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Betweenness to assess leaders in criminal networks: New evidence using the dual projection approach

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ABSTRACT

Brokerage is crucial for dark networks. In analyzing communications among criminals, which naturally induce bipartite networks, previous studies have focused on the classic Freeman's betweenness, conceived for one-mode matrices and possibly biasing the results. We explore different betweenness centrality including three inspired by the dual projection approach recently suggested by Everett and Borgatti 2013. We test these measures in identifying criminal leaders in a meeting participation network. Despite the expected high correlations among them, the measures yield different node rankings, capturing different characteristics of brokerage. Overall, the dual projection approaches show higher success than classic approaches in identifying the criminal leaders.

1. Introduction

Brokers are crucial in social networks: they can effectively manage the flows of resources and information, and are more likely to achieve positive assessment, career advancements, and higher rewards (Aldrich and Zimmer, 1986; Burt, 2005; Lin, 1999, 2008). Brokering skills are even more important for criminal networks, since criminals operate in stateless environments, where information flows are restricted due to the risk of detection (Kleemans and van Koppen, 2014; Kleemans and De Poot, 2008; Kleemans, 2014; Paoli, 2002; Reuter, 1983). In these contexts, criminals have to carefully balance the effective management of illicit activities with the security of the group (Morselli et al., 2007). The ability to access to criminal opportunities often decides success within criminal organizations (Kleemans and van Koppen, 2014; Kleemans, 2014). Studies showed that criminal leaders occupy brokering positions within organized crime, which is embedded in the surrounding social environment (Papachristos and Smith, 2014; Kleemans and Van De Bunt, 1999). Leaders usually bridge among other criminals but also among people from legitimate businesses and politics. They thus take advantage of different social ties providing access to criminal opportunities. These ties constitute the social opportunity structure and are not equally distributed among individuals (Kleemans and van Koppen, 2014; Kleemans, 2014).

Whereas the literature on criminal networks has consistently demonstrated the importance of brokering skills of criminal leaders, methodological considerations on the correct measurement of brokering remain scarce. Most studies on criminal groups rely on simple measures of centrality to assess the nodes' positions in communication networks. For example, in his popular monograph on criminal networks, Morselli (2009) employed degree centrality, betweenness (Freeman, 1979), eigenvector centrality (Bonacich, 1972), and flow betweenness (Freeman et al., 1991). Furthermore, a recent systematic review on drug supply networks identified fourteen studies examining the internal structure of the criminal groups (Bichler et al., 2017). Eight out of fourteen studies employed both degree and betweenness centrality measures, while three focused closeness centrality (also Hughes et al., 2016 focus on degree and betweenness in analysing three polydrug networks). Similarly, degree and betweenness measures were also adopted in the study of the social structure of bid rigging operations (Baker and Faulkner, 1993), trafficking for sexual exploitation (Mancuso, 2014), a Russian mafia group in an attempt to establish its activities in Rome (Varese, 2013), and in predicting criminal leadership in an Italian mafia group (Calderoni, 2014a). Overall, the literature suggests that in criminal networks degree centrality may entail visibility and thus vulnerability to law enforcement disruption, whereas betweenness centrality would ensure indirect control over the criminal activities but also better protection from the investigations (Morselli et al., 2007). This may also results in lower arrest or conviction chances or lower penalties (Morselli, 2010; Morselli et al., 2013; Calderoni, 2014b). Betweenness centrality thus distinguishes strategically

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positioned criminals, consistently both with the extensive literature on the advantages of brokerage and social capital in social networks (Coleman, 1988; Burt, 1992, 2005; Lin, 2001), and with the qualitative studies on brokerage within criminal groups (Morselli, 2001, 2003).

When using betweenness, studies on criminal networks normally employ the "classic" betweenness centrality measure proposed by Freeman, which computes the "frequency with which a point falls between pairs of other points on the shortest or geodesic paths connecting them" (Freeman, 1979, p. 221). The classic betweenness, however, has several shortcomings. First, it is routinely computed on binary networks and focuses on the geodesic paths only, thus neglecting the intensity of the relation and focusing only on the shortest paths. Second, the classic betweenness centrality normally requires one-mode networks (networks assessing the relations within a set of nodes of the same type, e.g. people or countries). Yet criminal network analysis often rely on data which would normally induce bipartite networks. For example, communication data such as telephone calls and meetings are naturally two-mode networks, where vertex sets are individuals and events are phone calls or meetings. The classic betweenness is often applied to these data through projection of the two-mode networks into one-mode networks. The projection makes it impossible to know which nodes participated in which events, it overestimates clustering, and may cause a general loss of information (Broccatelli, 2017; Everett and Borgatti, 2013). To overcome these issues, Everett and Borgatti (2013) have recently proposed a new approach that better takes into account the duality of the data. Their method is tailored to manage two-mode data, which are usually represented as bipartite networks. Combining the results of the analysis on one-mode projections with the original affiliation matrix, the loss of some precious information in the process of projection is avoided. More recently, Everett showed how this method can be applied to centrality problems (Everett, 2016). The aim of this work is to apply the dual-projection approach to the analysis of a criminal network (the Infinito network) for identifying the criminal leaders based on the individuals' participation in meetings. Individuals and meetings naturally induce a two-mode network, thus providing an ideal case study for testing the dual-projection approach. Centrality measures are the more suitable local indicators for the purpose of identifying the important nodes in a criminal network (Morselli, 2009; Carrington, 2011; Bright et al., 2015; Bichler et al., 2017). Computing vertex centralities is a well-established approach to assess the effective position of a person in a network. The role of a person in an organization is reflected by its position in the network of relations – then by its centrality. Given the relevance of brokerage in criminal networks, and previous analysis of the Infinito network suggesting that leaders exhibited relevant brokerage positions (Calderoni, 2014b, 2015; Calderoni et al., 2017), we focus on betweenness measures. By applying the new dual-projection method, we analyse in detail the betweenness centralities of the nodes in the Infinito network. In particular, given the list of mafia leaders, we test several betweenness measures existing in the literature. In addition to the classic betweenness measure, depending on the type of network considered, there are other suitable definitions of betweenness centrality, each one related to how the information spreads through the network (see Kivimäki et al., 2016).

