Using Social Network Analysis to Combat Organized Crime

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Introduction

In 2001, Nigel Coles noted the limited use of Social Network Analysis (SNA) in the study of criminal networks (for a summary, see Wasserman and Faust, 1994, and, more recently, Borgatti et al., 2024). However, this approach is specifically designed to represent and characterize the links, contacts, and exchanges between actors within groups. It does so in the form of specific mathematical objects called "graphs," which are made up of "nodes" (the members of the network) and "links" (the connections between them). Previously, research on the structure of criminal networks had focused on individual attributes and typologies (e.g., leaders *vs*. lieutenants) based on life stories, observations, or court documents. According to Coles, this resulted in a focus on "leaders," which introduced a major bias: these studies underestimated the effective role of intermediaries in circulating information and resources. Conversely, SNA reveals that neutralizing a less visible but "central" actor can more effectively weaken or dismantle a criminal network than arresting a leader (Berlusconi, 2016).

Since the publication of this initial article, literature using SNA to study criminal networks has grown and diversified. The areas of investigation now include Italian mafias (e.g., *'Ndrangheta*: Calderoni, 2012, 2014; Berlusconi et al., 2016; Calderoni and Superchi, 2019; *Cosa Nostra*: Cavallaro et al., 2020), illicit crops (Dutch cannabis network, Duijn et al., 2014), cybercrime (Nigerian fraud, Sarvari et al., 2014), international drug flows (Giommoni et al., 2017, 2022), collaboration between criminal organizations (Coutinho et al., 2020), and complementarities between legal and illicit trade (van Uhm et al., 2021).

SNA offers a variety of indicators to characterize networks, their members ("nodes"), and their relationships. These indicators include measures of "centrality" (the relative importance of each member or relationship; Tsai et al., 2019); detection of "communities" (groups of densely connected members within the network; Calderoni et al., 2017); and metrics of information fluidity or substitutability between actors (Cavallaro et al., 2020). These tools are used to empirically test dismantling strategies, such as the targeted elimination of central nodes, the isolation of logistics members, and the simulation of disruptions on critical links (Calderoni, 2012; Ficara et al., 2023).

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In line with this, this article uses SNA to evaluate the vulnerability of criminal networks based on two key operational issues: detecting and eliminating influential members and identifying missing links in police investigations.

This article will outline the main formalisms of SNA, limiting the use of mathematical language. Our analysis is based on the dataset provided by Cavallaro et al. (2020). This dataset was compiled from "Operation Montagna," which was conducted in Sicily until 2007. It is comprised of provisional detention orders, telephone wiretap transcripts, and surveillance reports. Our study proposes new formalisms and empirical results that differ from those of Cavallaro et al. Each operational issue is addressed in a dedicated section that links methodology, analysis, and implications for action.

1. Identifying leaders

Centrality is a key concept in SNA because it is used to identify the nodes that structure a network. The most illustrative example is that of a star: a node at the center is directly connected to all the others, while the latter are not directly connected to each other. Freeman (1979) demonstrates that the multi-connected node stands out in three ways in such a configuration. First, it has the largest number of direct links, i.e., the highest "degree." Second, it can reach any other node in the fewest possible steps. Its average distance from the other nodes is therefore small, a property called the node's "closeness." Third, it is found on all routes connecting the other nodes. Thus, it plays a necessary link role, measured by its "betweenness." In an ideal star, these three measures of centrality culminate at the same node.

To quantify these properties, Freeman (1979) suggests using the shortest elementary paths, also known as "geodesics," that connect them. An elementary path is a sequence of links that does not cross the same intermediate node twice. Only the paths that use the fewest intermediaries are retained between two nodes. For example, if we want to connect A to D and there are two paths, A-B-D and A-B-C-D, both of which are elementary paths, only the first path is considered, as if the second path did not exist. This convention, now standard practice, assumes that network actors always favor the shortest path. This remains a strong assumption.

Other, less restrictive measures assign a decreasing weight to all paths, whether geodesic or not. The "prestige" index proposed by Katz (1953) works as follows: Each route contributes to a node's centrality, but its influence decreases with distance, so a direct path counts more than a path with detours. Using both Freeman's indicators and Katz's index, the rest of this section will demonstrate how these approaches complement each other, shedding light on the flow of information in networks where communication channels may be more or less direct.

