with respect to the functionality of the StOCNET software. StOCNET is a freeware PC program, and can be obtained from the StOCNET website at

`http://stat.gamma.rug.nl/stocnet/`.

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1 Introduction

Two years ago, the development of an open software system called StOCNET for the advanced statistical analysis of social networks was announced by Zeggelink, Snijders, and Boer (2000) at the Sunbelt XX conference in Vancouver. Many different methods that exist for the analysis of social networks are covered by programs like GRADAP or UCINET. However, a number of recently developed statistical methods and the accompanying computer programs have not yet reached (potentially interested) empirical researchers in social networks. The main reason is that most of these methods are available in privately owned programs that are not quite fit for public distribution. StOCNET provides a Windows platform to make these statistical methods available.

After two years it is time for an update, and in this paper the current state of the developments is presented. A flexible and easily available data structure and user interface were developed such that new methods can easily be included and new tools can be developed by combining existing programs with routines of the StOCNET system. At this moment, the current operation, StOCNET version 1.1 (Boer, Huisman, Snijders, and Zeggelink, 2001), contains two statistical methods for social networks analysis: BLOCKS, for stochastic blockmodeling of relational data (Nowicki and Snijders, 2001), and SIENA, for the statistical analysis of longitudinal network data (Snijders, 2001). These modules are presented in this paper. Furthermore, modules that will be available in the near future are presented, as well as other functionalities of the StOCNET software to be implemented.

The paper starts with a brief introduction to the StOCNET project. In the following section, the current version of StOCNET (version 1.1), is presented. The supported options are described and an example data set consisting of friendship networks between university freshmen will be used to illustrate the StOCNET software.

The statistical methods forming the core of the StOCNET software are introduced in Section 4: BLOCKS and SIENA. The university freshmen data were analyzed with the procedures, and some results are presented. In Section 5 the functionalities that are under development are described and in the following section four programs that are planned to be included in the next year are introduced: p_2, PALNET, PACNET and ZO. The paper ends with directions for potential contributors and the presentation of the StOCNET website.

2 The StOCNET project

Methods for the analysis of social networks[1] are not covered in standard statistical packages. There exist a number of software packages that are specifically designed for social network analysis. The most widely known and widely used programs are GRADAP (Sprenger and Stokman, 1989) and UCINET (Borgatti, Everett, and Freeman, 1999). Other (less well known or only recently available) programs are FATCAT (Richards and Seary, 1993), MultiNet (Richards and Seary, 2000), and Pajek (Batagelj and Mrvar, 2002)[2]. These programs contain many state-of-the-art analysis methods, but they cover only specialized methods, or the coverage of established methods is not complete. Especially, and not surprisingly recently developed statistically oriented methods are underrepresented in these programs.

There are some privately owned computer programs implementing statistical analysis methods, constructed by the developers of the statistical methods. Stimulated by general developments in statistical analysis that were facilitated by expanded computing force, such as Gibbs sampling, computer-intensive techniques, partly based on simulation, have proved to be quite important contributions. These programs are not always easily available, user-friendly, and usually miss sufficient documentation. Therefore, the methods have not yet (or hardly) reached the empirical social network researchers.

The purpose of the StOCNET project is the development of an open software system for the advanced statistical analysis of social networks. The system serves three goals:

1. the incorporation of important recently developed methods in user-friendly and easily available software,
2. more efficiency in the implementation of new methods by setting up a system with common data structure and user interface, and
3. faster availability of new methods.

The aim is not competition with but complementarity to other social network analysis software. Whereas other programs usually are closed systems offering a wide range of mostly non-statistical methods, StOCNET is an open system focusing on more advanced statistical methods which, partly because of their being based on simulation methods, may require more expertise of the user.

A second aspect of the StOCNET project is the definition of requirements and formulation of instructions for potential contributors to the system. The

[1]See Wasserman and Faust, 1994, for an overview.

