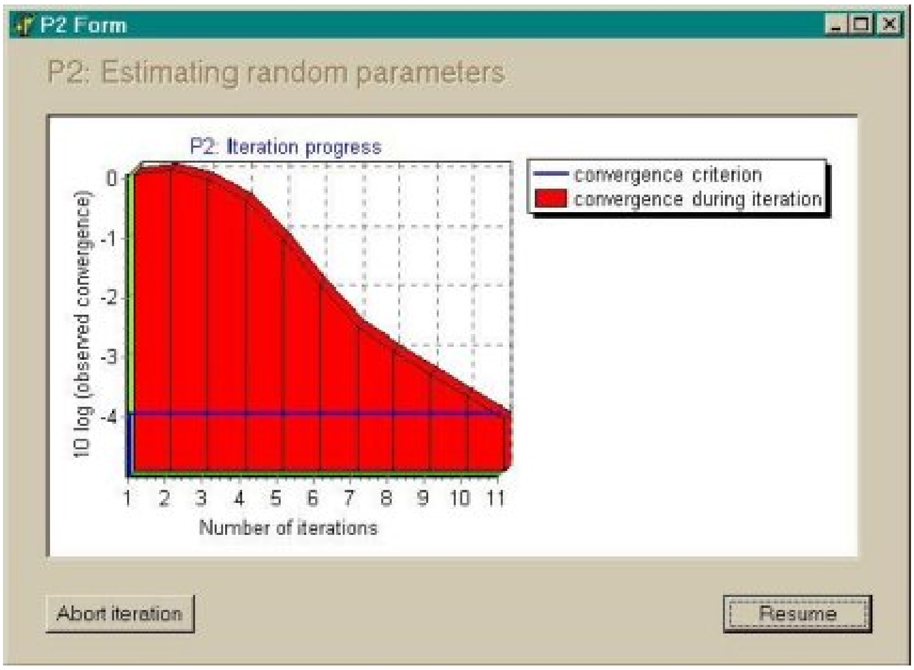
Manual p_2



version 2.0.0.7

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Contents

1 General Information

The p_2 program performs calculations for the p_2 model as proposed by Van Duijn and Snijders (see e.g. Lazega & Van Duijn, 1997; Van Duijn, 1995). The p_2 model is a model for the analysis of directed binary relationship data. It computes sender, receiver, density, and reciprocity effects. Covariates can be included to explain these effects. The p_2 program is incorporated in StOCNET (Boer, P. et al., 2001), an open software system for the analysis of social networks. StOCNET is freely distributed from the website http://stat.gamma.rug.nl/stocnet.

Part I

User's manual

2 A short introduction to the p_2 model

The p_2 model is designed for statistical analysis of social networks. Social networks consist of actors and variables indicating their ties. Often ties simply are recorded by asking actors with whom they have ties. However, there are many possible measures for ties and actors do not necessarily have to be persons, but could also be firms, countries, etc. The p_2 model analyzes complete networks. This means that within the networks everyone can possibly be tied to everyone else, although information on the presence of some ties are allowed to be missing. In practice, this is the case in closed settings, e.g. villages, organizations or school classes. The p_2 model allows for some observations from these complete networks to be missing.

2.1 Network data

The p_2 model analyzes dichotomous network data, representing ties that are either present (1) or absent (0). The data are collected in a square adjacency matrix Y with elements y_{ij} indicating a relation from actor i directed towards actor j (i indicates rows and j columns in Y). Below, an example of an adjacency matrix (Y) indicating the relations between actors a, b, c, and d is shown:

$$\begin{array}{c c}
 & \begin{array}{cccc} \mathrm{a} & \mathrm{b} & \mathrm{c} & \mathrm{d} \end{array} \\
\begin{array}{c} \mathrm{a} \\ \mathrm{b} \\ \mathrm{c} \\ \mathrm{d} \end{array} & \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{pmatrix}
\end{array}$$

From such an adjacency matrix, dyads can be derived (Wasserman & Faust, 1994). A dyad consists of two tie indicator variables Y for two directed ties between two actors, usually denoted by D_{ij}= (y_{ij}, y_{ji})= (y_1, y_2).

Three types of dyads are distinguished:

reciprocated (or mutual) dyad	$\rightarrow$	$(y_{a,b},\ y_{b,a})= (1,\ 1)$
asymmetric dyad	$\rightarrow$	$(y_{a,c},\ y_{c,a})= (0,\ 1)$
null dyad	$\rightarrow$	$(y_{a,d},\ y_{d,a})= (0,\ 0)$

2.2 The p_1 model

The p_2 model can be seen as an extension of the p_1 model introduced by Holland and Leinhardt (1981). The p_1 model specifies the probability for dyads in a network with n actors:

$$P\left(Y_{ij} = y_1, Y_{ji} = y_2\right)$$
$$= \exp\{y_1(\mu + \alpha_i + \beta_j) + y_2(\mu + \alpha_j + \beta_i) + y_1 y_2 \rho\}/k_{ij},$$

for $y_1, y_2 = 0, 1; i, j = 1, \ldots, n; i \neq j$.

