



# Non-response in social networks: The impact of different non-response treatments on the stability of blockmodels

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## ABSTRACT

Discerning the essential structure of social networks is a major task. Yet, social network data usually contain different types of errors, including missing data that can wreak havoc during data analyses. Blockmodeling is one technique for delineating network structure. While we know little about its vulnerability to missing data problems, it is reasonable to expect that it is vulnerable given its positional nature. We focus on actor non-response and treatments for this. We examine their impacts on blockmodeling results using simulated and real networks. A set of 'known' networks are used, errors due to actor non-response are introduced and are then treated in different ways. Blockmodels are fitted to these treated networks and compared to those for the known networks. The outcome indicators are the correspondence of both position memberships and identified blockmodel structures. Both the amount and type of non-response, and considered treatments, have an impact on delineated blockmodel structures.

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## 1. Introduction

Surveys and questionnaires are the most used techniques for gathering network data (Marsden, 2005, 2011; Wasserman and Faust, 1994). Because all methods have the potential for introducing different types of errors, including measurement errors, it is necessary to consider the implications of these errors in two ways. One is to consider how certain types of error can be reduced (a very good thing in its own right) and the other is to assess the impact of errors on the results obtained from using network analytic tools (given that measurement error is likely to be present). Of course, the two are not unrelated even though we focus here on the second assessment.

Our concern here is when all data from some egos regarding their alters in the network are missing and the implications this has for blockmodeling approaches to the study of network structure. The paper is organized as follows: Section 2 considers briefly errors in research designs regarding social networks with an emphasis on actor non-response. Blockmodeling of binary networks is discussed briefly in Section 3 and Section 4 presents possible non-response treatments. Section 5 describes how these treatments are used in our simulation study. Our results, in terms

of the stability of blockmodels, are presented in Section 6. We finish with a summary of the results (Section 7) together with some recommendations for further work.

## 2. Actor non-response

A broader set of error sources is shown in Fig. 1. The first cut is to distinguish boundary specification problems, questionnaire design, and errors due to respondents.

Boundary specification problems concern rules of inclusion for actors in studied networks (Laumann et al., 1983; Doreian and Woodard, 1994; Kossinets, 2006). Network instruments are another source for introducing errors. Three different question formats are often considered when designing instruments for collecting social network data: (i) free or fixed choice designs (Holland and Leinhardt, 1973; Kossinets, 2006); (ii) using recall or recognition of actors (Hlebec, 1993; Brewer, 2000; Brewer and Webster, 2000; Hlebec and Ferligoj, 2001; Bell et al., 2007); and (iii) seeking data for directed or symmetric ties (Stork and Richards, 1992; Ferligoj and Hlebec, 1999).

Errors due to actors (beyond those due to poor instrument design) can be divided also into three categories: (i) *complete* actor non-response; (ii) non-response regarding specific *ties* (Rumsey, 1993; Borgatti et al., 2006; Huisman and Steglich, 2008; Huisman, 2009; Žnidaršič et al., submitted for publication); and

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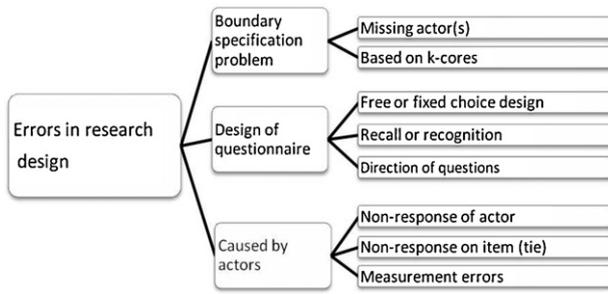


Fig. 1. Scheme of errors in research designs.

(iii) measurement errors in recorded ties (Holland and Leinhardt, 1973; Feld and Carter, 2002).

Rather than deal with all forms of errors due to actors, we confine our attention to complete actor non-response (regardless of the source). As noted above, non-response in social networks may appear in two forms. Item or tie non-response (Žnidaršič et al., submitted for publication) occurs, when an actor participates in the research but the data on particular tie(s) are absent, because the actor does not indicate the presence or absence of particular ties. The right panel of Fig. 2 shows tie non-response by three actors {C, H, K} (marked with gray squares with NA labels). In contrast, actor non-response occurs when all data from some actors are missing. This is shown in the left panel of Fig. 2 where the same three actors refused to respond or were excluded by design. The rows of missing ties are denoted with gray squares and NA labels.

Let  $n$  denote the number of vertices in a network and  $m$  the number of actors providing no responses. Each non-respondent implies  $(n - 1)$  missing ties. The actor response rate is  $(1 - m/n)$ . It is straightforward to show that the ‘relational response rate’ (the proportion of potentially observed ties that are measured) is also  $(1 - m/n)$  (Knoke and Yang, 2008). For the  $(n - m)$  respondents, there are  $(n - m)(n - m - 1)$  measured ties. Assuming that data are obtained for all of them, the proportion of these fully observed network ties is  $(n - m)(n - m - 1)/n(n - 1)$ . There are  $(n - m)m$  descriptions of ties between respondents and non-respondents and their proportion is equal to  $(n - m)m/n(n - 1)$ . The number of missing ties is  $m(n - 1)$  and their proportion is  $m(n - 1)/n(n - 1) = m/n$ . They consist of: (i) missing ties between non-respondents and respondents (the proportion of these ties is  $m(n - m)/n(n - 1)$ ) and (ii) completely missing ties (whose proportion is  $m(m - 1)/n(n - 1)$ ). The schematic representation of these types of ties is presented in the left panel in Fig. 3.

For example, if  $n = 15$  and  $m = 3$ : both the actor response rate and the relational response rate is 0.8; the proportion of fully described ties is 0.63; the proportion of described ties between respondents and non-respondents is 0.17; the proportion of missing ties between non-respondents and respondents is 0.17; and the proportion of completely missing ties is 0.03. The right panel in Fig. 3 shows these proportions for a network where  $n = 15$  and  $0 \leq m \leq 10$ . The relational response rate declines linearly with the number of actors not responding ( $m$ ), consistent with Knoke and Yang (2008). The proportions of the fully observed part of the network decline in a more extreme way. The proportion of missing ties increases in a non-linear fashion. The curve for the observed part of the network has a different non-linear pattern as  $m$  increases. The right panel of Fig. 3 suggests that non-response can be a major problem, one that gets worse as it increases.

In reviewing the network literature, Stork and Richards (1992) report response rates varying from 65% to 90%. Costenbader and Valente (2003) report, based on sample of 59 networks, a wider

range between 51% and 100%.<sup>1</sup> The extreme kind of examples shown on the right of Fig. 3 are possible in empirical research.

The effects of actor non-response on network properties such as network density, average vertex degree, out-degree or in-degree, clustering coefficients, transitivity, assortivity, and geodesic distances have been examined. (See, for example: Stork and Richards, 1992; Costenbader and Valente, 2003; Kossinets, 2006; Huisman, 2009.) Our concern regarding the impact of actor non-response focuses on a different network property. Robins et al. (2004:258) point out that “many network studies are based on the premise that in order to understand some social phenomenon of interest, it is necessary to understand the arrangement of network ties into larger network structures and sub-structures”. Blockmodeling (Doreian et al., 2005), one way of delineating the wider structures and substructures of a network, may be particularly vulnerable to the presence of non-response and, if so, results from it using could be misleading.

### 3. Blockmodeling

The results of blockmodeling procedures are partitions of the actors into clusters (called *positions*), and, simultaneously, partitions of the ties into *blocks* which are determined by the ties between actors in positions (Wasserman and Faust, 1994; Doreian et al., 2005). The actors within a cluster should have the same (or a very similar) pattern of ties based on a selected equivalence. The resulting blockmodel is a smaller representation of a network which captures its essential structure. This ‘reduced’ graph is an *image* of the network. The units in this image are positions made up of equivalent actors and the arcs (summarizing blocks) represent ties between positions.

Blockmodel partitioning is based on some type of equivalence with structural equivalence still being the most commonly used type. Units are structurally equivalent if they are connected to the rest of the network in identical ways. Batagelj et al. (1992b) proved that for structural equivalence there are only two possible ideal blocks: null (no ties between actors in a block, covered with zeroes in matrix representation), and complete (ties between all pairs of actors in a block).