[2]Some of the programs are available as freeware: see the INSNA website at `http://www.heinz.cmu.edu/project/INSNA/soft_inf.html`.

definition of requirements is aimed at data definition and output, thus developing StOCNET standards, with the purpose of reducing the programming task of the contributor. The requirements also include (precise) documentation of the method, which is facilitated because the set-up of the program, data definition, and technical specifications are already documented in StOCNET .

3 The StOCNET system

3.1 StOCNET sessions

An analysis within StOCNET takes place within a so-called session, and usually consists of five more or less sequential steps. The steps start with the data definition and result in specified output, after which all or some steps can be repeated. Within a session the user generally uses the same (selection of) data sets. Transformations, selections and the latest model specifications for these data are all saved in saving the session, and can easily be activated again when opening the same session a second time.

For most users, the sequential process of five steps will soon become a cyclic process, while possibly even skipping certain steps. The interactive features of StOCNET imply that any revised analysis can easily be undertaken in the current or in a new session. The different steps in a session can be entered by clicking the corresponding buttons in the StOCNET toolbar (see Figure 1).

Step 1. *Data definition*: specification and description of the network(s) and the actor attributes in separate data files. In this step, the network data and the attribute data are specified. Both may be contained in multiple data files. The network must be presented as an adjacency matrix (saved) in ASCII format. This means that each network is presented by n lines with n integer numbers separated by blanks, and each line is ended by a hard return. Once a file has been selected, the network in that file is added to the set of available networks for that session. The same holds for attribute files (actor and/or dyadic attributes). If there are k actor covariates, the data file must contain n lines, with on each line k numbers which are read as real numbers, and must be separated by blanks. The StOCNET user interface for this step is presented in Figure 1.

Step 2. *Transformation*: recoding of network values and/or actor variables, and specification of missing values. A full recode functionality is not yet implemented, but will be made available in later versions. For now, it is only possible to dichotomize the data by indicating the values that are to be transformed to value 1; all other values will be considered having value 0.