Here, ρ can be seen as a reciprocity parameter, since it is the only term that is involved when ties in both directions are present. The parameter μ can be recognized as an overall density parameter. For sender i in the tie indicator variable y_{ij}, α_i can be seen to be a sender parameter. For sender j in the opposed tie indicator variable y_{ji}, α_j can again be seen as a sender parameter. In a similar manner, the parameters β_j and β_i can be recognized as a receiver parameter for the tie indicator variables y_{ij} and y_{ji}, respectively. The parameter k_{ij} is a normalizing constant.
Note that in the p_1 model the dyads are mutually independent.

2.3 Extending the p_1 model to include covariates: p_2

The p_2 model allows covariates as predictors for the sender, receiver, density, and reciprocity effects. Within the p_2 model the sender and receiver effects are reformulated, using a regression model, as:

$$\alpha = X_1\gamma_1 + \mathbf{A},$$

and

$$\beta = X_2\gamma_2 + \mathbf{B},$$

where α and β are vectors containing the sender and receiver effects and X_1, X_2 are matrices with covariates for the sender and receiver effects with coefficients γ_1 and γ_2, respectively. $\mathbf{A}$ and $\mathbf{B}$ are random effects with (co)variances σ_A^2, σ_B^2, σ_{AB} and E($\mathbf{A}$)= E($\mathbf{B}$)= $\mathbf{0}$.

Between actors the random effects are assumed independent.
These substitutions can be regarded as a bivariate regression model for the pairs (α_i, β_i).

Replacing the sender and receiver effects by a function of covariates and random effects, reduces the number of parameters to be estimated. This allows the density and reciprocity parameters to vary over the dyads. In the p_1 model this was not allowed. The density and reciprocity parameters are reformulated as:

$$\mu_{ij} = \mu + Z_{1ij}\delta_{\mathbf{1}},$$

and

$$\rho_{ij} = \rho + Z_{2ij}\delta_{\mathbf{2}},$$

where Z_{1ij}, Z_{2ij} are matrices containing **dyadic attributes** for the density and the reciprocity effects with $\delta_{\mathbf{1}}$ and $\delta_{\mathbf{2}}$ vectors containing coefficients for the density and reciprocity effect, respectively. (Dyadic attributes have values for each pair of actors, $i, j = 1, \ldots, n$, $i \neq j$.) μ And ρ are the constant parts of μ_{ij} and ρ_{ij}. Because ρ_{ij} represents reciprocity, $\rho_{ij} = \rho_{ji}$ is assumed and therefore the dyadic attributes that are used as covariates for the reciprocity parameter are supposed to be equal as well ($Z_{2ij} = Z_{2ji}$).

2.4 Dyadic attributes (Z_{ij})

Covariates for the density and reciprocity parameters can vary over dyads. Hence, they are called dyadic attributes. They can be represented by a matrix. For attributes that are covariates for the reciprocity parameter, the matrix must be symmetrical.
Dyadic attributes can be collected for each combination of actors (each dyad), like network data are collected. Dyadic attributes can be derived from actor attributes as well. We often use differences and absolute differences of actor attributes in dyads. Below, there is an example with two male (coded '1') and two female (coded '0') actors. Both the difference between the actors and the absolute difference derived from this dummy variable are illustrated. (Of course, there are more possibilities for deriving dyadic attributes from actor attributes.)

actor	*sex*	*dummy*	*difference*				*absolute difference*			
a	male	1	0	0	1	1	0	0	1	1
b	male	1	0	0	1	1	0	0	1	1
c	female	0	-1	-1	0	0	1	1	0	0
d	female	0	-1	-1	0	0	1	1	0	0

Note that when covariates for the density parameter are derived from actor attributes, either the difference or the absolute difference can be applied. For covariates for the reciprocity parameter, only the absolute difference can be used, since this derivation is symmetrical regarding both directions of the dyads.
A model with a certain parameter for a sender covariate and the same (negative) parameter for a receiver covariate, is equivalent to a model with the same parameter for the density difference covariate if all these covariates are derived from the same actor covariate. Thus including all the above effects results in an unidentifiable model. Estimates from such a model will be poor. Do not use them!

2.5 Covariate effects

The p_2 model gives parameter estimates and standard errors for random effects (sender and receiver variance and their covariance) and for overall density and reciprocity effects. For specific covariates, the parameters and standard errors for their effects on the sender, receiver, density, and reciprocity effects are provided. For an overall test of the effect of a covariate, the p_2 program provides the Wald test statistic (see, e.g., Serfling, 1980, p. 157):

$$\mathbf{W} = \hat{\theta}'\hat{\mathbf{V}}^{\mathbf{-1}}\hat{\theta},$$

with θ containing all involved parameters for the covariate and $\hat{\mathbf{V}}$ the covariance matrix of these parameters. The Wald statistic tests the hypothesis that $\theta = \mathbf{0}$. $\mathbf{W}$ has an approximate χ^2 distribution with the dimension of θ as the number of degrees of freedom.