Regular equivalence, a generalization of structural equivalence, is one where units are equivalent if they link in equivalent ways to other units that are also equivalent (White and Reitz, 1983). For regular equivalence only null and regular block (which have at least one 1 in each row and in each column) are possible (Batagelj et al., 1992a). The concept of generalized equivalence (Doreian et al., 2005) is defined by a set of allowed blocks where the set of complete, null and regular blocks can be widened to row-dominant, column-dominant, row-regular, column-regular and other (also newly constructed) types of blocks.<sup>2</sup>

Batagelj et al. (1992a,b) distinguish indirect and direct blockmodeling approaches. The direct approach implies fitting a set of permitted block types to a network. This is done by minimizing a compatible criterion function which compares the agreement between ideal blocks and empirical blocks. Both direct and indirect approaches have been implemented in Pajek (Batagelj and Mrvar, 2010a,b); in an R-package called Blockmodeling (Žiberna, 2008); and in UCINET (Borgatti et al., 2002).

To study the consequences of non-response (Section 5) we confine our attention to structural equivalence, the most popular

<sup>1</sup> They excluded four networks from their analysis because their response rates were lower than 50%.

<sup>2</sup> Space limitations preclude a full listing of more block types but readers are referred to Doreian et al. (2005: Chapter 7, especially Table 7.1 and Figure 7.1.)

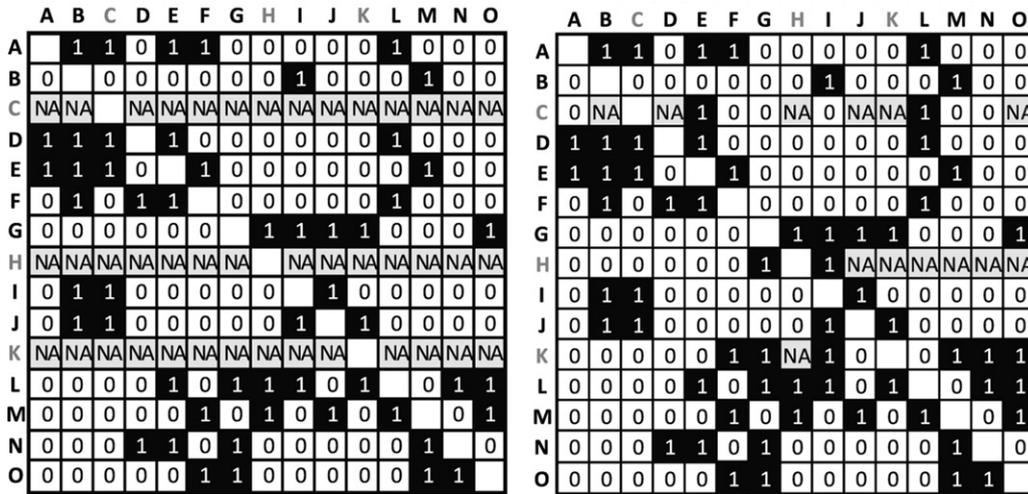


Fig. 2. Types of non-response in networks: actor non-response (left) and item non-response (right). Missing (or absent) data are denoted with gray squares and label NA.

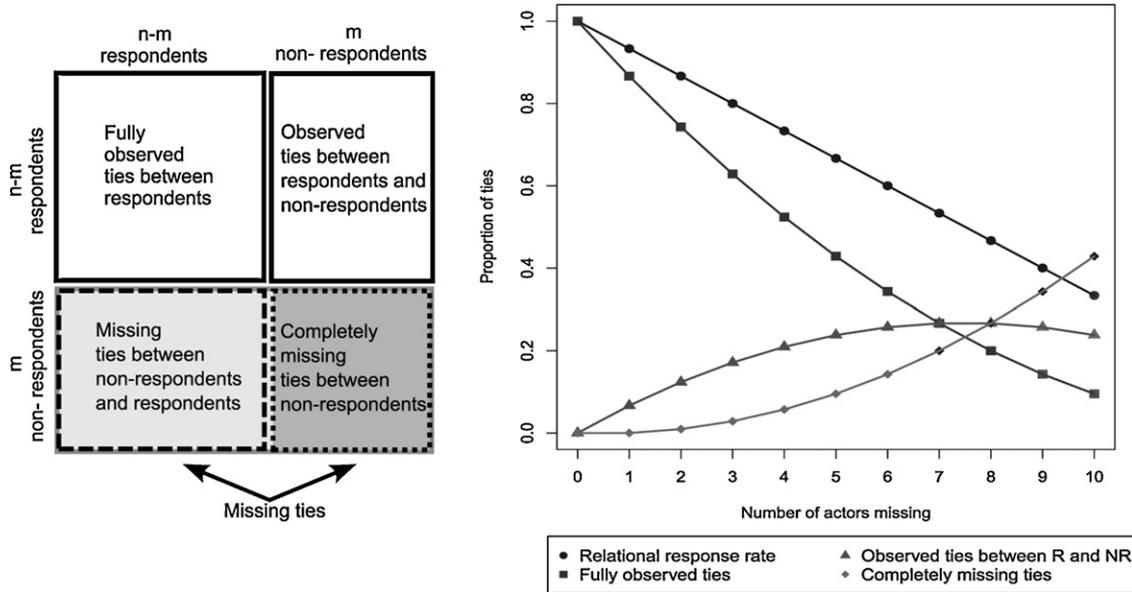


Fig. 3. Scheme of types of ties in network with actor non-response (left) and proportions of types of ties in network.

equivalence in SNA and use the direct approach.<sup>3</sup> The broad design of our study of the sensitivity of blockmodeling to treatments for non-response is straightforward. We start with a given (known) network that is either real or is generated using a specific set of parameters. We then introduce a controlled amount of actor non-response and treat the resulting network data for this non-response. Given the known network, we know also the true blockmodel. Blockmodels obtained by fitting the ‘treated’ network data are compared to the known true blockmodel. Two ways of comparing a pair of blockmodels are described next.

3.1. Comparison of two blockmodels

We compare a pair of blockmodels in two different ways. The first uses the Adjusted Rand Index (Hubert and Arabie, 1985) to measure the differences between the two partitions in terms of

their composition. Equally important – perhaps more important – is whether the identified blocks, given the positions for the treated network, correspond (or not) to the block types in the true blockmodel. Further, the correct block types need to be in their correct blockmodel locations. This is measured by a second index calculated as the proportion (or percent) of incorrectly located blocks.

3.1.1. The Adjusted Rand Index (ARI)

One widely used and popular index for comparing partitions or, more precisely, measuring the concordance between them is the Rand Index (Hubert and Arabie, 1985; Saporta and Youness, 2002). Its computation is based on how pairs of units are placed in two partitions *U* and *V* of the same data set of size *n*. The total number of possible combinations of pairs is  $\binom{n}{2}$  and they can be classified into four groups as presented in Table 1. The frequencies in the four cells of the table are denoted by *a*, *b*, *c* and *d*.

<sup>3</sup> The stability of blockmodeling for other types of equivalences were also studied (Žnidaršič, 2012).

**Table 1**  
The joint classification of pairs of units in two partitions.

Partition V	Partition U	
	Pair in same group	Pair in different groups
Pair in same group	a	b
Pair in different groups	c	d

The Rand Index is the fraction of agreement and is computed as:

$$RI = \frac{a + d}{a + b + c + d} = \frac{a + d}{\binom{n}{2}} \quad (1)$$

The distribution of the Rand Index is far from normal and depends on “the number of clusters, their proportions and separability (Saporta and Youness, 2002:347).” The Rand Index has some imperfections so that the expected value of the Rand Index of two random partitions does not take a constant value (Santos and Embrechts, 2009; Vinh et al., 2009). There is agreement in the literature that a correction (or normalization) for chance is necessary and that the Adjusted Rand Index is preferable (Yeung and Ruzzo, 2001; Steinley, 2004; Warrens, 2008; Santos and Embrechts, 2009; Vinh et al., 2009). The ARI is computed as

$$ARI = \frac{Rand\ Index - Expected\ Index}{Maximum\ Index - Expected\ Index} = \frac{\binom{n}{2}(a + d) - ((a + b)(a + c) + (c + d)(b + d))}{\binom{n}{2} - ((a + b)(a + c) + (c + d)(b + d))} \quad (2)$$

Its expected value is 0 and its maximal value is 1. Based on extensive simulations, Steinley (2004) presented some general guidelines for interpreting values of the ARI for determining the agreement between two partitions: (i)  $ARI \geq 0.9$  indicates excellent agreement; (ii)  $0.9 > ARI \geq 0.8$  suggests good agreement; (iii)  $0.8 > ARI \geq 0.65$  can be viewed as moderate agreement; and (iv)  $ARI \leq 0.65$  indicates poor agreement.