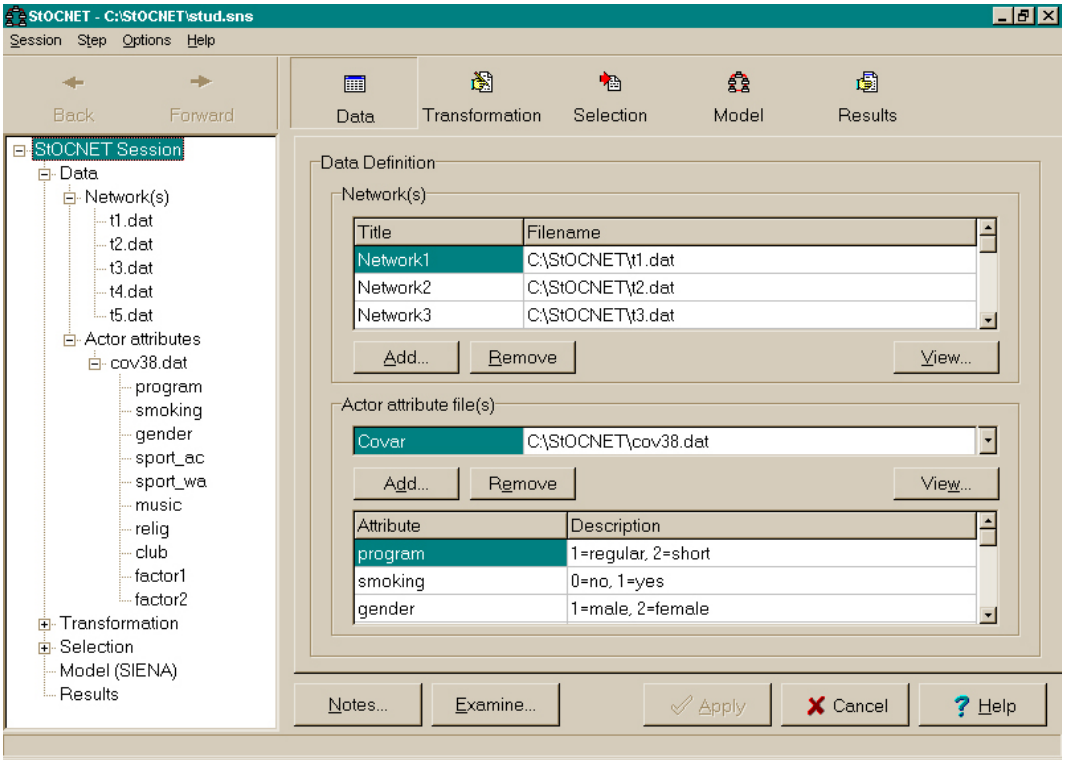

Figure 1: Step 1 in a StOCNET session — Data definition.

Step 3. *Selection*: selection of actors based on several possible criteria. This option is not yet available, but selection based on a range of actors, on values of attributes, or on calculated network statistics will be possible in later versions.

Step 4. *Model specifications and analysis*: choice of program for data analysis. Subsequently specification of the model parameters in the model specific user interface, and running the method. The models that are available in the current version are described in Section 4.

Step 5. *View results*: Inspection of the output and results from the analyses. StOCNET allows for a structured view through the output by selecting certain output items. The items are indicated in the output file by the symbol @1 for chapters, @2 for sections, @3 for sub-sections, and so on. These items are shown in the session tree in the left part of the StOCNET window, and the user can select an item by double clicking on it.

In every step of a StOCNET session, the left part of the window shows the session tree that contains global information on the history of the present session. The operation of this tree is similar to standard options in Windows Explorer, with the difference that here an overview is given of actions taken together with details of these actions. The details can be viewed by clicking the corresponding '+'. Double clicking the step name results in a move towards the corresponding step in this session. The session tree is shown in Figure 1.

3.2 Menu bar

The menu bar of the StOCNET program consists of four items. The first one, labeled *Session*, and the last one, labeled *Help* are standard Windows functionalities for opening/saving files (sessions) and on-line help, respectively. With the second item, labeled *Step*, the consecutive steps in a StOCNET session are entered. These steps are also available via separate buttons in the StOCNET toolbar (see Figure 1). The third option, labeled *Options*, contains options to set the toolbar on or off, set working directories, and set some running properties.

3.3 Example: friendships between university freshmen

A network of freshmen students was studied by Zeggelink, Stokman, van Duijn, and Wasseur (2001). The data were collected at five time points during the years 1996 and 1997, and are repeated measures of a friendship network of 38 university freshmen in sociology at a university in the Netherlands. The dichotomized relation studied is defined as "at least a friendly relationship".

Friendship data were collected on five time points: at the start of the academic year, and next at 3, 6, 13, and 35 weeks after the start of the year, respectively. We refer to these observation times as t_1 to t_5. Although most students did not know each other at the beginning of the year, some relationships that already existed at t_1 are taken into account. At the observation times, the relations of 38, 25, 26, 18, and 18 students, respectively, were completely observed[3].

At t_1 actor attribute data were collected. Three groups of attribute variables were distinguished: 1) opportunity variables (study program, smoking behavior), 2) visible attributes (gender), and 3) invisible attributes (doing sports, watching sports, playing music, religious involvement, club membership, study orientation, and social orientation); see Zeggelink et al. (2001) for a detailed description of all variables. Figure 1 shows the definition of the freshmen data in StOCNET .

[3]Between t_3 and t_4 one student left the network due to a change of discipline. The program SIENA can handle this kind of composition change.