3 Getting started

To run the p_2 program within StOCNET, specific actions are required. These are in short:

1. Select network data
2. If necessary, recode network data to be dichotomous (0/1)
3. Select p_2 model and files required for analysis
4. Specify the model
5. If necessary, use the advanced model specification
6. Run p_2
7. View results

In the next sections we will treat an example. The example will be discussed in a text box, like this one.

We will treat an example of an analysis using p_2 on network data concerning ties between American lawyers. This is a subsection of the data treated in Lazega and Van Duijn (1997).
Ties represent lawyers seeking advice among 35 partners of a law firm in two offices. Lawyers indicated to whom they go for advice. Actor attributes are 'seniority rank number' (starting with '1' for the highest rank and ending with '35' for the lowest rank) and 'office', the office in which the lawyers work (coded by '0' and '1') as covariates.
We also use a dyadic attribute 'cowork' for which the lawyers were asked with whom they have worked together.

4 Input data

The p_2 model is a model for the analysis of binary network data. This means that the dependent variable in the analysis needs to be a binary coded network. This network data is expected to be a square matrix with elements (i,j) representing a tie indicator variable for a tie from actor 'i' towards actor 'j' (i indicates rows and j columns). A tie has to be represented by "1", the absence of a tie by "0". Elements on the diagonal of the network data representing ties from actors towards themselves are not considered by the p_2 model, but are advised to be set to "0" for clarity.

If you do not have a binary coded network file, the network data can easily be transformed to the required binary format within StOCNET. For this option, see the StOCNET manual, Boer et al. (2002).

Covariates can either be actor attributes or dyadic attributes. Note that networks can be dyadic attributes as well. Separate files are expected for actor attributes and networks. Dyadic attributes derived from actor attributes (e.g. difference and absolute difference, see section 2.4) are generated by the p_2 program and do not need to be in a separate file. Covariates are not restricted to particular values. Thus when network files are used as dyadic attribute, they are not restricted to binary values.

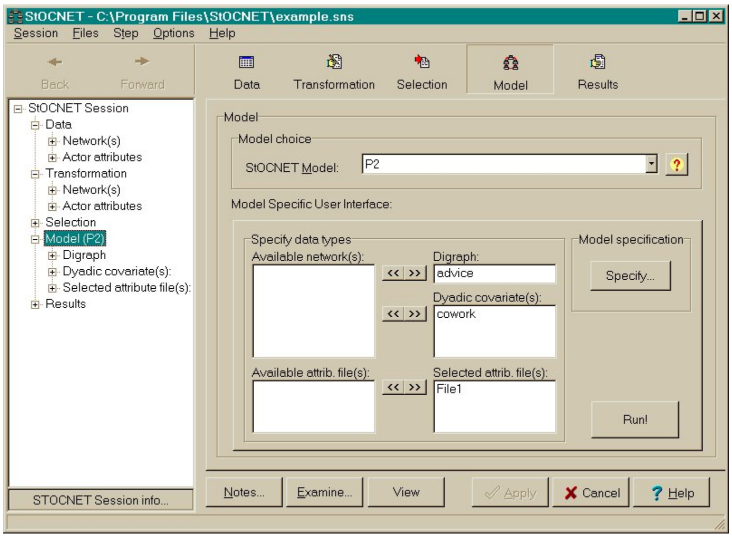
Note that the actor attributes and the dyadic attributes are supposed to cover the same actors as the dependent network. Thus the ordering of actors in all these files should be identical.

All data files should only contain data and all values have to be separated by tabs or spaces. If there is additional information in the files (e.g. variable names in the first line), the program will not work. Files are expected to be in ascii format with actors on subsequent lines and different values on a single line.

For each session, StOCNET asks the user to select files containing network data and files containing actor attributes. Here, select all the files that you want to use in different analyses. For specific analyses, StOCNET will ask the user which network is the dependent variable and which files containing actor attributes have to be used.

5 Model selection

Under the button 'StOCNET model' (step four in StOCNET), select the p_2 model in the pull-down menu in the box 'model choice'. After the p_2 model has been selected, the available network files and actor attribute files are displayed. From these files, select those that contain information that you want to use in the analysis. This will enable specification of covariates later on in the analysis.