### 3.1.2. The proportion of incorrect blocks

The second index for comparing blockmodels is the proportion of incorrect block types in a blockmodel compared to a reference blockmodel where all block types and their locations are known.

Let  $I_1$  be the image of the true (original) blockmodel and  $I_2$  the image of a blockmodel obtained from a network having non-response measurement errors. Consider the following example for two blockmodels:

$$I_1 = \begin{bmatrix} \text{com} & \text{null} \\ \text{null} & \text{com} \end{bmatrix} \quad I_2 = \begin{bmatrix} \text{com} & \text{null} \\ \text{null} & \text{null} \end{bmatrix} \quad (3)$$

The proportion of incorrect blocks ( $ErrB$ ) is the number of block disagreements (defined in relation to the known blocks and their locations in the reference blockmodel) divided by the number of blocks in the blockmodel<sup>4</sup>:

$$ErrB = \frac{\text{number of block disagreements}}{\text{number of blocks in a blockmodel}} = \frac{1}{4} \quad (4)$$

<sup>4</sup> We assume that the two blockmodels have the same number of positions and hence blocks. If an established blockmodel has a different number of positions than the reference blockmodel, we regard it as a very poor blockmodel and do not consider this further.

If the two blockmodels agree perfectly about block types then  $ErrB = 0$ . However, when the two images disagree regarding the locations of block types then  $ErrB > 0$ . In our example,  $I_2$  differs from the image matrix,  $I_1$ , of the reference blockmodel and the proportion of incorrect blocks is 0.25 (see Eq. (4)). According to our empirical evidence we will say that blockmodels are acceptable if  $ErrB$  will be below 0.2.

These two indices provide a clear and intuitively straightforward way of measuring the correspondence of two blockmodels. Their relevance is suggested by the importance of two central ideas of social network analysis (SNA) noted by Doreian (2008:3). “The first is that the structure of a social network, as a whole, is important to collective outcomes at the level of the network. The second is that the location occupied in a network is important for outcomes at the actor level”. In terms of blockmodeling networks, the image of the network captures the network level and the locations of actors are reflected in position memberships. Both have to be depicted accurately to examine these two basic network ideas empirically.

## 4. Missing data treatments

Stork and Richards (1992) suggest that the presence of non-respondents for collected network data can be treated in three different ways: (i) using a complete-case analysis, (ii) using an available-case analysis, and (iii) imputing data values as replacements of the missing data. The field of missing data approaches is developing quickly and the procedures can be roughly classified into four categories (Schafer and Graham, 2002): (i) complete-case analysis, (ii) reweighting, (iii) (single) imputations, and (iv) (maximum likelihood) model-based methods (e.g. EM algorithm). We expand the list of Stork and Richards to consider five different missing data treatments: the complete-case approach, imputations based on modal values, imputations by reconstruction, combination of reconstruction and imputation based on modal values and null tie imputations. The impacts of these procedures on delineated blockmodels are discussed in Section 6.<sup>5</sup>

### 4.1. The complete-case approach

With no outgoing ties for each non-respondent, there are rows of missing ties in the matrix representation of the observed network. Consider the example shown in Fig. 4(a) having three non-respondents B2, B6, and G1 (denoted with gray color and label NA). Note that some of the respondents (e.g. B1 and B5) report ties to other non-respondents. From the right panel of Fig. 4(a) there is an apparent blockmodel structure with two complete blocks on the diagonal and two null blocks off the diagonal.

The complete-case approach, known also as ‘listwise’ deletion of actors (Huisman and Steglich, 2008), removes not only the rows for the non-respondents but also their columns. Removing columns means that all ties between respondents and non-respondents (as reported by one actor) are removed from the analysis. The result is the smaller network as shown in Fig. 4(b).

<sup>5</sup> There exists a wide area of other approaches to missing data in social networks we do not consider here. Exponential random graph ( $p^*$ ) models (Robins et al., 2004) are an example of (likelihood) model-based treatments. Other possible non-response data treatments include: a reconstruction procedure where ties between non-respondents are imputed randomly with a probability proportional to the network density (Huisman, 2009); imputation by preferential attachment where the probability of a tie from actor  $i$  to actor  $j$  depends on the indegree of actor  $j$  (Huisman and Steglich, 2008) and ‘hot deck’ imputations where actor attributes are used. Huisman (2009) used both categorical data (about actors) and structural properties to locate a completely observed donor actor as a source to substitute ties for a non-responding actor. We do not consider actor attributes here.

	B1	B2	B3	B4	B5	B6	G1	G2	G3	G4	G5
B1		1	1	0	1	1	0	0	0	0	0
B2	NA		NA								
B3	1	1		1	1	0	0	0	0	0	0
B4	0	1	1		1	0	0	0	0	0	0
B5	1	1	1	0		1	0	0	0	0	0
B6	NA	NA	NA	NA	NA		NA	NA	NA	NA	NA
G1	NA	NA	NA	NA	NA	NA		NA	NA	NA	NA
G2	0	0	0	0	0	0	1		1	1	1
G3	0	0	0	0	0	0	0	1		1	0
G4	0	0	0	0	0	0	0	1	1		1
G5	0	0	0	0	0	0	0	1	1	0	

(a) Whole network with three non-respondents (B2, B6 and G1) provide no outgoing ties.

	B1	B3	B4	B5	G2	G3	G4	G5
B1		1	0	1	0	0	0	0
B3	1		1	1	0	0	0	0
B4	0	1		1	0	0	0	0
B5	1	1	0		0	0	0	0
G2	0	0	0	0		1	1	1
G3	0	0	0	0	1		1	0
G4	0	0	0	0	1	1		1
G5	0	0	0	0	1	1	0	

(b) The complete-case approach

	B1	B2	B3	B4	B5	B6	G1	G2	G3	G4	G5
B1		1	1	0	1	1	0	0	0	0	0
B2	1		1	1	1	NA	NA	0	0	0	0
B3	1	1		1	1	0	0	0	0	0	0
B4	0	1	1		1	0	0	0	0	0	0
B5	1	1	1	0		1	0	0	0	0	0
B6	1	NA	0	0	1		NA	0	0	0	0
G1	0	NA	0	0	0	NA		1	0	0	0
G2	0	0	0	0	0	0	1		1	1	1
G3	0	0	0	0	0	0	0	1		1	0
G4	0	0	0	0	0	0	0	1	1		1
G5	0	0	0	0	0	0	0	1	1	0	

(c) The reconstruction procedure with unavailable ties between non-respondents.

	B1	B2	B3	B4	B5	B6	G1	G2	G3	G4	G5
B1		1	1	0	1	1	0	0	0	0	0
B2	0		0	0	0	0	0	0	0	0	0
B3	1	1		1	1	0	0	0	0	0	0
B4	0	1	1		1	0	0	0	0	0	0
B5	1	1	1	0		1	0	0	0	0	0
B6	0	1	0	0	0		0	0	0	0	0
G1	0	1	0	0	0	0		0	0	0	0
G2	0	0	0	0	0	0	1		1	1	1
G3	0	0	0	0	0	0	0	1		1	0
G4	0	0	0	0	0	0	0	1	1		1
G5	0	0	0	0	0	0	0	1	1	0	

(d) The imputations based on modal (in-degree) values.

Fig. 4. Network with three non-respondents (B2, B6 and G1) and three treatments for dealing with missing data.

Robins et al. (2004) argue that this approach amounts to respecting the network boundary: non-respondents are removed to create a smaller network. The complete case analysis might be valid when non-respondents are missing completely at random. However, if this does not hold then the results may be biased because the sample of remaining actors may be unrepresentative (Schafer and Graham, 2002). Stork and Richards (1992:197) argue that the complete approach “seriously weakens any analysis at the system level”.