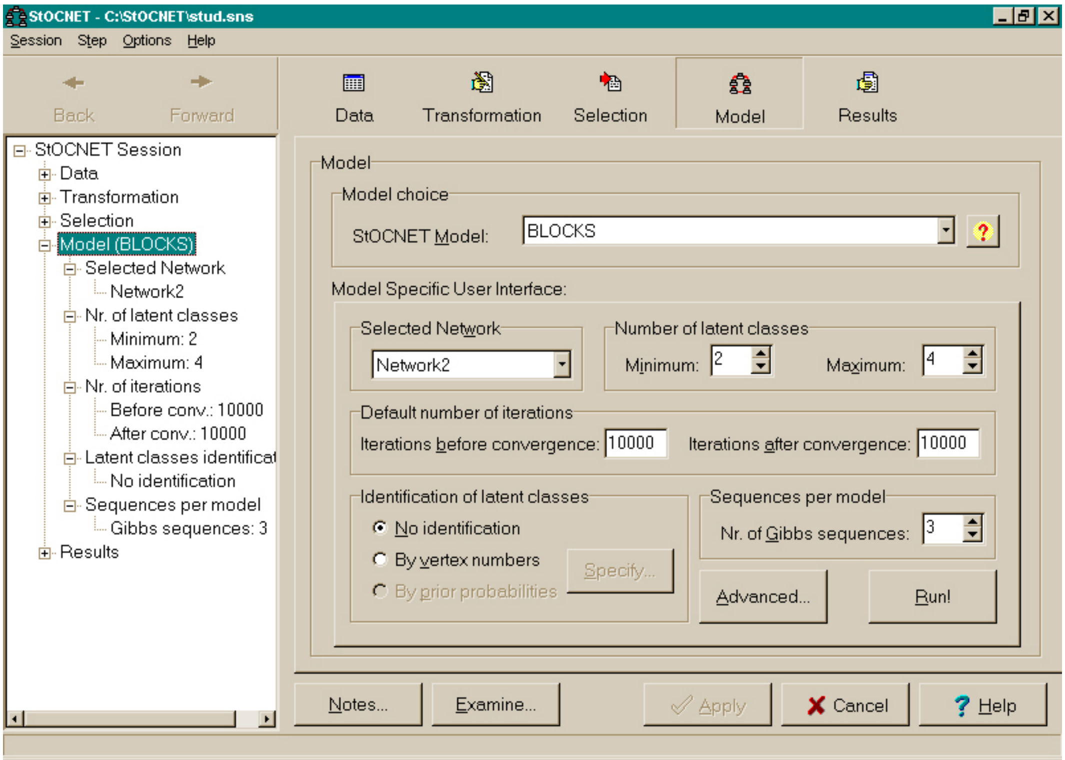

Figure 2: StOCNET user interface for the program BLOCKS.

4 Implemented modules

4.1 BLOCKS

The module BLOCKS (version 1.51) is designed for stochastic blockmodeling of relational data according to the methods described in Nowicki and Snijders (2001). For more detailed information on the program BLOCKS or stochastic blockmodeling, the reader is referred to Nowicki & Snijders (2001) and to the user's manual of BLOCKS (Snijders and Nowicki, 2001).

Posterior blockmodeling consists of finding equivalent groups of actors (with respect to relational patterns) based on the observed relations between the actors. When the observed data are assumed to be generated by some stochastic mechanism, this approach to blockmodeling is called stochastic blockmodeling. The method implemented in BLOCKS tries to find out a-posteriori how many different (latent) classes of actors can be distinguished and which actors belong to which class by estimating the posterior probability distribution of the configuration of the class structure given the network data. The parameter estimates are obtained with Gibbs sampling.

In Figure 2 the model specific user interface for BLOCKS is shown. The

Table 1: Goodness-of-fit of three blockmodels.

Blocks	I_y	H_x
2	0.633	0.673
3	0.572	0.576
4	0.558	0.500

options to be specified by the user are the network data, the number of latent classes, the number of iterations, and the number of Gibbs sequences in the estimation procedure. If prior information is available on the latent classes, the classes can be identified. Identification can be accomplished in two ways: 1) by specifying for each class one vertex number that has a high probability of belonging to that class, or 2) by specifying prior probabilities for a vertex to belong to a certain class.

University freshmen The data observed on t_2 are analyzed with the program BLOCKS to find distinct groups of students. Solutions with 2, 3, and 4 blocks of students were studied. In Table 1 the values of two fit indices, I_y and H_x (Nowicki and Snijders, 2001), are presented; I_y indicates the extra information contained in observing the relations, if grouping is known a priori; H_x indicates the clarity of the block structure. The indices have values between 0 and 1, with 0 indicating a good fit.

