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Measuring the robustness of network community structure using assortativity

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The existence of discrete social clusters, or 'communities', is a common feature of social networks in human and nonhuman animals. The level of such community structure in networks is typically measured using an index of modularity, *Q*. While modularity quantifies the degree to which individuals associate within versus between social communities and provides a useful measure of structure in the social network, it assumes that the network has been well sampled. However, animal social network data is typically subject to sampling errors. In particular, the associations among individuals are often not sampled equally, and animal social network studies are often based on a relatively small set of observations. Here, we extend an existing framework for bootstrapping network metrics to provide a method for assessing the robustness of community assignment in social networks using a metric we call community assortativity (r_{com}). We use simulations to demonstrate that modularity can reliably detect the transition from random to structured associations in networks that differ in size and number of communities, while community assortativity accurately measures the level of confidence based on the detectability of associations. We then demonstrate the use of these metrics using three publicly available data sets of avian social networks. We suggest that by explicitly addressing the known limitations in sampling animal social network, this approach will facilitate more rigorous analyses of population-level structural patterns across social systems.

Social network analysis has emerged as a useful method for quantitative analyses of complex systems including the structure of animal societies (Croft, James, & Krause, 2008; Farine & Whitehead, 2015; Krause, Croft, & James, 2007; Sih, Hanser, & McHugh, 2009; Wey, Blumstein, Shen, & Jordan, 2008; Whitehead, 2008a). In particular, network analysis has been useful for understanding fission–fusion dynamics in which social aggregations of individuals (e.g. flocks, schools and herds) represent nonrandom subsets of larger social groups, or 'communities'. In social networks that represent patterns of associations between individuals, social cohesion among subsets of individuals emerge as clusters of nodes that are tightly linked together (Kerth, Perony, & Schweitzer, 2011; Silk, Croft, Tregenza, & Bearhop, 2014; Sundaresan, Fischhoff, Dushoff, & Rubenstein, 2007). Variations in the patterns of clustering in social networks can arise from variations in the degree to which individuals show fidelity to a specific social community. At one extreme, associations may occur exclusively within social communities, producing a network consisting of a collection of independent social groups. At the other extreme, individuals may associate randomly (in which case assignments to communities would be arbitrary and meaningless), resulting in a network with little clustering. Many societies show intermediate patterns with relatively stronger associations within versus across social communities, for example when spatially discrete social groups are connected by individuals that affiliate with multiple groups. The pattern of community structure that emerges from nonrandom associations has widespread implications for evolution of cooperation (Marcoux & Lusseau, 2013; van Doorn & Taborsky, 2012), social selection (Farine & Sheldon, 2015; Formica et al., 2011), social communication (Bradbury & Vehrencamp, 2011), flow of information/disease (Adelman, Moyers, Farine, & Hawley, 2015; Aplin, Farine, Morand-Ferron, & Sheldon, 2012; Onnela, Arbesman,

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Gonzalez, Barabasi, & Christakis, 2011; Salathe & Jones, 2010) and the establishment and maintenance culture (Aplin et al., 2015).

While quantitative analyses of network structure present a powerful method to understand the socioecology of animals, the inferences we make about social dynamics often hinge on social network measures for which we cannot estimate robustness or uncertainty. Animal behaviourists have long been aware of the dangers of biased sampling design and the need to account for the possibility of errors in sampling that affect statistical results (Altmann, 1974). In social network analysis, the most common form of sampling error is estimate error arising from insufficient data collected when defining the relationships among all possible pairs of individuals (Farine & Strandburg-Peshkin, 2015; Farine & Whitehead, 2015). Incomplete sampling can easily affect the characterization of the global social structure of the study population (Kossinets, 2006; Lusseau, Whitehead, & Gero, 2008). Incorrect networks can also arise if associations are defined without a clear understanding of the underlying social dynamics, as is the case when one infers social relations based on associations in groups (Farine, 2015; Farine & Whitehead, 2015; Franks, Ruxton, & James, 2010; Whitehead & Dufault, 1999). Exhaustive sampling to generate weighted social networks will, in general, overcome issues of identification error and other types of sampling error (James, Croft, & Krause, 2009), whereas appropriate null models can account for any biases in the observation data (Farine & Whitehead, 2015). However, it is not always straightforward to assess the effects of sample size, and thus the potential impact of sampling error, on the precision of social network measures because these effects depend in part on the structure of the network itself (e.g. Whitehead, 2008b). Thus, robust methods that estimate uncertainty surrounding sampling effort when quantifying social network metrics greatly improve our inferences about social dynamics and structure of animal societies.