The indicators proposed by Freeman (1979) were originally designed for a very specific scenario: a network with no direction or weighting. In other words, the links connecting two nodes have no intensity. They simply indicate that a relationship exists without indicating its strength. An undirected link can signify a common affiliation, a meeting, or a friendship, for example. A directed link, on the other hand, indicates a prior relationship, a relationship of authority, or more generally, a flow from a source to a target. Similarly, an unweighted link simply attests to the existence of a relationship, while a weighted link specifies the frequency or intensity of this relationship: People may meet more or less often or exchange varying volumes of goods. By combining these two dimensions—direction and weighting—four *simple* network configurations are obtained. They are *simple* because there are many other properties of nodes and links that complicate this typology. For instance, we must study "multilayer" networks, in which several networks reporting links of different types overlap. Within certain limits, it is possible to add these layers to create larger networks. The properties of these extended networks depend on those of their layers.

The remainder of this paper will focus on undirected networks, whether weighted or not, as well as multilayer networks. Therefore, we will set aside questions of flows, prior relationship, and formal authority (as seen in an organizational chart). Our assumption is that the analysis of an undirected network can reveal positions of "real" authority even without this information. Whether we should disregard initiative relationships (e.g., who proposed a meeting or who receives on their turf) is more debatable. Although the raw data would enable us to create a directed graph, the current literature still neglects this enhancement. Existing cleaned databases reflect this omission. We will use one of these cleaned databases below. However, we will fully exploit the intensity of the links because these same databases provide the necessary information (e.g., the number of meetings).

The temptation to represent the same network in parallel in both weighted and unweighted forms dates back to Zachary's seminal work (1977). While studying a karate club, Zachary applied community detection algorithms to several versions of graphs representing this social network. This allowed him to verify the robustness of his conclusions: the actual disintegration of the network occurs at the fringes of the communities, as suggested by theory. The present study employs the same approach: Do we obtain similar results when deliberately simplifying the description of a complex network? In contexts where direction, weighting, and layers are taken into account—for example, in an international trade network—the use of a simplified representation is sometimes required for computational feasibility (Fagiolo, 2010). It may be surprising to note that the social sciences do not hesitate to use graphs in all their complexity. We will return to this point at the end of the article. In contrast, the "hard" sciences, such as statistical physics and epidemiology, often prefer—for reasons of scale—simplified models that perpetuate many of

the metrics inherited from classical SNA (see Watts, 2004, for a brief description of the uses of SNA metrics in the "new science of networks," as well as recent works by Barabasi and Posfai, 2016; Latora et al., 2017; Dorogovtsev and Mendes, 2022). The measures developed by Freeman (1979) and Katz (1953) can be adapted to weighted and multilayer structures. Therefore, they can serve as common sources for all the structures that interest us.

The data relating to Operation Montagna, made available by Cavallaro et al. (2020) on GitHub,[1] is presented in two *.csv* files. Each file describes a layer of relationships and has the same structure. Three columns record the ID of the first node, the ID of the second node, and the intensity of their interaction. Each row corresponds to a single observation. The first layer lists meetings and the second lists phone calls. For brevity, we refer to the "meetings" layer as "m," the "phone calls" layer as "p," and the combination between these two layers as "c." The identifiers of the members in the Sicilian Mafia network are numerical. Anonymization excludes all personal information. As mentioned earlier, the notion of initiative is not retained. A call from A to B followed by a call from B to A forms a single observation with an intensity of 2. From these files, it is possible to construct the corresponding graphs (Figure 1). In the visualization, the thickness of a link reflects the intensity of the interaction. To enhance understanding, two additional pieces of information are superimposed: node centrality, represented by symbol size, and community membership, indicated by color.[2]

The first two tables summarize descriptive indicators related to the graphs in Figure 1 and their aggregation. Table 1 shows that the phone calls network ("p"), the meetings network ("m"), and the combination of the two ("c") comprise 100, 101, and 154 nodes, respectively. Their "density"—the proportion of observed links relative to the maximum possible links—is low, ranging from 2.5% to 5%. In the "p" network, more than half of the members communicate with only one other member. In most cases, the intensity of these exchanges (the "strength," a weighted equivalent of the degree) does not exceed two. Calls therefore appear to be targeted and sporadic. In contrast, one actor stands out clearly as the most active: he maintains a direct link with nearly a quarter of the network's members and participates in 71 conversations. The fact that the averages for degrees and strengths are much higher than the medians confirms the graphs' highly heterogeneous nature. The "p" network is fragmented into five components, or subsets of nodes with no connections to other subsets. However, the "giant component" —the largest of these—comprises around nine out of ten nodes, with the remaining four components being very small. The "m" network has a similar profile but is around twice as dense. Members therefore seem to favor face-to-face exchanges, which are also concentrated around a few particularly active individuals.