#### 4.2. Imputations

Imputations of ties in social networks replace missing ties by estimates to create an apparently full data set. There are four types of simple imputation procedures where each missing value is imputed only once (Schafer and Graham, 2002; Huisman, 2009): (i) imputation of unconditional means; (ii) imputations from unconditional distributions; (iii) imputing using conditional means; and (iv) imputating using conditional distributions. Here, we focus on the first group of imputations. Huisman (2009) outlines three possible methods for imputing unconditional means in social networks. Only two of those methods are relevant here<sup>6</sup>.

<sup>6</sup> The third possibility of imputing unconditional means is the average number of outgoing relations of an actor or ‘person mean’. For complete actor non-response, where all outgoing ties are missing, this method is inapplicable.

##### 4.2.1. Using the total mean and the null tie imputation

The first method uses the average number of ties in the network. This is the ‘total mean’ of the observed ties which is also the density of a network. For binary networks this means imputing zeros instead of missing ties in sparse networks and ones in dense networks. Some threshold is required for this imputation. Huisman used 0.5 as the threshold in his simulation study. We note that Costenbader and Valente (2003) reported network densities between 0.01 and 0.49 for a sample of 59 networks.

Frequently used non-response data treatment is null tie imputation where zeroes are imputed instead of missing ties also in the case of denser networks.

##### 4.2.2. Using means of incoming ties

The third option imputes the average value of incoming ties of an actor which is known also as the ‘item mean’. For binary networks this implies imputing ones if actors are popular given their received ties. Operationally, this also requires a threshold. When this is set at 0.5, a tie is imputed if the actor is chosen by at least half of respondent actors (Fig. 4(d)). More precisely, for each missing outgoing tie  $x_{ij}$  ( $i \neq j$ ) of the non-respondent  $i$ , the mean value of all available incoming ties of actor  $j$  is imputed. For binary networks, this implies the imputation of the modal values of the incoming ties and this procedure is termed ‘imputations based on modal (indegree) values’ in this paper.

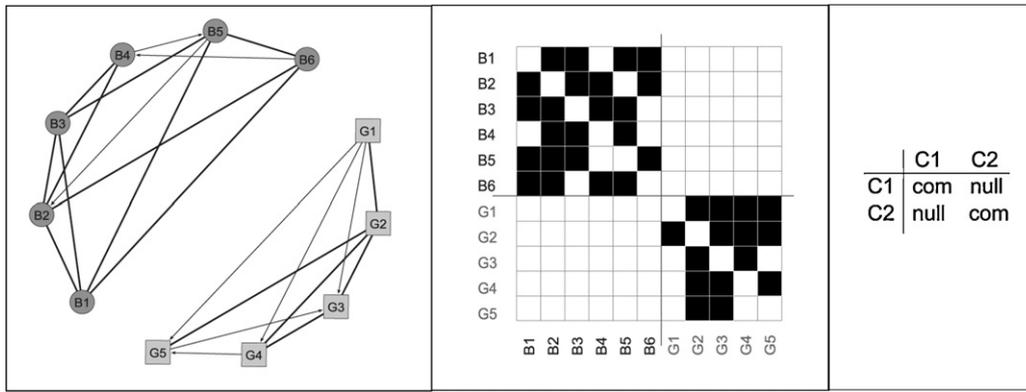


Fig. 5. Boy-girl network of liking ties (left), two partitions based on structural equivalence (middle) and image matrix (right).

4.2.3. Reconstruction

Reconstruction of the missing outgoing ties of non-respondents occurs when they are replaced by the observed incoming ties to those actors (Stork and Richards, 1992; Huisman, 2009). The result is that ties involving non-respondents and respondents become symmetric. Stork and Richards (1992) argued that reconstruction is not the same as imputation because, in the reconstruction procedure, no new ties are added. The reconstruction simply allows that the relationship between two persons, in essence, can be measured by using one report of the tie.

We note that the reconstruction procedure can be viewed in two different ways: (i) in the case of undirected networks it is an ‘available case approach’ which uses both the completely described ties between respondents and the partially described ties between respondents and non-respondents into account (Stork and Richards, 1992), (ii) in case of directed networks it is an imputation procedure because the missing tie is estimated from the opposite tie (Huisman, 2009).

However, for two non-respondents the reconstruction of ties between them is not possible. Some additional imputations are required to record data for them. In the simplest case, those unavailable ties (marked as NA in Fig. 4(c)) have zeroes imputed.<sup>7</sup> Two criteria must be met before attempting to reconstruct ties (Stork and Richards, 1992): (i) respondents and non-respondents should not systematically differ from each other and (ii) partially observed ties between respondents and non-respondents should be reliable descriptions of the relationships involving them.

4.2.4. Reconstruction plus imputations based on modal (indegree) values

It is possible to combine the reconstruction procedure with imputations based on modal indegree values for ties between non-respondents. More precisely, if actors  $i$  and  $j$  are non respondents, the tie  $x_{ij}$  between them cannot be replaced with reconstruction (ties between non-respondents are presented as NA in Fig. 4(c)). Therefore, the modal value of incoming ties of actor  $j$  (modal value of column  $j$ ) is computed and imputed instead of missing tie  $x_{ij}$ .<sup>8</sup>

5. The design of our simulation study

To investigate the vulnerability of blockmodels to different numbers of non-responding actors, along with various ways of

treating such missing data, we used simulation to study complete actor non-response where all outgoing ties of at least one actor are missing. We use the following terms: a whole network that is known; a measured network which is obtained from the whole network by removing all outgoing ties for some actors; and a measured and treated network obtained by treating actor non-responses in a measured network.

Section 5.1 describes the overall design of the simulations; Section 5.2 describes three types of whole networks; Section 5.3 outlines the introduction of non-response missing data and Section 5.4 presents five ways of treating the introduced missing data.

5.1. A scheme for simulations

For each whole binary network (presented in Section 5.2) blockmodels are established. Next, non-response is created using three different mechanisms (presented in Section 5.3), and five different non-response treatments are applied (Section 5.4). Blockmodels of whole and treated networks were compared using both indices presented in Section 3.1.

5.2. Whole networks

We use two types – real and simulated – whole networks. The real networks are used as demonstration examples before turning to the full simulation study.

5.2.1. Real whole networks

5.2.1.1. A gender based network of liking ties. The first real network presents a liking relationship between boys and girls in a classroom (used by Doreian et al., 2005:237) and is presented in Fig. 5 (left). There are two clear gender based subgroups, each with many internal ties (see the middle panel of Fig. 5). The best fitting model using structural equivalence having two clusters is shown in Fig. 5 (right). There are 12 inconsistencies and they are all null ties within the two diagonal blocks. (This served as a prototype for the near-symmetric blockmodel structure in Section 5.2.2.)

5.2.1.2. A student note borrowing network. Data for a note borrowing network for 15 undergraduate students attending lectures of a course were collected by Hlebec (1993) and used by Batagelj et al. (2004:460). The students were asked: ‘‘From whom would you borrow learning materials?’’ The number of choices was not fixed. This network is presented in Fig. 6 (left) together with a fitted blockmodel using structural equivalence (shown in the middle panel of Fig. 6). There are three clusters (positions) labeled C1, C2, and C3. Boys are represented by squares and the girls by circles. Position memberships in the network diagram on the left of Fig. 6 are indicated by the shading of the vertices. The fitted blockmodel is

<sup>7</sup> A more satisfactory imputation is presented in Section 4.2.4.  
<sup>8</sup> There are also other possibilities for imputing ties between non-respondents. For example, Huisman (2009) suggested random imputations where the probability of a tie is proportional to the observed network density. We do not consider this alternative here.