Our aim is to assess which measures better identify most leaders. Unsurprisingly, the different betweenness centrality measures are highly correlated. Yet, the measures provide different rankings of the nodes, suggesting that different measures may capture different brokerage features. The forthcoming analysis will thus explore the performance of the different betweenness measures both in the overall distribution of the absolute values and in the ranking of the nodes. Results show that leaders are on average higher in most betweenness centrality measures. Furthermore, the measures computed following the dual projection approach report a better performance, identifying the criminal leaders better than non-dual and classic measures. Lastly, inaccurate predictions may in fact offer interesting insight into the social organization of the criminal groups, as in the case of participants with high betweenness although they are not leaders.

The rest of the paper is organized as follows: the next section briefly reports some mathematical definitions about graph theory and centrality measures, describing also the dual projection approach. Section 3 describes the data and the methodology and discusses the results of the analysis of the Infinito network. Conclusions follow.

2. Preliminaries

In this section we first recall some definitions about graph theory which are essential for the subsequent discussion. We will assume familiarity with basic theoretical concepts (see Harary, 1969). Then we review some centrality measures and present the main ideas on the dual-projection approach for two-mode networks recently proposed by Everett and Borgatti (2013) in order to apply it to our case study in Section 3.

2.1. Graph theory

Let $G = (V, E)$ be a simple undirected graph with adjacency matrix $\mathbf{A}$. The Laplacian matrix $\mathbf{L}$ associated to $G = (V, E)$ is defined as $\mathbf{L} = \mathbf{D} - \mathbf{A}$, where $\mathbf{D}$ is a diagonal matrix whose entries are the nodes degrees $d_i = \sum_{j=1}^{n} a_{ij}$. $\mathbf{L}$ is a symmetric and semidefinite matrix; moreover, for connected graphs, the smallest null eigenvalue of $\mathbf{L}$ has algebraic and geometric multiplicity equal to one.

As far as weighted, undirected and simple graphs are concerned, we denote by $\mathbf{W}$ the weighted adjacency matrix with zero diagonal elements and all off-diagonal nonnegative entries equal to the weight w_{ij} associated to the edge $(i, j) \in E$. In this case, the Laplacian matrix $\mathbf{L^W}$ is defined as $\mathbf{L^W} = \mathbf{D^W} - \mathbf{W}$ where $\mathbf{D^W}$ is a diagonal matrix whose diagonal entries are given by $d_i = \sum_{j=1}^{n} w_{ij}$. Note that the spectral properties of the Laplacian matrix $\mathbf{L}$ still hold for L^W. The sum of nodes degrees is called the *volume* of the graph and it is denote by Vol(G). For the special case of unweighted graph, $\text{Vol}(G) = 2|E|$.

A graph is bipartite if the set of vertices V can be partitioned into two subsets V_1 and V_2, whose cardinalities are n_1 and n_2 respectively, such that there are not links between nodes in V_1 and V_2 and every edge of G joins V_1 with V_2. In this case, we can associate to the graph a binary matrix $\mathbf{E}$, called the affiliation matrix, of order $n_1 \times n_2$, where $e_{ij} = 1$ if a tie occurs between vertices $i \in V_1$ and $j \in V_2$. This representation is standard in the analysis of social networks, where, for instance, V_1 represents the actors and V_2 the events attended by them. A bipartite graph can be represented by a block square matrix of order $n_1 + n_2$, denoted by $\mathbf{B}$ (bipartite adjacency matrix) and defined as follows:

$$\mathbf{B} = \begin{bmatrix} \mathbf{0} & \mathbf{E} \\ \mathbf{E}^T & \mathbf{0} \end{bmatrix}$$

In this matrix the first n_1 rows and columns represent actors and the last n_2 rows and columns correspond to events.

To a bipartite graph can be also associated the projection matrices $\mathbf{EE}^T$ and $\mathbf{E}^T\mathbf{E}$ of order $n_1 \times n_1$ and $n_2 \times n_2$ respectively. In social networks analysis, the entries of $\mathbf{EE}^T$ ($\mathbf{E}^T\mathbf{E}$) indicate the number of events (actors) shared by each pair of actors (events). In particular, $\mathbf{EE}^T$ represents the adjacency matrix of the weighted graph in which nodes are actors and the weight on edge (i, j) is the number of events actors i and j share.

2.2. Centrality measures

Centrality is one of the major issues in network analysis (for example, see Newman, 2010, Chapter 7). The most intuitive centrality measure is the degree centrality, defined as the degree d_i of the node i, which indicates how many neighbours each node has. Degree has an immediate interpretation in two-mode data: the degree of an actor is the number of events she attends and the degree of an event is the number of people who attend it. But, this very rough measure may often disregard other relevant properties of a node. Among other widely used centrality measures, we focus on the class of betweenness centralities.