1 https://github.com/lcucav/criminal-nets/tree/master/disruption

2 These interactive networks are available in *.html* format upon request to the author.

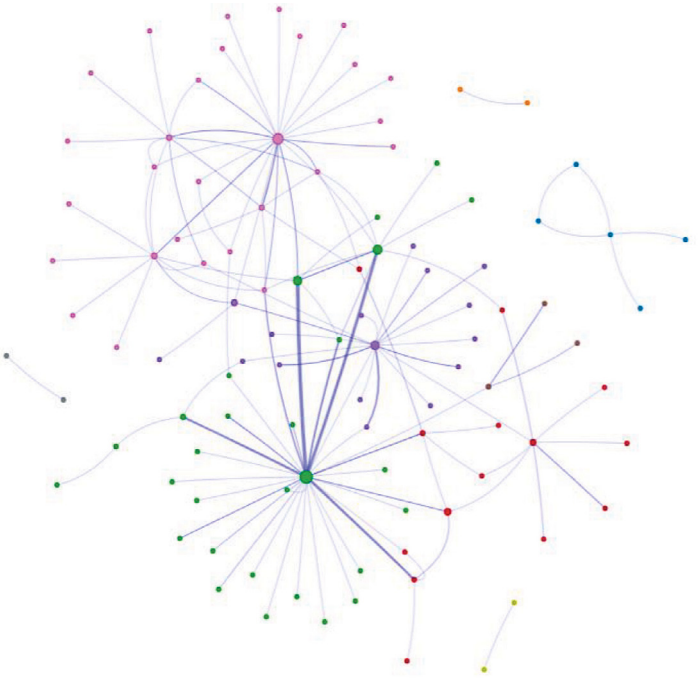

Fig. 1a. Phone calls network

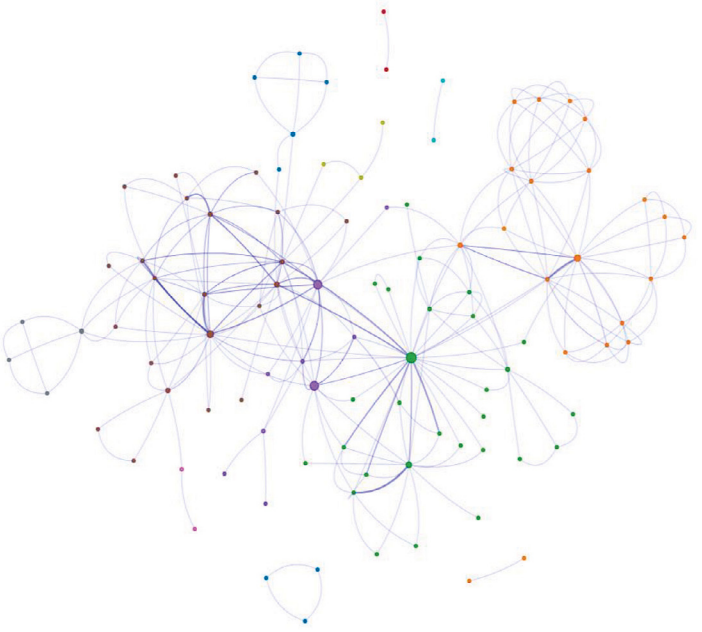

Fig. 1b. Meetings network

Figure 1. The structure of the "p" and "m" networks (relative node size according to betweenness centrality)

Table 1. Descriptive statistics on Montagna networks

Graph	# nodes	# links	# comp.	Density	Deg_mo	Deg_me	Deg_ma	Str_mo	Str_me	Str_ma
"p"	100	124	5	0,0251	2,4800	1	25	5,5200	2	71
"m"	101	256	5	0,0507	5,0693	3	24	9,0297	4	62
"c"	154	342	5	0,0290	4,4416	2	41	9,5065	3	116

Legend: # : number ; comp. : components ; Deg : degree ; Str : strength ; mo : mean ; me : median ; ma : max.

Table 2. Similarity statistics between "p" and "m" networks

Indices	Values	Descriptions
Jaccard_edges_unweighted	11.11	Jaccard index of shared links (presence)
Jaccard_edges_weighted	19.94	Jaccard index of common weight (intensity)
Node_overlap_Jaccard	30.51	% of players present in both networks
Spearman_strength_corr	0,3673	Correlation of strengths between networks
Spearman_strength_corr_p	0,0110	*p value* associated with the correlation
Edge_exclusive_m	0,8515	Fraction of links specific to "m"
Edge_exclusive_p	0,6935	Fraction of links specific to "p"

The "p" and "m" networks have nearly the same number of nodes, whereas the combined "c" network is considerably larger. Consequently, some individuals appear in only one layer. Table 2 provides several similarity measures that shed light on this partial overlap. Jaccard indices (ratio between intersection and union of networks), which are calculated based on the presence of links and their intensity (or strength), indicate that a significant proportion of members and connections remain specific to each layer. The two networks complement each other more than they overlap. Conversely, Spearman's rank correlation, or order similarity, applied to node strengths reveals significant agreement (the *p-value* is less than 0.05). This indicates that the most connected actors in the "m" network are also among the most connected in the "p" network. In other words, despite their different compositions, the two networks have comparable top-level structures.