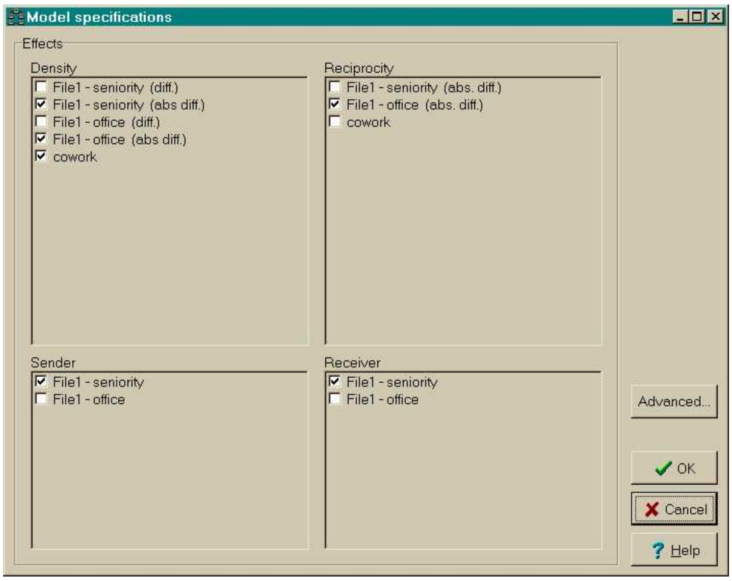
model selection window

Select one of the available network files under 'Digraph'. This network will then be the dependent variable in the analysis. If present, remaining networks can be selected as dyadic covariates. Further, select the attribute files that contain the actor attributes to be used as covariates in the analysis.
Pressing 'Model specification' will allow you to specify your model. Pressing 'Run!' starts the p_2 estimation process. If you have not specified a model, the empty model will be estimated on the network that is the dependent variable. We advice to estimate the empty model first in each new session. This provides a baseline model for models with covariate effects.

6 Model specifications

In 'model specifications', specify which covariates to include in the model. Covariates for the density, reciprocity, sender, and receiver

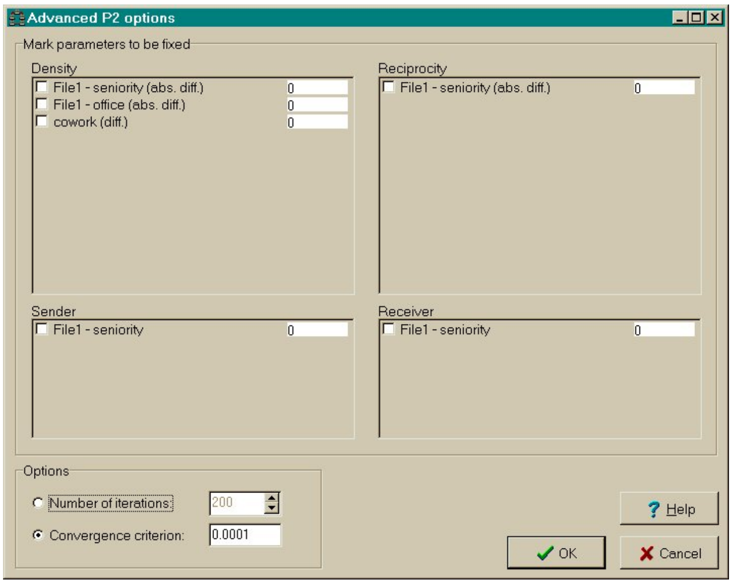
effects can be specified. As mentioned before, covariates for the density and reciprocity effects are called dyadic attributes. In the upper half of the 'model specifications' screen the dyadic attributes are displayed. These are dyadic attributes derived from actor attributes (differences and absolute differences over dyads) as well as selected network files. In the lower half of the 'model specifications' screen actor attributes are displayed. These are the possible covariates for the sender and receiver effects. Marking the checkboxes in front of any of the covariates will include them in the model.
Note that including a sender and receiver effect for a covariate corresponds to including a density difference effect for this covariate. Including all the above effects results in an unidentifiable model. Estimates from such a model will be poor. Do not use them!



model specifications window

Pressing the button 'advanced' will open the screen with 'advanced P2 options'. Here, all selected covariates are displayed. Marking the checkbox in front of these will fix the parameter of the covariate to a certain value. The value to which the parameter is fixed can be entered on the right of the covariate name. Novice users are advised not to use this option.

Below these options, a choice for the convergence criterion can be entered. Either the number of iterations or a measure for convergence can be entered. The measure for convergence is the maximum difference of all parameter estimates with the estimates from the previous iteration cycle.



advanced model specifications window

7 Output

The output of the p_2 program is displayed automatically in StOCNET after the iteration process has finished. For a new session, the output will be visible immediately. For an analysis in an existing session, the output will be appended to the previous output from this session. Then, in the output screen of StOCNET, scroll down to find the output of the last analysis.

The p_2 output is organized in several parts. First there is some basic information; the version number of p_2, the name of the output file, and the date and time:

```
P2 Version 2.0.0.6
example.out
December 17, 2002, 3:26:52 PM
```

General information on the specific analysis is provided afterwards. First, the digraph (the network that is the dependent variable in the analysis) is indicated. Second, the number of valid tie indicator variable observations is printed. Note that this depends on the number of actors in the network and the number of missing values in the data. Third, the iteration process is summarized. Other possible messages state the assigned number of iterations and the largest difference of parameter estimates between the last two performed iterations.

```
General Information:
Digraph: C:\program files\stocnet\ADVICE35.DAT
Number of valid tie indicator observations: 1190
Convergence criterion: 0.0001 reached after 8 iterations.
```

In this example the dependent network is advice.dat. From the number of valid tie indicator observations it is clear that there are no missing values in this dataset. Since the number of actors is 35, the total number of (directed) tie indicator observations is $35 \times 34 = 1190$. Thus, all possible tie indicator observations are valid.