Inspection of the fit indices shows that there is little improvement in model fit if more than 2 blocks are distinguished. Other results of the analysis (not reported here), show that the 2 blocks solution is the best, and distinguishing more groups does not result in stable results. In the data at t_2 two groups of students can be distinguished. Inspection of the attributes of the students shows that these two groups correspond exactly with one of the opportunity variables, program. The groups consist of those students in one of the two study programs: the regular four year program, or the short two year program for older students.

4.2 SIENA

The module SIENA (Simulation Investigation for Empirical Network Analysis; version 1.94) is a program that carries out the statistical estimation of models for the evolution of social networks according to the dynamic actor-oriented model of Snijders (2001). For more detailed information on the program or on stochastic actor-oriented models, the reader is referred to Snijders (2001) and to the user's manual of SIENA (Snijders and Huisman, 2001).

Stochastic actor-oriented models are used to model longitudinal network

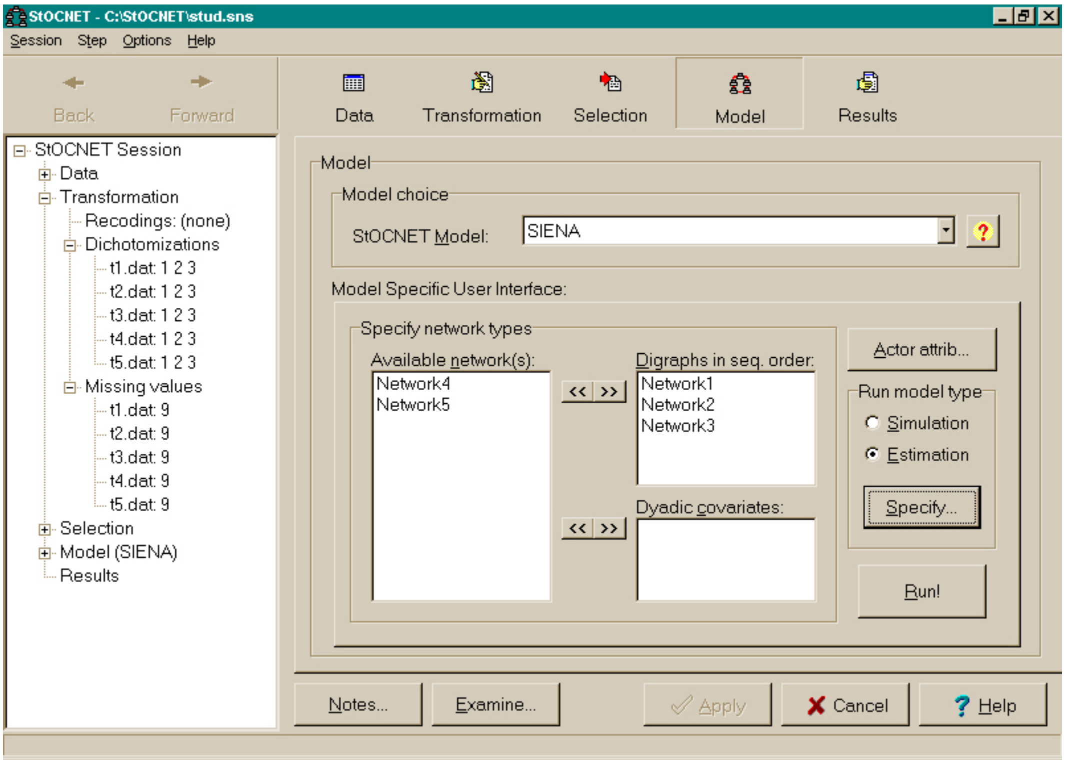

Figure 3: StOCNET user interface for the program SIENA.

data. The dependent variable is the evolving relation network, represented by repeated measurements of a directed graph. The network evolution is modeled as the consequence of actors initiating new relations or withdrawing existing relations such that a more rewarding configuration for the actor in the network emerges. This goal is modeled in a so-called objective function the actors try to maximize. The models are continuous-time Markov chains that are implemented as simulation models.