The content of Table 3 reinforces previous observations. It displays the centrality measures defined by Freeman (1979) in their original, unweighted form and their weighted adaptation, as presented by Wasserman and Faust (1994). For each network—phone calls, meetings, and the combination of the two—the five most central members, as determined by weighted betweenness, are listed.

Table 3. Top node centralities (ranked by weighted betweenness)

Tab. 3a. Centralities in the "m" network

Node	Degree	Strength	Close_unw	Close_w	Between_unw	Between_w
18	0,2400	37	0,4428	0,6747	0,3732	0,4907
29	0,1300	29	0,3962	0,6781	0,0898	0,4000
27	0,1600	44	0,4141	0,6683	0,1585	0,3972
47	0,1900	62	0,4161	0,6297	0,2198	0,2310
12	0,1600	35	0,3436	0,5628	0,1171	0,2023

Tab. 3b. Centralities in the "p" network

Node	Degree	Strength	Close_unw	Close_w	Between_unw	Between_w
18	0,2525	71	0,4053	0,8489	0,4182	0,4778
47	0,2121	54	0,3605	0,7829	0,2362	0,3632
29	0,0909	31	0,3816	0,8382	0,2195	0,2804
43	0,0505	15	0,3068	0,8034	0,0284	0,2327
61	0,1717	46	0,3853	0,7178	0,2817	0,2306

Tab. 3c. Centralities in the "c" network

Node	Degree	Strength	Close_unw	Close_w	Between_unw	Between_w
18	0,2680	108	0,4840	0,9185	0,4614	0,5507
29	0,1046	60	0,4132	0,9142	0,0731	0,3962
47	0,1895	116	0,4303	0,8855	0,2209	0,3882
43	0,0719	34	0,4107	0,8968	0,0380	0,3147
61	0,1242	50	0,4034	0,7307	0,1712	0,1642

Legend : unw : unweighted ; w : weighted ; Close : *closeness* ; Between : *betweenness*.

In all three graphs, node 18 is in the top position, monopolizing the largest number of "mandatory passages" in the flow of information. Its activity is especially notable in the "p" network. It is significantly less dominant in the "m" network, though it still occupies an important position. While Cavallaro et al. (2020) do not address this discrepancy, Calderoni and Superchi (2019) discuss it at length in their study of a Calabrian mafia network constructed using similar data. According to Calderoni and Superchi, the phone is a riskier channel than face-to-face contact. Using it reflects either organizational constraints (e.g., distance or logistics) or the urgency of a situation. Therefore, centrality in the phone calls network would not necessarily indicate a leading decision-making role. Some genuine leaders deliberately avoid this channel, preferring the discretion of face-to-face meetings. In their study, several of these leaders are completely absent from the "p" network.

However, the Sicilian case presents a peculiarity. Most of the central actors in "p" are also central in "m," indicating redundancy in structuring roles between the two layers. The clearest exception is node 61. Almost invisible in the meetings network with only four links, node 61 occupies a prominent position in the phone calls network, propelling it to a key position in the merged network. This configuration precisely corresponds to the profile described by Calderoni and Superchi (2019) of a supervisor or logistician involved in day-to-day coordination rather than strategic decisions.

Centrality measures are used not only to identify positions and roles. They are also used to develop strategies for combating criminal networks.

Figure 2 shows how the giant component of Montagna networks shrinks as nodes are removed, one by one, in order of their centrality score. The goal is to simulate a police strategy that neutralizes the fewest actors possible while completely dismantling the criminal structure. The removal order follows Freeman's three indices (1979) and Katz's index. First, the most central member is arrested, followed by the next most central member, and so on until the network is exhausted.

Consistent with the findings of Cavallaro et al. (2020), eliminating approximately 15% of the most central nodes ensures that the largest residual component does not exceed a few units, regardless of the chosen index. However, not all indices are equal. Betweenness centrality is the most effective: at each iteration, the size of the giant component is smaller than with the other indices. Conversely, Katz's index is the least effective, likely because it considers indirect paths and dilutes targeting. This relative inefficiency suggests that a measure too sensitive to the graph's overall complexity can be counterproductive, causing information overload.