Resampling techniques such as bootstrapping (Efron & Tibshirani, 1994) have been proposed as approaches to evaluate uncertainty in social network analysis (Lusseau et al., 2008; Whitehead, 2008b) A bootstrapping procedure involves randomly resampling the data stream (i.e. the observation of groups across time) with replacement such that some groups (or distinct observations) are repeated multiple times, while others are not included. Relevant metrics can be calculated from this bootstrap replicate network, and the process can be repeated many times (e.g. 1000 times, each time sampling the data differently) to generate a confidence interval of the network metric for a given set of data. This resampling technique has been used effectively in various empirical studies to estimate uncertainty in network metrics assuming that the sample is unbiased (e.g. Gero, Gordon, & Whitehead, 2013; Shizuka et al., 2014).

In this study, we discuss some considerations that need to be taken into account when applying bootstrapping methods to assess the robustness of community structure in networks. We focus particularly on the robustness of 'community assignment', a key step in the process of estimating community structure whereby nodes on a network are partitioned into discrete communities based on their patterns of connectivity. Our confidence in community assignment depends on both the degree to which individuals associate within versus across communities ('community fidelity') and the degree to which our sampling is incomplete ('sampling error'). Metrics of community structure such as modularity (see below) capture the degree of community fidelity when sampling is robust. Our goal is to develop a method to assess the influence of sampling error on community assignments, and provide a measure of certainty to accompany the modularity score Q. Our method combines bootstrapping with a coefficient of assortative mixing (Farine, 2014; Newman, 2002, 2003) to generate a single metric, which we call 'community assortativity' (r_{com}). We then test our methods using simulations and provide several applications of our procedure to empirical datasets of avian social networks.

BACKGROUND

Detection of Community Structure from Observation Data

Girvan and Newman (2002) first proposed a method for 'community detection', enabling the detection of unknown numbers of clusters within networks. This work initiated an explosion of studies on methods of partitioning networks into clusters of tightly linked nodes (i.e. sets of nodes that are more strongly connected to each other than they are to other nodes). There are now numerous methods for partitioning clusters on networks (Fortunato, 2010), and some of the most commonly used methods rely on the concept of modularity optimization. Modularity optimization techniques seek to partition a network in a way that maximizes the within-community rates of association or interactions. This maximum modularity value (Q) is the proportion of edges (or edge weights) that occur within communities relative to expected proportion of within-community edges if edges were distributed at random. This value is taken to be the measure of how much more community structure is present in the network compared to a random network with the same degree distribution. Importantly, the modularity value Q depends on the particular assignments of nodes into communities, and the robustness of the Q value also relies on the robustness of the assignments of nodes to communities.

Bootstrapping to Measure Robustness of Community Structure

Having measured community structure in a network using Q, the next step is to test whether this result is robust given the sampling effort. Lusseau et al. (2008) proposed that bootstrapping could be used to account for sampling error in estimating community structure: one could simply measure Q for each bootstrap replicate network and generate a confidence interval for the estimate of modularity. However, the confidence interval for the Q value generated by this bootstrapping procedure reflects the overall level of community structure per se, but does not represent confidence in the specific pattern of community structure (i.e. the assignments of individuals to different social communities). This is because applying the community detection anew to each bootstrap replicate often leads to different patterns of partitioning of the network (i.e. different numbers of clusters or the same number of clusters composed of different sets of nodes; Fig. 1). Yet, the particular membership of individuals in different social clusters is often the focus of social network research.

Measuring Confidence in Community Assignments Using Assortativity

We propose that the bootstrapping approach can be extended to evaluate the confidence of the original partitioning of the network into communities. We can estimate the effect of sampling effort as the probability that a pair of nodes that are assigned to the same community in the empirical network will also be assigned to the same community in bootstrapped replicate networks. At the level of the whole network, we can assess the robustness of community assignments using an index called 'assortativity', which is a correlation coefficient that measures the association patterns between different types of nodes (Farine, 2014; Newman, 2002, 2003). We can use this coefficient of assortativity to measure the degree to which pairs assigned to the same community in the empirical network also occur in the same community in bootstrap replicate networks (see