In Figure 3 the model specific user interface for SIENA is shown. The model specifications are presented in four groups: specification of network types (digraphs and dyadic covariates), actor attributes (varying and non-varying covariates, and times of composition change), estimation options (model specification and advanced estimation options), and simulation options (to simulate the network evolution).

University freshmen Data at four observation times (t_1 to t_4) are used to model the network evolution with the program SIENA[4]. The effects included in the actors' objective functions are reciprocity, balance, and popu-

[4]For a more detailed discussion of the results see Zeggelink et al., 2001

Table 2: Parameters for models estimated using observations t_1 to t_4 of the freshmen data. Only the parameters for which the t-value (estimate divided by standard error) is larger than 1.5 are depicted.

	$t_1 - t_2$		$t_2 - t_3$		$t_3 - t_4$		$t_1 - t_4$	
Effect	par.	(s.e.)	par.	(s.e.)	par.	(s.e.)	par.	(s.e.)
Rate (period 1)	5.26						7.01	
Rate (period 2)			2.96				3.06	
Rate (period 3)					5.30		5.28	
Density	–		-1.61	(0.48)	-2.17	(0.84)	-1.52	(0.56)
Reciprocity	2.61	(1.04)	3.51	(1.63)	3.07	(0.98)	2.92	(0.58)
Balance	9.25	(3.95)	6.62	(3.04)	9.18	(2.74)	7.25	(2.10)
Popularity	–		–		6.55	(2.05)	7.08	(1.23)
Program	-1.10	(0.19)	-0.78	(0.58)	–		-0.79	(0.13)
Smoking	-0.37	(0.22)	–		–		–	
Gender	-0.60	(0.22)	–		–		-0.40	(0.14)

larity (network effects), and program, smoking behavior, and gender (actor attributes). For the three attributes dissimilarity effects are calculated, that is, the preference for dissimilar others. Four different models are estimated: for the evolution from t_1 to t_2, t_2 to t_3, t_3 to t_4, and the complete period t_1 to t_4. The results (parameter estimates and standard errors) are presented in Table 2.

Table 2 shows that in each period on average about 5, 3, and 5 changes of relationship were made by the actors (rate parameters). In each period the actors have a preference for establishing reciprocated relations (large, positive reciprocity effects) and balanced network configurations (closed networks). Only in the last period the actors show a preference for initiating relations with popular alters (i.e., alters with large indegrees). The proximity variables program and smoking, and the visible attribute gender, are only important in the early stages of the evolutionary process. In the first period, actors initiate new relations with others in the same study program and smokers with other smokers. Also, women tend to choose other women, and men other men (negative dissimilarities).

From the fourth model it follows that the program and gender effects that are only important in the early stages of the process, are still strong enough to hold for the complete time period. The same is true for the significant popularity effect in the last period.

4.3 $p*$ SIENA

The SIENA program can also be used to estimate the parameters of the $p*$ model of Wasserman and Pattison (1996), using Markov chain Monte Carlo (MCMC) methods described in Snijders (2002). For more detailed

Table 3: Parameters estimates for the university freshmen data at observation time t_2, obtained with the program SIENA (MCMC and pseudolikelihood).

	MCMC		pseudolikelihood	
Effect	par.	(s.e.)	par.	(s.e.)
Number of ties	-3.61	(0.96)	-5.09	(0.39)
Reciprocity	3.99	(0.37)	1.97	(0.29)
Transitive triplets	0.17	(0.04)	0.57	(0.05)
Program	-0.75	(0.25)	-1.10	(0.26)
Smoking	-0.04	(0.03)	-0.14	(0.04)
Gender	-0.41	(0.16)	-0.80	(0.22)

information about the estimating the $p*$ model with SIENA the reader is referred to these articles and to the SIENA user's manual (Snijders and Huisman, 2001).