Disintegration occurs more quickly in the phone calls network ("p") than in the meetings network ("m"), and the difference between the various targeting strategies is less pronounced. This difference shows that global properties, such as connection density, influence a network's vulnerability to targeted node removal. A quick glance at Figure 1 suggests an explanation. "p" appears as a juxtaposition of stars, where the same nodes accumulate degree, closeness, and betweenness status. In contrast, "m" has more "gateway nodes" located at the junctions between communities.

These findings remain unchanged when working with weighted or unweighted versions of the graphs, which demonstrates the robustness of the results. Therefore, the betweenness indicator appears to be the most effective lever for designing a dismantling operation, requiring relatively few arrests.

As Cavallaro et al. (2020) acknowledge, this dismantling strategy is difficult to reconcile with reality due to the difficulty of understanding the true vulnerabili-

ty of such networks based on imperfect, incomplete, and static data. Other authors have developed techniques to estimate the complexity of the links between members of mafia organizations. These techniques help develop truly effective strategies for combating these organizations. This is the subject of the following section.

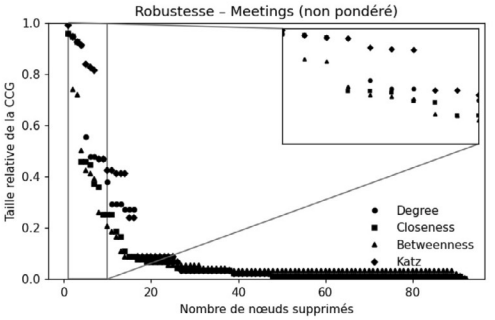

Fig. 2a. Robustness of the unweighted "m" network

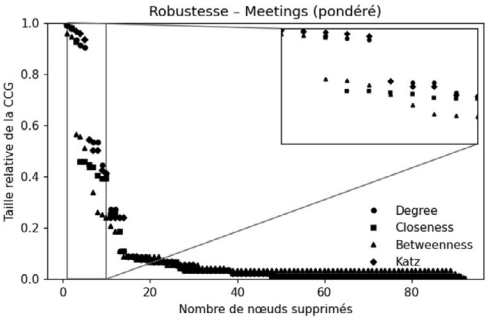

Fig. 2b. Robustness of the weighted "m" network

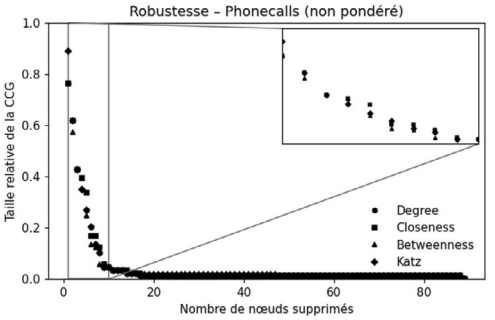

Fig. 2c. Robustness of the unweighted "p" network

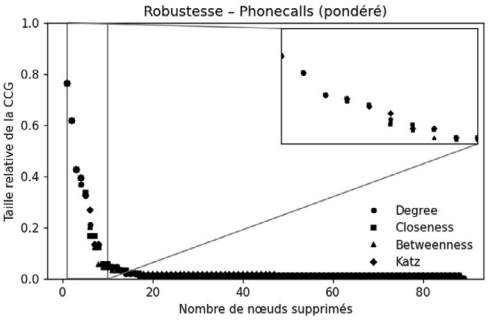

Fig. 2d. Robustness of the weighted "p" network

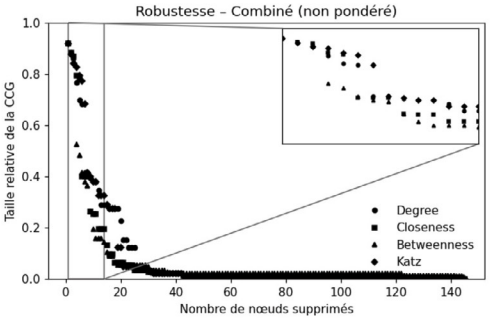

Fig. 2e. Robustness of the unweighted "c" network

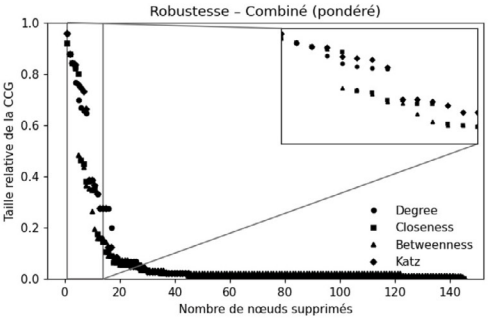

Fig. 2f. Robustness of the weighted "c" network

Figure 2. Robustness of the three networks in weighted and unweighted configurations

Reading. The x-axis represents an order of elimination of nodes ("iteration") from the initial structures. The markers represent the projection on the y-axis of the relative size of the remaining giant component at a given iteration. The first 10% of iterations are zoomed in on, with the x-scale made logarithmic to make the results easier to read.