The next part of the output displays the variances of the random effects. These are σ_A^2, σ_B^2, and σ_{AB}, referred to in section 2 of this manual:

```
Random effects:
                             parameter  standard
                              estimate  error
            sender variance:    0.7332  0.1633
          receiver variance:    0.6920  0.1561
  sender receiver covariance:  -0.3543  0.1227
```

> Here the amount of variation in sender and receiver activity is presented. That is, after controlling for the covariates in this analysis. Note that these effects covary negatively; the more lawyers tend to seek advice, the less likely it is advice is sought from them.

Following, the output displays fixed effects. First the overall fixed effects are displayed. These are the overall density and reciprocity effects as mentioned in section 2. For details on interpreting these effects, see section 8.

```
Overall effects:
                             parameter  standard
                              estimate  error
                    Density:   -1.3079  0.3884
                Reciprocity:    1.2648  0.2994
```

> The negative value of the density parameter indicates that the probability of a relation is smaller than 0.5 (see section 8) for covariate values equal to zero. The reciprocity parameter is positive, but not very large, indicating that advice relations have a tendency to be symmetrical, but not an extremely strong tendency.

Below are the values of the Wald statistic (see section 2) and the p-values under the approximating χ^2 distribution. The Wald statistic combines the separate t-tests for each covariate.

```
Overall covariate effects:
Overall effects of covariates including diff and absdiff manipulations.

                             Wald test
                Covariate    statistic  df  P
                seniority      25.2689   3  0.0000
                   office      25.3851   2  0.0000
                   cowork     133.8964   1  0.0000
```

The covariate seniority is used four times as covariate (sender, receiver, and density effects). Above is the combined effect of all the instances it was used. Office was used twice and and cowork just once. The interpretation of these effects should be based on the specific covariate effects that are shown below. All covariate effects are highly significant. (This is, of course, not always the case.)

Below are the parameters and standard errors of covariates for the sender, receiver, density, and reciprocity effects.

```
Sender covariates:
                            parameter  standard
               Covariate     estimate  error
               seniority       0.0528  0.0162
```

The seniority rank number is positively related to seeking advice. Thus, the higher the seniority rank number (i.e. the lower the seniority!), the more lawyers tend to seek advice. More senior lawyers seek less advice than less senior lawyers. Note that the magnitude of the parameters is related to the range of values of the covariate, just like unstandardized coefficients in regression analysis. Here the rank numbers range from 1 to 35. At first sight the parameter may not seem very large. However, taking into account the range of the covariate, the parameter is rather large.

```
Receiver covariates:
                            parameter  standard
               Covariate     estimate  error
               seniority      -0.0497  0.0160
```

The seniority rank number is negatively related to advice being sought. Thus, more advice is sought from the more senior lawyers (lawyers with a low seniority rank number).

```
Density covariates:
                            parameter  standard
               Covariate     estimate  error
      abs_diff_seniority      -0.0368  0.0096
         abs_diff_office      -0.9102  0.2240
                  cowork       2.0056  0.1733
```

The negative effect of the absolute difference in seniority rank number indicates that the probability of an advice relation decreases as the difference in seniority increases. The negative effect of the absolute difference of the office indicates that the probability of an advice relation outside the office is smaller than the probability of an advice relation within one's own office. Cowork is a dyadic covariate where lawyers indicated whether they work together with someone else. Working together with someone increases the chance of seeking advice from that person.

Notice that less senior lawyers tend to seek advice more and that advice is sought more from more senior lawyers. Thus advice appears to 'flow' from more senior lawyers to less senior lawyers. Considering this, a positive effect for the difference of seniority rank would be expected (lawyers with a large rank number seek more advice from lawyers with a low rank number). Leaving out seniority rank as sender and receiver covariate will indeed display this effect. Recall from section 2 that for the same covariate including a sender and receiver effect is equivalent to including a density difference effect.This problem of unidentifiability is comparable to the collinearity problem in regression analysis. You are kindly invited to try including covariates for the different effects to gain more insight in this phenomenon). Section 9 of this manual deals with this problem as well.

```
Reciprocity covariates:
                           parameter  standard
          Covariate         estimate  error
    abs_diff_office           0.3365  0.4763
```

Here, there is no increased probability for reciprocal relations as an effect of the absolute difference of office. Thus here the degree to which advice is a symmetric relation is not dependent on working in the same office.

8 Formulas for effects

In the output of the p_2 program parameter estimates are given with their standard errors. Dividing the former by the latter gives the t-test statistic. This is the test statistic for the null hypothesis that the parameter is zero. A commonly used rule of thumb is to accept that the parameter deviates from zero if the absolute value of the parameter estimate divided by the standard error is two or larger. More informative are the magnitude and sign of parameters. Note that the magnitude of parameters for covariates depends on the range of values of the covariates.