An exponential random graph model, that is, $p*$ model, is estimated if only one observation moment is specified in the SIENA program. The module carries out MCMC estimation for this model. If the algorithm works properly, the computed estimates are an approximations of the maximum likelihood estimates. However, it is discussed in Snijders (2002) that there are problems for estimating parameters of the likelihood distribution, and for many data sets it is impossible to achieve satisfactory estimates—perhaps it is next to impossible with any method. To use $p*$ SIENA it is advised first to read Snijders (2002). Also maximum pseudolikelihood estimates are given by SIENA (cf. Wasserman and Pattison, 1996).

If in the model specific user interface of SIENA (Figure 3) only one observed network data file is selected, the $p*$ SIENA model is estimated. A specification screen is opened in which the user must specify the network and/or covariate effects that are to be included in the model.

University freshmen The data observed at t_2, the first occurrence of the network, are analyzed with the program SIENA. The results are presented in Table 3. The network effects that are estimated are number of ties (density), reciprocity and transitive triplets. Although the models show the same general picure (also found in the longitudinal analysis), Table 3 shows some differences between the two estimation procedures. The MCMC method implemented in SIENA is recommended, because the properties of the pseudolikelihood estimators are unknown. It should be noted, however, that the convergence of the SIENA $p*$ model was doubtful. When the transitivity effect was deleted from the model, good convergence was obtained.

5 Planned functionalities

Some new StOCNET options and functionalities will become available in the next year. These planned activities are presented in this section.

1. Step 2: *Transformation.* In the current StOCNET version only two options are available in step 2, that is, dichotomization and specification of missing value codes for the network data. Future versions will contain a recode option to recode all available data (networks and attributes).

2. Step 3: *Selection.* In the planned version of the selection step, three different ways of selecting actors will be available.

   (a) The most straightforward way is to define a range of actors, for instance, the first ten or twenty actors in the adjacency matrix. The program will automatically select the corresponding rows and columns of the network data.

   (b) The second possibility is the selection of actors based on the values of the attributes. For instance, using the attribute gender, only female actors can be selected. For this purpose, first the attribute file containing the desired covariate has to be specified, then the covariate and its value to use as selection criterion.

   (c) The third selection method is the most complex one. It involves an examination of the network data and computation of some network statistics. Subsequently a subset of actors is selected that fulfills a certain network requirement, for instance, actors with (in/out)degree higher than one.

3. The *Examine button.* The planned selection based on network statistics implies an examination of the data before analyzing the data with the statistical modules. This examination functionality will become available via *Examine* buttons, which can be activated in every step of the StOCNET session (see Figures 1, 2, and 3). Based on the information available in each step and in earlier steps, descriptive statistics will be presented of the specified network(s).

4. *Export function for graphics.* It was decided not to develop a graphical module for the StOCNET system. The main reasons are the large amount of programming time such a module would take, and the availability of other programs with good graphic procedures. Instead, an export function will be included in future versions of StOCNET to create input files to make graphical presentations of networks in, for instance, KrackPlot (Krackhardt, Blythe, McGrath, 1994), Pajek (Batagelj and Mrvar, 2002), or Mage (Richardson and Presley, 2001).

5. The *help function*. The internal help function of StOCNET will be made available with the use of the manual (Boer et al., 2001), and the offered help topics will depend on the current step of the StOCNET session.

6 Modules available in the near future

6.1 p_2

The program p_2 (van Duijn, 1995) is designed for the analysis of binary social network data with actor and/or dyadic covariates. The p_2 model is a random effects model with the dyadic ties as the dependent variable. It can be regarded as an extension of the well-known p_1 model (Holland and Leinhardt, 1981), where the actor parameters are replaced by random effects and actor and dyadic attributes can be included.

The p_2 model can also be viewed as a type of logistic regression model for the ties, to which a reciprocity effect is added as well as random sender and receiver effects. The model parameters are estimated by maximizing (a first order Taylor approximation of) the likelihood function using the Iterative Generalized Least Squares (IGLS) algorithm for nonlinear multilevel models. For now, the estimation procedure was implemented in a GAUSS program. This program is in the process of being rewritten in Delphi to be included in StOCNET software. The analysis presented in the next paragraph was obtained with the (old) GAUSS program.