2. Detecting hidden relationships

Networks established on the basis of police investigations are incomplete by their very nature. Berlusconi et al. (2016) highlight the main reasons for this. The scope of an investigation is limited by a specific territory, time frame, and investigative resources. This necessarily leaves certain key players out of the picture, especially since many of them are very discreet. Additionally, the variety of communication channels and imperfect collection techniques mean that some exchanges go unnoticed. Therefore, the networks obtained lack both nodes and links.

Although it is impossible to retroactively expand the list of individuals under surveillance due to insufficient data, it is possible to refine the representation of relationships among those who have been identified. Berlusconi et al. (2016) explored this approach using data from Operation Oversize, which targeted approximately 50 *'Ndrangheta* members involved in international cocaine trafficking, murder, and theft in the early 2000s. Similar to Cavallaro et al. (2020), the authors obtained a single undirected, unweighted network from telephone wiretaps.

However, they plan to use only a simplified version without weighting. This decision stems from the practical observation that, although there are prediction methods for adding missing links, none can reliably estimate their strength. Therefore, the centrality measures used to reassess the importance of members can only be calculated in their unweighted form. This argument is valid but not without limitations, as we will demonstrate below.

Berlusconi et al. (2016) propose using two sets of indicators to fill in the missing links. The first set is local, being based on the similarity of direct neighbors of nodes. When two unconnected nodes have many contacts in common, it becomes plausible that a direct link exists between them, even if the telephone wiretaps has not confirmed it. The second set uses more global information. Similar to Katz's prestige index, it considers longer chains of relationships but assigns them less weight as the distance increases. When compared with court documents, such as investigation files, the suggested links are, for the most part, consistent in both (local and global) cases. The authors conclude that the simplest method, local measures based on the existence of direct common contacts, is sufficient to produce reliable predictions.

Here, we propose reexamining the indicators used to predict missing links by incorporating connection strength information. Inspired by Newman's (2005) work on "random walks" in weighted graphs, this approach suggests that the stronger a link is, the more likely it is to be used when an actor "moves" randomly from one node to another (using the analogy of road width).

Following Berlusconi et al. (2016), we use a local metric based on rank-2 proximity—that is, the probability that two actors who are not directly connected,

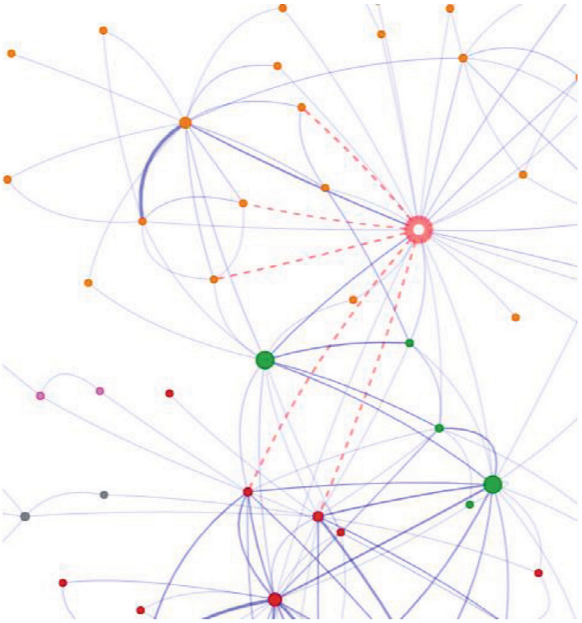

Fig. 3a. Hidden links in the "m" network for node 18 (zoom)

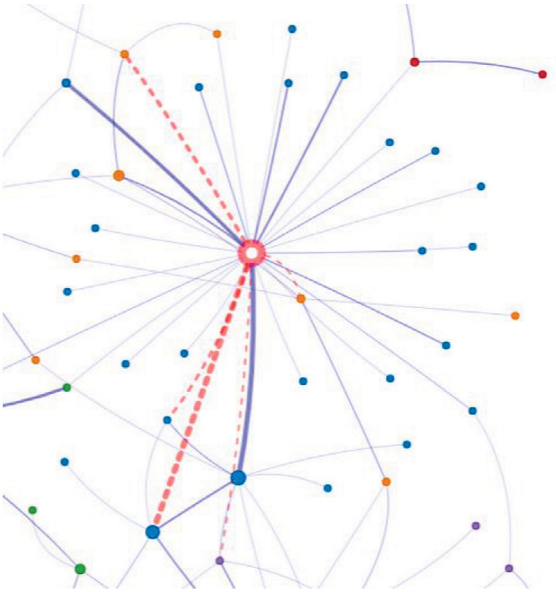

Fig. 3a. Hidden links in the "p" network for node 18 (zoom)