The density and reciprocity parameters have special formulas for their effects. The density parameter μ can be seen as a log-odds. The reciprocity parameter ρ can be viewed as the log of an odds-ratio.

The definition of μ_{ij} is the log of the odds:

$$P(Y_{ij} = 1|Y_{ji} = 0)/P(Y_{ij} = 0|Y_{ji} = 0) \qquad i, j = 1, \ldots, n; i \neq j.$$

The definition of ρ_{ij} is the log of the ratio:

$$\frac{P(Y_{ij} = 1|Y_{ji} = 1)/P(Y_{ij} = 0|Y_{ji} = 1)}{P(Y_{ij} = 1|Y_{ji} = 0)/P(Y_{ij} = 0|Y_{ji} = 0)} \qquad i, j = 1, \ldots, n; i \leq j.$$

$$= \frac{P(Y_{ij} = 1, Y_{ji} = 1)P(Y_{ij} = 0, Y_{ji} = 0)}{P(Y_{ij} = 1, Y_{ji} = 0)P(Y_{ij} = 0, Y_{ji} = 1)} \qquad i, j = 1, \ldots, n; i \leq j.$$

It represents the log of the increase in the odds that $Y_{ij} = 1$ given that $Y_{ji} = 1$. The second expression for ρ_{ij} shows that a higher value of ρ not only indicates an increased probability of a mutual tie (1,1), but also indicates an increased probability of a null dyad (0,0). Thus ρ is a parameter for both symmetric types of dyads (null and mutual).
As you can see, the density and reciprocity effects are intertwined.

Note that the above interpretations are valid when no covariates are included in the model. When covariates are added to the model the same interpretations hold, but only for actors with the same values on the covariates.

9 Limitations

The p_2 model has practical limitations for applying it and some more fundamental limitations concerning the estimation procedure.
A practical limitation may occur when two or more parameters "estimate" the same information. This will result in unidentifiable estimates, possibly causing overflow (implausibly large estimates). The same kind of problem is encountered with collinearity in regression analysis.
Selecting parameters for the sender effect, receiver effect, and density difference effect for the same covariate will result in this problem. In this case it is commonly observed that the convergence criterion gets stuck at a certain value.
The same problem may arise when a covariate carries very little information. This may be the case when most actors have the same value. Then again information that a covariate does not contain may intended to be estimated from the covariate.

Another practical limitation is the maximum number of actors in the network. Up to version 2.0.0.4 the maximum number of actors is 90. Note, however, that the number of observations of the tie indicator variables grows almost quadratically with the number of actors. So does the computing time. Therefore, when using large networks, expect long computing times.

For version 2.0.0.5 and higher we estimate the maximum number of actors to be 180. For 150 actors we know for sure that the program runs satisfactorily. However, expect long computing times for large networks. In the future we hope to optimize the computing procedure further and consequently shorten computing time.
A more fundamental problem lies in the estimation procedure applied by the p_2 program. The p_2 model is a generalized linear mixed model (thus applying a non-linear link function). The p_2 program uses an IGLS estimation procedure that applies a first order Taylor approximation of the non-linear link function (see Van Duijn, 1995, for a similar approach, see e.g. Goldstein, 1991). Such a procedure has been shown to sometimes underestimate variances in non-linear mixed models (Rodriguez and Goldman, 1995). In the near future we hope to offer alternative estimation procedures for the p_2 model.

Part II

Working with the p_2 executable

10 p_2 files

The p_2 program creates several files. All these files will carry the session name with different extensions.
Actors are assigned numbers according to their order in the network file. This ordering should correspond to the ordering of actors in the files containing actor attributes and dyadic attributes. Information from all the above files is combined in one single data file. This file has the extension '.dat'. Which files contain the required data (dependent network, covariates, and covariate networks) along with additional information is stored in the input file. This file has the extension '.in'. The model specification is stored in the (model-) design file. This file has the extension '.des'.

10.1 the data file

Within the p_2 program the data file is created automatically. In the data file each dyad is represented on two lines; one line for each directed tie indicator variable in a dyad.
In the data file, each entry on a line carries specific information. Entries need to be separated by spaces. In the first two entries in the data file the numbers (according to their order) of the actors are displayed. Each dyad is represented in two lines. The first line refers to the 'first' tie indicator variable, (Y_{ij}), indicating a tie from the actor on the first entry towards the actor on the second entry. The second line refers to the 'second', reversed tie indicator variable, (Y_{ji}). Below there is an overview of the contents of the data file (with actor covariates $c = 1, \ldots, C$ and network covariates $d = 1, \ldots, D$).