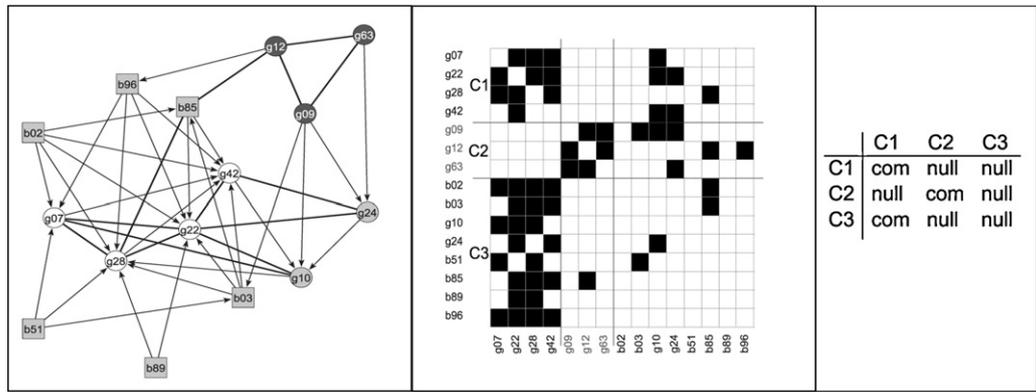


Fig. 6. A borrowing network (left), three partitions based on structural equivalence (middle) and image matrix (right).

on the right in Fig. 6 (and is the prototype for the non-symmetric blockmodel structure and used for the third simulated model type).

5.2.2. Simulated whole networks

5.2.2.1. A near-symmetric blockmodel structure. The starting simulated whole networks were constructed based on a specified image matrix with a given number of positions. Only complete and null blocks were fitted given structural equivalence. A two-cluster partition for a network with five actors in each cluster was used. The cluster membership is denoted by (1, 1, 1, 1, 1, 2, 2, 2, 2, 2). The image is shown in the left panel of Fig. 5. Ties were constructed to be consistent with this image matrix and were added with different combination of probabilities for complete blocks and null blocks (e.g. the probability of ties in a complete block was set to 0.9 and in null blocks it was set to 0.0, 0.1 or 0.2). Ten networks were generated for each combination of probabilities of ties in complete and null blocks (left panel in Table 2). This created 140 different whole networks. Every constructed network was checked to see if the structure obtained with blockmodeling procedure was consistent with the structure shown in Fig. 5 (right). The extent to which a network is symmetric was measured by reciprocity (Huisman, 2009) and was calculated for each whole network. The descriptive statistics for this measure over the 140 whole networks are (Min = 0.50, Q<sub>1</sub> = 0.70, Me = 0.79, Q<sub>3</sub> = 0.88, Max = 1.00) and confirm that these networks were highly symmetric.

5.2.2.2. The first non-symmetric blockmodel structure. The second structure for a simulated whole network is based on the image matrix in right panel of Fig. 6 with an additional complete block on the diagonal. Note that the top right ideal block in right panel of Fig. 6 is null and the lower left ideal block is complete. The membership of the three-cluster partition for a network with 15 vertices is denoted by (1, 1, 1, 1, 1, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3). The construction of the whole networks was done in the same manner as for

Table 2 Selected probabilities of ties in complete and null blocks for simulation of whole networks.

Blockmodel structure			
Near-symmetric		Non-symmetric	
Block type		Block type	
Complete	Null	Complete	Null
1	0.1, 0.2	1	0.1, 0.2
0.95	0.0, 0.1, 0.2	0.9	0.0, 0.1, 0.2
0.9	0.0, 0.1, 0.2	0.8	0.0, 0.1, 0.2
0.8	0.0, 0.1, 0.2		
0.7	0.0, 0.1, 0.2		

the near-symmetric structure with regard to null and complete blocks. Again, 10 networks were constructed for each combination of probabilities in different blocks (right panel in Table 2). The descriptive statistics for reciprocity across the 80 whole networks are (Min = 0.46, Q<sub>1</sub> = 0.55, Me = 0.61, Q<sub>3</sub> = 0.66, Max = 0.73).

5.2.2.3. The second non-symmetric blockmodel structure. The third structure for whole networks was constructed based on the image matrix shown in right panel of Fig. 6. Again, there are three clusters with the same cluster membership as the networks with the first non-symmetric blockmodel structure. The only difference is the presence of a null block on the diagonal. Ten networks were generated for each combination of probabilities of ties in null and in complete block. The summary description of the reciprocity measures ranges from 0.26 to 0.57 with a median of 0.42 (Q<sub>1</sub> = 0.37, Q<sub>3</sub> = 0.46). Replacing a diagonal complete block with a null block created networks with slightly lower reciprocity measures than for the networks from the first example of non-symmetric blockmodel structure.

5.3. Generating non-response missing data

Three different actor non-response mechanisms (or regimes for generating non-response missing data) were used. Each regime defines the probabilities that actors become non-respondents. These probabilities were: (i) actors are selected at random to become non-respondents, (ii) the probability of actors becoming non-respondents is proportional to 1/(outdegree + 1)<sup>2</sup>, and (iii) the probability of actors becoming non-respondents is proportional to 1/(indegree + 1)<sup>2</sup> (Huisman and Steglich, 2008; Huisman, 2009).

In Section 6, only results for randomly selected non-respondents are presented.<sup>9</sup> The random selection of non-respondents is unrelated to the network or actor characteristics and can be labeled as MCAR according to Rubin (1976). Huisman and Steglich (2008:302) argue that this model for missing data “may be realistic when there is no reason to assume that actors differ in their propensity to fill in network questionnaires”.

The number of non-respondents for the simulated whole networks based on near-symmetric blockmodel structure with 10 actors described in Section 5.2.2 ranges from 1 to 5 (with the proportion of non-response taking the values 0.1, 0.2, 0.3, 0.4 and 0.5). For simulating networks with three positions and 15 actors (two examples of non-symmetric blockmodel structures), the number of non-respondents ranges from 1 to 6 (with proportion of non-response taking the values 0.07, 0.13, 0.20, 0.27, 0.33, 0.40).

<sup>9</sup> Results for non-random missing mechanisms are due to small network sizes similar to random missing mechanism and can be found in Žnidaršič (2012).

#### 5.4. Treatments of missing non-response data

We treated the missing non-response data in five ways: with the complete-case approach; reconstruction; null tie imputation; imputation based on modal (indegree) values; and combination of reconstruction plus imputations based on a modal values (for ties between two non-respondents).

It is hard to state in advance the order of these approaches in terms of being radical with regard to treating missing data. From one viewpoint, the most radical of the five approaches is the complete-case approach because using it discards the most data. Yet, the extent to which 'substitute' data are used to replace missing data can be regarded as a criterion for being radical. Under this view, the complete-case approach is the least radical. Rather than try to resolve this issue ahead of time, we examine the impacts of all treatments with regard to their impact of the returned blockmodels following their use.

### 6. Results of simulation study

Results of the simulation study are presented in Fig. 7 for two symmetric blockmodel structures and in Fig. 8 for three non-symmetric blockmodel structures. First results of two real networks are given. In the following subsections only results of MCAR missing mechanism are presented. Detailed results for non-random missing mechanisms can be found in Žnidaršič (2012).

#### 6.1. Simulation study for two real networks

##### 6.1.1. A boy–girl liking ties network

In the boy–girl liking ties network (Section 5.2.1), non-respondents were selected *randomly* as described in Section 5.3. Five different treatments of non-response data (described in Sections 4 and 5.4) were used and, for every measured and treated network, a blockmodel was established and compared with structure shown in Fig. 5. The resulting factorial design has 75 cells (three non-response missing mechanisms, five treatments of non-response, and five numbers of actors with non-response). Within each cell, the generation of incomplete data was repeated 10 times for networks with one missing actor, 30 times for combinations of two missing actors and 100 times<sup>10</sup> for combinations of three or more non-respondents. For our purposes here, only excellent and good agreements are acceptable for deciding that two blockmodel partitions have the same position memberships. If  $mARI < 0.8$  then the correspondence of the position memberships is unacceptable.<sup>11</sup>

Fig. 7 (upper panel) presents the results for the boy–girl liking ties network when non-responding actors were selected at random. Boxplots for the Adjusted Rand Index the Proportion of incorrect block types are shown in the left and right panels respectively. Within each panel, boxplots for five missing data treatments NTI (null tie imputation), RE (reconstruction), MO (imputation based on modal (indegree) values), REMO (reconstruction plus imputation based on modal (indegree) values), and CC (complete-case approach) are shown. Each subset of boxplots represents results for different number of non-respondents (from 1 to 5). The stars \*

<sup>10</sup> The number of generated incomplete data networks increases with higher proportions of non-respondents because the number of all possible combinations of actors with non-response increases. For example, for a network where  $n = 10$  there are:  $\binom{10}{1} = 10$  possibilities for selecting one non-respondent;  $\binom{10}{2} = 45$  possibilities for selecting two non-respondents;  $\binom{10}{3} = 120$  and so on.