Figure 3. Evidence of hidden links in the "m" and "p" networks for node 18

Reading: The dashed links are the links revealed by the statistical procedure. Their thickness is an indicator of the value of the connection probabilities. The source node (member 18) appears with a white fill and a thick outline. It is the common point of all the missing links revealed.

but who have contacts in common, will form a link. The difference is that each link is weighted, so the probability of reaching a neighbor of a neighbor depends on the cumulative strength of the two segments traversed. For example, node A exchanges ten calls with B and only one with C, while B communicates ten times with D and C calls E only once. If A tries to reach an actor two steps away, the probability of reaching D is 10/11, compared to 1/11 for E. More generally, potential targets can be ranked in descending order of probability, regardless of the exact number of paths of length two connecting them to the source node.

Figure 3 illustrates the application of this procedure to the Montagna network. Node 18 is identified as the most central in terms of weighted betweenness in layers "m" and "p" and serves as the starting point. For each layer, the five most likely targets are selected. As with the unweighted method of Berlusconi et al. (2016), two topological effects are expected. First, communities become denser, and their mutual connections increase. Second, the average geodesic distance shortens, enabling faster information flow in the extended network.

This trend, which is driven by local procedures that add connections to densify and merge communities, as well as accelerate connections between nodes, echoes the network typology developed by Watts and Strogatz (1998). They demonstrated that various types of networks—social, technical, and biological—share two characteristics: a high clustering coefficient indicating that nodes form dense communities, and a short average node distance indicating that information flows quickly. These two properties define a "small world" network, a term borrowed from Milgram's (1967) experiment, which suggested that, on average, only six intermediaries are needed to connect two randomly selected people in the United States.

To position a network between the theoretical extremes of a random network, in which connections are distributed randomly, and a regular network, which has an ordered geometric structure (such as a grid or ring), Watts and Strogatz (1998) compare two indicators. For any network, let L be the average geodesic length and C be the clustering indicator. Add the index r for a random network. Let lambda be the ratio C/Cr, gamma be the ratio L/Lr, and alpha be the ratio lambda/gamma. Humphries and Gurney (2008) demonstrate that a network is statistically a small world when alpha is superior to 1. When L and C greatly exceed La and Ca, respectively, the network is regular. We use the two indicators L and C to qualify networks "m," "p," and "c" and test their robustness. The process takes place in three stages. First, we extract the giant component for each network and then rank its nodes in descending order of weighted betweenness values. Next, we apply the link addition procedure shown in Figure 3 to each node in turn, following this list. At each iteration, a single additional actor is assigned the probabilistic connections linking its second-rank neighbors. Finally, after each addition, we recalculate L and C to determine if the discovery of latent links moves

the graph toward the "small world," random, or regular domains. This check is essential because the effectiveness of a targeted neutralization strategy varies significantly depending on the target network's structural category.