University freshmen The data observed at t_2, analyzed earlier with the $p*$ model (in SIENA), are now analyzed with the p_2 model. Based on the results obtained earlier with the StOCNET modules, only the actor attributes program, smoking, and gender are included. The results are presented in Table 4.

In the p_2 analysis no significant sender and receiver effects were found. Similarity with respect to program and gender both had a significant and positive effect on density (i.e., there are more relations between students in the same program, between male students, and between female students). The similarity variables did not have a significant effect on reciprocity, but there is a general reciprocity effect. The receiver variance is much larger than the sender variance, due to the missing reports of 13 of the 38 students, whereas those missing students did receive choices of the others.

6.2 PALNET and PACNET

Pattison and Wasserman (1995) and Pattison, Wasserman, Robins, and Kanfer (2000) present methods for construction and fitting of structural

Table 4: Parameters estimates for the university freshmen data at observation time t_2, obtained with the program p_2 (only significant effects).

	Parameter	par.	(s.e.)
Sender	Variance σ_A^2	0.68	(0.19)
Receiver	Variance σ_B^2	1.21	(0.27)
Sender-receiver	Covariance σ_B^2	-0.09	(0.18)
Density	μ	-4.21	(0.38)
	Similarity program	1.90	(0.26)
	Similarity gender	1.16	(0.22)
Reciprocity	ρ	1.12	(0.30)

models for local (i.e., ego-centered) social networks and complete social networks, respectively.

Existing methods for the analysis of local networks are quite elementary. The methods proposed by Pattison and Wasserman (1995) gives researchers a tool to adequately summarize complex social networks. They define partial algebraic structures from the collection of network paths that have a focal individual as their source, and present a method for deriving algebraic representations from local network data. The statistical criteria used in the method are based on permutation distributions. The methods are implemented in the program PALNET with which partial algebras can be constructed from network paths with a fixed, maximum length.

The purpose of the program PACNET is to construct a partial algebra for a complete network, using statistical criteria based on conditional uniform random graph distributions. Both PALNET and PACNET are written in *C* and still only available from the authors. However, the programs are in the process of being implemented in the StOCNET system and will become available to a wider audience.

6.3 ZO

ZO (Zero-One; Snijders, 1991) is a program that calculates the probability distribution of any statistic for uniformly distributed graphs and digraphs with given degrees. More generally, it calculates distributions for matrices containing random binary data with given row and column sums and possibly structural zeros. Two methods to calculate the probability distributions are implemented: 1) by complete enumeration, which is only practical for small adjacency matrices, 2) a Monte Carlo method based on unequal probability sampling. With the implemented methods, p-values can be calculated for testing the conditionally uniform distribution with a given test statistic, for instance, the number of mutual relations.

The current (DOS) version of the program is in the process of being updated to a Windows version that will be added to the StOCNET system.

7 StOCNET contributors

In order to provide a new platform to make statistical programs available to a wider audience, the StOCNET system was set up in such a way that new modules can be implemented with as little effort as possible. New contributions can be implemented as executables or as DLLs, and their source codes are allowed to be written in a large variety of programming languages (e.g., Delphi, C, C^{++}).

The platform with its common data structure and user interface is provided by the StOCNET system, and the programs containing the statistical methods are treated as *black boxes*. All procedures will have similar interfaces and the contributors therefore only need to provide information with respect to data input, data representation, data output, parameter restrictions and so forth. Moreover, the procedures should have some general properties:

- proper documentation,
- the status of the calculations sent to the screen,
- user break possibility,
- proper error handling and error messages through error or log files, and
- correct memory handling and allocation.

News about StOCNET can be found at the StOCNET website at

`http://stat.gamma.rug.nl/stocnet/`.

Here, new versions of the program and the corresponding documentation will be presented and available for downloading. Also a brief history of the project is given, and of its goals and team members. Instructions for new contributors (including a questionnaire to be filled-in in order to facilitate inclusion of potential contributions) can be found as well, together with a list of potential contributors, whose programs are candidates for implementation in StOCNET .

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