<sup>11</sup> As a reminder of the guidelines for interpreting values of  $mARI$  (Steinley, 2004) are: excellent agreement ( $mARI \geq 0.9$ ); good ( $0.9 > mARI \geq 0.8$ ); moderate ( $0.8 > mARI \geq 0.65$ ); and poor ( $mARI \leq 0.65$ ).

represent the mean values of indices and are connected with lines within each treatment.

The results are unequivocal when there is only one non-responding actor. For all treatments of non-response missing data, there is perfect agreement with the whole network blockmodel:  $mARI = 1$  for all treatments, indicating complete agreement between positions of actors, and  $mErrB = 0$  so that all block types are correctly identified and placed. Differences between the results of treating missing data start to appear when there are at least two non-respondents. The results for the null tie imputations are the worst because boxplots show the widest range of  $ARI$  values for three to five non-respondents. All of the other missing data treatments perform quite well. Of these four methods, the treatment using modal (indegree) values affected the partitions the most although the  $mARI > 0.8$  and the blockmodel is stable for two or more non-respondents. The blockmodels for networks treated with the complete-case, reconstruction, and reconstruction plus imputations based on modal (indegree) values all lead to excellent agreements with the blockmodel for the whole network.

This network has a very strong structural signal: the near-complete and null blocks are very clear. The whole network has high reciprocity (with a reciprocity measure of 0.79). There is little surprise that small amounts of missing data (one or two non-respondents) do not prevent blockmodeling from identifying the intrinsic network structure in terms of the composition of positions and the identification of blocks. The strong signal also accounts for the poor performance of the null tie imputation treatment because it destroys reciprocity, particularly when there are three or more non-respondents.

##### 6.1.2. The student note borrowing network

The middle panel in Fig. 8 presents the simulation results for the student note borrowing network (Section 5.2) with less symmetric structure. Because this is a larger network ( $n = 15$ ), we consider a slightly wider range for the number of non-respondents ( $1 \leq m \leq 6$ ). For identifying the memberships of positions ( $ARI$ ), the null tie imputation method performs the worst. Overall, using reconstruction and reconstruction plus imputation based on modal (indegree) values come next with regard to poor performance when there are three or more non-respondents. Use of modal (indegree) values for imputations and the coupling of reconstruction with modal imputation come next. The best performance comes with the complete-case approach.

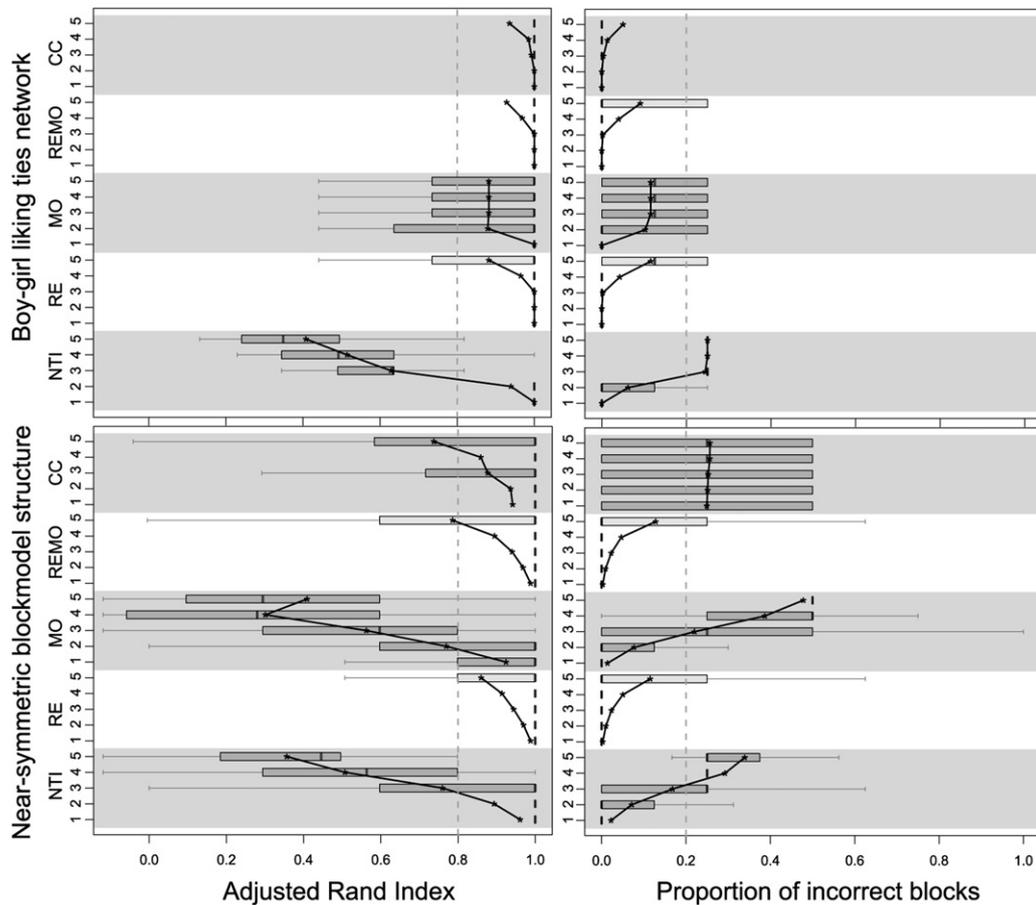
In terms of the identified blocks, all five treatment methods are indistinguishable when there is one non-respondent. Consistent with the  $ARI$  results, both the null imputation and reconstruction treatments degrade the blockmodeling results the most. On average, 20% of block types are identified incorrectly. In part, the block structure of Fig. 6 has a less clear structure than the one shown in Fig. 5 and its reciprocity is lower (0.46).

#### 6.2. Studies of simulated networks

While the two real networks that were examined above provide some clues about the potential consequences of the presence of certain forms of missing data, they do not provide an adequate foundation for assessing the general impact of the presence of non-respondents and, more importantly, the impact that treatments of missing data may have on the results produced by blockmodeling. For that we turn to simulating whole networks with known properties (described in Section 5.2.2).

##### 6.2.1. Results for the near-completely symmetric blockmodel structure

The factorial design for this blockmodel has 75 cells, the same as for the boy–girl liking ties network. The lower panel in Fig. 7



**Fig. 7.** Boxplots for the Adjusted Rand Index (left) and the proportion of incorrect block types (right) for two symmetric networks. Within each panel, boxplots for five missing data treatments NTI (null tie imputation), RE (reconstruction), MO (imputation based on modal (indegree) values), REMO (reconstruction plus imputations based on modal (indegree) values), and CC (complete-case approach) are given. Each subset of boxplots represents results for different number of non-respondents (from 1 to 5). The stars "\*" represent the mean values of indices and are connected with lines within each treatment.

contains boxplots and the mean values for the  $ARI$  (on the left) and the mean values for  $ErrB$  (on the right). In general, as the number of non-respondents increases, the  $mARI$  values decline for all missing data treatments. When we have one non-respondents the results from all treatment methods are acceptable. However, for higher number of non-respondents differences in the results emerge for all treatments. For two non-respondents, the mean values of  $ARI$  drop below 0.8 for imputations based on modal (indegree) values and its agreement is unacceptable for all higher numbers of non-respondents. Over the full range of non-respondents, there are two treatments that permit acceptable identification of position memberships: reconstruction and the combined use of reconstruction and imputation using modal (indegree) values. Of the two, the former performs slightly better.

The results from using the complete-case approach are unacceptable because more than one of four blocks is incorrectly identified ( $mErrB > 0.2$ ). The null tie imputations and the imputations based on mode become unacceptable for four and three non-respondents, respectively. As for  $mARI$ , the results from treating missing data with either reconstruction or the combination of reconstruction with using modal (indegree) values are acceptable over the full range of non-respondents considered here.