Organization of the data file

Entry	Contents
1, 2	Actors, represented by numbers according to their order in the network files and covariate files
3	Dummy variable coding a first line representing a dyad
4	Dummy variable coding a second line representing a dyad
5	Dependent network value for the (first and second) tie indicator variables
6	Variable stating '1' for first line denoting a dyad and the dependent network value of the first tie indicator variable on the second line denoting a dyad
7	Value of the first covariate for the actor on the first entry
8	Value of the first covariate for the actor on the second entry
5+(2*c)	Value of the c^{th} covariate for the actor on the first entry
6+(2*c)	Value of the c^{th} covariate for the actor on the second entry
5+(2*C)+(2*c)	Value of the difference on the c^{th} covariate. For the first line denoting a dyad: (*actor on first entry- actor on second entry*), for second line: (*actor on second entry- actor on first entry*).
6+(2*C)+(2*c)	Value of the absolute difference on the c^{th} covariate between actors on the first and second entry.
6+(2*C)+d	Covariate network value for the d^{th} covariate network.

```
1 2   1 0   1 1   1 2   0 0   -1 1   0 0   0
1 2   0 1   1 1   1 2   0 0    1 1   0 0   0
3 1   1 0   0 1   3 1   1 0    2 2   1 1   0
3 1   0 1   0 0   3 1   1 0   -2 2  -1 1   0
2 3   1 0   0 1   2 3   0 1   -1 1  -1 1   0
```

Part of the data file for the example presented in the previous sections. There are two actor covariates: 'seniority rank number' (note that actors are ordered according to this covariate), and 'office'. There is one network covariate: 'cowork'.

Each time you run the p_2 program, this data file will be produced. Whenever the same dependent network file and covariate files (actor and dyadic attribute) are selected, the data file will be identical. Perhaps this seem somewhat wasteful, but this operation takes just a minimal amount of time. For every differently specified analysis (with effects for different covariates), different parts of the data file will be used.

10.2 the input file

For creating the data file, the p_2 program needs to know in which files to find the dependent network, the covariates, and the networks that are covariates. For creating the output file, the p_2 program needs to know the names of the dependent network and all the covariates. This information is stored in the input file. For an example, see Appendix A.

Within StOCNET, the input file is created automatically from the information entered through the StOCNET interface. The input file consists of lines that are reserved for specific information.

Organization of the input file

Line	Information
1	number of actors (+ space)
1	number of files containing actor covariates (+ space)
1	number of networks that are covariates
2	File containing the dependent network
3	Missing value codes for the dependent network (separated by spaces) (optional)

subsequently, for all files containing actor covariates:

∗	file containing actor covariates
∗	Number of covariates in the file

subsequently, for all covariates within actor covariate files:

∗ Name of covariate
∗ Missing value for covariate (optional)

subsequently, for all files containing network covariates:

∗	file containing network
∗	missing values for the network (optional)
∗	name for the network

10.3 the design file

The design file contains information on how the model is specified. That is, which effects are specified for which covariates. For each covariate there is one line in the design file. Entries on the lines, separated by spaces, carry specific information. For an example, see appendix B.

Organization of the design file

Entry	Contents
1	Dummy for including a parameter for the sender effect
2	Dummy for including a parameter for the receiver effect
3	Dummy for including a parameter for the density effect for the difference
4	Dummy for including a parameter for the density effect for the absolute difference
5	Dummy for including a parameter for the reciprocity effect for the absolute difference
6	Dummy for fixing the parameter for the sender effect
7	Dummy for fixing the parameter for the receiver effect
8	Dummy for fixing the parameter for the density effect for the difference
9	Dummy for fixing the parameter for the density effect for the absolute difference
10	Dummy for fixing the parameter for the reciprocity effect for the absolute difference
11	Value on which to fix the parameter for the sender effect
12	Value on which to fix the parameter for the receiver effect
13	Value on which to fix the parameter for the density effect (difference)
14	Value on which to fix the parameter for the density effect (absolute difference)
15	Value on which to fix the parameter for the reciprocity effect (absolute difference)
subsequently, after lines for all covariates:	
$*$	assigned number of iterations
$*$	convergence criterion
$*$	dummy for using the assigned number of iterations(1) or the convergence criterion (0)

The executable of the p_2 program is simply called p2.exe. It can be found in the directory where you have installed StOCNET. Whenever there is an update available, you are strongly advised to use it. This will ensure that you have the version with the best bug fixes. Pressing 'run' in StOCNET will execute the p_2 program. However, if you have specified the input file and the design file correctly, the p_2 executable will work outside StOCNET as well.

If the p_2 program is used within StOCNET, references to files containing networks and covariates will be altered. The original filenames will preceded by a tilde (˜) . This is because StOCNET has the option for selecting specific actors (step 3; Selection). Therefore, StOCNET produces a new file with the name of the old file, preceded by a tilde. In StOCNET, it is this file that is referred to.