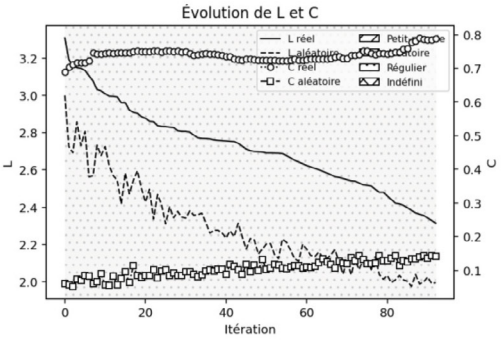

Fig. 4a. Robustness of the "m" network

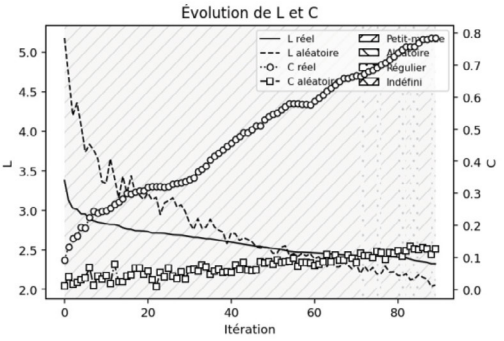

Fig. 4b. Robustness of the "p" network

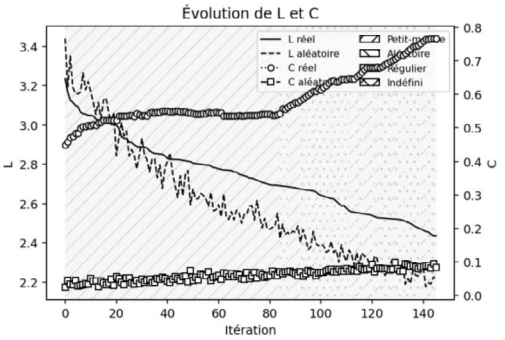

Fig. 4c. Robustness of the "c" network

Figure 4. Robustness of "m," "p," and "c" networks with hidden links

Reading. The x-axis of the graphs represents the addition of probable links node by node ("iteration") not identified by the police data (a maximum of five). The order in which the nodes are processed depends on their weighted betweenness centrality, starting with the highest scores. The y-axis indicates the values of L and C for these extended networks. For the "p" and "c" networks, the L values are sometimes higher in the random configuration than in the real configuration. This means that the presence of strong hubs creates additional shortcuts compared with the random reference graph. As long as the value of alpha remains above 1, the term "small world" remains valid in this case. The nature of the network ("small world," random, regular, undefined) appears as a background texture.

Figure 4 summarizes the effect of gradually adding missing links to the three studied networks. The meetings network ("m") exhibits characteristics of a regular network from the beginning and does not change over the course of the iterations. The phone calls network ("p") initially corresponds to a "small world" network, but as the number of iterations approaches seventy, it also adopts the

profile of a regular structure. The combined network ("c") behaves similarly to "p." In other words, a realistic extension that is limited in number and concentrated on the most central actors identified by the police investigation does not change the structural category. "m" remains regular, while "p" remains, in principle, a "small world."

This observation has practical implications. A "small world" reacts strongly to the targeted removal of nodes with high betweenness. Average distances increase, and the structure quickly segments into virtually isolated components. In network "p," this strategy remains effective even if a significant volume of links escaped investigation. Conversely, a regular network is more resistant to targeted attacks because all nodes play roughly the same role with more homogeneous betweenness. Consequently, the list of actors deemed "most central" lacks discrimination, and eliminating these members is almost acting at random. Therefore, it is necessary to arrest much more broadly to achieve a comparable level of fragmentation.

As we noted in the previous section, the giant component of "m" splits more slowly than that of "p" when nodes are removed in descending order of betweenness. The simulation presented here confirms and accentuates this difference because adding latent links reinforces the regularity of "m" without altering the structure of "p."

Regarding the Calabrian mafia network, Calderoni and Superchi (2019) point out that the resilience of a criminal organization depends on technical limitations, such as incomplete police coverage and fragmented data, as well as social factors related to internal relations between its members. However, we find their argument about the complementarity of channels to be the most interesting: the phone calls meets an imperative of efficiency, while face-to-face meetings satisfy a need for security. The coexistence of these two communication methods explains why the organization is resistant to attempts to dismantle it. The simulations conducted here support this idea: the observed robustness persists even when technical biases are neutralized by reestablishing plausible links. This proves that the organization's strength lies primarily in its dual architecture.

Conclusion

Although social network analysis is a valuable tool in the fight against organized crime, it also highlights the limitations that certain criminal structures impose on targeted arrest strategies due to their very organization.

This work focused on the organizational dimension, specifically the connections members establish with one another via various communication channels. However, SNA techniques can be applied to other contexts. For example, they can be used to map international drug flows, where each state becomes a node and each trade route a link. Giommoni et al. (2017, 2022) provide examples of this, such as heroin (2017) and, more recently, cocaine and heroin (2022). These authors demonstrate that routes are not chosen at random.

These commercial networks are represented by weighted and directed graphs, which complicates the interpretation of centrality and overall topology. Three additional concepts come into play in network topology: "Dependence," which refers to a hierarchical orientation of flows; "interdependence," which is linked to a more circular flow of goods; and "dominance," the driving force behind flows, which is defined according to supply (outgoing flows) or demand (incoming flows). In such a framework, Katz-type indicators, which are based on all paths, are more relevant than local measures. The term "influence" is often used instead of "centrality." However, this terminology, originating from international economics and input-output analysis, is not yet widely accepted in the SNA literature.

There are numerous theoretical and operational extensions that must be explored to adapt the SNA to the specific characteristics of drug trafficking and strengthen the effectiveness of anti-drug policies.

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