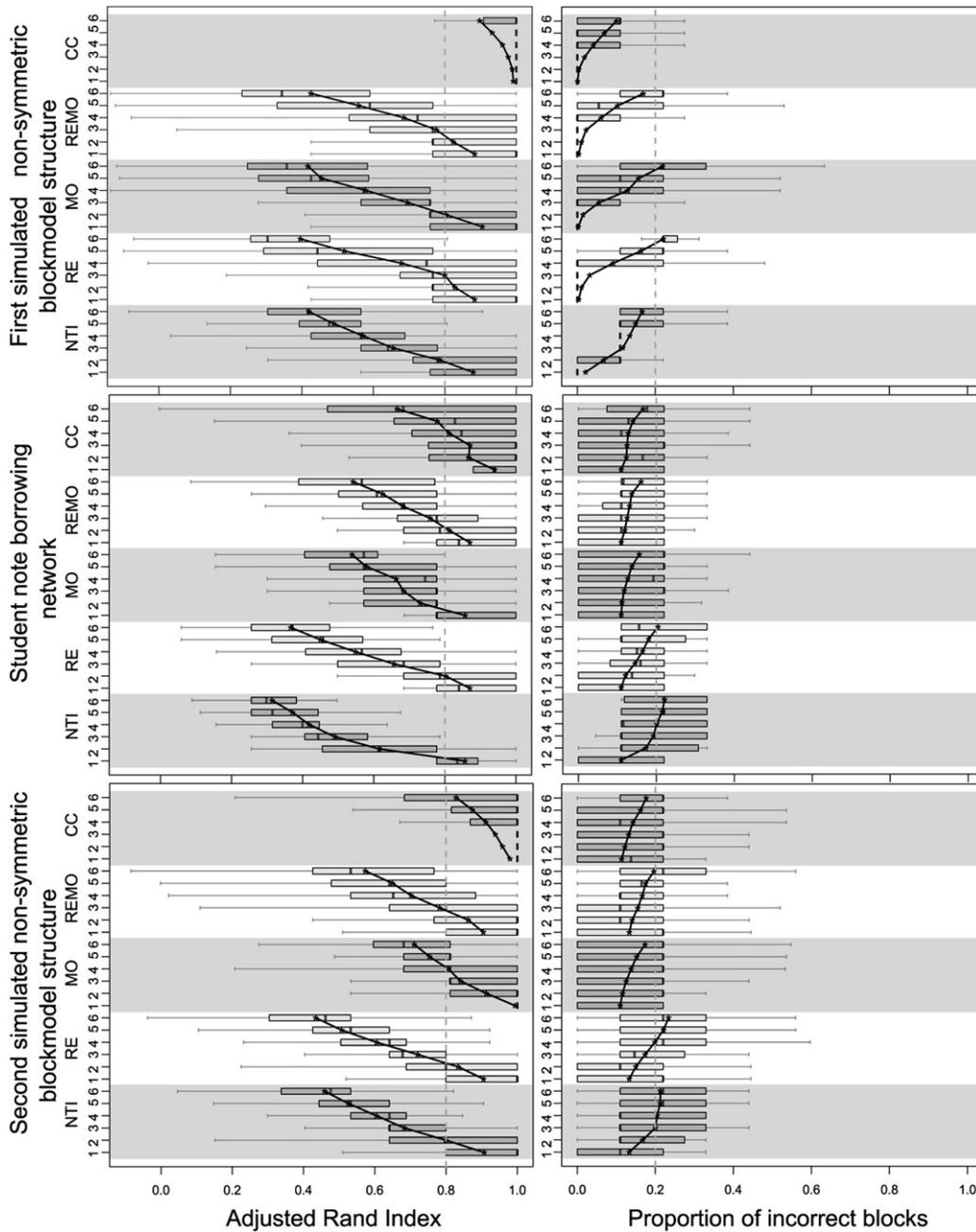
Only reconstruction and reconstruction together with imputation based on modal (indegree) values are the best according to the  $mARI$  and  $mErrB$ . Fig. 7 also shows that the differences in  $ARI$  and  $ErrB$  values are the smallest, another indicator of lower blockmodel instability.

### 6.2.2. Results for the first non-symmetric blockmodel structure

Fig. 8 (upper panel) presents the boxplots of  $mARI$  and  $mErrB$  for the blockmodel with all complete blocks on the diagonal and one complete block out of diagonal. The complete-case treatment is acceptable with regard to both position membership identification and block type designation for all values of non-respondents. For  $mARI$ , the other four treatments are borderline to the 0.8 threshold for two non-respondents. All four trajectories of mean values of  $ARI$  drop further as number of non-respondents increases and are not acceptable. In contrast, all treatments are acceptable in terms of  $mErrB$  for five non-respondents or less.

### 6.2.3. Results for the second non-symmetric blockmodel structure

All of the trajectories for mean values of  $ARI$  decline as number of non-respondents increases. It is clear that only the complete-case approach provides acceptable position membership identification for all numbers of introduced non-respondents. The graphical display of results for randomly missing actors in the non-symmetric blockmodel with a null diagonal block and all missing data treatments is provided on lower panel of Fig. 8. However, the five treatments form two groups. The first has the complete-case approach and imputations based on modal (indegree) values and the second has null tie imputation, reconstruction and the combination of reconstructions with using modal (indegree) values. The first group of treatments performs better than the second group and, more importantly, these differences are magnified as the number of non-respondents increases. By having low proportions of incorrect block identifications, the imputation using modal (indegree)



**Fig. 8.** Boxplots for the Adjusted Rand Index (left) and the proportion of incorrect block types (right) for three non-symmetric networks. Within each panel, boxplots for five missing data treatments NTI (null tie imputation), RE (reconstruction), MO (imputation based on modal (indegree) values), REMO (reconstruction plus imputations based on modal (indegree) values), and CC (complete-case approach) are given. Each subset of boxplots represents results for different number of non-respondents (from 1 to 6). The stars <sup>\*\*\*</sup> represent the mean values of indices and are connected with lines within each treatment.

values and complete-case approach perform the best for all values of non-respondents.

### 6.3. Summary of all effects

Even though the networks studied in Section 6 are small and quite simple in their block structures, the whole set of results is complex. Even so, it is clear that both the extent of actor non-response and the ways in which this form of error is treated can have dramatic results on the stability of blockmodeling results following the various treatments. The non-response missing mechanism has lower effect on the stability of blockmodeling compared to both the number of non-respondents and the used treatment,

however its impact on the stability of partitions is higher than on the stability of block structure.

We used ANOVA to investigate the effects of the number of non-respondents (variable labeled as *NR*), treatment of non-response data (*T*), non-response missing mechanism (*MM*) and type of the symmetry of the network (*S*). Networks with one non-respondent were excluded from this analysis because there is practically no variation in both indices of blockmodeling comparison (*ARI* and *ErrB*) and all treatments gave acceptable results. Five types of networks (two real networks and three simulated networks) were described by using a variable called *symmetry* with three categories reflecting levels of reciprocity (see Section 5.2.2): one was for the representatives of near-symmetric networks containing the boy-girl liking ties network and simulated near-symmetric

**Table 3**  
Analyses of variance for the Adjusted Rand Index and the proportion of incorrect block types.

Adjusted Rand Index				Proportion of incorrect block types			
Effect	$Df_1$	$F$	Partial $\eta^2$	Effect	$Df_2$	$F$	Partial $\eta^2$
NR	4	119,131	0.1287	NR	4	74,425	0.0845
T	4	84,481	0.0949	S * T	8	30,802	0.0710
S * T	8	33,703	0.0772	T	4	48,178	0.0564
S * NR * T	28	2304	0.0196	S	2	54,094	0.0325
MM * S * T	16	3001	0.0147	S * NR	7	14,137	0.0298
NR * T	16	2392	0.0117	S * NR * T	28	2113	0.0180
S * NR	7	3986	0.0086	NR * T	16	3049	0.0149
MM * T	8	3410	0.0084	MM * S * T	16	1029	0.0051
MM * S * NR * T	56	385	0.0066	MM * T	8	1383	0.0034
MM * S * NR	14	1233	0.0053	MM	2	4568	0.0028
MM * S	4	4230	0.0052	MM * NR	8	1101	0.0027
MM * NR * T	32	497	0.0049	MM * NR * T	32	227	0.0022
MM * NR	8	1081	0.0027	MM * S	4	1439	0.0018
MM	2	459	0.0003	MM * S * NR * T	56	81	0.0014
S	2	301	0.0002	MM * S * NR	14	226	0.0010

Residuals degrees of freedom:  $Df_2 = 3,224,790$ ; NR: number of non-respondents; T: treatment (of missing non-response data); S: symmetry (of the networks); MM: (non-response) missing mechanism.

blockmodel structures (mean reciprocity of those networks is 0.78); the second category has the variants of the first non-symmetric networks (mean reciprocity is 0.61); and the third category has the student note borrowing network and the second simulated non-symmetric blockmodel structures (mean reciprocity is 0.42).