11 Creating dyadic covariates for specific values of actor attributes

Sometimes the standard options of the p_2 program will not be satisfactory. Suppose you find a negative effect for the absolute difference of sex on the density (of relations). Roughly, this means that relations are less likely between actors of a different sex and consequently more likely when actors share the same sex. Now, you may wonder whether relationships between boys are equally more likely as relationships between girls. The common analysis with p_2 will not provide an answer to that question. What would provide an answer to that question is a network covariate coding whether dyads concern both boys or both girls (instead of just coding the same sex). This is what we mean by creating dyadic covariates for specific values of actor attributes. Note that this can be done for the density effect and for the reciprocity effect.
With some extra effort, the p_2 program can be used to create dyadic covariates indicating equality for specific values of actor covariates. To do this the input file and the design file need to be altered. These altered files can be used by the p_2 executable (outside StOCNET!) to create network files containing such dyadic covariates. Of course there are many other possibilities to produce a dyadic covariate indicating equality for a specific value of a covariate. How a dyadic covariate was produced, makes no difference to the p_2 program.

11.1 adjusting the input file

The first thing to do when you want to create a new network file for a specific value of an actor attribute is entering a '1' on the first empty line of the input file (that is, after the last non-empty line). This is a dummy indicating you want to create this file.

On the next line you enter the name of the variable you want to compute the new network file from.
On the next line enter the value for which you want to create the file. For this specific value the new network file will contain a '1' only if both actors have this specific value. Otherwise, the new network file will contain a '0'.
On the last line, enter the name of the new file. This should be a full name, including an extension (assuming that is what you want).
After taking the previous actions, the original input file should on the bottom part have something like the following added:

```
1
office
1
boston.net
```

After running the analysis, you will have a new network file (here: boston.net). If you do not want to create the new network file again, skip the above lines and add the network file to the other files in your analysis. This can either be done in StOCNET (see StOCNET manual or section 4 of this manual) or in the input file (see section 10.2).

11.2 adjusting the design file

The p_2 program immediately recognizes the new network file as a covariate. Thus you have to add a line with 15 entries (see section 10.2) on the bottom of the design part of the design file. If you want to estimate parameters for the newly created dyadic covariate, enter a '1' on the third entry for density and on fifth entry for reciprocity. All other entries have to be '0' unless you want to fix the parameter to a certain value (see section 10.3).

11.3 running p_2

When creating a new network file for a specific value of an actor attribute, the p_2 program cannot be run from within StOCNET. The easiest way to do this is by creating a shortcut to 'p2.exe'. In the properties of the shortcut, there are some changes needed. After the path, enter a space and the title of your session. This should look like:

```
"C:\Program Files\p2\p2.exe" example
```

The shortcut should start in the directory where the input file and design file are stored. If this is not the case, this should also be changed in the properties of your shortcut.

If 'p2.exe', the input file, and the design file are stored in the same directory, entering:

```
p2 example
```

and hitting enter in your (Windows) Dos-emulator will work as well.

12 Appendix A: Input file for example

```
35 1 1
C:\Program files\StOCNET\~ADVICE35.DAT

C:\Program files\StOCNET\~covp2.dat
2
seniority

office

C:\Program files\StOCNET\~COWORK35.DAT

cowork
```

Input file for the example first presented in section 3. There are two actor covariates (from the same file): 'seniority rank number' (note that actors are ordered according to this covariate), and 'office'. There is one network covariate: 'cowork'.

13 Appendix B: Design file for example

```
1 1 0 1 0 0 0 0 0 0 0 0 0 0 0
0 0 0 1 1 0 0 0 0 0 0 0 0 0 0
0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
200
0.0001
0
```

Design file for the example first presented in section 3. There are two actor covariates (from the same file): 'seniority rank number' (note that actors are ordered according to this covariate), and 'office'. There is one network covariate: 'cowork'.

14 References

Boer, P., Huisman, M., Snijders, T.A.B., & Zeggelink, E.P.H. (2001). *StOCNET: an open software system for the advanced statistical analysis of social networks*. Groningen: ProGAMMA / ICS. Website: http://stat.gamma.rug.nl/stocnet.

Boer, P., Huisman, M., Snijders, T.A.B., & Zeggelink, E.P.H. (2002). *StOCNET user's manual Version 1.3*. Available from website: http://stat.gamma.rug.nl/stocnet.

Goldstein, H. (1991). Nonlinear multilevel models, with an application to discrete response data. *Biometrika*, **78**, 45–51.

Serfling, R.J. (1980). *Approximation Theorems of Mathematical Statistics*. New York: John Wiley & Sons.

Lazega, E. & Van Duijn, M. (1997). Position in formal structure, personal characteristics and choices of advisers in a law firm: a logistic regression model for dyadic network data. *Social Networks*, 19, p. 375- 397.

Rodriguez, G. & Goldman, N (1995). An assessment of estimation procedures for multilevel models with binary responses. *Journal of the Royal Statistical Society, A*, 158, 73-89.

Van Duijn, M.A.J., 1995. Estimation of a random effects model for directed graphs. In: Snijders, T.A.B. et al. (Ed.) SSS '95. *Symposium Statistische Software, nr. 7. Toeval zit overal: programmatuur voor random-coffcint modellen*, p. 113–131. Groningen, iec ProGAMMA.

Wasserman, S. & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University Press.