Table 3 contains the ANOVA results for the Adjusted Rand Index (left panel) and the proportion of incorrect blocks (right panel). Main effects and all interactions (two, three-way, and four-way) are ordered according to their partial  $\eta^2$  values (all  $p$ -values are very close to zero).

Without surprise, the number of non-respondents in a network has the highest effect on the Adjusted Rand Index (partial  $\eta^2 = 0.1287$ ). From previous figures it is clear that larger the number of missing actors, lower the Adjusted Rand Index (ARI) and therefore the identification of position membership of an actor.

The type of non-response treatment has the second highest effect (partial  $\eta^2 = 0.0949$ ) where the null tie imputations performed the worst and the complete-case the best overall. The third largest effect on ARI is interaction between treatment and level of symmetry of the network (partial  $\eta^2 = 0.0772$ ): for the more symmetric networks, the best treatments are the reconstruction and the reconstruction plus imputations based on modal (indegree) values. The reverse holds for less symmetric networks where the imputations based on modal (indegree) values are better than both reconstruction procedures. Symmetry alone has the lowest effect (partial  $\eta^2 = 0.0002$ ) compared to other main effects and it has a strong effect only in combination with treatment as explained before.

The non-response missing mechanism has the highest effect in interaction with both the number of non-respondents and the treatment used (partial  $\eta^2 = 0.0147$ ) and in interaction with treatment (partial  $\eta^2 = 0.0084$ ). According to similar graphs as presented in Figs. 7 and 8 for non-random missing mechanisms (Žnidaršič, 2012) the following conclusions can be drawn: the complete-case approach performs slightly better with random missing mechanism, the null tie imputations are better when non-respondents are missing based on their outdegree, and on the other hand the reconstruction procedure performs worse in that case.

The second weakest effect is the main effect of non-response missing mechanism (partial  $\eta^2 = 0.0003$ ). The differences in the MCAR non-response mechanism and both non-random missing mechanisms based on outdegree and indegree are not clearly visible because of small networks and similar (out- and in-) degree distributions of actors in the networks.

The largest effect on the proportion of incorrect block types (right panel of Table 3) comes from the number of non-respondents (partial  $\eta^2 = 0.0845$ ), as in the case of ARI. The higher number of non-respondents leads to lower agreement between types and positions of blocks in blockmodels.

Treatment alone has lower effect (partial  $\eta^2 = 0.0564$ ) than in combination with symmetry (partial  $\eta^2 = 0.0710$ ). For the identification of block types and their position in the blockmodel (ErrB) the same conclusions are true as for identification of position membership of an actor (ARI): the complete-case approach performs good regardless of the symmetry of the network, for highly symmetric network also both reconstruction procedures are successful, and for highly non-symmetric network the imputation based on modal (indegree) values work better.

Looking at Figs. 7 and 8 again, we see that the values of proportion of incorrect block types are lower for the first simulated non-symmetric blockmodel structure than for other networks. This means that the effect of symmetry on blockmodel structure (ErrB) is a little bit weaker than the effect of treatment. If we compare the effects on ARI and ErrB we could say that the importance of symmetry is higher in identification of the blockmodel structure than in the position membership of actors.

The non-response missing mechanism has the largest effect in interaction with symmetry of networks and treatment (partial  $\eta^2 = 0.0051$ ). For near-symmetric blockmodel structures there are almost no differences in values of ErrB between three different non-response mechanisms for all treatments. The values of ErrB for the complete-case approach and the imputations based on modal (indegree) values are a little bit higher in the case of the first non-symmetric blockmodel structure and with non-respondents selected based on their outdegree compared to other two missing mechanisms.

## 7. Summary and recommendation

Providing a simple summary necessarily glosses over the diversity of the obtained results. Table 4 provides a summary statement for both the real networks and the three types of simulated networks. The networks in Table 4 are arranged from the most symmetric (on the left) to the least symmetric type (on the right). Both the correspondence of positions and the proportion of correctly identified blocks by location are important measures that merit attention. There were some cases where a partition/blockmodel was acceptable under one criterion but not the other. We do not discuss those cases here but note that the implications of them

**Table 4**  
Impact of non-response treatments on the stability of blockmodels.

Blockmodel	Symmetric				Non-symmetric					
	Boy–girl		Simulated		Simulated first		Borrowing		Simulated second	
	ARI	ErrB	ARI	ErrB	ARI	ErrB	ARI	ErrB	ARI	ErrB
Complete case	+	+	○	–	+	○	+	+	+	+
Reconstruction	+	+	+	+	○	+	–	–	–	–
Mode imputations	○	○	–	–	–	–	○	○	○	+
Null tie imputations	–	–	–	–	–	○	–	–	–	–
Reconstruction + mode	+	+	+	+	○	+	○	○	–	–

merit further examination. For each type of the network, the best overall treatment based on both the Adjusted Rand Index (*mARI*) and proportion of incorrect block types (*mErrB*) is presented by the + sign. The worst overall performance is represented by the – sign, and the moderate performances by the ○ sign.

Based on the study and the summary given in Tables 3 and 4 the following recommendations can be given:

- When choosing the type of blockmodel:
  - Structural equivalence is very stable for up to 50% of non-respondents. This is *not* the case for regular and generalized equivalence (Žnidaršič, 2012).
- During data collection:
  - Report the percentage of actor non-response (together with the size of the network).
  - Report the missing ties by coding them as such, for example, by NA, in the matrix representation of the network.
  - Never replace absent ties with zeroes because null tie imputation was the worst treatment regarding both micro (position membership) and macro level (block structure) depictions of the network.
- During data analysis (blockmodeling):
  - Estimate the reciprocity of the fully observed network (see left panel of Fig. 3) in order to decide about the best non-response treatment. If the reciprocity is low then we suggest using the complete-case approach or imputation based on modal (indegree) values. If the reciprocity is high than the use of the complete-case approach or one of reconstruction treatments is suggested.
  - Do not use complete-case approach if the aim of the study is to investigate the position of non-respondents in the network.

Of course, this study has some major limitations, especially the small size of the networks that we considered. This was dictated by computational constraints. The simulations were done using R in combination with Žiberna's (2008) blockmodeling package. For example, each simulation for the completely symmetric blockmodel structure were run in a computer lab<sup>12</sup> and ran for approximately three days. No doubt, the Žiberna program can be reprogrammed to run more efficiently and this reprogramming is underway. Other languages and faster machines may be better for the kinds of simulations considered here with the result that larger networks, with a broader range of blockmodel structures, can be considered. No doubt, the study of networks with other structures will reveal different performances than the outcomes shown here. What is not in doubt is that, when using blockmodeling, non-response is a serious problem with regard to blockmodeling outcomes (especially when not appropriately treated).

In addition to expanding the size of the networks that we consider, it will be useful to consider other forms of equivalence beyond

structural equivalence. The results are much worse than the results for structural equivalence (Žnidaršič, 2012).

With small networks, a limited range of blockmodel types, and only five non-response treatments, we have shown that actor non-response is a serious problem. It is likely that we need to consider some of the more complex ways of responding to non-response that were discussed in Section 4. Also, both the approach taken here and the results thus far are applicable to networks with multiple relations. Until these extensions are made, blockmodeling networks to delineate their underlying structure is fraught with hazard and attention to error in all of its forms is urgently needed. There are both substantive and methodological implications that follow from ignoring these problems.

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<sup>12</sup> The computers had an Intel Core 2 processor 1.86GHz and 2.00GB of RAM. Multiple machines were often running at the same time.

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